Final Report

Connor Ameres and Bradley

October 9th, 2016

Final Report

Sentiment Analysis

In order to create a sentiment analysis web application for customer service representitives of various companies to gather feedback about their airline, we first needed to be able to gather data from twitter. We found that the twitter streaming API would best suite our use case, because while we wanted our representitives to be able to responsed to be able to respond to potentially every single tweet for their airline. The rest API twitter provied didn't allow us to request more than 100 tweets at a time and our application would have to maintain a data structure to determine whether or not a tweet has been responded to.

In order to analyze the sentiment of every tweet we needed to create an additional service that would clasify the sentiment of the tweets streaming. In order to cut the cost of using a service like Google's Sentiment Analysis API, we used the VADER library. VADER is a part of a very popular python package, NLTK, and is designed to correctly classify social media tweets (see paper).

After the tweets were analyzed for sentiment, our main server would stream the tweets to all representitives connected to the website. From the website representitives would be able to respond directly to the person tweeting at the airline and address the potential concern the person might have.

We found that overall airlines are fairly effective in responding to tweets with sentiment, responding within minutes of complaints being made. We believe that this indicates some combination of sentiment analysis tools or an overstaffed consumer representive staff.

The Data

While we found that the *VADER* library performed very well for tweets (see correctly classified tweets in figure 1 and figure 2) we found that we would need to tune the algorithm in order to produce more false negatives than positives.

Figure 1: Correctly Classified Positive Tweet

The tweet in figure 1.3 shows an example of an incorrectly classified tweet. Two of Dr. Jeffery W. Ross' were correctly classified while this tweet has been classified incorrectly. Tweets like these stood out amongst other incorrectly classfied tweets. Other tweets might have elements like sarcasm which made for difficult classification, but Ross' tweet contains no sarcasm and the sentiment seems straightforward.

Figure 1.4 shows an incorrectly classified sarcastic tweet. We found that the great majority of tweets that streamed through our application were incorrectly classified due to the usage of the word *thank*.

Mapping Sentiment to Airports In inspecting the tweets streaming in, we found that the great majority of users were not including their location in their tweets. We wanted to be able to map out where user's were flying or which airport they might be located at to guage critical problems at particular locations. In order to achieve our goal we were able to extract the airport codes from the tweets that were passed in the tweets and mapped them to a particular latitude and longitude using a dataset source from openflights.org. After determing the sentiment of the tweet, we then were able to pin the user's location or location of arrival/departure on the map with their corresponding sentiment.

Sentiment Influence

In order to distinguish which airlines were performing particularly well with customers we measured the influence of a particular user based on the number of twitter followers a user has, because we could not measure the number of views

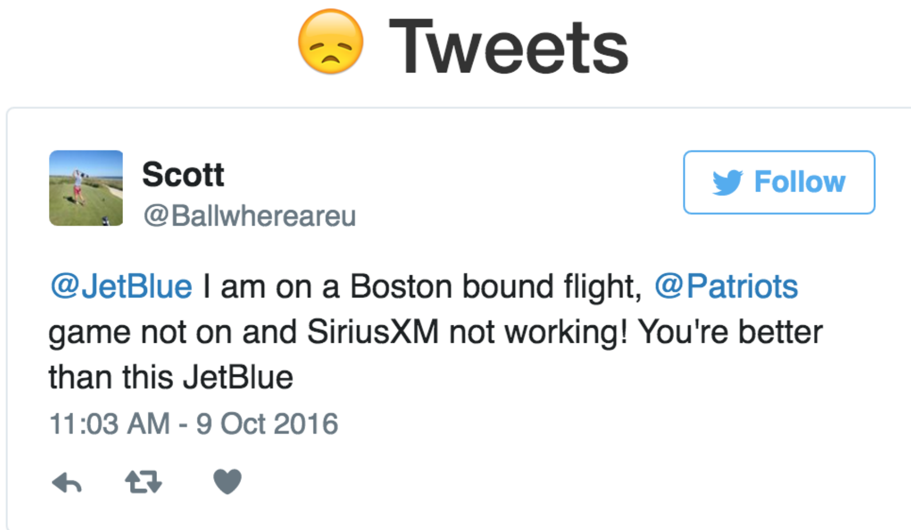

Figure 2: Correctly Classified Negative Tweet

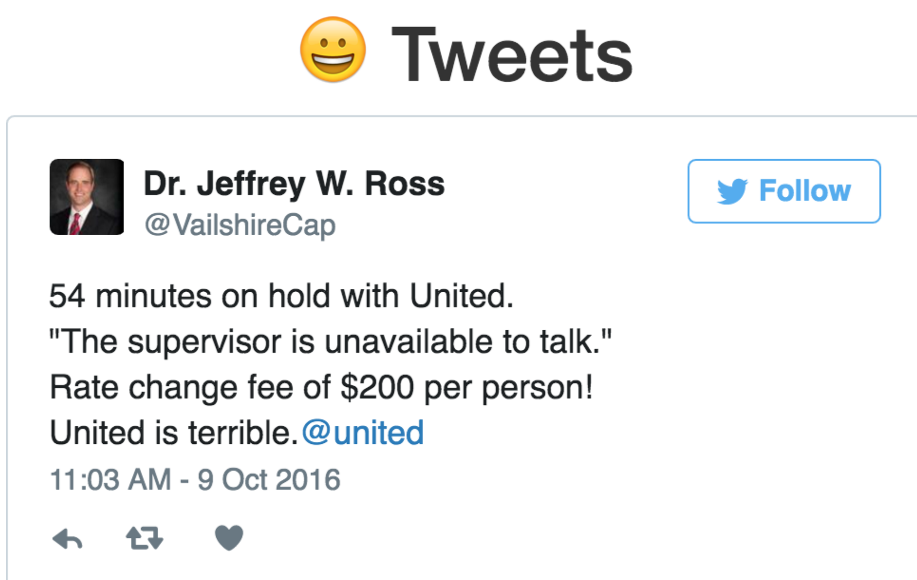

Figure 3: Incorrectly Classified Positive Tweet

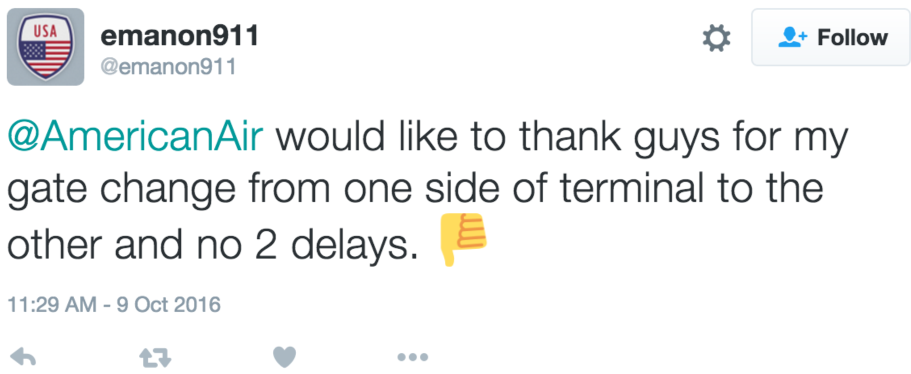

Figure 4: Incorrectly Classified Sarcastic Tweet

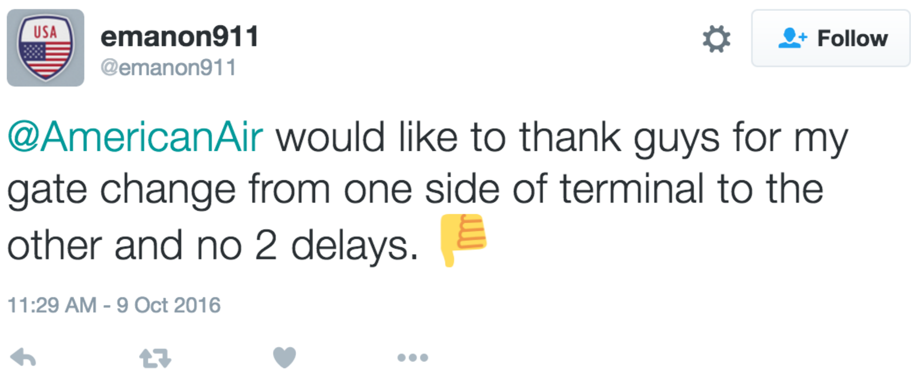

Figure 5: Pinning A Tweet on The Map

of the tweet. It was also decided that to preemtively respond to the tweet of a user with more followers would generate more views of a sales representives repsonse.

$$\text{Sentiment Influence} = \text{Sentiment} * \text{Influence}$$

Figure 6: Om Malik's Tweet

An example of a tweet with a large sentiment influence is Om Malik's tweet (see figure 4). Malik is a registered user on twitter with 1.5M followers. Simply put his tweets will garner more views than someone with a smaller network. Tweets from users like Om Malik become a high priority as the network effect is stronger for responses to these tweets.

Lastly, we created a visualization of sentiment analysis with a realtime chart of average sentiment influence over time. Representitives will be familiar to the real time chart based their usage in finance. In the chart in figure 5, we can see exactly when Om Malik tweeted at @JetBlue.

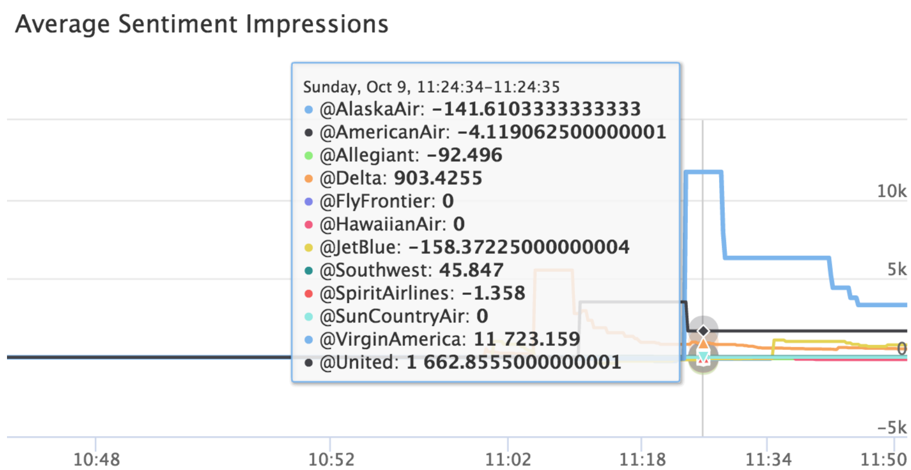

Figure 7: Sentiment Influence Chart