

Enrichment of ontological taxonomies using a neural network approach

Bachelorarbeit

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Contents

1	Introduction	1
2	Foundations	1
2.1	Wikidata	1
2.2	Taxonomy	1
2.3	Similarity	5
2.4	Similarity-based classification	5
2.5	Text processing	5
2.6	Problem statement	6
3	Analysis of the Wikidata taxonomy	7
4	Ontology learning	11
5	Neural networks	11
5.1	Recursive neural networks for graph representation	11
5.2	Deep neural networks for graph representation	14
5.3	Continuous Bag-of-Words	14
5.4	Skip-gram with negative sampling	14
5.5	Comparison	14
6	Algorithm	14
6.1	Baseline	14
6.2	Supplementing with other resources	14
7	Evaluation	14
7.1	Method	14
7.2	Generation of gold standard	14
7.3	Results	14

List of Figures

1	Example of Wikidata class: photographic film (Q6239)	1
2	The spectrum of ontology kinds. [23]	2
3	Example for k-nearest neighbors for 3 classes with k=4 and k=10. . .	6
4	Distance of subclasses to root class <i>entity</i> (Q35120). Wikidata (2016/11/07)	7
5	Percentage of unlinked classes with a specific amount of unique prop- erties. Wikidata (2016/11/07)	9
6	Frequency of properties in unlinked classes. Wikidata (2016/11/07) .	9
7	Percentage of unlinked classes with a specific amount of instances. Wikidata (2016/11/07)	10
8	Percentage of unlinked classes with a specific amount of subclasses. Wikidata (2016/11/07)	10
9	Percentage of unlinked, labeled, instantiated classes with a specific amount of unique properties. Wikidata (2016/11/07)	12
10	Frequency of properties in unlinked, labeled, instantiated classes. Wiki- data (2016/11/07))	12
11	Percentage of unlinked, labeled, instantiated classes with a specific amount of instances. Wikidata (2016/11/07))	13
12	Percentage of unlinked, labeled, instantiated classes with a specific amount of subclasses. Wikidata (2016/11/07)	13



Figure 1: Example of Wikidata class: photographic film (Q6239)

1 Introduction

Motivation. Related work. Solution. Evaluation.

2 Foundations

2.1 Wikidata

TODO: Define entity in Wikidata, how are classes identified, etc. Galárraga [11]
 Wikidata is a open, collaborative and user-driven knowledge base. Its main purpose is to serve as a structural knowledge store for other Wikimedia projects like Wikipedia.

2.2 Taxonomy

Ontologies are sets of concepts and relations, which formally define how knowledge can be related and ordered in a context. Additionally it is possible for ontologies to contain axioms used for validation and constraint enforcement. In comparison, a knowledge base like Wikidata can be seen as an instantiation of such an ontology,

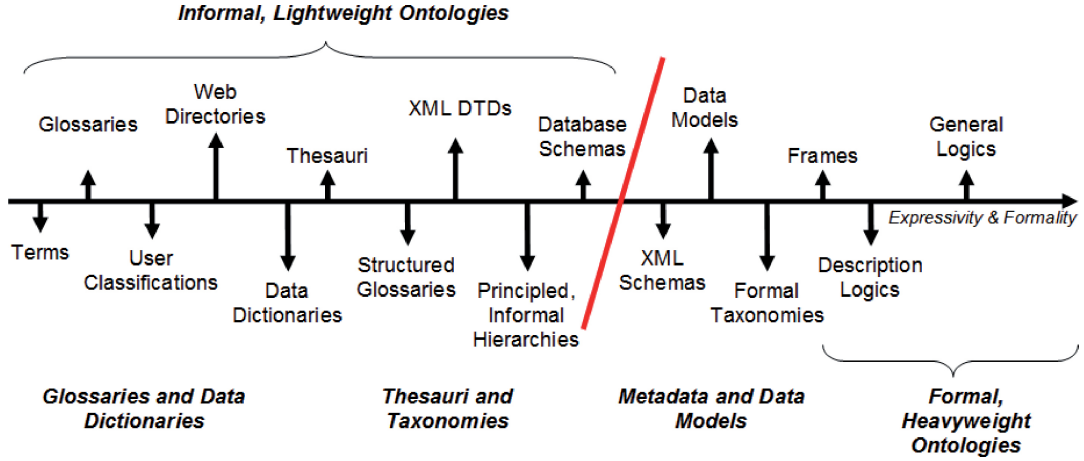


Figure 2: The spectrum of ontology kinds. [23]

since every knowledge base has to be conceptualized by an ontology [23]. Different types of ontologies can be grouped by their level of formality and expressiveness. Wong et al. [23] differentiates ontologies as lightweight and heavyweight ontologies (see Figure 2). *Taxonomies* are concept or class hierarchies. They typically represent a parent-child structure, which can be formalized with a single relationship called for example *subclass-of* in the case of Wikidata. The observed taxonomy in Wikidata belongs to the category of lightweight ontologies, specifically *principled, informal hierarchies*, as the only enforced rule for the subclass-of relation is that it should connect two entities [1].

For the purpose of developing a formal definition of the thesis' problem statement the notion of taxonomy needs to be formalized. Cimiano [6] defines a heavyweight ontology, which includes a taxonomy, as follows:

Definition (Ontology). An ontology is a structure

$$\mathcal{O} := (C, \leq_C, R, \sigma_R, \leq_R, \mathcal{A}, \sigma_A, \mathcal{T})$$

consisting of

- four disjoint sets C , R , \mathcal{A} , and \mathcal{T} whose elements are called concept identifiers, relation identifiers, attribute identifiers and data types, respectively,
- a semi-upper lattice \leq_C on C with top element root_C , called concept hierarchy or taxonomy,
- a function $\sigma_R : R \rightarrow C^+$ called relation signature,
- a partial order \leq_R on R , called relation hierarchy, where $r_1 \leq_R r_2$ implies $|\sigma_R(r_1)| = |\sigma_R(r_2)|$ and $\pi_i(\sigma_R(r_1)) \leq_C \pi_i(\sigma_R(r_2))$, for each $1 \leq i \leq |\sigma_R(r_1)|$, and

- a function $\sigma_{\mathcal{A}} : \mathcal{A} \rightarrow C \times \mathcal{T}$, called attribute signature,
- a set \mathcal{T} of datatypes such as strings, integers, etc.

Hereby, $\pi_i(t)$ is the i -th component of tuple t . [...] Further, a semi-upper lattice \leq fulfills the following conditions:

$$\begin{aligned}
& \forall x x \leq x \text{ (reflexive)} \\
& \forall x \forall y (x \leq y \wedge y \leq x \implies x = y) \text{ (anti-symmetric)} \\
& \forall x \forall y \forall z (x \leq y \wedge y \leq z \implies x \leq z) \text{ (transitive)} \\
& \forall x x \leq \text{top} \text{ (top element)} \\
& \forall x \forall y \exists z (z \geq x \wedge z \geq y \wedge \forall w (w \geq x \wedge w \geq y \implies w \geq z)) \text{ (supremum)}
\end{aligned}$$

So every two elements have a unique most specific supremum. "

A taxonomy can be modeled as a semi-upper lattice. This induces two important assumptions about the structure and to some degree completeness of the observed taxonomies. First, there is only one *root class*, top element of the lattice, of which every other class is (transitively) a subclass. Second, because of the supremum property, the taxonomy is fully connected, which means each class, but the root class, has a superclass. Wikidata's taxonomy does therefore not fulfill the definition by Cimiano [6], as it is not fully connected.

In the following, new definitions will be presented, which attempt to model an incomplete taxonomy based on the already presented data model and structure of Wikidata. First, basic concepts of graphs will be introduced.

Definition 1 (Directed graph). A directed graph G is an ordered pair $G = (V, E)$, where V is a set of vertices, and $E = \{(v_1, v_2) \mid v_1, v_2 \in V\}$ is a set of ordered pairs called directed edges, connecting the vertices.

Definition 2 (Predecessor). Let $G = (V, E)$ be a directed graph. $v_1 \in V$ is a predecessor of $v_2 \in V$, if there exists an edge so that $(v_1, v_2) \in E$. Let $v \in V$ be a vertex of G , then $\text{pred}_G(v) = \{w \mid (w, v) \in E\}$ is the set of predecessors of v .

Definition 3 (Successor). $v_1 \in V$ is a successor of $v_2 \in V$, if there exists an edge so that $(v_2, v_1) \in E$. Let $v \in V$ be a vertex of G , then $\text{succ}_G(v) = \{w \mid (v, w) \in E\}$ is the set of successors of v .

Definition 4 (Walk). Let $G = (V, E)$ be a directed graph. A walk W of length $n \in \mathbb{N}$ is a sequence of vertices $W = (v_1, \dots, v_n)$ with $v_1, \dots, v_n \in V$, so that $(v_i, v_{i+1}) \in E \forall i = 1, \dots, n-1$.

Definition 5 (Cycle). A walk $W = (v_1, \dots, v_n)$ of length n is called a cycle, if $v_1 = v_n$.

Definition 6 (Directed acyclic graph). A directed graph G is called directed acyclic graph, if there are no cycles in G .

In Wikidata, a class can have multiple superclasses, therefore a tree structure is not sufficient to model the taxonomy. However a directed acyclic graph, can model the taxonomy. The acyclic constraint is necessary to ensure that no class is transitively a subclass of itself. **TODO: define**

Definition 7 (Connectedness).

Definition 8 (Component).

Definition 9 (Taxonomy). A taxonomy $T = (C, S)$ is a directed acyclic graph, where C is a set of class identifiers, and S is the set of edges, which describe the subclass-of relation between two classes. such that c_1 is the subclass of c_2 , if $(c_1, c_2) \in S$.

Definition 10 (Subclass-of relation). The transitive binary relation \triangleleft_T on the taxonomy $T = (C, S)$ represents the subclass relationship of two classes in T . Given $c_1, c_2 \in C$, $c_1 \triangleleft_T c_2$, if there is a walk $W = (c_1, \dots, c_2)$ with length $n \geq 1$, which connects c_1 and c_2 . \triangleleft_T is transitive, $\forall c_1, c_2, c_3 \in C : c_1 \triangleleft_T c_2 \wedge c_2 \triangleleft_T c_3 \implies c_1 \triangleleft_T c_3$.

If the taxonomy defined by Cimiano [6] is mapped on this graph-based taxonomy model, the following assumption is true, for $T = (C, S)$:

$$|\{c \in C \mid \neg \exists s \in C : c \triangleleft_T s\}| = 1$$

Only one class in this taxonomy has no superclasses. This class is called *root class*. However in the case of Wikidata, this assumption does not hold true. The following state is the case:

$$|\{c \in C \mid \neg \exists s \in C : c \triangleleft_T s\}| > 1$$

There are classes other than the root class, which also have no superclasses. These classes will be called *unlinked classes*.

Definition 11 (Root class). Given a taxonomy $T = (C, S)$, the root class $root_T$ is a specific, predefined class with no superclasses in T . For $root_T$, $|succ_T(root_T)| = 0$ applies.

Definition 12 (Unlinked class). Given a taxonomy $T = (C, S)$ with a root class $root_T$, a class $u \in C$ is called unlinked class, if $u \neq root_T \wedge |succ_T(u)| = 0$.

In Wikidata, the root class is *entity* (Q35120) [2]. All other classes, which are not subclasses of *entity* (Q35120), are therefore either unlinked classes, or subclasses of unlinked classes. In Section 3, it will be shown that the Wikidata taxonomy graph is not fully connected. But the component, which contains root class *entity* (Q35120), contains 97% of all classes. This component will be referred to as *root taxonomy* in later sections.

2.3 Similarity

- semantic similarity e.g. distributional similarity
Lin [17]
Rodríguez and Egenhofer [21]
- geometrical similarity e.g. distance based-similarity, cosine similarity

For the task of ontology learning [14] as well as classification, e.g. k-nearest-neighbors, the concept of similarity is of importance. A basic intuition of similarity is for example given by Lin [17]. Similarity is related to the commonalities and differences between two objects. More commonalities implies higher similarity. Vice versa, more differences implies lower similarity. Two identical objects should have the maximum similarity. In addition, only identical objects should be able to achieve maximum similarity. Typically, similarity can be defined as a binary function, which maps two objects to a value in the interval $[0, 1]$. A value of 1 represents identical input objects. For this thesis, semantic and vector similarity measures will be used.

TODO: example for Commonalities, Differences

Vector similarity.

Semantic similarity measures are needed when comparing structures, which cannot be sufficiently represented as vectors. These are for example words and classes in ontologies **citations needed**. Rodríguez and Egenhofer [21] develops a semantic similarity measure for comparing entity classes in ontologies. Entity

2.4 Similarity-based classification

Chen et al. [4]

Zhang and Zhou [24]

Explain how kNN works. Nearest-neighbors classification is a lazy method, as it does not require training before testing. This is useful for applications with high amounts of data, large numbers of classes, and changing data [24]. For the considered use case of classification in Wikidata, these are very important strengths, as the number of classes in the taxonomy is very high and Wikidata is being constantly edited.

2.5 Text processing

- N-Gram
Jurafsky and Martin [15]
- Skip-Gram
Guthrie et al. [13]
- Counting-based word representations
Levy et al. [16]

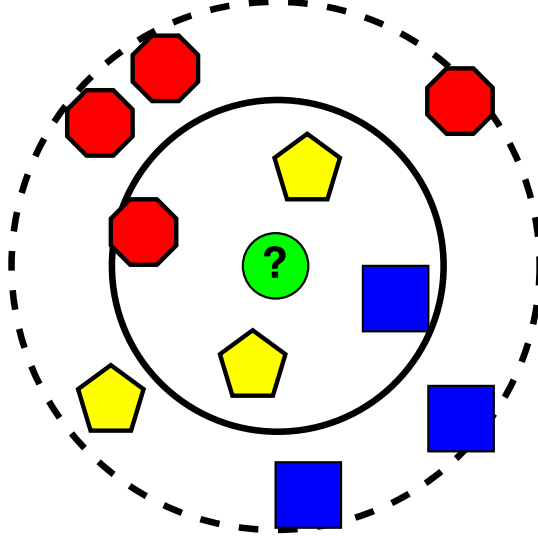


Figure 3: Example for k-nearest neighbors for 3 classes with $k=4$ and $k=10$.

- Predictive word representations
Levy et al. [16]

2.6 Problem statement

The task of this thesis is the classification of unlinked classes in Wikidata. In other words a function is needed, which given an unlinked class u of a taxonomy $T = (C, S)$ with a root class $root_T$, find an appropriate superclass for T . Doan et al. [9] suggests that for the task of placing a class into an appropriate position in T , either finding the most similar class, most specific superclass, or most general subclasses of u , are sensible approaches. This induces that the appropriate superclass for an unlinked class u is either the most similar class $c \in T$, or one of the superclasses of $succ_T(c)$. Therefore we can define the problem, as follows:

Definition 13 (Problem definition). *Given a taxonomy $T = (C, S)$ with root class $root_T$ and a similarity function sim over T , find a function f , which, given an unlinked class $u \in C$, returns a class $s = f(u)$, fulfilling the following criteria: **TODO: define as the parents of the most similar class? for example german would be similar to english, therefore the superclass for german should be language and not english***

$$\neg(s \triangleleft_T u) \text{ no child} \tag{1}$$

$$s = \max_{c \in C} (sim(u, s)) \text{ most similar class} \tag{2}$$

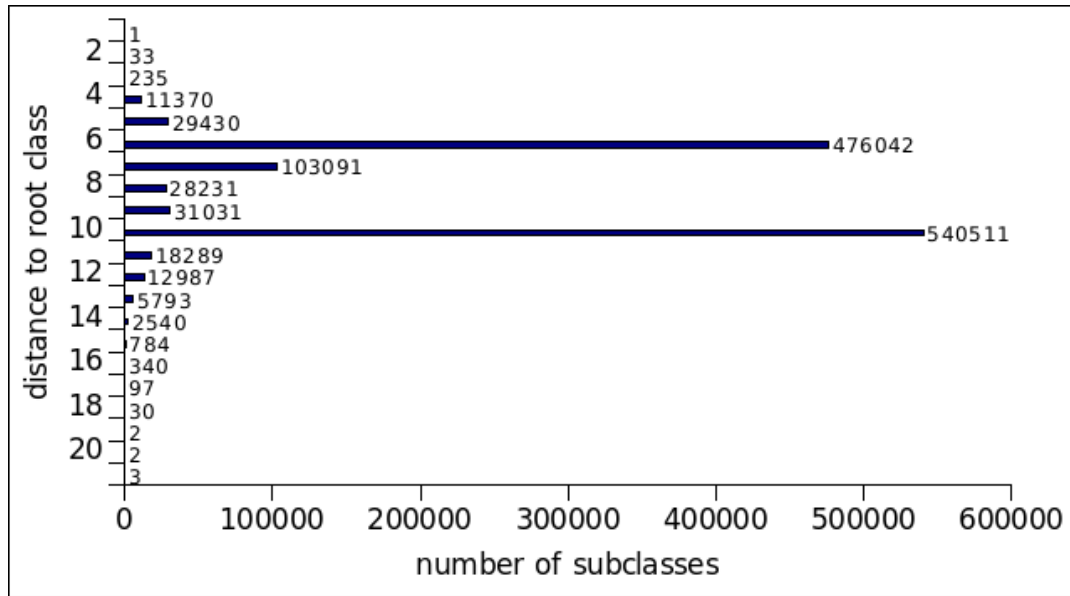


Figure 4: Distance of subclasses to root class *entity* (Q35120). Wikidata (2016/11/07)

3 Analysis of the Wikidata taxonomy

TODO: maybe separate this section into subsections For the task of developing an algorithm, which takes unlinked classes as input, it is necessary to know, what information the classes carry and if there are certain patterns among the classes. For this purpose an analysis of the taxonomy needs to be carried out, which may answer questions.

The taxonomy contained in the Wikidata dump of 2016/11/07 was analyzed. Classes were recognized as defined in Section 2.1. Unlinked classes were identified by checking whether a class does not have the *subclass of* (P279) property. The taxonomy contained a total of 1299501 classes at this time.

The state of the taxonomy was captured in regards to the root class *entity* (Q35120) (see Figure 4). 1260842 classes are currently subclasses of *entity* (Q35120). 97% of all classes are therefore nodes in the root taxonomy. This implies a high agreement in the Wikidata community on which class is considered root, and thereby also supports the modeling decision made in Section 2.2, which assumes that a taxonomy only has one root, and this root is *entity* (Q35120) in Wikidata. **Last sentences of this paragraph are mostly interesting trivia, but have currently no further use.** The longest shortest distance between the root and a leaf class is 20. The classes Q639064, Q15978631 and Q151055 fulfill this characteristics. Each of them is subclass of *Homo* (Q171283).

The characteristics of all unlinked classes and the root class were analyzed. This

set contains a total of 16373 classes. 13807 classes have an English label and 11534 classes have a corresponding English Wikipedia page.

Regarding the number of unique properties (or statement groups) per class (see Figure 5) the median is 3 and the average is ≈ 4.8 . Combined with the analyzed unique property frequency (see Figure 6), it can be seen that many unlinked classes are linked to other knowledge bases and taxonomies, e.g. Freebase or GND, using an identifier. Another observation is that 901 of the unlinked classes have properties related to taxons, which is a, to some degree, separate taxonomy in Wikidata, created with properties like *taxon name* (P225), *parent taxon* (P171), etc.

Most unlinked classes have only 0 to 1 instances, the median is 1 and the average is ≈ 4.65 instances per class (see Figure 7). There are however outliers with big numbers of instances, which skew the average number of instances per class. This may for example imply, that classes are created mainly for the purpose of grouping newly created instances.

The median and average for subclasses per class are 0 and ≈ 0.85 respectively (see Figure 8). This implies that the graph components of the unlinked classes are very small, and in most cases contain only the respective unlinked class.

The question has to be asked, whether an algorithm should try to handle the complete set of unlinked classes, or only a specific subset, which fulfills certain requirements. The answer depends on what information such an algorithm requires as input. The full set of unlinked classes is problematic for use in an algorithm as there are few shared characteristics over all classes. $\approx 16\%$ of classes are not labeled and $\approx 31.4\%$ of classes have no instances. Both labels and instances are useful characteristics for a class to have. The label allows the recognition of the class in natural text and also ensures that the class in the context of Wikidata was already curated, as the label is typically the first attribute, which is added by users ???. Instances represent classes and thereby describe them. For example, Rodríguez and Egenhofer [21] use instances to compute semantic similarity between classes. Therefore, I propose to only consider the set of classes, which have a label in the English language and at least 1 instance, as input for the algorithm. **TODO: Find a short name or acronym for this subset.**

Following this argument, the subset of labeled, instantiated and unlinked classes was analyzed. This set contains a total of 9157 classes. 7557 classes have an English Wikipedia page, which is $\approx 82.5\%$ of all analyzed classes in the subset, and an increase of $\approx 12\%$ in comparison to the full set of unlinked classes.

The average of unique properties per class increases from 4.8 to 5.5, while the median remains at 3 (see Figure 9). The frequency of different properties appearing in classes however is more distributed (see Figure 10). This implies that the classes of this subset are related to different topics, and share only few commonalities.

As expected the average of instances per class increased to ≈ 7.37 from ≈ 4.65 . However the median is still 1 (see Figure 11). $\approx 59\%$ of classes have only 1 instance.

At the same time the average of subclasses per class halved to ≈ 0.4 (see Figure 12). **can i just do such an assumption? the data supports it a bit, but i am not**

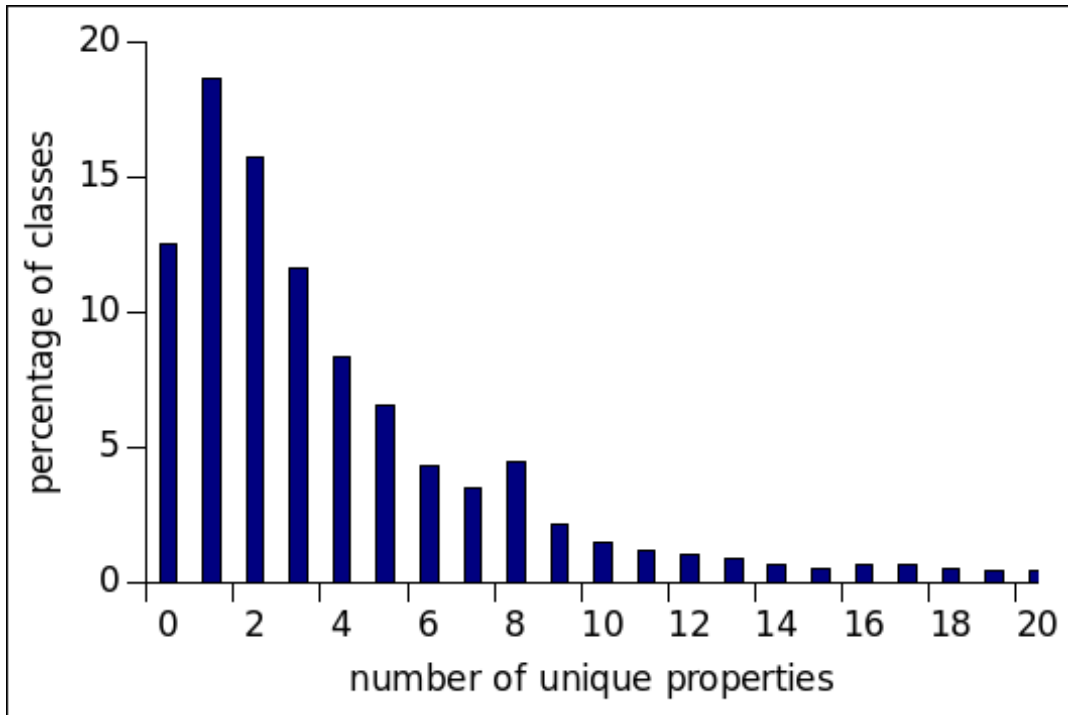


Figure 5: Percentage of unlinked classes with a specific amount of unique properties. Wikidata (2016/11/07)

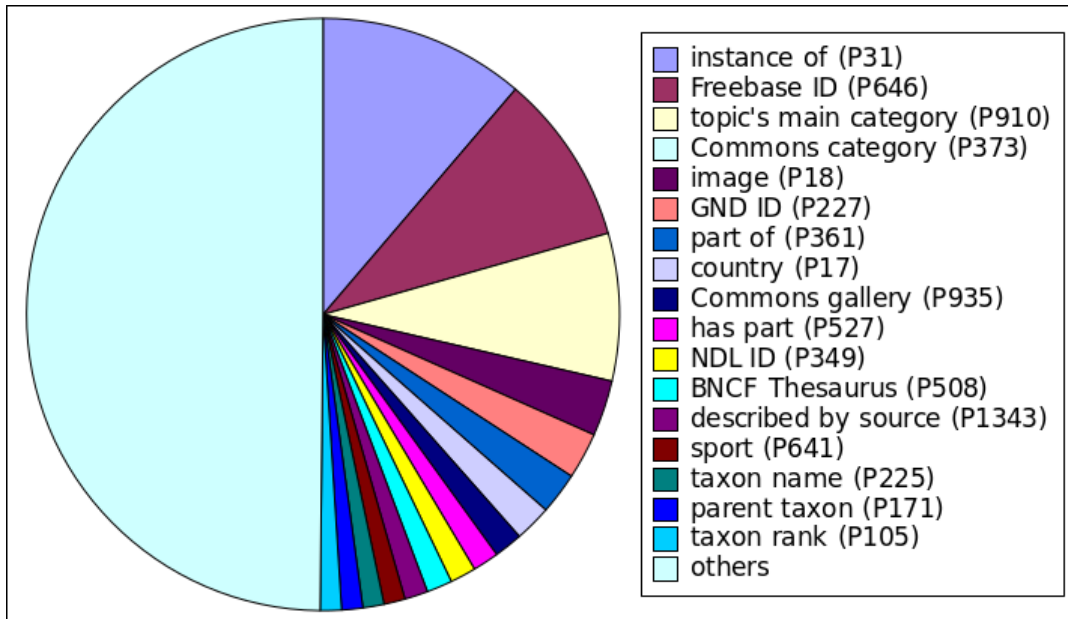


Figure 6: Frequency of properties in unlinked classes. Wikidata (2016/11/07)

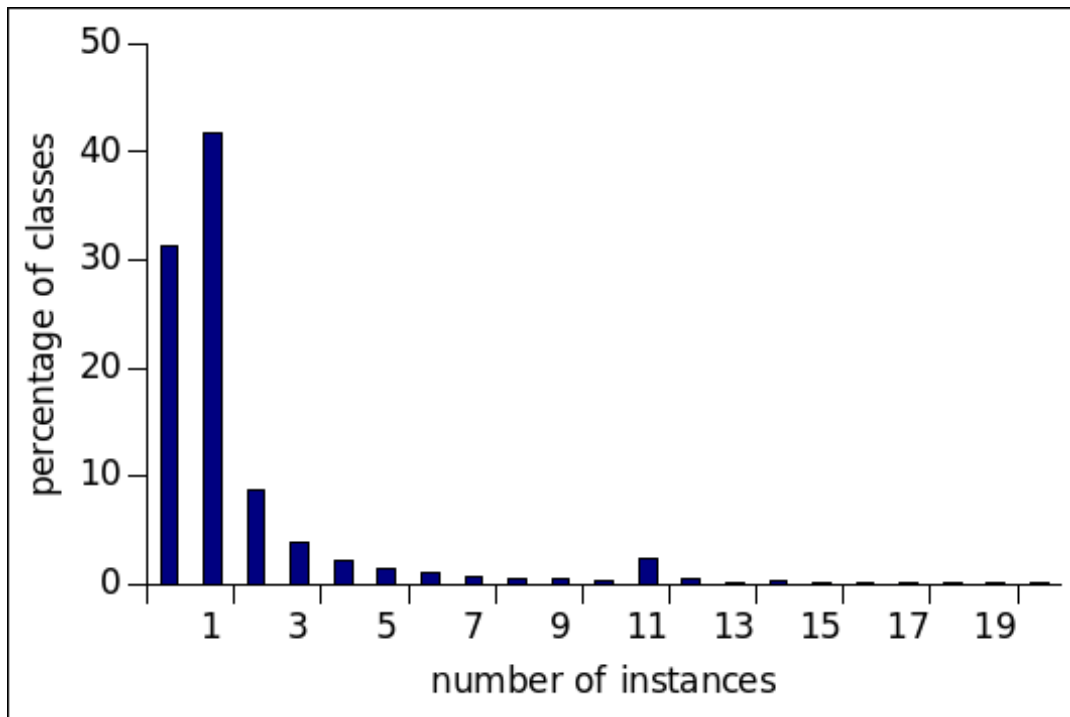


Figure 7: Percentage of unlinked classes with a specific amount of instances. Wiki-data (2016/11/07)

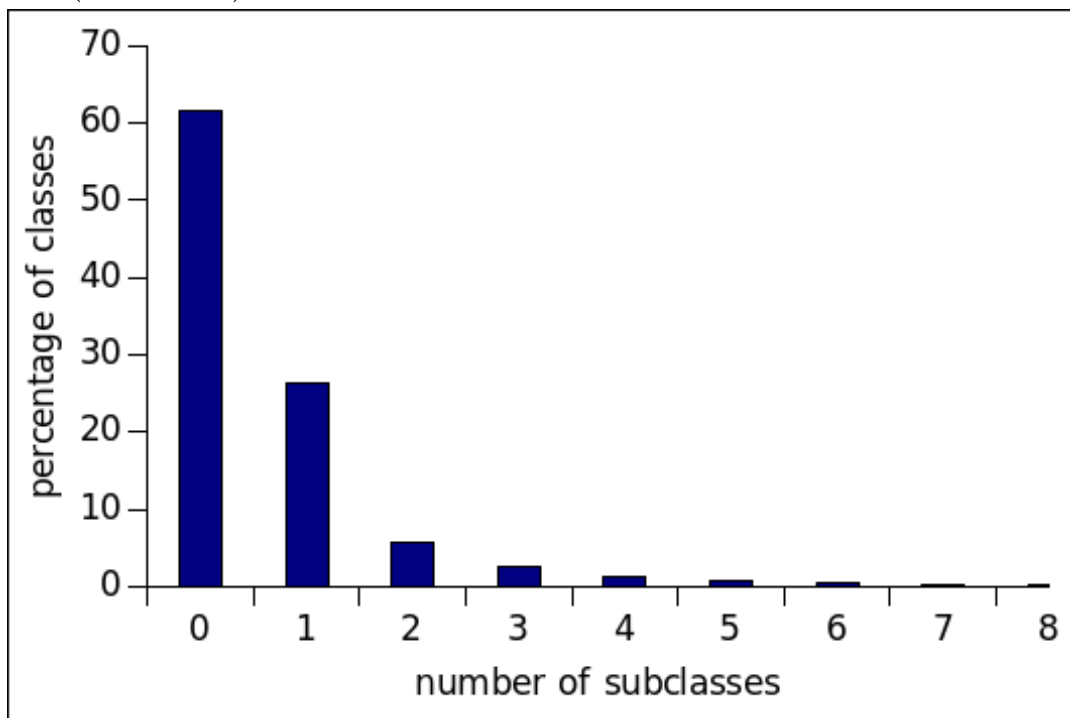


Figure 8: Percentage of unlinked classes with a specific amount of subclasses. Wiki-data (2016/11/07)

searching for counterclaims. and the assumption is not directly relevant to the thesis. Combined with the unchanged median of 1 instance per class, supports the assumption, that classes are mainly created for the purpose of grouping instances. While the extension of the taxonomy by connecting the newly created class to the main component of the taxonomy is **vernachlaessigt**.

The classes of the subset have, on average, a better level of description, more unique properties and instances, than the full set of unlinked classes. Between these classes the number of commonalities is lower, because the same properties occur not as frequently for different classes. The lack of commonalities between unlinked classes is not very problematic, as the algorithm would not compare unlinked classes with each other but with classes in the root taxonomy.

After completing the analysis, it can be seen that *entity* (Q35120) is the root class of the taxonomy, and Wikidata's taxonomy is in a good state, since 97% of classes are part of the root taxonomy. **TODO: not sure if i can just say that it is in a good state** Unlinked classes share few commonalities, and as shown above, a percentage of classes lack even basic information like a label. For developing an algorithm it is necessary to set a baseline, of what can be expected from the input. In this case, input is required to be labeled and have at least one instance. The benefit of this specific restriction is, that a basic level of descriptiveness can be assumed for every class. A label additionally allows supplementing the information, provided by Wikidata, to be supplemented with natural text sources, like Wikipedia, since it is now possible to recognize occurrences of the class in text.

4 Ontology learning

General concepts. Classification of considered problem in the task of ontology learning. Related work.

Cimiano et al. [5]

Wong et al. [23]

d'Amato et al. [7]

Petrucci et al. [19]

Fu et al. [10]

5 Neural networks

Notion of neural networks will be introduced.

5.1 Recursive neural networks for graph representation

Scarselli et al. [22]

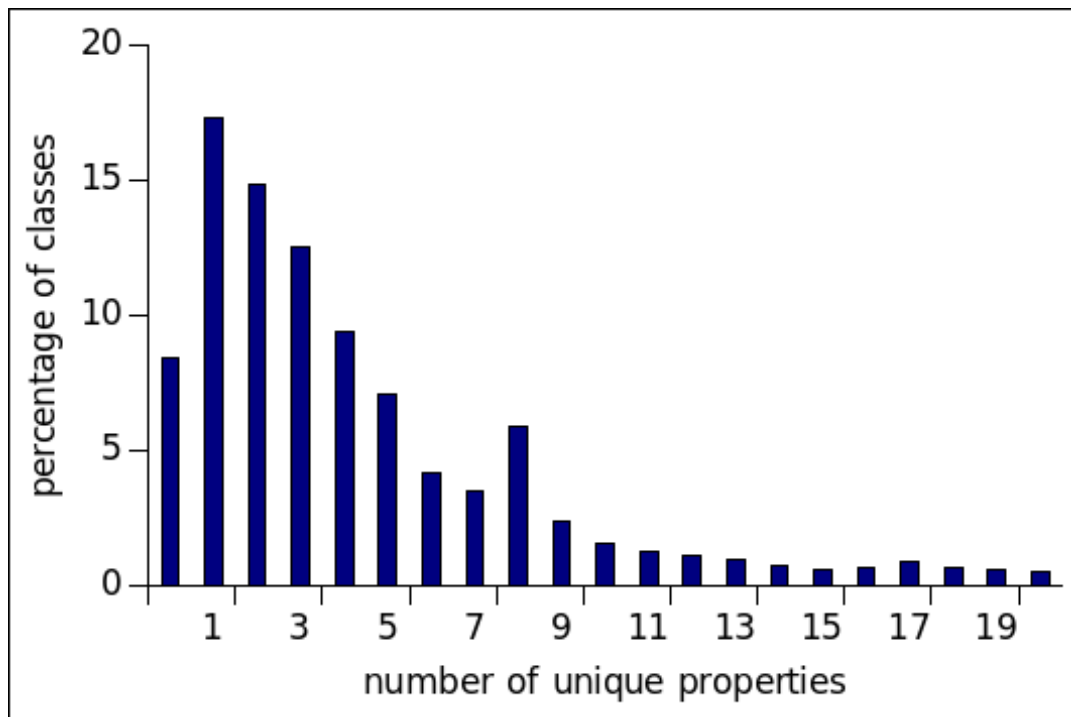


Figure 9: Percentage of unlinked, labeled, instantiated classes with a specific amount of unique properties. Wikidata (2016/11/07)

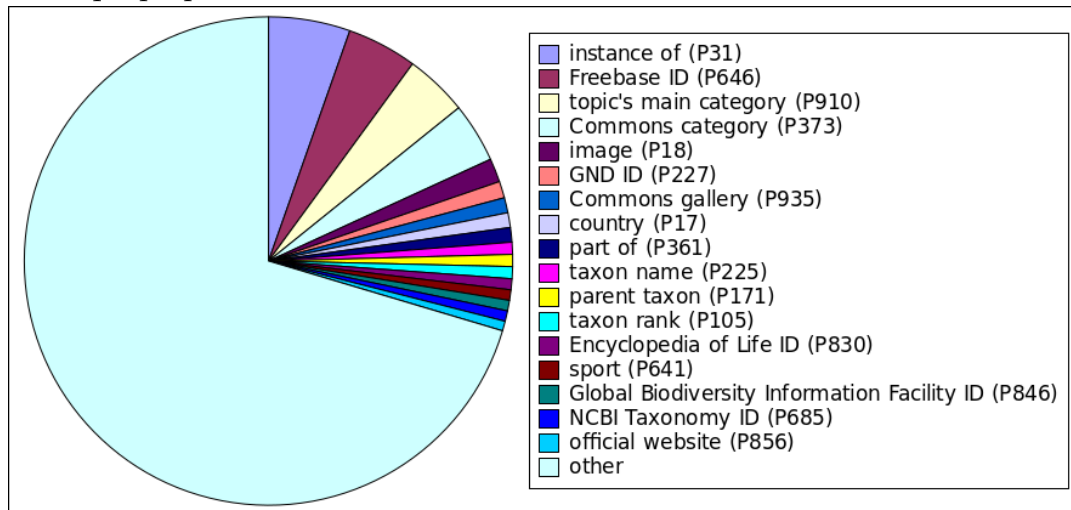


Figure 10: Frequency of properties in unlinked, labeled, instantiated classes. Wikidata (2016/11/07)

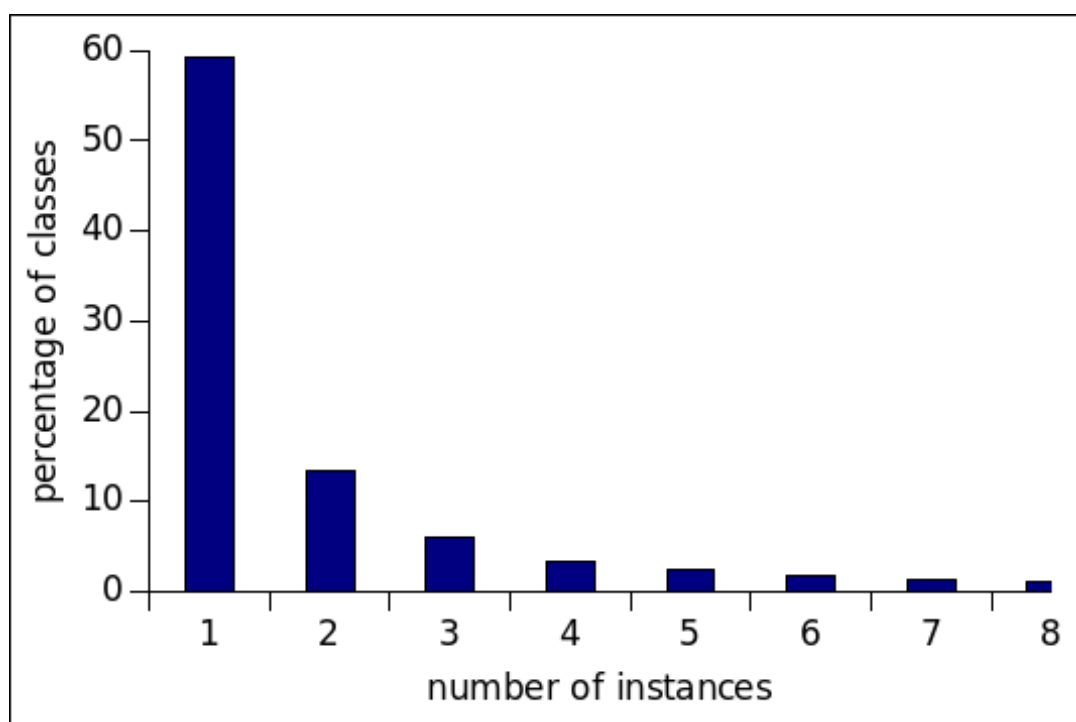


Figure 11: Percentage of unlinked, labeled, instantiated classes with a specific amount of instances. Wikidata (2016/11/07)

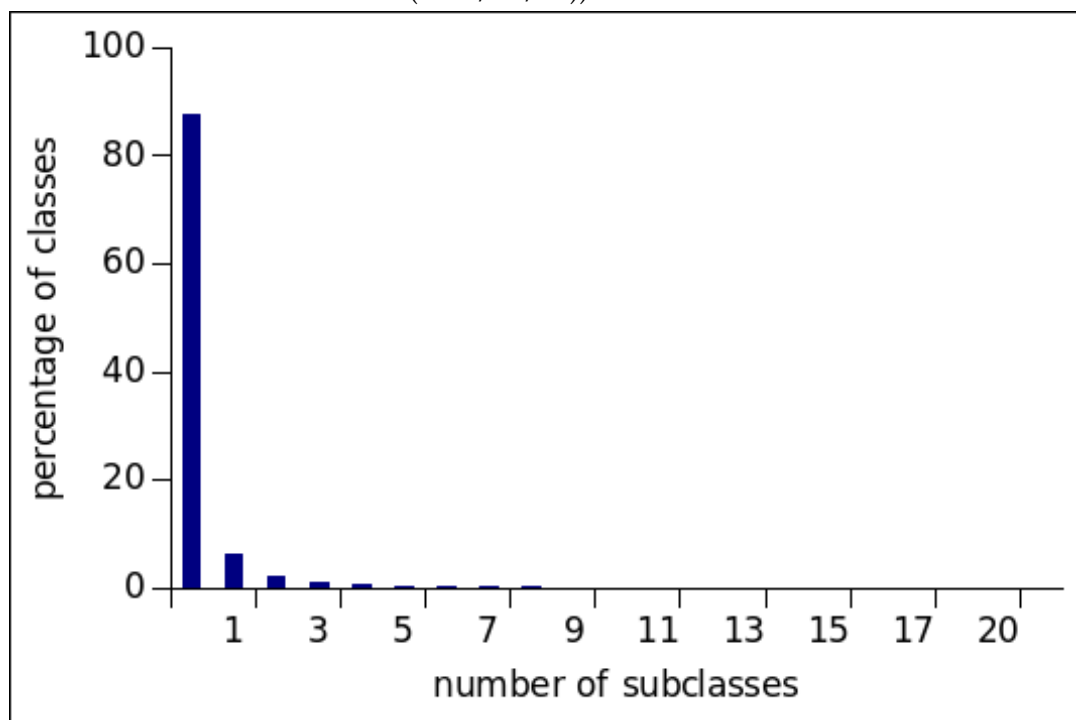


Figure 12: Percentage of unlinked, labeled, instantiated classes with a specific amount of subclasses. Wikidata (2016/11/07)

5.2 Deep neural networks for graph representation

Cao et al. [3]

Raghu et al. [20]

5.3 Continuous Bag-of-Words

Mikolov et al. [18]

5.4 Skip-gram with negative sampling

Mikolov et al. [18]

Levy et al. [16]

Goldberg and Levy [12]

graph representations are not really relevant as there is only one big component and the input classes are not part of that component.

5.5 Comparison

6 Algorithm

6.1 Baseline

- Hyper parameters
- Training data

6.2 Supplementing with other resources

e.g. Wikipedia

7 Evaluation

7.1 Method

Dellschaft and Staab [8]

7.2 Generation of gold standard

7.3 Results

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