Using Machine Learning to Detect Product Sentiment in Tweets

A proof-of-concept

Agenda

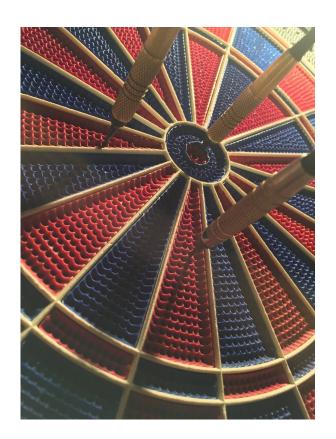
- ____
- Challenge statement: What and why
- My approach and caveats
- Overview of the data
- Machine learning results
- Recommendations
- Suggestions for Future Analysis

The challenge: Understanding consumer sentiment

- Voluntary product reviews are often highly polarized [1]
- Analysis of support tickets or customer complaints may highlight areas for improvement, but miss what works well
- It can be difficult to design surveys that avoid response bias

Can machine learning help?

- Can we use machine learning to separate tweets which contain positive or negative sentiment towards a brand or product from tweets which do not?
- What actionable insights could a machine learning model provide to a company interested in who wants to understand the factors driving both positive and negative sentiment?



My approach - A proof-of-concept

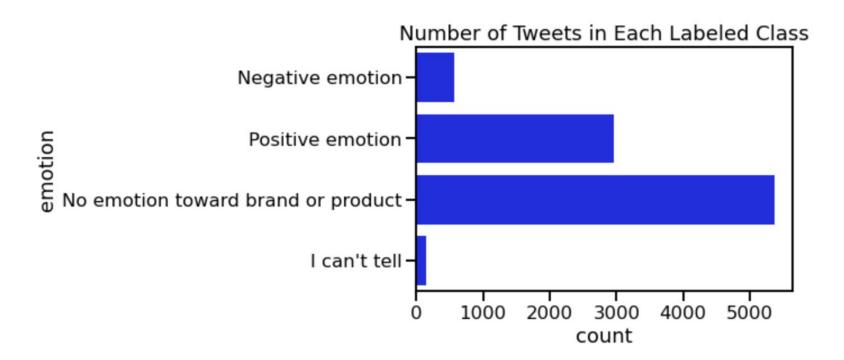
- Trained machine learning models on a set of tweets posted during SXSW
 - Models included Naive Bayes, Random Forest, and Logistic Regression
- Evaluated model classification performance compared to human classification
- Extracted predictors of sentiment from highest-performing models to show what insights could be gleaned

Data used for analysis

- ~9,000 tweets from SXSW, most of which contain mentions of Apple or Google products or brands [2]
- Tweets were originally classified by humans into these categories:
 - No sentiment towards a brand or product (or neutral emotion towards a brand or product)
 - Positive sentiment towards a brand or product
 - Negative sentiment towards a brand or product
- Dataset also included coding for which brands or products were mentioned, however this was not used

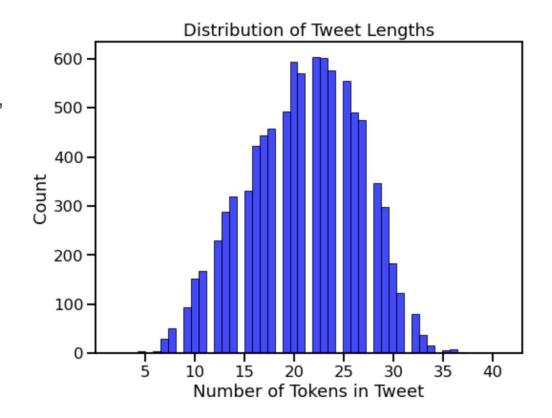
Tweet Dataset Overview

Class Distribution



Tweet Lengths (in word tokens)

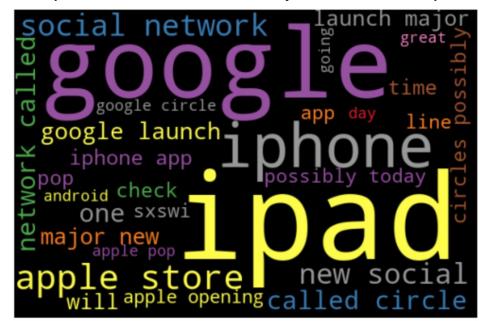
- Before removing stopwords, punctuation, and @mentions
- Most tweets are between 20 and 25 words



Word Frequencies - Entire Corpus

- Removed references to SXSW
- Product and brand-related words are very common

Word Cloud for Entire Corpus ("SXSW" and common stopwords removed)



Word Frequencies -Per Sentiment Class

No Sentiment Toward a Brand or Product



Positive Sentiment

Negative Sentiment





Machine Learning Results

Model Performance Summary

Multi-Class: Attempts to separate no sentiment towards brands and products from positive and negative sentiment

- Best model achieved ~60-65%
 balanced accuracy across all classes on unseen test data
- ~30% better than guessing randomly based on class distribution
- Performed about equally well when predicting any class
 - Confused Positive and No Sentiment more often than either of these with Negative

Binary: Attempts to separate positive from negative sentiment

- Best model achieved ~75% balanced accuracy across both classes on unseen test data
- ~25% better than guessing randomly based on class distribution
- Better at predicting positive sentiment than negative
 - Only ~10-15% of Positives misclassified as Negative
 - ~30-40% of Negatives misclassified as Positive

Summary and Recommendations

Summary of Results

TBD

Recommendations

TBD

Suggestions for Future Analysis

TBD

Thank you for reading!

For questions or comments, please contact:

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