Airline Tweets Sentiment Analysis

😔 ☺️

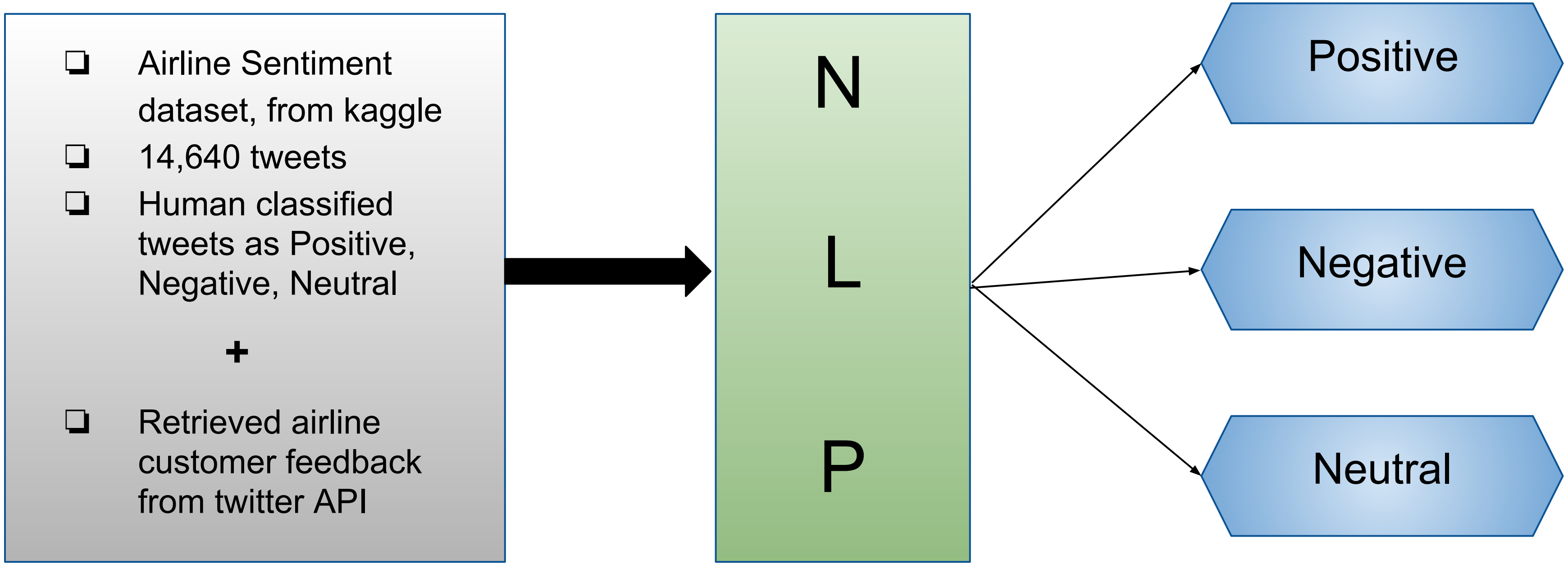
Alamy

Can machine learning help airline companies gauge customer satisfaction?

😊😞

By Sangita Gupta

Airline Sentiment Classification

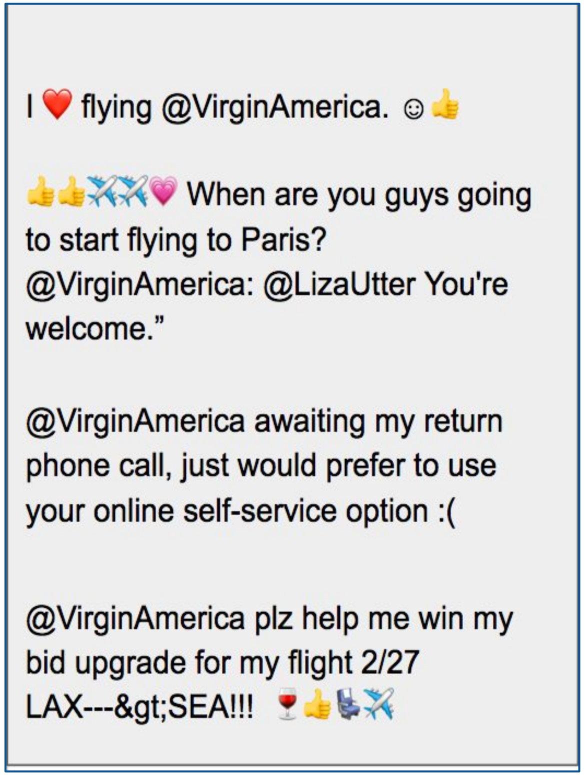


- ❏ Airline Sentiment dataset, from kaggle
- ❏ 14,640 tweets
- ❏ Human classified tweets as Positive, Negative, Neutral

+

- ❏ Retrieved airline customer feedback from twitter API

Conversion of tweets into airline sentiment



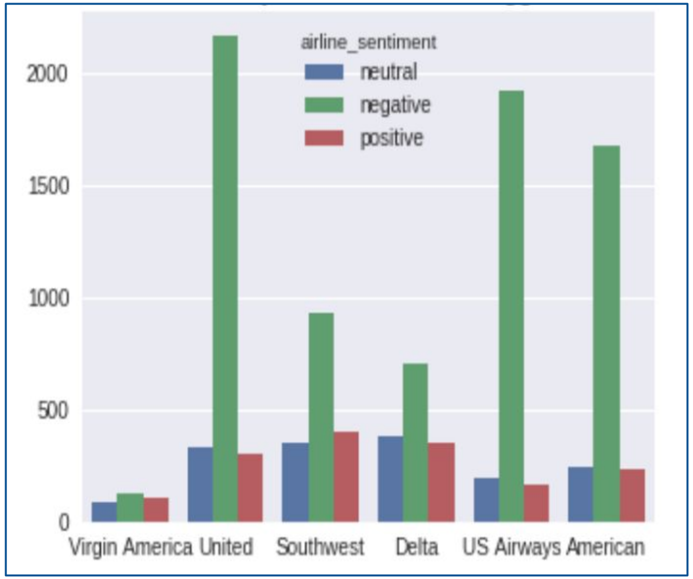
I ❤️ flying @VirginAmerica. ☺👍

👍👍✈️✈️💗 When are you guys going to start flying to Paris? @VirginAmerica: @LizaUtter You're welcome.”

@VirginAmerica awaiting my return phone call, just would prefer to use your online self-service option :(

@VirginAmerica plz help me win my bid upgrade for my flight 2/27 LAX---&gt;SEA!!! 🍷👍💺✈️

NLP



Natural Language Processing

A field of data science that can analyze text and make predictions using that text as data

Raw Tweets

Clean Tweets: remove urls, @users, numbers, punctuation

Data dimensionality reduction methods

Remove Stopwords: I, you, we, so, to, ...

Apply Lemmatization:

am, are, is ⇒ be
car, cars, car's, cars' ⇒ car

OR

Apply Stemming:

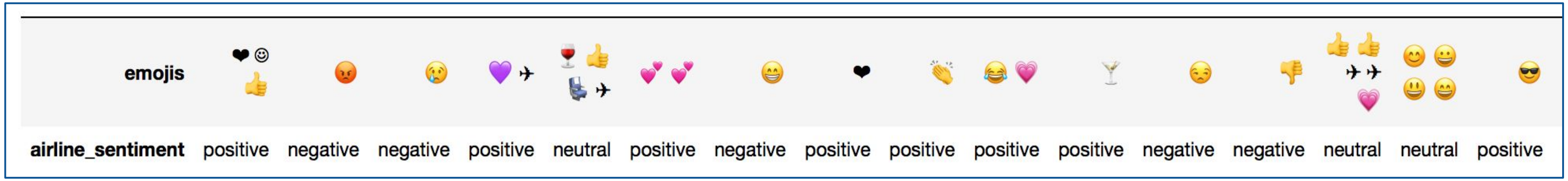
caresses, ponies, cats ⇒
caress, poni, cat

Processed Tweets

- ❑ **Raw Tweet:**
  - ❑ @VirginAmerica Applied for Status Match on Feb 1. Got confirmation email same day. Still no news though. You guys have dropped ball Late Flightly 😥
- ❑ **Cleaned and Emoji Encoded Tweet:**
  - ❑ applied for status match on feb got confirmation email same day still no news though you guys have dropped ball late flightly emoji_34
- ❑ **Stop Words Removed Tweet:**
  - ❑ applied status match feb got confirmation email day news guys dropped ball late flightly emoji_34
- ❑ **Stemming Applied to Tweet:**
  - ❑ appli statu match feb got confirm email day news guy drop ball late flightli emoji_34
- ❑ **Lemmatization Applied to Tweet:**
  - ❑ apply status match feb get confirmation email day news guy drop ball late flightly emoji_34

Handling Emojis

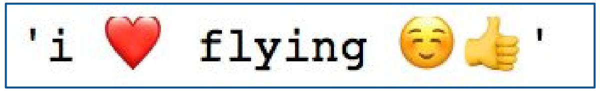
Extract emojis from tweets to see how they relate to the classified sentiment



emojis	❤ ☺ 👍	😡	😢	💜 ✈	🍷 👍 💺 ✈	💕 💕	😁	❤	👏	😂 💗	🍸	😒	👎	👍 👍 ✈ ✈ 💗	😊 😀 😃 😁	😎
airline_sentiment	positive	negative	negative	positive	neutral	positive	negative	positive	positive	positive	positive	negative	negative	neutral	neutral	positive

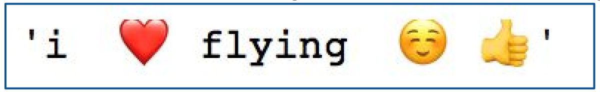
They look like good sentiment predictors. They are symbols so we have to encode them.

Users clump emojis together.



```
'i ❤️ flying ☺️👍'
```

So first separate the emojis into individual symbols.



```
'i ❤️ flying ☺️ 👍'
```

So now that they are separate, let’s encode them as features...

Encode Emojis

```
{'❤': 'EMOJI_1', '☺': 'EMOJI_2', '👍': 'EMOJI_3', '😡': 'EMOJI_4', '😢': 'EMOJI_5', '💜': 'EMOJI_6', '✈': 'EMOJI_7
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```

Transform text into numerical data

Divide tweets into words and create a document term matrix, where columns are unique words in the corpus of tweets and rows are tweets represented by a 0 or 1, depending on if the word is present or not.

Tokenize Text

The corpus of tweets are separated into words

The corpus is now like a bag of words

Document Term Matrix

The “bag of words” is then used to make a table

The columns are the unique words in the corpus

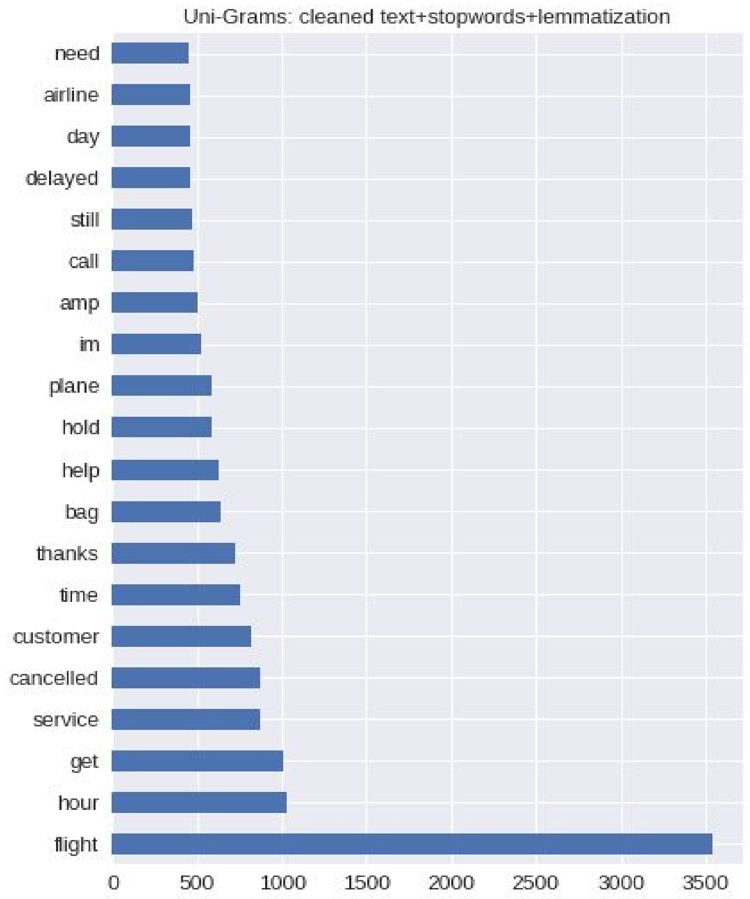
The rows are the individual tweets represented in numerical form

Vectorized Text

Each tweet is now represented by a series of ‘1’ and ‘0’ in the document term matrix

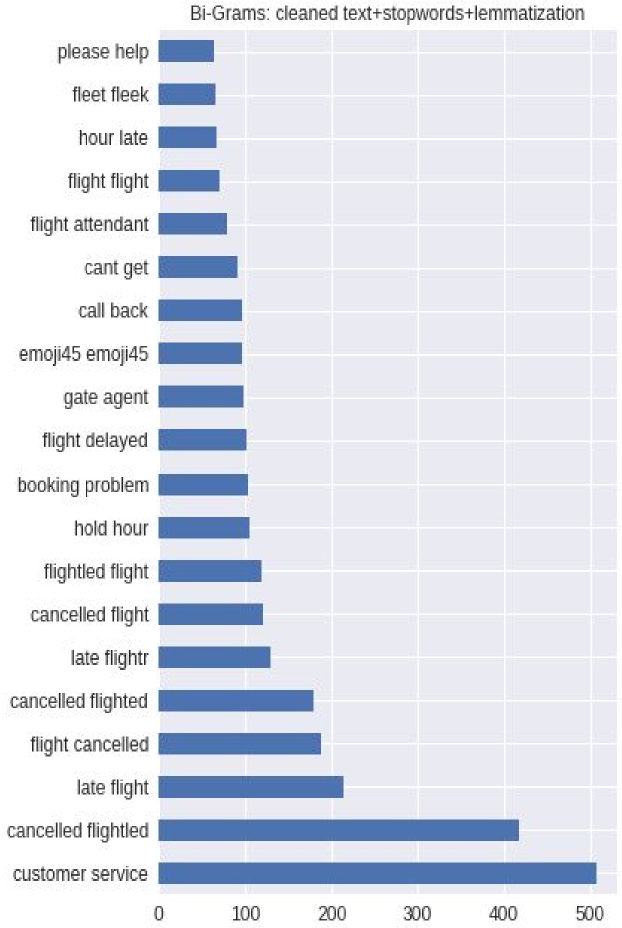
If the word exists in the tweet its value is ‘1’ if not, its ‘0’

Word Features: uni-grams



- ❑ Words in Natural Language Processing become features of the text dataset.
- ❑ These features are known as predictors in machine learning and are used to form predictions about an output label, also referred to as target.
- ❑ In NLP, single words or multiple successive words may be used as features, also referred to as n-grams.
  - ❑ An n-gram is a contiguous sequence of n words
- ❑ The graph to the left shows the top 20 “1-grams”, also known as “uni-grams”, for tweets in the dataset.
  - ❑ flight, hour, get, service cancelled, customer, time, thanks, bag, help, hold,plane, im, amp, call, still, delayed, day, airline, need

Word Features: bi-grams and tri-grams

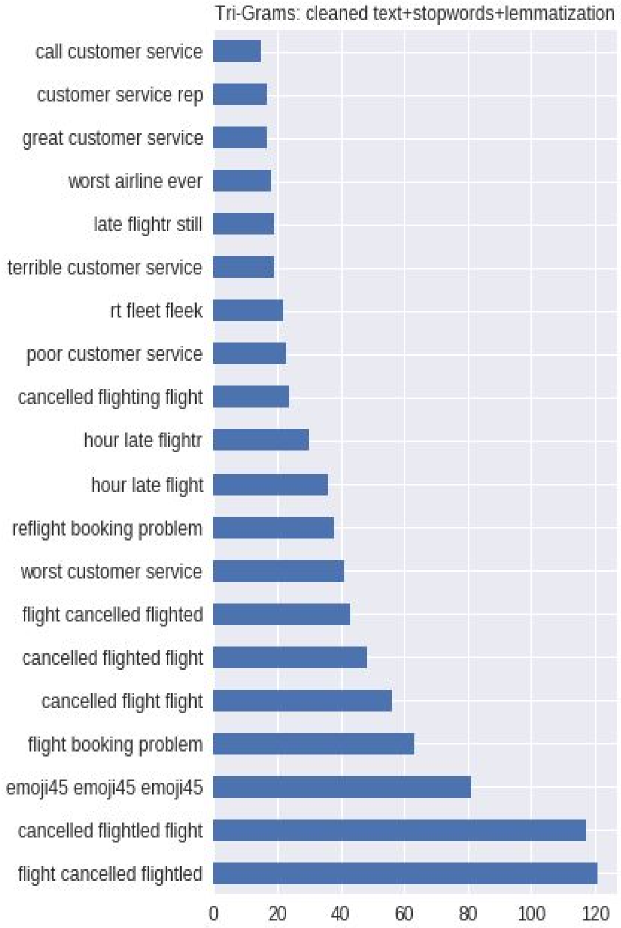


Top bi-grams:

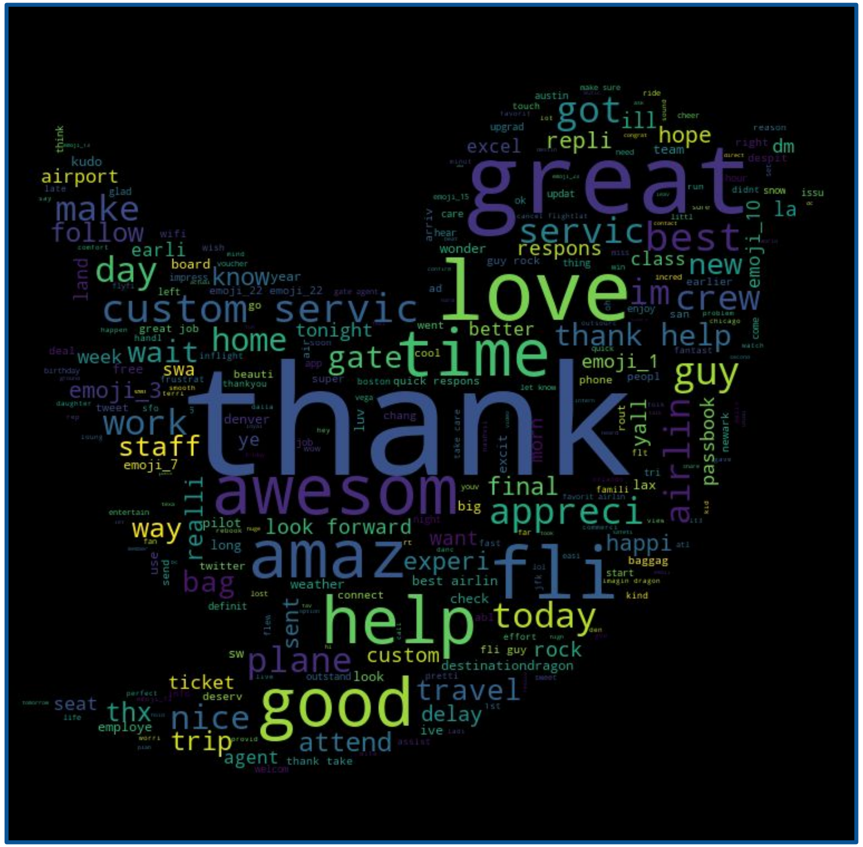
- ❏ Customer service
- ❏ late flight
- ❏ flight cancelled
- ❏ hold hour
- ❏ booking problem
- ❏ flight delayed
- ❏ gate agent
- ❏ emoji45 emoji45
- ❏ hour late
- ❏ please help

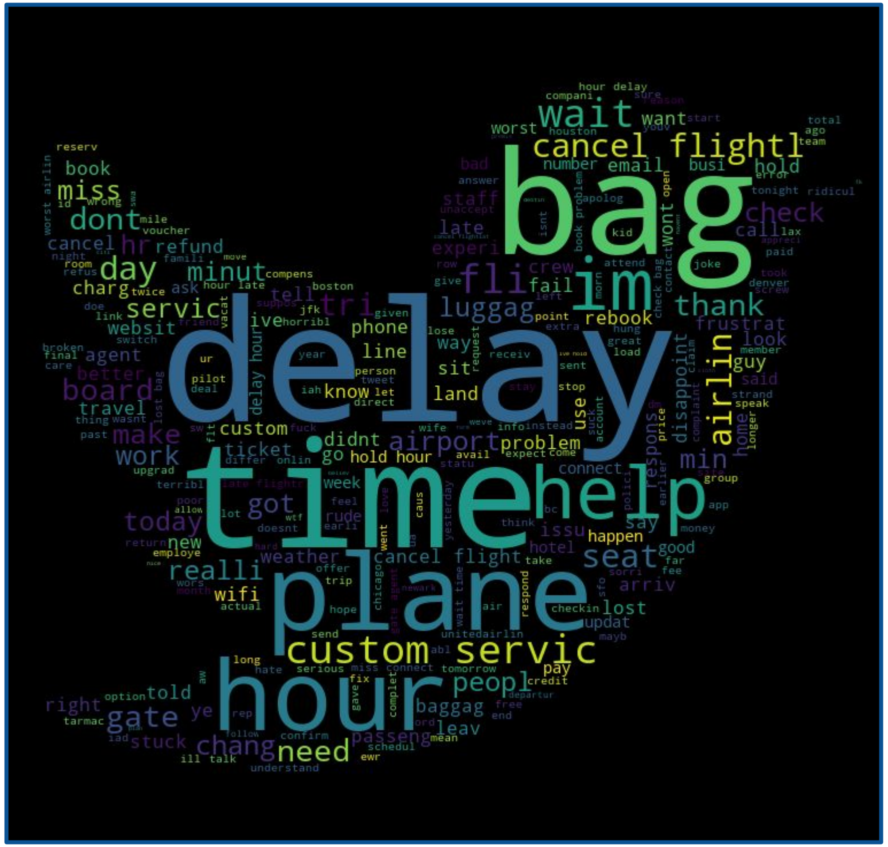
Top tri-grams:

- ❏ Flight cancelled flightled
- ❏ cancelled flightled flight
- ❏ emoji45 emoji45 emoji_45
- ❏ flight booking problems
- ❏ cancelled flight flight
- ❏ worst customer service
- ❏ great customer service
- ❏ reflight booking problem
- ❏ hour late flight
- ❏ call customer service



Word Frequency





Model Selection

Naive Bayes

Learning Mechanism

- Naive Bayes models the joint distribution (X,Y) and then predicts the probability P(Y|X)
    - X is set of input features
    - Y is the output labels
- It is thus called a generative model.

Model Assumptions

- Assumes that every word in a sentence is independent from the other words.
- So for Naive Bayes the following sentences would all be the same.

“this was a fun party”

“this party was fun”

“party fun was this”

Logistic Regression

Learning Mechanisms

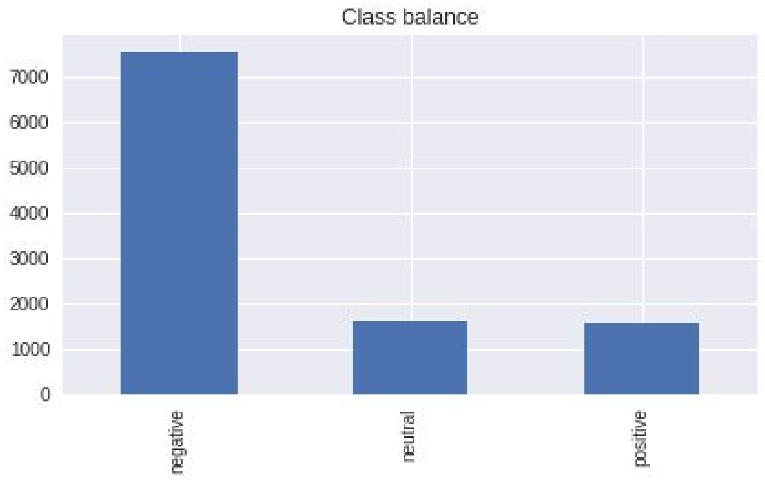
- Logistic Regression directly models the P(Y|X) from learning the input to the output mapping, by minimizing the prediction error.
- It is thus called a discriminative model, since it discriminates based on the error.

Model Assumptions

- It assumes non-collinearity of features.

- It splits the feature space linearly, so it deals fairly well even if some features are correlated.

Modeling



- Data is highly unbalanced.

Baseline Accuracy = 0.70

- We will be right 70% of the time if we always guess the most common class

Insights we want to gain

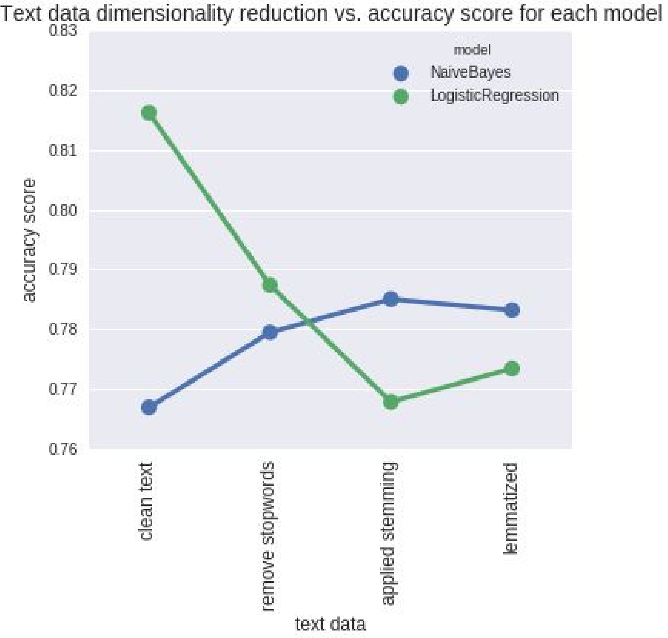
❏ What effects do ***emojis*** have on model predictions?

❏ What effects do different ***dimensionality reductions methods*** have on model predictions?

❏ What effects ***tuning*** the model's hyper parameters have on model predictions?

Model Accuracy

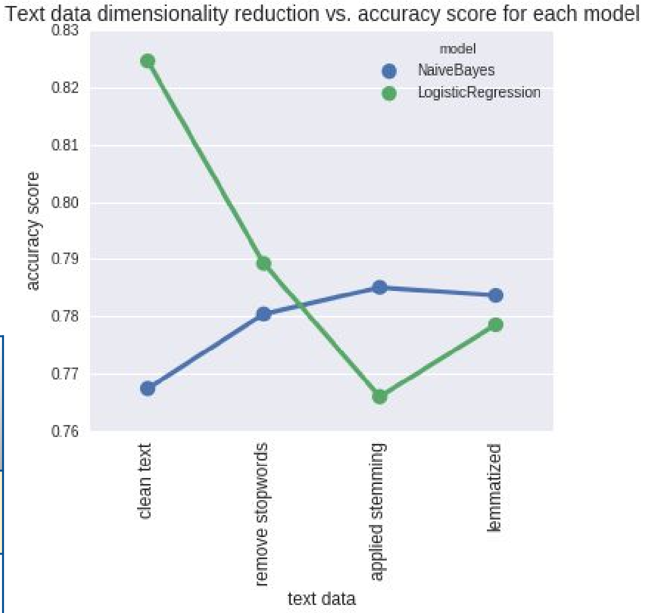
Emoji Not Encoded



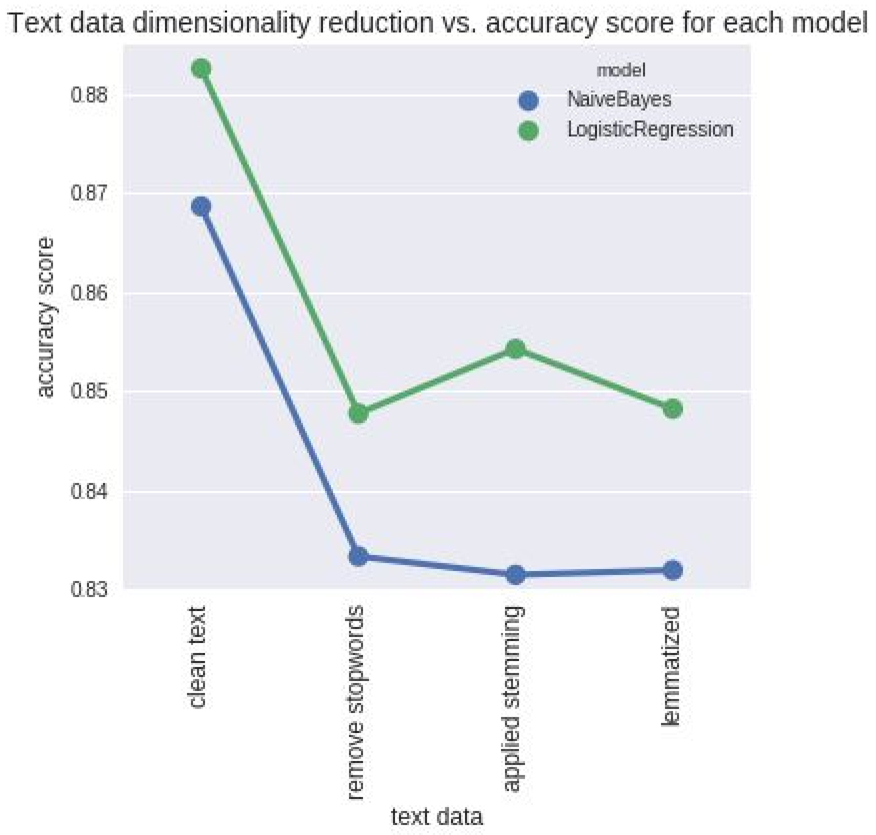
No Emoji Encode Text Processing	Naive Bayes	Logistic Regression
Clean Text	0.766953	0.816160
Stop Words	0.779482	0.787366
Stemming	0.785053	0.767872
Lemmatization	0.783201	0.773444

Emoji Encoded Text Processing	Naive Bayes	Logistic Regression
Clean Text	0.767418	0.824515
Stop Words	0.780412	0.789222
Stemming	0.785056	0.766014
Lemmatization	0.783664	0.778547

Emoji Encoded



Best Tuned Model Results



Parameters Tuned:

- ❏ Countvectorizer
  - ❏ min_df = 5, max_df = 0.95, ngram_range = (1,2)
- ❏ Logistic Regression model
  - ❏ C = 1.0
- ❏ Naive Bayes model
  - ❏ Alpha = 0 .10000000000000001

More parameters will be tuned when I deal with class imbalance.

Text Processing (Emoji Encoded Data)	Naive Bayes	Logistic Regression
Clean text	0.868617	0.882544
Stop Words	0.833333	0.847725
Stemming	0.831476	0.854225
Lemmatization	0.831941	0.848189

Conclusions about Models

Model accuracy effects from using emojis as sentiment predictors:

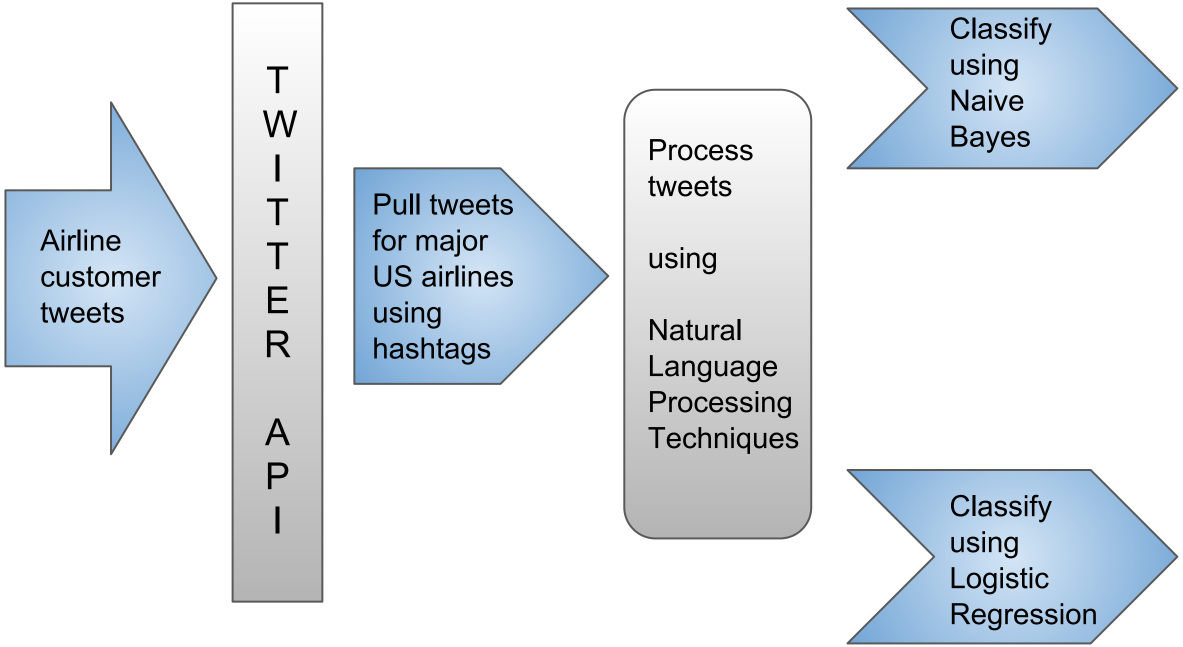
Text Processing	Naive Bayes	Logistic Regression
Clean Text	+ 0.0465%	+ 0.8355%
Stop Words	+ 0.0930%	+ 0.1856%
Stemming	+ 0.0003%	- 0.1858%
Lemmatization	+ 0.0463%	+ 0.5103%

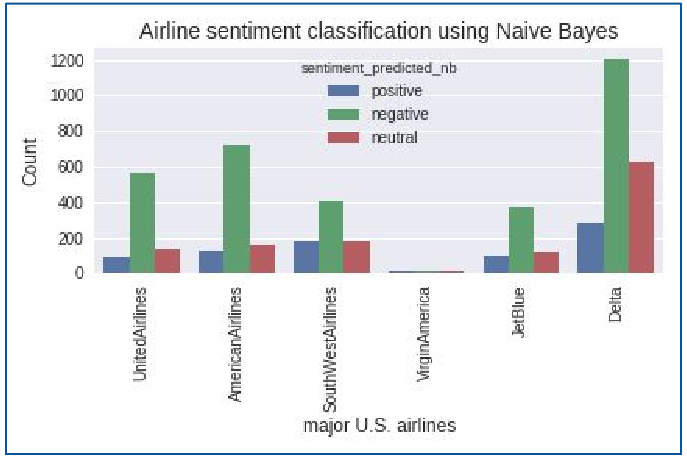
Model accuracy effects from tuning some hyper-parameters (emoji encoded data):

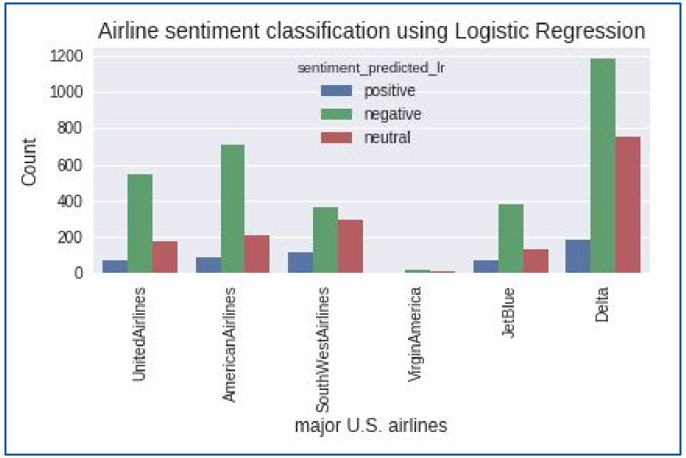
Text Processing	Naive Bayes	Logistic Regression
Clean Text	+ 10.12%	+ 5.803%
Stop Words	+ 5.292%	+ 5.850%
Stemming	+ 4.642%	+ 8.82%
Lemmatization	+ 4.828%	+ 6.9642%

- **Encoding Emojis:**
  - Logistic Regression model accuracy seems to improve a significant amount, with the exception when using stemming.
  - Naive Bayes also improves model accuracy, although less than Logistic Regression. However, when using stemming, Naive Bayes accuracy is unchanged, whereas Logistic Regression’s decreases.
- **Tuning model hyper-parameters:**
  - Logistic Regression and Naive Bayes have significant model accuracy gains by tuning hyper-parameters.
  - Naive Bayes has the highest accuracy gain when using data that is only cleaned and emoji encoded.
  - Logistic Regression has the highest accuracy gain when using data that has stemming applied.

Classify airline tweets from Twitter


Airline customer tweets
TWITTER API
Pull tweets for major US airlines using hashtags
Process tweets using Natural Language Processing Techniques
Classify using Naive Bayes
Classify using Logistic Regression





Airline Sentiment Classification

Tweet: Kudos to the #unitedairlines staff for helping us with our crazy reservations. Nice send-off from CHS
Sentiment Prediction NB: positive **Sentiment Prediction LR:** positive

Tweet: @united YESSSSSSSSSSSSSSSSSSSSSSSSSSS! I don't know how today can get any better, this is amazing! #ThankYou #UnitedAirlines #FlyingTheTahitiSkies
Sentiment Prediction NB: positive **Sentiment Prediction LR:** positive

Tweet: A peek inside Classified, where CEOs and celebrities dine in a hidden restaurant at Newark Liberty International Airport. https://t.co/bpmhavKTSh #TableReady #speakeasy #UnitedAirlines #exclusive
Sentiment Prediction NB: neutral **Sentiment Prediction LR:** neutral

Tweet: @united That's too bad. 😞 #YYJ would love some more #UnitedAirlines service choices✈️
Sentiment Prediction NB: positive **Sentiment Prediction LR:** negative

Tweet: Montreal, Canada to Phoenix, Arizona for only $271 CAD roundtrip with United. #UnitedAirlines #Montreal https://t.co/3PErNhmXZ0
Sentiment Prediction NB: negative **Sentiment Prediction LR:** neutral

Tweet: I am really pissed off with @united   Luggage missing since Jan 3 and no one from the airline has made any attempt to explain the problem #unitedairlines does not care
Sentiment Prediction NB: negative **Sentiment Prediction LR:** negative

Next Step: Dealing with class imbalance

- ❑ Resample the most frequent class to have a similar size as the other classes.
- ❑ Tune the penalty hyperparameter of Logistic Regression.
- ❑ Evaluate other algorithms which deal well with imbalanced datasets.
    - ❑ Decision trees may perform well on imbalanced datasets. The splitting rules that look at the class variable used in the creation of the trees, can force both classes to be addressed.

Questions?

To test out my airline sentiment classifiers go to:

http://34.212.204.117:5000/predict-sentiment-interface