

# Business Forecasting

Final Exam: Crime Data

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|--|-----------|
| <b>Business Forecasting Final Exam</b> | <b>3</b>  |
| <i>Introduction</i>                    | <i>3</i>  |
| <i>Import Data</i>                     | <i>3</i>  |
| <i>Plot and Inference</i>              | <i>4</i>  |
| <i>Central Tendency</i>                | <i>4</i>  |
| <i>Decomposition</i>                   | <i>5</i>  |
| <i>Naïve Method</i>                    | <i>7</i>  |
| <i>Simple Moving Averages</i>          | <i>12</i> |
| <i>Smoothing</i>                       | <i>15</i> |
| <i>Holt-Winters</i>                    | <i>22</i> |
| <i>ARIMA or Box-Jenkins</i>            | <i>28</i> |
| <i>Accuracy Summary</i>                | <i>35</i> |
| <i>Conclusion</i>                      | <i>36</i> |
| <i>Final Question</i>                  | <i>37</i> |

## Business Forecasting Final Exam

### Introduction

Crime in US has been steadily decreasing over the years. In the US, FBI tracks crime data. Data is tracked by type of crime. For this exercise, we will focus on robberies, theft, and larceny. See <https://www.fbi.gov/services/cjis/ucr> for more detail.

### Import Data

Note: For convenience and ease of analysis, I have merged the month and the year columns as date column in the CSV.

|    | A         | B    | C      | D    |
|----|-----------|------|--------|------|
| 1  | Month     | Year | Date   | Data |
| 2  | January   | 2008 | Jan-08 | 1392 |
| 3  | February  | 2008 | Feb-08 | 1031 |
| 4  | March     | 2008 | Mar-08 | 1301 |
| 5  | April     | 2008 | Apr-08 | 1420 |
| 6  | May       | 2008 | May-08 | 1574 |
| 7  | June      | 2008 | Jun-08 | 1587 |
| 8  | July      | 2008 | Jul-08 | 1731 |
| 9  | August    | 2008 | Aug-08 | 1743 |
| 10 | September | 2008 | Sep-08 | 1473 |
| 11 | October   | 2008 | Oct-08 | 1422 |

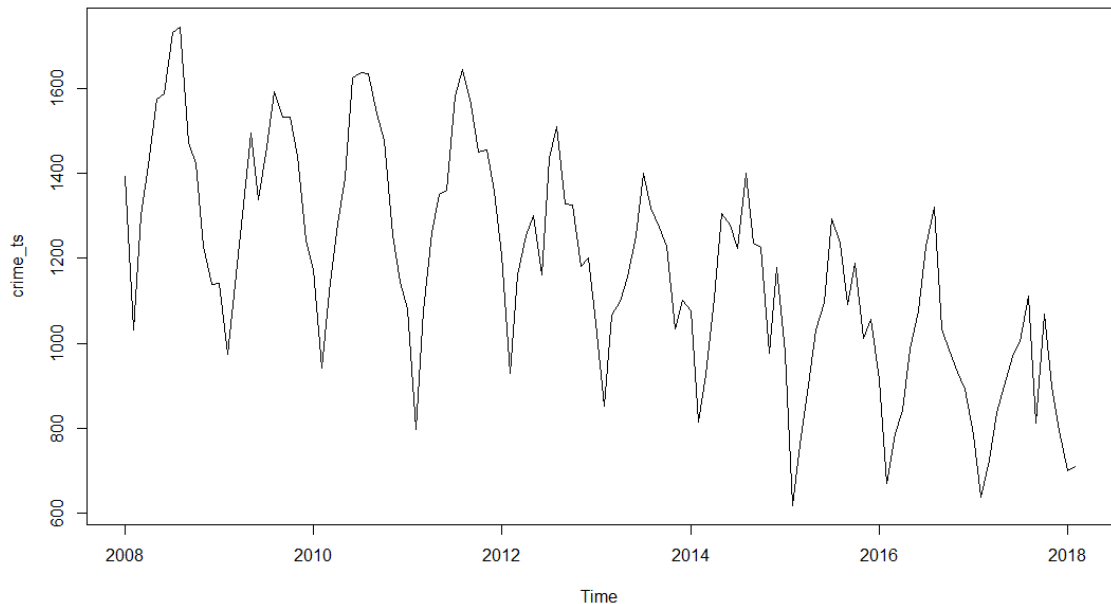
Please do the following steps once the csv file is on your desktop.

```
> library(readr)
warning message:
package 'readr' was built under R version 3.4.4
> crimes <- read_csv("C:/Users/asher/Desktop/Asher_MS/BF/Final/Crimes.csv")
Parsed with column specification:
cols(
  Month = col_character(),
  Year = col_integer(),
  Date = col_character(),
  Data = col_integer()
)
> view(crimes)
Error in view : object 'Crimes' not found
> view(crimes)

crime_ts <- ts(crimes$Data, start=c(2008,1),frequency = 12)
plot(crime_ts)
```

## Plot and Inference

- Show a time series plot.
- `plot(crime_ts)`



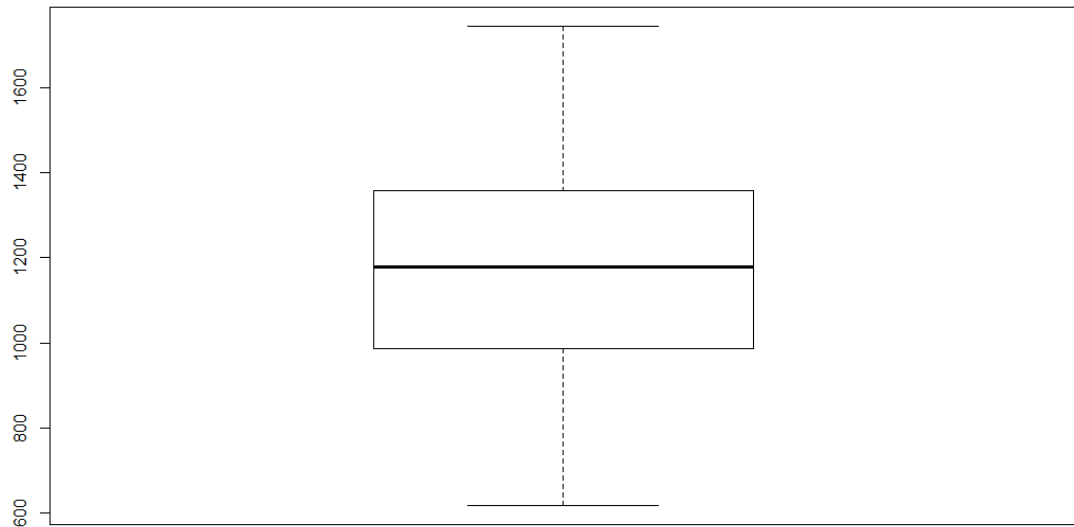
- Please summaries your observations of the times series plot
  - Overall the trend is downward, i.e. the crime rate is decreasing year by year.
  - We have a cyclical trend with regular upward and downward peaks.
  - Seasonality is observed as well. Crimes are high in the month of June-July and lowest in the month of Jan-Feb. From Jan to June there is rising trend and July to Dec is falling trend.

## Central Tendency

- What are the min, max, mean, median, 1<sup>st</sup> and 3<sup>rd</sup> Quartile values of the times series?

```
> plot(crime_ts)
> summary(crime_ts)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  619.0   991.5   1179.5   1179.1   1355.2   1743.0
```

- Show the box plot.  
`boxplot(crime_ts)`

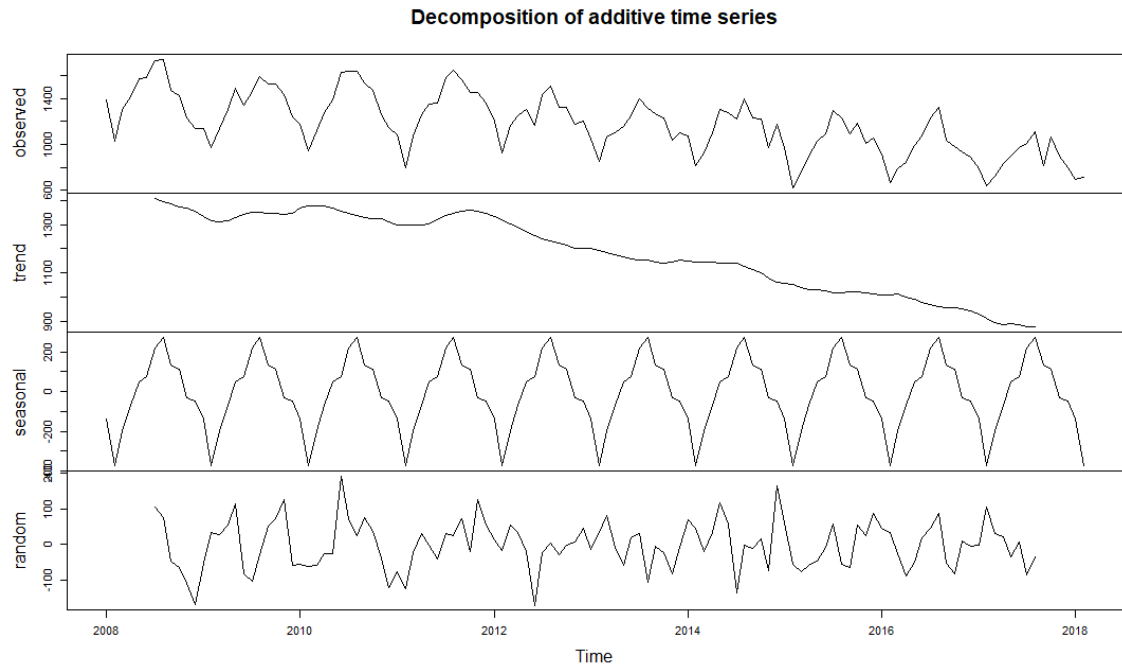


- Can you summarize your observation about the time series from the summary stats and box plot?
  - The mean and median are almost same, 1179.1 and 1179.5 respectively.
  - Min is 619 and max is 1743
  - First and third quartile value are 991.5 and 1355.2 respectively.

## Decomposition

- Plot the decomposition of the time series.

```
decomp<-decompose(crime_ts)
plot(decomp)
```



- Is the times series seasonal?
  - Yes, it is seasonal
- Is the decomposition additive or multiplicative?
  - It is additive
 

```
> decomp$type
[1] "additive"
```
- If seasonal, what are the values of the seasonal monthly indices?
 

```
> decomp$seasonal
```

|      | Jan        | Feb        | Mar        | Apr       | May      | Jun      | Jul       |
|------|------------|------------|------------|-----------|----------|----------|-----------|
| 2008 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2009 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2010 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2011 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2012 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2013 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2014 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2015 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2016 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2017 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |
| 2018 | -140.35579 | -374.62894 | -198.86505 | -69.94375 | 48.32477 | 77.65810 | 216.51968 |

|      | Aug       | Sep       | Oct       | Nov       | Dec       |
|------|-----------|-----------|-----------|-----------|-----------|
| 2008 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2009 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2010 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2011 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2012 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2013 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2014 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2015 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2016 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2017 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |
| 2018 | 272.14468 | 132.35255 | 111.50069 | -29.23542 | -45.47153 |

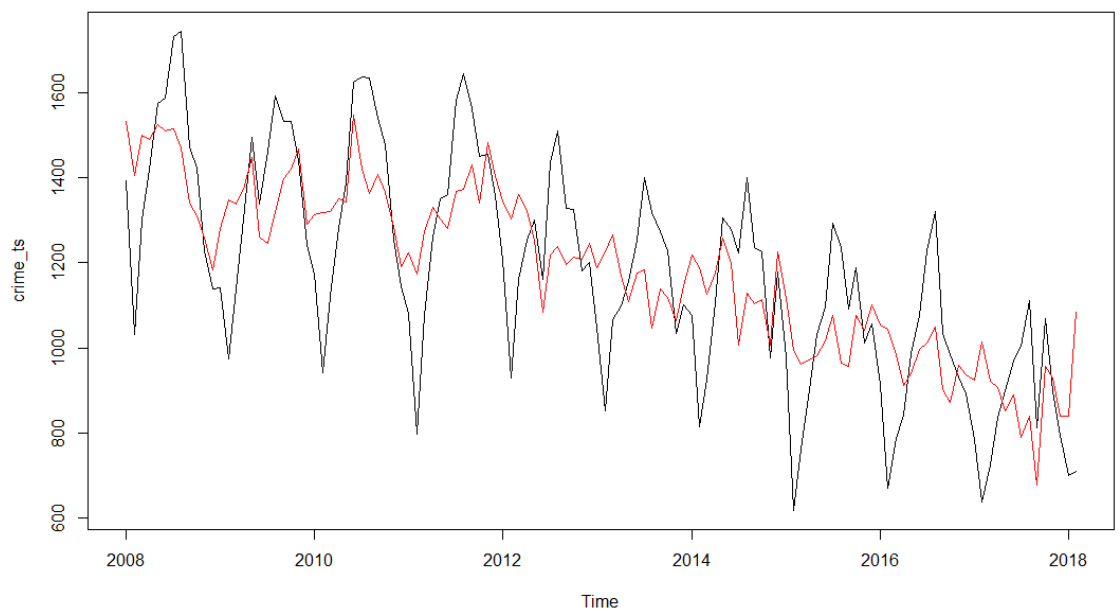
- For which month is the value of time series high and for which month is it low?

- Lowest in February and highest in August
- Can you think of the reason behind the value being high in those months and low in those months?
 

The weather is cold in February and hence people do not venture outdoors much. Also, the homeless are provided shelters by the government during this time.

August is summer time, people socialize more and the homeless take shelter on the curbside, hence crimes are possibly high.
- Show 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?
  - No Major fluctuations are observed

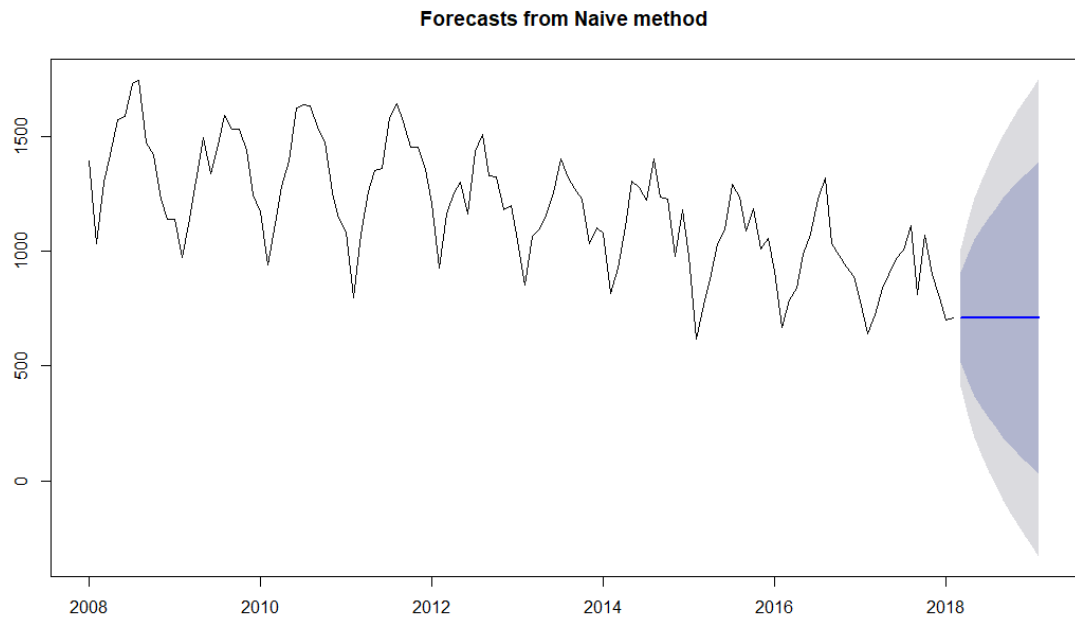
```
library(fpp)
temp_sesadjust<-seasadj(decomp)
plot(crime_ts)
lines(temp_sesadjust,col='red')
```



## Naïve Method

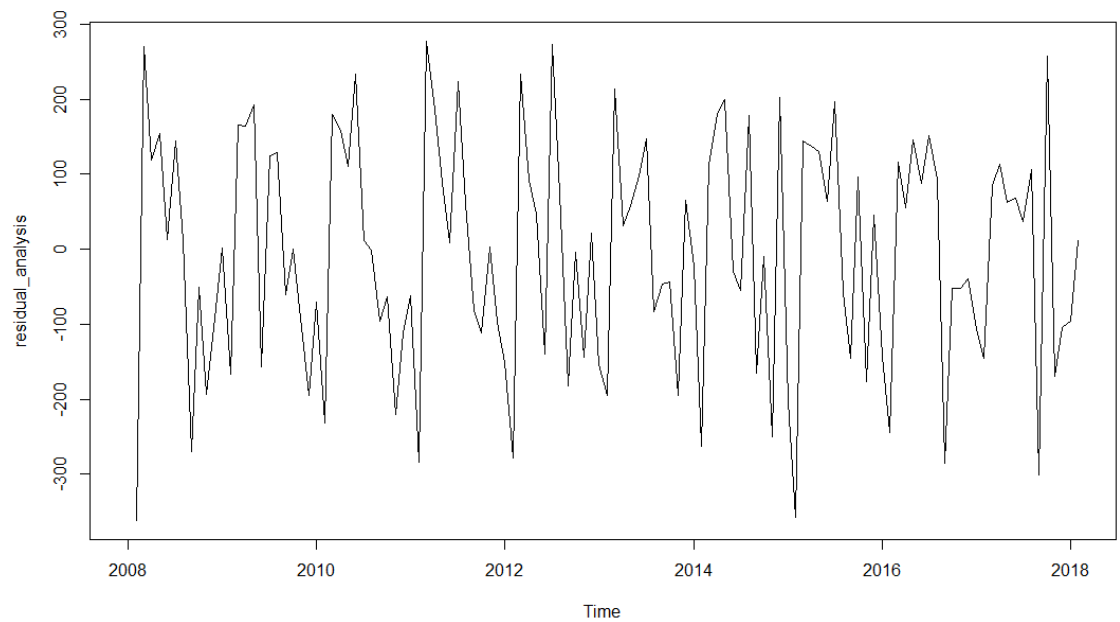
- Output
 

```
naive_forecast<-naive(crime_ts,12)
plot(naive_forecast)
```



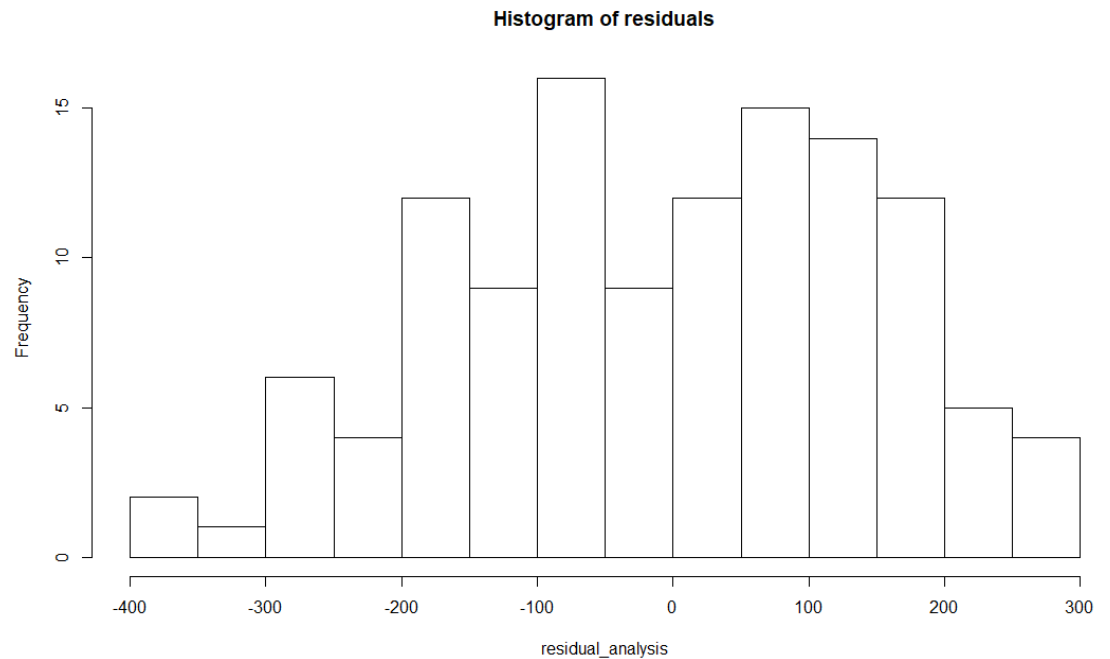
- Perform Residual Analysis for this technique.
  - Do a plot of residuals. What does the plot indicate?

The values fluctuate between -300 to 250. Values are significant when residuals are zero, which is not the case. The values are not very significant.



- Do a Histogram plot of residuals. What does the plot indicate?
  - Residual values are left skewed.

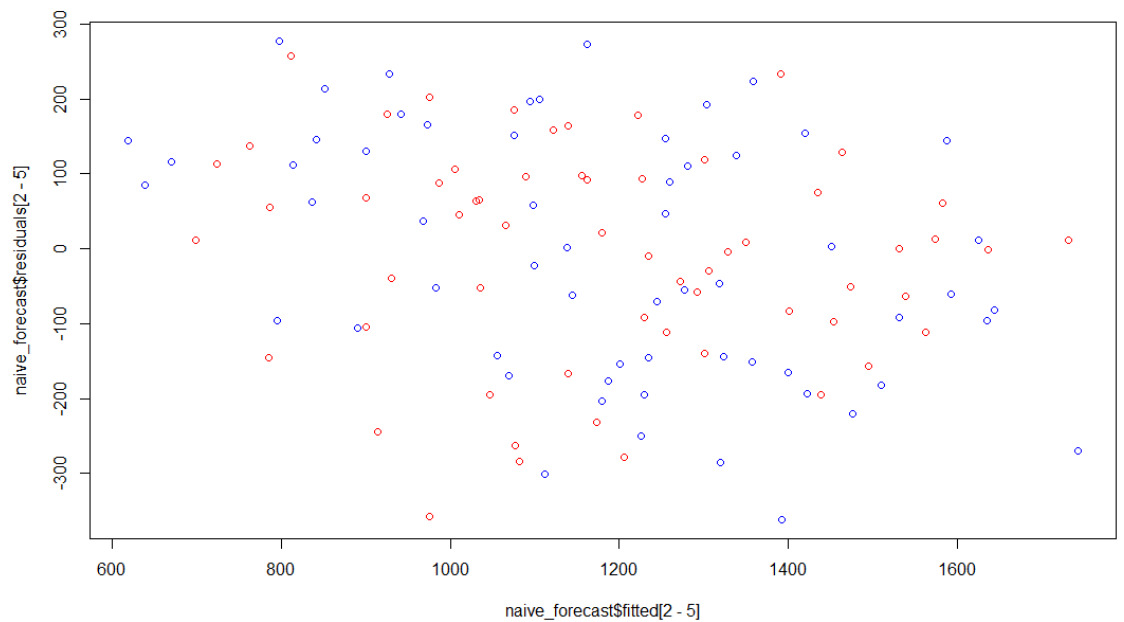




- Do a plot of fitted values vs. residuals. What does the plot indicate?

```
plot(naive_forecast$fitted[2-5],naive_forecast$residuals[2-5],col=c("red","blue"))
```

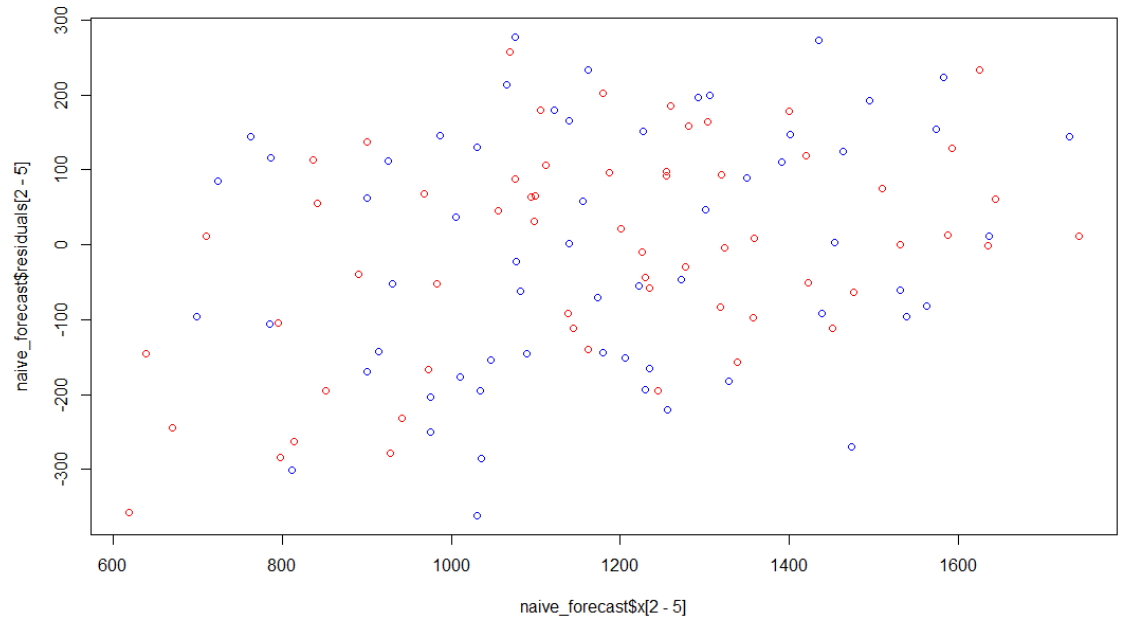
The variation in values is high, hence interpretation is difficult.



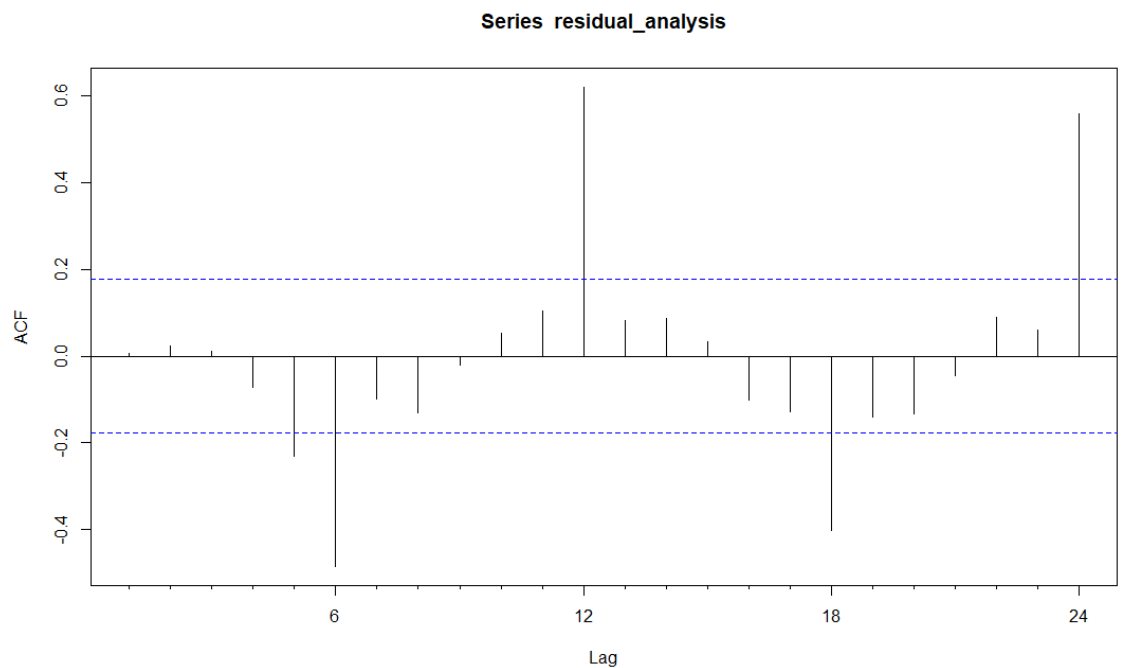
- Do a plot of actual values vs. residuals. What does the plot indicate?

```
plot(naive_forecast$x[2-5],naive_forecast$residuals[2-5],col=c("red","blue"))
```

The variation in values is high, hence interpretation is difficult.



- Do an ACF plot of the residuals? What does this plot indicate?  
`Acf(residual_analysis)`



We can say that very few values are significant.

- Print the 5 measures of accuracy for this forecasting technique

```
> accuracy(naive_forecast)
```

```
      ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
Training set -5.636364 153.4663 129.1074 -1.626318 12.00476 1.193129 0.006097097
```

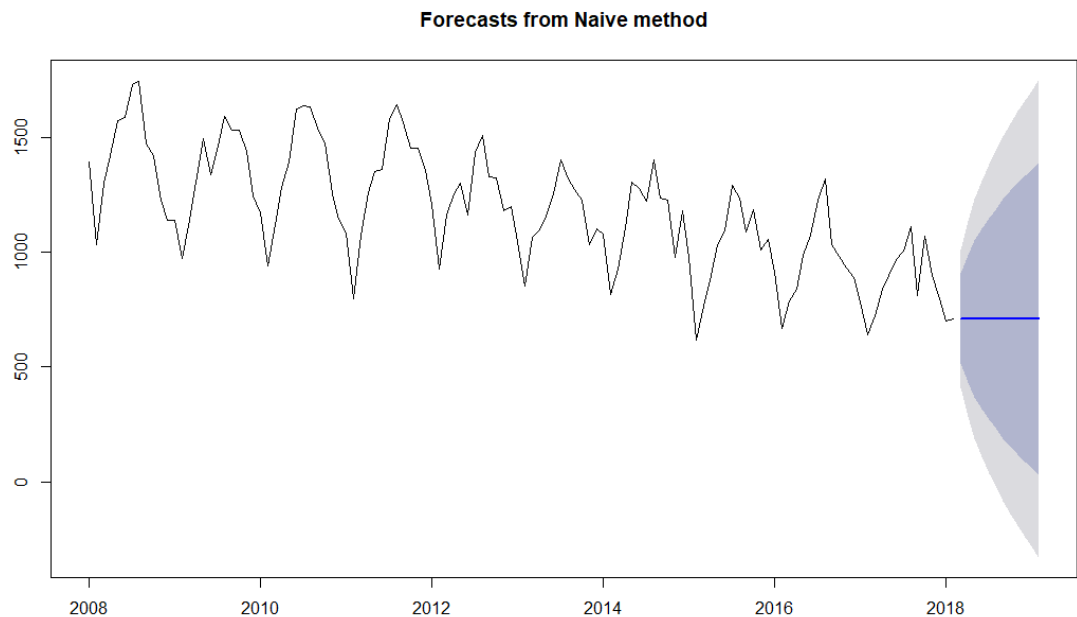
- Forecast
  - Time series value for next year. Show table and plot

```
naive_fore<- forecast(naive_forecast, h=12)
```

```
> naive_fore
```

|          | Point Forecast | Lo 80     | Hi 80     | Lo 95      | Hi 95    |
|----------|----------------|-----------|-----------|------------|----------|
| Mar 2018 | 710            | 513.32491 | 906.6751  | 409.21140  | 1010.789 |
| Apr 2018 | 710            | 431.85941 | 988.1406  | 284.62068  | 1135.379 |
| May 2018 | 710            | 369.34874 | 1050.6513 | 189.01886  | 1230.981 |
| Jun 2018 | 710            | 316.64981 | 1103.3502 | 108.42280  | 1311.577 |
| Jul 2018 | 710            | 270.22112 | 1149.7789 | 37.41624   | 1382.584 |
| Aug 2018 | 710            | 228.24637 | 1191.7536 | -26.77859  | 1446.779 |
| Sep 2018 | 710            | 189.64661 | 1230.3534 | -85.81183  | 1505.812 |
| Oct 2018 | 710            | 153.71883 | 1266.2812 | -140.75864 | 1560.759 |
| Nov 2018 | 710            | 119.97472 | 1300.0253 | -192.36580 | 1612.366 |
| Dec 2018 | 710            | 88.05874  | 1331.9413 | -241.17707 | 1661.177 |
| Jan 2019 | 710            | 57.70251  | 1362.2975 | -287.60293 | 1707.603 |
| Feb 2019 | 710            | 28.69749  | 1391.3025 | -331.96228 | 1751.962 |

```
plot(naive_fore)
```

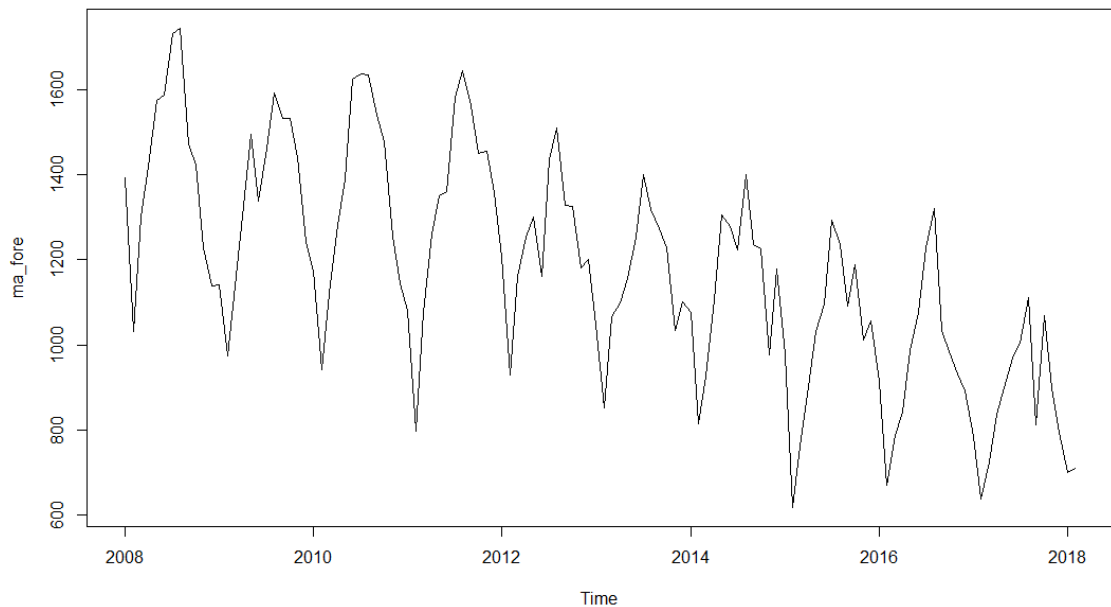


- Summarize this forecasting technique
  - How good is the accuracy?
    - The MAPE is 12.004, which is good. Hence there is 12% difference in actual and predicted values. Accuracy is good.

- What does it predict the value of time series will be in one year?  
The predicted value is 710
- Other observation
  - No such important observation

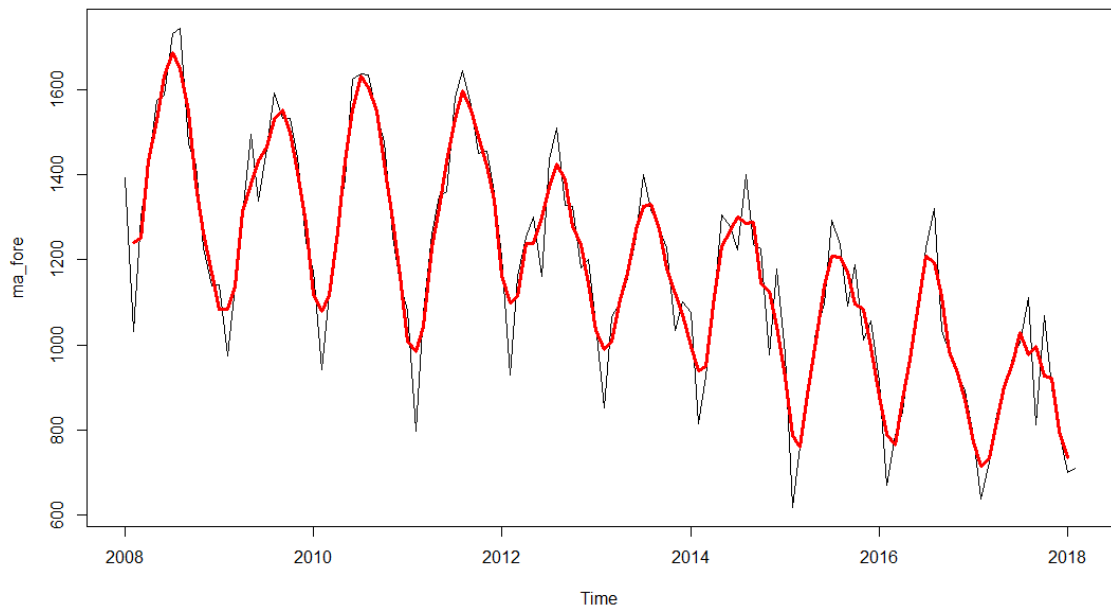
## Simple Moving Averages

- Plot the graph for time series.  
`ma_fore<-ma(crime_ts, order=1)`  
`plot(ma_fore)`

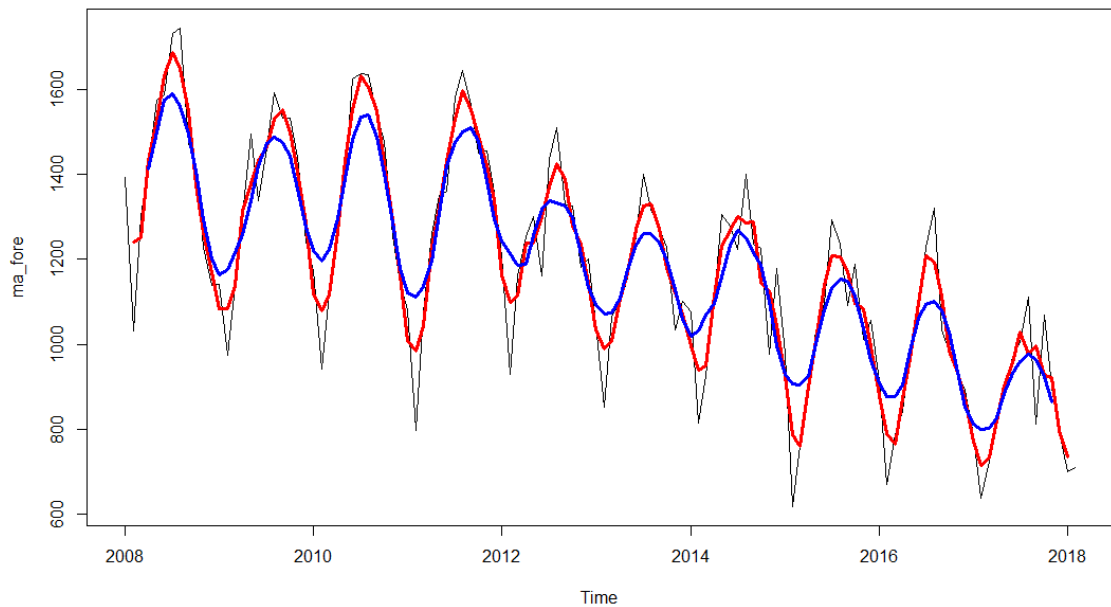


- Show the Simple Moving average of order 3 on the plot above in Red

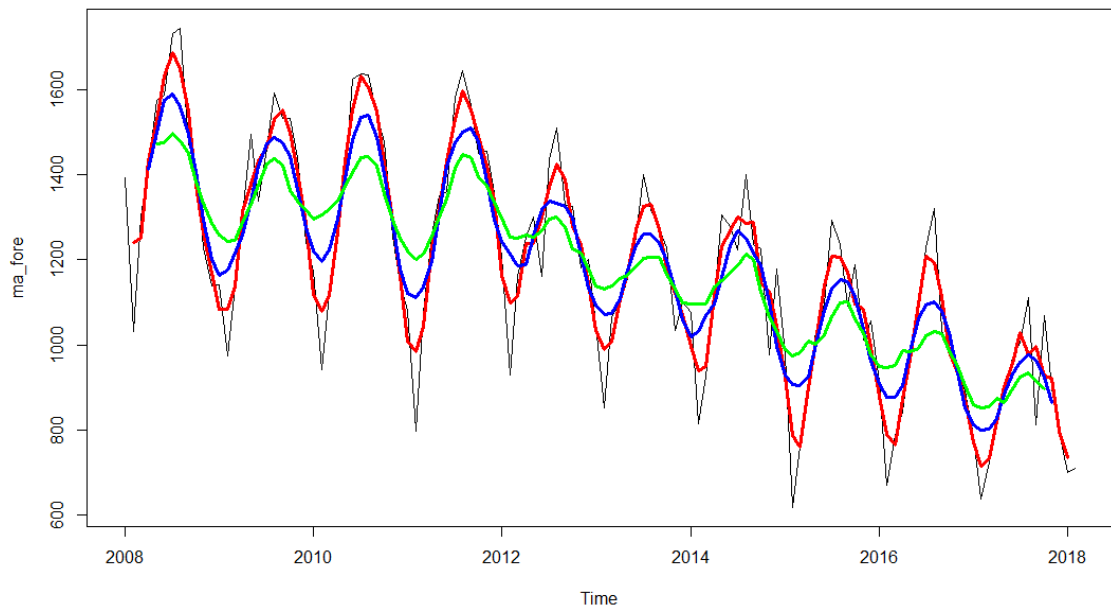
```
ma3_fore<-ma(crime_ts, order=3)
lines(ma3_fore,col="red",lwd=3)
```



- Show the Simple Moving average of order 6 on the plot above in Blue  
`ma6_fore<-ma(crime_ts, order=6)`  
`lines(ma6_fore,col="blue",lwd=3)`



- Show the Simple Moving average of order 9 on the plot above in Green  
`ma9_fore<-ma(crime_ts, order=9)`  
`lines(ma9_fore,col="green",lwd=3)`



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

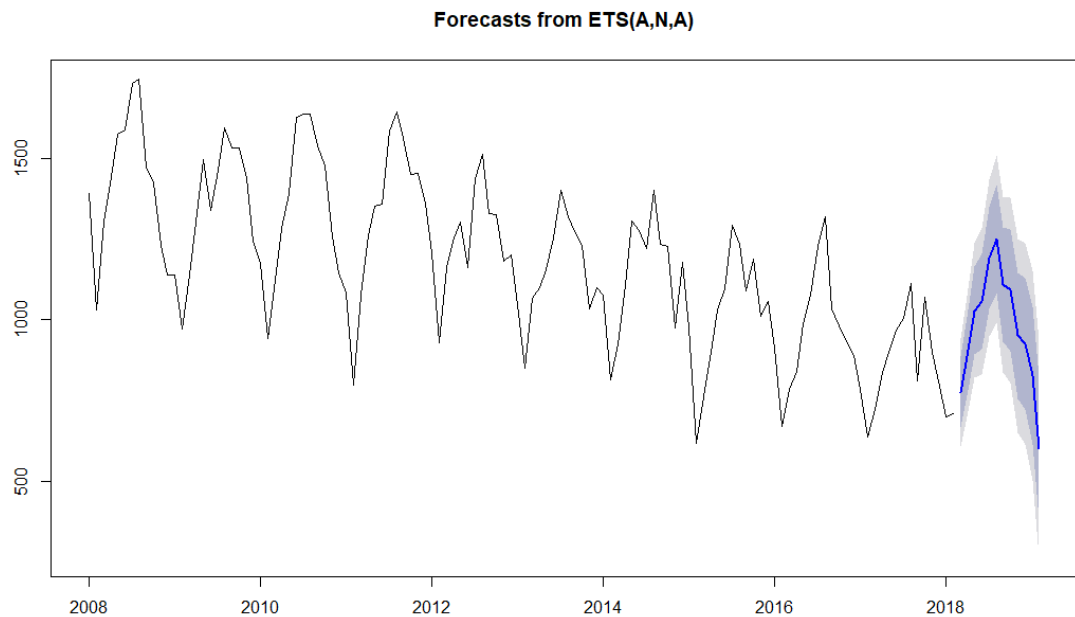
USING ETS:

```
ets_forecast <- ets(crime_ts)
fore_ets <- forecast.ets(ets_forecast, h=12)
fore_ets
```

|          | Point Forecast | Lo 80     | Hi 80     | Lo 95    | Hi 95     |
|----------|----------------|-----------|-----------|----------|-----------|
| Mar 2018 | 776.4469       | 667.0042  | 885.8895  | 609.0687 | 943.8250  |
| Apr 2018 | 906.9292       | 783.4354  | 1030.4230 | 718.0618 | 1095.7967 |
| May 2018 | 1028.3387      | 892.2367  | 1164.4406 | 820.1887 | 1236.4886 |
| Jun 2018 | 1057.1163      | 909.4791  | 1204.7536 | 831.3247 | 1282.9080 |
| Jul 2018 | 1190.9695      | 1032.6351 | 1349.3039 | 948.8180 | 1433.1210 |
| Aug 2018 | 1249.7781      | 1081.4249 | 1418.1312 | 992.3041 | 1507.2520 |
| Sep 2018 | 1108.7453      | 930.9370  | 1286.5537 | 836.8109 | 1380.6798 |
| Oct 2018 | 1091.2937      | 904.5082  | 1278.0792 | 805.6299 | 1376.9575 |
| Nov 2018 | 950.9327       | 755.5821  | 1146.2833 | 652.1698 | 1249.6956 |
| Dec 2018 | 926.0483       | 722.4928  | 1129.6039 | 614.7370 | 1237.3597 |
| Jan 2019 | 827.6569       | 616.2145  | 1039.0992 | 504.2836 | 1151.0301 |
| Feb 2019 | 601.5649       | 382.5165  | 820.6133  | 266.5593 | 936.5705  |

```
plot(fore_ets)
```

-



USING: Simple moving averages (forecast for accuracy table (extra))

```
ma_forecast<-forecast(ma_fore, h=12)
```

```
ma_forecast
```

```
accuracy(ma_forecast)
```

|          | Point Forecast | Lo 80     | Hi 80     | Lo 95    | Hi 95     |
|----------|----------------|-----------|-----------|----------|-----------|
| Mar 2018 | 776.4469       | 667.0042  | 885.8895  | 609.0687 | 943.8250  |
| Apr 2018 | 906.9292       | 783.4354  | 1030.4230 | 718.0618 | 1095.7967 |
| May 2018 | 1028.3387      | 892.2367  | 1164.4406 | 820.1887 | 1236.4886 |
| Jun 2018 | 1057.1163      | 909.4791  | 1204.7536 | 831.3247 | 1282.9080 |
| Jul 2018 | 1190.9695      | 1032.6351 | 1349.3039 | 948.8180 | 1433.1210 |
| Aug 2018 | 1249.7781      | 1081.4249 | 1418.1312 | 992.3041 | 1507.2520 |
| Sep 2018 | 1108.7453      | 930.9370  | 1286.5537 | 836.8109 | 1380.6798 |
| Oct 2018 | 1091.2937      | 904.5082  | 1278.0792 | 805.6299 | 1376.9575 |
| Nov 2018 | 950.9327       | 755.5821  | 1146.2833 | 652.1698 | 1249.6956 |
| Dec 2018 | 926.0483       | 722.4928  | 1129.6039 | 614.7370 | 1237.3597 |
| Jan 2019 | 827.6569       | 616.2145  | 1039.0992 | 504.2836 | 1151.0301 |
| Feb 2019 | 601.5649       | 382.5165  | 820.6133  | 266.5593 | 936.5705  |

```
> accuracy(ma_forecast)
```

|              | ME        | RMSE     | MAE     | MPE        | MAPE     | MASE      | ACF1       |
|--------------|-----------|----------|---------|------------|----------|-----------|------------|
| Training set | -6.398486 | 80.34939 | 62.6294 | -0.8653392 | 5.664747 | 0.5787813 | 0.05803802 |

```
> |
```

- What are your observations of the plot as the moving average order goes up?
  - Error of prediction increases with it.

## Smoothing

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

```
ses(crime_ts, h=12)
```

```
> ses(crime_ts, h=12)
```

|          | Point | Forecast | Lo 80     | Hi 80     | Lo 95      | Hi 95    |
|----------|-------|----------|-----------|-----------|------------|----------|
| Mar 2018 |       | 709.9989 | 512.50595 | 907.4918  | 407.95950  | 1012.038 |
| Apr 2018 |       | 709.9989 | 430.71569 | 989.2821  | 282.87209  | 1137.126 |
| May 2018 |       | 709.9989 | 367.95393 | 1052.0439 | 186.88627  | 1233.112 |
| Jun 2018 |       | 709.9989 | 315.04269 | 1104.9551 | 105.96551  | 1314.032 |
| Jul 2018 |       | 709.9989 | 268.42665 | 1151.5711 | 34.67242   | 1385.325 |
| Aug 2018 |       | 709.9989 | 226.28235 | 1193.7154 | -29.78172  | 1449.780 |
| Sep 2018 |       | 709.9989 | 187.52656 | 1232.4712 | -89.05359  | 1509.051 |
| Oct 2018 |       | 709.9989 | 151.45347 | 1268.5443 | -144.22261 | 1564.220 |
| Nov 2018 |       | 709.9989 | 117.57284 | 1302.4250 | -196.03857 | 1616.036 |
| Dec 2018 |       | 709.9989 | 85.52770  | 1334.4701 | -245.04739 | 1665.045 |
| Jan 2019 |       | 709.9989 | 55.04857  | 1364.9492 | -291.66119 | 1711.659 |
| Feb 2019 |       | 709.9989 | 25.92611  | 1394.0717 | -336.20014 | 1756.198 |

```
> |
```

- What is the value of alpha? What does that value signify?  
summary(ses(crime\_ts, h=12))

The value of alpha is 0.99. It signifies the optimal smoothing parameter for the model to get minimum error

```
> summary(ses(crime_ts, h=12))
```

Forecast method: Simple exponential smoothing

Model Information:  
Simple exponential smoothing

Call:  
ses(y = crime\_ts, h = 12)

Smoothing parameters:  
alpha = 0.9999

Initial states:  
l = 1391.4554

sigma: 154.1046

```
AIC      AICC      BIC
1819.256 1819.459 1827.668
```

Error measures:

|              | ME        | RMSE     | MAE      | MPE       | MAPE     | MASE    | ACF1        |
|--------------|-----------|----------|----------|-----------|----------|---------|-------------|
| Training set | -5.586269 | 152.8362 | 128.0557 | -1.612822 | 11.90683 | 1.18341 | 0.005428101 |

Forecasts:

|          | Point | Forecast | Lo 80     | Hi 80     | Lo 95      | Hi 95    |
|----------|-------|----------|-----------|-----------|------------|----------|
| Mar 2018 |       | 709.9989 | 512.50595 | 907.4918  | 407.95950  | 1012.038 |
| Apr 2018 |       | 709.9989 | 430.71569 | 989.2821  | 282.87209  | 1137.126 |
| May 2018 |       | 709.9989 | 367.95393 | 1052.0439 | 186.88627  | 1233.112 |
| Jun 2018 |       | 709.9989 | 315.04269 | 1104.9551 | 105.96551  | 1314.032 |
| Jul 2018 |       | 709.9989 | 268.42665 | 1151.5711 | 34.67242   | 1385.325 |
| Aug 2018 |       | 709.9989 | 226.28235 | 1193.7154 | -29.78172  | 1449.780 |
| Sep 2018 |       | 709.9989 | 187.52656 | 1232.4712 | -89.05359  | 1509.051 |
| Oct 2018 |       | 709.9989 | 151.45347 | 1268.5443 | -144.22261 | 1564.220 |
| Nov 2018 |       | 709.9989 | 117.57284 | 1302.4250 | -196.03857 | 1616.036 |
| Dec 2018 |       | 709.9989 | 85.52770  | 1334.4701 | -245.04739 | 1665.045 |
| Jan 2019 |       | 709.9989 | 55.04857  | 1364.9492 | -291.66119 | 1711.659 |
| Feb 2019 |       | 709.9989 | 25.92611  | 1394.0717 | -336.20014 | 1756.198 |



- What is the value of initial state?  
The value of initial state is 1391.4554
- What is the value of sigma? What does the sigma signify?  
The value of sigma is 154.1056. It signifies that the residuals have more variation around the residual mean.
- Perform Residual Analysis for this technique.

```
ses_fore <- ses(crime_ts, h=12)
ses_residual_ana <- residuals(ses_fore)
ses_residual_ana
```

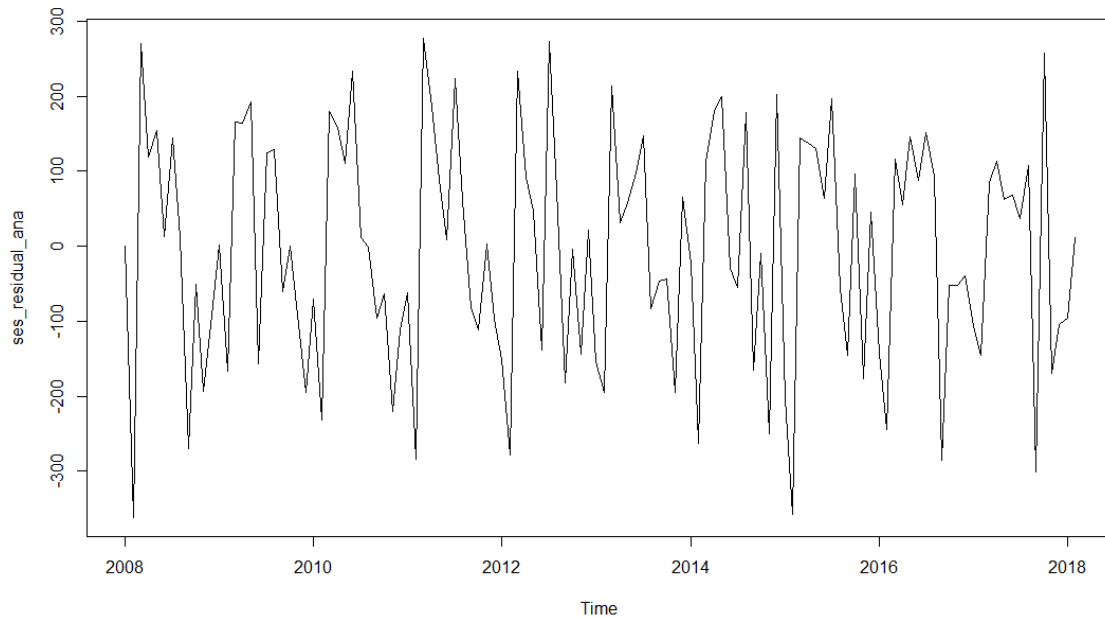
```
> ses_fore <- ses(crime_ts, h=12)
> ses_residual_ana <- residuals(ses_fore)
> ses_residual_ana
```

|      | Jan           | Feb           | Mar           | Apr           | May           |
|------|---------------|---------------|---------------|---------------|---------------|
| 2008 | 5.446450e-01  | -3.609999e+02 | 2.699638e+02  | 1.190271e+02  | 1.540119e+02  |
| 2009 | 1.990876e+00  | -1.669998e+02 | 1.659833e+02  | 1.640166e+02  | 1.920164e+02  |
| 2010 | -7.101955e+01 | -2.310071e+02 | 1.799768e+02  | 1.590180e+02  | 1.100159e+02  |
| 2011 | -6.201123e+01 | -2.840062e+02 | 2.769715e+02  | 1.850278e+02  | 9.001855e+01  |
| 2012 | -1.510097e+02 | -2.780151e+02 | 2.339721e+02  | 9.202345e+01  | 4.700922e+01  |
| 2013 | -1.539979e+02 | -1.950154e+02 | 2.139805e+02  | 3.202145e+01  | 5.800321e+01  |
| 2014 | -2.299339e+01 | -2.630023e+02 | 1.119736e+02  | 1.800112e+02  | 2.000180e+02  |
| 2015 | -2.029797e+02 | -3.570203e+02 | 1.439642e+02  | 1.380144e+02  | 1.300138e+02  |
| 2016 | -1.419955e+02 | -2.440142e+02 | 1.159755e+02  | 5.501163e+01  | 1.460055e+02  |
| 2017 | -1.060040e+02 | -1.460106e+02 | 8.498536e+01  | 1.130085e+02  | 6.301133e+01  |
| 2018 | -9.601053e+01 | 1.099038e+01  |               |               |               |
|      | Jun           | Jul           | Aug           | Sep           | Oct           |
| 2008 | 1.301544e+01  | 1.440013e+02  | 1.201443e+01  | -2.699988e+02 | -5.102707e+01 |
| 2009 | -1.569808e+02 | 1.249843e+02  | 1.290125e+02  | -6.098707e+01 | -6.113418e-03 |
| 2010 | 2.340110e+02  | 1.102346e+01  | -9.988950e-01 | -9.600010e+01 | -6.300962e+01 |
| 2011 | 9.009024e+00  | 2.240009e+02  | 6.102245e+01  | -8.199388e+01 | -1.110082e+02 |
| 2012 | -1.389953e+02 | 2.729861e+02  | 7.502736e+01  | -1.819925e+02 | -4.018243e+00 |
| 2013 | 9.800581e+01  | 1.470098e+02  | -8.298526e+01 | -4.600832e+01 | -4.300461e+01 |
| 2014 | -2.897995e+01 | -5.500290e+01 | 1.779945e+02  | -1.649822e+02 | -9.016538e+00 |
| 2015 | 6.401303e+01  | 1.970064e+02  | -5.698025e+01 | -1.450057e+02 | 9.698546e+01  |
| 2016 | 8.801464e+01  | 1.520088e+02  | 9.301524e+01  | -2.849907e+02 | -5.202857e+01 |
| 2017 | 6.800632e+01  | 3.700682e+01  | 1.070037e+02  | -3.009893e+02 | 2.579698e+02  |
| 2018 |               |               |               |               |               |
|      | Nov           | Dec           |               |               |               |
| 2008 | -1.930051e+02 | -9.101935e+01 |               |               |               |
| 2009 | -9.200000e+01 | -1.950092e+02 |               |               |               |
| 2010 | -2.200063e+02 | -1.120221e+02 |               |               |               |
| 2011 | 2.988872e+00  | -9.699970e+01 |               |               |               |
| 2012 | -1.440004e+02 | 2.098557e+01  |               |               |               |
| 2013 | -1.950043e+02 | 6.598045e+01  |               |               |               |
| 2014 | -2.500009e+02 | 2.029749e+02  |               |               |               |
| 2015 | -1.759903e+02 | 4.498236e+01  |               |               |               |
| 2016 | -5.200522e+01 | -4.000521e+01 |               |               |               |
| 2017 | -1.689741e+02 | -1.050169e+02 |               |               |               |
| 2018 |               |               |               |               |               |

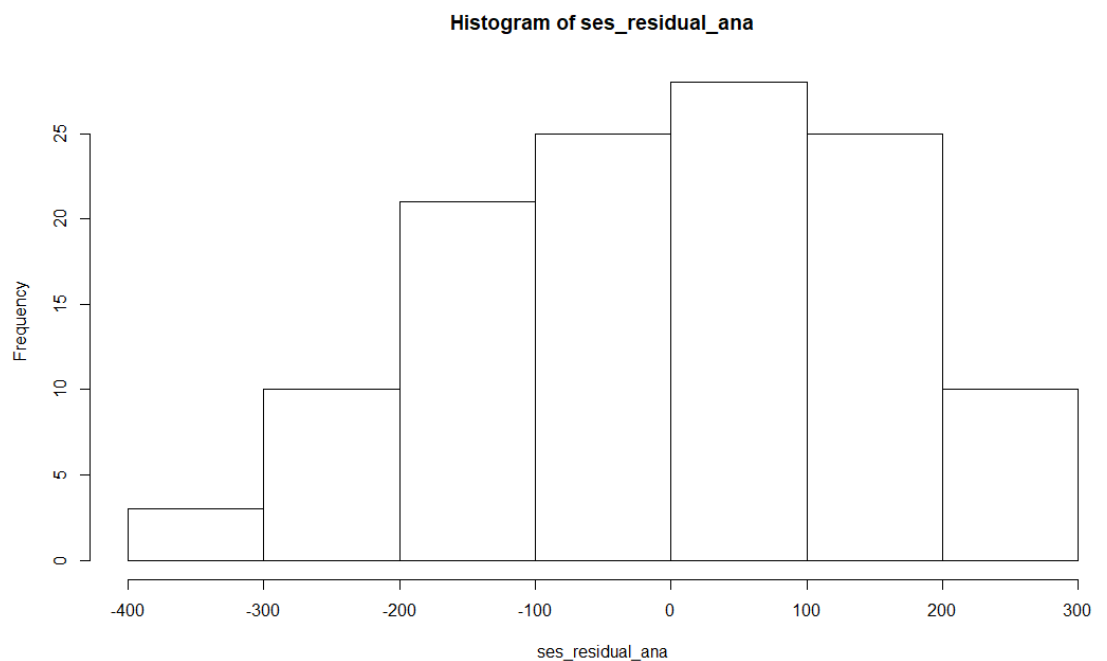
```
> plot(ses_residual_ana)
```

- Do a plot of residuals. What does the plot indicate?

```
plot(ses_residual_ana)
```

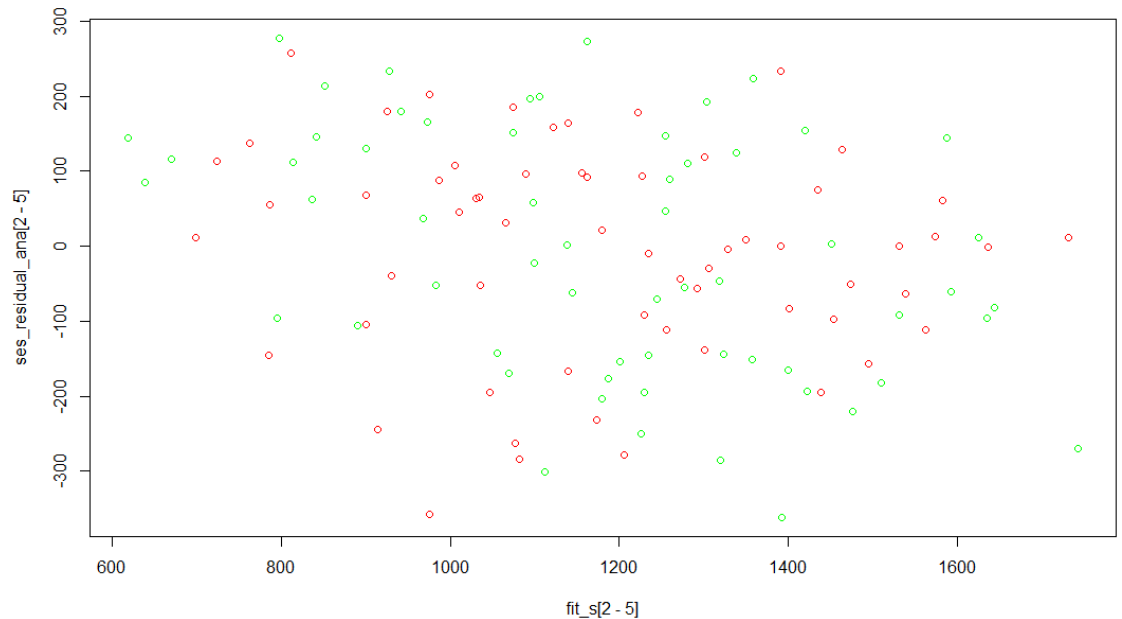


- Do a Histogram plot of residuals. What does the plot indicate?
  - From the plot we can see that data is left skewed.



- Do a plot of fitted values vs. residuals. What does the plot indicate?  
We observe cyclic and seasonal pattern in both, fitted and residual values.

```
fit_s<-ses_fore$fitted
plot(fit_s[2-5],ses_residual_ana[2-5], col=c("Red","Green"))
```

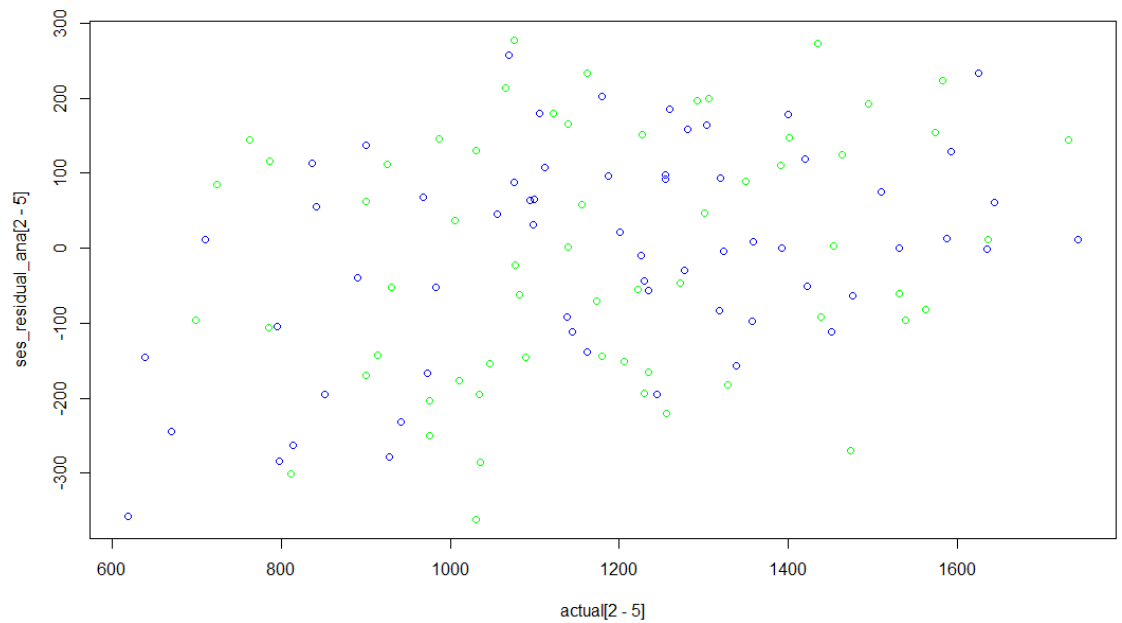


- Do a plot of actual values vs. residuals. What does the plot indicate?

We observe cyclic and seasonal pattern in both, fitted and residual values.

```
actual<-ses_fore$x
```

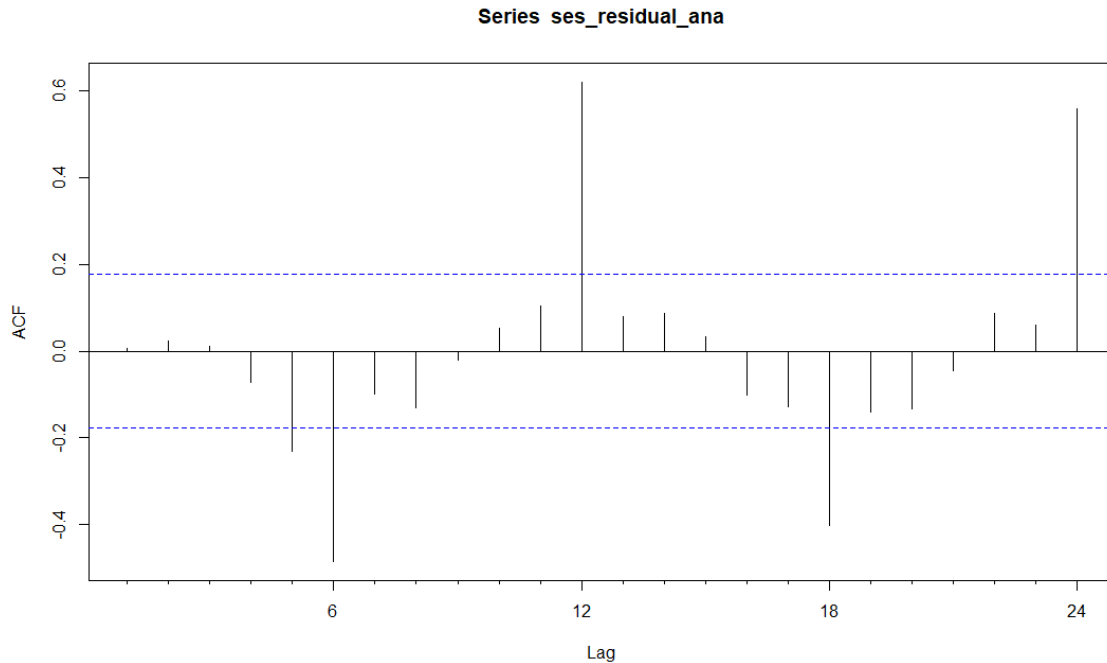
```
plot(actual[2-5],ses_residual_ana[2-5],col=c("Blue","Green"))
```



- Do an ACF plot of the residuals? What does this plot indicate?

```
Acf(ses_residual_ana)
```

We can say that only few values are significant, at 6, 12, 18, 24

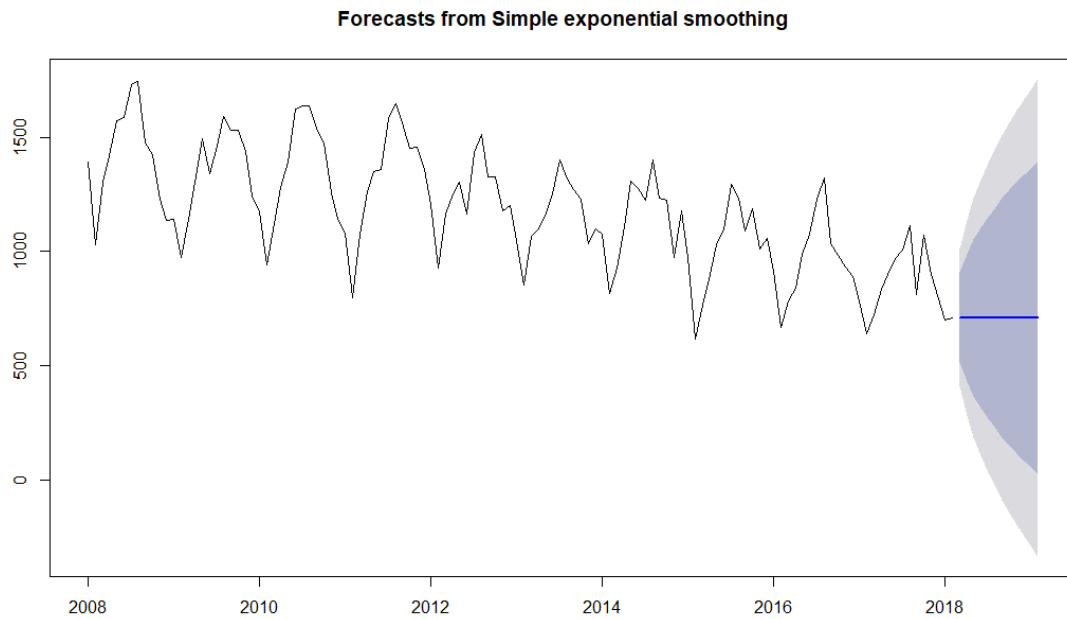


- Print the 5 measures of accuracy for this forecasting technique

```
< ACF(ses_residual_ana)
> accuracy(ses_fore)
      ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
Training set -5.586269 152.8362 128.0557 -1.612822 11.90683 1.18341 0.005428101
```

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

```
> forecast(ses_fore, h=12)
      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
Mar 2018      709.9989 512.50595 907.4918 407.95950 1012.038
Apr 2018      709.9989 430.71569 989.2821 282.87209 1137.126
May 2018      709.9989 367.95393 1052.0439 186.88627 1233.112
Jun 2018      709.9989 315.04269 1104.9551 105.96551 1314.032
Jul 2018      709.9989 268.42665 1151.5711  34.67242 1385.325
Aug 2018      709.9989 226.28235 1193.7154 -29.78172 1449.780
Sep 2018      709.9989 187.52656 1232.4712 -89.05359 1509.051
Oct 2018      709.9989 151.45347 1268.5443 -144.22261 1564.220
Nov 2018      709.9989 117.57284 1302.4250 -196.03857 1616.036
Dec 2018      709.9989  85.52770 1334.4701 -245.04739 1665.045
Jan 2019      709.9989  55.04857 1364.9492 -291.66119 1711.659
Feb 2019      709.9989  25.92611 1394.0717 -336.20014 1756.198
```



- Summarize this forecasting technique

```
> summary(ses_fore)

Forecast method: simple exponential smoothing

Model Information:
Simple exponential smoothing

Call:
ses(y = crime_ts, h = 12)

Smoothing parameters:
  alpha = 0.9999

Initial states:
  l = 1391.4554

sigma: 154.1046

      AIC      AICC      BIC
1819.256 1819.459 1827.668

Error measures:
      ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
Training set -5.586269 152.8362 128.0557 -1.612822 11.90683 1.18341 0.005428101
```

- How good is the accuracy?  
MAPE is 11.9 so accuracy is good
- What does it predict the value of time series will be in one year?  
The predicted value in 1 year is 709.99

- Other observation  
MPE, MAPE, MASE values show good accuracy, but RMSE, MAE show poor accuracy measures.

## Holt-Winters

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

```
holt<-HoltWinters(crime_ts)
holt_forecast<-forecast(holt, h=12)
holt_forecast
plot(holt_forecast)
```

Holt-winters exponential smoothing with trend and additive seasonal component.

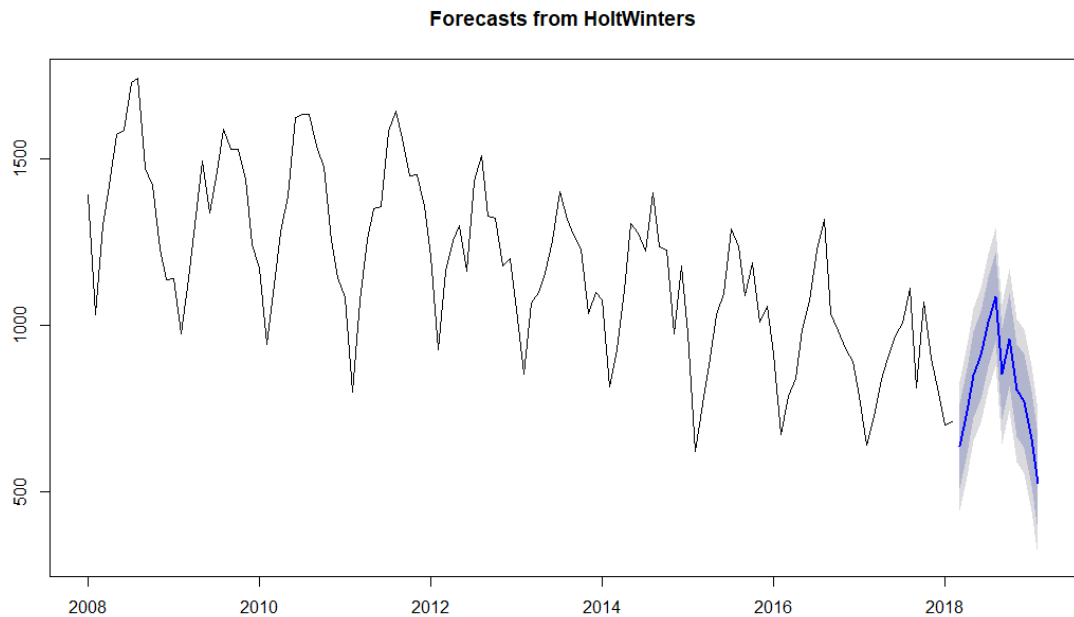
Call:  
Holtwinters(x = crime\_ts)

Smoothing parameters:  
alpha: 0.1583224  
beta : 0.005786356  
gamma: 0.4467106

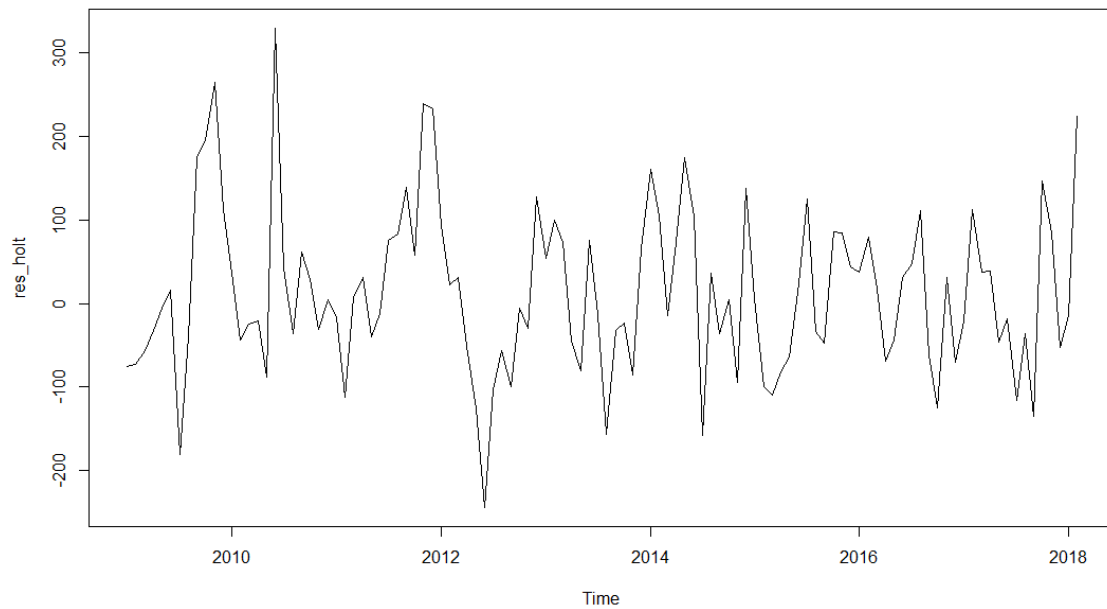
Coefficients:  
[,1]  
a 818.848314  
b -6.780014  
s1 -177.049490  
s2 -63.916884  
s3 52.668209  
s4 117.920159  
s5 225.125281  
s6 307.869360  
s7 81.796516  
s8 192.420461  
s9 45.961763  
s10 20.161964  
s11 -84.438994  
s12 -213.571013

> holt\_forecast

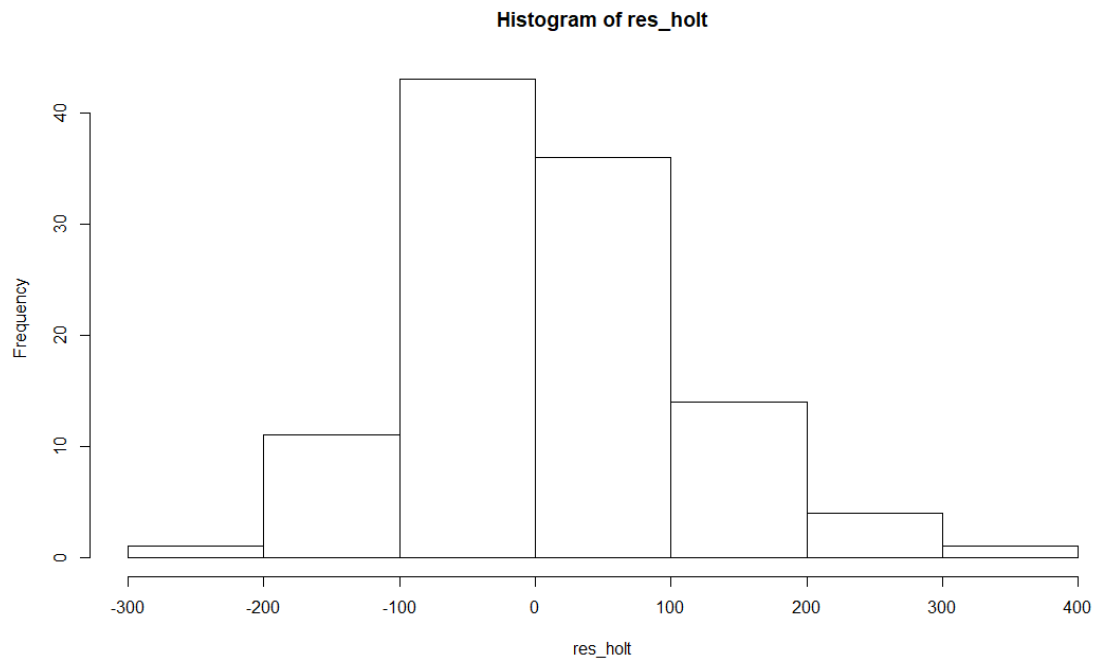
|          | Point | Forecast  | Lo 80    | Hi 80     | Lo 95    | Hi 95     |
|----------|-------|-----------|----------|-----------|----------|-----------|
| Mar 2018 |       | 635.0188  | 507.7725 | 762.2651  | 440.4124 | 829.6252  |
| Apr 2018 |       | 741.3714  | 612.5219 | 870.2209  | 544.3132 | 938.4296  |
| May 2018 |       | 851.1765  | 720.7254 | 981.6276  | 651.6687 | 1050.6842 |
| Jun 2018 |       | 909.6484  | 777.5971 | 1041.6998 | 707.6933 | 1111.6035 |
| Jul 2018 |       | 1010.0735 | 876.4231 | 1143.7239 | 805.6729 | 1214.4741 |
| Aug 2018 |       | 1086.0376 | 950.7893 | 1221.2859 | 879.1931 | 1292.8820 |
| Sep 2018 |       | 853.1847  | 716.3394 | 990.0300  | 643.8979 | 1062.4715 |
| Oct 2018 |       | 957.0287  | 818.5872 | 1095.4701 | 745.3007 | 1168.7566 |
| Nov 2018 |       | 803.7899  | 663.7530 | 943.8269  | 589.6220 | 1017.9579 |
| Dec 2018 |       | 771.2101  | 629.5783 | 912.8420  | 554.6030 | 987.8173  |
| Jan 2019 |       | 659.8292  | 516.6029 | 803.0554  | 440.7835 | 878.8748  |
| Feb 2019 |       | 523.9171  | 379.0968 | 668.7375  | 302.4336 | 745.4007  |



- **What is the value of alpha? What does that value signify?**  
The value of alpha is 0.1583. It signifies that the predictions are stable and random variations are smoothed.
- **What is the value of beta? What does that value signify?**  
The value of beta is 0.0057. It signifies that trend completely depends on the previous period value.
- **What is the value of gamma? What does that value signify?**  
The value of gamma is 0.4467. It signifies that the seasonality repeats according to cycles at regular time intervals
- **What is the value of initial states for the level, trend and seasonality? What do these values signify?**  
From the above:  
a is Level,  
b is Trend ,  
s1 to s12 are the initial seasonality values for each month
- **What is the value of sigma? What does the sigma signify?**  
`sd(complete.cases(holt_forecast$residuals))`  
0.2990297  
The value of sigma signifies the value of standard deviation.
- **Perform Residual Analysis for this technique.**
  - **Do a plot of residuals. What does the plot indicate?**  
`res_holt<-residuals(holt)`  
`plot(res_holt)`  
  
We can say that the variation in residuals is high.



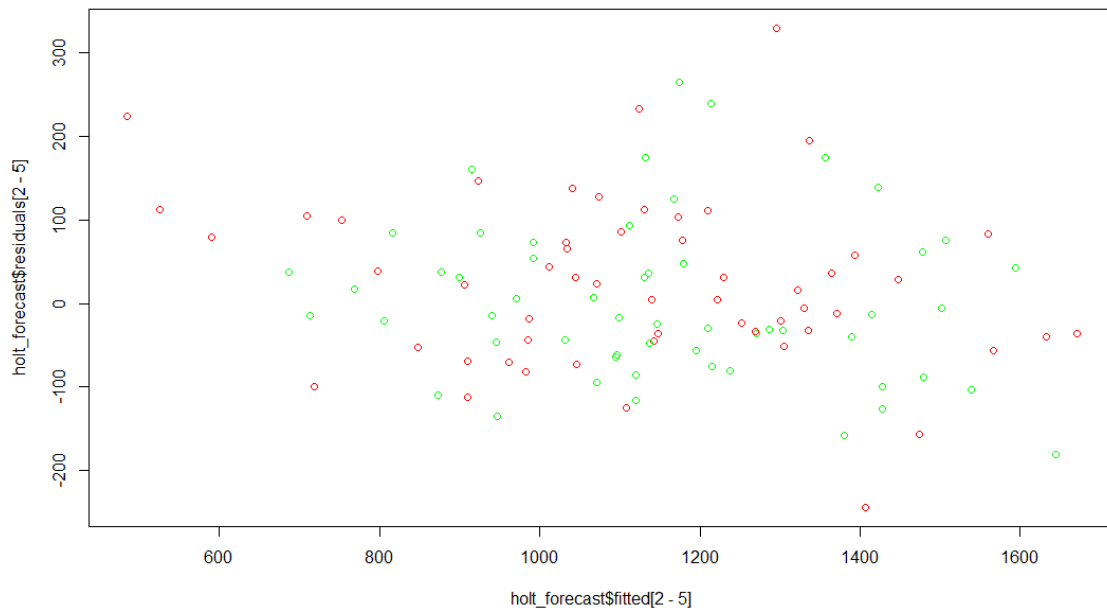
- Do a Histogram plot of residuals. What does the plot indicate?  
We can see that data is right skewed.



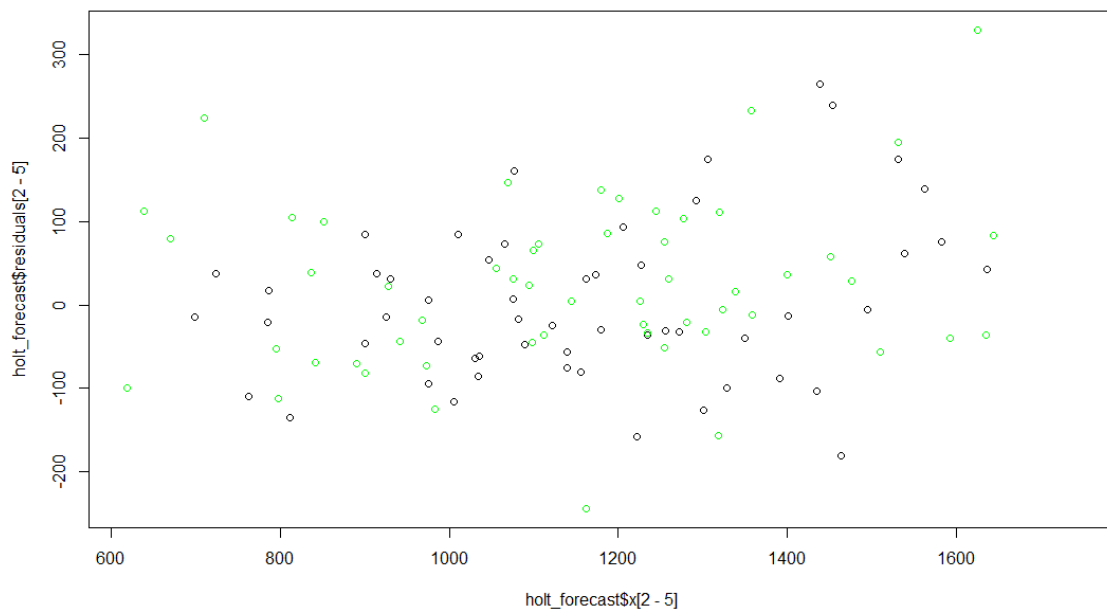
- Do a plot of fitted values vs. residuals. What does the plot indicate?

The fitted and residual variation is initially high, which eventually reduces  
`plot(holt_forecast$fitted[2-5],holt_forecast$residuals[2-5],col=c("red","green"))`

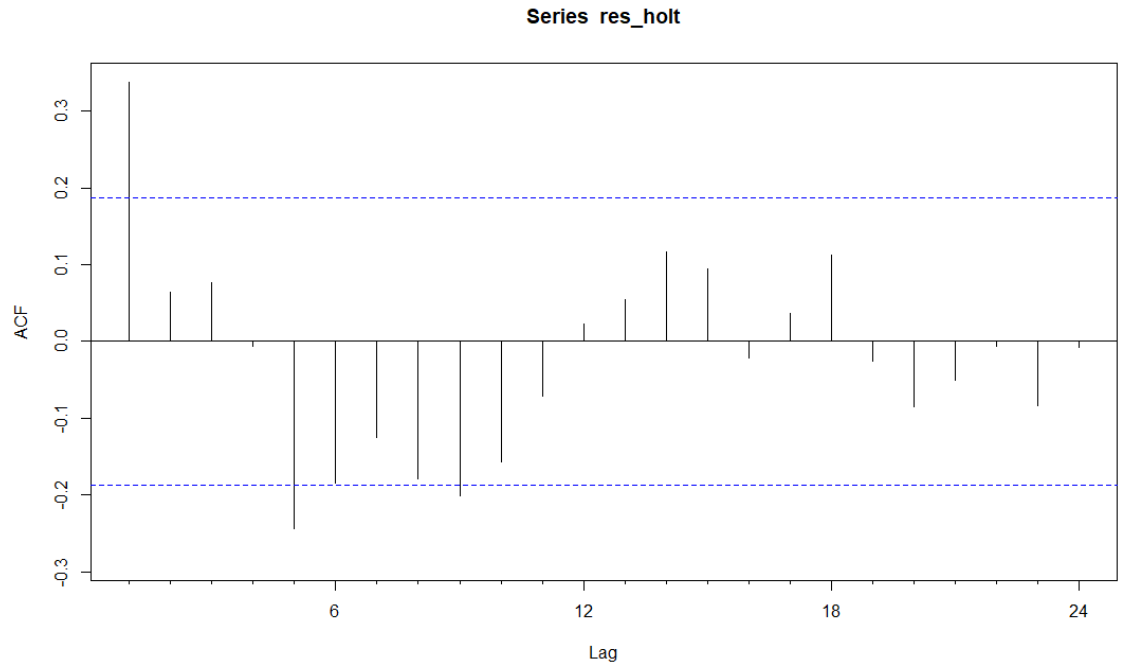




- Do a plot of actual values vs. residuals. What does the plot indicate?  
`plot(holt_forecast$x[2-5], holt_forecast$residuals[2-5], col=c("Green", "Black"))`  
 The forecasted and residual variation is initially high, which eventually reduces



- Do an ACF plot of the residuals? What does this plot indicate?  
 We can see that values are not very significant  
`Acf(res_holt)`



- Print the 5 measures of accuracy for this forecasting technique  
accuracy(holt\_forecast)

```
> accuracy(holt_forecast)
```

```

      ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
Training set 12.20904 99.58964 77.59005 0.7944291 6.939642 0.7170382 0.3374136

```

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

```
forecast(holt, h=12)
```

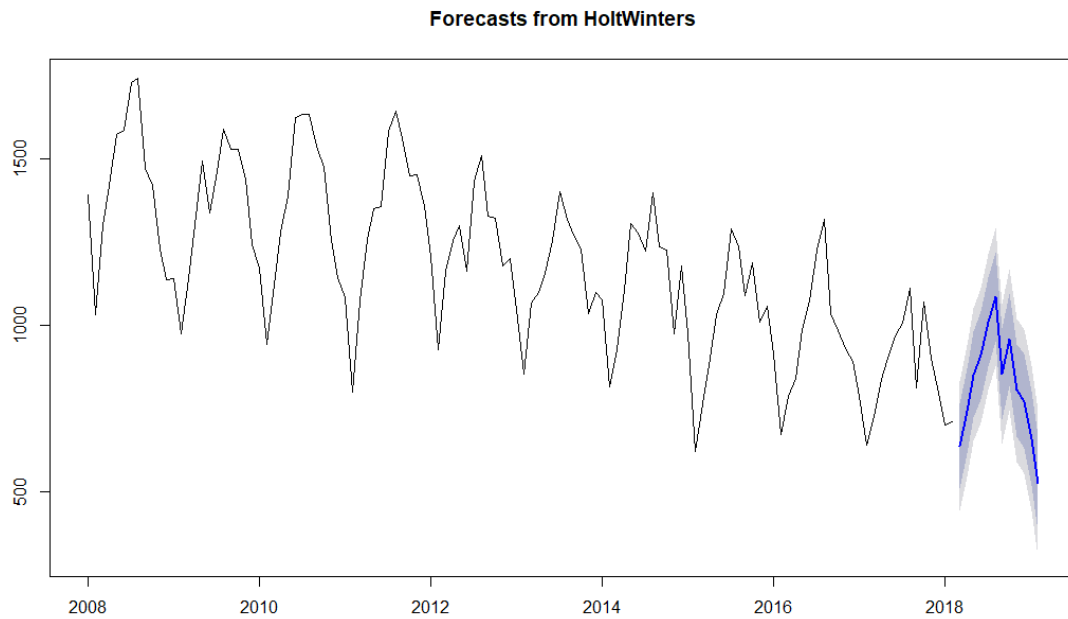
```
plot(forecast(holt, h=12))
```

```
> forecast(holt, h=12)
```

|          | Point Forecast | Lo 80    | Hi 80     | Lo 95    | Hi 95     |
|----------|----------------|----------|-----------|----------|-----------|
| Mar 2018 | 635.0188       | 507.7725 | 762.2651  | 440.4124 | 829.6252  |
| Apr 2018 | 741.3714       | 612.5219 | 870.2209  | 544.3132 | 938.4296  |
| May 2018 | 851.1765       | 720.7254 | 981.6276  | 651.6687 | 1050.6842 |
| Jun 2018 | 909.6484       | 777.5971 | 1041.6998 | 707.6933 | 1111.6035 |
| Jul 2018 | 1010.0735      | 876.4231 | 1143.7239 | 805.6729 | 1214.4741 |
| Aug 2018 | 1086.0376      | 950.7893 | 1221.2859 | 879.1931 | 1292.8820 |
| Sep 2018 | 853.1847       | 716.3394 | 990.0300  | 643.8979 | 1062.4715 |
| Oct 2018 | 957.0287       | 818.5872 | 1095.4701 | 745.3007 | 1168.7566 |
| Nov 2018 | 803.7899       | 663.7530 | 943.8269  | 589.6220 | 1017.9579 |
| Dec 2018 | 771.2101       | 629.5783 | 912.8420  | 554.6030 | 987.8173  |
| Jan 2019 | 659.8292       | 516.6029 | 803.0554  | 440.7835 | 878.8748  |
| Feb 2019 | 523.9171       | 379.0968 | 668.7375  | 302.4336 | 745.4007  |

```
> plot(forecast(holt, h=12))
```

```
> |
```



- Summarize this forecasting technique
  - How good is the accuracy?  
The MSE and MAPE is low, hence accuracy is high
  - What does it predict the value of time series will be in one year?  
The predicted value for Feb 2019 is 523.9171
  - Other observation  
No such notable observation.

## ARIMA or Box-Jenkins

- Is Time Series data stationary? How did you verify? Please post the output from one of the test

We perform the adf and kpss test to see if model is stationery. Since p value is <0.05 for ADF and not >0.05 for kpss, we can say that model is NOT stationery.

```
adf.test(crime_ts)
kpss.test(crime_ts)

> adf.test(crime_ts)

Augmented Dickey-Fuller Test

data: crime_ts
Dickey-Fuller = -9.1282, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

warning message:
In adf.test(crime_ts) : p-value smaller than printed p-value
> kpss.test(crime_ts)

KPSS Test for Level Stationarity

data: crime_ts
KPSS Level = 2.1832, Truncation lag parameter = 2, p-value = 0.01

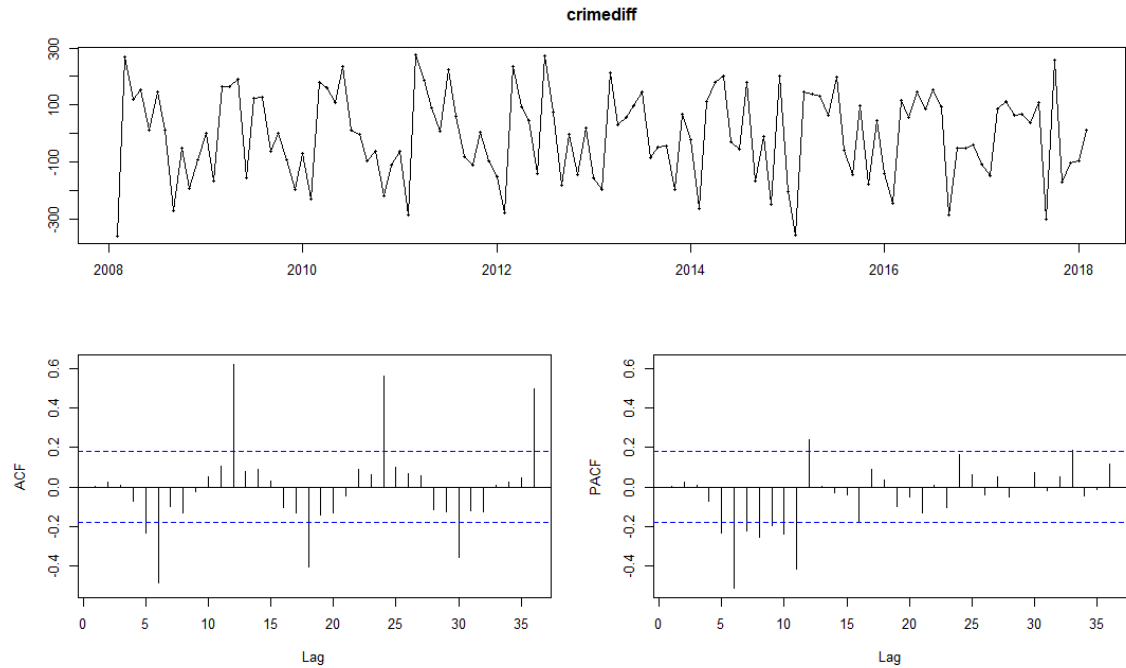
warning message:
In kpss.test(crime_ts) : p-value smaller than printed p-value
> |
```

- How many differences are needed to make it stationary?

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

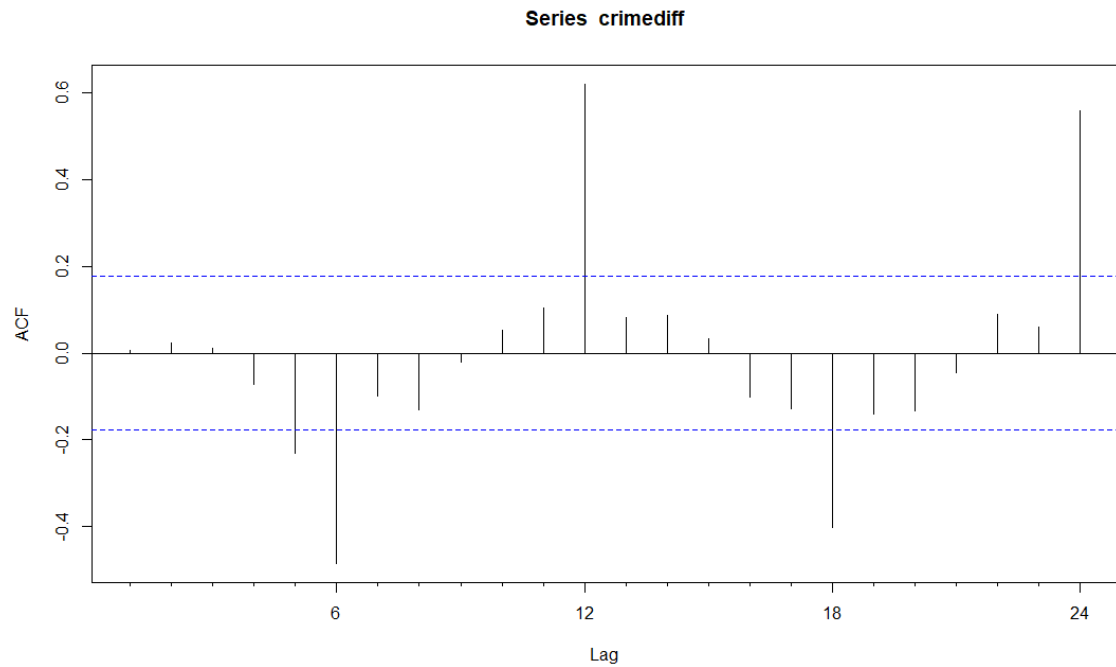
- Is Seasonality component needed?  
No, seasonal component is not needed.
- Plot the Time Series chart of the differenced series.

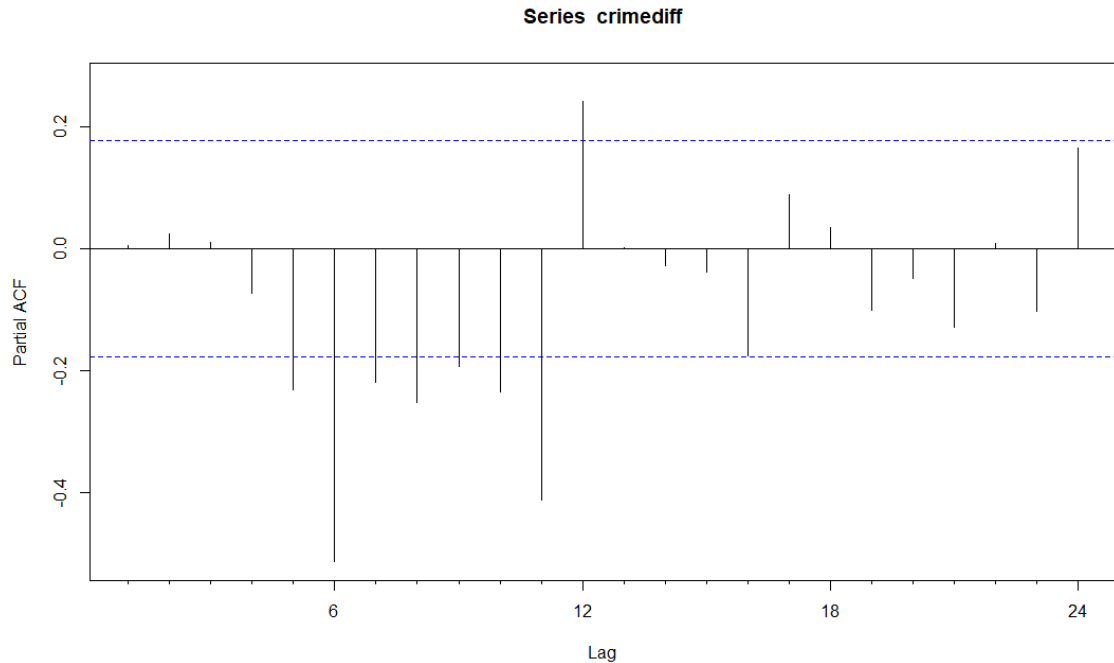
```
crimediff<- diff(crime_ts, differences=1)
tsdisplay(crimediff)
```



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

```
Acf(crimediff)
Pacf(crimediff)
```





- Based on the ACF and PACF, which are the possible ARIMA model possible?  
ARIMA(1,0,1)(0,1,1)  
auto.arima(crimediff)

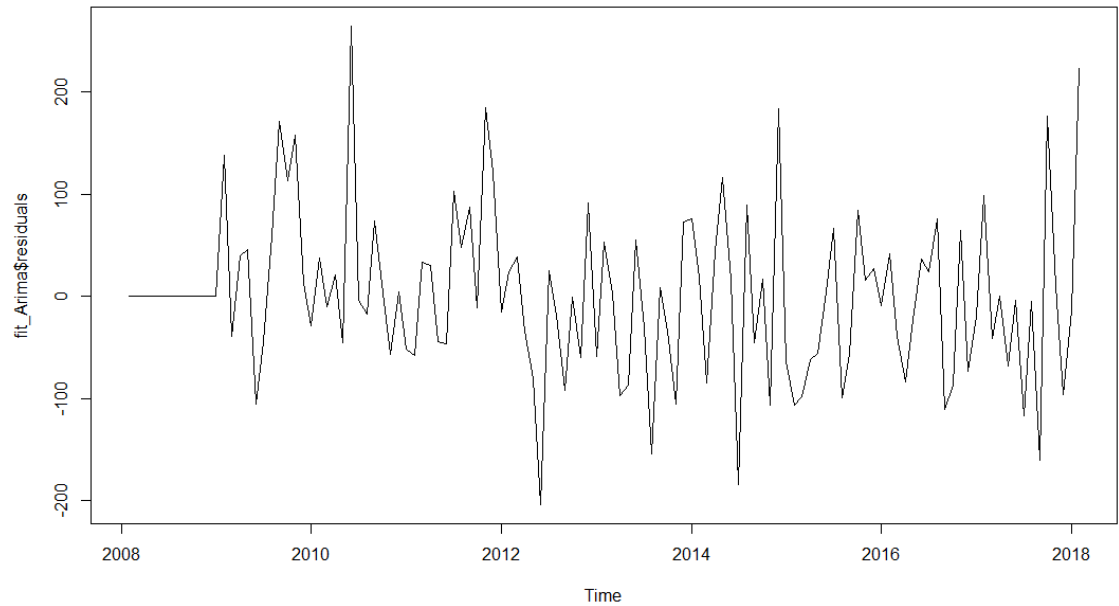
```
> auto.arima(crimediff)
Series: crimediff
ARIMA(1,0,1)(0,1,1)[12]

Coefficients:
      ar1      ma1      sma1
      0.4834 -0.9652 -0.7218
s.e.  0.1014  0.0512  0.1113

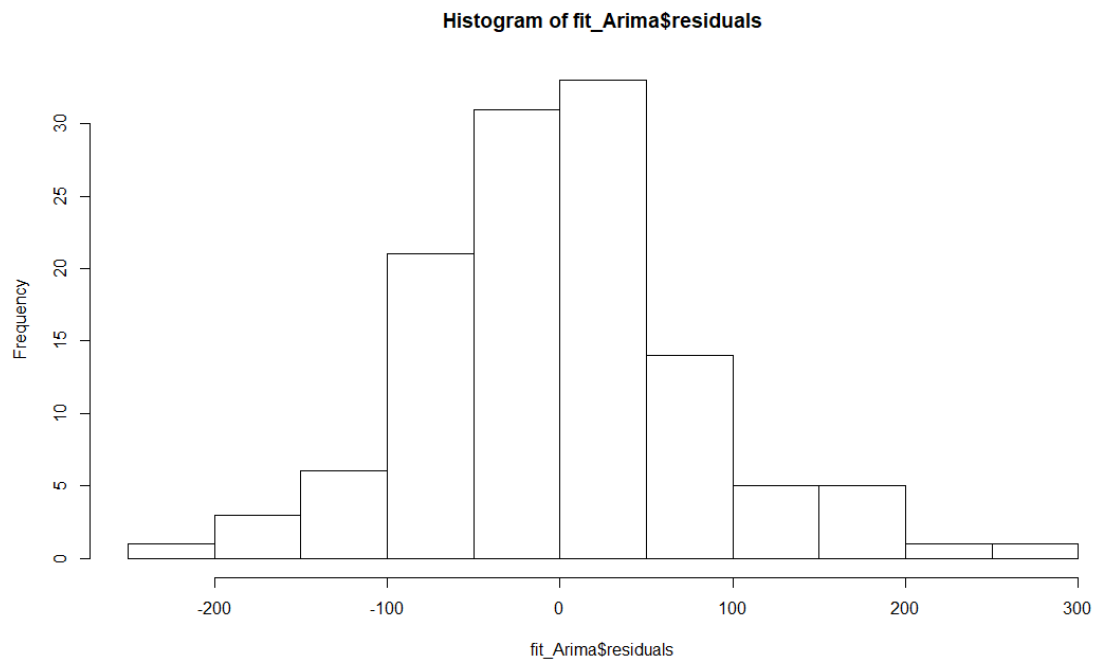
sigma^2 estimated as 7415:  log likelihood=-644.68
AIC=1297.37  AICC=1297.75  BIC=1308.13
> |
```

- Show the AIC, BIC and Sigma^2 for the possible models?  
  
sigma^2 estimated as 7415: log likelihood=-644.68  
AIC=1297.37 AICC=1297.75 BIC=1308.13
- Based on the above AIC, BIC and Sigma^2 values, which model will you select?  
ARIMA(1,0,1)(0,1,1)
- What is the final formula for ARIMA with the coefficients?  
p=1, d=0, q=1  
P=0, D=1, Q=1
- Perform Residual Analysis for this technique.
  - Do a plot of residuals. What does the plot indicate?  
Initially, residuals are zero, which fluctuate after 2010.

```
fit_Arima<-auto.arima(crimediff)
fit_Arima
plot(fit_Arima$residuals)
```



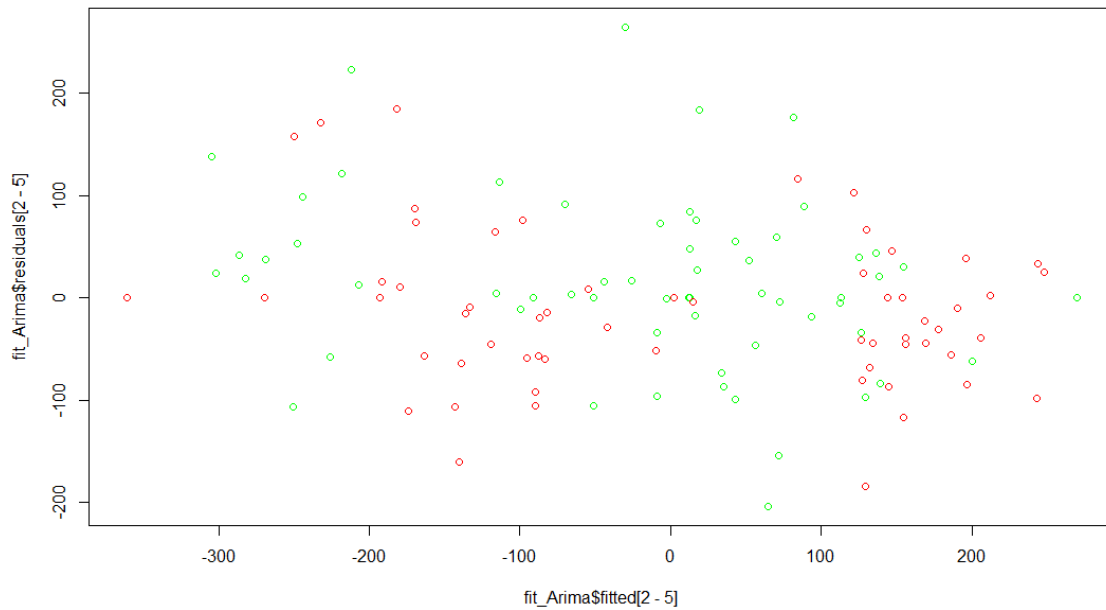
- Do a Histogram plot of residuals. What does the plot indicate?  
Data is almost symmetrical. Slightly right skewed  
`hist(fit_Arima$residuals)`



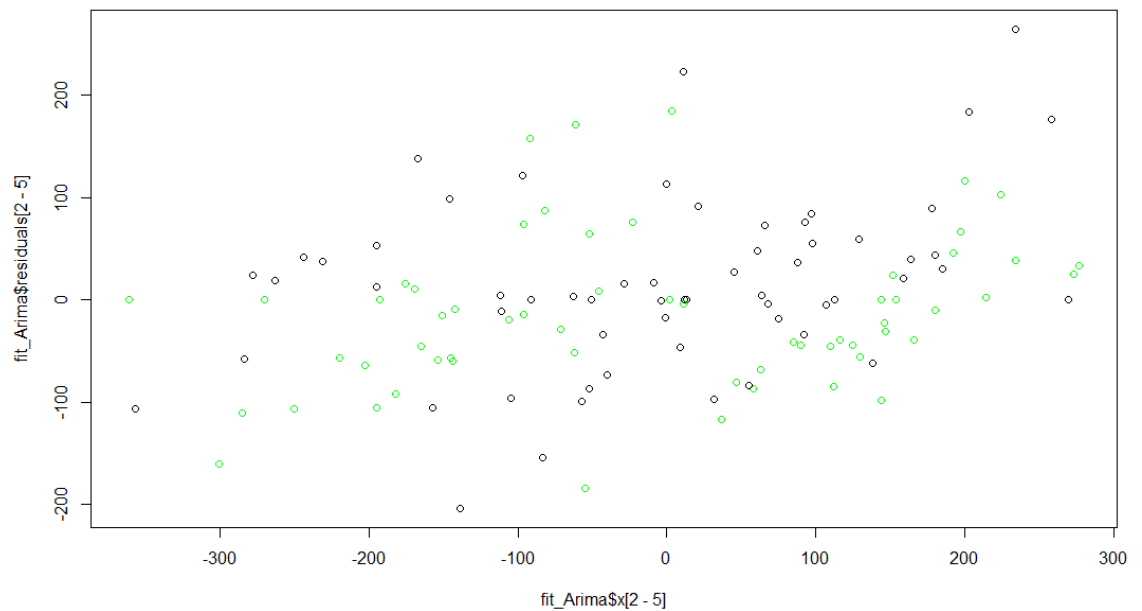
- Do a plot of fitted values vs. residuals. What does the plot indicate?

Initially, residuals are zero, which fluctuate later.

```
plot(fit_Arima$fitted[2-5],fit_Arima$residuals[2-5],col=c("red","green"))
```



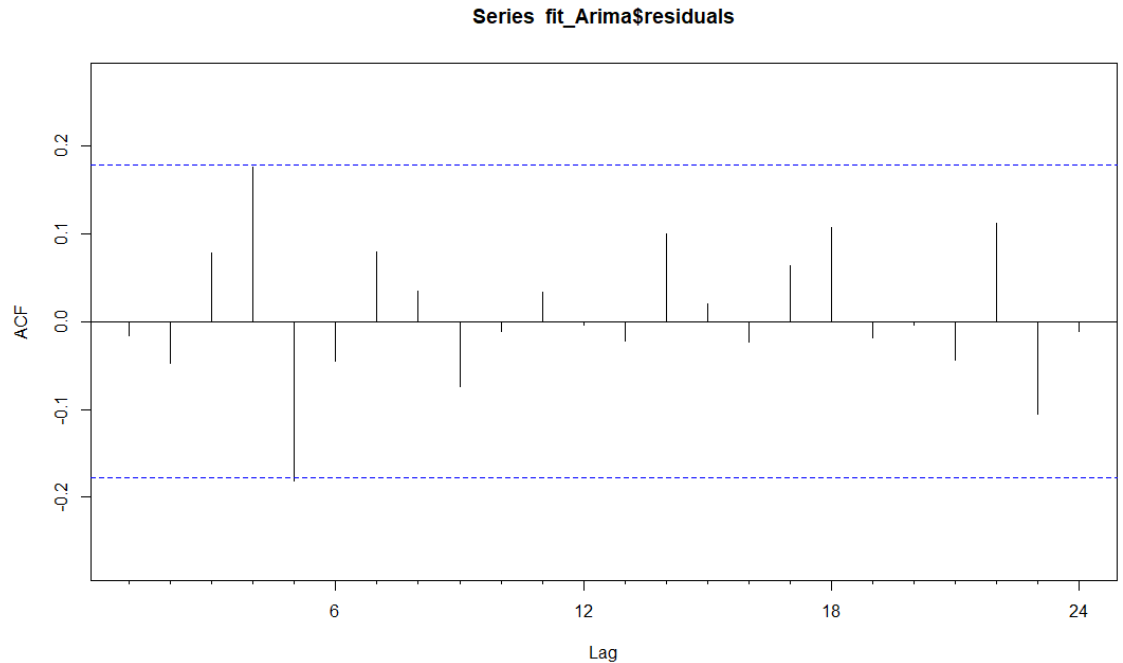
- Do a plot of actual values vs. residuals. What does the plot indicate?  
Initially, residuals are zero, which fluctuate later.  
(fit\_Arima\$x[2-5],fit\_Arima\$residuals[2-5],col=c("Green","Black"))



- Do an ACF plot of the residuals? What does this plot indicate?

We can see that only couple of values are significant  
Acf(fit\_Arima\$residuals)





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

```
> accuracy(fit_Arima)
```

```

              ME      RMSE      MAE  MPE  MAPE      MASE      ACF
Training set 0.5585606 80.59614 59.39053 Inf  Inf 0.6288069 -0.0152400
> |
```

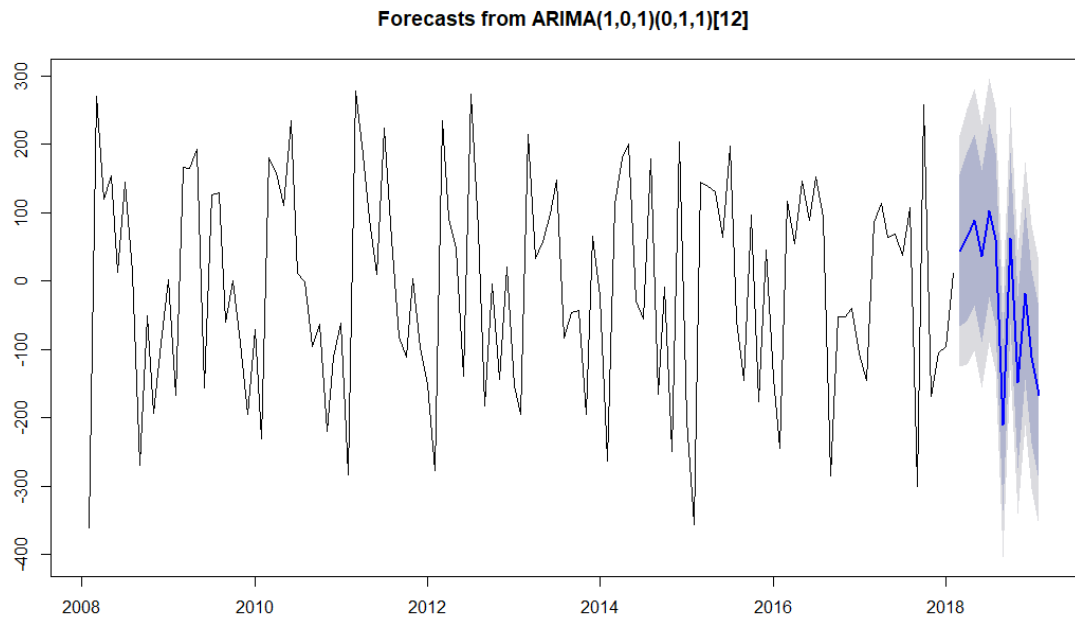
- Forecast
  - Next one year. Show table and plot

```
> forecast(fit_Arima, h=12)
```

|          | Point Forecast | Lo 80      | Hi 80     | Lo 95      | Hi 95     |
|----------|----------------|------------|-----------|------------|-----------|
| Mar 2018 | 44.04921       | -66.41948  | 154.51791 | -124.89808 | 212.99651 |
| Apr 2018 | 64.50171       | -58.04954  | 187.05296 | -122.92425 | 251.92768 |
| May 2018 | 89.14110       | -36.06586  | 214.34807 | -102.34643 | 280.62864 |
| Jun 2018 | 36.07212       | -89.74741  | 161.89164 | -156.35225 | 228.49648 |
| Jul 2018 | 103.18465      | -22.77760  | 229.14690 | -89.45799  | 295.82729 |
| Aug 2018 | 61.15065       | -64.84493  | 187.14624 | -131.54296 | 253.84427 |
| Sep 2018 | -210.95138     | -336.95473 | -84.94802 | -403.65688 | -18.24587 |
| Oct 2018 | 62.44329       | -63.56184  | 188.44842 | -130.26493 | 255.15151 |
| Nov 2018 | -148.34246     | -274.34781 | -22.33711 | -341.05101 | 44.36610  |
| Dec 2018 | -18.38280      | -144.38736 | 107.62177 | -211.09015 | 174.32455 |
| Jan 2019 | -110.83451     | -236.83532 | 15.16629  | -303.53611 | 81.86708  |
| Feb 2019 | -166.79065     | -292.77505 | -40.80626 | -359.46716 | 25.88585  |

```
> plot(forecast(fit_Arima, h=12))
```

```
> |
```



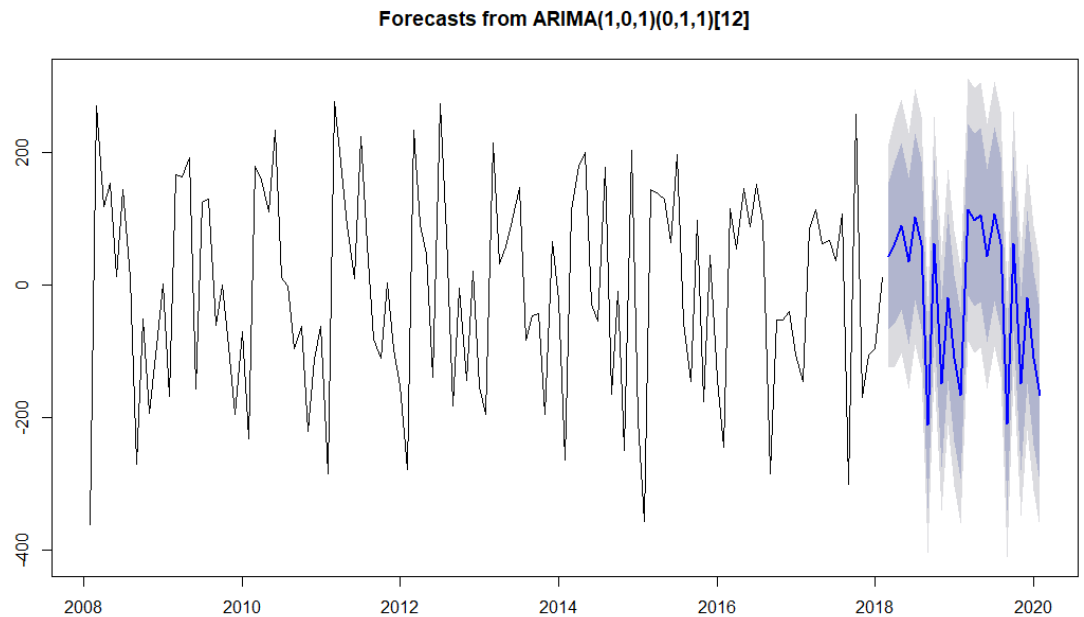
- Next two years. Show table and plot

```
> forecast(fit_Arima, h=24)
```

|          | Point Forecast | Lo 80      | Hi 80     | Lo 95      | Hi 95     |
|----------|----------------|------------|-----------|------------|-----------|
| Mar 2018 | 44.04921       | -66.41948  | 154.51791 | -124.89808 | 212.99651 |
| Apr 2018 | 64.50171       | -58.04954  | 187.05296 | -122.92425 | 251.92768 |
| May 2018 | 89.14110       | -36.06586  | 214.34807 | -102.34643 | 280.62864 |
| Jun 2018 | 36.07212       | -89.74741  | 161.89164 | -156.35225 | 228.49648 |
| Jul 2018 | 103.18465      | -22.77760  | 229.14690 | -89.45799  | 295.82729 |
| Aug 2018 | 61.15065       | -64.84493  | 187.14624 | -131.54296 | 253.84427 |
| Sep 2018 | -210.95138     | -336.95473 | -84.94802 | -403.65688 | -18.24587 |
| Oct 2018 | 62.44329       | -63.56184  | 188.44842 | -130.26493 | 255.15151 |
| Nov 2018 | -148.34246     | -274.34781 | -22.33711 | -341.05101 | 44.36610  |
| Dec 2018 | -18.38280      | -144.38736 | 107.62177 | -211.09015 | 174.32455 |
| Jan 2019 | -110.83451     | -236.83532 | 15.16629  | -303.53611 | 81.86708  |
| Feb 2019 | -166.79065     | -292.77505 | -40.80626 | -359.46716 | 25.88585  |
| Mar 2019 | 113.19226      | -16.49498  | 242.87949 | -85.14725  | 311.53176 |
| Apr 2019 | 97.92719       | -32.60138  | 228.45576 | -101.69903 | 297.55341 |
| May 2019 | 105.29982      | -25.42459  | 236.02422 | -94.62591  | 305.22554 |
| Jun 2019 | 43.88364       | -86.88649  | 174.65377 | -156.11202 | 243.87930 |
| Jul 2019 | 106.96094      | -23.81988  | 237.74175 | -93.05106  | 306.97293 |
| Aug 2019 | 62.97620       | -67.80710  | 193.75951 | -137.03961 | 262.99202 |
| Sep 2019 | -210.06886     | -340.85274 | -79.28498 | -410.08554 | -10.05217 |
| Oct 2019 | 62.86992       | -67.91405  | 193.65390 | -137.14690 | 262.88675 |
| Nov 2019 | -148.13621     | -278.92002 | -17.35241 | -348.15278 | 51.88035  |
| Dec 2019 | -18.28310      | -149.06605 | 112.49986 | -218.29837 | 181.73218 |
| Jan 2020 | -110.78631     | -241.56563 | 19.99300  | -310.79601 | 89.22339  |
| Feb 2020 | -166.76735     | -297.53086 | -36.00384 | -366.75288 | 33.21818  |

```
> plot(forecast(fit_Arima, h=24))
```

```
> plot(forecast(fit_Arima, h=12))
```



- Summarize this forecasting technique
  - How good is the accuracy?  
MASE is 0.62, which is low, hence accuracy is good.
  - What does it predict time series will be in one year and next two years?  
Prediction for Feb 2019 is -166.790  
Prediction for Feb 2020 is -166.767
  - Other observation  
Point forecast is highly fluctuating every month.

## Accuracy Summary

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

|                        | ME       | RMSE     | MAE      | MPE     | MAPE     | MASE     | ACF1     |
|------------------------|----------|----------|----------|---------|----------|----------|----------|
| Naïve                  | -5.63636 | 153.4663 | 129.1074 | -1.6263 | 12.004   | 1.1931   | 0.006097 |
| Simple Moving Averages | -6.3984  | 80.3493  | 62.6294  | 0.86532 | 5.6647   | 0.5787   | 0.05803  |
| Simple Smoothing       | -5.5862  | 152.83   | 128.0557 | -1.612  | 11.906   | 1.18341  | 0.00542  |
| Holt winters           | 12.20904 | 99.589   | 77.59    | 0.7944  | 6.939642 | 0.717038 | 0.3374   |
| ARIMA                  | 0.558    | 80.596   | 59.390   | inf     | inf      | 0.6288   | -0.0152  |

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

For naïve forecasts, we simply set all forecasts to be the value of the last observation. This method works remarkably well for many economic and financial time series.

Simple Moving Average is a method of time series smoothing and is a very basic forecasting technique. It does not need estimation of parameters, but rather is based on order selection.

The simple exponential smoothing method does not account for any trend or seasonal components, rather, it only uses the decreasing weights to forecast future results. This makes the method suitable only for time series without trend and seasonality.

Holt-Winters method, is one of the many methods or algorithms that can be used to forecast data points in a series, provided that the series is “seasonal”, i.e. repetitive over some period.

An autoregressive integrated moving average (ARIMA) model is a form of regression analysis that gauges the strength of one dependent variable relative to other changing variables. The model's goal is to predict future securities or financial market moves by examining the differences between values in the series instead of through actual values.

ME is best for ARIMA  
 RMSE is best for SMA  
 MAE is best for ARIMA  
 MPE is best for SMA  
 MAPE is best for SMA  
 MASE is best for SMA

## Conclusion

- Summarize your analysis of time series value over the time-period.
  - We observe a seasonality with crime rate being low in February and high in August.
  - Since there is overall downward trend, crime rate is predicted to drop in the coming years.
  - From Feb to June there is rising trend and Aug to Dec is falling trend.
- Based on your 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 our analysis and forecast, the crime rate is predicted to reduce over the next year and the following year as well
- Rank forecasting methods that best forecast for this time series based on historical values.
  - ARIMA
  - Simple Moving Averages
  - Holts Winters
  - Simple Smoothing
  - Naive

## Final Question

- If you were me, what final grade would you give yourself for this class?

I would give myself an A.

- Indicate the reasons why you gave yourself this grade?

I feel I have had an active participation in the class throughout, completed the assignments and exams satisfactorily in a timely manner.

---

R code:

```
#Final_exam_Asher
```

```
View(crimes)
crime_ts <- ts(crimes$Data, start=c(2008,1),frequency = 12)
plot(crime_ts)
summary(crime_ts)
boxplot(crime_ts)
decomp<-decompose(crime_ts)
plot(decomp)
decomp$type
decomp$seasonal
```

```
library(fpp)
temp_sesadjust<-seasadj(decomp)
plot(crime_ts)
lines(temp_sesadjust,col='red')
```

```
#Naive
naive_forecast<-naive(crime_ts,12)
plot(naive_forecast)
```

```
residual_analysis<-residuals(naive_forecast)
plot(residual_analysis)
```

```
histo<-hist(residual_analysis,breaks =10,main = "Histogram of residuals")
plot(naive_forecast$fitted[2-5],naive_forecast$residuals[2-5],col=c("red","blue"))
plot(naive_forecast$x[2-5],naive_forecast$residuals[2-5],col=c("red","blue"))
Acf(residual_analysis)
```

```
accuracy(naive_forecast)
```

```
naive_fore<- forecast(naive_forecast, h=12)
naive_fore
plot(naive_fore)
```

```
#SMA
ma_fore<-ma(crime_ts, order=1)
plot(ma_fore)
```

```
#forecast for accuracy table

ma_forecast<-forecast(ma_fore, h=12)
ma_forecast
accuracy(ma_forecast)

ma3_fore<-ma(crime_ts, order=3)
lines(ma3_fore,col="red",lwd=3)

ma6_fore<-ma(crime_ts, order=6)
lines(ma6_fore,col="blue",lwd=3)

ma9_fore<-ma(crime_ts, order=9)
lines(ma9_fore,col="green",lwd=3)

ets_forecast <- ets(crime_ts)
fore_ets<-forecast.ets(ets_forecast, h=12)
fore_ets
plot(fore_ets)

#smoothing
library (fpp)
ses(crime_ts, h=12)
summary(ses(crime_ts, h=12))

ses_fore <- ses(crime_ts, h=12)
ses_residual_ana <- residuals(ses_fore)
ses_residual_ana
plot(ses_residual_ana)

hist(ses_residual_ana)

fit_s<-ses_fore$fitted
fit_s
plot(fit_s[2-5],ses_residual_ana[2-5], col=c("Red","Green"))

actual<-ses_fore$x
plot(actual[2-5],ses_residual_ana[2-5],col=c("Blue","Green"))

Acf(ses_residual_ana)
accuracy(ses_fore)
forecast(ses_fore, h=12)
plot(forecast(ses_fore, h=12))
summary(ses_fore)

#Holt winters
holt<-HoltWinters(crime_ts)
holt_forecast<-forecast(holt, h=12)
holt_forecast
plot(holt_forecast)
```

```
sd(complete.cases(holt_forecast$residuals))

res_holt<-residuals(holt)
plot(res_holt)
hist(res_holt)

plot(holt_forecast$fitted[2-5],holt_forecast$residuals[2-5],col=c("red","green"))
plot(holt_forecast$x[2-5],holt_forecast$residuals[2-5],col=c("Green","Black"))
Acf(res_holt)
accuracy(holt_forecast)

forecast(holt, h=12)
plot(forecast(holt, h=12))

# ARIMA
crime_ts
adf.test(crime_ts)
kpss.test(crime_ts)
ndiffs(crime_ts)

crimediff<- diff(crime_ts, differences=1)
tsdisplay(crimediff)

Acf(crimediff)
Pacf(crimediff)
tsdisplay(crime_ts)

acf(crimediff, lag.max=20)

Acf(crimediff, lag.max=20, plot=FALSE)

Pacf(crimediff, lag.max=20)
Pacf(crimediff, lag.max=20, plot=FALSE)

fit_Arima<-auto.arima(crimediff)
fit_Arima
plot(fit_Arima$residuals)
hist(fit_Arima$residuals)
Acf(fit_Arima$residuals)

plot(fit_Arima$fitted[2-5],fit_Arima$residuals[2-5],col=c("red","green"))
plot(fit_Arima$x[2-5],fit_Arima$residuals[2-5],col=c("Green","Black"))
accuracy(fit_Arima)
forecast(fit_Arima, h=12)
plot(forecast(fit_Arima, h=12))

forecast(fit_Arima, h=24)
plot(forecast(fit_Arima, h=24))
```