MONASH University

MONASH BUSINESS SCHOOL

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

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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	
Hourly		
Half-hourly		

`ts` objects and `ts` function

`ts(data, frequency, start)`

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Monthly	12	c(1995,9)
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Weekly	52.18	c(1995,23)
Hourly		
Half-hourly		

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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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Weekly	52.18	c(1995,23)
Hourly	24 *or* 168 *or* 8,766	1
Half-hourly		

`ts` objects and `ts` function

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ts(data, frequency, start)
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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)
```

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	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))
```

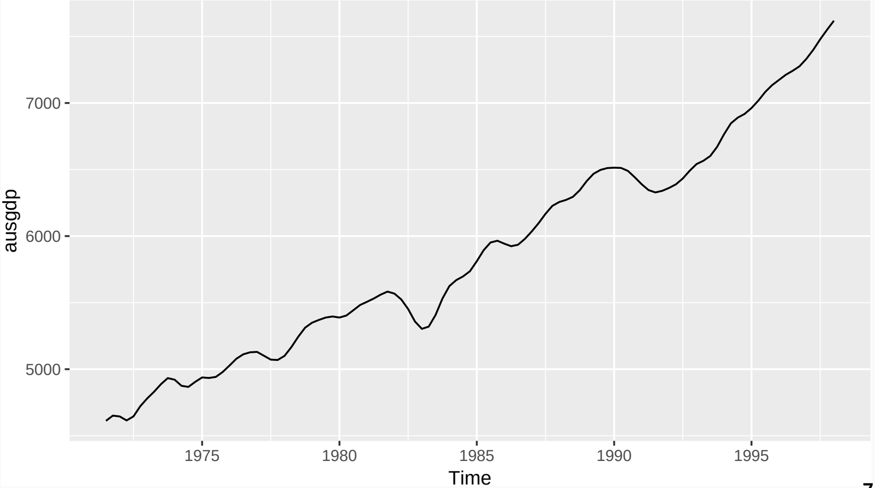
- Class: “ts”
- Print and plotting methods available.

```
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
```

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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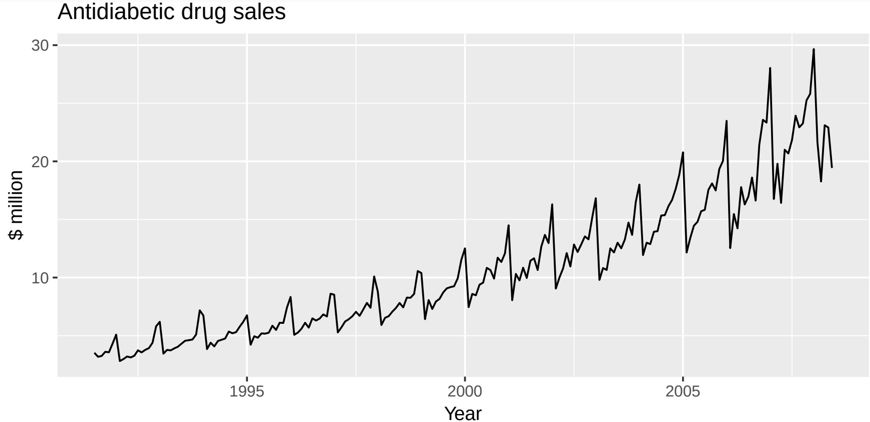
Time plots

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

Time plots

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

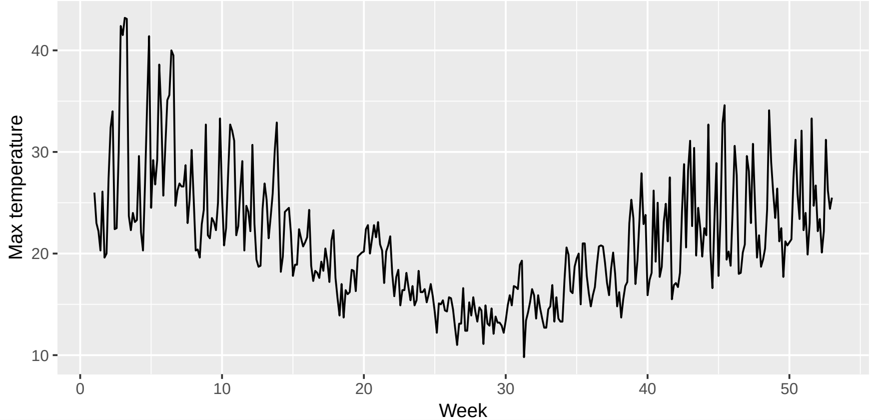


Your turn

- 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.

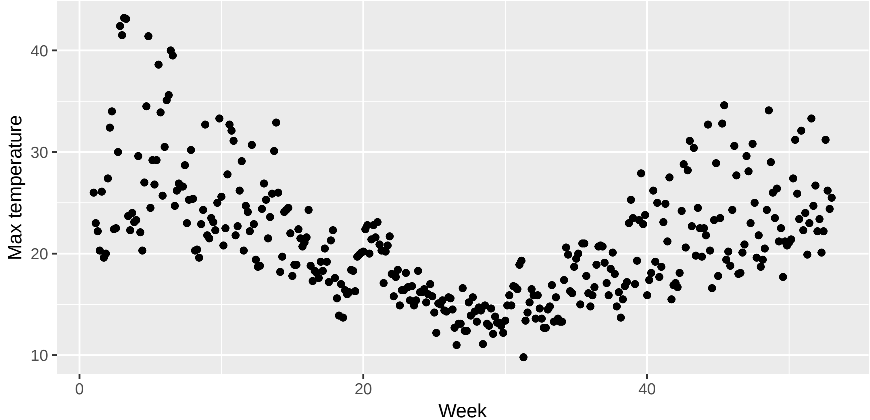
Are time plots best?

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

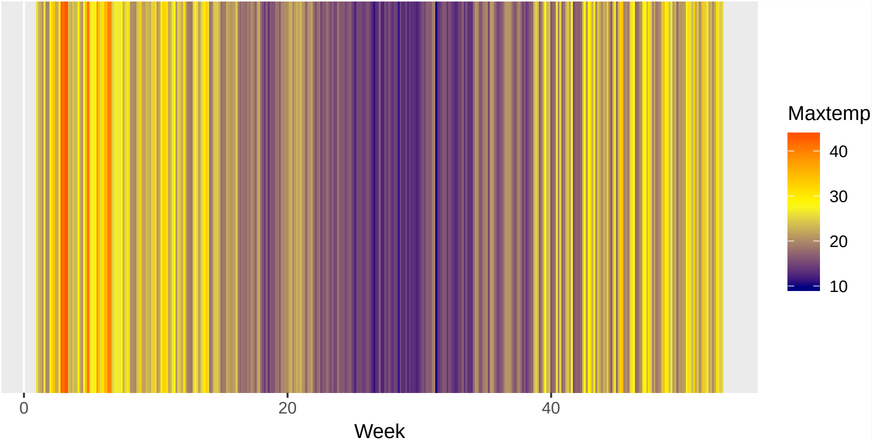


Are time plots best?

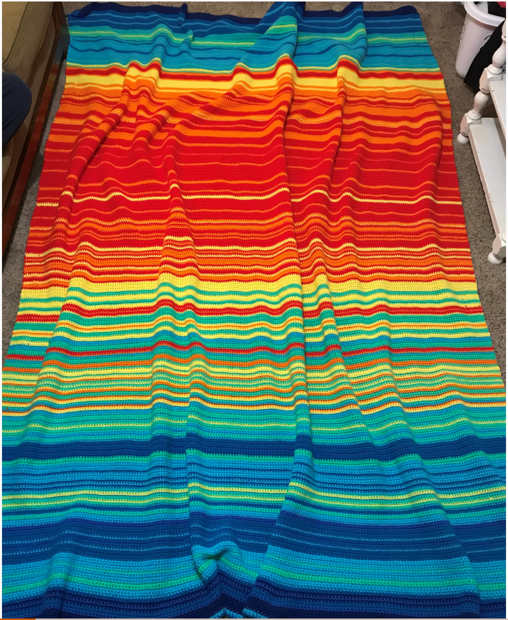
```r
qplot(time(elecdaily), elecdaily[,"Temperature"]) +
  xlab("Week") + ylab("Max temperature")
```



Are time plots best?



Are time plots best?

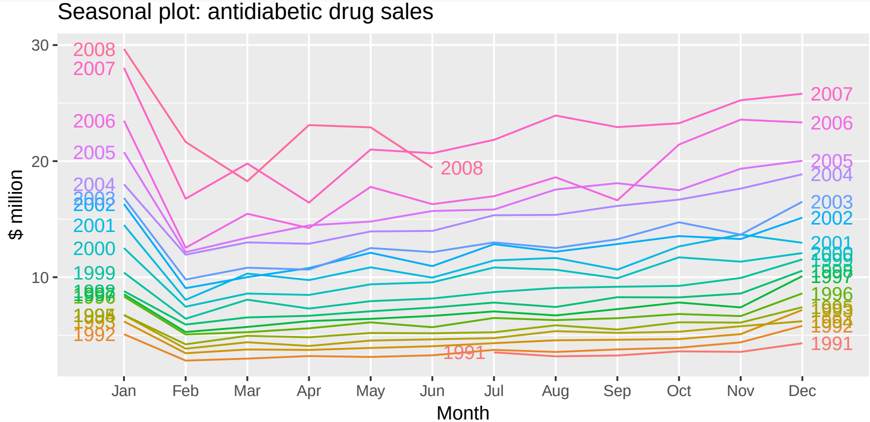


Outline

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

Seasonal plots

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

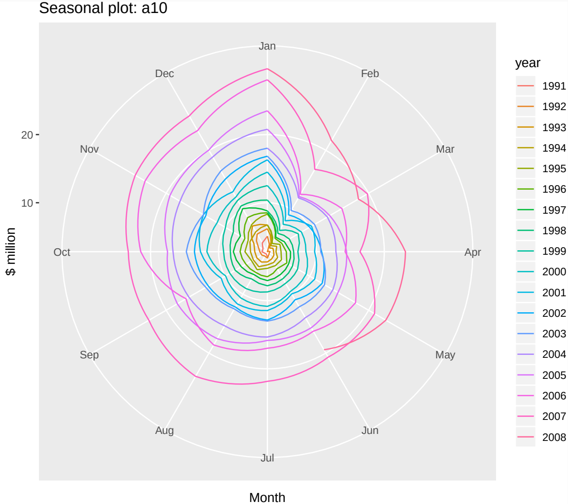


Seasonal plots

- 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()`

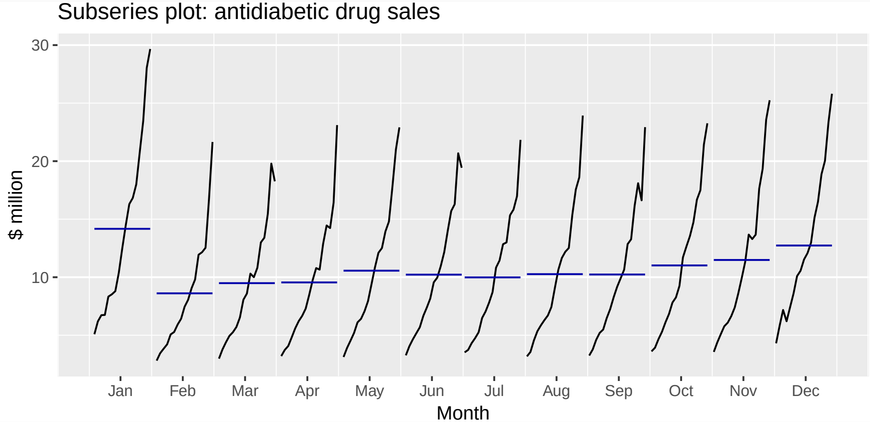
Seasonal polar plots

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



Seasonal subseries plots

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

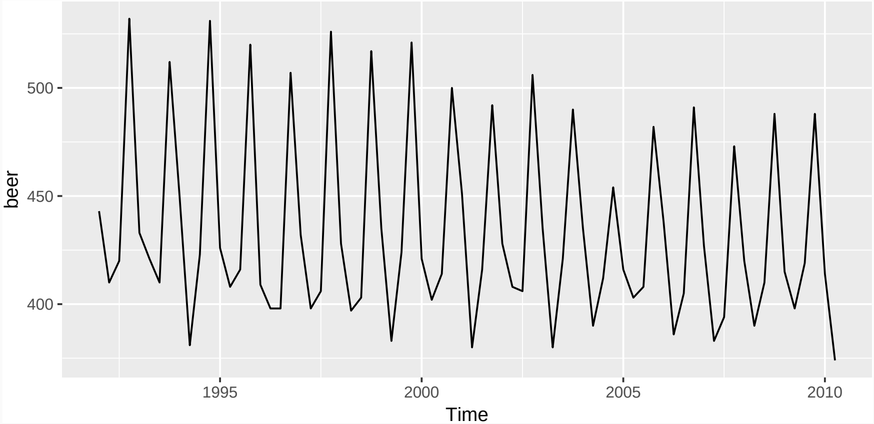


Seasonal subseries plots

- 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()`

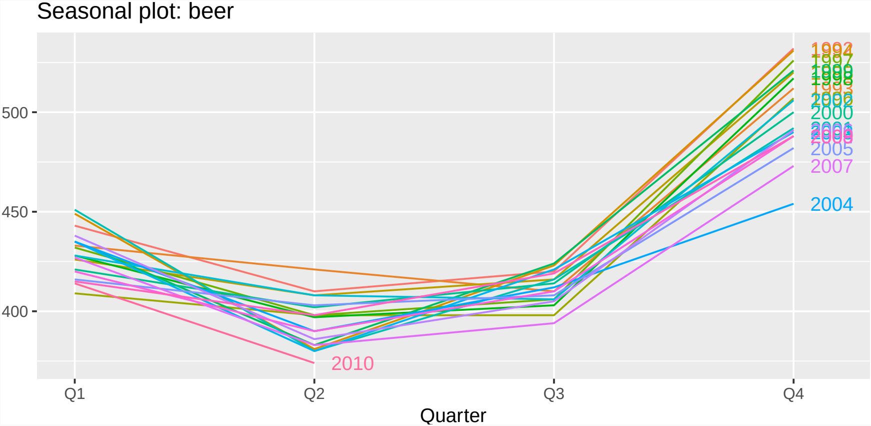
Quarterly Australian Beer Production

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



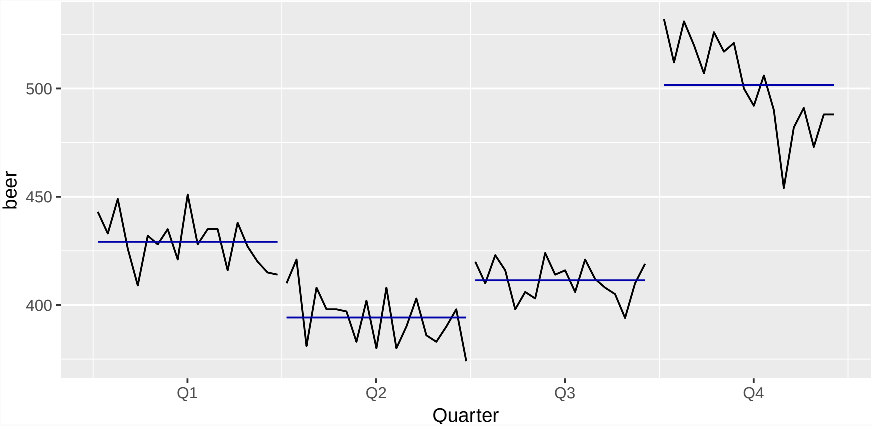
Quarterly Australian Beer Production

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



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).

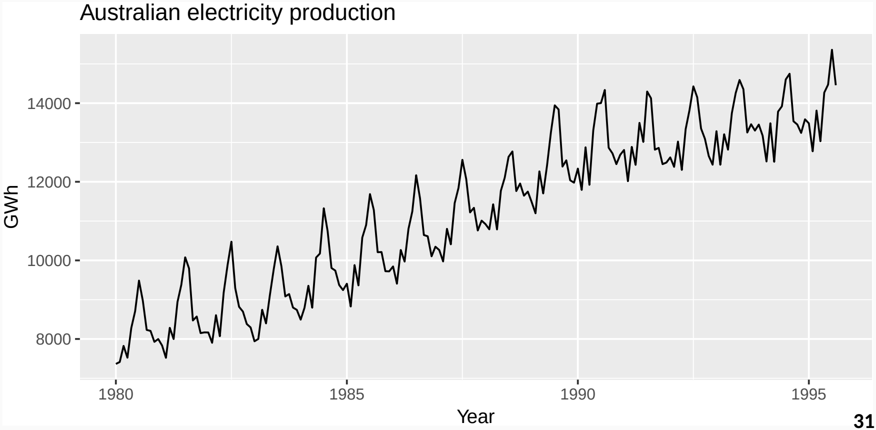
Time series components

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

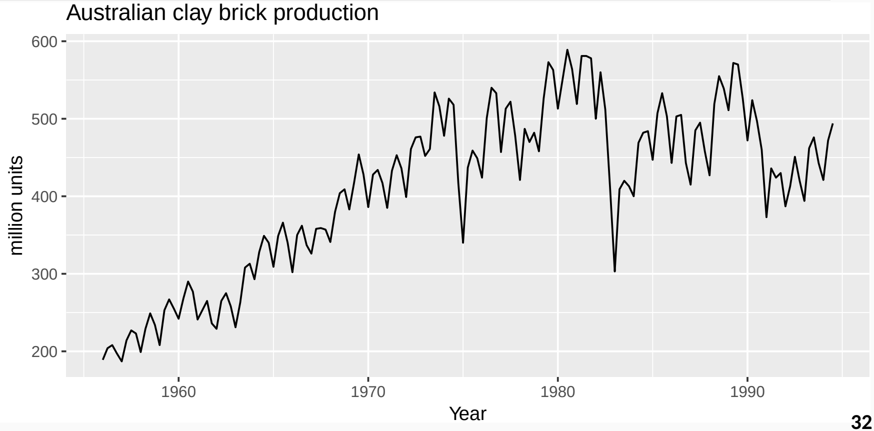
Time series patterns

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



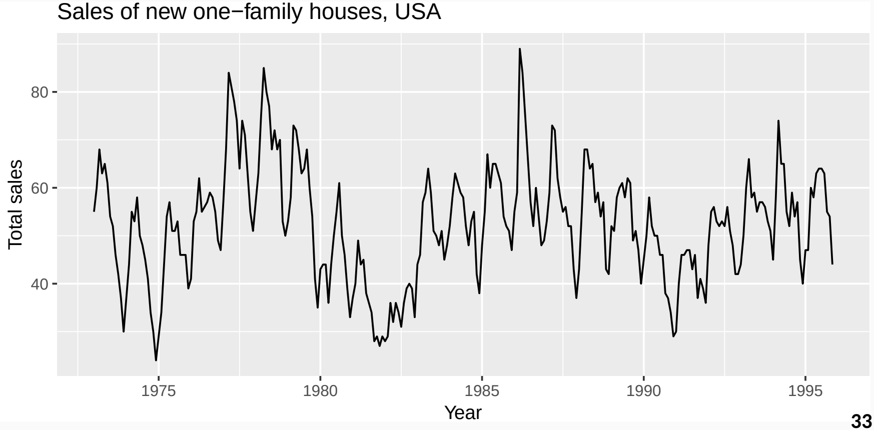
Time series patterns

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



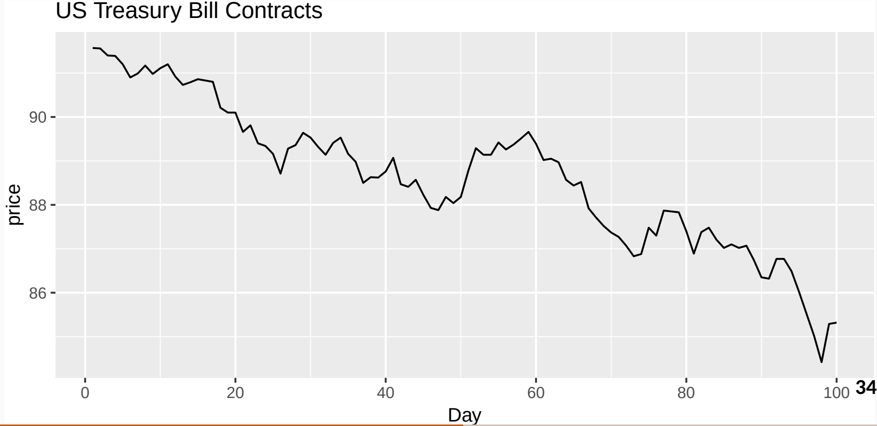
Time series patterns

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



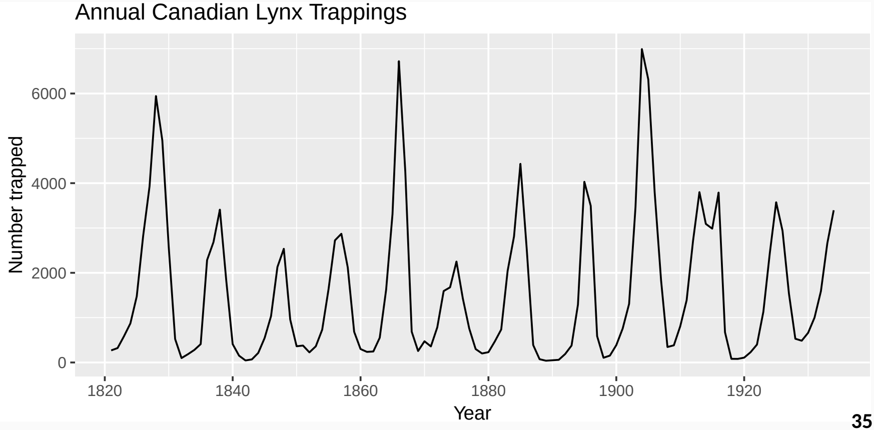
Time series patterns

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



Time series patterns

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



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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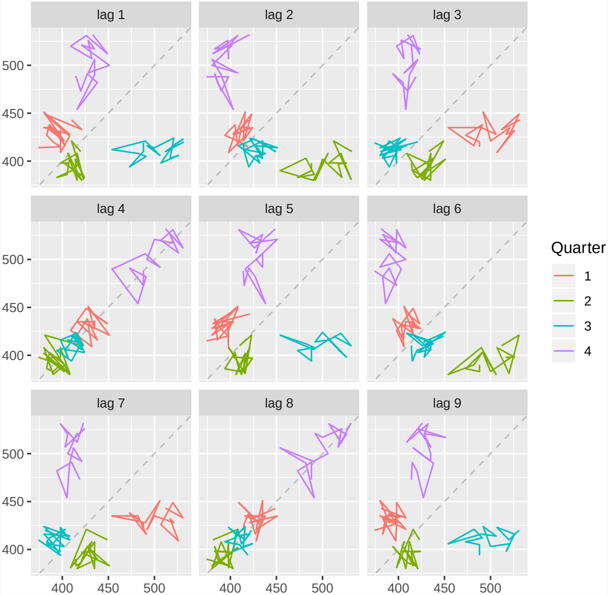
Example: Beer production

```
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.

Autocorrelation

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

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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.

We measure the relationship between:

- y_t and y_{t-1}
- y_t and y_{t-2}
- y_t and y_{t-3}
- etc.

Autocorrelation

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

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

$$\text{and} \qquad r_k = c_k / c_0$$

Autocorrelation

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$$\text{and} \qquad r_k = c_k/c_0$$

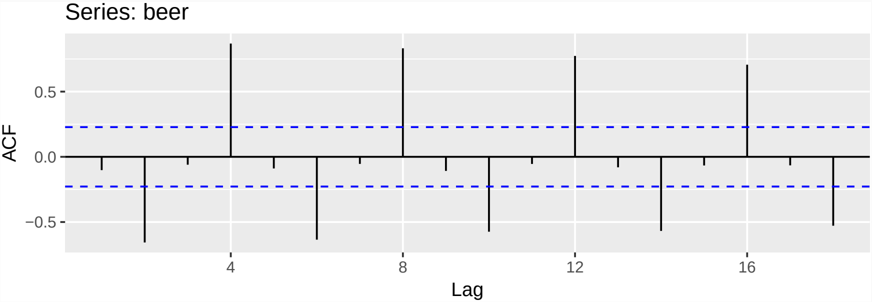
- r_1 indicates how successive values of y relate to each other
- r_2 indicates how y values two periods apart relate to each other
- r_k is *almost* the same as the sample correlation between y_t and y_{t-k}.

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

```r
ggAcf(beer)
```

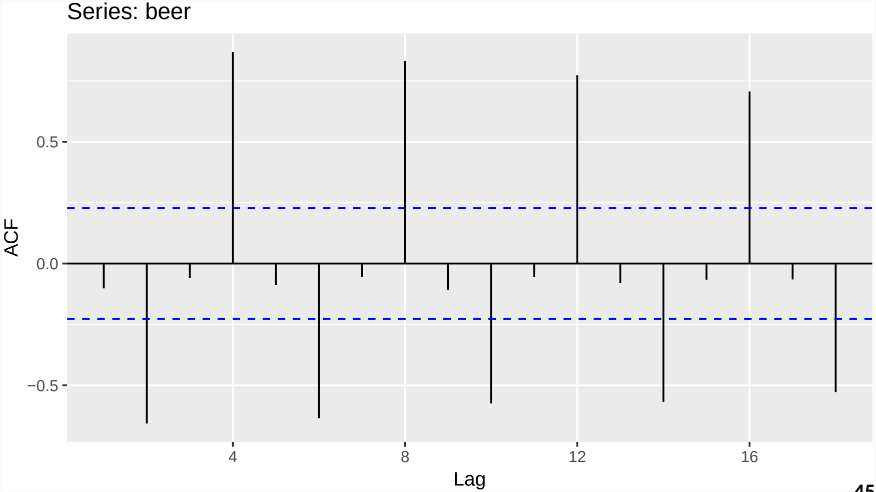


Autocorrelation

- 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, $\ldots$, make up the *autocorrelation* or ACF.
- The plot is known as a **correlogram**

ACF

```
ggAcf(beer)
```

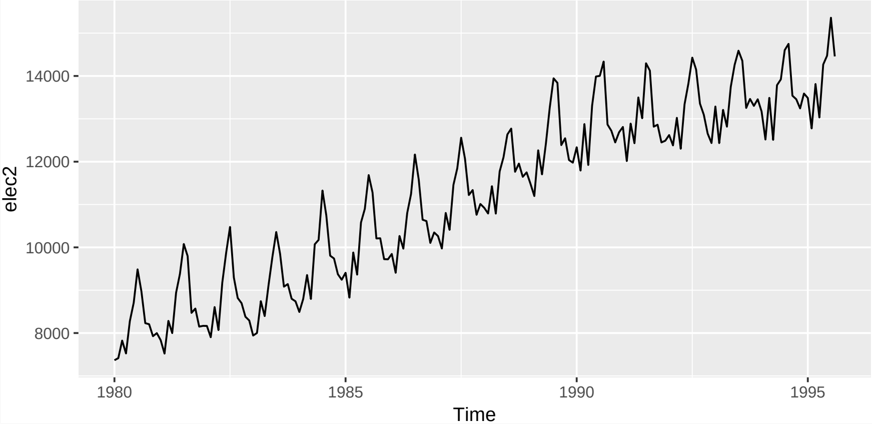


Trend and seasonality in ACF plots

- 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.

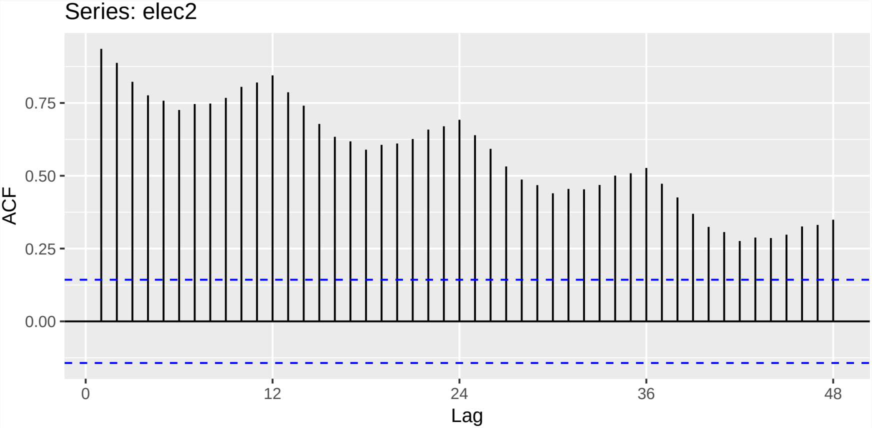
Aus monthly electricity production

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



Aus monthly electricity production

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



Aus monthly electricity production

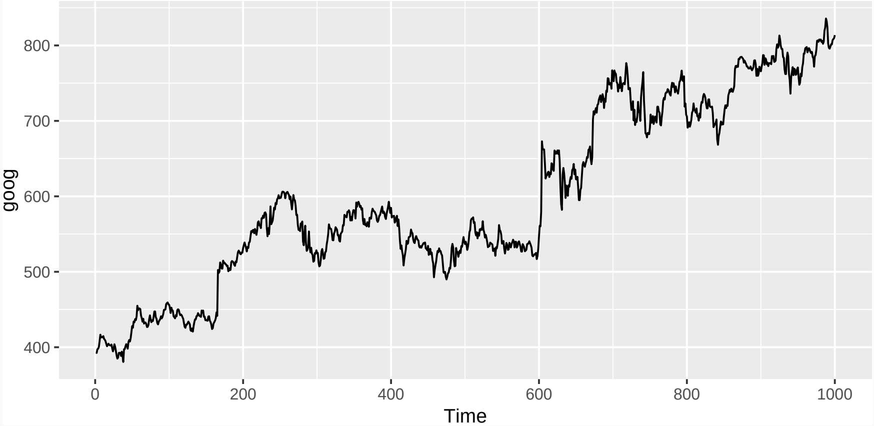
Time plot shows clear trend and seasonality.

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.

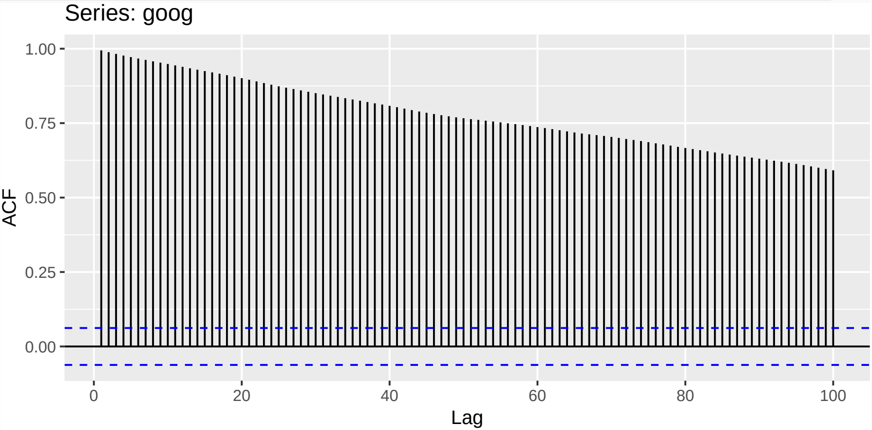
Google stock price

```
autoplot(goog)
```



Google stock price

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



Your turn

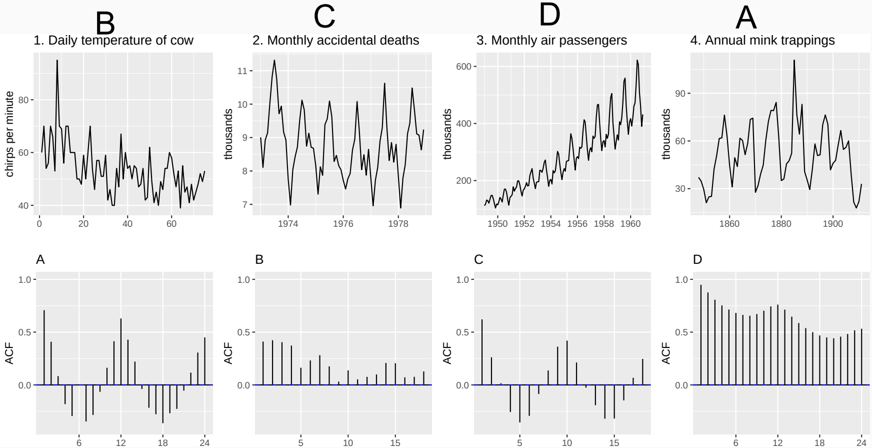
We have introduced the following graphics functions:

- `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?



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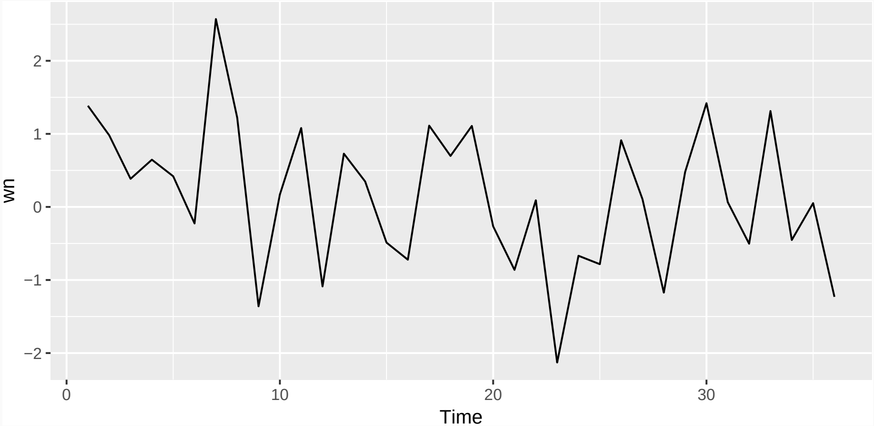
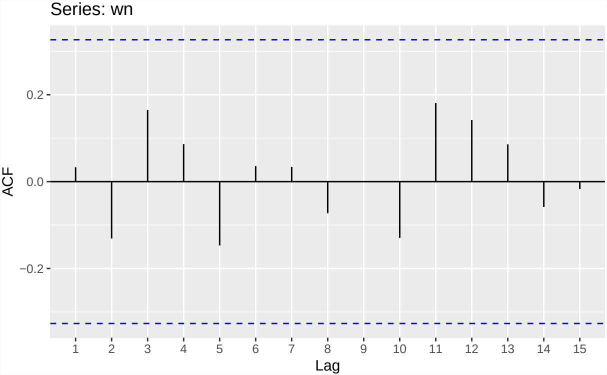
Example: White noise

```
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$(0,1/T)$.

Sampling distribution of autocorrelations

t rising, critical value drops.

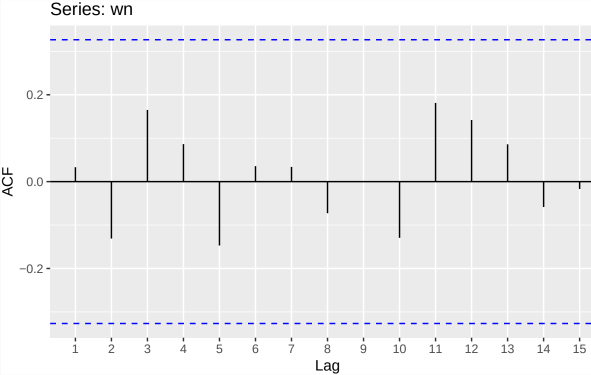
Sampling distribution of r_k for white noise data is asymptotically N(0,1/T).

- 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.)

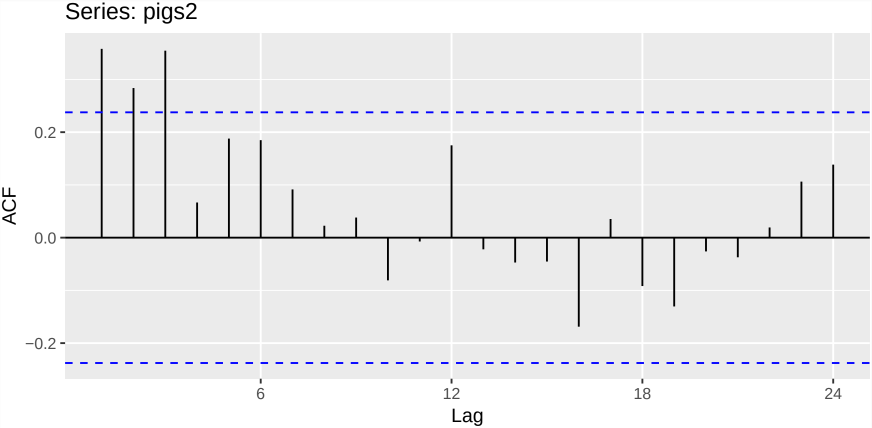


Example: Pigs slaughtered

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

Example: Pigs slaughtered

```
ggAcf(pigs2)
```



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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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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?