

*Dual Bachelor in Data Science and Telecommunications Technologies Engineering 2020-2025*

***Final Project***

***Machine Learning Applications***



**Alejo González García (100454351)**

**Alonso Madroñal de Mesa (100454449)**

**Daniel Toribio Bruna (100454242)**

**Andrés Navarro Pedregal (100451730)**

# **1.Introduction**

This project consists of a multiclass classification of previously preprocessed poems, that will be assigned to a period. In order to carry out this task, we make use of the tools explained in class regarding Natural Language Processing and Machine learning tools, such as feature extraction and selection.

# **2.Task 1: Text Preprocessing and vectorization**

## **2.1. The dataset**

In order to start the project, we first needed to obtain the dataset to work with. We could either download one available online or create it ourselves. We opted for the second option, and we obtained the information from the web [Poetry Foundation](https://www.poetryfoundation.org/poems/browse#page=1&sort_by=recently_added). Poner lo de licencia fines educativos?

For the creation we used a library called *request* to obtain the response of the GET request and then we obtained the JSON response where we have extracted information like author, title, link to the poem, tags and snippet. With the link to the poem and using BeautifulSoup we get the HTML information. Poems were mainly in two formats, text or images. For the first one we just extracted the text that was inside the div with class 'o-poem', and for the second one, we used an OCR, in this case, *pytesseract*, to extract the text from the image that was in the div with class ‘c-assetStack-media’.

This process was slow. Applying the OCR to thousands of images and sending GET requests to gather information of more than 50.000 of documents, at least in the way that we did it, took lot of time. As we could not afford to keep running the computer for one day, we gathered the data in small segments, and at the end we jointed all the datasets together. We just had to store the id of the last gathered poem and the next day start the scrapping beginning with the next Id.

The reason for this delay, was the way in which the page was created, it took lot of time, not due to our internet connection or computational power, but due to the fact that the server hosting the web page was answering our requests slowly.

In the web [Poetry Foundation](https://www.poetryfoundation.org/poems/browse#page=1&sort_by=recently_added) only 5535 poems from the 47388 total poems have a period assigned, so we will have two different datasets, one composed with all the poems that will be used for the topic modelling task, see Figure 1, and another with only the poems that have a period and they can be used for the classification task, see Figure 2.

The resulting dataset contains the following information:

* An id
* The title of the poem
* The author
* A snippet of the poem
* The link to where the poem is (text or image)
* The categories that the poem has
* The period of the poem
* The text of the poem



Figure 1. Sample of the dataset obtained without periods



Figure 2. Sample of the dataset obtained with periods

## **2.2. Preprocessing**

The first thing we are going to do is to remove missing values which means that poem text was missing. This happens because some of the images of the poems were not displayed because of the web. Then we removed the columns that do not give any useful information. These columns are id, snippet, and link.

During the creation of the datasets, we noted that some poems were not in English, but they were translated and published in the web, so we have “duplicated” poems in their original language and in English. To separate the English poems from the others we have used detect from the library *langdetect*. It is important to know that language detection algorithm is non-deterministic, which means that if you try to run it on a text which is either too short or too ambiguous, you might get different results everytime you run it. To avoid this, we have used a seed. At the end we have obtained that 420 poems are not in English, and as they are translated in the dataset, we can remove them.

After we extracted the poems from the web, we saw that some of the characters were not

properly encoded, so we fixed the characters that are important, for example the apostrophe,

to be able to expand the contractions with the method fix from library contractions. Then we

tokenize the text by words, convert the tokens into lower case and filter non alphabetic

tokens. For the homogenization we have chosen lemmatization to keep the semantic

meaning and have a better interpretability of the words. Lastly, we have removed the stop

words. In addition, we applied N-gram detection so that the words that appear very often

together are jointly categorized and we can see the joint words when later doing Topic

Modelling.

Also mention that, initially, we were removing just the alphanumeric characters and we

ended up removing all non-alphabetic characters. The reason why we took this decision was

that at the end, while doing the Topic Modelling, there was a topic full of numbers. We are

analysing poems and we detected that most of this numbers were obtained inevitable while

doing web scrapping as the indexes, page numbers and dates where mixed and collected.

No information gain is obtained if we keep the numbers, so we just removed them.

## **2.3. Text vectorization**

Once all the poems are preprocessed and cleaned, the next step is to transform them into a numerical representation that can be used as input for the learning algorithms. We decided to use the following vectorizations:

* Classical BoW or TF-IDF representation.
* Word2vec based representation.
* FastText
* Extraction of themes and vector representation of the documents using the LDA algorithm

After obtaining all the different vectorizations, the performance of each one of them with several classification methods will be compared. Then the pair of vectorization and classifier with the best results will be later analysed in order to extract even better results from it.

Prior to beginning with the vectorization step, we have to2 prepare the dictionary. After analysing the most frequent words in the data set, we can see that there are several words that appear much more times than the others. In order to try to identify these words, we obtained the following figure.

Gráfico, Gráfico de líneas

Descripción generada automáticamente

Figure 3. Most frequent tokens in the initial corpus

Also, similar graphs can be obtained in order to check the distribution of the words among the different documents of the dictionary. As it has been seen in class, neither the words that appear in all the documents nor the ones that hardly appear in any one are relevant for the algorithm. Thus, it will be useful to have an estimation of this distribution to manually select the discriminant conditions for the removal of both tails of the following histograms.

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| Gráfico, Gráfico de barras  Descripción generada automáticamente  Figure 4. Distribution of the number of tokens per poem | Gráfico  Descripción generada automáticamente  Figure 5. Distribution of the token appearances in the poems |

After analysing the distributions, the creation of the final dictionary was done. To filter these types of words, it was decided to remove those that did not appear in more than 10 poems and those that appeared in more than 75% of them. After removing these tokens, we have a dictionary of 22567 terms. We are now ready to vectorize our corpus of poems.

**BOW and TF-IDF**

BOW was implemented with doc2bow method and TF-IDF with TfidfModel from genism. After obtaining both the BoW and TF-IDF vectorizations, we plotted the representations of a given poem to compare them. As seen in Figures 6 and 7, while almost all tokens have the same value in the BoW representation, from the TF-IDF it can be seen that “leave” is a common word within the corpus, because its representation is now lower and “mistery” is relevant in this specific document, because its representation has increased a lot.

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| Figure 6. BoW representation of a poem | Figure 7. TF-IDF representation of a poem |