

ICA 12

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```
library(tseries)
```

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

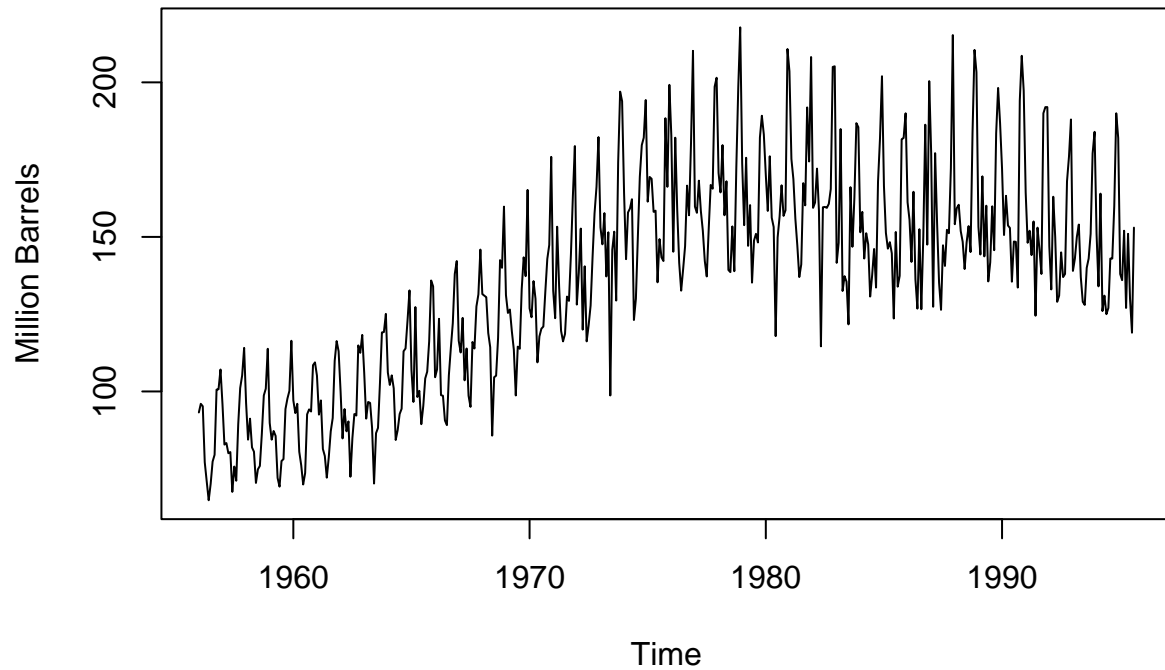
```
library(forecast)
```

Question 1

Import the data, convert it to a time series, and then plot it.

```
beer <- read.csv("beer.csv")  
beer_ts <- ts(beer[,2], start = c(1956,1), frequency = 12)  
plot(beer_ts, main = "Monthly Beer Production", ylab = "Million Barrels")
```

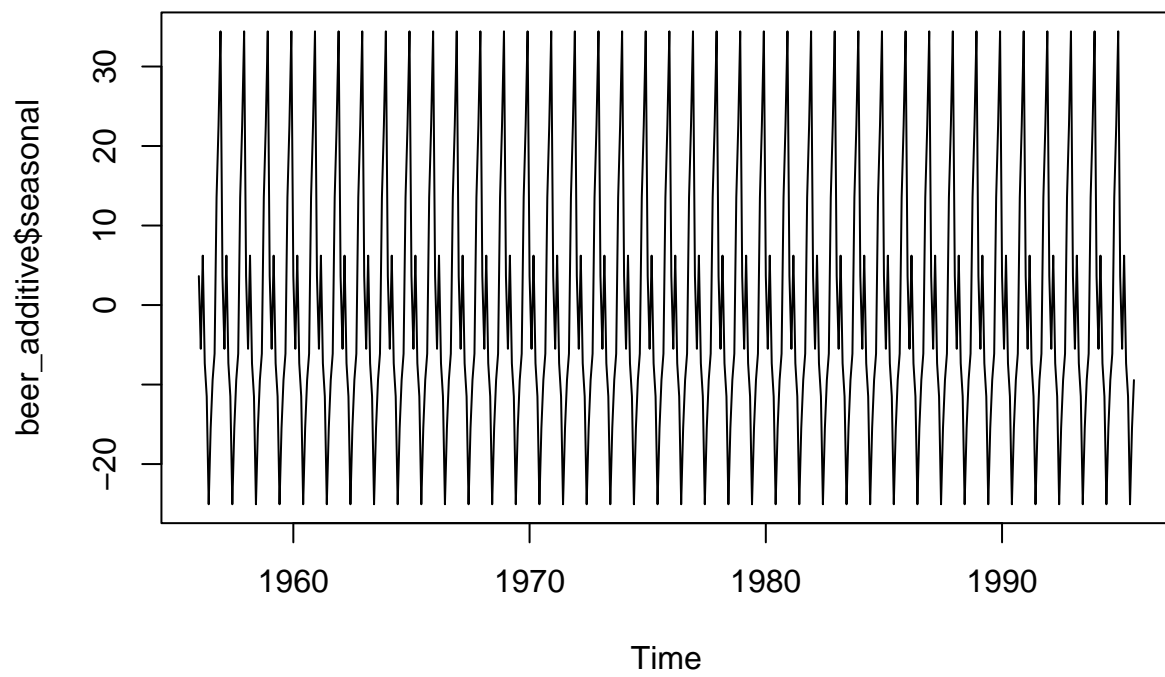
Monthly Beer Production



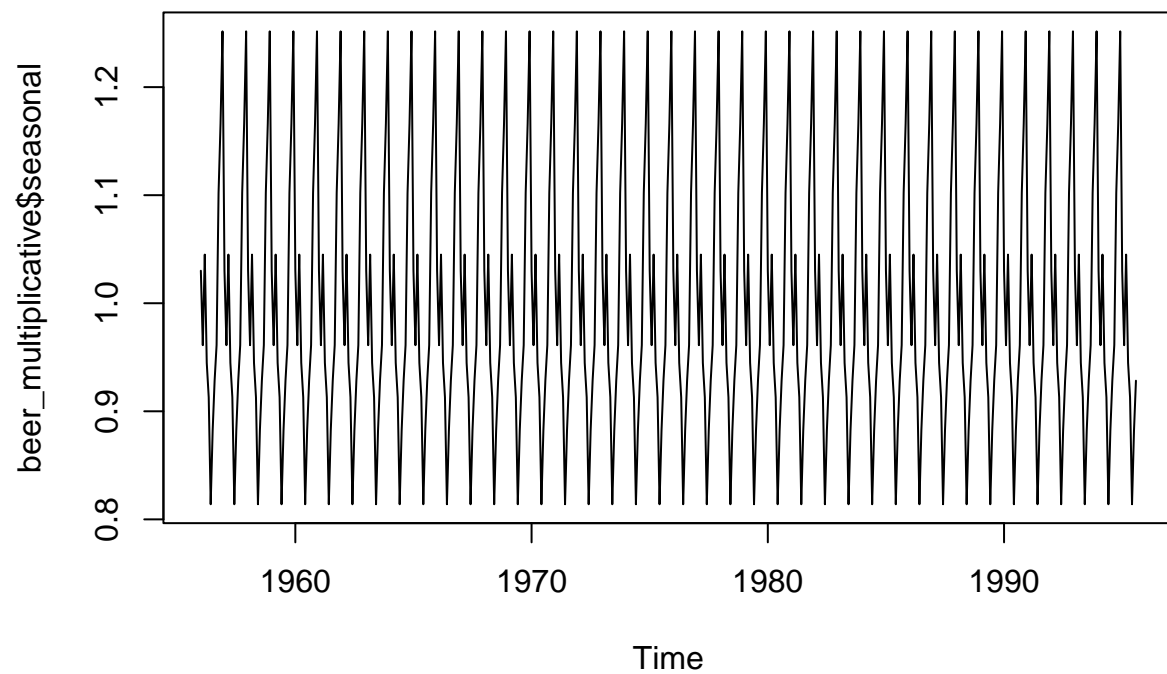
Question 2

Do additive and multiplicative decompositions of the data. Which one looks better? From the seasonal component, what part of the year typically has the largest beer consumption?

```
beer_additive <- decompose(beer_ts, type = "additive")
beer_multiplicative <- decompose(beer_ts, type = "multiplicative")
plot(beer_additive$seasonal)
```



```
plot(beer_multiplicative$seasonal)
```

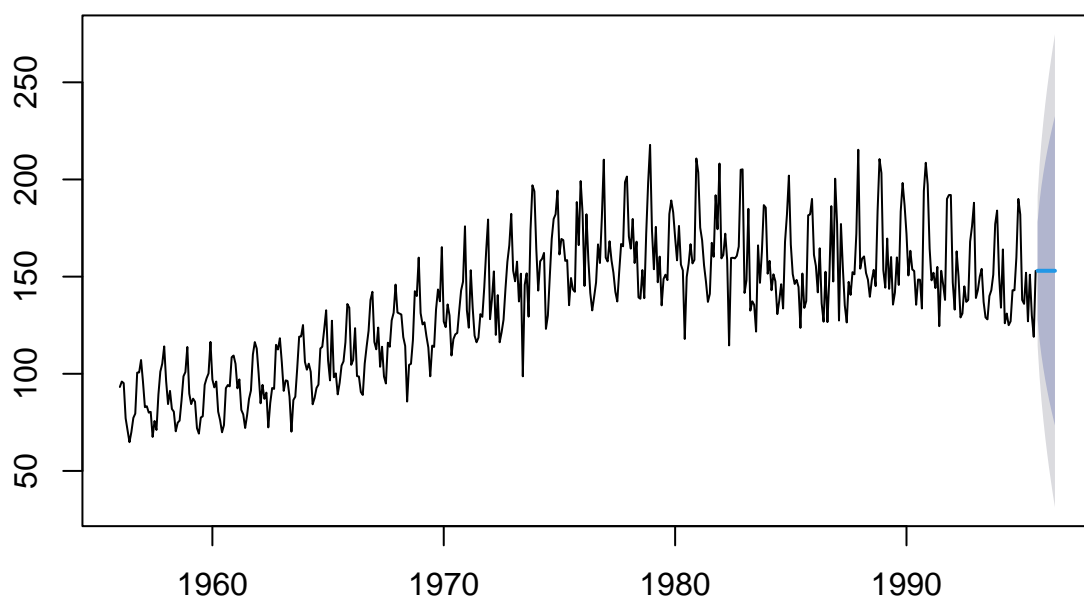


Question 3

Create the following forecast models for the data a. Naïve b. Seasonal naïve c. Holt-Winters d. ARIMA

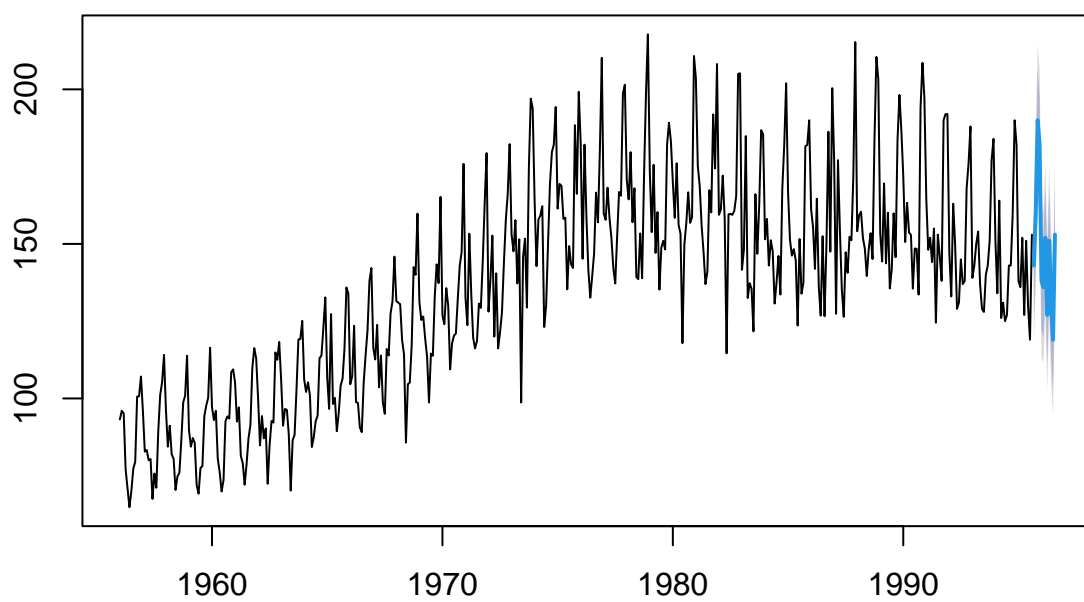
```
# naive model  
beer_naive <- naive(beer_ts)  
plot(beer_naive)
```

Forecasts from Naive method



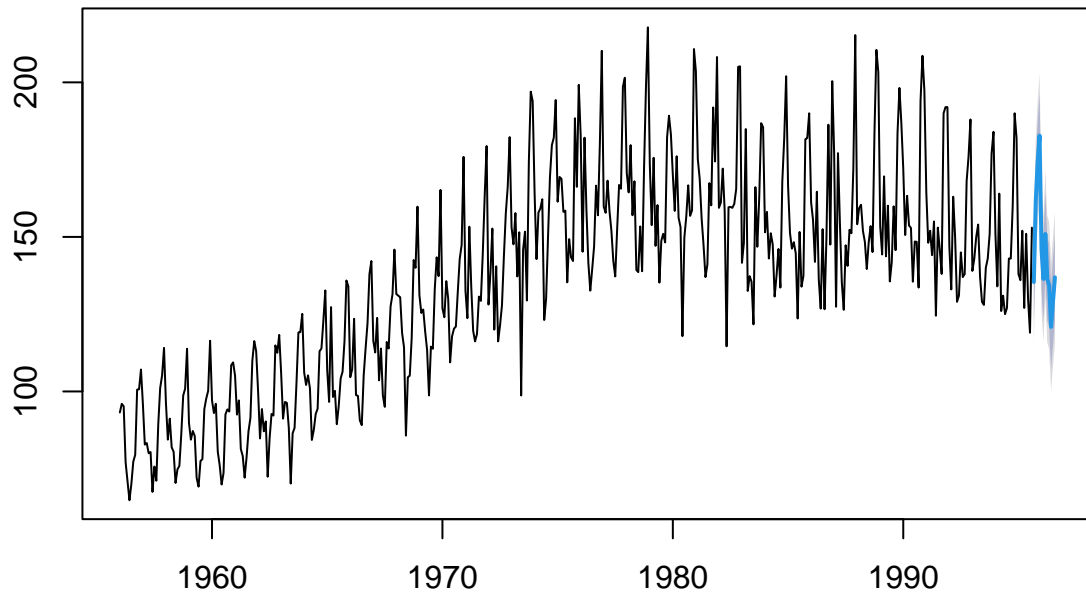
```
# seasonal naive model  
beer_snaive <- snaive(beer_ts, h = 12)  
plot(beer_snaive)
```

Forecasts from Seasonal naive method



```
# holt-winters  
beer_hw <- hw(beer_ts, h = 12)  
plot(beer_hw)
```

Forecasts from Holt–Winters' additive method



```
# automatic arima
beer_arima <- auto.arima(beer_ts)
#plot(beer_arima)
```

Question 4

Print out the summary of each model. Compare the MAPE's and MAE's.

```
summary(beer_naive)
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = beer_ts)
##
## Residual sd: 19.6333
##
## Error measures:
##           ME      RMSE      MAE      MPE      MAPE      MASE      ACF1
## Training set 0.1258947 19.63328 14.86695 -0.829328 10.81055 1.588547 -0.2276534
##
## Forecasts:
```

```
##          Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Sep 1995          153 127.83894 178.1611 114.51948 191.4805
## Oct 1995          153 117.41689 188.5831  98.58033 207.4197
## Nov 1995          153 109.41977 196.5802  86.34979 219.6502
## Dec 1995          153 102.67788 203.3221  76.03896 229.9610
## Jan 1996          153  96.73816 209.2618  66.95495 239.0451
## Feb 1996          153  91.36825 214.6318  58.74237 247.2576
## Mar 1996          153  86.43010 219.5699  51.19012 254.8099
## Apr 1996          153  81.83378 224.1662  44.16066 261.8393
## May 1996          153  77.51683 228.4832  37.55845 268.4416
## Jun 1996          153  73.43375 232.5663  31.31392 274.6861
```

```
summary(beer_snaive)
```

```
##
## Forecast method: Seasonal naive method
##
## Model Information:
## Call: snaive(y = beer_ts, h = 12)
##
## Residual sd: 12.5166
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE  MASE      ACF1
## Training set 1.613147 12.51656 9.358836 1.044984 6.683027    1 -0.09167538
##
## Forecasts:
##          Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Sep 1995          143 126.9594 159.0406 118.46799 167.532
## Oct 1995          160 143.9594 176.0406 135.46799 184.532
## Nov 1995          190 173.9594 206.0406 165.46799 214.532
## Dec 1995          182 165.9594 198.0406 157.46799 206.532
## Jan 1996          138 121.9594 154.0406 113.46799 162.532
## Feb 1996          136 119.9594 152.0406 111.46799 160.532
## Mar 1996          152 135.9594 168.0406 127.46799 176.532
## Apr 1996          127 110.9594 143.0406 102.46799 151.532
## May 1996          151 134.9594 167.0406 126.46799 175.532
## Jun 1996          130 113.9594 146.0406 105.46799 154.532
## Jul 1996          119 102.9594 135.0406  94.46799 143.532
## Aug 1996          153 136.9594 169.0406 128.46799 177.532
```

```
summary(beer_hw)
```

```
##
## Forecast method: Holt-Winters' additive method
##
## Model Information:
## Holt-Winters' additive method
##
## Call:
## hw(y = beer_ts, h = 12)
##
## Smoothing parameters:
```



```

##      alpha = 0.0783
##      beta  = 0.0056
##      gamma = 0.0931
##
## Initial states:
##      l = 86.5539
##      b = -0.0387
##      s = 30.367 19.4473 14.5135 -3.0423 -11.4326 -17.1747
##          -25.0948 -11.9055 -6.0042 7.8797 -1.9867 4.4333
##
##      sigma: 10.0972
##
##      AIC      AICc      BIC
## 5153.732 5155.068 5224.544
##
## Error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.006218262 9.926028 7.456388 -0.3199116 5.449987 0.7967217
##              ACF1
## Training set -0.1261593
##
## Forecasts:
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## Sep 1995      135.3961 122.4561 148.3362 115.6060 155.1863
## Oct 1995      161.5713 148.5858 174.5568 141.7117 181.4309
## Nov 1995      173.9555 160.9185 186.9925 154.0172 193.8939
## Dec 1995      182.7756 169.6807 195.8705 162.7486 202.8025
## Jan 1996      146.0442 132.8846 159.2037 125.9184 166.1699
## Feb 1996      136.3791 123.1480 149.6103 116.1438 156.6144
## Mar 1996      150.9540 137.6439 164.2640 130.5980 171.3100
## Apr 1996      136.3641 122.9675 149.7606 115.8759 156.8523
## May 1996      134.2043 120.7135 147.6951 113.5719 154.8366
## Jun 1996      120.8795 107.2865 134.4726 100.0907 141.6683
## Jul 1996      129.3088 115.6053 143.0124 108.3510 150.2666
## Aug 1996      136.9213 123.0988 150.7437 115.7816 158.0609

```

```
summary(beer_arima)
```

```

## Series: beer_ts
## ARIMA(0,1,3)(1,1,2)[12]
##
## Coefficients:
##      ma1      ma2      ma3      sar1      sma1      sma2
##    -1.0749 -0.0730 0.2637 -0.0550 -0.6694 -0.1656
## s.e.  0.0482  0.0774 0.0551  0.2572  0.2525  0.2066
##
## sigma^2 = 94.56: log likelihood = -1715.16
## AIC=3444.31 AICc=3444.56 BIC=3473.28
##
## Training set error measures:
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set -0.1585097 9.528211 7.015347 -0.3897423 5.09982 0.7495961
##              ACF1
## Training set -0.01034254

```