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Toxic Comment Classification

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ABSTRACT

Building a multi-headed model that's capable of detecting different types of toxicity like threats, obscenity, insult and identity-based hate. Discussing things you care about can be difficult. The threat of abuse and harassment online means that many people stop expressing themselves and give up on seeking different opinions. Platforms struggle to efficiently facilitate conversations, leading many communities to limit or completely shut down user comments. So far we have a range of publicly available models served through the perspective APIs, including toxicity. But the current models still make errors, and they don't allow users to select which type of toxicity they're interested in finding.

Keywords: *toxic comment classification*

1. INTRODUCTION

Discussing things you care about can be difficult. The threat of abuse and harassment online means that many people stop expressing themselves and give up on seeking different opinions. Platforms struggle to evidently facilitate conversations, leading many communities to limit or completely shut down user comments.

2. MOTIVATION

So far we have a range of publicly available models served through the Perspective API, including toxicity. But the current models still make errors, and they don't allow users to select which type of toxicity they're interested in finding. (E.g. some platforms may be ne with profanity, but not with other types of toxic content)

3. PROBLEM STATEMENT

Building a multi-headed model that's capable of detecting different types of toxicity like threats, obscenity, insult and identity-based hate.

4. DATASET

The dataset used was Wikipedia corpus dataset which was rated by human raters for toxicity. The corpus contains comments from discussions relating to use pages and articles dating from 2004-2015. The dataset was hosted on Kaggle.

5. DATA OVERVIEW

The dataset used was Wikipedia corpus dataset which was rated by human raters for toxicity. The corpus contains comments from discussions relating to use pages and articles dating from 2004-2015. The dataset was hosted on Kaggle.

The comments were manually classified into following categories:

Toxic
Severe toxic
Obscene
Threat
Insult
Identity hate

6. APPROACH

6.1 HOW PROBABILITY WAS CALCULATED?

Though there many multi class classifiers, we do not have a suitable multi label classier which was able to give probability with which target belongs to a label.

So, we used scikit-learn OneVsRestClassier with various estimators, with the help of predict_proba, we predicted the probability with which a comment belongs to a particular label.

7. ANALYSIS OF DATASET

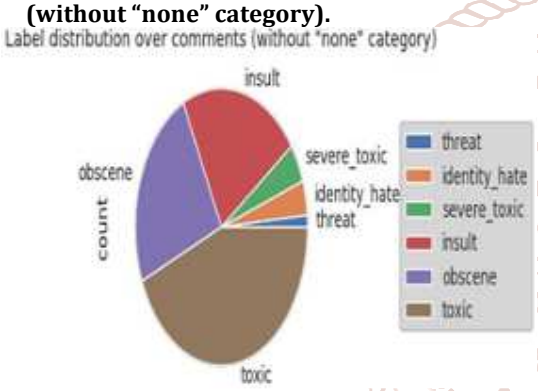
7.1 VISUALIZATION

7.1.1 COUNT THE NUMBER OF COMMENTS IN EACH CLASS

	count
none	134351
toxic	14352
obscene	7914
insult	7366
severe_toxic	1493
identity_hate	1314
threat	458

Three major labels are:
toxic
obscene
insult

7.1.2 Pie chart of Label Distribution over comments (without "none" category).



7.1.3 COUNT FOR EACH LABEL COMBINATION

Now, let's take a look at number of comment for each label combination. This helps us in finding correlation between categories.

	toxic	severe_toxic	obscene	threat	insult	identity_hate	none	count
0	0	0	0	0	0	0	1	134351
1	1	0	0	0	0	0	0	5335
2	1	0	1	0	1	0	0	3543
3	1	0	1	0	0	0	0	1654
4	1	0	0	0	1	0	0	1143
5	1	1	1	0	1	0	0	926
6	1	0	1	0	1	1	0	590
7	0	0	1	0	0	0	0	301
8	0	0	0	0	1	0	0	273
9	1	1	1	0	1	1	0	244

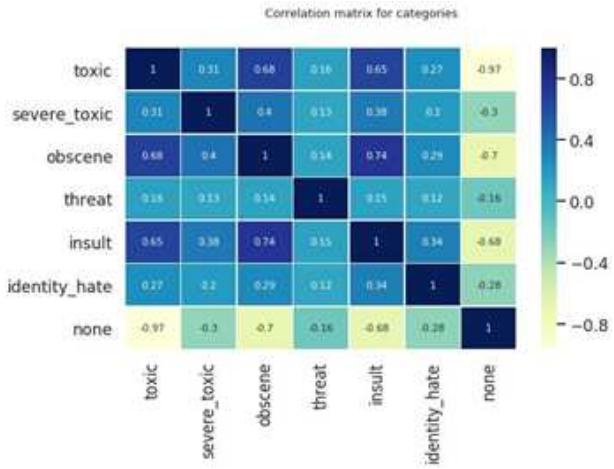
Following can be inferred from above table:
The table shows that number of comments with only none label are high.

Toxic which is the label high after none is present in all top 6 combinations.

Among the top combinations, obscene and insult comes 4 times in 6.

As the combinations increase the count drops very fast.

7.1.4 CORRELATION MATRIX



Following can be inferred from above matrix:
Toxic is highly correlated with obscene and insult.

Insult and obscene have highest correlation factor of 0.74

Interesting things to be observed:
Though, a severe toxic comment is also a Toxic comment, the correlation between them is only 0.31.

8. FEATURE ENGINEERING

8.1 CLEANING THE COMMENTS

Since, the comments in the dataset were collected from the internet they may contain 'HTML' elements in them. So, we removed the

HTML

We then converted each comment into lower case and then split it into individual words.

There were some words in the dataset which had length > 100, since there are no words in the English language whose length > 100, we remove such words.

First, we tried building the features removing stop words and then trained some models thinking that it may help the model in learning the semantics of toxicity, but we found out that the model learns better if there are stop words in the comment.

Possible reason is, generally a hate/toxic comment is used towards a person, seeing the data we found out that those persons are generally referred by pronouns, which are nothing but stop words.

8.2 STEMMERS AND LEMMATIZERS

1. Definitions:

Stemming usually refers to a crude heuristic process that chops o the ends of words in the hope of achieving this goal correctly most of the time, and often includes removal of derivational affixes.

Lemmatization usually refers to doing things properly with the use of a vocabulary and morphological analysis of words, normally aiming to remove endings only and to return the base or dictionary form of a word, which is known as the lemma.

2. Reasons to use:
We used both snowball stemmer, porter stemmer and WordNet lemmatizer.

For grammatical reasons, documents are going to use different forms of a word, such as organizes, organize and organizing. But they all represent thesame semantics. So, using stemmer/Lemmatizer for those three words gives a single word, which helps algorithm learn better.

3. Results:
On public dataset:
Snowball > WordNet > Porter

On private dataset:
WordNet > Snowball > Porter

Decreasing order of accuracy.

8.3 VECTORIZATION
Python's scikit-learn deals with numeric data only. To convert the text data into numerical form, tf-idf vectorizer is used. TF-IDF vectorizer converts a collection of raw documents to a matrix of Tf-idf features.

We set the predictor variable on the dataset with tf-idf vectorizer, in two different ways. First, by setting the parameter analyzer as 'word'(select words) and the second by setting it to 'char'(select characters). Using 'char' was important because the data had many 'foreign languages' and they were di cult to deal with by considering only the 'word' analyzer.

We set the parameter n-gram range (an n-gram is a continuous sequence of n-items from a given sample of text or speech). After trying various values, we set the n-gram as (1, 1) for 'word' analyzer and (1, 4) for 'char' analyzer. We also set the max_features as 30000 for both word and char analyzer after many trails.

We then combined the word and character features and transformed the dataset into two sparse matrixes for train and test sets, respectively using tf-idf vectorizer.

8.4 ADDING DATA RELATED FEATURES
We tried adding features to the dataset that are computed from the data itself. Those features are:

Length of comments
Number of exclamation marks - Data showed severe toxic comments with multiple exclamation marks.

Number of question marks
Number of punctuation symbols - Assumption is that angry people might not use punctuation symbols.

Number of symbols - there are some comments with words like f**k,

$#*t etc.

Number of words
Number of unique words - Data showed that angry comments are some- times repeated many times.

Proportion of unique words

Conclusion: All the above features had correlation of <0.06 with all labels. So, we decided that adding these features does not benefit the model.

9. MODEL BUILDING
Our basic pipeline consisted of count vectorizer or a tf-idf vectorizer and a classifier. We used OneVsRest Classifier model. We trained the model with Logistic Regression (LR), Random Forest (RF) and Gradient Boosting (GB) classifiers. Among them LR gave good probabilities with default parameters. So, we then improved the LR model by changing its parameters.

10. TRAINING, VALIDATION AND TEST METRICS
10.1 TRAINING AND VALIDATION SPLIT
To know whether was generalizable or not, we divided the into train and validation sets in 80:20 ratio. We then trained various models on the training data, then we ran the models on validation data and we checked whether the model is generalizable or not.

Also, we trained different models on training data and tested those on validation data, then we arrived at our best model.

10.2 TEST METRIC
We used Receiver Operating Characteristic (ROC) along with Area under the curve (AUC) as test metric.

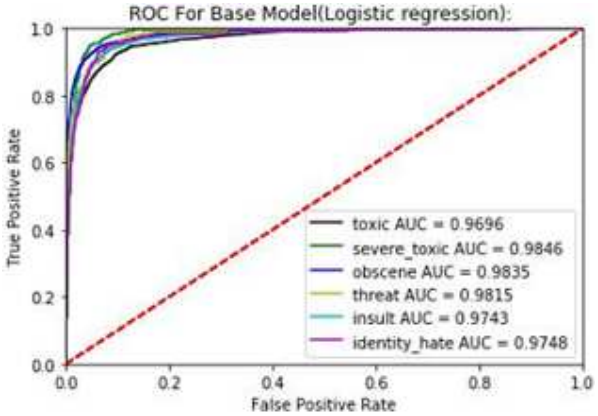
10.3 RESULTS FOR VARIOUS MODELS
10.3.1 BASE MODEL:
We created a model without any preprocessing or parameter tuning, we used this model as our model, and measured our progress using this model.

For this we used Logistic Regression as Classifier.

1. Cross Validation Results

Category	CV Score
Toxic	0.9501
Severe_toxic	0.9795
Obscene	0.9709
Threat	0.9733
Insult	0.9608
Identity_hate	0.9548
Average CV	0.9649

2. ROC-AUC Curve



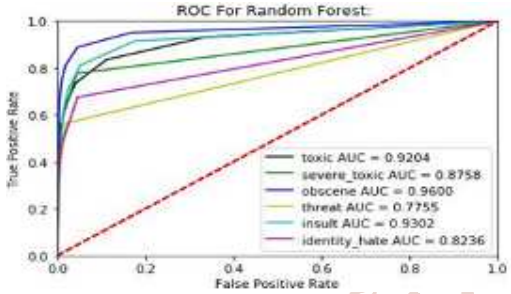
10.3.2 Random Forest:

Next, we created our model using Random Forest. We used n_estimators = 10 and random_state = 1 as parameters. We observed the following results:

1. Cross Validation Results

Category	CV Score
Toxic	0.8984
Severe_toxic	0.8479
Obscene	0.9491
Threat	0.6816
Insult	0.9183
Identity_hate	0.7782
Average CV	0.7782

2. ROC – AUC Curve



From the Cross Validation results table and ROC-AUC Curve, it is clear that Random Forest performs poorly compared to our base model itself, so we proceeded to tune parameters for Logistic Regression for better accuracy.

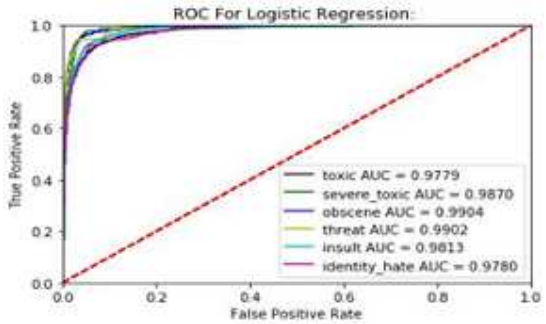
10.3.3 LOGISTIC REGRESSION

I. We created one model using C = 4 as parameter. The following results were observed.

1. Cross Validation Results

Category	CV Score
Toxic	0.9690
Severe_toxic	0.9850
Obscene	0.9825
Threat	0.9856
Insult	0.9750
Identity_hate	0.9774
Average CV	0.9791

2. ROC –AUC Curve



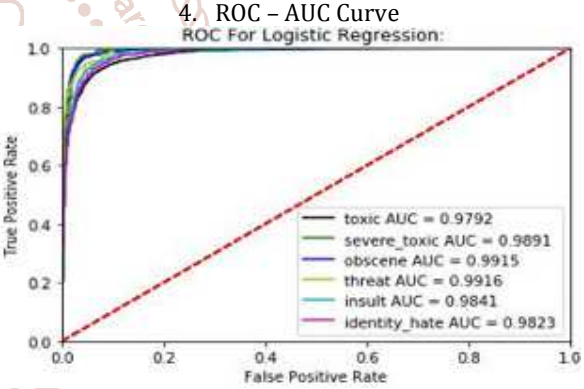
II. We created another Logistic Regression by selecting the best parameters by cross - validating the following parameters.

C	t_intercept	penalty	class_weight
1.05	True	'l2'	None
0.2	True	'l2'	'balanced'
0.6	True	'l2'	'balanced'
0.25	True	'l2'	'balanced'
0.45	True	'l2'	'balanced'
0.25	True	'l2'	'balanced'

3. Cross Validation Results

Category	CV Score
Toxic	0.9675
Severe_toxic	0.9864
Obscene	0.9827
Threat	0.9847
Insult	0.9761
Identity_hate	0.9764
Average CV	0.9790

4. ROC – AUC Curve



Though, (i) gave better score compared to (ii) on validation set, with difference in order of 0.0001. When run on the actual data (ii) was found to better than (i).

11. CONCLUSION

After checking the kaggle discussion board of the actual competition, standard Machine Learning approaches yield a maximum score of 0.9792, irrespective of any approach. In order to get a large margin over this score one has to employ Deep Learning (DL) techniques.

12. REFERENCES

[1] https://blog.citizennet.com/blog/2012/11/10/random-forests-ensembles-and-performa

[2] https://www.data-to-viz.com/

[3] https://www.kaggle.com/jagangupt a/stop-the-s-toxic-comments-eda