FINANCIAL TIME SERIES FORECATING

Presented By:-
Abhishek Sharma
Kumar Sourav
Nimesh K Verma

CONTENTS

INTRODUCTION

- Financial Time Series:-A financial time series is a sequence of data points such as stock prices, indixes, etc measured typically at successive points in time spaced at uniform time interval
- Financial Forecasting:- financial forecasting is basically estimating future value of a company stock or other financial instrument traded on a financial exchange based on previously observed values, rates, other market conditions

APPROACH

- Testing Different Prediction Models
- Artificial Neural Network
  Non Linear
- Statistical Model
  Linear

Artificial Neural Network

- Data Collection
- Data Processing
- Training, Validation and Testing Set
- Neural Network Paradigms:-
  - Number of hidden layers
  - Number of Hidden Neurons
  - Number of Output Neurons
  - Transfer Function

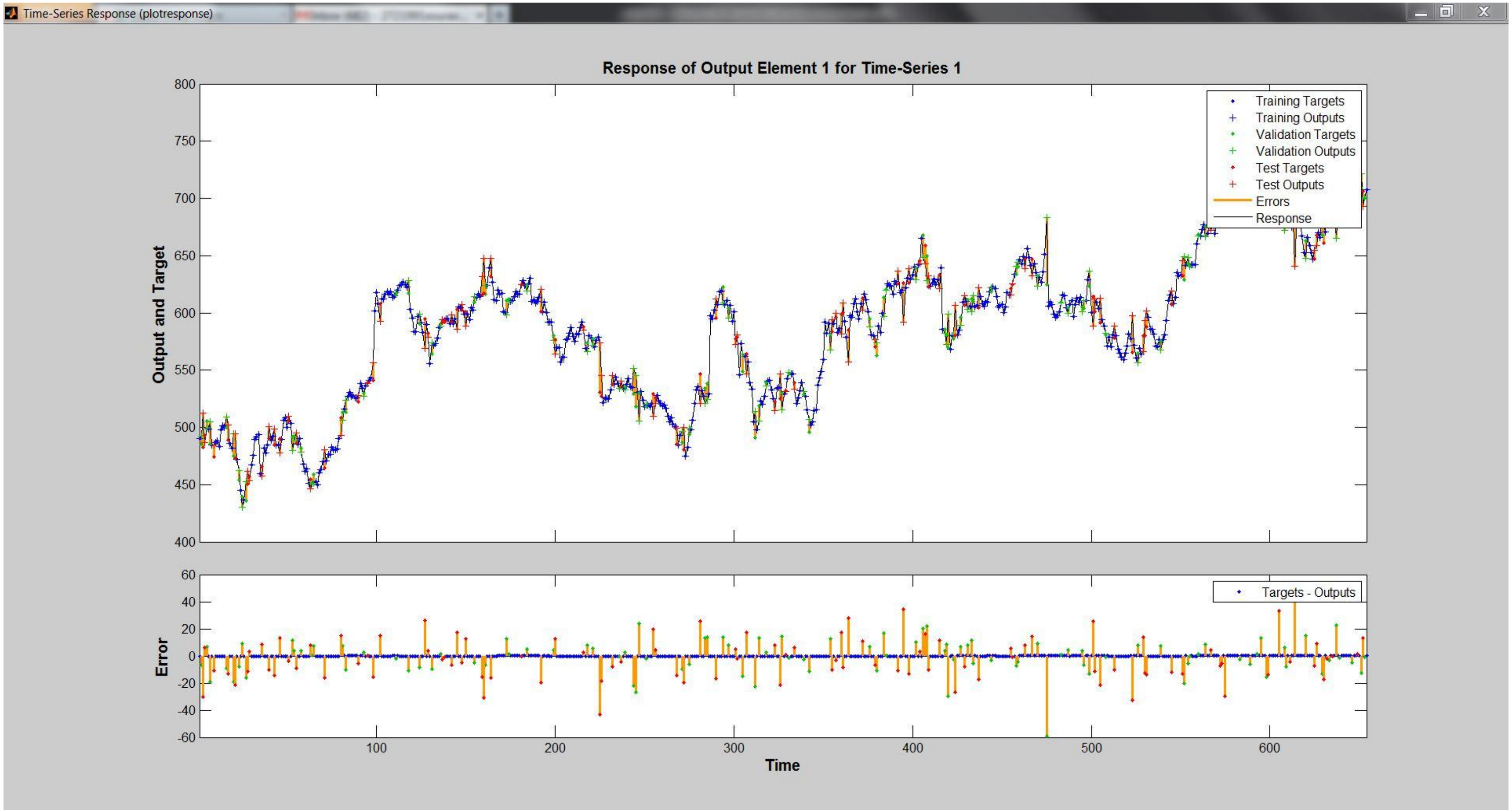
Artificial Neural Network Contd.

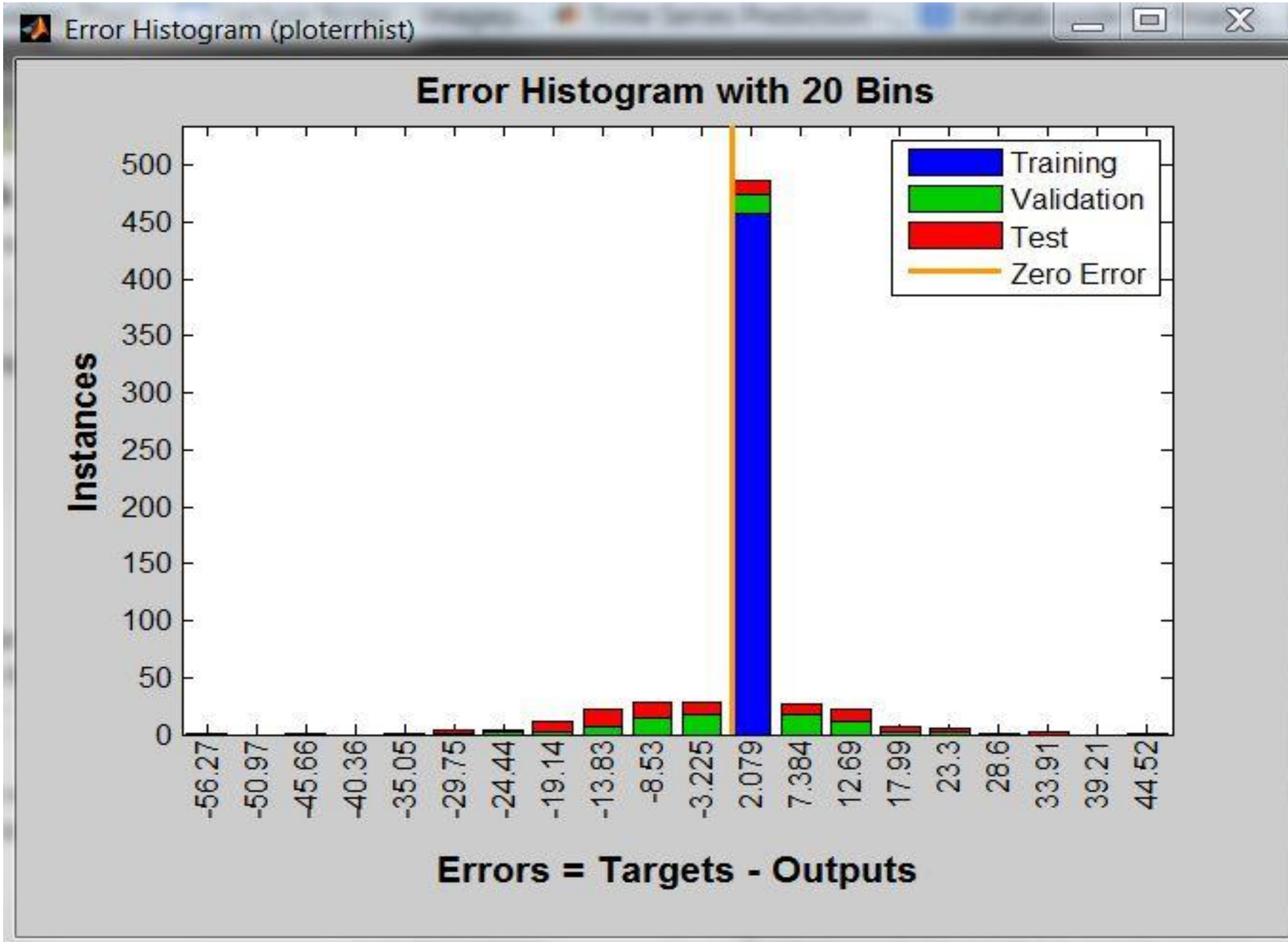
- Neural Network Training
  - Training Algorithm
  - Learning Rate and Momentum

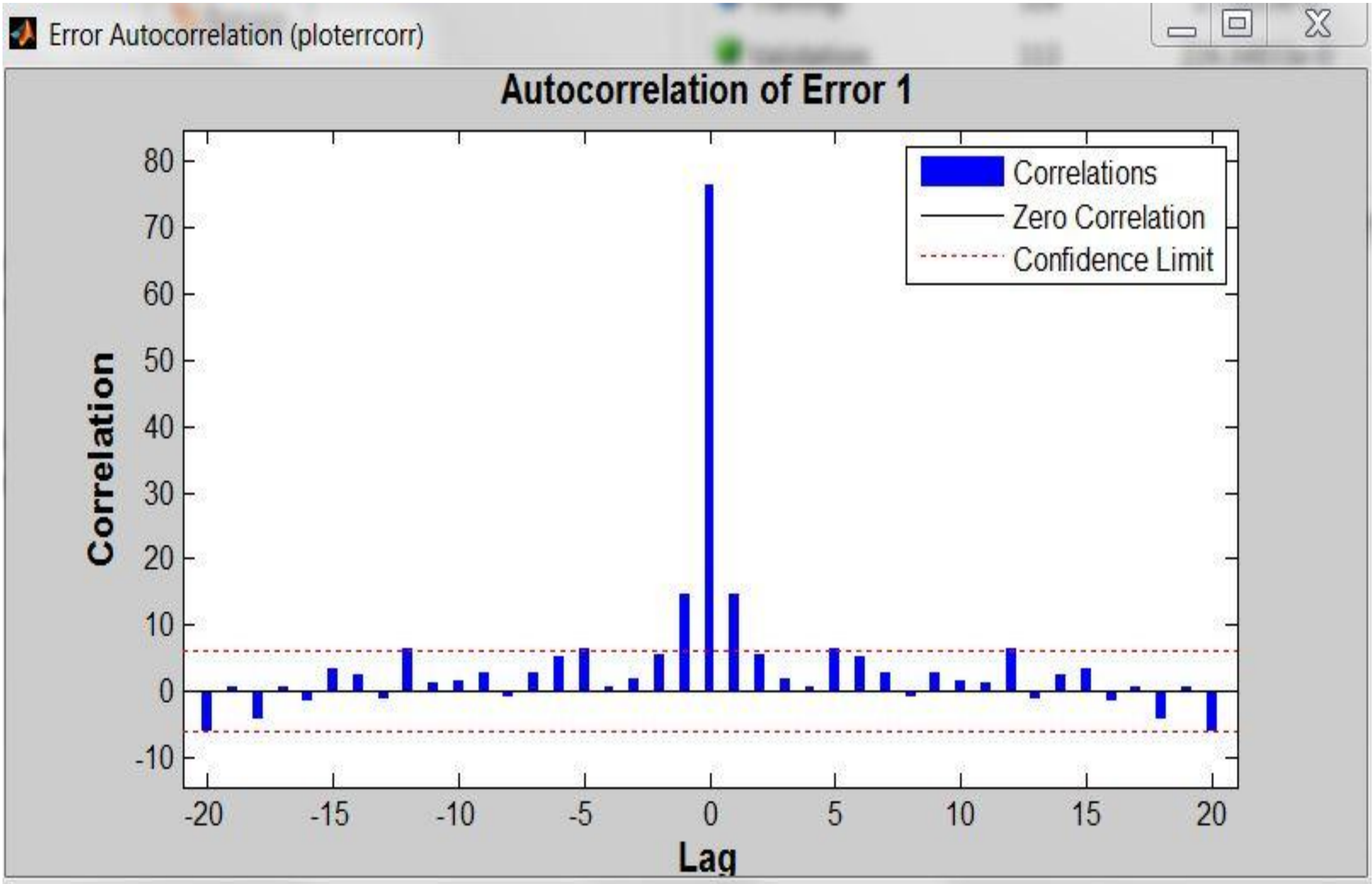
- Results
  - Error Histogram
  - Error Autocorrelation

Results

- Ann results depends on following factors
  - Data processing
  - Number of hidden layers, neurons and transfer functions
  - Training algorithms


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


Error Histogram (ploterrhist)
Error Histogram with 20 Bins
Training
Validation
Test
Zero Error
Instances
500
450
400
350
300
250
200
150
100
50
0
-56.27
-50.97
-45.66
-40.36
-35.05
-29.75
-24.44
-19.14
-13.83
-8.53
-3.225
2.079
7.384
12.69
17.99
23.3
28.6
33.91
39.21
44.52
Errors = Targets - Outputs



Error Autocorrelation (ploterrcorr)
Autocorrelation of Error 1
Correlations
Zero Correlation
Confidence Limit
Correlation
Lag
80
70
60
50
40
30
20
10
0
-10
-20
-15
-10
-5
0
5
10
15
20

Time Series -Revisited

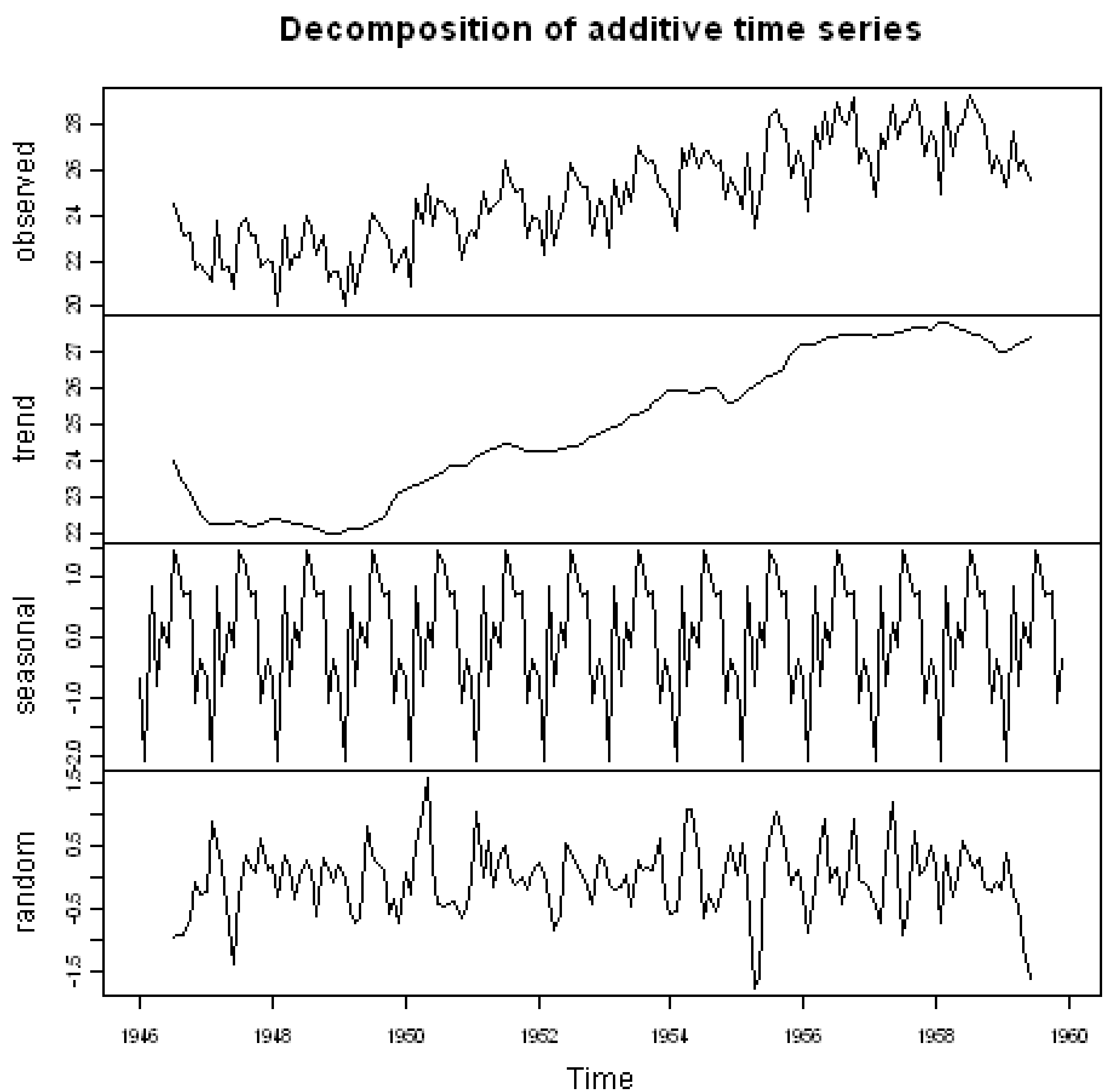
- A time series is a collection of observations of well-defined data items obtained through repeated measurements over time.

- Most of the times a time series can be decomposed into three components:

    Trend (long term direction),

    Seasonal (systematic, calendar related movements)

    Irregular (unsystematic, short term fluctuations).



Decomposition of additive time series
observed
trend
seasonal
random
Time
1946
1948
1950
1952
1954
1956
1958
1960

Decomposition of Times Series

- Additive Decomposition

Decomposition of the time series into its components, trend, seasonality, irregular and error , which are then summed up to give the forecast

The model equation is:

$$X'_t = T_t + S_t + C_t + \varepsilon_t$$

- Multiplicative Decomposition

Decomposition of the time series into its components, trend, seasonality, irregular and error , which are then Multiplied to give the forecast

The model equation is:

$$X'_t = T_t * S_t * C_t * \varepsilon_t$$

Moving Average

- **Simple Moving Average**

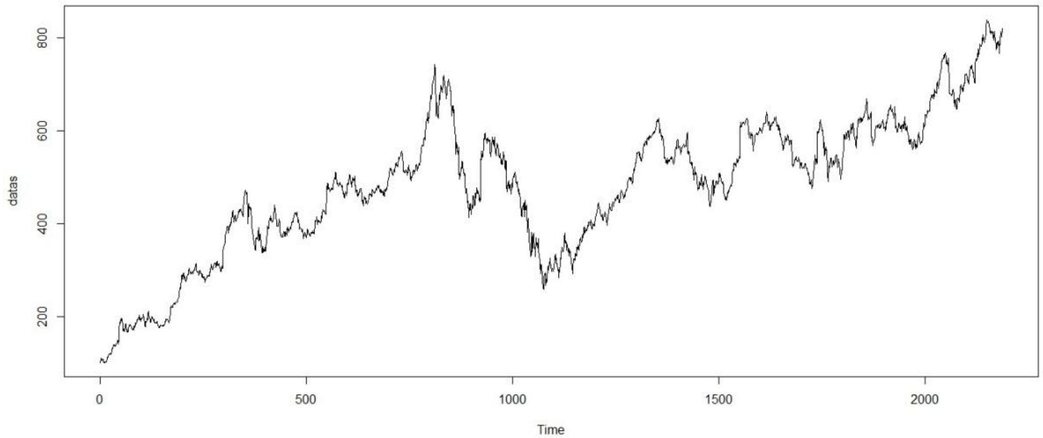
Smooth past data by arithmetically averaging over a specified period and projecting forward in time.

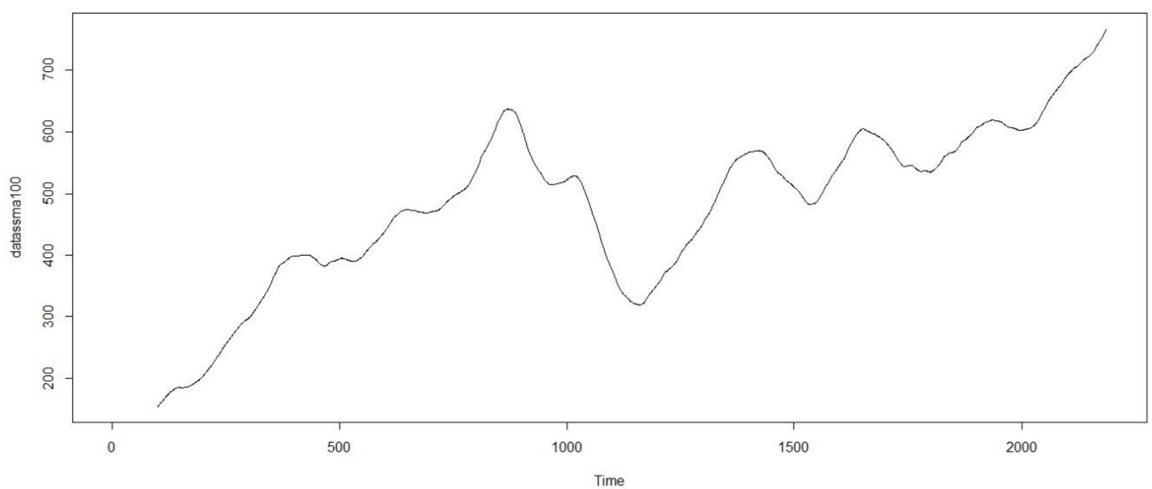
- **Exponential Moving Average**

summarized by the equation:

$$X'_t = \alpha X_t + (1-\alpha)X'_{t-1}$$

it is a weighted moving average with weights that decrease exponentially going backwards in time.


datas
200
400
600
800
0
500
1000
1500
2000
Time


datassma100
200
300
400
500
600
700
0
500
1000
1500
2000
Time

The Holt-Winters Forecasting Method

- Single Exponential Smoothing

$$\hat{y}_{n+1|n} = w_0 y_n + w_1 y_{n-1} + w_2 y_{n-2} + \ldots\ldots.$$

or $$\hat{y}_{n+1|n} = \sum_{i=0}^{\infty} w_i y_{n-i}$$

$$w_i = \alpha(1-\alpha)^i$$

$$\hat{y}_{n+1|n} = \alpha y_n + \alpha(1-\alpha)y_{n-1} + \alpha(1-\alpha)^2 y_{n-2} + \ldots$$

Since:

$$\hat{y}_{n+1|n} = \alpha y_n + (1-\alpha)(\alpha y_{n-1} + \alpha(1-\alpha)y_{n-2} + \ldots)$$

it can be seen that:

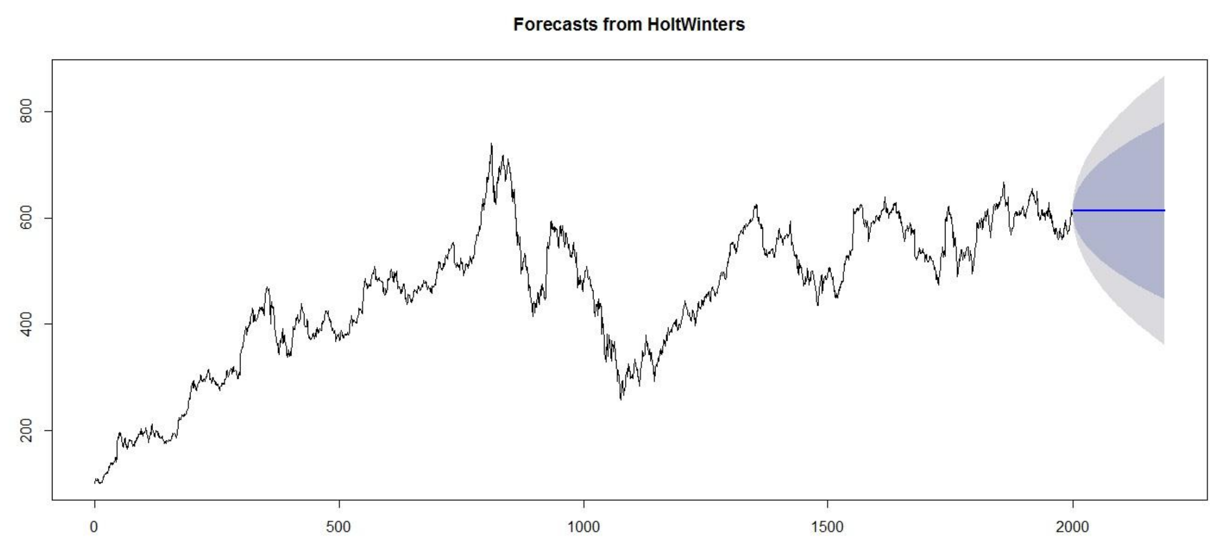
$$\hat{y}_{n+1|n} = \alpha y_n + (1-\alpha)\hat{y}_{n|n-1}$$

```
> datasforecast <- HoltWinters(datas, beta = FALSE, gamma=FALSE)
> datasforecast
Holt-Winters exponential smoothing without trend and without seasonal component.

Call:
HoltWinters(x = datas, beta = FALSE, gamma = FALSE)

Smoothing parameters:
 alpha: 0.9999582
 beta : FALSE
 gamma: FALSE

Coefficients:
      [,1]
a 819.0593
> 
```



Continued

- Holts Method

$$\hat{y}_{t/t-1} = m_{t-1} + b_{t-1}$$

m_n is the current level and b_n is the current slope.

$$m_t = \alpha_0 y_t + (1-\alpha_0)(m_{t-1} + b_{t-1}) \qquad 0 < \alpha < 1$$

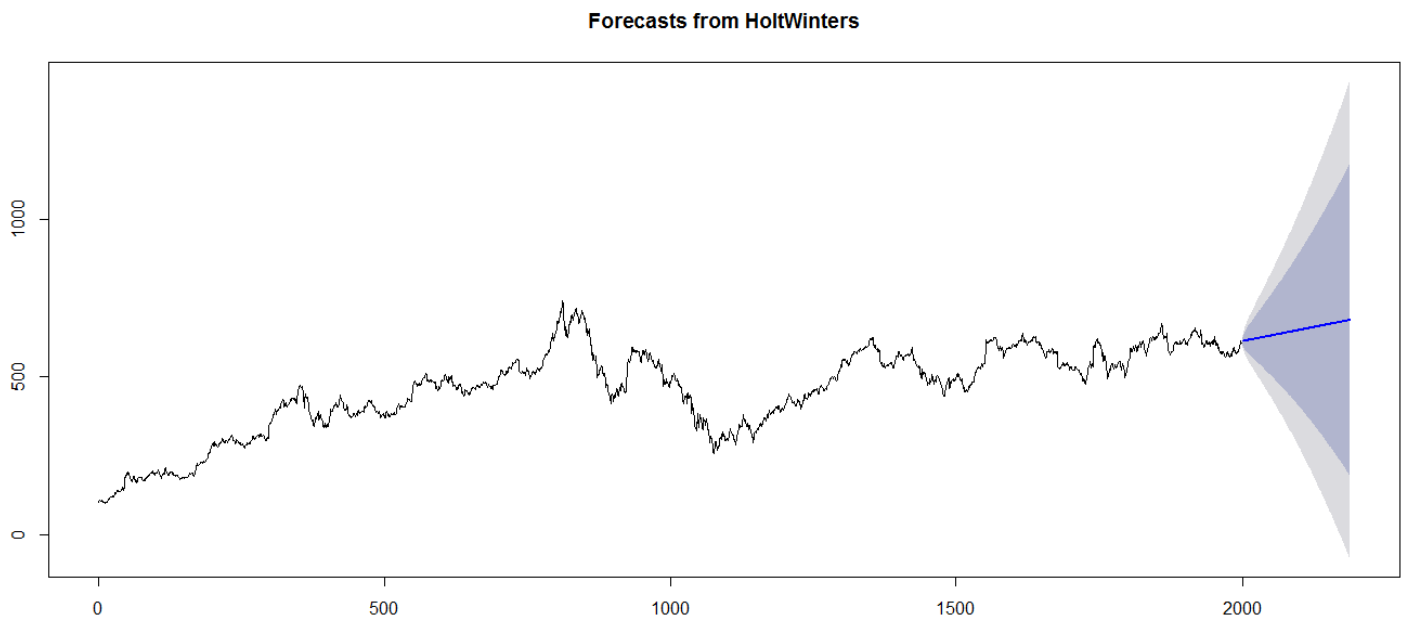
$$b_t = \alpha_1 (m_t - m_{t-1}) + (1-\alpha_1) b_{t-1}$$

```
> inputholts<- HoltWinters(inputseries, gamma=FALSE, l.start=100.335, b.start=7.975)
> inputholts
Holt-Winters exponential smoothing with trend and without seasonal component.

Call:
HoltWinters(x = inputseries, gamma = FALSE, l.start = 100.335,     b.start = 7.975)

Smoothing parameters:
 alpha: 0.9935594
 beta : 0.01892645
 gamma: FALSE

Coefficients:
         [,1]
a 613.3270917
b   0.3572637
> 
```



Also Attempted

- ARIMA
- BOX JENSKIN

Conclusion

- More number of hidden layer makes the calculation slow and there is a chance of over fitting
- The larger the window makes the prediction more close to the actual data
- As observed in our simulation the errors are less correlated as the window size is increased

Conclusion

- According to our results we found that ANN is better in prediction as compared to the Statistical Model