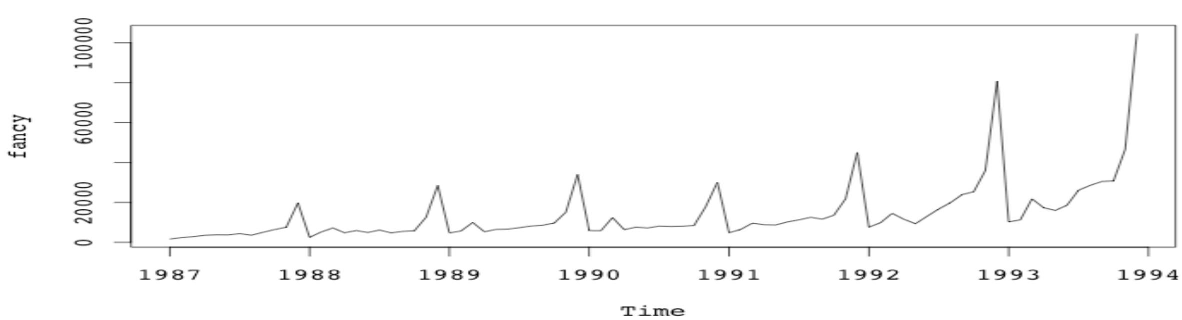
HOMEWORK-2
Nitin Gaonkar

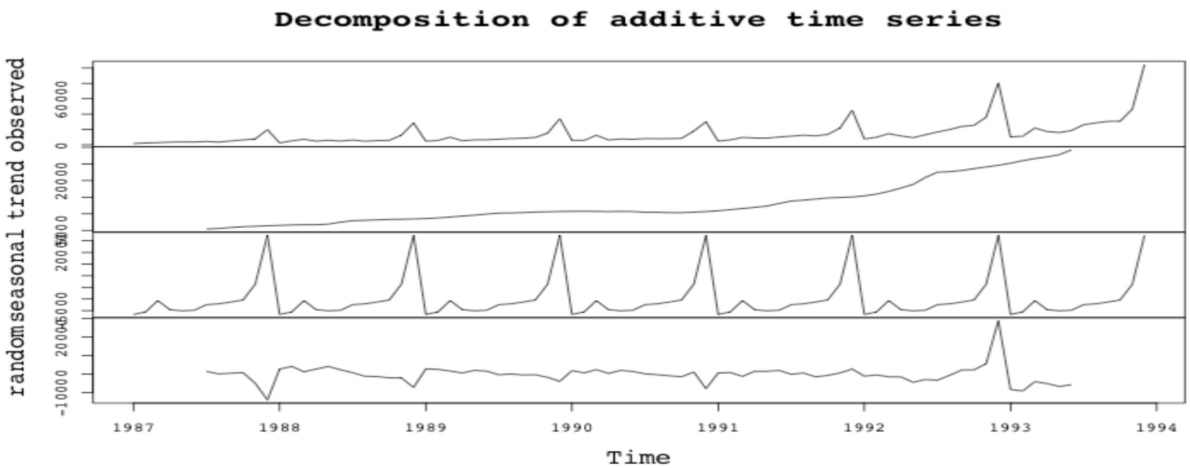
1.The data below (data set fancy) concern the monthly sales figures of a shop which opened in January 1987 and sells gifts, souvenirs, and novelties. The shop is situated on the wharf at a beach resort town in Queensland, Australia. The sales volume varies with the seasonal population of tourists. There is a large influx of visitors to the town at Christmas and for the local surfing festival, held every March since 1988. Over time, the shop has expanded its premises, range of products, and staff.

Below is the data set fancy used in this problem:

```
> fancy
          Jan       Feb       Mar       Apr       May       Jun       Jul       Aug
1987  1664.81   2397.53   2840.71   3547.29   3752.96   3714.74   4349.61   3566.34
1988  2499.81   5198.24   7225.14   4806.03   5900.88   4951.34   6179.12   4752.15
1989  4717.02   5702.63   9957.58   5304.78   6492.43   6630.80   7349.62   8176.62
1990  5921.10   5814.58  12421.25   6369.77   7609.12   7224.75   8121.22   7979.25
1991  4826.64   6470.23   9638.77   8821.17   8722.37  10209.48  11276.55  12552.22
1992  7615.03   9849.69  14558.40  11587.33   9332.56  13082.09  16732.78  19888.61
1993 10243.24  11266.88  21826.84  17357.33  15997.79  18601.53  26155.15  28586.52
          Sep       Oct       Nov       Dec
1987  5021.82   6423.48   7600.60  19756.21
1988  5496.43   5835.10  12600.08  28541.72
1989  8573.17   9690.50  15151.84  34061.01
1990  8093.06   8476.70  17914.66  30114.41
1991 11637.39  13606.89  21822.11  45060.69
1992 23933.38  25391.35  36024.80  80721.71
1993 30505.41  30821.33  46634.38 104660.67
```

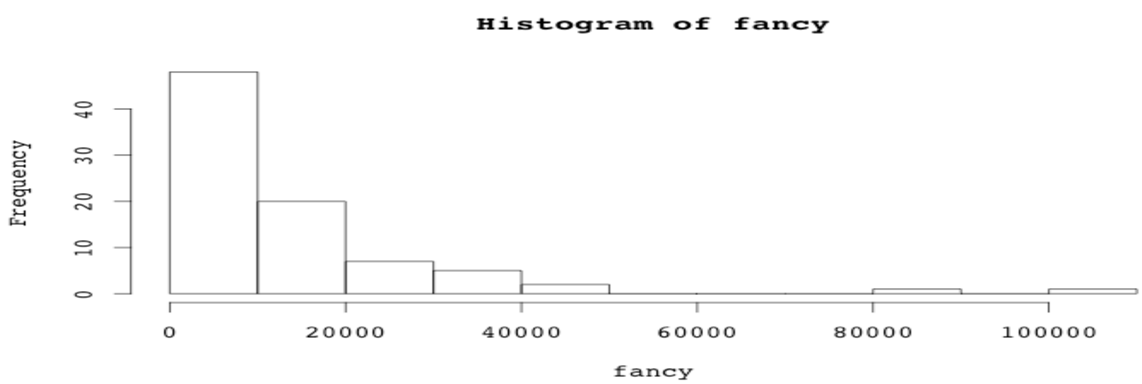
Below is the time series plot for the data set.





By looking at both the plots we can say that there is definitely an upward trend in the time series, we can see also see a strong seasonal pattern. We can see a high fluctuation in the sales at the end of the year due to the large influx of visitors to the town at Christmas.
Also we can notice that the as the year passed by the sales have increased, also we can see trend of year-end sales has also increased drastically since 1993.

b. As we can see from the below graph that the series is not normally distributed



So we have to log transform the data in order to get a better fit. Below is the graph after the data is log transformed.

We can see from the below graph that the data is better distributed than the above graph that is before transformation.

c. I ran the regression for the log of sales and the seasonal trend, below is the summary of the model:

```
> fit<-tslm(fancy_log ~ trend + season)
> summary(fit)

Call:
tslm(formula = fancy_log ~ trend + season)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.41644 -0.12619  0.00608  0.11389  0.38567 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 7.6058604  0.0768740  98.939  < 2e-16 ***
trend       0.0223930  0.0008448  26.508  < 2e-16 ***
season2     0.2510437  0.0993278   2.527 0.013718 *  
season3     0.6952066  0.0993386   6.998 1.18e-09 ***
season4     0.3829341  0.0993565   3.854 0.000252 ***
season5     0.4079944  0.0993817   4.105 0.000106 ***
season6     0.4469625  0.0994140   4.496 2.63e-05 ***
season7     0.6082156  0.0994534   6.116 4.69e-08 ***
season8     0.5853524  0.0995001   5.883 1.21e-07 ***
season9     0.6663446  0.0995538   6.693 4.27e-09 ***
season10    0.7440336  0.0996148   7.469 1.61e-10 ***
season11    1.2030164  0.0996828  12.068  < 2e-16 ***
season12    1.9581366  0.0997579  19.629  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1858 on 71 degrees of freedom
Multiple R-squared:  0.9527,    Adjusted R-squared:  0.9447 
F-statistic: 119.1 on 12 and 71 DF,  p-value: < 2.2e-16
```

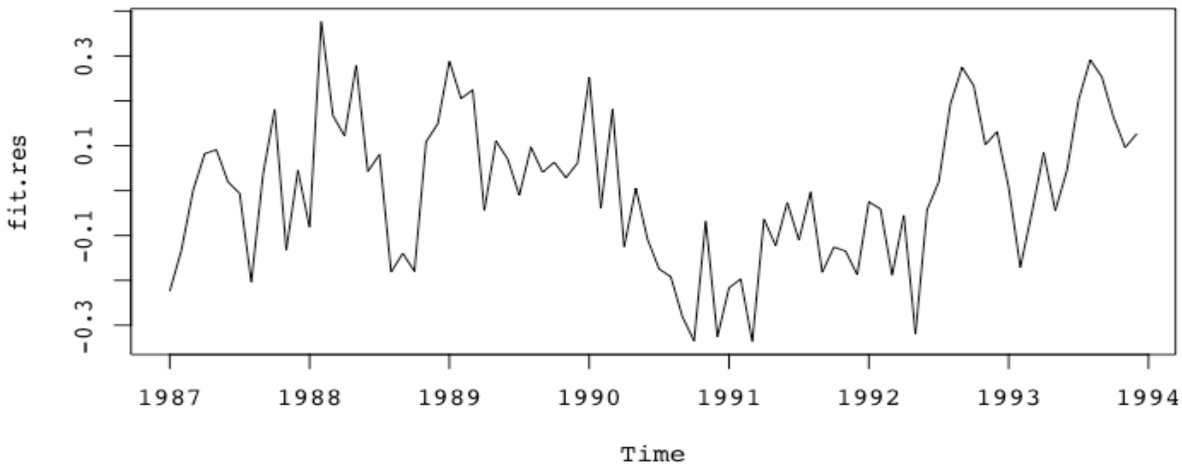
As we can see that the R squared value for the model is pretty good 0.9447, looks like a good fit, let's try the model with the surfing festival dummy variable.
Here I have created a dummy variable called as dummy fest. The Value of the dummy fest is 1 for the month of march from 1988 to 1993 and zero for the rest of the months.
We can see that the r square value has increased a bit but overall the model looks good.

```
> fit = tslm(fancy_log ~ trend + season + dummy_fest, data=my_data)
> summary(fit)

Call:
tslm(formula = fancy_log ~ trend + season + dummy_fest, data = my_data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.33673 -0.12757  0.00257  0.10911  0.37671 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) 7.6196670  0.0742471 102.626  < 2e-16 ***
trend       0.0220198  0.0008268  26.634  < 2e-16 ***
season2     0.2514168  0.0956790   2.628 0.010555 *  
season3     0.2660828  0.1934044   1.376 0.173275    
season4     0.3840535  0.0957075   4.013 0.000148 ***
season5     0.4094870  0.0957325   4.277 5.88e-05 ***
season6     0.4488283  0.0957647   4.687 1.33e-05 ***
season7     0.6104545  0.0958039   6.372 1.71e-08 ***
season8     0.5879644  0.0958503   6.134 4.53e-08 ***
season9     0.6693299  0.0959037   6.979 1.36e-09 ***
season10    0.7473919  0.0959643   7.788 4.48e-11 ***
season11    1.2067479  0.0960319  12.566  < 2e-16 ***
season12    1.9622412  0.0961066  20.417  < 2e-16 ***
dummy_fest  0.5015151  0.1964273   2.553 0.012856 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.179 on 70 degrees of freedom
Multiple R-squared:  0.9567,	Adjusted R-squared:  0.9487 
F-statistic:   119 on 13 and 70 DF,  p-value: < 2.2e-16
```

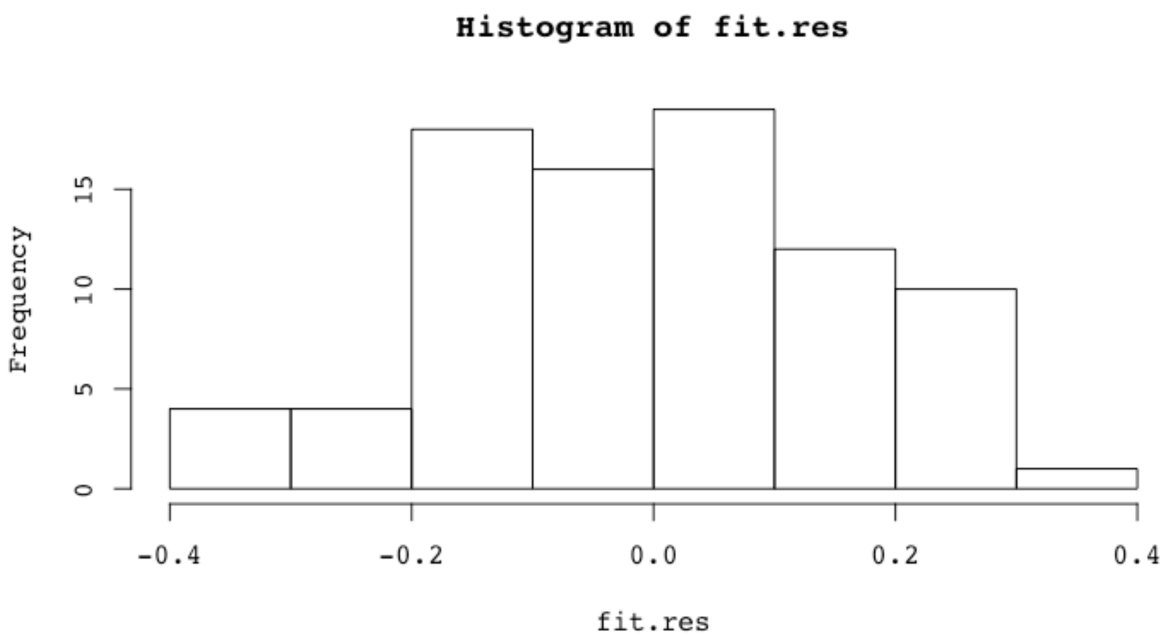
Below is the R code for dummy coding and regression:

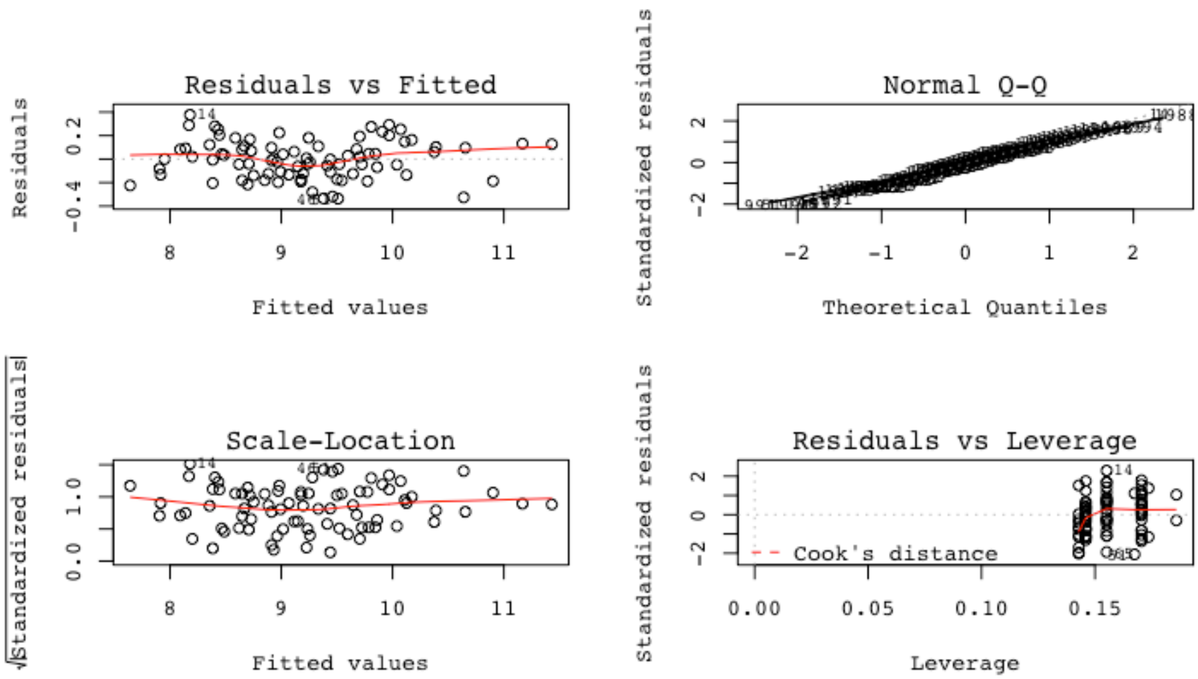
```
#regression
fit<-tslm(fancy_log ~ trend + season)
summary(fit)

#creating dummy variable for the festival in march

dummy_fest = rep(0, length(fancy))
dummy_fest[seq_along(dummy_fest)%%12 == 3] <- 1
dummy_fest[3] <- 0 #festival started one year later
dummy_fest = ts(dummy_fest, freq = 12, start=c(1987,1))

my_data <- data.frame(fancy_log,dummy_fest)

#regression
fit = tslm(log_fancy ~ trend + season + dummy_fest, data=my_data)
```

d. Below is the plot of the residual against time.



Below is the histogram of the residuals, we can see that it's not perfectly normally distributed but it fits ok.

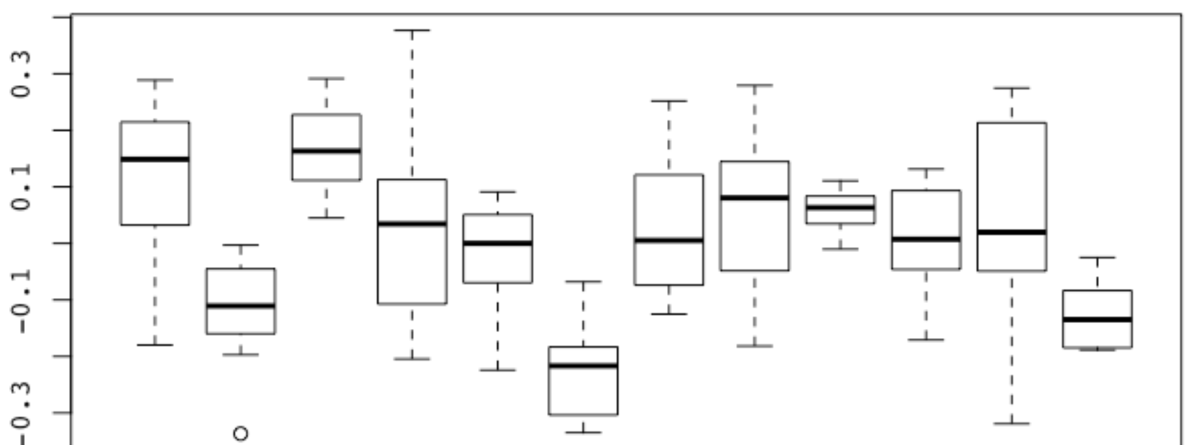




By looking at all the residual plot, we can comment that the QQ plot look good and the fitted value plot looks ok. So we have a decent model.

e.

we can see that the residual values vary for each month.



f.
Regression coefficients represent the mean change in the response variable for one unit of change in the predictor variable while holding other predictors in the model constant.
By looking at the models and seeing the p value we can say that all the predictor variables are significant except for season 3.

g. **Durbin-Watson test**

data: tslm(fancy_log ~ trend + season + dummy_fest, data = my_data)
DW = 0.88889, p-value = 9.78e-08
alternative hypothesis: true autocorrelation is greater than 0

- The null hypothesis (H0H0) is that there is no correlation among residuals, i.e., they are independent.
- The alternative hypothesis (HaHa) is that residuals are auto correlated.

we can see that the p value is significant thus we reject the null hypothesis.

h. Predicting the monthly sales for 1994, 1995 and 1996.

here's a forecast assuming the surfing festival is cancelled, and never happens again:

Below are the predictions and the predictors intervals.

```
> forecast(fit, newdata=future_data)
         Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
Jan 1994       9.509264  9.246995  9.771532  9.105002  9.913525
Feb 1994       9.782700  9.520432 10.044969  9.378439 10.186962
Mar 1994      10.249256  9.986988 10.511525  9.844995 10.653518
Apr 1994       9.959377  9.697108 10.221645  9.555115 10.363638
May 1994      10.006830  9.744562 10.269098  9.602569 10.411091
Jun 1994      10.068191  9.805923 10.330459  9.663930 10.472452
Jul 1994      10.251837  9.989569 10.514105  9.847576 10.656099
Aug 1994      10.251367  9.989099 10.513635  9.847106 10.655628
Sep 1994      10.354752 10.092484 10.617020  9.950491 10.759014
Oct 1994      10.454834 10.192566 10.717102 10.050573 10.859095
Nov 1994      10.936210 10.673942 11.198478 10.531949 11.340471
Dec 1994      11.713723 11.451455 11.975991 11.309462 12.117984
Jan 1995       9.777979  9.512777 10.043182  9.369195 10.186763
Feb 1995      10.051416  9.786214 10.316618  9.642632 10.460200
Mar 1995      10.517972 10.252770 10.783174 10.109188 10.926756
Apr 1995      10.228092  9.962890 10.493295  9.819308 10.636876
May 1995      10.275546 10.010343 10.540748  9.866762 10.684330
Jun 1995      10.336907 10.071704 10.602109  9.928123 10.745691
Jul 1995      10.520553 10.255351 10.785755 10.111769 10.929337
Aug 1995      10.520083 10.254880 10.785285 10.111299 10.928867
Sep 1995      10.623468 10.358266 10.888670 10.214684 11.032252
Oct 1995      10.723550 10.458347 10.988752 10.314766 11.132334
Nov 1995      11.204926 10.939723 11.470128 10.796142 11.613710
Dec 1995      11.982439 11.717236 12.247641 11.573655 12.391223
Jan 1996      10.046695  9.777950 10.315440  9.632451 10.460940
Feb 1996      10.320132 10.051387 10.588877  9.905887 10.734376
Mar 1996      10.786688 10.517943 11.055433 10.372443 11.200932
Apr 1996      10.496808 10.228063 10.765553 10.082564 10.911053
May 1996      10.544261 10.275516 10.813007 10.130017 10.958506
Jun 1996      10.605623 10.336878 10.874368 10.191378 11.019867
Jul 1996      10.789269 10.520524 11.058014 10.375024 11.203513
Aug 1996      10.788798 10.520053 11.057543 10.374554 11.203043
Sep 1996      10.892184 10.623439 11.160929 10.477939 11.306428
Oct 1996      10.992266 10.723521 11.261011 10.578021 11.406510
Nov 1996      11.473641 11.204896 11.742386 11.059397 11.887886
Dec 1996      12.251155 11.982409 12.519900 11.836910 12.665399
```

i. Transforming the predictions and the intervals.

Month	Year	Point forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	1994	13484.07	10373.35	17527.60	9000.20	20201.76
Feb	1994	17724.44	13635.50	23039.58	11830.53	26554.70
Mar	1994	28261.51	21741.71	36736.46	18863.71	42341.29
Apr	1994	21149.62	16270.48	27491.85	14116.72	31686.25
May	1994	22177.42	17061.20	28827.87	14802.76	33226.10
Jun	1994	23580.87	18140.88	30652.18	15739.52	35328.74
Jul	1994	28334.54	21797.90	36831.36	18912.46	42450.71
Aug	1994	28321.23	21787.66	36814.06	18903.57	42430.72
Sep	1994	31405.93	24160.73	40823.78	20962.51	47052.25
Oct	1994	34711.77	26703.93	45120.95	23169.06	52004.99
Nov	1994	56174.04	43214.96	73019.22	37494.48	84159.66

Dec	1994	122237.73	94038.07	158893.75	81590.00	183135.94
Jan	1995	17640.96	13531.52	22998.45	11721.68	26549.42
Feb	1995	23188.60	17786.84	30230.84	15407.84	34898.53
Mar	1995	36974.07	28360.99	48202.88	24567.70	55645.47
Apr	1995	27669.67	21224.04	36072.82	18385.32	41642.48
May	1995	29014.36	22255.47	37825.85	19278.81	43666.22
Jun	1995	30850.46	23663.85	40219.57	20498.83	46429.53
Jul	1995	37069.62	28434.29	48327.45	24631.19	55789.28
Aug	1995	37052.20	28420.90	48304.74	24619.62	55763.06
Sep	1995	41087.86	31516.48	53566.01	27301.15	61836.68
Oct	1995	45412.83	34833.92	59204.45	30174.91	68345.70
Nov	1995	73491.57	56371.73	95810.54	48832.04	110603.83
Dec	1995	159921.60	122667.90	208488.88	106261.15	240679.87
Jan	1996	23079.38	17640.45	30195.25	15251.77	34924.36
Feb	1996	30337.26	23187.93	39690.89	20048.05	45907.14
Mar	1996	48372.56	36972.99	63286.86	31966.48	73198.63
Apr	1996	36199.77	27668.86	47360.93	23922.24	54778.50
May	1996	37958.97	29013.48	49662.58	25084.79	57440.56
Jun	1996	40361.15	30849.57	52805.36	26672.22	61075.56
Jul	1996	48497.57	37068.54	63450.41	32049.09	73387.80
Aug	1996	48474.73	37051.09	63420.54	32034.03	73353.32
Sep	1996	53754.57	41086.67	70328.26	35523.12	81342.83
Oct	1996	59412.86	45411.52	77731.12	39262.34	89905.10
Nov	1996	96147.72	73489.37	125792.12	63538.23	145493.40
Dec	1996	209222.80	159916.81	273730.68	138262.59	316601.45

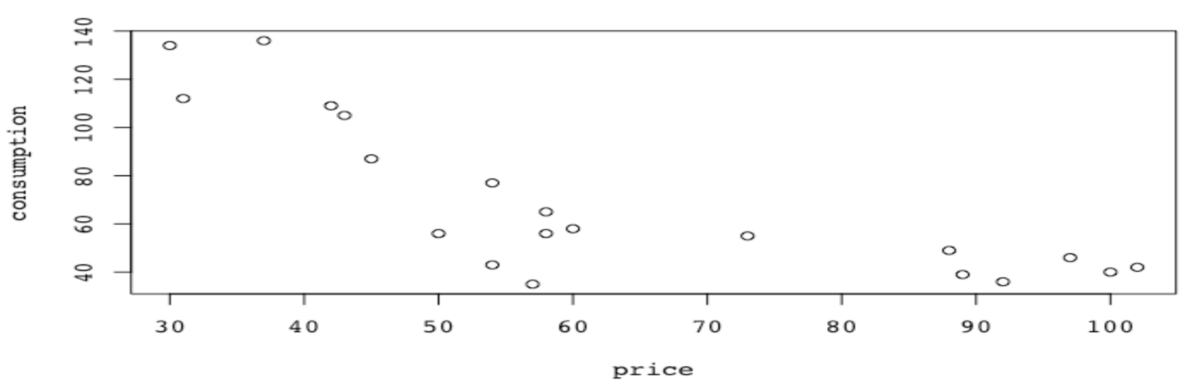
j. how could you improve these predictions by modifying the model?

We can use dynamic regression model which works better when we have autocorrelation remaining in the residual.

2. The data below (data set texasgas) shows the demand for natural gas and the price of natural gas for 20 towns in Texas in 1969.

```
> texasgas
   price consumption
1     30         134
2     31         112
3     37         136
4     42         109
5     43         105
6     45          87
7     50          56
8     54          43
9     54          77
10    57          35
11    58          65
12    58          56
13    60          58
14    73          55
15    88          49
16    89          39
17    92          36
18    97          46
19   100          40
20   102          42
```

Scatter plot,



b. The data is not linear so the slope needs to change in order to capture the change in the model.

c.
First model:

```
> fit <- lm(consumption ~ exp(price), df)
> summary(fit)

Call:
lm(formula = consumption ~ exp(price), data = df)

Residuals:
   Min     1Q Median     3Q    Max 
-35.86 -25.09 -13.86  20.64  65.14 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  7.086e+01  7.670e+00   9.238 2.98e-08 ***
exp(price)  -1.642e-43  1.711e-43  -0.959     0.35    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 33.19 on 18 degrees of freedom
Multiple R-squared:  0.04864,	Adjusted R-squared:  -0.004214 
F-statistic: 0.9203 on 1 and 18 DF,  p-value: 0.3501
```

The slope for price is -1.642

Residual variance:

> (summary(fit)$sigma)**2

[1] 1101.359

Second model

```
> library(segmented)
> lin.mod <- lm(consumption ~ price, df)
> segmented.mod <- segmented(lin.mod, seg.Z = ~price, psi=60)
> slope(segmented.mod)
$price
          Est. St.Err. t value CI(95%).l CI(95%).u
slope1 -3.1470  0.5102  -6.169   -4.2290   -2.0660
slope2 -0.3075  0.2220  -1.385   -0.7782    0.1632
```

The slope for B1 is -3.147
Slope for B2 is -0.308

Residual variance:

```
> (summary(segmented.mod) $sigma)**2
[1] 167.8511
```

Third model:

```
> fit3 <- lm(consumption ~ poly(price, 2), df)
> summary(fit3)

Call:
lm(formula = consumption ~ poly(price, 2), data = df)

Residuals:
     Min       1Q   Median       3Q      Max 
-25.5601  -5.4693   0.7502  11.0252  25.6619 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)       69.000      3.213  21.472 9.35e-14 ***
poly(price, 2)1 -114.043     14.371  -7.936 4.07e-07 ***
poly(price, 2)2   65.737     14.371   4.574 0.000269 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 14.37 on 17 degrees of freedom
Multiple R-squared:  0.8315,	Adjusted R-squared:  0.8117 
F-statistic: 41.95 on 2 and 17 DF,  p-value: 2.666e-07
```

Residual variance:

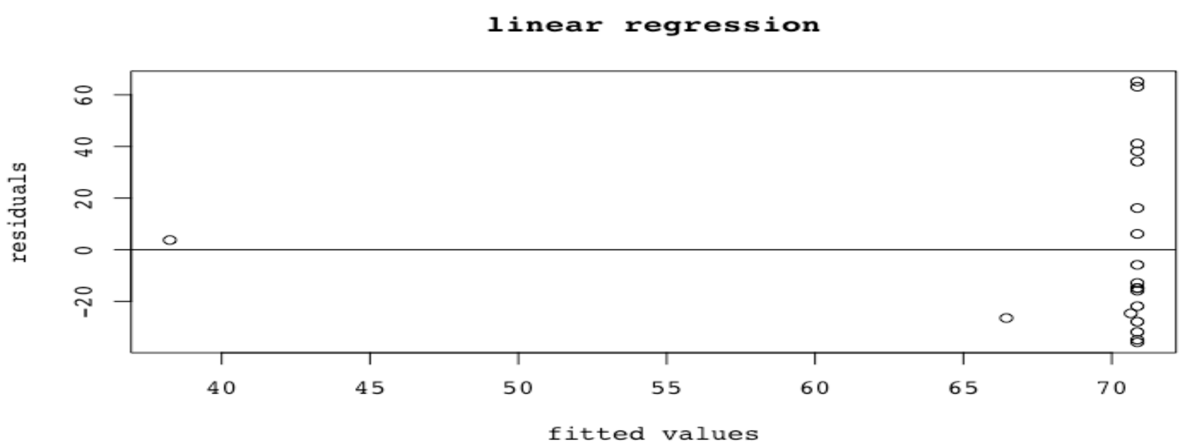
```
> (summary(fit3)$sigma)**2
[1] 206.5276
```

d. **For each model, find the value of R^2 and AIC, and produce a residual plot. Comment on the adequacy of the three models.**

First model:

Adjusted R-squared: -0.004
AIC: 200.736

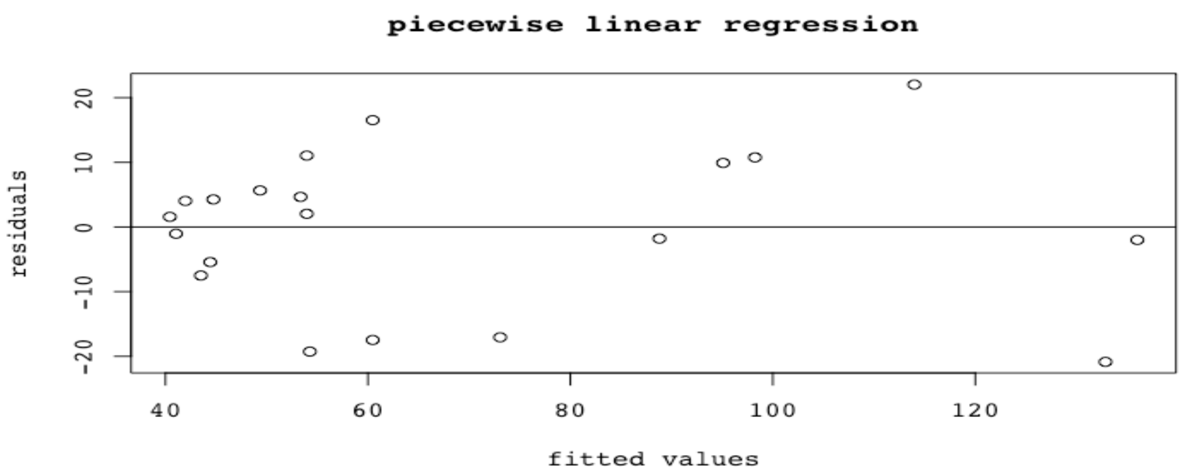
```
> resid <- residuals(fit)
> plot(fit$fitted.values, resid, ylab='residuals', xlab='fitted values',
+      main='linear regression')
> abline(0,0)
```



Second model:

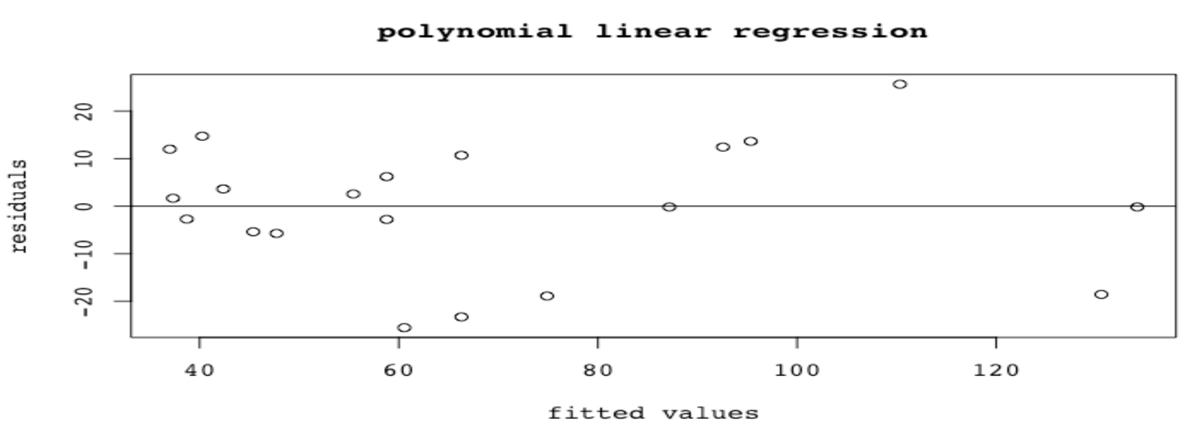
Adjusted R-squared: 0.847
AIC: 164.756

```
> resid <- residuals(segmented.mod)
> plot(segmented.mod$fitted.values, resid, ylab='residuals', xlab='fitted values',
+      main='piecewise linear regression')
> abline(0,0)
```



Third model, polynomial regression:

```
> plot(fit3$fitted.values, resid, ylab='residuals', xlab='fitted values',
+      main='polynomial linear regression')
> abline(0,0)
```



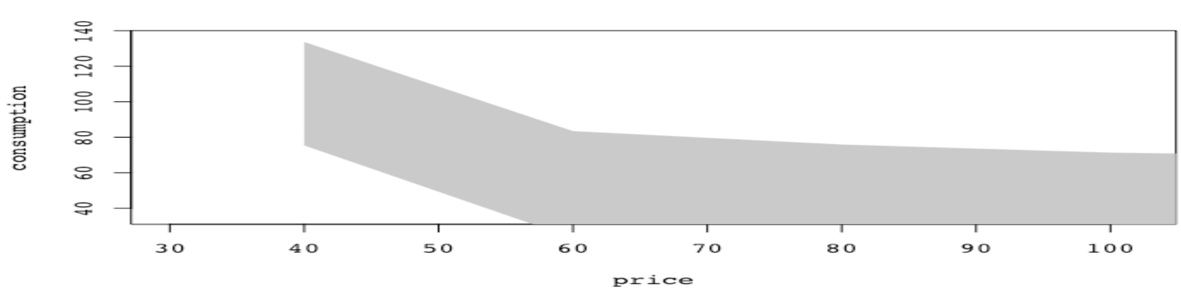
All three of the residual plots show heteroskedasticity. the linear regression model residual plot shows problems, nearly all the values are predicted to be around 71 and most of these predictions are inaccurate, the second mode has a slight larger r square and a slightly lower AIC than the polynomial mode so it's the best model.

e. **For prices 40, 60, 80, 100, and 120 cents per 1,000 cubic feet, compute the forecasted per capita demand using the best model of the three above.**

```
> new.data <- data.frame(price=c(40, 60, 80, 100, 120))
> predict(segmented.mod, new.data)
        1         2         3         4         5 
104.53618  53.34514  47.19593  41.04673  34.89752 
>
```

f. **Compute 95% prediction intervals. Make a graph of these prediction intervals and discuss their interpretation.**

```
> newx <- seq(min(new.data), max(new.data), length.out=5)
> intervals <- predict(segmented.mod, new.data, interval="predict")
> plot(consumption ~ price, data = df, type = 'n')
> polygon(c(rev(newx), newx), c(rev(intervals[ ,3]), intervals[ ,2]), col = 'grey80', border = NA)
```



By looking at the plot we can see that the intervals are fairly wide so we cannot accurately predict how much energy will be demanded.

6.7 Exercises

1. Show that a 3×53×5 MA is equivalent to a 7-term weighted moving average with weights of 0.067, 0.133, 0.200, 0.200, 0.200, 0.133, and 0.067.

   3 * 5 means we are getting the moving average of 5 terms first, and then we are finding MA on each 3 term series of the original MA

   Table below:

Values	5 MA	3*5 MA
V1		
V2		
V3	1/5*(V1+V2+V3+V4+V5)	
V4	1/5*(V2+V3+V4+V5+V6)	1/3*1/5*(V1+2V2+3V3+3V4+3V5+2V6+V7)
V5	1/5*(V3+V4+V5+V6+V7)	

So, 3 * 5 MA is:

= 1/3 * 1/5 * (V1 + 2V2 + 3V3 + 3V4 + 3V5 + 2V6 + V7)
= 1/15 (V1 + 2V2 + 3V3 + 3V4 + 3V5 + 2V6 + V7)

so respective weights are:

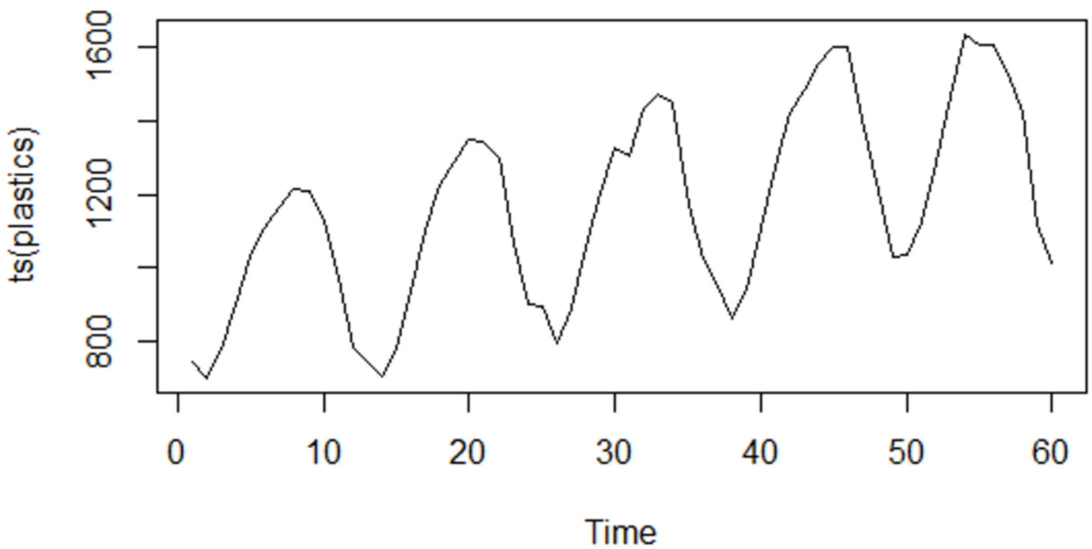
1/15= (=0.067) for V1
2/15= (=0.133 for V2
3/15= (=0.2) for V3
3/15= (=0.2) for V4
3/15= (=0.2) for V5
2/15= (=0.133) for V6
1/15= (=0.067) for V7

2. The data below represent the monthly sales (in thousands) of product A for a plastics manufacturer for years 1 through 5 (data set plastics).

Below is the data for the problem:

	1	2	3	4	5
Jan	742	741	896	951	1030
Feb	697	700	793	861	1032
Mar	776	774	885	938	1126
Apr	898	932	1055	1109	1285
May	1030	1099	1204	1274	1468
Jun	1107	1223	1326	1422	1637
Jul	1165	1290	1303	1486	1611
Aug	1216	1349	1436	1555	1608
Sep	1208	1341	1473	1604	1528
Oct	1131	1296	1453	1600	1420
Nov	971	1066	1170	1403	1119
Dec	783	901	1023	1209	1013

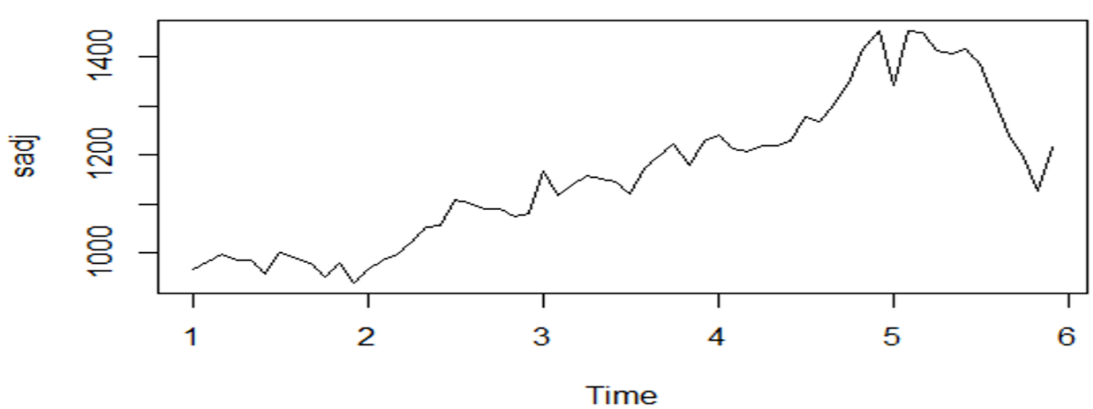
 # question a
plot(ts(plastics))



 # question b for multiplicative model , use the decompose function with type

tsmodel<- decompose(plastics, type="multiplicative")

trend_ind <- tsmodel$trend
seasonal_ind <- tsmodel$seasonal

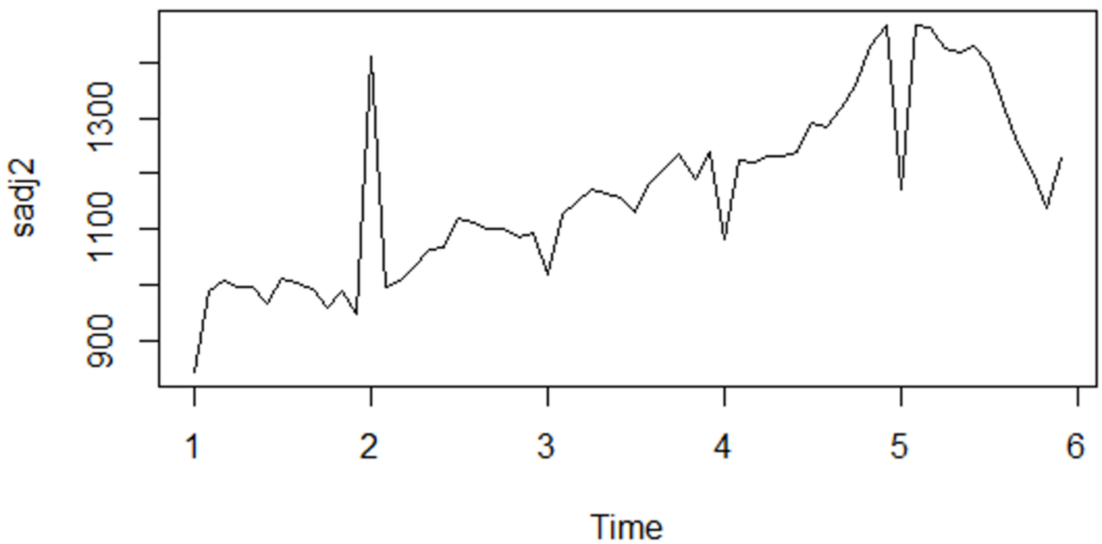


c. **Do the results support the graphical interpretation from part (a)?**

The plot shows that the summer months should have higher seasonal indices than the winter months and this is true.

 # d plot the seasonal adjusted data

sadj <- seasadj(tsmodel)
plot(sadj)



Question: e

# add the outlier 500 and then recompute everything
plastics500 <- plastics
plastics500[13] = plastics500[13] + 500

tsmodel2 <- decompose(plastics500, type="multiplicative")

sadj2 <- seasadj(tsmodel2)
plot(sadj2)

f. Does it make any difference if the outlier is near the end rather than in the middle of the time series?

It makes no difference whether an outlier is near the end or the middle of the time series.

g. Use a random walk with drift to produce forecasts of the seasonally adjusted data.

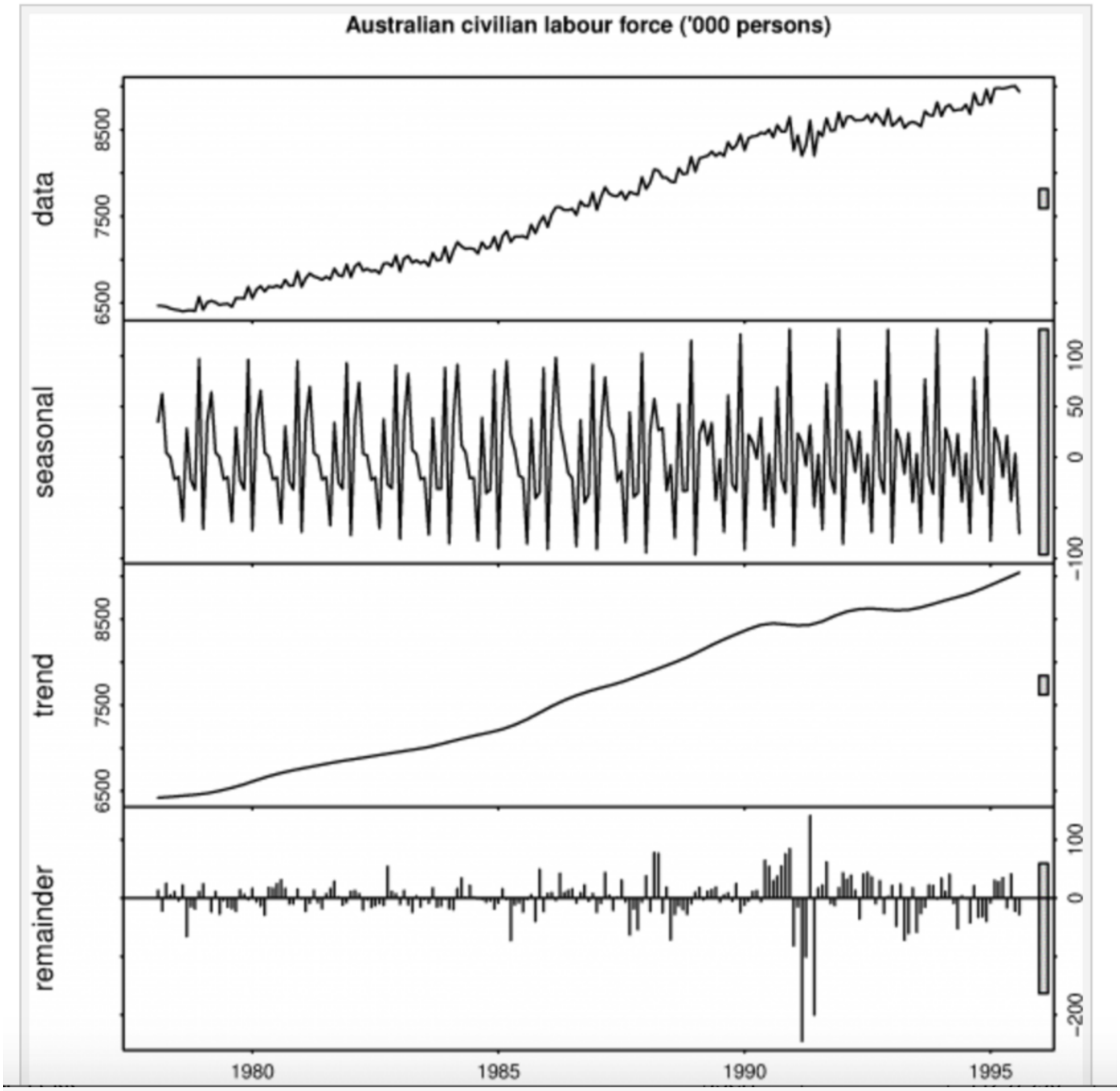
```
> fit5 <- rwf(sadj, drift=TRUE)
>
> summary(fit5)

Forecast method: Random walk with drift

Model Information:
$drift
[1] 4.213863

$drift.se
[1] 5.276238

$sd
[1] 40.52756

$call
rwf(y = sadj, drift = TRUE)


Error measures:
                        ME     RMSE      MAE         MPE     MAPE      MASE       ACF1
Training set -5.973412e-14 40.18263 30.59784 -0.03455045 2.578893 0.2572624 -0.1200898

Forecasts:
      Point Forecast   Lo 80    Hi 80    Lo 95    Hi 95
Jan 6       1220.179 1168.24 1272.117 1140.746 1299.611
Feb 6       1220.179 1168.24 1272.117 1140.746 1299.611
Mar 6       1220.179 1168.24 1272.117 1140.746 1299.611
Apr 6       1220.179 1168.24 1272.117 1140.746 1299.611
May 6       1220.179 1168.24 1272.117 1140.746 1299.611
Jun 6       1220.179 1168.24 1272.117 1140.746 1299.611
Jul 6       1220.179 1168.24 1272.117 1140.746 1299.611
Aug 6       1220.179 1168.24 1272.117 1140.746 1299.611
Sep 6       1220.179 1168.24 1272.117 1140.746 1299.611
Oct 6       1220.179 1168.24 1272.117 1140.746 1299.611
```

h. **Reseasonalize the results to give forecasts on the original scale.**

fit5 <- stl(ts, t.window=15,s.window="periodic", robust= True)
fit6 <- forecast (fit5, method="naïve")

```
> fit5 <- stl(ts, t.window=15,s.window="periodic", robust=TRUE)
> fit6 <- forecast(fit5, method="naive")
> summary(fit6)

Forecast method: STL +  Random walk

Model Information:
$drift
[1] 0

$drift.se
[1] 0

$sd
[1] 41.09468

$call
rwf(y = x, h = h, drift = FALSE, level = level)


Error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 3.292425 40.87774 31.97744 0.3318833 2.774289 0.2725834 0.03514162

Forecasts:
      Point Forecast     Lo 80     Hi 80     Lo 95     Hi 95
Jan 6       936.2531  883.8662  988.6400  856.1342 1016.3720
Feb 6       863.6074  811.2205  915.9943  783.4885  943.7263
Mar 6       942.2625  889.8756  994.6494  862.1436 1022.3814
Apr 6      1095.6329 1043.2460 1148.0198 1015.5140 1175.7518
May 6      1234.3115 1181.9246 1286.6985 1154.1927 1314.4304
Jun 6      1344.5774 1292.1905 1396.9644 1264.4585 1424.6963
Jul 6      1390.0138 1337.6269 1442.4008 1309.8950 1470.1327
Aug 6      1447.9805 1395.5936 1500.3674 1367.8616 1528.0994
Sep 6      1463.6068 1411.2199 1515.9937 1383.4879 1543.7257
Oct 6      1415.5186 1363.1316 1467.9055 1335.3997 1495.6375
Nov 6      1159.9252 1107.5383 1212.3122 1079.8063 1240.0441
Dec 6      1013.0000  960.6131 1065.3869  932.8811 1093.1189
Jan 7       936.2531  862.1668 1010.3394  822.9479 1049.5583
Feb 7       863.6074  789.5211  937.6937  750.3022  976.9126
Mar 7       942.2625  868.1762 1016.3488  828.9573 1055.5677
Apr 7      1095.6329 1021.5466 1169.7192  982.3277 1208.9381
May 7      1234.3115 1160.2252 1308.3979 1121.0063 1347.6168
Jun 7      1344.5774 1270.4911 1418.6637 1231.2722 1457.8826
Jul 7      1390.0138 1315.9275 1464.1002 1276.7086 1503.3191
Aug 7      1447.9805 1373.8942 1522.0668 1334.6753 1561.2857
Sep 7      1463.6068 1389.5205 1537.6931 1350.3016 1576.9120
Oct 7      1415.5186 1341.4323 1489.6049 1302.2133 1528.8238
Nov 7      1159.9252 1085.8389 1234.0115 1046.6200 1273.2305
Dec 7      1013.0000  938.9137 1087.0863  899.6948 1126.3052
```

3.
Figure 6.13 shows the result of decomposing the number of persons in the civilian labor force in Australia each month from February 1978 to August 1995.



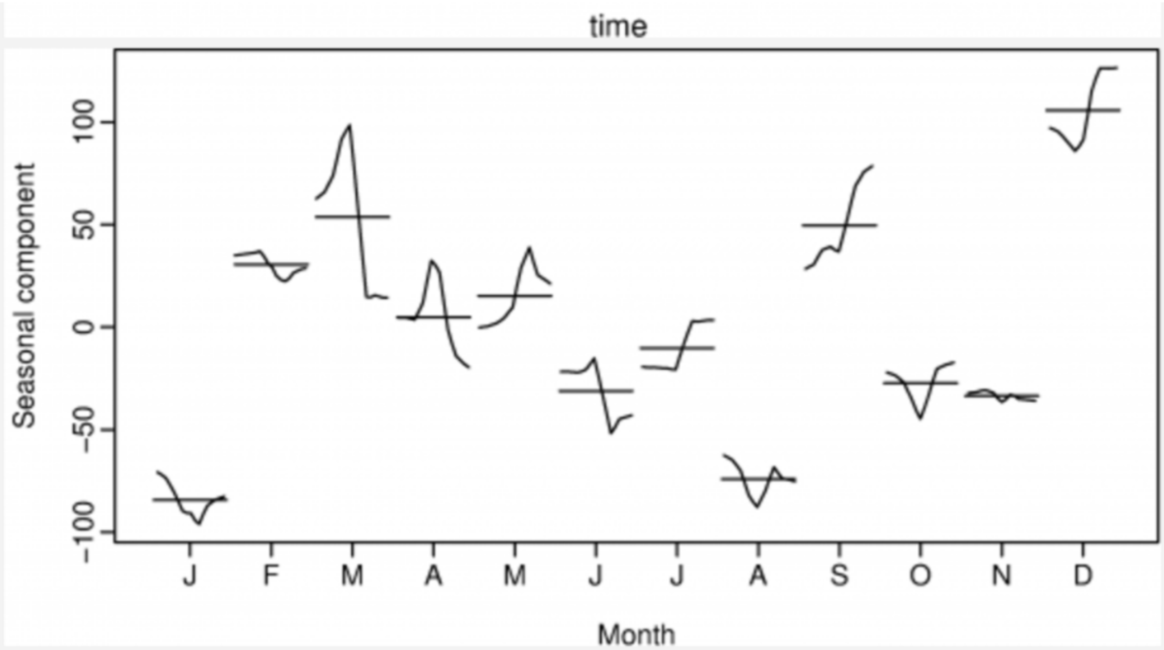


Figure 6.13: Decomposition of the number of persons in the civilian labor force in Australia each month from February 1978 to August 1995.

(a)

To describe the results of the seasonal adjustment we will look at both the trend component and seasonal component separately. We can clearly see from the trend component that the trend has constantly increased. From the periods 1978 to 1995 a constant upward trend can be seen with the exceptions of few stationary periods observed during the early 90's. By observing the monthly breakdown of the seasonal component we can see that few months for eg: March & December show higher velocities in their variations than other months.

(b)

From the residual or remainder graph, we can clearly see the large spikes or residues during the 1991-92 period. Thus, the recession of 1991-92 is clearly visible in the estimated components.