# Classifying Hate Speech on Twitter

Steve Donahue

# About Me

## Mathematician

Master of Arts

Twice-published

Programmer + Data Geek

## Educator

9 years teaching undergraduate courses

Rowan, Rutgers Universities

Camden and Cumberland CC’s

## Millenial

Musician

Athlete

World Traveler

# If you don’t have anything nice to say...

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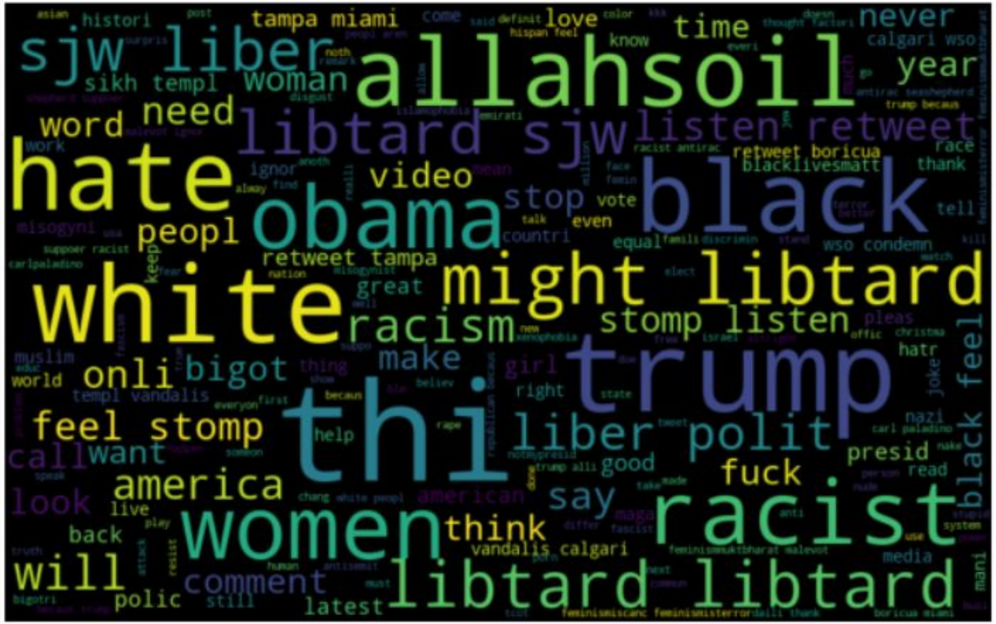


# The Process

Step 1:

Clean the tweets into normal, standardized language so they are comparable.

Step 2:

Determine that hate speech measurably different from normal speech through EDA.

# The Process

Step 3:

Develop various features from the cleaned data set for training ML algorithms.

Step 4:

Train, test, tune, and stack ML models for best results.

# Cleaning Raw Data

1. Remove unhelpful characters

   ( % * & ! etc)

2. Drop unhelpful words

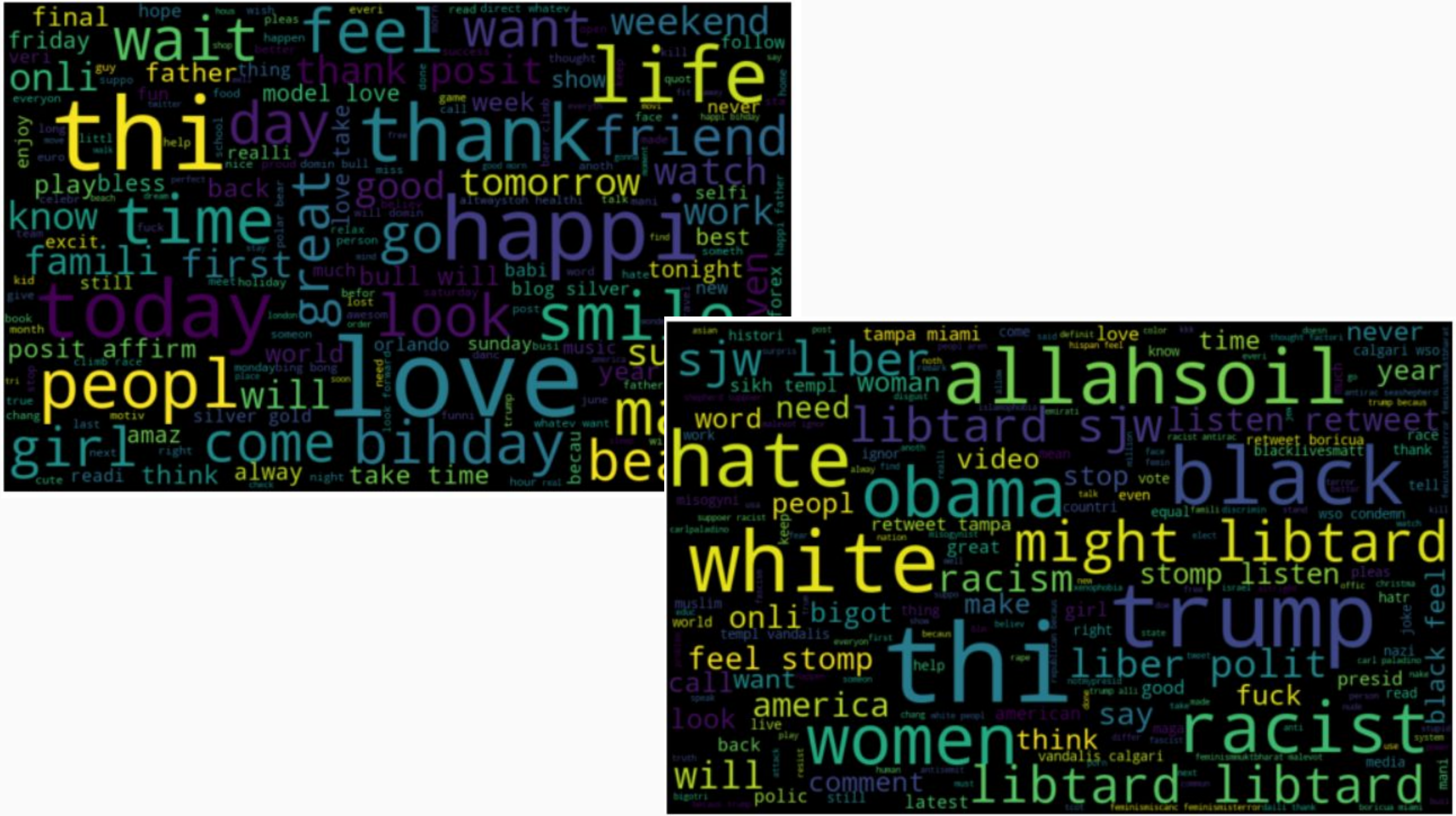
   (as the his etc)

3. Tokenize remaining words for standard language across all tweets.

   (loving -> love)

[2/2] huge fan fare and big talking before they leave. chaos and pay disputes when they get there. #allshowandnogo

huge fare talk befor they leav chao disput when they there #allshowandnogo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listen
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video
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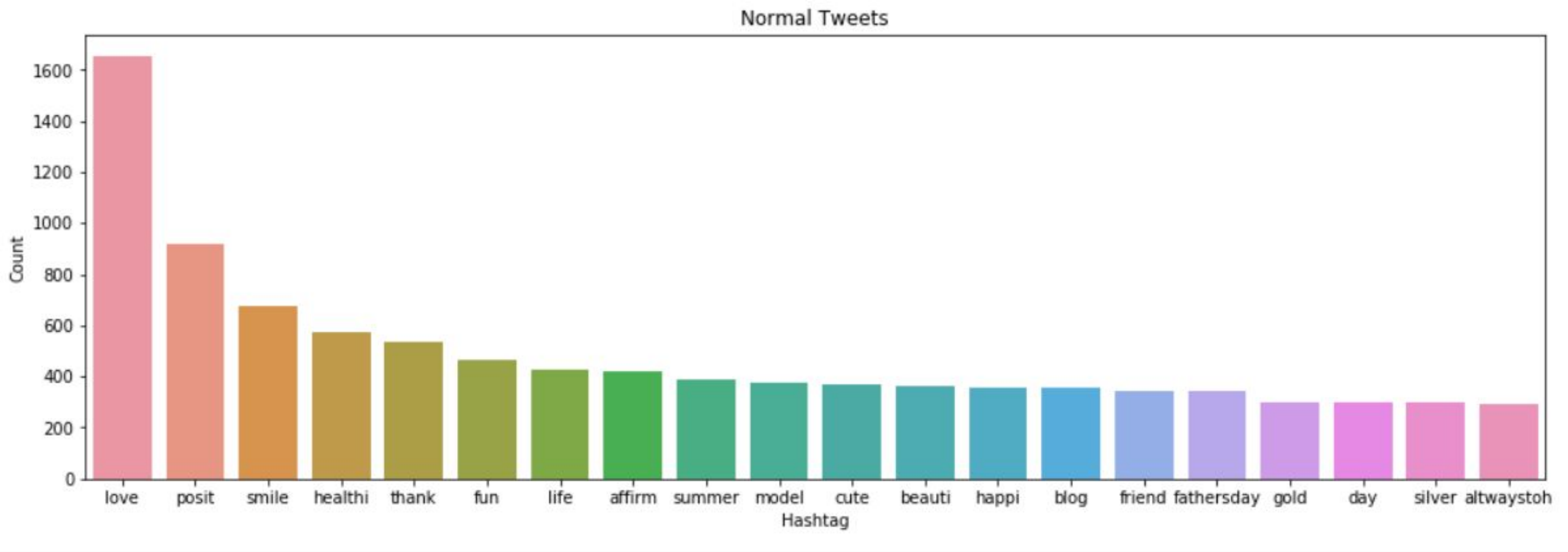
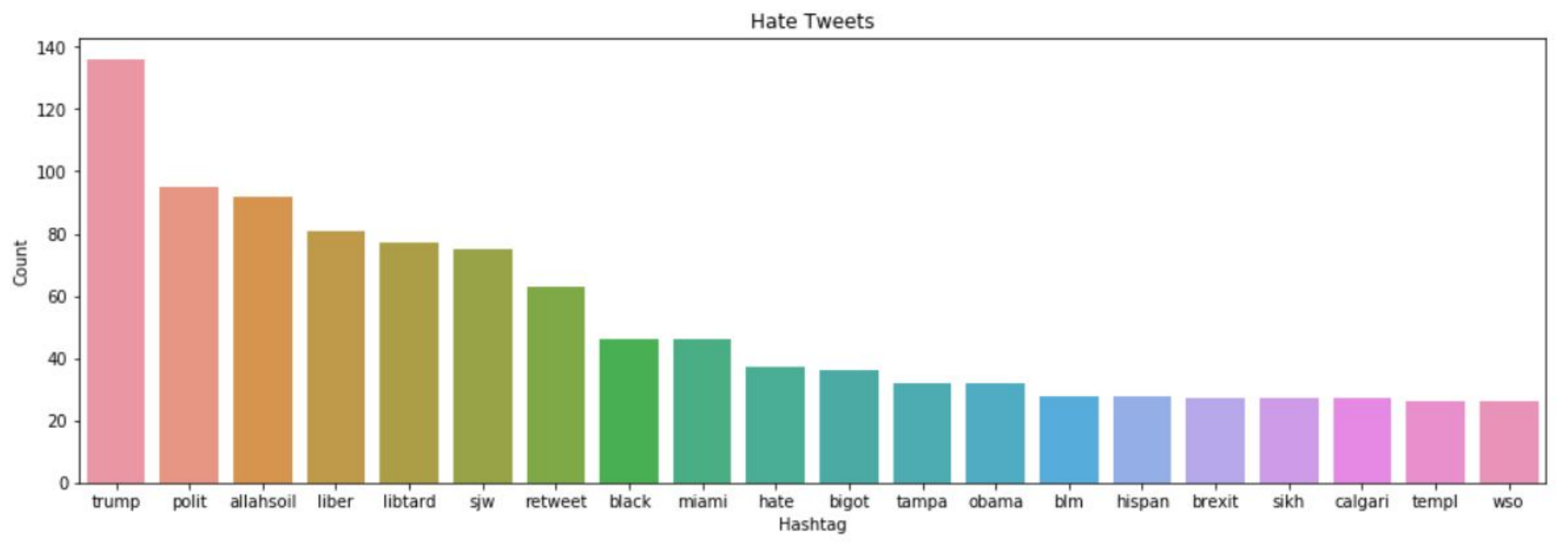
# Most popular hashtags in normal tweets



# Most popular hashtags in  tweets



# Feature Selection:

Bag of Words : select 1000 of the most common words for classification

TFIDF : Like Bag of Words, but with trained weights on key words

Word to Vector : Select 200 words, whose combinations create context
Trained using a neural network, and vectorized

Document to Vector : Like Words to Vector, but with the entire tweet.

# Stacked Machine Learning:

# The Twice-Cooked Technique

# Stacked Machine Learning:

## The Level 1

Start with the best ingredients:

| Classifier | F1 Score |
|---|---|
| LogReg (TFIDF) | .544 |
| Random Forest (TFIDF) | .562 |
| SVM (Word to Vector) | .571 |
| LogReg (Word to Vector) | .533 |
| Light GBM (Word to Vector) | .622 |

# Best Single Model Score

Light GBM (Tuned):

64.7% accuracy

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# Stacked Machine Learning:

## Level 2

Feed predictions from Level 1 to Level 2:

| Classifier | Competition Score |
|---|---|
| Log Reg | 70.7% accuracy |
| Light GBM | **73.5% accuracy** |

As of 03/31/19, this result places in the top 25% of 650 competitors.

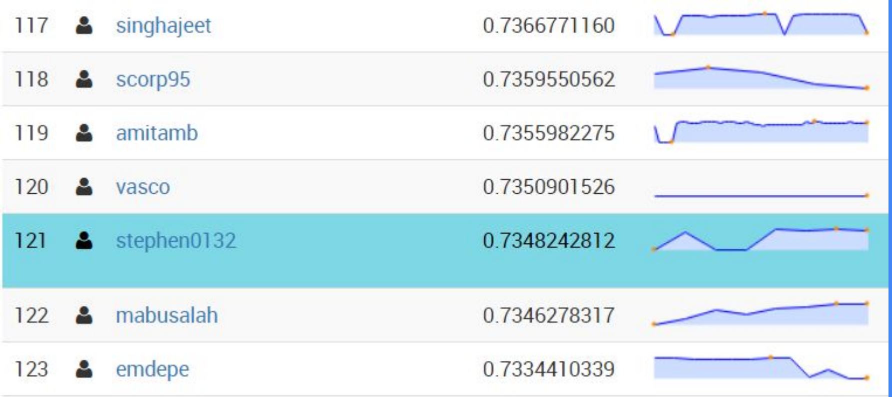
# Next Steps

Continued stacking

Feature Engineering

Data Set Balancing

## Score to beat:  85.8%



| | | | |
|---|---|---|---|
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| 118 | 👤 | scorp95 | 0.7359550562 |
| 119 | 👤 | amitamb | 0.7355982275 |
| 120 | 👤 | vasco | 0.7350901526 |
| 121 | 👤 | stephen0132 | 0.7348242812 |
| 122 | 👤 | mabusalah | 0.7346278317 |
| 123 | 👤 | emdepe | 0.7334410339 |