IT in Industry, Vol. 9, No.2, 2021

PublishedOnline12April 2021

A REVIEW ON WORD SENSE DISAMBIGUATION EMPHASIZING THE DATA RESOURCES ON WORDNET AND CORPUS

Chingakham PonyKumar Singh[1], Dr. HMamata Devi[2], Dr. Nongmaithem Ajith Singh[3]

[1]Research Scholar, Department of Computer Science, Manipur University, Manipur
[2]Associate Professor, Department of Computer Science, Manipur University, Manipur
[3]Assistant Professor, Department Of Computer Science, South East Manipur College, Manipur

Abstract

Word Sense Disambiguation is a disambiguating technique of finding the most relevant sense of an ambiguous word with the aid of its surrounding words. In this paper, we pointed out the various Word Sense Disambiguation approaches along with its different techniques, state of the art, comparative studies of the existing system highlighting its benefits and limitations across all the widely well known Indian and foreign languages. In this paper, we converse our study by emphasizing to all the studies that uses WordNet, IndoWordNet or corpus as the main data resources of the referred languages.

Keywords: **Word Sense Disambiguation(WSD), Natural Language Processing(NLP), Polysemy, Homonymy, WordNet.**

1. Introduction

Language is a structured system through which one's thought can be conveyed to other, which can be either in spoken or in any other forms. Communication among people happened due to the existence of language. Many a times it may happen that a word in any language may have multiple senses from which ambiguity arises leading to miscommunication. Lexical ambiguities are of three types:

- Polysemy ambiguity: It deals with a word or a phrase that have multiple senses but are related to one another.
- Homonymy ambiguity: It deals with a word or a phrase that have multiple senses but they are of totally unrelated senses.
- Categorical ambiguity: It deals with a word or a phrase that have multiple meaning but each meaning have different grammatical meaning[11].

Human beings using their own merit can decide the correct sense of a word relevant to the situation of its usage. While machines do not have such capability to handle such situation unless and until some rule based features are embedded into the machines' memory[6]. To distinguish the correct meaning of a word, its knowledge plays a vital role, whether it is referring to human or machine. Word Sense Disambiguation(WSD) is a disambiguating technique of finding the most relevant sense of an ambiguous word with the aid of its surrounding words[2, 20]. For example, the English word 'late' may have different senses as "after the usual or appointed time", "formerly", "dead" etc. Such word when used in a sentence like "Sam is the only son of late Daniel." needs to correctly find the referred sense and the process by which the most relevant sense of an ambiguous word can be found for a particular context is called Word Sense Disambiguation. Syntactic, positional, contextual factors act as the supporting roles in finding the appropriate sense of the word behind an argument[3]. Disambiguating can be performed for the entire words in a sentence(All Word Sense Disambiguation) or just a target word in a sentence. There are three main approaches of WSD:

ISSN(Online):22031731
ISSN (Print): 2204-0595

i. ***Knowledge based approach:*** While solving major NLP applications like machine translation and document classification which refers to just the outer knowledge of the text, one also need to acquire the hidden meaning of the text. Knowledge about the text and the domain of discourse play a vital role in understanding the text meaning, which Knowledge based NLP system using its various methods will further represent and implement this knowledge to solve NLP problems such as ambiguity resolution[22]. Any little piece of information can be seen as a group of cues which comprises of words, its inflection, its order etc[28]. Rather than suggesting the correct meaning of the text by the cues, they usually gave rise to many possible meanings. Hence many knowledge based approaches exist which relies mainly on knowledge resources like collocations, WordNet, thesaurus, ontology, etc[31]. Grammar rules, hand coded rules, explicit lexicon information etc. may also be used additionally for disambiguation purpose. Alternative option for disambiguating is by calculating the semantic similarity among the words irrespective of their positions by treating the text as an unordered bag of words. Lesk algorithm is one of the most popular knowledge-based algorithm which works by finding the maximum overlaps with words in a context[1].

ii. ***Machine learning based approach***: The main resource that this approach used is on the corpus evidence. Tagged or untagged corpus is usually used for training the model, which is a probabilistic/statistical model. Here, the main role of the classifier is to learn the features, which are used for extracting and assigning the correct sense of the word in example sentence. The number of occurrence of the target word around the given example with a fixed window size gives the value of the feature. There are three types of machine learning based approaches:

- *Supervised Techniques:* This technique works with hand labelled sense-annotated data sets[30]. Usually a classifier is used along with a training set which has a close interlink up with the sense inventory, wherein the target word is manually tagged with the most appropriate sense in the context. Supervised techniques give better performance than other techniques. Supervised WSD method includes Neural Networks, Decision lists, Decision tree, Naïve Bayes etc[18].
- *Unsupervised Techniques:* It is believed that words that have similar sense tend to have similar surrounding words. Clusters of words are used for deriving the word senses and later search for the fresh occurrence of the word in the derived cluster. Unsupervised WSD method includes Context Clustering, Co-occurrence Graphs, Word Clustering etc[18].
- *Semi-supervised Techniques:* In this technique, a smaller data set, which consists of only the critical information can be used to make the system learnt vital characteristics from it. This technique sometimes outperformed the unsupervised techniques.

iii. ***Hybrid approach:*** A mixture of knowledge based approach and machine based approach is used in this type of approach. Here the system may use machine readable dictionary to identify relations between senses and corpus to calculate mutual information score between the related senses. This approach is mainly used in a situation when uneven data are available for the implementation of the WSD system.

WSD can act as a stepping stone in various areas of Natural Language Processing(NLP) including machine translation, lexicography, parsing, automatic text summarization, hypertext navigation, speech processing and synthesis, spelling correction, reference resolution etc[23]. The most obvious application of Word Sense Disambiguation is Machine Translation. WSD also find its applications in many areas such as speech recognition (SR), information extraction (IE) and information retrieval (IR)[12].

The paper is organized as follows: Section 2 contains two parts. 2.1 gives the details about the related works done in foreign languages and 2.2 gives the details about the previous WSD related works done in Indian languages. Section 3 briefly explains the various evaluation metrics that can be used to calculate the performance of the WSD system and finally the overall conclusion and the future scope is given in section 4.

2. Related Works

Word Sense Disambiguation(WSD), since its first introduction by Warren Weaver in 1949, many researchers have been trying to automate the problem of WSD using various algorithms. Commendable works have been carried out by many researchers in WSD across many languages.

2.1 Foreign Languages

Tang Shancheng et al.[19] developed a word sense disambiguation system that works on all types of ambiguities. Here, three methods viz. TextCNN, TextLSTM and TextMultiTask methods were implemented so that comparisons with other deep learning WSD system can be made. It was observed

ISSN(Online):22031731
ISSN (Print): 2204-0595

that 11.48% improvement was seen when compared with other best existing methods like XYZ, I2R, CITYU, CFS_M etc. Myung Yun Kang et al.[20] proposed a new supervised model that embedded sense space to disambiguate the Korean language. The model was trained with a minimum frequency of 5(five) and a ten-fold cross validation was performed on the large training set. Results have shown that the embedded sense space outperformed the hybrid model. Grigori Sidorov and Alexander Gelbukh[29] proposed a unique Spanish WSD system based on the Spanish dictionary and was implemented using Lesk algorithm. By using the dictionary, handling important tasks like tagging, headword and window size become easier. To further improve the performance, Lesk algorithm was modified by adding a fuzzy comparison of synonymous words and a derivational morphology system. Nyein Thwet Thwet Aung et al.[5] developed a Myanmar WSD system that resolves the ambiguity of Myanmar words using Myanmar-English parallel corpus. The developed module was used to enhance the Myanmar-English machine translation system. The system gave a precision of 89%. Ali Saeed et al.[26] developed a novel benchmark Urdu corpus to perform all word sense disambiguation. The developed corpus will be of highly efficient as annotation of the ambiguous word was assigned after the consolidated result obtained from three annotators. Voting-Based approach was further used to increase the accuracy of the corpus. Farag Ahmed and Andreas Nurnberger[4] approach of disambiguating the translation work of Arabic to English was based on the statistical co-occurrence. Features selection was based on user query terms, topic context and word inflection forms. The cohesion nature of the Arabic words along with a special similarity score was used to translate the correct sense of the word in the English language. Boon Peng Yap et al.[27] shown how Word Sense Disambiguation can be used as ranking task for selecting the correct sense based on the context-gloss pair. This method outperformed all the other state-of-art WSD results. It also demonstrates the important usage of WordNet's example sentence in the generation of training data without the evolvement of external annotation.

ISSN(Online):22031731
ISSN (Print): 2204-0595

Table 1: Comparison of foreign languages word sense disambiguation systems

Authors & Year	Methodology	Language Used	Learning Model	Data Source and size	Accuracy	Advantages	Disadvantages
Ali Saeed, Rao Muhammad Adeel Nawab, Mark Stevenson, Paul Rayson(2008)	n-gram	Urdu	Knowledge Based	5064 words	57.71%	All the data sources, approaches and methods were clearly explained and presented.	Data size built up was very small.
Nyein Thwet Thwet Aung, Khin Mar Soe, Ni Lar Thein(2011)	Naïve Bayesian	Myanmar	Supervised Approach	Not mentioned	89%	Very efficient considering the first attempt and scarcity of data.	Works only with noun and verb. Uses only bag of words features but not collocation and co-occurrence features.
Alok Ranjan, Anirban Kundu, Abhay Singh, Raj Shekhar, Kunal Sinha(2015)	Modified LESK and Bag–of–word approaches	English	Hybrid Approach	Manually created test data sample. Data size not mentioned	Improve performance	Showed improvement in performance.	Too many steps involved to derive to the solution of disambiguation.

ISSN(Online):22031731
ISSN (Print): 2204-0595

PublishedOnline12April 2021

Tang Shancheng, Ma Fuyu, Chen Xiongxiong, Zhang Puyue (2018)	Sequence to sequence	Chinese	Supervised Approach	SemEval-2007 Task #5 was taken as test data	11.68% more than the 7 best performed methods	Reduce manual extraction of features. Worked on all types of ambiguities.	Data size taken up for disambiguation was considerably small.
Myung Yun Kang, Tae Hong Min, Jae Sung Lee(2018)	Embedding sense space	Korean	Supervised Approach	832650 sentences	Perform better	Used CBOW architecture of Word2Vec. Perform sense embedding as well as evaluation of it.	Hybrid Space model well only in the case of micro precision but not on macro precision.
Loic Vial, Benjamin Lecoutex, Didier Schwab(2020)	Neural Network	English	Supervised Approach	WordNet and SemCor corpus	99.99% using SemCor only and 100% using WordNet Gloss corpus	Improve coverage and capacity by keeping only the required senses. Outperformed all the other state-of-art WSD systems.	Monosemic words are excluded.
Aditi Salodkar, Mrunal Nagwanshi, Ms Bhavana	Tokenization, lemmatization, stemming, dictionary	English	Supervised Approach	Both data source and size were not mentioned	Not reported	Used basic concepts and implemented the application. Dictionary creation part is a bonus.	Only syntactic structure is considered.

ISSN(Online):22031731
ISSN (Print): 2204-0595

Gopchandani(2019)							
Farag Ahmed, Andreas Nurnberger(2019)	Naïve Bayesian	Arabic	Supervised Approach	Arabic/English Parallel Corpus	Precision:93%	Special properties of Arabic language were considered. Perform best feature selection for training the data.	Words with many senses were not considered leaving a big loophole.
Grigori Sidorov and Alexander Gelbukh(2001)	Lesk Algorithm	Spanish	Knowledge Based	30000 entries	Not reported	Tagging becomes easier, all the words were known to headwords and need not to care about window size.	Noun and adjective cannot be disambiguated accurately.
Boon Peng Yap, Andrew Koh, Eng Siong Chng(2020)	Neural Network	English	Supervised Approach	Baseline dataset:226036 training instances and augmented dataset:	Outperformed other state-of-art systems	Demonstrated the generation of additional training dataset from WordNet example sentence. Performance exceeds	Does not select all the context-gloss pair

ISSN(Online):22031731
ISSN (Print): 2204-0595

	37596 training instances	the state-of-art systems

ISSN(Online):22031731
ISSN (Print): 2204-0595

2.2 *Indian Languages*

Manisha Gupta et al.[7] used LESK algorithm, a knowledge based algorithm to disambiguate the word senses using the Hindi WordNet, which consist of 63,800 unique words and 23,687 synsets. For disambiguation purpose, the definition of the ambiguous words along with its ten surrounding words were derived and enriched, wherein modified LESK approach was applied. Pooja Sharma and Nisheeth Joshi[23] offer a solution by conducting an experiment using the relevant lexeme from the given context and the association between lexicons, which further stated that by removing the equivocalness of words and incorporating the word knowledge from external knowledge resources, the performance of the system can be improved. Richard Laishram et al.[9] made a primary attempt on building Word Sense Disambiguation system using a supervised method based on decision tree in Manipuri language. Conventional positional and context based features were suggested to capture the correct sense of the ambiguous word, which uses classification and regression tree (CART) based algorithm to train the classifier. Alok Ranjan Pal et al.[18] explains how a Naïve Bayes probabilities model can be used as a baseline method for sense classification in Bangla language. In the process of disambiguation, the Bengali text corpus was first normalised, where the Naïve Bayes rules were applied to resolve the actual sense of the ambiguous word. Further, lemmatization and bootstrapping were applied for improving the overall performance. Aditi Salodkar et al.[25] summarised a report on desktop application developed that uses a supervised learning algorithm to disambiguate the ambiguous word. Tokenization, lemmatization and stemming techniques were used for filtering the data in a corpus. Later, the filtered data was compared with the dictionary file to disambiguate the ambiguous word. P. Iswarya and V Radha[12] introduced an unsupervised learning approach in which part-of-speech(POS) and clustering techniques were used to handle the homonymy and categorical types of ambiguous words. This approach allows automatic selection of optimal k-value in the k-cluster and construction of sense collocation dictionary. Here, for

ISSN(Online):22031731

ISSN (Print): 2204-0595

disambiguating the word senses, POS taggers were used and the clustering & sense collocation dictionary were used for enhancing the performance of the system. Comparatively with other WSD methods, this approach has better processing time and results in better performance. The experimental analysis shows that the accuracy of the system achieved 1.86% improvement over the existing method. Sruthi Sankar K P et al.[16] proposed an unsupervised learning algorithm that used context similarity to disambiguate the word senses. The system used a corpus which was collected from various Malayalam web documents. Collocations together with most co-occurring words formed the training examples. Seed sets and sense clusters, which were generated from the collected corpus were used for disambiguating the ambiguous word. Silpa stemmer and Datuk corpus played a vital role in building Word Sense Disambiguation system for Malayalam. Here, an accuracy of 72% was achieved for the test set of 100 sets. Alok Ranjan et al.[6] developed a system using supervised and unsupervised approaches using live contexts for finding the best meaning of words. It introduced a mixed methodology having "Modified Lesk" and "Bag-of-Words" approaches, where the result of both the approaches were ORed and ANDed to get the correct sense of the ambiguous word. Himdweep Walia et. al[21] used a supervised method for Word Sense Disambiguating in Gurmukhi language. The Euclidean Distance between the test sets were calculated to form two lists, from which the k-nearest neighbour was found out with respect to the given test vector. For testing the performance of the system, a 5 fold cross-validation technique was used in the test set samples. Athaiya et.al[22] used a very unique algorithm called Genetic Algorithm, which is based on Darwin's theory for disambiguating the Hindi polysemous words using Hindi WordNet. Here, the result of overlapping of context and sense bag was used as an input to the Genetic algorithm, wherein the fitness of the population generated(consisting of n chromosome) was tested and the best fitted gene(sense) in the population was used for crossover & mutation and offsprings generated was taken as a new population. Shashank N S and Dr.Jagadish S Kallimani[17] developed a Word Sense

ISSN(Online):22031731

ISSN (Print): 2204-0595

Disambiguation system for Kannada language using LESK algorithm. Shallow Parser was used for POS tagging and a semantic module was created using POS and glosses. Another module consisting of polysemous word, POS and its contextual words was prepared and the comparison was made between these two modules to find the highest rank overlap of the senses of the target word with other surrounding words and in this way the polysemous word was disambiguated. Mohammad Shibli Kaysar et al.[24] showed how FP-Growth algorithm outperforms the Apriori algorithm and this work doesn't depend on the lexical and syntactic data. Comparison between the two algorithms were shown computationally and the FP-Growth algorithm smooth performance was illustrated at a larger extend. Purabi Kalita et al.[14] implemented Walker algorithm along with modified version of Assamese WordNet to disambiguate the Assamese words. Modification of Assamese WordNet was carried out by adding a component called FEATURE, which defines the subject category or the word domain. In XML format the WordNet data were represented to ease the extraction work and implementation of Walker Algorithm. Satisfactory result was obtained as an outcome of the experiment. Sreelakshmi Gopal and Rosna P Haroon[15] performed an experiment which uses two corpora viz ambiguous corpus and sense corpus along with the Naïve Bayes algorithm to disambiguate the Malayali ambiguous words. Naïve Bayes classifier was used for finding the conditional probability of the different senses of a word, which later selects the highest probability as the actual sense of the ambiguous word with reference to the context it is referring to. Gauri Dhopavkar et al.[13] analysed how rule based algorithm can effectively be used to perform word sense disambiguation of Marathi language. The system achieved an accuracy of about 75% and it disambiguates nouns, adjectives and verbs at word level ambiguity. Arindam Roy et al.[8] developed a simple yet effective Nepali WSD algorithm that integrated overlap based, conceptual distance based and semantic based approaches to resolve the ambiguity problem in Nepali language. Over the Overlap based approach, this algorithm showed how conceptual distance based and semantic based

ISSN(Online):22031731

ISSN (Print): 2204-0595

approaches were used to shot up the performance of the algorithm.

ISSN(Online):22031731

ISSN (Print): 2204-0595

Table 2: Comparison of Indian languages word sense disambiguation systems

Authors & Year	Methodology	Language Used	Learning Model	Data Source and size	Accuracy	Advantages	Disadvantages
Manisha Gupta, Seema Yadav, Shraddha Sharma, Dr. Surendra Yadav (2013)	LESK algorithm	Hindi	Knowledge Based	WordNet& Size: Unique word 63,800 Synset 28,687	Not reported	Giving importance to all the words in the sentences. Window size of 10 was considered for disambiguation.	Dependent on the length of the gloss. Only noun, verbs and adjective were considered. Words that were far away from the target words were not so useful. Restricts comparison to dictionary meaning. Glosses of synsets can also be considered.
Arindam Roy, Sunita Sarkar, Bipul Syam Purkayashtha(2014)	Overlap based, conceptual distance & semantic graph based	Nepali	Knowledge Based	Nepali WordNet	Noun-68% Adjective-58%	Effective use of Nepali WordNet to extract the word's senses.	Limited to noun and adjective only.

ISSN(Online):22031731
ISSN (Print): 2204-0595

Gauri Dhopavkar, Manali Kshirsagar, Latesh Malik(2015)	Rule Based Methods	Marathi	Knowledge Based	Marathi WordNet and Marathi Corpus	75%	Rules designed are simple and work effectively	Works only with single sentence that can identify and resolve word level ambiguity only.
Purabi Kalita, Anup Kumar Barman(2015)	Walker algorithm	Assamese	Knowledge Based	Assamese WordNet(82 sentences with an ambiguous word)	Satisfactory	Taking larger window size increases performance tremendously	Deals with only noun and adjective phrases.
Shashank N S and Dr. Jagadish S Kallimani(2017)	LESK algorithm with POS tagger	Kannada	Knowledge Based	Small size Kannada corpus	Not reported	Simple yet effective	Small size corpus, performance reduced, some cases exist for not able to find the overlap of the glosses.
Pooja Sharma and Nisheeth Joshi (2019)	LESK algorithm	Hindi	Knowledge Based	Hindi WordNet& data size was not given.	71.40%	Extensible as Selectional restriction may be applied later to improve the performance.	Knowledge source like POS tagger was not used.

ISSN(Online):22031731
ISSN (Print): 2204-0595

Richard Laishram, Krishnendu Ghosh, Kishorjit Nongmeikapam, Sivaji Bandyopadhyay (2014)	Conventional positional and context based features, Decision Tree	Manipuri	Supervised Approach	Sangai Express & Size: Sentences-672 Words-13,167	71.75%	Used decision tree algorithm which work best for agglutinative language like Manipuri. Conventional positioning and context based features were used to capture the sense of the word.	Worked on limited resource and non-unicode font.
Alok Ranjan Pal, Diganta Saha, Niladri Sekhar Dash, Antara Pal(2015)	Naïve Bayes , lemmatization and bootstrapping	Bengali	Supervised Approach	Bangla WordNet& Size: 35,89,220 inflected and non-inflected word among which 199,245 words are distinct lexical units.	84%	Used of lemmatization and bootstrapping increased the performance of the system.	Further better algorithm can be applied to increase the performance of the system
Sreelakshmi Gopal and Rosna P Haroon(2016)	Naïve Bayes Algorithm	Malayalam	Supervised Approach	Malayalam Corpus(1 lakh words)	90%	Use of conditional probability and synonyms yield better results.	Focused only on noun.

ISSN(Online):22031731
ISSN (Print): 2204-0595

PublishedOnline12April 2021

Himdweep Walia, Ajay Rana, Vineet Kansal(2018)	K-NN Algorithm	Gurmukhi (Popularly known as Punjabi)	Supervised Approach	Punjabi Corpora which has sense-tagged 100 words	Accuracy with respect to each word with highest being 76.4% and lowest being 53.6%	Technique used was a very good approach.	Data size and ambiguous words considered were too small.
Anidhya Athaiya, Deepa Modi, Gunjan Pareek(2018)	Genetic Algorithm	Hindi	Supervised Approach	Hindi WordNet	Accuracy ranges from 85-90% for different domains	Hybrid approach can be implemented later to deal with various types of word and to improve the performance	Deals only with nouns.
Mohammad Shibli Kaysar, Md. Asif Bin Khaledy, Mahady Hasanz, and Mohammad Ibrahim Khan(2019)	FP-Growth Algorithm	Bengali	Supervised Approach	1000 Bengali sentences	Around 80%	FP-Growth algorithm works quicker than the Apriori Algorithm. Does not depend	Limited sentences where used for the work

ISSN(Online):22031731
ISSN (Print): 2204-0595

						on lexical or syntactic data.	
P. Iswarya, V Radha(2016)	POS and clustering techniques	Tamil	Unsupervised Approach	WordNet. Data size not mentioned.	1.86% improveme nt	POS tagger for Tamil and English were used. Clustering and collocation were used for improving the performance. Processing time was reduced.	Context word tagging and assigning weights for the collocation were not done to further improve the performance.
Sruthi Sankar K P, P C Reghu Raj, Jayan V(2017)	Context Similarity	Malayalam	Unsupervised Approach	Datuk Corpus. Definition- 1,06,000 Words- 83,000	72%	Simple yet effective.	Generation of seed sets and sense clusters did not cover all word senses. Corpus size is small.

ISSN(Online):22031731
ISSN (Print): 2204-0595

3. Evaluation Metrics

Machine learning involves teaching systems to teach themselves to solve problems and performance measures are used to evaluate how well a computer teaches itself or learnt. Depending on the type of problem an appropriate measure is to be used. The effectiveness of a developed system is reflected in the accurateness of the results it determines. Hence most of the proposed systems evaluate the performance in terms of accuracy. Accuracy determines the reality measurement considering the devoid of mistakes in an unbiased manner. Also, some proposed systems represent their performance in terms of Precision, Recall and F-Score[15, 14, 20].In some systems, F1-score was also seen using as an evaluation metric, which work best for uneven class distribution[5, 8]. Lastly, comparison of a new system with the existing systems was also done to show the effectiveness from the newly developed system[12].

4. Conclusion

Different techniques were applied depending on the forms of the resources available and its suitability with the nature of the language. For foreign languages, most of the WSD systems are based on supervised approach and the studies are limited to just nouns, verbs and adjectives. It is observed that most of the Indian languages uses knowledge based and supervised approaches for implementing WSD Rare unsupervised approach is used to implement WSD across all the languages. It has been noted that for Indian languages, the system that specifically use Lesk algorithm restricts its comparison to just the dictionary meanings of words and only nouns, verbs and adjectives were considered for disambiguation purposes. Performance analysis shows that supervised algorithm performs best among all the approaches. It is observed that there is a variation in the accuracy when the same technique is applied to different categories of languages. Lots of further study can be done to build up a WSD system in Indian regional languages like Manipuri Language(Meiteilon) that maximally overcomes the above mentioned drawbacks. Further deep and aggressive studies considering improvisation of performance, covering the untouched language or little explored language will prove a good area for research.

ISSN(Online):22031731

ISSN (Print): 2204-0595

5. References

[1] Lesk, M.(1986).Automatic Sense Disambiguation Using Machine Readable Dictionaries: How to Tell a Pine Cone from an Ice Cream Cone. Proceedings of SIGDOC, 24-26.

[2] Yarowsky, D. (1992).Word-sense disambiguation using statistical models of Roget's categories trained on large corpora. Proceedings of the 14th International Conference on Computational Linguistics(COLING, Nantes, France) 454-460. doi:10.3115/992133.992140.

[3] C.Leacock, G.Towell and E.Voorhees(1993).Corpus-Based Statistical Sense Resolution. *ARPA* Workshop on Human Language Technology, 260-265. doi:10.3115/1075671.1075730.

[4] Farag Ahmed, Andreas Nurnberger(2008).Arabic/English Word Translation disambiguation using Parallel Corpora and Matching Schemes.12th EAMT conference, Hemburg, Germany, 6-11.

[5] Nyein Thwet Thwet Aung, Khin Mar Soe, Ni Lar Thein(2011).A Word Sense Disambiguation System Using Naïve Bayesian Algorithm For Myanmar Language,*International Journal of Scientific & Engineering Research Volume 2, Issue 9, ISSN 2229-5518, 1-7*.

[6] Alok Ranjan Pal, Anirban Kundu, Abhay Singh, Raj Shekhar, Kunalb Sinha(2013).A hybrid approach to word sense disambiguation combining supervised and unsupervised learning. *International Journal of Artificial Intelligence & Applications (IJAIA), Vol. 4, No. 4, 89-101*.

[7] Manisha Gupta, Seema Yadav, Shraddha Sharma, Dr. Surendra Yadav*(2013)*.Word Sense Disambiguation Using Hindi WordNet and Lesk Approach. *IPASJ International Journal of Computer Science (IIJCS) Volume 1, Issue 6, ISSN 2321-5992,12-17*.

[8] Arindam Roy, Sunita Sarkar, Bipul Syam Purkayashtha(2014).Knowledge Based Approaches To Nepali Word Sense Disambiguation.*International Journal of Natural Language Computing(IJNLC) Vol.3 No.3, 51-63*. doi:10.5121/ijnlc.2014.3305.

ISSN(Online):22031731

ISSN (Print): 2204-0595

[9] Richard Laishram, Krishnendu Ghosh, Kishorjit Nongmeikapam and Sivaji Bandyopadhyay(2014).A decision tree based word sense disambiguation system in Manipuri language, Advanced Computing: *An International Journal (ACIJ), Vol.5, No.4, 17-22*. doi:10.5121 /acij.2014.5403.

[10] Purabi Kalita, Anup Kumar Barman(2015).Word Sense Disambiguation: A Survey.*International Journal of Engineering and Computer Science ISSN: 2319-7242 Volume 4 11743-11748*.

[11] Alok Ranjan Pal, Diganta Saha(2015).Word sense disambiguation: a survey.*International Journal of Control Theory and Computer Modeling (IJCTCM) Vol.5, No.3, 1-16*. doi:10.5121 /ijctcm.2015.5301.

[12] Sruthi Sankar K P, P C Reghu Raj, JayanV(2016).Unsupervised Approach to Word Sense Disambiguation in Malayalam. *Procedia Technology 24 1507-1513*.doi:10.1016 /j.protcy.2016.05.106.

[13] Gauri Dhopavkar, Manali Kshirsagar, Latesh Malik(2015).Application of Rule Based Approach to Word Sense Disambiguation of Marathi Language Text. IEEE Sponsored 2nd International Conference on Innovations in Information Embedded and Communication systems(ICIIECS)1-5.doi:10.1109/ICIIECS.2015.7193146.

[14] P. Kalita and A. K. Barman(2015), Implementation of Walker algorithm in Word Sense Disambiguation for Assamese language.International Symposium on Advanced Computing and Communication (ISACC), Silchar, 136-140.doi: 10.1109/ISACC.2015.7377330.

[15] Sreelakshmi and Rosna P Haroon(2016).Malayalam Word Sense Disambiguation Using Naïve Bayes Classifier. International Conference On Advances In Human Machine Interaction (HMI), 1503-1507.doi:10.1016 /j.protcy.2016.05.106.

[16] P. Iswarya, V Radha(2017).Word Sense Disambiguation for Tamil Language using part-of-speech and clustering technique.*Journal of Engineering Science and Technology, Volume 12, No. 9, 2504-2512*.

ISSN(Online):22031731

ISSN (Print): 2204-0595

[17] Shashank N S, Dr. Jagadish S Kallimani(2017).Word Sense Disambiguation of polysemy words in Kannada language.*International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, Udupi, 641-644.doi: 10.1109/ICACCI.2017.8125913.

[18] Alok Ranjan Pal, Diganta Saha, Niladri Sekhar Dash, Antara Pal(2018).Word Sense Disambiguation in Bangla Language Using Supervised Methodology with Necessary Modifications.*Journal of The Indian Institution of Engineers, India Series. B 99 519-526*.doi:10.1007/s40031-018-0337-5.

[19] Tang Shancheng, Ma Fuyu, Chen Xiongxiong, Zhang Puyue(2018).Deep Chinese Word Sense Disambiguation Method Based on Sequence to Sequence, International Conference on Sensor Networks and Signal Processing (SNSP), 498-503. doi:10.1109/SNSP.2018.00099.

[20] Myung Yun Kang, Tae Hong Min, Jae Sung Lee(2018).Sense Space For Word Sense Disambiguation.IEEE International Conference on Big Data and Smart Computing (BigComp), Shanghai, 669-672. doi:10.1109/BigComp.2018.00122.

[21] H.Walia, A. Rana and V. Kansal(2018).A Supervised Approach on Gurmukhi Word Sense Disambiguation Using K-NN Method. 2018 8th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida (2018) 743-746, doi:10.1109/CONFLUENCE.2018.8442616.

[22] A. Athaiya, D. Modi and G. Pareek(2018).A Genetic Algorithm Based Approach for Hindi Word Sense Disambiguation. 3rd International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 11-14. doi:10.1109/CESYS.2018.8724117.

[23] Pooja Sharma and Nisheeth Joshi(2019).Knowledge-Based Method for Word Sense Disambiguation by Using Hindi WordNet. *International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-3, 3985-3989.*

[24] M. S. Kaysar, M. A. B. Khaled, M. Hasan and M. I. Khan(2019).Word Sense Disambiguation of Bengali Words using FP-Growth Algorithm. International Conference on Electrical, Computer and Communication Engineering (ECCE), Cox'sBazar, Bangladesh,1-5. doi:10.1109/ECACE.2019.8679405.

ISSN(Online):22031731

ISSN (Print): 2204-0595

[25] Aditi Salodkar, Mrunali Nagwanshi, Ms Bhavana Gopchandani(2019).Supervised Approach to Word Sense Disambiguation.*IOSR Journal of Engineering (IOSRJEN) ISSN(e): 2250-3021, ISSN(p) 2278-8719 Vol. 09,||S(IX) , 80-85.*

[26] Saeed, Ali & Nawab, Rao & Stevenson, R. & Rayson, Paul(2019).A Sense Annotated Corpus for All-Words Urdu Word Sense Disambiguation.*ACM Transactions on Asian and Low-Resource Language Information Processing. Volume 18. (2019) (40:1-40:14)*.doi:10.1145/3314940.

[27] Boon Peng Yap, Andrew Koh, Eng Siong Chng(2020). Adapting BERT for Word Sense Disambiguation with Gloss Selection Objective and Example Sentences, *Findings of the Association for Computational Linguistic MNLP 2020, 41-46, doi:10.18653/v1/2020.findings-emnlp.4*

[28] Kavi Mahesh, Sergei Nirenburg(1997).Knowledge-Based Systems for Natural Language Processing, CRC Press Handbook of Computer Science and Engineering 637-653.

[29] Grigori Sidorov and Alexander Gelbukh(2001), Word Sense Disambiguation in a Spanish Explanatory Dictionary(pp. 398-402).

[30] Daniel Jurafsky, James H Martin(2013).Speech and Language Processing (pp. 22-24).

[31] Tanveer Siddiqui, U. S Tiwary(2018).Natural Language Processing and Information Retrieval (pp. 156-173).

ISSN(Online):22031731

ISSN (Print): 2204-0595