US Net Imports

Introduction

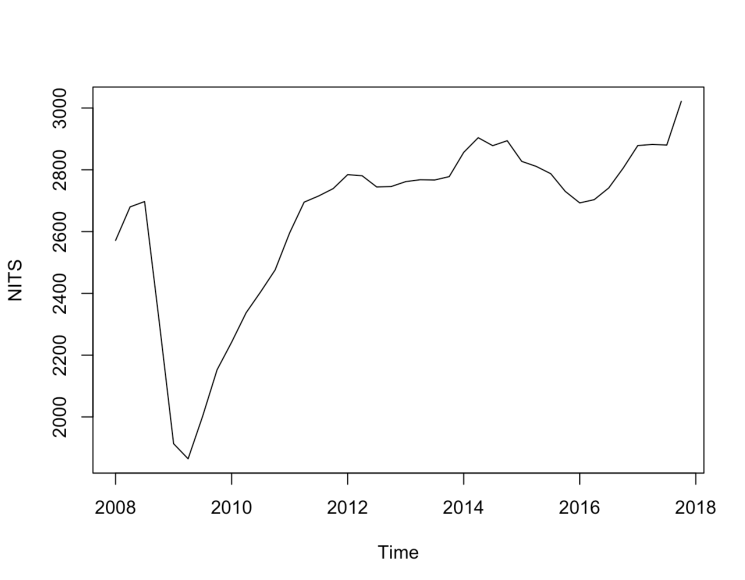
There has been a lot of discussions on trade policies lately. It would be good to understand the current trend of US Net Imports before we predict the implication due to the policy changes.
https://www.bea.gov/ is a great resource to learn more. Our dataset will be seasonally adjusted quarterly US net imports in Billions of Dollar for the last few years.

Import Data

- library(readr)
- Data_Spring_2018_NetImports <- read_csv("/Users/saurabhkarambalkar/Desktop/US_Net_Imports/Data_Spring_2018_NetImports.csv")
- netImport <- Data_Spring_2018_NetImports
- NITS <- ts(netImport$Imports,start=c(2008,01),frequency = 4)
- plot(NITS)

Plot and Inference

- Showing a time series plot.



- Summarising observations of the times series plot

  The time series plot does not show any significant seasonality as there is no regularity in it however we can see an upward positive trend. There is a dip in 2009.

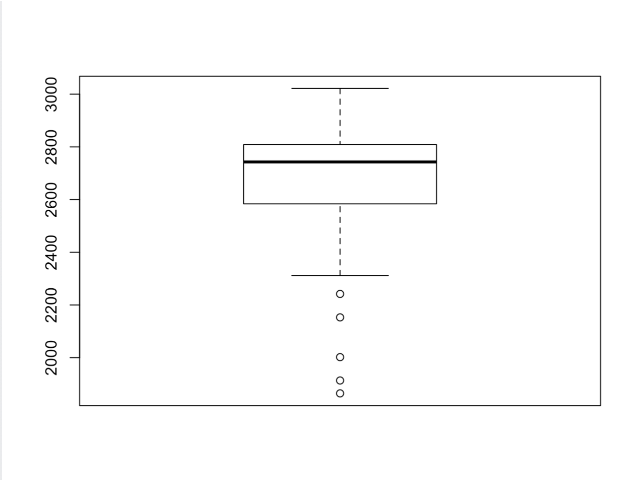
Central Tendency

- Finding out the min, max, mean, median, 1st and 3rd Quartile values of the times series?

```
> summary(NITS)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   1864    2590    2743    2646    2807    3022
```

- Showing the box plot.

```
> boxplot(NITS)
>
```

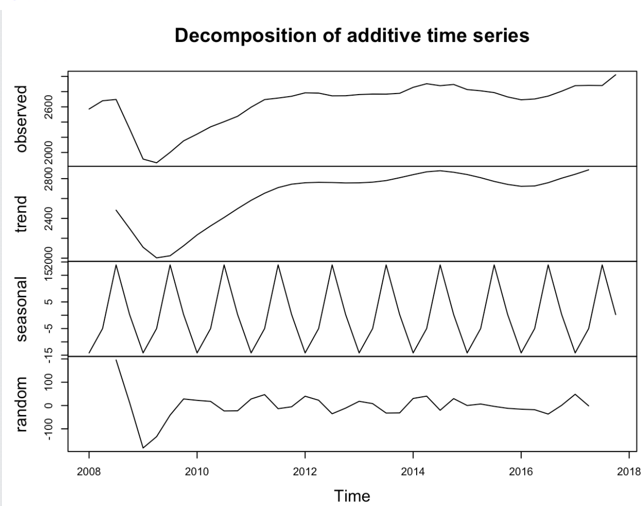


- Summarising the observations about the time series from the summary stats and box plot?
  The median of the time series is 2743. Range of first quartile is from 2300 to 2590. Second ranges from 2591 to 2750, third ranges from 2751 to 2800 while fourth ranges from 2801 to 2807. The data range is approximately 1158. Also, there are outliers in the box plot. The median is 2743 indicated by a thick line.

Decomposition

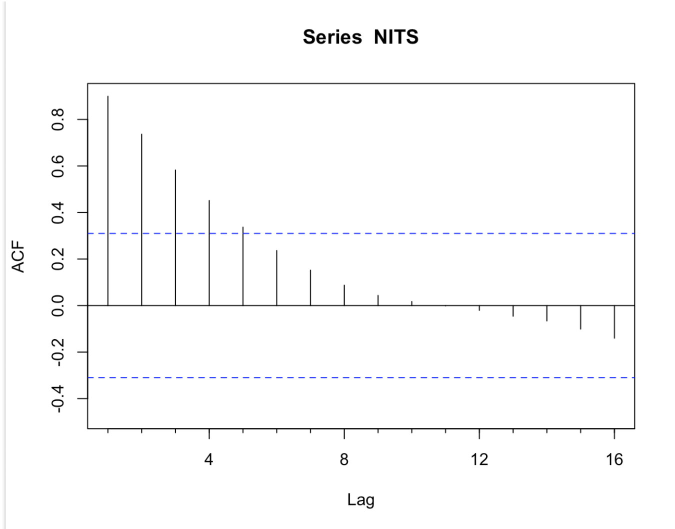
- Ploting the decomposition of the time series.

```
> decomp<-decompose(NITS)
> plot(decomp)
>
```



- Is the times series seasonal?

```
Acf(NITS)
```



The slowly decaying plot is indicative of trend. No, the time series is not seasonal.

- Is the decomposition additive or multiplicative?

```
> decomp$type
[1] "additive"
```

Additive. Adding the seasonal, random and trend component together we get the observed value. It is an Additive decomposition. Adding the values of the components(trend, seasonality and random, we can construct the original observed time series. This indicated that it is additive time series graph

- If seasonal, what are the values of the seasonal monthly indices?

Not applicable.

```
> decomp$seasonal
            Qtr1        Qtr2        Qtr3        Qtr4
2008 -14.1503472  -4.9961806  18.9038194   0.2427083
2009 -14.1503472  -4.9961806  18.9038194   0.2427083
2010 -14.1503472  -4.9961806  18.9038194   0.2427083
2011 -14.1503472  -4.9961806  18.9038194   0.2427083
2012 -14.1503472  -4.9961806  18.9038194   0.2427083
2013 -14.1503472  -4.9961806  18.9038194   0.2427083
2014 -14.1503472  -4.9961806  18.9038194   0.2427083
2015 -14.1503472  -4.9961806  18.9038194   0.2427083
2016 -14.1503472  -4.9961806  18.9038194   0.2427083
2017 -14.1503472  -4.9961806  18.9038194   0.2427083
```

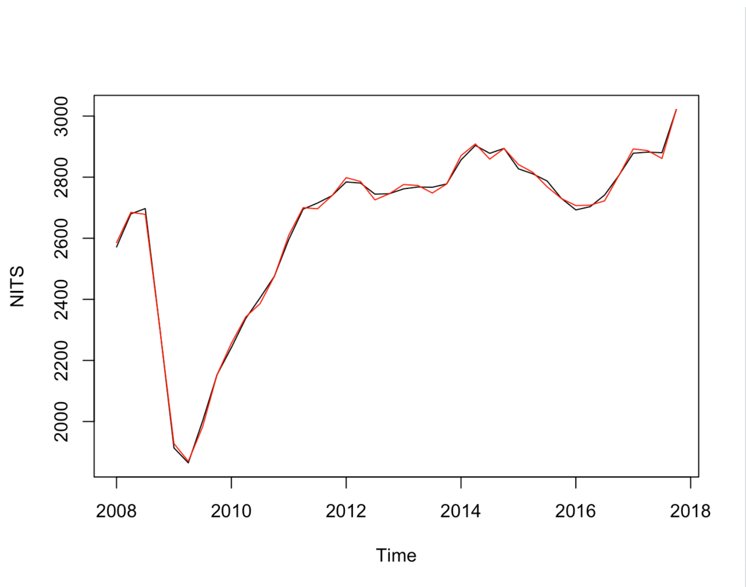
- For which month is the value of time series high and for which month is it low?

Value of time series is low for the Quarter 1 and high for Quarter 3.

- Reason behind the value being high in those months and low in those months. **Since there is no seasonality, it is ascertain to determine the increase and drop in values.**

- Showing the plot for time series adjusted for seasonality. Overlay this with the line for actual time series. Does seasonality have big fluctuations to the value of time series?

```
> tempSeasAdj <-seasadj(decomp)
> plot(NITS)
> lines(tempSeasAdj,col="red")
> |
```

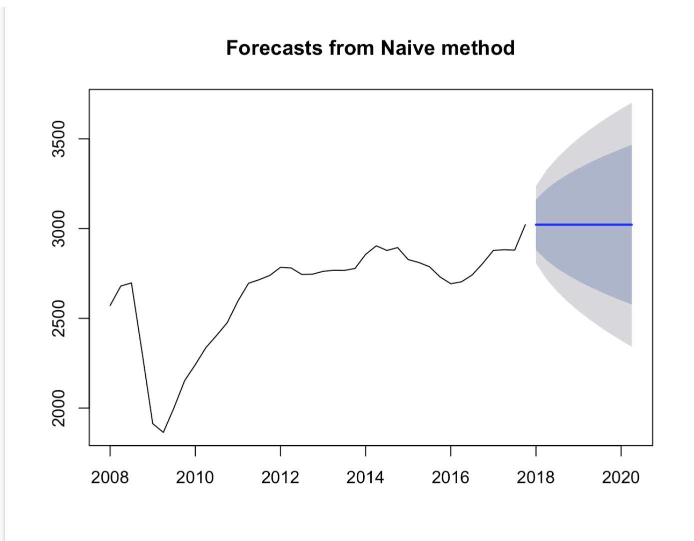


No, seasonality adjustment does not have any significant fluctuations to the value of original time series.

Naïve Method

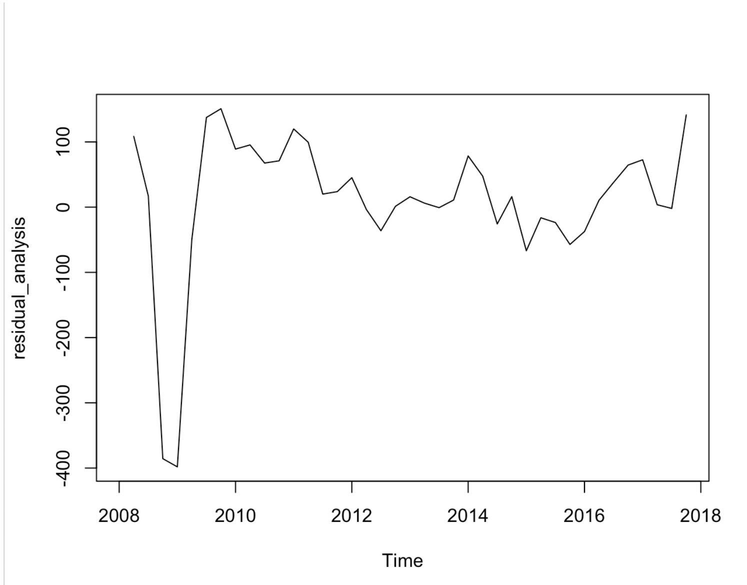
- Output

```
> naive_forecast1<-naive(NITS)
> plot(naive_forecast1)
```



- Performing Residual Analysis for this technique.
    - Plotting of residuals.

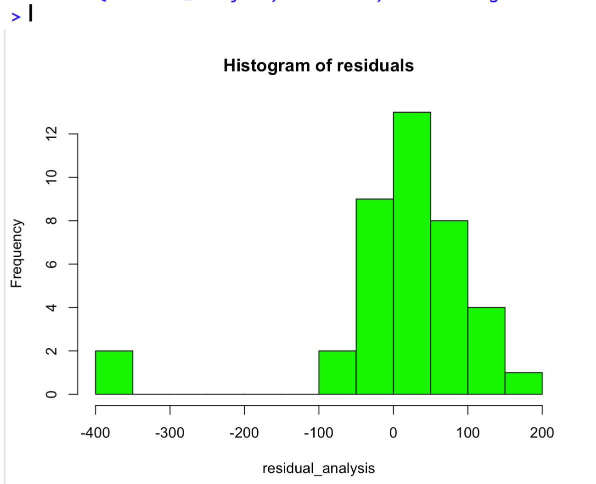
```
> residual_analysis<-residuals(naive_forecast1)
> plot(residual_analysis)
>
```



The time plot of the residuals shows that the variation of the residuals fluctuates significantly across the historical data and therefore the residual variance cannot be treated as constant.

- Histogram plot of residuals.

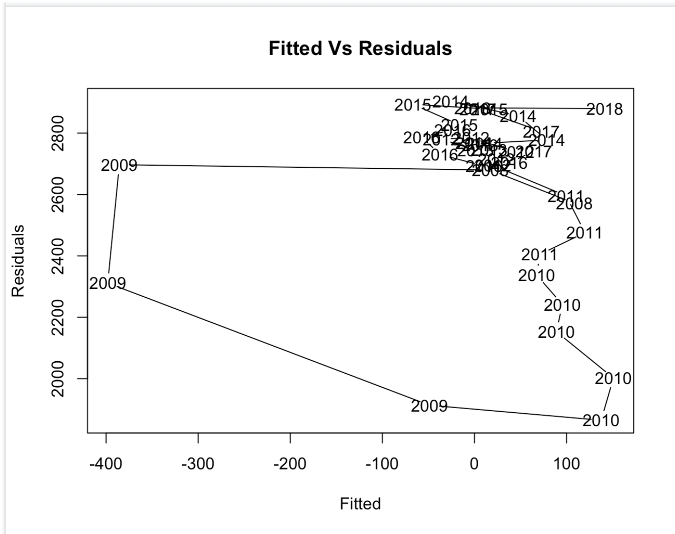
```
> h<-hist(residual_analysis, breaks=10,main="Histogram of residuals", col="green")
> |
```



The plot of histogram shows that it is skewed to the left. The fit of the distribution is not normal. We can see an outlier at -400.

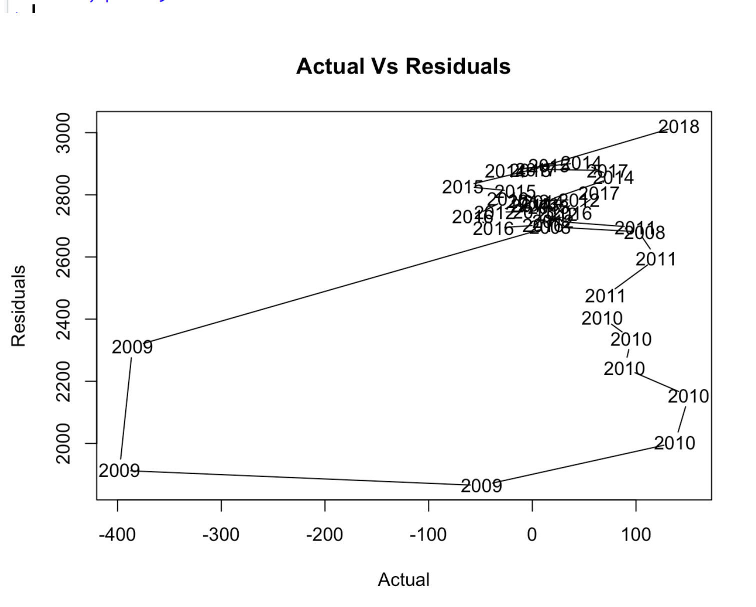
- Plot of fitted values vs. residuals.

```
> plot(naive_forecast1$fitted ~ naive_forecast1$residuals, main="Fitted Vs Residuals", xlab="Fitted", yla
b="Residuals")
```



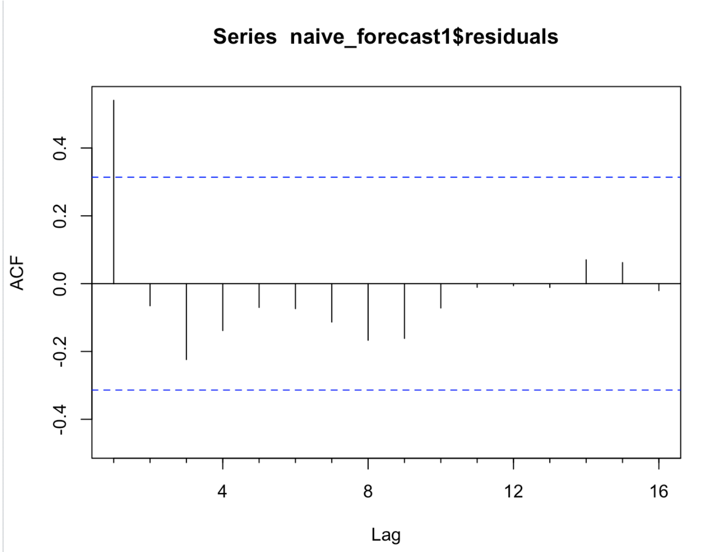
- Plot of actual values vs. residuals.

```
> plot(naive_forecast1$x ~ naive_forecast1$residuals, main="Actual Vs Residuals", xlab="Actual", ylab="Re
siduals", pch=19)
```



- An ACF plot of the residuals.

```
> Acf(naive_forecast1$residuals)
>
```



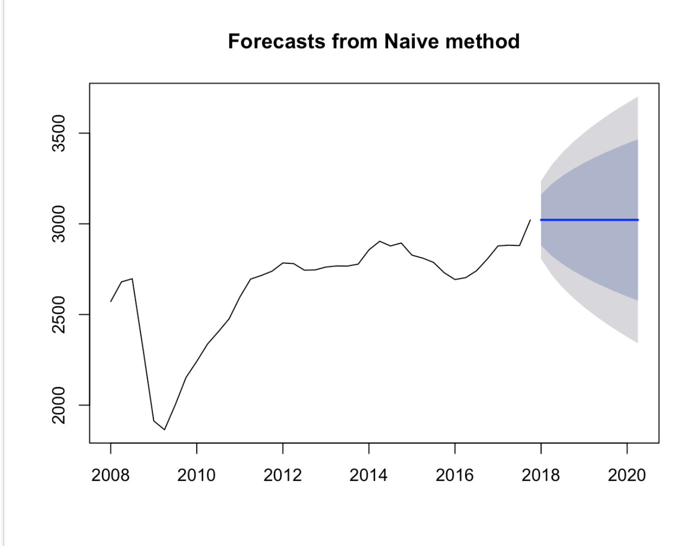
- Printing the 5 measures of accuracy for this forecasting technique

```
> accuracy(naive_forecast1)
                   ME     RMSE      MAE       MPE     MAPE      MASE      ACF1
Training set 11.54359 109.7054 68.08205 0.2970542 2.852688 0.3286562 0.5405785
> |
```

- Forecast
  - Time series value for next year. Showing table and plot

```
> naive_forecast1
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q1         3021.6 2881.006 3162.194 2806.580 3236.620
2018 Q2         3021.6 2822.770 3220.430 2717.516 3325.684
2018 Q3         3021.6 2778.084 3265.116 2649.174 3394.026
2018 Q4         3021.6 2740.412 3302.788 2591.560 3451.640
2019 Q1         3021.6 2707.222 3335.978 2540.800 3502.400
2019 Q2         3021.6 2677.216 3365.984 2494.910 3548.290
2019 Q3         3021.6 2649.623 3393.577 2452.710 3590.490
2019 Q4         3021.6 2623.940 3419.260 2413.431 3629.769
2020 Q1         3021.6 2599.818 3443.382 2376.540 3666.660
2020 Q2         3021.6 2577.002 3466.198 2341.647 3701.553
>
```

```
> plot(naive_forecast1)
>
```



- Summarising this forecasting technique

```
> summary(naive_forecast1)

Forecast method: Naive method

Model Information:
Call: naive(y = NITS)

Residual sd: 109.7062

Error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE      ACF1
Training set 11.54359 109.7054 68.08205 0.2970542 2.852688 0.3286562 0.5405785

Forecasts:
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q1         3021.6 2881.006 3162.194 2806.580 3236.620
2018 Q2         3021.6 2822.770 3220.430 2717.516 3325.684
2018 Q3         3021.6 2778.084 3265.116 2649.174 3394.026
2018 Q4         3021.6 2740.412 3302.788 2591.560 3451.640
2019 Q1         3021.6 2707.222 3335.978 2540.800 3502.400
2019 Q2         3021.6 2677.216 3365.984 2494.910 3548.290
2019 Q3         3021.6 2649.623 3393.577 2452.710 3590.490
2019 Q4         3021.6 2623.940 3419.260 2413.431 3629.769
2020 Q1         3021.6 2599.818 3443.382 2376.540 3666.660
2020 Q2         3021.6 2577.002 3466.198 2341.647 3701.553
```

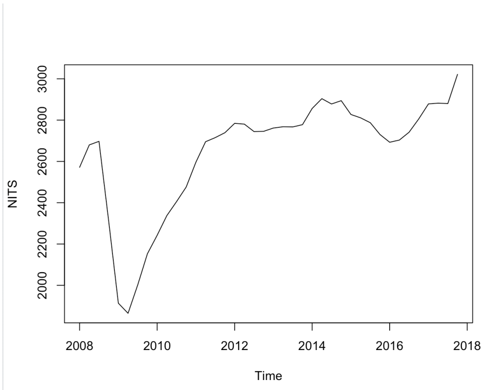
  - How good is the accuracy?
    The accuracy is not good as MAPE has a higher value.

  - What does it predict the value of time series will be in one year?
    The predicted value will be in the range of 2410 to 3629.

Simple Moving Averages

- Ploting the graph for time series.

```
> plot(NITS)
```

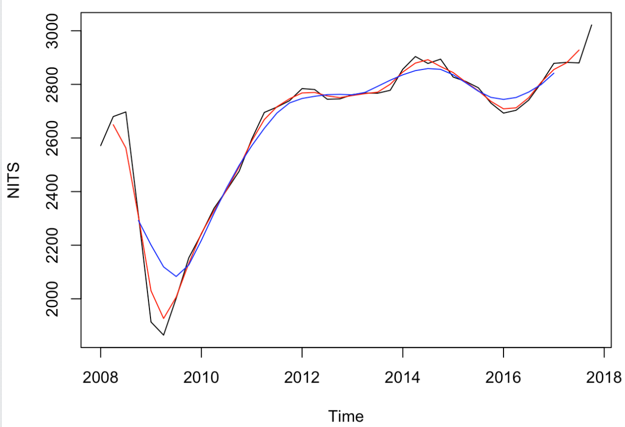


- Showing the Simple Moving average of order 3 on the plot above in Red

```
> MA3_forecast <- ma(NITS,order=3)
> lines(MA3_forecast,col="Red")
>
```

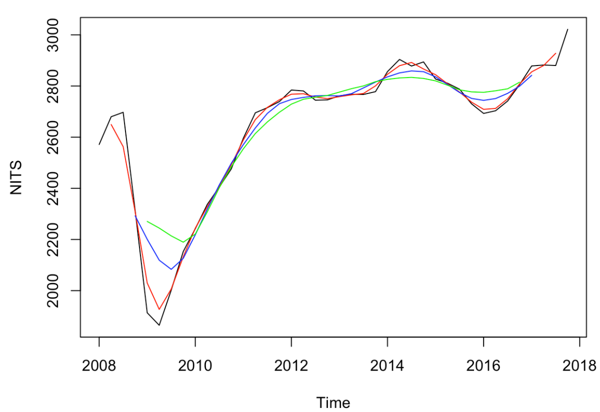
- Showing the Simple Moving average of order 6 on the plot above in Blue

```
> MA6_forecast <- ma(NITS,order=6)
> lines(MA6_forecast,col="Blue")
```



- Showing the Simple Moving average of order 9 on the plot above in Green

```
> MA9_forecast <- ma(NITS,order=9)
> lines(MA9_forecast,col="Green")
```



- Showing the forecast of next 12 months using one of the simple average order that you feel works best for time series

```
> MA9_forecast
         Qtr1     Qtr2     Qtr3     Qtr4
2008       NA       NA       NA       NA
2009 2270.533 2244.522 2213.967 2189.378
2010 2220.956 2307.833 2402.367 2484.267
2011 2554.422 2614.289 2659.533 2697.411
2012 2729.167 2748.278 2756.244 2763.200
2013 2776.233 2789.522 2800.344 2816.978
2014 2826.033 2831.511 2833.689 2829.600
2015 2820.144 2803.144 2785.078 2777.044
2016 2775.289 2781.378 2789.056 2815.078
2017       NA       NA       NA       NA
>
```

- What are your observations of the plot as the moving average order goes up?
  With the increase in order, there is a smoothness , so as we go towards a higher value the curve will be much smooth.

Smoothing

- Performing a smoothing forecast for next 12 months for the time series.

```
> simple_smoothing <- forecast(NITS,h=12)
> summary(simple_smoothing)

Forecast method: ETS(A,Ad,N)

Model Information:
ETS(A,Ad,N)

Call:
 ets(y = object, lambda = lambda, biasadj = biasadj, allow.multiplicative.trend =
    allow.multiplicative.trend)

  Smoothing parameters:
    alpha = 0.9999
    beta  = 0.9925
    phi   = 0.8

  Initial states:
    l = 2576.5503
    b = 7.0378

  sigma:  100.5086

     AIC     AICc      BIC
523.0334 525.5788 533.1666

Error measures:
                   ME     RMSE     MAE       MPE     MAPE      MASE      ACF1
Training set 4.922542 94.01716 56.0852 0.2528908 2.328826 0.2707432 0.2203102

Forecasts:
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
```

2018 Q1	3133.926	3005.119	3262.733	2936.933	3330.919
2018 Q2	3223.799	2959.257	3488.341	2819.216	3628.382
2018 Q3	3295.698	2885.967	3705.429	2669.069	3922.327
2018 Q4	3353.218	2795.526	3910.910	2500.302	4206.134
2019 Q1	3399.234	2694.588	4103.881	2321.571	4476.898
2019 Q2	3436.048	2587.594	4284.501	2138.450	4733.646
2019 Q3	3465.499	2477.561	4453.437	1954.578	4976.420
2019 Q4	3489.060	2366.551	4611.569	1772.330	5205.790
2020 Q1	3507.909	2255.968	4759.849	1593.231	5422.587
2020 Q2	3522.988	2146.761	4899.216	1418.230	5627.747
2020 Q3	3535.052	2039.548	5030.555	1247.877	5822.227
2020 Q4	3544.703	1934.723	5154.683	1082.451	6006.954

- What is the value of alpha? What does that value signify?

As seen from above, the value of alpha is 0.99 ,This value is very close to 1 which indicates that the most recent values have more weight.

- What is the value of initial state?

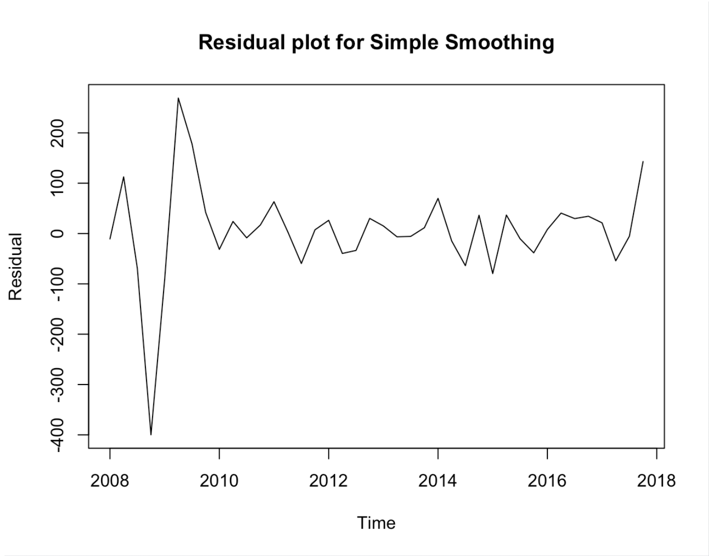
  Initial states:
  l = 2576.5503
  b = 7.0378

- What is the value of sigma? What does the sigma signify?

  sigma: 100.5086

- Perform Residual Analysis for this technique.
  - Do a plot of residuals. What does the plot indicate?

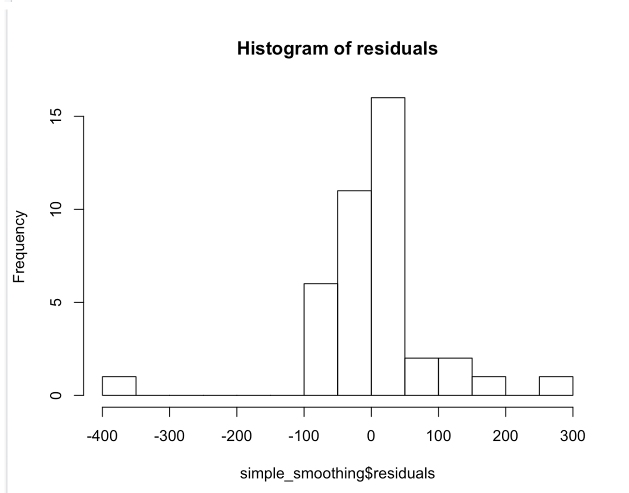
```
> plot(simple_smoothing$residuals,main="Residual plot for Simple Smoothing",ylab="Residual")
```



The above shown is residual plot which is same like the time series graph. The graph is smooth time series. Residual component has a high influence in time series

- Histogram plot of residuals.

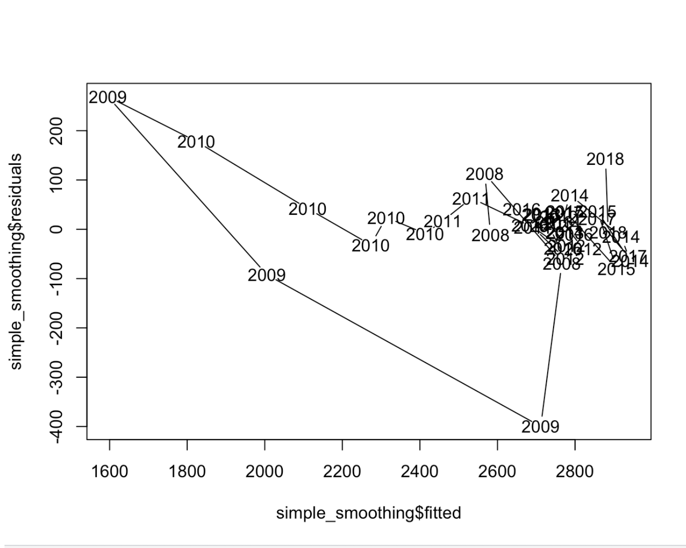
```
> hist(simple_smoothing$residuals,nclass = "FD",main="Histogram of residuals")
>
```



The histogram plot is not normally distributed and does not resemble any particular pattern.

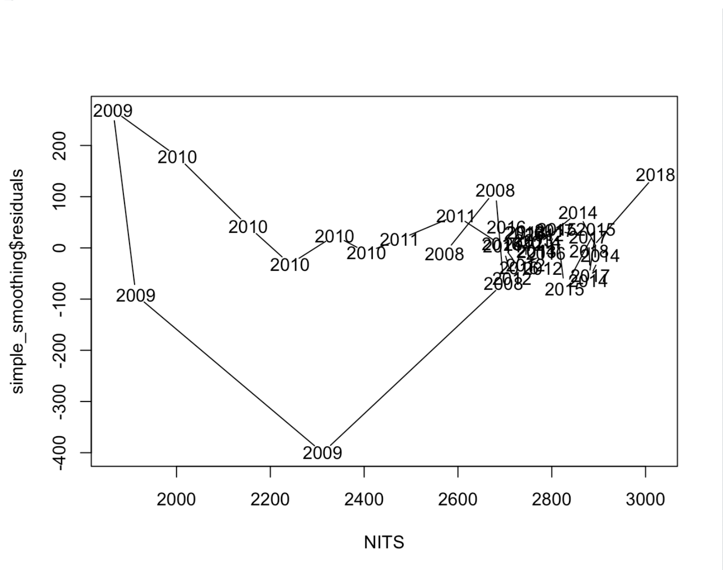
- Plot of fitted values vs. residuals.

```
> plot(simple_smoothing$fitted, simple_smoothing$residuals)
```



- Plot of actual values vs. residuals.

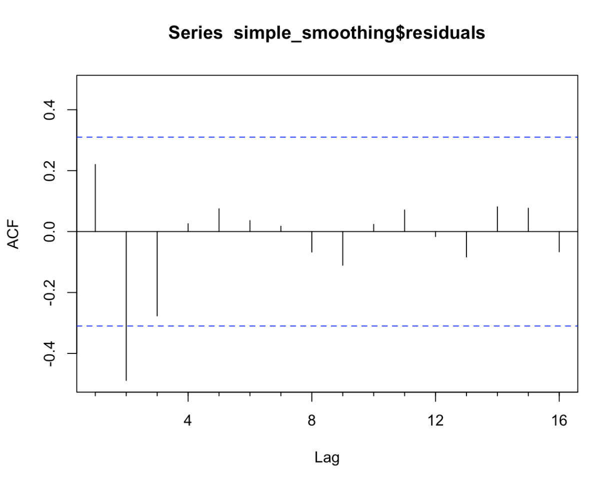
```
> plot(NITS,simple_smoothing$residuals)
> 
```



There is no significant relation.

- An ACF plot of the residuals.

```
> Acf(simple_smoothing$residuals)
>
```

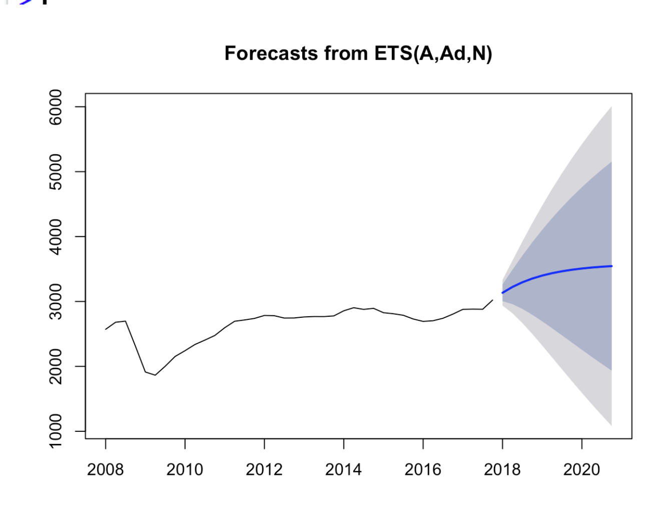


- Printing the 5 measures of accuracy for this forecasting technique

```
> accuracy(simple_smoothing)
                   ME     RMSE     MAE       MPE     MAPE      MASE      ACF1
Training set 4.922542 94.01716 56.0852 0.2528908 2.328826 0.2707432 0.2203102
>
```

- Forecast
  - Time series value for next year. Show table and plot

```
> f2<-forecast(simple_smoothing)
> plot(f2)
>
```



```
> f2
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q1       3133.926 3005.119 3262.733 2936.933 3330.919
2018 Q2       3223.799 2959.257 3488.341 2819.216 3628.382
2018 Q3       3295.698 2885.967 3705.429 2669.069 3922.327
2018 Q4       3353.218 2795.526 3910.910 2500.302 4206.134
2019 Q1       3399.234 2694.588 4103.881 2321.571 4476.898
2019 Q2       3436.048 2587.594 4284.501 2138.450 4733.646
2019 Q3       3465.499 2477.561 4453.437 1954.578 4976.420
2019 Q4       3489.060 2366.551 4611.569 1772.330 5205.790
2020 Q1       3507.909 2255.968 4759.849 1593.231 5422.587
2020 Q2       3522.988 2146.761 4899.216 1418.230 5627.747
2020 Q3       3535.052 2039.548 5030.555 1247.877 5822.227
2020 Q4       3544.703 1934.723 5154.683 1082.451 6006.954
```

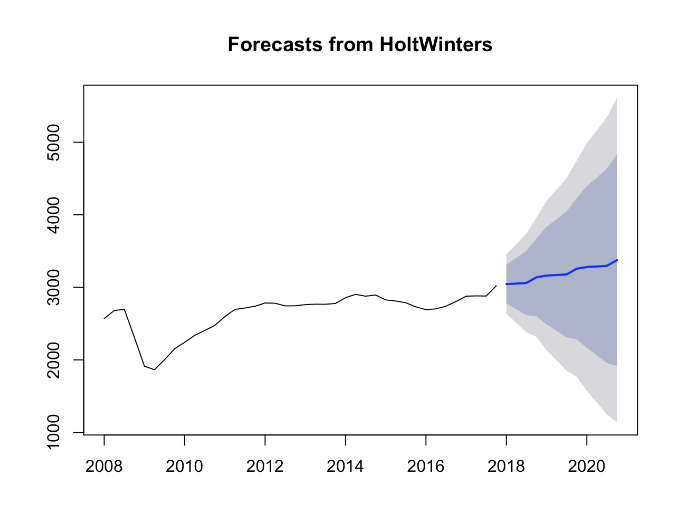
- Summarising this forecasting technique
    - How good is the accuracy?
      The accuracy is not good because of high residual component.

    - What does it predict the value of time series will be in one year?
      It will range from 1772 to 5205 in 2019.

Holt-Winters

- Performing Holt-Winters forecast for next 12 months for the time series.

```
> holt_Winters <- HoltWinters(NITS)
> forecast_HW <- forecast(holt_Winters,h=12)
> plot(forecast_HW)
>
```



> summary(forecast_HW)

Forecast method: HoltWinters

Model Information:
Holt-Winters exponential smoothing with trend and additive seasonal component.

Call:
HoltWinters(x = NITS)

Smoothing parameters:
 alpha: 0.7428379
 beta : 0.1730485
 gamma: 1

Coefficients:

	[,1]
a	2904.32028
b	29.47630
s1	110.70636
s2	88.73853

s3   67.93749
s4 117.27972

Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	41.5499	210.1229	145.5452	1.67805	5.850816	0.7025981	0.3363672

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2018 Q1	3044.503	2776.792	3312.213	2635.075	3453.931
2018 Q2	3052.011	2696.923	3407.100	2508.950	3595.073
2018 Q3	3060.687	2615.999	3505.374	2380.596	3740.778
2018 Q4	3139.505	2601.904	3677.106	2317.315	3961.695
2019 Q1	3162.408	2489.107	3835.710	2132.682	4192.134
2019 Q2	3169.917	2401.200	3938.633	1994.266	4345.568
2019 Q3	3178.592	2309.552	4047.632	1849.510	4507.674
2019 Q4	3257.410	2283.440	4231.381	1767.851	4746.970
2020 Q1	3280.313	2165.196	4395.431	1574.888	4985.738
2020 Q2	3287.822	2062.201	4513.443	1413.397	5162.247
2020 Q3	3296.497	1955.977	4637.017	1246.348	5346.646
2020 Q4	3375.316	1915.727	4834.904	1143.067	5607.564

- ○ What is the value of alpha? What does that value signify?
  alpha: 0.7428379. This value is very close to 1 which indicates that the most recent values have more weight.

- ○ What is the value of beta? What does that value signify?
  beta : 0. If the beta value =1 indicates that latest values have more weight.

- ○ What is the value of gamma? What does that value signify?
  gamma: 0.6033215

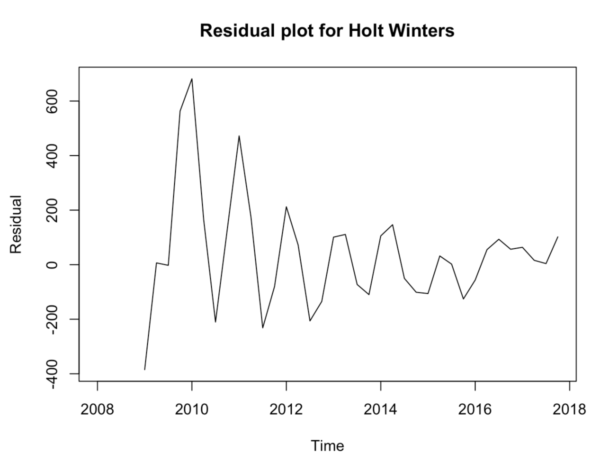
- ○ What is the value of initial states for the level, trend and seasonality? What do these values signify?
  The Beta and Gamma parameters are used for Holts exponential smoothing. Holts Winters exponential smoothing estimates the level, slope and seasonal component at the current point. Smoothing is controlled by 3 parameters: Alpha, beta and Gamma (they have the values between 0 to 1). The Gamma value close to or 1 indicates that the estimate of the seasonal component at the current time point is just based upon very recent observations

- ○ What is the value of sigma? What does the sigma signify?
  The sigma value is 107.6352. It is the standard deviation.

- Performing Residual Analysis for this technique.

  - ○ Plot of residuals.

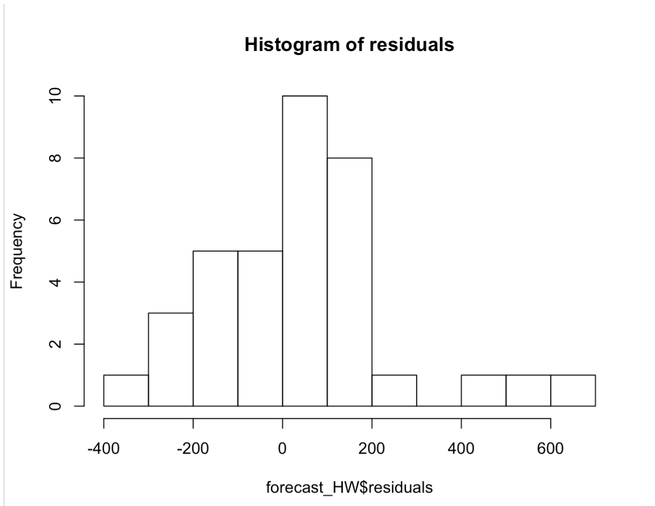
```
> plot(forecast_HW$residuals,main="Residual plot for Holt Winters",ylab="Residual")
```



The above shown is residual plot and it is different from the original time series.

- Histogram plot of residuals.

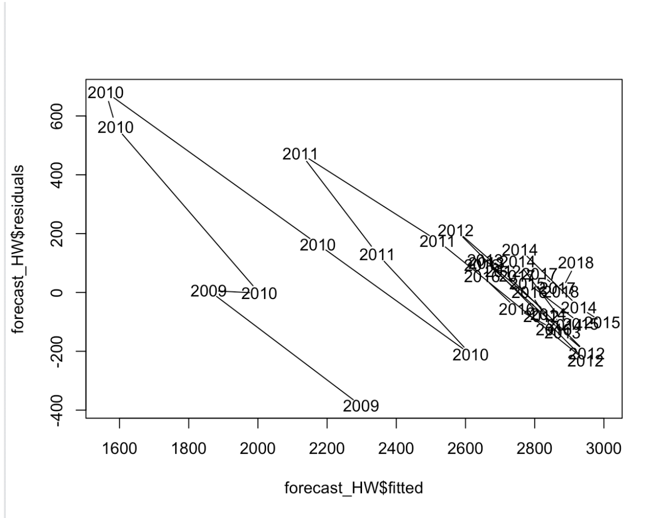
```
> hist(forecast_HW$residuals,nclass = "FD",main="Histogram of residuals")
```



The above is the histogram plot. There is no patterns that is observed. The centre has the high values frequency.

- Plot of fitted values vs. residuals.

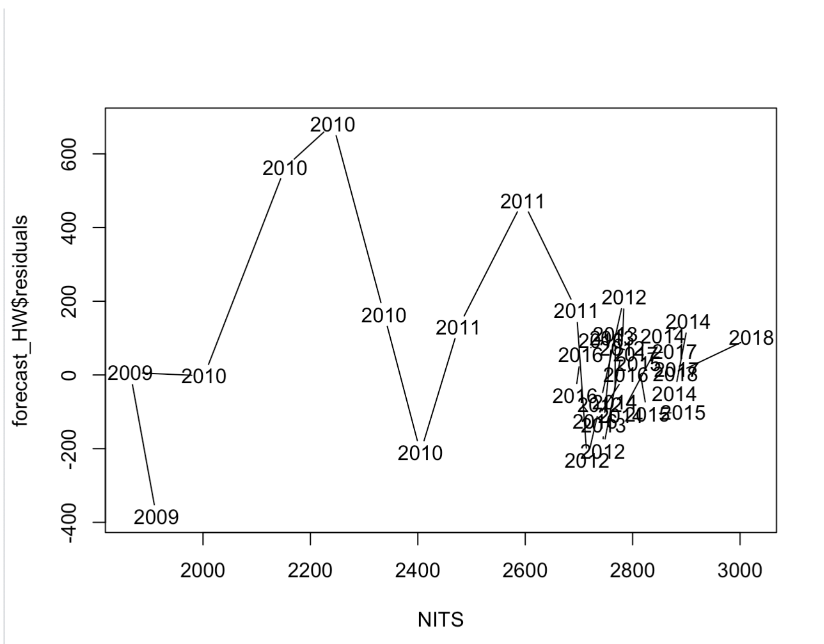
```
> plot(forecast_HW$fitted,forecast_HW$residuals)
```



There is no patterns observed and the residues are dispersed. At some places there are cluster of residues.

- Plot of actual values vs. residuals.

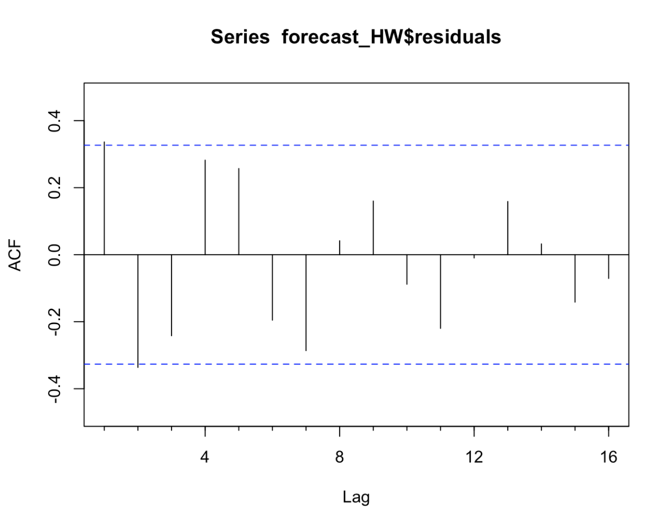
```
> plot(NITS,forecast_HW$residuals)
>
```



There is no patterns observed and the residues are dispersed. At some places there are cluster of residues.

- An ACF plot of the residuals.

```
> Acf(forecast_HW$residuals)
>
```



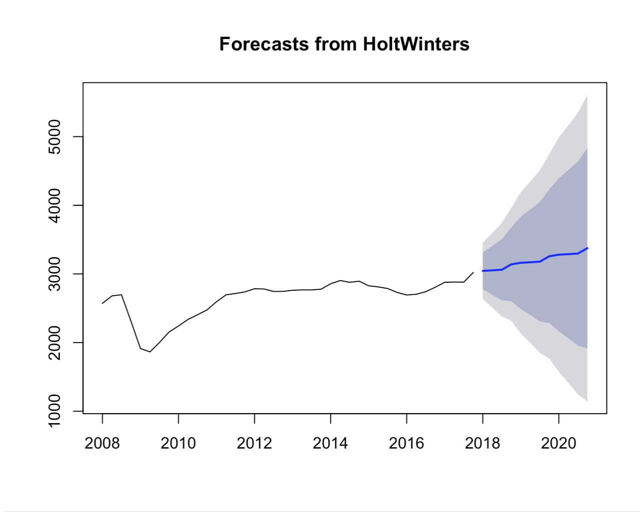
The fading graph is indicative of trend.

- Printing the 5 measures of accuracy for this forecasting technique

```
> accuracy(forecast_HW)
                  ME     RMSE      MAE     MPE     MAPE      MASE      ACF1
Training set 41.5499 210.1229 145.5452 1.67805 5.850816 0.7025981 0.3363672
>
```

- Forecast
  - Time series value for next year. Showing table and plot

```
> plot(forecast_HW)
>
```



- Summarising this forecasting technique
  - How good is the accuracy?
    The accuracy is very good because of low residual component.
  - What does it predict the value of time series will be in one year?

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2018 Q1	3044.503	2776.792	3312.213	2635.075	3453.931
2018 Q2	3052.011	2696.923	3407.100	2508.950	3595.073
2018 Q3	3060.687	2615.999	3505.374	2380.596	3740.778
2018 Q4	3139.505	2601.904	3677.106	2317.315	3961.695
2019 Q1	3162.408	2489.107	3835.710	2132.682	4192.134
2019 Q2	3169.917	2401.200	3938.633	1994.266	4345.568
2019 Q3	3178.592	2309.552	4047.632	1849.510	4507.674
2019 Q4	3257.410	2283.440	4231.381	1767.851	4746.970
2020 Q1	3280.313	2165.196	4395.431	1574.888	4985.738
2020 Q2	3287.822	2062.201	4513.443	1413.397	5162.247
2020 Q3	3296.497	1955.977	4637.017	1246.348	5346.646
2020 Q4	3375.316	1915.727	4834.904	1143.067	5607.564

ARIMA or Box-Jenkins

- Finding out whether the Time Series data stationary?
- No, the Time series data is not stationary.

  There are test to tell if series is stationary. ADF test says differences is required if p-value is > 0.05. Kipps test says differences is required if p-value is < 0.05.

```
> adf.test(NITS)

        Augmented Dickey-Fuller Test

data:  NITS
Dickey-Fuller = -2.907, Lag order = 3, p-value = 0.2175
alternative hypothesis: stationary

> kpss.test(NITS)

        KPSS Test for Level Stationarity

data:  NITS
KPSS Level = 1.1832, Truncation lag parameter = 1, p-value = 0.01
```

- How many differences are needed to make it stationary?

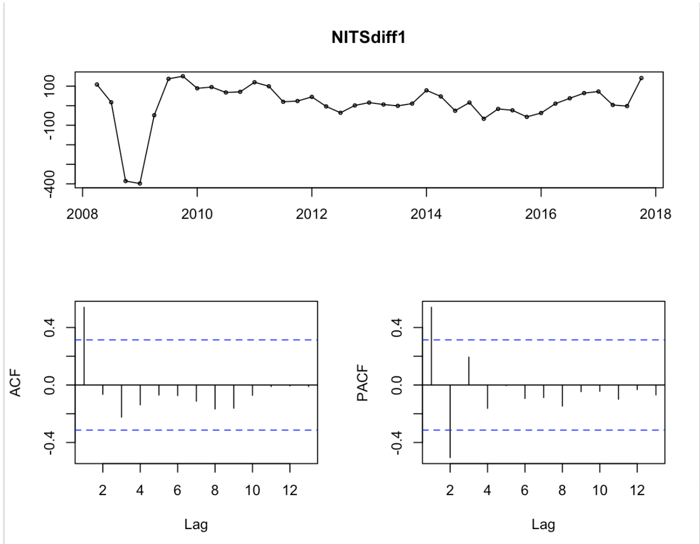
```
> ndiffs(NITS)
[1] 1
```

- Is Seasonality component needed?

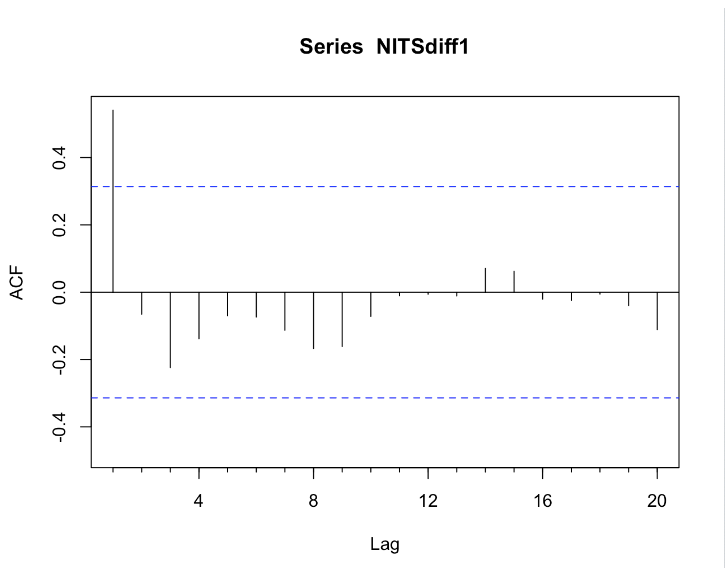
  No.

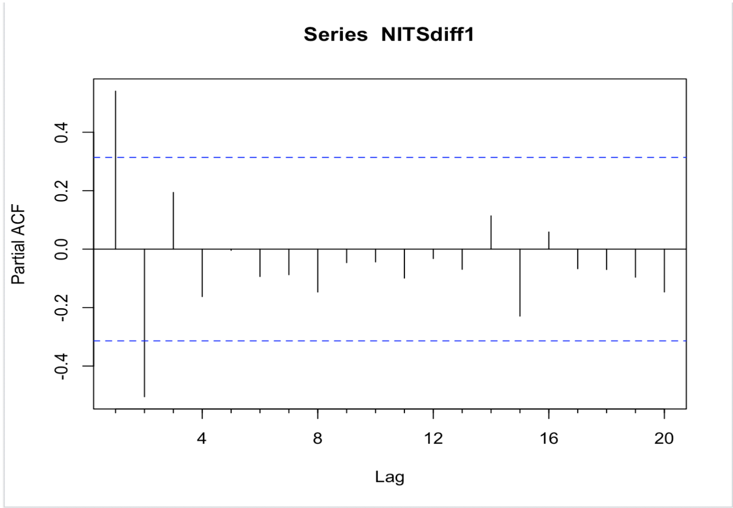
- Ploting the Time Series chart of the differenced series.

```
> tsdisplay(NITSdiff1)
>
```



- Ploting the ACF and PACF plot of the differenced series.





- Based on the ACF and PACF, which are the possible ARIMA model possible?
  ARMA(2,1)

- Showing the AIC, BIC and Sigma^2 for the possible models?

```
> auto_fit <- auto.arima(NITS)
> auto_fit
Series: NITS
ARIMA(2,1,1)

Coefficients:
         ar1      ar2     ma1
      0.5013  -0.3525  0.6409
s.e.  0.1958   0.1824  0.1657

sigma^2 estimated as 5322:  log likelihood=-221.93
AIC=451.87   AICc=453.04   BIC=458.52
```

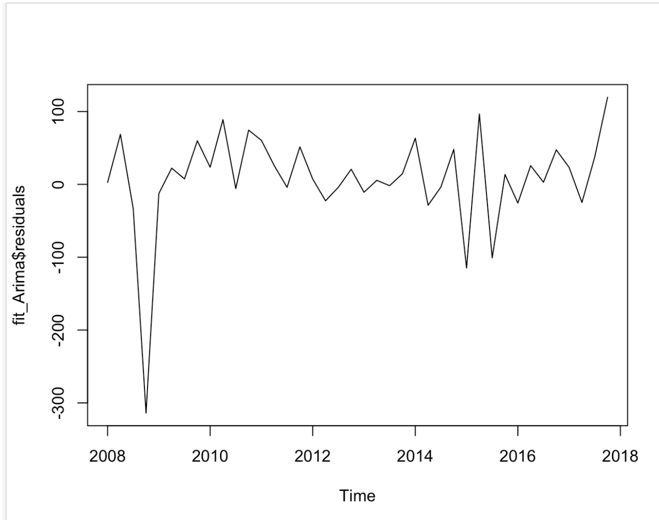
- Based on the above AIC, BIC and Sigma^2 values, which model will you select?
  ARIMA(2,1,1)

- What is the final formula for ARIMA with the coefficients?
  ARIMA(2,1,1) So, p=2 , d=1, q=2

- Performing Residual Analysis for this technique.

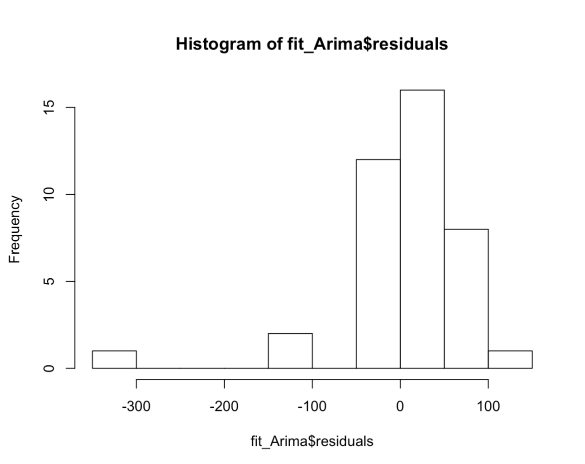
  - Plot of residuals.

```
> plot(fit_Arima$residuals)
>
```



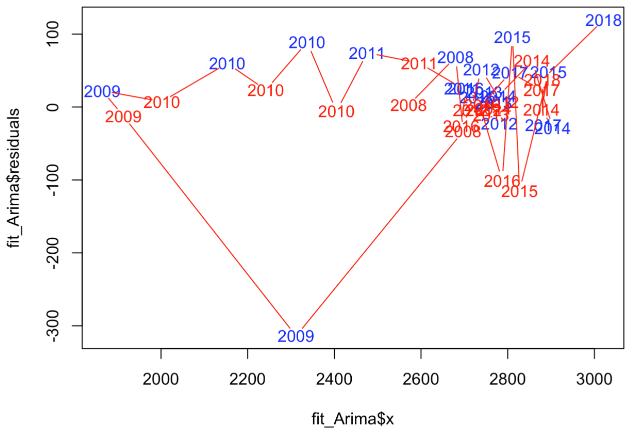
- Histogram plot of residuals.

```
> hist(fit_Arima$residuals)
>
```



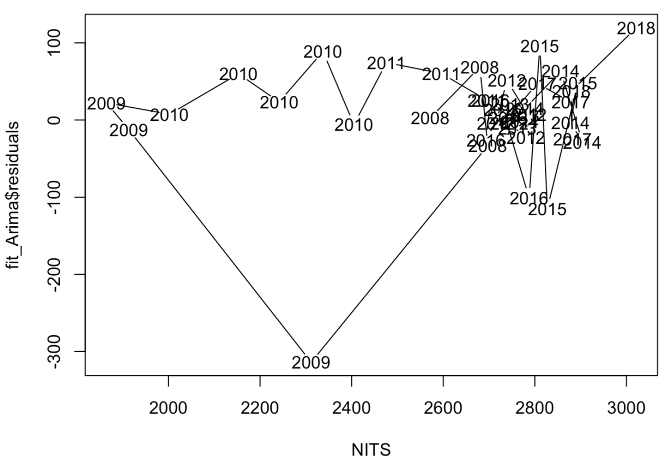
- Plot of fitted values vs. residuals.

```
> plot(fit_Arima$x,fit_Arima$residuals, col=c("red","blue"))
```



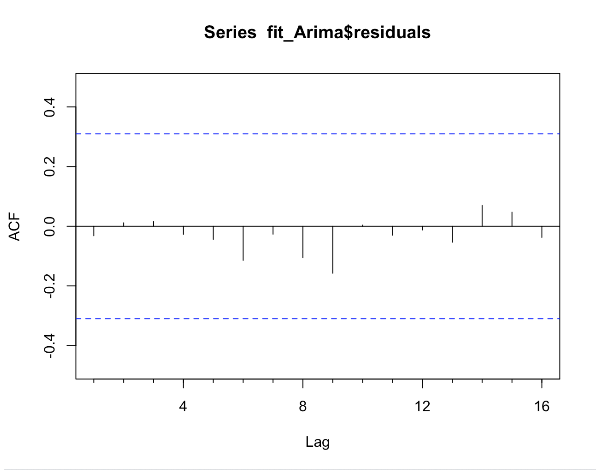
- Plot of actual values vs. residuals.

```
> plot(NITS,fit_Arima$residuals)
>
```



- An ACF plot of the residuals.

```
> Acf(fit_Arima$residuals)
>
```



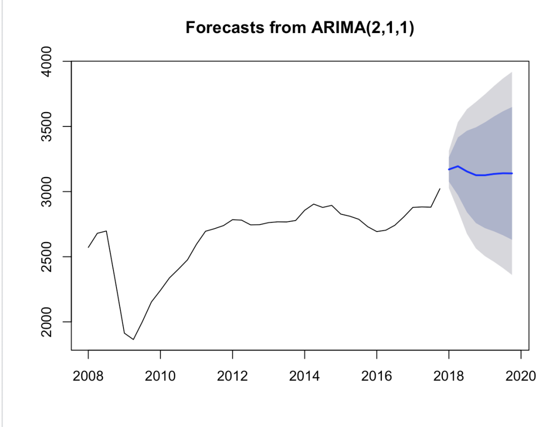
- Printing the 5 measures of accuracy for this forecasting technique.

```
> accuracy(fit_Arima)
                   ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 7.607852 69.20748 42.97381 0.263098 1.657254 0.2074498 -0.03197029
```

- Forecast
  - Next one year. Showing table and plot

```
> forecast(fit_Arima)
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q1       3169.929 3076.438 3263.419 3026.947 3312.910
2018 Q2       3194.406 2973.382 3415.430 2856.379 3532.433
2018 Q3       3154.390 2841.935 3466.844 2676.532 3632.247
2018 Q4       3125.701 2758.169 3493.233 2563.609 3687.793
2019 Q1       3125.426 2719.395 3531.456 2504.455 3746.396
2019 Q2       3135.400 2694.557 3576.243 2461.189 3809.612
2019 Q3       3140.498 2664.831 3616.165 2413.028 3867.968
2019 Q4       3139.537 2630.082 3648.992 2360.393 3918.681
```

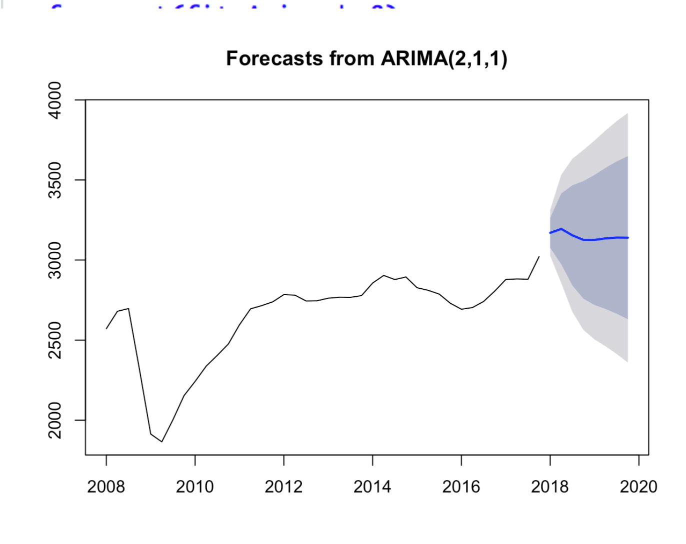
```
> plot(forecast(fit_Arima))
>
```



- Next two years. Showing table and plot

```
> forecast(fit_Arima,h=8)
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q1       3169.929 3076.438 3263.419 3026.947 3312.910
2018 Q2       3194.406 2973.382 3415.430 2856.379 3532.433
2018 Q3       3154.390 2841.935 3466.844 2676.532 3632.247
2018 Q4       3125.701 2758.169 3493.233 2563.609 3687.793
2019 Q1       3125.426 2719.395 3531.456 2504.455 3746.396
2019 Q2       3135.400 2694.557 3576.243 2461.189 3809.612
2019 Q3       3140.498 2664.831 3616.165 2413.028 3867.968
2019 Q4       3139.537 2630.082 3648.992 2360.393 3918.681
```

```
> plot(forecast(fit_Arima,h=8))
```



- Summarising this forecasting technique
    - How good is the accuracy?
      Accuracy is good as MASE is low.

    - What does it predict time series will be in one year and next two years?
      In the next one year, the lowest will be 2360 and highest will be 3918. In the next two years, lowest is 2034 and highest is 4329.

Accuracy Summary

- Showing a table of all the forecast method above with their accuracy measures.

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
NAÏVE	11.543	109.705	68.082	0.297	2.852	0.328	0.54
SIMPLE SMOOTHING	4.922	94.017	56.082	0.252	2.328	0.27	0.22
HOLT WINTERS	41.549	210.122	145.545	1.678	5.85	0.702	0.336
ARIMA	7.607	69.207	42.973	0.263	1.657	0.207	-0.0319

- Separately defining each forecast method and why it is useful. Showing the best and worst forecast method for each of the accuracy measures.

  The **naïve method** is a good method but it does not cover the seasonal components and just concentrates on present and predicted values.

  Simple Exponential Smoothing – This model smooths the data using the exponential window function and is used to assign exponentially decreasing weights over time. More useful when recent observations need to be given more weightage than past observations.

  Holt Winter is a good method of forecasting as it covers all the components.

  Moving average depends on the order, with the increase in order the curve is smooth but for lower orders it is not recommendable.

  ARIMA a powerful tool for accurate short-range forecast.
  Models are quite flexible and can represent a wide range of characteristics of time series occurring in practices but a large amount of data is required. In our case, it works well given the huge range of data. Model has to be periodically completely refitted or new model developed.

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
BEST	SIMPLE SMOOTHING	ARIMA	ARIMA	SIMPLE SMOOTHING	ARIMA	ARIMA	SIMPLE SMOOTHING
WORST	HOLT WINTERS	HOLT WINTERS	HOLT WINTERS	HOLT WINTERS	HOLT WINTERS	HOLT WINTERS	NAÏVE

Conclusion

- Summarising the analysis of time series value over the time-period.
  The time series does not show any seasonality however there is an evident trend. There is a steep decline in the year 2009 post which, we observe a positive trend in general. The time series is divided quarterly hence evaluated for four different parts of year.

- Based on the analysis and forecast above, do you think the value of the time series will increase, decrease or stay flat over the next year? How about next 2 years?
  Based on the analysis and forecast above, the value of the time series tend to stay almost constant throughout 2018 however it increases in the last quarter. In 2019, we observe that, there is an increasing trend in general throughout all the quarters.

- Rank forecasting methods that best forecast for this time series based on historical values.
  1. **ARIMA**
  2. **Simple Smoothing**
  3. **Naïve**
  4. **Holt Winters**
  5. **Moving Average**