Data mining and machine learning project

DEVELOPMENT OF AN APPLICATION TO ANALIZE REAL-TIME TWEETS ABOUT EARTHQUAKES

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Motivation

Social network have entered our lives massively. The idea behind our work is to analyze tweets and to use them as a sort of sensor to detect study and detect their usage in case of natural disaster like earthquakes.

We developed an application for real-time monitoring of earthquake event detection. To do that, we analyzed tweets related to that topic using text analysis techniques; at the end we created a model able to classify tweets.

Dataset (I)

In order to build our classifier raw tweets have been scraped using a twitter scraping tool called Twint written in Python. Given location, tags to search for and a timestamp (or a date interval), returns the informations about the tweets matching those parameters.
To build the training set, two different queries have been used:

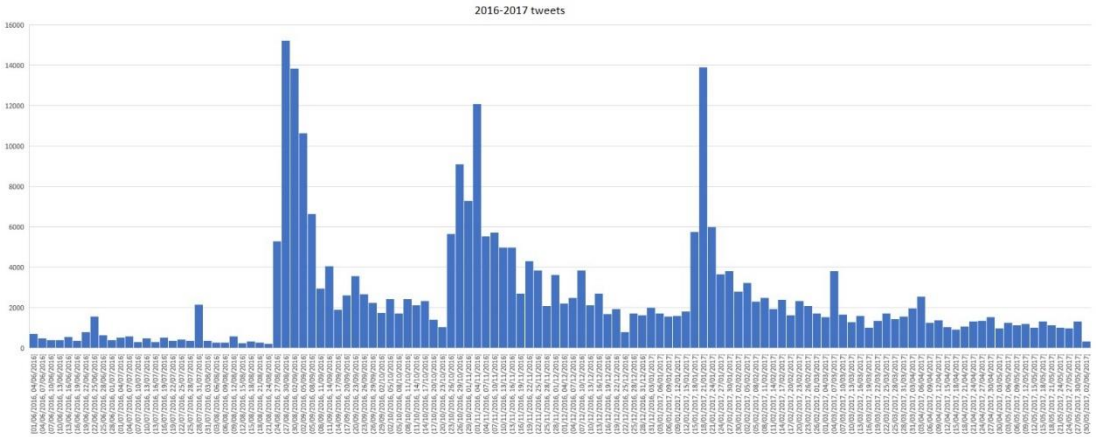
- The first query selects tweets in Italy matching the tag #terremoto
- The second query selects the tweets in Italy without tags

Another database was created by collecting (in the same way) tweets between the dates 2017-06-30 and 2016-06-01.

Dataset (II)

Once the database about tweets of 2016-2017 were created, we realized an histogram to check if there are spikes of tweets corresponding to catastrophic earthquakes in order to perform an analysis.

As we can see, there 3 major spikes relative to the 24-08-206, 30-10-2016 and 28-01-2017 huge earthquakes.



Training set

All labels (earthquakes, non-earthquakes) on tweets have been added manually. We ended up having a balanced data set of
circa 300 tweets per class, 600 tweets in total.

Pre-processing

All the preprocessing steps were performed using Weka API and java.

After the tweets have been fetched, all of them have been pre-processed to extract only the raw text and remove all meta-information associated. All useless information have been discarded, like hashtags, mentions, links etc.
Finally, all character have been converted to lower case.

Classification model

Once the raw tweets have been elaborated during the pre-processing steps, we managed to try different classification models to find the one that provides the best results.

Different classifiers have been applied to our training set, in particular we focused on SMO (Sequential Minimal Optimization), J48 (weka's implementation of the C4.5 algorithm), kNN (k-Nearest Neighbors, we focused on two kNN models, with k equal to 1 and 3) an the NB (the naïve Bayesian classifier, based on the Bayes' s theorem).

Classification model (II)

- SMO

```
Correctly Classified Instances         551               90.625  %
Incorrectly Classified Instances        57                9.375  %
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0,832    0,020    0,977      0,832   0,899      0,822    0,906     0,897     earthquake
                 0,980    0,168    0,854      0,980   0,913      0,822    0,906     0,847     non-earthquake
Weighted Avg.    0,906    0,094    0,915      0,906   0,906      0,822    0,906     0,872
```

- J48

```
Correctly Classified Instances         536               88.1579 %
Incorrectly Classified Instances        72               11.8421 %
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0,868    0,105    0,892      0,868   0,880      0,763    0,952     0,934     earthquake
                 0,895    0,132    0,872      0,895   0,883      0,763    0,952     0,959     non-earthquake
Weighted Avg.    0,882    0,118    0,882      0,882   0,882      0,763    0,952     0,946
```

Classification model (III)

- 1NN

```
Correctly Classified Instances         547               89.9671 %
Incorrectly Classified Instances        61               10.0329 %
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0,875    0,076    0,920      0,875   0,897      0,800    0,960     0,953     earthquake
                 0,924    0,125    0,881      0,924   0,902      0,800    0,960     0,958     non-earthquake
Weighted Avg.    0,900    0,100    0,901      0,900   0,900      0,800    0,960     0,956
```

- 2NN

```
Correctly Classified Instances         536               88.1579 %
Incorrectly Classified Instances        72               11.8421 %
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0,822    0,059    0,933      0,822   0,874      0,769    0,971     0,963     earthquake
                 0,941    0,178    0,841      0,941   0,888      0,769    0,971     0,975     non-earthquake
Weighted Avg.    0,882    0,118    0,887      0,882   0,881      0,769    0,971     0,969
```

Classification model (IV)

- 3NN

```
Correctly Classified Instances         521               85.6908 %
Incorrectly Classified Instances        87               14.3092 %
=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0,780    0,066    0,922      0,780   0,845      0,723    0,967     0,957     earthquake
                 0,934    0,220    0,809      0,934   0,867      0,723    0,966     0,974     non-earthquake
Weighted Avg.    0,857    0,143    0,866      0,857   0,856      0,723    0,966     0,965
```

- NB

```
Correctly Classified Instances         511               84.0461 %
Incorrectly Classified Instances        97               15.9539 %

                 TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                 0,734    0,053    0,933      0,734   0,821      0,697    0,949     0,929     earthquake
                 0,947    0,266    0,780      0,947   0,856      0,697    0,949     0,942     non-earthquake
Weighted Avg.    0,840    0,160    0,857      0,840   0,839      0,697    0,949     0,935
```

Classification model (V)

To evaluate each classification model, we used an n-fold cross-validation (with n = 10).
The results obtained about accuracy for each classifier are summarized here:

Classifier	Accuracy (%)
SMO	90.62%
J48	88.16%
1NN	89.97%
2NN	88.16%
3NN	85.70%
NB	84.05%

SMO Classifier

To have a better view about the classifier we studied their confusion matrix and other measures. Here, we showed those results for the SMO classifier.

```
=== Confusion Matrix ===

   a   b   <-- classified as
 253  51 |   a = earthquake
   6 298 |   b = non-earthquake
```

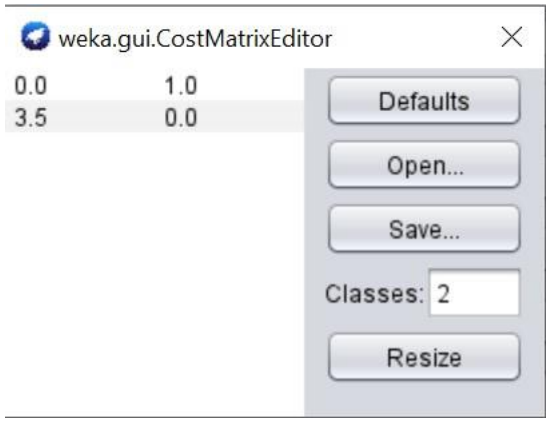
```
Correctly Classified Instances         551               90.625  %
Incorrectly Classified Instances        57                9.375  %

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0,832    0,020    0,977      0,832    0,899      0,822    0,906     0,897     earthquake
                 0,980    0,168    0,854      0,980    0,913      0,822    0,906     0,847     non-earthquake
Weighted Avg.    0,906    0,094    0,915      0,906    0,906      0,822    0,906     0,872
```

Note about classifier

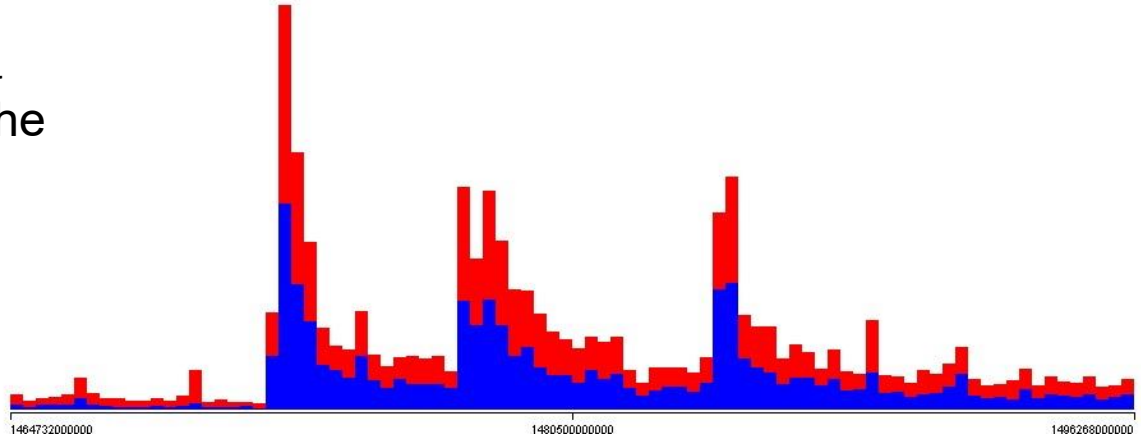
We performed a cost sensitive classification schema, because we wanted to give an higher weight to the “earthquake” class than to “non-earthquake” class.



Using the classifier on the database

Since the SMO classifier provided us the best results, we used it in the application. To exploit a further test, we applied the model build on the database containing the 2016-2017 tweets, containing the “terremoto” hashtag.

We can see that the classifier has labeled a good amount of tweets as “earthquake” at the peaks seen previously.



Toward the application

Once we found the right classifier, we started implementing the application using java language. The application fetches real-time tweets containing the keyword “terremoto”, performs a real_time classification of each fetched tweet; if a positive tweet is found, the information about the tweet are stored in a mysql database. At the end of the fetch step, the user can visualize the results in a dedicated are of the application.