

Toxic Comment Classification

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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	C
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	C
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 \dots	0	0	0	0	0	C
159567	ffea4adeee384e90	You should be a shamed of yourself $\ln \pi$ is	0	0	0	0	0	C
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	C

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

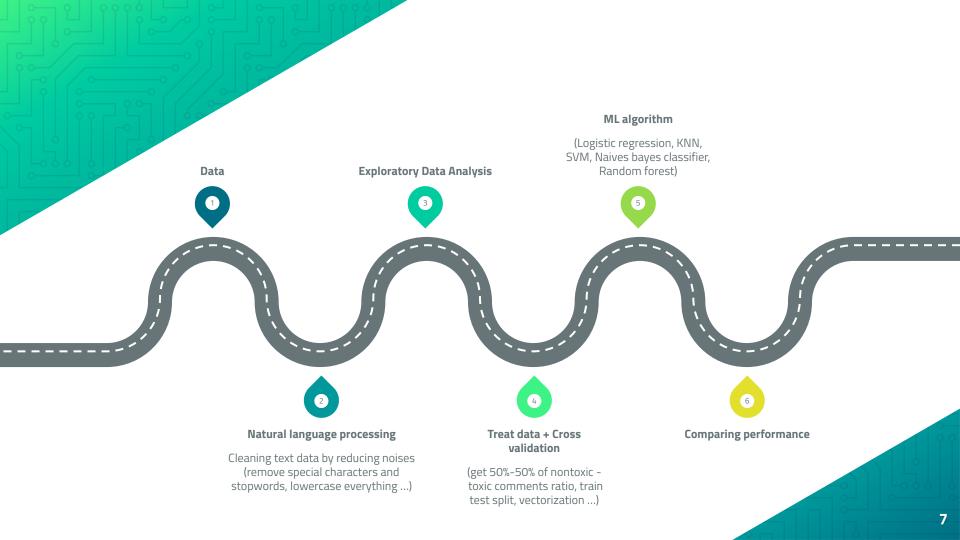
2 labels:

- 0 : False
- 1 : True



Build a classification model that is able to predict the toxicity of comment

Evaluate and compare the performance between ML models





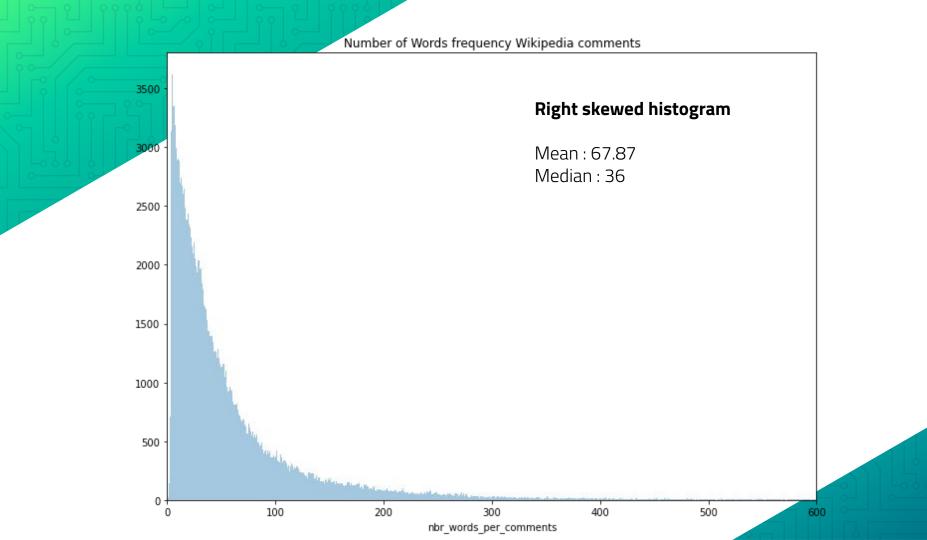
- No null values to deal with
- Read comments properly using neattext library

Comment

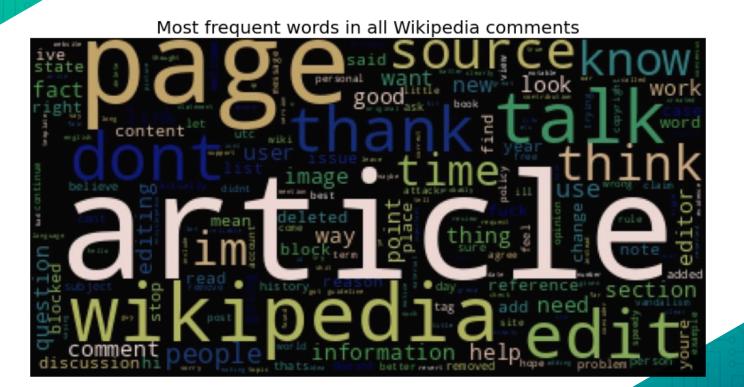
'"\nMore\nI can\'t make any real suggestions on improvement - I wondered if the section statistics should be later on, or a subsection of ""types of accidents"" -I think the references may need tidying so that they are all in the exact same format ie date format etc. I can do that later on, if no-one 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 backlog on articles for review so I guess there may be a delay until a reviewer turns up. It\'s listed in the relevant 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



The most frequent words in Wikipedia comments are Wikipedia related





- 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

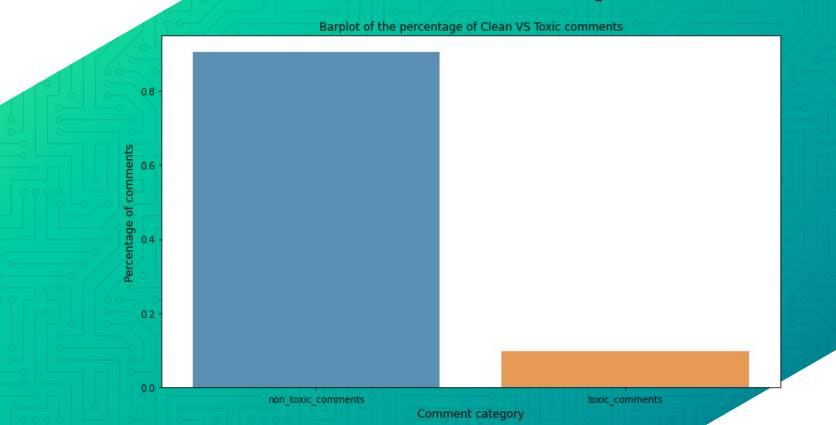
Data analysis

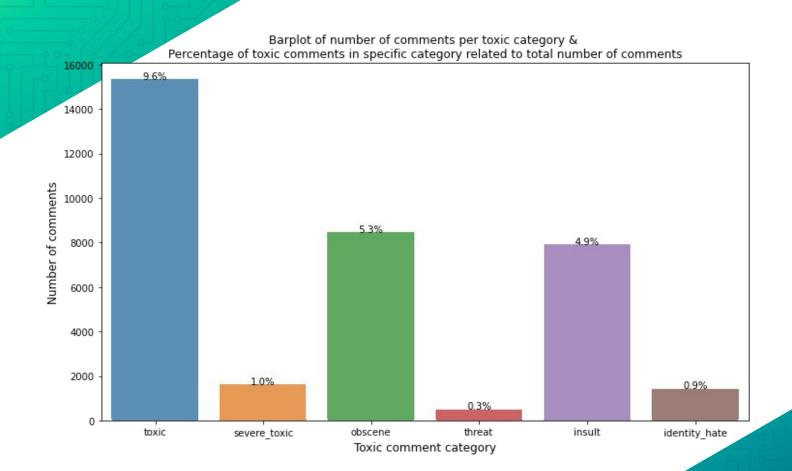
Number of toxic comment for each category:

toxic	15294
severe toxic	1595
obscene	8449
threat	478
insult	7877
identity hate	1405

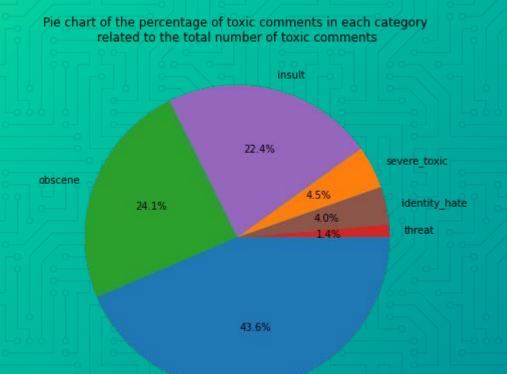
- No null values to deal with
- Read comments properly using neattext library
- NLP and pre-processing: Clean data by removing punctuation, stopwords, lower casing ...
- Check repartition of toxic comments:
 - 90% of the comments have no form of toxicity at all.

Only around 10% comments have a form of toxicity



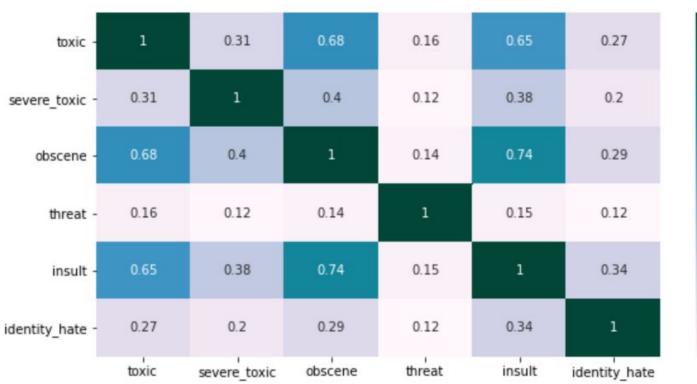


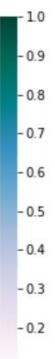
Toxic, Insults & Obscene comments compose the majority of toxic comments



toxic

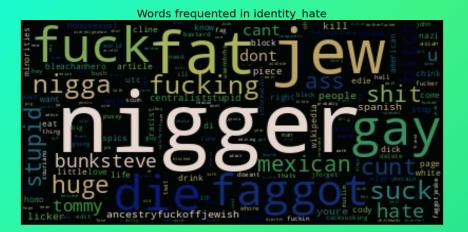
Correlation Matrix of toxic categories

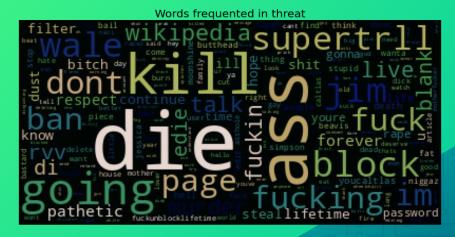




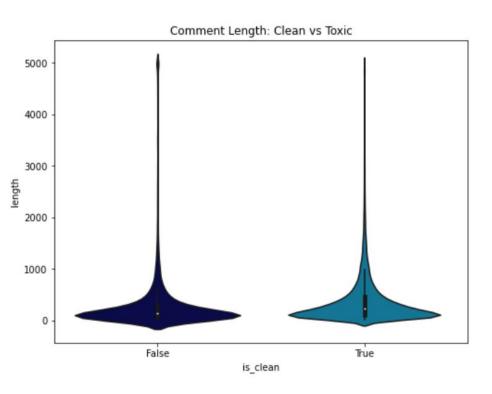


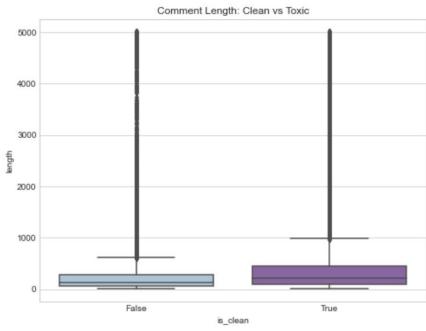




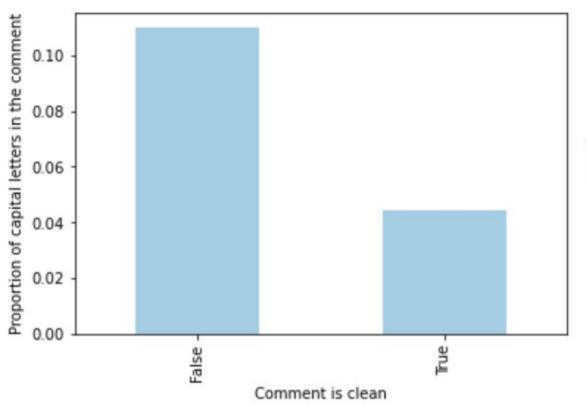


Length and toxicity



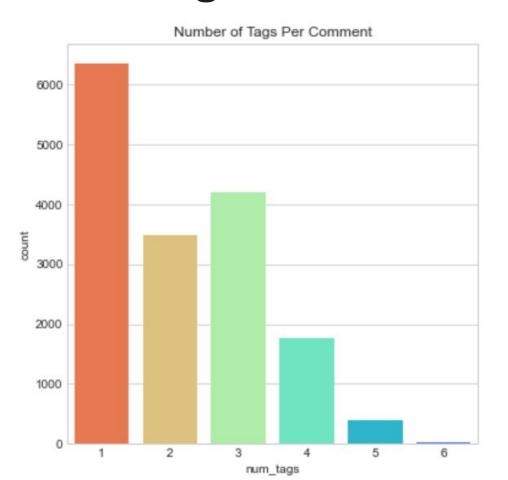


Capital letters in toxic comments



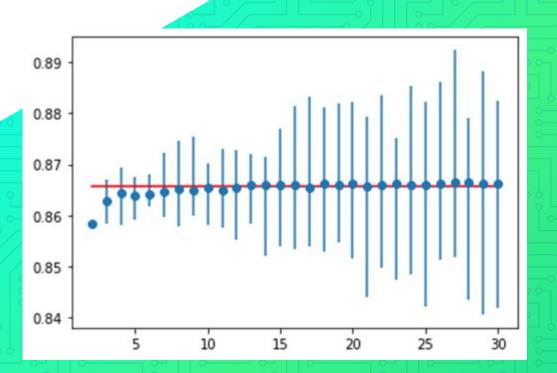
is_clean	length	capitals	proportion	
False	305.672604	42.980770	0.109680	
True	406.885138	14.236993	0.044497	

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=0.005 (0.050,0.075)
> folds=12, accuracy=0.866 (0.855,0.873)
  folds=13, accuracy=0.866 (0.858,0.872)
     <del>lds-14, accuracy-0.066 (0.852,0.871</del>
> 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):

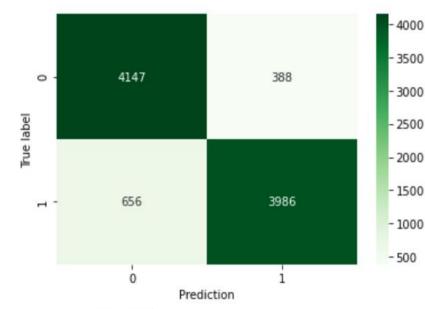
- measure of the ability of a classifier to distinguish between classes.
- summary of the ROC curve.

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

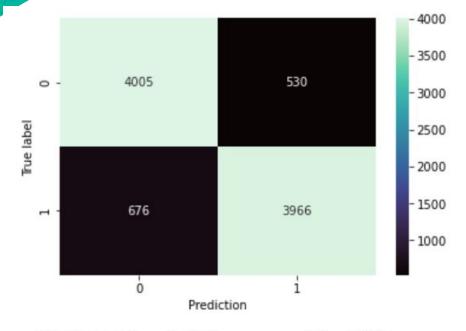
Log loss: 0.381

TN 4147 FP 388

FN 656

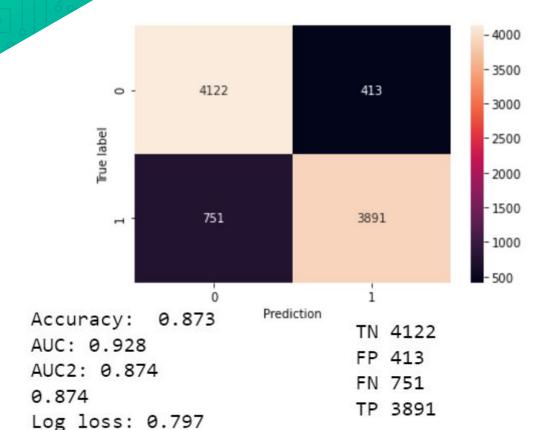
TP 3986

SVM



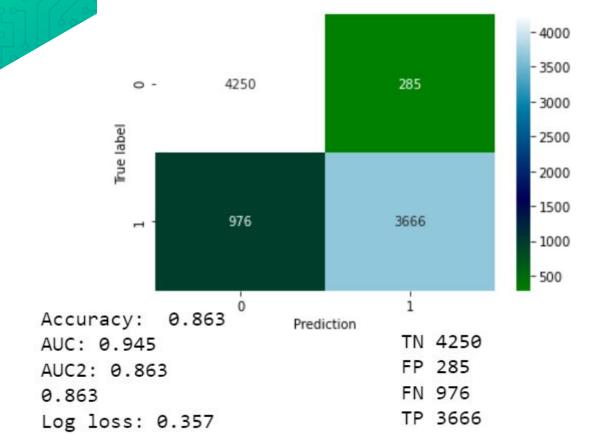
Accuracy: 0.869 TN 4005 AUC2: 0.869 FP 530 0.869 FN 676 Log loss: 0.381 TP 3966

Multinomial Naive Bayes



27

Random Forest



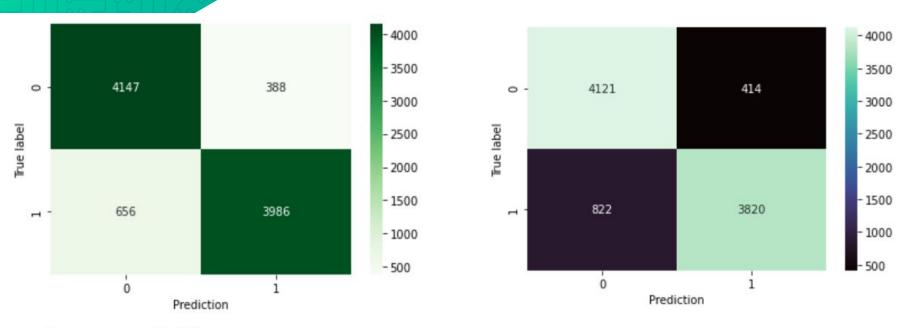
Comparison for Toxic column

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

word frequency & importance/weight



Accuracy: 0.886

AUC: 0.947 AUC2: 0.887

0.887

Log loss: 0.381

TN 4147 FP 388 FN 656

TP 3986

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

TN 4121 FP 414 FN 822 TP 3820

30

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?

