Are You A Hater?

Hate Speech on the Internet

Leon Zhou

"And the haters gonna hate, hate, hate, hate, hate..."
- Taylor Swift

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The Problem

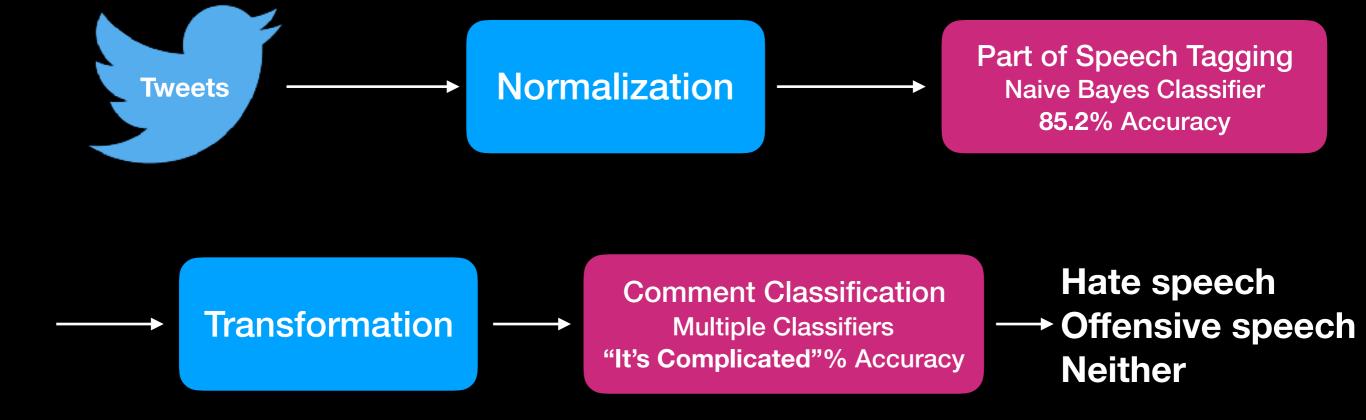
Hate Speech

```
['the', 'blacks', 'in', 'california', 'are', 'typical', 'n
```

Other Speech (offensive, non-offensive)

```
['using', 'y', 'mx', 'b', 'to', 'measure', 'the', 'slope', 'of', 'that', 'ass', 'girl']
['yal', 'hoes', 'dont', 'need', 'a', 'valentine', 'yal', 'need', 'jesus']
['told', 'that', 'hoe', 'she', 'special', 'like', 'the', 'mcrib', 'at', 'mcdonalds']
```

Workflow



RT @ComedyPics: If Kanye took Kim to McDonald's then ya hoes don't deserve \$200 Dates http://t.co/20K4I1fRT

Retweets and Mentions

Hyperlinks

Hashtags

Characters

Retweets and Mentions Hyperlinks Hashtags Unicode Characters



if kanye took kim to mcdonalds then ya hoes dont deserve 200 dates

Retweets and Emoji Hyperlinks Hash

Hashtags Unicode Characters



if kanye took kim to mcdonalds then ya hoes dont deserve 200 dates

[CS, PPSS, VBD, PPO, TO, NNS, WRB, NP, DOZ, NN, VB, CD, NNS]

(85.2% accuracy) (theoretically)

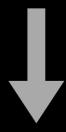
Retweets and Mentions

Emoji

Hyperlinks

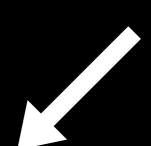
Hashtags

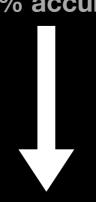
Unicode Characters



if kanye took kim to mcdonalds then ya hoes dont deserve 200 dates

[CS, PPSS, VBD, PPO, TO, NNS, WRB, NP, DOZ, NN, VB, CD, NNS] (85.2% accuracy)







Unigrams

NN

to TO
mcdonalds NNS
then WRB
ya NP
hoes DOZ

dont

Bigrams

to mcdonalds TO NNS
mcdonalds then NNS WRB
then ya WRB NP
ya hoes NP DOZ
hoes dont DOZ NN

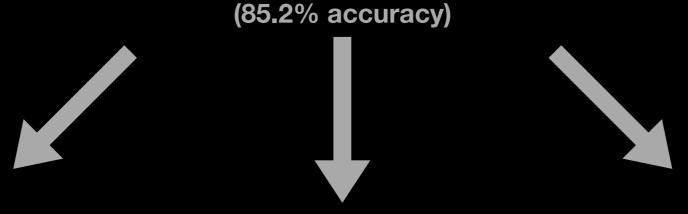
Trigrams

to mcdonalds then mcdonalds then ya then ya hoes ya hoes dont TO NNS WRB NNS WRB NP WRB NP DOZ NP DOZ NN

Unicode Retweets and **Hyperlinks** Hashtags **Emoji Mentions Characters**

if kanye took kim to mcdonalds then ya hoes dont deserve 200 dates

[CS, PPSS, VBD, PPO, TO, NNS, WRB, NP, DOZ, NN, VB, CD, NNS]



Unigrams	Bigrams	Trigrams
----------	----------------	-----------------

TO to to mcdonalds mcdonalds NNS mcdonalds then then **WRB** then ya NP ya va hoes DOZ hoes hoes dont NN dont

TO NNS **NNS WRB WRB NP** NP DOZ DOZ NN

to mcdonalds then mcdonalds then ya then ya hoes ya hoes dont

TO NNS WRB NNS WRB NP **WRB NP DOZ** NP DOZ NN

[..., 0, 0, 0.001, 0, 1, 0, 0.561, 0, 0, 0.003, 0, 0, 0, 0, 0, 0, 0, 0.421, ...]

Class O (Hate Speech) F1 Score, 3 Classes - Stratified									
Param									
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS			
Decision Tree	0.2650	0.0916	0.2519	0.0758	0.0918	0.2298	0.0000	0.2650	
Gradient Boosted Trees	0.0338	0.2593	0.2473	0.0343	0.2393	0.0259			
Logistic Regression	0.0000	0.2011	0.0000	0.2505	0.1953	0.0000			
Naive Bayes	0.1184	0.1118	0.1122	0.1186	0.1127	0.1183			

0.0000

0.1924

0.0000

0.0664

0.0707

Stochastic Gradient Desc.

0.0000



Took majority opinion of five best models:

e.g.
$$\begin{bmatrix} [0,0,0,1,2] \\ \downarrow \\ 0 \end{bmatrix} < 0.25$$





Thank You

Appendix

Not Perfect

Some words critical to identification lost in processing

```
DEBUG:root:Incoming words:
DEBUG:root:['i', 'dont', 'trust', 'these', 'b']
DEBUG:root:Outgoing words:
DEBUG:root:['i', 'dont', 'trust', 'these', 'birches']
```

Solution: manually added high-impact slang, profanity

```
DEBUG:root; To raise words:

DEBUG:root ['yaya', ho', 'cut' ', 'avi', 'tho', 'rt', 'i', 'had', 'no', 'idea', 'she', 'was', 'sleep']

DEBUG:root ['may', 'o', 'cut' 'vi', 'the', 'i', 'had', 'no', 'idea', 'she', 'was', 'sleep']
```

Other words are just "acceptable losses"

Part of Speech Classification

- Naive Bayes Classifier (nltk.NaiveBayesClassifier)
- Trained on Brown corpus (nltk.corpus.Brown)
- 85.2% Accuracy and F1-Score

Contextual Features

Characteristic Features

```
def word_feature_extraction(sentence, index):
    word = sentence[index]
    previous_word = "<START>"
    next_word = "<END>"
    if index > 0:
        previous_word = sentence[index - 1]
    if index < len(sentence) - 1:
        next_word = sentence[index + 1]
    suffix1 = word[-1]
    suffix2 = word[-2:]
    suffix3 = word[-3:]
    numeric = True if word.isnumeric() else False</pre>
```

Diving Deep

Input

Conv1D

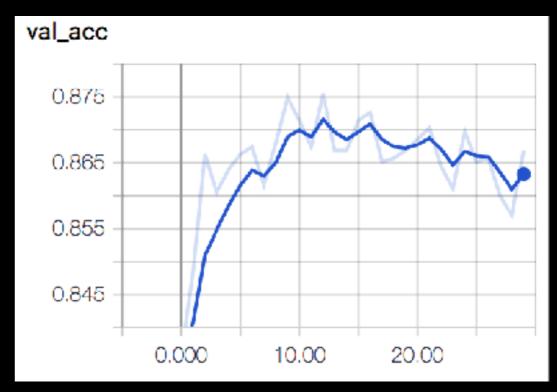
MaxPool
1D

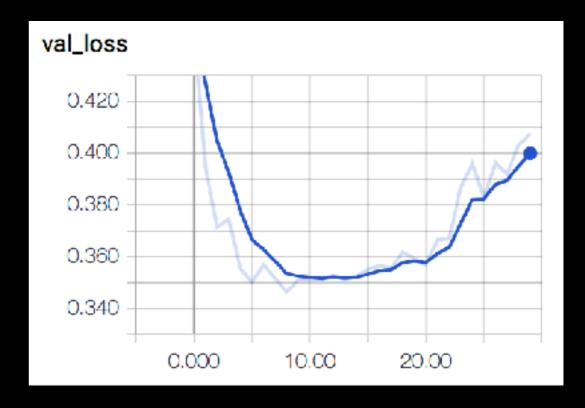
Dropout

Dense

Dropout

Output





Diving Deep

Input

Conv1D

MaxPool
1D

Dropout
x2

Epoch 11 Avg. F1-Score: 0.84 Class 0 F1-Score: 0.00

Dense Dropout

Output

Epoch 12 Avg. F1-Score: 0.85 Class 0 F1-Score: 0.16

Convolutional Neural Network

```
batch_size = 50
num_epochs = 30
kernel_size1 = 50
kernel_size2 = 20
pool_size1 = 10
pool_size2 = 10
conv_depth1 = 32
conv_depth2 = 64
drop_prob1 = 0.25
drop_prob2 = 0.4
hidden_size = 512
```

```
Test Loss after Epoch 12: 0.336706623265
Test Accuracy after Epoch 12: 0.877605917988
```

Results

Each model only trained on one type of feature

Run with stratified sampling

Each square corresponds to a distinct trained model

Average F1 Score, 3 Classes - Stratified Sampling

		Param					Avg. Avgf	
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS		
Decision Tree	0.8626	0.6746	0.8605	0.6707	0.6663	0.8546	0.1172	0.8878
Gradient Boosted Trees	0.7109	0.8878	0.8761	0.7092	0.8836	0.7081		
Logistic Regression	0.6981	0.8660	0.7002	0.8763	0.8558	0.6985		
Naive Bayes	0.3677	0.1172	0.1210	0.3725	0.1248	0.3716		
Stochastic Gradient Desc.	0.7791	0.6845	0.7876	0.6886	0.8072	0.6850		

The Catch

Class Imbalance

	Precision	Recall	F1 Score	Support
Hate Speech	0.07	0.44	0.12	427
Offensive	0.78	0.27	0.40	5747
Neither	0.27	0.56	0.36	1261
Avg. / Total	0.65	0.33	0.37	7435

Naive Bayes - Unigram

Each square corresponds to a distinct trained model

Average F1 Score, 3 Classes - Stratified Sampling

		Param						
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS		
Decision Tree	0.8626	0.6746	0.8605	0.6707	0.6663	0.8546	0.1172	0.8878
Gradient Boosted Trees	0.7109	0.8878	0.8761	0.7092	0.8836	0.7081		
Logistic Regression	0.6981	0.8660	0.7002	0.8763	0.8558	0.6985		
Naive Bayes	0.3677	0.1172	0.1210	0.3725	0.1248	0.3716		
Stochastic Gradient Desc.	0.7791	0.6845	0.7876	0.6886	0.8072	0.6850		

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Neither	0.27	0.56	0.36	1261
Avg. / Total	0.65	0.33	0.37	7435

Naive Bayes - Unigram

Each square corresponds to a distinct trained model

Class 0 (Hate Speech) F1 Score, 3 Classes - Stratified

		Param						
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS		
Decision Tree	0.2650	0.0916	0.2519	0.0758	0.0918	0.2298	0.0000	0.2650
Gradient Boosted Trees	0.0338	0.2593	0.2473	0.0343	0.2393	0.0259		
Logistic Regression	0.0000	0.2011	0.0000	0.2505	0.1953	0.0000		
Naive Bayes	0.1184	0.1118	0.1122	0.1186	0.1127	0.1183		
Stochastic Gradient Desc.	0.0707	0.0000	0.0664	0.0000	0.1924	0.0000		

If one model can't do the job, why not five?

Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS
Decision Tree	0.2650	0.0916	0.2519		0.0918	0.2298
Gradient Boosted Trees		0.2593		0.0343	0.2393	
Logistic Regression						
Naive Bayes	0.1184	0.1118	0.1122	0.1186	0.1127	0.1183
Stochastic Gradient Desc.	0.0707	0.0000	0.0664	0.0000	0.1924	0.0000

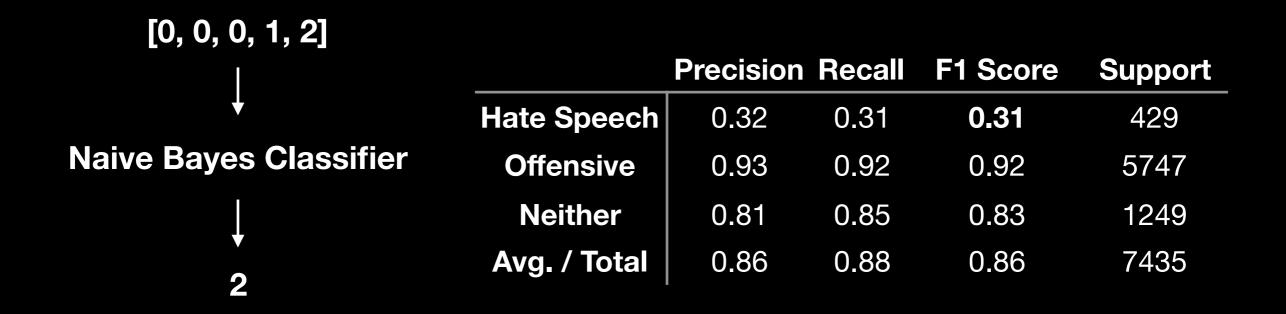
Took the majority opinion of model outputs as decision

		Precision	Recall	F1 Score	Support
[0, 0, 0, 1, 2]	Hate Speech	0.42	0.14	0.21	429
	Offensive	0.89	0.97	0.93	5747
0	Neither	0.85	0.71	0.77	1249
	Avg. / Total	0.86	0.88	0.86	7435

If one model can't do the job, why not five?

Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS
Decision Tree	0.2650	0.0916	0.2519		0.0918	0.2298
Gradient Boosted Trees		0.2593			0.2393	
Logistic Regression						
Naive Bayes	0.1184	0.1118	0.1122	0.1186	0.1127	0.1183
Stochastic Gradient Desc.						

Fit a second layer classifier to make decision



Binary Classification

Not interesting - just target the curse words

Offensive category already largest - lumping it into hateful or other category skews

Hateful + Offensive Classification F1 Score (Binary) - Stratified

		Param					COF	
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS		
Decision Tree	0.9594	0.8555	0.9609	0.8545	0.8520	0.9575	0.1666	0.9689
Gradient Boosted Trees	0.9051	0.9689	0.9632	0.9056	0.9646	0.9061		
Logistic Regression	0.9087	0.9630	0.9085	0.9664	0.9574	0.9086		ı
Naive Bayes	0.4713	0.1666	0.1822	0.4802	0.1754	0.4751		
Stochastic Gradient Desc.	0.9328	0.9076	0.9274	0.9089	0.9330	0.9091		

PCA

Class 0 (Hate Speech) F1 Score, 3 Classes - Stratified, PCA to 50 Elements

		Param					COF	
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS		
Decision Tree	0.1099	0.0799	0.1584	0.0995	0.0798	0.1455	0.0000	0.2681
Gradient Boosted Trees	0.0308	0.1706	0.0521	0.0397	0.0693	0.0393		
Logistic Regression	0.0000	0.0565	0.0000	0.1487	0.0687	0.0000		
Naive Bayes	0.2681	0.0815	0.0890	0.1741	0.0769	0.1519		
Stochastic Gradient Desc.	0.0314	0.0000	0.0702	0.0000	0.1389	0.0000		

Class 0 (Hate Speech) F1 Score, 3 Classes - Stratified, PCA to 250 Elements

		Param					COF	
Model	Unigram	Uni-POS	Bigram	Bi-POS	Trigram	Tri-POS		
Decision Tree	0.1296	0.0707	0.1622	0.0852	0.0824	0.0876	0.0000	0.2653
Gradient Boosted Trees	0.0394	0.1434	0.0568	0.0352	0.0731	0.0308		
Logistic Regression	0.0000	0.0596	0.0000	0.1532	0.0696	0.0000		
Naive Bayes	0.2653	0.0815	0.0890	0.1707	0.0769	0.1610		
Stochastic Gradient Desc.	0.1923	0.0136	0.0047	0.0000	0.1412	0.0181		

Hate Speech (n.):

speech that demeans on the basis of race, ethnicity, gender, religion, age, disability, or any other similar ground

Takeaways and Improvements

- It's a **HARD** problem
 - Intricacies and subtleties in language use
- Do the EDA

This will be summarized and made much less wordy

- My definition of offensive is not same as readers'
 - Very conservative, any profanity
- Design with class imbalance in mind from the start
- Relationship between tweets; many near duplicates due to twitter's reply system
- Improvements to POS may reduce errors
- Models that take in multiple groups of features