

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

***Final Project***

***Machine Learning Applications***



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# **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 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.

|  |  |
| --- | --- |
| 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 gensim. After obtaining both 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 “mystery” is relevant in this specific document, because its representation has increased a lot.

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

**Word2Vec and FastText**

Word2Vec was implemented with Word2Vec from genism and FastText with FastText from genism. For both, we are using vector\_size=100, window=5, min\_count=5. The vector size is just 100 because in this way the classification models requires less time to train. After obtaining both vectorizations, we search for the most similar words to “love”. The results are displayed in the following table:

|  |  |
| --- | --- |
| Word2Vec | FastText |
| tenderness | unlove |
| beauty | loveth |
| hate | lover |
| lover | love\_hate |
| true | lover\_lover |

*Table 7. Most similar words to “love”*

We can see that both gives good results, but FastText gives more explicit similar words.

**Topic modeling using the LDA algorithm**

We have implemented LDA for topic modelling with genism. In order to find the optimal number of topics, we will use the coherence metric “c\_v” to evaluate different number of topics, in this case, 5, 10, 15, 20, 25. The results are displayed in the following image:

Gráfico, Gráfico de líneas

Descripción generada automáticamente

Figure 8. Coherence scores for each number of topics

We can see that the best coherence score is obtained for 15 topics. We have made the WordClouds of these topics to visualize the words that characterize them:

PONER WORDCLOUD Y DAR INTERPRETACION DE ALGUNOS

# **3.Task 2: Classification**

Our objective is to classify the poems according to the period when they were written. For this task we have used the embeddings obtained in the text vectorization part as mentioned previously. We have considered random forest, support vector machine and K-nearest neighbours.

Before training the models, we have carried out a small exploratory data analysis of the target variable. The following figure summarises this:

Gráfico, Gráfico de barras

Descripción generada automáticamente

Figure 9. Count of poems in each period

We can see that our dataset is very imbalanced. The poems with period Modern are the 28% of the data, followed by Victorian with 11.8%. As we have a small number of observations, we cannot make under-sampling, so we have considered to keep all poems and use as a benchmark for the accuracy the 28% of the majority class.

In order to select the best pair of text vectorization and classification algorithm, we took advantage of the Pipeline and GridSearchCV functions of sklearn. Each one of the algorithms has its own characteristics and parameters to be tuned, so in the following the chosen implementation of each one of them will be briefly explained. We have also to divide the train and test poems with train\_test\_split from sklearn.

**Random Forest**

The first algorithm to be tested will be Random Forest, using the function RandomForestClassifier implemented in sklearn. In order to try to extract the best of it, the RF algorithm (and so will be done with the rest of the algorithms) was tested under different parameters, obtaining the optimum one by means of a grid search. This grid contains two variations for the ‘criterion’ of the RF classifier (gini and entropy) and tests different values for the ‘max\_depht’ of the forests ranging from 5 to 35 with a step of 10.

**Support Vector Machine**

The next algorithm used was the support vector machine classifier. This was implemented by means of the SVC function of sklearn. The chosen SVM algorithm was the RBF non-linear Kernel version, as there is hardly expected to be any linearity among the data, and two different values are included in the grid search for the parameter C (the regularization parameter): 1 and 10. For SVM we used the sparse representations of the data to be more computationally efficient.

**K-Nearest Neighbours**

In the last place, the KNN Classifier will be applied. For the selection of the optimal parameters of the classifier, a grid search is used that will compute this classification for values for the number of neighbours (‘n\_neighbors’) ranging from 5 to 40 and using two different metrics for the weights (‘weights’): uniform and distance.

With the embeddings of Word2Vec and FastText, we had to compute the mean to have uniform lengths and be able to skip errors in the training of the models. We will also consider a pre-trained embeddings, en\_core\_web\_md, which are obtained with a model trained in a huge corpus.

As a summary of the performance of each pair we have the following table:

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | BoW | TF-IDF | Word2Vec | FastText | Pre-trained |
| RF | 0.37 | 0.38 | 0.39 | 0.38 | 0.45 |
| SVM | 0.51 | 0.47 | 0.35 | 0.35 | 0.54 |
| KNN | 0.24 | 0.46 | 0.37 | 0.36 | 0.44 |

Figure 10. Accuracies of the text vectorizations with classification models

We can see that the best accuracy is obtained with the pre-trained embeddings and the SVM model. This could happen as our embeddings are obtained in a relatively small dataset and the words are better represented in the pre-trained embeddings.

**Feature extraction and selection**

As the best accuracy was obtained with pre-trained embeddings and we saw that they were of a length of 300, we decided to explore the consequences of reducing the dimensionality of this embeddings to the half and see if the same information could be explained in fewer dimensions and we could reduce the computational cost. To achieve this, we will use the ideas of the feature extraction and selection, to see use the most important variables after the dimension reduction. We have tried PCA, CCA and LDA for feature extraction and mutual information for feature selection. All the techniques are implemented with sklearn functions. The accuracies are displayed in the following table:

|  |  |  |  |
| --- | --- | --- | --- |
|  | PCA | CCA | LDA |
| Mutual information | 0.51 | 0.52 | 0.53 |

Figure 11. Accuracies after feature extraction and selection

We can see that PCA gives the lowest accuracy since it is an unsupervised algorithm, good for dimensionality reduction, but not as good as CCA or LDA, if we want a supervised approach, like we have seen in class. We have only considered mutual information because is computationally efficient compared to the other ones seen in class, for example, HSIC.

We can also see that the accuracy was not improved, and it has decreased 0.01 so we must try another approach to obtain a higher accuracy. In the following image we can see the confusion matrix of the LDA reduction:

Gráfico

Descripción generada automáticamente con confianza baja

Figure 12. Confusion matrix of the LDA reduction

We can see that most of the predictions are associated with the principal class. As we can not apply over-sampling, neither under-sampling, we have opted to group classes by their historical period following the mapping of the web. This mapping is:

Interfaz de usuario gráfica, Aplicación

Descripción generada automáticamente con confianza media

Figure 13. Mapping of the historical period with the art periods

**Joining classes**

By applying the previous mapping our distribution depending on the periods are:

Gráfico, Gráfico de barras

Descripción generada automáticamente

We can see that now the dataset is less imbalanced with the following proportions:

1901-1950: 44.289593%

1951-Present: 26.443439%

1781-1900: 19.131222%

1550-1780: 9.828054%

Pre-1550: 0.307692%

After training the model that gave us the best accuracy (pre-trained embeddings with SVM), we have obtained an accuracy of 0.79 and the following confusion matrix:

Gráfico, Gráfico de dispersión

Descripción generada automáticamente

Figure 14. Confusion matrix after joining classes

# **4.Conclusions**