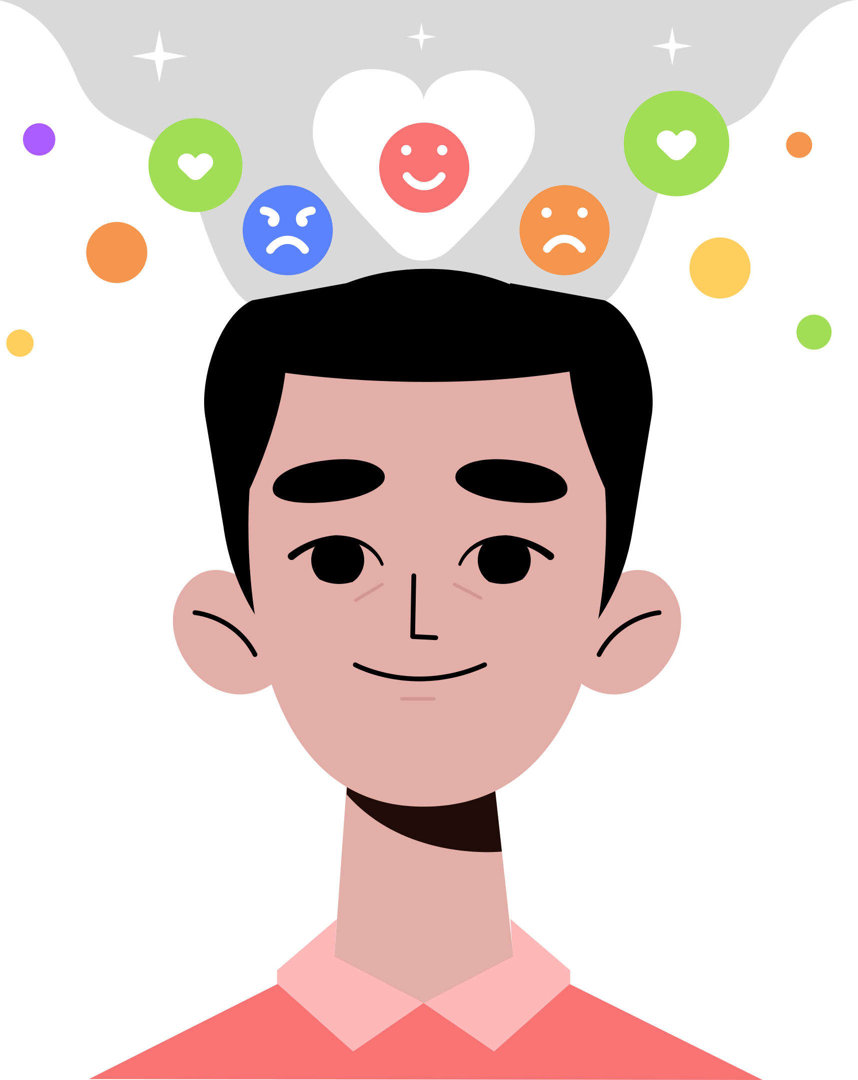


# Twitter Sentiment Classifier

Gaining actionable insight from social media data

The outline for today's presentation will begin with a discussion of the business problem being addressed. More on that in a bit. Next we will talk about the twitter data used for building a machine learning classifier. Next, we will discuss methods for gaining insight from twitter data, and we will discuss methods for building a sentiment classifier. After that we can see some results and go over some conclusions. We will finish with a brief discussion of future work. Now, lets put our attention back on the business problem and go over that in more detail.

Product Sentiment Analysis: Proof of Concept

## 01 Business Problem

Process and classify twitter text data to gain insights on a brand and associated products.

## 02 Data

Labeled twitter data relating sentiment to brands and products

## 03 Methods

Methods for gaining insight from twitter data and for building a classifier

## 04 Results

Evaluation of model performance and insights gained from test models

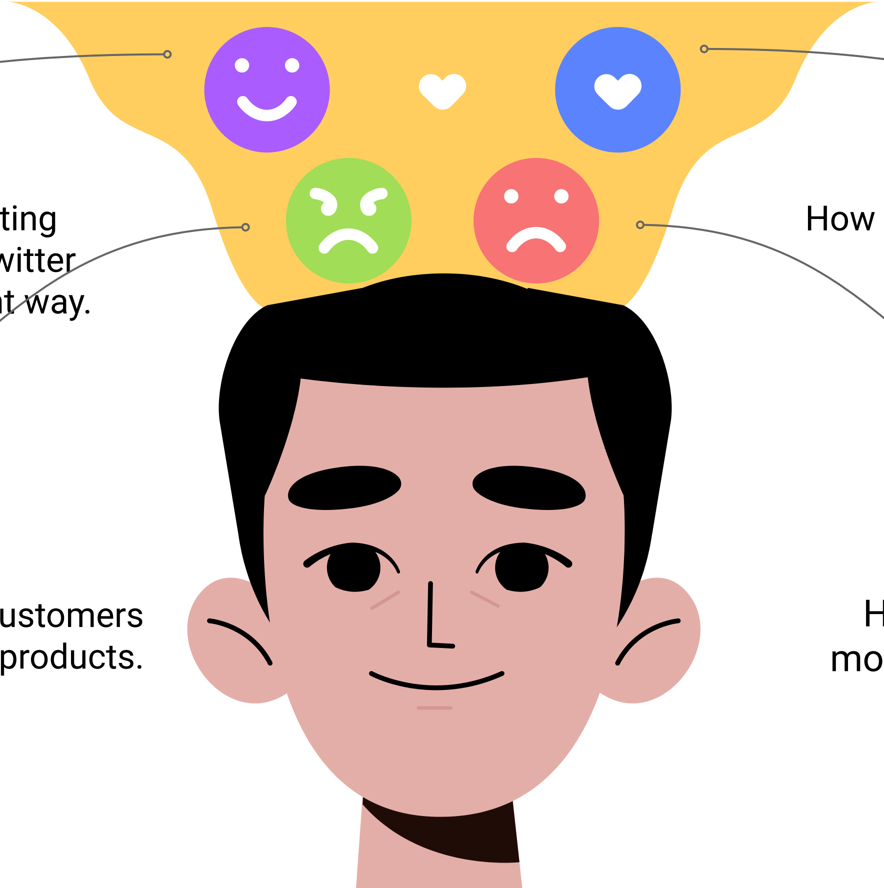
## 05 Conclusions

Conclusions?

## 06 Future Work

Future Work?

A company wants to explore ways to gain actionable insights from twitter text data in a more efficient way. They want a PROOF OF C of how a MLC could help. They are interested in SENTIMENT, which is to say how their customers feel about their brand and products. Finally, we need to know How can we trust the MLC to make fair predictions?



01

**Twitter Data**

explore options for generating actionable insights from twitter text data in a more efficient way.

02

**Proof of Concept**

How could machine learning be deployed to help?

03

**Sentiment**

interested in what their customers feel about their products.

04

**Balanced Accuracy**

How well can we trust the model to make predictions?

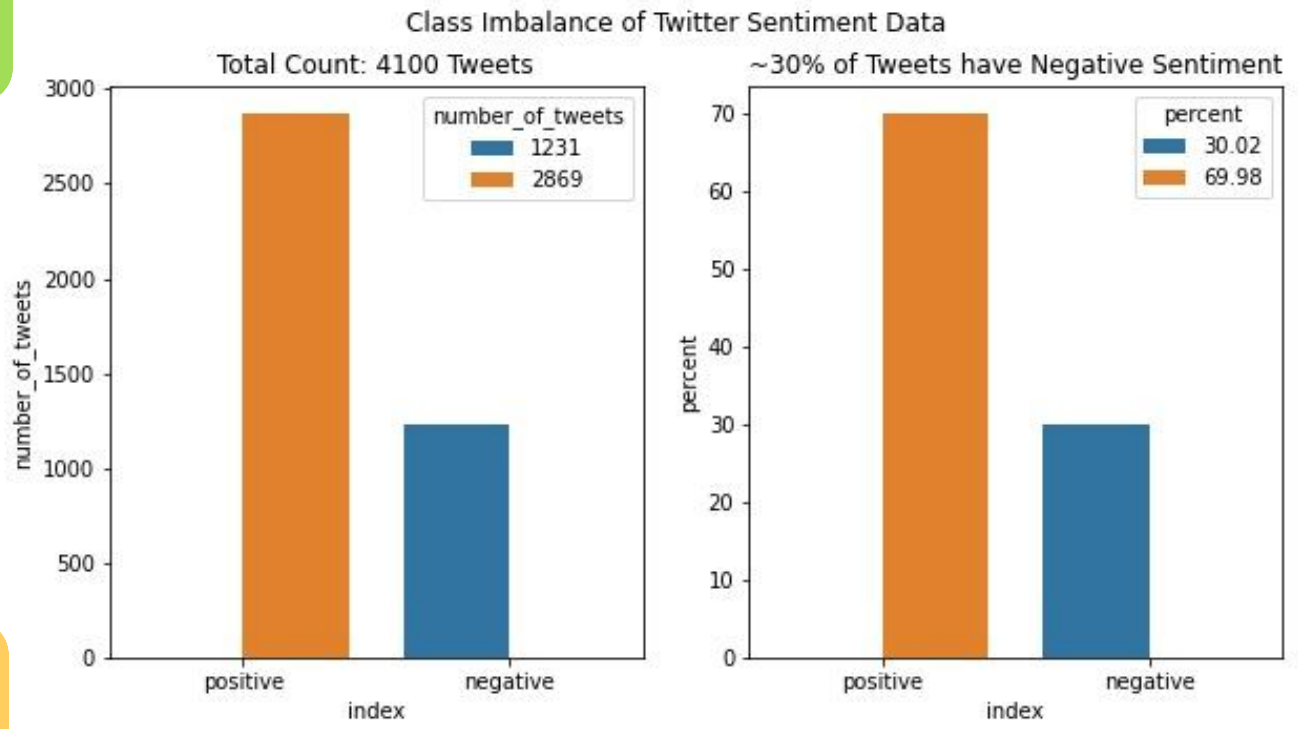
# The Data

Crowdsourced labeled tweets from 2011 SXSW event (Apple/Google)

**Labeled Twitter Data**

Sourced from CrowdFlower

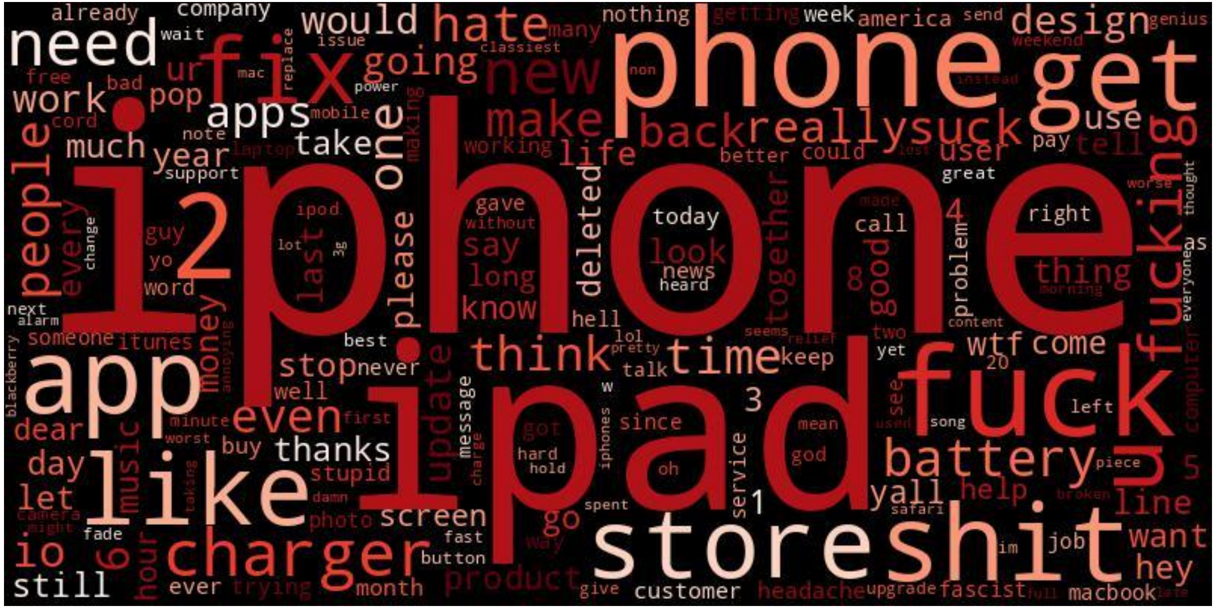
Additional sentiment labeled data available from CrowdFlower (Apple)



# Methods: Natural Language Processing

## Word Clouds

Use word frequencies to construct quick visualization of what customers do not like apple a company or product




## PMI Scores

Calculate Pointwise Mutual Information to create bigrams, trigrams, and quadrgrams

| | word_triplets | PMI |
|---|---|---|
| 0 | (heat, million, sun) | 21.286869 |
| 1 | (button, heat, million) | 20.412400 |
| 2 | (classiest, fascist, company) | 18.129017 |
| 3 | (back, button, heat) | 17.876347 |
| 4 | (fascist, company, america) | 17.851483 |
| 5 | (news, apps, fade) | 16.106960 |
| 6 | (ipad, design, headache) | 13.715867 |
| 7 | (ipad, news, apps) | 12.436422 |
| 8 | (ipad, back, button) | 12.298918 |
| 9 | (iphone, battery, life) | 10.537000 |

# Methods: Classification Evaluation

# Model Performance Matrix

**Key Metric: Balanced Accuracy**

average of recall obtained on each class

| **ACTUAL** | | |
|---|---|---|
| Positive Tweet | **True Positive Tweet**<br>A tweet that is correctly predicted to contain positive sentiment by model. | **False Negative**<br>The model incorrectly identifies a tweet that contains positive sentiment as one that contains negative sentiment. Given the context of the business problem, this would mean extra noise added when trying to isolate for negative sentiment of brand/product. |
| Negative Tweet | **False Positive**<br>A false positive would occur when the model incorrectly identifies a tweet containing negative sentiment as a tweet that contains positive sentiment. Given the context of the business model, this would mean more truly negative sentiment will be left out of analyzing key word pairs for negative tweets. | **True Negative Tweet**<br>A tweet that is correctly predicted to contain negative sentiment by model. |
| **Predicted** | Positive Tweet | Negative Tweet |

# Results: Balanced Random Forest Classifier

**81%**

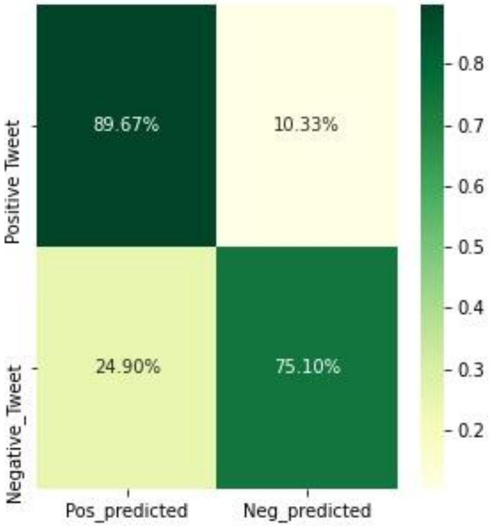
**Balanced Accuracy**

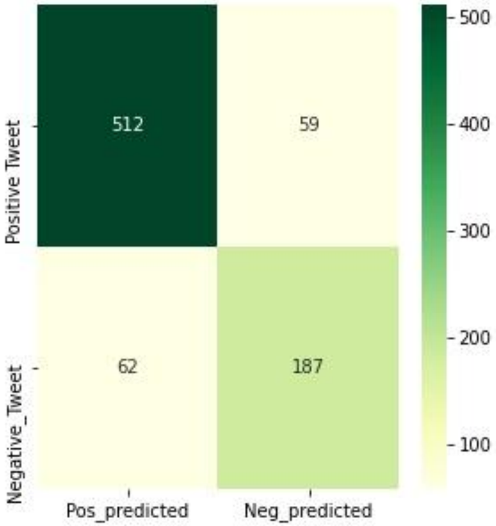
Despite being red, Mars is a cold place

**Tuned**

**Hyperparameters**

Tuned for balanced accuracy with gridsearchCV




See the appendix for more model results. The one shown here is the best performing supervised model.

# Results: BERT_base Sentiment Classifier

**~87.3%**

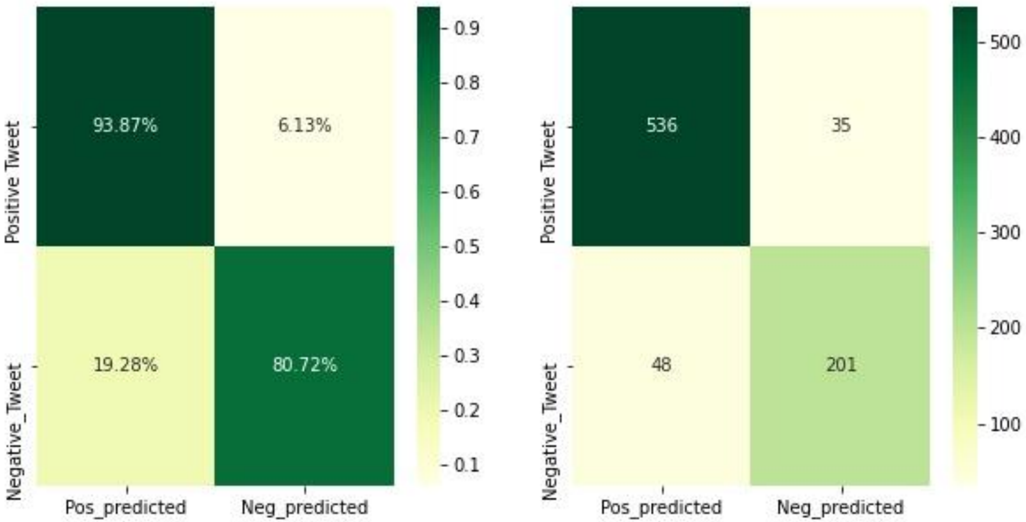
**Balanced Accuracy**

Despite being red, Mars is a cold place

**pre-trained**

**Convoluted network**

Transfer learning takes advantage of gigantic model




See the appendix for more model results. The one shown here is the best performing BERT model.

# Conclusions and Future Work

Either classifier could be used to predict sentiment on new brand-centric social media data for the company's own products or that of a competitor

- Use the BERT classifier to predict the sentiment on new unlabeled twitter data filtered for product or brand of interest (Apple/Google) from another source to find more actionable insights to further proof of concept.

- Use the BERT classifier to predict the sentiment on new twitter data to help balance existing dataset and retrain the other models.

- leverage a state-of-the-art early stopping algorithm (ASHA) using Ray Tune and PyTorch

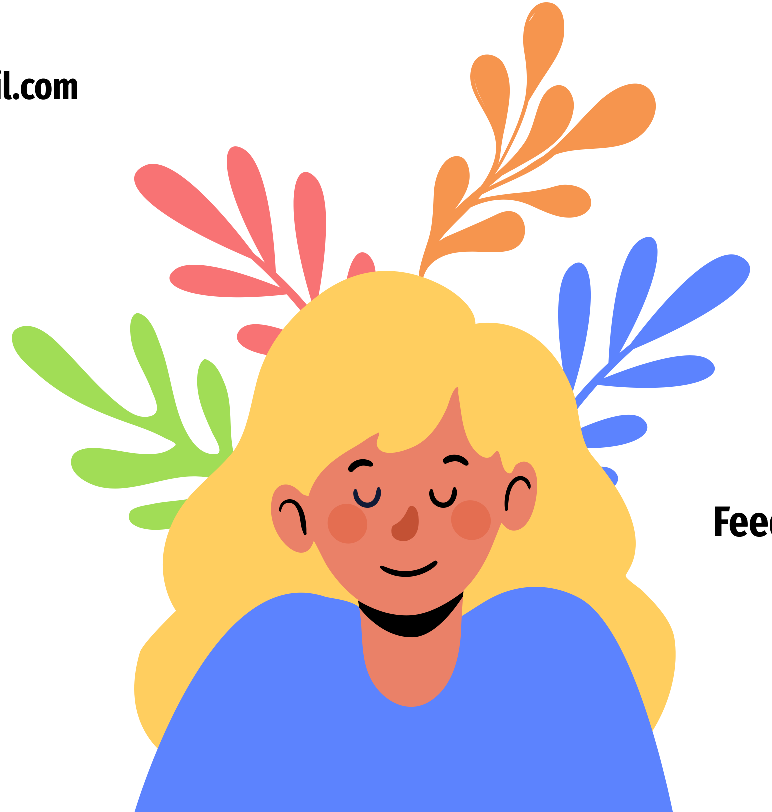
# Thank You

## Email

ddey2985@gmail.com

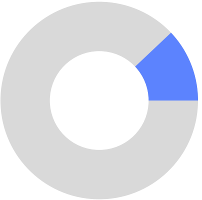
## Github

Project Link



## Blog

Blog Link



## Thanks

Feedback Welcome