On Link Predictions in Complex Networks with an Application to Ontologies and Semantics

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For my wife.

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1 Introduction

When Alan Turing started to occupy himself seriously with artificial intelligence (AI), it was still something most had never heard of. In the 1940s, Isaac Asimov wrote his first stories about intelligent robots; his most prominent books were not published before the 1950s. Most earlier literature did not think of man creating intelligent machines. Before science fiction, human creations were mostly unintelligent beings: from the Jewish Golem myth, to Frankenstein's monster, or Hoffmann's Clara in *Der Sandmann*, all these artificial humans did not come close to human intelligence. It must have seemed way off that humans might actually engineer something intelligent.

Before Turing occupied himself with AI, he lay the foundation of modern computers and computer science with his work *On computable numbers with an application to the Entscheidungsproblem* and the definition of what was later called the *Turing machine* (Turing, 1937).

Turing proposed computing machines[1] to solve the so-called *Entscheidungsproblem* formulated by Hilbert at the beginning of the 20th century:

> Das Entscheidungsproblem ist gelöst, wenn man ein Verfahren kennt, das bei einem vorgelegten logischen Ausdruck durch endlich viele Operationen die Entscheidung über die Allgemeingültigkeit bzw. Erfüllbarkeit erlaubt.[2] (Hilbert and Ackermann, 1928, p. 73)

Alonzo Church was the first to show that there is no such formula using the *lambda calculus* (Church, 1936a,b). Turing found a different solution. He defined the later on so-called Turing machine, a hypothetical machine that consists of a set of rules and an input. Today's computers still do not do anything more than a Turing machine does. If a programming language can be used to simulate a Turing machine, given the theoretical fact that it has unlimited computational capacity, it is called *Turing complete*. The universal Turing machine (UTM) is a Turing machine that can read and execute programs: It can simulate or execute other Turing machines. With regards to the *Entscheidungsproblem*, Turing defined the so-called halting problem: Can there be a Turing machine that can, given the rules and input of another Turing machine, determine whether the Turing machine will come to a halt (i.e., whether the program will finish or run on infinitely). Turing found and proved that no such Turing machine exists.[3] Since the halting problem

[1] In the time before modern computers based on Turing machines, the word computer referred to a person doing calculations. The computing machines of Turing are essentially computing instructions that can be executed by human computers.

[2] Translation: The *Entscheidungsproblem* is solved if there is a procedure that can decide in a number of finite steps whether a given logical expression is universal or satisfiable.

[3] All one can do is follow (i.e., execute) the set of instructions, the program code. But since an infinite

is equivalent to the *Entscheidungsproblem*, Turing could show that there was no way to solve the *Entscheidungsproblem* (Turing, 1937). He thereby came to the same answer to Hilbert's question as Church a few months earlier and what came to be known as the Church–Turing thesis. Before the first computer was ever build or used, Turing had already defined the foundations of every modern computer and also outlined its limitations.

Turing shows that the UTM can carry out any work any Turing machine can compute. Despite other claims, he does not show that a UTM can compute what any machine could compute.[4] It is "common in modern writing on computability and the brain ... to hold that Turing's results somehow entail that the brain, and indeed any biological or physical system whatever, can be simulated by a Turing machine" (Copeland, 2008). If this was true, our own mind should be explainable in terms of a Turing machine, what Copeland (2002) calls the narrow mechanism. Hence our mind would underlie the same restrictions that apply to UTM. But as Copeland (2008) put it: "Yet it is certainly possible that psychology will find the need to employ models of human cognition that transcend Turing machines". Copeland (2002) calls the assumption that the brain is a machine, but possibly one that cannot be mimicked by a Turing machine, the wide mechanism. Although it still remains unclear what the philosophical implications of the Church–Turing thesis, the negation of the *Entscheidungsproblem*, are for our own minds (cf. Jack Copeland, 2008, p. 15), Turing seems to have had no doubts that, regardless of the limitation of computers, AI was a solvable problem:

> The original question, "Can machines think?" I believe to be too meaningless to deserve discussion. Nevertheless I believe that at the end of the century use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted. (Turing, 1950, p. 442)

In 1950, he invented the *imitation game*, today referred to as the *Turing test*, a game in which a human person asking questions has to decide whether his or her opponent, the one answering the questions, is human or not. Turing (1950, p. 442) says the following:

> I believe that in about fifty years' time it will be possible, to programme computers ... to make them play the imitation game so well that an average interrogator will not have more than 70 per cent chance of making the right identification after five minutes of questioning.

running program never comes to a halt, one cannot determine if any infinite running program ever comes to a stop in an endless number of steps.

[4]There might still be non-Turing machines.

Even though his belief in the progress to be made during the 20th century turned out to be exaggerated, his ideas started what we call AI. The imitation game is actually played on a regular basis, and, despite other claims made in 2014,[5] the systems have not yet accomplished the final goal of making the computer behave, act, and think like a human being. One important point towards this goal is work being done on natural language semantics and the computational processing of it. An intelligent machine has to master a couple of obstacles, among them are basic necessities that are still not solved, like natural language processing (NLP) and understanding (i.e., the treatment and understanding of semantics or even pragmatics), as well as image processing and interpretation, before one can come to more advanced technologies such as knowledge retrieval or logical inferences, not to mention creativity and self-awareness.

Besides a computational treatment of syntactic structures, the main goal is the understanding of human language and hence semantics. The branch of formal semantics takes insights from logics, and philosophy to treat language in a formal, hence computable, way. Montague (1974) realized not only that the semantics of a sentence come from the composition of its parts, and is therefore parallel to the syntax, as well as that first-order logics could be used to describe a subset of English. Frege, often seen as one of the founding fathers of modern logic, is often credited with the *principle of compositionality*:

> **The principle of compositionality:** The meaning of a complex expression is a function of the meanings of its parts and of the way they are syntactically combined. (Partee, 2011, p. 16)

Following the principle of compositionality, the combination of words make up the meaning of a sentence. But what is the meaning of a word? This is the second big question in the computational treatment of natural language semantics. Theories such as those of the lexical field, or Harris' distributional structure (Harris, 1954), have been applied to construct word semantics. Work on lexical fields and semantic domains, including semantic relations like synonymy or hyponymy, can be formalized in terms of logics and hence in the form of ontologies. We will see how ontologies can be used to describe the meaning of lexical units or objects and how such ontologies are put to use. Ontologies in the computer science context do not describe the essence of all that is, as in the philosophical use of the word, but rather small parts of the world or domains. Such ontologies are either manually compiled, a time- and money-consuming task, or they are automatically derived from texts, databases, and other knowledge resources. A combination of both is also very common.

[5]The University of Reading claimed that the Turing test was passed at its *Turing Test 2014* (`http://www.reading.ac.uk/news-and-events/releases/PR583836.aspx`), while this interpretation is very much doubtable (`http://www.wired.com/2014/06/turing-test-not-so-fast/`).

Ontologies are a building block of question answering (QA) systems. Examples for such ontologies can be found in modern Internet technologies. Apple's Siri is a question answering system that uses an ontology, Wolfram Alpha, at the core. Google is working on an apparently automatically derived ontology to support its search, making it a semantic search engine apart from its statistical knowledge employed today.

The IBM Watson *Jeopardy!* challenge is a good example of the capabilities of AI, and it is built on techniques from NLP and on information or knowledge bases in the form of ontologies. IBM Watson is a QA system. It was built to take part in the *Jeopardy!* TV show where three contestants are presented with an answer, like *This US president was the only president to be elected three times*, to which the correct question has to be formulated (e.g., *Who was Franklin D. Roosevelt?*). The Watson system first has to analyze the given input, the answer, to identified clues, such as *US president* and *elected three times*, transform these into a logical form that can be used to query a database (e.g., a list of US presidents), and infer information such as the fact that Franklin D. Roosevelt (FDR) won three elections.

To perform such inferences on data, one needs an ontology that formalizes possible relations and connections between entities, and thereby allows not having to store every single bit of information, but just enough so that the information is given at least implicitly, like the fact that FDR was elected three times through three relations of the form *FDR won us_presidential_election_1932* and so on.

The IBM team uses a range of different ontologies, among them Freebase,[6] part of the Google Knowledge Graph, and DBpedia, an ontology extracted from Wikipedia. Furthermore they applied WordNet to do fine-grained distinctions between words.

In NLP, and in the IBM Watson *Jeopardy!* task as such, different ontologies serve two different purposes: On the one hand, there are those ontologies that contain world knowledge on different entities, such as the US presidents, and that are mainly used to infer and find knowledge about entities of the real world. On the other hand, ontologies like WordNet are used to find the meaning of a single word of, in the case of WordNet, English, which does not necessarily refer to a physical entity of the extra-linguistic world. Concepts such as *love* or *democracy*, as well as actions in the form of verbs or modifiers in the form of adverbs and adjectives, are described in relation and contrast to each other.

As will be shown, both domains, word and world knowledge, make up the human lexicon and both are essential to process natural language and to find answers to questions or to perform orders given in natural language.

One property of ontologies that offers the possibility to extend the information over

[6]Google announced in December of 2014 that it is not going to develop Freebase any further. The data will be loaded into Wikidata, a collaboratively edited database of facts.

what is directly observable in an ontology is the so-called inference and reasoning. But reasoning only works in small defined areas, where such relations have been defined. One can for example define a relation *sibling* as a relation between any two entities that share common parents without the necessity for the human collecting the data to know this relation and manually assign this relation to the entities in question.

A set of entities connected by relations, such as in ontologies, necessarily makes up a network. The nodes or vertices of the network are the entities, connected by the relations, the edges in the network jargon. While it is commonly known that ontologies are based on semantic networks, and that they form (directed) graphs (cf. Hesse, 2002, p. 478), I have found almost no work actually treating ontologies as networks. There have been graph analyses of WordNet and other ontologies, but the findings have not yet been used to improve the quantity or quality of the ontology in question.

Network or graph theory is, nonetheless, often applied in NLP and especially in semantics, especially to word networks based on co-occurrences or collocations. These networks are built from words and their co-occurrence with other words in large corpora. The co-occurrence can either be estimated by direct neighbors, by word windows around focus words, or by the dependency or syntactic structure, which might not necessarily correspond to the word order. A network built from occurrences connects words in syntagmatic relations to other words. When looking at words that share neighbors in such a graph, these words are paradigmatically related and occur in similar contexts. Words that share many common neighbors can be thought of as being semantically similar. The meaning of a word can then be represented as the connections it has in the network, or as a word vector, where the occurrence of every word in the defined neighborhood of a word is counted.

Although these networks do not reach the fine-grained sense distinctions a manually composed ontology contains and do not offer the possibility to perform logical inference, they have the major advantage of being knowledge free and being built without the necessity of human interference. Still, distributional semantics can make some interesting, though for a linguist maybe not surprising, distinctions based on the distribution of words. For example, Biemann (2009) was able to distinguish female and male first names based on their distribution. Mikolov *et al.* (2013) have shown that word vectors are compositional to a certain degree. The word vector for *London* minus the word vector for *England* is pretty similar to the word vector of *Paris* minus the word vector of *France*.

Since ontologies add human knowledge and analysis of the usage of words to pure distribution, they achieve better results but do not have the broad coverage of the distributional approach. The time and work that is put into ontologies is on the one hand the reason for its accuracy, but on the other hand a mayor downside when it comes to

coverage. This leads to the two main problems that occur when working with ontologies: First, they are very work intensive to build and second, they might still be missing needed information; that is, they are incomplete.

Some automatic or semi-automatic approaches to extending ontology data without the need to employ human knowledge and human labor have been proposed. These will be reviewed later. Many of these approaches use text structures (i.e., syntactical or hierarchical text structures such as headings or paragraphs) to identify useful and meaningful relations that can be added to the data set. But what if the necessary information is already given, even if it is hidden, in the ontology data?

It is assumed that ontologies can be represented and treated as networks and that these networks show properties of so-called complex networks. Just like ontologies "our current pictures of many networks are substantially incomplete" (Clauset *et al.*, 2008, p. 3ff.). For this reason, networks have been analyzed and methods for identifying missing edges have been proposed. The goal of this thesis is to show how treating and understanding an ontology as a network can be used to extend and improve existing ontologies, and how measures from graph theory and techniques developed in social network analysis and other complex networks in recent years can be applied to semantic networks in the form of ontologies. Given a large enough amount of data, here data organized according to an ontology, and the relations defined in the ontology, the goal is to find patterns that help reveal implicitly given information in an ontology. The approach does not, unlike reasoning and methods of inference, rely on predefined patterns of relations, but it is meant to identify patterns of relations or of other structural information taken from the ontology graph, to calculate probabilities of yet unknown relations between entities.

The methods adopted from network theory and social sciences presented in this thesis are expected to reduce the work and time necessary to build an ontology considerably by automating it. They are believed to be applicable to any ontology and can be used in either supervised or unsupervised fashion to automatically identify missing relations, add new information, and thereby enlarge the data set and increase the information explicitly available in an ontology. As seen in the IBM Watson example, different knowledge bases are applied in NLP tasks. An ontology like WordNet contains lexical and semantic knowledge on lexemes while general knowledge ontologies like Freebase and DBpedia contain information on entities of the non-linguistic world. In this thesis, examples from both kinds of ontologies are used: WordNet and DBpedia.

WordNet is a manually crafted resource that establishes a network of representations of word senses, connected to the word forms used to express these, and connect these senses and forms with lexical and semantic relations in a machine-readable form. As will be shown, although a lot of work has been put into WordNet, it can still be improved.

While it already contains many lexical and semantical relations, it is not possible to distinguish between polysemous and homonymous words. As will be explained later, this can be useful for NLP problems regarding word sense disambiguation and hence QA.

Using graph- and network-based centrality and path measures, the goal is to train a machine learning model that is able to identify new, missing relations in the ontology and assign this new relation to the whole data set (i.e., WordNet). The approach presented here will be based on a deep analysis of the ontology and the network structure it exposes. Using different measures from graph theory as features and a set of manually created examples, a so-called training set, a supervised machine learning approach will be presented and evaluated that will show what the benefit of interpreting an ontology as a network is compared to other approaches that do not take the network structure into account.

DBpedia is an ontology derived from Wikipedia. The structured information given in Wikipedia infoboxes is parsed and relations according to an underlying ontology are extracted. Unlike Wikipedia, it only contains the small amount of structured information (e.g., the infoboxes of each page) and not the large amount of unstructured information (i.e., the free text) of Wikipedia pages. Hence DBpedia is missing a large number of possible relations that are described in Wikipedia. Also compared to Freebase, an ontology used and maintained by Google, DBpedia is quite incomplete. This, and the fact that Wikipedia is expected to be usable to compare possible results to, makes DBpedia a good subject of investigation.

The approach used to extend DBpedia presented in this thesis will be based on a thorough analysis of the network structure and the assumed evolution of the network, which will point to the locations of the network where information is most likely to be missing. Since the structure of the ontology and the resulting network is assumed to reveal patterns that are connected to certain relations defined in the ontology, these patterns can be used to identify what kind of relation is missing between two entities of the ontology. This will be done using unsupervised methods from the field of data mining and machine learning.

The thesis is structured as follows: In Chp. 2, the most important concepts of graph/network theory, regarding the scope of this thesis, are introduced. It will also be shown what distinguishes complex networks from simple networks. In Chp. 2.2, it is shown how especially graphs, and mathematical concepts in general, can be helpful for the understanding of the functioning of the human mind. It will be shown how early approaches have taken similar (graph-based) notions to understanding lexical processing in the human mind and to what extent graph theory is more than just a helpful computational model and could indeed explain the function of the mind itself.

In Chp. 3, an overview of important theories in semantics is given, to a degree that

is helpful to follow the argumentation and experiments given in this thesis. Especially lexical semantics, including frame semantics (Chp. 3.1), field theories (Chp. 3.2), distributional approaches (Chap. 3.3), and semantic relations (Chp. 3.4), are introduced. Semantic fields, domains, and relations are important to understand the architecture of WordNet. Domains are important when it comes to computational treatment of polysemy and the nature of DBpedia and similar ontologies. Furthermore, the fundamental notions of ontologies, their conception and formalization, are treated briefly in Chp. 3.5. These will not only be helpful for working with WordNet, but also for working with the DBpedia.

In Chp. 4.1, non-graph-based approaches to automatically extending ontologies are introduced and explained. In Chp. 4.2, approaches from extending and completing networks are discussed with regards to their applicability in the context of this thesis. Chapter 4.3 shortly presents possible machine learning algorithms that are evaluated later on.

In Chp. 5, both the architecture (Chp. 5.2) and the network structure (Chp. 5.3) of WordNet are analyzed to be able to deduce useful features for a machine learning algorithm. Afterwards the state of the art regarding polysemy identification in WordNet is presented and discussed; then useful features of WordNet for this task are presented in Chp. 5.4, before the data preparation and the machine learning algorithms to be applied are discussed. Afterwards these algorithms and the obtained results are evaluated and presented in Chp. 5.5.

In Chp. 6, DBpedia, its creation (Chp. 6.1), and the ontology and network structure (Chp. 6.1.4 and Chp. 6.2) are presented. In Chp. 6.3, already existing approaches to automatically extending DBpedia are presented and it is shown how these can be extended using the findings of social network analysis. Afterwards the proposed features are used in a machine learning task and the results are evaluated.

The results will be presented and discussed. The findings will be analyzed in their context. Further open questions will be shortly discussed, and possible future work will be laid out.

2 Graph Theory and Complex, Natural Networks

Networks are a universal, natural way of organization. In the world around us, one can find things that are treated or represented as a network, as well as many structures that are in fact organized in the form of networks. In biology there are the blood circuit, the nervous system, the brain, and even genes; in human interaction one finds social networks; in engineering there are networks of transportation and communication (e.g., the Internet or the world wide web). Especially social networks will be of great interest for this thesis and will often be referred to.

Newman (2010, p. 1) defines a network in its simplest form as a "collection of points joined together in pairs by lines. In the jargon of the field the points are referred to as *vertices* or *nodes* and the lines are referred to as edges".

The mathematical field of graph theory forms the basis of network analysis. A graph G is a set $G = (V, E)$, where V is a set of vertices and E is a set of edges. Vertices are connected by edges. An edge between $v_1 \in V$ and $v_2 \in V$ is usually written as $\{v_1, v_2\}$. In the same way a network is defined.

In the following, the basic terminology of graph theory will be introduced, measures commonly used in network analyses will be presented,[7] and theories about network and language evolutions will be discussed to a degree that is helpful in understanding the argumentation of the following chapters.

2.1 Properties of Graphs and Networks

2.1.1 Vertices, Edges, In- and Out-Degree

Vertices or nodes are connected to each other by edges. The number of edges a vertex is connected by is called its degree. The degree k of vertex i can be calculated as

$$k_i = \sum_{j=1}^{n} A_{ij}, \tag{1}$$

where n is the number of vertices and A is the adjacency matrix. In matrix A, we can see whether or not an edge between some vertex i and another vertex j exists. If A_{ij} is 1, the two vertices are connected by an edge.

[7] The overview, including the formulas, shown in the following follow, if not stated differently Newman (2010). The examples, matrices and graphs, are my own.

$$A = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix}$$

In a graph, edges can be undirected (see Fig. 1(a) or the corresponding matrix A[8]) or directed (see Fig. 1(b) or matrix A'). Directed graphs are called digraphs. When the edges are directed (i.e., pointing in one direction from one vertex to another) they are often referred to as arcs. An edge $\{a, c\}$ hence is an edge whose source vertex is a and whose target vertex is c.

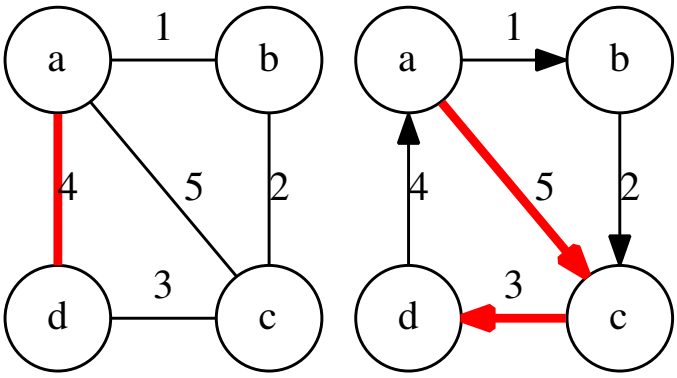
$$A' = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

In a digraph, the in- and out-degree can be distinguished. In-degree is the number of edges pointing to the vertex, while the out-degree is the number of edges pointing from the vertex to others. In the undirected case in Fig. 1(a), vertex a has a degree of three. In the digraph in Fig. 1(b), vertex a has an out-degree of two (sum of the first row of A') and an in-degree of one (sum of the first column of A'). The total degree is hence three. The average degree of a network is the sum of the degrees of all vertices, divided by the number of vertices.

A sequence of neighboring edges forms a path. The length of a path connecting two vertices is called their distance. The geodesic path is the shortest path between two vertices. The longest geodesic path between two vertices of a network is called the *network diameter*. A path connecting two vertices over three edges has the length three. If there is no possible shorter path, this is also the shortest distance. Distance measures will be of special importance throughout this thesis. Especially networks with an overall high centrality have a low geodesic distance.

Looking at Fig. 1, one can see the difference between a digraph and an undirected graph regarding the distance: In the undirected graph in Fig. 1(a), one can see that the shortest distance from a to d is through edge 4. Other paths do exist (e.g., through edges

[8]The matrix is orthogonal, which means that its inverse is also its transpose.



(a) Undirected graph (b) Directed graph

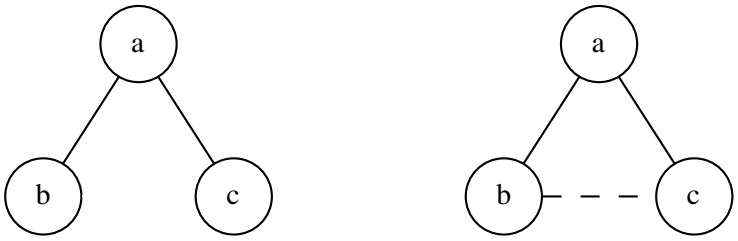
Figure 1: Simple example graphs.

$5, 3$ or $1, 2, 3$) but these are longer (length of two and three). In the digraph in Fig. 1(b), the shortest path between a and d is the path through edges $5, 3$. The other possible path through $1, 2, 3$ is longer. Furthermore there is no path from a to d through edge 4, since the edge's direction is from d to a.

For example, in social networks, two friends would have a distance of one, because there is one edge connecting them directly (i.e., the path is of the length one). The friend of a friend has the distance two; There is a shortest path of two edges connecting one vertex to the friend of a friend. Given three vertices in a social network where two vertices are connected, there is often assumed to be a missing connection between the two yet unconnected vertices, especially if many such constellations indicate this connection. In this case, these three vertices make up an unconnected triad. In social networks, it is usually assumed that given many common neighbors, two vertices are expected to be connected as well. This is commonly known as *homophily*, same-love. Homophily is

> the principle that we tend to be similar to our friends. Typically, your friends don't look like a random sample of the underlying population: Viewed collectively, your friends are generally similar to you (Easley and Kleinberg, 2010, p. 86).

In Fig. 2(a) an example of a connection between two persons is given. Following the homophily assumption that a friend of a friend is likely to be a friend as well, one can assume the connection given in the dotted line in Fig. 2(b). This is called the *closed triangle assumption* or *triadic closure*.



(a) Open triangle: three nodes connected by two edges.

(b) Closed triangle: assumed connection.

Figure 2: Closed triangle assumption.

The degree to which vertices are connected to their possible neighbors in a network is called the clustering coefficient or its transitivity. It can be calculated as

$$C = \frac{number\ of\ closed\ triads}{number\ of\ geodesic\ paths\ of\ length\ two}. \tag{2}$$

2.1.2 Components, Cliques, Clusters, and Communities

The terms components, cliques, clusters, and communities all refer to subsets of vertices of a graph that are, in one way or another, connected to each other.

A component is a subset of vertices of a graph such that there exists a path from any vertex to any other vertex of the component. In directed graphs, theses paths have to be directed. In many cases, and it will be shown for WordNet as well, a network consists of more than one component: Not every vertex can be reached by a path from any other vertex.

A network that consists of only one large component is called *connected*. A fully connected graph is one where each vertex is connected to any other vertex of the network directly by an edge.

Cliques are sets of vertices such that there exists an edge (i.e., a path of length one) from any member of the clique to every other vertex of the clique and such that no other vertex could be added that fulfills the first requirement.

Clustering is "the division of network nodes into groups within which the network connections are dense, but between which they are sparser" (Newman and Girvan, 2004, p. 1). Not every vertex of a cluster, or community, is connected to every other vertex, but the vertices of a cluster are, overall, more interconnected within their cluster than

they are to vertices of other clusters. Still, there can be paths from one cluster to another cluster. A connected component can, and in social networks this is almost surely the case, contain many clusters.

Looking for example at the members of a parliament and treating the members as vertices and their interactions as edges, one would surely find that there is more interaction between the members of the same fraction, the same committee, and things like these than between members of different fractions or committees. The fractions and committees are the natural clusters of such a network.

Clusters are harder to identify than the straightforwardly defined components and cliques. There might be cases where vertices lie on the intersection of different clusters and might belong to not just one of them. Clustering algorithms in general aim to identify groups or similar elements. In networks this means to identify the sets that are strongly interconnected. In Chp. 4.3.2, clustering algorithms with an application to machine learning and network analysis will be discussed.

2.1.3 Multigraphs, Trees, and Bipartite Graphs

Vertices of a graph can be connected by more than one edge, called *multiedges*. Such graphs are called *multigraphs*. A matrix of a multigraph would not only contain Boolean values of 0 and 1, but can also contain any number $\mathbb{R}^{\geq 0}$ as can be seen in matrix B. In other cases, graphs can contain self-loops (i.e., vertices that are connected through an edge to themselves). Matrix B is a matrix of a multigraph containing self-loops (see second row, second column).

$$B = \begin{bmatrix} 0 & 1 & 2 \\ 2 & 3 & 1 \\ 1 & 4 & 0 \end{bmatrix}$$

The ontologies we are going to examine are multigraphs. Entities of an ontology can be connected to one another by more than one relation.

A special form of a connected graph that contains no loops is a tree. An interesting property of a tree is "that a tree of n vertices always has exactly $n-1$ edges." (Newman, 2010, p. 128). Even though the tree does not have to be directed, a tree always implies a hierarchical structure since multiple inheritance is not permitted (i.e., a vertex cannot have more than one direct parent vertex as can be seen in Fig. 3). This leads to the *conditio sine qua non* that a tree of n vertices always has exactly $n-1$ edges.

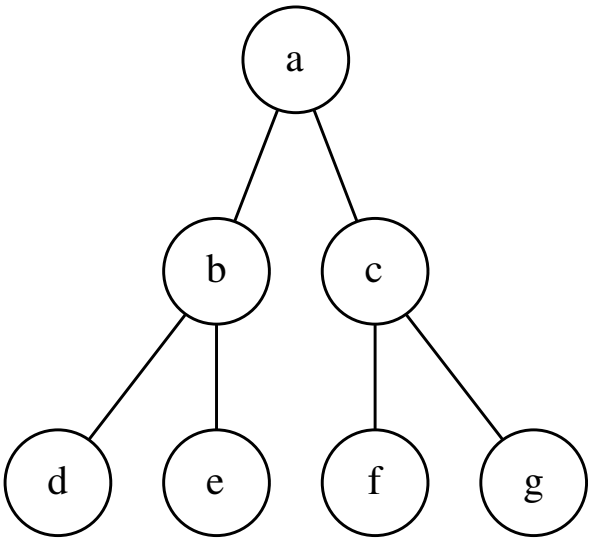


Figure 3: A small, simple tree.

Another special graph that will be of interest later on is the so-called *bipartite graph*. A bipartite graph consists also of vertices and edges, but the vertices are of two different kinds (see Fig. 4). An example of such a graph can be a network of co-working in the movie business. Three actors $\{a, c, e\}$ are linked to the movies $\{b, d\}$ they appear in. The vertices are of the kind *movie* and *actor*. Such *affiliation networks* are widely used in social network analyses. There are no direct connections between the actors, they are only connected through the movies both appear in. One can also reduce these graphs to monopartite graphs (i.e., actors are seen as connected if they worked together on a movie). The latter graph of course is not as meaningful as the original bipartite graph.

2.1.4 Measure of Centrality and Importance of Vertices

An important measure for vertices in a network is the centrality. The degree centrality is the degree of a vertExample A vertex with a relatively high degree in a network can be described as central.

The overall centrality of a network can be measured using Freeman's (1978) general formula of centrality:

$$C_D = \frac{\sum_{i=1}^{n}[C_D(a*) - C_D(a_i)]}{n^2 - 3n + 2}, \tag{3}$$

where n is the number of vertices, a_i the particular node, and $a*$ the maximum degree of

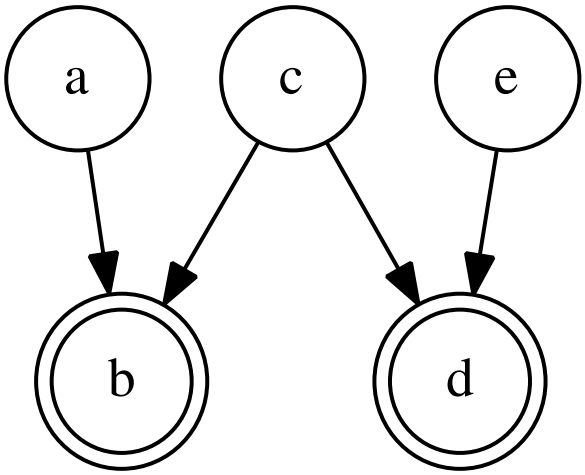


Figure 4: A simple bipartite graph with two different kinds of vertices: {a,c,e} and {b,d}.

a vertex in the network. The centrality C_D of a network is thus defined as the sum from $i = 1, \ldots, n$ of the centrality of the vertex where the degree is at the maximum minus the centrality of a vertex a_i divided by the number of vertices n^2 minus 3 times n plus 2 (Freeman, 1978, p. 226ff.).

Beside the very basic degree centrality measure, other measures like the *eigenvector centrality*, *betweenness*, *closeness*, and *PageRank* are commonly applied in network analysis. All the measures that are to be presented here will be used later on in link prediction tasks.

Eigenvector Centrality

Newman (2010, p. 169) says that

> [i]n many circumstances a vertex's importance in a network is increased by having connections to other vertices that are themselves important. This is the concept behind eigenvector centrality. Instead of awarding vertices just one point for each neighbor, as in degree centrality, eigenvector centrality gives each vertex a score proportional to the sum of the scores of its neighbors.

Bonacich (1987, p. 1173) defines the eigenvector centrality as shown in Eq. 4 and Eq. 5. The centrality of vertex i is calculated as the sum over edges between i and any connected

vertex j multiplied by the centrality of j (C_j) times β plus a:

$$c_i(\alpha\beta) = \sum_j (\alpha + \beta c_j) A_{ij}, \tag{4}$$

or

$$c(\alpha\beta) = \alpha(I - \beta A)^{-1} A1, \tag{5}$$

where A is the adjacency matrix of the graph and I is the identity matrix:[9]

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Vector '1' is a column vector of all ones.[10] The constants α and β determine the importance or influence of the degree of a vertex.

Quite similar to the Eigenvector centrality is the so-called Katz centrality (Katz, 1953). The two constant values α and β in Eq. 6 result in the fact that even if the centrality of a vertex is 0, it will still be awarded β:

$$\lambda x_i = \alpha \sum_{j=1}^{n} a_{ij} x_j + \beta, i = 1, \ldots, n. \tag{6}$$

Given any vertex that is pointed to by many vertices that themselves have no other vertices pointing to them, the Eigenvector centrality would be low or 0, while the Katz measure still rewards these links. The constant α is used to control the weight of the eigenvector in relation to β (Newman, 2010, p. 172).

Betweenness Centrality

Another important measure in (social) networks is the so-called *betweenness*. It is "based on the assumption that information is passed from one person to another only along the

[9]The identity matrix, being its own inverse, is the matrix multiplication equivalent to 1: A $n \times m$ matrix R multiplied by $I_{n,m}$ is R.

[10]Multiplying an adjacency matrix by a vector of all ones sums up the values of each column of a matrix which corresponds to the degree of a vertex.

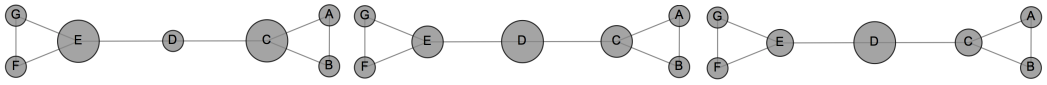


Figure 5: Weighted graphs: (a) weighted by degree, (b) weighted by betweenness centrality, and (c) weighted by closeness centrality.

shortest paths linking them" (Freeman *et al.*, 1991, p. 142). This means, if one is looking at the spread of information in a social network, those vertices are *best informed* that lie on a high number of shortest paths between any two vertices. A vertex can have a very high degree but still a very small betweenness, and vice versa. If the number of geodesic paths between the vertices j and k is g_{jk}, and the number of these paths between j and k going through vertex i is $g_{jk}(i)$, the betweenness centrality of i is the quotient

$$b_{jk}(i) = \frac{g_{jk}(i)}{g_{jk}}. \tag{7}$$

Now, one has to sum up this value for all pairs of vertices where $i \neq j \neq k$ to get the overall betweenness centrality of i.

Closeness Centrality

Closeness, as defined by Freeman (1978, cf. p. 221), indicates the length of the average geodesic distance between a vertex i and any other vertex of a network.

$$C_c(i) = \left[\frac{\sum_n^{i=1} d(i,j)}{n-1} \right]^{-1} \tag{8}$$

Dividing the average distance between i and j by the number of total vertices minus 1 $(n-1)$ normalizes the value of $C_c(i)$. This equation is problematic in networks with unconnected components (Freeman, 1978, cf. p. 226): When there are vertices to which no path exists, the sum is infinite. Inverting an infinite number leads to a value of 0 as the outcome of the equation. Opsahl *et al.* (2010, p. 245) suggest to "sum the inversed distance instead of the inverse sum of distances".

PageRank

The last measure to introduce at this point is *PageRank*. Page *et al.* (1998) developed this ranking system at Stanford before founding Google on the basis of PageRank. On the World Wide Web, it assigns each web page a rank not based on its in-degree alone but on the in-degree of the vertices pointing to the page.[11] Again we take a vertex i to be ranked. The sum over all vertices j in B_i pointing to i is normalized by a factor c. The rank of j is divided by N_i (i.e., the number of links i is pointing to).

$$R(i) = c \sum_{j \in B_i} \frac{R(j)}{N_i} \tag{9}$$

This function is different from the ones shown above because it only takes into account the in-degree of the vertex itself and its nearest neighbors. One does not need information on the whole network to calculate the importance of a node. In case of a huge network like the World Wide Web, this is an advantage.

The measures of degree, betweenness, and closeness are compared in Fig. 5(a)–(c). The size of the vertices indicates the corresponding value of the measure in question.

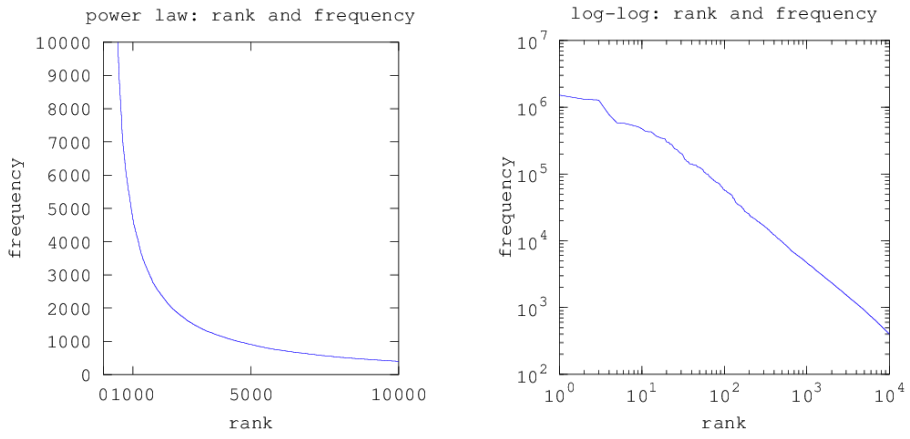
2.1.5 Small-World Networks and Scale-Free Distribution

Social networks have been of special interest in the social sciences for decades. It has been found that social networks show a property that is called the *small-world phenomenon*.

Small-world networks and social networks as such expose two distinguishing features. First, they have a short average geodesic path and, second, a high clustering coefficient (compared to random graphs). Both features result in the common observation that a friend of a friend tends to be a friend as well.

One of the first pieces of systematic research in the field of social networks that became extraordinarily popular, so popular indeed that its findings are now part of general knowledge, was the work of Milgram (1967). Milgram sent out letters to randomly chosen people in the US and asked them to hand the letter to a first-name acquaintance of theirs in order for the letter to reach a specific person located in Boston. The letters that actually made it to their destination got there through about six stations (on average 5.8 steps). This is commonly known as the *six degrees of separation* and it can be seen as the

[11] The WWW is a directed multigraph (see Chp. 2.1.3).



(a) (b)

Figure 6: Plot of frequency and rank of words based on the Brown Corpus: (a) the data following a power law and (b) the same data plotted on logarithmic scale.

short average geodesic path of the social network of US citizens.

Not only was the average path from a randomly chosen starting point to the destination relatively short, but most of the letters came to their destination through the hands of only a few people connected to the destination person. Travers and Milgram (1969) call these people authorities, since they seem to be very well connected not only to the destination person as well as to others they were getting the letters from. These authorities are also called *hubs*, and they have ever since been found in many networks with a small geodesic distance. Those networks of course also tend to be clustered: groups of vertices (strongly connected) build clusters, and their degree distributions follow a power law: Very few vertices have a very high degree, while most vertices have a very low degree.

A good example of a power-law distribution is given by the so-called *Zipf's law*.[12] Zipf (1965) found that the distribution of the frequency of words is inversely proportional to their rank. A distribution of this kind can be plotted to a graph as can be seen in Fig. 6(a). This distribution follows a power law of the form $p(x) = Cx^{-\alpha}$.

An interesting observation on the plotting of this kind can be seen in Fig. 6(b): When plotted on a logarithmic scale, the graph pretty much follows a straight line.[13]

[12]Adamic (2002) shows that Zipf's law and the Pareto distribution are equivalent. The difference consists in the usage of the two axes that are inverted.

[13]According to Newman (2004), this observation was first made by Auerbach (1913) in his work on the

Power-law distributions are scale free. This means they show the same distribution no matter what the scale is. To understand what *scale free* means, one can have a look at Fig. 6(a) and Fig. 7, which show the same data scaled by a factor of 2. The distribution "is the same *whatever scale we look at it on*" (Newman, 2004, p. 334).

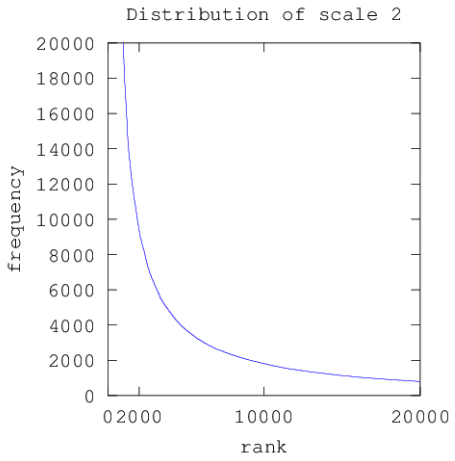


Figure 7: The same data as in Fig. 6(b) but scaled by a factor of 2.

The degree distribution of many real-world networks follows such power laws with the limitation that the number of vertices is not infinite. But power laws have not only been found in word frequencies or degree distributions of networks. In sociology, it has been shown that the distribution of the size of cities and distribution of wealth among people follows a power law: Compared to the number of cities in the world, only very few have a very high number of inhabitants, while a very large number have only very few inhabitants (though probably not only one). In other words, large cities attract ever more inhabitants. Similarly it has been found that people with a large fortune, which are only very few people, tend to increase their wealth further, while the great number of people have much less wealth. This has been called the *rich-get-richer* principle. We will come back to how such structures (i.e., that words with many connections tend to attract ever more connections) arise in (language) networks later on (see Chp. 2.2).

density of population (*Bevölkerungsdichte*).

2.1.6 Terminology

A number of terms that can be used synonymously have been introduced already, and there are still more terms in use that have not been mentioned yet: graph and network, vertex and node, edges, arcs, and links, vertex and site, edge and bonds, or in the social sciences vertex and actor, and edge and tie. In Chp. 3.5, the terms entities and relations in the context of ontologies will be introduced. These terms correspond, when the ontology is referred to as a network, to vertex and edge in graph theory. Throughout this thesis, I will use either vertex or entity and edge or relation, depending on the context and the connotation, either meaning the element of the graph or the entity of the ontology. Sometimes the relations of an entity will be called its attributes or properties.

2.2 Language Networks and Computational Models of Language

Graph and network theory have been used in different ways in linguistics, especially in the study of semantics, language evolution, language acquisition, as well as in neurosciences. Some questions that are of interest for the evaluation of the results of this thesis are based on the following models. Questions such as *How do networks in natural language arise? How can network or (hierarchical) graph models explain the processes of the human mind and how accurate are they?* have to be kept in mind when using network methods to model natural language.

The idea of computation in language processing in the human mind is not new. Chomsky (1988) suggests that language understanding, learning, and evolution depends on the human mind's capability to carry out computations. Hauser, Chomsky, and Fitch call this the *faculty of language in a narrow sense*, which they define as "the core computational mechanisms of recursion" (Hauser *et al.*, 2002, p. 1573). And in his *computational theory of mind* (CTM), Pinker (2005, p. 22) defines the mind as a "naturally selected system of organs of computation". In the early 1990s, Steven Pinker proposed a dual mechanism: The brain contains on the one hand a lexicon where words are stored and on the other hand a grammar apparatus to infer, among other things, regular forms of words (Pinker, 1991; Pinker and Prince, 1991). Pinker denies the idea of either a "homogeneous associative memory structure or alternatively, of a set of genetically determined computational modules in which rules manipulate symbolic representations" (Pinker, 1991, p. 253), and he thereby contradicts Chomsky. Pinker's distinction implies that there must be a differ-

ence between the retrieval of an irregular past-tense verb stored in the human memory and a regular verb generated by a rule-based mechanism. The lexicon must contain not only word–meaning pairs for the word stems but also irregular word forms that cannot be mentally computed using grammatical rules. Other research that will be shortly reviewed now has been undertaken that back this idea.

When it comes to the actual storage of words in the brain, several different approaches to investigate the structure can be distinguished. One indication of the internal network structure of the brain are findings that semantically related words take less retrieval time than a mere phonological relationship. In these studies, subjects were shown a prime–target sequence (e.g., 'swan/goose' and 'gravy/grave'). The semantical relation in the brain in the first case was stronger, resulting in less reaction time than the phonological relation between the semantically unrelated words *gravy* and *grave* (Marslen-Wilson and Tyler, 1997, p. 592).

Furthermore, Marslen-Wilson and Tyler (1997) took a prime/target approach comparing the relation between a stem and its past-tense form, whether regular or irregular, in comparison between different neurological damage. Two aphasic patients with ungrammatical speech were compared to one patient with right and left hemisphere damage and a group of healthy subjects. The results suggest that the two aphasic patients are not able to use regular past-tense forms but are able to retrieve irregular forms. This suggests damage to the part of the brain where the grammatical mental computation is done. The other patient neither shows semantic priming nor is he able to retrieve irregular verb forms, suggesting that his mental lexicon is damaged. His grammatical apparatus for mental computation is not affected; he is able to use regular verb forms.

Other studies undertaken by Indefrey *et al.* (1997) and Jaeger *et al.* (1996) using positron emission tomography (PET) show that different regions of the brain are used to form regular verb forms and to retrieve irregular ones. According to Indefrey *et al.* (1997, p. 548), both "regular and irregular morphological production induced significant rCBF [regional cerebral blood flow] increases in midbrain and cerebellum, but showed no overlap in cortical areas".

A study on German irregular plural forms using event-related brain potentials (ERPs) provides, according to the authors, "a clear electrophysiological distinction between regular and irregular inflections" (Weyerts *et al.*, 1997, p. 961), supporting the hypothesis of

a dual mechanism.[14]

Ullman *et al.* (1997) analyze the capacities of patients with Alzheimer's disease (AD), which leads to impairments of the lexical memory, on the one hand, and Parkinson's disease (PD), which leads to impairments of the grammatical rules, on the other hand. Their findings also suggest that the distinction between the lexicon and the grammatical apparatus is correct. They find that patients with impairments of the lexical memory (AD patients) have more trouble finding irregular verbs than converting even unknown verbs to the regular past tense. PD patients showed the opposite pattern.

Manning *et al.* (2012) study how the retrieval of words in the human mind is influenced by their semantic similarity. Electrocorticographic recordings of 46 "neurosurgical patients who were implanted with subdural electrode arrays and depth electrodes during presurgical evaluation of a treatment for drug-resistant epilepsy" (Manning *et al.*, 2012, p. 8872), memorizing and remembering words on a list, show how individuals store related words. Manning *et al.* (2012) chose a latent semantic analysis (LSA) to describe the semantics of a given word. They say:

> If a participant shows a strong correspondence between neural and semantic similarity ..., then we consider them to exhibit neural clustering in the sense that neural patterns associated with words that are similar in meaning (according to LSA) will be clustered nearby in their neural space (where each point in neural space is a pattern of neural activity) (Manning *et al.*, 2012, p. 8873f.).

They calculate the cosine similarity between the semantic vectors as well as the similarity between the patterns of brain activity during memorizing and recall of semantically related words. Using an underlying LSA to explain the meaning of their findings, these results indicate that the words are, in a network sense, similarly connected. This experiment shows that there is a relation between a network of words and the neural network in the human mind, or as they put it: "This indicates that temporal and frontal networks organize conceptual information by representing relationships among stored concepts" (Manning *et al.*, 2012, p. 8876), as in a network or even more as in an ontology.

[14] A differing view from Indefrey *et al.* (1997) on the localization of the human linguistic capacities is held by Grodzinsky (2000). The exact region or regions responsible for human linguistic abilities remain unclear. This is mostly because of the unsatisfactory accuracy of the applied neuroimaging methods (PET and ERP).

The presented studies suggest (1) that a mental lexicon exists in the human brain that connects semantically related words more closely than other words, i.e., a network structure,[15] and that (2) a part of the brain fulfills mental computations using grammatical rules to convert regular nouns and verbs.

2.3 Graphs of Language

From these and similar considerations and findings in medicine, psychology, and biology, different theories about how language networks evolve have been proposed. In the following, some approaches will be presented. Starting with an older computational model of a hierarchically ordered tree-like structure of lexico-semantic information, models of how networks evolve and develop will be presented that finally lead to a model of language network growth that can explain some statistical features of complex networks representing human language. Afterwards, the properties that can be expected from a language network and complex network compared to simple or ordered networks can be defined.

2.3.1 Hierarchical Structures of the Mind

Quillian (1967) uses a tree-like, hierarchically structured taxonomy model for the "simulation of some basic semantic capabilities" (Quillian, 1967, p. 459) in the form of a computer program. His model of "memory as a 'semantic network' [is] representing factual assertions about the world" (Quillian, 1969, p. 459) in a hierarchical class model. Quillian stores each word with "a configuration of pointers to other words in the memory; this configuration represents the word's meaning" (Collins and Quillian, 1969, p. 240), and in his opinion it is a reverse-engineered model of the human semantic capacity. [16]

Collins and Quillian's (1969) model allows one to make predictions about the time it should take to retrieve information. They argue that if the information is hierarchically organized in the form of a tree, where children vertices inherit the information of their parent vertices, the retrieval time for information inherited from the parent should be longer than that for information belonging to the vertex itself.

As an example they use the concept of a *canary bird*. Like all birds, canaries have

[15] This lexicon also contains irregular forms of words that cannot be formed using grammatical rules.

[16] These considerations are very early examples of semantic networks that finally lead to the development of ontologies. The words are the vertices; the pointers are edges of the network.

feathers and can fly.[17] Like all animals, birds have skin. Since a canary is a bird, and a bird is an animal, it has skin as well. Moreover, a canary is yellow and can sing. Collins and Quillian predict that there should be a higher retrieval time for information that is inherited. To show this, subjects have to decide whether a sentence is true or false and while their reaction time is measured.

The subjects are shown sentences like: "A canary can sing.", "A canary can fly.", or "A canary has skin." (all taken from Collins and Quillian (1969, p. 241)). These sentences are all true, but the authors assume that there should be difference in the time necessary to retrieve the needed information. They suspect that *singing* is a property of the canary itself, while *flying* is a property of birds and hence one level higher in the hierarchy, and that *having skin* is a property of animals and hence one further step higher in the tree.

They measure the reaction time and find that it takes about 75 ms "to move from a vertex to its superset" (Collins and Quillian, 1969, p. 244). They conclude that "there was substantial agreement between the predictions and the data" (Collins and Quillian, 1969, p. 246).

However, later studies could not verify these findings (McCloskey and Glucksberg, 1979; Murphy and Brownell, 1985). Furthermore, McClelland and Rogers (2003) argue that the hierarchical model has some issues. They are asking

> just which superordinate should be included, and which properties should be stored with them? At what point in development are they introduced? What are the criteria for creating such categories? And how does one deal with the fact that properties that are shared by many items, which could be treated as members of the same category, are not necessarily shared by all members? (McClelland and Rogers, 2003, p. 311)

From their study of language acquisition and forms of dementia, McClelland and Rogers suggest a network model: Information is "latent in the connections among the neurons in the brain that processes semantic information" (McClelland and Rogers, 2003, p. 310). The generalized properties (e.g., that all birds fly) are derived from clusters of the network, or from the distance between word vectors in a vector space.

Interestingly enough, McClelland and Rogers (2003) deny a hierarchical organization

[17] Exceptions like an ostrich or a penguin would have to be marked as a bird that cannot fly. It is "more economical to store generalized information with superset vertices rather than with all the individuals to which such a generalization might apply" (Collins and Quillian, 1969, p. 246).

and instead propose – without further looking into this – that neighborhood and the connectivity of a concept implicitly provide this information.

2.3.2 Complex Network Growth and Models of Language Network Evolution

After seeing how language can be treated as a graph or network, the question has to be asked how such networks evolve. There have been different proposals for different kinds of networks. The most important ones are to be presented and compared here.

Random Networks (Erdös and Rényi)

In 1959, Erdös and Rényi proposed a model of random graphs. They start with n vertices and connect those with N edges with a probability P (Erdös and Rényi, 1959, p. 290). Such a network's degree distribution follows a Poisson distribution. The Poisson distribution indicates the probability that a certain state occurs. If we know that a graph has n vertices and N edges, the average number of edges a vertex has, its degree, should be $A = \frac{n}{N}$. The Poisson distribution shows the probability of the state $A \pm x$ to occur. An example of an Erdös and Rényi graph is given in Fig. 8.

With a lack of data on real-world networks, this model could not be tested extensively. The model constructs a random network that is not like real-world, complex networks, as we have seen them already and will analyze later on in this thesis. The model is missing the most basic features of complex networks: Neither the power law distribution, and thus the scale-free feature, nor the small-world property of natural networks can be explained using this model (Barabási and Réka, 1999, p. 510).

Small-World Networks (Watts and Strogatz)

One feature of complex networks that the above shown model does not predict is the small-world phenomenon. Watts and Strogatz (1998) propose a model that explains how small-world networks emerge.

Having a network of n vertices and k edges per node, Watts and Strogatz "rewire each edge at random with probability p" (Watts and Strogatz, 1998, p. 440), where $p = 0$ results in an ordered network (see Fig. 9(a)), and $p = 1$ results in an unordered network (see Fig. 9(c)). While an ordered network has a long average path length L (a large-world network), and a high clustering coefficient C, a network of $0 < p > 1$ (see Fig.

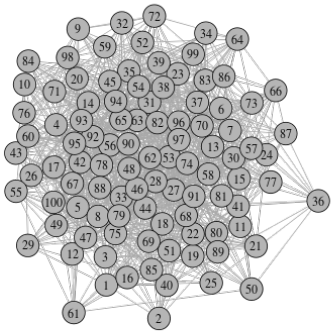


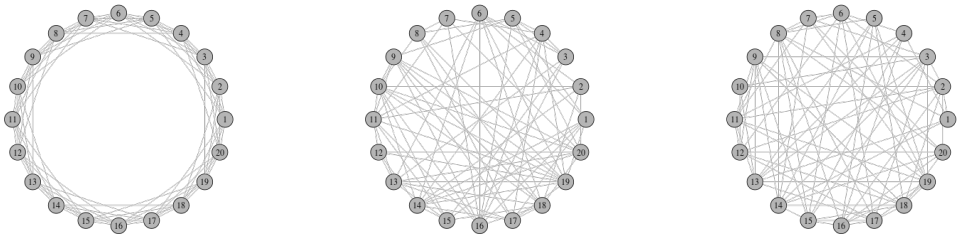
Figure 8: An Erdös and Rényi random graph with 100 vertices and a connectivity probability of 0.2.

9(b)) leads to a less clustered network with a short average path length or small-world network. Even for "small p, each short cut has a highly nonlinear effect on L, contracting the distance not just between the pair of vertices that it connects, but between their immediate neighbourhoods" (Watts and Strogatz, 1998, p. 440). But this model stills misses the power-law distribution that is typically found in complex networks, and it is no explanation of how such networks evolve since it does not incorporate growth of any kind.

Preferential Attachment (Barabási and Réka)

Network models of language allow one to analyze the supposed structure of the mind and to predict and analyze the evolution of language. Barabási and Réka (1999) describe a model of network growth using preferential attachment:[18] Having a network, this models predicts that "new vertices in the growing network are preferentially attached to an existing vertex with a probability proportional to the degree of such a node" (Ferrer and Solé, 2001, p. 2263). This is equivalent to the rich-get-richer principle introduced before. The model leads to a power law distribution, which is generally seen as a natural result

[18]Preferential attachment applies Bayesian models which are also used (e.g., to predict the growing of the mind (cf. Tenenbaum *et al.*, 2011)). Bayesian models complement network approaches and are used widely in language models in psychology, linguistics, and medicine.



(a) Probability $p = 0$. (b) Probability $p = 0.5$. (c) Probability $p = 1$.

Figure 9: Watts and Strogatz graphs with $n = 20$ and $k = 4$.

of the way a system, like a network, grows over time. Barabási and Réka state that this indicates that "the development of large networks is governed by robust self-organizing phenomena that go beyond the particulars of the individual systems" (Barabási and Réka, 1999, p. 509).[19]

In formal terms, the probability $P(k_i)$ that a new vertex in a network starting with m_0 vertices and adding a new vertex at every time step t with $m \leq m_0$ edges will connect to an existing vertex i depends on the degree k_i of that node:

$$P(k_i) = \frac{k_i}{\sum jk_j}.$$

This leads to a random network with $t + m_0$ vertices and m_t edges that is "following a power law with the an exponent $y_{model} = 2.9 \pm 0.1$" (Barabási and Réka, 1999, p. 5).

An example is given in Fig. 10. Comparing this graph to an Erdös and Rényi random graph, one can see that the distribution of edges per vertex is not distributed in Poisson fashion, but that some vertices have a reasonably higher degree than others. This also leads to clustering as Fig. 10 shows.

This model predicts degree distributions that follow a power law, more or less like it can be observed in networks of natural language or, in general, in scale-free, small-world networks.

In Fig. 11, the degree distributions of the models presented above are given. In

[19] In protein networks, for example, scale-free distribution follows from preferential attachment in the growing process, which seems to be a result of gene duplication (cf. Barabasi and Oltvai, 2004, p. 106).

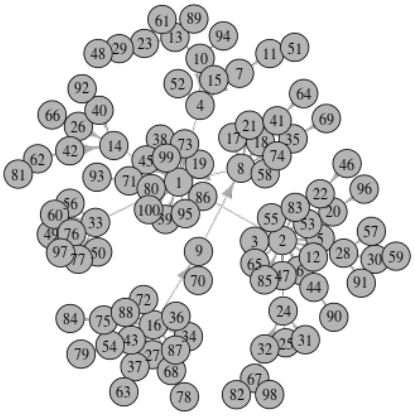


Figure 10: A Barabási and Réka graph with 100 vertices.

accordance with what has been stated above and as one can see, neither the degree distribution shown in Fig. 11(a) nor the one in Fig. 11(b) follows a power law. Only the model of Barabási and Réka (1999), Fig. 11(c), shows a degree distribution that is found in most natural networks, such as social networks, and, as will be shown in later chapters, in ontologies.

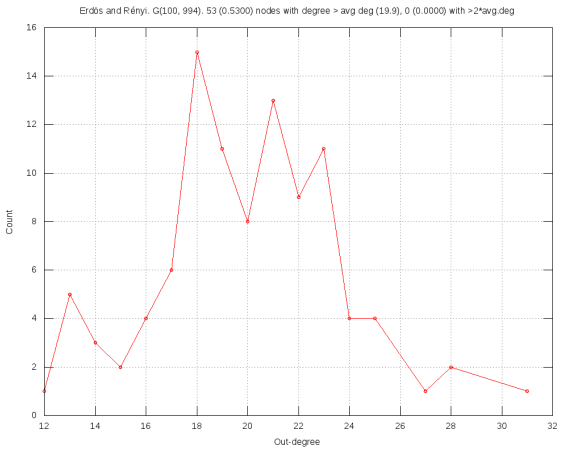
Language Network Models (Steyvers and Tenenbaum)

Steyvers and Tenenbaum compare the Barabási and Réka model to findings in natural language networks[20] and find that preferential attachment as proposed by Barabási and Réka (1999) does not explain the structure of semantic networks.

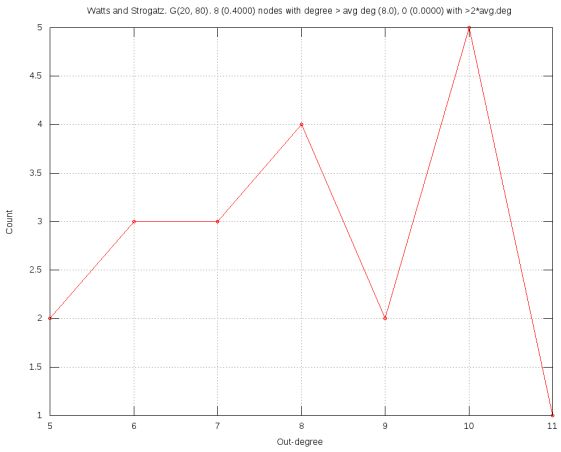
From a language evolution[21] point of view, Steyvers and Tenenbaum argue that "[w]ords that enter the network early are expected to show higher connectivity" (Steyvers and Tenenbaum, 2005, p. 44). Also existing complex concepts (i.e., those with a high

[20]Unfortunately, they restrict themselves to an analysis of networks and ignore the large amount of linguistic research in the areas of language evolution and language change.

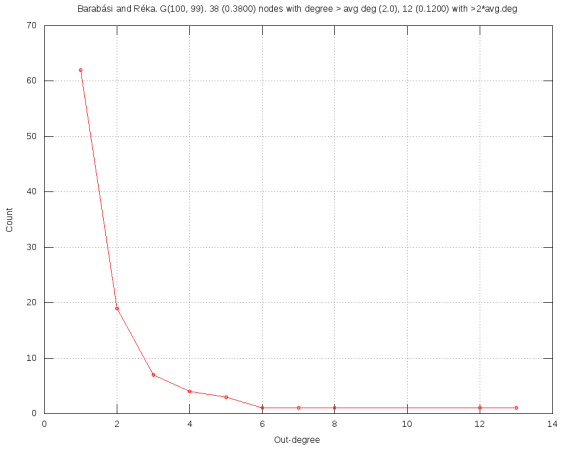
[21]Steyvers and Tenenbaum's model could just as well be applicable to individual language acquisition, even though it cannot account for all the diverse processes that happen during the acquisition or evolution of natural languages.



(a) Degree distribution of Erdös and Rényi random graph in Fig. 8.



(b) Degree distribution of Watts and Strogatz graph in Fig. 9(c).



(c) Degree distribution of Barabási and Réka graph in Fig. 10.

Figure 11: Degree distributions of Erdös and Rényi, Watts and Strogatz, and Barabási and Réka models.

connectivity or degree) in a language are more likely differentiated over time. This means complex and very wide terms tend to be differentiated into narrower terms. There are of course a lot of other processes that can be discussed concerning the evolution of a natural language, but this process is leading to concepts with a high connectivity (i.e., hubs or authorities) and thereby to a small-world network.

Two models for the growth of language networks are proposed by the authors: The first explains the growing of an undirected network, while the second one explains the growth of a directed network (e.g., a semantic relationship network of words such as WordNet or other language ontologies).

The first growth model can be formulated as follows: Given is a fully connected network of size n that grows over time, at each time point t with $t(n)$ vertices, a randomly chosen vertex i is differentiated by adding a new vertex with M connections ($M < n$) to randomly chosen vertices in the neighborhood of i. This leads to the effect that a "new vertex can be thought of as differentiating the existing node, by acquiring a similar but slightly more specific pattern of connectivity" (Steyvers and Tenenbaum, 2005, p. 57). Now the probability that vertex i is chosen has to be defined. The probability $P_i(t)$ is corresponding to the connectivity of the vertex i (i.e., its degree):

$$P_i(t) = \frac{k_i(t)}{\sum_{n(t)}^{i-1} k_i(t)}.$$

The degree of i at t, $k_i(t)$, is divided by the sum of degrees from $i-1$ to $n(t)$ (i.e., all vertices at time t)

To choose a vertex j in the neighborhood H_i of i that the vertex to be added will be connected to, the probability $P_{ij}(t)$ is calculated in proportion to the utility of the corresponding node:

$$P_{ij}(t) = \frac{1}{k_i(t)}.$$

This is repeatedly done until M vertices from H_i have been chosen. Then the new vertex is connected to them. These steps are repeated until the desired network size is reached. The network produced by the model can then be compared to a real-world network of the same size.

The second model of network growth results in a directed network. The process is very similar to the first model. The only difference is the connection of the new node:

Still, the vertices it will be connected to are chosen with the probability $P_{ij}(t)$, but the direction of the connecting edges is chosen randomly.

While this model fits the examined features of language graphs, it should be mentioned that a model of the growth or evolution of a language network should also account for the loss of words (i.e., at randomly chosen time steps the network should to be pruned and poorly connected concepts should be erased). A diachronic analysis of language shows not only a differentiation of words and hence a semantic shift, as well as that concepts that are poorly connected and therefore less frequently used, cease to exist in the vocabulary of a single person or even a language community (cf. Pagel *et al.*, 2013). This property is, in my opinion, missing in the model. Also, Dorogovtsev and Mendes (2001) point out, because of a semantic shift, existing concepts should at time be *rewired* to other concepts.

2.4 Conclusion

The use of network models of language and the application of methods of graph theory were explained and legitimized taking findings from linguistics and from other relevant fields of research.

Basic concepts of graph theory as well as sophisticated measures of network structure and vertex centrality have been introduced and will be utilized to analyze the structure of networks extracted from ontologies and as features for machine learning tasks to extend the ontologies. As will be shown in Chp. 4, many interesting ideas from social networks analyses might also be applicable to ontologies. The network structure, nonetheless, will be the main basis for the application of machine learning to identify and classify missing edges in the network structure. Furthermore, properties of complex, natural networks, the degree distribution, and the small-world phenomenon (i.e., the short average geodesic path and high clustering coefficient) have been introduced. These features distinguish complex network from (e.g., random networks as proposed by Erdös and Rényi (1959)).

Looking at the neurological network in the human brain, a definition of the semantics of a word or concept was found that is not only true for semantic networks as are the ontologies used in this thesis. Manning *et al.* (2012, p. 8873f.) find "that neural patterns associated with words that are similar in meaning ... will be clustered nearby in their neural space" of the human brain. Hence, the meaning of a word is defined as its connections or relations to other words or, more general, as a *pattern of connectivity* (cf. Steyvers and Tenenbaum, 2005). As will be shown in the following chapter, similar

definitions of meaning have been made in semantics. Based on these definitions, applying machine learning algorithms to predict patterns can be employed to build or complete word networks.

Trees, as a special network structure, and hierarchies can also be found in representations of human grammar (e.g., *phrase structure grammars* (PSGs)). Hierarchical structures like these are considered to be a unique feature of human communication. Other animals are capable of learning *finite-state grammars* (FSGs) but fail to learn the recursive rules of a PSG. Fitch and Hauser explain that other species than humans "suffer from a specific and fundamental computational limitation on their ability to spontaneously recognize or remember hierarchically organized acoustic structures" (Fitch and Hauser, 2004, p. 380) and conclude with the thesis that the "acquisition of hierarchical processing ability may have represented a critical juncture in the evolution of the human language faculty" (Fitch and Hauser, 2004, p. 380). This is again a further indication of the existence of data structured in hierarchical form and for an organ of computation which supports the use of computational methods to model language. It is no explanation for why this form of organization, a network, is employed, though.

Phrases can be embedded in other phrases; sentences form a syntax tree. Analogous to a syntax tree, semantic relations between entities in human language are also organized in the form of a tree. We find structures, especially trees, that can be interpreted as a network on all levels of the human language.

Seeing that the evolution of language and of vocabulary, at least when looked at as a network, is generally similar to the growth of a neural network is not surprising since it is the neural network of the human brain that stores, retrieves, and manipulates language. Network structures are a very robust way of organization. The structure of the data system (the human brains neural network) seems naturally reflected in the internal structure of language processed by this system. In this way, the structure of the language capacity is adapted to the medium. Of course the human neural network does not function as the much simpler network model applied in the following. One does not find vertices representing words in the neural network of the brain, but still patterns of network activity seem to correspond to distinct words, concepts, and their understanding and processing. Therefore, using this resemblance and the term network to indicate a similarity between technical processes and mental processes can be very problematic.

The notion of *artificial neural networks* (ANNs) in so-called deep learning has become very popular in recent years. ANNs were developed having in mind the (simplified)

understanding of how the human neural network behaves.

While the practical advantages of such techniques are indisputable, the notion that such systems are inspired or even work like the human brain has to be rejected. Many people in machine learning have contradicted this understanding of neural networks. For example Michael Jordan has pointed out in an interview that to "infer that something involving neuroscience is behind it ... is just patently false" (Gomes, 2014).

When networks and ideas from psychology, and especially neurology, were first used to explain semantics, Fillmore (1975, p. 124) found that the analogies to the human mind and brain might "sound like extremely naive psychology". In an interview with *The New York Times*, Andrew Ng, one of the heads behind the Google Brain project, admits that it is a "loose and frankly awful analogy ... that our numerical parameters correspond to synapses". [22]

[22]Source: `http://www.nytimes.com/2012/06/26/technology/in-a-big-network-of-computers-evidence-of-machine-learning.html`.

3 Lexical Semantics and Ontologies

> Most of what's called "semantics" is, in my opinion, syntax. It is the part of syntax that is presumably close to the interface system that involves the use of language. So there is that part of syntax and there certainly is pragmatics in some general sense of what you do with words and so on. But whether there is semantics in the more technical sense is an open question. I don't think there's any reason to believe that there is. (Chomsky, 2001, p. 73)

This quote of Chomsky will be referred to a few times in the following. In my opinion its main message is not *there is no semantics*, but rather that semantics cannot be anything coming from outside the language, but can only be understood from the language structure. In this sense, it is a very structuralist statement, although Chomsky denies the fruitfulness of empirical linguistics and, as such, many structuralist attempts.

In the following, different theories of semantics that are vital to understanding computational semantics are going to be introduced shortly to an extent necessary and useful for the understanding and the argumentation in the following chapters of this thesis.

This is not an introduction to semantics. In this sense, this section does neither aim at an as-broad-as-possible overview, nor is the chronological order of the development of these theories very important. Hence the subsections are arranged in a logical order.

Starting from the quote above, the first theory to be introduced very shortly here is formal or Montague semantics. It is the attempt to translate natural language into a logical form. A phrase like

(1) fierce black cat

corresponds to a logical form like

(2) $\lambda x[fierce(x) \wedge black(x) \wedge cat(x)]$

which means that the entity x is fierce, black, and a cat (cf. Copestake *et al.*, 2005, p. 284). Predicate logics can be used to formalize all kinds of relations, not only relations expressed in natural language. For example, if the cat had a name, this could be represented using a relation *hasName* as shown in Example 3.

(3) $\exists x[cat(x) \wedge hasName(x, Anton)]$

While complete semantic parsing, based on predicate logics, is for many reason not possible, among them the incompleteness of Montague Semantics (i.e., its inability to account for more than a snippet or natural English), the more simplistic approach of semantic role labeling is often applied to parse sentences and to derive logical relations from the syntactic structure of natural language.[23] These relations are of special interest in NLP, both in parsing texts as well as in ontologies. When parsing natural language texts, often a more simplistic representation is chosen. A possible logical form for Example 4[24] is given in Example 5, which also corresponds to the dependency structure of the sentence.

(4) Julius gave Anne a rose.

(5) give(Julius, Anne, a rose)

Example 5 shows a *give* relation (predicate) with three arguments for the agent (subject), recipient (indirect object), and the theme (direct object). The semantic role has to be distinguished from the grammatical or syntactical role. This very basic, compared to a full logical analysis, assumption of semantic roles is in fact being applied in NLP quite regularly (cf. Jaworski and Przepiórkowski, 2014; Lally *et al.*, 2012)

The logic-based approach to derive meaning from syntax, and thereby showing the strong relationship between both, is a very effective tool to describe the semantics of a complex phrase. But it stops at a very basic point: the words or lexical units. Formal semantics can show how different parts of phrases are combined and how the compositionality constructs meaning, but it does not describe the meaning of any lexical unit. What or who are *Julius* and *Anne*, what is *to give* and what is *a rose*? And of course a word like *love* does not receive its meaning from the syntactical structure but rather from its paradigmatic relations.

While the main contributions to formal semantics were made in the Anglo-American research community, the structuralism of Europe developed a different concept of describing meaning during the last century. These theories, among others, are to be presented in the following since there is a direct link between how natural language semantics is treated and how ontologies work.

[23] Lohnstein (2011) shows and explains what he calls the isomorphism between syntactic and semantic structures ("...Isomorphie zwischen syntaktischen und semantischen Strukturen") (Lohnstein, 2011, p. 153).

[24] This example is taken from Wittenberg *et al.* (2014).

3.1 Frame Semantics and Encyclopedic Knowledge

> "[E]verything you know about the concept is part of its meaning .... From this it follows that there is no essential difference between (linguistic) semantic representation and (general) knowledge representation" (Croft and Cruse, 1993, p. 336f).

Frame semantics takes a very broad concept of meaning. Unlike other approaches that are to be discussed later on in this chapter, frame semantics explicitly includes non-linguistic knowledge, world knowledge or general knowledge, of concepts into the representation of the concept's meaning. This is for one meant to be close to the meaning representation humans have of concepts, words, or facts, as well as to be a base for AI, where the understanding of human utterances makes knowledge about concepts important. Therefore, researchers from cognitive linguists, like Fillmore (1975), as well as computer scientists, such as Minsky (1974), contributed to this theory of semantics.

Fillmore distinguishes between a scene and a frame, where the scene is the situation itself, and the frame makes up for the linguistic material available or connected to that scene (cf. Fillmore, 1975, 1977). The frame or domain is nothing that necessarily exists in the language itself. It is derived from experience and can be seen as the (non-linguistic) context of a word. Fillmore states that

> frames and scenes, in the mind of a person who has learned the associations between them, activate each other; and that furthermore frames are associated in memory with other frames by virtue of their shared linguistic material, and that scenes are associated with other scenes by virtue of sameness or similarity of the entities or relations or substances in them, or their contexts of occurrence. (Fillmore, 1975, p. 124)

For example, when in a garage, both speaker and listener have frames of cars and tools associated with the scene (garage) that can be used; for example, cars have engines, they drive fast, and much more.

Fillmore proposes his frame theory as an "integrated view of language structure, language behavior, language comprehension, language change, and language acquisition" (Fillmore, 1977, p. 55); in fact he gives detailed examples from those fields, as well as from issues of language translation that cannot be repeated here.

The frame, the base, itself gives meaning to the unit. If one understands the scene, the event, or activity in question, "then, given that knowledge, we can know exactly what the vocabulary pertaining to that semantic domain means" (Fillmore, 1977, p. 60). The scene itself is independent of the frame and the lexical material. When a child learns a new word within a frame, the scene does not alter, only the associated frame is changed (cf. Fillmore, 1977, p. 66).

Langacker (1987) refines Fillmore's notion of the frame, such that the "semantic value of a symbolic expression is given only by the base and profile together" (Langacker, 1987, p. 187). The profile is "a substructure of designation" (Langacker, 1987, p. 183); it is what distinguishes a word from others connected to the same base/domain/frame.

One often finds network-related terms in cognitive linguistics and especially in the field of frame semantics: "[a]lthough in theory all knowledge about an entity is accessible – that is, the whole knowledge network is accessible – some knowledge is more central ..., and the pattern of centrality and peripherality is a major part of what distinguishes the meaning of one word from that of another" (Croft and Cruse, 1993, p. 337). Frame theory is based on a supposed understanding of the neural network of the human brain, although this might "sound like extremely naive psychology" (Fillmore, 1975, p. 124). Minsky's early work is highly influenced by the metaphor of *network*. Therefore it seems unsurprising that there is a straight line from the notion of frames to that of networks and ontologies representing general knowledge used in NLP today.

As mentioned above, the knowledge represented by a frame is not entirely linguistic, as well as contains general knowledge or knowledge derived from experience. It is no coincidence that Minsky was involved in establishing this theory. From his background in AI he realized that a lexical resource to be used in AI needs to be more than a dictionary. If a machine is to understand language (i.e., complex sentences, texts, and discourses) it needs knowledge beyond linguistic knowledge of the single words. Text and language understanding is more then parsing syntactic structures; it is more than understanding grammatical relations or dependencies. It is even more than the understanding of basic lexical units, the words of a language. In today's state-of-the-art NLP systems, a number of different resources are used. Besides linguistic ontologies like WordNet, different general knowledge ontologies are used to understand statements, or to find answers to questions. There is a straight line from the notion of the frame to these ontologies. In Chp. 6, DBpedia, an ontology often used in NLP tasks, covering different real-world concepts, persons, and places, will be introduced, analyzed, and extended.

3.2 Field Theories

Jost Trier first famously described a concept he called *Wortfeld*. *Wortfeld* is often translated as *semantic field*. Geckeler (1982, p. 89) argues that the English term *semantic field* and the French term *champ sémantique*, are not very good translations. Since the term *semantic* does not solely refer to the lexical dimension of meaning. Therefore, he prefers the terms *lexical field* and *champ lexical* (Geckeler, 1982, p. 85). Although this distinction does not seem to be universally accepted and the term semantic field is still used to refer to the German *Wortfeld*, I will use *lexical field* in this context.

A lexical field contains semantically related lexical units. Words in a lexical field can replace each other in a paradigm, but differ from each other semantically in one way or another. They have distinguishing semantic features, later called semes. Trier (1931) gave his prominent example of a lexical field study using the Middle High German *wîsheit*. His diachronic study compares the field at a first state around 1200 and a second state around 1300. While *wîsheit* is the superordinate of *kunst* and *list* around 1200, the field changes over time and in the 1300s, *wîsheit*, *kunst*, and *wissen* make up the field, but *wîsheit* no longer includes the other members of the field (see Table 1).

In the first state *wîsheit* (knowledge) is the hypernym of *kunst* (courtly knowledge) and *list* (other knowledge). In the work of Meister Eckhart around 1300, the field has changed: *wîsheit* (closer to the modern German *Weisheit* (wisdom); especially in a mystical and religious sense), *kunst* (art), and *wizzen* (knowledge) are now members of the field. The word *list* shifted closer to its modern meaning (cunning).

Table 1: Lexical field *wîsheit*. Left: ca. 1200; right: ca. 1300.

wîsheit	
kunst	*list*

wîsheit
kunst
wizzen

Trier states that the meaning of a word depends on its neighbors in the field (Trier, 1931, p. 3); the position of the word in a field determines its meaning. The user's knowledge of the composition of the field affects his or her understanding of the word. In Trier's understanding, the members of a field are like a mosaic: only by *seeing* all members of a field can one grasp the whole meaning.

Geckeler (1982, p. 199) names the most important properties of a lexical field:

- Lexical fields are not taxonomies.
- The distinguishing traits of the members of a field do not have to be evident in the things themselves. This is especially true for adjectives such as *young/old*, *beautiful/ugly*, and so on.
- Lexical fields do not consist of associations.
- The fields do not depend on the usage of a word.

Lexical fields consist not only of similar or nearly synonymous words but also of antonymous pairs of words. What the members of fields do have in common is a mutual semantic trait. *Young/old* denote the age of a person, *beautiful/ugly* appearance. In the structural analysis of a lexical field, three terms are of special relevance: *lexeme*, *archilexeme*, and *seme*. Lexeme corresponds to the (simple) words as the units of a language. The archilexeme is the head of a lexical field. Lexemes in a lexical field are distinguished by semantic features, the semes. The seme is a distinguishing trait of a lexeme.

Examining the semes of the lexemes of a field is called a componential analysis. Pottier (1978, p. 404) defines the difference between a *chair* and a *stool* as the existence or non-existence of a back.

Table 2: Componential analysis of seats (Pottier, 1978, p. 404).

Seme / **Lexeme**	**Used for Sitting**	**On legs**	**With a Back**
Chair	+	+	+
Stool	+	+	−

The archilexeme of the lexical field is *seats*, the members of the field are the lexemes. The seme *used for sitting* can be called an *archiseme*. Both words in the example above share the semes *used for sitting* and *on legs*. *Existence of a back* can be seen as a differentiating seme in the lexical field of seating.

One problem with the seme analysis is the question of where these distinctions arise from. The idea was taken from phonology, where a phoneme is the smallest, possibly

meaning-changing unit of the language. In phonology this distinction arises from the language itself.

What do *chair* and *stool* have in common that allows them to be members of the same field? The componential analysis assumes that there is some common semantic trait, here that the object is made for *sitting*, and that there are fine-grained differences between the words that distinguishes them from each other: they stand in opposition to each other in a paradigm. This analysis, of course, seems to be mainly extra-linguistic: There is nothing *having-a-back-like* about the word *chair* that distinguishes it from *stool*. The distinction is rather found on the signifieds than on the signifiers. This of course does not do right to the structuralist claim of how linguistics should be done. Or as Lyons (1977, p. 267) put it: "What is lacking ..., as most field-theorists would probably admit, is a more explicit formulation of the criteria which define a lexical field than has yet been provided".

Despite of the justifiable criticism against lexical fields and the fact that it never found its way into the curriculum of North American linguistics, it contributed some interesting points that are still of importance today as will be shown in this and the following chapters. Not only semantic relations as well as modern ontologies are based on the ideas of Trier and others.

The dilemma of how the lexical fields are constructed, if not by opposition of semes, and by facts we know about objects, can be solved using another structuralist approach. Based on Trier's ideas and on Wittgenstein's and Harris' assumption that the usage, or the distribution, of words in the language make up the meaning, Gliozzo and Strapparava (2009) describe in great detail how to computationally construct lexical fields, which they call semantic domains, by looking at the distribution of words in large text corpora. To answer the question asked above, what *chair* and *stool* have in common – they are similar in the sense that they share very similar contexts in speech, or that they are, in certain contexts, interchangeable.

3.3 Distributional Semantics

> Die Bedeutung eines Wortes ist sein Gebrauch in der Sprache. (PU §43 [Ludwig Wittgenstein: Philosophische Untersuchungen,. 1953])[25]

These words of Wittgenstein are supposedly the most often cited reference when intro-

[25] *The meaning of a word is its use in the language* (translated by the author).

ducing the notion of distributional semantics. The sentence itself remains a little vague. But Wittgenstein continues to ask:

> Aber besteht der gleiche Sinn der Sätze nicht in ihrer gleichen Verwendung? (PU §20b [Ludwig Wittgenstein: Philosophische Untersuchungen, 1953])[26]

or as Firth famously put it:

> You shall know a word by the company it keeps. (Firth, 1957, p. 11)

Wittgenstein's rhetorical question indicates that two expressions share the same meaning if they are interchangeable. Firth shows that it is the context of an expression that indicates its meaning. Hence, one can conclude that two words that share a similar environment are likely to share a similar meaning as well. Most researchers account the notion of distribution in the sense used here to Harris (1968). Harris analyzes language on a purely distributional basis, and in a way his conclusions remind one in a strange way of Chomsky when Harris states that "it frequently happens that when we do not rest with the explanation that something is due to meaning, we discover that it has a formal regularity of 'explanation'." (Harris, 1968, p. 785). This is close to Chomsky's opinion on semantics that the main transmission of meaning does not lie in an inexplicable and obscure *meaning*, but in structural findings; here the distribution of words.[27]

Miller and Charles (1991) define semantic similarity as follows: "the more often two words can be substituted into the same contexts the more similar in meaning they are" (Miller and Charles, 1991, p. 1).

This does not mean, however, that two words that are being substituted on a regular basis are synonymous. Far from that, phrases such as the following do not indicate that *good*, *tasty*, *spicy*, and *bad* are synonyms.

(6) *good food*

(7) *tasty food*

(8) *spicy food*

[26] *But does not the equality of meaning of the sentences exist in their equal use?* (translated by the author).

[27] Still, Chomsky explicitly neglects corpus-based, empirical, and hence distributional approaches to linguistics. Chomsky writes: "I think that we are forced to conclude that grammar is autonomous and independent of meaning, and that probabilistic models give no particular insight into some of the basic problems of syntactic structure" (Chomsky, 1957, p. 17) and in an interview he even says: "Corpus linguistics doesn't mean anything" (Andor, 2004, p. 97).

(9) *bad food*

They show a range of different relations from partly synonymous (Example 6 and Example 7) to antonymous (Example 6 and Example 9, or Example 7 and Example 9).

Of the theories presented here, distributional semantics is closest to what is called structuralism. Looking at the syntagmatic relations of a word, presuming the text corpus is large enough, gives hints about its paradigmatic relations. The adjectives {*good, tasty, spicy, bad*} are paradigmatically related and can, depending on the context, substitute each other. All these adjectives stand in syntagmatic relations with *food* and in paradigmatic opposition with each other.

Looking at a word in a large corpus, its occurrences, or more exactly its co-occurrences, with other words are counted. Assuming the examples above to be our corpus, a possible word co-occurrence matrix is shown in Table 3.

Table 3: Exemplary co-occurrence matrix.

	good	tasty	spicy	bad	food
good	0	0	0	0	1
tasty	0	0	0	0	1
spicy	0	0	0	0	1
bad	0	0	0	0	1
food	1	1	1	1	0

This simplistic approach, Boolean values to indicate if words co-occur, is seldom utilized. One can also count the absolute number of co-occurrence to weight the connection between two words. The window of words taken into account (i.e., the number of neighbors to the right or to the left) can be set higher than 1. Other approaches do not look at the direct co-occurrence, but at syntactic relations between words by parsing the sentences (Pado, 2002; Padó, 2007).

The distance between two words can be used to weight the co-occurrence. Also, more elaborated statistical measures (e.g., the log likelihood (G^2) (Dunning, 1993) to find only significant co-occurrences) have been proposed and employed to identify significant word pairs (cf. Biemann and Quasthoff, 2009).

The co-occurrence matrix in Table 3 can be read and interpreted in the same way the network matrices have been treated before. Each row or column corresponds to one

word and its neighbors in the word network. In this case the matrix forms a graph where the word *food* is connected to each of the adjectives by one edge. Words with similar syntagmatic relations would have the same neighbors and hence be similar. The paradigmatically related words are those that have many common neighbors in the graph. Adjectives like those in the examples above are similar to a certain degree because they are interchangeable and have similar syntagmatic relations. Another very common way of treating the co-occurrences of a word in computational semantics is a vector model. Looking at only one row of the matrix, one gets the word vector in Table 4. Therefore, both approaches, networks and word vectors, are basically identical. Both approaches of course offer different means of computing, for example, the similarity. It has to be mentioned that word vectors usually start at this point and that more sophisticated (similarity) measures are applied to form the actual word vector (e.g., in latent semantic analysis (LSA)).

Table 4: Exemplary word vector: food.

	good	tasty	spicy	bad	food
food	1	1	1	1	0

Given a word like *food*, one could expect that a partly synonymous word like *dish* would have a similar pattern of connection in the network, as well as having a very similar vector to that of *food* seen above. If words share only very few, statistically insignificant, or no connections, they are not similar.

For word vectors of cities and countries it has been found that these vectors are, to some degree, compositional. For example, Mikolov *et al.* (2013, p. 7) show that, given word vectors for *Paris* ($\vec{P}$), *France* ($\vec{F}$), *Rome* ($\vec{R}$), and *Italy* ($\vec{I}$), it holds: $\vec{P} - \vec{F} + \vec{I} \approx \vec{R}$. This means, the word vector of *Paris* minus the word vector of *France* is very similar to the word vector of *Rome* minus the word vector of *Italy*. This shows that there is more similarity between *Paris* and *Rome* than just being a large European city: Both are their nation's capital. The similarity of these vectors or the connectedness of words in a network is a very useful finding for NLP tasks such as part-of-speech (POS) tagging since words of the same paradigm share the same POS. Biemann (2009) and Biemann and Riedl (2013) show how the distribution of words can be used to build and improve,

respectively, POS taggers. Knowing that a word that is not in the vocabulary of a POS tagger is distributionally similar to a known word allows one to assign the same POS to the out-of-vocabulary word (Biemann and Riedl, 2013). The approach presented in Biemann (2009) is solely based on distribution and shows that the distribution allows for very fine distinctions of POS. The adjectives in examples 6 to 9 can be expected to be the neighbors of both *food* and *dish*, and in fact both words are of the same POS. Furthermore, Biemann (2009) shows that it is possible to distinguish between female and male first names. Also the author is able to form clusters of similar words (e.g., the city names used in the example above). The finding that names form clusters, allows to be used for named entity recognition and tagging. A great part of the work done on semantic networks in recent years was undertaken on distributional data. Many findings that were made in different kinds of networks, among them the lexical networks presented here, will be used and be ported to applications in ontologies.

Only quite recently has distributed computing (i.e., the usage of a cluster of personal computers) made distributional analysis of huge text corpora possible without the need of having a super computer. Huge text corpus here means at least a few million sentences that are processed and analyzed. Only such large numbers of sentences make the assumptions taken from them meaningful.

Unlike ontologies and other hand-crafted resources, distributional semantics is what is called knowledge free: It does not reside on *a priori* information. While it is much more computationally intensive, it requires less human work to analyze huge amounts of texts statistically. Still, the results are not yet as accurate as man-made resources, as will be shown later on. Despite its accordance with the requirements of structuralism, distributional semantics differs from even the structuralist approaches presented earlier. Unlike semantic fields, it is heavily based on empiricism and includes paradigmatic as well syntagmatic relations. The distinction between the kinds of relations that exist between the words (i.e., the semantic relations) is still an open problem; also some experiments show that a distinction between different relations should be possible (Erk and Padó, 2008; Mikolov *et al.*, 2013; Socher *et al.*, 2013). The negation of words (e.g., *bad* versus *not bad* versus *not not bad*) and their representation in a vector model are problematic. Or in general the question "how textual logic would best be represented in a continuous vector space model remains an open problem" (Hermann *et al.*, 2013, p. 74f.).

In comparison to frame semantics, distributional semantics does not at all include extra-linguistic knowledge. As Harris formulates it, the co-occurrences of a word "may

still be 'due to meaning' in one sense, but it accords with a distributional regularity" (Harris, 1968, p. 785). All the vagueness of semantic fields and frames is avoided; only empirical distributional regularities remain.

3.4 Semantic Relations

The distributional approach connects words both in a syntagmatic way, the neighbors in the network, as well as in a paradigmatic way, words with a similar pattern of connectivity. It does not specify how the relation between two words is exactly, only in terms of similarity. The following chapter will shortly recap the basic semantic relations, especially those that are going to be of interest when examining ontologies, i.e., those relations realized in WordNet and other ontologies. Because they will be discussed in more detail, especially with regards to the specific implementation within WordNet in Chp. 5, only a very short overview will be given here.

3.4.1 Synonymy

Synonymy as the total semantic identity of two words is a very rare feature. Different words hardly ever mean exactly the same in all contexts of a natural language.[28] Cruse (1986, p. 88) defines cognitive synonymy of X and Y if both are syntactically identical and any sentence S containing X has equivalent truth conditions to an identical sentence S^1 where X is replaced by Y.

Even though *big* and *large* can substitute each other in some contexts, they cannot substitute each other in every context. While a *big boy* is a boy that is behaving like an adult, a *large boy* is an overweight boy. *Big/large* are therefore only partly synonymous.

3.4.2 Hyponymy

The relations of *hypernymy* (token > type relation) and its inverse *hyponymy* (type < token relation) are hierarchical relations, or, in terms of set theory, relations of inclusion. A hypernym includes all its hyponyms. A is the hypernym of B ($A \supset B$) if B is a hyponym of A ($B \subset A$). For example, *tree* is a hypernym of *oak* and *oak* is a hyponym of *tree*. The set of all trees also includes *cherry*, *linden*, and other kinds of trees. All these

[28] Technical vocabulary and scientific language as special forms of a language are exceptions.

trees are co-hyponyms; they share the same hypernym. Most hypernym–hyponym pairs make up a *taxonomy*.

The hyponymy relation is sometimes called a *kind-of* relation. As Löbner (2003, p. 133) states in his introduction to semantics, a car is a type of *(motor) vehicle*, but a boy is not a type of child. Cruse (2000, p. 152) illustrates some problems arising when hyponymy is defined as *X is a kind/type/sort of Y*. When saying *a kitten is a sort/type/kind of cat*, Cruse argues, this sounds rather odd. He therefore tries to find definitions of hyponymy aside the inclusion definitions given above.

In computational approaches, hyponymy is often called a $IS-A$ relation. If we apply the $IS-A$ relation to *kitten/cat*, this problem does not arise at all. It is perfectly fine to say that a *kitten is a cat* or a *boy is a child*. A quite regular case of hyponym–hypernym pairs is that of the endocentric compounds, where the compound is a hyponym of the head of the compound (e.g., a *lifeboat* is a kind of *boat*)[29].

3.4.3 Meronymy

A related concept is the *meronymy* relation, or part–whole relation. A meronym A of B is not a hierarchical subconcept of B, but a part of B itself. A *hand* has *fingers* and a *palm*. The inverse relation is called a *holonym*. Concept B does not logically include A; it is more of the physical constitution or definition of B to include A. Computationally, especially with respect to ontologies, this relation is often included in the $HAS-A$ or a $PART-OF$ relation. We speak of meronymy only if both relations apply. As Cruse (1986, p. 161) shows, a *wife has a husband* and *changing diapers is part of being a mother* do not indicate a meronymy relation. Only if both conditions are satisfied do we speak of meronymy: *A hand has a finger*, and *a finger is part of a hand*.

3.4.4 Antonymy and Opposition

Antonymous words are mutually exclusive and mark points of a scale, like *large* and *small*. We call this opposition *antonymy*. Two expressions are contradictory if "the truth of one implies the falsity of the other and [...] contrary if only one proposition can be true but both can be false" (Fellbaum *et al.*, 1990, p. 29). Logically incompatible, antonymous word pairs are not necessarily complementary, meaning that the negation of one does not

[29]Of course there are many exceptions, where a compound's meaning is not directly derived from its parts. A *skinhead* is not special form of a head

equal its antonym. *Not large* is not the same as *small* but can also lie in between these two on a scale (cf. Löbner, 2003, p. 124); the words are bi-polar. The negated form does not inevitably "express the opposite value of an attribute but something like 'everything else' " (Fellbaum *et al.*, 1990, p. 35).

Lyons (1977, p. 286) states that the opposition of two words arises from "some dimension of similarity", meaning that only two words that are similar up to a certain point, and are different from each other in one property, can be antonymous. Murphy (2003, p. 170) says that in antonymy "only one relevant property of the words is contrasted". Both *brother* and *sister* denote a sibling. The only difference is the gender of the sibling referred to[30]. This can be called a *binary semantic property* (see Table 5). Both words are *semantically complementary*. They are not the opposite of each other, but complementary and exclusive.

Table 5: Binary semantic property of siblings.

Expression	**Sibling**	**Female**
brother	+	−
sister	+	+

As Murphy (2003, p. 167) puts it: "The boundary between synonymy and antonymy is not always so clear". She states that antonyms are co-hyponyms with exclusive senses, while (near-)synonymous words are co-hyponyms with similar or "overlapping senses" (Murphy, 2003, p. 167).

Fellbaum (1995) shows that semantically related words across part of speech (POS) also co-occur at very a high rate. A word pair like *dead* (noun) and *live* (verb) co-occur more often than the antonym pair *live/die*. This shows that there is of course a semantic relation between both concepts and that lexical entities from different POS are being used contrastively. From a semantic point of view, leaving out the paradigmatic or grammatical level, the relation between words across different POS is just as strong as those of the same POS. Still, this effect should not be confused with antonymy.

In a NLP context, one would still be interested in the information that the pair *dead/live* describes a kind of opposition.

[30]This kind of antonymy is called a relational antonymy.

3.5 Ontologies

3.5.1 Conception

Unlike in *metaphysics* in philosophy, the term ontology in the context of information and computer sciences does not refer to a system that tries to explain or categorize everything-that-is in one coherent scheme. Instead the term refers to a system describing special relations or meaning in a concrete domain, based on ideas taken from early semantic networks as they have been introduced in Chp. 2.2. Furthermore, ontologies are closely related to lexical fields and frame semantics.

An often cited definition of an ontology states that an ontology is an "explicit specification of a conceptualization" (Gruber, 1993). This definition has been criticized for being overly broad (e.g., by Smith and Welty (2001)), and, at the same time, for excluding especially some linguistic ontologies (i.e., WordNet (Stuckenschmidt, 2009)). To understand the definition one has to also define what *explicit specification* and *conceptualization* are.

Taking these critiques into account, Gruber later defines ontologies in the context of information sciences as

> a set of representational primitives with which to model a domain of knowledge or discourse. The representational primitives are typically classes (or sets), attributes (or properties), and relationships (or relations among class members). The definitions of the representational primitives include information about their meaning and constraints on their logically consistent application (Gruber, 2009).

This second definition gives some clues about the way an ontology formalizes knowledge. Classes, attributes, and properties are used to build a consistent system of knowledge that is logically connected. If such a system is treated as an *open world*, it is said to be incomplete: Not every existing entity, relation, or class has to be modeled in the ontology. Non-existence in the ontology is no proof of falsehood. Entities of an ontology may as well have other neither explicitly, nor implicitly, mentioned properties.

The *closed-world* assumption means that what is not existent in the model is treated as false (Stuckenschmidt, 2009, p. 35). The ontologies that are going to be examined in this thesis are open-world ontologies. They are incomplete but can be extended by new elements.

The objects an ontology describes are called instances or entities. Instances are members of a class. Classes are defined as having special attributes or properties. They are ordered hierarchically. Child classes inherit properties of their parent class. A class can have different attributes which might be used to describe the instances of a class. If we imagine a class *mammal*, all child classes and all their instances share some common attributes: Their offspring is born alive, they have skin, and fur or hair. But child classes might have special properties. Felines have four feet, fur and so on, while the members of the class *Homo sapiens* walk upright on two feet and have a mostly hairless or at least furless skin. One instance of *Homo sapiens* might have the name *Peter*. It has a birthday, hair color, address, sex, and more properties that distinguish this instance from others of the same class.

Instances can be members of different classes or, in terms of set theory, members of different sets. Set theoretical concepts (e.g., the inclusion, union, intersection, and so on) form the basis of ontology formalization.

3.5.2 Ontology Formalizations

Ontologies can be formalized in different ways. The membership of an instance to a class, or of a class to a parent class, might be expressed using sets. Relationships between classes or instances, properties, and attributes, as well as inheritance and hierarchy can be described using description logics. Standard notations such as the Resource Description Framework (RDF) or the Web Ontology Language (OWL) can be used to write description logic equivalent statements in the form of an XML notation. The following chapters give a short overview of those formalisms.

3.5.2.1 Description Logics

The fundamental concepts of ontology formalization lie within the so-called description logics (DL). DL are a defined subset of predicate logic expressions. They can be defined to be more or less expressive, depending on the application (cf. Nardi and Brachman, 2003, p. 7). DL are a family of knowledge representation formalisms

> that represent the knowledge of an application domain (the 'world') by first defining the relevant concepts of the domain (its terminology), and then using

> these concepts to specify properties of objects and individuals occurring in the domain (the world description) (Baader and Nutt, 2003, p. 47).

The formalization of a domain (e.g., classes, relations or hierarchies) is called the DL TBox (*terminological box*) while the data is called ABox (*assertional box*) (cf. Nardi and Brachman, 2003, p. 17). The TBox is intensional. This information does not change. The ABox describes objects, i.e., their concrete relations or attributes. New information might be added to an ABox.

The most basic relations in a DL are those of set theory (e.g., the inclusion ($A \subseteq B$) or equivalence ($A \equiv B$)). A can be defined as atomic concept B as happened here, or the right side of the equation could be a complex logical expression. In this fashion, definitions of the TBox are specified.

An ABox consists of expressions on entities or individuals. For example, an entity (e) can be assigned to a class (C) $e : C$. Given that a relation `bandMember` was defined in the TBox, the expression in Ex. 10 and Example 11 can be made. The examples are taken from the data set of DBpedia and have been translated to a possible DL expression.

(10) bandMember(The_Beatles, Paul_McCartney)

(11) bandMember(The_Beatles, John_Lennon)

The information that both musicians played in the same band should be automatically available through reasoning. Later we will come back to the complex of inference when it comes to link predictions in large networks built from ontology data, the ABox.

Table 6 gives a brief overview of possible DL notations. Some of these notations have direct equivalents in the semantic relations that were shown before. The subset/superset ($\subseteq$ / $\supseteq$) correspond to hyponymy and hypernymy. The equivalence ($\equiv$) is similar to synonymy.[31] It has already been explained that the antonym of an expression is not necessarily its negation ($\neg$). But antonyms are mutually exclusive. An entity is either a member of the set *uncle* (U) or of the set *aunt* (A): $U \vee A$.

The universal restriction ($\forall$) can be used to assign some property to every member of a class (e.g., every person has a name), while the existential restriction ($\exists$) is used to allow an entity to have a value (e.g., an academic title) without saying that every instance has to have one. Using this set of notions, other, more sophisticated relations between entities or classes, such as meronymy, can be defined and used in an ontology.

[31] In Chp. 5, I will claim that the synonymy relation in WordNet actually defines an equivalence.

Table 6: Logical operators, restrictions, and set theoretic expressions used in description logics.

$\forall$	universal restriction: $\forall x$, for all x
$\exists$	existential restriction: $\exists x$, there is at least one x
$\neg$	negation (non)
$\wedge$	conjunction (et)
$\vee$	disjunction (vel)
$\cap$	intersection
$\cup$	union
$\subseteq$ / $\supseteq$	subset/superset
$\equiv$	equivalence
:	assertion

The more expressive a DL is, the more complex, or even impossible is the reasoning. DL are based on the *open-world assumption* (i.e., concepts that cannot be found in an ontology), or information missing in a data set is not necessarily *false*. Other information might exist that just has not been formalized. Reasoning on data makes some implicit information accessible.

3.5.2.2 RDF

The *Resource Description Framework* (RDF) is a World Wide Web Consortium (W3C) specification for the description of any kind of resource. A resource can be a website, a web service, as well as other resources like physical objects of the real world. It is a description framework (i.e., a set of terms used to describe objects) "for describing just about anything" (McBride, 2004, p. 51).

The description principle of RDF is a directed graph. Directed graphs have been examined in Chp. 2. To reference the objects that are being described, *universal resource identifiers* (URIs) are used. The most widely known examples are web addresses. URIs consist of a *schema* (e.g., *http*), an *authority* (e.g., *w3c.org*), a path, the simplest being */*, and optional *query* or *fragment*. In the case of a web address, the URI references exactly one website (cf. Berners-Lee, 1994). Full URIs can be seen in Listing 1.

In the ontologies that are examined in this thesis, URIs are used to reference objects,

such as persons, institutions, and concepts, as well as their descriptions. Objects are linked using attributes. But attributes can also take *literal* or *numerical* values.

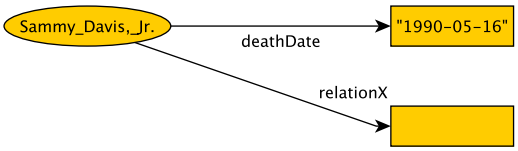


Figure 12: An exemplary RDF graph.

This can be seen in Fig. 12. The elliptic nodes, labeled by URIs, represent resources. The edges stand for attributes or relations labeled as well by a URI. The rectangular nodes stand for literal values. Empty nodes are equivalent to the ∃-quantor in predicate logic: There is at least one, not further defined, value or object in this relation. The different types of nodes are going to be of importance to distinguish when it comes to predicting relations in an ontology. Literal values and empty nodes might not be of great interest or use in the predictions of new attributes of a given object. As seen in Fig. 12, literal values such as the population of a city or country or the age or birthday of a person are likely to contain special values that are not common to, or shared by, a cluster of elements. The graphical representation in the form of a graph (see Fig. 12) is not the only possible formalization of RDF data.

The description framework consists of terms to describe relations between objects. RDF has several possible formal description languages. The two most important notations in the context of this thesis are N-triples and the RDF/XML notation.[32] N-triples consist of three elements, in this case URIs (see Listing 1).

Listing 1: N-Triple taken from DBpedia

```
<http://dbpedia.org/resource/Sammy_Davis,_Jr.>
      <http://dbpedia.org/property/deathDate>
"1990-05-16"
```

The first refers to the object that is being described. The second refers to the relation that exists between the first object and the third element in the triple. In this case the third element is not a URI-referenced object like the first or the second, but a literal value. N-triples are widely used to exchange resource descriptions or the ABox of a DL. Lists of such triples make up the data of DBpedia (see Chp. 6).

[32]Many other ways to formalize RDF exist that cannot be presented here.

The RDF/XML notation describes the same relation between two objects but makes use of the *Extensible Markup Language* (XML). The syntax is more sophisticated and can be processed by widely used XML processors. XML is often used to exchange data between different systems. Not the whole expressibility of RDF/XML can be discussed here. For further information see (e.g., Carroll and Klyne (2004)).

RDF is capable of describing concrete objects or abstract ideas, but it cannot be used to describe a domain or knowledge in the way ontologies do. RDF is therefore not an adequate instrument to model ontologies, but rather to describe relations. An extension of RDF called RDFS solves some problems that occur when using RDF. It adds the possibility to declare subsets of classes and the use of negation (cf. McBride, 2004, p. 63). Still, more expressiveness is needed to formalize description logics. Some of these shortcomings were resolved with the development of OWL.

3.5.2.3 OWL – Web Ontology Language

To make full use of the expressiveness of descriptions logics, the *Web Ontology Language* (OWL) was developed. Usually, OWL is written in an XML notation.

Among OWL's distinct expressions are the possibility to declare properties that may exist only between objects of some defined classes (Antoniou and Harmelen, 2003, p. 92). Given the relations seen in examples 10 and 11, the restriction to a relation $bandMember(x, y)$ is that x is in fact a member of the class $Band$ ($x : Band$), and that y is a *person* ($y : Person$). The first is called a relation's *domain*, the latter is called the *range*.

Classes can be *disjoint*, meaning that there cannot exist objects that are members of both classes A and B, or, in other words, the intersection $A \cap B$ is empty. For example, the set of male and female members of a group have no intersection and are disjoint. Disjointness implies that the intersection is an empty set, but an empty intersection does not imply the disjointness of two sets.

Similarly, OWL allows one to define subsets ($A \subset B$) and unions ($A \cup B$). Properties can also be defined to have a special data type.

OWL is defined in three versions, each with its own level of expressiveness: *OWL Full* is a superset of *OWL DL*, which is itself a superset of *OWL Lite*. *OWL Full* is hence the most expressive variant of OWL, and it is undecidable. The subset *OWL DL* is a version that is based on description logics. It is decidable and there are reasoning algorithms that work with *OWL DL*. *OWL Lite* was intended as a much simpler version of OWL. Still, it

has been shown that it is in fact just as expressive as *OWL DL* (Grau *et al.*, 2008).

In the context of this thesis, it is relevant to know that there are differences between RDF and OWL, especially those described above, and that OWL can be used as an ontology language to define the terminology of an ontology (TBox), while RDF is in this context mostly used to define relations between entities or classes that are defined in an ontology (ABox).

As one can easily see from the descriptions above, the relations used in RDF that are defined in an ontology using OWL make up not only a graph as well as a network of entities and their properties and relations.

The ABox of an ontology is made up by directed triples, describing relations between one entity and another entity or describing a property of an entity. Looking at Listing 1 above, one could also think of a triple as describing a graph. In the graph notation, the first and the third element each refer to a vertex of the graph. As mentioned before, a graph can be written as an edge list. For example, given two vertices v_1 and v_2 that are connected by an edge, the corresponding notation is $\{v_1, v_2\}$.

In case of ontology data, the triple has to be interpreted as directed. The first element points to the third element, not vice versa.

3.6 Conclusion

In Chp. 2, definitions of semantics based on a network were given that are, in many aspects, very close to what has been shown in this chapter. The idea that the meaning of a word is based on its relation to other words[33], or the word's neighbors, can be found in the distributional approaches, in frame semantics, and in lexical field theories. Trier states that "Worte im Feld stehen in gegenseitiger Abhängigkeit voneinander. Vom Gefüge des Ganzen her empfängt das Einzelwort seine inhaltliche begriffliche Bestimmtheit"[34] (Trier, 1973, p. 41). He compares the meaning of a word to a mosaic, where only the knowledge of all neighboring words gives the meaning of the word. Instead of mosaic one could also speak of a network. In a network, and in an ontology as well, the meaning of a concept or word is given by its neighbors, by the entities or vertices it is related to.

Semantic relations define how words are connected. Where the picture of the mosaic

[33]These relations, ultimately, result from the usage of the words.

[34]Translation: Words of a field stand in mutual dependency with each other. From the structure of the field the single word receives its conceptual determination.

and network only gives the fact that a relation exists, semantic relations define, similar to ontologies, how words are dependent on each other. Frame semantics furthermore states that the extra-linguistic knowledge of entities is important and tries to formalize them in a coherent way. Like formal semantics, ontologies are grounded in logics, in description logics to be precise. This reliable philosophical–mathematical framework makes ontologies very adaptive to different domains and needs, and allows one to apply logical reasoning and inference.

Ontologies are not restricted to purely intra-linguistic information, but can be open to world knowledge as has been proposed in frame semantics. Relations between entities can take different forms and further define the meaning of an entity. Synonymy, antonymy, hyponymy, meronymy are all basic relations not only in the human language as well as in the relationships between things. They are therefore commonly used in ontologies. Based on relations between entities, the data naturally forms a graph or a network.

Distributional semantics, an approach that looks at words in context (i.e., at the realization in syntagmatic and paradigmatic relations) aims to find these regularities in large amounts of data. Distributional semantics has only been recognized within the last 20 years as being very useful and is today probably the most often used approach to semantics in NLP. This is of course due to the possibilities modern computers and the Internet offer. Today it is widely used not only in state-of-the-art search engines (e.g., in the form of latent semantic analysis (LSA) (Deerwester *et al.*, 1990) as well as in a variety of other NLP tasks such as POS tagging (Biemann and Riedl, 2013), word-sense disambiguation (Biemann and Giesbrecht, 2011), and others).

Distributional semantics does not need human interaction and knowledge; it is usually referred to as knowledge free and is hence much easier to apply. Still, the results are not as semantically exact as hand-made resources. Ontologies have very exact relations and can have very fine-grained sense distinctions. But this advantage comes at a price: Creating ontologies, both the formalization and the data, is very time intensive. Therefore, the goal of this thesis is to improve existing ontologies without the need of human interaction or with only very limited interaction. For both ontologies that are to be analyzed and extended here (i.e., WordNet and DBpedia), the proposed methods are based on findings and techniques developed in social sciences, biology, and physics in recent years. These methods and ideas are to be reviewed in the following before adapting the ideas to ontologies, taking into account what has been said about graphs and networks in the chapter before. Afterwards, the two ontologies in question are analyzed first to identify possibly

missing information and, secondly, to find features that might help in identifying missing relations between two entities automatically.

4 Relation Extraction and Prediction

The structure and properties of networks, as seen in Chp. 2.1, show a special feature of networks: The information given in a network is present not only in the vertices and their edges as well as in the overall structure. A good example is the centrality measures introduced before: They are calculated by looking at least at the direct neighbors, but most of them take the whole network into account. The information given in the complexity of a network is more than the pure sum of its vertices.

The structure of networks has been used to make assumptions about the probability of the existence of non-defined edges between vertices. The information given in the graph is used to predict possible relations between two vertices that the graph, or an ontology that will be treated as a graph in the context of this thesis, does not actually represent, but that the network structure makes plausible.

This has lately been used especially in online social networks or in the context of marketing and advertisement, as will be shown in Chp. 4.2. In Chp. 4.3, I will present existing machine learning techniques to compute such probabilities, before discussing the conceptual difference between a social network and a semantic network and the implications these differences have on the methods that are to be applied to predicting links or identifying missing edges in semantic networks.

Before turning to techniques based on networks, classical text-based approaches to extending ontologies shall be discussed.

4.1 Extending Ontologies: Relation Extraction from Text

Ontology creation and development is a time-consuming, often manually undertaken, task. Enrichment and automatic extension of ontologies have therefore been a field of intense study in the last decades.

This thesis is going to focus on methods adopted from graph and network analysis and ontologies will be looked at as graphs. Still, there have been different approaches to enrich ontologies, especially semantic ontologies like WordNet.

In the following, I will evaluate existing methods of ontology enrichment through relation extraction from natural language texts. These approaches do not take the ontology (e.g., WordNet or DBpedia and its network structure) into account, but rather work with freely available texts from different domains. The methods are based on the idea that

natural language texts contain and convey knowledge in the form of (syntactic) structures and that language can be parsed, processed, and information extracted. Three related, yet quite different, approaches shall be examined here.

Hearst (1992) proposes a method to extract hyponymy–hypernymy relations from texts only taking into account the surface structure of sentences (i.e., only a shallow analysis based on POS tagging). This method is evaluated in Hearst (1998).

Lüngen and Lobin (2010) introduce a method to transform information given in table of contents to a *Multilayered Semantic Network* (MultiNet). Unlike the first approach, a deep syntactic analysis of the dependency structure is undertaken to identify entities and relations. Furthermore, the text structure and organization are taken into account.

Others, such as McCord *et al.* (2012), take parsing trees and the deep structure of sentences into account when looking for recognizable patterns to match information given in texts to semantic relations such as those of DBpedia.

Hearst (1998) presents a method she calls *lexico-syntactic pattern extraction* to find relations between words. The method is meant to support a lexicographer in his work (e.g., the developers of WordNet). The goal is to find constructions "that frequently and reliably indicate the relation of interest" (Hearst, 1992, p. 540). Hearst (1998, p. 134) gives some examples of such constructions in texts:

(12) ... works by such authors as Herrick, Goldsmith, and Shakespeare.

(13) Bruises, ..., broken bones, or other injuries

Example 12 shows a typical itemization of names that are subsumed by the preceding noun phrase (NP) *authors*. The pattern that matches such constructions is

(14) *such NP as* {*NP,* }* {*, and/or*} *NP*.

The first NP is a hypernym of the following NPs:

- $hyponym(Herrick, author)$,
- $hyponym(Goldsmith, author)$, and
- $hyponym(Shakespeare, author)$.

The pattern of interest in example 13 is of the form

(15) *NP* {*, NP*}* {*,*} *or other NP*.

The NP in the first slot are all hyponyms of the NP in the last position.[35] In total, Hearst identifies eight such patterns that unambiguously and reliably indicate a hypernymy/hyponymy relation.

One way of finding such patterns is to derive a list of words that are already connected by the relation in question in WordNet and to extract sentences from large text corpora that contain the two words. Looking at the derived sentences should give a good overview of possible constructions and hence patterns.

However, adding newly found relations to WordNet comes with some problems. Since the structure of WordNet is not word based, but rather word sense based (see Chp. 5.2 for a deeper analysis of the WordNet structure), one has to decide which one is the word sense present in the relation. The word sense has to be disambiguated to the WordNet senses. This is, as will be explained later, not an easy task. More over, if one word form does not exist, the lexicographer has to decide to what word sense (called synonymous set of short *synset*) to add this word form or to create a new synset.

Another problem arises when text genres other than encyclopedic texts are used to find new relations. Especially in newspapers, a genre for which a great amount of corpus data is available, authors often present subjective interpretations.

Hearst (1998, p. 17) found that this leads to some noise when extracting relations from newspaper articles.

The weakness of this approach lies in its inability to find patterns for relations other than hyponymy/hypernymy. Nonetheless, the method was used in the creation of WordNet and helped identify hyponymous words.

While Hearst (1998) only mentions the possibility to apply a deeper analysis, Lüngen and Lobin (2010) transfer the idea of finding patterns in language structures that indicate a certain semantic relation, not necessarily a lexical relation, to table of contents (TOC) of academic text books. They find that the hierarchical order of text structures, such as sections, paragraphs, and others, in combination with morpho-syntactic information can be used to identify semantic relations between terms in headings.

The number of possible relations identified by different patterns is quite large. The

[35] Although this notion a widely accepted in the field of natural language processing, it is probably rejected by many scientists in other fields (cf. Kripke, 1980). Hyponymy is not used in a strictly linguistic sense here. It is used to refer to a logical categorization of objects in nature. Important in the field on NLP is that a pattern like this one allows to categorize entities, here represented by proper names. It gives meaning to a proper name that otherwise to a computer is only a string of characters without any meaning.

structure of headings, especially in academic textbooks, indicates per se a hierarchical relation that also exists between the single elements of the TOC. In a first step, a number of syntactic and grammatical analyses are undertaken (e.g., lemmatization and syntactic parsing). Statistical methods can be applied to find technical terms that are specific to a domain (see bold-faced terms in Fig. 13). Between these terms, depending on the hierarchical and syntactical order, the relations are established.

Hebborn (2013, p. 204) gives the example shown in Fig. 13, where an exemplary excerpt from a TOC can be seen.

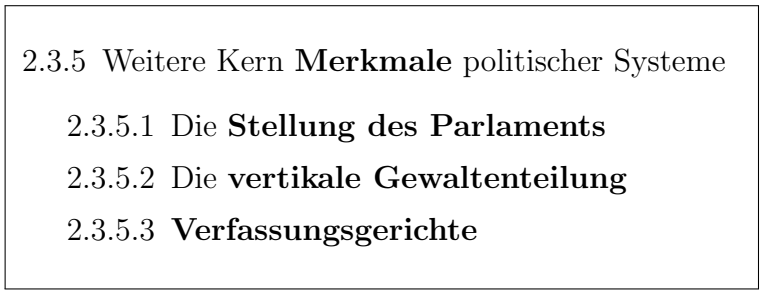


Figure 13: Sample of hierarchically structured text.

A human reader easily understands that the subordinated sections and paragraphs extend or explain the superordinate section. The terms that are related are in bold.[36]

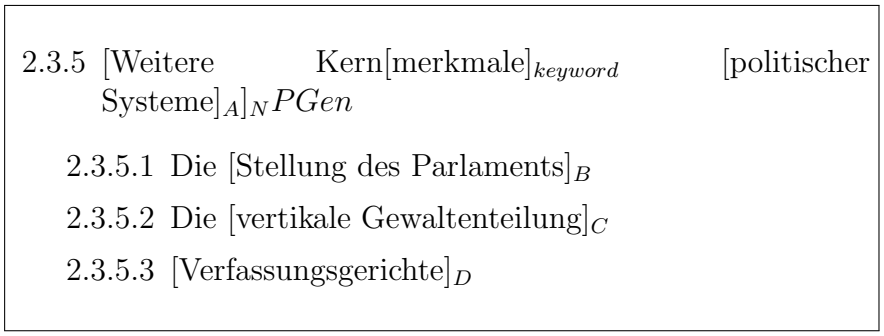


Figure 14: Sample of hierarchically structured text with marked terms.

In Fig. 14, the important elements are labeled:[37] The keyword *Merkmal* (English: property), in plural, here in the form of a compound, in the superordinate heading (*Further main properties of political systems*) is the head of a $NPGen$ (*of political systems*) along with the term A, *politischer Systeme* (*political systems*) that indicates the focus of

[36]The accentuation does not exist in the original TOC but were added by Hebborn.
[37]Based on Hebborn (2013, p. 204); extended by appropriate tags.

the following headings. The subordinate headings contain the terms $B - D$. This structure implicitly comprises relations of the kind $has(term_A, term_X)$ (e.g., *has(politisches System, Verfassungsgericht)*). The focus term in the superordinate heading is explained or extended in the subordinate headings.

This approach is very fruitful when working with general knowledge ontologies, or when creating such an ontology. The approach seems unfitting for WordNet, where a relatively small set of semantic relations exists, and where the focus is not on general knowledge terms. It could, nonetheless, be applied to DBpedia and other similar ontologies to fill existing gaps. Still, because of its relatively free use of relations, one might have to create further rules to match these relations to those defined in the ontology. An example of how to match relations given in texts to relations in an ontology will be given in the following approach.

Based on the syntactic structure of utterances, the isomorphism or parallelism between syntactic and semantic structures can be exploited to assign semantic roles to phrases. For example, in question answering (QA) systems such as the already mentioned IBM Watson, finding information on different entities is needed to understand a question and to find the appropriate answer. In IBM Watson, relation extraction is used at different points in the workflow. Watson uses, besides other knowledge sources, DBpedia.

In contrast to the approach of Hearst, deep dependency parsing in used in Watson. A parser returns a parsing tree indicating syntactic and semantic dependencies between constituents. While a solely surface analysis depends on situations where the structure of a sentence corresponds to a predefined pattern, the parsing allows one to identify entities in nested structures or complex phrases. Also multi-word tokens are easily identified as single vertices in such a dependency tree.

The parser used by IBM is a so-called slot grammar (SG) (McCord, 1980). In SG, verbs are assigned basic semantic types indicating their sense. This information is stored within the system's lexicon module (McCord, 1993, p. 127).

During the work on the Watson *Jeopardy!* challenge, the semantic type system was extended to include WordNet synset information and to match nouns to related verb frames. This can be used to define semantic relations by choosing a class of verbs or verb senses to be responsible to express the relation (McCord *et al.*, 2012, p. 5). Having a verb frame *writeVerb*, each verb belonging to this frame is expected to express a writing relation. The semantic typing system and the WordNet synsets are used to match different verbs, such as *write*, *compose*, and others, as well as constructions such as *the composer*

of to this frame that establishes an *authorOf* relation.

The dependency structure of a sentence[38] like

(16) In 1936, he wrote his last play, "The Boy David"; an actress played the title role (McCord *et al.*, 2012, p. 10).

can easily be displayed in a predicate–argument structure such as

writeVerb("he", "his last play, 'The Boy David"')[39]

while still keeping in memory the internal structure of the object phrase. The relation can be reduced to

(17) *writeVerb(he, The Boy David).*

Dissolving the pronoun to the correct entity is then the actual problem in this question-answering problem. The underlying question to answer is "Who wrote *The Boy David*?". From different ontologies as well as a large number of natural language texts that are processed in the same way as the example question above, the system tries to find the answer. It has to look for a relation like the one in Example 17, where the first slot of the relation, the *he*, is filled with the actual author name: J. M. Barrie.

These and other approaches to extending sparse information of ontologies or to analyzing relations in natural language texts are based on text corpora, i.e., external sources of information. In the following, approaches to extending networks will be presented that make no use of external knowledge but focus on the network structure itself.

4.2 Predicting Missing Links

Alternatively to the approaches mentioned so far, some recent work from the field of social network analyses (SNAs), especially link prediction and inferring missing links, will be presented and discussed. These will later on be ported and applied to extending ontologies.

Social networks are formed by (human) interaction, and they are "structures whose vertices represent people or other entities embedded in a social context, and whose edges

[38]The example might appear a little odd. This is due to the fact that IBM Watson was used to take part in the US TV show *Jeopardy!*, where the contestants have to find a fitting question to a given answer.

[39]Only the two important slots, *subj* and *obj* (i.e., direct object), are shown here; other arguments have already been removed.

represent interaction, collaboration, or influence between entities" (Liben-Nowell and Kleinberg, 2007, p. 1).

Liben-Nowell and Kleinberg (2007, p. 1) define the link-prediction problem in social networks as follows:

> Given a snapshot of a social network at time t, we seek to accurately predict the edges that will be added to the network during the interval from time t to a given future time t'.

This definition sets link prediction close to the "problem of inferring missing links from an observed network" (Liben-Nowell and Kleinberg, 2007, p. 2), and as we will see, most studies in the field do not take different time points into account but work on static networks as will be the case for the problems given in this thesis.

Link prediction in SNA has been an active field of research[40] in the last decade. Most of the link prediction studies undertaken on either Facebook, co-authorship graphs, or other social networks are pretty similar in their approach to predict unseen links and with regards to the kinds of links they predict (e.g., suggesting new friends, predicting future interactions between users, or other behaviors).

The first three approaches presented in the following are all based on the Facebook graph. They do not try to identify possible edges between existing users (i.e., vertices in the network) but predict personal information from what one likes, friends outside of the social network, or the home residence by looking at their friends' activities.[41] Afterwards, other approaches are presented that try to find missing links from networks using some heuristics based on human/social behavior or using machine learning techniques.

On Facebook the users are connected to other users, their friends, as well as to sites representing entities like companies, places, and so on that the users like. Furthermore, Facebook users are connected with properties like their age, sex, and many more.

Kosinski *et al.* (2013) examine a relatively large sample of vertices (here users and their personal information) and edges (page likes) from Facebook. From these, they remove, one after another, attributes such as the age, gender, political or religious views,

[40] A good review of methods used can be found in Sarkar *et al.* (2011).

[41] In case of the first two studies presented here one should mention that the possible threat to user's, or even non-user's, privacy was a main concern of the researchers. Others have warned about the possibility to predict the user's personality (Golbeck *et al.*, 2011) or to identify people in anonymized data (Butler, 2007). The third paper presented in this section is less critical and was published by Facebook employees. It shows what Facebook actually does with the user data.

relationship status, and sexual orientation of the users. The pages a user likes are used as features to predict the user's personal information. They further take the user's network size and density as well as information they derive from questionnaires filled out by the users into account (e.g., they estimate the user's intelligence).

The authors try to predict two different kinds of properties of a user: numerical values (density, size, intelligence, or age) and sets of dichotomous attributes, including the political view (i.e., *liberal* or *conservative*), sexuality (i.e., *heterosexual* or *homosexual*). Despite some odd findings (e.g., that liking curly fries is, according to the machine learning model they trained, a good indicator of intelligence[42]), Kosinski *et al.* (2013) are able to classify users quite well. The highest accuracy was obtained when predicting the ethnicity (95%) followed by the gender (93%) and political views (85%) as well as the sexual orientation (homosexuality of males 88%, females 75%).

To classify the numeral values, Kosinski *et al.* (2013) employ a regular regression model. To predict the other values they use a logistic regression model. Regression is, alongside other machine learning techniques, going to be explained in Chp. 4.3.

In a narrow sense, these predictions are not link predictions since they do not add or predict links between vertices (users or sites in Facebook) but predict attributes connected to the user or even attributes defined outside of Facebook (e.g., the intelligence is inferred from questionnaires the participants filled out). Information like gender, age, sexual orientation, or political views contains attributes that are present in the Facebook graph and could therefore be treated as vertices themselves. Still, this is not what this thesis is about.

Horvát *et al.* (2012) aim at a different goal. Taking a part of the Facebook graph, containing users and their friendships, plus the user's address book outside of Facebook, Horvát *et al.* predict the probability of two non-members being friends if they have common friends on Facebook. Although the accuracy is not very high, it is still higher than a baseline of randomly assigned edges (Horvát *et al.*, 2012, p. 5ff.).

The findings are, from a user's or better non-user's point of view, maybe even more alarming than the ones seen before. In this case, one can speak of a good example of the prediction of edges in a network, thereby extending it. The approach does not aim at finding links between existing vertices but at extending the network by new vertices.

As features for their prediction, Horvát *et al.* (2012) take the degree, the shortest path

[42]There is of course no significant correlation or even causality.

and few other measures into account. These measure are then used to train a random-forest classifier, and to build decision trees. This machine learning approach will also be discussed in Chp. 4.3.

A third study that is to be presented here was undertaken by three Facebook employees. Backstrom *et al.* (2010) propose an algorithm to predict "the location of an individual from a sparse set of located users with performance that exceeds IP-based geolocation" (Backstrom *et al.*, 2010, p. 61).[43] They state that about 6% of the ca. 100 million users in the US entered a home address. From these, they were able to parse about 60%. This gives about 3.5 million addresses that can be geolocated. They observed that with an increasing distance the probability of friendship decreased. This observation allows one to predict the location of users without an address on Facebook by taking into account the locations of their friends. The likelihood of one user living close to its next friends, the ones he has the most contact with, is very high and makes these predictions possible. But since this assumption only holds true for social networks, this approach is not adequate to be used to predict other relations. After looking at these possibilities to predict different features of vertices in a social network, link prediction or the identification of possibly missing edges within a social network is the main purpose of the following approaches.

Often used, or extended, is the approach of Adamic and Adar (2003) (cf. Davis *et al.*, 2011; Liben-Nowell and Kleinberg, 2007; Sarkar *et al.*, 2012; Scellato *et al.*, 2011). Adamic and Adar (2003) look at faculty home pages (i.e., personal websites of faculty members of a university), which are thought of as representing the user's social environment and can therefore be used to "learn a great deal about both virtual and real-world communities of people" (Adamic and Adar, 2003, p. 212). To build a network out of these home pages, four sources are used: the text of a home page, the out- and in-links, and mailing lists of the different departments involved. Combining these, a network structure arises that is believed to show the same clusters as the actual involvement of the persons. The network should therefore exhibit structures that arise from university department structures or from projects in different departments. The analysis was undertaken for different universities (e.g., Stanford University and Massachusetts Institute of Technology).

Looking at the in- and out-links, the mailing list membership, and the home page text, Adamic and Adar (2003) "predict whether one person is associated with another [...]. [The] matchmaking algorithm is based on the well-established result in sociology

[43]IP-based geolocation works by looking up a user's IP in a special database that returns a close approximation of the location of the user.

that friends tend to be similar .... Hence the more things two people have in common, the more likely they are to be friends, and the more likely they are to link to each other on their homepages" (Adamic and Adar, 2003, p. 222). This has been called homophily before, and it is what is meant when Adamic and Adar (2003) speak of similarity: the similarity of connections.

Liben-Nowell and Kleinberg (2007, p. 4) treat link prediction as "computing a measure of proximity or 'similarity' between vertices x and y, relative to the network topology". To calculate this similarity, they apply a number of measures, some of them very similar. The most basic approach is the length of the shortest path between the two vertices. Also, the measure presented in Katz (1953) is applied: It defines the sum over all path, up to a certain length, between the two vertices, where, because of a parameter β, the longer path contributes only very little to the sum.

Since two different time points of the same social network are being examined, evolution models such as preferential attachment can be used as well. Furthermore, PageRank and random walk models, as well as clustering algorithms are used. Liben-Nowell and Kleinberg (2007, p. 8) state that many of the measures they applied overlap each other.

Based on the closed triangle assumption or the homophily that Adamic and Adar (2003) use to predict connections, they apply a measure based on the common neighborhood. It is a score for common neighbors (i.e., the intersection of the set of neighbors of x ($\Gamma(x)$) and the set of neighbors of y ($\Gamma(y)$)).

Widely used in information retrieval and similarity calculations tasks is the Jaccard coefficient (Jaccard, 1912), which divides the intersection of two sets by the union of the two sets and thereby calculates the similarity of the two sets:

$$\frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|}.$$

Taskar *et al.* (2003) take a different step in predicting links in social networks. They are not only asking "Is there a link between two vertices" as well as , *what type of link* it is. Just as Adamic and Adar (2003), Taskar *et al.* look at faculty website and their interaction in the form of hyperlinks and similarity (i.e., topics mentioned on the sites themselves), which gives them a broad network. They use a method called relational Markov network (RMN) to make predictions. RMNs find cliques in the data which are

then used to make predictions.[44] What makes this approach interesting is the fact that it takes into account what kind of link may exist between the vertices. For every two vertices an attribute *exists* is defined, which gives information on whether a link between the two vertices can exist or not. This can be applied to ontologies with respect to possible *domain/range* restrictions.

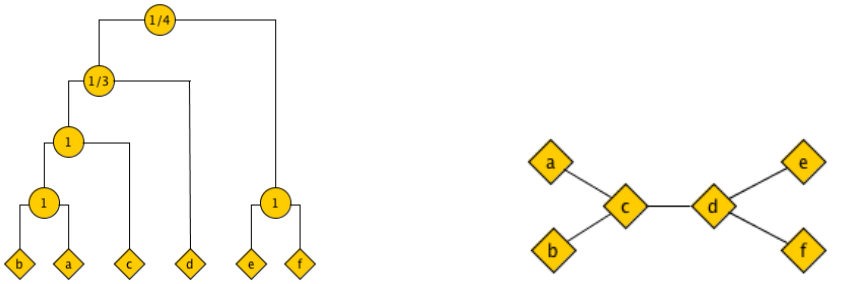
Another example of using supervised machine learning in link prediction is given in Hasan *et al.* (2006). Hasan *et al.* use different features given in co-authorship networks, though not all of them are topological features of the network. The shortest path is one of the network measures utilized but also the common neighbors, as seen above, and the clusters. Among the tested classification algorithms (e.g., support vector machines, decision trees, multilayer perceptron, and Naive Bayes) they find that all of them work comparably well with an accuracy between 80% and 90%. These classifiers will also be evaluated in this thesis.

Looking at the research done in SNA, one can find some clues to link prediction that might be applied to ontologies as well. First, one can see that a profound analysis and understanding of the data helps in finding ways to predict unseen structures. Considering link prediction as a classification task is a second one. The consideration that two people are likely to interact if they share a lot of common acquaintances is not true for language networks such as WordNet,[45] but might be applied to DBpedia data set. A problem arising when working with ontologies is that of domain or range restrictions, which are not formalized in graphs. Taskar *et al.* (2003) have shown how these restrictions might be handled to avoid false predictions that contradict the ontology. In the following chapters I will explain how these range restrictions can be handled in WordNet and DBpedia.

The next step in evaluating existing methods is to look at other mathematical models that have been proposed to make predictions in complex, non-social networks. Predicting links in social networks is based on some basic assumptions made on the structure of human interaction. Two vertices that share many common neighbors are more likely to be related (at some point) because humans tend to meet their friend's friends and people with similar interests and hobbies. But this is not true for other networks, for example gene networks or semantic networks. Techniques that can be employed to successfully

[44] As we will see in the analysis of the WordNet graph, cliques are no help in predicting links in semantic word nets like WordNet.

[45] In WordNet, many neighbors are unconnected because of the structure of the WordNet ontology. Synonyms, for example, are child nodes of a common synset but are not connected themselves.



(a) Hierarchical organization D with vertices {a,. . . ,f} of G.

(b) Original graph G with vertices {a,. . . ,f}.

Figure 15: HRG: hierarchical random graph model.

predict links in social networks can therefore not directly be ported to other types of networks. A more general approach that is not limited to social networks since it is not based on properties of social interaction, will be reviewed in the following.

Clauset *et al.* (2008, p. 99.) state that "our current pictures of many networks are substantially incomplete". This is due to the incompleteness of most networks available.[46]

To predict the missing links they introduce their approach of *hierarchical random graphs* (HRGs). HRGs are arbitrary hierarchical structures that correspond in their topology (i.e., in terms of statistical properties such as degree distribution, or path length etc.) to the original graph. Clauset *et al.* (2008) claim that the hierarchical structure itself can explain these features of a graph. The algorithm produces a set of different random graphs representing the original graph's features (i.e., "hierarchical random graphs with probability proportional to the likelihood that they generate the observed network . . . each of which is a reasonably likely model of the data" (Clauset *et al.*, 2008, p. 98)). These hierarchical random graphs are then combined.

Figure 15(a) shows the dendrogram D of graph G that can be seen in Fig. 15(b). The vertices {a,. . . ,f} are the vertices taken from G. The non-leaf vertices of the tree indicate the probability of potential edges between the vertices on the left and the right subtree. Reading from left to right, the vertices e and f are less likely to be connected to a or b than for example d.

Looking at the hierarchical graph in Fig. 15, one can see that closely related vertices (e.g., a and b) are very likely to be connected, while, moving up the tree, this probability decreases. This also corresponds to one's intuition when looking at the original graph.

[46]Hence the need to extend networks, just as ontologies, by predicting missing edges.

This kind of clusters can be called *assortative*.

But the HRG model is also capable of representing what the authors call *disassortative* structures, which indicate that the vertices are unlikely to be related directly, even though they are connected by a short geodesic path.

The algorithm comes with some problems with regard to the problem of this thesis. First, it ignores different kinds of edges as they exist in ontologies. The different kinds of relations are expected to yield important information. It also ignores the directedness of the graph. Both are features that might be of great interest in the context of ontologies.

Another problem that is not solely related to this algorithm but to most clustering algorithms is the treatment of clusters as disjoint sets: No intersection between these sets exists; that is, no vertex can be a member of more than one cluster.

Even though the authors state that their approach, calculating HRGs for the network, should be more efficient than doing calculations for every possible pair of vertices of a graph to check the possibility of them being connected,[47] the approach of calculating random graphs that fit the network and combining these graphs is, when done on large networks such as semantic networks, highly computationally intense.

Both WordNet and DBpedia seem unfitting for this approach. WordNet's structure, as will be shown in the following chapter, is different from many other networks and looks incompatible to the ideas underlying HRGs. Also, both ontologies are very large, too large for these computations to be finished in a reasonable time. In the appendix to Clauset *et al.* (2008), Clauset *et al.* state that the algorithm works well with networks of a few thousand vertices. WordNet and DBpedia have a few hundred thousand vertices. The authors admit that "equilibration could take exponential time in the worst case" (Appendix to Clauset *et al.* (2008)).

4.3 Possible Machine Learning Algorithms

4.3.1 Machine Learning

From the great amount of available machine learning algorithms, three main directions can be identified: classification, clustering, and association. All three shall be shortly introduced here. Afterwards, those algorithms that have either been used in similar tasks

[47] The goal is to avoid checking every possible combination of vertices, by restricting the possible pairs before doing such calculations. How this can be achieved will be shown in the following chapters.

(see Chp 4.2, Chp. 5.4.2, and Chp. 6.3.1) or seem to fit the requirements for the task of this thesis will be explained in more detail.

Machine learning algorithms, be they clustering, classification, or association algorithms, work on instances. These instances represent events or entities that are thought of as manifesting some underlying patterns. An instance consists of a number of (meaningful) features, a so called feature vector, that can be used to distinguish, relate, or compare instances.

Machine learning algorithms can be either supervised or unsupervised. Supervised approaches are based on a labeled data set that has been (manually) classified or measured in some way. The set of instances is split into two subsets, one used to train the algorithm and one for testing, used to evaluate the formula on previously unseen data. A special case of validation is the x-fold cross validation, where the whole set is split up in x subsets of the same size and in each iteration $\frac{x-1}{x}$ sets are used for training and the remaining $\frac{1}{x}$ of the whole set for testing/evaluating.

Unsupervised approaches are not based on a training set, but are meant to find meaningful distinctions or similarities between the instances of the data themselves, without a manual annotation.

Classification tasks are supervised and work on a predefined set of already classified instances. Often the class is binary (e.g., classifying emails as either *spam* or *not-spam*) but it can also have multiple classes, e.g., in number recognition the elements have to be assigned one of the digits from 0 to 9. The instances have one class attribute. The goal of classification is to learn or identify non-obvious rules of attribute combinations that predict the class of each instance. The necessary rules can be obtained using different algorithms: from decision trees to support vector machines. New instances, data not previously learned in the training set can then be classified using these rules.

Clustering algorithms are unsupervised and used to form (meaningful) subsets of instances of a data set. These clusters can be previously unknown. The task is to find patterns that make it very likely that different instances are somehow connected. Two different kinds of clustering algorithms are of relevance here: The first group is used to cluster networks; that is, it is used to identify densely connected communities within a graph. The second kind works on feature sets and can be thought of as clustering similar vectors. If one thinks of instances as vectors in a vector space, one can also calculate the distance between two vectors, using the Euclidean distance or other calculations like the cosine similarity. Those vectors with a small distance form a cluster. In the end it

is a question of data representation, either as a network or as a set of vectors, which algorithms can be used. Most data can be represented in both fashions.

Association techniques are unsupervised and most often used in marketing and sales contexts. To my knowledge association rules were first described by Agrawal *et al.* (1993) and applied to sales data to show "an association between departments in the customer purchasing behavior" (Agrawal *et al.*, 1993, p. 215). Association rules do not classify instances; they are, in a way, similar to clustering approaches though: They do not look at the properties of single instances themselves, but they look for patterns of their co-occurrence. Looking at marketing contexts, the idea is to find any kind of association rule between items that are, for example, often purchased together or by the same customer. This information can be used to build a recommendation system, for example.

The most important measures of quality in evaluating machine learning models are the precision, the recall, and the accuracy. These measures are taken from information retrieval (IR) and can be applied most successfully to classification tasks. They are computed using the fractions of correctly identified, or classified, instances versus those that were not found.

Table 7: Evaluation in IR: true positives, false positives, true negatives, and false negatives.

		Assigned class	
		false	**true**
Actual class	**false**	fn	tn
	true	fp	tp

The documents the system regards as relevant are called hits. In IR, the precision is the fraction of relevant hits divided by the number of total hits. As can be seen in Table 7, the relevant hits are called *true positives* (tp); the number of irrelevant hits are called *false positives* (fp). The documents the system correctly identifies as irrelevant are called *true negatives* (tn). Those documents that the system incorrectly regards as irrelevant are called *false negatives* (fn).

Transferring this idea to a classification task, precision is the fraction of correctly

classified instances divided by sum of correctly and incorrectly classified instances:

$$precision = \frac{tp}{tp + fp}. \tag{10}$$

Recall in IR refers to the coverage of the correctly identified hits divided by number of relevant documents (i.e., those that are correctly classified (tp) and those that are incorrectly regarded as irrelevant (fn)).

$$recall = \frac{tp}{tp + fn} \tag{11}$$

Most systems tend to have either a high precision but a low coverage (recall) or tend to have a high coverage with a low precision. To estimate how well the system is balanced, the so-called F measure is used:

$$F = 2 * \frac{precision * recall}{precision + recall}. \tag{12}$$

The accuracy is the number of documents that are correctly classified (tp and tn) divided by the total number documents (i.e., the sum of tp, tn, fp, and fn):

$$accuracy = \frac{tp + tn}{tp + tn + tp + fn}. \tag{13}$$

In IR as well as in classification tasks, the goal is to find a system or model that provides both high precision and high recall. For a multiclass classification task, the calculation of precision, recall, F-measure, and accuracy has to be done for each class separately. The results can then be averaged.

4.3.2 Machine Learning Algorithms

In the following, possible algorithms will be introduced before being tested on actual network data in the following chapters. The set of algorithms to test is based on two considerations: The first is if they have been applied to similar tasks or in similar contexts in the past. The second is based on the idea of treating link prediction as a classification task (i.e., to decide whether or not two vertices are connected).

First, supervised classification algorithms will be presented. Afterwards clustering algorithms, sometimes also called unsupervised classification, will be presented for both

vector and network data before looking at association rule mining.

4.3.2.1 Classification

Logistic Regression

Logistic regression is a supervised classification algorithm. Besides the misleading name, "it should be emphasized that this is a model for classification rather than regression" (Bishop, 2006, p. 205). The name is derived from the sigmoid function, also known as the logistic function. The logistic function is given by le Cessie and van Houwelingen (1992, p. 192) as follows:

$$p(X_i) = \frac{e^{X_i\beta}}{1 + e^{X_i\beta}}. \tag{14}$$

$p(X_i)$ is the so-called hypothesis (i.e., the probability that instance X_i is of class $Y_i = 1$), where X is a matrix containing all instances and the corresponding features, and β a vector containing the parameters that are to be used in the logistic regression.

To calculate how well the parameters in β fit the data (i.e., the classes given by Y), the cost is calculated. The overall cost is basically the sum of the difference between the class and the hypotheses. It can be calculated as follows:

$$\sum_{i=1}^{m}[Y_i log(p(X_i)) - (1 - Y_i) log(1 - p(X_i)]. \tag{15}$$

The logistic regression further needs some algorithm to find the optimal values of β (i.e., those values of β that minimize the cost function given above). There are different algorithms that can be used to iterate over possible values of β (e.g., gradient descent). Its result is a sum over the products of the parameters and the features and takes the form of a polynomial: $\beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 {X_{i1}}^2 + \beta_4 {X_{i2}}^2$. Each feature of the data set corresponds to one parameter of the polynomial expression. To predict a new instance, the instance's features and the parameters are used in the sigmoid function. The results lie between 0 and 1. This can be interpreted as either *false* for a value < 0.5 or *true* for a value ≥ 0.5.

Bayes Classifier

The Naive Bayes algorithm is a supervised algorithm and hence uses a set of instances that are already classified to a specific class. To use the Naive Bayes classifier, we need the vectors containing the features $\vec{d_1} \ldots \vec{d_n}$ for the instances $d_1 \ldots d_n$, and the possible classes be $c_1 \ldots c_n$. Given the data set (i.e., the instances and their feature vectors), one can calculate the probability that a certain value for a feature predicts the assigned class.

John and Langley (1995, p. 340)[48] give a simple example: Given a data set with a class attribute $\{true, false\}$ and a nominal feature that is either $\{a, b\}$ containing the instances $\{(true, a), (true, b), (true, a), (false, b), (false, b)\}$, the probability of class *true* is $P(true) = 3/5$. The probability of *true* given a is 2/3, i.e., $P(true|a) = 2/3$. The probability of class *true* for the value b is correspondingly $P(true|b) = 1/3$. These probabilities are absolutely independent of any other existing features, which is why this algorithm is called naïve. The algorithm calculates the probability of an instance belonging to any of the possible classes given the feature vector $\vec{d}$. Each feature value has its own probability of predicting any of the possible classes. These predictions are, based on the naïve assumptions of being independent, combined and the instance is assigned the class with the highest probability.

In a more general way, considering this information, Bayes' theorem is given as (Aas and Eikvil, 1999, p. 13f.) the probability of class c_j given $\vec{d}$:

$$P(c_j|\vec{d}) = \frac{P(c_j)P(\vec{d}|c_j)}{P(\vec{d})}. \tag{16}$$

Since the probability $P(\vec{d})$ is independent of the class, the formula can be reduced to the following:

$$P(c_j|\vec{d}) = P(c_j)P(\vec{d}|c_j). \tag{17}$$

The naïve idea "that all attributes of the examples are independent of each other given the context of the class ... is clearly false in most real-world tasks" (McCallum and Nigam, 1998, p. 1). Nevertheless, accepting this naïve assumption, we can calculate the

[48] The original data set was slightly altered to fit the other examples used in this section.

probability of class c_j given vector $\vec{d}$ as

$$P(c_j|\vec{d}) = P(c_j) \prod_{i=1}^{M} P(d_i|c_j) \tag{18}$$

such that its overall probability of the class $P(c_j)$ is multiplied by the product of the probabilities of each feature d_i given class c_j.

Support Vector Machines

Support vector machines (SVMs) are very widely applied in all different kinds of supervised classification tasks. They are claimed to be "the most robust and accurate methods among all well-known algorithms" (Wu *et al.*, 2007, p. 10), and it "requires only a dozen examples for training, and is insensitive to the number of dimensions" (Wu *et al.*, 2007, p. 10).

Looking at a two-class classification problem such as the question of whether or not two vertices of a network are likely to be connected, the algorithm treats the instances and their n features as vectors in an $n + x$-dimensional space.[49] From the infinite number of possible hyperplanes that divide the space into two sets, the algorithm identifies the hyperplane with the highest margin to the two sets. The margin is defined as the shortest distance of any data point of each class to the hyperplane.

To train an SVM, the SVM optimization problem has to be solved. Two parameters are used in the implementation of Chang and Lin (2011) that will be used later on: a margin parameter C and a (Gaussian) radial basis function kernel (RBF kernel) parameter γ. The implementation uses a grid search to determine the best combination of values for C and γ.

Decision Trees

Without going into too great detail about the mathematical foundations of decision trees such as ID3 (Quinlan, 1986) or C4.5 (Quinlan, 1993), the basis of these supervised classification algorithms shall be described here. Starting from a root node, decision trees split up in different branches; at the end of these, the leaves indicate the classes.

[49] SVM use mapping techniques to increase the number of dimensions.

At each split the algorithm takes into account the available attributes in the data set and chooses the attribute with the highest information gain (i.e., the feature that best distinguishes between the classes). For each value, or range of values, of the attribute, a new branch is built. This is repeated recursively until each remaining instance that reaches or satisfies the conditions defined on the way there is of the same class.

To classify an instance, the algorithm follows the tree top-down. The tree can be thought of as a series of if/else conditions: Attribute x_y of instance y satisfies some condition c, and the next condition is checked recursively until the class can be assigned. At each split it checks the defined feature and its value. Then it follows the path according to the value of the feature. The number of steps depends on the depth of the tree as well as on the instance. Some features might unambiguously split the data set in the classes if they reach certain values, but sometimes a number of different features have to be checked against the values defined in the model. This way the algorithms end up at leaves that indicate the class.

Random Forests

Following the definition of Breiman (2001, p. 6) a "random forest is a classifier consisting of a collection of tree-structured classifies where ... each tree casts a unit vote for the most popular class".

A random forest is a collection of random trees (hence forest). The number is not fixed and can be changed according to the needs. The trees are random in the way that at every node in the tree, n random features from the training set are chosen to split the tree on. The decision what feature to choose is not based on the information gain or entropy of the feature but purely random, which distinguishes this approach from the decision trees seen above.

The depth of the tree can be set and an accordingly large or small random tree is built. The random trees are then combined and used to vote on the class of any given input instance x.

Due to the randomness, the number of trees and the number of random features selected at every split have a great influence on the performance, while a single feature might not have the strong influence it has on decision trees. A higher number of random features does not necessarily result in better classifications. In fact, Breiman (2001, p. 14) found that "using a single randomly chosen input variable to split on at each node could

produce good accuracy".

Unlike decision trees that can be read and give strict instructions on how to select the appropriate class, random-forest models are shrouded by (random) trees. There can be a few hundred underlying trees. In the end, each instance is assigned the class that most of these trees voted on. Accordingly, the random-forest model outputs a likelihood for each class.

Deep Learning and Neural Networks

Deep learning has become a buzz word just as big data in recent years. Deep learning comprises the idea that, given enough computational resources and enough data, a system can learn in an unsupervised fashion. Often cited in this context is the joint venture of Google and members of Stanford University presented in Le *et al.* (2012) that has become widely popular due to the fact that the neural network employed was able to not only categorize pictures of faces into clusters as well as to identify cat faces. All this was undertaken in an unsupervised fashion, using 16,000 cores in 1,000 machines during a period of three days.

Underlying the idea of deep learning are artificial neural networks (ANNs). ANNs consist of artificial neurons (i.e., vertices in an artificial neural network). Given some input vertices (e.g., the features of the instances to be classified), a number of hidden layers perform calculations and transformations on the input and subsequently produce the output (i.e., the corresponding class of an instance).

In each layer, a sigmoid activation function is used. It takes the output of the layer before as an input and using different parameters at each layer, in the ANN terminology called weights, performs relatively simple calculations. Combining these simple functions can result in complex functions by adding extra layers.[50]

Given is the input, instances, their features, and classes, as well as the output, the class. Now one has to decide on the number of hidden layers and one has to assign the weights or parameters in such a way that the output corresponds to the class. Again, there is a cost or error function that computes the difference between the classification made by the algorithm, called forward-propagation, and the classes given in the data set. To minimize the cost, back-propagation can be used. Back-propagation was first

[50]For example, given a hidden layer that computes the logical function OR and AND with a third layer that computes the OR function, one gets an XNOR function.

described in Rumelhart *et al.* (1986). First the error value for the last layer, the output layer, is calculated. Using this value, the error of the previous layer is calculated and so forth until the input layer is reached. In each layer, the weights are changed according to the error that is back-propagated.

It is often stated (e.g., in Le *et al.* (2012)) that the architecture of artificial neural networks is similar to that of a human neural network, although "with around 10 million parameters ... our network is still tiny compared to the human visual cortex, which is 10^6 times larger in terms of the number of neurons and synapses (Le *et al.*, 2012, p. 3). It has already been mentioned that such statements have to be interpreted with care.

4.3.2.2 Clustering

In the following, vector-based and network-based approaches of clustering are presented. While the first kind treats instances as vectors and searches for clusters containing only instances with a small distance between each other, network approaches are looking for sets of densely connected vertices.[51]

Clustering is an unsupervised machine learning approach: Vectors, representing the instances, are compared and those that are most similar are clustered together.

k-Means

Given the number of clusters k and a data set with n data points, the algorithm has to find the centers for the k clusters in a way "to minimize ... the sum of the squared distances between each point and its closest center" (Arthur and Vassilvitskii, 2007, p. 1027). Doing this exactly is an NP-hard[52] problem (Drineas *et al.*, 2004).

Lloyd (1982) presents what today usually is referred to as the k-means algorithm. The k-means algorithm is a straightforward vector-space-based clustering algorithm. It clusters the set of vectors into k clusters. In a first step, k centroids are chosen randomly (i.e., k points in the vector space representing the k clusters). Then the algorithm iterates over two phases: First, all instances are assigned to their nearest cluster centroid. Then the center of the cluster is moved to the mean (i.e., the centroid is reassigned). These

[51] Of course one could transform each network to a vector and many vectors to networks. Working with numbers though, distance measures on vectors work better than a network representation of the same data.

[52] Non-deterministic polynomial-time hard problems are believed to be unsolvable in polynomial time.

steps are repeated until it converges (i.e., until the clusters no longer change during the iterations).

As Arthur and Vassilvitskii (2007, p. 1027) state, "the empirical speed and simplicity of the *k-means* algorithm come at the price of accuracy." In fact, the choice of the initial centroids is a weak point of the algorithm, since choosing the *wrong* initial centroids leads to less than optimal clusters.

Usually the Euclidean distance is used to find the nearest cluster centroid. Other measures are possible. The cost function is then the minimum distance to the centroids, which means that assigning a vector to a cluster other than the nearest cluster increases the cost. To avoid problems arising from poorly chosen centroids in the first step, the process is often repeated several times using different initial centroids.

Arthur and Vassilvitskii (2007) propose a modified version of the algorithm called *k-means++*. Instead of choosing k centroids purely at random in the first step, they only choose the first centroid at random from the whole set of data points. The remaining $k-1$ clusters are subsequently chosen taking into account "the shortest distance from a data point x to the closest center we have already chosen" (Arthur and Vassilvitskii, 2007, p. 1029), such that the centroids are not near each other.

Network Clustering: Based on Edge Betweenness

There is very wide range of different algorithms to identify communities in networks (e.g., based on the edge betweenness (Newman and Girvan, 2004), using greedy optimization of modularity (Clauset *et al.*, 2004), based on propagating labels (Raghavan *et al.*, 2007), using eigenvectors (Newman, 2006), using multi-level optimization (Blondel *et al.*, 2008), the maximal modularity score (Brandes *et al.*, 2008), short random walks (Pons and Latapy, 2005), or the similarity of the neighborhood (Biemann, 2006)). Some have complexity that is linear to the number of edges or vertices; some are not that efficient. Here, only one commonly used approach shall be presented.

Using the edge betweenness to identify communities in networks was proposed in Newman and Girvan (2004). The betweenness measures, a "measure that favors edges that lie between communities and disfavors those that lie inside communities" (Newman and Girvan, 2004, p. 3), has been discussed before (see Chp. 2.1.4). Here the edge betweenness is calculated (i.e., those edges are identified that lie on the most shortest paths between the vertices of the network).

The assumption underlying this approach is that clusters are densely connected among its members but not to members of other clusters. Given different clusters that are connected by only a few edges, these edges can be expected to have a very high betweenness since they connect all the vertices from one cluster to those of the other clusters. This is because "all paths through the network from vertices in one community to vertices in the other must pass along one of those few edges" (Newman and Girvan, 2004, p. 3).

The algorithm works by first calculating the betweenness for each edge. Then the edge with the highest betweenness is removed. Afterwards the betweenness is recalculated to again find those remaining edges with the highest betweenness. These values can change between the steps. These steps are repeated and can be stopped at any given moment. The components of the network resulting from removing the edges can be considered the originals networks communities or clusters. Because of the recalculation of the betweenness values in every iteration, the run time of this algorithm is quite long for larger networks.

4.3.2.3 Association Rules

Apriori Algorithm

The Apriori algorithm is unsupervised and was developed for marketing tasks. Hence the instances are called item sets. The goal is to mine rules from a large set of shopping baskets containing different items to find items that are regularly combined and purchased together. Although these techniques were developed 20 years ago, only online shopping sites with millions of data sets made these techniques widely popular and known to the general public.

The algorithm itself is quite simple and easy to implement. It first counts the occurrences of each set of co-occurring items of size $n = 1$ and compares the counts to a predefined value called minimum support (i.e., the minimum occurrence of the item). Afterwards the algorithm increases n by one and iterates over the set until no new sets that satisfy the minimum support value can be found.

The second important value is the confidence value of a rule. Having found all large item sets (i.e., all sets with at least minimum support), the system can formulate rules that predict what items are usually bought together. Agrawal *et al.* (1993, p. 487) give the example that people who "purchase tires and auto accessories also get automotive

services done". Such a rule has to meet a predefined confidence rule which is the fraction of cases in the data set in which this rules makes a correct prediction. If given a data set containing *tire purchase* and *auto accessories* in four item sets, but only two of these contain *automotive services* as well, the confidence of this rule is only 0.5.

While the minimum support defines the item sets that are used to conclude rules from, the confidence defines how accurate these rules have to be in the data set. If the minimum support is very low, many rules have to be considered. These rules might even reach the necessary confidence. For example, if an item was only purchased once, the confidence that this item predicts the purchase of the other items in the item set would be 1. This is why it is important to set both values to a reasonably high, but not too high, value.

The fact that the algorithm only works with nominal data is a restriction. Each feature is identified by a name and counted. Numerical values are not recognized or treated as such.

4.4 Conclusion

One common problem that arises when working with both networks and ontologies is the sparsity of data. In both cases, the creation of new data is very time-consuming. Therefore, since the rise of electronic ontologies such as WordNet, a number of researchers have tried to extract structured information, entities, and their relations, from unstructured sources, especially free texts.

Exploiting the syntactic relations in human language, given by either syntax or hierarchical text structures, it was shown how ontologies can be extended by identifying patterns of texts (or syntactic structures) that describe a certain relation between two entities. Having identified a new relation between two entities of an ontology, this relation can be added to the ontology's ABox, or the data set.

Problems arise from mainly two points: For one, when using WordNet or other semantic networks with a high degree of homonymy, the problem of word sense disambiguation to identify the right word sense in the dictionary has to be solved. The second problem is related to the relation itself: For WordNet it was found that only hypernymy/hyponymy relations could be identified with a high accuracy based on natural language texts. For other ontologies the problem of mapping the relation given by the texts to the set of terms defined by the ontology arises: One has to find different patterns for every relation given in the ontology to reasonably extend an existing ontology. The pattern-based approach

therefore has its limitations, especially when working with ontologies and even more so when working with WordNet.

While all these approaches rely on external sources to extend ontologies and the networks they expose, findings in the work with social networks indicate that the structure of the network itself (e.g., the neighborhood of the vertices in question) can give approximations to what vertices are likely to be connected or not.

Some of the approaches introduced in this chapter are based on human observations while a great number of approaches apply different machine learning algorithms. These algorithms, plus some others that have not yet been used but that seem to be promising or are heavily used in other neighboring fields, have been introduced here and will be tested on the WordNet or DBpedia ontologies in the following.

From the comparison of social-network-based and non-social-network-based approaches in this chapter, we can conclude that the best method of solving the problem of identifying missing relations can only be chosen after the structure of the network, of the ontology, has been analyzed. For example, while in social networks some behaviors of human beings can be employed to predict connections between them (e.g., the homophily, the fact that friends tend to be similar in their connectedness within the network), these are no fit for other complex networks, such as gene networks, or, as will be shown shortly in more detail, ontologies like WordNet. A deep understanding of the source the data was taken from or arises from is just as important as an understanding of the structure of the data itself to choose correct features to identify missing relations.

The structure is thought of as not only providing the missing information as well as indicating how this information might be contained. What this means in detail will be clarified in the following chapters in regards to WordNet and DBpedia.

As has been pointed out by Clauset *et al.* (2008), checking every vertex of a large network against any other vertex might be very uneconomical. Looking at the problems that are to be solved regarding WordNet and DBpedia, and at the ontologies themselves, ways have to be described to circumvent this problem. Helpful with this problem might be a special property of ontologies: Relations are restricted as to what classes of vertices they can connect in the first place. This is called a relation's range or domain restriction. The restrictions can forbid some vertices to be connected by certain relations or might even forbid two vertices to be connected at all. Furthermore it is expected that the structure of the networks will show densely connected areas, called clusters, where new relations might be probable, but it might also show where connections might be missing. Based on

a deep analysis of the networks exposed by the ontologies, one should be able to determine what kind of machine learning is the most promising approach to solving the problem, as well as what kinds of features of the ontology and networks should be the most useful ones.

5 WordNet: Analyses and Predictions

In the following, the structure of the WordNet ontology, and of the corresponding graph, will be examined. This will show what kind of relations exist in WordNet, how these relations can be used in the subsets of WordNet, corresponding to the POS nouns, verbs, adjectives, and adverbs. This will also disclose some shortcomings of the WordNet data.

WordNet is widely used in many NLP tasks. Since it contains accurate and detailed information on English nouns, verbs, adjectives, and adverbs, it can be used to calculate similarity between words, find related words, and group words among others. But WordNet is based on word sense rather then words or lemmas. The relation between most word senses sharing a common lemma remains unclear in WordNet. A further difficulty is the very fine sense distinction that is not reachable with today's NLP methods.

Stokoe (2005) undertakes a study on the impact of word sense disambiguation, especially in cases of homonymy and polysemy, for information retrieval (IR) methods. The author concludes that "making fine-grained sense distinctions can offer increased retrieval effectiveness" (Stokoe, 2005, p. 409). Lacking other resources, WordNet is used as a basis of distinguishing homonymy from polysemy. As Biemann (2012) shows, the fine-grained sense distinction of WordNet is a hinderance in word sense disambiguation (i.e., the task of assigning a word in context a given sense in WordNet). Many closely related senses are not distinguishable, and therefore the accuracy is limited to an upper bound of 80%.

While others have tried to group closely related word senses to reduce the number of senses generally (e.g. Snow *et al.*, 2007), only word senses sharing a common lemma are to be considered in this thesis. Hence, the approach tries to distinguish between word senses that share a common lemma by chance (homonymy) and those that share a common lemma because of an underlying semantic relation (polysemy) based on some kind of cognitive process that is to be discussed further in the following.

The general idea that it should be possible to exploit the network structure to either identify missing links or to add new relations to the ontology, and the relation between all semantically related or polysemous word senses is such a missing relation. In Chp. 5.1, polysemy and homonymy will be examined more closely.

Chapter 5.2 will show the WordNet architecture in more detail. In Chp. 5.3, a network analysis will be undertaken on the WordNet data, treating the word forms and word senses and their interrelations as a graph. Analyzing the ontology structure and the network will give hints as to what measures or features are promising to be used in a machine learning

task.

In Chp. 5.4, the state of the art in identifying polysemy in WordNet will be presented, before a new approach is presented that makes use of the network structure and machine learning.

In Chp. 5.5, these features are used to classify data and the results are evaluated and compared to other possible approaches.

5.1 Ambiguity: Polysemy and Homonymy

While all lexical units are possibly vague or ambiguous, polysemy is a special case of semantic ambiguity and it is common in natural languages. It is often found in jokes, punch lines, metaphorical, and metonymical uses of language. In polysemy, one lexeme has several related meanings (Lyons, 1995, p. 58). Croft and Cruse (2004, p. 111) define polysemic units as "derived from the same lexical source, being the result of processes of extension such as metaphor and metonymy".

Homonymy, from Greek meaning *having the same name*, describes the fact that different objects are referred to by the same word form. We speak of a true homonym when the same string of characters (homograph) and the same sound (homophone) refer to different, unrelated things. In cases of polysemy, the different senses of homograph/homophone words are related. Polysemy is an interesting aspect in human language, because it shows human creativity and also allows a glimpse at how the evolution of languages works. Furthermore, as will be explained later on, knowing what words are related instead of just arbitrarily being homographs might improve word sense disambiguation and question-answering tasks.

In the following, only the written forms (i.e., homographs) is considered, since WordNet does not offer information on pronunciations.

5.1.1 Homonymy

On first sight, homonymy seems like a very straightforward matter. Homonymy in a broad sense refers to two or more words that have the same graphical representation and the same pronunciation. Since we are only looking at written words, homophony is not relevant, since no information on the pronunciation is available. The cases that are of interested here are, actually, homographs (i.e., words that share the same spelling). Words

like *lead* (/liːd/), meaning a *position of leadership*, and *lead* (/lɛd/), Latin *plumbum*, a heavy metal, are homographs but not homophones. Still, in the computational processing based on texts, not spoken language, these have to be treated as homonyms as well.

Working only with the written form of language here, we can call two words homonymous if they are written identically, but have no semantical or etymological relation. The biggest problem of this definition is the last part, the etymology. There are cases where the semantical relation between two words that once might have existed is not known or not obvious to the users of today's form of a language anymore. Due to semantic shift, the meaning of a word may have changed and the common meaning that two once polysemous words shared, might be lost.

A very common example is that of $bank_1$, meaning a financial institution, and that of $bank_2$ meaning *the slope of a river or water*. The first is derived from the Italian *banco*, while the etymology of the second can be traced back to a Germanic origin. The same example shows how problematic this distinction can be. The Romance word *Italian/Spanish banco, French banque* and thereby $bank_2$ originally derive from the same Germanic word meaning *bench, counter, hillock*.[53] Still, the two lexemes $bank_1$ and $bank_2$ should be considered homonymous. They are, as Lyons (1995, p. 28) puts it, "semantically unrelated: there is assumed to be no connexion – more precisely, no synchronically discernible connexion".

The easiest way to define homonymy, and also a very fruitful one in a computational approach,[54] is to ignore the etymological roots of two homonymous words. The etymology is not relevant for the understanding of a word's sense and mapping this sense to other, related meanings.

5.1.2 Polysemy

Polysemy is regarded as either regular polysemy[55] or irregular polysemy. First, regular polysemy will be defined, before taking a closer look at those cases that do not match this definition and are hence to be treated as irregular polysemy.

[53] *Bank* meaning bench still exists in German in this form. Other Germanic languages have similar forms. The English word *bench* shows signs of the regular phonological change of English.

[54] When looking at homonymous words, the important question for an NLP task is whether two words are semantically related. Polysemous words are, but homonymous words, even if they might share some common ancestor or a sense lost over time, are not. In natural language understanding, this distinction is important.

[55] The terms systematic or productive polysemy can also be used synonymously.

Apresjan (1974, p. 16) defines regular polysemy as follows:

> Polysemy of the word A with the meanings a_i and a_j is called regular if, in the given language, there exists at least one other word B with the meanings b_i and b_j, which are semantically distinguished from each other in exactly the same way as a_i and a_j and if a_i and b_i, a_j and b_j are nonsynonymous.

What Apresjan calls *regular polysemy* is a very common phenomenon, and the process of transferring the meaning or a sense of one word to another follows some rules.

The word *olive* for example has the following senses:[56]

1. olive – small ovoid fruit of the European olive tree; important food and source of oil
2. olive, European olive tree, *Olea europaea* – evergreen tree cultivated in the Mediterranean region since antiquity and now elsewhere; has edible shiny black fruits
3. olive – hard yellow often variegated wood of an olive tree; used in cabinetwork
4. olive – one-seeded fruit of the European olive tree usually pickled and used as a relish
5. olive – a yellow-green color of low brightness and saturation

One can easily see that the senses all bear a common feature: their relation to the olive tree (sense 2).[57] The wood taken from this tree is also called olive (sense 3) and so are the fruits (sense 4), the food made from the fruits (sense 1) and the color of the fruit (sense 5). One could say *an olive (tree) has olive (wood) and olives (fruit)* (cf. meronymy). The relation between the senses seems to be of metonymic nature: Either a part stands for the whole (*pars pro toto*), or the name of the whole is used to refer to its parts.

If we now look at other trees with fruits (e.g., a cherry) we find a very similar pattern. Cherry can refer to a tree, wood,[58] fruit, food, and color. The same is true for other trees as well.

A more general process is that of the relation between fruit and food. The food is often called the same as the fruit. The same is true in many cases of the naming of food

[56] Taken from WordNet.

[57] One could just as well argue that all of them are related to the fruit. Still, using the tree as a common reference point makes this approach consistent with non-fruit-bearing trees.

[58] WordNet 3.1 is missing this sense of *cherry*.

gained from animals. For example, *chicken* can refer to the bird and the meat.[59] This case of regularity (i.e., the metonymic usage of the animal name for products gained from the animal) is called grinding.

According to frame semantics, the interpretation of a polysemous word has to be done by taking into account both profile and base of the word. Katz and Fodor (1963) give the following prominent example of a polysemous word *bachelor*:

1. a young knight serving under the standard of another knight
2. one who possesses the first and lowest academic degree
3. a man who has never married
4. a young fur seal when without a mate during the breeding time.

Fillmore argues that the word was borrowed from one frame, the one expressed in sense no. 3, based on analogy and then transferred to a new domain, the one expressed in sense no. 4, instead of claiming that the sense of bachelor was extended from the range of humans to animals (cf. Fillmore, 1977, p. 68). Pustejovsky formalizes the vague notion analogy found in polysemous words: He states that "every lexical item exhibits some degree of ambiguity, what I call logical polysemy" (Pustejovsky, 1993, p. 73). This view leads to the conclusion that the meaning of a word cannot at all be named but can only be concluded from the context.

While the classical lexicographic approach to semantics, the sense enumeration as Pustejovsky calls it, is suitable for (hypothetic, non-natural) *monomorphic languages* (i.e., "[a] language where lexical items and complex phrases are provided a single type and denotation" (Pustejovsky, 1998, p. 56))[60], Pustejovsky finds speaking of background knowledge suitable for meaning shifts in *unrestricted polymorphic languages*, where "there is nothing inherent in the language that constrains the meaning of the words in context" (Pustejovsky, 1998, ibid.). The *weakly polymorphic languages* lie in between the two extremes, and hence where "semantic operations of lexically determined type changing (e.g., type coercions) operate under well-defined constraints" (Pustejovsky, 1998, p. 57).

[59] In English, many words used to refer to food gained from animals, such as *beef*, *pork*, or *venison*, are Anglo-Norman loanwords and hence of Romance origin. Still, the process of deriving the term for meat from the animal is still working as examples such as *chicken*, *pheasant*, or *lamb* show. Furthermore, the Anglo-Norman words themselves are derived using grinding in old northern French dialects.

[60] Such as programming languages or logic-based languages.

Pustejovsky's (1998) generative lexicon overcomes some flaws of traditional sense enumeration lexicons, where every entry stands for a sense. Sense enumerations not only have to provide an entry for every possible or thinkable use of a word, but the entries are also not flexible and not open to creative usage of the word: The "numbers of, and distinctions between, senses within an entry are 'frozen' " (Pustejovsky, 1993, p. 73). Furthermore, these entries do no account for the connection and relatedness of the meanings. Polysemous words (i.e., their meanings) share one entry in the lexicon. But this does not offer insight into the processes that lie behind the meaning shift that is undertaken to use a word in a different context (Pustejovsky, 1998, p. 47). The core element of the generative lexicon is the *qualia* structure. It "tells us ... [that] a concept is the set of semantic constraints by which we understand a word when embedded within the language" (Pustejovsky, 1998, p. 86) and hence supplies "the structural template over which semantic transformations may apply to alter the denotation of a lexical item or phrase" (Pustejovsky, 1998, p. 86). Pustejovsky (1998, p. 45) gives the following example of different senses of the word *want*:

(18) Mary wants another cigarette.

(19) Bill wants a beer.

(20) Mary wants a job.

Want has to be interpreted differently in all three examples. Words like *want* and others are not strictly polysemous or ambiguous, Pustejovsky (1998, p. 87) calls them "simply *underspecified*, with respect to the particular activity being performed".

Example 18 can be paraphrased as *Mary wants to smoke another cigarette*, while Example 19 would be *Bill wants to drink a beer*, and the Example 20 can be something like *Mary wants to find a job* or something similar.[61] The actual type found in the exemplary sentences is that of an NP or in the form of semantic types that of $<< e, t >, t >$. Now it is assumed that *want* expects an argument of type t, i.e, a phrase like *to drink a beer*. This can be seen in the interpretations given above. This is a case of type coercion, where a verb coerces its expected type to its argument. The argument places have to be filled to avoid a type error. To fill the argument place, the qualia of the noun is used. The qualia consists of four different roles: *constitutive*, *formal*, *telic*, and *agentive*. The formal level indicates what an object is (e.g., its orientation, shape, dimensionality, or color). The

[61] The interpretation as *wants to have a job* would not help much, since *have* can be used as a light or underspecified verb as well.

information given here distinguishes the object from others in a broader domain. The constitutive role names an object's material, weight, or parts and components. The telic role gives the purpose or function and the agentive role the cause of an object/event.

In the attribute value matrix below (Pustejovsky, 1998, p. 100), an excerpt of the features of the noun *beer* is shown. The telic role *drink(e,y,x)* gives the necessary interpretation to the sentence in Example 19 (i.e., that of *want to drink x*). The telic role indicates the purpose of the noun (i.e., being drunk).

$$\left[\begin{array}{ll} \textbf{beer} & \\ ARGSTR = & \left[\begin{array}{ll} ARG1 = & \textbf{x:liquid} \end{array}\right] \\ QUALIA = & \left[\begin{array}{ll} FORMAL = & \textbf{x} \\ TELIC = & \textbf{drink(e,y,x)} \end{array}\right] \end{array}\right]$$

An example of this behavior can be seen in some adjectives whose meaning is highly dependent on the context. Examples 21–23 show the adjective *sad* in different contexts. One sees different, yet related, meanings that all derive from one common, more abstract meaning.

(21) a sad poem

(22) a sad poet

(23) a sad day

Example 21 refers to a poem that is about something unhappy or that is doleful or distressing. In any case, it is not the same as in Ex. 22, where a person is in pain or sorrow. A day cannot be *sad* in this sense; it does not experience these kinds of feelings. Instead, it is a day when something that is saddening has happened or a day causing someone to be sad.

Pustejovsky (1991) argues that adjectives like *sad* operate on the heads qualia structure and therefore modify them in different ways. Still, the entry for *sad* in the generative lexicon only exists once and does not need to be changed.

Therefore, Copestake and Briscoe (1996) treat "this type of polysemy as a question of selecting the appropriate aspect of meaning of the complement, rather than a change in the meaning of the NP itself" (Copestake and Briscoe, 1996, p. 32). They further argue that this kinds of words are vague and not ambiguous.

Copestake and Briscoe (1996) subdivide the field of regular polysemy further into *constructional polysemy* and *sense extension*. *Constructional polysemy* is used to describe cases in which a "lexical item is assigned one (often more abstract) sense and processes of syntagmatic combination or 'composition' ... are utilized to specialize this sense appropriately". An example can be the lexical unit *reel*, which is assigned the meaning of *container* and is then disambiguated according to context or syntagmatic relations to refer to a *reel of film* or *fishing reel*[62] (cf. Copestake and Briscoe, 1996, p. 31).

The second group of regular polysemous words, following Copestake and Briscoe (1996), is characterized by *sense extension*. This second group also includes the cases of grinding where the animal's name can be used for a product made from it (e.g., meat or fur/skin). For grinding they propose a rule that transforms one feature structure to another, from animal to meat as shown in Lexical Rule 1 (cf. Copestake and Briscoe, 1996, p. 41), where **c_subst.** stands for comestible substance.

Lexical Rule 1. $\langle\rangle\langle$ *grinding* $\rangle\langle\rangle$

$\langle 0\ QUALIA\rangle$ = ***animal***

$\langle 1\ QUALIA\rangle$ = ***c_subst.***

While these are metonymic (i.e., *pars pro toto*) sense extensions, there also exists a metaphorical sense extension. These include calling people by the name of an animal and therefore transfer some, not predictable, connotation of that animal to the person in question. For example, the epithet *Lion*, which was, for centuries, attributed to many kings, can refer to many positive attributes of lions: their strength, their courage, or the notion of the lion as the ruler of animal kingdom[63]. These examples are a metaphorical word usage (i.e., they are comparisons without the use of a word of comparison). Calling someone a lion means that the person is as strong as a lion or has courage like a lion. Such "associations ... would not be encoded in the qualia structure" (Copestake and Briscoe, 1996, p. 37). We will shortly come back to similar cases of irregular polysemy.

Nunberg describes "productive linguistic processes that enable us to use the same expression to refer to what are intuitively distinct sorts of categories of things" (Nunberg, 1996, p. 109), which he calls *predicate transfer* and defines in more detail as "[t]he principal

[62]Furthermore, container nouns can be used to refer to their content.

[63]The Frankish historian Fredegar referred to Clovis I as a lion and interpreted this in terms of his courage (Jaeger *et al.*, 1996, p. 22).

... that the name of a property that applies to something in one domain can sometimes be used as the name of a property that applies to things in another domain, provided the two properties correspond in a certain way" (Nunberg, 1996, p. 111). In a more formal way, he defines the condition on predicate transfer as

Definition 1. *"Let $\mathcal{P}$ and $\mathcal{P}'$ be sets of properties that are related by a salient transfer function g_t: $\mathcal{P} \rightarrow \mathcal{P}'$. Then if F is a predicate that denotes a property $P \in \mathcal{P}$, there is also a predicate F', spelt like F, which denotes the property P', where $P' = g_t(P)$." (Nunberg, 1996, p. 112)*

In the example to be shown below (24), the correspondence P and P' can be described using a salient function h from a set A, where F denotes a property $P \in A$, to a disjoint set B so that F'

$$\lambda P.\lambda y(\forall x_{domh}.h(x) = y \rightarrow P(x)), \tag{19}$$

or

$$\lambda P.\lambda y(\exists x_{domh}.h(x) = y \wedge P(x)), \tag{20}$$

representing the *universal* and the *existential* interpretation of the utterance.

Nunberg (1996, p. 115) gives a straightforward example of a metonymic relation that can be explained using the functions above:

(24) Who is the ham sandwich?

This is from the context of a restaurant. Here, at least from the point of view of the service personal, "customers acquire their most usefully distinctive properties in virtue of their relations to the dishes they order" (Nunberg, 1996, p. 115). Without going too deep into detail, one can say that the predicate F is taken from the set P, which roughly compasses the menu of the establishment, and that F' refers to an object of P', being the customers, and where the common property or relation is given by the order.

The example given by Nunberg is interesting, yet for the direction taken in this thesis not of too much importance, since only lexicalized words, and then only those cases of polysemy that can be found in WordNet, are of interest. Still, the formalism given in Definition 1 gives an interesting explanation of processes that take place in the creation of polysemy. In my eyes it is not only true in regular cases, as those similar to Example 24, but also for the irregular ones looked at in the following.

Before looking at examples of irregular cases of polysemy, one should recall what has been said about the application of animal names to humans: that the characteristics "cannot be predicted from knowledge of the animal sense" and that "properties ascribed to a person ... are stereotypical associations with the animal, which would not be encoded in the qualia structure" (Copestake and Briscoe, 1996, p. 37). Two things are noteworthy in this statement: For one, the non-predictability[64] of the property transferred from one usage of a word to the other seems to be evidence that we are not dealing with regular polysemy here.

The case of grinding is not concerned by this ascertainment. Grinding is a regular process, even though it might be used to refer to different products derived from an animal. But these products, even if not necessarily predictable, are not open to all properties of the given animal. Other than irregular polysemy: When someone is called a *pig* for example, this is likely to refer to cleanliness or tidiness of that person, or more precisely the lack of it, or the body size of a person. Still, such metaphorical usage of words can also be constructed ad hoc depending on context. Copestake and Briscoe simply call this "stereotypical associations with the animal", which is also the reason why it would not be found in the qualia-structure. Even though the characteristics that are transferred "cannot be predicted from knowledge of the animal sense", they are taken, nonetheless, from the world knowledge about that animal.[65] Taking into account what has been said in Definition 1, the properties of one thing in one domain can be used to refer to something else by the same name in a different domain. Given the relations shown in equations 19 and 20, we can see that this definition can indeed be used to also describe processes of irregular polysemy.

The case of *irregular polysemy* is one that seems much harder to process automatically by a computer than regular cases, where explicit rules can be stated. Often a single nuance of the connotation or world knowledge about an entity is transferred to a new situation. A look at the word senses of *chicken*, quoted from WordNet, shows the problem:

1. chicken, *poulet*, *volaille* – the flesh of a chicken used for food

[64]From a computational point of view, there are no clear rules, so the program can make no a priori assumptions about the meaning transfer.

[65]Of course there is also distributional evidence of these associations: Looking at a large corpus of English text, such as the one given in the *Wortschatz Leipzig* project (`http://corpora.informatik.uni-leipzig.de/`), a very frequent co-occurrence of *pig* is indeed *fat*. In other words, there is more than just stereotypes: There is structural evidence in the usage of the words, which could be taken into account.

2. chicken, *Gallus gallus* – a domestic fowl bred for flesh or eggs; believed to have been developed from the red jungle fowl
3. wimp, chicken, crybaby – a person who lacks confidence, is irresolute and wishy-washy
4. chicken – a foolhardy competition; a dangerous activity that is continued until one competitor becomes afraid and stops.

Sense 1 and 2 follow the pattern of grinding. But sense 3 and 4 are different. A *chicken*, as in sense 2, is attributed as easily scared. From this attribute, not a lexical property of *chicken* (sense 2), but an attribute taken from the world knowledge, sense 3, is derived. When calling someone a *chicken* this does not mean he or she has feathers, lays eggs, or anything like that; only the attribute *easily scared* is transferred to the new context: The person is easily scared like a chicken. Sense 4 is derived from sense 3: Two competitors play against each other until one becomes the *chicken* (sense 3).

The processes, which take place in the above-described cases of polysemy, require a certain amount of world knowledge.[66] A person living on an isolated island who has never seen a chicken, and therefore is not accustomed to its characteristics, could not understand why a *wimp* may be called a *chicken*.

Copestake and Briscoe (1996, p. 28f.) propose rules, like the one in lexical rule 1, for this kind of meaning transfer as well. Their rules allow names of animals being used for referents other than animals, e.g., humans, but it does not however formalize an abstraction of meaning such that the underlying meaning transfer from the animal to the denoted human would be made explicit.

This is of course a problem for a computer automatically processing language. The connection that exists between the senses 3 and 4 of *chicken* on the one hand and sense 2 of *chicken* on the other hand is not directly evident in the lexical material or in the network of WordNet. The computer, so to say, lacks the necessary general knowledge. Also, the metaphorical usage of words bears connotations. While lion is usually a positive byname, chicken and pig are not. This is not evident to a computer and the underlying meaning transfer is not directly observable or deduce-able from a resource like WordNet.

[66] Admittedly to a degree that is not available in WordNet directly.

5.2 Architecture of WordNet

In WordNet, a word is defined as "a conventional association between a lexicalized concept and an utterance that plays a syntactic role" (Miller *et al.*, 1990a, p. 3). The term *word* normally refers to both the meaning and the realization. Therefore, *word form* will be used to refer to the physical realization of the word and *word meaning* or *word sense* will be used to refer to the concept. This division of words into form and meaning raises the question of how these two concepts are represented and connected.

Synonymy is the most basic lexical relation between word forms in WordNet. Synonymy is described by a set of words forms that constitute the word sense, so-called synonymy sets (*synsets*). Synsets contain word forms that are synonymous.[67] While real synonymy is usually defined as two words that can be substituted in every linguistic situation and where this substitution never changes the truth value (*true* or *false*) of an expression, WordNet defines synonymy as follows:

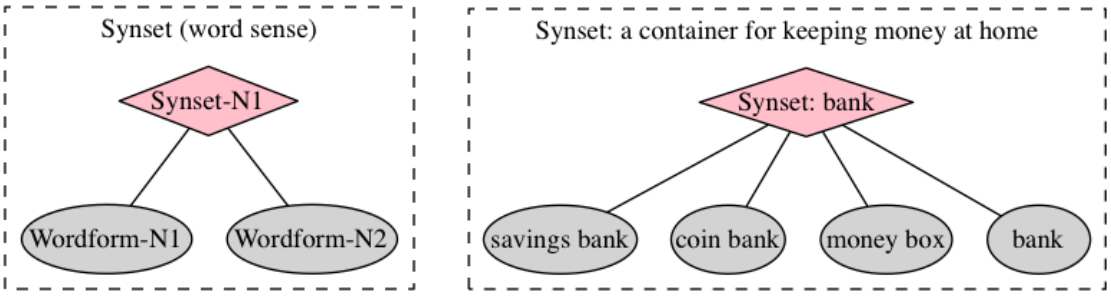
> two expressions are synonymous in a linguistic context C if the substitution of one for the other in C does not alter the truth value (Miller *et al.*, 1990a, p. 6).

Synsets are formed by a set of word forms that in a defined context C can be substituted for each other. These word forms are therefore in terms of C synonymous. A synset does not however describe the meaning of the set of word forms. The meaning is formed by the synset's members and the relations the synset has, the synset's neighbors.

In Fig. 16(a), a prototypical synset is shown: The synset is made up of word forms that together constitute the meaning. Figure 16(b) gives an example from WordNet: the synset *bank* as in a container for keeping money at home. As one can see, the word form bank is used to refer to this word sense and only in combination with other word forms like *money box* can one understand the meaning of *bank* in this example compared to other synsets that contain *bank* word forms but have a different meaning.[68]

[67] English is quite rich in synonyms. A possible explanation is the large number of loanwords from the Nordic languages (e.g., *meat*, derived from the Nordic word for food, replaces the Anglo-Saxon *flesh*), as well as loanwords that were used by different social classes after the Normans conquered England (again, many Norman words replaced the Old English animals names in the context of food), and of course the expansion of English over huge parts of the world resulting in the development of synonyms (e.g., *autumn/fall*; although this pair can be treated as synonymous, there are still diatopic differences).

[68] This dependence on the neighbors or a word to define the meaning has already been shown in the chapters before for lexical fields in what Trier called the mosaic, but also for other approaches like frame theory and also a basic assumption in medical studies.



(a) Structure of Synset, formed by word forms.

(b) Structure of synset *bank*, a container for keeping money at home.

Figure 16: Word senses, synsets, and word forms in WordNet.

Synonymy (S) is a symmetric relation,[69] meaning that it is equal to its inverse function ($S \equiv S^{-1}$). If a and b are synonymous (S) (i.e., aSb), the inverse S^{-1} is also synonymous (i.e., bSa). This implies that $aSb \implies bSa$.

Furthermore, and this is true for at least *true* or *full* synonymy as well as the actual formalization of synonymy in WordNet, but may not always be true for all uses of synonymy in linguistics, it is transitive: $aSb \wedge bSc \implies aSc$. Also, one could say that synonymy is reflexive: aSa.[70] If a relation is symmetric, transitive, and reflexive, it is an equivalence relation: $a \sim b$ or simply $a = b$.[71]

These conditions are actually the mathematical explanation for the clustering of the WordNet graph. Every synset contains equivalent elements. There are no elements that belong to more than one synset. In other words, the intersection between every two synsets s_1 and s_2 of a graph G is empty or they are disjoint: $\forall s_1, s_2 \in G : s_1 \cap s_2 = \emptyset$.

Following the definition of synonymy given above, WordNet distinguishes different parts of speech (e.g., nouns, verbs, adjectives, and adverbs). Since an adjective cannot replace a noun without changing the truth value of the expression, the relation of synonymy is always restricted to elements of the same POS.

The synonymy relation clusters, or partitions, all vertices of the network into synsets.

[69] This is also shortly mentioned in Miller *et al.* (1990a, p. 7). The two following types of relations, transitive and reflexive, are not mentioned. Nor are the implications on the network these properties have.

[70] *By definition* two expressions are synonymous if the replacement of one for the other does not change the truth value of the expression in a context C. This is not the case if one *replaces* one word with itself.

[71] This is at least true for fully synonymous words in natural language, but also for synsets in WordNet with the restriction that word forms making up a synset are not necessarily equivalent to each other in terms of lexical relations, such as antonymy.

These synsets represent the meaning. Their parts make up the synset and define the meaning, while at the same time the synset is the entity that contains the meaning and defines the meaning of its parts. This reminiscent of Trier's statement that from the parts the whole receives its meaning.

WordNet is not one fully connected component. It actually consists of four components, or subnetworks – one for nouns, adjectives, adverbs, and verbs – which are only loosely connected by morphosemantic relations between related word forms. In the following the different POS contained in WordNet will be discussed and their interconnection will be shown. WordNet distinguishes between *lexical relations* (i.e., relations between the lexical units or word forms) and *semantic relations* (i.e., relations between word meanings or synsets).

5.2.1 Nouns

Synonymy, as defined above, is one of the main structuring features of nouns in WordNet. The lexemes in WordNet are not organized in a hierarchical tree, but Synsets are organized hierarchically. Hyponymy and hypernymy are semantic relations between synsets in WordNet.[72] These relations are the inverse of each other. Furthermore, they are transitive and asymmetrical (Lyons, 1977, p. 292) as well as irreflexive. Transitive relations have already been defined above. In turn, an asymmetric relation R between two synsets a and b (aRb) is defined in a way that the inverse (bRa) is always false. Furthermore, as an asymmetric relation it is defined as irreflexive, meaning no relation of the kind aRa is defined.[73] From this it also follows that $a \neq b$. In mathematics a relation having the features of being transitive, asymmetrical, and irreflexive is called a *partial order* and orders a set of elements.

The set of all nouns is therefore ordered hierarchically. A hyponym inherits all features of its hypernym and "adds at least one feature that distinguishes it from its superordinate and from any other hyponyms of that superordinate" (Miller *et al.*, 1990b, p. 8). Multiple inheritance is possible. If A is a superordinate or hypernym and B is its hyponym, then the logical expression $\forall x[B(x) \rightarrow A(x)]$ applies. In terms of set theory one can say $B \subset A$.

[72] This is also a feature in the WordNet structure that is very similar to that in lexical field theory: Not the lexeme themselves are ordered hierarchically, but the fields (i.e., synsets) are.

[73] Lyons (1977, p. 308) claims that *dog* can be its own hypernym when asking whether a dog (1) is a dog (2) or a bitch. But *dog* (2) must be distinguished from *dog* (1). Usage (1) refers to the set of all animals of the species *Canis lupus familiaris*. Usage (2) only refers to the male members of this set, excluding the female members that are called bitch.

For example, the set of all *trees* is a subset of *plants*. If an object belongs to the class or set of *trees* it can also be said to be a *plant* and share the common features of plants such as using photosynthesis.

The main distinctive feature in the organization of nouns in WordNet, is their hierarchical structure. Originally, this did not mean a fully connected graph: 25 unique beginners were identified that subdivide the nouns into multiple hierarchies which "correspond to relatively distinct semantic fields, each with its own vocabulary" (Miller *et al.*, 1990b, p. 16). They can be seen in Table 8.

Miller (1998, p. 28) says that a unique beginner "corresponds roughly to a primitive semantic component in a compositional theory of lexical semantics". Like lexical fields, they are not built on lexical differences but on differences found in the nature of things, be they physical, biological, or philosophical, and are therefore of an ontological, in a philosophical sense, nature.[74] The unique beginners are mainly used in the organization of the lexicographer's work. Each one represents one file that the lexicographers work on.

Table 8: List of 25 unique beginners in the noun set of WordNet.

{act, activity}	{food}	{possession}
{animal, fauna}	{group, grouping}	{process}
{artifact}	{location}	{quantity, amount}
{attribute}	{motivation, motive}	{relation}
{body}	{natural object}	{shape}
{cognition, knowledge}	{natural phenomenon}	{state}
{communication}	{person, human being}	{substance}
{event, happening}	{plant, flora}	{time}
{feeling, emotion}		

During the compilation of WordNet however, some of these unique beginners have been grouped together, leading to only 11 unique beginners that are assigned the attribute *nouns.tops* in the WordNet database. Although it is often[75] stated that the unique be-

[74]While this association between nature and language has be disputed in linguistics for many decades now, the more pragmatic approach in NLP still constantly relates utterances to objects in the real word. The knowledge NLP is interested in, is to understand what objects or things in the real world a person is referring to. From a linguistic point of view and for the speaker of a language, this is of course quite obvious.

[75]In Miller (1998, p. 28), the possibility of one top most synset or root vertex of the noun tree was

ginners do not have a superordinate synset, this is, at least in the most recent version of WordNet 3.1, not true. The synsets marked as *nouns.tops* are in fact hyponyms of *entity*. Hence, all nouns are organized in one single tree. A distinguishing feature of those top vertices or unique beginners is that they, due to their usage as an auxiliary construction, do not contain word forms.

Meronymy is the part–whole relation (*has-a*). Given a synset $X = \{x_1, x_2, \ldots, x_n\}$ and a synset $Y = \{y_1, y_2, \ldots, y_n\}$, the meronymy between X and Y is defined if $\forall x[X(x) \rightarrow hasA(y, x)]$ is true: If x is an element of X, then y *has a* x applies for every x.

Meronymy, and its inverse holonymy, is also said to be transitive and asymmetrical (Cruse, 1986, p. 165). But it is, just as the hypernymy relation, also irreflexive. There is no synset that can be its own meronym. Meronymy and holonymy are only available in the noun set. As a relation that is transitive and asymmetrical, meronymy therefore forms a partial order, just like hypernymy/hyponymy.

Besides these semantic relations that exist between synsets, WordNet also contains a set of lexical relations. One lexical relation is antonymy. Antonymy is not a very rich feature of nouns. Still some nouns do have antonyms (e.g., *war* is an antonym of *peace*). Antonymy is very common within the field of descriptive adjectives.

Nouns (i.e., noun word forms) can also be related to word forms of other POS by morphological relations indicating derivational processes. An adjective can refer to a similar concept or situation as a noun from which it is derived. This will be discussed later.

The *derivationally related* relation exists between word forms of different POS. It indicates, besides the morphological processes underlying the word formation, a relation in meaning since it transfers the meaning from one POS to another (e.g., *music* (noun) and *musical* (adjective)). This information can be of great use for the purposes of this thesis, since it may connect word forms belonging to a polysemous word, but it should not exist between word forms of a homonymous word.

Figure 17 shows an exemplary graph of a possible organization of nouns in WordNet. One can see that some relations are restricted to synsets (i.e., in terms of an ontology, the relation's range and domain are restricted to entities of the type synset). Other relations are lexical and therefore only exist between the lexical units or word forms. The relation of synonym in the graph is dotted since this relation is not explicitly stated by a relation

rejected, saying that there exists no linguistic justification for it and that this vertex would only be a "generic concept" (Miller, 1998, p. 28). Still, WordNet 3.1 does exhibit exactly this behavior.

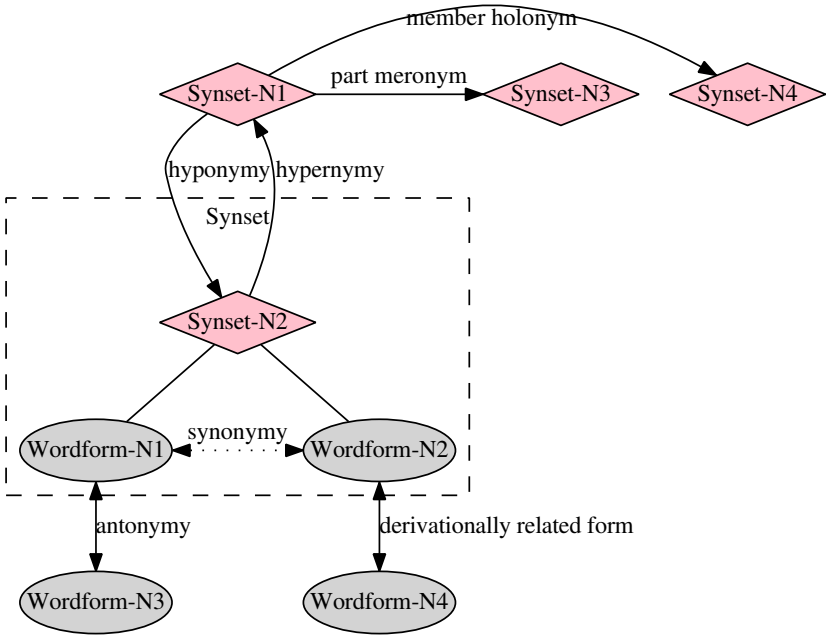


Figure 17: Exemplary organization of nouns in WordNet.

linking the synonymous word forms, but can be assumed from the fact that both word forms are members of the same synset.

5.2.2 Adjectives

Adjectives are also organized in synsets. Unlike the noun set, the adjective synsets are not hierarchically ordered. Fellbaum *et al.* (1990, p. 27) say that "[t]he semantic organization of adjectives is more naturally thought of as an abstract hyperspace of N dimensions rather than as a hierarchical tree". WordNet distinguishes two main categories of adjectives: descriptive adjectives and relational adjectives. Descriptive adjectives can be used as attributes, while relational adjectives can be used as modifiers. Unlike in the field of nouns, antonymy is a very rich feature among descriptive adjectives.

Antonymy in WordNet is a *lexical relation* between word forms. The synsets {*high, tall, top, up*} and {*low, down, inferior, short, little*} are opposites of each other, but they are not antonymous. While *high/low*, *up/down*, and *tall/short* are antonyms, *high/down* or *tall/low* are not.

One condition of antonymy regularly cited is the *association test* (Charles and Miller,

1989; Fellbaum *et al.*, 1990; Justeson and Katz, 1991, 1992). In case of antonymy, the use of a lexical item automatically invokes its antonym. Given a descriptive adjective, people are asked to name associated words. The answers turn out to be mostly their antonyms: *Good* invokes *bad*, and *high* invokes *low*. Also, the antonym of a word x is not always $\neg x$. Saying that someone is *not rich* does not say that he or she is *poor* (cf. Miller *et al.*, 1990a, p. 7). Still, *poor* and *rich* are antonyms, or as said in Chp. 3.4.4, they lie on opposite ends of a scale of wealthiness. *High* and *low* are antonymous adjectives. They are said to be possible values of an attribute *HEIGHT* (cf. Fellbaum *et al.*, 1990, p. 27). Most attributes are bipolar: The values of *HEIGHT* can lie between *low* and *high*.

This explains why the opposed pair of *high/down* is not treated as antonyms in WordNet. For one, they are not values of the same attribute *HEIGHT*, and secondly they "are not familiar antonym pairs" (Fellbaum *et al.*, 1990, p. 28). Of course, the second condition, the association test with English speakers, is connected to the first one.

Antonymy is "not the same as the conceptual opposition between word meanings" (Fellbaum *et al.*, 1990, p. 28). Except some descriptive adjectives of Germanic origin (e.g., *good/bad*), most antonymous pairs of descriptive adjectives in English are derived through morphological rules by adding a negation suffix like *un-, in-*, and others. This is the reason why Fellbaum *et al.* (1990) call antonymy a relation between word forms: "Morphological rules apply to word forms, not word meaning" (Fellbaum *et al.*, 1990, p. 28). Following this statement, it is argued that antonymy is not a semantic relation, but a lexical relation: "Antonymy is a lexical relation between word forms, not a semantic relation between word meanings" (Miller *et al.*, 1990b, p. 7).

Opposing pairs, such as *high/down*, do not have a special relation in WordNet. Looking for an opposing adjective when no direct antonyms are available means looking for synonyms that have an explicit antonym. All descriptive adjectives in WordNet have at least indirect antonyms.

The second main class of adjectives in WordNet is that of relational adjectives. These adjectives can be compared to a modifying noun. Relational adjectives are used to indicate some form of association to a noun. Fellbaum *et al.* (1990, p. 34) give the examples of *dental* having to do with *teeth*, or *fraternal*, associated with *brother*. But not only adjectives of Latin origin can be used as relational adjectives. Using derivation, some nouns, such as *music*, "give rise to two homonymous adjectives; one relational adjective

restricted to predicative use, the other descriptive" (Fellbaum *et al.*, 1990, p. 34).[76] This results in polysemous adjectives, here *musical*, which have two senses as in musical instrument (an instrument used to play music) and *musical child*, a child with a musical ability. In contrast to descriptive adjectives, relational adjectives are not related to a scalable attribute of a noun. Instead, these adjectives are semantically closely related to the corresponding noun (i.e., they "refer to the same concept, but they differ formally (morphologically)" (Fellbaum *et al.*, 1990, p. 35)). Also, they mostly have no direct or indirect antonyms.

Other adjectives include what Fellbaum *et al.* (1990) call reference-modifying adjectives and the color adjectives. The latter ones naturally have no antonyms but can have synonyms.[77]

Color adjectives are widely used in metaphors and metonymy and are a rich source of polysemous words. Polysemous usage of color adjectives is not always regular, as was the example of *olive* above. In most cases there will be some semantic connection and not only coincidental accordance of word forms, but these connections might not be obvious.[78] Examples of metonymic usage of color adjectives include the *reds*, referring, according to WordNet, to Marxists, or the name *greys* for the soldiers of the Confederate army wearing grey uniforms, similar to the term *redcoat* for the red-wearing soldiers of the British army during the revolutionary war. These metonymical usages stand *pars pro toto* for the soldiers wearing the color. Furthermore, adjectives can be used as verbs to mean that something turns its color, e.g., *to blue*, or *to yellow*.

Figure 18 shows a possible graph of an adjective synset in WordNet. The relations of synonymy and antonymy have already been discussed. Apart from these lexical relations among word forms, adjective synsets are not ordered hierarchically by relations such as hyponymy or hypernymy. Instead they can be linked by *also see* or *similar to*. If we are looking at an adjective synset such as {good}, this will be linked to the corresponding comparison {better} by *also see*. *Similar to* indicates an almost synonymous relation but not between word forms, but between synsets. Again the synset {good} might be related

[76] Fellbaum *et al.* (1990) state the relation between the two lexemes of the adjective *musical* as homonymous. Polysemous would be more appropriate here to make a distinction to homonymy as defined in Chp. 5.1.

[77] In WordNet, *purple* and *violet* are subsumed in one synset, though such adjectives are highly discussable, culture dependent, and often up to subjective estimation.

[78] For example, Ammer (1993, p. 192) traces back the meaning of the expression that is not very often used anymore *you're yellow* meaning someone is a coward to the connection of *yellow* with betrayal. Judas Iscariot has often been portrayed wearing yellow clothes.

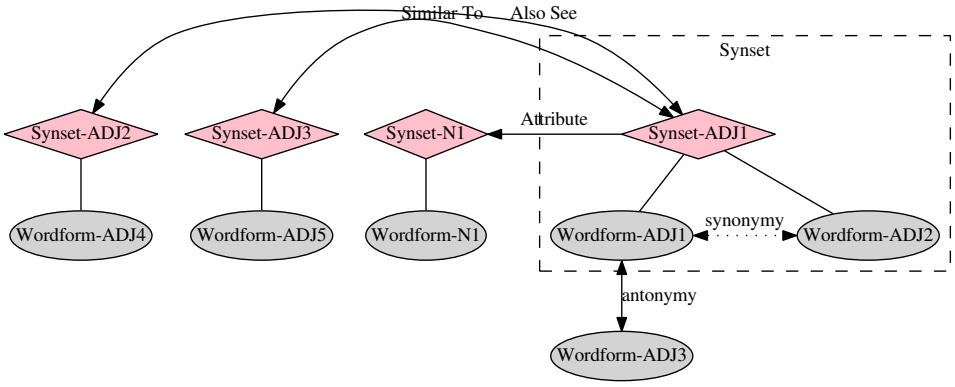


Figure 18: Exemplary organization of adjectives in WordNet.

to that of {fresh}. Saying an *apple is good* or an *apple is fresh* is not the same, but they are closely related. A fresh apple is expected to be good and vice versa, though this is no categorical causal nexus.

An adjective synset {good} might be used as an attribute in a special context. It is then linked to a noun synset it can be used to describe (e.g., the {quality}). As can be seen in Fig. 19, adjectives can also be related to word forms from other POS through a *derivationallyRelated* connection, which indicates a relation through derivation.

5.2.3 Adverbs

The modeling of adverbs in WordNet is similar to that of adjectives, though more simplistic. The adverb graph mostly only consists of a collection of unrelated synsets. Sometimes word forms have antonyms or some adverbs are derived from adjectives and therefore *derivationally related* to an adjective synset (cf. Miller, 1998, p. 64ff.). This can be seen in Fig. 19. As one can see, the structure of adverbs is not very elaborate. The complexity of the graph is low; there are no larger clusters or even connected components. The level of information given in an adverb graph is therefore expected to be very low.

5.2.4 Verbs

Not only in grammars or syntactic theories, as well as in most semantic theories such as frame semantics (Fillmore, 1976), semantics in construction grammars (Pollard and

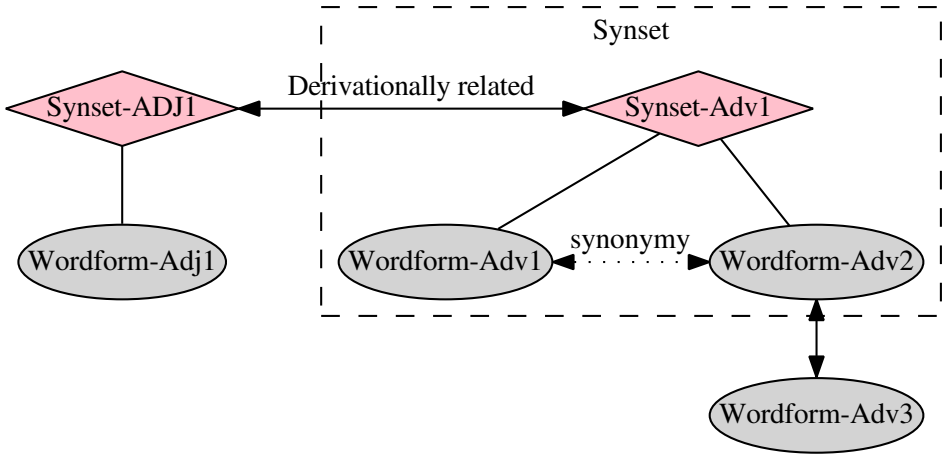


Figure 19: Exemplary organization of adverbs in WordNet.

Sag, 1988), or formal semantics, the verb is the linchpin of the theory. Since WordNet treats verbs just as other POS, they are not assigned any kind of further grammatical information. For example they contain no information on combinatory restrictions (e.g., they are not restricted to what nouns they can be combined with or the number or kind of grammatical object they bind). The meaning of a verb can change with the arguments it takes. The most common verbs in English (e.g., *have, be, run, make, set, go, take*) do not have one meaning but a multitude of possible senses.[79]

Fellbaum (1990, p. 40) says that verbs in *Collins English Dictionary* have on average 2.11 senses while nouns only have 1.74. This finding can also be made in WordNet: Verbs are much more polysemous than nouns. Homograph word forms make up 30.38% of the nouns, while 74.94% of the verbs are homographs.

WordNet currently contains 13,767 verb synsets. These are organized in different files corresponding to semantic domains such as "verbs of bodily care and functions, change, cognition, communication, competition, consumption, contact, creation, emotion, motion, perception, possession, social interaction, and whether verbs" (Fellbaum, 1990, p. 41) and

[79]Fellbaum (1990, p. 40) cites Gentner and France (1988), who conducted an experiment where verbs were used in violation to their selectional restriction for nouns. When subjects where asked to paraphrase the sentences, they reinterpreted the verbs in relation to the nouns and assigned a new semantic meaning, differing from the verb's known senses. They conclude that "noun representations may be typically more internally cohesive than verb representations and therefore less easily altered. ... Change of meaning does occur to accommodate contextual constraints, but that change involves computations over the internal structure of the word meanings, particularly that of the verb" (Gentner and France, 1988, p. 379).

one file containing verbs of states that are not semantically connected otherwise.

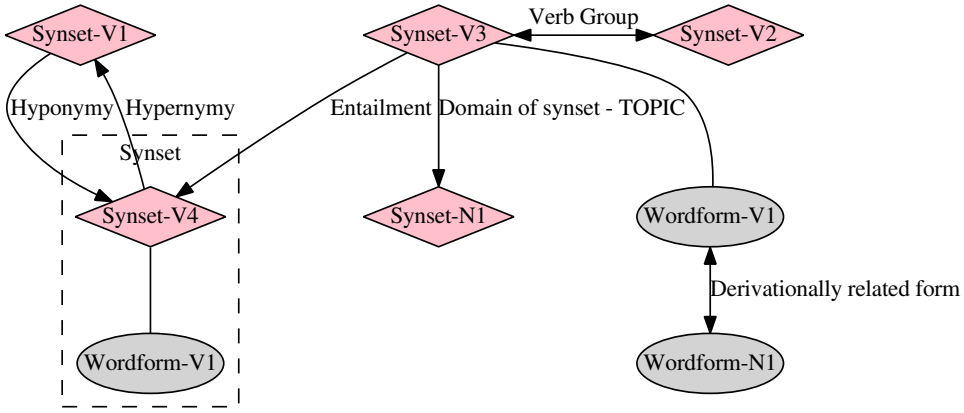


Figure 20: Exemplary organization of verbs in WordNet.

Figure 20 shows an exemplary verb structure in WordNet. One can see the hierarchical structure that is established through hyponymy and hypernymy relations. Even though there are very few synonymous verbs, verbs are also organized in synsets. These mostly contain only one word form. The relation *verbgroup* is used to group verb synsets that are closely related though not synonymous and can be thought of as similar to frames in frame semantics, as well as to the notion of fields mentioned earlier. This relation is of special interest since it is expected to relate polysemous verb synsets. It is for example used to relate the following two senses of *have*: *have or possess, either in a concrete or an abstract sense* and *have as a feature*. This relation is not applied in a coherent way in WordNet (i.e., it is often missing where it could have been applied).

Not yet mentioned was the entailment relation. Entailment includes various relations. Fellbaum (1998, p. 77) defines entailment as a "relation between two verbs *V1* and *V2* that holds when the sentence *Someone V1* logically entails the sentence *Someone V2*". The relation in WordNet exists between two synsets as can be seen in Fig. 20. For example, *Someone snores* entails *Someone sleeps*. One of the relations subsumed under entailment is troponymy, "which relates synset pairs such that one expresses a particular manner of the other (e.g., {whisper}-{talk} and {punch}-{strike})" (Fellbaum, 2006, p. 667). Further entailment relations in WordNet according to Fellbaum (1998, p. 77ff.) are backward entailment {divorce–marry}, presupposition {buy–pay}, and cause {show–see} (Fellbaum, 1998, p. 83).

An interesting feature of verb synsets is the possible relation *domain*. A domain can designate a topic (i.e., a noun synset). Verb synsets like {run}, {jump}, and {play} can be associated with the domain {sports}.

5.2.5 Overview and Shortcomings

Table 9 gives an overview over the existing relations in WordNet with respect to the type (i.e., a lexical or semantic relation) the POS in question, and a short example.

In order to understand how a network-based link prediction in WordNet might be done, one should also look at these relations in more detail. Table 10 shows the relations with regard to the word classes and the number of their occurrences in absolute numbers.

Especially the small relations will be of great interest. Derivationally related word forms are a good indicator of closely related meanings that might indicate polysemy if the two word forms are homographs. The same is true for the *attribute*, *pertainym*, *similar to*, *see also*, *verb group*, *entailment*, and *cause* relation. These are often referred to as the *cousin relations* in WordNet.

These relations, even though small in number and apparently unequally distributed, are, if they connect homograph word forms, a first indicator of polysemy but will only apply to a small percentage of the possibly polysemous cases. In the WordNet graph, these relations will lead to short distances; in the case of a lexical relation this geodesic path will be 1, in case of semantic relations 3.[80] Furthermore, these relations also tightly relate otherwise further separated meanings, which are not directly connected otherwise. This should lead to a small-world structure.

Some etymologically related word forms will tend to have small shortest geodesic path due to relations that connect (derivationally) related forms. Unfortunately, this is only true for very few polysemic cases in WordNet. In general one can expect forms that are closely related, maybe with a geodesic path of <3 or a little over that, to be polysemous or have at least a very high probability of being related. This does not mean that word forms that are separated by a geodesic path with a much longer or indefinite path length can be related.

This analysis of the structure of WordNet that was undertaken in this chapter reveals

[80]Semantic relations connect the synsets. Therefore the distance between the word forms within the synsets is 3.

Table 9: Relations in WordNet.

Relation	**Type**	**Part of Speech**	**Examples**
synonymy	lexical	N,V,Adj, Adv	{buy, purchase}
antonymy	lexical	N,V,Adj, Adv	good, bad
hyponymy	semantic	N,V	{oak,...}, {tree,...}
hypernymy	semantic	N,V	{tree,...}, {oak,...}
meronymy	semantic	N	{leg,...}, {chair,...}
holonymy	semantic	N	{chair,...}, {leg,...}
entailment	semantic	V	{jump,...}, {fall,...}
cause	semantic	V	{burn,...}, {combust,...}
also see	lexical	V,Adj	jump, jump on
verb group	semantic	V	{burn,fire,...}, {incinerate}
domain of synset	semantic	V,N	{run,...}, {sport,...}
similar to	semantic	Adj	{good,...}, {fresh,...}
attribute	semantic	Adj, N	{good,...}, {quality,...}
derivationally related	lexical	N,V,Adj, Adv	good, goodness

Table 10: Overview: relations per word class.

Relation	**Noun**	**Adjective**	**Verb**	**Adverb**
synonymy	146312	30070	25061	5592
antonymy	1560	3547	690	540
hyponymy	84427	0	13256	0
hypernymy	84427	0	13256	0
meronymy	22196	0	0	0
holonymy	22196	0	0	0
entailment	0	0	408	0
cause	0	0	221	0
see also	0	2690	349	0
verb group	0	0	1744	0
domain of synset	6352	1427	1284	110
member of domain	9242	0	0	0
similar to	0	21434	0	0
attribute	639	639	0	0
derivationally related	22100	8994	13274	7
pertainym	0	3751	0	0
participle	0	59	0	0

some shortcomings and possible problems that might arise when using WordNet in the context of NLP.

In the scope of NLP, WordNet is sometimes found to be too fine-grained. In word sense disambiguation (WSD), some homonymous words are found in too many, sometimes very closely related synset, which makes WSD in correspondence to WordNet a very hard or maybe even impossible task (cf. Mccarthy, 2006; Navigli, 2009). Biemann (2012) mentions an upper bound of 80%, which WSD algorithms do not exceed due to the "fine-grained sense structure of WordNet" (Biemann, 2012, p. 4038).

Biemann and Riedl (2013) also found that WordNet's coverage in some domains is very low. Depending on the texts that are to be processed, one might find homonyms whose senses are not fully represented by WordNet. Biemann and Riedl use Wikipedia and find that *anime* was contained in two synsets but none was of the sense *Japanese animation movie*. Such findings might further hinder WSD tasks based on WordNet.

A further problem that might arise when using WordNet is its limitation to semantic relations.[81] Verbs have no information on the numbers of objects or kinds of objects they bind or possible selection restrictions. Sometimes verbs that share a common word form can be distinguished using such features.

The so-called cousin relations have been found to be a good indication of polysemy between word forms. It has also been stated that these relations, unfortunately, are only used very seldom and are missing in most cases.

5.3 Network Analysis

In this chapter, the network topology of WordNet will be analyzed. This analysis gives insight into the structure and characteristics of the network. Together with the in-depth analysis of the ontology structure, this information will be used to choose features for the link-prediction task.

5.3.1 WordNet as a Graph

The network has a total of $324,602$ nodes. These vertices include all word forms and synsets contained in WordNet, and they are connected by $584,528$ edges. The graph is not connected; it consists of $5,051$ weakly connected components.

[81] Even though there exists some morphological relations as well.

The degree distribution shows how many vertices have a certain degree. As has been mentioned before, small-world networks expose a degree distribution that can be fitted to a power law. If such a distribution is fitted to a log–log scale, one can see the scale-free distribution as a more or less straight line. Furthermore, a small-world network is defined as having relatively short geodesic paths (due to vertices with a very high degree, so-called hubs or authorities) and as having a high clustering coefficient.

The small-world phenomenon is important because the paths between every two vertices in the network are relatively short. This behavior has especially been noticed for social networks, as well as other complex networks, and as such for semantic networks.

In Figure 21, the degree distribution of the WordNet network is when the directedness of the edges is respected. Figure 21(a) shows the in-degree distribution and the corresponding power law $p(x) = x^{\alpha}$, where $\alpha = -2.708156$.[82] Figure 21(b) shows the out-degree distribution and the power law $p(x) = x^{-3.498834}$ fitted to it.

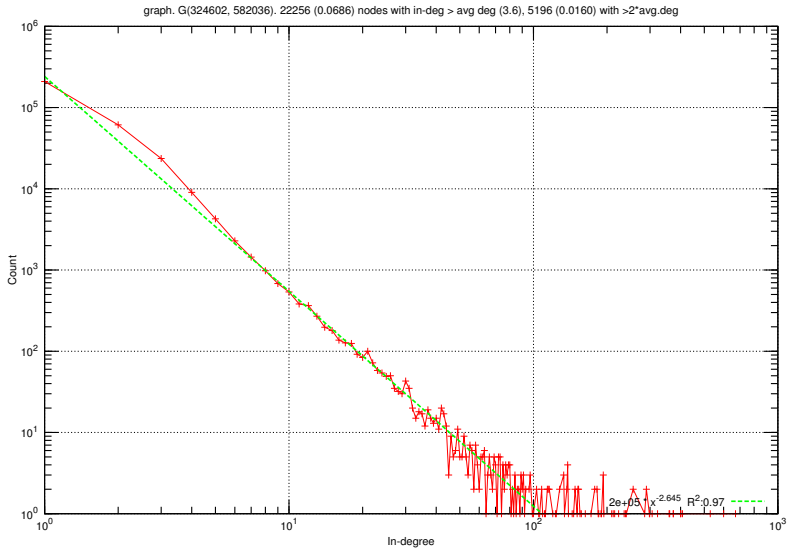
Figure 22 shows the degree distribution when the direction of the edges is ignored, and the fitted power law $p(x) = x^{-2.820797}$. The overall findings in these three degree distributions show the typical behavior one would expect of a small-world, scale-free network. Still, the clustering coefficient is much smaller than would be expected from a small-world network: 0.004.

As suspected from these findings, the geodesic path in the graph, (i.e., the average shortest path or degree of separation) is found to be ~ 9.7 edges. This is within the range of geodesic distances normally found in social networks. The network diameter (i.e., the farthest geodesic path between two vertices) is 27.

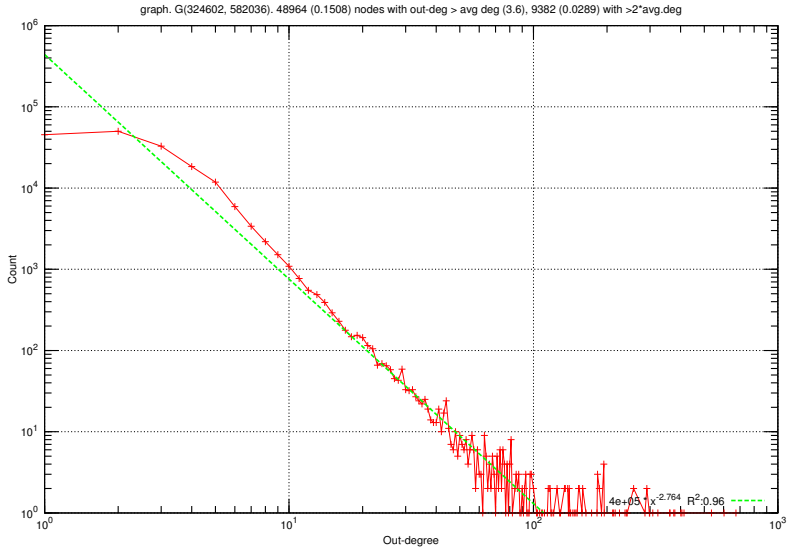
Small world networks contain few vertices with a very high degree, while most vertices have a degree close to the average or lower. These vertices result in the degree distribution seen above and in the short geodesic paths. In WordNet, the synset containing the word forms {*metropolis*, *city*, *urban-center*} has the highest out- and in-degree: 674 and 671, respectively, which results in a total degree of $1,345$.

In this case, most relations are instance relation. Instead of using the hypernym relation, the WordNet architecture offers the instance relation. Instance is a subtype

[82]The power-law distribution is limited by the lowest possible value, which is 0, and the highest, which is, as we will see, $1,345$. The lowest value being 0 is due to the fact that every word form belongs to a synset. Since all vertices are either a word form or a synset, the lowest possible degree is 1. Looking at a directed graph, some word forms might have a 0 out-degree and synsets a 0 in-degree. So the lowest possible value, when treating the graph as directed, is 0 and 1 when treating the graph as directed.



(a) In-degree distribution with fitted power law.



(b) Out-degree distribution with fitted power law.

Figure 21: WordNet degree distribution (directed network).

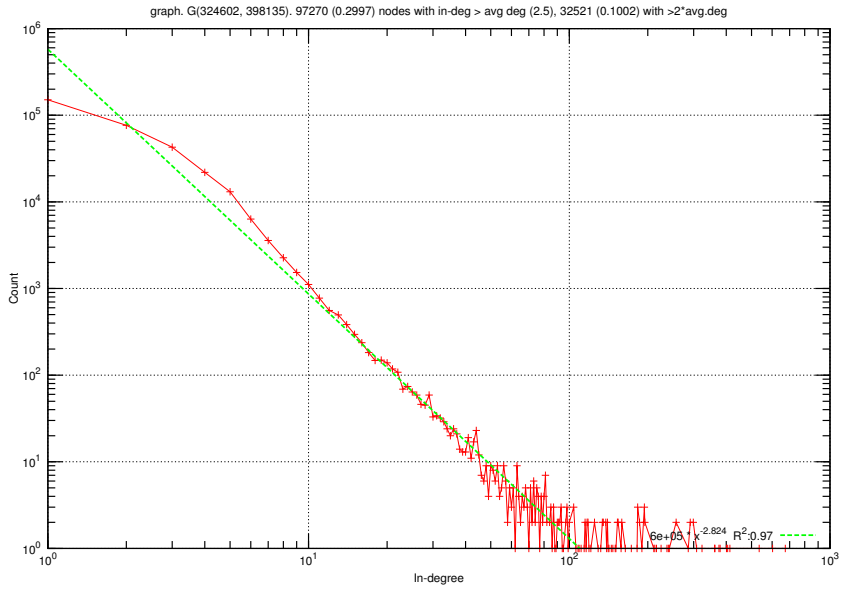


Figure 22: WordNet degree distribution (ignoring direction) with fitted power law.

of hypernym or hyponym.[83] Hubs or authorities are interesting since they connect one synset to another synset with a relatively short path. A synset such as *Dakar* can be an instance of *city* as well as another geographical entities such as *port*. This offers a rich source of possibly polysemous use of words (e.g., city names can refer to the city, and the port, airport, and so on).

But not only synsets containing a lot of instances, such as cities, can have many relations and thus a high degree. The {law, jurisprudence} synset's (see Fig. 23) in-degree is 613, its out-degree 615, and the total degree sums up to $1,228$. This synset is connected to others by the *topic_of* relation, which is the inverse of the domain relation. This relation connects nouns, adjectives, verbs, and adverbs. Synsets like {law, jurisprudence} connect the different subsets (e.g., nouns, adjectives, verbs, and adverbs) of WordNet and are therefore of special interest. A hub like this builds shortcuts between related vertices in the graph.

The degree distribution, and the low average geodesic path length it is caused by, fits the definition of a small world. Still, the clustering coefficient is very low in WordNet. The clustering coefficient indicates how well connected the vertices and its neighbors are.

[83] An instance in an ontology is a vertex that is not an abstract category, but an entity. In this case the instances are city names.

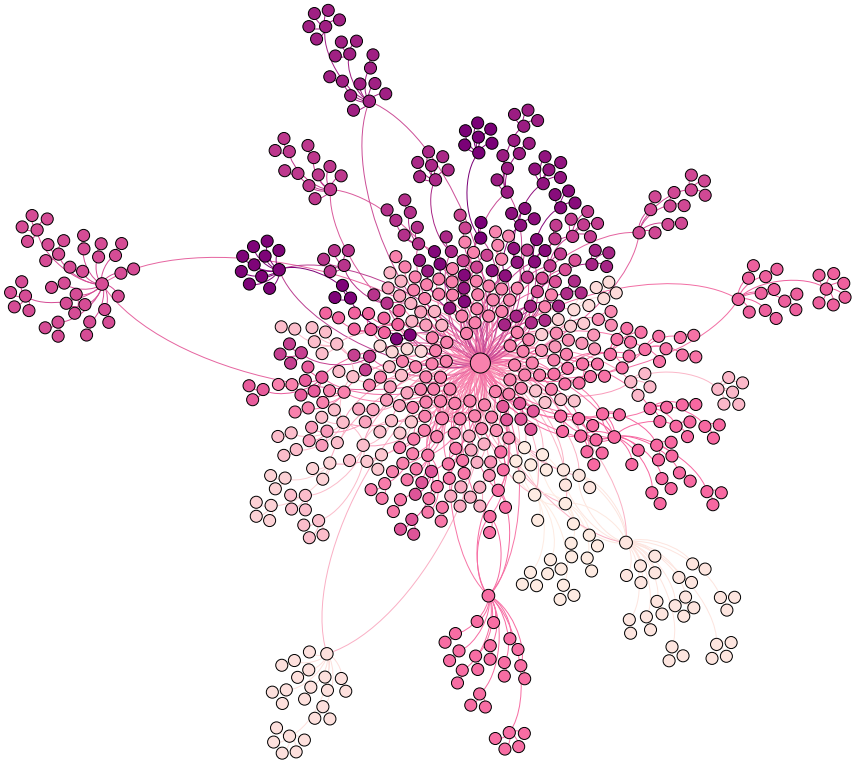


Figure 23: Schematic plot of synset {law, jurisprudence} and its first- and second-degree neighbors.

The synset structure, a synset is connected to the word forms, but the word forms are not connected to themselves (see Fig. 16), causing the very low clustering coefficient of 0.004. Also, given the hierarchical structure of the synsets, not all child synsets of a superconcept are connect (e.g., most co-hyponyms subsumed under the synset {metropolis, city, urban center} are not connected in any way). This is a behavior that is not expected of social networks for example.

In other words, WordNet exposes an unusual network topology that is caused by design choices made in the ontology (e.g., that synonyms and co-hyponyms are not directly connected). While many complex networks and their topology can be explained relying on the preferential attachment model by Barabási and Réka (1999), WordNet's structure does not match the features for social networks. It has been claimed by Steyvers and Tenenbaum (2005) that WordNet and other semantic networks evolve similarly to the preferential attachment model, but with a certain probability of new vertices to be connected not only to an existing node with a probability that depends on the vertex degree, as well as to other neighbors of this vertExample Steyvers and Tenenbaum (2005) claim that this process can be thought of as refining an existing representation of a word's meaning by adding a new vertex with a similar, still different, pattern of connectivity. An example for such a behavior might be the already mentioned synset of {law, jurisprudence} that is defined by many connections in very different domains.

The short average geodesic path and the degree distribution indicate a network growth model that can be explained suspecting new vertices being added following preferential attachment. New vertices are, at first sight, more likely to connect to already well-connected vertices in the graph. This would also be expected by the Steyvers and Tenenbaum (2005) growth model. Still, this latter model would predict a much higher clustering coefficient, even higher than that of preferential attachment.

To further investigate the supposed evolution of a static network, the large-scale structure of a network can be examined by looking at the communities of the network. Especially in large networks, such as the WordNet network, plotting the community structure can give a good impression of the topology of the network. The so-called *network community profile* (NCP) (Leskovec *et al.*, 2008a,b, 2010) can give such an overview.

In Leskovec *et al.* (2010), different social and information networks are compared and their NCPs analyzed. Leskovec *et al.* (2010, p. 4) define a good community as a set of vertices that "have many internal edges and few edges pointing to the rest of the network". This phenomenon is known as *conductance*. The lower the conductance, the

more community-like is the set of nodes. The NCP is a function over the size of possible communities in a network. The NCP plot for the WordNet network can be seen in Fig. 24.

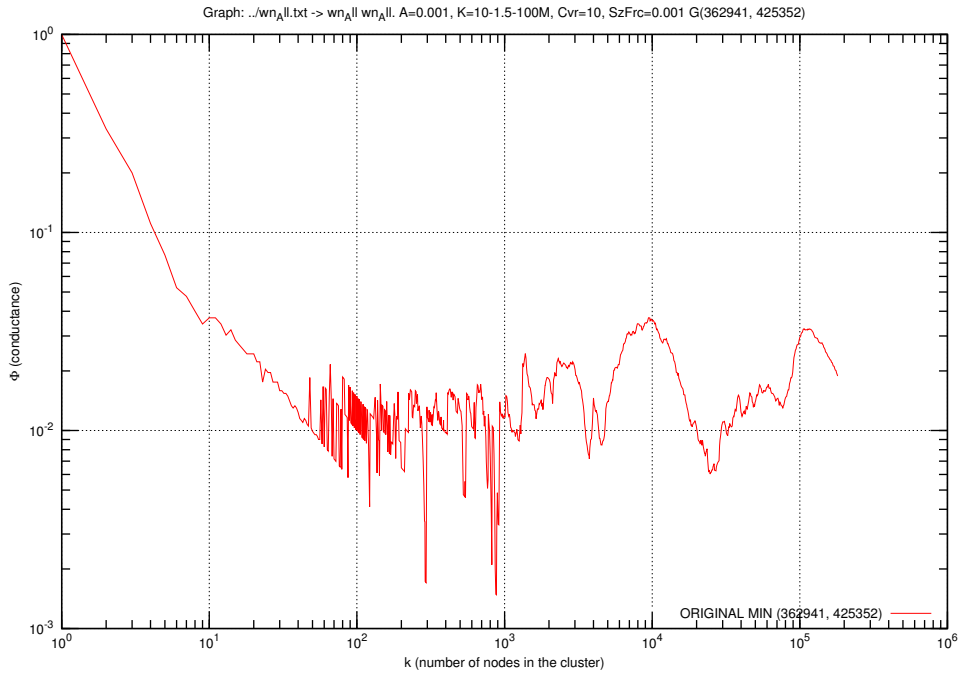


Figure 24: NCC plot of WordNet.

The local minima of the plot indicate the size k of the communities and the corresponding low conductance. As one can see, the best community sizes for the WordNet networks (i.e., those with the lowest conductance) lie between 10^2 and 10^3 vertices per community.

This plot shares some typical properties with other complex networks such as large social or information networks. Leskovec *et al.* (2010) found that the best community sizes for most of the large networks they examined lie between 10^2 and 10^5, more likely to be near 10^2.

NCP plots of small social networks are normally sloping downward. This means, with increasing size, the conductance also increases, which means that smaller communities can be added up to larger, still meaningful communities. Complex networks do not normally show this behavior. Most large networks expose an upward sloping plot, meaning that the communities get less community-like when growing in size.

The graph in Fig 24 first slopes down and after reaching the local minima slopes slightly up again. Following the analysis of Leskovec *et al.* (2010, p. 41) on the typical NCP for different network evolution models, a network created using pure preferential attachment is expected to slope up more before reaching an almost flat line.

When comparing the WordNet plot to the plots generated by different evolution models, none perfectly fits the given plot. While preferential attachment can explain the degree distribution and the short geodesic paths, it does not account for the community structure of WordNet. The model proposed by Steyvers and Tenenbaum (2005) also accounts for the degree distribution, but not for the low clustering coefficient that is caused by the design choices in WordNet. Both models fail to predict or explain the existence of the components WordNet is made of. The existence of such components seems to be responsible for the slope of the NCP plot. Therefore, they can not be readily used to give insight into how missing relations should be connected. We will see later on that, for other networks such as DBpedia, the evolution models give a very good indication of where relations might be missing.

5.3.2 Graphs of Single POS

When looking at the graphs built of only those vertices of the same POS, one can expect to see some structural properties that can also be concluded from the analysis of the WordNet architecture. For one, one might expect to find non-connected graphs with relatively long geodesic paths in comparison to the graph that is built of all word forms and synsets. This is due to the fact that a lot of WordNet's structure is found in inter-POS relations (e.g., derivational relations that are missing within these subsets).

In a first attempt to extract subsets from WordNet, I defined the subsets as all vertices belonging to one POS plus its immediate neighbors (including those of other POS). This definition leads to unexpected and unusable results (e.g., that all subsets, including the adverb subset, exposed a power law degree distribution which cannot be expected from the WordNet analysis). This was due to the fact that the subsets are interconnected through a relatively small number of hubs (e.g., a noun synset acting as the domain of many adjective or adverb synsets). Especially adjectives and nouns are related through *derivation* and *domain* relations. The latter is also true for adverbs that are related to nouns via the *domain* relation and not to verbs as one might expect for their use in

language.[84] Nouns are furthermore strongly connected to verbs. This shows the central role of the noun subset of vertices in WordNet. Such highly connected vertices are expected to have a high betweenness value, since many shortest paths between vertices of different POS-based subsets are expected to run through them.

The definition was redefined to only those relations between two vertices of which both are members of the same POS. Doing so, all information on interconnection is lost. Also the vertices do not show their full degree, only that existent within the subset. The whole graph is more than the sum of these subsets since those connections from one POS to any other POS are missing.

The Noun Graph

The noun graph is a weakly (but fully) connected graph (i.e., there is a path from every vertex to every other vertex of the graph). The graph is *weakly* connected because the direction of the edges has to be ignored to find a path from every vertex to any other vertex of the graph.[85]

The connectedness of the noun subset is caused by the fact that all nouns are organized in a taxonomy, sharing one common root node, while the adjectives and adverbs are not.

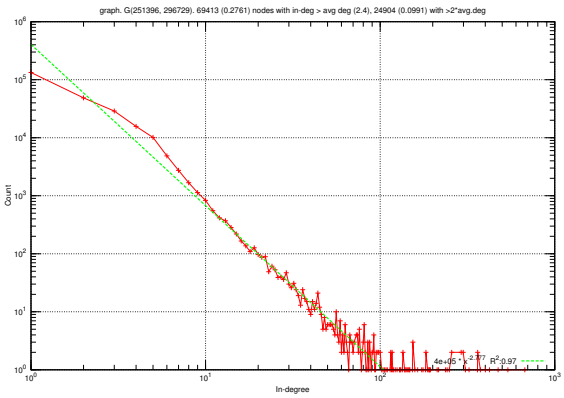
The noun graph consists of 251.396 vertices and 412.772 edges. The longest geodesic path between two vertices is 22, and the average geodesic path length is ~ 9.55 and hence slightly shorter than that of the whole graph.

The vertices with the highest degree (i.e., the hubs) are those already mentioned before.

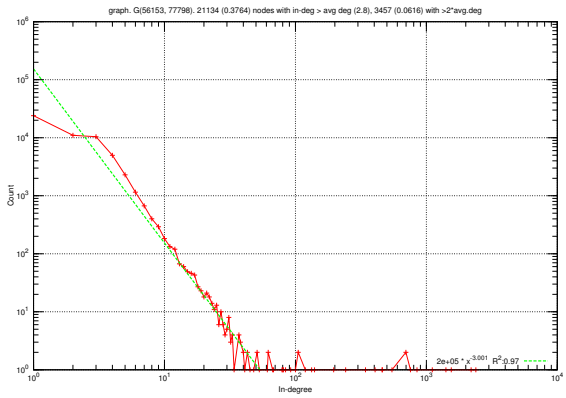
Since the noun subset makes up more than half of WordNet, it is not surprising that it shows very similar properties as the whole WordNet graph. The degree distribution of the noun graph, as shown in Fig. 25(a), is similar to that of the whole graph. It fits a power law with $\alpha = -2.67$. With regard to the small-world phenomenon, the clustering coefficient of the subset is 0.004 as well.

The NCC plot in Fig. 26(a) is also very similar but indicates a stronger clustering at the size of around 10^3.

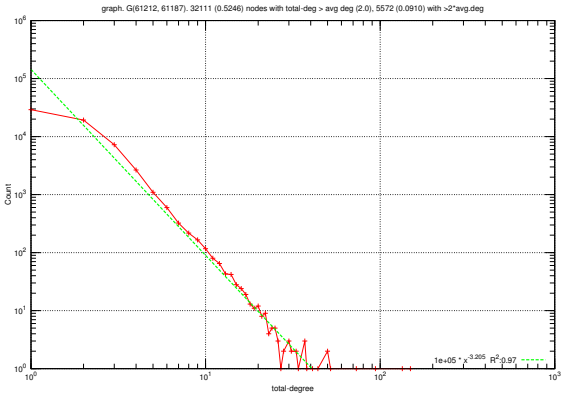
[84] One has to keep in mind that this grammatical or syntactical information is not present in WordNet.
[85] Every synset points to its members, but the members do not point back.



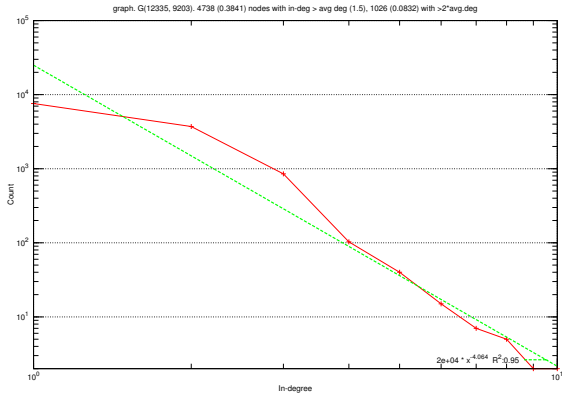
(a) Degree distribution of the noun subset and fitted power law with $\alpha = -2.67$.



(b) Degree distribution of the verb subset and fitted power law with $\alpha = -2.91$.



(c) Degree distribution of the adjective subset and fitted power law with $\alpha = -3.36$.



(d) Degree distribution of the adverb subset and fitted power law with $\alpha = -5.52$.

Figure 25: Degree distribution, in- and out-degree combined, of the four WordNet subsets with the appropriate power law fitting. Note the different scaling of the plots.

The Verb Graph

The verb subset contains $56,138$ vertices and 78.741 edges. It is thus significantly smaller than the noun graph. The clustering coefficient is 0.004 and thus the same as in the noun graph. The average geodesic path length is ~ 11 and hence longer than that of the whole WordNet graph. The length of the furthest geodesic path between two vertices (i.e., the diameter of the graph) is 33. Although verbs do not share one common root node, the verb graph consists of only one weakly connected component. This is mainly due to the fact that verbs are organized in verb groups, similar to frames in frame semantics.

The degree distribution that the verb graph exposes (see Fig. 25(b)) resembles that of the total graph and that of the noun subset, but the power law shows a steeper slope and more noise around the count of 10^4 as well as around 10. The power laws α value lies around -2.91. The NCP plot (see Fig. 26(b)) is more constant without clear cuts or local minima with a slight downward slope. This means there is no clear tendency as to the size of optimal clusters. The higher the number of vertices in the cluster, the better are these clusters. This general downward slope is not surprising: The whole connected component apparently makes up the best cluster of the graph.

The Adjective Graph

The nouns and the verbs are organized in a hierarchical order. The adjectives do not form such hierarchies. This results in $3,774$ small unconnected components. The graph consists of $61,212$ vertices and $77,456$ edges. The average geodesic path, which converges to infinity due to the unconnectedness, can nonetheless be calculated using methods such as random walks.

Still, this results in very long paths, on average 17.77, and diameter of the adjective graph is even 44 edges long. The degree distribution of the adjective graph seen in Figure 25(d) follows in general a very similar power law with $\alpha = -3.36$ as the noun or verb graph, even with similar limits and similar noise around the end of the distribution. The clustering coefficient is, again, 0.004.

Since the graph is not wholly connected, the NCP plot shows several local minima of cluster sizes k between 10^2 and 10^3. Not surprisingly the NCP plot in Figure 26(d) shows an upward slope indicating that the bigger k gets, the less likely are those clusters optimal clusters. This conforms with the architecture of WordNet and the existence of components, i.e., the non-connectedness of the adjective subset.

The Adverb Graph

Like adjectives, adverbs are not organized in a connected structure, but in many smaller components, 3,198 in number. It consists of 12,335 vertices but only 9,566 edges. This is due to the fact that most of the graph is made of synsets only consisting of the synset and one word form. The clustering coefficient is 0.

Since the 3,301 components mostly only consist of one synset the average path length between the connected vertices is only 1.39. The longest geodesic path is only 4. This shows how small those connected components are.

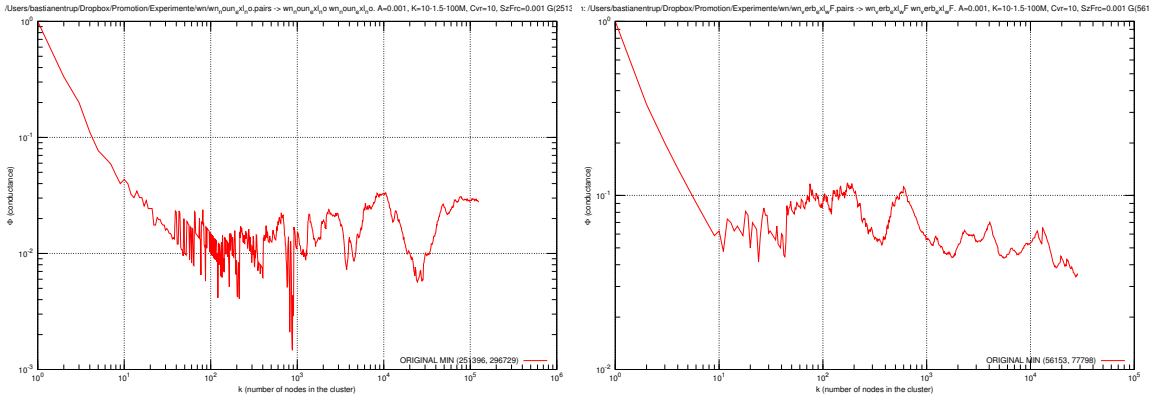
The degree distribution does not fit the power law with $\alpha = -5.52$ well (see Fig. 25(d)). The plot is less noisy as well as not as steep as the ones seen for the whole graph and the other subsets.

The overall skewed NCP plot shown in Fig. 26(d) indicates this strange behavior of the graph. The mixture of small average degree, small connectedness, and the large number of unconnected components as well as the relatively small number of vertices leads to this finding. The optimal cluster size k lies slightly above 10, indicating the relatively small components described above.

5.3.3 Network Analysis: Overview

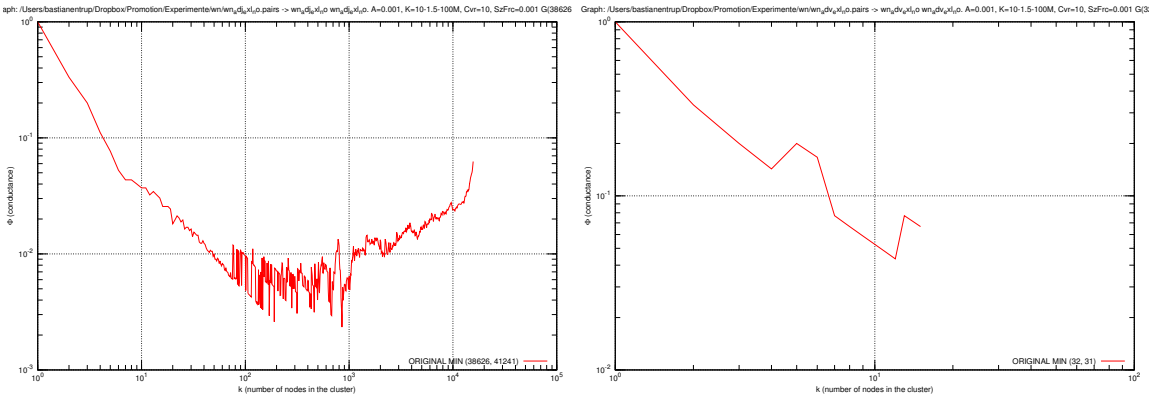
Mehler (2008) hypothesizes that "agents build communities in the form of small worlds in order to generate knowledge networks which themselves are small worlds" and that "word networks tend to evolve as small worlds though *very differently*" (Mehler, 2008, p. 622). The analysis of the WordNet network structure supports this assumption, although it comes with the constraint that the clustering coefficient is quite low. The network analysis of WordNet has shown that WordNet is a small-world network with respect to the degree distribution, and hence the existence of hubs and a small average geodesic path, but that the clustering coefficient is much lower than in other complex networks such as neural or social networks.

Small-world networks expose a degree distribution that follows a power law and a high clustering coefficient. Social networks show just these features. Some vertices have a great number of connections (i.e., a high degree) while others have close to zero connections. In social networks, vertices are very likely to be connected to the same vertices as their neighbors, hence the high clustering coefficient. The synset structure of WordNet causes this low clustering coefficient (0.0004). From the analysis of the WordNet ontology, one



(a) NCC plot of the noun subset.

(b) NCC plot of the verb subset.



(c) NCC plot of the adjective subset.

(d) NCC plot of the adverb subset.

Figure 26: NCP plots of the WordNet POS subsets.

can suspect that this very low value is caused by the structure of the synsets and how large synsets are connected to their members; theses synonymous word forms are not connected to each other. Also, co-hyponyms are not necessarily connected. The semantic relations that were found in WordNet order the network hierarchically, while only the lexical relations interconnect vertices in different parts of the hypernym/hyponym tree. All this leads to a relative sparseness of edges in the network.

These assumptions based on the ontology structure are confirmed by the network analysis. Especially looking at the subsets built by the different POS shows how sparsely connected the parts of WordNet can be: Adjectives and adverbs form many unconnected components. Also, the community structure caused by the components leads to the low clustering coefficient. The verb subset shows an NCP plot that indicates that the whole component is the most community-like set within the verbs, while especially the unconnected sets of adverbs and adjectives show that the components found in the data are actually very small: between 100 vertices for the adjectives, and only 10 for the adverbs.

Steyvers and Tenenbaum (2005) describe a model that should be able to explain the WordNet structure. After looking at the degree distribution of the WordNet graph and the subsets separately, as well as the NCP plots, their model seems unlikely to explain WordNet's structure. While the NCP plot of the noun subset in Fig. 26(a) resembles that of a network generated using preferential attachment found by Leskovec *et al.* (2008a, p. 42), the other subsets as well as the total graph do not.

The assumption that vertices that exist for a longer time in the graph, are, over time, more likely to be well connected, is not generally true. Other factors might be the frequency of usage as well as the POS. The Steyvers and Tenenbaum (2005) assumption that the meaning of a word becomes more differentiated the longer the word is used cannot be proved using WordNet. The analysis undergone here cannot confirm the findings and interpretations of Steyvers and Tenenbaum (2005). The model does not account for the existence and evolution over the large number of components, and it was shown what a strong influence this division has on the network analysis. Actually, to confirm their finding, Steyvers and Tenenbaum (2005) only look at WordNet's biggest components, ignoring the strong division of the network into components.

WordNet's structure is hence different from other complex networks. One can conclude that measures or features that take the neighbor of a vertex into account, as seen in the social networks approaches to link prediction, as well as purely geodesic-path-based

approaches, will not be good fits for this network structure. A new set of features has to be found that differs from previous attempts on other networks to meet WordNet's special properties.

It has been assumed that the so-called cousin relations might be very precise indicators of polysemy as defined in the context of this thesis. Still, looking at the frequency of usage of these relations, the coverage is expected to be very low. From the existence of different components in the subsets, as well as the range and domain restrictions that de facto exist for some relations, one can conclude that the relations that interconnect different POS might be of special interest. Also, it can be assumed that some POS are more likely to take part in the polysemy relation that is to predicted in the following. The geodesic path has been claimed to be very precise, but it is not sufficient to classify an instance as being polysemous of homonymous.

Having in mind these properties and the topology of WordNet and its subsets, appropriate properties of vertices and the graphs can be taken into account when attributes for the machine learning algorithms are being chosen. WordNet's structure is very different to that of social networks. Second degree neighbors that a vertex shares many connections with are not good candidates to connected the vertex to. This is due to the synset structure as well as the hierarchical structure formed by hyponymy and hypernymy.

It has been stated before that checking every possible combination of any two vertices of a graph for similarity or probability of connectedness is not very economical (cf. Clauset *et al.*, 2008). Since only forms with the same lemma can be polysemous or homonymous, the number of possible candidates to check (i.e., the number of pairs of word forms in WordNet with a shared lemma) is reduced significantly compared to checking every vertex against any other vertex of the network. While this solution here is caused by the definition of the relation in question, we will further see when looking at the DBpedia later on how the network topology can also be used to solve the problem.

5.4 Link Prediction: Polysemy

5.4.1 State of the Art: Finding Polysemy in WordNet

The CoreLex resource (Buitelaar, 1998) defines a set of 39 basic types. These basic types are assigned to noun synsets in WordNet and are meant to indicate a property of all subordinate synsets. For example, the basic types *animal* or *food* are assigned to different WordNet vertices and thus define the type of these vertices and their hyponyms. All

synsets that are a child element of *animal* are animals and all child elements *food* are foods.

As mentioned before, nouns are hierarchically ordered and the topmost (empty) synsets are called unique beginners. The basic types are an extension to the existing hypernymy/hyponymy tree of the WordNet noun subnet and aim to be more exact and especially useful for the identification of regular polysemy.

Many of the approaches presented here are based on, or are related to, CoreLex and thus restricted to nouns. The general idea is to provide a taxonomy of basic types that can be used to identify regular polysemy based on the definition by Apresjan (1974) seen before. Taking for example the grinding rule, it is expected to find regular patterns of co-occurrence of homograph words both in the set of vertices subsumed under *animal* and *food*.

Based on the CoreLex resource, Boleda *et al.* (2012) and Utt and Padó (2011) present an approach to identify regular polysemy (i.e., common patterns used by speakers that form polysemous words such as in grinding). The authors identify common pairs of basic types, like the one shown above, that indicate a productive (i.e., regular) polysemy pattern (cf. Utt and Padó, 2011). If given a word like *lamb* with many word forms in WordNet, the system looks up the sense's basic types. If it finds one sense corresponding to the type *animal* and another of the type *food*, this pattern can also be found for *chicken* and others.

Utt and Padó (2011) state that "[i]n polysemy . . . sense variation is systematic, i.e., appears for whole sets of words" (Utt and Padó, 2011, p. 265) and go on to define polysemy, with respect to the mentioned 39 basic types, as "high-frequency (systematic) basic ambiguities . . . , and low-frequency (idiosyncratic) basic ambiguities as homonymous" (ibid.). The basic types a lemma is connected to are expected to show patterns of reoccurring combinations of basic types indicating regular polysemy. The more of these patterns a lemma is related to, the more polysemous it is.

Even though in the context of the paper this definition is an understandable reduction, it is, in my opinion, problematic in many aspects. Polysemy is not only regular polysemy which is what is in fact defined here. In many cases more subtle or deep relations between two senses play a role that cannot be explained by these regular patterns.

Taking the *lamb* example, *lamb* can also mean "a sweet innocent mild-mannered person (especially a child)" (WordNet), which refers not to the fact that lamb is an animal or food but to the (subjective) characterization of a lamb as innocent. Utt and Padó see

polysemy as a property of words, not of word forms. If among the word forms they find at least two that fit one of the defined patterns, this word is treated as polysemous. This is in my opinion an oversimplification and should be avoided. There are cases in which some word forms belonging to one lemma are indeed related while others belonging to the same lemma are obviously not (e.g., *bank* may refer to a financial institution and the building that institution resides in (polysemy) as well as to a slope of land (homonymous)). To avoid this pitfall, or to at least reduce the negative effect, Utt and Padó (2011) calculate a ratio whose values lie between 0 and 1.

Afterwards they define a cutoff value of the ratio >0 to distinguish between polysemous words and homonymous words. Utt and Padó (2011, p. 268) state that they "consider polysemy and homonymy the two points on a gradient, where the words in the middle show elements of both". Although this is a nice thought, it of course leads to nothing since they still define a border (i.e., cutoff value) between both. Also the necessity to define such a ratio in the first place is only necessary because polysemy is defined on the word level and not on the sense level. The question remains how to treat the different senses and related word forms of *bank*: In WordNet, most of the senses of *bank* are connected to the financial institution, only four to mound or river bank. Is bank thus polysemous since most senses are related, or is it homonymous since there are two quite different clusters of meaning? Many people would surely agree that *bank* is homonymous. Regarding the problem of identifying word forms that are related in WordNet, and WordNet is based on senses, not on words or lemmas, neither of the two possibilities solves the problem. The only possibility is to adapt the problem and the definition of homonymy and polysemy to WordNet and look at the relations on the level of word forms. Also, when thinking of the possible use-case in word WSD, working with sense instead of words is necessary since the task is to distinguish between the different senses based on the usage of a word.

Peters and Peters (2000) examine how the-top level vertices (*nouns.TOPS*) of the WordNet hierarchies could be used to identify regular polysemy. The top-level vertices each enfold a tree of hypernym/hyponym relations beneath it. The idea is similar to that of CoreLex but uses the structure of the WordNet data set and uses the different files. Each file corresponds to one top-level vertex used to store parts of the noun tree.

Every noun in WordNet is a child of at least one of these unique beginners, i.e., categories that structure the whole noun subgraph (e.g., *artifact: a man-made object* or *group: any number of entities (members) considered as a unit*). Peters and Peters (2000) identify cases where polysemous lemmas are members of both *artifact* or *group*.

For example, the name of an institution can refer to an organization (*group*) and the corresponding building (*artifact*). This also shows the metonymic character of regular polysemy since it can be argued that the building – belonging to, owned, or rented by the institution – is part of that institution.

To identify more cases, they also added other hypernyms within a given geodesic path (≤ 4) to find pairs of other (super) concepts that show a similar regularity. So taking a word form w_1 and word form w_2 that share the same lemma, not only their corresponding unique beginner is taken into account, as well as their hypernyms up to the geodesic path of 4.

The polysemy concept used by Peters and Peters (2000) is similar to the one used here as it only looks at pair-wise combinations of word forms and at words, i.e., sets of word forms that correspond in appearance but necessarily in meaning, to identify polysemy. It is the internal WordNet structure, the non-existence of the word concept, and the organization in synsets formed by word forms that makes this treatment of polysemy a property of word forms, and not of words, plausible in this context.

The goal of the Peters and Peters is to extend WordNet by looking for missing pairs (i.e., cases where one sense is missing). One pair is that of *container/quantity* (e.g., cup is the container as well as the amount of substance in it). The same pattern of regular polysemy could be applied to every container (e.g., an amphora) to build the sense of the quantity, as in *He drank the whole amphora of wine.* According to this goal, their evaluation only looks at those cases that were identified to see if they are found in WordNet and thereby right (true positives), or wrong (true negatives) (i.e., those pairs that did not shown the pattern) without taking into account those cases that were not covered by their approach (false positives) (i.e., patterns that might not be identified in the first place).[86]

Another interesting, diverging, method is introduced by Veale (2004). Instead of looking at structural similarities, he proposes a system that compares the glossaries of synsets containing potentially polysemous word forms to identify those that are in fact related. Since this method is not applicable in the context of this thesis (i.e., using the network structure to identify missing relations) because it ignores the structure of WordNet altogether, I will not elaborate on the details of how this similarity is computed.

My approach differs from the ones cited above. First, after looking at the different approaches and at the structure of WordNet, I consider polysemy a relation on the level

[86]Another approach that is based on the systems mentioned so far is presented by Barque and Chaumartin (2009), but it does not offer much new information, insight, or ideas.

of word forms (i.e., the elements that make up a word sense) and not on the level of *words*, a concept that does not exist in WordNet in this form. Some word forms can be seen as polysemous: their sense is related and they share a lemma, while other forms only share a lemma but the senses are not related. There is no binary opposition on the word level between polysemous and homonymous words but only between related (or polysemous) and unrelated (or homonymous) pairs of word forms. A word can therefore exhibit polysemous senses (cf. *to bank* (money) and *bank* as financial institution) and homonymous senses (cf. the before mentioned senses of *bank* and one meaning shore or sandbank) at the same time. Some senses of bank form a set of polysemous semantically related meanings while at the same time they share a common form (homograph) with others only by chance. Secondly, I do not restrict my approach to only nouns. Restricting the research to only nouns seems to be a result of two factors. One is the hierarchical structure of the noun graph that supports disambiguation. CoreLex is based on nouns and often used. Furthermore, the hierarchical structure makes computing the similarity easier than in other subnets that do not offer hierarchies. The other reason is the fact that many researchers in the field have information retrieval tasks in mind and nouns are by far the most searched for word class. But the distinction between polysemous and homonymous might also play a role in word sense disambiguation and machine translation tasks where there is no restriction to only nouns.

Also, the approach presented here does not ignore irregular cases of polysemy. The goal is to identify both those cases that are formed by regular rules, as well as those formed using some other kind of similarity between object, be this relation metaphorical or metonymic.

5.4.2 Feature Selection: the Network Approach

As Davis *et al.* (2011) put it: "Choosing features that sufficiently represent the information inherent in the network topology is a serious challenge". In Chp. 2, a number of measurements were introduced that can be utilized to support machine learning algorithm on semantic networks; also some approaches to link prediction in social networks were introduced in Chp 4.

If we try to predict polysemy in WordNet, we will find that polysemous concepts are often, though not always, related in WordNet. Especially the *cousin* relations and morpho-syntactic relations like derivation seem promising. As seen from the network

analysis, WordNet consists of different components. Also, the network is relatively sparse and has a low clustering coefficient. This results in the fact that homograph word forms do not always have common neighbors and do not necessarily denote closely related concepts, even though they share a common semantic trait.

Calculating semantic similarity might be a possible step towards the classification since it is assumed that polysemous word forms belong to word senses that share some common semantic trait. Some similarity measures are based on the networks topology and will be applied to the task presented in this thesis. Some are not and will only be mentioned for the sake of completeness.

In the following, the set of graph-based measures and similarity measures will be introduced. Some notion on the reasons for choosing these measures will be given. All selected features can be found in Table 11.

5.4.2.1 Features Based on Similarity

In Snow *et al.* (2007), an approach to word sense merging in WordNet is presented. Because of the observation that WordNet senses are too fine-grained, they propose an alternate version of WordNet where synsets are merged. Even though this is not directly related to the distinction between polysemy and homonymy, their methods are of great interest to the problem concerned in this work.

Snow *et al.* (2007) use a supervised support vector machine classifier, the two classes being whether to merge two synsets or not. If two synsets are found to be closely enough related, they are merged (i.e., a new synset is formed containing the word forms of both original synsets).[87] Snow *et al.* (2007) use three measures that are based on path calculations, three based on information content, and two gloss-based and therefore not strictly graph-based measure. The similarity measures include the following that are of interest for this thesis: Resnik and Yarowsky (1999), Lin (1998), Jiang and Conrath (1997), Banerjee and Pedersen (2003), Hirst and St-Onge (1998), Leacock *et al.* (1998), and Wu and Palmer (1994).[88]

The original Lesk measure (Lesk, 1986) was proposed for use in WSD. The neighborhood of a word to be disambiguated was compared to the glosses of possible word forms available in WordNet. Starting from this assumption, Banerjee and Pedersen (2003) pro-

[87] To evaluate the approach they use hand-labeled data sets of groupings of WordNet senses. The first one is presented in Kilgarriff (2001); the second one can be found in Philpot *et al.* (2005).

[88] Snow *et al.* (2007) use the WordNet::Similarity package described in Pedersen *et al.* (2004).

pose their *extended gloss overlap* measure, which assumes that the more words two glosses share, the more closely related are the corresponding synsets. This is also true for synsets that are not directly related in WordNet (e.g., the glosses for *car* and *tire* do share a certain amount of lexical material). They also include the glosses of related synsets (e.g., hypernyms as well as other relations). In contrast to Lesk (1986), they do not simply count overlapping words. They add a higher score to overlapping phrases, since "phrasal n-word overlap is a much rarer occurrence than a single word overlap" (Banerjee and Pedersen, 2003, p. 806).

The Hirst and St-Onge (1998) measure is based on the path between two synsets and takes into account the direction of these relations. A change in the direction is used as an indicator of a weaker similarity. If a path consists of only hypernymy or hyponymy relations, both concepts are more similar or related than in cases where both hypernymy and hyponym relations exist in the path between two concepts. Similarly based on the path between two vertices are the measures described in Leacock *et al.* (1998) and Wu and Palmer (1994).

Lin (1998) proposes a different measure of similarity that can be applied to WordNet, as well as to other word representations (e.g., vectors). Two synsets to be evaluated are compared in relation to their mutually shared hypernyms taking into account the probability of a synset being the hyponym of the found hypernyms. This is called information content (Cover and Thomas, 1991). The measures of Jiang and Conrath (1997) and Resnik and Yarowsky (1999) are also based and the information content of the closest common hypernym and are computed on a corpus of raw texts.

Analyzing what other approaches seem promising (e.g., including some features from Snow *et al.* (2007)), especially the measures of semantic similarity, the features in Table 11 will be included in the machine learning approach proposed in this thesis.

Other approaches to polysemy/homonymy distinction (cf. Boleda *et al.*, 2012; Buitelaar, 1998; Peters and Peters, 2000; Utt and Padó, 2011) have to be examined and compared with those features chosen here. However, the CoreLex basic types will not be used as a feature, since it is an external source of knowledge and the idea of this thesis is to show how information contained in an ontology, especially in form of graph-based measures, can be used to predict not yet existing connections.

Table 11: Proposed feature set for the machine learning task.

Abbreviation	**Source or Description**	**POS**
Resnik and Yarowsky	Resnik and Yarowsky (1999)	N, V
Lin	Lin (1998)	N, V
Jiang and Conrath	Jiang and Conrath (1997)	N, V
Hirst and St. Onge	Hirst and St-Onge (1998)	N
Leacock, Miller, and Chodorow	Leacock *et al.* (1998)	N, V
Wu and Palmer	Wu and Palmer (1994)	N, V
minDist2SharedHypernym	Snow *et al.* (2007)	N,V
isA-Rel	*is-A* relation between word forms	N,V
areDerivationalRelated	is one word form derived from the other? Snow *et al.* (2007)	all
closeness	the closeness value of the node	all
betweenness	the betweenness value of a node	all
POS	the part of speech of word form	all
shortestPath	geodesic path between the two nodes	all
word sense degree	degree of the word sense nodes	all
synset degree	degree of the synset nodes	all
eigenvector centrality	the eigenvector centrality values of the nodes	all
page rank	the page rank values of the vertices Page *et al.* (1998)	all
POS	the part of speech of word form	all
sharedLemmas	number of lemmas shared by the synsets	all
isSameVerbFrame	geodesic path between the two nodes	V

5.4.2.2 Network-Based Features

Apart from measures of semantic similarity, some basic features deduced from the WordNet ontology structure, and from the network topology and the position or centrality of the vertices of the networks, are to be considered.

The minimum geodesic path of two presumingly polysemous word senses to their closed common hypernym is a feature derived from a quite similar feature mentioned in Snow *et al.* (2007). All hypernyms of both word forms are compared; the shared ones are stored. Then the geodesic path between the two word forms and the shared hypernym are calculated and the nearest one is selected.

The authors look at the possibility, of whether word senses contained in the synsets in question are derivationally related or whether they share a common antonym or pertainym. They found that especially the binary feature of two word senses being derivationally related (or not) when used as an explicit feature increased the F-score up to 9.8%. Indicating whether two word forms share an antonym only improved the prediction in the verb subset, while indicating common pertainyms did not improve the performance. On the contrary, it impaired the results. Both features are not to be expected from polysemous word forms.

Indicating a shared verb group improved the results of Snow *et al.*. Interesting might be their measure of closest shared hypernym and accordingly the maximal shared hypernym. Again, theses feature are only available for verbs and nouns. Other features they included are not of interest in the approach undertaken in this thesis, because they are not based on the network itself.

Apart from the features used in Snow *et al.*, the WordNet ontology structure indicates that other relations might be of special interest as well. The `isA-Rel` feature calculates whether the two synsets the word forms belong to are either a hypernym or hyponym of the other. The assumption is that a word sense that subsumes another word sense using the same lemma is polysemous (e.g., the synset {human, man} subsumes {man} (male human being)).

The `shortestPath` indicates the length of the geodesic path connecting both word forms. It can be assumed that those word forms closely connected in WordNet are more likely to be polysemous than those connected through a long path. Furthermore the `areDerivationalRelated` feature will be used, indicating whether or not one word form was derived from the other; this in itself indicates polysemy. Such derivationally relations

also lead to a short geodesic path. But Snow *et al.* (2007) suggest that using this relation explicitly as a features improves the results in their experiments. This will be evaluated here as well. The same is true `isSameVerbFrame`, which can only be used for verbs.

Besides these relations that are based on the WordNet structure, network-based measures (i.e., the degree, closeness, betweenness, eigenvector centrality, and page rank of the vertex, are used as features). Vertices with high closeness are likely to be connected to more vertices than others. Vertices with a high betweenness are likely to be connected to many vertices via relatively short paths, and a high degree itself indicates a higher connectedness than vertices with a very low degree. The degree will not only be calculated for the word form itself, but also for its synset. Vertices with these features might show relatively short paths to other vertices, but this might not always be a sign of semantic relatedness. Also, the POS of the word form in question is added as a feature.

Another feature that seems promising is calculating the number of lemmas shared by the two synsets the word forms in question are taken from. Though not a graph feature, it is information that is available in the graph without using any external knowledge.

All these features will be evaluated individually to see their impact on the performance of the machine learning algorithm used and to finally arrive at an optimal feature set for the task.

5.4.3 Data Preparation

In order to use the network data given in WordNet, I extract the graph from WordNet using the MIT Java Wordnet Interface.[89] Most calculations are done in R using an R–Java interface[90] and igraph[91] for R. Instead of using the WordNet::Similarity package (Pedersen *et al.*, 2004) for Perl directly, I use David Hope's of the University of Sussex Java implementation[92], which also uses the MIT Java Wordnet Interface. I changed the implementation to my needs, i.e., I added methods to compare MIT Java Wordnet Interface objects to each other instead of comparing just strings, representing words, with each other. To evaluate different machine learning algorithms the WEKA software is used (Hall *et al.*, 2009).

The process starts by obtaining a list of all word forms. Then these word forms are

[89] `http://projects.csail.mit.edu/jwi/`.
[90] `http://www.rforge.net/Rserve/`.
[91] `http://igraph.org/`.
[92] `http://www.sussex.ac.uk/Users/drh21/`.

compared to each other to find those forms that are homographs. The retrieved sets of homograph word forms are then processed in pairs of two, each word form to every other word form in the set, and the above-mentioned calculations are made using either the Java implementation of WordNet or the igraph R package. Since performance in question of run-time is of no high priority in this case because this data extraction is only performed once and the stored data can then be reused for evaluation and training purposes, using the R-Java interface, which in fact is quite slow and would not be sufficient for any real time purposes, can be justified. Any application that needed to do calculations on the fly would need to implement other approaches.

The data set consists of instances. Each instance contains two homograph word forms, the features that are to be chosen, and the class. It can be thought of as a table containing information on the two individual word forms and on the relations between these according to the feature set that is to be explained in Chp. 5.5. Each instance in the training and test set was manually assigned a class: either *yes* or *no*, indicating whether the two word forms are related or not (polysemous vs. homonymy).

5.5 Evaluation and Results

5.5.1 Homograph Nouns

5.5.1.1 Data Set and Baseline

44,449 noun word forms in WordNet are homographs of at least one other word form. This makes up 30.38% of the all noun word forms.

Table 12 shows the number of instances containing a noun and a member of the other subnets. Almost half of the instances contain two nouns (49.09%). Many noun and verb word forms share a lemma: 40.35% of instances contain, besides a noun, a verb, while 9.62% of the instances connect a noun word form to an adjective word form, and only 0.93% of the instances in the noun set contain an adverb as second word form. In total, 124,034 instance, pairs of homograph word form and the features to be extracted, exist in WordNet.

From these, a subset of 2,511 was manually classified as either sharing a similar/common meaning or as being just arbitrarily a homograph. 1,237 pairs have been classified as related, while 1,274 have been classified as being unrelated. Using a simple prediction of the most common class (i.e., *no*) as a baseline, an algorithm has to top at least 50.74%

Table 12: Instances of the kind *noun* ↔ *POS*.

Part of Speech **Total No. of Instances**	**Total No. of Occurrences** 124,034	**Percentage**
nouns	60,893	49.09%
adjectives	11,938	9.62%
verbs	50,053	40.35%
adverbs	1,150	0.93%

of correctly classified instances.

In the following, some algorithms that have been found to exceed the base line will be evaluated. First, the model with the highest accuracy, precision, and recall will be presented. The model was obtained training a random forest. This algorithm was also used by Horvát *et al.* (2012), as has been shown before. Parts of this evaluation have already been presented in Entrup (2014).

5.5.1.2 Evaluation: Random Forest

A good feature divides the data unambiguously, if possible, into the given classes. None of the features proposed here can account for this behavior on its own. The best measure to determine if two word forms share a common meaning seems to be, at first glance, the geodesic path. This is at the same time the easiest and best known measure of similarity in WordNet. Figure 27 shows the data plotted according to the geodesic path on both axes and the two classes. While the geodesic path is a very good indicator for the class *yes* (i.e., a good indicator of semantic relatedness) it is, unfortunately, not a secure indicator of two word forms being unrelated: Instances below a certain geodesic path, around 6, are definitely of class *yes*. Yet, being high or even infinite does not indicate the other class. Still, the probability of an instance being classified as *no* rises with the length of the geodesic path.

The random forest is black-box when it comes to evaluating the impact of the attributes used. Since this is a known problem of many algorithms, I chose a way of evaluating the feature set inspired by Snow *et al.* (2007): One feature at a time is removed from the set and a new model trained leaving all other properties the same. This is called an ablation study. The gain and loss resulting from this new evaluation give an indication of how

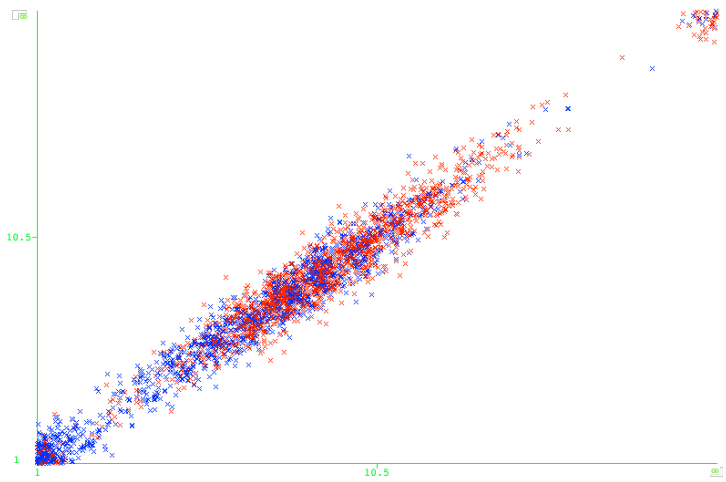


Figure 27: Classes of instances *yes*/*blue* and *no*/*red* plotted according to the geodesic path.

important the features are in the context of the model.

Since the random-forest model randomly chooses features for every vertex it builds, the impact of one feature might be relatively small. As Breiman (2001) shows, even features with a small information content can, when combined in the right way, result in a very good model.

In the following, the different features that have been proposed will be evaluated and compared. First, the features in Table 13 will be examined and the impact of the features will be evaluated. Afterwards, a subset of high-quality features will be extracted. These will be compared to machine learning models based on other feature sets that have been used in polysemy detection in WordNet before: the CoreLex basic types of Buitelaar (1998) and unique beginners used in Peters and Peters (2000).

Using only the features shown in Table 13, a random-forest model has been trained that is based on 100 random trees, each constructed while considering 17 random features and 10 seeds. The model reaches a precision of 0.87 out of 1. The algorithm achieves 87.02% of correctly classified instances and thus outperforms the baseline by 36.28 points.

The gain or loss when one feature is left out and the model trained again using the exact same properties is shown in Table 13; a negative number indicates a gain in accuracy if the feature is left out.

The graph measures of closeness and betweenness result in a good gain of precision. Even the simple measure of degree, the page rank, and the eigenvector centrality have a

Table 13: Ablation study: accuracy difference obtained by removal of single feature in the noun set. Features in italics are used for evaluation later on.

Attribute	**Loss**		**Attribute**	**Loss**
word 1 degree	0.52		*word 2 pos*	0.48
word 1 closeness	5.98		*word 2 degree*	−0.24
word 1 betweenness	1.19		*word 2 closeness*	0.16
word 1 eigenvector centrality	0.68		*word 2 betweenness*	0.24
word 1 page rank	1.23		*word 2 eigenvector centrality*	0.32
word 1 synset degree	3.46		*word 2 page rank*	0.36
is-A rel.	0.78		*word 2 synset degree*	0.52
areDerivationalRelated	0.52		*minDis2SharedHypernym*	0.20
sharedLemmas	0.92		Lin	0.36
Hirst and St. Onge	0.36		Resnik and Yarowsky	0.36
Leacock and Chodorow	0.48		Jiang and Conrath	0.84
Wu and Palmer	0.28		geodesic path	−1.95

high impact. The graph-based measures that were proposed in this thesis (see features in italics in Table 13) perform mostly well or even very well.

Surprisingly enough, the shortest path, as mentioned above a good indicator of class *yes*, is better left out: It has a negative impact on the performance. The other semantic similarity measures (see non-italic features in Table 13), which are all based on paths between two vertices, add little to the precision.

After this evaluation step, the path-based, semantic similarity measures were completely left out and only the graph-based measures were used. This new feature set, now only containing basic network measures such as degree, closeness, betweenness, eigenvector centrality, page rank, plus the number of shared lemmas in the synsets, the distance to the next common hypernym, if applicable, and the information if both word forms are derivationally related, results in a precision of 90.12% of correctly classified instances. Recall, precision, and F-measure are all around 0.9, as can be seen in Table 14.

The semantic similarity measures that were thought to indicate semantic relatedness and could thus be used to find polysemous word forms in WordNet do not have a positive impact after all. Using only graph-based measures (see italic features in Table 13) yields a higher precision and outperforms classic similarity measures on WordNet. An overview

Table 14: Precision and recall or the random-forest algorithm on the noun set using only basic network measures.

	Precision	**Recall**	F **Measure**	**Class**
	0.904	0.894	0.899	yes
	0.898	0.908	0.903	no
weighted average	0.901	0.901	0.901	both

Table 15: Correctly and incorrectly classified instances in the noun set using only basic network-based measures.

Correctly Classified Instances	2,263	**90.12%**
Incorrectly Classified Instances	248	**9.88%**
Total No. of Instances	2,511	

of the model's performance is given in Table 15.

To compare the graph-based features to the CoreLex basic types, every noun was annotated by the appropriate basic type assigned by the CoreLex resource. The assumption is that those basic types show regular patterns of polysemy that the algorithm used for classification should be able to identify. The actual rules proposed by Buitelaar (1998), Utt and Padó (2011), and Boleda *et al.* (2012) were not used. Also, this is of course no direct comparison to those results. But it should give insight into the quality of the features used.

The CoreLex approach can only be used to identify regular polysemy. The ratio of correctly classified instances can therefore be expected to drop compared to the graph-based approach. In addition, only nouns can be assigned basic types. All instances of nouns sharing a lemma with other POS will not show any significant patterns.[93] This again can be expected to result in a drop of accuracy.

Using only the basic types to train a model and evaluating it as before results in 64.99% correctly classified instances.[94] This is 25.13 points less accurate than the method

[93]Even though it was stated by Buitelaar (1998) that a similar resource could be made available for other POS as well, this seems questionable since only nouns employ a deep hierarchical tree. Verbs only form shallow trees, and adverb and adjectives have no hierarchical order at all.

[94]The numbers given in the following are always the highest possible rates of accuracy of a random-

proposed in this thesis.[95]

As has already been mentioned, the CoreLex basic types cannot be used to classify instances containing other POS than nouns. Using only just-noun instances and no other POSs, and only the basic types as features, results in 66.77% accuracy. Using the graph-based measures instead results in 82.9%. Thus, they are still 16.13 points more accurate.

Instead of using the basic types, Peters and Peters (2000) used patterns of WordNet unique beginners to identify polysemous word forms. On the set of instances containing different POS, a model trained using only the unique beginners results in 62.01% of correctly classified instances and is thus outperformed by the CoreLex basic types and the measures of network topology. On only noun instances, it reaches an accuracy of 63.52%. Buitelaar (1998) states that the basic types are more fine-grained and therefore more meaningful than using the unique beginners that were later used by Peters and Peters (2000). Here, using the random-forest model, this statement seems to be valid. As will be shown when looking at other algorithms, this is not necessarily true, at least when using this data set.

A combination of the graph-based measures presented in this thesis, the CoreLex basic types, and the unique beginners yields the best results: 93.31% correctly classified instances on the set containing instances of nouns and other POS and 87.9% when only pairs comparing nouns to nouns are used. An overview of all results is given in Table 16.

Table 16: Comparison of feature sets.

Data Set	**Attributes**	**Accuracy (%)**	**Precision**	**Recall**	F **Measure**
All	network measures	90.12	0.9	0.9	0.9
Instances	basic types	61.61	0.62	0.62	0.62
	unique beginners	62.01	0.64	0.62	0.60
	all	93.39	0.93	0.93	0.93
Only	network measures	82.9			
Noun	basic types	66.23	0.67	0.66	0.66
Pairs	unique beginners	63.46	0.63	0.64	0.63
	all	87.9	0.88	0.88	0.88

forest model of 100 trees. The number of randomly selected features varies.

[95]Different models were trained using different algorithms. Still the random-forest model was the most accurate one.

5.5.1.3 Evaluation: Other Algorithms

In Chp. 4.2, a number of other machine learning algorithms have been proposed. At this point, the introduced algorithms (i.e., support vector machines, naive Bayes classifier, the J48 decision tree, multilayer perceptron (neural network), and logistic regression) are to be evaluated on the different feature sets.

Table 17: Comparison: support vector machines.

Data Set	**Attributes**	**Cost Value**	**gamma value**	**Accuracy in %**
All Instances	network measures	128	8.0	73.64
	basic types	2.0	0.125	62.37
	unique beginners	8192	8.0	62.49
	all	2048	0.5	81.00

Overall, the results are quite similar to those of the random-forest algorithms with regards to what feature sets work best. Nonetheless, no algorithm comes close to the results obtained using the random-forest algorithm.

Support vector machines and appropriate values of γ (gamma) and c (cost), using the implementation presented in Chang and Lin (2011), the proposed feature set of only graph-based measures still outperforms the other features sets by far (73.64% compared to 62.36% for basic types and 62.49% for unique beginners, respectively). Combining all feature sets results in 82% correctly classified instances (see Fig. 17).

Table 18: Comparison: Naive Bayes classifier.

Data Set	**Attributes**	**Accuracy in %**
All Instances	network measures	68.42
	basic types	56.67
	unique beginners	60.10
	all	72.48

Using the Naive Bayes classifier (see Fig. 18), the graph-based features still perform best. In this case, even the unique beginners perform better than the CoreLex basic types.

The precision is, overall, much lower than that of the random-forest model and even that of the SVM.

Table 19: Comparison: J48 decision tree.

Data Set	**Attributes**	**Accuracy in %**
All Instances	only network measures	77.82
	basic types	60.14
	unique beginners	62.01
	all	81.08

A similar picture gives the evaluation of the results obtained from the J48 decision tree (see Fig. 19), although the accuracy is a little higher: graph-based measures perform best, followed by the unique beginners and the CoreLex basic types.

Table 20: Comparison: multilayer perceptron neural network using back-propagation.

Data Set	**Attributes**	**Accuracy in %**
All Instances	only network measures	70.37
	basic types	61.45
	unique beginners	57.11
	all	78.1

Using a neural network, a multilayer perceptron, with back-propagation, the network-based feature set proposed in this thesis reaches a value of 70.37% accuracy (see Table 20) compared to the basic types with 61.45%, and the unique beginners with only 57.11%. All three feature sets combined reach 78.1% accuracy.

The logistic regression could be expected to perform less accurately than the other, more sophisticated, algorithms. Indeed, it yields the lowest results. The picture remains similar: The graph-based measures out-perform the other proposed feature sets (see Table 21).

These short evaluations confirm the results stated above and found using the random-forest algorithm. There is no bias between the feature sets and a special algorithm, but the results are quite comparable over a number of different algorithms. The statement that

Table 21: Comparison: logistic regression.

Data Set	**Attributes**	**Accuracy in %**
All Instances	only network measures	62.80
	basic types	60.57
	unique beginners	57.15
	all	72.48

the CoreLex basic types are better suited to identify regular polysemy than the unique beginners in WordNet can, at least when using a data set containing not only nouns and not only regular polysemic cases, not be confirmed.

In the following steps, the algorithms presented here will not be evaluated any further. Only the random-forest algorithm will be used for the remaining POS sets.

5.5.2 Homograph Adjectives

5.5.2.1 Data Set and Baseline

Out of the total 38,917 instances containing adjectives, $\approx$ 40% contain an adjective as second word form as well; 30.67% of the instances contain a noun, 15.25% contain adjectives and verbs, and 7% adjectives and adverbs. Table 22 gives an overview over both the percentages and the total number of instances. The numbers show that adjectives tend to be more polysemous than nouns.

Table 22: Homograph pairs of the kind *adjective* $\leftrightarrow$ *POS*.

Part of Speech **Total No. of Instances**	**Total No. of Occurrences** 38,917	**Percentage**
nouns	11,938	30.67%
adjectives	18,319	40.07%
verbs	5,934	15.25%
adverbs	2,726	7%

For the test and training set, 1,291 instances have been classified manually. Of these,

1,122 instances were classified as *yes*, and 169 instances as *no*. A basic baseline, assigning each instance the most common class (*yes*) reaches 86.91% of correctly classified instances. A model for machine learning has to top this relatively high value.

5.5.2.2 Evaluation of the Feature Set

The random-forest model was trained using 100 trees and 5 random features at each vertex of these trees. Interestingly enough, very simple and few pieces of information extracted from the WordNet graph are enough to reach a total of 91.17% correctly classified instances, as can be seen in Table 23. This is a gain of accuracy of 4.26 points compared to the baseline.

Table 23: Correctly and incorrectly classified instances in adjective test set.

Correctly Classified Instances	1,177	**91.17%**
Incorrectly Classified Instances	114	**8.83%**
Total No. of Instances	1,291	

The features, similar to those used in the noun set, and their impact (i.e., the loss or gain to the model if left out) can be seen in Table 24.

Table 24: Ablation study: accuracy difference obtained by removal of single feature in adjective set.

Attribute	**Loss**	**Attribute**	**Loss**
word 1 degree	0.31	word 2 degree	0.72
word 1 closeness	0.85	word 2 closeness	1.01
word 1 betweenness	0.54	word 2 betweenness	0.00
word 1 eigenvector centrality	0.39	word 2 eigenvector centrality	0.08
word 1 page rank	0.70	word 2 page rank	0.47
word 1 synset degree	0.16	word 2 synset degree	0.62
geodesic path	0.77	word 2 pos	0.93
sharedLemmas	1.16	areDerivationalRelated	0.39

Again, the combination of useful attributes is more important than the information

gain of one single attribute. Attributes need to divide the data set in a useful way. Since there exists no single features that divides the whole data set in the desired way, the goal is best achieved using more attributes that in turn interlock and therefore, in their combination, result in a good model for the data.

The difference between the loss values of the features is, compared to the noun set, relatively small. Good performance is shown by the graph measures (i.e., closeness, betweenness, eigenvector centrality, and page rank) of the two vertices involved. Remember that the second word form may be, or is likely to be, of another POS. Especially the closeness of both vertices has a high impact, 0.85 and 1.01. The betweenness of the first word form has a relatively high gain value, while the betweenness of the second vertex involved has no relevance for the model. The impact of the first vertex graph measures is overall higher than that of the second vertex: The eigenvector centrality and the quite similar page rank both have a considerable gain compared to the same measures of the second word form. Only the degree of the second word form seems to add more information than the counterpart of the first word form. This is also true for the degree of the related synset. While the vertices degree indicate lexical relations, the synset's degree indicates the number of semantic relations a word sense has.

The number of shared lemmas of the two synsets involved results in a gain in accuracy. The information if two word forms are derivationally related yields a relatively small amount of information. Although it can be thought of being a very good indicator of class *yes*, it is a very rare relation in WordNet. Therefore it only exists in few instances in the test and training set.

The degree values of the synsets have a lower impact than the same measures of the word forms. This could indicate that the lexical relations that result in the degree of the word forms add more to the model than the semantic relations connected to the synsets.

There is a considerable correlation between the POS of the second word sense and the likelihood of it being related to an adjective in the first place. This can be seen in Fig. 28: Instances containing nouns are much more likely to be of class *no* (red) than instances where both word sense belong to the adjective subnet.

Unlike the model used in the noun set, the model evaluated here actually gains from using the geodesic path (see Fig 29 for details) between the two word forms in question. A major difference is that the noun is connected (i.e., there exists a path from every vertex of the set to any other) while the adjective set is unconnected.

Table 25 gives more detailed information on the precision in regard to the different

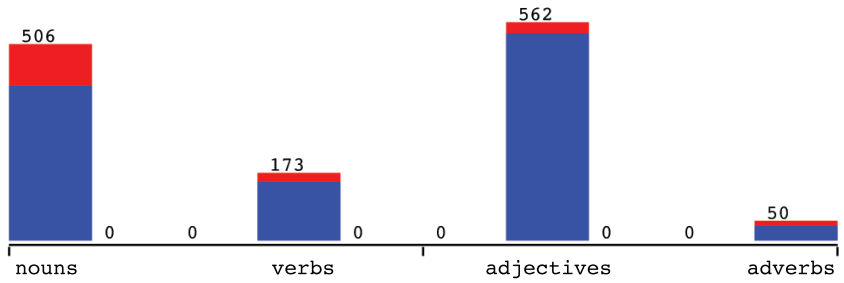


Figure 28: Instances containing word senses from an adverb and the other given POS and their membership of class *yes* (blue) or *no* (red).

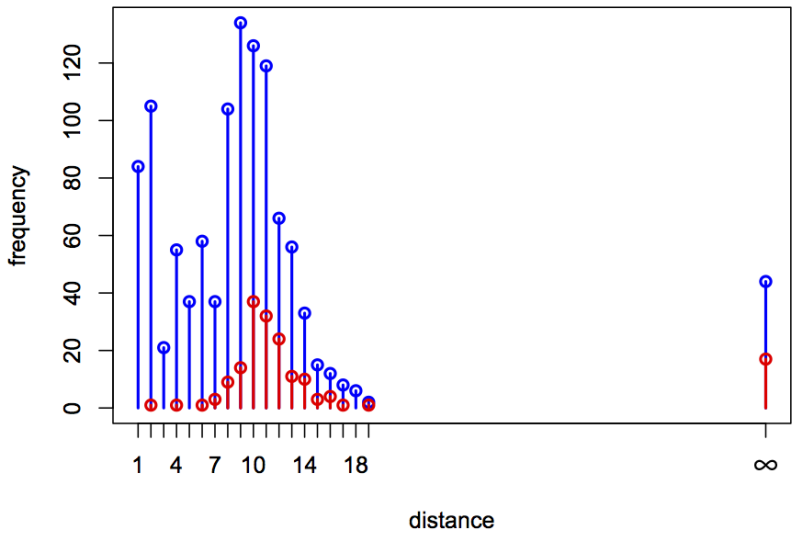


Figure 29: Correlation of geodesic path and class (*yes/blue* and *no/red*) in the adjective test and training set.

classes. In the adjective set the classification task is even harder than in the noun set, since the *no*-class is strongly underrepresented in the test and training sets, and supposedly in the whole of all instances.

Table 25: Precision and recall of the random-forest algorithm on the adjective test set.

	Precision	**Recall**	F **Measure**	**Class**
	0.923	0.98	0.951	yes
	0.778	0.456	0.575	no
Weighted Average	0.904	0.912	0.901	

Admittedly, the results also show the weakness of the model. While it is relatively easy to reach the 88.61% of the baseline, this is shown by the high precision and recall for the *yes* class[96]. it is much harder to find and identify those relatively few cases of *no*, which is reflected by the, in comparison the other class, pretty low precision, recall, and F measure. While 78% of the instances that were classified as belonging to *no* were classified correctly, only 46% of all cases of *no* were identified in the first place.

5.5.3 Homograph Adverbs

5.5.3.1 Data Set and Baseline

Out of 6,403 instances containing at least one adverb, 17.69% contain an adverb and a noun word form, 42.57% an adverb and an adjective, and 10.15% between an adverb and a verb, and 29.73% instances describe homography between two adverbs.

Out of these possible instances, 925 instances have been classified manually: 688 as *yes* and 237 as *no*. This results in a baseline, if every instance is assigned the most common class, of 74.38%.

5.5.3.2 Evaluation of the Feature Set

As can be seen in Table 27, the random-forest model trained using 100 trees and 5 random features yields a total of 87.35% correctly classified instances and 12.65% incorrectly

[96]Remember that the baseline assigns each instance the class *yes* and therefore reaches a recall of 100%, while the precision is lower due to the fact that all *no* instances were also classified as *yes*.

Table 26: Instances of the kind *adverb* ↔ *POS*.

Part of Speech **Total No. of Instances**	**Total No. of Occurrences** 6,403	**Percentage**
nouns	1,150	17.96%
adjectives	2,726	42.57%
verbs	650	10.15%
adverbs	1,904	29.73%

Table 27: Correctly and incorrectly classified instances in adverb test set.

Correctly Classified Instances	808	**87.35%**
Incorrectly Classified Instances	117	**12.65%**
Total No. of Instances	925	

classified instances. This outperforms the baseline of 74.38% by 12.97 points. To train the model, the features in Table 28 were used.

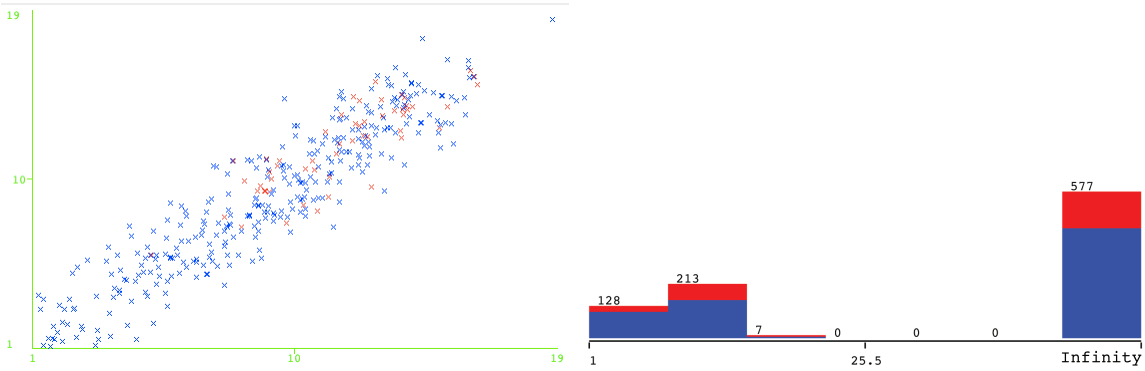
The geodesic path feature has a relatively high impact on the adverb model taking into account how sparse the adverb subnet is (i.e., how few of the adverb vertices actually are connected to vertices outside of the subnet). Many vertices are only connected with their synset but not with any other vertex in the network. Therefore, most adverbs have an infinite geodesic path to any other vertex of WordNet. Figure 30(a) shows those instances that actually are connected. The blue crosses are those pertaining to *yes*; the red ones belong to the *no* class. As one can see, there is correlation between *yes* and a geodesic path lower than around 10. Figure 30(b) shows all instances in the set. But also an infinitely long geodesic path between two vertices indicates neither *yes* nor *no*.

A higher degree of a word form (e.g., it is connected to an adjectives it is derived from) indicates that the adverb word form is more likely to be sharing meaning with other word forms. This can be seen in Fig. 31: The higher the degree, the more dominant are the blue (class *yes*) dots compared to the red ones (those instances classified as *no*). The same holds for the synset's degree.

Again, we find that a word form's or node's closeness is a very good feature. Figure 32(a) shows the closeness values of the first word form and the corresponding classes.

Table 28: Precision difference obtained by removal of the single feature in adverb set.

Attribute	**Loss**	**Attribute**	**Loss**
word 1 degree	0.43	word 2 degree	0.86
word 1 closeness	3.35	word 2 closeness	3.57
word 1 betweenness	0.21	word 2 betweenness	0.54
word 1 eigenvector centrality	0.43	word 2 eigenvector centrality	−0.33
word 1 page rank	1.51	word 2 page rank	0.21
word 1 synset degree	1.84	word 2 synset degree	−0.33
sharedLemmas	0.21	word 2 pos	−0.11
geodesic path	0.86	areDerivationalRelated	0.54



(a) geodesic path of instances plotted against the classes: *yes/blue*, *no/red*.

(b) geodesic path of instances on x axis, number of instances on y axis. The colors indicate the classes: *yes/blue*, *no/red*.

Figure 30: Classes in adverb set relative to geodesic path.

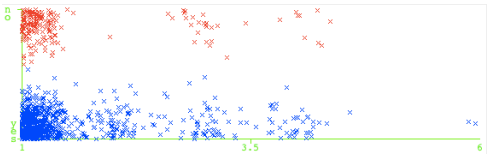
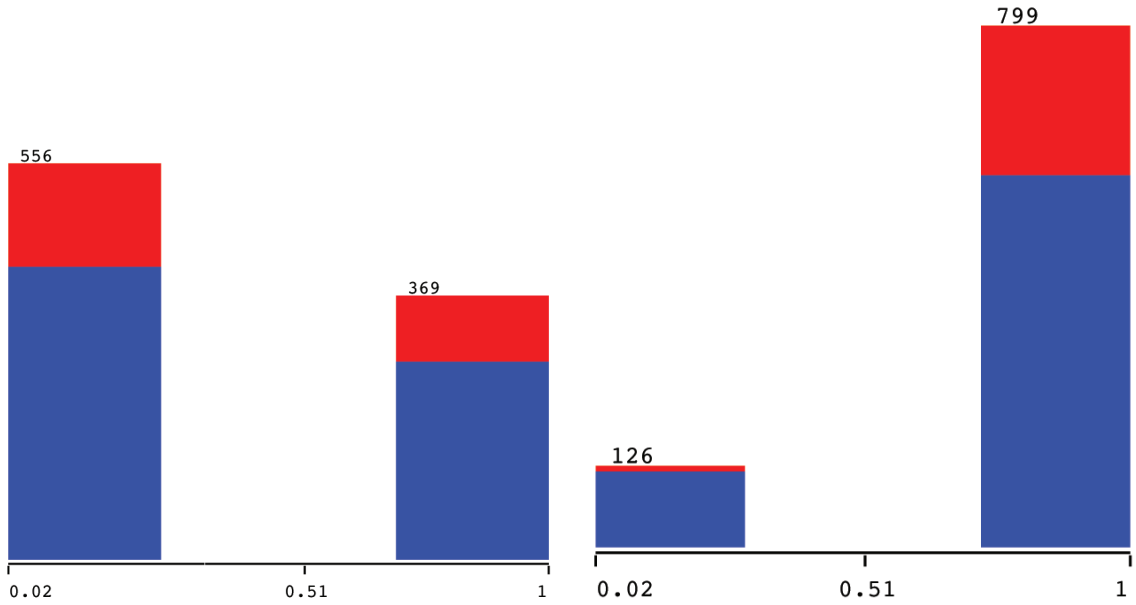


Figure 31: Correlation of degree (word form 1) and class in the adverb test and training set.

Figure 32(b) shows the same for the second word form. These are only simplified illustrations, one bar for values lower than 0.5 and one for higher values. Still, one can see that especially in the second word form, a low value indicates a higher probability of the class *yes*.



(a) Simplified plot of closeness values and classes in relation to word sense 1.

(b) Simplified plot of closeness values and classes in relation to word sense 2.

Figure 32: Closeness of the two word sense vertices involved in the instances.

The page rank and eigenvector value of the first word sense have a high impact on the model trained and evaluated here. Besides the POS feature that was already mentioned, also the synset's degree of the second word form involved and the eigenvector centrality of the second word form have a negative influence on the model's performance.

Table 29: Precision and recall of the random-forest algorithm on the adverb test set.

	Precision	**Recall**	***F* Measure**	**Class**
	0.9	0.933	0.916	yes
	0.783	0.7	0.739	no
Weighted Average	0.874	0.874	0.871	

Like the adjective model, this model works better on the *yes* class than on the instances

classified as *no*. Details can be found in Table 29. Still, it is an improvement compared to the baseline that, of course, only reaches 0.0 points in precision and recall on the *no* class, since it does not classify any instance as *no*. The model presented here reaches a precision of 78% on those instances. The instances classified as *no* are in 78% of the cases actually of the class *no*. The recall of 70% indicates that 7 our of 10 of all no cases were actually found. In total, the precision reaches 0.9 and recall reaches 0.93.

5.5.4 Homograph Verbs

5.5.4.1 Data Set and Baseline

As can be seen in Table 30, 47.42% of the instances contain two verbs, 46.47% a noun, 5.5% an adjective, and only 0.6% an adverb. Again, most instances exist between forms of the same POS, while those sharing a lemma with a noun, because of the general dominance of nouns in WordNet, make up the second largest group.

Table 30: Instances of the kind *verb* $\leftrightarrow$ *POS*.

Part of Speech **Total No. of Instances**	**Total No. of Occurrences** 107,715	**Percentage**
nouns	50,053	46.47%
adjectives	5,934	5.5%
verbs	51,078	47.42%
adverbs	650	0.6%

Out of the 107,715 possible instances, 1,019 have been classified manually, resulting in 926 instances classified as *yes* and only 93 classified as *no*. Again, using the most common class (*yes*) and assigning it to every instance as the most basic approach results in a baseline of 90.87%. This pretty high baseline has to be topped by a model trained using the proposed feature set.

5.5.4.2 Evaluation of the Feature Set

Using the random-forest algorithm, 100 trees with 14 random features per vertex of the tree, results in 94.11% correctly classified instances and only 5.89% incorrectly classified instances (see Table 31). It thus outperforms the baseline by 3.24 points.

Table 31: Correctly and incorrectly classified instances in verb set.

Correctly Classified Instances	959	**94.11%**
Incorrectly Classified Instances	60	**5.89%**
Total No. of Instances	1,019	

Table 32 shows the features that have been used to train the model. Most features have, if removed, only very small impact. If removed from the set, some even result in a gain of correctly classified instances. Working well on both vertices involved in the instances is the page rank measure resulting in a drop of 1.19 for the first vertex and 1.08 points for the second vertex respectively. A similar influence has, again, the closeness of the second word sense node. Little impact is seen in the synset degree (i.e., the semantic relations the connected synset has). The number of shared lemmas and the distance to the closest common hypernym are also of little impact. All other features have no or even a negative influence of the model and could be left out to train a model to be used in a real-life scenario. Almost no influence can be found in the geodesic path.

Table 32: Precision difference obtained by removal of the single feature in the verb set.

Attribute	**Loss**	**Attribute**	**Loss**
word 1 degree	0.00	word 2 degree	−0.10
word 1 closeness	−0.20	word 2 closeness	0.88
word 1 betweenness	−0.10	word 2 betweenness	0.00
word 1 eigenvector centrality	0.10	word 2 eigenvector centrality	−0.10
word 1 page rank	1.19	word 2 page rank	1.08
word 1 synset degree	0.19	word 2 synset degree	0.29
geodesic path	0.11	word 2 pos	−0.10
sharedLemmas	0.10	areDerivationalRelated	0.00
is-a relation	0.00	minDis2SharedHypernym	0.10
same verbframe	−0.10		

The semantic similarity measures have been left out in this evaluation since they were shown to have a negative impact on the model in the noun set. Also the low impact of the geodesic path in the feature set is an indicator that theses measures are (almost) no

improvement to the model. Still, a model was trained including the appropriate semantic similarity measures. This second model did not result in a significant gain in precision and only one more instance was classified correctly. Again, the semantic similarity measures can be left out; the network measures turn out to be the a good feature set for this classification task. Table 33 shows that 80% of the cases the algorithm identified an instance as belonging to class *no* were correctly classified by the model. The recall (i.e., the number of instances of the class that were actually identified and correctly classified) is much lower, around 0.48 out of 1.

Table 33: Precision and recall of the random-forest algorithm on the verb set.

	Precision	**Recall**	***F* Measure**	**Class**
	0.95	0.987	0.968	yes
	0.789	0.484	0.6	no
Weighted Average	0.935	0.941	0.935	

This can also be seen in the confusion matrix in Table 34: Only 45 out of 93 instances of class *no* were correctly classified, while most cases of the class *yes* were classified correctly.

Table 34: Confusion matrix: verb classification.

		Assigned Class	
		false	**true**
Actual Class	**false**	12	914
	true	45	48

5.6 Results

The structure of WordNet is not arbitrary but formed in a systematic manner that helps identifying new, not yet formalized relations that can then be added in a coherent way. The sparseness of the network as well as what we know about other semantic networks makes the assumption that there are missing connections plausible. The network measures

are therefore a good feature set to classify instances, sets of two nodes and their features and class, as either showing these new relations or not.

A new set of features derived from the network structure was proposed that can be used to identify both regular and irregular polysemy and that can also be used on all four POS present in WordNet.

After training, testing, and evaluating the proposed feature set consisting of basic network centrality measures and features derived from WordNet's ontology structure, these have been found to be a very good fit for the task of identifying related and unrelated homograph word forms (i.e., polysemous from homonymous word forms). Indeed the features perform even better than similarity measures and other features that have been proposed to identify polysemy in WordNet.

Table 35: Overview: the different models' performances.

Part of Speech	random forest: trees	features	**Baseline**	**Model Performance**	**Gain**
nouns	100	17	50.74%	**90.12%**	**39.38**
adjectives	100	5	86.91%	**91.17%**	**4.26**
adverbs	100	5	74.38%	**87.35%**	**12.97**
verbs	100	14	90.87%	**94.11%**	**3.24**

After evaluating different classification algorithms on the noun set, only the random-forest model was used for training and testing of the other models. Furthermore, the noun set was used to compare the network-based features that have been proposed to identify polysemy in WordNet (i.e., the WordNet unique beginners (cf. Peters and Peters, 2000) and the CoreLex basic types (Buitelaar, 1998)). These features come with some down sides: They can only be applied to the hierarchical structure of the noun set and not to adverbs, adjectives, and also not readily to verbs. Furthermore, they are only thought of as indicating regular polysemy, thereby treating irregular polysemy as mere homonymy.

Regarding the evaluation of the proposed feature set, an overview of the results, the baseline that had to be topped, the actual percentage of correctly classified instances, and the resulting gain compared to the baseline, is given in Table 35. The gain values seem to vary considerably. This is related to the very different baselines: While only every second homograph instance containing a noun is regarded as being related (i.e., can be called

polysemous), over 90% of the instances containing a verb are of the class *yes* and hence polysemous. Therefore the range of possible out-performance of the baseline varies.

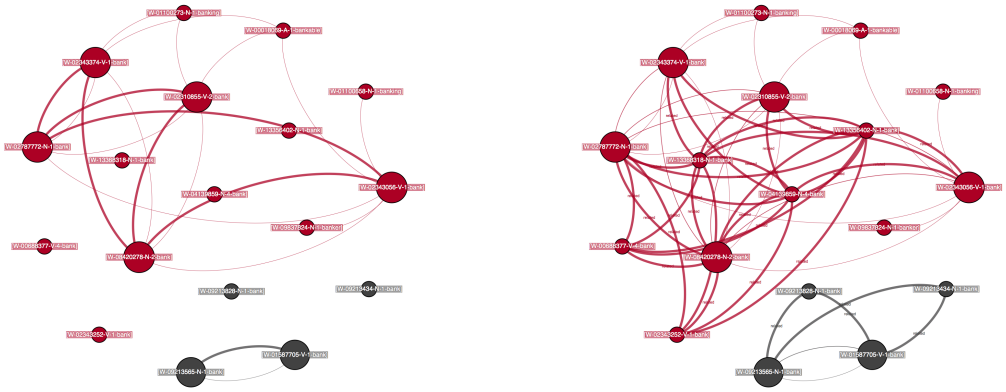
In the end, all models reach an accuracy of around 90%, regardless of the baseline. The verb set reaches over 94.11%, the adverbs reach 87.35%, while nouns, 90.12%, and adjectives, 91.17%, lie between these values.

When looking at the undertaken evaluation of the single features, one can find some features that work consistently well. The degree of either the vertex itself (i.e., the number of lexical relations a word form has) or of the related synset (i.e., the number of semantic relations a word sense has) often has a positive influence on the performance. The number of shared lemmas, if > 1, of the two involved synsets often exhibits a close relation between the two synsets and therefore indicates polysemy. The page rank was found to be helpful in the adverb set as well as in the verb set, while the geodesic path between the two vertices involved had almost no impact on verbs, a negative impact on nouns, and a positive impact on adjectives and adverbs.

Before evaluating the data sets, the geodesic path and related measures of semantic similarity that have been proposed and used for similar task, e.g., in Snow *et al.* (2007), were thought of as indicating the relatedness and therefore showing non-arbitrary homography of two word forms in WordNet. After the evaluation of the different sets, this cannot be confirmed: Both the verb and especially the noun set do not profit from using the geodesic path as a feature. Furthermore, the noun set model's performance even worsens when the semantic similarity measures are used.

The highest impact have the closeness values of one or both nodes. The closeness indicates the close neighborhood of a vertex to any other vertex. A high closeness value therefore indicates a good connectedness (i.e., relatively short geodesic paths to any other vertex in the network). This does not, however, indicate that a high closeness is necessarily an indication of either polysemy or homonymy. Since the random-forest model is a black box consisting of many independent decision trees that are combined to classify an instance, it was tried to estimate both the impact a single features has as well as how this feature might be used to classify an instance. Different features can be combined to get results the single features cannot offer. In this sense, it cannot be said whether a high or low closeness is generally a good indicator for either of both classes, only that the closeness is an important feature in identifying the correct class.

Basically, using the proposed graph and ontology based features, non-arbitrary homography between different word sense could be identified in WordNet Using the same



(a) Nodes with the lemma *bank* and their interconnections before applying the machine learning model presented here.

(b) Nodes with the lemma *bank* and their interconnections after applying the machine learning model presented here.

Figure 33: Changes in the WordNet graph: connected and unconnected word forms of *bank*.

or similar network-based features, it should also be possible to predict other relations between word forms or word senses in WordNet, as well as in other ontologies. For example, the so-called cousin relations are not consequently used in every possible case. The approach presented here, using network-based features, might also be used to identify cases where these relations are missing in WordNet.

Finally, looking at Fig. 33, which shows a very small subset of WordNet nodes, one can see the impact the new found edges have on WordNet. In Fig. 33(a), the interconnections of the word forms with the lemma *bank* in WordNet are shown. Four vertices are unconnected to the others. In contrast, Fig. 33(b) shows the same subset with the newly identified relations of semantic relatedness. Now all forms of *bank* that are semantically related are directly connected. Furthermore, one can see that two components emerge: one (red) with those forms of *bank* related to the financial system, the other one (grey) related to a slope (of land). There are no interconnections between the components, and the four nodes, before not connected to the rest of the graph, are now connected to the correct component.

6 DBpedia: Analyses and Predictions

6.1 DBpedia: an Ontology Extracted from Wikipedia

6.1.1 Knowledge Bases

The meaning of a word is not solely defined by its semantic or lexical relations such as those used in WordNet. Looking at WordNet, we know that a *bird* is a *vertebrate* and hence an *animal*. We do not know that birds are animals that fly, have feathers, lay eggs, sing, and are related to dinosaurs. This is not all part of the meaning of a word, but it is the knowledge (almost) every speaker of English has about a bird.

A computer does not have this information. Early on (e.g., in Minsky (1974)) it was stated that an intelligent machine must have this kind information at hand, and it is similar to what Fillmore (1975) proposed to be called the *frame* of a lexical unit.

To have access to this and similar information, a computer needs a special database called a knowledge base (KB). A KB contains some kind of information in an organized or structured way. A triple store for examples contains triples of the kind *subject–predicate–object*. Often these triples follow an underlying ontology that describes implications of relations or what kind of objects can be connected with certain relations. KBs contain either specific domain knowledge or general knowledge. Depending on the purpose of a NLP or AI system one is planning to build, one might need different kinds of KBs for different purposes.

In the WordNet use case, it was shown that using different similarity and distance measures taken from graph and network theory can be used to train a machine learning model to predict new relations from a set of manually made classifications. The task presented in this chapter differs not only in the usage of a different ontology, DBpedia, but also in its scope. Since DBpedia is expected to be very sparse and missing connections, the assumption is that by looking at the network and ontology structure of DBpedia it should be possible to fill the existing gaps in the KB.

6.1.2 What Is DBpedia?

DBpedia, *DB* stands for database, is extracting structured information from Wikipedia to make this source of knowledge accessible, inter-linkable, and especially machine readable. Assigning one identifier and a stable URI to each entity, nets of linked open data are being established that can be used to enrich existing information by freely adding

new relations. Exploiting the availability of Wikipedia in different languages, it is multilingual and connects different information from different languages under one common identifier. Furthermore, it links to entities outside Wikipedia/DBpedia and offers links to other knowledge bases (WordNet, YAGO, Freebase, the *Gemeinsame Normdatei*[97] (GND), GeoNames, and others).

Unlike many other sources of knowledge, DBpedia is domain independent and covers all the areas that are covered by Wikipedia. Offering Wikipedia data in a structured form can be used as a knowledge base in different kinds of tasks, such as semantic search (cf. Perez-aguera *et al.*, 2010), named entity disambiguation (cf. Mendes *et al.*, 2011), or the disambiguation of geographical identifiers (cf. Volz *et al.*, 2007).

6.1.3 Extraction of Data from Wikipedia

Most information in DBpedia is taken from Wikipedia. Wikipedia consists in great part of unstructured data in the form of free text, but almost every page of Wikipedia contains structured data in the form of so-called infoboxes as well. These are often displayed in the right upper corner of a Wikipedia page (but can also be in other places). The infoboxes use underlying templates that transform data given in the form of a table, similar to key value pairs, to what it later displayed to the user.

These key values pairs can take a form such as

(25) birth_date ={{Birth date—1940—10—9—df=yes}},

which is taken from the page `John_Lennon`. During the process of creating DBpedia, all wikipages are parsed and such structured information is transformed into triples of the kind `John_Lennon birthdate 1940-10-9`.[98]

Unfortunately there is no single infobox template that is coherent over all pages or languages in Wikipedia. Instead there are different templates that can be used to describe entities. For example, describing a person, the birth date can be expressed as `birthdate` or as `dateofbirth`.

The name of a wikipage is unique and can hence be used as an identifier. Each wikipage contains an abstract that is also available as free text in DBpedia. Links to versions in different languages are created according to Wikipedia's linking.

[97] English: Integrated Authority File.

[98] This is only a simplified presentation. In the real data set these objects consist of full URIs.

Wikipedia furthermore contains redirect pages (i.e., a page that points to a page with a different name). This is how Wikipedia handles synonyms, and this can of course also be exploited in DBpedia. Correspondingly, Wikipedia contains disambiguation sites that point from one name to different pages that represent different entities with the same name. This way homonyms are handled, identified, and disambiguated.

Geodata (i.e., coordinates of places from Geonames[99]) is available and stored in DBpedia. Wikipedia also contains a rich set of hierarchical categories and links to resources such as YAGO that contain their own categories. All these categories are available in DBpedia as classes or types. Furthermore, DBpedia is based on an ontology that defines its own category system.

The DBpedia data set contains several subsets of different size. When the term DBpedia data set is used henceforth, it refers to the so-called *mapping-based* version. While the generic infobox extraction creates triples as seen above, the mapping-based approach maps all information found in an infobox to the corresponding DBpedia relation if possible. The different templates using `birthdate` or `dateofbirth` are both mapped to one DBpedia relation. Since not all information can be mapped, this data set is a little smaller than the generic data set. Still, it is connected to the underlying ontology and does not contain ambiguous relations.

6.1.4 DBpedia Ontology

The mapping-based data set describes 843,169 entities from 170 classes in over 7 million triples using 720 properties described in DBpedia ontology (Bizer *et al.*, 2009).

The classes are organized in a shallow hierarchy: The class `Person` for example subsumes the class `Artist`, which is the superclass of `Actor` and `MusicalArtist` among others. Subclasses inherit properties of their superclasses. An entity of the class `Actor` is a `Person` as well. Other upper-level classes are `Place`, `Organisation`, and `Work`.

A member of the class `Person` can have, among others, the properties `name`, `birthdate`, `birthplace`, or `spouse`. `Artists` have `activeyears`, `awards`, `genre`, and many more properties. Some of these classes and their relations can be seen in Fig. 34. An `Artist` inherits the relations from its superclass, and every instance can have the properties of a `Person`. But not every `Person` can have the properties of `Artist`. The relations can have exact range and domain restrictions. For example, the `birthplace` relation is defined as

[99] `http://www.geonames.org`.

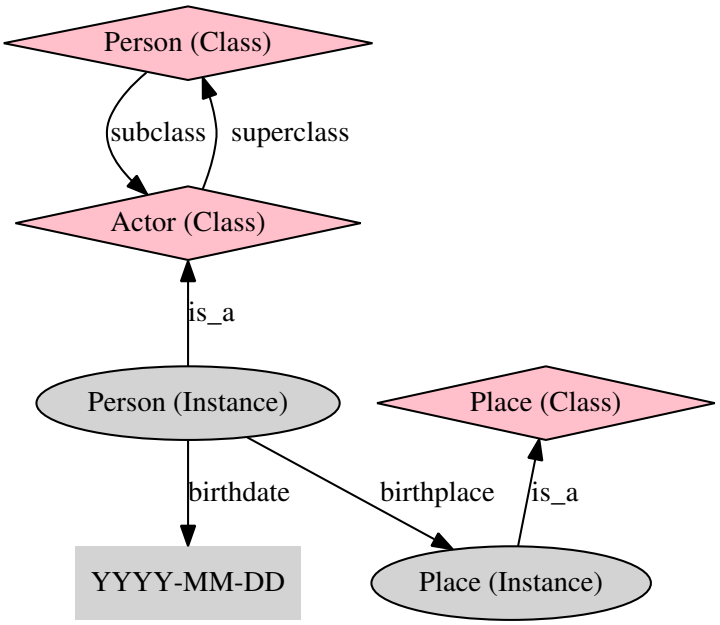


Figure 34: Exemplary graph: DBpedia classes and instances and their interrelations.

can be seen in Listing 2:

Listing 2: XML/OWL declaration of the birthplace relation

```
<owl:ObjectProperty rdf:about="http://dbpedia.org/ontology/birthPlace">
        <rdfs:domain rdf:resource="http://dbpedia.org/ontology/Person"/>
        <rdfs:range rdf:resource="http://dbpedia.org/ontology/Place"/>
</owl:ObjectProperty>
```

This OWL definition can be read as follows: The relation `http://dbpedia.org/ontology/birthPlace` (which is a URI) can only point from a member of the class `http://dbpedia.org/ontology/Person` to an instance of the class `http://dbpedia.org/ontology/Place`. In other words, only a person can have a birthplace, and only a place can be a birthplace. Fictional characters and animals do not have this relation (according to the DBpedia ontology).

The domain and range restrictions as well as the whole ontology were manually created from Wikipedia infobox templates.

6.1.5 Similar Approaches

The DBpedia project is not the only effort undertaken to make the knowledge and information contained in Wikipedia machine-accessible and machine-readable. Freebase

(Bollacker *et al.*, 2007) and YAGO (Mahdisoltani *et al.*, 2015) are two other knowledge bases that exploit Wikipedia to offer structured information.

YAGO is quite similar to DBpedia in its design and coverage. Just as DBpedia it parses Wikipedia to extract semi-structured data from links, redirection pages, and infoboxes. Just as DBpedia it works with an underlying ontology that defines classes, relations, and so on. DBpedia is available in different languages. YAGO takes the idea of a multilingual knowledge base a step further and does not offer different versions of its data in different languages but parses the multilingual versions of Wikipedia to extract information from them and to combine the information found across different languages in one data set. In other words, if certain information only exists in one version of Wikipedia (e.g., only in German for a certain German actor or city), this information is not available in the English version of DBpedia. YAGO aims at combining the different information from different Wikipedia sites and adds new entities as well as new facts (Mahdisoltani *et al.*, 2015).

Freebase is a "collaboratively built, graph-shaped database of structured general human knowledge" (Bollacker *et al.*, 2007, p. 1962). As such it contains tuples and supports querying the database using the Metaweb Query Language (MQL) just as DBpedia does using SPARQL. Furthermore, Freebase offers an API to not only read as well as write data to Freebase. Unlike DBpedia or YAGO, Freebase does not directly exploit information given in Wikipedia. The information is collaboratively assembled and can come, and does come, from many different sources. Freebase is not based on one underlying ontology as DBpedia or YAGO are. In contrast it offers the possibility to "design ... simple types and properties" (Bollacker *et al.*, 2007, p. 1963). Hence different types and properties exist that reflect different views on objects and facts at the same time. The downside of this approach is the inability to conduct logical reasoning on the data. Still, categorizing all possible knowledge in one coherent ontology would have been a very ambitious task, especially when working collaboratively. Freebase is open source. In 2010 it was acquired by Google and serves as a basis for Google's Knowledge Graph.[100]

[100] As of December 2014, Freebase was announced to be closed. Existing data are meant to be transferred to the similar Wikidata project.

6.1.6 Shortcomings of DBpedia

DBpedia is an automatically extracted, non-domain-specific ontology and its data set, the ABox, is incomplete. This is a problem that exists is many ontologies.

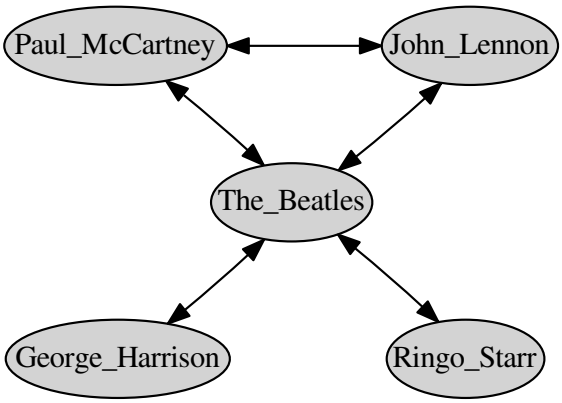


Figure 35: Connectivity between the four Beatles in DBpedia.

In Fig. 35, a small and simplified example taken from DBpedia can be seen. It shows the small social network of *The Beatles*, i.e., only the members of *The Beatles* and their direct relations to each other.

It can be seen that the shortest distance between `John_Lennon` and `Paul_McCartney` on the one side, and `George_Harrison` and `Ringo_Starr` on the other side, is 2, while `Paul_McCartney` and `John_Lennon` are directly connected (shortest path of length 1). They are all connected through `The_Beatles`. One would expect these nodes to be more interconnected. We know from our experience and external knowledge that they are connected, not just through their membership in `The_Beatles`. In Wikipedia, the corresponding pages are more interlinked. This information is apparently missing in DBpedia.

Furthermore, their connection to `The_Beatles` tells us, nonetheless, that they have to be connected in other ways as well. Possible properties for these connections within DBpedia ontology are *associatedAct* or *associatedMusicalArtist*.

As has been shown for the Facebook data, people that are closely connected share common attributes (e.g., all the Beatles are from Liverpool, they are likely to know Yoko

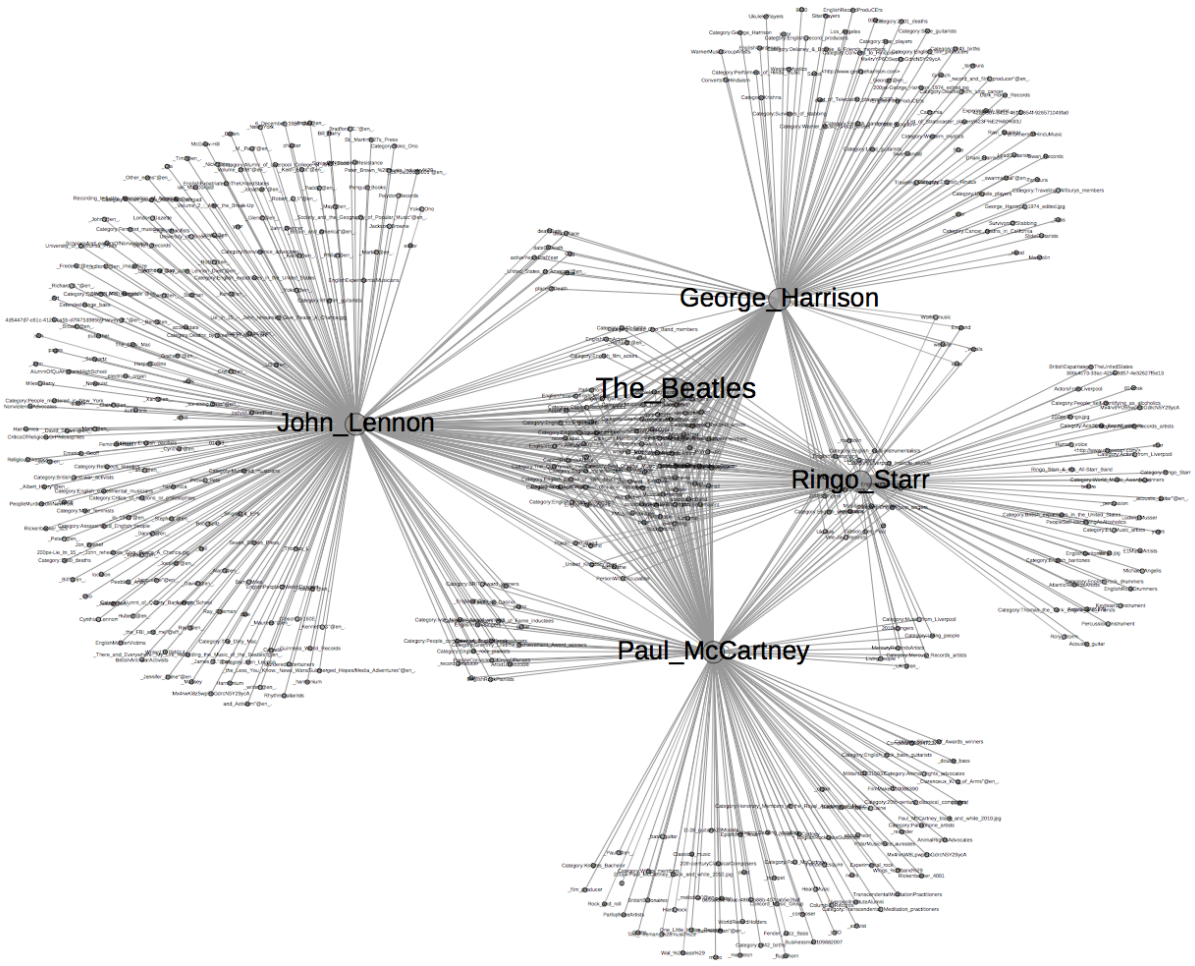


Figure 36: *The Beatles* and their neighbors in DBpedia.

Ono, they are English singers, and they all worked with Apple records). This information is also not complete in DBpedia. All this seems to be obvious to a human reader, but it is not for a computer, the user of the DBpedia ontology. Figure 36 provides a picture of the characteristics the four Beatles actually share according to DBpedia.

6.2 Network Analysis

The data set will be examined to find the typical properties of a non-random, or complex, network. These properties can be used to calculate new, not yet available relations between the entities.

As mentioned before, there are several characteristics of natural networks that arise in different domains and distinguish these from random networks. The distinguishing marks form a formal basis not only for the analysis of networks but also for predictions, classifications, and other computational tasks performed on network data. Steyvers and Tenenbaum (2005) mention five characteristics: sparsity, connectedness, short path lengths, neighborhood clustering, and power-law degree distribution.

If the relatedness of the network of entities of the entire ontology is similar to that usually found in natural social network, techniques used to compute attributes in a social network might also be employed to calculate attributes of other entities in the ontology.

The degree distribution of many natural, complex networks follows a power law of the form

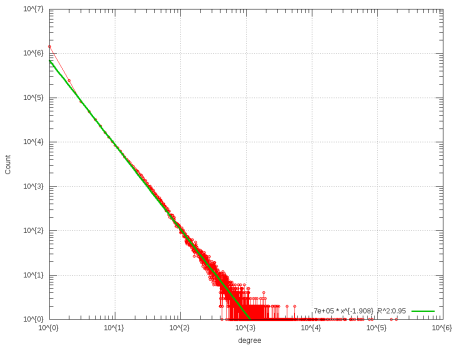
$$P(k) \sim k^{-\gamma}.$$

The in-degree distribution, plotted on a log–log scale in Fig. 37(a), fits the power law with $\gamma = 1.91$ pretty well. The out-degree plot (see Fig. 37(b)) is more skewed and does not fit the power law with $\gamma = 3.79$ too well. Ignoring the directedness, as seen in Fig. 37(c), the degree distribution is quite close to the power law with $\gamma = 2.11$.

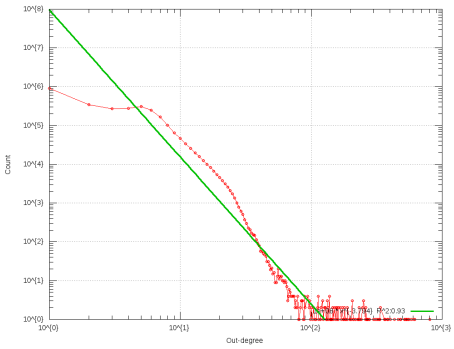
This distribution is caused by hubs or authorities, vertices with a very high degree. These hubs also cause a small geodesic path l. Caused by the evolution of growth of complex networks, small-world networks expose a clustering coefficient C (i.e., the sum over the number of links between any vertex and the vertices its direct neighbors are connected to), which is, on average, relatively high.[101]

These measures, l, γ, and C, have been analyzed in Zlatić *et al.* (2006) for a number

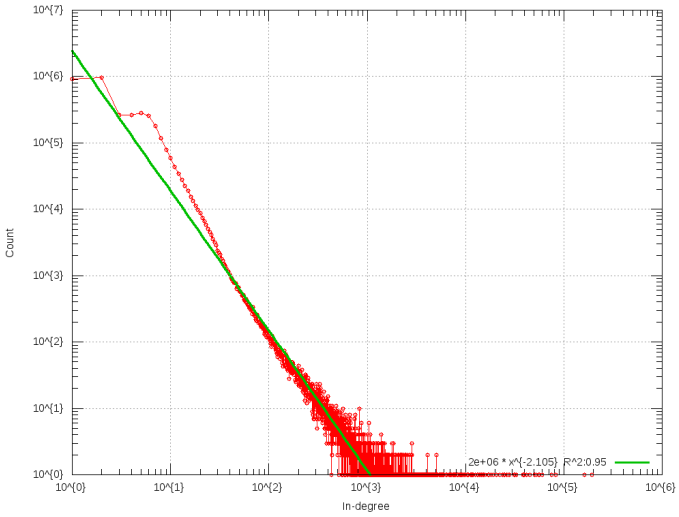
[101] This means it is expected to be higher than in a random network.



(a) In-degree distribution with fitted power law (green line), $\gamma = 1.91$.



(b) Out-degree distribution with fitted power law (green line), $\gamma = 3.79$.



(c) DBpedia degree distribution (ignoring direction) with fitted power law (green line), $\gamma = 2.11$.

Figure 37: DBpedia degree distribution.

Network	l	γ	C
Wikipedia	3.28	2.37	0.0098
DBpedia	5.5	2.11	0.0003

Table 36: The average path length l, the power-law exponent γ, and the clustering coefficient C for Wikipedia and DBpedia. Wikipedia values for l and γ are taken from Zlatić *et al.* (2006), C is given in Mehler (2006).

of Wikipedia sites of different languages and, overall, the study shows that the reported features are quite similar for Wikipedia sites of different languages. They also report the tendency that with a larger number of vertices, the clustering coefficient drops.

The in- and out-degree distribution of Wikipedia, as well as the undirected degree distribution, is overall very similar to the findings for DBpedia above. In Table 36, an overview over the different measures, the γ values, the average path length l, and the clustering coefficient C, for the English Wikipedia, which is also the basis for DBpedia version used in this paper, is shown. Only the numbers for an undirected network, ignoring the direction of the edges between the vertices, are shown. The numbers for the clustering coefficient C are taken from Mehler (2006).

Comparing these values of Wikipedia to those of DBpedia shows that the numbers do not match each other. The average shortest path, for Wikipedia only 3.28 edges, is longer in DBpedia but not unlikely for an SWN: $l = 5.5$. [102] The clustering coefficient is calculated to be 0.0003 in DBpedia (see Table 36), and hence very low. The C value of Wikipedia is around 30 times higher.

Although smaller differences can be expected from the different structures of Wikipedia and DBpedia (e.g., DBpedia introduces types that are not represented in Wikipedia structure and some other links to other ontologies, such as the friend-of-a-friend ontology), the differences, especially for l and C, are quite large and all of them point to one underlying problem: missing links.

[102] This is also shown when one looks at the diameter (i.e., the longest shortest path between any two vertices in the network), which equals 41 edges of length.

6.3 Approach to Link Identification in DBpedia

6.3.1 Related Work

Much of the information that is contained in Wikipedia is *lost* during the process of extracting it from Wikipedia to DBpedia. Different approaches are perceivable to enrich DBpedia. For example, extracting relations from free text in Wikipedia using pattern recognition techniques (e.g., Blessing and Kuhn, 2014) might be used to add new triples to DBpedia data set.

Approaches to enriching ontologies automatically, based solely on the ontologies themselves, have been proposed. This field of research is called ontology mining and aims at discovering underspecified knowledge in ontological knowledge bases (d'Amato *et al.*, 2010). Due to the great workload that is necessary to build high-quality ontologies, methods have to be found to make knowledge more accessible even from data that do not explicitly contain this information. Recent progress in this field includes the automatic induction of a schema by statistically analyzing relational data sets and thereby inducing the ontology and its rules based on observed interactions of entities (Völker and Niepert, 2011). Patterns of links between instances are extracted that can be used to heuristically find information on the type of an instance and possible relations a type might have (Paulheim, 2012). And Paulheim and Bizer (2013) show that the classical inference system does not work well on DBpedia, and they therefore propose an inference system that takes probabilities into account.

Paulheim and Bizer (2013) find that inferring the types of entities using reasoning on the RDF data of DBpedia leads to false conclusions. The existence of only one false statement results in nonsensical types of entities. For example, "there are more than 38,000 statements about `dbpedia:Germany`, i.e., an error rate of only 0.0005 is enough to end up with ... a complete nonsensical reasoning result" (Paulheim and Bizer, 2013, p. 2). This means that, even if the RDF data are over 99.9% correct, this could still result in wrong results. Also, reaching 99.9% is almost impossible in the first place. Paulheim and Bizer (2013, p. 2) state:

> These problems exist because traditional reasoning is only useful if (a) both the knowledge base and the schema do not contain any errors and (b) the schema is only used in ways foreseen by its creator.... Both assumptions are not realistic for large and open knowledge bases.

Since certain relations only occur with defined types (e.g., due to range/domain restrictions), the types should be inferable from the relations an entity has. Therefore, the probability of an entity belonging to a certain class based on the observations of relations is calculated. If only very few relations (e.g., one of the above mentioned 38,000) predict a certain type, the confidence or probability will be very low. Since many relations might be overrepresented in the data set, the probability is weighted based on the deviation of the property in the whole data set. The approach is hence a probability-based kind of inference and reaches a precision of up to 0.99.

The idea presented in Völker and Niepert (2011) is to use the ontology's ABox, i.e., the relational data, to conclude how these relations must be defined. In other words, the assumption is "that the semantics of any RDF resource, such as a predicate for example, is revealed by patterns we can observe when considering the usage of this resource in the repository" (Völker and Niepert, 2011, p. 129). To identify these patterns or rules, association rule mining, the Apriori algorithm, is used. This assumption is tested mining DBpedia's ABox and evaluating the resulting rules against DBpedia's TBox. Since the "expressivity of the DBpedia ontology is relatively low (it equals the complexity of the $\mathcal{ALCF}$ (D) description logic)" (Völker and Niepert, 2011, p. 134), and the rules are tested against DBpedia itself, it can assumed that not all false classifications would actually be false but could just be missing in the ontology itself. This approach reaches a precision of up to 0.854, while having a low recall of only 0.258.

In Paulheim (2012), missing types of instances are calculated by looking at the co-occurrence of types. While a large and very expressible ontology could be used to infer types using the axioms of the ontology, "most of the ontologies used in Linked Open Data do not provide that rich level of axiomatization" (Paulheim, 2012). Hence, the types cannot be inferred from the ontology. To overcome this problem and to add missing types in the data set of DBpedia, the author employs the Apriori algorithm. Given the fact that an entity is assigned the class `Singer` and the class `AmericanMusicians`, one might like to infer the fact that the entity is also of the type `AmericanSinger`.

Using association rule mining, a pattern or rule can be identified that states the following: if an entity e_1 is a member of the classes c_1 and c_2, it is also a member of class c_3. To make sure the rules conform to the ontology, rules are checked for their plausibility (e.g., if any class that is to be assigned is disjoint from any already explicitly assigned class of the entity, this class cannot be assigned). Also, classes are only inferred in a combination observable for the data. As the author states, there are no entities

that are both an `Athlete` and an `AmericanMusician`, and therefore no rule predicting this combination would be accepted. The system reaches an accuracy between 82.9% and 85.6% (Paulheim, 2012, p. 5). The author concludes a similar system could be defined that predicts "missing statements other than types" (Paulheim, 2012). This is exactly what will be done in the following, based on both the structure of the ontology and network, taking into account the assumed evolution of the network.

Given the small-world-like structure of Wikipedia and the differing structure of DBpedia, one can assume that DBpedia could be, in its structure, much more like a social network. Hence applying some of the methods taken from SNA mentioned above might be applicable to DBpedia as well. The approaches to type inference proposed in Völker and Niepert (2011), Paulheim (2012), and Paulheim and Bizer (2013) are based on DBpedia as well. The usage of association rules and especially the Apriori algorithm as proposed in Völker and Niepert (2011) and Paulheim (2012) seems promising. Still, having in mind that general prediction of missing statement is a broader field than the prediction of missing types, the accuracy to be expected from a similar approach based on the Apriori algorithm can be assumed to be considerably lower. In the following, a method to predict potential relations between entities of DBpedia based on the ontology structure and some general assumptions about prediction in complex networks is proposed and the underlying assumptions explained.

6.3.2 Identifying Missing Links and the Network Structure of DBpedia

Most of DBpedia is constructed using structured information given in Wikipedia infoboxes. This leaves out all the unstructured information, including the links between Wikipedia pages, since these links cannot easily be matched to the relations given in the DBpedia ontology.

To identify these missing links, some of the assumption about networks and DBpedia presented above are combined to formulate an approach that finds missing connections between vertices of the DBpedia graph with a very high precision. In a first step, a method for identifying vertices that are likely to be connected is presented; afterwards the same approach is used to predict the kind of relation existing between these vertices.

Here, a network-based approach trying to predict the most likely connected vertices is used. Afterwards, network-based methods will be used to predict the kind of relation missing between the two vertices.

Looking at the research done in SNA, one can find some clues to link prediction that might be applied to ontologies as well. First, one can see that a profound analysis and understanding of the data helps in finding ways to predict not seen structures. Different notions of similarity (e.g., short geodesic path between two vertices and common neighbors) are applied to find those vertices most likely to be missing a connection or to be connected in the future.

As has been shown, link prediction has been an active field of research in the last decade. The dawn of online social networks, such as Facebook or Twitter, and co-authorship graphs, enable researchers to conduct SNA on a new scale. Still, as stated in Clauset *et al.* (2008, p. 99), "our current pictures of many networks are substantially incomplete". When looking at the comparison of Wikipedia graph and DBpedia graph above, one can extend this statement to *our current pictures of many ontologies are substantially incomplete*.

As said before, the difference between the clustering coefficient in Wikipedia and DBpedia leaves room for improvements to DBpedia. While the low clustering coefficient of the WordNet graph was, in combination with the analysis of the ontology structure, an indication that the neighbors of a vertex do not play a vital role in WordNet when it comes to link prediction, the conclusion drawn from the numbers here has to be different. The structure of DBpedia is sparser than that of Wikipedia, and the difference between both is expected to be missing. As the Beatles example above shows, there are missing connections.

The network structure is of course a result of how the ontology is expected to develop over time (i.e., its evolution): The power-law distribution, the average geodesic path, and the clustering coefficient indicate an evolution model based on preferential attachment with some kind of variance that causes neighbors to be interconnected like the model given by Steyvers and Tenenbaum (2005). Hence, new vertices are connected not only to those vertices with a high degree but also to the vertex' neighbors. These second degree neighbors that are not yet connected to the vertex in question are possible candidates for the classification of a missing connection.

A basic assumption that will define what vertices are to be checked for missing relations in DBpedia can be formulated: Given a vertex A, plus it's neighbors (e.g., B) and second-degree neighbors (e.g., C), the higher value for l and relatively small value of C, indicate that the probability of A being connected to C is higher than the probability of it being connected to a random vertex of the graph.

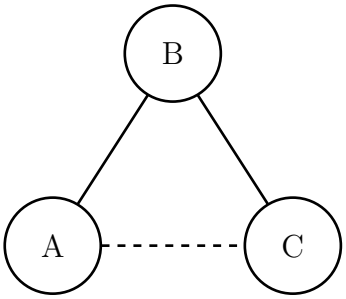


Figure 38: Unconnected triad with assumed connection (dotted edge) between two vertices A and C.

Often the vertices A and C will not only have one common neighbor, here B, as the simplified Fig. 38 might suggest, but they can have many common neighbors. Following this assumption, unconnected triads from DBpedia will be classified as either missing a connection between A and C, or not. What appears to be a quite straightforward task is hindered by the fact that DBpedia is incomplete. The unconnected triads are containing false negatives (i.e., cases where there should be a connection but where there is none). This complicates the application of machine learning techniques, since noisy data has to be cleaned to get a data set to draw conclusions from. To achieve this goal, all connected triads where A and C are in fact connected are extracted from DBpedia, ignoring the unconnected and therefore possibly erroneous instances. Using the relations between the three vertices (i.e., the relation from A to B ($rel(A, B)$), from B to C ($rel(B, C)$) as well as the connection $rel(A, C)$ from A to C), association rules are mined using the Apriori algorithm. These rules are of the kind *if* $rel(A, B)$ *equals to* x *and* $rel(B, C)$ *equals* y*, then* $rel(A, C)$ *equals* z. Furthermore, each rule is assigned a confidence value, which indicates the probability with which the rule predicts the assigned class (i.e., the relation between A and C).

The rules obtained are applied to the unclosed triads, where A and C are unconnected. In the first step it will be evaluated if a rule can be applied and, if so, if A and C should be connected. The problem here is that while there is a good set of connected cases in DBpedia, there is no such set for unconnected cases, since the yet unconnected cases are believed to be erroneous. Afterwards, in a second step, the cases that are missing a connection are assigned a fitting relation and the results are evaluated.

In the following, the different data sets to be used in the different tasks and evaluations are introduced. The different data sets are necessary to predict both where connections

are missing and what kind of connection or relation is missing. Furthermore, different machine learning algorithms use different kinds of features.

Afterwards these data sets will be used in different setups. Two unsupervised methods to predicting missing connection are to be tested: the Apriori algorithm that is often used in ontology mining and that has already been applied to DBpedia, and the k-means clustering algorithm. For the link classification task, the Apriori algorithm will be used.[103]

6.4 The Data Sets

DBpedia's ABox can be downloaded in the form of triples of the kind <*node*> <*relation*> <*node*>.[104] These triples follow the underlying DBpedia ontology and make up a network of relations between the entities in DBpedia.

Data Set `dbp0`

To build a data set as a basis of further investigation and evaluation, the mapping-based DBpedia set has been cleaned (i.e., all relations not belonging to DBpedia ontology have been removed and all instances that have no correspondence in Wikipedia[105] will be ignored in the evaluation process).

Data Set `dbp1`

This data set will be used to train a machine learning algorithm to identify whether two second degree neighbors in the network should be connected. Two vertices A and C that share at least one common neighbor,e.g., B, are extracted. The relations from A to any member of the set of common neighbors of A and C (i.e., the intersection of the set of neighbors of A $\Gamma(A)$ and C Γ), and from any member of this set to C are stored and will be used to find patterns that predict the connectedness of the triad.

One item hence consists of the set of relations $rel(A, B)$, and the relations $rel(B, C)$.

[103]Supervised methods are less feasible. Although there are many relations in the DBpedia data set, these are not fit for training a supervised algorithm. The reason is that the data set contains a lot of noise in the form of missing information (i.e., false negatives).

[104]Here, Version 31 was used. It can be downloaded from `http://wiki.dbpedia.org/Downloads31`.

[105]In many cases, an entity given in DBpedia cannot be mapped to a Wikipedia page. DBpedia contains special entities that represent, for example, career steps or life phases of athletes. These support entities do not exist in Wikipedia and can hence not be evaluated. Therefore, these entities, or rather items or triads containing such entities, were left out of the process.

These sets contain at least one relation but may very well contain many more relations from and to different common neighbors of A and C. To process these data, the sets of relations are transformed to a vector model: If relation x exists between A and any B, then it is counted as 1; otherwise the value is 0 or a missing value. The same is done for all relations $rel(B, C)$. In other words, for any pair of A and C, the data set contains two vectors indicating the existence of a certain relation between A and any common neighbor, and one vector containing the relation from any common neighbor to vertex C.

Since no rules based on the absence of relations are desired (these would be thousands) the vector model is altered in the way that only the connected values remain and the unrelated are missing. Thus the algorithm does not try to find rules containing non-existing, 0 or missing values. In total, the data set contains 917 attributes (i.e., different possible relations $rel(A, B)$, and $rel(B, C)$).

For evaluation purposes, a local installation of Wikipedia database was used to determine what page of Wikipedia, which corresponds to the DBpedia entities, links other sites.[106] This data is not used for training, but only to estimate the quality of the results.

The `dbp1` data set was extracted as both a training set with 272,566 items and as a test set with 721,299 items.

Data Set `dbp2`

The `dbp2` data set will be used for clustering. Besides the relations as in `dbp1`, it contains the closeness, betweenness, degree, and the page rank value of vertices A and C. Furthermore, the Jaccard similarity coefficient of the number of common neighbors of node A and C are available in the data set. For the set of neighbors of A (a_n) and the set of neighbors of C (c_n), the Jaccard coefficient J is computed as the size of the intersection of both sets, divided by the size of the union of both sets:

$$J(A, C) = \frac{|a_n \cap c_n|}{|a_n \cup c_n|}.$$

Also, the number of paths of length 2 is given as a feature. An overview showing all features in more detail is given in Table 37. The greater number of relations is less frequent and not shown in the table.

The `dbp2` data set consists of 949,193 items. Of these, 470,942 are connected and

[106] DBpedia offers a data set with all links between all wikipages as well.

Table 37: Graph-based features of DBpedia data set (`dbp2`).

Feature Name		**Feature Name**
$J(A, C)$		no. of shortest paths
degree A		degree C
closeness A		closeness C
betweenness A		betweenness C
page rank A		page rank C

contain $rel(A, C)$ as a class attribute. An overview over the most frequent classes is given in Table 38.

Data Set `dbp3`

The data set `dbp3` is different from `dbp1` and `dbp2`. First, it contains full, connected triads: the relation from A to B, from B to C, and from A to C. This last relation will be used to find rules to classify missing relations in unconnected triads. Again these relations are given in the form of a vector, where a relation between two vertices is either indicated as being presented or absent.

Since the total number of possible relations in the data set is very high, it seems most promising to restrict oneself to the most common classes in the data set. In Table 38, an overview over the most common classes is given. Some relations (e.g., those related the biological taxonomies, like `kingdom`, `class`, `family`) are by definition hierarchical and transitive and are hence ignored in the following for the sake of clarity. For each of the remaining classes, 4,000 items were extracted, i.e., triads where the existing relation between A and C is a member of the set of classes. Furthermore, 10,000 unconnected triads, according to Wikipedia, were added to the data set. A test set with 10,000 items yet unconnected in DBpedia, but according to Wikipedia connected, was extracted as well.

The choice to use a fixed number of occurrences per class regardless of the actual distribution of classes in the data set was due to the fact that the distribution of classes is very skewed. While some classes make up for over 10% of the total data set, most classes only exist in less than 1% of the items (see Table 38). Therefore, a good restriction on the

Table 38: Most frequent classes in `dbp2`.

Class	**No. of Instances**	**in %**
team	50,417	10.71
country	47,895	10.17
isPartOf	38,949	8.27
genre	30,649	6.51
order	23,193	4.92
class	22,041	4.68
kingdom	21,932	4.66
family	21,579	4.58
phylum	17,251	3.66
birthPlace	16,608	3.53
recordLabel	15,358	3.26
location	11,817	2.51
timeZone	9,957	2.11
producer	8,814	1.87
artist	7,218	1.53
deathPlace	6,731	1.43
hometown	5,361	1.14
division	5,349	1.15
writer	4,219	0.9
region	4,202	0.89
associatedMusicalArtist	4,169	0.89

minimum support is very hard to find: For the very common classes there are hundreds of rules, while no rules for the less common classes could be identified. Such a setup would be very unpractical in supervised approaches, where the class distribution itself can indicate the overall probability of a class. The Apriori algorithm is insusceptible for this effect.

An overview of the selected classes is given in Table 43.

6.5 Identification of Missing Links: Evaluation and Results

Two methods of unsupervised learning seem promising to solve the task of identifying missing relations using the data set `dbp1` described above: clustering and association rule mining, using k-means and the Apriori algorithm.

Starting with an approach based on the Apriori algorithm, a quantitative analysis and evaluation of the method presented here will be given.

6.5.1 Setup: Apriori

The Apriori algorithm, which was described in Chp. 4.3.2, is used to extract rules from the data set `dbp1` described above. The vector model of relations is used to find rules of the form *if the set of relations from A to any B contains the relation x, and the set of relations from any B to C contains the relation y, the two vertices A and C are connected.*

For several reasons only the in fact connected items were used in the Apriori algorithm. For one, the proportion between the connected and unconnected triads is strongly biased towards those cases that are unconnected. Furthermore, we are not interested in rules predicting when a triad is not connected in the data set. Also, the data are expected to contain noise: The yet unconnected items are believed to be missing connections (false negatives in the learning set) and are hence not well suited for learning.

The minimum support was set to 0.01, which equates to a minimum number of 2,726 items exposing one rule.[107] The confidence was set to 0.9. The confidence is the a measure of certainty of a discovered rule (i.e., the probability with which the rule predicts the class, being connected, or having a relation)). In other words, only if an identified rule predicts the class *connected* in at least 90% of the times, and exists in at least 2,729 items, the rule is accepted.

[107] This is a quite conservative choice which, as will be seen later on, guarantees only high-quality rules to be generated.

The evaluation of this first step is undertaken as follows: For each triad or item taken from DBpedia graph in the database, the Wikipedia database is queried to find if a connection between A and C exists. This information is only used for evaluation and not during training of the machine learning algorithm.

6.5.2 Quantitative Evaluation: Apriori

If only the connections between A and B, and B and C are taken as features, the algorithm identifies 62 rules. The rules generated as described above are then applied to the items of the `dbp1` test set, which contains the yet unconnected triads. The rules generated by the algorithm find only very few true positives, and both precision and recall are very low. Different combinations of features and sets of training items were tested.

If the right pattern of features is found and the rule matches the item, this prediction is compared to Wikipedia. If both the prediction and Wikipedia indicate a connection, this event is counted as a true positive. If the rule predicts a connection that does not exist in Wikipedia, this event is counted as a false positive (see Table 39). From these two values the precision can be calculated. Taking the number of items that are unconnected in DBpedia but that are connected in Wikipedia, the recall can be calculated as well.

Here the unsupervised approach reaches its limits. The similarity feature is hard to consider in Apriori rules since the algorithm does not handle numerical values. Nonetheless, it is suspected that the similarity (i.e., the ratio of shared neighbors of yet unconnected vertices) can play a role in identifying these cases.

To test this assumption, the evaluation was undertaken again. This time, the similarity J for the two vertices in question was calculated and a cut-off value for J specified: The similarity, or the cut-off value, lying between 0 and 1, was raised in every step until it reached 1. Only those cases that top the cut-off value for J were considered in each step.

As can be seen in Fig 39, the precision rises with a higher similarity and reaches its highest point of 0.74 for a similarity of 0.8. The recall, which is very low to begin with, drops further and approximates 0. It reaches a low at 0.004 for a similarity of 0.9.

The best results are hence reached using the 62 a priori rules and accepting a classification only if the similarity of the two vertices in question tops a predefined threshold of 0.8.

The numbers in Table 39 seem quite promising: Almost 74% of all instances are classified correctly; the error rate is close to 26%. These numbers are not very good,

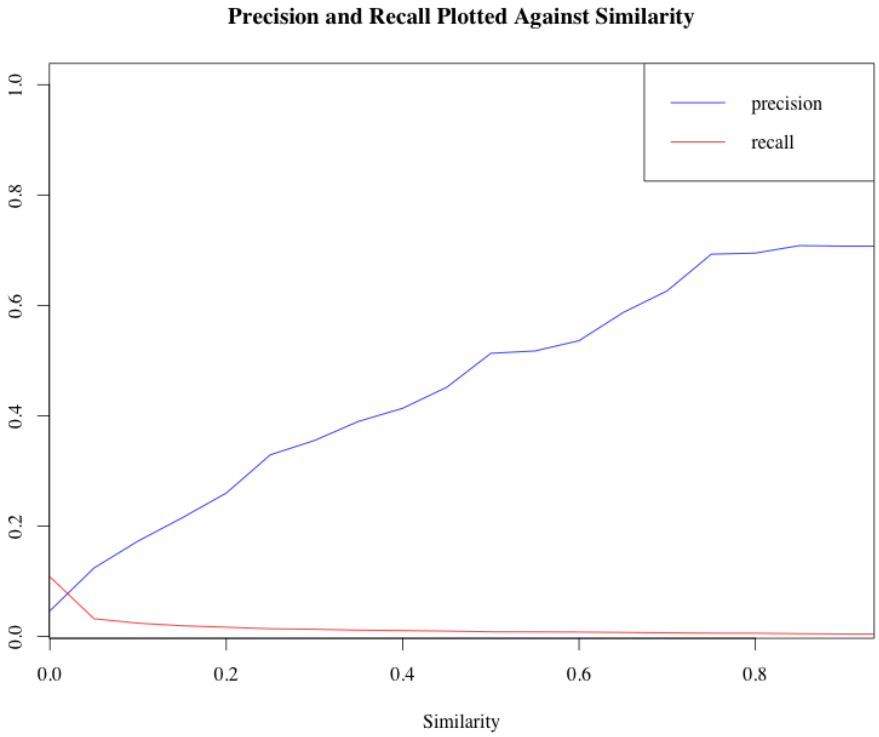


Figure 39: Precision and recall in relation to the similarity.

Table 39: Correctly and incorrectly classified missing connections in DBpedia using the a priori approach.

Correctly Classified Instances	678,420	**73.98%**
Incorrectly Classified Instances	42,879	**26.02%**
Total No. of Instances	721,299	

but in fact they are even worse than they look at first glance. One has to look at the true positive and false positive values (see Table 40) to find the real problem behind this approach. While most classified items are correctly classified as being unconnected, only 236 missing connections out of 721,299 triads could be identified. The recall is very low and the approach is missing many connections (i.e., the false negatives: 678,184).

After looking at the results of this first evaluation step, it seems very likely that the relations between three vertices A, B, and C, where A and B and B and C are known to be connected, do not necessarily predict the existence of a connection between vertices A and C.

In the following, clustering will be applied trying to solve the same problem, before drawing a final conclusion on the step of link prediction in DBpedia.

Table 40: True positives and other values for the classification of missing connections in DBpedia using the a priori approach.

		in Wikipedia	
		connected	**unconnected**
the algorithm	**connected**	236 (tp)	83 (fp)
	unconnected	678,184 (fn)	62,796 (tn)

6.5.3 Setup: Clustering

To evaluate how well-connected and unconnected triads can be distinguished using a clustering approach, the data set `dbp2` was used. Since clustering works well with numerical features, this data set contains the relations, the similarity J, plus the measures of centrality (see Table 37).

The k-means algorithm described in Chp. 4.3.2 was used. It takes the data set as a vector in an n-dimensional space and tries to find two centroids, where each vector is assigned the class of its closest centroid. The actual classes derived from Wikipedia are not used by the algorithm. It tries to find a natural distinction between the two sets. While supervised learning can weigh certain features according to the class, unsupervised learning, especially clustering, has to find distinctions in the data set that make a split into two classes most plausible. Therefore the precision is expected to be lower than the results found in the WordNet data set using supervised learning.

6.5.4 Quantitative Evaluation: Clustering

In a first step, the clustering is performed using the above-mentioned subset with all relations and all numerical features.

The k-means algorithm divides the set into two clusters, one for each class; 871,491 instances are identified as being unconnected, class *false*, and 77,702 as being connected, class *true*.

Table 41: Confusion matrix: clustering DBpedia instances.

		assigned class	
		false	**true**
actual class	**false**	702,887	47,113
	true	168,604	30,589

The cases that are classified as *true* and that are of the class *true* are the true positives (30,585). The false negatives are those that are connected in Wikipedia, but not according to the clustering (168,604). The cases that have been correctly classified as being unconnected are the true negatives (702,887), while those instances that were classified as being connected but that are not connected according to Wikipedia are the false positives (47,113). All values are given in Table 41.

The precision is calculated as the fraction of the true positives over the sum of true positives and false positives and equates to 0.4. The recall is the fraction of the true positives over the sum of the true positives and the false negatives and equates to 0.39.

These numbers do not change considerably if the numerical features are ignored and only the relations are used. As seen above, this seems to indicate that the relations make no good feature to predict the existence of a connection between two vertices A and C in an unconnected triad.

Since the numbers are very unsatisfactory, the relations will be ignored and only the numerical features, the network-based measures that were already used for the WordNet problem, are considered.

In this data set, 5% of the instances (i.e., 48,052 instances) are assigned the class *true*. Table 42 shows the confusion matrix.

As one can see, 727,187 instances of the class *false* are correctly classified as *false* (true

Table 42: Confusion matrix: clustering DBpedia instances using only network-based measures.

		assigned class	
		false	**true**
actual class	**false**	727,287	22,713
	true	173,854	25,339

negatives); 173,854 instances that actually are of the class *true* have been classified as belong to class *false* (false negatives); 25,229 instances have been correctly identified as being connected (true positives), while 22,713 instances that are of the class *false* were wrongfully assigned the class *true* (false positives).

Even though the overall error rate is only 20.71%, or 196,567 instances out of 949,193, which means that almost 80% of the data set was clustered correctly, over 17 thousand instances were not correctly identified, and even worse, over 22 thousand instances were incorrectly classified as being related. The precision value is only 0.53 and hence 0.14 points higher than when the relations are included in the form of a vector, and the recall is only 0.13 for the *true* class. Hence, ignoring the relations, and only using numerical features calculated on the network structure works a little better than considering the relations. Using only the network-based measures yields results in 0.14 points higher than when the relations are included. Still, the results are very unsatisfactory. The problem of automatically identifying where edges are missing DBpedia network could, at least using Wikipedia as a gold standard and using the setup presented here, not be solved.

6.6 Unsupervised Classification of Missing Links

6.6.1 Setup: Link Classification Using Apriori Algorithm

The step before consisted of predicting whether two second degree neighbors are missing a relation or not. Since this information is given in Wikipedia, the task of classifying the missing relation can still be fulfilled even though the results above are far from optimal.

The data set `dbp3` is used to predict not whether two yet unconnected vertices are missing a direct connection or edge but to predict what kind of edge is missing. The task

is to assign a fitting relation defined in DBpedia ontology to triads that are connected in Wikipedia but not in DBpedia using the Apriori algorithm.

The confidence was set to 0.9 (i.e., only if a pattern corresponds to the class, the kind of relation between two vertices, in at least 90% of the times, the rule is accepted). The minimum support was set to 0.001. To test the identified rules, the `dbp3` test set is used and the classification is manually evaluated using Wikipedia.

The data set is made up by unconnected second degree neighbors that share a set of common neighbors and their relation to these neighbors as set or a vector indicating the existence or non-existence of a certain relation between entity A and any common neighbor B, and any of these neighbors and C. Other setups would have been conceivable (e.g., using each path from A through any B to C as a feature and mining rules on this data set). Still, the chosen setup, and the vector representing the relations, is thought of as exhibiting more information since it shows all relations that exist on any path of length 2 from A to C. As shall be explained later, this setup does in fact have some advantages over other possible data sets.

6.6.2 Evaluation

The Apriori algorithm identifies 42 (see Table 46 in Appendix A) rules of the following form: If one $rel(A, B)$ is of kind x, and one $rel(B, C)$ is of kind y, then the relation $A--C$ is expected to be of kind z. The predictions are then checked against the information found in Wikipedia.

Table 43 gives an overview of the classes to be predicted and the corresponding number of correct and incorrect classifications related to the class. In total, considering all classes shown in Table 43, the rules result in a total of 78.49% correctly classified instances and 20.51% error rate. The recall can only be estimated. Out of 100 unconnected entities, the rules shown here predict a relation in 12.5 cases. Given that there could be more than one relation missing between two entities, this coverage is expected to be even a little smaller. The most commonly assigned class is `region`, which is assigned to almost 17% of all instances in the test set. The cases correctly classified as `region` make up 16.73% of the data set; the incorrectly classified cases only make up 0.4%.

Looking at the ratio between correctly and incorrectly classified instances, one can see that not every class is predicted equally well (see Table 43). The large red portions of the bars in Fig. 40 show this: The `isPartOf` relation for example is more often wrongly

Table 43: Classes and the percentage of correct and incorrect classifications compared to the whole test set.

Predicted Relation	Percent Incorrect	Percent Correct
associatedMusicalArtist	15.14	1.20
author	1.99	3.98
country	15.54	0.00
isPartOf	6.77	10.36
location	0.00	0.00
region	16.73	0.40
team	7.97	0.00
writer	8.37	1.99
hometown	5.98	3.59
	78.49	**20.51**

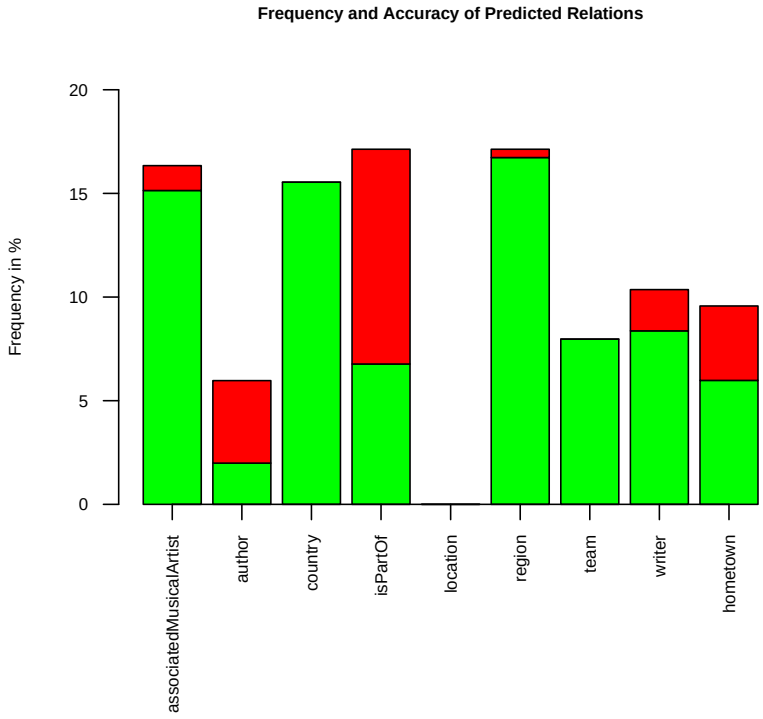


Figure 40: Classification results with all selected classes: predicted relations in %. Green: correct classifications, red: incorrect classifications.

assigned (10.36%) than used in correct classifications (6.77%). Also the error rate of the `author` and `hometown` relation is higher than the correct classifications, and the `location` relation is not assigned one single time in the test set. This is due to the fact that no rule satisfying the minimum support and confidence values was identified in the data set.

Table 44: Apriori rules to predict relation in DBpedia (excerpt I).

Rel. *A–B*	**Rel.** *B–C*	**Prediction**	**Counter**
`isPartOf`	`isPartOf/part`	`isPartOf`	4,960
`isPartOf`	`isPartOf`	`isPartOf`	1,510
`associatedBand`	`associatedBand`	`associatedMusicalArtist`	2,689
`associatedMusical Artist`	`formerBandMember`	`associatedMusicalArtist`	2,557
`producer`	`bandMember/writer`	`writer`	1,874
`careerStation`	`team`	`team`	496
`city/state`	`country`	`country`	668
`region/department`	`country`	`country`	266
`department`	`region/isPartOf`	`region`	438

Two different rules predicting a `isPartOf` relation are given in Table 44. The first applies if A is part of any common neighbor B and any B is part of C and there also exists a relation `part` between B and C[108]. The semantics behind `part` is similar to `isPartOf` but has a range restriction on `dbpedia-owl:Place`. The second rule applies if A is part of any B and any B is part of C. While the first rule results in 92% incorrect classifications, the second rule, contrarily, makes correct classifications in 87% of the cases.

The error rate of the `hometown` relation classifications is also very high. In the test set, eight different rules predict this relation; in some cases, numerous rules predict the same relation in the case of two concrete entities. In the following, an example will be shown that is related to the Canadian band *Barenaked Ladies*. In total, five of the eight rules in the rule set apply to the entity and all five rules classify `Toronto` as the band's hometown.

First, one should have a look at Wikipedia to see if this assumed relation is indeed correct. The information to be identified is not given in the infobox of a Wikipage, but in

[108]One has to remember that due to the setup of the data set, B can represent any shared neighbor of both vertices, but not strictly and necessarily the same neighbor in both conditions!

the free text of the page as can be seen in the screenshot of the corresponding wikipage in Fig. 41.

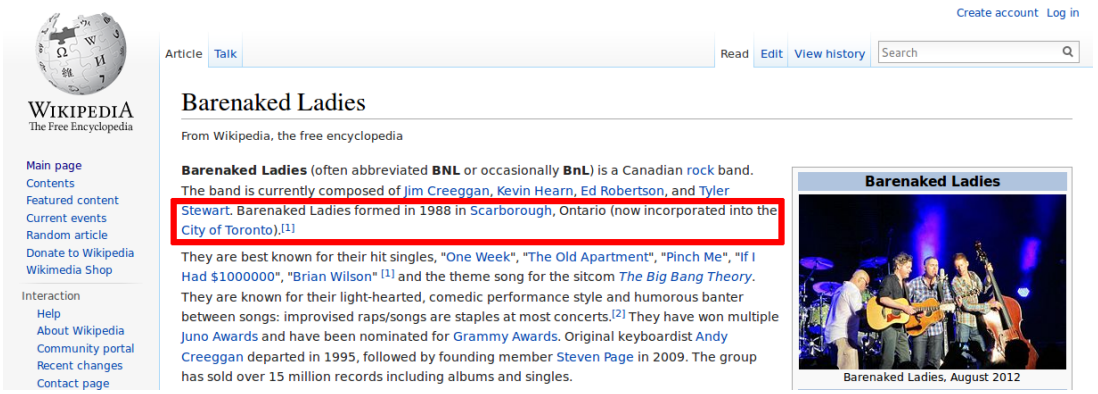


Figure 41: Screenshot of Wikipedia page: `Barenaked_Ladies`.

The applied rules predict the relation in different ways. A quite simplistic rule states that if `Barenaked_Ladies` has the hometown `Scarborough,_Ontario`, and both entities share a common neighbor that is part of `Toronto`, then the `Barenaked_Ladies` are from `Toronto`. Another rule indicates that if at least one band member of the band is from `Toronto`, then the band is from Toronto. Despite its simplicity and that there obviously must be many exceptions, this rule is often correct and can even predict cases where there is no clear evidence even in the free text of the corresponding wikipage and where parsing-based approaches, as those discussed before (cf. Blessing and Kuhn, 2014; McCord *et al.*, 2012), would not be able to identify the desired relation. Within the test set, there is the example of a Norwegian heavy metal band called `I_(band)`, which, according to the presented rule here, originates from the city of Bergen. The free text mentions Bergen only as a place were the band had their first, and apparently only, public performance. To answer the question of whether the band itself is from Bergen, one can look at the band members and can find that they are in fact from Bergen. This is what the rule states. Of course, there might, and there in fact are, exceptions from this and other similar rules.

Especially these geography-related rules have been found to be used in a rather unexpected way in the original data set. While evaluating the predictions made by the rules, some seem rather odd at first glance. For example, the `Harwich_Town_railway_station` was said to be related to `Essex` by a `country` relation. Since Essex is not a country, and the range restriction of the relation states that it has to be a country, this seems wrong.

Still, `Essex` is a country according to DBpedia. Other types (e.g., a region) would have been more appropriate. Also, US states are de facto of the type country, according to the relation they take part in. Also, the `hometown` relation has a range restriction on the type `Settlement`. Still, settlement is apparently a very broad term in DBpedia and can also refer to countries. The `hometown` and `country` relations are actually quite often used in DBpedia, and hence the rules presented here also predict that some country would be the hometown of some person. This is not wrong according to the ontology and is also frequently done in the original data set, but it still shows that some relations of DBpedia seem clearly underspecified with regards to their range or domain restriction.

Overall, the error rate of the proposed rule set is quite high. To minimize the error rate, one could leave out not only the rules that predict classes that are often wrongly classified, but just as well rules that seem not very convincing to the human implementing the rules in (e.g., SPARQL (a recursive abbreviation for *SPARQL Protocol And RDF Query Language*), a graph-based query language for RDF data).

To reach a higher accuracy in the classifications, the four classes with either no classifications or a high error rate, `author`, `isPartOf`, `hometown` and `location`, and the corresponding rules will be ignored. Applying the remaining rules to the test set results in the values shown in Table 45. Summing up the percentages of correctly classified instances results in an accuracy of 94.67% and hence an error rate of 5.33%.

Table 45: Apriori rules to predict relation in DBpedia (excerpt II).

Predicted Relation	**Percent Incorrect**	**Percent Correct**
associatedMusicalArtist	1.78	22.49
country	0.00	23.08
region	0.59	24.85
team	0.00	11.83
writer	2.96	12.43
	5.33	**94.67**

These numbers are visualized in Fig. 42: The large green portions of the bars indicate the correct classifications. The `team` and `country` relations are always assigned correctly; the rules predict these relations with a very high accuracy.

In Table 44, two rules predicting the relation `associatedMusicalArtist` are shown.

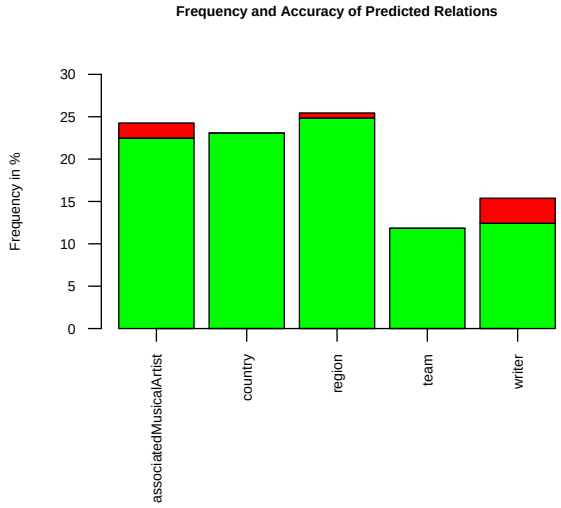


Figure 42: Classification results with only well-performing classes: predicted relations in %. Green: correct classifications, red: incorrect classifications.

Each of these two rules is applied over 2.5 thousand times in the data set. The first says that if A is connected to a common neighbor with C by the relation `associatedBand`, and a common neighbor of both C and A is connected to C by `associatedBand` as well, A and C are related through `associatedMusicalArtist`. In other words, if A, B and C are all bands, and A and B as well as B and C are associated, A and C are also associated.

The second rules states that if the set of shared neighbors of A and C contains an `associatedMusicalArtist` of A, and a `formerBandMember` or C, A and C are missing a relation `associatedMusicalArtist`. There might of course be exceptions to this special rule.

Listing 3: The band members of the `Ramones` and the newly identified relations between them.

```
Johnny_Ramone      associatedMusicalArtist Dee_Dee_Ramone
Johnny_Ramone      associatedMusicalArtist Joey_Ramone
Johnny_Ramone      associatedMusicalArtist Tommy_Ramone
Johnny_Ramone      associatedMusicalArtist Marky_Ramone
Johnny_Ramone      associatedMusicalArtist Richie_Ramone
Johnny_Ramone      associatedMusicalArtist Clem_Burke
Johnny_Ramone      associatedMusicalArtist C._J._Ramone
```

The examples in Listing 3 show cases where one of the most common classes is assigned to otherwise unconnected entities, the members of the punk-rock band *Ramones*. Unlike one might think, the members of the Ramones are not familiarly related and the names of band members are pseudonyms. In the list shown here, the only exception seems to be `Clem_Burke`. In fact, Clem Burke was the drummer of the band *Blondie* and worked with the Ramones during a limited period of time during which he went by the pseudonym *Elvis Ramone*. Each of these relations is predicted by two different, yet similar, rules. If there exists a relation `associatedBand` between A and a member of the set of shared neighbors of A and C, as well as between one of the shared neighbors and C, and if there further is a relation `formerBandMember` to C, the rule predicts the relation `associatedMusicalArtist`. The second rule only differs in the fact that it checks if A and any B are connected by an `associatedMusicalArtist` relation.

This also shows, in part, what the difficulty in identifying such rules manually might be. In total, a number of 10 different rules are identified that predict the relation `associatedMusicalArtist`. While one can easily think of a number of possible relations in a triad that could be expected to result in this class for $rel(A, C)$, one would need to study the ontology intensively and might still not think of every possible rule. Given the fact that there are almost 500 possible relations in DBpedia and at least 3 relations involved in a rule, this results in 500^3 (i.e., 125 million) possible combinations. Given the fact that there is no reason why only one relation could exist between two entities, this number has to be increased further.

As mentioned before, single triads containing exactly one relation from A to B and from exactly this B to C, hence forming a possible path of length 2 between the two entities in question, would have been a possible alternative to the vector model used here. Mining rules on a data set built in this fashion was found to result in a large number of nonsensical relations. For example, the often used `team` relation that is never incorrectly assigned in this data set led to rules that would predict this relation to exist between two teams themselves. This is not strictly forbidden by the ontology and hence the predictions are made, but they contradict the common meaning. The underlying problem is that some relations expose a *fuzzy* semantic, as shown above, and are hence used in wide variety of ways. Furthermore, relations like the `team` are lacking a defined domain restriction (e.g., `person`) since only a person can be a member of a team.

6.7 Conclusion

DBpedia is an automatically derived ontology based on structured information given in Wikipedia pages. It is already widely used in NLP tasks although the knowledge base is quite incomplete. Just how incomplete can be seen when comparing the network analysis of DBpedia to that of Wikipedia. DBpedia is a complex network (i.e., it shows a degree distribution that follows a power law). It is hence a small-world network with a short average geodesic path length between any two vertices of the network, and it has a clustering coefficient higher than a random network with a similar average degree.

Since the structure of DBpedia is based on the Wikipedia structure, entities that are connected in Wikipedia and unconnected in DBpedia are assumed to be missing a relation. Therefore, the second step (i.e., classifying the missing relations between any two entities) can be accomplished by comparing both resources. First, an analysis of Wikipedia's and DBpedia's network structure shows that Wikipedia has a shorter average geodesic path length than DBpedia. As has been shown in the small-world network model (Watts and Strogatz, 1998), adding very few wide-spanning relations between entities otherwise only connected by a large geodesic path can cause a very small average path length in the whole network. In other words, the fact that the average geodesic path length of DBpedia is shorter than that of Wikipedia might only indicate very few missing relations. Comparing the clustering coefficients of both networks shows that Wikipedia's clustering coefficient was over 30 times higher than that of DBpedia. Since the clustering coefficient is the ratio of second degree neighbors the vertex is also connected to, or, in other words, the degree to which a vertex is connected in its neighborhood, the much smaller value in DBpedia indicates that a great number of missing relations is missing within the vertex' neighborhood, the neighbors of its neighbors.

This assumption is further confirmed when analyzing the network's structure and looking at how this structure would evolve. Taking into account that the degree distribution follows a power law, one can assume that an evolution model using preferential attachment can explain this finding. Furthermore, the clustering coefficient is higher than a pure preferential attachment model (Barabási and Réka, 1999) would predict. As has been proposed by Steyvers and Tenenbaum (2005), a model that fits the structure of semantic networks has to be extended in a way that newly added vertices are connected not only to other already well-connected vertices as well as to vertices in the neighborhood. The probability by which this is done influences the clustering coefficient.

From these findings in the network, and from the consideration made in social network analysis that neighbors tend to be similar in their connectedness to their neighborhood, the assumption was emerged that looking in the neighborhood of a vertex for missing connections would be a good starting point for a link prediction task. Hence the connected and unconnected triads, pairs of second degree neighbors that are not connected yet, were extracted. The Wikipedia graph gives indications at what pairs should be connected, and this information can be used to check the quality of any prediction made.

Two tasks have been identified in order to extends the ontology based on the network it exposes: First, those second degree neighbors that shall be connected have to be identified; second, the relation between those two entities has to be classified.

Examining the state-of-the-art methods in ontology mining, techniques that have already been applied to derive missing type relations in DBpedia, the Apriori algorithm was identified as a possibly suitable algorithm. Another possible unsupervised approach that was tested was the k-means clustering algorithm.

Testing different setups, it was found that the results of the task of identifying possibly related entities using the Apriori algorithm were very unsatisfactory. The relations and paths between the entities in question seem unfitting to fulfill this task. Furthermore, including network-based centrality measures, clustering was employed to solve the task of identifying possibly connected vertices. Here the centrality measures caused an increase in accuracy of 0.14 points. In the end, this problem could not be solved using unsupervised approaches relying on the ontology and network structure using the features proposed here. The reason for this is believed to be found in the creation and the structure of Wikipedia itself. Many wikipages make reference to other sites of Wikipedia in a way that DBpedia, in its current form, does not account for: Many people are connected based on common professions; places are connected by geographic closeness. Most of these relations are missing in DBpedia, and the interlinked pages are otherwise poorly connected since their degree of relatedness is expected to be very low. It is assumed here that this property of Wikipedia structure might be hindering a successful identification, at least when Wikipedia is used as a gold standard to define what entities should be connected and what entities should not be connected.

The task of classifying missing relations was solved using the known difference between DBpedia and its defined gold standard, Wikipedia. By comparing both resources, one can know exactly where there are missing relations.

It was stated before that approaches of parsing the free text of Wikipedia can be used

to extract relations that are given in natural language. Here, however, the network and the ontology structure are considered as features to identify rules that can classify what relation is missing. For a defined, and admittedly relatively small set of possible relations, the method evaluated here was found to reach an accuracy of 94.67%. In order to build an industrial level system, one could remove relations that are predicted with a low accuracy, as it was done here, one could also have a look at single rules and only use those rules that work with a high accuracy, as it was suggested above.

The rules proposed here can easily be translated to SPARQL, the language used to query DBpedia. The example given in Listing 4 corresponds to the rule that for any n that has a hometown of x and is part of z, n has also the hometown z.[109].

Listing 4: SPARQL query

```
PREFIX p: <http://dbpedia.org/property/>
PREFIX o: <http://dbpedia.org/ontology/>
PREFIX dbpedia: <http://dbpedia.org/resource/>

SELECT DISTINCT ?n '<http://dbpedia.org/ontology/hometown>' ?z '.'
WHERE {
 ?n p:hometown ?x.
 ?x o:isPartOf ?z.
 }
Limit 100
```

During the manual evaluation, some relations were found to exhibit a rather strange distribution (i.e., they were used to relate entities that did not seem to be matching an intuitive semantics of the relations). Especially the geography-related connections were found to be underspecified with regards to their range or domain restrictions. A relation like `hometown` can essentially be used in the same way as `country` or `region`. Furthermore, the `country` relation, although restricted to countries, can also refer to regions like `Essex` that are clearly not an independent country and have not been an independent country or kingdom for many centuries.

These missing restrictions, as well as the de facto pretty vague typing system, might be problematic for ontology mining tasks as the one presented here. If there is no clear distinction between certain relations, they are redundant. Furthermore, the expressiveness is clearly reduced if a certain number of the possible almost 500 relations cannot be clearly

[109]DBpedia offers an online tool to run such queries. at `http://dbpedia.org/snorql/`. The number of results is limited though.

distinguished from each other. This reduced expressiveness, of course, might result itself in less precise results in ontology mining.

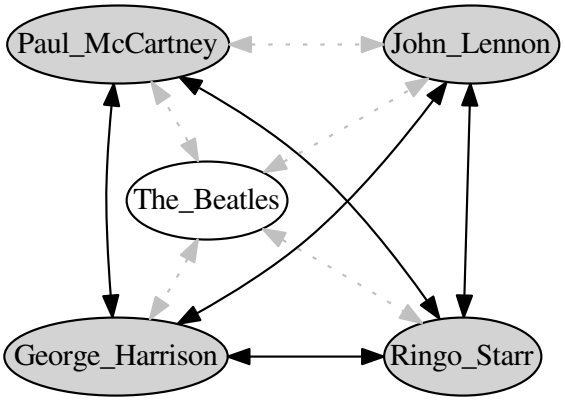


Figure 43: Existing relations (grey, dotted) and newly added relations (black) between the four Beatles in DBpedia.

Nonetheless, it was found while evaluation and checking the predicted relations against Wikipedia that some predicted relations could not be easily identified in Wikipedia, since even the free text in the wikipage did not contain this information. The example of the Norwegian metal band *I* was given above, where only a closer look at the band members revealed the information that the band must be from the city of Bergen. Hence, the network of entities not only encompasses much of the information given in the form of natural language in Wikipedia, but even indicates information that cannot be found or observed directly in Wikipedia but that can only be concluded from information given by its neighbors.

At the beginning of the chapter, the four Beatles and their interconnections were mentioned. It was stated that although they share a number of neighbors in the network, they are not connected to each other, as would be expected from both our world knowledge and the existing linkings from the corresponding wikipages. Following the approach presented here, the four Beatles can now be identified as `associatedMusicalArtist` by a number of rules given in Table 46 in Appendix A. Figure 43 shows the newly added relations between the band members.

7 Discussion, Conclusion, and Future Work

Networks naturally evolve all around us. They are often found in nature. For example, the neurons of the brain form networks, the blood circuit is a network, genes can be treated as a network, and so on. But not only natural organisms and structures take the form of a network. Human interaction takes the form of networks too, such as social networks, communication networks, transportation networks.

Networks are suited to be used in these different tasks because of their robustness. Thinking of the network of streets in a city, there is a way from every point to any other point even if certain streets are closed. Thinking of the Internet, even if one undersea cable were malfunctioning, there would always be a route using another cable. In this sense, even the non-existence or a damage to one of the edges of a network does not jeopardize the whole network.

Therefore, this form of organizing objects of any kind is often *chosen* in nature and in human action. Humans choose the organization in the form of networks either consciously, as in the organization of train tracks across a country, or unconsciously, as the networks arising from human language show. Underlying the idea of treating language as a network is the assumption that language networks, just as many other kinds of human interaction and especially social networks or communication networks, evolve as a result of the working of the human mind that is network like. It has been claimed in this thesis that the similarities between the organization of the human brain and the human language are not a coincidence, but an isomorphism, where the organization of the first is reflected in the second[110].

The neural network of the human brain is thought of as exposing patterns of connectivity, it shows patterns of interactions of different clusters of neurons in the network that correspond to the semantics of words or concepts. Even though the analogy between the neural network of a brain and that of word networks is very skewed since word networks never reach the fine-grained, detailed, and large structure the simplest neural networks in biology reach, the idea of treating the interaction of words as a network offers new ways to understand language, and, as was the goal of this thesis, can be used to extend existing systems in NLP.

Furthermore, networks not only make good models of interactions because they are

[110]Similarly, it has been claimed in Mehler (2008) that wikis are formed as a result of the small-world structure of their users.

fitting, but they also offer a concise mathematical approach to problems. As has been shown, graph theory offers the possibilities to undertake calculations on networks that help understand its structure, its evolution, and might finally be used to extend networks.

Especially the evolutions of different networks was looked at in greater detail. The idea is, by looking at the status quo of a network, to understand what processes drove the objects or vertices in the network to be organized in the way they are now. By understanding which processes can explain the structure we see, we can conclude how future growth should function and how a networks structure is supposed to behave when it grows (i.e., if new vertices or edges are added).

Looking at the semantic theories that were proposed and employed during the last century, the idea of networks arises in most of the more common theories. Starting with the lexical fields, where words are thought of as entities whose meaning is defined in relation to its neighbors, and frame semantics, where the extra-linguistic situation, the extra-linguistic knowledge, and the lexical units themselves are related and interact with each other, to semantic relations that define the word meaning in hierarchical or vertical lexical and semantic relations, to the above already mentioned paradigmatic and syntagmatic relations words expose in distributional approaches to semantics based on large text corpora. Co-occurrence graphs are built from large amounts of texts and the co-occurrence of two words establishes a relation between them. The more often two words co-occur, the stronger the tie. Such syntagmatic co-occurrence graphs also exhibit paradigmatic relations (i.e., a certain degree of similarity as these words can substitute each other, of course not without changing the meaning or truth value of an utterance).

Modern ontologies combine many properties of the above-mentioned semantic theories in a coherent, mathematical framework. A straight line of evolution has been made out in this thesis that connects the ideas of lexical fields, frame semantics, and lexical relations to ontologies used in information sciences and NLP. Furthermore, the distributional approaches are closely related to ontologies in the way they form networks and hence in the ways they can be treated mathematically. Starting with Frege and Leibniz, over Montague semantics, mathematical logics was introduced into the treatment of linguistics. Logic is also used to define ontologies and to infer meaning from ontologies. It seems therefore only plausible that since ontologies form networks and are based on logics, they should be treated in mathematical ways, using reasoning and graph theory.

Ontologies have been found to be of very great use to many problems in NLP. But they have almost just as often been found to have major shortcomings: either their

incompleteness due to the limitation given by their manual creation of their incompleteness or erroneousness due to an automatically extraction.

Different ways have been proposed to extend or refine ontologies by (e.g., including data from other data or knowledge bases, or by parsing natural language and thereby exploiting the fact that syntax gives indications to relations expressed in natural languages and hence to the semantics of words or concepts). Most approaches are based on external *unstructured* data (i.e., texts). The term *unstructured* refers to the fact that the structure is not machine readable without further preprocessing. Texts and language of course follow a defined structure. This structure is so complex that automatic approaches, unlike the human mind, have problems to understand, identify, and use these structures. Lacking a thinking machine that understands language the way humans do, researchers have build sets of rules that have been found to express certain relations.

Although these techniques are used regularly, problems arise especially when working with ontologies and trying to add new information to an existing ontology. For one, an ontology defines a closed set of vocabulary that can be used to describe relations. If a relation is identified in a text, it has to be mapped to the ontology. The other problem arises from the entities in questions. Especially in WordNet, a *word*, a certain string of characters, is not unambiguously existent in the ontology. Some kind of sense disambiguation has to be performed to map what is found in a data set or in an human utterance to what exists in the ontology.

Because of the difficulties arising from these approaches, this thesis looks at the network the data (i.e., the ontology) exposes. Ontologies and other knowledge bases can be treated as networks too. It has often been stated that RDF triples form a graph and that a large amount of such triples makes up a network. Still, most approaches treating ontologies as networks so far have only been concerned with structural properties of such graphs in relation to other complex networks such as collaboration networks (cf. Mehler, 2007).

Both networks and ontologies suffer from the fact they many of them are incomplete and missing information (cf. Clauset *et al.*, 2008). Therefore, the methods presented in this thesis are based on the mathematical foundation of graph theory as well as on findings made in different research fields such as computational social sciences that, when looking at social networks, some vertices are much more likely to be connected than others. An extensive review of different techniques, approaches, and studies undertaken in this and neighboring fields has been presented here. In social networks, especially the

neighborhood of two vertices indicates a relation. In other words, two vertices in a social network that are connected tend to have similar neighborhoods. This is called homophily.

Based on assumptions made in the social science, research from physics and other areas of research, and based on basic concepts of graph and network theory, this thesis presented two very different approaches to find, predict, and classify missing relations in two different kinds of ontologies that are regularly used in NLP tasks: WordNet and DBpedia.

WordNet is a manually crafted resource that interlinks word senses and word forms with each other. It contains information on nouns, adjectives, adverbs, and verbs, and organizes these in the form of a network by establishing different lexical and semantical relations between them. It is one of the most often used resources in English NLP. Although undoubtedly a very helpful resource, it has often been criticized for either being to fine grained in its distinction of meaning, or for missing certain information.

As has been shown in this thesis, a lot of work has been put into the distinction of polysemous and homonymous *words* in WordNet. Looking at the linguistic literature regarding polysemy, a polysemous word can be defined as being underspecified or very broad in meaning, and therefore it can be used in very different contexts and thus refer to different concepts. The most basic example is the so-called grinding rule, where animal names are regularly used to refer to products gained from the animal, be it fur, skin, or meat. Animal names also offer the possibility to be used to refer to people, and in this case there is no a priori rule of what property connected to the animal is transferred to the new referent. If someone is called a *lion* or *tiger* it might be due to their strength, but it might also refer to their power, or even cruelness. These connotations are available to humans, but they are not part of WordNet.[111]

Homonymy, in a narrow sense, refers to the fact that the same sound (homophony) and the same form (homography) refer to distinct, unrelated things in the extra-linguistic world. In the setting of this thesis, only homograph cases can be considered since WordNet does not offer any information on the pronunciation of words. Homonyms are hence arbitrarily similar forms of words that have no semantic connection. Resulting from this, the thesis arose that polysemous word forms should be semantically more closely related.

Since WordNet is based on word forms and word senses, the term word is of no use in this context. In the context of WordNet, and especially when looking at what the use of

[111]Other resources such as FrameNet contain more circumstantial knowledge of lexical units, since they are thought of as belonging to the meaning of a word as well.

the knowledge of a *word* being polysemous or homonymous is, i.e., knowing if a certain sense of it is semantically related to the other senses, the problem has to be redefined: The task is to identify if two (homograph) word forms, and hence the meaning connected to them, are related or unrelated. Using different similarity measures for social networks and WordNet, was originally assumed to be a fruitful approach to identifying polysemy in WordNet.

Furthermore, the different centrality measures, closeness, betweenness, degree, and page rank, plus some measures based on considerations made from the analysis of the ontology structure of WordNet, among them the number of shared lemmas of two synsets or the existence of certain relations (e.g., indicating derivationally relatedness) were extracted for any pair of homograph word forms in WordNet.

A large set of these instances was then manually tagged as either being related (i.e., sharing a common meaning or being underspecified) or as being unrelated and hence homonymous. This is of course not the usual definition of polysemy and homonymy, but it is the one applicable to WordNet and it also fulfills the task to know if two word senses share a common semantic trait or if these senses are just purely at random expressed using homograph word forms.

The task of finding homograph word forms restricts the possible candidates in the network to a relatively small set of instances. It has been claimed before that checking every vertex of a complex network against any other vertex would not be a good strategy (Clauset *et al.*, 2008). In this task, the set of instances is naturally restricted. The instances, containing the word forms and synsets in question, plus the set of features defined in this thesis, and the class attribute, were used in different machine learning algorithms, to train a model that could be applied to yet unseen instances to classify the two word forms in question as polysemous or homonymous.

The best results were obtained using a random-forest algorithm (i.e., a set of decision trees based on random feature selection, where each tree casts a vote and where the finally assigned class is the most often voted for class). Other algorithms have been tested as well. None of them came close to the results of the random-forest model though.

Interestingly enough, the features of semantic similarity, including the geodesic path between the two word forms, were found to have a negative influence on the model's performance of the noun and verb sets. The shortest path does have a positive influence on the results for adjectives and adverbs.

Other features that have previously been proposed to identify polysemy in WordNet

were compared to the feature set presented in this thesis, namely the CoreLex basic types (Buitelaar, 1998) that have been used by Utt and Padó (2011) and Boleda *et al.* (2012) among others, and the WordNet unique beginners that were used in Peters and Peters (2000).

Both approaches rely on the identification of patterns of co-occurrence of either basic types or unique beginners that would predict regular polysemy. Three main problems arise here: The approaches are only applicable to nouns, they are only able to identify regular cases of polysemy, and they, especially the basic types, do not work well on the word form level, but rather treat all homograph word forms as one word and assign either the label polysemy or homonymy to it, even though many words show both related and unrelated senses[112]. The goal in this thesis was instead to work on the word form level and hence identify those word senses that are in fact similar. Furthermore, the approach presented here is not restricted to nouns or to regular cases of polysemy.

As could be expected from these restrictions, the beforehand proposed methods did not perform well on the new task (i.e., identifying polysemy over different POS, including irregular cases, and looking at the word forms and not at sets of word forms).

Using the proposed set of graph-based features (i.e., the centrality measures, plus the measures based on the WordNet structure) yielded an accuracy between 87.35% for adverbs,and 94.11% for verbs, where as the results for adjectives (91.17%) and nouns (90.12%) lie between these values.

Using the same features, it is expected to also be possible to identify other missing relations in WordNet. The so-called cousin relations for example are only used very seldom in WordNet. Since they offer very rich information on the connectedness of otherwise unconnected word senses or forms, it might be useful to add these relations in as many cases as possible, without the need to do this work manually.

The second ontology is not a purely linguistic ontology, but it contains general knowledge and it is in its structure much more similar to social and other complex networks than WordNet. DBpedia is an ontology that is automatically derived from the structured data of Wikipedia (e.g., the infoboxes, redirect pages and others). While this information is quite precise and accurate, it is missing many links that exist in Wikipedia that are not identified during the extraction of DBpedia and that cannot be mapped to relations defined in the ontology.

[112]Related and unrelated with regards to their semantics in todays language and not with regards to other historical stages of the language.

A comparison between Wikipedia and DBpedia on network level shows these differences. The average geodesic path in DBpedia is longer than that of Wikipedia. This indicates that some, but maybe only very few, connections between vertices are missing that are otherwise separate by far in the network. As has been shown in the small-world model (Watts and Strogatz, 1998), adding only very few of these connections can reduce the length of the average geodesic path greatly. Looking at the clustering coefficient C, one can see that Wikipedia's C value is much higher than that of DBpedia. This indicates that there are missing connections in the direct neighborhood of the vertices in DBpedia network. Therefore, unconnected triads are examined in this thesis. The second-degree neighbors of any vertex are looked at, and if the vertices are unconnected the idea is to estimate if a connection is missing or not. Furthermore, this approach reduces the complexity of the task, since not every vertex has to be checked against any other vertex of the network. The resulting classifications, either missing a relation or not, can be compared to the Wikipedia graph.

In a second step, it was tried to classify the missing relation (i.e., in the case that a connection is missing) a machine learning algorithm tries to identify the most plausible relation defined in DBpedia ontology. Looking at the field of ontology mining, the Apriori algorithm was identified as a promising technique to solve the given task. It was used before to automatically derive ontologies based on DBpedia (Völker and Niepert, 2011) and to infer missing types in DBpedia (Paulheim and Bizer, 2013). Especially the identification of missing types is to some degree similar to the tasks in this thesis.

Since the Apriori algorithm only counts occurrences of events, it does not distinguish between numerical values and nominal values. The algorithm can be applied straightforwardly but only to nominal features. The occurrence of different relations between the unconnected vertices is taken into account. It is assumed that certain patterns arise (i.e., the occurrence of two relations between two vertices should indicate whether they are connected or not). One main problem is the noise in the data set (i.e., errors that exist and therefore hinder machine learning). This noise is caused by the fact that many unconnected vertices in DBpedia should in fact be connected.

Trying to solve the first problem, the Apriori algorithm identifies 62 rules that seem to indicate a connection, but there are many exceptions from these rules. Applying the identified rules to unconnected vertices in DBpedia set and checking the predictions against the Wikipedia graph showed that the rules are not very accurate. The results are unsatisfactory, and the task of identifying missing relations using DBpedia relations

and the Apriori and the k-means algorithms remains unsolved. Other approaches might be conceivable, for example using supervised learning and bootstrapping for example to overcome the problem of noise.

The second task was to classify the kind of relation missing between two entities. Since DBpedia is extracted from Wikipedia, it is expected to show a similar interlinking. From the Wikipedia graph, it is known what entities are connected and are possibly missing a link in DBpedia. An Apriori rule mining approach was undertaken to identify patterns of connections between two (unconnected) entities sharing a common neighborhood that could be used to classify the missing relation. Using only a small subset of the possible almost 500 different relations in DBpedia, 42 rules were mined that can be used to identify what relation is missing between two second-degree neighbors that should be connected. After analyzing the accuracy of the rules, it was decided to exclude further relations that were shown to perform inaccurately. Other possible ideas to reduce the error rate might be excluding only certain rules from the rule set that can be shown to perform inaccurately.

Applying the proposed rule set results in an accuracy of 94.67%. Since the data set only contains a very small subset of possible relations, the recall or coverage of these rules is assumed to be rather low. Examining how the proposed rules work and what the reasons for bad performance might be, some issues that might be causing the problems with some of the classes or rules could be identified.

For one, it was found that many relations are rather redundant in both their application in DBpedia and with regards to their semantics. This can be seen in many already existing triples in DBpedia data set but just as well in some of the predictions made here. The `hometown` relation for example is often used where one would expect a `country` or `region` relation. In other words, some relations are just too similar and therefore hard to distinguish. This might be causing problems when trying to predict these relations as it was found in this thesis. Related to this problem, many relations are underspecified with regards to their domain and range restrictions. The `hometown` relation is similar to the other mentioned relations because it has no restriction to towns or cities, but to settlements. But in DBpedia settlements can be anything, from a country to a village. Hence, the relations are very similar since they do not differ in their range and domain restrictions in a way that would be expected. Others such as the `team` relation might be expected to only exist between a person and a sports team. Instead, anything could be connected to a team by this relation without contradicting the ontology.

Another reason for the non-optimal performance of many of the above-mentioned

geographic relations might be found in the linking structure of Wikipedia and is hence related to the chosen *gold standard*. Wikipedia offers rich interlinking between (e.g., villages or cities pertaining to a common region or district). While this information is actually given in a more or less structured way, it is not given in a way readily readable for DBpedia extraction mechanism. Wikipedia automatically inserts special navigation boxes at the bottom of a page based on the information given in the Wikipage. The line {{`List of European capitals by region`}} in a wikipage causes Wikipedia to insert a list of other European capitals for the user. Since this is done on runtime and based on the category system of Wikipedia, this information is not extracted for DBpedia. In DBpedia this results in many missing connections that exist according to the Wikipedia linking table. Furthermore, since these relations are missing for every Wikipage in DBpedia, there are not many examples for these missing relations in the data set to mine corresponding rules from. Most of these relations cannot usefully be mapped to the existing DBpedia relations. They were not taken into account when the DBpedia ontology was designed.

This last point is the main reason why the link predictions task, identifying whether a link is missing or not, based on triads does not work with an acceptable accuracy. Wikipedia graph is just not a perfect gold standard for the kind of relations that are missing and that are of interest in DBpedia. The low coverage of the link classification task can also partly be traced back to this systematic mismatch between both data sets, Wikipedia and DBpedia.

Other attempts to extract relations from Wikipedia include text-parsing approaches. Interestingly enough the evaluation undertaken in this thesis shows that a graph- or network-based approach is, in some cases, even more accurate than a parsing approach. It was shown that some of the predictions or classifications that the approach presented here make were also not given in the text of the related Wikipage. In the example presented in Chp. 6.6.2, a `hometown` relation between a band and a city was established. This information was taken from the interconnection of the wikipages and was not contained in the single page. Only by reading other related pages (i.e., those regarding the band members) could the information that the band was indeed from the city be confirmed by a human reader. A parsing-based approach would not be able to identify this information given by the network structure.

Both approaches to identifying different relations, in different contexts, using different machine learning or data mining techniques, indicate that interpreting language as a network can be of great use in many NLP tasks, as shown here for ontologies. Ontologies

build complex networks, and as other networks they are often incomplete. But just as it has been shown for social networks and other complex networks in recent years, the network structure contains in itself a lot of information that can be exploited to extend the network and hence the ontology in question. Given two solid candidates, two entities of the ontologies or two vertices in the network, one is likely able to predict certain properties of these vertices (e.g., what kind of relation should be connecting them). While the network structure of both language and ontologies has often been stressed before, this thesis presents the first approach to extend knowledge given in an ontology by exploiting its network structure.

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A Appendix

Table 46: Complete list of Apriori rules to predict relations in DBpedia.

Relation *A–B*	**Relation** *B–C*	**Prediction**	**Counter**
careerStation	team	team	496
recordLabel/ associatedBand	associatedMusicalArtist	associatedMusicalArtist	174
isPartOf	part	isPartOf/ part	4960
bandMember	hometown	hometown	75
associatedBand	bandMember/ associatedBand	associatedMusicalArtist	2689
city/ state	country	country	668
hometown	location	hometown	55
associatedMusicalArtist	formerBandMember	associatedMusicalArtist	2557
hometown	hometown	hometown	120
department	region	region	6
formerBandMember/ bandMember	associatedBand	associatedMusicalArtist	468
department	country	country	0
bandMember	country	hometown	19
arrondissement	isPartOf	region	16
province	isPartOf	region	17
region/ department	country	country	266
department	region/ isPartOf	region	438
subsequentWork/ producer	bandMember	writer	337
bandMember	birthPlace	hometown	68
state	country	country	395
producer	writer/ bandMember	writer	1874
associatedBand	associatedBand/ formerBandMember	associatedMusicalArtist	2557

formerBandMember	hometown	hometown	49
bandMember	associatedMusicalArtist	associatedMusicalArtist	338
formerBandMember	birthPlace	hometown	69
recordLabel/ associatedBand	associatedBand	associatedMusicalArtist	174
previousWork	author	author	18
isPartOf	isPartOf	isPartOf	1510
hometown	birthPlace	hometown	61
currentMember	team	team	61
formerBandMember	associatedMusicalArtist	associatedMusicalArtist	468
arrondissement	region	region	6
hometown/associatedBand	country	hometown	232
district	country	country	232
series/ subsequentWork	writer	writer	75
isPartOf	state	isPartOf	4
associatedMusicalArtist	bandMember /associatedBand	associatedMusicalArtist	2689
formerBandMember	country	hometown	19
hometown/ associatedBand	isPartOf	hometown	216
successor	region	region	113
bandMember	associatedBand	associatedMusicalArtist	338
subsequentWork	author	author	20