Plaint-or-Tweet

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Introduction

For our final project we decided to implement some sentiment analysis techniques on social media data, and in particular on tweets from the social network Twitter. We used a dataset from Kaggle [?] which contains 1.6 million tweets labelled as positive or negative (the dataset is balanced: there are 800k positive tweets and 800k negative tweets). We chose this topic because it is of course interesting from a research point of view, but it has also many applications in industry: for example we discovered some companies that provide sentiment analisys on social media as one of their main services [?] , these services are especially useful to other companies, for example to understand what their customers think about the release of new products (and in many similar scenarios).

Models

As we have seen during coursework, the naive bayes classifier has proved to be a good model for spam classification, and it is therefore reasonable to expect good results also in sentiment analysis. We decided to implement many variations of naive bayes to have a deeper understanding on how the representations of a tweet (and in general of a text) affects the performances of this class of models.

Classic Naive Bayes

We implemented the multivariate bernoulli event model, in which each tweet T is associated to a boolean vector V and $V[i] = 1$ if and only if the i-th word of the dictionary is present in tweet T.
Another classical model we implemented is the multinomial event model: for each tweet we create a vector where the i-th value is the number of times the i-th word of the dictionary appears inside the tweet; note that this representation is a bit different from the one seen during coursework but we get equivalent formulas for the parameters and this representation makes the implementation of the model easier. In the multinomial event model we also tried to associate to each word its tf-idf score instead of the number of occurrences: the tf-idf value is a score associated to a word inside a tweet, that increases the more the word is repeated inside the tweet and decreases the more the word is repeated in the whole training set. This is an improper way of using the multinomial event model because we are not using vectors of positive integers, but we are using positive real values; however this variation has been used a lot in practice and it seems to perform well.
In both these models, we also tried to use the n-grams: we don't consider only the single words as features, but also groups of adjacent words (for example with bigrams, we consider couple of adjacent words as features).

Embeddings

A relatively new idea that has been really successful in natural language processing, is the one of word embeddings: we associate to each word a vector of real values, learned via deep learning techniques. The two most common algorithms to create word embeddings are FastText and Word2Vec, we tried both of them to get the embeddings of words[1], and to get the embedding of a tweet we average the embeddings of the words it contains. To make predictions from the tweet embeddings we used three versions of naive bayes. We tried the multinomial event model on the raw values of the embedding, the only difficulty here is that the embedding might contain negative values and this could result in negative probabilities in the multinomial event model: to fix this, we translate all the values to make them positive (we do this looking at the minimum value in the training set, for each feature), the intuition behind this model is to consider the values of the embeddings as score (as it is done with tf-idf), but of course this

[1]Since their performance is basically the same, in the tests we show just FastText results

might not be true in general, since the main property of word embeddings is that similar words will be close to each other. We also tried the multinomial event model discretizing each features in k buckets (and in this case, the features will not “mix up”, ie: each feature will be treated indipendently), this is something often done in the multinomial event model when dealing with continuous values, so we expected some decent results from this model. The last model we used is a gaussian naive bayes: assuming that the features are gaussian is another common way to deal with continuous values in naive bayes, however in this case the values are artificial, and we didn't expect them to be gaussian, so from this model we expected bad results.
Word embeddings are generally used as input for complex models such as neural networks, we thought it was interesting to see if also simpler models such as naive bayes can take profit from these successful representations.
Note that there are many other ways to create the embedding of a tweet from the word embeddings, for example we could do a weighted average (weighting the words according to some score, for example tf-idf), or we could concatenate the word embeddings (truncating too long tweets, and padding too short tweets).

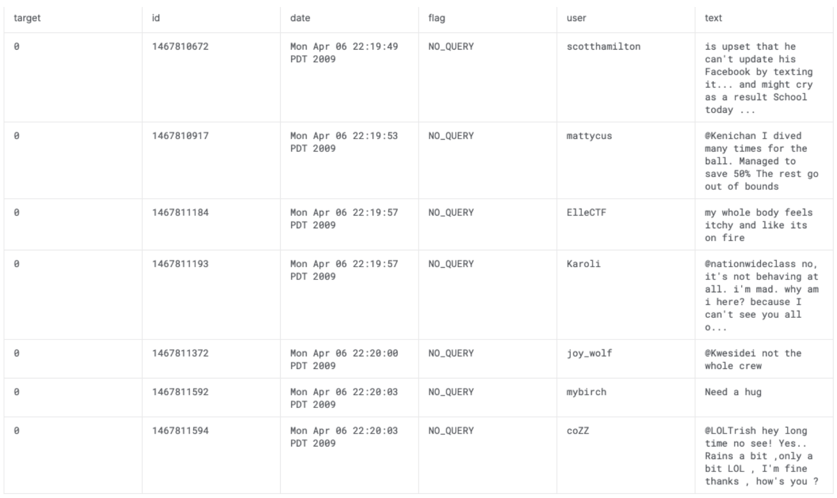
Notes on implementation

The core of the models has been implemented from scratch, but for the data preparation we used some scikit-learn function: for example we implemented the multinomial event model assuming in input vectors of positive values, and we used a scikit-learn function to transform a tweet to a vector (of frequencies or of tf-idf scores). Since the dataset is really large, the efficiency of the learning and testing procedures has been a critical factor to take into account. We managed to get reasonably efficient algorithms leveraging numpy and scipy functions: speaking at a very high level, the key idea has been to compute most of the needed values across all the training set (or all the test set) instead of iterating over the train sample (or test sample) and compute such values in a trivial way.

Preprocessing

Data preprocessing is a vital step in any Machine Learning pipeline, and it is particularly meaningful when dealing with natural language. The fact is that natural language is inherently ambiguous, and in many NLP tasks, we care a lot about the quality of our data which has to be high enough in order to achieve good results. In this case, we tackled the Sentiment Analysis task on the Twitter dataset which consists of a collection of user tweets with their annotated sentiment (either positive or negative) and some additional information such as the tweet identifier, the author, etc ...

As the first step, we cleaned the dataset from all the columns and retained only those related to text and (ground truth) sentiment annotation. We even performed some minor transformations on class labels which were originally defined in {0,4} to have values in {0,1}.



target	id	date	flag	user	text
0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by texting it... and might cry as a result School today ...
0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Managed to save 50% The rest go out of bounds
0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all. i'm mad. why am i here? because I can't see you all o...
0	1467811372	Mon Apr 06 22:20:00 PDT 2009	NO_QUERY	joy_wolf	@Kwesidei not the whole crew
0	1467811592	Mon Apr 06 22:20:03 PDT 2009	NO_QUERY	mybirch	Need a hug
0	1467811594	Mon Apr 06 22:20:03 PDT 2009	NO_QUERY	coZZ	@LOLTrish hey long time no see! Yes.. Rains a bit ,only a bit LOL , I'm fine thanks , how's you ?

Figure 1: Overview of the Twitter dataset.

We noticed that users tend to make mistakes when posting new tweets either because they contain typos (i.e. grammatical issues) or because they replace English words with abbreviations or idiomatical terms (i.e. slung or Internet jargon). Therefore, we chose to perform major treatments on our data and tried to correct these errors in order to enhance the quality of our corpus (e.g. replace duplicated characters, 'hellooo' becomes 'helloo' and 'tooo much' becomes 'too much').

We decided to apply lemmatization and tokenization, which are common operations in NLP tasks, on our dataset, and in order to do that we relied on the spaCy pipeline [**?**] because of its efficiency and because nowadays many companies that deal with natural natural language processing have chosen to use it [?].

While it is common to tokenize sentences into words before passing them to a model, we thought it would be interesting to use lemmas instead of the original words since different variations of the original lemma have the same meaning (e.g. ’be’, ’been’ and ’am’ refer to the same concept) and models should benefit from this process since they will have the chance to see multiple times the same lemma in different contexts.

Moreover, we managed to filter out from our corpus those common words that do not contribute to adding meaning to our sentences: the so-called stopwords. There are a plethora of valid collections of stopwords available on the web (e.g. NLTK [?], Gensim [?]) and we decided to use those offered by spaCy.

Effects of preprocessing

At first, we expected this process to lead to good results since it simplifies the problem by removing a possibly long list of words whose presence can be neglected, but we had to change our mind about that.

Here, we can see some interesting results when testing our intuition on data preprocessing either for the Multivariate Bernoulli or the Multinomial Naïve Bayes with word embeddings. Nevertheless, if we observe these ROC curves we discover some unexpected results: both the models achieved the best results when trained on non-preprocessed data.

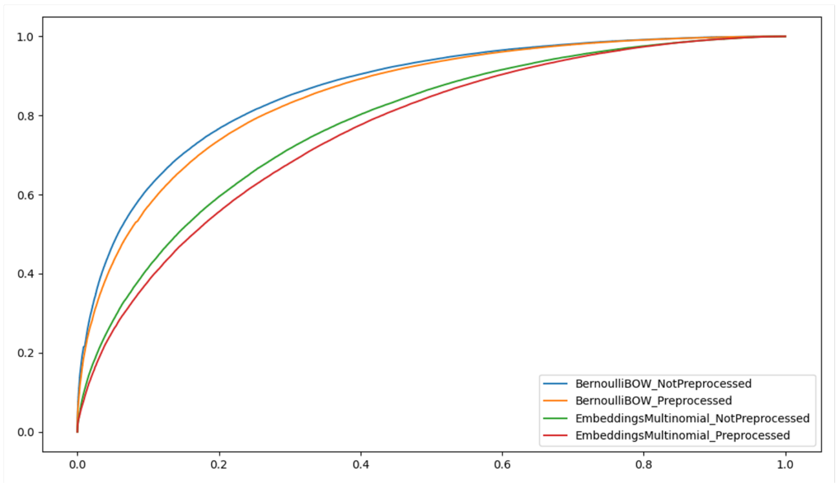


Figure 2: ROC curve with 80% training and 20% test.

We struggled to understand the reasons why this scenario occurs, and we found two principal causes of performance decrease. First, lemmatization is not always a good idea, and in some cases using the original words instead of their lemma is the best choice. More in general, this is a strong text manipulation technique, and common sense tells us that if it does not allow us to gain a significant performance gain, we should better avoid it [**?**]. Second, it's not always a good idea to remove stopwords, especially if the stopwords come from a general dictionary, in fact some words considered stopwords in a context might be useful words in another context. Using the spaCy stopwords the performance of our model decreased, instead using an ad-hoc set of stopwords (which contained only a few words such as articles and pronouns) we got some slightly better results compared to the case where no preprocessing at all is done.

Table 1: Comparing the results of preprocessing on our Bernoulli model. We randomly splitted the dataset in 80% training set, 20% test set

Preprocessing	Accuracy
complete (spaCy pipeline)	0.7690
none	0.7828
ad-hoc stopwords removal	0.7834

Tests and metrics

Classic Naïve Bayes vs Embeddings

In figure 3 are represented the ROC curves obtained with the models using no preprocessing. The dataset split is here set to 80% for the train set and 20% for the test set. The simplest approaches eventually brought the best results. In fact, using word embeddings, the final accuracy was much lower than the one obtained with the classic Naïve Bayes with bag of words. Both the simple Bernoulli and the multinomial Naïve Bayes that counts words occurrences have reached the maximum accuracy with very similar results.

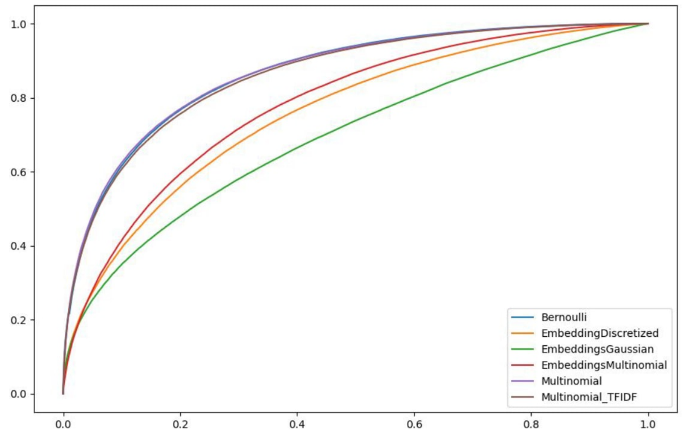


Figure 3: ROC curves that compare the classic Naïve Bayes models with bag of words and word embedding approaches.

In table 2 are shown some metrics about the models resulted from classic approaches. All of their performances are very similar with around 80% of Accuracy and F1-score and 88% of AUROC.

Table 2: Results obtained with bag of words Bernoulli and Multinomial models.

Model	Accuracy	F1	AUROC
Bernoulli	0.797	0.799	0.880
Multinomial	0.802	0.802	0.884
Multinomial TF-IDF	0.805	0.804	0.886

Additionally, some hyperparameter tuning has been applied. The intention has been to find the best n-grams to maximize the final results. In order to do that, 20% of the dataset has been dedicated to the cross validation set.

Kaggle notebooks

In this section we describe how we compared our models to a couple of top-rated notebooks on Kaggle. We also tried to run these notebooks without removing stopwords from their datasets, to gain some further insight on the role their role in the learning process.

The model we chose to compare to these notebooks is our most performing one: Multinomial Naive Bayes with Tf-Idf. The first selected notebook on Kaggle is the most performing one to use the same technique [11]. After resizing our dataset split to theirs, in order to make the comparison as equal as possible, we were happy to see that it's area under the ROC score was slightly lower than ours, as showed in table 2. However, by running the same notebook without executing the preprocessing parts, its performance fairly improved.

Table 3: Comparing our model to notebook [11], with and without preprocessing

Model	AUROC
notebook	0. 839
our model	0.841
notebook without preprocessing	0.849

We also wanted to see if more complex models could capture the irregularities in word embeddings better than our Naive Bayes. We searched Kaggle for the notebook with best results on word embeddings and found this one [12], based on a LSTM neural network. We were truly surprised to see that its accuracy was lower than the one reached by our Tf-Idf, as showed in table 3.

Table 4: Comparing our model to notebook [12], with and without stopword removal

Model	Accuracy
notebook	0. 0.779
our model	0.799
notebook without removing stopwords	0.816

However, by emptying the lists of stopwords to be removed from the dataset and running the notebook again, its accuracy enjoyed a significant boost. The difference between the two executions of notebook [12] is a substantial result to support the intuition that some stopwords contain useful information that we want to keep in our dataset.

Further tests

We trained our model with a dataset and tested it against a different one, to this aim were used am IMDb dataset of cinematographic reviews [?] and a Reddit one about various NFL games [?], results for the Bag-Of-Words Naïve Bayes (1,3)-gram model without preprocessing can be seen in figures 4 and 5.

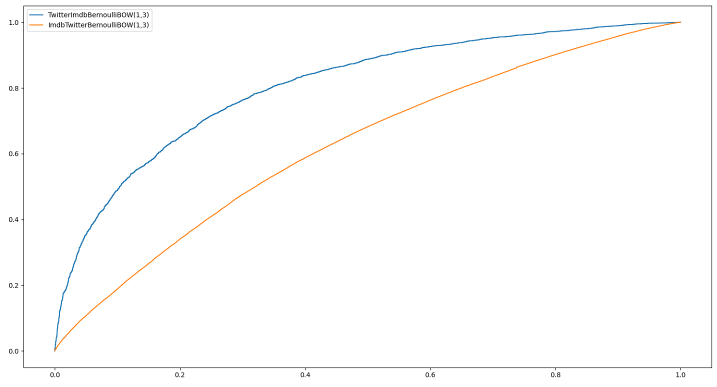


Figure 4: Comparison between Imdb-Twitter and Twitter-Imdb.

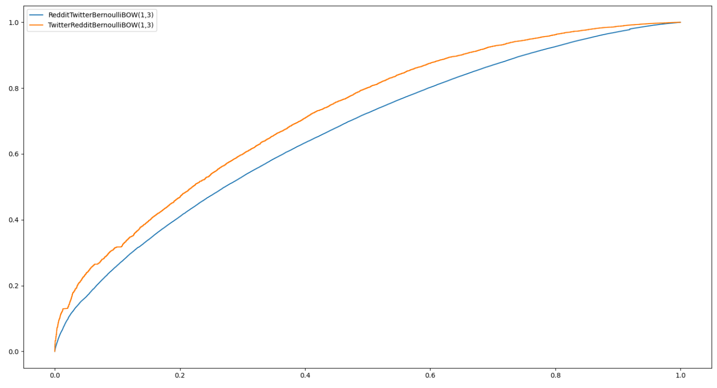


Figure 5: Comparison betwen Reddit-Twitter and Twitter-Reddit.

This is something usually not done since different datasets will have different distributions hence we expect bad results and this is what we found except one single case. Training our model with the Twitter dataset and testing it with the IMDb one strangely gives us rather good metrics, this can be seen in table 5, is exposed only the comparision betwen Twitter and IMDb since results are more interesting. This could happen since Twitter's dataset has a very large number of examples, other datasets other than being smaller are also very specific: the Reddit one is only about a specific set of american football games and the IMDb one is about cinematographic reviews, reasonably in this case lexicon is also more specific. Sentiment140 on the other hand covers a larger class of human language and is less prone to be biased.

Table 5: Comparing metrics for some train test combinations.

Train-Test	Accuracy	F1	AUROC
Twitter-IMDb	0.732	0.723	0.806
IMDb-IMDb	0.891	0.887	0.963
IMDb-Twitter	0.550	0.330	0.625
Twitter-Twitter	0.797	0.800	0.880

Conclusions

The model giving us the best results comparing it to other Kaggle's notebooks is multinomial naïve Bayes with tfidf, we were in general surprised of how FastText performs worse than naïve Bayes; it seems to us that this model perform better when the dataset is simple as is the case of Sentiment140 while more complex have lower scores. Preprocessing also is not necessairly the best way, we obtained the best results when applying an ad-hoc preprocessing carefully choosing which words to ignore, a too broad preprocessing makes us lose too much information and have lower scores.