

Le-Anne Lee | DSI 12



Overview

Introduction

Problem Statement

Understanding Airline Customer Tweets

Findings from Modelling

Future Implementation

Impact of Social Media



Average Daily Time Spent on Social Networking Worldwide



More than half of the world's population use social media

144

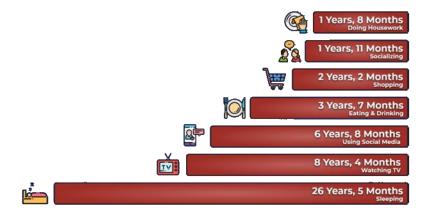
minutes per day

3.8bil

people in 2020

Impact of Social Media

Average Time Spent in a Lifetime





Source: Broadbandsearch

Source: Bureau of Labour Statistics

Sentiment Analysis

What it does

- Interpretation and classification of emotions within text
- Time-consuming to sieve through large amounts of data

Business Outcome

- Identify customer sentiment towards brands / services
- Automatically analyse customer feedback to tailor services to meet their needs























































Problem Statement



How can airlines exploit twitter data to better respond to customer's needs?

About the Data

- Airline tweets gathered in Feb 2015
- 14640 tweets

- Contains:
 - tweet id
 - airline sentiment
 - airline sentiment confidence
 - airline
 - name
 - retweet count
 - text
 - tweet coordinate
 - tweet created
 - tweet location
 - user timezone
 - negative reason

Understanding your customers









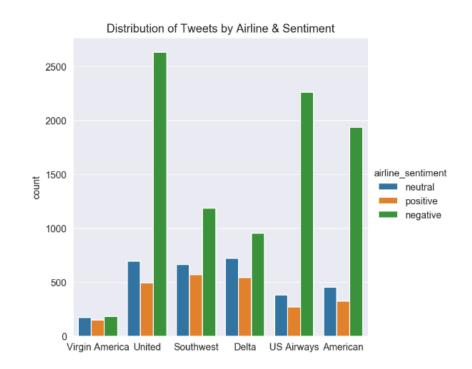


Data Insights

Distribution of tweets by Airline & Sentiment

Implications:

People tend to tweet more when they have something negative to say



Data Insights

02

Incorrect Tagging of Original Dataset

- All 2222 observations tagged as Delta posts were referring to @JetBlue

	text	airline
6746	@JetBlue Yesterday on my way from EWR to FLL j	Delta
6747	@JetBlue I hope so because I fly very often an	Delta
6748	@JetBlue flight 1041 to Savannah, GA	Delta
6749	@JetBlue They weren't on any flight, they just	Delta
6750	@JetBlue everyone is here but our pilots are n	Delta

O3 #CUSTOMER_SERVICE_HOTLINE

```
@JetBlue I have a internal bleed in my foot, and I am flying next Tuesday, what should I. Do :( these. Leeds come randomly. I
@JetBlue no, I am fine to fly! Haha, they come at random, with the hemophilia, but what if i need extra assistance
8570
@JetBlue is it true there's a new A320 livery and a new website...?!
@JetBlue BEST SEAT ON A E190 to board early. READY. SET. GO!
8568
@JetBlue I can't pay 30 bucks xD
@JetBlue my mom wanted me to change her seat along with my sister, but their two different reservations and idk
@JetBlue can't change it. True blue points and I can't get to a phone
8558
@JetBlue can you DM?
@JetBlue is flight 51 on 4/24/15 moved back? When I booked it said we arrive 11:31 but now it says 12:08 😥
8297
@JetBlue I can't do that flight. I need a Late Flightr one! I need you to change my flight. You guys changed it and now I can't
do that time!
8296
@JetBlue I can't. I don't have acces to a phone rn. My iPhone broke. :/ would rather change it now then Late Flightr.
@JetBlue should I check in my awesome bag on my flight or carry it on... Decisions...
8294
@JetBlue okie doke! Knowing you, you will fix this ;)
@JetBlue thanks to the gent on the phone who fixed my BOS-MCO flight and the fee waiver! A320 now :) #flyfi ! I forget her name
```

O3 #THE_SPAMMER

03 #NEWS_SOURCE

```
'@JetBlue Fliers to Gain Access to WSJ Content - Analyst Blog - Nasdaq http://t.co/dWEse7Xidr'
```

'@JetBlue Airways Stock Rating Lowered by Vetr Inc. (JBLU) - Dakota Financial News http://t.co/QW2eBEEMVg'

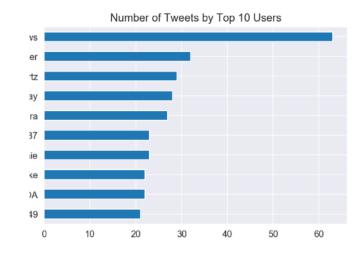
"@JetBlue's new CEO Robin Hayes battles to appease passengers and Wall Street - Business In Savannah http://t.co/KKAY8XaPs1"

03

Highest number of tweets by the same user: 60 out of 14640 over tweets.

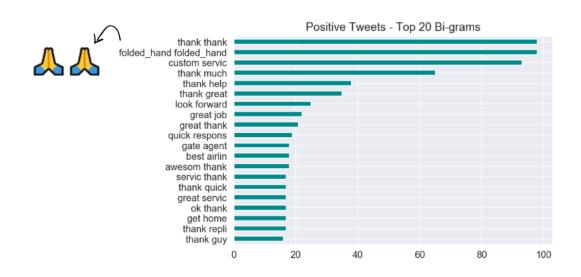
Implications:

No concern that the data is overly skewed by one user

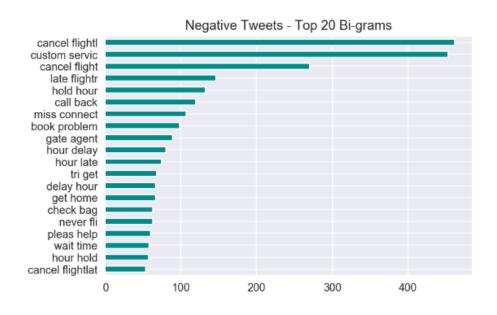


Common Words

#POSITIVE



Common Themes #NEGATIVE



Data Preprocessing

- Retain emojis
- Retain stopwords
- Spelling errors
- Short forms

Modelling Results

Model	Accuracy Score
Logistic Regression	0.801
Naive Bayes	0.748
Decision Tree	0.681
Random Forest Classifier	0.761
Ada Boost	0.755
Gradient Boost	0.751
XG Boost	0.774

Model	Accuracy Score
Vanilla RNN Model	0.781
RNN with LSTM	0.750
RNN with LSTM & Dropout	0.778

Summary of Findings

Model Performance

- Performed best on negative tweets
- Precision for Neutral tweets was only 70%

Areas of Improvement

- POS Tagging
- Topic Modeling
- Word2Vec
- Include more positive and neutral posts

Model Deployment



Sentiment Analysis



Topic Modelling

Removal of Spam Tweets



Negative Tweets to be Addressed by Customer Service



Conclusion

- Model was able to accurately classify 80.1% of tweets
- Pre-processing of features is the most important
- Future work includes:
 - classification of spam tweets
 - topic modelling



