Stock Trading and Market Analysis Project

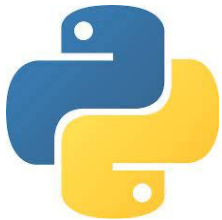
Angelo Vacca, Kasper Seglem, William Ruiz

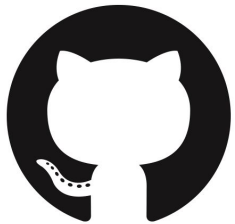
Introduction

- Dataset and Tools
- Trello
- What We've Done
- Stock Correlation
- Correlations by Year
- LSTM Prediction
- LSTM with Correlation
- Random Prediction
- Analysis and Findings

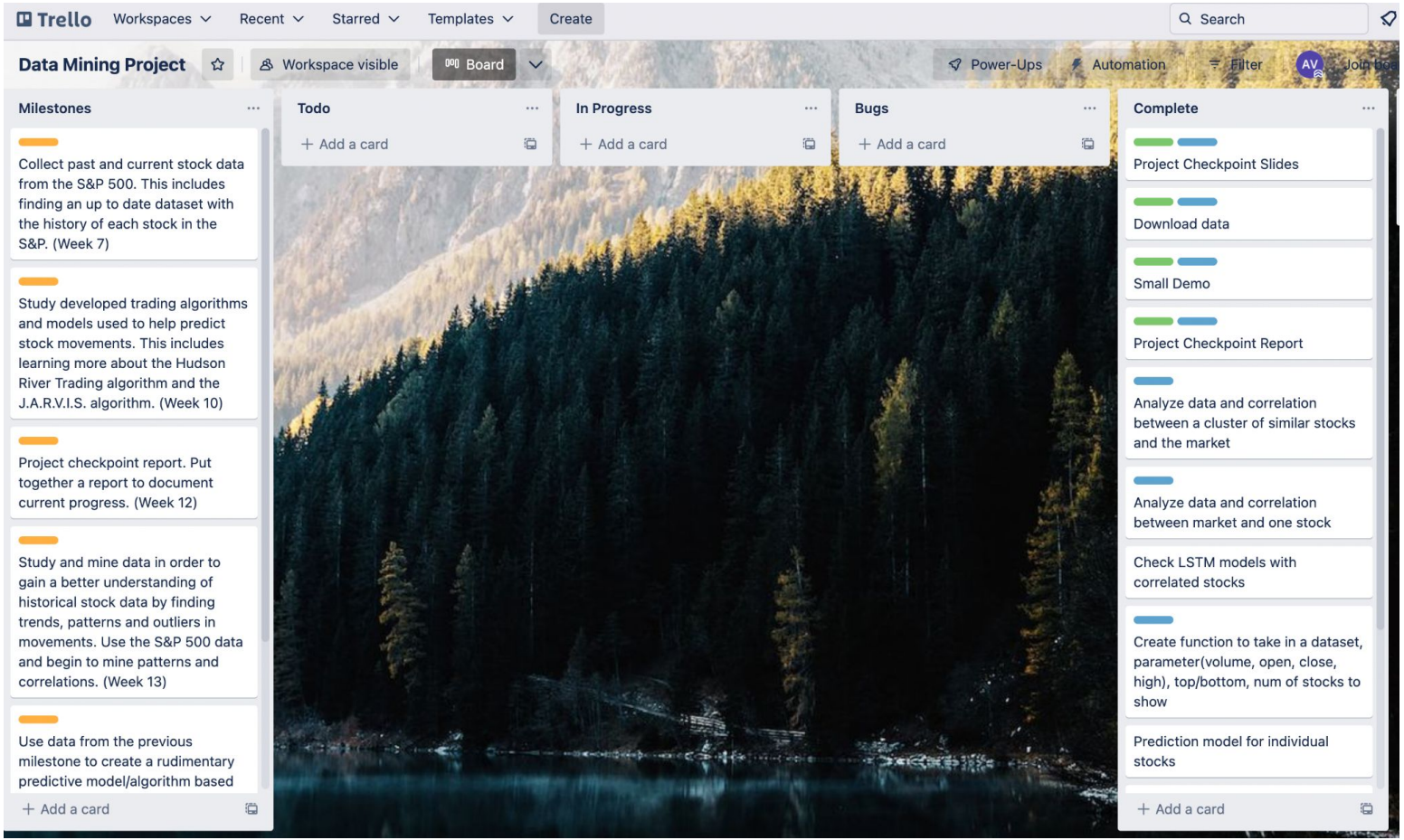
Dataset and Tools

- S&P 500 companies
  - 2013 to 2018 (5 years)
  - date, open, high, low, close, volume, Name
  - 2013-02-08, 67.7142, 68.4014, 66.8928, 67.8542, 158168416, AAPL
  - 20 year data
- Python
  - matplotlib
  - numpy
  - pandas
  - Seaborn
  - Tensorflow
- GitHub





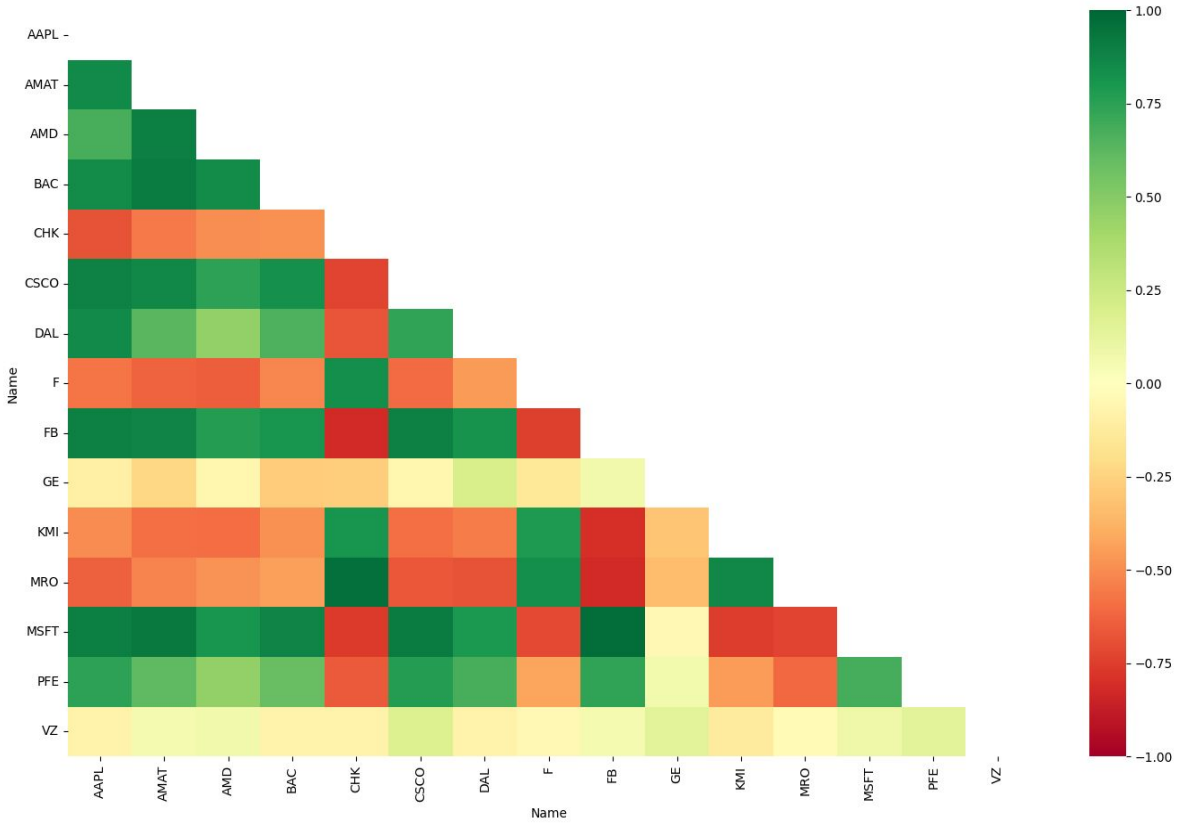
Trello Board

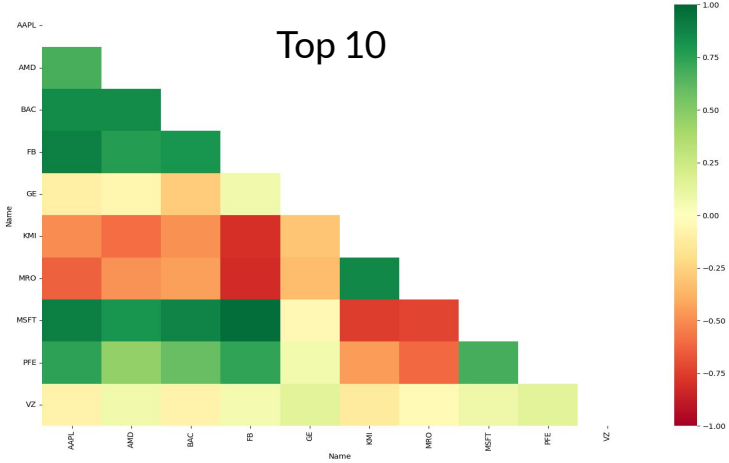


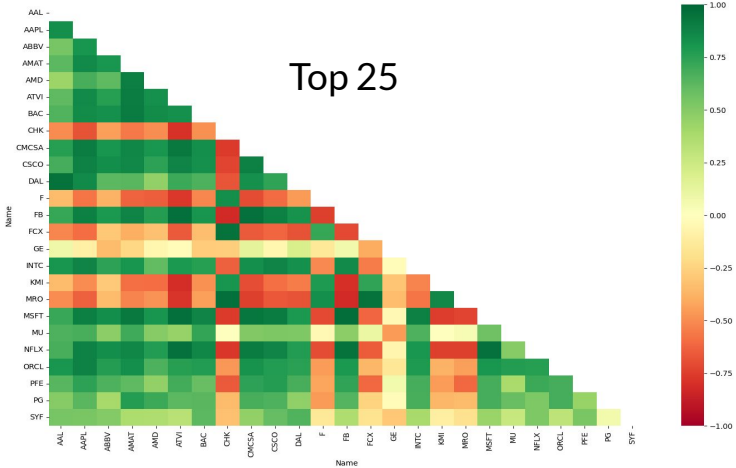
What We've Accomplished

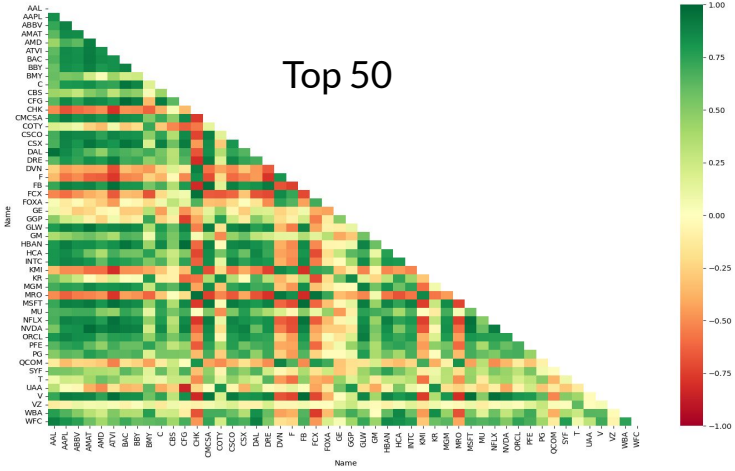
- Studied trading algorithms
- Found and cleaned up dataset
- Found correlation between stocks
- Compared correlations by year
- LSTM prediction model
- LSTM model with correlated stocks
- Random prediction model

Correlated Stocks




Top 10
AAPL
AMD
BAC
FB
GE
KMI
MRO
MSFT
PFE
VZ
Name
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Top 25
AAL
AAPL
ABBV
AMAT
AMD
ATVI
BAC
CHK
CMCSA
CSCO
DAL
F
FB
FCX
GE
INTC
KMI
MRO
MSFT
MU
NFLX
ORCL
PFE
PG
SYF
Name
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Top 50
Name
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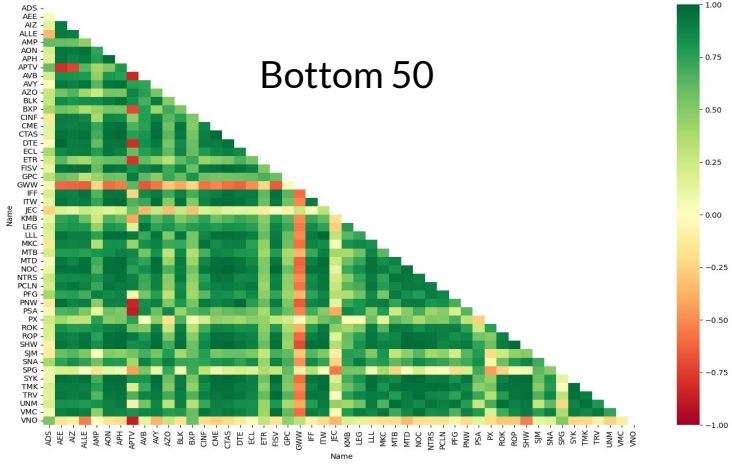
−1.00


Bottom 50
Name
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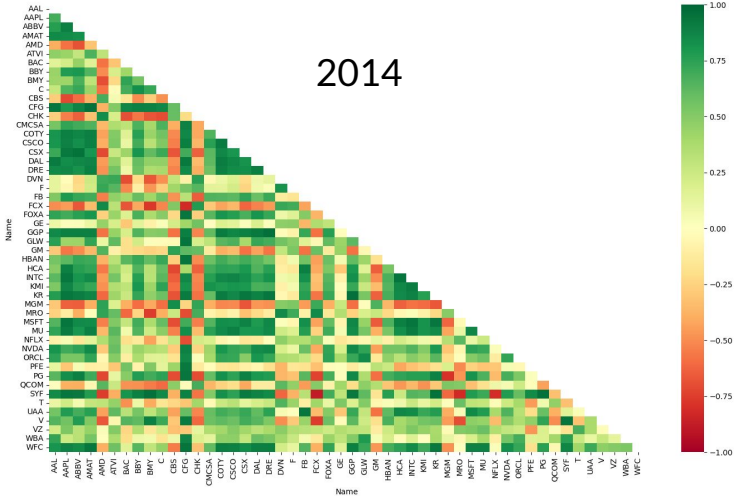
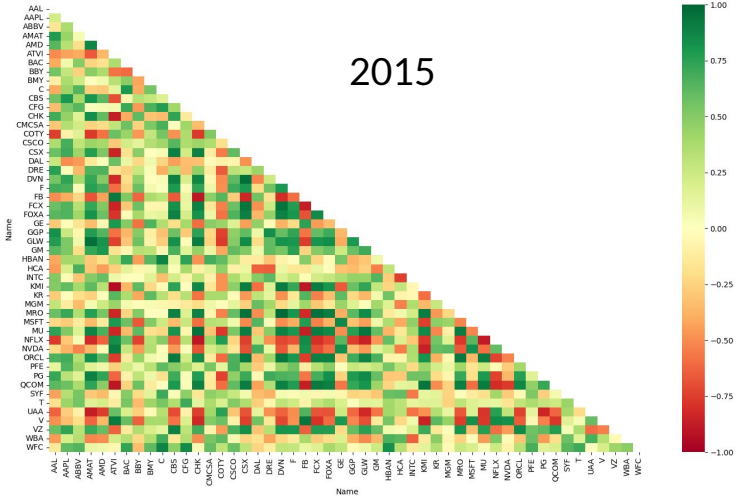
−1.00


2014
Name
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


2015
Name
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0.75
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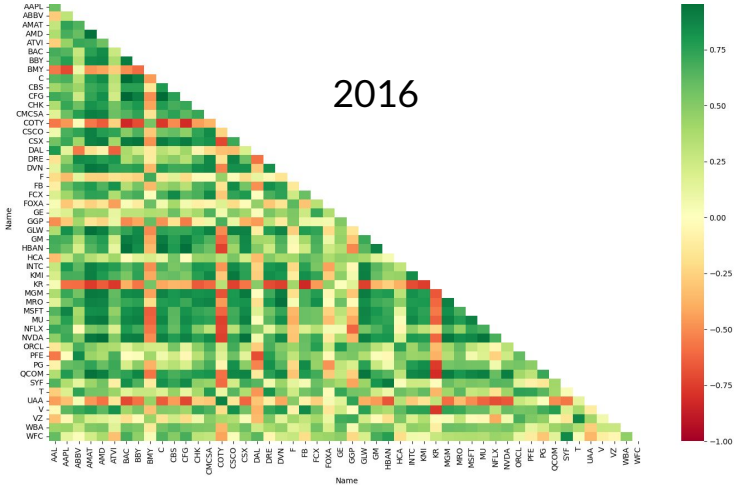
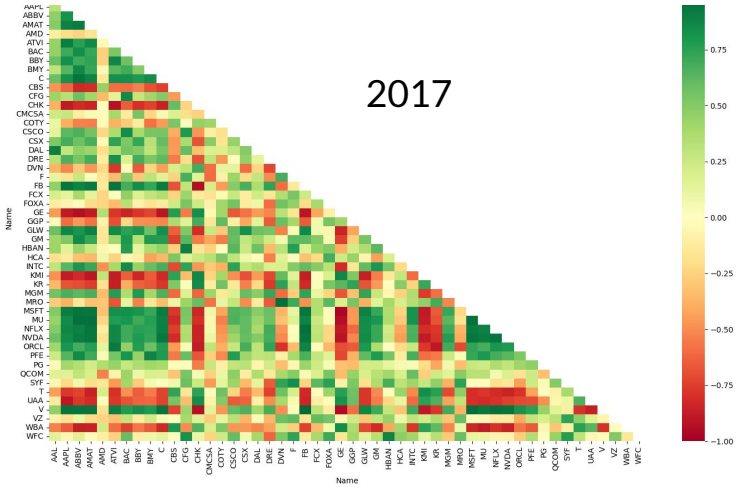
−0.50
−0.75
−1.00


2016
Name
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

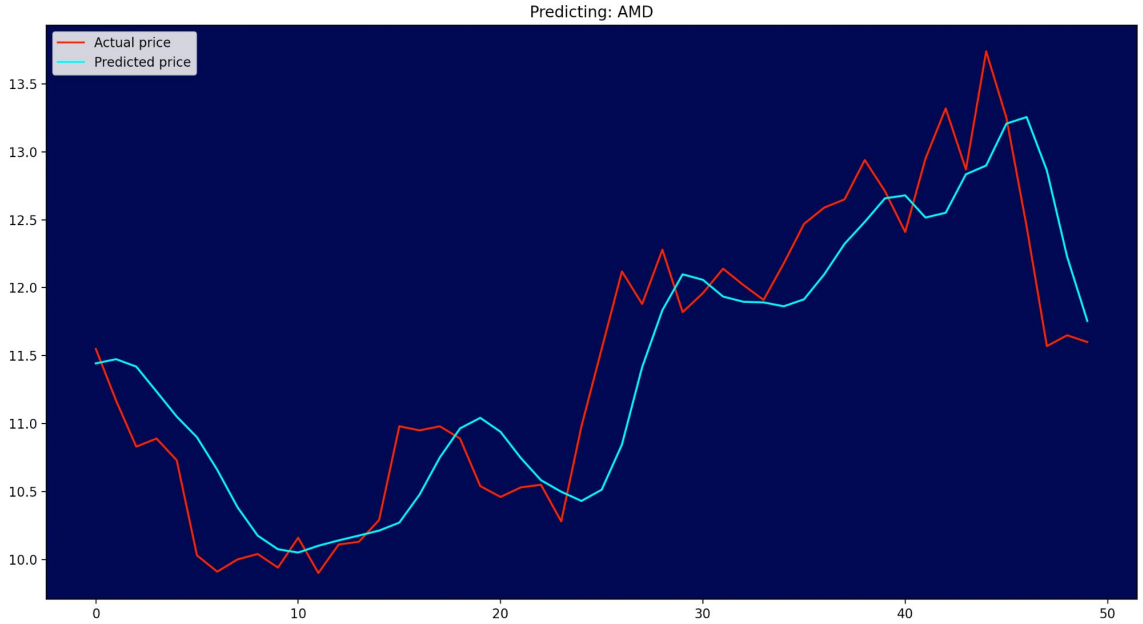

2017
Name
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

About Correlation

- Can vary greatly depending on time frame
- Correlation does not imply causation
- Helpful tool for diversifying portfolio
    - Negatively correlated stocks for limited losses
- Delayed correlation may work
    - Industry trends

Using machine learning to predict prices

- Using Long Short-Term Memory machine learning model
  - We were able to utilize the LSTM model in order to roughly predict stock prices
  - Utilized the “close” attribute of the stock data to train the model to predict prices



Using machine learning to predict prices

- Using the Random Tree Classifier model
  - This model allowed us to utilize all of the attributes of the stock data
  - We could also add more information to the table by calculating trends
  - More accurate model and could be utilized for actual trading vs basic prediction
- Initial findings (AMD: 09/15/2017 - 02/07/2018)

```
Initial money: 1000
Total money: 1064.0800000000004
Total shares: 0
Total trades: 48
Percent gain or loss: 6.408000000000036%
```

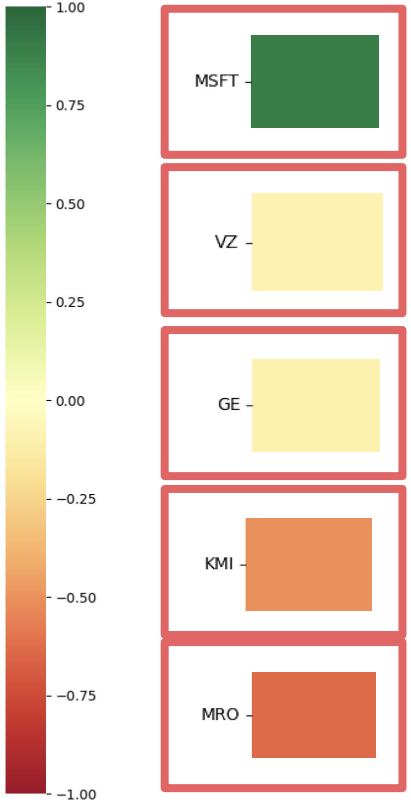
Using machine learning to predict prices

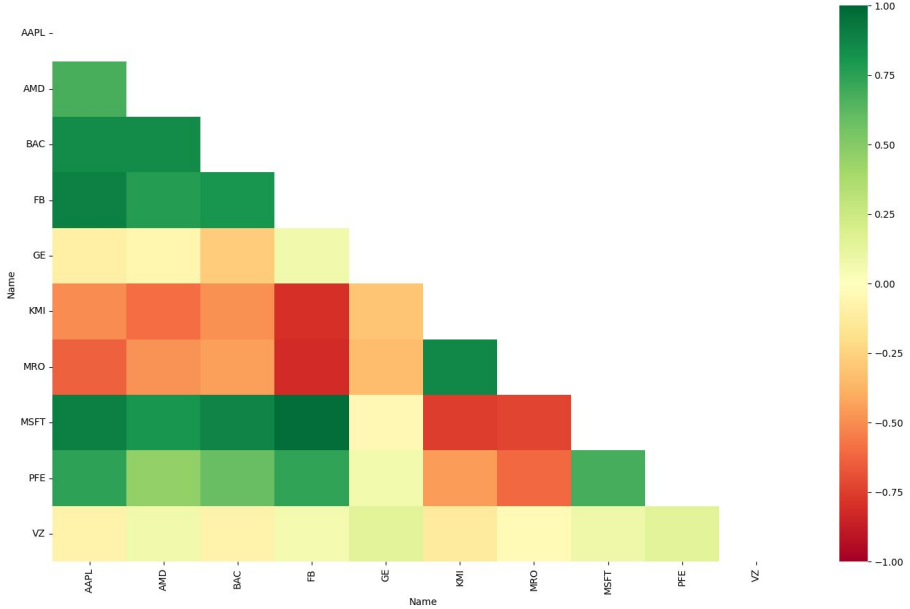
- Using the Random Tree Classifier model
- More intensive run:

```
Initial money: 1000
Total money: 1090.7799999999997
Total shares: 0
Total trades: 55
Percent gain or loss: 9.077999999999964%
```

```
Total money: 1000
Total money: 1015.08
Total money: 988.85999999
Total money: 988.85999999
Total money: 513.38999999
Total money: 1001.5799999
Total money: 1001.5799999
Total money: 961.67999999
Total money: 43.629999999
Total money: 481.28999999
Total money: 947.86999999
Total money: 933.58999999
Total money: 470.33999999
Total money: 66.729999999
Total money: 1016.55
Total money: 260.28999999
Total money: 1081.33
Total money: 1088.1999999
Total money: 1090.7799999
Total money: 1090.7799999
```

LSTM with Correlation (AAPL model)





Findings

- Use correlation data to build predictive models
  - We were able to utilize our correlated stocks in order to train predictive models that fit well for more than one company
  - Highly correlated stocks tend to have a more accurate predictive price versus non-correlated stocks
- LSTM
  - Using a Long Short Term Memory model we were able to predict stock prices for various companies
  - Trained multiple models to predict many different stocks
- Random Tree Classifier
  - Using the Random Tree Classifier we were able to utilize more parameters to train a model
  - Using the predictions we can calculate the amount of money we could make
  - Found that on average we would make money, around 7% profit over 100 days
- Testing
  - As we hoped, we were able to create models with positive returns when tested on market data

Evaluation

- Work has be evaluated by observing if our algorithm successfully predicts the actual change in the market.
- Metrics for evaluation will be the accuracy or error of our predictions, especially when compared to that of other prediction algorithms.
- Our models have been tested by letting it invest and make its own decisions
- We have compared our work with the standard trading trends in the market
- We have compared our work with random guesswork

Milestones

- Study other trading algorithms and models (Week 7) COMPLETED
- Collect past and current stock data (Week 10) COMPLETED
- Find correlation between the top S&P 500 stocks COMPLETED
- Project Checkpoint Report (Week 12) COMPLETED
- Study and mine data for patterns, trends, outliers, etc. (Week 13) COMPLETED
- Create a predictive model/algorithm based off patterns and trends from mined data (Week 14)COMPLETED
- Create/use a site to host the application (Week 15) Possible
- Final Project Report (Week 16)

We are happy with our results!

Questions?