

TomatoProject.R

HP

2020-12-19

```
# Read CSV File
```

```
my_data <- read.csv("E:/NDSU/NDSU_ Classes/Applied Regression/Project/Final Project/Tomato5.csv")
```

```
#See the Summary of the data
```

```
summary(my_data)
```

```
##      Date      Sales.Per.Day
## Length:83      Min.   : 20
## Class :character 1st Qu.: 545
## Mode  :character Median :1420
##              Mean   :1434
##              3rd Qu.:2075
##              Max.   :4930
```

```
#Check out the Library
library(fpp2)
```

```
## Warning: package 'fpp2' was built under R version 4.0.3
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo
```

```
## -- Attaching packages ----- fpp2 2.4 --
```

```
## v ggplot2 3.3.2    v fma      2.4
## v forecast 8.13    v expsmooth 2.3
```

```
## Warning: package 'ggplot2' was built under R version 4.0.3
```

```
## Warning: package 'forecast' was built under R version 4.0.3
```

```
## Warning: package 'fma' was built under R version 4.0.3
```

```
## Warning: package 'expsmooth' was built under R version 4.0.3
```

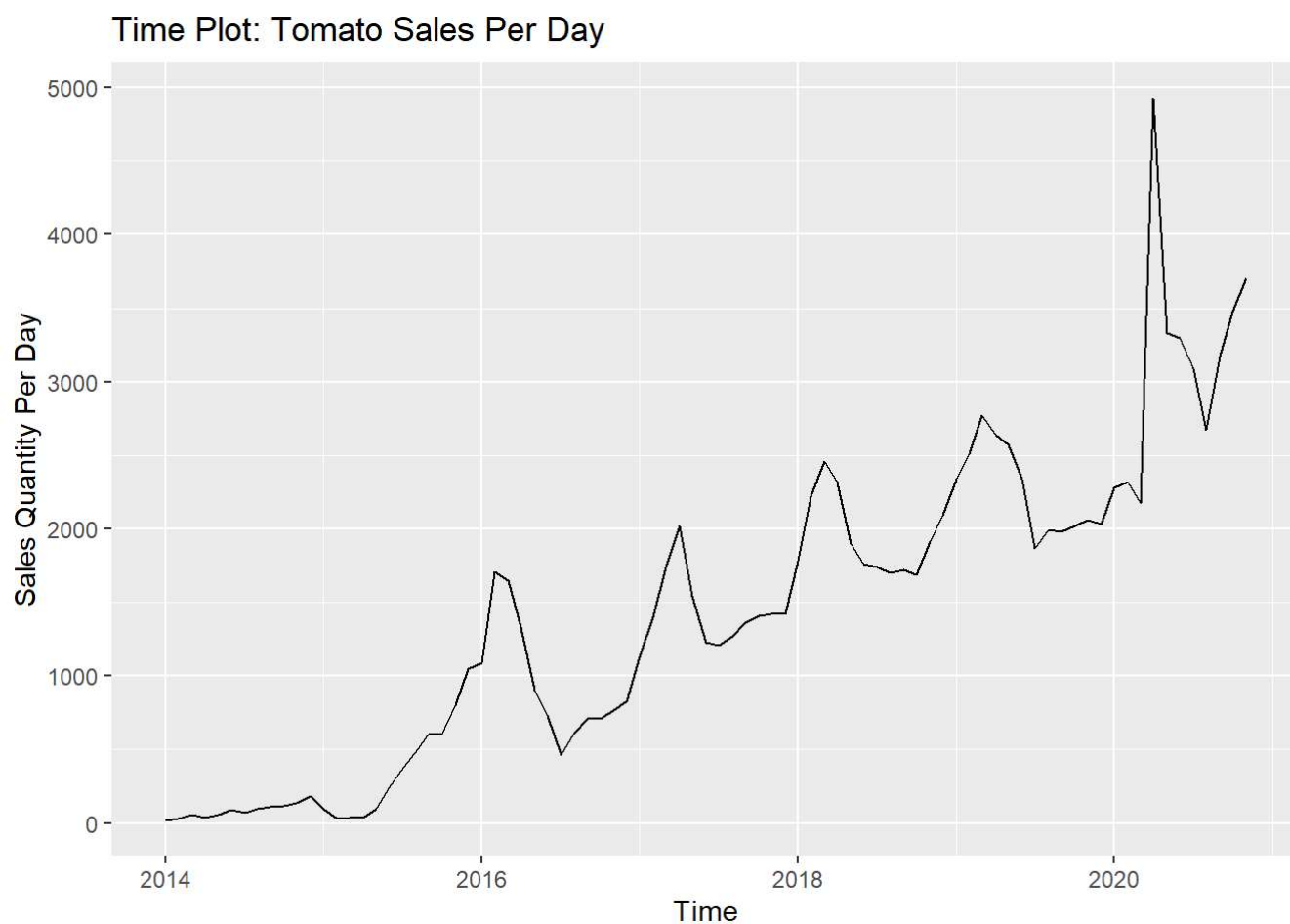
##

```
#Convert the data frame into time series data
```

```
Y<-ts(my_data[,2],start=c(2014,1),frequency = 12)
```

```
#Plot the main time series v alues
```

```
autoplot(Y)+ggtitle("Time Plot: Tomato Sales Per Day")+  
  ylab("Sales Quantity Per Day")
```



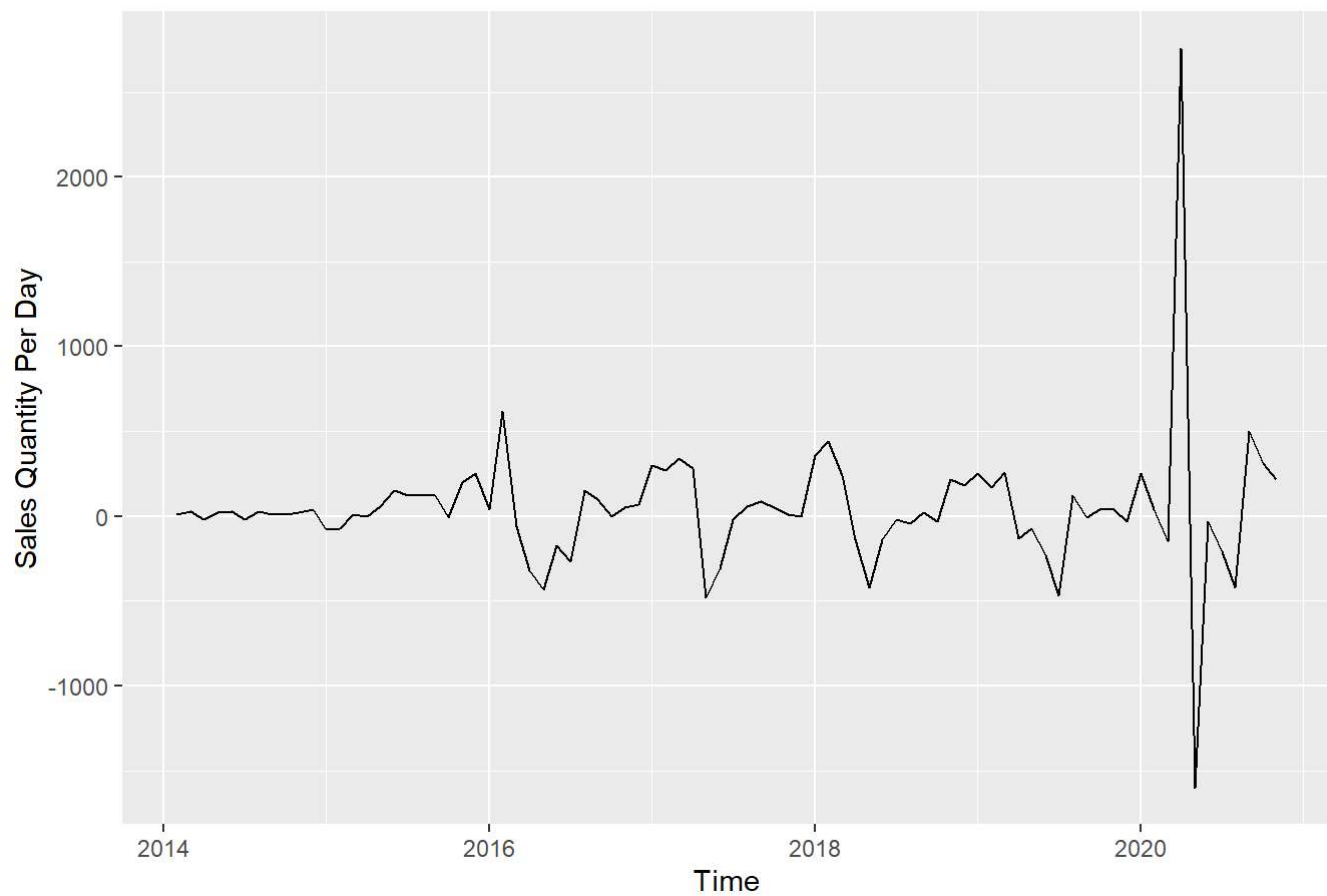
```
#Differencing the Y value
```

```
DY<-diff(Y)
```

```
#Plot the modified time series values
```

```
autoplot(DY)+ggtitle("Time Plot: Tomato Sales Per Day")+  
  ylab("Sales Quantity Per Day")
```

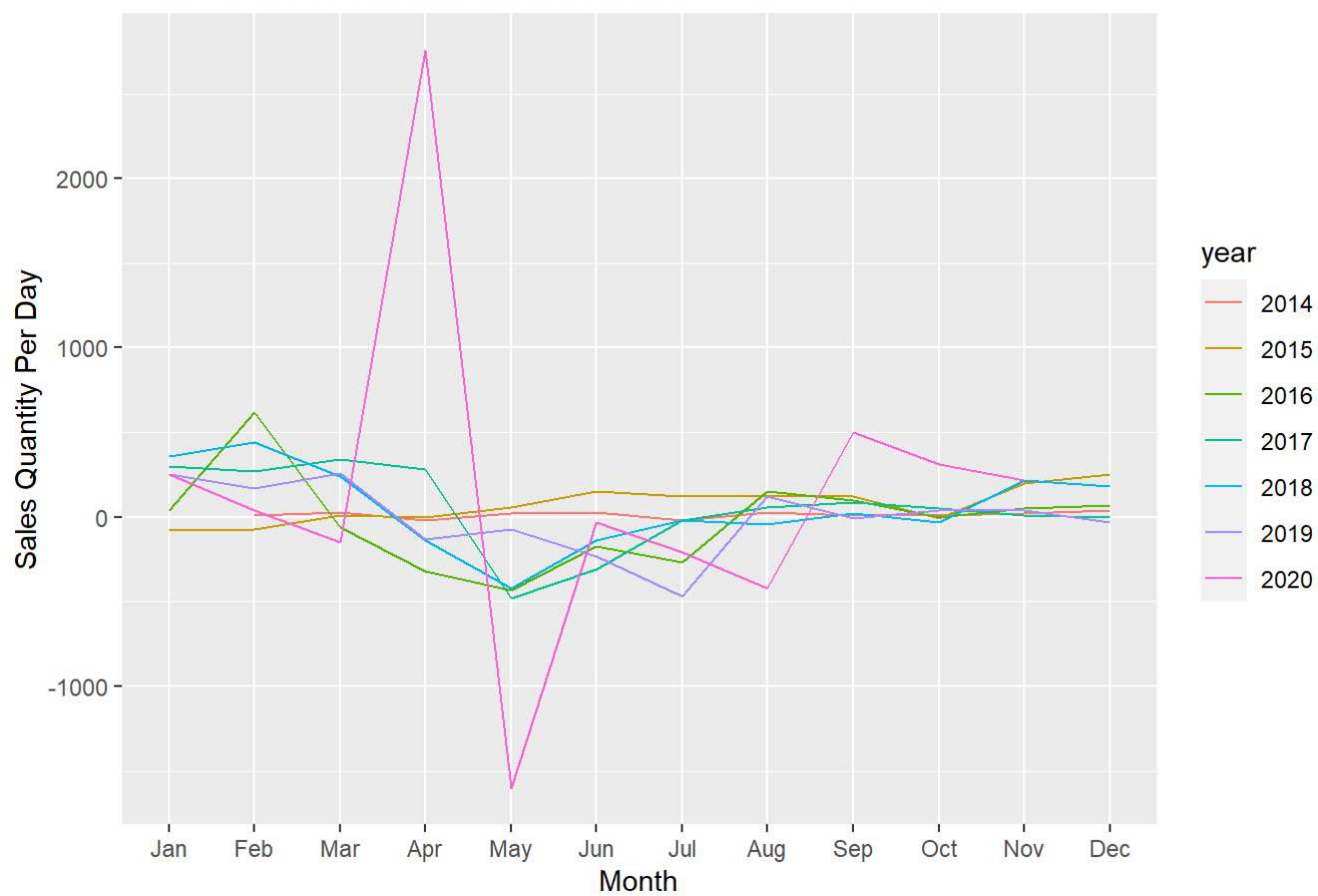
Time Plot: Tomato Sales Per Day



```
#Plot a seasonal chart
```

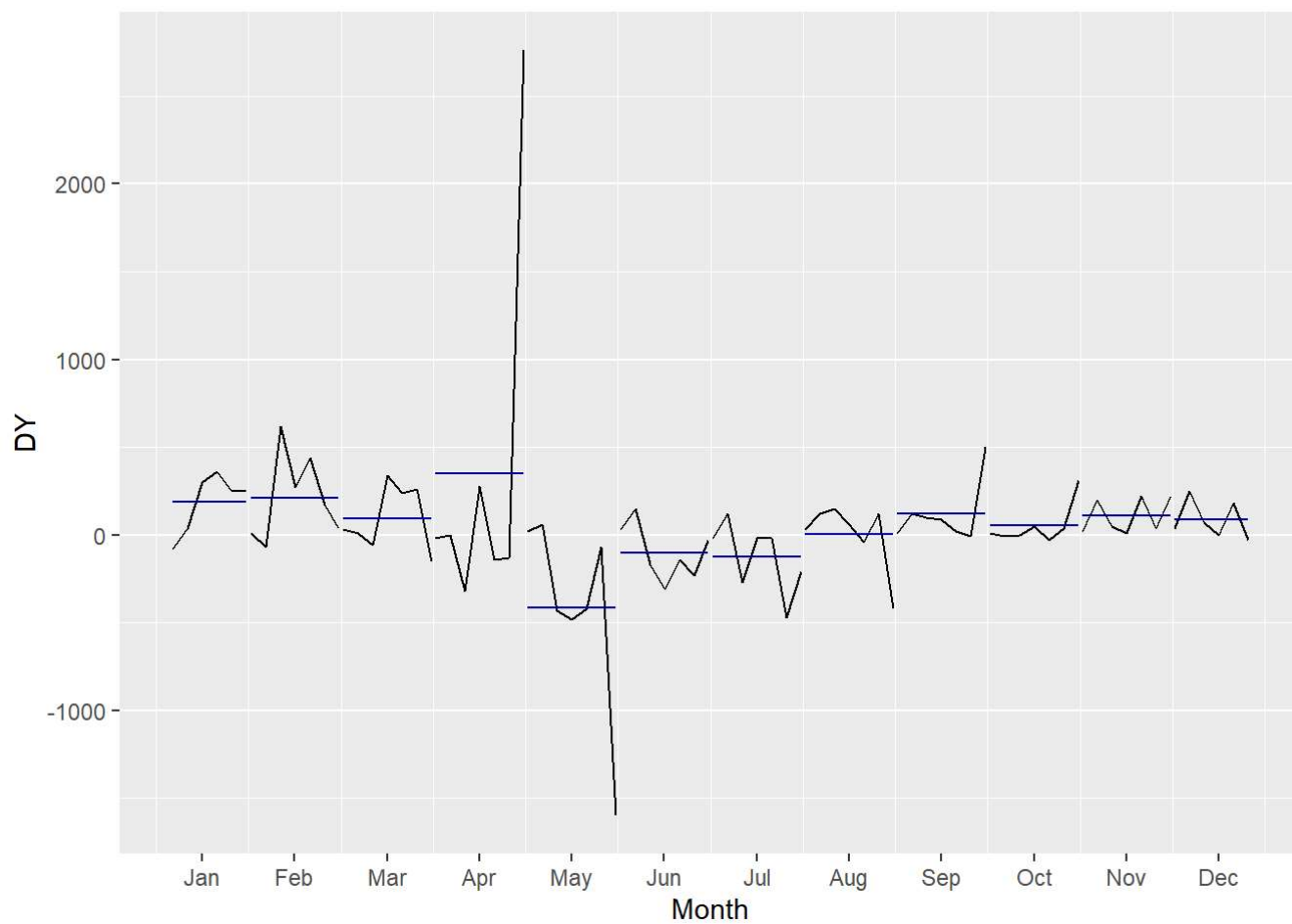
```
ggseasonplot(DY)+  
  ggtitle("Seasonal Plot: Change in Daily Sales")+  
  ylab("Sales Quantity Per Day")
```

Seasonal Plot: Change in Daily Sales



#Plot a subseries chart

```
ggsubseriesplot(DY)
```



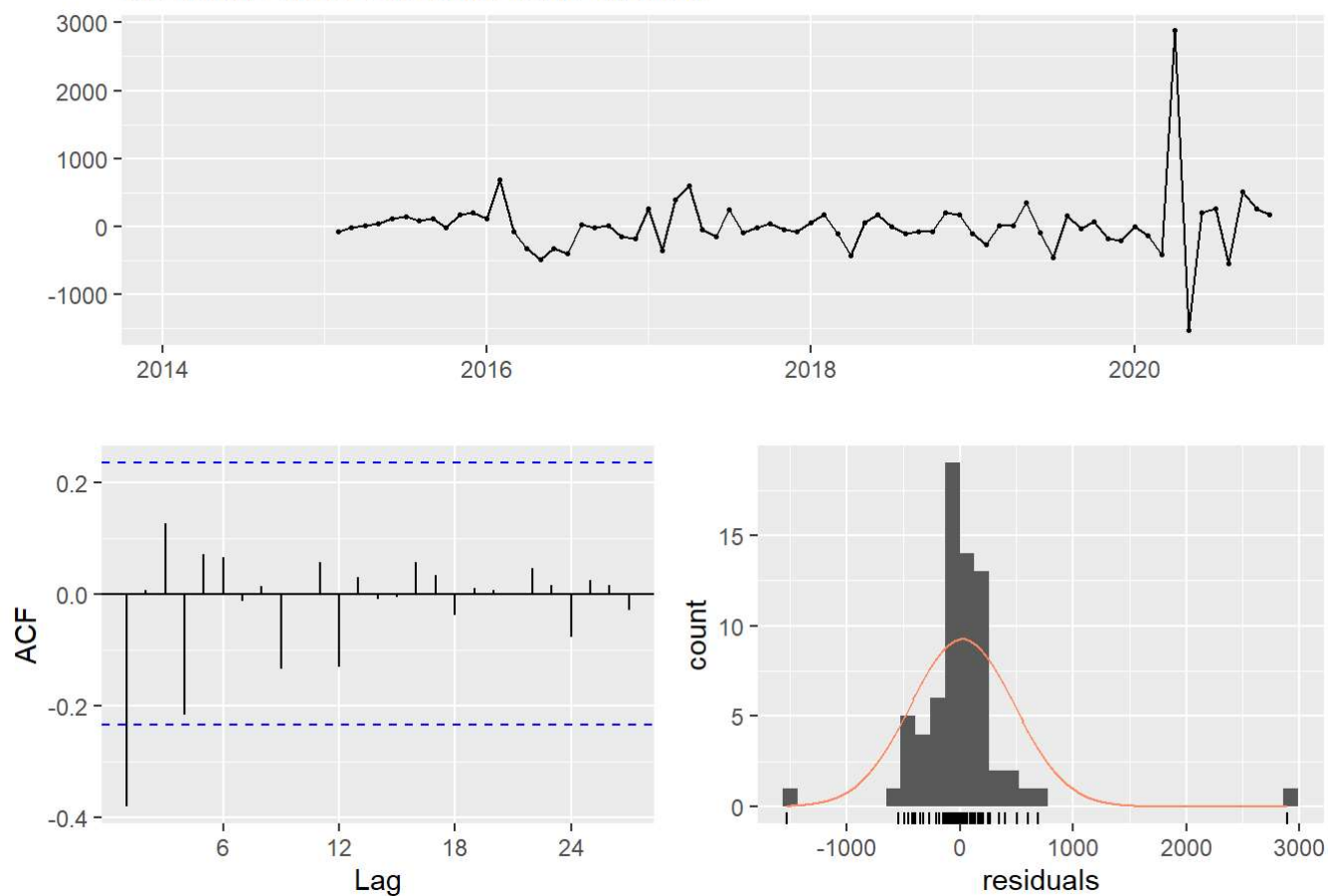
```
#Seasonal Naive Method as our benchmark #Residual sd: 45.699  
# $y_t = y_{t-s} + e_t$   
  
fit<-snaive(DY)  
print(summary(fit))
```

```
##
## Forecast method: Seasonal naive method
##
## Model Information:
## Call: snaive(y = DY)
##
## Residual sd: 456.9902
##
## Error measures:
##           ME      RMSE      MAE MPE MAPE MASE      ACF1
## Training set 22.28571 456.9902 237.4286 NaN  Inf    1 -0.381392
##
## Forecasts:
##           Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Dec 2020           -30 -615.65645  555.6564 -925.6842  865.6842
## Jan 2021            250 -335.65645  835.6564 -645.6842 1145.6842
## Feb 2021             40 -545.65645  625.6564 -855.6842  935.6842
## Mar 2021          -150 -735.65645  435.6564 -1045.6842  745.6842
## Apr 2021          2760 2174.34355 3345.6564 1864.3158 3655.6842
## May 2021         -1600 -2185.65645 -1014.3436 -2495.6842 -704.3158
## Jun 2021           -30 -615.65645  555.6564 -925.6842  865.6842
## Jul 2021          -210 -795.65645  375.6564 -1105.6842  685.6842
## Aug 2021          -420 -1005.65645  165.6564 -1315.6842  475.6842
## Sep 2021           500  -85.65645 1085.6564 -395.6842 1395.6842
## Oct 2021           310 -275.65645  895.6564 -585.6842 1205.6842
## Nov 2021           220 -365.65645  805.6564 -675.6842 1115.6842
## Dec 2021           -30 -858.24329  798.2433 -1296.6888 1236.6888
## Jan 2022           250 -578.24329 1078.2433 -1016.6888 1516.6888
## Feb 2022            40 -788.24329  868.2433 -1226.6888 1306.6888
## Mar 2022          -150 -978.24329  678.2433 -1416.6888 1116.6888
## Apr 2022          2760 1931.75671 3588.2433 1493.3112 4026.6888
## May 2022         -1600 -2428.24329 -771.7567 -2866.6888 -333.3112
## Jun 2022           -30 -858.24329  798.2433 -1296.6888 1236.6888
## Jul 2022          -210 -1038.24329  618.2433 -1476.6888 1056.6888
## Aug 2022          -420 -1248.24329  408.2433 -1686.6888  846.6888
## Sep 2022           500 -328.24329 1328.2433 -766.6888 1766.6888
## Oct 2022           310 -518.24329 1138.2433 -956.6888 1576.6888
## Nov 2022           220 -608.24329 1048.2433 -1046.6888 1486.6888
##           Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Dec 2020           -30 -615.65645  555.6564 -925.6842  865.6842
## Jan 2021            250 -335.65645  835.6564 -645.6842 1145.6842
## Feb 2021             40 -545.65645  625.6564 -855.6842  935.6842
## Mar 2021          -150 -735.65645  435.6564 -1045.6842  745.6842
## Apr 2021          2760 2174.34355 3345.6564 1864.3158 3655.6842
## May 2021         -1600 -2185.65645 -1014.3436 -2495.6842 -704.3158
## Jun 2021           -30 -615.65645  555.6564 -925.6842  865.6842
## Jul 2021          -210 -795.65645  375.6564 -1105.6842  685.6842
## Aug 2021          -420 -1005.65645  165.6564 -1315.6842  475.6842
## Sep 2021           500  -85.65645 1085.6564 -395.6842 1395.6842
## Oct 2021           310 -275.65645  895.6564 -585.6842 1205.6842
## Nov 2021           220 -365.65645  805.6564 -675.6842 1115.6842
## Dec 2021           -30 -858.24329  798.2433 -1296.6888 1236.6888
## Jan 2022           250 -578.24329 1078.2433 -1016.6888 1516.6888
```

```
## Feb 2022      40  -788.24329   868.2433 -1226.6888 1306.6888
## Mar 2022     -150 -978.24329   678.2433 -1416.6888 1116.6888
## Apr 2022     2760 1931.75671  3588.2433 1493.3112 4026.6888
## May 2022    -1600 -2428.24329 -771.7567 -2866.6888 -333.3112
## Jun 2022     -30  -858.24329   798.2433 -1296.6888 1236.6888
## Jul 2022    -210 -1038.24329   618.2433 -1476.6888 1056.6888
## Aug 2022    -420 -1248.24329   408.2433 -1686.6888  846.6888
## Sep 2022     500  -328.24329  1328.2433  -766.6888 1766.6888
## Oct 2022     310  -518.24329  1138.2433  -956.6888 1576.6888
## Nov 2022     220  -608.24329  1048.2433 -1046.6888 1486.6888
```

```
checkresiduals(fit)
```

Residuals from Seasonal naive method



```
##
## Ljung-Box test
##
## data: Residuals from Seasonal naive method
## Q* = 19.838, df = 16, p-value = 0.2276
##
## Model df: 0. Total lags used: 16
```

```
#Fit on ARIMA Model
```

```
fit_arima<-auto.arima(Y,d=1,D=1,stepwise = FALSE,approximation = FALSE,trace=TRUE)
```

```
##
## ARIMA(0,1,0)(0,1,0)[12] : 1058.163
## ARIMA(0,1,0)(0,1,1)[12] : 1055.437
## ARIMA(0,1,0)(0,1,2)[12] : 1057.277
## ARIMA(0,1,0)(1,1,0)[12] : 1056.817
## ARIMA(0,1,0)(1,1,1)[12] : 1057.51
## ARIMA(0,1,0)(1,1,2)[12] : 1059.262
## ARIMA(0,1,0)(2,1,0)[12] : 1055.746
## ARIMA(0,1,0)(2,1,1)[12] : Inf
## ARIMA(0,1,0)(2,1,2)[12] : Inf
## ARIMA(0,1,1)(0,1,0)[12] : 1048.205
## ARIMA(0,1,1)(0,1,1)[12] : 1045.49
## ARIMA(0,1,1)(0,1,2)[12] : 1047.594
## ARIMA(0,1,1)(1,1,0)[12] : 1046.676
## ARIMA(0,1,1)(1,1,1)[12] : 1047.695
## ARIMA(0,1,1)(1,1,2)[12] : Inf
## ARIMA(0,1,1)(2,1,0)[12] : 1045.821
## ARIMA(0,1,1)(2,1,1)[12] : 1046.245
## ARIMA(0,1,1)(2,1,2)[12] : 1048.633
## ARIMA(0,1,2)(0,1,0)[12] : 1050.324
## ARIMA(0,1,2)(0,1,1)[12] : 1047.704
## ARIMA(0,1,2)(0,1,2)[12] : 1049.823
## ARIMA(0,1,2)(1,1,0)[12] : 1048.902
## ARIMA(0,1,2)(1,1,1)[12] : 1049.962
## ARIMA(0,1,2)(1,1,2)[12] : 1052.05
## ARIMA(0,1,2)(2,1,0)[12] : 1048.09
## ARIMA(0,1,2)(2,1,1)[12] : 1048.635
## ARIMA(0,1,3)(0,1,0)[12] : 1052.554
## ARIMA(0,1,3)(0,1,1)[12] : 1049.701
## ARIMA(0,1,3)(0,1,2)[12] : 1051.709
## ARIMA(0,1,3)(1,1,0)[12] : 1051.01
## ARIMA(0,1,3)(1,1,1)[12] : 1051.98
## ARIMA(0,1,3)(2,1,0)[12] : 1049.677
## ARIMA(0,1,4)(0,1,0)[12] : Inf
## ARIMA(0,1,4)(0,1,1)[12] : Inf
## ARIMA(0,1,4)(1,1,0)[12] : Inf
## ARIMA(0,1,5)(0,1,0)[12] : Inf
## ARIMA(1,1,0)(0,1,0)[12] : 1049.598
## ARIMA(1,1,0)(0,1,1)[12] : 1047.438
## ARIMA(1,1,0)(0,1,2)[12] : 1049.634
## ARIMA(1,1,0)(1,1,0)[12] : 1048.681
## ARIMA(1,1,0)(1,1,1)[12] : 1049.675
## ARIMA(1,1,0)(1,1,2)[12] : Inf
## ARIMA(1,1,0)(2,1,0)[12] : 1047.582
## ARIMA(1,1,0)(2,1,1)[12] : 1047.805
## ARIMA(1,1,0)(2,1,2)[12] : 1050.195
## ARIMA(1,1,1)(0,1,0)[12] : 1050.324
## ARIMA(1,1,1)(0,1,1)[12] : 1047.682
## ARIMA(1,1,1)(0,1,2)[12] : Inf
## ARIMA(1,1,1)(1,1,0)[12] : 1048.892
## ARIMA(1,1,1)(1,1,1)[12] : Inf
## ARIMA(1,1,1)(1,1,2)[12] : Inf
## ARIMA(1,1,1)(2,1,0)[12] : Inf
```



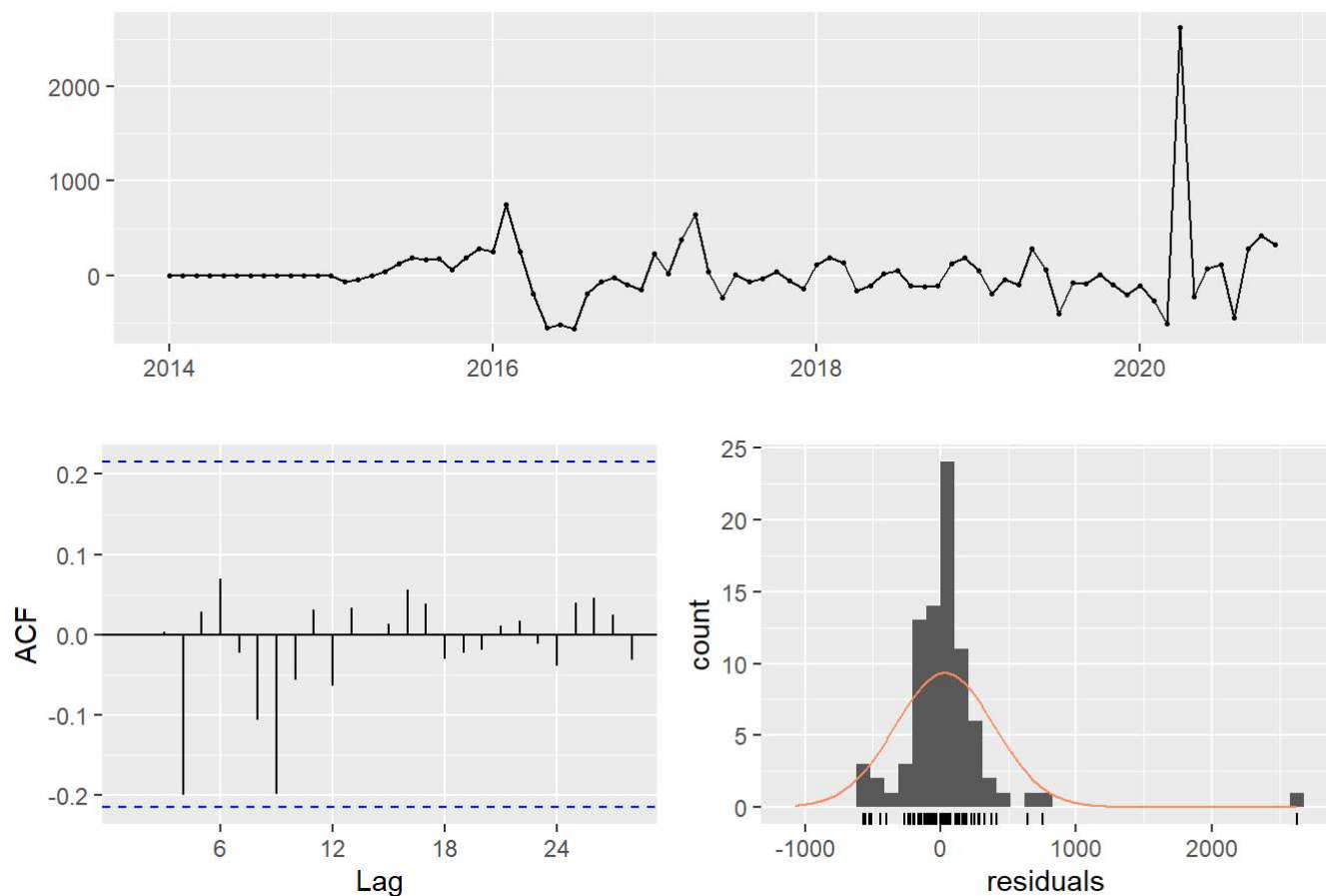
```
## ARIMA(1,1,1)(2,1,1)[12] : 1048.343
## ARIMA(1,1,2)(0,1,0)[12] : 1052.574
## ARIMA(1,1,2)(0,1,1)[12] : 1049.636
## ARIMA(1,1,2)(0,1,2)[12] : Inf
## ARIMA(1,1,2)(1,1,0)[12] : 1050.751
## ARIMA(1,1,2)(1,1,1)[12] : Inf
## ARIMA(1,1,2)(2,1,0)[12] : Inf
## ARIMA(1,1,3)(0,1,0)[12] : 1053.972
## ARIMA(1,1,3)(0,1,1)[12] : Inf
## ARIMA(1,1,3)(1,1,0)[12] : 1053.14
## ARIMA(1,1,4)(0,1,0)[12] : Inf
## ARIMA(2,1,0)(0,1,0)[12] : 1049.993
## ARIMA(2,1,0)(0,1,1)[12] : 1048
## ARIMA(2,1,0)(0,1,2)[12] : 1050.295
## ARIMA(2,1,0)(1,1,0)[12] : 1049.123
## ARIMA(2,1,0)(1,1,1)[12] : 1050.314
## ARIMA(2,1,0)(1,1,2)[12] : Inf
## ARIMA(2,1,0)(2,1,0)[12] : 1048.55
## ARIMA(2,1,0)(2,1,1)[12] : 1049.092
## ARIMA(2,1,1)(0,1,0)[12] : 1051.34
## ARIMA(2,1,1)(0,1,1)[12] : Inf
## ARIMA(2,1,1)(0,1,2)[12] : Inf
## ARIMA(2,1,1)(1,1,0)[12] : Inf
## ARIMA(2,1,1)(1,1,1)[12] : Inf
## ARIMA(2,1,1)(2,1,0)[12] : Inf
## ARIMA(2,1,2)(0,1,0)[12] : 1053.558
## ARIMA(2,1,2)(0,1,1)[12] : Inf
## ARIMA(2,1,2)(1,1,0)[12] : Inf
## ARIMA(2,1,3)(0,1,0)[12] : 1055.236
## ARIMA(3,1,0)(0,1,0)[12] : 1051.835
## ARIMA(3,1,0)(0,1,1)[12] : 1050.262
## ARIMA(3,1,0)(0,1,2)[12] : 1052.65
## ARIMA(3,1,0)(1,1,0)[12] : 1051.371
## ARIMA(3,1,0)(1,1,1)[12] : 1052.656
## ARIMA(3,1,0)(2,1,0)[12] : 1050.918
## ARIMA(3,1,1)(0,1,0)[12] : 1053.633
## ARIMA(3,1,1)(0,1,1)[12] : Inf
## ARIMA(3,1,1)(1,1,0)[12] : Inf
## ARIMA(3,1,2)(0,1,0)[12] : Inf
## ARIMA(4,1,0)(0,1,0)[12] : 1052.497
## ARIMA(4,1,0)(0,1,1)[12] : 1050
## ARIMA(4,1,0)(1,1,0)[12] : 1051.35
## ARIMA(4,1,1)(0,1,0)[12] : 1054.7
## ARIMA(5,1,0)(0,1,0)[12] : 1054.525
##
##
##
## Best model: ARIMA(0,1,1)(0,1,1)[12]
```

```
print(summary(fit_arma))
```

```
## Series: Y
## ARIMA(0,1,1)(0,1,1)[12]
##
## Coefficients:
##          ma1      sma1
##       -0.4452 -0.4181
## s.e.   0.1164  0.1709
##
## sigma^2 estimated as 162703:  log likelihood=-519.56
## AIC=1045.13   AICc=1045.49   BIC=1051.87
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 30.57467 365.1016 183.916 -3.745538 17.46485 0.3396107
##              ACF1
## Training set -0.001002148
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 30.57467 365.1016 183.916 -3.745538 17.46485 0.3396107
##              ACF1
## Training set -0.001002148
```

```
checkresiduals(fit_arma)
```

Residuals from ARIMA(0,1,1)(0,1,1)[12]



```
##  
##  Ljung-Box test  
##  
## data:  Residuals from ARIMA(0,1,1)(0,1,1)[12]  
## Q* = 10.395, df = 15, p-value = 0.7942  
##  
## Model df: 2.    Total lags used: 17
```

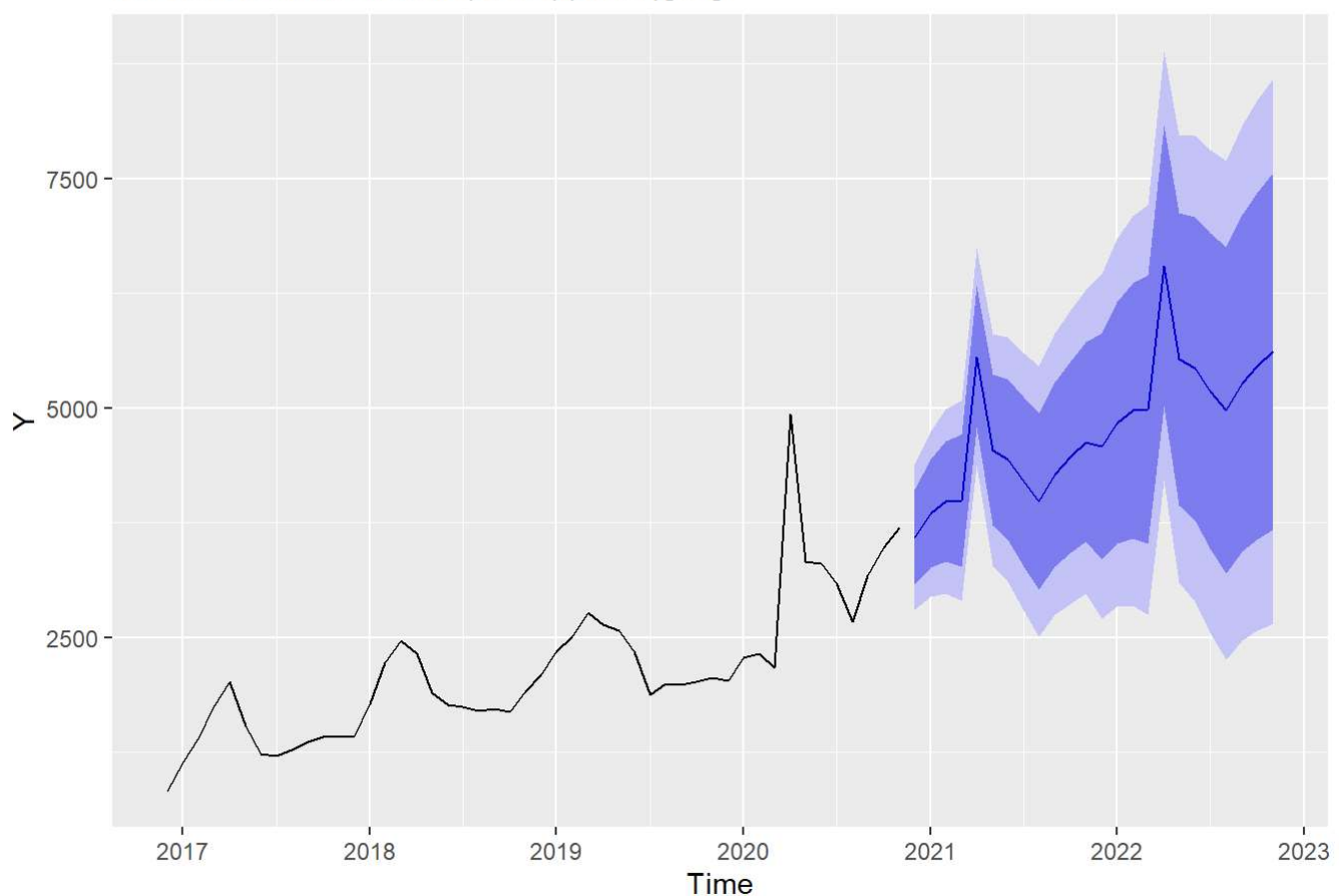
```
sqrt(162703)
```

```
## [1] 403.3646
```

```
#Forecasting on ARIMA Model
```

```
fcst<-forecast(fit_arma,h=24)  
autoplot(fcst,include=48)
```

Forecasts from ARIMA(0,1,1)(0,1,1)[12]



```
print(summary(fcst))
```

```
##
## Forecast method: ARIMA(0,1,1)(0,1,1)[12]
##
## Model Information:
## Series: Y
## ARIMA(0,1,1)(0,1,1)[12]
##
## Coefficients:
##          ma1      sma1
##       -0.4452 -0.4181
## s.e.   0.1164  0.1709
##
## sigma^2 estimated as 162703:  log likelihood=-519.56
## AIC=1045.13  AICc=1045.49  BIC=1051.87
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 30.57467 365.1016 183.916 -3.745538 17.46485 0.3396107
##              ACF1
## Training set -0.001002148
##
## Forecasts:
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Dec 2020      3591.388 3074.449 4108.328 2800.798 4381.979
## Jan 2021      3847.541 3256.381 4438.701 2943.440 4751.643
## Feb 2021      3979.102 3322.053 4636.151 2974.232 4983.972
## Mar 2021      3993.106 3276.198 4710.015 2896.690 5089.523
## Apr 2021      5559.518 4787.377 6331.658 4378.631 6740.404
## May 2021      4540.993 3717.316 5364.670 3281.287 5800.699
## Jun 2021      4438.388 3566.214 5310.562 3104.513 5772.263
## Jul 2021      4194.946 3276.833 5113.059 2790.813 5599.078
## Aug 2021      3981.996 3020.136 4943.856 2510.958 5453.034
## Sep 2021      4279.213 3275.511 5282.915 2744.183 5814.243
## Oct 2021      4468.395 3424.526 5512.263 2871.935 6064.854
## Nov 2021      4631.550 3549.005 5714.096 2975.940 6287.161
## Dec 2021      4582.788 3351.041 5814.536 2698.993 6466.583
## Jan 2022      4838.941 3526.300 6151.582 2831.430 6846.453
## Feb 2022      4970.502 3581.673 6359.331 2846.471 7094.533
## Mar 2022      4984.506 3523.457 6445.556 2750.024 7218.989
## Apr 2022      6550.917 5021.053 8080.782 4211.192 8890.643
## May 2022      5532.393 3936.678 7128.107 3091.958 7972.827
## Jun 2022      5429.788 3770.835 7088.740 2892.639 7966.937
## Jul 2022      5186.346 3466.478 6906.213 2556.036 7816.655
## Aug 2022      4973.396 3194.699 6752.093 2253.114 7693.678
## Sep 2022      5270.613 3434.971 7106.255 2463.241 8077.985
## Oct 2022      5459.794 3568.921 7350.667 2567.954 8351.635
## Nov 2022      5622.950 3678.414 7567.486 2649.039 8596.861
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Dec 2020      3591.388 3074.449 4108.328 2800.798 4381.979
## Jan 2021      3847.541 3256.381 4438.701 2943.440 4751.643
## Feb 2021      3979.102 3322.053 4636.151 2974.232 4983.972
## Mar 2021      3993.106 3276.198 4710.015 2896.690 5089.523
## Apr 2021      5559.518 4787.377 6331.658 4378.631 6740.404
```

```
## May 2021      4540.993 3717.316 5364.670 3281.287 5800.699
## Jun 2021      4438.388 3566.214 5310.562 3104.513 5772.263
## Jul 2021      4194.946 3276.833 5113.059 2790.813 5599.078
## Aug 2021      3981.996 3020.136 4943.856 2510.958 5453.034
## Sep 2021      4279.213 3275.511 5282.915 2744.183 5814.243
## Oct 2021      4468.395 3424.526 5512.263 2871.935 6064.854
## Nov 2021      4631.550 3549.005 5714.096 2975.940 6287.161
## Dec 2021      4582.788 3351.041 5814.536 2698.993 6466.583
## Jan 2022      4838.941 3526.300 6151.582 2831.430 6846.453
## Feb 2022      4970.502 3581.673 6359.331 2846.471 7094.533
## Mar 2022      4984.506 3523.457 6445.556 2750.024 7218.989
## Apr 2022      6550.917 5021.053 8080.782 4211.192 8890.643
## May 2022      5532.393 3936.678 7128.107 3091.958 7972.827
## Jun 2022      5429.788 3770.835 7088.740 2892.639 7966.937
## Jul 2022      5186.346 3466.478 6906.213 2556.036 7816.655
## Aug 2022      4973.396 3194.699 6752.093 2253.114 7693.678
## Sep 2022      5270.613 3434.971 7106.255 2463.241 8077.985
## Oct 2022      5459.794 3568.921 7350.667 2567.954 8351.635
## Nov 2022      5622.950 3678.414 7567.486 2649.039 8596.861
```

#Check with Original vs Predicted Value

```
YTest<-ts(my_data[,2],frequency=12,start=c(2014,1),end=c(2019,12))
fitTest<-auto.arima(YTest,d=1,D=1,stepwise=FALSE,approximation = FALSE,trace=TRUE)
```

```

##
## ARIMA(0,1,0)(0,1,0)[12] : 808.3935
## ARIMA(0,1,0)(0,1,1)[12] : 795.9805
## ARIMA(0,1,0)(0,1,2)[12] : Inf
## ARIMA(0,1,0)(1,1,0)[12] : 799.3952
## ARIMA(0,1,0)(1,1,1)[12] : Inf
## ARIMA(0,1,0)(1,1,2)[12] : Inf
## ARIMA(0,1,0)(2,1,0)[12] : 799.3141
## ARIMA(0,1,0)(2,1,1)[12] : Inf
## ARIMA(0,1,0)(2,1,2)[12] : Inf
## ARIMA(0,1,1)(0,1,0)[12] : 808.2001
## ARIMA(0,1,1)(0,1,1)[12] : 794.7672
## ARIMA(0,1,1)(0,1,2)[12] : Inf
## ARIMA(0,1,1)(1,1,0)[12] : 799.4682
## ARIMA(0,1,1)(1,1,1)[12] : Inf
## ARIMA(0,1,1)(1,1,2)[12] : Inf
## ARIMA(0,1,1)(2,1,0)[12] : 798.6091
## ARIMA(0,1,1)(2,1,1)[12] : Inf
## ARIMA(0,1,1)(2,1,2)[12] : Inf
## ARIMA(0,1,2)(0,1,0)[12] : 809.5609
## ARIMA(0,1,2)(0,1,1)[12] : 797.0715
## ARIMA(0,1,2)(0,1,2)[12] : Inf
## ARIMA(0,1,2)(1,1,0)[12] : 801.3493
## ARIMA(0,1,2)(1,1,1)[12] : Inf
## ARIMA(0,1,2)(1,1,2)[12] : Inf
## ARIMA(0,1,2)(2,1,0)[12] : 800.9482
## ARIMA(0,1,2)(2,1,1)[12] : Inf
## ARIMA(0,1,3)(0,1,0)[12] : 811.8644
## ARIMA(0,1,3)(0,1,1)[12] : 799.4181
## ARIMA(0,1,3)(0,1,2)[12] : Inf
## ARIMA(0,1,3)(1,1,0)[12] : 803.7328
## ARIMA(0,1,3)(1,1,1)[12] : Inf
## ARIMA(0,1,3)(2,1,0)[12] : 803.2117
## ARIMA(0,1,4)(0,1,0)[12] : 813.9531
## ARIMA(0,1,4)(0,1,1)[12] : Inf
## ARIMA(0,1,4)(1,1,0)[12] : Inf
## ARIMA(0,1,5)(0,1,0)[12] : Inf
## ARIMA(1,1,0)(0,1,0)[12] : 808.7955
## ARIMA(1,1,0)(0,1,1)[12] : 795.0395
## ARIMA(1,1,0)(0,1,2)[12] : Inf
## ARIMA(1,1,0)(1,1,0)[12] : 799.8518
## ARIMA(1,1,0)(1,1,1)[12] : Inf
## ARIMA(1,1,0)(1,1,2)[12] : Inf
## ARIMA(1,1,0)(2,1,0)[12] : 798.9885
## ARIMA(1,1,0)(2,1,1)[12] : Inf
## ARIMA(1,1,0)(2,1,2)[12] : Inf
## ARIMA(1,1,1)(0,1,0)[12] : 809.6018
## ARIMA(1,1,1)(0,1,1)[12] : 797.0715
## ARIMA(1,1,1)(0,1,2)[12] : Inf
## ARIMA(1,1,1)(1,1,0)[12] : 801.3309
## ARIMA(1,1,1)(1,1,1)[12] : Inf
## ARIMA(1,1,1)(1,1,2)[12] : Inf
## ARIMA(1,1,1)(2,1,0)[12] : 800.9665

```

```
## ARIMA(1,1,1)(2,1,1)[12] : Inf
## ARIMA(1,1,2)(0,1,0)[12] : 811.8635
## ARIMA(1,1,2)(0,1,1)[12] : Inf
## ARIMA(1,1,2)(0,1,2)[12] : Inf
## ARIMA(1,1,2)(1,1,0)[12] : 803.7221
## ARIMA(1,1,2)(1,1,1)[12] : Inf
## ARIMA(1,1,2)(2,1,0)[12] : Inf
## ARIMA(1,1,3)(0,1,0)[12] : Inf
## ARIMA(1,1,3)(0,1,1)[12] : Inf
## ARIMA(1,1,3)(1,1,0)[12] : Inf
## ARIMA(1,1,4)(0,1,0)[12] : Inf
## ARIMA(2,1,0)(0,1,0)[12] : 809.8791
## ARIMA(2,1,0)(0,1,1)[12] : 796.9422
## ARIMA(2,1,0)(0,1,2)[12] : Inf
## ARIMA(2,1,0)(1,1,0)[12] : 801.4879
## ARIMA(2,1,0)(1,1,1)[12] : Inf
## ARIMA(2,1,0)(1,1,2)[12] : Inf
## ARIMA(2,1,0)(2,1,0)[12] : 800.7361
## ARIMA(2,1,0)(2,1,1)[12] : Inf
## ARIMA(2,1,1)(0,1,0)[12] : 811.8761
## ARIMA(2,1,1)(0,1,1)[12] : Inf
## ARIMA(2,1,1)(0,1,2)[12] : Inf
## ARIMA(2,1,1)(1,1,0)[12] : Inf
## ARIMA(2,1,1)(1,1,1)[12] : Inf
## ARIMA(2,1,1)(2,1,0)[12] : Inf
## ARIMA(2,1,2)(0,1,0)[12] : Inf
## ARIMA(2,1,2)(0,1,1)[12] : Inf
## ARIMA(2,1,2)(1,1,0)[12] : Inf
## ARIMA(2,1,3)(0,1,0)[12] : Inf
## ARIMA(3,1,0)(0,1,0)[12] : 812.1188
## ARIMA(3,1,0)(0,1,1)[12] : 798.8604
## ARIMA(3,1,0)(0,1,2)[12] : Inf
## ARIMA(3,1,0)(1,1,0)[12] : 803.8553
## ARIMA(3,1,0)(1,1,1)[12] : Inf
## ARIMA(3,1,0)(2,1,0)[12] : 802.6333
## ARIMA(3,1,1)(0,1,0)[12] : Inf
## ARIMA(3,1,1)(0,1,1)[12] : Inf
## ARIMA(3,1,1)(1,1,0)[12] : Inf
## ARIMA(3,1,2)(0,1,0)[12] : Inf
## ARIMA(4,1,0)(0,1,0)[12] : 813.9395
## ARIMA(4,1,0)(0,1,1)[12] : 799.9092
## ARIMA(4,1,0)(1,1,0)[12] : 804.6628
## ARIMA(4,1,1)(0,1,0)[12] : 816.3976
## ARIMA(5,1,0)(0,1,0)[12] : 816.3737
##
##
##
## Best model: ARIMA(0,1,1)(0,1,1)[12]
```

```
fctest<-forecast(fitTest,h=11)
print(summary(fctest))
```

```
##
## Forecast method: ARIMA(0,1,1)(0,1,1)[12]
##
## Model Information:
## Series: YTest
## ARIMA(0,1,1)(0,1,1)[12]
##
## Coefficients:
##          ma1      sma1
##      0.2540  -0.7301
## s.e.  0.1294   0.2615
##
## sigma^2 estimated as 33097:  log likelihood=-394.17
## AIC=794.33  AICc=794.77  BIC=800.56
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
## Training set 0.783362 161.8688 110.6011 -1.825139 12.66811 0.2421922 0.01522368
##
## Forecasts:
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Jan 2020      2200.752 1965.244 2436.259 1840.5741 2560.929
## Feb 2020      2461.146 2084.469 2837.823 1885.0689 3037.224
## Mar 2020      2638.349 2160.534 3116.164 1907.5945 3369.104
## Apr 2020      2573.680 2012.673 3134.687 1715.6940 3431.666
## May 2020      2338.253 1704.888 2971.617 1369.6057 3306.900
## Jun 2020      2189.398 1491.134 2887.661 1121.4958 3257.299
## Jul 2020      2024.009 1266.386 2781.633  865.3241 3182.695
## Aug 2020      2094.998 1282.339 2907.657  852.1429 3337.853
## Sep 2020      2138.197 1273.999 3002.394  816.5211 3459.872
## Oct 2020      2151.263 1238.433 3064.093  755.2101 3547.315
## Nov 2020      2241.560 1282.560 3200.559  774.8969 3708.223
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## Jan 2020      2200.752 1965.244 2436.259 1840.5741 2560.929
## Feb 2020      2461.146 2084.469 2837.823 1885.0689 3037.224
## Mar 2020      2638.349 2160.534 3116.164 1907.5945 3369.104
## Apr 2020      2573.680 2012.673 3134.687 1715.6940 3431.666
## May 2020      2338.253 1704.888 2971.617 1369.6057 3306.900
## Jun 2020      2189.398 1491.134 2887.661 1121.4958 3257.299
## Jul 2020      2024.009 1266.386 2781.633  865.3241 3182.695
## Aug 2020      2094.998 1282.339 2907.657  852.1429 3337.853
## Sep 2020      2138.197 1273.999 3002.394  816.5211 3459.872
## Oct 2020      2151.263 1238.433 3064.093  755.2101 3547.315
## Nov 2020      2241.560 1282.560 3200.559  774.8969 3708.223
```

#Testing With Original Data

```
original_2020<-tail(Y,11)
print(original_2020)
```


##	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
## 2020	2280	2320	2170	4930	3330	3300	3090	2670	3170	3480	3700