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Word Sense Disambiguation

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Abstract

This project focuses on Word Sense Disambiguation (WSD), a task in natural language processing that aims to determine the correct meaning of a word based on its context. The project aims to create a dataset for training WSD models using both automatic and manual methods. The dataset creation involves four steps: identifying highly polysemous words from the Elexis WSD dataset, extracting sentence pairs from the ccKres corpus using clustering methods, manual verification and correction of sentence pairs, and converting the existing Elexis WSD dataset to WiC format. The resulting dataset will be used to train WSD models that can determine if two occurrences of a word in different contexts have the same meaning or not. The project aims to contribute to the development of accurate WSD models for improving the accuracy of machine translation and other NLP tasks.

Keywords

Natural Language Processing, NLP, Word Sense Disambiguation, WSD, Clustering, Slovene

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Introduction

Word sense disambiguation (WSD) is an important task in natural language processing that consists of determining the correct meaning of a word based on its context, using a predetermined list of potential meanings. This process is usually performed unconsciously by humans. WSD can be viewed as a classification problem in which the goal is to assign an occurrence of a word to its appropriate sense class based on a dictionary of possible meanings. The context in which the word occurs, including neighboring words, serves as evidence for the classification task. WSD is applicable in various domains, such as machine translation, information retrieval and hypertext navigation, content and thematic analysis, speech processing, knowledge acquisition, information extraction, etc. [1]

The goal of this project is to prepare a dataset for training WSD models using both automatic and manual methods. The project consists of four steps. To create the dataset, we will first create a list of highly polysemous words from the existing Elexis WSD dataset. Then, sentence pairs containing these words will be extracted from the ccKres corpus using clustering methods and automatic truth value assignment. The sentence pairs will be manually verified, and their truth values corrected as needed. We will also convert the existing Elexis WSD dataset to WiC format and create as many positive and negative examples as possible, which we will then join to the newly generated dataset. The resulting dataset will be used to train WSD models that can determine whether two occurrences of a word in different contexts have the same meaning or not.

Overall, this project aims to contribute to the development of WSD models that can accurately determine the correct meaning of polysemous words in natural language text, which is essential for improving the accuracy of machine translation and other NLP tasks.

Related work

Preliminary challenge in WSD [2] is the ambiguity of language itself. Despite extensive research in this field, there is still no clear understanding of the two main categories of lexically ambiguous words, homonymy and polysemy [3]. Polysemy refers to a single lexical item with more than one semantic specification, while homonymy involves multiple morphological specification with the same sound and/or spelling under different dictionary entries. The word homonym can thus be used for both homophone and homograph, which adds complexity to the issue of homonymy. Therefore, in the task of disambiguation, it is important to have a clear definition of polysemy and consistently follow the chosen approach [4].

Furthermore, there is still not a clear understanding of the difference between the two main types of linear and non-linear polysemy. Non-linear polysemy mainly consists of metaphor and metonymy, whereas linear polysemy can be

further categorized into autohyponymy, automeronymy, autosuperordination, and autoholonymy [3].

Important and frequently observed problem related to a drop in accuracy with WSD [5] is the so-called domain adaptation problem, where the system is trained on one domain but applied to a different domain. The goal of domain adaptation is to train a neural network on one dataset for which label or annotation secure good performance on another dataset from a different domain. Therefore, the challenge is to make classifiers perform well on the target dataset [6].

Current approaches rely heavily on supervised learning techniques. While they have shown promising results in WSD, they require large amounts of data for training, which can be time consuming and costly, additionally they call for annotated data. Further research is needed to develop techniques that at the same time do not rely heavily on annotated data, handle the ambiguity of language, and can be used across domains. As has been previously established, many approaches in different areas of NLP, models that are only trained on a particular domain, usually perform poorly on text from a different domain. To achieve this, semi-supervised and unsupervised approaches that can leverage large amounts of unannotated text would have to be developed [7].

WSD models for Slovene

While there have been many WSD models developed for English and other languages, for Slovene there is still a lack of different WSD models. One of the well-known ones is the one developed by RSDO [8]. Besides this one, there is also the Slovenian version of the parallel-sense annotated corpus ELEXIS-WSD [9]. We decided to use this dataset to help us find highly polysemous words. Elexis is a manually curated and annotated dataset consisting of five annotation layers for 10 European languages, including Slovene. This dataset features five annotation layers, including WSD, which is used to identify highly polysemous words. The Slovene dataset was processed using a highly accurate tool called CLASSLA tagger. Two different POS tagsets were used, which could cause confusion for the taggers. To solve this problem, the detailed tagging guidelines UD-POS [10] for Slovene were consulted. Another problem with this process was the distinction between different categories, such as DET vs PRON and CCONJ vs ADV. In order to obtain more content words, named entity components that are not proper nouns were assigned their appropriate part of speech. Finally, some corrections were made to the lemmatisation, such as manually correcting the lemmatisation of prepositions. Despite these challenges, the tokenisation process was error-free.

WiC dataset

We will also be using the WiC dataset [11] that is based on three lexical resources: WordNet, VerbNet, and Wiktionary. Word-in-Context is a binary classification task that aims to determine whether a word used in two different contexts corresponds to the same meaning or not. The dataset consists of examples with a target word and two sentences containing the target word. Each example is either positive or negative, depending on whether the two sentences have the same meaning of the target word. The dataset was compiled by obtaining all possible positive and negative examples from various sources. The test and development sets were created with the intention of obtaining a diverse and balanced set. Some of the examples were also reserved for testing and development data set, respectively. The remaining examples were used for initial training.

Our working process

We have implemented an unsupervised method for our word disambiguation task. This method does not rely on external sources of knowledge, sense inventories or machine readable dictionaries [12]. However, it does require a dataset with labeled word senses and an annotated corpus, both of which we do have.

We first created a `.txt` file with the 250 most polysemous lemmas found in Elexis-WSD. Then we narrowed down the list to 30 words per group member for the purpose of assigning senses to polysemous words. Our candidate words represent the 90 most polysemous words in the Elexis-WSD corpus.

Our next step was to create a `.csv` file that contained all sentences found in ccKres that included polysemous words from each group member's lists. To do that, we used `.xml` files in `ccKres_LEMATIZIRAN`. The files are structured so that the polysemous lemma is in the first column, and the sentence containing it is in the second column. We created one `.csv` file for each group member.

Then we had to vectorize each sentence in each group member `.csv` file, which was done using the `SentenceTransformer` model [13]. We embedded the whole sentence and then used PCA to remove columns with less correlation. Then we used the k-means clustering algorithm with a value of k set to 10, which means that we have be dividing the data into 10 distinct clusters, with each cluster corresponding to a potential sense of a polysemous word. We found the centroid of each cluster so that the algorithm could represent the central tendencies of each sense, which will help us in disambiguating the word sense of a given usage by comparing it to the centroids of the potential senses and selecting the one that is closest. Lastly, centroids and sentences containing them have been printed into a `.txt` file for each of the participants.

The final part of the project involved manually annotating sentence pairs. The primary objective of this annotation task was to determine whether the lemmas in each sentence pair had the same or a different meaning. We created a program that randomly generated pairs of sentences containing the same lemma. A csv file was generated which is composed of several columns. The first column is the lemma, the second one is the first sentence, the third one is the second sentence, the fourth one contains labels, in the fifth column the meaning of the first sentence is noted, and in the sixth and final column, the meaning of the second sentence is noted. For the fourth column, we used the labels "T" and "F" to represent true and

false. This was our main and primary focus for this word disambiguation task. On top of that, for determining the meanings in the fifth and sixth columns, we referred to the meanings proposed in Elexis. In Elexis lemmas that have multiple possible meanings, have all the different meanings labeled with a number. We used these numbers in our WiC dataset.

While performing the manual annotation, we encountered several problems. These mostly came up when we were trying to refer to the meaning according to the meanings determined in Elexis. The main problem was that some of the meanings of the lemmas were not one of the proposed ones in Elexis. Because we wanted to be consistent, we in such cases mostly noted in the dataset that a particular meaning has not been noted in Elexis and proposed a new meaning. Furthermore, we stumbled across many examples which had a metaphorical meaning which was also not noted in Elexis. For those examples, we mostly noted the literal meaning of the lemma. Moreover, there were also some examples where we encountered flexible word classes [14]. In such examples we also had to decide how to compare the meanings of the lemmas. It adds additional complexity to the task to have two sentences where a lemma is a different part of speech. One such example that we encountered was with the lemma `stran` (in English, this lemma could be equivalent to the words page, side, party (in legal language), away). We had a pair of sentences where one had the word `stran` used as an adverb, and the other one as a noun. That is also something that could be addressed later on.

Future work

While our annotation process has provided valuable insights, further research can be conducted to expand on this work. One of the base ideas is that additional sentence pairs could be annotated and a wider range of lemmas used. Additionally, it would contribute to the existing research in this area to explore non-linear polysemy, mainly metaphors. That would solve one of the issues we encountered while manually annotating a particular meaning of lemmas. In addition, manual annotation could also be performed to determine whether lemmas are homophones, homographs, or are in a different relation.

It would also contribute to our existing project if a model for word disambiguation was implemented. By incorporating such a model, we would be able to assess its performance on our annotated sentences through manual evaluation. The model's error rate could be computed by comparing its disambiguation results with our manually assigned labels.

One of the possible future steps of the project would be to manually assess the algorithm's work using the Elexis-WSD corpus. We could also indicate whether the polysemous word is used in its literal or figurative meaning.

Momentarily we have only tried working with the unsupervised method but would like to implement an unsupervised method such as decision trees, support vector machines, naïve bayes or maximum entropy. For the supervised learning method, a classifier is trained on manually created training data and is used to assign senses to instances of that word. During the testing phase, the classifiers use the learned information to identify the best sense for each occurrence of the word. Overall, supervised approaches tend to be more precise than other methods [12]. Besides the mentioned ones, two more classes of methods can be used for word sense disambiguation: knowledge-based and hybrid methods. Semi-supervised WSD methods utilize both annotated and unannotated data. It involves using a small set of labeled data, a larger set of unlabeled data, and a set of classifiers. The algorithm is then applied to both datasets, with the annotated dataset expanding while the unlabeled dataset shrinks until a certain threshold is reached. This algorithm has been shown to achieve high accuracy when applied to smaller datasets, but there are uncertainties involved in selecting parameter values such as pool size and number of iterations. Knowledge based methods avoid the need for large training datasets and exploit the knowledge contained in WordNet, Wikipedia, dictionaries etc. They have an advantage over corpus based algorithms because one does not need an annotated corpus to implement these methods. Corpus based algorithms, however, are more precise than knowledge based ones [12].

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