A REVIEW: WORD SENSE DISAMBIGUATION

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ABSTRACT

Word sense disambiguation is branch of Artificial Intelligence (AI) which deals with the Natural Language Processing. Word sense disambiguation deals with the polysemy of word, in natural language processing a single word are having two or more meanings where respective context discriminates the meaning. Human beings are quite intelligent to get meaning of the word as they are having biological neural network. Computers can be trained in such a way that they should work same as biological neural networks. There are different suggested approach for the disambiguation such that knowledge-based, supervised, semi-supervised, and unsupervised. The objective of this research is to improve better communication in between the computer and human being. The discussed model used supervised learning approach with linked allocation for calculating word space and tree approach for word sense

Keyword: - *Word Sense Disambiguation, Learning Models.*

1. INTRODUCTION

In Natural Language Processing (NLP), Word-Sense Disambiguation (WSD) focuses on crucial problem concerned with identifying which sense of a word is used in a sentence to get exact and accurate meaning of sentence. There are so many words used in the English language have various different senses and meanings. WSD is concerned with the problem of selecting the correct meaning with respect to sense. The solution to this problem impacts improving relevance of search engines with real time information. The human brain (Biological Neural Network) is quite adroit at word-sense disambiguation. Simple context is all that is needed for humans to understand the correct sense or meaning of a word. The human language developed in a way that reflects the innate ability provided by the brain's biological neural networks. In computer science and Information technology, it has been a long-term challenge to train computers for natural language processing and predictions by machine learning or Artificial Intelligence. Presently so many application or technologies are there that they working on this problem of disambiguation but still there is scope for improvement and accuracy.

In today's modern world, people are heavily invested in a computer's ability to solve various problems in their daily lives. From finding directions via GPS to calculating their tax returns, most people are reliant on computer devices in one way or another. For better user experience and improved interfacing between man and machine, there needs to be clear communication between them. One obstruction in the way is the problem of ambiguity in word senses. In an effort to reduce this problem and enhance the intelligence of computers, we propose our research for Word Sense Disambiguation. For example, consider a word bank in English which has different meanings: any of various as a commercial bank, blood bank and river bank. Word sense disambiguation replaces the ambiguous word by the proper one depending on the surrounding context of the sentence. Here we are focusing on the English language and in same, there are so many ambiguous words whose meaning said by the surrounding and position of the word in the sentence.

2. APPROACHES FOR WDS

- THERE ARE FOUR CONVENTIONAL APPROACHES TO WSD

1. KNOWLEDGE BASED APPROACH

Knowledge based algorithms uses various lexical resources such as Machine Readable Dictionaries (MRDs), WordNet to identify the correct sense of words. These Algorithms are easy to implement and was first to be developed while trying to solve the problem of WSD. A knowledge based system only needs access to commercial dictionary resources to start process of word disambiguation.

Drawback of these algorithms is that their performance is limited on the speed of searching and retrieval of these resources. As the size of the resources increase, so does the latency and hence performance decreases.

Example Lesk Algorithm

2. MACHINE LEARNING BASED

There are three different learning methods comes under the Machine learning approach as,

2.1 Supervised methods

Supervised methods are based on the hypothesis that the context can provide enough indication on its own to disambiguate words (hence, common sense and reasoning are deemed unnecessary).
A learning set is prepared for the system to predict the actual meaning of an ambiguous word using a few sentences, having a specific meaning for that particular word. A system finds the actual sense of an ambiguous word for a particular context based on that defined learning set.

Supervised approach always gives superior performance than any other methods. However, these supervised methods are subject to a new knowledge acquisition holdup since they rely on considerable amounts of manually sense-tagged resources for training, which are arduous and expensive to create.
Example Naïve Bayes Method, Decision Tree Method

2.2 Semi-supervised methods

Many word sense disambiguation algorithms use semi-supervised learning which allows both labelled and unlabelled data because of the lack of training data. The bootstrapping method starts from a small amount of seed data for each word: either a small number of sure fire decision rules (e.g., 'play' in the context of 'bass' almost always states the musical instrument) or manually tagged training corpus. Using any of the supervised method, seeds are used to train an initial classifier. This classifier is then used on the untagged portion of the corpus to extract a larger training set, in which only the most assured classifications are included. This procedure repeats, each new classifier being trained on a successively larger training data, until the complete data is consumed, or until a given maximum number of iterations are reached.
Examples Yarowsky Bootstrapping Method, Label Propagation Algorithm

2.3 Unsupervised method

Unsupervised learning methods are the greatest challenge for WSD researchers. The underlying assumption is that similar meaning words occur in similar contexts, and thus senses can be induced from text by clustering word occurrences using some measure of similarity of context, a task referred to as word sense discrimination or induction. To disambiguate a word they use some measure of similarity in context to get the correct sense.

Performance has been observed to be lower than for the other methods described above, but it is hoped that unsupervised learning will overcome the knowledge acquisition bottleneck because they are not dependent on manual effort.

Examples Co-occurrence Graphs/ Hyper-Lex Algorithm, WSD using parallel corpora

3. LITERATURE REVIEW

Literature survey is performed with consideration of four different Word Sense Disambiguation approaches as,

KNOWLEDGE BASED APPROACH:-

Chandrakant D. Koake and Sachin D. Babar [1](2019)

I this research papers authors have proposed in adaptive approach for the lexical ambiguity in the Word Sense Disambiguation. The proposed and evaluated recurrent neural network with semCore and OMSTI gives better result for the polysemy words.

Myung Yun Kang, Tae Hong Min, Jae Sung Lee [8](2018)

Authors have extended the word vector space model to reject a more fine-grained meaning in context vectors by incorporating embedded sense space. They have used a large Korean sense-tagged corpus and built an embedded sense space with knowledge based learning and evaluated the effectiveness of the sense embedding for word sense disambiguation. The results of their experiment with a Korean sense-tagged corpus showed that the proposed method, i.e., embedded sense space model, is more effective than the word space model. Embedded sense space model is not useful because sense context or disambiguated word context is not available in a normal query.

Udaya Raj Dhungana, Subarna Shakya, Kabita Baral and Bharat Sharma [12](2015)

In this paper, they used the knowledge based approach. They have used adapted Lesk algorithm to disambiguate the polysemy word in Nepali language. They grouped each sense of a polysemy word based on the verb, noun, adverb and adjective with which the sense of the polysemy word can be used in a sentence. The experiment is performed on 348 words (including the different senses of 59 polysemy words and context words) with the test data containing 201 Nepali sentences shows the accuracy of their system to be 88.05%.

Michael Lesk [16](1986)

The paper written by Michael Lesk in 1986 has been proved to be revolutionary work in Word Sense Disambiguation (WSD). In this paper, he presented his famous Lesk algorithm which has been the pivotal algorithm for knowledge based approach WSD. The Lesk algorithm uses various machine readable dictionaries (MRDs) to find correct senses of words. The algorithm searches for overlaps in various senses or signatures of a word. Senses having maximum overlap are chosen as the correct senses of the word. Lesk has concluded that the algorithm produces an accuracy of about 50-70% depending on the MRD used.

SUPERVISED LEARNING APPROACH:-

Edilson A. Corrêa, Alneu A. Lopes, Diego R. Amancio[1] (May 2018)

In this system the supervised learning approach is used for the WSD, the words of documents are represented in the form of nodes. If two nodes are connected if and only if they are semantically similar. The big challenge authors have addressed is the formation of network form the words and assigning the sense to the word from the appearance and context of the word. The adopted learning algorithm in bipartite networks proves better result mostly when local features are correctly mapped with the context of data. The challenge to this method is that failure of the edge while mapping sense of the word. This method performs well even if small amount of data is available for training.

Tinghua Wang, Junyang Rao, Qi Hu[3](2014)

In this system the supervised learning approach with the formation of BoW of context is used for word sense disambiguation. There are three different proposed phases as Preprocessing, Kernel and Classification. In preprocessing the Bag of Words (BoW) is formed, Semantic diffusion kernel in which the SDK is applied before classification to improve the performance of SVM. In third and last phase the Support vector machine (SVM) is used for the classification purpose. The limitations of supervised training here are class labels and co-occurrence information is required .The limitation of BoW is that the disordering grammar and order will leads towards the wrong context of word.

Abdulgabbar Saif, Nazlia Omar, Ummi Zakiah Zainodin, Mohd Juziaddin Ab Aziz [5](2018)

In this approach authors has addressed to the very first step of the WSD that is building of sense tag. Building of sense tag data is main challenge for the supervised learning technique that achieved promising result in word sense disambiguation. The manual knowledge based approach is labor and time consuming. Proposed method starts with the mapping Arabic Wordnet and Wikipedia to select the Wikipedia article for the corresponding sense in Wordnet. In mapping step cross language method is used to measure similarity between features of Wikipedia and Wordnet sense separately. The proposed approach works I three different stages as candidate Extraction, Candidate Alignment and Instance Extraction.

Ali Alkhatlan, Jugal Kalita, Ahmed Alhaddad [6](2018)

In this paper work in Arabic has been limited despite the fact that there are half a billion native Arabic speakers. In this work, we present multiple approaches for the problem of WSD in Arabic utilizing recent developments and successes in learning word embeddings with approaches such as GloVe, and Word2vec. The primary shortcoming of word embeddings is the single vector representation of a word’s meaning, although many words are polysemous. Author’s main contribution in this work is to computationally obtain an embedding for each sense, using an Arabic WordNet (AWN) to overcome the problem of WSD. They also compute word semantic similarity giving thought to multiple Arabic stemming algorithms. Finally, authors make available a large pre-processed corpus that is ready to be used for further experiments and a WSD test data based on AWN,1 seeking to fill gaps in Arabic NLP (ANLP) compared to English.

Tamilselvi P, S.K. Srivatsa [7](2012) In this paper, a supervised approach for word sense disambiguation using neural network with minimal feature sets was implemented. As we know there are three layers on neural network with one hidden layer in which the hidden neurons ranging from 5 to 20 with the increase of 5 neurons at a time are constructed for disambiguation. Disambiguation is tried with minimum two features, bigram and maximum three features, trigram. Number of input for the network is based on the number of features taken for disambiguation process. Bigram takes only two features including ambiguous word and trigram takes only three features (including ambiguous word). Performance is measured using four different error functions. Out of 60 different network architecture, In-trigram based pattern recognition network with 20 neurons produced outstanding performance with 85.72% accuracy.

Ignacio Iacobacci, Mohammad Taher Pilehvar, Roberto Navigli [11](2016)

The main focus of this paper is on word embedding. i.e. is to collect the semantic information from the collection of the datasets. It is an example of knowledge-based approach. Word embedding is usually a collection of names for a set of language modeling and advanced learning techniques in the natural language processing. In this the results are evaluated by using two methods:

1. 1. Lexical Sample WSD Experiments.
2. 2. All words WSD Experiments.

The main interests were on the training parameters of embedding and WSD features which were impacting on the WSD performance. The maximum accuracy observed during this experiment was 69.9%.

Niladri Chatterjee and Rohit Misra[15](2009)

In this paper, the team members have presented a trainable model for Word Sense Disambiguation (WSD). The model uses concepts of information theory to find appropriate sense of a word when the context of word is provided. Given training text, the model learns to classify each occurrence of target word to correct sense. The model presented uses the Principle of Maximum Entropy, considering the sense of target word as a random variable with various outcomes. The model then estimates the probability of each sense by measuring the 'bias' of surrounding words. The sense with highest probability is chosen as correct sense of the target word. The model has been proved to deliver accuracy as high as 85%.

3. UNSUPERVISED LEARNING APPROACH

Yoan Gutiérrez, Sonia Vázquez, Andrés Montoyo [2](2017)

In this paper they have addressed to the very first step of the Word sense disambiguation by page rank algorithm to assign sense tags to the word or formation of co occurrence network. The proposed two different approaches for same as Knowledge based approach which basically used machine readable dictionaries like WordNet and second is the corpus based approach which uses co-occurrence to measures the similarity in between the words.

K.P. Sruthi Sankar, P.C. Reghu Raj, V. Jayan, [8](2016)

In this paper the work is to develop a WSD system for Malayalam, a language spoken in India, predominantly used in the state of Kerala. The proposed system uses a corpus which is collected from various Malayalam web documents. For each possible sense of the ambiguous word, a relatively small set of training examples (seed sets) are identified which represents the sense. Collocations and most co-occurring words are considered as training examples. Seed set expansion module extends the seed set by adding most similar words to the seed set elements. These extended sets act as sense clusters. The most similar sense cluster to the input text context is considered as the sense of the target word.

Alok Pal, Anupam Munshi and Diganta Saha [13](2013)

The key focus of this paper is to speed-up the process of Word Sense Disambiguation by using filtering method which finds appropriate senses of the given ambiguous word through part-of-speech tagging. The exact part-of-speech of the ambiguous word at that particular instance is obtained. In the next method, online dictionaries are referred such as WordNet etc. which are related to the part-of-speech to disambiguate the correct sense of that particular ambiguous word.

In the training data phase, brown corpus is used for part of speech tagging and WordNet as an online dictionary. In this method to speed up the process of WSD, some of the relevant glosses (words) is filtered out and accuracy is increased.

4. SEMI SUPERVISED LEARNING APPROACH

Bridget T. McInnes, Mark Stevenson [4](2014)

In this paper the suggested method includes both supervised and unsupervised learning approaches. Supervised learning makes use of information or labels form training data where unsupervised approach rely on the UMLS (United Medical Language Systems).Authors have proposed two different scenarios in supervised approach as mean_similarity and max_similarity. In mean similarity the degree of similarity between the concepts of each ambiguous word possible senses computed and combined mean of similarity. Authors have concluded that the supervised learning approach generated 98% accurate results for the abbrev dataset (Dataset of abbreviations only).

- Bartosz Broda, Maciej Piasecki [9](2009)

In this paper, word sense ambiguity is resolved by using semi-supervised approach and results have showed that the approach is very close in its precision to the supervised approach. Drawbacks of using supervised and unsupervised approach is that in the supervised approach it requires laborious and costly manual preparation of the training data. On the other hand, unsupervised approach express significantly lower accuracy and the results are not satisfied for solving the problem. The main task of this model is to reduce the human involvement, but assign the senses manually using lexical semantic resource known as WordNet. Here, Lexicographer (LexCSD) is used is gather the corpus from the given keyword. This keyword is then split into clusters and some common keywords are found from the given word. It is analysed to search for the common characteristics or senses in each cluster. Evaluation is done later by crosschecking the MRDs.

Pratibha Rani, Vikram Pudi, Dipti Misra Sharma [10](2017)

In this paper, the authors have presented a generic Word Sense Disambiguation (WSD) method using semi-supervised approach. They explain that current WSD systems use extensive domain resources and require advanced linguistic knowledge. Therefore, to improve these factors, they propose a system that extracts context based list from a small amount of seed data containing sense tagged and untagged training data. Their experiments in Hindi and Marathi language domains show that the system gives good performance without language specific information with exception of sense IDs present in the training set, with approximately 60-70% precision.

Lokesh Nandanwar, Kalyani Mamulkar [14](2013)

This is a survey paper which tells about three approaches used in word sense disambiguation:

1. Supervised Approach.

2. Semi-Supervised Approach.

3. Unsupervised Approach.

These approaches are found to be very useful and successful in the field of word sense disambiguation. They are categorized based on the main source of knowledge which is used to differentiate senses and amount of annotated corpora required.

For the following approaches described above semi-supervised approach requires less amount of annotated corpora as compared to supervised approach. Here, annotated means adding some opinion to the text and corpora means data which is required. By observing and testing the approaches, supervised approach gives better performance as compared to the other approaches.

SUMMARY OF SURVEY

Table -1 is mirror of literature survey with three parameters as supervised learning, Un-supervised Learning and Semi supervised learning as,

Year	Learning	Algorithms/Model	Advantages	Limitations	Accuracy
2019[1]	Supervised	Recurrent Neural Network	This model performs well even if small amount of data is available for training	Complex Model	92 %
2017[2]	Un-supervised	Page-rank	Generates more accurate results	Lexical knowledge of the words is required.	62%
2014[3]	Supervised	Bag of Words (BoW), Semantic Diffusion kernel.	Applying Semantic diffusion kernel before Support Vector Machine (SVM) in classification improves performance.	Generates better results for Homonymy words.	84.09%
2014[4]	Both Supervised and Un-supervised.	Mean Similarity and Max Similarity	Supervised learning generates more accurate results on Abbrev dataset.	Applicable for United Medical Language System(UMLS) only	98%
2018[6]	Supervised	GloVe and Word2vec	To computationally obtain an embedding for each sense, using an Arabic WordNet (AWN) to overcome the problem of WSD	Vector Space Models (VSMs) is hard to construct	--

2012[7]	Supervised	Neural Network	Out of 60 different network architecture, In-trigram based pattern recognition network with 20 neurons produced outstanding performance with 85.72% accuracy	Complex network architecture	85.72%
2016[8]	Unsupervised	Sense Tagged	The proposed system develops sense clusters using the seed sets. Then based on the similarity between the given input text and the sense clusters,	Human intervention. required	72%
2018[9]	Knowledge Based	Vector space model	Sense Space Model more effective than Word space model	Not practical because sense context is not available in normal queries. Did not show any practical improvement over the word space model	79%
2017[10]	Semi-supervised learning	LexCSD algorithm ,Clustering algorithm, NB algorithm	Reduced human involvement	Limited to unsupervised methods which has a lower accuracy and produce results which are not satisfying for many applications	--
2017[11]	Semi-supervised learning	Contextual similarity property based on hypothesis of Yarowsky (1993)	Generic Method issue table for resource-poor languages and it can be used for various languages without requiring a large sense tagged corpus.	Provides comparatively low accuracy for English language as compared to other systems.	69.9%
2016[12]	Supervised Learning	Knowledge-based word embedding	Word Embedding can be used to improve state-of-the-art Supervised WSD.	Best performance is obtained when standard WSD features are augmented with the additional knowledge from Word2vecvectors.	--

2015[13]	Supervised Learning	Adapted Lesk algorithm	Accuracy is increased by 3.484% in compared to the accuracy of previous systems of Nepali Language.	Requires large amount of training data.	88.05%.
2013[14]	Unsupervised Learning	Filtering Method using unsupervised method	Correct sense of an ambiguous word is found using the Part-of-Speech Tagging before the disambiguation procedure.	Execution time might be increased	72.86%
2009[15]	Supervised Learning	Principle of Maximum Entropy, Bayesian theorem	High accuracy of around 85% through the language independent model.	Same concept applied to Supervised methods might reward higher accuracy.	85%
1986[16]	Supervised Learning	Lesk Algorithm	Laid the foundation of Supervised Learning, providing 50-70% accuracy	Accuracy is limited to technology of lexical resources.	50-70%

4. CONCLUSIONS

Word Sense Disambiguation (WSD) is an open problem concerned with selecting the correct sense of a polysemous word. To bridge the gap between humans and computers and to provide better interfacing, the accuracy of the systems working on this task, need to be improved. In this survey, we have addressed the need to increase accuracy of existing WSD systems, fig-C and Fig-D shows the system architecture, Flowchart respectively. The model uses a Back propagation neural network model to maximize accuracy.

As future work, proposed system can be developed. Carefully planned execution and programming of the system will provide required high accuracy. Then after development, test cases will be generated and accuracy of system can be tested successfully

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