Stance detection on tweets about the covid-19 vaccination topic

Project of the Data Mining course 2020/2021

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Sommario

1. Introduction

Our goal was to create an application that can analyze tweets to discover Italian people's opinion about anticovid-19 vaccines.

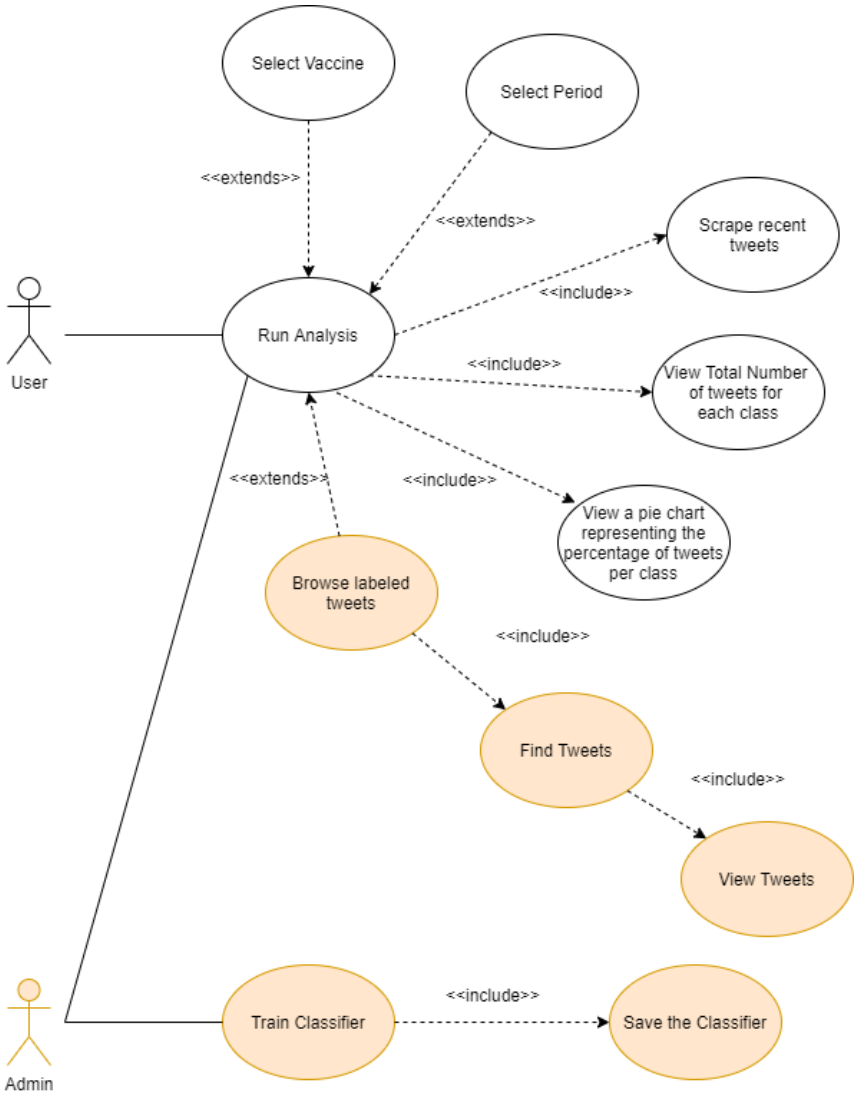
In particular, the user can specify the period he want to analyze and the vaccine he is interested in. The system updates the dataset of tweets (by scraping them from Twitter) and then the targeted tweets are automatically labeled in one of three classes (negative, positive, or neutral) depending on the stance expressed in the tweet itself. Finally, the application shows a pie-chart that plots the number of tweets for each class.

To develop the final classifier used in the application, it was necessary to pass through a supervised learning stage, which allowed us to test different classifiers and choose the one that gave us better results.

2. Analysis

2.1.Use case diagram analysis

The figure shows a basic use case diagram. The use cases colored in orange are possible only for the admin.



2.2. Requirements

The system should have these functional requirements:

- Update in real time the tweet when a user performs a request
- Perform a classification of the tweets and obtain the labelled tweets
- Show the summarized results of the classification

The system should have these non-functional requirements:

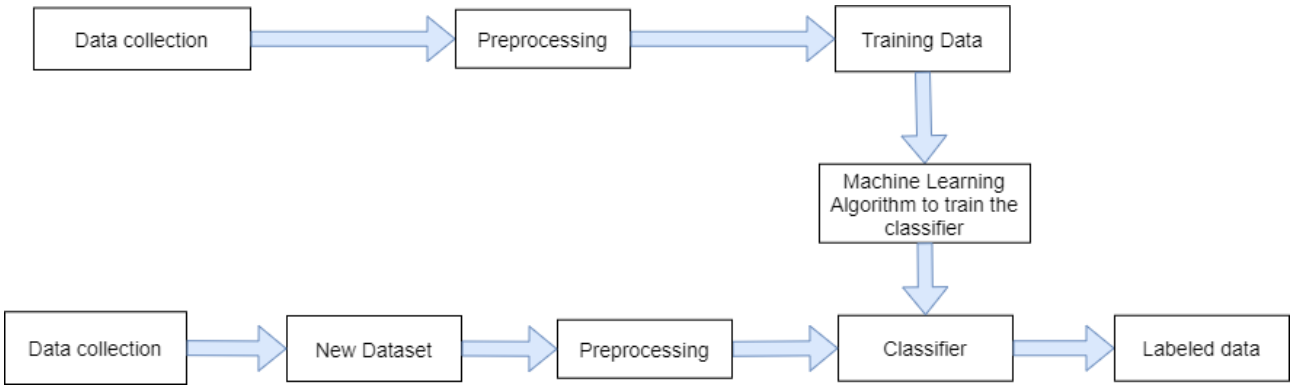
- Simplicity of the system's usage
- Fast response to the requests
- Good level of accuracy

3. Workflow

In order to perform the stance detection on the tweets, it was necessary to train an appropriate classifier (**supervised learning stage**). Then, using the classifier learned in this previous phase, we can apply it to the new unlabeled tweets in order to classify them.

To apply classification algorithms on the tweets and to construct the classifier, the tweets must pass through a **preprocessing phase** in which they are cleaned from all the features that are not useful for the classification task. Then each tweet must also be transformed into a numerical vector (**feature representation**).

The following image shows the workflow adopted in order to obtain the classifier and to use it for the classification of new tweets:



In the following we will explain more in detail the meaning of each phase.

3.1. Data collection

The raw tweets are scraped from Twitter using the *Twint*[1] library. Using the functions offered from this library, we can set some options in order to scrape tweets according to some parameters. In particular we set:

- The date, in order to scrape tweets posted only on a specific period.
- The language, in order to scrape only Italian tweet.
- Some keywords to scrape the tweets only related to the vaccination topic.

The scraped tweets are characterized by the following attributes (whose name is self-explanatory):

- id
- date
- time
- username
- tweet
- likes_count

[1] All information about *Twint* can be retrieved from GitHub repository: https://github.com/twintproject/twint

In the following image is shown the code used for scraping. In the file “keywords.txt” are contained the keywords that are used linked with the *OR* conjunction in order to scrape tweets related to the vaccination topic. We tested different sets of keywords and we choose the one that gives the better results in terms of scraping (so the one that allows to scrape more tweets related to the vaccination topic).

```
string = ""
condition = " OR "
start = True
with open('keywords.txt', 'r') as file:
    for line in file:
        if start == True:
            start = False
        else:
            string += condition

        string += line.strip()

print(string)
```

```
vaccino OR vaccini OR vaccinato OR vaccinata OR vaccinati OR vaccinate OR vacci
nazione OR anticovid OR Astrazeneca OR Pfizer OR Moderna OR Sputnik OR Johnson
OR #iomivaccino OR #iovaccino OR #sivaccino OR #novaccino OR #vaccinoCovid OR #
vaccinoAnticovid OR janssen OR CureVac OR Novavax OR Sinovac OR vaxzevria OR tr
ombosi vaccini OR trombosi vaccino
```

```
#os.remove("none.csv")
c = twint.Config()
c.Lang = 'it'
c.Search = string
c.Custom["tweet"] = ["id","date","time","username","tweet","likes_count"]
c.Since = "2021-02-01"
c.Until = "2021-05-31"
c.Store_csv = True
c.Filter_retweets = True
c.Output = "tweet.csv"
```

```
twint.run.Search(c)
```

```
1399141465163538434 2021-05-31 01:11:34 +0200 <Ussignur_> @MarioBordonaro @ro
ughnuances @Nic_Trevi @pbecchi @fdragoni @borghi_claudio @MT_Meli_ peccato ch
e questi vaccini non impediscano il contagio, quindi questo motivo non è un m
otivo valido. Inoltre le persone che hanno un qualche rischio sono già state
vaccinate. Funziona questo vaccino o no? E se no, perché volete farne di più?
Non impedisce il contagio.
```

3.2. Data pre-processing

In the pre-processing phase raw tweets are elaborated in order to clear them. In particular, we do the following steps:

- Remove all the links, emoji and images contained in the tweets
- Remove all the hashtag symbols (#) from the tweets. For example, if a tweet contains “#word” we transform it in “word”. We decided to maintain the word associated to the hashtag because it is often important to understand the stance of the tweet (for example there can be hashtags like #iomivaccino or #vaccinomorte that are indicative of the opinion about vaccines expressed in the tweet)
- Remove all the mentions to other users in the tweet
- Put the text of the tweets in lower case
- Remove all the punctuation
- Remove all the extra-spaces

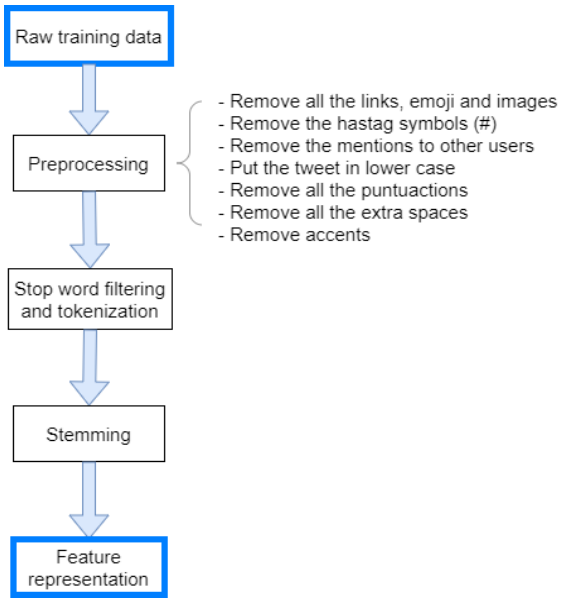
As an example, the tweet *"@valy_s È una cosa normale. L'immunità di gregge è a senso unico. Se vaccini tutti non sconfiggerai mai la malattia. Quando lo capiranno, torneremo a vivere normalmente! Se vuoi fermare la pandemia, studiala e crea una medicina. Il vaccino serve a poco!"* is transformed into *“e una cosa normale l immunita di gregge e a senso unico se vaccini tutti non sconfiggerai mai la malattia quando lo capiranno torneremo a vivere normalmente se vuoi fermare la pandemia studiala e crea una medicina il vaccino serve a poco”.*

3.3. Text representation: tokenization, stop-word filtering and stemming

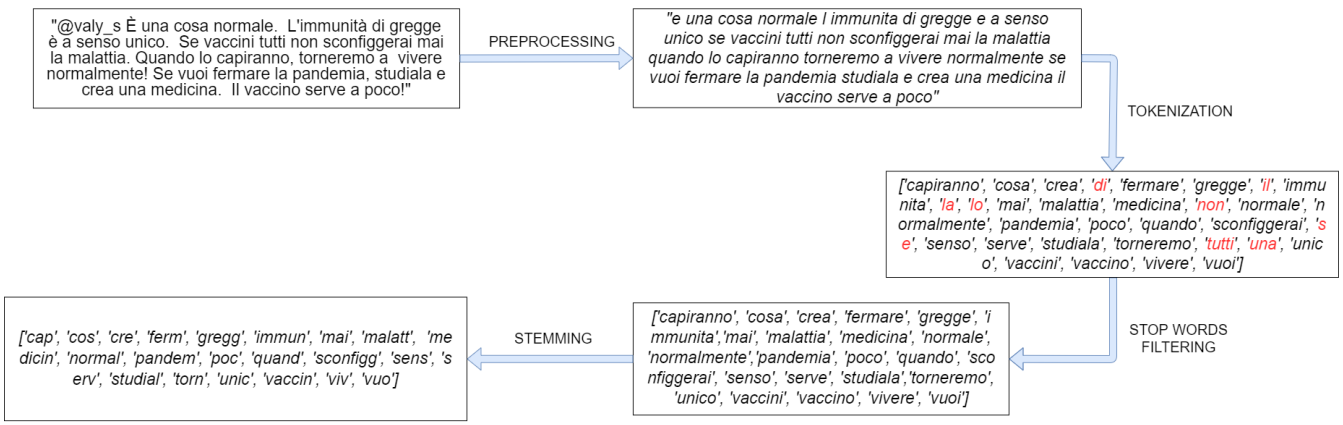
In order to apply classification algorithms to the tweets we have to represent them as numerical vectors. In particular we have to follow the following steps:

- Extract tokens from tweets (**tokenization phase**). We use the BOW representation testing different values of n-gram (we consider only unigrams and unigrams and bigrams together)
- Remove stop-words (**stop-word filtering**) from the set of extracted tokens
- Eventually perform a **stemming phase**, in order to reduce each token to its "root form"
- Perform a **tf-idf transformation**, where the importance of each stem is computed using the *Inverse Document Frequency*

The following image shows all the phases we carried out to transform each tweet into a numerical vector. For clarity, also the pre-processing phase is considered.



In the following image is shown an example of how a tweet is transformed when it passes through each one of these phases:



3.4. Training the model

In this phase, the classifier is learned from a manually labelled training set.

We trained different models and we tested them using the cross-validation procedure. Finally, the classifier that gave us better results (in terms of accuracy, precision and recall per class) was chosen as the final classifier to be adopted for the classification of tweets.

To train the model different experiments were performed, considering different classifiers and different text representations techniques. We decided to test 7 different classifiers:

- Multinomial classifier
- Bernoulli classifier
- Linear support vector classifier
- Random forest classifier
- K-nn classifier
- Adaboost classifier
- Decision tree classifier

3.5. Classification of unlabelled tweets

In this phase the unlabelled tweets are classified using the classifier trained in the supervised learning stage (the one that gives better results), after passing through the pre-processing phase and the text representation phase.

3.6. Concept drift analysis

Since the lexicon used by Twitter's users can change over time, a concept drift analysis must be carried out. If the presence of concept drift is detected, the model must be updated in order to reduce the effects of the concept drift.

For analysing the presence of concept drift, we adopted the following strategy (in the following with "initial training set" we will refer to the training set made up of 906 tweets from January and with "initial classifier" to the classifier trained using the initial training set):

- We manually labelled 60 tweets (20 tweets for each class) of the months of February, March and April. For each month we sort the tweets in descending order using the number of likes they received, and we classify them starting from the one with the higher number of likes and going on until there were 20 tweets per class.
- Then we test the initial classifier on each one of the labelled sets of February, March and April.
- Then a new classifier was constructed using the initial training set and the 60 labelled tweets from February. This new classifier was tested on the tweets of March.
- We compared the scores of the initial classifier and the new classifier. If the scores of the new classifier are better than the initial one, it means that there is concept drift.
- The same procedure can be repeated constructing in an incremental way the new classifier: we considered the initial training set and the labelled tweets from February and March and we tested it using the tweets from April.

4. Choosing the classifier

4.1. Initial choice

Initially the training set was constructed by scraping tweets from "01-01-2021" to "31-01-2021" and manually labelling 906 instances (302 instances for each class).

Using the 5 folds cross-validation procedure[2] we train and test 7 different classifiers.

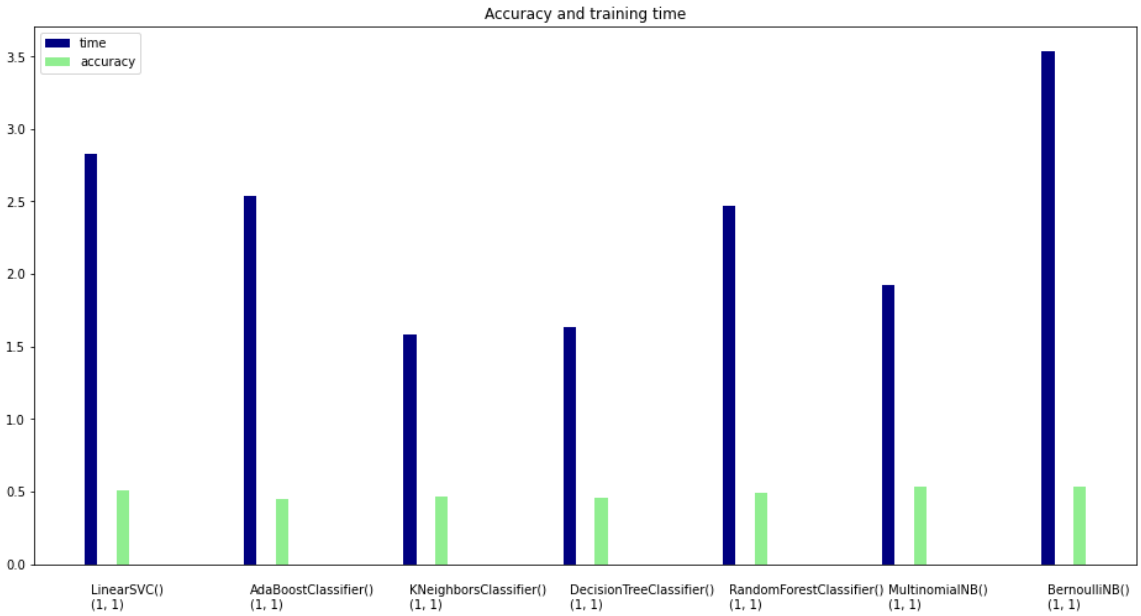
We made some experiments in which we defined different sets of stop-words, but we saw that the better results were obtained by using the default set of Italian stop-words offered by *SK-Learn Library*. We also try to do some experiments without the stemming phase, but better results are achieved by adopting the stemming phase. For the sake of brevity, we will report only the results obtained with the experiments performed with the default set of Italian stop-words and the stemming phase.

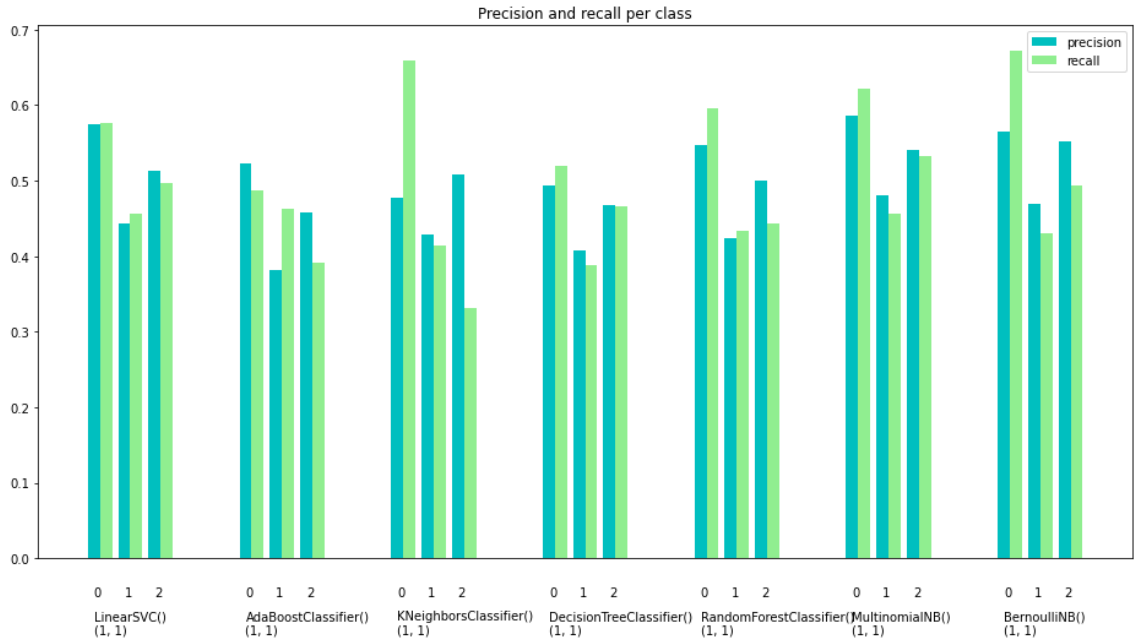
In the following, we report the results obtained testing the different classifiers using the tokenization with only unigrams (n-gram = (1,1)) and with unigrams and bigrams (n-gram = (1,2)). We also report some histograms that show the overall accuracy and the training time for each classifier and for each classifier, the precision, the recall and the f1-score for each one of the three classes.

4.1.1. Results for n-gram = (1,1)

Classifier	***Class***	***Precision***	***Recall***	***F-score***	***Accuracy***	***Time (s)***	***Confusion matrix***
BernoulliNB()	*0*	*0.57*	*0.67*	*0.61*	*0.53*	*1.92*	*203 60 39* *90 130 82* *66 87 149*
	1	*0.47*	*0.43*	*0.45*			
	2	*0.55*	*0.49*	*0.52*			
MultinomialNB()	*0*	*0.59*	*0.62*	*0.6*	*0.53*	*1.78*	*188 67 47* *74 138 90* *59 82 161*
	1	*0.48*	*0.46*	*0.47*			
	2	*0.54*	*0.53*	*0.54*			
LinearSVC	*0*	*0.57*	*0.58*	*0.58*	*0.51*	*2.42*	*174 77 51* *73 138 91* *56 96 150*
	1	*0.44*	*0.46*	*0.45*			
	2	*0.51*	*0.49*	*0.51*			
RandomForestClassifier()	*0*	*0.56*	*0.58*	*0.56*	*0.51*	*3.09*	*176 79 47* *85 135 82* *56 98 148*
	1	*0.43*	*0.45*	*0.44*			
	2	*0.53*	*0.49*	*0.51*			
KNeighborsClassifier() N = 5	*0*	*0.48*	*0.66*	*0.55*	*0.47*	*1.76*	*199 70 33* *113 125 64* *105 97 100*
	1	*0.43*	*0.41*	*0.42*			
	2	*0.51*	*0.33*	*0.4*			
AdaBoostClassifier	*0*	*0.52*	*0.49*	*0.5*	*0.45*	*2.56*	*147 99 56* *78 140 84* *56 128 118*
	1	*0.38*	*0.46*	*0.41*			
	2	*0.46*	*0.39*	*0.42*			
DecisionTreeClassifier()	*0*	*0.5*	*0.52*	*0.51*	*0.45*	*2.53*	*158 74 70* *91 118 93* *68 102 132*
	1	*0.4*	*0.39*	*0.4*			
	2	*0.45*	*0.44*	*0.44*			

[2] The experiments were performed using a 5-fold cross validation procedure. Using a 5-fold cross validation procedure, at each iteration the model is constructed and tested using 60 instances as test set, and the remaining instances as training set.

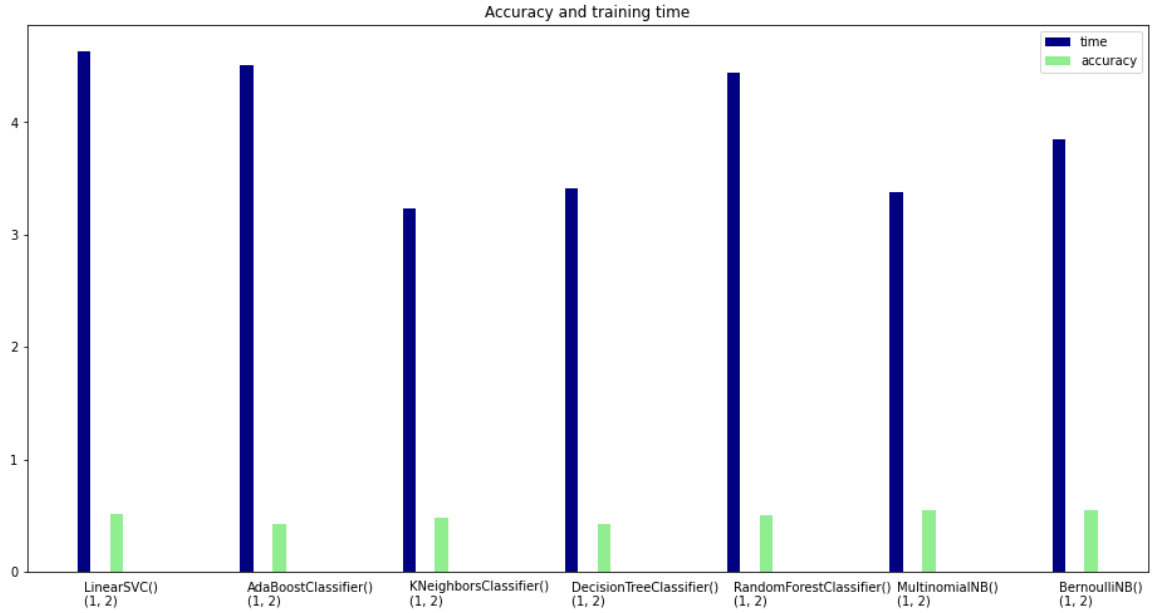


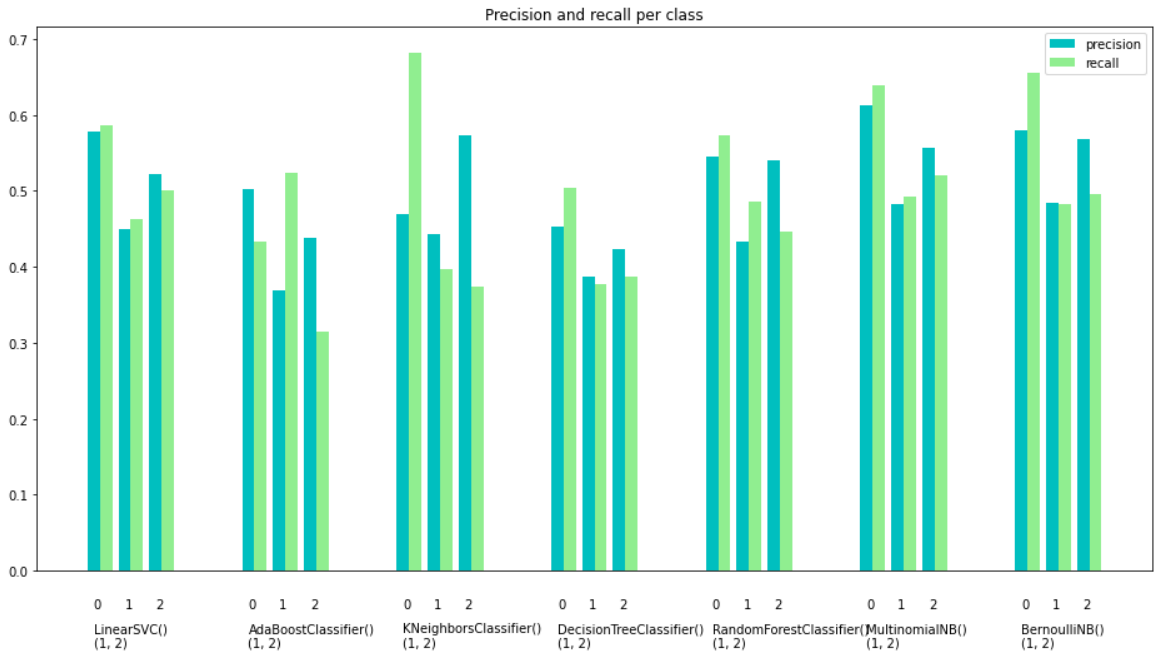


4.1.2. Results for n-gram = (1,2)

Classifier	***Class***	***Precision***	***Recall***	***F-score***	***Accuracy***	***Time (s)***	***Confusion matrix***
BernoulliNB()	*0*	*0.58*	*0.66*	*0.52*	*0.55*	*3.84*	*198 66 38*
	1	*0.49*	*0.48*	*0.48*			*80 146 76*
	2	*0.57*	*0.5*	*0.53*			*63 89 150*
MultinomialNB()	*0*	*0.61*	*0.64*	*0.63*	*0.55*	*3.38*	*193 72 37*
	1	*0.48*	*0.49*	*0.49*			*65 149 88*
	2	*0.56*	*0.52*	*0.54*			*57 88 157*
LinearSVC	*0*	*0.58*	*0.59*	*0.58*	*0.52*	*4.63*	*177 77 48*
	1	*0.45*	*0.46*	*0.46*			*72 140 90*
	2	*0.52*	*0.5*	*0.51*			*57 94 151*

RandomForestClassifier()	*0*	*0.55*	*0.57*	*0.56*	*0.5*	*4.44*	*173 89 40*
	1	*0.43*	*0.49*	*0.46*			*80 147 75*
	2	*0.54*	*0.44*	*0.49*			*64 103 135*
KNeighborsClassifier() N = 5	*0*	*0.47*	*0.68*	*0.56*	*0.48*	*3.23*	*206 67 29*
	1	*0.44*	*0.4*	*0.42*			*127 120 55*
	2	*0.57*	*0.37*	*0.45*			*105 84 113*
DecisionTreeClassifier()	*0*	*0.45*	*0.5*	*0.48*	*0.42*	*3.41*	*152 85 65*
	1	*0.39*	*0.38*	*0.38*			*94 114 94*
	2	*0.42*	*0.39*	*0.4*			*89 96 117*
AdaBoostClassifier	*0*	*0.5*	*0.43*	*0.47*	*0.42*	*4.51*	*131 114 57*
	1	*0.37*	*0.52*	*0.43*			*79 158 65*
	2	*0.44*	*0.31*	*0.36*			*51 166 95*





4.1.3. Interpretation of the results

As we can see from the previous tables in both cases of n-gram = (1,1) and n-gram = (1,2), the best overall accuracy is reached by the Multinomial classifier and the Bernoulli classifier. The better overall accuracy is equal to 55%. This is probably because in the tweets sarcasm and irony are often used, and this makes the classification task more complex. Moreover, there can be cases in which also for a human is difficult to assign a class to a tweet, due to the fact that the expressed opinion is not so much clear.

We decided to consider only unigrams. In fact, considering unigrams and bigrams do not improve so much the classifiers (with respect to the case in which we consider only unigrams) but instead the training time is almost doubled.

For the final classifier we decided to adopt the Bernoulli classifier.

4.2. Updating the classifier: concept drift analysis

When doing the concept drift analysis, we realized that our initial classifier presented some problems. In particular (despite the accuracy given by the cross-validation results using the training set of February was equal to 53%) it was not able to recognize the actual class of the tweets of the following months. In fact, the classifier tested on the manually labelled dataset of March and April gives us very bad results (it recognizes almost all the tweets as belonging to the neutral class).

Updating the classifier with the tweets of February (as explained in the section 3.6), we realized that the classifier gave us the expected results.

We give the cause to the fact that the tweets of January are very different (both in terms of vocabulary and in the topics covered) from those of the following months. Therefore, the model built using only the tweet of January is not able to classify well the tweets of the subsequent months.

For this reason, **we finally decided to adopt for our application the Bernoulli classifier trained on the labelled dataset of January and February**.

Here are the results of the concept drift analysis:

Results for the concept drift analysis

Month	***Class***	***Precision***	***Recall***	***F-score***	***Accuracy***	***Confusion matrix***
March	*0*	*0.39*	*0.54*	*0.39*	*0.45*	*7 4 9* *5 13 2* *6 7 7*
	1	*0.35*	*0.65*	*0.35*		
	2	*0.37*	*0.59*	*0.37*		
April	*0*	*0.52*	*0.5*	*0.3*	*0.47*	*14 3 3* *4 10 6* *9 7 4*
	1	*0.7*	*0.5*	*0.2*		
	2	*0.6*	*0.5*	*0.24*		

Results for the classifier trained with the training set of January (only the confusion matrix is reported)

Month	***Confusion matrix***
March	*0 0 20* *0 2 18* *1 0 19*
April	*0 0 20* *0 0 20* *0 1 19*

5. Implementation

The whole application is implemented in *Python* exploiting the *SK-learn* library. The cross-validation and the concept drift analyses are implementer using the *Jupyter* notebook. The application is developed using *PyCharm*.

For what regard the **Jupyter notebook**[3] we have different modules:

- Scraper.ipynb → in which there is the code for scraping tweets
- ExtractOccurences → in which there is the code to count occurrences for each class label
- Preprocessing.ipynb → in which there is the code for the pre-processing
- CrossValidation.ipynb → in which there is the code for perform the cross-validation
- TrainingModel.ipynb → in which the chosen model is trained and saved in the file "InitialModel.pkl"
- ConceptDrift.ipynb → in which the concept drift analysis is implemented
- Utilities.ipynb → that contains some utilities functions
- UtilitiesConceptDrift.ipynb → that contains some utilities functions for the concept drift

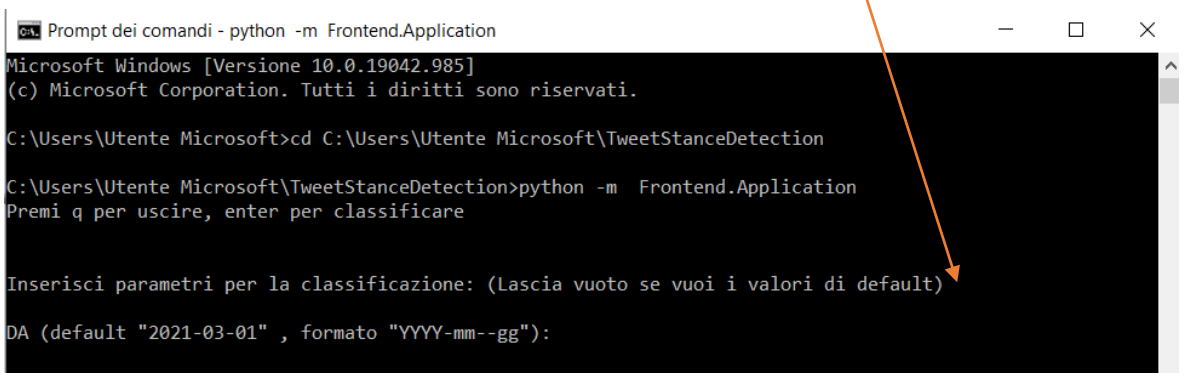
The **application**[4] consists of different packages:

- Backend → is the package that contains the following modules:
    - Scraper.py → module that implements the scraping
    - Preprocess.py → module that implements the pre-process
    - Classification.py → module that performs the classification
- Frontend → that contains the module Application.py to launch the application and to collect input setting from the user
- TrainingModel → is the package that contains the code for training the model. It contains the module Training.py

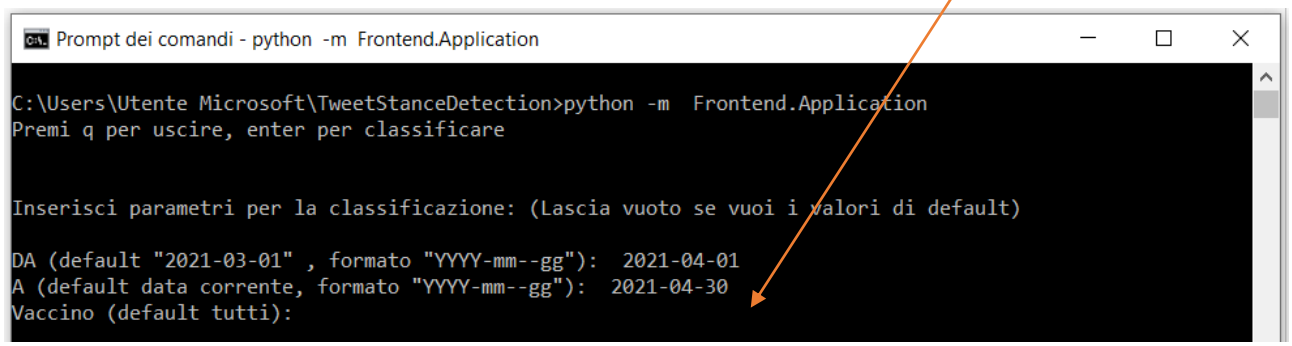
[3] The code is available on this GitHub repository: https://github.com/Matteo-Castrignano/Text-Mining
[4] The code is available on this GitHub repository: https://github.com/EricaDallatomasina/DMML-project

6. Example of usage of the application

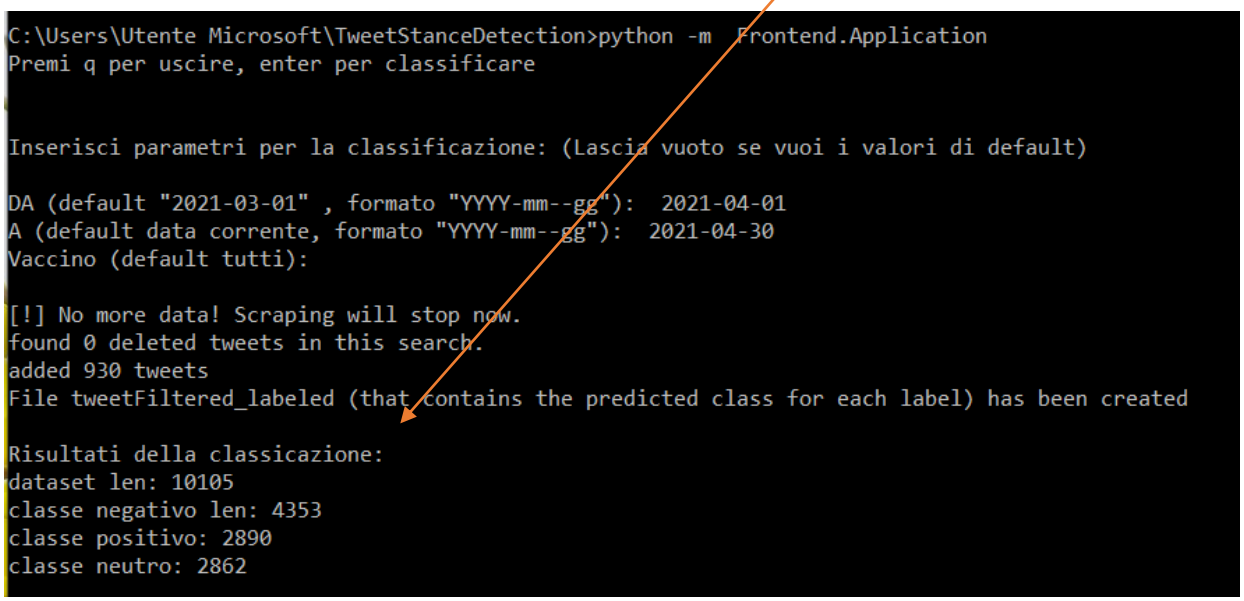
1. When the application is lauched, it asks for the user to insert the parameters for the classification



2. The user inserts the parameters



3. The application shows the results of the classification



4. The application shows the pie chart with the results of the classification