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# Using Machine Learning Algorithms for Word Sense Disambiguation: A Brief Survey

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***Abstract---* In the entire vocabulary of Human language, numerous words have more than one distinct meaning and thus present a contextual ambiguity which is a worth of one of the many language based problems needs procedure based resolution. Approaches to WSD are often classified according to the main source of knowledge used in sense differentiation. Methods that rely primarily on dictionaries, thesauri, and lexical knowledge bases, without using any corpus evidence, are termed dictionary-based or knowledge based. Natural language tends to be ambiguous. Comparing and evaluating different WSD systems is extremely difficult, because of the different test sets, sense inventories, and knowledge resources adopted. In this research we shall address the problem of Word Sense Disambiguation by a combination of learning algorithms. The study is aimed at comparing the performance of using machine learning algorithms for Word Sense Disambiguation (WSD).**

***Index Terms*—Context, Machine Learning, Word Net, Word Sense Disambiguation.**

## I. INTRODUCTION

Words can have more than one distinct meaning. Word sense ambiguity is a central problem for many established Human Language Technology applications (e.g., machine translation, information extraction, question answering, information retrieval, text classification, and text summarization) .This is also the case for associated subtasks (e.g., reference resolution, acquisition of sub- categorization patterns, parsing, and, obviously, semantic interpretation). For this reason, many international research groups are working on WSD, using a wide range of approaches. However, to date, no large-scale, broad-coverage, accurate WSD
system has been built. With current state-of-the-art accuracy in the range 60–70%, WSD is one of the most important open problems in NLP. In natural language processing (NLP), word sense disambiguation (WSD) is defined as the task of assigning the appropriate meaning (sense) to a given word in a text or discourse. As an example, consider the following three sentences:

1. Many cruise missiles have fallen on Baghdad.
2. Music sales will fall by up to 15% this year.
3. U.S. officials expected Basra to fall early.

Any system that tries to determine the meanings of the three sentences will need to represent somehow three different senses for the verb fall. In the first sentence, the missiles have been launched on Baghdad. In the second sentence, sales will decrease, and in the third the city will surrender early. WordNet 2.0 contains thirty-two different senses for the verb fall as well as twelve different senses for the noun fall. Note also that the first and third sentence belong to the same, military domain, but use the verb fall with two different meanings. Thus, a WSD system must be able to assign the correct sense of a given word, in these examples, fall, depending on the context in which the word occurs. Providing innovative technology to solve this problem will be one of the main challenges in language engineering to access advanced knowledge technology systems.

## II. MOTIVATION

WSD is one of the most important open problems in the Natural Language Processing (NLP) field. Despite the wide range of approaches investigated and the large effort devoted to tackle this problem, it is a fact that to date no large scale broad coverage and highly accurate word sense disambiguation system has been built.

WSD is:

- Accessible to anyone with an interest in NLP.
- Persuade you to work on word sense disambiguation.
- It's an interesting problem.
- Lots of good work already done, still more to do.
- There is infrastructure to help you get started.
  Persuade you to use word sense disambiguation in your text applications. Machine learning is a branch of artificial intelligence which studies mechanisms to mimic the ability of humans to learn. Machine learning strives to get the computer to learn tasks such as discriminating between objects, segregating similar objects from dissimilar ones and learning from experience.

Various Machine Learning (ML) approaches have been demonstrated to produce relatively successful Word Sense Disambiguation (WSD) systems. There are still unexplained differences among the performance measurements of different algorithms, hence it is warranted to deepen the investigation into which algorithm has the right 'bias' for this task. These tasks are formally known as supervised, unsupervised and reinforcement learning in the machine learning parlance. In supervised learning, the system is presented with a set of data which is labeled into various categories and involves learning a function which maps the data to the categories.

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This function is then used to map an unseen instance of the data to its corresponding category. Unsupervised learning on the other hand works on unlabelled data and involves grouping this data based on its characteristics, i.e., infer potential categories from unlabelled data. Reinforcement learning is a system which learns an effective way of doing a task from the experience of doing the task and feedback from the environment on the outcome.

## III. BASIC APPROACHES TO WSD

Approaches to WSD are often classified according to the main source of knowledge used in sense differentiation. Methods that rely primarily on dictionaries, thesauri, and lexical knowledge bases, without using any corpus evidence, are termed dictionary-based or knowledge-based. Methods that eschew (almost) completely external information and work directly from raw unannotated corpora are termed unsupervised methods (adopting terminology from machine learning). Included in this category are methods that use word-aligned corpora to gather cross-linguistic evidence for sense discrimination. Finally, supervised and semi-supervised WSD make use of annotated corpora to train from, or as seed data in a bootstrapping process. Almost every approach to supervised learning has now been applied to WSD, including aggregative and discriminative algorithms and associated techniques such as feature selection, parameter optimization, and ensemble learning. Unsupervised learning methods have the potential to overcome the new knowledge acquisition bottleneck (manual sense-tagging) and have achieved good results. These methods are able to induce word senses from training text by clustering word occurrences and then classifying new occurrences into the induced clusters/senses and the Web. The objective of clustering is to take a set of instances that incorporate ideas from both. The algorithm acts as a search strategy that dictates how to proceed through the instances. The actual choice of which clusters to split or merge is decided by a criteria function represented as either a similarity matrix or context vectors and cluster together instances that are more like each other than they are to the instances that belong to other clusters. Clustering algorithms are classified into three main categories, hierarchical, partitional, and hybrid methods. Frequently, research in machine learning (ML) of natural language takes the form of comparative ML experiments, either to investigate the role of different information sources in learning a task, or to investigate whether the bias of some learning algorithm fits the properties of natural language processing tasks better than alternative learning algorithms.

### A. Knowledge based WSD

Work on WSD reached a turning point when large-scale lexical resources such as dictionaries, thesauri, and corpora became widely available. The work done earlier on WSD was theoretically interesting but practical only in extremely limited domains. Many researchers have used machine-readable dictionaries (MRDs) as a structured source of lexical knowledge to deal with WSD. These approaches, by exploiting the knowledge contained in the dictionaries, mainly seek to avoid the need for large amounts of training material. Most of them can be located in MRDs, and include part of speech, semantic word associations, syntactic cues, selection preferences, and frequency of senses, among others.

### B. AI-Based Approaches

In the 1960's and 1970's, there was a lot of growth in AI research, and consequently, most of the methods that tackled WSD during this period used AI approaches. These systems relied on a wealth of both language and world knowledge, to determine the meaning of a word in context. Majority of these systems were grounded in language understanding theories and attempted to model deep knowledge of linguistic theory, especially in the area of syntax and semantics. Consequently, these systems tried to produce a semantic representation for an entire sentence in an attempt to capture its meaning, and from which word ambiguity problems would be solved. However, due to the pervasive nature of both structural and lexical ambiguity in natural language, a sentence can have several possible interpretations. In order to determine the correct interpretation, these systems adopted a strategy of combining syntactic, semantic and world knowledge and enforcement of constraint satisfaction, to produce syntactic and semantic representation of an entire sentence.
The scheme adopted for world knowledge representation as well as the process used to integrate syntactic, semantic and world knowledge, serve as the main distinguishing factors amongst these systems. \

### C. Dictionary-based Approaches

In the 1980's, there was a surge in computing machinery and a corresponding increase in the availability of electronic linguistic resources, popularly known as MRDs, as most publishers started to produce electronic versions of their products. This precipitated the shift from AI-based systems to the emergence of dictionary-based approaches. MRDs presented a viable solution to the knowledge acquisition bottleneck facing AI-based approaches since they provided comprehensive lexical coverage of natural language. This meant that systems no longer suffered vocabulary limitations, spurring interest in language processing of unrestricted text. One of the first attempts to utilize these resources for WSD was Lesk (1986). His work was based on the observation that the coherence of a sentence is dependent on the cohesion of the words in it, meaning that the choice of one sense in a text is a function of the senses of the words close to it. He devised an algorithm that chooses the correct sense of a word by calculating the word overlap between the context sentence and the dictionary definition of the word in question. Lesk's work influenced most of the subsequent work in knowledge-based WSD Other machine readable resources that have been used in knowledge-based WSD include thesauri such as *ROGET's* thesaurus that has been used severally by different researchers including Masterman (1957)and Yarowsky (1992), and lexicons. A major hindrance to dictionary-based techniques such as those based on Lesk's idea is their crucial dependence on similarity in wording between a text and the MRD. Dictionary definitions are usually too short to generate an overlap from which an adequate set of indicators can be obtained.

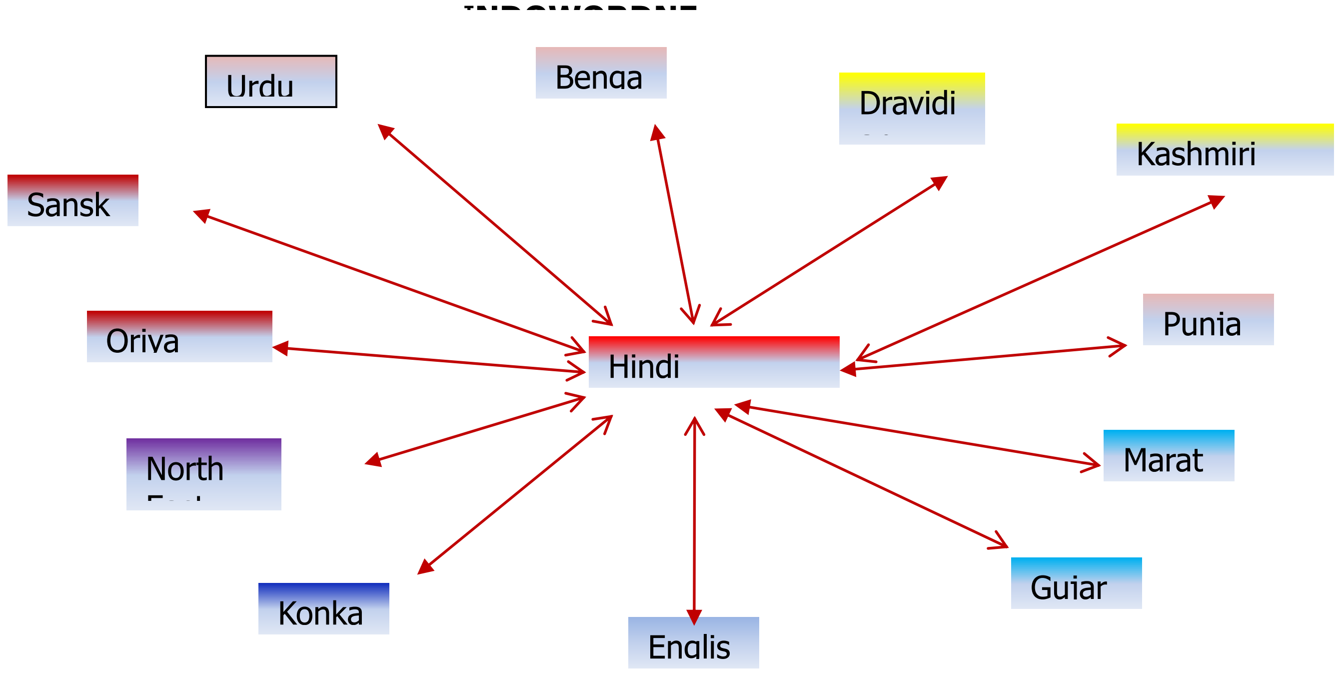


**Fig. I Wordnet for Different languages**

Also, despite their well-structured information and increased vocabulary coverage, pre-coded knowledge sources suffer from limitations in domain-specific coverage and in coping with the introduction of new words.

D. Corpus based WSD

WSD is one of the most important open problems in the Natural Language Processing. In the last fifteen years, empirical and statistical approaches have had a significantly increased impact on NLP. Of increasing interest are algorithms and techniques that come from the machine-learning (ML) community since these have been applied to a large variety of NLP tasks with remarkable success. The types of NLP problems initially addressed by statistical and machine-learning techniques are those of language ambiguity resolution, in which the correct interpretation should be selected from among a set of alternatives in a particular context (e.g., word-choice selection in speech recognition or machine translation, part-of-speech tagging, word-sense disambiguation, co-reference resolution, etc.). These techniques are particularly adequate for NLP because they can be regarded as classification problems, which have been studied extensively in the ML community. Regarding automatic WSD, one of the most successful approaches in the last ten years is supervised learning. Generally, supervised systems show better results in comparison to unsupervised ones, a conclusion that is based on experimental work and international competitions. This approach uses semantically annotated corpora to train machine learning (ML) algorithms to decide which word sense to choose in which contexts. The words in such annotated corpora are tagged manually using semantic classes taken from a particular lexical semantic resource (most commonly WordNet).

## IV. LEARNING ALGORITHMS

Machine learning is the subfield of artificial intelligence that is concerned with the design and development of algorithms that allow computers to improve their performance over time based on data, such as from sensor data or databases. A major focus of machine learning research is to automatically produce (induce) models, such as rules and patterns, from data. Hence, machine learning is closely related to fields such as data mining, statistics, inductive reasoning, pattern recognition, and theoretical computer science. Machine learning usually refers to the changes in systems that perform tasks associated with artificial intelligence (AI). Such tasks involve recognition, diagnosis, planning, robot control, prediction etc.

Depending on the feedback we can distinguish between the following forms of learning: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the learning algorithms receive inputs and the correct outputs, and searches for a function which approximates the unknown target function. In unsupervised learning, the agent receives only input data and uses an objective function (such as a distance function) to extract clusters in the input data or particular features which are useful for describing the data. In reinforcement learning, the agent receives an input and an evaluation (reward) of the action selected by the agent, and the learning algorithm has to learn a policy which maps inputs to actions resulting in the best performance.

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### *A. Analytical Perspective*

The computational analysis of machine learning algorithms and their performance is a branch of theoretical computer science known as computational learning theory. Because training sets are finite and the future is uncertain, learning theory usually does not yield absolute guarantees of the performance of algorithms. Instead, probabilistic bounds on the performance are quite common. Interpretation of WSD as a classification task: given a possibly ambiguous word and its context as input features, a classifier assigns the contextually correct class (sense) to it. Information about the local context and information about keywords in the context Parameter optimization for machine-learned WSD. The distinguishing feature of Memory-Based Learning (MBL) in contrast with minimal-description-length-driven or eager ML algorithms (e.g. decision trees and decision lists) is that MBL keeps all training data in memory, and only abstracts at classification time by extrapolating a class from the most similar item(s) in memory to the new test item. This strategy is often referred to as lazy learning.

## V. RELATED WORK

Since the 1950s, many approaches have been proposed for assigning senses to words in context, although early attempts only served as models for toy systems. Currently, there are two main methodological approaches in this area: knowledge-based and corpus-based methods. Knowledge-based methods use external knowledge resources, which define explicit sense distinctions for assigning the correct sense of a word in context. Corpus-based methods use machine-learning techniques to induce models of word usages from large collections of text examples. Both knowledge-based and corpus-based methods present different benefits and drawbacks. Common problems faced in natural language processing are data sparseness and inconsistency in vocabulary. When the number of features increases, the sparseness is unavoidable. Smoothing is really required to overcome the above problem for improving the performance.

A. Azzini, C. da Costa Pereira, M. Dragoni, and A. G. B. Tettamanz[1] proposed a supervised approach to word sense disambiguation based on neural networks combined with evolutionary algorithms. Large tagged datasets for every sense of a polysemous word are considered, and used to evolve an optimized neural network that correctly disambiguates the sense of the given word considering the context in which it occurs. The viability of the approach has been demonstrated through experiments carried out on a representative set of polysemous words.

Rion Snow Sushant Prakash, Daniel Jurafsky, Andrew Y. Ng[2] formulated sense merging as a supervised learning problem, exploiting human-labeled sense clustering as training data. They train a discriminative classifier over a wide variety of features derived from WordNet structure, corpus-based evidence, and evidence from other lexical resources. Their learned similarity measure outperforms previously proposed automatic methods for sense clustering on the task of predicting human sense merging judgments, yielding an absolute F-score improvement of 4.1% on nouns, 13.6% on verbs, and 4.0% on adjectives. Finally, they propose a model for clustering sense taxonomies using the outputs of our classifier, and they make automatically sense-clustered Word Nets of various sense granularities.

Yoong Keok Lee and Hwee Tou Ng and Tee Kiah Chia[3] participated in the SENSEVAL-3 English lexical sample task and multilingual lexical sample task. They adopted a supervised learning approach with Support Vector Machines, using only the official training data provided. No other external resources were used. The knowledge sources used were part of speech of neighboring words, single words in the surrounding context, local collocations, and syntactic relations.

Gerard Escudero, Llu´ıs M`arquez and German Rigau[6] described an experimental comparison between two standard supervised learning methods, namely Naïve Bayes and Exemplar–based classification, on the Word Sense Disambiguation (WSD) problem. The aim of the work is twofold. Firstly, it attempts to contribute to clarify some confusing information about the comparison between both methods appearing in the related literature. In doing so, several directions have been explored, including: testing several modifications of the basic learning algorithms and varying the feature space.

Dinakar Jayarajan [9] presented a new representation for documents based on lexical chains. This representation addresses both the problems achieves a significant reduction in the dimensionality and captures some of the semantics present in the data. They represent an improved algorithm to compute lexical chains and generate feature vectors using these chains.

Yee Seng Chan and Hwee Tou Ng, David Chiang[10] presented conflicting evidence on whether word sense disambiguation WSD) systems can help to improve the performance of statistical machine translation (MT) systems. In this paper, we successfully integrate a state-of-the-art WSD system into a state-of-the-art hierarchical phrase-based MT system. They show for the first time that integrating a WSD system improves the performance of a state-of-the- art statistical MT system on an actual translation task. Furthermore, the improvement is statistically significant.

Andres Montoyo, Armando Su´arez, German Rigau, Manuel Palomar [11] concentrated on the resolution of the lexical ambiguity that arises when a given word has several different meanings. This specific task is commonly referred to as word sense disambiguation (WSD). The task of WSD consists of assigning the correct sense to words using an electronic dictionary as the source of word definitions. They present two WSD methods based on two main methodological approaches in this research area: a knowledge-based method and a corpus-based method..

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S.K.Jayanthi and S. Prema[13] prompted a number of investigations into the relationship between information retrieval (IR) and lexical ambiguity in web mining. The work is such an exploration. Starting with a review of previous research that attempted to improve the representation of documents in IR systems, this research is reassessed in the light of word sense ambiguity. The results of these experiments lead to the conclusions that query size plays an important role in the relationship between ambiguity and IR in web content mining. Word Sense Disambiguation (WSD) is tested and analyzed for some of the existing Information Retrieval engines like Google, Clusty, yahoo, Altavista and msn search using Brill's tagger, and the derived results for the IR systems recommends how to accommodate the sense information in the selected document collection.

Antonio J Jimeno-Yepes[14], Alan R Aronson found that the graph-based approach, using the structure of the Meta thesaurus network to estimate the relevance of the Meta thesaurus concepts, does not perform well compared to the first two methods. In addition, the combination of methods improves the performance over the individual approaches. On the other hand, the performance is still below statistical learning trained on manually produced data and below the maximum frequency sense baseline.

P.Tamilselvi, S.K.Srivatsa[15] implemented disambiguation system with three different set of features with three different distance measuring functions combined with three different classifiers for word sense disambiguation. Using Neural Networks with enormous number of features, accuracy measured from 33.93% to 97.40% for words with more than two senses and 75% of accuracy for words with two senses.

M. Nameh, S.M. Fakhrahmad, M. Zolghadri Jahromi [17] presented a supervised learning method for WSD, which is based on Cosine Similarity. As the first step, they extract two sets of features; the set of words that have occurred frequently in the text and the set of words surrounding the ambiguous word. Then they presented the results of evaluating the proposed schemes and illustrate the effect of weighting strategies proposed.

A.R.Rezapour, S. M. Fakhrahmad and M. H. Sadreddini[18] presented a supervised learning method for WSD, which is based on K-Nearest Neighbor algorithm. They extracted two sets of features; the set of words that have occurred frequently in the text and the set of words surrounding the ambiguous word. In order to improve the classification accuracy, they proposed a feature weighting strategy. The results are encouraging comparing to state of the art.

Arindam Chatterjee, Salil Joshii, Pushpak Bhattacharyya, Diptesh Kanojia and Akhlesh Meena [19] shows that in almost all disambiguation algorithms, the sense distribution parameter $P(S/W)$, where $P$ is the probability of the sense of a word $W$ being $S$, plays the deciding role. The widely reported accuracy figure of around 60% for all-words-domain-independent WSD is contributed to mainly by $P(S/W)$, as one ablation test after another re-veals. Their experience of working with hu-man annotators who mark with WordNet sense ids, general and domain specific corpora brings to light the interesting fact that producing sense ids without looking at the context is a heavy cognitive load. Sense annotators do form hypothesis in their minds about the possible sense of a word, but then look at the context for clues to accept or reject the hypothesis. Such clues are minimal, just one or two words, but are critical nonetheless. Without these clues the annotator is left in an indecisive state as to whether or not to put down the first sense coming to his mind.

## VI. RESEARCH ISSUES

Word Sense Disambiguation is very challenging field of research. There are many researches challenges that have to solve out:

* Different dictionaries and thesauruses provide different division of words into sense. So it is difficult to choose a dictionary for the purpose.
* Sometimes the common sense is needed to disambiguate the meaning of words
  e.g.
  { Sita and Geeta are sisters - (they are sister to each other)
  { Sita and Geeta are mothers - (each is independently mother)
  It is very difficult to prepare a system which can understand such common sense.
* Word meaning is infinitely variable and context sensitive. It does not divide up easily into distinct or discrete sub meanings.
* To date there is no large scale, broad coverage, much efficient WSD system exists. Accuracy achieved by previous research is up to 60
* In last few years Word Net has been widely adopted as the sense inventory of choice in WSD, however sense inventory is too fine grained for many tasks and this makes the disambiguation very difficult.
* The comparative results of machine learning show that even most sophisticated methods have not been able to make a qualitative jump and get close to the solution of problem.
* The knowledge acquisition bottleneck is perhaps the major impediment to solving the WSD problem
* Word meaning does not divide up to discrete senses.

## VII. PROPOSED WORK

* To study the machine learning algorithms using clustering for WSD.
* To develop or optimize an algorithm which will perform best for classifying words in WSD.
* More specifically, to use learning algorithms for Word Sense Disambiguation.
* To optimize the performance of machine learning algorithms already developed for WSD, and
* To develop new algorithm which combines the best features of other

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## VIII. CONCLUSIONS

The above literature survey concludes that supervised learning algorithms are mostly used for removing disambiguation from the words. In some research they combined two algorithms to optimize the performance. In some research papers they have performed clustering also to improve the performance. But still there is much more to do to improve the performance of machine learning algorithms for word sense disambiguation. Using machine learning algorithm for some specific data of words reaches 86.74 % accuracy Knowledge-based approaches achieve good performance, even though below standard WSD baselines. We have presented several approaches and analyzed their performance and drawbacks. Finally, we have proposed several directions for further research which might improve performance, and some of these could be used to improve the WSD.

## REFERENCES

[1] A. Azzini, C. da Costa Pereira, M. Dragoni, and A. G. B. Tettamanzi," Evolving Neural Networks for Word Sense Disambiguation", Eighth International Conference on Hybrid Intelligent Systems, 2008.
[2] Rion Snow Sushant Prakash, Daniel Jurafsky, Andrew Y. Ng ,"Learning to Merge Word Senses", Computer Science Department Stanford University,2007.
**[3]** Yoong Keok Lee and Hwee Tou Ng and Tee Kiah Chia," Supervised Word Sense Disambiguation with Support Vector Machines and Multiple Knowledge Sources", Department of Computer Science National University of Singapore, 2004.
[4] Dan Klein, Kristina Toutanova, H. Tolga Ilhan, Sepandar D. Kamvar and Christopher D. Manning," Combining Heterogeneous Classifiers forWord-Sense Disambiguation", Computer Science Department Stanford University, 2002.
[5] T. Theodosiou1, N. Darzentas,L. Angelis1 and C. A. Ouzounis," PuReD-MCL: a graph-based PubMed document clustering methodology", Vol. 24 no. 17, 2008.
[6] Gerard Escudero, Llu´ıs M`arquez and German Rigau," Naive Bayes and Exemplar-Based approaches to Word Sense Disambiguation Revisited", Proceedings of th 14th European Conference, 2000.
[7] David Martinez Iraolak," Supervised Word Sense Disambiguation: Facing Current Challenges", Informatikan Doktore titulua eskuratzeko aurkezturiko Tesia Donostia, 2004.
[8] Rada Mihalcea," Word Sense Disambiguation", the 18th European Summer School in Logic, Language and Information 31 July - 11 August, 2006.
[9] Dinakar Jayarajan," Using Semantics in Document Representation: A Lexical Chain Approach ", Department of Computer Science and Engineering Indian Institute of technology Madras, June 2009.
[10] Yee Seng Chan and Hwee Tou Ng, David Chiang,"Word Sense Disambiguation Improves Statistical Machine Translation", Department of Computer Science National University of Singapore, 2007.
[11] Andres Montoyo, Armando Su´arez, German Rigau,"Combining Knowledge- and Corpus-based Word-Sense-Disambiguation Methods", Journal of Artificial Intelligence Research ,2005.
[12] Hwee Tou Ng," Exemplar-Based Word Sense Disambiguation: Some Recent Improvements", DSO National Laboratories 20 Science Park Drive Singapore, 1996.
[13] S.K.Jayanthi and S. Prema," Word Sense Disambiguation in Web Content Mining Using Brill's Tagger Technique", International Journal of Computer and Electrical Engineering, Vol. 3, June 2011.
[14] Antonio J Jimeno-Yepes, Alan R Aronson, "Knowledge-based biomedical word sense disambiguation: comparison of approaches", Jimeno-Yepes and Aronson BMC Bioinformatics 2010.
[15] P.Tamilselvi , S.K.Srivatsa ," Case Based Word Sense Disambiguation Using Optimal Features", IPCSIT vol.16, IACSIT Press, Singapore,2011.
[16] David Martinez, Oier Lopez de Lacalle, Eneko Agirre," On the Use of Automatically Acquired Examples for All-Nouns Word Sense Disambiguation", University of the Basque Country 20018, Journal of Artificial Intelligence Research 33,79-107,2008.
[17] M. Nameh, S.M. Fakhrahmad, M. Zolghadri Jahromi," A New Approach to Word Sense Disambiguation Based on Context Similarity", Proceedings of the World Congress on Engineering 2011 Vol I, July 6 - 8, 2011.
[18] A. R. Rezapour, S. M. Fakhrahmad and M. H. Sadreddini ," Applying Weighted KNN to Word Sense Disambiguation", Proceedings of the World Congress on Engineering 2011 Vol III WCE 2011, July 6 - 8, 2011.
[19] Arindam Chatterjee, Salil Joshii, Pushpak Bhattacharyya, Diptesh Kanojia and Akhlesh Meena, "A Study of the Sense Annotation Process: Man v/s Machine", International Conference on Global Wordnets , Matsue, Japan,, Jan, 2012.

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