SHIV NADAR UNIVERSITY

Project Report – Part 1

Machine Learning Implementation on 'Stock Price Forecasting'

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Acknowledgement and Motivation

We would like to express my deepest appreciation to our Professor **Dr. Madan Gopal** who provided me the possibility to complete this report. A special gratitude we give to our Assistant Professor **Ashish Kushwaha**, whose contribution in stimulating suggestions and encouragement which helped us to coordinate my project.

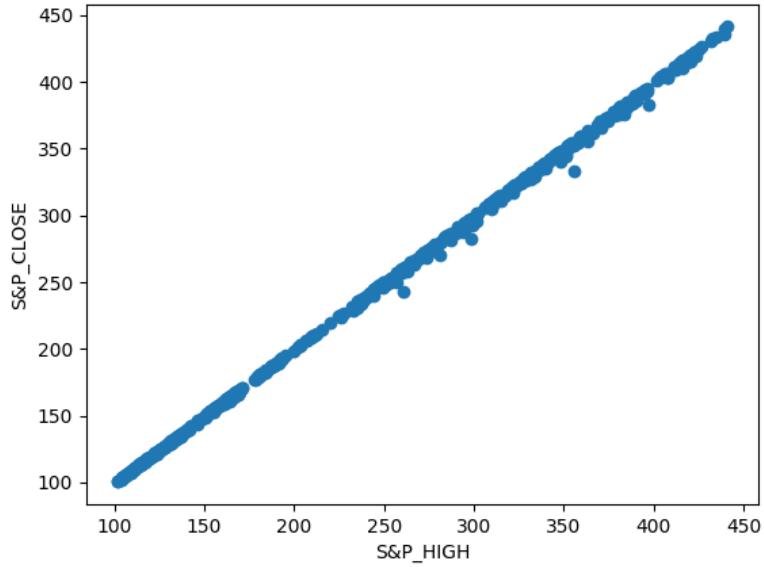
‘Stock Price Forecasting’ is an interesting field of study and a money oriented practical application of Machine Learning. A lot of research work is being carried out to predict the stock prices by financial institutes and is the topic of the hour. This trending topic intrigued us and we found the dataset to be challenging enough to be considered as our project.

Feature Analysis

There are 21 features in our dataset. The stocks market parameters listed in the dataset are listed from 1/4/1980 – 12/4/1992. Feature to be predicted is **S&P Close**. There are total 679 examples given in the dataset (roughly 4 example per month).

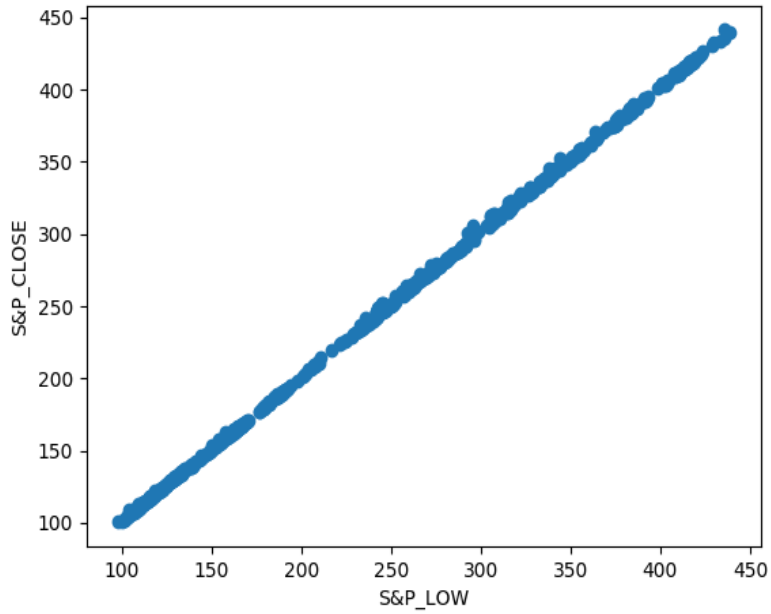
1. **S&P_HIGH**

It's a parameter of Standard & Poor listed 500 biggest companies of America. This parameter tells us the highest intra-day value achieved by these companies.



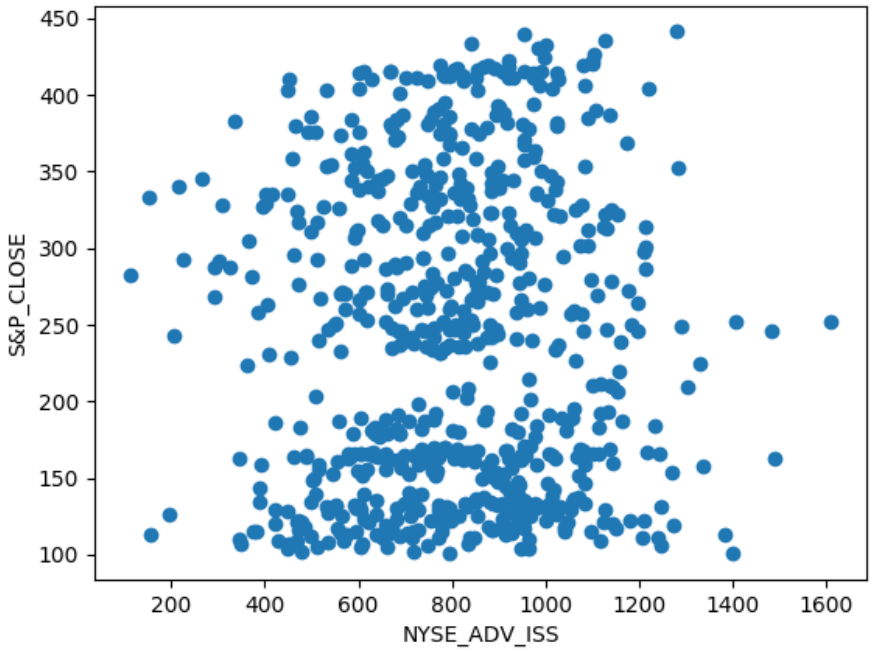
2. **S&P_LOW**

It's a parameter of Standard & Poor listed 500 biggest companies of America. This parameter tells us the highest intra-day value achieved by these companies.



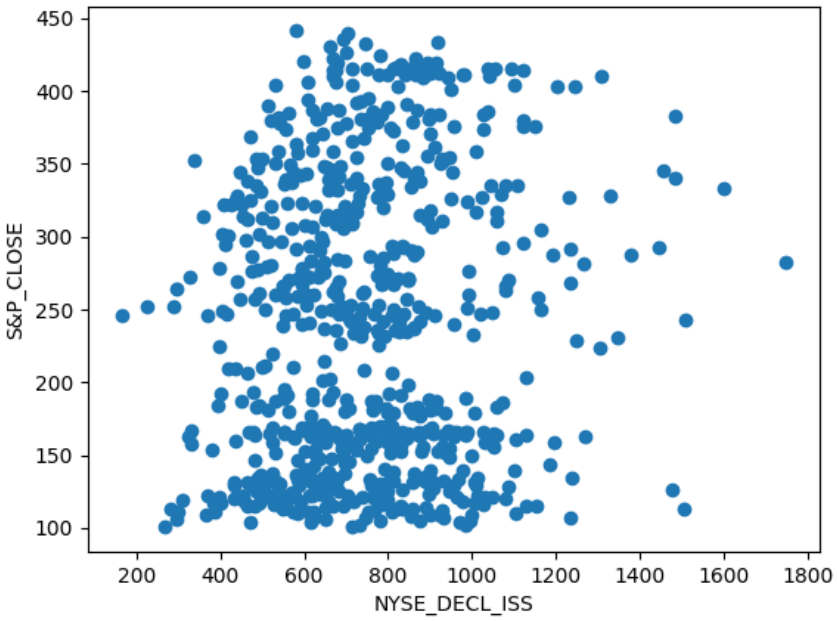
3. **NYSE_ADV_ISS**

This parameter indicates how many companies had an increase in their stock prices. This feature will eventually be removed as it has very low correlation value with the output label.



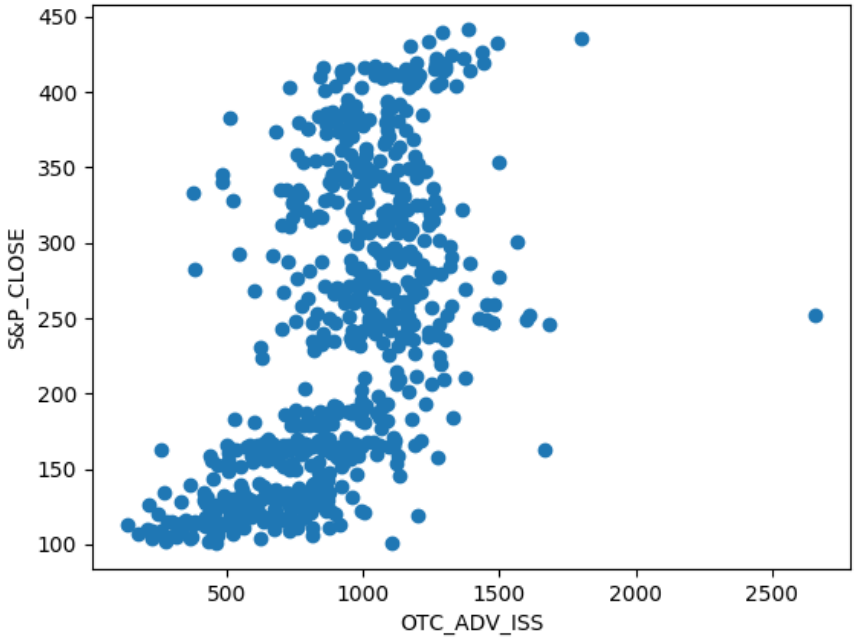
4. **NYSE_DECL_ISS**

This parameter indicates how many companies had a decrease in their stock prices. This feature will eventually be removed as it has very low correlation value with the output label.



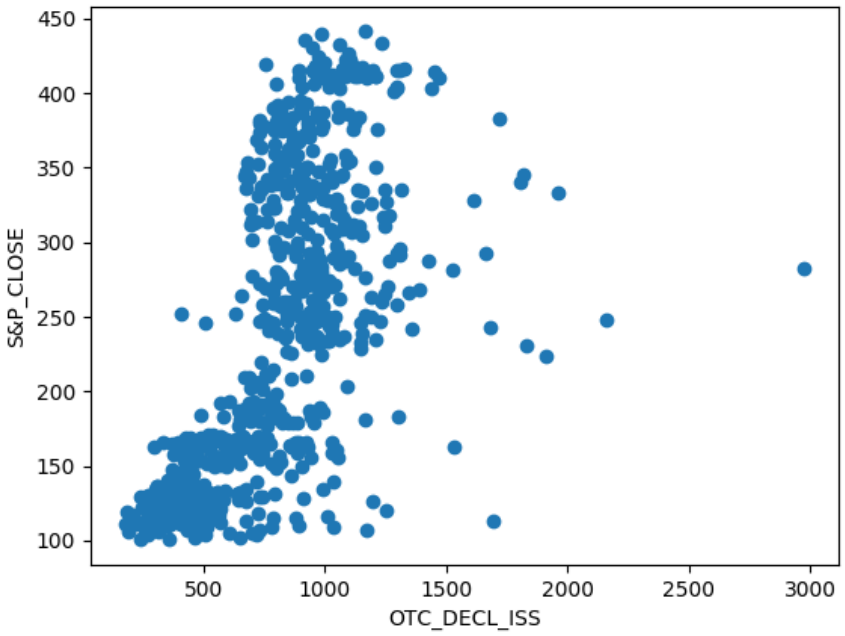
5. **OTC_ADV_ISS**

Over-the-Counter (penny stocks) parameter indicates how many penny stocks had a surge in its value.



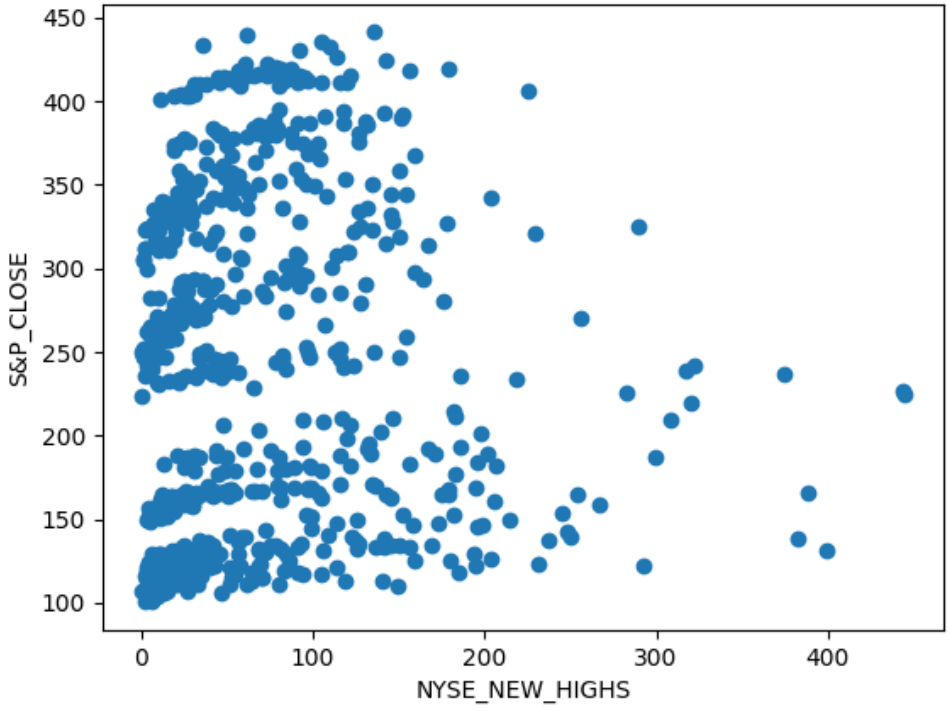
6. **OTC_DECL_ISS**

Over-the-Counter (penny stocks) parameter indicates how many penny stocks had a decrease in its value.



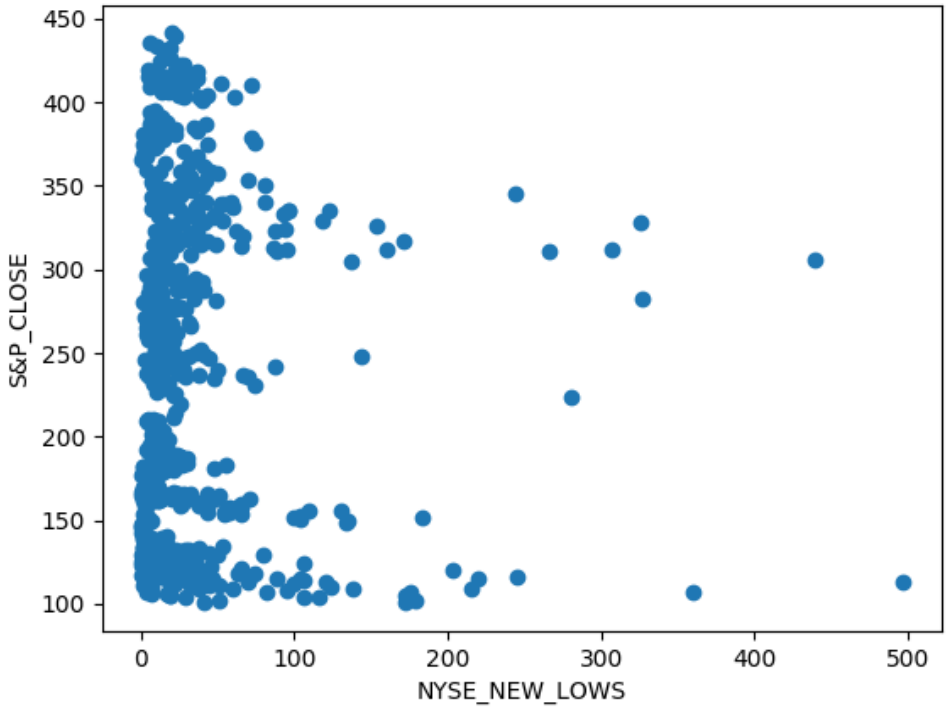
7. **NYSE_NEW_HIGHS**

Parameter tells number of best performing shares.



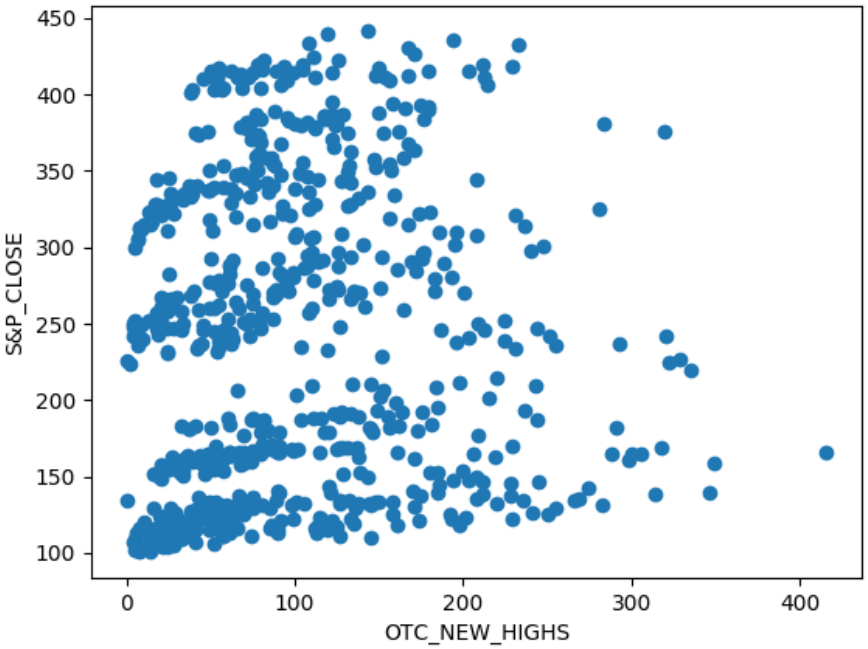
8. **NYSE_NEW_LOWS**

Parameter tells number of worst performing shares.



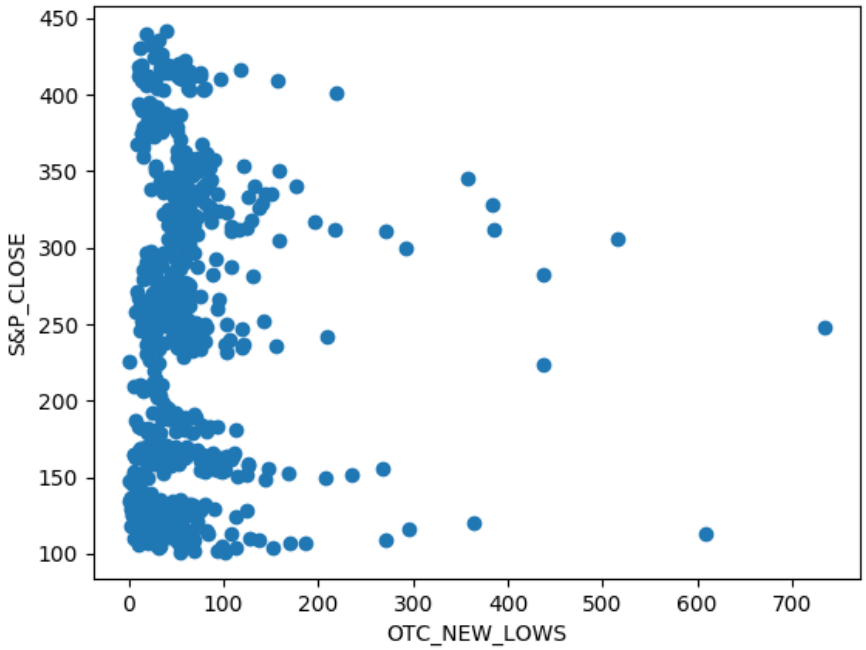
9. **OTC_NEW_HIGHS**

Parameter tells number of penny stocks which are best performing.



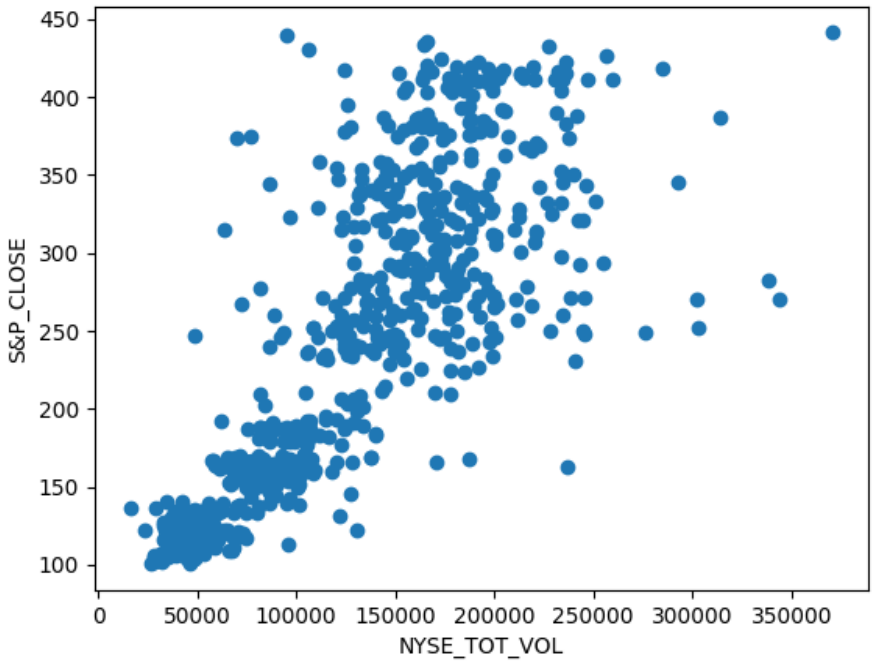
10. **OTC_NEW_LOWS**

Parameter tells number of penny stocks which are worst performing.



11. **NYSE_TOT_VOL**

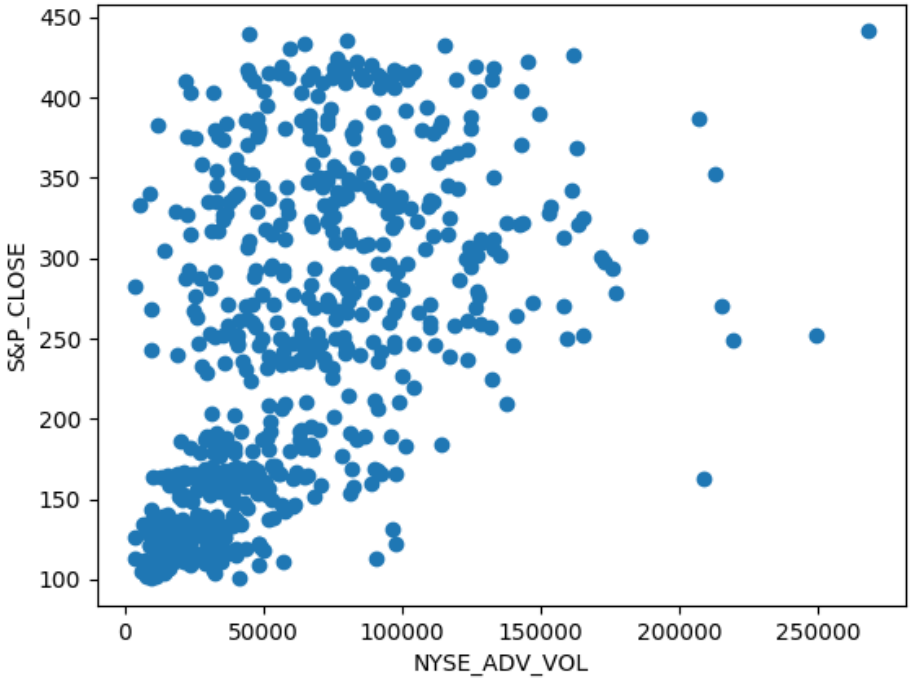
Total number of shares traded in the exchange.



12. **NYSE_ADV_VOL**

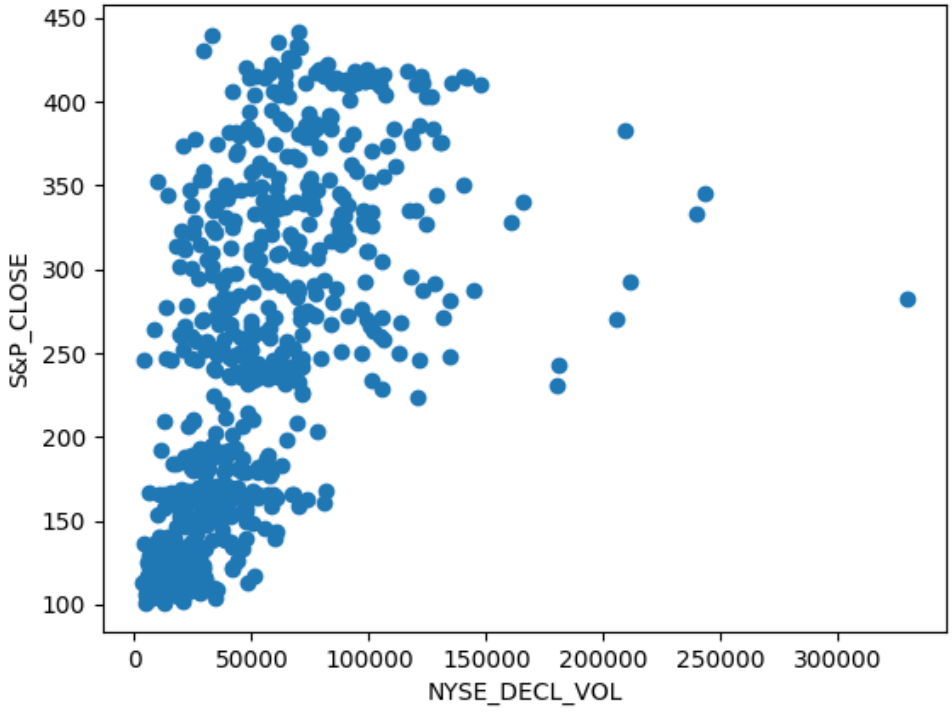
Total number of positive performing shares traded in the exchange.

13.



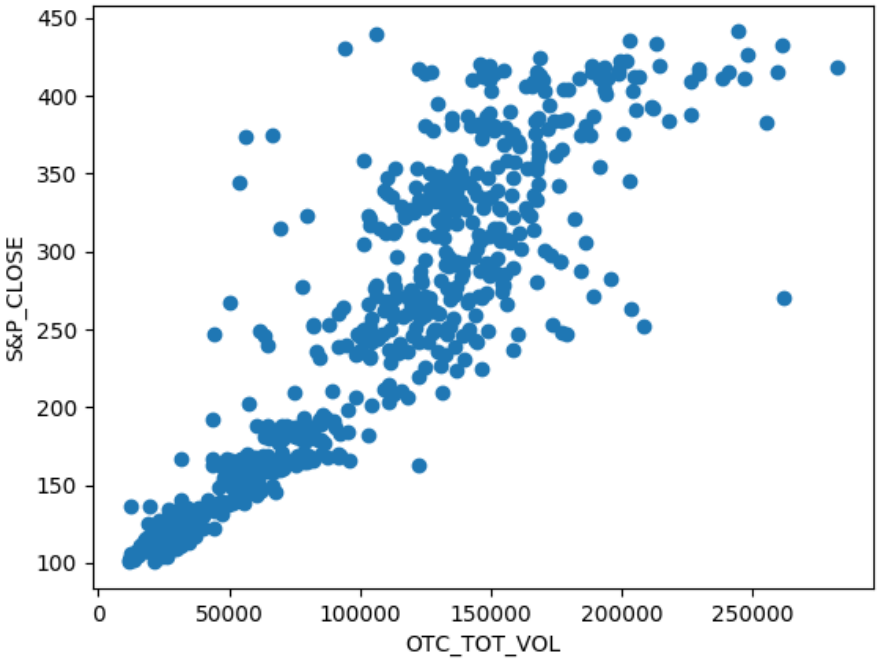
NYSE_DECL_VOL

Total number of negatively performing shares traded in the exchange.



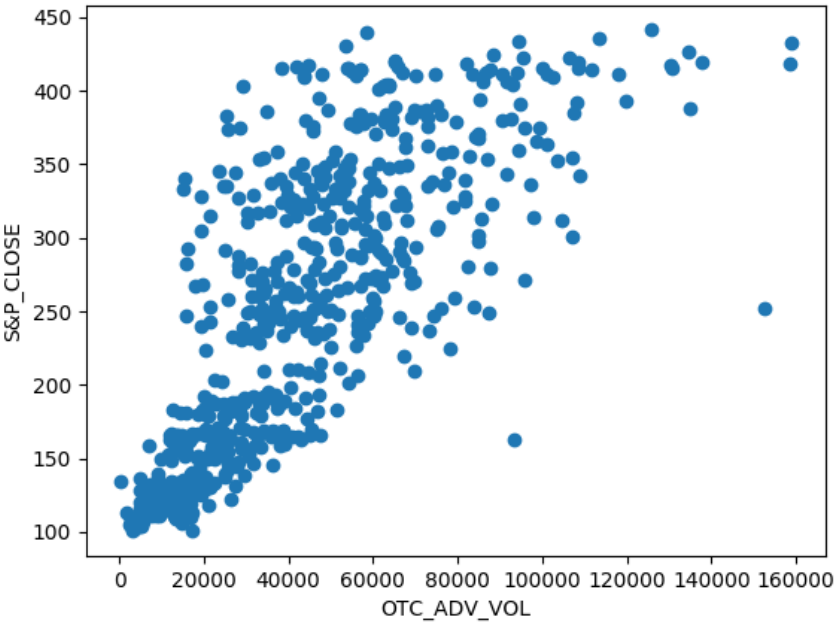
14. **OTC_TOT_VOL**

Total number of penny stock shares traded in the exchange.



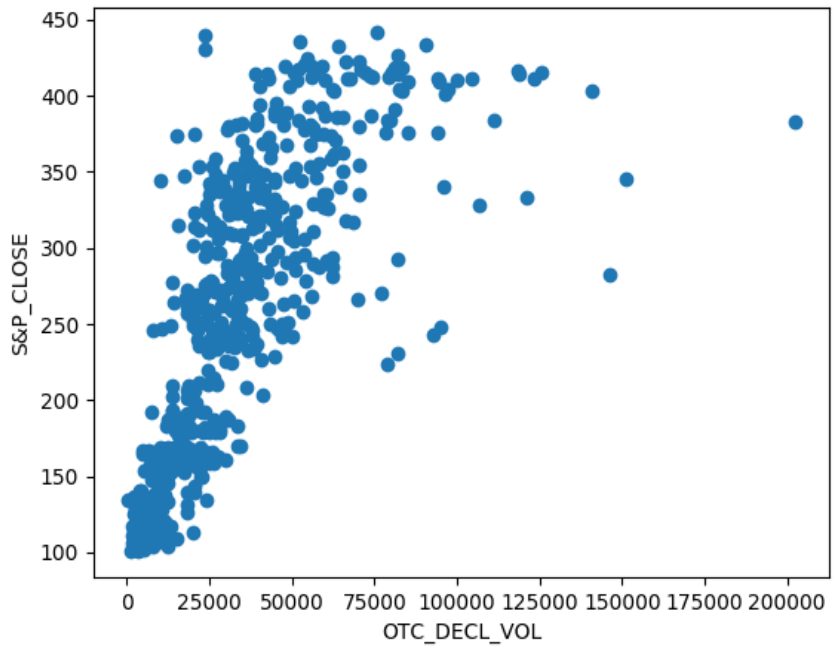
15. **OTC_ADV_VOL**

Total number of positive performing penny stock shares traded in the exchange.



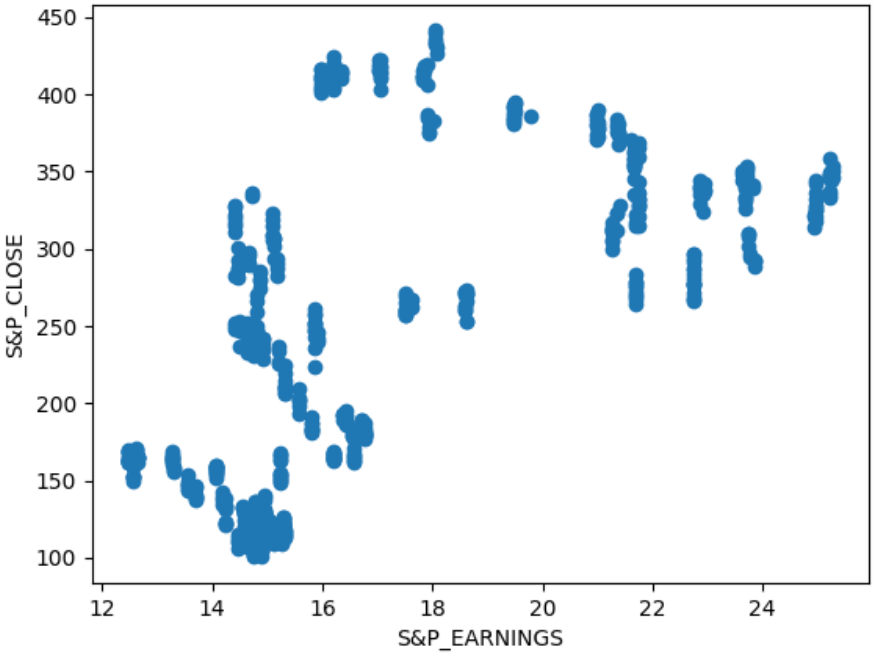
16. **OTC_DECL_VOL**

Total number of negatively performing penny stock shares traded in the exchange.



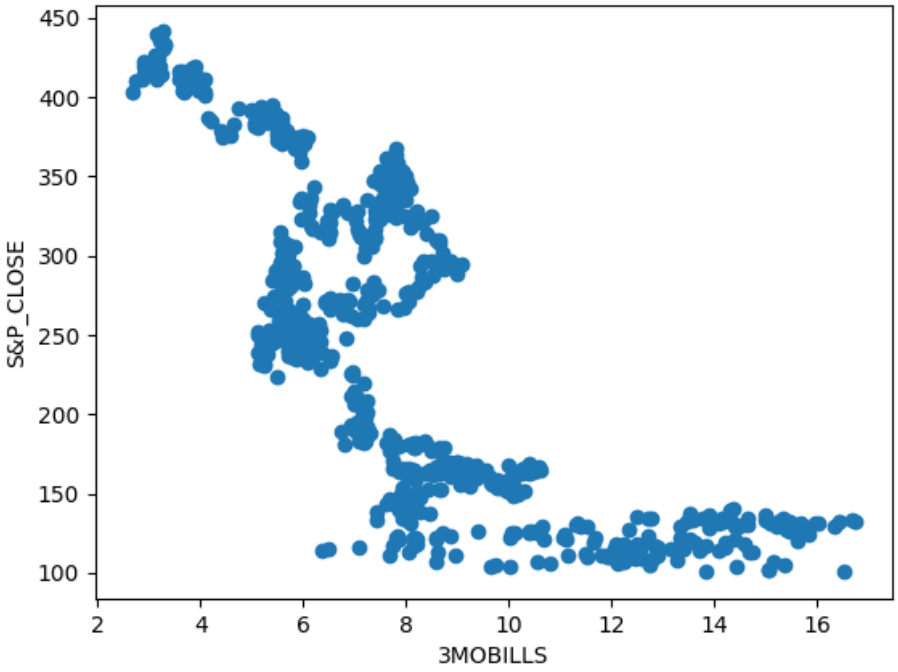
17. **S&P EARNINGS**

This feature hasn't been understood yet.



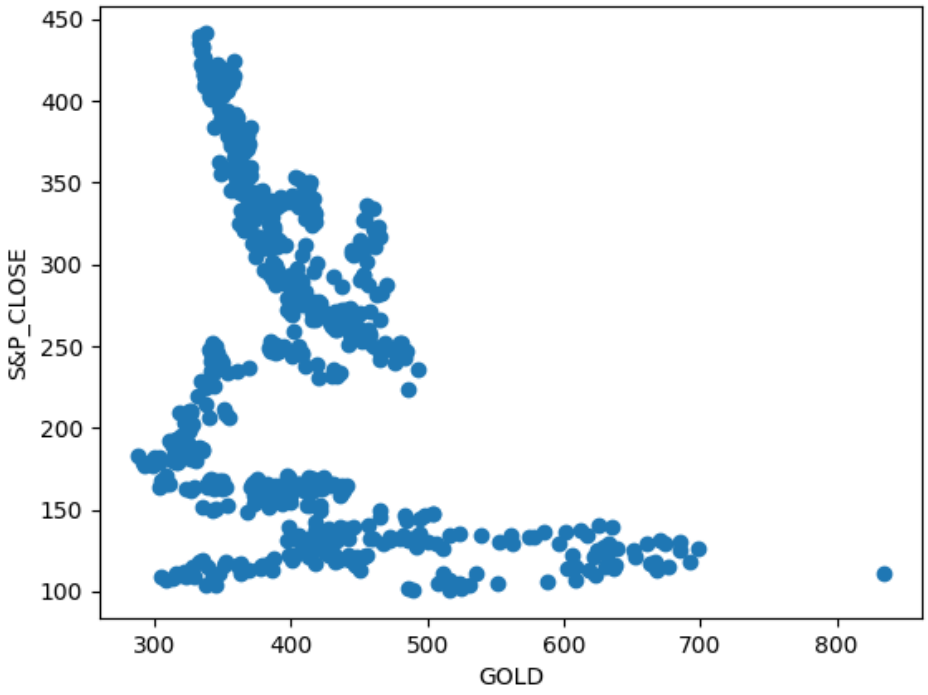
18. **3 MOBILLS**

This feature hasn’t been understood yet.



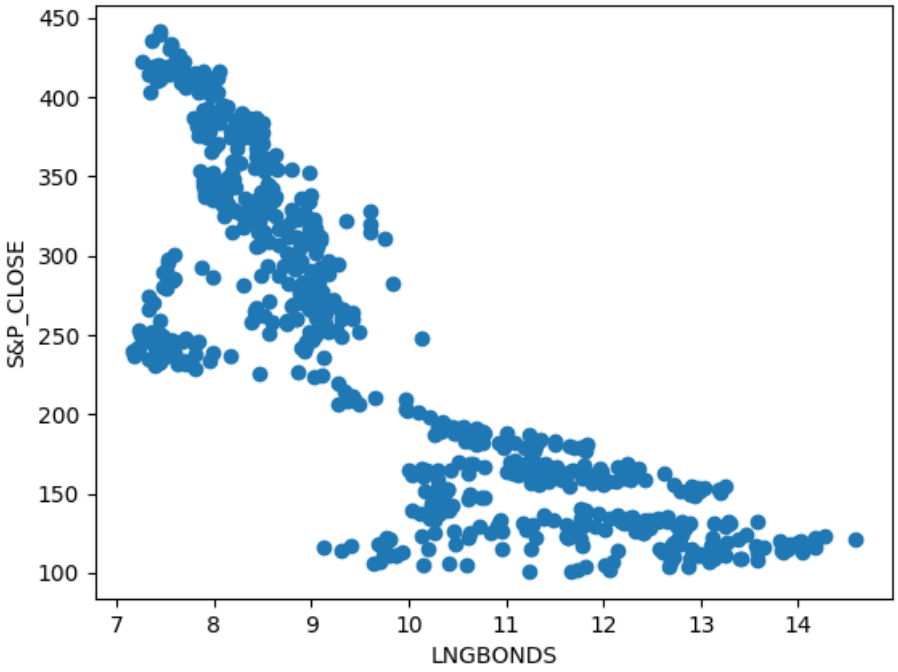
19. **LONGBONDS**

This feature hasn’t been understood yet.

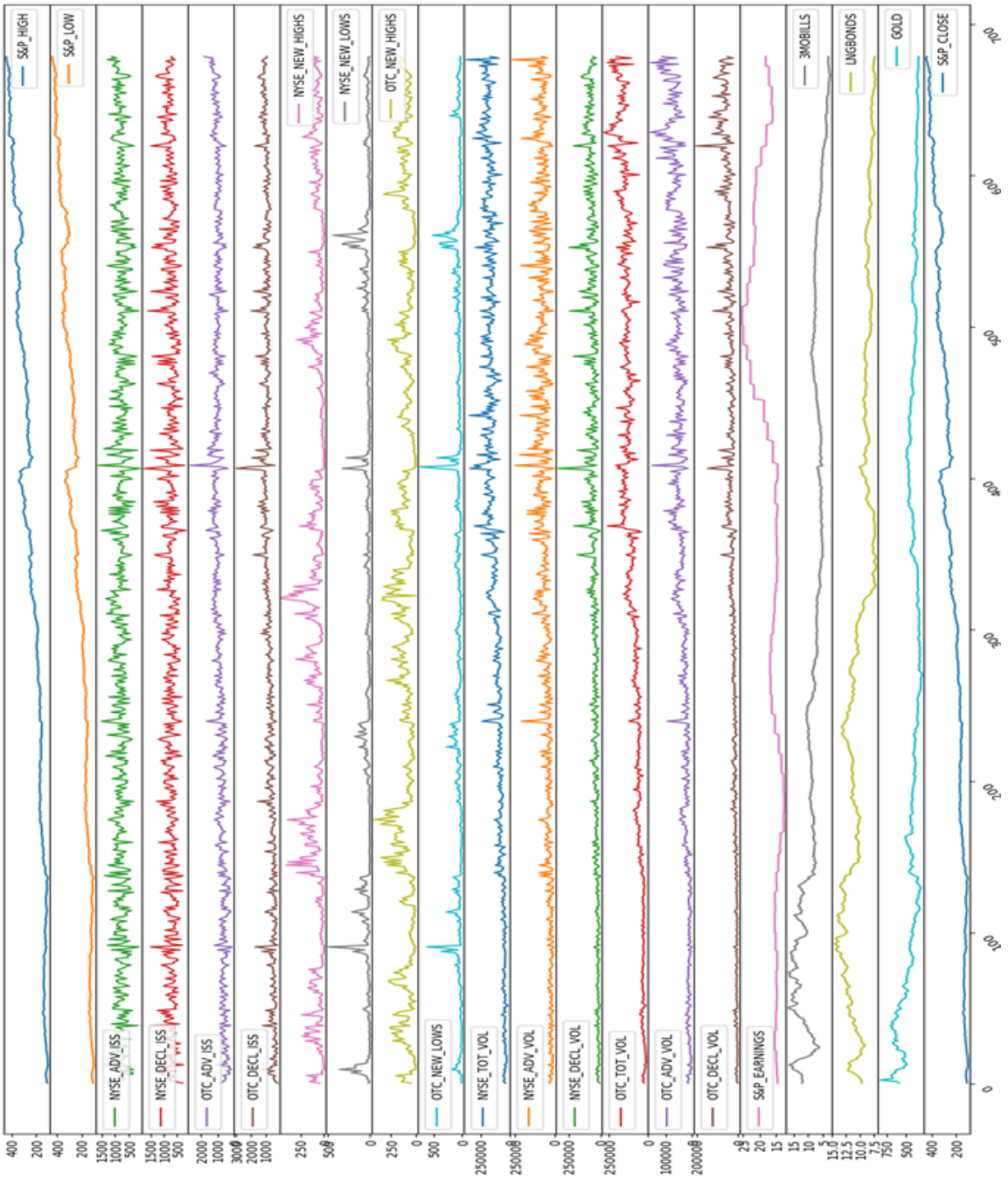


20. **GOLD**

How does S&P close affect the prices of gold



Correlation, Covariance and Interdependencies



Graph for each feature

The above stated graph shows each and every feature without scaling and reduction. This is rough and unprocessed representation of the dataset provided to us. Through this we can easily visualize which parameters have high and low volatility (idea of standard deviation.

Observation

Observation from correlation matrix shown below was quite interesting as we were able to reduce the features with its help. We also tried to reduce some features by gaining some domain knowledge. The need for applying **Principal Component Analysis (PCA)** was eventually eliminated as the features were reduced through above steps.

Elimination

The features having correlation value with the output label (**S&P_CLOSE)** less than 0.07 were removed straight away to reduce the features. The contribution of these features seemed not-worth mentioning as they had a very little effect on our variable to be predicted.

Elimination value (Correlation) ≤ 0.07

Hence, eliminating 3 features (**NYSE_ADV_ISS, NYSE_DEC_ISS, NYSE_NEW_LOWS**)

Removing Outliers

After removing the 3 features due to their less correlation with our output variable. The next step was to remove the outliers in the dataset. For this a new matrix was created and Z was calculated for each feature.

Z = (x - mean)/(standard deviation)

$Z = [(x-\mu)/\sigma]$

Higher the value of Z more that particular point is away from the mean and hence higher the tendency of being an outlier. 5% of the 679 examples showing maximum value of Z were considered as an outlier and replaced with mean value of the feature on the original dataset.

Normalization

In order to have a uniform range of all the features, each point was divided by the maximum value of that feature. Normalization was done so that weights of

all the features remain constant and weights of particular features do not shoot up due to its high values.

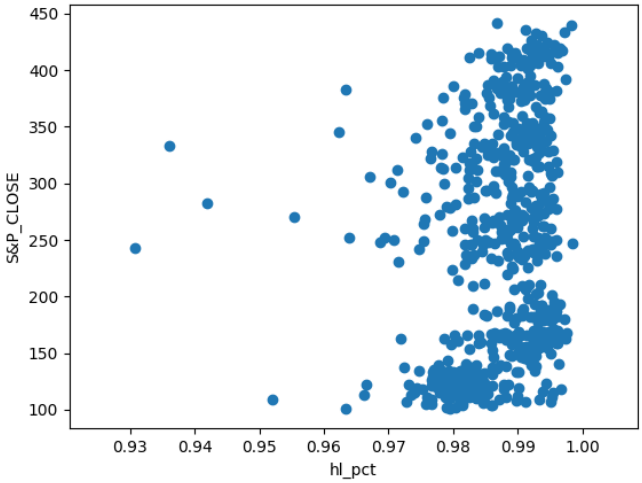
Merging

The features having correlation value with each other more than 0.80 were merged and their ratio was taken to describe the measure.

Merging Value (Correlation) ≥0.80

(S&P_LOW÷ S&P_HIGH).

Hence, merging 2 features (**S&P_HIGH, S&P_LOW**) by creating one feature describing their ratio (Value remains less than 1 because the ratio taken into consideration is (**S&P_LOW÷ S&P_HIGH**).

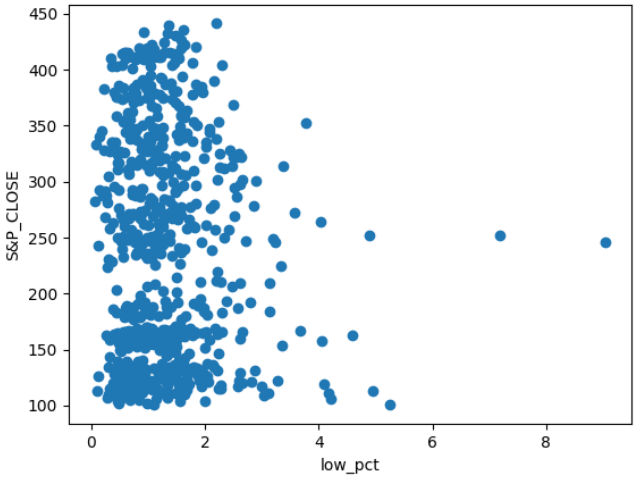


As we can see from the graph, correlation between **hl_pct** (**S&P_LOW÷ S&P_HIGH**) is approximately 0.20 which has actually ruined the both the features and incorporating this reduces our accuracy significantly.

(NYSE_ADV_ISS / NYSE_DECL_ISS)

Now, merging these two features which showed a very low correlation with **S&P_CLOSE.**

Here, we tried not removing these features like we stated before whereas we incorporated these features and reduced (merged) them into one. This further gave us a variable **l_pct (NYSE_ADV_ISS/NYSE_DECL_ISS)** which was even badly correlated. Hence, removing them seem to be the best option.



Even after applying the domain knowledge for the dataset, **PCA** may find to be useful for finding relation between two features which may not seem to be correlated to be each other with the help of domain knowledge.

//This remains a topic of research for the Project Report Part 2.

Algorithms (Applied)

Linear Regression Application

Before reducing the matrix

In the MATLAB script *"MultiVar_LinearRegression.m",* linear regression with multiple variables has been implemented for forecasting stock prices. Training been done on 80% of data while testing of the data is done on the rest 20%. The accuracy of the results tends to be 82.9055%. In this script, all the features have been used and algorithm is applied on modified Z-score matrix.

Learning rate (α) was chosen 0.01. Earlier, the iterations were 2000 due to which cost function converged to 19.04. After increasing the iterations to 19000, the cost function reduced and converged to 0, which was the best case scenario considering other values of α.

The value of cost function (J) started from 2.3*10^4 all the way finally to 0.1959

Z-Score Matrix

The same algorithm was applied in the script *"FeatureReduction_DropCol.m",* but this time 3 features were removed due to very less correlation value with label.

Features removed were **"NYSE_ADV_ISS", "NYSE_DECL_ISS"** and **"NYSE_NEW_LOWS".** Learning rate and iterations were kept constant and it was found that accuracy improved slightly (from 82.9055 to 82.9282%).

We further modified our dataset and this time we calculated and removed 5% outliers from each feature using the Z-Score matrix (Z score matrix is derived from input matrix using formula $(x-\mu)/\sigma$).

Normalisation of the data

Also we normalised data by dividing each and every value by the maximum value of the feature(column). We couldn't calculate the accuracy of the same due some errors in the code.

// Errors in the code in the Normalisation of the data

	S&P_HIGH	S&P_LOW	NYSE_ADV_	NYSE_DECL_ISS	OTC_ADV_ISS \
S&P_HIGH	1	0.98921	0.027696	0.070367	0.441661
S&P_LOW	0.98921	1	0.029383	0.068093	0.443318
NYSE_ADV_ISS	0.027696	0.029383	1	-0.747096	0.418409
NYSE_DECL_ISS	0.070367	0.068093	-0.7471	1	-0.296923
OTC_ADV_ISS	0.441661	0.443318	0.418409	-0.296923	1
OTC_DECL_ISS	0.512928	0.510169	-0.31316	0.414572	0.13941
NYSE_NEW_HIGHS	0.114472	0.115436	0.264967	-0.144023	0.243061
NYSE_NEW_LOWS	0.039511	0.037496	-0.17377	0.133222	-0.11693
OTC_NEW_HIGHS	0.117964	0.119606	0.192845	-0.101059	0.2423
OTC_NEW_LOWS	0.083889	0.08203	-0.20175	0.162851	-0.075596
NYSE_TOT_VOL	0.654376	0.649211	0.082871	0.03254	0.491941
NYSE_ADV_VOL	0.448152	0.448401	0.443408	-0.340354	0.659569
NYSE_DECL_VOL	0.509694	0.506232	-0.3162	0.449111	0.164604
OTC_TOT_VOL	0.763859	0.76039	0.050106	0.068306	0.503244
OTC_ADV_VOL	0.658665	0.659158	0.241018	-0.12313	0.672055
OTC_DECL_VOL	0.701928	0.698137	-0.14879	0.270539	0.285644
S&P_EARNINGS	0.398762	0.399117	0.003419	-0.046785	0.204454
3MOBILLS	-0.595194	-0.59508	-0.04873	-0.085397	-0.440344
LNGBONDS	-0.637751	-0.63839	-0.03346	-0.071388	-0.415445
GOLD	-0.270311	-0.27194	-0.04457	-0.02878	-0.147413
S&P_CLOSE	0.990155	0.991352	0.034361	0.063351	0.446691

	OTC_DECL_ISS	NYSE_NEW	NYSE_NEW	OTC_NEW_HIGHS \
S&P_HIGH	0.512928	0.114472	0.039511	0.117964
S&P_LOW	0.510169	0.115436	0.037496	0.119606
NYSE_ADV_ISS	-0.313159	0.264967	-0.17377	0.192845
NYSE_DECL_ISS	0.414572	-0.14402	0.133222	-0.101059
OTC_ADV_ISS	0.13941	0.243061	-0.11693	0.2423
OTC_DECL_ISS	1	-0.08346	0.179113	-0.053603
NYSE_NEW_HIGHS	-0.083459	1	-0.40892	0.692775
NYSE_NEW_LOWS	0.179113	-0.40892	1	-0.443418
OTC_NEW_HIGHS	-0.053603	0.692775	-0.44342	1
OTC_NEW_LOWS	0.267055	-0.36164	0.558165	-0.36112
NYSE_TOT_VOL	0.484212	0.131598	0.022368	0.13369
NYSE_ADV_VOL	0.157004	0.239072	-0.07514	0.207599
NYSE_DECL_VOL	0.65035	0.023611	0.068259	0.046604
OTC_TOT_VOL	0.510016	0.149377	0.004689	0.175437
OTC_ADV_VOL	0.301085	0.233477	-0.07973	0.249181
OTC_DECL_VOL	0.697915	0.05152	0.087368	0.069535
S&P_EARNINGS	0.238436	-0.02502	0.074871	-0.005268
3MOBILLS	-0.472261	-0.11598	0.069657	-0.116251
LNGBONDS	-0.461451	-0.16277	0.047874	-0.138487
GOLD	-0.132365	-0.12919	-0.06624	-0.083731
S&P_CLOSE	0.50671	0.116314	0.03758	0.11976

	OTC_NEW_LOW	NYSE_ADV_	NYSE_DECL_VOL \
S&P_HIGH	0.083889	0.448152	0.509694
S&P_LOW	0.08203	0.448401	0.506232
NYSE_ADV_ISS	-0.201747	0.443408	-0.3162

NYSE_DECL_ISS	0.162851	-0.34035	0.449111
OTC_ADV_ISS	-0.075596	0.659569	0.164604
OTC_DECL_ISS	0.267055	0.157004	0.65035
NYSE_NEW_HIGHS	-0.361639	0.239072	0.023611
NYSE_NEW_LOWS	0.558165	-0.07514	0.068259
OTC_NEW_HIGHS	-0.36112	0.207599	0.046604
OTC_NEW_LOWS	1	-0.01961	0.152415
NYSE_TOT_VOL	0.08286	0.598977	0.549733
NYSE_ADV_VOL	-0.019612	1	0.155866
NYSE_DECL_VOL	0.152415	0.155866	1
OTC_TOT_VOL	0.062016	0.518812	0.545424
OTC_ADV_VOL	-0.040272	0.646756	0.351376
OTC_DECL_VOL	0.156646	0.322257	0.701488
S&P_EARNINGS	0.084673	0.269203	0.252182
3MOBILLS	-0.004215	-0.39358	-0.45094
LNGBONDS	-0.006069	-0.38439	-0.4248
GOLD	-0.133859	-0.1548	-0.17104
S&P_CLOSE	0.081887	0.454136	0.501967

	OTC_TOT_VOL	OTC_ADV_	OTC_DECL_	S&P_EARNINGS \
S&P_HIGH	0.763859	0.658665	0.701928	0.398762
S&P_LOW	0.76039	0.659158	0.698137	0.399117
NYSE_ADV_ISS	0.050106	0.241018	-0.14879	0.003419
NYSE_DECL_ISS	0.068306	-0.12313	0.270539	-0.046785
OTC_ADV_ISS	0.503244	0.672055	0.285644	0.204454
OTC_DECL_ISS	0.510016	0.301085	0.697915	0.238436
NYSE_NEW_HIGHS	0.149377	0.233477	0.05152	-0.025016
NYSE_NEW_LOWS	0.004689	-0.07973	0.087368	0.074871
OTC_NEW_HIGHS	0.175437	0.249181	0.069535	-0.005268
OTC_NEW_LOWS	0.062016	-0.04027	0.156646	0.084673
NYSE_TOT_VOL	0.77334	0.667572	0.661055	0.344188
NYSE_ADV_VOL	0.518812	0.646756	0.322257	0.269203
NYSE_DECL_VOL	0.545424	0.351376	0.701488	0.252182
OTC_TOT_VOL	1	0.744618	0.724416	0.34066
OTC_ADV_VOL	0.744618	1	0.503022	0.322319
OTC_DECL_VOL	0.724416	0.503022	1	0.333766
S&P_EARNINGS	0.34066	0.322319	0.333766	1
3MOBILLS	-0.592407	-0.53356	-0.5624	-0.185076
LNGBONDS	-0.577489	-0.54897	-0.56023	-0.26942
GOLD	-0.201811	-0.19117	-0.21767	-0.177139
S&P_CLOSE	0.762227	0.662706	0.695342	0.398632

	3MOBILLS	LNGBONDS	GOLD	S&P_CLOSE
S&P_HIGH	-0.595194	-0.63775	-0.27031	0.990155
S&P_LOW	-0.595078	-0.63839	-0.27194	0.991352
NYSE_ADV_ISS	-0.048728	-0.03346	-0.04457	0.034361
NYSE_DECL_ISS	-0.085397	-0.07139	-0.02878	0.063351
OTC_ADV_ISS	-0.440344	-0.41545	-0.14741	0.446691
OTC_DECL_ISS	-0.472261	-0.46145	-0.13237	0.50671
NYSE_NEW_HIGHS	-0.115983	-0.16277	-0.12919	0.116314

NYSE_NEW_LOWS	0.069657	0.047874	-0.06624	0.03758
OTC_NEW_HIGHS	-0.116251	-0.13849	-0.08373	0.11976
OTC_NEW_LOWS	-0.004215	-0.00607	-0.13386	0.081887
NYSE_TOT_VOL	-0.554455	-0.52391	-0.17266	0.652264
NYSE_ADV_VOL	-0.393577	-0.38439	-0.1548	0.454136
NYSE_DECL_VOL	-0.450936	-0.4248	-0.17104	0.501967
OTC_TOT_VOL	-0.592407	-0.57749	-0.20181	0.762227
OTC_ADV_VOL	-0.533563	-0.54897	-0.19117	0.662706
OTC_DECL_VOL	-0.562402	-0.56023	-0.21767	0.695342
S&P_EARNINGS	-0.185076	-0.26942	-0.17714	0.398632
3MOBILLS	1	0.669188	0.189963	-0.594758
LNGBONDS	0.669188	1	0.146586	-0.637985
GOLD	0.189963	0.146586	1	-0.27114
S&P_CLOSE	-0.594758	-0.63799	-0.27114	1

Multivariate Linear Regression

Objective

In this MATLAB script, linear regression with multiple variabes has been coded and tried to be implemented for forecasting stock prices. Training has been done on 80% of data and prediction has been tried to be done on the rest 20% data. The accuracy of the results comes to be about 82.9055%. In this script, all features have been used and Z-score has been used on the input matrix.

```
clc
clear
close all

fileToRead = 'S&Pdata';

%Training would be done on 80% of data (1:550 out of 679)
rangeTaken = 1:550;

% Import the complete spreadsheet file
[xlsObjectComplete, xlsHeads] = xlsread(fileToRead);
% xlsHeads contains the headings in the form of a string

xlsHeads = xlsHeads(2:22);  % Remove the 'DATE' heading

% Filter just the S&P Close into a vector (Take the last col only)
SP_Close = xlsObjectComplete(rangeTaken, 22);

inputMatrix = xlsObjectComplete(rangeTaken, 2:21);

thetaWeights = zeros(21, 1);

% Learning rate, or rate of descent
alpha = 0.01;
iterations = 19000; % Obtained after a few hit and trials.

%--------------------------------------------------------------------------
```

- Normalization

```
%--------------------------------------------------------------------------

X = inputMatrix;
X_norm = X;
mu = zeros(1, size(X, 2));
sigma = zeros(1, size(X, 2));

for feature_index = 1:size(X,2)

    % Find mean
    feature_mean = mean(X(:,feature_index));
    % (datatpoint - mean)
    X_norm(:,feature_index) = X(:,feature_index) - feature_mean;
```

```
    % Find StdDev
    feature_std = std(X_norm(:,feature_index));
    % (datatpoint - mean)/(stdDev)
    X_norm(:,feature_index) = X_norm(:,feature_index) / feature_std;

    sigma(feature_index) = feature_std;
    mu(feature_index) = feature_mean;
end

% Repeat the above code for getting complete normalized input matrix

X = xlsObjectComplete(:, 2:21);
X_norm_Complete = X;
mu = zeros(1, size(X, 2));
sigma = zeros(1, size(X, 2));

for feature_index = 1:size(X,2)

    % Find mean
    feature_mean = mean(X(:,feature_index));
    % (datatpoint - mean)
    X_norm_Complete(:,feature_index) = X(:,feature_index) -
 feature_mean;

    % Find StdDev
    feature_std = std(X_norm_Complete(:,feature_index));
    % (datatpoint - mean)/(stdDev)
    X_norm_Complete(:,feature_index) =
 X_norm_Complete(:,feature_index) / feature_std;

    sigma(feature_index) = feature_std;
    mu(feature_index) = feature_mean;
end

X_norm_Complete = [ones(679, 1), X_norm_Complete];
% X_norm_Complete stores ALL the input variables of ALL features in a
% normalized manner, and a one vector is appended in the beginning.
 This
% will be exported to Excel/CSV later.

%-------------------------------------------------------------------------
```

- Gradient descent algo

```
%-------------------------------------------------------------------------

m = length(SP_Close);

X_norm = [ones(m, 1) X_norm];   % The normalized X
X = [ones(m, 1) inputMatrix];

y = SP_Close;
```

```
for i = 1 : iterations
    temp = thetaWeights - (alpha/m) * X_norm' * (X_norm * thetaWeights
 - y);
    thetaWeights = temp;

    jHistory(i) = (1 / (2*m) ) * sum(((X_norm * thetaWeights)-y).^2);
end

%-------------------------------------------------------------------------
```

- Cost function algo

```
%-------------------------------------------------------------------------

J = 0;
fprintf('Cost function:\n');
J = (1 / (2*m) ) * sum(((X_norm * thetaWeights)-y).^2)

%-------------------------------------------------------------------------
```

Cost function:

J =

0.1959

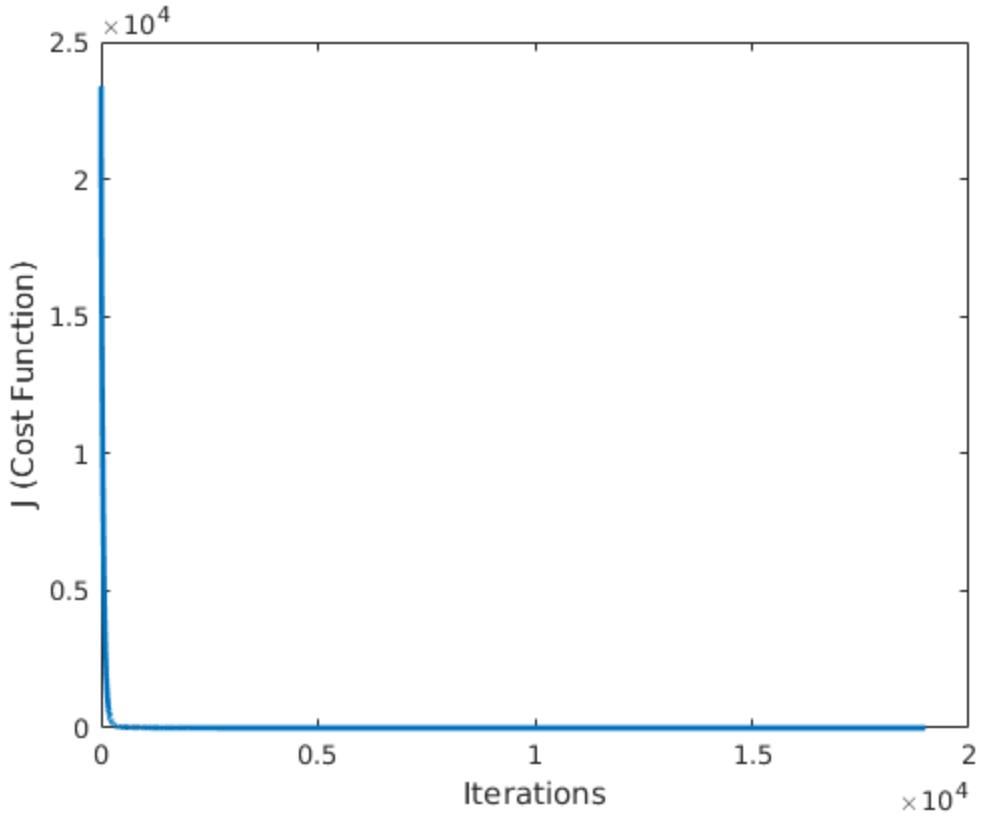
- Output variable (predicted)

```
%-------------------------------------------------------------------------
% Take the 20% (551:679) of all the output variables for testing
SP_Close_ToBePredicted = xlsObjectComplete(551:679, 22);

% Preallocate yHat with zeros
yHat = zeros(129, 1);

% Caculate the predicted output vaiable
% y = theta(0)*x(0) + theta(1)*x(1) + ... + theta(21)*x(21);
% 21, because we've 21 features.
for i = 1 : 21
    someTempVar = (thetaWeights(i) * X_norm_Complete(551:679, i));
    yHat = yHat + someTempVar;
end

difference = SP_Close_ToBePredicted - yHat;
accuracy = (difference./SP_Close_ToBePredicted)*100;
mean = mean(accuracy);

% Print the accuracy calculated
actualAccuracy = 100-mean

% Export the normalized input matrix file to Excel/CSV
% xlswrite('matToExcel.xlsx', X_norm_Complete);

%-------------------------------------------------------------------------
```

```
actualAccuracy =

   82.9055
```

- Plot the results

```
%-------------------------------------------------------------------------

% Plotting the cost function


graph = plot(1:iterations, jHistory);
set(graph,'LineWidth',2);
xlabel('Iterations'); ylabel('J (Cost Function)');
jHistory = jHistory';
```



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Multivariate Linear Regression with Reduced Features

Objective

In this MATLAB script, linear regression with multiple variabes has been code, built on the same script used earlier, but with 3 of the features reduced because correlation calculations. It gives a very slightly better accuracy (82.9282%) compared to the previous script.

```
clc
clear
close all

fileToRead = 'S&Pdata';

%Training would be done on 80% of data (1:550 out of 679)
rangeTaken = 1:550;

% Import the complete spreadsheet file
[xlsObjectComplete, xlsHeads] = xlsread(fileToRead);
% xlsHeads contains the headings in the form of a string vector

% Filter just the S&P Close into a vector
SP_Close = xlsObjectComplete(rangeTaken, 22);

xlsHeads = xlsHeads(2:21);  % Remove the 'DATE' heading
completeOP = xlsObjectComplete(:, 22);
xlsObjectComplete = xlsObjectComplete(:, 2:21); % Remove the date & OP
 coloumn

%------------------------------------------------------------------------
```

- Feature reduction

```
xlsObjectComplete( :, [3, 4, 8] ) = [];   % Remove 3, 4, 8 col
%------------------------------------------------------------------------

inputMatrix = xlsObjectComplete(rangeTaken, 1:17);

thetaWeights = zeros(17+1, 1);

% Learning rate, or rate of descent
alpha = 0.01;
iterations = 19000; % Obtained after a few hit and trials.

%------------------------------------------------------------------------
```

- Normalization

```
%------------------------------------------------------------------------
```

```
X = inputMatrix;
X_norm = X;
mu = zeros(1, size(X, 2));
sigma = zeros(1, size(X, 2));

for feature_index = 1:size(X,2)

    % Find mean
    feature_mean = mean(X(:,feature_index));
    % (datatpoint - mean)
    X_norm(:,feature_index) = X(:,feature_index) - feature_mean;

    % Find StdDev
    feature_std = std(X_norm(:,feature_index));
    % (datatpoint - mean)/(stdDev)
    X_norm(:,feature_index) = X_norm(:,feature_index) / feature_std;

    sigma(feature_index) = feature_std;
    mu(feature_index) = feature_mean;
end

% Repeat the above code for getting complete normalized input matrix

X = xlsObjectComplete(:, 1:17);
X_norm_Complete = X;
mu = zeros(1, size(X, 2));
sigma = zeros(1, size(X, 2));

for feature_index = 1:size(X,2)

    % Find mean
    feature_mean = mean(X(:,feature_index));
    % (datatpoint - mean)
    X_norm_Complete(:,feature_index) = X(:,feature_index) -
 feature_mean;

    % Find StdDev
    feature_std = std(X_norm_Complete(:,feature_index));
    % (datatpoint - mean)/(stdDev)
    X_norm_Complete(:,feature_index) =
 X_norm_Complete(:,feature_index) / feature_std;

    sigma(feature_index) = feature_std;
    mu(feature_index) = feature_mean;
end

X_norm_Complete = [ones(679, 1), X_norm_Complete];
% X_norm_Complete stores ALL the input variables of ALL features in a
% normalized manner, and a one vector is appended in the beginning.
 This
% will be exported to Excel/CSV later.


%------------------------------------------------------------------------
```

- Gradient descent algo

```
%-------------------------------------------------------------------------

m = length(SP_Close);

X_norm = [ones(m, 1) X_norm];   % The normalized X
X = [ones(m, 1) inputMatrix];

y = SP_Close;

for i = 1 : iterations
    temp = thetaWeights - (alpha/m) * X_norm' * (X_norm * thetaWeights
 - y);
    thetaWeights = temp;

    jHistory(i) = (1 / (2*m) ) * sum(((X_norm * thetaWeights)-y).^2);
end

%-------------------------------------------------------------------------
```

- Cost function algo

```
%-------------------------------------------------------------------------

J = 0;
fprintf('Cost function:\n');
J = (1 / (2*m) ) * sum(((X_norm * thetaWeights)-y).^2)


%-------------------------------------------------------------------------
```

```
Cost function:

J =

    0.1955
```

- Output variable (predicted)

```
%-------------------------------------------------------------------------
% Take the 20% (551:679) of all the output variables for testing
SP_Close_ToBePredicted = completeOP(551:679, 1);

% Preallocate yHat with zeros
yHat = zeros(129, 1);
for i = 1 : 17
    someTempVar = (thetaWeights(i) * X_norm_Complete(551:679, i));
    yHat = yHat + someTempVar;
end

difference = SP_Close_ToBePredicted - yHat;
accuracy = (difference./SP_Close_ToBePredicted)*100;
mean = mean(accuracy);
```

```
actualAccuracy = 100-mean


% Perform Outlier remover
outputX = outlierRemover(X_norm_Complete, xlsObjectComplete, 1, 1.75);
outputX = outlierRemover(X_norm_Complete, outputX, 2, 1.75);
outputX = outlierRemover(X_norm_Complete, outputX, 3, 1.45);
outputX = outlierRemover(X_norm_Complete, outputX, 4, 1.5);
outputX = outlierRemover(X_norm_Complete, outputX, 5, 1.9);
outputX = outlierRemover(X_norm_Complete, outputX, 6, 1.9);
outputX = outlierRemover(X_norm_Complete, outputX, 7, 1.4);
outputX = outlierRemover(X_norm_Complete, outputX, 8, 1.7);
outputX = outlierRemover(X_norm_Complete, outputX, 9, 1.8);
outputX = outlierRemover(X_norm_Complete, outputX, 10, 1.85);
outputX = outlierRemover(X_norm_Complete, outputX, 11, 1.7);
outputX = outlierRemover(X_norm_Complete, outputX, 12, 1.9);
outputX = outlierRemover(X_norm_Complete, outputX, 13, 1.95);
outputX = outlierRemover(X_norm_Complete, outputX, 14, 2);
outputX = outlierRemover(X_norm_Complete, outputX, 15, 2.2);
outputX = outlierRemover(X_norm_Complete, outputX, 16, 1.75);
outputX = outlierRemover(X_norm_Complete, outputX, 17, 2.5);

normalizedInputMatrix = maxNormalization(outputX);
% Export to CSV
% xlswrite('outlierOutput.xlsx', X_Outlier);


actualAccuracy =

   82.9282
```

Published with MATLAB® R2017a

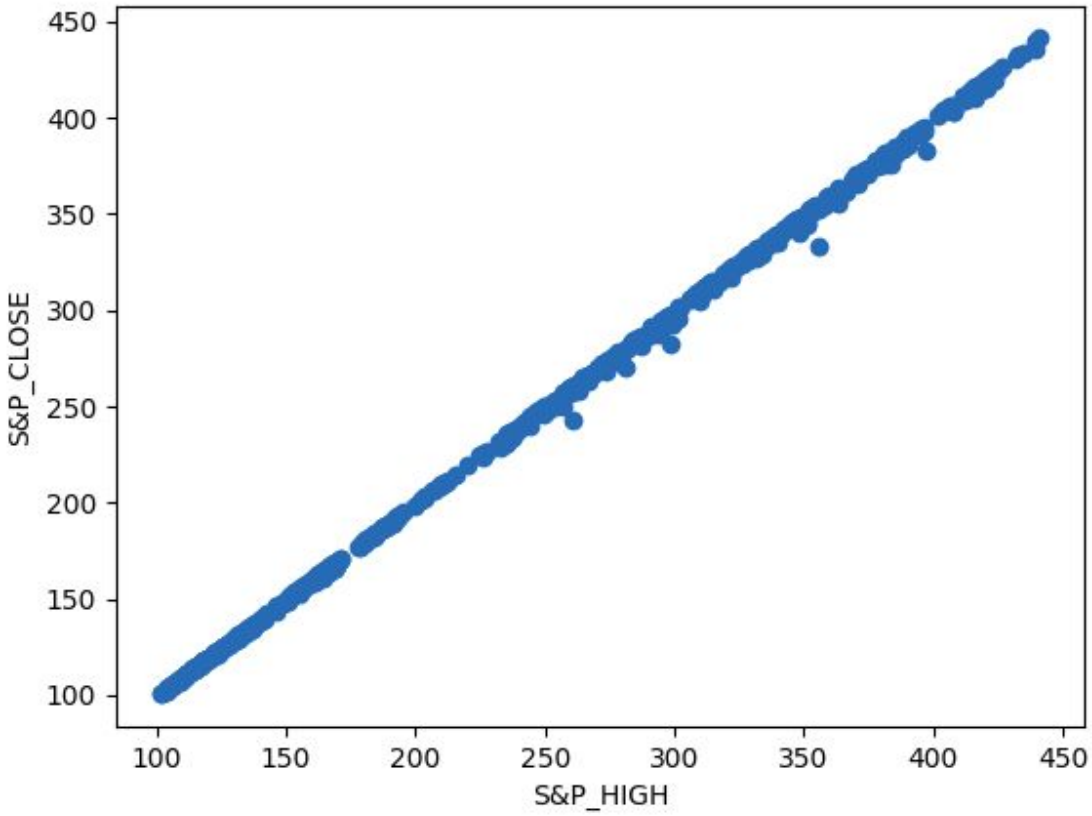
PART - II

Flaw in Normalization Method of Earlier Report

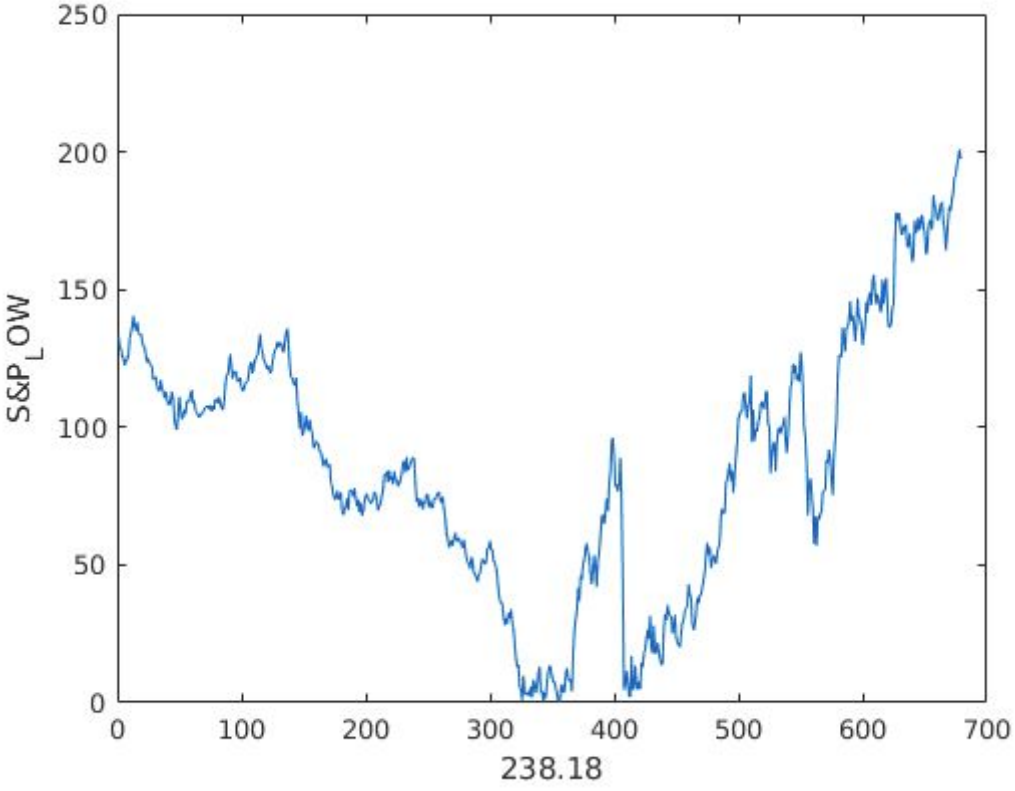
Earlier method opted for normalization was to calculate Z-score of every feature:

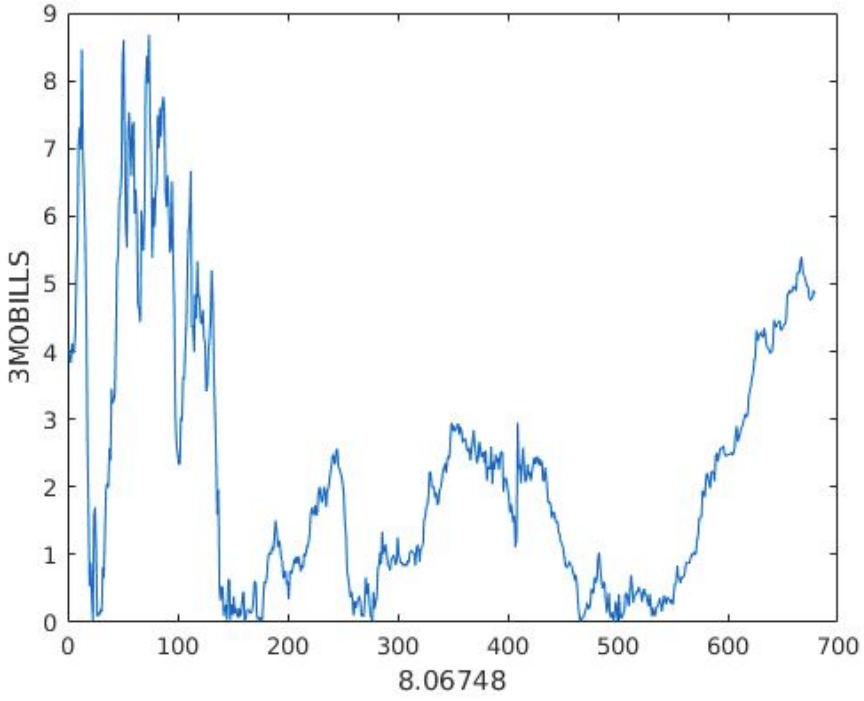
$$Z = (x-\mu)/\sigma$$

Where μ is the mean value of the feature and σ is the standard deviation. Higher the value of Z more is the tendency of being an outlier. This was the basis of normalisation of earlier report. But we realized Since our dataset contains timestamp values (features dependant on previous time values) the initial values and the end values were treated as outliers.

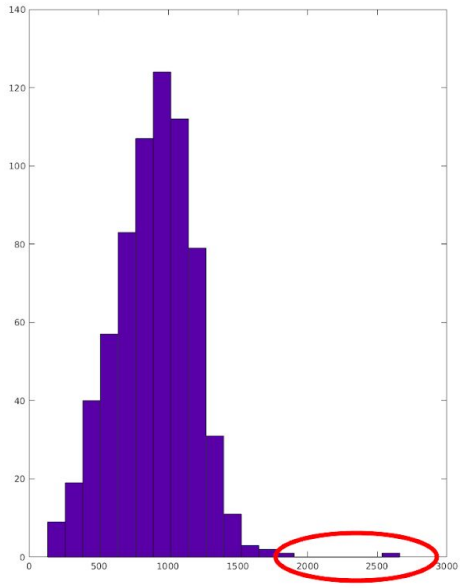


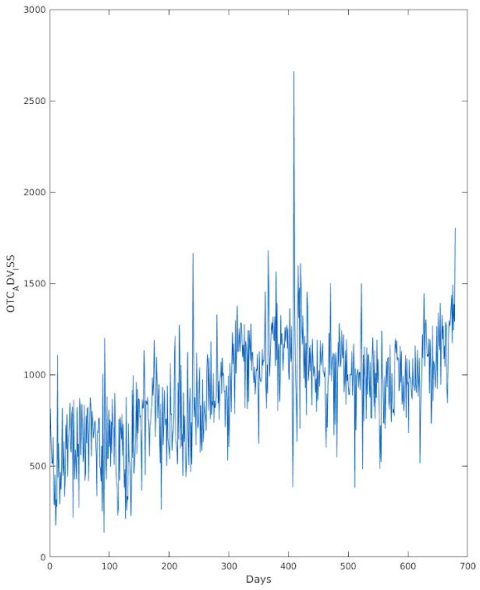
As evident from the above diagram most of the end and starting date,valuable data is lost to the mean value. We further plotted the **| y - μ |** value of all the features and identified the timestamp features. The similarity between timestamp feature graph is that it results in the 'V' shape graph **| y - μ |**. The Normalisation failed in 10 features which are listed as (S&P Low, S&P High, Gold, 3 MOBILS, Long Bonds, S&P Earning, OTC_ decline_volume, OTC_ total_volume, OTC_ advance_volume, OTC_ decline_issues)

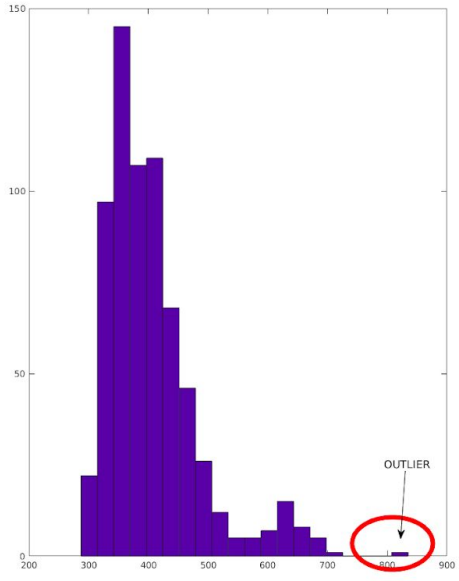

250
200
150
100
50
0
S&P_LOW
0
100
200
300
400
500
600
700
238.18

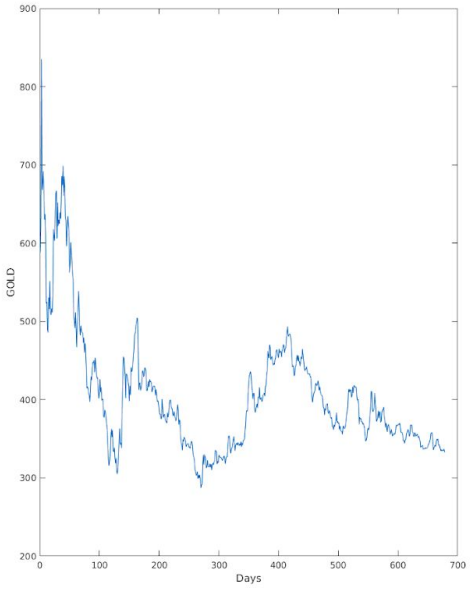

9
8
7
6
5
4
3
2
1
0
3MOBILLS
0
100
200
300
400
500
600
700
8.06748

It is evident from the graph the **| y - μ |** value is maximum at the corners which results in losing out crucial data.
As as result the Z-score method to remove outliers were only implemented to non-timestamp features. From these Z-score values histogram diagrams were generated to see the frequency of each Z values in each interval. The threshold frequency of occurrence was considered to be 5.

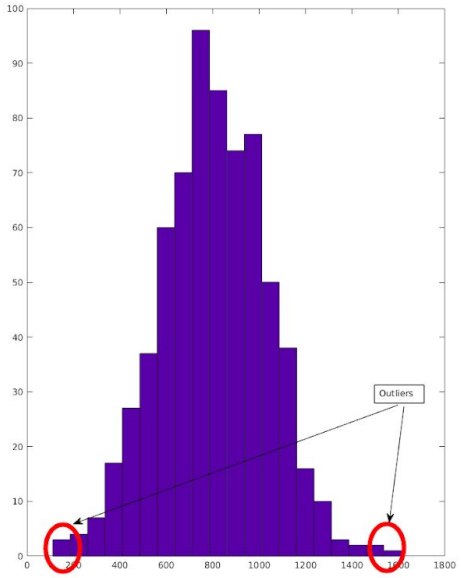


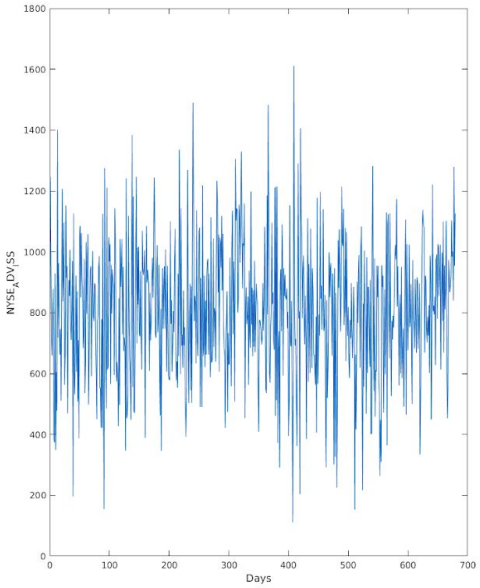


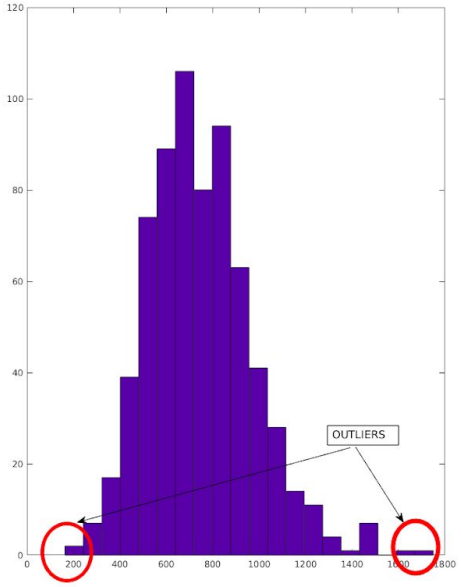


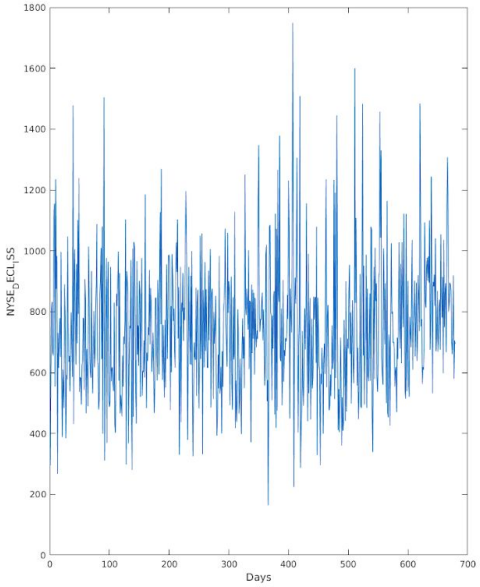


Only the corner bars were considered as outliers cause they were attaining extreme values. Also it was made sure that important end values were not during the process.









Flaw in Scaling Method of Earlier Report

In the earlier report submitted the scaling process used to bring the features in the range of 0-1 was to divide the particular values of the feature with its maximum value. The flaw in this method is that the resultant values were not swinging from 0 to 1

instead from an arbitrary value to 1. As a result true scaling wasn't achieved. The final method applied for bringing the swing from 0-1 is as follows.

$$(Xj - \textit{mean value of feature}) \,/\, (\textit{maximum value of feature}) - (\textit{minimum value of feature})$$

Algorithms Applied Further

Linear Regression

1. Mvregress was applied for the implementation of Linear Regression.
2. Before applying mvregress, the “cost function” coded by us was applied.

Linear Regression was applied on the following 4 matrices.
1. Raw Data Matrix : This is an untouched matrix provided to us
2. Normalised_Matrix : In this matrix outliers are removed and all the features are scaled from 0 to 1
3. Principal Component Analysis Matrix : The PCA algorithm was applied 19 times on the Normaised_Matrix.
4. Reduced features matrix : In this matrix based on the Domain knowledge and correlation matrix which features having minimum correlation value with respect output label was removed

For the project submission part 1 of midterm evaluation, we had used our own model of linear regression by creating our own code in MATLAB.Training had been done on 80% of data while testing of the data was done on the rest 20%. The accuracy of the results was 82.9055%.

Several attempts were made to improve our code, but that wasn’t possible and we simply couldn't improve our code.

So finally, we used an inbuilt function of MATLAB called mvregress(), which directly returns the weights after giving it our inputs and the output to be predicted.

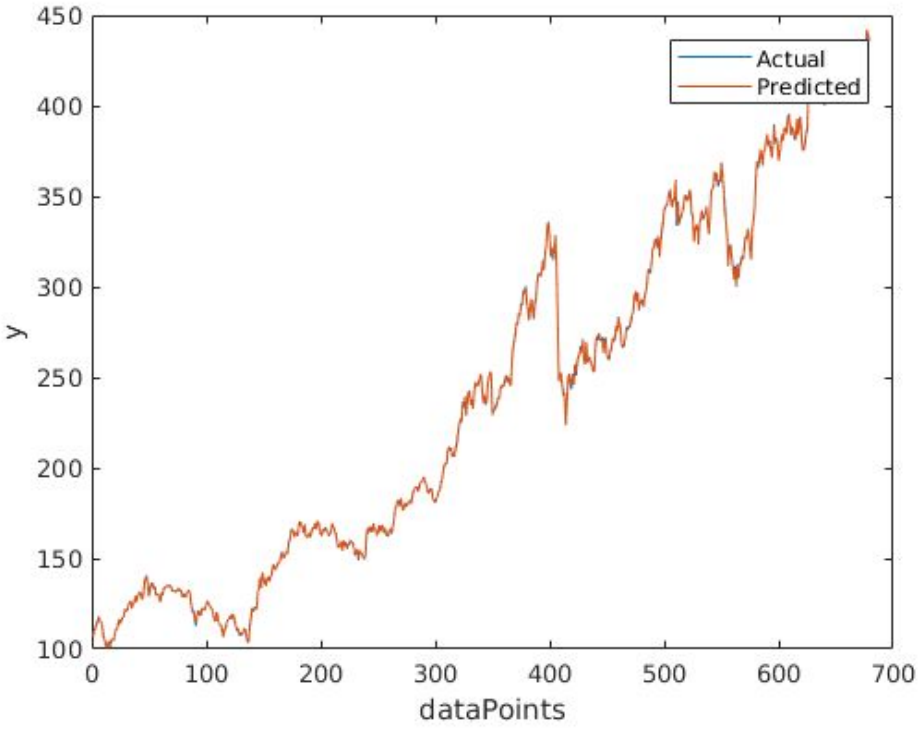
Accuracy formula used by us in linear Regression is as follows

Accuracy = 1 - Σ(y - predicted output)/Σ(y - mean of y)

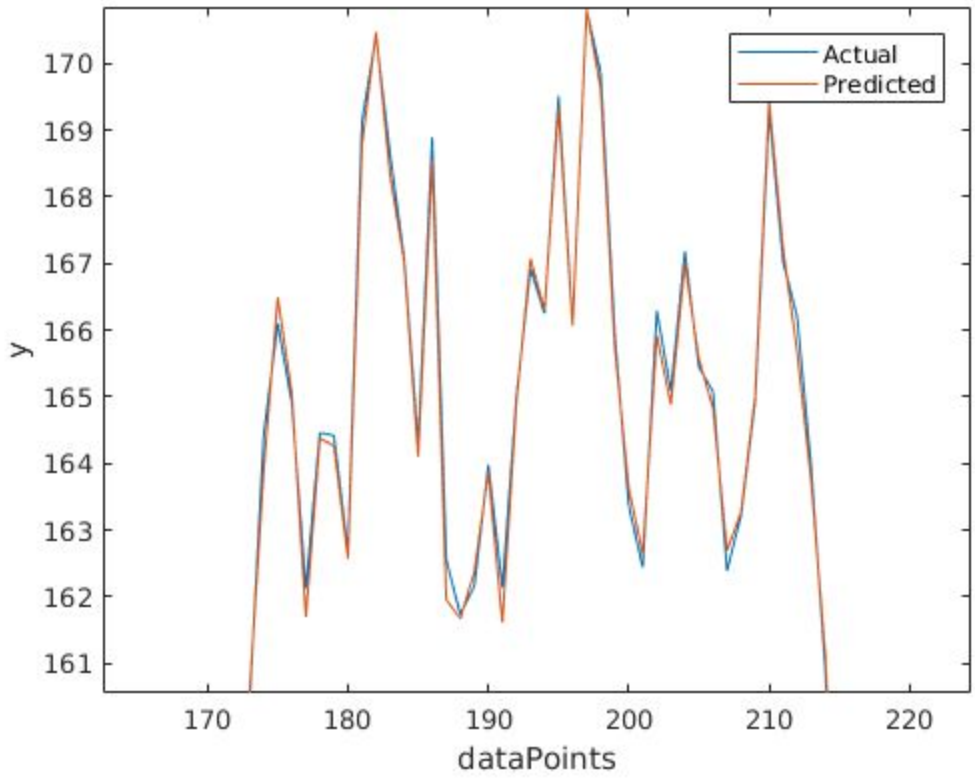
Training on raw data

At first, mvregress() was applied on raw data, and the results were a bit surprising.

Accuracy	MSE
0.100	0.4627



As can be seen from the graph, the actual values and the predicted ones were almost similar and were seeming to overlap. On a closer look though, we find:

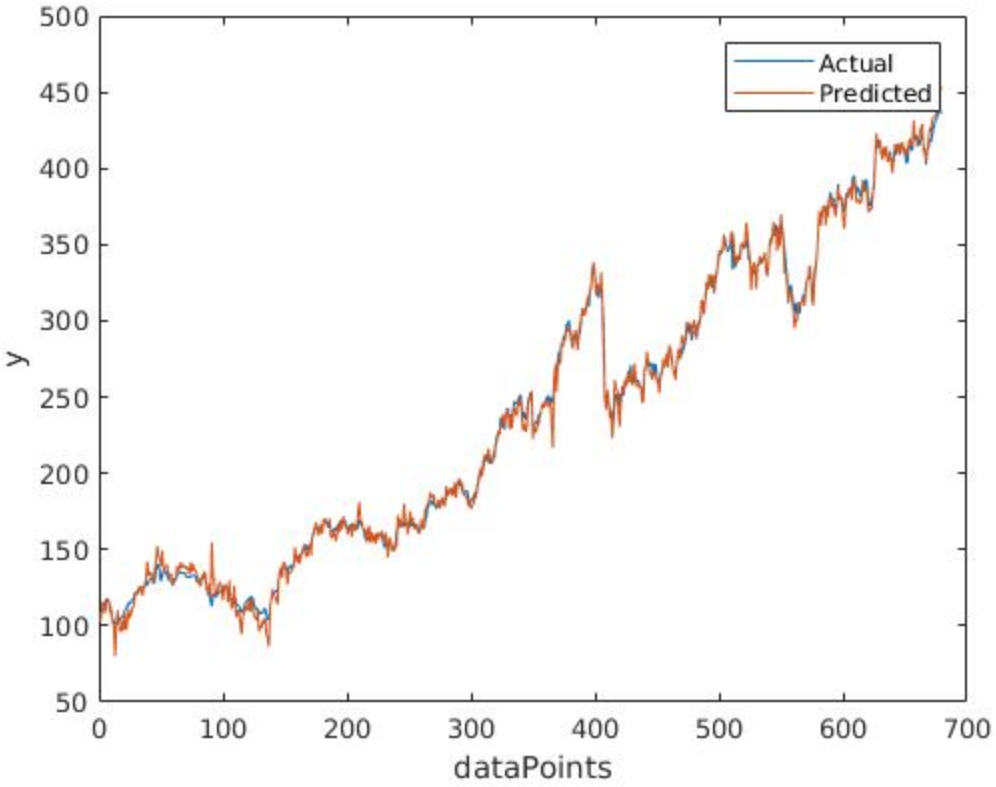


We find that there are differences, but very minute.

Training on normalized data

Training was now done on normalizzed data. This normalization was done on the basis of calculating the Z scores of some specific features and deciding upon a threshold. If there would be data points below the threshold values, those points would be replaced by the mean of the rest of the column's data.

Accuracy	MSE
0.9971	28.5097



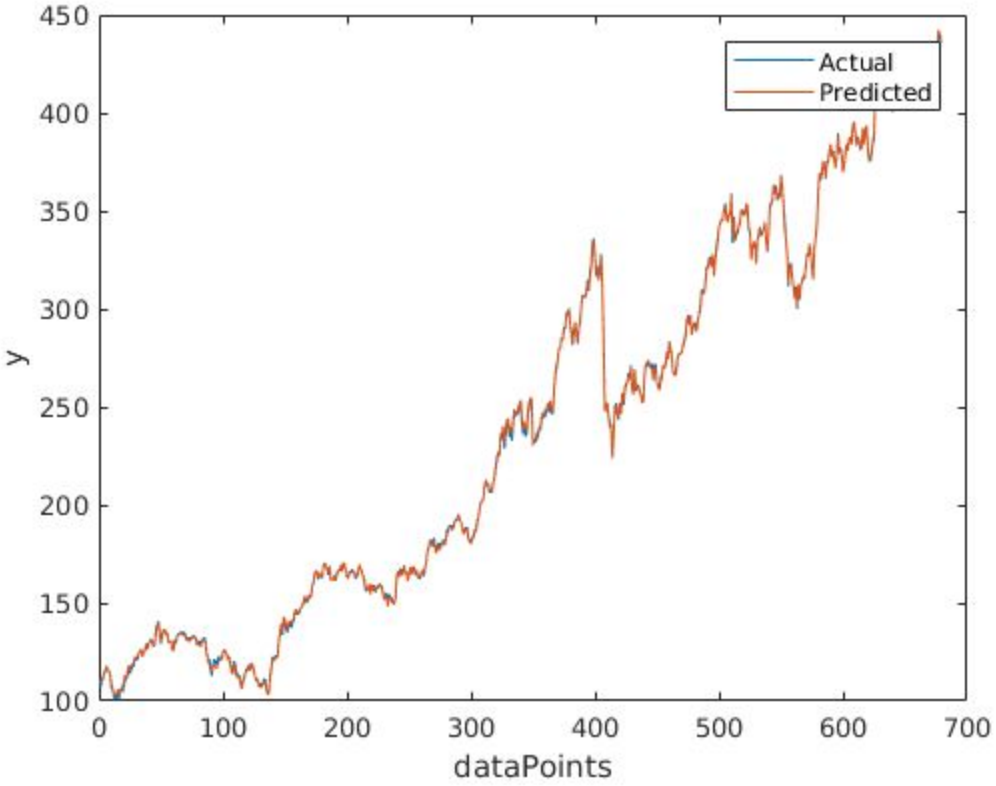
Both the accuracy kind of deteriorated, but it was better than the raw data's case, because 100% accuracy is too good to be true, so in comparison to that, a 99% accuracy seems applicable.

Feature Reduction using PCA

Principal Component Analysis was tried to be incorporated in order to reduce some of the features of our dataset. MATLAB's inbuilt function `pca()` was put to use for this by directly passing the input matrix to this function.

PCA - Level 1

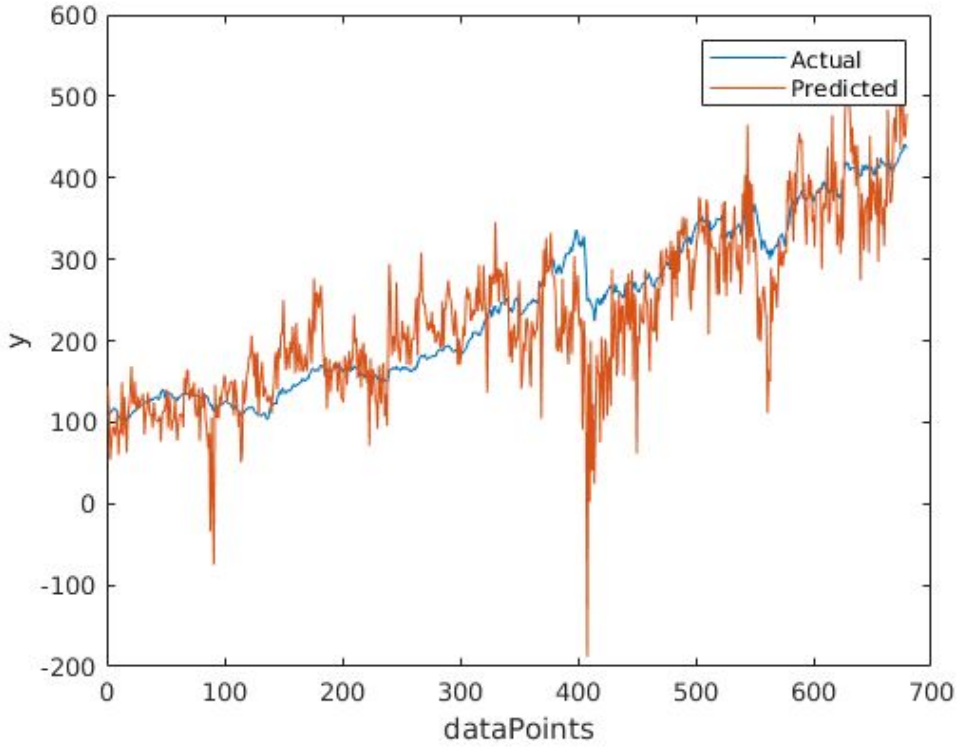
Accuracy	MSE
0.9999	1.2822



The accuracy seems to have improved to 0.9999, and so does the MSE. MATLAB seems to decide feature reduction based on some inbuilt logic and do it on our dataset.

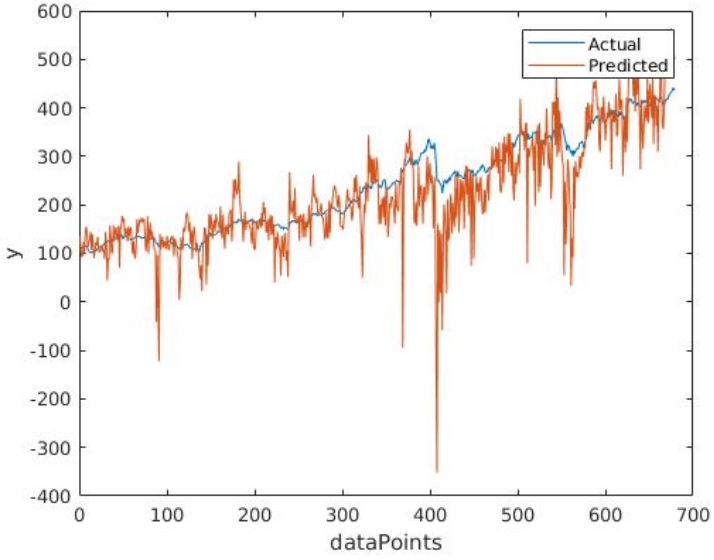
PCA - Level 2

Accuracy	MSE
0.6592	3363.1



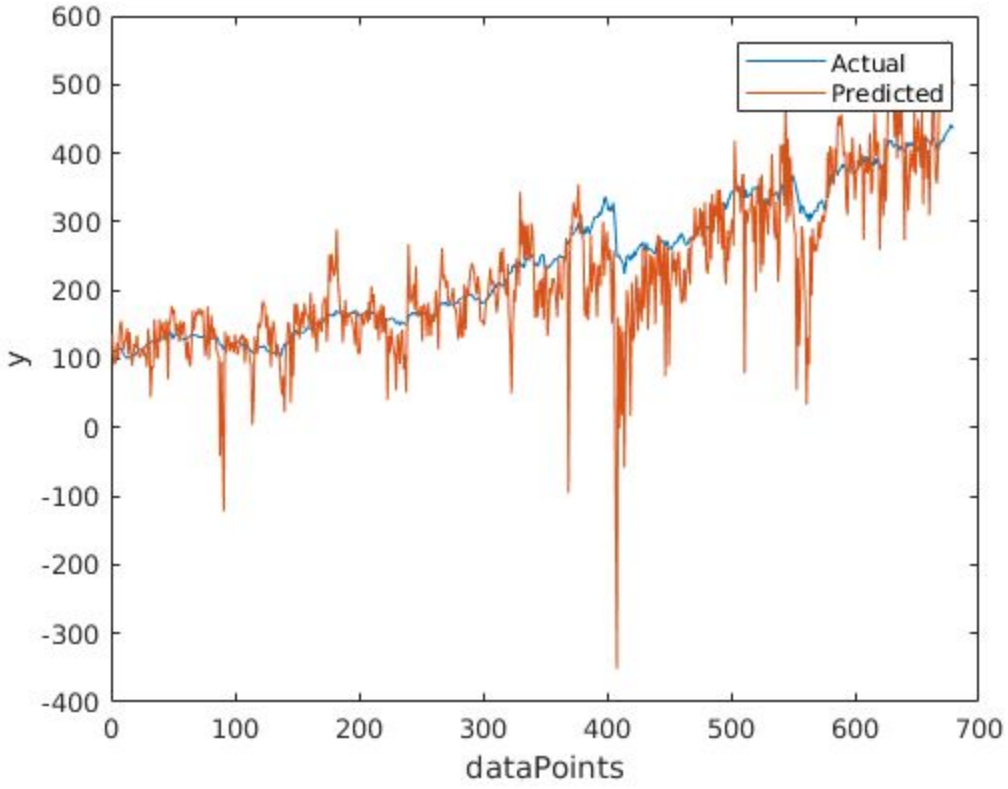
PCA - Level 3

Accuracy	MSE
0.5469	4471



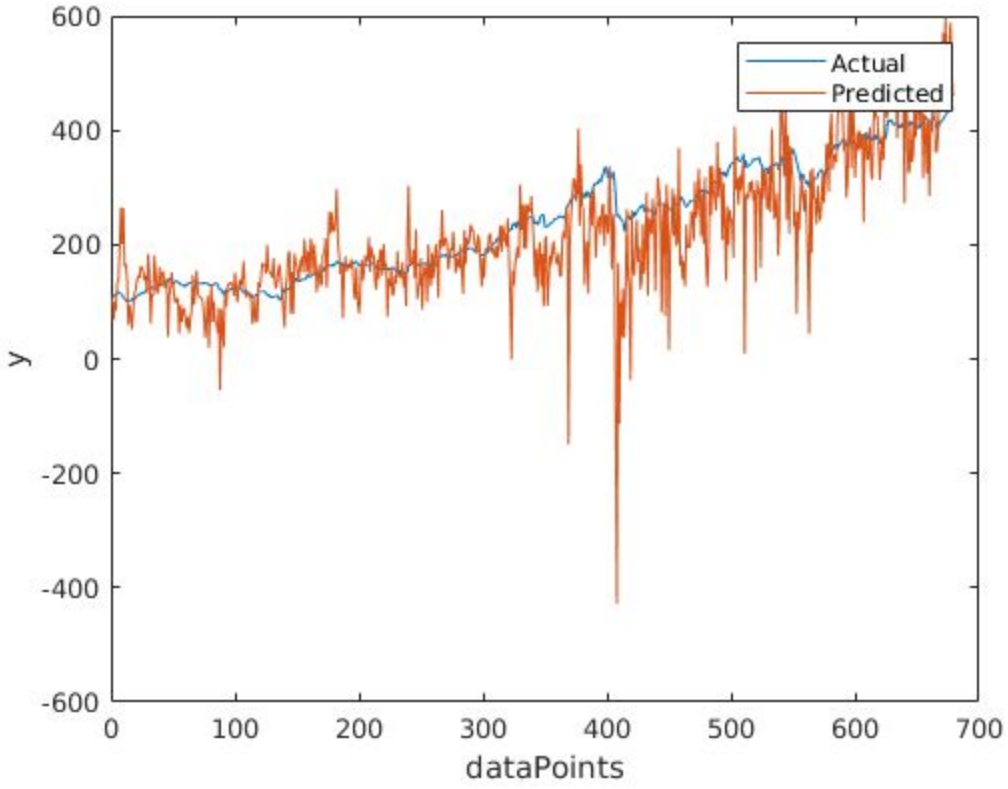
PCA - Level 4

Accuracy	MSE
0.5469	4471



PCA - Level 5

Accuracy	MSE
0.4144	5778.6



As we can see, the accuracy seems to be decreasing after apply PCA multiple times PCA only once was good enough to do some feature reduction.

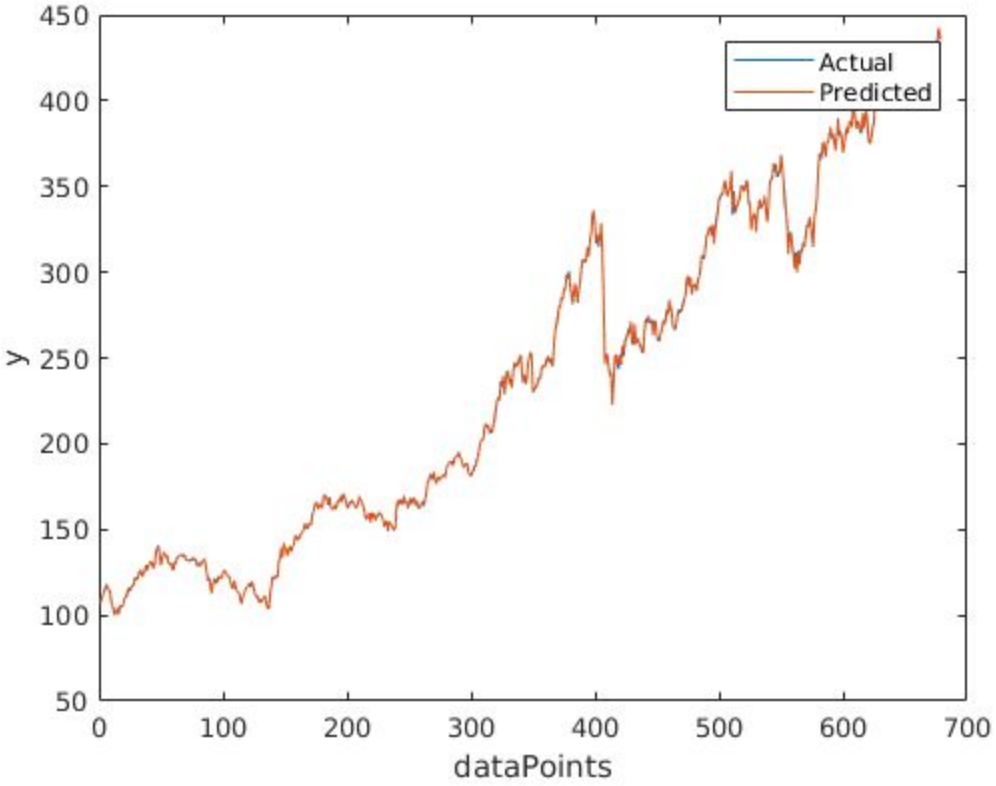
,

Feature Reduction using correlation

Feature reduction was tried using the correlation coefficient matrix between each of the feature and output vector, which was made earlier in part 1 of the report. Since correlation coefficient gives values between 0 and 1, a threshold is now decided for this as follows - 10%, 15%, 30%, 50%, 55% and 60% of the correlation value. Values below the decided threshold value would be discarded (the whole feature would be discarded). Following were the results obtained:

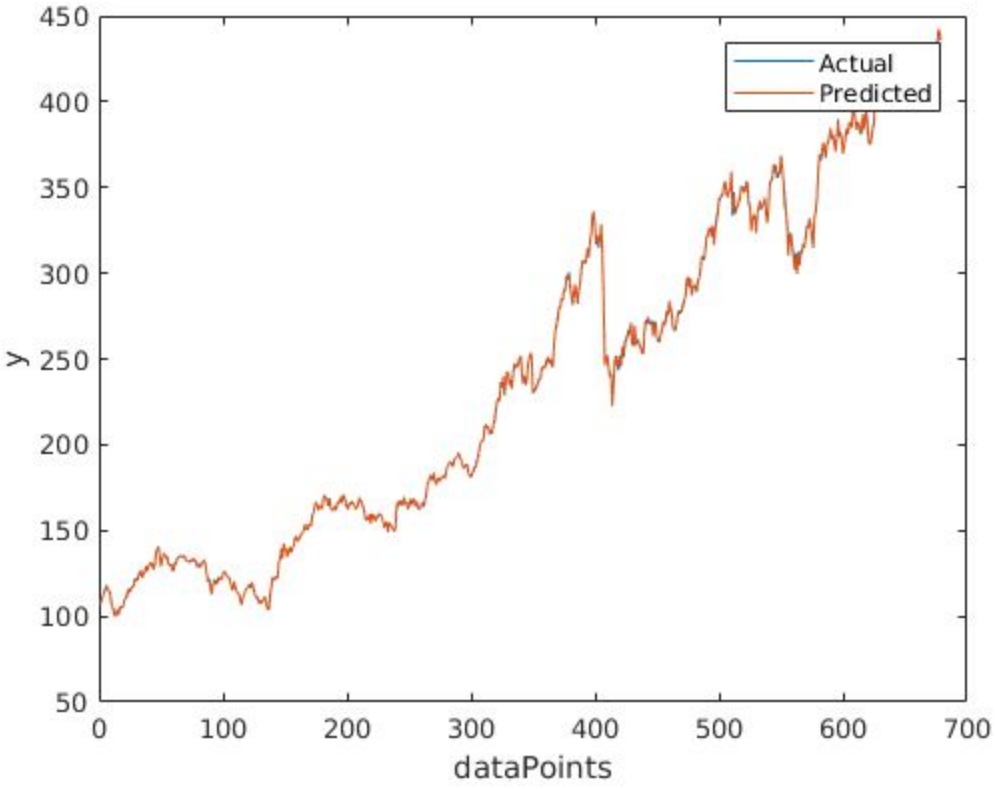
Threshold <10%

Acuuracy	MSE
0.9999	0.5127



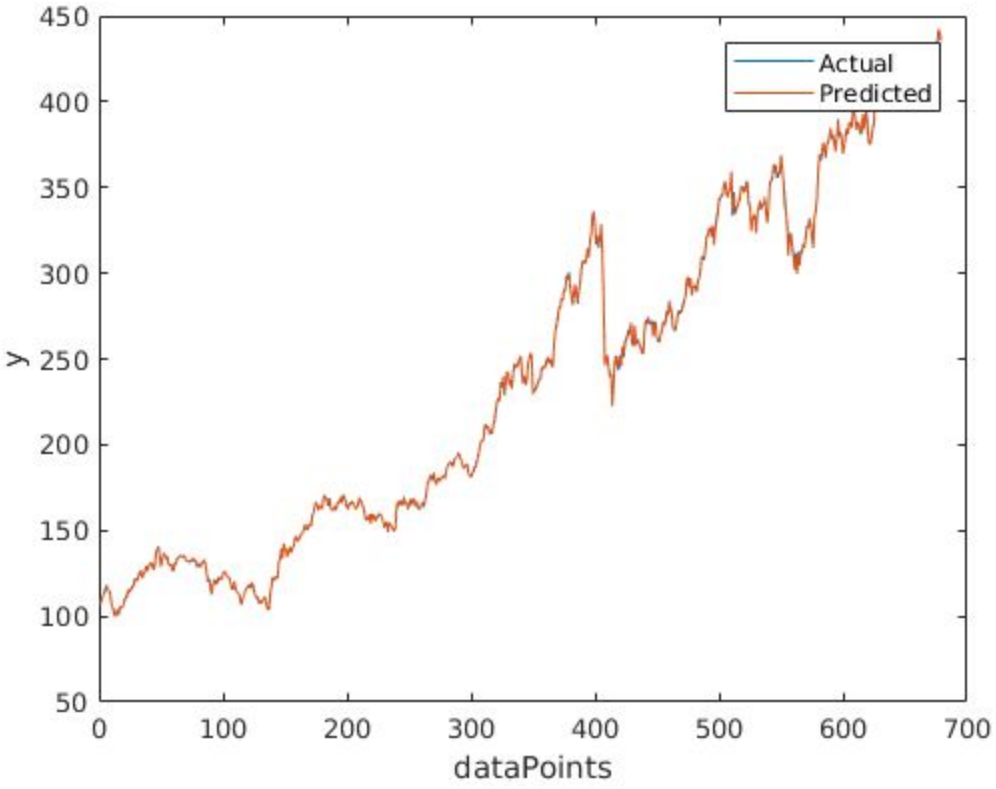
Threshold <15%

Accuracy	MSE
0.9999	0.5254



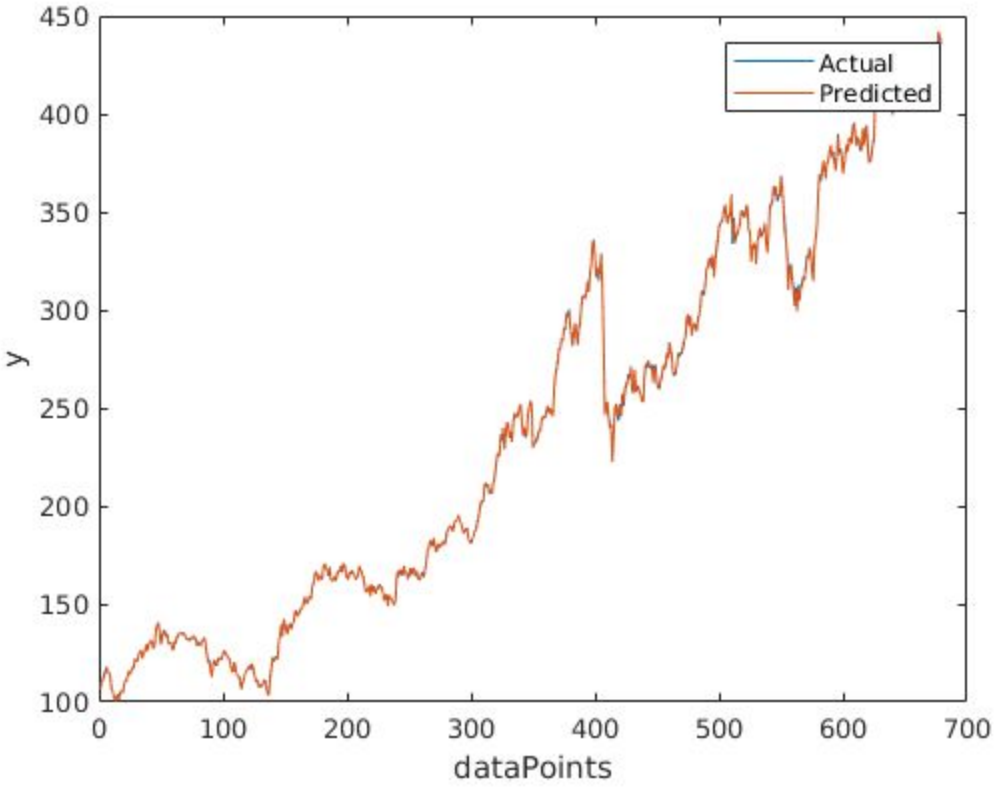
Threshold <30%

Accuracy	MSE
0.9999	0.5275



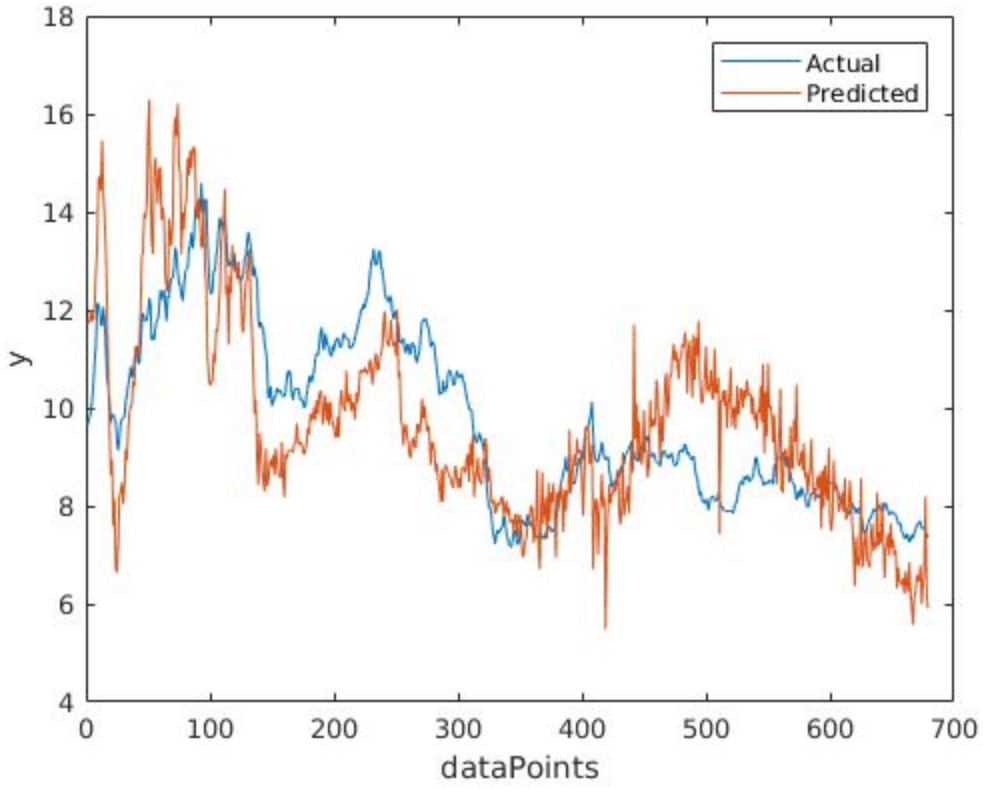
Threshold <50%

Accuracy	MSE
0.9999	0.5483



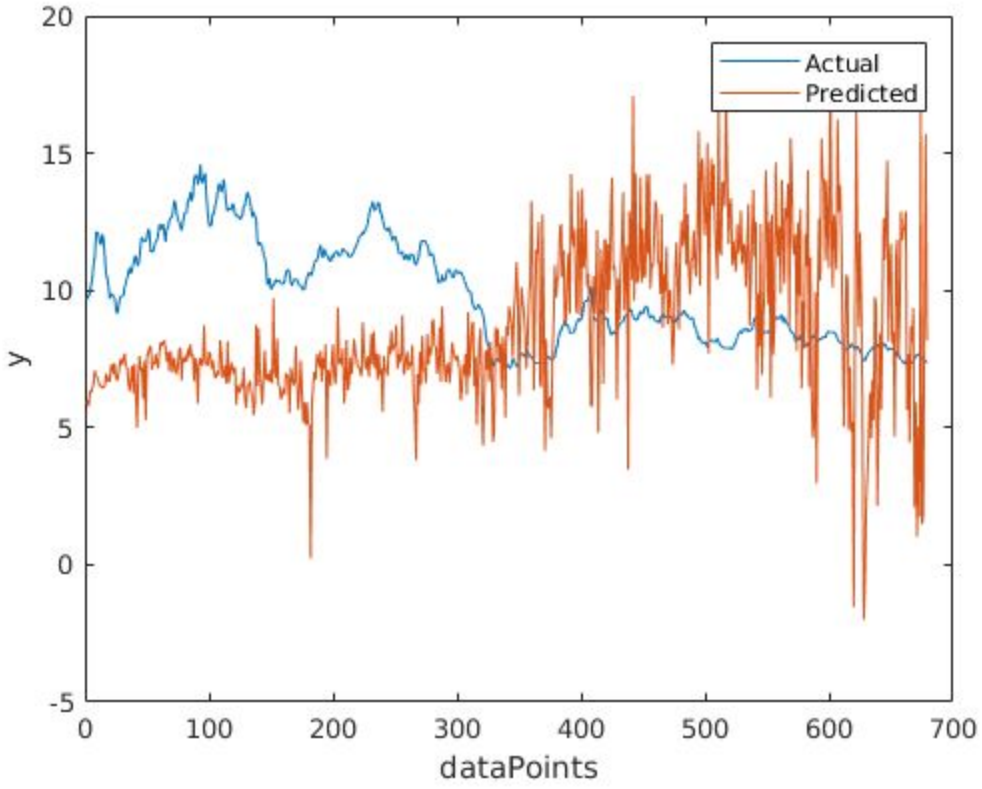
Threshold <55%

Accuracy	MSE
0.4043	2.0759



Threshold <60%

Accuracy	MSE
-3.8393	16.8647



As can be seen from the above graphs, the MSE would always gradually increase, but the accuracy would remain constant and starts deteriorating after increasing the threshold of removal point to large threshold value.

The results can be summarized in the following table:

Reduction scheme	Accuracy	MSE	Comments
Raw data	100.00%	0.4627	Too good to be true
Normalized data	0.9971	28.5097	Good accuracy, but MSE is large
PCA1	0.9999	1.2822	Good accuracy with good MSE
PCA2	0.6592	3.36E+03	Both deteriorating
PCA3	0.5469	4.47E+03	Both deteriorating

PCA4	0.5469	4.47E+03	Both deteriorating
PCA5	0.4144	5.78E+03	Worst accuracy and MSE
(Threshold <10%)	0.9999	0.5127	[NYSE_ADV_ISS, NYSE_DECL_ISS, NYSE_NEW_LOWS , OTC_NEW_LOW] - **removed**
(Threshold <15%)	0.9999	0.5254	[OTC_NEW_HIGHS , NYSE_NEW_HIGHS, previous] - **removed**
(Threshold <30%)	0.9999	0.5275	[GOLD, previous] - **removed**
(Threshold <50%)	0.9999	0.5483	[S&P_Earning, NYSE_ADV_VOL, OTC_ADV_ISS, previous] - **removed**
(Threshold <55%)	0.4043	2.0759	[NYSE_DECL_VOL, OTC_DECL_ISS, previous] - **removed**
(Threshold <60%)	-3.8393	16.8647	[3MOBILS, previous] - **removed**

Support Vector Machines

Support Vector Machine was applied on the following 4 matrices.

1. Raw Data Matrix : This is an untouched matrix provided to us

2. Normalised_Matrix : In this matrix outliers are removed and all the features are scaled from 0 to 1

3. Principal Component Analysis Matrix : The PCA algorithm was applied 19 times on the Normaised_Matrix.

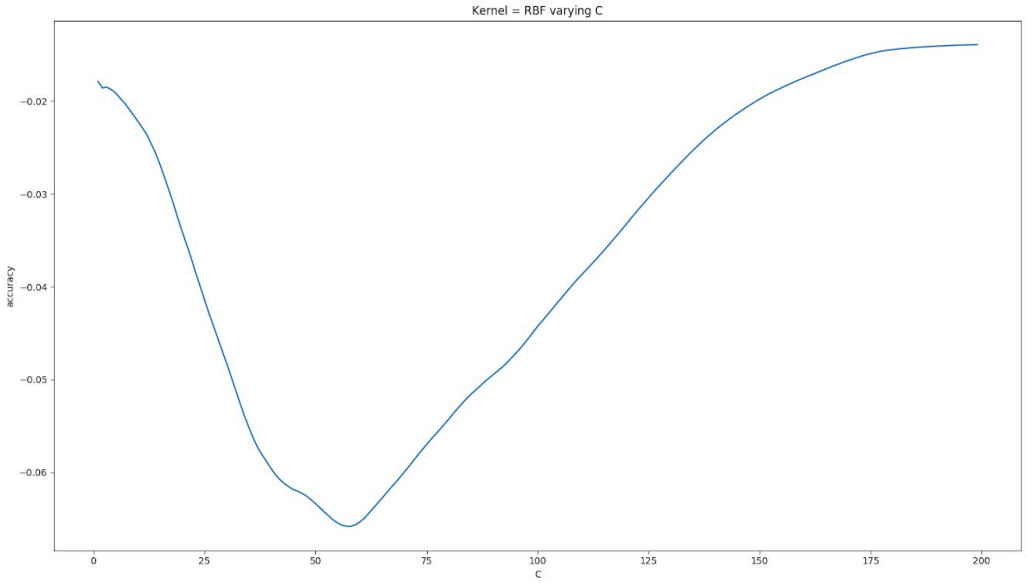
4. Reduced features matrix : In this matrix based on the Domain knowledge and correlation matrix which features having minimum correlation value with respect output label was removed

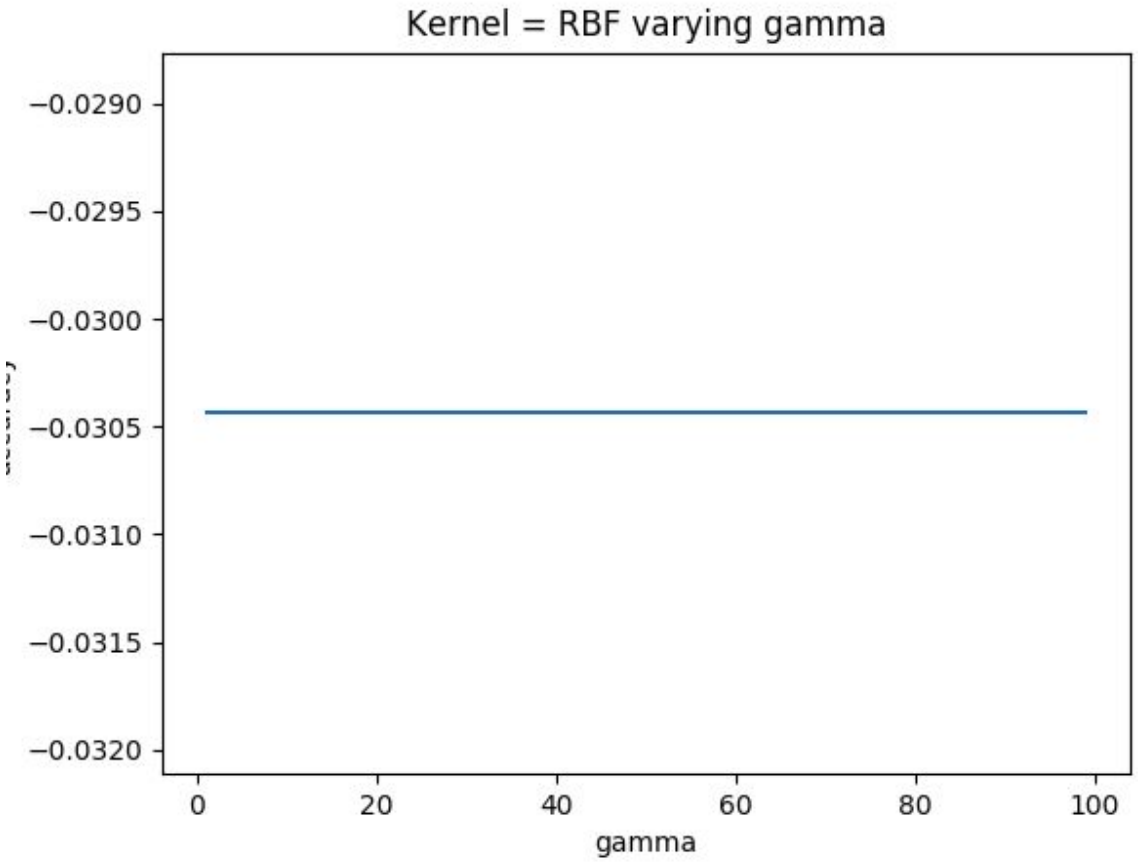
Four kernels of SVM were applied on the matrices which are RBF, Linear, Poly , Sigmoid their best values of C and gamma were also founded by plotting various graphs. The SVM algorithm was applied on 80% of the data and 20% was used for testing.

Raw Data

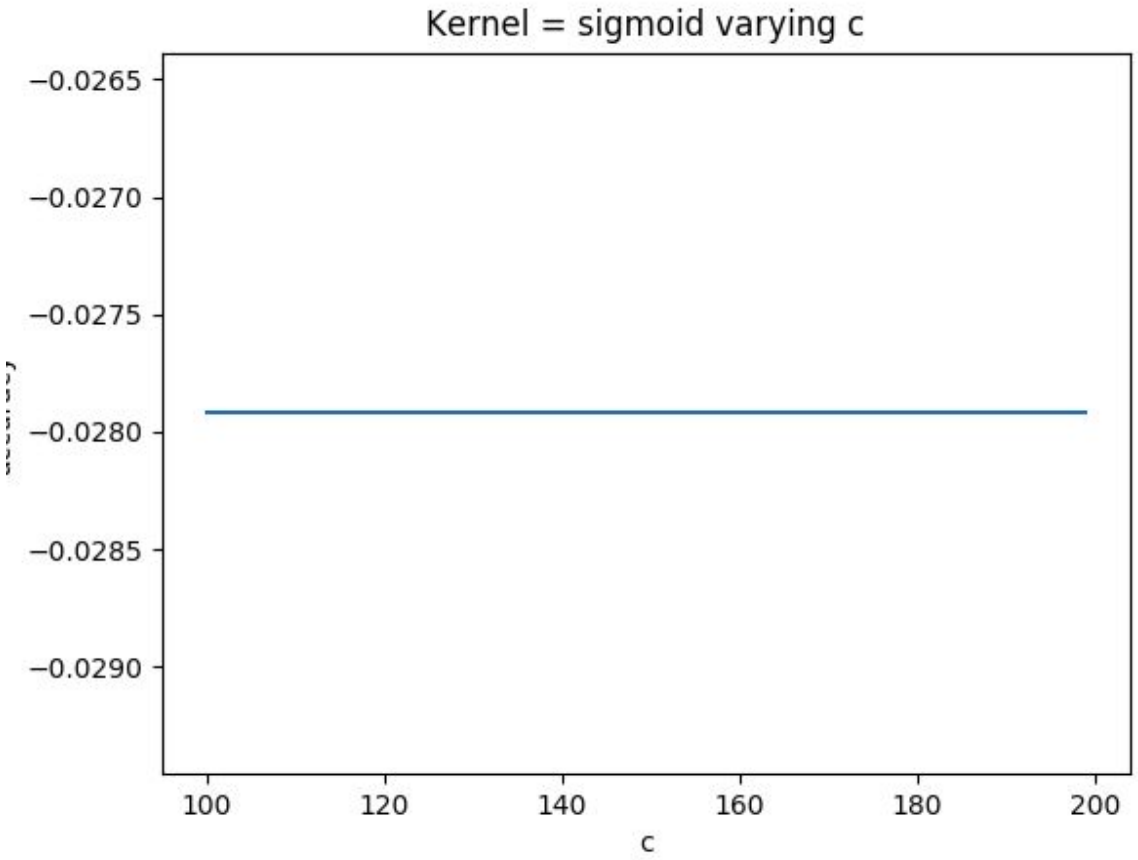
RBF	Poly	Linear	Sigmoid
1%	Not Computable	Not Computable	-2%

SVM displayed very poor accuracy on RBF and Sigmoid, also upon applying Poly and Linear the program kept running and was forced to exit().





As it is evident from the above graph by varying gamma the accuracy of RBF kernel doesn't change and stays constant.

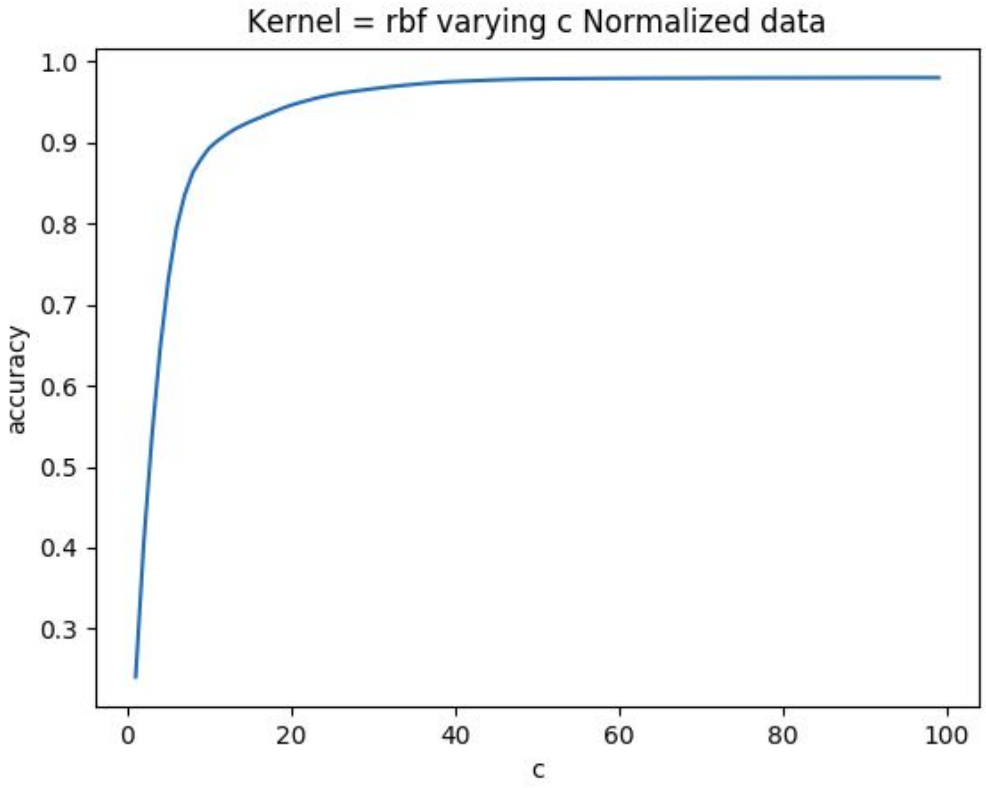


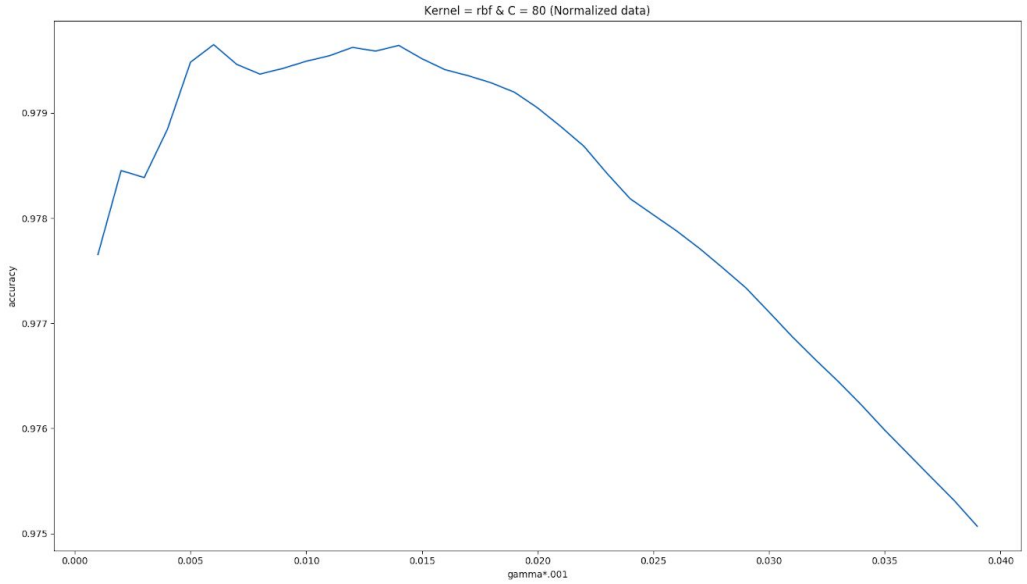
The value of sigmoid function remains constant even if the value of C is varied.

Normalised Data

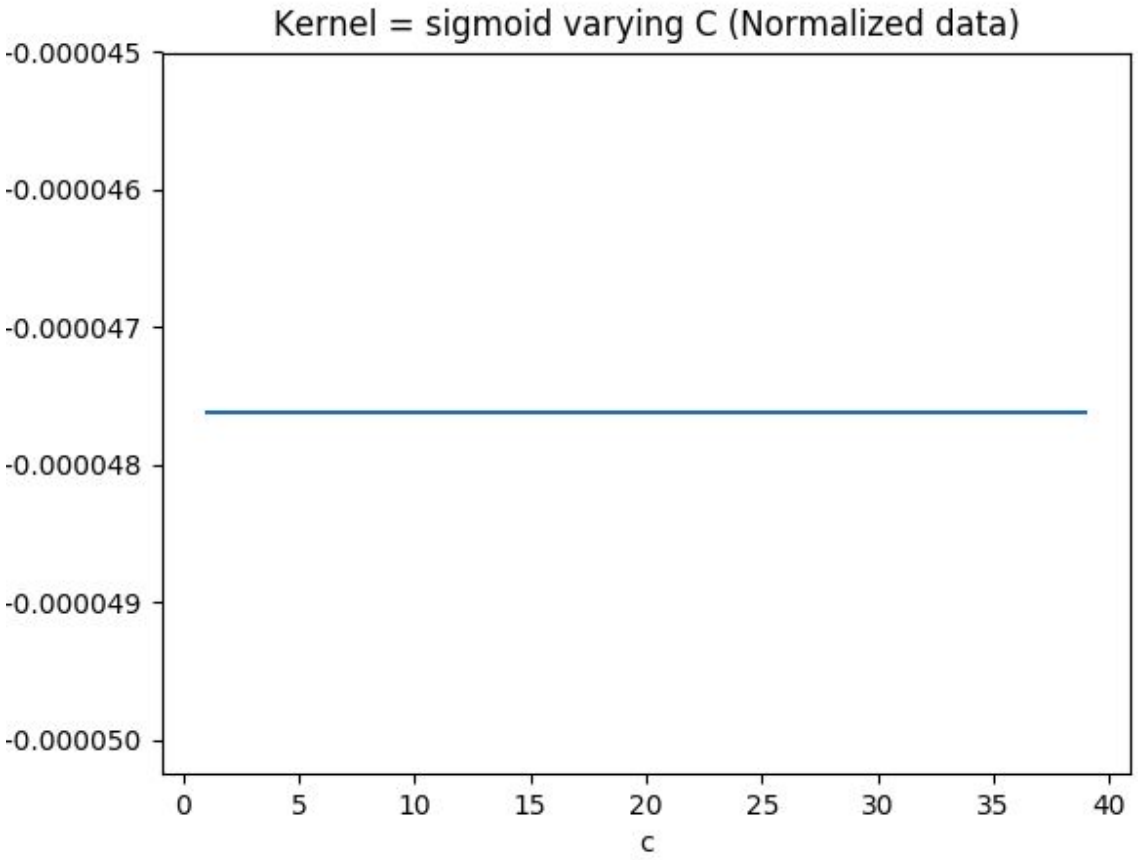
RBF	Poly	Linear	Sigmoid
98%	**Not Computable**	**97.8%**	**-0.1%**

This time SVM showed good results, RBF and Linear kernels were showing accuracy as high as 98%. The value of C and gamma were found out for RBF using the graphs, as it can be seen below the best accuracy is when C = 80 after that incrementing the value of C doesn't have any effect on accuracy and it saturates





The above image clearly shows that at gamma = 0.006 maximum accuracy was achieved, and after that it started decreasing upon incrementing gamma.



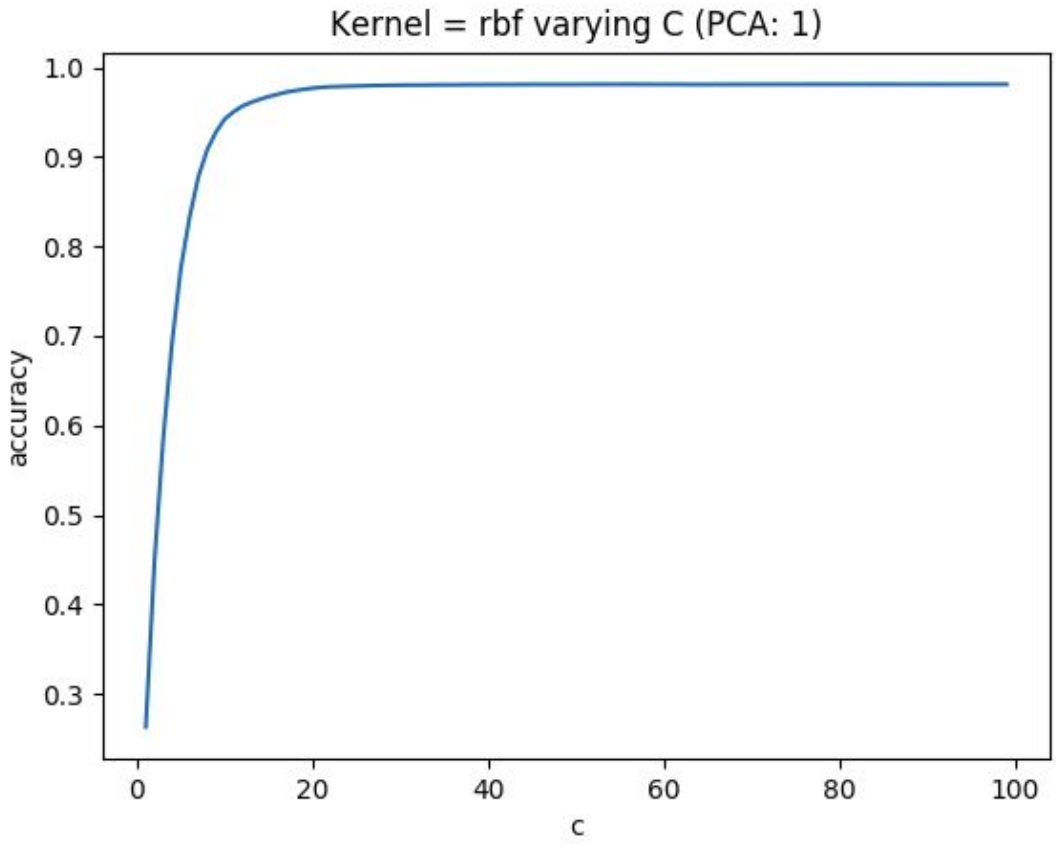
Sigmoid kernel can be seen as giving constant poor accuracy even when C was varied.

Principal Component Analysis Matrix

PCA algorithm was applied to normalised matrix as many as 19 times the results are listed below:

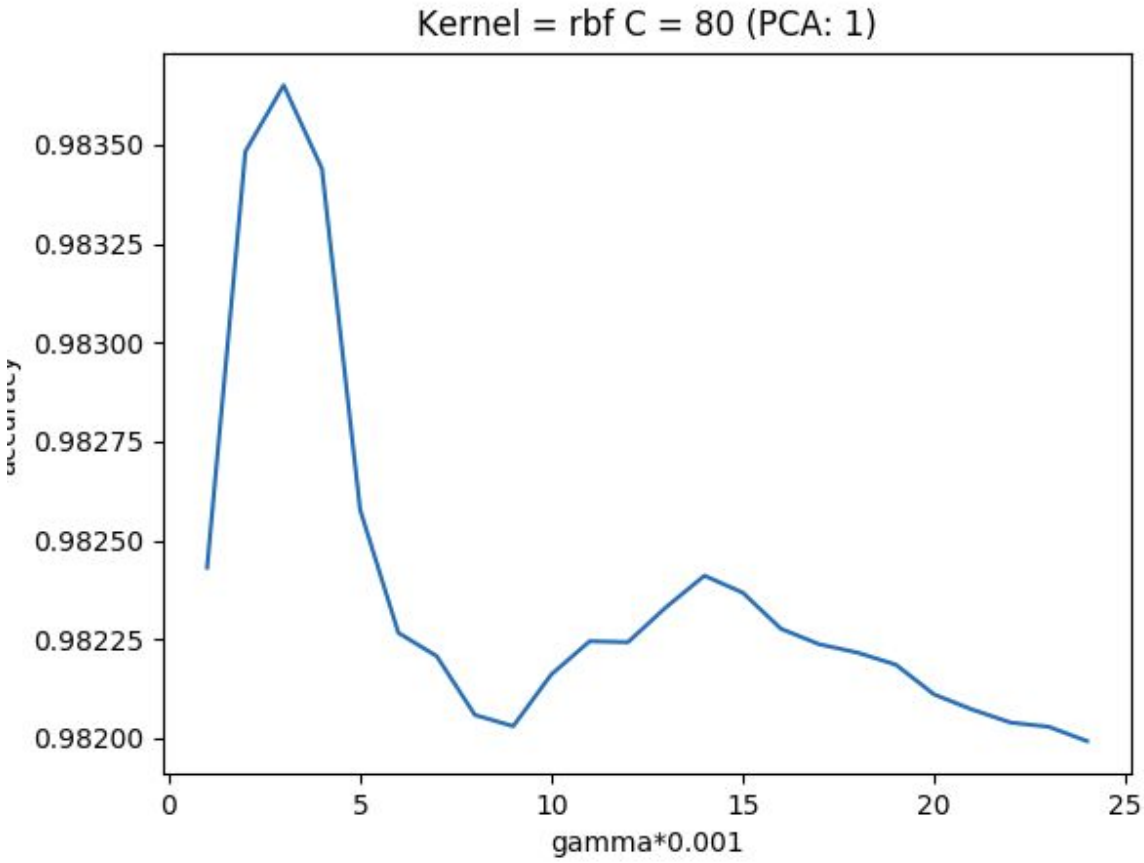
	RBF	Poly	Linear	Sigmoid
PCA 1	**98.36%**	**Not Computable**	**98.07%**	**-0.2%**
PCA 2	**97.2%**	**Not Computable**	**98.05%**	**-0.2%**
PCA 3	**97.2%**	**Not Computable**	**98.5%**	**-0.1%**
PCA 4	**97.4%**	**Not Computable**	**98%**	**-0.3%**

PCA 5	**-**	**Not Computable**	**98.57%**	**-0.2%**
PCA 6	**-**	**Not Computable**	**97.55%**	**-0.1%**

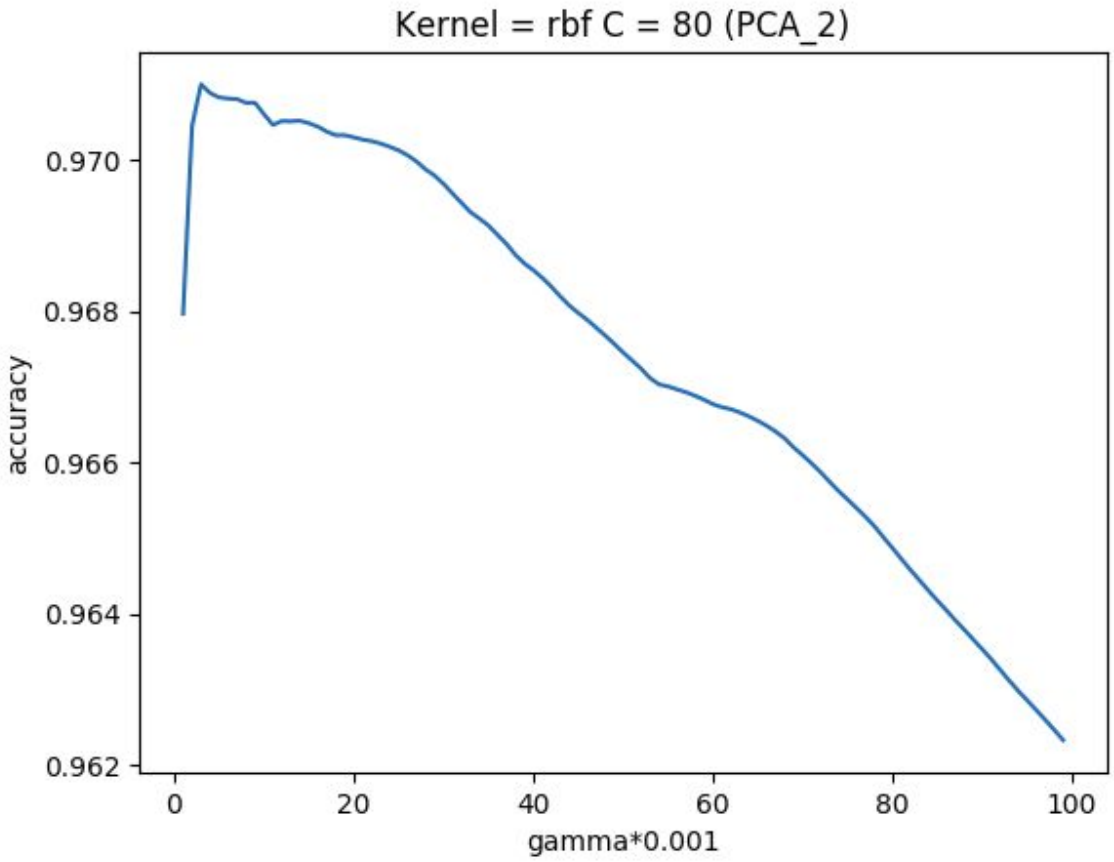


Sigmoid function was giving absurd values and Poly function always had to be forcefully terminated on the other hand RBF and Linear kernel were giving decent values. In the above diagram RBF was implemented after applying PCA algorithm on the normalised dataset only for one time. The best value of C that came out was 80. After keeping C constant at 80 gamma value was found out which was 98.4%, on further increasing the

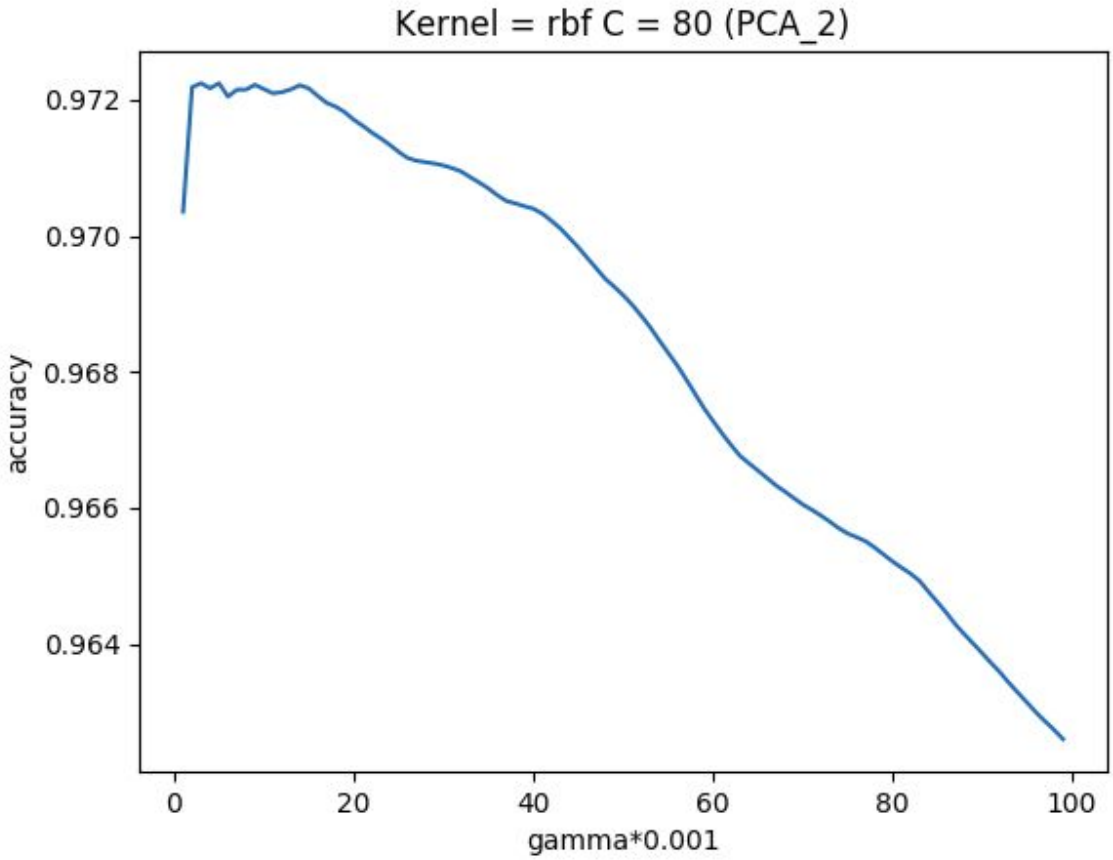
gamma the accuracy value deteriorated more it achieved maximum at 0.004.

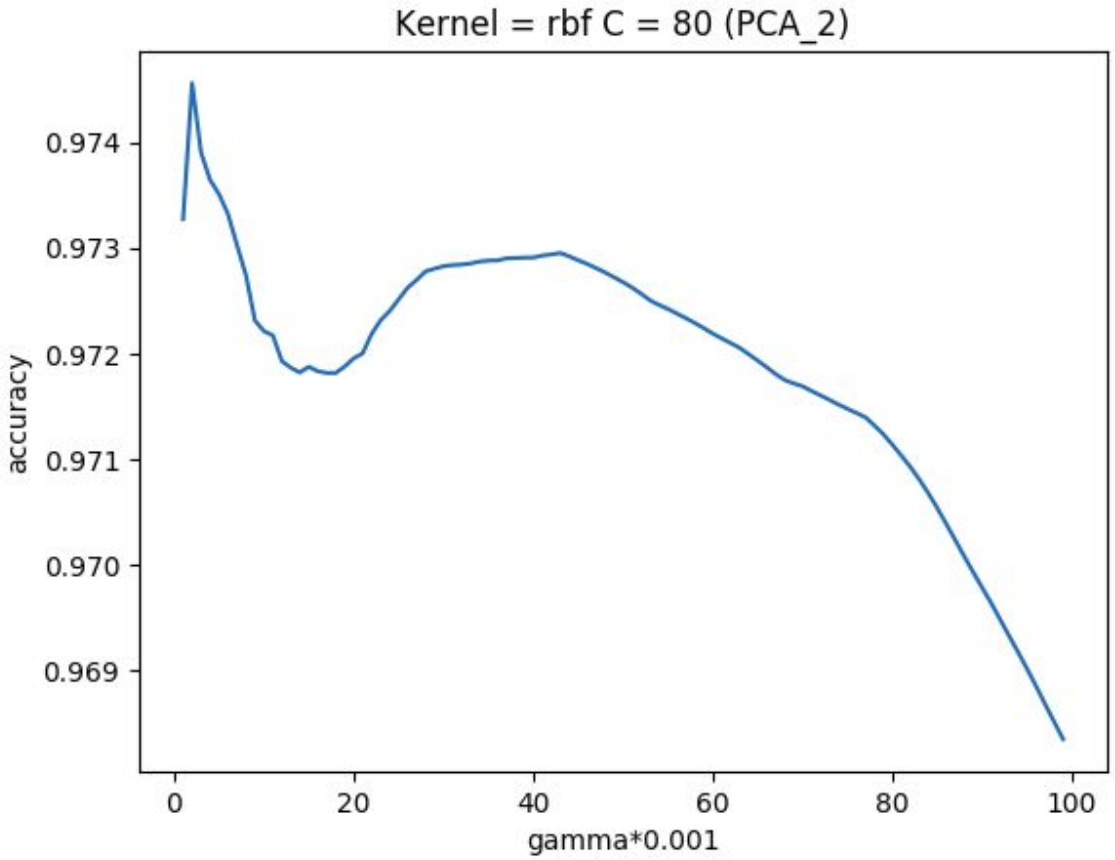


In the below graph RBF was implemented after PCA function was called two time here we observed that value of C was similar to previous PCA 1 which is 80.



The best value of gamma also came out to be 0.008 which was same as the previous case of PCA_2. Upon observing this, the value of C and Gamma was kept constant for all the PCA dataset at 80 and 0.004.


Kernel = rbf C = 80 (PCA_2)
accuracy
0.972
0.970
0.968
0.966
0.964
0
20
40
60
80
100
gamma*0.001



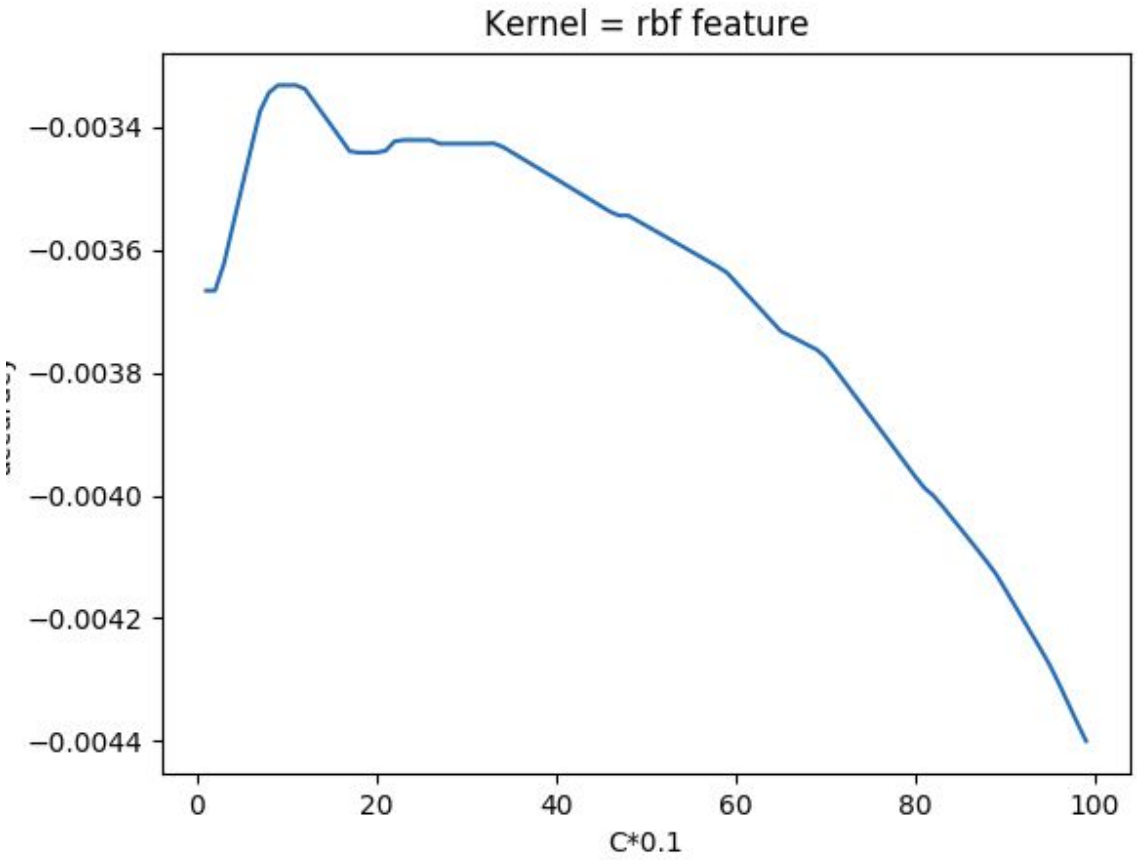
PCA 3 also gave similar results maximum value peaked at C = 80 and gamma = 0.004.

Reduced Feature Dataset

Upon Reducing the features with less than 10% correlation with output matrix, SVM algorithm no longer worked. Accuracy always remained a negative number and many kernels were not able to do computation on the reduced feature dataset.

	RBF	Poly	Linear	Sigmoid
Reduced Feature(<10% correlation)	**-0.3%**	**Not Computable**	**Not Computable**	**Not Computable**

Since accuracy was effected so much it was decided not to apply SVM on further feature reduced matrix.


Kernel = rbf feature
−0.0034
−0.0036
−0.0038
−0.0040
−0.0042
−0.0044
0
20
40
60
80
100
C*0.1

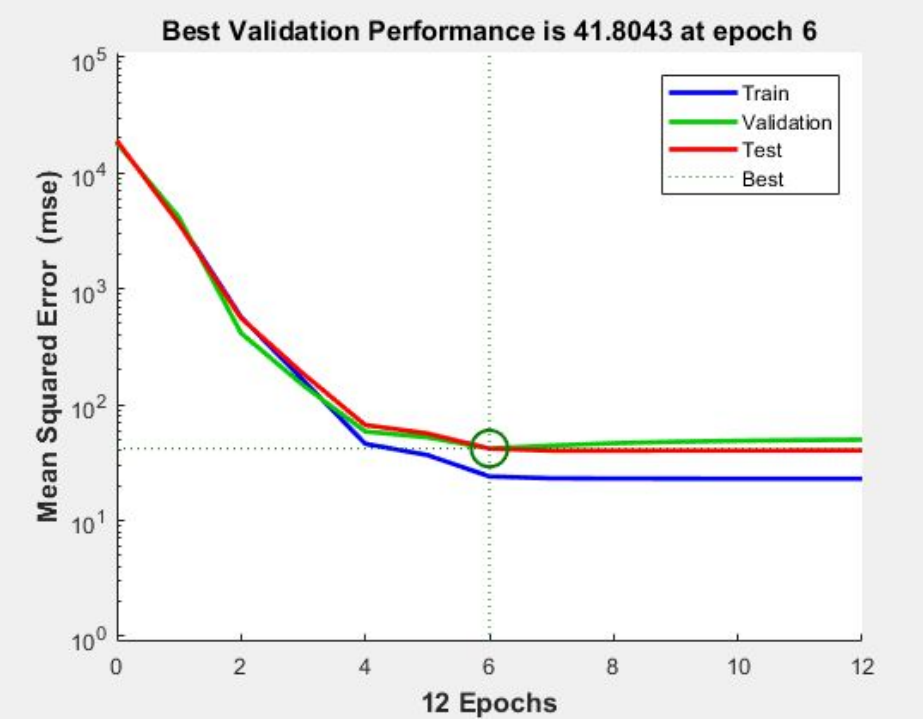
Neural Networks

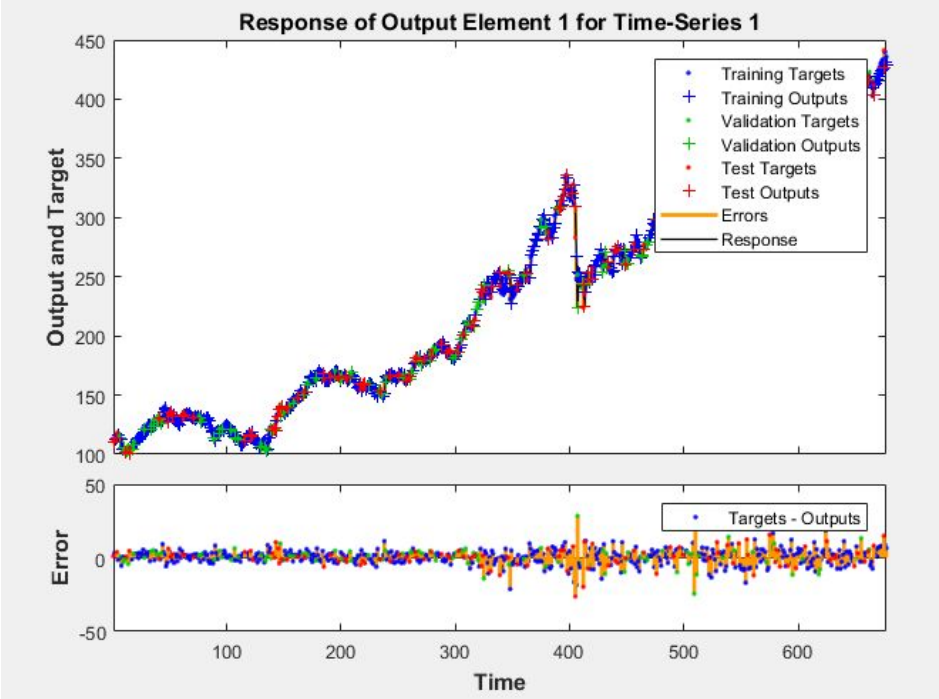
1. There are 4 type of matrices to which the algorithm has been applied which are as follows -
    1. Raw_Data_Matrix
    2. Normalised_Matrix
    3. Principal_Component_Analysis_Matrix

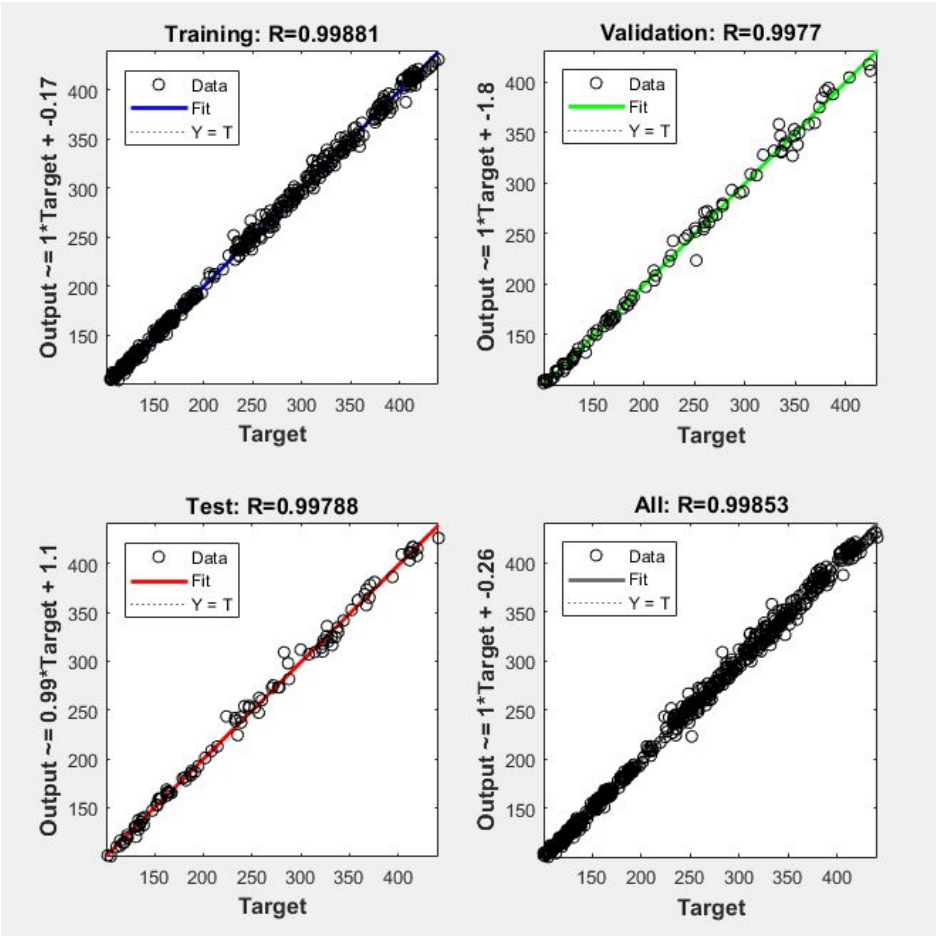
On Raw_Data_Matrix

Application of Nonlinear_Autoregressive_Response

The application of NAR with the Target (S&P_CLOSE) resulted in the following graph with MSE(Mean Square Error) increasing as we move forward in the timesteps.
Here MSE has been taken as the Measure for performance.
Training - 70%
Validation - 15%
Testing - 15%

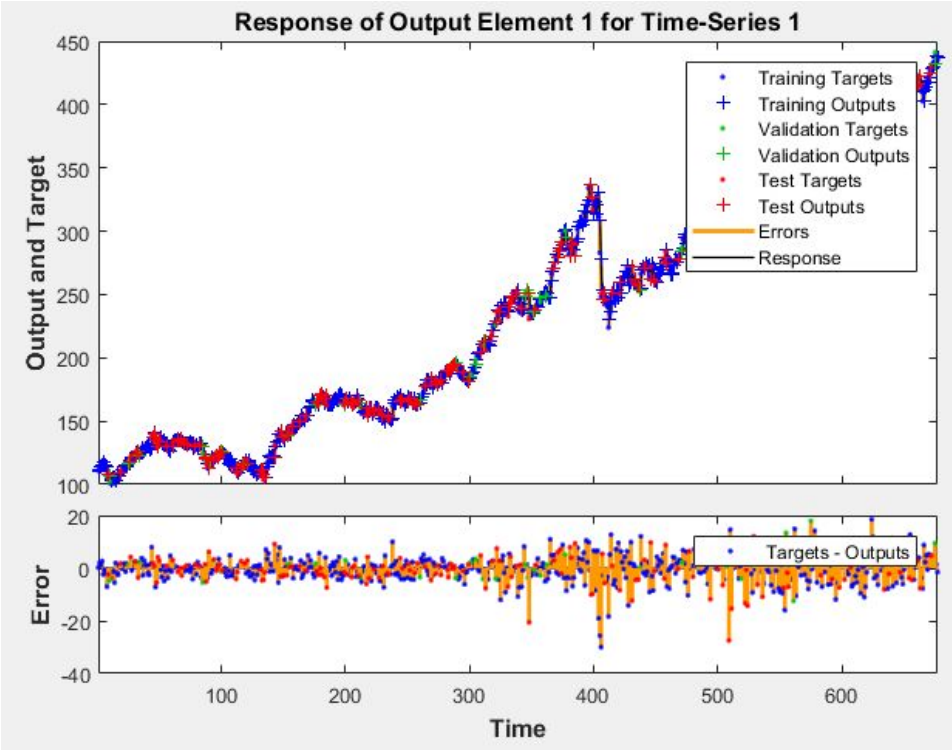


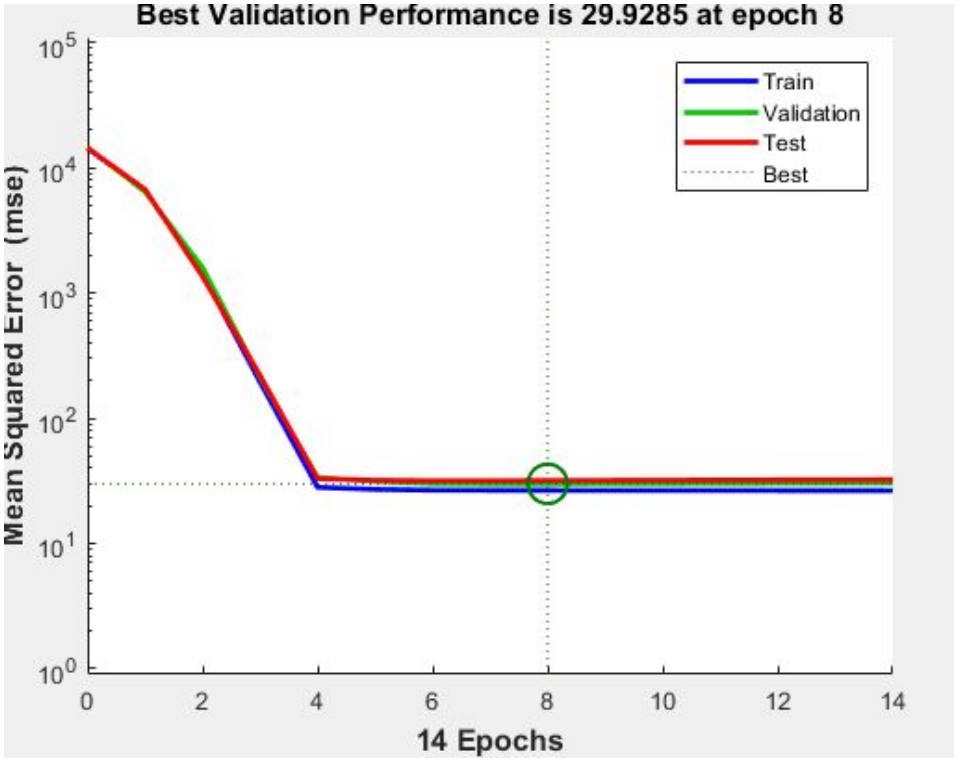

Response of Output Element 1 for Time-Series 1
Training Targets
Training Outputs
Validation Targets
Validation Outputs
Test Targets
Test Outputs
Errors
Response
Output and Target
Targets - Outputs
Error
Time

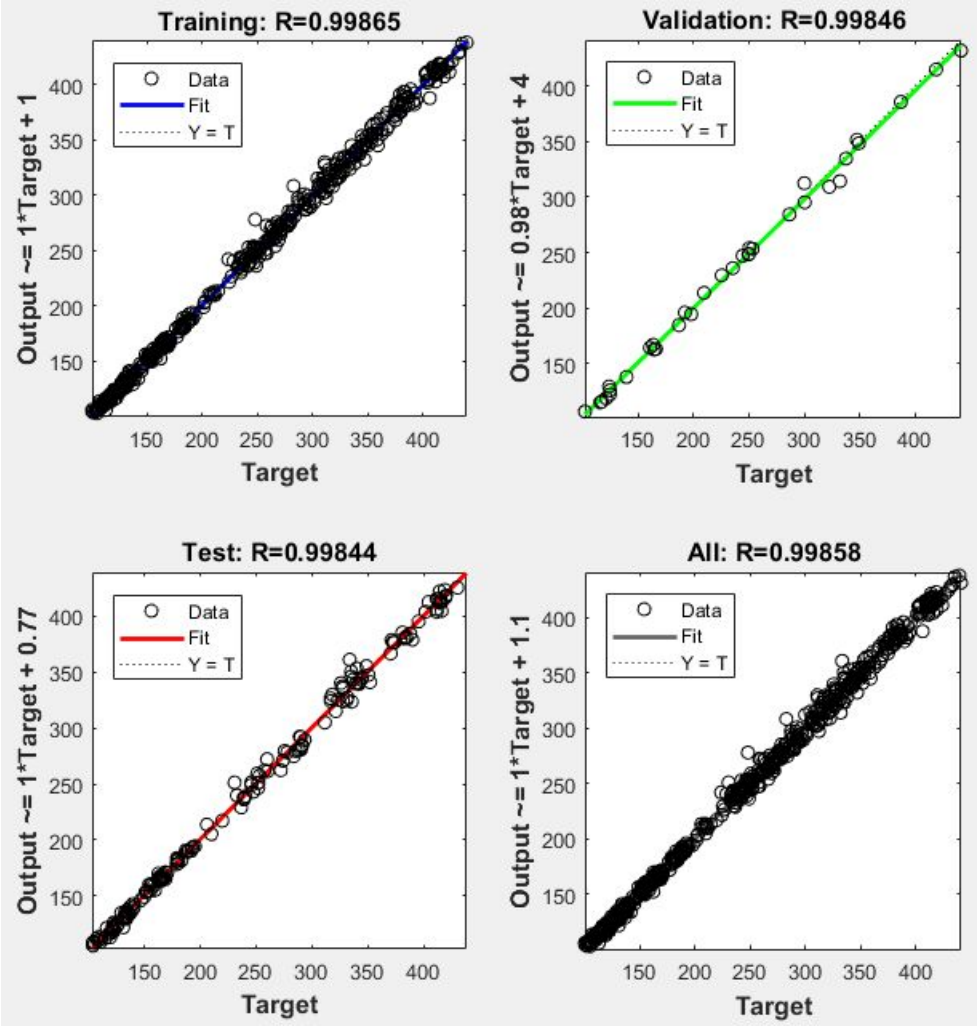

Training: R=0.99881
Validation: R=0.9977
Test: R=0.99788
All: R=0.99853
Data
Fit
Y = T
Output ~= 1*Target + -0.17
Output ~= 1*Target + -1.8
Output ~= 0.99*Target + 1.1
Output ~= 1*Target + -0.26
Target

Performance Plot

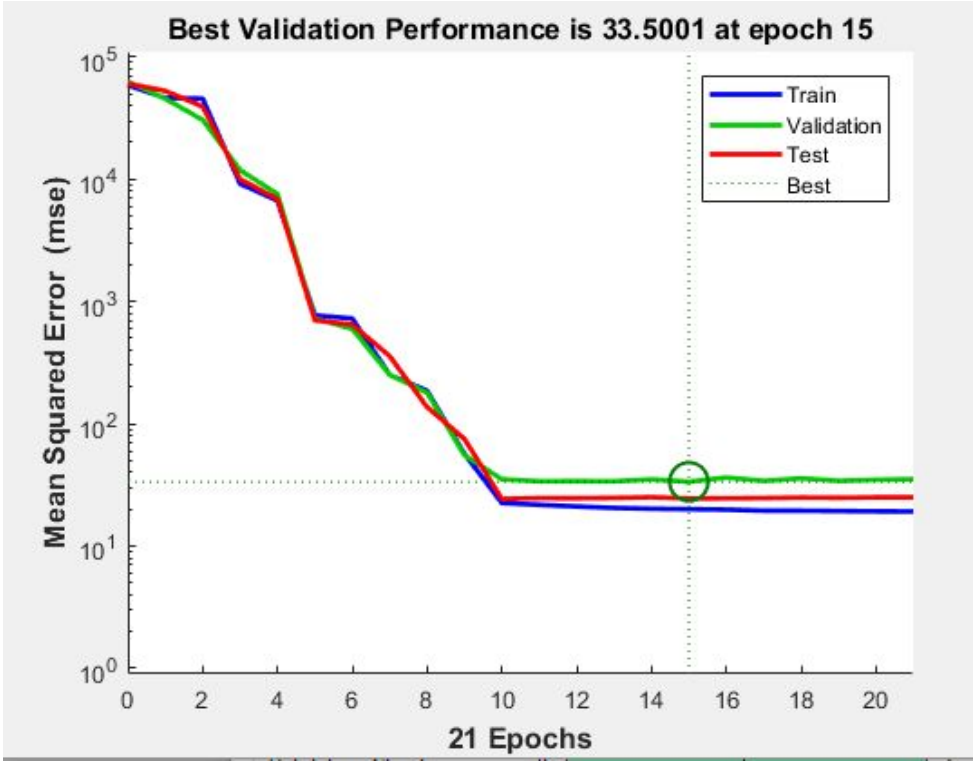
Training - 70 % Testing - 5% Validation - 25%

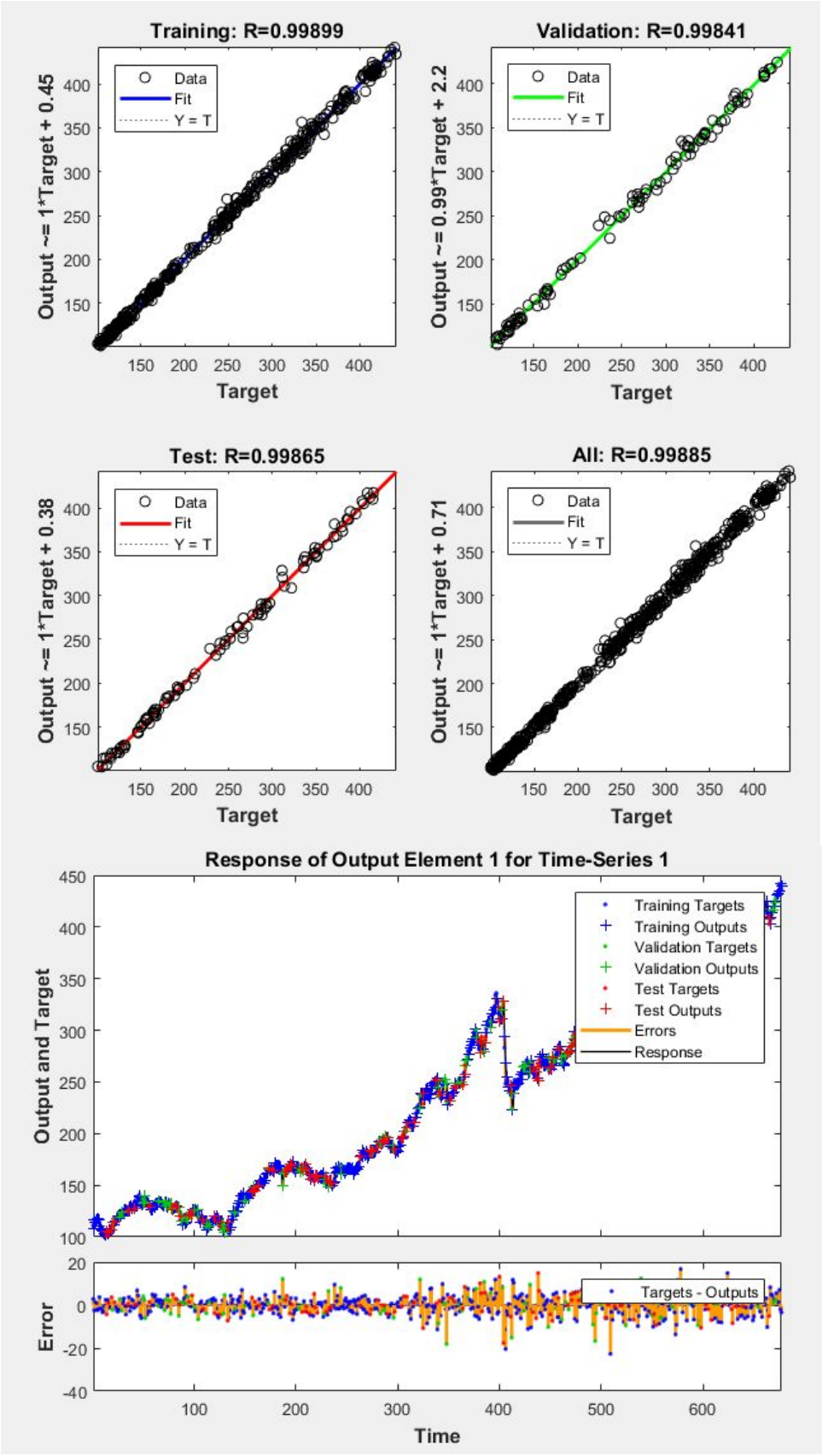



Best Validation Performance is 29.9285 at epoch 8
Mean Squared Error (mse)
14 Epochs
Train
Validation
Test
Best
10^5
10^4
10^3
10^2
10^1
10^0
0
2
4
6
8
10
12
14

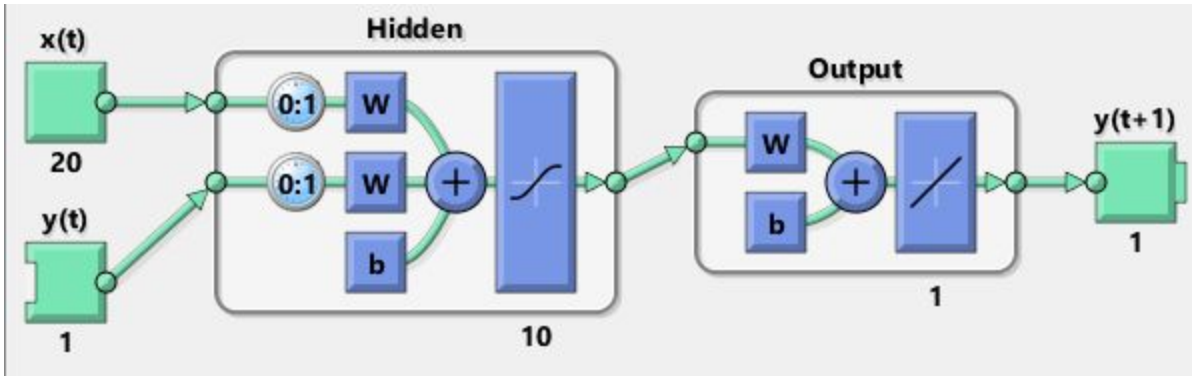


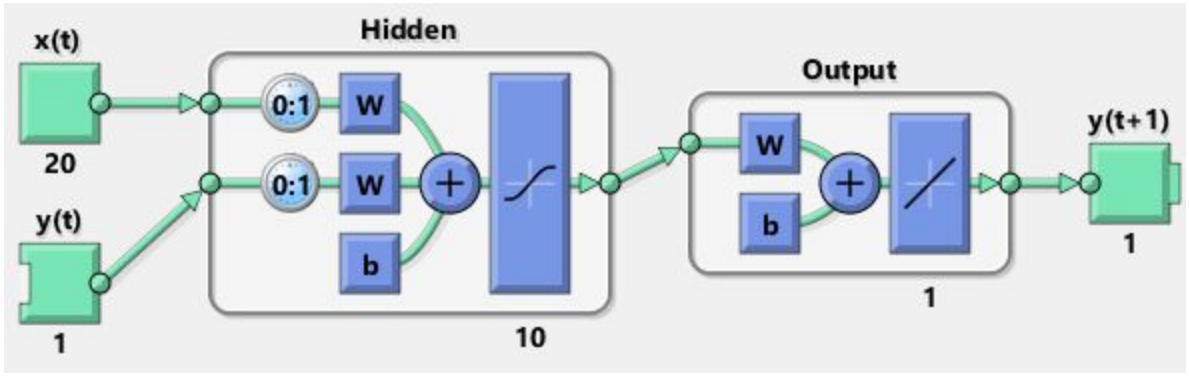
Application of Nonlinear_Autoregressive Exogenous Inputs (NARX)

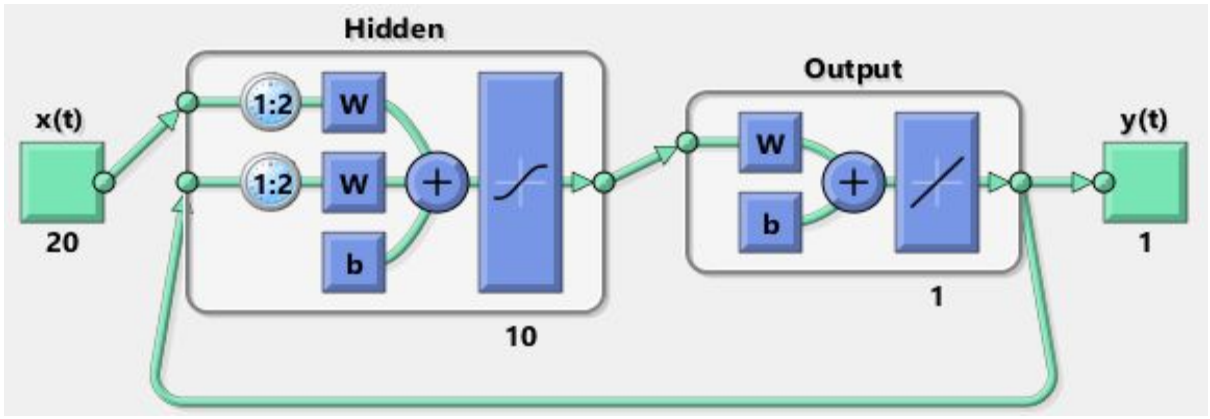




In this the Neural Network is trained at a configuration where
Training Data - 70%
Validation Data - 15%
Testing Data - 15%

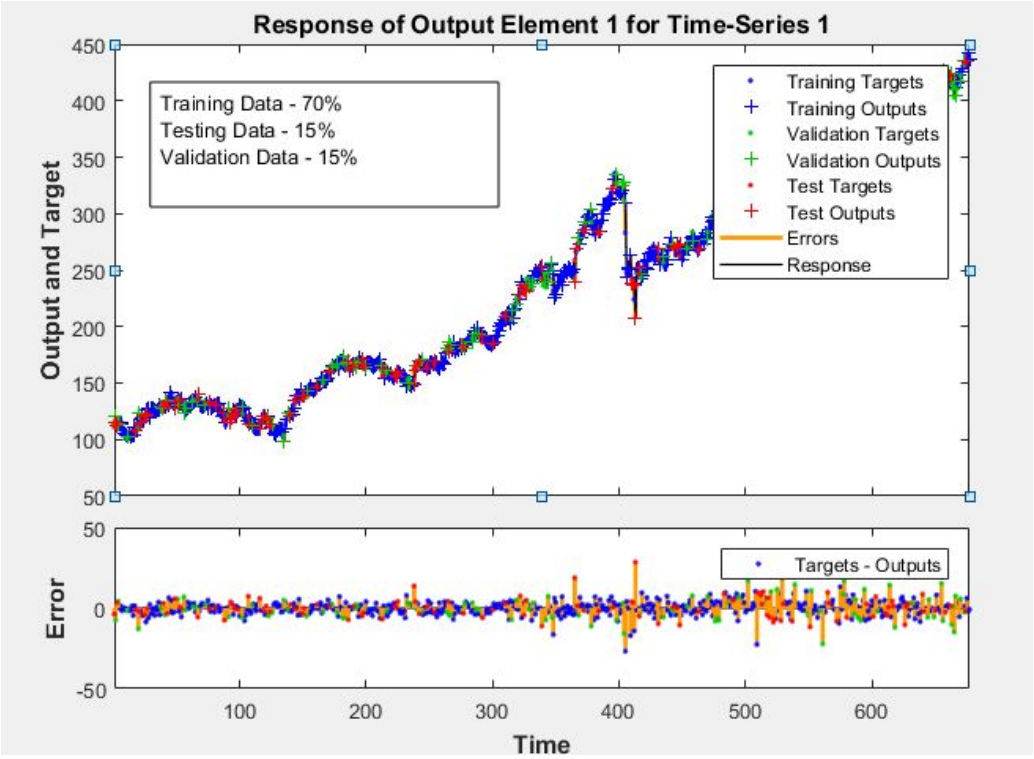


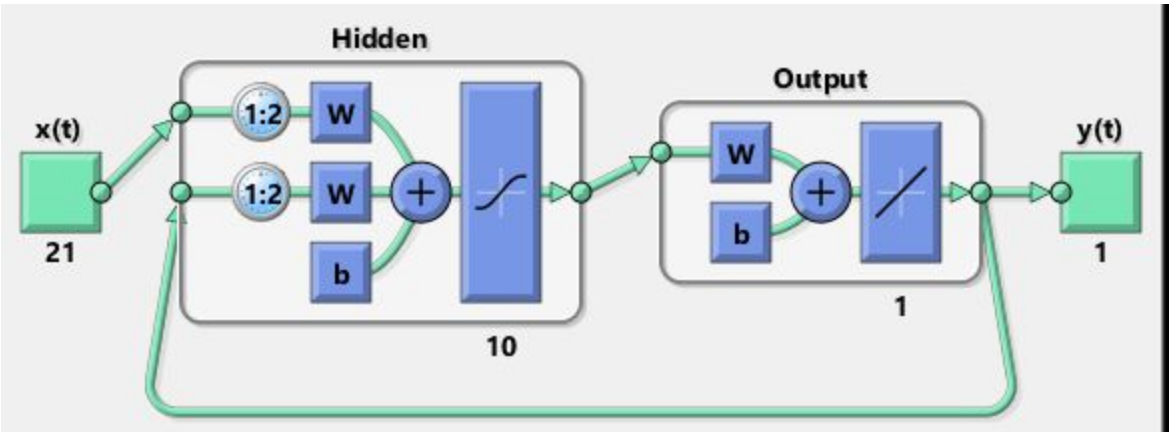


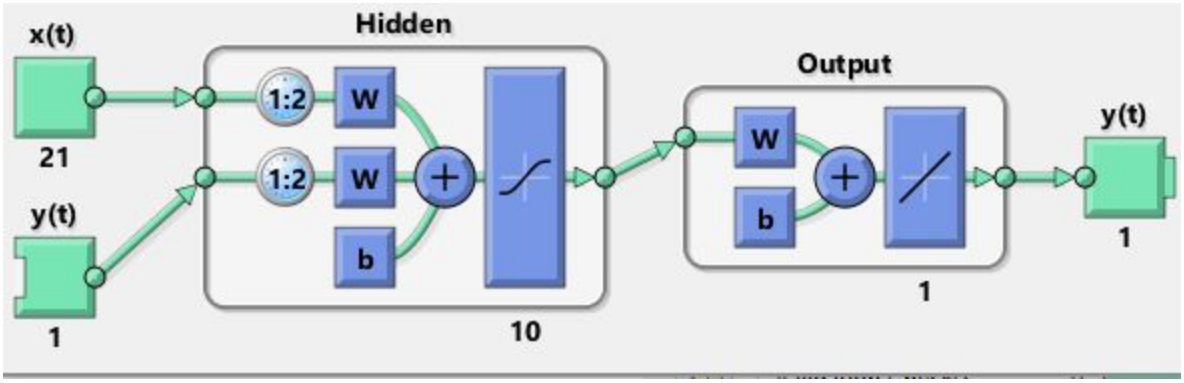


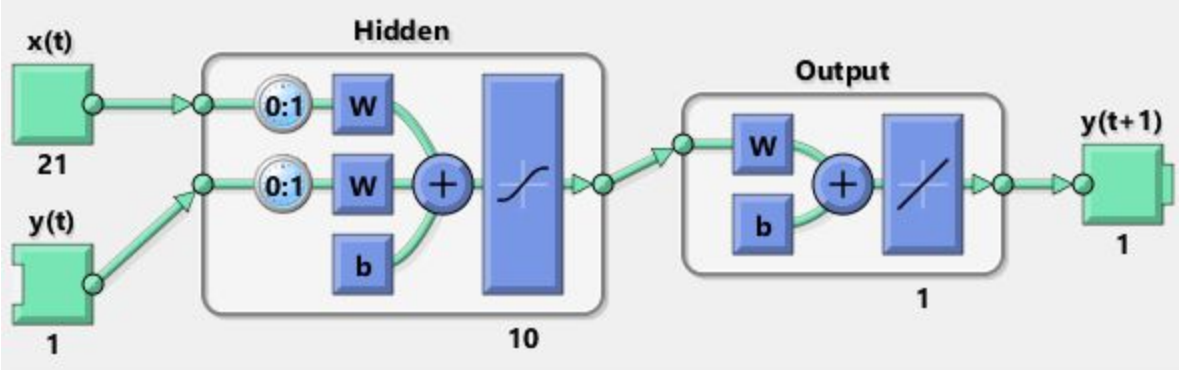
On Normalised_Data_Matrix

Application of Nonlinear_Autoregressive Exogenous Inputs (NARX)


Response of Output Element 1 for Time-Series 1
Training Data - 70%
Testing Data - 15%
Validation Data - 15%
Training Targets
Training Outputs
Validation Targets
Validation Outputs
Test Targets
Test Outputs
Errors
Response
Output and Target
Targets - Outputs
Error
Time

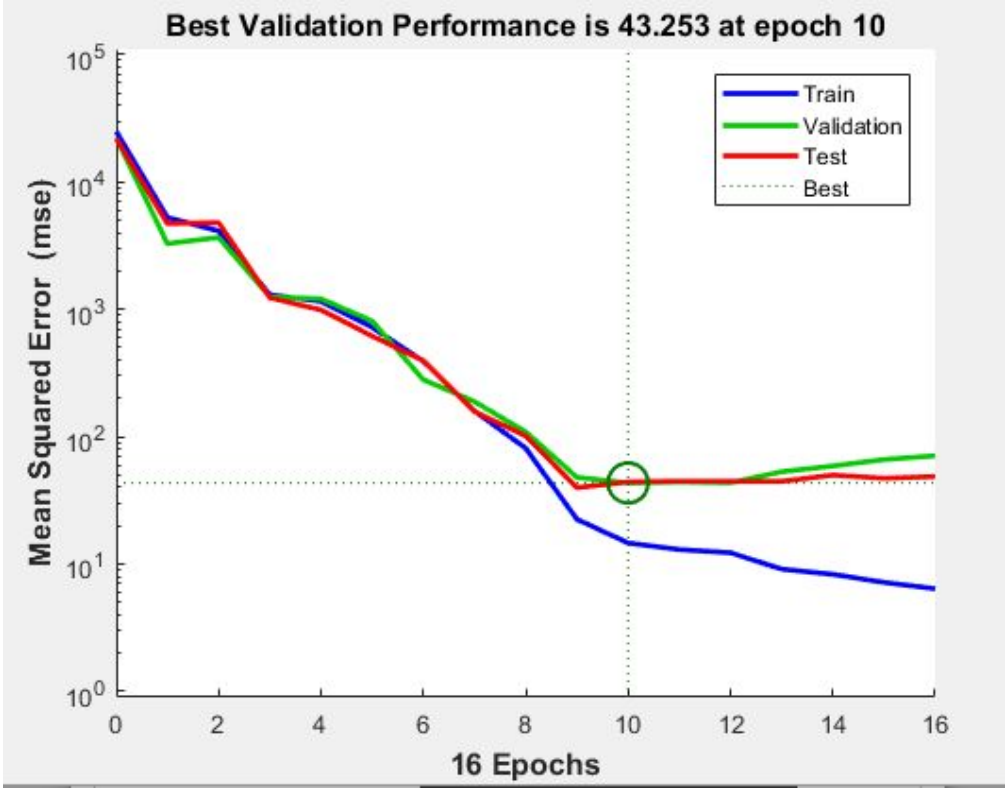

Hidden
Output
x(t)
y(t)
1:2
W
b
21
10
1

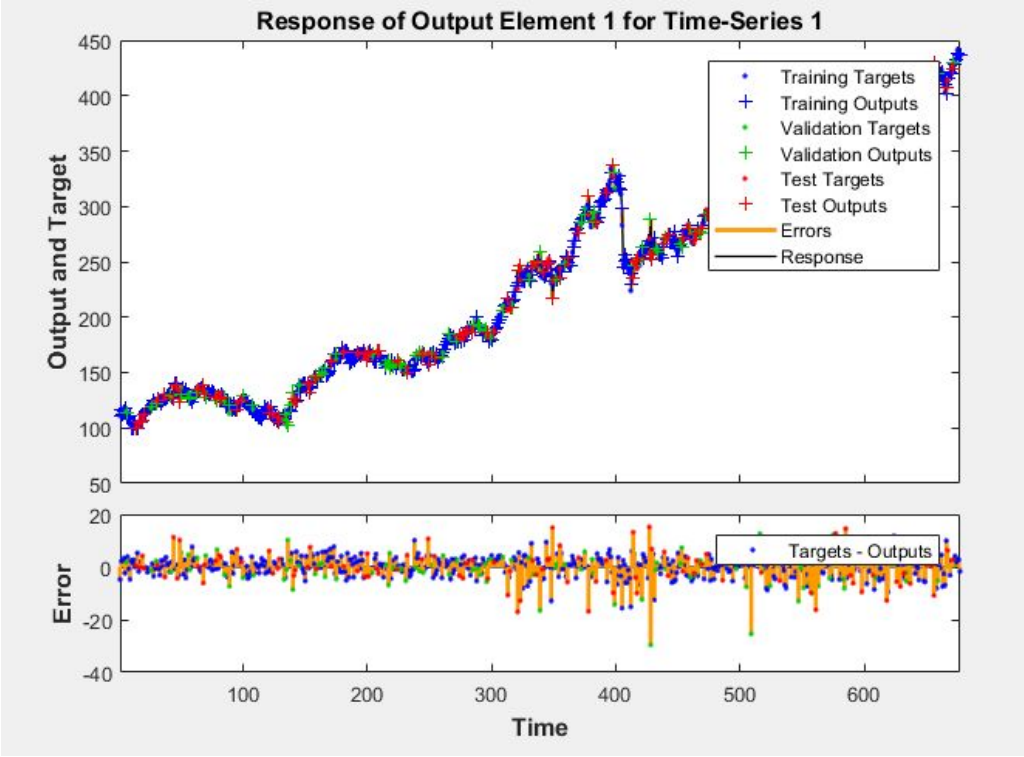

x(t)
Hidden
Output
y(t)
21
y(t)
1:2
W
b
1
10
1

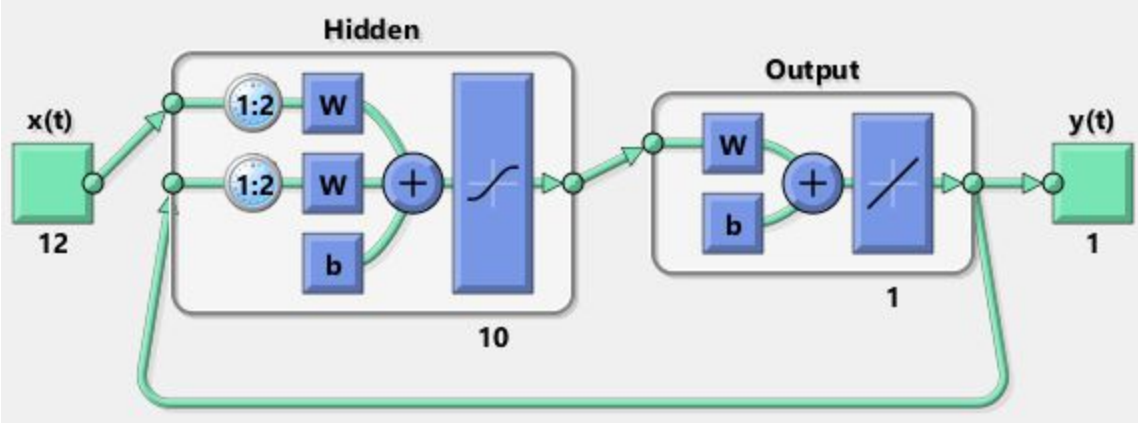


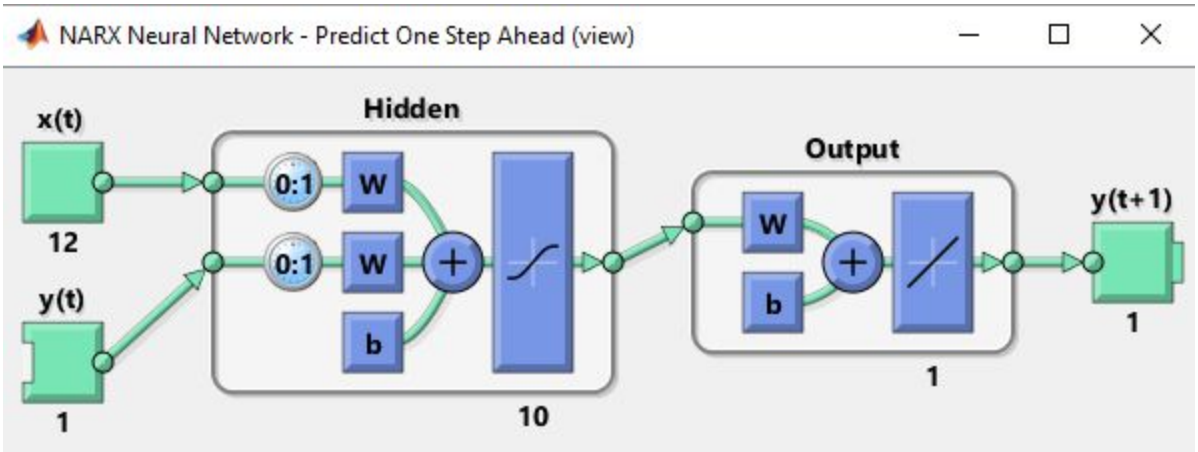
On Principal Component Analysis Matrix

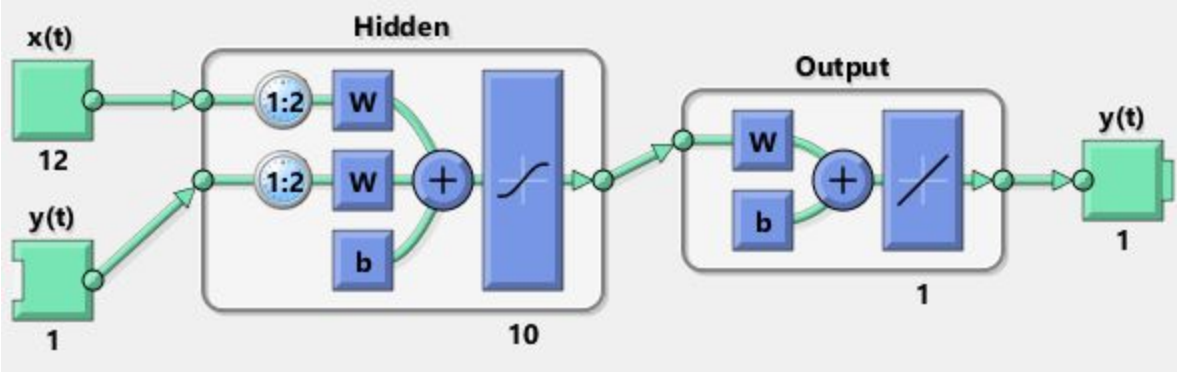
Application of Nonlinear_Autoregressive Exogenous Inputs (NARX)




Response of Output Element 1 for Time-Series 1
Output and Target
Error
Time
Training Targets
Training Outputs
Validation Targets
Validation Outputs
Test Targets
Test Outputs
Errors
Response
Targets - Outputs


Hidden
Output
x(t)
y(t)
1:2
W
b
12
10
1
1


NARX Neural Network - Predict One Step Ahead (view)
x(t)
y(t)
Hidden
Output
y(t+1)
0:1
W
b
12
1
10
1
1



Raw Data	valPerformance	test performance	Close loop Performance	multiStepPerformance	stepAheadPerformance
NARX(Raw)	87.9897	2.70E+03	616.8959	29.56	435.8385
NARX(Z)	31.2154	37.578	5.16E+04	70.9248	25.223
NARX(PCA)	41.3106	63.615	3.64E+03	682.2212	26.2605

Inference from Observation :

It can be stated that no algorithm is better than another in absolute terms. Simple algorithm of linear regression was giving close to 99% accuracy when the raw data was given to it. On the same other hand when the same raw data was passed through SVM the prediction failed miserably.

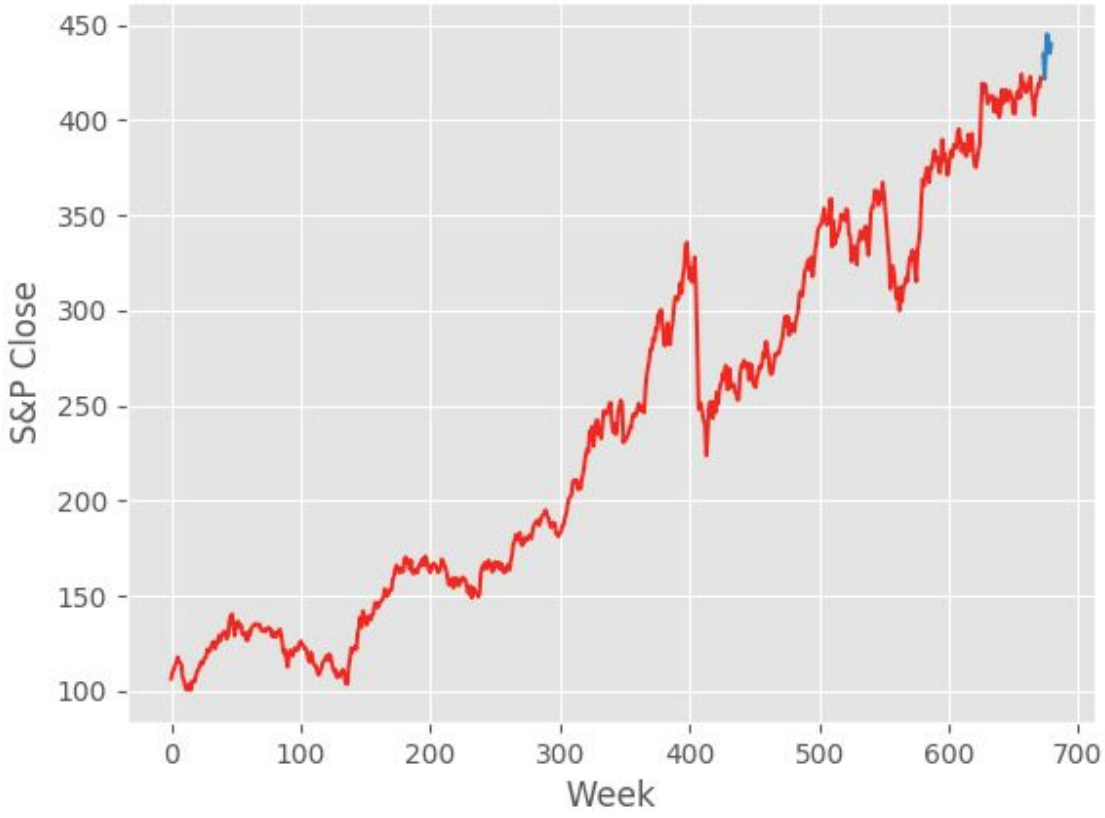
Same was observed with Normalised data set, it failed miserably with linear regression but performed extremely well with SVM.

PCA matrix also failed with Linear Regression as it was returning high mean absolute error but when the same matrix was passed through SVM it gave close to 98% accuracy, the linear kernel of SVM reported 98.76% accuracy even when the PCA was applied 11 times. Feature Reduced Data set gave extremely low mean absolute error although as much as 10 features were removed which had correlation less the 50% but they same matrix performed horribly with SVM.
The current knowledge about Neural Networks is not enough and we cannot infer anything from the same. However, the Neural Networks were implemented.

Predicted Values:

The following are the predicted values of S&P close of next 7 weeks

435.19
424.39
432.75
447.23
441.35
437.38
440.86



Conclusion

There are many things to conclude from this dataset and the algorithms applied by us.

No Domain Knowledge

Consider the situation where we do not have the idea of the features and the domain knowledge of the dataset. Different values of different features are provided to us but with no knowledge about the subject of the dataset.

In that regard, we find that **PCA** acts as a great tool in reducing the dimensionality in those datasets.

With Domain Knowledge (Based on this project)

Even after having the domain knowledge, feature reduction based on taking ratio of the values was not that beneficial.

But the domain knowledge played a significant role in removing the features while in feature reduction.

Currently, we are talking only in the terms of data exploration, Feature Scaling and Feature Reduction. In further reports the main focus would be on achieving greater accuracy by applying different algorithms on our dataset.

Part 2

After applying different algorithms on our dataset we have achieved the observations listed in the page no. 72.