

# **ETC3550**

## **Applied forecasting for business and economics**

Ch2. Time series graphics

[OTexts.org/fpp3/](https://OTexts.org/fpp3/)

# Outline

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

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# Class packages

```
# Data manipulation and plotting functions  
library(tidyverse)  
# Time series manipulation  
library(tsibble)  
# Forecasting functions  
library(fable)  
# Time series graphics and statistics  
library(feasts)  
# Tidy time series data  
library(tsibbledata)
```

# tsibble objects

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

It contains:

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

# tsibble objects

## Example

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

```
## # 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

Common time index variables can be created with these functions:

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

# The key to many time series

Year	Length	Sex	Time
1896	100m	men	12.0
1928	100m	women	12.2
1900	200m	men	22.2
1948	200m	women	24.4
1896	400m	men	54.2
1964	400m	women	52.0



# The key to many time series

```
olympic_running %>% as_tsibble(  
  key = id(Length, Sex), index = Year)
```

```
## # A tsibble: 312 x 4 [4Y]  
## # Key:      Length, Sex [14]  
##   Year Length Sex    Time  
##   <dbl> <fct>  <chr> <dbl>  
## 1  1896 100m   men    12  
## 2  1900 100m   men    11  
## 3  1904 100m   men    11  
## 4  1908 100m   men   10.8
```

# Australian GDP

```
aus_economy <- global_economy %>%  
  filter(Code == "AUS")
```

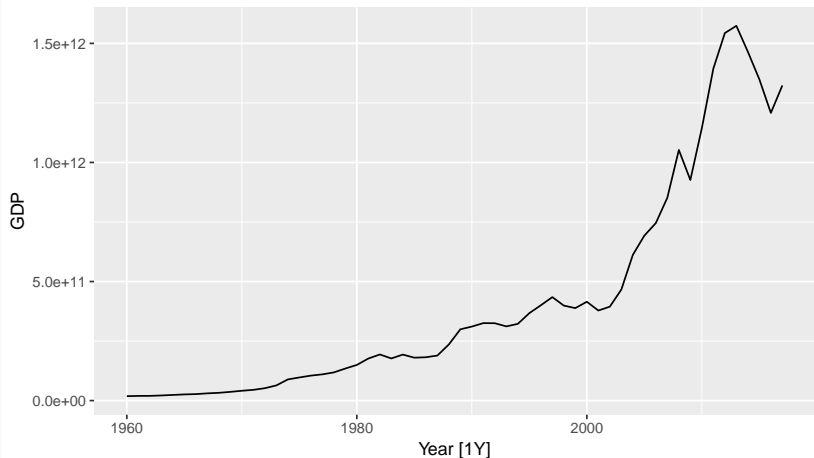
```
## # A tsibble: 58 x 9 [1Y]
```

```
## # Key:          Country [1]
```

##		Country	Code	Year	GDP	Growth	CPI
##		<fct>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>
##	1	Austra~	AUS	1960	1.86e10	NA	7.96
##	2	Austra~	AUS	1961	1.96e10	2.49	8.14
##	3	Austra~	AUS	1962	1.99e10	1.30	8.12
##	4	Austra~	AUS	1963	2.15e10	6.21	8.17
##	5	Austra~	AUS	1964	2.38e10	6.98	8.40
##	6	Austra~	AUS	1965	2.59e10	5.98	8.69
##	7	Austra~	AUS	1966	2.73e10	2.38	8.98

# Australian GDP

```
aus_economy %>% autoplot(GDP)
```

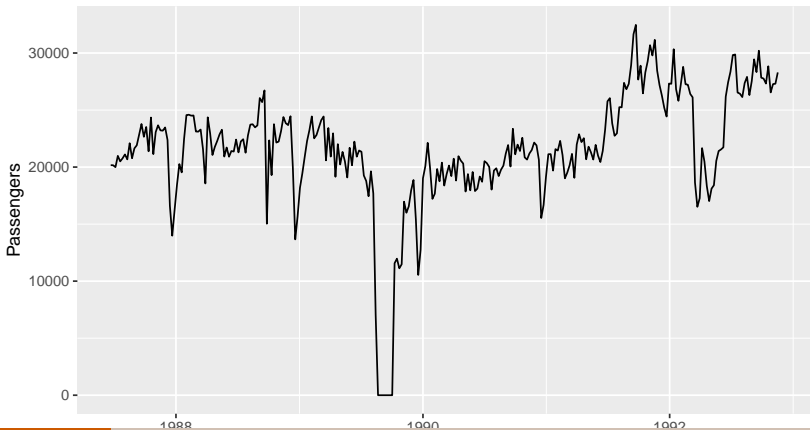


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# Time plots

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



# Time plots

```
a10 <- PBS %>%  
  filter(ATC2 == "A10") %>%  
  summarise(Cost = sum(Cost)/1e6)
```

```
## # A tsibble: 204 x 2 [1M]
```

```
##       Month  Cost
```

```
##       <mth> <dbl>
```

```
## 1 1991 Jul   3.53
```

```
## 2 1991 Aug   3.18
```

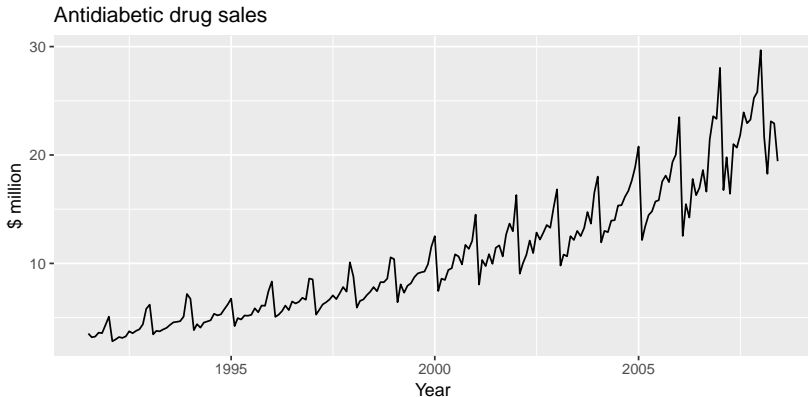
```
## 3 1991 Sep   3.25
```

```
## 4 1991 Oct   3.61
```

```
## 5 1991 Nov   3.57
```

# Time plots

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



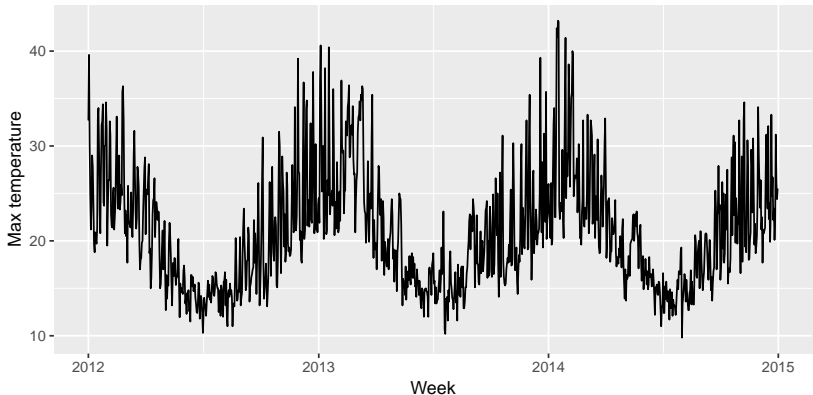
## Your turn

- Create plots of the following time series: Bricks from `aus_production`, Lynx from `pel_t`, Google from `gafa_stock`
- Use `help()` to find out about the data in each series.
- For the last plot, modify the axis labels and title.



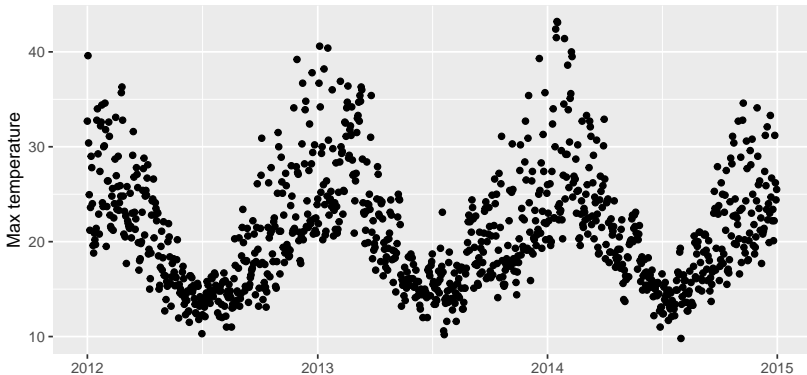
# Are time plots best?

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

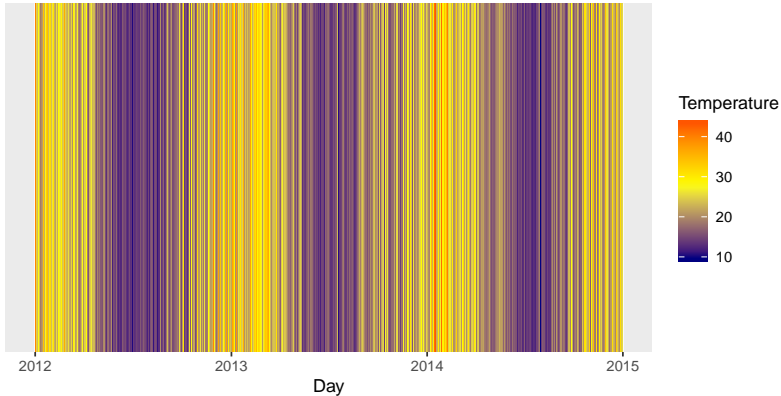


# Are time plots best?

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



# Are time plots best?



# Are time plots best?

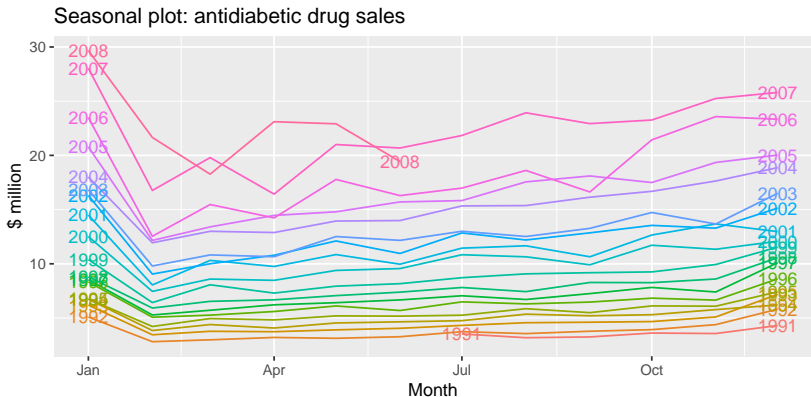


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# Seasonal plots

```
a10 %>% gg_season(Cost, labels = "both") +  
  ylab("$ million") +  
  ggtitle("Seasonal plot: antidiabetic drug sales")
```



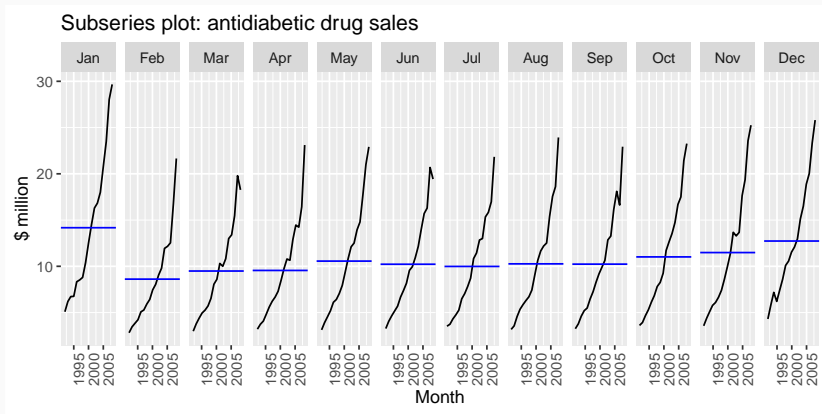
# Seasonal plots

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

# Seasonal subseries plots

a10 %>%

```
gg_subseries(Cost) + ylab("$ million") +  
ggtitle("Subseries plot: antidiabetic drug sales")
```



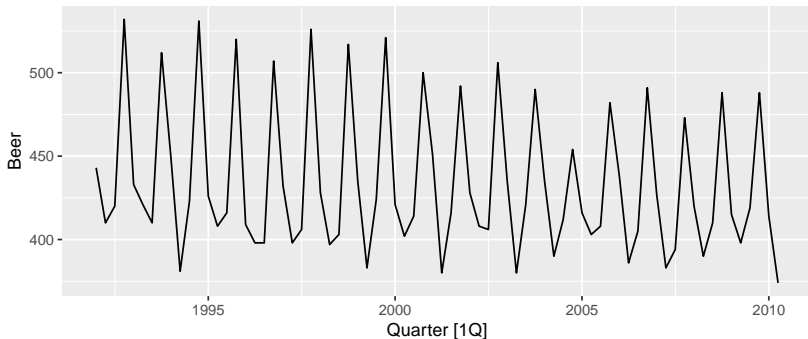


# Seasonal subseries plots

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

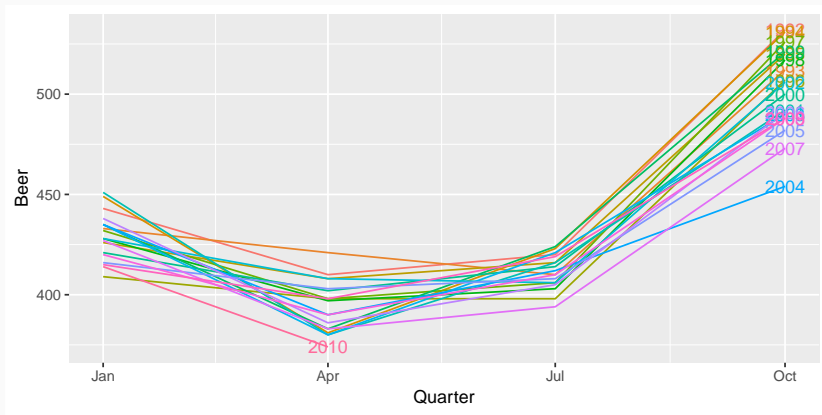
# Quarterly Australian Beer Production

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



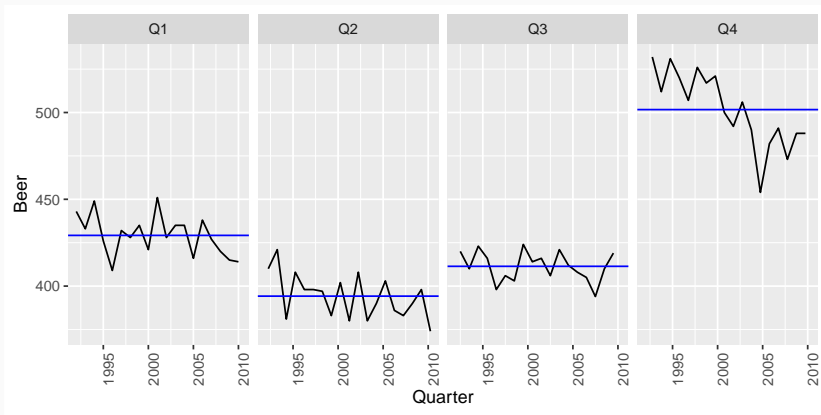
# Quarterly Australian Beer Production

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



# Quarterly Australian Beer Production

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



## Your turn

Look at the quarterly tourism data for the Snowy Mountains

```
snowy <- filter(tourism,  
  Region == "Snowy Mountains",  
  Purpose == "Holiday")
```

- Use `autoplot()`, `gg_season()` and `gg_subseries()` to explore the data.
- What do you learn?

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# Time series patterns

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

**Seasonal** pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).

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

# Time series components

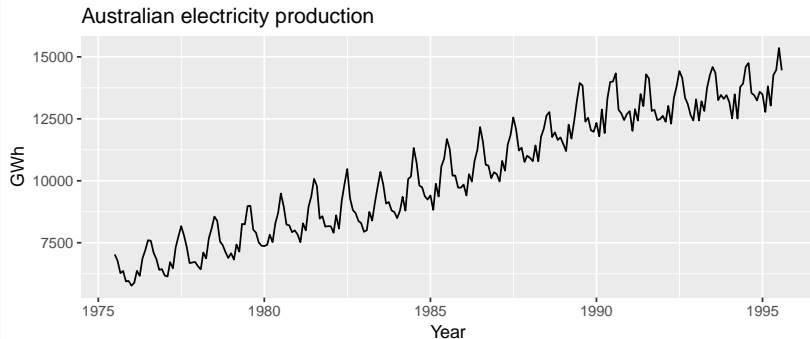
## Differences between seasonal and cyclic patterns:

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



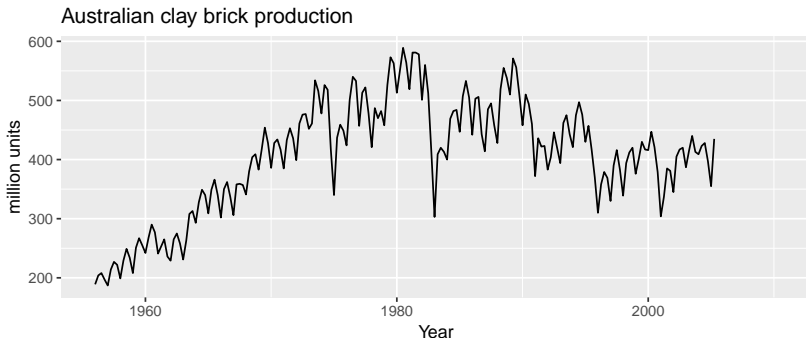
# Time series patterns

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



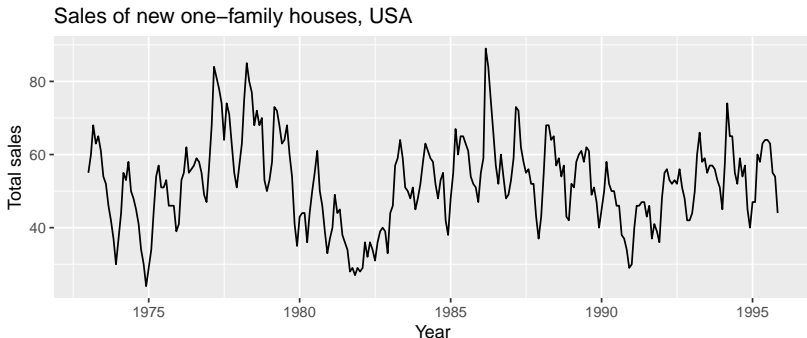
# Time series patterns

```
aus_production %>%  
  autoplot(Bricks) +  
  ggtitle("Australian clay brick production") +  
  xlab("Year") + ylab("million units")
```



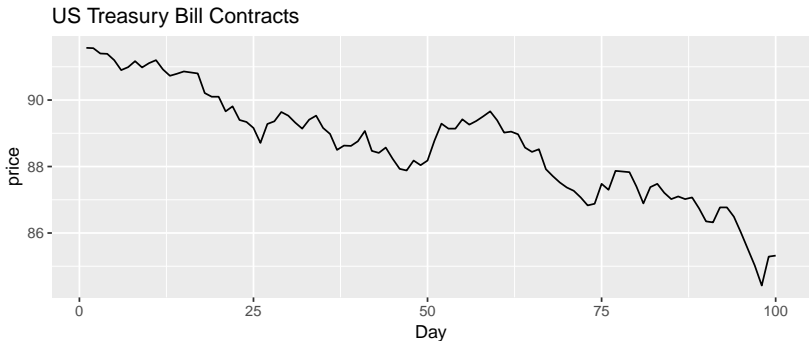
# Time series patterns

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



# Time series patterns

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



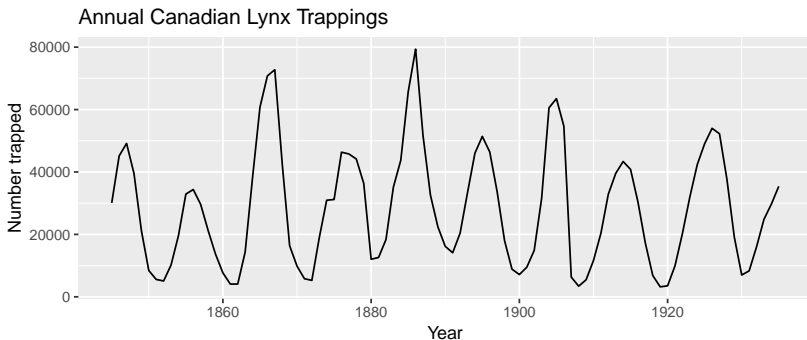
# Time series patterns

```
pelt %>%
```

```
  autoplot(Lynx) +
```

```
  ggtitle("Annual Canadian Lynx Trappings") +
```

```
  xlab("Year") + ylab("Number trapped")
```



# Seasonal or cyclic?

## Differences between seasonal and cyclic patterns:

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

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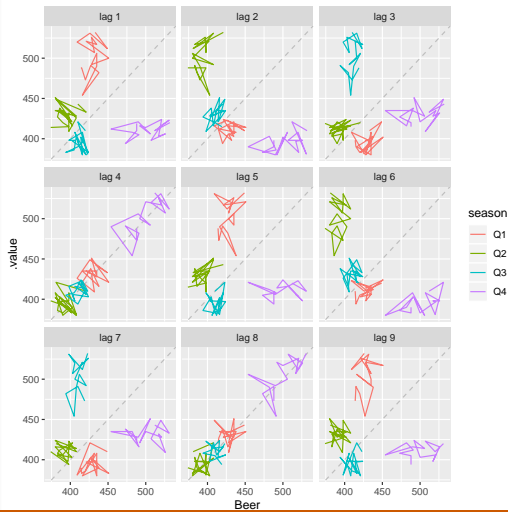
# Example: Beer production

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

```
## # A tibble: 74 x 7 [1Q]  
##       Quarter Beer Tobacco Bricks Cement  
##       <qtr> <dbl>    <dbl>  <dbl>  <dbl>  
## 1 1992 Q1    443    5777    383   1289  
## 2 1992 Q2    410    5853    404   1501  
## 3 1992 Q3    420    6416    446   1539  
## 4 1992 Q4    532    5825    420   1568  
## 5 1993 Q1    433    5724    394   1450  
## 6 1993 Q2    421    6036    462   1668
```

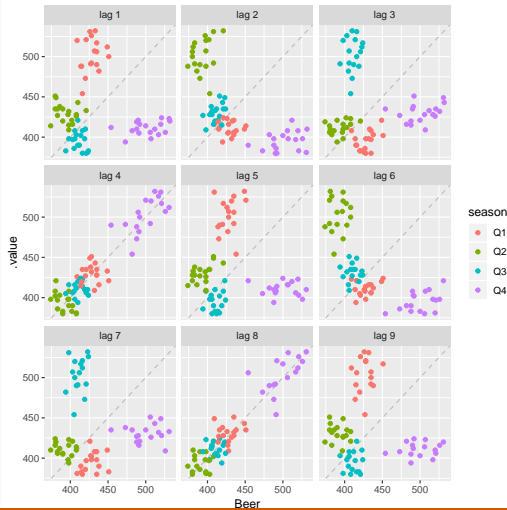
# Example: Beer production

```
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.

# Autocorrelation

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

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

# Autocorrelation

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

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

We measure the relationship between:

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

# Autocorrelation

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

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

and  $r_k = c_k / c_0$



# Autocorrelation

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

and  $r_k = c_k / c_0$

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

# Autocorrelation

Results for first 9 lags for beer data:

```
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
```

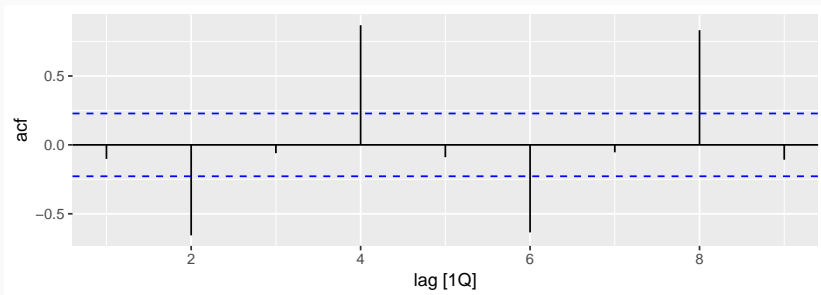
```
## 7    7Q -0.0542
```

```
## 8    8Q  0.832
```

# Autocorrelation

Results for first 9 lags for beer data:

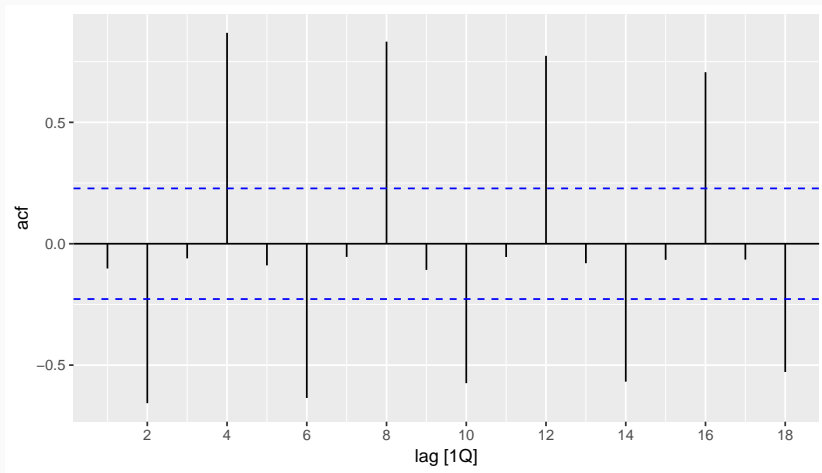
```
new_production %>% ACF(Beer, lag_max = 9) %>% autoplot()
```



# Autocorrelation

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

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

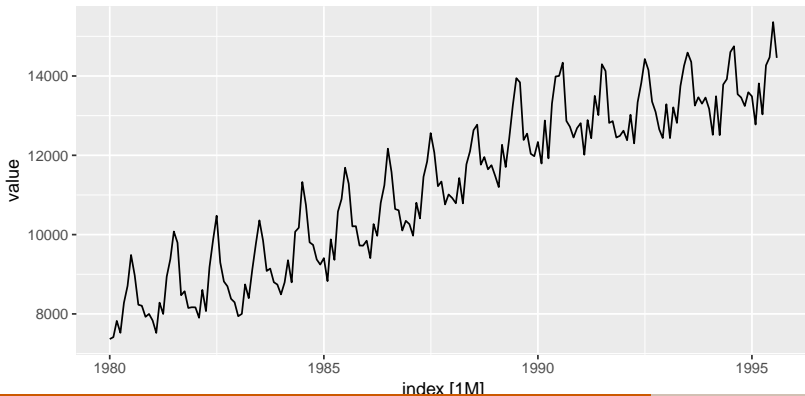


# Trend and seasonality in ACF plots

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

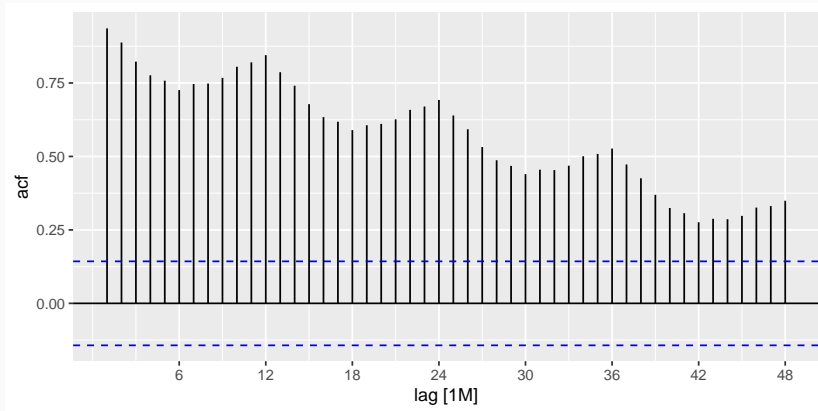
# Aus monthly electricity production

```
elec2 <- as_tsibble(fma::elec) %>%  
  filter(year(index) >= 1980)  
elec2 %>% autoplot(value)
```



# Aus monthly electricity production

```
elec2 %>% ACF(value, lag_max=48) %>%  
  autoplot()
```





# Aus monthly electricity production

Time plot shows clear trend and seasonality.

The same features are reflected in the ACF.

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

# Google stock price

```
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.
```

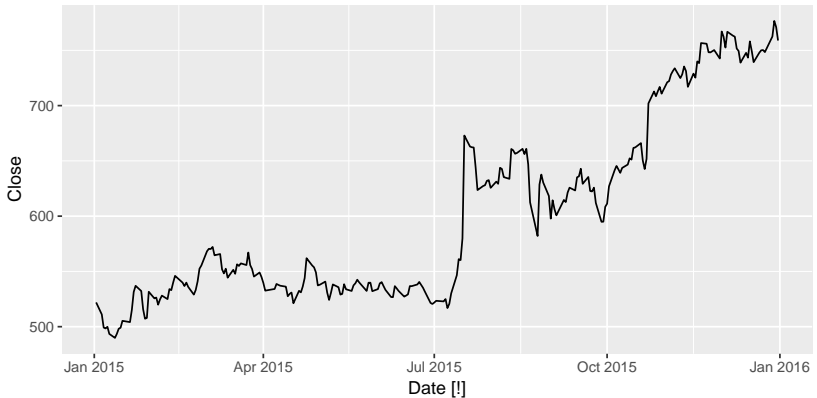
```
## 4 2015-01-07  498.
```

```
## 5 2015-01-08  500.
```

```
## 6 2015-01-09  493.
```

# Google stock price

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



# Google stock price

```
google_2015 %>%  
  ACF(Close, lag_max=100)  
# Error: Can't handle tsibble of irregular interval.
```

# Google stock price

```
google_2015 %>%  
  ACF(Close, lag_max=100)  
# Error: Can't handle tsibble of irregular interval.
```

```
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.
```

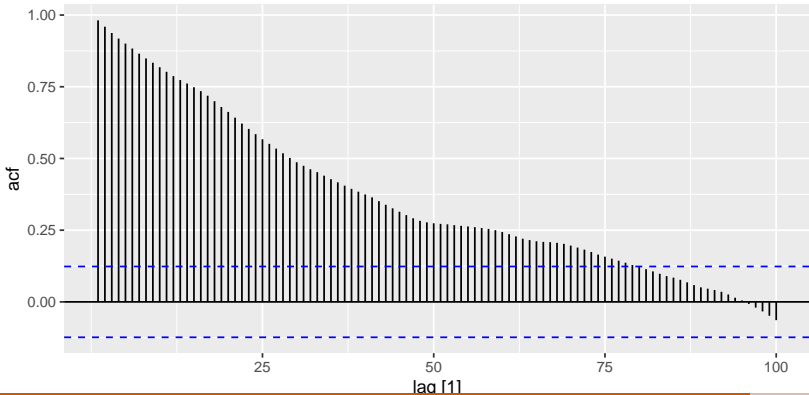
# Google stock price

```
google_2015 <- google_2015 %>%  
  mutate(trading_day = row_number()) %>%  
  update_tsibble(index=trading_day, regular=TRUE)  
google_2015
```

```
## # A tsibble: 252 x 3 [1]  
##   Date      Close trading_day  
##   <date>    <dbl>      <int>  
## 1 2015-01-02 522.        1  
## 2 2015-01-05 511.        2  
## 3 2015-01-06 499.        3  
## 4 2015-01-07 498.        4  
## 5 2015-01-08 500.        5  
## 6 2015-01-09 493.        6
```

# Google stock price

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



# Your turn

We have introduced the following functions:

- `gg_lag`
- `ACF`

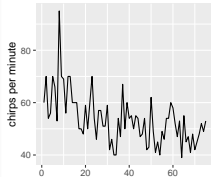
Explore the following time series using these functions. Can you spot any seasonality, cyclicity and trend? What do you learn about the series?

- Bricks from `aus_production`
- Lynx from `pel_t`
- Victorian Electricity Demand from `aus_elec`

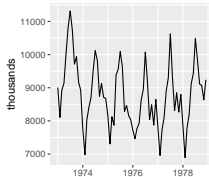


# Which is which?

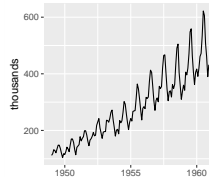
1. Daily temperature of cow



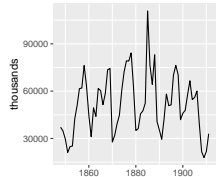
2. Monthly accidental deaths



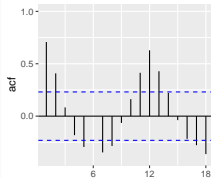
3. Monthly air passengers



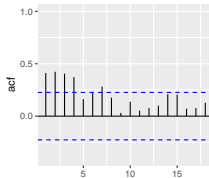
4. Annual mink trappings



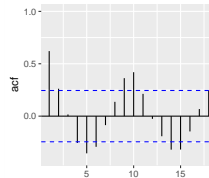
A



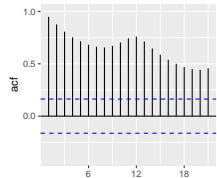
B



C



D

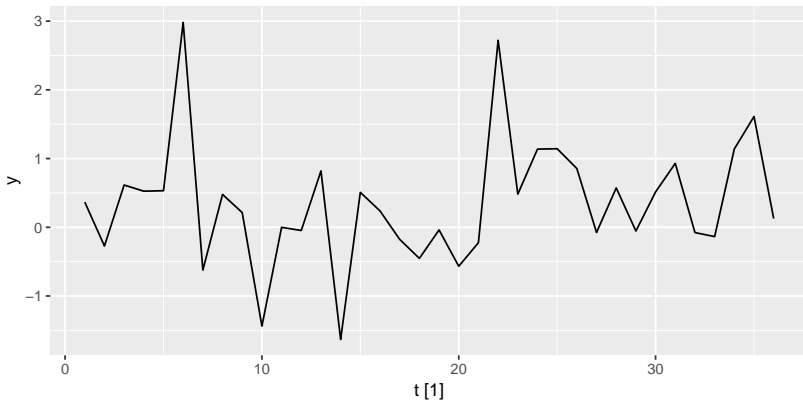


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- 5 Lag plots and autocorrelation
- 6 White noise

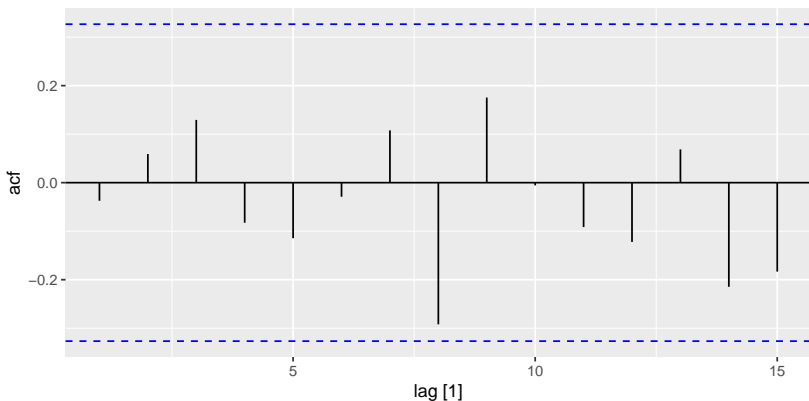
# Example: White noise

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



# Example: White noise

$r_1$	$r_2$	$r_3$	$r_4$	$r_5$	$r_6$	$r_7$	$r_8$	$r_9$	$r_{10}$
-0.037	0.059	0.129	-0.083	-0.115	-0.029	0.108	-0.292	0.175	-0.006



# Sampling distribution of autocorrelations

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- 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**.

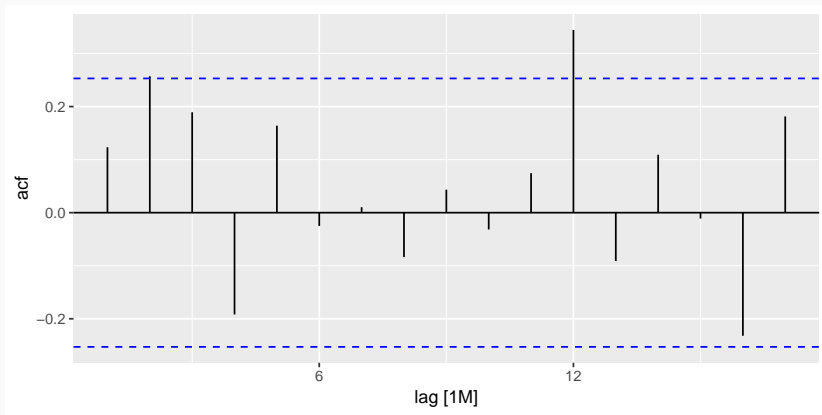
# Example: Pigs slaughtered

```
pigs <- aus_livestock %>%  
  filter(State == "Victoria", Animal == "Pigs",  
         year(Month) >= 2014)  
pigs %>% autoplot(Count/1e3) +  
  xlab("Year") + ylab("Thousands") +  
  ggtitle("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.)

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- Indicate some slight seasonality.

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

# Your turn

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