Toxic Comment Classification

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Bullying, including cyberbullying, is a serious impediment to achieving the Sustainable Development Goals (SDGs).

Book: Developmental Science and Sustainable Development Goals for Children and Youth - Tracing the Connections Between Sustainable Development, Bullying, and Cyberbullying

R. Sittichai, T. Ojanen, J. Burford - 2018

Bullying has documented impacts on:

Educational access

Mental health

Depression and suicidale rate

Multiple SDGs and their targets

Wikipedia Toxic Comment Classification

	id	comment_text	toxic	severe_toxic	obscene	threat	insult	identity_hate
0	0000997932d777bf	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	000103f0d9cfb60f	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0
2	000113f07ec002fd	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0
3	0001b41b1c6bb37e	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0
4	0001d958c54c6e35	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
159566	ffe987279560d7ff	":::::And for the second time of asking, when ...	0	0	0	0	0	0
159567	ffea4adeee384e90	You should be ashamed of yourself \n\nThat is ...	0	0	0	0	0	0
159568	ffee36eab5c267c9	Spitzer \n\nUmm, theres no actual article for ...	0	0	0	0	0	0
159569	fff125370e4aaaf3	And it looks like it was actually you who put ...	0	0	0	0	0	0
159570	fff46fc426af1f9a	"\nAnd ... I really don't think you understand...	0	0	0	0	0	0

159571 rows × 8 columns

15971 rows, 8 columns

Source: https://www.kaggle.com/c/jigsaw-toxic-comment-classification-challenge/overview

Dataset

Comments from Wikipedia's discussions page

6 classes of comment:

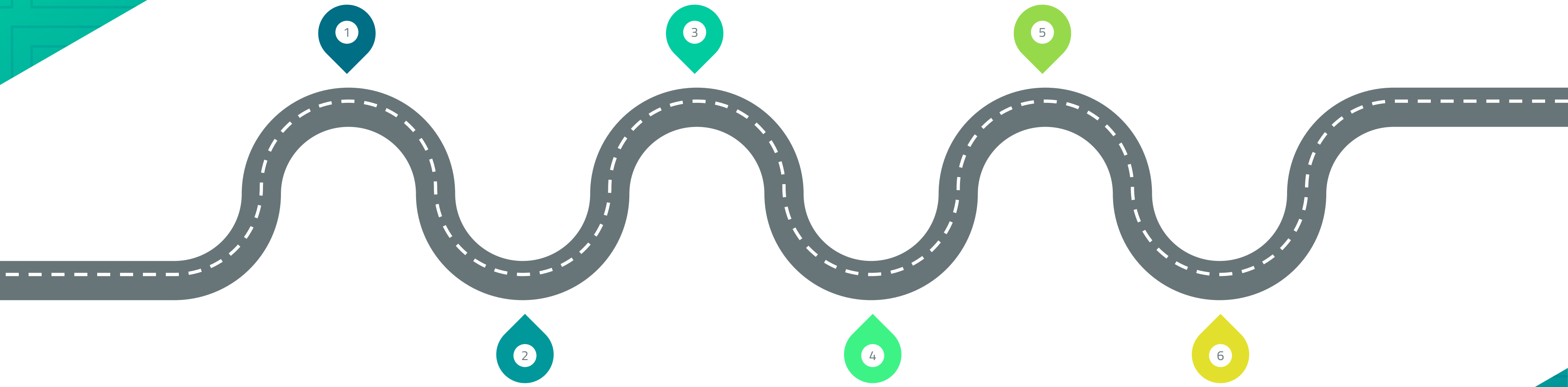
- Toxic
- Severe toxic
- Obscene
- Threat
- Insult
- Identity hate

2 labels:

- **0 : False**
- **1 : True**

Objective

- Build a classification model that is able to predict the toxicity of comment
- Evaluate and compare the performance between ML models



Data

Natural language processing

Cleaning text data by reducing noises (remove special characters and stopwords, lowercase everything ...)

Exploratory Data Analysis

Treat data + Cross validation

(get 50%-50% of nontoxic - toxic comments ratio, train test split, vectorization ...)

ML algorithm

(Logistic regression, KNN, SVM, Naives bayes classifier, Random forest)

Comparing performance

Data analysis

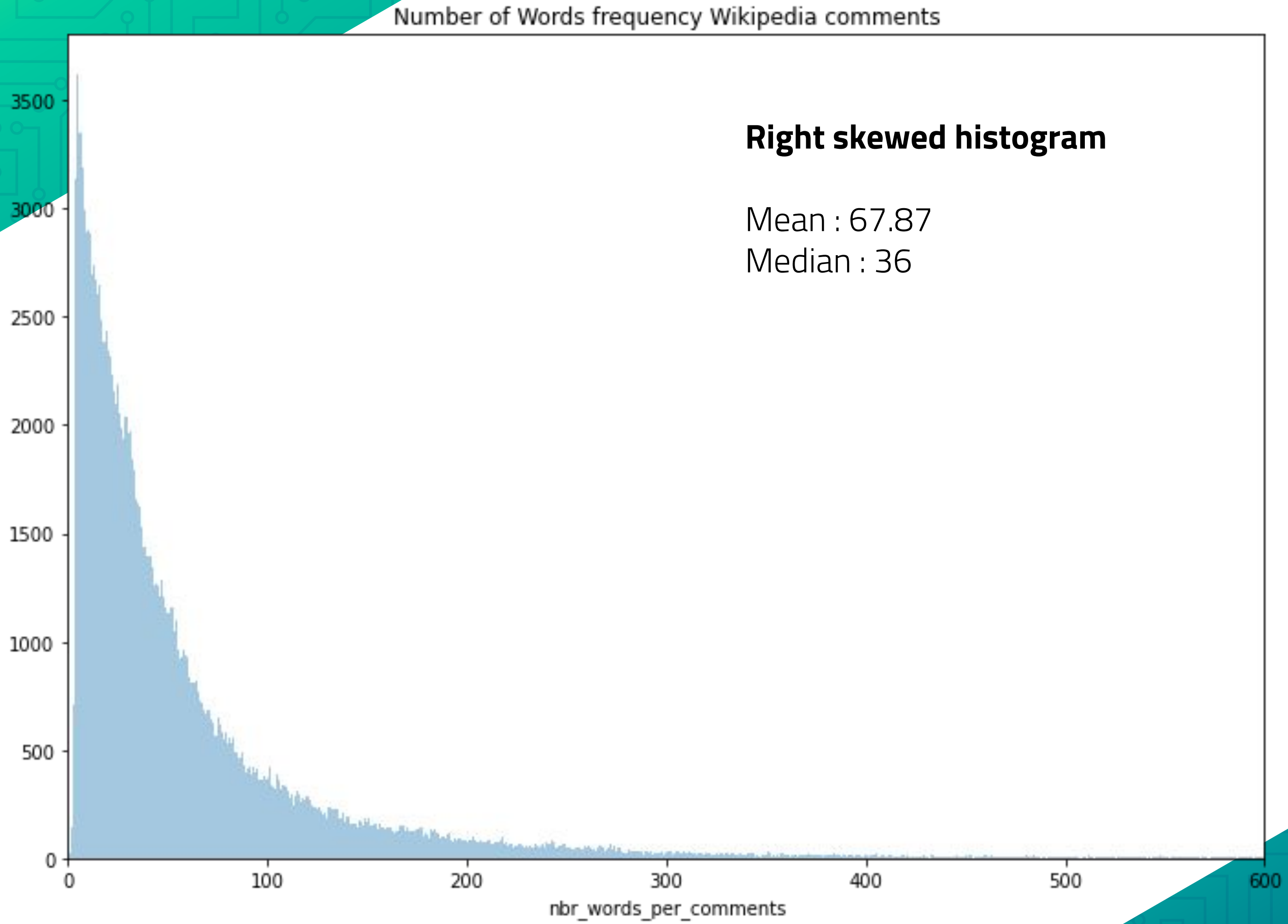
- No null values to deal with
- Read comments properly using **neattext** library

Comment

```
'"\nMore\nI can\'t make any real suggestions on improvement - I wondered if the section statistics should be later
on, or a subsection of ""types of accidents""  -I think the references may need tidying so that they are all in th
e exact same format ie date format etc. I can do that later on, if no-one else does first - if you have any prefer
ences for formatting style on references or want to do it yourself please let me know.\n\nThere appears to be a ba
cklog on articles for review so I guess there may be a delay until a reviewer turns up. It\'s listed in the releva
nt form eg Wikipedia:Good_article_nominations#Transport  "'
```

Description:

```
Key        Value
Length   : 622
vowels   : 196
consonants: 290
stopwords: 62
punctuations: 20
special_char: 21
tokens(whitespace): 113
tokens(words): 116
```



Right skewed histogram

Mean : 67.87
Median : 36

The most frequent words in Wikipedia comments are Wikipedia related

Most frequent words in all Wikipedia comments

Data analysis

- No null values to deal with
- Read comments properly using **neattext** library
- NLP and pre-processing: Clean data by removing punctuation, stopwords, lower casing …

Natural language processing (NLP)

linguistics, computer science, artificial intelligence

Interactions between computers and human language. Allow computer to process and analyze large amounts of natural language data (human language).

NLP tools and process :

- Normalization: take into account all the form of the same word *(have, having)*
- Stemming: finding a root of the words *(have, having)* ⇒ *hav*
- Tokenization: splitting a sentence into tokes (words, ponctuation …)
- Vectorization: process of converting text into numerical representation

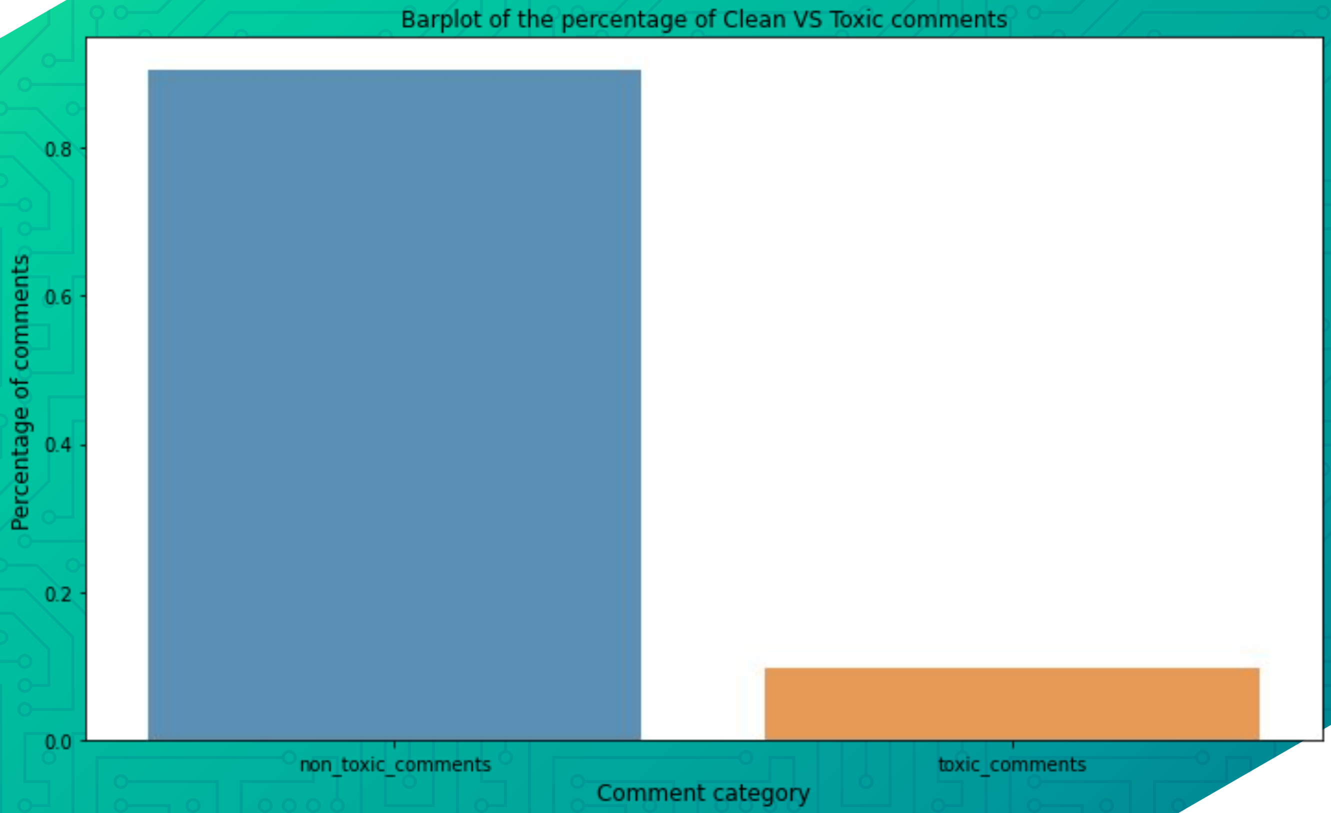
Data analysis

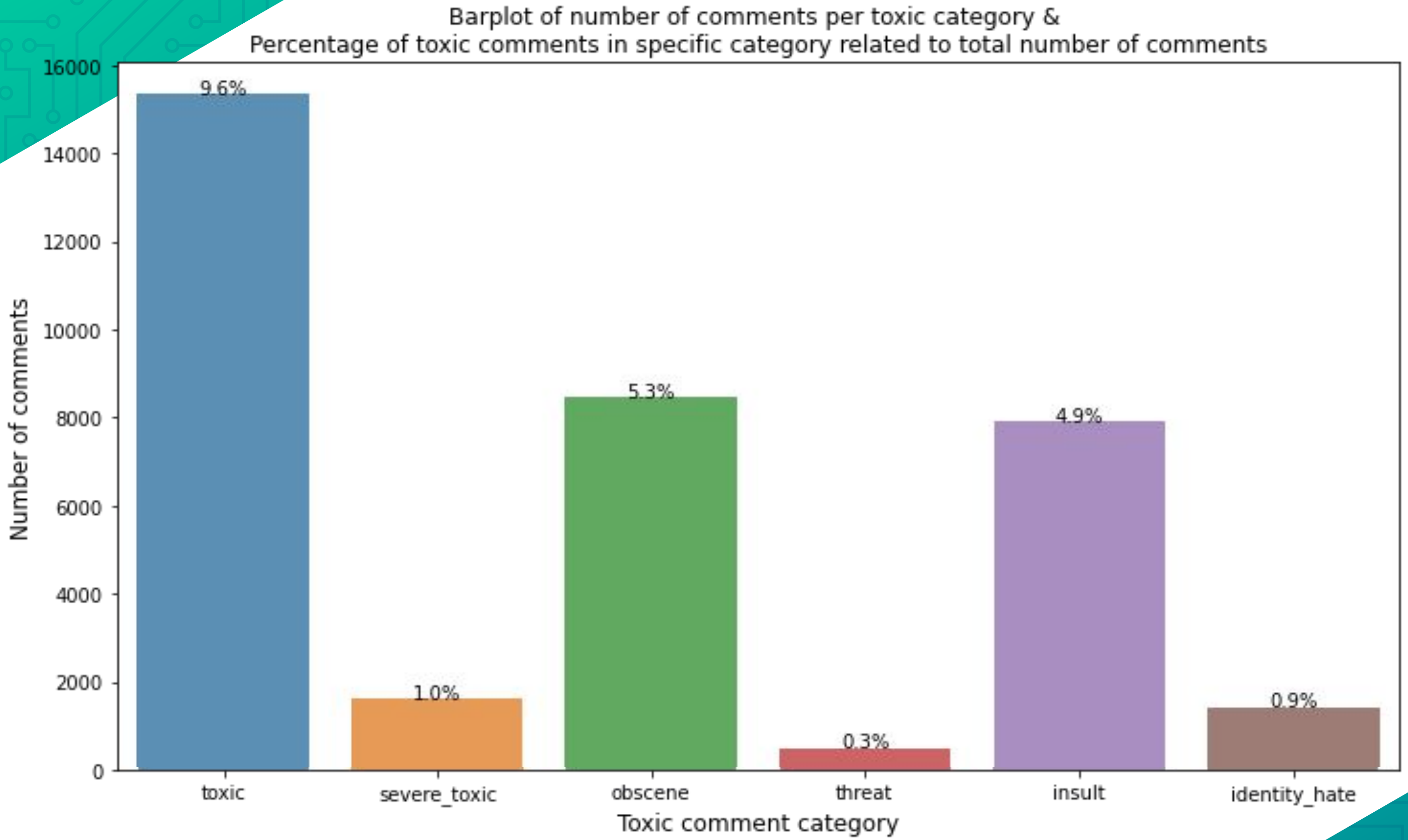
```
Number of toxic comment for each category:

 toxic            15294
severe_toxic      1595
obscene           8449
threat             478
insult            7877
identity_hate     1405
```

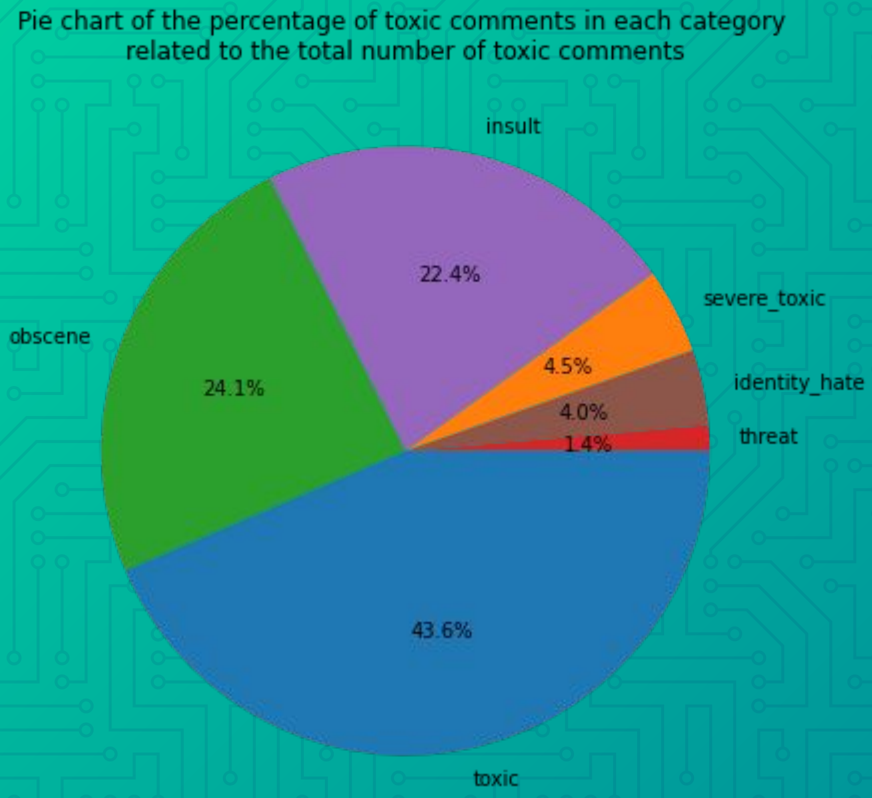
- No null values to deal with
- Read comments properly using **neattext** library
- NLP and pre-processing: Clean data by removing punctuation, stopwords, lower casing ...
- Check repartition of toxic comments:
    - 90% of the comments have no form of toxicity at all.

Only around 10% comments have a form of toxicity

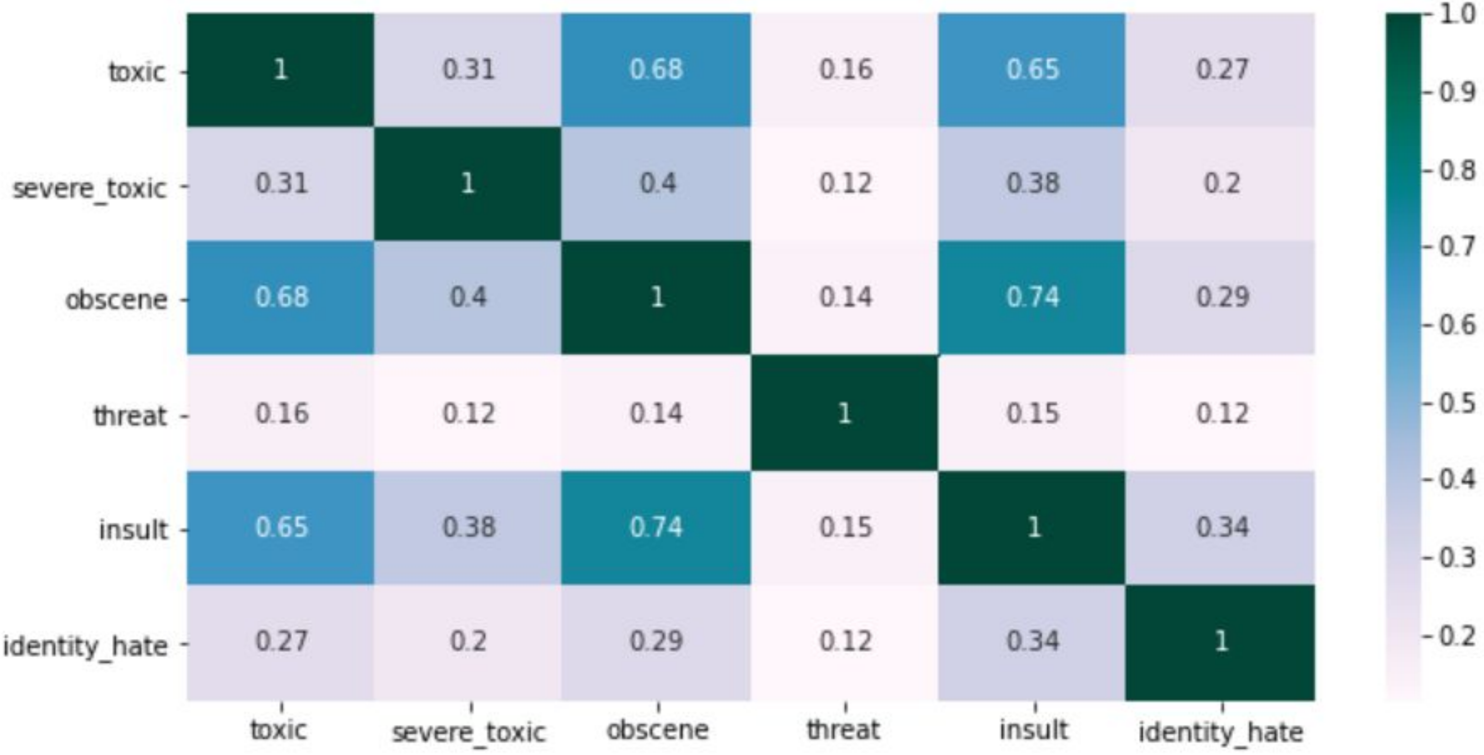



Barplot of number of comments per toxic category &
Percentage of toxic comments in specific category related to total number of comments
9.6%
1.0%
5.3%
0.3%
4.9%
0.9%
Number of comments
0
2000
4000
6000
8000
10000
12000
14000
16000
toxic
severe_toxic
obscene
threat
insult
identity_hate
Toxic comment category

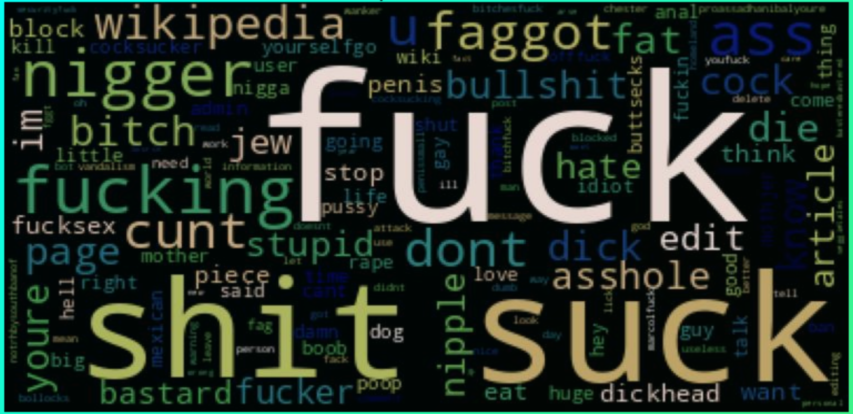
Toxic, Insults & Obscene comments compose the majority of toxic comments



Correlation Matrix of toxic categories



Words frequented in obscene

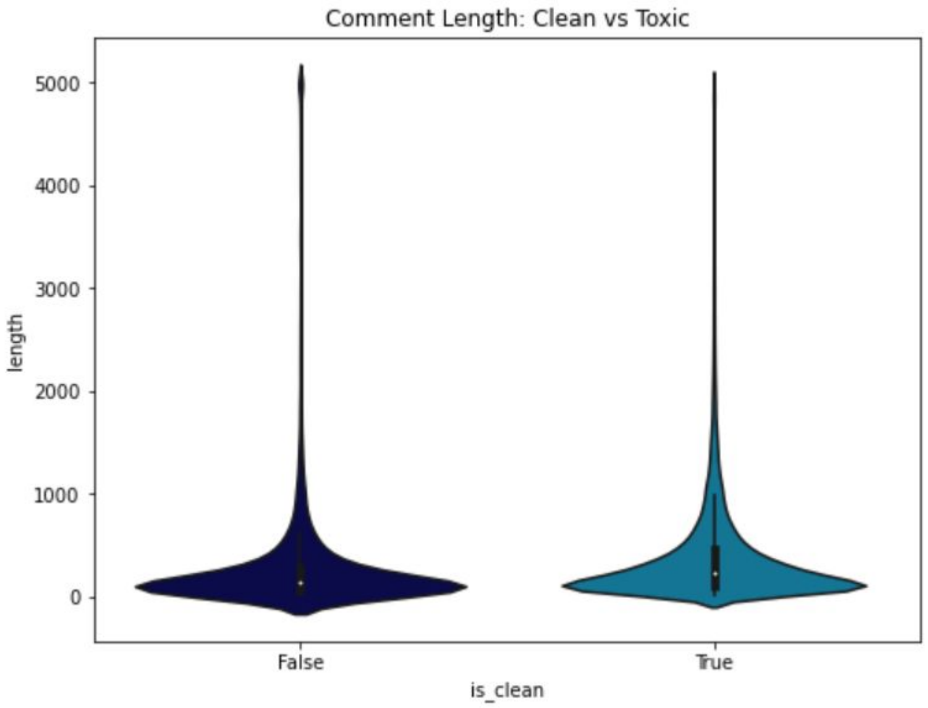


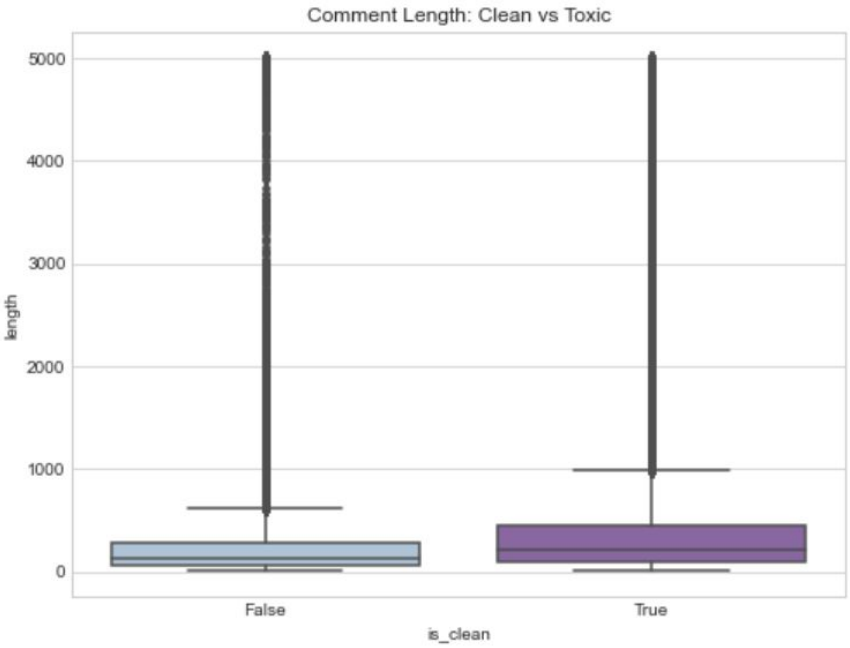
Words frequented in insult

Words frequented in identity_hate

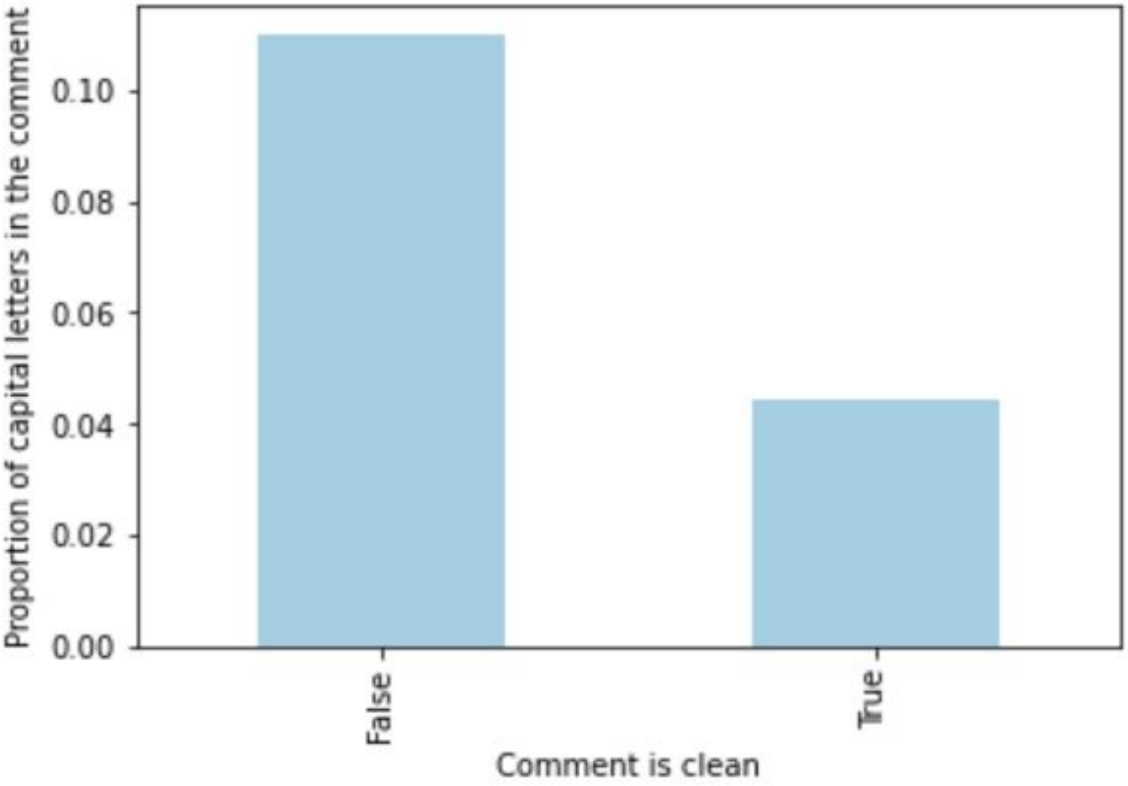
Words frequented in threat

Length and toxicity



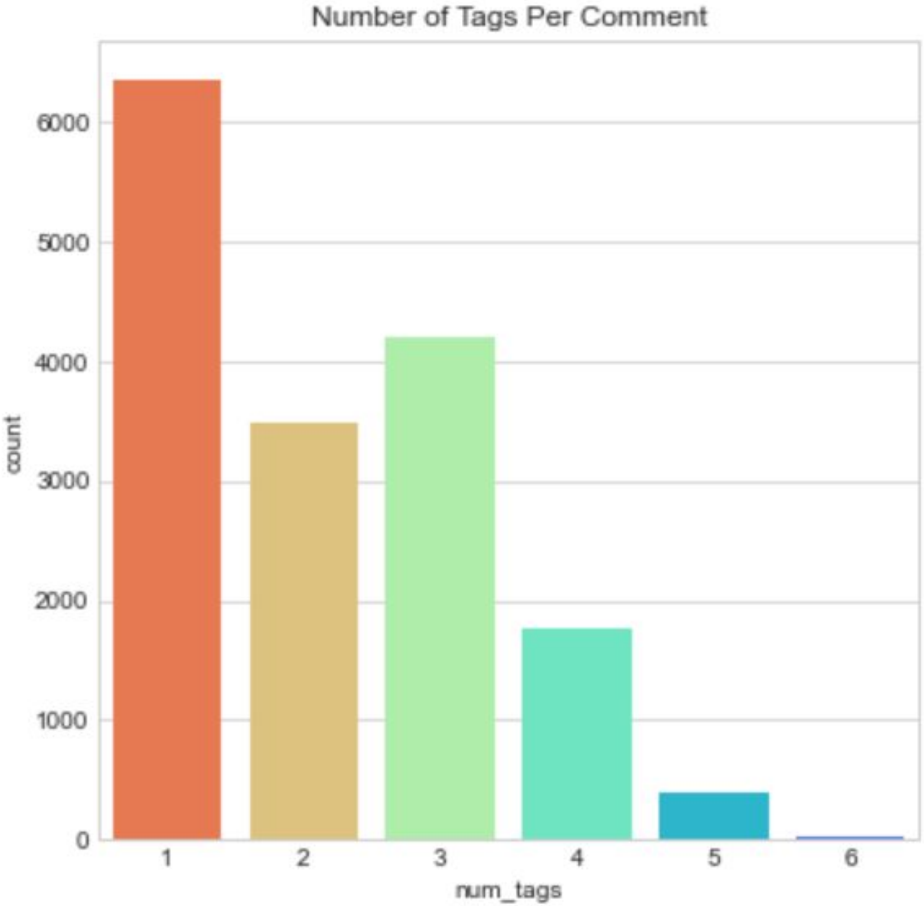


Capital letters in toxic comments



	length	capitals	proportion
is_clean			
False	305.672604	42.980770	0.109680
True	406.885138	14.236993	0.044497

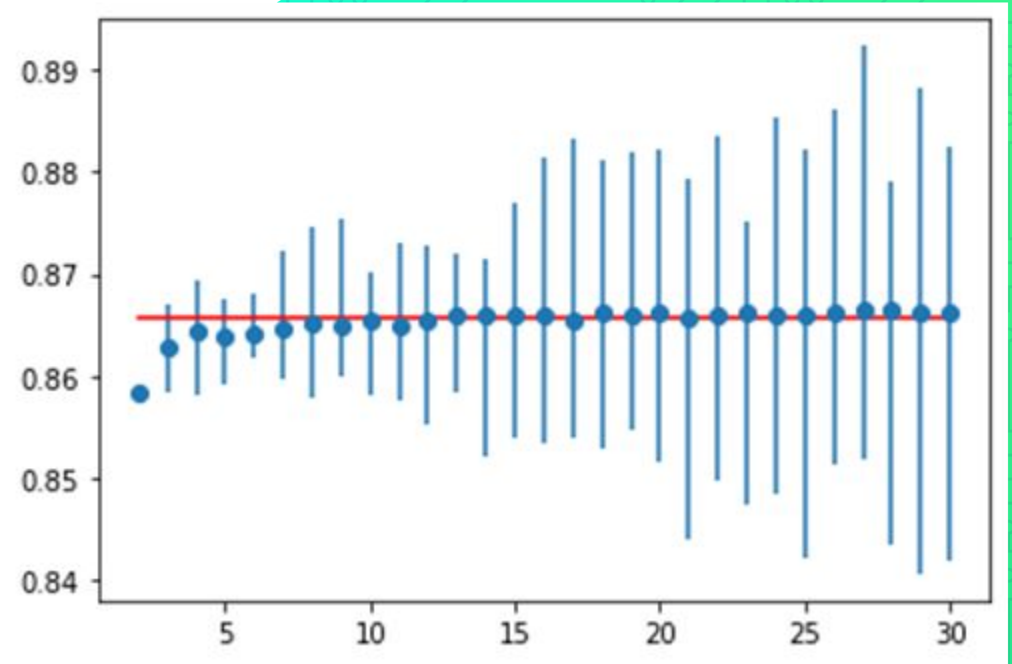
Number of tags for each toxic comment



We took a subset of the dataset to create 6 datasets (one for each level of toxicity)

We balanced each datasets to have a 50-50 frequency of toxic-nontoxic words

Logistic regression. Cross-validation




```
Ideal: 0.866
> folds=2, accuracy=0.858 (0.858,0.859)
> folds=3, accuracy=0.863 (0.858,0.867)
> folds=4, accuracy=0.864 (0.858,0.869)
> folds=5, accuracy=0.864 (0.859,0.868)
> folds=6, accuracy=0.864 (0.862,0.868)
> folds=7, accuracy=0.865 (0.860,0.872)
> folds=8, accuracy=0.865 (0.858,0.874)
> folds=9, accuracy=0.865 (0.860,0.875)
> folds=10, accuracy=0.865 (0.858,0.870)
> folds=11, accuracy=0.865 (0.858,0.873)
> folds=12, accuracy=0.866 (0.855,0.873)
> folds=13, accuracy=0.866 (0.858,0.872)
> folds=14, accuracy=0.866 (0.852,0.871)
> folds=15, accuracy=0.866 (0.854,0.877)
> folds=16, accuracy=0.866 (0.853,0.881)
> folds=17, accuracy=0.865 (0.854,0.883)
> folds=18, accuracy=0.866 (0.853,0.881)
> folds=19, accuracy=0.866 (0.855,0.882)
> folds=20, accuracy=0.866 (0.852,0.882)
> folds=21, accuracy=0.866 (0.844,0.879)
> folds=22, accuracy=0.866 (0.850,0.883)
> folds=23, accuracy=0.866 (0.847,0.875)
> folds=24, accuracy=0.866 (0.849,0.885)
> folds=25, accuracy=0.866 (0.842,0.882)
> folds=26, accuracy=0.866 (0.851,0.886)
> folds=27, accuracy=0.867 (0.852,0.892)
> folds=28, accuracy=0.866 (0.843,0.879)
> folds=29, accuracy=0.866 (0.841,0.888)
```

Logistic regression.

AUC (Area Under the Curve):

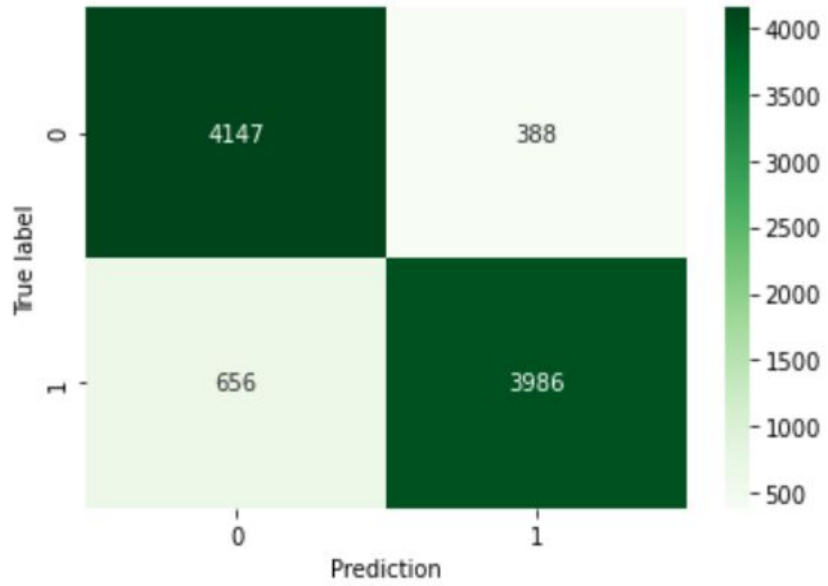
- measure of the ability of a classifier to distinguish between classes.
- summary of the ROC curve.

The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes.

Log Loss:

- applies to the prediction process in machine learning related to probabilities

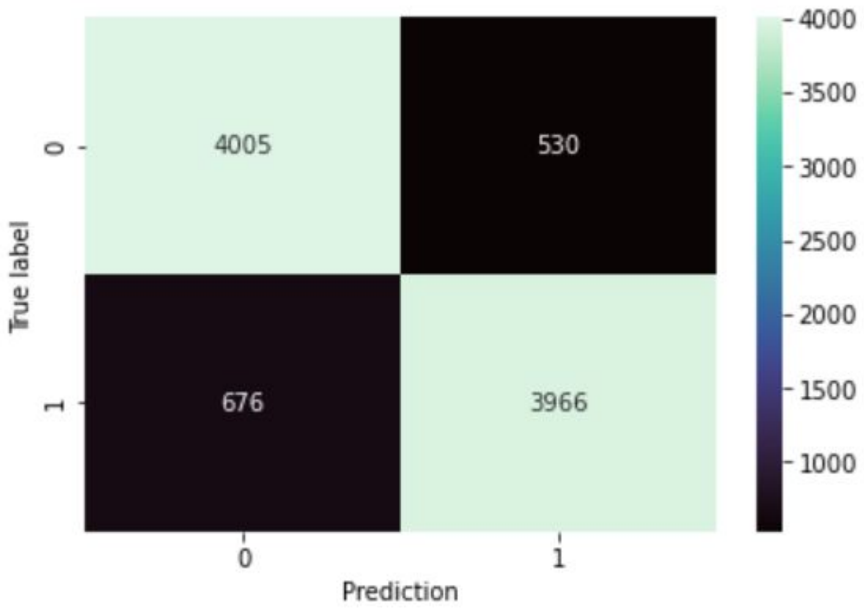
The lower the log loss, the more accurate predictions your AI will make, meaning its overall accuracy and functionality will rise.




```
Accuracy:  0.886
AUC: 0.947
AUC2: 0.887
0.887
Log loss: 0.381
```

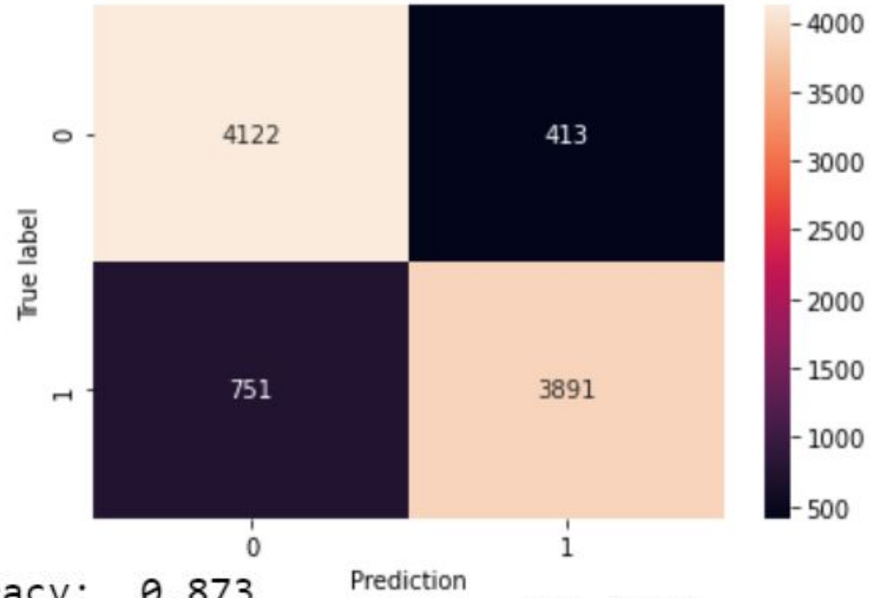
```
TN 4147
FP 388
FN 656
TP 3986
```

SVM




```
Accuracy:  0.869          TN 4005
AUC2: 0.869               FP 530
0.869                     FN 676
Log loss: 0.381           TP 3966
```

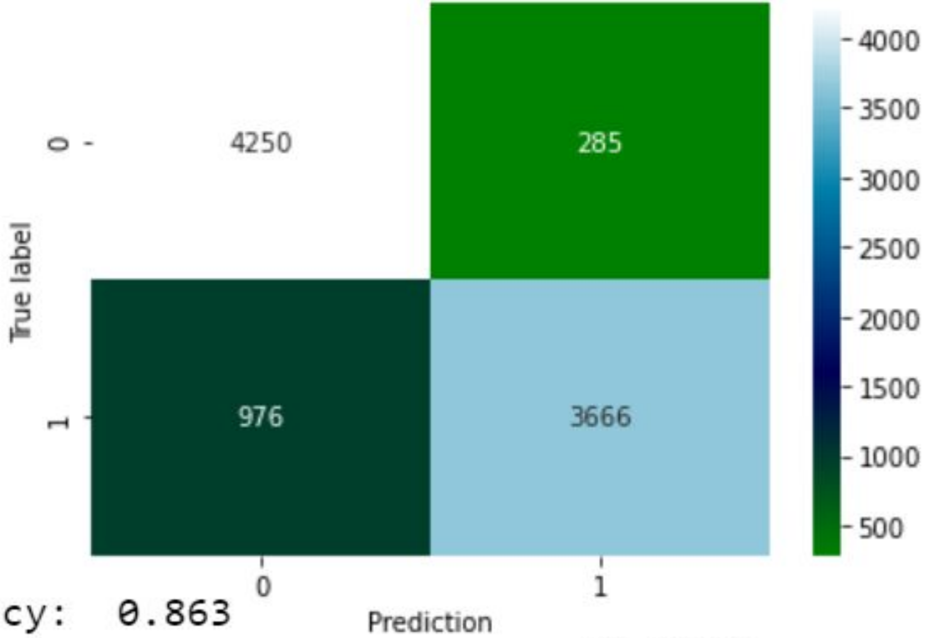
Multinomial Naive Bayes



Accuracy: 0.873
AUC: 0.928
AUC2: 0.874
0.874
Log loss: 0.797

TN 4122
FP 413
FN 751
TP 3891

Random Forest




```
Accuracy:  0.863
AUC: 0.945
AUC2: 0.863
0.863
Log loss: 0.357
```

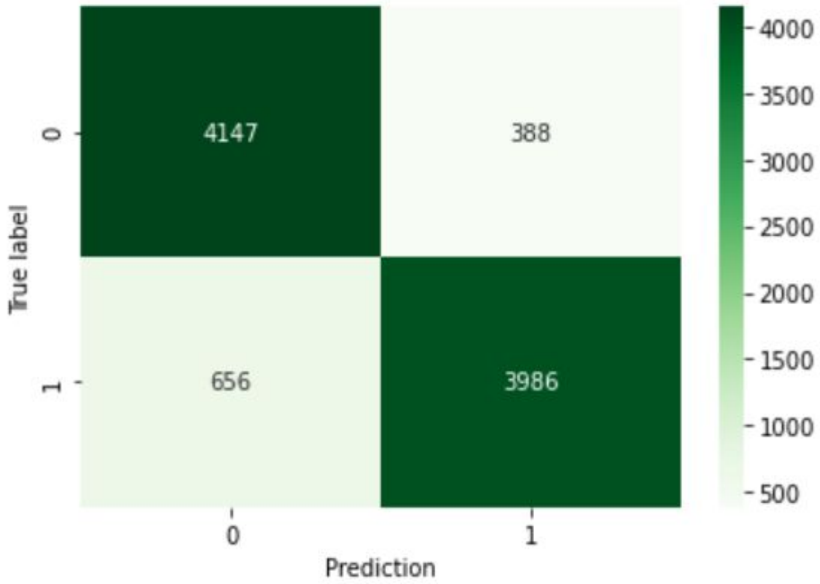
```
TN 4250
FP 285
FN 976
TP 3666
```

Comparison for Toxic column

Algorithm	KNN	Logistic regression	SVM	Naive Bayes	Random Forest
Accuracy	0.728	0.886	0.869	0.873	0.863
AUC	0.814	0.887	0.869	0.874	0.863
Log loss		0.381	0.381	0.797	0.357

CountVectorizer vs TFDIF

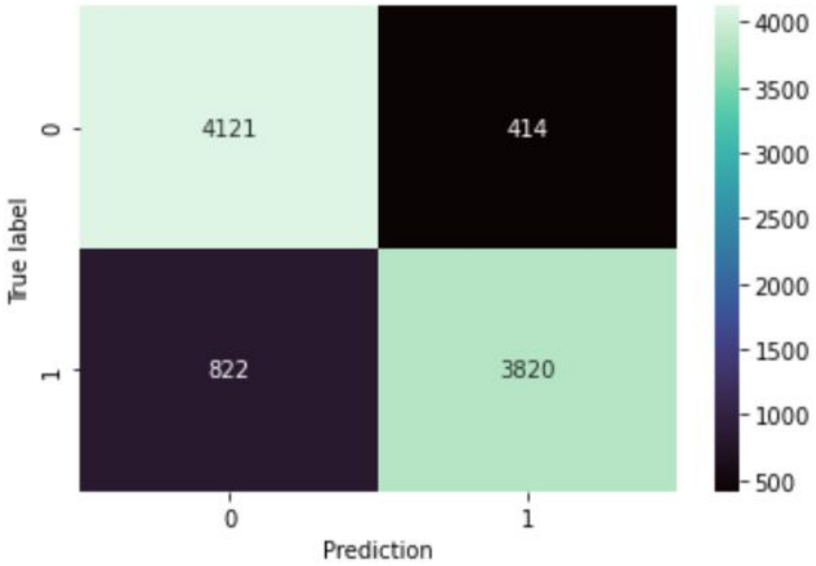
word frequency



Accuracy: 0.886
AUC: 0.947
AUC2: 0.887
0.887
Log loss: 0.381

TN 4147
FP 388
FN 656
TP 3986

word frequency & importance/weight



Accuracy: 0.865
AUC: 0.943
AUC2: 0.866
0.866
Log loss: 0.301

TN 4121
FP 414
FN 822
TP 3820

Classifier Chain

	Model	Accuracy	AUC	Log loss
0	Chain-LogisticRegression	0.918	0.698	2.838

To go further.

More time for tuning:

- Find the best **parameters**
- Find the best **vectorization** library

Compare the models accuracy of deep NLP VS no NLP

Build an app to detect and erase toxic comments

Thank you for your Time !

If you have any questions?

Deep Learning

Embedding + conv1d

- accuracy : 0.808
- Loss: 1.64
- 20 epochs

LSTM model

- accuracy : 0.854
- Loss: 0.543
- 20 epochs