WORD SENSE DISAMBIGUATION: A REVIEW

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I. INTRODUCTION

In the process of natural language, a lot of words have different connotations. The correct sense of a word depends upon the context in which the word occurs. Word sense disambiguation known as the process of selecting the most correct sense of the word in a given sentence. Furthermore, Most of natural language processing applications, such as the extraction of information, machine translation, and Analysing of content are supported by the process of word sense disambiguation which can be an essential pre-processing step for them. Figure 1 shows the general process of word sense disambiguation.

Figure 1: General model of word sense disambiguation

Furthermore, in English language words can have fully opposite meanings in different contexts. An example to show that, the sentence “*The bank of Yemen was robbed*”, *bank* here means the institution of finance. On the other hand, in the “*My home town is on the southern bank of Yemen*” the word *bank* here means a shore of a river or a land.

There are many approaches for word sense disambiguation one of them is knowledge based word sense disambiguation which in our case assign the senses to each word “bank” and indicates which sense is correct by word overlapping between the word in the given sentence and the word from WordNet, then the correct sense is the one which have the maximum number of overlapping, in our case we have the sense “*finance*” which can be in the following words [finance, deposit, money, activity, accept], and the following words for the sense “*land*” [river, water, body, land] the total of overlapping will be:

- First Sentence: (land = 0, finance = 2)
- Second Sentence: (land = 1, finance = 0)

Therefore, the finance sense is assigned to the first sentence and the land sense assigned to the second sentence. However, large number of suitable sense in WordNet is undistinguishable from each other in this method. Whereas the supervised methods are obtained to be more suitable than other approaches such as unsupervised method and knowledge base approaches.

II. CHALLENGES IN WORD SENSE DISAMBIGUATION

1. Differences between dictionaries

In some cases, many senses are closely related to each other so it's difficult to separate the words into senses.

2. Part-of-speech tagging

Sense tagging and Part of speech tagging are closely correlated to each other. So the decision of whether these tasks should be decoupled or kept together becomes much more difficult.

3. Human Interaction

Human interaction provides the better result than computer to find the sense of words. But it is difficult for human to memorize all the possible senses of words.

4. Common sense

Sometimes it is difficult to parse the meaning of words without common sense. For example, “Ram and Shyam are fathers” and “Ram and Shyam are brothers”. In first sentence each is independently a father whereas in second sentence they are brothers of each other.

5. Sense Inventory and algorithms task-dependency

It is difficult to find the accurate sense of word between multiple languages. An example, the ambiguity of word “mouse” where is it animal or computer device is not pertinent in Arabic-English machine translation.

III. RELATED WORK

1. A Research paper was proposed by Pradeep Sachdeva 2014, “An Improved Approach to Word Sense Disambiguation” [1].

The problem: Improvement of the Previous Algorithms which use only two factors to found the similarity between the nearby and target words, first factor calculating the intersection between the glosses of the nearby and target words. Second factor by identifying the exact occurrence of the nearby word's sense in the hierarchy (hypernyms) of the target word's senses.

Solution:

Providing a **Knowledge based algorithm** for disambiguating words using the tool of computational linguistics. This approach includes more factors for calculating similarity which are the whole hierarchy, intersection, and distance which has not been involved by any of the previous approaches. Choosing the correct sense based on the highest score.

Data set: Only noun words polysemous content of SemCor dataset.

Result: The proposed Knowledge based approach as shown in table 1 resulted with a higher precision for the three top result measurement which is better than other approaches.

Table 1: results of knowledge based approach with different approaches tested for nouns.

Measure		Precision	Recall	F1 Measure
PROPOSED APPROACH	Top 1 Result	53.3	43.6	47.9
	Top 2 Result	60.01	59.9	59.95
	Top 3 Result	61.9	61.9	61.9
Graph Connectivity Measure[7]		37.8	37.8	37.8
Adapted Lesk [3]		34.05	34.05	34.05
First Sense [8]		68.8	68.8	68.8

2. Another research paper was mentioned by Bridget T. McInnes, and Mark Stevenson “Determining the difficulty of Word Sense Disambiguation” 2013 [2].

The problem: Automatic processing of biomedical documents is made difficult by the fact that many of the terms they contain are ambiguous.

Solution: Suggested both unsupervised and supervised methods to estimate the WSD performance on an ambiguous terms of biomedical including abbreviations, phrases and words.

Data Set: MSH-WSD dataset The National Library of Medicine’s MSH Word Sense Disambiguation (MSH-WSD) dataset contains 203 ambiguous terms and abbreviations from the 2010 MEDLINE baseline.

Result: Results show that the supervised methods are good predictors of WSD difficulty in some cases, but that their results are not consistent across different data sets. These methods also require labelled training data, limiting their usefulness. The unsupervised approaches do not have this limitation and can be applied to a wider range of ambiguities.

Table 2: Result of WSD accuracy using unsupervised and supervised approaches.

Dataset	Measure	WSD	
		Unsupervised	Supervised
NLM-WSD	# Senses	−0.30	−0.17
	MFS	0.15	0.89
	Entropy	−0.17	−0.88
Abbr	# Senses	−0.46	−0.14
	MFS	0.18	−0.57
	Entropy	−0.33	0.32
MSH-WSD	# Senses	−0.05	−0.06
	MFS	0.11	0.14
	Entropy	0.11	0.17
Combined	# Senses	−0.11	−0.11
	MFS	−0.05	0.03
	Entropy	0.03	−0.09

3. Another research work was mentioned by Rada Mihalcea “Using Wikipedia for Automatic Word Sense Disambiguation” 2007, [3].

The problem: Building accurate WSD in automatic way using Wikipedia as a basis of sense annotations.

Solution: proposed a supervised method, where the occurrence of each sense tagged of a specific word is converted into a feature parameter which is then used in an automatic learning process.

Data Set: Nouns of Wikipedia sense corpus and SENSEVAL dataset.

Result: The supervised method relies wholly on monolingual data, which can avoid the possible constraints forced by approaches that need parallel texts, which may be difficult to find.

Table 3: Average number of examples and senses using SENSEVAL and WIKIPEDIA datasets.

Dataset	#s	#ex	baselines		word sense
			MFS	LeskC	disambig.
SENSEVAL	4.60	226	51.53%	58.33%	68.13%
WIKIPEDIA	3.31	316	72.58%	78.02%	84.65%

4. Another research paper was studied by Anagha Kulkarni, “Word Sense Disambiguation for Vocabulary Learning”, 2006 [4].

The problem: Improvement of English vocabulary by performing sense disambiguation for homonyms to help ESL students in vocabulary learning.

Solution: Both supervised and unsupervised methods are used in vocabulary learning to find word sense disambiguation. Learning of word meaning pairs was done instead of words.

Data set: 30 homonyms of ESL dictionary.

Result: the result indicates that unsupervised methods were less accurate than supervised approaches. A user study reveals that students equipped with WSD-enabled vocabulary tutor perform significantly better than students using vocabulary tutor without the WSD capabilities.

Table 4: Result of 30 homonyms using supervised classification models.

	Homonym	Number of senses	Baseline Accuracy (%)	Best Accuracy (%)	Cohen's Kappa	Classification Algorithm	Window Size (w)
1	panel	2	84.92	99.82	0.993	MNB	25
2	transmission	2	51.91	99.15	0.983	MNB	70
3	procedure	2	82.04	99.40	0.980	MNB	85
4	foundation	3	79.17	98.81	0.965	MNB	85
5	principal	2	64.39	98.05	0.957	SVM	40
6	bond	2	81.78	98.67	0.956	SVM	70
7	aid	2	59.76	97.71	0.952	SVM	85
8	tape	2	75.16	98.14	0.951	MNB	40
9	monitor	2	84.36	98.58	0.947	MNB	85
10	code	2	66.18	97.10	0.936	MNB	85
11	volume	3	51.00	96.00	0.934	MNB	85
12	suspend	2	81.48	97.53	0.919	MNB	40
13	contract	3	83.67	97.73	0.919	MNB	40
14	qualify	3	79.81	97.12	0.909	MNB	70
15	major	3	90.24	98.32	0.904	MNB	40
16	conceive	2	80.92	96.95	0.898	SVM	70
17	pose	3	58.26	94.78	0.893	MNB	25
18	trigger	2	59.40	94.33	0.883	SVM	25
19	brief	3	75.81	95.70	0.883	SVM	10
20	parallel	2	53.70	94.14	0.882	MNB	85
21	supplement	2	73.18	95.45	0.882	MNB	70
22	channel	2	53.25	93.49	0.869	MNB	10
23	depress	2	60.66	93.44	0.862	MNB	40
24	manual	2	68.80	93.59	0.850	SVM	10
25	factor	2	91.24	97.72	0.848	MNB	85
26	shift	3	70.71	92.55	0.837	MNB	70
27	function	2	90.84	97.01	0.830	MNB	55
28	issue	3	80.90	92.96	0.767	MNB	85
29	complex	3	58.51	86.86	0.735	MNB	70
30	appreciate	2	68.63	86.27	0.690	SVM	40

5. Although, a research paper was mentioned in 2014 by Arindam Roy “Knowledge based approaches to Nepali Word Sense Disambiguation”, [7]. They use three types of knowledge base approaches to perform WSD which are semantic graph based, conceptual distance, and overlap based. They use only noun and adjectives of Nepali WordNet as data set. The result shows that in overlap based the accuracy were 54% and 42% approximately. While the mixture of semantic graph based and conceptual distance resulted to be more accurate than overlap based approach.

6. Another research paper was studied in 2008 by Shrestha [8], they used Lesk algorithm for Nepali WSD. The authors changed the Lesk algorithm in way that just the words in the sentence without their gloss, hypernym, examples and synset are chosen as context words. They use the Nepali WordNet as dataset which resulted this method is more accurate than other approaches.

7. Furthermore, a research was done in 2014 by Dhungana [5], they use adapted Lesk Method to disambiguate the Nepali words. They use 348 words with the test data containing 201 sentences of Nepali language which resulted that this algorithm more accurate and increased by 16.41% which is better than the accuracy of the approach proposed by Shrestha [8].

8. One more work was mentioned in 2014 by Richard Laishram Singh “A Decision Tree Based WSD System in Manipuri Language” [6]. Proposed contextual and positional features for WSD using a WordNet of Manipuri language as a dataset.

IV. DISCUSSION

Three approaches most widely used in word sense disambiguation which are knowledge based approach, supervised approach and unsupervised approach, here will discuss the advantages and disadvantage of each approach.

Table 5: Advantages and disadvantages of WSD approaches

Approach	Advantage	Disadvantage
Knowledge-Based	These algorithms give higher Precision.	These algorithms are overlap based, so they suffer from overlap sparsity and performance depends on dictionary definitions.
Supervised	This type of algorithms are better than the two approaches w.r.t. implementation perspective.	These algorithms don't give satisfactory result for resource scarce languages.
Unsupervised	There is no need of any sense inventory and sense annotated corpora in these approaches.	These algorithms are difficult to implement and performance is always inferior to that of other two approaches.

IV. CONCLUSION

In this study, we have reviewed the task of word sense disambiguation, WSD is the toughest open problems of NLP. Some of WSD challenges has been discussed, many problems occurs in WSD because it depends on knowledge drawn from different resources. WSD also deals with complexities of languages. Knowledge based, supervised approach, unsupervised approach and semi supervised approaches are used in WSD. Supervised approach performs well as a compared to all other approach because training data totally depends on specific domain.

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