Sentiment Analysis assignment

The challenge consists of a sentiment analysis problem where we want to identify tweets which are hate tweets and which are not (non-hate tweets).

The approach consists of the following steps:
1. Data cleaning
2. Data exploration
3. Modeling with Logistic Regression and Random Forests
4. Modeling with NN

Data cleaning

Follows the first five rows of the dataset:

	id	is_train	target	text
0	1	1	0.0	@user when a father is dysfunctional and is so selfish he drags his kids into his dysfunction. #run
1	2	1	0.0	@user @user thanks for #lyft credit i can't use cause they don't offer wheelchair vans in pdx. #disapointed #getthanked
2	3	1	0.0	bihday your majesty
3	4	1	0.0	#model i love u take with u all the time in urð±!!! ðððð¦ð¦ð¦
4	5	1	0.0	factsguide: society now #motivation

Looking at it we can observe some encoding problems and particularities about the twitter messages that need to be cleaned. If we look into it with more detail we can find the following irregularities that we will normalise:

1. @user - masked user names for anonymity. We'll consider it irrelevant for the problem at hands and thus we will remove it;

2. \#getthanked - hashtags contain relevant information (it can be seen here https://www.analyticsvidhya.com/blog/2018/07/hands-on-sentiment-analysis-dataset-python/) so we'll keep them and remove only the \# symbol;

3. Abbreviations - in a more in-depth study it should be normalised to one form, in this case we will do it for a short list of abbreviations;

4. Contractions and abbreviations - (can't) vs (can not) vs (cannot) - some of these scenarios will be converted to a common form;

5. Stop words - words like 'the', 'to', etc do not add information to the approach that will be used and will end up contributing just as noise for the final model;

6. Stemming will be applied with the same purpose of finding a common form for a common meaning. This reduces the vocabulary by reducing words to the same root / stem;

7. All the text will be transformed into lowercase;

8. Remove HTML encoding - Example: ‘&amp’, …;

9. Remove URLs;

10. Correct words as 'sooo goooood’ to ‘soo good’ - only allows to repeat the same character twice. We will still have ‘so good’ and ‘soo good’ but it reduces the number of possibilities.

After this preprocessing we get:

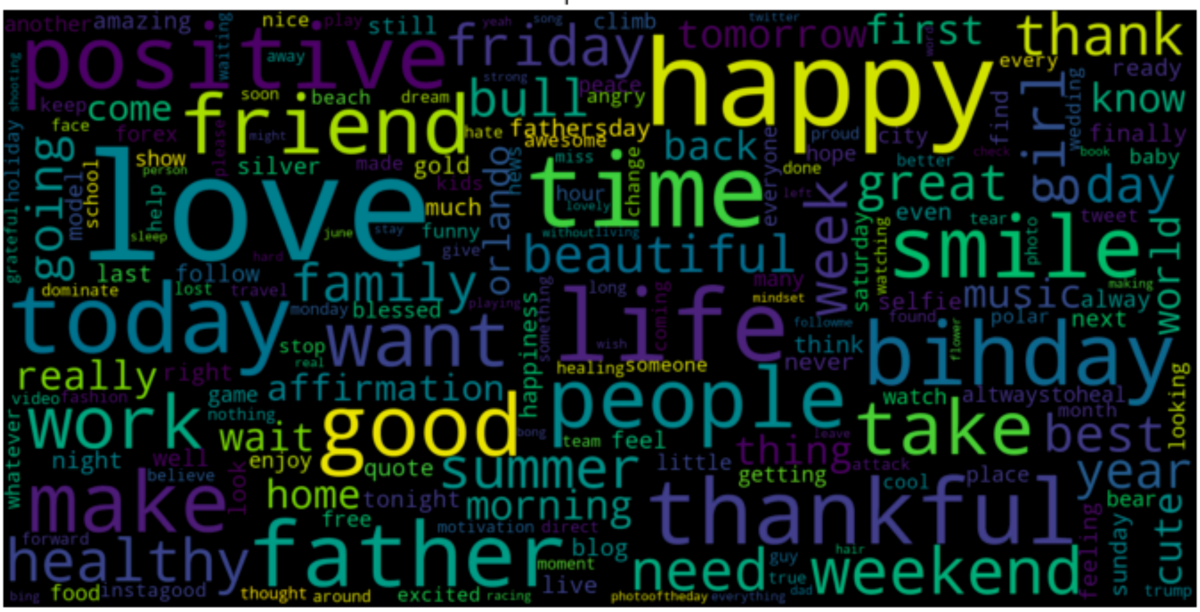
	id	is_train	target	text	clean_text	clean_text_stemmed
0	1	1	0.0	@user when a father is dysfunctional and is so selfish he drags his kids into his dysfunction. #run	father dysfunctional selfish drags kids dysfunction	father dysfunct selfish drag kid dysfunct
1	2	1	0.0	@user @user thanks for #lyft credit i can't use cause they don't offer wheelchair vans in pdx. #disapointed #getthanked	thanks lyft credit cannot cause offer wheelchair vans disapointed getthanked	thank lyft credit cannot caus offer wheelchair van disapoint getthank
2	3	1	0.0	bihday your majesty	bihday majesty	bihday majesti
3	4	1	0.0	#model i love u take with u all the time in urð±!!! ðððð¦ð¦ð¦	model love take time	model love take time
4	5	1	0.0	factsguide: society now #motivation	factsguide society motivation	factsguid societi motiv

Although the *WordCloud* is not a scientific method it does help to visually identify which words are more prevalent.

By using this method I ended up finding also some irregularities that are now clean.

Hate speech WordCloud

Non-hate speech WordCloud



From the images above we can see that the ‘hate speech’ words that are drawn make sense - usually related with politics, races, gender, negative words, swearing, etc. In the ‘non-hate speech’ *WordCloud* we can find a lot of positive words. It is important to notice that we are considering only 1-gram here, which does not capture the context in which the word is inserted - ‘happy’ and ‘not happy’ will contribute equally for the word ‘happy’.

In both cases there's a lot of noisy words that could be excluded in a more detailed analysis.

Data exploration - comparison between classes

The training set is imbalanced having 2242 (0.07%) samples of hate speech and 29720 (0.93%) samples of non-hate speech. In order to compare the percentage that a certain word shows up in one class vs the other we will re-scale to be as if there are the same number of samples for each class. That will be shown by the columns 'hate_pct_scaled' and ‘non_hate_pct_scaled'.

	hate	non_hate	total	hate_scaled	non_hate_scaled	total_scaled	hate_pct_scaled	non_hate_pct_scaled
love	27	2819	2846	27	213	240	0.112500	0.887500
trump	213	182	395	213	14	227	0.938326	0.061674
like	139	920	1059	139	70	209	0.665072	0.334928
people	95	792	887	95	60	155	0.612903	0.387097
libtard	149	3	152	149	1	150	0.993333	0.006667
white	140	83	223	140	7	147	0.952381	0.047619
black	134	126	260	134	10	144	0.930556	0.069444
happy	12	1694	1706	12	128	140	0.085714	0.914286
racist	108	37	145	108	3	111	0.972973	0.027027
time	22	1127	1149	22	86	108	0.203704	0.796296

The image above shows the ten words that show up most often (after scaling, based on total_scaled column). In red words that show up mostly in tweets that are classified as hate speech and in green non-hate speech.
From this sample we can already observe that:

1. As expected, it is possible to classify as hate speech and non-hate speech tweets based on single words - love, happy, trump, libtard, white, black, …
2. There are words that appear almost as often in both categories: like, people,…
3. There are words that although they are not really related with each category, they still show up more often in one category than the other due to the dataset that we are working on (word ‘time’)

One way to identify more words that can be excluded because they do not contain information regarding the labels we want - considered as noise - is to look for scaled percentages that are around 50% - they appear in both categories (hate and non-hate) with the same frequency.

	hate	non_hate	total	hate_scaled	non_hate_scaled	total_scaled	hate_pct_scaled	non_hate_pct_scaled
never	34	386	420	34	30	64	0.531250	0.468750
think	33	376	409	33	29	62	0.532258	0.467742
girl	28	362	390	28	28	56	0.500000	0.500000
year	29	307	336	29	24	53	0.547170	0.452830
live	23	325	348	23	25	48	0.479167	0.520833
even	23	320	343	23	25	48	0.479167	0.520833
still	24	302	326	24	23	47	0.510638	0.489362
look	24	286	310	24	22	46	0.521739	0.478261
many	23	266	289	23	21	44	0.522727	0.477273
ever	23	242	265	23	19	42	0.547619	0.452381

In the current solution these words were not removed. The reason is that we will work with n-grams and they might still make sense in the context of more than one word. A more in-depth study is needed in order to understand the relevance of these words.

Data split

The training dataset was split into two datasets: training (75%) and validation (15%). A third one should be used (test) in order to tune the hyper parameters of the model with the validation set but fine-tuning was not performed. So the model is trained with the training dataset and validated on the validation data set allowing us to observe the bias / overfit to the training data.

Modeling with Logistic Regression and Random Forests

When modeling, the first step we want to take is to define the performance metrics that we will use. The problem states that it will use f1 score to evaluate the results, nevertheless we will also look into recall and precision to better understand where is our model misclassifying (hate vs non-hate speech). Accuracy will not be very informative in this context due to the data imbalance.

Now we will create some models (logistic regression and random forests) based on word of bags (bow) and term frequency–inverse document frequency (tf-idf) and explain its predictions by evaluating what features have more weight (both positive and negative).

Regarding feature engineering only two approaches were taken:
- Word of bags - which consists in the word count of each tweet;
- Tf-idf - which is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

From the perspective of tf-idf, if a word shows up only in one tweet and it does not show up anywhere else it means that this word is extremely relevant for that tweet. This case is not what we want because it will also only be valid for that one tweet and we want to create a model that is able to generalize: this is why we will exclude words that show up too often as well as words that show up only in very few samples. This also applies to the word of bags approach.

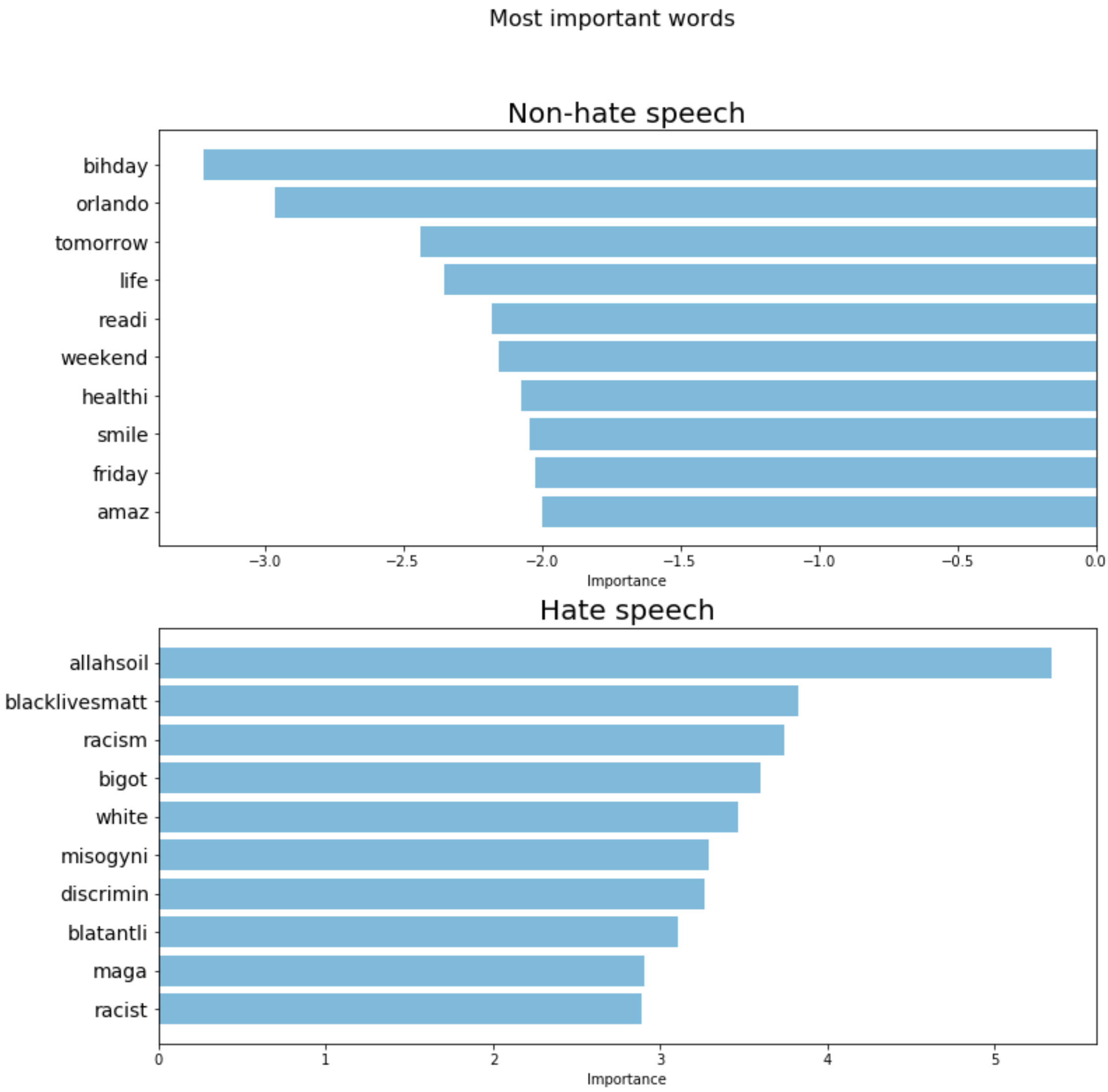
In both cases it was used 1-gram, 2-gram and 3-gram of the tweets.

<u>Logistic Regression</u>

For this model the only non-default parameter that was used was the 'class_weight' that was set to balanced. This allows the model to deal with the data imbalance and give higher weight to the 'hate speech' class samples (class fewer samples).

- Bag of words - The logistic regression with the bag of words features output the following results: accuracy = 0.943, precision = 0.570, recall = 0.735, f1 = 0.642

Below we can see the feature importance after fitting the model.



- Tf-idf - The logistic regression with the tf-idf features output the following results: accuracy = 0.939, precision = 0.547, recall = 0.762, f1 = 0.637

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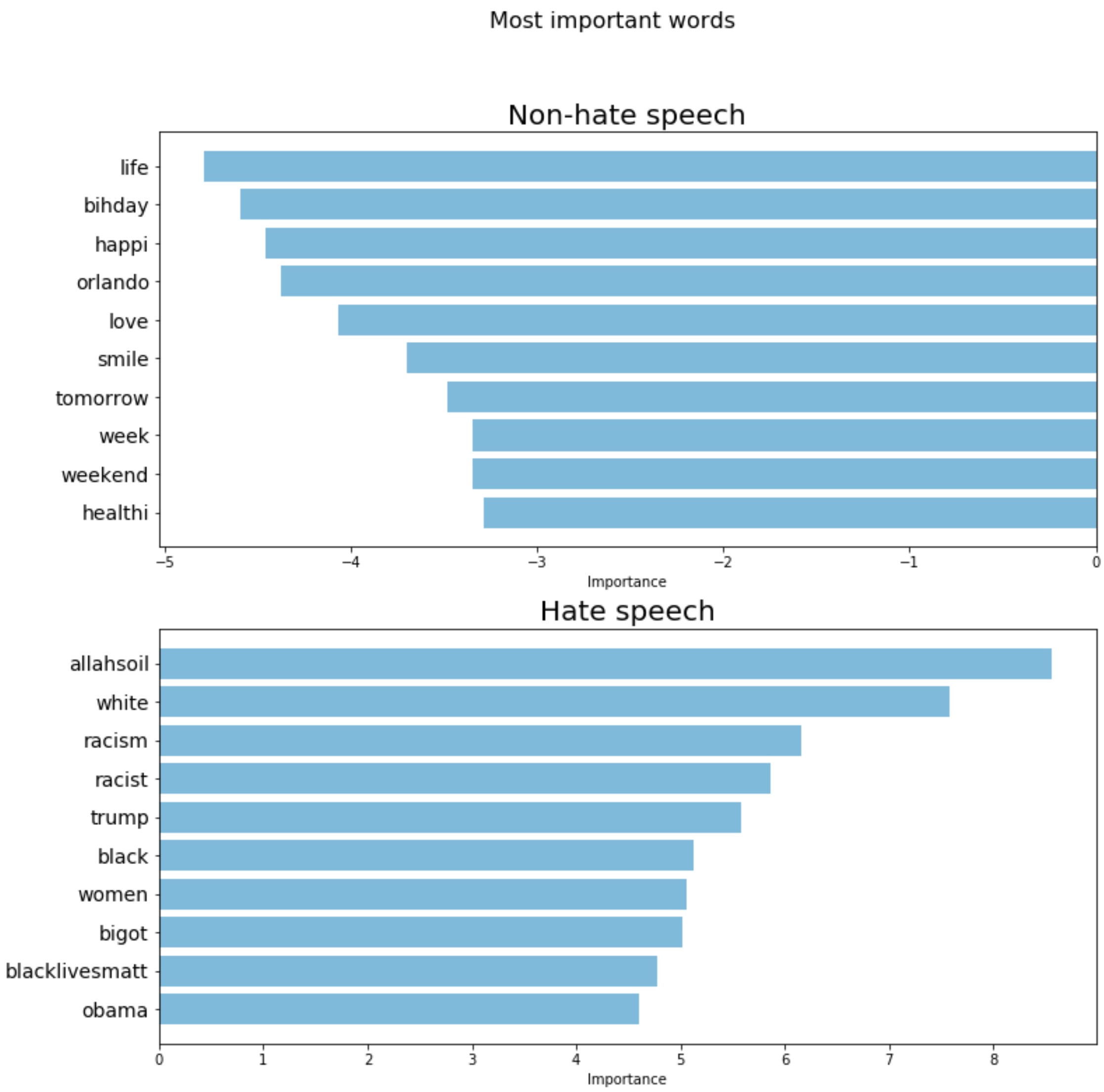


Looking at the results/metrics we can say that we have a high recall and low precision. This means that our classifiers think there's a lot of tweets that are 'hate speech'. This means that we did classify correctly a lot of 'hate speech' category but there's a lot of positive classifications that should be 'non-hate speech'.

Random Forests

For this model the only non-default parameter that was used was the 'class_weight' that was set to balanced. This allows the model to deal with the data imbalance and give higher weight to the 'hate speech' class samples (class fewer samples).

- Bag of words The random forest with the bag of words features output the following results: accuracy = 0.952, precision = 0.682, recall = 0.601, f1 = 0.639

- Tf-idf - The random forest with the tf-idf features output the following results: accuracy = 0.962, precision = 0.819, recall = 0.580, f1 = 0.679

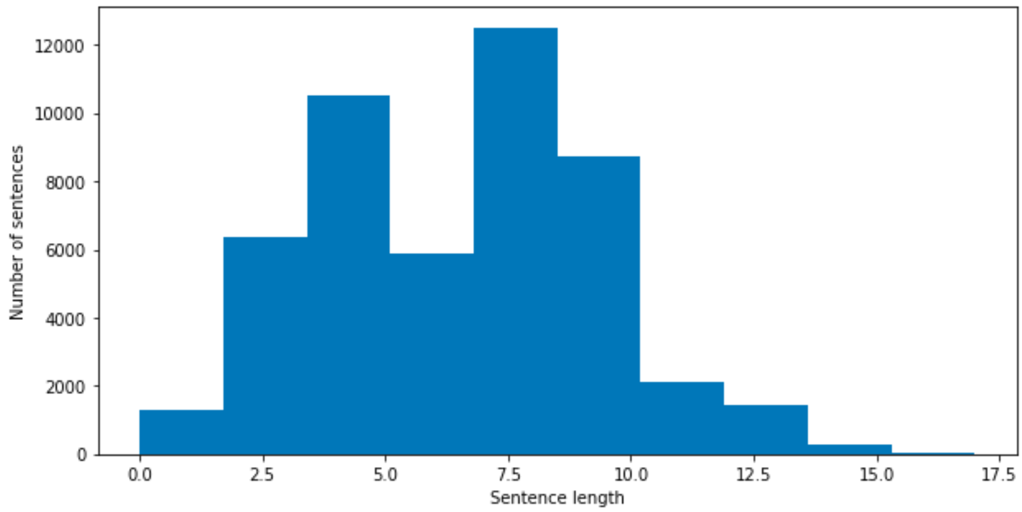
Here, in the case of random forest with tf-idf features, we have the opposite scenario: low recall and high precision. This means that our classifier is much more conservative: the tweets it classifies as 'hate speech' are actually correct but it is missing a lot of them as well.

Modeling with NN

The NN approach that will be used here is simple: input layer that will receive the whole sentences/tweets. Each tweet is converted into a vector (where each entry is a word) that will be fed to the NN, then each of the entries of that vector (each word) is mapped to it's representation in the vector space - word embedding. After having all the words represented by a vector, we have a flatten layer that will then feed a sigmoid in order to have an output between 0 and 1.

It could have been more elaborated by using a CNN or RNN (that are used to take into account sequences) with pre-trained word embeddings that would map words into a vector space where closely related words in terms of meaning would be grouped together. This means that words like 'black' and 'white' would most probably be similar with other colours like 'yellow' or 'green' but it could also relate with the word 'racism', specially if we retrain the word embedding to our particular case / subject.

In order to use as input the whole sentence we need to determine the maximum size (number of words) of our tweets. Below is an histogram with word counts of each tweet in our dataset.



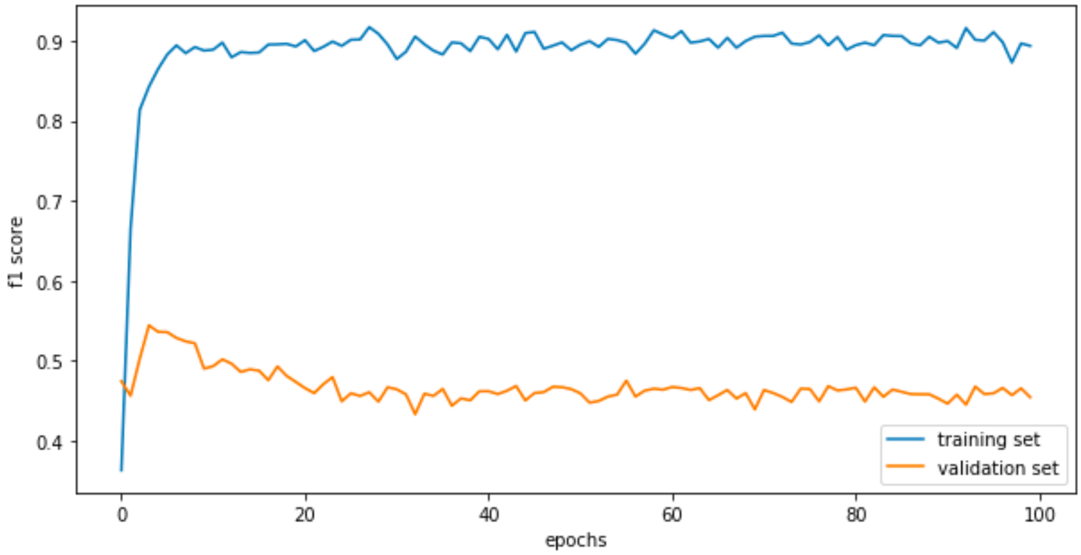
The architecture of our simple NN is the following:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 16, 150)           4423650
_________________________________________________________________
flatten_1 (Flatten)          (None, 2400)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 2401
=================================================================
Total params: 4,426,051
Trainable params: 4,426,051
Non-trainable params: 0
_________________________________________________________________
```

Which gave us the following results:

accuracy = 0.936, precision = 0.547, recall = 0.524, f1 = 0.535

If we look at the f1 score during training we can see that there's overfit to the training data making this model unreliable.



Although these results are worse when compared with previous results it is important to state that the approach is completely different and it lacks a fundamental step when we talk about NN: hyper parameter tuning: number of layers, number of neurons, dropout, learning rate, activation functions, etc.

So in the end, this is just a dummy/naive example to allow for further discussion if I step into the next stage of the recruitment process.

Summary of results

- LR_bow: accuracy = 0.943, precision = 0.570, recall = 0.735, f1 = 0.642
- LR_tfidf: accuracy = 0.939, precision = 0.547, recall = 0.762, f1 = 0.637
- RF_bow: accuracy = 0.952, precision = 0.682, recall = 0.601, f1 = 0.639
- RF_tfidf: accuracy = 0.962, precision = 0.819, recall = 0.580, f1 = 0.679
- NN: accuracy = 0.936, precision = 0.547, recall = 0.524, f1 = 0.535

Looking at the results the best f1_score was obtained using random forests with tf-idf features.

Comments

Follow some ideas that would improve the results:
- Cross-validation in order to tune the hyper parameters of the models (for instance, through grid search);
- Convert more 'slang' from the twitter to a common form;
- Ensemble modeling - example: since logistic regression proved to be best at 'recall' and random forest at 'precision' both could be combined to get a better overall output;
- In the case of NN use pre-trained word embedding and more suited architecture for this purpose - https://arxiv.org/abs/1408.5882 ;
- For NN try different optimisation algorithms and loss functions;