MONASH University

MONASH BUSINESS SCHOOL

ETC3550 Applied forecasting for business and economics

Ch2. Time series graphics

OTexts.org/fpp3/

Outline

Outline

`tsibble` objects

A `tsibble` allows storage and manipulation of time series in R.

It contains:

- Measured variable(s): numbers of interest
- Key variable(s): unique identifiers for each series
- An index: time information about the observation

tsibble objects

Example

```
library(tsibble)
y <- tsibble(year = 2012:2016, y = c(123,39,78
print(y)
```

```
## # A tsibble: 5 x 2 [1Y]
##    year     y
##   <int> <dbl>
## 1  2012   123
## 2  2013    39
## 3  2014    78
## 4  2015    52
```

Seasonal periods

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

Seasonal periods

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

Seasonal periods

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

Seasonal periods

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

Seasonal periods

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

Seasonal periods

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

Seasonal periods

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

Seasonal periods

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		

Seasonal periods

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		

Seasonal periods

Type of data	frequency	start example
Annual	1	1995
Quarterly	4	c(1995,2)
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Weekly	52.18	
Hourly		
Half-hourly		

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Half-hourly		

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Monthly	12	c(1995,9)
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Weekly	52.18	c(1995,23)
Hourly	24 *or* 168 *or* 8,766	
Half-hourly		

Seasonal periods

Type of data	frequency	start example
Annual	1	1995
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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	

Seasonal periods

Type of data	frequency	start example
Annual	1	1995
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Monthly	12	c(1995,9)
Daily	7 *or* 365.25	1 *or* c(1995,234)
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Hourly	24 *or* 168 *or* 8,766	1
Half-hourly	48 *or* 336 *or* 17,532	1

Australian GDP

```
ausgdp <- as_tsibble(x, index = Time)
```

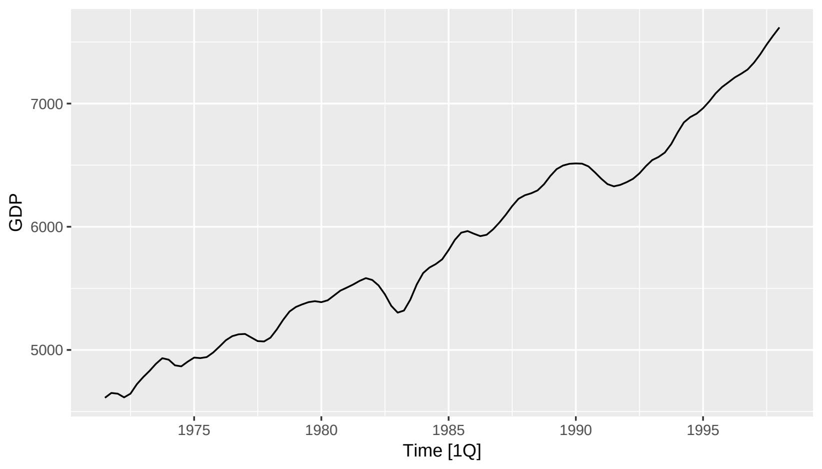
- Object: “tsibble”
- Print and plotting methods available.

```
ausgdp
```

```
## # A tsibble: 107 x 2 [1Q]
##         Time   GDP
##        <qtr> <dbl>
##   1 1971 Q3   4612
##   2 1971 Q4   4651
##   3 1972 Q1   4645
##   4 1972 Q2   4615
##   5 1972 Q3   4645
```

Australian GDP

```r
ausgdp %>% autoplot(GDP)
```



Residential electricity sales

```
elecsales
```

```
## # A tsibble: 20 x 2 [1Y]
##     Year   GWh
##    <dbl> <dbl>
##  1  1989 2354.
##  2  1990 2380.
##  3  1991 2319.
##  4  1992 2469.
##  5  1993 2386.
##  6  1994 2569.
##  7  1995 2576.
##  8  1996 2763.
##  9  1997 2844.
```

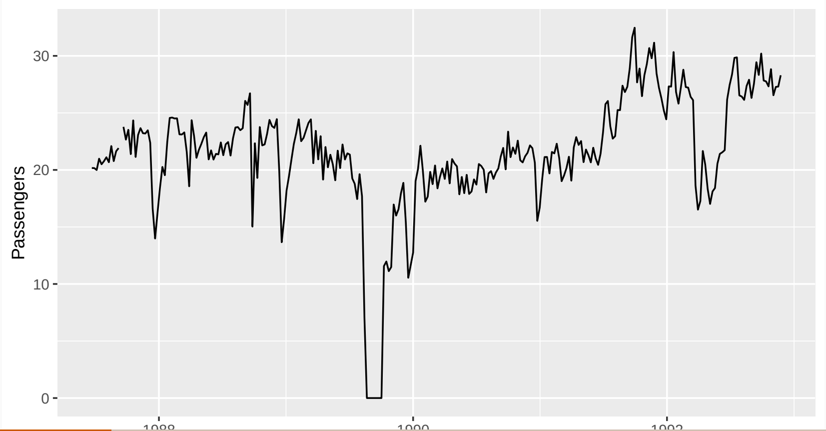
Class packages

```
library(tidyverse) # Data manipulation functio
library(fable) # Forecasting functions
library(feasts) # Time series graphics and sta
library(tsibbledata) # Tidy time series data
library(fma) # Lots more time series data
```

Outline

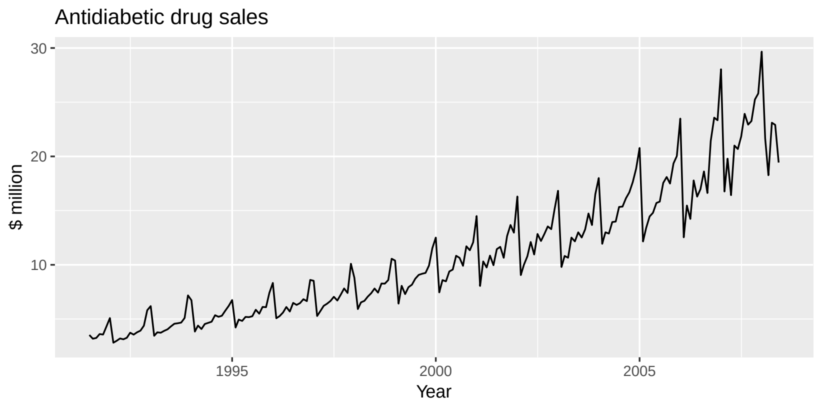
Time plots

```
melsyd %>%
  filter(Class == "Economy.Class") %>%
  autoplot(Passengers)
```



Time plots

```
a10 %>% autoplot(Scripts) + ylab("$ million") + xlab("Y
  ggtitle("Antidiabetic drug sales")
```

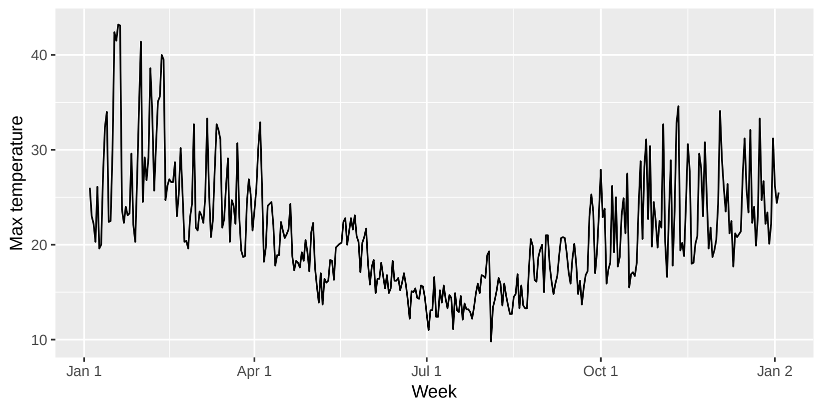


Your turn

- 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.

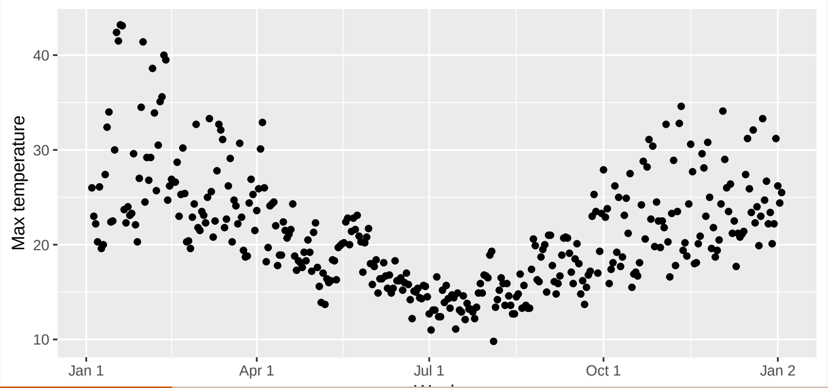
Are time plots best?

```
elecdaily %>%
  autoplot(Temperature) +
  xlab("Week") + ylab("Max temperature")
```

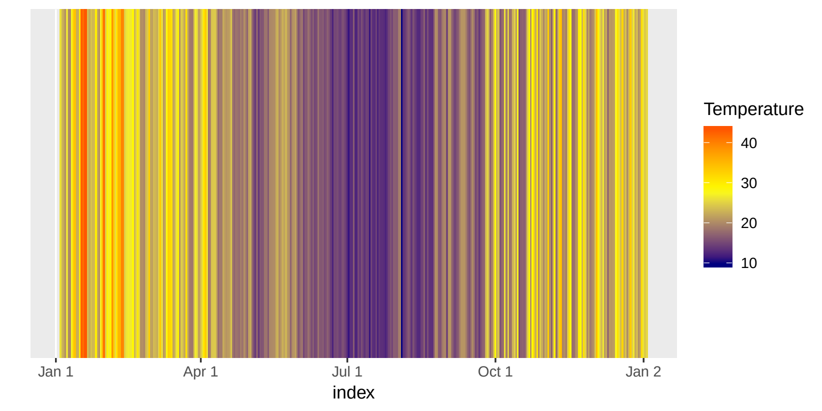


Are time plots best?

```
elecdaily %>%
  ggplot(aes(x = index, y = Temperature)) +
  geom_point() +
  xlab("Week") + ylab("Max temperature")
```



Are time plots best?

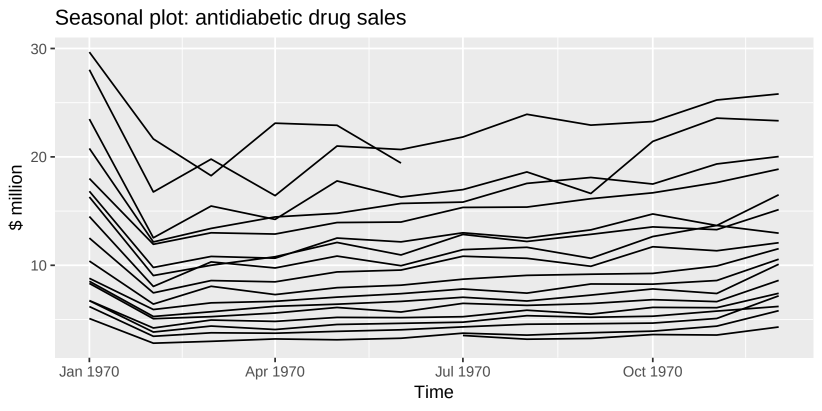


Are time plots best?

Outline

Seasonal plots

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



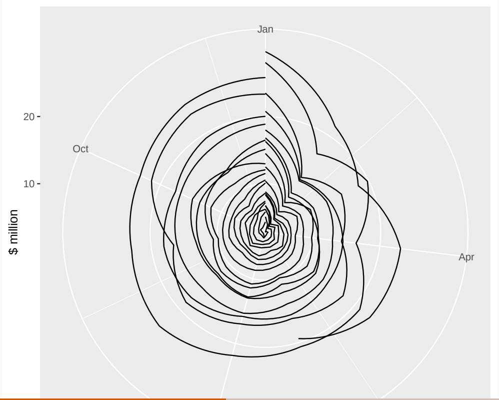
Seasonal plots

- 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

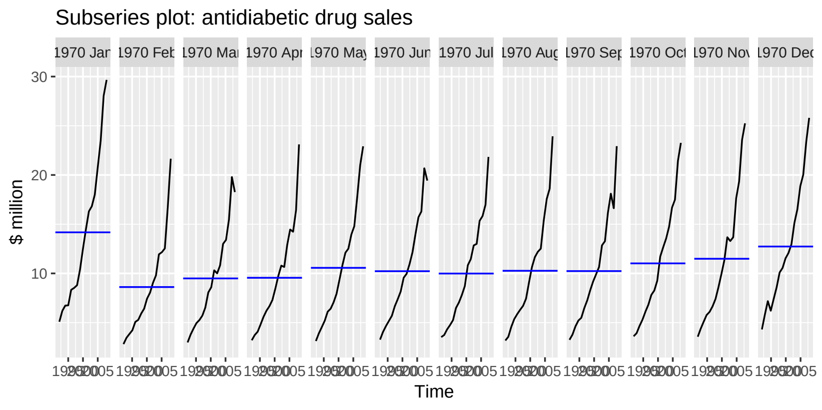
```r
a10 %>% ggseasonplot() + coord_polar() +
  ylab("$ million")
```

```
## Plot variable not specified, automatically selected
```



Seasonal subseries plots

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

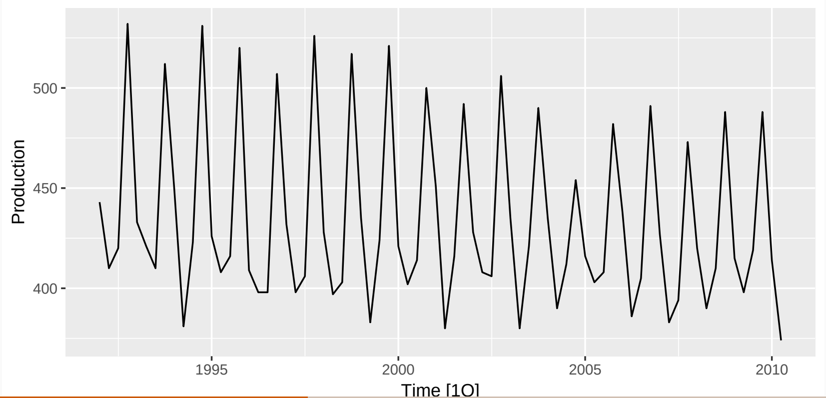


Seasonal subseries plots

- 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()`

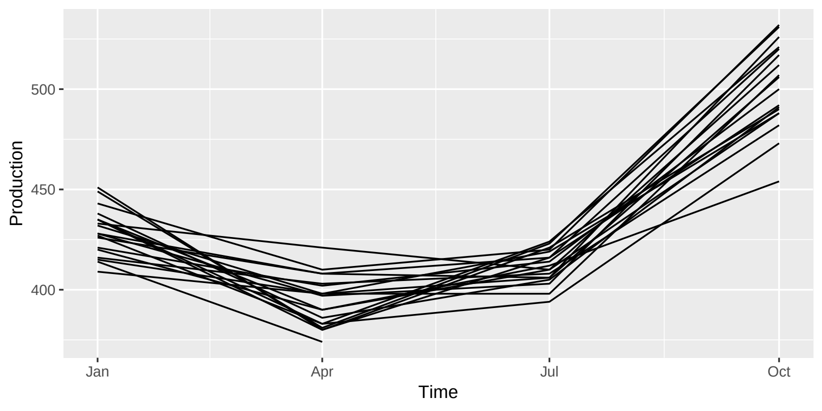
Quarterly Australian Beer Production

```
beer <- ausbeer %>%
  filter(year(Time) >= 1992)
beer %>% autoplot(Production)
```



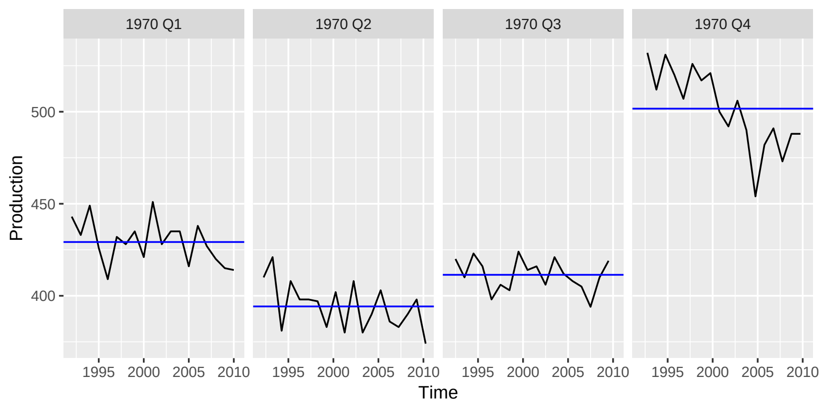
Quarterly Australian Beer Production

```
beer %>% ggseasonplot(Production, year.labels=
```



Quarterly Australian Beer Production

```
beer %>% ggsubseriesplot(Production)
```



Your turn

The `arrivals.csv` 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?

Outline

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).

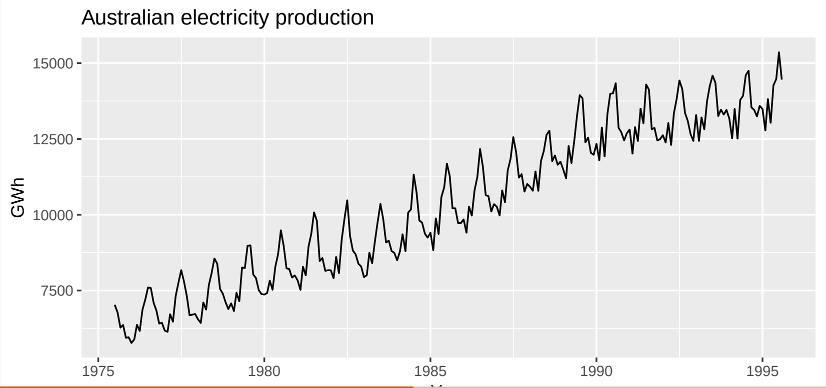
Time series components

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

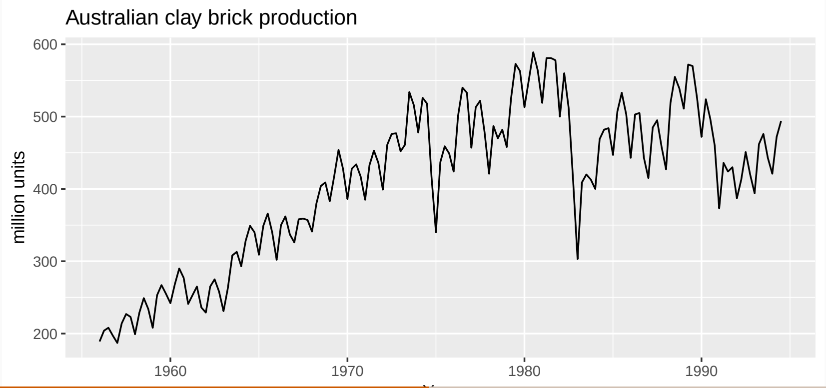
Time series patterns

```
as_tsibble(fma::elec) %>% filter(index >= 1980) %>%
  autoplot(value) +
  ggtitle("Australian electricity production") +
  xlab("Year") + ylab("GWh")
```



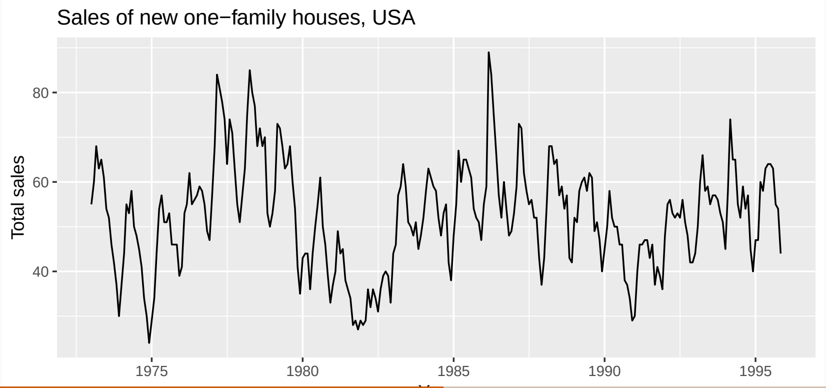
Time series patterns

```r
as_tsibble(fma::bricksq) %>%
  autoplot(value) +
  ggtitle("Australian clay brick production") +
  xlab("Year") + ylab("million units")
```



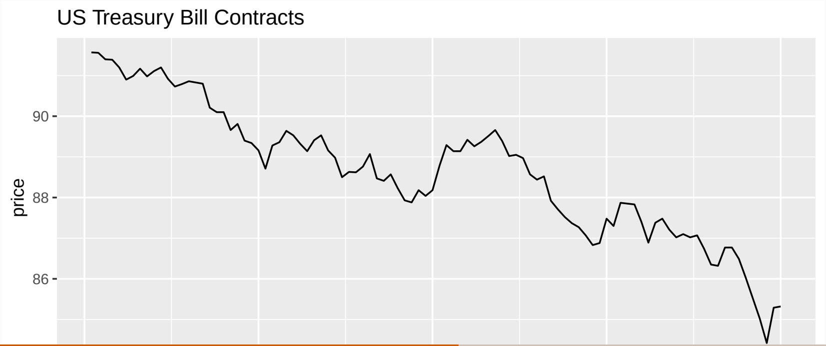
Time series patterns

```r
as_tsibble(fma::hsales) %>%
  autoplot(value) +
  ggtitle("Sales of new one-family houses, USA") +
  xlab("Year") + ylab("Total sales")
```



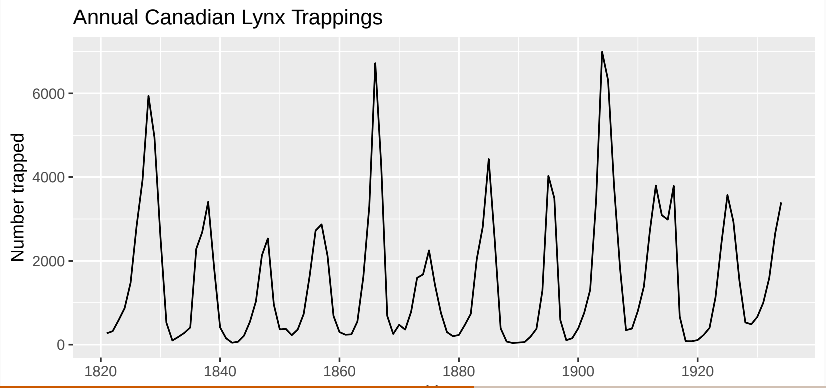
Time series patterns

```r
as_tsibble(fma::ustreas) %>%
  autoplot(value) +
  ggtitle("US Treasury Bill Contracts") +
  xlab("Day") + ylab("price")
```



Time series patterns

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



Seasonal or cyclic?

Differences between seasonal and cyclic patterns:

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Seasonal or cyclic?

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- 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.

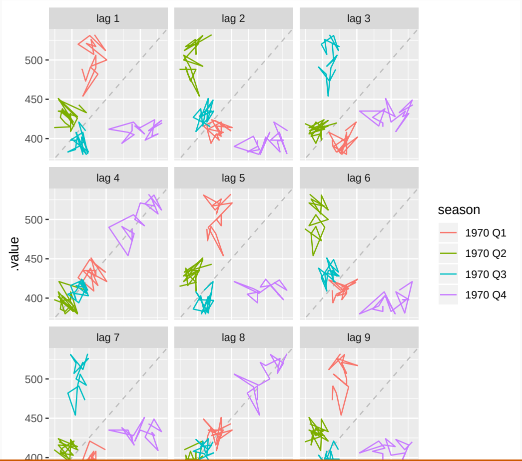
Outline

Example: Beer production

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

Example: Beer production

```
## Warning: Removed 1 rows containing missing
## (geom_path).
```



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

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

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

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

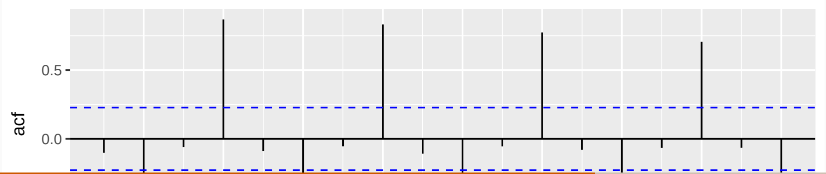
- r_1 indicates how successive values of y relate to each other
- r_2 indicates how y values two periods apart relate to each other
- r_k is *almost* the same as the sample correlation between y_t and y_{t-k}.

Autocorrelation

Results for first 9 lags for beer data:

```
## # A tsibble: 4 x 2 [1Q]
##      lag      acf
##    <lag>    <dbl>
## 1     1Q -0.102
## 2     2Q -0.657
## 3     3Q -0.0603
## 4     4Q  0.869
```

```
beer %>% ACF(Production) %>% autoplot
```

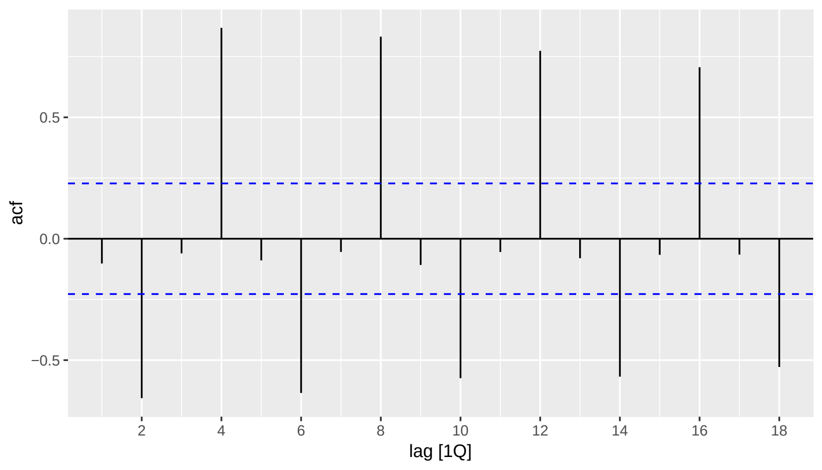


Autocorrelation

- 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**

ACF

```
beer %>% ACF(Production) %>% autoplot
```

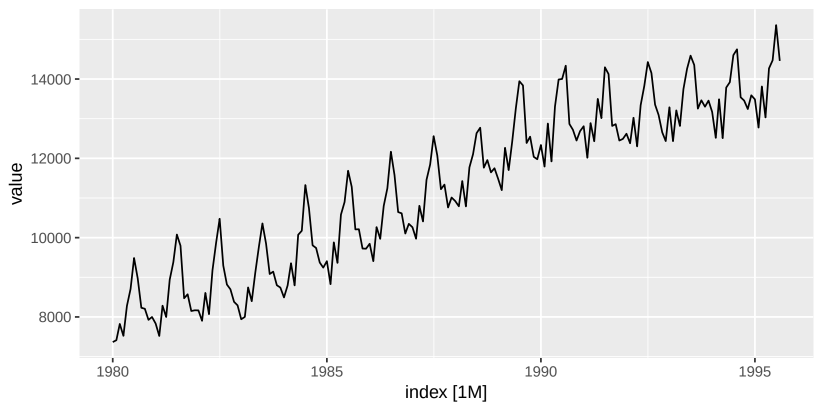


Trend and seasonality in ACF plots

- 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.

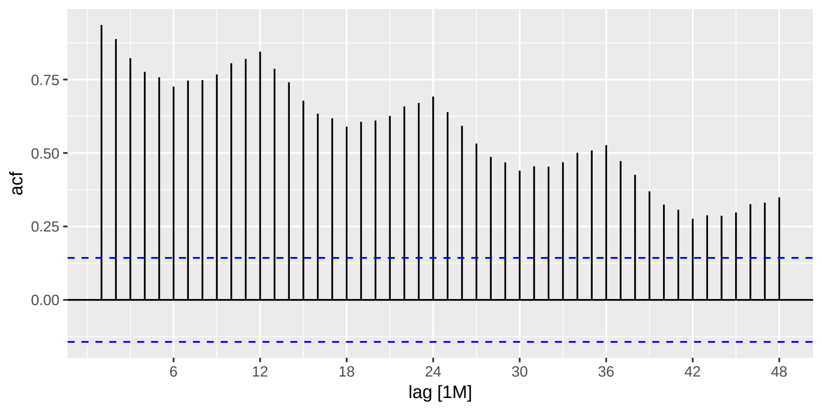
Aus monthly electricity production

```
elec2 <- as_tsibble(fma::elec) %>% filter(year
elec2 %>% autoplot(value)
```



Aus monthly electricity production

```
elec2 %>% ACF(value, lag.max=48) %>% autoplot(
```



Aus monthly electricity production

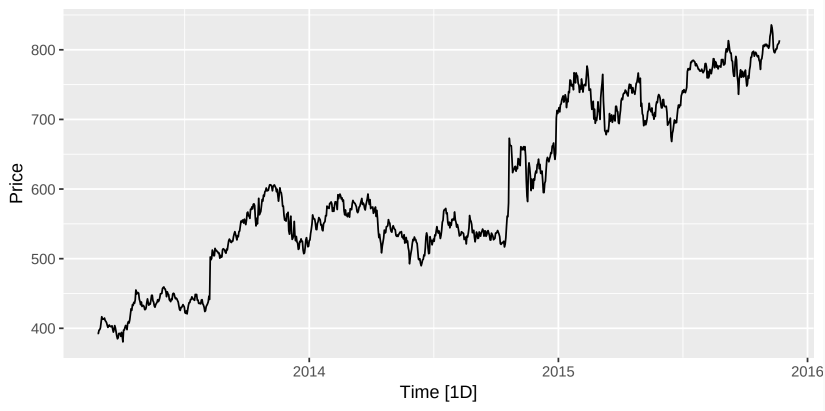
Time plot shows clear trend and seasonality.

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.

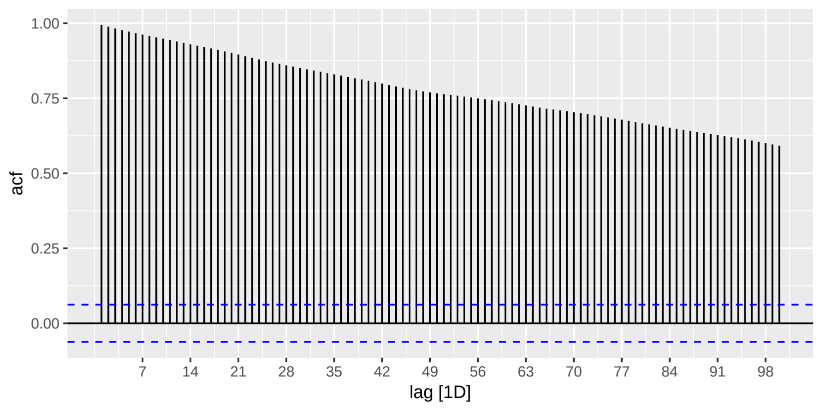
Google stock price

```
goog %>% autoplot(Price)
```



Google stock price

```
goog %>% ACF(Price, lag.max=100) %>% autoplot
```



Your turn

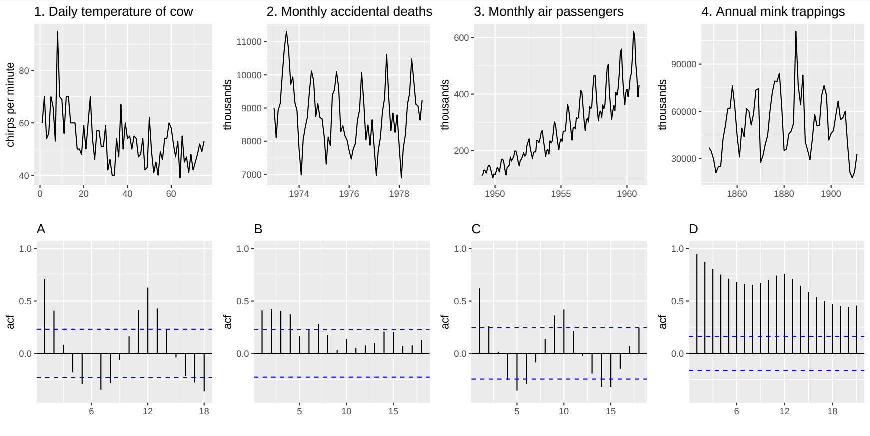
We have introduced the following functions:

- `gglagplot`
- `ACF`

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`

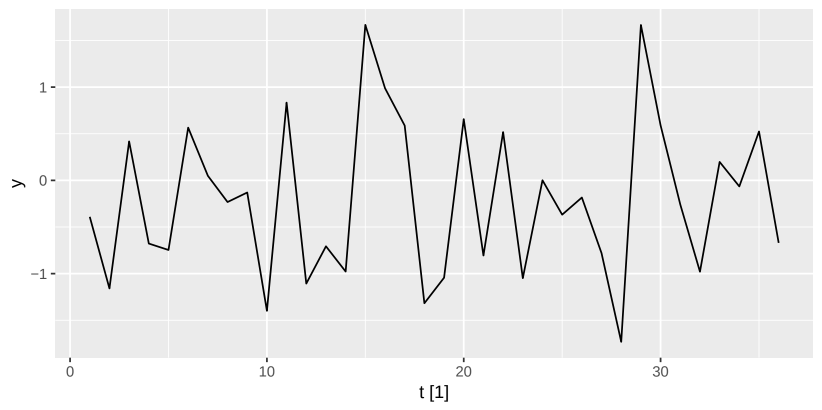
Which is which?



Outline

Example: White noise

```
wn <- tsibble(t = seq_len(36), y = rnorm(36),
wn %>% autoplot(y)
```



Example: White noise

Outline

Sampling distribution of autocorrelations

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

Sampling distribution of autocorrelations

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

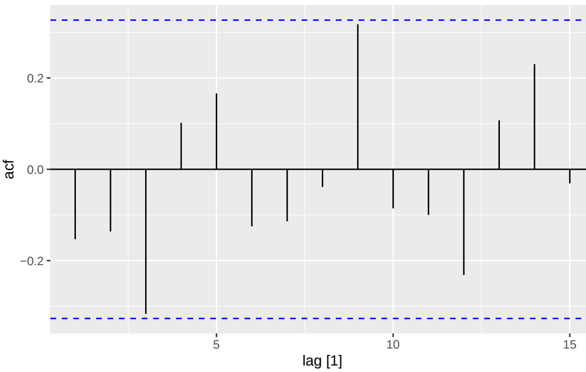
- 95% of all r_k for white noise must lie within $\pm 1.96/\sqrt{T}$.
- If this is not the case, the series is probably not WN.
- Common to plot lines at $\pm 1.96/\sqrt{T}$ when plotting ACF. These are the ***critical values***.

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.)

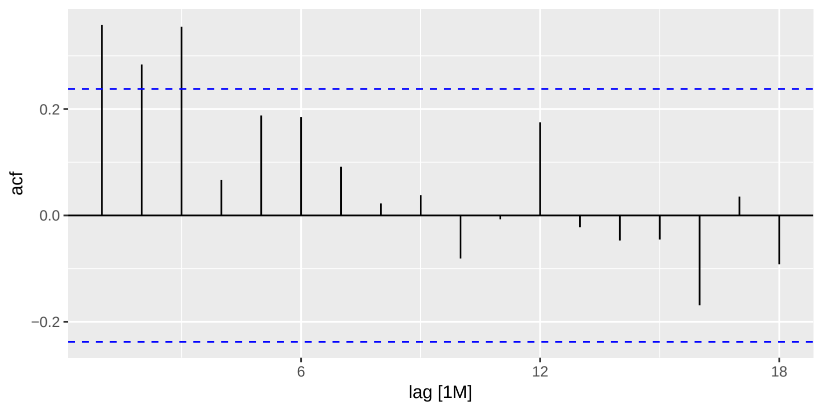


Example: Pigs slaughtered

```r
pigs2 <- as_tsibble(fma::pigs) %>% filter(year(index) >
pigs2 %>% autoplot(value) +
  xlab("Year") + ylab("thousands") +
  ggtitle("Number of pigs slaughtered in Victoria")
```

Example: Pigs slaughtered

```
pigs2 %>% ACF(value) %>% autoplot()
```



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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- ACF shows some significant autocorrelation at lags 1, 2, and 3.
- r_{12} relatively large although not significant. This may indicate some slight seasonality.

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.)

- Difficult to detect pattern in time plot.
- ACF shows some significant autocorrelation at lags 1, 2, and 3.
- r_{12} relatively large although not significant. This may indicate some slight seasonality.

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 <- goog %>%
  mutate(diff = Price - lag(Price))
```

Does `dgoog` look like white noise?