Predicting Stock Prices

- Sam Stoltenberg

Introduction

Here we walk through our results from predicting stock data with an LSTM network. A basic overview of the process:

- Scraped 127 million data points over a year
- Scrubbed the data for the Neural Network
- Built a graphing app to visualize the data
- Built three networks for predicting Apple's price, and related prices.
- Built two networks for predicting the prices of seven stocks tomorrow and the next for two day forecasts.

Questions

I. What feature changes have the most impact on changes in tomorrow’s price?
II. What are the limitations faced when predicting stock data?
III. How can we best build an array of networks for predicting stock data?

About the Data

Scraped from an investment firm consisting of

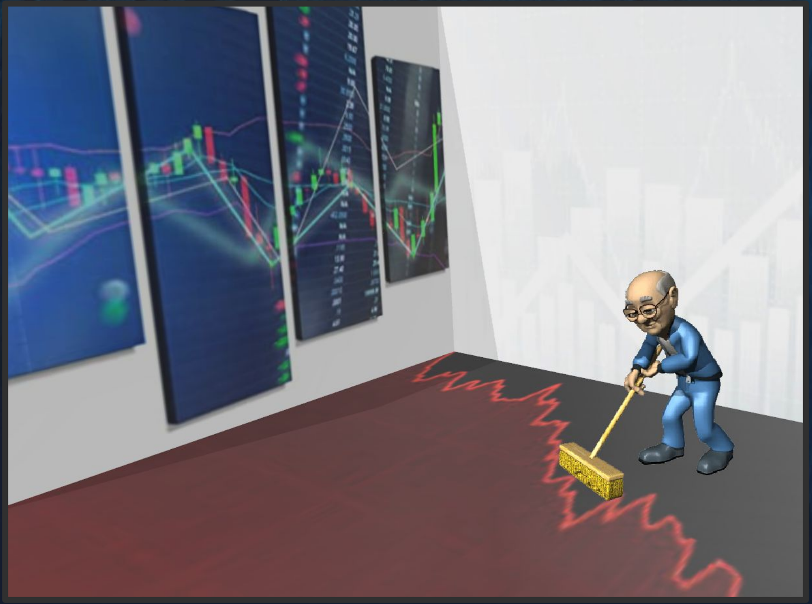
- Daily data from August 9th, 2019 -> Today
- 7,681 symbols
- Five tables
  - Prices
  - Analyst Opinions
  - Performance Stats
  - Company Information
  - Stock Split Data

Scrubbing the Data

- All choices made during the scrubbing process have a direct effect on the network's predictions, thus they and their effects must be carefully thought out.

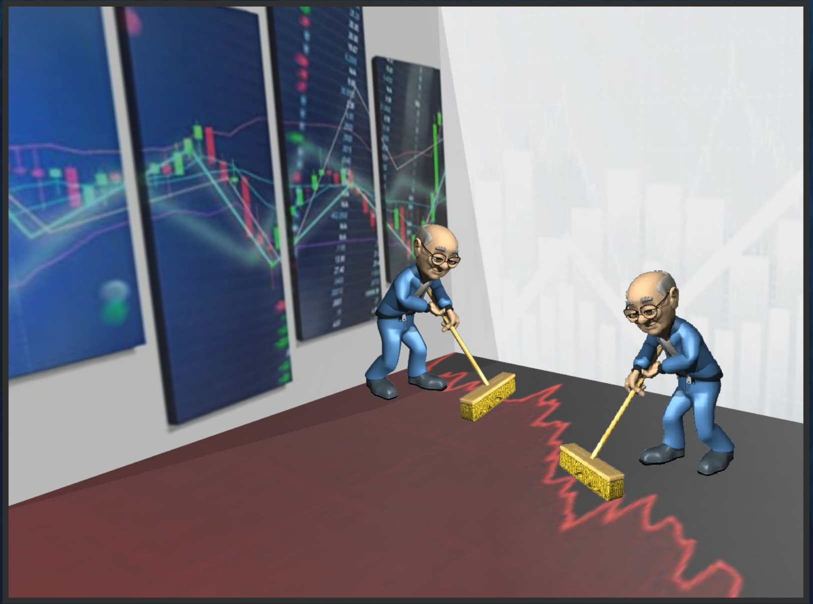
- We remove many features and symbols where data could potentially be negative, as filling it with zero could have drastic consequences.

- After scrubbing we ended up with roughly 2,000 symbols, and predicted with only 7 from the S&P 500.



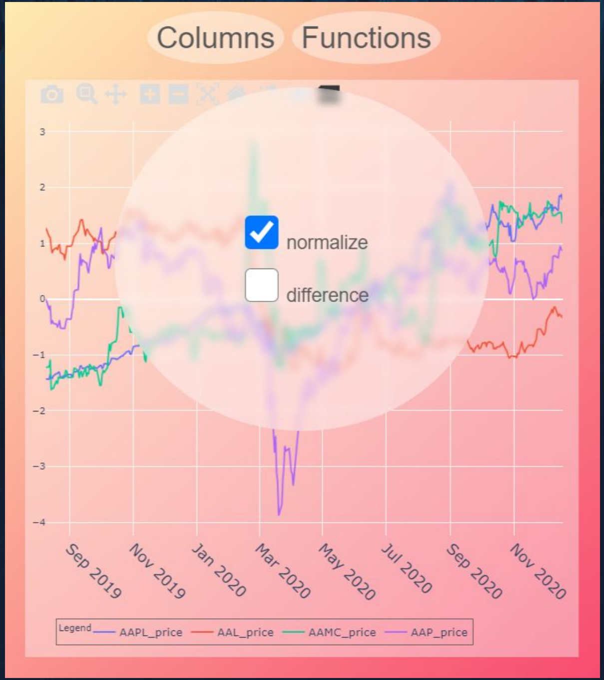
Scrubbing the Data Part 2

- Match all table's indexes
- Performance and Pricing data were filled by the moving average with a maximum of three consecutive null values.
- Removed roughly 5,000 symbols that still contained null values.
- Removed six features of performance that contained sparse data.
- Analyst data was numerically mapped. Ex:
    - Buy -> 5, Sell -> 1
- Null company data was filled with"unknown" or 0.



Visualized Data

View our cleaned data [Here]

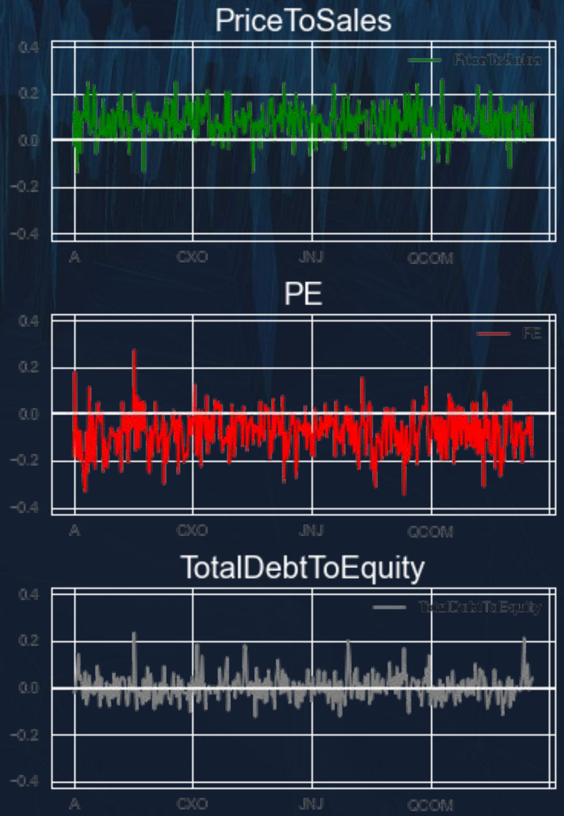


Correlation Search

We searched for which features had the greatest correlation to price tomorrow and the next day. By finding which features correlated we could remove 20 features that did not.

On the right you'll see three separate correlations indicating what price is most likely to do the next day:

- In green PriceToSales has a positive correlation to price.
- In red PE has a negative correlation to price.
- In gray TotalDebtToEquity has no positive or negative correlation thus we would remove this feature



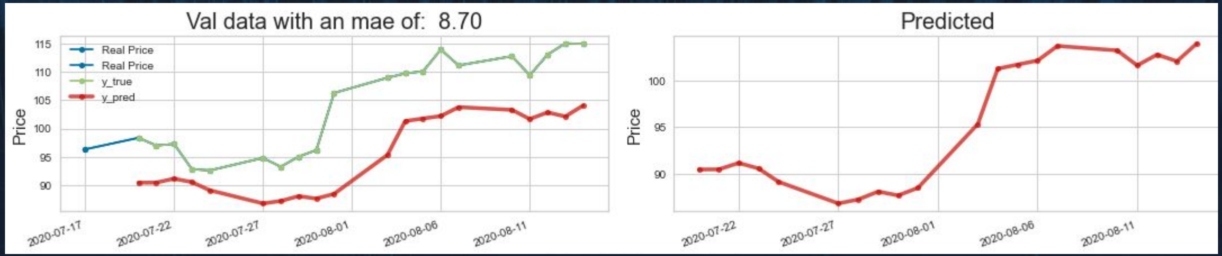
Quick Note

We use the abbreviation “mae” to represent mean absolute error. The mean absolute error is literally the mean of the errors of the data, or for our stock data how far in cents (on average) is the prediction off. Also our “val” data is data that hasn’t been seen by the model.

Base Network and Hand Tuning

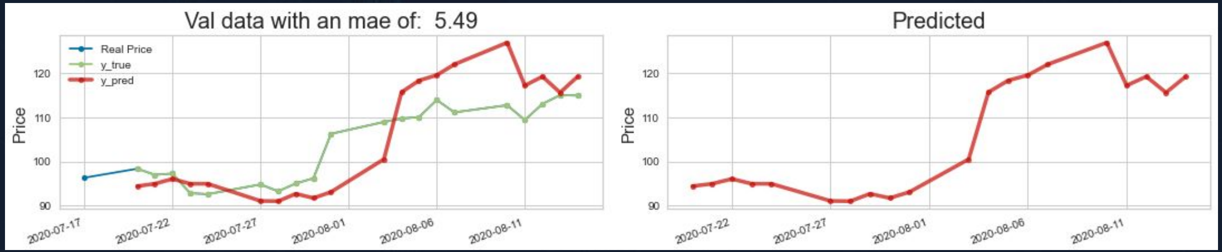
Our first base network was predicting tomorrow's price of Apple with all of the previous day's data of Apple.

Base Network



Hand Tuned Network

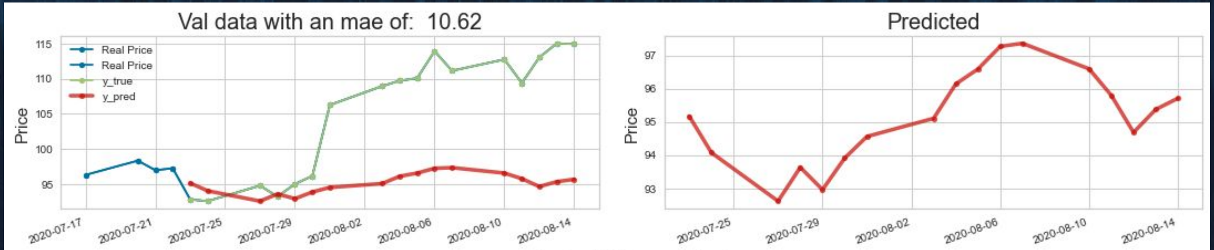
You can see the hand tuned network is much closer to the actual data with an mae of 5.49.



Base Network and Hand Tuning (cont…)

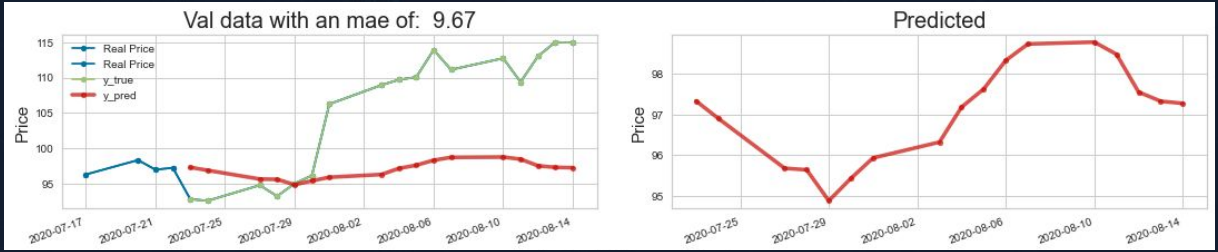
Our next base network was for predicting Apples price with four days of all other stocks' prices.

Base Network



The results of our hand tuned network improved slightly with an mae of 9.67

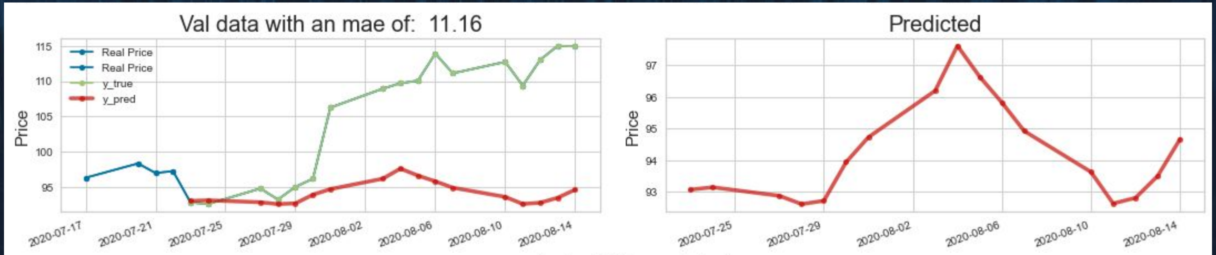
Hand Tuned Network



Base Network and Hand Tuning (cont…)

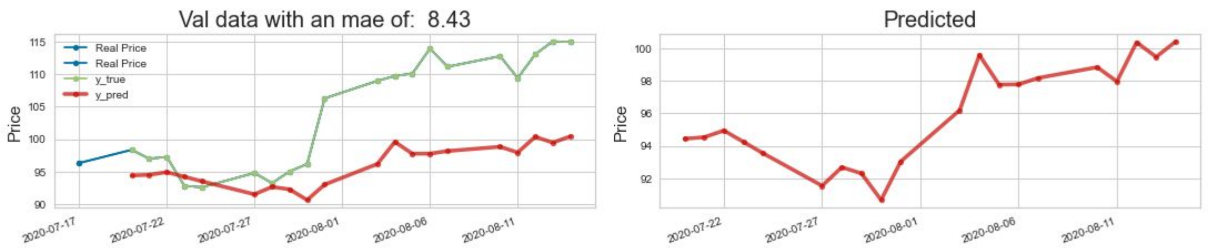
Our final base network was for predicting Apple’s price with four days of data from Apple’s industry

Base Network



Hand Tuned Network

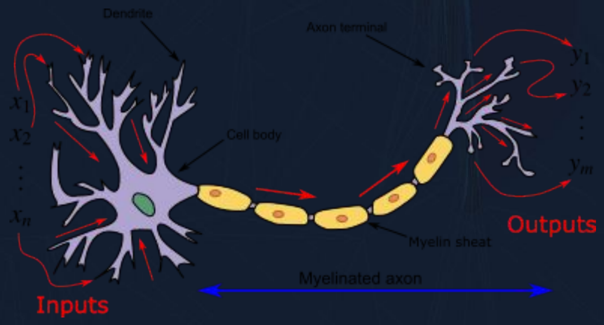
The results of our hand tuned network improved with an mae of 8.43



Final Network

We first attempted to build an array of networks to predict all of the data. After that didn't work due to processing limitations we built the following networks to predict two days of a single sector's prices:

- A network to predict tomorrow's prices
- A network to predict prices of the day after
- Combining these networks we can forecast the next two day's prices of a sector.



Hyper Parameter Tuning

Cross-Validation

We tuned our two networks by:

- Breaking down the creation of a network to variables such as:
  - How many hidden layers to use
  - How many previous days to use for each prediction
- Grid searched 1.2 million hyper-parameters combinations for each network taking roughly 5 hours each.
- Implemented k-fold cross-validation.

Final Network Scores

For predicting tomorrow's prices for "Technology Hardware" we achieved an mae of 2.62 vs 2.69 of our base network.

For the following day's prices we achieved an mae of 3.04 vs 3.49 of our base network.

Stock data is almost random, so we will never achieve a prediction accuracy anywhere close to a perfect mae of 0. We'll have to see how well it does forecasting for real results!

Conclusion

I. Changes in PE and PriceToSales have the greatest effect on tomorrow's price. So if PE is up I would recommend buying that stock.

II. Our number one limitation for predicting the data was GPU RAM. We ran into out of memory errors quickly if we tried predicting on all of the data. I recommend exploring big data machine learning options to reduce that limitation.

III. The best array of networks for predicting stock data we found was training a network for each of the x days of data you want to predict into the future.   I recommend exploring different methods for creating a network, and thinking outside of the box.

Next Steps

- Cluster data on absolute correlation
- iteratively add columns and test prediction quality
- Try with and without differencing

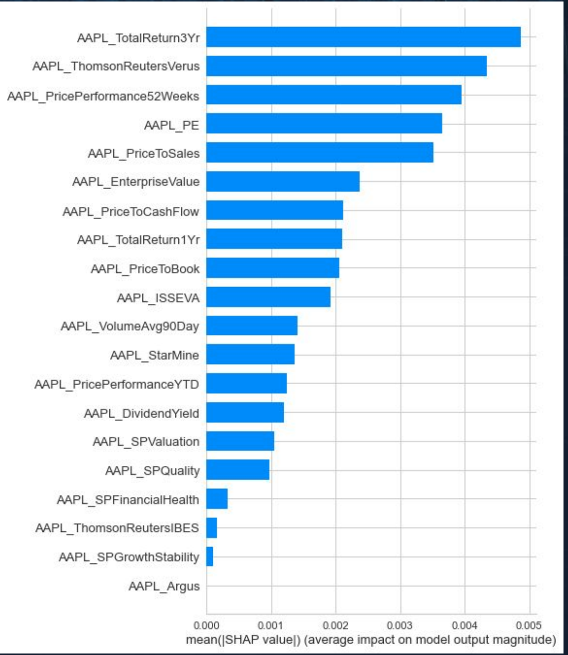
Thank you!

Appendix

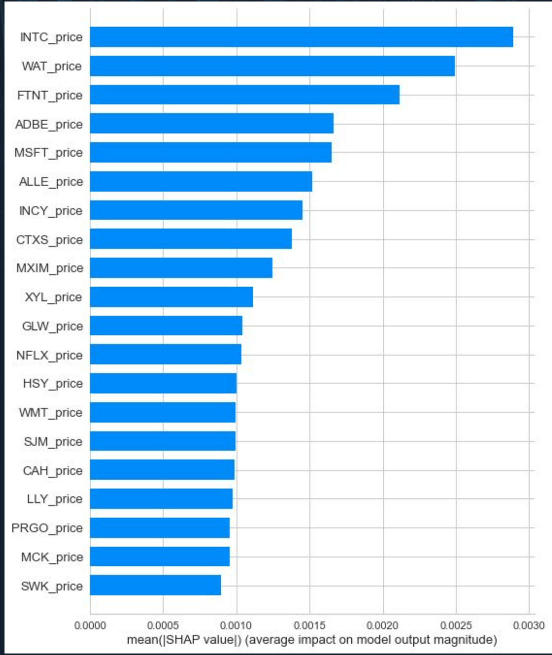
Appendix (cont…) Interpretations

Here we have model interpretations for three of our models showing how much each feature affected the prediction.

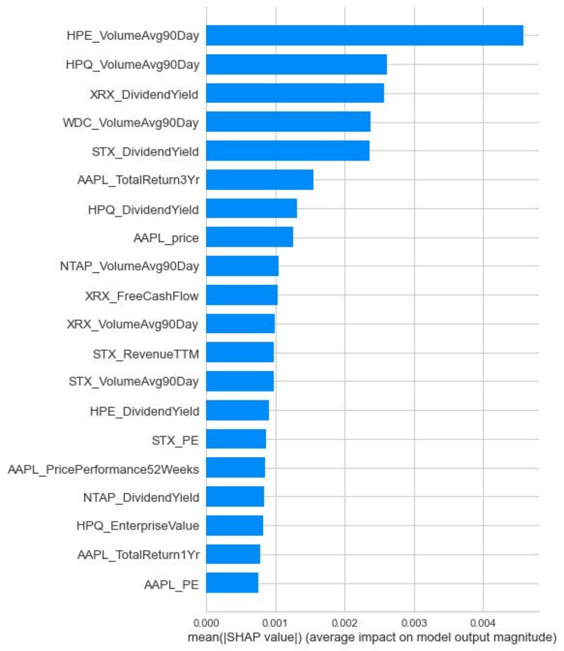
AAPL with AAPL data



AAPL with all prices



AAPL with sector data



Appendix (cont…) Hyper parameters

Here we show the best hyper parameters from our two auto-tuned networks.

Tomorrow

```
parameters = {
    'n_days': 3,
    'add_hidden_lstm': 1,
    'use_input_regularizer': 0,
    'input_dropout_rate': 0.1,
    'add_gaussian_noise': 0,
    'use_hidden_regularizer': 0,
    'hidden_dropout_rate': 0.0,
    'n_hidden_layers': 1,
    'hidden_neurons': 64,
    'optimizer': 'rmsprop',
    'patience': 0,
    'use_early_stopping': 0,
    'batch_size': 64,
    'gaussian_noise_quotient': 1.0,
    'input_regularizer_penalty': 0.01,
    'hidden_lstm_neurons': 64,
    'hidden_regularizer_penalty': 0.1}
```

Day After Tomorrow

```
parameters = {
    'n_days': 3,
    'add_hidden_lstm': 0,
    'use_input_regularizer': 0,
    'input_dropout_rate': 0.3,
    'add_gaussian_noise': 0,
    'use_hidden_regularizer': 0,
    'hidden_dropout_rate': 0.1,
    'n_hidden_layers': 1,
    'hidden_neurons': 32,
    'optimizer': 'adam',
    'patience': 0,
    'use_early_stopping': 0,
    'batch_size': 64,
    'gaussian_noise_quotient': 3.0,
    'input_regularizer_penalty': 0.01,
    'hidden_regularizer_penalty': 0.01,
    'hidden_lstm_neurons': 64}
```