Hate Speech and Offensive Language

Text Classification and Clustering

Emanuela Elli (892901) Federica Madon (825628) Tommaso Strada (829351)



About the dataset

The dataset is about **tweets** that may contain *hate speech*, offensive *language* or *neither*. There are **24783 rows** and **6 columns**.



Columns



Number of CrowdFlower users who coded each tweet



neither

Number of CF users who judged the tweet to be neither offensive nor non-offensive



hate_speech

Number of CF users who judged the tweet to be hate speech



class

Label for majority of CF users



offensive_language

Number of CF users who judged the tweet to be offensive

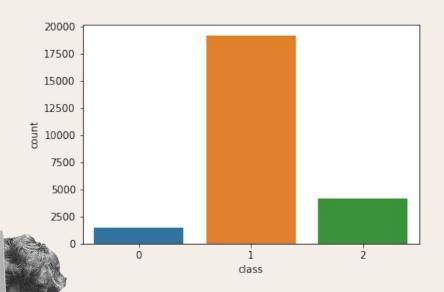


tweet

Text of the tweet

Labels

XXXXX



- Hate Speech
 - "We hate niggers, we hate faggots and we hate spics"
- Offensive Language
 - "RT @HerMoufPiece: Hairy pussy bitch you the type that got herps"
- Neither

"Got my vans on.. My pockets chunky"

Framework







01

02

03

Pre Processing

Text Classification

Text Clustering



Pre-Processing



Binary labels



Reduction of label to a binary variable → type with 1 for hate_speech and offensive_language and 0 for neither of them

Lowercase



Reduction of characters to lowercase

Useless Characters



Dropping of urls, mentions, punctuation, emojis, numbers and extra white space.

Removal of *repeating characters* (more than twice)

"Amp" & NaN



Correction of a **typographical error**: "Amp" \rightarrow "And" Removal of 2 rows with NaN values

Tokenization



Tokenization of tweets



Before Pre-Processing

- "We hate niggers, we hate faggots and we hate spics"
- "RT @HerMoufPiece: Hairy pussy bitch you the type that got herps"
- "Got my vans on.. My pockets chunky"



After Pre-Processing

- ['We', 'hate', 'niggers', 'we', 'hate', 'faggots', 'and', 'we', 'hate', 'spics']
- ['Hairy', 'pussy', 'bitch', 'you', 'the', 'type', 'that', 'got', 'herps']
- ['Got', 'my', 'vans', 'on', 'My', 'pockets', 'chunky']







Dataset

The dataset is divided in:

- **70% training set** → 17346 rows
- **30% test set** → 7435 rows

Fixing imbalanced classes in the **training set** with Smote (Synthetic Minority Oversampling Technique) method.

Pre-Processing

Pre-Processing is applied only on the **training set**. The tweets of the **test set** are only removed of the **punctuation**.

Text Representation

TF-IDF

- For using this representation the STOPWORDS are removed in the training set
- Using of lemmatization on tweets already divided in tokens
- Using of n-grams (unigram, bigram, trigram)

Word2vec

- Using of unigram
- Google pretrained model

Text Classification with TF-IDF

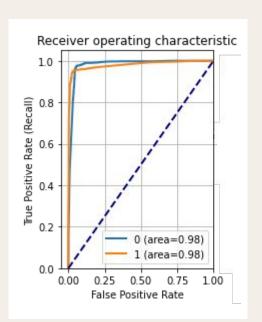
	XGBOOST	Naive Bayes	SVM
Unigram	Accuracy: 0.74 AUC: 0.89	Accuracy: 0.84 AUC: 0.93	Accuracy: 0.78 AUC: 0.90
Bigram	Accuracy: 0.73 AUC: 0.89	Accuracy: 0.75 AUC: 0.93	Accuracy: 0.74 AUC: 0.88
Trigram	Accuracy: 0.73 AUC: 0.89	Accuracy: 0.75 AUC: 0.92	Accuracy: 0.73 AUC: 0.88

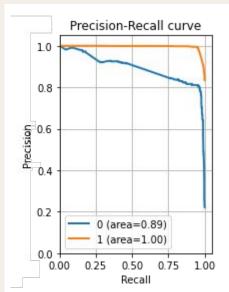
Text Classification with Word2vec

	XGBOOST	Naive Bayes	SVM
Unigram	Accuracy: 0.95 AUC: 0.98	Accuracy: 0.90 AUC: 0.92	Accuracy: 0.95 AUC: 0.97

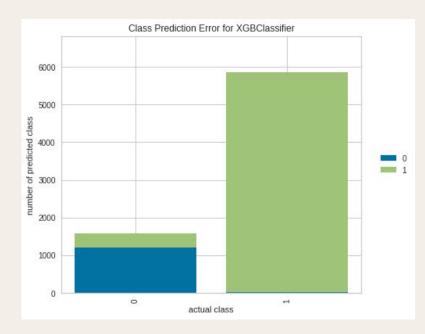
Word2vec - XGBOOST

Results on training set





Results on test set







Text Clustering

Dataset

A **sample** is extracted from the dataset. This sample respects the **imbalance** between the new two classes of the labels.

Pre-Processing

- Pre-Processing is applied on all the dataset
- Tweets are also removed from the STOPWORDS
- After tokenization, lemmatization is applied

Text Representation

Word2vec

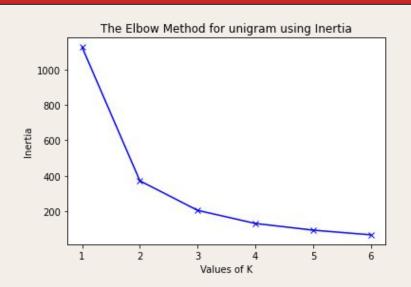
- Using of CBOW architecture:size = 300 andalpha = 0.03
- Using of n-grams (unigram, bigram, trigram)

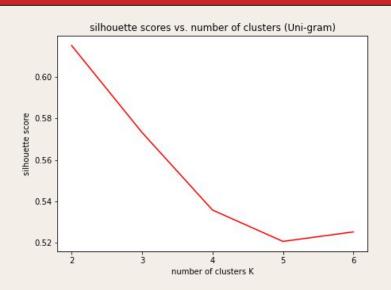
How many clusters?

The Elbow Method and Silhouette Method are computed for each type of n-gram to determine the **optimal number of clusters**. The plots below are about unigrams.

Elbow Method

Silhouette Method



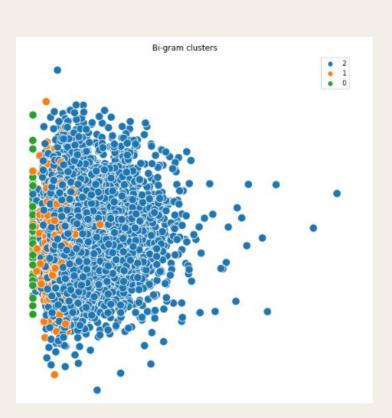


It turns out that **three clusters** are the ideal quantity. The results are analog for bigram and trigram.

Text Clustering with Word2vec

	K-Means	Agglomerative	
Unigram	Silhouette index: 0.15 Davies bouldin index: 1.94	Silhouette index: -0.24 Davies bouldin index: 0.58	
Bigram	Silhouette index: 0.74 Davies bouldin index: 0.95	Silhouette index: -0.59 Davies bouldin index: 0.56	
Trigram	Silhouette index: 0.96 Davies bouldin index: 6.41	Silhouette index: -0.73 Davies bouldin index: 0.55	

K-means - Bigram



Top 10 most frequent words for cluster 0 [('trash anyway', 3), ('you pussy', 3), ('whipped cream', 2), ('he yank', 2), ('shy people', 2), ('female trash', 2), ('next door', 2), ('oreo milkshake', 2), ('hat ghetto', 2), ('could

Top 10 most frequent words for cluster 1 [('street', 9), ('uncle om', 7), ('hoe lol', 6), ('when i', 5), ('fucking retard', 5), ('fucking pussy', 5), ('jig', 5), ('ring', 5),

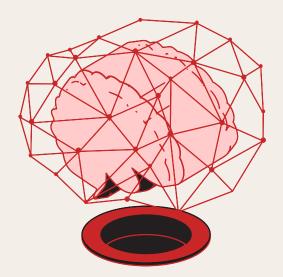
get', 2)1

```
Top 10 most frequent words for cluster 2
[('bitch', 2140), ('i', 1348), ('hoe', 814),
('is', 525), ('like', 517),
('pussy', 401), ('nigga', 350), ('as', 305),
('get', 301), ('but', 282)]
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('unfollow', 5), ('tryin', 5)]

Text Classification

For classification (even if only for unigrams) with the **Word2vec representation** we get a considerable improvement on the results for our dataset



Conclusion

Text Clustering

The available dataset is probably **not suitable** for this type of task since the results obtained in *terms of metrics* seem to be quite satisfactory but *visually* they do not seem to show *particular patterns or features* that allow us to clearly distinguish groups of tweets

Future Developments



Validation Test

Dividing the test set into validation and test set with cross validation

Spelling Correction

Using a function to correct spelling mistakes

Normalization

Using a function to normalize all the vocabulary for all the models

N-grams for Word2Vec classification

Implementing Word2Vec classification also with bigram and trigram

Another dataset

Test the chosen model of classification on another dataset with tweets

Relevant Websites:

- https://medium.com/@dilip.voleti/classification-using-word2vec-b1d79d375381
- https://www.kaggle.com/nlp-model-to-predict-hate-speech#Importing-the-dataset
- https://www.kaggle.com/hate-offensive-language
- https://github.com/Hate-Speech-Detection
- https://medium.com/unsupervised-text-clustering-using-natural-language-processing-nlp
- https://ai.intelligentonlinetools.com/ml/k-means-clustering-example-word2vec/
- https://www.guru99.com/word-embedding-word2vec.html

Relevant Papers:

- Razavi, Amir H., et al. "Offensive language detection using multi-level classification." Advances in Artificial Intelligence: 23rd Canadian Conference on Artificial Intelligence, Canadian Al 2010, Ottawa, Canada, May 31–June 2, 2010. Proceedings 23. Springer Berlin Heidelberg, 2010.
- Davidson, Thomas, et al. "Automated hate speech detection and the problem of offensive language." Proceedings of the international AAAI conference on web and social media. Vol. 11. No. 1. 2017.

