Problem Statement

Will our customers like our new phone?

Our new mobile phone will soon be released into a saturated and competitive marketplace.

How will we know if our customers like or dislike it?

And how quickly can we get that information?

Business Value

Faster Consumer Feedback

We could simply observe sales data, but it would likely have a significant lag between those sales and current consumer opinion.

The internet, on the other hand, is a never ending stream of opinions, and some of those opinions will be about our phone.

If we can harness that information, we could gather consumer feedback in real time...

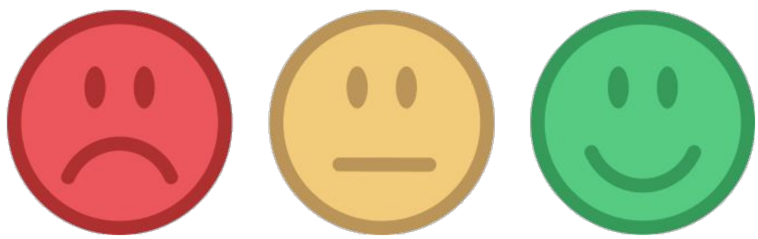
Business Value

Increase Market Knowledge

And we could increase our market knowledge of not only our products but those of our competitors.

Methodology

Twitter Sentiment Analysis



With the goal of harnessing some of the publicly available knowledge online, I used the following methodology to create a Sentiment Analysis model to evaluate the polarity, negative, neutral or positive, of what people are tweeting on Twitter.

Methodology

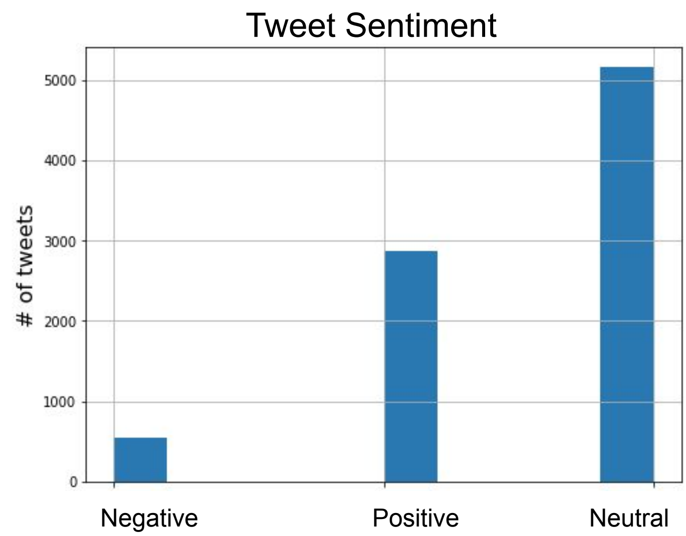
Collect Twitter Data

Keynote: Instagram Founders Kevin Systrom & Mike Krieger with Josh Constine during the 2019 SXSW Conference and Festivals at Austin Convention Center on March 11, 2019 in Austin, Texas. (Photo by Chris Saucedo/Getty Images for SXSW)

I used a dataset of tweets from #SXSW because attendees or people interested in SXSW are also likely to be interested in technology; like our phone.

Methodology

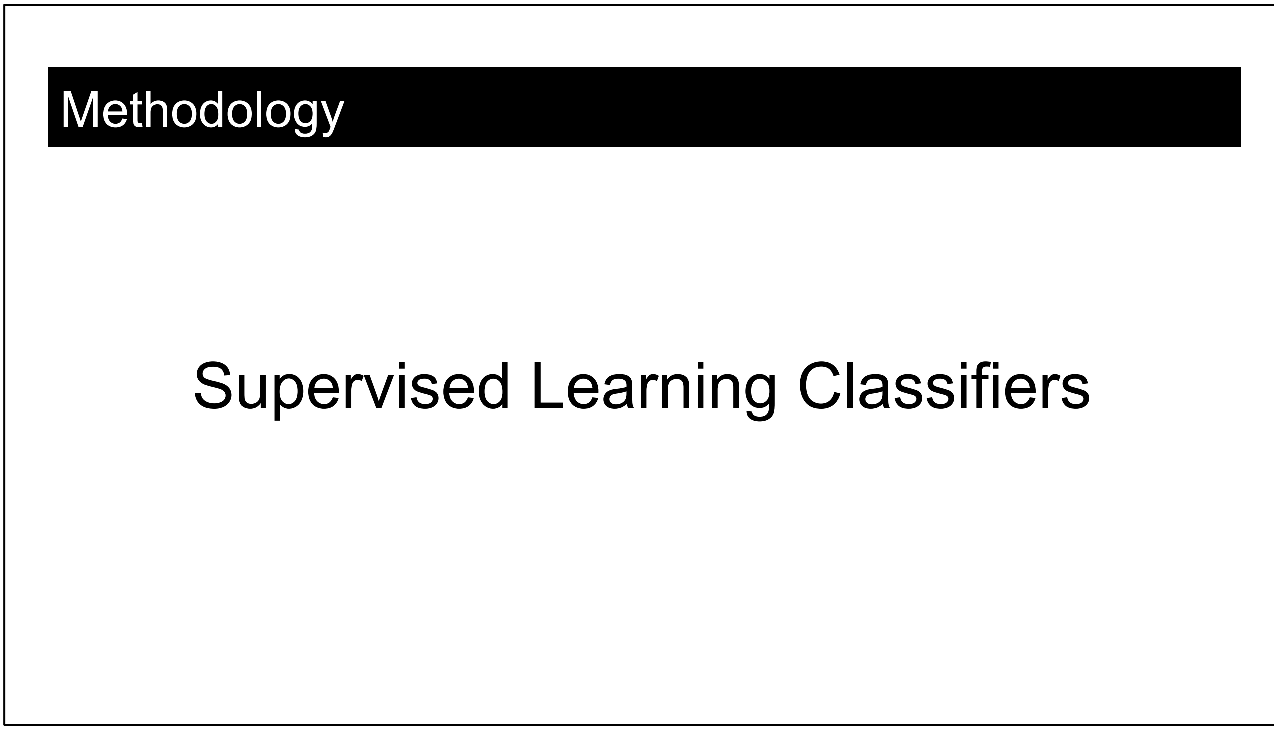
Oversampling



This dataset, while relevant, is highly imbalanced.

And while getting a distribution of sentiment like this towards our phone, where positive tweets far exceed the negative ones would be ideal, it makes it hard for a machine learning model to learn how to classify those tweets.

To compensate, I used Oversampling where possible to generate new data to balance the three classes when training the model.



I used supervised learning classification, meaning I knew the classes of a set of tweets, and I wanted to train a model that could accurately predict those classes, and more importantly new ones that the model wasn't trained on.

I iterated on three different classifiers, two machine learning and and one Neural Network.

Methodology

Model	Ave Macro Recall	Negative Recall	Neutral Recall	Positive Recall	Overall Accuracy
Baseline - Random Pick	0.33	0.33	0.33	0.33	0.33
Naive Bayes	0.61	0.61	0.56	0.67	0.60
Support Vector Machine	0.59	0.61	0.62	0.53	0.59
Neural Network	0.54	0.27	0.78	0.57	0.68

The three types of models were evaluated on the following metrics: average accuracy of the classes (average macro recall), a balanced accuracy/recall among the classes, and overall accuracy.

The one that did the best was a Naive Bayes Classifier that used oversampling.

It achieved an average accuracy among the classes of 61%, a fairly balanced accuracy among the classes of 61%, 56% and 67% for negative, neutral and positive respectively, and an overall accuracy of 60%

Methodology

Sentiment Analysis is HARD

Using several types of models, I was only able to achieve 60% accuracy when classifying the sentiment of the tweets.

I contend that is pretty good considering that humans only agree on sentiment 80% of the time. [1]

And a computer model is going to have a hard time evaluating complex negations, exaggerations, jokes or sarcasm.

Some tweets with these types of features would be easy for a human evaluator to classify and others would not and may require extensive background knowledge of the situation, culture, or personality of the person tweeting.

That said, I think 60% accuracy is good enough to move forward with some valuable business recommendations.

Recommendations

Create a Real Time Customer Feedback and Response System

Create a Real Time Customer Feedback and Response System.

We can use Twitter's API to filter tweets with hashtags and text deemed to be related to our mobile phone.

These tweets can then be classified by our model and then monitored and reviewed to keep track of their content and the current sentiment regarding our phone.

With this knowledge, we will be able to quickly address any consumer concerns and amplify any praise.

Recommendations

Create An Alert System

Building upon the previous recommendation, an alert system could be established to monitor for significant changes in sentiment towards our phone; prompting us to take action.

Recommendations

Conduct Market Research

We can use the model to do market research on our competitors.

If our model can tell us about the sentiment of Twitter users towards our phone, it can also tell us what people are feeling about our competitors phones and we can act on that knowledge.

Future Work

Improve the Model with More Tweets

Improve the Model with More Tweets

The dataset used to train this model is relatively small, about 8500 tweets. Retraining the model on a larger dataset should improve its performance.

Future Work

Expand the Scope of the Sentiment Analysis Monitoring

Expand the Scope of the Sentiment Analysis Monitoring

There is plenty of other publicly available text data that can be acquired and monitored for sentiment.

This data may be on other social media platforms or public forums, or could be product reviews.

While product reviews often have an associated rating, that rating may differ from the overall sentiment of the review.

Classifying this other data will require a new model because its structure would differ from a tweet.

Future Work

Add Granularity To the Sentiment Analysis

Add Granularity To the Sentiment Analysis

Some text data is going to be more negative or more positive than others.

By creating a scale from very negative to somewhat negative to neutral to somewhat positive to very positive, more nuance will be able to be found in the sentiment analysis, and actions can be taken based on the severity of the situation.

Thank You