Stock Price Prediction With RNN's and NLP

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Objective

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The objective of this study is to see how user **sentiment** towards a particular stock affects its future price. We will be using data from **twitter/reddit** for user **sentiment** and **Yahoo Finance** for historical stock price data.

Data

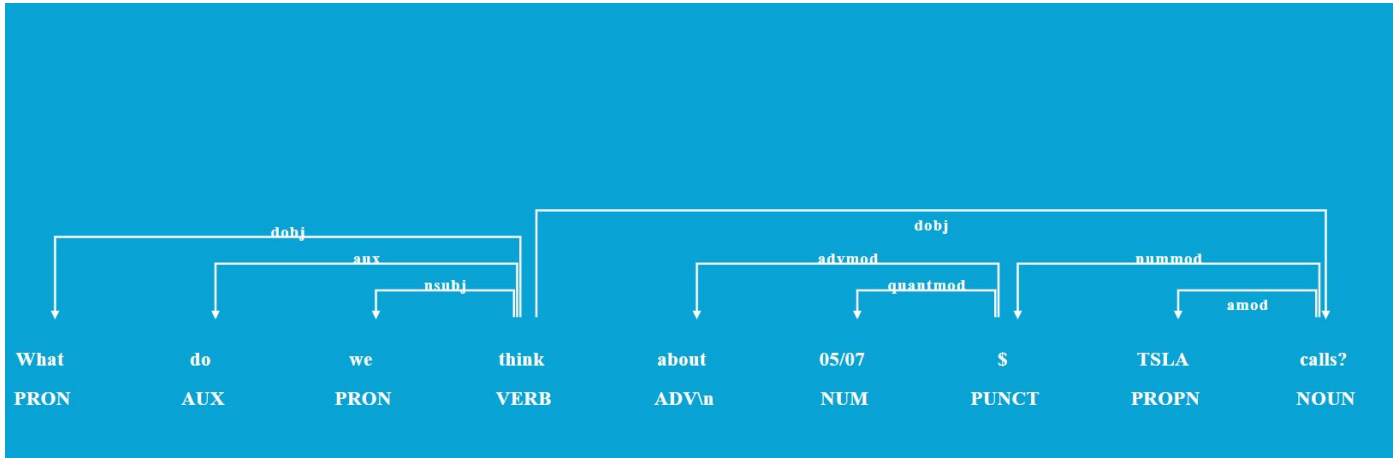
Data:

The data used consisted of **24 months** worth of historical **Tesla** stock price data which accounted for **505 dates** (since the stock market does not work on weekends) and about **7k+ posts** from reddit and twitter.

EDA

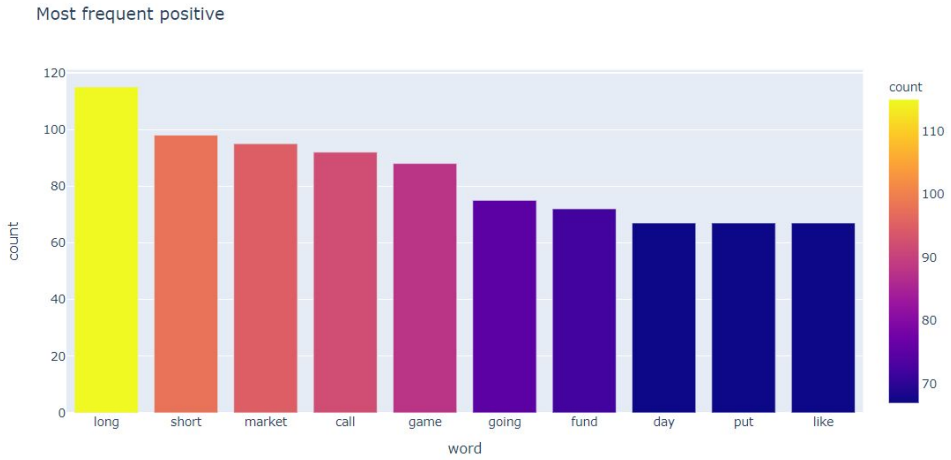
EDA:

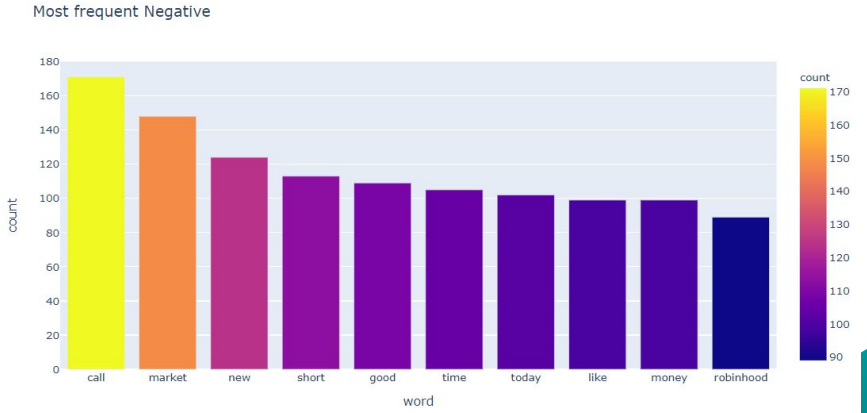
In order to detect user sentiment we have to first teach the model how essentially read. To do this, I used spaCy's Textblob pipeline component. With Textblob, we can part of speech tagg and find sentiment analysis with textual data.



EDA Continued:

After the reddit data was **tokenized** and **tagged**, I was able to pull the sentiment and subjectivity from each post. With this information we are able to see if a post leans positive or negative.





EDA: Continued:

Here we can see how sentiment compares to (subjectivity) which is another feature used to determine how how subjective the model is determining the post to be (1 = more subjective, 0 = less subjective). We can see that the less subjective the tweets, the more sentiment neutral. Below is sentiment to closing price. We can see that major spikes in sentiment(blue line) seem to indicate if the price going up or down in the near future.

Model

Base Model:

The data used for the model was a combination of both the reddit/twitter post data and historic stock price. To make dataframe applicable to the model, I first had to **group** all the post by the date and extract the **average value** for **subjectivity** and **sentiment**. This created a dataframe with just **closing price**, **sentiment** and **subjectivity**. Then I needed to create the **target** column which in this case was tomorrows closing price. After having the data in a serviceable manner, I could then feed it into the **LSTM RNN** model(**Long-Short-Term-Memory Recurrent Neural Network**). The main difference between an **LSTM** and a regular **RNN** is that, **LSTM remember** the important data and pass it on down the sequence to make predictions. **RNN**'s, however tend to **forget** if a sequence is long enough due to the vanishing gradient problem.

Base Model Continued:

For the base model, I used a simple architecture with 2 **LSTM** layers and 1 **Dense** layer. The base model was fitted on a **batch size** of 1 and with 100 **epochs**. The results were as followed:

```
13/13 [==============================] - 0s 3ms/step - loss: 5.7300e-04 - mean_absolute_percentage_error: 13011.9111
Training Loss: 0.000573
Training MAPE: 1.3e+04
----------
4/4 [==============================] - 0s 3ms/step - loss: 0.0546 - mean_absolute_percentage_error: 15.3176
Test Loss: 0.0546
Test MAPE: 15.3
RMSE: 141.54787328211893
```

Final Model:

For the final model, I tried different combinations of **layers**, including **dropout layers**, **L2 regularization** and **early stopping**. I also increased/decreased the number of **epochs** and nothing seemed to make a significant difference. The only parameter that made a noticeable difference was increasing the **batch size**.

Final Model Countinued:

For the fina; model, I used a simple architecture with 2 **LSTM** layers, 3 **Dense** layers, **batch size** of 20 and 100 **epochs**. The results were as followed:

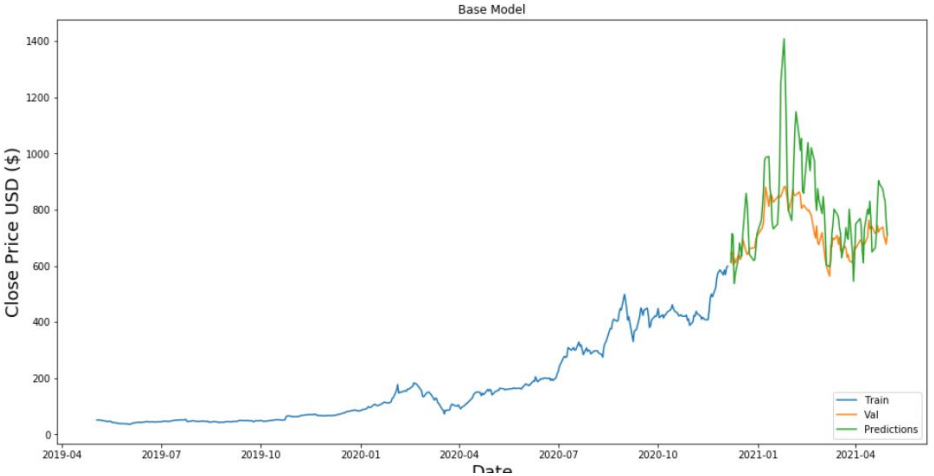
```
13/13 [==============================] - 0s 4ms/step - loss: 7.0885e-04 - mean_absolute_percentage_error: 2057.1589
Training Loss: 0.000709
Training MAPE: 2.06e+03
----------
4/4 [==============================] - 0s 4ms/step - loss: 0.0064 - mean_absolute_percentage_error: 5.6810
Test Loss: 0.00638
Test MAPE: 5.68
RMSE: 48.41230817504435
```

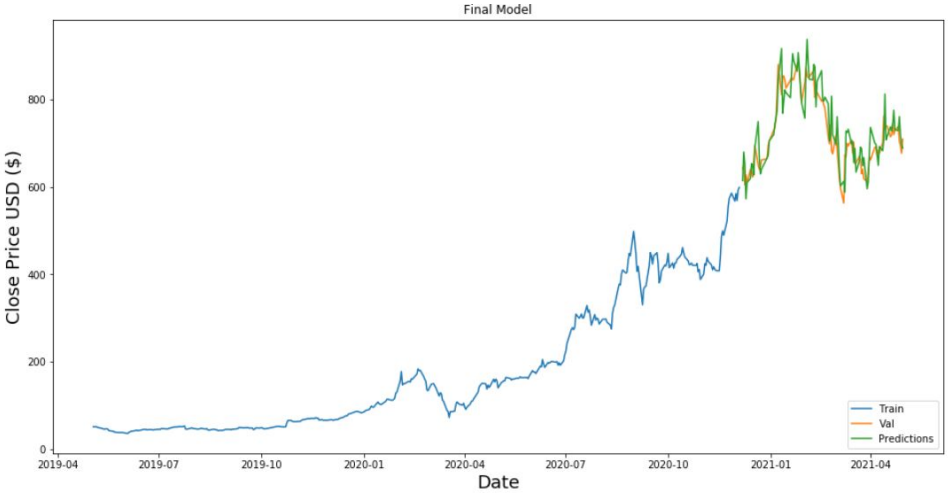
Results

Results:

Compared to the base model, I was able to lower the **Test Mean absolute squared error** rate by **250**%. **Test RMSE** dropped from **141.54** to **48.41**. The **training MAPE** also seems to be astronomically higher then the **test MAPE** but that is due to the fact the model is trained to predict future values .

Results Continued:





Summary/ Conclusion:

- **LSTM**'s work very well on forecasting time series data.
- Sentiment can signal if there's going to be a significant decrease or increase in the near future.

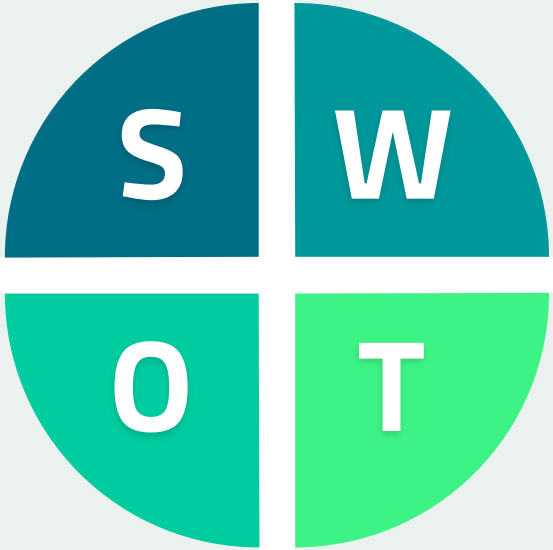
SWOT ANALYSIS

STRENGTHS

The model is able to remember better then a regular RNN and learn more from the data .

WEAKNESSES

Lack of data due to API limitations



Functionalizing will make the model run more efficiently. Also increasing data will increase the accuracy

OPPORTUNITIES

Different languages might trip up the sentiment analysis

THREATS

Next Steps:

1. Finish Functionalizing to make more user friendly
2. Add more data sources to the web scraper
3. Create a frontend
4. Address the language problem from web scraping
5. Incorporate more data
6. Add crypto currency functionality

Thank you

Thank you for sitting through my presentation!

- Sources Used:
  - Presentation template by SlidesCarnival
  - https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21
  - APmonitor.com's youtube channel
  - spaCy.io