Refinement of the Wikidata taxonomy with neural networks

Proposal for Bachelor thesis

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November 27, 2016

1 Motivation

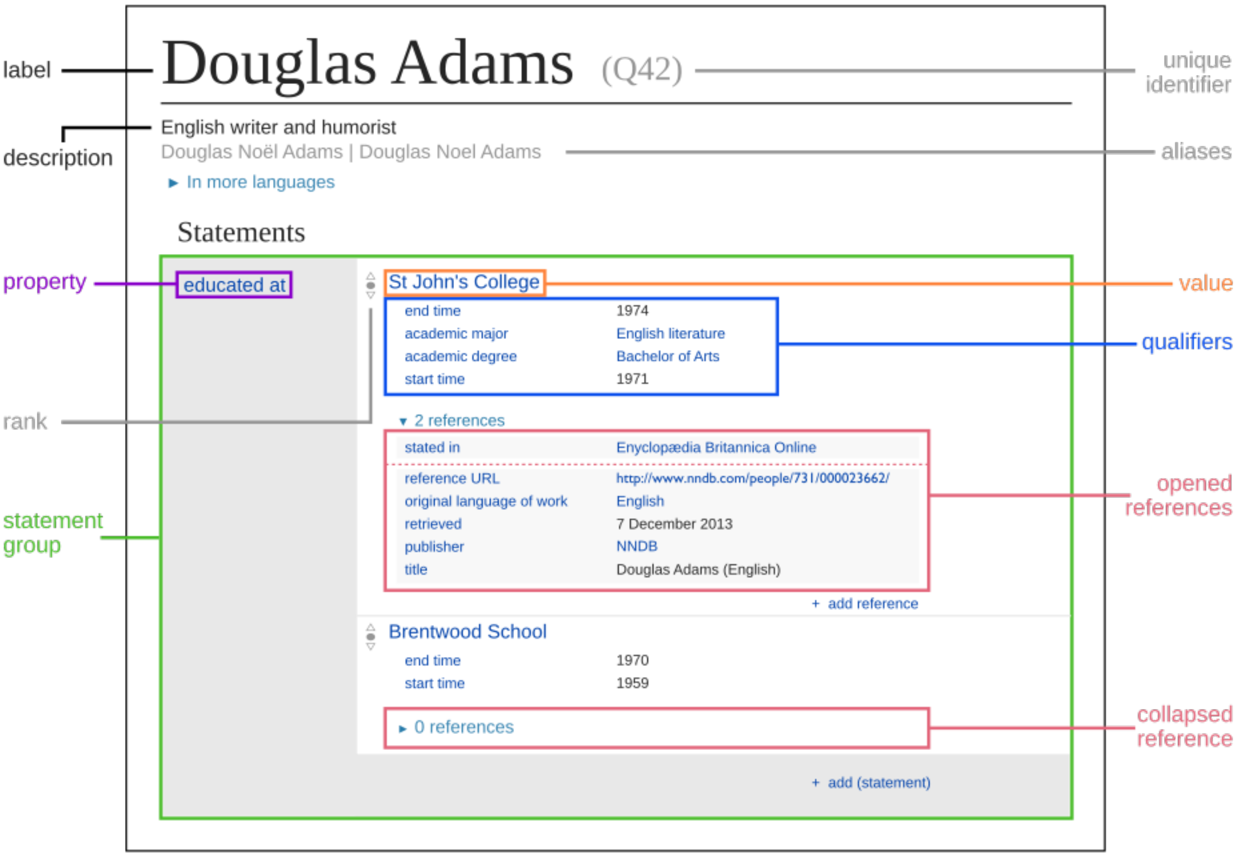
Wikidata is an open, free, multilingual and collaborative knowledge base. It acts as a structured knowledge source for other Wikimedia projects. It tries to model the real world, meaning every concept, object, animal, person,etc., therefore Wikidata can always be considered to be incomplete. Wikidata is mostly edited and extended by humans, which implies entries in Wikidata can be erroneous. On 7th November 2016 it contained 24,438,781 entities [2].

Most entities in Wikidata are items. Items consist of labels, aliases and descriptions in different languages. Sitelinks connect items to their corresponding Wiki articles. Most importantly items are described by statements. Statements are in their simplest form a pair of property and value. They can be annotated with references and qualifiers. See figure 1 for an example.

The other category of entities in Wikidata are properties. Properties are used to describe data values of items. A property always has a data type, which are for example item or date. Two important properties are *instance of (P31)* and *subclass of (P279)*. The data type of both properties are item, which means they are used to connect two items with a subclass or instance relationship.

The *subclass of (P279)* property allows the creation of a taxonomy in Wikidata. Figure 2 shows a fragment of Wikidata's taxonomy. It can, for example, be seen that *electrical apparatus (Q2425052)* is the superclass of *Computer (Q68)*, *clock (Q376)*, and 4 other classes. Taxonomies like this can be used for different tasks. [9] for example develops a method of word classification in thesauri, which exploits the structure of taxonomies. Other uses may be found in information retrieval and reasoning.

As of the 7th November 2016 over a million classes are present in this taxonomy. A root class in a taxonomy is a class, which has no more generalizations. Root classes should therefore describe the most basic concepts. For example *entity (Q35120)* can be considered to most general class, comparable to the Object class in Java. According to



Douglas Adams (Q42)

English writer and humorist
Douglas Noël Adams | Douglas Noel Adams
▸ In more languages

Statements

educated at

St John's College

end time	1974
academic major	English literature
academic degree	Bachelor of Arts
start time	1971

▾ 2 references

stated in	Enyclopædia Britannica Online
reference URL	http://www.nndb.com/people/731/000023662/
original language of work	English
retrieved	7 December 2013
publisher	NNDB
title	Douglas Adams (English)

+ add reference

Brentwood School

end time	1970
start time	1959

▸ 0 references

+ add (statement)

Figure 1: Graphic representing the datamodel in Wikidata with a statement group and opened reference; `https://commons.wikimedia.org/wiki/File:Graphic_representing_the_datamodel_in_Wikidata_with_a_statement_group_and_opened_reference.svg`

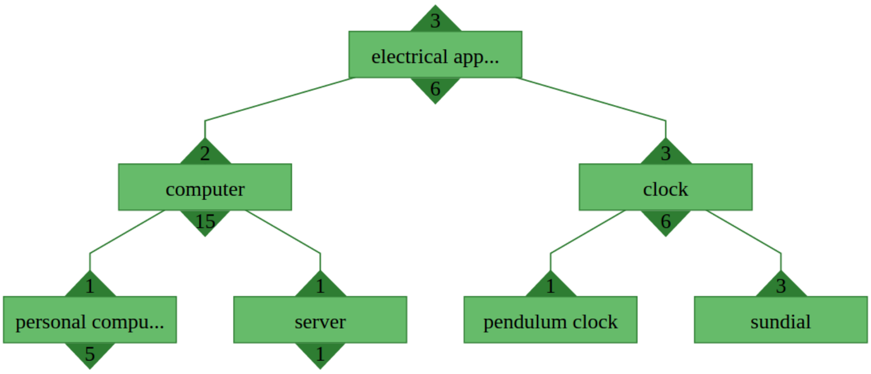


Figure 2: Fragment of Wikidata's taxonomy created with [12]

this view, we would assume that a good taxonomy has only very few, possibly only one root class.
At the current state (2016-11-07) Wikidata contains 7142 root classes, of which 5332 have an English label. There are many root classes for which we easily can find generalizations. For example both *Men's Junior European Volleyball Championship (Q169359)* and *Women's Junior European Volleyball Championship (Q169956)* are root classes. By just looking at their labels we can find an appropriate superclass, *European Volleyball Championship (Q6834)*, for both of them. A superclass should be considered appropriate, if it is a generalization of the child class and also the most similar respectively nearest class to the child class. Tools, which solve this task, may help the Wikidata community in improving the existing taxonomy. Similar problems in the field of ontology and taxonomy learning are already well researched (see section "Related Work"). However neural networks are comparably scarcely applied in this research area. Neural networks have proven to be very powerful for other complex tasks, e.g. speech recognition [8]. Accordingly it may be interesting to see, how neural networks can be used for the task of refining the taxonomies of knowledge bases by reducing the number of root classes.

2 Problem statement

To define the problem following definitions are needed:

Definition 1 (Directed Graph)**.** A 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 the vertices.

Definition 2 (Predecessor, Successor)**.** 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 vertice of G, then $pred(v) = \{w \mid (w, v) \in E\}$ is the set of predecessors of v.
$v_1 \in V$ 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 vertice of G, then $succ(v) = \{w \mid (v, w) \in E\}$ is the set of successors of v.

Definition 3 (Walk)**.** Let $G = (V, E)$ be a directed graph.
A walk W of length $n \in \mathbb{N}$ is a sequence of vertices $W = (v_1, \ldots, v_n)$ with $v_1, \ldots, v_n \in V$, so that $(v_i, v_{i+1}) \in E \; \forall i = 1, \ldots, n - 1$.

Definition 4 (Cycle)**.** A walk $W = (v_1, \ldots, v_n)$ of length n is called a cycle, if $v_1 = v_n$.

Definition 5 (Path)**.** A walk $P = (v_1, \ldots, v_n)$ is a path from v_1 to v_n, if $v_i \neq v_j$ for all $i, j = 1, \ldots, n$ with $i \neq j$.

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

Definition 7 (Statement)**. TODO 1: Define statement.**

Definition 8 (Class)**.** A class is a tuple $(id, label, Statements, Instances, wiki)$:

- $id \in \mathbb{N}$, which is a numerical Wikidata item ID;
- $label$, which is the, to id corresponding, English label in Wikidata;
- $Statements$ is a set of statements about the class;
- $Instances \in \mathcal{P}(\mathbb{N})$ is the set of numerical Wikidata item IDs, which are instances of the class;
- $wiki$ is the, to the class corresponding, English Wikipedia article text.

Definition 9 (Taxonomy)**.** A taxonomy $T = (C, S)$ is a acyclic graph, where C is a set of classes, and S is a set of subclass-of relations between these classes.

Definition 10 (Subclass Relation)**.** Let $T = (C, S)$ be a taxonomy.
The transitive, ordered relation $\lhd_{subclass}$ is defined.
Let $c_1, c_2 \in C$. $c_1 \lhd_{subclass} c_2$, if there is a path $P = (c_1, \ldots, c_2)$ from c_1 to c_2 in T.

Definition 11 (Root class)**.** Let $T = (C, S)$ be a taxonomy.
$r \in C$ is called root class of T, if $|succ(r)| = 0$.
$root(T) = \{r \in C \mid |succ(r)| = 0\}$ is the set of all root classes in T.

Finally we can define our problem as the following task:

Problem. Let W_1 be the taxonomy of Wikidata, where only labeled root classes are considered. On 7th November 2016 the following state applies $|root(W_1)| = 5332$.
$W_1 = (C, S)$ is the input for the described problem.
Let W_2 be the refined output taxonomy.
A refinement method is needed to significantly reduce the number of root classes in the Wikidata taxonomy. After the refinement method is applied on W_1, which outputs W_2, the following should be true: $|root(W_2)| \ll |root(W_1)|$.

The refinement process can be reduced to the following smaller task:
Let $r \in root(W_1)$.
Find a $c \in C$ with $\neg(c \lhd_{subclass} r)$, so that c is the most similar superclass of r.
Connecting r to c with an edge produces the output taxonomy $W_2 = (C, S \cup \{(r, c)\})$.
Accordingly $|root(W_2)| = |root(W_1)| - 1$ applies.
Repeating this smaller task will eventually yield $|W_2| \ll |W_1|$.

The problem can therefore be defined as developing a method, which finds, given a taxonomy $W = (C, S)$ and a root class $r = root(W)$, the most similar superclass of r.

TODO 2: Define similarity between classes. How? Many aspects to consider.
TODO 3: Probably need to define neural networks.

3 Related work

The research fields of ontology learning and neural networks are of interest to the proposed thesis.

[9] defines two algorithms, tree-descending and tree-ascending algorithm, which allow the semantic classification of words, using the taxonomic relations between words. Evaluation of the tree-ascending algorithm showed that it was better at predicting a superconcept for a correct class than the kNN method (k-nearest-neighbors). A combination of kNN and tree-ascending was also tested and was shown to be to some degree better than both kNN and tree-ascending.
The problem of [9] is similar to the described problem. Both try to solve a classification of data, which is not naturally in a vector representation: words and Wikidata classes. Also both have a taxonomy given, which can be exploited to make a better informed decision, because the taxonomy contains additional semantic information.

[3] develops a deep neural network, which is able to create a graph representation model. Each vertex of the graph is represented as a low dimensional vector. The method was tested on real datasets and outperformed some state-of-the-art systems.
The given problem will be solved with neural networks. Most existing neural networks are using vectors as input. Therefore it is of interest to find methods, which are able to represent graph structures, like taxonomies, as vectors. So the taxonomic structure can be exploited in further calculations.

[11] is an older paper, which develops neural networks using generalized recursive neurons for the classification of structured patterns (e.g. concept graphs). Because the encoding of structures has drawbacks for neural networks. The author proposes the use of another neural network, which encodes the structure into a vector, so it can be used in the feed-forward classification network.
Like [3] the idea of encoding/representing the taxonomy as a vector for further usage seems to be a relevant concept. Representing each class as a vector will also allow a simpler definition of similarity between classes, using for example cosine similarity.

[10] describes a recurrent neural network with short-term memory capabilities through Gated Recursive Units. The neural network is used for ontology learning, specifically creation of new formulas based on encyclopedic text. It is argued that recurrent networks are especially capable for this task, because they proved to do well in handling natural languages. This is the case, because the architecture of recurrent neural networks allows the use of context and does most importantly not limit the size of the context window [8], which is important for natural language prediction. The architecture of the developed network consists of two neural networks, with different tasks, sentence tagging and sentence transduction. Both outputs are then combined to create the resulting formula. This paper shows that recurrent networks are able to make semantic decisions about

encyclopedic text, which is available for the given problem in the form Wiki articles. Additionally the architecture of the paper's network show that is possibly to combine different neural networks to solve a complex problem.
TODO 4: Should I add other related works?

In conclusion the related work suggests a solution, which consists of multiple neural networks, which are connected in a series. In the first step multiple networks will be used to represent the different aspects (taxonomic structure, Wiki article, statements, etc.) of the class as vectors, which then will be combined to one feature vector per class. In the following step a supervised classification method can be applied on the vector representations, which should result in finding the most similar superclass of the entered class.

4 Methodology

TODO 5: Deprecated. Rewrite.
The main task of this work will be to develop a method for extending taxonomic relations of root classes based on neural networks. The task can be divided into the following subtasks:

The root classes in the knowledge base have to be identified and analyzed. This should result in a comparison of similarities and characteristics of root classes in Wikidata. The purpose of this task is to identify, which data is available and how it is structured.

Two categories of to this challenge related work has to analyzed. The first category of related work is concerned with the topic of ontology and taxonomy learning. The second category is concerned with different applications of neural networks, and ways to represent complex data for usage in neural networks. Goal of this task should be to find an appropiate mapping of Wikidata root classes to feature vectors, which can be used by neural networks.

After the mapping of classes is defined, data can be collected per hand or possibly by crawling for training neural networks. The author will create a ground truth for the collected data.

Finally different neural networks can be implemented and trained using existing libraries. The configurations of the networks will be improved by means of experimentation and literature review until a small enough error in testing is achieved.

The real data, all 7142 root classes, will be applied on the best performing network(s). The results will be reviewed by the author. If it is possible a survey with the Wikidata community will be executed. A (random?) subset of the results will be presented to the community, and the participants of the survey will be asked, whether they think the generated suggestions of the network are accurate and could be entered into Wikidata. Such a survey would be really important to confirm the validity and relevance of this work.

5 Expected results

TODO 6: What should I expect? NNs are powerful, so it is likely to work, if the architecture is well designed and the chosen data is good.

6 Time plan

TODO 7: Add a time plan.

List of Figures

References

[1] Wikidata game. https://tools.wmflabs.org/wikidata-game/.

[2] Wikidata statistics. https://tools.wmflabs.org/wikidata-todo/stats.php.

[3] Shaosheng Cao, Wei Lu, and Qiongkai Xu. Deep neural networks for learning graph representations. In Dale Schuurmans and Michael P. Wellman, editors, AAAI, pages 1145–1152. AAAI Press, 2016.

[4] 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.

[5] Alexander Maedche, Viktor Pekar, and Steffen Staab. Ontology Learning Part One — on Discovering Taxonomic Relations from the Web, pages 301–319. Springer Berlin Heidelberg, Berlin, Heidelberg, 2003.

[6] Alexander Maedche and Steffen Staab. Ontology learning for the semantic web. IEEE Intelligent Systems, 16(2):72–79, March 2001.

[7] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. CoRR, abs/1301.3781, 2013.

[8] Tomas Mikolov, Martin Karafiát, Lukás Burget, Jan Cernocký, and Sanjeev Khudanpur. Recurrent neural network based language model. In INTERSPEECH 2010, 11th Annual Conference of the International Speech Communication Association, Makuhari, Chiba, Japan, September 26-30, 2010, pages 1045–1048, 2010.

[9] Viktor Pekar and Steffen Staab. Taxonomy learning - factoring the structure of a taxonomy into a semantic classification decision. In Proceedings of the 19th Conference on Computational Linguistics, COLING-2002, August 24 - September 1, 2002 , Taipei, Taiwan, 2002, 2002.

[10] Giulio Petrucci, Chiara Ghidini, and Marco Rospocher. Using recurrent neural network for learning expressive ontologies. CoRR, abs/1607.04110, 2016.

[11] Alessandro Sperduti and Antonina Starita. Supervised neural networks for the classification of structures. IEEE Transactions on Neural Networks, 8(3):714–735, may 1997.

[12] Serge Stratan. Wikidata taxonomy browser (beta). `http://sergestratan.bitbucket.org/`.

[13] Wilson Wong, Wei Liu, and Mohammed Bennamoun. Ontology learning from text: A look back and into the future. ACM Comput. Surv., 44(4):20:1–20:36, September 2012.