Wiki sense bag creation using multilingual word sense disambiguation

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ABSTRACT

Performance of word sense disambiguation (WSD) is one of the challenging tasks in the area of natural language processing (NLP). Generation of sense annotated corpus for multilingual word sense disambiguation is out of reach for most languages even if resources are available. In this paper we propose an unsupervised method using word and sense embedding or improving the performance of these systems using untagged. Corpora and create two bags namely ontological bag and wiki sense bag to generate the senses with highest similarity. Wiki sense bag provides external knowledge to the system required to boost the disambiguation accuracy. We explore Word2Vec model to generate the sense

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1. INTRODUCTION

Increasing demands by the user to access text data in various languages opens up the doors ofmultilingual natural language processing (NLP) and word sense disambiguation (WSD) has proved to be a key step in performance improvement of many NLP systems.The accuracy of word sense disambiguation systems is far from being satisfactory and multilingual WSD has not achieved satisfactory results due to insufficient resource availability [1]. The availability of multilingual dictionaries has enhanced sense disambiguation using multilingual content which depicts the need for multilingual WSD [2]. It also opens up a different way ofapproaching multilingual WSD by making use of BabelNet, a wide ontological structure exploring semantic knowledge. This is the motivation for working on multilingual word sense disambiguation by exploring the available resources.

Relying only on multilingual knowledge-based system may hamper the growth of WSD systems and though multilingual dictionaries provide wide coverage exploring the interconnected ontology structure, various issues still remain to be seen such as proper nouns are not part of the dictionary and correlation between most frequent words and rare contextual words lack dictionary coverage. External knowledge in terms of raw text is needed which is provided using word and sense embedding [3]. Our research makes use of word and sense embeddings to create a semantic word cloud by designing a wiki bag in addition to the sense bag. Wiki bag is designed using Wikipedia as it is the largest encyclopedia which covers most of the database essential for disambiguation. The paper is organized being as: section 2 presents the literature review which highlights the research work of various researchers, section 3 describes the proposed methodology used which includes working with multilingual input, multilingual dictionary BabelNet and the working of WSD engine. Section 4 focuses on results and discussions and section 5 sums up with conclusion.

2. LITERATURE REVIEW

Word2Vec model [4]–[13] provides an efficient tool for estimating vector model using the corpus. A sense bag was created [14] making use of dictionary resources such as synset members, example sentences, hypernymy and hyponymy subsets. A survey was presented on WSD [15] highlighting the motivation for solving the ambiguity of words and providing description of the task. The concept of Word sense disambiguation in multilingual setting [16] introduces by making use of large encyclopedic ontological network BabelNet. Precision achieved was 54.3% when tested on SemEval 2010 dataset. In 2013, Aziz and Specia [17] discusses expressing meanings in terms of paraphrases.

The role of WSD for multilingual scenario of NLP text was surveyed using English-Spanish languages [18]. WSD in multilingual machine translation (MT) is based on the concept that resource full language helps a resource low language by projecting parameters like sense distributions, and corpus co-occurrences [19]. The accuracy observed was 75% for three languages with domain specific corpus. WSD in NLP applications is also discussed [20]. Cross-lingual WSD systems was discussed [21], and evaluated on SemEval 2010 task. Machine translation is one of the important applications of WSD and is discussed [22], [23]. A survey of text classification of Kurdish language is beautifully presented [24]–[27] where they applied stemmer algorithm to find the stem to perform classification. WSD network approach, sentiment analysis and survey is explored [28]–[31]. It is observed that not much work is reported on WSD in multilingual setting to the best of our knowledge and it needs to be explored using various state of the art WSD methods.

3. PROPOSED METHODOLOGY

The proposed methodology is presented in the Figure 1 and we present the concept of representing multilingual input data in section 3.1. It includes accepting multilingual input which will benefit the engine. External knowledge is also provided to the system using sense embeddings.

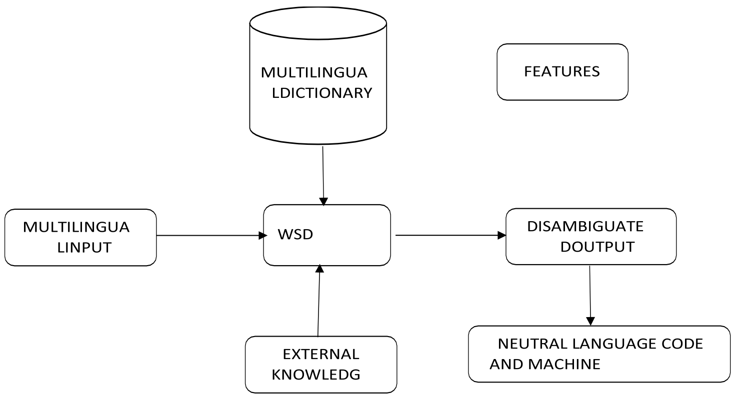

Figure 1. Proposed multilingual word sense disambiguation (WSD) framework

3.1. Multilingual input

We consider here input from various languages like German and French and make use of Babel Net multilingual dictionary described in section 3.2. This is done to explore various languages and taking help from other languages improves the system accuracy. Ambiguous word in one language may not be ambiguous in other language and this will benefit the system engine for improving the accuracy.

3.2. BabelNet

TheBabelNet is a huge multilingual ontological network incorporating lexical semantic and syntactic knowledge from various languages [1]. It represents a labelled graph specifying semantic relations between various nodes and edges. It combines the knowledge of various language WordNet and largest multilingual encyclopedia. Section 3.3 represents the working of WSD with thealgorithm for the same.

3.3. Word sense disambiguation (WSD) engine

WSD engine takes the multilingual input by exploring various languages altogether at the same time. It combines the translations of target word and other context words to produce more accurate sense predictions. Sense disambiguation begins by gathering the data required for disambiguation where the different senses of the ambiguous word are collected in S represented as synonymset from the BabelNet. Context words are collected in Ctx and the algorithm then proceeds by picking up the multilingual translations of the ambiguous and clue words stored in Tx and Ty respectively. Translations are considered in French and German languages as foreign languages are explored. The algorithm iterates through each synset s € S to collect the translations of each of its senses [7].

Algorithm also iterates through each context word ci € Ctx to collect the translations in Ty in sense-specific German and French translations. Element ti is selected from Tx and element tj is selected fromTy and a multilingual context μ'is created by combining ti and tj with the Ctx. The variable μ' is used to build a graph G= {V, E} by computing the paths in BabelNet which connects the synsets of ti with those of other words in μ'as shown in Figure 2. By selecting at each step, a different element fromT, a new graph is created where different sets of Babel synsets get activated by the context words in Ctx. The result of this procedure is a subgraph of BabelNet containing the senses of the words in the context and all edges and intermediate senses found in BabelNet along all paths connecting them. Figure 2 shows the disambiguation graph created to disambiguate the English language target word *'bank'*. In the graph, some of the possible senses of this word are activated including the correct sense ($bank^2_{ENGLISH}$) but also related yet incorrect one is activated ($bank^9_{ENGLISH}$).

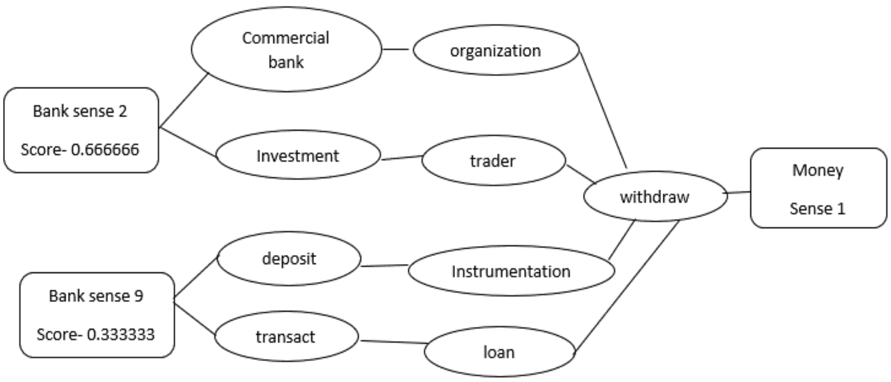

Figure 2. Disambiguation graph for English language

3.4. Scoring distribution

Scoring distribution is calculated using the Inverse path length sum measure. It scores each sense by summing over the inverse length of all paths which connect it to other senses in the graph. It is very useful for sense disambiguation and improves the accuracy.

$$\text{scorej} = \frac{1}{e^{length(p)-1}} \tag{1}$$

Where paths(sj) is the set of simple paths connecting sj to the senses of other context words. Length (p) is the number of edges in the path p and each path is scored with the exponential inverse decay of the path length. Scores are calculated and stored in Δscore and in the final step; cosine distance similarity measure is calculated to find the maximum score which determines the closeness between the ambiguous word and the context words. The cosine distance formula is presented in (2):

$$\text{Cos}\left(\text{S}, \text{SC (T)}\right) = \frac{\sum_{i=1}^{n} S * SC(T)}{\sqrt{\sum_{i=0}^{n} S^2} * \sqrt{\sum_{i=1}^{n} SC(T)^2}} \tag{2}$$

where S is vector representing the score of ambiguous words, SC (T) is vecto rrepresenting the score of context words. Global score consists of selecting the highest score represented and as a result of execution ofalgorithm; the scoring distribution which is maximum is returned to select the best disambiguation sense. Sections 3.5 and 3.6 represents the use of deep learning tools to represent the dictionary framework in numericrepresentation. Table 1 represents the scoring distribution using the above formula for the two senses of bank namely building sense $bank^9_{ENGLISH}$ and financial institution $bank^2_{ENGLISH}$.

Table 1. Scoringdistribution

Language	$bank^2_{ENGLISH}$	$bank^9_{ENGLISH}$
bankEN	0.666666666	0.3333333333
bankGERMAN	0.333333333	0
banqueFRENCH	0.444444444	0

3.5. Synset dictionary framework

Our study explores the ontology of each sense definition from the dictionary namely hypernym, hyponym, holonymy, and gloss. as synset members alone are not sufficient for identifying the correct sense. Some of synsets have a very small number of synset members and the other reason is to bring down topic drift which may have occurred because of polysemoussynset members. It is also observed that adding gloss of hypernym/hyponym gives better performance compared to synset members of hypernym/hyponym [5].

3.6. Word and sense embedding

There is a need to bring the clue words and ambiguous words together which is done using word embeddings. It represents embedding continuous vector space with lesser dimensions and word embedding are trained using word2Vec tool [4]. The training proceeds by presenting different context-target words pair from the corpus thus preparing an ensemble model for all the ambiguous words in the vocabulary as presented in Figure 3. The corpus ensemble model of vectors represents the closeness of the context-target pair for specific sense and to the best of our knowledge, this is the first of the kind attempt to generate sense specific word vector model which represents close proximity between the context words and ambiguous word in the vector space. Section 3.6 represents our contribution of sense bag creation.

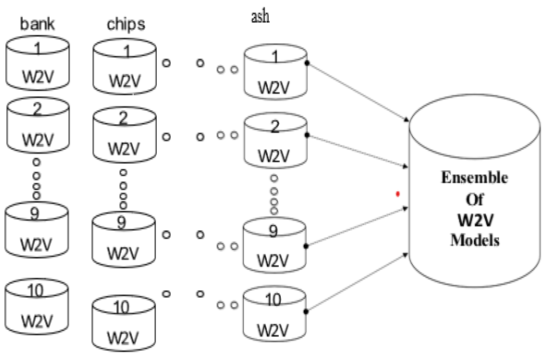

Figure 3. Corpus based ensemble vector model

3.7. Sense bag creation

Sense specific vector model is represented by extracting features from the lexical ontology as well as encyclopedic knowledge. Words are represented by retrieving the context words from the ontological structure of each sense such as synset members, gloss or example sentence, relations such as hypernym or hyponym. Word2Vec model is a layered neural network structure that processes the text by converting them into vectors; a numerical form which brings related words together. The input to the neural network is window of words, hidden layer comprises of weight matrix and output is vector representation of words. Wiki sense bag is also created which is vector representation of Wikipedia of ambiguous words. This is done so as to provide additional world knowledge to the Word sense disambiguation engine as Wiki sense bag covers maximum vocabulary needed to bring context-target pairs closure in the vector space. Wiki bag creation is represented in Figure 4 and Similarity measure is calculated in section 3.8.

3.8. Similarity measure

The similarity measure is calculated by considering the cosine similarity between the word representation of context vector and sense bag representation. It helps to generate a similarity score which helps in the disambiguation process. Cosine similarity measure has proven to be more useful in the word sense disambiguation process.

$$\mathrm{Cos}\ (\mathrm{vec(w)}, \mathrm{vec\ (SB)}) = \frac{\sum_{i=1}^{n} w * SB}{\sqrt{\sum_{i=1}^{n} w^2} * \sqrt{\sum_{i=1}^{n} SB^2}} \quad (3)$$

Where vec (w) is the word embedding for word w, SB represents the sense bag and vec (SB) is the sense embedding representing the combined score of ontology bag and the wiki sense bag. Sense disambiguation (SD) is performed by summing the scores of (1)-(3) which represents multilingual Word sense disambiguation similarity score, word embedding and sense embedding scores of ontology bag and wiki sense bag to boost the disambiguation accuracy. The output of the WSD engine results in disambiguated sense which is converted into neutral language code to be used for MT. Section 3.9 represents the formation of neutral language code.

-3.1438863e-03	2.5703609e-03	2.3864100e-03	-1.6323227e-03
6.4692349e-04	2.6351425e-03	-4.3628053e-03	4.3827966e-03
-4.7720312e-03	-3.4716928e-03	3.4759669e-03	4.3763947e-03
3.2847153e-03	2.3355209e-03	2.8738815e-03	-2.2687481e-03
-4.8421333e-03	3.0184705e-03	-2.1880846e-03	1.8512266e-03
1.6703347e-03	-6.8748498e-04	-6.2847714e-04	-3.0067556e-03
3.0463885e-03	-3.5307638e-03	2.7850315e-03	3.9292048e-04
-2.6362720e-03	-3.6856441e-03	2.7092642e-04	1.5298135e-04
-4.8553180e-03	3.8366476e-03	-2.4513335e-03	3.6468427e-03
2.3314022e-03	1.7899536e-03	-4.3625557e-03	3.3640813e-03
-1.8001328e-03	1.4276117e-03	-1.1264355e-03	-4.4314810e-03
4.2599617e-03	1.2551763e-03	3.8926408e-03	2.4237178e-04
-4.3531498e-03	2.6536058e-03	-3.3246232e-03	4.0993919e-03

Figure 4. Wiki sense bag creation

3.9. Neutral language code

Words after disambiguation are converted into unique representation termed as neutral language code is formed using binary combination of 30-bit unique code where each bit represents significant information about the disambiguated polysemy noun represented in Table 2. Neutral language code is unique in the sense that it covers all the information other than sense identification and parts of speech. Results are presented in the next section.

Table 2. Neutral language code

Noun	Code
Bank	000100011010110010101111001 1xx
	000-parts of speech
	0001-unique identification
	1101-Type of noun
	011-number
	001-gender
	11110000-tenses
	xx - reserved bits

4. RESULTS AND DISCUSSION

Word sense disambiguation framework comprises of multilingual input and evaluation is performed on a manually created corpus for English language consisting of 25 polysemous nouns, for English lexical sample task. Experiments were performed with 5000 instances out of which 70% was used for training and 30% for testing. Test instances were also collected from various search engines books and the accuracy observed for multilingual word sense disambiguation is 40% as compared to 25% observed for monolingual word sense disambiguation. Table 3 presents comparison of the two systems and results are presented for 10 polysemy nouns. For simplicity we consider two senses each for polysemy nouns. The system was tested using multilingual approach and observed accuracy was improved by 15 %. The overall accuracy observed was 40%. Observations and findings are presented in section 4.1.

Table 3. Monolingual versus multilingual word sense disambiguation

English	Sense	Accuracy in % for Monolingual word sense disambiguation	Accuracy in % for Multilingual word sense disambiguation
Chips	Silicon chip	25	45
	Wafers	24	40
Table	Furniture	30	35
	Row/column	32	43
Bat	Mammal	25	45
	Sports	27	45
Bank	Finance	32	45
	Riverbank	32	47
Tank	Military tank	25	44
Plant	Industry plant	35	44
	Tree	35	47
Stock	Capital	30	43
	Storage	29	40
Palm	Hand	28	44
	Name of tree	26	43
Account	Bank account	35	43
	Write up	35	45

4.1. Observations and findings

The problem of similar score faced in monolingual approach was eliminated using multilingual word sense disambiguation. Observed accuracy is 40% which is far less than the baseline accuracy observed for most frequent sense. It is also observed that proper nouns like Madhura, Shreyas from our instances were not part of the dictionary definitions which failed to generate proper scores. Also, dictionary definition being short lacks strong clues which fail the disambiguation accuracy.

Features of BabelNet senses are extracted from the synset (S), gloss of synset member (G), hypernymy (H), hyponymy (HP), synset gloss of hypernymy-hyponymy relation (HG), holonymy (HO) and gloss of holonymy (HOG). We tested these features on 2000 instances and results are represented by taking the maximum of the global scores received represented in Table 4. It is observed from the Table 4 that combining all the features of BabelNet senses together gives us an improved accuracy of 50%. It shows that combining all the features together yields significant improvement in the disambiguation process. Multilingual approach implements graph-based disambiguation and we observed that many clue words from the context were not in close proximity with the ambiguous words. Many words closely related are at distance from one another and this being one of the important findings results in less score which affects the disambiguation process. Words in similar context needs to come close for improve the accuracy. Word and sense embeddings are presented in section 4.2.

Table 4. Synset dictionary framework

Features	Global score	Accuracy in %
S	0.0869	24
S+G	0.1923	27
S+G+H	0.1666	33
S+G+H+HP	0.0588	38
S+G+H+HP+HG	0.3333	42
S+G+H+HP+HG+HO	0.0526	47
S+G+H+HP+HG+HO+HOG	0.5238	50

4.2. Word and sense embeddings

We evaluated our approach for testing the system on word and sense embeddings separately and then combining the two results for disambiguation process. Word embeddings are taken from the raw corpus and make use of gensim word2Vec model for our study. We compared our work with other state of the art methods in terms of precision and recall represented in Table 5. It is observed that our approach with word embeddings came close to baseline accuracy and unsupervised most frequent sense (UMFS) approach. Our approach gives a feasible way to extract predominant senses in an unsupervised setup. Our approach is domain independent so that it can be easily adapted to a domain specific corpus. To get the domain specific word and sense embeddings, we simply have to run the word2vec program on the domain specific corpus. Also, our approach is language independent and portable across mobile devices as smart phones being the most preferred mode of communication. Conclusion is summed up in the next section.

Table 5. Performance comparison of sense embeddings with other methods

System	Precision	Recall
Most frequent sense baseline	0.552	0.552
Lesk algorithm	0.097	0.053
Adapted lesk	0.240	0.234
UMFS (Bhingardive)	0.433	0.432
Multilingual WSD with word and sense embeddings	0.489	0.489

5. CONCLUSION

In this research work, we presented multilingual approach to word sense disambiguation and used BabelNet as multilingual lexicon for disambiguation. Multilingual word sense disambiguation exploits graph-based method to collect evidences from translations in various languages. We also explored the synset dictionary framework by making use of features from BabelNet dictionary. We created separate model for each ambiguous word sense and made an ensemble of the word2Vec models for disambiguation purpose using word embeddings. Our research contribution includes sense bag creation by using the ontological features of the BabelNet lexicon and encyclopedic knowledge from Wikipedia. It is observed that multilingual word sense disambiguation achieved good results in comparison to monolingual system as additional knowledge from various languages help to boost the accuracy. The results also show that our method of multilingual word sense disambiguation with sense embedding improves the accuracy of the system. The approach is open to explore other languages. We will explore our approach for other parts of speech and other languages especially Indian languages like Marathi, Hindi, and Bangla. We plan in the near future to create generalized sense representation for multiple languages so as to provide a general framework for knowledge rich multilingual word sense disambiguation.

REFERENCES

[1] R. Navigli and S. P. Ponzetto, "Joining forces pays off: multilingual joint word sense disambiguation," in *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, Jul. 2012, pp. 1399–1410.

[2] D. O, S. Kwon, K. Kim, and Y. Ko, "Word sense disambiguation based on word similarity calculation using word vector representation from a knowledge-based graph," in *Proceedings of the 27th International Conference on Computational Linguistics*, Aug. 2018, pp. 2704–2714.

[3] Y. Wang, M. Wang, and H. Fujita, "Word Sense Disambiguation: A comprehensive knowledge exploitation framework," *Knowledge-Based Systems*, vol. 190, p. 105030, Feb. 2020, doi: 10.1016/j.knosys.2019.105030.

[4] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," *1st International Conference on Learning Representations, ICLR 2013 - Workshop Track Proceedings*, Jan. 2013.

[5] S. Bhingardive, S. Shaikh, and P. Bhattacharyya, "Neighbors help: bilingual unsupervised WSD using context," 2013, vol. 2, pp. 538–542.

[6] R. Fu, J. Guo, B. Qin, W. Che, H. Wang, and T. Liu, "Learning semantic hierarchies: a continuous vector space approach," *IEEE Transactions on Audio, Speech and Language Processing*, vol. 23, no. 3, pp. 461–471, Mar. 2015, doi: 10.1109/TASLP.2014.2377580.

[7] K. Taghipour and H. T. Ng, "Semi-supervised word sense disambiguation using word embeddings in general and specific domains," in *NAACL HLT 2015 - 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference*, 2015, pp. 314–323, doi: 10.3115/v1/n15-1035.

[8] X. Chen, Z. Liu, and M. Sun, "A unified model for word sense representation and disambiguation," in *EMNLP 2014 - 2014 Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*, 2014, pp. 1025–1035, doi: 10.3115/v1/d14-1110.

[9] I. Iacobacci, M. T. Pilehvar, and R. Navigli, "Embeddings for word sense disambiguation: an evaluation study," in *54th Annual Meeting of the Association for Computational Linguistics, ACL 2016 - Long Papers*, 2016, vol. 2, pp. 897–907, doi: 10.18653/v1/p16-1085.

[10] A. Trask, P. Michalak, and J. Liu, "sense2vec - A fast and accurate method for word sense disambiguation in neural word embeddings," 2015.

[11] H. Sugawara, H. Takamura, R. Sasano, and M. Okumura, "Context representation with word embeddings for WSD," in *Communications in Computer and Information Science*, vol. 593, Springer Singapore, 2016, pp. 108–119.

[12] L. Specia, M. Stevenson, and M. Nunes, "Learning expressive models for word sense disambiguation," 2007.

[13] S. Thater, H. Fürstenau, and M. Pinkal, "Word meaning in context: a simple and effective vector model," *AFNLP*. pp. 1134–1143, 2011.

[14] S. Bhingardive, D. Singh, M. V Rudra, H. Redkar, and P. Bhattacharyya, "Unsupervised most frequent sense detection usingword embeddings," in *NAACL HLT 2015 - 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference*, 2015, pp. 1238–1243, doi: 10.3115/v1/n15-1132.

[15] R. Navigli, "Word sense disambiguation: a survey," *ACM Computing Surveys*, vol. 41, no. 2, pp. 1–69, Feb. 2009, doi: 10.1145/1459352.1459355.

[16] R. Navigli and S. Ponzetto, "Multilingual WSD with just a few lines of code: the BabelNet API," 2012, pp. 67–72.

[17] W. Aziz and L. Specia, "Multilingual WSD-like constraints for paraphrase extraction," 2013, pp. 202–211.

[18] A. Montoyo, R. Romero, S. Vázquez, C. Calle, and S. Soler, "The role of WSD for multilingual natural language applications," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 2448, Springer Berlin Heidelberg, 2002, pp. 41–48.

[19] M. M. Khapra, S. Shah, P. Kedia, and P. Bhattacharyya, "Projecting parameters for multilingual word sense disambiguation," in *EMNLP 2009 - Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: A Meeting of SIGDAT, a Special Interest Group of ACL, Held in Conjunction with ACL-IJCNLP 2009*, 2009, pp. 459–467, doi: 10.3115/1699510.1699570.
[20] P. Resnik, "WSD in NLP applications," Springer Netherlands, 2007, pp. 299–337.
[21] C. Silberer and S. Ponzetto, "UHD: Cross-lingual word sense disambiguation using multilingual co-occurrence graphs," pp. 134–137, 2010.
[22] D. Vickrey, L. Biewald, M. Teyssier, and D. Koller, "Word-sense disambiguation for machine translation," in *HLT/EMNLP 2005 - Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference*, 2005, pp. 771–778, doi: 10.3115/1220575.1220672.
[23] R. Marvin and P. Koehn, "Exploring word sense disambiguation abilities of neural machine translation systems," *AMTA*, vol. 1, pp. 125–131, Mar. 2018, doi: 10.2/JQUERY.MIN.JS.
[24] T. A. Rashid, A. M. Mustafa, and A. M. Saeed, "A Robust Categorization System for Kurdish Sorani Text Documents," *Information Technology Journal*, vol. 16, no. 1, pp. 27–34, Dec. 2016, doi: 10.3923/itj.2017.27.34.
[25] A. M. Saeed, T. A. Rashid, A. M. Mustafa, R. A. A.-R. Agha, A. S. Shamsaldin, and N. K. Al-Salihi, "An evaluation of Reber stemmer with longest match stemmer technique in Kurdish Sorani text classification," *Iran Journal of Computer Science*, vol. 1, no. 2, pp. 99–107, Jan. 2018, doi: 10.1007/s42044-018-0007-4.
[26] A. M. Mustafa and T. A. Rashid, "Kurdish stemmer pre-processing steps for improving information retrieval," *Journal of Information Science*, vol. 44, no. 1, pp. 15–27, Jan. 2018, doi: 10.1177/0165551516683617.
[27] T. A. Rashid, A. M. Mustafa, and A. M. Saeed, "Automatic kurdish text classification using KDC 4007 dataset," in *Lecture Notes on Data Engineering and Communications Technologies*, vol. 6, Springer International Publishing, 2018, pp. 187–198.
[28] Y. Choi, J. Wiebe, and R. Mihalcea, "Coarse-grained +/-effect word sense disambiguation for implicit sentiment analysis," *IEEE Transactions on Affective Computing*, vol. 8, no. 4, pp. 471–479, Oct. 2017, doi: 10.1109/TAFFC.2017.2734085.
[29] R. R . Karwa and M. B. Chandak, "Word sense disambiguation: hybrid approach with annotation up to certain level – a review," *International Journal of Engineering Trends and Technology*, vol. 18, no. 7, pp. 328–330, Dec. 2014, doi: 10.14445/22315381/ijett-v18p267.
[30] E. A. Corrêa, A. A. Lopes, and D. R. Amancio, "Word sense disambiguation: a complex network approach," *Information Sciences*, vol. 442–443, pp. 103–113, May 2018, doi: 10.1016/j.ins.2018.02.047.
[31] A. H. Aliwy and H. A. Taher, "Word sense disambiguation: survey study," *Journal of Computer Science*, vol. 15, no. 7, pp. 1004–1011, Jul. 2019, doi: 10.3844/jcssp.2019.1004.1011.

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