

ETC3550/ETC5550

Applied forecasting

Ch2. Time series graphics

OTexts.org/fpp3/



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- 3 Example: Australian pharmaceutical sales
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- 5 Seasonal and subseries plots
- 6 Lag plots and autocorrelation
- 7 White noise

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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 5488888896.    8.10     4.45    9166764
## 3 1962 Afghanistan 5466666678.    9.35     4.88    9345868
## 4 1963 Afghanistan 7511111191.   16.9      9.17    9533954
## 5 1964 Afghanistan 8000000044.   18.1      8.89    9731361
## 6 1965 Afghanistan 10066666638.   21.4     11.3    9938414
## 7 1966 Afghanistan 13999999967.   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 5488888896.    8.10     4.45    9166764
## # 3 1962 Afghanistan 5466666678.    9.35     4.88    9345868
## # 4 1963 Afghanistan 7511111191.   16.9      9.17    9533954
## # 5 1964 Afghanistan 8000000044.   18.1      8.89    9731361
## # 6 1965 Afghanistan 10066666638.   21.4     11.3    9938414
## # 7 1966 Afghanistan 13999999967.   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

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```
## # 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 5488888896.    8.10     4.45    9166764
## # 3 1962 Afghanistan 5466666678.    9.35     4.88    9345868
## # 4 1963 Afghanistan 7511111191.   16.9      9.17    9533954
## # 5 1964 Afghanistan 8000000044.   18.1      8.89    9731361
## # 6 1965 Afghanistan 10066666638.   21.4     11.3    9938414
## # 7 1966 Afghanistan 13999999967.   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
```

	Year	Country	GDP	Imports	Exports	Population
	Index	Key	Measured variables			
## 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      50  
## 2 2019      23  
## 3 2019      34  
## 4 2019      30  
## 5 2019      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>

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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
## 5 ACT    Female  Remanded ATST        1 2006  Q1
```

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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_~1 ATC2  ATC2_~2 Scripts  Cost
##   <mth> <chr>       <chr>    <chr> <chr>  <chr>  <chr>    <dbl> <dbl>
## 1 1991 Jul Concessional Co-payments A Alimen~ A01 STOMAT~  18228 67877
## 2 1991 Aug Concessional Co-payments A Alimen~ A01 STOMAT~  15327 57011
## 3 1991 Sep Concessional Co-payments A Alimen~ A01 STOMAT~  14775 55020
## 4 1991 Oct Concessional Co-payments A Alimen~ A01 STOMAT~  15380 57222
## 5 1991 Nov Concessional Co-payments A Alimen~ A01 STOMAT~  14371 52120
## 6 1991 Dec Concessional Co-payments A Alimen~ A01 STOMAT~  15028 54299
## 7 1992 Jan Concessional Co-payments A Alimen~ A01 STOMAT~  11040 39753
## 8 1992 Feb Concessional Co-payments A Alimen~ A01 STOMAT~  15165 54405
## 9 1992 Mar Concessional Co-payments A Alimen~ A01 STOMAT~  16898 61108
## 10 1992 Apr Concessional Co-payments A Alimen~ A01 STOMAT~ 18141 65356
## # ... with 67,586 more rows, and abbreviated variable names 1: ATC1_desc,
## # 2: ATC2_desc
```

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_~1 ATC2   ATC2_~2 Scripts   Cost  
##       <mth> <chr>        <chr>    <chr> <chr> <chr>    <chr> <dbl>    <dbl>  
## 1 1991 Jul Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  89733 2.09e6  
## 2 1991 Aug Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  77101 1.80e6  
## 3 1991 Sep Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  76255 1.78e6  
## 4 1991 Oct Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  78681 1.85e6  
## 5 1991 Nov Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  70554 1.69e6  
## 6 1991 Dec Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  75814 1.84e6  
## 7 1992 Jan Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  64186 1.56e6  
## 8 1992 Feb Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  75899 1.73e6  
## 9 1992 Mar Concessional Co-paymen~ A     Alimen~ A10  ANTIDI~  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
```

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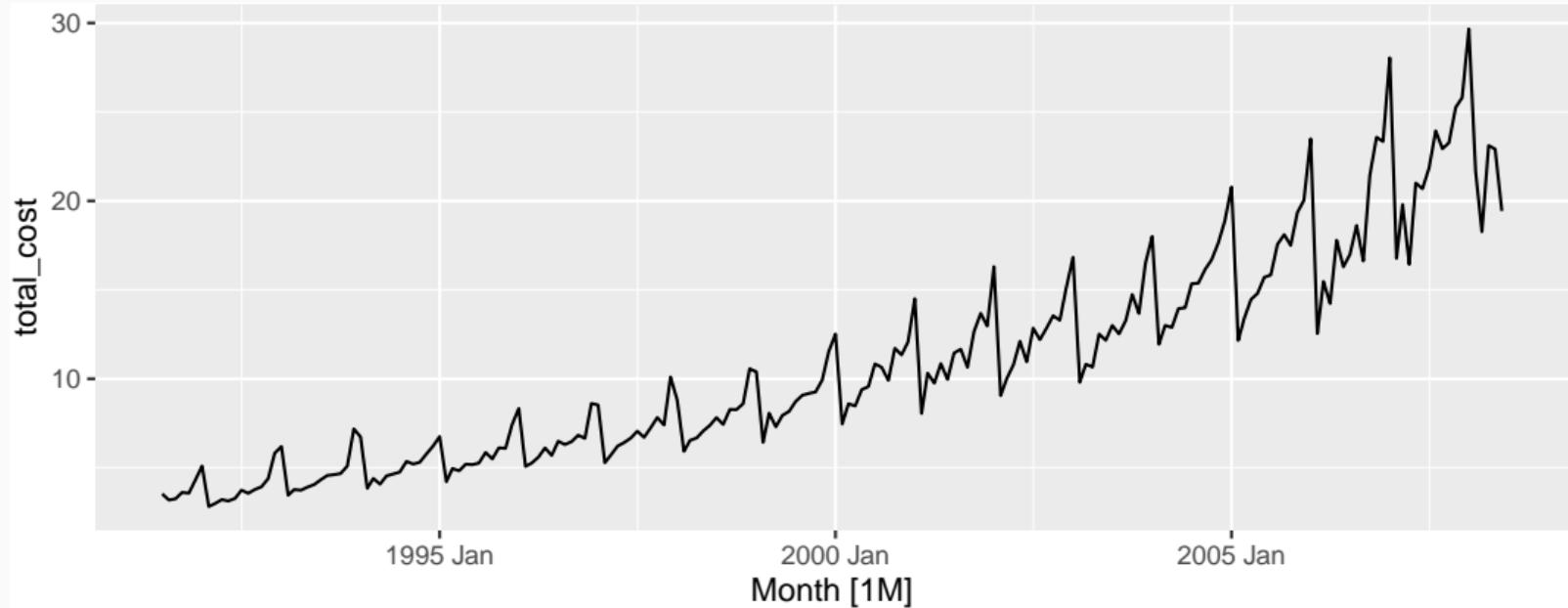
Lag plots and autocorrelation

7

White noise

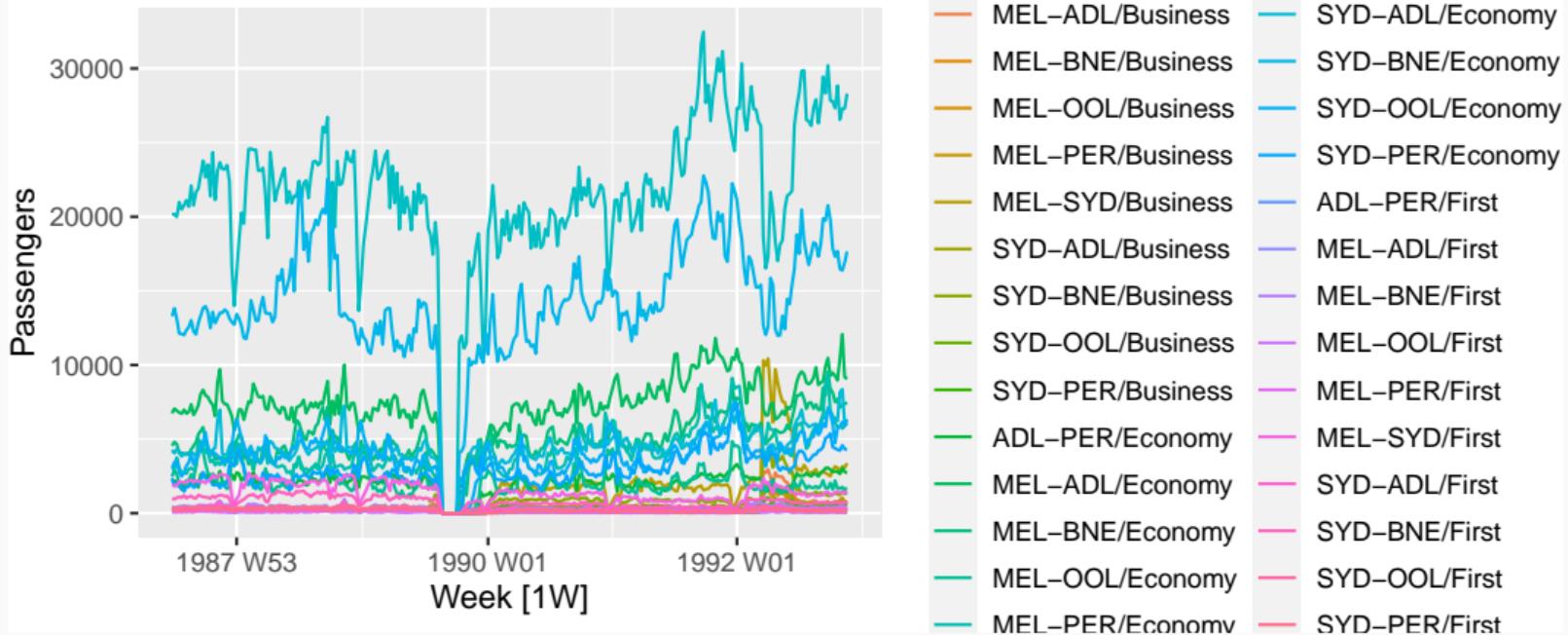
Time plots

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



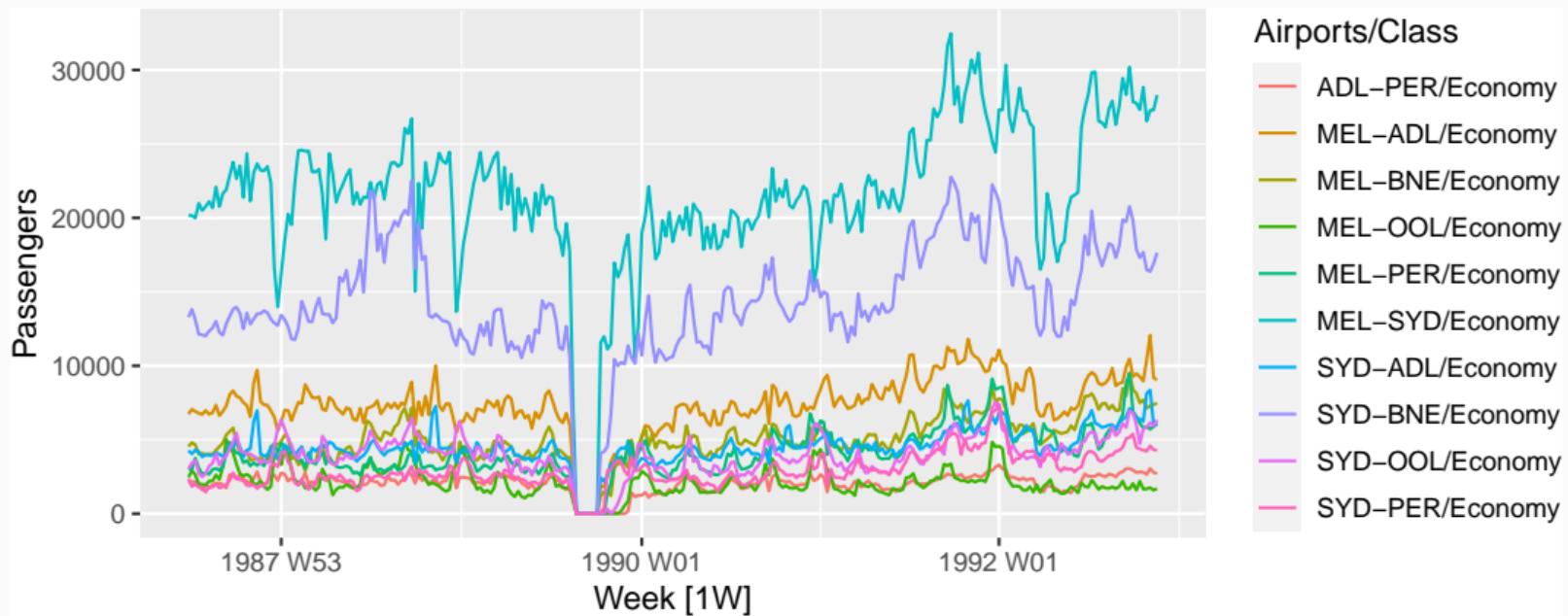
Ansett airlines

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



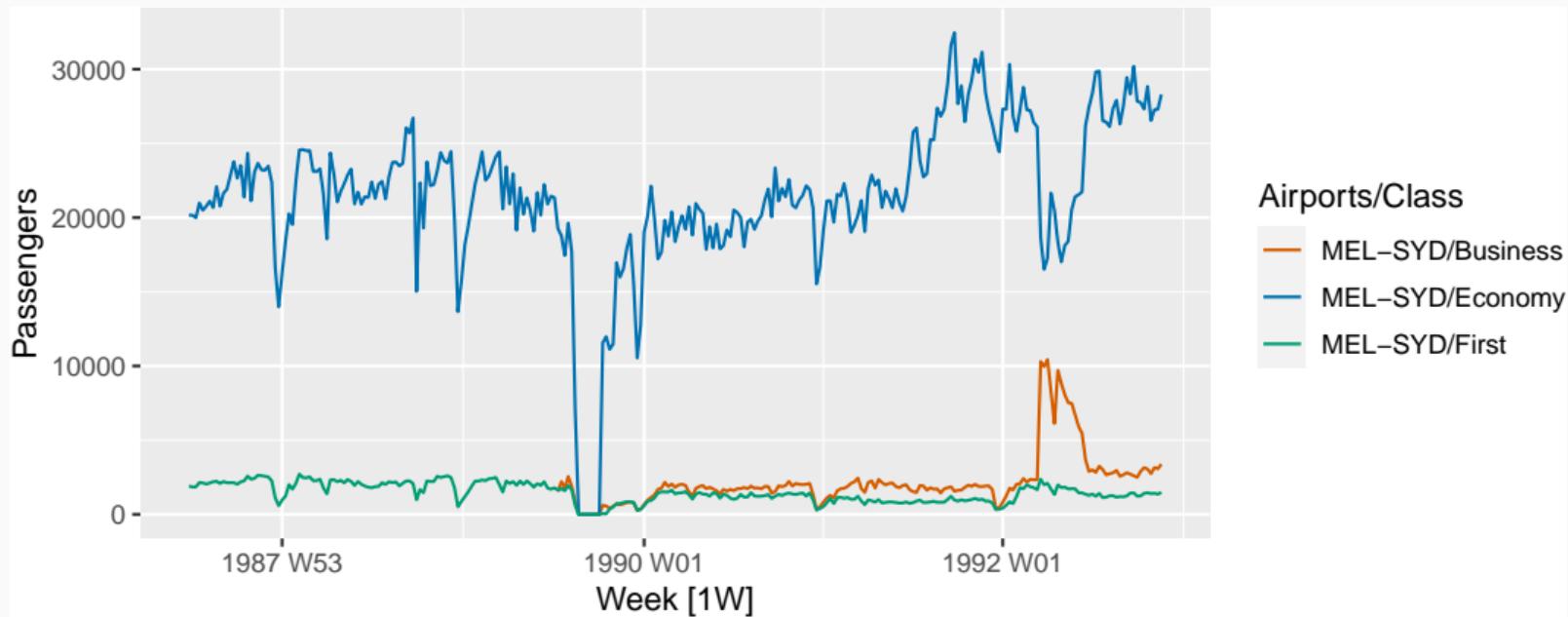
Ansett airlines

```
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).

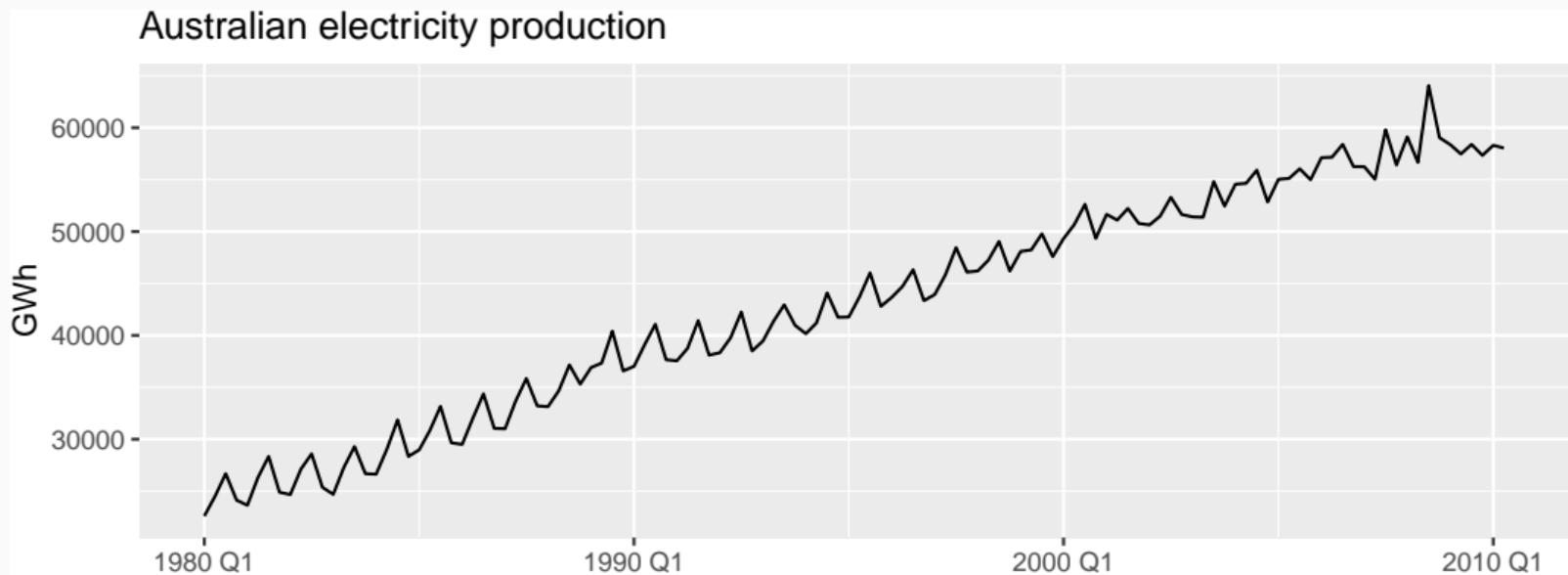
Time series components

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

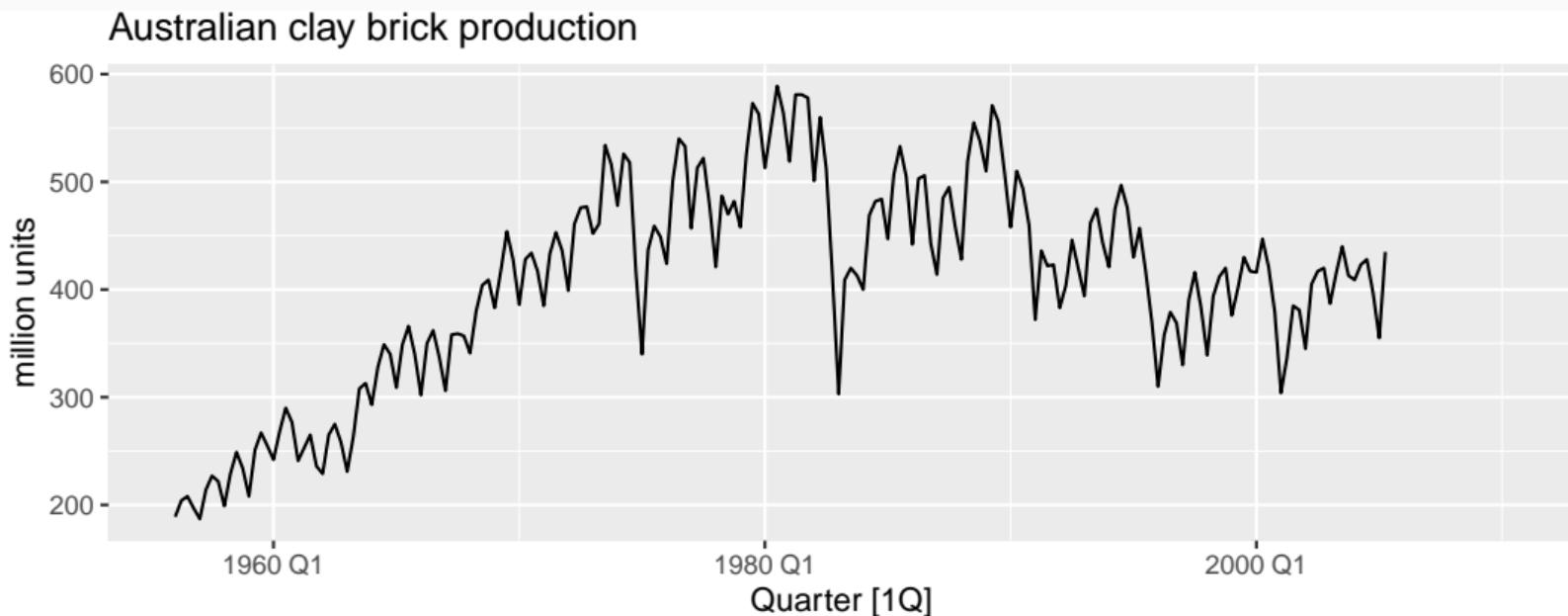
Time series patterns

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



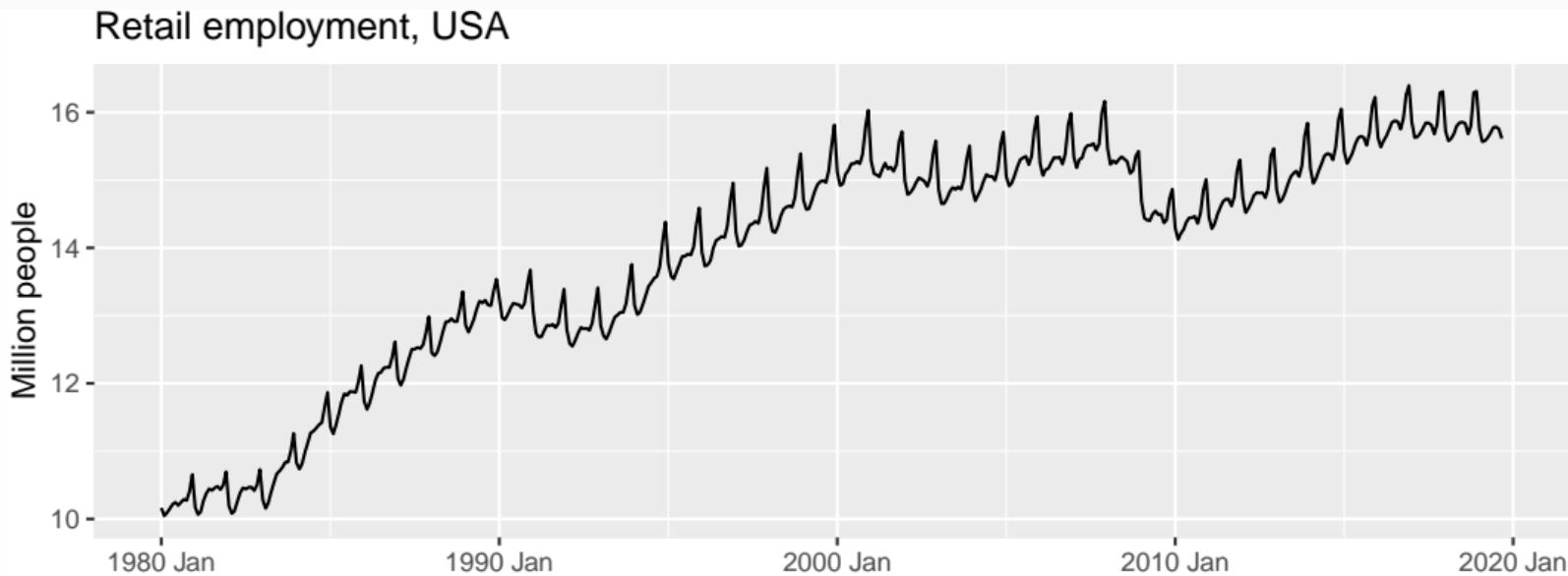
Time series patterns

```
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")
```



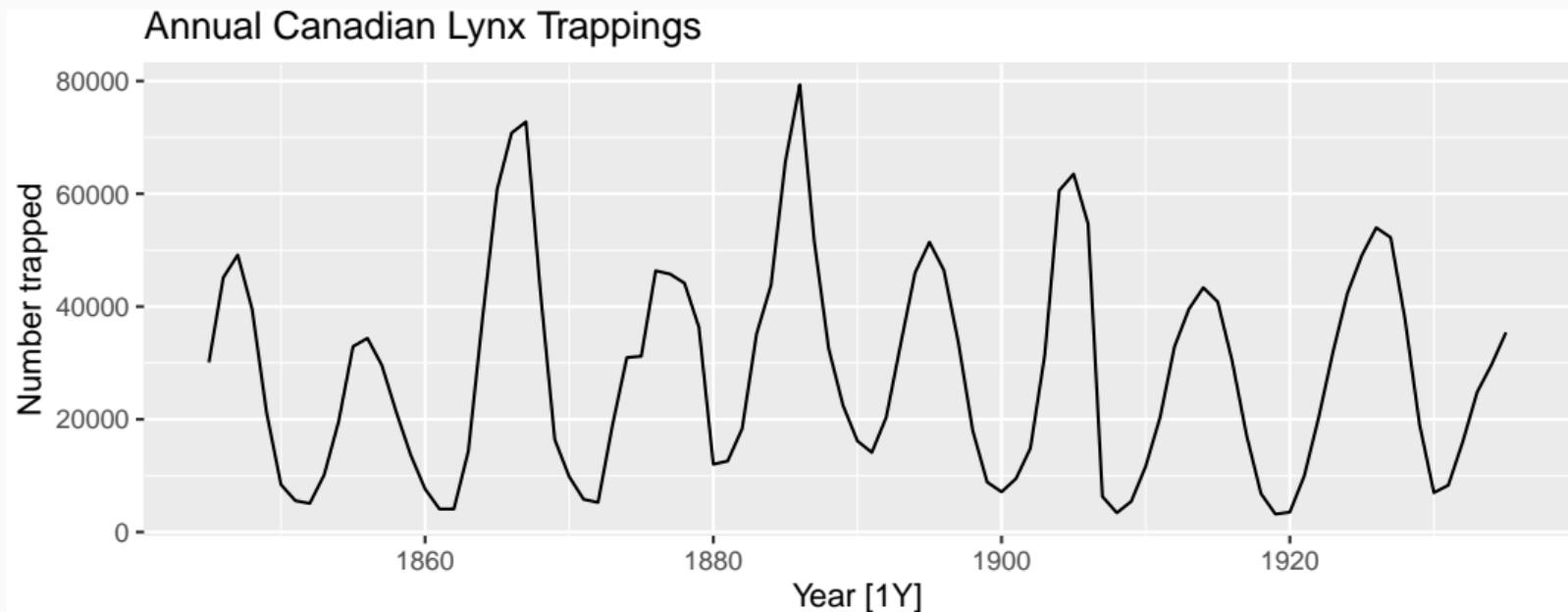
Time series patterns

```
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.

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Seasonal and subseries plots

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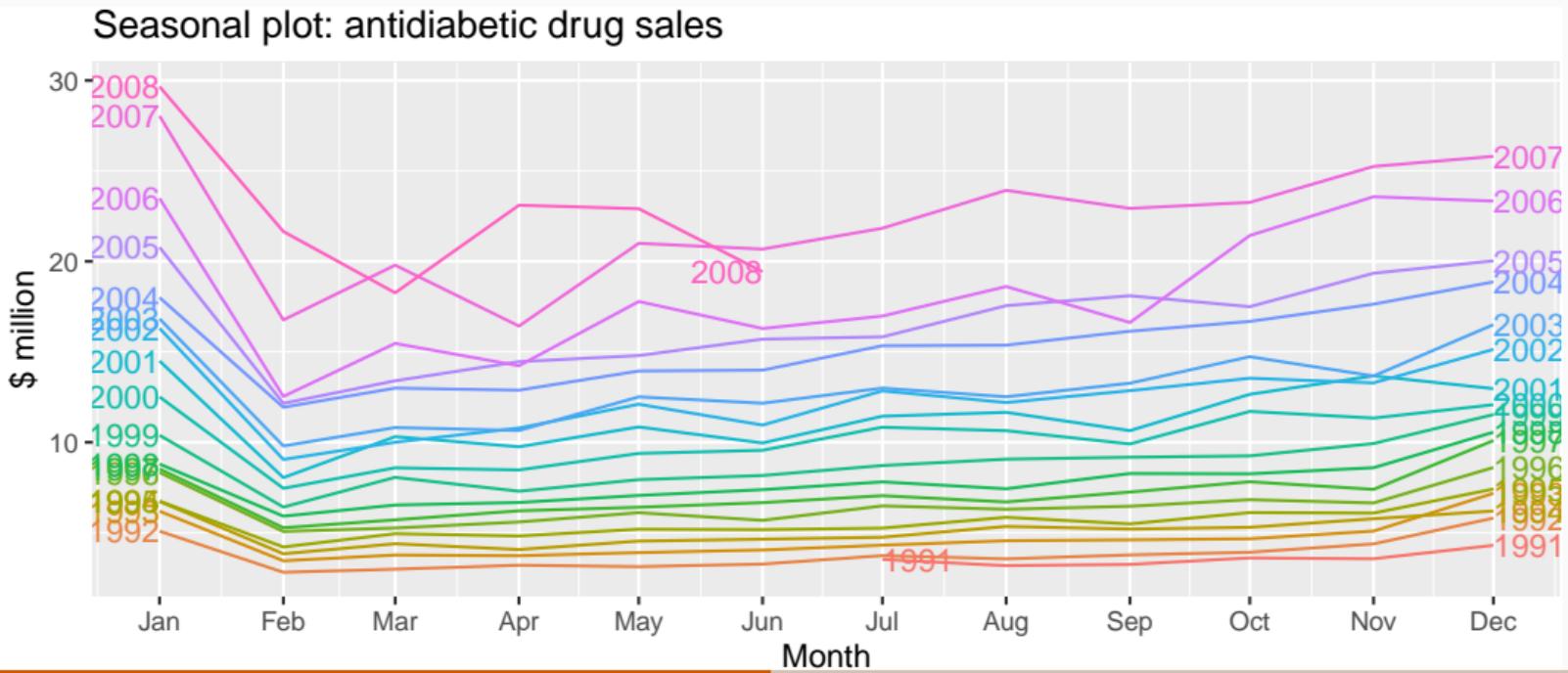
Lag plots and autocorrelation

7

White noise

Seasonal plots

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



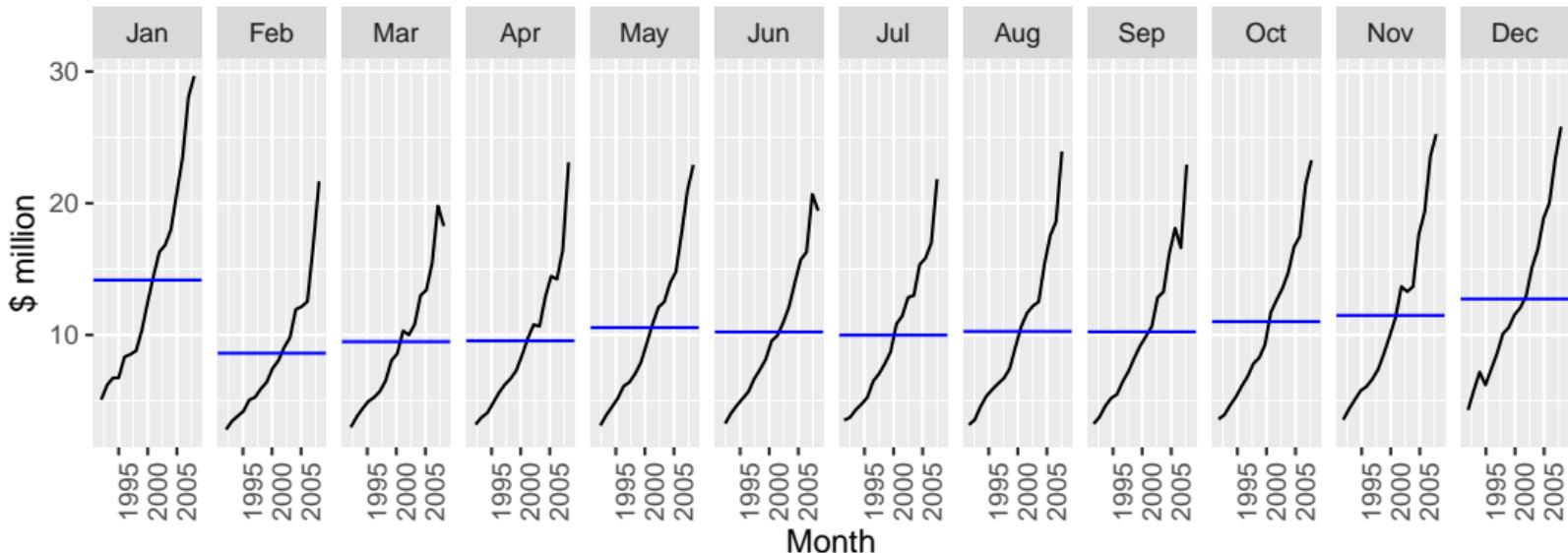
Seasonal plots

- 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")
```

Subseries plot: antidiabetic drug sales

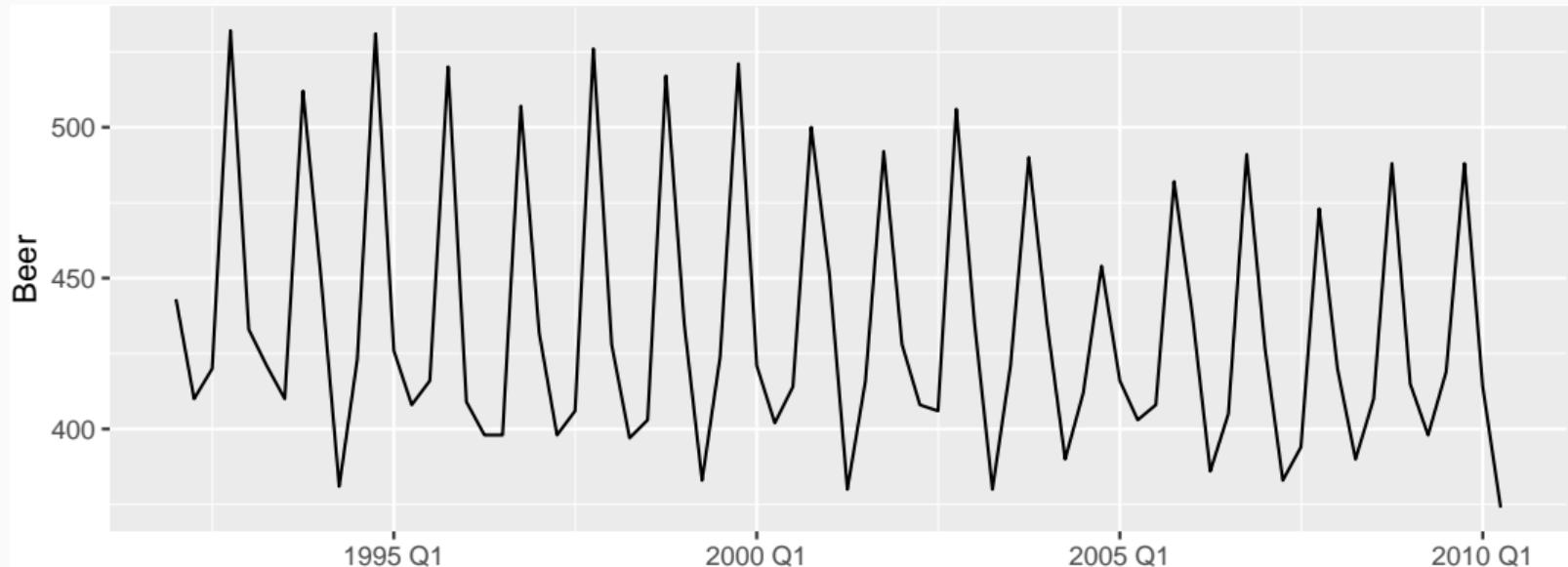


Seasonal subseries plots

- 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()`

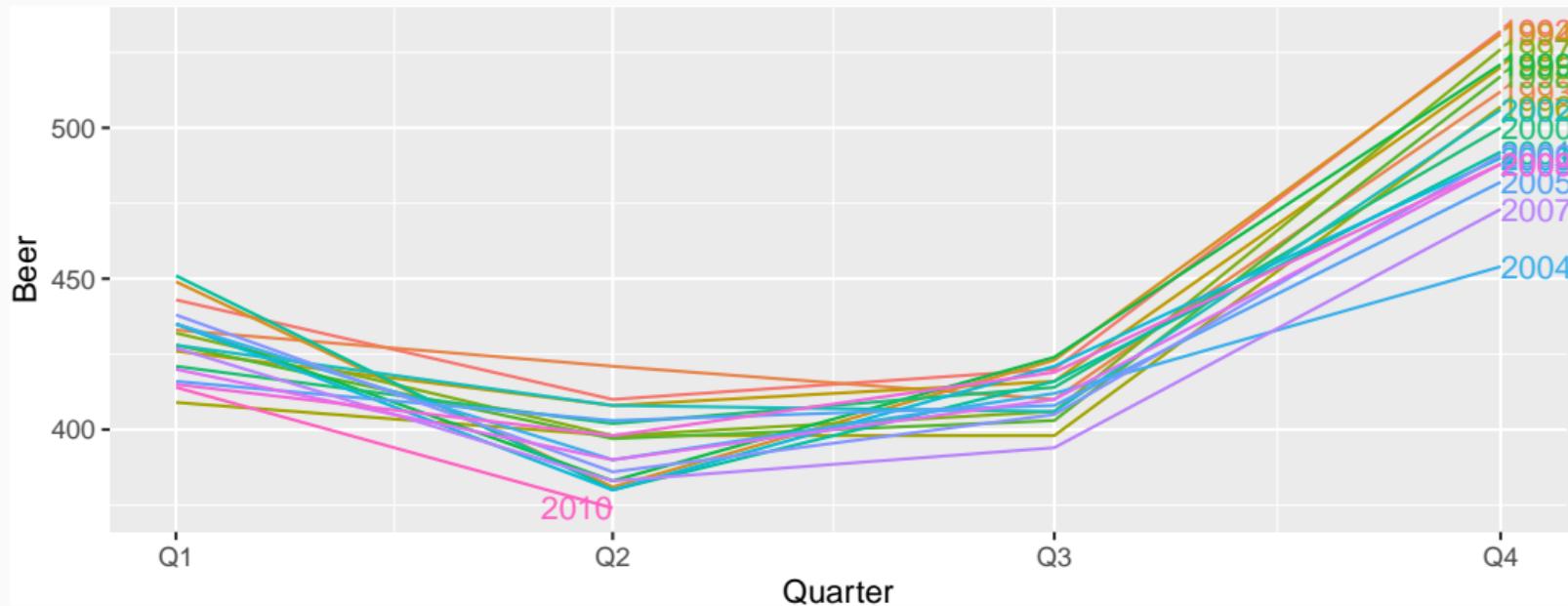
Quarterly Australian Beer Production

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



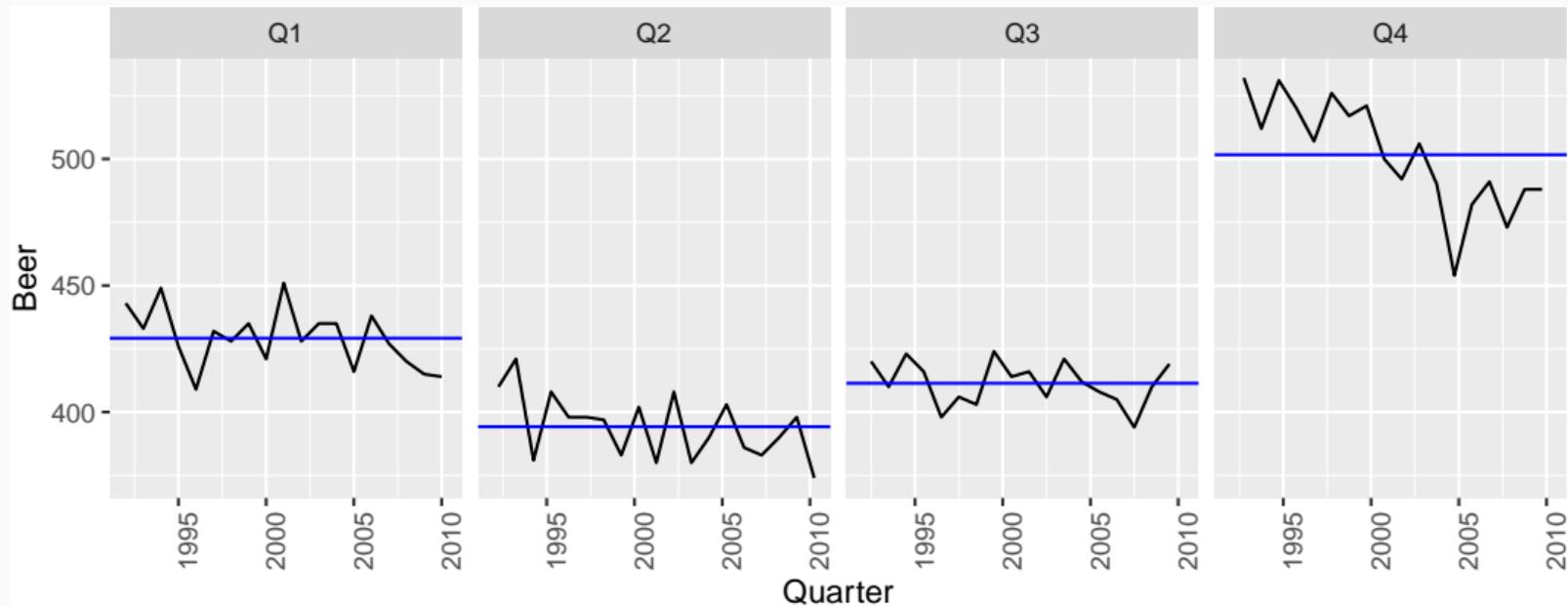
Quarterly Australian Beer Production

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



Quarterly Australian Beer Production

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



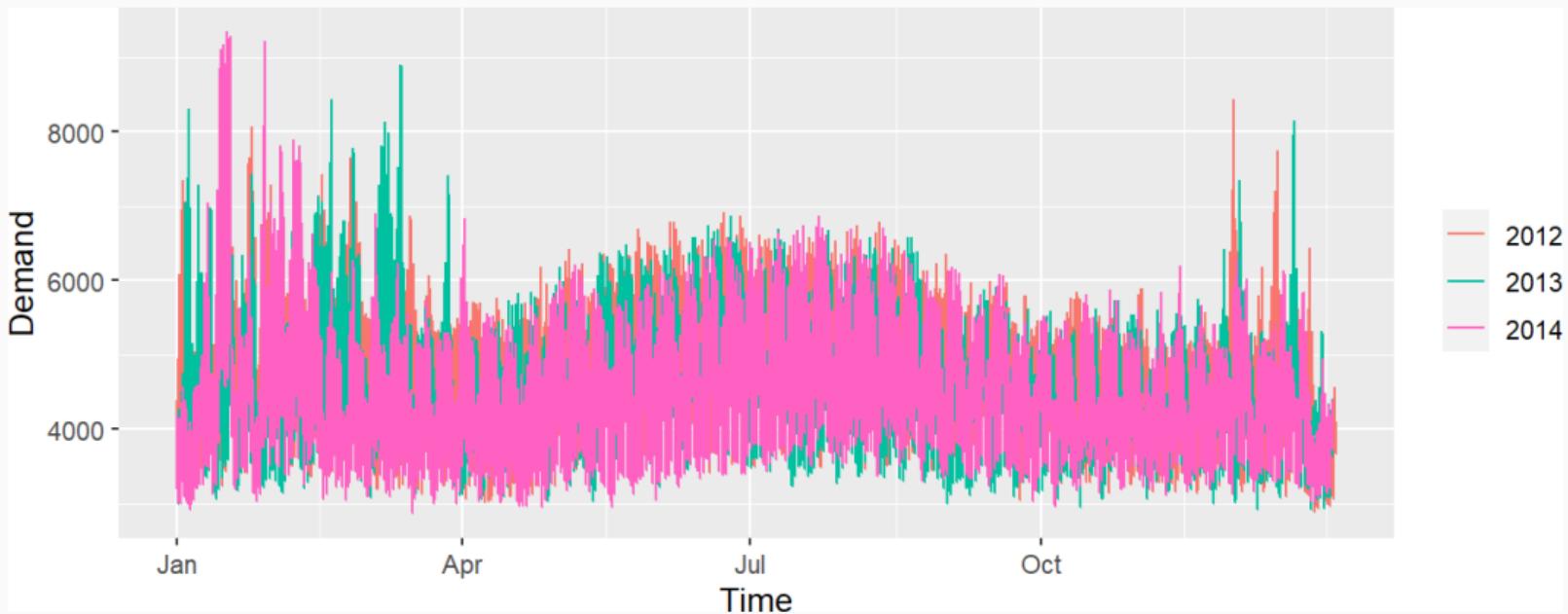
Multiple seasonal periods

```
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
## # i Use `print(n = ...)` to see more rows
```

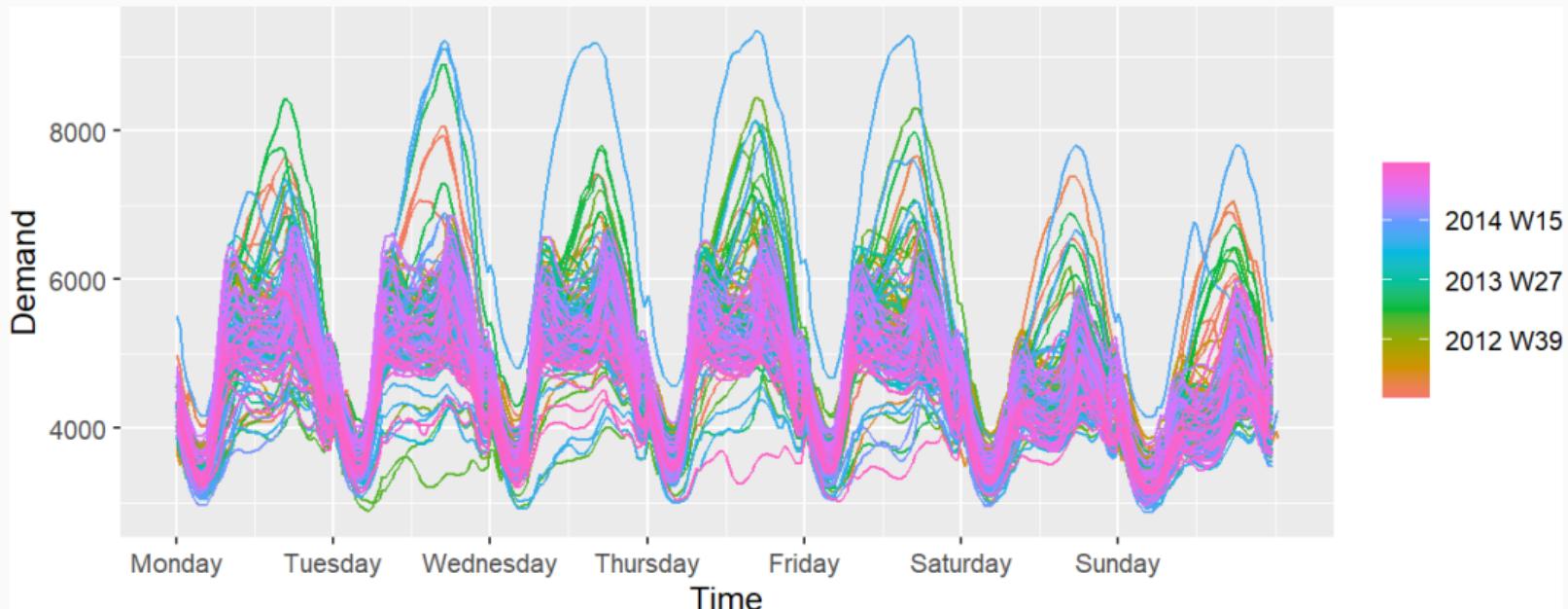
Multiple seasonal periods

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



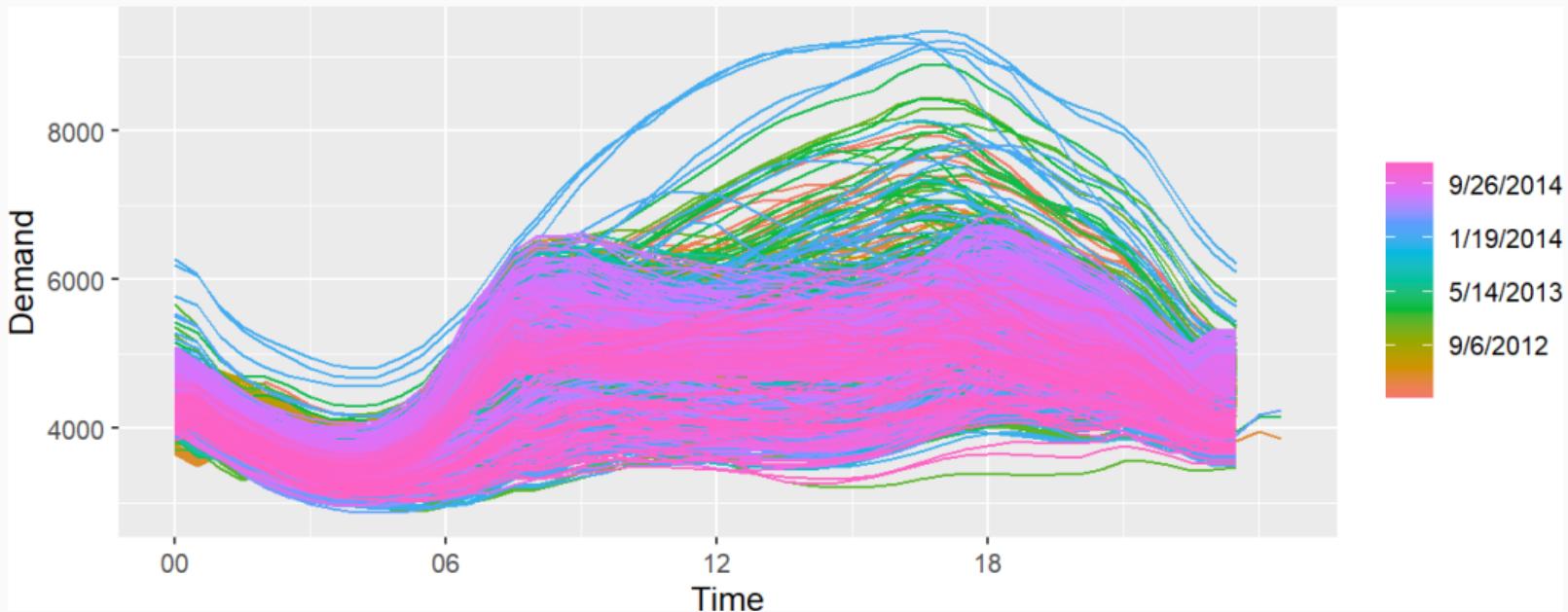
Multiple seasonal periods

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



Multiple seasonal periods

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



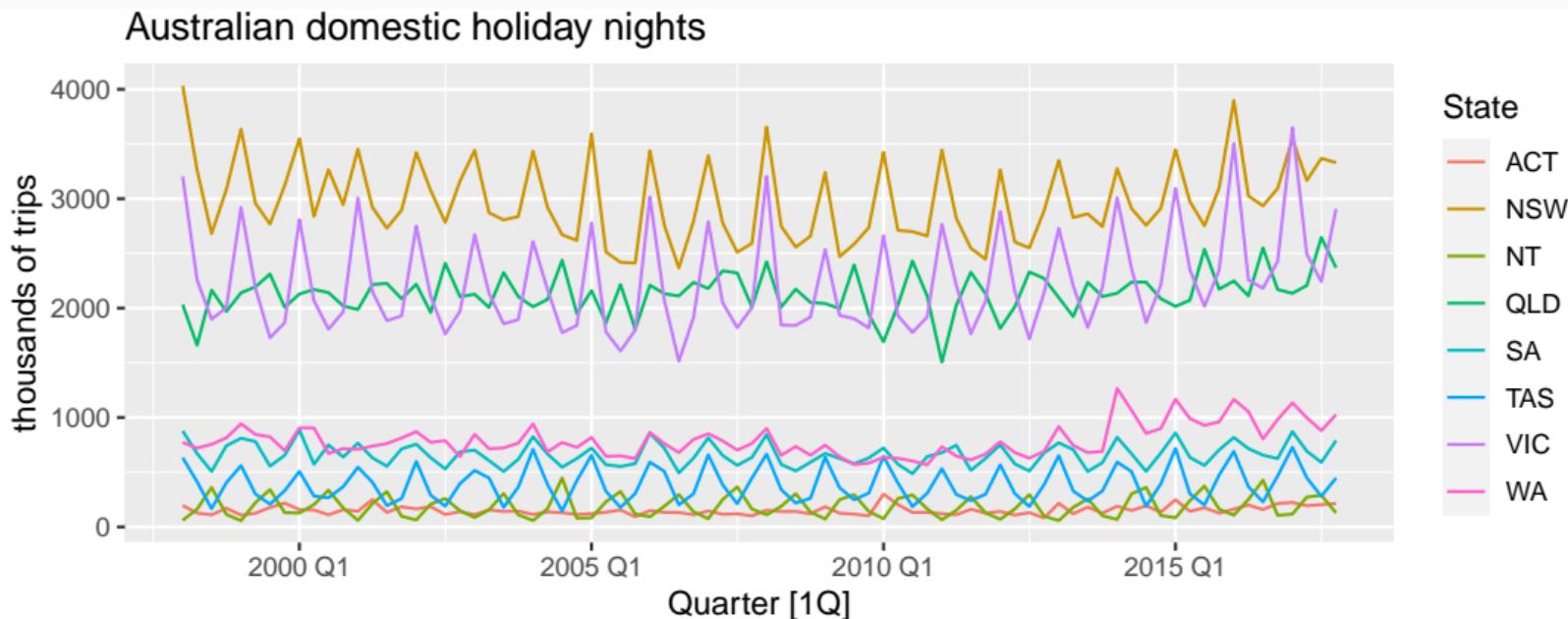
Australian holidays

```
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.
```

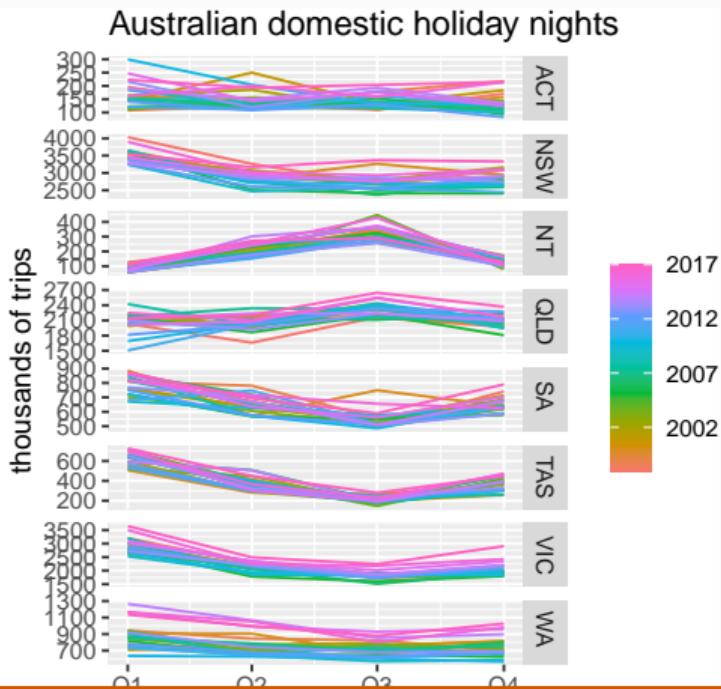
Australian holidays

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



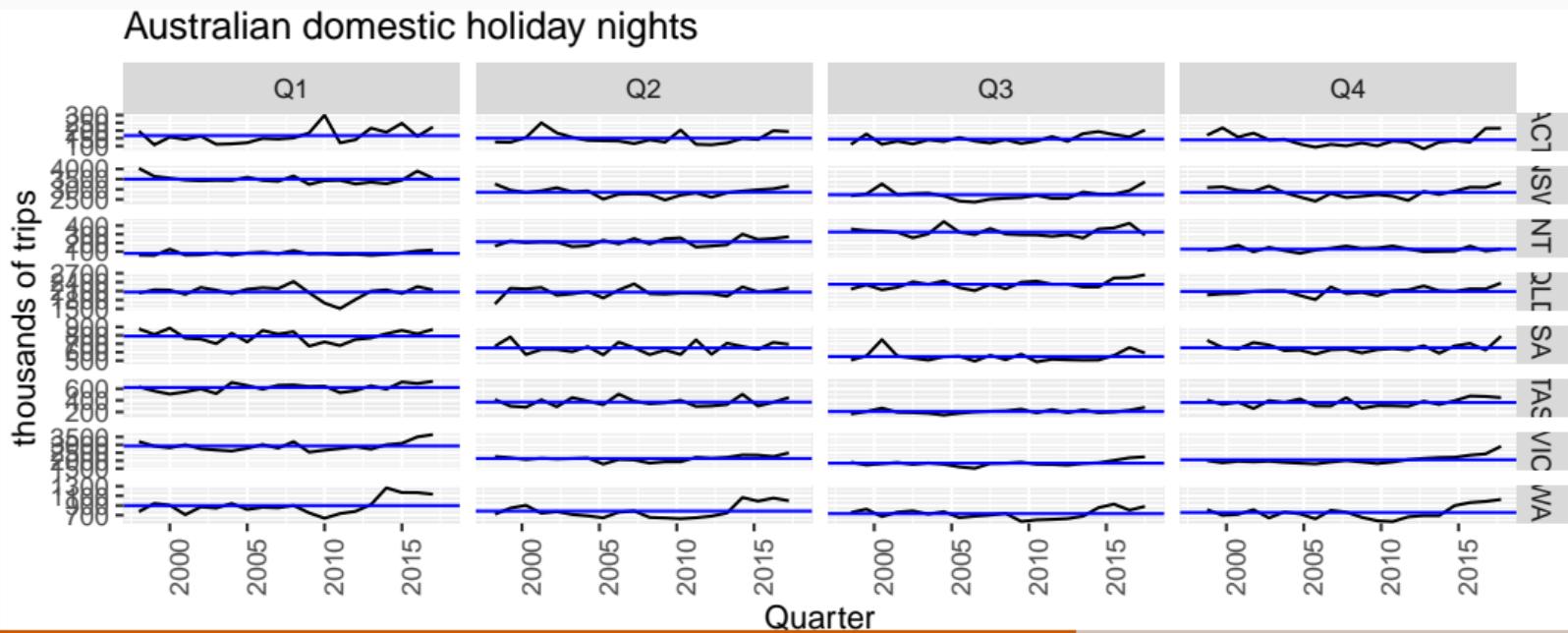
Seasonal plots

```
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

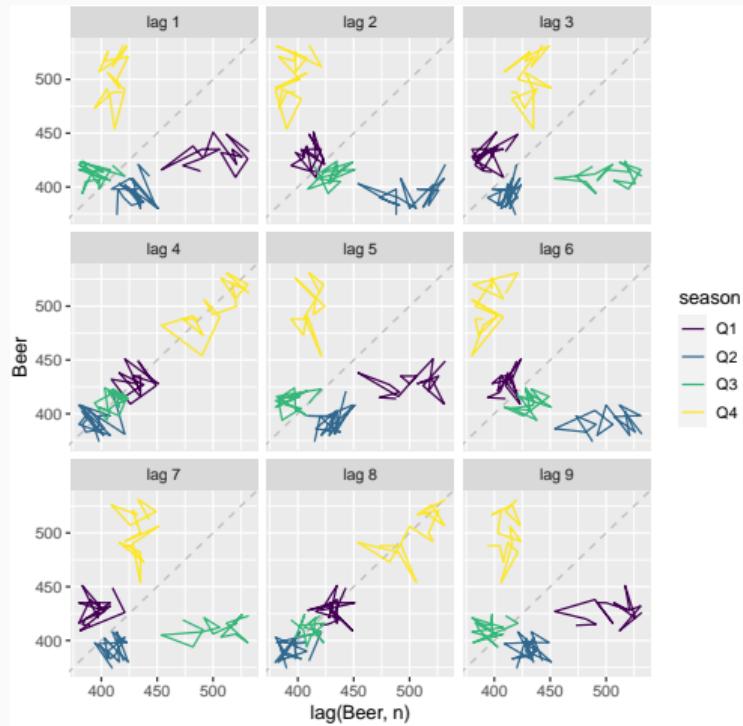
Example: Beer production

```
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
```

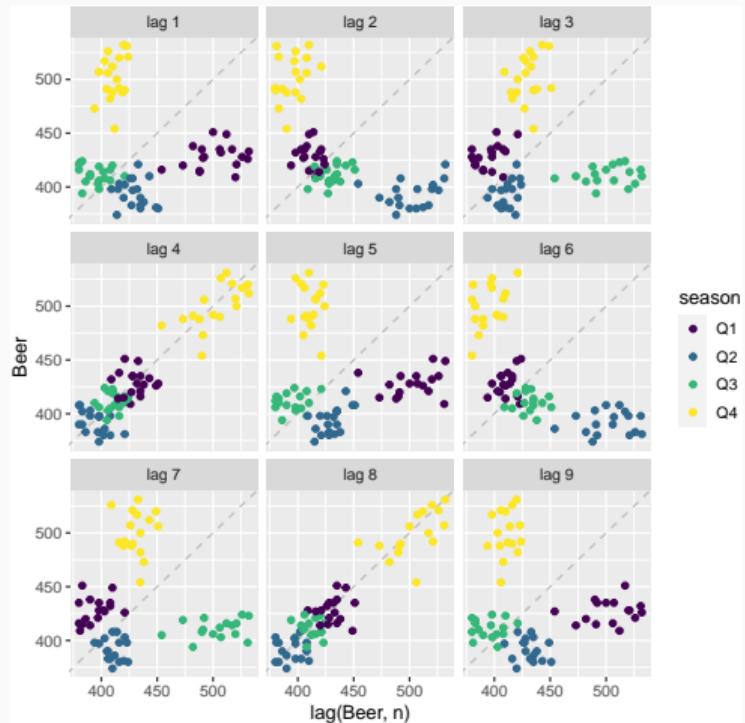
Example: Beer production

```
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:

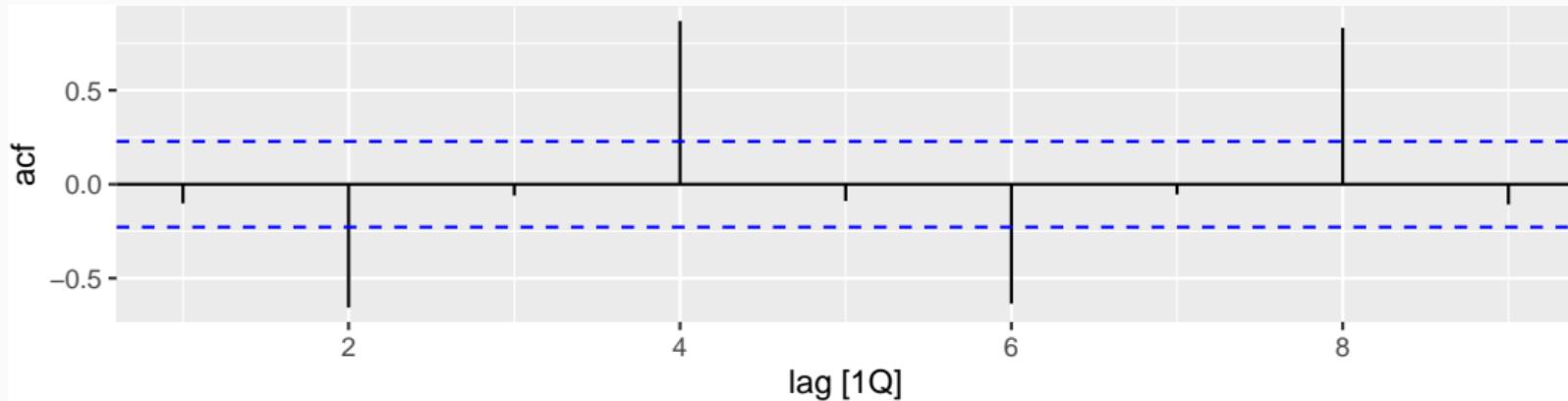
```
new_production %>% ACF(Beer, lag_max = 9)
```

```
## # A tsibble: 9 x 2 [1Q]
##      lag     acf
##    <lag>   <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:

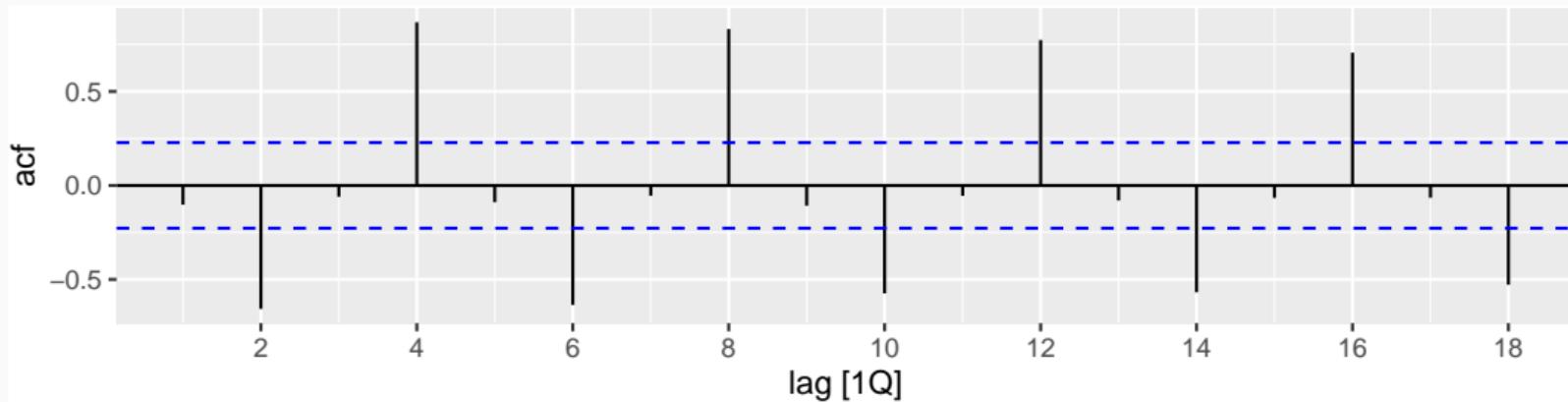
```
new_production %>% ACF(Beer, lag_max = 9) %>% autoplot()
```



- 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()
```



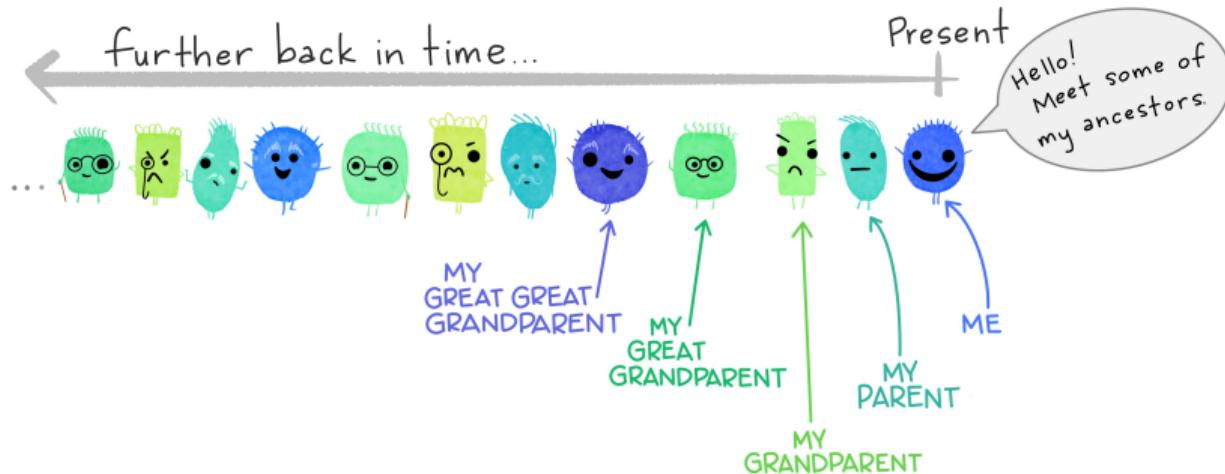
- r_4 higher than for the other lags. This is due to **the seasonal pattern in the data**: the peaks tend to be **4 quarters** apart and the troughs tend to be **2 quarters** apart.
- r_2 is more negative than for the other lags because troughs tend to be 2 quarters behind peaks.

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)

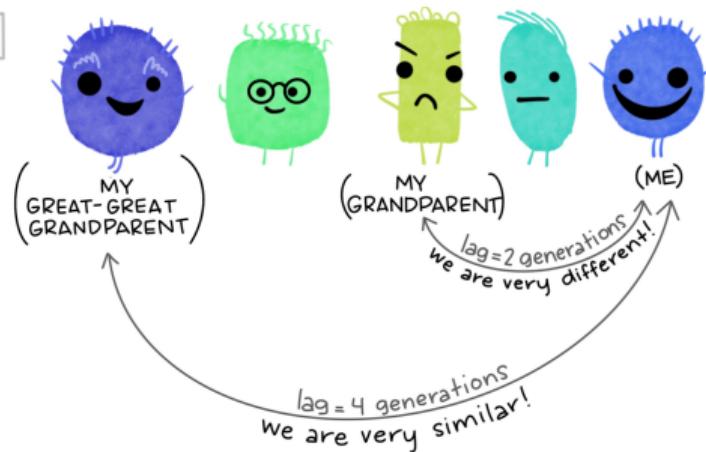


Autocorrelation functions

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

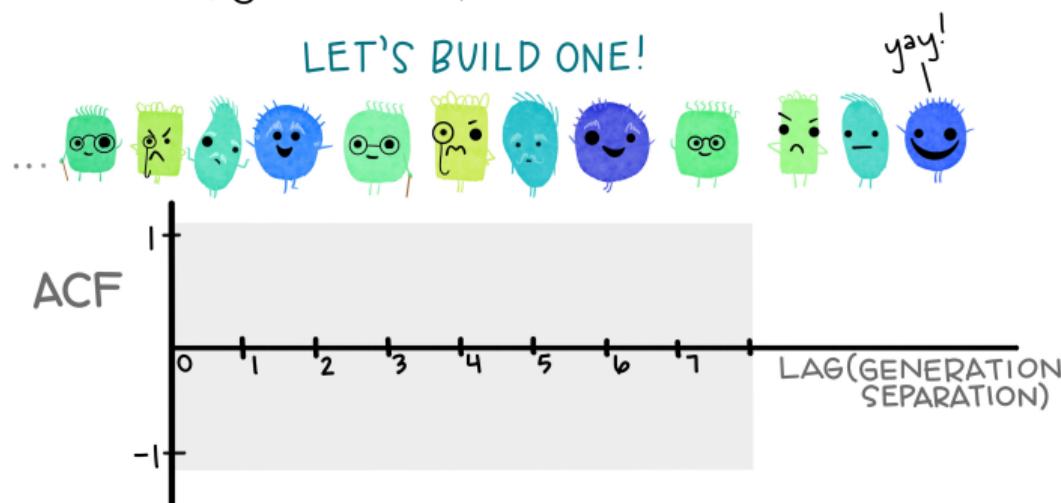
FOR EXAMPLE:



Autocorrelation functions

THE autocorrelation function (ACF)

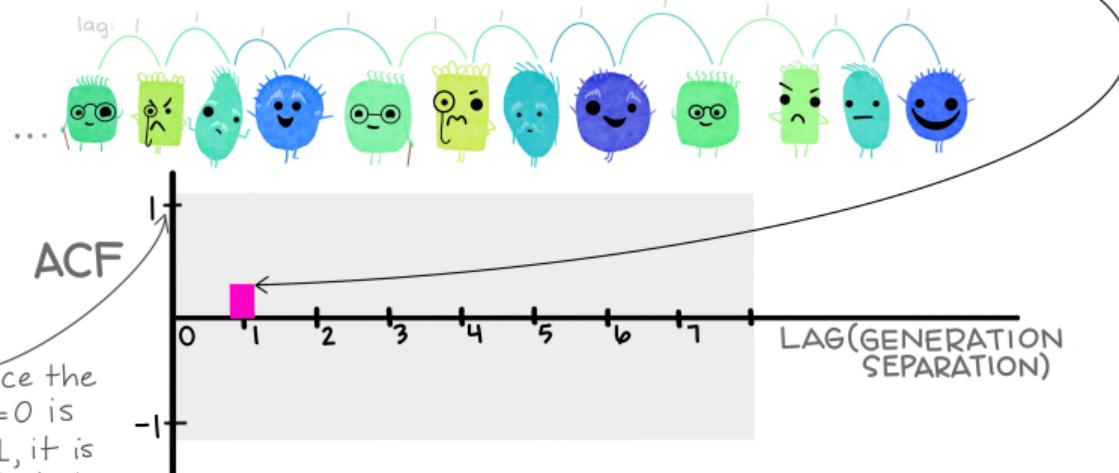
The ACF is a plot of autocorrelation between a variable and itself separated by specified lags (in our case, generations)



Autocorrelation functions

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

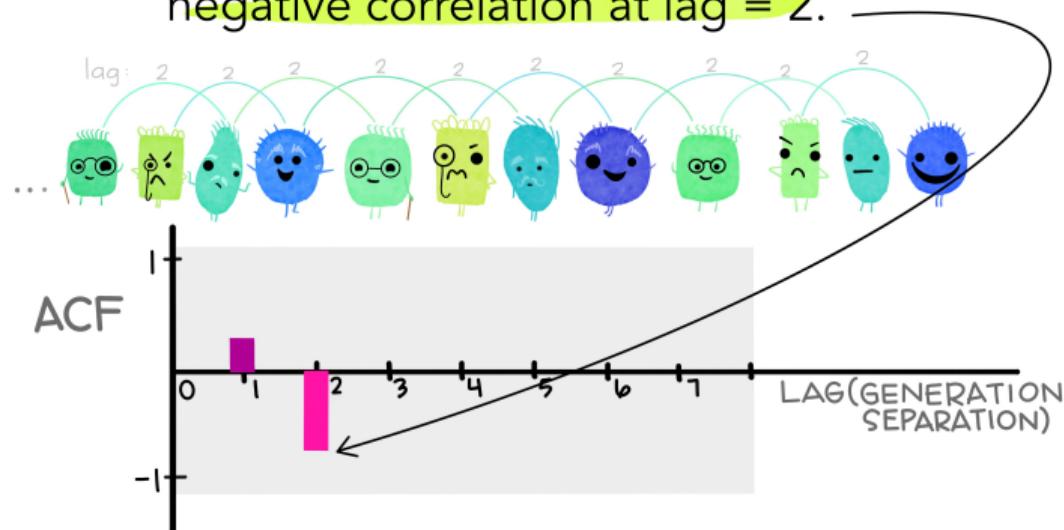
They are **somewhat positively correlated**:



Autocorrelation functions

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

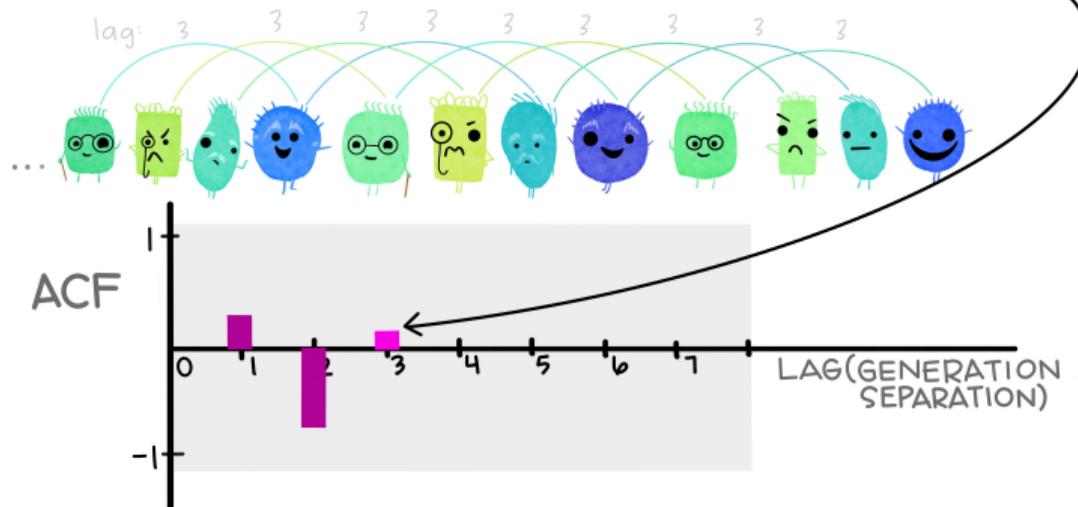
Since they tend to be very different, we find a **negative correlation at lag = 2**.



Autocorrelation functions

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

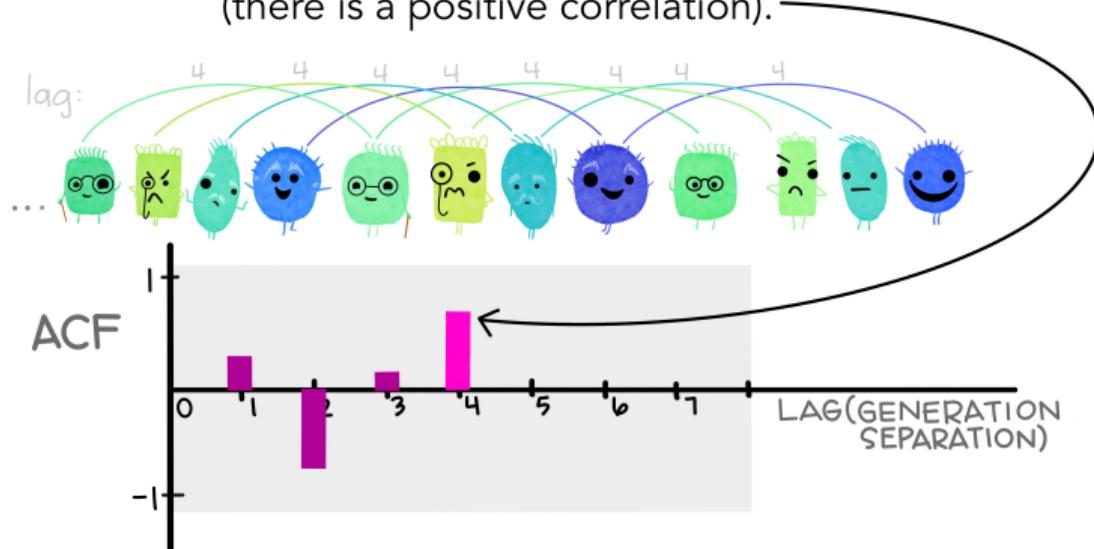
They are slightly positively correlated.



Autocorrelation functions

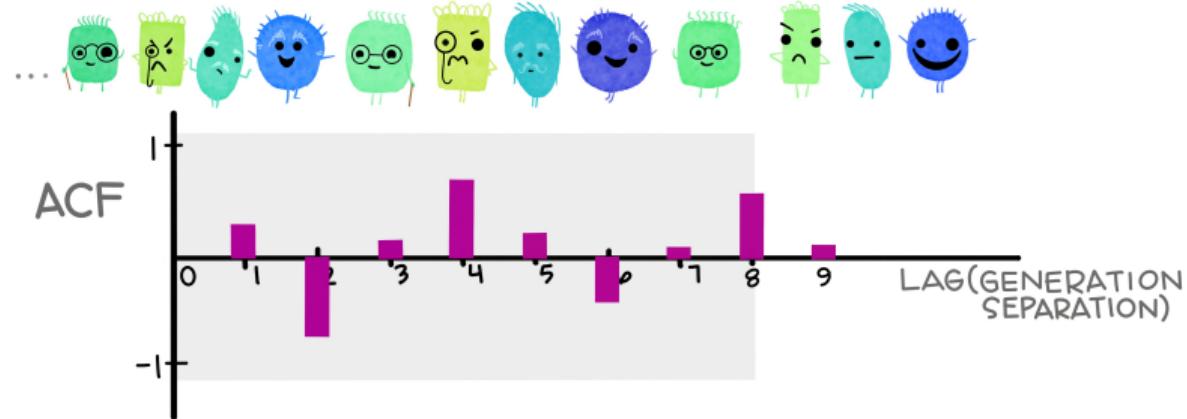
At lag = 4, we find the correlation between **monsters** and their **great-great grandparent**.

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



Autocorrelation functions

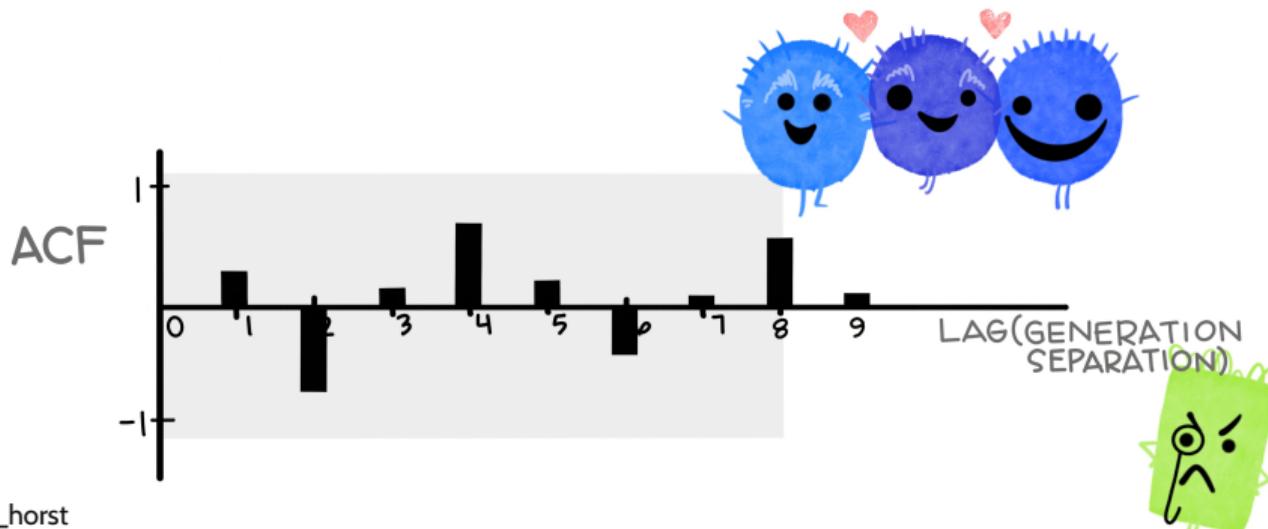
...and we continue finding the correlations as we increase the lag (generations) between the monsters...



Autocorrelation functions

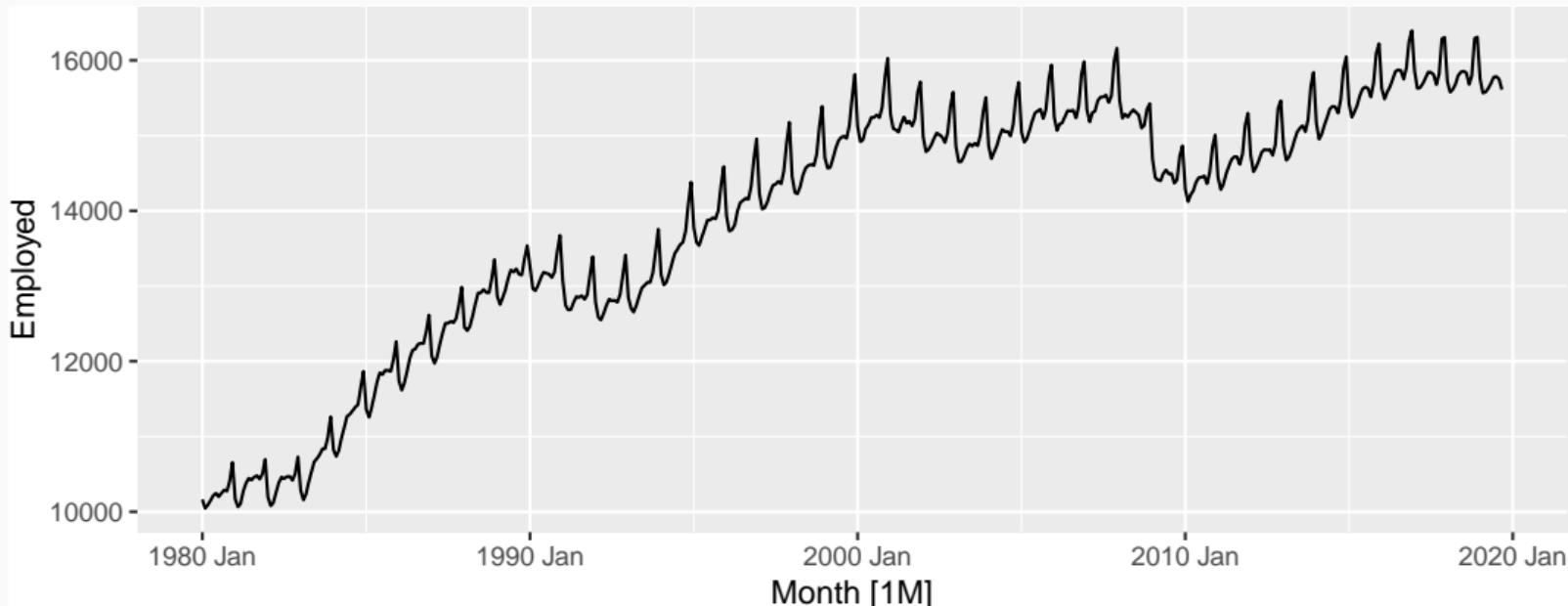
in summary:

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



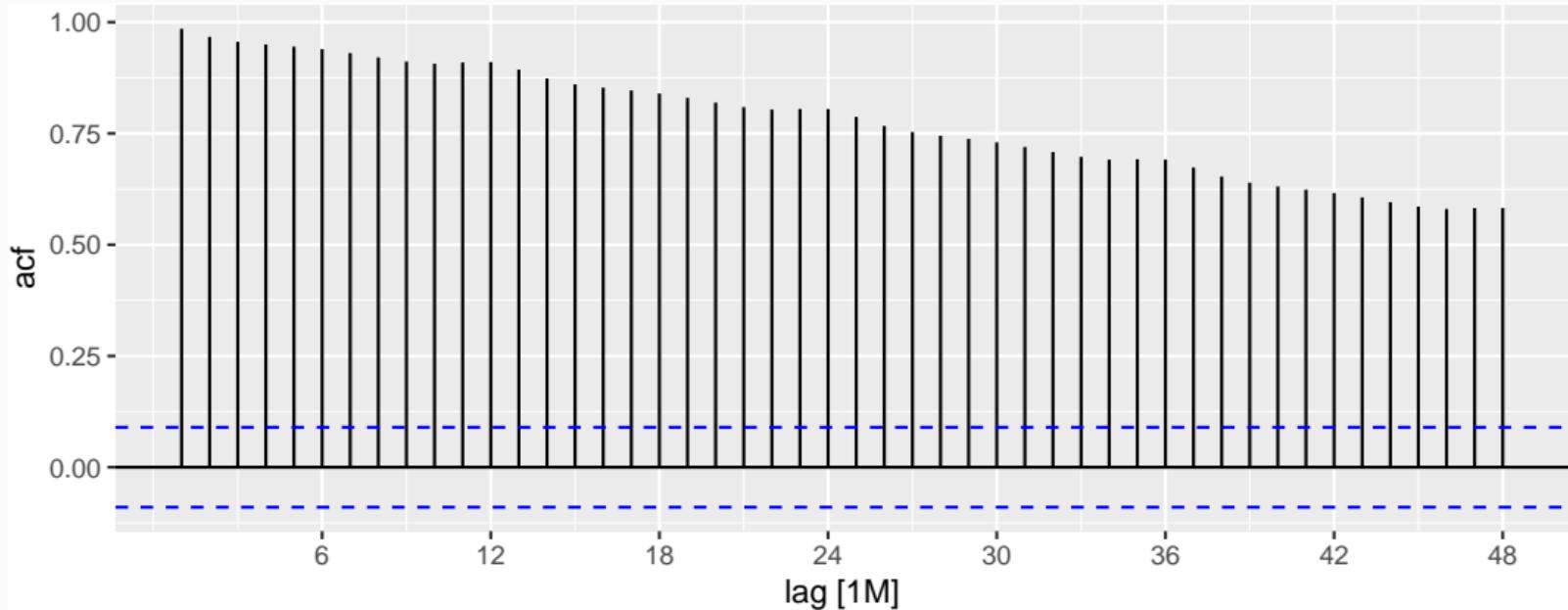
US retail trade employment

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



US retail trade employment

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



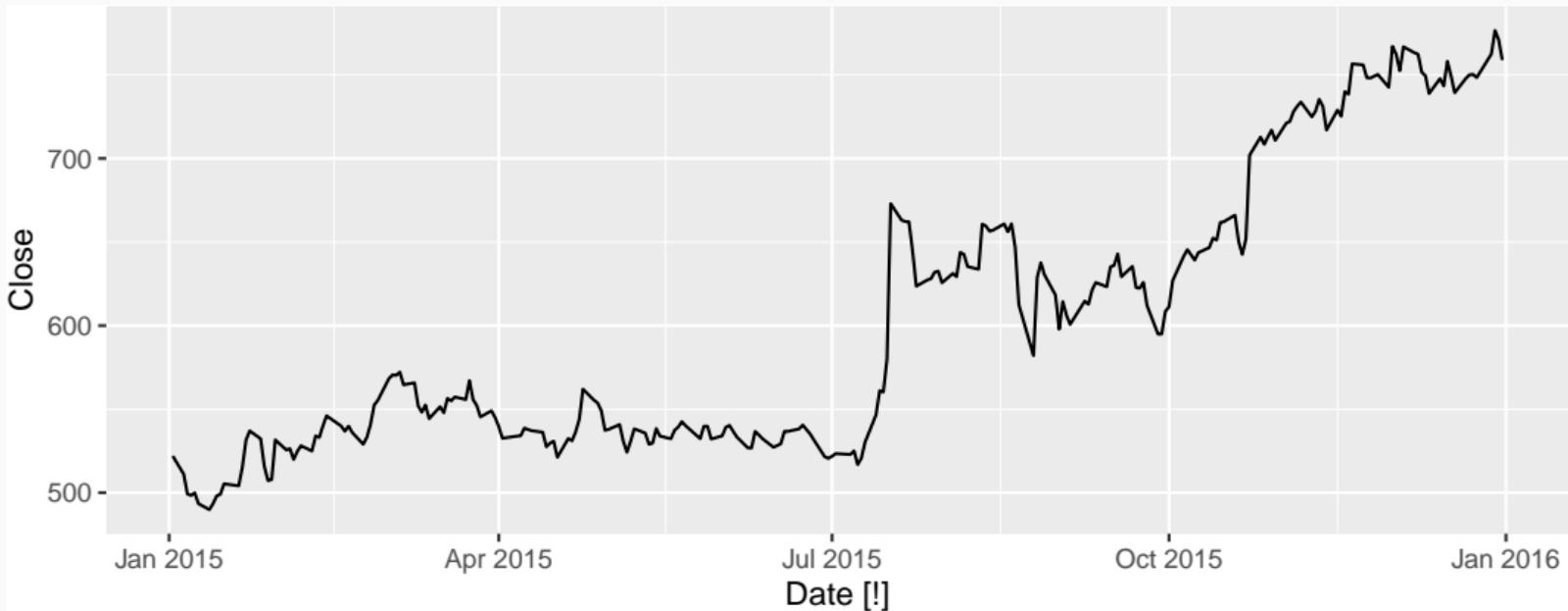
Google stock price

```
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)
```



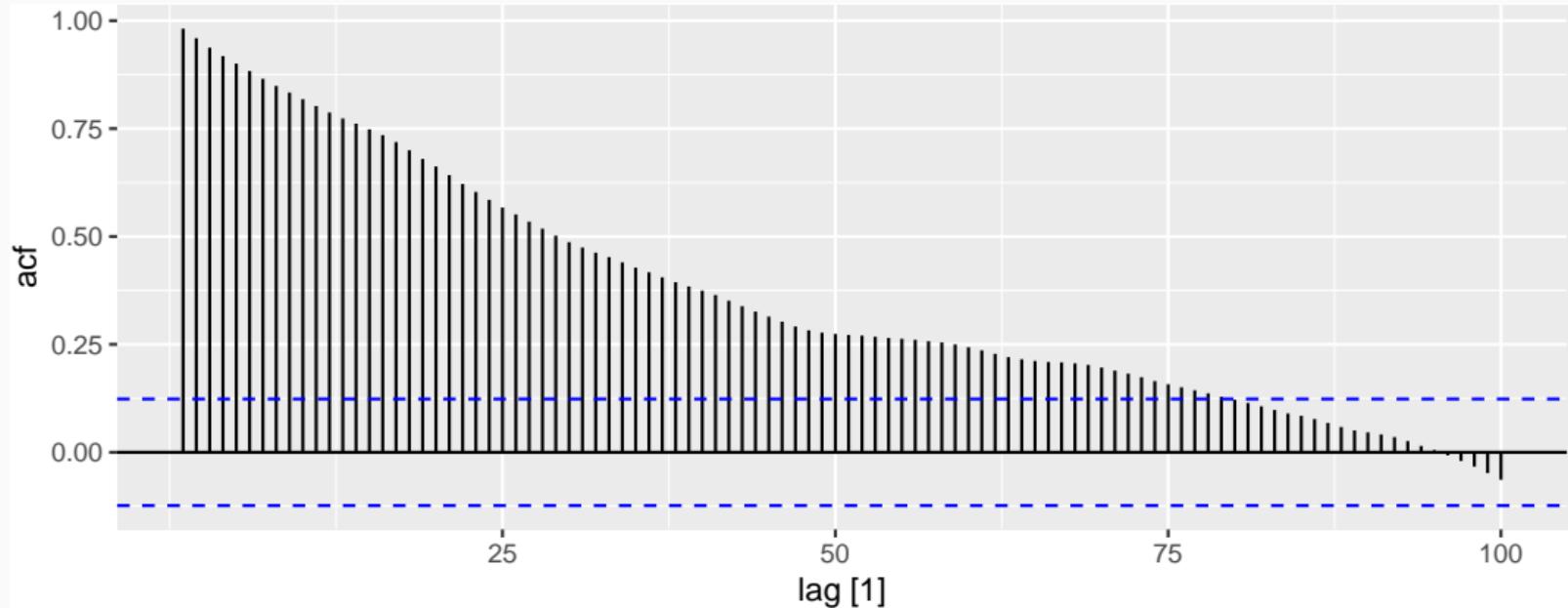
Google stock price

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

## # A tsibble: 100 x 2 [1]
##      lag    acf
##      <dbl> <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
## # i Use `print(n = ...)` to see more rows
```

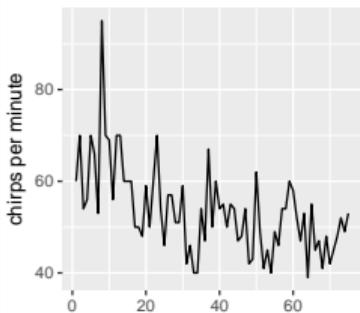
Google stock price

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

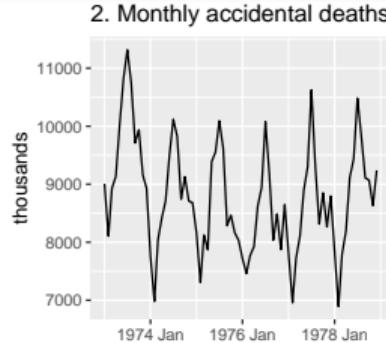


Which is which?

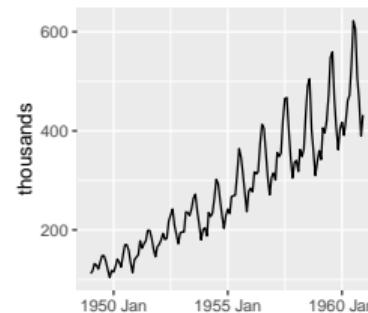
1. Daily temperature of cow



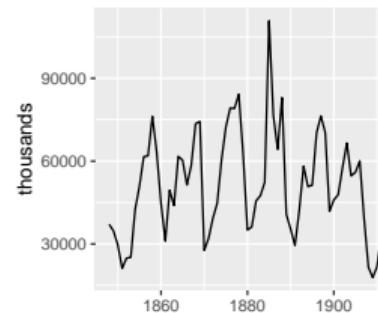
2. Monthly accidental deaths



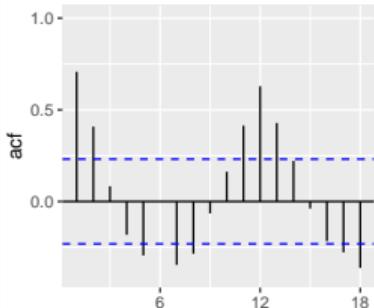
3. Monthly air passengers



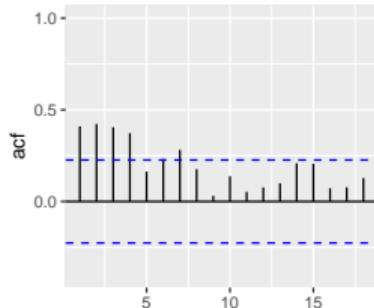
4. Annual mink trappings



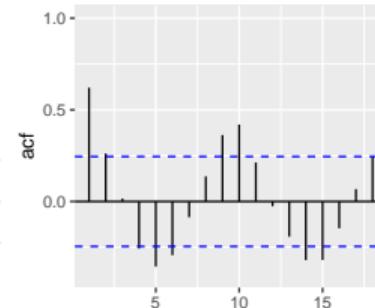
A



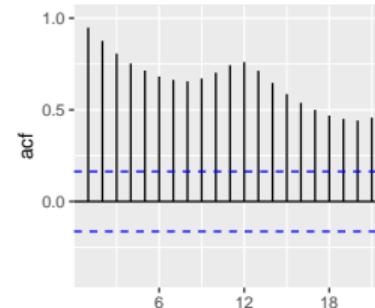
B



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

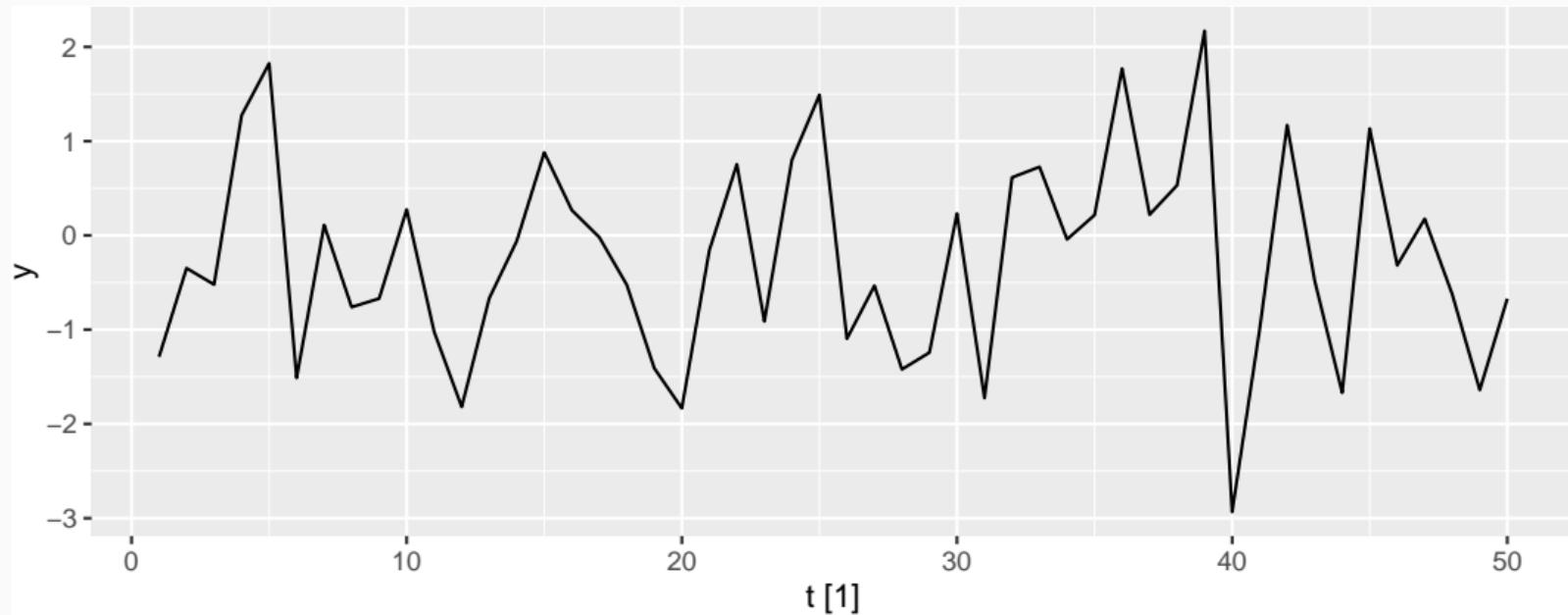
Lag plots and autocorrelation

7

White noise

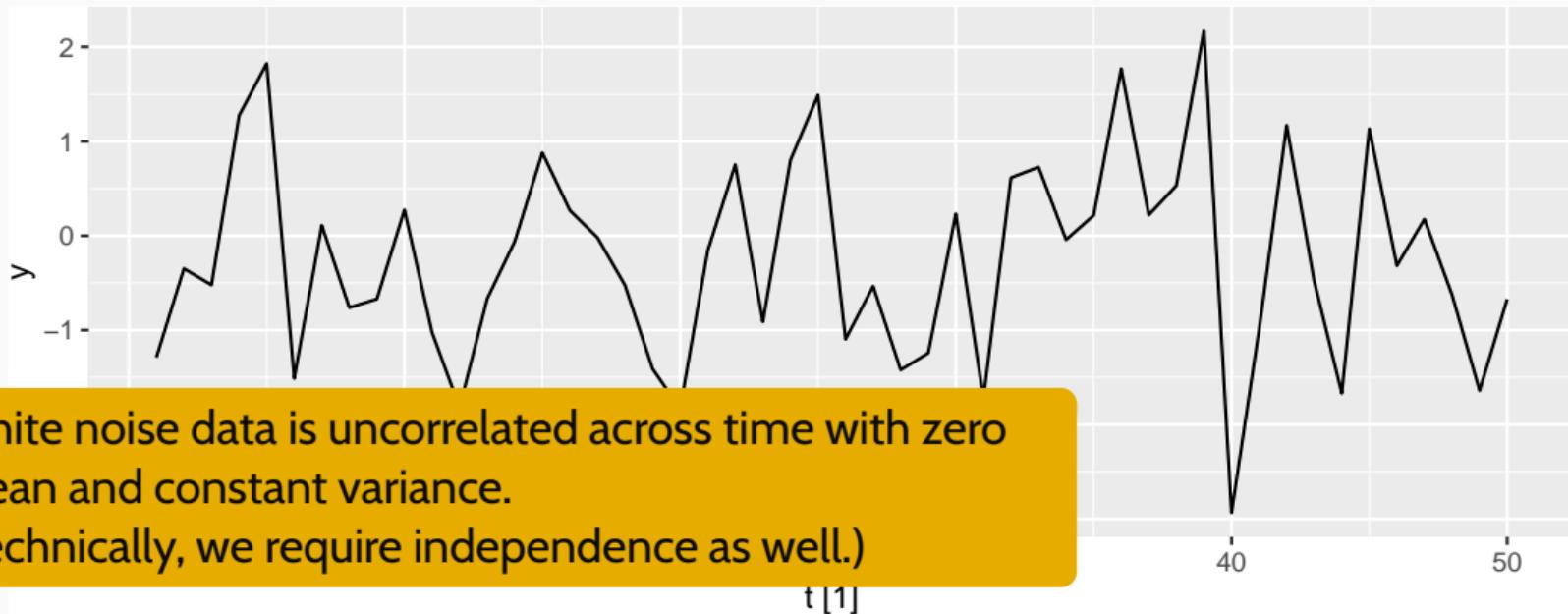
Example: White noise

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



Example: White noise

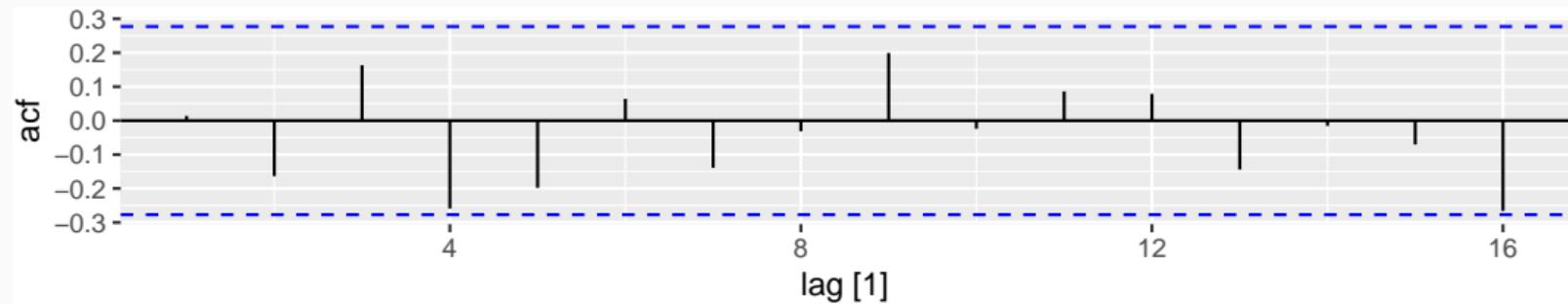
```
set.seed(30)
wn <- tsibble(t = 1:50, y = rnorm(50), index = t)
wn %>% autoplot(y)
```



Example: White noise

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

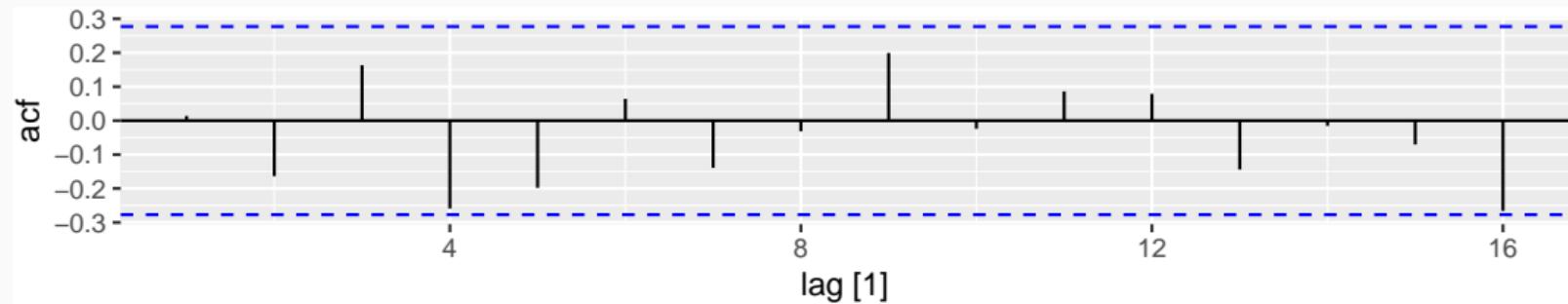
r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
0.014	-0.163	0.163	-0.259	-0.198	0.064	-0.139	-0.032	0.199	-0.024



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 $N(0, 1/T)$.

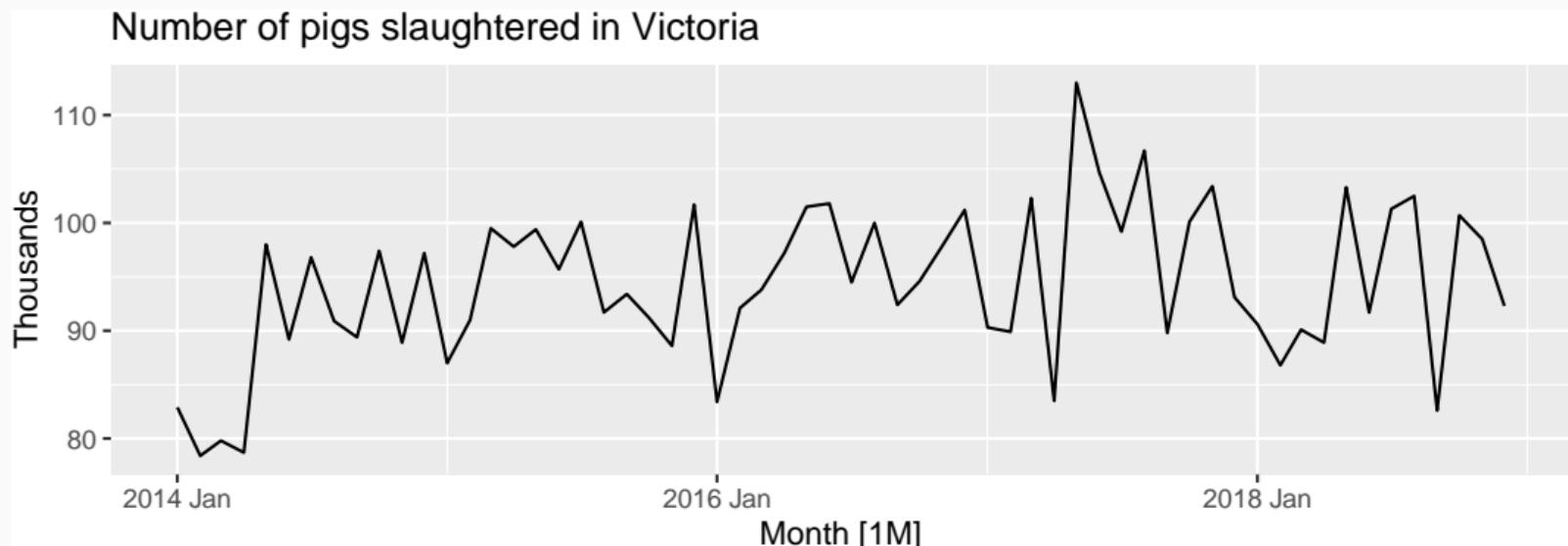
Sampling distribution of autocorrelations

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**.

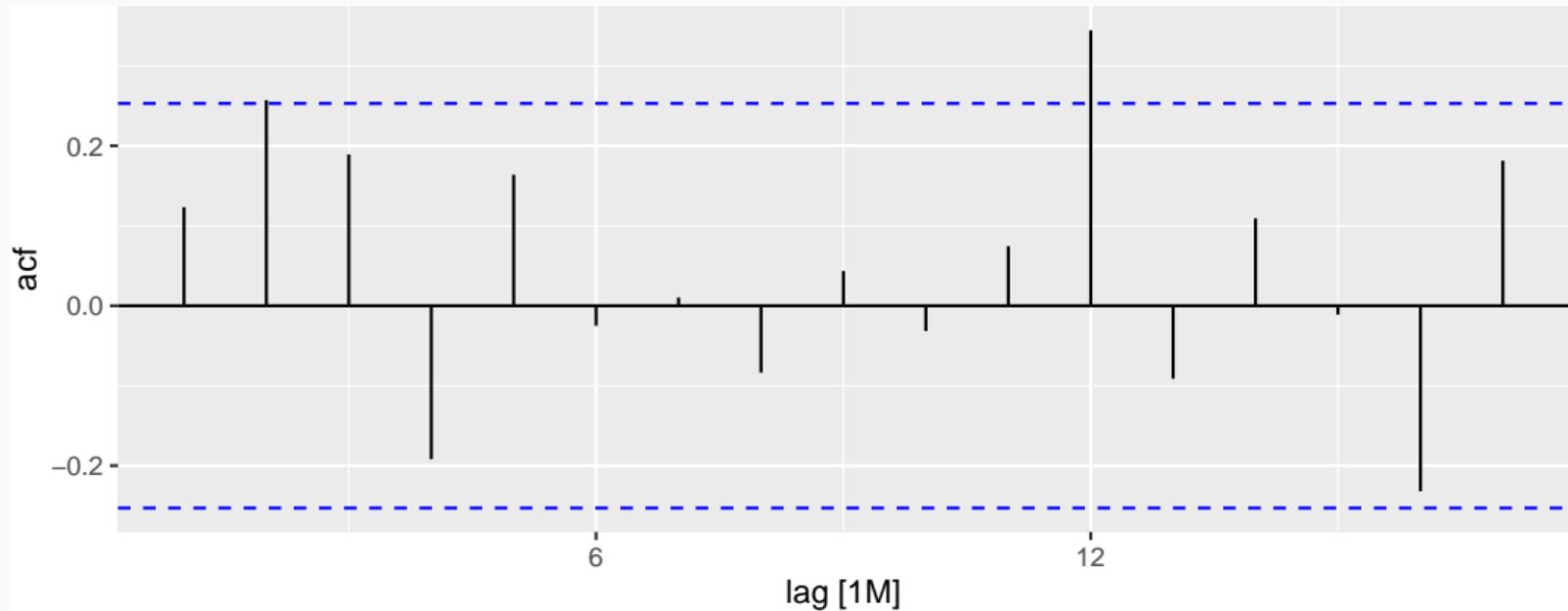
Example: Pigs slaughtered

```
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(diff = difference(Close))
```

Does diff look like white noise?

2.10 Exercises (not an assignment but helpful!)

- Use help function: `?autoplot`
- Try exercises that you are less familiar with