TOWARDS MULTILINGUAL READABILITY ASSESSMENT

by

Ion Madrazo Azpiazu

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Ion Madrazo Azpiazu

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Sole Pera, Ph.D.	Chair, Supervisory Committee
Tim Andersen, Ph.D.	Member, Supervisory Committee
Nere Lete, Ph.D.	Member, Supervisory Committee

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ABSTRACT

An *abstract* is a brief summary of the document. A typical abstract provides a brief introduction, enough to provide context for the document, explains the purpose of the thesis or project, and summarizes the major results and conclusions. Keep in mind that a casual observer is likely to judge the content of the document by the abstract and title alone. (There is an old addage: "in a joke, the punchline comes at the end; in a paper [or thesis], it comes in the abstract.") A single concise paragraph usually suffices for the abstract. If it spills onto a second page, it is probably too long.

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LIST OF ABBREVIATIONS

IR – Information Retrieval

NLP – Natural Language Processing

PoS – Part of Speech

LIST OF SYMBOLS

$\sqrt{2}$ square root of 2

λ lambda symbol, normally used in lambda calculus but it sometimes gets used for wavelength as well

CHAPTER 1

INTRODUCTION

Reading is an important skill in the academic environment, a competence that can be critical for students' educational opportunities and their careers [43]. As reported by Lennon and Burdick [35] reading for learning takes place when the reader comprehends 75% of a text. This represents an appropriate balance that allows the reader to positively understand the text, while also finding challenges in the reading process that will motivate him to improve his skills [35]. Outside the educational environment, reading generally takes place for comprehension rather than for learning. In this context, it is critical to provide people with texts they can fully understand. For example, patients that properly understand documents disclosed to them before surgery, are known to be less anxious before the operation and obtain more satisfactory results during posterior treatment [42]. However, recent studies[33, 42, 40] show that even medical documents that are supposed to be suited for average readers, tend to be too specialized and even well-educated adults have trouble understanding them. Whether for learning or understanding, the complexity of texts to be read needs to be determined.

Every reader has different reading skills and the levels of difficulty of the texts they need depends also upon their personal objective. Therefore, providing institutions and readers with tools that can measure the complexity of a text so that they can assess

whether it is adequate for a user is imperative. *Readability Assessment (RA)* tools [1] are certainly aimed for handling such a task by providing a mean to determine the degree of ease with which a reader can understand a given text, i.e. the *Readability Score (RS)* of the text.

Historically, teachers have been the main stakeholders of RA formulas, using them to select new materials for their courses and curriculum design. However, lately, more stakeholders have found benefits in using RA tools outside the academic environment. Automatic text simplification[46, 44], summarization for people with reading difficulties[28], book recommendation [41], literacy assessment[48], or legal and medical document complexity assessment[33, 37, 42, 40] are only a few examples of applications that take advantage of the complexity levels generated by existing RA tools. Even in commercial environments, book publishers require professional linguistic services in order to tag their publications with a readability level required for their intended audience, a task that could similarly be completed by an automatic tool.

In estimating the complexity of texts, traditional formulas, such as Flesh [30], became very popular in the late 1940's among educators for manually determining text difficulty. Most of these formulas relied on *shallow features*, which could easily be adapted to multiple languages and provide a simple way of determining text complexity. The multilingualism achieved by traditional formulas offered numerous benefits in contexts where the readability of more than one language was needed, i.e., book translation or learning a second language. However, traditional formulas were known to lack precision. For example, they could classify nonsense text as *simple to read*, just because it contained short and frequently-used words [25]. The insufficient

[1] RA tool and RA formula are used interchangeably in this document.

precision encouraged researchers to study and develop better and more sophisticated methods for RA that depended upon more in-depth text analysis [31, 16]. These new formulas continued taking advantage of shallow features, but incorporated more complex features based on the syntax and semantics of text. With the addition of new text complexity indicators, the tools became more precise, but at the same time more constrained regarding their language adaptability [19, 29]. In fact, they used increasingly more language-dependent techniques, which made the systems unadaptable to estimate RS for text in languages other than the one they were designed for. As a result, the multilingualism that was possible in the early stages disappeared.

With multilingualism and precision in mind, we propose to develop **MRAS**, a **M**ultilingual **R**eadability **A**ssessment **S**ystem. This tool should both show results comparable to monolingual state-of-the-art systems and maintain the multilingualism the early tools in the RA field had. For doing so, we will (1) explore features and methods used in literature, (2) design novel features that positively influence the readability level estimating process and (3) analyze how all those features can be adapted to be used in multilingual RA. MRAS will be *open source* and *easily connected* to different applications that require RA as a service, potentially permitting the analysis of all sorts of texts, including text snippets, books, websites and even short and unstructured texts, such as the ones found in social media. In doing so, we will create a system that will adapt itself to the input text language and use an adequate subset of features for the corresponding language for readability prediction, creating, to the best of our knowledge, the first multilingual readability assessment system.

As a byproduct of our research work, we will create a leveled dataset with readability-labeled documents for different languages, which currently is unavailable. In addition, we will create an in-depth report surveying existing strategies for readability predic-

tion.

It is important to note that, for practical purposes, the proposed application will only be tested in three different languages: *English*, for state of the art comparison purposes and as reference of germanic languages. *Spanish*, as a reference for romance languages, and *Basque* as an example of a pre-indoeuropean and minority language.

CHAPTER 2

RELATED WORK

From the past six decades, different RA systems have been developed with high diversity in terms of both languages and features [29, 19]. Initial readability formulas, such as Flesh [30], Dale-Chall [21], and Gunning FOG [13] made use of **shallow features**, mostly based on ratios of characters, terms, and sentences. These formulas, were basic enough even to be computed manually, providing a simple way of estimating a text's complexity, even if the formulas lacked precision in some cases [25]. This simplicity, however, made them easy to be adapted to estimate readability scores in different languages [45].

In recent years, readability formulas have evolved to supervised learning based systems that use a combination of traditional shallow features and new natural language processing based ones, which consider language aspects, such as syntax or semantics of texts. However, incorporating new features has brought a drawback to the area, evidenced by the fact that current systems are too focused in certain languages, making them only functional in the languages they were created for. Current state-of-the-art is composed by methods focused on specific languages, as discussed below:

For **English**, the RA system presented in [16] predicted only two levels of difficulty, simple or complex, using elaborated features, such as ambiguity among the terms in

the texts. Other authors [28], oriented their system for assessing the difficulty level of a text for people with intellectual disabilities by developing features that were intended to detect how well a text was structured. A readability prediction system for finalcial documents was presented in [20], which was based on features such as the presence of active voice or number of hidden verbs. It is also important to mention two commercial RA tools, Lexile[1] and AR [2], which are widely used among English speaker academic professionals. Even if their algorithms are not public, they are known to use shallow features showing how common terms of a text are and how long sentences are in average [35]. The literature pertaining to RA for text in English is abundant. For more in-depth discussion on RA formulas refer to [29, 19].

In contrast to English, **Spanish** RA has not seen any significant improvement regarding features in recent years, as most of the existing works are still based on shallow features. Among the well-known RA tools for Spanish, SSR [45] was based on the analysis of sentence length and number of rare words per sentences, whereas LC and SCI [17] were based on density of low frequency words in text. Other systems [47, 27] presented strategies to combine the aforementioned methods to improve RA estimation.

Compared to other languages, **Basque** RA is reduced to only one system. Due to the fact that Basque is considered a minority language and shares little similarity with most spoken languages, limited research has been done in the area. So far, ErreXail [32] is the only system created for Basque RA. ErreXail was developed to predict two different readability values, simple or complex, using features mostly based on ratios of common natural language processing labels, such as Part-of-Speech tags or

[1]https://www.lexile.com/

[2]http://www.renaissance.com/products/accelerated-reader/atos-analyzer

morphology annotations.

Similar to Basque, the literature for **Arabic** RA is limited as well. Al-Ajlan and Al-Khalifa [12] developed a RA tool based on only two features: average letters per term and average terms per sentence. These, features were analyzed using a Support Vector Machine classifier in order to classify text as simple or complex.

Opposed to RA tools for previous languages, structural features do not seem to have such a success for **Chinese** RA. Therefore, most of the research works related to Chinese RA have been focused only on lexical features, such as Tf-Idf of terms [22, 23].

In contrast to the aforementioned techniques, the authors of [26] presented a RA system for **Italian** aimed at assessing readability at sentence level, which combined traditional, lexical, and syntactical methods.

Rather than focusing on the general reader, François and Fairon [31] developed a RA system for **French** with foreign language learners in mind. The objective was to determine which features were more important for a foreign language learner to understand a text. They tested lexical, syntactical and semantic features and showed that semantic ones performed poorly in their case.

Even if the number of RA systems that tackle individual languages is high, they are usually focused on a specific set of features and materials they can analyze. In addition, to best of our knowledge, none the RA systems presented are **multilingual**. MRAS will not only be multilingual, but will also be based on a comprehensive set of existing and novel features which will be general enough to potentially be able to handle all sorts of reading materials. All those characteristics will make MRAS a unique system in the area.

CHAPTER 3

METHOD

MRAS is a readability assessment system capable of automatically predicting the readability level of any given document, being able to handle multiple document types, differing in format, length and language. For doing so MRAS takes advantage of several tools described in section 3.1, as well as various text processing strategies described in 3.2. This chapter also provides an overview of the design of MRAS in section 3.3 and further in-depth detail in sections 3.4 and 3.5.

3.1 Tools

Whether for text processing or for feature extraction, MRAS takes advantage of several existing tools and techniques, which we describe below.

3.1.1 NLP Toolkits

For developing MRAS we analysed several NLP toolkits available in he market.

Freeling NLP

Freeling [39, 38] is a NLP tookit developed for the easing various natural language analysis tasks. Freeling includes, but is not limited to, tokenization, PoS tagging, syntactic parsing, dependency parsing and semantic labelling. Furthermore, Freeling

is, to the best of our knowledge, the only tool kit supporting 14 languages with this depth of analysis, supporting Asturian (as), Catalan (ca), German (de), English (en), French (fr), Galician (gl), Croatian (hr), Italian (it), Norwegian (nb), Portuguese (pt), Russian (ru), Slovene (sl), Spanish (es), and Welsh (cy).

SyntaxNet

should I mention why not this one?

Katea

Katea is set of NLP tools developed for Basque. Katea is composed by Morpheus [11] (morpho-syntactic analysis), eustagger [15] (lemmatization and syntactic function indentification), eihera [14] (named entity detection), ixati [11] (shallow parsing) and maltixa [18] (dependency parsing).

3.1.2 WordNet

Wordnet [36] is a lexical database for English where terms, i.e., nouns, verbs and adjectives, are grouped into sets of synonyms, expressing different concepts. These concepts are related by each other by several semantic relationships, such as hyperonymie or hyponimie. An example of this structure can be seen in figure 3.1, where *motor vehicle* has *vehicle* as hypernym and *car* and *truck* as hyponyms. Note that this structure forms a tree. This fact will be used later, for building some features.

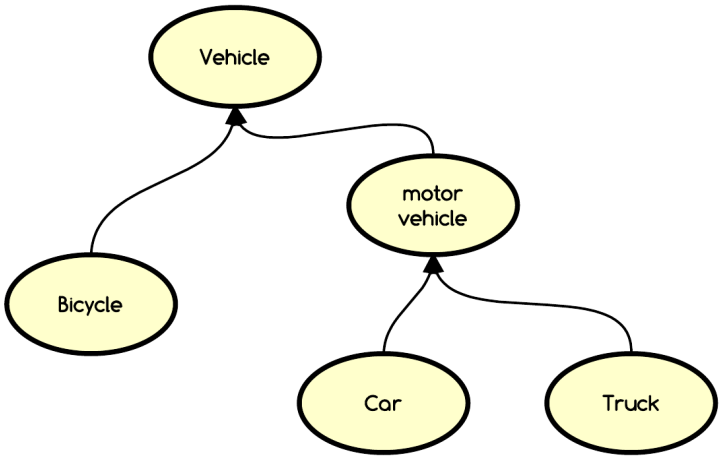

Figure 3.1: Wordnet example

3.2 Text processing

The preprocessing step is the one that takes place first for any document handled by MRAS. The aim of preprocessing is to identify the document to decide further process MRAS needs to perform over it, and to prepare the document for future feature extraction. More detail of mentioned processes is given below.

3.2.1 Document type detection

One of the main features of MRAS is its versatility, since MRAS is capable to predict readability values for documents of different format, length and language. Given this variety of documents, each of them cannot be treated the same way, different strategies need to be applied for different texts. Therefore, each document used by MRAS is classified using 3 criteria: format, length and language.

should we go deeper? explain how each criteria is determined?

3.2.2 Tokenization

Tokenization is the process of splitting a text into smaller parts, i.e. tokens. A token represents each sensical part of a text, which usually corresponds to a term, a number, or a punctuation mark. However, sometimes tokens can be formed by a combination of the previous, i.e., *aren't* or *people's*. An example of how a sentence is tokenized can be seen in Table 3.1.

Did they win the olimpics?					
did	they	win	the	olimpics	?

Table 3.1: Tokenization example

3.2.3 Stopping

Stopping or stopword removal refer to the process of removing stopwords from a text. A stopword is a term that does not add any important information to the task that is performed, usually adding unnecessary noise that hinders valuable information among a document. The frequency of a term is a good indicator for stopwords since, usually the terms that most appear in a text are the ones that less information contain. Some examples of general purpose stopwords are *a*, *the* or *is*, however depending on the domain, terms such as *computer* can also be stopwords given its high frequency. The purpose stopping is usually 2-way, speeding up later processes and noise reduction, and is usually performed without the need of any specific tool, just using a stopword list.

3.2.4 Stemming/Lemmatization

The goal of both stemming and lemmatization is to achieve a normalized version of a term. This normalization, is usually helpful for search and comparison task as it

reduced the search space among all the terms. As an example, when computing a metric about the verb *play* it might be interesting to compute it for all its word-forms (*play*, *plays*, *played*). This process is usually simpler if all the word-forms are normalized to one canonical form. Stemming and Lemmatization differ in the way the normalized form is obtained. While lemmatization is able to achieve real canonical form (i.e. lemma) of a word (the one appearing in the dictionary), stemming simply chops common prefixes and suffixes to obtain an approximation of it. When both techniques are available MRAS will use lemmatization over stemming, however, some languages do not have any lemmatization technique available. Freeling will be used for lemmatization in Spanish and English, while katea will serve for the same purpose in Basque.

3.2.5 Part of Speech Tagging

Part of Speech Tagging is the process of labelling each token with a tag that represent the function each token has in a sentence. PoS tags usually differ from language to language[1], however, the most predominant tags, such as verb, adjective or noun, exist among all the languages. An example of Part of Speech tagging can be seen in Table 3.3.

did	they	win	the	olimpics	?
Verb	Pronoun	Verb	Determiner	Noun	Symbol

Table 3.2: Part of Speech tagging example

[1]As an example, the Penn Treebank project defines 36 PoS tags for English, which can be seen here https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html

3.2.6 Shallow parsing

Shallow parsing, also called chunking, refers to the process of grouping tokens into chunks. A chunk consists usually a small phrase of about 1 to 4 terms. Those terms are somehow connected to each other and together express a senseful concept. There are two types of chunks, depending if they express a noun or verb phrase. An example of a shallow parsing of a sentence can be seen in figure 3.2.

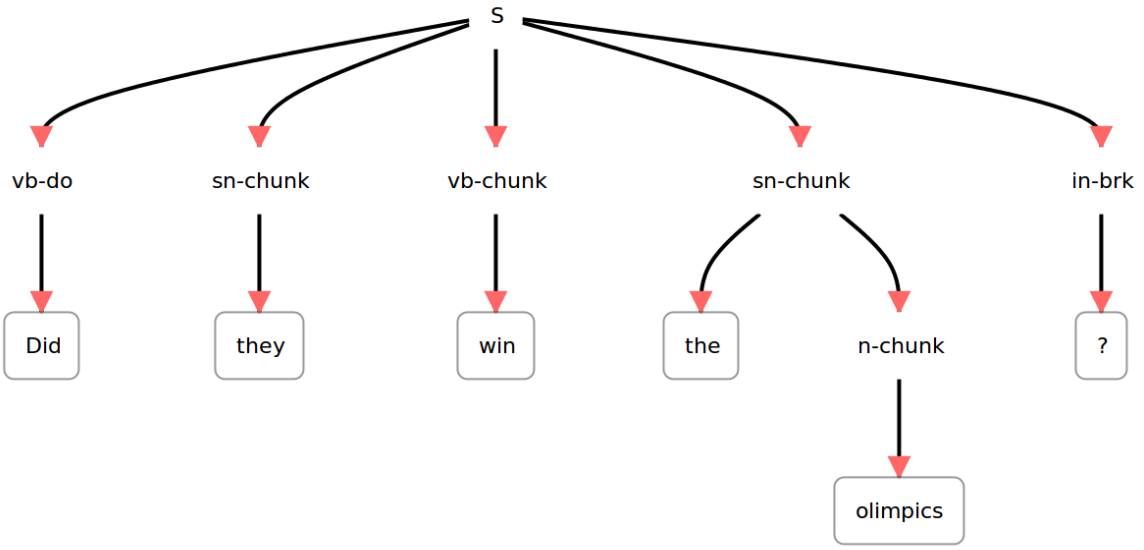

Figure 3.2: Shallow parsing example

3.2.7 Dependency parsing

Dependency parsing goes further than shallow parsing, determining relationships between tokens rather than just grouping them. Given these relationships, a dependency tree is generated, which usually has a root node representing the main verb of the sentence, which has the subject and objects of the sentence as children. An example of a dependency parsed sentence can be seen in figure 3.3.

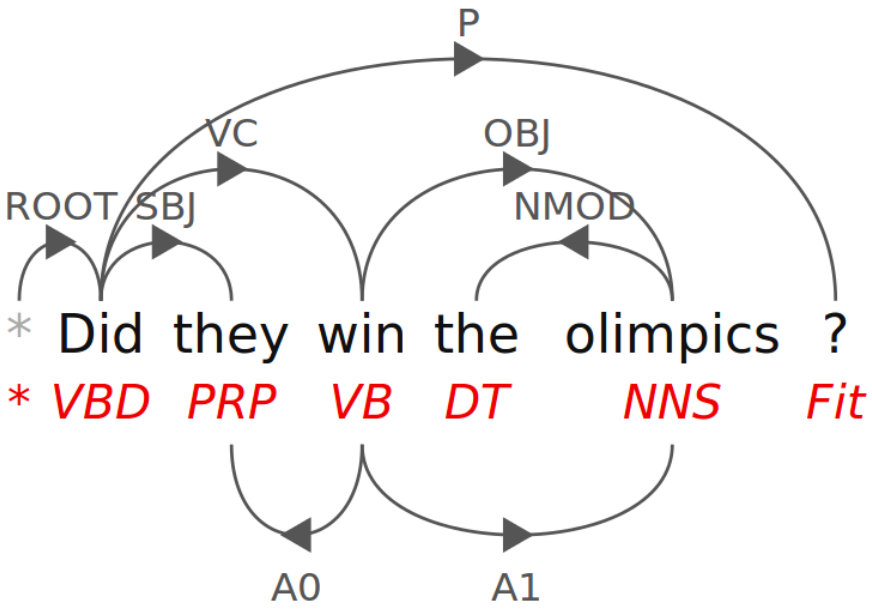

Figure 3.3: Dependency parsing example

3.2.8 Named entity detection

A named entity is a token or group of tokens that represent and known entity such as a person, a location, or an organization. Depending on the complexity of the tool that performs this analysis, those entities can also be linked to a knowledge base such as Dbpedia [34] where more structured information about the entity can be found.

Usain	Bolt	won	the	race	in	Rio	de	Janeiro	.
person	person					location	location	location	

Table 3.3: Named entity detection example

3.3 Design overview

MRAS is based on a supervised learning approach that relies on knowledge acquired from a leveled corpora. In designing MRAS we followed the steps illustrated in Figure 3.4 and discussed below.

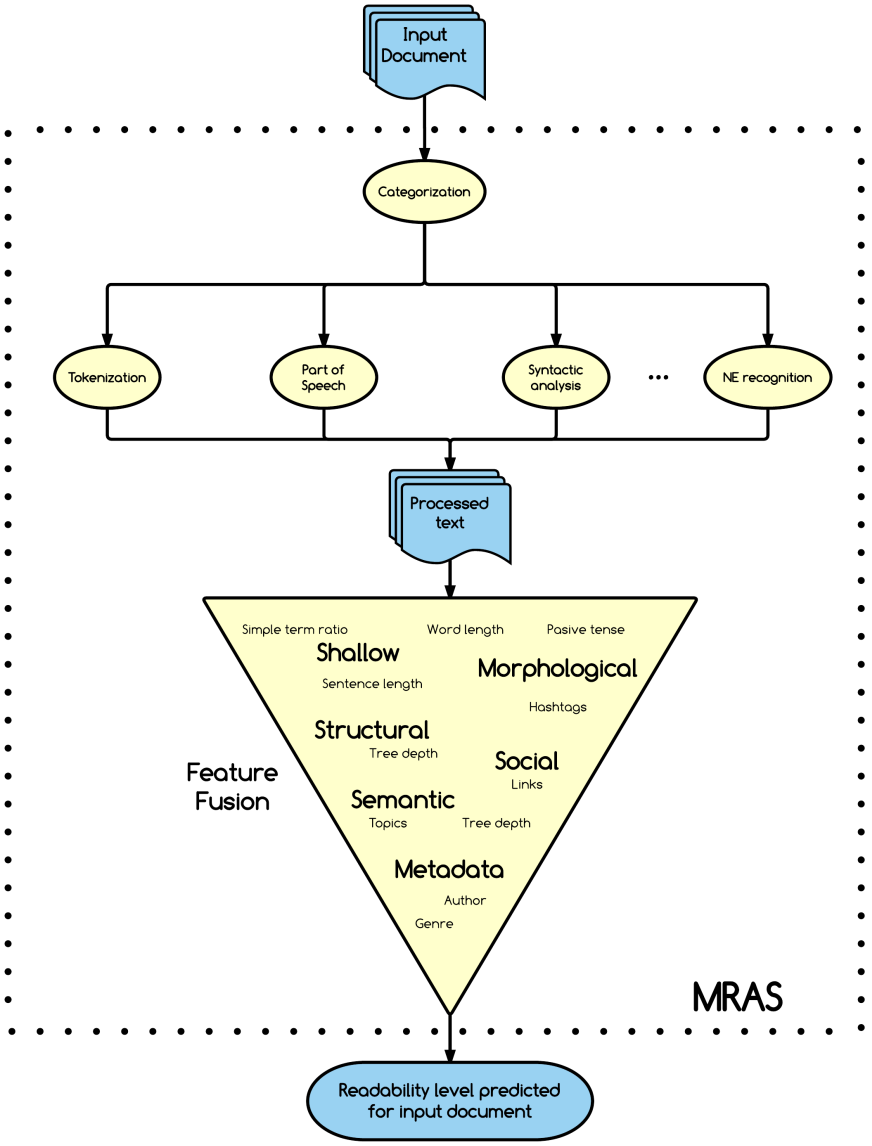

Figure 3.4: MRAS

MRAS receives two different inputs: a collection C of documents for each of which a readability label is already assigned, and a document d which its readability is unknown for MRAS and, thus, will be predicted. Both inputs are taken through a preprocessing step described in section **??**, which cleans, filters and normalizes their content, to prepare them for the feature extraction step described in section **??**. These features, serve as a numeric representation for each document. MRAS is capable of learning patterns over the representations extracted from each document in C and use these patters to predict readability scores for new unlabelled documents such as d.

3.4 Feature extraction

Feature engineering is one of the most important aspects of this thesis. A good feature set determines the the quality of a classifier, and therefore the quality of a readability assessment system. A description of each feature included in MRAS is provided below separated in different linguistic levels.

3.4.1 Shallow features

Shallow features [30, 21, 13] have historically shown to be of good use when predicting readability. Even if they sometimes lack precision [25], they serve as a good baseline for readability assessment systems. A description for each shallow feature is provided below.

Word length

Everyday terms are usually short in most languages, they are preferred for spoken language over their longer analogues, in order to maintain more fluent conversations. In the opposite side, difficult terms are longer the more technical or scientific they are. Therefore, short terms the one youngsters first learn and better comprehend. To take advantage of this fact, MRAS bases 4 features on it, average length of terms and average length of their lemmas, considering or not stopwords for both cases.

Sentence length

Sentences oriented people with low understanding skill are usually short. They just focus on simple ideas and facts with very simple argumentations. On the opposite side, documents oriented to more technical and complex aspects contain more argumentation and therefore more subclauses in the sentences, resulting in longer sentences. MRAS benefits of this fact generating two features, average word length of sentence with and without stop words.

Simple terms

3.4.2 Morphological features

Morphological features capture how terms are formed from their root. Even if this aspect is not relevant in some languages, such as English, it has been shown to be a strong predictor for readability scores in morphology rich languages such as Basque [32]. A description of morphological features included in MRAS is described below.

Morphological phenomena frequencies

Inflection ratio

difference in size between the wordform and the lemma

3.4.3 Structural features

Structural features are the ones that describe how a text is organized. They can both describe structure within the sentence (syntactical structure) or structure between sentences (pragmatical structure). The features that have been implemented in MRAS can be seen below.

Structural complexity

based on a neural network and distributional semantics

3.4.4 Semantic features

Semantic features go beyond the tokens and structure of the text in order to analyse the concepts laying on it.

Semantic closeness

How close is a text from the terms of each group? Using simple cosine similarity and using the cloud of points created using distributional semantics.

Concept densisty

Followability

Ngram frequencies

3.4.5 Social features

RA can be used in more than just plain text. Internet is evolving into a new social era and so are text resources. Increasingly more resources contain social information, such as hashtags, mentions, or links, a type of information that is usually ignored by readability formulas.

3.4.6 Metadata features

Metadata based features can be useful in environments where text access is limited (i.e. copyrighted material). An exploration of this type of features will also be done in order expand the types of texts MRAS can handle.

3.5 Fusioning Strategy

CHAPTER 4

EVALUATION

Even if MRAS is designed to be language independent, for practical purposes the evaluation will only be conducted in three languages that we think can faithfully represent the diversity of existing languages. For this purpose, we have chosen a germanic, a romance, and a pre-indioeuropean language, i.e. English, Spanish, and Basque respectively.

4.0.1 Datasets

The ideal dataset for developing MRAS would be a multilingual leveled dataset that would contain the exact same documents written in different languages, as well as human judgments, in terms of readability scores for each document. However, to the best of our knowledge, such a dataset does not currently exist. Consequently, we have identified various sets of leveled documents for each individual language that can suit MRAS' needs and can be used for evaluation purposes. Details on the datasets considered for evaluation purposes can be seen in Table 4.1.

4.0.2 Metrics

The performance of MRAS will be evaluated by means of (1) common classification evaluation methods, such as absolute error [24], (2) regression evaluation methods

	Dataset	Description
English	Lexile [1]	Contains book titles associated with its readability level
	Stantarized tests [2, 3]	Tests for English level, they contain various texts per test
	Other [4, 5, 6]	News for kids, exercises for learning English
Spanish	Lexile [1]	Contains book titles associated with its readability level
	Learning resources [7, 8, 9]	Various exercises for learning Spanish
Basque	Learning resources [1]	Various exercises for learning Basque
Multilingual	Parallel corpus [10]	Contains same texts translated into Spanish and English

Table 4.1: Data resources identified for MRAS development and validation

such as MSE (Mean Square Error) [24] and (3) methods common in the readability assessment domain, such as adjacent accuracy [31].

4.0.3 Overall Assessment

The study and performance analysis of this thesis will aim at answering the following questions:

- Which learning model performs better for MRAS? Which feature subset?
- Which features add more value in terms of predicting readability? Do they add same value for each language?
- How does MRAS perform compared to baseline shallow feature based formulas? and compared to state of the art systems?
- Would MRAS give the same prediction for a text that is translated manually into another language? and for a text that is automatically translated?
- How efficiently can MRAS predict the readability levels of written text in a language for which it has not been trained? If we train MRAS for two languages can we use it to predict the readability of a text in a third one?

- If we have a really small dataset for one language, would adding more data from another language improve the prediction results of the first one?

CHAPTER 5

MRAS IN ACTION

hashtag rec in twitter

CHAPTER 6

CONCLUSIONS

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