B06

R語言
時間序列資料分析

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本章大綱&學習目標

- 學習資源: 參考書目
- R軟體中的時間序列**物件**
- 時間序列資料**輸入與輸出**
- 時間序列資料的**處理:** `lubridate` **套件**
- **時間序列圖**
- 時間序列資料的**平滑化**
- 時間序列資料統計**模型與預測:**
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  - AR, MA, ARMA, ARIMA
- 財務金融資料分析套件: quantmod & tidyquant

CRAN Task View: Time Series Analysis

https://cran.r-project.org/web/views/TimeSeries.html

CRAN Task View: Time Series Analysis

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Contact:	Rob.Hyndman at monash.edu
Version:	2023-07-26
URL:	https://CRAN.R-project.org/view=TimeSeries
Source:	https://github.com/cran-task-views/TimeSeries/
Contributions:	Suggestions and improvements for this task view are very welcome and can be made through issues or pull requests on GitHub or via e-mail to the maintainer address. For further details see the Contributing guide.
Citation:	Rob J Hyndman, Rebecca Killick (2023). CRAN Task View: Time Series Analysis. Version 2023-07-26. URL https://CRAN.R-project.org/view=TimeSeries.
Installation:	The packages from this task view can be installed automatically using the ctv package. For example, `ctv::install.views("TimeSeries", coreOnly = TRUE)` installs all the core packages or `ctv::update.views("TimeSeries")` installs all packages that are not yet installed and up-to-date. See the CRAN Task View Initiative for more details.

Base R ships with a lot of functionality useful for time series, in particular in the stats package. This is complemented by many packages on CRAN, which are briefly summarized below. There is overlap between the tools for time series and those designed for specific domains including Econometrics, Finance and Environmetrics.

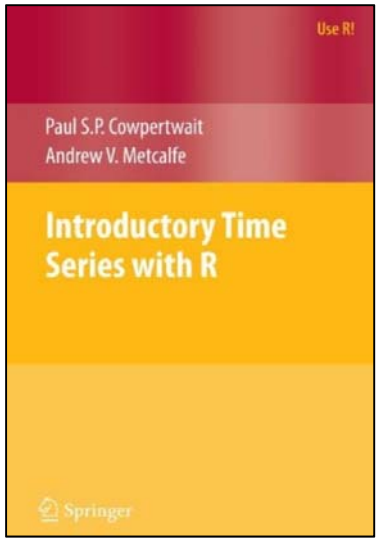
The packages in this view can be roughly structured into the following topics. If you think that some package is missing from the list, please let us know, either via e-mail to the maintainer or by submitting an issue or pull request in the GitHub repository linked above.

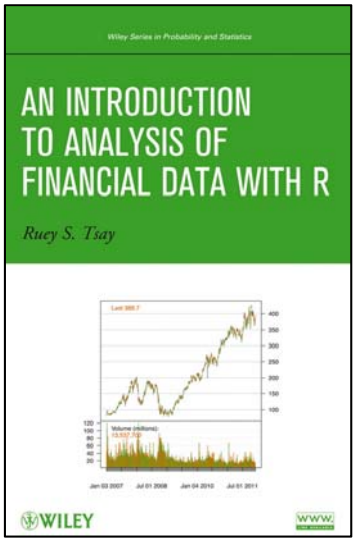
Basics

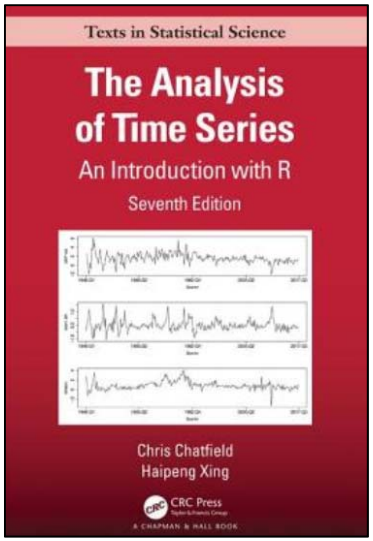
- *Infrastructure* : Base R contains substantial infrastructure for representing and analysing time series data. The fundamental class is `"ts"` that can represent regularly spaced time series (using numeric time stamps). Hence, it is particularly well-suited for annual,

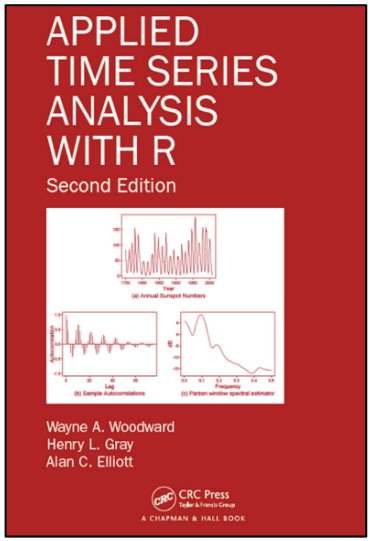
Basics、Times and Dates、Time Series Classes、Forecasting and Univariate Modeling、Frequency analysis、Decomposition and Filtering、Seasonality、Stationarity, Unit Roots, and Cointegration、Nonlinear Time Series Analysis、Entropy、Dynamic Regression Models、Multivariate Time Series Models、Analysis of large groups of time series、Functional time series、Matrix and tensor-valued time series、Continuous time models、Resampling、Time Series Data、Miscellaneous

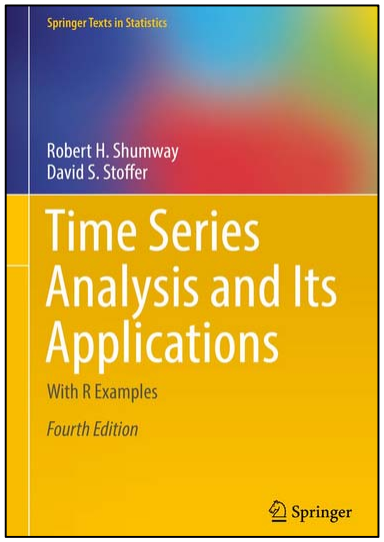
Time Series Analysis Uing R

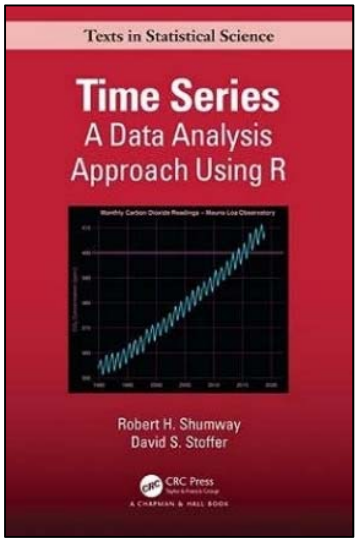


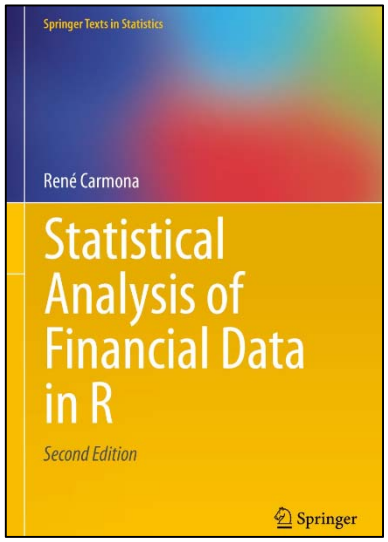


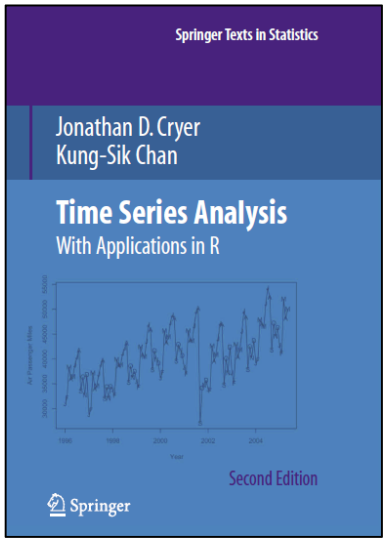




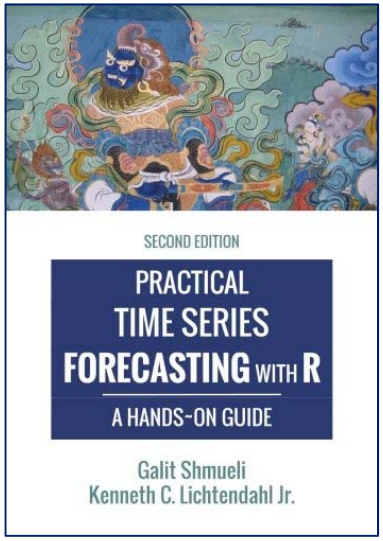


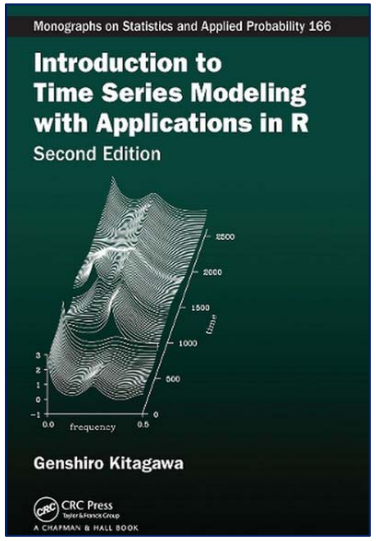


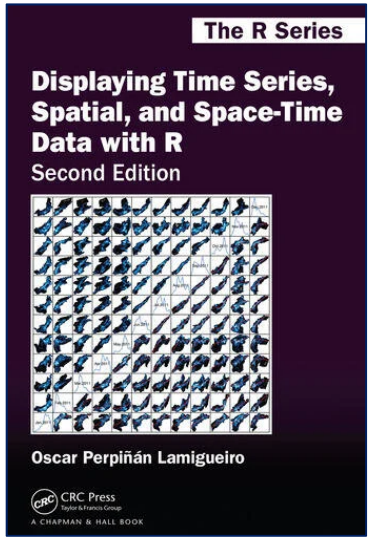


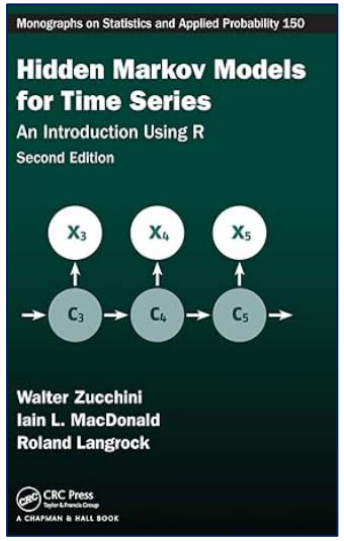


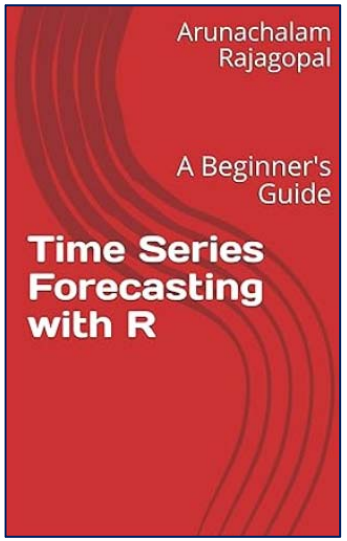
Time Series Analysis Uing R

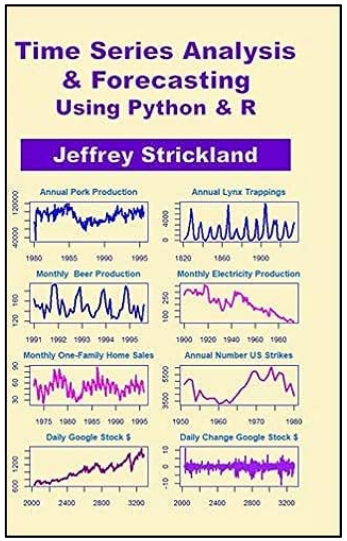


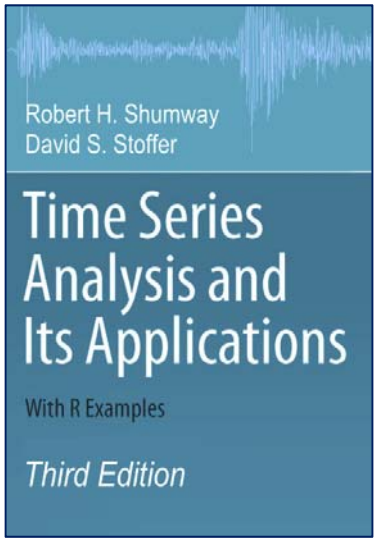


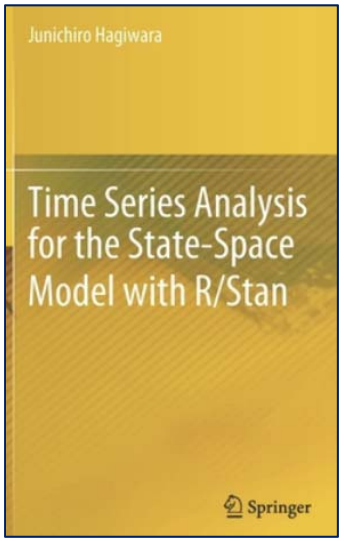




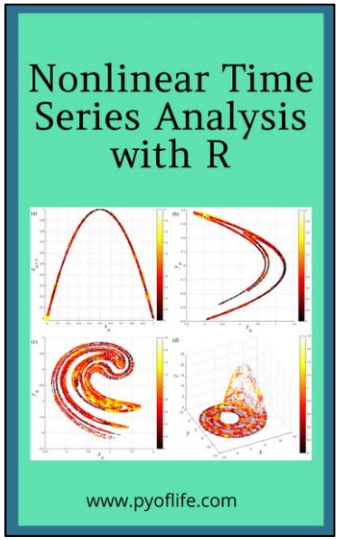


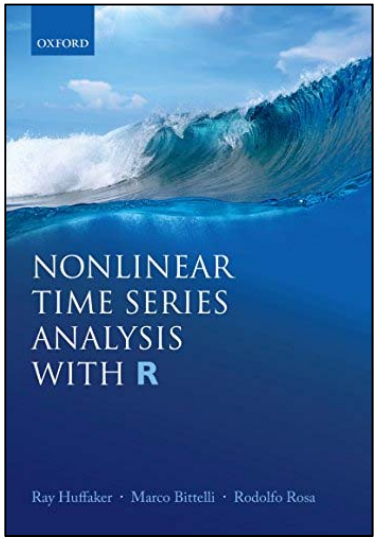


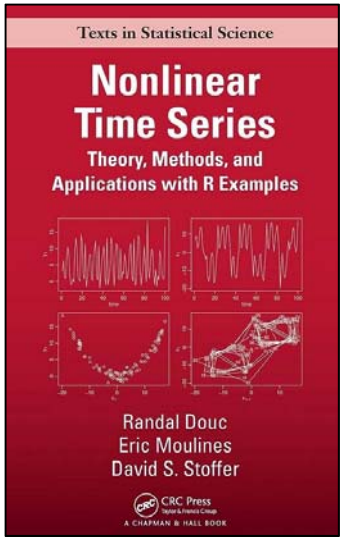


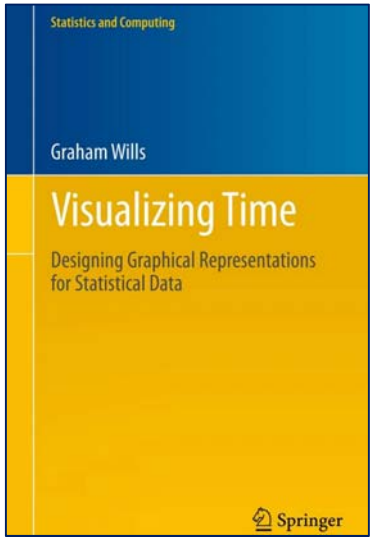


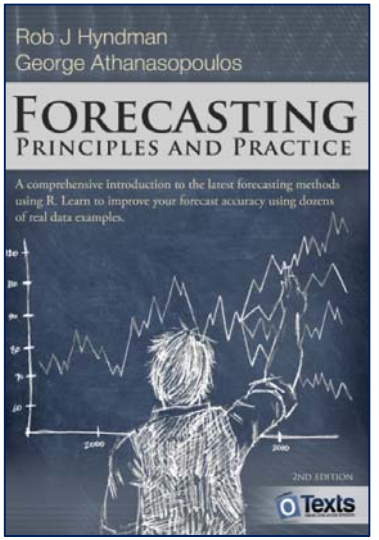
Time Series Analysis Uing R

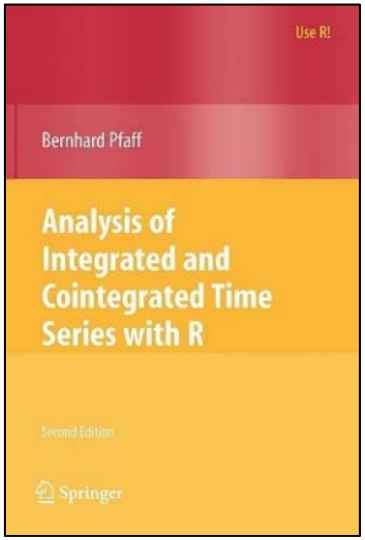


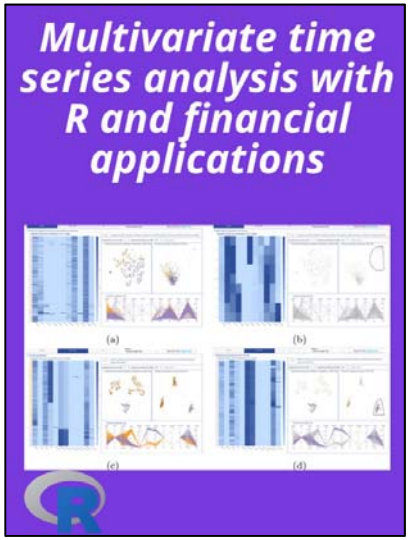


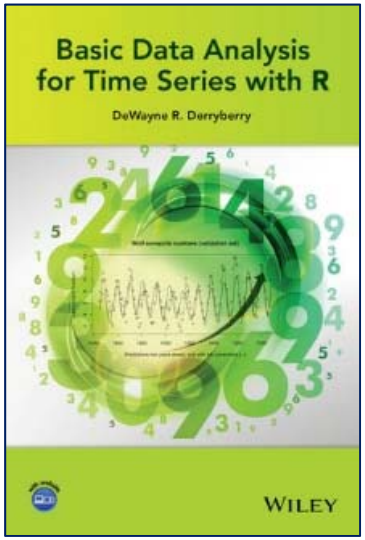












Overview of Time Series Objects in R

時間序列類別	套件	說明
ts, mts	stats: R statistical functions	This package contains functions for statistical calculations and random number generation.
timeSeries	timeSeries: Financial Time Series Objects (Rmetrics)	'S4' classes and various tools for financial time series: Basic functions such as scaling and sorting, subsetting, mathematical operations and statistical functions.
ti	tis: Time Indexes and Time Indexed Series	Functions and S3 classes for time indexes and time indexed series, which are compatible with FAME frequencies.
zoo	zoo: S3 Infrastructure for Regular and Irregular Time Series (Z's Ordered Observations)	An S3 class with methods for totally ordered indexed observations. It is particularly aimed at irregular time series of numeric vectors/matrices and factors. zoo's key design goals are independence of a particular index/date/time class and consistency with ts and base R by providing methods to extend standard generics.
xts	xts: eXtensible Time Series	Provide for uniform handling of R's different time-based data classes by extending zoo, maximizing native format information preservation and allowing for user level customization and extension, while simplifying cross-class interoperability.

Overview of Date and Date.Time Objects in R

類別	套件	說明
Date	base	Represent calendar dates as the number of days since 1970.01.01
POSIXct	base	Represent calendar dates and times within the day as the (signed) number of seconds since the beginning of 1970 as a numeric vector. Supports various time zone specifications (e.g. GMT, PST, EST etc.)
POSIXlt	base	Represents local dates and times within the day as named list of vectors with date.time components.
chron	chron: Chronological Objects which Can Handle Dates and Times	Provides chronological objects which can handle dates and times.
Yearmon (yearqtr)	Zoo: S3 Infrastructure for Regular and Irregular Time Series (Z's Ordered Observations)	Represent monthly (quarterly) data. Internally it holds the data as year plus 0 for January, 1/12 for February, 2/12 for March (Quarter 1, 1/4 for Quarter 2) and so on in order that its internal representation is the same as tsclass with frequency = 12 (4).
timeDate	timeDate: Rmetrics - Chronological and Calendar Objects	The 'timeDate' class fulfils the conventions of the ISO 8601 standard as well as of the ANSI C and POSIX standards. Beyond these standards it provides the "Financial Center" concept which allows to handle data records collected in different time zones and mix them up to have always the proper time stamps with respect to your personal financial center, or alternatively to the GMT reference time. It can thus also handle time stamps from historical data records from the same time zone, even if the financial centers changed day light saving times at different calendar dates.

日期 Dates
The Date Class (base R)

- R以"Date" 類別表示(不包括時間)日期: 年月日。
- Internally, Date objects are stored as the number of days since **January 1, 1970**, using negative numbers for earlier dates.
- The **as.numeric** function can be used to convert a Date object to its internal form.

```
> as.numeric(as.Date("1970/1/1"))
[1] 0
```

Code	Value
%d	Day of the month (decimal number)
%m	Month (decimal number)
%b	Month (abbreviated)
%B	Month (full name)
%y	Year (2 digit)
%Y	Year (4 digit)

```
> as.Date("1985-6-16")
[1] "1985-06-16"
> as.Date("2019/02/17")
[1] "2019-02-17"
> as.Date(1000, origin = "1900-01-01")
[1] "1902-09-28"
> as.Date("2/15/2011", format = "%m/%d/%Y")
[1] "2011-02-15"
>
> as.Date("April 26, 1993", format = "%B %d, %Y")
[1] "1993-04-26"
> as.Date("22JUN01", format = "%d%b%y")
[1] "2001-06-22"
> seq(as.Date('1976-7-4'), by = 'days', length = 10)
 [1] "1976-07-04" "1976-07-05" "1976-07-06" "1976-07-07" "1976-07-08" "1976-07-09" "1976-07-10"
 [8] "1976-07-11" "1976-07-12" "1976-07-13"
> seq(as.Date('2010-2-1'), to = as.Date('2010-4-1'), by = '2 weeks')
[1] "2010-02-01" "2010-02-15" "2010-03-01" "2010-03-15" "2010-03-29"
```

請先執行!!

```
> (lct <- Sys.getlocale("LC_TIME"))
[1] "C"
> Sys.setlocale("LC_TIME", "C")
[1] "C"
```

```
> Sys.getlocale("LC_TIME")
[1] "Chinese (Traditional)_Taiwan.950"
```

日期時間
The POSIXt classes (base R)

- R的"時間"用"POSIXct"或 "POSIXlt" 類別表示，
- 內部時間是以 "1970年1月1日" 起至今的秒數表示。
- (UTC, Universal Time, Coordinated, 世界協調時間)
- (GMT, Greenwich Mean Time, 格林威治標準時間)

```
> Sys.time()
[1] "2028-10-14 21:16:07 台北標準時間"
# extract date
> substr(as.character(Sys.time()), 1, 10)
[1] "2028-10-14"
# extract time
> substr(as.character(Sys.time()), 12, 19)
[1] "21:16:07"
> date()
[1] "Tue Oct 14 21:16:09 2028"
```

```
> now <- Sys.time()
> as.POSIXct(now)
[1] "2027-06-03 17:46:44 CST"
> as.POSIXlt(now)
[1] "2027-06-03 17:46:44 CST"
> class(now)
[1] "POSIXct" "POSIXt"
```

```
sec, min, hour,
mday (# day number within the month),
mon (#January=0),
year (#+1900),
wday (#day of the week starting at 0=sunday),
yday (#day of the year after 1 january=0)
```

```
> my.date <- as.POSIXlt(Sys.time())
> my.date
[1] "2028-10-14 21:18:31 台北標準時間"
> my.date$sec
[1] 31.304
> my.date$min
[1] 18
> my.date$hour
[1] 21
```

```
> my.date$mday
[1] 14
> my.date$mon
[1] 9
> my.date$year + 1900
[1] 2028
> my.date$wday
[1] 2
> my.date$yday
[1] 287
```

Two POSIXt sub-classes: POSIXlt / POSIXct 類別

- Functions to convert between character representations and objects of classes "POSIXlt" and "POSIXct" representing calendar dates and times.
  - Character input is first converted to class "POSIXlt" by **strptime**.
  - Numeric input is first converted to "POSIXct".
- Any conversion that needs to go between the two date-time classes requires a time zone: conversion from "POSIXlt" to "POSIXct" will validate times in the selected time zone.

Code	Meaning	Code	Meaning
%a	Abbreviated weekday	%A	Full weekday
%b	Abbreviated month	%B	Full month
%c	Locale-specific date and time	%d	Decimal date
%H	Decimal hours (24 hour)	%I	Decimal hours (12 hour)
%j	Decimal day of the year	%m	Decimal month
%M	Decimal minute	%p	Locale-specific AM/PM
%S	Decimal second	%U	Decimal week of the year (starting on Sunday)
%w	Decimal Weekday (0=Sunday)	%W	Decimal week of the year (starting on Monday)
%x	Locale-specific Date	%X	Locale-specific Time
%y	2-digit year	%Y	4-digit year
%z	Offset from GMT	%Z	Time zone (character)

```
> as.POSIXct("1969-12-31 23:59:59", format = "%Y-%m-%d %H:%M:%S", tz = "UTC")
[1] "1969-12-31 23:59:59 UTC"
> as.POSIXlt(Sys.time(), "GMT")
[1] "2017-08-27 13:17:45 GMT"
```

strptime {base}: Date-time Conversion Functions to and from Character

```
> x1 <- c("20040227", "20050412", "19930922")
> strptime(x1, format = "%Y%m%d")
[1] "2004-02-27 CST" "2005-04-12 CST" "1993-09-22 CST"
>
> x2 <- c("27/02/2004", "27/02/2005", "14/01/2003")
> strptime(x2, format = "%d/%m/%Y")
[1] "2004-02-27 CST" "2005-02-27 CST" "2003-01-14 CST"
>
> x3 <- c("1jan1960", "2jan1960", "31mar1960", "30jul1960")
> strptime(x3, "%d%b%Y")
[1] "1960-01-01 CST" "1960-01-02 CST" "1960-03-31 CST" "1960-07-30 CDT"
```

```
> dates <- c("02/27/92", "02/27/92", "01/14/92", "02/28/92", "02/01/92")
> times <- c("23:03:20", "22:29:56", "01:03:30", "18:21:03", "16:56:26")
> x <- paste(dates, times)
> strptime(x, "%m/%d/%y %H:%M:%S")
[1] "1992-02-27 23:03:20 CST" "1992-02-27 22:29:56 CST"
[3] "1992-01-14 01:03:30 CST" "1992-02-28 18:21:03 CST"
[5] "1992-02-01 16:56:26 CST"
```

時間序列資料輸入與輸出: 純文字檔

mydate.txt

```
1;73;2017/01/27 11:30:20
2;52;2017/03/05 12:01:40
3;57;2017/05/12 03:20:00
1;74;2017/08/27 14:00:00
2;51;2017/10/17 21:03:50
3;60;2017/12/08 08:40:30
```

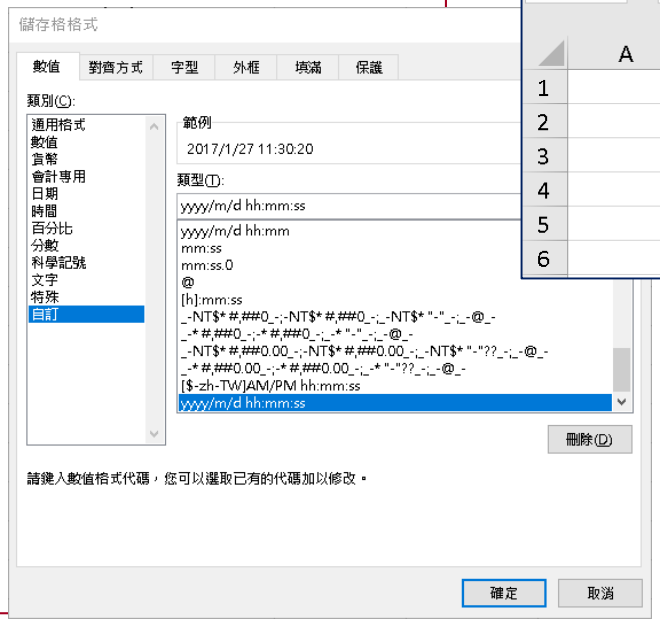
```
> mydate <- read.table("mydate.txt",
                       sep = ";")
> mydate
  V1 V2                  V3
1  1 73 2017/01/27 11:30:20
2  2 52 2017/03/05 12:01:40
3  3 57 2017/05/12 03:20:00
4  1 74 2017/08/27 14:00:00
5  2 51 2017/10/17 21:03:50
6  3 60 2017/12/08 08:40:30
> lapply(mydate, class)
$V1
[1] "integer"

$V2
[1] "integer"

$V3
[1] "factor"
```

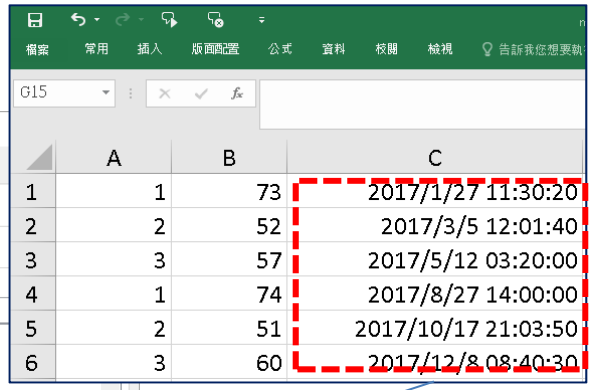
```
> # 方法一
> varNames <- c("ID", "Values", "DateTime")
> mydate <- read.table("mydate.txt", sep = ";",
                       col.names = varNames)
> mydate
  ID Values             DateTime
1  1     73 2017/01/27 11:30:20
2  2     52 2017/03/05 12:01:40
3  3     57 2017/05/12 03:20:00
4  1     74 2017/08/27 14:00:00
5  2     51 2017/10/17 21:03:50
6  3     60 2017/12/08 08:40:30
> lapply(mydate, class)
$ID
[1] "integer"
$Values
[1] "integer"
$DateTime
[1] "factor"

> mydate$DateTime <- strptime(mydate$DateTime,
                              "%Y/%m/%d %H:%M:%S")
> lapply(mydate, class)
$ID
[1] "integer"
$Values
[1] "integer"
$DateTime
[1] "POSIXlt" "POSIXt"
```

```
> # 方法二
自定讀取類別
```

時間序列資料輸入與輸出: EXCEL檔

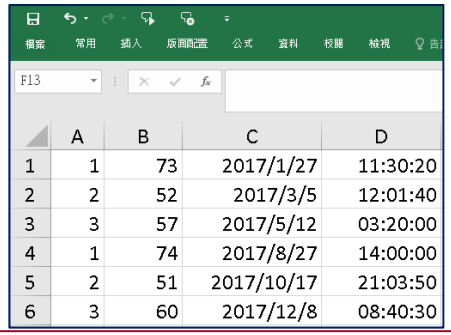
```
> library(readxl)
> mydate <- read_excel("mydate.xlsx", col_names = FALSE)
> mydate
# A tibble: 6 x 3
   ...1  ...2 ...3
  <dbl> <dbl> <dttm>
1     1    73 2017-01-27 11:30:20
...
6     3    60 2017-12-08 08:40:30
> lapply(mydate, class)
$...1
[1] "numeric"

$...2
[1] "numeric"

$...3
[1] "POSIXct" "POSIXt"
```





	A	B	C
1	1	73	2017/1/27 11:30:20
2	2	52	2017/3/5 12:01:40
3	3	57	2017/5/12 03:20:00
4	1	74	2017/8/27 14:00:00
5	2	51	2017/10/17 21:03:50
6	3	60	2017/12/8 08:40:30

滑鼠右鍵



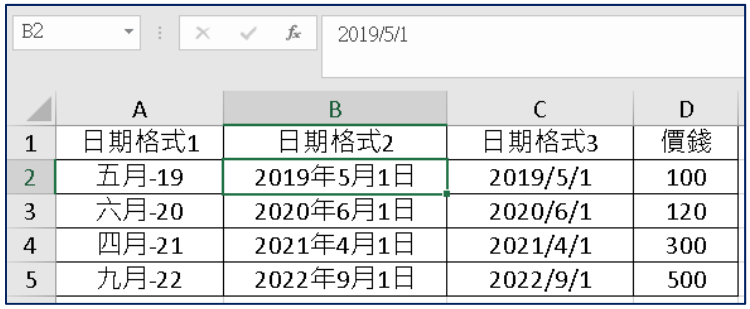
	A	B	C	D
1	1	73	2017/1/27	11:30:20
2	2	52	2017/3/5	12:01:40
3	3	57	2017/5/12	03:20:00
4	1	74	2017/8/27	14:00:00
5	2	51	2017/10/17	21:03:50
6	3	60	2017/12/8	08:40:30

```
> mydate2 <- read_excel("mydate2.xlsx", col_names = FALSE)
> mydate2
# A tibble: 6 x 4
   ...1  ...2 ...3                ...4
  <dbl> <dbl> <dttm>              <dttm>
1     1    73 2017-01-27 00:00:00 1899-12-31 11:30:20
...
6     3    60 2017-12-08 00:00:00 1899-12-31 08:40:30
```

Further modification is needed!

```
library(writexl)
write_xlsx(iris, path = "iris.xlsx")
write_xlsx(list(sheet1 = iris[, 1:2], sheet2 = iris[, 3:4]), path = "iris.xlsx")
```

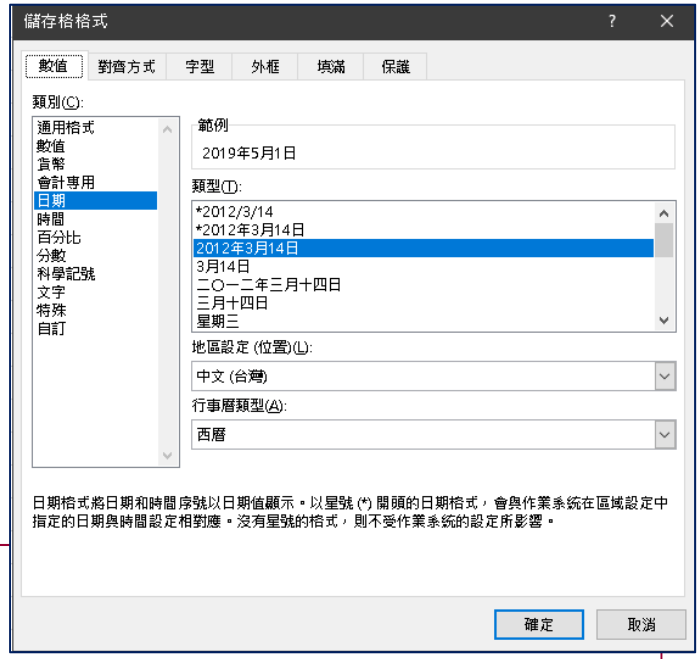
時間序列資料輸入與輸出: 中文格式



B2 | 2019/5/1

	A	B	C	D
1	日期格式1	日期格式2	日期格式3	價錢
2	五月-19	2019年5月1日	2019/5/1	100
3	六月-20	2020年6月1日	2020/6/1	120
4	四月-21	2021年4月1日	2021/4/1	300
5	九月-22	2022年9月1日	2022/9/1	500

TimeData-cht.xlsx




```
> library(readxl)
> TimeData_xlsx <- read_excel("data/TimeData-cht.xlsx")
> TimeData_xlsx
# A tibble: 4 x 4
  日期格式1           日期格式2           日期格式3           價錢
  <dttm>              <dttm>              <dttm>              <dbl>
1 2019-05-01 00:00:00 2019-05-01 00:00:00 2019-05-01 00:00:00   100
2 2020-06-01 00:00:00 2020-06-01 00:00:00 2020-06-01 00:00:00   120
3 2021-04-01 00:00:00 2021-04-01 00:00:00 2021-04-01 00:00:00   300
4 2022-09-01 00:00:00 2022-09-01 00:00:00 2022-09-01 00:00:00   500
> str(TimeData_xlsx)
tibble [4 x 4] (S3: tbl_df/tbl/data.frame)
 $ 日期格式1: POSIXct[1:4], format: "2019-05-01" "2020-06-01" "2021-04-01" ...
 $ 日期格式2: POSIXct[1:4], format: "2019-05-01" "2020-06-01" "2021-04-01" ...
 $ 日期格式3: POSIXct[1:4], format: "2019-05-01" "2020-06-01" "2021-04-01" ...
 $ 價錢     : num [1:4] 100 120 300 500
```

時間序列資料輸入與輸出: 中文格式

TimeData-cht.csv

日期格式1,	日期格式2,	日期格式3,	價錢
五月-19,	2019年5月1日,	2019/5/1,	100
六月-20,	2020年6月1日,	2020/6/1,	120
四月-21,	2021年4月1日,	2021/4/1,	300
九月-22,	2022年9月1日,	2022/9/1,	500

TimeData-cht.csv

```
> TimeData_csv <- read.csv("data/TimeData-cht.csv",
+                          stringsAsFactors = FALSE,
+                          fileEncoding = "big5")
> TimeData_csv
  日期格式1     日期格式2 日期格式3 價錢
1   五月-19 2019年5月1日   2019/5/1  100
2   六月-20 2020年6月1日   2020/6/1  120
3   四月-21 2021年4月1日   2021/4/1  300
4   九月-22 2022年9月1日   2022/9/1  500
> str(TimeData_csv)
'data.frame':       4 obs. of  4 variables:
 $ 日期格式1: chr  "五月-19" "六月-20" "四月-21" "九月-22"
 $ 日期格式2: chr  "2019年5月1日" "2020年6月1日" ...
 $ 日期格式3: chr  "2019/5/1" "2020/6/1" "2021/4/1" ...
 $ 價錢     : int  100 120 300 500
```

```
> TimeData_csv$日期格式2 <- as.POSIXct(strptime(TimeData_csv$日期格式2, format="%Y年%m月%d日"))
> TimeData_csv$日期格式2
[1] "2019-05-01 CST" "2020-06-01 CST" "2021-04-01 CST" "2022-09-01 CST"
>
> TimeData_csv$日期格式3 <- as.POSIXct(TimeData_csv$日期格式3, format="%Y/%m/%d")
> TimeData_csv$日期格式3
[1] "2019-05-01 CST" "2020-06-01 CST" "2021-04-01 CST" "2022-09-01 CST"
```

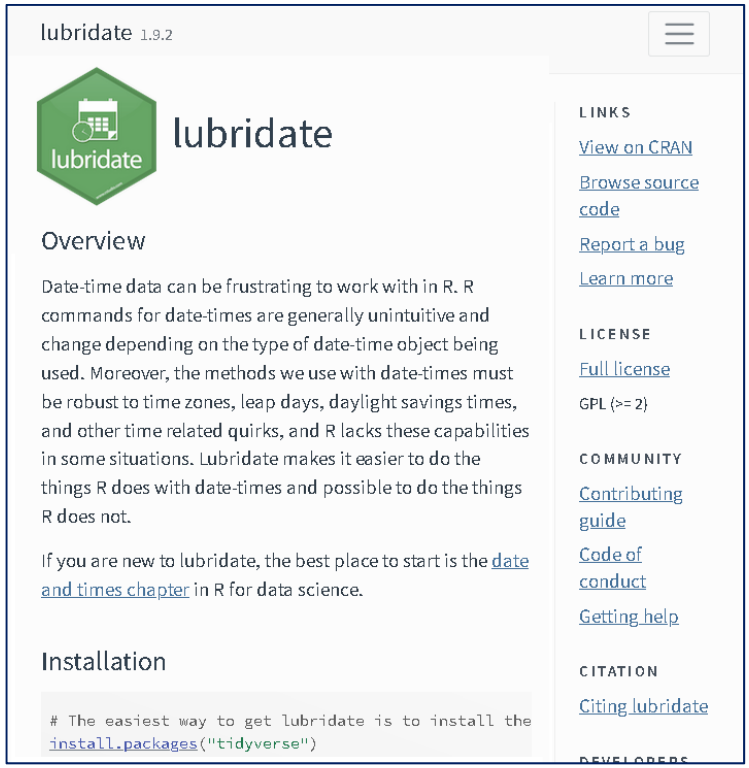
時間序列資料輸入與輸出: 中文格式

```
> months_map <- c("一月"=1, "二月"=2, "三月"=3, "四月"=4,
+                 "五月"=5, "六月"=6, "七月"=7, "八月"=8,
+                 "九月"=9, "十月"=10, "十一月"=11, "十二月"=12)
> date_str <- TimeData_csv$日期格式1
> parts <- strsplit(date_str, "-"); parts
> month <- months_map[sapply(parts, function(x) x[1])]; month
> year <- as.numeric(sapply(parts, function(x) x[2])) + 2000; year
> date_str <- paste(year, month, "1", sep="-")
> TimeData_csv$日期格式1 <- as.POSIXct(date_str, format="%Y-%m-%d")
> TimeData_csv
   日期格式1  日期格式2  日期格式3 價錢
1 2019-05-01 2019-05-01 2019-05-01  100
2 2020-06-01 2020-06-01 2020-06-01  120
3 2021-04-01 2021-04-01 2021-04-01  300
4 2022-09-01 2022-09-01 2022-09-01  500
> str(TimeData_csv)
'data.frame':       4 obs. of  4 variables:
 $ 日期格式1: POSIXct, format: "2019-05-01" "2020-06-01" "2
 $ 日期格式2: POSIXct, format: "2019-05-01" "2020-06-01" "2
 $ 日期格式3: POSIXct, format: "2019-05-01" "2020-06-01" "2
 $ 價錢     : int  100 120 300 500
```

```
> months_map
  一月   二月   三月   四月   五月   六月   七月   八
     1      2      3      4      5      6      7
> parts
[[1]]
[1] "五月" "19"

[[2]]
[1] "六月" "20"

[[3]]
[1] "四月" "21"

[[4]]
[1] "九月" "22"

> month
五月 六月 四月 九月
   5    6    4    9
> year
[1] 2019 2020 2021 2022
> date_str
[1] "2019-5-1" "2020-6-1" "2021-4-1" "2022-9-1"
```

時間序列資料的處理

lubridate: Make Dealing with Dates a Little Easier



Garrett Grolemund, Hadley Wickham (2011). Dates and Times Made Easy with **lubridate**. *Journal of Statistical Software*, 40(3), 1-25.

Base R method	**lubridate** method
`date <- as.POSIXct("01-01-2010", format = "%d-%m-%Y", tz = "UTC")`	`date <- dmy("01-01-2010")`
`as.numeric(format(date, "%m"))` or `as.POSIXlt(date)$month + 1`	`month(date)`
`date <- as.POSIXct(format(date, "%Y-2-%d"), tz = "UTC")`	`month(date) <- 2`

Table 1: **lubridate** provides a simple way to parse a date into R, extract the month value and change it to February.

Base R method	**lubridate** method
`date <- seq(date, length = 2, by = "-1 day")[2]`	`date <- date - days(1)`
`as.POSIXct(format(as.POSIXct(date), tz = "UTC"), tz = "GMT")`	`with_tz(date, "GMT")`

Table 2: **lubridate** easily displays a date one day earlier and in the GMT time zone.

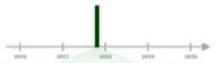
- https://lubridate.tidyverse.org/
- https://rawgit.com/rstudio/cheatsheets/main/lubridate.pdf
- https://cran.r-project.org/web/packages/lubridate/index.html
- Do more with dates and times in R: https://cran.r-project.org/web/packages/lubridate/vignettes/lubridate.html

Cheatsheet, lubridate

Dates and times with lubridate : : CHEATSHEET

lubridate

Date-times



2017-11-28 12:00:00

2017-11-28 12:00:00
A **date-time** is a point on the timeline, stored as the number of seconds since 1970-01-01 00:00:00 UTC

*dt <- **as_datetime**(1511870400)*
"2017-11-28 12:00:00 UTC"

2017-11-28
A **date** is a day stored as the number of days since 1970-01-01

*d <- **as_date**(17498)*
"2017-11-28"

12:00:00
An hms is a **time** stored as the number of seconds since 00:00:00

*t <- hms::**as_hms**(85)*
00:01:25

PARSE DATE-TIMES (Convert strings or numbers to date-times)

1. Identify the order of the year (**y**), month (**m**), day (**d**), hour (**h**), minute (**m**) and second (**s**) elements in your data.
2. Use the function below whose name replicates the order. Each accepts a tz argument to set the time zone, e.g. ymd(x, tz = "UTC").

2017-11-28T14:02:00 — **ymd_hms(), ymd_hm(), ymd_h()**. ymd_hms("2017-11-28T14:02:00")

2017-22-12 10:00:00 — **ydm_hms(), ydm_hm(), ydm_h()**. ydm_hms("2017-22-12 10:00:00")

11/28/2017 1:02:03 — **mdy_hms(), mdy_hm(), mdy_h()**. mdy_hms("11/28/2017 1:02:03")

1 Jan 2017 23:59:59 — **dmy_hms(), dmy_hm(), dmy_h()**. dmy_hms("1 Jan 2017 23:59:59")

20170131 — **ymd(), ydm()**. ymd(20170131)

July 4th, 2000 — **mdy(), myd()**. mdy("July 4th, 2000")

4th of July '99 — **dmy(), dym()**. dmy("4th of July '99")

2001: Q3 — **yq()** Q for quarter. yq("2001: Q3")

07-2020 — **my(), ym()**. my("07-2020")

2:01 — hms::**hms()** Also lubridate::**hms()**, **hm()** and **ms()**, which return periods.* hms::hms(seconds = 0, minutes = 1, hours = 2)

2017.5 — **date_decimal**(decimal, tz = "UTC") date_decimal(2017.5)

now(tzone = "") Current time in tz (defaults to system tz). now()

today(tzone = "") Current date in a tz (defaults to system tz). today()

fast_strptime() Faster strptime. fast_strptime("9/1/01", "%y/%m/%d")

parse_date_time() Easier strptime. parse_date_time("09-01-01", "ymd")

GET AND SET COMPONENTS

Use an accessor function to get a component.
d ## "2017-11-28"
day(d) ## 28

Assign into an accessor function to change a component in place.
day(d) <- 1
d ## "2017-11-01"

2018-01-31 11:59:59 — **date(x)** Date component. date(dt)

2018-01-31 11:59:59 — **year(x)** Year. year(dt)
isoyear(x) The ISO 8601 year.
epiyear(x) Epidemiological year.

2018-01-31 11:59:59 — **month**(x, label, abbr) Month. month(dt)

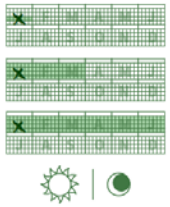
2018-01-31 11:59:59 — **day(x)** Day of month. day(dt)
wday(x, label, abbr) Day of week.
qday(x) Day of quarter.

2018-01-31 11:59:59 — **hour(x)** Hour. hour(dt)

2018-01-31 11:59:59 — **minute(x)** Minutes. minute(dt)

2018-01-31 11:59:59 — **second(x)** Seconds. second(dt)

2018-01-31 11:59:59 UTC — **tz(x)** Time zone. tz(dt)



week(x) Week of the year. week(dt)
isoweek() ISO 8601 week.
epiweek() Epidemiological week.

quarter(x) Quarter. quarter(dt)

semester(x, with_year = FALSE) Semester. semester(dt)

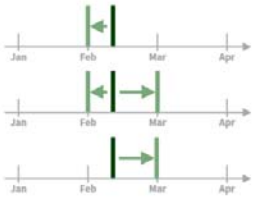
am(x) Is it in the am? am(dt)
pm(x) Is it in the pm? pm(dt)

dst(x) Is it daylight savings? dst(d)

leap_year(x) Is it a leap year? leap_year(d)

update(object, ..., simple = FALSE) update(dt, mday = 2, hour = 1)

Round Date-times



floor_date(x, unit = "second") Round down to nearest unit. floor_date(dt, unit = "month")

round_date(x, unit = "second") Round to nearest unit. round_date(dt, unit = "month")

ceiling_date(x, unit = "second", change_on_boundary = NULL) Round up to nearest unit. ceiling_date(dt, unit = "month")

Valid units are second, minute, hour, day, week, month, bimonth, quarter, season, halfyear and year.

rollback(dates, roll_to_first = FALSE, preserve_hms = TRUE) Roll back to last day of previous month. Also **rollforward()**. rollback(dt)

Stamp Date-times

stamp() Derive a template from an example string and return a new function that will apply the template to date-times. Also **stamp_date()** and **stamp_time()**.

1. Derive a template, create a function
   sf <- stamp("Created Sunday, Jan 17, 1999 3:34")
2. Apply the template to dates
   sf(ymd("2010-04-05"))
   ## [1] "Created Monday, Apr 05, 2010 00:00"

Tip: use a date with day > 12

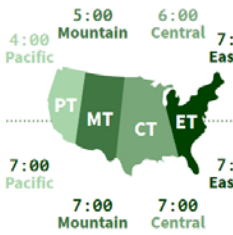
Time Zones

R recognizes ~600 time zones. Each encodes the time zone, Daylight Savings Time, and historical calendar variations for an area. R assigns *one* time zone per vector.

Use the **UTC** time zone to avoid Daylight Savings.

OlsonNames() Returns a list of valid time zone names. OlsonNames()

Sys.timezone() Gets current time zone.



with_tz(time, tzone = "") Get the **same date-time** in a new time zone (a new clock time). Also **local_time**(dt, tz, units). with_tz(dt, "US/Pacific")

force_tz(time, tzone = "") Get the **same clock time** in a new time zone (a new date-time). Also **force_tzs()**. force_tz(dt, "US/Pacific")

posit™

Cheatsheet, lubridate

Math with Date-times

Lubridate provides three classes of timespans to facilitate math with dates and date-times.

Math with date-times relies on the **timeline**, which behaves inconsistently. Consider how the timeline behaves during:

A normal day

```
nor <- ymd_hms("2018-01-01 01:30:00",tz="US/Eastern")
```

The start of daylight savings (spring forward)

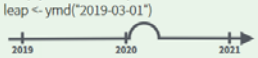
```
gap <- ymd_hms("2018-03-11 01:30:00",tz="US/Eastern")
```

The end of daylight savings (fall back)

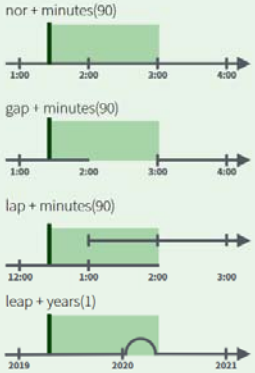
```
lap <- ymd_hms("2018-11-04 00:30:00",tz="US/Eastern")
```

Leap years and leap seconds

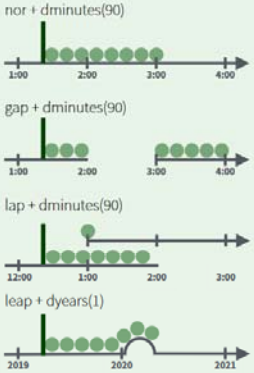
```
leap <- ymd("2019-03-01")
```



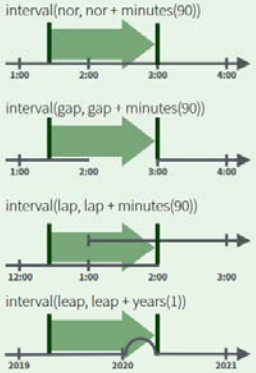
Periods track changes in clock times, which ignore time line irregularities.



Durations track the passage of physical time, which deviates from clock time when irregularities occur.



Intervals represent specific intervals of the timeline, bounded by start and end date-times.



Not all years are 365 days due to **leap days**.

Not all minutes are 60 seconds due to **leap seconds**.

It is possible to create an imaginary date by adding **months**, e.g. February 31st

```
jan31 <- ymd(20180131)
jan31 + months(1)
## NA
```

%m+% and **%m-%** will roll imaginary dates to the last day of the previous month.

```
jan31 %m+% months(1)
## "2018-02-28"
```

add_with_rollback(e1, e2, roll_to_first = TRUE) will roll imaginary dates to the first day of the new month.

```
add_with_rollback(jan31, months(1),
roll_to_first = TRUE)
## "2018-03-01"
```

PERIODS

Add or subtract periods to model events that happen at specific clock times, like the NYSE opening bell.

Make a period with the name of a time unit ***pluralized***, e.g.

```
p <- months(3) + days(12)
p
"3m 12d 0H 0M 0S"
```

Number of months · Number of days · etc.

years(x = 1) x years.
months(x) x months.
weeks(x = 1) x weeks.
days(x = 1) x days.
hours(x = 1) x hours.
minutes(x = 1) x minutes.
seconds(x = 1) x seconds.
milliseconds(x = 1) x milliseconds.
microseconds(x = 1) x microseconds
nanoseconds(x = 1) x nanoseconds.
picoseconds(x = 1) x picoseconds.

period(num = NULL, units = "second", ...) An automation friendly period constructor. period(5, unit = "years")

as.period(x, unit) Coerce a timespan to a period, optionally in the specified units. Also **is.period()**. as.period(p)

period_to_seconds(x) Convert a period to the "standard" number of seconds implied by the period. Also **seconds_to_period()**. period_to_seconds(p)

DURATIONS

Add or subtract durations to model physical processes, like battery life. Durations are stored as seconds, the only time unit with a consistent length. **Difftimes** are a class of durations found in base R.

Make a duration with the name of a period prefixed with a ***d***, e.g.

```
dd <- ddays(14)
dd
"1209600s (~2 weeks)"
```

Exact length in seconds · Equivalent in common units

dyears(x = 1) 31536000x seconds.
dmonths(x = 1) 2629800x seconds.
dweeks(x = 1) 604800x seconds.
ddays(x = 1) 86400x seconds.
dhours(x = 1) 3600x seconds.
dminutes(x = 1) 60x seconds.
dseconds(x = 1) x seconds.
dmilliseconds(x = 1) x $\times 10^{-3}$ seconds.
dmicroseconds(x = 1) x $\times 10^{-6}$ seconds.
dnanoseconds(x = 1) x $\times 10^{-9}$ seconds.
dpicoseconds(x = 1) x $\times 10^{-12}$ seconds.

duration(num = NULL, units = "second", ...) An automation friendly duration constructor. duration(5, unit = "years")

as.duration(x, ...) Coerce a timespan to a duration. Also **is.duration()**, **is.difftime()**. as.duration(i)

make_difftime(x) Make difftime with the specified number of units. make_difftime(99999)

INTERVALS

Divide an interval by a duration to determine its physical length, divide an interval by a period to determine its implied length in clock time.

Make an interval with **interval()** or **%--%**, e.g.

Start Date · End Date

```
i <- interval(ymd("2017-01-01"), d)      ## 2017-01-01 UTC--2017-11-28 UTC
j <- d %--% ymd("2017-12-31")            ## 2017-11-28 UTC--2017-12-31 UTC
```

a %within% b Does interval or date-time *a* fall within interval *b*? now() %within% i

int_start(int) Access/set the start date-time of an interval. Also **int_end()**. int_start(i) <- now(); int_start(i)

int_aligns(int1, int2) Do two intervals share a boundary? Also **int_overlaps()**. int_aligns(i, j)

int_diff(times) Make the intervals that occur between the date-times in a vector. v <-c(dt, dt + 100, dt + 1000); int_diff(v)

int_flip(int) Reverse the direction of an interval. Also **int_standardize()**. int_flip(i)

int_length(int) Length in seconds. int_length(i)

int_shift(int, by) Shifts an interval up or down the timeline by a timespan. int_shift(i, days(-1))

as.interval(x, start, ...) Coerce a timespan to an interval with the start date-time. Also **is.interval()**. as.interval(days(1), start = now())

posit

Parsing Dates and Times

```
> library(lubridate)
>
> today()
[1] "2023-09-10"
> current1 <- now()
> current1
[1] "2023-09-10 08:17:32 UTC"
> class(current1)
[1] "POSIXct" "POSIXt"
>
> current2 <- date()
> current2
[1] "Sun Sep 10 16:17:32 2023"
> class(current2)
[1] "character"
```

```
> my_date <- ymd("20230910")
> my_date
[1] "2023-09-10"
> class(my_date)
[1] "Date"
>
> mdy("09-10-2023")
[1] "2023-09-10"
> dmy("10/09/2023")
[1] "2023-09-10"
>
> ymd_hms("20131219101707")
[1] "2013-12-19 10:17:07 UTC"
> ymd_hms("2013 Dec 19 10:17:07")
[1] "2013-12-19 10:17:07 UTC"
>
> mdy("Dec 19, 2013")
[1] "2013-12-19"
>
> mdy_hms("December 19, 2013 10:17:07")
[1] "2013-12-19 10:17:07 UTC"
>
> dmy_hms("19-Dec, 2013 10:17:07")
[1] "2013-12-19 10:17:07 UTC"
```

```
> two_dates <- ymd_hms("2023-01-01 01:15:00", "2023-02-01 01:30:00")
> minute(two_dates)
[1] 15 30
> mean(minute(two_dates))
[1] 22.5
```

時區 (Time Zone)

- The default time zone for the lubridate functions is Greenwich Mean Time (**GMT**, formerly)/Universal Time, Coordinated (**UTC**)
- Taipei: CST (China Standard Time), Offset: UTC + 8 hours
- London: BST (British Summer Time) (Apr. ~ Oct.), Offset: UTC/GMT + 1 hour

```
> OlsonNames() ## typically around six hundred names
  [1] "Africa/Abidjan" "Africa/Accra" "Africa/Addis_Ababa" "Africa/Algiers"
  [5] "Africa/Asmara" "Africa/Asmera" "Africa/Bamako" "Africa/Bangui"
  [9] "Africa/Banjul" "Africa/Bissau" "Africa/Blantyre" "Africa/Brazzaville"
...
[589] "US/Mountain" "US/Pacific" "US/Samoa" "UTC"
[593] "W-SU" "WET""Zulu"
attr(,"Version")
[1] "2022e"
```

```
> Sys.timezone()
[1] "UTC"
> Sys.setenv(TZ = "UTC")
> ymd_hms("2023-08-17 08:50:00", tz = "Asia/Taipei")
[1] "2023-08-17 08:50:00 CST"
> ymd_hms("2023-08-17 19:25:00", tz = "Europe/London")
[1] "2023-08-17 19:25:00 BST"
>
> departure <- ymd_hms("2023-08-17 08:50:00", tz = "Asia/Taipei")
> departure
[1] "2023-08-17 08:50:00 CST"
> with_tz(departure, "Europe/London")
[1] "2023-08-17 01:50:00 BST"
```

```
> changed <- force_tz(departure, "America/Chicago")
> changed
[1] "2023-08-17 08:50:00 CDT"
> with_tz(changed, "Europe/London")
[1] "2023-08-17 14:50:00 BST"
```

Central Daylight Time
中部夏令時間

Setting and Extracting Information

```
> departure <- ymd_hms("2023-08-17 08:50:00", tz = "Asia/Taipei")
> year(departure)
[1] 2023
> month(departure)
[1] 8
> week(departure)
[1] 33
> yday(departure)
[1] 229
> mday(departure)
[1] 17
> wday(departure)
[1] 5
> hour(departure)
[1] 8
> minute(departure)
[1] 50
> second(departure)
[1] 0
```

Date Component	Extractor Function
Year	`year()`
Month	`month()`
Week	`week()`
Day of year	`yday()`
Day of month	`mday()`
Day of week	`wday()`
Hour	`hour()`
Minute	`minute()`
Second	`second()`
Time zone	`tz()`

```
> second(departure) <- 25
> departure
[1] "2023-08-17 08:50:25 CST"
```

```
> month(departure, label = TRUE)
[1] 八月
Levels: 一月 < 二月 < 三月 < 四月 < 五月 < 六月 < 七月 < 八月 < 九月 < 十月 < 十一月 < 十二月
> month(departure, label = TRUE, abbr = FALSE)
[1] 八月
Levels: 一月 < 二月 < 三月 < 四月 < 五月 < 六月 < 七月 < 八月 < 九月 < 十月 < 十一月 < 十二月
> wday(departure, label = TRUE)
[1] 週四
Levels: 週日 < 週一 < 週二 < 週三 < 週四 < 週五 < 週六
```

英文: **August**, **Aug**

```
> Sys.getenv()
> Sys.setenv(LANG = "en")
> Sys.setenv(LANG = "zh")
```

Time Intervals

```
> summer_camp_start <- ymd_hms("2023-07-20 08:00:00")
> summer_camp_end <- ymd_hms("2023-08-03 12:00:00")
> camp_period <- interval(summer_camp_start, summer_camp_end)
> camp_period
[1] 2023-07-20 08:00:00 UTC--2023-08-03 12:00:00 UTC
>
> # Toronto
> # Current:     EDT – Eastern Daylight Time
> # Next Change: EST – Eastern Standard Time
>
> JSM2023 <- interval(ymd(20230805, tz = "Canada/Eastern"),
+                     ymd(20230810, tz = "Canada/Eastern"))
> JSM2023
[1] 2023-08-05 EDT--2023-08-10 EDT

> int_overlaps(JSM2023, camp_period)
[1] FALSE
> union(JSM2023, camp_period)
[1] 2023-07-20 04:00:00 EDT--2023-08-10 EDT
>
> # Other functions that work with intervals:
> # int_start, int_end, int_flip, int_shift, int_aligns, union,
> # intersect, setdiff, %within%.
```

Arithmetic with Date Times

```
> # Periods record a time span in units larger
than seconds
> ymd(20230805) + 1
[1] "2023-08-06"
> ymd(20230805) + days(1)
[1] "2023-08-06"
> days(0:5)
[1] "0S" "1d 0H 0M 0S" "2d 0H 0M 0S" "3d 0H 0M
0S" "4d 0H 0M 0S" "5d 0H 0M 0S"
> weeks(1:5)
[1] "7d 0H 0M 0S"  "14d 0H 0M 0S" "21d 0H 0M
0S" "28d 0H 0M 0S" "35d 0H 0M 0S"
> months(1)
[1] "1m 0d 0H 0M 0S"
> ymd(20230805) + months(1)
[1] "2023-09-05"
> years(1:2)
[1] "1y 0m 0d 0H 0M 0S" "2y 0m 0d 0H 0M 0S"
> ymd(20230805) + years(1:2)
[1] "2024-08-05" "2025-08-05"
```

```
> # Durations: record the time span in
seconds
> dweeks(1)
[1] "604800s (~1 weeks)"
> ddays(6)
[1] "518400s (~6 days)"
> dhours(1)
[1] "3600s (~1 hours)"
> dminutes(1)
[1] "60s (~1 minutes)"
> dseconds(60)
[1] "60s (~1 minutes)"
```

Arithmetic with Date Times

- **Question**: January 31st + one month.
  Should the answer be
  (1) February 31st (which doesn't exist)
  (2) March 4th (31 days after January 31), or
  (3) February 28th (assuming its not a leap year)

```
> jan31 <- ymd("2013-01-31")
> jan31
[1] "2013-01-31"
```

```
> #(1)
> jan31 + months(1)
[1] NA
> jan31 + months(0:11)
 [1] "2013-01-31" NA "2013-03-31" NA "2013-05-31" NA
 [7] "2013-07-31" "2013-08-31" NA "2013-10-31" NA "2013-12-31"
>
> #(2)
> floor_date(jan31, "month")
[1] "2013-01-01"
> floor_date(jan31, "month") + months(0:11) + days(31)
 [1] "2013-02-01" "2013-03-04" "2013-04-01" "2013-05-02" "2013-06-01" "2013-07-02"
 [7] "2013-08-01" "2013-09-01" "2013-10-02" "2013-11-01" "2013-12-02" "2014-01-01"
>
> #(3)
> # %m+% and %m-%: roll dates back to the last day of the month
> jan31 %m+% months(0:11)
 [1] "2013-01-31" "2013-02-28" "2013-03-31" "2013-04-30" "2013-05-31" "2013-06-30"
 [7] "2013-07-31" "2013-08-31" "2013-09-30" "2013-10-31" "2013-11-30" "2013-12-31"
```

Creating ts Time Series Object

```
ts(data = NA, start = 1, end = numeric(), frequency = 1,
   deltat = 1, ts.eps = getOption("ts.eps"), class = , names = )
as.ts(x, ...)
is.ts(x)
```

Year	Observation
2012	123
2013	39
2014	78
2015	52
2016	110

ts(data, frequency, start)

Type of data	frequency	start example
Annual	1	1995
Quarterly	4	c(1995,2)
Monthly	12	c(1995,9)
Daily	7 *or* 365.25	1 *or* c(1995,234)
Weekly	52.18	c(1995,23)
Hourly	24 *or* 168 *or* 8,766	1
Half-hourly	48 *or* 336 *or* 17,532	1

```
Observation <- ts(c(123, 39, 78, 52, 110), start = 2012)
```

```
> ts_matrix
        [,1]  [,2]  [,3]
 [1,] -0.33  0.14  0.52
 [2,]  0.44  2.63  0.58
 [3,] -1.05 -0.37 -1.33
 [4,] -0.42 -2.10 -0.59
 [5,]  0.69  0.05 -0.59
 [6,]  0.85  0.74  0.64
 [7,] -0.74 -1.97  0.20
 [8,] -0.67 -0.13  0.28
 [9,]  0.42  1.69  1.18
[10,]  1.66 -2.16  0.90
[11,]  0.30 -1.83  0.90
[12,] -0.03 -1.21  0.60
[13,] -0.10 -0.49 -0.40
[14,] -0.35  0.19 -1.01
[15,] -0.68 -1.26  2.20
[16,]  1.34 -0.64 -0.05
[17,]  1.15  1.28  0.90
[18,]  0.55  0.34 -2.00
[19,] -0.03 -0.17  0.59
[20,]  0.53  0.42 -1.25
```

```
> ts_obj
         Series 1 Series 2 Series 3
Jan 1961    -0.33     0.14     0.52
Feb 1961     0.44     2.63     0.58
Mar 1961    -1.05    -0.37    -1.33
Apr 1961    -0.42    -2.10    -0.59
May 1961     0.69     0.05    -0.59
Jun 1961     0.85     0.74     0.64
Jul 1961    -0.74    -1.97     0.20
Aug 1961    -0.67    -0.13     0.28
Sep 1961     0.42     1.69     1.18
Oct 1961     1.66    -2.16     0.90
Nov 1961     0.30    -1.83     0.90
Dec 1961    -0.03    -1.21     0.60
Jan 1962    -0.10    -0.49    -0.40
Feb 1962    -0.35     0.19    -1.01
Mar 1962    -0.68    -1.26     2.20
Apr 1962     1.34    -0.64    -0.05
May 1962     1.15     1.28     0.90
Jun 1962     0.55     0.34    -2.00
Jul 1962    -0.03    -0.17     0.59
Aug 1962     0.53     0.42    -1.25
```

```
> ts_matrix <- matrix(round(rnorm(60), 2), 20, 3)
> ts_matrix
> ts_obj <- ts(ts_matrix, start = c(1961, 1), frequency = 12)
> ts_obj
> class(ts_obj)
[1] "mts"    "ts"     "matrix"
> is.mts(ts_obj)
[1] TRUE
```

The R Graph Gallery: Time Series

The R Graph Gallery https://r-graph-gallery.com/time-series.html

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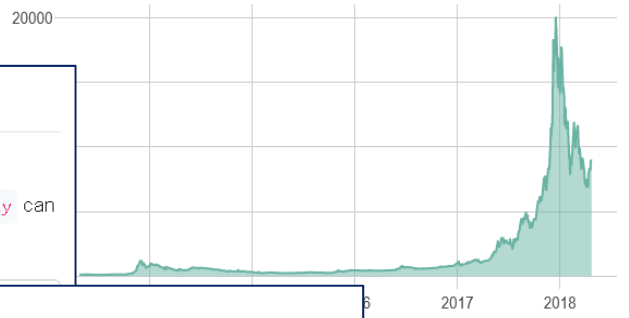
Time Series

INTERACTIVE VERSION: PLOTLY

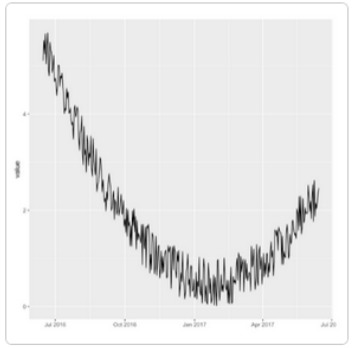
The `ggplotly()` function of the `plotly` library makes it a breeze to build an interactive version. Try to hover circles to get a tooltip, or select an area of interest for zooming. Double click to reinitialize.

GET CODE



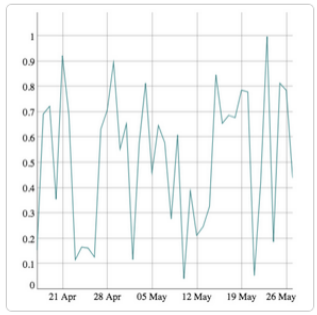
TIME SERIES WITH GGPLOT2

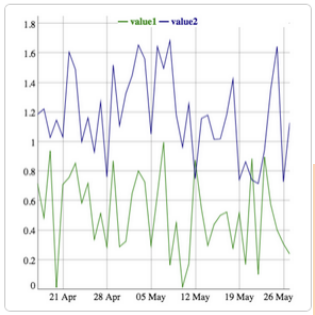
`ggplot2` offers great features when it comes to visualize time series. The `date` format will be recognized automatically, resulting in neat X axis labels. The `scale_x_data()` makes it a breeze to customize those labels. Last but not least, `plotly` can turn the resulting chart interactive in one more line of code.

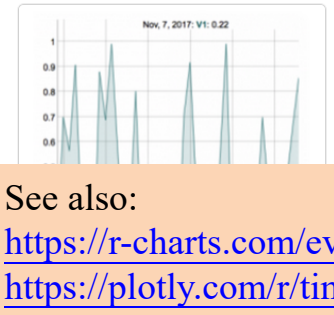


TIME SERIES WITH DYGRAPH

The dygraphs package is a html widget. It allows to make interactive time series chart: you can zoom and hover data points to get additional information. Start by reading the chart #316 for quick introduction and input description. Then, the graph #317 gives an overview of the different types of charts that are offered. To go further, check the graph #318 (interactive version below).







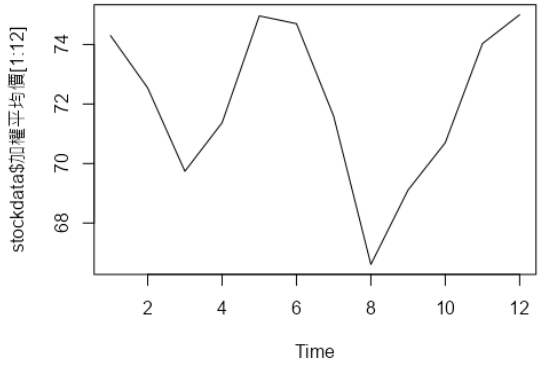
See also:
https://r-charts.com/evolution/time-series-ggplot2/
https://plotly.com/r/time-series/

matplot {graphics}, geom_line {ggplot2}

民國100年5家半導體公司股票月成交資訊(元,股)

半導體公司		年度	月份	最高價	最低價	加權平均價	成交筆數	成交金額	
台積電	100	1	78.3	69.6	74.3	263,999	100,578,274,926	1,353,616,348	5.22
台積電	100	2	77	69.9	72.54	235,159	74,985,055,548	1,033,654,452	3.98
台積電	100	3	72.2	65.7	69.74	276,434	88,459,924,495	1,268,289,393	4.89
台積電	100	4	73.9	68	71.37	211,611	70,177,023,098	983,177,475	3.79
台積電	100	5	76.9	73	74.96	213,185	74,005,599,560	987,256,484	3.8
台積電	100	6	78.2	70.4	74.7	260,507	96,761,306,205	1,295,262,736	4.99
台積電	100	7	73.9	68.5	71.59	238,386	73,569,965,426	1,027,567,656	3.96
台積電	100	8	72.8	62.2	66.61	305,409	84,617,942,159	1,270,302,342	4.9
台積電	100	9	72.1	65.9	69.11	266,720	74,225,030,814	1,073,997,108	4.14
台積電	100	10	74	68.1	70.7	181,361	59,947,670,693	847,821,278	3.27
台積電	100	11	76	71.3	74.03	197,579	65,432,526,407	883,753,804	3.41
台積電	100	12	76.8	72	75	179,107	53,687,756,290	715,808,271	2.76
威盛	100	1	33.4	29.3	30.97	55,107	4,580,913,795	147,912,893	21.54
威盛	100	2	32.65	28.35	30.54	26,901	2,060,809,696	67,459,942	9.82
威盛	100	3	35.45	28.5	32.01				
威盛	100	4	32.8	27.55	30.35				
威盛	100	5	32.6	25.95	29.4				
威盛	100	6	37.25	31.2	34.68				
威盛	100	7	38.15	32.45	35.47				
威盛	100	8	35.4	26.6	30.13				
威盛	100	9	29	23.1	26.17				
威盛	100	10	25.15	20.4	23.39				
威盛	100	11	25.7	18.7	22.74				
威盛	100	12	20.2	14.8	16.96				
聯發科	100	1	424	378	403.55	106,530	57,621,649,341	142,786,216	12.98
聯發科	100	2	380	325.5	348.98	97,339	46,409,931,806	132,985,689	12.08
聯發科	100	3	355	312.5	339.96	117,960	52,887,228,668	155,567,203	14.14

```
stockdata <- read.table("stock-data.txt", skip = 1, header = T)
head(stockdata, 5)
sapply(stockdata, class)
for(at in 7:9){
  stockdata[,at] <- as.numeric(gsub(",", "", stockdata[,at]))
}
```



ts.plot {stats}

Plot Multiple Time Series

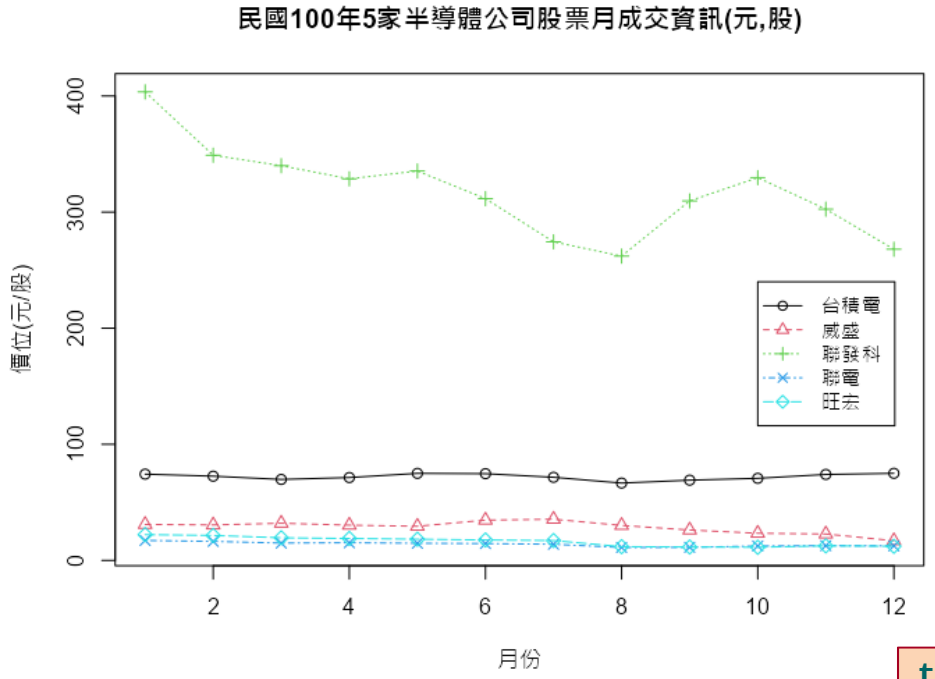
```
ts.plot(stockdata$加權平均價[1:12])
```

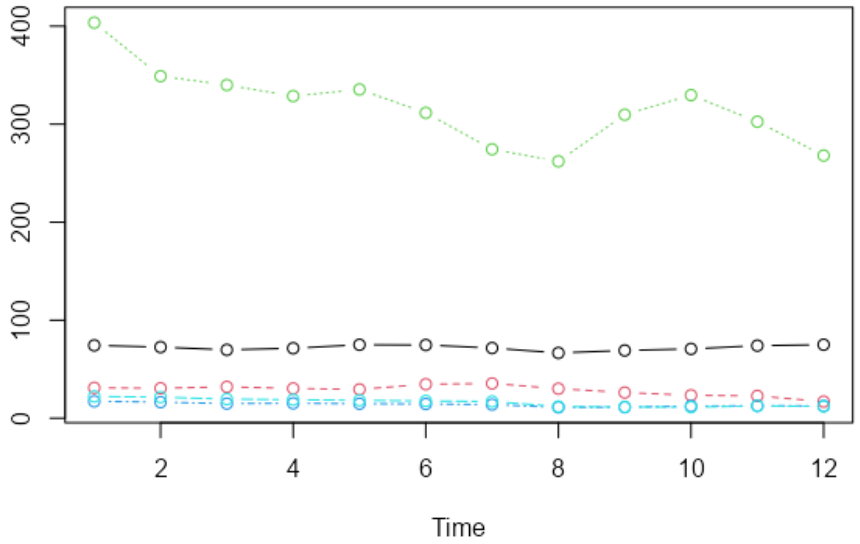
使用 matplot {graphics}

```
mat <- as.data.frame(matrix(stockdata$加權平均價, ncol = 5))
colnames(mat) <- unique(stockdata$半導體公司)
mat

matplot(1:12, mat, type = "o", lty = 1:5, col = 1:5, pch = 1:5,
        main = "民國100年5家半導體公司股票月成交資訊(元,股)",
        xlab = "月份", ylab = "價位(元/股)")
legend(10, 240, legend = colnames(mat), lty = 1:5, col = 1:5,
       pch = 1:5, cex = 0.9)
```

type = "l"

```
> mat
   台積電  威盛 聯發科  聯電  旺宏
1   74.30 30.97 403.55 17.19 22.19
2   72.54 30.54 348.98 16.38 21.49
3   69.74 32.01 339.96 14.92 19.48
4   71.37 30.35 328.65 15.21 18.88
5   74.96 29.40 335.42 14.76 18.25
6   74.70 34.68 311.57 14.51 17.60
7   71.59 35.47 274.39 13.89 17.09
8   66.61 30.13 262.09 11.13 11.84
9   69.11 26.17 309.66 11.25 11.55
10  70.70 23.39 329.66 12.39 11.31
11  74.03 22.74 302.52 12.68 12.54
12  75.00 16.96 268.01 12.51 12.17
```



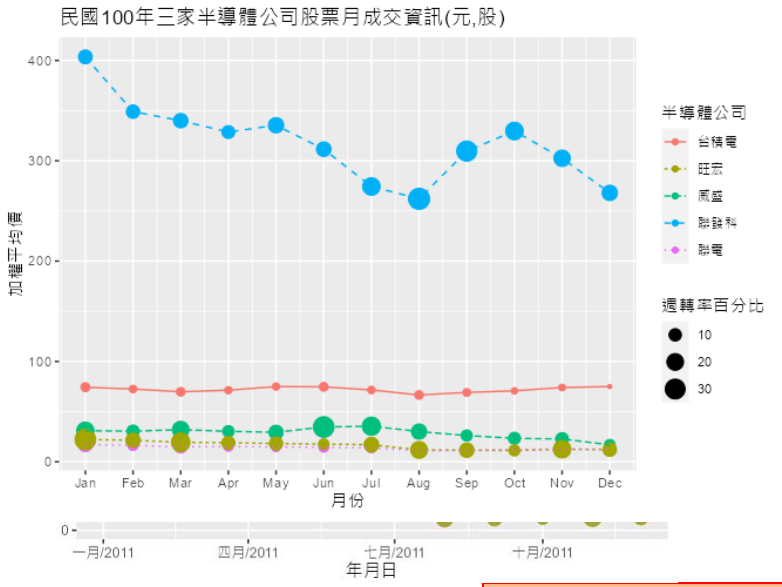


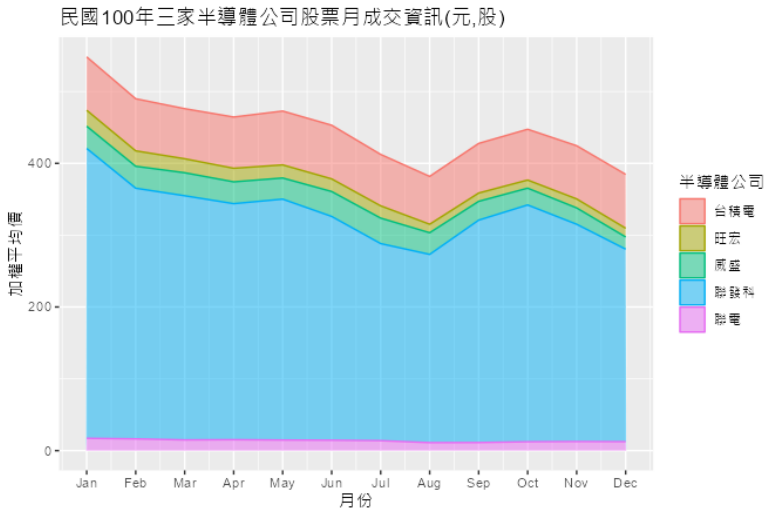

```
ts.plot(mat, lty = 1:5, col = 1:5, type = "b")
```

使用 geom_line {ggplot2}

```
library(ggplot2)
ggplot(stockdata, aes(x = 月份, y = 加權平均價, colour = 半導體公司)) +
  geom_point(aes(size = 週轉率百分比))+
  geom_line(aes(lty = 半導體公司)) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(title="民國100年三家半導體公司股票月成交資訊(元,股)")
```

```
ggplot(stockdata, aes(x = 月份, y = 加權平均價, colour = 半導體公司)) +
  geom_area(aes(fill = 半導體公司), alpha = 0.5) +
  scale_x_continuous(breaks = 1:12, labels = month.abb) +
  labs(title="民國100年三家半導體公司股票月成交資訊(元,股)")
```



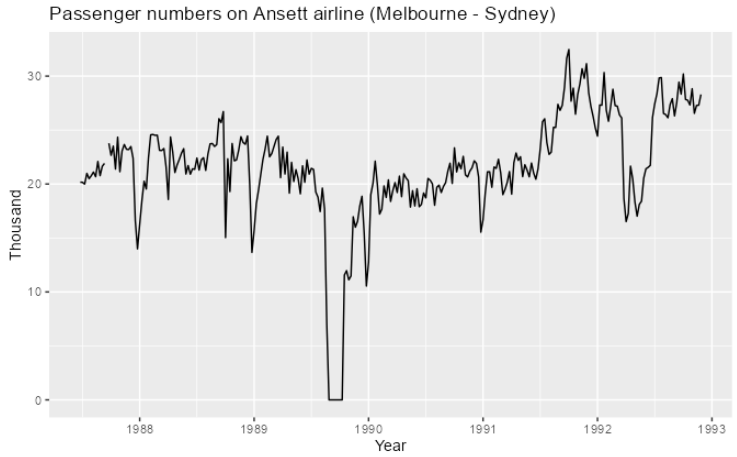



```
stockdata$年月日 <- as.Date(paste0("2011/", stockdata$月份, "/01"))
ggplot(...) +
  scale_x_date(date_labels = "%b/%Y")
```

使用 autoplot for ts, mts Object

```
> library(forecast)
> library(ggplot2)
> library(fpp) # Forecasting: principles and practice
>
> data(melsyd) # Total weekly air passenger numbers on Ansett airline flights between
Melbourne and Sydney, 1987-1992.
> head(melsyd)
Time Series:
Start = c(1987, 26)
End = c(1987, 31)
Frequency = 52
         First.Class Business.Class Economy.Class
1987.481       1.912             NA        20.167
1987.500       1.848             NA        20.161
1987.519       1.856             NA        19.993
1987.538       2.142             NA        20.986
1987.558       2.118             NA        20.497
1987.577       2.048             NA        20.770
> class(melsyd)
[1] "mts" "ts"
> colnames(melsyd)
[1] "First.Class"    "Business.Class" "Economy.Class"
> time(melsyd)
Time Series:
Start = c(1987, 26)
End = c(1992, 48)
Frequency = 52
  [1] 1987.481 1987.500 1987.519 1987.538 1987.558 1987.577 1987.596 1987.615
1987.635...
```

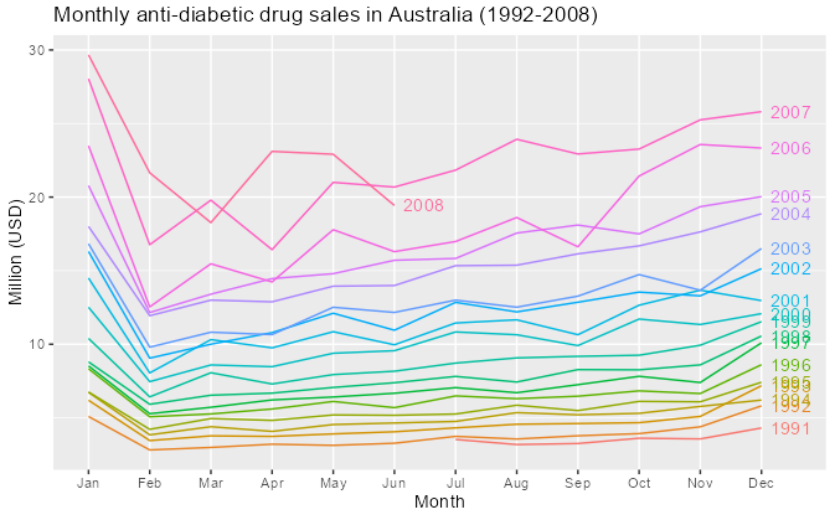
```
> autoplot(melsyd[, "Economy.Class"]) +
+   xlab("Year") +
+   ylab("Thousand") +
+   ggtitle("Passenger numbers (Melbourne - Sydney)")
```

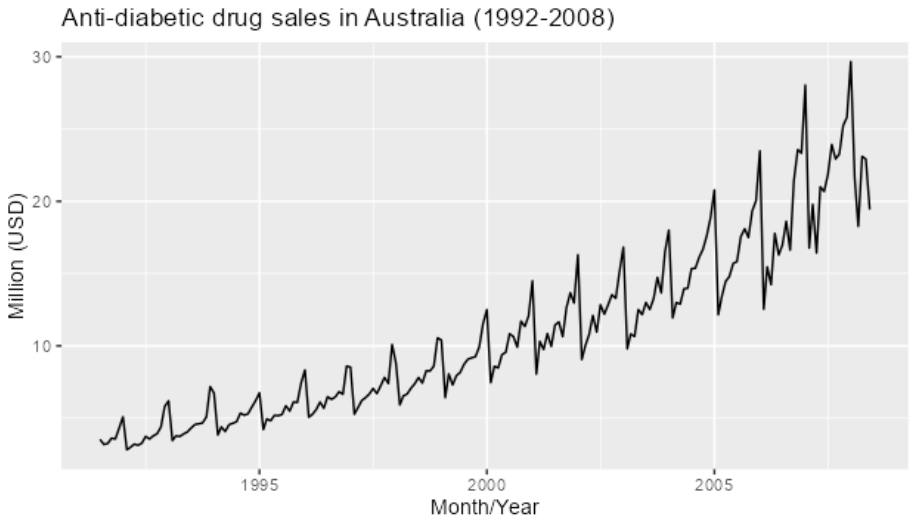


使用 ggseasonplot for ts Object

```
> data(a10) # Monthly anti-diabetic drug (抗糖尿病藥) sales in Australia from 1992 to 2008.
> a10
           Jan       Feb       Mar       Apr       May       Jun       Jul       Aug
1991                                                             3.526591  3.180891
1992  5.088335  2.814520  2.985811  3.204780  3.127578  3.270523  3.737851  3.558776
...
2007 28.038383 16.763869 19.792754 16.427305 21.000742 20.681002 21.834890 23.930204
2008 29.665356 21.654285 18.264945 23.107677 22.912510 19.431740
> class(a10)
[1] "ts"
> ggseasonplot(a10, year.labels = TRUE) +
+   xlab("Month")+
+   ylab("Million (USD)") +
+   ggtitle("Monthly anti-diabetic drug sales in Australia (1992-2008)")
```

```
autoplot(a10) +
  xlab("Month")+
  ylab("Million (USD)") +
  ggtitle("Anti-diabetic drug sales)")
```





plotly package supports the time-series classes: ts, mts, zoo, xts, data.frame, tbl

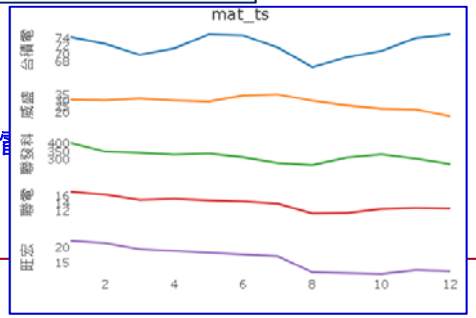
```
library(plotly)
# data.frame with one date/time column
date_mat <- data.frame(date = seq(as.Date("2011/1/1"),
                                  by = "month",
                                  length.out = 12),
                       mat)
sapply(date_mat, class)
ts_plot(date_mat)
```

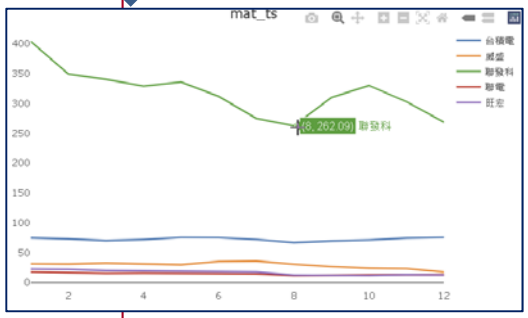
```
> mat
   台積電  威盛 聯發科  聯電  旺宏
1   74.30 30.97 403.55 17.19 22.19
2   72.54 30.54 348.98 16.38 21.49
3   69.74 32.01 339.96 14.92 19.48
4   71.37 30.35 328.65 15.21 18.88
5   74.96 29.40 335.42 14.76 18.25
6   74.70 34.68 311.57 14.51 17.60
7   71.59 35.47 274.39 13.89 17.09
8   66.61 30.13 262.09 11.13 11.84
9   69.11 26.17 309.66 11.25 11.55
10  70.70 23.39 329.66 12.39 11.31
11  74.03 22.74 302.52 12.68 12.54
12  75.00 16.96 268.01 12.51 12.17
```

```
> date_mat
         date 台積電  威盛 聯發科  聯電  旺宏
1  2011-01-01  74.30 30.97 403.55 17.19 22.19
2  2011-02-01  72.54 30.54 348.98 16.38 21.49
3  2011-03-01  69.74 32.01 339.96 14.92 19.48
4  2011-04-01  71.37 30.35 328.65 15.21 18.88
5  2011-05-01  74.96 29.40 335.42 14.76 18.25
6  2011-06-01  74.70 34.68 311.57 14.51 17.60
7  2011-07-01  71.59 35.47 274.39 13.89 17.09
8  2011-08-01  66.61 30.13 262.09 11.13 11.84
9  2011-09-01  69.11 26.17 309.66 11.25 11.55
10 2011-10-01  70.70 23.39 329.66 12.39 11.31
11 2011-11-01  74.03 22.74 302.52 12.68 12.54
12 2011-12-01  75.00 16.96 268.01 12.51 12.17
```

```
> # convert data.frame to ts, and then using ts_plot
> mat_ts <- as.ts(mat, start = c(2011, 1), frequency = 12)
> mat_ts
Time Series:
Start = 1
End = 12
Frequency = 1
   台積電  威盛 聯發科  聯電  旺宏
 1  74.30 30.97 403.55 17.19 22.19
...
12  75.00 16.96 268.01 12.51 12.17
> class(mat_ts)
[1] "mts"    "ts"     "matrix"
> str(mat_ts)
 Time-Series [1:12, 1:5] from 1 to 12: 74.3
 - attr(*, "dimnames")=List of 2
  ..$ : NULL
  ..$ : chr [1:5] "台積電" "威盛" "聯發科" "聯電
> ts_plot(mat_ts)
> ts_plot(mat_ts, type = "multiple")
```

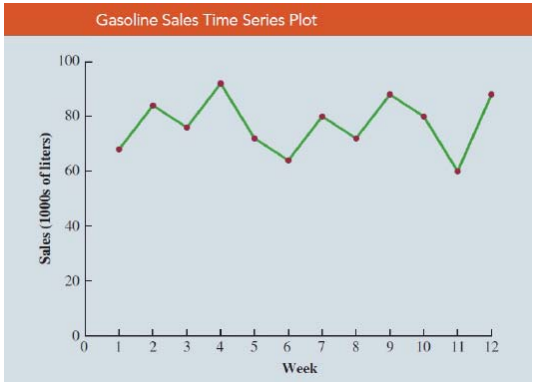
```
> mat_ts
Time Series:
Start = 1
End = 12
Frequency = 1
   台積電  威盛 聯發科  聯電  旺宏
 1  74.30 30.97 403.55 17.19 22.19
 2  72.54 30.54 348.98 16.38 21.49
 3  69.74 32.01 339.96 14.92 19.48
 4  71.37 30.35 328.65 15.21 18.88
 5  74.96 29.40 335.42 14.76 18.25
 6  74.70 34.68 311.57 14.51 17.60
 7  71.59 35.47 274.39 13.89 17.09
 8  66.61 30.13 262.09 11.13 11.84
 9  69.11 26.17 309.66 11.25 11.55
10  70.70 23.39 329.66 12.39 11.31
11  74.03 22.74 302.52 12.68 12.54
12  75.00 16.96 268.01 12.51 12.17
```



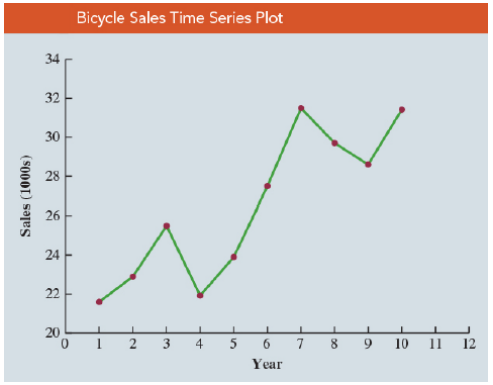


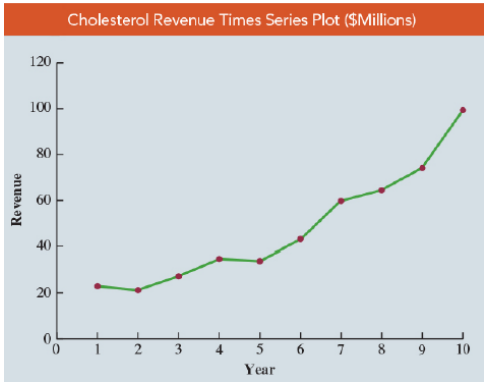
基本時間序樣態
(Basic Time Series Patterns)

Horizontal Pattern



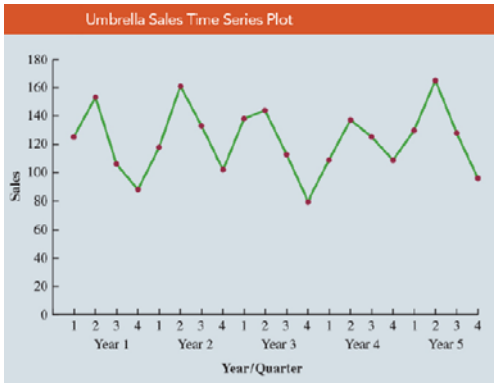
Trend Pattern



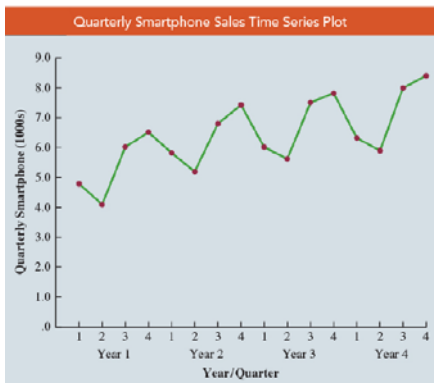


Images Source: Anderson et al., 2019, Statistics for Business & Economics (14th Edition), Cengage Learning Ltd

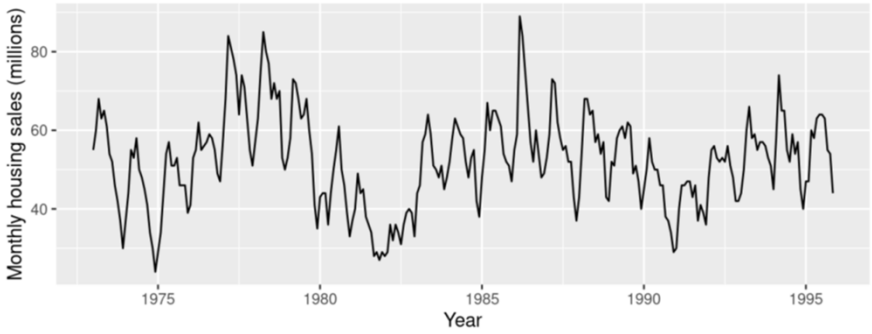
Seasonal Pattern



Trend and Seasonal Pattern



Cyclical Pattern



- If the frequency is unchanging and associated with some aspect of the calendar, then the pattern is seasonal.
- If the fluctuations are not of a fixed frequency then they are cyclic.
- In general, the average length of cycles is longer than the length of a seasonal pattern.
- The magnitudes of cycles tend to be more variable than the magnitudes of seasonal patterns.

自我相關函數 (Autocorrelation Function, ACF)

- Autocorrelation is the correlation between two observations at different points in a time series.

- A time series $y_1,\ y_2, \dots,\ y_T$.
- mean: $\bar{y} = \frac{\sum_{t=1}^{T} y_t}{T}$.
- The autocorrelation function at lag k:

$$ACF(k) = \frac{\sum_{t=1}^{T-k}(y_t - \bar{y})(y_{t+k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2} = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^{T}(y_t - \bar{y})^2}$$

Week	Sales
1	68
2	84
3	76
4	92
5	72
6	64
7	80
8	72
9	88
10	80
11	60
12	88

$lag(k = 1)$

Week	Sales
1	68
2	84
3	76
4	92
5	72
6	64
7	80
8	72
9	88
10	80
11	60
12	88

$lag(k = 2)$

Week	Sales
1	68
2	84
3	76
4	92
5	72
6	64
7	80
8	72
9	88
10	80
11	60
12	88

$lag(k = 3)$

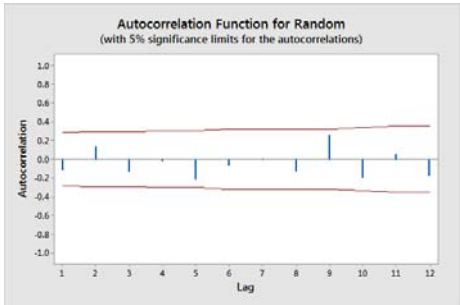
Week	Sales
1	68
2	84
3	76
4	92
5	72
6	64
7	80
8	72
9	88
10	80
11	60
12	88

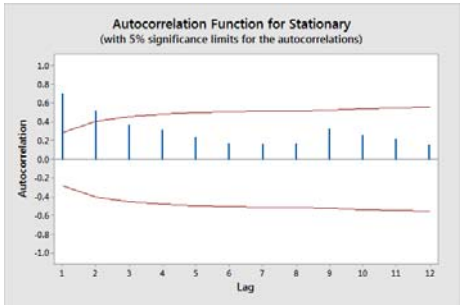
$lag(k = 4)$

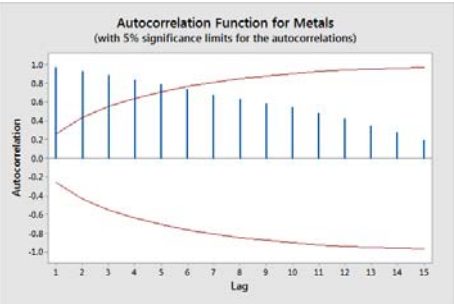
correlogram: $ACF(k)$ against k

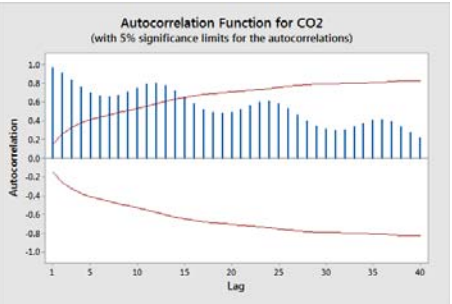
自我相關函數 (Autocorrelation Function, ACF)

- **Randomness/White Noise**:
  - ACF should be near zero for all lags.
  - Non-random data have at least one significant lag.
  - When the data are not random, you need to incorporate lags into a regression analysis to model the data appropriately.
- **Stationarity**:
  - The time series does not have a trend, has a constant variance, a constant autocorrelation pattern, and no seasonal pattern.
  - Stationary time series : ACF declines to near zero rapidly.
  - ACF drops slowly for a non-stationary time series.
- **Trends**:
  - When trends are present in a time series, shorter lags typically have large positive correlations.
  - ACF taper off slowly as the lags increase.
- **Seasonality**:
  - ACF are larger for lags at multiples of the seasonal frequency than for other lags. (wavy correlations)
  - When a time series has both a trend and seasonality, the ACF plot displays a mixture of both effects.







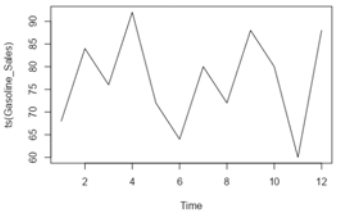


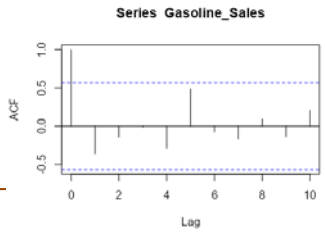
Images source: https://statisticsbyjim.com/time-series/autocorrelation-partial-autocorrelation/

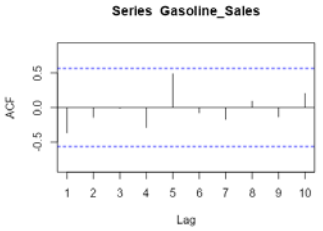
自我相關函數
(Autocorrelation Function, ACF)

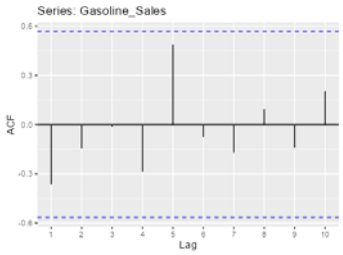
```
> Gasoline_Sales <- ts(c(68, 84, 76, 92, 72, 64, 80, 72, 88, 80, 60, 88))
> Gasoline_Sales
Time Series:
Start = 1
End = 12
Frequency = 1
 [1] 68 84 76 92 72 64 80 72 88 80 60 88
> acf(Gasoline_Sales) # base package
> Acf(Gasoline_Sales) # forecast package
> ggAcf(Gasoline_Sales) # forecast package
```

```
plot(ts(Gasoline_Sales))
```

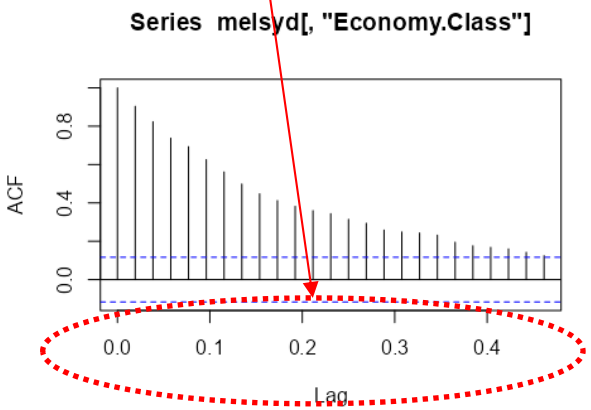


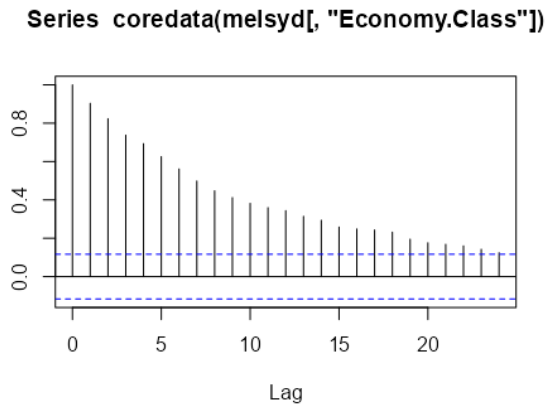


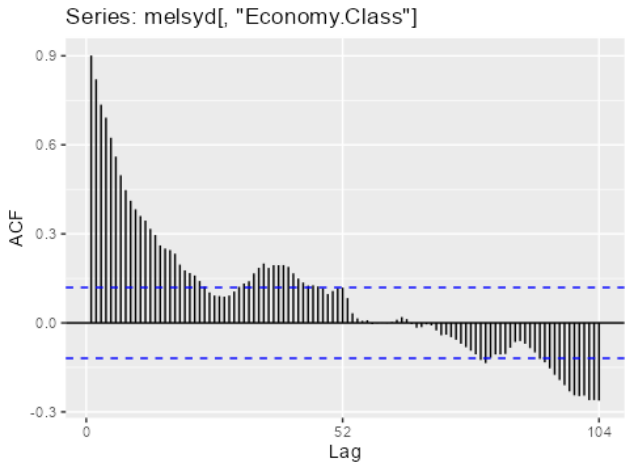





```
class(melsyd[, "Economy.Class"])
acf(melsyd[, "Economy.Class"], na.action = na.pass)
acf(coredata(melsyd[, "Economy.Class"]), na.action = na.pass)
Acf(melsyd[, "Economy.Class"])
ggAcf(melsyd[, "Economy.Class"])
```







Durbin Watson Test

(An autocorrelation test)

- One of the key assumptions in linear regression is that there is no correlation between the residuals, e.g. the residuals are independent. Perform a Durbin-Watson test to detect the presence of autocorrelation in the residuals of a regression.
- The Durbin Watson Test is a measure of autocorrelation (i.e, serial correlation), the AR(1) process, in residuals from regression analysis.

Hypothesis:

$H_0 = no\ first\ order\ autocorrelation.$

$H_1 = first\ order\ correlation\ exists.$

(For a first order correlation, the lag is one time unit).

Assumptions:

- The errors are $N(0, \sigma^2)$.
- The errors are stationary.

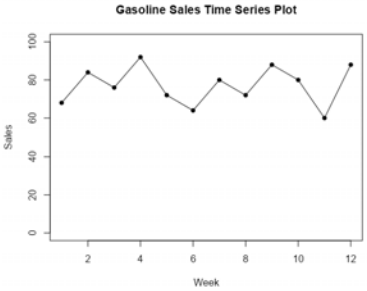
Test statistic:

$$DW = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}$$

where e_t are residuals from an OLS regression.

DW = 2: is no autocorrelation.
DW = 0 ~ 2 is positive autocorrelation.
DW > 2 ~ 4 is negative autocorrelation.
A rule of thumb is that test statistic values in the range of 1.5 to 2.5 are relatively normal.

```
> library(readxl)
> Gasoline <- read_excel("Gasoline.xlsx")
> Gasoline
# A tibble: 12 × 2
    Week Sales
   <dbl> <dbl>
 1     1    68
 2     2    84
...
12    12    88
> plot(Sales ~ Week, data = Gasoline, type = "o",
+      main = "Gasoline Sales Time Series Plot",
+      ylim = c(0, 100), pch = 16)
>
> Gasoline_lm <- lm(Sales ~ Week, data = Gasoline)
> library(lmtest)
> dwtest(formula = Gasoline_lm,
         alternative = "two.sided")

        Durbin-Watson test
data:  Gasoline_lm
DW = 2.5478, p-value = 0.5156
alternative hypothesis: true autocorrelation is not 0
```



判斷趨勢:

移動平均 (moving average，簡稱均線)

- 移動平均法使用n期的資料進行平均。
- **簡單移動平均** $SMA_t = \frac{x_t + x_{t-1} + x_{t-2} + \cdots + x_{t-n}}{n+1}$
- 期數選擇影響很大，該如何選擇:
  - 事件發展有無週期性。若有，應以此週期為期數，藉以消除週期影響。
  - 對趨勢平均性的要求。期數愈多，修勻效果愈平均。
  - 對趨勢反映近期變化敏感程度的要求。想得到長期趨勢，期數選擇要大。短期趨勢則選擇小期數。
- **加權移動平均** $WMA_t = w_0 x_t + w_1 x_{t-1} + \cdots + w_n x_{t-n}$
- **指數移動平均** $EMA_t = \alpha x_t + \alpha(1-\alpha)x_{t-1} + \alpha(1-\alpha)^2 x_{t-2} + \cdots$

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t \qquad F_1 = Y_1.$$

F_{t+1}: forecast of the time series for period $(t+1)$

Y_t: actual value of the time series in period t

F_t: forecast of the time series for period t

α: smoothing constant $\quad (0 \le \alpha \le 1)$

$$\begin{aligned} F_4 &= \alpha Y_3 + (1-\alpha)F_3 \\ &= \alpha Y_3 + \alpha(1-\alpha)Y_2 + (1-\alpha)^2 Y_1 \end{aligned}$$

Smoothing and Moving Average in R

smooth: Forecasting Using Smoothing Functions

https://cran.r-project.org/web/packages/smooth/index.html

`es()` - Exponential Smoothing;
`ssarima()` - State-Space ARIMA, also known as Several Seasonalities ARIMA;
`ces()` - Complex Exponential Smoothing;
`ges()` - Generalised Exponential Smoothing;
`ves()` - Vector Exponential Smoothing;
`sma()` - Simple Moving Average in state-space form;

TTR: Technical Trading Rules

https://cran.r-project.org/web/packages/TTR/index.html

```
SMA(x, n = 10, ...)
EMA(x, n = 10, wilder = FALSE, ratio = NULL, ...)
DEMA(x, n = 10, v = 1, wilder = FALSE, ratio = NULL)
WMA(x, n = 10, wts = 1:n, ...)
EVWMA(price, volume, n = 10, ...)
ZLEMA(x, n = 10, ratio = NULL, ...)
VWAP(price, volume, n = 10, ...)
VMA(x, w, ratio = 1, ...)
HMA(x, n = 20, ...)
ALMA(x, n = 9, offset = 0.85, sigma = 6, ...)
```

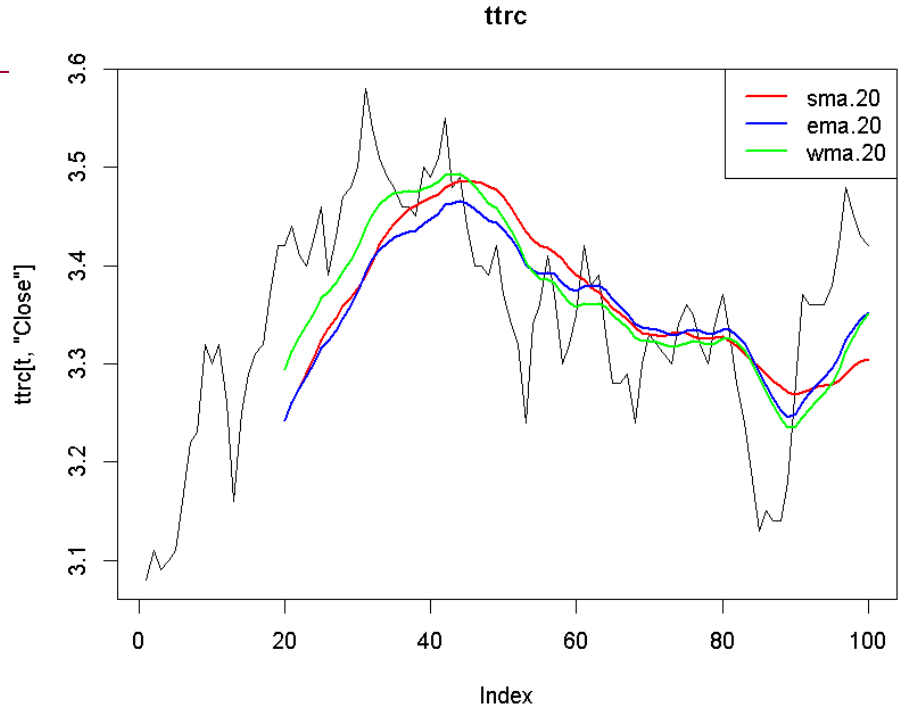
- SMA: Simple moving average.
- EMA: Exponential moving average.
- WMA: Weighted moving average.
- DEMA: Double-exponential moving average.
- EVWMA: Elastic, volume-weighted moving average.
- ZLEMA: Zero lag exponential moving average.
- VWMA: Volume-weighed moving average (same as VWAP).
- VWAP: Volume-weighed average price (same as VWMA).
- VWA: Variable-length moving average.
- HMA: Hull moving average.
- ALMA: Arnaud Legoux moving average.

移動平均範例

ttrc {TTR}: Technical Trading Rule Composite data

Historical Open, High, Low, Close, and Volume data for the periods January 2, 1985 to December 31, 2006. Randomly generated.

```
> # install.packages("TTR")
> library(TTR)
> data(ttrc)
> dim(ttrc)
[1] 5550    6
> head(ttrc)
        Date Open High  Low Close  Volume
1 1985-01-02 3.18 3.18 3.08  3.08 1870906
2 1985-01-03 3.09 3.15 3.09  3.11 3099506
3 1985-01-04 3.11 3.12 3.08  3.09 2274157
4 1985-01-07 3.09 3.12 3.07  3.10 2086758
5 1985-01-08 3.10 3.12 3.08  3.11 2166348
6 1985-01-09 3.12 3.17 3.10  3.16 3441798

> t <- 1:100
> sma.20 <- SMA(ttrc[t, "Close"], 20)
> ema.20 <- EMA(ttrc[t, "Close"], 20) # Arms' [illegible]
> wma.20 <- WMA(ttrc[t, "Close"], 20)
>
> plot(ttrc[t,"Close"], type = "l", main =  "ttrc")
> lines(sma.20, col = "red", lwd = 2)
> lines(ema.20, col = "blue", lwd = 2)
> lines(wma.20, col = "green", lwd = 2)
> legend("topright", legend = c("sma.20", "ema.20", "wma.20"),
+        col = c("red", "blue", "green"), lty = 1, lwd = 2)
```



預測正確率 (Forecast Accuracy)

- $ForecastError = ActualValue - Forecast$
- $PercentageError = ForecastError / ActualValue * 100\%$
- The mean absolute error (MAE): the average of the absolute values of the forecast errors.
- The mean squared error (MSE): the average of the sum of squared forecast errors.
- The mean absolute percentage error (MAPE): average of the absolute value of percentage forecast errors.

Naive forecasting method: the simplest of all the forecasting methods that uses the most recent week's sales volume as the forecast for the next week.

Week	Time Series Value	Forecast	Forecast Error	Absolute Value of Forecast Error	Squared Forecast Error	Percentage Error	Absolute Value of Percentage Error
1	68						
2	84	68	16	16	256	19.05	19.05
3	76	84	−8	8	64	−10.53	10.53
4	92	76	16	16	256	17.39	17.39
5	72	92	−20	20	400	−27.78	27.78
6	64	72	−8	8	64	−12.50	12.50
7	80	64	16	16	256	20.00	20.00
8	72	80	−8	8	64	−11.11	11.11
9	88	72	16	16	256	18.18	18.18
10	80	88	−8	8	64	−10.00	10.00
11	60	80	−20	20	400	−33.33	33.33
12	88	60	28	28	784	31.82	31.82
		Totals	20	164	2864	1.19	211.69

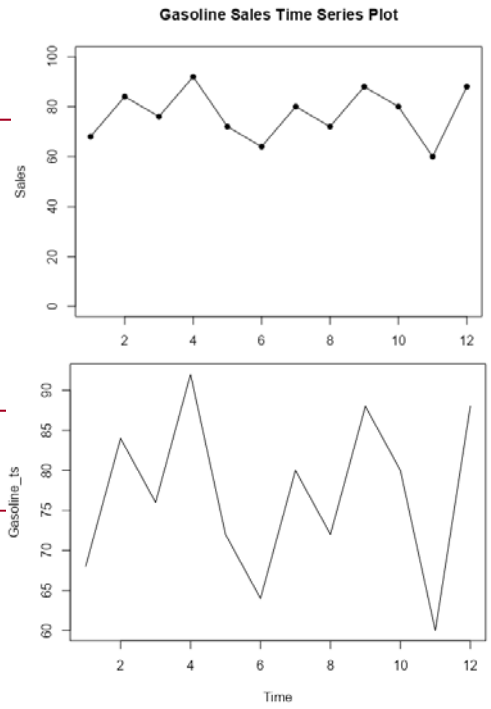
MAE = 164/11=14.91 MSE = 2864/11=260.36 MAPE = 211.69/11 = 19.24%

Images Source: Anderson et al., 2019, Statistics for Business & Economics (14th Edition), Cengage Learning Ltd

範例: Naive Method

```
> library(readxl)
> Gasoline <- read_excel("Gasoline.xlsx")
> Gasoline
# A tibble: 12 × 2
    Week Sales
   <dbl> <dbl>
 1     1    68
 2     2    84
 3     3    76
 4     4    92
 5     5    72
 6     6    64
 7     7    80
 8     8    72
 9     9    88
10    10    80
11    11    60
12    12    88
>
> Gasoline_fc_naive <- naive(Gasoline_ts)
> Gasoline_fc_naive$fitted
Time Series:
Start = 1
End = 12
Frequency = 1
 [1] NA 68 84 76 92 72 64 80 72 88 80 60
> summary(Gasoline_fc_naive)
> accuracy(Gasoline_fc_naive)
                    ME     RMSE      MAE        MPE     MAPE  MASE        ACF1
Training set 1.818182 16.13579 14.90909 0.1082169 19.24431     1 -0.4553872
```

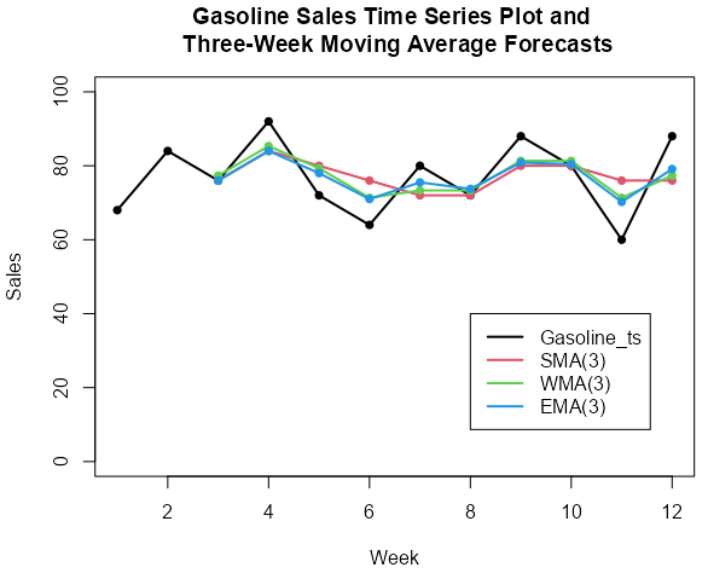
```
> plot(Sales ~ Week, data = Gasoline, type = "o",
+      main = "Gasoline Sales Time Series Plot",
+      ylim = c(0, 100), pch = 16)
>
> library(forecast)
> Gasoline_ts <- ts(Gasoline$Sales)
> plot(Gasoline_ts)
```




```
> summary(Gasoline_fc_naive)

Forecast method: Naive method

Model Information:
Call: naive(y = Gasoline_ts)

Residual sd: 16.1358

Error measures:
                    ME     RMSE      MAE        MPE     MAPE MASE        ACF1
Training set 1.818182 16.13579 14.90909 0.1082169 19.24431    1 -0.4553872

Forecasts:
   Point Forecast    Lo 80    Hi 80      Lo 95    Hi 95
13             88 67.32116 108.6788  56.374438 119.6256
14             88 58.75570 117.2443  43.274701 132.7253

22             88 22.60775 153.3922 -12.008809 188.0088
```

範例: Moving Average and Forecast Accuracy

```
> library(TTR)
> Gasoline_fc_sma3 <- SMA(Gasoline_ts, n = 3)
> Gasoline_fc_wma3 <- WMA(Gasoline_ts, n = 3)
> Gasoline_fc_ema3 <- EMA(Gasoline_ts, n = 3)
>
> accuracy(Gasoline_fc_sma3, Gasoline_ts[2:12])
             ME     RMSE      MAE       MPE     MAPE
Test set  0 12.78888 10.66667 -2.310057 14.35661
> accuracy(Gasoline_fc_wma3, Gasoline_ts[2:12])
                  ME    RMSE      MAE       MPE     MAPE
Test set 0.2222222 13.5592 11.92593 -2.129945 15.99248
> accuracy(Gasoline_fc_ema3, Gasoline_ts[2:12])
                  ME     RMSE      MAE       MPE     MAPE
Test set 0.6909722 13.44512 11.98264 -1.502064 15.9555
```



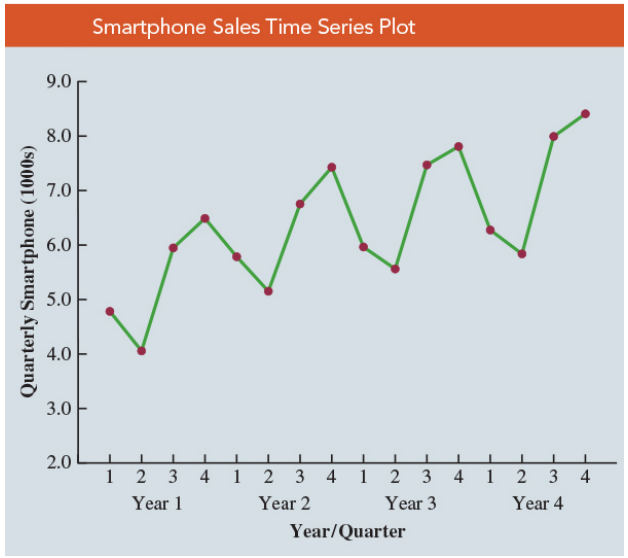

```
> # Gasoline Sales Time Series Plot and Three-Week Moving Average Forecasts
> plot(Gasoline_ts, type = "o", ylim = c(0, 100), lwd = 2, pch = 16,
+      xlab = "Week", ylab = "Sales",
+      main = "Gasoline Sales Time Series Plot and \n Three-Week Moving Average Forecasts")
> points(Gasoline_fc_sma3, type = "o", lwd = 2, col = 2, pch = 16)
> points(Gasoline_fc_wma3, type = "o", lwd = 2, col = 3, pch = 16)
> points(Gasoline_fc_ema3, type = "o", lwd = 2, col = 4, pch = 16)
> legend(8, 40, legend = c("Gasoline_ts", "SMA(3)", "WMA(3)", "EMA(3)"),
+        col = 1:4, lty = 1, lwd = 2)
```

模型與預測: 多重回歸法

- The general form of the estimated **multiple regression equation** for modeling both the quarterly seasonal effects and the linear trend in the smartphone time series

$$\hat{Y}_t = b_0 + b_1\ Qtr1 + b_2\ Qtr2 + b_3\ Qtr3 + b_4 t$$

Seasonality and Trend



$\hat{Y}_t$ = estimate or forecast of sales in time period t

dummy variable

$Qtr1 = 1$ $(Qtr2 = 1)$ $(Qtr3 = 1)$

if time period t corresponds to the first (second) (third) quarter of the year; 0 otherwise.

The estimated multiple regression equation

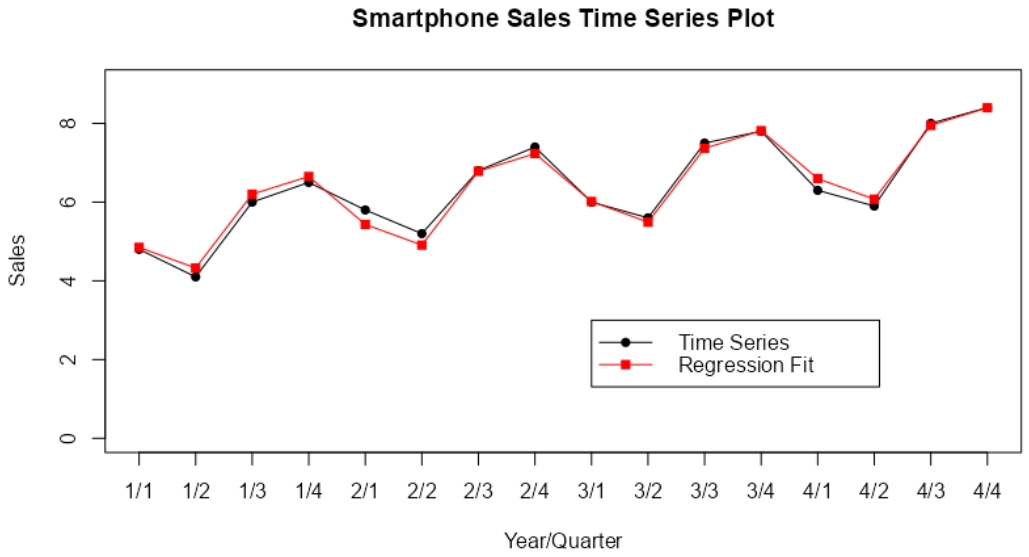
$$Sales(1000s) = 6.069 - 1.363\ Qtr1 - 2.034\ Qtr2 - 0.304 Qtr3 + 0.1456\ t$$

Forecast for Time Period 17 (Quarter 1 in Year 5):

$$Sales(1000s) = 6.069 + 1.363(1) + 2.034(0) + 0.304(0) + 0.1456(17) = 7.18$$

範例: Fit A Multiple Regression Model to Smartphone Sales Time Series Data


```
> SmartphoneSales <- read_excel("SmartphoneSales.xlsx")
> SmartphoneSales
# A tibble: 16 x 3
    Year Quarter `Sales (1000s)`
   <dbl>   <dbl>           <dbl>
 1     1       1             4.8
 2     1       2             4.1
 3     1       3             6
 4     1       4             6.5
 5     2       1             5.8
 6     2       2             5.2
 7     2       3             6.8
 8     2       4             7.4
 9     3       1             6
10     3       2             5.6
11     3       3             7.5
12     3       4             7.8
13     4       1             6.3
14     4       2             5.9
15     4       3             8
16     4       4             8.4
> SmartphoneSales_ts <- ts(SmartphoneSales$`Sales (1000s)`,
+                          start =1, frequency = 4)
>
> plot(SmartphoneSales_ts, type = "o", pch = 16,
+      ylim = c(0, 9), xlab = "Year/Quarter", ylab = "Sales",
+      xaxt = "n",
+      main = "Smartphone Sales Time Series Plot")
> axis(1, at = seq(from = 1, by = 0.25, length.out = length(SmartphoneSales_ts)),
+      labels = paste0(rep(1:4, each = 4), "/", rep(1:4, 4)))
```



範例: Smartphone Sales Time Series

```
> SmartphoneSales$Quarter <- factor(SmartphoneSales$Quarter, levels = 4:1)
> SmartphoneSales$Period <- 1:nrow(SmartphoneSales)
> SmartphoneSales_lm <- lm(`Sales (1000s)` ~ Quarter + Period, data = SmartphoneSales)
> summary(SmartphoneSales_lm)
Call:
lm(formula = `Sales (1000s)` ~ Quarter + Period, data = SmartphoneSales)

Residuals:
    Min      1Q  Median      3Q     Max
-0.2988 -0.1569 -0.0075  0.1150  0.3663

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  6.06875    0.16250  37.347 6.12e-13 ***
Quarter3    -0.30438    0.15368  -1.981   0.0732 .
Quarter2    -2.03375    0.15511 -13.112 4.66e-08 ***
Quarter1    -1.36313    0.15745  -8.657 3.06e-06 ***
Period       0.14563    0.01211  12.023 1.14e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2167 on 11 degrees of freedom
Multiple R-squared:  0.9763,  Adjusted R-squared:  0.9676
F-statistic: 113.2 on 4 and 11 DF,  p-value: 7.376e-09
> points(x = seq(from = 1, by = 0.25, length.out = length(SmartphoneSales_ts)),
+        y = SmartphoneSales_lm$fitted.values,
+        type = "o", pch = 15, col = "red")
> legend(3, 3, legend = c("Time Series", "Regression Fit"), lty = 1,
+        col = c("black", "red"), pch = c(16, 15))
```

$$Sales(1000s) = 6.069 - 1.363\ Qtr1 - 2.034\ Qtr2 - 0.304 Qtr3 + 0.1456\ t$$

Forecast quarterly sales for next year. Next year is year 5 for the smartphone sales time series; that is, time periods 17, 18, 19, and 20.

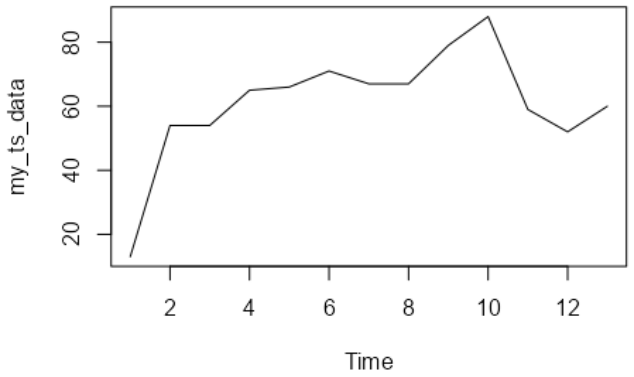
```
> predict(SmartphoneSales_lm,
          newdata = data.frame(Quarter =
                      factor(1:4),
                    Period = 17:20))
      1       2       3       4
7.18125 6.65625 8.53125 8.98125
```

時間序列模型基本概念:
穩定、平穩、穩態 (Stationary)

The foundation of time series analysis is stationarity.

A time series $\{r_t\}$ is said to be *strictly stationary* if the joint distribution of $(r_{t_1}, \ldots, r_{t_k})$ is identical to that of $(r_{t_1+t}, \ldots, r_{t_k+t})$ for all t, where k is an arbitrary positive integer and $(t_1, \ldots, t_k)$ is a collection of k positive integers.

WIKIPEDIA
The Free Encyclopedia

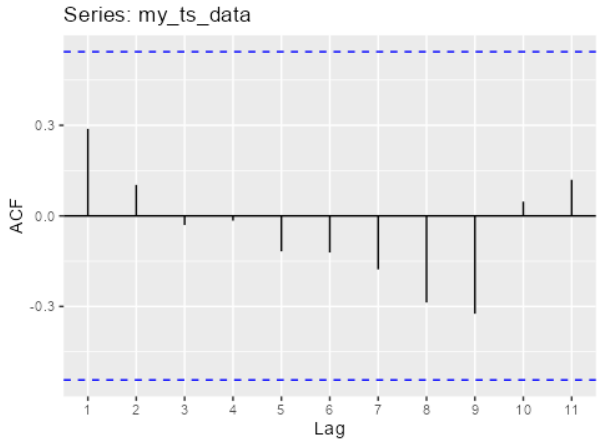


ADF Test (Augmented Dickey-Fuller)

https://en.wikipedia.org/wiki/Augmented_Dickey%E2%80%93Fuller_test

H_0: The time series is non-stationary.

```
> library(tseries)
> my_ts_data <- ts(c(13, 54, 54, 65, 66, 71, 67, 67,
+                    79, 88, 59, 52, 60))
> plot(my_ts_data)
> ggAcf(my_ts_data)
> adf.test(my_ts_data)

        Augmented Dickey-Fuller Test

data:  my_ts_data
Dickey-Fuller = -1.6549, Lag order = 2, p-value = 0.7039
alternative hypothesis: stationary
```



時間序列模型基本概念
AR, MA, ARMA, ARIMA 模型

自迴歸模型: Autoregressive Model, $AR(p)$

$$Y_t = c + \sum_{k=1}^{p} \phi_k Y_{t-k} + \epsilon_t$$

A time series r_t is called a white noise if $\{r_t\}$ is a sequence of independent and identically distributed random variables with finite mean and variance.

$\{\epsilon_t\}$ is a white noise process with mean 0 and variance σ^2

移動平均模型: Moving Average Model, $MA(q)$

$$Y_t = c + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t$$

移動平均自迴歸模型
Autoregressive Moving Average Model, $ARMA(p, q)$

有些書是用減號的

$$Y_t = c + \sum_{k=1}^{p} \phi_k Y_{t-k} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t$$

$$\text{ARMA}(1,1) \quad Y_t = \phi Y_{t-1} + \epsilon_t + \theta \epsilon_{t-1}$$

時間序列模型基本概念
(差分)整合移動平均自迴歸模型，$ARIMA(p,d,q)$

Box-Jenkins backshift operator ⇨ $B^p X_t = X_{t-p}$

$ARMA(p,q)$ $Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + a_t - \sum_{j=1}^{q} \theta_j a_{t-j}$

- p為自我迴歸項數。
- q為移動平均項數。
- d為使之成為平穩序列所做的差分次數(階數)。

⇨ $\left(1 - \sum_{i=1}^{p} \phi_i B^i\right) Y_t = \left(1 - \sum_{j=1}^{q} \theta_j B^j\right) a_t$

⇨ $\phi_p(B) Y_t = \theta_q(B) a_t$

where $\phi_p(B) = (1 - \sum_{i=1}^{p} \phi_i B^i)$ and $\theta_q(B) = (1 - \sum_{j=1}^{q} \theta_j B^j)$.

When time series exhibit nonstationary behavior, then the ARMA model presented above can be extended and written using differences:

$$\begin{aligned} W_t &= Y_t - Y_{t-1} = (1-B)Y_t \\ W_t - W_{t-1} &= Y_t - 2Y_{t-1} + Y_{t-2} \\ &= (1-B)^2 Y_t \\ &\vdots \end{aligned}$$

⇨ $W_t - \sum_{k=1}^{d} W_{t-k} = (1-B)^d Y_t,$ ⇨

Replacing in the ARMA model with the differences defined above yields the formal ***ARIMA*(p,d,q) model**:

$\phi_p(B)(1-B)^d Y_t = \theta_q(B) a_t$

$ARIMA(p,d,q)$建模步驟

1. 繪製時間序列圖並進行初步分析：
- 觀察是否存在異常值或顯著的季節性和趨勢成分。
- 如果方差隨時間顯著波動，可以考慮使用Box-Cox變換來穩定方差。

2. 檢測和確保時間序列的平穩性：
- 通過ADF (Augmented Dickey-Fuller Test)檢定或KPSS (Kwiatkowski–Phillips–Schmidt–Shin Test)檢定檢測時間序列的平穩性。
- 如果時間序列不是平穩的，進行一階或更高階的差分，直到序列變得平穩。

3. 識別ARIMA模型的階數：
- 對平穩的時間序列繪製ACF圖和PACF圖。
- 根據ACF和PACF圖，判別可能的ARIMA(p,d,q)模型。

4. 模型配適和選擇：
- 使用選定的p, d, q值來配適ARIMA模型。
- 通過AIC或AICc來選擇最佳模型。

5. 模型診斷:
- 繪製模型殘差的ACF圖。
- 進行白噪檢定來評估模型的適合度。
- 如果模型殘差不滿足白噪條件，可以考慮重新選擇模型並進行配適。

6. 模型預測：
- 找到滿足條件的模型，可以使用該模型來進行未來的預測。
- 評估模型的預測效能，計算預測誤差的度量（如MAE, RMSE等）。

7. 結果報告和解釋：
- 對模型的結果進行解釋和報告。
- 提供模型的預測結果和相應的信賴區間。

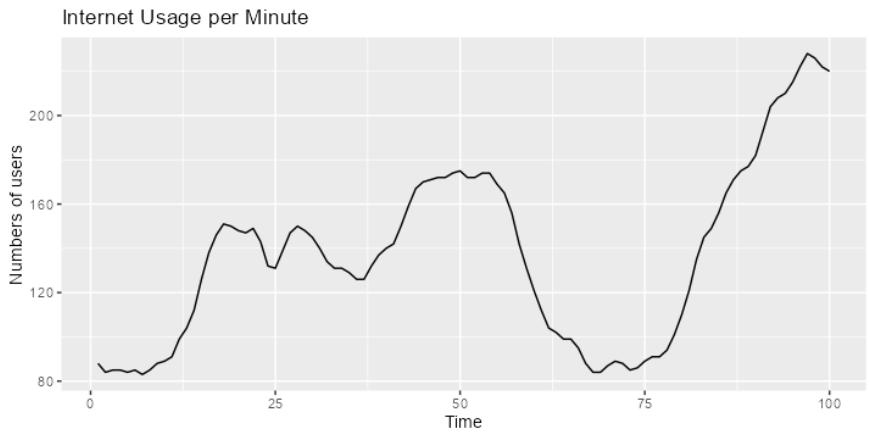
model	acf	pacf
AR(p)	dies away geometrically	zero after lag p
MA(q)	zero after lag q	dies away geometrically
ARMA(p,q)	dies away geometrically	dies away geometrically

ARIMA 範例:

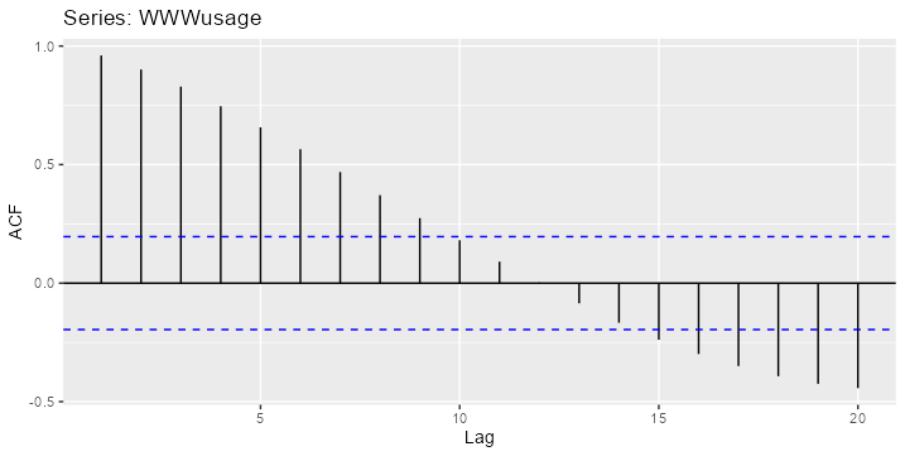
WWWusage {datasets}: Internet Usage per Minute

WWWusage {datasets}:
A time series of the numbers of users connected to the Internet through a server every minute.

```
library(forecast)
autoplot(WWWusage) +
  xlab("Time")+
  ylab("Numbers of users") +
  ggtitle("Internet Usage per Minute")
```




```
ggAcf(WWWusage)
```



ARIMA 範例:

WWWusage {datasets}: Internet Usage per Minute

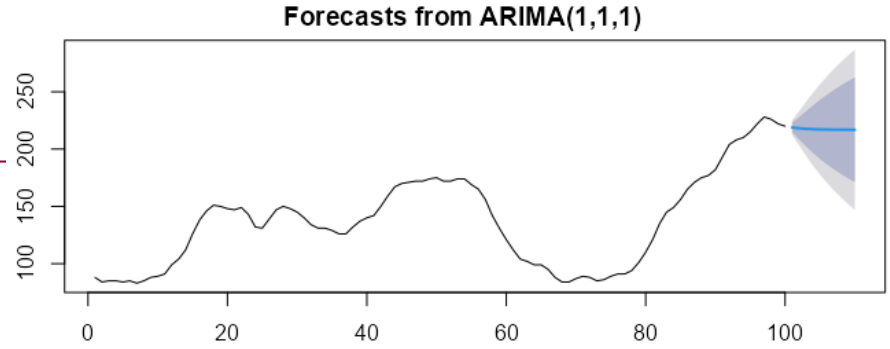
```
> WWWusage_arima <- Arima(WWWusage, order = c(2, 1, 2))
> WWWusage_arima
Series: WWWusage
ARIMA(2,1,2)

Coefficients:
         ar1     ar2     ma1     ma2
      0.0215  0.3407  1.2001  0.4394
s.e.  0.2981  0.2356  0.2799  0.1729

sigma^2 = 10.1:  log likelihood = -253.68
AIC=517.36   AICc=518.01   BIC=530.34
```

auto.arima: Fit best ARIMA model to univariate time series. Returns best ARIMA model according to either AIC, AICc or BIC value. The function conducts a search over possible model within the order constraints provided.

```
> WWWusage_arima_best <- auto.arima(WWWusage)
> WWWusage_arima_best
Series: WWWusage
ARIMA(1,1,1)

Coefficients:
         ar1     ma1
      0.6504  0.5256
s.e.  0.0842  0.0896

sigma^2 = 9.995:  log likelihood = -254.15
AIC=514.3   AICc=514.55   BIC=522.08
```

```
> forecast(WWWusage_arima_best, h = 10)
    Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
101       218.8805 214.8288 222.9322 212.6840 225.0770
...
110       216.8413 171.1478 262.5348 146.9592 286.7235
```

```
> plot(forecast(WWWusage_arima_best, h = 10))
```



多變量自迴歸模型
The Stationary Vector Autoregression Model

- The Stationary Vector Autoregression Model VAR(2):

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & \pi_{12}^1 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \pi_{11}^2 & \pi_{12}^2 \\ \pi_{21}^2 & \pi_{22}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

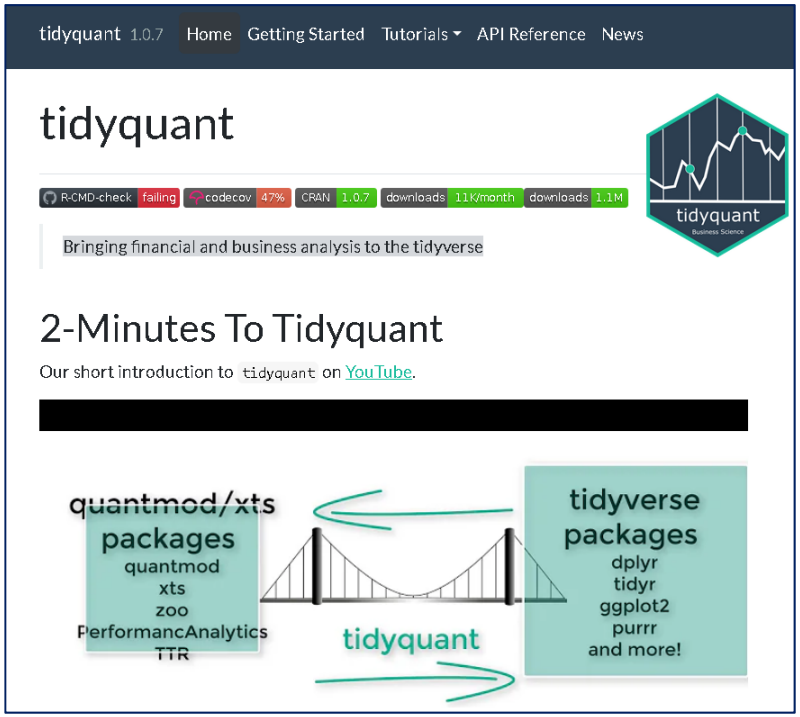
quantmod: Quantitative Financial Modeling Framework

tidyquant: Bringing financial and business analysis to the tidyverse

quantmod: Specify, build, trade, and analyse quantitative financial trading strategies.

http://www.quantmod.com/

https://business-science.github.io/tidyquant/



- Core Functions:
  - Getting Financial Data from the web: `tq_get()`
  - Manipulating Financial Data: `tq_transmute()` and `tq_mutate()`
  - Performance Analysis and Portfolio Analysis: `tq_performance()` and `tq_portfolio()`
- Comparing Stock Prices, Evaluating Stock Performance, Evaluating Portfolio Performance
- https://cran.r-project.org/web/packages/tidyquant/vignettes/TQ03-scaling-and-modeling-with-tidyquant.html