Machine Learning Engineer Nanodegree

Capstone Project

Thiago Vieira June 7th, 2019

I. Definition

Project Overview

The goal of this project it's to build a model for authorship attribution classification using as a background the work developed in VJO2011 e OOJ2013 that is available in The Laboratory of Vision, Robotics and Imaging of Federal University of Parana.

The use of electronic documents like e-mails continue to grow exponentially, and even though reliable technology is available to trace a particular computer/or IP address where the document has been produced, the fundamental problem is to identify who was behind the keyboard when the document was produced (OOJ2013). Practical applications for author identification have grown in several different areas such as criminal law (identifying writers of ransom notes and harassment letters), civil law (copyright and estate disputes), and computer security (mining email content).

This problem is very relevant for my work since I'm developing several NLP classification models to label court decisions and the importance of a case to the federal attorney. I intend to apply the knowledge obtain from this project to my work and share it, as well.

Problem Statement

Authorship attribution can be defined as the task of inferring characteristics of a document's author from the textual characteristics of the document itself. The challenge here is to estimate how similar two documents are from each other, based on patterns of linguistic behavior in documents of known and unknown authorship. This is known in the literature as authorship attribution or authorship analysis.

Metrics

Based on the context of NLP and the multiclass problem property, I'll use the following metrics to compare models:

- Accuracy link;
- F1 score (trade-off between TP and FP) link;
- Recall link;
- Precision link;
- Confusion Matrix link.

Given the context of the problem and to replicate the same metrics used in the base references, These set of metrics is suitable to the problem because it's the most used in the NLP field.

II. Analysis

Data Exploration

The dataset used and proposed by VJO2011 contains 100 different authors whose texts were uniformly distributed over 10 different subjects: Miscellaneous, Law, Economics, Sports, Gas- tronomy, Literature, Politics, Health, Technology, and Tourism. In this database all the subjects have ten different authors.

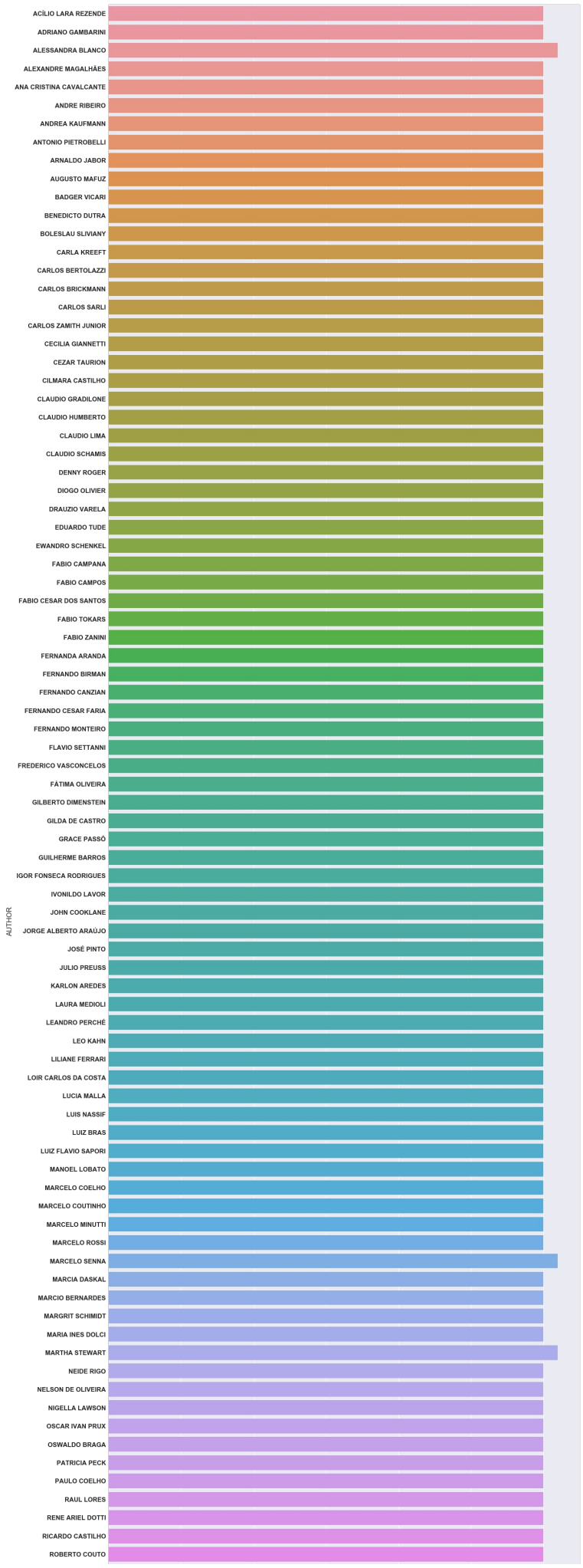
For each author it was chosen 30 short articles, thus summing up 3000 pieces of documents. The articles usually deal with polemic subjects and express the authors personal opinion. In average, the articles have 600 tokens (words) and 350 Hapax (words occurring once). One aspect worth of remark is that this kind of articles can go through some revision process, which can remove some personal characteristics of the texts. Besides, authorship attribution using short articles poses an extra challenge since the number of features that can be extracted are directly related to the size of the text.

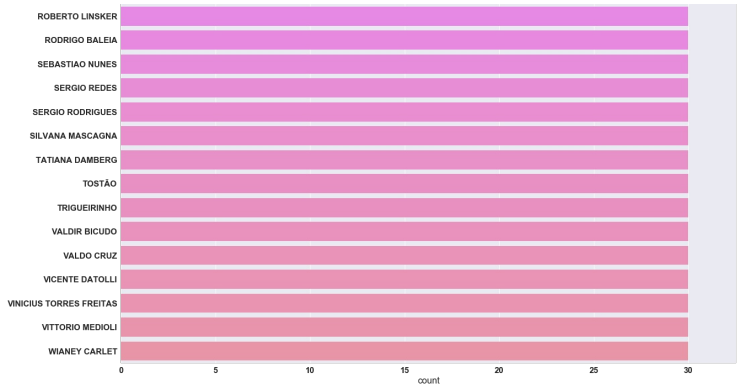
At first it was create a csv file to store all the text from the initial dataset provided by the original work. The dataset was distribuited in folders organized by subjects and authors in folder `data/raw/BASE DE DADOS - PAULO JR VARELA`. In notebook `notebooks/00-Make-Dataset.ipynb` this csv file is built and stored at folder `data` as `data_raw.csv`.

Exploratory Visualization

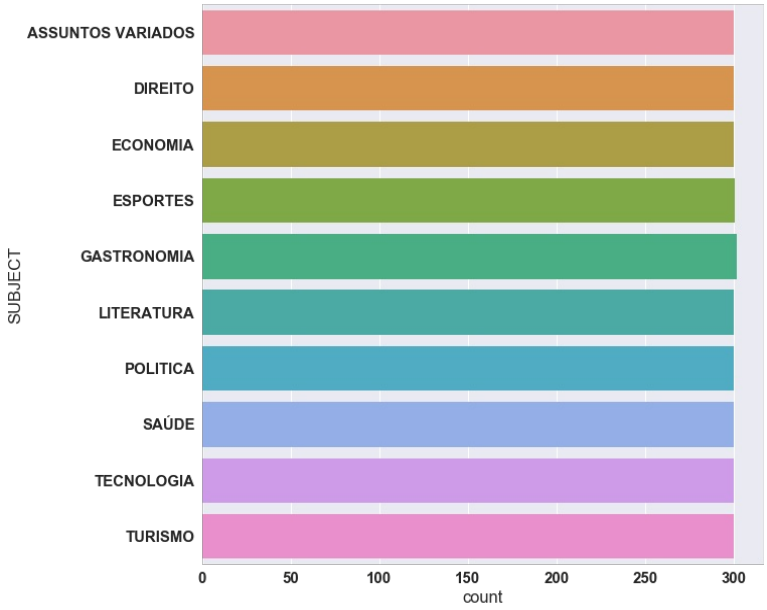
It was verified that the authors and subject distribuitions were in accordance to the reported by the original work as it's shown in the figures below:

- Authors





- Subjects

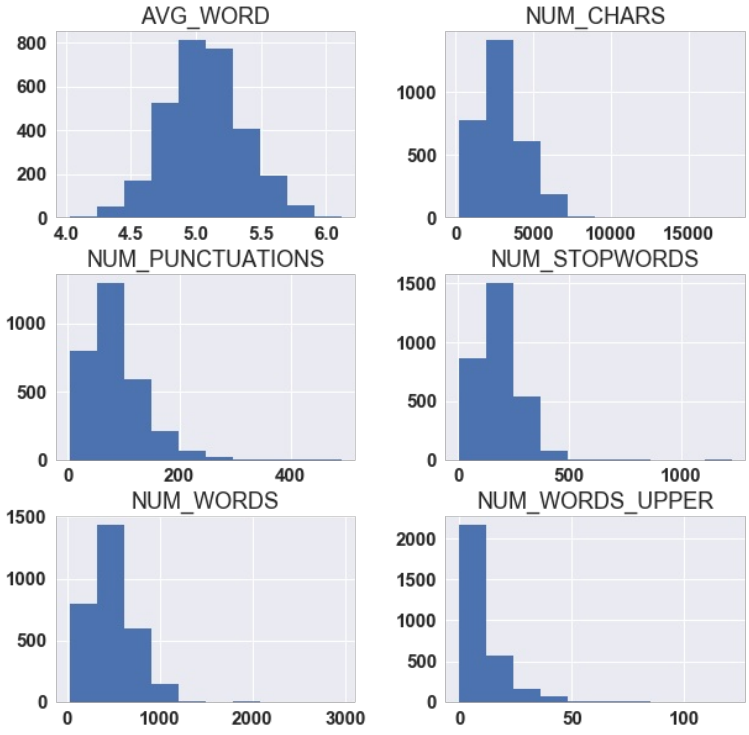


New Features

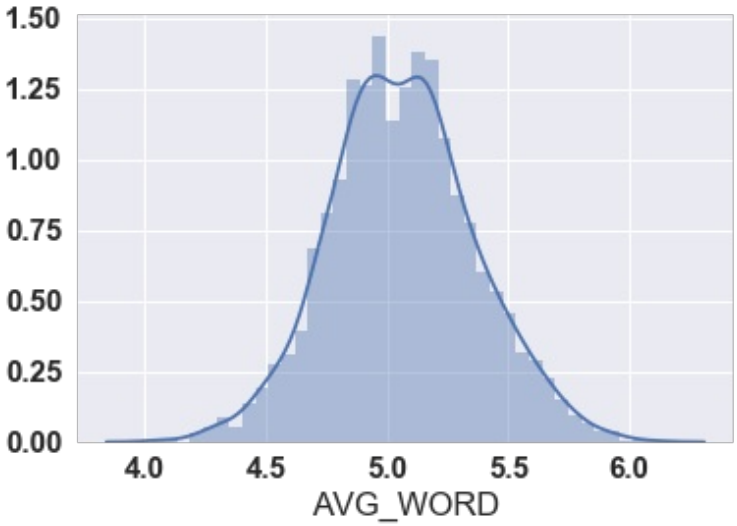
Then in notebook notebooks/01-Make-Features.ipynb I created new features based on the text characteristics as Number of stopwords, Number of punctuations, Number of title case words, Number of chars, Number of words and Average word length. In this notebook the text is also cleaned and a new csv file containing all these transformations is create and stored in /data/data_feat.csv.

Some Exploratory Data Analysis is made in ``notebooks/02-EDA.ipynb` over the new features and text data.

By the new created features, their distribuitions are as follow:



It's importante to notice the normal shape distribuition of average word length:



WordCloud

Another visual analysis applied was a technique to better visualize the most appeared words in the text. First, I generate a wordcloud using all cleaned text and I obtained the following figure:

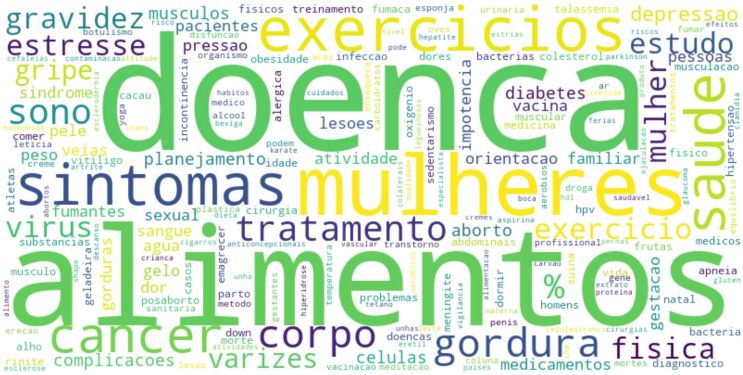
We can use this analysis to find and remove potential non relevant words to add to a stopword list.

Then, I generate the wordcloud for each of the subjects sinche there are many authors. In this approach, the wordcloud was generated based on the most relevant words in each subject by using TF-IDF feature extractions technique:

- Assuntos Variados

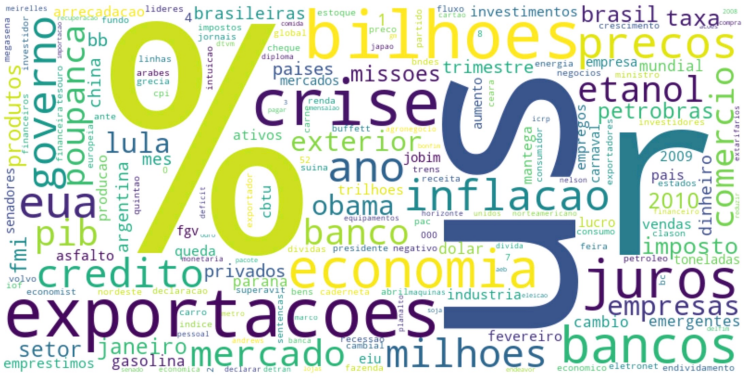
- Esporte

- Saúde



- Gastronomia

- Economia



- Direito

- Literatura

- Política

- Tecnologia

- Turismo

Algorithms and Techniques

Several algorithms and techniques were used and applied based on literacture on NLP classification problems. Most of then were used without any hyperparameter tunning.

For the classical machine learning techniques tested like Logistic Regression, Stochastic Gradient Descendent and Multi Layer Perceptron the input text was preprocessed using TF-IDF and for more advanced techniques like Deep Neural Networks, Convolutional Neural Networks and Recurrent Neural Networks it was also used word embeddings (link)[https://en.wikipedia.org/wiki/Word_embedding].

Basically, I tested the following classification algorithms and feature representation:

- Logistic Regression;
- Stochastic Gradient Descendent;
- Multi Layer Perceptron;
- Shallow Neural Network;
- Deep Neural Network;
- Convolutional Neural Network;
- Recurrent Neural Network;
- FastText.

Benchmark

In the image below, it's shown some works on authorship attribution published in the literature. Comparing different works is not a straightforward task since most of the works use different databases and classifiers.

Published works on authorship attribution.

Ref.	Classifier	Database	Rec. rate (%)
[23]	SVM	Web pages	66–80
[7]	SVM	German newspaper	80
[10]	SVM	3 sister's letters	75
[24]	kNN	Novels	66–76
[5]	Distance	Brazilian novels	78
[19]	SVM	Brazilian newspaper	72
[6]	Bayes	Mexican poems	60–80
[21]	Bayes	Turkish newspaper	80
[25]	SVM	Brazilian newspaper	74

For this project, I'll use as a benchmark model the accuracy of the work in VJO2011 e OOJ2013, which were a 74% and 77% using with a SVM classifier + a feature selection using a multi-objective algorithm and compression models approach, respectively.

Since there are 100 authors in the database, analyzing the confusion matrix would be complicated, these works provided the analysis of the confusion matrix grouped by subject. Such a matrix can show that the recognition rate in terms of subjects is about 86% in VJO2011 and 80% in OOJ2013.

III. Methodology

Data Preprocessing

The text data was cleaning in notebooks/01-Make-Features.ipynb where I removed bad characteres, stopwords, and create new features.

Othertwo data preprocessing technique were used to prepare the text for the models. They are TF-IDF and Glove word embeddings.

Implementation

In VJO2011 experiments they used 7 documents for training and the remaining 23 for testing. In order to be able to compare the results, we adopted the same protocol. The documents were randomly divided into training and testing.

Let's summarize all the implementation done in this project in parts.

Feature Extractions

- It was implementend some function to new features in notebooks/01-Make-Features.ipynb;

Visualization

- It was implementend some function to visualize data in notebooks/02-EDA.ipynb, like generate_wordcloud, top_tfidf_feats, top_feats_in_doc, top_mean_feats and top_feats_by_class used to show relevant words in wordcloud figures;

Classic Machine Learning

- It was implementend some function to train the model and show results in notebooks/03-ML.ipynb, like conf_matrix, train, evaluate_, train_evaluate, show_roc, show_report used to better organized the experimentation process;

Neural Networks

Here, the models were implementend using the framework Keras.

- It was implementend some function to train the model and show results in notebooks/04-ML.ipynb - notebooks/05-DNN.ipynb - notebooks/06-CNN.ipynb - notebooks/07-RNN.ipynb - notebooks/04-ML.ipynb, like plot_history, Metrics, evaluate_, train_evaluate, show_roc, show_report used to better organized the experimentation process and add metrics to traning process;

Word Embeddings

Here, some implementations used the Glove Word Embeddings downloaded from NILC. More precisely, the GLOVE 100 that can be downloaded in this link.

Refinement

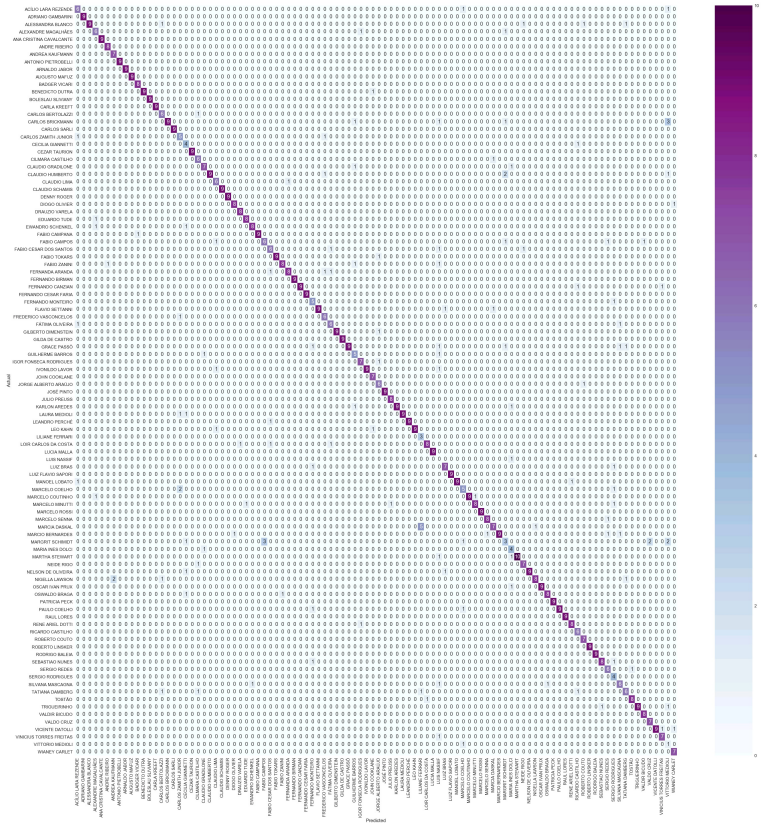
The best classical algorithms was applied to a GridSearch with cross validation to find a better hyperparameter setting as shown in notebooks/03-ML.ipynb.

This processed resulted in the best model in this project as shown below:

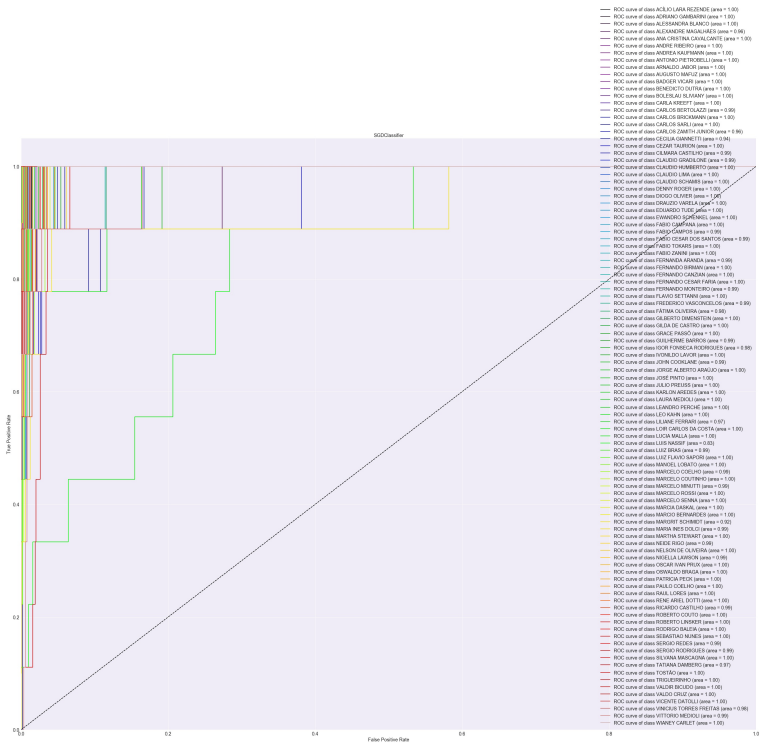
```
Train acc: 1.0
Test acc: 0.8423973362930077
Train f1-score: 1.0
Text f1-score: 0.8423973362930077
```

The classification report over all author gave an average of precision, recall and f1-score of 0.85, 0.84 and 0.83, respectively over the 901 test samples.

- Confusion Matrix



- ROC CURVE



Then I added the average word length feature to the model, as it's follow a normal distribuition. But, it made the accuracy decrease:

```
Train acc: 0.9895337773549001
Test acc: 0.7280799112097669
Train f1-score: 0.9895337773549001
Text f1-score: 0.7280799112097669
```

IV. Results

Model Evaluation and Validation

Let's, again, summarize all the models evaluations done in this project in parts. I'm not going to show all tests on all models since many of them resulted in poor results, but I'll show the best of each approach.

Machine Learning Evaluations - **notebooks/03-ML.ipynb**

As mentioned before, the best result was:

```
Train acc: 1.0
Test acc: 0.8423973362930077
Train f1-score: 1.0
Text f1-score: 0.8423973362930077
```

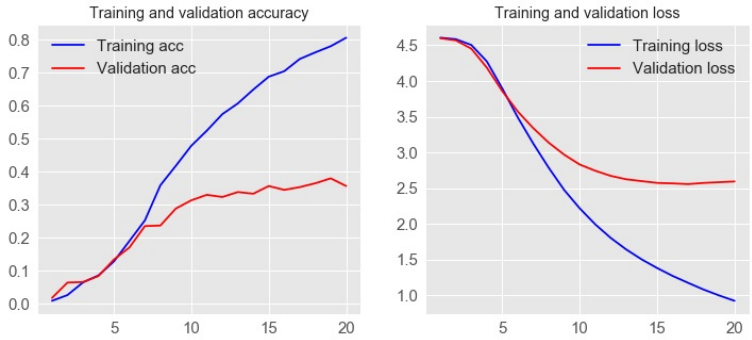
Shallow Neural Network Evaluations - **notebooks/04-NN.ipynb**

Better result was with word embedding and maxpooling:

```
embedding_dim = 50

model = Sequential()
model.add(layers.Embedding(input_dim=vocab_size,
                           output_dim=embedding_dim,
                           input_length=maxlen))
model.add(layers.GlobalMaxPool1D())
model.add(layers.Dense(10, activation='relu'))
model.add(layers.Dense(100, activation='softmax'))
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['sparse_categorical_accuracy','accuracy'])
```

```
Training Accuracy: 0.8518
Testing Accuracy:  0.3561
```

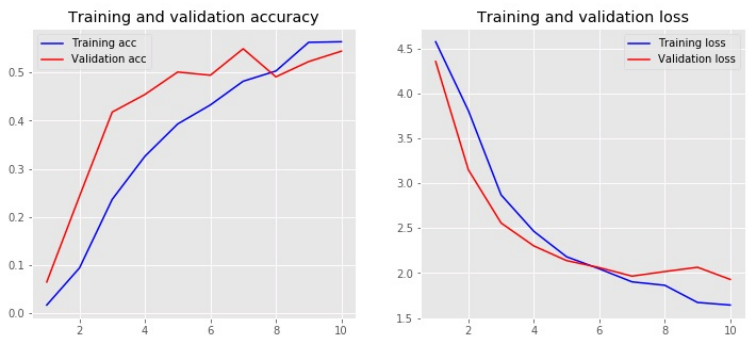


Deep Neural Network Evaluations - **notebooks/05-DNN.ipynb**

Better result was with TF-IDF and Dropout:

```
input_dim = 600
model = Sequential()
model.add(layers.Dense(10, input_dim=input_dim, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='softmax'))
```

```
Training Accuracy: 0.9713
Testing Accuracy:  0.5441
```



Convolutional Neural Network Evaluations - **notebooks/06-CNN.ipynb**

Better result was with word embedding:

```
embedding_dim = 100

model = Sequential()
model.add(layers.Embedding(input_dim=vocab_size,
                           output_dim=embedding_dim,
                           input_length=maxlen))
model.add(layers.Conv1D(128, 5, activation='relu'))
model.add(layers.GlobalMaxPooling1D())
model.add(layers.Dense(10, activation='relu'))
model.add(layers.Dense(100, activation='softmax'))
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
Training Accuracy: 0.9009
Testing Accuracy:  0.2479
```

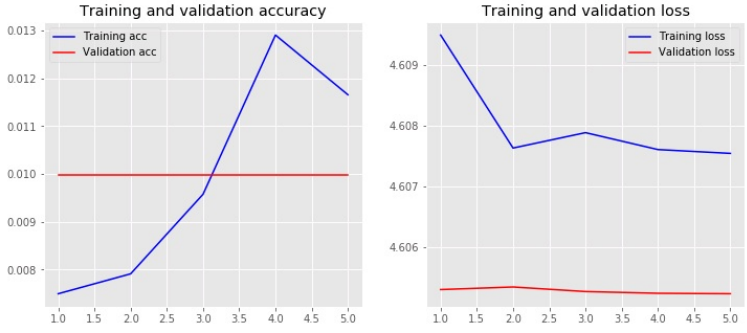
Recurrent Neural Network Evaluations - **notebooks/07-RNN.ipynb**

Better result was with word embedding and LSTM, but probably it has some problem beacause the classification was very bad:

```
embedding_dim = 100

model = Sequential()
model.add(layers.Embedding(input_dim=vocab_size,
                           output_dim=embedding_dim,
                           input_length=maxlen))
model.add(layers.SpatialDropout1D(0.3))
model.add(layers.LSTM(100, dropout=0.2, recurrent_dropout=0.2))
model.add(layers.Dense(100, activation='softmax'))
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

```
Training Accuracy: 0.0121
Testing Accuracy:  0.0100
```



FastText Evaluations - **notebooks/08-FastText.ipynb**

Using supervised learning it obtained a accuracy of 0.324. Using n-grams did not improve the score.

```
N   601
P@1 0.324
R@1 0.324
```

As we can see, the best model was the one with a Stochastic Gradient Descendent classifier with log loss. But, we can observed that it is overfitted. Another result, also with Stochastic Gradient Descendent but using hinge loss, that can not provide probabilities, did a good job but with the cost of worst accuracy and better recall.

Justification

Looking only for model accuracy, my model did a better job on predicting the text author using the same sample split. As the original work did not provide f1-score or the seed used for the train/test split, I can't be sure that my result is really better.

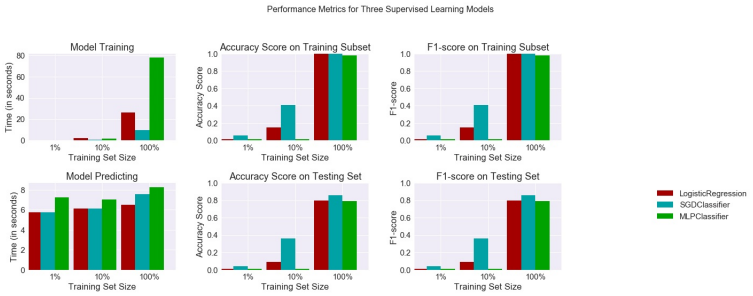
My best accuracy was 0.84 on the overfitted model and 0.72 in a less overfitted model. The orignal result was 0.74.

The solution presented is more like a baseline for future work than a proper solution. As the original work was more intended to show a new approach then to provide a solution to the problem since the dataset is very small.

V. Conclusion

Free-Form Visualization

Here I'd like to plot the graph of the model selection that I borrowed from the course and it showed very useful. I'd like to make this graph with all models built, but it was more difficult that I imagine. This plot helped me to find the better classical machine learning algorith for the problem and to analise it in a much faster way.



Reflection

The goal of this project it's to build a model for authorship attribution classification using as a background the work developed in VJO2011 e OOJ2013 that is available in The Laboratory of Vision, Robotics and Imaging of Federal University of Parana.

During the project, I have done the following:

- Collect the data;
- Create the dataset;
- Cleanead the data;
- Create new features;
- Did some EDA and visualizations analysis;
- Processed the text data with TF-IDF and Word Embeddings;
- Built classical machine learning models;
- Built Deep Neural Networks models;
- Preprocced the text to follow FastText schema;
- Tested a SOTA text classification framework, FastText.

The most challenge thing about this project was to learn the basics Keras and FastText, so I could use them. The other difficult thing was the lack of data, this dataset is very small.

As my final thoughts, I think the simpler approach resulted in a satisfatory solution to the problem and it was better than the benchmark result.

Improvement

I think that the best model could be improved by building a ensemble model to balanced the miss classified authors. It could be made a more deep analysis on the most miss classified text to seek for insights, like words that could be generating this errors.

It's necessary to double check some deep neural networks embeddings preprocessing, because some model failed terribly and maybe this could be the reason.

Alse I could build a topic model using LDA - Latent Dirichlet allocation and use it as feature to improve the classification performance.

Another final improvement is to gather more data by these same authors.