

Data Analytics

Assignment -5

Name : R Siva Girish

SRN : PES1201700159

Dataset : Sensex Dataset 2014 - 2019

The dataset is based on Sensex data collected over the years 2014 to 2019. Until current date. This dataset consists of attribute date, open, high, low, close and volume. Volume is the number of trading instances taking place. But we are more interested in the closing value of the share. Hence we shall evaluate a time series model over the entire dataset to forecast the closing values of share in the next few years.

| | Date | Open | High | Low | Close | Volume |
|----|------------|--------------|--------------|--------------|--------------|--------|
| 1 | 2014-10-16 | 26260.349609 | 26462.080078 | 25933.980469 | 25999.339844 | 10700 |
| 2 | 2014-10-17 | 25950.000000 | 26248.539063 | 25910.769531 | 26108.529297 | 9400 |
| 3 | 2014-10-20 | 26434.160156 | 26517.900391 | 26368.939453 | 26429.849609 | 9300 |
| 4 | 2014-10-21 | 26552.449219 | 26615.410156 | 26407.000000 | 26575.650391 | 8400 |
| 5 | 2014-10-22 | 26782.570313 | 26818.330078 | 26712.210938 | 26787.230469 | 6000 |
| 6 | 2014-10-27 | 26959.570313 | 26994.960938 | 26726.839844 | 26752.900391 | 6500 |
| 7 | 2014-10-28 | 26788.730469 | 26907.140625 | 26764.150391 | 26880.820313 | 6800 |
| 8 | 2014-10-29 | 27017.439453 | 27126.300781 | 26971.160156 | 27098.169922 | 8100 |
| 9 | 2014-10-30 | 27098.939453 | 27390.599609 | 27088.650391 | 27346.330078 | 7000 |
| 10 | 2014-10-31 | 27439.060547 | 27894.320313 | 27438.279297 | 27865.830078 | 11600 |

❖ Time Series Models

- A time series is a set of observations, each one being recorded at a specific time t
- Time Series modelling is a method by which we can predict the future values of a variable and gain useful insights regarding the trends followed by the data.
- Our Goal is to run Holt Winter model on the dataset and measure its accuracy.

❖ Holt Winter Model

- Converting data to Time Series data

Code:

```
Close_Values<-ts(Sensex$Close,frequency=365,start=c(2014,10,16),end = c(2019,10,15))
```

#Here we convert the closing values of the share to time series data so that it can be modeled.

- Applying Holt Winter model

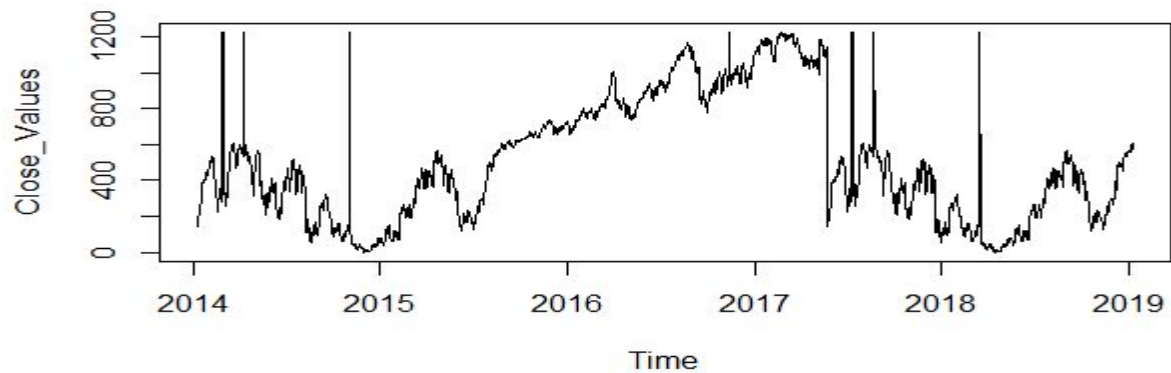
Code:

```
CHWF1<-HoltWinters(Close_Values,beta=NULL,gamma=NULL)
```

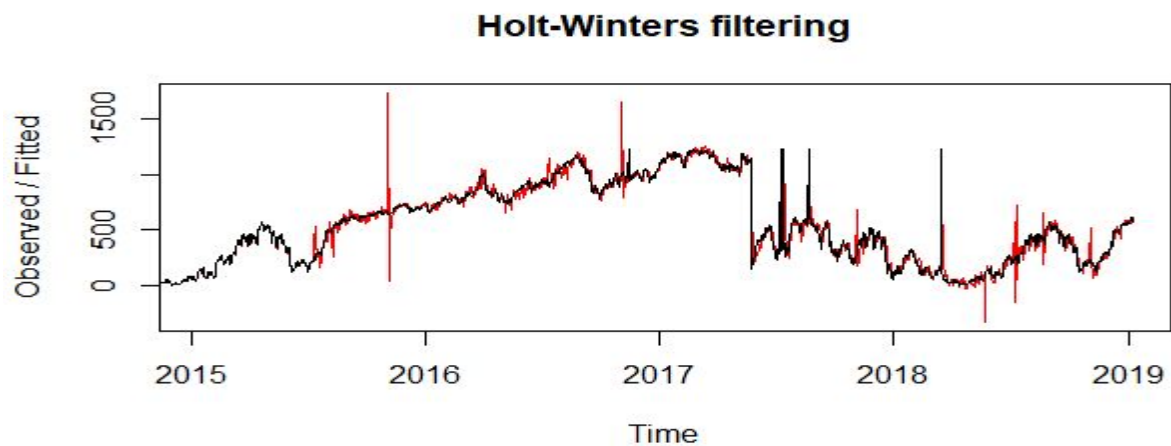
#Modeling the time series data as a holt winter model.

- Forecasting The data

```
fc<-forecast(CHWF1,h=365) [Forecasting for an entire year]
```

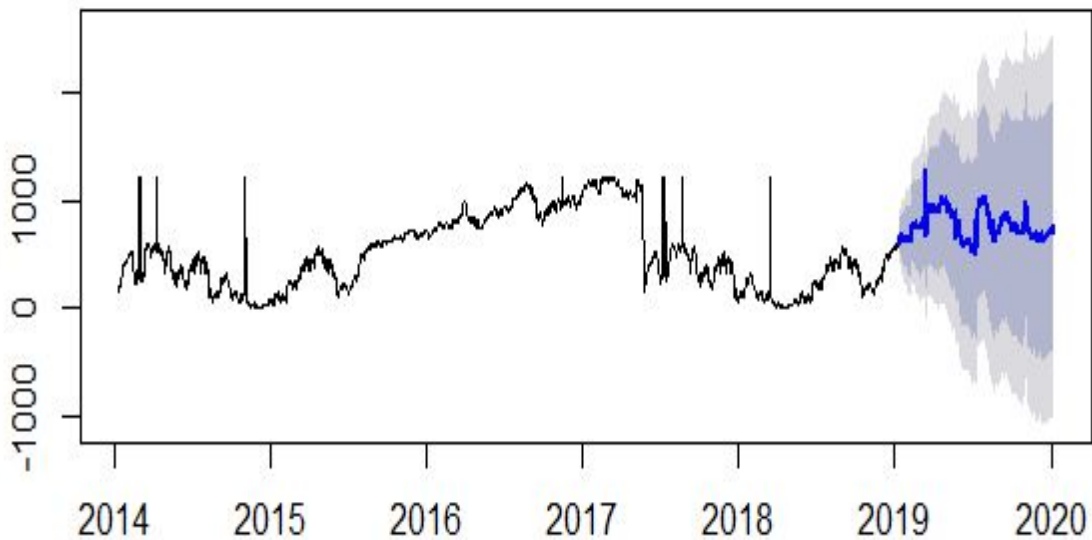


In the time series dataset the frequency has been set to 365 days and the time series data is indexed starting from the first record of data to the most recent to get data year wise.



By Setting the Beta parameter of the HoltWinters function to NULL we will obtain a model with exponential smoothing practically suppressing all the outliers.

Forecasts from HoltWinters



The model plotted above is the forecast of the HoltWinter model till the year 2020.

```
> accuracy(fc)
              ME      RMSE      MAE      MPE      MAPE      MASE
Training set -0.03696946 91.36239 40.3543 -1.173932 18.70256 0.09098835
              ACF1
Training set 0.09533314
> |
```

The Mean absolute percentage Error(Mape) is 18.7025% therefore the accuracy of the model is (100% - Mape).

Accuracy of the model = $100 - 18.7025 = 81.2975$

~81%

❖ Linear Model

- Linear model for this dataset is not possible as it doesn't have any dependent variables.
- All variables are independent therefore we merged the Gold prices for 5 years in our dataset.
- Against USDollars, GBP and Euro prices of gold respectively.

| | Date | USD..AM. | USD..PM. | GBP..AM. | GBP..PM. | EURO..AM. | EURO..PM. |
|----|------------|----------|----------|----------|----------|-----------|-----------|
| 1 | 2019-10-18 | 1487.50 | 1490.00 | 1154.15 | 1155.64 | 1336.67 | 1337.28 |
| 2 | 2019-10-17 | 1484.45 | 1492.65 | 1151.64 | 1162.63 | 1336.60 | 1341.59 |
| 3 | 2019-10-16 | 1482.55 | 1485.10 | 1166.32 | 1155.85 | 1344.52 | 1343.27 |
| 4 | 2019-10-15 | 1494.75 | 1487.80 | 1183.69 | 1178.34 | 1357.08 | 1353.30 |
| 5 | 2019-10-14 | 1494.20 | 1490.60 | 1188.79 | 1182.94 | 1354.04 | 1352.12 |
| 6 | 2019-10-11 | 1498.35 | 1479.15 | 1197.93 | 1166.01 | 1359.90 | 1338.33 |
| 7 | 2019-10-10 | 1508.20 | 1494.80 | 1232.35 | 1222.75 | 1368.69 | 1356.38 |
| 8 | 2019-10-09 | 1503.40 | 1507.25 | 1228.43 | 1232.93 | 1369.00 | 1372.65 |
| 9 | 2019-10-08 | 1500.00 | 1505.85 | 1225.50 | 1233.14 | 1365.30 | 1372.28 |
| 10 | 2019-10-07 | 1502.15 | 1501.25 | 1221.40 | 1218.11 | 1369.36 | 1365.54 |
| 11 | 2019-10-04 | 1509.50 | 1499.15 | 1223.75 | 1220.01 | 1374.70 | 1366.78 |
| 12 | 2019-10-03 | 1504.00 | 1517.10 | 1221.70 | 1223.84 | 1372.25 | 1380.26 |
| 13 | 2019-10-02 | 1484.05 | 1492.60 | 1213.21 | 1215.13 | 1359.84 | 1364.68 |

Showing 1 to 15 of 13,093 entries, 7 total columns

LBMA Gold Dataset (Dataset used for merging gold prices)

| | Date | Open | High | Low | Close | Volume | USD..PM. | GBP..PM. | EURO..PM. |
|----|------------|--------------|--------------|--------------|----------|--------|----------|----------|-----------|
| 1 | 2014-10-16 | 26260.349609 | 26462.080078 | 25933.980469 | 25999.34 | 10700 | 1237.75 | 773.545 | 971.851 |
| 2 | 2014-10-17 | 25950.000000 | 26248.539063 | 25910.769531 | 26108.53 | 9400 | 1234.25 | 768.237 | 967.053 |
| 3 | 2014-10-20 | 26434.160156 | 26517.900391 | 26368.939453 | 26429.85 | 9300 | 1244.50 | 771.161 | 974.321 |
| 4 | 2014-10-21 | 26552.449219 | 26615.410156 | 26407.000000 | 26575.65 | 8400 | 1250.25 | 774.340 | 982.283 |
| 5 | 2014-10-22 | 26782.570313 | 26818.330078 | 26712.210938 | 26787.23 | 6000 | 1243.75 | 775.405 | 982.037 |
| 6 | 2014-10-27 | 26959.570313 | 26994.960938 | 26726.839844 | 26752.90 | 6500 | 1228.75 | 761.543 | 966.835 |
| 7 | 2014-10-28 | 26788.730469 | 26907.140625 | 26764.150391 | 26880.82 | 6800 | 1229.25 | 760.580 | 964.572 |
| 8 | 2014-10-29 | 27017.439453 | 27126.300781 | 26971.160156 | 27098.17 | 8100 | 1223.50 | 757.632 | 959.006 |
| 9 | 2014-10-30 | 27098.939453 | 27390.599609 | 27088.650391 | 27346.33 | 7000 | 1202.00 | 750.406 | 952.456 |
| 10 | 2014-10-31 | 27439.060547 | 27894.320313 | 27438.279297 | 27865.83 | 11600 | 1164.25 | 729.206 | 931.325 |
| 11 | 2014-11-03 | 27943.039063 | 27969.820313 | 27785.400391 | 27860.38 | 9500 | 1167.75 | 730.986 | 935.397 |
| 12 | 2014-11-05 | 27907.189453 | 28010.390625 | 27857.650391 | 27915.88 | 8700 | 1142.00 | 715.539 | 914.991 |
| 13 | 2014-11-07 | 27902.710938 | 27980.929688 | 27739.560547 | 27868.63 | 10500 | 1154.50 | 728.759 | 928.801 |

Showing 1 to 15 of 1,186 entries, 9 total columns

➤ On this merged dataset we perform a linear regression on Closing values of Sensex to USD,GBP and EURO gold prices.

```
> #Applied Linear regression on closing values of Sensex dataset
> linmod<-lm(Nmer$Close~Nmer$USD..PM.+Nmer$GBP..PM.+Nmer$EURO..PM.)
> summary(linmod)
```

Call:

```
lm(formula = Nmer$Close ~ Nmer$USD..PM. + Nmer$GBP..PM. + Nmer$EURO..PM.)
```

Residuals:

```
      Min       1Q   Median       3Q      Max
-6584.1 -2291.0  -168.9   2336.3  6979.3
```

Coefficients:

```
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  19243.883   1708.779   11.262  <2e-16 ***
Nmer$USD..PM.    20.463     2.186    9.359  <2e-16 ***
Nmer$GBP..PM.    35.597     1.720   20.693  <2e-16 ***
Nmer$EURO..PM.  -42.216     2.258  -18.692  <2e-16 ***
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 3047 on 1182 degrees of freedom
Multiple R-squared:  0.55,    Adjusted R-squared:  0.5488
F-statistic: 481.5 on 3 and 1182 DF,  p-value: < 2.2e-16
```

Conclusion :

The accuracy of the model is around 82% which is good but it could possibly be made better. Log functions cannot be applied to this data set as it is the case that some undefined values enter our time series data set and the Mape becomes infinite. Hence this model can neither be log transformed to get a better fit. Linear Regression on this dataset upon merging with gold values gives us an Adjusted R Squared Value of around 55%. Which is very poor. Therefore we must test other models such as Autoregressive Moving Average models (ARMA) to find a better fit for the sensex data. Which may lead to a better fit.