Introduction to time series data and visualization

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Contents

1 Reference

- Hyndman and Athanasopoulos (June 2017), Forecasting: Principles and Practice.

1.1 R packages

```
library(fpp2)
library(ggfortify)
library(forecast)
source("multiplot.r")
```

2 Examples of time series data

2.1 Annual data

2.1.1 Electricity sales

Annual **electricity sales** to residential customers in South Australia from 1989 to 2008. Electricity (used for hot water has been excluded).[1]

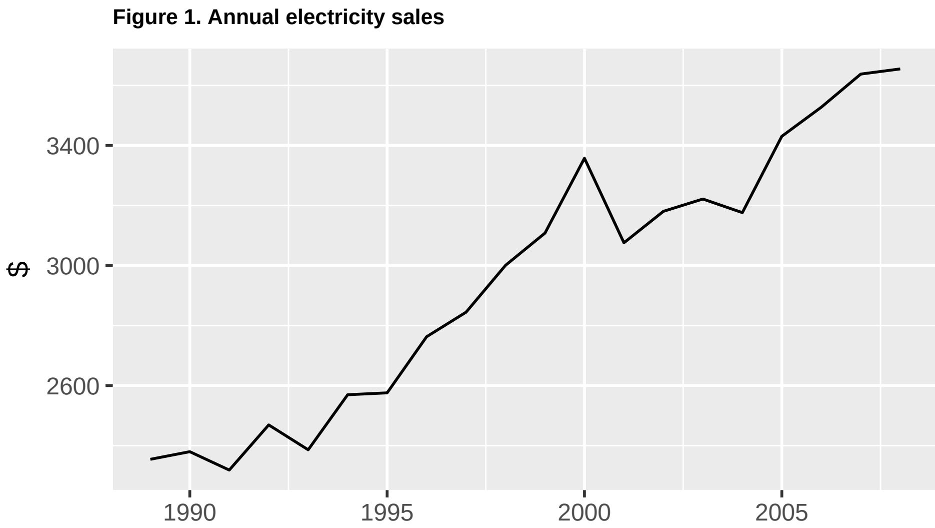
```
elecsales
```

```
## Time Series:
## Start = 1989
## End = 2008
## Frequency = 1
##  [1] 2354.34 2379.71 2318.52 2468.99 2386.09 2569.47 2575.72 2762.72
##  [9] 2844.50 3000.70 3108.10 3357.50 3075.70 3180.60 3221.60 3176.20
## [17] 3430.60 3527.48 3637.89 3655.00
```

```
# start(elecsales) # 1989 1
# end(elecsales)   # 2008 1
# frequency(elecsales)  # 1
```

[1] Australian Energy Market Operator.

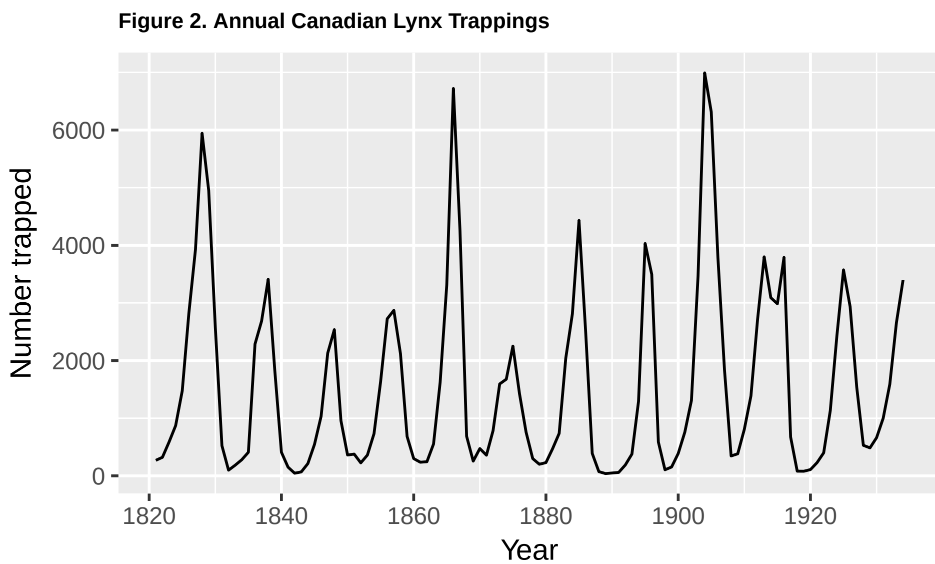
```r
autoplot(elecsales)+
        ggtitle("Figure 1. Annual electricity sales")+
        ylab("$")+
        theme(plot.title = element_text(size=8, face="bold"))
```



2.1.2 Canadian Lynx trappings[2]

Annual **numbers of lynx trappings** for 1821-1934 in Canada.

```r
autoplot(lynx) +
        ggtitle("Figure 2. Annual Canadian Lynx Trappings") +
        xlab("Year") +
        ylab("Number trapped")+
        theme(plot.title = element_text(size=8, face="bold"))
```



[2] Brockwell, P. J. and Davis, R. A. (1991) Time Series and Forecasting Methods. Second edition. Springer. Series G (page 557).

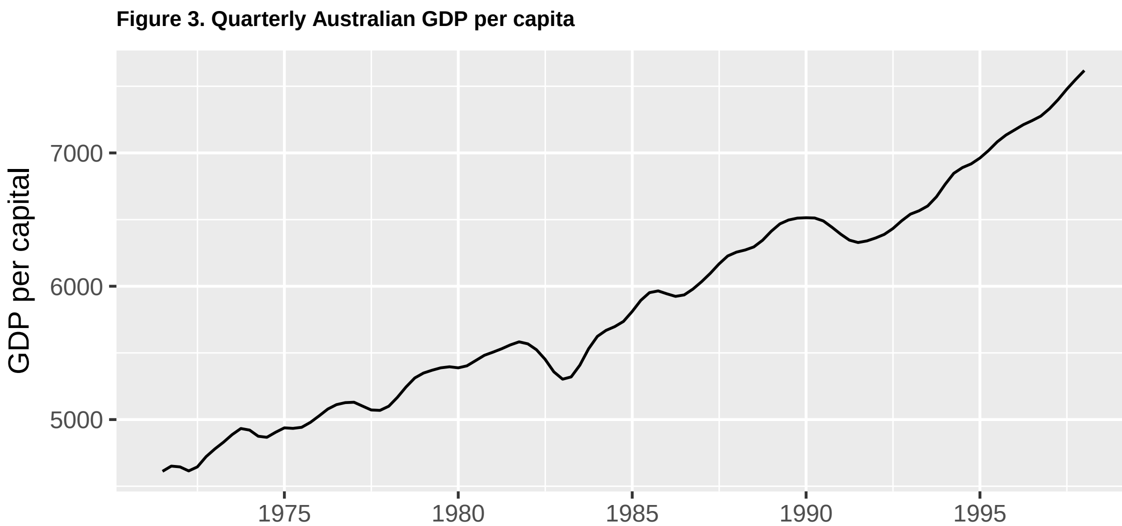
2.2 Quarterly data

2.2.1 Australian GDP per capita, 1971:Q3 - 1998:Q1[3]

```
head(ausgdp,14)
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 1971           4612 4651
## 1972 4645 4615 4645 4722
## 1973 4780 4830 4887 4933
## 1974 4921 4875 4867 4905
```

```
# start(ausgdp)  # 1971 3
# end(ausgdp)    # 1998 1
# frequency(ausgdp)  #4
autoplot(ausgdp)+
        ggtitle("Figure 3. Quarterly Australian GDP per capita")+
         ylab("GDP per capital")+
        theme(plot.title = element_text(size=8, face="bold"))
```



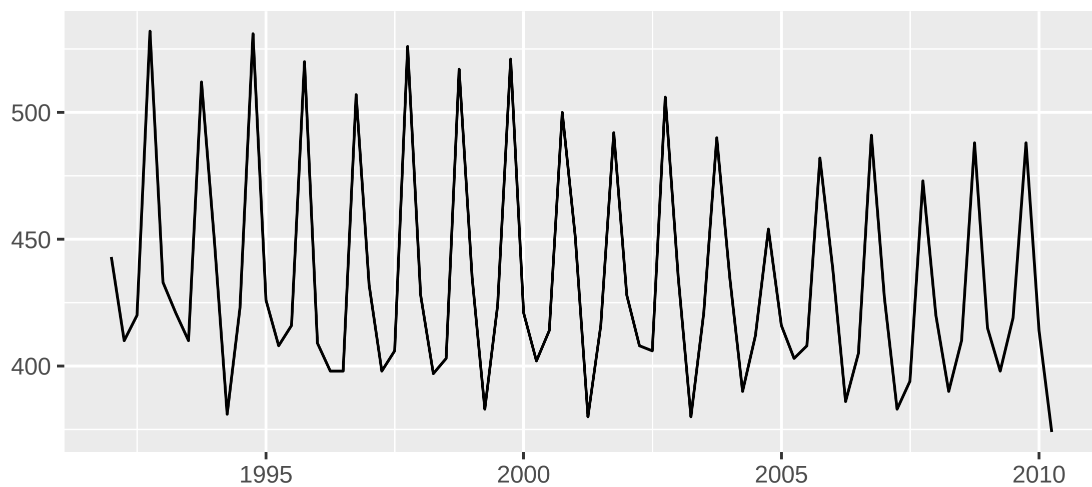
[3]Hyndman, R.J., Koehler, A.B., Ord, J.K., and Snyder, R.D., (2008) Forecasting with exponential smoothing: the state space approach, Springer.

2.2.2 Beer production[4]

Total quarterly beer production in Australia (in megalitres) from 1956:Q1 to 2010:Q2

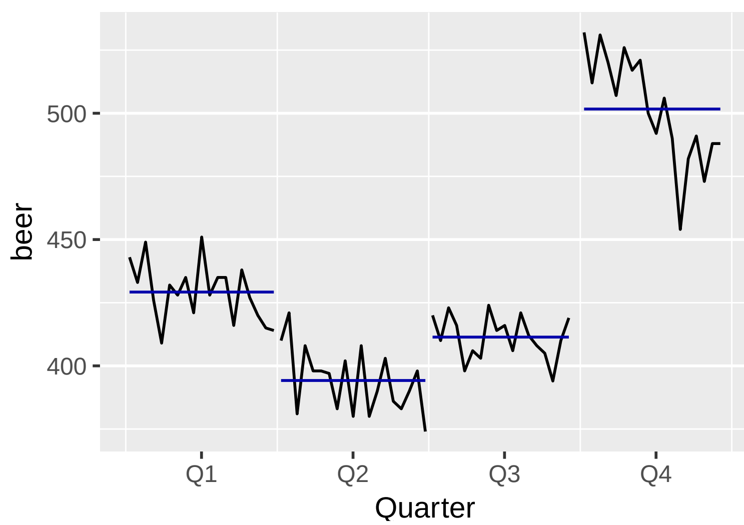
```
beer <- window(ausbeer,start=1992)
autoplot(beer)+
        ggtitle("Figure 4. Quarterly beer production (Time series plot)")+
        theme(plot.title = element_text(size=8, face="bold"))
```

Figure 4. Quarterly beer production (Time series plot)



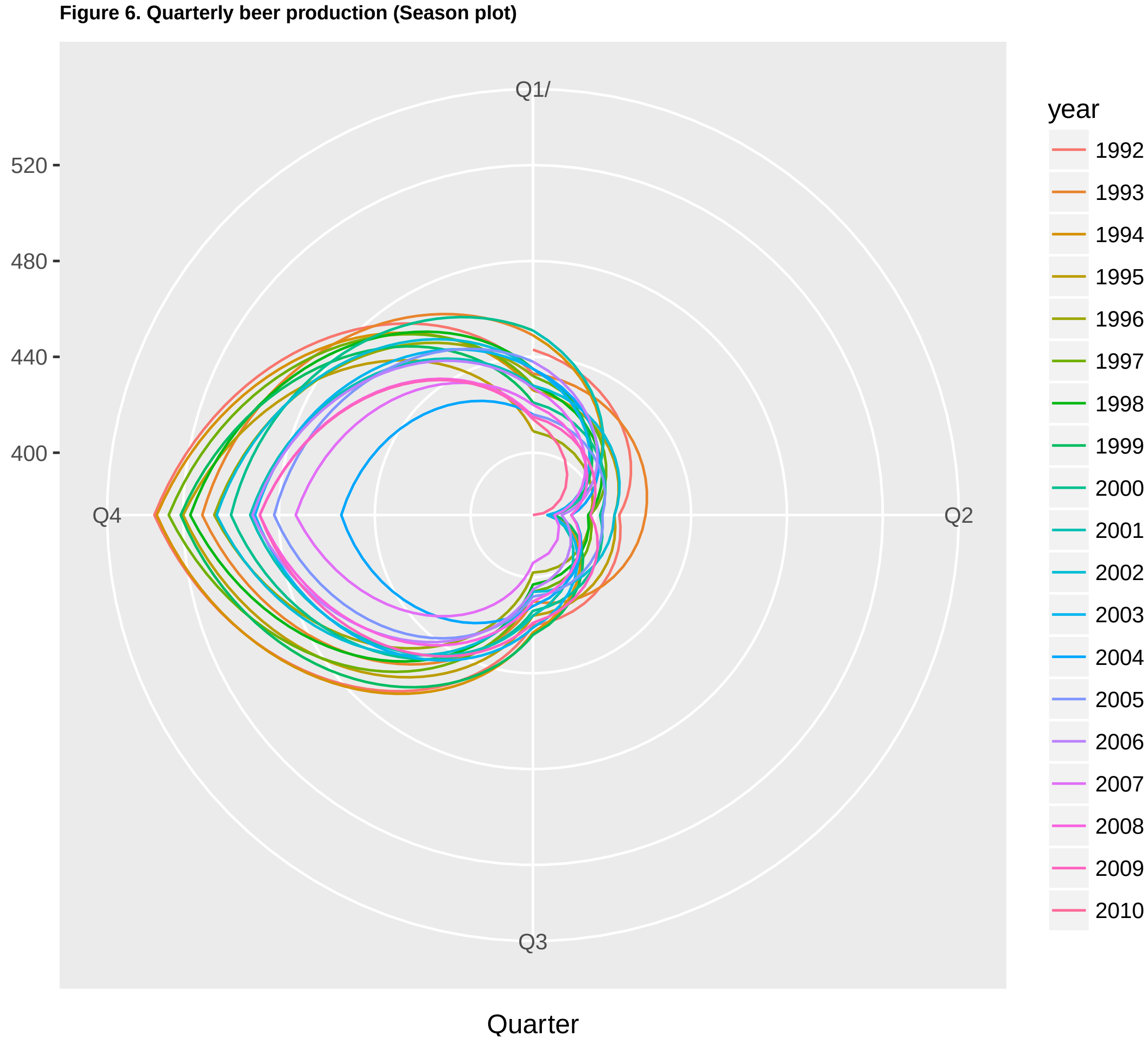

```
ggsubseriesplot(beer)+
        ggtitle("Figure 5. Quarterly beer production (Subseries plot)")+
        theme(plot.title = element_text(size=8, face="bold"))
```

Figure 5. Quarterly beer production (Subseries plot)



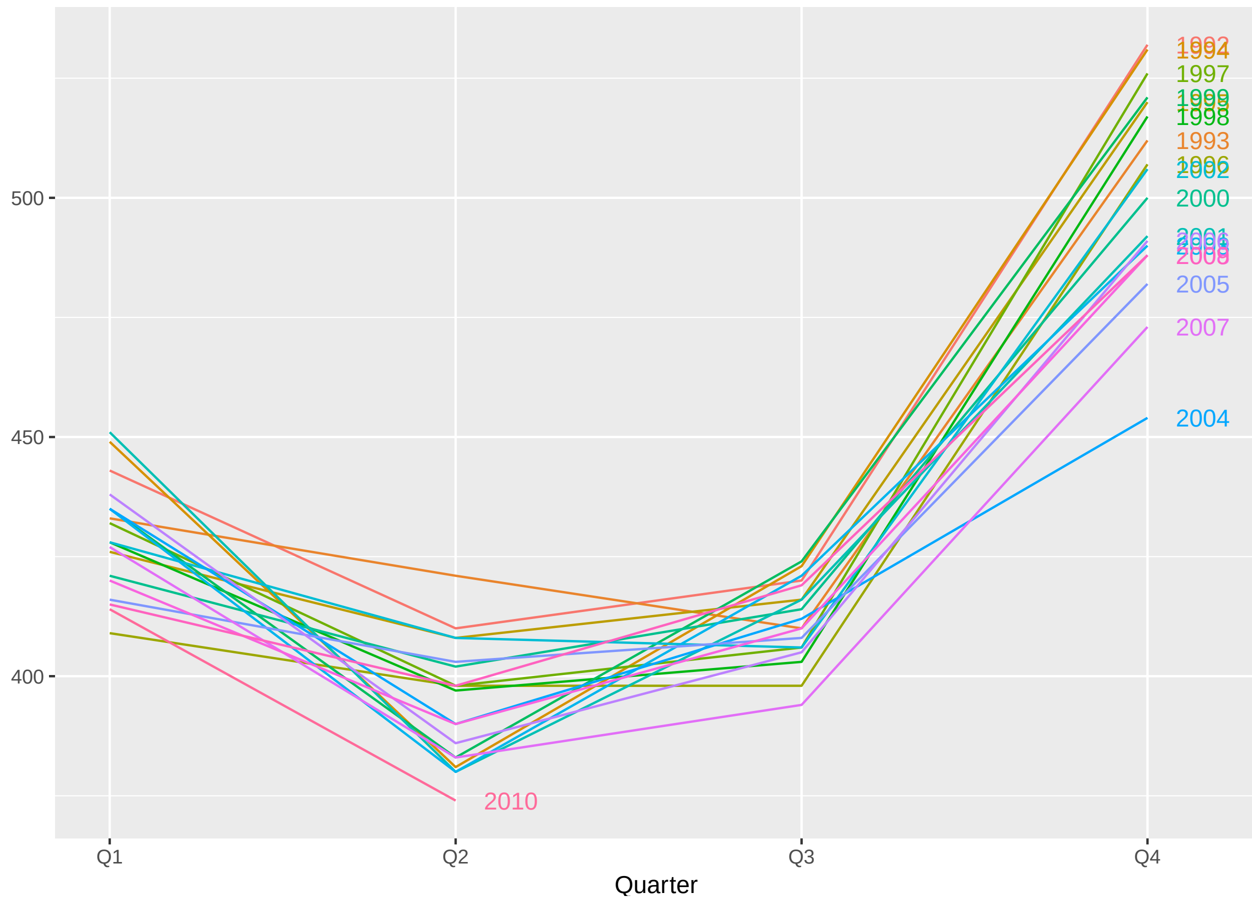
[4] Australian Bureau of Statistics. Cat. 8301.0.55.001.

```
ggseasonplot(beer, polar = TRUE)+
        ggtitle("Figure 6. Quarterly beer production (Season plot)")+
        theme(plot.title = element_text(size=8, face="bold"))
```



```r
# Alternative option
ggseasonplot(beer, year.labels=TRUE)+
        ggtitle("Figure 7. Quarterly beer production (Season plot)")+
        theme(legend.text=element_text(size=8, face="bold"))
```

Figure 7. Quarterly beer production (Season plot)



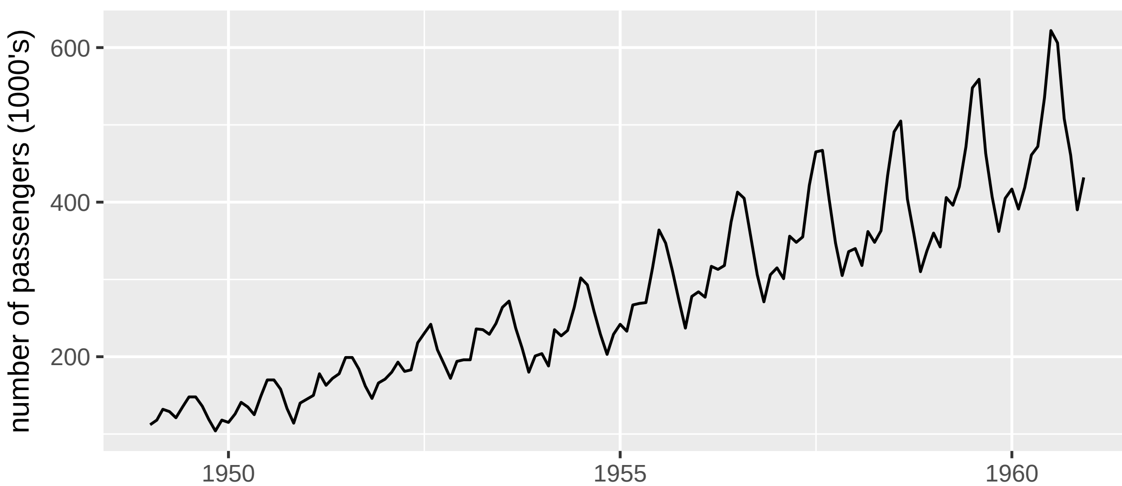
2.3 Monthly data

2.3.1 Air Passengers[5]

Monthly totals of international airline passengers from 1949 to 1960.

```
data("AirPassengers")
# start(AirPassengers)
# end(AirPassengers)
# frequency(AirPassengers)
p<-autoplot(AirPassengers)+
        ggtitle("Figure 8. Monthly totals of international airline passengers")+
        ylab("number of passengers (1000's)")+
        theme(plot.title = element_text(size=8, face="bold"))
p
```

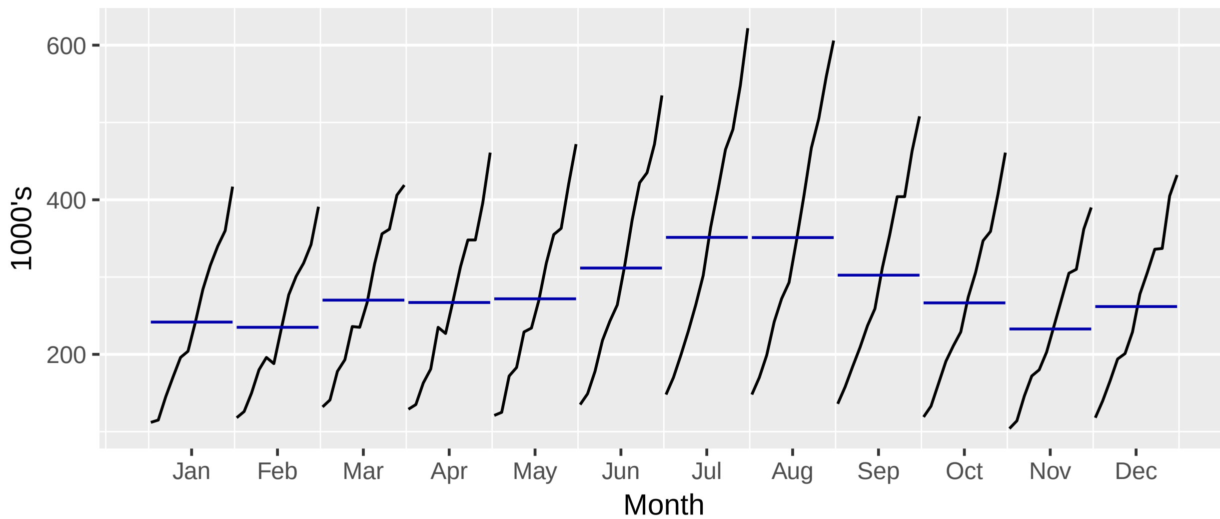
Figure 8. Monthly totals of international airline passengers




```
ggsubseriesplot(AirPassengers)+
        ylab("1000's")+
        ggtitle("Figure 9. Monthly airline passengers")+
        theme(plot.title = element_text(size=8, face="bold"))
```

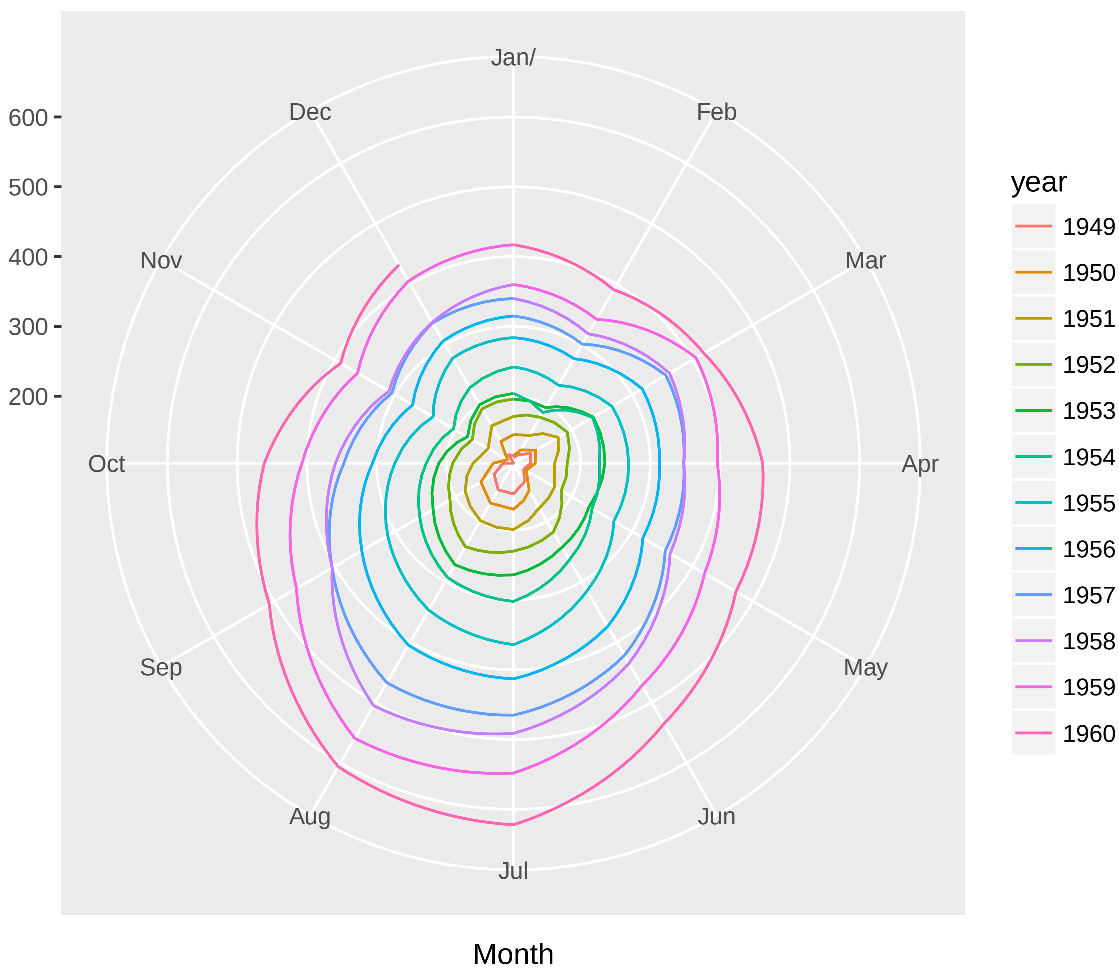
[5]Box, G. E. P., Jenkins, G. M. and Reinsel, G. C. (1976) Time Series Analysis, Forecasting and Control. Third Edition. Holden-Day. Series G.

Figure 9. Monthly airline passengers



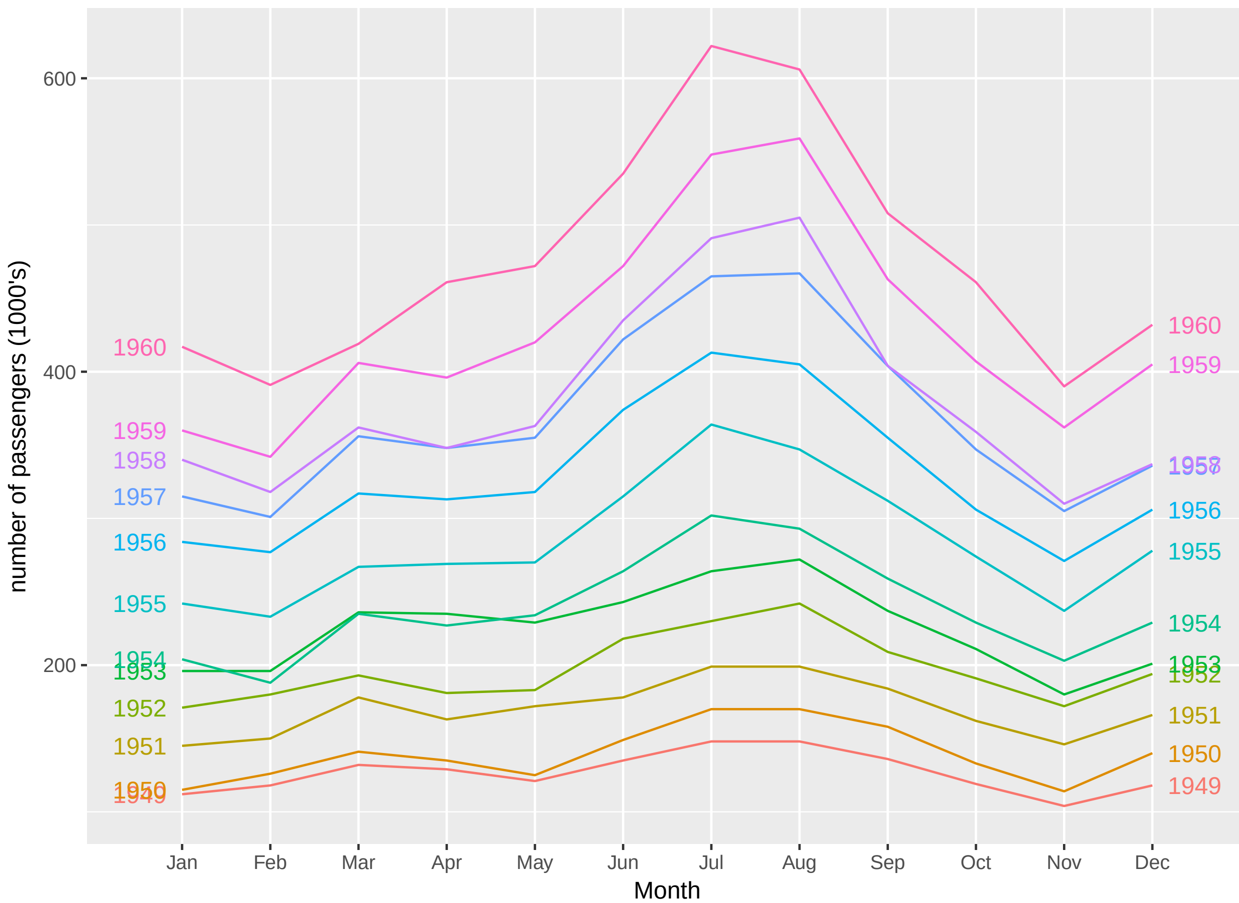

```r
ggseasonplot(AirPassengers, polar = TRUE)+
        ggtitle("Figure 10. Monthly airline passengers (Season plot 1)")+
        theme(plot.title = element_text(size=8, face="bold"))
```

Figure 10. Monthly airline passengers (Season plot 1)



```r
ggseasonplot(AirPassengers, year.labels=TRUE,year.labels.left=TRUE)+
        ggtitle("Figure 11. Monthly airline passengers (Season plot 2)")+
        ylab("number of passengers (1000's)")+
        theme(plot.title = element_text(size=8, face="bold"))
```

Figure 11. Monthly airline passengers (Season plot 2)

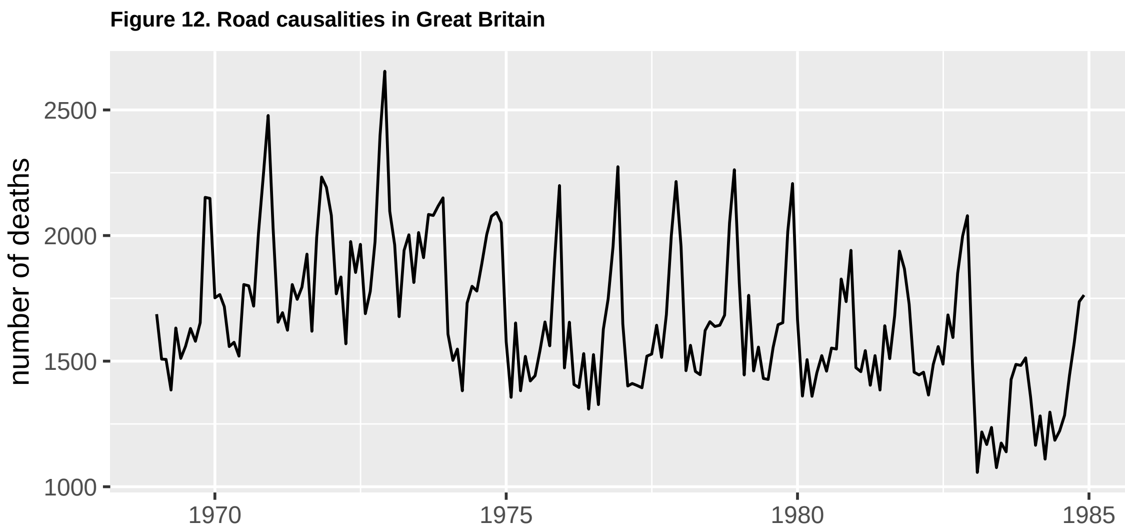


2.3.2 Road causalities in Great Britain 1969-84[6]

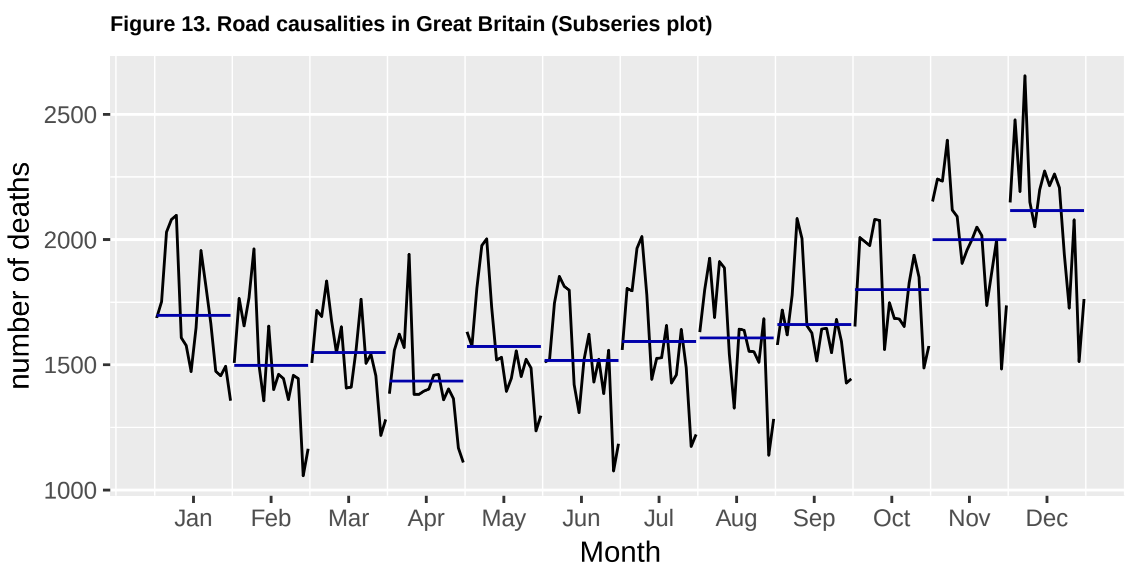
UKDriverDeaths is a time series giving the monthly totals of car drivers in Great Britain killed or seriously injured Jan 1969 to Dec 1984. Compulsory wearing of seat belts was introduced on 31 Jan 1983.

```r
data("UKDriverDeaths")
autoplot(UKDriverDeaths)+
        ggtitle("Figure 12. Road causalities in Great Britain")+
        ylab("number of deaths")+
        theme(plot.title = element_text(size=8, face="bold"))
```

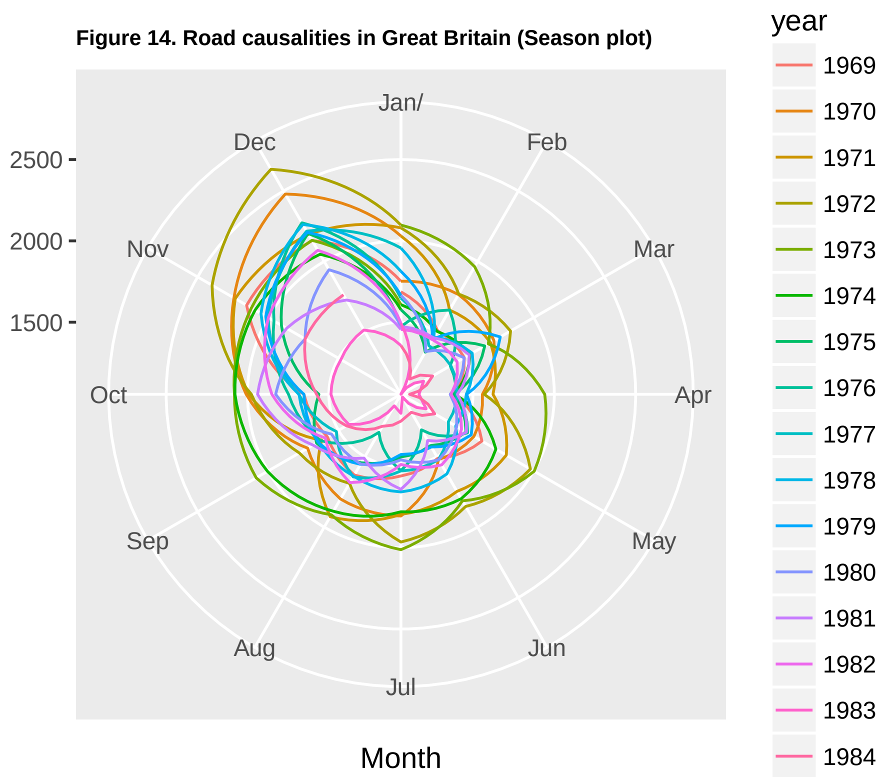
[6] https://rdrr.io/r/datasets/UKDriverDeaths.html




```
ggsubseriesplot(UKDriverDeaths)+
        ggtitle("Figure 13. Road causalities in Great Britain (Subseries plot)")+
        ylab("number of deaths")+
        theme(plot.title = element_text(size=8, face="bold"))
```




```
ggseasonplot(UKDriverDeaths,polar=TRUE)+
        ggtitle("Figure 14. Road causalities in Great Britain (Season plot)")+
        theme(plot.title = element_text(size=8, face="bold"))
```



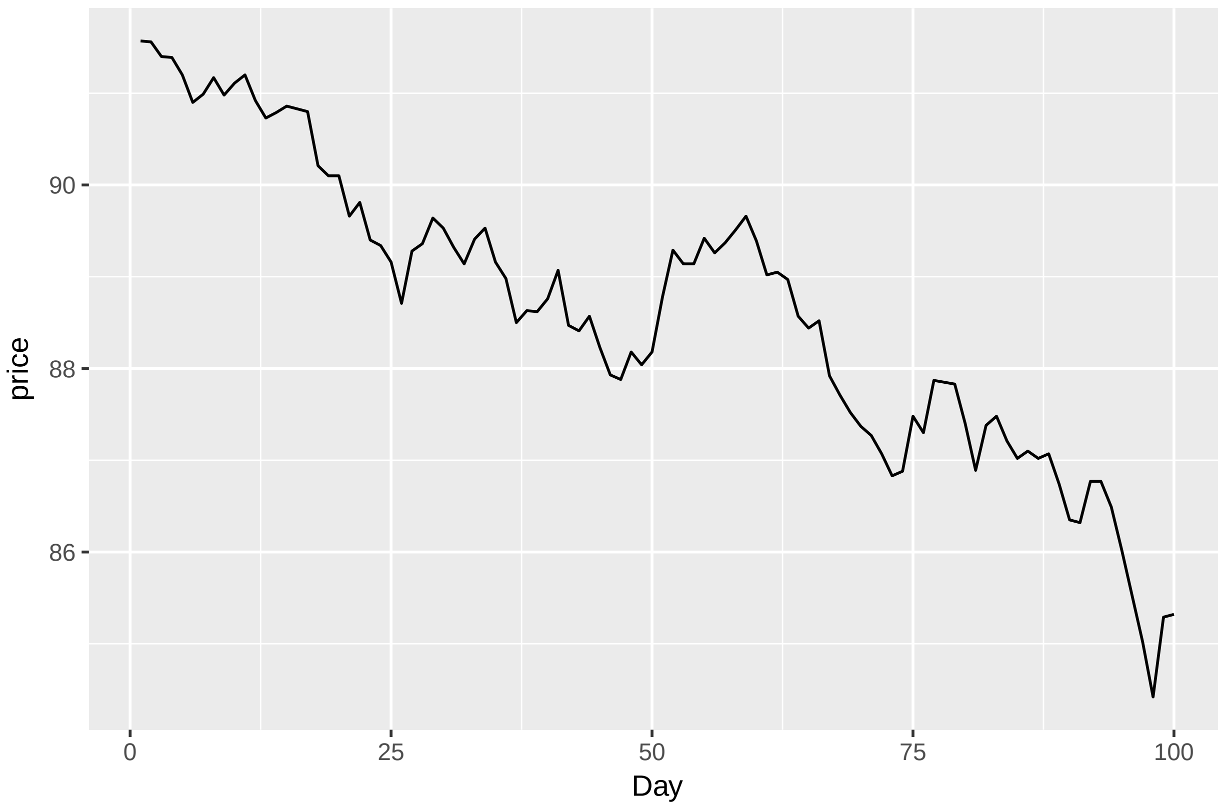
2.4 Other frequency

US treasury bill[7] contracts on the Chicago market for 100 consecutive trading days in 1981.

```
autoplot(ustreas) +
ggtitle("Figure 15. US Treasury Bill Contracts") +
xlab("Day") + ylab("price")+
        theme(plot.title = element_text(size=8, face="bold"))
```

[7]Makridakis, Wheelwright and Hyndman (1998) Forecasting: methods and applications, John Wiley & Sons: New York. Chapter 1.

Figure 15. US Treasury Bill Contracts



3 Patterns in time series data

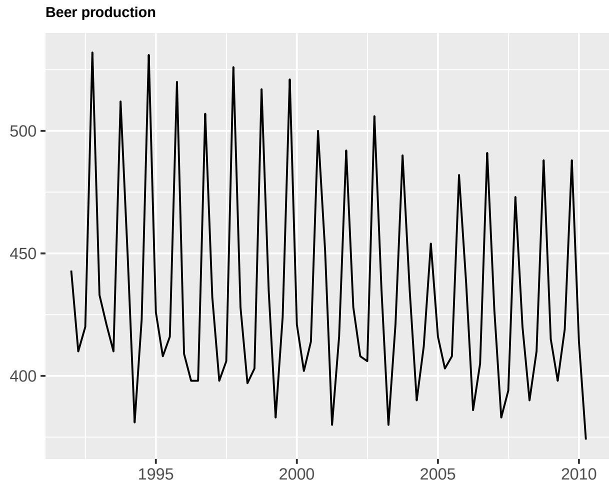
Three patterns are observed in time series data:

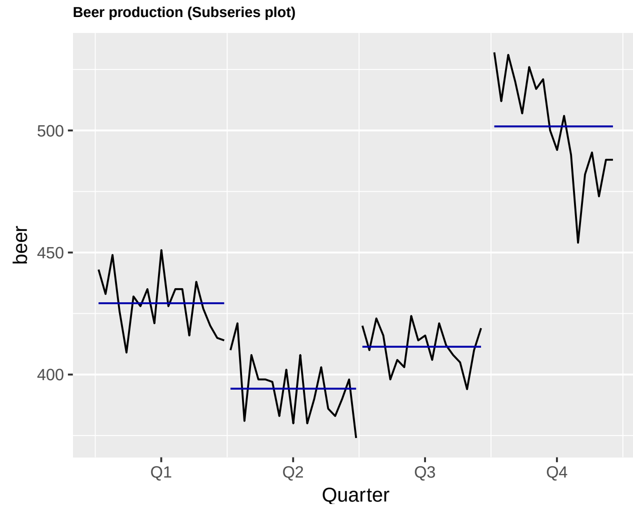
1. **Trend pattern** exists when there is a long-term increase or decrease in the data.
2. **Seasonal pattern** exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).
3. **Cyclical pattern** exists when data exhibit rises and falls that are not of fixed period (duration usually of at least 2 years).

4 Measuring temporal dependence

4.1 Common tools

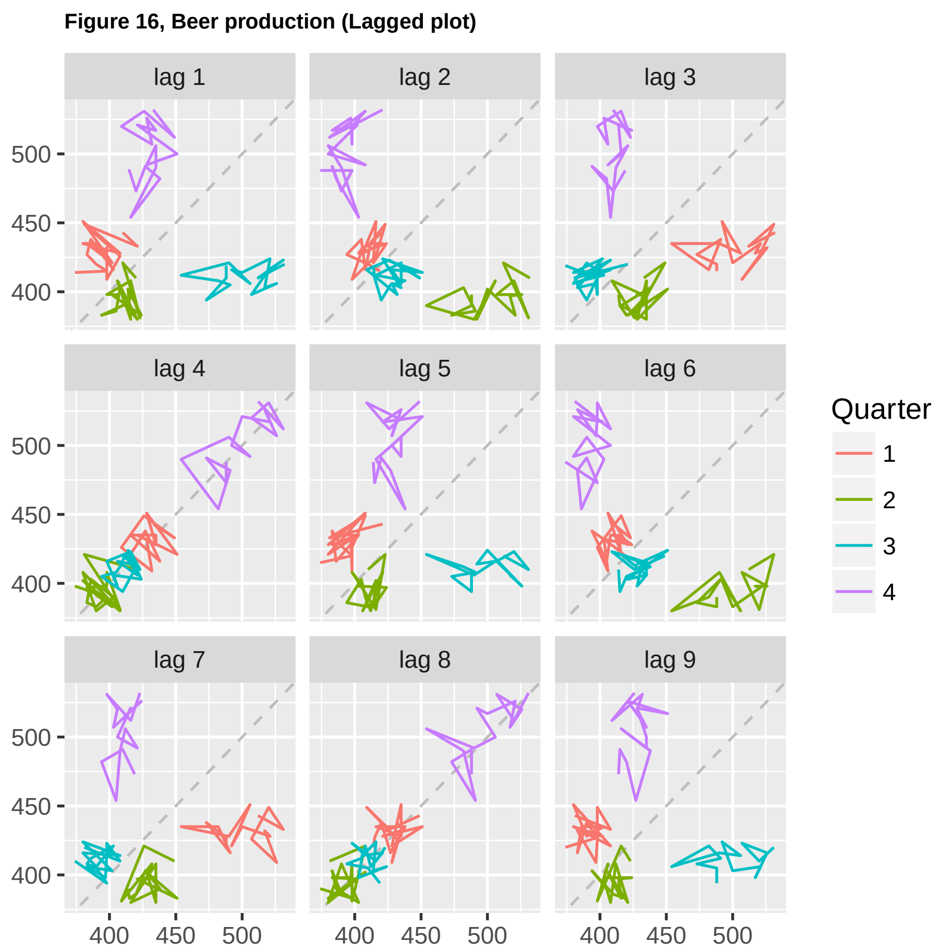
```
beer <- window(ausbeer, start=1992)
p00<-autoplot(beer)+ggtitle("Beer production")+
        theme(plot.title = element_text(size=8, face="bold"))
p01<-ggsubseriesplot(beer)+ggtitle("Beer production (Subseries plot)")+
        theme(plot.title = element_text(size=8, face="bold"))
multiplot(p00,p01,cols=2)
```





1. **Lagged scatterplots:** Each graph shows y_t plotted against y_{t-k} for different values of k.

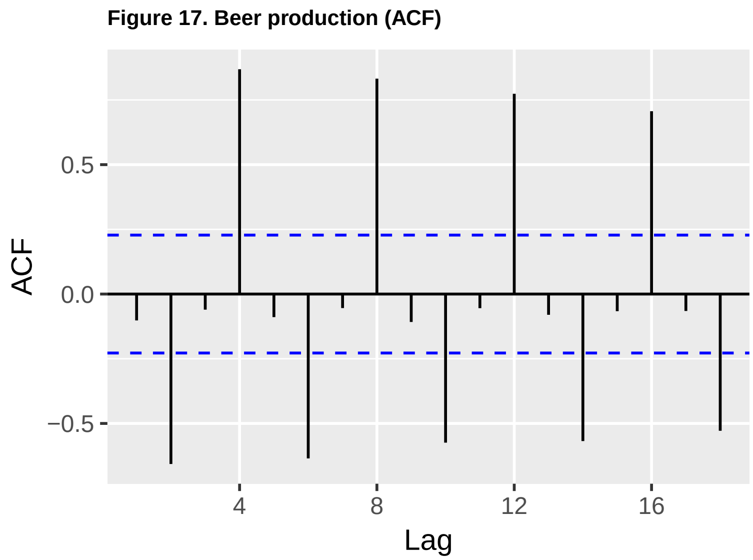
```
forecast::gglagplot(beer)+ggtitle("Figure 16, Beer production (Lagged plot)")+
        theme(plot.title = element_text(size=8, face="bold"))
```



2. **Autocorrelation plots (aka correlogram):** The autocorrelations are the correlations associated with these scatterplots. Mathematically, the autocorrelation function at lag k may be defined as

$$\rho(k) = \frac{cov(y_t, y_{t-k})}{\sqrt{var(y_t)\ var(y_{t-k})}}.$$

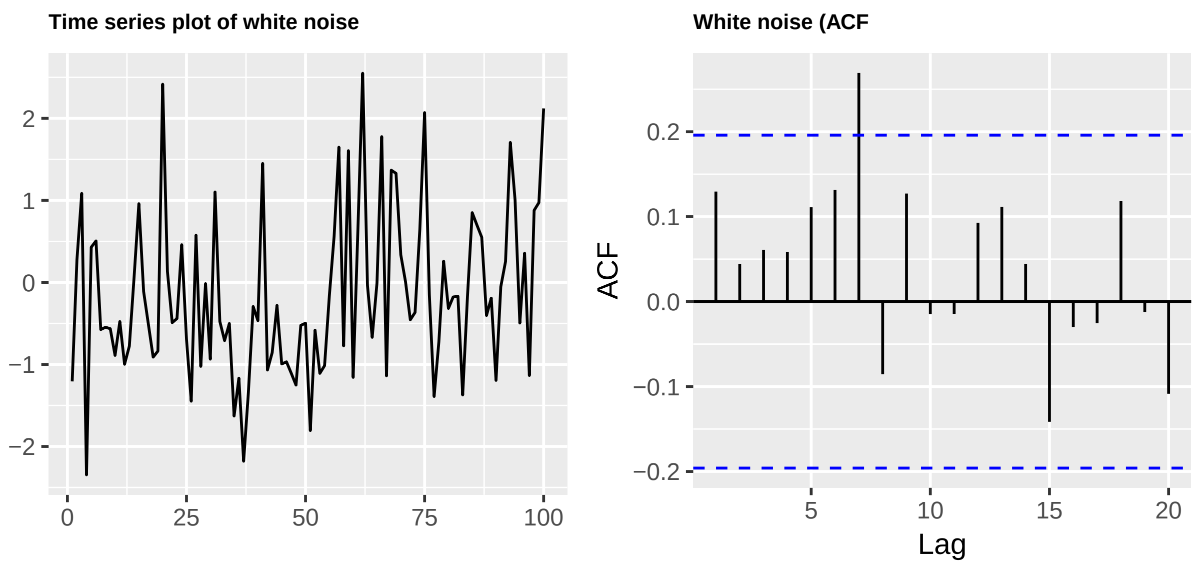
```
ggAcf(beer)+ggtitle("Figure 17. Beer production (ACF)")+
        theme(plot.title = element_text(size=8, face="bold"))
```



4.2 Autocorrelation plots for a white noise process

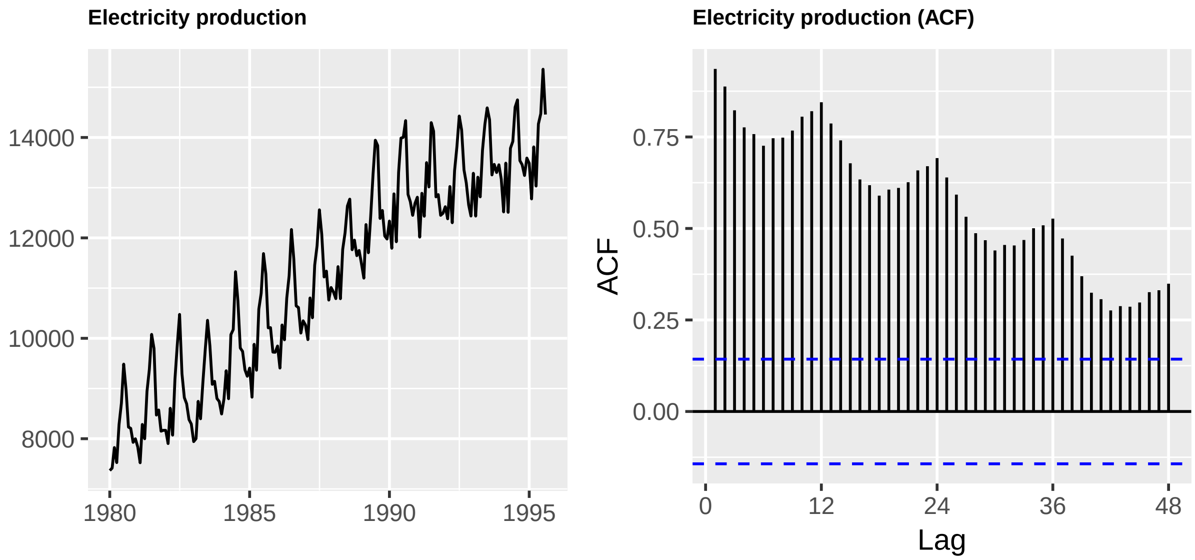
A stochastic process $\{y_t\}$ is called a white noise process if y_t satisfies
1. $E(y_t) = 0 \; \forall t$
2. $var(y_t) = cov(y_t, y_t) = \sigma^2$ is a constant.
3. $\gamma(t, s) = cov(y_t, y_s) = 0 \; \forall t \neq s$.

```
set.seed(1234)
y<-ts(rnorm(100))

p1<-autoplot(y)+ggtitle("Time series plot of white noise")+
        theme(plot.title = element_text(size=8, face="bold"))
p2<-ggAcf(y, lag.max = 20)+
        ggtitle("White noise (ACF")+
        theme(plot.title = element_text(size=8, face="bold"))

multiplot(p1,p2,cols=2)
```



4.3 Autocorrelation plots for data with trend and seasonality

```
elec <- window(elec, start=1980)
p3<-autoplot(elec)+
        ggtitle("Electricity production")+
        theme(plot.title = element_text(size=8, face="bold"))
p4<-ggAcf(elec, lag.max=48)+
        ggtitle("Electricity production (ACF)")+
        theme(plot.title = element_text(size=8, face="bold"))
multiplot(p3,p4, cols=2)
```



Remark:

1. When data have a trend, the autocorrelations for small lags tend to be large and positive.
2. When data are seasonal, the autocorrelations will be larger at the seasonal lags (i.e., at multiples of the seasonal frequency)
3. When data are trended and seasonal, you see a combination of these effects.