

Neural Net Stock Trend Predictor



Advisor:

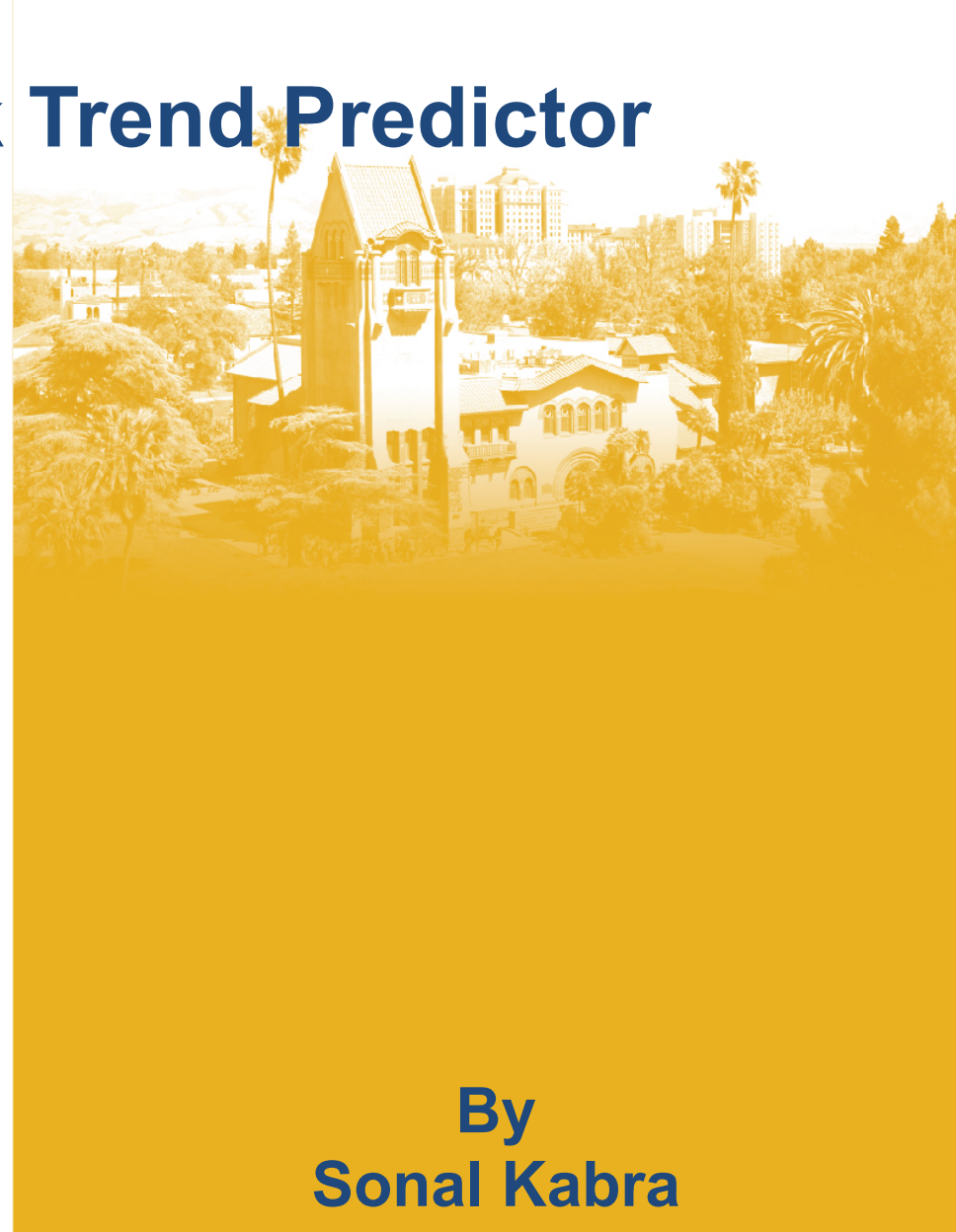
Dr. Chris Pollett

Committee Members:

Dr. Robert Chun

Mr. Paul Thienprasit

By
Sonal Kabra



- Purpose
- Introduction
- Review of Existing Work
- Prior Experiments
- Our Approach
- Neural Networks
- Models Developed
- Results
- Conclusion

- This project consisted of experiments and implementations of several neural nets to predict Stock Market movement and indicates whether the stock under study should be -- Bought, Neutral, or Sold to generate profit.
- All of our neural nets were designed to predict stock prices for the following week.

- Since the beginning of the stock market in 1817 in the United States, accurate stock prediction has been a goal of investors.
- One difficulty in accurately predicting stocks is the high number of variables on which they depend.

- Our neural nets used financial data from Quandl.
- Below is some example data showing attributes this data has.

Date	Open	High	Low	Close	Volume (BTC)
1/19/2016	387.04	387.04	387.01	387.01	5.24961215
1/18/2016	382.11	390	375.01	387.1	19467.04404
1/17/2016	388.43	393.31	378.76	382.02	20715.0043
1/16/2016	359.16	392.5	352.5	388.4	74056.46019
1/15/2016	429.27	429.43	357.02	359.16	123870.5349
1/14/2016	431.09	435	426	429.25	13304.53779
1/13/2016	431.99	436.36	416	431.11	33149.40771
1/12/2016	449.26	449.98	427.01	432.04	20739.28438
1/11/2016	449.34	452.49	443.42	449.26	14809.00262
1/10/2016	449.23	450.26	441.01	449.35	13778.25597
1/9/2016	454	456.01	447.07	449.23	8950.479347
1/8/2016	458.41	465	446.55	454	29967.85309

- Most investors follow two analytical methods:
- **Fundamental Analysis**
 - Studies company fundamental factors
 - Helps the investors to find the stocks worth investing
- **Technical Analysis**
 - Identifies the future uptrend or downtrend patterns.

- **Stock Prediction is not a new concept.**
- **Kara et al. [1]**
 - Two models: a neural network and an SVM, each used to predict the direction of stock price index movement.
 - Both use ISE National 100 Index for the dataset
 - Both use a total of 10 technical analysis indicators
 - The neural network had an accuracy of 75.74% and the SVM had an accuracy of 71.52%.

- Instead of predicting Up/Down signals, it will predict stock trade signals namely “Buy, Sell or Neutral” for next week.
- Instead of combining all the technical indicator, neural net will train separately for each indicator.

- Whenever human invests in stocks, they try to study the past data to find the similar pattern.
- The earlier experiments used K-nearest neighbor and decision tree machine learning regression techniques.
- By using those techniques, earlier experiments predict the closing price of the same day.

- The algorithm states that the prediction values are similar for the objects that are in close proximity of each other.
- Thus, we can assume that the prediction values will be almost equal for such objects.

- KNN has a high error range for both stocks
- The predictions are completely off from the right prices.

```
Training for FB.....  
AVG score is  0.0584505431993  
This is the result for FB.....  
Predicted adjusted close value for today is 126.51
```

```
Training for CSC0.....  
AVG score is  -0.284828431011  
This is the result for CSC0.....  
Predicted adjusted close value for today is 30.32
```

Actual Prices: FB: 149.78 CSC0: 34.3

- Helps to make predictions by mapping given observations to conclusions.
- Divide the information into small gatherings based on maximizing information gain.

```
Training for FB.....  
AVG score is  0.989572154988  
This is the result for FB.....  
Predicted adjusted close value for today is 150.45
```

```
Training for CSC0.....  
AVG score is  0.98784596313  
This is the result for CSC0.....  
Predicted adjusted close value for today is 33.88
```

Actual Prices: FB: 149.78 CSC0: 34.3

Our Approach



- Effective for short-term trading.
- Observes money flow, momentum, and volatility.
- Supplements in confirmation of trend or pattern
- 2 Types:
 - Leading Indicators
 - Lagging Indicators

- Is a lagging indicator.
- Formula:

$$SMA = \frac{p_M + p_{M-1} + \cdots + p_{M-(n-1)}}{n}$$

- **5-Day and 10-Day Moving Average Crossover Strategy**

- It is a leading indicator
- It tells whether the given stock is overbought or oversold.
- Formula:

$$RSI = 100 - \left(\frac{100}{(1+RS)} \right)$$

- The project is using the 14-Day period for the RSI.
- The RSI value above 70 indicates an oversold region, while below 30 indicates the overbought region.

- It is used to find buying and selling trend of the stock.
- It calculates the positive and negative flow of the volume on its price.
- If the current closing price is more than the previous close price:

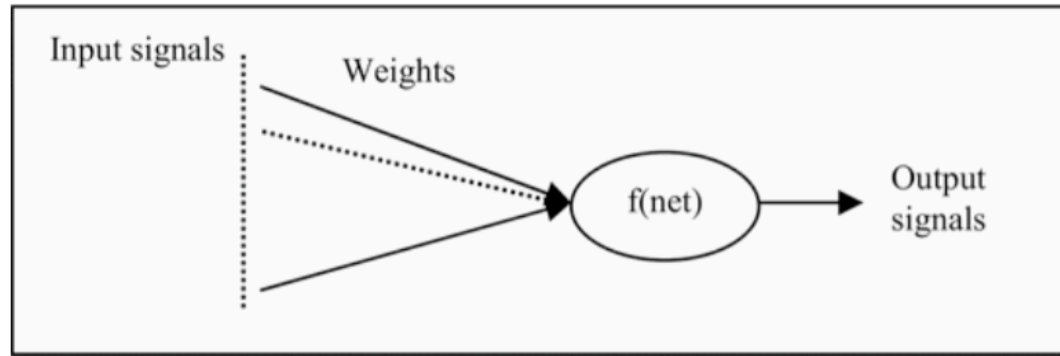
$$\text{Current OBV} = \text{Previous OBV} + \text{Current Volume}$$

- If the current closing price falls below the previous close price:

$$\text{Current OBV} = \text{Previous OBV} - \text{Current Volume}$$

- Else it will just assign the previous OBV to current OBV.

- Are computational models that replicate the behavior and adapt the features of biological neural systems.
- Has thousands of artificial neurons just like the human brain has neuron nodes.



- Input layer comprises of nodes or all input features in the Training set.
- Hidden layer comprises of the node responsible for the processing and learning of data from the Input Layer.
- Output layer comprises of a class node.

- Backpropagation algorithm.
- The problem is set up as minimization of a loss function.
- RPROP Algorithm

- Keras (Neural Network Library)
- Sklearn (Machine learning and data analysis library)
- Numpy (for mathematical calculations)
- Matplotlib (Plotting the results)
- Quandl API (Stock data)
- Pandas (storing stock data structure)

- S&P 500 market
- Blankets a diverse set of multinational corporations
- Collect the dataset from Quandl.
- Python Quandl API

- All the features in the data set are not in similar range.
- The values in datasets are normalized in the range of $[-1,1]$.
- **The formula is:**

$$X_{std} = (X - X_{min}) / (X_{max} - X_{min})$$

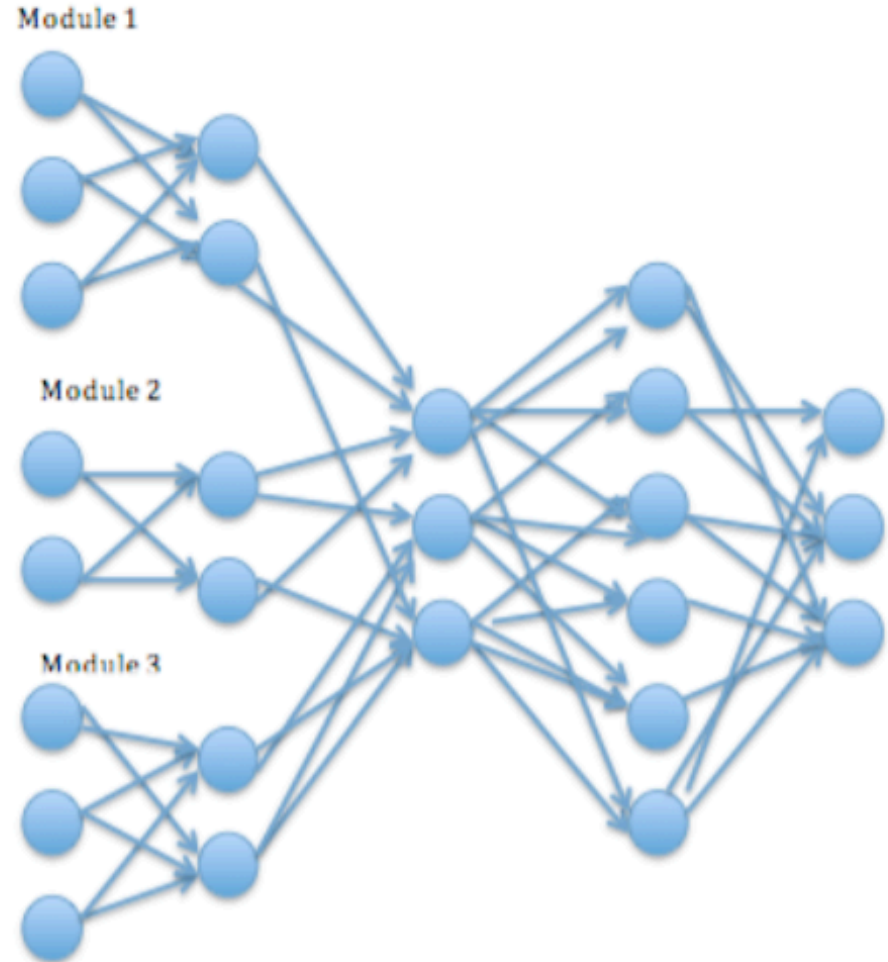
- The data is partitioned into the training (70% of the dataset), the validation (20%) data set, and test (10%)
- The 100 contiguous data points are randomly held from the generated dataset.
- The neural net is trained on around 800 stock data points and later tested on 100.

- 4-layer neural network.
- 30 input nodes: Three nodes for each day till ten days.
- Input features: 5-Day SMA, 10-Day SMA and Closing price of that day.
- 2 hidden layers: 60 and 60.
- The activation used is tanh.

- 4-layer neural network.
- 20 input nodes: Two nodes for each day till ten days.
- Input features: 14-Day RSI, and Closing price of that day.
- 2 hidden layers: 40 and 40.
- The activation used is tanh.

- 4-layer neural network.
- 30 input nodes: Three nodes for each day till ten days.
- Input features: On balance volume of the day, Volume of the day, and Closing price of that day.
- 2 hidden layers: 60 and 60.
- The activation used is tanh.

- All the models are merged into final layer of the neural network as shown in the following figure.
- The whole architecture is trained together, instead of training each model differently.



- The architecture is same as previous model.
- The test data set generated in this experiment is not random.
- The training is strictly forced to use the early days of stock data, and testing is done in recent days of stock data.

- As this is a multi-classification problem ("Buy," "Sell," or "Neutral"), the accuracy metric used is a Confusion Matrix.
- Accuracy defined is the number of correctly classified points in comparison to the total number classifications made.

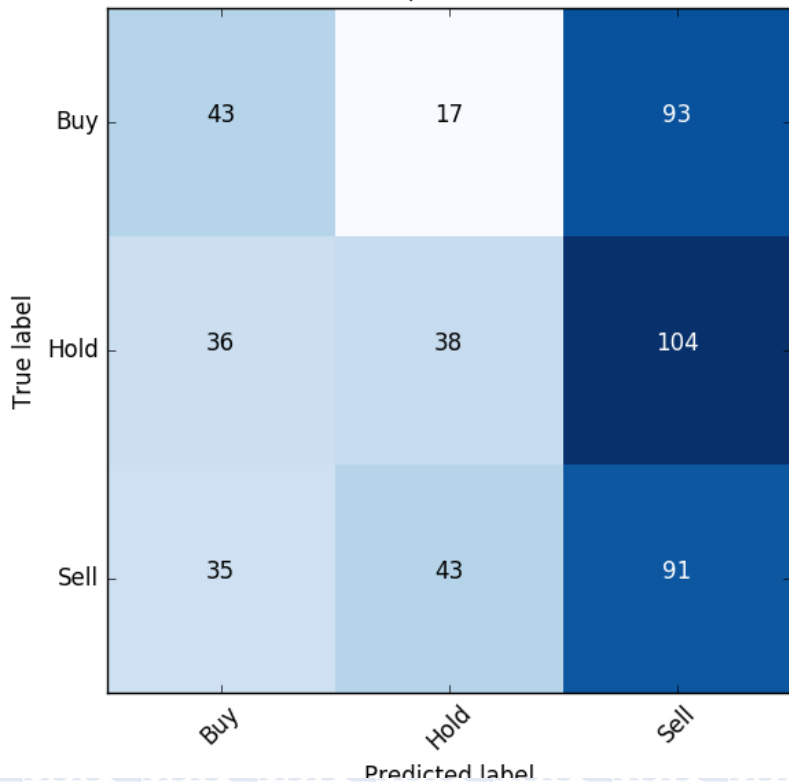
$$\text{Accuracy} = \frac{\text{True_Buy} + \text{True_Sell} + \text{True_Neutral}}{\text{Total number of Observations}}$$

- To calculate the profitability for each model following formula is used to calculate the normalized weekly return of a stock.:

$$\text{Return Threshold (}=1\%) * \frac{(\text{Total_Positive} + \text{Total_Negative}) - (\text{False_Positive} + \text{False_Negative})}{\text{total observations}}$$

- The average risk-free rate of weekly return is 0.035%

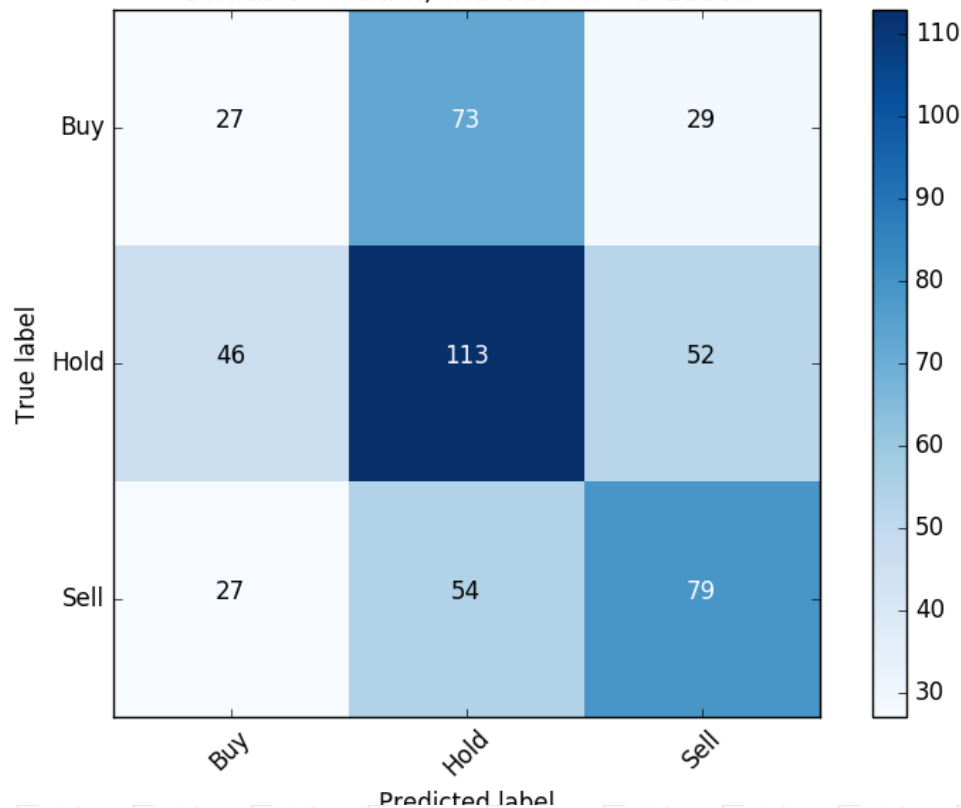
Confusion matrix, without normalization



HD[Acc.37.60%(+/-3.47%)]

1.04

Confusion matrix, without normalization

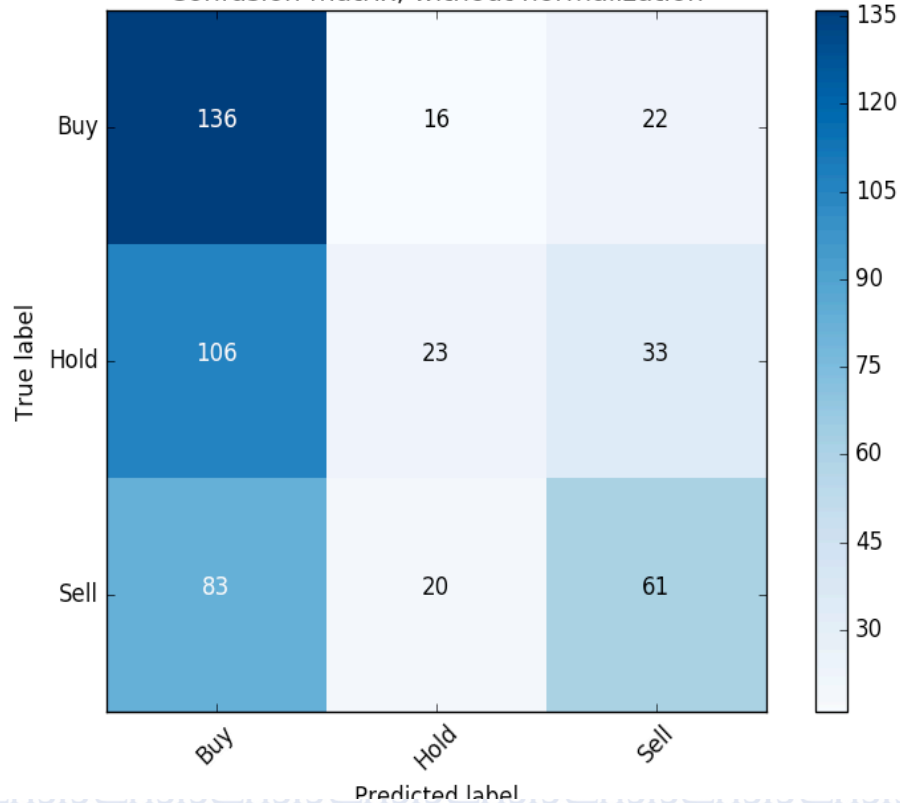


C [Acc. 47.00%(+/-4.16%)]

2.72

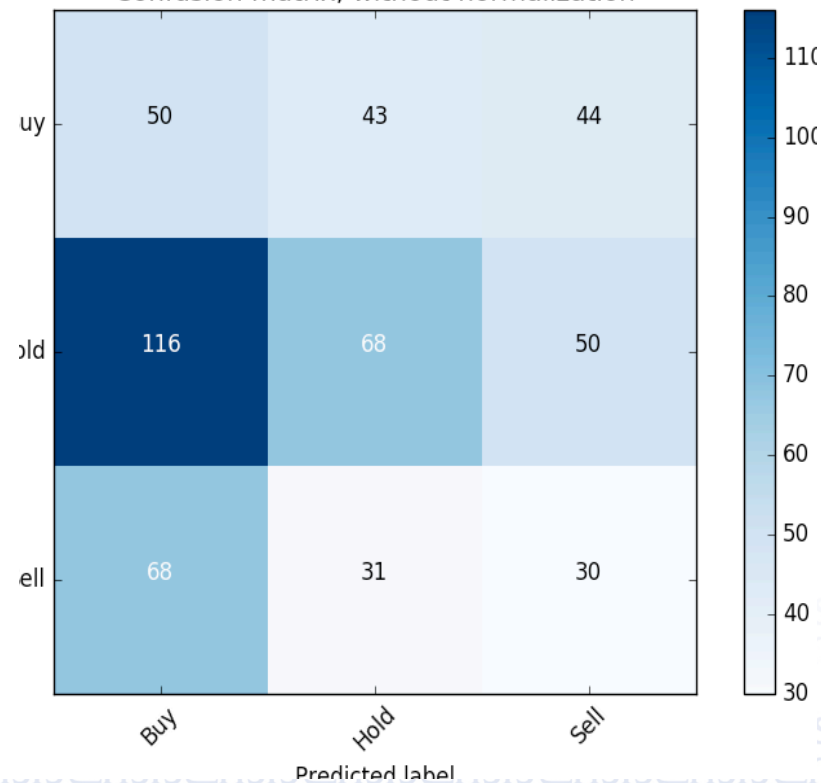
Stocks	Percentage weekly return
AAPL	0.066%
MCD	0.088%
XOM	0.076%
CAT	0.104%
C	0.1%
HD	0.012%

Confusion matrix, without normalization



CAT [Acc.37.40%(+/-6.41%)]
1.87

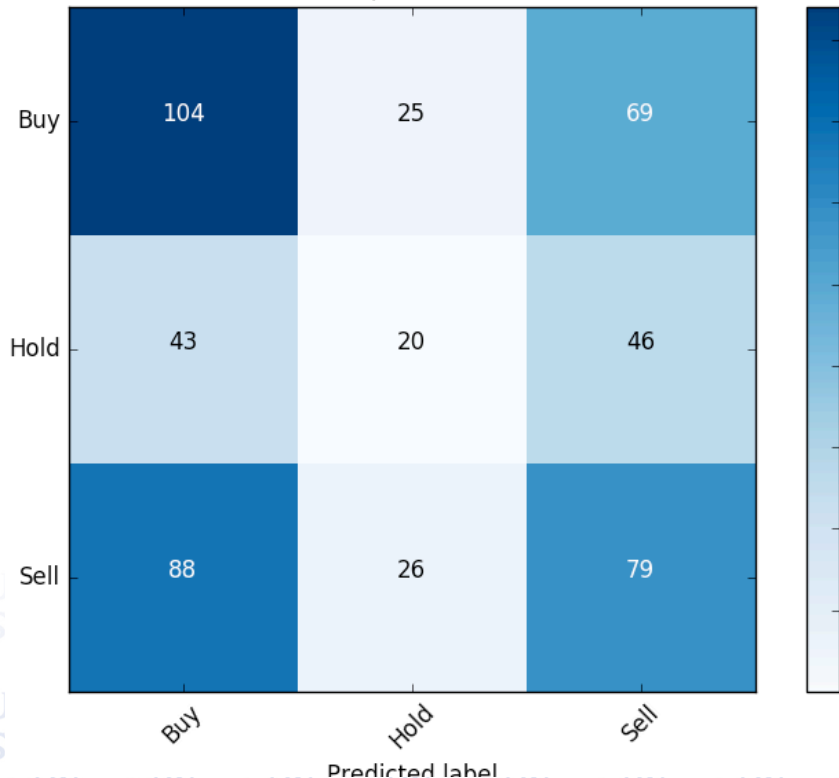
Confusion matrix, without normalization



XOM [Acc.29.60%(+/-8.16%)]
0.71

Stocks	Percentage weekly return
AAPL	0.126%
MCD	0.068%
XOM	-0.064%
CAT	0.184%
C	0.078%
HD	0.008%

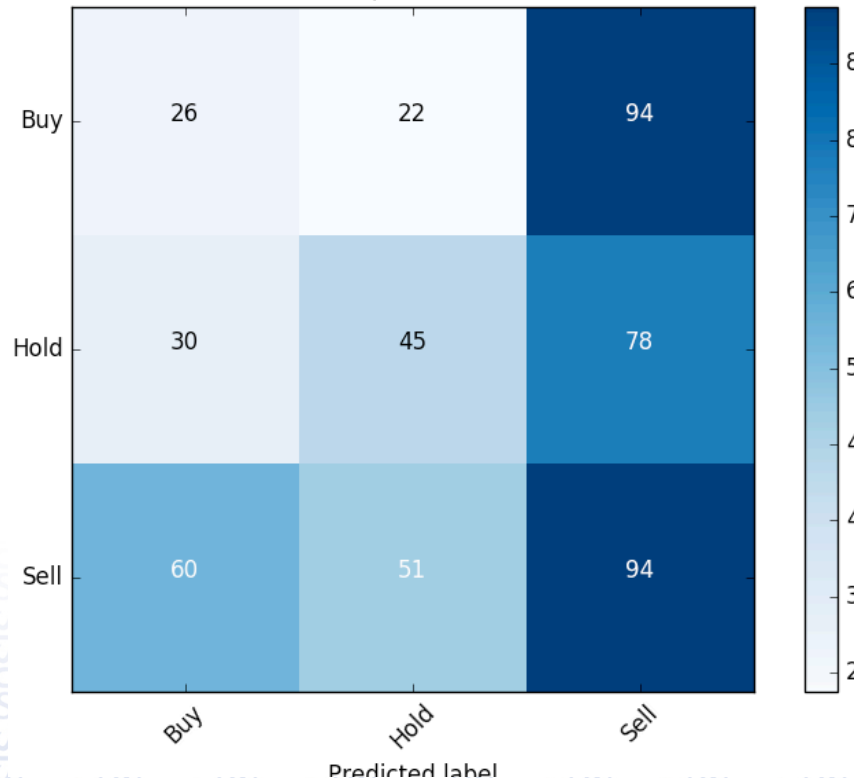
Confusion matrix, without normalization



C [Acc. 46.80%(+/-4.58%)]

1.16

Confusion matrix, without normalization

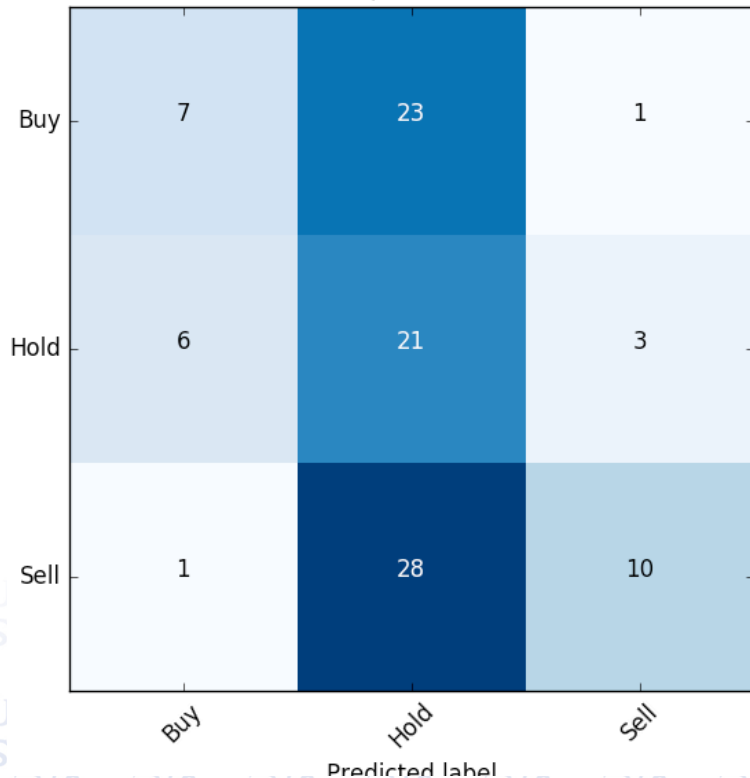


HD [Acc. 34.20%(+/-1.16%)]

0.77

Stocks	Percentage weekly return
AAPL	0.052%
MCD	-0.002%
XOM	-0.006%
CAT	0.028%
C	0.052%
HD	-0.068%

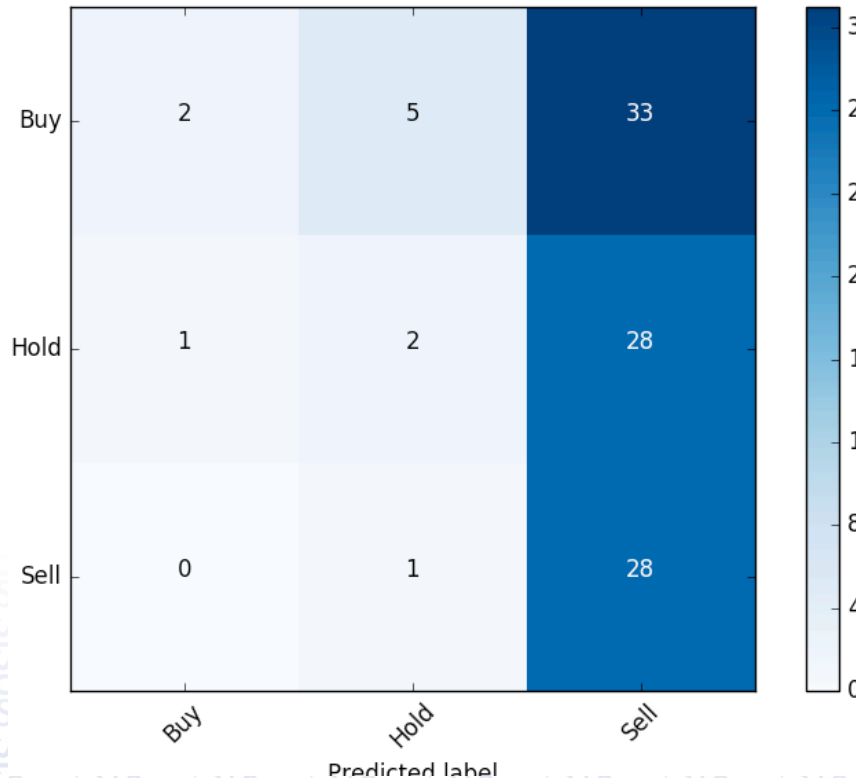
Confusion matrix, without normalization



CAT [Acc.44.36%(+/-4.76%)]

8.5

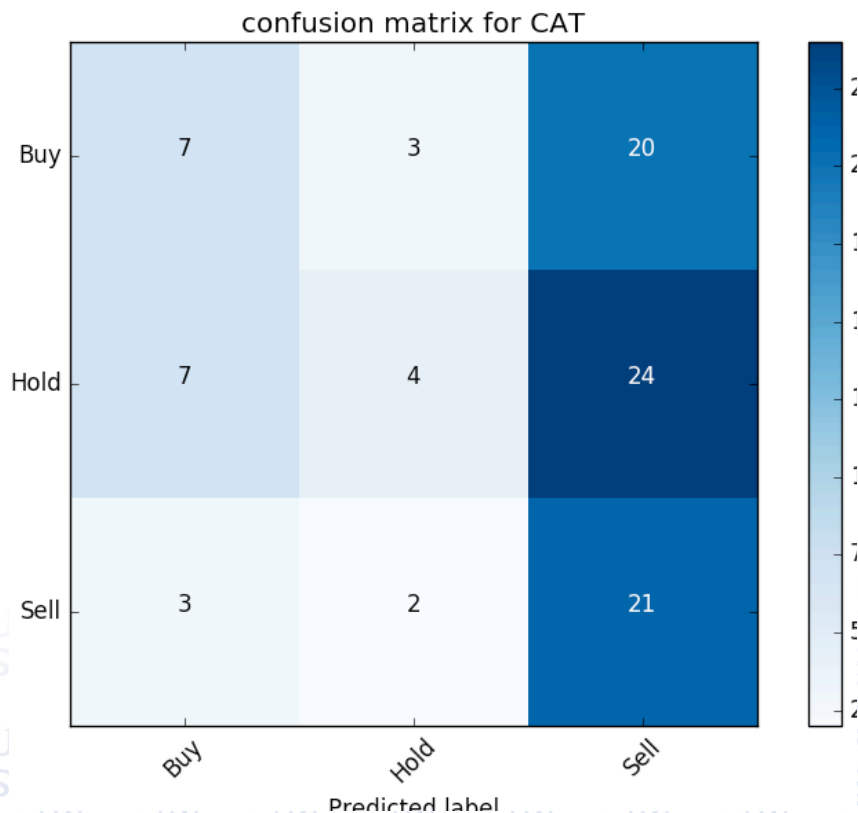
confusion matrix for HD



HD [Acc.34.26%(+/-1.76%)]

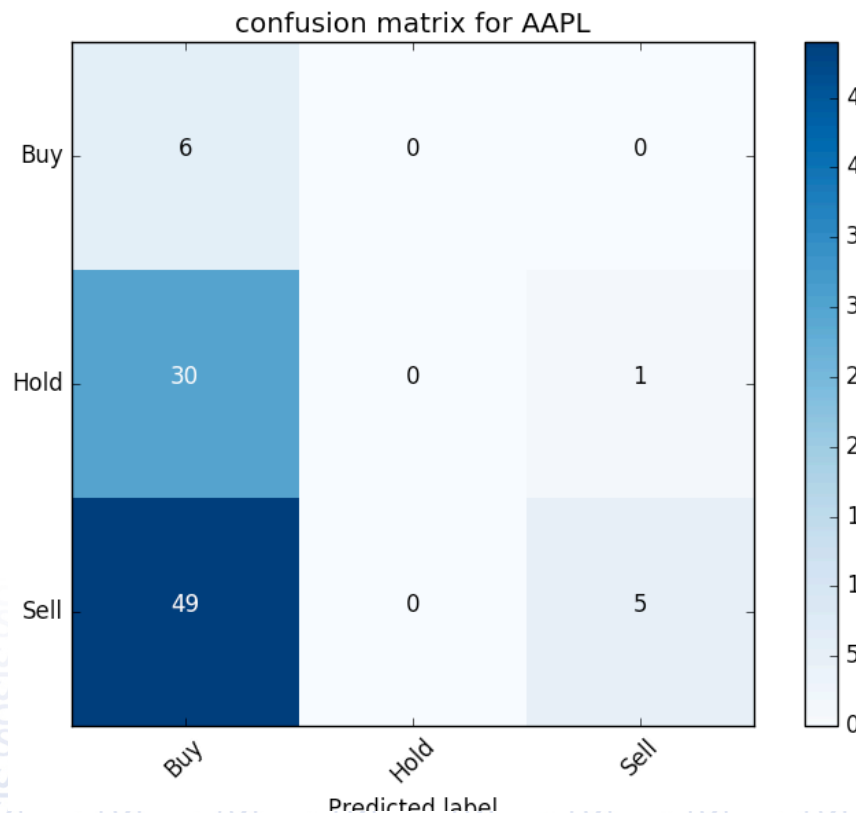
0.90

Stocks	Percentage weekly return
AAPL	0.19%
MCD	0.06%
XOM	-0.001%
CAT	0.15%
C	0.06%
HD	-0.03%



CAT [Acc.37.53%(+/-3.72%)]

1.21



AAPL[Acc.26.22%(+/-5.88%)]

0.22

Stocks	Percentage weekly return
AAPL	-0.38%
MCD	-0.36%
XOM	0.001%
CAT	0.184%
C	-0.01%
HD	-0.18%

Why some models may performed poorly:

- Model Complexity
- Training Data
- Market Noise

- From the Confusion matrices for above simulations, Merged Model Randomized still gives better results than the Merged Model in Sequence.
- If we consider only moving average crossover model, then that model gives more returns than rest of them.
- Therefore, for future development one can surely use Moving average crossover model.

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THANK YOU..!!!

