# Investigating Social Value of Food Products using Population’s Sentiments

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# Research Goal

Our project aims to leverage text mining and sentiment analysis tools to shed more light on what what importance the community places on different foods (social value) so as the better understand if the community’s sentiments towards different foods are aligned with their economic value

# Sentiment Classifier with Supervised Learning for Positive or Negative Sentiment

- We trained our model using the bert-base-uncased model, and the full version of BERT (12 layers and 768 dimensions).

**Training and Model Evaluation**

- Sentiment140 dataset, consisting of 1.6 million  pre-labeled (positive,or negative) tweets used for training.
- Achieved an accuracy of 82.6% on our test data, with bootstrap 95% confidence intervals of 81.5% to 83.8%.
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**Testing Model on Food**

- Extracted Tweets from the Twitter API using the Tweety package
- Specified two lists of ten keywords each. The first list contained foods that were exclusively agricultural products (‘apple’, ‘bread’, ‘coffee’), whereas the second list contained foods that were more variable, including processed foods and meats such as ‘ice cream’ and ‘steak’.

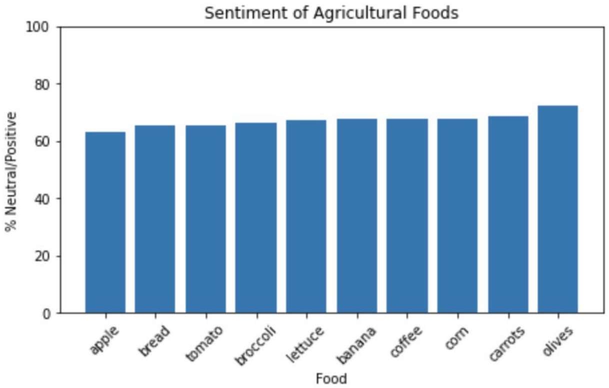
# Results

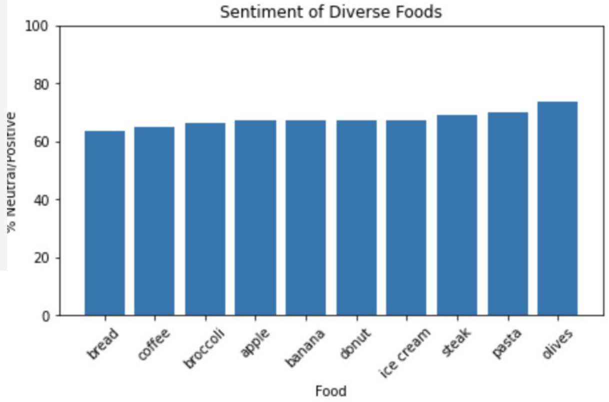
★ No visible differences in sentiment towards tweets with different kinds of foods in them.

★ For each food category, around 65-70% of tweets were classified as neutral/positive.

★ Neutral sentiment may be skewing results.

★ lack of signal in distinguishing sentiment between these groups led us to consider training model on data we annotated ourselves



# Data Annotation

- We created annotation guidelines specifically for sentiments( positive, negative or neutral) on tweets about food.
- Randomly selected tweets

<u>Confusion Matrix</u>

| | Positive | Neutral | Negative |
|---|---|---|---|
| Positive | 21 | 6 | 0 |
| Neutral | 10 | 47 | 0 |
| Negative | 0 | 1 | 3 |

Observed Agreement = 0.81
Cohen’s Kappa = 0.61

# Sentiment Classifier Using Annotated Data on Coffee

## Annotations

- We selected coffee as a demo food product to use for our annotations analysis. We annotated 1000 tweets with the keyword ‘coffee’ as positive, neutral or negative.

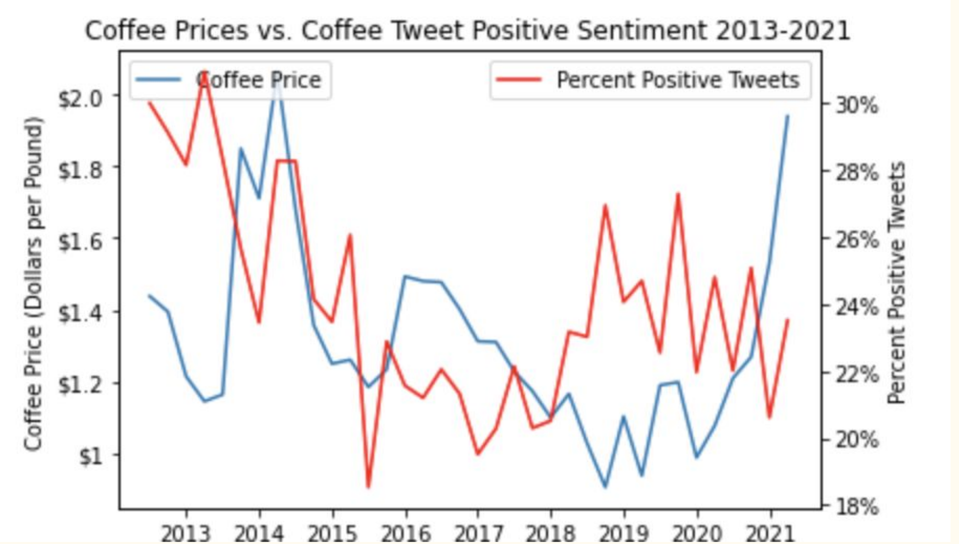
## Model Training and Evaluation

- We then trained our formerly created BERT sentiment classifier on these annotations. We achieved 71% accuracy with confidence intervals of 63% and 78% against an accuracy majority class baseline of 57%, indicating a 14% improvement in accuracy against a baseline model.

# Time Series Analysis Between Coffee Sentiment and Price

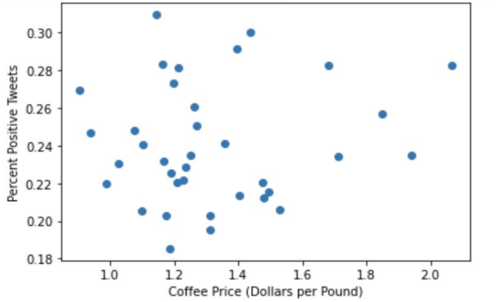
Time Series Data Aggregation and Analysis

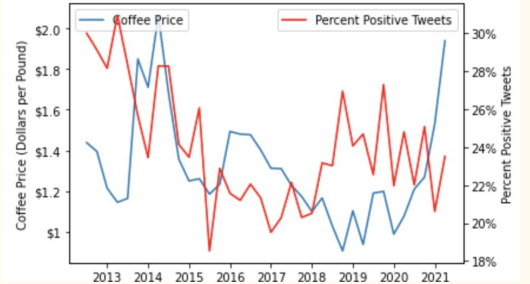
- We classified the sentiment of 50,000 tweets spanning a period of 9 years and then compared the resulting time series to coffee price data over the same time period and assessed whether there was any correlation between the two datasets.
- We viewed no visual correlation in the data and a Pearson correlation coefficient measure revealed no statistically significant correlation between the two time series.

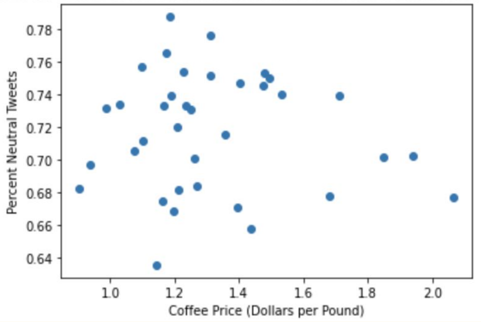


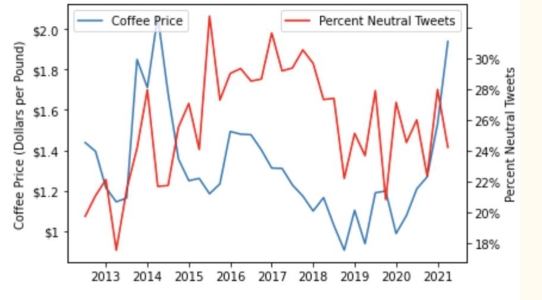
# Correlating Sentiment to Price

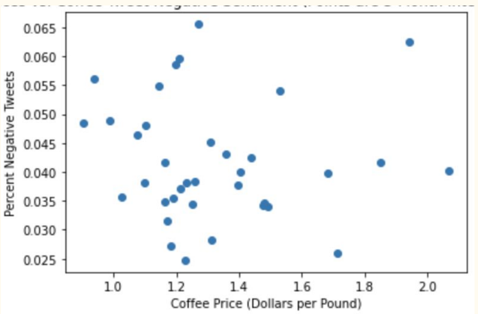
- ★ On the Left panel, we show the trend in coffee prices from 2013 - 2021.
- ★ We overlay our sentiment trends, positive, neutral and negative respectively for the same period.
- ★ On the right panel, from the top to bottom, we provide scatter plots of coffee prices versus sentiment, positive, neutral and negative respectively for the period of 2013-2021.
- ★ Time resolution = 3 months

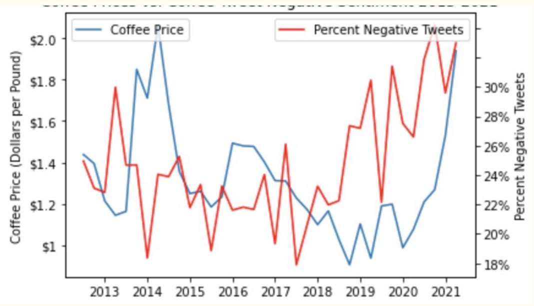


# Conclusion

- ★ we used sentiment140 dataset, consisting of 1.6 million pre-labeled (positive or negative) tweets used for training of our sentiment classifier.
- ★ We developed annotation guidelines specifically for sentiments( positive, negative or neutral) on tweets about food. We obtained a Cohen’s Kappa value of 0.61.
- ★ We then created 1,000 annotations using these guidelines for the food product coffee and trained our sentiment classifier using these data. Using the resulting classifier, we classified the sentiment of 50,000 tweets with the keyword ‘coffee’ over the course of 9 years and assessed whether there was a relationship with coffee prices over this time period.
- ★ Our results showed that there was no statistically significant relationship between these variables over the given time period.

# Next Steps

★ In the future, we plan to annotate other food tweets, train our sentiment classifier on these annotations and assess the relationship between food sentiment and other kinds of variables.

★ One limitation to our model is that we only used 1000 labeled tweets to train our classifier. In the future, we would like to increase the number of labeled examples so as to improve our classifier.

★ In addition, we will include in this looking at fad foods such as oat milk or kale to see if our food sentiment data correlates with spikes in popularity of these foods.

# Thank you!