

# Master thesis proposal

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## 1 Introduction

Reading is an important skill of not only in the educational context, but in daily tasks. People that get good understanding from the texts they read, tend to take better decisions when they face medical or educational problems, which can lead to better career opportunities in the future. Studies [Ibrahim et al., 2016] [Petkovic et al., 2015] [Patel et al., 2015] show that even medical resources that are supposed to be suited for average readers, tend to be too specialized and even well educated adults have trouble understanding. Therefore, it is important not only to provide students with encouraging texts for improving their reading skills, but also to be able to produce texts, in medical or legal contexts, that are simple enough to be understood by people with average or poor reading skills. That is where the readability assessment formulas take place, providing a simple way of assessing a text's complexity level, so that the public for each text can be determined.

A readability score refers to the degree of ease with which a reader can understand a given text, which is usually conditioned by features such as vocabulary or syntax. Historically, teachers have been the main stakeholders of the use of readability formulas, making use of it for obtaining new materials for their courses and curriculum design. However, lately, readability scores have been discovered to have more uses than the ones in academic environments. Automatic text simplification [Štajner et al., 2015] [Saggion et al., 2015] or summarizing for people with reading difficulties [Feng, 2009a], book recommendation [Pera and Ng, 2014], literacy assessment [Weiss et al., 2005], or even legal [Ogloff and Otto, 1991] and medical document complexity assessment [Ibrahim et al., 2016] [Petkovic et al., 2015] [Patel et al., 2015]

are examples of the benefits a readability score can provide.

At the early stages of readability, formulas such as Flesh [Flesch, 1948], Dale-Chall [Chall and Dale, 1995] and Gunning FOG [Albright et al., 1996] showed up as the most used formulas by educators for manually determining text difficulty. Most of those formulas made use of shallow features such as, average word length or average sentence length. However, they soon left place to more complex formulas [François and Fairon, 2012] [Aluisio et al., 2010], that started to put together both natural language processing and machine learning techniques. The new formulas usually continued using the shallow features mentioned above, but added new more complex features based on syntax or semantics of the text. With the addition of new features, the tools became more precise, but more constrained, making them difficult to port to other languages than the one they were designed for, making the multilingualism that was possible in the early stages disappear.

Having seen the lack of multilingualism among the state of the art systems for readability prediction, we pursue to develop a multilingual readability assessment tool . This tool should both show results comparable to monolingual state of the art systems, and maintain the multilingualism the early tools in the readability field had. For doing so we will make a exploration of the features and methods used in literature, and adapt them to be multilingual. Furthermore, we will develop novel features that will aim at suiting the lack systems in the literature have regarding some languages. In doing so, we will produce a system that will adapt itself to the input text language, and use an adequate subset of features for that certain language for giving a prediction, creating, to the best of our knowledge, the first multilingual readability assessment system.

Should I explain something about evaluation here? About the comparison of features and analysis of their influence in each language?

It is important to note, that for practical purposes, the 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 latin languages, and *Basque* as an example of a non-indoeuropean language.

## 2 Thesis statement

In this project we aim to develop a multilingual readability predictor taking advantage of machine learning techniques and features extracted using natural language processing techniques. As a secondary goal, we will survey the features and methods currently used in the state of the art, and create a comparison features and their importance in the readability prediction for each language. As a byproduct of the development and testing, we will create various datasets that can be of good use for other researchers in the area.

## 3 Related work

In the recent years, different RA systems have been developed with high diversity regarding both languages and features.

For **English**, [Feng et al., 2010] presented a comparison of the common readability features used for English. [Aluisio et al., 2010] aimed their system for evaluating text simplification methods with a system, that made use of some more elaborated features such as ambiguity in terms. [Feng, 2009b] oriented their system for assessing the difficulty level of a text for people with intellectual disabilities, developing some features that were intended to detect how well a text was structured. **TO DO**

For **Spanish** [Štajner and Saggion, 2013] [Drndarević et al., 2013] ... **TO DO**

For **Basque**, for the best of our knowledge, only one system have been developed. Due to the fact that Basque is considered a minority language and shares very little similarities with the most spoken languages. Very little research have been done in the area. Therefore, currently, Errexail [Gonzalez-Dios et al., 2014] is the only system created for Basque readability assessment. This system was aimed for text simplification purposes and was developed to predict two different values, simple or complex. The aim for this was to detect which texts needed some simplification and which texts did not. The system makes use of simple features mostly based on ratios of common Natural language processing tags.

For **Chinese**, [Chen et al., 2011] developed a RA system only based on lexical metrics based on the TF-Idf measure. This metric in conjunction with a mutual information measure was able to determine which terms were most relevant for each of the readability levels. These terms were afterwards used to predict the level of readability for the inputs texts. However, this technique was not topic independent, as once trained for a certain topic the terms were no longer useful for other topics. Previously, [Collins-Thompson and Callan, 2004] developed a system that already tried to solve, the topic dependence problem for Chinese. This system was based on Tf-Idf too and as the authors stated, removing some top scoring words of the Tf-Idf ranking, lead the system to be more independent of the topic. Apparently, the top scoring words were highly specialized words to the topic selected for training.

For **Arabic**, [Al-Ajlan et al., 2008] developed a readability assessment told based on only two features. The features were based on simple ratios based on sentence, terms and letter counts. Those, features were used with a SVM classifier in order to be able to classify text as simple or complex.

For **Italian**, [Dell’Orletta et al., 2011] presented a readability assessment system aimed for text simplification. Since the text simplification tool the authors were developing was based on sentences. The authors of this system decided, that rather than developing a system for determining text readability, their system would work at sentence level. Therefore, the text simplification tool, would have more information of which sentence needed simplification and which did not. The model generated for sentence level is shown to be generalizable to full text level, by the use of simple averages. The more complex sentences a text have, the more probabilities it have to be complex in overall.

For **French**, [François and Fairon, 2012] developed a readability assessment system with the foreign language learners in mind. The objective was to determine which features were more important for a foreign language learner to understand a text. In addition, they provided a metric new to the area called adjacent accuracy that tried to measure systems’ performance in a more accurate and relevant.

## 4 Methodology

The proposed method relies in two different areas of data science, Natural language processing and machine learning. Advantage of one or both areas is taken in each of the steps that conform the pipeline of the algorithm explained below.

### 4.1 Pipeline description

The pipeline of the algorithm is composed by the following steps: Texts processing, feature extraction, feature processing and prediction. A visual description of the general pipeline of the system can be seen on figure 1. A more in-depth explanation of each step can be seen in the following sections.

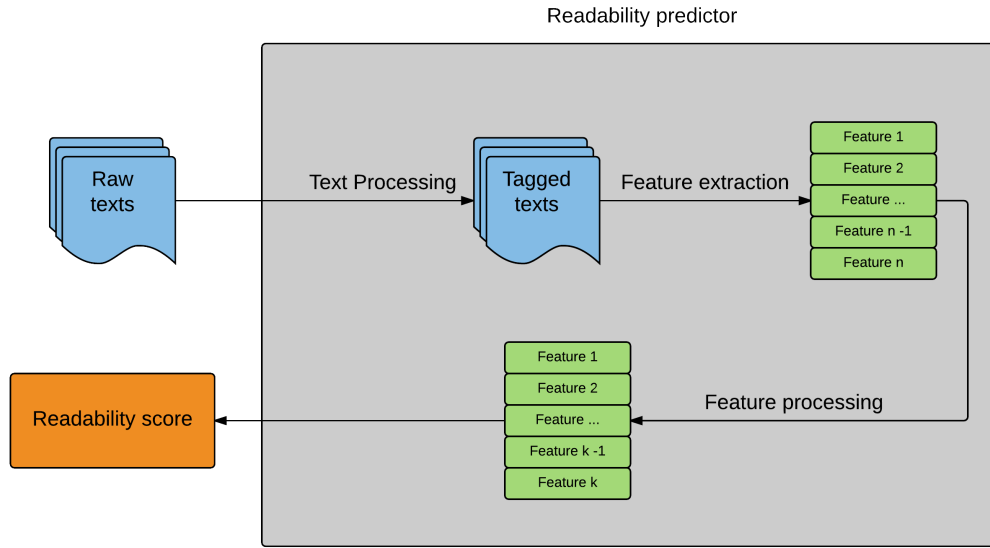


Figure 1: General pipeline

### 4.2 Text processing

The text processing step is the step where the raw text is given structure and, therefore, value. This structure and information will later be used for

extraction features that will help the system predict a readability score.

The tool that has been chosen for natural language processing is Freeling NLP [?]. Freeling is an open source Natural language processing library that supports 11 different languages. The tool solves common NLP tasks, such as, Tokenization, sentence detection, Part of speech tagging or dependency parsing. Each of this processes will be helpful for building certain features later.

The **tokenization** is the base module for any NLP processing. Tokenization refers to taking a raw text and normalizing it into pieces that make text processing possible. This will also make possible, to implement tradition shallow features such as, FleschKincaid [?].

The **Part of speech** analysis determines the function each token has in the sentence. This, together with **dependency parsing** techniques, make possible the analysis of syntactic structures in the sentences.

Other tools outside Freeling, such as **WordNet** or **Latent semantic analysis** techniques, will make possible to analyses texts at semantic level, for detecting structures that refer to concepts rather than to tokens themselves.

### 4.3 Feature extraction

This section describes the features proposed for the system. These features range from the most simple and commonly used ones such as the shallow features, to a more complex set of features such as the ones base on semantics.

**Shallow features**

**Part of Speech tags**

**N-grams**

...

Description of all the features used. Why should this feature be valuable, give hypotheses and intuition behind the use of each feature. Give examples

when needed.

## **4.4 Feature processing and selection**

Describe algorithms used for feature processing and selection, why should they help get better results?

## **4.5 Learning and prediction**

Describe algorithms for learning and prediction. Pros and cons of each algorithm, why should this algorithm adapt better to our problem?

# **5 Evaluation**

## **5.1 Datasets**

Information about how we get and extract the datasets.

### **5.1.1 English**

- Lexile
- List all for proposal...

### **5.1.2 Spanish**

- Lexile
- List all for proposal...

### **5.1.3 Basque**

- Ikasbil

## **5.2 Metrics**

- Error rate, accuracy
- Adjacent accuracy, double adjacent accuracy...

- Average error distance

### 5.3 Tests

- Which features add the most value? Correlation, information gain etc.
- Do features correlate similarly with the readability score for each language?
- Feature preprocessing, does it help?
  - Discretization
  - Feature subset selection techniques
- Comparison of learning models, which learning model fits best the problem?
  - KNN
  - Bayesian models
  - SVM
  - Neural network
  - Regression (Adding a sense of order in class values)
  - Ordinal classification (Adding a **stronger** sense of order in class values)
- **Comparison** of the system vs **baselines** such as fleish for each language individually.
- Comparison **vs state of the art** systems for each language.
- Multi vs monolingual
- If we take a bilingual corpus, does the system predict same values? And if we take a text and translate it to another language? Does the readability values maintain using an automatic translator?



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