Forecasting Netflix Stock Price

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Problem Statement

Background:

Volatile stock market

- Based on periodicity/seasonality
- Sway of news and opinions
- Earnings, expectations, and emotion

Objective:

Will investor sentiment contribute to the accurate prediction of volatility in Netflix next day closing price?

- Netflix is included in the S&P 500 and a FANNG stock
- Use LSTM to accurately predict the next day closing price and its drops and rises

Data

- **Yahoo! Finance:** Two-year (April 22, 2020 to April 22, 2022) historical closing prices of Netflix
- **Twitter API:** Query matching “$NFLX” for the two-year period
    - Only English tweets
    - No retweets

Methodology

VADER	• Lexicon-based library that is designed to handle social media data
BERT model	• Use of Transformer that learns contextual relations between words • Pre-trained on a large dataset of financial text
LSTM model	• Extract periodic patterns from time-series data • Ability to capture relevant temporal patterns and forget irrelevant patterns

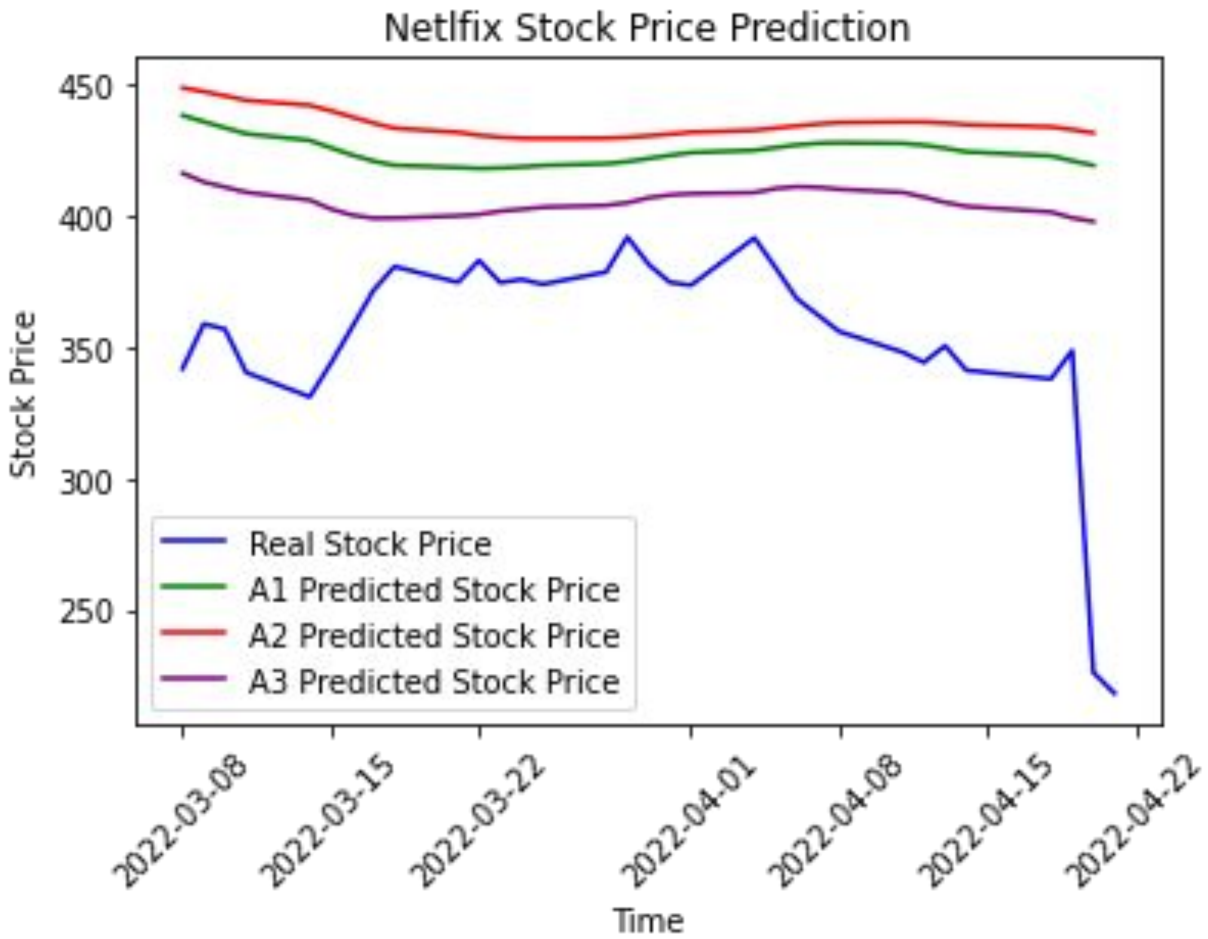
Methodology

- Preprocess tweet data
  - Replace emojis with words using Python package demoji
  - Took a random sample of 40,000 and 80,000 tweets
  - Used VADER to generate polarity of each tweet
  - Evaluated subset labels for no processed and processed tweets
- Hugging Face FinancialBERT fine-tuned using VADER-generated labels
- Apply original FinancialBERT model and fine-tuned FinancialBERT model to the rest of the tweets
- Build LSTM models
  - Only closing price
  - Closing price and sentiment
- Compare results using MAE score and visualizations

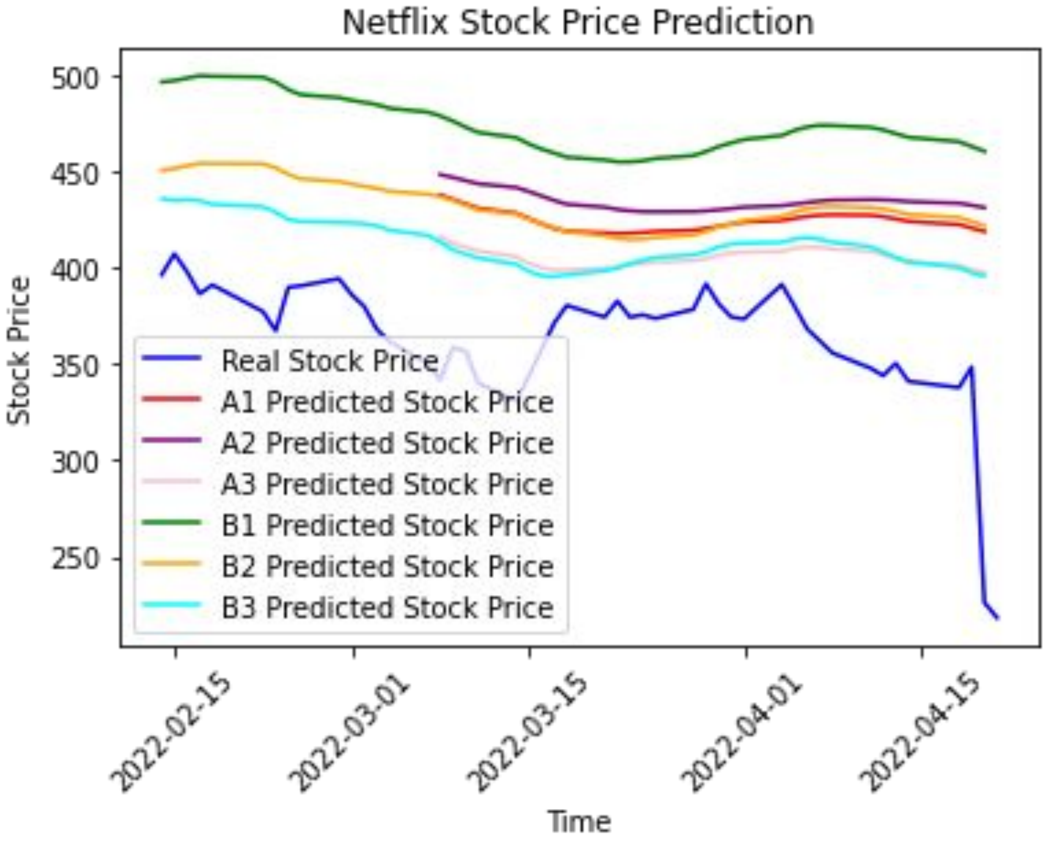
Summary of Results

- Fine-tuning FinancialBert with a subset of 40,000 and 80,000 had an accuracy of 0.33
- FinancialBert did not face much difficulty of classifying tweets as anticipated
- LSTM model with only closing price had the best results with a time step of 5 (using 2 year data)
- The addition of sentiment to the LSTM model improved the accuracy and ability to predict rises and falls of next day closing prices
- Best model: Experiment E.2 Bidirectional Multilayer LSTM

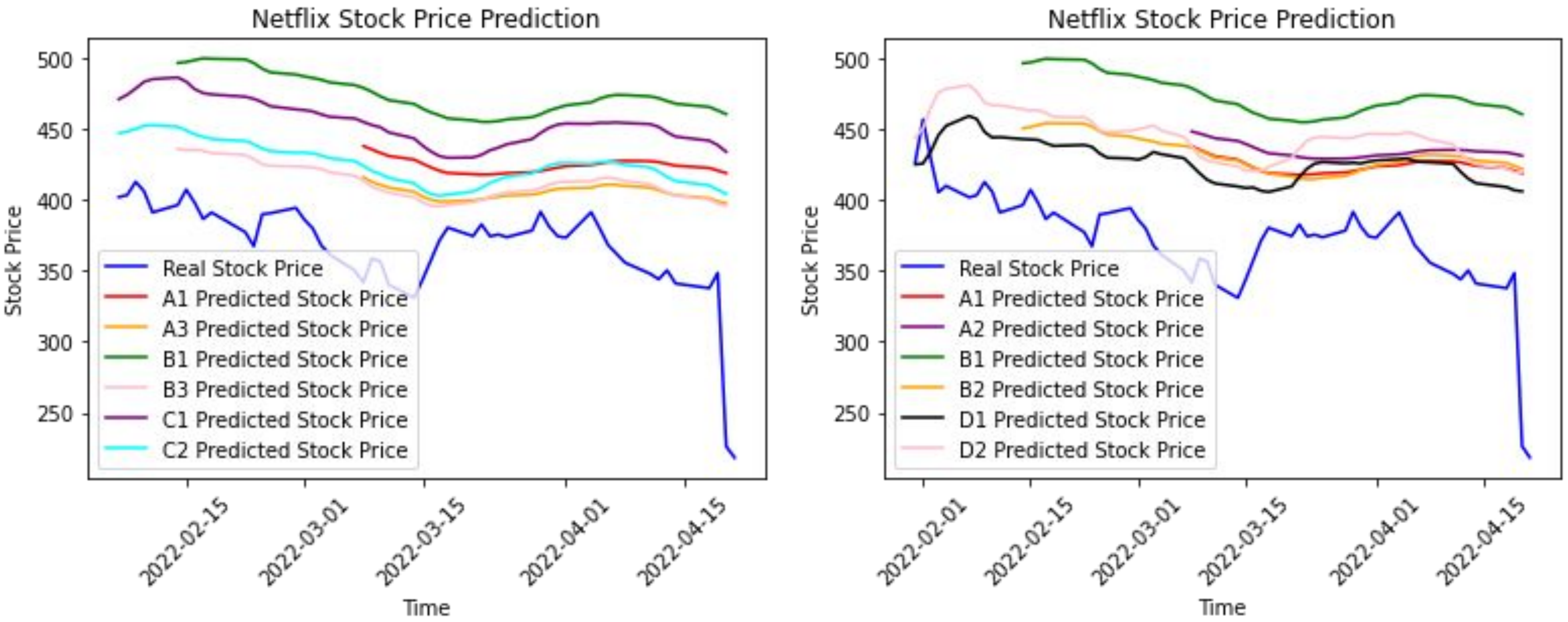
Experiment	Description	Training	Validation	Testing	Process Time (seconds)	Epochs	Total Parameters	Hyperparameters
Experiment A: Input – Closing Price, Time Step – 30								
A.1	Multi-Layer LSTM	0.09	0.11	0.14	8.89	6	11,191	LSTM - 30 Dropout - 0.3 LSTM - 30 Dropout - 0.3 Dense - 1
A.2	Multi-Layer LSTM	0.07	0.10	0.16	7.50	10	54,781	LSTM - 30 Dropout - 0.3 LSTM - 60 Dropout - 0.3 LSTM - 60 Dropout - 0.3 Dense - 1
A.3	Multi-Layer Bidirectional LSTM	0.11	0.13	0.10	6.80	6	18,631	Bidirectional LSTM - 30 Dropout - 0.5 LSTM - 30 Dropout - 0.5 Dense - 1


Netlfix Stock Price Prediction
450
400
350
300
250
Stock Price
Real Stock Price
A1 Predicted Stock Price
A2 Predicted Stock Price
A3 Predicted Stock Price
2022-03-08
2022-03-15
2022-03-22
2022-04-01
2022-04-08
2022-04-15
2022-04-22
Time

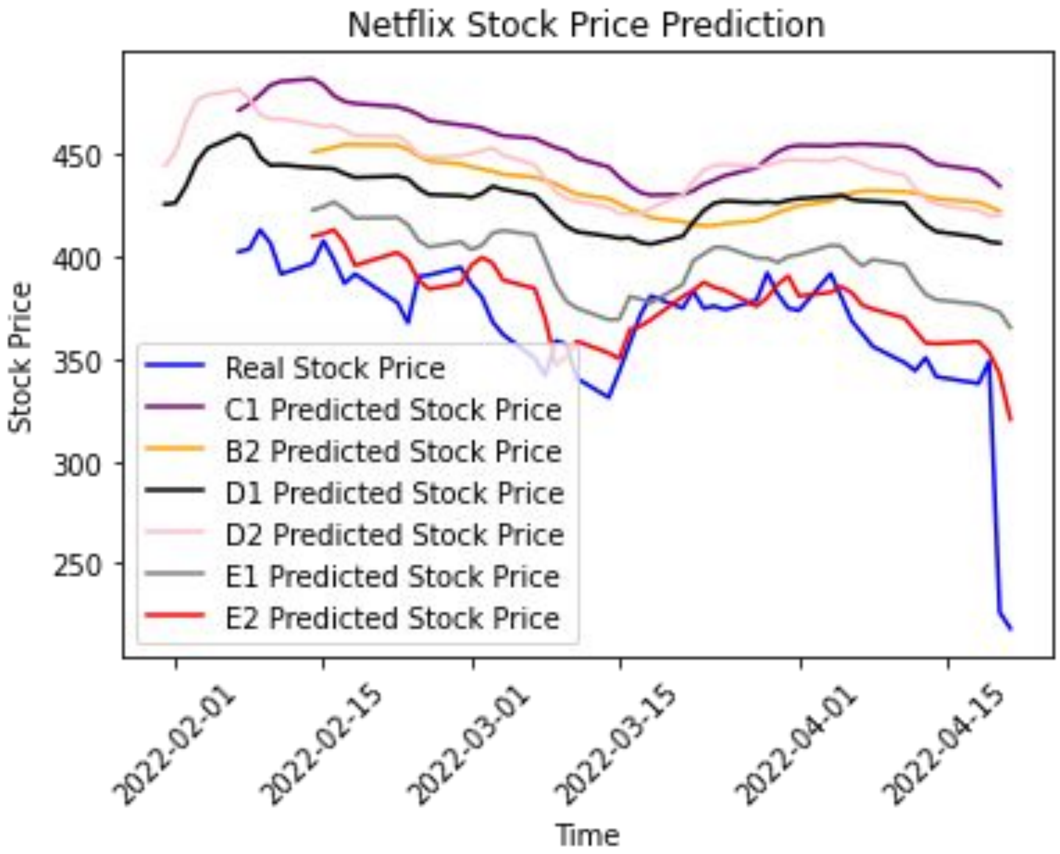
Experiment	Description	Training	Validation	Testing	Process Time (seconds)	Epochs	Total Parameters	Hyperparameters
Experiment B: Input – Closing Price, Time Step – 15								
B.1	Multi-Layer LSTM	0.09	0.11	0.23	4.26	4	11,191	LSTM - 30 Dropout - 0.3 LSTM - 30 Dropout - 0.3 Dense - 1
B.2	Multi-Layer LSTM	0.06	0.09	0.14	7.52	9	54,781	LSTM - 30 Dropout - 0.3 LSTM - 60 Dropout - 0.3 LSTM - 60 Dropout - 0.3 Dense - 1
B.3	Multi-Layer Bidirectional LSTM	0.11	0.13	0.10	8.47	6	18,631	Bidirectional LSTM - 30 Dropout - 0.5 LSTM - 30 Dropout - 0.5 Dense - 1


Netflix Stock Price Prediction
Stock Price
500
450
400
350
300
250
Real Stock Price
A1 Predicted Stock Price
A2 Predicted Stock Price
A3 Predicted Stock Price
B1 Predicted Stock Price
B2 Predicted Stock Price
B3 Predicted Stock Price
2022-02-15
2022-03-01
2022-03-15
2022-04-01
2022-04-15
Time

Experiment C: Input – Closing Price, Time Step – 10								
C.1	Multi-Layer LSTM	0.09	0.10	0.18	6.06	4	11,191	LSTM - 30 Dropout - 0.3 LSTM - 30 Dropout - 0.3 Dense - 1
C.2	Multi-Layer Bidirectional LSTM	0.11	0.13	0.12	6.46	5	18,631	Bidirectional LSTM - 30 Dropout - 0.5 LSTM - 30 Dropout - 0.5 Dense - 1
Experiment D: Input – Closing Price, Time Step – 5								
D.1	Multi-Layer LSTM	0.08	0.10	0.11	4.45	6	11,191	LSTM - 30 Dropout - 0.3 LSTM - 30 Dropout - 0.3 Dense - 1
D.2	Multi-Layer Bidirectional LSTM	0.10	0.11	0.15	5.82	4	18,631	Bidirectional LSTM - 30 Dropout - 0.5 LSTM - 30 Dropout - 0.5 Dense - 1


Netflix Stock Price Prediction
Stock Price
Time
Real Stock Price
A1 Predicted Stock Price
A3 Predicted Stock Price
B1 Predicted Stock Price
B3 Predicted Stock Price
C1 Predicted Stock Price
C2 Predicted Stock Price
Netflix Stock Price Prediction
Stock Price
Time
Real Stock Price
A1 Predicted Stock Price
A2 Predicted Stock Price
B1 Predicted Stock Price
B2 Predicted Stock Price
D1 Predicted Stock Price
D2 Predicted Stock Price

Experiment E: Input – Closing Price and Finbert Labels, Time Step – 5								
E.1	Multi-Layer LSTM	0.07	0.06	0.07	6.90	17	11,311	LSTM - 30 Dropout - 0.3 LSTM - 30 Dropout - 0.3 Dense - 1
E.2	Multi-Layer Bidirectional LSTM	0.09	0.04	0.04	9.21	19	18,871	Bidirectional LSTM - 30 Dropout - 0.5 LSTM - 30 Dropout - 0.5 Dense - 1


Netflix Stock Price Prediction
Stock Price
Time
450
400
350
300
250
2022-02-01
2022-02-15
2022-03-01
2022-03-15
2022-04-01
2022-04-15
Real Stock Price
C1 Predicted Stock Price
B2 Predicted Stock Price
D1 Predicted Stock Price
D2 Predicted Stock Price
E1 Predicted Stock Price
E2 Predicted Stock Price

Result Interpretation and Analysis

Dataset:

- Noise from ads and non-opinion tweets

VADER-labeled dataset:

- Conversion of emojis to words may have created a bias and effected overall sentiment classification
- Manual check over not processed and processed tweets was biased

LSTM models:

- Smaller timestep was able to predict better due to the shorter time range
- Bidirectional LSTM layer was able to capture relevant patterns reading the input forwards as well as backwards
- Model with sentiment was more accurate in price range and also able to predict the rises and dips better than just closing price -- still lagging a bit but sentiment is also due to lag after it drops as well

Recommendations for Future Work

- Try other sentiment labelling methods:
  - Other BERT models like ones that are trained using tweet data
  - SVM and Naive Bayes
- Clean and preprocess tweet data further
  - Remove noise
  - Compare if there is a difference between sentiment labeling with emoji conversion and no emoji conversion
- Collect more tweets and historical data to have be able to train the LSTM models further and see if there is further improvement in its predictions
- Source tweets using mentions of its username or company name for more general opinions

Conclusion

- Dataset used to fine-tune needs to cleaned and labelled more accurately
- FinancialBERT model was able to accurately label dataset
- LSTM models are able to take the temporal correlations of the patterns in closing price as well as in sentiment to predict next day closing price
- Sentiment does help in the predicting more accurate and trends of next day closing prices
- Smaller time steps and bidirectional wrapper allow for more accuracy in volatility

Thank You!