## Sentiment Analysis ML Report

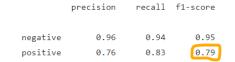
## Models

- A Logistic Regression based classifier using the bag-of-words representation of texts as vectors. Simple data pre-processing employed (removing punctuation and contractions). Works well and is computationally and development-time-wise effecient. Useful as a baseline.
- A Naive Bayes based classifier with tokenization and slightly more advanced data preprocessing (regex to remove links, etc.). Still the same principle though. Useful as a sanity check because it can model feature importance so it can be verified that the words that indicate positive/negative sentiments make sense (e.g. "wonderful" and "fantastic" strongly indicate positive sentiment according to the model which makes sense).

## **EDA** and Metrics

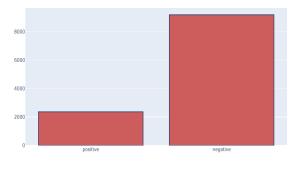
During data exploration, it was clear that the training data distribution was biased (more negative than positive observations/texts). So I opted for evaluating the models using precision and recall as summarized by the **f1-score** instead of possibly misleading accuracy scores.

Logistic Regression had a score of 79%



Naive Bayes scored 74% on test data

	precision	recall	f1-score
Negative	0.98	0.92	0.95
Positive	0.64	0.88	0.74



Both fared comparably on regular accuracy (about 92% correct predictions) so I chose to use the Logistic Regression for the API.

## **Model Tuning**

I varied two hyperparameters:

- Amount of training data (from 50 to 80%) using a fixed amount (20%) of test data
  - To understand the tradeoff between high variance and high bias
  - o 80% yielded the best f1-scores on test data
- Type of data pre-processing
  - Did not seem to have a significant effect whether or not I removed punctuation, etc. (or used twitter specific tokenizers)

I just varied these parameters manually in a notebook since the models were so simple. If I was to spend more time on this project, I would want to look at tuning regularization and other parameters using a more automated cross validation setup.