



ETC3550: Applied forecasting for business and economics

Ch2. Time series graphics

OTexts.org/fpp2/

Outline

- 1 Time series in R
- 2 Time plots
- 3 Seasonal plots
- 4 Seasonal or cyclic?
- 5 Lag plots and autocorrelation
- 6 White noise

ts objects and ts function

A time series is stored in a ts object in R:

- a list of numbers
- information about times those numbers were recorded.

Example

| Year | Observation |
|------|-------------|
| 2012 | 123 |
| 2013 | 39 |
| 2014 | 78 |
| 2015 | 52 |
| 2016 | 110 |

```
y <- ts(c(123,39,78,52,110), start=2012)
```

ts objects and ts function

For observations that are more frequent than once per year, add a frequency argument.

E.g., monthly data stored as a numerical vector z:

```
y <- ts(z, frequency=12, start=c(2003, 1))
```

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start | example |
|--------------|-----------|-------|---------|
|--------------|-----------|-------|---------|

Annual

Quarterly

Monthly

Daily

Weekly

Hourly

Half-hourly

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-----------|---------------|
|--------------|-----------|---------------|

| | | |
|--------|---|--|
| Annual | 1 | |
|--------|---|--|

| | | |
|-----------|--|--|
| Quarterly | | |
|-----------|--|--|

| | | |
|---------|--|--|
| Monthly | | |
|---------|--|--|

| | | |
|-------|--|--|
| Daily | | |
|-------|--|--|

| | | |
|--------|--|--|
| Weekly | | |
|--------|--|--|

| | | |
|--------|--|--|
| Hourly | | |
|--------|--|--|

| | | |
|-------------|--|--|
| Half-hourly | | |
|-------------|--|--|

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-----------|---------------|
| Annual | 1 | 1995 |
| Quarterly | | |
| Monthly | | |
| Daily | | |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-----------|---------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | |
| Monthly | | |
| Daily | | |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-----------|---------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | | |
| Daily | | |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-----------|---------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | 12 | |
| Daily | | |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-----------|---------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | 12 | c(1995,9) |
| Daily | | |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-------------|---------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | 12 | c(1995,9) |
| Daily | 7 or 365.25 | |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-------------|------------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | 12 | c(1995,9) |
| Daily | 7 or 365.25 | 1 or c(1995,234) |
| Weekly | | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

| Type of data | frequency | start example |
|--------------|-------------|------------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | 12 | c(1995,9) |
| Daily | 7 or 365.25 | 1 or c(1995,234) |
| Weekly | 52.18 | |
| Hourly | | |
| Half-hourly | | |

ts objects and ts function

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ts objects and ts function

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| Daily | 7 or 365.25 | 1 or c(1995,234) |
| Weekly | 52.18 | c(1995,23) |
| Hourly | 24 or 168 or 8,766 | |
| Half-hourly | | |

ts objects and ts function

ts(data, frequency, start)

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|--------------|--------------------|------------------|
| Annual | 1 | 1995 |
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ts objects and ts function

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| Daily | 7 or 365.25 | 1 or c(1995,234) |
| Weekly | 52.18 | c(1995,23) |
| Hourly | 24 or 168 or 8,766 | 1 |
| Half-hourly | 48 or 336 or 17,532 | |

ts objects and ts function

ts(data, frequency, start)

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|--------------|---------------------|------------------|
| Annual | 1 | 1995 |
| Quarterly | 4 | c(1995,2) |
| Monthly | 12 | c(1995,9) |
| Daily | 7 or 365.25 | 1 or c(1995,234) |
| Weekly | 52.18 | c(1995,23) |
| Hourly | 24 or 168 or 8,766 | 1 |
| Half-hourly | 48 or 336 or 17,532 | 1 |

Australian GDP

```
ausgdp <- ts(x, frequency=4, start=c(1971,3))
```

- Class: "ts"

- Print and plotting methods available.

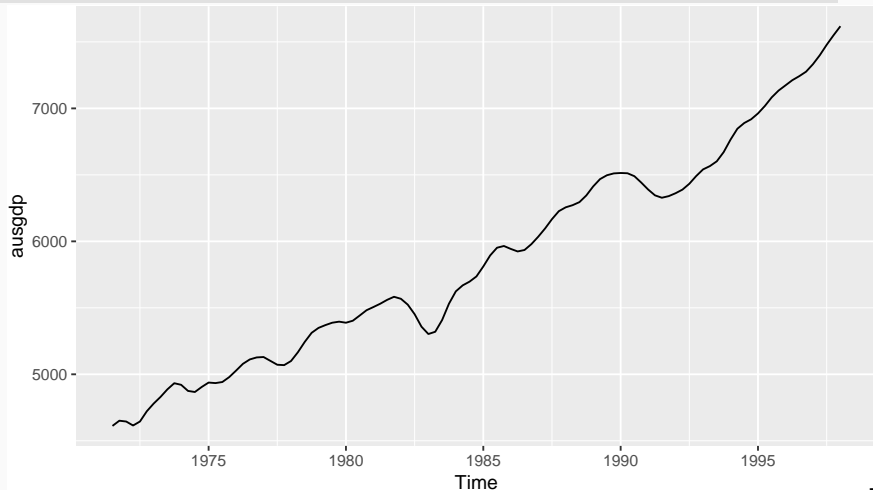
```
ausgdp
```

```
##          Qtr1 Qtr2 Qtr3 Qtr4
## 1971                4612 4651
## 1972 4645 4615 4645 4722
## 1973 4780 4830 4887 4933
## 1974 4921 4875 4867 4905
## 1975 4938 4934 4942 4979
## 1976 5028 5079 5112 5127
## 1977 5130 5101 5072 5069
## 1978 5100 5166 5244 5312
```

```
## 1979 5240 5270 5280 5280
```

Australian GDP

`autoplot(ausgdp)`



Residential electricity sales

```
elecsales
```

```
## Time Series:
```

```
## Start = 1989
```

```
## End = 2008
```

```
## Frequency = 1
```

```
## [1] 2354.34 2379.71 2318.52 2468.99 2386.09
```

```
## [6] 2569.47 2575.72 2762.72 2844.50 3000.70
```

```
## [11] 3108.10 3357.50 3075.70 3180.60 3221.60
```

```
## [16] 3176.20 3430.60 3527.48 3637.89 3655.00
```

Class package

```
> library(fpp2)
```

Class package

```
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```

This loads:

- some data for use in examples and exercises

Class package

```
> library(fpp2)
```

This loads:

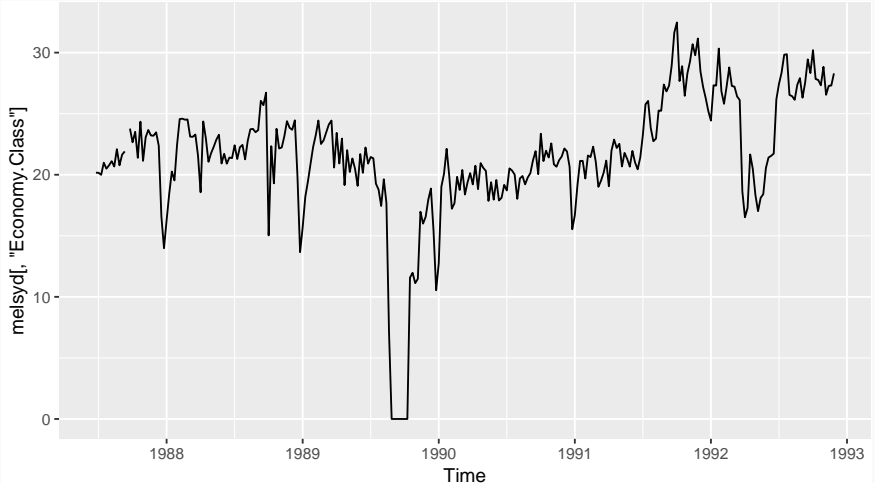
- some data for use in examples and exercises
- **forecast** package (for forecasting functions)
- **ggplot2** package (for graphics functions)
- **fma** package (for lots of time series data)
- **expsmooth** package (for more time series data)

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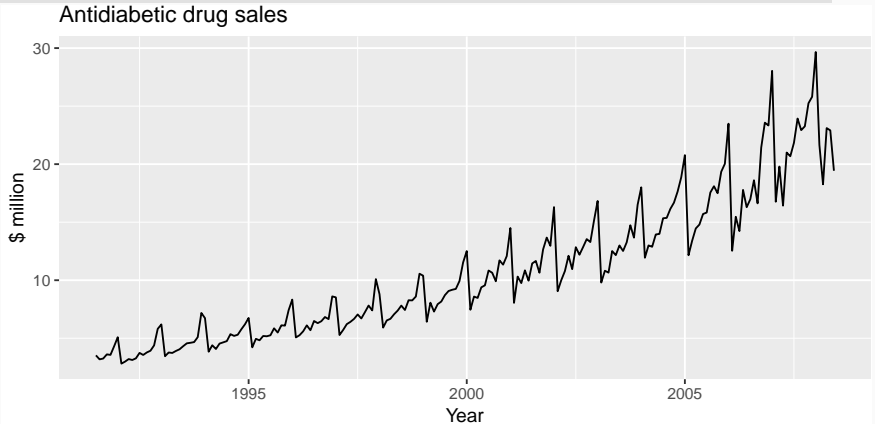
Time plots

```
autoplot(melsyd[, "Economy.Class"])
```



Time plots

```
autoplot(a10) + ylab("$ million") + xlab("Year") +  
  ggtitle("Antidiabetic drug sales")
```

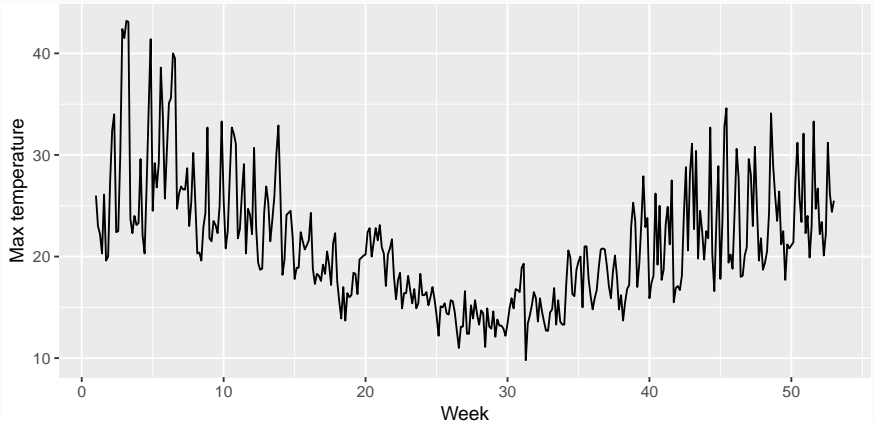


Your turn

- Create plots of the following time series: `dole`, `bricksq`, `lynx`, `goog`
- Use `help()` to find out about the data in each series.
- For the last plot, modify the axis labels and title.

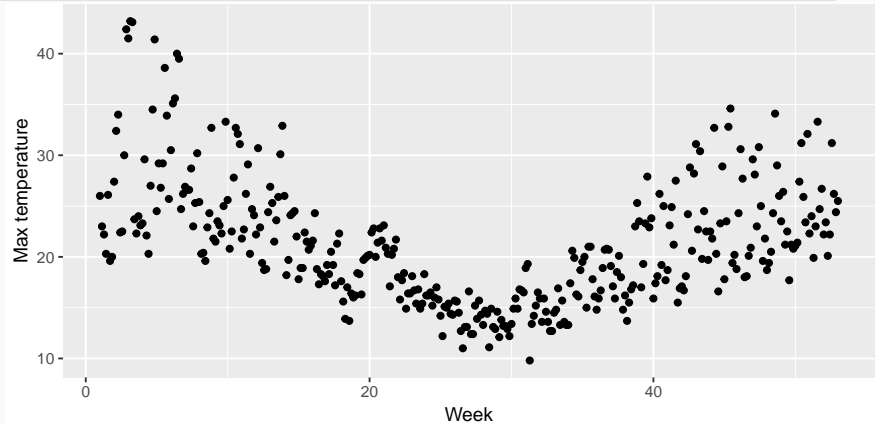
Are time plots best?

```
autoplot(elecdaily[, "Temperature"]) +  
  xlab("Week") + ylab("Max temperature")
```

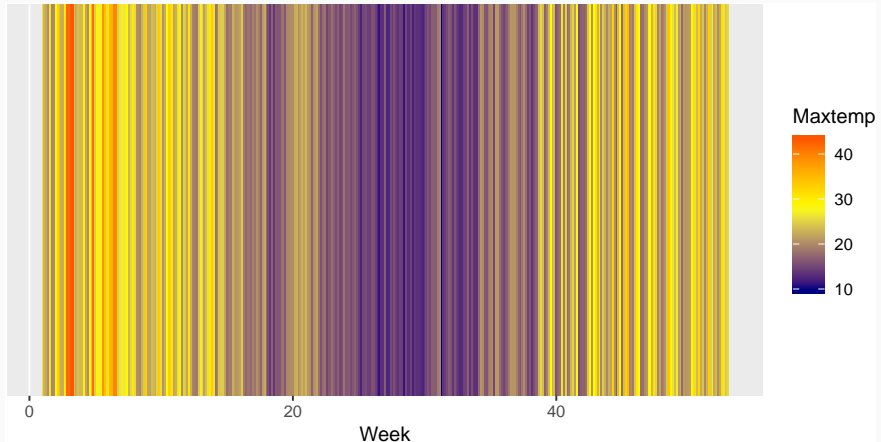


Are time plots best?

```
qplot(time(elecdaily), electdaily[, "Temperature"]) +  
  xlab("Week") + ylab("Max temperature")
```



Are time plots best?



Are time plots best?



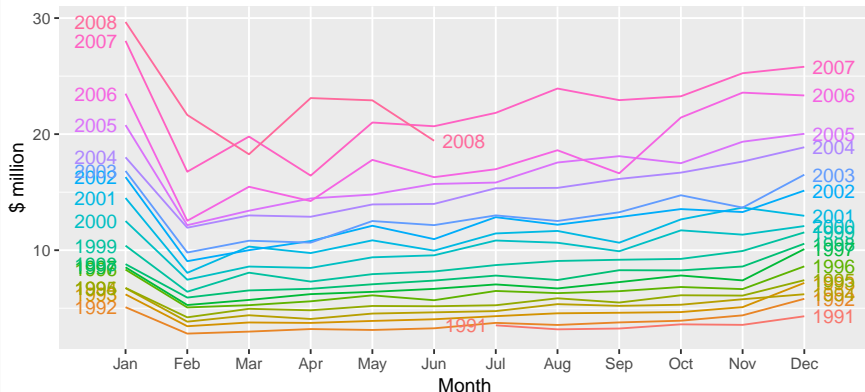
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Seasonal plots

```
ggseasonplot(a10, year.labels=TRUE, year.labels.left=TRUE) +  
  ylab("$ million") +  
  ggtitle("Seasonal plot: antidiabetic drug sales")
```

Seasonal plot: antidiabetic drug sales



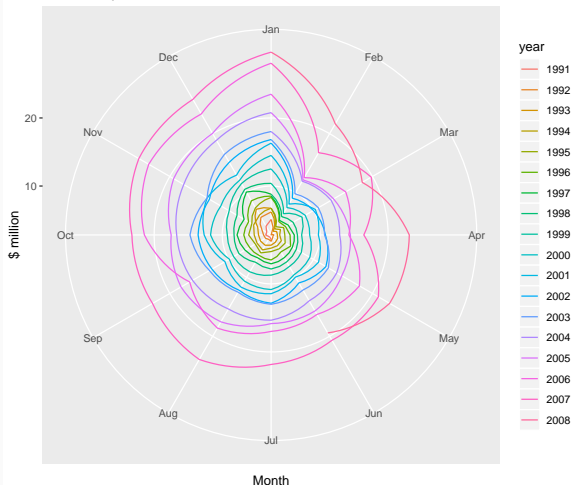
Seasonal plots

- Data plotted against the individual “seasons” in which the data were observed. (In this case a “season” is a month.)
- Something like a time plot except that the data from each season are overlapped.
- Enables the underlying seasonal pattern to be seen more clearly, and also allows any substantial departures from the seasonal pattern to be easily identified.
- In R: `ggseasonplot()`

Seasonal polar plots

```
ggseasonplot(a10, polar=TRUE) + ylab("$ million")
```

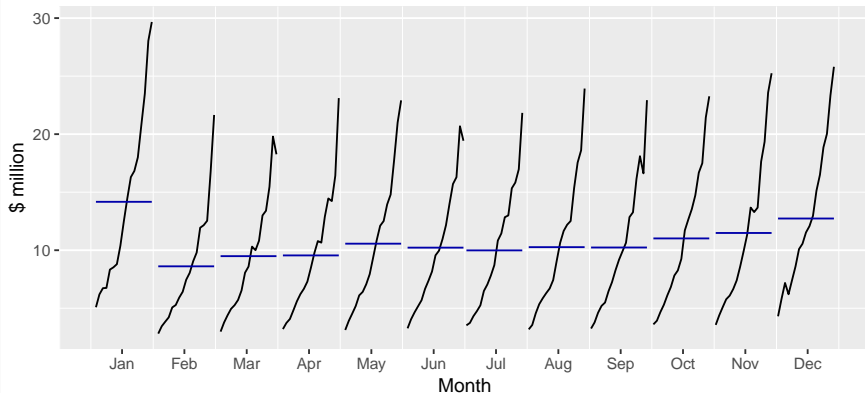
Seasonal plot: a10



Seasonal subseries plots

```
ggsubseriesplot(a10) + ylab("$ million") +  
  ggtitle("Subseries plot: antidiabetic drug sales")
```

Subseries plot: antidiabetic drug sales

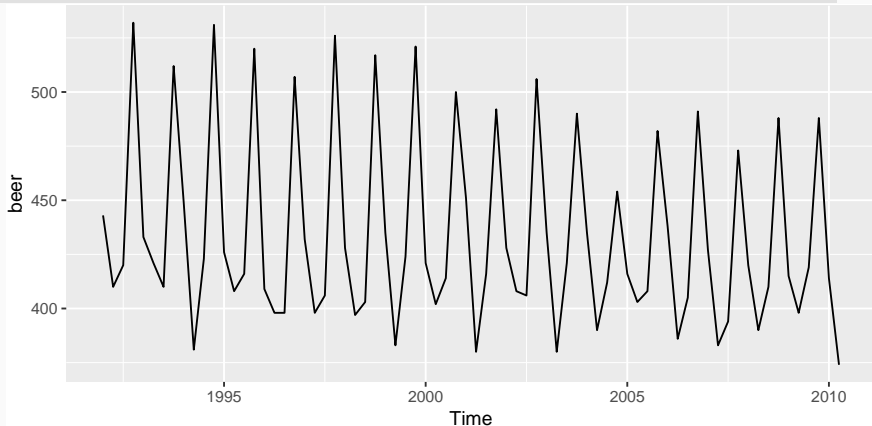


Seasonal subseries plots

- Data for each season collected together in time plot as separate time series.
- Enables the underlying seasonal pattern to be seen clearly, and changes in seasonality over time to be visualized.
- In R: `ggsubseriesplot()`

Quarterly Australian Beer Production

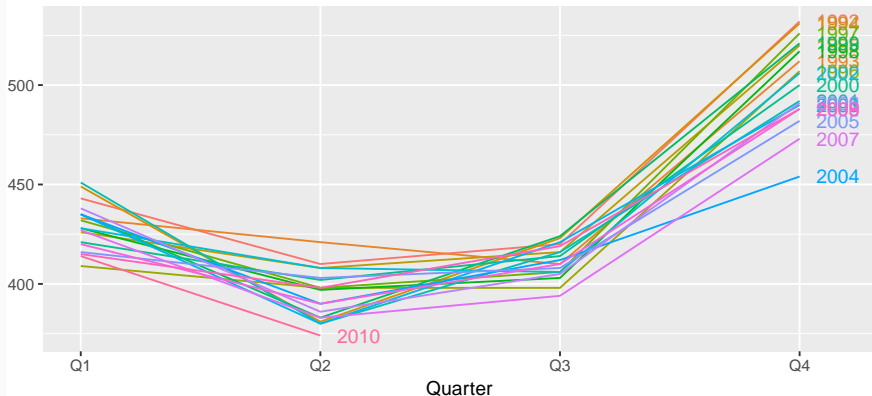
```
beer <- window(ausbeer, start=1992)  
autoplot(beer)
```



Quarterly Australian Beer Production

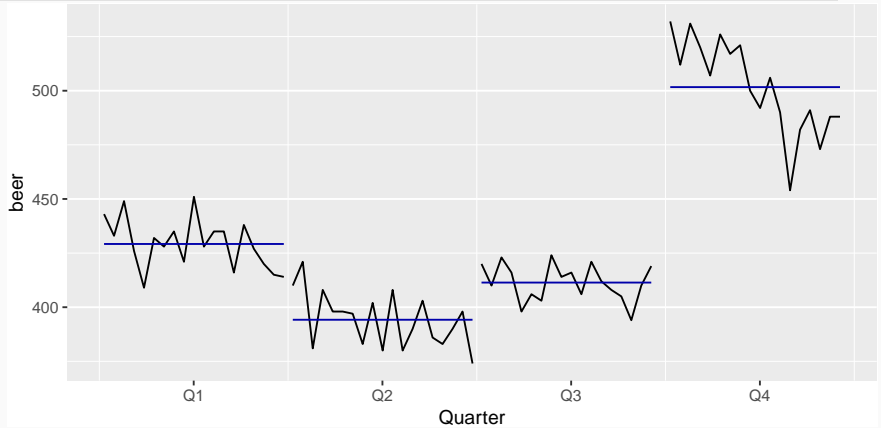
```
ggseasonplot(beer, year.labels=TRUE)
```

Seasonal plot: beer



Quarterly Australian Beer Production

`ggsubseriesplot(beer)`



Your turn

The `arrivals` data set comprises quarterly international arrivals (in thousands) to Australia from Japan, New Zealand, UK and the US.

- Use `autoplot()` and `ggseasonplot()` to compare the differences between the arrivals from these four countries.
- Can you identify any unusual observations?

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Time series patterns

Trend pattern exists when there is a long-term increase or decrease in the data.

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).

Cyclic pattern exists when data exhibit rises and falls that are *not of fixed period* (duration usually of at least 2 years).

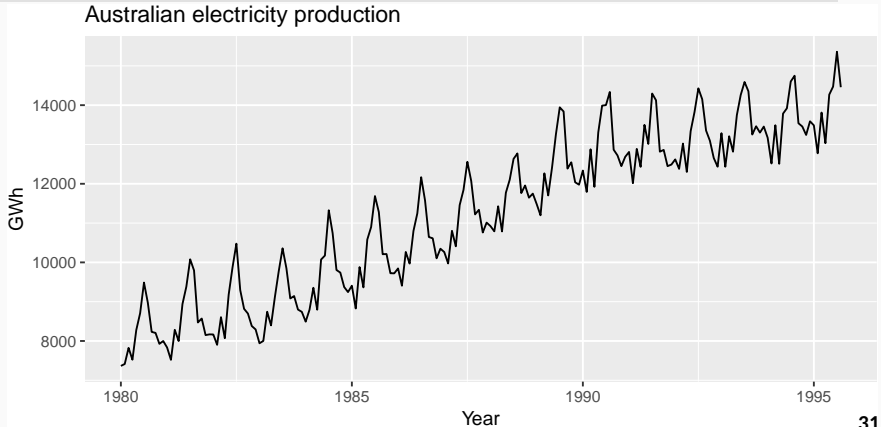
Time series components

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

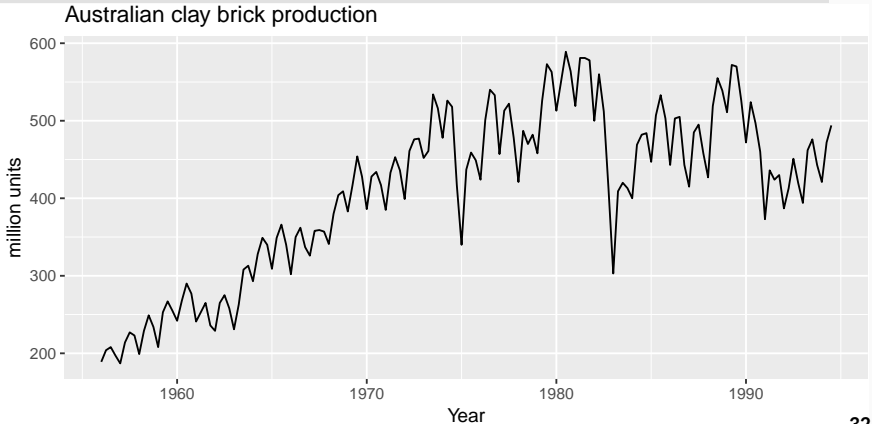
Time series patterns

```
autoplot(window(elec, start=1980)) +  
  ggtitle("Australian electricity production") +  
  xlab("Year") + ylab("GWh")
```



Time series patterns

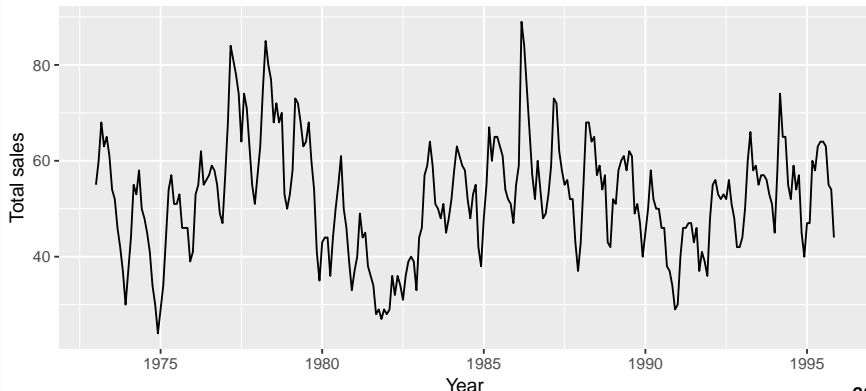
```
autoplot(bricksq) +  
  ggtitle("Australian clay brick production") +  
  xlab("Year") + ylab("million units")
```



Time series patterns

```
autoplot(hsales) +  
  ggtitle("Sales of new one-family houses, USA") +  
  xlab("Year") + ylab("Total sales")
```

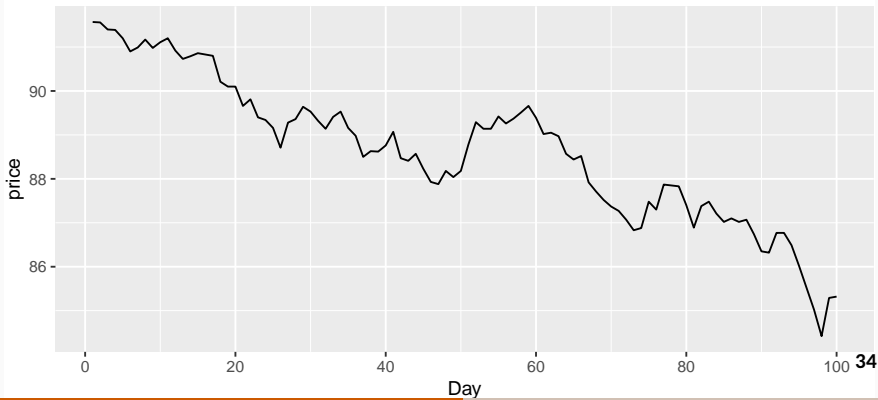
Sales of new one-family houses, USA



Time series patterns

```
autoplot(ustreas) +  
  ggtitle("US Treasury Bill Contracts") +  
  xlab("Day") + ylab("price")
```

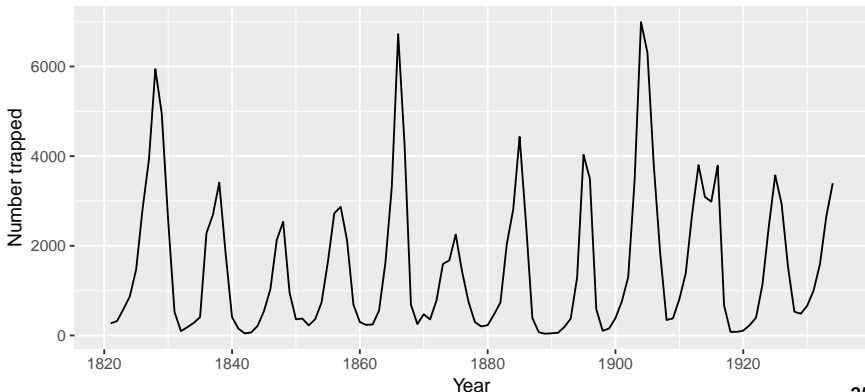
US Treasury Bill Contracts



Time series patterns

```
autoplot(lynx) +  
  ggtitle("Annual Canadian Lynx Trappings") +  
  xlab("Year") + ylab("Number trapped")
```

Annual Canadian Lynx Trappings



Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

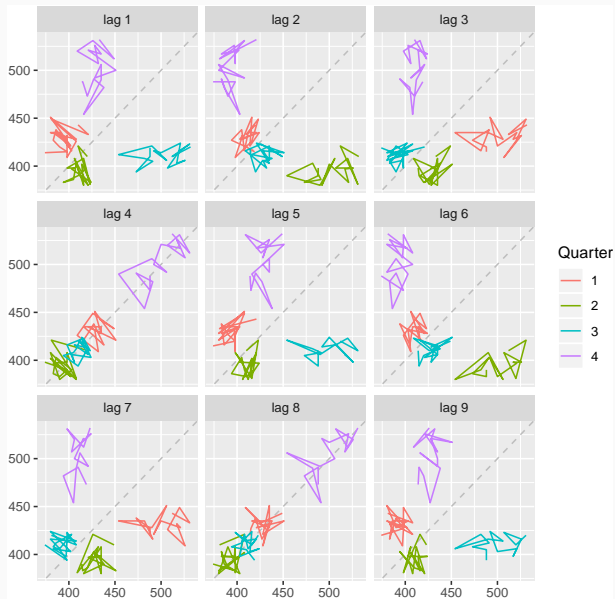
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Example: Beer production

```
beer <- window(ausbeer, start=1992)  
gglagplot(beer)
```

Example: Beer production



Lagged scatterplots

- Each graph shows y_t plotted against y_{t-k} for different values of k .
- The autocorrelations are the correlations associated with these scatterplots.

Covariance and **correlation**: measure extent of **linear relationship** between two variables (y and X).

Autocorrelation

Covariance and **correlation**: measure extent of **linear relationship** between two variables (y and X).

Autocovariance and **autocorrelation**: measure linear relationship between **lagged values** of a time series y .

Autocorrelation

Covariance and **correlation**: measure extent of **linear relationship** between two variables (y and X).

Autocovariance and **autocorrelation**: measure linear relationship between **lagged values** of a time series y .

\begin{tabbing} We measure the relationship
between: ~ ~ = y_t and y_{t-1} \> y_t and y_{t-2} \> y_t and y_{t-3} \>
> etc. \end{tabbing}

Autocorrelation

We denote the sample autocovariance at lag k by c_k and the sample autocorrelation at lag k by r_k . Then define

$$c_k = \frac{1}{T} \sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})$$

and $r_k = c_k / c_0$

Autocorrelation

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$$c_k = \frac{1}{T} \sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})$$

and $r_k = c_k / c_0$

- r_1 indicates how successive values of y relate to each other
- r_2 indicates how y values two periods apart relate to each other
- r_k is *almost* the same as the sample correlation between y_t and y_{t-k} .

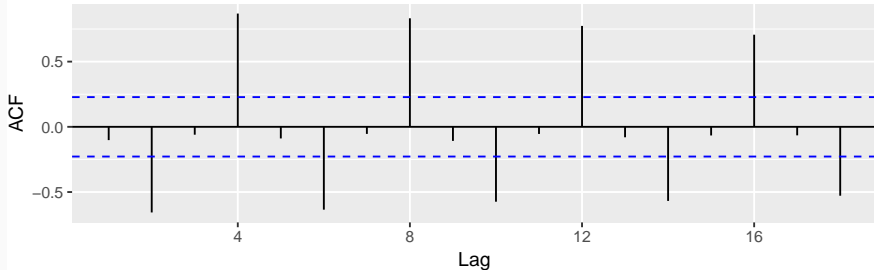
Autocorrelation

Results for first 9 lags for beer data:

| r_1 | r_2 | r_3 | r_4 | r_5 | r_6 | r_7 | r_8 | r_9 |
|--------|--------|--------|-------|--------|--------|--------|-------|--------|
| -0.102 | -0.657 | -0.060 | 0.869 | -0.089 | -0.635 | -0.054 | 0.832 | -0.108 |

`ggAcf(beer)`

Series: beer

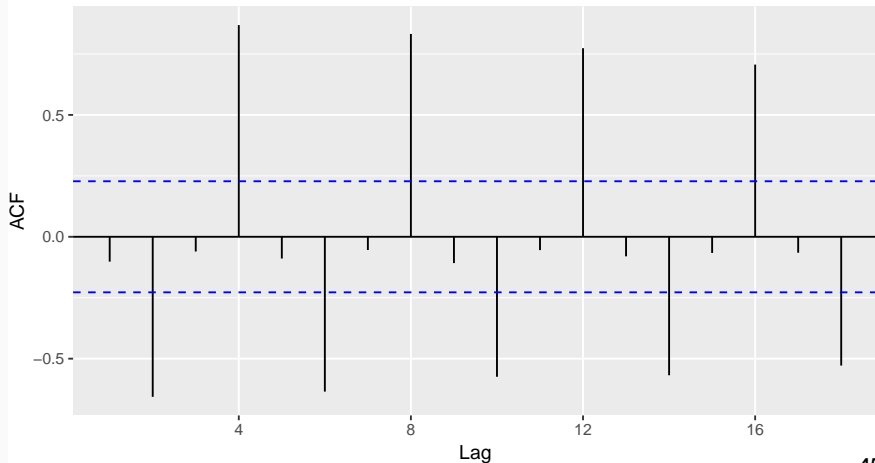


Autocorrelation

- r_4 higher than for the other lags. This is due to **the seasonal pattern in the data**: the peaks tend to be **4 quarters** apart and the troughs tend to be **2 quarters** apart.
- r_2 is more negative than for the other lags because troughs tend to be 2 quarters behind peaks.
- Together, the autocorrelations at lags 1, 2, ..., make up the *autocorrelation* or ACF.
- The plot is known as a **correlogram**


```
ggAcf(beer)
```

Series: beer

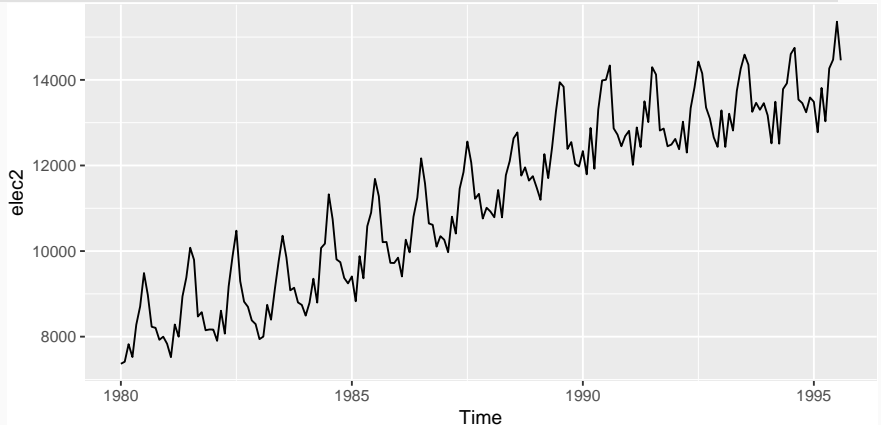


Trend and seasonality in ACF plots

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

Aus monthly electricity production

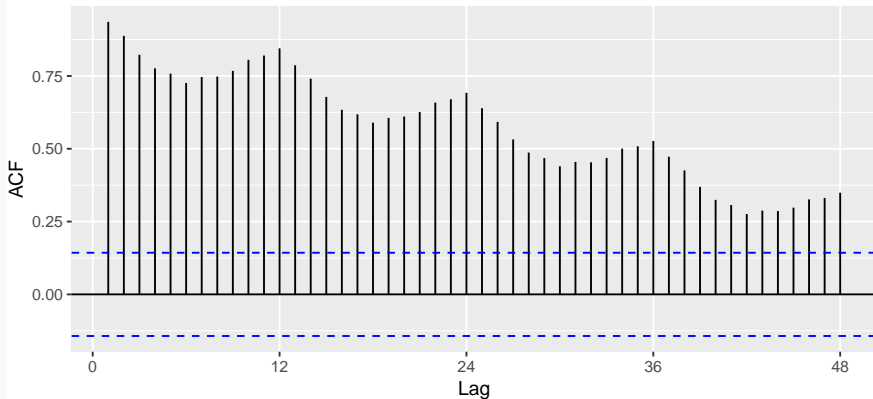
```
elec2 <- window(elec, start=1980)  
autoplot(elec2)
```



Aus monthly electricity production

```
ggAcf(elec2, lag.max=48)
```

Series: elec2



Aus monthly electricity production

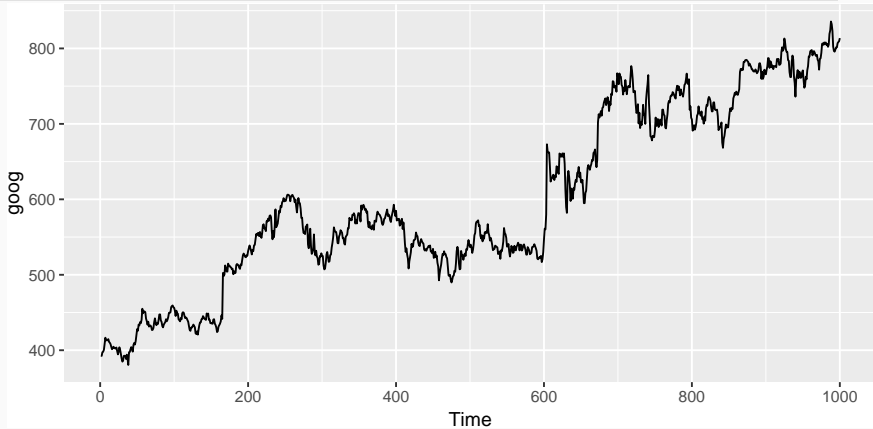
Time plot shows clear trend and seasonality.

The same features are reflected in the ACF.

- The slowly decaying ACF indicates trend.
- The ACF peaks at lags 12, 24, 36, ..., indicate seasonality of length 12.

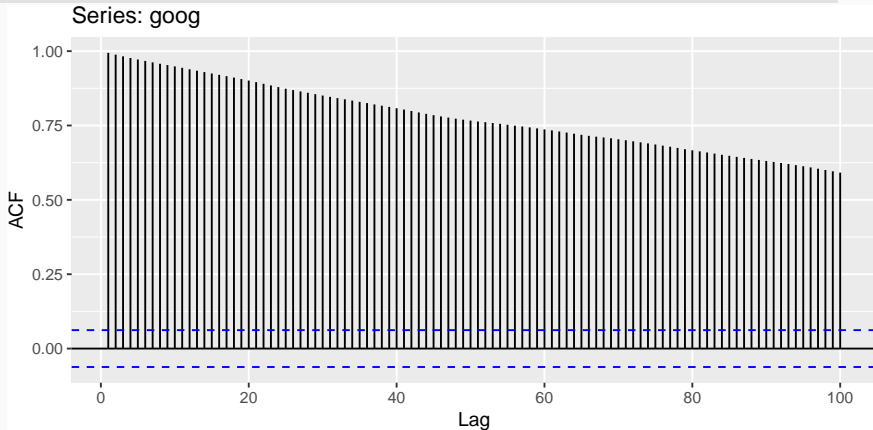
Google stock price

```
autoplot(goog)
```



Google stock price

```
ggAcf(goog, lag.max=100)
```



Your turn

We have introduced the following graphics functions:

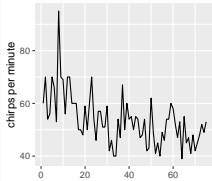
- `gglagplot`
- `ggAcf`

Explore the following time series using these functions. Can you spot any seasonality, cyclicity and trend? What do you learn about the series?

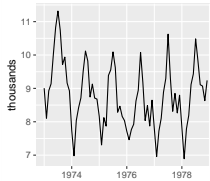
- `hsales`
- `usdeaths`
- `bricksq`
- `sunspotarea`
- `gasoline`

Which is which?

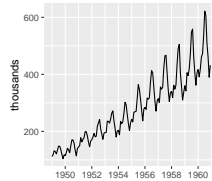
1. Daily temperature of cow



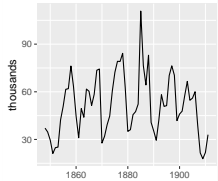
2. Monthly accidental deaths



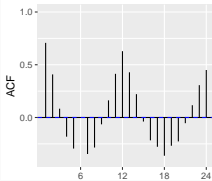
3. Monthly air passengers



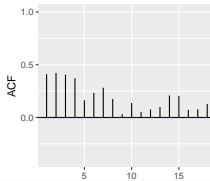
4. Annual mink trappings



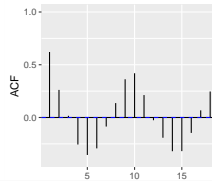
A



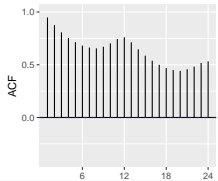
B



C



D

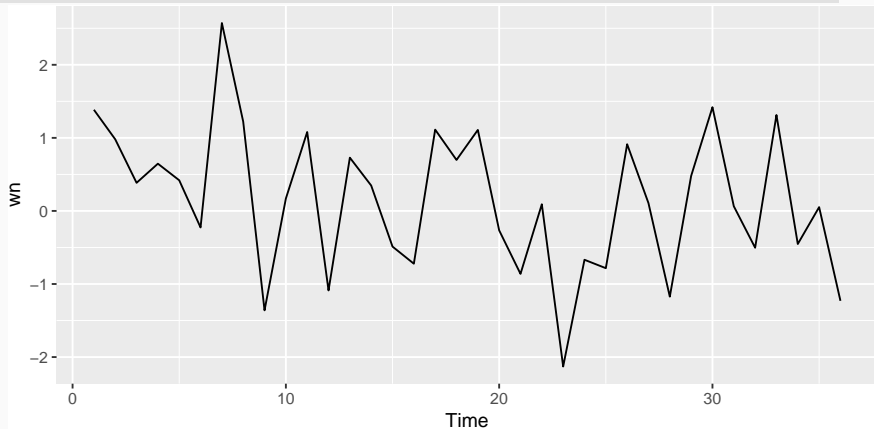


Outline

- 1 Time series in R
- 2 Time plots
- 3 Seasonal plots
- 4 Seasonal or cyclic?
- 5 Lag plots and autocorrelation
- 6 White noise

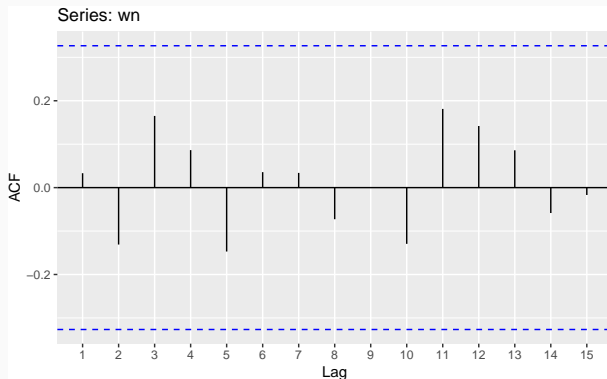
Example: White noise

```
wn <- ts(rnorm(36))  
autoplot(wn)
```



Example: White noise

| | |
|----------|-------|
| r_1 | 0.03 |
| r_2 | -0.13 |
| r_3 | 0.17 |
| r_4 | 0.09 |
| r_5 | -0.15 |
| r_6 | 0.04 |
| r_7 | 0.03 |
| r_8 | -0.07 |
| r_9 | 0.00 |
| r_{10} | -0.13 |



Sample autocorrelations for white noise series.

We expect each autocorrelation to be close to zero.

Sampling distribution of autocorrelations

Sampling distribution of r_k for white noise data is asymptotically $N(0, 1/T)$.

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Sampling distribution of r_k for white noise data is asymptotically $N(0, 1/T)$.

- 95% of all r_k for white noise must lie within $\pm 1.96/\sqrt{T}$.
- If this is not the case, the series is probably not WN.
- Common to plot lines at $\pm 1.96/\sqrt{T}$ when plotting ACF. These are the **critical values**.

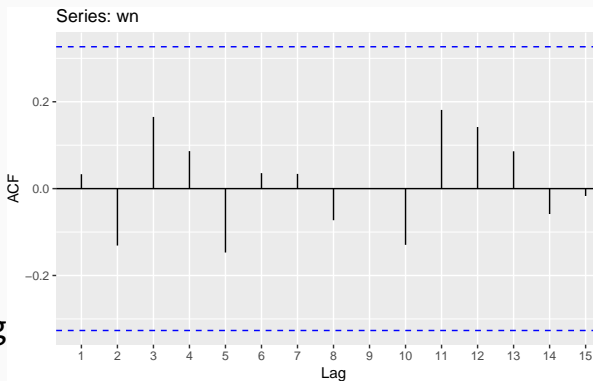
Autocorrelation

Example:

$T = 36$ and so critical values at

$$\pm 1.96 / \sqrt{36} = \pm 0.327.$$

All autocorrelation coefficients lie within these limits, confirming that the data are white noise. (More precisely, the data cannot be distinguished from white noise.)



Example: Pigs slaughtered

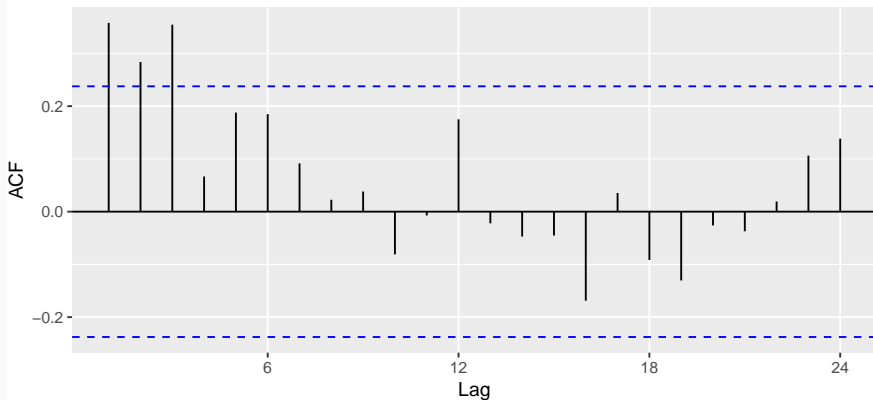
```
pigs2 <- window(pigs, start=1990)
autoplot(pigs2) +
  xlab("Year") + ylab("thousands") +
  ggtitle("Number of pigs slaughtered in Victoria")
```



Example: Pigs slaughtered

```
ggAcf(pigs2)
```

Series: pigs2



Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 1990 through August 1995. (Source: Australian Bureau of Statistics.)

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- r_{12} relatively large although not significant. This may indicate some slight seasonality.

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These show the series is **not a white noise series**.

Your turn

You can compute the daily changes in the Google stock price using

```
dgoog <- diff(goog)
```

Does dgoog look like white noise?