Large-scale Taxonomy Induction Using Entity and Word Embeddings

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ABSTRACT

Taxonomies are an important ingredient of knowledge organization, and serve as a backbone for more sophisticated knowledge representations in intelligent systems, such as formal ontologies. However, building taxonomies manually is a costly endeavor, and hence, automatic methods for taxonomy induction are a good alternative to build large-scale taxonomies. In this paper, we propose TIEmb, an approach for automatic unsupervised class subsumption axiom extraction from knowledge bases using entity and text embeddings. We apply the approach on the WebIsA database, a database of subsumption relations extracted from the large portion of the World Wide Web, to extract class hierarchies in the Person and Place domain.

KEYWORDS

Ontology Induction, Entity Embeddings, Text Embeddings

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1 INTRODUCTION

Semantic ontologies and hierarchies are established tools to represent domain-specific knowledge with dozens of scientific, industrial and social applications [7] and, in knowledge bases, the natural way to structure the knowledge. A basic building block of an ontology is a class, where the classes are organized with “is-a” relations, or class subsumption axioms (e.g., each city is a place). It is crucial to define a high quality class hierarchy for a knowledge base in order to allow effective access to the knowledge base from various Natural Language Processing, Information Retrieval, and any Artificial Intelligence systems and tools.

However, manually curating a class hierarchy for a given knowledge graph is time consuming and requires a high cost. For example the DBpedia Ontology [11], which is a central hub for many applications in the Semantic Web domain [23], has been manually created based on the most commonly used infoboxes within Wikipedia. Many recent studies propose automatic extraction of class hierarchies [8, 10, 27]. The importance of automatic approaches for the induction class hierarchy becomes more apparent when we deal with large scale automatically acquired knowledge bases such as the WebIsA database (WebIsADb) [24].

The WebIsADb is a large collection of more than 400 million hypernymy relations. Relations are extracted from the CommonCrawl,1 by means of Hearst-like patterns [9]. Being extracted from raw text from the very diverse Web sources, and using heuristics of varying reliability, the WebIsADb provides a good coverage, but rather low precision, and cannot be applied as a taxonomy as is.

In recent years, word embedding models have been used heavily in many NLP applications. Such approaches take advantage of the word order in text documents, explicitly modeling the assumption that closer words in the word sequence are statistically more dependent. In the resulting semantic vector space, similar words appear close to each other, and simple arithmetic operations can be executed on the resulting vectors. One of the widely used approach is the word2vec neural language model [14, 15]. Word2vec is a particularly computationally-efficient two-layer neural net model for learning word embeddings from raw text. Another widely used approach is GloVe [21], which in comparison to word2vec is not a predictive model, but a count-based model, which learns word vectors by doing dimensionality reduction on a co-occurrence counts matrix. The studies suggest that both models show comparable performances on many NLP tasks [12].

Such word embedding approaches have been adapted for knowledge base embeddings, or entity embeddings. For example, the RDF2vec approach [22] is able to embed large knowledge bases, like DBpedia. The approach first performs graph transformations

1http://commoncrawl.org/
on the complete knowledge base, and then learns entity embeddings using neural language models.

In this paper, we propose the \textit{TIEmb} approach for automatic unsupervised class subsumption axiom extraction from knowledge bases using entity and text embeddings. The underlying assumptions behind our approach are: (i) the majority of all instances of the same class are positioned close to each other in the embedded space; (ii) each class in the knowledge base can be represented as a cluster of the instances in the embedded space, defined with a centroid and an average radius; (iii) clusters that completely or partially subsume each other, indicate class subsumption axiom.

Figure 1 shows an example of three class clusters projected into a two-dimensional feature space. Each of the classes is represented with the class instances, centroid and a radius. As we can observe, the centroids of the "Football Player" and "Basketball Player" classes are within the radius of the "Athlete" class, which indicates that the centroids of the "Football Player" and "Basketball Player" are subclasses of the "Athlete" class.

The contributions of this paper are the following ones:

- We present a novel unsupervised approach to induce class subsumption axioms using entity and word embeddings.
- We show that such approach can be applied on large knowledge bases, like DBpedia and the WebIsADb.
- Finally, we provide the resulting class subsumption axioms in the Person and Place domains extracted from the WebIsADb. This goes in the direction of semantifying the WebIsADb, and the CommonCrawl in general.

The rest of this paper is structured as follows: in section 2, we give an overview of related work. We present our approach in section 3, followed by two evaluations in section 4, one being on DBpedia, one on the WebIsADb. We conclude with a summary and an outlook on future work.

2 RELATED WORK

The backbone of ontologies typically consist of hierarchy of hypernymy relations, namely "IsA" relations, typically pairs of the kind \((t, h)\) where \(t\) is a concept/term and \(h\) one of its generalizations. Hence, in the construction of knowledge bases, the induction of taxonomies represents an intermediate fundamental step. However, manually constructing taxonomies is a very demanding task, requiring a large amount of time and effort. A quite recent challenge, referred to as ontology learning, consists of automatically or semi-automatically creating a lexicalized ontology using textual data from corpora or the Web (see [2, 26] for a survey on the task). As a result, the heavy requirements of manual ontology construction are drastically reduced.

The task of lexicalized taxonomy induction can be started with the extraction of domain specific hypernymy relations from texts. To this end, [10] use Hearst-like patterns [9] to bootstrap the extraction of terminological sisters terms and hypernyms. Instead, in [27] the extraction of hypernymy relations is performed with a classifier, which is trained on a set of manually annotated definitions from Wikipedia, being able to detect definitional sentences and to extract the definiendum and the hypernym. In the above mentioned systems, the harvested hypernymy relations are then arranged into a taxonomy structure.

In general, all such lexical-based approaches suffer from the limitation of not being sense-aware, which results in spurious taxonomic structures. To cope with such limitations, in [4] the authors adopt a corpus-based unsupervised distributional semantics method to harvest fully disambiguated sense inventories, as well as a new approach to clean distributional semantics-based acquired knowledge graphs [5].

In all the above web-based approaches, a problem arises when the systems open to the Web. In fact, in the last year the majority of the Web search engines do not allow to programmatically query the Web. The WebIsADb [24] addresses the "unavailability" of the Web indices, providing a large database (more than 400M tuples) of hypernymy relations extracted from the CommonCrawl web corpus.\(^2\)

Another group of approaches - instead of inducing a taxonomy from scratch - involve statistical evidence to induce structured hierarchies on existing data sources. In [28] (among others) a schema is statistically induced from the large amount of RDF triples on the Web. Enabling suitable schemas for all those application where logical inference is required.

Recently, word embeddings representations are involved in the task of knowledge hierarchical organization [6], [30], [8]. However, these methods are only considering hypernym-hyponym relationship extraction between lexical terms, using word embeddings. Instead, in our approach we focus on extracting class subsumption axioms, where each class is represented with a set instances.

3 APPROACH

Our approach makes use of vector space embeddings. Those are projections of each instance – e.g., a word or an entity in a graph – into a low dimensional vector space. The core assumption that we
We perform two experiments: (i) applying the proposed approach on the DBpedia dataset using the DBpedia ontology as a gold standard (see Section 4.1); (ii) applying the proposed approach on the WeblsA dataset in unsupervised manner (see Section 4).

4.1 Embedding the DBpedia Ontology

DBpedia is a public knowledge graph which is derived from structured information in Wikipedia, mainly infoboxes. For every Wikipedia page, a node in the DBpedia knowledge graph is generated, and the links to other Wikipedia pages contained in the infoboxes are

Algorithm 1: Algorithm for class subsumption axioms extraction from a knowledge base

Data: KB: Knowledge base, VKB: Knowledge base embeddings for the knowledge base KB

Result: A: Set of class subsumption axioms

1: A := ∅
2: # Calculate the centroid and radius for each class in the knowledge base
3: CKB = {c | ∃i typeOf c ∧ i ∈ KB}
4: foreach class c ∈ CKB do
5: Ức = {i | i typeOf c ∧ i ∈ KB ∧ ∃v_i ∈ VKB}
6: Ứ centroid = ∑i∈Ức v_i
7: Ứ radius = √∑i∈Ức (v_i - Ứ centroid)^2
8: end
9: # Extract class subsumption axioms
10: foreach class c_1 ∈ C do
11: Ứ A_1 := ∅
12: foreach class c_2 ∈ C do
13: Ứ if c_1 ⊑ c_2 then
14: Ứ continue
15: end
16: Ứ distance_{c_1,c_2} = distance(c_1,centroid, c_2,centroid)
17: Ứ if distance_{c_1,c_2} ≤ Ứ radius and c_1.radius < c_2.radius
18: Ứ axiom = c_1 ⊑ c_2
19: Ứ add [axiom, distance] to A_{c_1}
20: end
21: end
22: sort A_{c_1} in ascending order
23: add A_{c_1}.first() to A
24: end
25: # Compute transitive closure
26: change = true
27: while change == true do
28: Ứ foreach axiom a ∈ A do
29: Ứ change = false
30: Ứ subclass = axiom.getSubClass()
31: Ứ superclass = axiom.getSuperClass()
32: Ứ superClassesAxioms = {c | axiom ∈ A ∧ axiom = superclass ⊑ c}
33: Ứ foreach classAxiom s ∈ superClassesAxioms do
34: Ứ if s.class == subclass then
35: UNCTIONinue
36: Ứ end
37: Ứ axiom = subclass ⊑ s
38: Ứ if axiom ∉ A then
39: Ứ add axiom to A
40: Ứ change = true
41: Ứ end
42: end
43: end
44: end
45: return A
| Method    | Precision | Recall | F-score |
|-----------|-----------|--------|---------|
| rel out   | 0.056     | 0.076  | 0.064   |
| rel in    | 0.097     | 0.209  | 0.132   |
| rel in & out | 0.104   | 0.219  | 0.141   |
| TLEmb     | 0.594     | 0.465  | 0.521   |

The results are shown in Table 1. The results show that we are able to identify 46.5% of all the class subsumption axioms, and from the ones we discovered, 59.4% exist in DBpedia. Furthermore, the results show that using entity embeddings significantly outperforms the baseline feature generation approaches.

The error analysis showed that the algorithm often extracts subsumption axioms for classes on the same level in the hierarchy, or sibling classes, e.g., `dbo:Bird ⊆ dbo:Mammal`. The reason for such false positives is that the centroids of the classes are positioned very close to each other in the embeddings space. Furthermore, some of the false positives would not necessarily be incorrect, but those axioms simply do not exist in the DBpedia ontology, e.g., `dbo:Senator ⊆ dbo:OfficeHolder`. Since the DBpedia ontology, like all data sets on the Semantic Web, follows the open world assumption, 59.4% are only a pessimistic estimate for our approach’s precision (see [18] for a discussion).

As a second comparison, we tried to compare our approach to the approach proposed by Völker and Niepert [28], who propose to use association rule mining for deriving subsumption axioms. The core idea of their approach is that if instances of class A are often also of class B, then A should be a subclass of B. However, the approach was not able to generate any axioms on the dataset we used, since in this dataset, only the most specific class is assigned to each instance, hence, co-occurrences such as those which their approach tries to exploit are rarely found in the dataset.

### 4.2 Inducing Ontologies from the WebIsADb

The WebIsA database (WebIsADb) is a database of word pairs which reflect subsumption relations. It was generated from the Common-Crawl by applying a set of patterns like Hearst patterns [9], e.g., \( X \) is a \( Y \) or \( Y \) such as \( X \) to the large corpus of text in the common crawl. Given that the input is raw text from the Web, and all the patterns are heuristic, the corpus is assumed to provide high coverage, but low precision. Thus, simply arranging all the axioms from the WebIsADb into a graph would not constitute a taxonomy, but rather a densely connected graph with many cycles.

In the second set of experiments, we apply the proposed approach on the WebIsADb in order to extract meaningful class hierarchies for the underlying data. As the WebIsADb contains 120,992,248 entities, extracting a single class hierarchy for the complete database is not a trivial task. Therefore, we narrowed the experiments to extract 2 domain specific class hierarchies, i.e., `Person` and `Place`.

To extract the class hierarchy, first we need to select the domain specific instances from the WebIsADb and identify a finite set of classes for which we need to extract class subsumption axioms. To do so, we use domain specific classes from DBpedia as filters. First, we select all the subclasses of `dbo:Person` (184 in total) and `dbo:Place` (176 in total) in DBpedia, and use them as the initial set of classes for each domain separately. Then, we select all the instances of these classes in WebIsADb. To identify the rest of the domain specific classes in WebIsADb, we expand the set of classes by adding all siblings of the corresponding class within the WebIsADb. For example, we use `dbo:SoccerPlayer` to select all the instances of type “soccer player” in WebIsADb, e.g., “Cristiano Ronaldo” is such an instance. In the next step, we expand the initial set of classes with all the classes assigned to the “soccer player” instances, e.g., from the instance “Cristiano Ronaldo”, we will add the following classes...
in the set of Person classes: "Player", "Portuguese Footballer", "Star", "Great Player", etc.

Once we have defined the set of classes for each domain, we select all the instances for each class, which represents the input knowledge base for Algorithm 1. We experiment with entity and word embeddings. As entity embeddings we use DBpedia RDF2vec embeddings, which are built similarly as described in the previous section, only this time we also use the instance transitive types. To link the WebIsADb instances to DBpedia, we use exact string matching.

For word embeddings, we use GloVe embeddings [21], trained on the complete Common Crawl. The model provides 300-dimensional embedding vectors for 2.2 million tokens. In case of multiple tokens in the WebIsADb instance, the final vector is calculated as the average of the vectors of all the tokens in the instance.

Again, we compare our approach to the association rule mining-based approach proposed in [28]. To do so, for each instance, we generate a transaction of all the instance’s types. Then, for each of the classes separately, we learn class subsumption axioms using the standard Apriori algorithm [1]. We consider all the rules with support and confidence value above 50.

To evaluate the induced class subsumption axioms, we use the DBpedia ontology as a reference class hierarchy, i.e., (i) we count how many of the class subsumption axioms defined in the DBpedia ontology we identified in WebIsADb (DBpedia coverage); (ii) we count how many more axioms were discovered compared to the DBpedia Ontology (Extra Coverage); (iii) we manually determine the precision on 100 randomly selected axioms from all of the extracted axioms.

First, we manually map each DBpedia class to the corresponding WebIsADb class. For the Person domain, we were able to map 0.99% of the classes, and there is 1466.67% extra class coverage for the same domain in WebIsADb. For the Place domain, we were able to map 0.71% of the classes, and there is 1161.93% extra class coverage for the same domain in WebIsADb. The results for the Person and the Place domain are shown in Table 2 and 3, respectively. We can observe that although the coverage of axioms is slightly lower using
Figure 3: Excerpt of the Place top level hierarchy

the graph embeddings and TIEmb, we are able to mine subsumption axioms at much higher precision.

The extracted class subsumption axioms can be found online.4 Excerpts of the top levels of the Person and Place hierarchies are shown in Figure 2 and Figure 3, respectively.

5 CONCLUSION AND OUTLOOK

Taxonomies are an important backbone of formal knowledge representations. However, at large scale, they cannot be created manually with reasonable efforts, thus, automatic approaches have to be used. In this paper, we have accordingly shown that using word and knowledge base embeddings are suitable approaches for inducing large scale taxonomies from knowledge graphs such as DBpedia or the WebIsADB. The approach relies on vector space embeddings of entities and exploits the proximity preserving properties of such embeddings approaches such as GloVe or RDF2vec.

Using WebIsADB, we were able to create hierarchies of thousands of classes at decent precision. We created two example hierarchies, i.e., persons and places, but the approach is capable of generating class hierarchies for any seed concept at hand. In general, the approach cannot only be used for taxonomy induction, but also for the problem of type prediction [19]. Here, again exploiting the proximity relations in the embedding space, each instance can be assigned to the types with the closest cluster centroid(s).

In the future, it will be interesting to see how embeddings coming from text and graphs can be combined reasonably. This will allow for even more concise induction of taxonomies. Furthermore, we want to investigate how higher-level semantic knowledge, such as class restrictions or complementarity, can be mined using an embedding-based approach. That way, using the Common Crawl as a representative sample of the knowledge that exists on the Web, we will be able to create large-scale semantic knowledge representations directly from Web data.

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