DeepFX: foreign exchange market prediction using technical features and sentiment analysis

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Prediction

The motivation of this project was to use deep learning principles, specifically Recurrent Neural Networks (RNNs) in order to predict foreign currency exchange market fluctuations. The inputs can be split up into two categories: sentiment data (Reddit World News Headlines with a custom embedding) and technical indicators (computed from market time series data). These inputs were process, **combined,** and fed into a deep LSTM-based RNN in order to categorically predict whether the future value of GBP/USD foreign exchange rate would increase or decrease.

Data

The input data for our network can be split up into two categories: sentiment and technical indicator data. Daily values were collected from 8-08-2008 to 7-01-2016 when the market was open.

Sentiment Data: News headlines were scraped from the Reddit World News subreddit for dates. The raw text of the top twenty-five headlines (defined by number of upvotes) was preprocessed and merged into one long sentiment input per day.

Technical Data: GBP/USD daily foreign exchange rates (High, Low, Open, and Close) were downloaded from Yahoo Finance. Additionally, we obtained the closing values for correlated assets such as currency exchanges EURO/GBP, EURO/USD, GBP/JPY, USD/JPY, GBP/CNY, and USD/CNY, as well as global market indicators such as the Dow Jones Index, NASDAQ, FTSE 100, Nikkei 225, Treasury Yield (a measure of interest rate), and VIX (a general market volatility measure).

Output Labels: Close of GBP/USD rate on each day was compared to that of previous day. An increase in the closing price —> 1, a decrease —> 0.

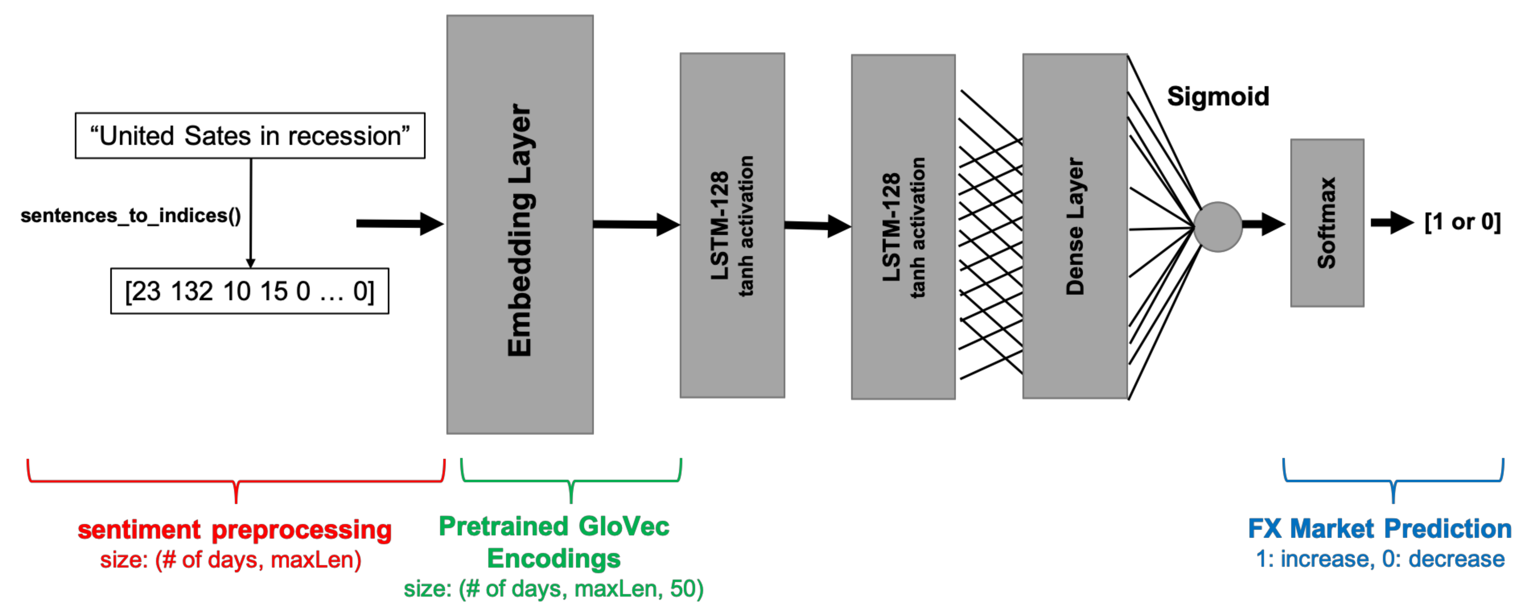
Features

Accurate feature extraction was the most critical component of our predictive model. We used two different approaches to define features for 1-sentiment and 2-technical data:

Sentiment Features

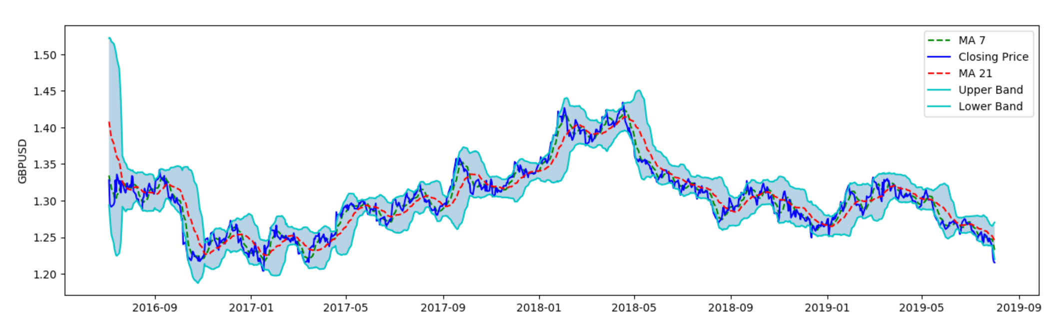
For each market day twenty-five headlines from reddit.com/r/worldnews were concatenated into one long text string. Words in the string were converted to dictionary indices and mapped to pre-trained GloVe 50 dimensional vectors using an embedding layer.

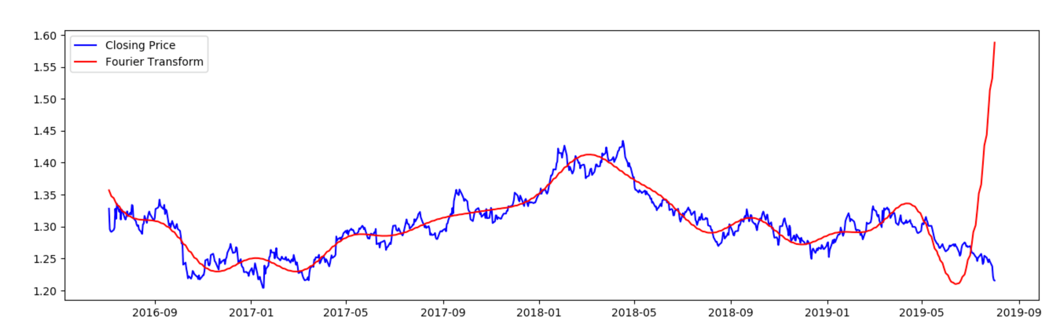
These embedded words were then used to train two LSTM layers with binary cross-entropy loss to generate 128 activations (or "forex-related embeddings") to be used as features in the main network.



Technical Features

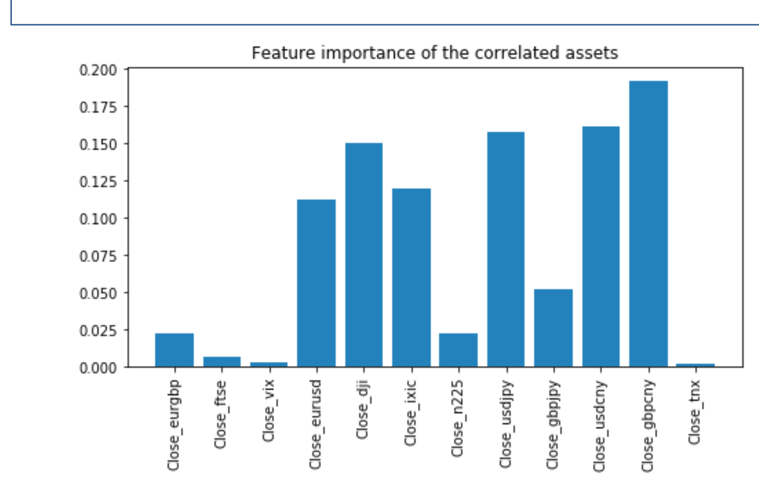
GBP/USD closing prices were processed using conventional technical analysis techniques. For ~2,000 days of closing price data we computed 7 and 21-day moving averages, Bollinger Bands, exponential moving averages, momentum, and 40-component Fourier transform. We combined these features with unaltered closing prices of the correlated assets mentioned previously.

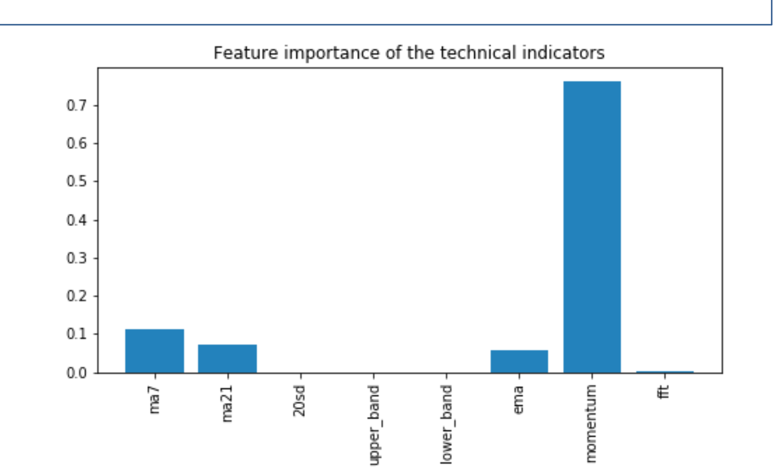




Assessing Feature Performance

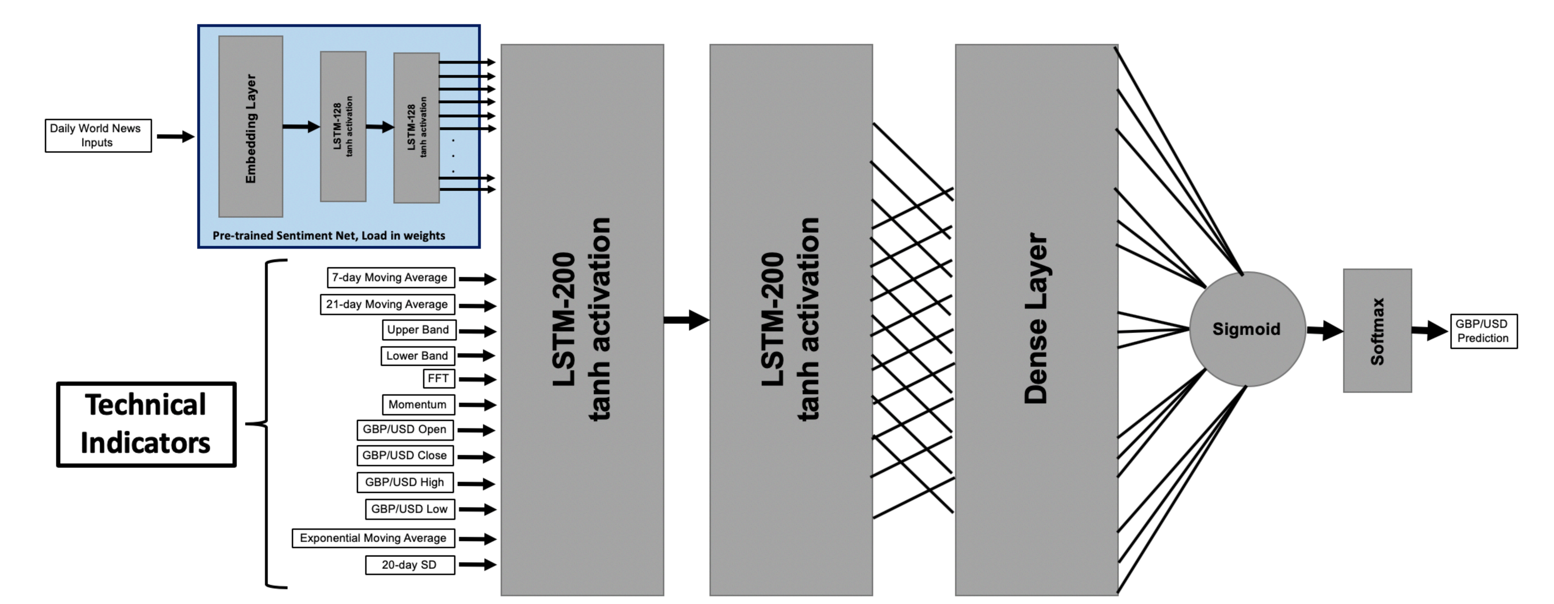
We implemented gradient-boosted decision trees using the XGBoost module in Python in order to assess importance of the correlated asset and technical features.





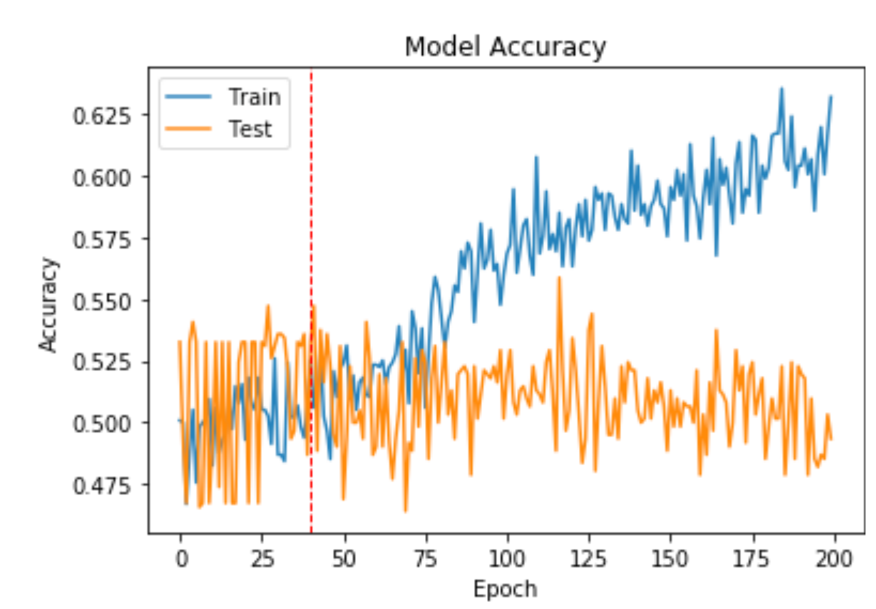
Model

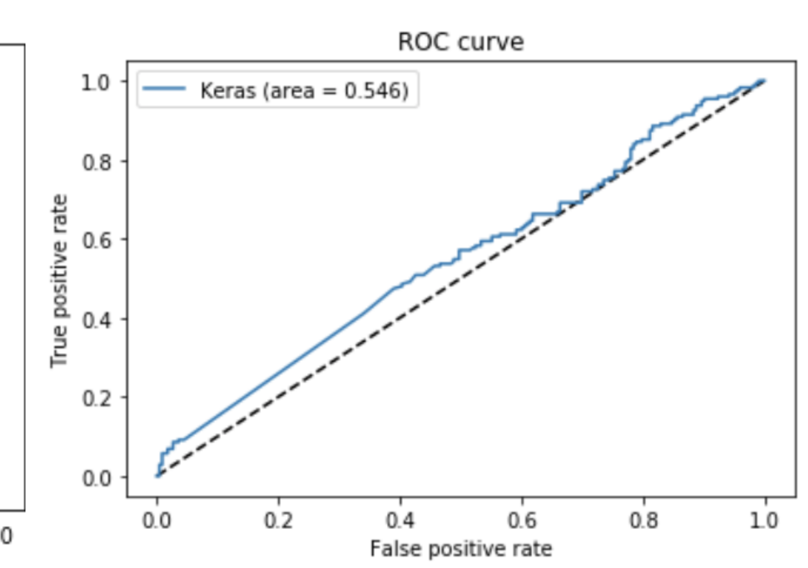
We use a 2-layer LSTM to embed the pre-trained GloVe word embeddings in 128 dimensions. We then feed those as features to a 2-layer LSTM along with correlated asset and technical indicator features to predict whether the market will move up or down.



Results

Our model has a max accuracy of ~55% on most training runs. We obtain similar accuracy results to those reported in the literature. ~40 training epochs is optimal before overfitting begins to occur. The ROC curve corroborates this.





Conclusions & Future Work

Conclusions:

- Combining technical data with sentiment data gives better results than technical data alone, with about 55% accuracy.
- This is the accuracy of state-of-the art forex deep learning models *(ref [X])* and according to their GBP/USD backtesting over a period 3 years one can obtain 10% annual return.

Future Work:

- Collect more headline data from sources other than Reddit. Use finance-specific embeddings.
- Find more assets correlated to national GDP and run NLP on financial reports
- Make half-day or quarter-day predictions (which would also help add more training data)
- Try GANs
- Make multi-class softmax predictions to discern magnitude of increase or decrease.
- Generalize results to other currency markets to diversify portfolio

References

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