# Word-Sense disambiguation system for text readability

Rodrigo Alarcon
Computer Science Department,
Universidad Carlos III de Madrid,
Madrid, Spain

Lourdes Moreno
Computer Science Department,
Universidad Carlos III de Madrid,
Madrid, Spain

Paloma Martinez
Computer Science Department,
Universidad Carlos III de Madrid,
Madrid, Spain

## ABSTRACT

People with cognitive, language and learning disabilities face accessibility barriers when reading texts with complex or specialized words. In order for these needs to be addressed, and in accordance with accessibility guidelines, it is beneficial to provide the definitions of complex words to the user. In this sense, human language can, at times, be ambiguous, and many words may be interpreted in multiple ways depending on the context. To offer a correct definition, it is often necessary to carry out Word Sense Disambiguation. In this paper, a system that is based on Natural Language Processing and Language Resources in the field of easy reading to provide a contextualized definition for a complex word is presented. An expert linguistic, specialized in easy reading and plain language, has evaluated the Word Sense Disambiguation system. This research work is part of the EASIER project that offers an accessible platform to provide users with the easiest possible Spanish text to understand and read.

## CCS CONCEPTS

• **Human-centered computing**; • **Accessibility**; • **Accessibility technologies**; • **Computing methodologies**; • **Artificial intelligence**; • **Natural language processing**;

## KEYWORDS

Web accessibility, Readability, WCAG, Tool, Word-sense disambiguation, Natural Language Processing, Cognitive disabilities

**ACM Reference Format:**

Rodrigo Alarcon, Lourdes Moreno, and Paloma Martinez. 2020. Word-Sense disambiguation system for text readability. In *9th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion (DSAI 2020), December 02–04, 2020, Online, Portugal.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3439231.3439257

## 1 INTRODUCTION

Currently, we have access to an overwhelming amount of information, yet this information is not accessible to all people. Certain individuals face accessibility barriers when reading texts that contain long sentences, unusual words, complex language structures, etc.

Although people with cognitive, language and learning disabilities are directly affected, cognitive accessibility barriers affect other user groups such as the deaf, deaf-blind, elderly, illiterate and immigrants who speak a different native language. According to the PISA report, the majority of the adult population in Spain has difficulties understanding dense texts [1]. In addition, 1.7% of the population is functionally illiterate and there are 277,472 people with some manner of intellectual disability.

To provide universal access to information and make texts more accessible, one of the most noteworthy initiatives is the Easy Reading guidelines, which propose recommendations on how to adapt texts so that they are easier to read and understand. In Spain, there are regulations in this regard, such as the UNE 153101:2018 (Easy to read. Guidelines and recommendations for the elaboration of documents) standard [2]. A second is the Plain Language initiative which promotes the use of simple language in information society content[1].

Related work is Web Content Accessibility Guidelines (WCAG) [3] within the Web Accessibility Initiative (WAI) of the W3C that contain specific standards that improve the understanding of texts. Along these lines, another notable initiative is the Accessibility Working Group for Cognitive and Learning Disabilities (COGA TF) [4].

In all these works, the guideline of using a language with a simple lexicon is repeated as being essential; techniques such as offering definitions of unusual words and distinguishing them so as to be recognizable by users are also recommended. Following this guideline is costly since, in practice, there are no resources that offer automatic support, making manually compliance not feasible in most cases. As part of the solution, there are Text Simplification methods found in the Natural Language Processing (NLP) field which could provide systematic support to improve the accessibility of textual content and promote compliance with cognitive accessibility guidelines [3][5].

While recent research, only focus on finding the sense of a word in a context, this work adds the procedure of finding the correct definition for a word in a certain context. This has been a key factor in defining the motivation of this research work: to create mechanisms which offer definitions for complex words.

Description of the accessibility guidelines concerning improving the accessibility of textual content are provided below. Section 3 presents related work. The description of the WordSense Disambiguation (WSD) system and the EASIER platform in which it is integrated is presented in Section 4. Section 5 includes the evaluation of the WSD system. Finally, conclusions and future lines of research are presented.

[1]Plain Language network web page https://plainlanguagenetwork.org/plain-language/que-es-el-lenguaje-claro/ [Accessed 18 November 2020].


*DSAI 2020, December 02–04, 2020, Online, Portugal*

ACM ISBN 978-1-4503-8937-2/20/12…$15.00
https://doi.org/10.1145/3439231.3439257

**Table 1: Success criterion 3.1.3 techniques (WCAG 2.1)**

| Option | Main technique | Techniques |
|---|---|---|
| Option A: If the word or phrase has a unique sense within the web page: | G101: Providing the definition of a word or phrase used in an unusual or restricted way | G55: Linking to definitions<br>•H40: Using description lists<br>•H60: Using the link element to link to a glossary<br>G112: Using inline definitions<br>•H54: Using the dfn element to identify the defining instance of a word<br>G62: Providing a glossary<br>G70: Providing a function to search an online dictionary |
| Option B: If the word or phrase has different senses within the same web page: | G101: Providing the definition of a word or phrase used in an unusual or restricted way | G55: Linking to definitions<br>•H40: Using description lists<br>•H60: Using the link element to link to a glossary<br>G112: Using inline definitions<br>•H54: Using the dfn element to identify the defining instance of a word |

## 2 ACCESSIBILITY GUIDELINES

Web Content Accessibility Guidelines (WCAG) [6], part of the W3C's WAI provide guidelines regarding how to make content more accessible for individuals with intellectual and learning disabilities. The WCAG includes certain guidelines which, if followed, assist in making web content accessible for individuals with intellectual and learning disabilities.

The Success Criterion 3.1.3 (Unusual Words) indicates that there must be a mechanism available for identifying specific definitions of words or phrases used in an unusual or restricted way, including idioms and jargon. This Success Criterion 3.1.3 is included in Guideline 3.1 (Readable) which recommends making text content readable and understandable. Likewise, this guideline belongs to Principle 3 (Understandable), which states that the information and operation of the user interface must be understandable.

Certain disabilities make it difficult for nonliteral word usage and specialized words or usage to be understood. This Success Criterion may help people with cognitive, language, and learning disabilities who have difficulty understanding words and phrases or those who have difficulty using context to aid understanding.

The Success Criterion 3.1.3 provides techniques which can provide assistance to these groups of people with disabilities. Fundamentally, said techniques state that the definition of a word used in an unusual or restricted way on a web page must be provided.

As shown in Table 1, in order to follow the techniques and provide the definition for unusual words, it is necessary to differentiate between two situations: if a word has a unique meaning within the web page or if different senses for the same word appear within the same web page. Therefore, in order to apply these techniques, the first step is to differentiate between these two situations. Moreover, it is necessary to contextualize the meaning of the unusual word in the textual content. As a solution, in this work, we propose using a WSD system which employs NLP methods.

## 3 RELATED WORK

Human language is ambiguous, and it is possible for many words to be interpreted in multiple ways depending on the context. The computational identification of meaning for words in context is called Word Sense Disambiguation [7]. As new words continue to be added to our language, this task becomes increasingly complex. Furthermore, as it is influenced by the domain in which the knowledge is created, producing resources to support knowledge based WSD is extremely costly. Considering this disadvantage, machine learning approaches have proved to be a good solution by using predictive strategies. Research can be found which has used supervised, unsupervised, and semi-supervised approaches.

Knowledge-based approaches require extensive lexical resources to determine the sense of a target word. Lesk [8] follows a knowledge-based approach by overlapping the word context and the sense definitions from a machine readable dictionary. Next, the sense that has a greater number of words in common with the context of the target word is chosen. This approach is dependent on finding the exact words in the definition, resulting in poor performance.

Supervised approaches require sense tagged corpora to train an algorithm to determine which sense is correct. For example, a team in the Senseval-3 competition [9] followed a supervised approach by training Support Vector Machines supported by the neighboring word's POS tags, single words around the context and syntactic relations, showing good recall when compared with the other participants in the task.

More recently, unsupervised approaches are among the most researched by using comparable corpora strategies [10]. Additionally, with the introduction of word embeddings, many investigations combine these concepts. Moradi [11] trained a Word2Vec model to evaluate similarity measures to disambiguate Persian language by considering semantic relationships between words.

Semi-supervised approaches appear by attempting to improve the disadvantages of each of the previous approaches. Generally, they consist in training classifiers from a small amount of labeled data and a large amount of unlabeled data. A recent work [12], proposes a semi-supervised method to improve a Long Short Term Memory (LSTM) model using self-learning and constructing the model by using the few labeled data to which they had access.

At the same time, many competitions have been organized with the goal of solving WSD problems. The SemEval-2007 competition [13] was focused on correctly disambiguating and identifying the semantic relationship between words. The SemEval-2013 [14] competition addressed this task by presenting a multilingual sense-annotated corpus, one of which was in Spanish, tagged with WordNet, Babelnet, and Wikipedia. The SemEval-2015 [15] addressed both WSD and Entity Linking (EL) to analyze and find ways to solve these tasks with similar methods by providing resources that integrate encyclopedic knowledge and lexicographic information.

However, others have tackled this problem from another point of view. Such is the case of Google, which uses its BERT language representation model (Bidirectional Encoder Representations from Transformers) [16] to solve different tasks in NLP by fine tuning their pretrained models. A research project carried out based on this approach [17] consisted in fine tuning a BERT model for WSD using WordPiece embeddings as part of the entries. Good results were obtained, overperforming the results of current approaches in F1-scores. The core process of our WSD system follows the aforementioned approach.

This task greatly supports other areas, such as simplification systems [18] oriented to people with cognitive disabilities. For the benefit of people with disabilities with communication and language problems, research has been found on systems that include WSD such as [19], to provide predictive text functionality, and [20], concerned with the selection of a correct pictogram.

# 4 WORD-SENSE DISAMBIGUATION (WSD) SYSTEM

In this section, the EASIER project, in which the WSD system has been integrated, will be introduced and subsequently described.

## 4.1 EASIER Project

The WSD task which supports the accessibility requirement (Success Criterion 3.1.3 (Unusual Words)) has been integrated into the EASIER [21] platform [2] [3] described in this section.

The difficulties in understanding texts containing unusual words that may create accessibility barriers for people with language and learning disabilities led to the creation of the EASIER project. It is a system that provides various resources which improve cognitive accessibility in Spanish such as synonyms, definitions, and pictograms for complex words within a text. To provide the definition resource, it was necessary to integrate a WSD task, which is the focus of this work.

The EASIER system is a web system that provides an accessible web interface. It was designed to be compliant with the WCAG 2.1 (Level AA) [6]. Furthermore, accessibility cognitive guidelines [4] were followed. Accessibility requirements such as making the purpose of page obvious, using clear and understandable content, and making each step of the simplification process as clear as possible, including instructions, were taken into consideration. Additionally, a consistent visual design, using graphic symbols that help the user, was used (see Figure 1).


**Figure 1: Screenshot of the EASIER system web interface (desktop version)**

Its functionality is as follows. Through the web interface, a user can enter a text and, subsequently, a web page with the results is returned. The system provides the same text, which was entered, but with the complex words highlighted (See Figure 1). When the user interacts with the complex words, synonyms, definitions and pictograms are provided. Adhering to a responsive design, a user interface for mobile devices is also provided.

Moreover, browser extensions have been developed for the Chrome and Mozilla browsers that offer the function of identifying complex words and providing synonyms for text a user selects on any web page.

In order to provide these language resources, the system integrates various NLP tasks. Firstly, in order to detect complex words within a text, lexical simplification based on Machine Learning is carried out using the Support-Vector Machine (SVM) classification algorithm [22].

In relation to providing a definition of the complex word detected during the previous step, dictionaries are then used and the WSD task is implemented as described in this paper.

Lastly, this service provides a pictogram of the complex word. This is obtained through the ARASAAC[4] resource which offers graphic elements for people with communication disabilities. The ARASAAC resource provides an available database of pictograms. Pictograms are a tool used by people with cognitive or communication disabilities.

[2]Easier project git http://github.com/LURMORENO/easier [Accessed 18 November 2020].
[3]Easier project webpage http://163.117.129.208:8080/ [Accessed 18 November 2020].
[4]Arasaac resource webpage http://www.arasaac.org/index.php [Accessed 18 November 2020

## 4.2 WSD System

This section introduces the WSD system's procedure used to select the correct definition for a specific word. In order to understand the core of the system, the BERT model the system relies on is subsequently explained.

*4.2.1 Meaning lookup procedure.* Figure 2 shows an example of the WSD selection procedure. Two dictionaries are used: the "Real Academia de la Lengua Española" Dictionary (RAE)[5] and the "Diccionario Facil"[6], the latter a dictionary of Easy Reading definitions created by the "Plena Inclusión Madrid"[7] association's experts and users with cognitive disabilities.

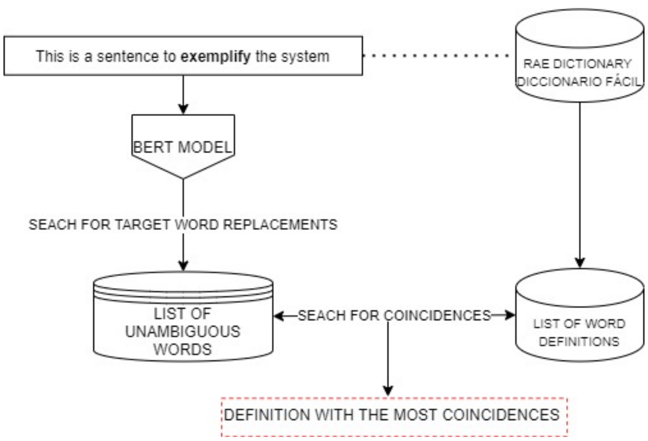


**Figure 2: Example of WSD system procedure**

The system receives a sentence along with the target word, then creates a list of the target word definitions extracted from the RAE or Easy Dictionary. With the help of the BERT model in the system, the word is masked in the sentence to which it belongs, then the model predicts which words can be substituted for the masked word. This results in a list of words that share a common meaning, thus disambiguating the target word. Later, with the help of a Spanish Spacy[8] model, we tokenize the sentence and search for verbs, nouns, and adverbs. The words in the sentence that has lexical content are then extracted and added to the list. Finally, these words are lemmatized to enrich the list.

Due to the fact that the first list created by our system contains words with similar semantics, these two lists are compared, and the coincidences are counted. The hypothesis followed is that the definition provided by the second list, which has more coincidences of words than the first list, is the correct definition associated with the target word and, consequently, that chosen by the WSD system. If no coincidences are found, the system selects the first definition in the list (First in).

[5]RAE Web Page https://dle.rae.es/ [Accessed 18 November 2020]
[6]Diccionario facil resource webpage http://www.diccionariofacil.org/ [Accessed 18 November 2020].
[7]Plena Inclusion association webpage https://plenainclusionmadrid.org/ [Accessed 18 November 2020].
[8]Spacy web page https://spacy.io/ [Accessed 18 November 2020].

*4.2.2 Bert model.* The core module uses a multilingual, pretrained BERT model[9] released by Google. To import this model, we use the PyTorch interface for BERT by Hugging Face[10] and, as this is a pretrained model, a specific input is required. Said input is as follows:

- The sentence must be surrounded by specific tokens: [CLS] and [SEP] indicating the beginning and the end of the sentence, respectively.
- Tokens that conform with the fixed vocabulary used in BERT.
- Token ID'S from BERT's tokenizer (one of them must be the target word).
- Mask ID's to distinguish between tokens and padding elements.
- Segment ID's to distinguish between sentences. In this instance, said value is always the same since we input one sentence every iteration.
- Positional embeddings.

We need to use BERT´s tokenizer because of its unique way of representing words. This tokenizer was created with a WordPiece model, therefore splits the words into smaller sub-words or characters. The model first checks if the whole is in the vocabulary, if not it tries to break the word into sub-words. Take for example de word "embedding" where the tokenizer outputs four sub-words: "em", "##bed", "##ding", "##s". This happens because within the word, the tokenizer finds coincidences between sub-words and the tokenizer´s vocabulary. Later, the sentence is converted to a list of vocabulary indexes and Segment ID´s (just one).

As a next step we generate an object from the model. This object has four dimensions: The layer number (12 layers), the batch number (1 sentence), the number of tokens and the feature number (768). At first, the values of the object are grouped by layers, but to our purposes, we need it to be grouped by tokens and we change the previous dimension into the following: number of tokens, number of layers, number of features with the help of the permute function of Pytorch.

Finally, to create our word vectors we combine some of the layer vectors. To know which layers, provide the best results, we follow Jay Allamar´s approach on Name entity recognition, where they perform a concatenation of the last four layers of the model. It is worth mentioning that depending of the task, this strategy could have different results.

These model embeddings are useful for semantic searches and information retrieval. The main difference between this type of embedding and others, such as Word2Vec or FastText, is that BERT produces word representations that are dynamically informed by the context words, while Word2Vec words are represented as unique indexed values. In common word embeddings, each word is represented with a single vector, ignoring polysemic words. In a sense, with this word embedding, each word could have several vectors, one for each of its possible senses. Therefore, these models allow the task of word disambiguation to be addressed when one attempts to discover the meaning of a word.

[9]Pytorch implementation: https://github.com/shehzaadzd/pytorch-pretrained-BERT [Accessed 18 November 2020].
[10]Hugging Face git repository https://github.com/huggingface/transformers [Accessed 18 November 2020].

**Table 2: Results in WSD System**

| | # Instances | % Correct |
|---|---|---|
| BERT Model | 117 | 64.95 |
| First in | 408 | 72.06 |
| Total | 525 | **70.48** |

## 5 WSD SYSTEM EVALUATION

The evaluation of the WSD system was made by a linguistic expert specialized in easy reading and plain language. The expert received a set of sentences associated with the target word and the definition selected by the system. The expert verified whether the definition selected by the system was correct, taking the context of the word in the sentence into consideration.

Table 2 shows the results of the evaluation of the WSD system. 525 instances were evaluated, of which 70.48 % were rated as correct, thus indicating our approach has a fair performance.

The BERT model approach was able to process 117 instances with a score of 64.95 % rated as correct. By applying the "First in" strategy, 408 instances were processed, from which 72.06 % were rated as correct. These results demonstrate that our approach performs well when dealing with polysemous words but faces some issues on recall. To help understand our results, examples are illustrated below.

With regards to the positive results, we noticed that the system selects larger definitions. This is due to the fact that the more coincidences the system finds, the larger the definition is, as shown in Table 3. In this instance, the coincidences were the words "declarar" (state) and "exponer" (present). Furthermore, we noticed that the system prefers "Diccionario Fácil" definitions whenever possible. This occurs because this database offers the definition of a word and an example of the word in a sentence. We believe that this is an advantage because there are some definitions in the RAE dictionary that are quite short and do not provide sufficient explanation. Table 4 shows an example of this in which the RAE dictionary provides a very short definition (a), from among all the possible definitions. However, the system chooses a correct and more explanatory definition (c).

By analyzing scenarios in which the system does not find any coincidences, we found that, generally speaking, there are no coincidences in generic sentences such as those found in Table 5, where the model does not have much context to analyze and outputs generic words like "resulta" (results), "consiste" (consists), and "ayuda" (help). Moreover, in some cases, we found that the system does not find coincidences because the definition is in another grammatical form. This issue can be corrected by lemmatizing the words in the definition and searching for coincidences.

Lastly, certain scenarios were found by analyzing negative results. As seen in in Table 5, the system presents problems when faced with generic sentences. In this case it outputs generic words, therefore selecting incorrect definitions. Another issue found was that when the system encounters the same number of coincidences among definitions, it selects the last processed definition. There must be a mechanism capable of selecting the correct definition in this scenario.

## 6 CONCLUSIONS

The main objective of this work is to offer correct definitions for complex words resulting in an improvement in cognitive accessibility by increasing the understanding and readability of texts. To accomplish this objective, a WSD system has been created that uses a context-aware approach supported by a multilingual BERT model, which provides a definition of a word, taking its context into account. This system has been integrated into the EASIER project, which provides various resources that improve cognitive accessibility in Spanish such as synonyms, definitions, and pictograms for complex words within a text.

The system has been evaluated by a linguistic expert, obtaining a precision score of 70.48%. The system showed positive results by selecting correct definitions. However, the coverage was low. It was observed that there were missing coincidences due to the fact that certain definitions for words were in a different grammatical form than the words that the WSD system provided. To improve this and as future work, content words of the definition can be lemmatized and added to the WSD process. Additionally, an issue was also observed in some cases in which the same number of coincidences among definitions were found. A mechanism to solve this must be developed, taking the main objective of this work into consideration.

**Table 3: WSD system positive results example 1**

| Sentence | "... confianza para todos los ciudadanos", ha **explicado**. (*"... trust for all citizens," he explained*) |
|---|---|
| Target Word | explicado" (*explained*) |
| Definition options | Declarar o exponer cualquier materia, doctrina o texto difícil, con palabras muy claras para hacerlos más perceptibles. (*state or present any material, doctrine or difficult text with very clear words so as to make it more understandable*)<br>Enseñar en la cátedra. (*teach from a podium*)<br>Justificar, exculpar palabras o acciones, declarando que no hubo en ellas intención de agravio. (*justify, exculpate words or actions, stating that there was no insult or injury intended*)<br>Dar a conocer la causa o motivo de algo. (present the cause of or motive for something) |
| Definition selected by the system | Declarar o exponer cualquier materia, doctrina o texto difícil, con palabras muy claras para hacerlos más perceptibles. (*state or present any material, doctrine or difficult text with very clear words so as to make it more understandable*) |

**Table 4: WSD system on selecting a more explanatory definition**

| | |
|---|---|
| Sentence | "Deben ser reconocidos por su contribución a la mejora en el intercambio y **procesamiento** de datos e información entre todos los agentes del sistema." *(They should be recognized for their contribution to the improvement in the exchange and processing of data and information between all of the system's agents.)* |
| Target Word Definition options | "procesamiento" *(processing)*<br>a) Acto de procesar. (the act of processing)<br>b) Acto por el cual se declara a alguien como presunto autor de unos hechos delictivos a efectos de abrir contra él un proceso penal. *(an action by which an individual who has allegedly committed a crime is formally charged and criminal proceedings are initiated)*<br>c) Aplicación sistemática de una serie de operaciones sobre un conjunto de datos, generalmente por medio de máquinas, para explotar la información que estos datos representan. *(The systematic application of a series of operations on a set of data, normally by machines, to exploit the information said data represents.)* |
| Definition selected by the system | Aplicación sistemática de una serie de operaciones sobre un conjunto de datos, generalmente por medio de máquinas, para explotar la información que estos datos representan. *(The systematic application of a series of operations on a set of data, normally by machines, to exploit the information said data represents.)* |

**Table 5: WSD system negative result**

| | |
|---|---|
| Sentence | "Y todo ello **redunda** en una mejor salud" *("And all of this results in improved health.")* |
| Target Word Definition options | "redunda" (*results*)<br>*a)* Dicho especialmente de un líquido: Rebosar, salirse de sus límites o bordes por demasiada abundancia. *(Used especially when referring to a liquid: spill over the edges or borders because the quantity exceeds the capacity.)*<br>b) Dicho de una cosa: Venir a parar en beneficio o daño de alguien o algo. *(Used when referring to a thing: to create a benefit for or a damage to someone or something.)* |
| Definition selected by the system | Dicho especialmente de un líquido: Rebosar, salirse de sus límites o bordes por demasiada abundancia. (*Used especially when referring to a liquid: spill over the edges or borders because the quantity exceeds the capacity.)* |

# ACKNOWLEDGMENTS

This work was supported by the Research Program of the Ministry of Economy and Competitiveness - Government of Spain, (DeepEMR project TIN2017-87548-C2-1-R), and the Accessible Technologies award - INDRA Technologies and the Fundación Universia (www.tecnologiasaccesibles.com). We would also like to express our sincerest gratitude to the association of people with cognitive disabilities "Plena Inclusión Madrid" (plenainclusionmadrid.org), who granted us the use of its easy reading dictionary ("Diccionario Fácil").

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