



# Apple Twitter Sentiment Analysis

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A PROTOTYPE RNN



# Business Problem

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Traditional market analysis is:

- Expensive
- Time Consuming
- Low in Information Content

A NLP model can allow for more efficient processing of large amounts of available data on public sentiment on social media

# Project Goals

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- Determine what kind of model would be best of this task
- Test the effects of various model features
- Construct a prototype sentiment analysis model

# Data

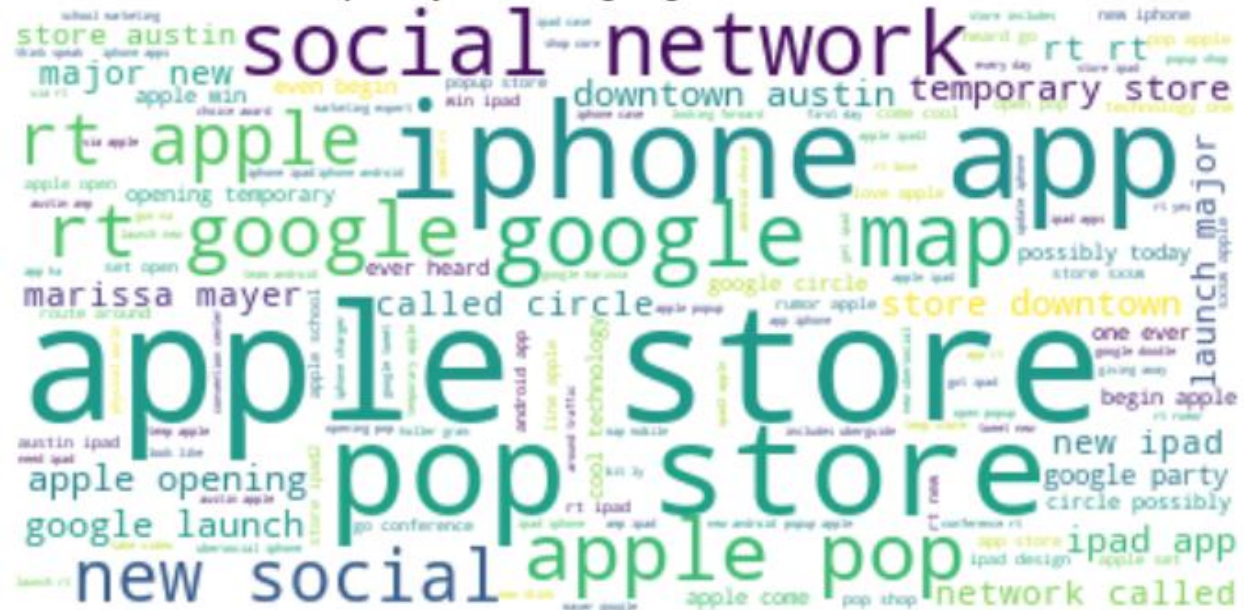
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Data was taken from data.world and consists of:

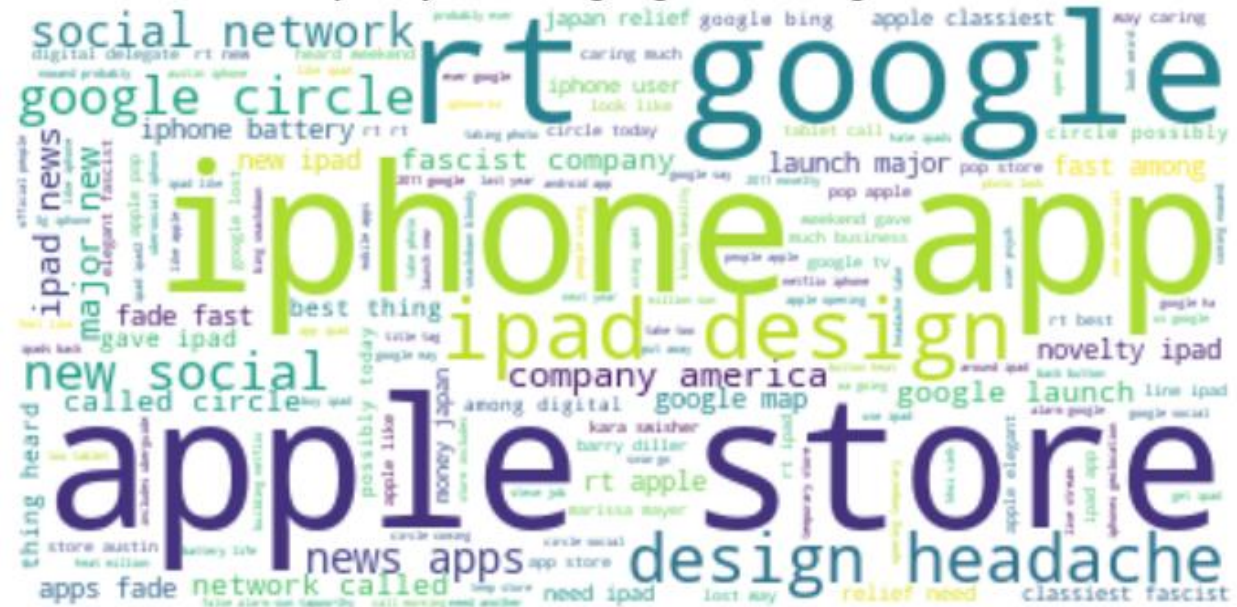
- 9203 tweets from the #SXSW hashtag
- All tweets contain keywords mentioning Apple or Google products
- Tweets were labeled by crowd sourcing as having either positive, negative or neutral sentiment to the brand
- 61% of the tweets were neutral, 33% positive, and only 6% negative

# Visualizing the Data

### Most Frequently Occurring Bigrams in Positive Tweets



### Most Frequently Occurring Bigrams in Negative Tweets



# Models and Features Tested

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## Models

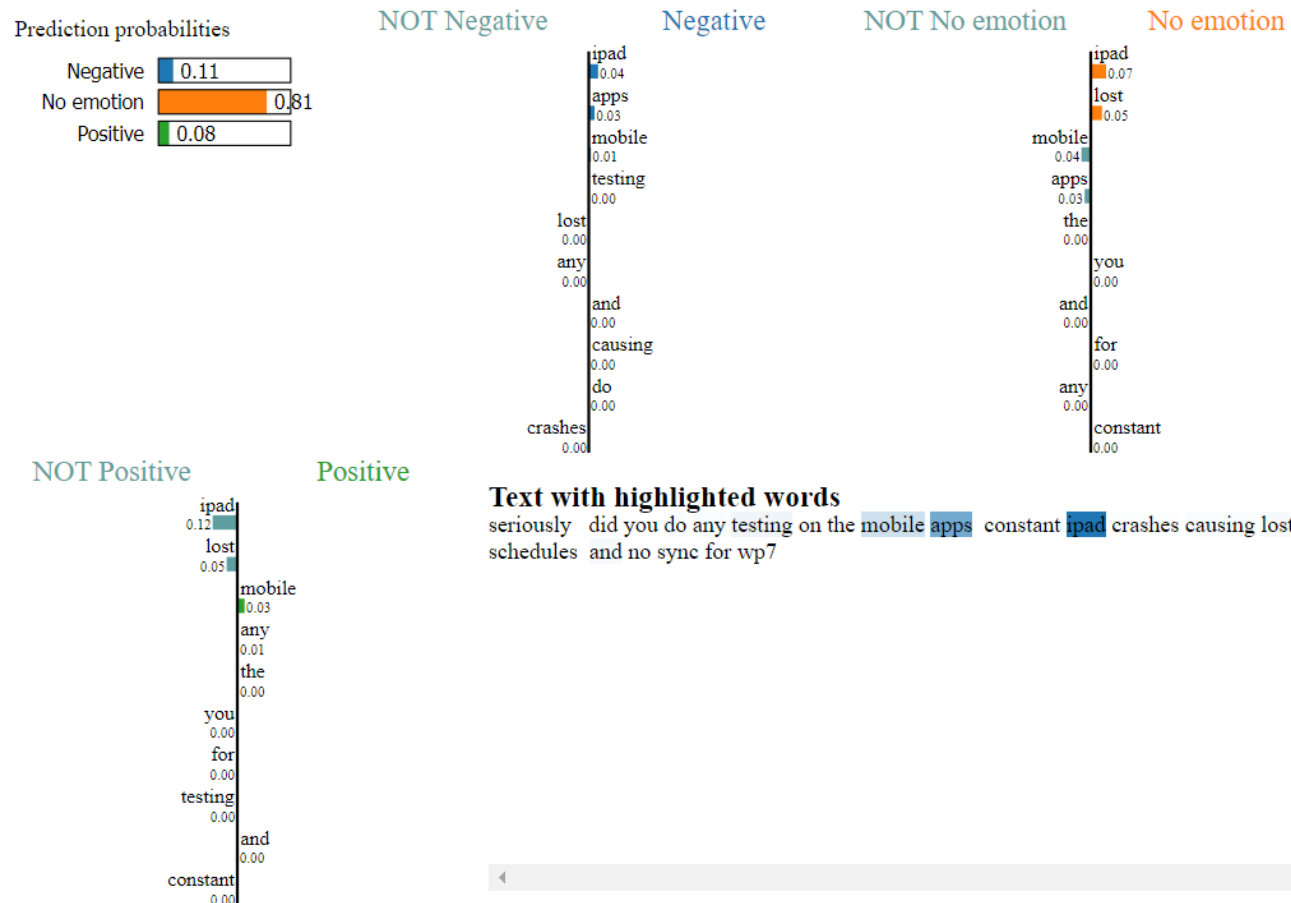
- Naïve Bayesian
- Logistic
- Random Forest
- SVC
- RNN

## Features

- GloVe vs Custom embedding
- Class Weighting
- Augmentation with Synonyms
- Depth
- Number of Nodes

# Limits of Tradition Models in NLP

```
In [230]: exp_forest.show_in_notebook(text=data[idx])
```

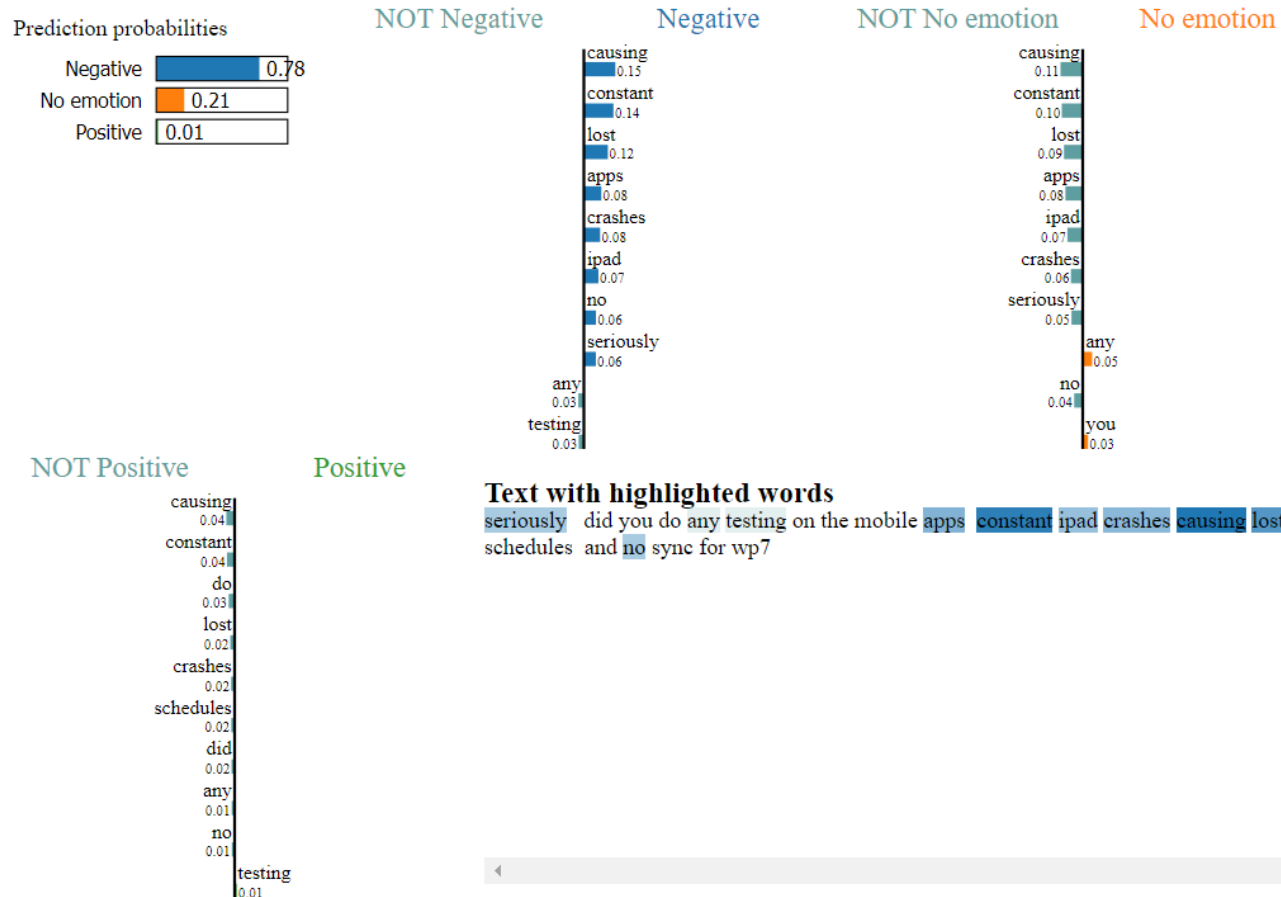


We can see in this example that:

- 1) The model failed to recognize this was a negative tweet
- 2) It failed because it was unable to recognize the relevant features



```
In [232]: exp_pipe.show_in_notebook(text=data[idx])
```



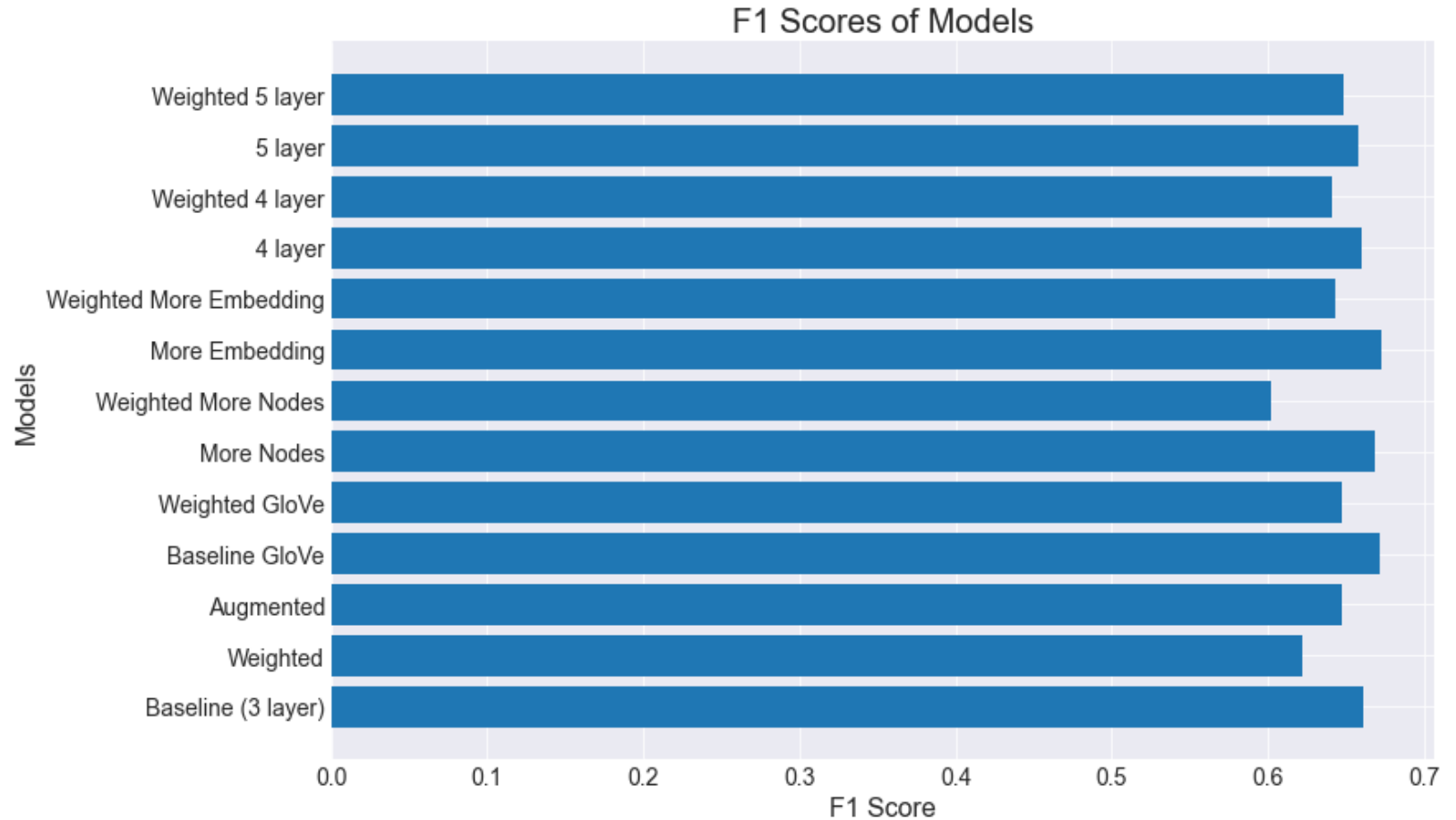
# Advantage of RNN in NLP

We can see in this example that:

- 1) The RNN correctly identified this was a negative tweet
- 2) It correctly picked up on some of the clearly negative wording, though not perfectly

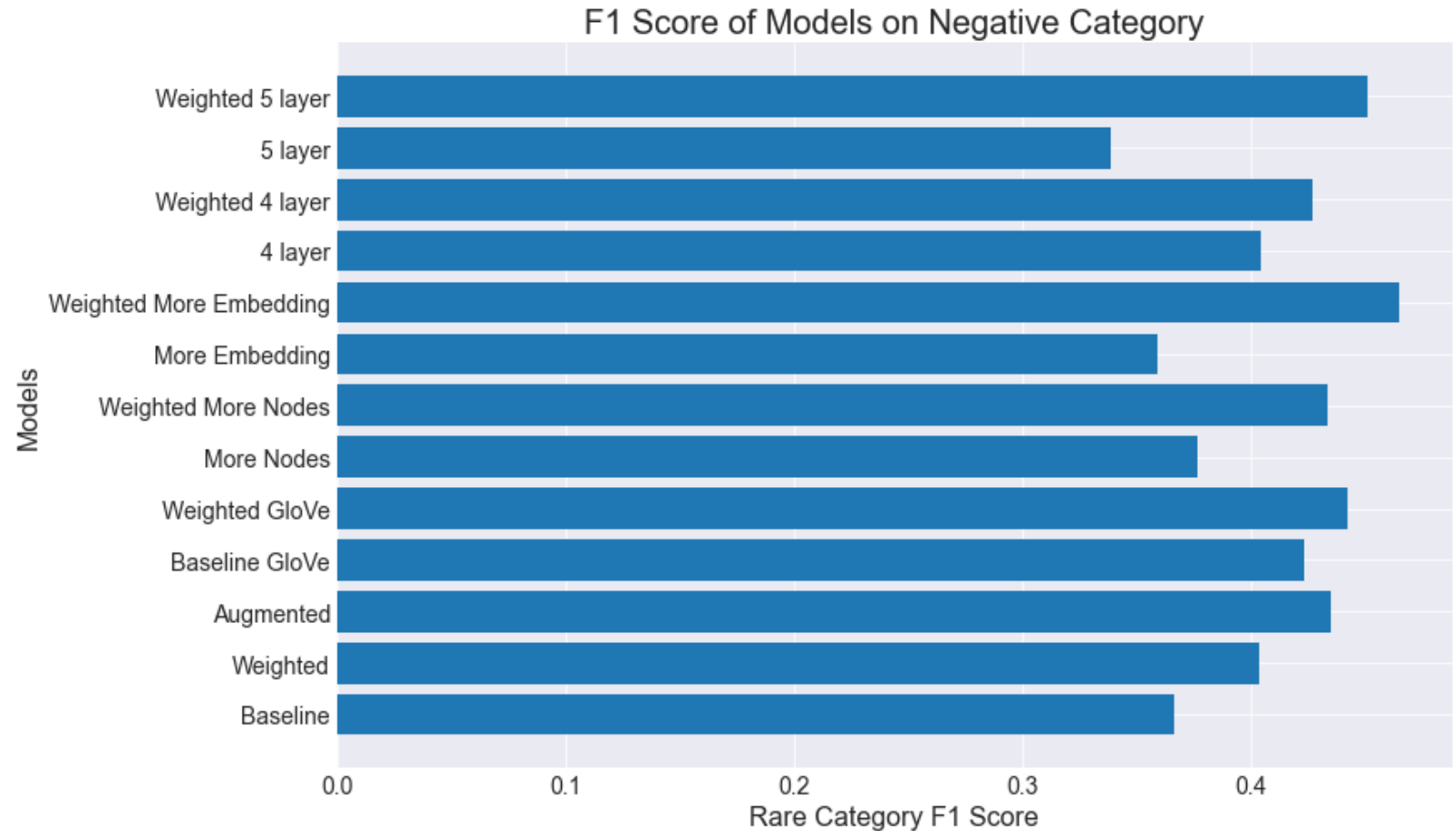


# Comparing Model Features by Overall Performance



- Weighted models tended to do worse overall
- GloVe embedding showed some improvement
- Synonym augmentation did not improve performance
- Differences in structure were minimal on this data set

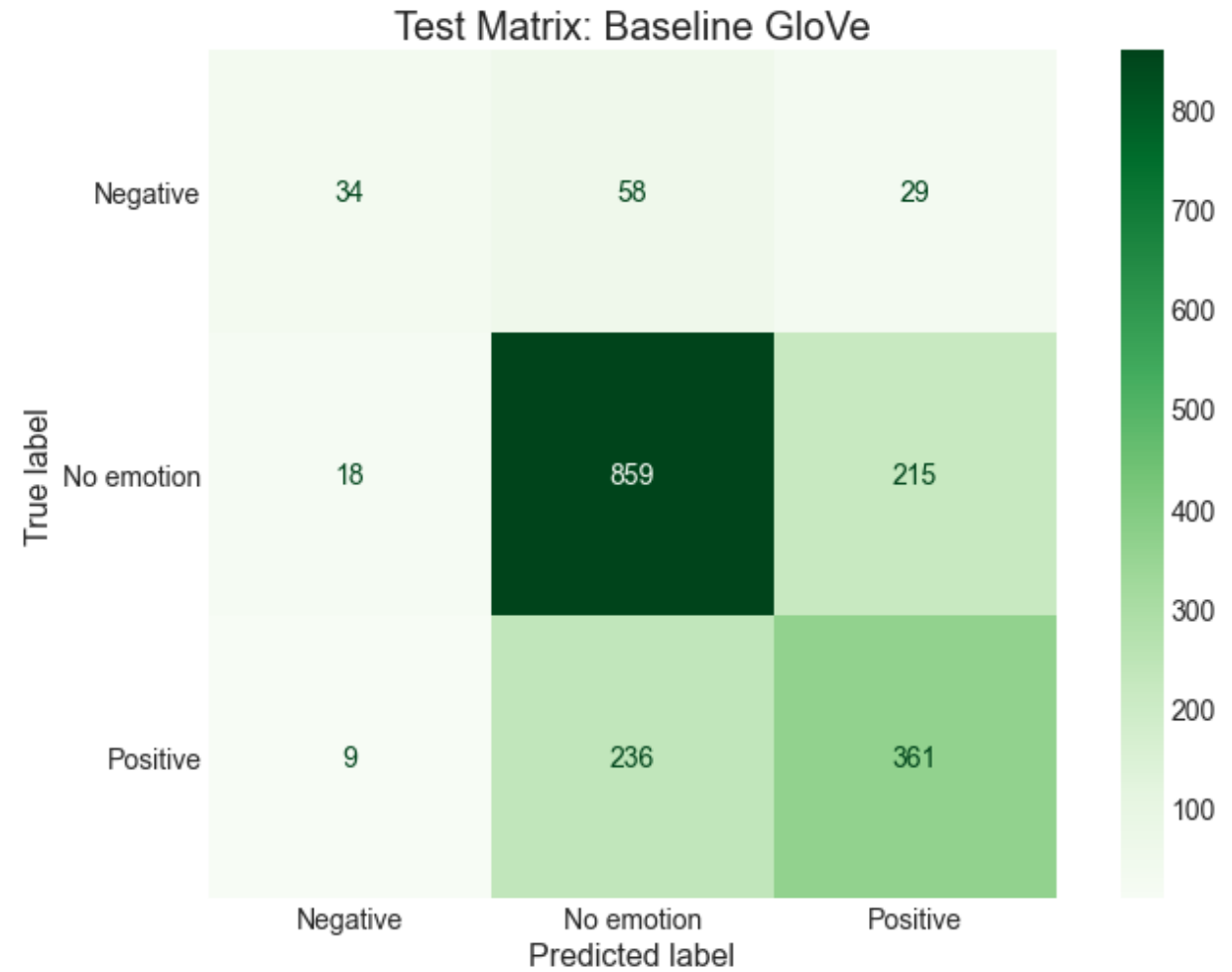
# Comparing Model Features by Performance on Rare Data



- Weighted models tended to do better on rare data
- Pretrained or more embedding improved performance on rare data
- Deeper networks were somewhat better on rare data

# Final Model On Test Data

GloVe model had the highest weighted F1 score of 68%



# Conclusions

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- RNN are promising tools for sentiment analysis and should be used in this kind of analysis *given sufficient data*
- Improvements by using RNNs can be small if the data is limited, there was only a 4% improvement in F1 score (68% for RNNs versus 64%) using a dataset this small

# Limitations

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- Data was specifically taken from a hashtag that was more likely to contain tweets talking about brands and products. This potentially places limits on its generalizability
- Given the extreme class imbalance in this data set, the performance on the rare category is not very likely to be reliable

# Contact Information

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Github for this project

<https://github.com/nonlocal-lia/sentiment-analysis-project>

