Improving Hypernymy Extraction with Distributional Semantic Classes

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Abstract

In this paper, we show for the first time how distributionally-induced semantic classes can be helpful for extraction of hypernyms. We present a method for (1) inducing sense-aware semantic classes using distributional semantics and (2) using these induced semantic classes for filtering noisy hypernymy relations. Denoising of hypernyms is performed by labeling each semantic class with its hypernyms. On one hand, this allows us to filter out wrong extractions using the global structure of the distributionally similar senses. On the other hand, we infer missing hypernyms via label propagation to cluster terms. We conduct a large-scale crowdsourcing study showing that processing of automatically extracted hypernyms using our approach improves the quality of the hypernymy extraction both in terms of precision and recall. Furthermore, we show the utility of our method in the domain taxonomy induction task, achieving the state-of-the-art results on a benchmarking dataset.

Keywords: semantic classes, distributional semantics, hypernyms, co-hyponyms, word sense induction

1. Introduction

Hypernyms are useful in various applications, such as question answering (Zhou \textit{et al.}, 2015) or query expansion (Gong \textit{et al.}, 2005) as they can help to overcome sparsity of statistical models. Hypernyms are also the building blocks for learning taxonomies from text (Bordea \textit{et al.}, 2016). Consider the following sentence: “This café serves fresh mangosteen juice”. Here the infrequent word “mangosteen” may be poorly represented or even absent in the vocabulary of a statistical model, yet it can be substituted by lexical items with better representations, which carry close meaning, such as its hypernym “fruit” or one of its close co-hyponyms, e.g. “mango”.

Currently available approaches to hypernymy extraction focus on the extraction of individual binary hypernymy relations (Hearst, 1992) [Snow \textit{et al.}, 2004] [Weeds \textit{et al.}, 2014] [Shwartz \textit{et al.}, 2016] [Glavaš and Ponzetto, 2017]. Frequencies of the extracted relations usually follow a power-law, with a long tail of noisy extractions containing rare words. We propose a method that performs post-processing of such noisy binary hypernyms using distributional semantics. Namely, we use the observation that distributionally related words are often co-hyponyms (Wandmacher, 2005) [Heylen \textit{et al.}, 2008] and operationalize it to perform filtering of noisy relations by finding dense graphs composed of both hypernyms and co-hyponyms.

The contribution of the paper is an unsupervised method for post-processing of noisy binary hypernymy relations based on clustering of distributional sense graphs. We are the first to use distributional semantic classes to improve hypernymy extraction, as opposed to prior methods, which used distributional yet sense-unaware local features. The implementation of our method and the induced language resources (distributional semantic classes and cleansed hypernymy relations) are available online [https://github.com/uhh-it/mangosteen].

2. Related Work

Hypernymy extraction methods. In her pioneering work, Hearst (1992) proposed to extract hypernyms based on lexical-syntactic patterns from text. Snow \textit{et al.} (2004) learned such patterns automatically based on a set of hypernym-hypernym pairs. Pantel and Pennacchiotti (2006) presented another approach for weakly supervised extraction of similar extraction patterns. These approaches use some training pairs of hypernyms to bootstrap the pattern discovery process. For instance, Tjong Kim Sang (2007) used web snippets as a corpus for similar extraction of hypernyms. More recent approaches exploring the use of distributional word representations for extraction of hypernyms and co-hyponyms include (Roller \textit{et al.}, 2014) [Weeds \textit{et al.}, 2014] [Necsulescu \textit{et al.}, 2015] [Vylomova \textit{et al.}, 2016]. They rely on two distributional vectors to characterize a relation between two words, e.g. on the basis of the difference of such vectors or their concatenation.

Recent approaches to hypernym extraction went into two directions: (1) unsupervised methods based on huge corpora, to ensure extraction coverage via Hearst (1992) patterns (Seitner \textit{et al.}, 2016); (2) learning patterns in a supervised way based on a combination of syntactic patterns and distributional features (Glavaš and Ponzetto, 2017). In our experiments, we use a web-scale database of noisy hypernyms extracted by Seitner \textit{et al.} (2016), a large-scale repository of automatically extracted hypernyms. Note that while methods, such as (Mirkin \textit{et al.}, 2006) and (Shwartz \textit{et al.}, 2016) use distributional features for extraction of hypernyms, in contrast to our method, they do not take into account (1) word senses, (2) distributional semantic classes (global sense clusters).

Semantic class induction. This line of research starts with (Lin and Pantel, 2001), where sets of similar words are clustered into concepts. While this approach performs a hard clustering and does not label clusters, these drawbacks are addressed in (Pantel and Lin, 2002), where words can belong to several clusters, thus representing senses, and in
3. Unsupervised Induction of Distributional Sense-Aware Semantic Classes

As illustrated in Figure 1, our method consists of induction of a sense inventory from a text corpus using the method of Faralli et al. (2016), and clustering of these senses. Word senses in the induced resource are specific to a given target word, e.g. words “apple” and “mango” have distinct “fruit” senses, represented by a list of related senses. On the other hand, sense clusters represent a global and not local clustering of senses, i.e. the “apple” in the “fruit” sense can be a member of only one cluster. This is similar to WordNet, where one sense can only belong to one single synset.

3.1. Word Sense Induction from a Text Corpus

Each word sense \( s \) in the induced sense inventory \( \mathcal{S} \) is represented by a list of neighbours \( \mathcal{N}(s) \). Extraction of this network is performed using the method of Faralli et al. (2016) and involves three steps: (1) building a distributional thesaurus, i.e. a graph of related undisambiguated terms; (2) word sense induction via clustering of ego networks (Everett and Borgatti, 2005) of related words using the Chinese Whispers algorithm (Biemann, 2006); (3) disambiguation of related words and hypernyms. The word sense inventory used in our experiment was extracted from a 9.3 billion tokens corpus, which is a concatenation of Wikipedia (dump of June 2016), ukWac (Ferraresi et al., 2008), LCC (Richter et al., 2006) and Gigaword (Graff and Cieri, 2003). Note that analogous graphs of senses can be obtained using word sense embeddings, see (Neelakantan et al., 2014; Bartunov et al., 2016).

3.2. Representing Senses with Ego Networks

To perform global clustering of senses, we represent each induced sense \( s \) (cf. Section 3.1) by a second-order ego network (Everett and Borgatti, 2005). An ego network is a graph consisting of all related senses of the ego sense \( s \) reachable via a path of length one or two: \( \{ s_j : (s_j \in \mathcal{N}(s)) \lor (s_i \in \mathcal{N}(s), s_j \in \mathcal{N}(s_i)) \} \). Each edge weight \( w_{rs} \) between two senses is taken from the induced sense inventory network and is equals to a distributional semantic relatedness score between \( s_i \) and \( s_j \). To minimize the impact of the word sense induction errors we filter out ego networks with a highly segmented structure. Namely, we cluster each ego network with the Chinese Whispers algorithm and discard networks for which the cluster containing the target sense \( s \) contains less than 80% nodes of the respective network. Besides, all nodes of a network not appearing in the cluster containing the ego sense \( s \) are also discarded.

3.3. Global Sense Graph Construction

The goal of this step is to merge ego networks of individual senses constructed at the previous step into a global graph. We compute weights of the edges of the global graph by counting the number of co-occurrences of the same edge in different networks. For filtering out noisy edges, we remove all edges with the weight less than a threshold \( t \).

3.4. Clustering of Word Senses

The core of our method is the induction of semantic classes by clustering the global graph of word senses. We use the Chinese Whispers algorithm to make every sense appear only in one cluster \( c \). Results of the algorithm are groups of strongly related word senses that represent different concepts. Hypernymy is by definition a relation between nouns. Thus optionally, we remove all single-word senses that do not correspond to nouns using the Pattern library (De Smedt and Daelemans, 2012). We use two clustering versions in our experiments: the fine-grained model clusters 208,871 induced word senses into 1,870 semantic classes, and the coarse-grained model that groups 18,028 word senses into 734 semantic classes.

4. Denoising Hypernyms using the Induced Distributional Semantic Classes

By labeling the induced semantic classes with hypernyms we can thereby remove wrong ones or add those that are missing as illustrated in Figure 2. Each sense cluster is labeled with the noisy input hypernyms, where the labels are the common hypernyms of the cluster word (cf. Table 1). Hypernyms that label no sense cluster are filtered out. In addition, new hypernyms can be generated.

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"Pantel and Ravichandran, 2004," where authors aggregate hypernyms per cluster, which come from Hearst patterns. The main difference to our approach is that we explicitly represent senses both in clusters and in their hypernym labels, which enables us to connect our sense clusters into a global taxonomic structure. To this end, we are the first to use semantic classes to improve hypernymy extraction.
5. Evaluation

To evaluate our approach, we conduct two intrinsic and one extrinsic experiment. The first experiment aims to estimate the fraction of spurious sense clusters, the second one evaluates the quality of the post-processed hypernyms. Finally, we evaluate the labeled sense classes in application to the taxonomy induction task.

5.1. Experiment 1: Plausibility of the Hypernymy-Labeled Semantic Classes

Comparison to gold standard resources allow us to gauge the relative performances of various configurations of our method. To measure the absolute quality of the best configuration selected in the previous section, we rely on microtask-based crowdsourcing with CrowdFlower.

Task Design. We used two crowdsourcing tasks based on word intruder detection (Chang et al., 2009) to measure how humans perceive the extracted lexical-semantic structures. Namely, the tasks are designed to evaluate the quality of the extracted sense clusters and their labels. A crowdworker is asked to identify words that do not match the context represented by words from a sense cluster or its label. To generate an intruder, following the original design of (Chang et al., 2009), we select a random word from a cluster and replace it with a word of similar frequency that does not belong to any cluster (bias here is low as the evaluated model contains 27,149 out of 313,841 induced word senses).

Evaluation Metrics. We compute accuracy as the fraction of tasks where annotators correctly identified the intruder, thus the words from the cluster are consistent.

Results. Overall, 68 annotators provided 2,035 judgments about the quality of sense clusters. Regarding hypernyms, 98 annotators provided 2,245 judgments. The majority of the induced semantic classes and their labels are highly plausible according to human judgments: the accuracy of the sense clusters based on the intruder detection is 0.859 (agreement of 87%), while accuracy of hypernyms is 0.919 (agreement of 85%). The crowdworkers show a substantial agreement according to Randolph κ coefficient computed 0.739 for the cluster evaluation task and 0.705 for the hypernym evaluation task (Meyer et al., 2014).

A major source of errors for crowdworkers are rare words and entities. While clusters with well-known entities, such as “Richard Nixon” and “Windows Vista” are correctly labeled, examples of other less-known named entities sometimes wrongly labeled as implausible, e.g., cricket players. Another source of errors during crowdsourcing were wrongly assigned hypernyms: in rare cases, sense clusters are labeled with hypernyms like “thing” or “object” that are too generic even under tf-idf weighting.

5.2. Experiment 2: Improving Binary Hypernymy Relations

In this experiment, we test whether our post-processing based on the semantic class improves the quality of hypernymy relations (cf. Figure 1).

Generation of Binary Hypernyms. We evaluated the best pruned model (ℓ = 100). Each sense cluster of this model is split into the set $H_{\text{cluster}}$ of binary hypernyms, as illustrated in Figure 2. Overall, we gathered 85,290 hypernym relations for 17,058 unique hyponyms. Next, we gathered the set $H_{\text{orig}}$ of 75,486 original hypernyms for exactly the same 17,058 hypernyms. For each word from the sense cluster we looked up top five hypernyms under the best ones when sorting them by extraction frequency from the hypernym relation database of (Seitner et al., 2016) as in our model each sense cluster is labeled with five hypernyms from the same database. The database of (Seitner et al., 2016) is extracted using lexical patterns. Note that any other method for extraction of binary hypernyms can be used at this point, e.g. (Shwartz et al., 2016; Glavaš and Ponzetto, 2017). For the comparison, we gathered up to five hypernyms for each word, using (1) the most frequent hypernym relations from (Seitner et al., 2016) vs. (2) the cluster labeling method as described above.
Task Design. We drew a random sample of 4,870 relations using lexical split by hyponyms (all relations from \(H_{\text{cluster}}\) and \(H_{\text{orig}}\) of one hyponym were included in the sample). These relations were subsequently annotated by human judges using crowdsourcing. We asked crowdworkers to provide a binary judgment about the correctness of each hypernymy relation.

Results. Overall, 298 annotators completed 4,870 unique tasks resulting in total 33,719 binary human judgments about hypernyms. We obtained a fair agreement among annotators of 0.548 in terms of the Randolph \(\kappa\) (Meyer et al., 2014). Since CrowdFlower reports a confidence for each answer, we selected \(N \approx 3\) most confident answers per pair and aggregated them using weighted majority voting. The ties were broken pessimistically, i.e. by treating a hypernym as irrelevant. Results for \(N \in \{3, 5, 6\}\) varied less than by 0.002 in terms of F-score. Table 2 presents results of the experiment. Since each pair received a binary score, we calculated Precision, Recall, and F-measure of two compared methods. Our denoising method improves the quality of the original hypernyms by a large margin both in terms of precision and recall, leading to an overall improvement of 10 F-score points. The improvements of recall are due to the fact that to label a cluster of co-hyponyms it is sufficient to lookup hypernyms for only a fraction of words in the clusters. However, binary relations will be generated between all cluster hypernyms and the cluster words potentially generating hypernyms missing in the input database. For instance, a cluster of fruits can contain common entries like “apple” and “mango” which ensure labeling it with the word “fruit”. Rare words in the same cluster, like “mangosteen”, which have no hypernyms in the original resource due to the sparsity of the pattern-based approach, will also obtain the hypernym “fruit” as they are distributionally related to frequent words with reliable hypernym relations.

5.3. Experiment 3: Improving Domain Taxonomy Induction

In this section, we show how the labeled semantic classes can be used for induction of domain taxonomies.

SemEval 2016 Task 13. We use the taxonomy extraction evaluation dataset by Bordea et al. (2016), featuring gold standard taxonomies for three domains (Food, Science, Environment) and four languages (English, Dutch, French, and Italian) on the basis of existing lexical resources, such as WordNet and Eurovoc (Steinberger et al., 2006). We used the English part of the task and the official evaluation setup based on the Fowlkes&Mallows Measure (F&M), a cumulative measure of the similarity of two taxonomies.

Taxonomy Induction using Semantic Classes. Our method for taxonomy induction takes as input a vocabulary of the domain and outputs a taxonomy of the domain. The method consists of three steps: (1) retrieving sense clusters relevant to the target domain; (2) generation of binary relations though a Cartesian product of words in a sense cluster and its labels; (3) attaching disconnected components to the root (the name of the domain). We retrieve domain-specific senses for each domain of the SemEval datasets by a lexical filtering. First, we build an extended lexicon of each domain on the basis of the seed vocabulary of the domain provided in the SemEval dataset. Namely, for each seed term, we retrieve all semantically similar terms. To filter out noisy expansions, related terms are added to the expanded vocabulary only if there are at least \(k = 5\) common terms between the seed vocabulary and the list of related terms. Second, we retrieve all sense clusters that have at least one term from the expanded vocabulary among its sense clusters or hypernyms. Whereafter we generate binary hypernymy relations by linking every word in the semantic class to each hypernym label as shown in Figure 2. Finally, we link roots of each disconnected components to the root of the taxonomy, e.g. “food” for the Food domain.

Results. Table 3 presents results of the taxonomy extraction experiment. We evaluated two best models of our method: a coarse and fine grained clusterings featuring respectively 734 and 1870 semantic classes with different levels of pruning: \(t \in \{0, 100\}\). As one can observe, our model based on the labeled sense clusters significantly outperforms the substring-based baseline and all participating system by a large margin on all domains. For the “Science (Eurovoc)” and “Food” domains our method yields results comparable to WordNet while remaining unsupervised and knowledge-free. Besides, for the “Science” domain our method outperforms WordNet, indicating on the high quality of the extracted lexical semantic knowledge. Overall, the coarse-grained model which used more pruning yielded better results as compared to fine-grained unpruned model for all domains but “Science (Eurovoc)”.

6. Conclusion

We presented a unsupervised method for induction of sense-aware semantic classes using distributional semantics and graph clustering and showed how these can be used for post-processing of noisy hypernymy databases extracted from text. To evaluate our approach, we performed three experiments. A large-scale crowdsourcing study indicated a high plausibility of extracted semantic classes according to human judgment. Besides, we demonstrated that our approach helps to improve precision and recall of a hypernymy extraction method. Finally, we showed how the proposed semantic classes can be used in domain taxonomy induction.
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