

Enrichment of ontological taxonomies using a neural network approach

Bachelorarbeit

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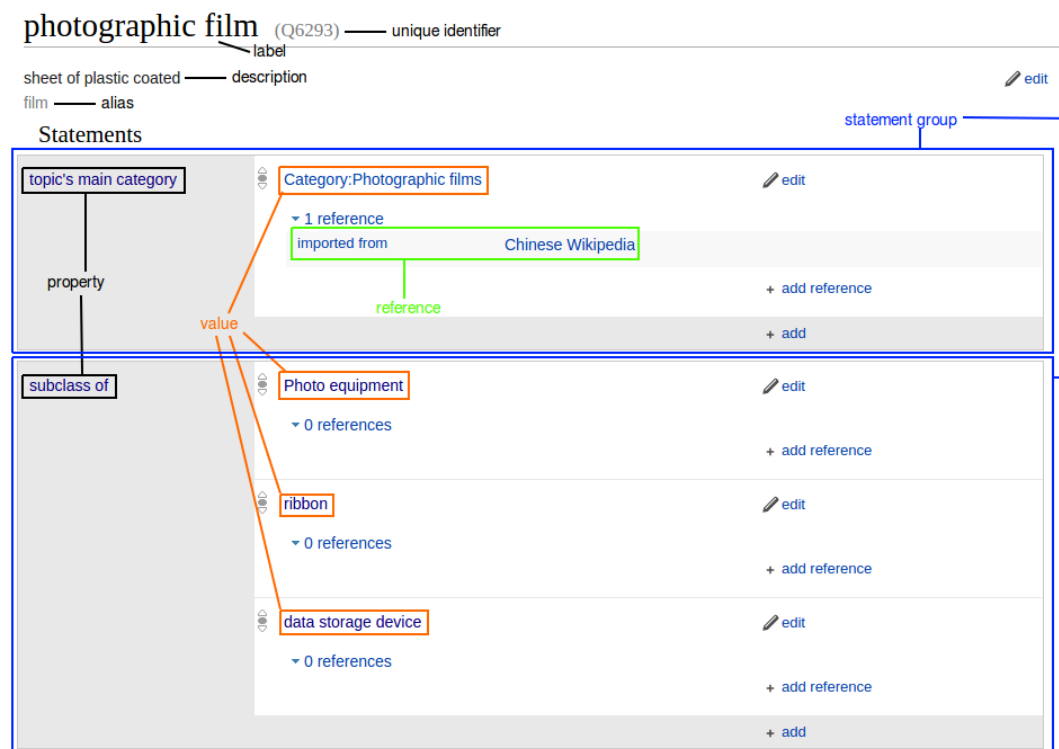


Figure 1: Example of Wikidata class: photographic film (Q6239)

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,

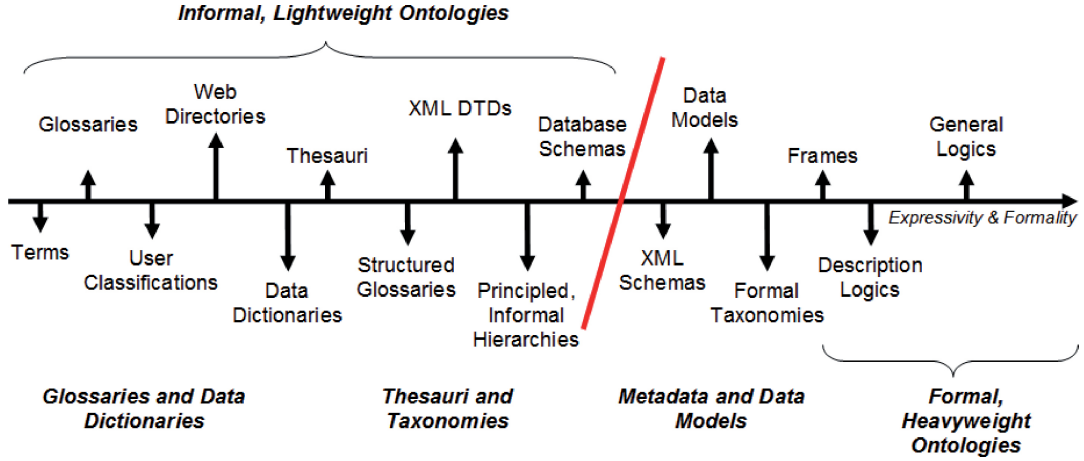


Figure 2: The spectrum of ontology kinds. [23]

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.

Definition 7 (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 8 (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 9 (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 10 (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. **TODO: Something is missing here maybe. The problem statement could follow here, but the required definition of similarity is missing. Maybe switch the order of similarity and taxonomy.**

2.3 Similarity

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

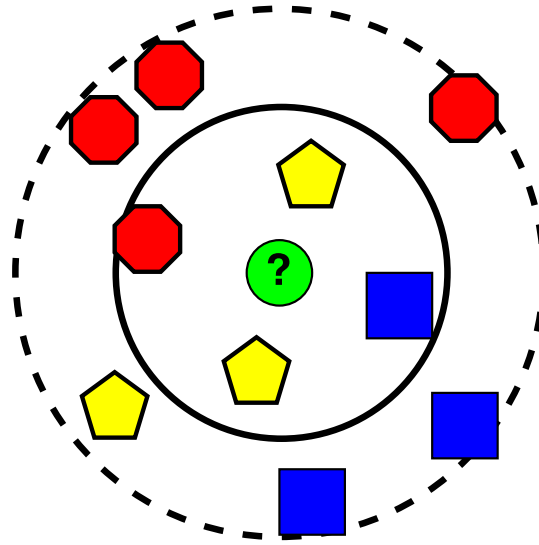


Figure 3: Example for k-nearest neighbors for 3 classes with $k=4$ and $k=10$.

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. 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]
- 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 11 (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***

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

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

3 Analysis of the Wikidata taxonomy

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. Additionally other knowledge can be gained through the analysis.

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). 1260842 classes are currently subclasses of *entity* (Q35120). 97% of all classes are therefore nodes in the same graph component as the root class. 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 4) the median is 3 and the average is ≈ 4.8 . Combined with the analyzed unique property frequency (see Figure 7), it can be seen that many unlinked classes are linked to other knowledge bases, 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 5). 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 6). 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]

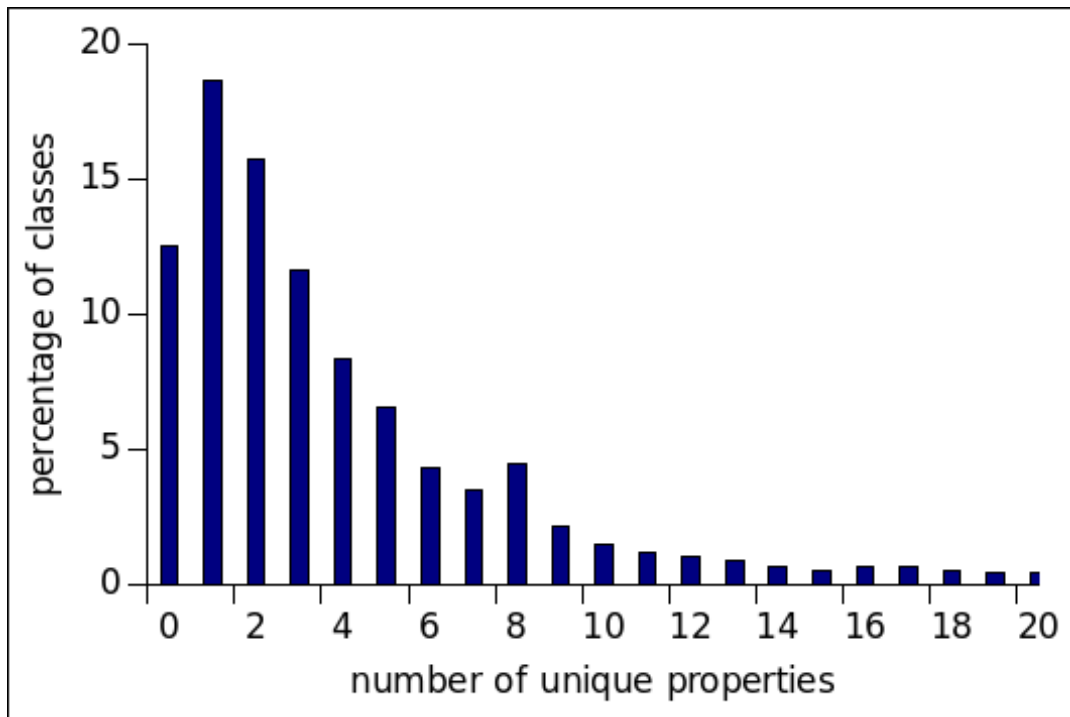


Figure 4: Percentage of unlinked classes with a specific amount of unique properties. Wikidata (2016/11/07)

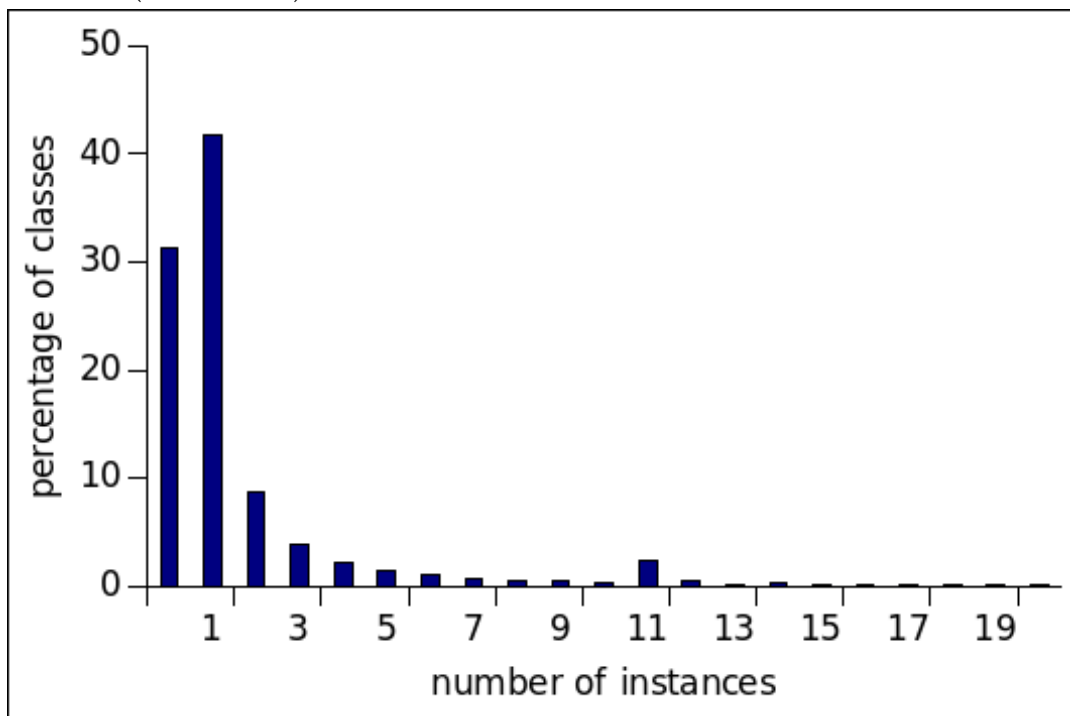


Figure 5: Percentage of unlinked classes with a specific amount of instances. Wikidata (2016/11/07)

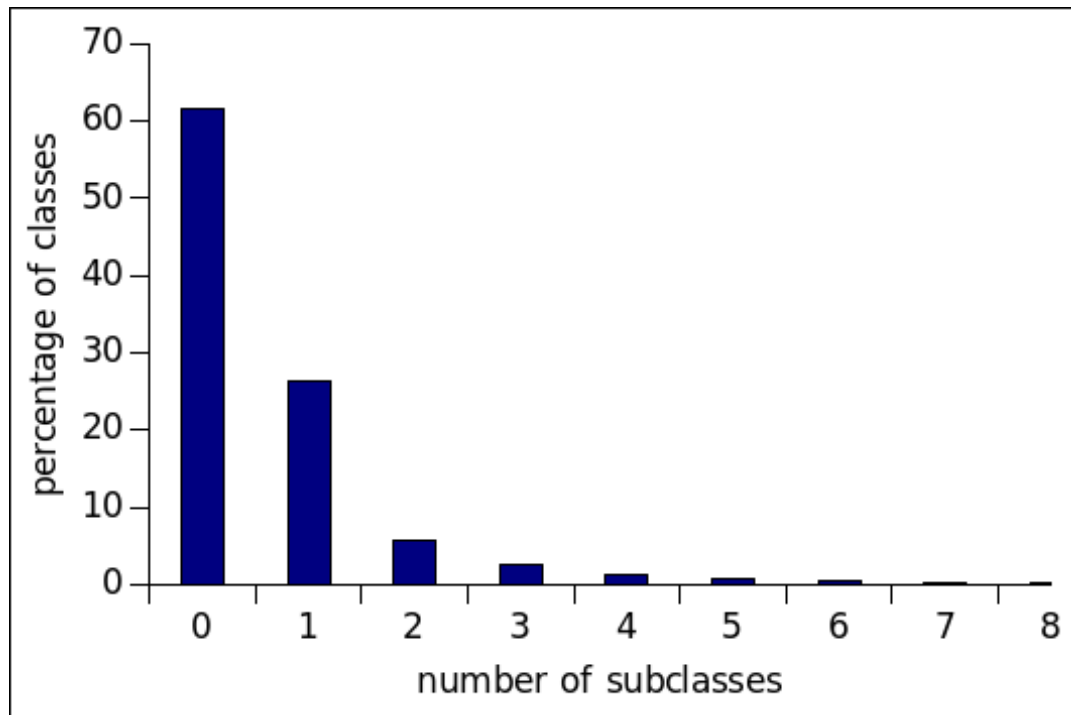


Figure 6: Percentage of unlinked classes with a specific amount of subclasses. Wikidata (2016/11/07)

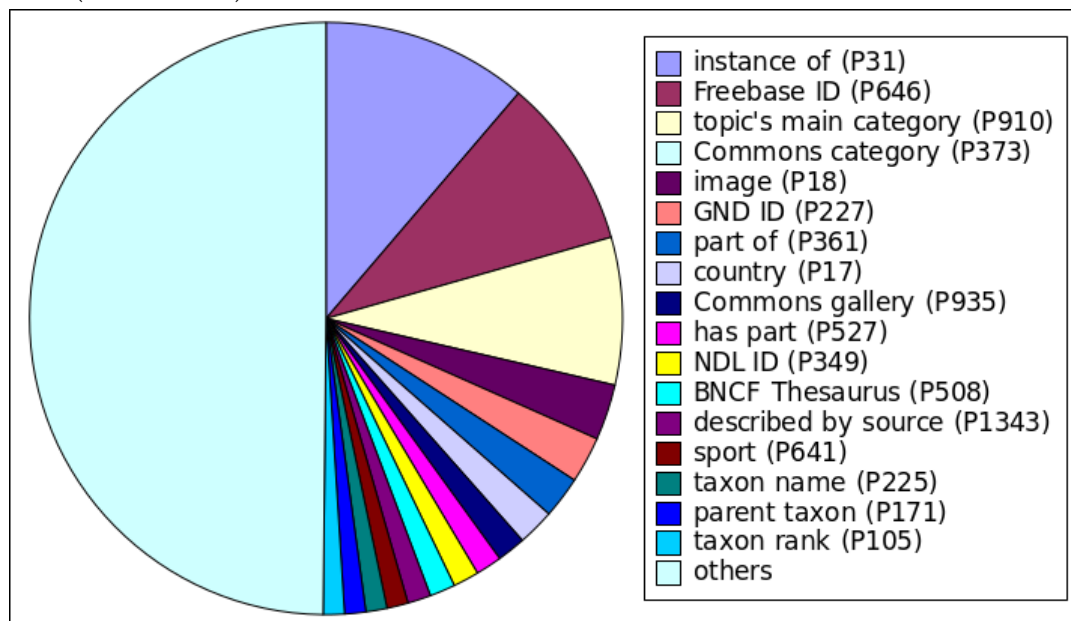


Figure 7: Frequency of properties in unlinked classes. Wikidata (2016/11/07)

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.

Following this argument, the subset of labeled, instantiated and unlinked classes was analyzed. This set contains a total of 9157 classes.

TODO: final conclusion The fact that most classes are linked to other knowledge bases and Wikipedia articles would allow an algorithm to supplement the structured information provided by Wikidata with additional information gathered from these resources.

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]

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]

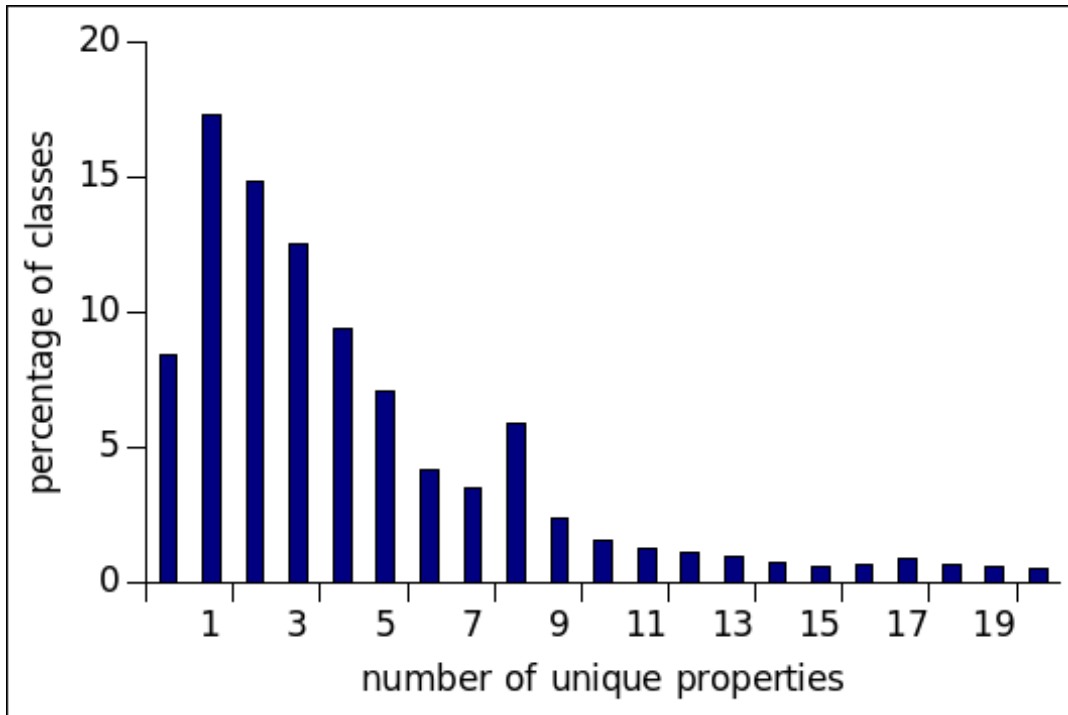


Figure 8: Percentage of unlinked, labeled, instantiated classes with a specific amount of unique properties. Wikidata (2016/11/07)

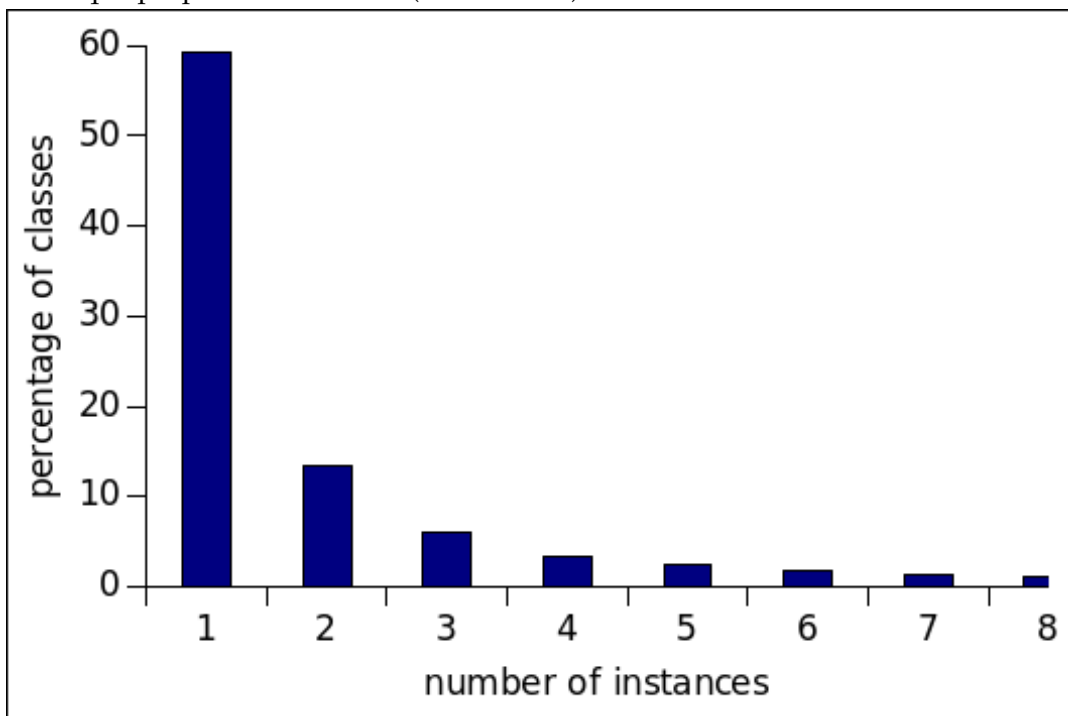


Figure 9: Percentage of unlinked, labeled, instantiated classes with a specific amount of instances. Wikidata (2016/11/07)

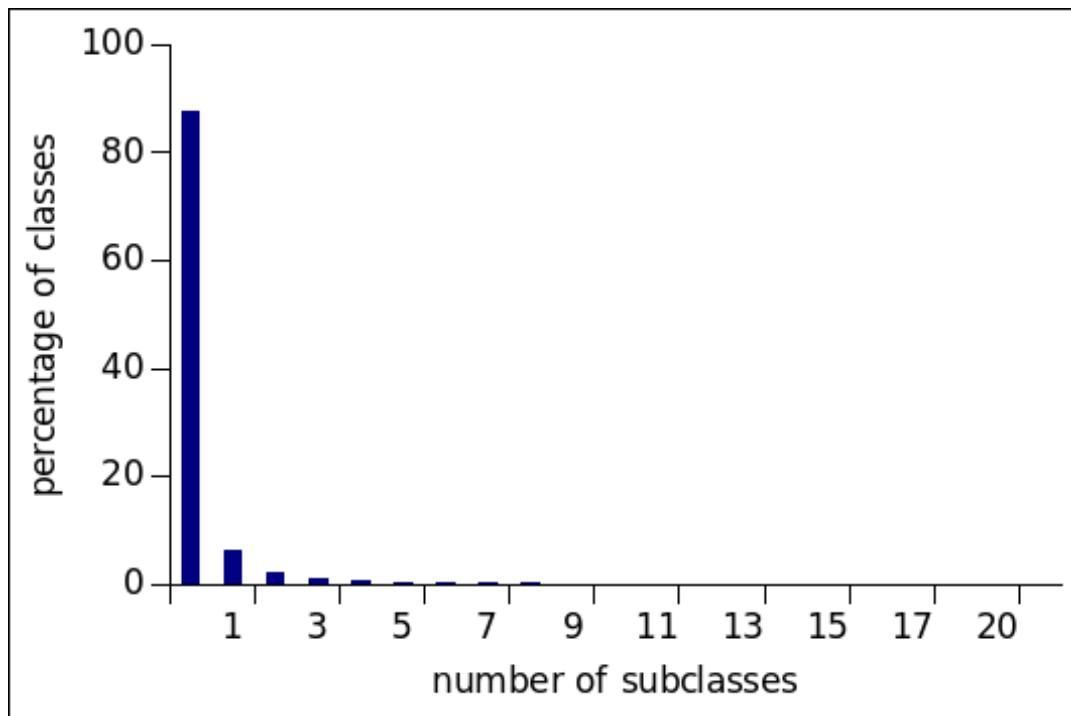


Figure 10: Percentage of unlinked, labeled, instantiated classes with a specific amount of subclasses. Wikidata (2016/11/07)

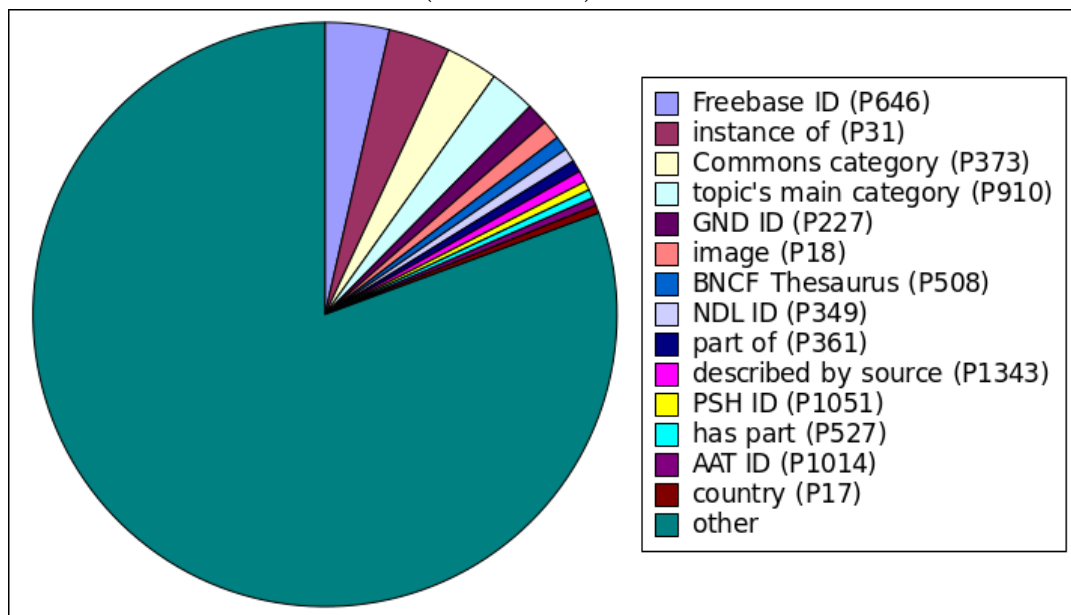


Figure 11: Frequency of properties in unlinked, labeled, instantiated classes. Wikidata (2016/11/07)

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

References

- [1] Property talk:p279. https://www.wikidata.org/wiki/Property_talk:P279,.
- [2] Talk:q35120. <https://www.wikidata.org/wiki/Talk:Q35120,.> Accessed: 2017-01-29.
- [3] Shaosheng Cao, Wei Lu, and Qionghai Xu. Deep neural networks for learning graph representations. In Dale Schuurmans and Michael P. Wellman, editors, AAAI, pages 1145–1152. AAAI Press, 2016. URL <http://dblp.uni-trier.de/db/conf/aaai/aaai2016.html#CaoLX16>.
- [4] Yihua Chen, Eric K. Garcia, Maya R. Gupta, Ali Rahimi, and Luca Cazzanti. Similarity-based classification: Concepts and algorithms. J. Mach. Learn. Res., 10:747–776, June 2009. ISSN 1532-4435. URL <http://dl.acm.org/citation.cfm?id=1577069.1577096>.

- [5] P. Cimiano, A. Mädche, S. Staab, and J. Völker. Ontology learning. In S. Staab and R. Studer, editors, Handbook on Ontologies, International Handbooks on Information Systems, pages 245–267. Springer, 2nd revised edition edition, 2009. URL <http://www.uni-koblenz.de/~staab/Research/Publications/2009/handbookEdition2/ontology-learning-handbook2.pdf>.
- [6] Philipp Cimiano. Ontology Learning and Population from Text: Algorithms, Evaluation and Applications. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2006. ISBN 0387306323.
- [7] Claudia d’Amato, Steffen Staab, Andrea G. B. Tettamanzi, Tran Duc Minh, and Fabien L. Gandon. Ontology enrichment by discovering multi-relational association rules from ontological knowledge bases. In Sascha Ossowski, editor, SAC, pages 333–338. ACM, 2016. ISBN 978-1-4503-3739-7. URL <http://dblp.uni-trier.de/db/conf/sac/sac2016.html#dAmatoSTMG16>.
- [8] Klaas Dellschaft and Steffen Staab. On how to perform a gold standard based evaluation of ontology learning. In Proceedings of the 5th International Conference on The Semantic Web, ISWC’06, pages 228–241, Berlin, Heidelberg, 2006. Springer-Verlag. ISBN 3-540-49029-9, 978-3-540-49029-6. doi: 10.1007/11926078_17. URL http://dx.doi.org/10.1007/11926078_17.
- [9] AnHai Doan, Jayant Madhavan, Pedro Domingos, and Alon Halevy. Learning to map between ontologies on the semantic web. In Proceedings of the 11th International Conference on World Wide Web, WWW ’02, pages 662–673, New York, NY, USA, 2002. ACM. ISBN 1-58113-449-5. doi: 10.1145/511446.511532. URL <http://doi.acm.org/10.1145/511446.511532>.
- [10] Ruiji Fu, Jiang Guo, Bing Qin, Wanxiang Che, Haifeng Wang, and Ting Liu. Learning Semantic Hierarchies via Word Embeddings. Acl, pages 1199–1209, 2014.
- [11] Luis Galárraga. Rule Mining in Knowledge Bases. PhD thesis, Telecom Paris-Tech, 2016.
- [12] Yoav Goldberg and Omer Levy. word2vec explained: deriving mikolov et al.’s negative-sampling word-embedding method. CoRR, abs/1402.3722, 2014. URL <http://arxiv.org/abs/1402.3722>.
- [13] David Guthrie, Ben Allison, W. Liu, Louise Guthrie, and Yorick Wilks. A closer look at skip-gram modelling. In Proceedings of the Fifth international Conference on Language Resources and Evaluation (LREC-2006), Genoa, Italy, 2006.
- [14] Maryam Hazman, Samhaa R El-Beltagy, and Ahmed Rafea. A Survey of Ontology Learning Approaches. International Journal of Computer Applications, 22(9):975–8887, 2011.

- [15] Daniel Jurafsky and James H. Martin. N-Grams. In Speech and Language Processing, chapter N-Grams. 2014.
- [16] Omer Levy, Yoav Goldberg, and Ido Dagan. Improving distributional similarity with lessons learned from word embeddings. Transactions of the Association for Computational Linguistics, 3:211–225, 2015. ISSN 2307-387X. URL <https://transacl.org/ojs/index.php/tacl/article/view/570>.
- [17] Dekang Lin. An information-theoretic definition of similarity. In Proceedings of the Fifteenth International Conference on Machine Learning, ICML '98, pages 296–304, San Francisco, CA, USA, 1998. Morgan Kaufmann Publishers Inc. ISBN 1-55860-556-8. URL <http://dl.acm.org/citation.cfm?id=645527.657297>.
- [18] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. CoRR, abs/1301.3781, 2013. URL <http://arxiv.org/abs/1301.3781>.
- [19] Giulio Petrucci, Chiara Ghidini, and Marco Rospocher. Using recurrent neural network for learning expressive ontologies. CoRR, abs/1607.04110, 2016. URL <http://arxiv.org/abs/1607.04110>.
- [20] M. Raghu, B. Poole, J. Kleinberg, S. Ganguli, and J. Sohl-Dickstein. On the expressive power of deep neural networks. ArXiv e-prints, June 2016.
- [21] M. Andrea Rodríguez and Max J. Egenhofer. Determining semantic similarity among entity classes from different ontologies. IEEE Trans. on Knowl. and Data Eng., 15(2):442–456, February 2003. ISSN 1041-4347. doi: 10.1109/TKDE.2003.1185844. URL <http://dx.doi.org/10.1109/TKDE.2003.1185844>.
- [22] F. Scarselli, M. Gori, Ah Chung Tsoi, M. Hagenbuchner, and G. Monfardini. The Graph Neural Network Model. IEEE Transactions on Neural Networks, 20(1):61–80, jan 2009. ISSN 1045-9227. doi: 10.1109/TNN.2008.2005605. URL <http://ieeexplore.ieee.org/document/4700287/>.
- [23] Wilson Wong, Wei Liu, and Mohammed Bennis. Ontology learning from text: A look back and into the future. ACM Comput. Surv., 44(4):20:1–20:36, September 2012. ISSN 0360-0300. doi: 10.1145/2333112.2333115. URL <http://doi.acm.org/10.1145/2333112.2333115>.
- [24] Min-Ling Zhang and Zhi-Hua Zhou. A k-Nearest Neighbor Based Algorithm for Multi-label Classification. volume 2, pages 718–721 Vol. 2. The IEEE Computational Intelligence Society, 2005. URL http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1547385.