→

Energy Analytics
HW 4

Chanukya
113419663

1) MA to 7 terms

Let $M_1, M_2, M_3, M_4, M_5, M_6, M_7$ be the terms

$$MA = \frac{\frac{M_1+M_2+M_3+M_4+M_5}{5} + \frac{M_2+M_3+M_4+M_5+M_6}{5} + \frac{M_3+M_4+M_5+M_6+M_7}{5}}{3}$$

$$= \frac{1}{15}M_1 + \frac{2}{15}M_2 + \frac{3}{15}M_3 + \frac{3}{15}M_4 + \frac{3}{15}M_5 + \frac{2}{15}M_6 + \frac{1}{15}M_7$$

$\frac{1}{15} \approx 0.067$ $\quad \frac{2}{15} = 0.133$

$\frac{3}{15} = .200$ $\quad \frac{4}{15}$

Hence Proved

HW4

Chanukya

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```
#Q2
library(fpp2)
```

```
## Loading required package: ggplot2
```

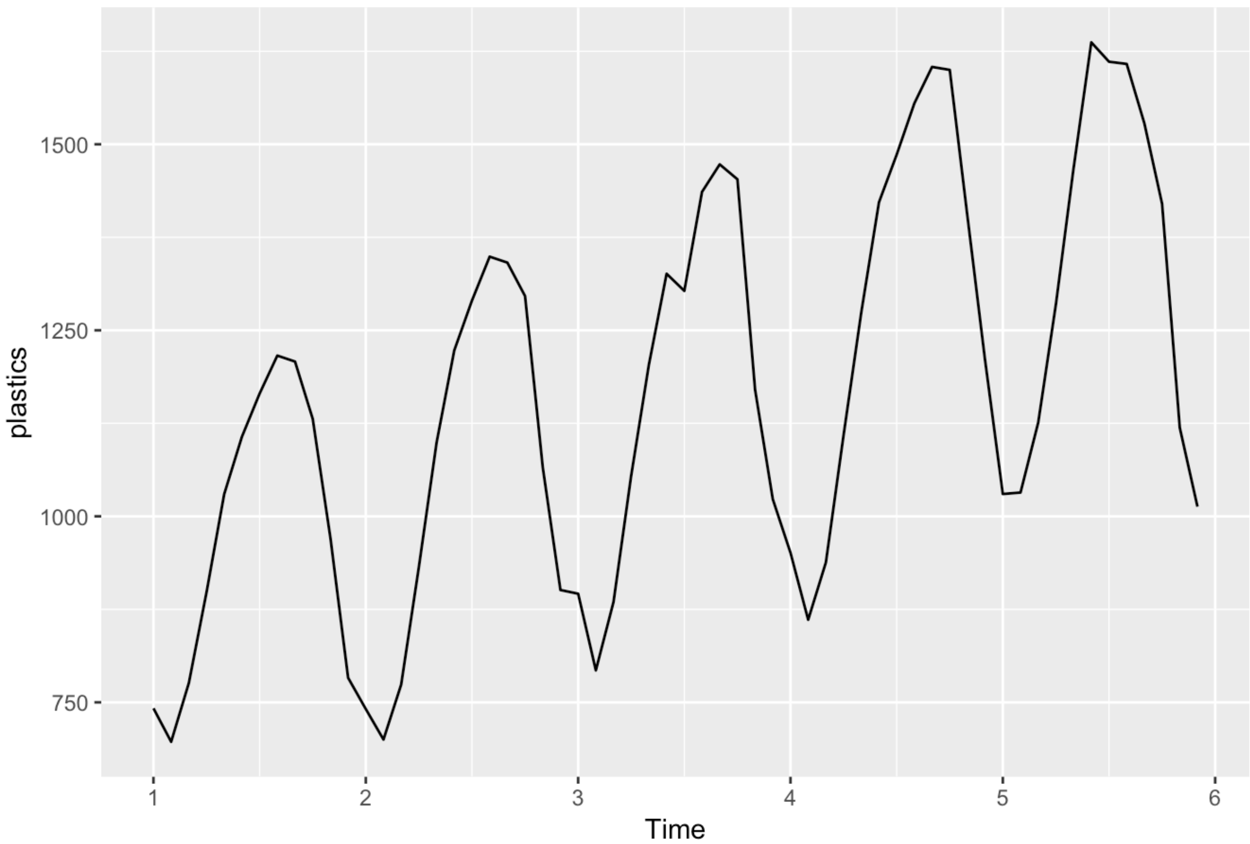
```
## Loading required package: forecast
```

```
## Warning: package 'forecast' was built under R version 3.5.2
```

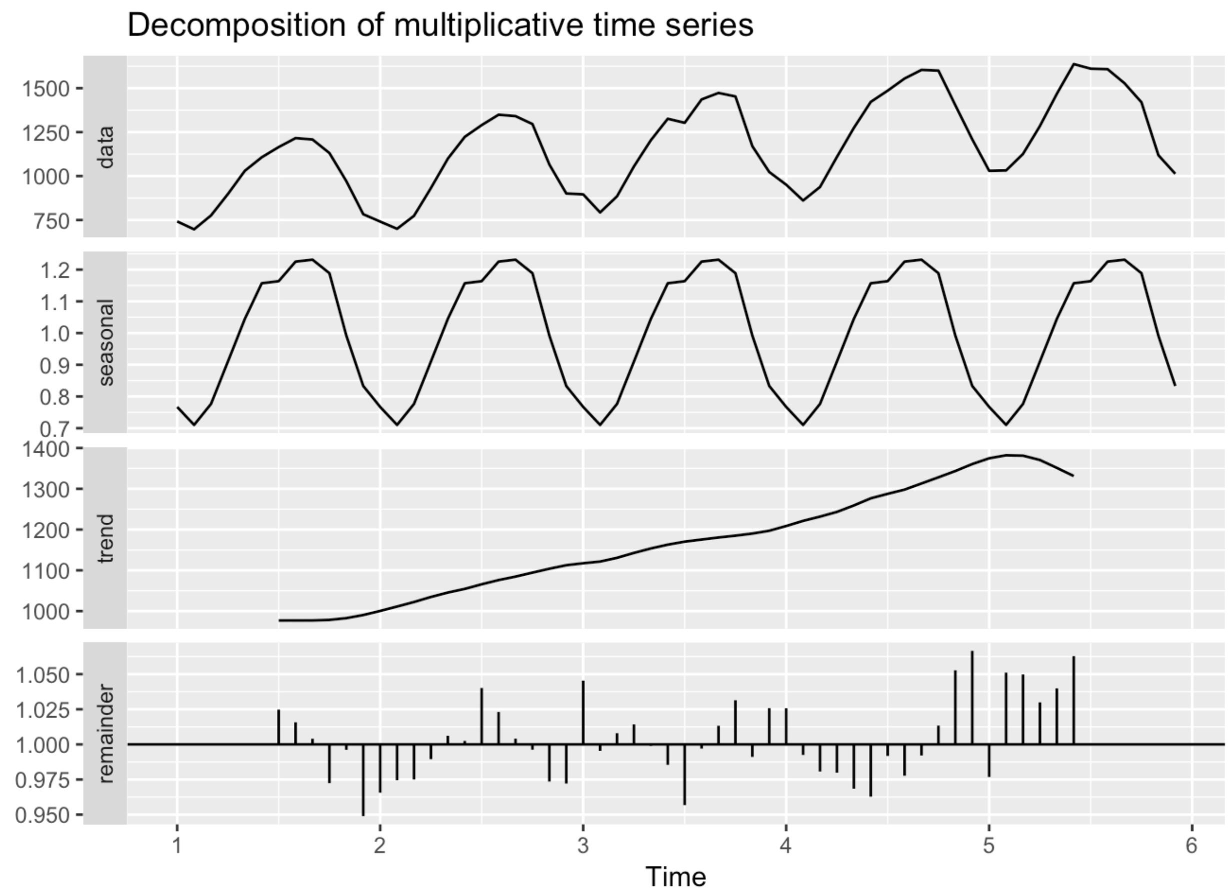
```
## Loading required package: fma
```

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

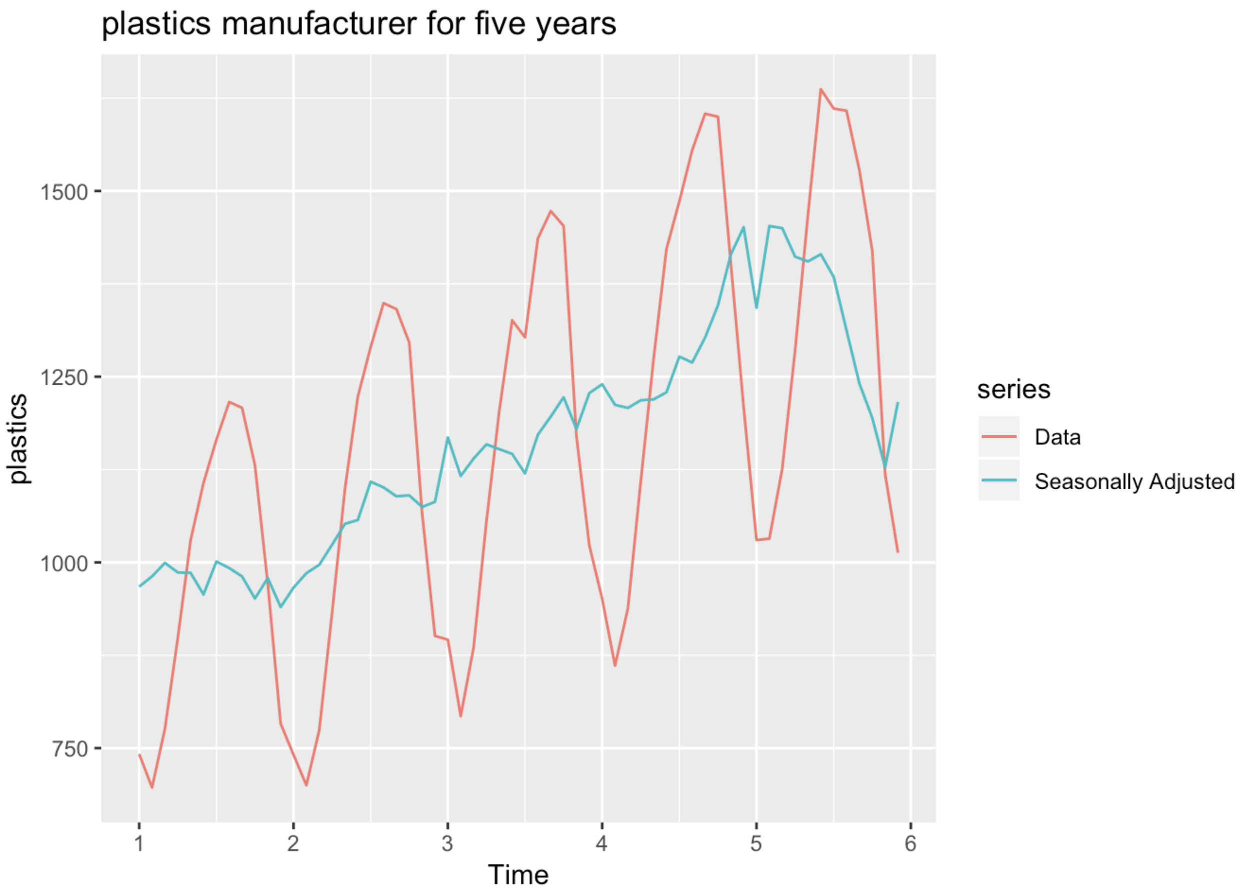
```
#2a)
autoplot(plastics)
```



```
# The graph is seasonal in a upward trend



#2b)

plastics_mult <- decompose(plastics, "multiplicative")
autoplot(plastics_mult)
```



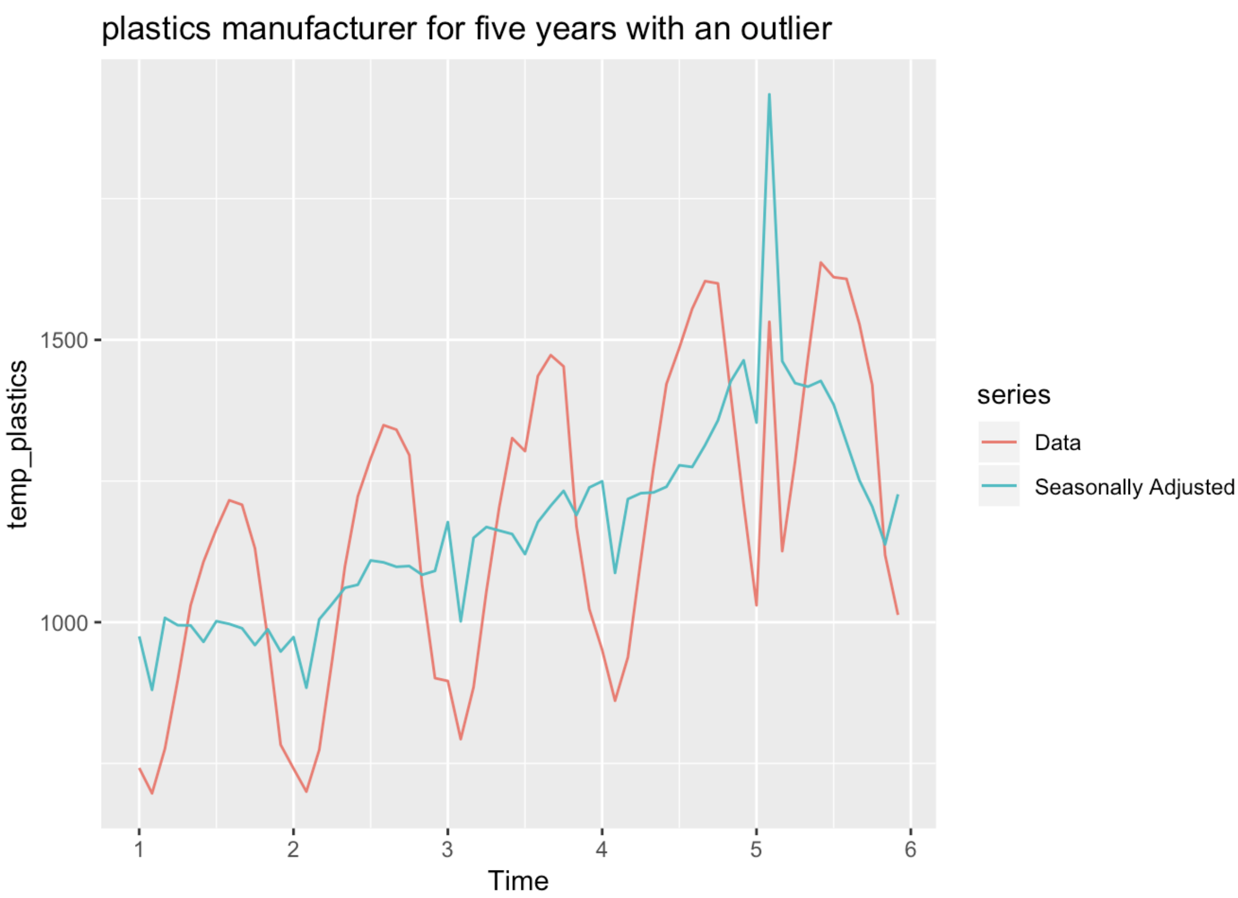

```
#2c)

# They support the inference of the result of 2a

#2d)
autoplot(plastics, series="Data") +autolayer(seasadj(plastics_mult), series="S
easonally Adjusted")+ggtitle("plastics manufacturer for five years")
```




```
#2e)
temp_plastics <- plastics
temp_plastics[50]
```

```
## [1] 1032
```

```
temp_plastics[50] <- temp_plastics[50]+500
tmp_plastics_mult <- decompose(temp_plastics, "multiplicative")
autoplot(temp_plastics, series = "Data") +autolayer(seasadj(tmp_plastics_mul
t),series = "Seasonally Adjusted") +ggtitle("plastics manufacturer for five ye
ars with an outlier")
```



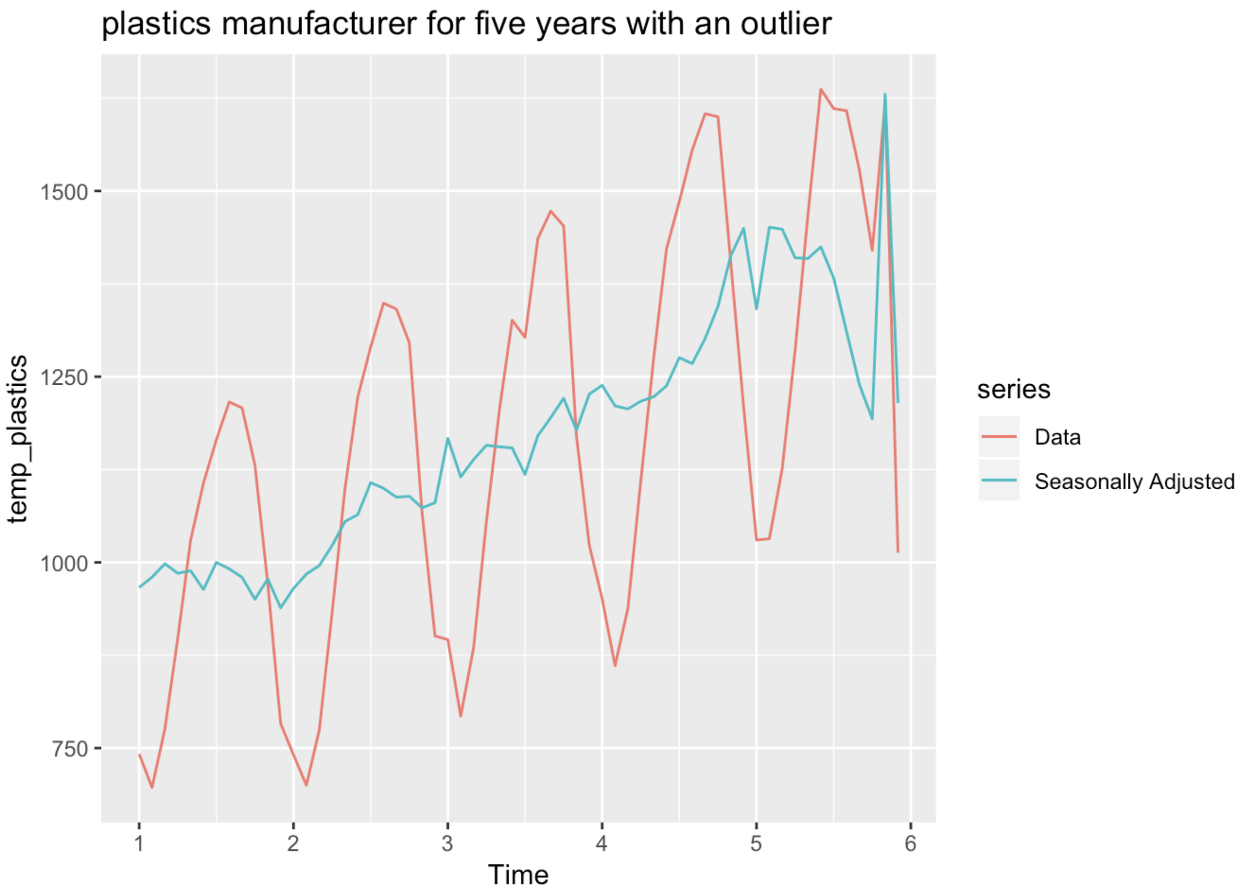

```
# The outlier really effects the seasonally adjusted data.

#2f)
length(plastics)
```

```
## [1] 60
```

```
temp_plastics <- plastics
temp_plastics[59]
```

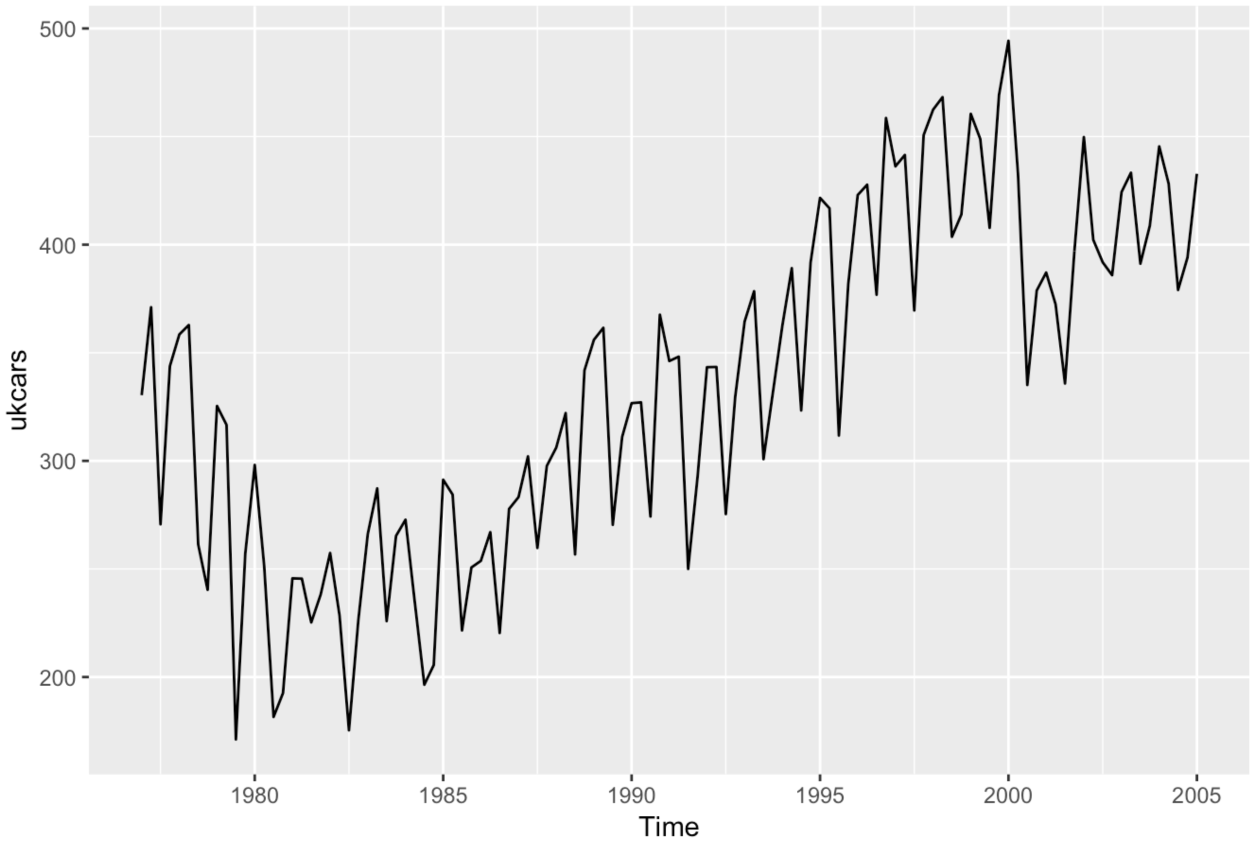
```
## [1] 1119
```

```
temp_plastics[59] <- temp_plastics[59]+500
tmp_plastics_mult <- decompose(temp_plastics, "multiplicative")
autoplot(temp_plastics, series = "Data") +autolayer(seasadj(tmp_plastics_mul
t),series = "Seasonally Adjusted") +ggtitle("plastics manufacturer for five ye
ars with an outlier")
```

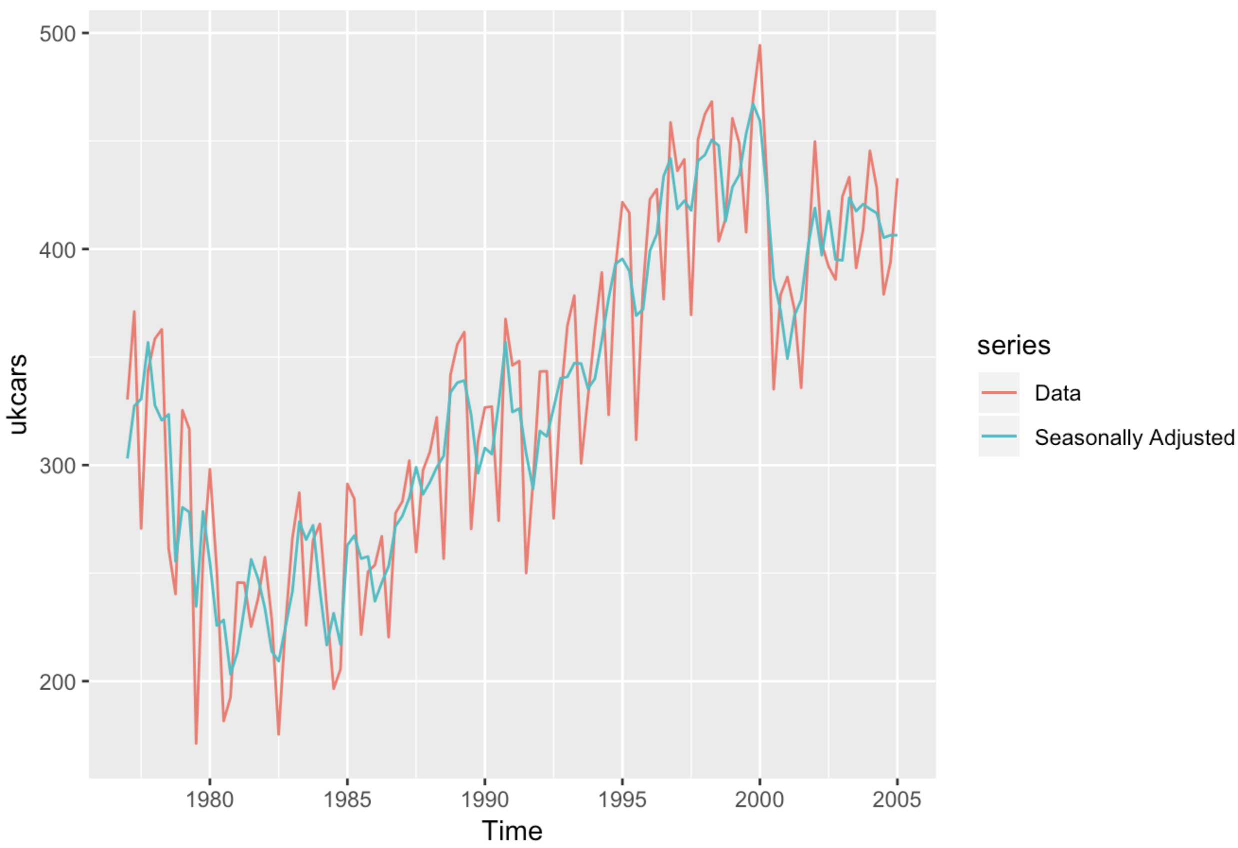



```
# We can see from the plot that the effect is less when the outlier is at the
end.
```

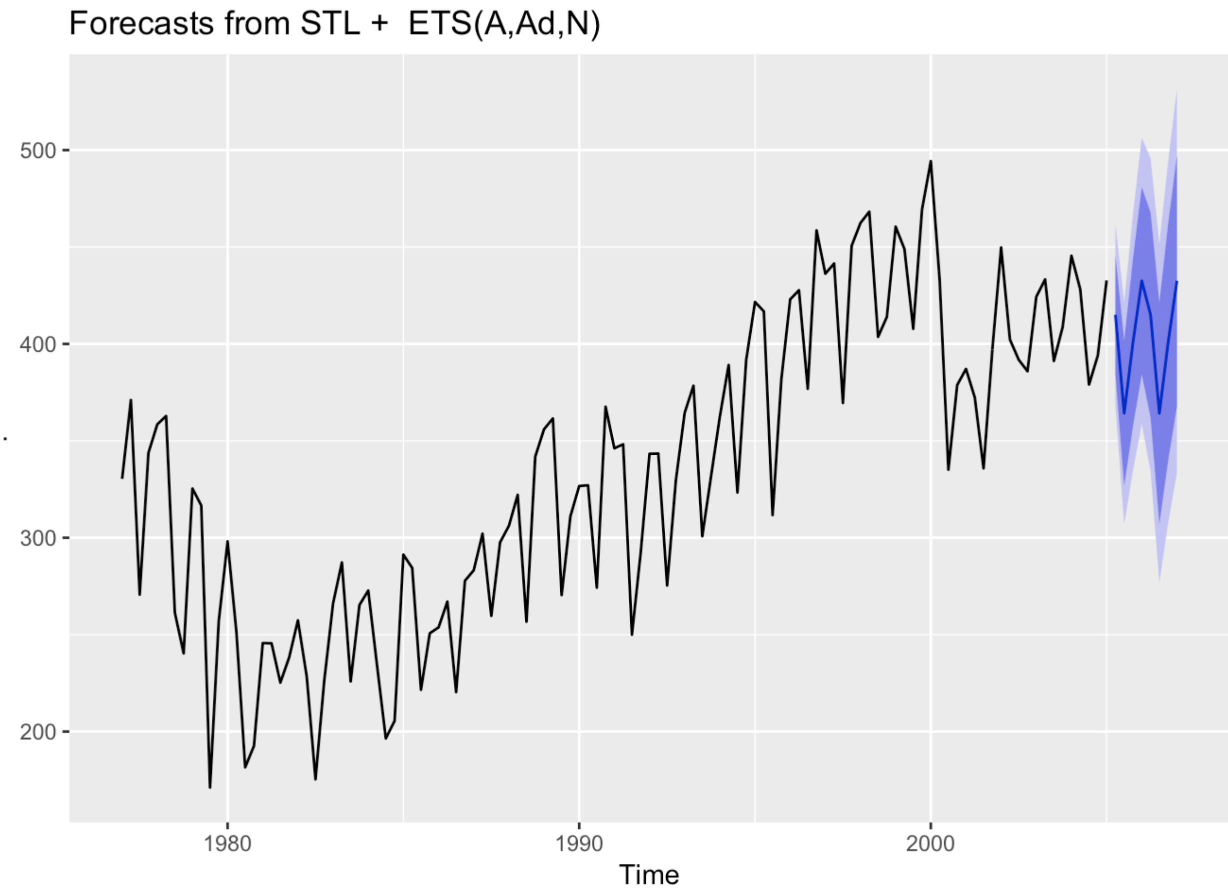
```
#3a)
#head(ukcars)
library(fpp2)
autoplot(ukcars)
```



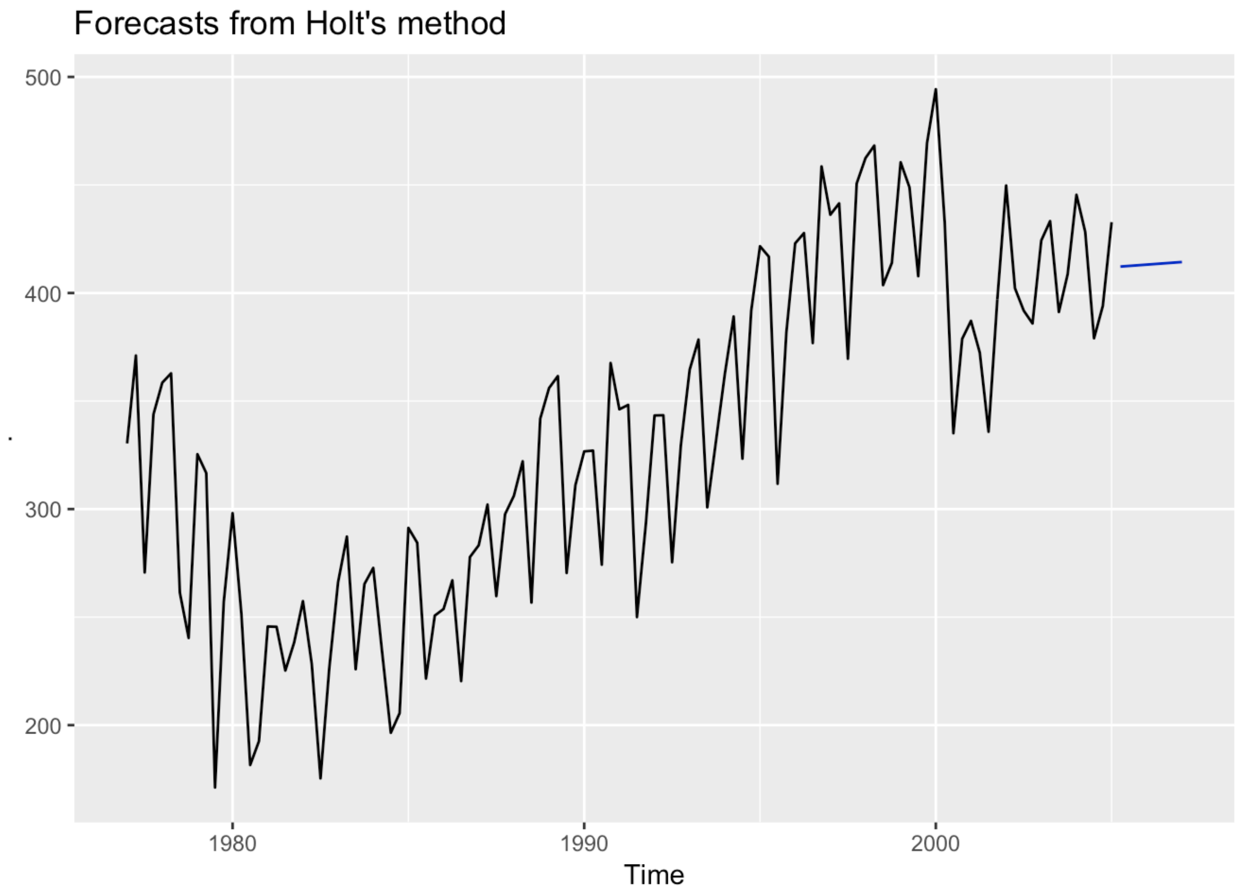

```
# The data is seasonal. Initially it had a downward trend but later i did have
an upward trend.

#3b)
fit <-stl(ukcars,s.window=4)
autoplot(ukcars, series="Data") +autolayer(seasadj(fit), series="Seasonally Ad
justed")
```



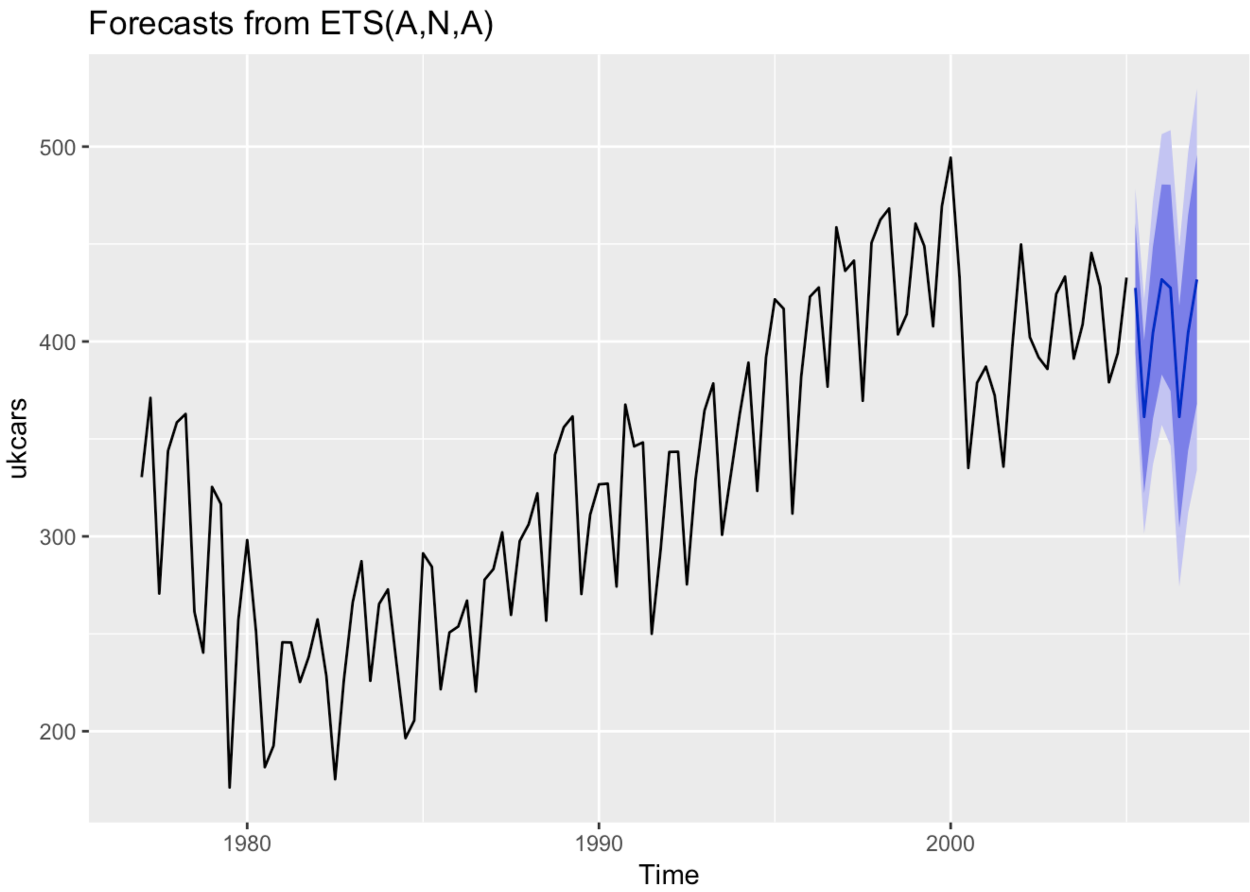

```
#3c)
#h =8 because 2 years
AAN_ukcars <- ukcars %>% stlf(h = 8, etsmodel = "AAN", damped = TRUE)
autoplot(AAN_ukcars)
```




```
#3d)
holt_ukcars <- ukcars%>%holt(h=8,PI=FALSE)
autoplot(holt_ukcars)
```




```
#3e)
ukcar_ets <- ets(ukcars)
# got ETS(A, N, A) model.
autoplot(forecast(ukcar_ets, h = 8))
```




```
#3f)
accuracy(AAN_ukcars)
```

```
##                     ME     RMSE      MAE        MPE     MAPE     MASE
## Training set 1.551267 23.32113 18.48987 0.04121971 6.042764 0.602576
##                     ACF1
## Training set 0.02262668
```

```
accuracy(holt_ukcars)
```

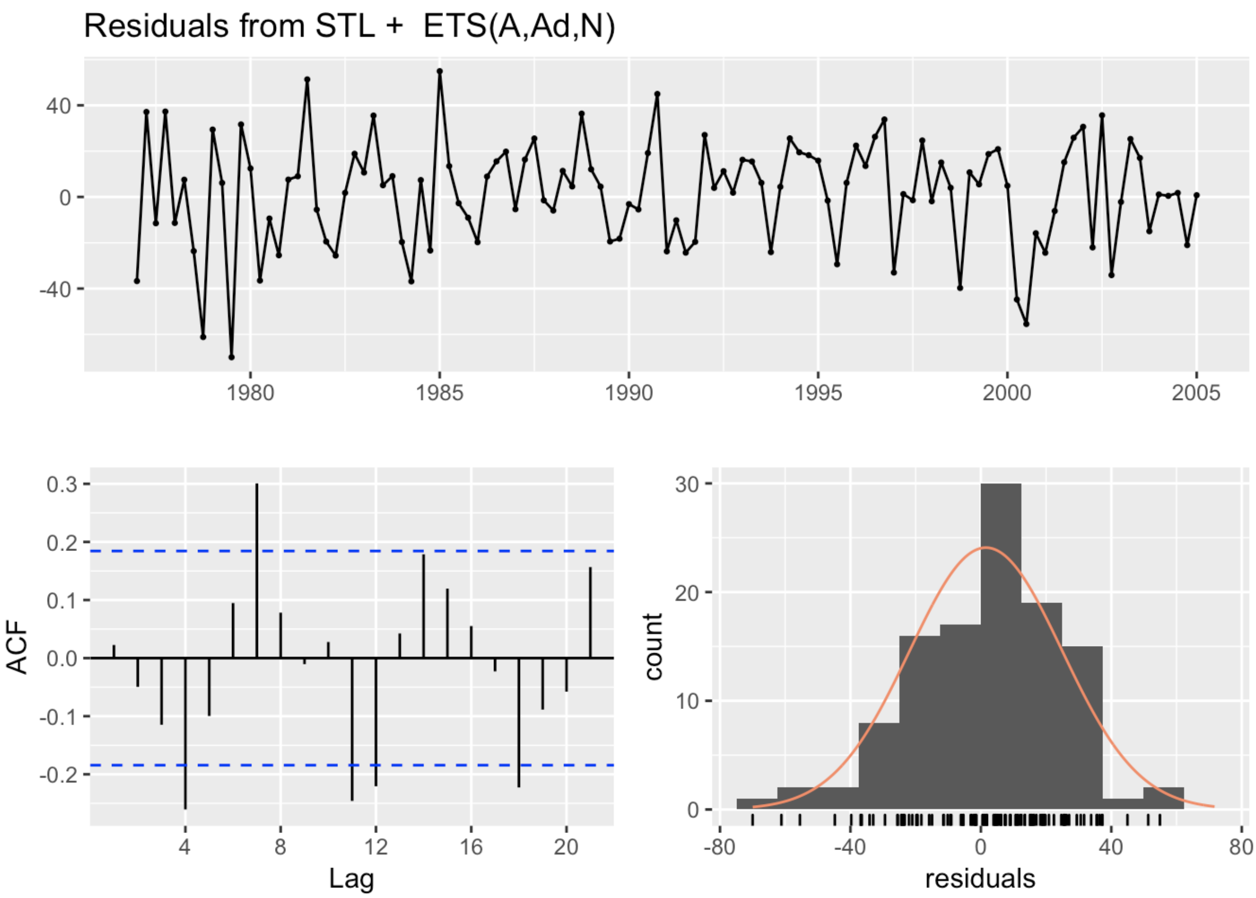
```
##                     ME     RMSE      MAE        MPE     MAPE     MASE
## Training set 2.439974 42.17556 35.11596 -0.3846216 11.55863 1.144412
##                     ACF1
## Training set 0.09392347
```

```
accuracy(ukcar_ets)
```

```
##                     ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 1.313884 25.23244 20.17907 -0.1570979 6.629003 0.6576259
##                     ACF1
## Training set 0.02573334
```

```
# AAN gives the better model

#3g)
# ANN is the optimal model among the three

#3h)
checkresiduals(AAN_ukcars)
```

```
## Warning in checkresiduals(AAN_ukcars): The fitted degrees of freedom is
## based on the model used for the seasonally adjusted data.
```

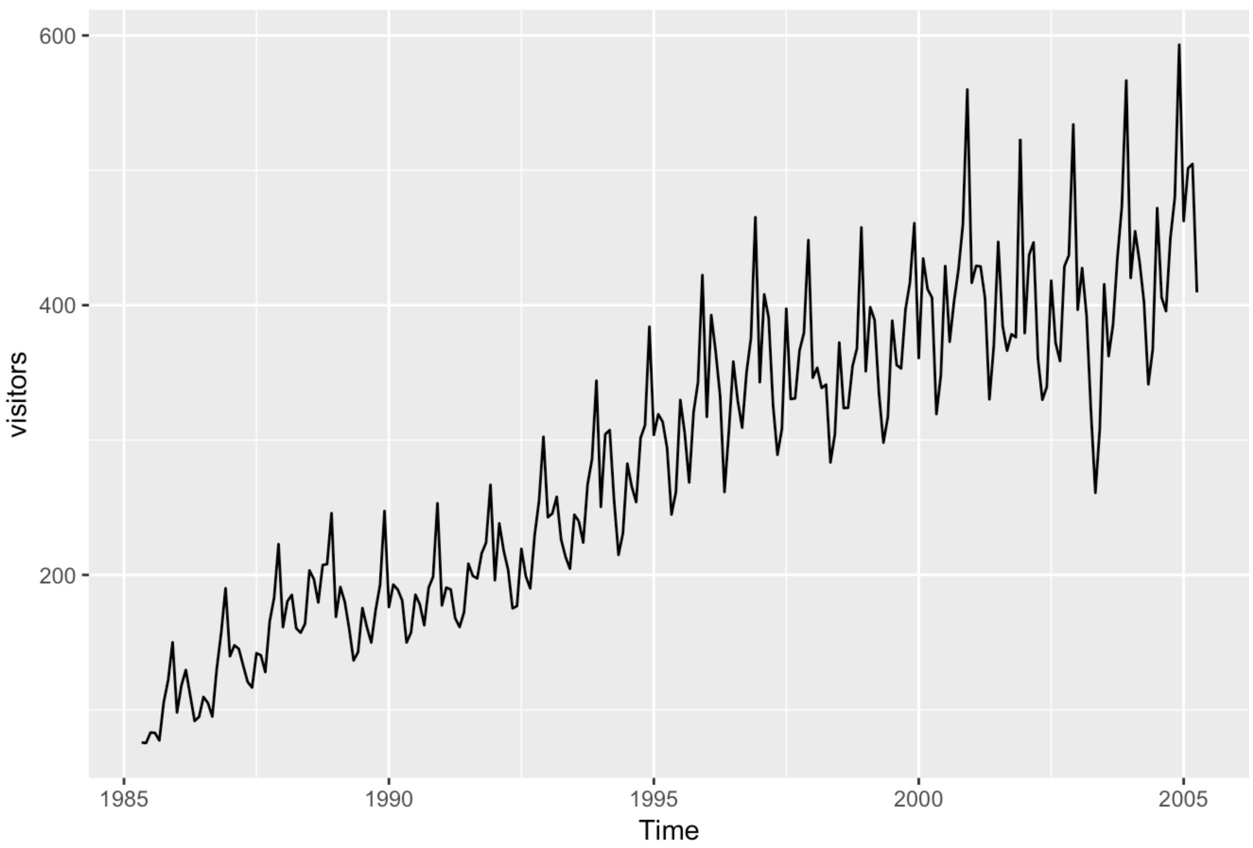



```
##
##  Ljung-Box test
##
## data:  Residuals from STL +  ETS(A,Ad,N)
## Q* = 24.138, df = 3, p-value = 2.337e-05
##
## Model df: 5.   Total lags used: 8
```

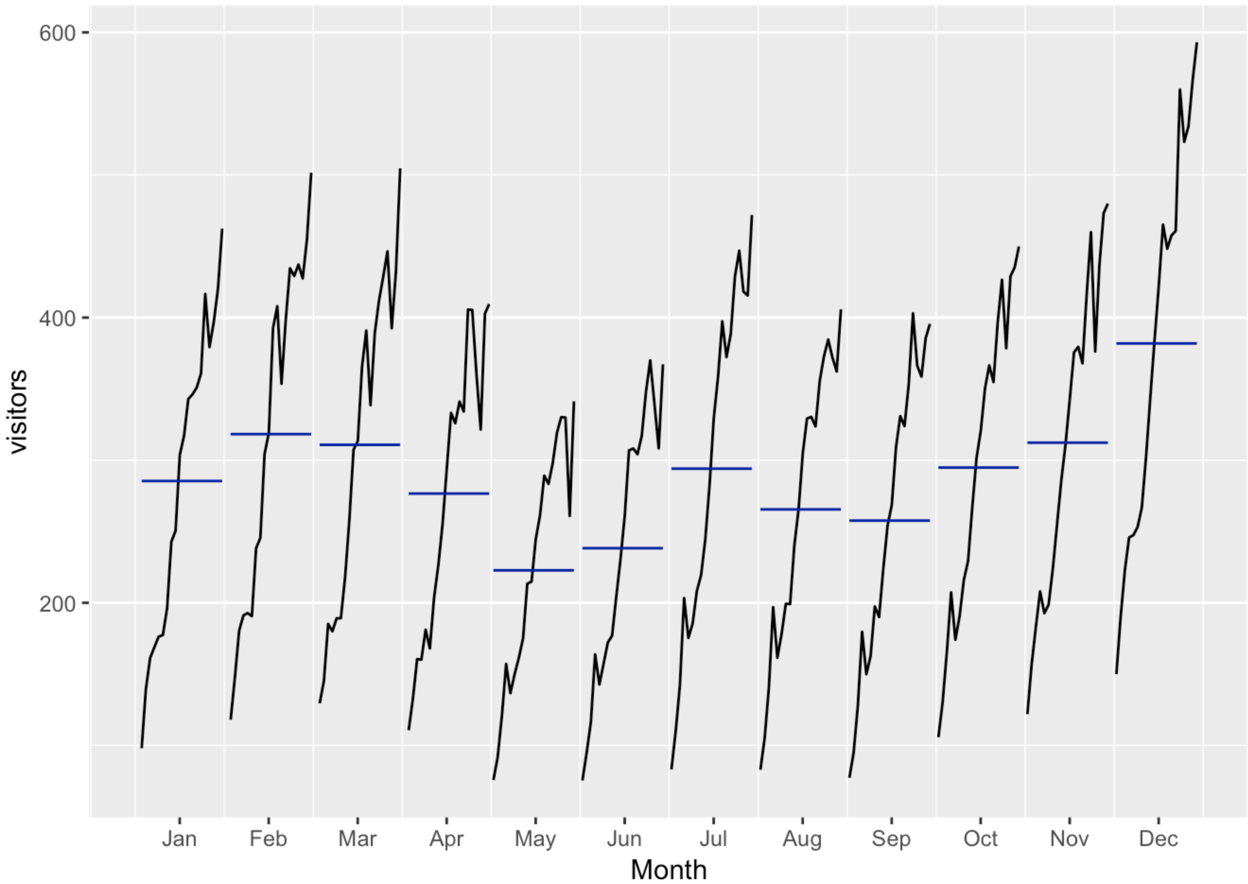
```
# they are exactly normally distributed. From ACF plot we can conclude there i
s little information in residuals.



#4a)
head(visitors)
```

```
##         May   Jun   Jul   Aug   Sep   Oct
## 1985  75.7  75.4  83.1  82.9  77.3 105.7
```

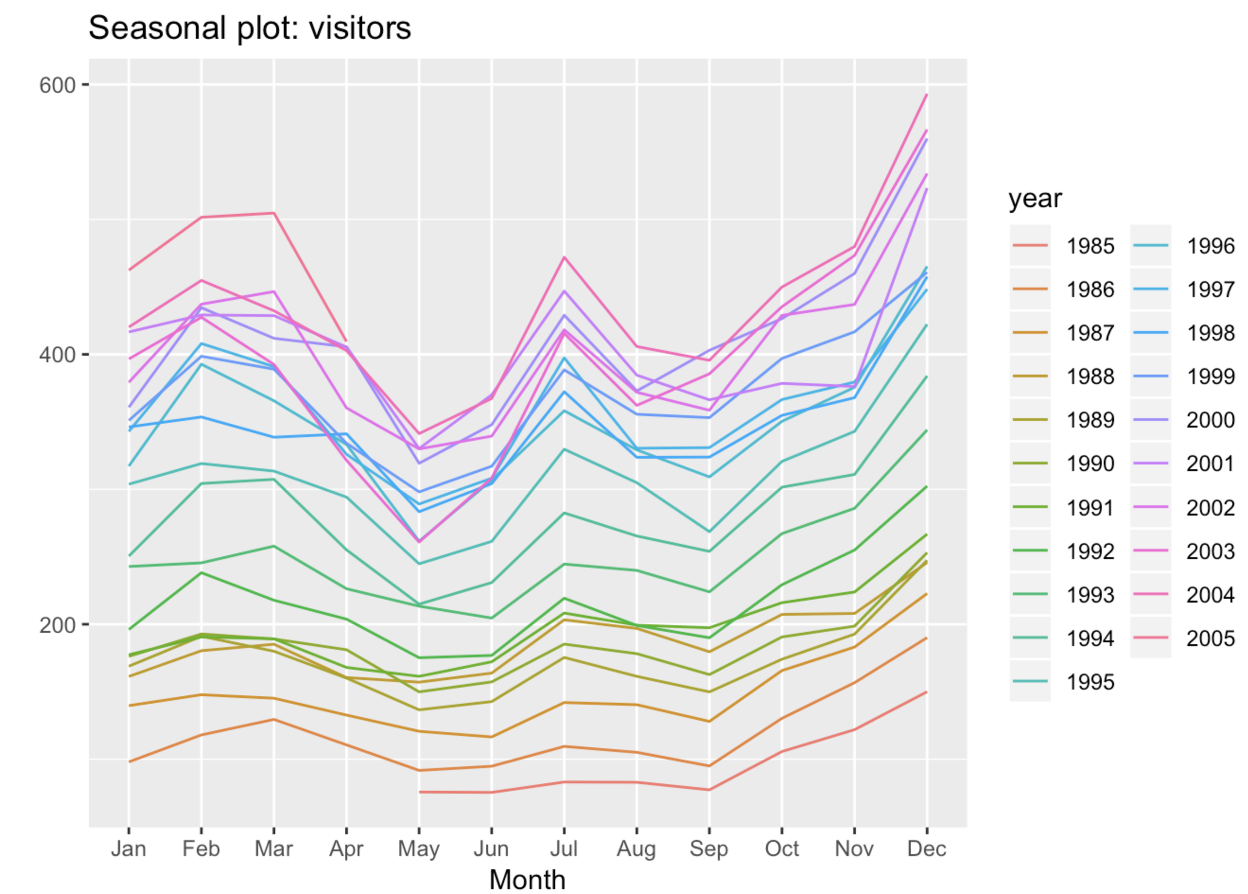
```
autoplot(visitors)
```




```
ggsubseriesplot(visitors)
```



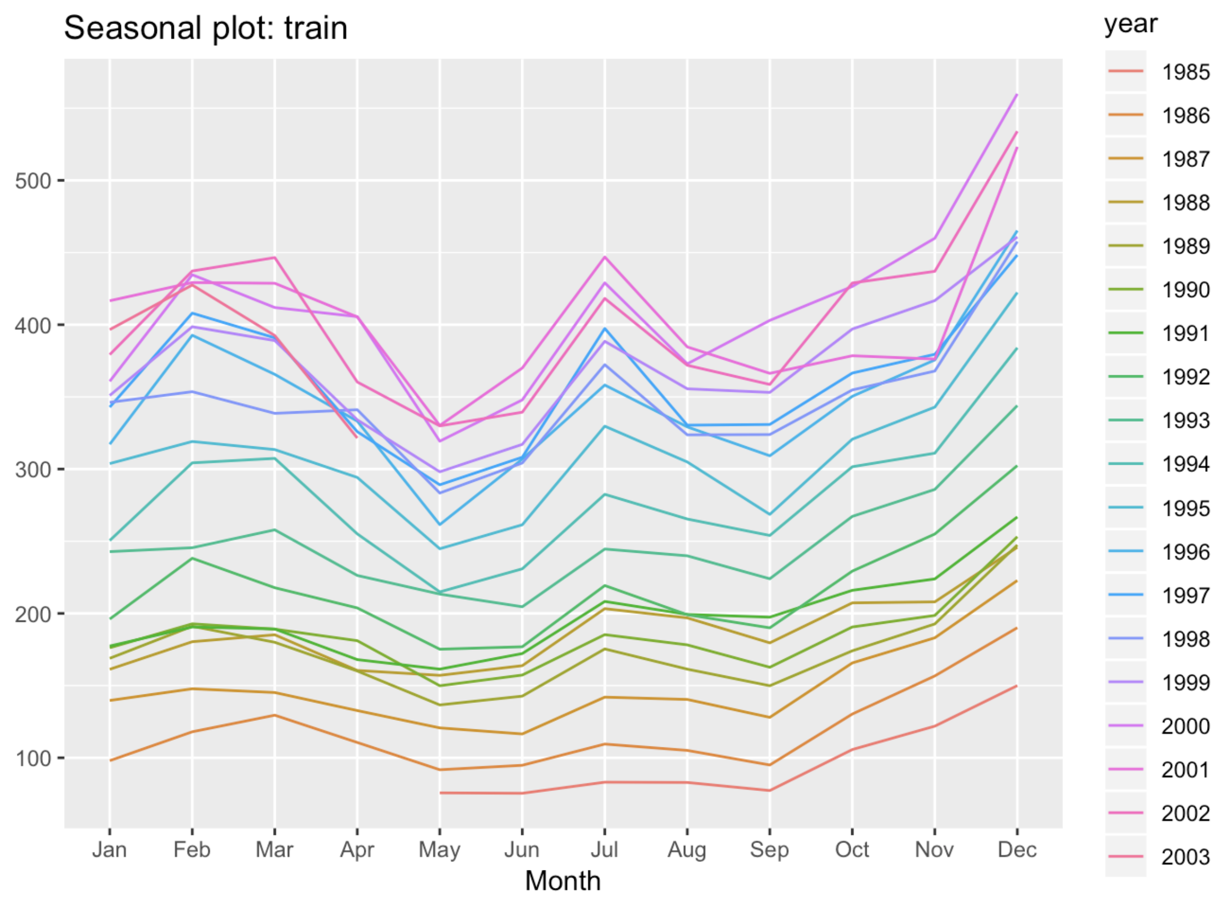

```
ggseasonplot(visitors)
```



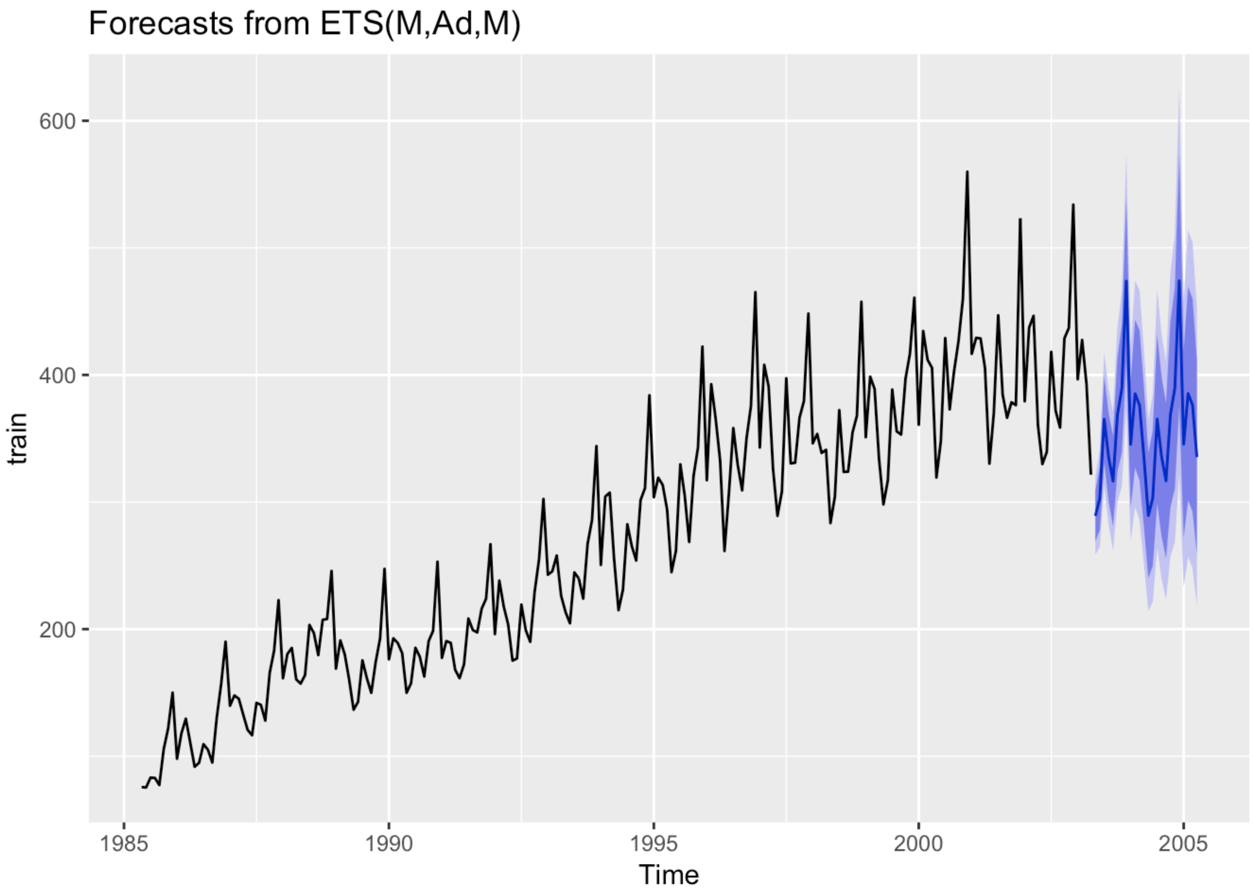
```
#highest number of visitors are during the month of decemeber. Lease number of visitors are during the month of may
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

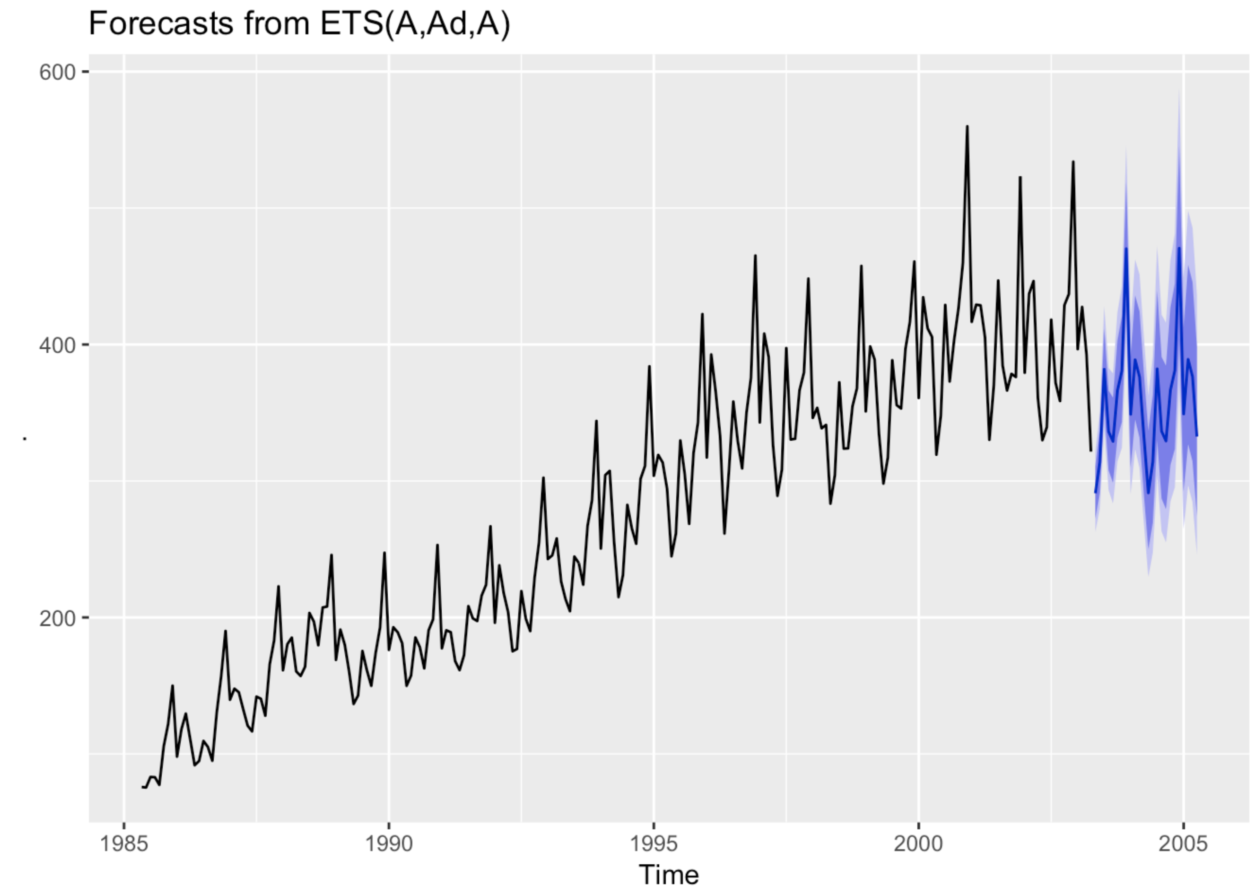
```
train <- subset(visitors,end = length(visitors) - 24)
test <-  subset(visitors,start = length(visitors) - 23)

#4c)
ggseasonplot(train)
```



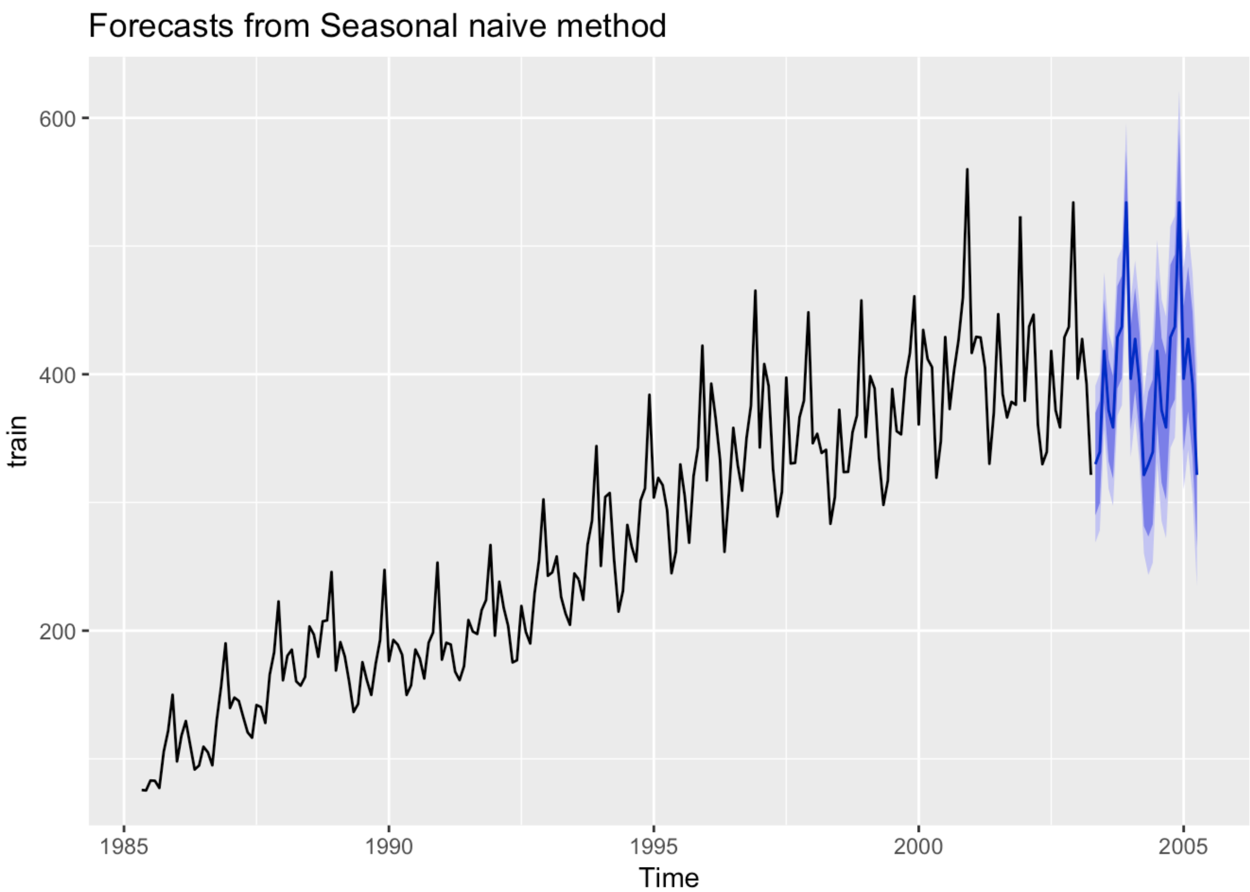

```
#change of amplitude with change in seasons varies from season to season, so i
t is better to use multplicative method

#4d)
train_ets <- forecast(ets(train), h= 24)
autoplot(train_ets)
```



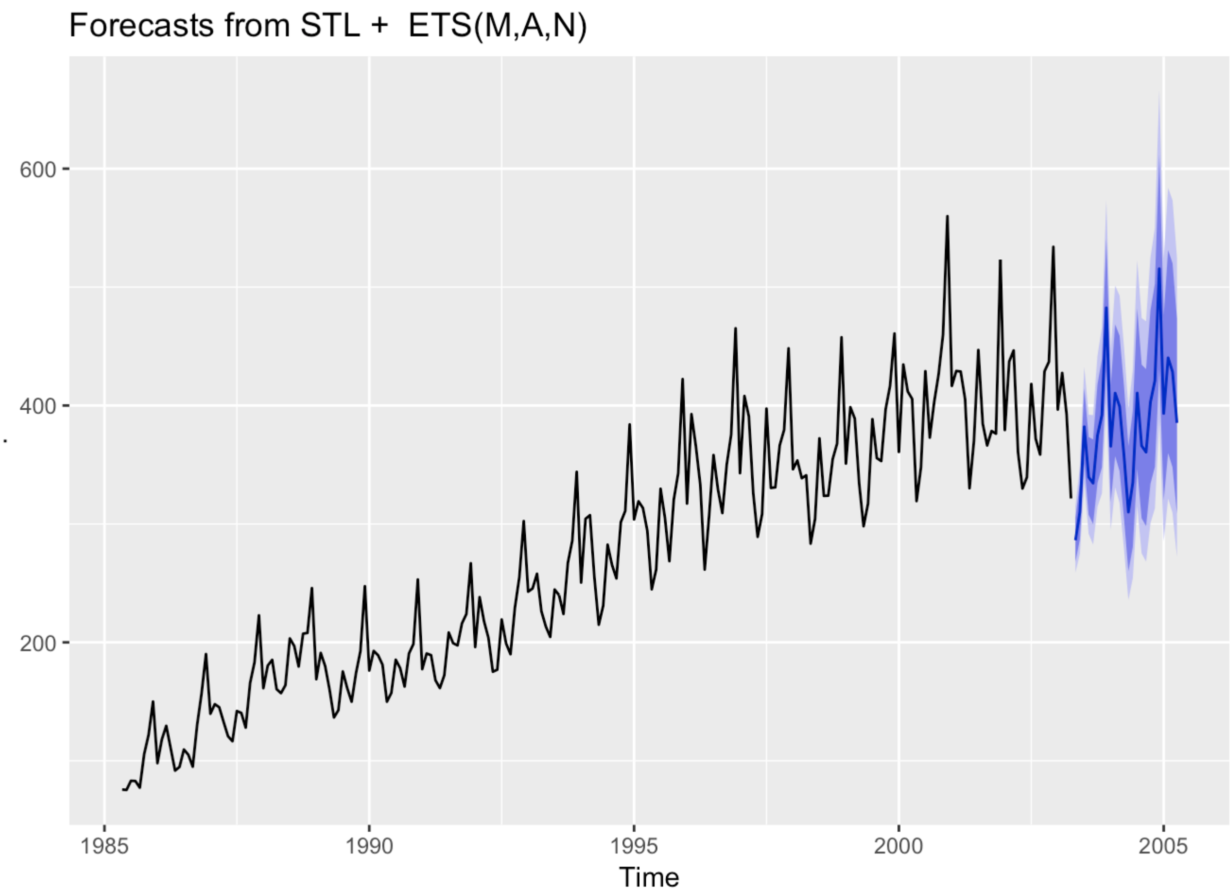

```
train_ets_boxcox<- train %>%
  ets(lambda = BoxCox.lambda(train)) %>%
  forecast(h = 24)
autoplot(train_ets_boxcox)
```




```
train_snaive <- forecast(snaive(train), h= 24)
autoplot(train_snaive)
```



```
train_ets_boxcox_stlm<- train %>%
  stlm(lambda = BoxCox.lambda(train), method= "ets") %>%
  forecast(h = 24)
autoplot(train_ets_boxcox_stlm)
```




```
#e)
accuracy(train_ets,test)
```

```
##                      ME     RMSE      MAE        MPE      MAPE     MASE
## Training set  0.7640074 14.53480 10.57657  0.1048224  3.994788 0.405423
## Test set     72.1992664 80.23124 74.55285 15.9202832 16.822384 2.857773
##                     ACF1 Theil's U
## Training set -0.05311217        NA
## Test set      0.58716982  1.127269
```

```
accuracy(train_ets_boxcox,test)
```

```
##                     ME     RMSE      MAE        MPE      MAPE      MASE
## Training set  1.001363 14.97096 10.82396  0.1609336  3.974215 0.4149057
## Test set     69.458843 78.61032 72.41589 15.1662261 16.273089 2.7758586
##                     ACF1 Theil's U
## Training set -0.02535299        NA
## Test set      0.67684148  1.086953
```

```
accuracy(train_snaive,test)
```

```
##                     ME     RMSE      MAE      MPE      MAPE     MASE
## Training set 17.29363 31.15613 26.08775 7.192445 10.285961 1.000000
## Test set     32.87083 50.30097 42.24583 6.640781  9.962647 1.619375
##                   ACF1 Theil's U
## Training set 0.6327669        NA
## Test set     0.5725430 0.6594016
```

```
accuracy(train_ets_boxcox_stlm,test)
```

```
##                     ME     RMSE       MAE        MPE     MAPE     MASE
## Training set -0.818467 13.18586  9.313846 -0.2679515  3.45496 0.357020
## Test set     45.718265 52.25443 47.966445  9.9332803 10.78695 1.838658
##                     ACF1 Theil's U
## Training set -0.09848974        NA
## Test set      0.50475313 0.7342067
```

```
#snaive and train_ets_boxcox model performed alnist equally, and snaive stood
out among all models
```