

PROJECT TITLE:

"JIGSAW MULTILINGUAL TOXIC COMMENT CLASSIFICATION" **KAGGLE COMPETITION**

PERSONAL DETAILS:

This project is successfully developed by team of 2.

Team Name: Error-404

The details of the two members:

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PROJECT OVERVIEW:

People tend to leave online conversations due to people posting toxic or disrespectful comments. You need to make a machine learning model to recognize if a comment is normal or toxic. If we can recognize such harmful contributions, we will have a healthier, more open internet.

MODELS USED:

Logistic Regression of bag of words model and Term FrequencyInverse Document Frequency model.

- ➔ A bag-of-words representation is simple to generate but far from perfect. If we count all words equally, then some words end up being emphasized more than we need.

➔ Tf-idf is a simple twist on the bag-of-words approach. It stands for term frequency–inverse document frequency. Instead of looking at the raw counts of each word in each document in a dataset, tf-idf looks at a normalized count where each word count is divided by the number of documents this word appears in. That is:

$$\text{bow}(w, d) = \# \text{ times word } w \text{ appears in document } d$$

$$\text{tf-idf}(w, d) = \text{bow}(w, d) * N / (\# \text{ documents in which word } w \text{ appears})$$

N is the total number of documents in the dataset. The fraction $N / (\# \text{ documents ...})$ is what's known as the inverse document frequency. If a word appears in many documents, then its inverse document frequency is close to 1. If a word appears in just a few documents, then the inverse document frequency is much higher.

Alternatively, we can take a log transform instead using the raw inverse document frequency. Logarithm turns 1 into 0, and makes large numbers (those much greater than 1) smaller. (More on this later.)

ACCURACY REPORT SCREENSHOT:

```
In [43]: #confusion matrix for bag of words
from sklearn.metrics import confusion_matrix
cm_bow=confusion_matrix(test_toxic,lr_bow_predict,labels=[1,0])
print(cm_bow)
#confusion matrix for tfidf features
cm_tfidf=confusion_matrix(test_toxic,lr_tfidf_predict,labels=[1,0])
print(cm_tfidf)
```

```
[[ 324 11026]
 [  86 108135]]
[[    0 11350]
 [    0 108221]]
```

```
In [37]: #Accuracy score for bag of words
from sklearn.metrics import accuracy_score
lr_bow_score=accuracy_score(test_toxic,lr_bow_predict)*100
print("lr_bow_score :",lr_bow_score)

#Accuracy score for tfidf features
lr_tfidf_score=accuracy_score(test_toxic,lr_tfidf_predict)*100
print("lr_tfidf_score :",lr_tfidf_score)

lr_bow_score : 90.7067767267983
lr_tfidf_score : 90.50773180787984
```

```
In [42]: #Classification report for bag of words
from sklearn.metrics import classification_report
lr_bow_report=classification_report(test_toxic,lr_bow_predict,target_names=['Toxic','Non-toxic'])
print(lr_bow_report)

#Classification report for tfidf features
lr_tfidf_report=classification_report(test_toxic,lr_tfidf_predict,target_names=['Toxic','Non-toxic'])
print(lr_tfidf_report)
```

	precision	recall	f1-score	support
Toxic	0.91	1.00	0.95	108221
Non-toxic	0.79	0.03	0.06	11350
accuracy			0.91	119571
macro avg	0.85	0.51	0.50	119571
weighted avg	0.90	0.91	0.87	119571

	precision	recall	f1-score	support
Toxic	0.91	1.00	0.95	108221
Non-toxic	0.00	0.00	0.00	11350
accuracy			0.91	119571
macro avg	0.45	0.50	0.48	119571
weighted avg	0.82	0.91	0.86	119571

CONCLUSION:

In this project of toxic data classification, using the logistic regression model of machine learning algorithms for Bag of Words model the accuracy is 90.7% and for the Term Frequency-Inverse Document Frequency model the accuracy is 90.5%.

WE HOPE THAT YOU ARE SATISFIED WITH OUR TEAM WORK.

THANK YOU!