A Novel Word Sense Disambiguation Approach Using WordNet Knowledge Graph

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ABSTRACT
Various applications in computational linguistics and artificial intelligence rely on high-performing word sense disambiguation techniques to solve challenging tasks such as information retrieval, machine translation, question answering, and document clustering. While text comprehension is intuitive for humans, machines face tremendous challenges in processing and interpreting a human’s natural language. This paper presents a novel knowledge-based word sense disambiguation algorithm, namely Sequential Contextual Similarity Matrix Multiplication (SCSMM). The SCSMM algorithm combines semantic similarity, heuristic knowledge, and document context to respectively exploit the merits of local context between consecutive terms, human knowledge about terms, and a document’s main topic in disambiguating terms. Unlike other algorithms, the SCSMM algorithm guarantees the capture of the maximum sentence context while maintaining the terms’ order within the sentence. The proposed algorithm outperformed all other algorithms when disambiguating nounson the combined gold standard datasets, while demonstrating comparable results to current state-of-the-art word sense disambiguation systems when dealing with each dataset separately. Furthermore, the paper discusses the impact of granularity level, ambiguity rate, sentence size, and part of speech distribution on the performance of the proposed algorithm.

1. Introduction

Many Natural Language Processing (NLP) applications rely on Word Sense Disambiguation (WSD), either directly or indirectly. The list includes, but is not limited to Machine Translation (MT), Information Retrieval (IR), Question Answering (QA), Named Entity Recognition (NER), and text summarization. WSD is considered one of the oldest tasks of computational linguistics dating back to the 1940s. It started as a distinct task when machine translation was first developed. The first challenge that triggered WSD task is MT in the 1940s. Since then, researchers have been developing models and algorithms to improve the accuracy of this task using various approaches; supervised, semi-supervised, and knowledge-based systems. WSD is an essential task in many other applications, such as IR, information extraction, knowledge acquisition, and NLP. With the introduction of supervised machine learning in the 1990s, various supervised approaches attempted to solve the WSD task. More recent studies are exploring semi-supervised and unsupervised approaches using knowledge base in the form of graph systems such as WordNet\textsuperscript{1} and BabelNet\textsuperscript{2}.

Human beings can usually detect the appropriate sense unconsciously, whereas programming a machine to perform such a function is challenging. Within the NLP domain, WSD is the task to determine the appropriate meaning (sense) of words given a surrounding context. WSD is considered a classification task, where the system’s main task is to classify a specific word to one of its senses as defined by a lexical dictionary. One typical example is the word ‘bank’, which has eighteen different senses defined in WordNet\textsuperscript{3} lexical database, namely ten as a noun, and the rest as a verb, as shown in Fig. 1.

WSD systems are divided into four main categories based on their approach: supervised, semi-supervised, unsupervised, and knowledge-based. Supervised systems require a large sense-annotated training dataset. Semi-supervised
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**Noun**

- **S:** (n) bank (sloping land (especially the slope beside a body of water)) "they pulled the canoe up on the bank"; "he sat on the bank of the river and watched the currents"
- **S:** (n) depository financial institution, bank, banking concern, banking company (a financial institution that accepts deposits and channels the money into lending activities) "he cashed a check at the bank"; "that bank holds the mortgage on my home"
- **S:** (n) bank (a long ridge or pile) "a huge bank of earth"
- **S:** (n) bank (an arrangement of similar objects in a row or in tiers) "he operated a bank of switches"
- **S:** (n) bank (a supply or stock held in reserve for future use (especially in emergencies))
- **S:** (n) bank (the funds held by a gambling house or the dealer in some gambling games) "he tried to break the bank at Monte Carlo"
- **S:** (n) bank, cant, camber (a slope in the turn of a road or track; the outside is higher than the inside in order to reduce the effects of centrifugal force)
- **S:** (n) savings bank, coin bank, money box, bank (a container (usually with a slot in the top) for keeping money at home) "the coin bank was empty"
- **S:** (n) bank, bank building (a building in which the business of banking transacted) "the bank is on the corner of Nassau and Witherspoon"
- **S:** (n) bank (a flight maneuver; aircraft tips laterally about its longitudinal axis (especially in turning)) "the plane went into a steep bank"

**Verb**

- **S:** (v) bank (tip laterally) "the pilot had to bank the aircraft"
- **S:** (v) bank (enclose with a bank) "bank roads"
- **S:** (v) bank (do business with a bank or keep an account at a bank) "Where do you bank in this town?"
- **S:** (v) bank (act as the banker in a game or in gambling)
- **S:** (v) bank (be in the banking business)
- **S:** (v) deposit, bank (put into a bank account) "She deposits her paycheck every month"
- **S:** (v) bank (cover with ashes so to control the rate of burning) "bank a fire"
- **S:** (v) count, bet, depend, swear, rely, bank, look, calculate, reckon (have faith or confidence in) "you can count on me to help you any time"; "Look to your friends for support"; "You can bet on that!"; "Depend on your family in times of crisis"

![Figure 1: Senses for the term bank](image)

systems employ a bootstrapping process with a small seed of a sense-annotated training dataset and a large corpus of un-annotated senses. Unsupervised approaches use context clustering [22], word clustering [39], or other graph-based algorithms such as the PageRank algorithm [5]. Finally, knowledge-based approaches rely on the structure and features of a Knowledge Graph (KG), such as taxonomic relations, non-taxonomic relations, concept’s Information Content (IC), and paths.

Among all four WSD categories, supervised and knowledge-based are the most promising approaches [16]. However, supervised approaches require a large annotated dataset, which is challenging to produce. Due to the limited number of sense-annotated datasets, these systems face challenges to excel and demonstrate a noticeable improvement over other systems. Moreover, for the most part, supervised systems require training dataset, in addition to being computationally expensive and time-consuming. Finally, most WSD supervised systems are unable to intuitively explain their results since they usually use a training function that leads to a calculated decision-making process.

Knowledge-based systems however, do not require a training dataset because they rely on a massive dictionary or KG. Moreover, knowledge-based systems can easily explain their results since they normally follow an intuitive process. With the advancement of Linked Open Data (LOD) and domain-specific KGs, these systems have a higher potential to outperform other approaches due to the advantage of broader KG coverage [34], but achieving this requires a semantically rich KG and a comprehensive semantic similarity measure. The later is used to perform a WSD task by assigning a weight to each sense of the ambiguous word based on its semantic similarity with other terms within the sentence, document, or both. The sense with the highest weight is selected as the correct sense.
In addition to the semantic similarity measure, word sense heuristics and document context are two important ingredients that have also been used in the literature for disambiguating words [34, 44, 14]. The word sense heuristic is expressed by the frequency distribution of the word’s senses based on their usage in the training dataset (i.e., SemCor and OMSTI). The document context provides an ambiguous word with a global context that enables the selection of the appropriate sense. In this paper, we investigated the use of semantic similarity, word sense heuristics, and document context, to develop a novel knowledge-based WSD algorithm, namely Sequential Contextual Similarity Matrix Multiplication (SCSMM). The proposed algorithm follows the disambiguation process of the human brain by exploiting the local context within the sentence, prior knowledge of the term’s usage, and the global context of the document, which are represented by the semantic similarity between terms, terms frequency heuristics, and the document context, respectively.

The rest of the paper is organized as follows: Section 2 describes in detail the related work, motivations behind this study and contributions. Section 3 introduces the proposed method for the WSD system. In Section 4, we describe the experimental environment and discuss experimental results. Finally, conclusions are drawn and future research work is suggested in Section 5.

2. Related Work

The main objective of WSD is to classify a word into its correct sense given a context. This task has been investigated within the computational linguistics field since the 1940s, and since then, many algorithms and techniques have been developed. WSD is a challenging task for several reasons, one of which is related to the discrepancies of senses choices between dictionaries. One dictionary might provide more senses for a word than another. To overcome such a challenge, many researchers relied on a single comprehensive machine-readable lexical dictionary such as WordNet4, Wikipedia5, and BabelNet6.

Another difficulty is derived from the evaluated test datasets and the inter-annotator agreement. The datasets to evaluate any system must be judged and annotated by humans because human judgment is considered a gold standard. Compiling test datasets is not an easy task, as it is difficult for humans to remember or know all senses for all words, including their precise meanings and differences from other senses. The gold standard datasets are usually measured by the inter-annotator agreement. Based on [15, 38, 47, 34, 23] the inter-annotator agreement using WordNet ranges between 67% and 80% on fine-grained inventory. Such a low range of inter-annotator agreement encouraged the research community to develop and further investigate coarse-grained databases. In fact, some of the coarse-grained inventory has achieved up to 90% inter-annotator agreement [18, 34, 23]. Nonetheless, significant effort has been made to compile high-quality datasets that are considered the primary gold standard for WSD systems (i.e., SensEval2, SensEval3, SemEval 2007, SemEval 2013, and SemEval 2015). These datasets are further discussed in Section 4.1.2.

A vast number of research approaches, techniques and models have attempted to solve the WSD challenge as a standalone task or as part of a larger NLP application [27, 34, 10, 37, 19, 45, 6]. Either way, these approaches are grouped into four conventional categories. Supervised approaches require the use of a training dataset (i.e., a sense-annotated corpus). However, these corpora are hard to produce due to the complexity of identifying the best combination of words’ senses based on their definitions from WordNet. To our knowledge, there are currently two such datasets available: SemCor [30] and One Million Sense-Tagged Instances) (OMSTI) [49], which will be discussed in Section 4.1.1. Supervised approaches also require a Machine Learning (ML) technique that will, through training, create a feature vector for each ambiguous word, train a classifier to appropriately assign the correct sense class to an ambiguous target word, and finally, test it using a dataset to evaluate the model [51, 40]. Early development of supervised WSD approaches include rule-based, probabilistic, or statistical models. Many comprehensive surveys have covered the mathematical details of each model in [34, 19, 10, 37, 45, 6].

Semi-supervised approaches take a middle ground strategy by using a secondary small sense-annotated corpus as seed data, then applying a bootstrapping process such as the one presented in [29]. The bootstrapping technique requires only a small amount of tagged data that acts as seed data. This data then undergoes a supervised method to train an initial classifier, which is, in return, used on another untagged portion of the corpus to generate a larger training dataset. Only high-confidence classifications are considered as candidates for the final training dataset. Those same steps are then repeated in numerous iterations, and the training portion successively increases until the entire corpus

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4https://wordnet.princeton.edu/
5https://www.wikipedia.org/
6https://babelnet.org/
is trained, or a maximum number of iterations caps the process. The main advantage of the bootstrapping approach is that it requires a small seed dataset to begin the training process. The seed data could be manually-annotated or generated by a small number of surefire decision rules.

Unlike the previous two categories, unsupervised approaches do not require prior knowledge of the text; hence, no manual sense-annotated corpus is required. Nonetheless, most techniques in this category still require a training corpus for an unsupervised training task. Algorithms from this group have been further categorized into three groups: context clustering, co-occurrence graphs, and word clustering.

Finally, knowledge-based approaches do not require an intensive training process. However, they disambiguate words in context by exploiting large scale knowledge resources (i.e., dictionaries, ontologies, and KG). The most common methods within this category, which is the focus of this study, are described in detail below.

2.1. Definition Overlap Systems

The definition overlap, or Lesk algorithm named after its author, is based on the commonality of words between two sentences, where the first sentence is the context of word \( w_t \) and the the second is the definition of a given sense from the knowledge base [25]. The definition with the highest word overlap is considered the correct sense. However, the Lesk algorithm has major limitations, i.e., being highly sensitive to the exact word match and having a concise definition within WordNet. To overcome this limitation, Nanerjee and Padersen [8] expanded on Lesk’s algorithm to include related concepts within the knowledge base. Related concepts are identified through direct relations with the candidate sense (e.g., hypernyms or meronyms).

2.2. Semantic Similarity Systems

Since the introduction of WordNet, many semantic similarity measures have been developed. Some of the most relevant measures were discussed in [7, 11]. This technique follows the intuition that words that appear in a sentence are coherently contextual, and should therefore be highly related within a conceptual knowledge base such as WordNet.

Pedersen et al. [42] introduced a variation to the Lesk overlap approach by proposing an exhaustive evaluation of all possible combinations of sentences that can be constructed by all candidate senses within a context window. The context window is the words surrounding a target word. The Pedersen algorithm can be expressed as a general disambiguation framework based on a semantic similarity score. The framework can be described as follows: for a target word \( w_i \), \( \hat{S} \) is chosen such that it maximizes the sum of the most similar sense with all other words’ senses based on the following equation [42, 34]:

\[
\hat{S} = \arg \max_{S \in \text{Senses}(w_i)} \sum_{w_j \in T : w_j \neq w_i} \max_{S' \in \text{Senses}(w_j)} \text{score}(S, S'),
\]

where \( T = (w_1, ..., w_n) \) is the set of all words in a text, \( \text{Senses}(w_i) \) is the full set of senses of \( w_i \in T \). The formula measures the contributions of all context words with the most suitable sense. Pedersen’s algorithm, as shown in Algorithm 1, can use any semantic similarity measure. However, their results as reported in [42] are much lower than some of the recent approaches of this category, as shown below:

A more recent study conducted by Mittal and Jain [31] utilized an average of three semantic similarity measures, some of which include Wu and Palmer (\( \text{Sim}_{wu} \)) measure [52], Leacock and Chodorow path-based measure (\( \text{Sim}_{lch} \)) [24], and a node counting distance measure. The average of all three similarity measures is assigned as a similarity value between each sense of an ambiguous word and all neighboring words (context) [31].

2.3. Heuristic Systems

Based on linguistic properties, heuristics are applied to evaluate word senses. The main idea is based on the ranking of sense distribution within a training dataset. Three main heuristic models have been developed to solve the WSD task: Most Frequent Sense (MFS), one sense per discourse, and one sense per collocation.

1. MFS is based on the frequency distribution of senses within the training dataset (i.e., SemCor and OMSTI). For a word \( w \), the sense with the highest frequency is ranked first \( w^1 \), and the sense with the second highest frequency is ranked second \( w^2 \), and so on. Table 1 depicts the ranking of the noun senses for ‘plant’ within SemCor dataset. In fact, senses in WordNet itself are ranked based on their frequency of occurrence in semantic concordance texts\footnote{https://wordnet.princeton.edu/documentation/wndbSwn} [34].
Algorithm 1: Maximum Relatedness Disambiguation [42]

Input: $w_t$: Target word

Output: $i$: Index of maximum related sense

1. foreach $s_{ti} \in Senses_{of}(w_t)$ do
   2. Initialize $score_i \leftarrow 0$
   3. foreach word $w_j \in \text{ContextWindow}(w_t) = \{w_j: j \neq i\}$ do
      4. Initialize $maxScore_j \leftarrow 0$
      5. foreach $s_{jk} \in Senses_{of}(w_j)$ do
         6. if $maxScore_j < \text{relatedness}(s_{ti}, s_{jk})$ then
            7. $maxScore_j = \text{relatedness}(s_{ti}, s_{jk})$
      8. if $maxScore_j > \text{threshold}$ then
         9. $score_i + = maxScore_j$
   10. Return $i$ such that $score_i \geq score_j, \forall j, 1 \leq j \leq n, n = \text{number of words in the sentence}$.

Table 1
WordNet sense ranking based on SemCor frequencies

| Sense   | Definition                                      | Frequency |
|---------|------------------------------------------------|-----------|
| plant-1 | Buildings for carrying on industrial labor      | 338       |
| plant-2 | A living organism lacking the power of locomotion | 207       |
| plant-3 | Something planted secretly for discovery by another | 2         |
| plant-4 | An actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience | 0         |

2. One sense per discourse argues that the meaning of a word is most likely preserved within a specific text/domain, rather than in general.

3. One sense per collocation narrows the preservation of meaning within collocation instead of a domain.

Once the challenging part of ranking the senses within the knowledge base is complete, disambiguating a word would be as simple as selecting the most frequent sense from the training dataset; which is referred to as MFS baseline. The first sense selection from WordNet is also considered a baseline approach. These baseline approaches yield a moderate accuracy between 55.2% and 67.8% as reported in SemEval-07 and SemEval-15, respectively [44].

2.4. Graph-based Systems

Several other methods exploited the knowledge base structure and attempted to construct a sub-graph to determine the appropriate sense within a sentence. Navigli and Lapata constructed a graph containing all possible combinations of the ambiguous words’ senses, where each node of the new graph represents a sense of one of the word sequence, while edges correspond to relationships between senses. Once the graph is constructed, each node is assessed based on the shortest path measure to determine the most suitable sense for each word that provides the highest context [36].

2.5. Knowledge-based Benchmarking Systems

The following are the knowledge-based systems that have been used as a benchmark and will be compared to our system.

Lesk: The original Lesk algorithm is based on a gloss overlap between the definitions of the ambiguous word’s senses and its sentence (i.e., context). The sense definition with the maximum overlap with the word’s sentence is selected as the correct sense [25]. Lesk$\text{ext}$ is an extension of the original gloss overlap, which extended the gloss to include terms that share one or more relations with the ambiguous term in the KG. They also employed the Term Frequency-Inverse Document Frequency (TF-IDF) weights to compute the final similarity between the extended gloss and the context [8]. Finally, Lesk$\text{ext+emb}$ incorporated Latent Semantic Analysis (LSA) to select the appropriate sense using semantic vector similarity instead of TF-IDF vector similarity. They re-weighted the terms using an Inverse Glass Frequency (IGF), viewing all extended glosses as a corpus compared to the Inverse Document Frequency (IDF) approach. Beyond using the distributional semantic space, the latter overcame the bag of words overlap limitation...
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in the original Lesk algorithm by using a vector cosine similarity [9]. However, the Lesk algorithm is dependent on the matching of terms between the compared texts. Moreover, the algorithm would fail if the compared text contains synonym terms rather than the exact terms. In addition, none of the overlap approaches take into consideration the sequence of terms within the sentence itself.

UKB: UKB employed a graph-based PageRank approach on the entire WordNet graph, which is a completely different approach from Lesk’s. To optimize the PageRank algorithm over WordNet, they constructed a subgraph for a text window (typically a sentence or a few contiguous sentences). The subgraph included the senses of all open-class (ambiguous) terms and the rest of the text as a context [5]. An extended version of UKB, namely UKB\textsubscript{gloss}, used extended WordNet to transform the glosses into disambiguated synsets. This implementation of UKB also incorporated sense frequencies to initialize context words [3]. The latest release of UKB is UKB\textsubscript{gloss18}, which includes the optimal parameters for the software to guarantee optimal performance. For example, they used a window of over 20 words as a context of each target word and 30 iterations for the personalized PageRank algorithm. They also confirmed that using WordNet versions 1.7.1 and 2.0 resulted in better performance since they match the annotated datasets [4]. Furthermore, the authors highlighted the use of an undirected graph as a limitation for the PageRank algorithm [3].

Babelfy: A graph-based approach integrated entity linking and WSD based on random walks with restart algorithm [50] over BabelNet, which is an extensive multi-graph semantic network integrating entities from WordNet and Wikipedia or Wiktionary. Babelfy employs the densest subgraph heuristic for selecting the most suitable sense of each text fragment. For a target word, Babelfy considers the entire document instead of the sentence alone [33]. This approach is also bound by the PageRank algorithm limitations with respect to WordNet KG.

WSD-TM: This is a graph-based WSD system that uses a topic modeling approach based on a variation of the Latent Dirichlet Allocation (LDA) algorithm. This approach applies the whole document as a context to disambiguate all open-class words within the document. WSD-TM views document as synsets and synset words rather than topics and topic words, then performs the LDA algorithm based on that assumption [14].

Baselines: Senses in WordNet are ranked based on their frequency of occurrence in semantic concordance texts\textsuperscript{8}. Therefore, selecting the first sense of the target word in WordNet is presented as a baseline. Another baseline is based on the MFS extracted from the training dataset (SemCor and/or OMSTI).

2.6. Critical Analysis of the Related Work

Although the above-mentioned benchmarking systems are all knowledge-based, they can be further classified into three subcategories based on their implemented algorithm. The first subcategory is the definition overlap, the second is the graph-based (i.e., PageRank), while the third is topic modeling. The Lesk systems follow the definition overlap, which limit the similarity between two texts on the term’s exact match. Furthermore, the original Lesk algorithm adopts a bag-of-words approach. Although it was enhanced with a vector-based approach in subsequent literature, none of the overlap methods considered the broader context of the document.

The UKB systems employ a graph-based method (i.e., PageRank). The PageRank algorithm is time-consuming and requires intensive computational power to weigh the links between WordNet concepts. Furthermore, some of these systems employ the Lesk algorithm for the initial weights linking any two concepts [28], while others use a collection of semantic similarity measures including JCN, LCH, and Lesk [46, 3]. The personalized PageRank optimizes the performance by using a subgraph approach. However, this is achieved at the cost of context reduction, as the optimal results of UKB considers a window size of 20 words, which could span multiple sentences [4].

The WSD-TM system relies on the document topic as the main disambiguating context. Despite the importance of the global document context, WSD-TM overlooks the importance of the word’s local surroundings, which is considered a local context. Furthermore, this system also employs Lesk similarity to model relationships between synsets as one of its priors to the LDA algorithm. A major limitation that applies to most systems in these three categories is that they follow a bag-of-words approach, ignoring the sequence of the terms within the sentence, which we believe is a critical factor to disambiguate a word within its sentence and discourse contexts.

Research published in neuroscience journals shows that human brain models suggest that semantic memory is a construction of conceptual knowledge based on a widely-distributed network [41]. Based on some models, the brain networks consist of neurons, neuronal populations, or brain regions that can be viewed as nodes, and the structural or functional connectivity viewed as edges linking these nodes together [26]. Fig. 2 describes such a network with functional relationships connecting various brain regions (nodes). Furthermore, structural or functional connectivity

\textsuperscript{8}https://wordnet.princeton.edu/documentation/wndb5wn
refers to the anatomical pathways between neurons, neuronal populations, or brain regions, depending on the spatial scales of interest. These structural and functional connections form a biological route for information transfer and communication [41, 20]. If we compare the KG to our brain, viewing concepts as nodes and relations as structural and functional connections, we can rely on widely-distributed KG to extract various semantic knowledge, including similarity and relatedness between nodes using the structural and functional relationships, respectively.

Inspired by the brain models, we attempt to overcome the limitations mentioned above as follows: we argue that the sequential connectivity of terms has an essential part in forming the overall context of the sentence. Beneath the sequential connectivity, there exists structural and functional relationships that construct the term’s context. These relationships are measured by semantic similarity and relatedness within the KG.

Consider the following two sentences:

- “John has all his faculty members at the meeting table.”
- “John has all his faculties and could think clearly and logically”

The word faculty (lemma of faculties) has two distinct meanings (see Fig. 3), and without the rest of the sentence or other external context (e.g., knowing that John is a Dean at a university), it is challenging to distinguish the correct meaning. Since humans use and rely on context to disambiguate words, machines are even more dependent on it.

If we remove all words that follow faculty from both sentences, it will not be easy, as a human being, to understand the correct meaning. This difficulty is derived from the fact that the term faculty is ambiguous. However, as we add more context to the sentence, the meaning becomes more evident in each sentence. More importantly, our brain will
be able to establish functional connectivities between the terms of the sentence and infer additional knowledge, such as John could be working at a university as a Chairperson or a Dean.

Initially, our brain could not understand the meaning of faculties because it could not make the connection between the term and its surrounding context {‘John’, ‘has’, ‘all’, ‘his’}. However, as soon as the context was enriched with {‘members’, ‘at’, ‘the’, ‘meeting’, ‘table’}, our brain was able to create a context from the joint meanings of the core terms in the sentence {‘John’, ‘faculty’, ‘member’, ‘meeting’, ‘table’}, hence, disambiguating the sentence. Surprisingly enough, the three terms {‘member’, ‘meeting’, ‘table’} are also ambiguous, with even more senses to choose from (refer to Fig. 4). However, our brains can connect the various meanings of each term and determine the context of the full sentence. Our main observation here demonstrates that humans tend to connect terms/things based on the various associations that connect them, in addition to its prior heuristic knowledge about the ambiguous terms. The prior heuristic knowledge is represented by the common use of the terms presented in the sequence.

To summarize, the four points below are essential for disambiguating words within a sentence; hence, we incorporate them into our proposed WSD algorithm:

- The sequence of the terms within the sentence;
- The connectivity between various concepts (i.e., senses) of ambiguous terms;
- Basic heuristic knowledge of each term and its various concepts (i.e., senses);
- The broader context of the document.

The limitations in current WSD systems motivates us to pursue the following objectives:

- Address the limitations in existing knowledge-based WSD methods;
- Investigate the effect of semantic similarity measures, word sense heuristic, document context, and average sentence size on disambiguating words;
- Propose a new algorithm that exploits semantic similarity, word sense heuristic, and document context to solve All-Words WSD task;
- Evaluate our approaches by using gold-standard benchmarks and state-of-the-art methods to demonstrate their robustness and scalability.

To achieve the above-mentioned objectives, we propose a novel SCSMM algorithm within a comprehensive knowledge-based WSD system. Our proposed algorithm follows the disambiguation process of the human brain by exploiting the local context within the sentence, prior knowledge of the term’s usage, and the global context of the document, represented by the semantic similarity between terms, terms frequency heuristics, and document context, respectively.

3. Proposed Method

This section presents a novel, context-aware WSD algorithm based on a KG semantic similarity measure. Our main intuition is derived from the brain’s basic steps to analyze and disambiguate words in context (i.e., sentence and document) as described in Section 2.6. Fig. 5 describes the main tasks of the proposed WSD method, starting from parsing the XML content of the dataset and the NLP preprocessing tasks, followed by the construction of a document’s context. The document context consists of all context words within each document (terms with a single sense) that have a nonzero TF-IDF value. The three main WSD processes, which make up the WSD algorithm, are then executed for each sentence in the document. These include the construction of Contextual Similarity Matrix (CSM)s queue, followed by the main SCSMM algorithm, and finally the identification of the senses that contribute the most to the global context in the back-tracing algorithm. In the cases where any ambiguous terms remain, the carry-forward process is executed to disambiguate them.

The complete WSD process, as described in Algorithm 2, consists of the CSM queue construction, a novel SCSMM and a back-tracing algorithm for an All-Words (AW) WSD task. The proposed method follows a knowledge-based approach using WordNet as a sense dictionary and the main knowledge resource. Before starting the WSD process,
standard NLP preprocessing steps take place, such as sentence tokenization, stop-words removal, lemmatization, and Part Of Speech (POS) tagging. Before delving into the algorithm, the next section presents the core components that construct the CSM. These are the semantic similarity, sense heuristic, and document context.

### 3.1. CSM Core Components

The similarity matrix algorithm described in Algorithm 3 employs the aforementioned semantic similarity measure as the similarity measure between the senses of every term and its consecutive term $SCM(t_i, t_{i+1})$. The local context generated by the consecutive terms’ similarities is then complemented by the heuristic of each sense and the global context from the document context similarity. As a result, each cell in the CSM matrix resembles the local context, prior knowledge, and document context (refer to lines 7-9 in Algorithm 3).

1- **Semantic Similarity**: A semantic similarity measure represents a direct and local context between consecutive
Figure 5: Flowchart for the proposed WSD algorithm
Algorithm 2: WSD Algorithm Using SCSMM

Input: \( S \): Sentence with a list of ambiguous words
Output: \( \hat{S} \): Sentence with annotated sense

1 Data Structures:
2 \( CSM\text{Que} \): Contextual Similarity Matrices Queue
3 \( MtxProductStack \): A Stack for the produced matrices resulting from the product of consecutive matrices

4 for \( i \leftarrow 0 \) to \(|\text{TermsOf}(S)| - 1\) do
5 \( CSM\text{Que} \leftarrow \text{Enqueue} \) Call getSemSimMatrix\((S_i, S_{i+1})\)
6 \( MtxProductStack \leftarrow \text{Call SCSMM}(CSM\text{Que})\)
7 \( \hat{S} \leftarrow \text{Call BMCC}(MtxProductStack)\)

The main idea is to find the maximum pairwise context between senses of the two consecutive terms. However, it is possible to have more than one local context from two words based on the combination of their senses. Various knowledge-based semantic similarity measures have been evaluated in order to determine the best similarity measure for our algorithm. These measures are presented in [7]. We further evaluate these measures in Section 4.3.

2- Sense Heuristic: In addition to the semantic similarity between senses, each sense has heuristic information that reflects its use frequency. These heuristics are observed from the available training datasets: SemCor and OMSTI. The heuristic function is based on the senses frequency distribution within the training dataset. More formally, for a term \( w_i \) that has a set of senses \( \{S\} \), and a sense \( s_{ij}, 1 \leq j \leq |S| \), the heuristic function is described as below:

\[
H(s_{ij}) = \begin{cases} 
  P(s_{ij} | w_i), & s_{ij} \in \{S\} \\
  \frac{1}{\text{Count}(w_i)}, & s_{ij} \notin \{S\} \\
  1, & w_i \notin \{W\} 
\end{cases}
\]  

(2)

where \( P(s_{ij} | w_i) \) is the conditional probability of the sense \( s_{ij} \) given its term \( w_i \), that is computed based on their respective counts within the dataset as follows:

\[
P(s_{ij} | w_i) = \frac{\text{Count}(s_{ij})}{\text{Count}(w_i)}
\]

(3)

Algorithm 3: Get Semantic Similarity matrix method

Input: \( P_{r_{term}} \): First term
\( C_{r_{term}} \): Second term
Output: \( SimMtx \): Similarity Matrix

1 Data Structures:
2 \( CSM \): Contextual Similarity Matrix

1 Initialization:
4 \( CSM \leftarrow \text{NewMatrix}[\text{Sense}(P_{r_{term}})]][\text{Sense}(C_{r_{term}})]\{0\}
5 foreach \( s_i \in \text{Sense}(P_{r_{term}}) \) do
6 foreach \( s_j \in \text{Sense}(C_{r_{term}}) \) do
7 /* Get the semantic similarity */ \( CSM[i][j] \leftarrow \text{SSR}(s_i, s_j) \)
8 /* Apply heuristics as a weighted frequency of each sense */ \( CSM[i][j] \ast= H(s_i) \ast H(s_j) \)
9 /* Apply document context similarity of each sense */ \( CSM[i][j] \ast= \text{DocCtxSim}(s_i) \ast \text{DocCtxSim}(s_j) \)
10 return \( CSM \)
Table 2
Similarity matrix between terms walk<sub>v</sub> and bank<sub>n</sub>

|       | bank1 | bank2 | bank3 | bank4 | bank5 | bank6 | bank7 | bank8 | bank9 | bank10 |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|
| walk1 | 0.051 | 0.053 | 0.047 | 0.045 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk2 | 0.048 | 0.044 | 0.044 | 0.037 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk3 | 0.069 | 0.072 | 0.063 | 0.059 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk4 | 0.042 | 0.039 | 0.039 | 0.033 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk5 | 0.069 | 0.072 | 0.063 | 0.059 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk6 | 0.065 | 0.068 | 0.060 | 0.056 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk7 | 0.067 | 0.077 | 0.061 | 0.058 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk8 | 0.066 | 0.075 | 0.061 | 0.058 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk9 | 0.088 | 0.069 | 0.092 | 0.055 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |
| walk10| 0.065 | 0.063 | 0.059 | 0.053 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000  |

Note that if the training dataset does not contain the term \( w_i \), its heuristic is set to one, and it will not affect the similarity matrix.

3. Document Context: As described in the semantic similarity, multiple sense-pairs might have high similarity, which indicates various contexts. To determine the appropriate context in the sentence, we crosscheck each sense with the document context obtained from all non-ambiguous terms in the document. Formally, for a given document with sets of ambiguous and non-ambiguous (context) terms \( D = \{A \cup \{C\}\} \), and each ambiguous term \( w_i \ (w_i \in \{A\}) \) has a set of senses \( \{S_{w_i}\} \), then the sense \( s_{ij} \ (s_{ij} \in S_{w_i}) \) has a context similarity weight \( weight_{\text{CtxD}}(s_{ij}|C) \) with the document context \( C \) expressed as the average similarity with all context terms \( c_k \in \{C\} \) as depicted in the equation below:

\[
weight_{\text{CtxD}}(s_{ij}|C) = \frac{1}{|C|} \times \sum_{c_k \in C} sim_{jc}(s_{ij}, c_k)
\] (4)

Illustrative Example:
Consider the sentence “I’m walking to the bank”, with the two ambiguous words ‘walk’ and ‘bank’. The similarity matrix (Table 2) shows high similarities between the sense pairs walk\(_v^9\) – bank\(_n^3\), and walk\(_v^7\) – bank\(_n^2\) of 0.092 and 0.077, respectively. These represent a local context for each pair of senses. For more details of these senses and their definitions, refer to Fig. 6.

For our system to disambiguate such a short sentence with no additional context, it relies only on the semantic similarity. Therefore, the senses walk\(_v^9\) and bank\(_n^3\) would be selected since they have the highest similarity of 0.092 compared to all other combinations. However, when adding heuristics, the results change completely towards another pair walk\(_v^1\) and bank\(_n^2\) with the highest similarity of 0.0236. Intuitively, people would think that the first meaning of walk (walk\(_v^1\)) and one of the first two senses of bank would be more meaningful contexts than the rest. This intuition is clearly visible in Table 3 with the top two senses of bank (bank\(_n^1\) and bank\(_n^2\)). Note that the heuristic weights for walk\(_v^1\) is 0.9, and for bank\(_n^1\) and bank\(_n^2\) are 0.35 and 0.5, respectively. Heuristics were computed using both of SemCor and OMSTI datasets.

Finally, if we are provided with additional context about the sentence, such as non-ambiguous terms within the same document (i.e., river), our brain will shift towards a more concrete context based on the document’s main topic, and so does our system. The first sense will have higher similarity than the second one, with the first sense walk\(_v^1\) of 0.153 and 0.151, respectively. The final correct senses in this case would be walk\(_v^1\) and bank\(_n^1\). On the other hand, if the document contained more financial terms (i.e., central_bank), the other sense would be selected. Based on the above, we employed the document’s context similarity, which improves the overall similarity between the senses.

3.2. Sequential Contextual Similarity Matrix Multiplication Algorithm
Once all CSMs are constructed for the sentence, the WSD algorithm starts by building a similarity matrix queue (CSMQueue) from all CSMs, maintaining their sequence (refer to Algorithm 2 lines 4-5). Line 6 in the algorithm generates the final matrix based on the sequential multiplication of the matrices, as presented in the SCSMM algorithm (Algorithm 4). Fig. 7 illustrates the sequential multiplication process of the consecutive local CSMs for a sample
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Verb

- S: (v) walk (use one's feet to advance; advance by steps) "Walk, don't run!"; "We walked instead of driving"; "She walks with a slight limp"; "The patient cannot walk yet"; "Walk over to the cabinet"
- S: (v) walk (accompany or escort) "I'll walk you to your car"
- S: (v) walk (obtain a base on balls)
- S: (v) walk (traverse or cover by walking) "Walk the tightrope"; "Paul walked the streets of Damascus"; "She walks 3 miles every day"
- S: (v) walk (give a base on balls to)
- S: (v) walk (live or behave in a specified manner) "walk in sadness"
- S: (v) walk (be or act in association with) "We must walk with our dispossessed brothers and sisters"; "Walk with God"
- S: (v) walk (walk at a pace) "The horses walked across the meadow"
- S: (v) walk (make walk) "He walks the horse up the mountain"; "Walk the dog twice a day"
- S: (v) walk, take the air (take a walk; go for a walk; walk for pleasure) "The lovers held hands while walking"; "We like to walk every Sunday"

(a) Verb senses for the term walk

Noun

- S: (n) bank (sloping land (especially the slope beside a body of water)) "they pulled the canoe up on the bank"; "he sat on the bank of the river and watched the currents"
- S: (n) depository financial institution, bank, banking concern, banking company (a financial institution that accepts deposits and channels the money into lending activities) "he cashed a check at the bank"; "that bank holds the mortgage on my home"
- S: (n) bank (a long ridge or pile) "a huge bank of earth"
- S: (n) bank (an arrangement of similar objects in a row or in tiers) "he operated a bank of switches"
- S: (n) bank (a supply or stock held in reserve for future use (especially in emergencies))
- S: (n) bank (the funds held by a gambling house or the dealer in some gambling games) "he tried to break the bank at Monte Carlo"
- S: (n) bank, cant, camber (a slope in the turn of a road or track; the outside is higher than the inside in order to reduce the effects of centrifugal force)
- S: (n) savings bank, coin bank, money box, bank (a container (usually with a slot in the top) for keeping money at home) "the coin bank was empty"
- S: (n) bank, bank building (a building in which the business of banking transacted) "the bank is on the corner of Nassau and Witherspoon"
- S: (n) bank (a flight maneuver; aircraft tips laterally about its longitudinal axis (especially in turning)) "the plane went into a steep bank"

(b) Noun senses for the term bank

Figure 6: Definitions for the terms ‘walk’ and ‘bank’ in WordNet

sentence with four ambiguous words. Finally, the algorithm applies a back-tracing process to determine the most contributing senses to the maximum global context. Next, we describe the SCSMM algorithm in detail, followed by the back-tracing algorithm.

Similarity Matrices Multiplication: Once all CSMs are constructed between consecutive terms (see Fig. 7, matrices M1, M2, and M3), the matrix multiplication algorithm (Algorithm 4) starts by multiplying M1 and M2, and the resulting matrix M4 is then multiplied by M3, and so on. The sequential multiplication of matrices guarantees a global context across all words within the sentence. It also guarantees the maximum context value while maintaining the order of the terms within the sentence. The order of words in a sentence is critical to better understand and disambiguate the sentence. Finally, starting with the latest produced matrix, the back-tracing algorithm traces back all senses that contributed to the maximum global context.

Back-tracing Senses: The final step of the SCSMM algorithm is the back-tracing stage (Algorithm 2, line 7). In this stage, we identify the most contributing sense to the sentence’s global context (Algorithm 5). Fig. 8 and 9 illustrate
Table 3
Similarity matrix with heuristics between terms \( \text{walk}_n \) and \( \text{bank}_n \)

|     | bank1   | bank2   | bank3   | bank4   |
|-----|---------|---------|---------|---------|
| walk1 | 0.0158  |         |         |         |
| walk2 | 0.0003  | 0.0236  |         |         |
| walk3 | 0.0004  | 0.0006  | 0.0001  |         |
| walk4 | 0.0001  | 0.0002  | 0.0000  | 0.0000  |
| walk5 | 0.0001  | 0.0002  | 0.0000  | 0.0000  |
| walk6 | 0.0001  | 0.0002  | 0.0000  | 0.0000  |
| walk7 | 0.0001  | 0.0002  | 0.0000  | 0.0000  |
| walk8 | 0.0001  | 0.0002  | 0.0000  | 0.0000  |
| walk9 | 0.0002  | 0.0002  | 0.0000  | 0.0000  |
| walk10 | 0.0001 | 0.0002  | 0.0000  | 0.0000  |

Algorithm 4: Sequential Contextual Similarity Matrix Multiplication

**Input**: \( CSMQue \): Contextual Similarity Matrices Queue

**Output**: \( MtxProductStack \): A Stack stores the product of the consecutive matricides

1. **Data Structures**:
   - \( Pr_{matrix} \): Stores the previous matrix
   - \( Cr_{matrix} \): Stores the current matrix
   - \( MtxProductStack \): A Stack stores the product of the consecutive matricides

2. **Initialization**:
   - \( Pr_{matrix} \) ← Dequeue \( CSMQue \)
   - \( MtxProductStack \) ← \( Pr_{matrix} \)

3. **while** \( CSMQue \) ≠ Empty **do**
   - \( Cr_{matrix} \) ← Dequeue \( CSMQue \)
   - \( MRes \) ← \( Pr_{matrix} \) ⋅ \( Cr_{matrix} \)
   - \( MtxProductStack \) ← \( MtxProductStack \) ⋅ \( MRes \)
   - \( Pr_{matrix} \) ← \( Cr_{matrix} \)

**Result**: \( MtxProductStack \)

the back-tracing stage as follows: back-tracing begins by selecting the maximum value from the final produced matrix. This value represents the maximum contextual weight for a given sentence. This value is then decomposed into its row and column vectors from the previous matrix multiplication. In step three, we select senses with the maximum product. These are senses that contributed the most to the global context. Finally, steps two and three repeat until no elements are left to decompose.

As described above, our algorithm is intuitive and its results are explicable. It begins with a local context and then improves the context with heuristics and document context. Finally, it selects the most appropriate sense that contributes to the maximum global context while maintaining terms order.

3.3. Document Carry-forward Terms:

In a few cases, our algorithm is unable to disambiguate a term using the SCSMM algorithm. This would happen where a term has no local context (zero similarity) with its surrounding terms. In such cases, we first attempt to disambiguate the term using its sentence as a context, including all recently-disambiguated terms. We then select the sense with the maximum similarity with the sentence context. However, if a term could still not be disambiguated within its own sentence, the term is then carried forward to be disambiguated after the entire document is processed. These terms are referred to as Document Carry Forward (DocCF) terms, which are processed after all sentences have been disambiguated to provide a maximum context for these terms. For each DocCF term, the sense with the maximum average similarity with all terms in the document is selected.
Algorithm 5: Back-tracing the maximum context contributing senses

**Input**: $MtxProductStack$: A Stack stores the product of the consecutive matricides

**Output**: $SensesList$: A stock of list of selected Senses

1. **Data Structures**:
   - $Pr_{matrix}$: Stores the previous matrix
   - $Cr_{matrix}$: Stores the current matrix
   - $location\langle r, c, val \rangle$: triple $\langle$row, col, value$\rangle$ of the location of maximum value in the matrix

2. **Initialization**:
   - $Pr_{matrix} \leftarrow MtxProductStack$
   - $location\langle r, c, val \rangle \leftarrow \text{Max}(Pr_{matrix})$

3. **while** $MtxProductStack \neq \text{Empty}$ **do**
   - $SensesList \leftarrow \text{Push}\langle \text{Sense}(c) \rangle$
   - $Cr_{matrix} \leftarrow MtxProductStack$
   - /* The index of column that contributes the most to the context */
   - $c \leftarrow \text{Max}(\{\text{Row}_{Cr_{matrix}}, \text{Col}_{Pr_{matrix}}\})$
   - $location \leftarrow \{r, c, val\}$
   - $Pr_{matrix} \leftarrow Cr_{matrix}$
   - $SensesList \leftarrow \text{Push}\langle \text{Sense}(c) \rangle$
   - $SensesList \leftarrow \text{Push}\langle \text{Sense}(r) \rangle$

4. **return** $SensesList$

4. Evaluation and Experimental Results

4.1. Experimental Setup

We compared the results of our proposed SCSMM-WSD approach to the state-of-the-art systems based on well-known evaluation datasets. We also employed the commonly used training dataset in this field to obtain sense heuristic. We also compared our approach to the baseline approaches represented by selecting the first sense in WordNet and the MFS using both training datasets. To obtain heuristics, we retrieved the senses’ annotations from the SemCor and
OMSTI training datasets (see Section 4.1.1). The SemCor annotations are available as part of the SemCor installation package in the 'cntlist' file, and the OMSTI annotations were preloaded to the SQL database from the 'keys' file downloaded from [44].

4.1.1. Training Datasets

The two large sense-annotated corpora (SemCor and OMSTI) have been used in many supervised approaches for training their models. Both datasets are tagged with WordNet senses; one of which is manually annotated, while the other is automatic.

- **SemCor** [30]: a manually-annotated corpus extracted from the original Brown corpus. The dataset is annotated with POS, lemmas, and word senses based on WordNet KG. SemCor consists of 352 documents: 186 documents include tags for all POS words (nouns, verbs, adjectives, and adverbs), while the remaining 166 contain tags only for verbs. The total number of sense annotations in all documents is 226,040. To our knowledge, SemCor is

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10http://lcl.uniroma1.it/wsdeval/home
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Table 4
SensEval/SemEval evaluation datasets

| Dataset Name | Task | Method | # of Senses |
|--------------|------|--------|-------------|
| SensEval2 (SE2) [17] | | LS, AW | 1066 517 445 254 2282 |
| SensEval3 (SE3) [48] | | LS, AW | 900 588 350 12 1850 |
| SemEval-07 (SE07) [43] | | LS | 159 296 - - 455 |
| SemEval-13 (SE13) [35] | | LS, AW | 1644 - - - 1644 |
| SemEval-15 (SE15) [32] | | LS, AW | 531 251 160 80 1022 |

Table 5
Statistics of WSD gold standard dataset

| Criteria | SE2 | SE3 | SE07 | SE13 | SE15 |
|----------|-----|-----|------|------|------|
| #Doc | 3 | 3 | 3 | 13 | 4 |
| #Sent* | 242 | 297 | 120 | 301 | 133 |
| #Terms | 2282 | 1850 | 455 | 1644 | 1022 |
| AvgSentSize | 9 | 6 | 3 | 5 | 7 |
| Single sense | 442 | 311 | 26 | 348 | 189 |
| Ambiguity rate | 81% | 83% | 94% | 79% | 82% |

the largest manually-annotated corpus with WordNet senses, and is the main corpus used in various literature to train supervised WSD systems [2, 55].

- **OMSTI** [49]: an automatically-annotated corpus with senses from WordNet 3.0. As the name suggests, it contains one million sense-annotated instances. To automatically tag senses, OMSTI used an English-Chinese parallel corpus\(^{11}\) with an alignment-based WSD approach [13]. OMSTI has already shown its potential as a training corpus by improving the performance of supervised systems [49, 21].

4.1.2. Evaluation Datasets (Gold Standard)

A comprehensive evaluation framework has been presented in [44] with the integration of the primary WSD datasets. These datasets were presented as part of the SemEval International Workshop on Semantic Evaluation\(^{12}\) between 2002 and 2015. The framework included datasets from five main competitions, as presented in Table 4.

We further analyzed the datasets to determine the average sentence size, context size, and ambiguity rate within each dataset. Table 5 depicts the statistics for each dataset. The average sentence size is calculated based on the number of annotated terms/processed sentence. Sentences that do not contain any terms are omitted. The context size is measured by the number of terms that have a single sense, hence unambiguous terms. Finally, the percentage of ambiguity is computed based on the number of ambiguous terms to the total number of terms. For example, SemEval-07 has the highest ambiguity rate of 94%, with only 26 out of 455 terms that are not ambiguous (only one sense), and the smallest average sentence size with an average of only three terms/sentence. Note that the ambiguity rate is inversely correlated with context size, which could degrade the disambiguation score, as presented in the results in Section 4.5.

Furthermore, out of those ambiguous terms, Table 6 depicts the granularity level for each POS on all datasets combined. The granularity level reflects the average number of senses for each term, and negatively impacts disambiguation performance. Having a high granularity level makes the disambiguation decision very difficult even for humans, explaining the relatively low inter-agreement score between annotators. The annotators’ inter-agreement score ranges between 72% to 80% on AW task. The average granularity level for verbs is the highest compared to all other POS; on average, each verb term has 10.95 senses compared to 5.71, 4.7, and 4.4 senses for the nouns, adjectives, and adverbs, respectively. The fourth row presents the maximum number of senses within each POS, where the maximum number of senses in verbs reaches up to 59, compared to 33, 21, and 13 senses for the nouns, adjectives, and adverbs, respectively. Both nouns and verbs are highly granular, explaining most systems’ results as will be described in Section 4.5.

\(^{11}\)http://www.euromatrixplus.net/multi-un/

\(^{12}\)Current workshop website: http://alt.qcri.org/semeval2020/
Table 6
Ambiguous terms statistics for all gold standard datasets

|                  | Noun | Verb | Adjective | Adverb |
|------------------|------|------|-----------|--------|
| # of terms       | 4300 | 1652 | 955       | 346    |
| # of ambiguous   | 3442 | 1555 | 732       | 208    |
| Average granularity | 5.7  | 11.0 | 4.7       | 4.4    |
| Max #senses      | 33   | 59   | 21        | 13     |
| Mode             | 2    | 4    | 2         | 2      |
| Median           | 5    | 7    | 4         | 3      |

The mode and median also explain the results in Section 4.5, as most ambiguous verbs have four senses compared to two senses in all other POS.

4.2. Evaluation Metric
Three main metrics are used to evaluate any WSD system performance: Precision, Recall, and F1-score. These measures are commonly used in the IR field. Assuming, within a dataset, there is a set of manually annotated test words \( T = (w_1, ..., w_n) \), and for any system, the set of all evaluated/retrieved words is represented as \( E = (w_1, ..., w_k) : k <= n \), and the set of correctly evaluated words \( C = (w_1, ..., w_m) : m <= k \). Then we can evaluate the system as follow:

- **Precision**: the percentage of correctly identified words given by the system:
  \[
P = \frac{\text{Number of correct words}}{\text{Number of evaluated words}} = \frac{m}{k},
\]
  where \( k = |E| \) the total number of evaluated words, and \( m = |C| \) the total number of correctly evaluated words.

- **Recall**: the percentage of correctly identified words given by the system out of all test words in the dataset:
  \[
  R = \frac{\text{Number of correct words}}{\text{Number of test words}} = \frac{m}{n},
\]
  where \( n = |T| \) the total number of evaluated words, and \( m = |C| \) the total number of correctly evaluated words. If a system is able to evaluate every test word in \( T \), then, we can say that the system has a 100% coverage; hence, \( P = R \).

- **F1-score**: is a balanced \( F_\alpha \)-score where \( \alpha = 0.5 \). The \( F_1 \)-score is given by the following equation:
  \[
  F_1 \text{-score} = \frac{2PR}{P + R} \tag{7}
  
  The general \( F_\alpha \)-score measures the trade-off between the precision and recall as follows:
  \[
  F_\alpha \text{-score} = \frac{1}{\alpha \frac{1}{P} + (1 - \alpha) \frac{1}{R}} \tag{8}
  
4.3. Evaluated Semantic Similarity measures
In this section, we present various semantic similarity measures that have been evaluated in our experiment. The similarity measure with the best performance is employed to construct the similarity matrix for our algorithm, as shown in Algorithm 3, Line 7. These measures have been discussed in detail in [7]. Table 7 depicts the performance of the top four measures (\( LCH, WUP, JCN, \) and \( PATH \)) on all dataset. As shown in these results, the JCN measure provides the best WSD performance across all datasets. The only exception is on \( SemEval2013 \) where both \( PATH \) and \( LCH \) outperformed \( JCN \). However, using the combined datasets, \( JCN \) outperformed all other methods. Hence, it is the measure used in our SCSMM algorithm.
### Table 7
F1-score for top four semantic similarity methods

| Method | SSR  | SE2  | SE3  | SE07 | SE13 | SE15 | All  |
|--------|------|------|------|------|------|------|------|
| LCH    | 72.51| 69.89| 61.01| 64.42| 66.29| 67.67| 67.67|
| WUP    | 73.17| 68.78| 62.89| 63.56| 66.48| 67.37| 67.37|
| JCN    | 78.14| 72.67| 64.78| 63.44| 68.38| 69.67| 69.67|
| PATH   | 73.17| 70.11| 61.01| 64.66| 66.29| 67.98| 67.98|

### 4.4. Implementation

Fig. 10 describes the architecture for the proposed WSD system. The WSD system is built based on the Web API architecture, which includes controllers and models. We further extend the architecture to provide a separate services component that handles the main WSD system logic. The architecture consists of two Web API systems: WSD API and PyNLTK API. WSD API is responsible for the core WSD algorithm, while PyNLTK API carries out any NLP processing tasks, including gloss-based similarity (i.e., Lesk).

![WSD System Architecture](image)

**Figure 10: WSD system architecture**

The main WSD application is a C# Web API application with three separate layers: controllers, services, and models. The controllers handle the API routing process and trigger the appropriate system logic from the services layer. In return, the services component is responsible for implementing the core WSD algorithm. It also connects with the models to add, retrieve, and update data from the database. Furthermore, the services layer is also responsible for establishing any internal or external API calls such as the calls to the PyNLTK API to perform any NLP preprocessing required, or the calls the BabelNet API\(^\text{13}\) to obtain BabelNet synsets, which is required for the NSARI embedding evaluation.

The second PyNLTK API application is a python-based implementation. The main role of this component is to compute text-based similarity measures such as the *LESK* similarity.

The data is retrieved from three distinct sources. The first is an SQL server database that stores the heuristics datasets (SemCor and OMSTI). The second consists of filesystems that contains pre-calculated embedding vectors for WordNet KG from two embedding models: NASARI [12], and TransE from [54]. The last is the Natural Language Toolkit (NLTK) corpora as part of the NLTK\(^\text{14}\) package. We employed the Brown and SemCor corpora to compute concepts’ IC.

\(^\text{13}\)https://babelnet.org/
\(^\text{14}\)https://www.nltk.org/
Table 8
Configuration parameters for the SCSMM system

| Name        | Description                              | Best Config. |
|-------------|------------------------------------------|--------------|
| SSR         | Semantic similarity measure              | JCN          |
| H(x)        | Heuristic dataset used s=SemCor, so=SemCor+OMSTI | H(s)         |
| DocCtx      | Document context used in the CSM flag    | True         |
| DocCF       | Document carry-forward flag              | True         |
| POS_Of_Int  | The list of POS of interest that are being processed | \{n,v,adj,adv\} |
| DocCtxPOS   | The list of POS used as in the document context | \{n,v\}     |

Table 9
F1-score for each gold standard datasets

| System         | SE2  | SE3  | SE07 | SE13 | SE15 | All  |
|----------------|------|------|------|------|------|------|
| Lesk_ext       | 50.6 | 44.5 | 32.0 | 53.6 | 51.0 | 48.7 |
| Lesk_ext+emb   | 63.0 | 63.7 | 56.7 | 66.2 | 64.6 | 63.7 |
| UKB            | 56.0 | 51.7 | 39.0 | 53.6 | 55.2 | 53.2 |
| UKB_gloss      | 60.6 | 54.1 | 42.0 | 59.0 | 61.2 | 57.5 |
| Babelfy        | 67.0 | 63.5 | 51.6 | 66.4 | 70.3 | 65.5 |
| UKB_gloss18    | 68.8 | 66.1 | 53.0 | 68.8 | 70.3 | 67.3 |
| WSD-TM         | 69.0 | 66.9 | 55.6 | 65.3 | 69.6 | 66.9 |
| WN1st_sense    | 66.8 | 66.2 | 55.2 | 63.0 | 67.8 | 65.2 |
| MFS_s         | 65.6 | 66.4 | 54.5 | 63.8 | 67.1 | 64.8 |
| MFS_so        | 66.5 | 60.4 | 52.3 | 62.6 | 64.2 | 62.8 |
| SCSMM_Hs      | 66.9 | 67.2 | 55.4 | 63.0 | 68.4 | 65.6 |
| SCSMM_Hs      | 68.1 | 67.2 | 55.4 | 63.0 | 68.4 | 66.0 |
| SCSMM_Hs + DocCtx | 68.4 | 66.8 | 56.9 | 63.4 | 69.0 | 66.2 |
| SCSMM_Hs + DocCF | 68.1 | 67.1 | 56.3 | 63.0 | 68.7 | 66.0 |
| SCSMM_Hs + DocCtx + DocCF | 68.9 | 67.6 | 57.1 | 63.5 | 69.5 | 66.7 |

Table 8 outlines the main parameters that control our system, where the right most column shows the optimal configuration that leads to optimal performance. Note that we include all POS in the evaluation for the POS_Of_Int. However, since adjectives and adverbs merely describe nouns and verbs, respectively, they are not considered a context in DocCtxPOS parameter.

4.5. Experimental Results and Performance Analysis

To validate the robustness of the proposed method, we evaluated its performance with the five gold standard datasets presented in Table 4. We further present the results of the combined datasets to demonstrate the overall performance of the evaluated systems. The performance is measured by the F1-score discussed in Section 4.2. We present the proposed SCSMM method using two heuristics deployments; the first uses heuristics from the SemCor dataset (H_s), and the second uses both SemCor and OMSTI datasets\(^{15}\) (H_so). In addition, we present three additional configurations for the SCSMM algorithm. These configurations demonstrate the effects of document context and document carry-forward on the performance of the proposed algorithm.

Table 9 depicts the F1-score for each individual dataset in addition to the overall performance on all five datasets combined. The results of all configurations of the proposed SCSMM algorithm are compared to the current state-of-the-art knowledge-based systems presented in [25, 5, 3, 33]. In addition, we present the baseline approaches using WN1st_sense, MFS_s, and MFS_so.

The proposed SCSMM algorithm has the best performance when the document context is included in the CSM, and when the DocCF disambiguation option is enabled. SCSMM outperforms all other systems on two datasets, the SE3 and SE07, while matching the WSD-TM system on SE2. We noticed that our system is outperformed on SE13, as it is ranked fifth compared to other systems on the same datasets. We believe this is due to the following reasons:

1. This dataset is not diverse, as it includes only nouns, while with other datasets, various POS contribute positively.

\(^{15}\)The training dataset were downloaded from \texttt{http://lcl.uniroma1.it/wsdeval/training-data}
Table 10
F1-score for each POS on all gold standard datasets

| System            | Noun | Verb | Adj | Adv |
|-------------------|------|------|-----|-----|
| Lesk\textsubscript{ext} | 54.1 | 27.9 | 54.6 | 60.3 |
| Lesk\textsubscript{ext+emb} | 69.8 | 51.2 | 51.7 | 80.6 |
| UKB               | 56.7 | 39.3 | 63.9 | 44.0 |
| UKB\textsubscript{gloss} | 62.1 | 38.3 | 66.8 | 66.2 |
| Babelfy           | 68.6 | 49.9 | 73.2 | 79.8 |
| WSD-TM            | 69.7 | 51.2 | 76.0 | 80.9 |
| WSD-TM            | 69.7 | 51.2 | 76.0 | 80.9 |

Table 10 depicts the F1-score of the combined five datasets on each POS. As can be seen from the results, our system outperforms all other systems when disambiguating nouns using the SCSMM\textsubscript{H=DocCtx + DocCF} with a F1-score of 69.9. This is due to the proposed sequential algorithm that captures the maximum combination of the local similarities within each sentence. This can also be explained by the fact that nouns are structured and connected within WordNet compared to all other POS. Note that Lesk\textsubscript{ext+emb} and WSD-TM outperform our system on verbs.

4.5.1. Discussion of Experimental Results

Despite the various scores achieved by the evaluated systems, Table 9 shows a performance correlation across all systems. The results demonstrate a consensus on the best and worst scores per dataset. For instance, most systems perform best on SE15 and worst on SE07. Based on the observation above, we present and analyze the effect of POS distribution, granularity level, ambiguity rate, and sentence size on the performance of WSD systems in general and the proposed SCSMM algorithm in particular.

**POS Distribution:** The diversity of POS within each dataset appears to correlate with the F1-score. Fig. 11 depicts the F1-score for our proposed SCSMM algorithm with the POS distribution for each dataset. As shown in the figure, SE2 and SE15 contain similar POS distribution, in particular, the weights of verbs within the datasets has a higher impact on the performance of any WSD system, including the proposed algorithm. SE2 and SE15 contain almost the same percentage of verbs (23% and 25%), respectively, and have a similar F1-score. As for SE3, verbs occupy 32% of the dataset. Consequently, the performance of all systems has deteriorated for this dataset compared to SE2 and SE15. Finally, having verbs outweigh nouns by almost double in SE07, all systems showed the lowest F1-score on this dataset compared to all other datasets.

Finally, the trigger dataset for analyzing the POS distribution is SE13. Although SE13 contains three of the best qualities a dataset could have, yet, it performs poorly compared to other diverse datasets. SE13 contains only nouns,
which are well structured in WordNet. It has the lowest ambiguity rate (79%, as shown in Table 5), and it has the lowest granularity level of 5.9 as a dataset (see Fig. 13). As a result, we conclude that a diverse distribution of POS within a dataset improves our WSD algorithm.

**Granularity Level**: Granularity level is one of the most apparent factors that affect the performance of any WSD system including the proposed algorithm. Fig. 12 exhibits the performance of the proposed system and all other evaluated systems compared to the granularity level for each POS. The columns in the figure represent the granularity levels, while the lines represent the F1-score for the evaluated systems. The figure clearly illustrates that the more granular senses within POS, the lower the system’s performance. The same holds true for the granularity level within each dataset regardless of the POS distribution. Fig. 13 presents the F1-score for all systems on each dataset compared to the granularity level of each dataset.

**Context vs. Ambiguity Rates**: Both SE2 and SE15 have almost the same POS distribution within their respective datasets (see Fig. 11) and the exact same granularity level (see Fig. 13). On the other hand, the other three datasets have different POS distribution and relatively higher granularity level. So what are the advantages of SE15 over SE2
that yield better performance? We believe this is due to the context and ambiguity rates. The ambiguity rate represents the percentage of ambiguous terms within each POS or dataset. Fig. 14 depicts the POS distribution for each dataset in addition to the context and ambiguity rates within each POS. Except for the nouns, SE15 has a higher context rate than SE2, which explains the results of the F1-score for each POS within these two datasets. Table 11 shows the F1-scores for the proposed SCSMM algorithm for each POS on SE2 and SE15 datasets. The results correlate with the context and ambiguity rates within each POS. For example, SE2 has a higher context rate for the nouns than SE15; thus, it performed better. On the other hand, SE15 performed better than SE2 on all other POSs due to their higher context rates.

**Figure 13:** The granularity level of datasets compared to F1-score

**Figure 14:** Distribution of POS with (context to ambiguous) ratio

**Average Sentence Size:** The average sentence size is the most important factor that affects the performance of our SCSMM algorithm and other systems, as it is more challenging to extract a context from fewer words. The same is true for a large number of words. The average sentence size is shown in Table 5, which explains the lower performance of SE13 compared to SE2, as the average sentence size is shorter for SE13. However, although SE15 has a shorter...
average sentence size than SE2, it performed better. This result can be justified by the context rate factor discussed above, or an indication of an optimal average sentence size.

5. Conclusion

In this paper, we presented a novel knowledge-based WSD approach. Unlike other systems, our proposed SCSMM algorithm exploits the merits of local context, word sense heuristics, and the global context while maintaining the words order. The proposed SCSMM algorithm exceeds the current state-of-the-art KG-based systems when disambiguating nouns. Moreover, we evaluated the performance of current WSD systems, including our proposed method, on well-known gold standard datasets from the SemEval workshop series. Based on the datasets analysis and the trends of the evaluated systems, we conclude that WSD systems are negatively impacted by the granularity level of the dataset and the included POS. On the other hand, a more diverse POS within the dataset improves the results of the proposed WSD algorithm. Similarly, the higher the context rate, the better the F1-score. Finally, the results show that very short sentences (i.e., fewer than three words) can negatively affect the proposed SCSMM algorithm.

We believe that as KGs are enriched with more relationships between entities, and more domain-based KG are exploited, knowledge-based systems will outperform other WSD approaches. Furthermore, knowledge-based systems are intuitive, and their results are easily explained, understood, and justified by humans. The proposed method does not capture the exact topic of the document, but rather utilizes all context words in the document to disambiguate terms. To address this limitation, future research could investigate the adaptation of topic modeling and text clustering algorithms, such as the LDA algorithms used in [14], or the \(\beta\)-hill climbing technique presented in [1] to improve the document context and its similarity with ambiguous terms. Future work could include the investigation of a comprehensive semantic similarity and relatedness measure, making use of both taxonomic and not-taxonomic relations existing in the KG in order to capture true contextual relatedness between terms.

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Biography

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