Business Forecasting

Mac Sales

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Business Forecasting Mid-Term Exam

Introduction

Apple makes great consumer technology products. Even with cheaper options available, their market share and profits keep increasing. We will look at quarterly sales data for Mac to forecast future sales. Data has been provided to you as well as the commands to import the dataset as a time series.

Import Data

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

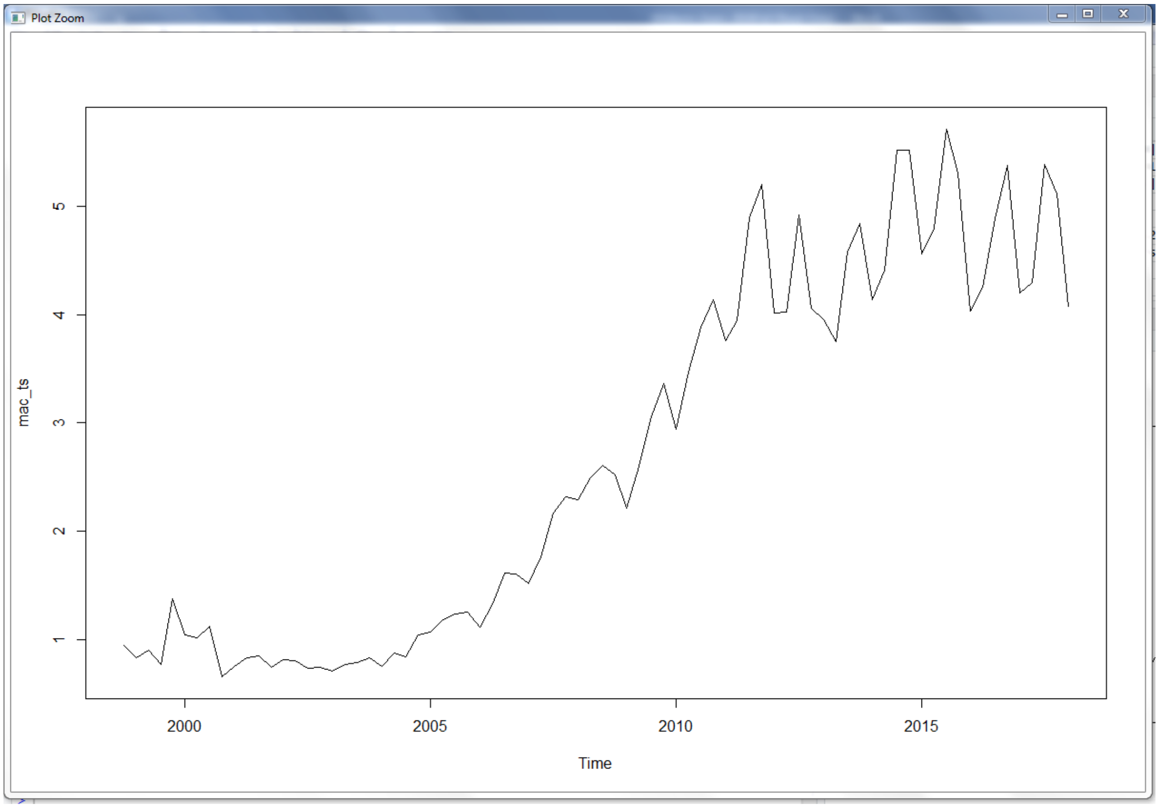
- library(readr)
- apple_data <- read_csv("C:/Users/rrparikh/Desktop/apple_data.csv")
- View(apple_data)
- plot(mac_sales)
- mac_ts <- ts(mac_sales,start=c(1998,4),frequency = 4)
- plot(mac_ts)

Plot and Inference

- Show a time series plot.

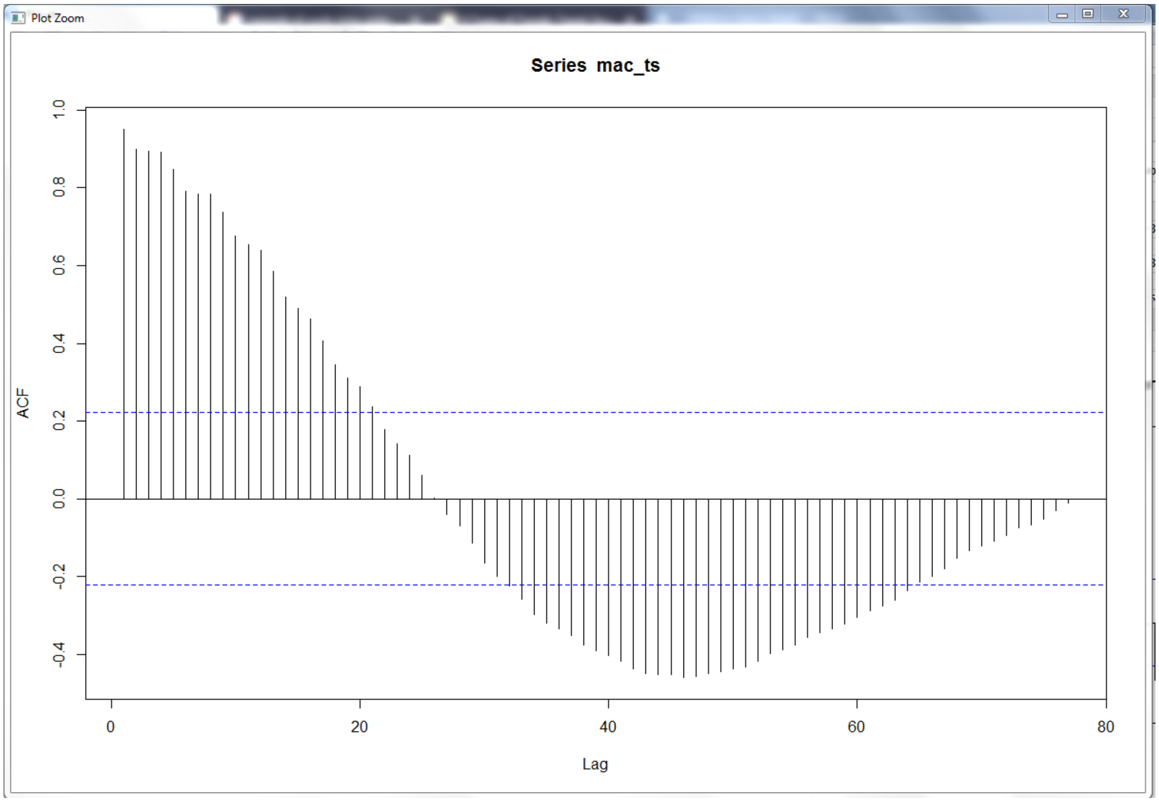
  mac_ts <- ts(apple_data$Mac,start=c(1998,4),end=c(2018,1),frequency = 4)

  plot(mac_ts)



- Please summaries your observations of the times series plot

Time series has trend, seasonality and cycle the as shown below

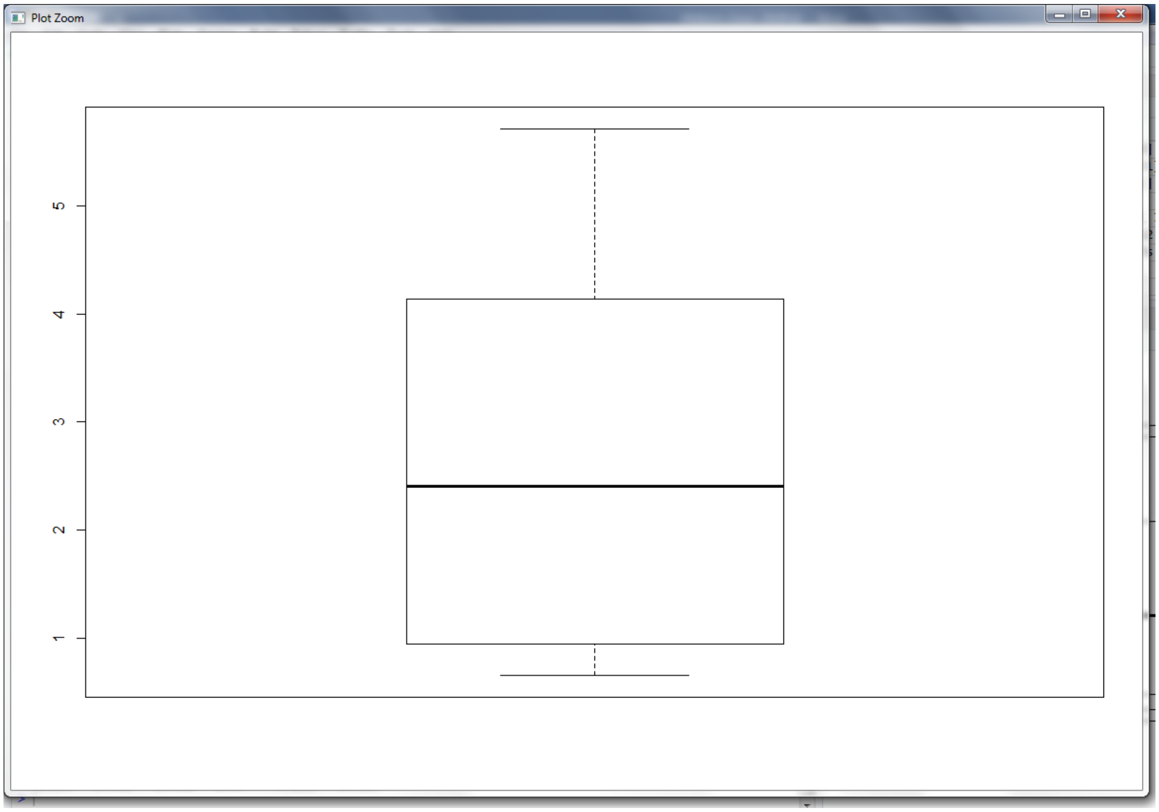


Central Tendency

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

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.659   0.962   2.408   2.677   4.136   5.710 
```

- Show the box plot.

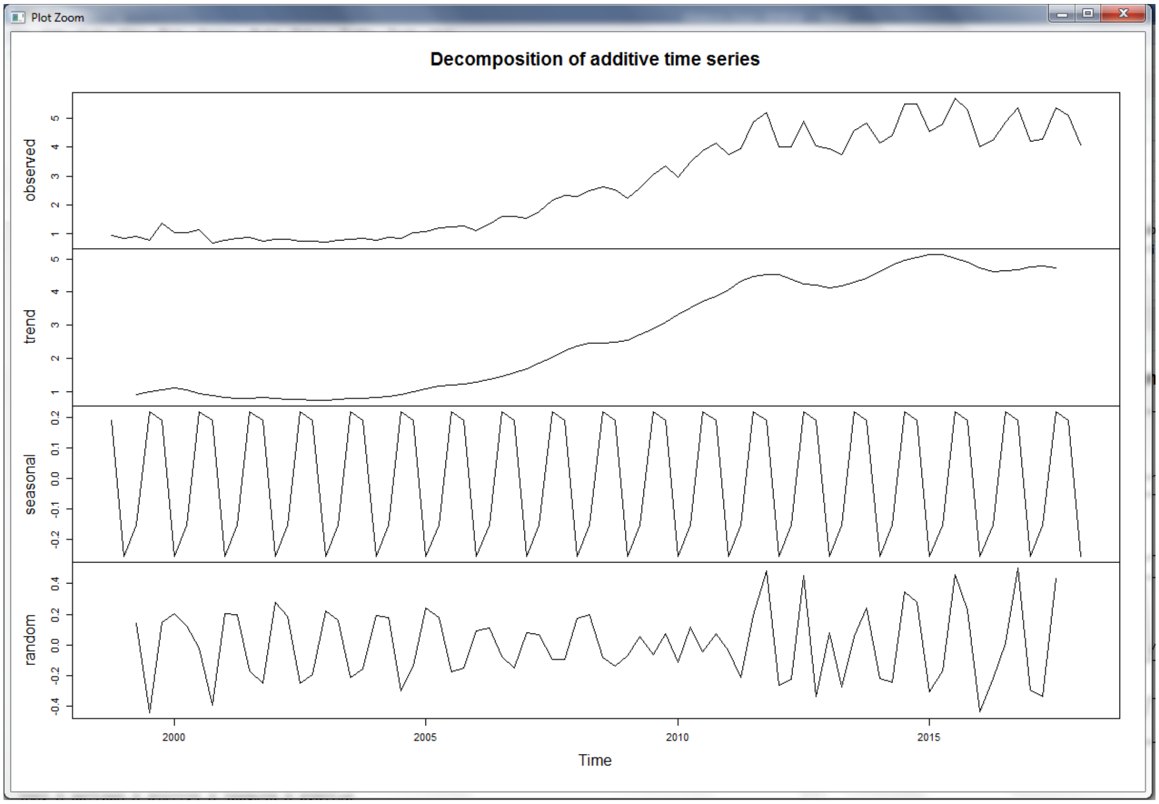


- Can you summarize your observation about the time series from the summary stats and box plot?

Mean is greater than median; the time series is skewed. There are outliers that in very few quarters there is either very high or very low Mac books sales, but on an average quarterly sale is 2.677, but most of the time 2.408 as there is skewness.

Decomposition

- Plot the decomposition of the time series.



- Is the times series seasonal?

Yes, it has seasonal component

- Is the decomposition additive or multiplicative?

additive

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

```
     seasonal
Q4  0.1963016
Q1 -0.2631489
Q2 -0.1546814
Q3  0.2215288
```

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

Quarter 4-September, October, November, December - it is high

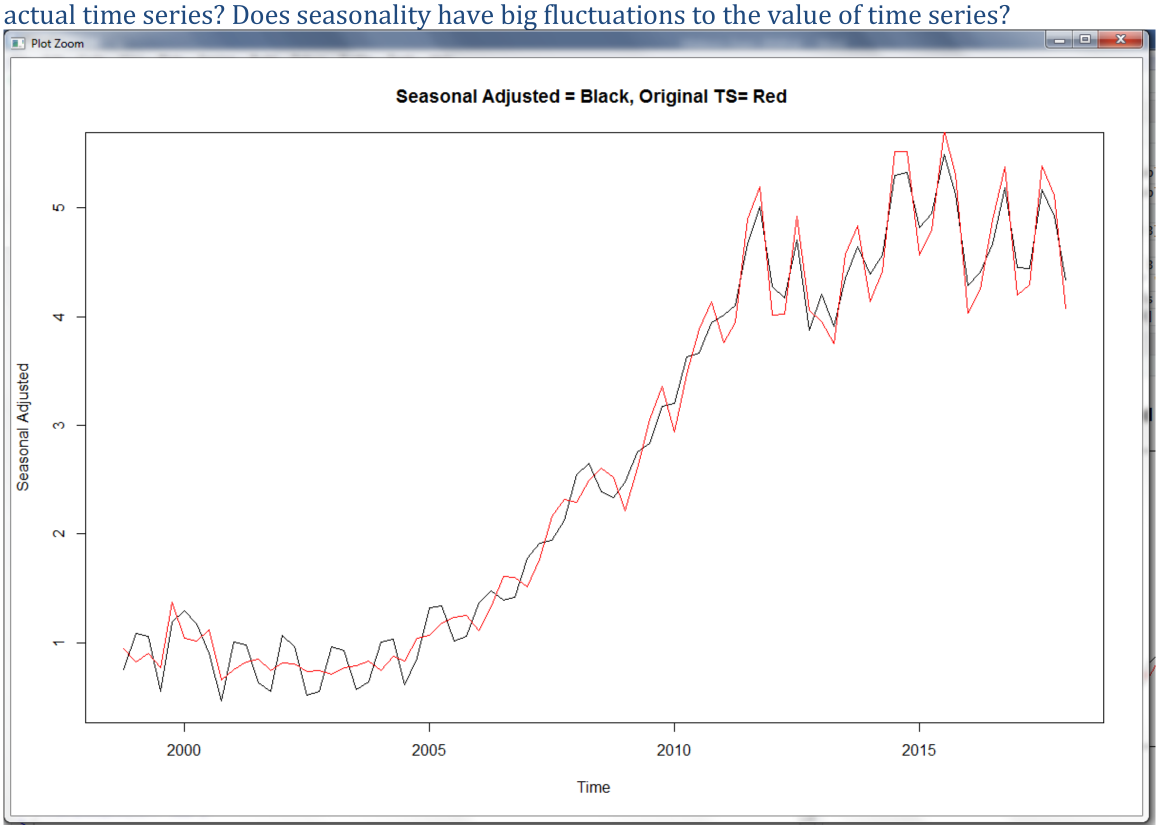
Quarter 1- January, February, March, April it is low

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

Quarter 4 it is high may be because Apple gives good deals or offers for festivals like: black Friday, Thanks giving, new year, Christmas

Quarter 1 it is low because whoever wanted to buy, will mostly buy during festive season with good offers and deals. Moreover, one more reason is people ran out of budget after festive celebration and winter vacation.

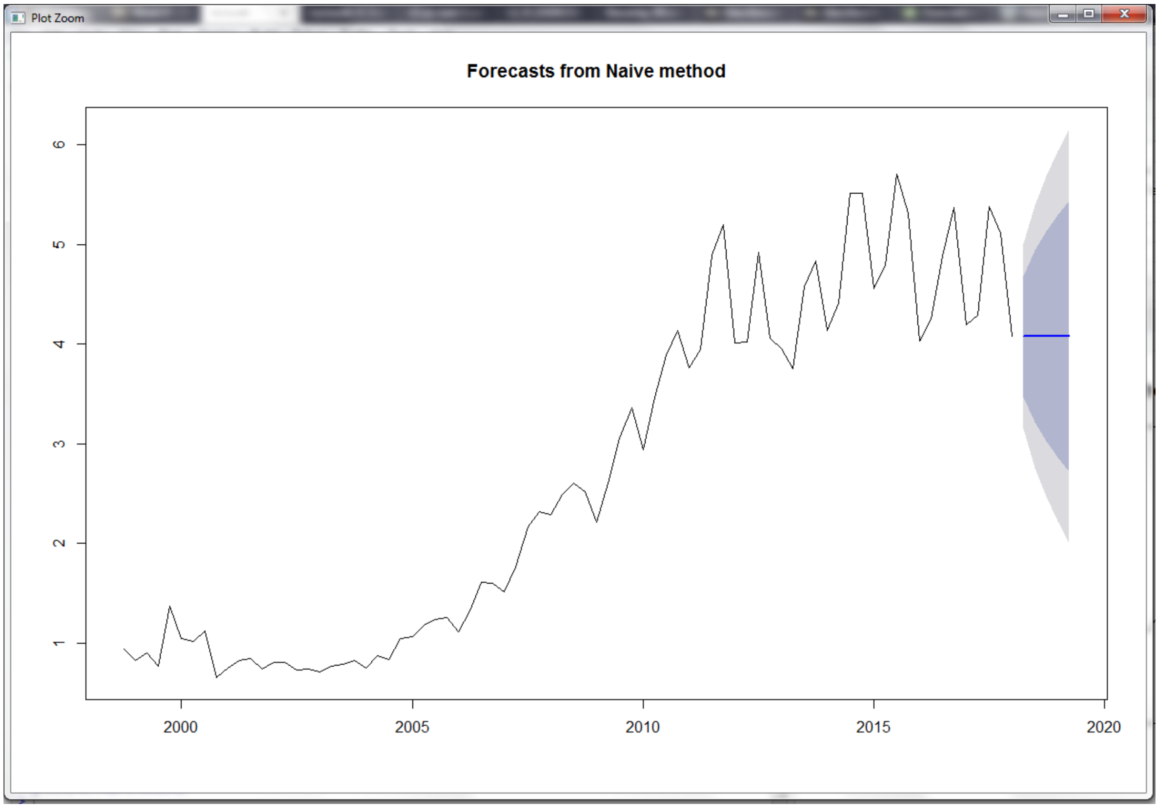
- Show the plot for time series adjusted for seasonality. Overlay this with the line for actual time series? Does seasonality have big fluctuations to the value of time series?



No, overall seasonality does not have big fluctuations to the value of the time series.

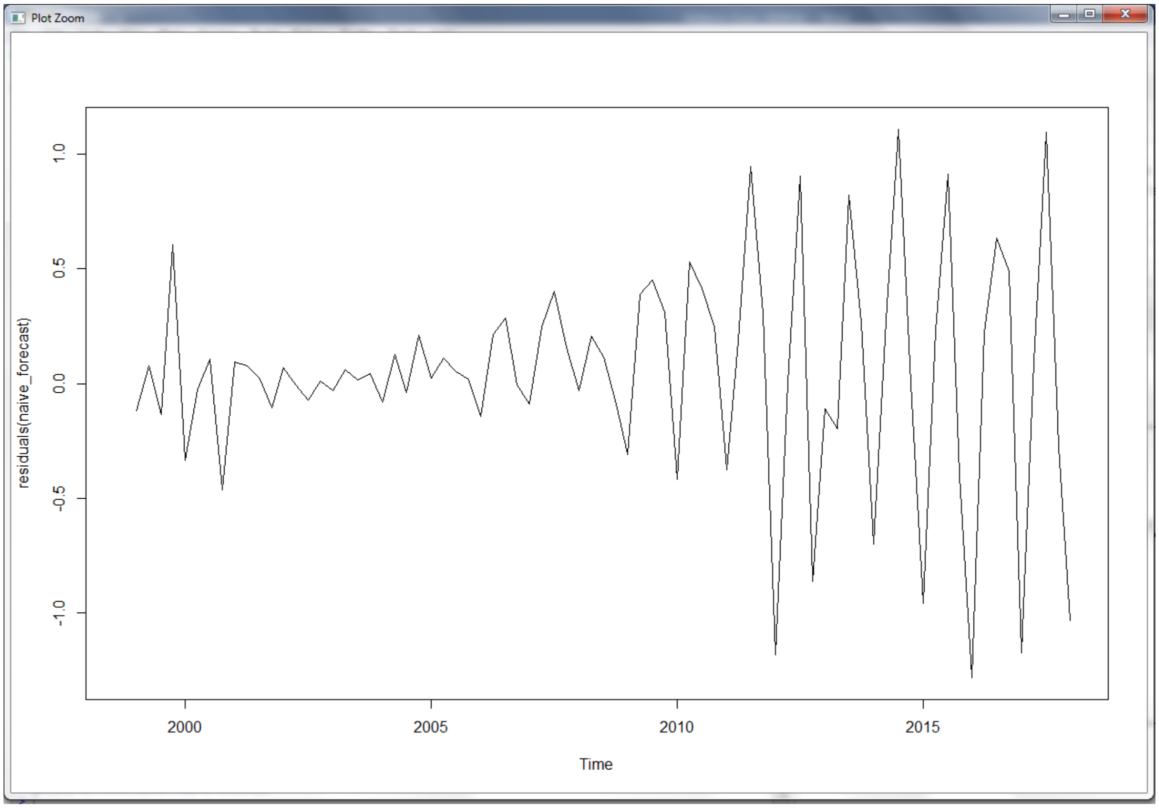
Naïve Method

- Output



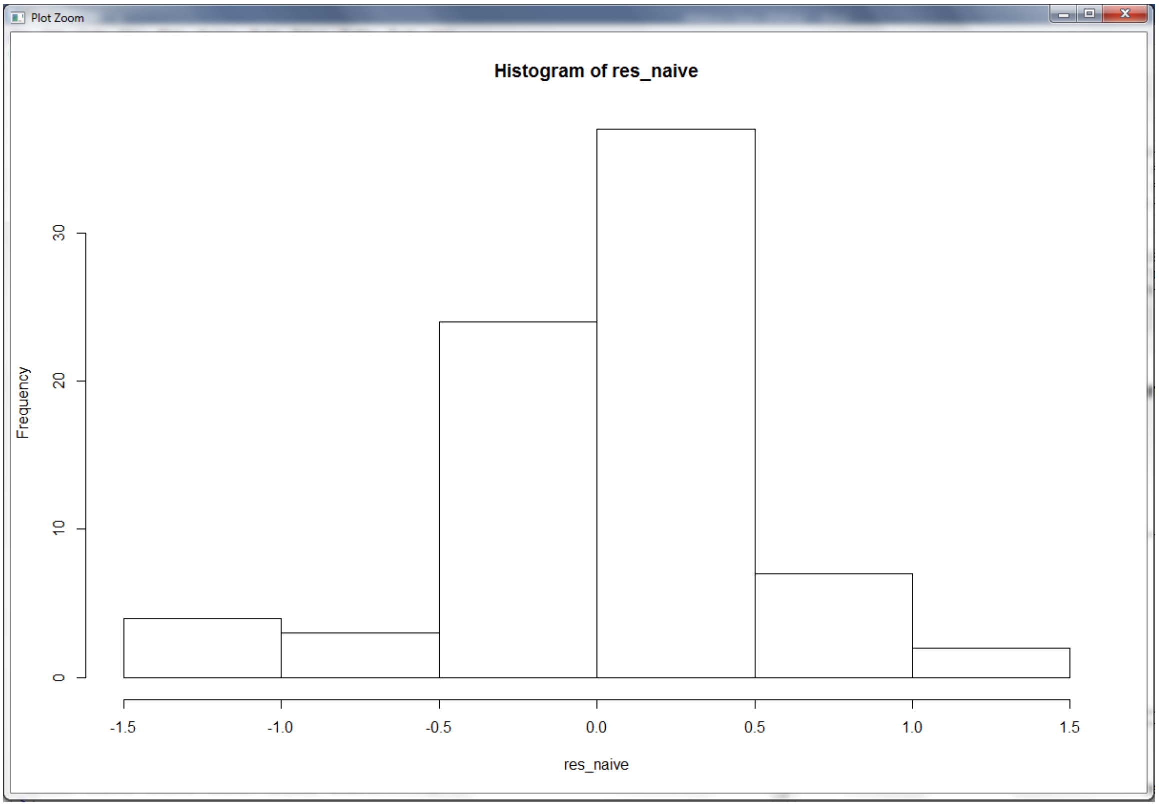
- Perform Residual Analysis for this technique.
    - Do a plot of residuals. What does the plot indicate?

There is a pattern in residual, indicates that it is not a good model



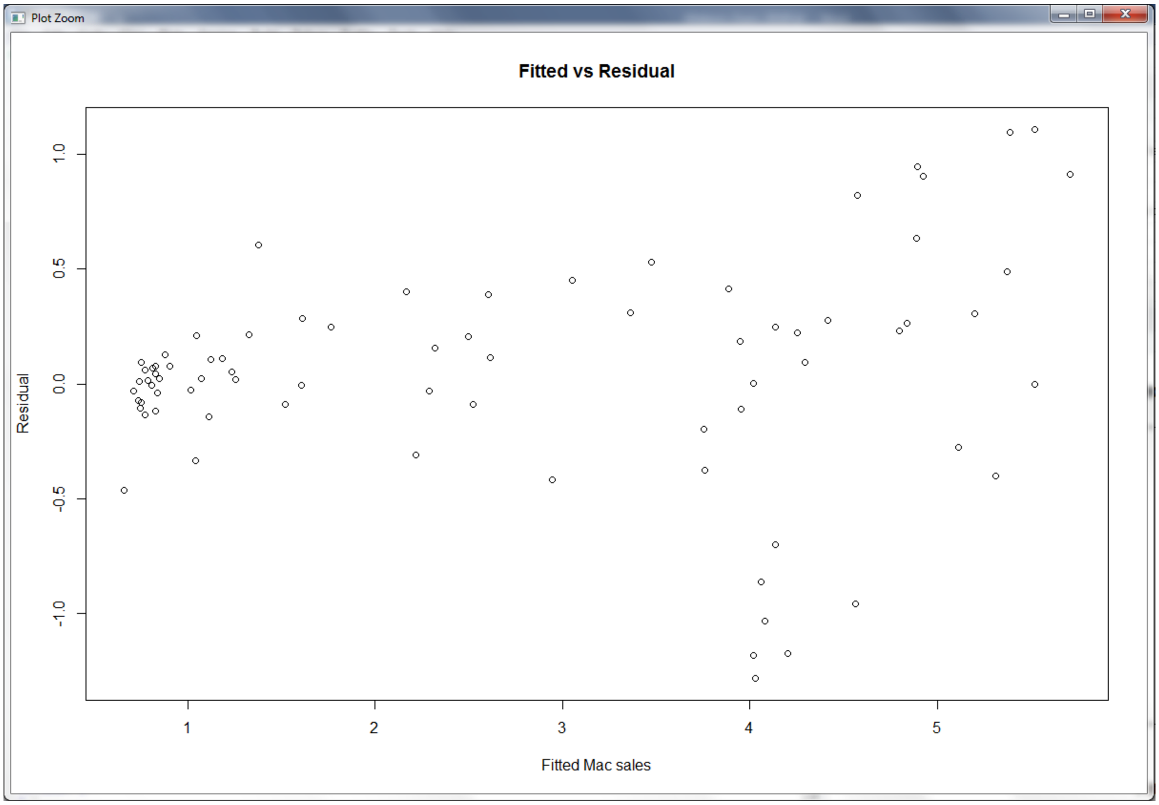
- Do a Histogram plot of residuals. What does the plot indicate?

Histogram suggests that residual is not normally distributed but skewed



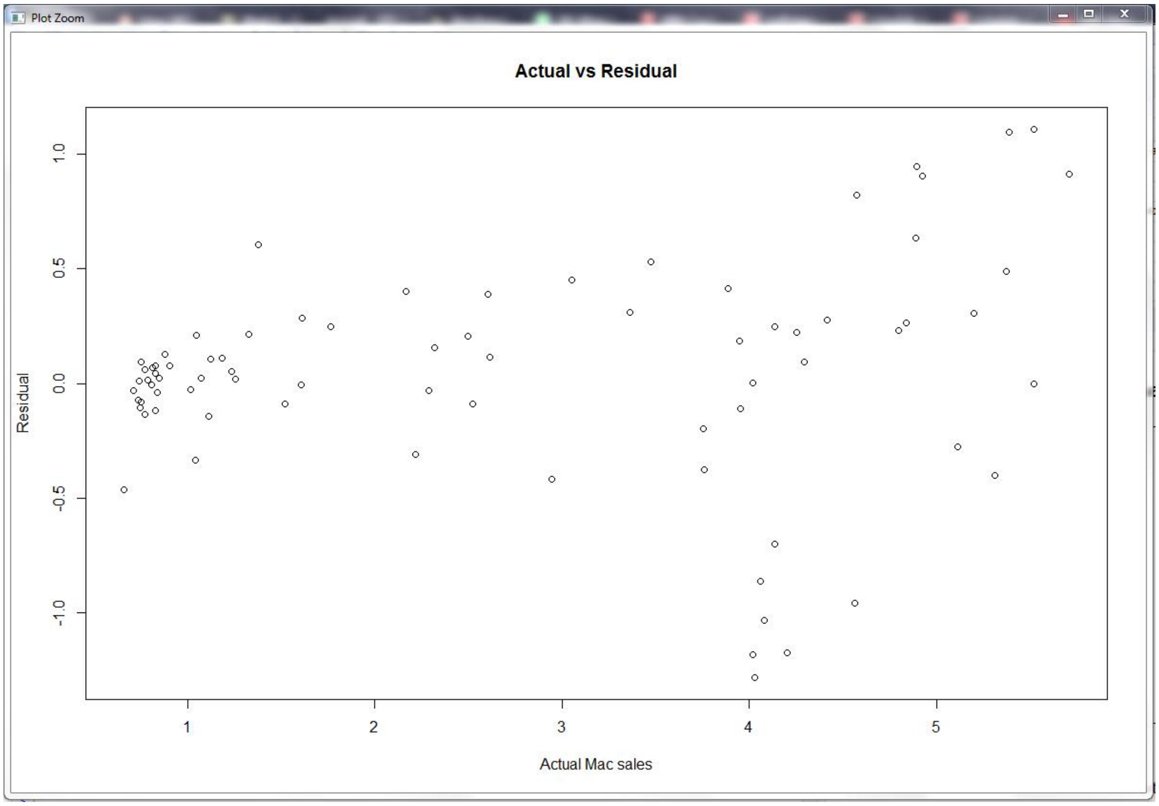
- Do a plot of fitted values vs. residuals. What does the plot indicate?

The Plot indicates funnel shape (variance increasing with x), indicates there is scope for improvement in the forecasting model



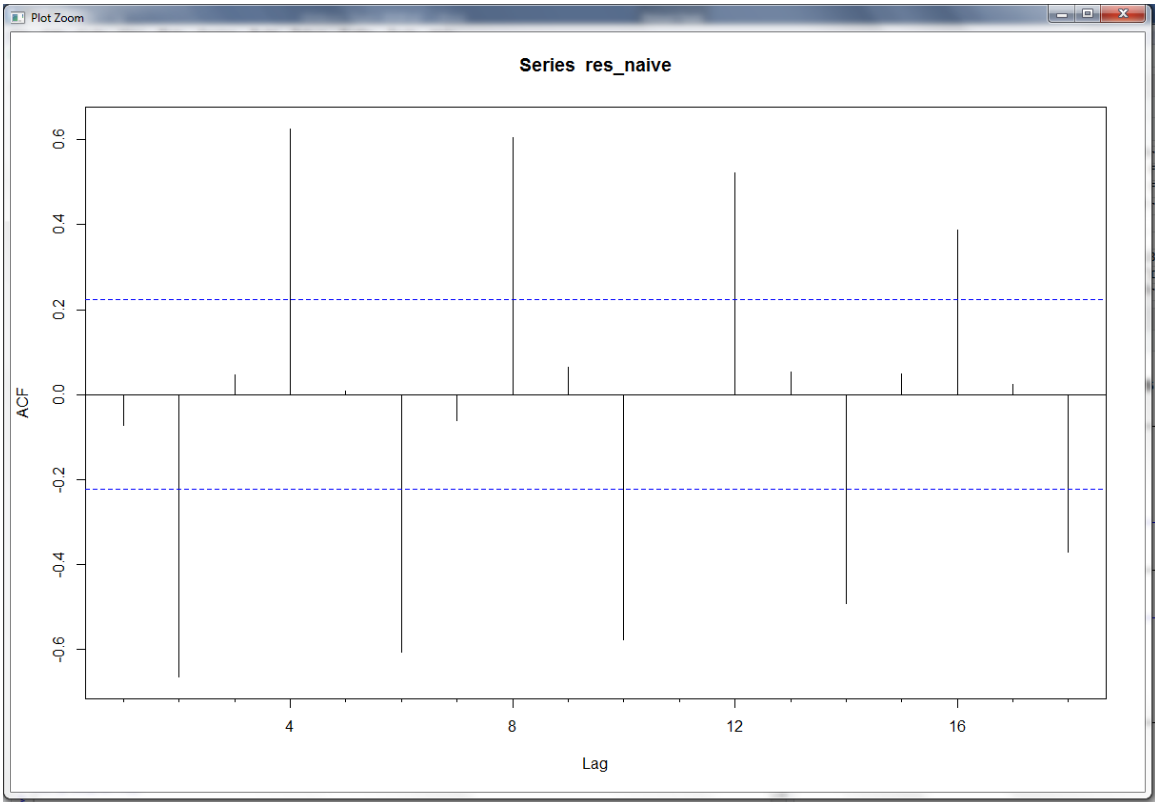
- Do a plot of actual values vs. residuals. What does the plot indicate?

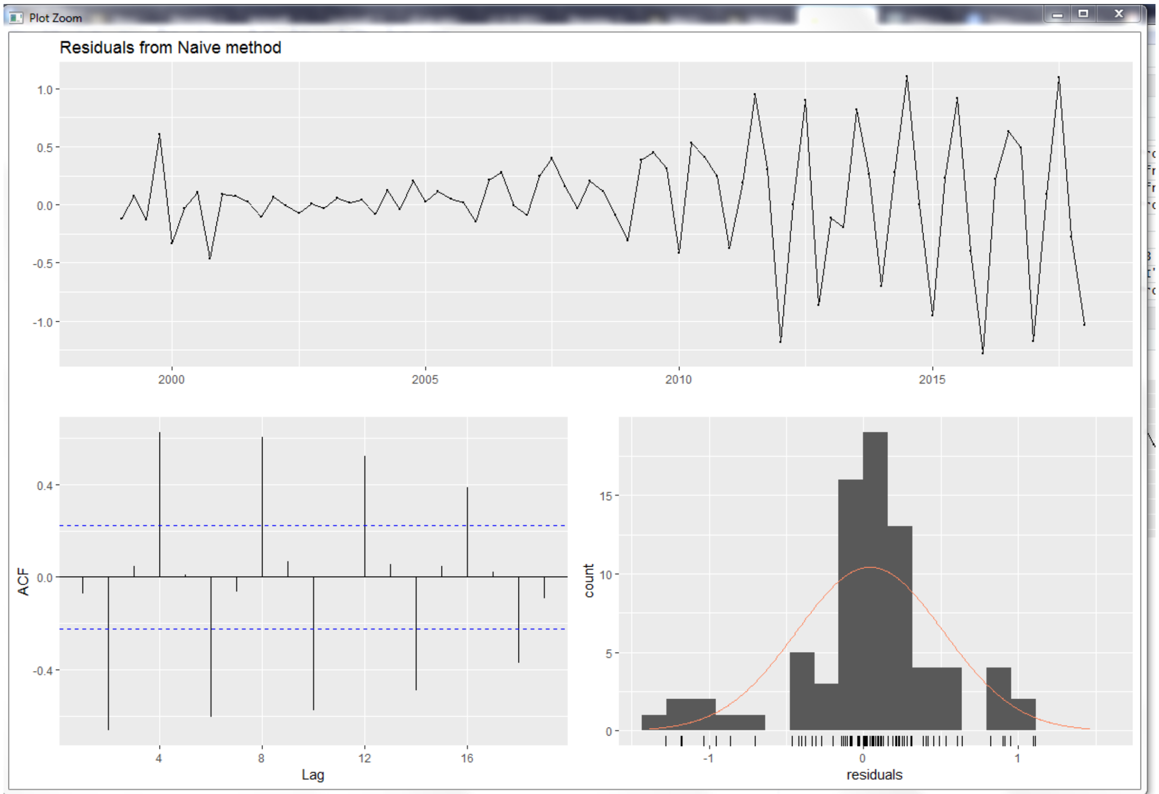
The Plot indicates funnel shape (variance increasing with x), indicates there is scope for improvement in the forecasting model



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

Residuals has correlations, suggesting that forecast is not good





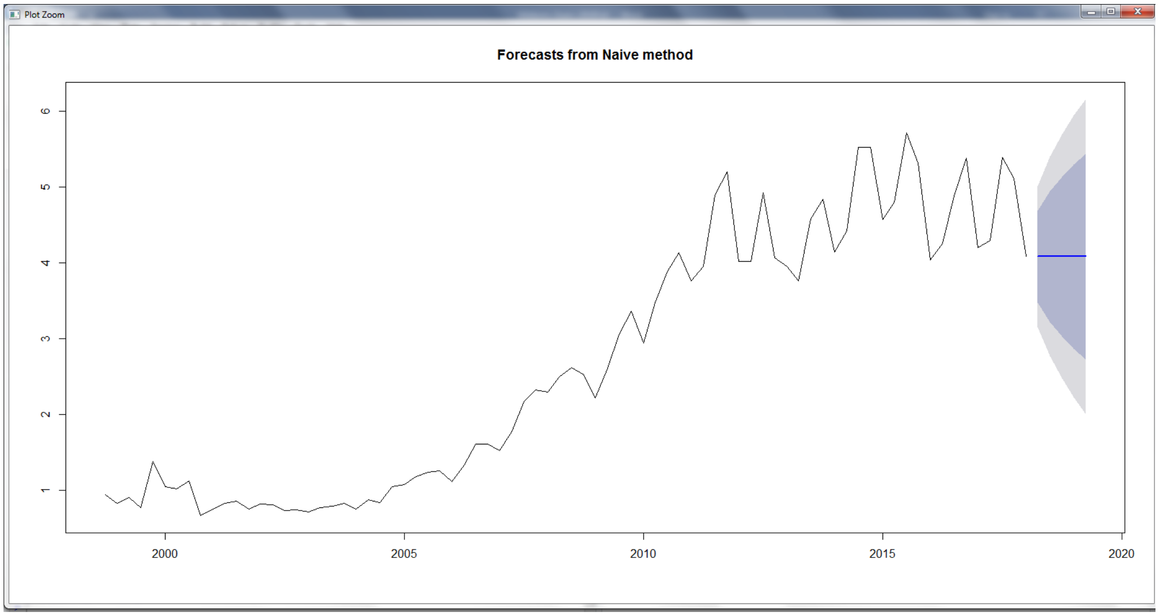
- Print the 5 measures of accuracy for this forecasting technique

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.0407013	0.4738365	0.3272727	0.6541332	12.01044	0.8748711

ACF1
-0.07297452

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

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2018 Q2	4.078	3.470754	4.685246	3.149298	5.006702
2018 Q3	4.078	3.219225	4.936775	2.764616	5.391384
2018 Q4	4.078	3.026219	5.129781	2.469440	5.686560
2019 Q1	4.078	2.863508	5.292492	2.220595	5.935405
2019 Q2	4.078	2.720157	5.435843	2.001358	6.154642



- Summarize this forecasting technique
    - How good is the accuracy?

```
> accuracy(training_naive,test)
                      ME      RMSE       MAE       MPE     MAPE      MASE        ACF1 Theil's U
Training set  0.06488333 0.3529115 0.2386167  1.488774 11.53233 0.6493746 -0.13250584        NA
Test set     -0.03841176 0.5742937 0.5232353 -2.247557 11.12935 1.4239394  0.07894378 0.7507823
```

When we compare test and training data
MPE is negative(–) meaning it is overestimating
Test data has high RMSE, meaning no so good
MAPE is approx. equal, overall it is not so good forecasting method.

- What does it predict the value of time series will be in one year?

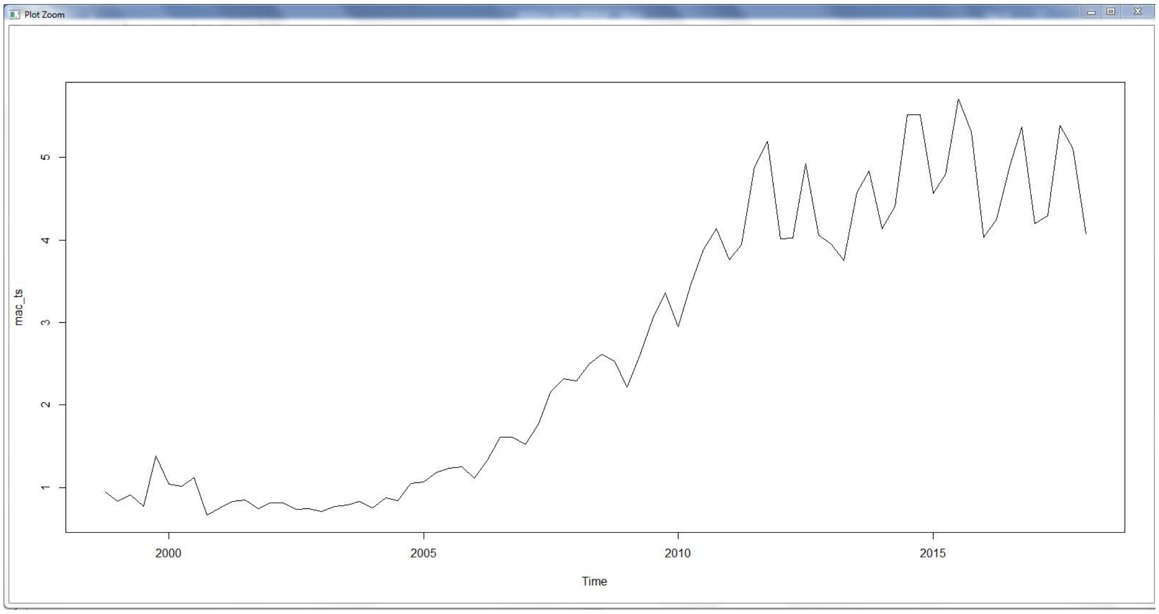
Value of Mac sales next year should be 4.078

- Other observation

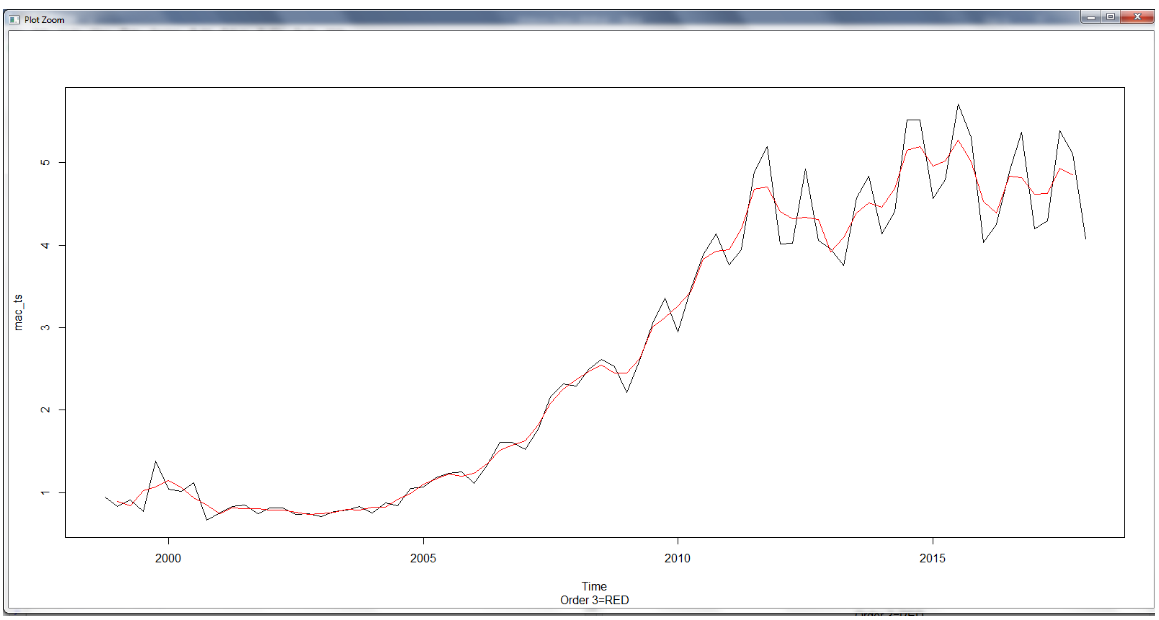
Time Series has seasonality and trend both, there this forecasting method is not suitable to forecast sales for Mac.

Simple Moving Averages

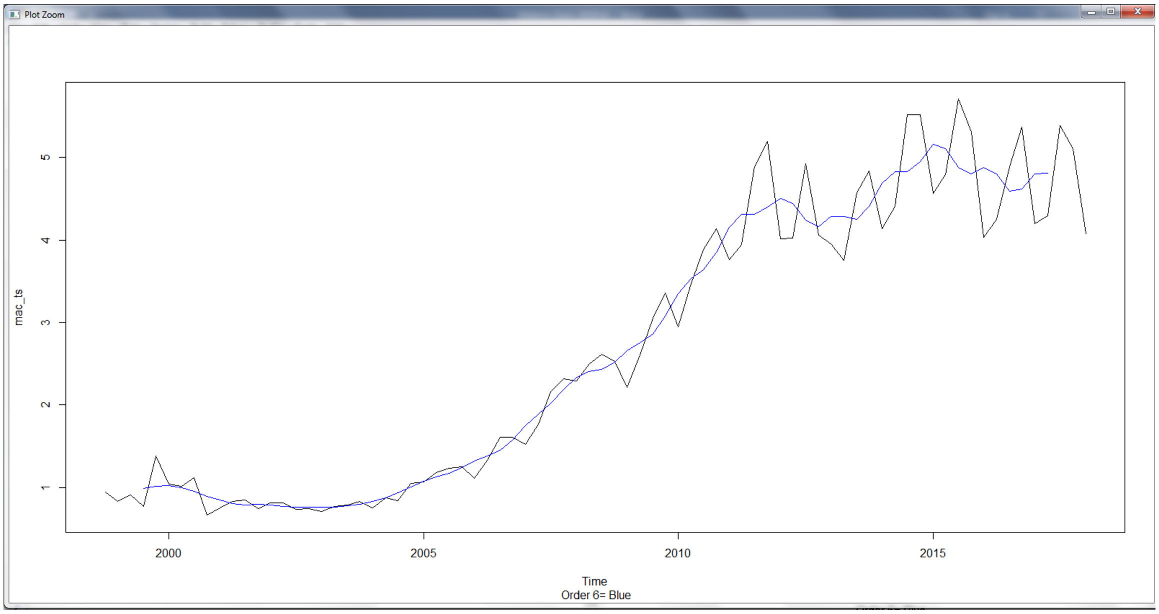
- Plot the graph for time series.



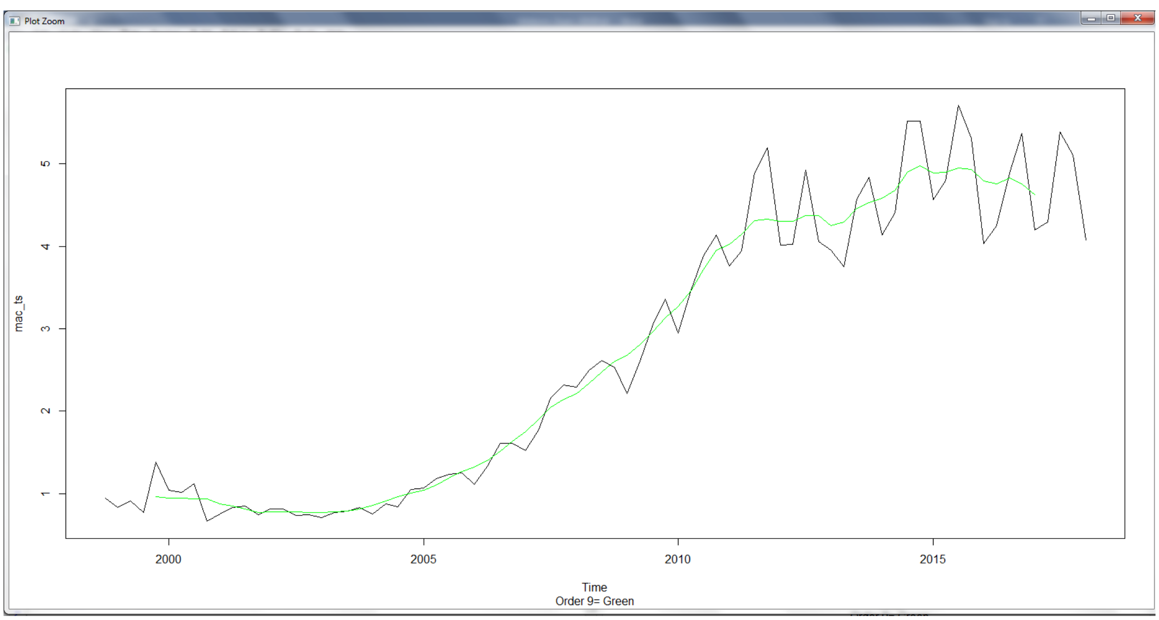
- Show the Simple Moving average of order 3 on the plot above in Red



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



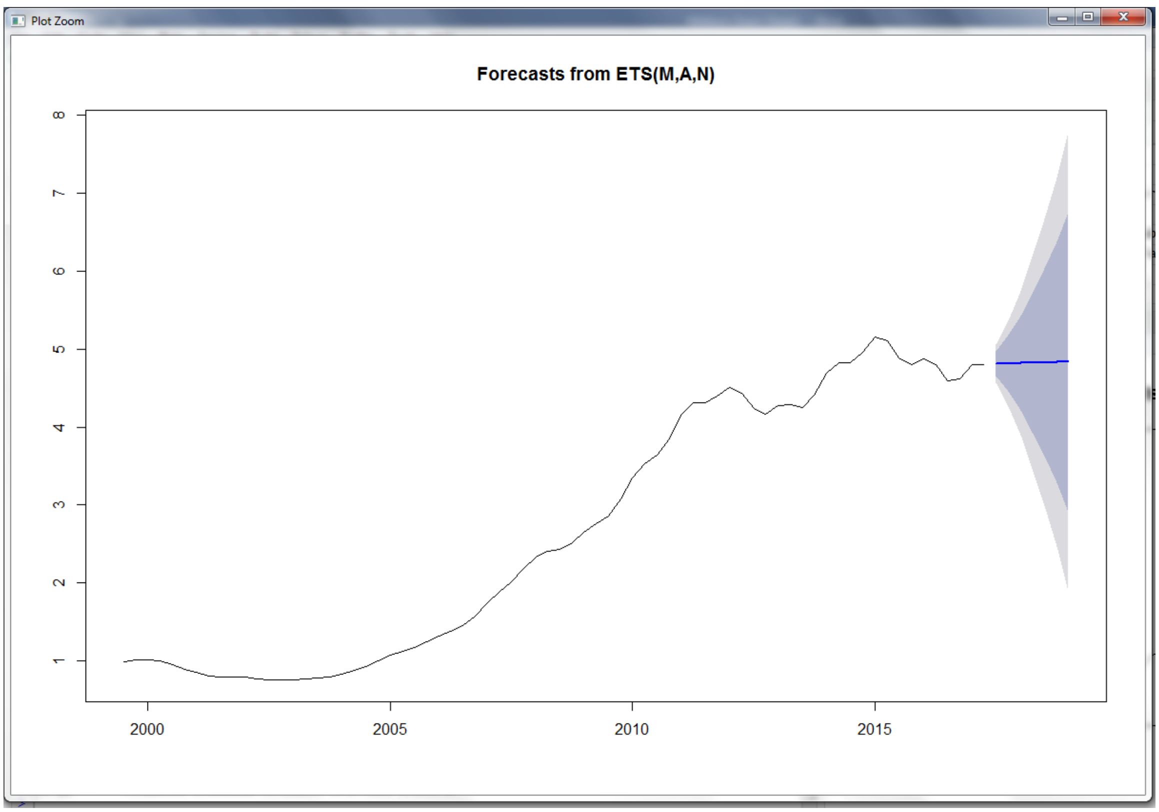
- Show the Simple Moving average of order 9 on the plot above in Green



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

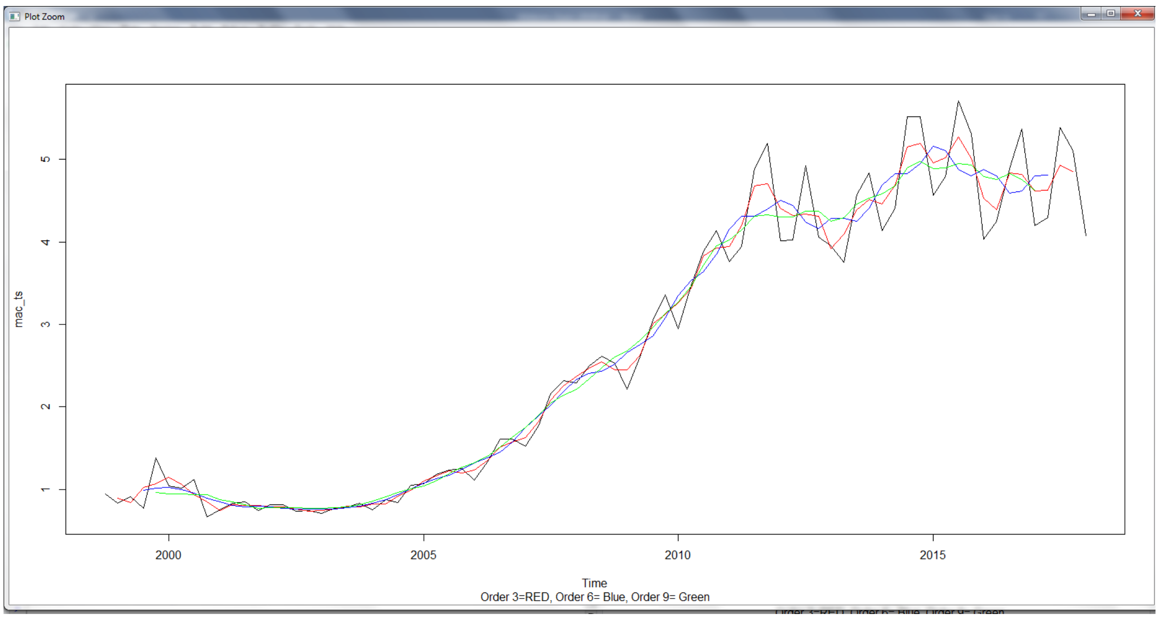
I find simple moving average with order 6 to the best fit and using below is the forecasting for next 1 year

```
   Point Forecast     Lo 80    Hi 80    Lo 95    Hi 95
2017 Q3       4.811885 4.650140 4.973630 4.564517 5.059253
2017 Q4       4.816252 4.454442 5.178062 4.262912 5.369593
2018 Q1       4.820619 4.214813 5.426425 3.894118 5.747120
2018 Q2       4.824986 3.937431 5.712541 3.467588 6.182384
2018 Q3       4.829353 3.626311 6.032395 2.989459 6.669247
2018 Q4       4.833720 3.284198 6.383243 2.463930 7.203510
2019 Q1       4.838087 2.913021 6.763153 1.893953 7.782222
```



- What are your observations of the plot as the moving average order goes up?

As the order is increasing the curve is becoming smooth, green one with order 9 is smoother then red (order 3) and blue (order 6). But, as the order is increasing we are losing data points, so there is trade of here either lose data points or get more smoother line.



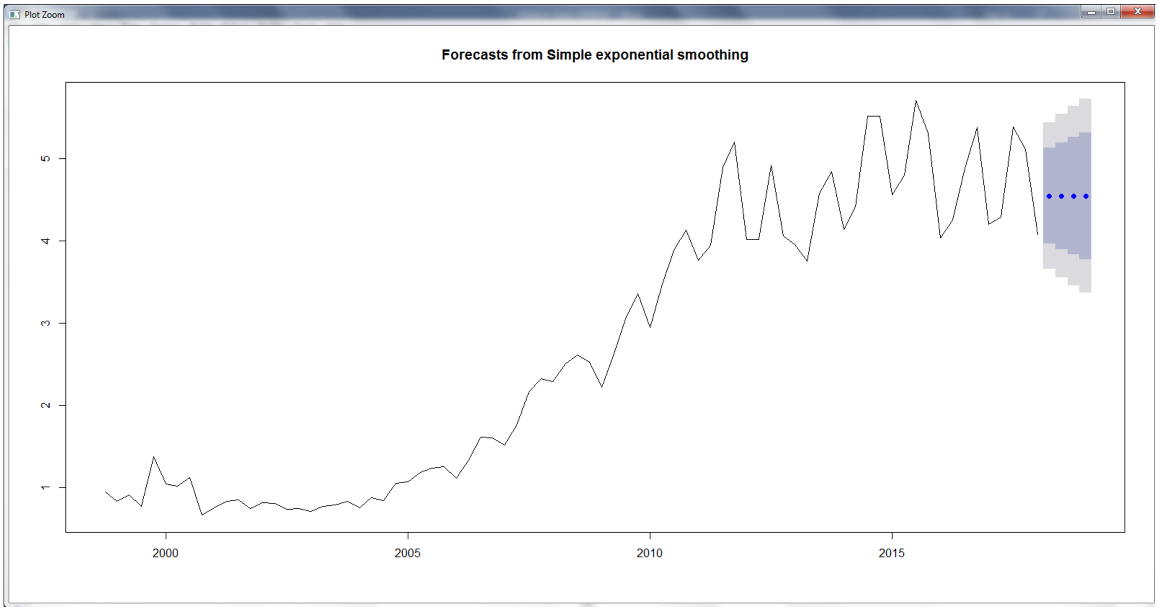
Simple Smoothing

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

```
#Simple smoothing

SSE_simle_mac1 <- ses(mac_ts,4)
plot(SSE_simle_mac1)
plot(SSE_simle_mac1$residuals)
Acf(SSE_simle_mac1$residuals)
hist(SSE_simle_mac1$residuals)
checkresiduals(SSE_simle_mac1)
fit <- SSE_simle_mac1$fitted
#o	Do a plot of fitted values vs. residuals
df <- as.data.frame(apple_data$Mac)
str(df)df
```

df[,"fitted"] <- as.numeric(fit)
df[,"Res"] <- as.numeric(SSE_simle_mac1$residuals)
head(df,10)
plot(x=df$`apple_data$Mac`, y=df$Res, ylab="Residual", xlab="Actual Mac Sales Data")
plot(x=df$fitted, y=df$Res, ylab="Residual", xlab="Fitted Mac Sales Data")




```
SSE_simle_mac_forcast
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q2       4.545139 3.975805 5.114473 3.674418 5.415861
2018 Q3       4.545139 3.908025 5.182254 3.570757 5.519521
2018 Q4       4.545139 3.846793 5.243486 3.477110 5.613168
2019 Q1       4.545139 3.790513 5.299766 3.391038 5.699241
```

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

```
   Smoothing parameters:
    alpha: 0.5022709
```

It signifies that here the more weights are assigned to observations from middle years, in this case may be more weights are assigned to data from year around 2010 to 2013.

- What is the value of initial state?

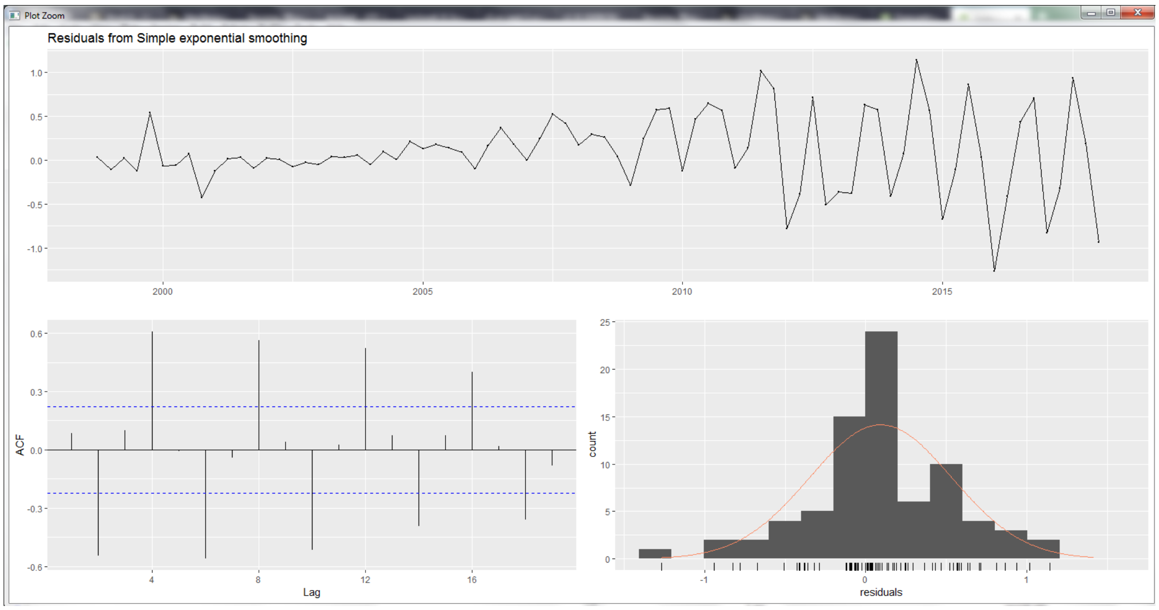
0.944 is the initial state

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

0.4413109, there is a correlation

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

Below is the plot, there is a trend and seasonality in the plot, also its not summing zero around the mean, there residual has some information left, thus forecast model need improvement.

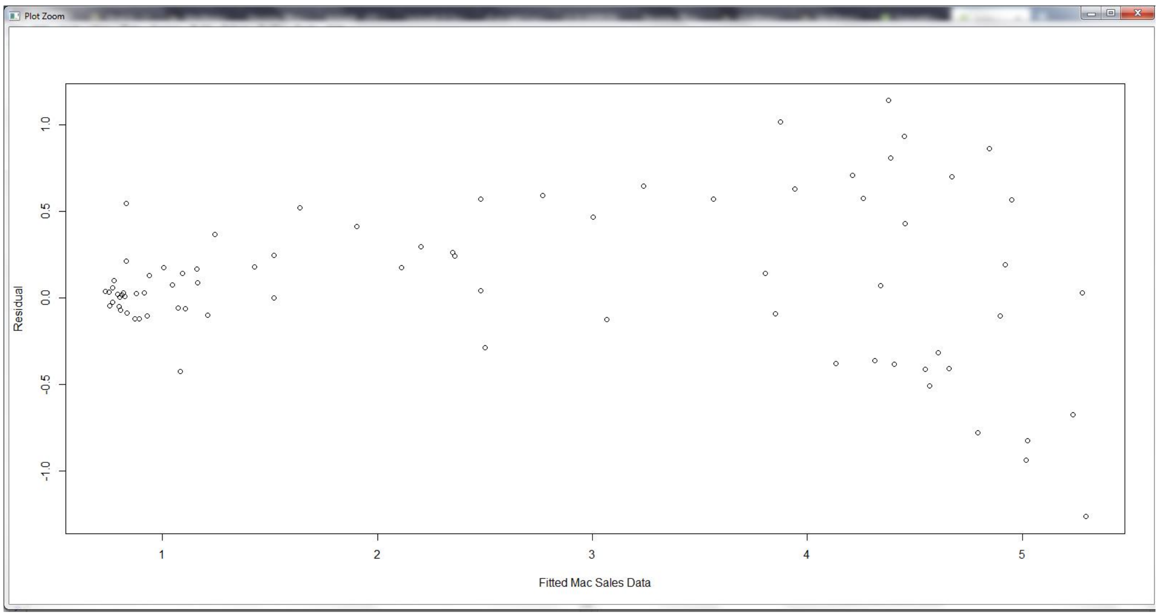


- Do a Histogram plot of residuals. What does the plot indicate?

Above has histogram plot, its skewed, indicates that the forecasting model has scope for improvement

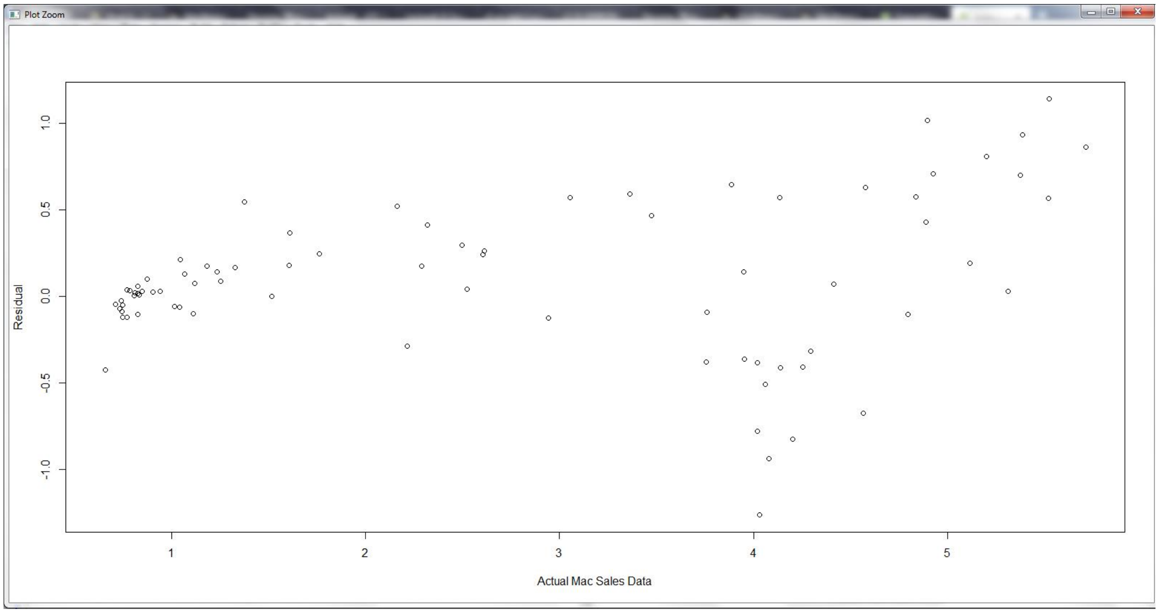
- Do a plot of fitted values vs. residuals. What does the plot indicate?

Below is the plot, Residual has funnel like pattern, which indicates forecast method has chance of improvement.

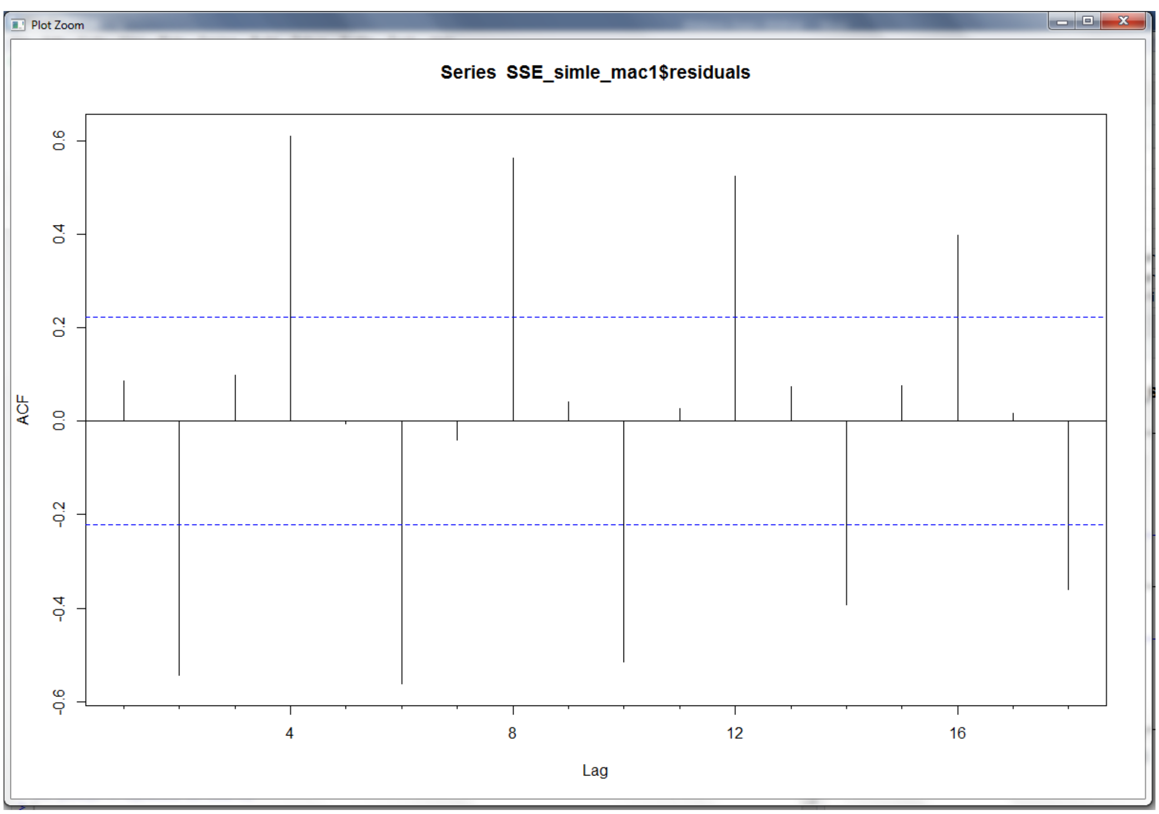
- 

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

Funnel shape like pattern, also outliers. Indicates scope for improvement.

- 

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

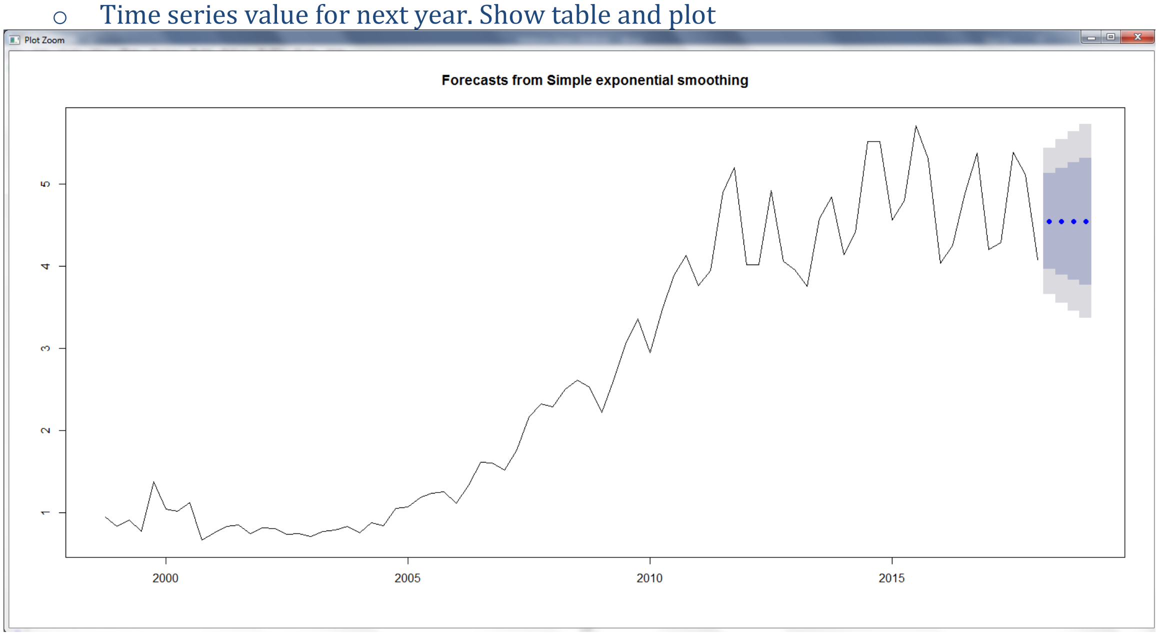


It indicates there is increasing and decreasing lags shows seasonality in the residual of the forecast, so there is scope of improvement in the forecast model.

- Print the 5 measures of accuracy for this forecasting technique

- `accuracy(SSE_simle_mac1)`
- `                    ME      RMSE       MAE      MPE   MAPE       M`
  `ASE       ACF1`
- `Training set 0.09266392 0.4481574 0.326483 2.404932 11.762 0.8727`
  `599 0.08573371`

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




```
SSE_simle_mac_forcast
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q2       4.545139 3.975805 5.114473 3.674418 5.415861
2018 Q3       4.545139 3.908025 5.182254 3.570757 5.519521
2018 Q4       4.545139 3.846793 5.243486 3.477110 5.613168
2019 Q1       4.545139 3.790513 5.299766 3.391038 5.699241
```

- Summarize this forecasting technique
    - How good is the accuracy?

```
> accuracy(training_ses,test)
                     ME      RMSE       MAE       MPE     MAPE      MASE       ACF1 Theil's U
Training set 0.08579681 0.3445459 0.2445838 2.2956868 11.27351 0.6656136 0.01972387        NA
Test set     0.09073468 0.5801470 0.5260086 0.4824222 10.89136 1.4314868 0.07894378 0.7672276
```

ME and RMSE is greater for test set
MPE is positive meaning it is underestimating model
MAPE is reduced for test set
Overall, we can say this is not that good model.

- What does it predict the value of time series will be in one year?

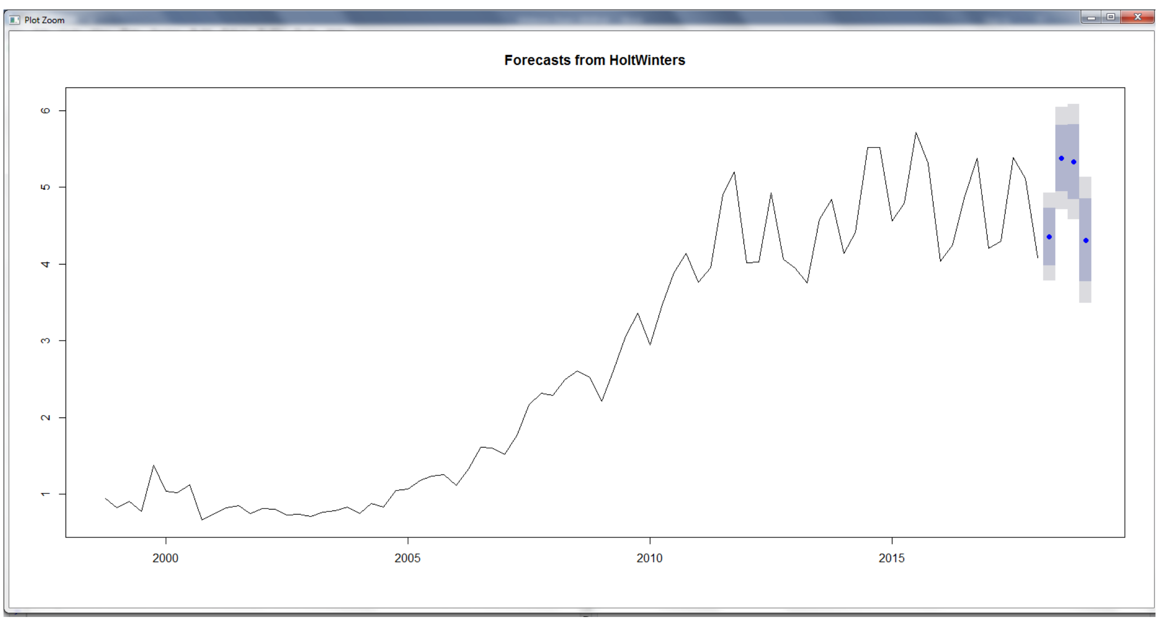
Value will be 4.5451

- Other observation

It's better than naïve, but the Acf show correlation and histogram show skewness, therefore there is chance of improvement.

Holt-Winters

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




```
> hw_mac
Holt-Winters exponential smoothing with trend and additive seasonal
component.

Call:
HoltWinters(x = mac_ts)
```

```
Smoothing parameters:
 alpha: 0.591872
 beta : 0
 gamma: 0.9719223

Coefficients:
         [,1]
a   4.7632368
b   0.0579750
s1 -0.4684586
s2  0.4965668
s3  0.3928622
s4 -0.6848847
```

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

```
alpha: 0.591872 signifies level reacts to slight backdated observ
ations (in case if it close to 1, we say more weights are given t
o recent observations but it's not the case here)
```

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

```
   beta: 0
Signifies trend is not changing over time
```

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

```
gamma: 0.9719223
```

seasonality smoothing is close to 1 so it signifies more weights are given to recent observations

- What is the value of initial states for the level, trend and seasonality? What do these values signify?

Initial states for level is 0.944, 0.827, 0.905, 0.772 it signifies that level are calculated using these values and formula: `Lt = @Yt/St-s + (1-@)(Lt-1 + T t-1)`

Initial states for trend is 0,0,0,0 it signifies that trend are remains constant, also trend is calculat ed using formula Tt = &(Lt-Lt-1) + (1-&)Tt-1

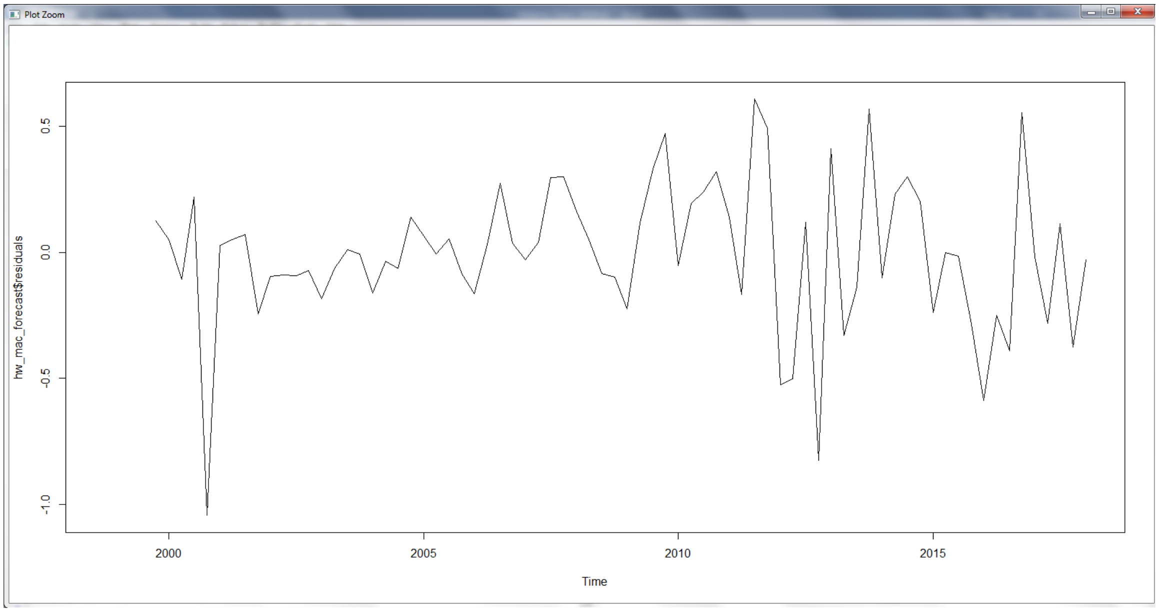
Initial states for seasonality is 1,1,1,1 it signifies that gamma use this and it calculates the values using formula !(Yt/Lt)+(1-!)St-s

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

Sigma is NA, meaning no correlation exists(Acf also shows no correlation)

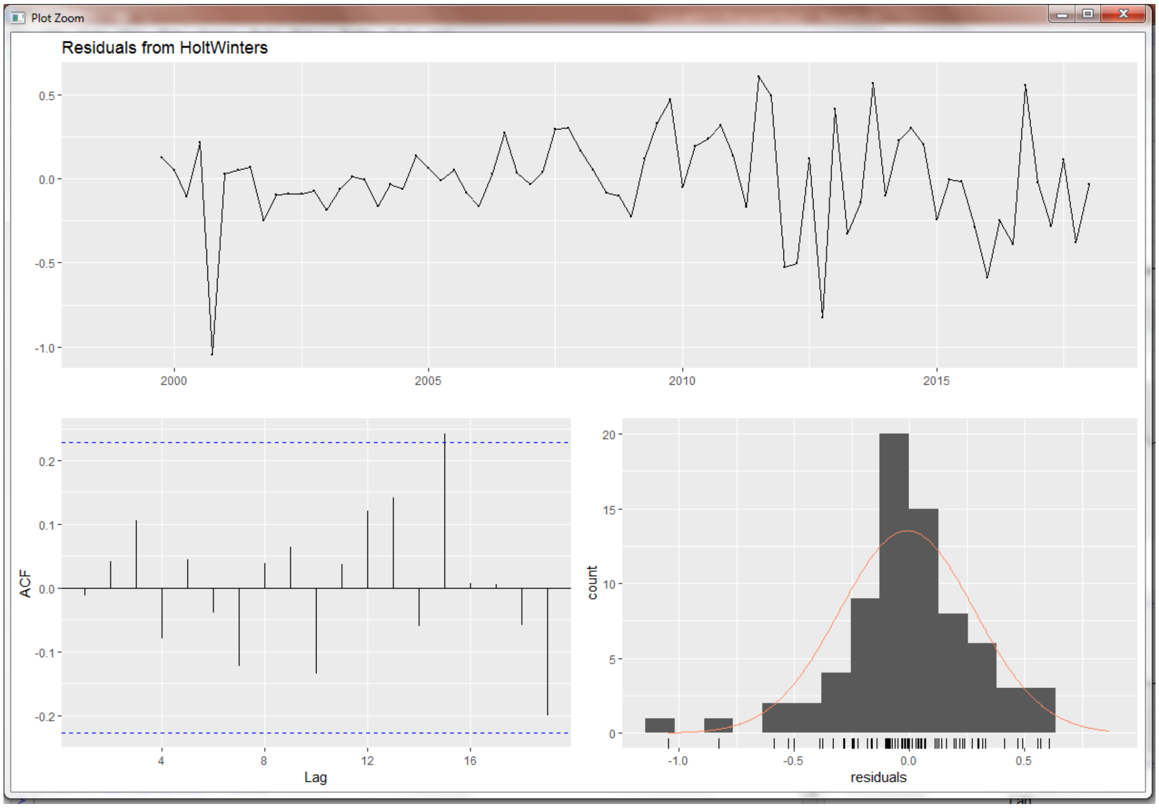
- Perform Residual Analysis for this technique.
  - Do a plot of residuals. What does the plot indicate?

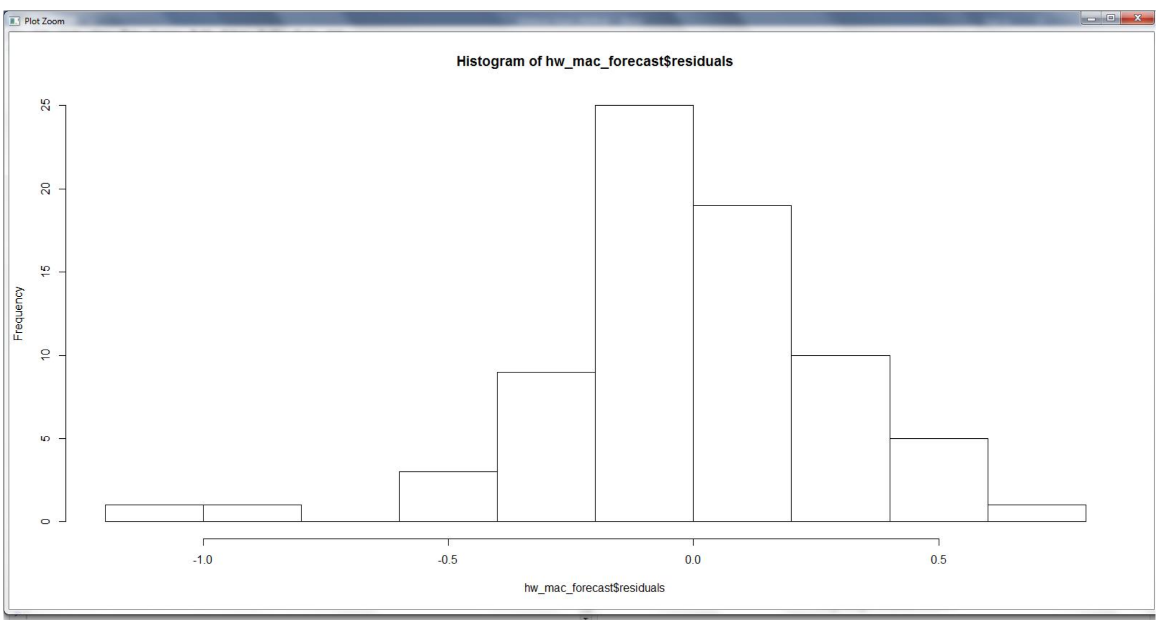
It looks random, indicates residuals do not have any information thus our forecast model is good



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

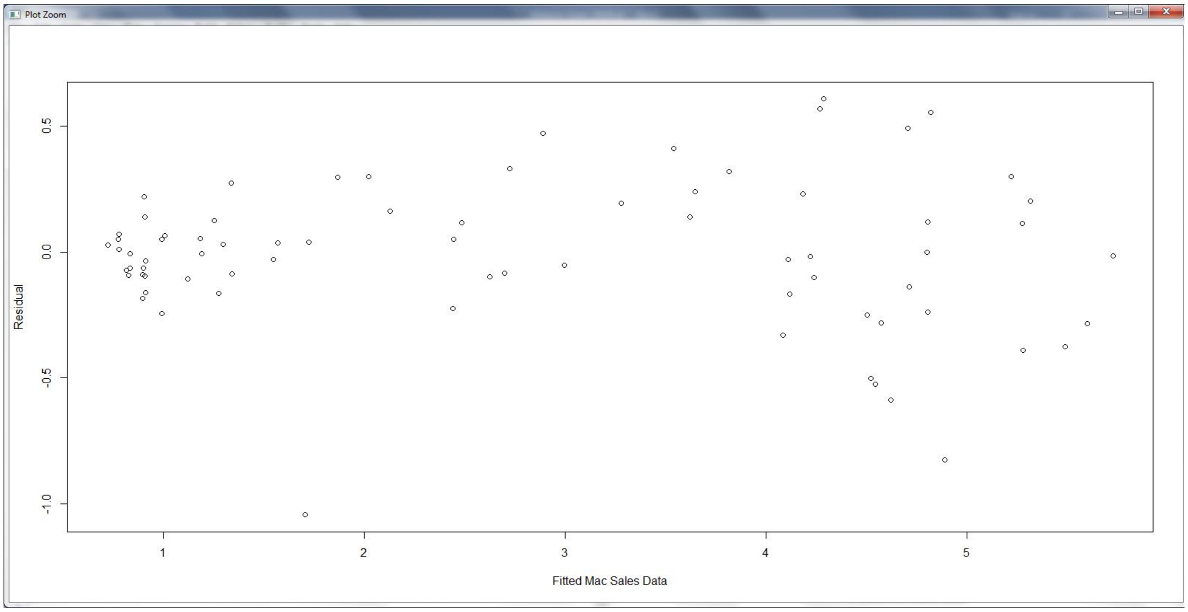
It is still slightly skewed, but better the previous forecasting models.





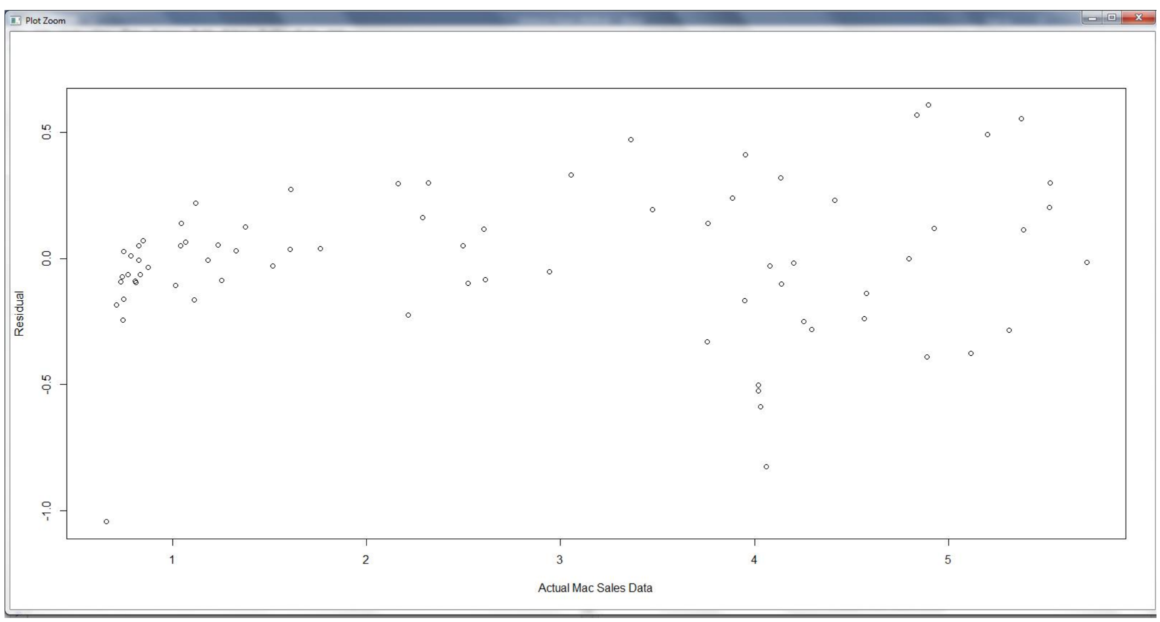
- Do a plot of fitted values vs. residuals. What does the plot indicate?

Variance is not increasing much with x, at right bottom side there is little more variance, but overall it is good, we can say will approximately zero sum around the mean.



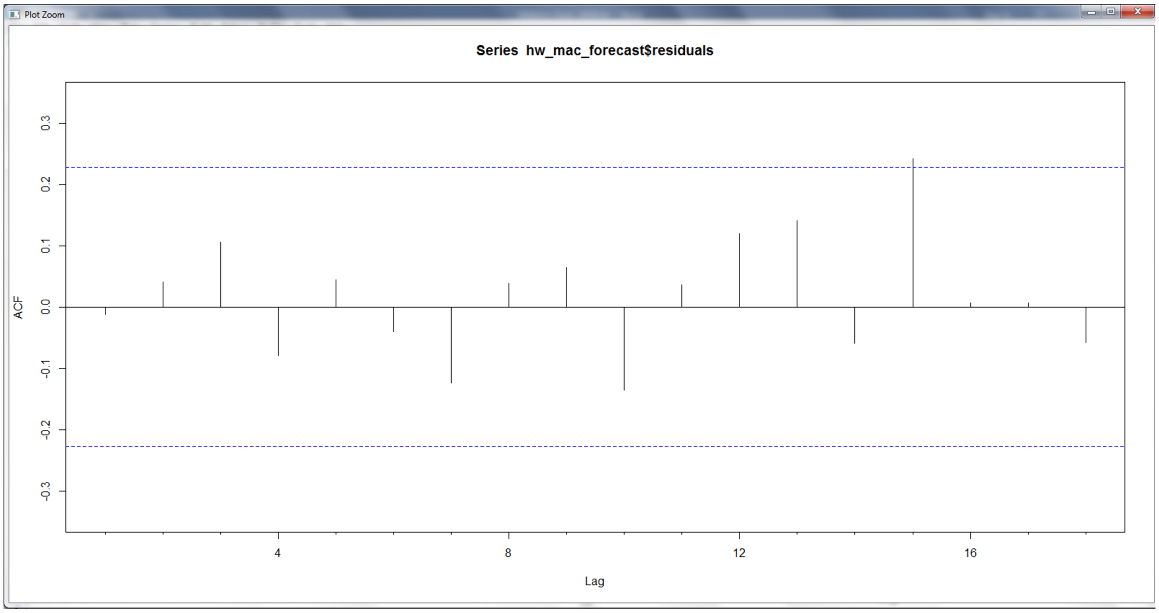
- Do a plot of actual values vs. residuals. What does the plot indicate?

Variance is not increasing much with x, at right bottom side there is little more variance, but overall it is good, we can say will approximately zero sum around the mean.



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

Indicates no correlation, although only one data point touches the lag, rest seems good, thus its random and good forecast

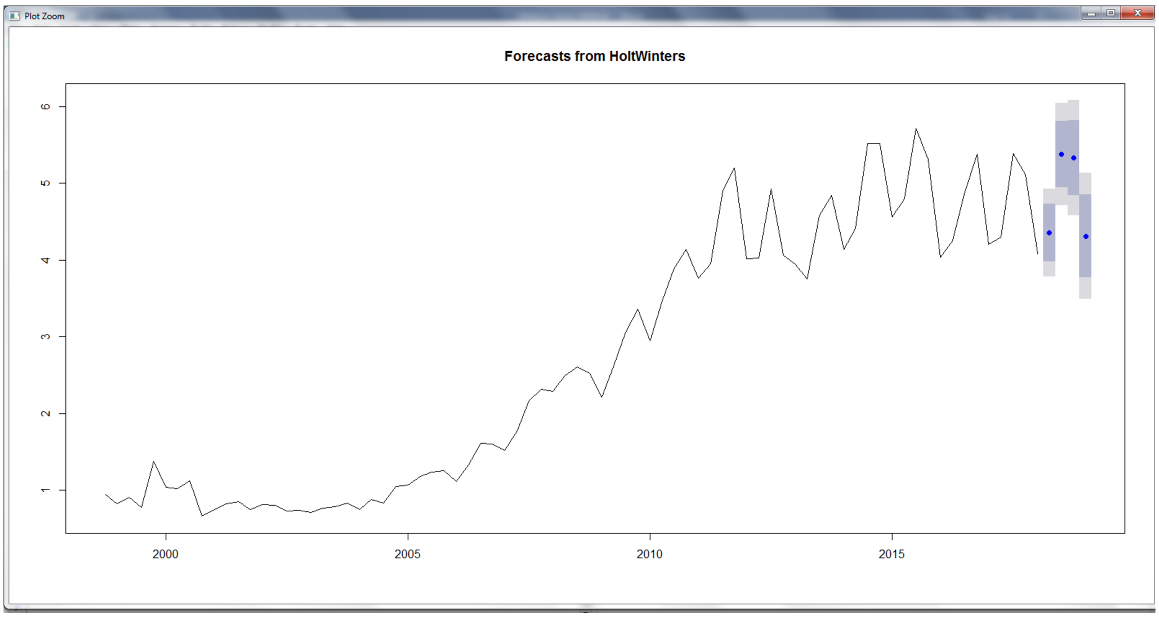


- Print the 5 measures of accuracy for this forecasting technique

```
> accuracy(hw_mac_forecast)
                     ME      RMSE       MAE       MPE     MAPE
MASE        ACF1
Training set -0.0089909 0.2905301 0.2094488 -2.914616 9.993218 0.559
9021 -0.01148062
```

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

```
hw_mac_forecast
        Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018 Q2       4.352753 3.978062 4.727445 3.779712 4.925794
2018 Q3       5.375754 4.940351 5.811156 4.709863 6.041644
2018 Q4       5.330024 4.841397 5.818652 4.582733 6.077315
2019 Q1       4.310252 3.773653 4.846851 3.489595 5.130909
```



- Summarize this forecasting technique
    - How good is the accuracy?

```
> accuracy(training_holts_winter_forecast,test)
                      ME      RMSE       MAE       MPE      MAPE      MASE          ACF1 Theil's U
Training set  0.009034717 0.2897909 0.2011297 -3.376620 11.446244 0.5473571 -0.0005915045        NA
Test set     -0.212286648 0.5134969 0.4362363 -5.159953  9.458764 1.1871792  0.6311920233 0.7013054
```

- What does it predict the value of time series will be in one year?

```
For  2018 Q2 4.352753

     2018 Q3 5.375754

     2018 Q4 5.330024

     2019 Q1 4.310252
```

- Other observation

Holts Winter forecast is better than the naïve and simple smoothing, which is also clear from the residual analysis. Also, when we compare the errors like RMSE, MAPE of Holts winter with the other two, its lesser, thus this is more accurate.

Accuracy Summary

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

```
> accuracy(hw_mac_forecast)
                     ME      RMSE       MAE       MPE     MAPE      MASE        ACF1
Training set -0.0089909 0.2905301 0.2094488 -2.914616 9.993218 0.5599021 -0.01148062
> accuracy(SSE_simle_mac1)
                     ME      RMSE      MAE      MPE   MAPE      MASE       ACF1
Training set 0.09266392 0.4481574 0.326483 2.404932 11.762 0.8727599 0.08573371
> accuracy(naive_forecast)
                    ME      RMSE       MAE       MPE     MAPE      MASE        ACF1
Training set 0.0407013 0.4738365 0.3272727 0.6541332 12.01044 0.8748711 -0.07297452
```

Hw_mac_forecast = accuracy of Holts winter

SSE_simple_mac1= accuracy of Simple Smoothing

Naïve_forecast = accuracy of Naïve

Among 3 best accuracy is of Holts winter forecasting method as RMSE, MAPE and MASE is th e lowest among all 3, whereas the Naive is worst.

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

Naïve Forecast: This forecast is a simple model assumes that the recent data provides the best predictions of the future.

That is Y’t+1=Yt

It is useful in the scenario to validate the result obtained from the complex forecasting model.

For the time series of mac sales accuracy is the worst among the 3, forecast model

Simple Smoothing Forecast: In this forecast model, the weights are assigned to the observations based on its relevance. If the more recent observations have more information than more weights are assigned to them and weights are decreased in the exponential order

Y^t+1(point forecast) = @Yt + @(1-@)Yt-1 +…..

@= smoothing factor

It is useful in short term forecasting where it assumes extreme fluctuations represent randomness in a series of historical observation. Also where there is no proper upward or downward trend present.

In our case this is average of model.

Holts Winter Forecast: It is built on simple smoothing forecast concept, here it has been adjusted for trend and seasonality both, which is done 2 scientists Holts and Winter. It comprises of forecast equation and 3 smoothing equations.

Smoothing equations involves calculation of level, trend and seasonality based on respective smoothing constant, which is calculated such that SSE should be minimum.

Once we have level, trend and seasonality, forecast model is built using forecast equation.

Following are calculations

- Forecast equation: Y^t+p = (Lt + p*Tt)*St-s+p
- Level equation: Lt = @Yt/St-s + (1-@)(Lt-1 + T t-1)
- Trend Equation: Tt = &(Lt-Lt-1) + (1-&)Tt-1
- Seasonal Equation: !(Yt/Lt)+(1-!)St-s

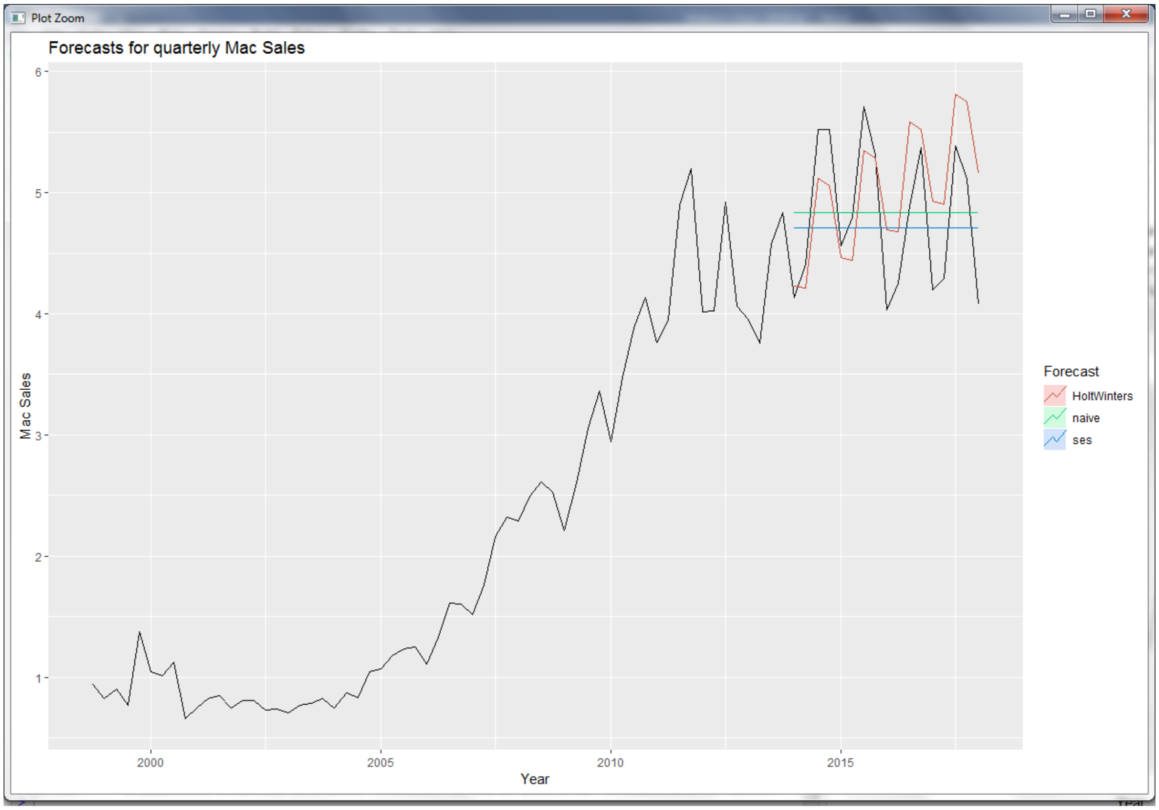
  Where Lt = new smoothed Value
  @ = smoothing constant for level
  Yt = Actual forecast at time t
  & = Smoothing constant for trend
  Tt = trend estimate
  p = period for which to calculate forecast on
  Y^t+p = Forecast for p period into the future
  s = length of seasonality
  ! = Seasonality constant
  St = seasonality estimate.

It has advantage of simple smoothing and we have considered seasonality in the model, so it gives more accurate more forecast model.

In our case, Mac sale, it has the **best accuracy** among the, 3 models.

Holts Winters Forecasting model is the Best and Naïve Forecasting Model is the worst in case of the Mac Sale.

Below is the accuracy test and comparison of the three:-




```
> accuracy(training_naive,test)
                      ME      RMSE       MAE       MPE     MAPE      MASE        ACF1 Theil's U
Training set  0.06488333 0.3529115 0.2386167  1.488774 11.53233 0.6493746 -0.13250584        NA
Test set     -0.03841176 0.5742937 0.5232353 -2.247557 11.12935 1.4239394  0.07894378 0.7507823
> accuracy(training_ses,test)
                     ME      RMSE       MAE      MPE     MAPE      MASE       ACF1 Theil's U
Training set 0.08579681 0.3445459 0.2445838 2.2956868 11.27351 0.6656136 0.01972387        NA
Test set     0.09073468 0.5801470 0.5260086 0.4824222 10.89136 1.4314868 0.07894378 0.7672276
> accuracy(training_holts_winter_forecast,test)
                       ME      RMSE       MAE       MPE      MAPE      MASE          ACF1
Training set  0.009034717 0.2897909 0.2011297 -3.376620 11.446244 0.5473571 -0.0005915045
Test set     -0.212286648 0.5134969 0.4362363 -5.159953  9.458764 1.1871792  0.6311920233
             Theil's U
Training set        NA
Test set     0.7013054
```

Conclusion

- Summarize your analysis of time series value over the time-period.

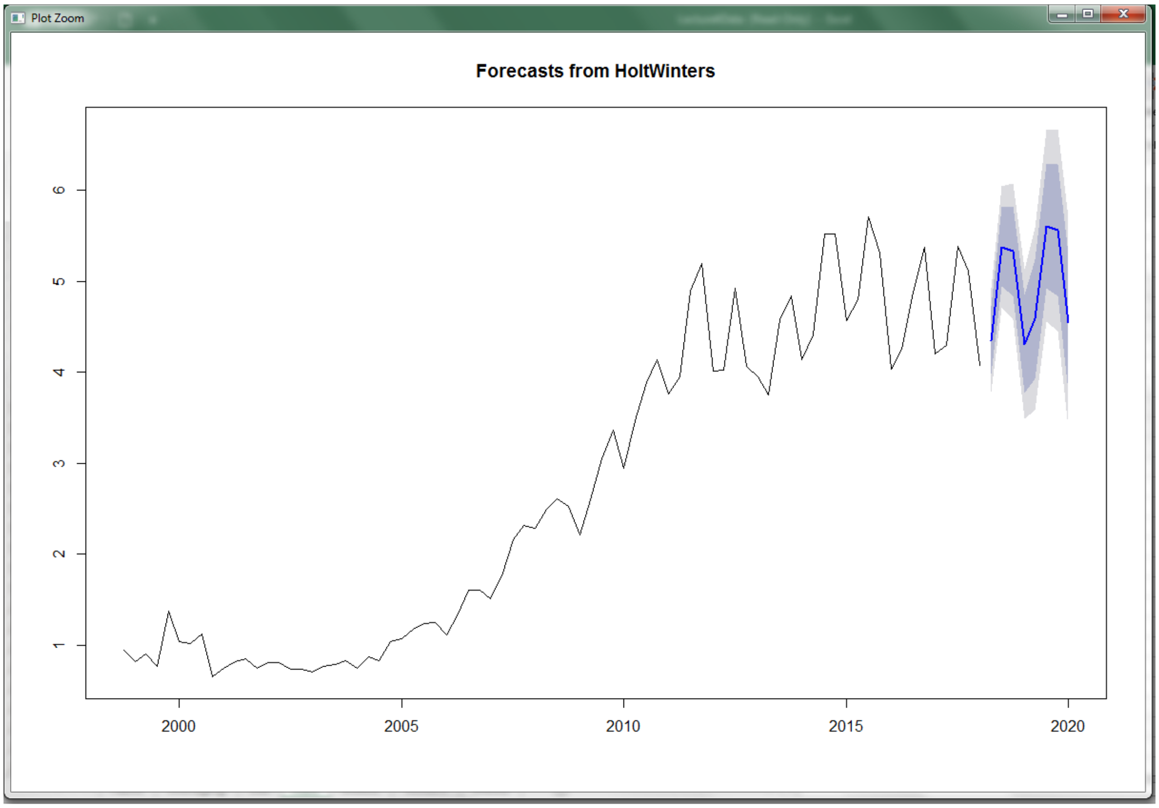
Over all time series has followed a trend, initial year had prominent seasonality and increasing trend till year 2010, since 2011 there is kind of comparatively less percentage increasing in sales, that is its fluctuating in between 3 to 5.5, so as per the forecasting model over time of 1-2 years it will remain in the region with slight increase 3.3 to 6.6.

- 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?

Highlighted is the value, according to the seasonality it will increase and decrease

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2018 Q2	4.352753	3.978062	4.727445	3.779712	4.925794
2018 Q3	5.375754	4.940351	5.811156	4.709863	6.041644

```
2018 Q4       5.330024 4.841397 5.818652 4.582733 6.077315
2019 Q1       4.310252 3.773653 4.846851 3.489595 5.130909
2019 Q2       4.584653 3.932631 5.236675 3.587471 5.581835
2019 Q3       5.607654 4.918949 6.296359 4.554370 6.660937
2019 Q4       5.561924 4.838394 6.285454 4.455380 6.668468
2020 Q1       4.542152 3.785397 5.298907 3.384796 5.699509
```



- Rank forecasting methods that best forecast for this time series based on historical values.

Holts Winter is the Best Method

Attaching the code

```
View(apple_data)
plot(x=apple_data$mac,y=apple_data$Period)
mac_ts <- ts(apple_data$Mac,start=c(1998,4),end=c(2018,1),frequency=4)
plot(mac_ts)

autoplot(mac_ts)
summary(mac_ts)
sd(mac_ts)
hist(mac_ts)
plot.ts(mac_ts)
Acf(mac_ts,lag=78)
```

```
boxplot(apple_data$Mac, main="Mac Sales")
?boxplot
plot(x <- apple_data$mac, y <- apple_data$Time)
boxplot(mac_ts)

#decomposition
summary(mac_ts)
decompose_mac <- decompose(mac_ts)

attributes(decompose_mac)
dec_sea_mac <- seasadj(decompose_mac)
plot(decompose_mac)
plot(dec_sea_mac, ylab="Seasonal Adjusted", main="Seasonal Adjusted = Black, Original TS= Red ")
lines(mac_ts,col='RED')
trendcycle()

stl_decomp <- stl(mac_ts,s.window ="periodic")
plot(stl_decomp)
attributes(stl_decomp)
stl_dec_mac <- seasadj(stl_decomp)
plot(mac_ts)
lines(stl_dec_mac, col='RED')
lines(trendcycle(stl_decomp), col='BLUE')
?trendcycle
?decompose
install.packages("TTR")

library(TTR)
# Naive Forecast
naive_forecast <- naive(mac_ts,5)
par(mfrow= c(1,1))
plot(naive_forecast)
lines(naive_forecast$fitted, col='RED')

lines(residuals(naive_forecast, col='GREEN'))

res_naive <- residuals(naive_forecast)
plot(res_naive)
plot(naive_forecast$fitted, col='RED', sub="Fitted = Red, Residual=Black")
lines(res_naive)
?hist
cov(res_naive)

sd(res_naive)
hist(res_naive)
accuracy(naive_forecast)
summary(res_naive)
Acf(res_naive)


df[,"res_naive"] <- as.numeric(res_naive)
df[ ,"fit_naive"] <- as.numeric(naive_forecast$fitted)

plot(x=df$`apple_data$Mac`,y=df$res_naive,xlab="Actual Mac sales", ylab="Residual",main="Actual vs Residual")
plot(x=df$`apple_data$Mac`,y=df$res_naive,xlab="Fitted Mac sales", ylab="Residual",main="Fitted vs Residual")

lines(naive_forecast$fitted, col='RED')
plot(res_naive)
```

```
accuracy()
?accuracy
?residuals
residu
?checkresiduals
checkresiduals(naive_forecast)


#moving average
plot(mac_ts, sub="Order 3=RED")
ma3_mac <- ma(mac_ts,order=3)
lines(ma3_mac,col="RED")

plot(mac_ts, sub=" Order 6= Blue")
ma6_mac <- ma(mac_ts,order=6)
lines(ma6_mac,col="Blue")

plot(mac_ts, sub="Order 9= Green")
ma9_mac <- ma(mac_ts,order=9)
lines(ma9_mac,col="GREEN")

#Simple smoothing
?HoltWinters
SSE_simle_mac<- HoltWinters(mac_ts,beta=FALSE,gamma=FALSE)
plot(SSE_simle_mac)
SSE_simle_mac_forcast <- forecast(SSE_simle_mac,4)
plot(SSE_simle_mac_forcast)

plot(SSE_simle_mac_forcast$residuals)
Acf(SSE_simle_mac_forcast$residuals)
hist(SSE_simle_mac_forcast$residuals)
?ses
SSE_simle_mac_forcast$lower

SSE_simle_mac1 <- ses(mac_ts,4)
plot(SSE_simle_mac1)
plot(SSE_simle_mac1$residuals)
Acf(SSE_simle_mac1$residuals)
hist(SSE_simle_mac1$residuals)
checkresiduals(SSE_simle_mac1)
fit <- SSE_simle_mac1$fitted
#o        Do a plot of fitted values vs. residuals
df <- as.data.frame(apple_data$Mac)
str(df)df

df[,"fitted"] <- as.numeric(fit)
df[,"Res"] <- as.numeric(SSE_simle_mac1$residuals)
head(df,10)
plot(x=df$`apple_data$Mac`, y=df$Res, ylab="Residual", xlab="Actual Mac Sales Data")
plot(x=df$fitted, y=df$Res, ylab="Residual", xlab="Fitted Mac Sales Data")
accuracy(SSE_simle_mac1)

#Holtswinter
hw_mac<- HoltWinters(mac_ts)
plot(hw_mac)
hw_mac_forecast <- forecast(hw_mac,8)
plot(hw_mac_forecast)
accuracy(hw_mac_forecast)
```

```
str(df)
mac_ts
?HoltWinters

plot(hw_mac_forecast$residuals)
Acf(hw_mac_forecast$residuals)
hist(hw_mac_forecast$residuals)
checkresiduals(hw_mac_forecast)

fit_hw_mac <- hw_mac_forecast$fitted
df[,"fit_hw"] <- as.numeric(fit_hw_mac)
df[,"res_hw"]<- as.numeric(hw_mac_forecast$residuals)
plot(x=df$`apple_data$Mac`, y=df$res_hw, ylab="Residual", xlab="Actual Mac Sales Data")
plot(x=df$fit_hw, y=df$res_hw, ylab="Residual", xlab="Fitted Mac Sales Data")
View(df)

#accuracy test

?window
training <- window(mac_ts, start=c(1998,4), end=c(2013,4))
test <- window(mac_ts, start=c(2014,1))
training_naive <- naive(training,17)
training_ses <- ses(training,17)
training_holts_winter <- HoltWinters(training)
training_holts_winter_forecast <- forecast(training_holts_winter,17)

autoplot(window(mac_ts, start=c(1998,4))) +
  autolayer(training_naive, series="naive", PI=FALSE) +
  autolayer(training_ses, series="ses", PI=FALSE) +
  autolayer(training_holts_winter_forecast, series="HoltWinters", PI=FALSE) +
  xlab("Year") + ylab("Mac Sales") +
  ggtitle("Forecasts for quarterly Mac Sales") +
  guides(colour=guide_legend(title="Forecast"))

accuracy(training_naive,test)
accuracy(training_ses,test)
accuracy(training_holts_winter_forecast,test)
accuracy(training_holts_winter,test)


sd(df$Res)
sd(df$res_hw)
```