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Inferring Structure from Complex Systems

Lab 7

Github link: https://github.com/egagli/amath563/blob/main/labs/7/Lab7_Template.ipynb

1. Please provide the following specifics of your RNN model

a. RNN architecture type (e.g. Vanilla, LSTM, GRU)

GRU, adapted from lab 7 notes pdf.

b. RNN Input dimension and hidden layer dimension

1 input dimension and 16 hidden layer dimensions.

c. Type of nonlinearity

Tanh activation.

d. Other Network Layers (FC, dropout, etc.)

FC layer from hidden dimension to output.

e. Additional RNN modifications (e.g. DeepRNN, Bi-directional RNN)

N/a

f. Training Epochs

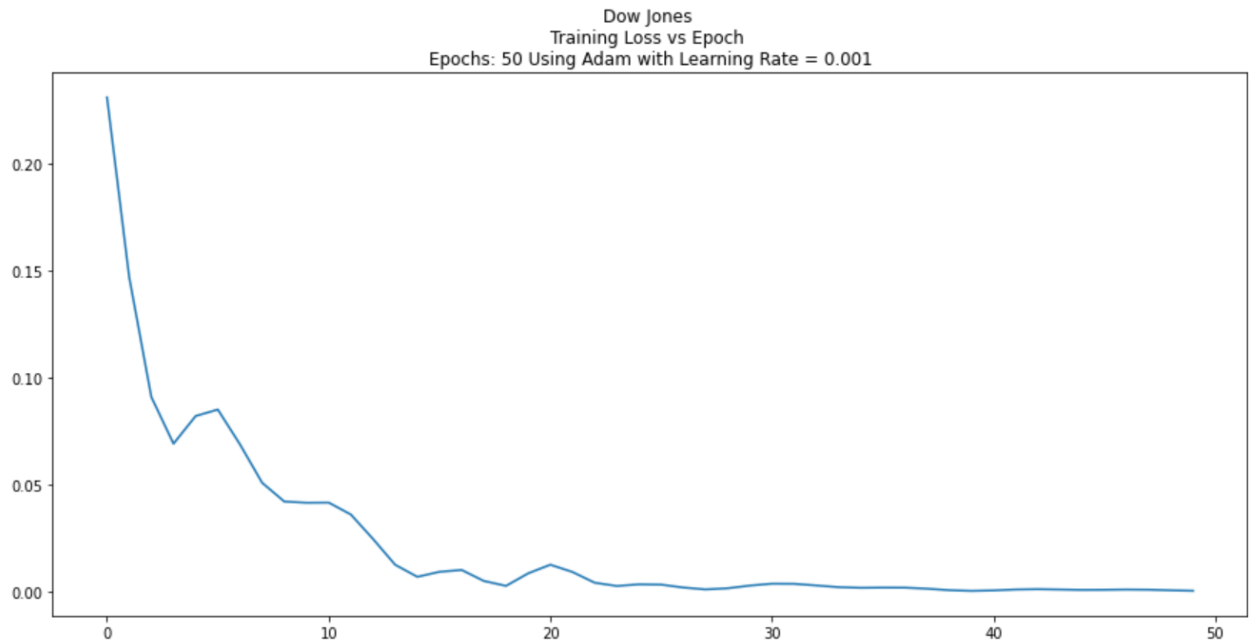
50 epochs.

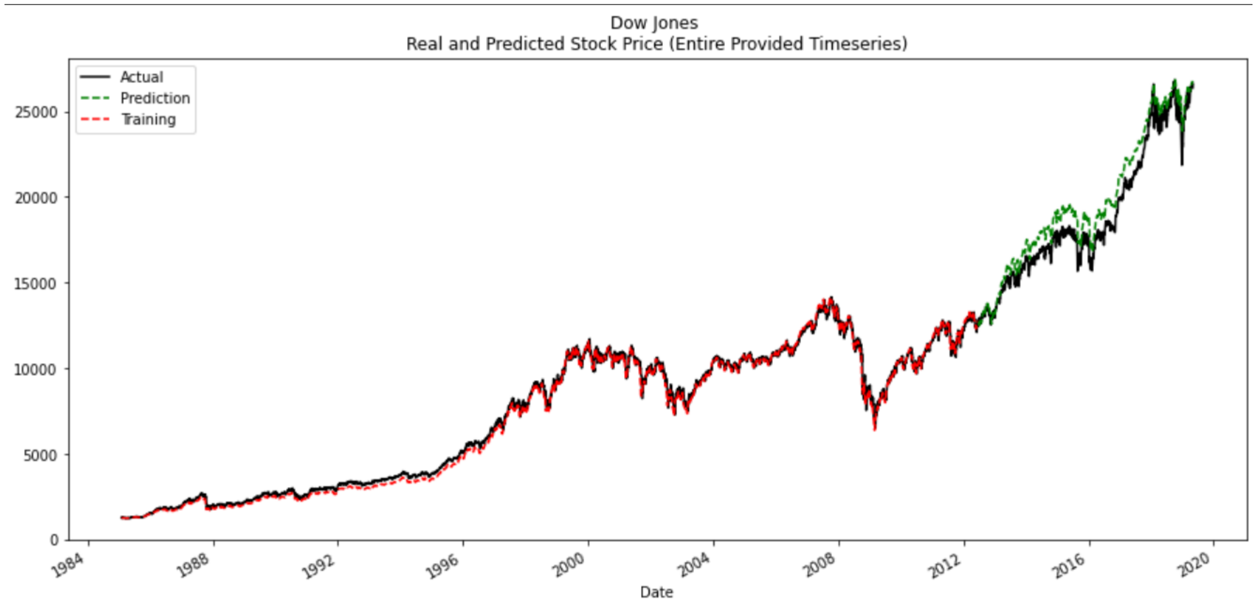
g. Learning Rate

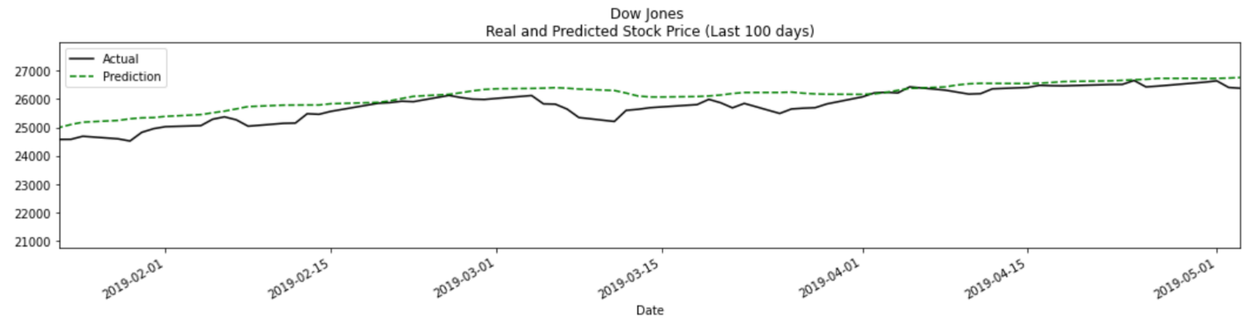
Adam with a learning rate of 0.001.

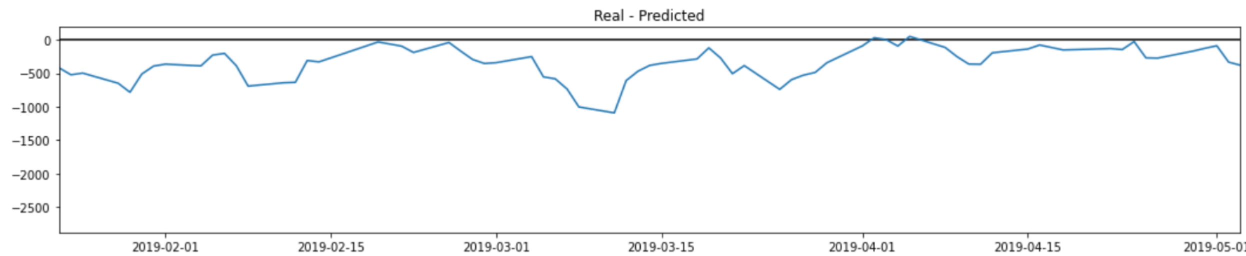
2. Please include figures showing the ground truth vs RNN predicted for the last 100 days of the following datasets:

a. Dow Jones

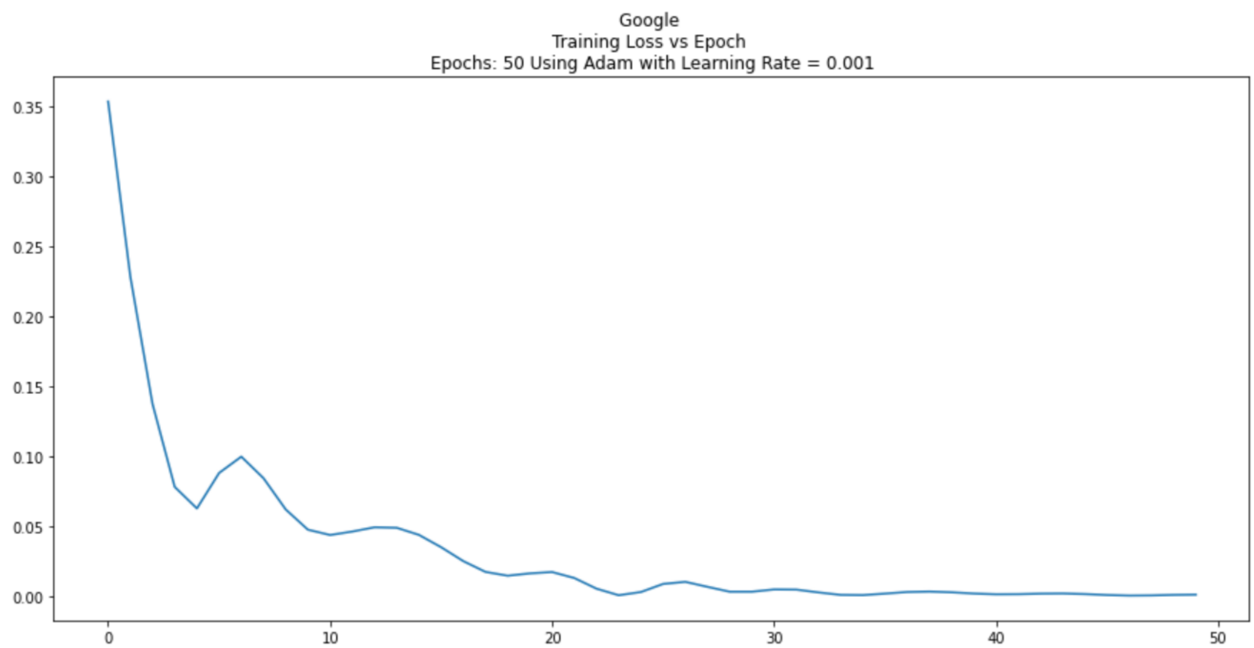


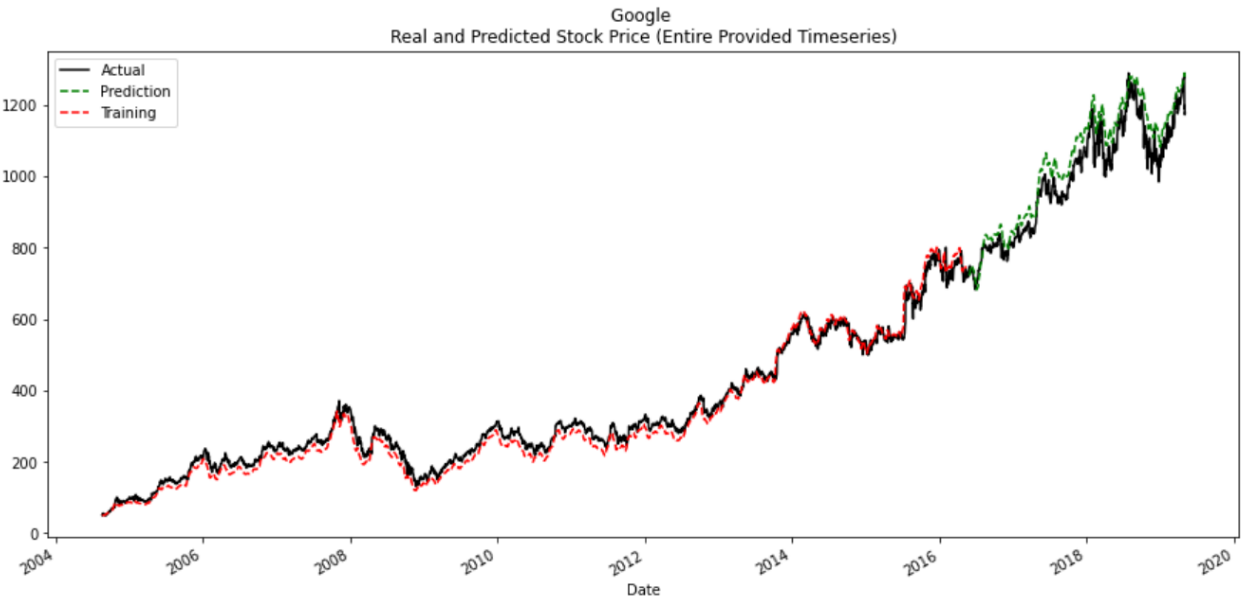


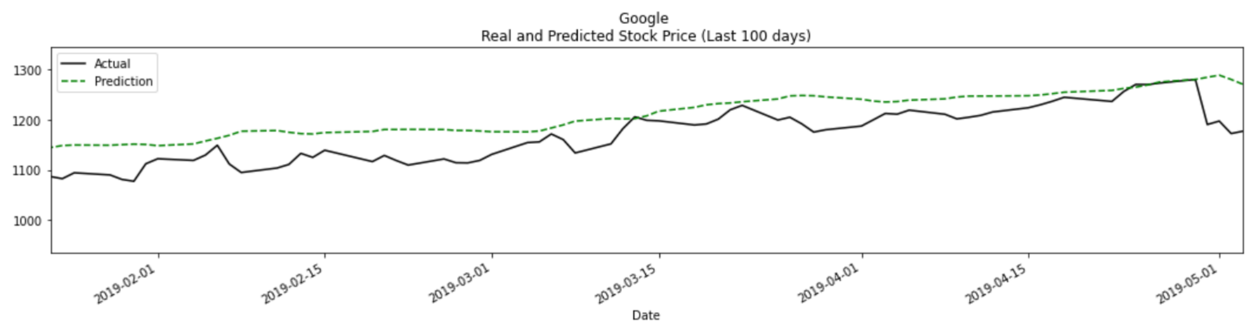

Dow Jones
Real and Predicted Stock Price (Last 100 days)
Actual
Prediction
Date

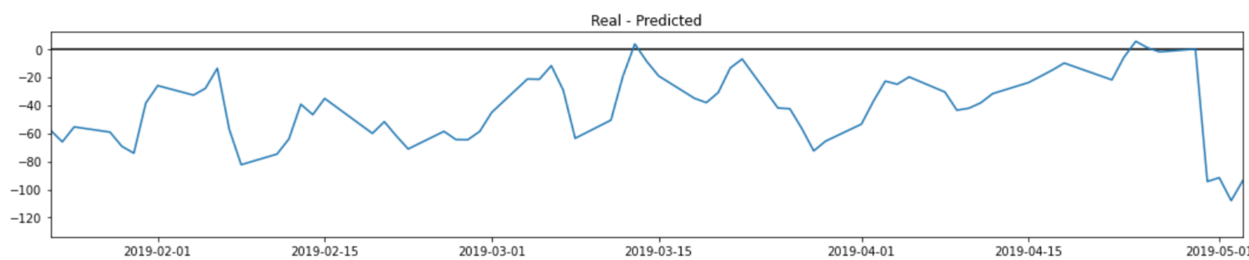

Real - Predicted

b. Google

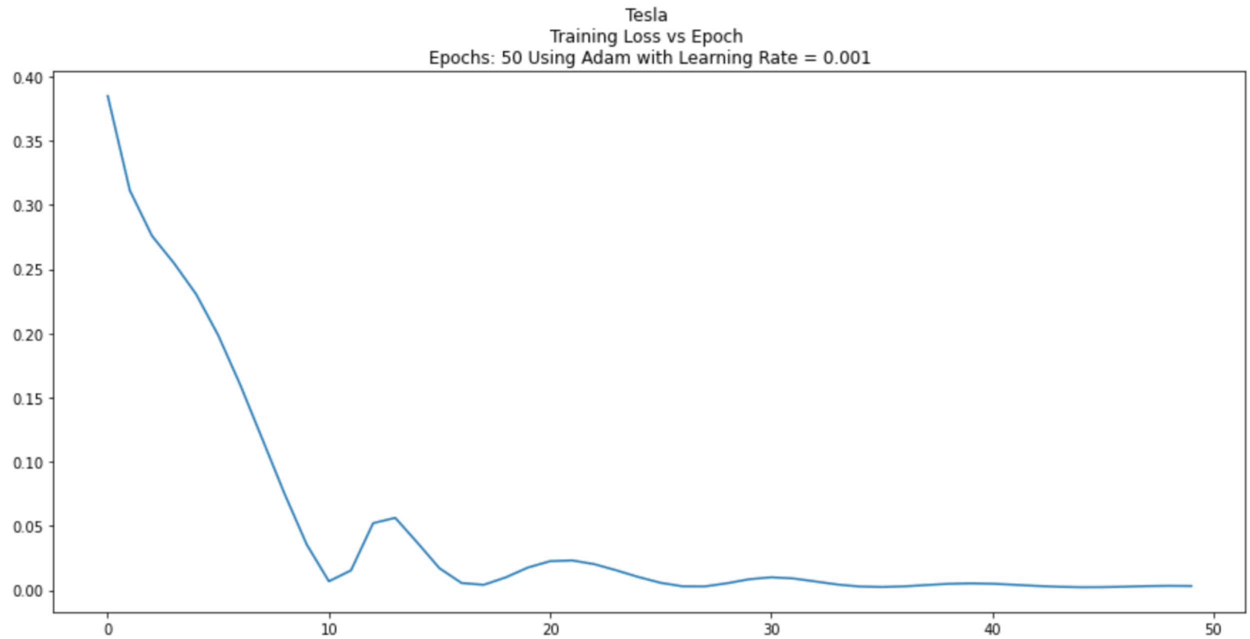

Google
Training Loss vs Epoch
Epochs: 50 Using Adam with Learning Rate = 0.001

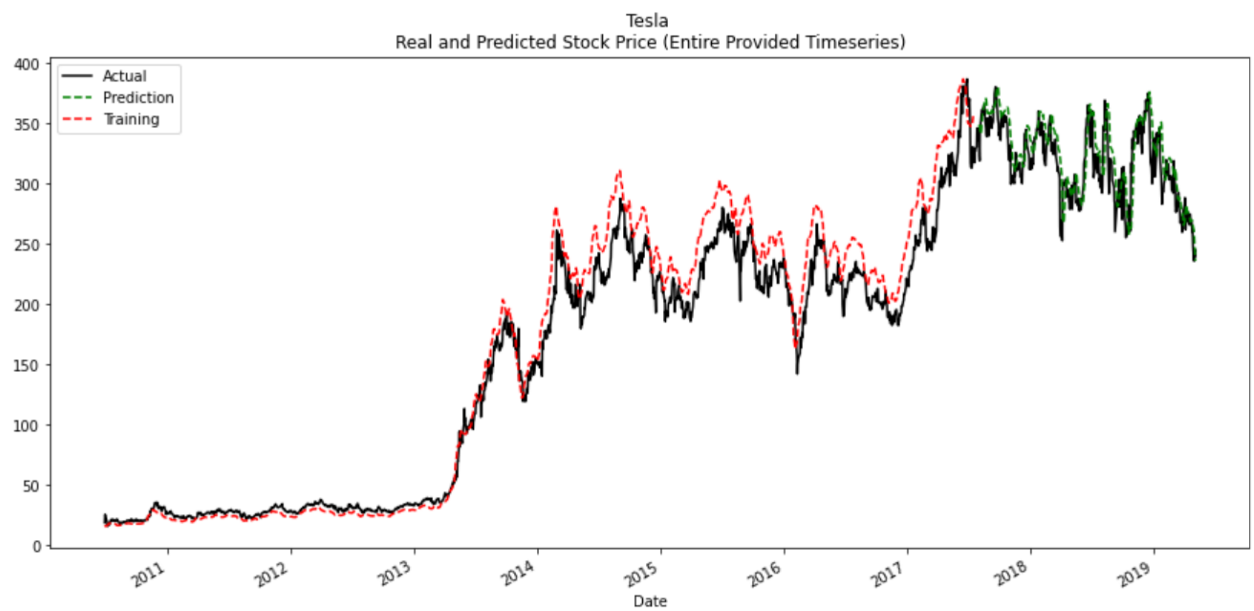

Google
Real and Predicted Stock Price (Entire Provided Timeseries)
Actual
Prediction
Training
Date

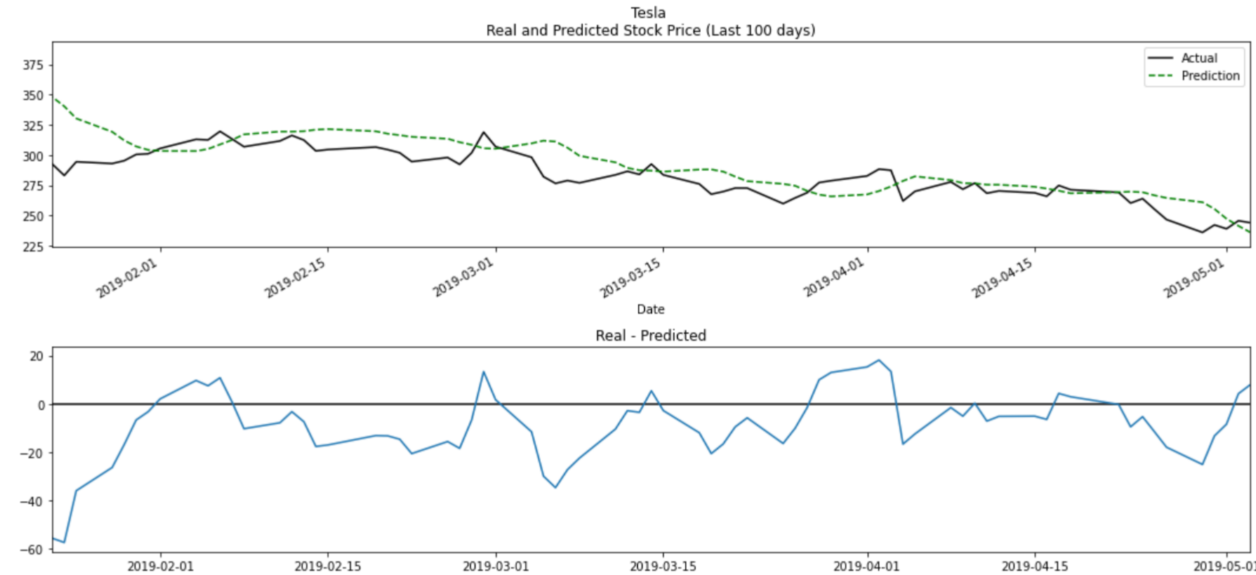

Google
Real and Predicted Stock Price (Last 100 days)
Actual
Prediction
Date


Real - Predicted

c. Tesla


Tesla
Training Loss vs Epoch
Epochs: 50 Using Adam with Learning Rate = 0.001
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50


Tesla
Real and Predicted Stock Price (Entire Provided Timeseries)
Actual
Prediction
Training
400
350
300
250
200
150
100
50
0
2011
2012
2013
2014
2015
2016
2017
2018
2019
Date



3. What aspects of the data was your RNN model successful at capturing/predicting? How did it struggle? How can you explain these issues? Are they limitations to the models, or are they due to the nature of the data? Explain your reasoning.

My RNN was overall very good at capturing the stock prices, though I'm sure I've overfit the model. Even still, the test data seemed to have low overall MSE which shows the strength of the model. I purposely kept the number of hidden dimensions low because of overfitting concerns, but when I cranked up the hidden dimensions my MSE got even lower. Looking at the graphs above, the model captures overall trends very well, but struggles with the more high frequency fluctuations. The predictions consistently overestimate stock price, though the magnitude of these overestimates is proportionally small to the overall stock price. This is likely not a limitation of the model, but instead a limitation of the data. Stock market data has so many confounding variables, depends more on speculation rather than historical trends or current value metrics, and is quite chaotic, especially to current events and trader sentiment. Consider, for example, if we lived in a capitalist dystopia and it were possible that a (theoretical, of course) madman Tesla CEO could manipulate stock prices with a quick random tweet from his phone. This is not something that a RNN could capture well–it's hard to model an erratic narcissist. There are just way too many externalities in the stock market that building a good model is very hard (I would argue impossible). At best, these types of models might assist human traders in recognizing anomalies, probably more with day trading during very normal and non-newsworthy conditions. I think it's quite telling that we don't see RNNs in widespread use to make money on the stock market. Most of this is just speculation on my part and having conversations with my ML, quant, and finance bro friends, definitely not an expert.