

# Twitter Sentiment About Apple and Google products

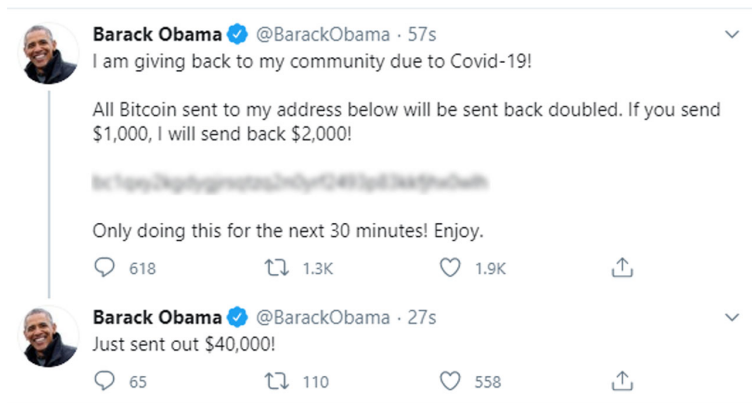
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# Introduction

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# Background

- Judge Emotion About Brands and Products
- Contributors evaluated tweets about multiple brands and products. The crowd was asked if the tweet expressed positive, negative, or no emotion towards a brand and/or product. If some emotion was expressed they were also asked to say which brand or product was the target of that emotion.
  - Added: August 30, 2013 by Kent Cavender-Bares
  - Data Rows: 9093
- Source: <https://www.crowdfunder.com/data-for-everyone/>



judge-1377884607\_tweet\_product\_company.csv  
[Request more info](#)

	tweet_text	emotion_in_tweet_is_directed_at	is_there_an_emotion_directed_at_a_brand_or_product
1	.@wesley83 I have a 3G iPhone. After	iPhone	Negative emotion
2	@jessedee Know about @fiudapp ? Aweso	iPad or iPhone App	Positive emotion
3	@swonderlin Can not wait for #iPad 2	iPad	Positive emotion
4	@sxsw I hope this year's festival isn	iPad or iPhone App	Negative emotion
5	@sxtxstate great stuff on Fri #SXSW:	Google	Positive emotion

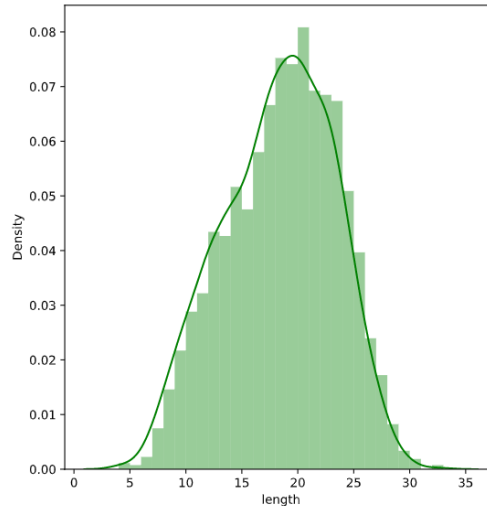
Showing 1-5 of 8,721 rows, 3 columns [See all](#) [Switch to column overview](#)

# Exploratory Data Analysis

- Both positive and negative sentiment tweets have mean word count of 18 and standard deviation of 5.
- Tweet word length have no correlation to sentiment.

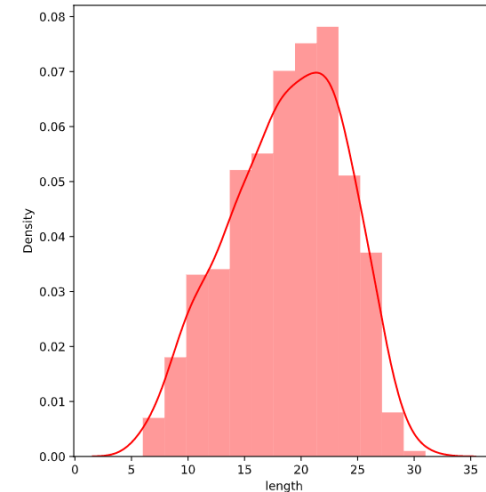
Distribution of text length for positive sentiment tweets.

	length
count	2672.0
mean	18.2
std	4.95
min	4.0
25%	15.0
50%	19.0
75%	22.0
max	33.0



Distribution of text length for negative sentiment tweets.

	length
count	519.0
mean	18.72
std	5.13
min	6.0
25%	15.0
50%	19.0
75%	23.0
max	31.0



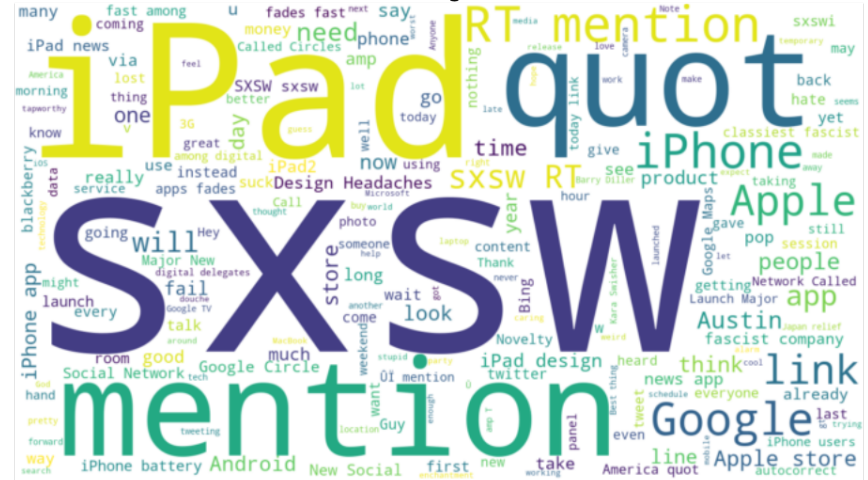
# Exploratory Data Analysis

- Top words for both positive and negative tweets:
  - SXSW, mention, iPad, iPhone, Apple, Google
- Simple keyword search won't indicate positive or negative sentiment.

Most common words in positive sentiment tweets.

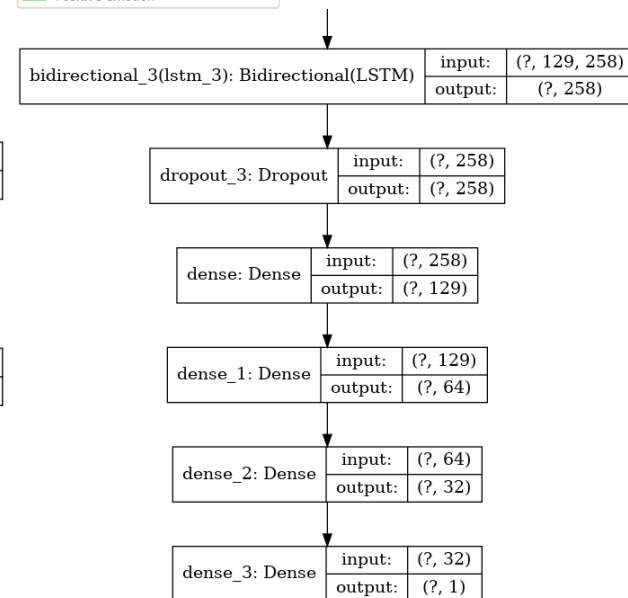
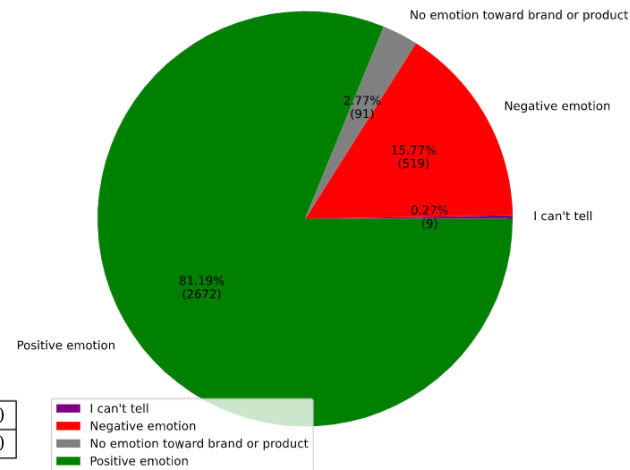
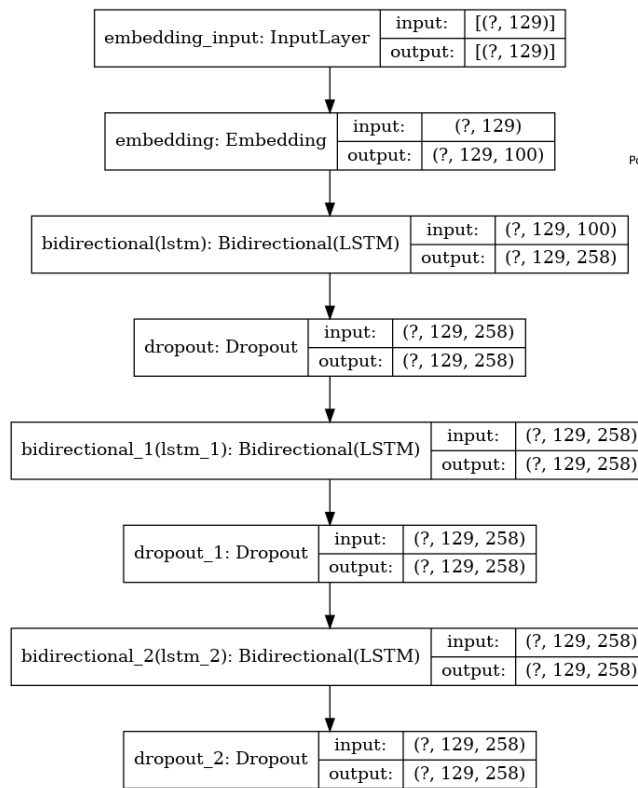


Most common words in negative sentiment tweets.



# Best Model

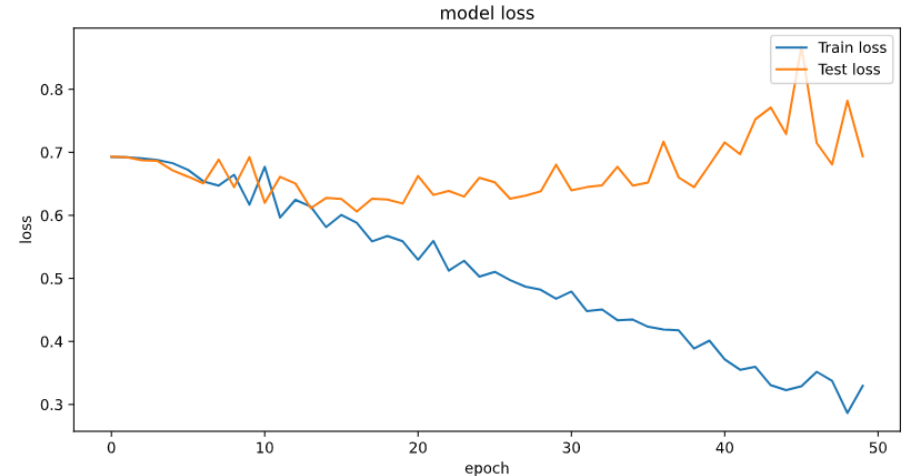
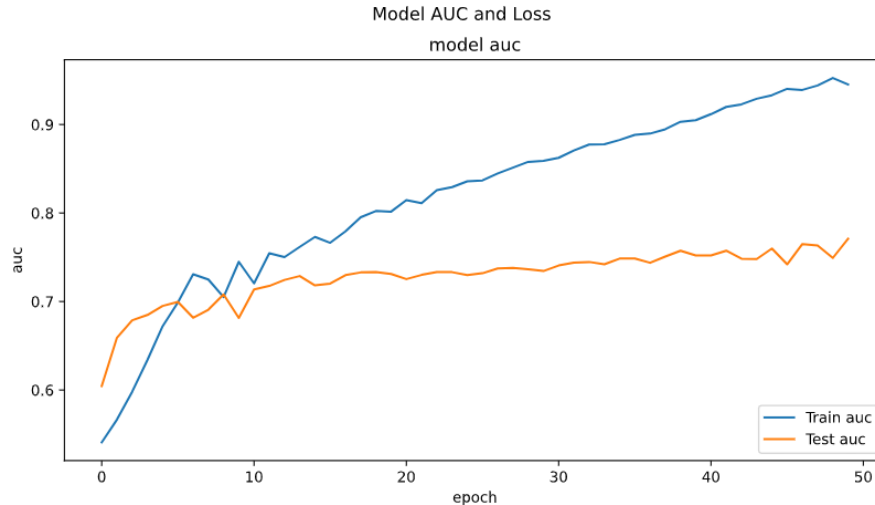
- Word count and keyword search don't identify sentiment, therefore we will try to fit a deep learning model.
- There are a lot more positive emotions than the rest.
  - In order to fully utilize all our available data, we will make the target into only two categories: positive and non-positive.
  - Then undersample based on the number of non-positive data.
- Many variation of the word\_embedding-LSTM-dropout-dense layer models were explored, this is the one with the best performance.



# Best Model Performance

- Average precision is 0.71.
- Average recall is 0.70.
- AUC score is around 0.70.
- Further training doesn't improve performance.
- This model can be used to predict how customers like the product

	precision	recall	f1-score	support
0	0.76	0.65	0.70	165
1	0.66	0.76	0.71	145
accuracy			0.70	310
macro avg	0.71	0.71	0.70	310
weighted avg	0.71	0.70	0.70	310



# Recommendations and Future Works

1) Gather more data.

- Sometimes more data improve model performance, but too much may increase training complexity by too much!

2) Build a continuous learning model.

- In case there are new terms and slogans: language changes over time.

3) Pick an acceptable classification threshold value from the AUC ROC curve.

- Pick an acceptable risk.



# Summary

- Using water well pump data to predict the pumps are “functional”, “functional needs repair”, or “non functional”.
- Random Forest is the best model.
- Model performs well without too much complexity added by choosing high `n_estimators` and `n_top_features`.
- Recommendation:
  - Use simpler model to real time update model as more data come on. Could train multiple simple model based on date intervals as well.
  - Develop libraries and visualization tools for categorical Random Forest Classifier
    - To later help with root cause investigation and mitigation plan design.
  - The goal should be lower the false “functional” rate, since this slows the true “non functional” or “functional needs repair” replacement or repair process.

Thank you for you attention!

Any questions?

