

ETC3550/ETC5550

Applied forecasting

Ch2. Time series graphics

OTexts.org/fpp3/



Outline

- 1 Time series in R
- 2 Example: Australian prison population
- 3 Example: Australian pharmaceutical sales
- 4 Time plots
- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

Outline

1 Time series in R

2 Example: Australian prison population

3 Example: Australian pharmaceutical sales

4 Time plots

5 Seasonal and subseries plots

6 Lag plots and autocorrelation

7 White noise

tsibble objects

```
global_economy
```

```
## # A tsibble: 15,150 x 6 [1Y]
## # Key:      Country [263]
## #       Year Country          GDP Imports Exports Population
## #   <dbl> <fct>        <dbl>    <dbl>    <dbl>      <dbl>
## 1 1960 Afghanistan 5377777811.    7.02     4.13    8996351
## 2 1961 Afghanistan 548888896.     8.10     4.45    9166764
## 3 1962 Afghanistan 546666678.     9.35     4.88    9345868
## 4 1963 Afghanistan 751111191.    16.9     9.17    9533954
## 5 1964 Afghanistan 800000044.    18.1     8.89    9731361
## 6 1965 Afghanistan 1006666638.    21.4    11.3    9938414
## 7 1966 Afghanistan 1399999967.    18.6     8.57   10152331
## 8 1967 Afghanistan 1673333418.    14.2     6.77   10372630
## 9 1968 Afghanistan 1373333367.    15.2     8.90   10604346
## 10 1969 Afghanistan 1408888922.    15.0    10.1    10854428
```

tsibble objects

```
global_economy
```

```
## # A tsibble: 15,150 x 6 [1Y]
## # Key:      Country [263]
## #       Year Country          GDP Imports Exports Population
## #   Index <fct>     <dbl>    <dbl>    <dbl>     <dbl>
## 1 1960 Afghanistan 5377777811.    7.02     4.13    8996351
## 2 1961 Afghanistan 548888896.    8.10     4.45    9166764
## 3 1962 Afghanistan 546666678.    9.35     4.88    9345868
## 4 1963 Afghanistan 751111191.   16.9     9.17    9533954
## 5 1964 Afghanistan 800000044.   18.1     8.89    9731361
## 6 1965 Afghanistan 1006666638.   21.4    11.3    9938414
## 7 1966 Afghanistan 1399999967.   18.6     8.57   10152331
## 8 1967 Afghanistan 1673333418.   14.2     6.77   10372630
## 9 1968 Afghanistan 1373333367.   15.2     8.90   10604346
## 10 1969 Afghanistan 1408888922.   15.0    10.1    10854428
```

tsibble objects

```
global_economy
```

```
## # A tsibble: 15,150 x 6 [1Y]
## # Key:      Country [263]
## #       Year Country          GDP Imports Exports Population
## #   Index   Key        <dbl>    <dbl>    <dbl>     <dbl>
## # 1 1960 Afghanistan 5377777811.    7.02     4.13 8996351
## # 2 1961 Afghanistan 548888896.    8.10     4.45 9166764
## # 3 1962 Afghanistan 546666678.    9.35     4.88 9345868
## # 4 1963 Afghanistan 751111191.   16.9     9.17 9533954
## # 5 1964 Afghanistan 800000044.   18.1     8.89 9731361
## # 6 1965 Afghanistan 1006666638.   21.4    11.3 9938414
## # 7 1966 Afghanistan 1399999967.   18.6     8.57 10152331
## # 8 1967 Afghanistan 1673333418.   14.2     6.77 10372630
## # 9 1968 Afghanistan 1373333367.   15.2     8.90 10604346
## # 10 1969 Afghanistan 1408888922.   15.0    10.1 10854428
```

tsibble objects

```
global_economy
```

```
## # A tsibble: 15,150 x 6 [1Y]
## # Key:      Country [263]
## #       Year Country          GDP Imports Exports Population
## #   Index   Key
## # 1 1960 Afghanistan 537777811.    7.02   4.13  8996351
## # 2 1961 Afghanistan 548888896.    8.10   4.45  9166764
## # 3 1962 Afghanistan 546666678.    9.35   4.88  9345868
## # 4 1963 Afghanistan 751111191.   16.9    9.17  9533954
## # 5 1964 Afghanistan 800000044.   18.1    8.89  9731361
## # 6 1965 Afghanistan 1006666638.   21.4   11.3   9938414
## # 7 1966 Afghanistan 1399999967.   18.6   8.57  10152331
## # 8 1967 Afghanistan 1673333418.   14.2   6.77  10372630
## # 9 1968 Afghanistan 1373333367.   15.2   8.90  10604346
## # 10 1969 Afghanistan 1408888922.   15.0   10.1   10854428
```

tsibble objects

tourism

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:      Region, State, Purpose [304]
##   Quarter Region  State Purpose Trips
##       <qtr>  <chr>    <chr>  <chr>    <dbl>
## 1 1998   Q1 Adelaide SA Business  135.
## 2 1998   Q2 Adelaide SA Business  110.
## 3 1998   Q3 Adelaide SA Business  166.
## 4 1998   Q4 Adelaide SA Business  127.
## 5 1999   Q1 Adelaide SA Business  137.
## 6 1999   Q2 Adelaide SA Business  200.
## 7 1999   Q3 Adelaide SA Business  169.
## 8 1999   Q4 Adelaide SA Business  134.
## 9 2000   Q1 Adelaide SA Business  154.
## 10 2000  Q2 Adelaide SA Business  169.
```

tsibble objects

tourism

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:      Region, State, Purpose [304]
##   Quarter Region  State Purpose Trips
##   Index     <chr>    <chr>  <chr>    <dbl>
## 1 1998   Q1 Adelaide SA  Business  135.
## 2 1998   Q2 Adelaide SA  Business  110.
## 3 1998   Q3 Adelaide SA  Business  166.
## 4 1998   Q4 Adelaide SA  Business  127.
## 5 1999   Q1 Adelaide SA  Business  137.
## 6 1999   Q2 Adelaide SA  Business  200.
## 7 1999   Q3 Adelaide SA  Business  169.
## 8 1999   Q4 Adelaide SA  Business  134.
## 9 2000   Q1 Adelaide SA  Business  154.
## 10 2000  Q2 Adelaide SA  Business  169.
```

tsibble objects

tourism

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:      Region, State, Purpose [304]
## #   Quarter Region  State Purpose Trips
## #   Index     Keys          <dbl>
## # 1 1998 Q1 Adelaide SA Business 135.
## # 2 1998 Q2 Adelaide SA Business 110.
## # 3 1998 Q3 Adelaide SA Business 166.
## # 4 1998 Q4 Adelaide SA Business 127.
## # 5 1999 Q1 Adelaide SA Business 137.
## # 6 1999 Q2 Adelaide SA Business 200.
## # 7 1999 Q3 Adelaide SA Business 169.
## # 8 1999 Q4 Adelaide SA Business 134.
## # 9 2000 Q1 Adelaide SA Business 154.
## # 10 2000 Q2 Adelaide SA Business 169.
```

tsibble objects

tourism

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:      Region, State, Purpose [304]
##   Quarter Region  State Purpose Trips
##   Index     Keys          Measure
## 1 1998 Q1 Adelaide SA Business 135.
## 2 1998 Q2 Adelaide SA Business 110.
## 3 1998 Q3 Adelaide SA Business 166.
## 4 1998 Q4 Adelaide SA Business 127.
## 5 1999 Q1 Adelaide SA Business 137.
## 6 1999 Q2 Adelaide SA Business 200.
## 7 1999 Q3 Adelaide SA Business 169.
## 8 1999 Q4 Adelaide SA Business 134.
## 9 2000 Q1 Adelaide SA Business 154.
## 10 2000 Q2 Adelaide SA Business 169.
```

tsibble objects

tourism

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:      Region, State, Purpose [304]
## # Quarter Region  State Purpose Trips
## # Index     Keys          Measure
## # 1 1998 Q1 Adelaide SA Business 135.
## # 2 1998 Q2 Adelaide SA Business 110.
## # 3 1998 Q3 Adelaide SA Business 166.
## # 4 1998 Q4 Adelaide SA Business 127.
## # 5 1999 Q1 Adelaide SA Business 137.
## # 6 1999 Q2 Adelaide SA Business 200.
## # 7 1999 Q3 Adelaide SA Business 169.
## # 8 1999 Q4 Adelaide SA Business 134.
## # 9 2000 Q1 Adelaide SA Business 154.
## # 10 2000 Q2 Adelaide SA Business 169.
```

Domestic visitor nights in thousands by state/region and purpose.

tsibble objects

- A tsibble allows storage and manipulation of multiple time series in R.
- It contains:
 - ▶ An index: time information about the observation
 - ▶ Measured variable(s): numbers of interest
 - ▶ Key variable(s): optional unique identifiers for each series
- It works with tidyverse functions.

The tsibble index

Example

```
mydata <- tsibble(  
  year = 2012:2016,  
  y = c(123, 39, 78, 52, 110),  
  index = year  
)  
mydata
```

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

The tsibble index

Example

```
mydata <- tibble(  
  year = 2012:2016,  
  y = c(123, 39, 78, 52, 110)  
) %>%  
  as_tsibble(index = year)  
mydata
```

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

The tsibble index

For observations more frequent than once per year, we need to use a time class function on the index.

```
z  
## # A tibble: 5 x 2  
##   Month     Observation  
##   <chr>          <dbl>  
## 1 2019      Jan        50  
## 2 2019      Feb        23  
## 3 2019      Mar        34  
## 4 2019      Apr        30  
## 5 2019      May        25
```

The tsibble index

For observations more frequent than once per year, we need to use a time class function on the index.

```
z %>%
  mutate(Month = yearmonth(Month)) %>%
  as_tsibble(index = Month)
```

```
## # A tsibble: 5 x 2 [1M]
##      Month Observation
##      <mth>     <dbl>
## 1 2019 Jan      50
## 2 2019 Feb      23
## 3 2019 Mar      34
## 4 2019 Apr      30
```

The tsibble index

Common time index variables can be created with these functions:

Frequency	Function
Annual	<code>start:end</code>
Quarterly	<code>yearquarter()</code>
Monthly	<code>yearmonth()</code>
Weekly	<code>yearweek()</code>
Daily	<code>as_date(), ymd()</code>
Sub-daily	<code>as_datetime()</code>

Outline

1 Time series in R

2 Example: Australian prison population

3 Example: Australian pharmaceutical sales

4 Time plots

5 Seasonal and subseries plots

6 Lag plots and autocorrelation

7 White noise

Australian prison population



Read a csv file and convert to a tsibble

```
prison <- readr::read_csv("data/prison_population.csv")
```

```
## # A tibble: 3,072 x 6
##   date      state gender legal    indigenous count
##   <date>    <chr>  <chr>  <chr>    <chr>        <dbl>
## 1 2005-03-01 ACT    Female Remanded ATSI         0
## 2 2005-03-01 ACT    Female Remanded Other        2
## 3 2005-03-01 ACT    Female Sentenced ATSI         0
## 4 2005-03-01 ACT    Female Sentenced Other        0
## 5 2005-03-01 ACT    Male   Remanded ATSI        7
## 6 2005-03-01 ACT    Male   Remanded Other       58
## 7 2005-03-01 ACT    Male   Sentenced ATSI         0
## 8 2005-03-01 ACT    Male   Sentenced Other        0
## 9 2005-03-01 NSW   Female Remanded ATSI       51
## 10 2005-03-01 NSW   Female Remanded Other      131
## # ... with 3,062 more rows
```

Read a csv file and convert to a tsibble

```
prison <- readr::read_csv("data/prison_population.csv") %>%
  mutate(Quarter = yearquarter(date))
```

```
## # A tibble: 3,072 x 7
##   date      state gender legal    indigenous count Quarter
##   <date>    <chr> <chr>  <chr>    <chr>      <dbl>    <qtr>
## 1 2005-03-01 ACT   Female Remanded ATSI        0 2005 Q1
## 2 2005-03-01 ACT   Female Remanded Other       2 2005 Q1
## 3 2005-03-01 ACT   Female Sentenced ATSI       0 2005 Q1
## 4 2005-03-01 ACT   Female Sentenced Other      0 2005 Q1
## 5 2005-03-01 ACT   Male   Remanded ATSI       7 2005 Q1
## 6 2005-03-01 ACT   Male   Remanded Other      58 2005 Q1
## 7 2005-03-01 ACT   Male   Sentenced ATSI       0 2005 Q1
## 8 2005-03-01 ACT   Male   Sentenced Other      0 2005 Q1
## 9 2005-03-01 NSW  Female Remanded ATSI      51 2005 Q1
## 10 2005-03-01 NSW  Female Remanded Other     131 2005 Q1
```

Read a csv file and convert to a tsibble

```
prison <- readr::read_csv("data/prison_population.csv") %>%  
  mutate(Quarter = yearquarter(date)) %>%  
  select(-date)
```

```
## # A tibble: 3,072 x 6  
##   state gender legal    indigenous count Quarter  
##   <chr>  <chr>  <chr>      <chr>     <dbl>    <qtr>  
## 1 ACT    Female  Remanded  ATSI        0 2005 Q1  
## 2 ACT    Female  Remanded  Other       2 2005 Q1  
## 3 ACT    Female  Sentenced ATSI        0 2005 Q1  
## 4 ACT    Female  Sentenced Other       0 2005 Q1  
## 5 ACT    Male    Remanded  ATSI       7 2005 Q1  
## 6 ACT    Male    Remanded  Other      58 2005 Q1  
## 7 ACT    Male    Sentenced ATSI        0 2005 Q1  
## 8 ACT    Male    Sentenced Other       0 2005 Q1  
## 9 NSW    Female  Remanded  ATSI      51 2005 Q1
```

Read a csv file and convert to a tsibble

```
prison <- readr::read_csv("data/prison_population.csv") %>%  
  mutate(Quarter = yearquarter(date)) %>%  
  select(-date) %>%  
  as_tsibble(  
    index = Quarter,  
    key = c(state, gender, legal, indigenous)  
)
```

```
## # A tsibble: 3,072 x 6 [1Q]  
## # Key:      state, gender, legal, indigenous [64]  
##   state gender legal  indigenous count Quarter  
##   <chr>  <chr>  <chr>    <chr>     <dbl>   <qtr>  
## 1 ACT    Female  Remanded ATSI        0 2005 Q1  
## 2 ACT    Female  Remanded ATSI        1 2005 Q2  
## 3 ACT    Female  Remanded ATSI        0 2005 Q3  
## 4 ACT    Female  Remanded ATSI        0 2005 Q4
```

Outline

- 1 Time series in R
- 2 Example: Australian prison population
- 3 Example: Australian pharmaceutical sales
- 4 Time plots
- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

Australian Pharmaceutical Benefits Scheme



Australian Pharmaceutical Benefits Scheme

The **Pharmaceutical Benefits Scheme** (PBS) is the Australian government drugs subsidy scheme.

Australian Pharmaceutical Benefits Scheme

The **Pharmaceutical Benefits Scheme** (PBS) is the Australian government drugs subsidy scheme.

- Many drugs bought from pharmacies are subsidised to allow more equitable access to modern drugs.
- The cost to government is determined by the number and types of drugs purchased. Currently nearly 1% of GDP.
- The total cost is budgeted based on forecasts of drug usage.
- Costs are disaggregated by drug type (ATC1 x15 / ATC2 84), concession category (x2) and patient type (x2), giving $84 \times 2 \times 2 = 336$ time series.

Working with tsibble objects

PBS

```
## # A tsibble: 67,596 x 9 [1M]
## # Key:      Concession, Type, ATC1, ATC2 [336]
## # Month Concession  Type   ATC1  ATC1_desc ATC2  ATC2_desc Scripts  Cost
## # <mth> <chr>       <chr>  <chr>  <chr>    <chr>  <chr>    <dbl> <dbl>
## 1 1991 Jul Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  18228 67877
## 2 1991 Aug Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  15327 57011
## 3 1991 Sep Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  14775 55020
## 4 1991 Oct Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  15380 57222
## 5 1991 Nov Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  14371 52120
## 6 1991 Dec Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  15028 54299
## 7 1992 Jan Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  11040 39753
## 8 1992 Feb Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  15165 54405
## 9 1992 Mar Concessional Co-pay~ A     Alimenta~ A01  STOMATOL~  16898 61108
## 10 1992 Apr Concessional Co-pay~ A    Alimenta~ A01  STOMATOL~  18141 65356
## # ... with 67,586 more rows
```

Working with tsibble objects

We can use the filter() function to select rows.

```
PBS %>%  
  filter(ATC2 == "A10")
```

```
## # A tsibble: 816 x 9 [1M]  
## # Key:      Concession, Type, ATC1, ATC2 [4]  
##       Month Concession  Type   ATC1  ATC1_desc ATC2  ATC2_desc Scripts    Cost  
##       <mth> <chr>      <chr>  <chr>  <chr>     <chr>  <dbl>    <dbl>  
## 1 1991 Jul Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  89733 2.09e6  
## 2 1991 Aug Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  77101 1.80e6  
## 3 1991 Sep Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  76255 1.78e6  
## 4 1991 Oct Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  78681 1.85e6  
## 5 1991 Nov Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  70554 1.69e6  
## 6 1991 Dec Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  75814 1.84e6  
## 7 1992 Jan Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  64186 1.56e6  
## 8 1992 Feb Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  75899 1.73e6  
## 9 1992 Mar Concessional Co-pa~ A  Alimenta~ A10  ANTIDIAB~  89445 2.05e6
```

Working with tsibble objects

We can use the `select()` function to select columns.

```
PBS %>%  
  filter(ATC2 == "A10") %>%  
  select(Month, Concession, Type, Cost)
```

```
## # A tsibble: 816 x 4 [1M]  
## # Key:      Concession, Type [4]  
##   Month Concession  Type      Cost  
##   <mth> <chr>       <chr>     <dbl>  
## 1 1991 Jul Concessional Co-payments 2092878  
## 2 1991 Aug Concessional Co-payments 1795733  
## 3 1991 Sep Concessional Co-payments 1777231  
## 4 1991 Oct Concessional Co-payments 1848507  
## 5 1991 Nov Concessional Co-payments 1686458  
## 6 1991 Dec Concessional Co-payments 1843079  
## 7 1992 Jan Concessional Co-payments 1564702  
## 8 1992 Feb Concessional Co-payments 1732508
```

Working with tsibble objects

We can use the `summarise()` function to summarise over keys.

```
PBS %>%
  filter(ATC2 == "A10") %>%
  select(Month, Concession, Type, Cost) %>%
  summarise(total_cost = sum(Cost))
```

```
## # A tsibble: 204 x 2 [1M]
##       Month total_cost
##       <mth>     <dbl>
## 1 1991 Jul     3526591
## 2 1991 Aug     3180891
## 3 1991 Sep     3252221
## 4 1991 Oct     3611003
## 5 1991 Nov     3565869
## 6 1991 Dec     4306371
## 7 1992 Jan     5088335
## 8 1992 Feb     2814520
```

Working with tsibble objects

We can use the `mutate()` function to create new variables.

```
PBS %>%  
  filter(ATC2 == "A10") %>%  
  select(Month, Concession, Type, Cost) %>%  
  summarise(total_cost = sum(Cost)) %>%  
  mutate(total_cost = total_cost / 1e6)
```

```
## # A tsibble: 204 x 2 [1M]  
##       Month total_cost  
##     <mth>      <dbl>  
##   1 1991 Jul      3.53  
##   2 1991 Aug      3.18  
##   3 1991 Sep      3.25  
##   4 1991 Oct      3.61  
##   5 1991 Nov      3.57  
##   6 1991 Dec      4.31  
##   7 1992 Jan      5.09
```

Working with tsibble objects

We can use the `mutate()` function to create new variables.

```
PBS %>%  
  filter(ATC2 == "A10") %>%  
  select(Month, Concession, Type, Cost) %>%  
  summarise(total_cost = sum(Cost)) %>%  
  mutate(total_cost = total_cost / 1e6) -> a10
```

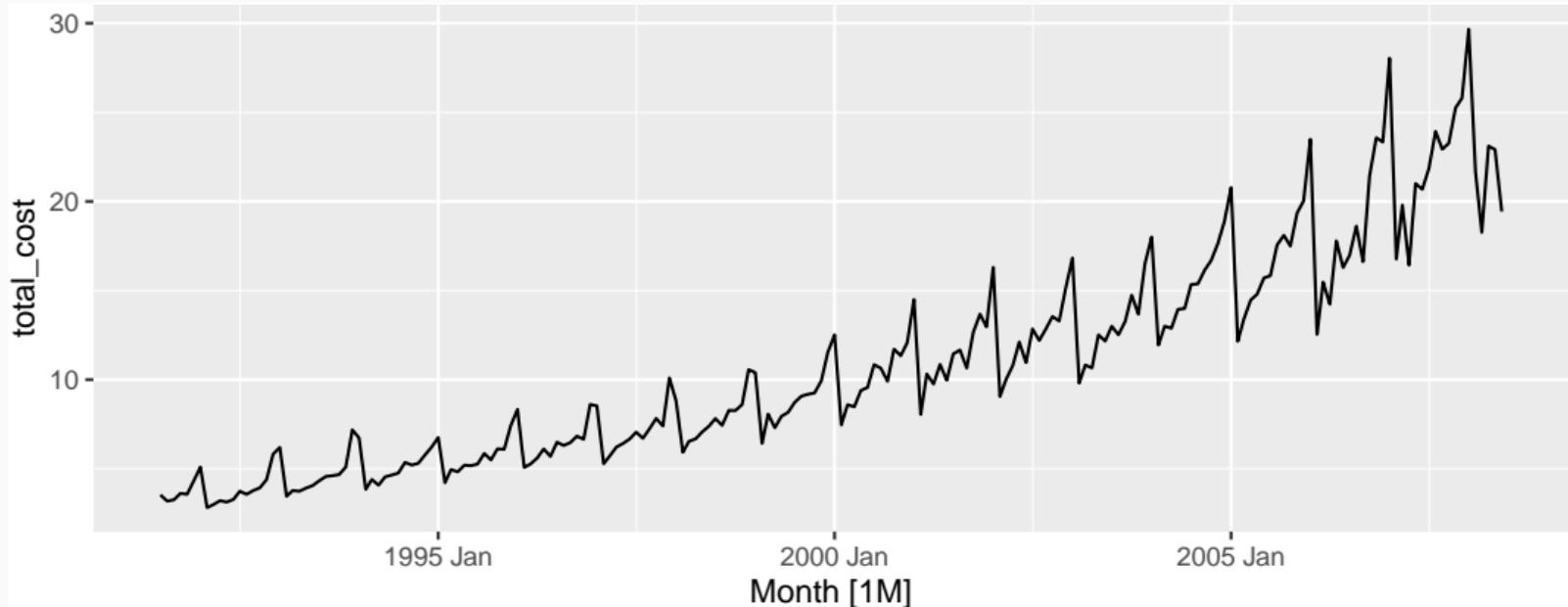
```
## # A tsibble: 204 x 2 [1M]  
##       Month total_cost  
##     <mth>     <dbl>  
##   1 1991 Jul     3.53  
##   2 1991 Aug     3.18  
##   3 1991 Sep     3.25  
##   4 1991 Oct     3.61  
##   5 1991 Nov     3.57  
##   6 1991 Dec     4.31  
##   7 1992 Jan     5.09
```

Outline

- 1 Time series in R
- 2 Example: Australian prison population
- 3 Example: Australian pharmaceutical sales
- 4 Time plots
- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

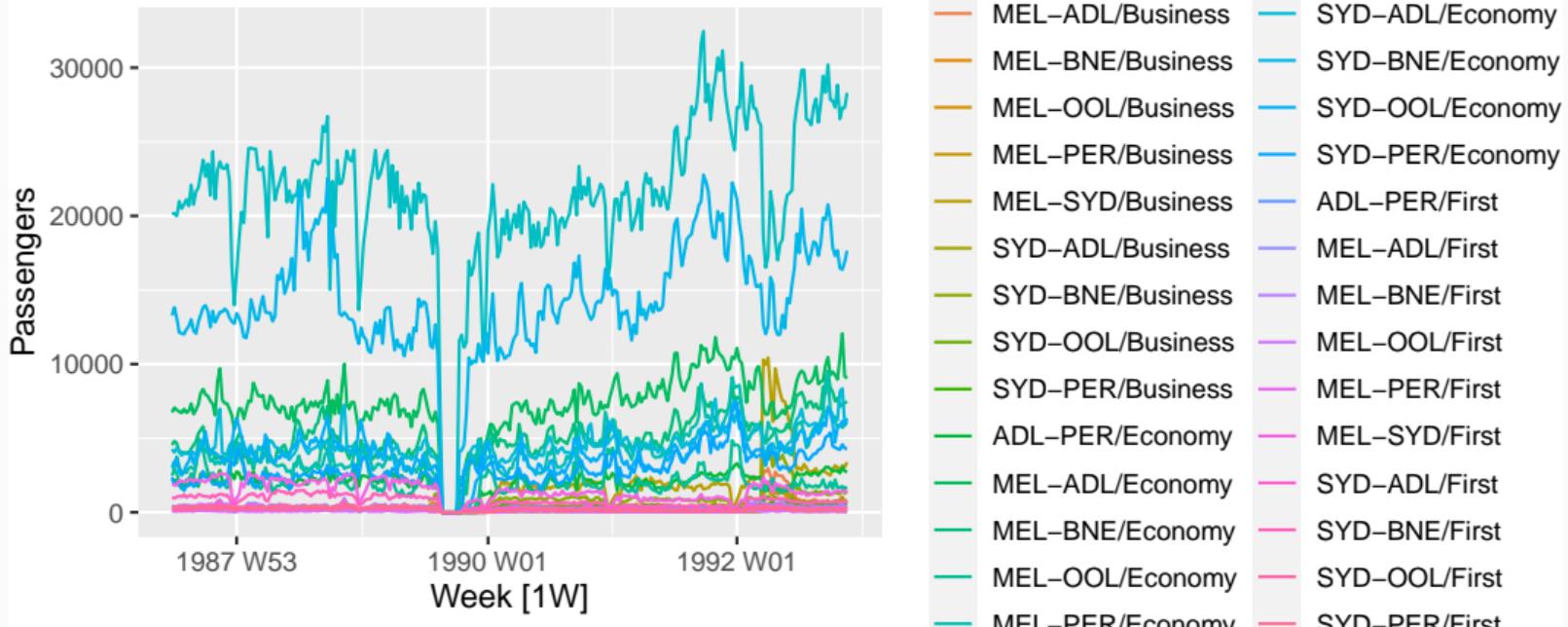
Time plots

```
a10 %>%  
  autoplot(total_cost)
```



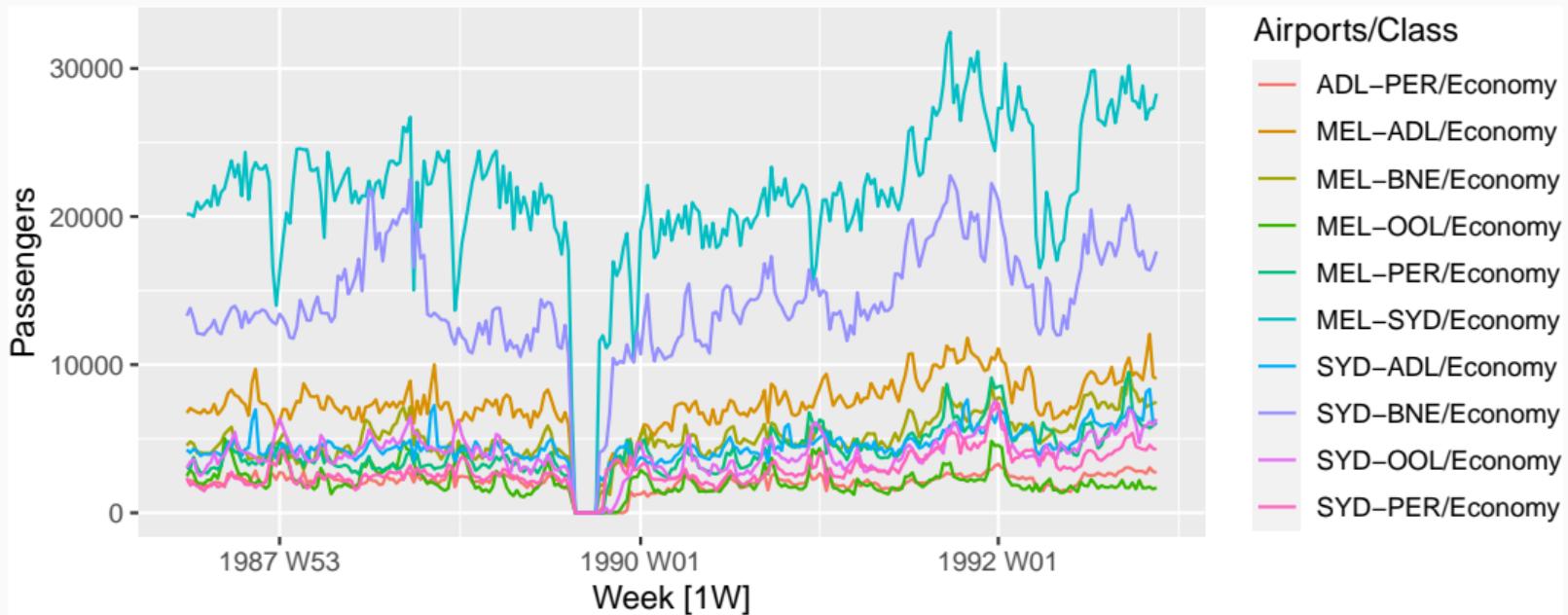
Ansett airlines

```
ansett %>%  
  autoplot(Passengers)
```



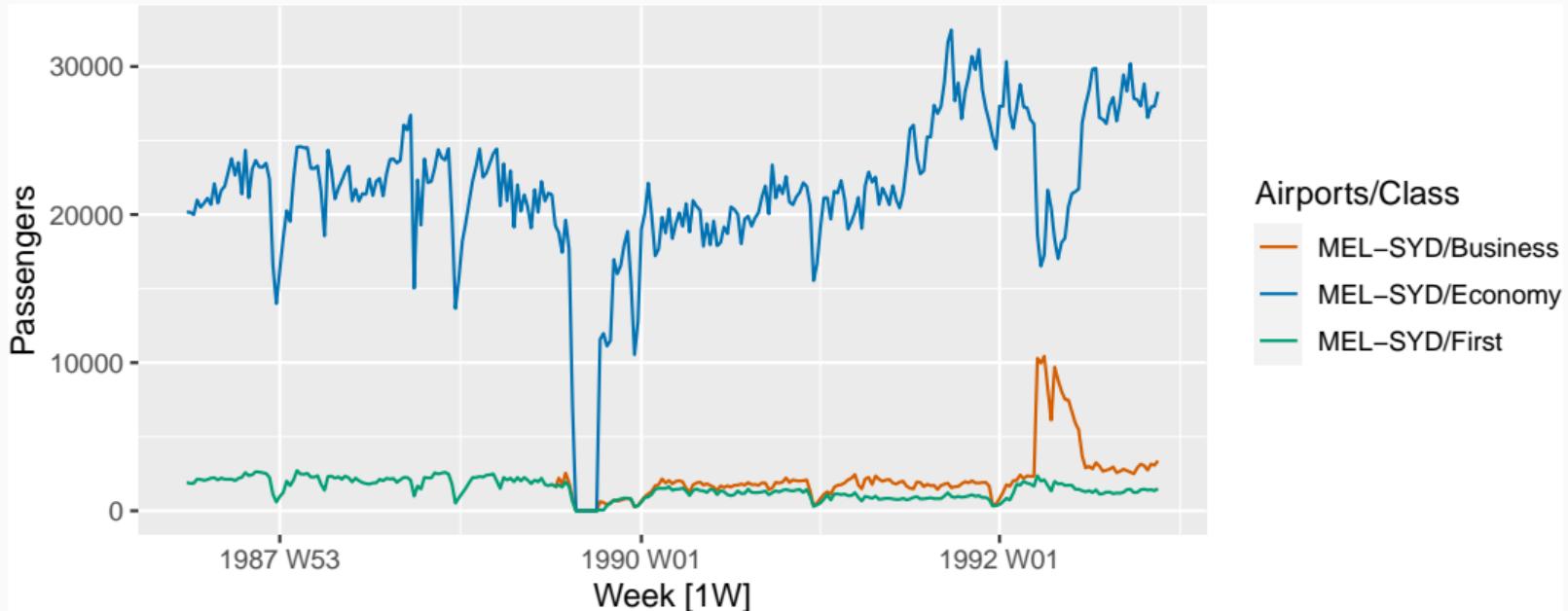
Ansett airlines

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



Ansett airlines

```
ansett %>%
  filter(Airports == "MEL-SYD") %>%
  autoplot(Passengers)
```



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).

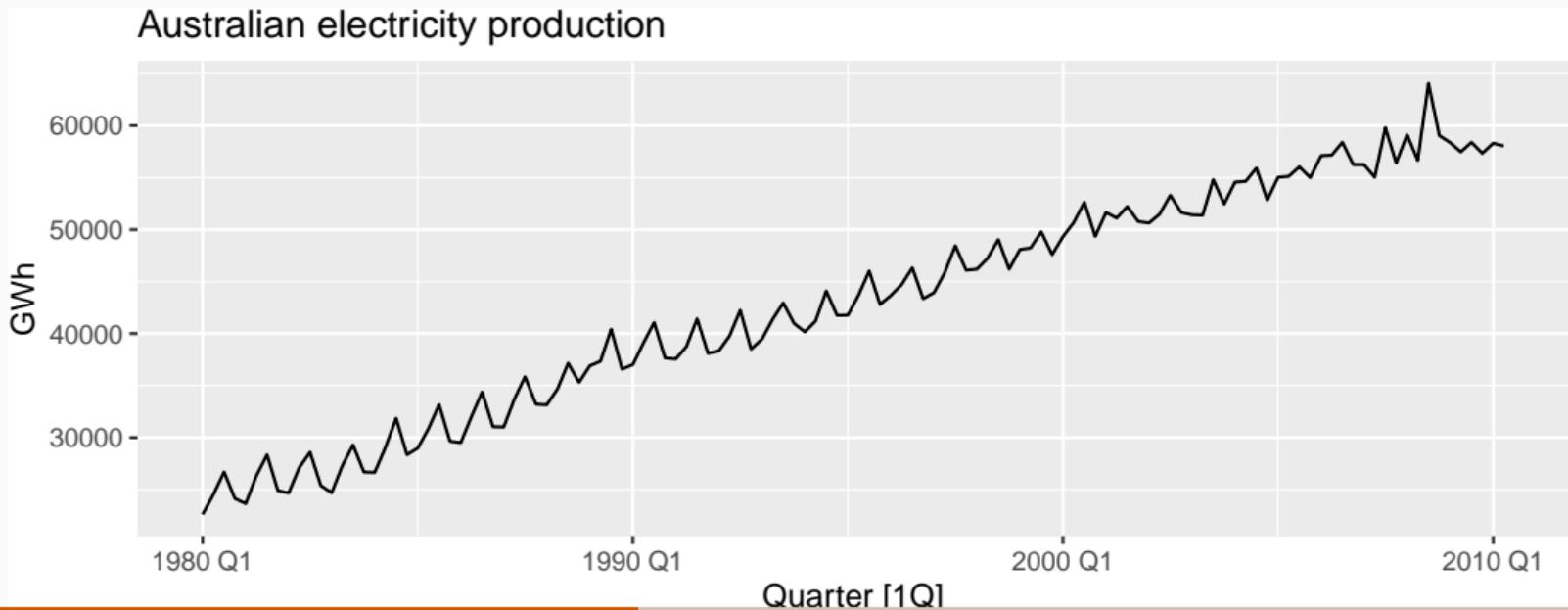
Time series components

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

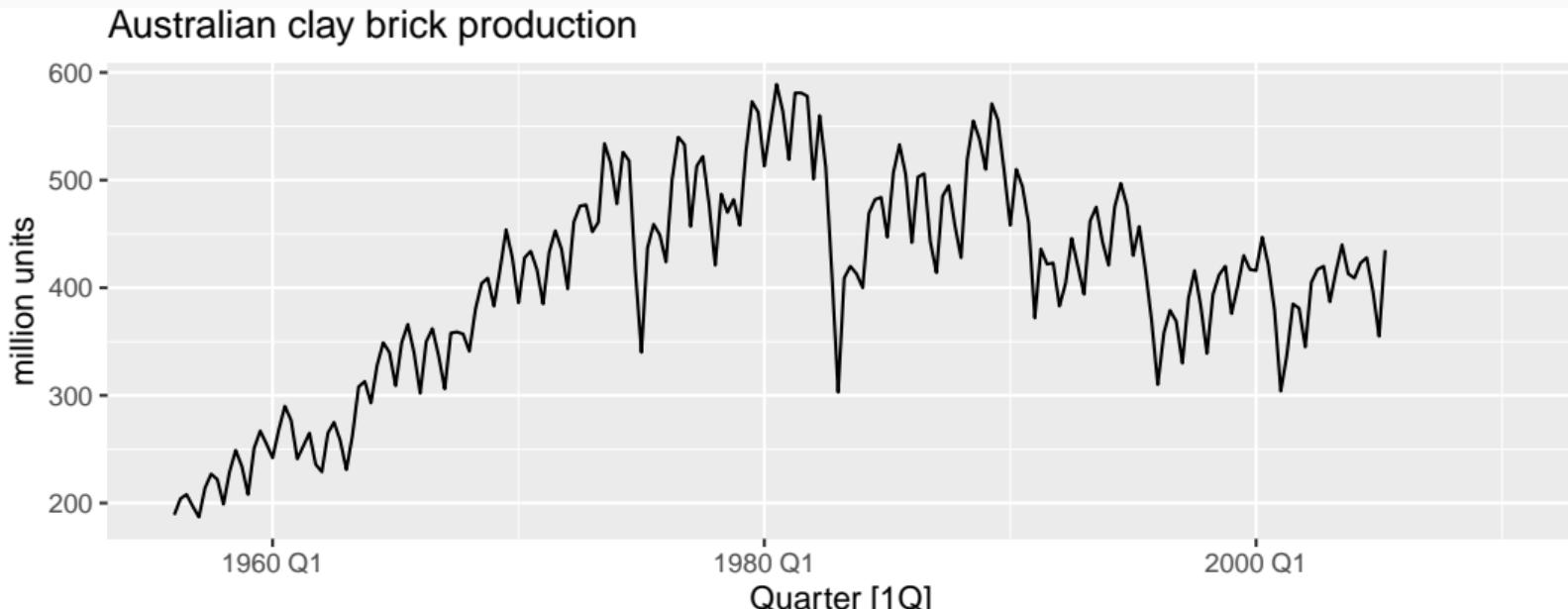
Time series patterns

```
aus_production %>%
  filter(year(Quarter) >= 1980) %>%
  autoplot(Electricity) +
  labs(y = "GWh", title = "Australian electricity production")
```



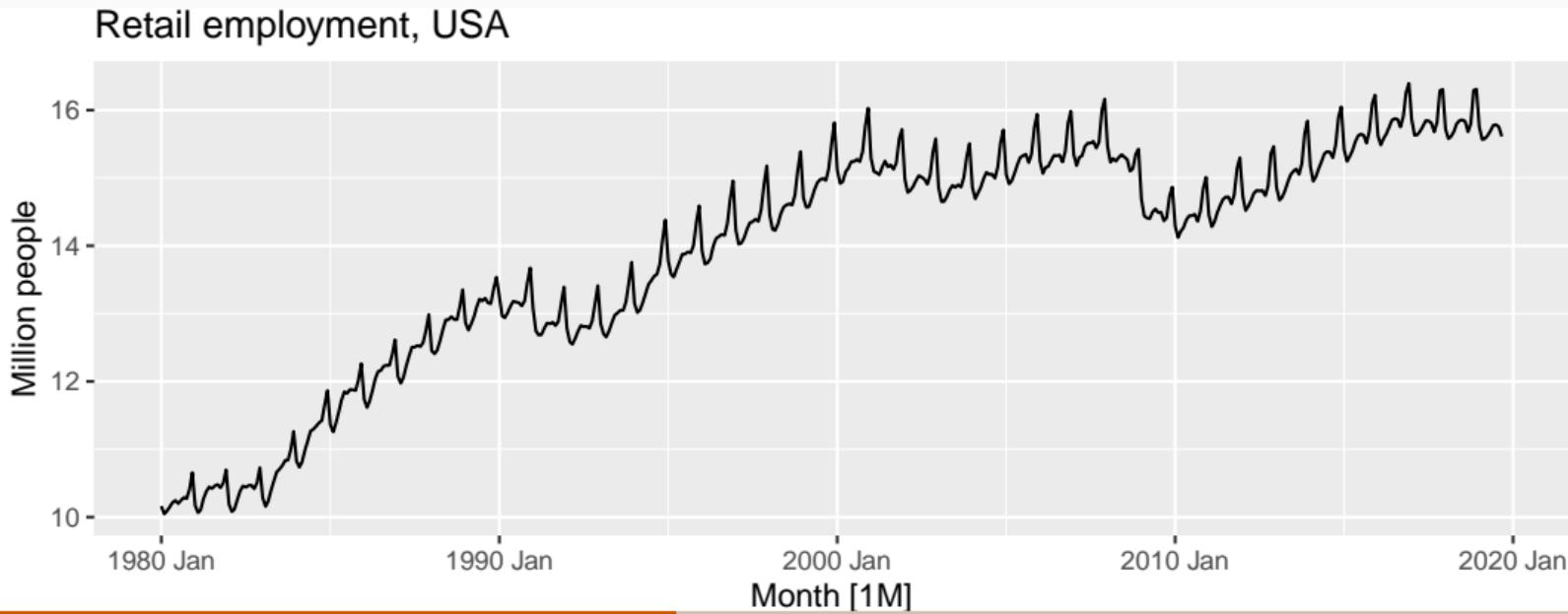
Time series patterns

```
aus_production %>%
  autoplot(Bricks) +
  labs(y = "million units", title = "Australian clay brick production")
```



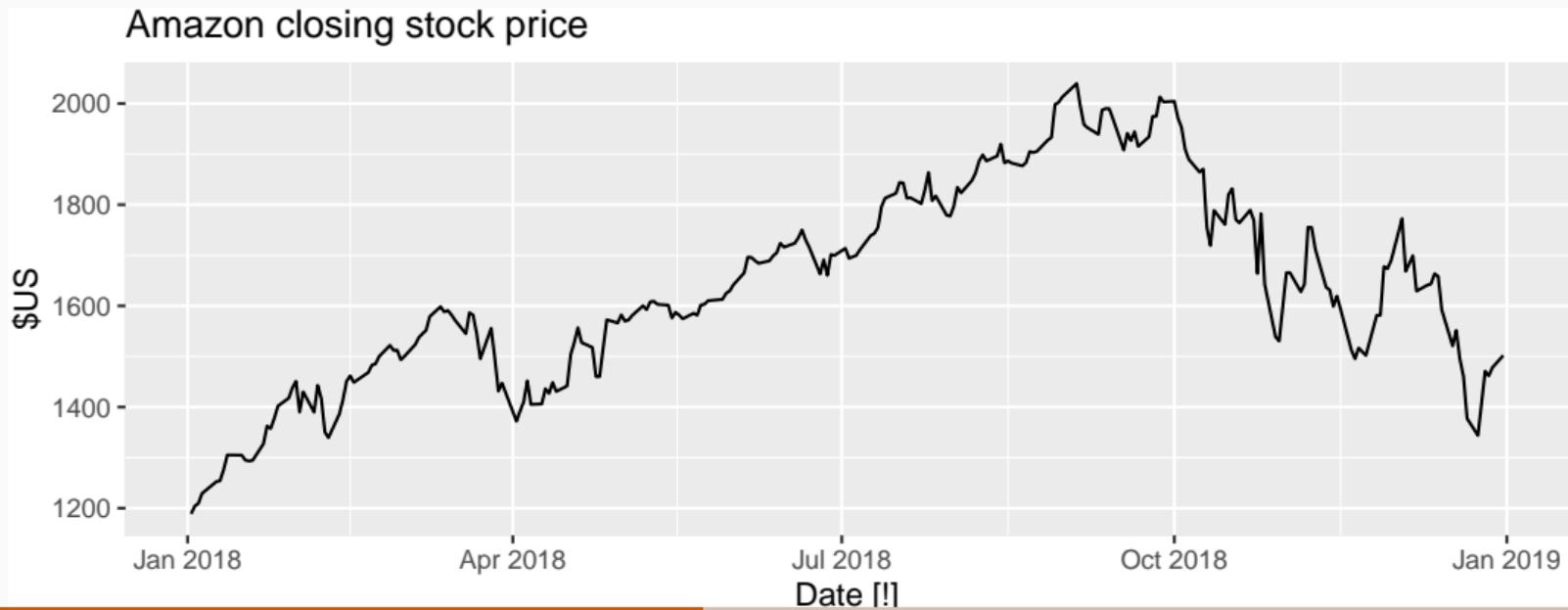
Time series patterns

```
us_employment %>%
  filter>Title == "Retail Trade", year(Month) >= 1980) %>%
  autoplot(Employed / 1e3) +
  labs(y = "Million people", title = "Retail employment, USA")
```



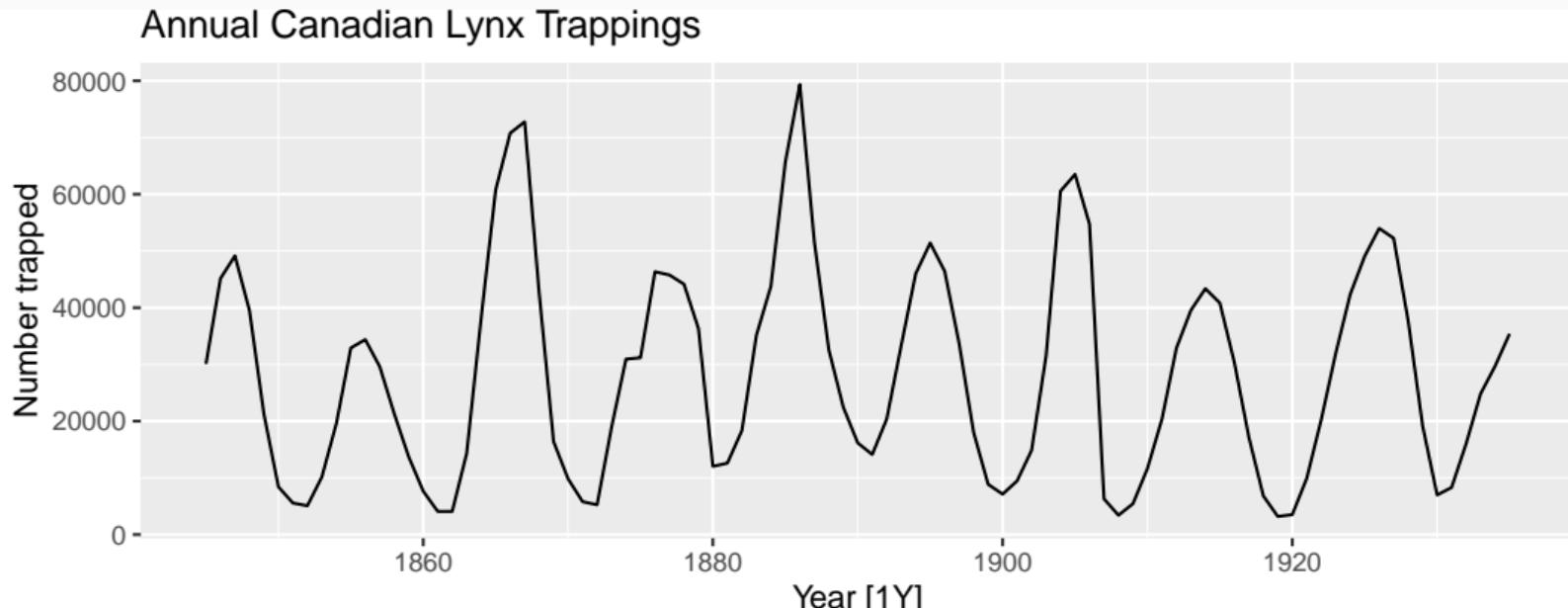
Time series patterns

```
gafa_stock %>%
  filter(Symbol == "AMZN", year(Date) >= 2018) %>%
  autoplot(Close) +
  labs(y = "$US", title = "Amazon closing stock price")
```



Time series patterns

```
pelt %>%  
  autoplot(Lynx) +  
  labs(y="Number trapped", title = "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

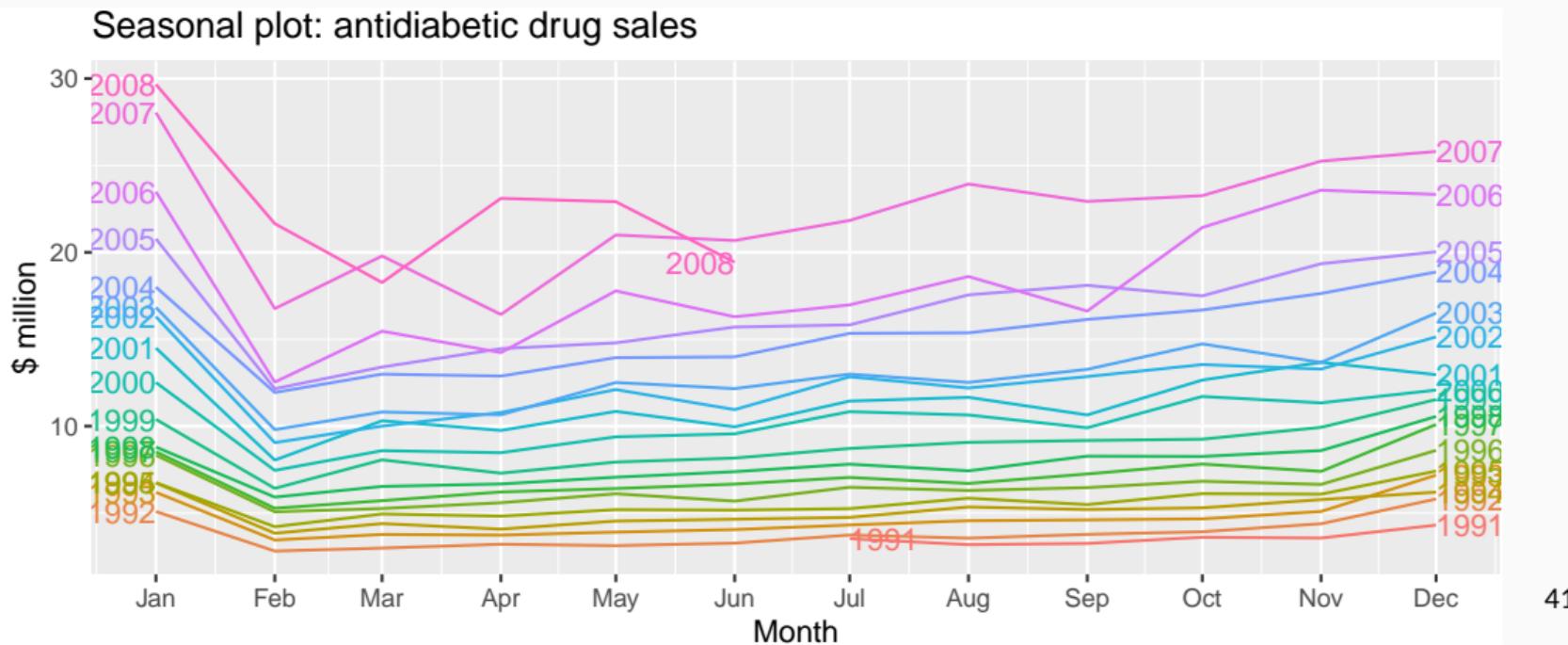
The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

Outline

- 1 Time series in R
- 2 Example: Australian prison population
- 3 Example: Australian pharmaceutical sales
- 4 Time plots
- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

Seasonal plots

```
a10 %>% gg_season(total_cost, labels = "both") +  
  labs(y = "$ million", title = "Seasonal plot: antidiabetic drug sales")
```

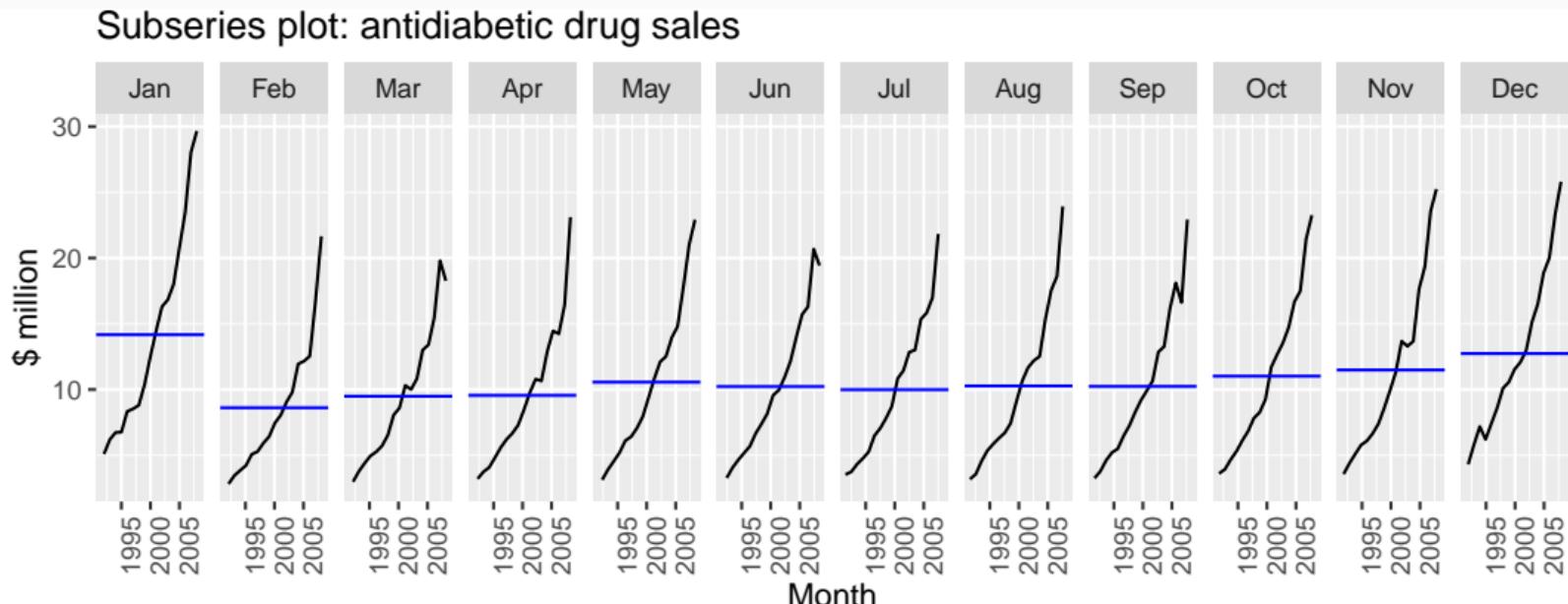


Seasonal plots

- 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: `gg_season()`

Seasonal subseries plots

```
a10 %>%  
  gg_subseries(total_cost) +  
  labs(y = "$ million", title = "Subseries plot: antidiabetic drug sales")
```

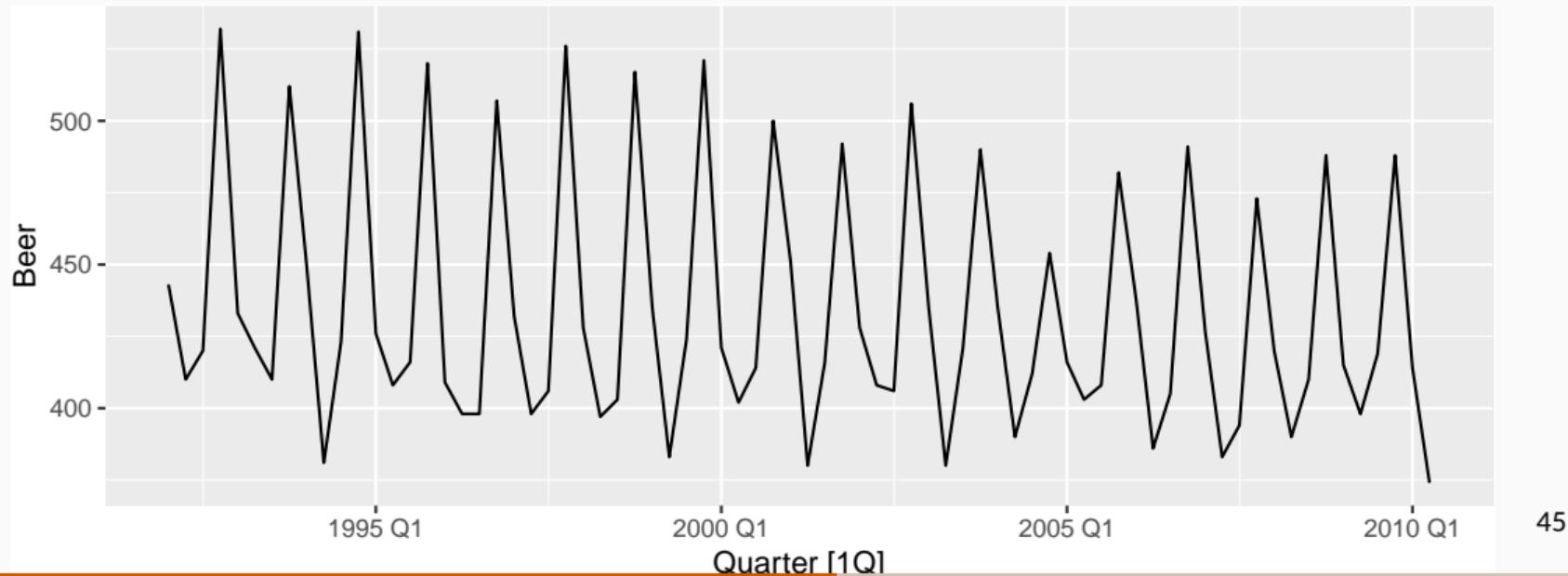


Seasonal subseries plots

- 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: `gg_subseries()`

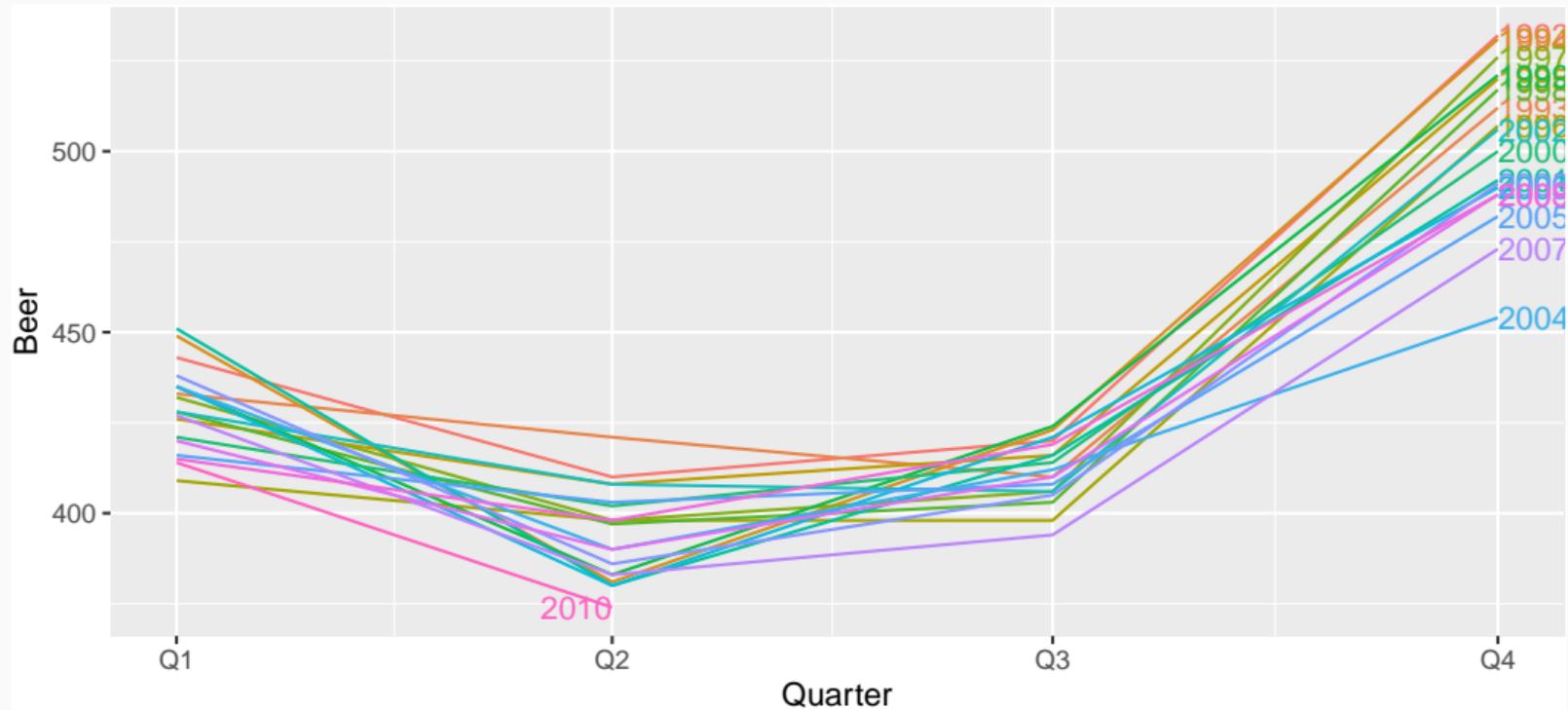
Quarterly Australian Beer Production

```
beer <- aus_production %>%
  select(Quarter, Beer) %>%
  filter(year(Quarter) >= 1992)
beer %>% autoplot(Beer)
```



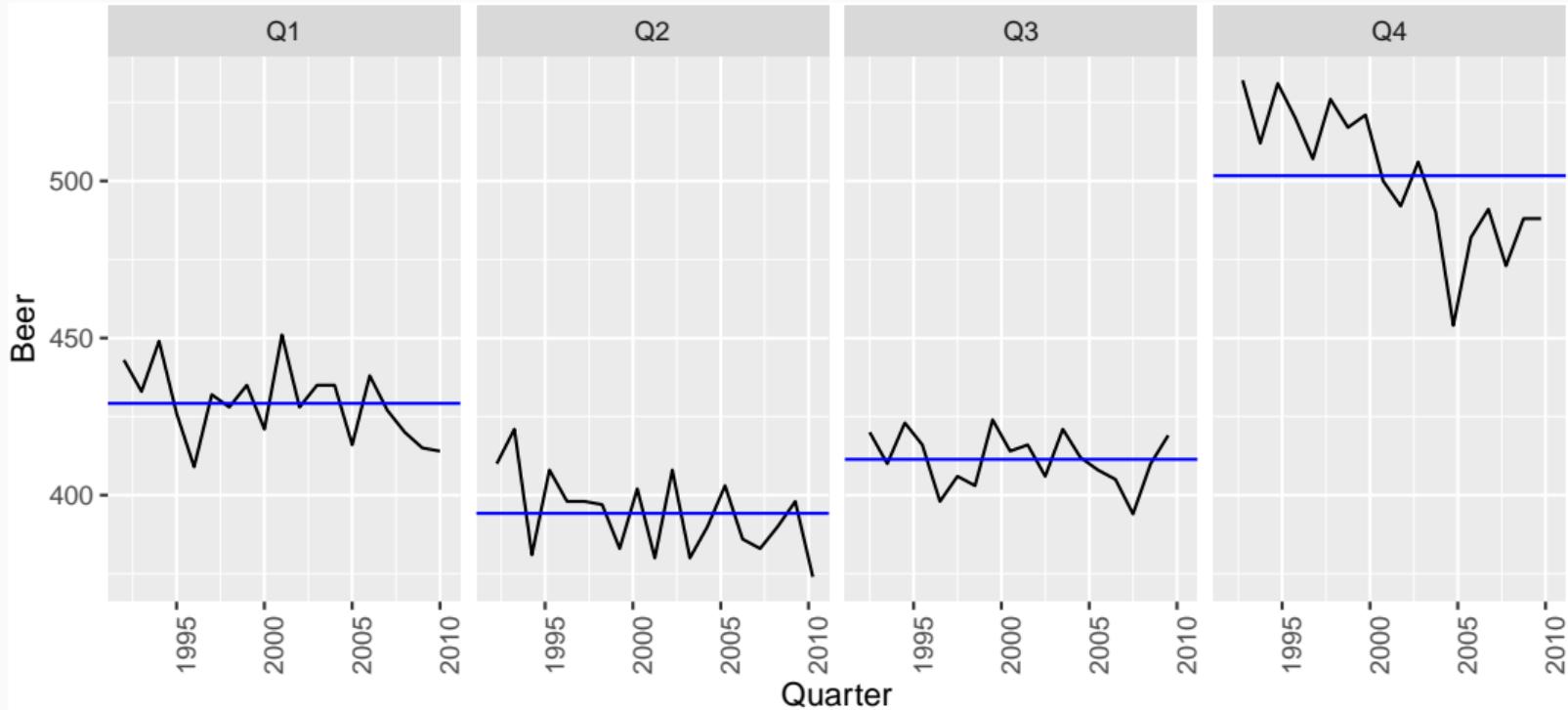
Quarterly Australian Beer Production

```
beer %>% gg_season(Beer, labels="right")
```



Quarterly Australian Beer Production

```
beer %>% gg_subseries(Beer)
```



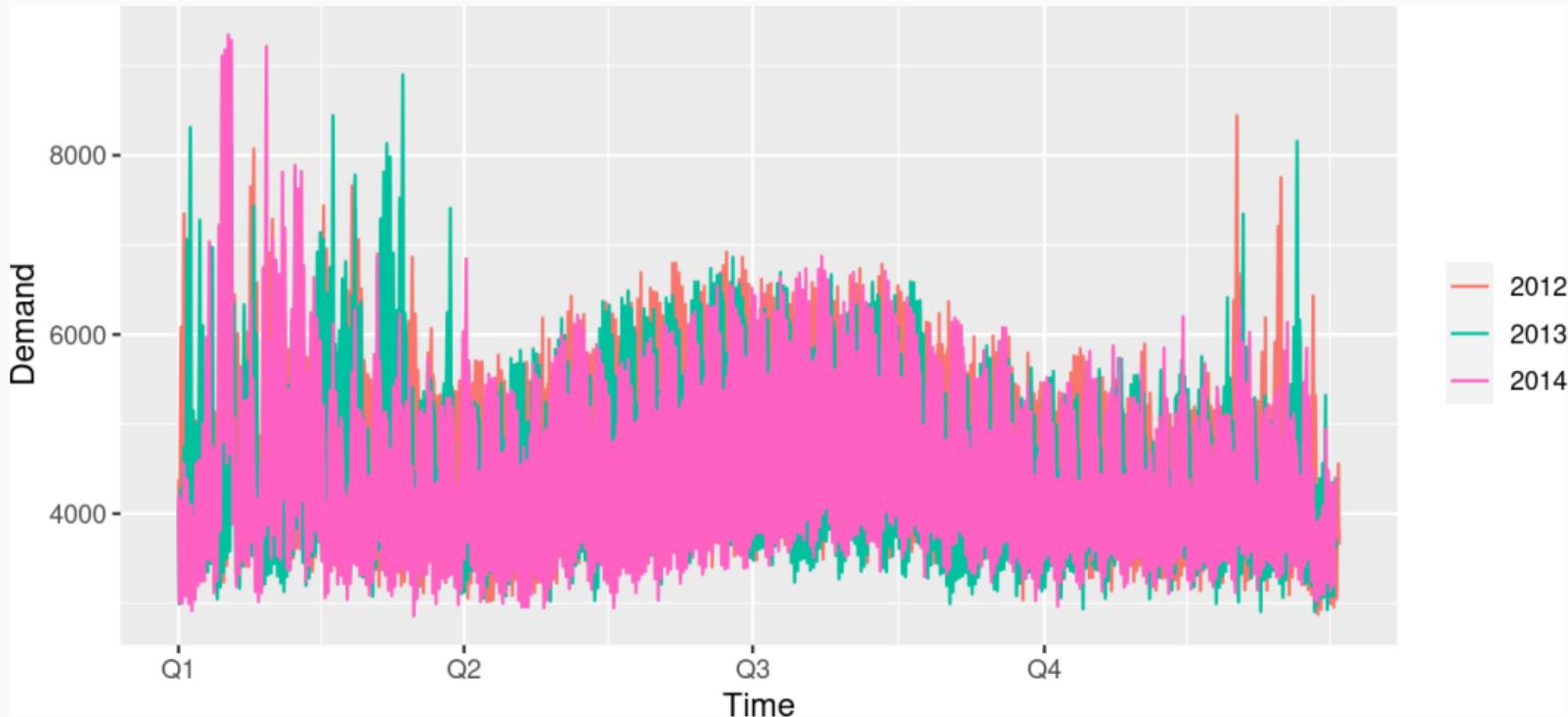
Multiple seasonal periods

```
vic_elec
```

```
## # A tsibble: 52,608 x 5 [30m] <Australia/Melbourne>
##   Time                 Demand Temperature Date      Holiday
##   <dttm>              <dbl>     <dbl> <date>    <lgl>
## 1 2012-01-01 00:00:00  4383.     21.4 2012-01-01 TRUE
## 2 2012-01-01 00:30:00  4263.     21.0 2012-01-01 TRUE
## 3 2012-01-01 01:00:00  4049.     20.7 2012-01-01 TRUE
## 4 2012-01-01 01:30:00  3878.     20.6 2012-01-01 TRUE
## 5 2012-01-01 02:00:00  4036.     20.4 2012-01-01 TRUE
## 6 2012-01-01 02:30:00  3866.     20.2 2012-01-01 TRUE
## 7 2012-01-01 03:00:00  3694.     20.1 2012-01-01 TRUE
## 8 2012-01-01 03:30:00  3562.     19.6 2012-01-01 TRUE
## 9 2012-01-01 04:00:00  3433.     19.1 2012-01-01 TRUE
## 10 2012-01-01 04:30:00  3359.     19.0 2012-01-01 TRUE
## # ... with 52,598 more rows
```

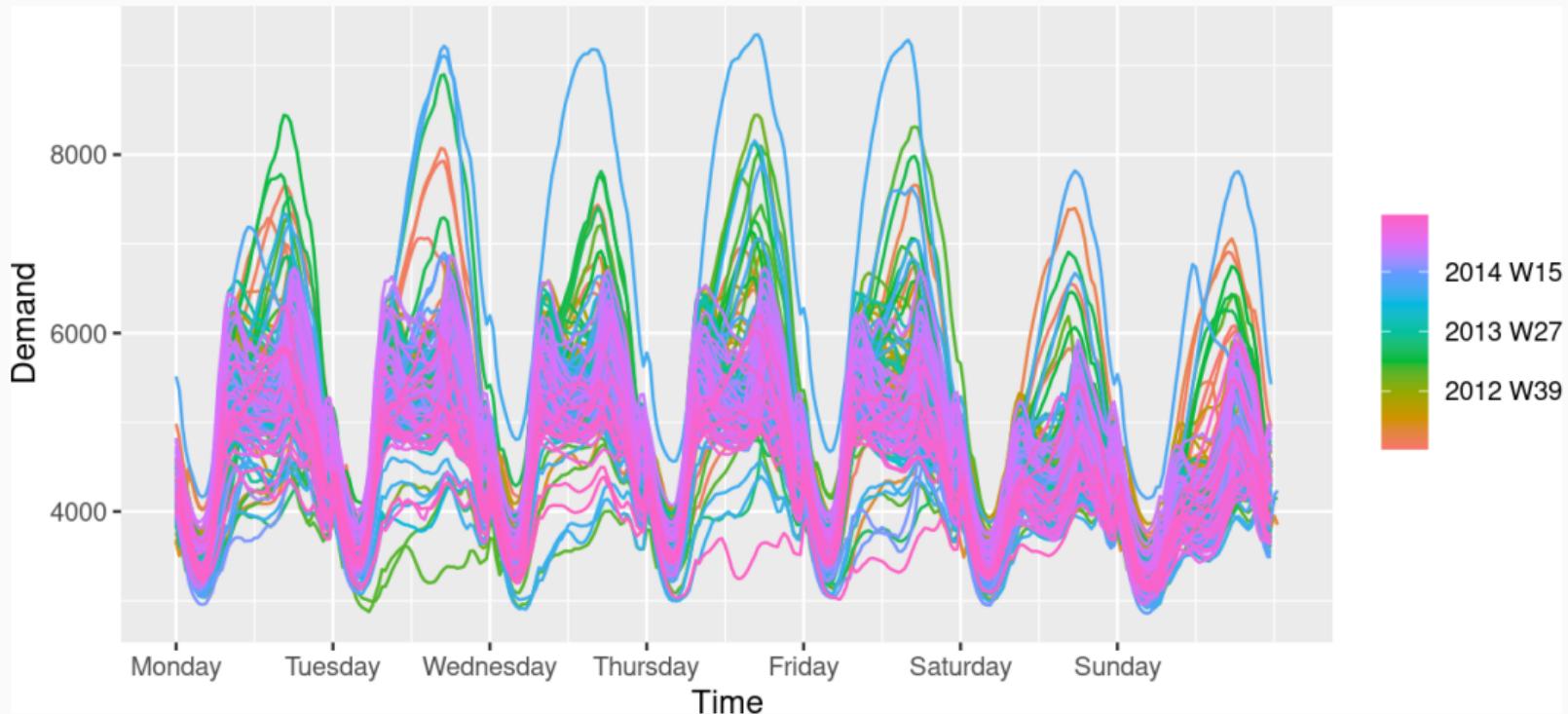
Multiple seasonal periods

```
vic_elec %>% gg_season(Demand)
```



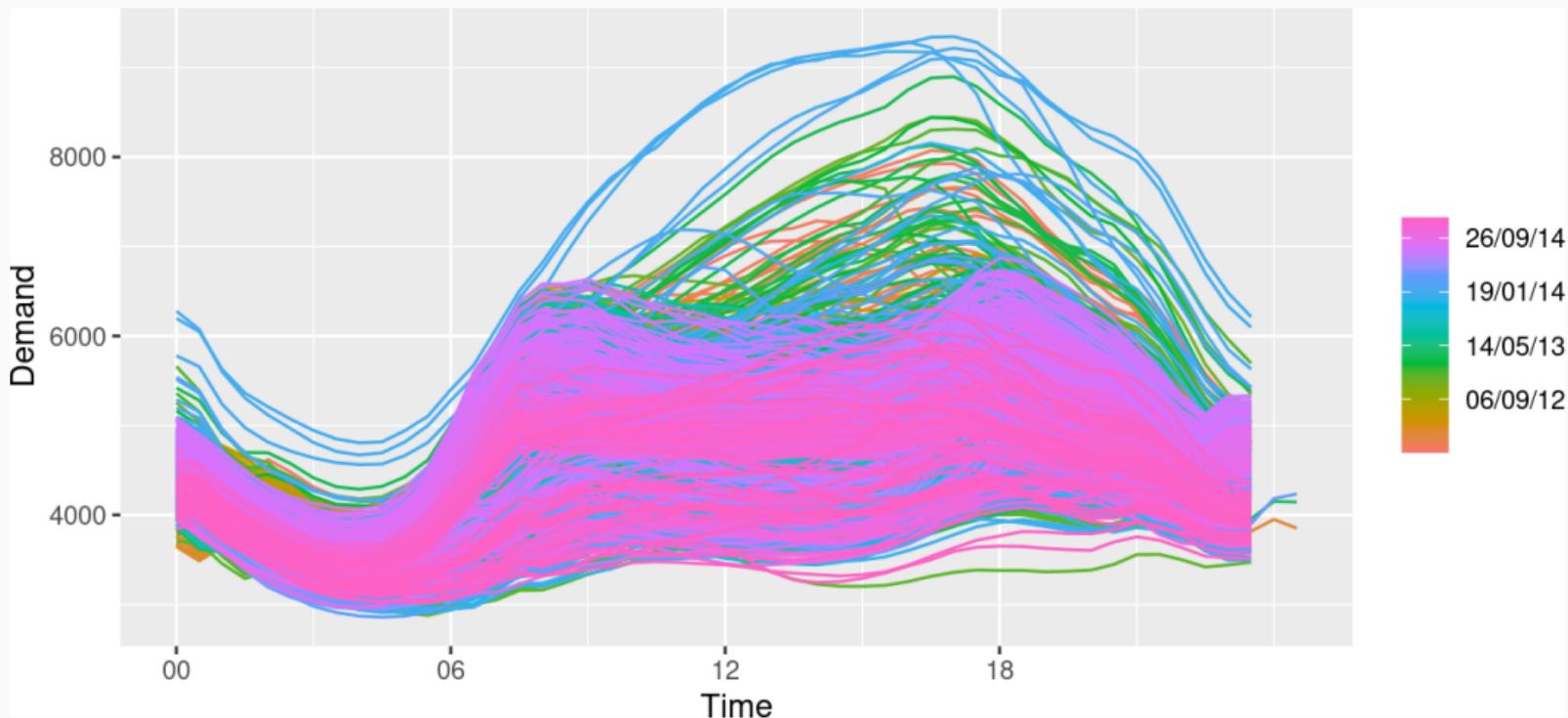
Multiple seasonal periods

```
vic_elec %>% gg_season(Demand, period = "week")
```



Multiple seasonal periods

```
vic_elec %>% gg_season(Demand, period = "day")
```



Australian holidays

```
holidays <- tourism %>%
  filter(Purpose == "Holiday") %>%
  group_by(State) %>%
  summarise(Trips = sum(Trips))
```

```
## # A tsibble: 640 x 3 [1Q]
## # Key:      State [8]
##      State Quarter Trips
##      <chr>   <qtr>  <dbl>
## 1 ACT     1998  Q1    196.
## 2 ACT     1998  Q2    127.
## 3 ACT     1998  Q3    111.
## 4 ACT     1998  Q4    170.
## 5 ACT     1999  Q1    108.
## 6 ACT     1999  Q2    125.
## 7 ACT     1999  Q3    178.
## 8 ACT     1999  Q4    218.
## 9 ACT     2000  Q1    158.
```

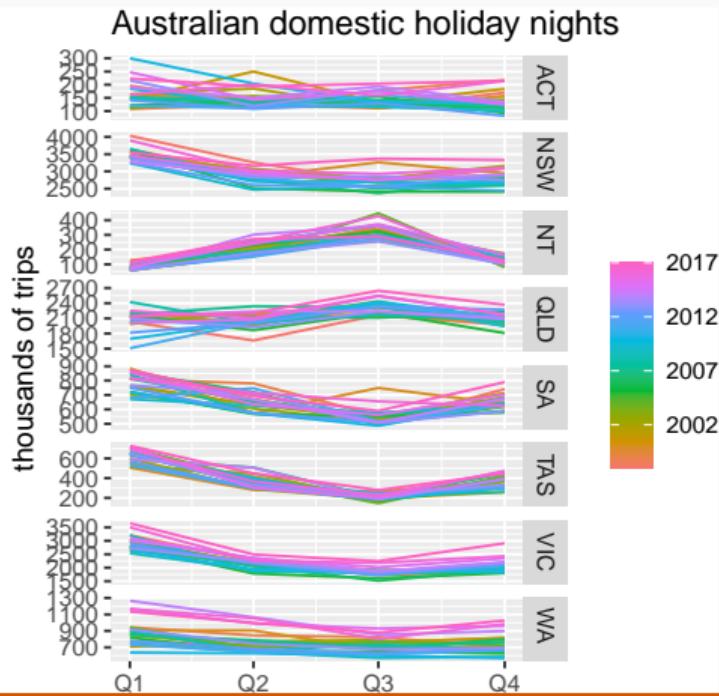
Australian holidays

```
holidays %>% autoplot(Trips) +  
  labs(y = "thousands of trips", title = "Australian domestic holiday nights")
```



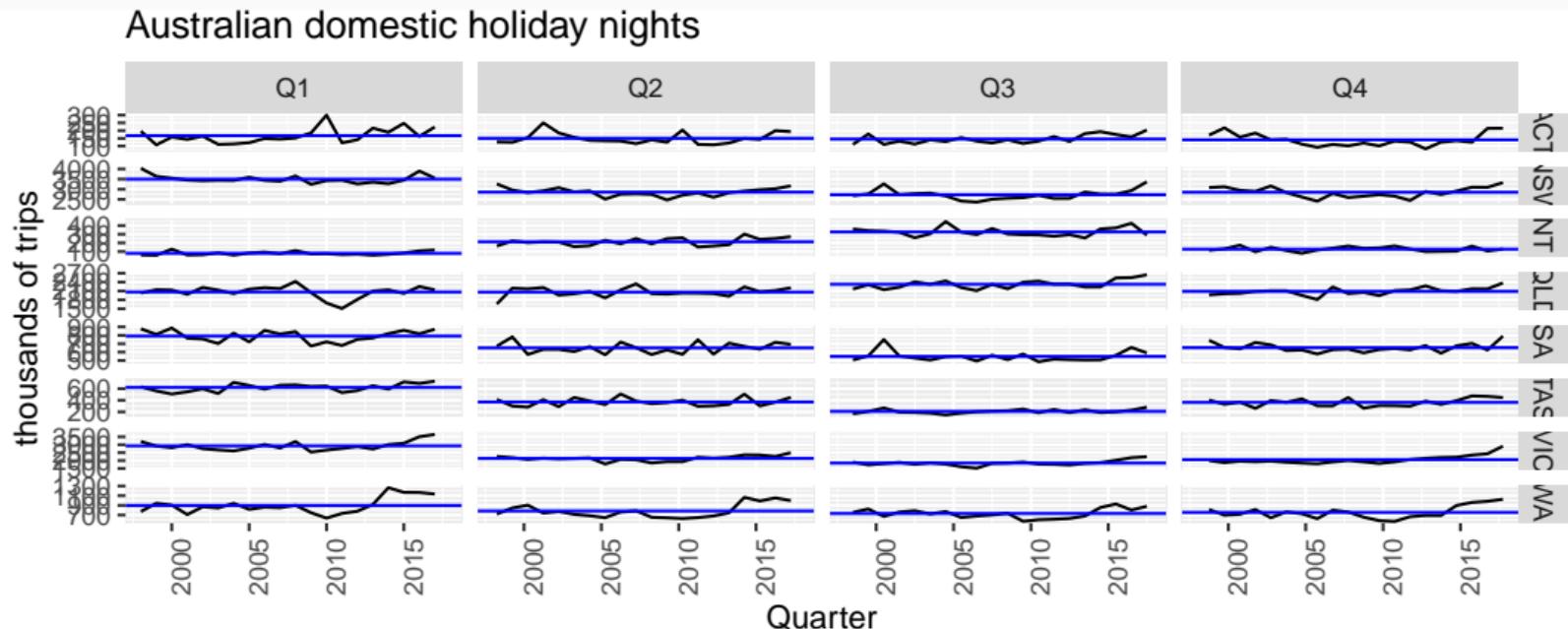
Seasonal plots

```
holidays %>% gg_season(Trips) +  
  labs(y = "thousands of trips", title = "Australian domestic holiday nights")
```



Seasonal subseries plots

```
holidays %>%
  gg_subseries(Trips) +
  labs(y = "thousands of trips", title = "Australian domestic holiday nights")
```



Outline

- 1 Time series in R
- 2 Example: Australian prison population
- 3 Example: Australian pharmaceutical sales
- 4 Time plots
- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

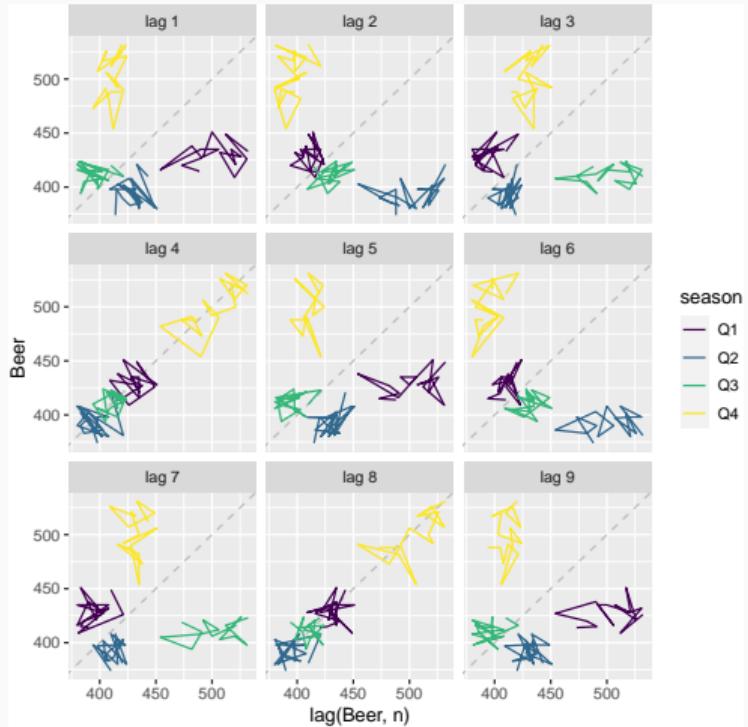
Example: Beer production

```
new_production <- aus_production %>%
  filter(year(Quarter) >= 1992)
new_production

## # A tsibble: 74 x 7 [1Q]
##   Quarter Beer Tobacco Bricks Cement Electricity Gas
##   <qtr> <dbl>    <dbl>   <dbl>   <dbl>      <dbl> <dbl>
## 1 1992   Q1     443     5777    383    1289      38332  117
## 2 1992   Q2     410     5853    404    1501      39774  151
## 3 1992   Q3     420     6416    446    1539      42246  175
## 4 1992   Q4     532     5825    420    1568      38498  129
## 5 1993   Q1     433     5724    394    1450      39460  116
## 6 1993   Q2     421     6036    462    1668      41356  149
## 7 1993   Q3     410     6570    475    1648      42949  163
## 8 1993   Q4     512     5675    443    1863      40974  138
## 9 1994   Q1     449     5311    421    1468      40162  127
## 10 1994  Q2     381     5717    475    1755      41199  159
## # ... with 64 more rows
```

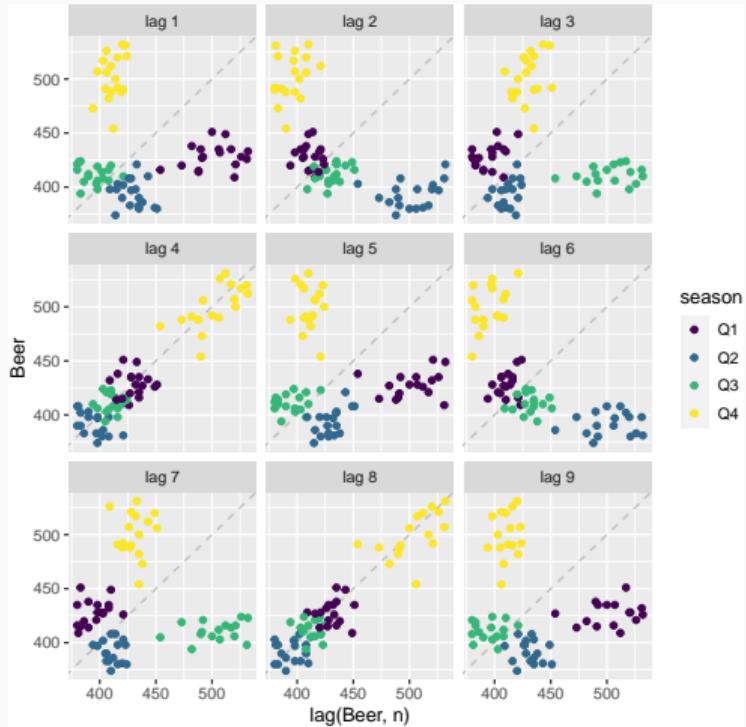
Example: Beer production

```
new_production %>% gg_lag(Beer)
```



Example: Beer production

```
new_production %>% gg_lag(Beer, geom='point')
```



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.
- ACF (autocorrelation function):
 - ▶ $r_1 = \text{Correlation}(y_t, y_{t-1})$
 - ▶ $r_2 = \text{Correlation}(y_t, y_{t-2})$
 - ▶ $r_3 = \text{Correlation}(y_t, y_{t-3})$
 - ▶ etc.

Autocorrelation

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 .

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

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

and $r_k = c_k/c_0$

Autocorrelation

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

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

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:

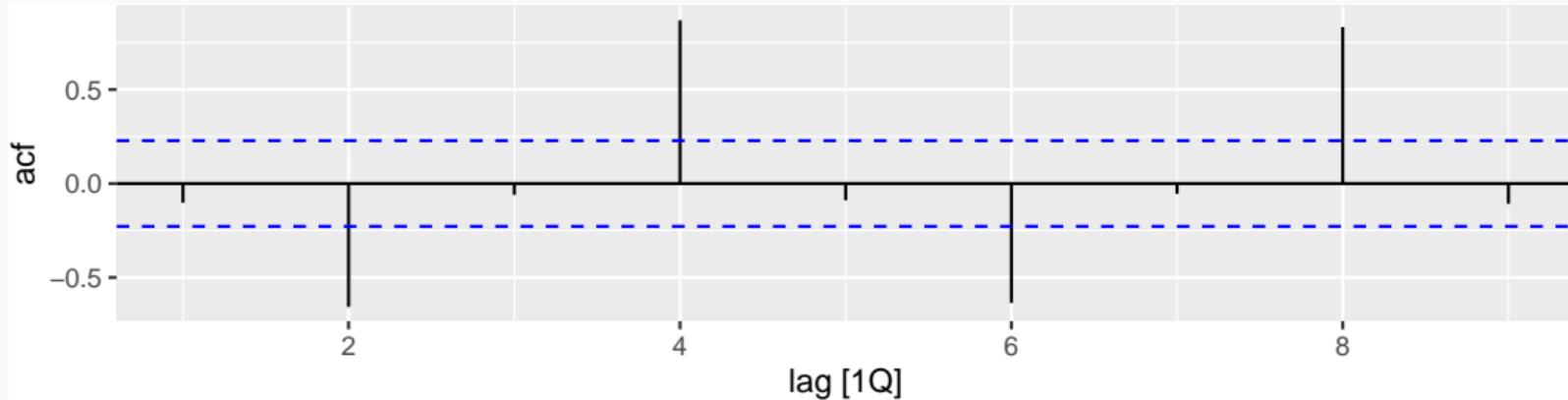
```
new_production %>% ACF(Beer, lag_max = 9)
```

```
## # A tsibble: 9 x 2 [1Q]
##   lag      acf
##   <dbl>    <dbl>
## 1 1Q -0.102
## 2 2Q -0.657
## 3 3Q -0.0603
## 4 4Q  0.869
## 5 5Q -0.0892
## 6 6Q -0.635
## 7 7Q -0.0542
```

Autocorrelation

Results for first 9 lags for beer data:

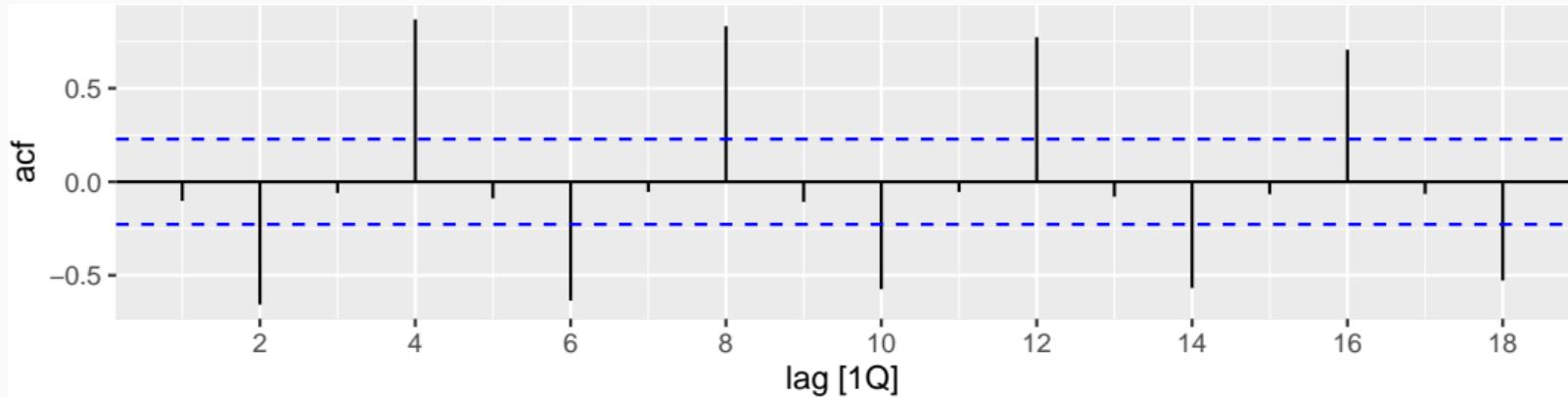
```
new_production %>% ACF(Beer, lag_max = 9) %>% autoplot()
```



- Together, the autocorrelations at lags 1, 2, ..., make up the *autocorrelation* or ACF.
- The plot is known as a **correlogram**

Autocorrelation

```
new_production %>% ACF(Beer) %>% autoplot()
```



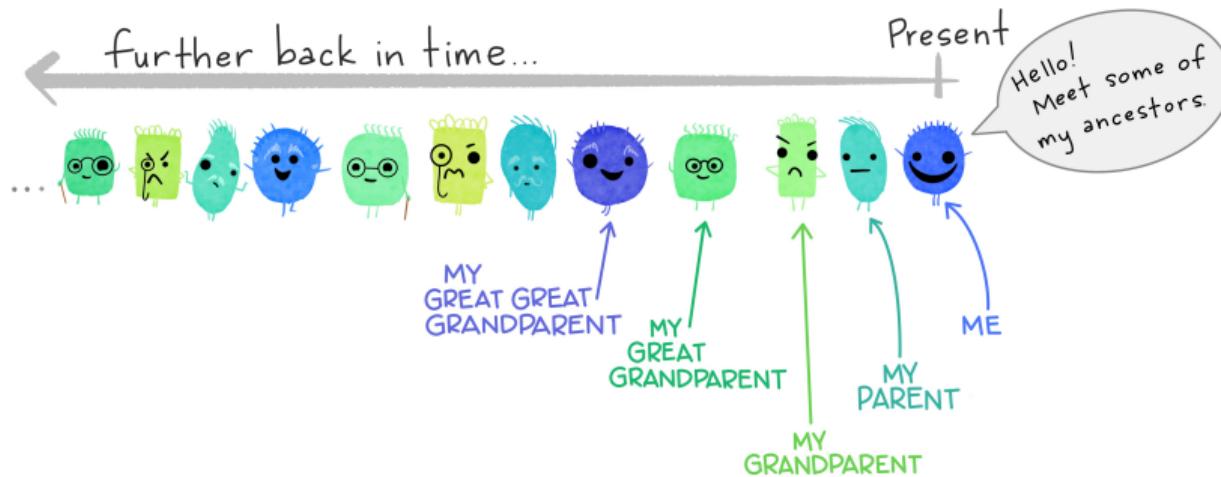
- r_4 higher than for the other lags. This is due to **the seasonal pattern in the data**: the peaks tend to be **4 quarters** apart and the troughs tend to be **2 quarters** apart.
- r_2 is more negative than for the other lags because troughs tend to be 2 quarters behind peaks.

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.

Autocorrelation functions

intro to the
autocorrelation function (ACF)

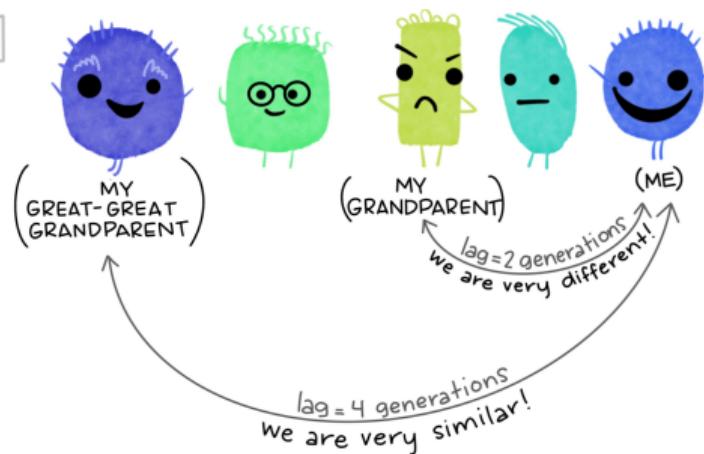


Autocorrelation functions

in our family MONSTERS tend to be...

- A little similar to their parent and great-grandparent
- Very different from their grandparent
- Very similar to their great-great grandparent

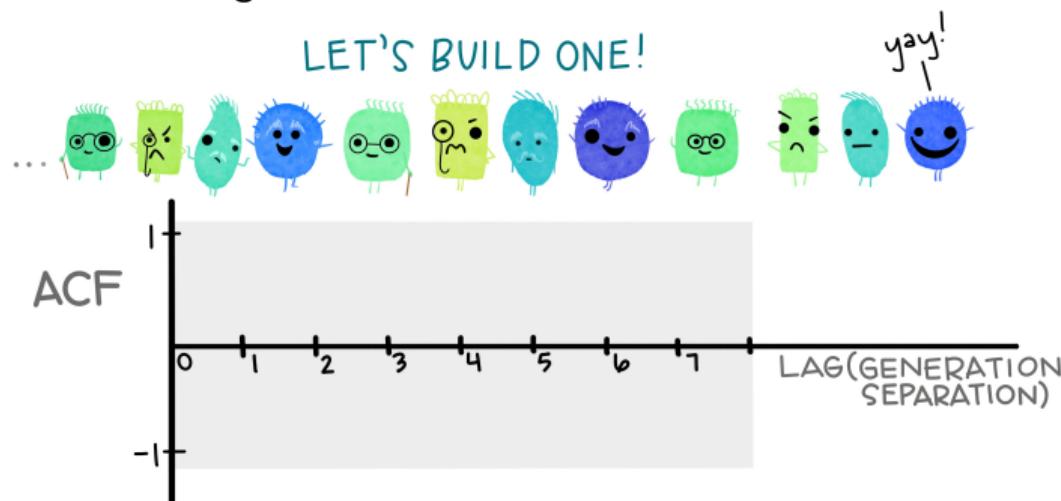
FOR EXAMPLE:



Autocorrelation functions

THE autocorrelation function (ACF)

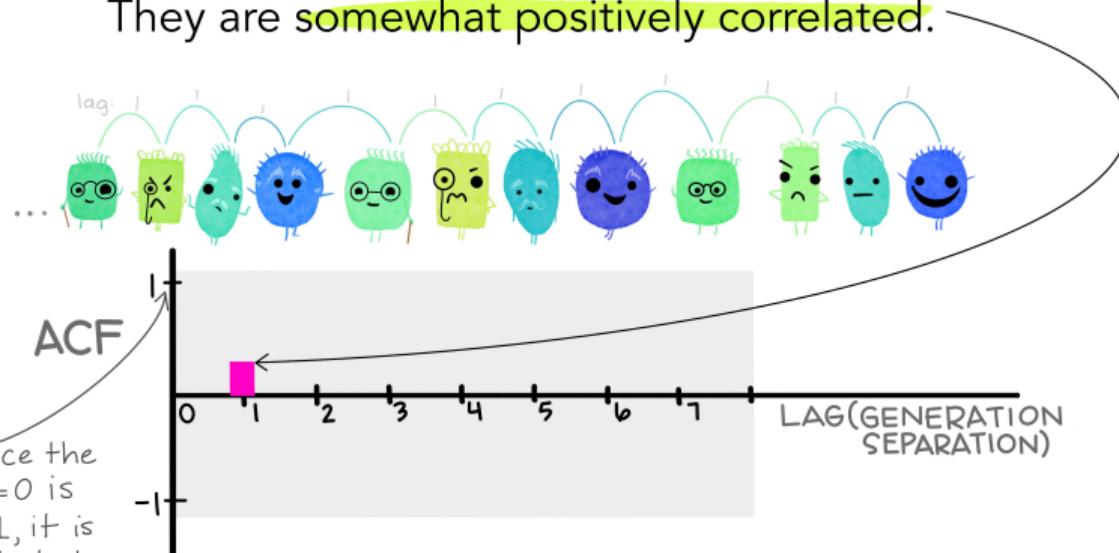
The ACF is a plot of autocorrelation between a variable and itself separated by specified lags (in our case, generations)



Autocorrelation functions

At lag = 1, we find the correlation between
monsters and their **parent**.

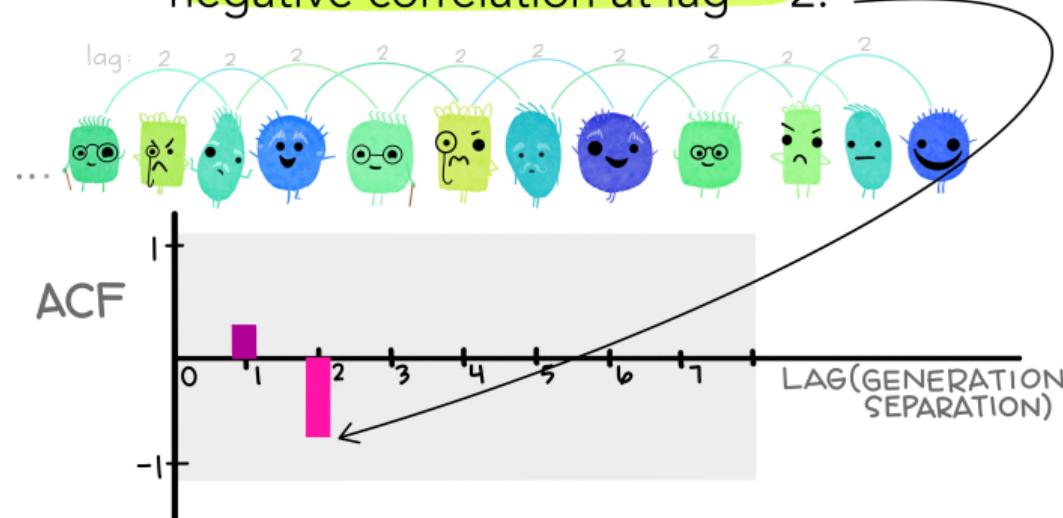
They are **somewhat positively correlated**.



Autocorrelation functions

At lag = 2, we find the correlation between
monsters and their **grandparent**.

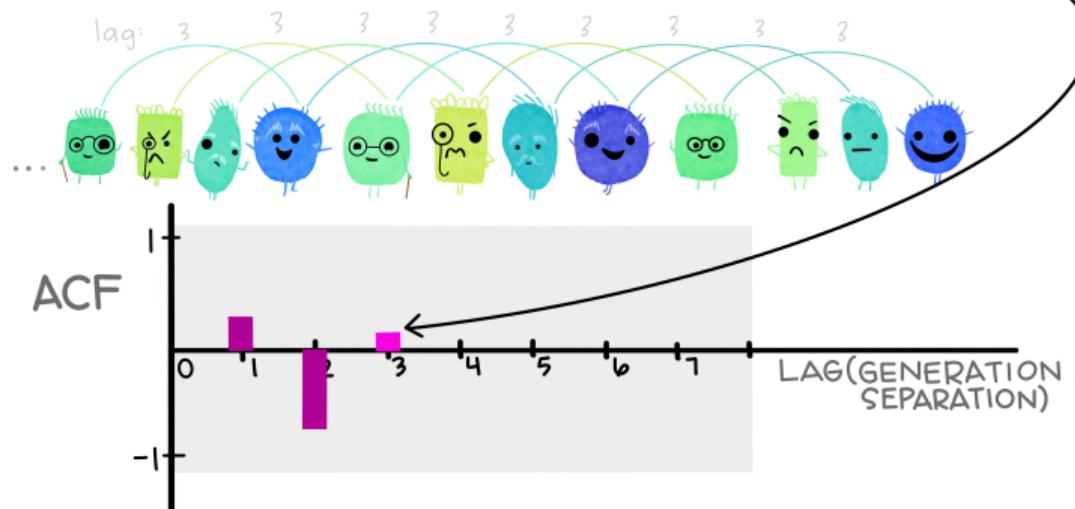
Since they tend to be very different, we find a
negative correlation at lag = 2.



Autocorrelation functions

At lag = 3, we find the correlation between
monsters and their **great-grandparent**.

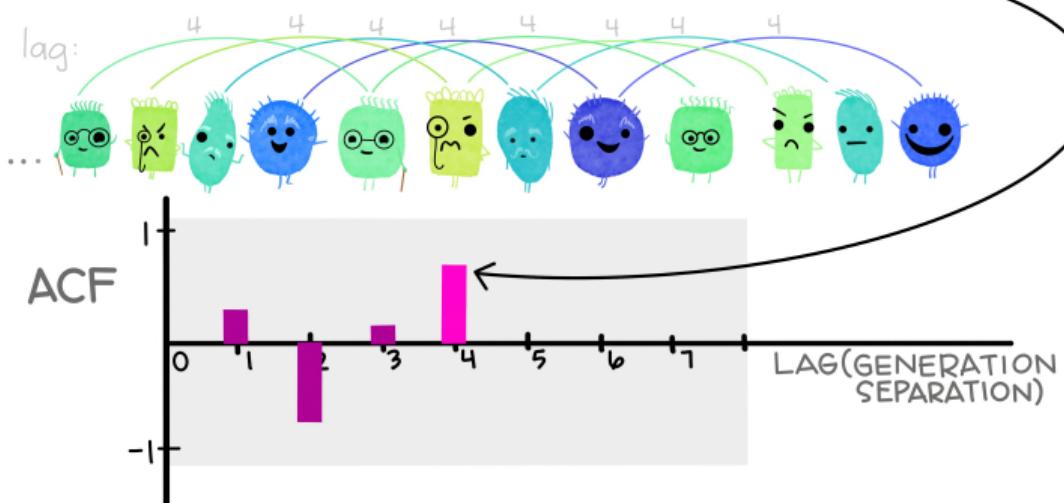
They are slightly positively correlated.



Autocorrelation functions

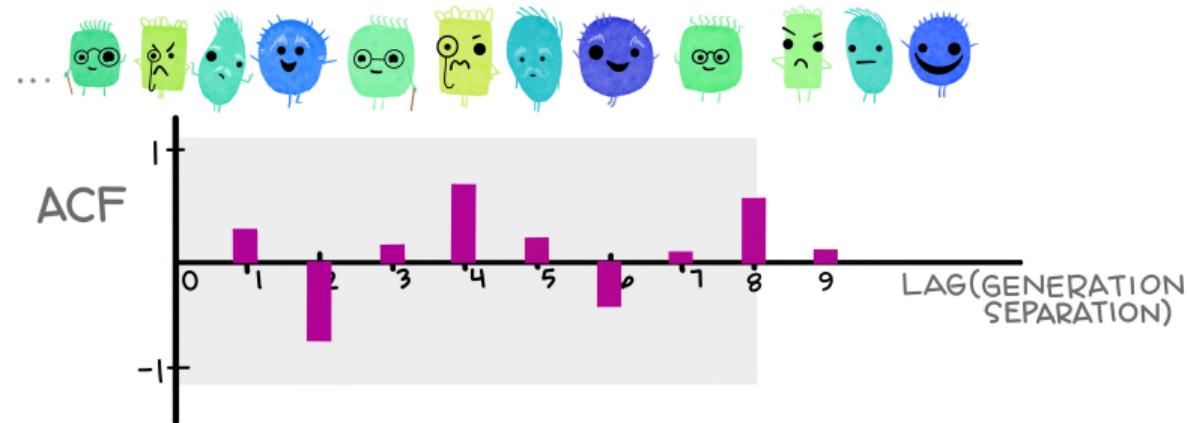
At lag = 4, we find the correlation between **monsters** and their **great-great grandparent**.

They tend to be very similar
(there is a positive correlation).



Autocorrelation functions

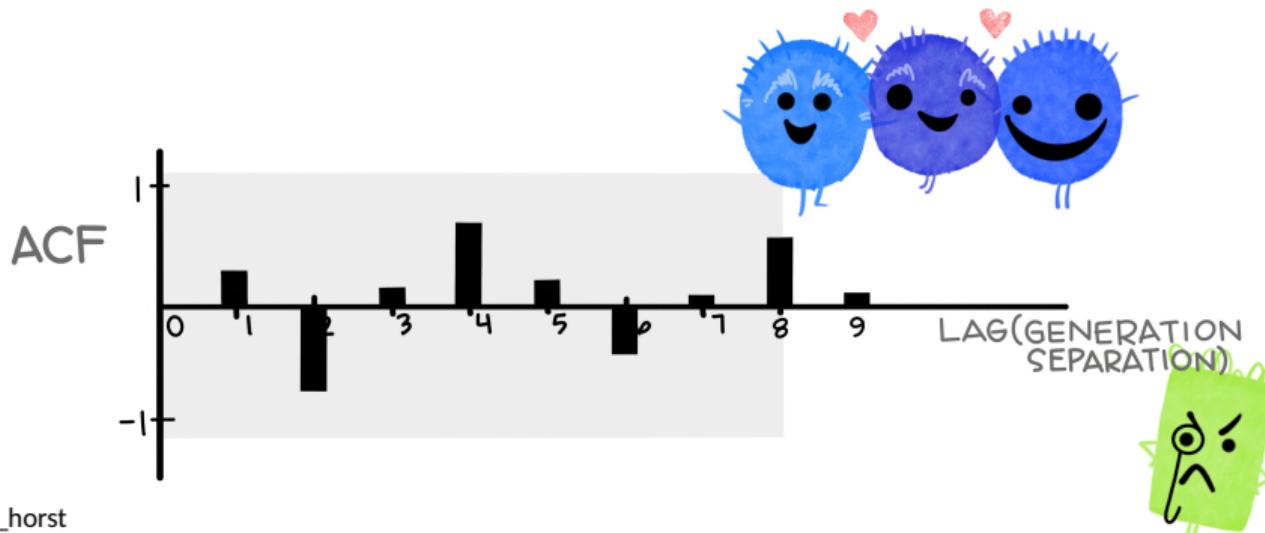
...and we continue finding the correlations as we increase the lag (generations) between the monsters...



Autocorrelation functions

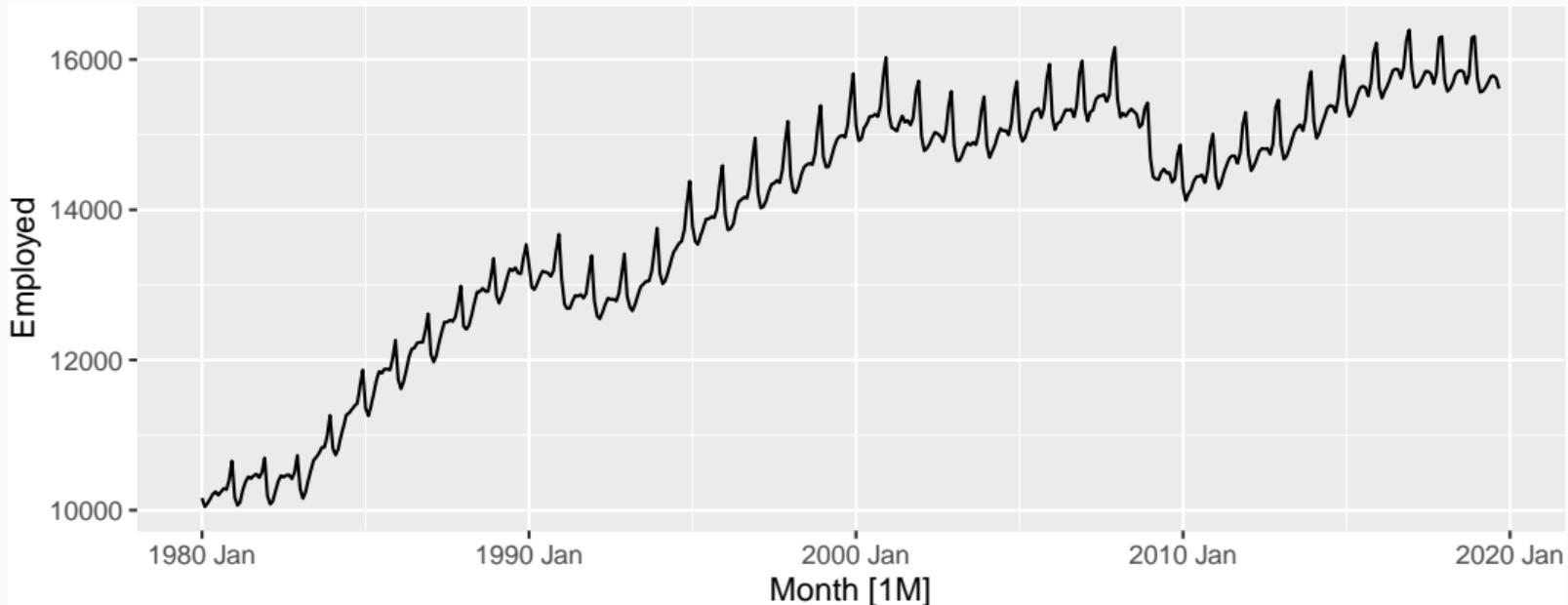
in summary:

The autocorrelation function (ACF) tells us the correlation between observations and those that came before them, separated by different lags (here, monster generations)!



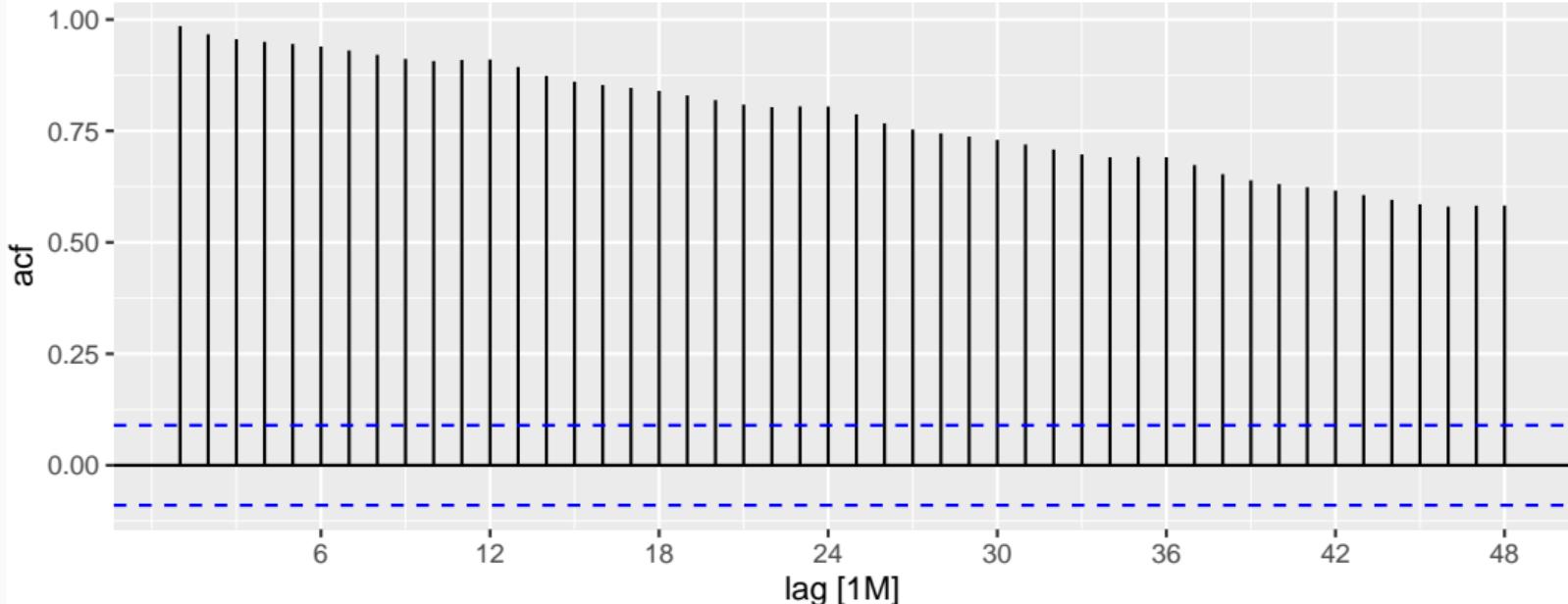
US retail trade employment

```
retail <- us_employment %>%
  filter>Title == "Retail Trade", year(Month) >= 1980)
retail %>% autoplot(Employed)
```



US retail trade employment

```
retail %>%  
  ACF(Employed, lag_max = 48) %>%  
  autoplot()
```



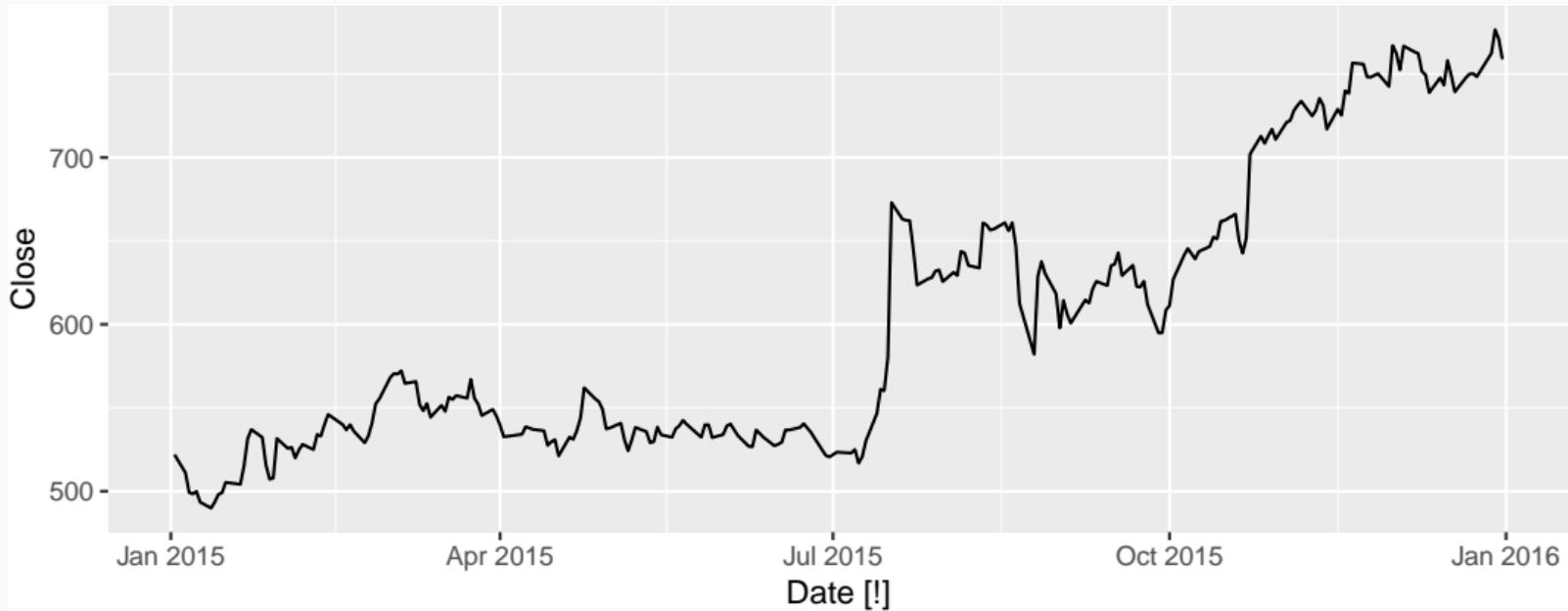
Google stock price

```
google_2015 <- gafa_stock %>%
  filter(Symbol == "GOOG", year(Date) == 2015) %>%
  select(Date, Close)
google_2015
```

```
## # A tsibble: 252 x 2 [!]
##   Date      Close
##   <date>    <dbl>
## 1 2015-01-02  522.
## 2 2015-01-05  511.
## 3 2015-01-06  499.
## 4 2015-01-07  498.
## 5 2015-01-08  500.
## 6 2015-01-09  493.
## 7 2015-01-12  490.
## 8 2015-01-13  493.
## 9 2015-01-14  498.
## 10 2015-01-15 499.
```

Google stock price

```
google_2015 %>% autoplot(Close)
```



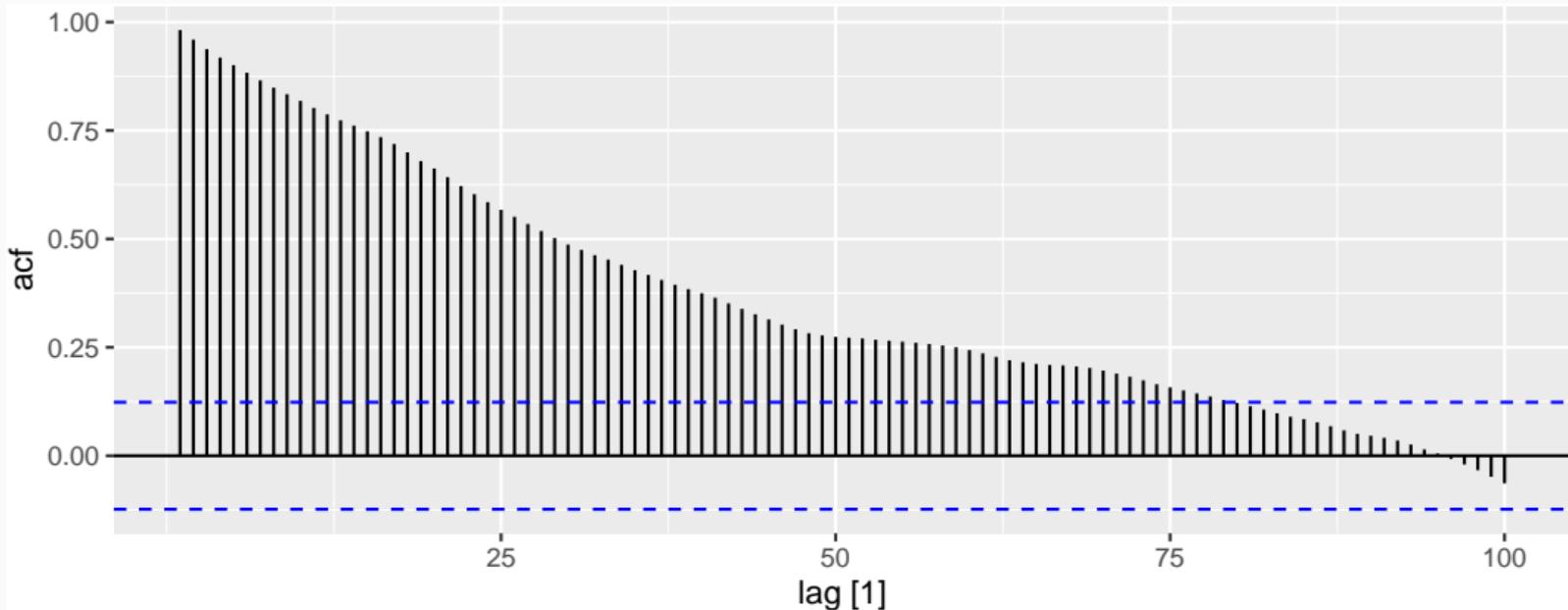
Google stock price

```
google_2015 %>%  
  ACF(Close, lag_max=100)
```

```
## # A tsibble: 100 x 2 [1]  
##   lag     acf  
##   <lag> <dbl>  
## 1 1 0.982  
## 2 2 0.959  
## 3 3 0.937  
## 4 4 0.918  
## 5 5 0.901  
## 6 6 0.883  
## 7 7 0.865  
## 8 8 0.849  
## 9 9 0.834  
## 10 10 0.818  
## # ... with 90 more rows
```

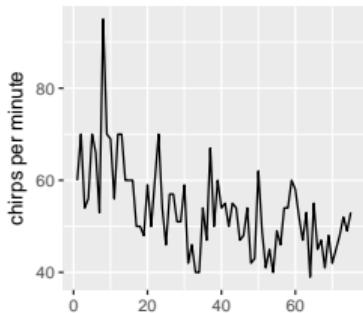
Google stock price

```
google_2015 %>%
  ACF(Close, lag_max = 100) %>%
  autoplot()
```

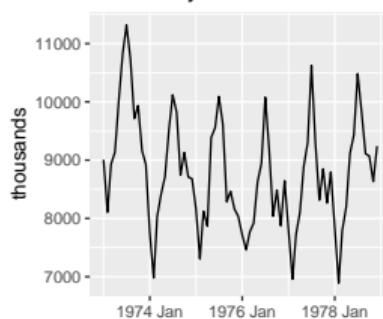


Which is which?

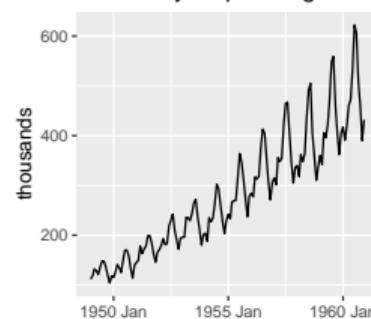
1. Daily temperature of cow



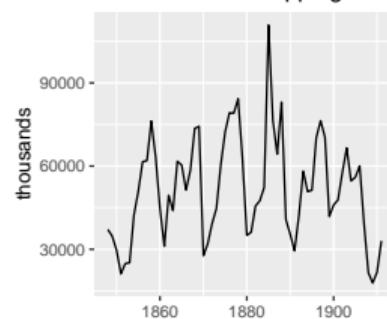
2. Monthly accidental deaths



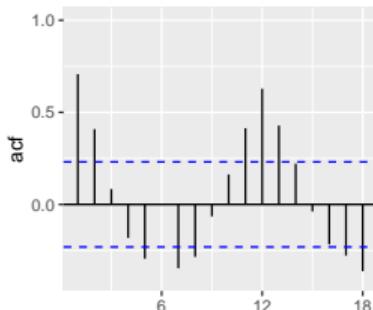
3. Monthly air passengers



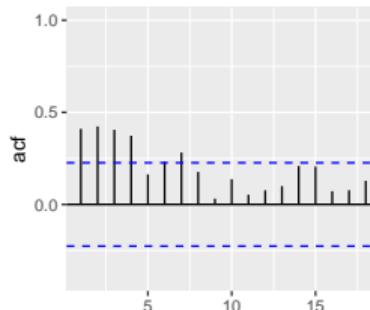
4. Annual mink trappings



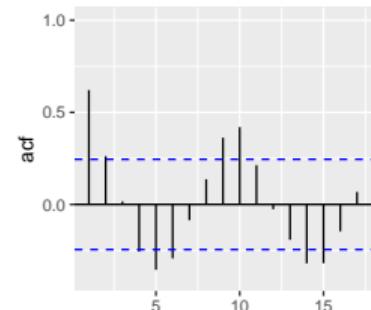
A



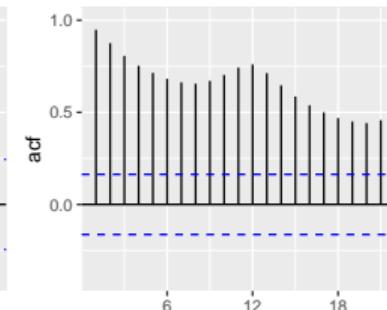
B



C



D

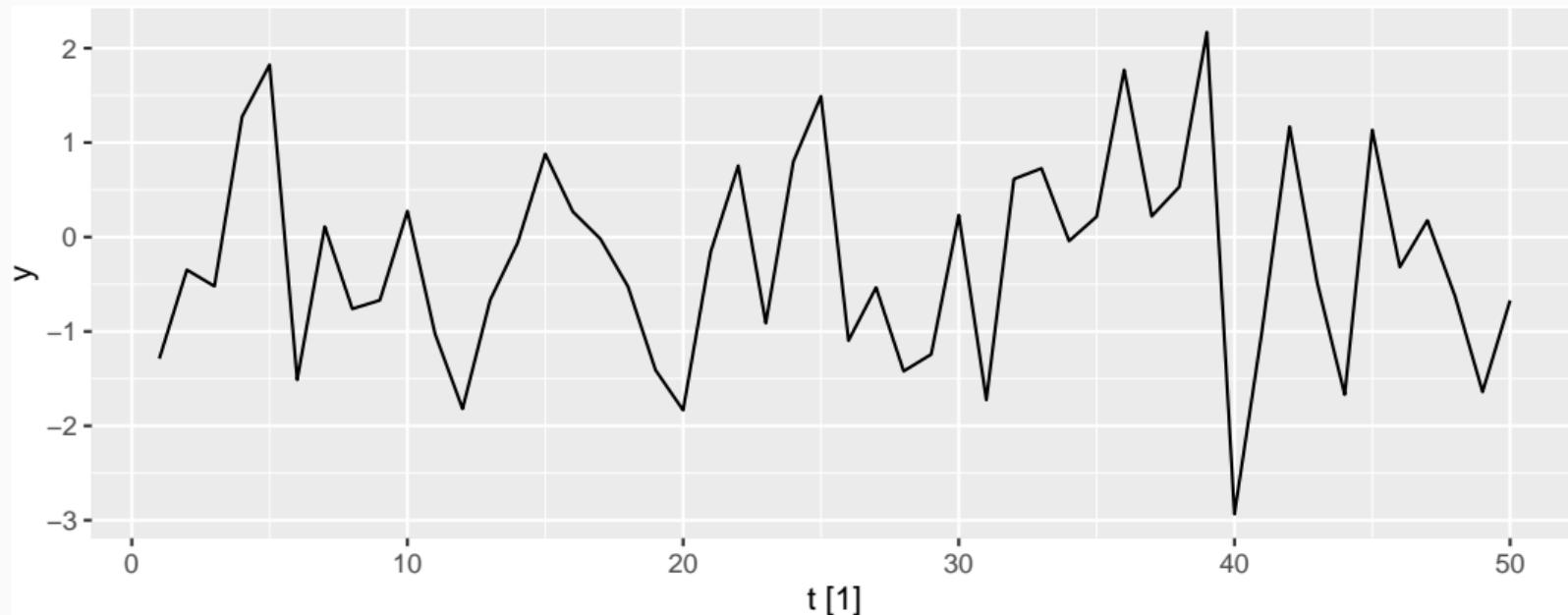


Outline

- 1 Time series in R
- 2 Example: Australian prison population
- 3 Example: Australian pharmaceutical sales
- 4 Time plots
- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

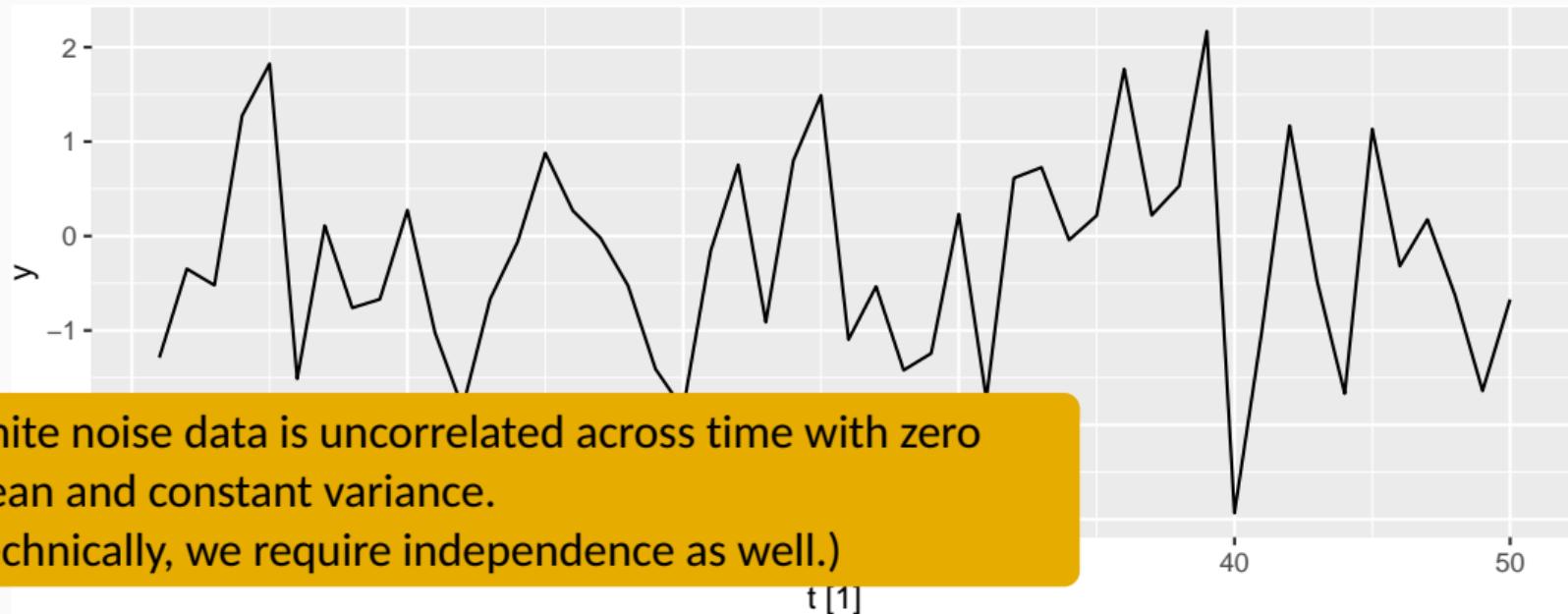
Example: White noise

```
set.seed(30)
wn <- tsibble(t = 1:50, y = rnorm(50), index = t)
wn %>% autoplot(y)
```



Example: White noise

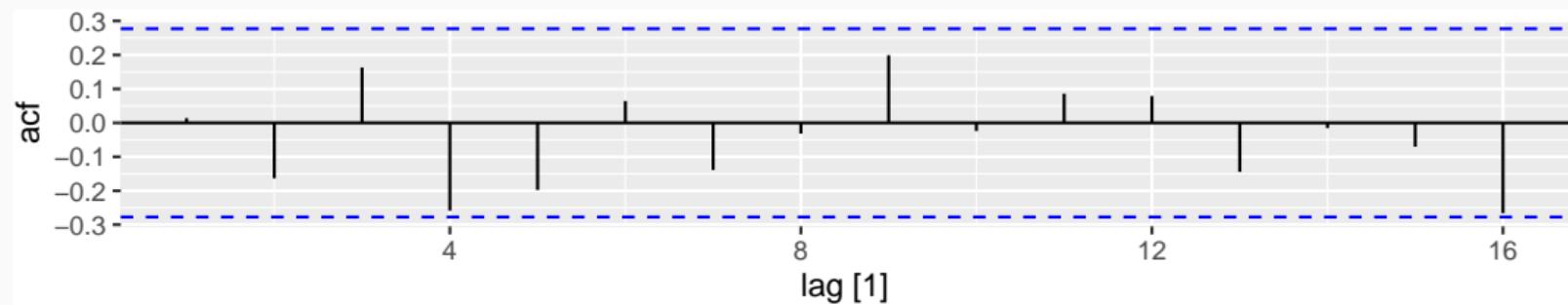
```
set.seed(30)
wn <- tsibble(t = 1:50, y = rnorm(50), index = t)
wn %>% autoplot(y)
```



Example: White noise

```
wn %>% ACF(y)
```

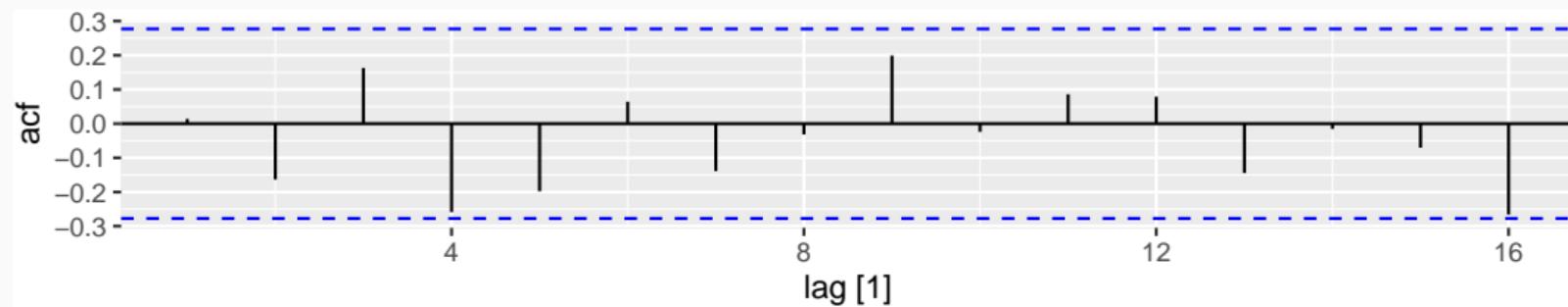
r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
0.014	-0.163	0.163	-0.259	-0.198	0.064	-0.139	-0.032	0.199	-0.024



Example: White noise

```
wn %>% ACF(y)
```

r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
0.014	-0.163	0.163	-0.259	-0.198	0.064	-0.139	-0.032	0.199	-0.024



- Sample autocorrelations for white noise series.
- Expect each autocorrelation to be close to zero.
- Blue lines show 95% critical values.

Sampling distribution of autocorrelations

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

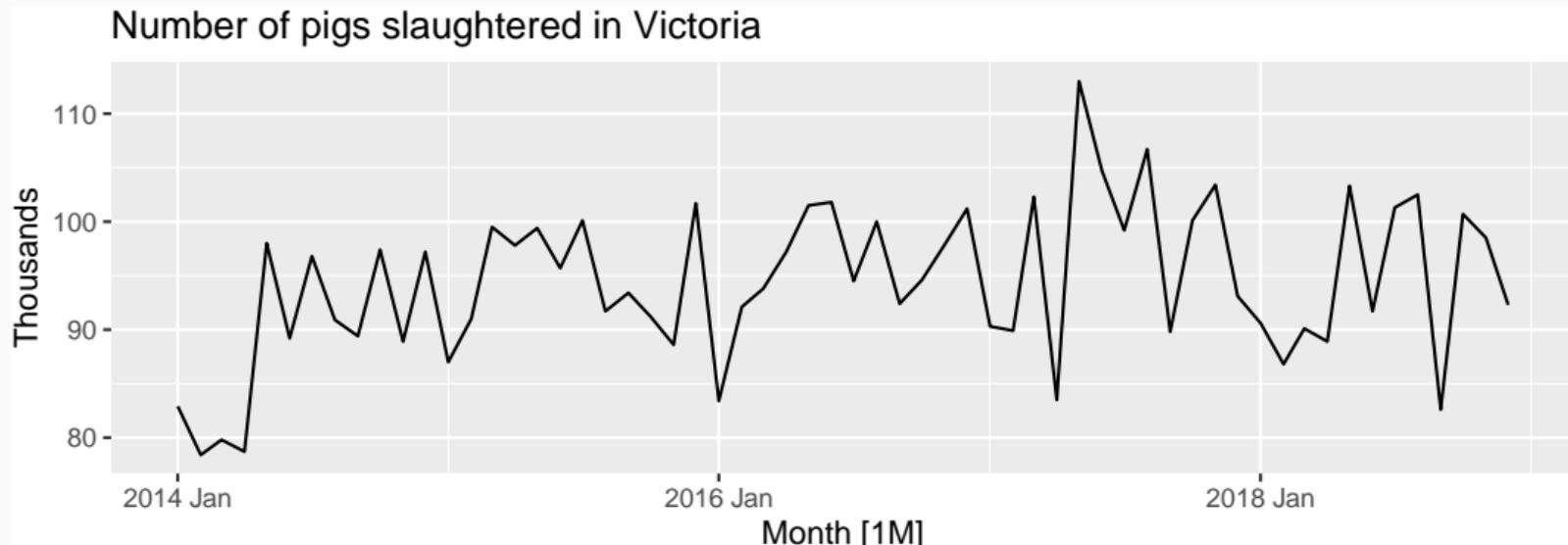
Sampling distribution of autocorrelations

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**.

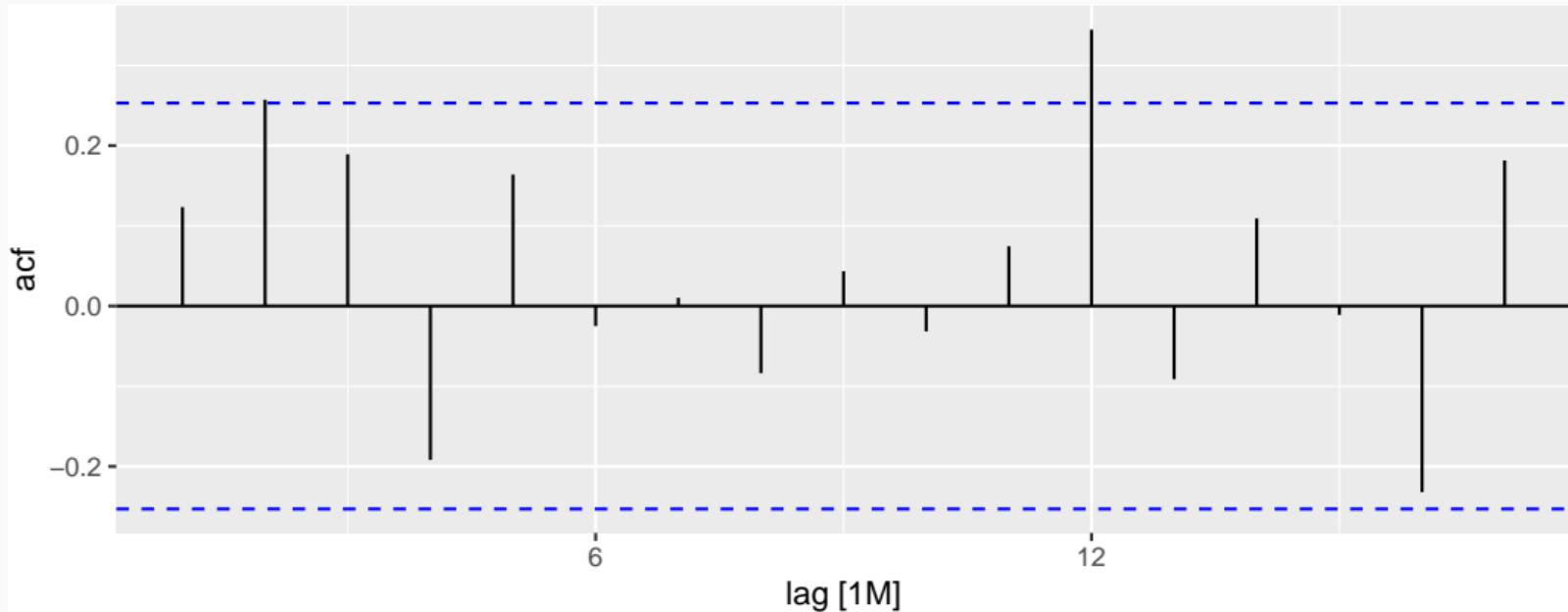
Example: Pigs slaughtered

```
pigs <- aus_livestock %>%
  filter(State == "Victoria", Animal == "Pigs", year(Month) >= 2014)
pigs %>% autoplot(Count/1e3) +
  labs(y = "Thousands", title = "Number of pigs slaughtered in Victoria")
```



Example: Pigs slaughtered

```
pigs %>% ACF(Count) %>% autoplot()
```



Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

- Difficult to detect pattern in time plot.
- ACF shows significant autocorrelation for lag 2 and 12.
- Indicate some slight seasonality.

Example: Pigs slaughtered

Monthly total number of pigs slaughtered in the state of Victoria, Australia, from January 2014 through December 2018 (Source: Australian Bureau of Statistics.)

- Difficult to detect pattern in time plot.
- ACF shows significant autocorrelation for lag 2 and 12.
- 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 in 2018 using

```
dgoog <- gafa_stock %>%  
  filter(Symbol == "GOOG", year(Date) >= 2018) %>%  
  mutate(trading_day = row_number()) %>%  
  update_tsibble(index=trading_day, regular=TRUE) %>%  
  mutate(diff = difference(Close))
```

Does diff look like white noise?