Time Series forecasting

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Project Objective: Demand for 2 products A and B are provided for period Jan 2002 till Jul 2017. We are required to check the trends, seasonality and perform best model fit of the time series and forecast the demands for both the products from Sep 2017 till Dec 2018

1. Assumptions: There are no specific assumptions made in the explanation of the solutions
2. Dataset: The provided data is in the .csv file and a sample format is provided below

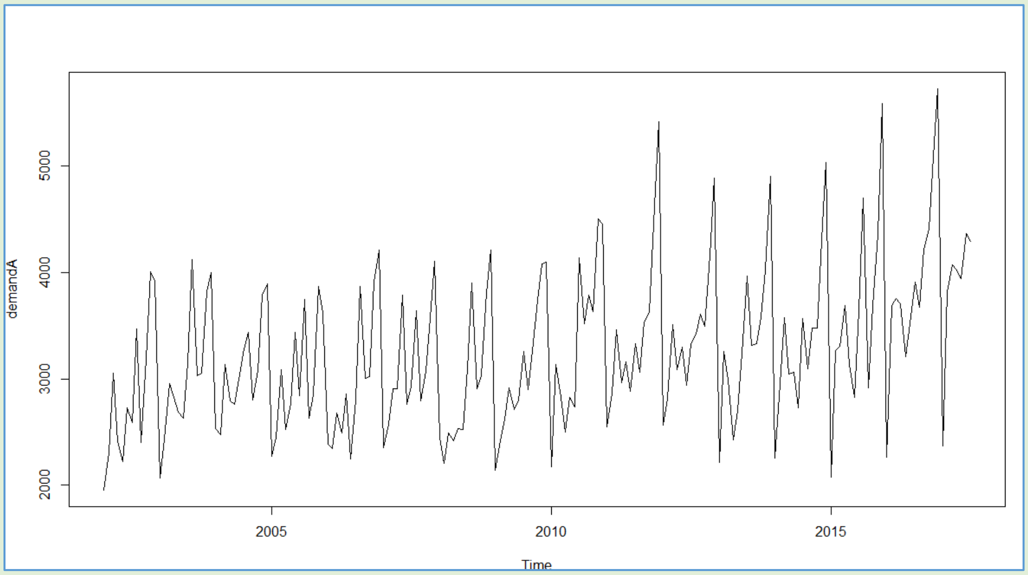
	A	B	C	D	E	F
1	Year	Month	Item A	Item B	Diff A	Diff B
2	2002	1	1954	2585		
3	2002	2	2302	3368	348	783
4	2002	3	3054	3210	752	-158
5	2002	4	2414	3111	-640	-99
6	2002	5	2226	3756	-188	645
7	2002	6	2725	4216	499	460
8	2002	7	2589	5225	-136	1009
9	2002	8	3470	4426	881	-799
10	2002	9	2400	3932	-1070	-494
11	2002	10	3180	3816	780	-116
12	2002	11	4009	3661	829	-155
13	2002	12	3924	3795	-85	134
14	2003	1	2072	2285	-1852	-1510
15	2003	2	2434	2934	362	649
16	2003	3	2956	2985	522	51
17	2003	4	2828	3646	-128	661
18	2003	5	2687	4198	-141	552
19	2003	6	2629	4935	-58	737
20	2003	7	3150	5618	521	683
21	2003	8	4119	5454	969	-164
22	2003	9	3030	3624	-1089	-1830
23	2003	10	3055	2898	25	-726

3.

4. **Exploratory Data Analysis**
   4.1. **Environmental Set Up and Data Import**: The provided dataset will be analyzed in R STUDIO by importing it using the *read.csv* function. Simple Time Series Forecasting methods like ARIMA etc. will be used to forecast the demands for the 2 products. Data will be divided in the train and test and will be validated using the MAPE technique
   4.2. Install packages and invoke libraries: Variety of packages used and invoked libraries.
      4.2.1. tseries
      4.2.2. reshape2
      4.2.3. fpp2
      4.2.4. Forecast

Q1: Before a formal extraction of time series components is done, can you check for seasonal changes in the data for the two series separately? Particularly whether there are more variability in a season compared to the others, whether seasonal variations are changing across years etc. Compare the behavior of the two series

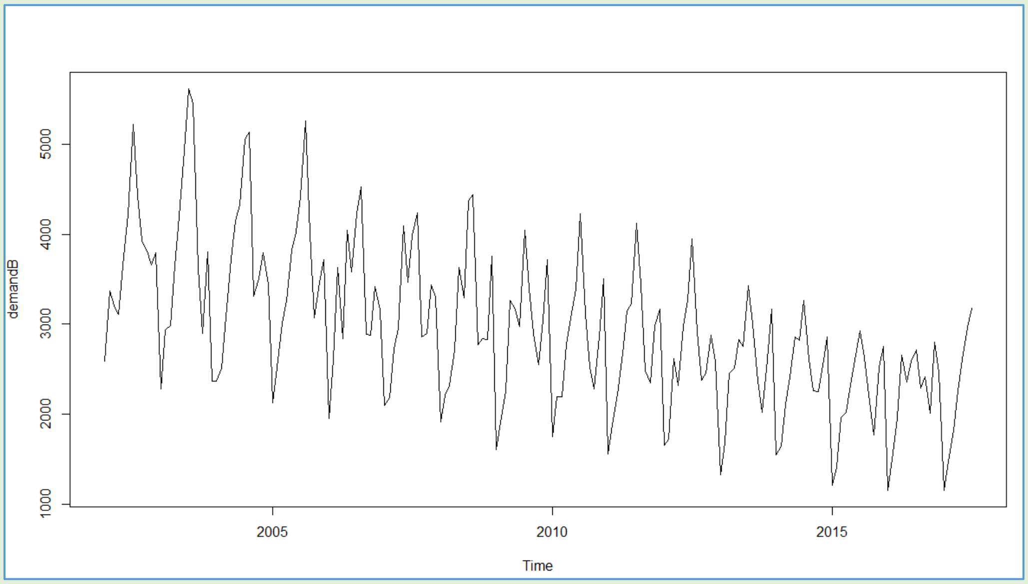
Visualization for Product A



Visualizing the data it can be seen that there exists no trend for product A as it shows steady demand for the product over the period and also no seasonality

Visualization for Product B:

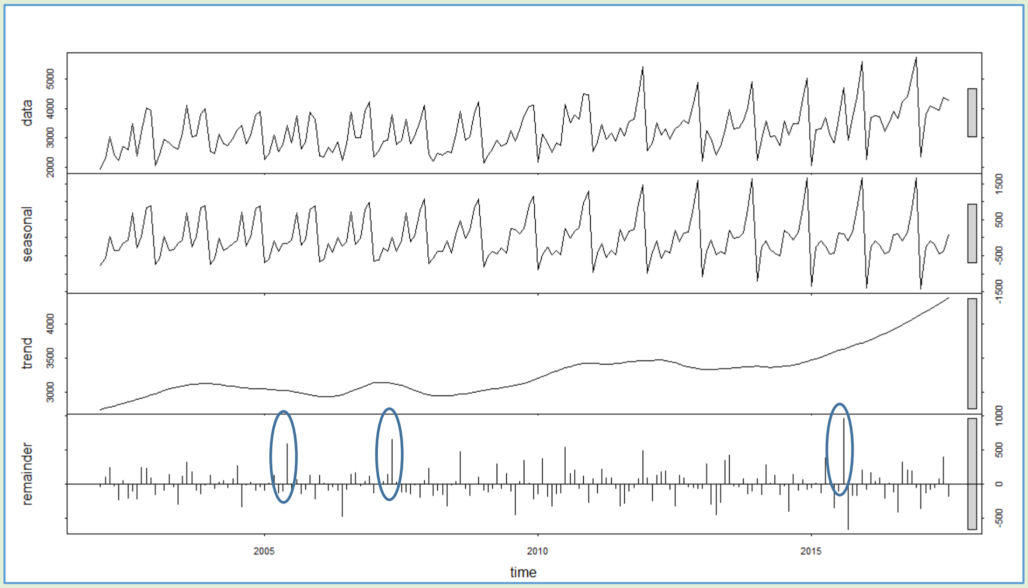
The below graph depicts that there is gradual declining trend for the product and seasonality also exists to a certain extent



Q2: Decompose each series to extract trend and seasonality, if there are any. Which seasonality is more appropriate – additive or multiplicative? Explain the seasonal indices. In which month(s) do you see higher sales and which month(s) you see lower sales? Any difference in the nature of demand of the two items?

```
# decomposition

demandAstl = stl(demandA, s.window = 7)
plot(demandAstl)
```

Decomposition is done using the 'stl' function in R. It is assumed that there are no seasonal patterns for A, s.window has been used with number 7.



The decomposed graph is divided in 4 parts.

1st part is the actual data plotted

2nd part is the seasonal component

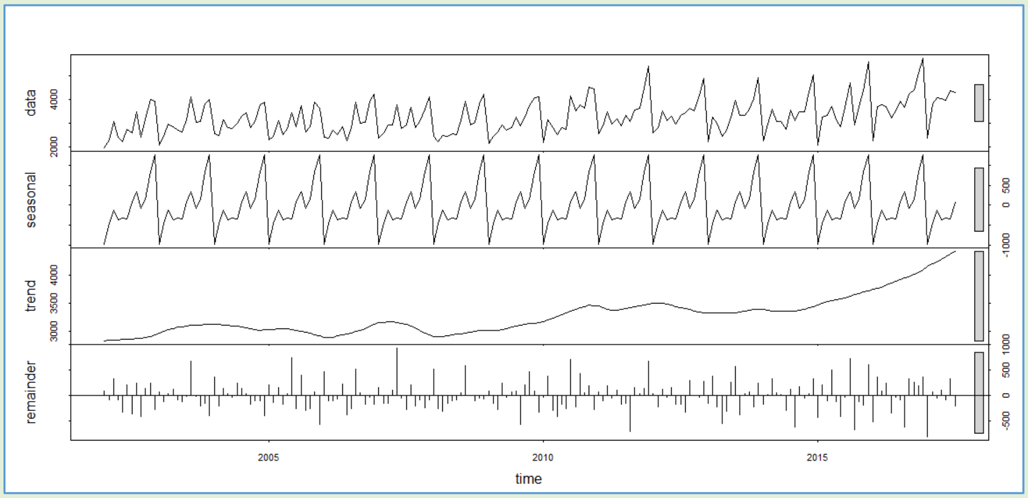
3rd part is the trend of the data. This part is very similar to the first part but only in a smoothed manner

4th part is the unexplained or the remainder part which the decomposition could not explain. It can be observed that there are few occasions that the decomposition could not identify the spikes in the data (marked in circles). These can be investigated to see what could have been the reasons for the spikes. Since no information is available not much comments could be done.

Since we have assumed that there are no seasonality we considered a number while decomposing and we could see that the seasonality is not evenly spread. However if you look at the grey bars at the right hand corner, its length of the bar decides the significance of either trend or seasonality.

Lesser the length of the bar the more significant that component and thus it can be seen that the seasonality is significant than the trend of the data.

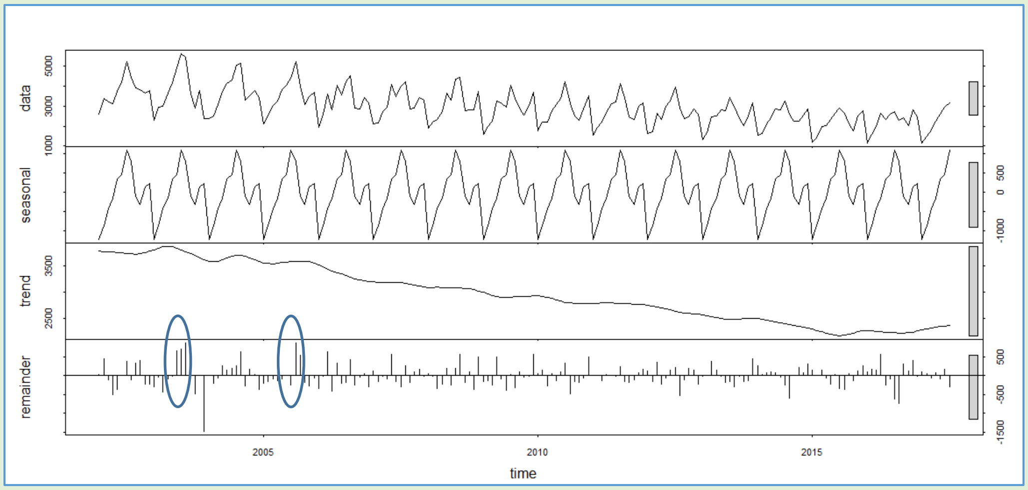
Let us also observe the data assuming there is seasonality and we use ‘p’ for the s.window



It can be observed that due to seasonality assumption the seasonal part of the graph is now much more aligned. It can also be seen that the grey line is still smaller than the trend and thus making seasonality significant. Rest of the graph remains the same.

Similar can be observed for demand for product B

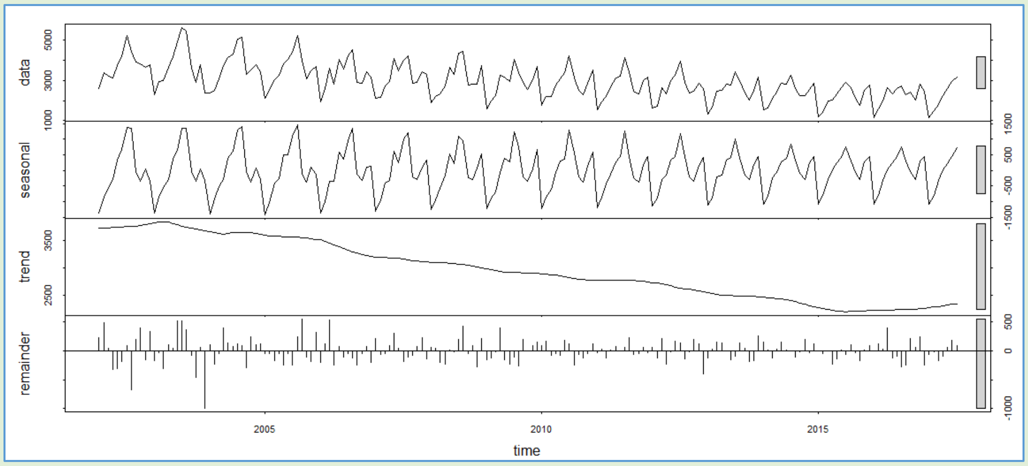
Assumption that there exists no seasonality and thus using s.window as 7



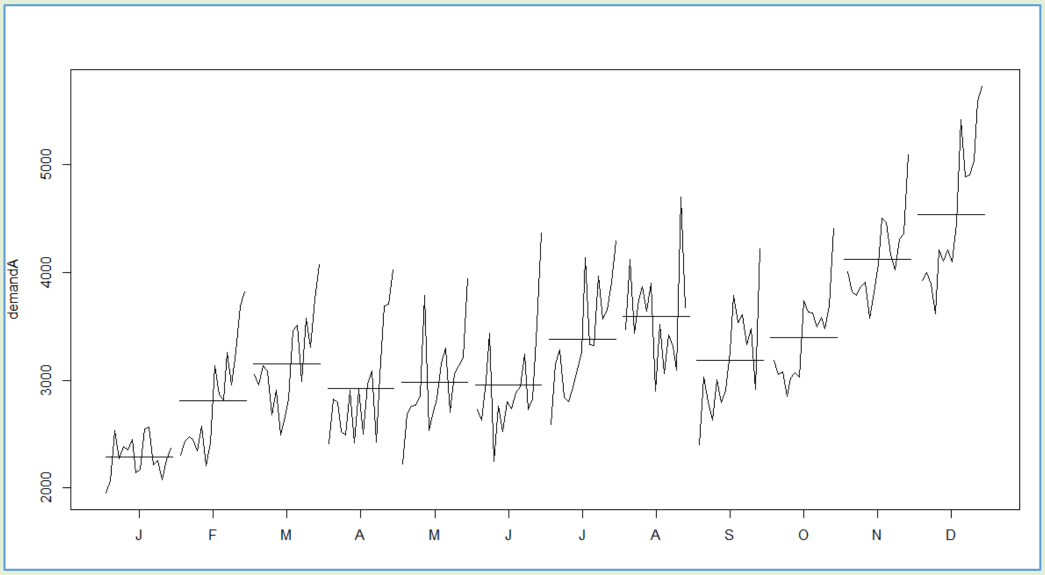
It can be observed that the seasonality pattern is much aligned and also the grey bar is also shorter than the trend.

There are again at times when the decomposition could not identify spikes as shown in the circles. The trend also shows that there is a declining trend for the product.

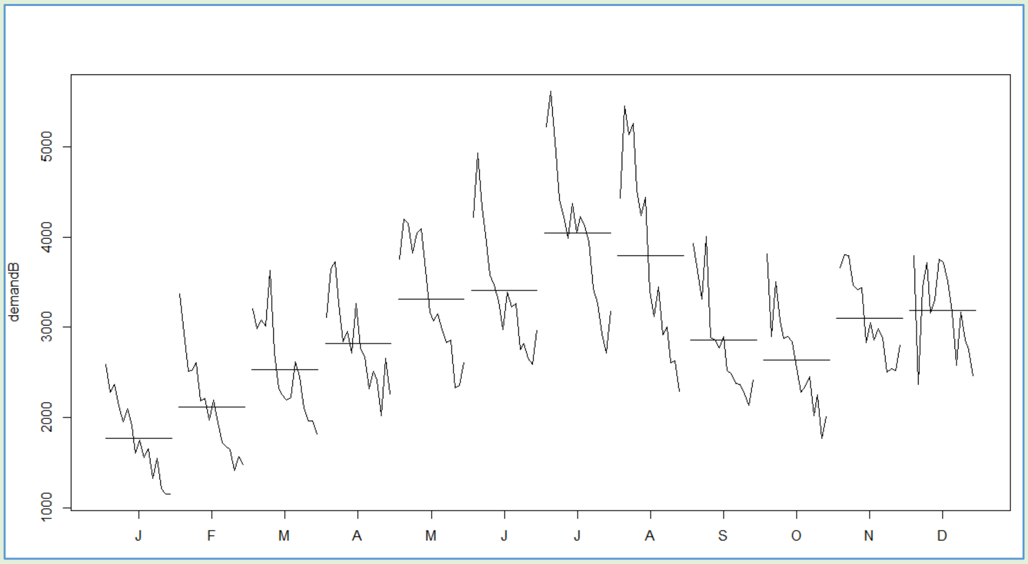
With seasonality assumed the significance still remains for seasonality. Rest everything remains the same.



Visualization using month plot for product A: With the below graph it is evident that the sales are high during the last 2 months i.e. Nov and Dec and lowest during Jan. The sales stabilize during Apr, May and Jun post which spikes are seen in the next couple of months only to witness reduced sales in Sep and gradually reach the peak



Month plot for product B: For Product B, it is evident that sales are high during the months of Jul. Lowest sales being in Jan and they gradually increase every month to reach peak in Jul and later dip further month on month except a small recovery during Nov and Dec



With the above product demands being broken down into monthly sales and considering the entire product demand analysis it can be said that

i. The nature of the products are very different since the demand for product A is a steady one.
ii. There can be some seasonality but overall the demand for the product A is steady.
iii. The peak periods of the product A also is towards the end of the year as compared to B which is somewhere at the middle of the year.
iv. Product B is on the declining trend. This could mean that the product is at its end of life cycle or it requires reinventing the wheel so as to sustain it into the market.

Q3. Can you extract the residuals for the two decomposition exercises and check if they form a stationary series? Do a formal test for stationarity writing down the null and alternative hypothesis. What is your conclusion in each case?

The products are defined in the below time series object in R

demandA and demandB

To perform an ARIMA model test, it is a mandatory requirement that the data has to be stationary. Typically data with trends or seasonality will not stationary series. However to test if the data is stationary or not Augmented Dickey Fuller test is done. In this test

The test is a Hypothesis testing done where

Null hypothesis is the data is not stationary

Alternative hypothesis is that the data is stationary

In our case the test is conducted on the time series defined objects demandA and demandB

```
# Doing the stationary test using the ADF test
adf.test(demandA)
adf.test(demandB)
```

The results for both the TS objects demandA and demandB are given below

```
        Augmented Dickey-Fuller Test

data:  demandA
Dickey-Fuller = -7.8632, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

```
        Augmented Dickey-Fuller Test

data:  demandB
Dickey-Fuller = -12.967, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

Given the p value of 0.01 for both the time series objects, and considering the threshold value of p-value to be 0.05 it can be said that the alternative hypothesis will be accepted which means that the data is stationary and an ARIMA model can be built on this data

Q4. Before the final forecast is undertaken one would like to compare a few models. Use the last 21 months as hold-out sample fit a suitable exponential smoothing model to the rest of the data and calculate MAPE. What are the values of α, β and γ? What role do they play in the modeling? For the same hold-out period compare forecast by decomposition and compute MAPE. Which model gives smaller MAPE? Give a comparison for the two demands

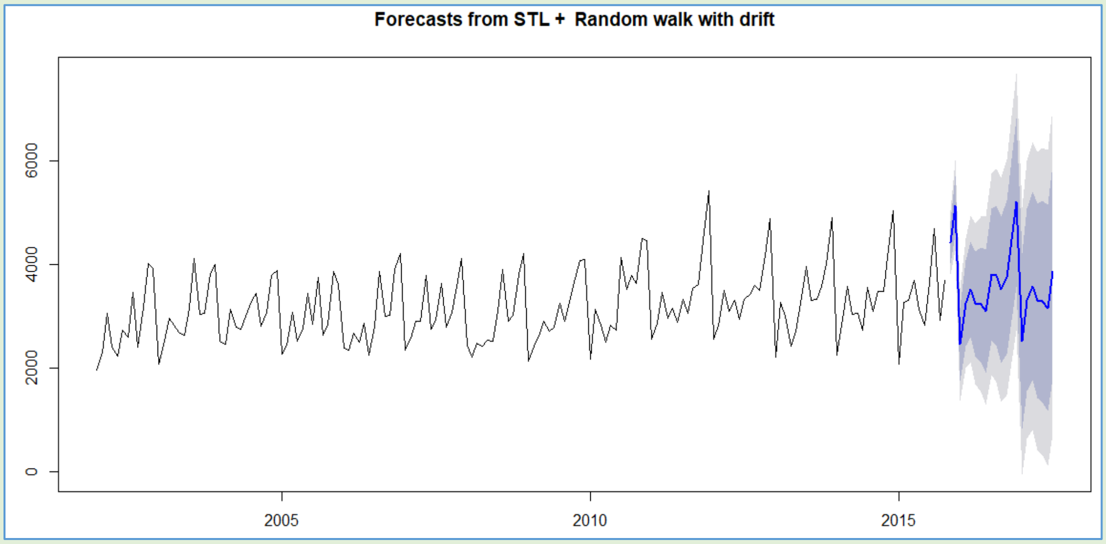
R Codes for doing an exponential smoothing forecast with MAPE

```
# Demand Forecasting and calculation of MAPE under exponential smoothing
forecast.demandA <- forecast(DmndTrnA, method="rwdrift", h=21)
plot(forecast.demandA)
forecast.demandA
forecast.demandB <- forecast(DmndTrnB, method="rwdrift", h=21)
plot(forecast.demandB)
forecast.demandB
VecA<- cbind(demandAtest,forecast.demandA$mean)
ts.plot(VecA, col=c("blue", "red"), main="Demand A vs Forecast")
MAPE <- mean(abs(VecA[,1]-VecA[,2])/VecA[,1])
MAPE
VecB<- cbind(demandBtest,forecast.demandB$mean)
ts.plot(VecB, col=c("blue", "red"), main="Demand A vs Forecast")
MAPE <- mean(abs(VecB[,1]-VecB[,2])/VecB[,1])
MAPE
# Forecast for simple exponential smoothing
fcdemandA = ses(demandAtest, h =5)
plot(fcdemandA)
fcdmndA = ses(demandA, h =3)
plot(fcdmndA)
ts.plot(demandA, fcdmndA$fitted, col=c("brown", "gold"))
round(accuracy(fcdmndA),2)
fcdmndA$model
fcdmndA$mean
fcdmndA2 = ses(demandA, alpha = 0.2)
fcdmndA2
fcdmndA5 = ses(demandA, alpha = 0.5)
fcdmndA5
fcdmndA8 = ses(demandA, alpha = 0.8)
fcdmndA8
ts.plot(demandA,fcdmndA2$fitted, fcdmndA5$fitted, fcdmndA8$fitted, col=c("black","red","blue"))
```

MAPE for both products

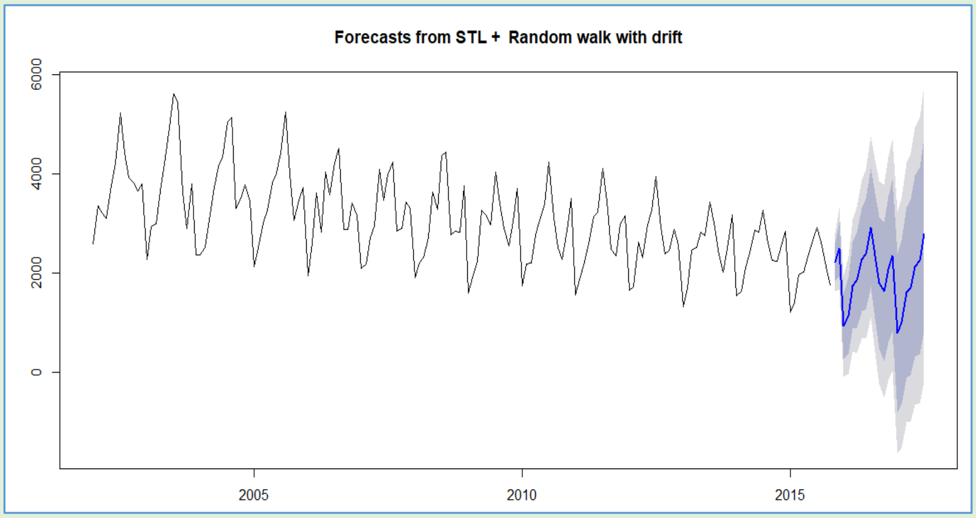
```
> VecA<- cbind(demandAtest,forecast.demandA$mean)
> ts.plot(VecA, col=c("blue", "red"), main="Demand A vs Forec
ast")
> MAPE <- mean(abs(VecA[,1]-VecA[,2])/VecA[,1])
> MAPE
[1] 0.105762
> VecB<- cbind(demandBtest,forecast.demandB$mean)
> ts.plot(VecB, col=c("blue", "red"), main="Demand A vs Forec
ast")
> MAPE <- mean(abs(VecB[,1]-VecB[,2])/VecB[,1])
> MAPE
[1] 0.1694894
```

Demand Forecast for A using the random walk with drift



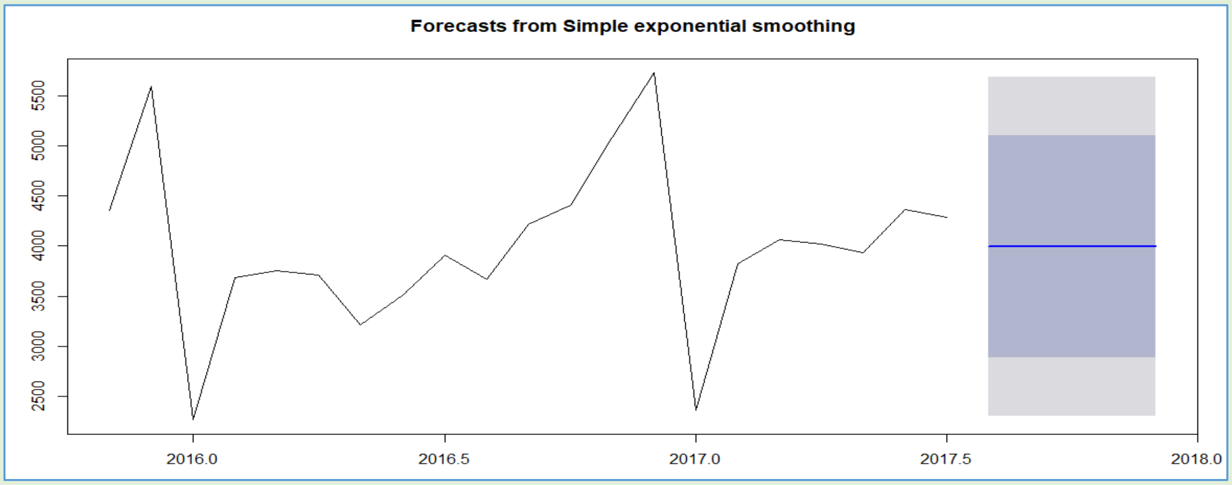

```
> forecast.demandA
         Point Forecast     Lo 80    Hi 80      Lo 95    Hi 95
Nov 2015       4420.996 4018.426 4823.565  3805.3185 5036.673
Dec 2015       5138.832 4566.093 5711.571  4262.9033 6014.760
Jan 2016       2453.320 1747.698 3158.942  1374.1643 3532.475
Feb 2016       3252.907 2433.346 4072.468  1999.4968 4506.317
Mar 2016       3521.415 2599.807 4443.024  2111.9363 4930.894
Apr 2016       3240.289 2224.932 4255.646  1687.4340 4793.144
May 2016       3226.707 2123.782 4329.632  1539.9290 4913.485
Jun 2016       3100.183 1914.501 4285.865  1286.8389 4913.527
Jul 2016       3805.255 2540.682 5069.828  1871.2578 5739.253
Aug 2016       3785.818 2445.537 5126.099  1736.0353 5835.601
Sep 2016       3513.509 2100.192 4926.827  1352.0266 5674.992
Oct 2016       3748.572 2264.495 5232.650  1478.8720 6018.273
Nov 2016       4483.568 2930.697 6036.439  2108.6563 6858.479
Dec 2016       5201.404 3581.454 6821.354  2723.9044 7678.904
Jan 2017       2515.892  830.374 4201.410   -61.8855 5093.670
Feb 2017       3315.479 1565.733 5065.225   639.4737 5991.485
Mar 2017       3583.988 1771.212 5396.763   811.5868 6356.388
Apr 2017       3302.861 1428.134 5177.589   435.7127 6170.010
May 2017       3289.280 1353.573 5224.986   328.8724 6249.687
Jun 2017       3162.755 1166.955 5158.555   110.4424 6215.068
Jul 2017       3867.828 1812.741 5922.915   724.8432 7010.812
```

Demand Forecast for B using the random walk with drift




```
> forecast.demandB
         Point Forecast        Lo 80    Hi 80       Lo 95
Nov 2015      2222.7378 1842.98553 2602.490  1641.95680
Dec 2015      2496.3945 1956.11808 3036.671  1670.11302
Jan 2016       936.5148  270.88704 1602.143   -81.47503
Feb 2016      1146.8242  373.71543 1919.933   -35.54362
Mar 2016      1752.3607  882.98798 2621.733   422.76988
Apr 2016      1853.1222  895.31451 2810.930   388.28174
May 2016      2273.2389 1232.82680 3313.651   682.06591
Jun 2016      2391.3840 1272.90557 3509.862   680.81885
Jul 2016      2927.5475 1734.64951 4120.446  1103.16745
Aug 2016      2344.5098 1080.19483 3608.825   410.90692
Sep 2016      1808.2158  475.00392 3141.428  -230.75583
Oct 2016      1634.3589  234.39799 3034.320  -506.69655
Nov 2016      2085.0967  620.24105 3549.952  -155.20671
Dec 2016      2358.7534  830.62095 3886.886    21.67650
Jan 2017       798.8738 -791.11063 2388.858 -1632.79752
Feb 2017      1009.1831 -641.38861 2659.755 -1515.14848
Mar 2017      1614.7196  -95.30920 3324.748 -1000.54376
Apr 2017      1715.4811  -52.98854 3483.951  -989.15984
May 2017      2135.5978  309.60587 3961.590  -657.01586
Jun 2017      2253.7429  371.06317 4136.423  -625.56727
Jul 2017      2789.9064  851.30012 4728.513  -174.93607
```

Under simple exponential smoothing, the value forecasted is a single value for any period as shown in the below graph



Using the Holt Winter Model

Forecast graphical representation for product A

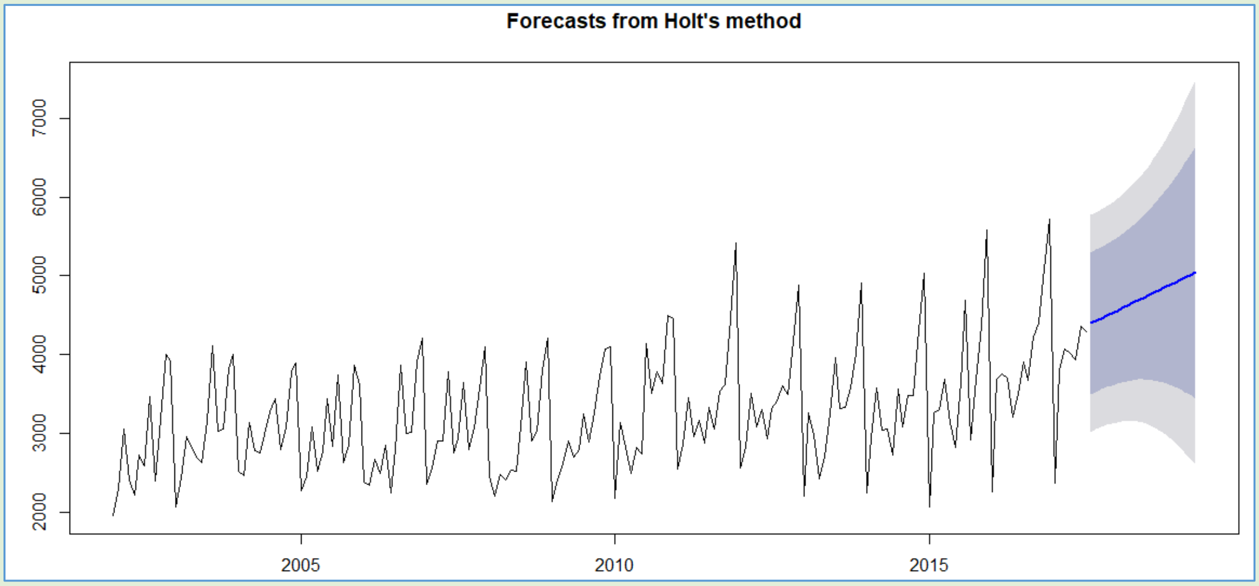


Table depicting the values forecasted

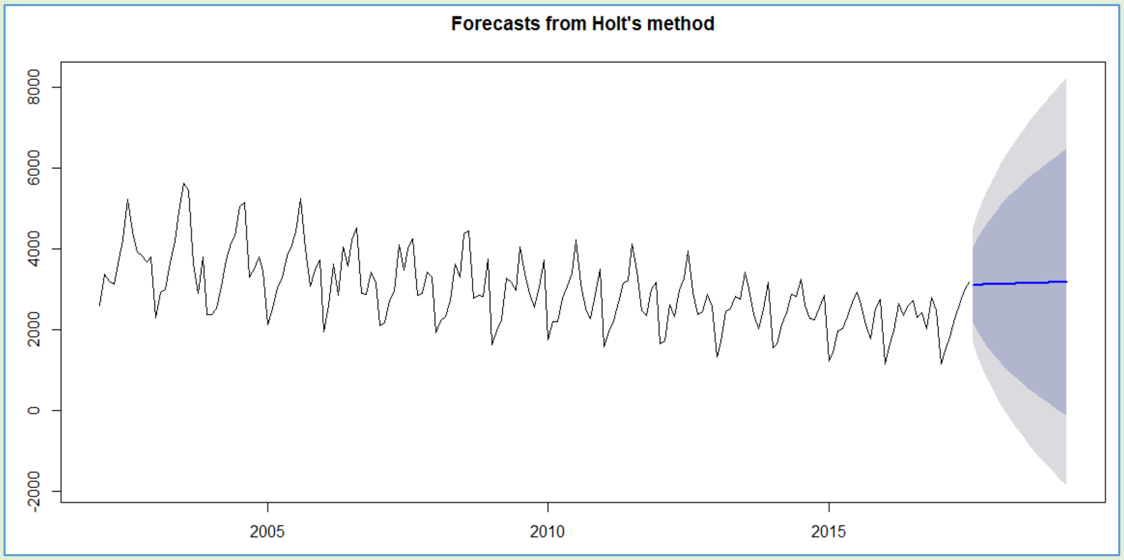
```
> fcdmndA_Holt
```

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Aug 2017	4397.713	3498.450	5296.977	3022.409	5773.018
Sep 2017	4430.042	3529.612	5330.473	3052.953	5807.132
Oct 2017	4462.371	3559.320	5365.422	3081.274	5843.468
Nov 2017	4494.700	3587.009	5402.390	3106.507	5882.892
Dec 2017	4527.028	3612.136	5441.921	3127.821	5926.236
Jan 2018	4559.357	3634.192	5484.522	3144.439	5974.275
Feb 2018	4591.686	3652.719	5530.653	3155.660	6027.712
Mar 2018	4624.015	3667.321	5580.708	3160.878	6087.151
Apr 2018	4656.343	3677.675	5635.011	3159.600	6153.087
May 2018	4688.672	3683.537	5693.807	3151.451	6225.893
Jun 2018	4721.001	3684.745	5757.257	3136.184	6305.818
Jul 2018	4753.330	3681.213	5825.446	3113.669	6392.990
Aug 2018	4785.658	3672.929	5898.387	3083.886	6487.431
Sep 2018	4817.987	3659.939	5976.035	3046.906	6589.068
Oct 2018	4850.316	3642.338	6058.293	3002.874	6697.758
Nov 2018	4882.644	3620.258	6145.031	2951.991	6813.298
Dec 2018	4914.973	3593.854	6236.093	2894.495	6935.451
Jan 2019	4947.302	3563.297	6331.307	2830.649	7063.955
Feb 2019	4979.631	3528.766	6430.496	2760.724	7198.537
Mar 2019	5011.959	3490.439	6533.480	2684.994	7338.925
Apr 2019	5044.288	3448.491	6640.085	2603.727	7484.849

MAPE A

```
> MAPE_Holt
[1] 0.1733669
```

For Product B



MAPE B

```
> MAPE_Holt_B
[1] 0.2190072
```

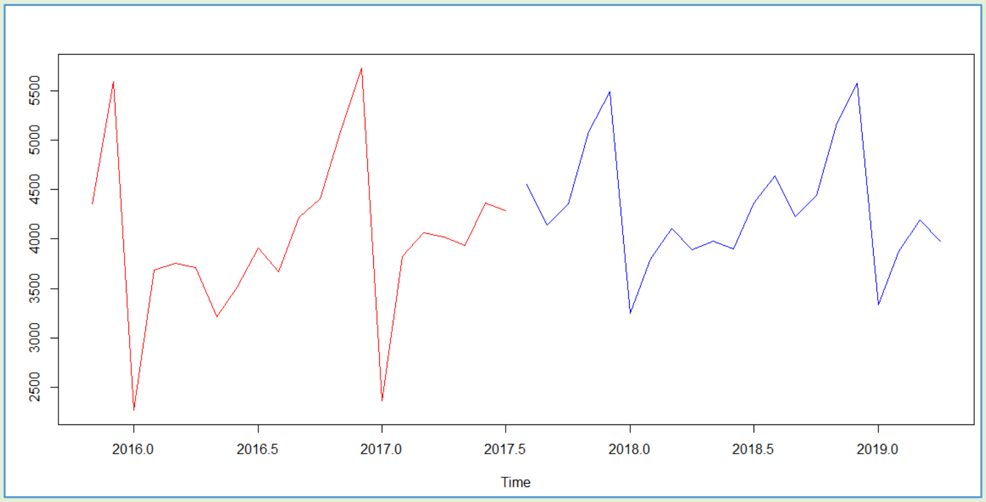
> fcdmndB_Holt

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Aug 2017	3106.126	2177.34388	4034.908	1685.67627	4526.576
Sep 2017	3109.574	1942.32632	4276.822	1324.42265	4894.726
Oct 2017	3113.022	1748.31346	4477.731	1025.88032	5200.164
Nov 2017	3116.470	1579.41990	4653.520	765.75464	5467.186
Dec 2017	3119.918	1427.95228	4811.884	532.27965	5707.557
Jan 2018	3123.366	1289.48914	4957.243	318.69327	5928.039
Feb 2018	3126.814	1161.21178	5092.417	120.68471	6132.944
Mar 2018	3130.262	1041.19253	5219.332	-64.69416	6325.219
Apr 2018	3133.710	928.04415	5339.376	-239.56495	6506.985
May 2018	3137.158	820.72887	5453.588	-405.51477	6679.831
Jun 2018	3140.606	718.44634	5562.766	-563.76768	6844.980
Jul 2018	3144.054	620.56387	5667.545	-715.29127	7003.400
Aug 2018	3147.502	526.57107	5768.434	-860.86613	7155.871
Sep 2018	3150.950	436.04908	5865.852	-1001.13282	7303.033
Oct 2018	3154.398	348.64916	5960.148	-1136.62475	7445.421
Nov 2018	3157.846	264.07723	6051.615	-1267.79162	7583.484
Dec 2018	3161.294	182.08263	6140.506	-1395.01681	7717.606
Jan 2019	3164.742	102.44960	6227.035	-1518.63028	7848.115
Feb 2019	3168.190	24.99089	6311.390	-1638.91842	7975.299
Mar 2019	3171.638	-50.45730	6393.734	-1756.13176	8099.409
Apr 2019	3175.086	-124.03924	6474.212	-1870.49088	8220.664

```
Holt's method

Call:
 holt(y = demandB, h = 21)

  Smoothing parameters:
    alpha = 0.7611
    beta  = 1e-04

  Initial states:
    l = 3478.2099
    b = 3.5827

  sigma:  724.7326

     AIC     AICc      BIC
3447.264 3447.596 3463.420
```

Use of “hw” function in Holt winter model

For product A: Graphical representation of forecast trends colored in “Blue”



MAPE A

```
> MAPE_HW
[1] 0.08203897
```

The Alpha, Beta and Gamma Values are as below for product A

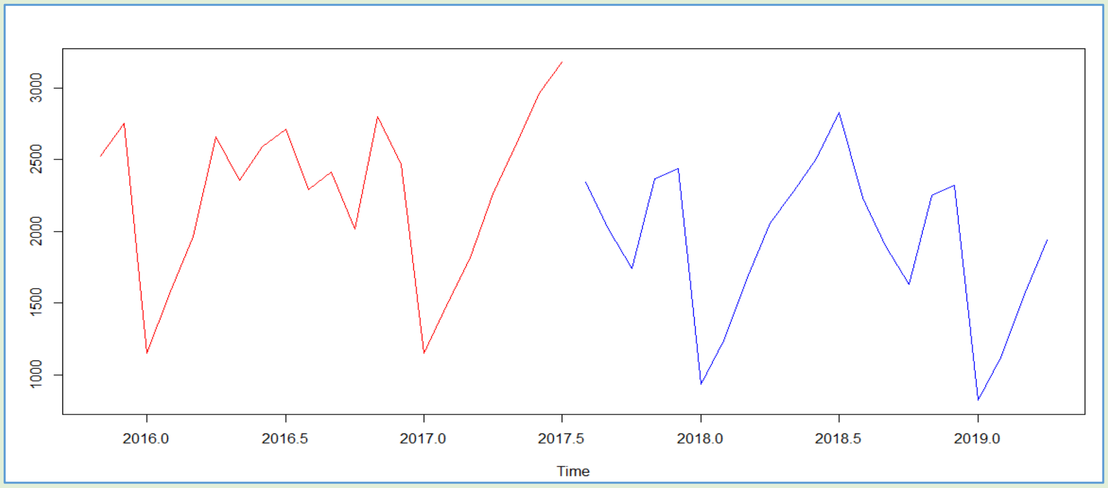
```
Smoothing parameters:
  alpha = 0.1331
  beta  = 1e-04
  gamma = 4e-04
```

	Jan	Feb	Mar	Apr	May	Jun	Jul
2017							
2018	3250.725	3793.940	4109.453	3893.741	3977.923	3899.630	4361.673
2019	3334.871	3878.086	4193.599	3977.887			

	Aug	Sep	Oct	Nov	Dec
2017	4552.034	4140.217	4354.567	5088.377	5488.777
2018	4636.179	4224.362	4438.712	5172.522	5572.923
2019					

Use of "hw" function in Holt winter model

For product B: Graphical representation of forecast trends colored in "Blue"



MAPE B

```
> MAPE_HW_B
[1] 0.07989064
```

The Alpha, Beta and Gamma Values are as below for product B

```
Smoothing parameters:
  alpha = 1e-04
  beta  = 1e-04
  gamma = 0.3467
```

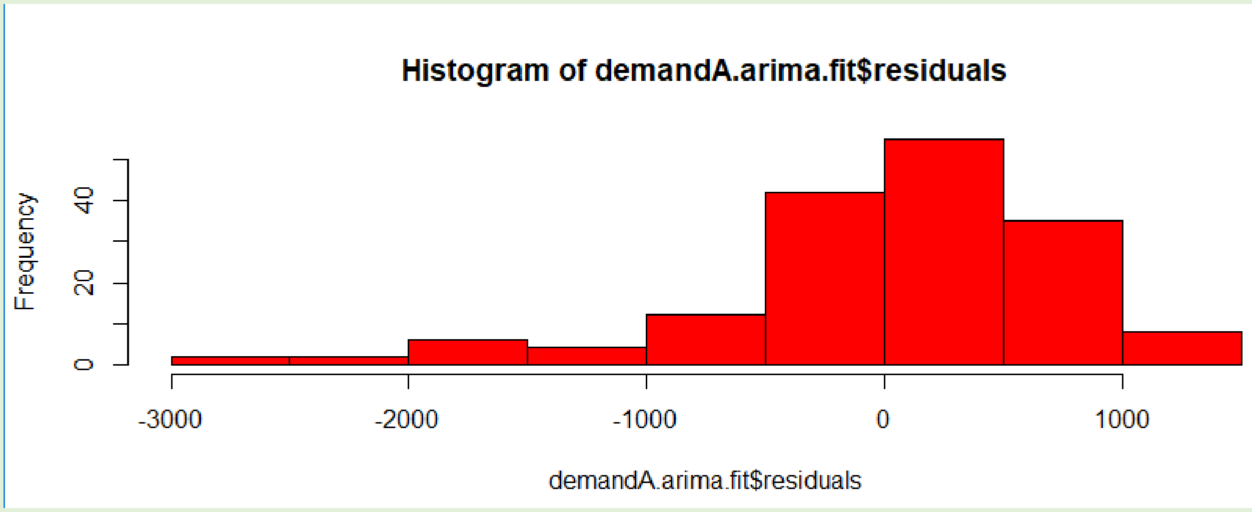
```
> demandBHW$mean
           Jan       Feb       Mar       Apr       May       Jun
2017
2018  937.1552 1239.7282 1679.0992 2056.5112 2281.9294 2511.2094
2019  821.1228 1123.6958 1563.0669 1940.4788
           Jul       Aug       Sep       Oct       Nov       Dec
2017           2346.8725 2016.8723 1744.5830 2366.0301 2436.7843
2018 2832.0218 2230.8402 1900.8400 1628.5507 2249.9978 2320.7520
2019
```

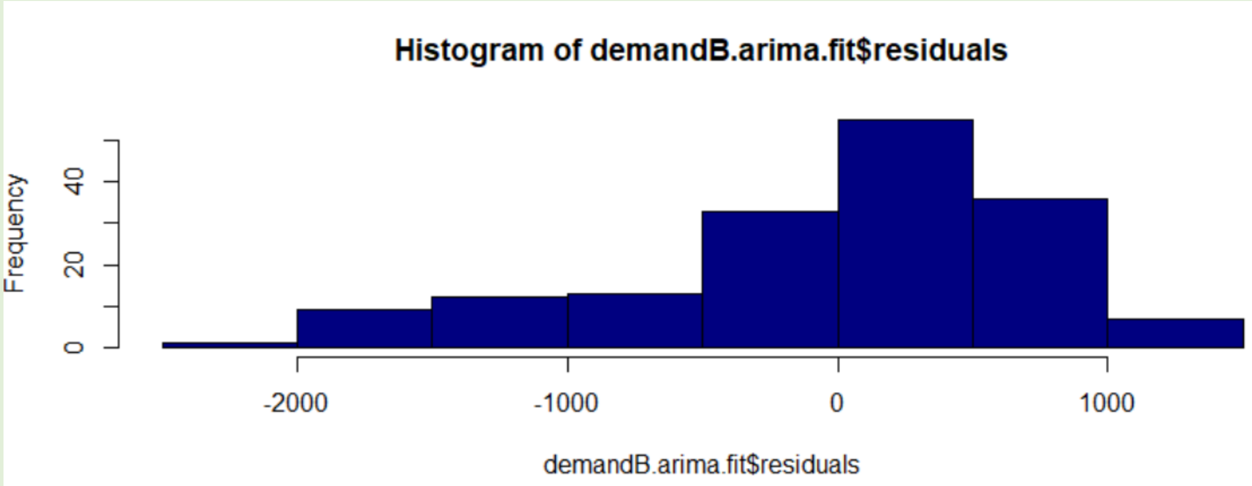
Under the Auto Correlation Factor (ARIMA model)

Code sheet

```
#AutoRegression ACF
plot(acf(demandAtrain, lag=50))
plot(acf(demandBtrain, lag=50))


demandA.arima.fit = arima(demandAtrain, c(1,1,0))
demandA.arima.fit
hist(demandA.arima.fit$residuals, col="red")
demandB.arima.fit = arima(demandBtrain, c(1,1,0))
demandB.arima.fit
hist(demandB.arima.fit$residuals, col="navy")
Box.test(demandB.arima.fit$residuals, lag=30, type="Ljung-Box")
# setwd ("C:/Users/Amit Kulkarni/Documents/R Programming/packages")

demandA.arima.fit_FC = forecast(demandA.arima.fit, h=15)
plot(demandA.arima.fit_FC)
demandA.arima.fit_FC

demandB.arima.fit_FC = forecast(demandB.arima.fit, h=15)
plot(demandB.arima.fit_FC)
demandB.arima.fit_FC
```

Under the Auto regression model, the observed values are regressed amongst themselves. The 2nd one regressed with the 1st, 3rd with 2nd, 4th with 3rd so on so forth. This basically tries to identify that if there is any impact of the distant past observation that is having influence on the current one.






```
Coefficients:
          ar1
      -0.3167
s.e.   0.0738

sigma^2 estimated as 593831:  log likelihood = -1330.96,  aic = 2665.92
```

Portmanteau test using Box.Plot function for product B and A

```
> Box.test(demandB.arima.fit$residuals, lag=30, type="Ljung-Box")

        Box-Ljung test

data:  demandB.arima.fit$residuals
X-squared = 350.91, df = 30, p-value < 2.2e-16
```

```
> Box.test(demandA.arima.fit$residuals, lag=30, type="Ljung-Box")

        Box-Ljung test

data:  demandA.arima.fit$residuals
X-squared = 360.23, df = 30, p-value < 2.2e-16
```

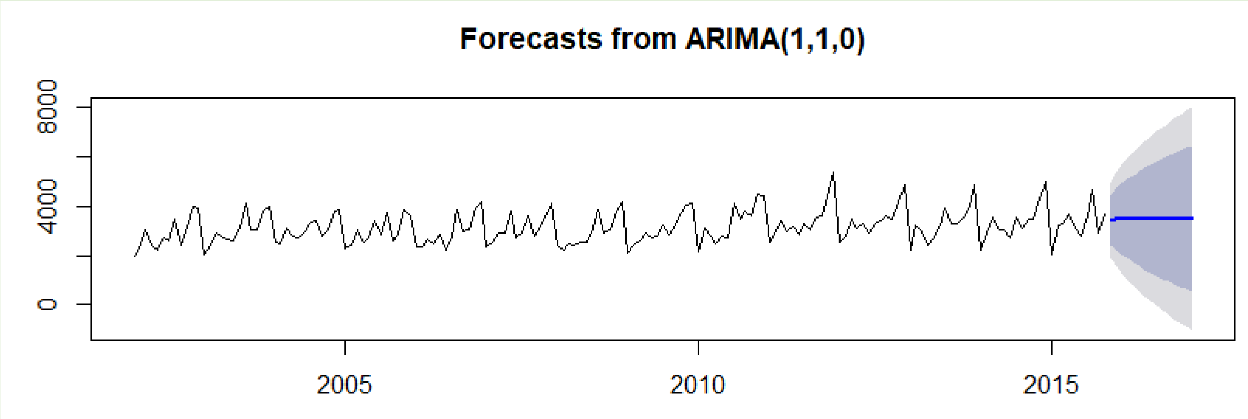
This is to test if the residuals are independent or not.

Ho = the residual values are independent

Ha = the residual values are not independent

Since the p values are very low the model selection is not the best and other models need to be evaluated

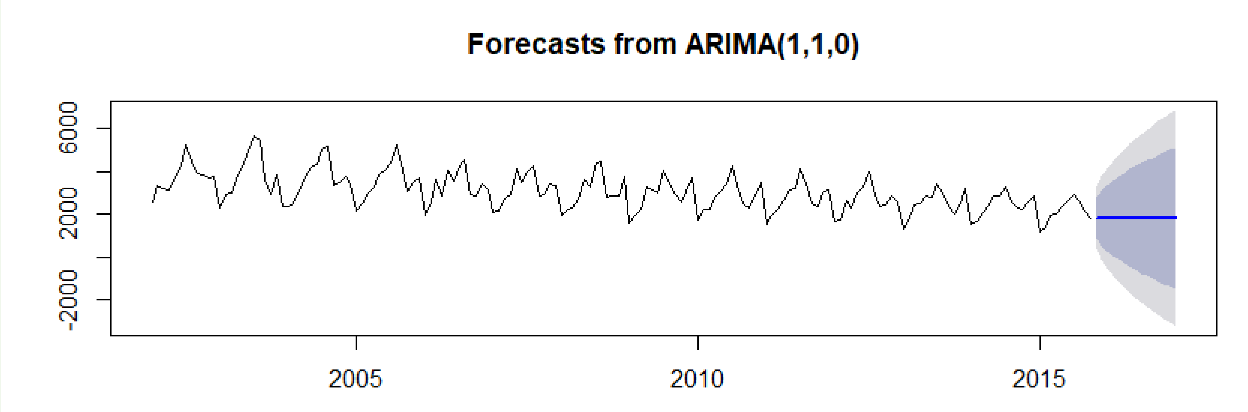
Forecast using the ARIMA model graphically and values for product A




```
> demandA.arima.fit_FC
```

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Nov 2015	3441.540	2453.9704	4429.109	1931.1827	4951.897
Dec 2015	3518.950	2322.8263	4715.074	1689.6365	5348.264
Jan 2016	3494.438	2069.7999	4919.075	1315.6423	5673.233
Feb 2016	3502.200	1895.6747	5108.725	1045.2318	5959.167
Mar 2016	3499.742	1725.7359	5273.748	786.6339	6212.849
Apr 2016	3500.520	1574.7607	5426.279	555.3253	6445.715
May 2016	3500.274	1433.5141	5567.033	339.4378	6661.109
Jun 2016	3500.352	1301.7232	5698.980	137.8396	6862.864
Jul 2016	3500.327	1177.2709	5823.383	-52.4807	7053.134
Aug 2016	3500.335	1059.1948	5941.475	-233.0666	7233.736
Sep 2016	3500.332	946.5597	6054.105	-405.3257	7405.990
Oct 2016	3500.333	838.6909	6161.975	-570.2974	7570.963
Nov 2016	3500.333	735.0253	6265.640	-728.8401	7729.506
Dec 2016	3500.333	635.1083	6365.557	-881.6500	7882.316
Jan 2017	3500.333	538.5601	6462.106	-1029.3077	8029.973

Forecast using the ARIMA model graphically and values for product B




```
> demandB.arima.fit_FC
         Point Forecast         Lo 80    Hi 80      Lo 95    Hi 95
Nov 2015       1815.370   871.40154 2759.339   371.6947 3259.046
Dec 2015       1810.145   553.01152 3067.279  -112.4749 3732.766
Jan 2016       1810.775   296.63108 3324.918  -504.9082 4126.458
Feb 2016       1810.699    78.04386 3543.354  -839.1683 4460.566
Mar 2016       1810.708  -115.91881 3737.335 -1135.8135 4757.230
Apr 2016       1810.707  -292.06461 3913.479 -1405.2047 5026.619
May 2016       1810.707  -454.55455 4075.969 -1653.7116 5275.126
Jun 2016       1810.707  -606.14455 4227.559 -1885.5485 5506.963
Jul 2016       1810.707  -748.77203 4370.186 -2103.6784 5725.093
Aug 2016       1810.707  -883.86057 4505.275 -2310.2785 5931.693
Sep 2016       1810.707 -1012.49258 4633.907 -2507.0042 6128.418
Oct 2016       1810.707 -1135.51386 4756.928 -2695.1490 6316.563
Nov 2016       1810.707 -1253.60024 4875.014 -2875.7466 6497.161
Dec 2016       1810.707 -1367.30186 4988.716 -3049.6382 6671.052
Jan 2017       1810.707 -1477.07369 5098.488 -3217.5197 6838.934
```

Summary of MAPE

	MAPE		
Product	Exponential smoothing	Holt Winter model	Holt Winter HW function
A	0.1057	0.1733	0.08203897
B	0.1694	0.219	0.07989064

Referring to the table it can be seen that the Holt winter with hw function model has the least MAPE value making it an efficient model for both the products

Conclusion:

The typical trend that the products show are
For A: The demand is stable and with some intensity of seasonality. Typically this product does makes maximum sales during the year end, I will ensure that sufficient stocking of the product is done. In our models as well the product demand is in sync with the previous cycle and it will have its ups and downs. Stocking of the product is necessary during the peak business days. Since the product information is not provided, not much can be said but as a store's manager I will ensure that this product is stocked basis the seasonality

For B: It is very evident that the product is on a declining trend. There are spikes in sales during July and August of the year but the product sold is fairly less compared to the previous year. The forecast of the demand also in our model predicts that there will be a downward trend with respect to the sales within the stores.
The product could be an outdated or an outgoing or out of fashion so people tend to demand less but there is going to be some time that people will buy this product and thus the stocking of the product is done accordingly.
As a store's manager, my focus will be to ensure that I push the product to ultimate consumers unless it is out of vogue.