

Adidas_Sales_Forecast.R

DELL

Fri Dec 07 14:06:29 2018

```
#Loading the dataset
```

```
library(ggplot2)
```

```
library(readr)
```

```
library(fpp)
```

```
## Loading required package: forecast
```

```
## Loading required package: fma
```

```
## Loading required package: expsmooth
```

```
## Loading required package: lmtest
```

```
## Loading required package: zoo
```

```
##
```

```
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      as.Date, as.Date.numeric
```

```
## Loading required package: tseries
```

```
library(fpp2)
```

```
##
```

```
## Attaching package: 'fpp2'
```

```
## The following objects are masked from 'package:fpp':
```

```
##
```

```
##      ausair, ausbeer, austa, austourists, debitcards, departures,
```

```
##      elecequip, euretail, guinearice, oil, sunspotarea, usmelec
```

```
#reading data from csv file
```

```
data = read.csv("C:/Users/DELL/Downloads/adidas_revenue1.csv")
```

```
data
```

##	date	Revenue	US.GDP	Europe.GDP	CHN.GDP.US	Price.Index	NIKE
## 1	2000Q1	1517	12359.09	1728.244	257.6491	246.5	2161.6
## 2	2000Q2	1248	12592.53	1749.600	290.4375	326.4	2272.7
## 3	2000Q3	1677	12607.68	1769.259	310.5510	322.5	2636.7
## 4	2000Q4	1393	12679.34	1789.253	352.6953	321.0	2198.7
## 5	2001Q1	1558	12643.28	1819.140	290.9745	329.4	2170.1
## 6	2001Q2	1368	12710.30	1833.713	322.9186	329.8	2483.3
## 7	2001Q3	1790	12670.11	1845.879	342.3183	313.3	2613.7
## 8	2001Q4	1396	12705.27	1861.936	383.2037	302.1	2336.8
## 9	2002Q1	1638	12822.26	1878.783	317.6722	296.5	2260.3
## 10	2002Q2	1507	12893.00	1893.801	352.7202	301.0	2682.2
## 11	2002Q3	1868	12955.77	1914.837	377.6277	298.9	2796.3
## 12	2002Q4	1510	12964.02	1927.341	422.4808	292.2	2514.7
## 13	2003Q1	1669	13031.17	1933.872	360.3185	294.0	2400.9
## 14	2003Q2	1392	13152.09	1943.995	393.0824	296.3	2985.1
## 15	2003Q3	1853	13372.36	1969.849	426.3864	300.7	3024.9
## 16	2003Q4	1353	13528.71	1988.492	480.4693	309.2	2837.1
## 17	2004Q1	1623	13606.51	2010.120	417.3614	327.1	2904.0
## 18	2004Q2	1401	13706.25	2031.765	467.5954	333.0	3487.1
## 19	2004Q3	1758	13830.83	2046.182	505.7028	332.7	3561.8
## 20	2004Q4	1078	13950.38	2065.015	564.7315	321.3	3148.3
## 21	2005Q1	1674	14099.08	2076.923	488.7694	310.3	3308.2
## 22	2005Q2	1516	14172.69	2101.559	541.2070	311.3	3721.4
## 23	2005Q3	1924	14291.76	2124.553	593.7716	304.9	3862.0
## 24	2005Q4	1522	14373.44	2153.840	669.4382	297.6	3474.7
## 25	2006Q1	2459	14546.12	2179.109	587.2396	292.9	3612.8
## 26	2006Q2	2428	14589.58	2214.849	658.7748	295.3	4005.4
## 27	2006Q3	2949	14602.63	2240.239	708.9029	295.9	4194.1
## 28	2006Q4	2248	14716.93	2275.903	814.7579	297.4	3821.7
## 29	2007Q1	2538	14726.02	2314.019	739.2749	299.8	3926.9
## 30	2007Q2	2400	14838.66	2338.311	851.0275	301.4	4383.2
## 31	2007Q3	2941	14938.47	2362.323	925.6537	305.6	4655.1
## 32	2007Q4	2420	14991.78	2392.426	1077.6908	310.7	4339.5
## 33	2008Q1	2621	14889.45	2416.113	988.8873	322.3	4544.4
## 34	2008Q2	2521	14963.36	2419.735	1148.3868	334.9	5088.0
## 35	2008Q3	3083	14891.64	2411.679	1210.5950	335.8	5432.2
## 36	2008Q4	2574	14576.99	2382.319	1299.1836	332.0	4590.1
## 37	2009Q1	2577	14375.02	2317.899	1083.2955	323.0	4440.8
## 38	2009Q2	2457	14355.56	2310.312	1229.2481	320.8	4713.0
## 39	2009Q3	2888	14402.48	2320.823	1318.1139	326.8	4798.5
## 40	2009Q4	2458	14541.90	2339.329	1479.6432	332.5	4405.6
## 41	2010Q1	2674	14604.84	2349.078	1283.5211	338.0	4733.0
## 42	2010Q2	2917	14745.93	2377.207	1465.6673	347.7	5076.9
## 43	2010Q3	3468	14845.46	2396.736	1585.3964	354.0	5175.0
## 44	2010Q4	2931	14939.00	2415.849	1806.4896	431.9	4842.0
## 45	2011Q1	3273	14881.30	2439.892	1596.0131	567.3	5079.0
## 46	2011Q2	3064	14989.56	2445.959	1841.4921	655.8	5766.0
## 47	2011Q3	3744	15021.15	2454.501	1998.1746	576.6	6081.0
## 48	2011Q4	3241	15190.25	2455.081	2198.1463	505.5	5546.0
## 49	2012Q1	3824	15291.03	2459.268	1868.2618	431.7	5656.0
## 50	2012Q2	3517	15362.42	2457.575	2081.9618	410.7	6236.0
## 51	2012Q3	4173	15380.80	2461.767	2186.1221	379.0	6474.0
## 52	2012Q4	3369	15384.25	2459.338	2424.1446	369.2	5955.0

## 53	2013Q1	3751	15491.88	2462.191	2067.9449	370.9	6187.0
## 54	2013Q2	3383	15521.56	2480.438	2330.3550	389.3	6697.0
## 55	2013Q3	3879	15641.34	2492.943	2487.0690	387.0	6971.0
## 56	2013Q4	3391	15793.93	2503.542	2763.2571	378.1	6431.0
## 57	2014Q1	3480	15757.57	2523.399	2285.6911	382.6	6972.0
## 58	2014Q2	3400	15935.83	2528.024	2542.9235	390.0	7425.0
## 59	2014Q3	4044	16139.51	2545.888	2693.4092	380.3	7982.0
## 60	2014Q4	3610	16220.22	2567.073	2960.9904	360.6	7380.0
## 61	2015Q1	4083	16349.97	2600.116	2458.1909	336.7	7460.0
## 62	2015Q2	3907	16460.89	2616.887	2756.1993	333.2	7779.0
## 63	2015Q3	4758	16527.59	2637.050	2777.8913	333.5	8414.0
## 64	2015Q4	4167	16547.62	2656.240	2970.8388	331.3	7686.0
## 65	2016Q1	4769	16571.57	2672.910	2498.3069	329.4	8032.0
## 66	2016Q2	4199	16663.52	2683.968	2720.2047	324.1	8244.0
## 67	2016Q3	5413	16778.15	2699.526	2856.3504	322.4	9061.0
## 68	2016Q4	4687	16851.42	2725.422	3040.1019	325.4	8180.0
## 69	2017Q1	5671	16903.24	2745.103	2622.0142	344.6	8432.0

```
#converting into time series data
```

```
data<-ts(data, start=c(2000,1), end=c(2017,1), frequency = 4)
```

```
data
```

##	date	Revenue	US.GDP	Europe.GDP	CHN.GDP.US	Price.Index	NIKE
## 2000 Q1	1	1517	12359.09	1728.244	257.6491	246.5	2161.6
## 2000 Q2	2	1248	12592.53	1749.600	290.4375	326.4	2272.7
## 2000 Q3	3	1677	12607.68	1769.259	310.5510	322.5	2636.7
## 2000 Q4	4	1393	12679.34	1789.253	352.6953	321.0	2198.7
## 2001 Q1	5	1558	12643.28	1819.140	290.9745	329.4	2170.1
## 2001 Q2	6	1368	12710.30	1833.713	322.9186	329.8	2483.3
## 2001 Q3	7	1790	12670.11	1845.879	342.3183	313.3	2613.7
## 2001 Q4	8	1396	12705.27	1861.936	383.2037	302.1	2336.8
## 2002 Q1	9	1638	12822.26	1878.783	317.6722	296.5	2260.3
## 2002 Q2	10	1507	12893.00	1893.801	352.7202	301.0	2682.2
## 2002 Q3	11	1868	12955.77	1914.837	377.6277	298.9	2796.3
## 2002 Q4	12	1510	12964.02	1927.341	422.4808	292.2	2514.7
## 2003 Q1	13	1669	13031.17	1933.872	360.3185	294.0	2400.9
## 2003 Q2	14	1392	13152.09	1943.995	393.0824	296.3	2985.1
## 2003 Q3	15	1853	13372.36	1969.849	426.3864	300.7	3024.9
## 2003 Q4	16	1353	13528.71	1988.492	480.4693	309.2	2837.1
## 2004 Q1	17	1623	13606.51	2010.120	417.3614	327.1	2904.0
## 2004 Q2	18	1401	13706.25	2031.765	467.5954	333.0	3487.1
## 2004 Q3	19	1758	13830.83	2046.182	505.7028	332.7	3561.8
## 2004 Q4	20	1078	13950.38	2065.015	564.7315	321.3	3148.3
## 2005 Q1	21	1674	14099.08	2076.923	488.7694	310.3	3308.2
## 2005 Q2	22	1516	14172.69	2101.559	541.2070	311.3	3721.4
## 2005 Q3	23	1924	14291.76	2124.553	593.7716	304.9	3862.0
## 2005 Q4	24	1522	14373.44	2153.840	669.4382	297.6	3474.7
## 2006 Q1	25	2459	14546.12	2179.109	587.2396	292.9	3612.8
## 2006 Q2	26	2428	14589.58	2214.849	658.7748	295.3	4005.4
## 2006 Q3	27	2949	14602.63	2240.239	708.9029	295.9	4194.1
## 2006 Q4	28	2248	14716.93	2275.903	814.7579	297.4	3821.7
## 2007 Q1	29	2538	14726.02	2314.019	739.2749	299.8	3926.9
## 2007 Q2	30	2400	14838.66	2338.311	851.0275	301.4	4383.2
## 2007 Q3	31	2941	14938.47	2362.323	925.6537	305.6	4655.1
## 2007 Q4	32	2420	14991.78	2392.426	1077.6908	310.7	4339.5
## 2008 Q1	33	2621	14889.45	2416.113	988.8873	322.3	4544.4
## 2008 Q2	34	2521	14963.36	2419.735	1148.3868	334.9	5088.0
## 2008 Q3	35	3083	14891.64	2411.679	1210.5950	335.8	5432.2
## 2008 Q4	36	2574	14576.99	2382.319	1299.1836	332.0	4590.1
## 2009 Q1	37	2577	14375.02	2317.899	1083.2955	323.0	4440.8
## 2009 Q2	38	2457	14355.56	2310.312	1229.2481	320.8	4713.0
## 2009 Q3	39	2888	14402.48	2320.823	1318.1139	326.8	4798.5
## 2009 Q4	40	2458	14541.90	2339.329	1479.6432	332.5	4405.6
## 2010 Q1	41	2674	14604.84	2349.078	1283.5211	338.0	4733.0
## 2010 Q2	42	2917	14745.93	2377.207	1465.6673	347.7	5076.9
## 2010 Q3	43	3468	14845.46	2396.736	1585.3964	354.0	5175.0
## 2010 Q4	44	2931	14939.00	2415.849	1806.4896	431.9	4842.0
## 2011 Q1	45	3273	14881.30	2439.892	1596.0131	567.3	5079.0
## 2011 Q2	46	3064	14989.56	2445.959	1841.4921	655.8	5766.0
## 2011 Q3	47	3744	15021.15	2454.501	1998.1746	576.6	6081.0
## 2011 Q4	48	3241	15190.25	2455.081	2198.1463	505.5	5546.0
## 2012 Q1	49	3824	15291.03	2459.268	1868.2618	431.7	5656.0
## 2012 Q2	50	3517	15362.42	2457.575	2081.9618	410.7	6236.0
## 2012 Q3	51	4173	15380.80	2461.767	2186.1221	379.0	6474.0
## 2012 Q4	52	3369	15384.25	2459.338	2424.1446	369.2	5955.0

```
## 2013 Q1 53 3751 15491.88 2462.191 2067.9449 370.9 6187.0
## 2013 Q2 54 3383 15521.56 2480.438 2330.3550 389.3 6697.0
## 2013 Q3 55 3879 15641.34 2492.943 2487.0690 387.0 6971.0
## 2013 Q4 56 3391 15793.93 2503.542 2763.2571 378.1 6431.0
## 2014 Q1 57 3480 15757.57 2523.399 2285.6911 382.6 6972.0
## 2014 Q2 58 3400 15935.83 2528.024 2542.9235 390.0 7425.0
## 2014 Q3 59 4044 16139.51 2545.888 2693.4092 380.3 7982.0
## 2014 Q4 60 3610 16220.22 2567.073 2960.9904 360.6 7380.0
## 2015 Q1 61 4083 16349.97 2600.116 2458.1909 336.7 7460.0
## 2015 Q2 62 3907 16460.89 2616.887 2756.1993 333.2 7779.0
## 2015 Q3 63 4758 16527.59 2637.050 2777.8913 333.5 8414.0
## 2015 Q4 64 4167 16547.62 2656.240 2970.8388 331.3 7686.0
## 2016 Q1 65 4769 16571.57 2672.910 2498.3069 329.4 8032.0
## 2016 Q2 66 4199 16663.52 2683.968 2720.2047 324.1 8244.0
## 2016 Q3 67 5413 16778.15 2699.526 2856.3504 322.4 9061.0
## 2016 Q4 68 4687 16851.42 2725.422 3040.1019 325.4 8180.0
## 2017 Q1 69 5671 16903.24 2745.103 2622.0142 344.6 8432.0
```

```
#extracting sales data
y=data[,2]
y
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 2000 1517 1248 1677 1393
## 2001 1558 1368 1790 1396
## 2002 1638 1507 1868 1510
## 2003 1669 1392 1853 1353
## 2004 1623 1401 1758 1078
## 2005 1674 1516 1924 1522
## 2006 2459 2428 2949 2248
## 2007 2538 2400 2941 2420
## 2008 2621 2521 3083 2574
## 2009 2577 2457 2888 2458
## 2010 2674 2917 3468 2931
## 2011 3273 3064 3744 3241
## 2012 3824 3517 4173 3369
## 2013 3751 3383 3879 3391
## 2014 3480 3400 4044 3610
## 2015 4083 3907 4758 4167
## 2016 4769 4199 5413 4687
## 2017 5671
```

```
#Set training dataset and testing dataset
train_data = window(y,start=c(2000,1), end=c(2013,4))
test_data = window(y,start=2014)
train_data
```

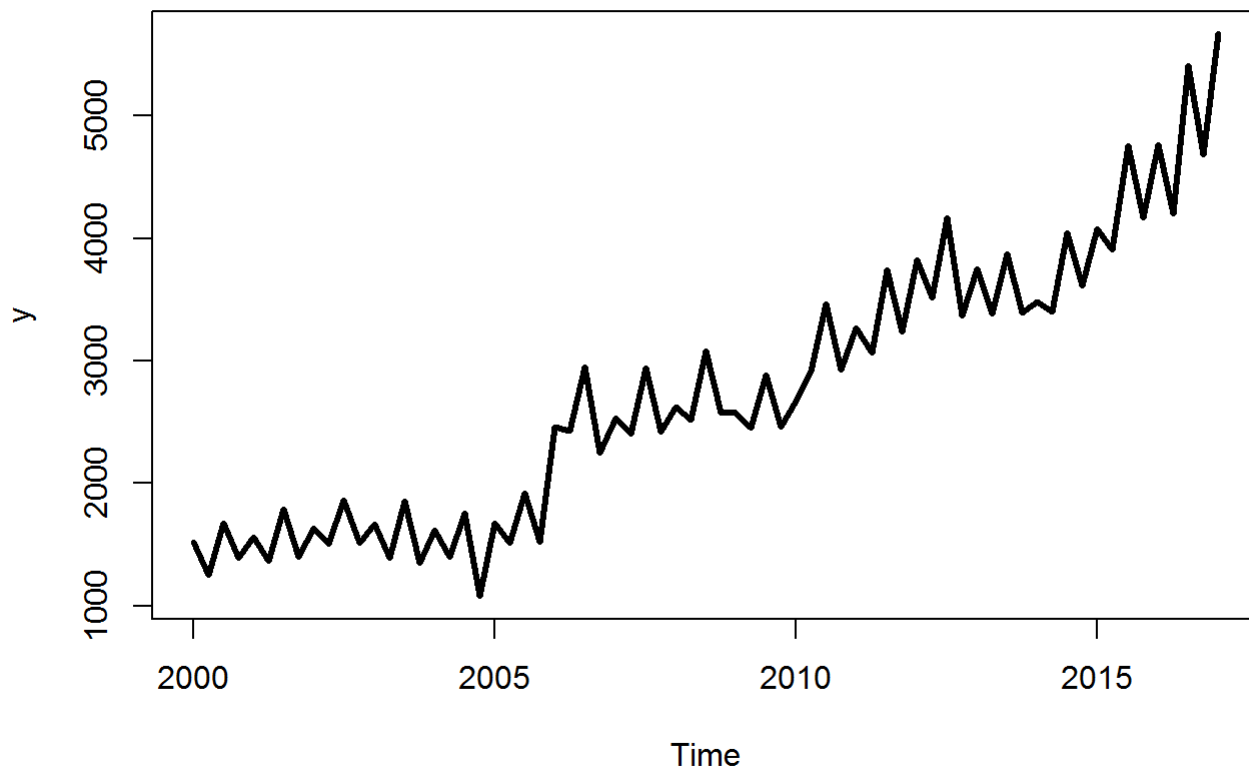
```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 2000 1517 1248 1677 1393
## 2001 1558 1368 1790 1396
## 2002 1638 1507 1868 1510
## 2003 1669 1392 1853 1353
## 2004 1623 1401 1758 1078
## 2005 1674 1516 1924 1522
## 2006 2459 2428 2949 2248
## 2007 2538 2400 2941 2420
## 2008 2621 2521 3083 2574
## 2009 2577 2457 2888 2458
## 2010 2674 2917 3468 2931
## 2011 3273 3064 3744 3241
## 2012 3824 3517 4173 3369
## 2013 3751 3383 3879 3391
```

```
test_data
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 2014 3480 3400 4044 3610
## 2015 4083 3907 4758 4167
## 2016 4769 4199 5413 4687
## 2017 5671
```

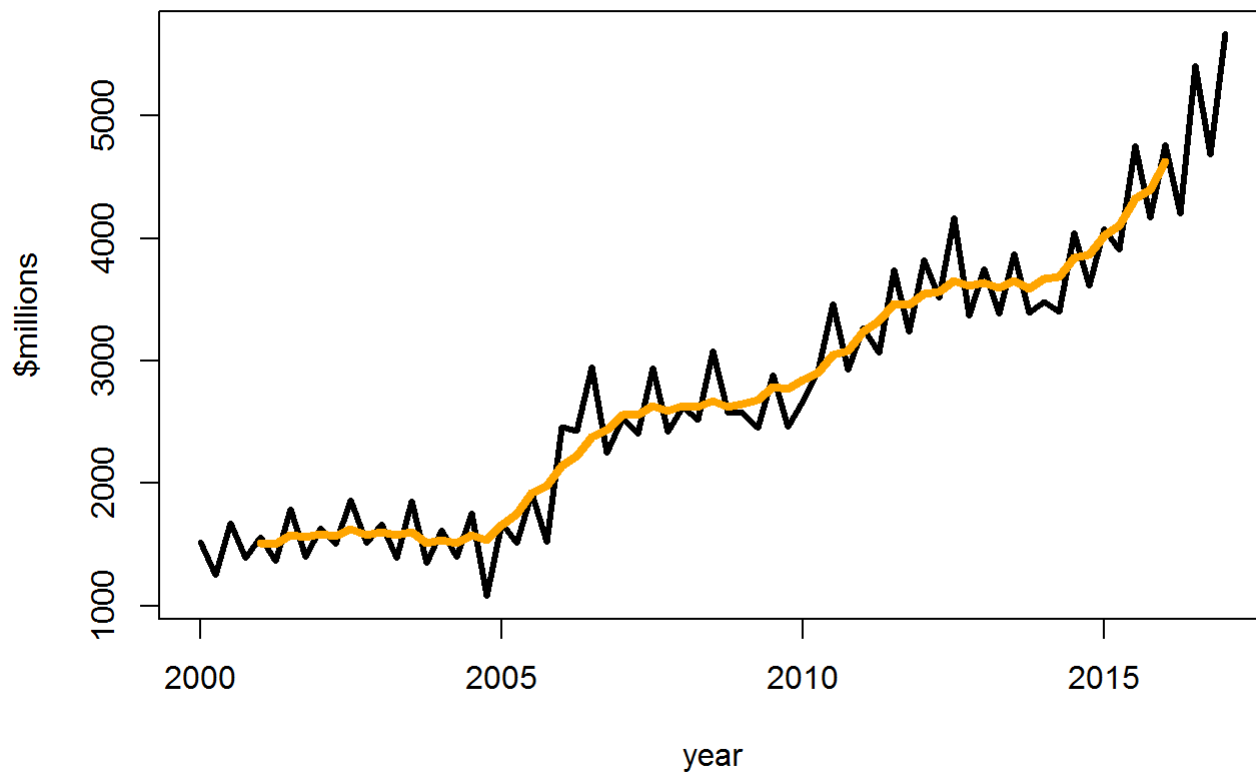
```
#plot raw dataset
plot(y,main="Adidas Quarterly Sales", lwd=3)
```

Adidas Quarterly Sales



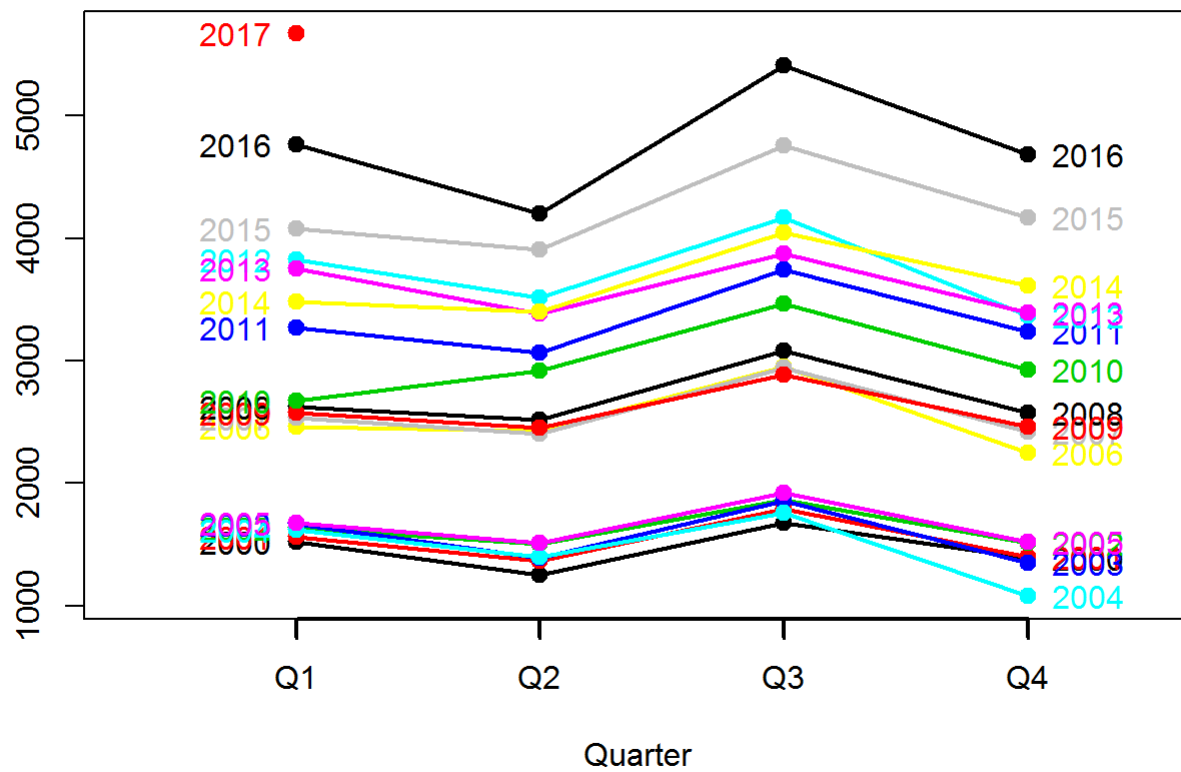
```
plot(y,main="Adidas Revenue", xlab="year", ylab="$millions", lwd=3)
lines(ma(y,9),col="orange",lwd=4)
```

Adidas Revenue



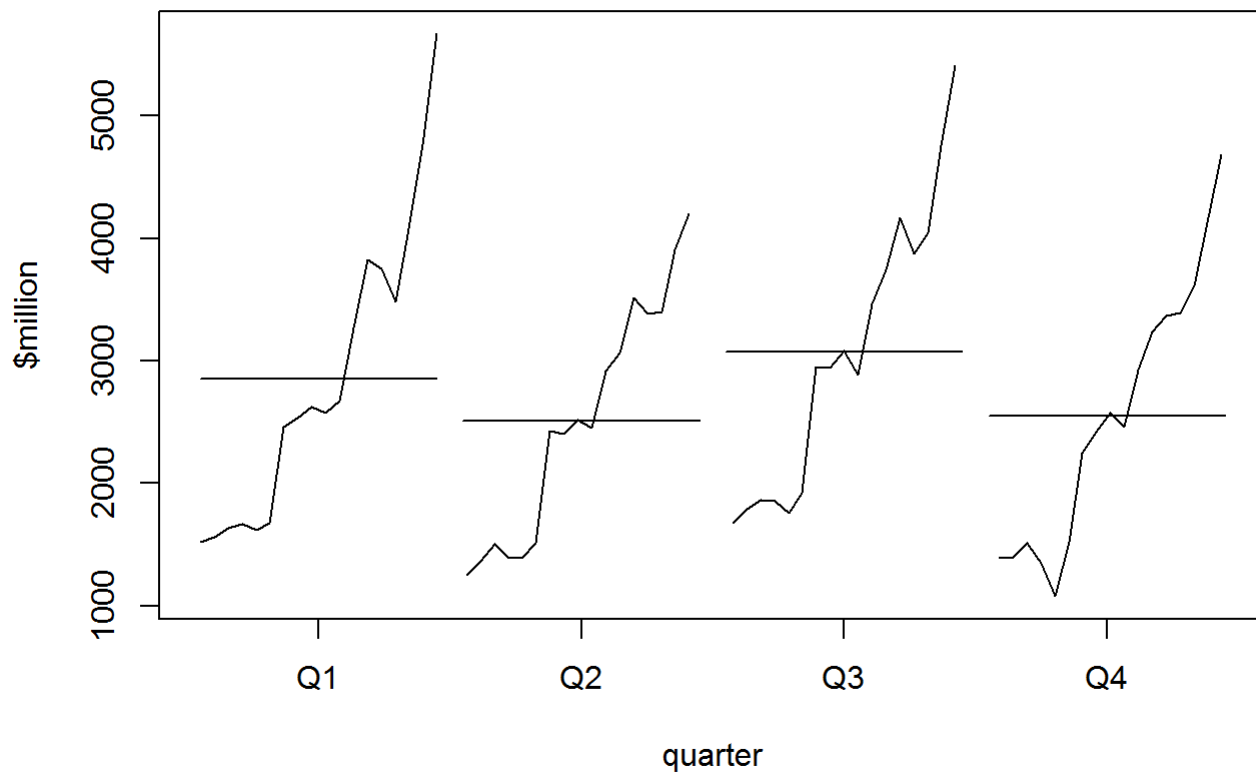
```
#seasonlity plot  
seasonplot(y,main="Seasonal plot: Adidas sales",  
           year.labels = TRUE, year.labels.left = TRUE,  
           col=1:20, pch=19,lwd=2)
```


Seasonal plot: Adidas sales



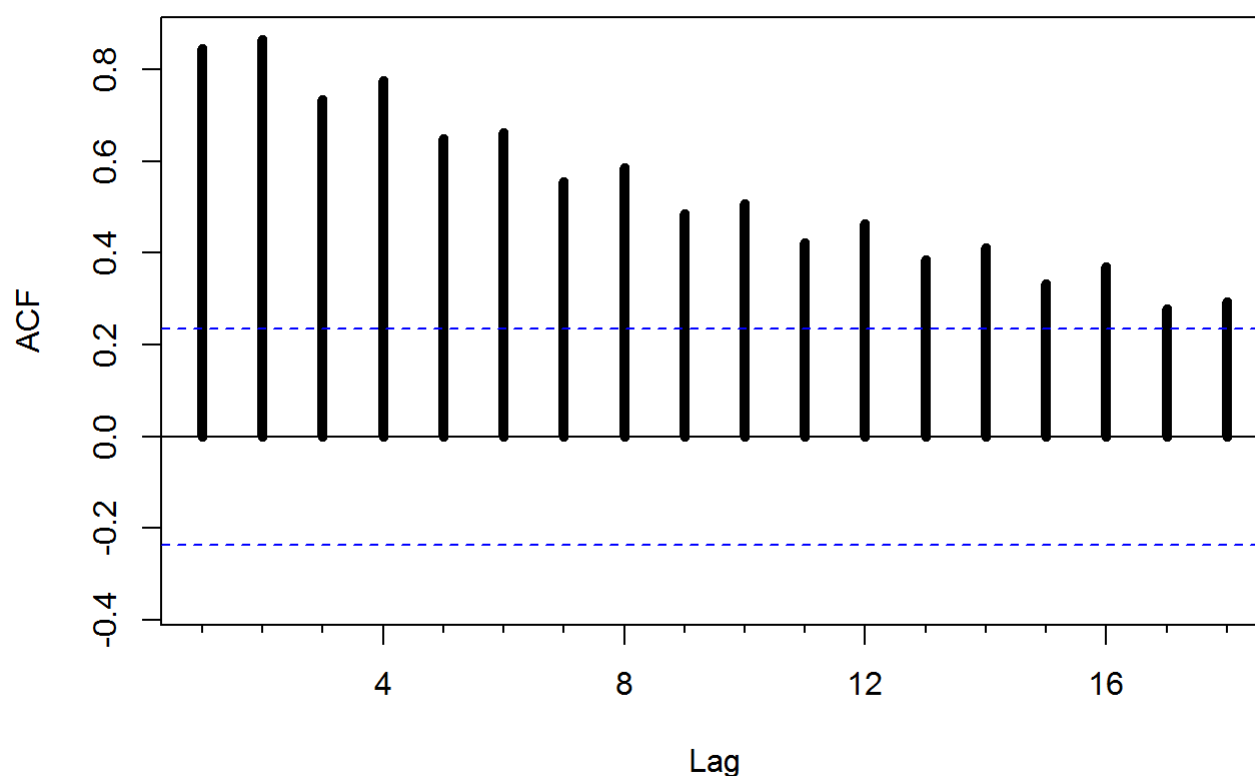
```
monthplot(y, main="Seasonal plot: Adidas sales",
          xlab="quarter", ylab = "$million")
```

Seasonal plot: Adidas sales



```
#Autocorrelation  
Acf(y, lwd=5, main="Adidas Quarterly Sales")
```

Adidas Quarterly Sales



*#Looking at the raw dataset, ADIDAS sales have a strong seasonal and increasing trend
#pattern. Out of four quarters, the third quarter generally has better performance.
#It also has a strong correlation with its lagged data.*

#Simple forecasting methods:Mean,Naive, Seasonal Naive

h=6

fit.mean=meanf(train_data,h=h)

fit.naive=naive(train_data,h=h)

fit.snaive=snaive(train_data,h=h)

plot with forecasts and actual values

*plot(fit.mean, PI=FALSE,
 main="Forecasts for quarterly")*

lines(fit.naive\$mean,col=2)

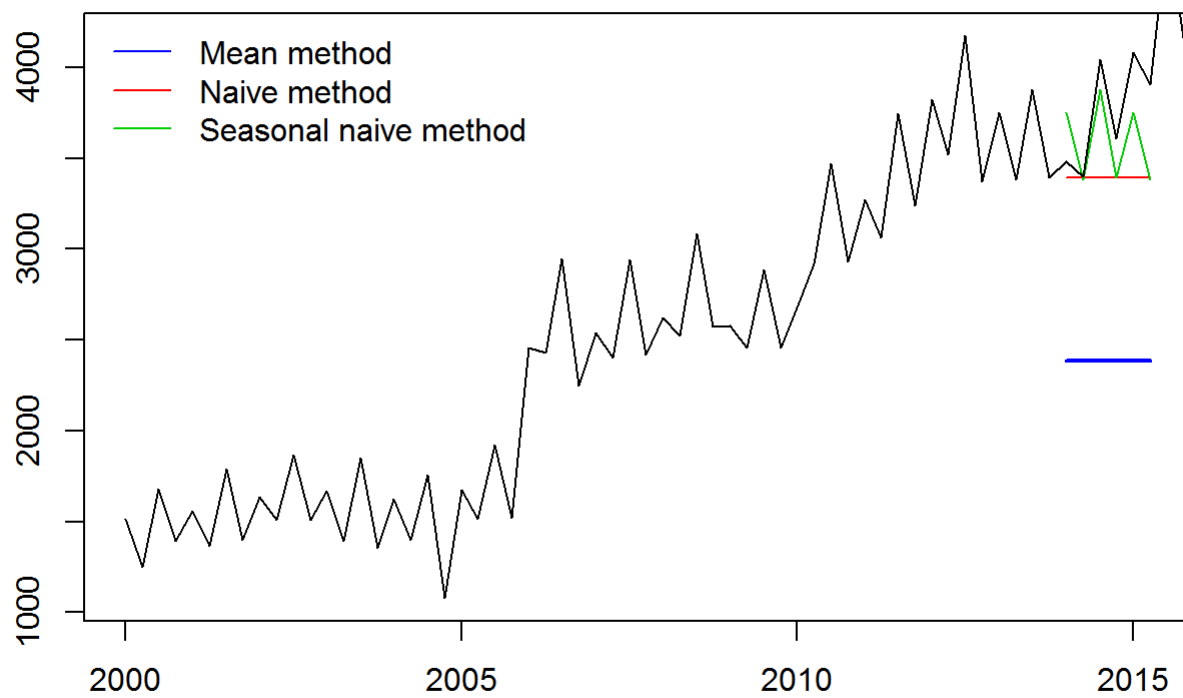
lines(fit.snaive\$mean,col=3)

lines(y)

legend("topleft",lty=1,col=c(4,2,3),

legend=c("Mean method","Naive method","Seasonal naive method"),bty="n")

Forecasts for quarterly

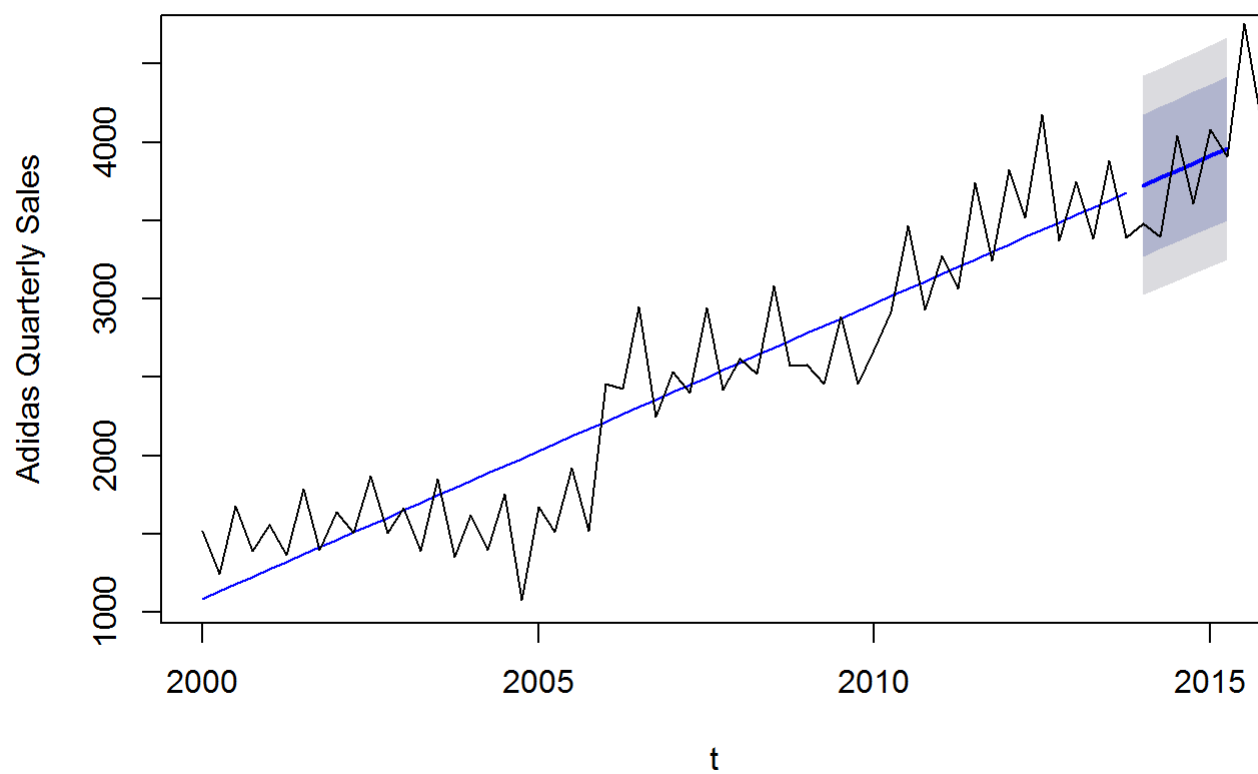


```
#Linear Trend model  
reg <- tslm(train_data ~ trend)  
fit.tslm=forecast(reg, h=h,level=c(80,95))  
summary(fit.tslm)
```

```
##
## Forecast method: Linear regression model
##
## Model Information:
##
## Call:
## tslm(formula = train_data ~ trend)
##
## Coefficients:
## (Intercept)      trend
##    1040.73      47.06
##
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -4.05727e-15 330.5585 264.7163 -2.184255 13.04242 1.158009
##              ACF1
## Training set 0.1474735
##
## Forecasts:
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2014 Q1      3723.344 3270.858 4175.829 3024.130 4422.557
## 2014 Q2      3770.407 3317.087 4223.727 3069.903 4470.910
## 2014 Q3      3817.470 3363.288 4271.652 3115.635 4519.306
## 2014 Q4      3864.534 3409.463 4319.605 3161.324 4567.743
## 2015 Q1      3911.597 3455.610 4367.584 3206.973 4616.222
## 2015 Q2      3958.661 3501.731 4415.590 3252.579 4664.742
```

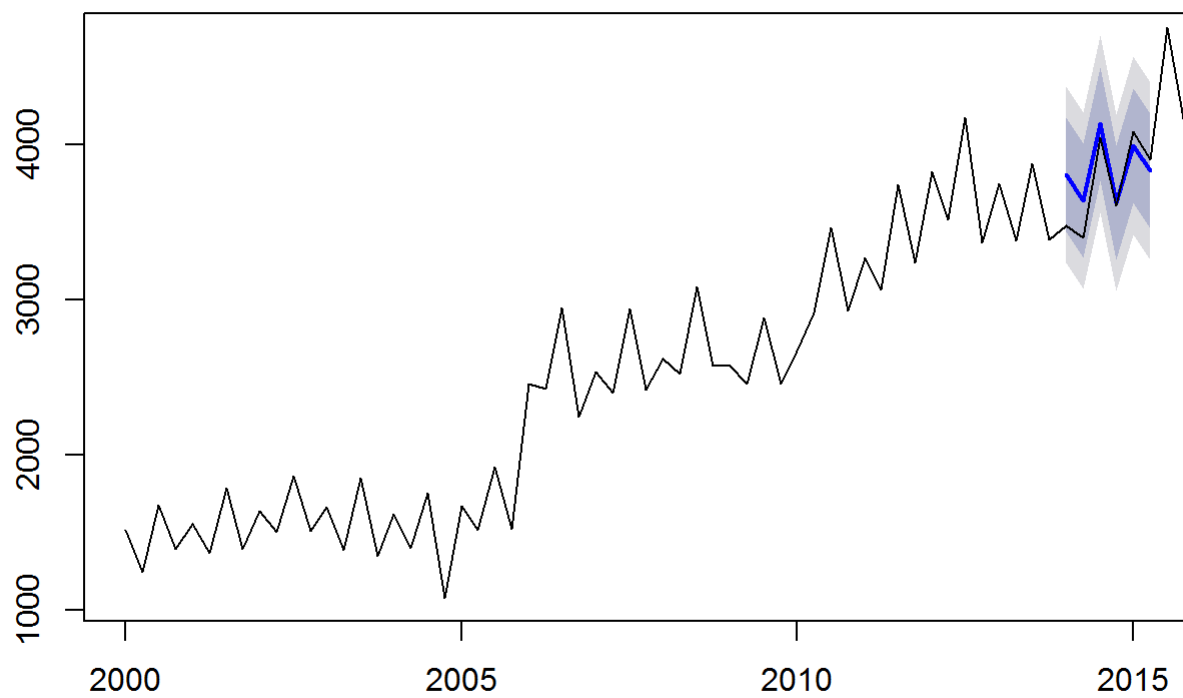
```
plot(fit.tslm, ylab="Adidas Quarterly Sales",
      xlab="t")
lines(fitted(reg),col="blue")
lines(y)
```

Forecasts from Linear regression model

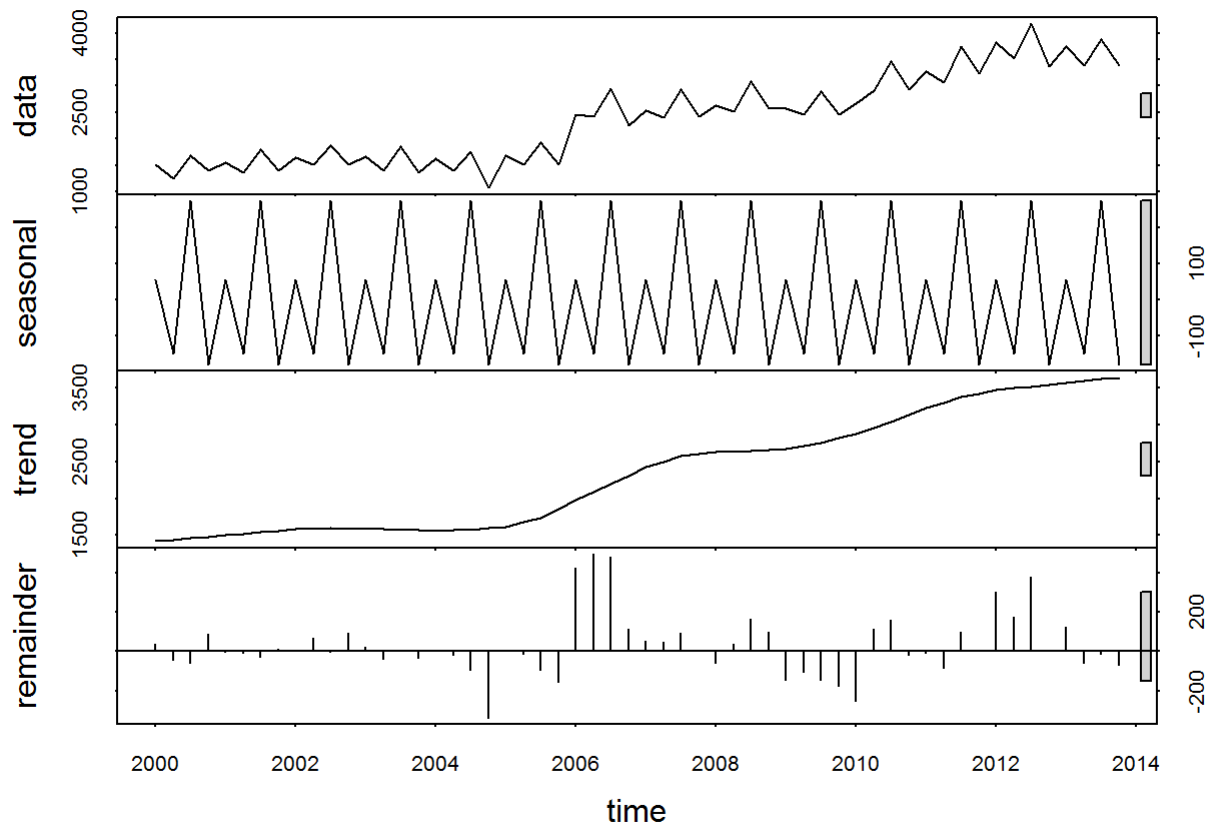


```
#trend & seasonal  
ts <- tslm(train_data ~ trend + season)  
fit.lmts = forecast(ts, h=h)  
plot(fit.lmts)  
lines(y)
```

Forecasts from Linear regression model



```
#STL Decomposition  
y.stl <- stl(train_data, t.window=15, s.window="periodic", robust=TRUE)  
plot(y.stl)
```



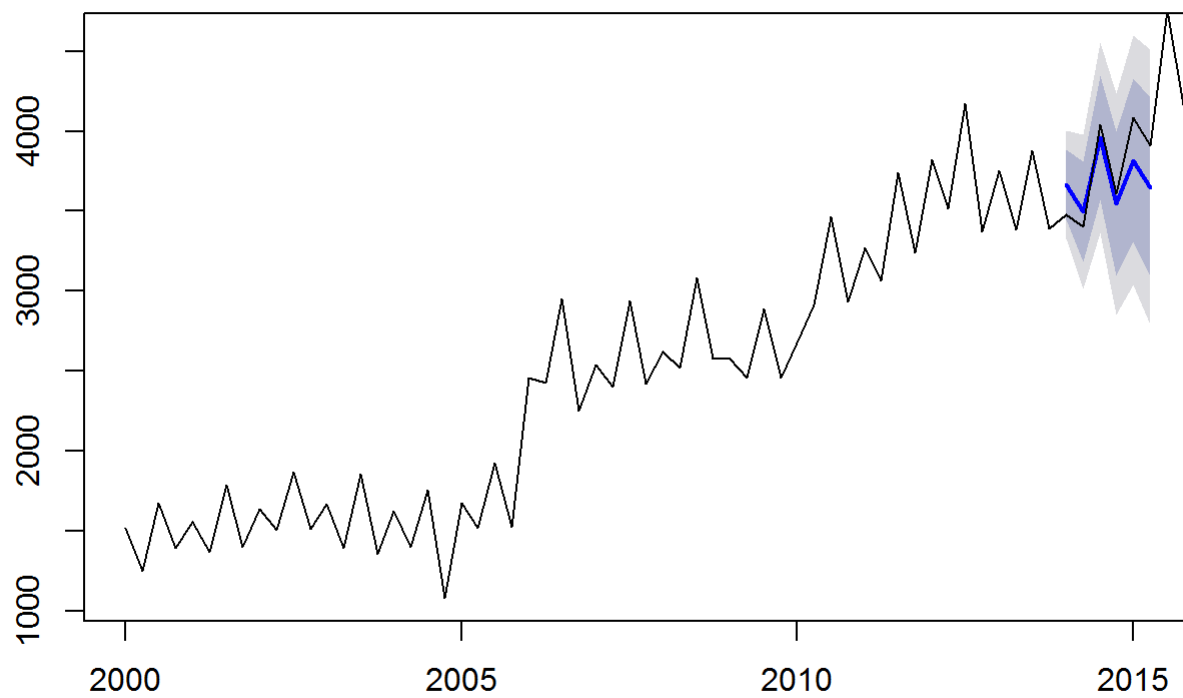
```
#STL Forecasting  
fit.stl <- forecast(y.stl, method="rwdrift", h=h)  
summary(fit.stl)
```



```
##
## Forecast method: STL + Random walk with drift
##
## Model Information:
## Call: rwf(y = x, h = h, drift = TRUE, level = level)
##
## Drift: 38.3479 (se 22.7383)
## Residual sd: 170.1858
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -7.974611e-12 168.6314 116.8932 -0.5536722 5.136756 0.5113525
##              ACF1
## Training set -0.1616575
##
## Forecasts:
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2014 Q1      3664.484 3444.444 3884.524 3327.962 4001.006
## 2014 Q2      3496.375 3182.475 3810.276 3016.306 3976.445
## 2014 Q3      3960.785 3573.038 4348.531 3367.777 4553.792
## 2014 Q4      3544.392 3092.883 3995.900 2853.869 4234.915
## 2015 Q1      3817.876 3308.885 4326.866 3039.442 4596.309
## 2015 Q2      3649.767 3087.646 4211.888 2790.077 4509.457
```

```
plot(fit.stl)
lines(y)
```

Forecasts from STL + Random walk with drift

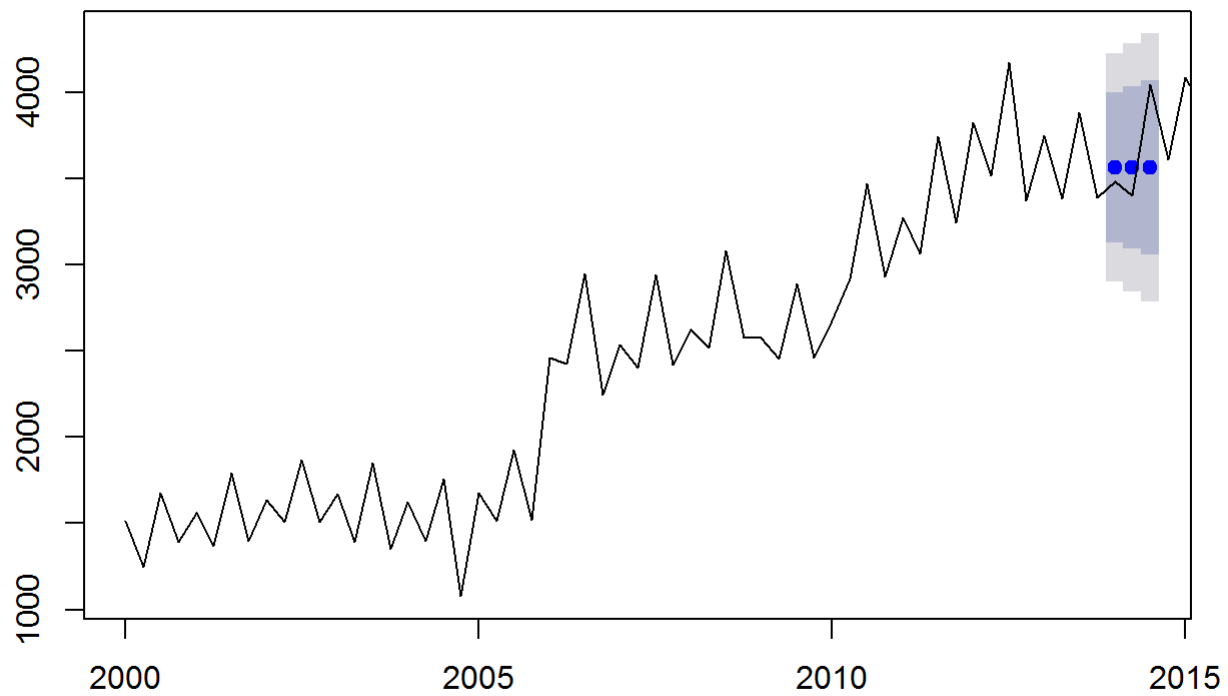


```
#SIMPLE EXPONENTIAL SMOOTHING  
fit.expo <- ses(train_data, h = 3)  
summary(fit.expo)
```

```
##
## Forecast method: Simple exponential smoothing
##
## Model Information:
## Simple exponential smoothing
##
## Call:
## ses(y = train_data, h = 3)
##
## Smoothing parameters:
##   alpha = 0.426
##
## Initial states:
##   l = 1465.8592
##
## sigma: 338.6906
##
##      AIC      AICc      BIC
## 881.7929 882.2544 887.8689
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 87.89642 332.5876 267.6454 1.968379 11.80674 1.170822
##              ACF1
## Training set -0.3854825
##
## Forecasts:
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2014 Q1      3562.769 3128.719 3996.818 2898.947 4226.590
## 2014 Q2      3562.769 3090.974 4034.564 2841.220 4284.317
## 2014 Q3      3562.769 3056.032 4069.505 2787.782 4337.756
```

```
plot(fit.expo)
lines(y)
```

Forecasts from Simple exponential smoothing

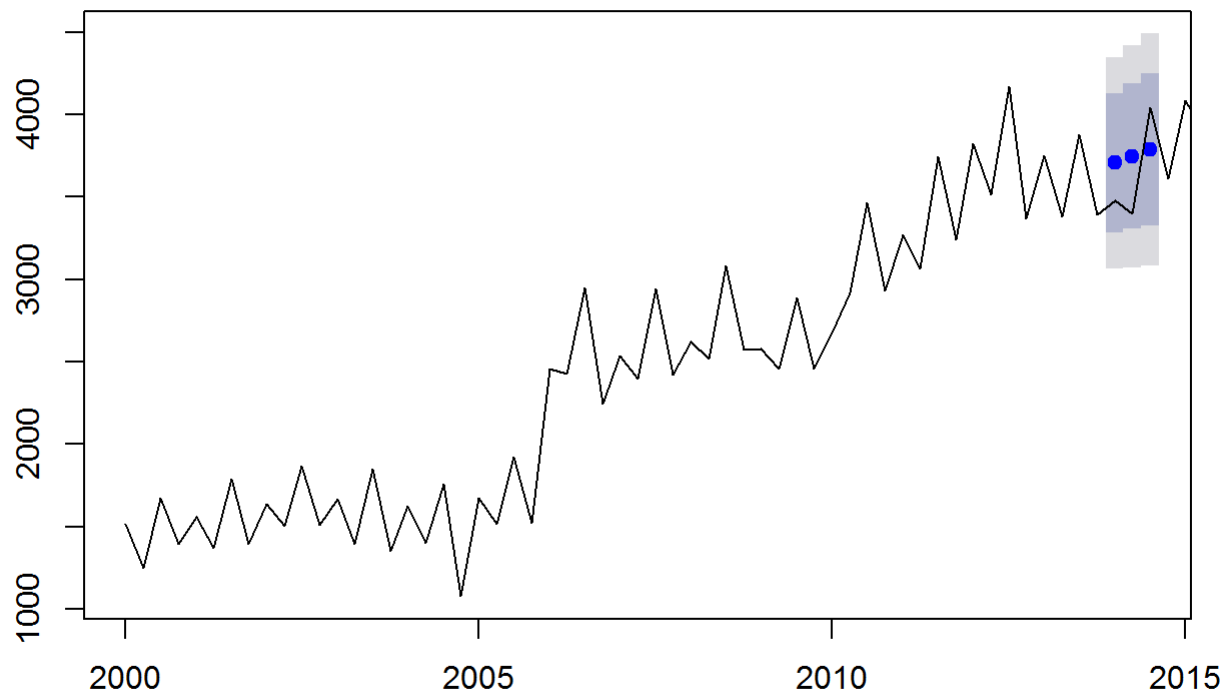


```
#HOLT-WINTERS LINEAR  
fit.hlinear <- holt(train_data, h=3)  
summary(fit.hlinear)
```

```
##
## Forecast method: Holt's method
##
## Model Information:
## Holt's method
##
## Call:
## holt(y = train_data, h = 3)
##
## Smoothing parameters:
##   alpha = 0.3108
##   beta  = 1e-04
##
## Initial states:
##   l = 1423.3542
##   b = 40.7112
##
## sigma: 328.1225
##
##      AIC      AICc      BIC
## 880.1290 881.3290 890.2558
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -1.989548 316.1868 258.6053 -2.498491 11.88473 1.131276
##              ACF1
## Training set -0.2567311
##
## Forecasts:
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2014 Q1      3705.698 3285.193 4126.204 3062.590 4348.807
## 2014 Q2      3746.399 3306.039 4186.758 3072.927 4419.870
## 2014 Q3      3787.099 3327.732 4246.466 3084.557 4489.640
```

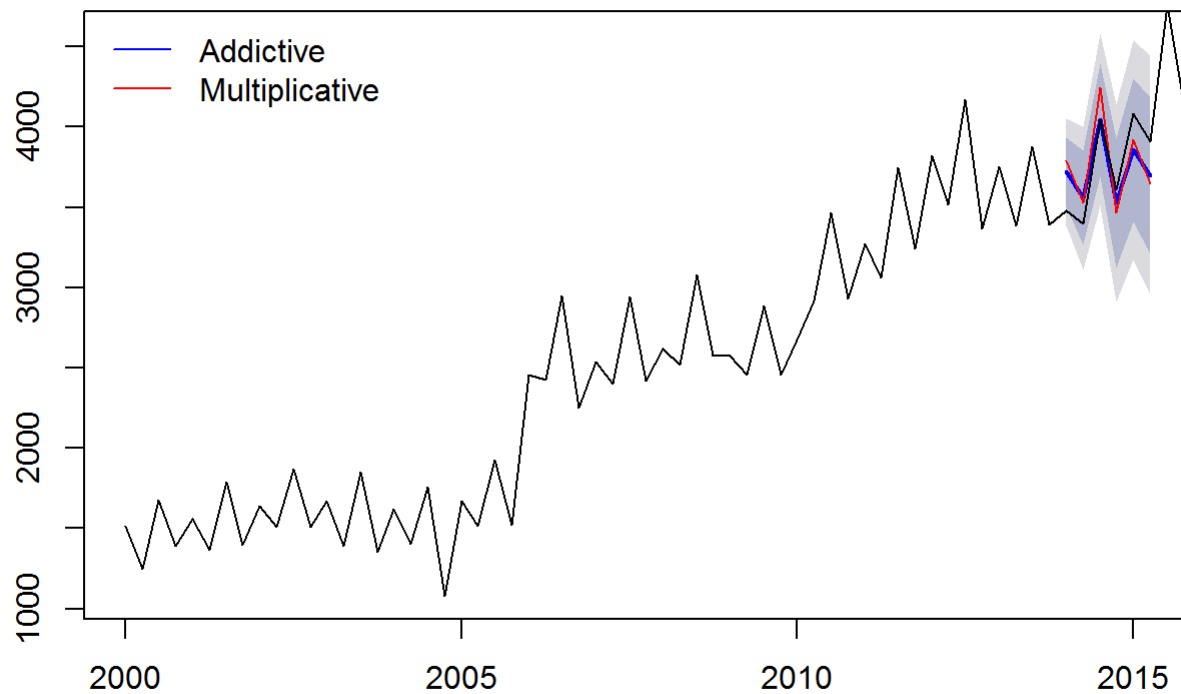
```
plot(fit.hlinear, main = "Holt's Linear Trend")
lines(y)
```

Holt's Linear Trend



```
#HOLT-WINTERS SEASONAL METHOD:MULTIPLICATIVE AND ADDITIVE
fit.hwm <- hw(train_data, seasonal="multiplicative", h=h)
fit.hwa <- hw(train_data, seasonal="additive", h=h)
plot(fit.hwa, col = 4)
lines(fit.hwm$mean, col = 2)
lines(y)
legend("topleft",lty=1,col=c(4,2),
      legend=c("Addictive","Multiplicative"),bty="n")
```

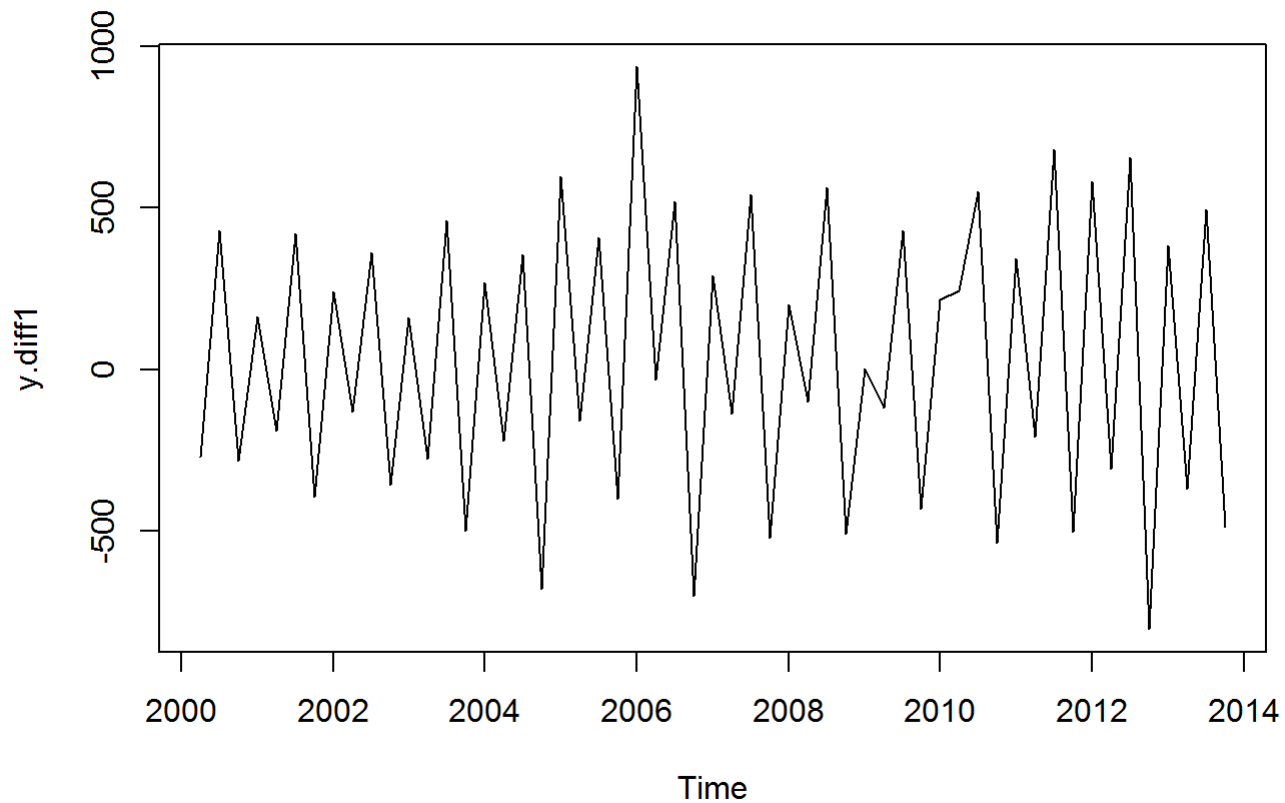
Forecasts from Holt-Winters' additive method



```
#ARIMA
y.diff1 = diff(train_data, differences = 1)
adf.test(y.diff1, alternative = "stationary")
```

```
##
## Augmented Dickey-Fuller Test
##
## data: y.diff1
## Dickey-Fuller = -2.4882, Lag order = 3, p-value = 0.3778
## alternative hypothesis: stationary
```

```
plot(y.diff1)
```

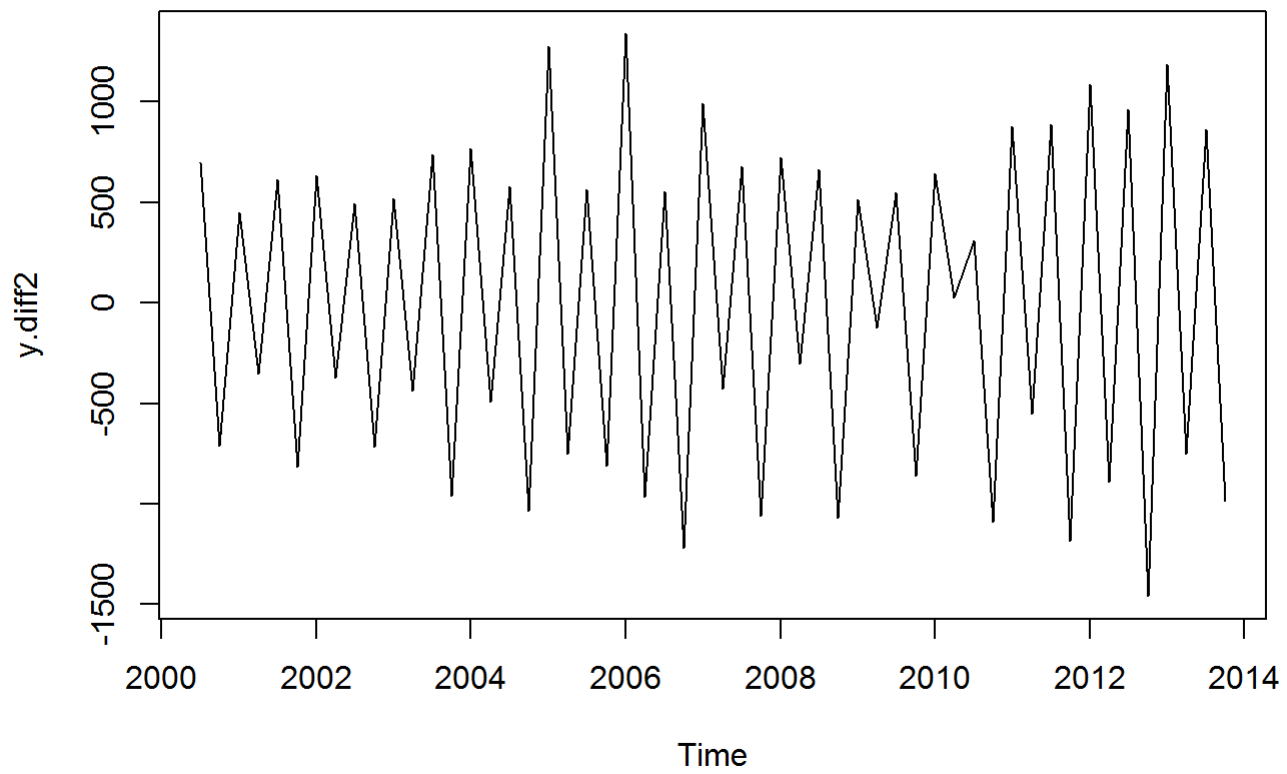


```
y.diff2 = diff(train_data, differences = 2)
adf.test(y.diff2, alternative = "stationary")
```

```
## Warning in adf.test(y.diff2, alternative = "stationary"): p-value smaller
## than printed p-value
```

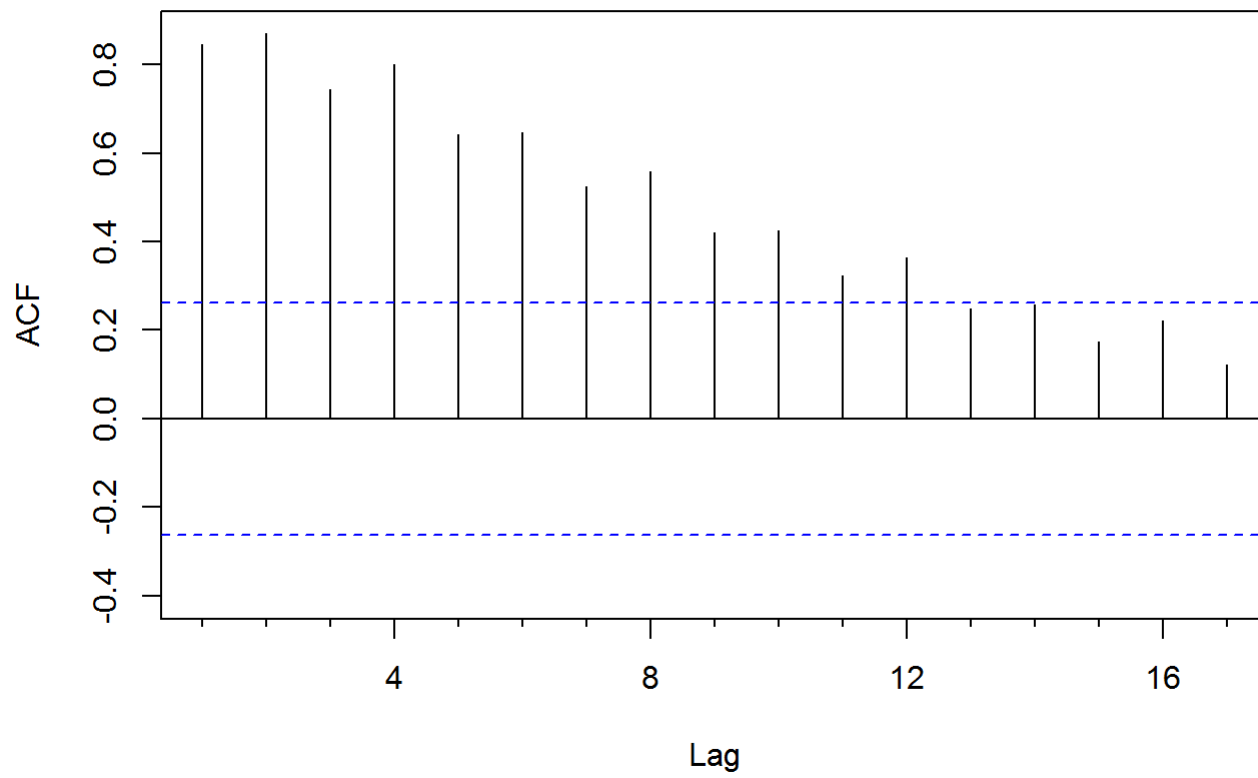
```
##
## Augmented Dickey-Fuller Test
##
## data: y.diff2
## Dickey-Fuller = -5.1456, Lag order = 3, p-value = 0.01
## alternative hypothesis: stationary
```

```
plot(y.diff2)
```

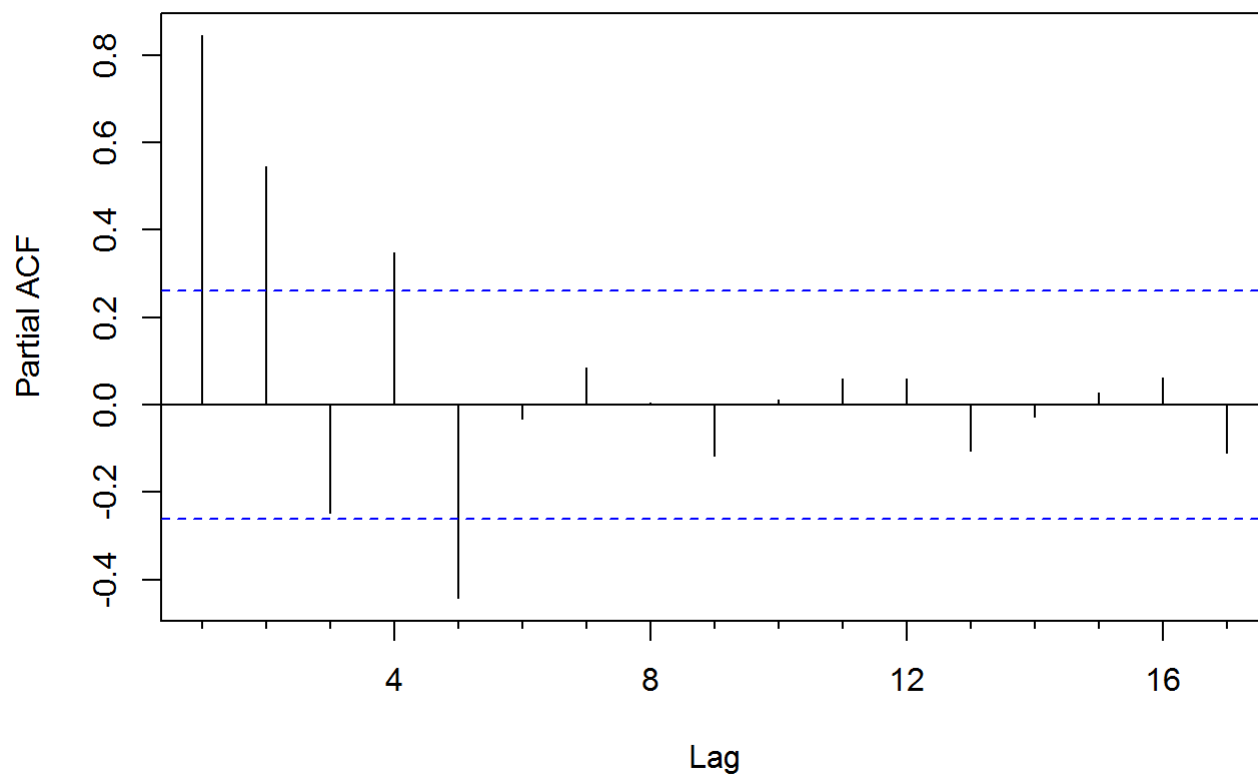
```
Acf(train_data)
```

Series train_data



```
Pacf(train_data)
```

Series train_data

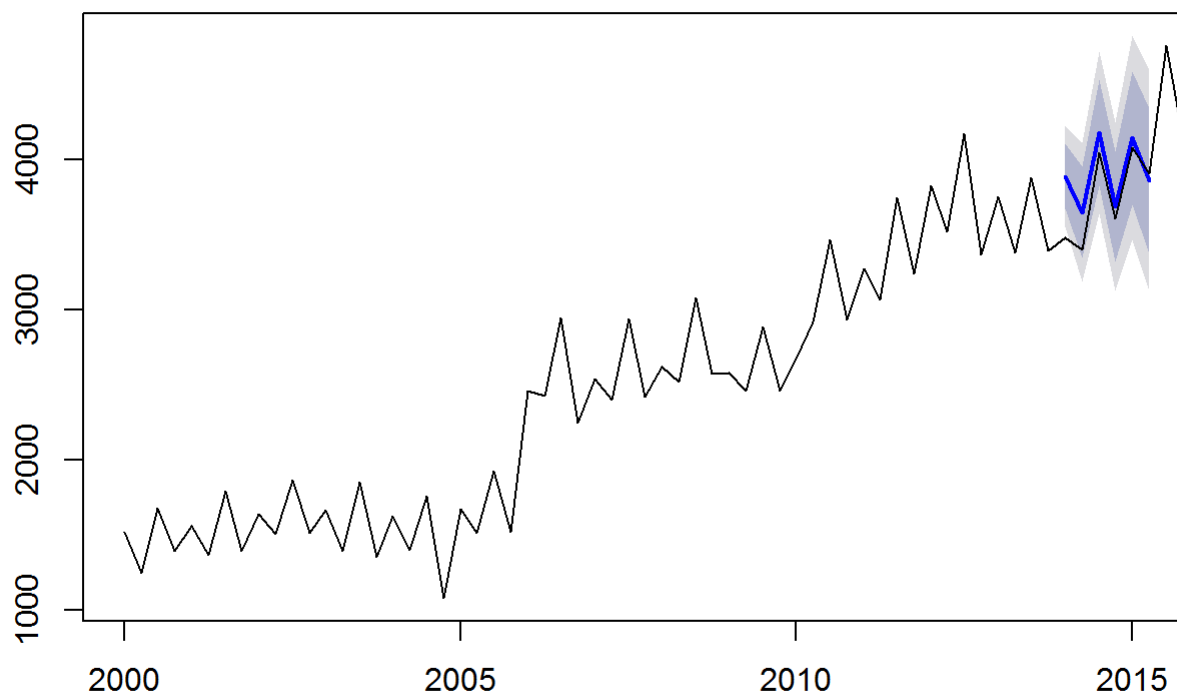


```
#Auto ARIMA
y.arima <- auto.arima(train_data)
fit.arima <- forecast(y.arima, h=h)
summary(fit.arima)
```

```
##
## Forecast method: ARIMA(3,0,0)(0,1,0)[4] with drift
##
## Model Information:
## Series: train_data
## ARIMA(3,0,0)(0,1,0)[4] with drift
##
## Coefficients:
##          ar1      ar2      ar3      drift
##      0.9518 -0.0746 -0.2485  42.2554
## s.e.  0.1348   0.1953   0.1367  15.2852
##
## sigma^2 estimated as 29069:  log likelihood=-339.59
## AIC=689.18   AICc=690.49   BIC=698.94
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set 1.006213 157.8494 123.0373 -0.5617156 5.473664 0.5382301
##              ACF1
## Training set 0.02318496
##
## Forecasts:
##      Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 2014 Q1      3889.926 3671.426 4108.427 3555.759 4224.094
## 2014 Q2      3649.406 3347.757 3951.056 3188.074 4110.739
## 2014 Q3      4179.491 3827.375 4531.608 3640.976 4718.007
## 2014 Q4      3685.368 3318.475 4052.261 3124.254 4246.482
## 2015 Q1      4144.244 3699.497 4588.992 3464.062 4824.427
## 2015 Q2      3857.592 3375.351 4339.833 3120.068 4595.116
```

```
plot(fit.arma)
lines(y)
```

Forecasts from ARIMA(3,0,0)(0,1,0)[4] with drift



#Accuracy Summary

```

a.mean=accuracy(fit.mean,test_data)
a.naive=accuracy(fit.naive,test_data)
a.snaive=accuracy(fit.snaive,test_data)
a.linear=accuracy(fit.tslm,test_data)
a.st=accuracy(fit.lmts,test_data)
a.ses=accuracy(fit.expo, test_data)
a.stl=accuracy(fit.stl, test_data)
a.holt=accuracy(fit.hlinear, test_data)
a.multi=accuracy(fit.hwm, test_data)
a.add=accuracy(fit.hwa, test_data)
a.arima=accuracy(fit.arima, test_data)

a.table<-rbind(a.mean, a.naive, a.snaive, a.linear, a.st, a.ses, a.stl, a.holt, a.multi, a.add,
a.arima)

row.names(a.table)<-c('Mean training','Mean test', 'Naive training', 'Naive test', 'S. Naive tra
ining', 'S. Naive test' , 'Linear training', 'Linear test','season-trend training', 'season-trend
test', 'STL training', 'STL test',"ses training", "ses test","Holt's Linear training", "Holt's
Linear test", 'Muti training', 'Multi test','add training', 'add test','ARIMA training', 'ARIMA
test')

# order the table according to MASE
a.table<-as.data.frame(a.table)
a.table<-a.table[order(a.table$MASE),]
a.table

```

##	ME	RMSE	MAE	MPE
## add training	5.936575e+00	156.5048	112.4352	-0.1179359
## Muti training	1.308620e+01	166.8032	112.6028	-0.1602071
## ses training	-7.974611e-12	168.6314	116.8932	-0.5536722
## ARIMA training	1.006213e+00	157.8494	123.0373	-0.5617156
## season-trend test	-8.451355e+01	176.0549	139.3619	-2.4960244
## add test	1.955155e+01	175.0263	152.6493	0.2612656
## ses test	6.505367e+01	178.4244	158.6734	1.4694336
## ARIMA test	-1.470048e+02	208.3561	163.4742	-4.1314244
## Multi test	-1.287246e+01	210.9563	200.8146	-0.5256939
## season-trend training	4.061359e-15	253.5765	207.0419	-1.1739508
## Linear test	-8.700208e+01	239.6415	219.6462	-2.7434039
## S. Naive training	1.647885e+02	333.3575	228.5962	5.9459772
## STL test	7.856461e+01	297.1688	242.2562	1.5780522
## S. Naive test	1.643333e+02	298.2493	254.6667	4.0670576
## Holt's Linear training	-1.989548e+00	316.1868	258.6053	-2.4984905
## Linear training	-4.057270e-15	330.5585	264.7163	-2.1842548
## STL training	8.789642e+01	332.5876	267.6454	1.9683790
## Holt's Linear test	-1.050652e+02	281.0279	276.3328	-3.4403750
## Naive test	3.630000e+02	452.3074	363.0000	9.1985708
## Naive training	3.407273e+01	431.1145	384.2909	-0.5467924
## Mean training	6.473790e-14	829.4148	716.7819	-13.6030199
## Mean test	1.371964e+03	1398.2485	1371.9643	36.2157926
##	MAPE	MASE	ACF1	Theil's U
## add training	5.257339	0.4918508	-0.007430929	NA
## Muti training	5.405616	0.4925838	-0.019884166	NA
## ses training	5.136756	0.5113525	-0.161657496	NA
## ARIMA training	5.473664	0.5382301	0.023184964	NA
## season-trend test	3.867160	0.6096424	0.545497353	0.3115035
## add test	4.121876	0.6677684	0.553473346	0.3667693
## ses test	4.181376	0.6941210	0.458407323	0.4051990
## ARIMA test	4.552960	0.7151221	0.378847178	0.3348381
## Multi test	5.376758	0.8784688	0.385913179	0.4257386
## season-trend training	10.909320	0.9057104	0.787718765	NA
## Linear test	6.009932	0.9608483	-0.438685321	0.5751233
## S. Naive training	9.220278	1.0000000	0.780659978	NA
## STL test	6.355203	1.0597564	-0.236360619	0.7812646
## S. Naive test	6.662843	1.1140462	0.359303768	0.6720790
## Holt's Linear training	11.884729	1.1312760	-0.256731105	NA
## Linear training	13.042421	1.1580085	0.147473485	NA
## STL training	11.806736	1.1708221	-0.385482533	NA
## Holt's Linear test	7.675478	1.2088252	-0.285759503	0.6549705
## Naive test	9.198571	1.5879532	-0.101774408	1.1757093
## Naive training	17.396986	1.6810909	-0.764711029	NA
## Mean training	34.890539	3.1355816	0.844401211	NA
## Mean test	36.215793	6.0016945	-0.101774408	3.4094174