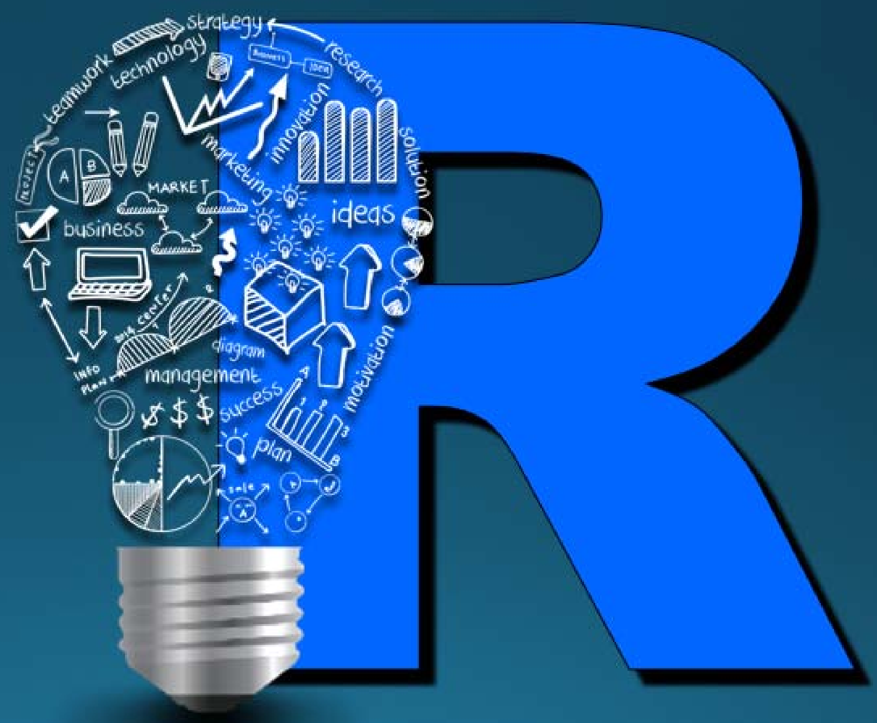
Q01

R 語言問卷分析(1)

問卷資料檔處理
資料檢核與轉換
敘述統計



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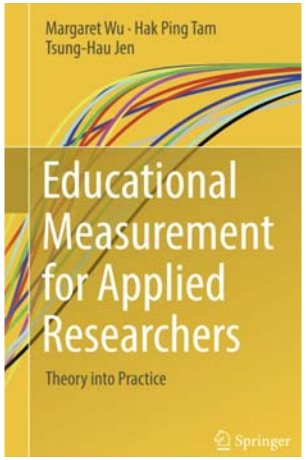
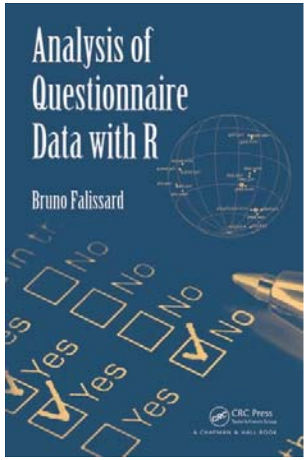
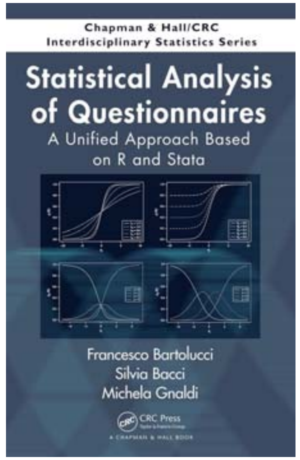
https://hmwu.idv.tw

大綱

- 資料檔管理與轉換
- 資料檢核與轉換
- 敘述統計量

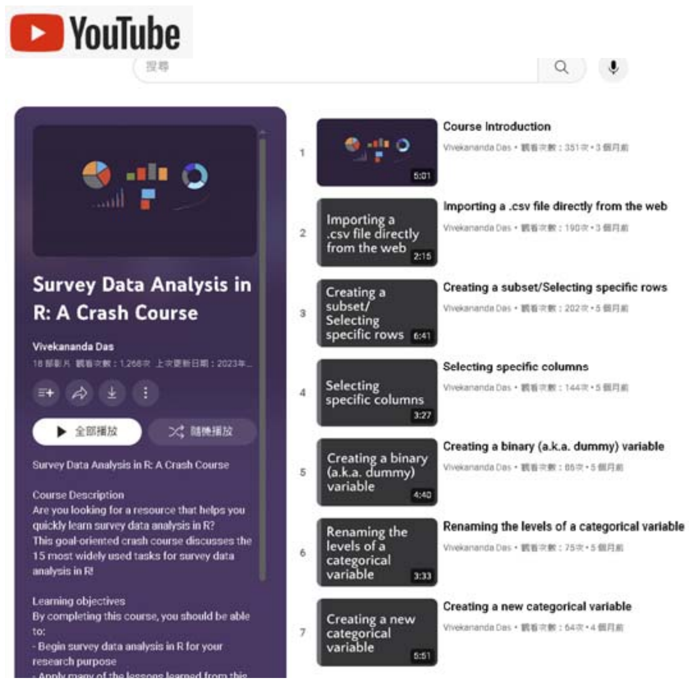






本講義部份內容掃瞄自以下所列之上課用書，並無它用。
吳明隆, SPSS操作與應用：問卷統計分析實務（附光碟） 五南出版社

參考資料與學習資源



- Questionnaires and Surveys: Analyses with R
https://ladal.edu.au/surveys.html
- Survey Data Analysis with R
https://stats.oarc.ucla.edu/r/seminars/survey-data-analysis-with-r/
- Essentials for Analyzing Survey Data Using R
https://rpubs.com/kiffercard/Essentials-for-Analyzing-Survey-Data-Using-R
- Analyzing Survey Data in R
https://rpubs.com/Onduma/surveydata
- Getting Started with R for Survey Analysis
https://www2.hawaii.edu/~georgeha/Handouts/R_Handout_Getting_Started_with_R.html
- Analyzing Survey Data in R: A Crash Course (Part 1)
https://vivdas.medium.com/analyzing-survey-data-in-r-a-crash-course-part-1-9dfa4b110115
- Survey Data Analysis in R: A Crash Course
https://www.youtube.com/playlist?list=PLLnN822fMufOrlQpfGW_7vvZF34Ppu50d

資料類型

- Continuous Data 連續型資料:
  - 年收入、年資、身高、... (quantitative 計量)
- Discrete (Categorical) Data 類別資料:
  - 性別、種族、教育程度、... (qualitative 屬質)
- "Ordinal" 順序變數，次序變數:
  - 非常同意，同意，普通，不同意，非常不同意
  - 優，佳，劣
- "Nominal"名目變數:
  - 宗教信仰、交通工具、音樂類型
- Ordinal methods cannot be used with nominal variable
- Nominal methods can be used with nominal, ordinal variables.

問卷、試卷與量表的編製

試卷、問卷與量表都是用於收集資料的工具，但它們各有不同的用途和特點：

1. 試卷（Test or Exam）：

- 目的：試卷主要用於測試知識、技能或能力，常見於教育和專業認證領域。
- 特點：試卷通常有標準答案和評分標準，用以評估受試者的表現水平。

2. 問卷（Questionnaire）：

- 目的：問卷用於廣泛收集資訊，如個人的意見、態度、感受或行為等。
- 特點：問卷可以包括開放性問題和封閉性問題，並且結構可以很靈活，適用於定性或定量研究。

3. 量表（Scale）：

- 目的：量表專注於評估特定變數的程度或強度（如李克特量表），常用於心理測量和醫學研究，如測量焦慮、滿意度或其他心理特徵。
- 特點：量表通常包含一系列相關問題，透過統計方法來測量特定的心理或行為特徵，並有明確的計分方式。

	應用範圍	設計重點	計分系統
試卷	主要用於教育和測試	強調評分的公正和標準化	有固定答案和評分標準
問卷	調查研究，收集多樣化的資料	強調問題的多樣性和覆蓋範圍	可能沒有統一的計分方式
量表	專注於特定特徵的測	強調測量的精確性和信度	有明確的計分系統來評估特定狀態或特性

問卷/量表編製的方法及步驟

- **擬定編製量表的計畫:** 預算、樣本、完成時間等。
- **確定主題**：清晰定義希望通過問卷獲得什麼資訊，有助於聚焦問卷的內容。
- **蒐集資料、確定目標群體**：確定目標受眾。這將影響問卷的設計，包括語言的選擇和問題的難易程度。
- **擬定量表的架構、設計問題 (編製題目)**：
  - 封閉式問題：提供預設的答案選項，便於量化分析。例如，單選題或是多選題。
  - 開放式問題：允許受訪者以自由形式回答填寫 ，適合收集質性資料。
  - 問題的順序：合理安排問題的順序可以幫助提高回答率和質量。通常將簡單或不敏感的問題放在前面，逐漸過渡到更複雜或私人的問題。
- **問卷的預試**：在問卷發放之前，進行預測調查以檢測問題的表述是否明確，答案選項是否恰當，並確保問卷能夠有效地測量預期的指標。
- **項目分析、編製正式題目**
- **問卷的執行**：決定問卷的發放方式（例如，紙質問卷、在線問卷等），並設計有效的收集和追蹤回應的策略。
- **建立信度與效度**：
  - 信度的考驗: 穩定性係數(重測信度)、內部一致性係數(Cronbachα、折半信度)
  - 效度的考驗: 效標關聯效度、團體差異的分析、因素分析
- **資料分析**：量化分析及質性資料分析。
- **報告撰寫：**根據問卷調查的結果撰寫報告。報告應該包括研究的背景、方法、主要發現、結論和建議。

大約要比預定的題數多編二分之一的題目。如一個分量表若需要10題，此時就需編15題。

提出問題的標準
- 問題是否與研究目的一致
- 問題的類型是否合適(開放/封閉式)
- 問題是否令人難以回答(敏感問題)
- 問題是否涉及個人的穩私
- 問題是否有暗示作用
- 問題是否超出作答者的能力

編製題目的原則
- 用字淺顯易懂
- 每個問題只涵蓋一個觀念
- 避免主觀及情緒化的字眼
- 問題的選項應清楚界定
- 不用假設或猜測的語句
- 句子避免過長

如何擬定量表的架構
- 決定量表的因素(向度、分量表)
- 決定預編的題數、正式量表的題數
- 決定量表的量尺(五點、六點等)

分析流程: 建立資料檔

一、基本資料

1. 我的班級：□甲班　□乙班
2. 我的性別：□男生　□女生
3. 第二定期考查的數學成績：_____分

二、數學學習問卷

符合程度

低 ←——→ 高

1. 我會努力去面對具有挑戰性的數學題目 ………… □ □ □ □ □
2. 同學對我數學學習上的肯定，使我更喜歡數學 ………… □ □ □ □ □
3. 課堂上的數學題目我大多做得出來 ………… □ □ □ □ □
4. 我喜愛參與數學課堂中的學習活動 ………… □ □ □ □ □
5. 上數學課時我的精神特別好 ………… □ □ □ □ □
6. 遇到較為困難的數學題目時，我不會逃避 ………… □ □ □ □ □
7. 我有能力幫助同學解答相關的數學問題 ………… □ □ □ □ □
8. 老師對我的數學學習能力與態度十分肯定 ………… □ □ □ □ □

Microsoft Excel - 數學效能_1.xls

檔案(F) 編輯(E) 檢視(V) 插入(I) 格式(O) 工具(T) 資料(D) 視窗

Arial 10

O16 fx

	A	B	C	D	E	F	G	H	I	J	K
1	班級	性別	數學成就	a1	a2	a3	a4	a5	a6	a7	a8
2	1	1	60	5	1	5	2	1	5	3	3
3	1	1	42	5	2	5	2	2	4	4	2
4	1	1	78	5	2	5	2	2	3	3	1
5	1	2	65	5	2	5	2	2	4	3	4
6	1	2	68	1	1	5	2	3	5	2	5
7	1	1	57	4	2	5	2	2	4	3	6
8	1	1	55	4	2	5	2	2	5	4	4
9	1	1	97	4	2	5	2	3	4	3	3
10	1	2	87	1	2	5	3	2	3	5	3
11	1	2	92	4	2	4	3	2	4	5	6
12	1	2	75	1	2	4	3	4	3	4	2
13	1	1	55	2	2	4	3	5	5	4	5
14	1	1	64	2	2	4	3	5	4	3	5
15	1	1	71	2	2	4	2	5	3	4	5
16	1	1	78	2	2	4	2	3	4	5	5
17	1	2	84	2	2	4	2	4	5	4	5

數學效能_1

就緒

```
> library(readxl)
> math_data <- read_excel("data/數學效能_1.xlsx")
> head(math_data)
# A tibble: 6 × 11
   班級  性別 數學成就    a1    a2    a3    a4    a5    a6    a7    a8
  <dbl> <dbl>    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1     1     1       60     5     1     5     2     1     5     3     3
2     1     1       42     5     2     5     2     2     4     4     2
...
> tail(math_data)
# A tibble: 6 × 11
   班級  性別 數學成就    a1    a2    a3    a4    a5    a6    a7    a8
  <dbl> <dbl>    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
...
4     2     1       89     5     5     5     5     2     4     4     5
5     2     2       87     5     5     5     2     2     4     5     5
6     2     2       76     5     5     4     5     3     4     4     5
> str(math_data)
tibble [50 × 11] (S3: tbl_df/tbl/data.frame)
 $ 班級    : num [1:50] 1 1 1 1 1 1 1 1 1 1 ...
 $ 性別    : num [1:50] 1 1 1 2 2 1 1 1 2 2 ...
 $ 數學成就: num [1:50] 60 42 78 65 68 57 55 97 87 92 ...
 $ a1      : num [1:50] 5 5 5 5 1 4 4 4 1 4 ...
...
 $ a8      : num [1:50] 3 2 1 4 5 6 4 3 3 6 ...
> summary(math_data)
      班級            性別            數學成就              a1              a2              a3     
 Min.   :1.00   Min.   :1.00   Min.   : 42.00   Min.   :1.00   Min.   :1.00   Min.   :1.0  
 1st Qu.:1.00   1st Qu.:1.00   1st Qu.: 65.50   1st Qu.:2.00   1st Qu.:1.00   1st Qu.:3.0  
 Median :2.00   Median :1.00   Median : 75.50   Median :3.50   Median :2.00   Median :4.0  
 Mean   :1.52   Mean   :1.44   Mean   : 75.78   Mean   :3.38   Mean   :1.96   Mean   :3.5  
 3rd Qu.:2.00   3rd Qu.:2.00   3rd Qu.: 87.00   3rd Qu.:4.00   3rd Qu.:2.00   3rd Qu.:4.0  
 Max.   :2.00   Max.   :2.00   Max.   :100.00   Max.   :5.00   Max.   :5.00   Max.   :5.0  
```

資料合併

- 兩資料檔具有共同變數: 配對變數
- 若有部份變數是另一個資料檔中所沒有的: 非配對變數
- 先開啟的檔: 作用中的資料檔
- 合併有兩種:
  - 觀察值合併 (垂直合併, **`rbind`**) : 其變數應為「配對變數」，將觀察值加在「作用中的資料檔」的後面
  - 變項合併 (水平合併, **`cbind`**): 需有一「關鍵變數」(例如: 編號、編碼值、...)，新合併的資料檔中觀察值個數不變。
- 資料合併指令
  - Base R: **`merge`**
  - Tidyverse **`dplyr`**: **`join{dplyr}`**: **`anti_join, full_join, inner_join, left_join, right_join, semi_join`**

合併觀察值: rbind

```
> math_data1 <- read_excel("data/數學學習_1.xlsx")
> math_data1
# A tibble: 5 × 4
  編號    性別 數學成就 數學態度
  <chr> <dbl>    <dbl>    <dbl>
1 1001      1       87       38
2 1002      1       84       42
...
5 1005      2       92       40
> math_data2 <- read_excel("data/數學學習_2.xlsx")
> math_data2
# A tibble: 5 × 4
  編號    性別 數學成就 數學態度
  <chr> <dbl>    <dbl>    <dbl>
1 1006      2       74       36
2 1007      2       94       34
...
5 1010      1       70       54
> math_data_all <- rbind(math_data1, math_data2)
> math_data_all
# A tibble: 10 × 4
   編號    性別 數學成就 數學態度
   <chr> <dbl>    <dbl>    <dbl>
 1 1001      1       87       38
 2 1002      1       84       42
 3 1003      1       75       25
 4 1004      2       78       33
 5 1005      2       92       40
 6 1006      2       74       36
 7 1007      2       94       34
 8 1008      2       85       28
 9 1009      1       68       30
10 1010      1       70       54
```

合併「數學學習_1. xlsx 」和「數學學習_2 .xlsx 」

	編號	性別	數學成就	數學態度
1	1001	1	87	38
2	1002	1	84	42
3	1003	1	75	25
4	1004	2	78	33
5	1005	2	92	40

	編號	性別	數學成就	數學態度
1	1006	2	74	36
2	1007	2	94	34
3	1008	2	85	28
4	1009	1	68	30
5	1010	1	70	54

```
> math_data2_tmp <- math_data2[, sample(1:4)]
> rbind(math_data1, math_data2_tmp)
# A tibble: 10 × 4
   編號    性別 數學成就 數學態度
   <chr> <dbl>    <dbl>    <dbl>
 1 1001      1       87       38
 2 1002      1       84       42
 3 1003      1       75       25
...
10 1010      1       70       54
>
> math_data2_tmp$TEST <- sample(1:5)
> math_data2_tmp
# A tibble: 5 × 5
  編號    性別 數學態度 數學成就  TEST
  <chr> <dbl>    <dbl>    <dbl> <int>
1 1006      2       36       74     5
2 1007      2       34       94     3
...
4 1009      1       30       68     1
5 1010      1       54       70     2
> rbind(math_data1, math_data2_tmp)
Error in rbind(deparse.level, ...) : 
  numbers of columns of arguments do not match
```

合併變數: cbind

合併「數學學習_1.xls、數學學習_3.xls 」。

```
> math_data1 <- read_excel("data/數學學習_1.xlsx")
> math_data1
# A tibble: 5 × 4
  編號   性別 數學成就 數學態度
  <chr> <dbl>    <dbl>    <dbl>
1 1001      1       87       38
2 1002      1       84       42
..
5 1005      2       92       40
> math_data3 <- read_excel("data/數學學習_3.xlsx")
> math_data3
# A tibble: 5 × 4
  編號   數學效能 數學焦慮 數學投入
  <chr>     <dbl>    <dbl>    <dbl>
1 1001         54       48       25
2 1002         32       38       40
..
5 1005         44       45       28
>
> cbind(math_data1, math_data3)
  編號 性別 數學成就 數學態度 編號 數學效能 數學焦慮 數學投入
1 1001    1     87       38   1001      54       48       25
2 1002    1     84       42   1002      32       38       40
3 1003    1     75       25   1003      48       46       32
4 1004    2     78       33   1004      42       41       19
5 1005    2     92       40   1005      44       45       28
```

	編號	性別	數學成就	數
1	1001	1	87	
2	1002	1	84	
3	1003	1	75	
4	1004	2	78	
5	1005	2	92	

	編號	數學效能	數學焦慮	數學投入
1	1001	54	48	25
2	1002	32	38	40
3	1003	48	46	32
4	1004	42	41	19
5	1005	44	45	28

```
> math_data3_tmp <- math_data3[sample(1:5), ]
> math_data3_tmp
# A tibble: 5 × 4
  編號   數學效能 數學焦慮 數學投入
  <chr>     <dbl>    <dbl>    <dbl>
1 1005         44       45       28
...
5 1001         54       48       25
> cbind(math_data1, math_data3_tmp)
  編號 性別 數學成就 數學態度 編號 數學效能 數學焦慮 數學投入
1 1001    1     87       38   1005      44       45       28
2 1002    1     84       42   1003      48       46       32
3 1003    1     75       25   1004      42       41       19
4 1004    2     78       33   1002      32       38       40
5 1005    2     92       40   1001      54       48       25
```

```
merge(math_data1, math_data3, by = "編號")
```

rbind and cbind

```
> begin.experiment <- data.frame(name=c("A", "B", "C", "D", "E", "F"),
+ weights=c(270, 263, 294, 218, 305, 261))
> middle.experiment <- data.frame(name=c("G", "H", "I"),
+ weights=c(169, 181, 201))
> end.experiment <- data.frame(name=c("C", "D", "A", "H", "I"),
+ weights=c(107, 104, 104, 102, 100))
> # merge the data for those who started and finished the experiment
> (common <- intersect(begin.experiment$name, end.experiment$name))
[1] "A" "C" "D"
> (b.at <- is.element(begin.experiment$name, common))
[1]  TRUE FALSE  TRUE  TRUE FALSE FALSE
> (e.at <- is.element(end.experiment$name, common))
[1]  TRUE  TRUE  TRUE FALSE FALSE
> experiment <- rbind(cbind(begin.experiment[b.at,], time="begin"),
+                     cbind(end.experiment[e.at,], time="end"))
> experiment
   name weights  time
1     A     270 begin
3     C     294 begin
4     D     218 begin
11    C     107   end
2     D     104   end
31    A     104   end
```

```
> begin.experiment
  name weights
1    A     270
2    B     263
3    C     294
4    D     218
5    E     305
6    F     261
> middle.experiment
  name weights
1    G     169
2    H     181
3    I     201
> end.experiment
  name weights
1    C     107
2    D     104
3    A     104
4    H     102
5    I     100
```

```
> tapply(experiment$weights, experiment$time, mean)
   begin      end
260.6667 105.0000
```

merge {base}: Merge Two Data Frames

- Merge (adds variables to a dataset) two data frames horizontally by common columns or row names (key variables, either string or numeric). , or do other versions of database join operations.

```
merge(x, y, by = intersect(names(x), names(y)),
      by.x = by, by.y = by, all = FALSE, all.x = all, all.y = all,
      sort = TRUE, suffixes = c(".x",".y"),
      incomparables = NULL, ...)
```

```
# merge two data frames by ID
total <- merge(data.frame.A, data.frame.B, by="ID")

# merge two data frames by ID and Country
total <- merge(data.frame.A, data.frame.B, by=c("ID","Country"))
```

https://stat.ethz.ch/R-manual/R-devel/library/base/html/merge.html

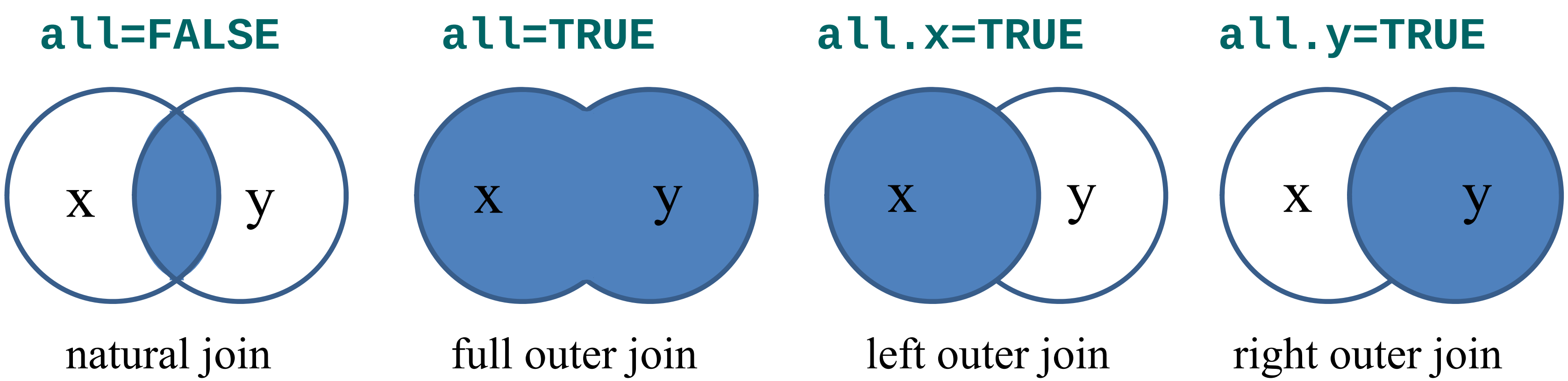
merge {base}, 合併的準則

- `merge{base}`合併的準則:
  - (default) the data frames are merged on the columns with names they both have.
  - The rows in the two data frames that match on the specified columns are extracted, and joined together.
  - If there is more than one match, all possible matches contribute one row each.

- `merge{base}`重要`Arguments`:
  - `by, by.x, by.y` : The names of the columns that are common to both x and y. The default is to use the columns with common names between the two data frames.
  - `all.x, (all.y)`: logical;
    - if `TRUE`, then extra rows will be added to the output, one for each row in `x` that has no matching row in `y`.
    - These rows will have NAs in those columns that are usually filled with values from `y`.
    - The default is `FALSE`, so that only rows with data from both `x` and `y` are included in the output.
  - `all = TRUE (FALSE)` is shorthand for `all.x = TRUE (FALSE)` and `all.y = TRUE (FALSE)`. Logical values that specify the type of merge.
    - The default value is `all=FALSE` (meaning that only the matching rows are returned).

Different Types of Merge

- **Natural join**: To keep only rows that match from the data frames, specify the argument `all=FALSE` **(by default)**.
- **Full outer join**: To keep all rows from both data frames, specify `all=TRUE`. Note that this performs the complete merge and fills the columns with NA values where there is no matching data.
- **Left outer join**: To include all the rows of your data frame `x` and only those from `y` that match, specify `all.x=TRUE`.
- **Right outer join**: To include all the rows of your data frame `y` and only those from `x` that match, specify `all.y=TRUE`.



dplyr: `inner_join` `full_join` `left_join` `right_join`

merge {base}, Example (1)

```
> authors <- data.frame(
+     surname = I(c("Tukey", "Venables", "Tierney", "Ripley", "McNeil")),
+     nationality = c("US", "Australia", "US", "UK", "Australia"),
+     deceased = c("yes", rep("no", 4)))
> books <- data.frame(
+     name = I(c("Tukey", "Venables", "Tierney",
+              "Ripley", "Ripley", "McNeil", "R Core")),
+     title = c("Exploratory Data Analysis",
+               "Modern Applied Statistics ...",
+               "LISP-STAT",
+               "Spatial Statistics", "Stochastic Simulation",
+               "Interactive Data Analysis",
+               "An Introduction to R"),
+     other.author = c(NA, "Ripley", NA, NA, NA, NA, "Venables & Smith"))
>  authors
   surname nationality deceased
1    Tukey          US      yes
2 Venables   Australia       no
3  Tierney          US       no
4   Ripley          UK       no
5   McNeil   Australia       no
> books
      name                         title     other.author
1    Tukey     Exploratory Data Analysis             <NA>
2 Venables Modern Applied Statistics ...           Ripley
3  Tierney                     LISP-STAT             <NA>
4   Ripley            Spatial Statistics             <NA>
5   Ripley         Stochastic Simulation             <NA>
6   McNeil     Interactive Data Analysis             <NA>
7   R Core          An Introduction to R Venables & Smith
```

https://stat.ethz.ch/R-manual/R-devel/library/base/html/merge.html

merge {base}, Example (1)

```
> (m1 <- merge(authors, books, by.x = "surname", by.y = "name"))
   surname nationality deceased                         title other.author
1   McNeil   Australia       no     Interactive Data Analysis         <NA>
2   Ripley          UK       no            Spatial Statistics         <NA>
3   Ripley          UK       no         Stochastic Simulation         <NA>
4  Tierney          US       no                     LISP-STAT         <NA>
5    Tukey          US      yes     Exploratory Data Analysis         <NA>
6 Venables   Australia       no Modern Applied Statistics ...       Ripley
> (m2 <- merge(books, authors, by.x = "name", by.y = "surname"))
      name                         title other.author nationality deceased
1   McNeil     Interactive Data Analysis         <NA>   Australia       no
2   Ripley            Spatial Statistics         <NA>          UK       no
3   Ripley         Stochastic Simulation         <NA>          UK       no
4  Tierney                     LISP-STAT         <NA>          US       no
5    Tukey     Exploratory Data Analysis         <NA>          US      yes
6 Venables Modern Applied Statistics ...       Ripley   Australia       no
```

```
> merge(authors, books, by.x = "surname", by.y = "name", all = TRUE)
   surname nationality deceased                         title     other.author
1   McNeil   Australia       no     Interactive Data Analysis             <NA>
2   R Core        <NA>     <NA>          An Introduction to R Venables & Smith
3   Ripley          UK       no            Spatial Statistics             <NA>
4   Ripley          UK       no         Stochastic Simulation             <NA>
5  Tierney          US       no                     LISP-STAT             <NA>
6    Tukey          US      yes     Exploratory Data Analysis             <NA>
7 Venables   Australia       no Modern Applied Statistics ...           Ripley
```

https://stat.ethz.ch/R-manual/R-devel/library/base/html/merge.html

merge {base}, Example (2)

```
> (x <- data.frame(k1 = c(NA,NA,3,4,5), k2 = c(1,NA,NA,4,5), data = 1:5))
  k1 k2 data
1 NA  1    1
2 NA NA    2
3  3 NA    3
4  4  4    4
5  5  5    5
> (y <- data.frame(k1 = c(NA,2,NA,4,5), k2 = c(NA,NA,3,4,5), data = 1:5))
  k1 k2 data
1 NA NA    1
2  2 NA    2
3 NA  3    3
4  4  4    4
5  5  5    5
> merge(x, y, by = c("k1","k2")) # NA's match
  k1 k2 data.x data.y
1  4  4      4      4
2  5  5      5      5
3 NA NA      2      1
> merge(x, y, by = "k1") # NA's match, so 6 rows
  k1 k2.x data.x k2.y data.y
1  4    4      4    4      4
2  5    5      5    5      5
3 NA    1      1   NA      1
4 NA    1      1    3      3
5 NA   NA      2   NA      1
6 NA   NA      2    3      3
> merge(x, y, by = "k2", incomparables = NA) # 2 rows
  k2 k1.x data.x k1.y data.y
1  4    4      4    4      4
2  5    5      5    5      5
```

merge {base}, Example (3)

```
> stories <- read.table(header=TRUE, text='
+    storyid  title
+     1        lions
+     2       tigers
+     3        bears
+ ')
> data <- read.table(header=TRUE, text='
+     subject storyid rating
+           1       1    6.7
+           1       2    4.5
+           1       3    3.7
+           2       2    3.3
+           2       3    4.1
+           2       1    5.2
+ ')
>
> merge(stories, data, by="storyid")
  storyid  title subject rating
1       1  lions       1    6.7
2       1  lions       2    5.2
3       2 tigers       1    4.5
4       2 tigers       2    3.3
5       3  bears       1    3.7
6       3  bears       2    4.1
```

```
>  stories2 <- read.table(header=TRUE, text='
+    id        title
+     1        lions
+     2       tigers
+     3        bears
+ ')
>
> merge(stories2, data, by.x="id", by.y="storyid")
  id  title subject rating
1  1  lions       1    6.7
2  1  lions       2    5.2
3  2 tigers       1    4.5
4  2 tigers       2    3.3
5  3  bears       1    3.7
6  3  bears       2    4.1
```

http://www.cookbook-r.com/Manipulating_data/Merging_data_frames/

Merge on Multiple Columns

```
> animals <- read.table(header=T, text='
+    size type         name
+   small  cat         lynx
+     big  cat        tiger
+   small  dog    chihuahua
+     big  dog "great dane"
+ ')
>
> observations <- read.table(header=T, text='
+    number  size type
+         1   big  cat
+         2 small  dog
+         3 small  dog
+         4   big  dog
+ ')
>
> merge(observations, animals, c("size","type"))
   size type number       name
1   big  cat      1      tiger
2   big  dog      4 great dane
3 small  dog      2  chihuahua
4 small  dog      3  chihuahua
```

問卷編碼範例: 基本資料

高中職學校行政主管時間管理現況及其策略運用調查問卷

親愛的教育先進：您好！

【說明】

研 究 生 ○○○ 敬上

一、基本資料

1. 性別：□(1)男 □(2)女
2. 年齡：□(1) 30 歲以下 □(2) 31-40 歲 □(3) 41-50 歲 □(4) 51-60 歲 □(5) 61 歲以上
3. 婚姻：□(1)未婚 □(2)已婚 □(3)離異 □(4)喪偶
4. 最高學歷：□(1)專科(含)以下 □(2)大學 □(3)研究所 40 學分班 □(4)碩士 □(5)博士
5. 服務年資：□(1) 5 年以下 □(2) 6-10 年 □(3) 11-15 年 □(4) 16-20 年 □(5) 21-25 年 □(6) 26 年以上
6. 學校屬性：□(1)公立 □(2)私立
7. 學校類別：□(1)高中 □(2)高職
8. 學校規模(日間部)：□(1) 24 班以下 □(2) 25-48 班 □(3) 49 班以上

原始題項	變項名稱	變項標記	數值範圍	水準數值標記
一、基本資料				
1	性別		1-2	1:男生 2:女生
2	年齡		1-5	1:30 歲以下 2:31--40 歲 3:41--50 歲 4:51--60 歲 5:61 歲以上
3	婚姻		1-4	1:未婚 2:已婚 3:離異 4:喪偶
4	學歷		1-5	1:專科以下 2:大學 3:40 學分班 4:碩士 5:博士
5	服務年資		1-6	1:5 年以下 2:6--10 年 3:11--15 歲 4:16--20 年 5:21--25 歲 6:26 年以上
6	學校屬性		1-2	1:公立 2:私立
7	學校類別		1-2	1:高中 2:高職
8	學校規模		1-3	1:24 班以下 2:25--8 班 3:49 班以上

資料來源:吳明隆, SPSS操作與應用：問卷統計分析實務，五南出版社

問卷編碼範例: 次序變項

二、時間管理認知

填答說明：請根據您的認知，在各題適當的□內打「✓」

	非常同意	同意	普通	不同意	非常不同意
01.我覺得時間管理是每個人應具備的一種技巧。	□	□	□	□	□
02.我認為時間管理是減輕壓力的一項重要因素。	□	□	□	□	□
03.對時間使用的覺察與反省是改善時間管理的必要步驟。	□	□	□	□	□
04.良好的時間管理者，會清楚自己的工作目標。	□	□	□	□	□
05.我認為良好的時間管理，有助於提高生活品質。	□	□	□	□	□
06.善於時間管理的人，其能力更加使人信賴。	□	□	□	□	□
07.善於時間管理的人，會更擅長於授權。	□	□	□	□	□
08.善於時間管理的人，更能掌握突發事件。	□	□	□	□	□
09.善於管理時間的人，會懂得運用人力資源。	□	□	□	□	□
10.做好時間管理，會更能有效地去完成目標。	□	□	□	□	□

原始題項	變項名稱	變項標記	數值範圍	水準數值標記
二、時間管理認知				
01	A1		1-5	
02	A2		1-5	
03	A3		1-5	
04	A4		1-5	
05	A5		1-5	

資料來源:吳明隆, SPSS操作與應用：問卷統計分析實務，五南出版社

問卷編碼範例: 排序資料

三、時間分配

由下列項目中，排列出最能反應您平日工作時間分配的情況，請將數字依序填入□內，時間花費最多的填1，其次填2，以此類推……。

□組織發展 □行政領導 □事務管理 □教學視導 □學生輔導
□公共關係 □研習進修 □偶發事件 □其　他

原始題項	變項名稱	變項標記	數值範圍	水準數值標記
三、時間分配				
	B3_1	組織發展	1-9	
	B3_2	行政領導	1-9	
	B3_3	事務管理	1-9	
	B3_4	教學視導	1-9	
	B3_5	學生輔導	1-9	
	B3_6	公共關係	1-9	
	B3_7	研習進修	1-9	
	B3_8	偶發事件	1-9	
	B3_9	其他	1-9	

資料來源:吳明隆, SPSS操作與應用：問卷統計分析實務，五南出版社

問卷編碼範例: 排序資料

四、互動對象

除面對學生外，學校行政主管因爲工作的關係，經常須與家長、社區民眾、長官或其他人士溝通。在下列項目中，請您依互動頻率多寡，將數字依序填入□內，互動頻率最高填1，其次填2，以此類推……。

□上級長官 □校外夥伴 □學校同事 □學生家長 □社區民眾
□民意代表 □同學朋友 □家人親戚 □其　　他

原始題項	變項名稱	變項標記	數值範圍	水準數值標記
四、互動對象				
	C4_1	上級長官	1-9	
	C4_2	校外夥伴	1-9	
	C4_3	學校同事	1-9	
	C4_4	學生家長	1-9	
	C4_5	社區民眾	1-9	
	C4_6	民意代表	1-9	
	C4_7	同學朋友	1-9	
	C4_8	家人親戚	1-9	
	C4_9	其　他	1-9	

資料來源:吳明隆, SPSS操作與應用：問卷統計分析實務，五南出版社

問卷編碼範例: 複選題

五、困擾因素

在工作上，時常會影響您對時間管理的困擾因素有哪些？（此題爲複選題，至多選五項），請在□內打「✓」

□01 對許多事承諾太多無法拒絕。
□02.書面資料及公文處理費時。
□03.權責不清，不易做決定。
□04.經常缺乏計畫，手忙腳亂。
□05.工作經常拖延，無法依原訂進度執行。
□06.電話干擾不斷。
□07.不速之客造訪。
□08.與人溝通協調，占用太多時間。
□09.許多事須親自處理，授權不易。
□10.經常參加會議及各項活動。
□11.學校偶發事件處理。
□12.上級長官臨時交辦事項。
□13.同仁沒有時間管理觀念。
□14.家庭問題。

原始題項	變項名稱	變項標記	數值範圍	水準數值標記
五、困擾因素				
	D5_1		0-1	0:未勾選　1:勾選
	D5_2		0-1	0:未勾選　1:勾選
	D5_3		0-1	0:未勾選　1:勾選
	D5_4		0-1	0:未勾選　1:勾選
	D5_5		0-1	0:未勾選　1:勾選
	D5_6		0-1	0:未勾選　1:勾選
	D5_7		0-1	0:未勾選　1:勾選
	D5_8		0-1	0:未勾選　1:勾選
	D5_9		0-1	0:未勾選　1:勾選
	D5_10		0-1	0:未勾選　1:勾選
	D5_11		0-1	0:未勾選　1:勾選

資料來源:吳明隆, SPSS操作與應用：問卷統計分析實務，五南出版社

問卷編碼範例: 次序變項

六、時間管理策略運用狀況

填答說明：請仔細閱讀下列敘述句後，根據您的意見，在各題適當的□內打「✓」

	完全符合	大部分符合	有一半符合	多數不符合	完全不符合
01.我會訂定明確的工作目標，並據此發展周詳的計畫。……………	□	□	□	□	□
02.我會以事情的輕重緩急來編排行事優先順序。………………………	□	□	□		
04.我會先行檢查一下明日的行程並預做準備。………………………………	□	□	□		
05.我會利用行政團隊成員的優點，合作把工作完成。………………	□	□	□		
06.我會隨時把握機會與工作成員做良好的溝通。………………………	□	□	□		
07.我會事先做合適的時間分配，使工作都能如期完成。……………	□	□	□		
08.發展計畫時，我會思考可能的阻礙，事先做好因應的措施。….	□	□	□		
09.我覺得自己是一個很會做時間管理的人。………………………………	□	□	□		
10.我會善用記事本等工具，記錄每天重要的訊息和行程。…………	□	□	□		
11.我會利用布告欄記載重要行事，讓同仁做好時間分布和管理。	□	□	□		
12.我會使用電腦等工具，協助工作較有效率地完成。………………	□	□	□		
13.我會利用電腦網頁公布工作要項，使校務運作更順暢。…………	□	□	□		
14.我會在文件的關鍵處加標記，以便加快重讀時的速度。…………	□	□	□		
15.我會將工作上的困難、想法與心得記錄下來，以便未來查考。	□	□	□		

原始題項	變項名稱	變項標記	數值範圍	水準數值標記
六、時間策略運用				
01	E1		1-5	
02	E2		1-5	
03	E3		1-5	
04	E4		1-5	
05	E5		1-5	
06	E6		1-5	
07	E7		1-5	
08	E8		1-5	
09	E9		1-5	
10	E10		1-5	
11	E11		1-5	
12	E12		1-5	
13	E13		1-5	
14	E14		1-5	
15	E15		1-5	

資料來源:吳明隆, SPSS操作與應用：問卷統計分析實務，五南出版社

試卷之試題分析: 二元計分類型及多元計分類型

二元計分類型

答案

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	ID	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	P11	P12	P13	P14	P15
2	ANS	3	2	4	2	2	3	4	4	1	2	1	4	1	2	3
3	ST001	3	2	4	3	4	3	4	4	1	3	2	4	3	2	4
4	ST002	2	2	4	2	2	1	3	4	1	3	3	1	1	2	3
5	ST003	3	2	4	4	4	3	4	4	1	4	2	1	1	2	3
6	ST004	3	2	4	4	4	3	4	4	1	2	2	4	1	2	3
7	ST005	1	2	4	2	2	3	4	4	1	2	1	4	1	2	4
8	ST006	3	2	4	1	4	3	1	2	1	3	3	2	2	2	3
9	ST007	2	2	2	1	4	3	2	4	1	4	3	2	4	2	3
10	ST008	3	2	2	3	4	3	2	4	1	2	2	4	1	2	1
11	ST009	4	2	4	3	4	1	3	4	1	2	1	4	1	2	4
12	ST010	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2	3
13	ST011	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2	3
14	ST012	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	3	4
15	ST013	3	1	4	2	2	4	3	1	2	2	4	1	2	3	1
16	ST014	3	1	4	2	2	3	4	1	1	2	2	4	3	4	4
17	ST015	3	2	4	2	2	3	4	4	1	2	1	4	1	2	3
18	ST016	2	2	4	1	4	3	4	4	1	3	2	4	1	2	3
19	ST017	3	2	4	2	2	3	3	4	1	3	2	4	1	2	4
20	ST018	3	1	4	2	2	3	3	4	1	2	1	2	1	2	1

受試者的反應資料

多元計分類型

題項B101~B106、 B201~B206

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	ID	B101	B102	B103	B104	B105	B106	B201	B202	B203	B204	B205	B206
2	ST001	4	4	4	4	4	4	4	4	4	4	4	4
3	ST002	4	4	4	4	4	4	4	4	4	4	4	4
4	ST003	3	3	3	3	3	3	3	3	3	3	3	3
5	ST004	3	3	3	3	4	3	3	3	3	3	3	3
6	ST005	3	3	3	3	3	3	3	3	3	3	3	3
7	ST006	3	3	4	4	4	4	3	3	3	3	3	3
8	ST007	3	3	3	3	3	3	3	3	3	3	3	3
9	ST008	3	3	3	3	3	3	3	3	3	3	3	3
10	ST009	3	3	3	3	3	3	3	3	3	3	3	3
11	ST010	3	3	3	3	3	3	3	4	3	3	3	3
12	ST011	3	3	4	4	4	4	3	3	3	3	3	4
13	ST012	3	3	3	3	3	3	4	4	4	4	4	4
14	ST013	4	4	4	4	4	4	4	4	4	4	4	4
15	ST014	3	3	3	3	3	3	3	3	4	4	3	4
16	ST015	4	4	4	4	4	4	4	4	4	4	4	4

分析要點:

- 二元計分 (答對率)
- **項目分析(itemanalysis):** 以單題為單位來進行分析
- **誘答力分析 (選擇題選項分析)**
  - 一道選擇題的選項分析除可了解考生在正確選項的選答情形外，更能了解「不正確選項」發揮的誘答效果，所以選項分析又可稱「誘答力分析」。所謂誘答力是指「不正確選項」吸引考生選答的程度，通常以該選項選答人數占全體到考考生人數的百分比來表示，百分比數值越大，表示誘答力越高。
  - 誘答功能判斷標準：(a) 低分組學生至少有一人選。(b)低分組選的人數不得低於高分。
- **描述性統計**
- **計算難度**

二元計分的難度計算有2種方式:
(1) 答對人數/全部受試者
(2) 高低分組(前後27%、前後33%、前後25%)之平均數
計算高分組及低分組在每一題答對的人數百分比, 記為 PH 及 PL。每一題之難度: $P = (PH + PL)/2$。

- **計算鑑別度:** $D = PH - PL$
- **高低分組平均數t檢定之t值: 決斷值，criticalratio, CR值**
- **計算題目與總分相關係數**
- **計算總量表刪題後信度、題目信度**

試題難度與鑑別度

若試題理想難度預設值為0.5

試題難易度等級表

難易度	難易度等級
P≧0.80	極容易
0.60≦P<0.80	容易
0.40 ≦P<0.60	難易適中
0.20 ≦P<0.40	困難
P<0.20	極困難

將學生分為高分組和低分組 (例如: 27%) 。

- 難度就是答對率，難度值越高代表題目越簡單，越低表示越困難。$P = (PH + PL)/2$
- 鑑別度 = 高分組答對率-低分組答對率。值越高表示越具鑑別度。 $(D = PH - PL)$
- 高鑑別度的題目能有效區分高低分組學生的能力。
- 鑑別度與難度有密切關係。難度越接近0.5，鑑別度越高，難度越接近極端值，鑑別度越低。

美國學者伊博（1979）的評鑑標準

鑑別指數	試題評鑑
0.40以上	非常優良
0.30~0.29	優良，但可能需修改
0.20~0.29	尚可，但通常需修改
0.19以下	劣，須淘汰或修改

$-1 \leq D \leq 1$

- $D = 0$，無鑑別度
  試題太簡單，高分組與低分組學生全部答對
  試題太困難，高分組與低分組學生全部答錯
- $D = +1$
  高分組學生全部答對，低分組學生全部答錯。
- $D = -1$
  低分組學生全部答對，高分組學生全部答錯。

計算難度及鑑別度值的目的: 整體試卷難度分配、各單元及目標的難度分配、難度值過高的題目、難度值過低的題目(尤其是鑑別度又低)。

抽樣調查的樣本數

- 問卷調查之抽樣樣本數多寡，並無定論。
  - 一般問卷，正式抽樣樣本數，最好為350人以上。
  - 一般而言，樣本數要占母群體10%。
  - 若母群體人數少於500，則樣本數最好占母群體20%以上。
  - 若母群體人數較少，則樣本數最好占母群體30%以上。
- 需考量研究者的時間、精力、財力等因素。
- 抽取具<u>代表性</u>的樣本比抽取<u>多數但不具代表性</u>的樣本更具外在效度。
- 如有組別，最少每組需20以上。最少不得低於15人，理想為30人以上。

N: 母群體樣本數。k: 常數 (與信賴係數相關)。P: 一般設爲0.5。

$$n \geq \frac{N}{(\frac{\alpha}{k})^2 \frac{N-1}{P(1-P)} + 1}$$

以企業組織員工爲研究對象 (5000人), 則在隨機取樣時, 至少樣本要抽取多少, 統計推論才是可靠?

母體數: $N = 5000$, 顯著水準: $\alpha = 0.05$,

信賴係數: $1 - 0.05 = 0.95$, $k = 1.96$, $P = 0.5$。

若$N = 10000$, 則$n \approx 370$。若$N = 40000$, 則$n \approx 381$。

$$\begin{aligned} n &\geq \frac{N}{(\frac{\alpha}{k})^2 \frac{N-1}{P(1-P)} + 1} \\ &= \frac{5000}{(\frac{0.05}{1.96})^2 \frac{5000-1}{0.5(1-0.5)} + 1} \\ &= \frac{5000}{14.0125} \\ &= 356.516 \\ &\approx 357 \end{aligned}$$

計算抽樣調查的樣本數

How to Choose Sample Size for a Simple Random Sample

Margin of Error (誤差範圍)

The margin of error expresses the maximum expected difference between the true population parameter and a sample estimate of that parameter. To be meaningful, the margin of error should be qualified by a probability statement (often expressed in the form of a confidence level).

For example, a pollster might report that 50% of voters will choose the Democratic candidate. To indicate the quality of the survey result, the pollster might add that the margin of error is +5%, with a confidence level of 90%. This means that if the survey were repeated many times with different samples, the true percentage of Democratic voters would fall within the margin of error 90% of the time.

$$\bar{x} \pm z_{\alpha/2}\frac{\sigma}{\sqrt{n}} \qquad E = z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$$

Let E = the desired margin of error:

Sample statistic	Population size	Sample size
Mean	Known	$n = \dfrac{z^2\sigma^2\left[\frac{N}{N-1}\right]}{E^2 + \left[\frac{z^2\sigma^2}{N-1}\right]}$
Mean	Unknown	$n = \dfrac{z^2\sigma^2}{E^2}$
Proportion	Known	$n = \dfrac{(z^2 \cdot p \cdot q) + E^2}{E^2 + \frac{z^2 \cdot p \cdot q}{N}}$
Proportion	Unknown	$n = \dfrac{(z^2 \cdot p \cdot q) + E^2}{E^2}$

$$n \geq \frac{N}{\left(\frac{\alpha}{k}\right)^2 \frac{N-1}{P(1-P)} + 1}$$

- Level of significance: α ($\alpha = 0.05$)
- Confidence level: $1-\alpha$ ($1-\alpha = 0.95$)
- Margin of error: E ($E = 0.04$)
- Critical standard score: $z_{\alpha/2}$ ($z_{\alpha/2} = 1.96$)
- Size of the population: N
- Variance of the population: σ^2
- Population proportion: p, $q = 1-p$

Determining the sample size: interval estimation, hypothesis testing

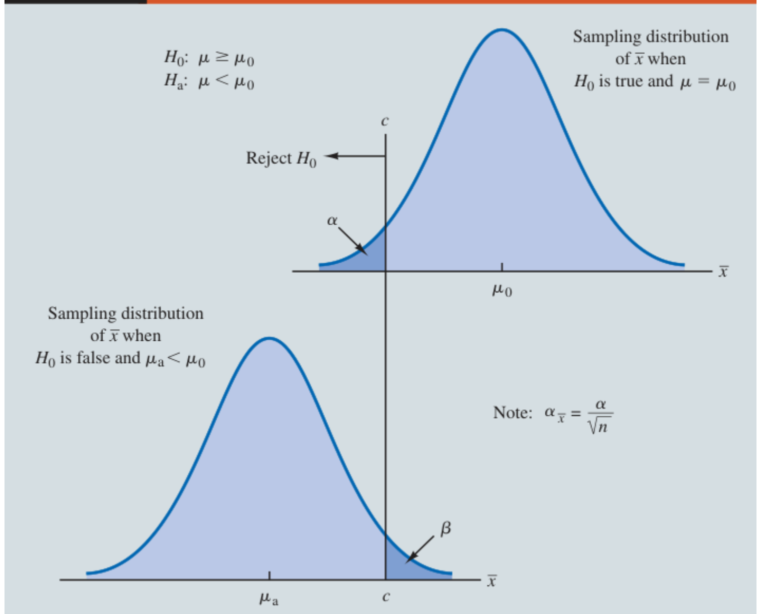
Let E = the desired margin of error:

$$\bar{x} \pm z_{\alpha/2}\frac{\sigma}{\sqrt{n}} \qquad E = z_{\alpha/2}\frac{\sigma}{\sqrt{n}}$$

SAMPLE SIZE FOR AN INTERVAL ESTIMATE OF A POPULATION MEAN

$$n = \frac{(z_{\alpha/2})^2\sigma^2}{E^2}$$

FIGURE 9.10 Determining the Sample Size for Specified Levels of the Type I (α) and Type II (β) Errors



$$H_0\text{: } \mu \geq \mu_0$$
$$H_a\text{: } \mu < \mu_0$$

$$\mu_0 - z_\alpha\frac{\sigma}{\sqrt{n}} = \mu_a + z_\beta\frac{\sigma}{\sqrt{n}}$$

SAMPLE SIZE FOR A ONE-TAILED HYPOTHESIS TEST ABOUT A POPULATION MEAN

$$n = \frac{(z_\alpha + z_\beta)^2\sigma^2}{(\mu_0 - \mu_a)^2} \tag{9.7}$$

where

z_α = z value providing an area of α in the upper tail of a standard normal distribution
z_β = z value providing an area of β in the upper tail of a standard normal distribution
σ = the population standard deviation
μ_0 = the value of the population mean in the null hypothesis
μ_a = the value of the population mean used for the Type II error

Note: In a two-tailed hypothesis test, use (9.7) with $z_{\alpha/2}$ replacing z_α.

資料檔之管理與轉換

- **從Excel讀取資料，並設定變數屬性**
- **選擇觀察值**
  - 選擇部份特定條件的觀察值
  - 觀察值的隨機樣本
  - 使用過濾變數
- **分割檔案 (群組資料): 以群組進行分析**
- **資料轉換**
  - 自動重新編碼、重新編碼
  - 轉換成等級觀察值、Visual Binning
- **計算變數、橫向計數**
- **排序、遺漏值處理、資料整合**

資料檢核
- summary statistics
- index plot, histogram, box-plot
- heatmap

資料檢核

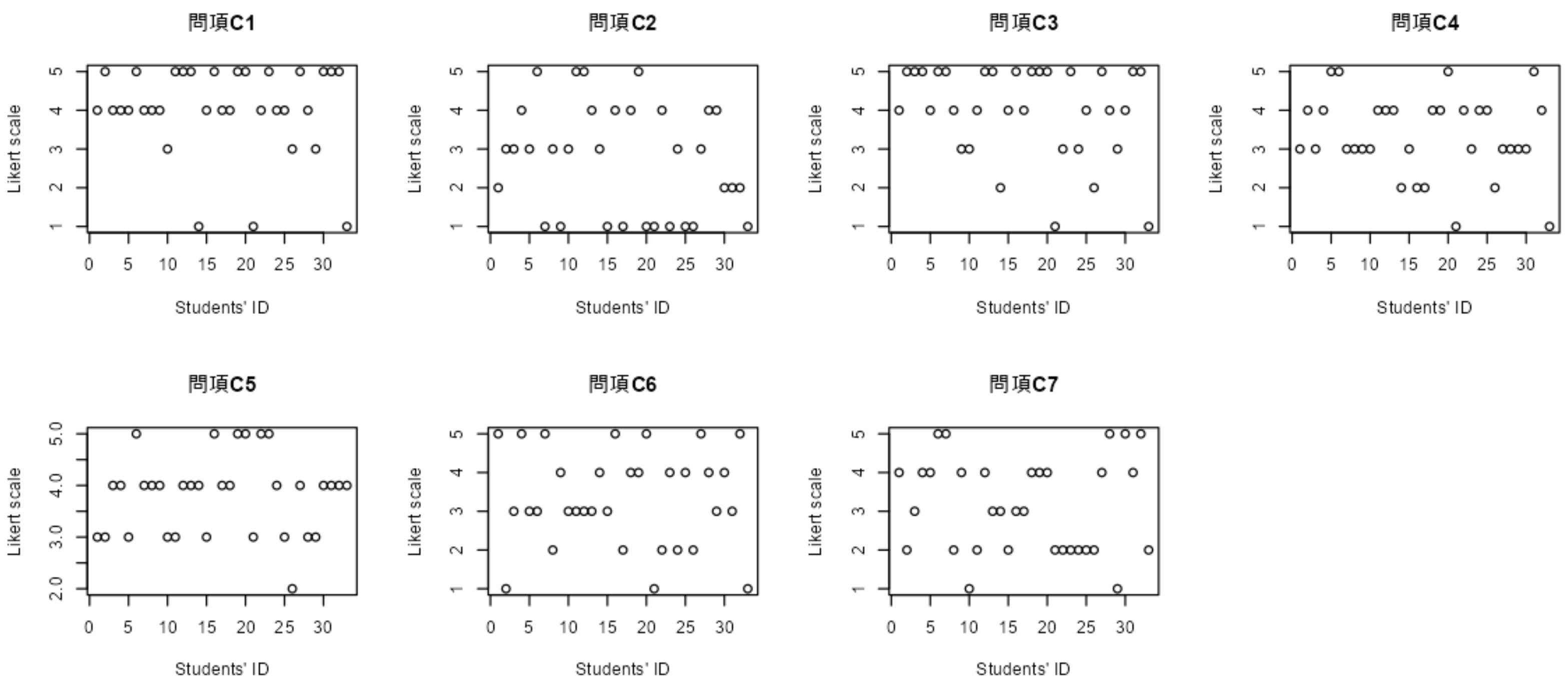
```
> CBRS <- read.csv("data/CBRS.csv", fileEncoding = "BIG5")
> head(CBRS)
  學生編號 組別 問項C1 問項C2 問項C3 問項C4 問項C5 問項C6 問項C7
1        1    B      4      2      4      3      3      5      4
...
6       24    A      5      5      5      5      5      3      5
> dim(CBRS)
[1] 33  9
> CBRS$組別 <- as.factor(CBRS$組別)
>
> MBRS <- read.csv("data/MBRS.csv", fileEncoding = "BIG5")
> head(MBRS)
  學生編號 組別 問項M1 問項M2 問項M3 問項M4 問項M5 問項M6 問項M7 問項M8 問項M9 問項M10 問項M11 問項M12
1        1    B      3      3      2      3      2      1      2      2      2       1     2        2
...
6        7    A      5      5      4      5      5      5      3      4      2       1     1        3
> dim(MBRS)
[1] 33 14
> MBRS$組別 <- as.factor(MBRS$組別)
>
> CBRS_MBRS <- merge(CBRS, MBRS, by = "學生編號")
> CBRS_MBRS$組別.y <- NULL
> colnames(CBRS_MBRS)[2] <- "組別"
```

	A	B	C	D	E	F	G	H	I
1	學生編號	組別	問項C1	問項C2	問項C3	問項C4	問項C5	問項C6	問項C7
2	1	2	4	2	4	3	3	5	4
3	12	1	5	3	5	4	3	1	2
4	13	2	4	3	5	3	4	3	3
5	22	1	4	4	5	4	4	5	4
6	23	2	4	3	4	5	3	3	4
7	24	1	5	5	5	5	5	3	5
8	37	1	4	1	5	3	4	5	5
9	38	2	4	3	4	3	4	2	2
10	39	1	4	1	3	3	4	4	4
11	40	2	3	3	3	3	3	3	1
12	41	1	5	5	4	4	3	3	2
13	2	1	5	5	5	4	4	3	4
14	3	1	5	4	5	4	4	3	3
15	4	2	1	3	2	2	4	4	3

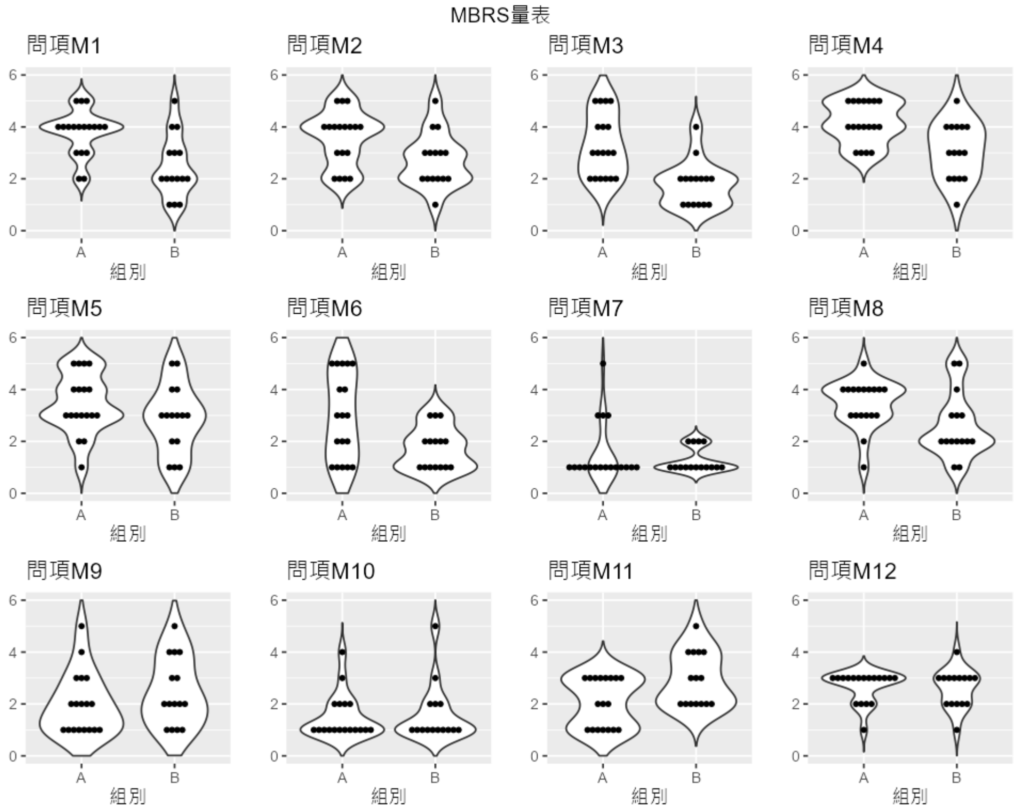
	A	B	C	D	E	F	G	H	I	J	K
1	學生編號	組別	問項M1	問項M2	問項M3	問項M4	問項M5	問項M6	問項M7	問項M8	問項M9
2	1	2	3	3	2	3	2	1	2	2	2
3	2	1	4	4	5	5	5	5	1	5	3
4	3	1	4	4	2	5	5	5	1	4	3
5	4	2	2	2	1	2	1	1	1	1	2
6	6	2	2	2	2	1	2	2	1	1	4
7	7	1	5	5	4	5	5	5	3	4	2
8	9	2	3	2	1	2	3	1	1	2	4
9	10	1	4	5	4	5	4	3	1	4	3
10	12	1	3	3	2	4	2	2	1	3	5
11	13	2	4	3	2	4	3	1	1	4	2
12	14	1	4	4	4	4	3	4	1	4	2
13	15	2	2	3	2	3	3	2	1	3	3
14	16	1	2	2	2	3	3	1	1	4	4
15	17	2	2	3	4	4	5	3	2	5	4

資料檢核: 索引圖

```
par(mfrow = c(2, 4))
lapply(3:9, function(x) plot(CBRS[,x],
                             xlab = "Students' ID",
                             ylab = "Likert scale",
                             main = names(CBRS)[x]))
```



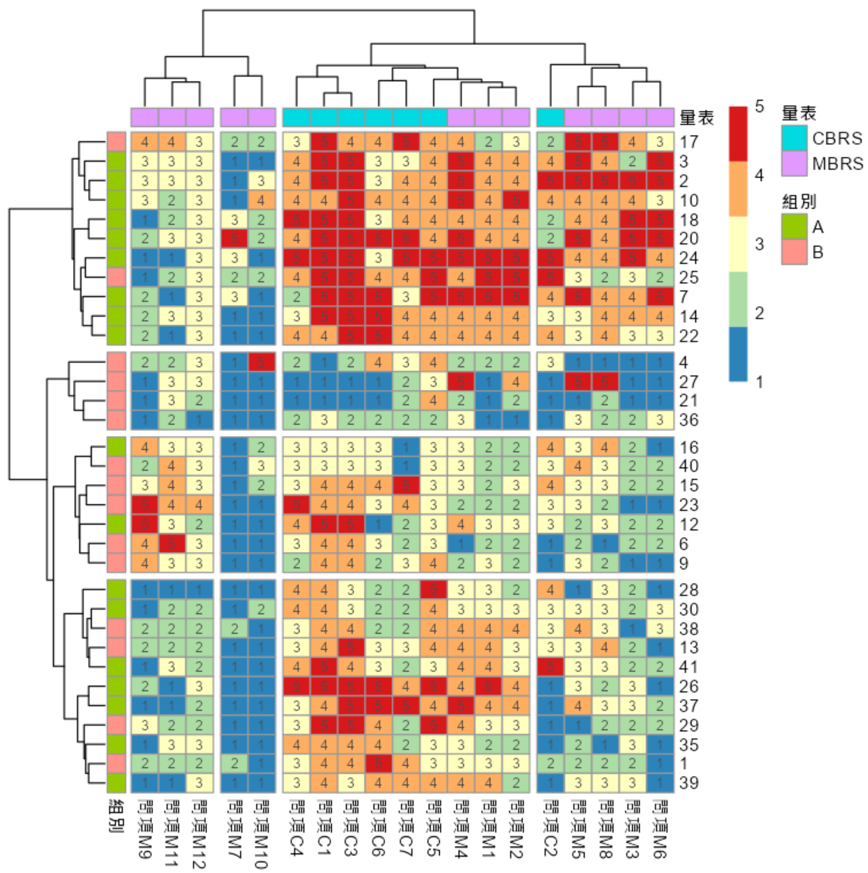
資料檢核: 小提琴圖




```
library(ggplot2)
library(grid)
library(gridExtra)

my_violin <- function(x){
  ggplot(MBRS, aes(x = 組別, y = MBRS[, x])) +
    geom_violin(trim = FALSE) +
    geom_dotplot(binaxis = 'y', stackdir = 'center') +
    scale_y_continuous(limits = c(0, 6)) +
    labs(title = names(MBRS)[x], y = "")

}

violin_list <- lapply(3:14, my_violin)
grid.arrange(grobs = violin_list, nrow = 3, ncol = 4, top = "MBRS量表")
```

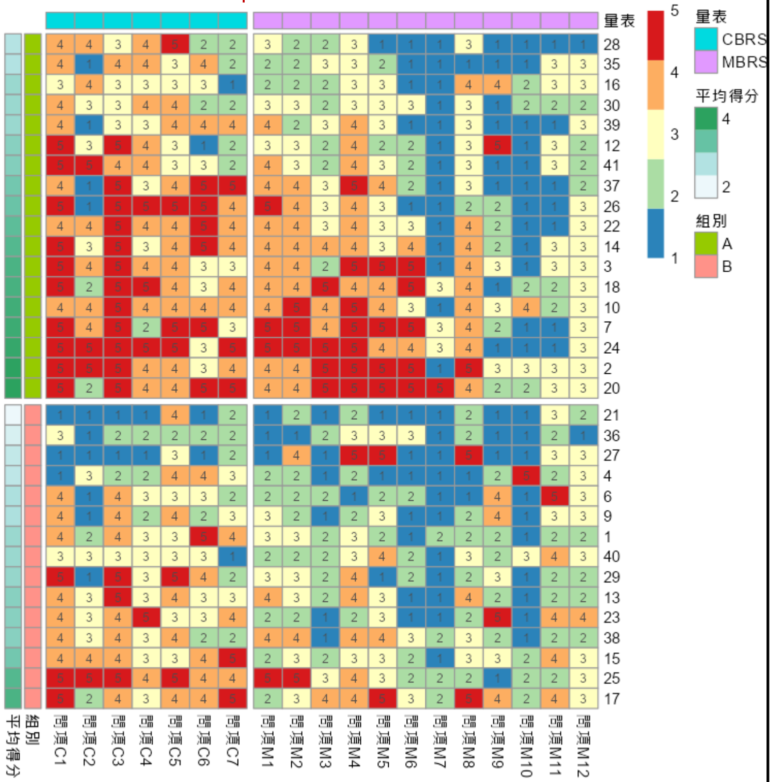
資料檢核: 熱圖 (群集分析)

```
CBRS_MBRS <- merge(CBRS, MBRS, by = "學生編號")
CBRS_MBRS$組別.y <- NULL
colnames(CBRS_MBRS)[2] <- "組別"

CBRS_MBRS_X <- CBRS_MBRS[, 3:ncol(CBRS_MBRS)]
rownames(CBRS_MBRS_X) <- CBRS_MBRS[, 1]
colnames(CBRS_MBRS_X)

col_groups <- data.frame(量表 = c(rep("CBRS", 7),
rep("MBRS", 12)))
row.names(col_groups) <- colnames(CBRS_MBRS_X)
col_groups

row_groups <- data.frame(組別 = CBRS_MBRS$組別)
rownames(row_groups) <- rownames(CBRS_MBRS_X)
row_groups

library(RColorBrewer)
library(pheatmap)

pheatmap(CBRS_MBRS_X,
         color = rev(brewer.pal(5, "Spectral")),
         annotation_row = row_groups,
         annotation_col = col_groups,
         cutree_rows = 4,
         cutree_cols = 4,
         display_numbers = TRUE,
         number_format = "%.0f",
         clustering_method = "ward.D2")
```

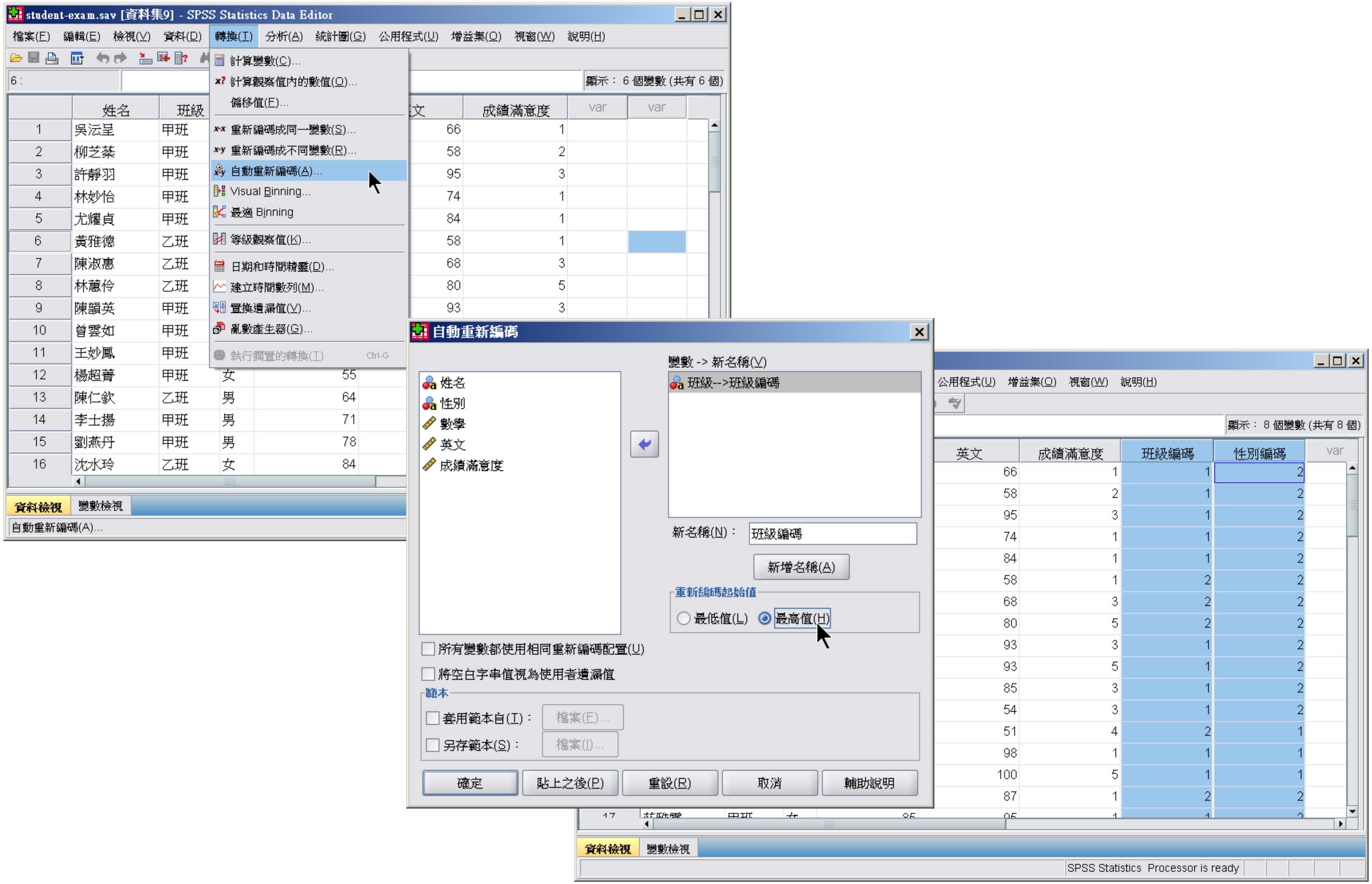


資料檢核: 熱圖 (以組別區分)

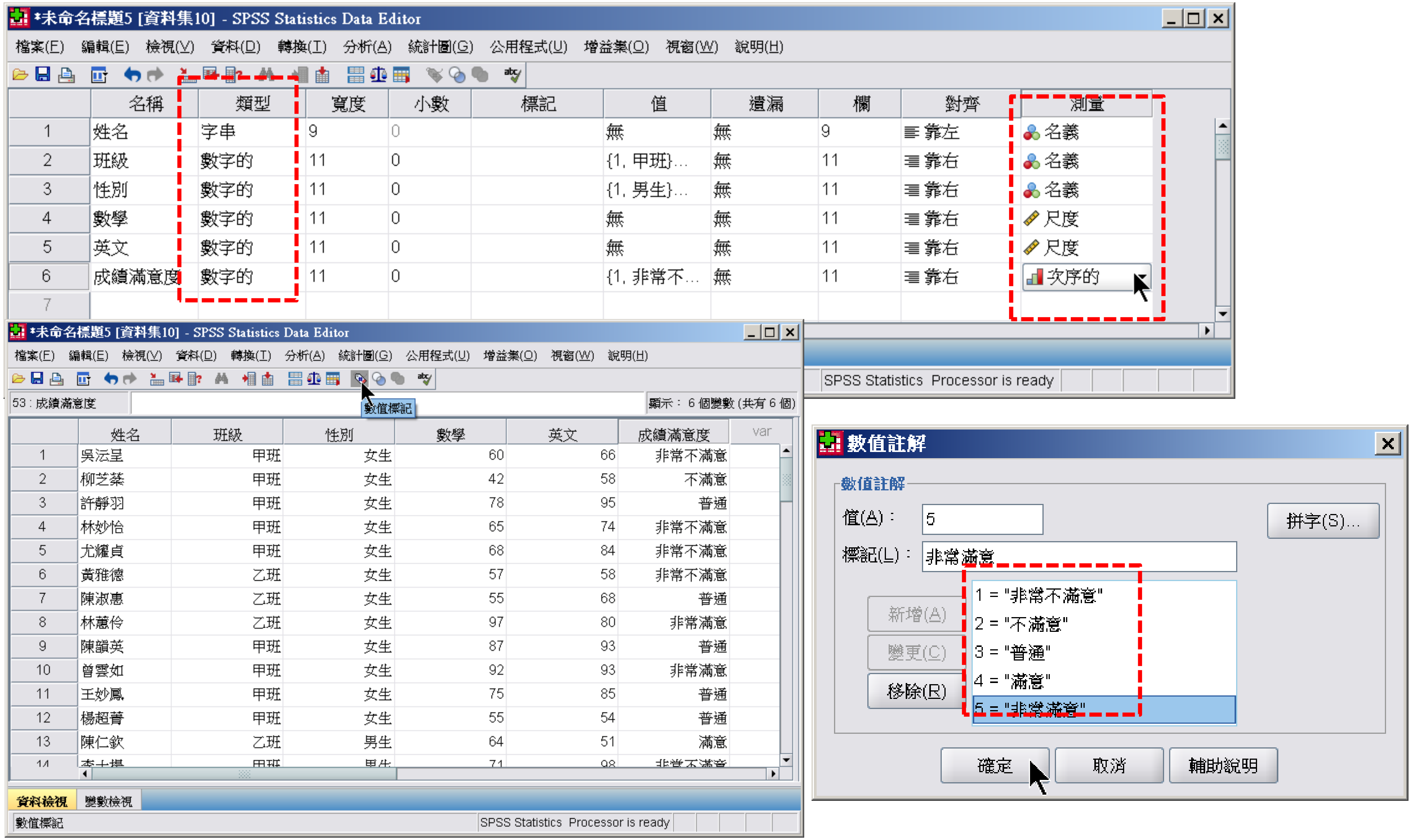
```
library(tidyverse)
CBRS_MBRS_means <- rowMeans(CBRS_MBRS[, 3:ncol(CBRS_MBRS)])
CBRS_MBRS_ALL <- cbind(CBRS_MBRS, means = CBRS_MBRS_means)
CBRS_MBRS_sort <- arrange(CBRS_MBRS_ALL, 組別, means)

CBRS_MBRS_X_sort <- CBRS_MBRS_sort[, 3:(ncol(CBRS_MBRS_sort)-1)]
rownames(CBRS_MBRS_X_sort) <- CBRS_MBRS_sort[,1]
colnames(CBRS_MBRS_X_sort)

row_group2 <- data.frame(組別 = CBRS_MBRS_sort$組別,
                         平均得分 = round(CBRS_MBRS_sort$means, 2))

rownames(row_group2) <- rownames(CBRS_MBRS_X_sort)
colnames(row_group2)

col_group2 <- data.frame(量表 = c(rep("CBRS", 7),
  rep("MBRS", 12)))
rownames(col_group2) <- colnames(CBRS_MBRS_X_sort)
colnames(col_group2)

# 列位依組別及每生之平均排序，欄位依量表及每項目平均排序。
pheatmap(CBRS_MBRS_X_sort,
         color = rev(brewer.pal(5, "Spectral")),
         annotation_row = row_group2,
         annotation_col = col_group2,
         display_numbers = TRUE,
         number_format = "%.0f",
         cluster_rows = FALSE,
         cluster_cols = FALSE,
         gaps_row = 18,
         gaps_col =7)
```



SPSS編碼範例:
SPSS需要對變量編碼(文字轉數字)，R不用



SPSS範例: 設定變數屬性，並以「數值標記」檢視



讀入資料，視情況編碼並轉成適當類別

```
> library(readxl)
> student_score_s1 <- read_excel("data/學生成績Data1.xlsx", sheet = 1)
> head(student_score_s1)
# A tibble: 6 × 6
  姓名    班級   性別    數學   英文  成績滿意度
  <chr>   <chr> <chr> <dbl> <dbl>       <dbl>
1 吳沄呈  甲班   女        60    66           1
...
6 黃雅德  乙班   女        57    58           1
>
> student_score_s1$班級編碼 <- ifelse(student_score_s1$班級 == "甲班", 1, 2)
> head(student_score_s1)
> # A tibble: 6 × 7
  姓名    班級   性別    數學   英文  成績滿意度  班級編碼
  <chr>   <chr> <chr> <dbl> <dbl>       <dbl>    <dbl>
1 吳沄呈  甲班   女        60    66           1        1
...
6 黃雅德  乙班   女        57    58           1        2

> satisfy_scale <- c("非常不滿意", "不滿意", "普通", "滿意", "非常滿意")
> student_score_s1$成績滿意度文字因子 <- satisfy_scale[student_score_s1$成績滿意度]
> student_score_s1$成績滿意度文字因子 <- factor(student_score_s1$成績滿意度文字因子,
+                                         levels = satisfy_scale, ordered = TRUE)
> str(student_score_s1)
tibble [50 × 8] (S3: tbl_df/tbl/data.frame)
 $ 姓名              : chr [1:50] "吳沄呈" "柳芝菜" "許靜羽" "林妙怡" ...
 $ 班級              : chr [1:50] "甲班" "甲班" "甲班" "甲班" ...
 $ 性別              : chr [1:50] "女" "女" "女" "女" ...
 $ 數學              : num [1:50] 60 42 78 65 68 57 55 97 87 92 ...
 $ 英文              : num [1:50] 66 58 95 74 84 58 68 80 93 93 ...
 $ 成績滿意度        : num [1:50] 1 2 3 1 1 1 3 5 3 5 ...
 $ 班級編碼          : num [1:50] 1 1 1 1 1 2 2 2 1 1 ...
 $ 成績滿意度文字因子: Ord.factor w/ 5 levels "非常不滿意"<"不滿意"<..: 1 2 3 1 1 1 3 5 3 5 ...
```

保留日後要運算

	A	B	C	D	E	F
1	姓名	班級	性別	數學	英文	成績滿意度
2	吳沄呈	甲班	女	60	66	1
3	柳芝菜	甲班	女	42	58	2
4	許靜羽	甲班	女	78	95	3
5	林妙怡	甲班	女	65	74	1
6	尤耀貞	甲班	女	68	84	1
7	黃雅德	乙班	女	57	58	1
8	陳淑惠	乙班	女	55	68	3
9	林蕙伶	乙班	女	97	80	5
10	陳韻英	甲班	女	87	93	3
11	曾雲如	甲班	女	92	93	5
12	王妙鳳	甲班	女	75	85	3
13	楊超菁	甲班	女	55	54	3
14	陳仁欽	乙班	男	64	51	4
15	李士揚	甲班	男	71	98	1
16	劉燕丹	甲班	男	78	100	5
17	沈水玲	乙班	女	84	87	1
18	莊雅雲	甲班	女	85	95	1
19	彭景雯	甲班	女	76	94	2

工作表1 工作表2 工作表3

選擇符合條件的觀察值

```
# 選擇女性樣本
student_score_s1[student_score_s1$性別 == "女", ]

# 選擇甲班及英文大於80分之樣本
student_score_s1[(student_score_s1$班級 == "甲班") |
                   (student_score_s1$英文 >= 80), ]

# 選擇男性、數學大於等於80分及英文大於70分之樣本
student_score_s1[((student_score_s1$性別 == "男") &
                   (student_score_s1$數學 >= 80)) |
                   (student_score_s1$英文 > 70), ]

# 選擇隨機樣本
student_score_s1[sample(1:nrow(student_score_s1), 10), ]

# 選擇11號~20號的姓名、數學、英文
student_score_s1[11:20, c("姓名", "數學", "英文")]

# 選擇某一時間內的資料
student_score_s1$時間 <-  seq(as.Date("2028/04/02"), by = "day",
                            length.out = nrow(student_score_s1))
selected_date <- (as.Date("2028/04/08") < student_score_s1$時間) &
  (student_score_s1$時間 < as.Date("2028/04/20"))
student_score_s1[selected_date, ]

# 刪除成績滿意度為「非常不滿意」
student_score_s1[!(student_score_s1$成績滿意度 == 1), ]
student_score_s1[!(student_score_s1$成績滿意度文字因子 == "非常不滿意"), ]
```

比較群組: 敘述統計、次數

```
> library(psych)
> describe(student_score_s1[, sapply(student_score_s1, is.numeric)])
           vars  n  mean    sd median trimmed   mad min max range  skew kurtosis   se
數學          1 50 75.78 13.96   75.5   75.92 16.31  42 100    58 -0.16    -0.80 1.97
英文          2 50 79.32 16.12   85.0   80.83 16.31  38 100    62 -0.68    -0.54 2.28
成績滿意度    3 50  2.56  1.47    2.0    2.45  1.48   1   5     4  0.43    -1.25 0.21
班級編碼      4 50  1.56  0.50    2.0    1.57  0.00   1   2     1 -0.23    -1.98 0.07
> describeBy(student_score_s1[, sapply(student_score_s1, is.numeric)],
+            student_score_s1$班級)

 Descriptive statistics by group
group: 乙班
           vars  n  mean    sd median trimmed   mad min max range  skew kurtosis   se
數學          1 28 78.11 14.06     77   78.21 16.31  55 100    45 -0.09    -1.24 2.66
英文          2 28 78.29 15.82     85   79.42 16.31  38  99    61 -0.63    -0.51 2.99
成績滿意度    3 28  2.93  1.49      3    2.92  1.48   1   5     4  0.12    -1.51 0.28
班級編碼      4 28  2.00  0.00      2    2.00  0.00   2   2     0   NaN      NaN 0.00
-------------------------------------------------------------------
group: 甲班
           vars  n  mean    sd median trimmed   mad min max range  skew kurtosis   se
數學          1 22 72.82 13.57   73.5   73.28 14.83  42  94    52 -0.33    -0.68 2.89
英文          2 22 80.64 16.78   87.5   82.28 13.34  41 100    59 -0.72    -0.73 3.58
成績滿意度    3 22  2.09  1.34    1.5    1.89  0.74   1   5     4  0.86    -0.54 0.29
班級編碼      4 22  1.00  0.00    1.0    1.00  0.00   1   1     0   NaN      NaN 0.00
```

```
> table(student_score_s1$性別)
女 男
29 21
> table(student_score_s1$成績滿意度文字因子)
非常不滿意     不滿意       普通       滿意   非常滿意
        17         10          9          6          8
```

```
> table(student_score_s1$性別, student_score_s1$成績滿意度文字因子)
      非常不滿意 不滿意 普通 滿意 非常滿意
  女          13      3    6    2        5
  男           4      7    3    4        3
```

two-way 列聯表

```
> tbl <- table(student_score_s1$性別, student_score_s1$成績滿意度文字因子)
> sum(tbl)
[1] 50
> tbl

     非常不滿意 不滿意 普通 滿意 非常滿意
  女         13      3    6    2        5
  男          4      7    3    4        3
>
> # overall
> prop.table(tbl)
     非常不滿意 不滿意  普通 滿意 非常滿意
  女       0.26   0.06 0.12 0.04     0.10
  男       0.08   0.14 0.06 0.08     0.06
>
> # by row
> prop.table(tbl, margin = 1)
     非常不滿意     不滿意       普通       滿意   非常滿意
  女 0.44827586 0.10344828 0.20689655 0.06896552 0.17241379
  男 0.19047619 0.33333333 0.14285714 0.19047619 0.14285714
>
> # by column
> prop.table(tbl, margin = 2)
     非常不滿意    不滿意      普通      滿意  非常滿意
  女  0.7647059 0.3000000 0.6666667 0.3333333 0.6250000
  男  0.2352941 0.7000000 0.3333333 0.6666667 0.3750000
```

```
> margin.table(tbl)
[1] 50
> margin.table(tbl, margin = 1)
女 男
29 21
> margin.table(tbl, margin = 2)
非常不滿意     不滿意       普通       滿意   非常滿意
        17         10          9          6          8
```

See also: `cumsum`

自動重新編碼: 算名次

```
> Average <- rowMeans(student_score_s1[, c("數學", "英文")])
> Rank <- rank(- Average)
> student_score_output <- data.frame(student_score_s1$姓名,
+                                    平均 = Average,
+                                    排名 = Rank)
> student_score_output
   student_score_s1.姓名 平均 排名
1                 吳沄呈 63.0 40.0
2                 柳芝蓁 50.0 49.0
...
49                陳冠鈺 87.5 15.0
50                黃之伶 81.0 26.0
>
> student_score_output[order(student_score_output$平均, decreasing = TRUE), ]
   student_score_s1.姓名 平均 排名
46                吳宜帆 98.5  1.0
34                劉祐民 95.0  2.5
...
2                 柳芝蓁 50.0 49.0
45                李洋瑩 49.0 50.0
```

重新編碼使用狀況:

- 反項題重新計分。
- 連續變項數值分為數個等級。
- 背景變項水準數值重新合併。

重新編碼(分組)

```
> x <- c(24, 13, 26, 21,  7,  9, 2, 1, 30, 14, 20, 16, 6, 4, 12, 8,
11, 22, 18, 3)
> ifelse(x <= 10, 1, ifelse(x <= 20, 2, 3))
 [1] 3 2 3 3 1 1 1 1 3 2 2 2 1 1 2 1 2 3 2 1
```

- 將年齡資料轉換為年齡群組1~20, 21~40, 41~60, 61歲以上，並編碼為A, B, C, D。

```
> set.seed(12345)
> age <- sample(1:100, 20)
> age
 [1] 73 87 75 86 44 16 31 48 67 91  4 14 65  1 34 40 33 97 15 78
```

- 將”A”與”E”編碼為1，”C”編碼為2，”B”與”D”編碼為3。

```
> set.seed(12345)
> code <- sample(LETTERS[1:5], 20, replace=T)
> code
 [1] "D" "E" "D" "E" "C" "A" "B" "C" "D" "E" "A" "A" "D" "A" "B" "C"
[17] "B" "C" "A" "E"
```

提示: %in%

See also: `cut(), recode{car}`

重新編碼: 分數百分數轉換成等級

- 美國大學成績平均績點(GPA)(四分制)的計算方式如右表，請寫一R函式，將某同學之各科修課成績百分數score轉成等級及GPA。

等級 (Grade)	百分數	GPA
A	80 – 100 分	4
B	70 – 79 分	3
C	60 – 69 分	2
D	50 – 59 分	1
E	49 分以下	0

```
> set.seed(12345)
> score <- sample(0:100, 10, replace=T)
> score
 [1] 72 88 76 89 46 16 32 51 73 99
```

```
gpa.table <- data.frame(grade=c("A", "B", "C", "D", "E"),
                        pscore=c("80-100", "70-79", "60-69", "50-59", "49-0"),
                        GPA=c(4, 3, 2, 1, 0))
gpa.table
set.seed(12345)
score <- sample(0:100, 10, replace=T)

score_to_gpa <- function(x){

    group.id <- ifelse(x >= 80, 1,
                  ifelse(x >= 70, 2,
                         ifelse(x >=60, 3,
                                ifelse(x >= 50, 4, 5))))
    data.frame(score=x, gpa.table[group.id,], row.names = NULL)
}
```

```
> score_to_gpa(score)
   score grade pscore GPA
1     72     B  70-79   3
2     88     A 80-100   4
3     76     B  70-79   3
4     89     A 80-100   4
5     46     E   49-0   0
6     16     E   49-0   0
7     32     E   49-0   0
8     51     D  50-59   1
9     73     B  70-79   3
10    99     A 80-100   4
```

分組

cut {base}: Convert Numeric to Factor

- **cut{base}** divides the range of **x** into intervals and codes the values in **x** according to which interval they fall. The leftmost interval corresponds to level one, the next leftmost to level two and so on.

```
cut(x, breaks, labels = NULL,
    include.lowest = FALSE, right = TRUE, dig.lab = 3, ordered_result = FALSE, ...)
```

```
> x <- rnorm(50)
> (x.cut1 <- cut(x, breaks = -5:5))
 [1] (-1,0]  (-2,-1] (-2,-1] (-1,0]  (-1,0]  (-2,-1] (0,1]   (0,1]   (-1,0]  (1,2]   (0,1]
...
[45] (1,2]   (0,1]   (-1,0]  (-2,-1] (0,1]   (0,1]
Levels: (-5,-4] (-4,-3] (-3,-2] (-2,-1] (-1,0] (0,1] (1,2] (2,3] (3,4] (4,5]
> table(x.cut1)
x.cut1
(-5,-4] (-4,-3] (-3,-2] (-2,-1]  (-1,0]   (0,1]   (1,2]   (2,3]   (3,4]   (4,5]
      0       0       1      10      18      13       8       0       0       0
> (x.cut2 <- cut(x, breaks = -5:5, labels = FALSE))
 [1] 5 4 4 5 5 4 6 6 5 7 6 5 7 5 7 6 4 7 7 4 5 6 5 5 5 6 5 6 5 4 7 ...
[47] 5 4 6 6
> table(x.cut2)
x.cut2
 3  4  5  6  7
 1 10 18 13  8
> hist(x, breaks = -5:5, plot = FALSE)$counts
 [1]  0  0  1 10 18 13  8  0  0  0
```

cut {base} Examples

```
> #the outer limits are moved away by 0.1% of the range
> cut(0:10, 5)
 [1] (-0.01,2] (-0.01,2] (-0.01,2] (2,4]     (2,4]     (4,6]     (4,6]     (6,8]
 [9] (6,8]     (8,10]    (8,10]
Levels: (-0.01,2] (2,4] (4,6] (6,8] (8,10]
>
> age <- sample(0:80, 50, replace=T)
> summary(age)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   1.00   21.00   35.00   38.16   52.75   80.00
> cut(age, 5)
 [1] (48.4,64.2]  (16.8,32.6]  (16.8,32.6]  (48.4,64.2]  (16.8,32.6]  (32.6,48.4]
...
[49] (16.8,32.6]  (48.4,64.2]
Levels: (0.921,16.8] (16.8,32.6] (32.6,48.4] (48.4,64.2] (64.2,80.1]
> mygroup <- c(0, 15, 20, 50, 60, 80)
> (x.cut <- cut(age, mygroup))
 [1] (50,60] (20,50] (15,20] (20,50] (20,50] (20,50] (15,20] (0,15]  (0,15]  (60,80]
...
Levels: (0,15] (15,20] (20,50] (50,60] (60,80]
> table(x.cut)
x.cut
 (0,15] (15,20] (20,50] (50,60] (60,80]
      7       5      22       8       8
```

Note: Instead of `table(cut(x, br))`, `hist(x, br, plot = FALSE)` is more efficient and less memory hungry. Instead of `cut(*, labels = FALSE)`, `findInterval()` is more efficient.

計算: 變數的四則運算

- 變數的四則運算

```
> sqrt(student_score_s1$數學) * 10
> rowMeans(student_score_s1[, c("數學", "英文")])
```

- 橫向計數: 單一變數 (例: 不及格)

```
> table(ifelse(student_score_s1$數學 < 60, "不及格", "及格"))
不及格   及格
   8     42
```

- 橫向計數: 多個變數(例: 不及格科數)

```
> output <- data.frame(student_score_s1[, c("數學", "英文")],
+                      不及格科數 = apply(student_score_s1[, c("數學", "英文")], 1,
+                                         function(x) sum(x < 60)))
> output
  數學 英文 不及格科數
1   60   66          0
2   42   58          2
3   78   95          0
4   65   74          0
...
```

橫向計數: 多個變數 (例:每個人在所有問題選項中「滿意」「不滿意」的個數。)

```
> table(CBRS$問項C1)
 1  3  4  5
 3  3 14 13
> agree_scale <- c("非常不同意", "不同意", "普通", "同意", "非常同意")
> C1 <- factor(CBRS$問項C1, levels =1:5, labels = agree_scale, order = T)
> str(C1)
 Ord.factor w/ 5 levels "非常不同意"<"不同意"<..: 4 5 4 4 4 5 4 4 4 3 ...
> table(C1)
C1
非常不同意     不同意       普通       同意   非常同意
         3          0          3         14         13
```

排序

```
> arrange(student_score_s1, 成績滿意度, 數學,  英文)
# A tibble: 50 × 8
   姓名    班級   性別    數學   英文 成績滿意度 班級編碼 成績滿意度文字因子
   <chr>  <chr> <chr> <dbl> <dbl>      <dbl>    <dbl> <ord>
 1 張亞慧 甲班   女        55    68          1        1 非常不滿意
 2 黃怡昕 乙班   女        56    72          1        2 非常不滿意
 3 李洋瑩 甲班   女        57    41          1        1 非常不滿意
 4 黃雅德 乙班   女        57    58          1        2 非常不滿意
 5 吳沄呈 甲班   女        60    66          1        1 非常不滿意
 6 林妙怡 甲班   女        65    74          1        1 非常不滿意
 7 蔡舜遠 甲班   男        67    61          1        1 非常不滿意
 8 尤耀貞 甲班   女        68    84          1        1 非常不滿意
 9 張鈞興 乙班   男        71    68          1        2 非常不滿意
10 黃千筠 甲班   女        71    92          1        1 非常不滿意
# … with 40 more rows
# ℹ Use `print(n = ...)` to see more rows
>
```

具遺失(缺失)值資料 (Missing Data)

Missing data (missing values for certain variables for certain cases): **item non-response**.

When data are missing for all variables for a given case: **unit non-response**.

When data are missing for a variable for all cases: **latent** or **unobserved**.

	A	B	C	D	E	F	G
1	ID	C	Y	X1	X2	X3	X4
2	s1	1	78.3	69.6	74.3	NA	5.22
3	s2	2	77	69.9	72.54	NA	3.98
4	s3	3	72.2	65.7	69.74	NA	4.89
5	s4	1	33.4	NA	30.97	NA	21.54
6	s5	2	32.65	28.35	30.54	NA	9.82
7	s6	3	35.45	28.5	32.01	NA	19.81
8	s7	1	424	378	403.55	NA	12.98
9	s8	2	NA	NA	NA	NA	NA
10	s9	3	355	312.5	339.96	NA	14.14
11	s10	1	18.2	15.5	17.19	NA	13.93
12	s11	2	18.3	15.3	16.38	NA	6.92
13	s12	3	16.1	13.9	14.92	NA	10.15
14	s13	1	23.75	20.2	22.19	NA	32.81

若資料出現遺失值:

計算及演算法無法進行。

影響估計量的性質。

(e.g. means, percentages, percentiles, variances, ratios, regression parameters, etc.).

影響統計推論。

(e.g., the properties of tests and confidence intervals.)

遺失值的處理

- The missing values may give clues to systematic aspects of the problem.

- **如何處理遺失值:**
  - 不處理，換分析演算法。
  - 刪除法。
  - 用一全域值做填補: Use a global constant to fill the value will misguide the mining process. (例如: 缺考給0分; 影像訊號=前景-背景)
  - 用平均或中位數等統計量做填補: Use the attribute mean or median for all samples belonging to the same class as the given tuple.
  - 補值法 (Missing value imputation) (most popular)

置換遺漏值

- **Neutral-value (中性值) substitution**: You can use neutral value of the likert scale. In your case neutral value would be 3.5 but if your overall average score is less than 3.5 then you could not able to use this method.

- **Mean-value substitution**: only when the number of respondents with missing data and the number of items missing were 20% or less.

- **Imputation methods**: e.g, Approximate Bayesian bootstrap with Propensity score

- Downey, R. G., & King, C. V. (1998). Missing data in Likert ratings: A comparison of replacement methods. The Journal of general psychology, 125(2), 175-191. (被引用 1009 次)
- Shrive, F. M., Stuart, H., Quan, H., & Ghali, W. A. (2006). Dealing with missing data in a multi-question depression scale: a comparison of imputation methods. BMC medical research methodology, 6, 1-10. (被引用 832 次)
- Carpita, M., & Manisera, M. (2011). On the imputation of missing data in surveys with Likert-type scales. Journal of Classification, 28, 93-112. (被引用 68 次)
- Wu, W., Jia, F., & Enders, C. (2015). A comparison of imputation strategies for ordinal missing data on Likert scale variables. Multivariate behavioral research, 50(5), 484-503. (被引用 115 次)
- Applied Missing Data Analysis with SPSS and R
https://bookdown.org/mwheymans/bookmi/missing-data-in-questionnaires.html

遺失機制 (Missingness Mechanism)

collected data

$$X = \{X_o, X_m\}$$

observed elements　　　　missing elements

The missingness indicator matrix R corresponds X,
and each element of R is 1 if the corresponding element of X is missing,
and 0 otherwise.

define the missingness mechanism as
the probability of R conditional on
the values of the observed and missing elements of X:

$$Pr(R|X_o, X_m)$$

Missing by Design
Missing Completely at Random

- **依設計產生的遺失 (Missing by Design)**
  - **Excluded** some participants from the analysis because they are not part of the population under investigation.
  - missingness codes: (i) refused to answer; (ii) answered don't know; (iii) had a valid skip or (iv) was skipped by an enumerator error.

- **完全隨機遺失 (Missing Completely at Random, MCAR)**
  - missingness is independent of their own unobserved values and the observed data.

$$Pr(R|X) = Pr(R)$$

  - *例*: Miscoding or forgetting to log in answer.
  - **Imputation methods** rely on the missingness being of the MCAR type.

Missing at Random (MAR)
Missing Not at Random (MNAR)

- 隨機遺失 (Missing at Random, MAR) $Pr(R|X) = Pr(R|X_o)$
  - missingness does not depend on their unobserved value but does dependent on the observed data.
  - *例 1*: male participants (observed data) are more likely to refuse to fill out the **depression survey**, but it does not depend on the level of their depression (unobserved value).
  - *例2*: if men are more likely to tell you their weight than women, **weight** is MAR.
  - We can ignore missing data (= omit missing observations) if we have MAR or MCAR.

- 非隨機遺失 (Missing Not at Random, MNAR)
  - Missingness that depends on the missing value itself.
  - *例*: question about **income**, where the high rate of missing values (usually 20%~50%) is related to the value of the income itself (very high and very low values will not be answered).
  - MNAR data is a more serious issue. (not ignorable)

一些注意事項

- Assuming data is **MCAR**, too much missing data can be a problem.
  - Usually a safe maximum threshold is 5% of the total for large datasets.
  - If missing data for a certain feature or sample is more than 5% then you probably should leave that feature or sample out.
- If some variable is missing almost 25% of the data points.
  - Consider either dropping it from the analysis or gather more measurements.
  - Keep the other variables are below the 5% threshold.
- 類別變數的補值(categorical variable): replacing categorical variables is usually not advisable.
  - Some common practice include replacing missing categorical variables with the mode of the observed ones (questionable).
- 我的資料有需要做補值嗎?
- 補值後的資料不可改變「原資料結構」!
- 常聽到:「資料補值後，分類演算法的正確率提昇了」?!

R Packages for Dealing With Missing Values

https://cran.r-project.org/web/packages/package-name/

- **`Amelia (Amelia II)`**: A Program for Missing Data
- **`hot.deck:`** Multiple Hot-Deck Imputation
- **`HotDeckImputation`**: Hot Deck Imputation Methods for Missing Data
- **`impute`**: (Bioconductor) Imputation for Microarray Data
- **`mi`**: Missing Data Imputation and Model Checking
- **`mice`**: Multivariate Imputation by Chained Equations
- **`missForest:`** Nonparametric Missing Value Imputation using Random Forest
- **`missMDA`**: Handling Missing Values with Multivariate Data Analysis (e.g., imputePCA, imputeMCA,)
- **`mitools`**: Tools for Multiple Imputation of Missing Data
- **`norm:`** Analysis of Multivariate Normal Datasets with Missing Values
- **`VIM`**: Visualization and Imputation of Missing Values
- R packages support for missing values imputation.
  - **`Hmisc:`** Harrell Miscellaneous
  - **`survey`**: analysis of complex survey samples
  - **`Zelig`**: Everyone's Statistical Software
  - **`rfImpute{randomForest}`**: Imputations by randomForest
  - **`imputation{rminer}`**: Data Mining Classification and Regression Methods, Missing data imputation (e.g. substitution by value or hotdeck method).
  - **`impute.svd{bcv}`**: Cross-Validation for the SVD (Bi-Cross-Validation), Missing value imputation via a low-rank SVD approximation estimated by the EM algorithm.
  - **`mlr`**: Machine Learning in R provides several imputation methods.
    https://mlr-org.github.io/mlr-tutorial/release/html/index.html

Package "**`imputation`**" was removed from the CRAN. (Archived on 2014-01-14)

列表刪除法 (List-wise Deletion)

- Also called the **complete case analysis**.
- All units with missing data for a variable are removed and the analysis is performed with the remaining units (complete cases).
- This is the default approach in most statistical packages.
- The use of this method is only justified if the missing data generation mechanism is **MCAR**.
- In R, using the function `na.omit()` or extract complete observations using the function `complete.cases()`.

```
> mdata <- matrix(rnorm(15), nrow=5)
> mdata[sample(1:15, 4)] <- NA
> mdata <- as.data.frame(mdata)
> mdata
           V1         V2          V3
1 -0.62222501  1.0807983          NA
2  0.07124865  0.5216675 -0.08334454
3  1.70707399  0.1004917  0.88197789
4          NA -0.6595201 -0.08387860
5          NA  1.6138847          NA
> (x1 <- na.omit(mdata))
          V1        V2          V3
2 0.07124865 0.5216675 -0.08334454
3 1.70707399 0.1004917  0.88197789
> (x2 <- mdata[complete.cases(mdata),])
          V1        V2          V3
2 0.07124865 0.5216675 -0.08334454
3 1.70707399 0.1004917  0.88197789
> mdata[!complete.cases(mdata),]
         V1         V2         V3
1 -0.622225  1.0807983         NA
4        NA -0.6595201 -0.0838786
5        NA  1.6138847         NA
```

快速分析一下，得知資料大概狀況

Mean/Median Substitution

- A very simple but popular approach is to substitute means for the missing values.
- The method preserves sample size and does not reduce the statistical power associated with sample size in comparison with list-wise or pairwise deletion.
- This method produces biased estimates and can severely distort the distribution of the variable in which missing values are substituted.
- This results in underestimates of the standard deviations and distorts relationships between variables (estimates of the correlation are pulled toward zero).

Due to these **distributional problems**, it is often recommended to ignore missing values rather than impute values by mean substitution (Little and Rubin, 1989.)

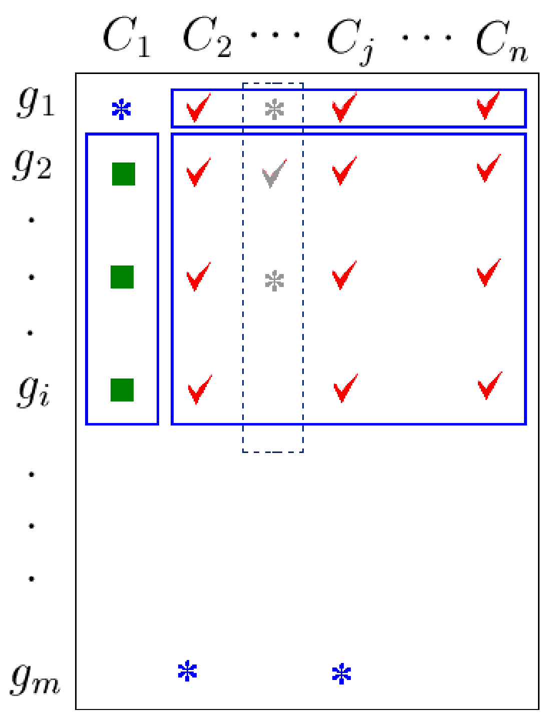
```
mean.subst <- function(x) {
   x[is.na(x)] <- mean(x, na.rm = TRUE)
   x
}
```

```
median(x, na.rm = TRUE)
```

```
> mdata
           V1        V2          V3
1 -0.62222501  1.0807983          NA
2  0.07124865  0.5216675 -0.08334454
3  1.70707399  0.1004917  0.88197789
4          NA -0.6595201 -0.08387860
5          NA  1.6138847          NA
> mdata.mip <- apply(mdata, 2, mean.subst)
> mdata.mip
              V1         V2          V3
[1,] -0.62222501  1.0807983  0.23825158
[2,]  0.07124865  0.5216675 -0.08334454
[3,]  1.70707399  0.1004917  0.88197789
[4,]  0.38536588 -0.6595201 -0.08387860
[5,]  0.38536588  1.6138847  0.23825158
```

K-Nearest Neighbour Imputation

- The k-nearest neighbour imputation searches for the k-nearest observations (respective to the observation which has to be imputed) and replaces the missing value with the mean of the found *k* observations.
- It is recommended to use the (weighted) median instead of the arithmetic mean.
- **KNN** minimize data modeling assumptions and take advantage of the correlation structure of the data.



KNNimpute

Model:

$$\{g_{(k)}, k = 1, 2, \cdots, K\} = \underset{k}{\text{args}} \max_{i \in \mathrm{C}} \mathrm{Corr}(g_1, g_i)$$

$$\{g_{(k)}, k = 1, 2, \cdots, K\} = \underset{k}{\text{args}} \min_{i \in \mathrm{C}} \mathrm{Dist}(g_1, g_i)$$

C: Observed C_i's without missing values

Imputation:

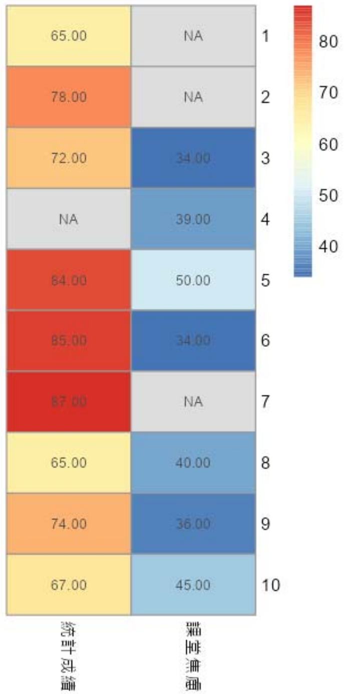
Average $\widehat{C_1(g_1)} = \frac{1}{K} \sum_{k=1}^{K} C_1(g_k)$

Weighted Average $\widehat{C_1(g_1)} = \frac{\sum_{k=1}^{K} w_k C_1(g_k)}{\sum_{k=1}^{K} w_k}$

$$w_k = \frac{1}{\sum_{j \in \mathrm{C}} [C_j(g_k) - C_1(g_1)]^2}$$

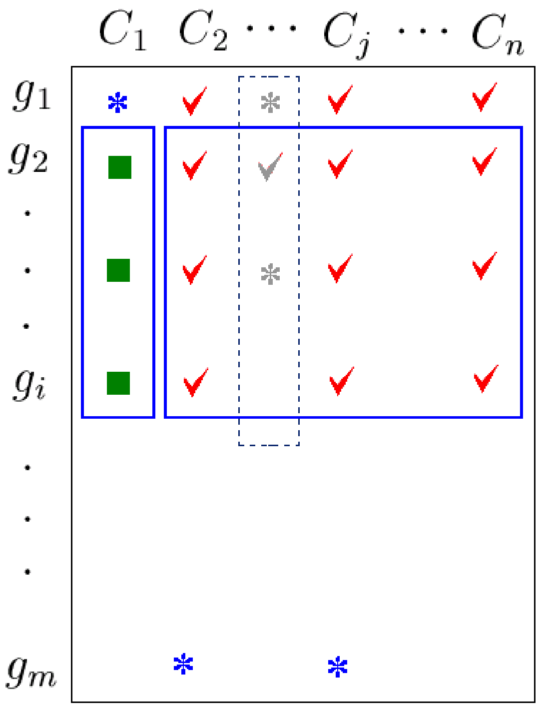
knn.impute{bnstruct}

```
> library(bnstruct)
>
> missing_data <- read.csv("data/置換遺漏值.csv")
> missing_data
   編號 統計成績 課堂焦慮
1     1       65       NA
2     2       78       NA
...
10   10       67       45
> str(missing_data)
'data.frame':         10 obs. of  3 variables:
 $ 編號    : int  1 2 3 4 5 6 7 8 9 10
 $ 統計成績: int  65 78 72 NA 84 85 87 65 74 67
 $ 課堂焦慮: int  NA NA 34 39 50 34 NA 40 36 45
> summary(missing_data)
      編號            統計成績          課堂焦慮
 Min.   : 1.00   Min.   :65.00   Min.   :34.00
 1st Qu.: 3.25   1st Qu.:67.00   1st Qu.:35.00
 Median : 5.50   Median :74.00   Median :39.00
 Mean   : 5.50   Mean   :75.22   Mean   :39.71
 3rd Qu.: 7.75   3rd Qu.:84.00   3rd Qu.:42.50
 Max.   :10.00   Max.   :87.00   Max.   :50.00
                 NA's   :1       NA's   :3
> library(pheatmap)
> pheatmap(missing_data[, 2:3],
+          display_numbers = T,
+          cluster_rows = FALSE,
+          cluster_cols = FALSE)
> knn.impute(as.matrix(missing_data$統計成績),  k = 5)
> knn.impute(as.matrix(missing_data),  k = 5)
```



Regression Methods

- Using fitted regression values to replace missing values.
- The model must be chosen so that it does not yields invalid fitted values. e.g., negative values.
- This technique might be more accurate than simply substituting a measure of central tendency, since the imputed value is based on other input variables.
- This technique underestimates standard errors by underestimating the variance in x.



Regression

Model:

$$C_1 = \beta_0 + \sum_{j \in \mathrm{C}} \beta_j C_j$$

C: Observed C_i's without missing values

Imputation:

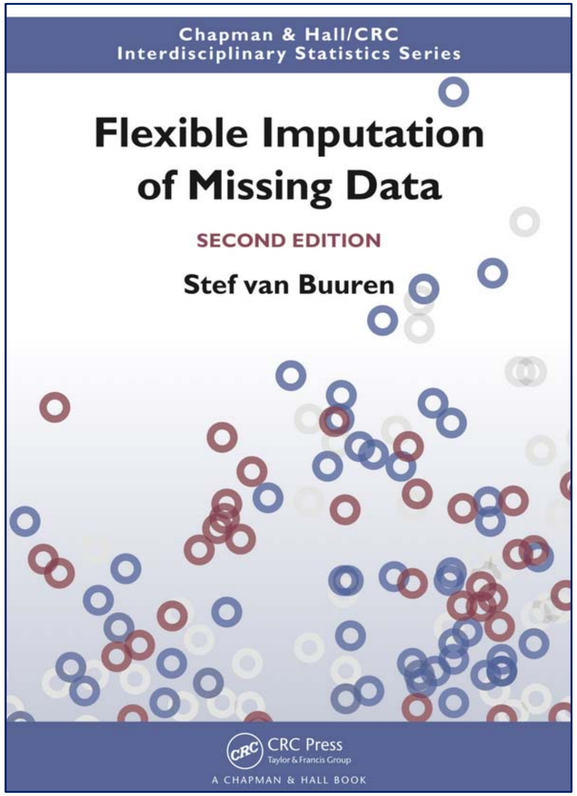
$$\widehat{C_1(g_1)} = \hat{\beta}_0 + \sum_{j \in \mathrm{C}} \hat{\beta}_j C_j(g_1)$$

R Package: mice

- **mice**: Multivariate Imputation by Chained Equations in R by Stef van Buuren.

- Imputing missing values on:
  - Continuous data: Predictive mean matching, Bayesian linear regression, Linear regression ignoring model error, Unconditional mean imputation etc.
  - Binary data: Logistic Regression, Logistic regression with bootstrap
  - Categorical data (More than 2 categories) - Polytomous logistic regression, Proportional odds model etc.
  - Mixed data (Can work for both Continuous and Categorical) - CART, Random Forest, Sample (Random sample from the observed values).

電子書
Flexible Imputation of Missing Data



https://stefvanbuuren.name/fimd

Source: http://www.listendata.com/2015/08/missing-imputation-with-mice-package-in.html

Imputation using MICE Package

```
> mydata <- airquality
> mydata[4:10,3] <- rep(NA,7)
> mydata[1:5,4] <- NA
>
> #Use numerical variables as examples here.
> #Ozone is the variable with the most missing datapoints.
> data <- mydata[-c(5,6)]
> summary(mydata)
     Ozone           Solar.R          Wind             Temp           Month            Day
 Min.   :  1.00   Min.   :  7.0   Min.   : 1.700   Min.   :57.00   Min.   :5.000   Min.   : 1.0
 1st Qu.: 18.00   1st Qu.:115.8   1st Qu.: 7.400   1st Qu.:73.00   1st Qu.:6.000   1st Qu.: 8.0
 Median : 31.50   Median :205.0   Median : 9.700   Median :79.00   Median :7.000   Median :16.0
 Mean   : 42.13   Mean   :185.9   Mean   : 9.806   Mean   :78.28   Mean   :6.993   Mean   :15.8
 3rd Qu.: 63.25   3rd Qu.:258.8   3rd Qu.:11.500   3rd Qu.:85.00   3rd Qu.:8.000   3rd Qu.:23.0
 Max.   :168.00   Max.   :334.0   Max.   :20.700   Max.   :97.00   Max.   :9.000   Max.   :31.0
 NA's   :37       NA's   :7       NA's   :7        NA's   :5
>
> #Check the missing percentages for features (columns) and samples (rows)
> pMiss <- function(x){sum(is.na(x))/length(x)*100}
> apply(mydata, 2, pMiss)
    Ozone   Solar.R      Wind      Temp     Month       Day
24.183007  4.575163  4.575163  3.267974  0.000000  0.000000
> apply(mydata, 1, pMiss)
  [1] 16.66667 16.66667 16.66667 33.33333 66.66667 33.33333 16.66667 16.66667 16.66667
33.33333 16.66667  0.00000
...
[145]  0.00000  0.00000  0.00000  0.00000  0.00000 16.66667  0.00000  0.00000  0.00000
```

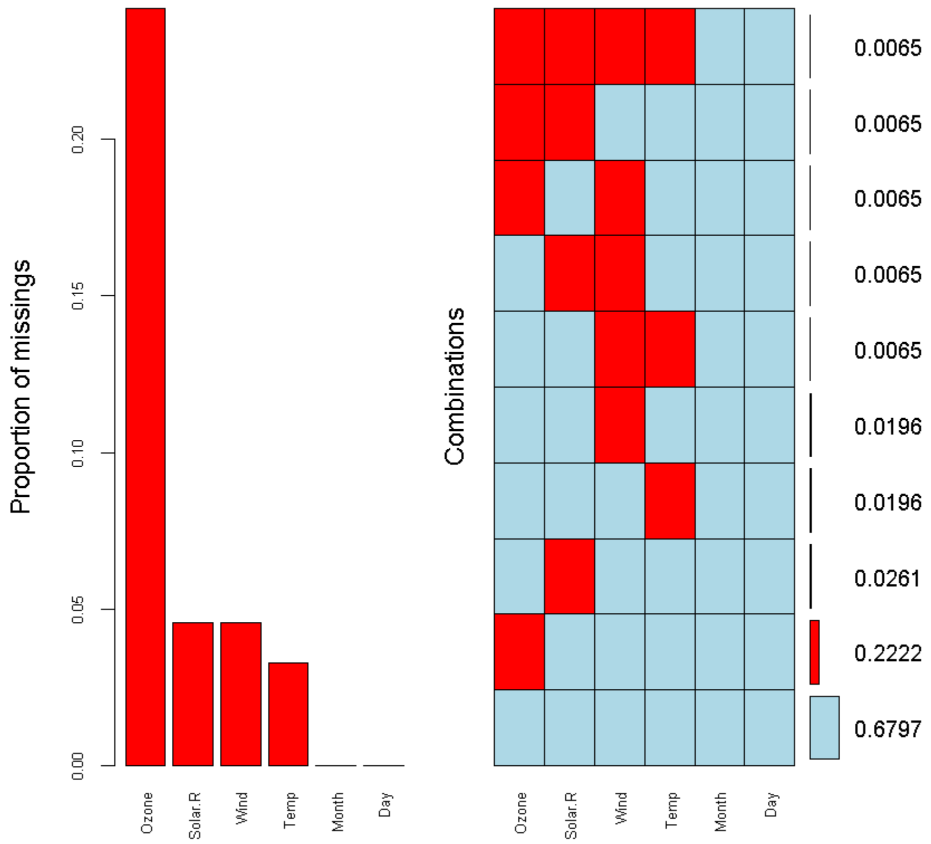
Sourec: http://www.r-bloggers.com/imputing-missing-data-with-r-mice-package/

Visualizing the Pattern of Missing Data

```
> library(mice)
> md.pattern(mydata)
    Month Day Temp Solar.R Wind Ozone
104     1   1    1       1    1     1  0
 34     1   1    1       1    1     0  1
  4     1   1    1       0    1     1  1
  3     1   1    1       1    0     1  1
  3     1   1    0       1    1     1  1
  1     1   1    1       0    1     0  2
  1     1   1    1       1    0     0  2
  1     1   1    1       0    0     1  2
  1     1   1    0       1    0     1  2
  1     1   1    0       0    0     0  4
        0   0    5       7    7    37 56
```

```
> library(VIM)
> mydata.aggrplot <- aggr(mydata,
col=c('lightblue','red'), numbers=TRUE,
prop = TRUE, sortVars=TRUE,
labels=names(mydata), cex.axis=.7, gap=3)

 Variables sorted by number of missings:
 Variable      Count
    Ozone 0.24183007
  Solar.R 0.04575163
     Wind 0.04575163
     Temp 0.03267974
    Month 0.00000000
      Day 0.00000000
```

#104 samples are complete, 34 samples miss only the Ozone measurement, 4 samples miss only the Solar.R value and so on.



Number of Observations Per Patterns for All Pairs of Variables

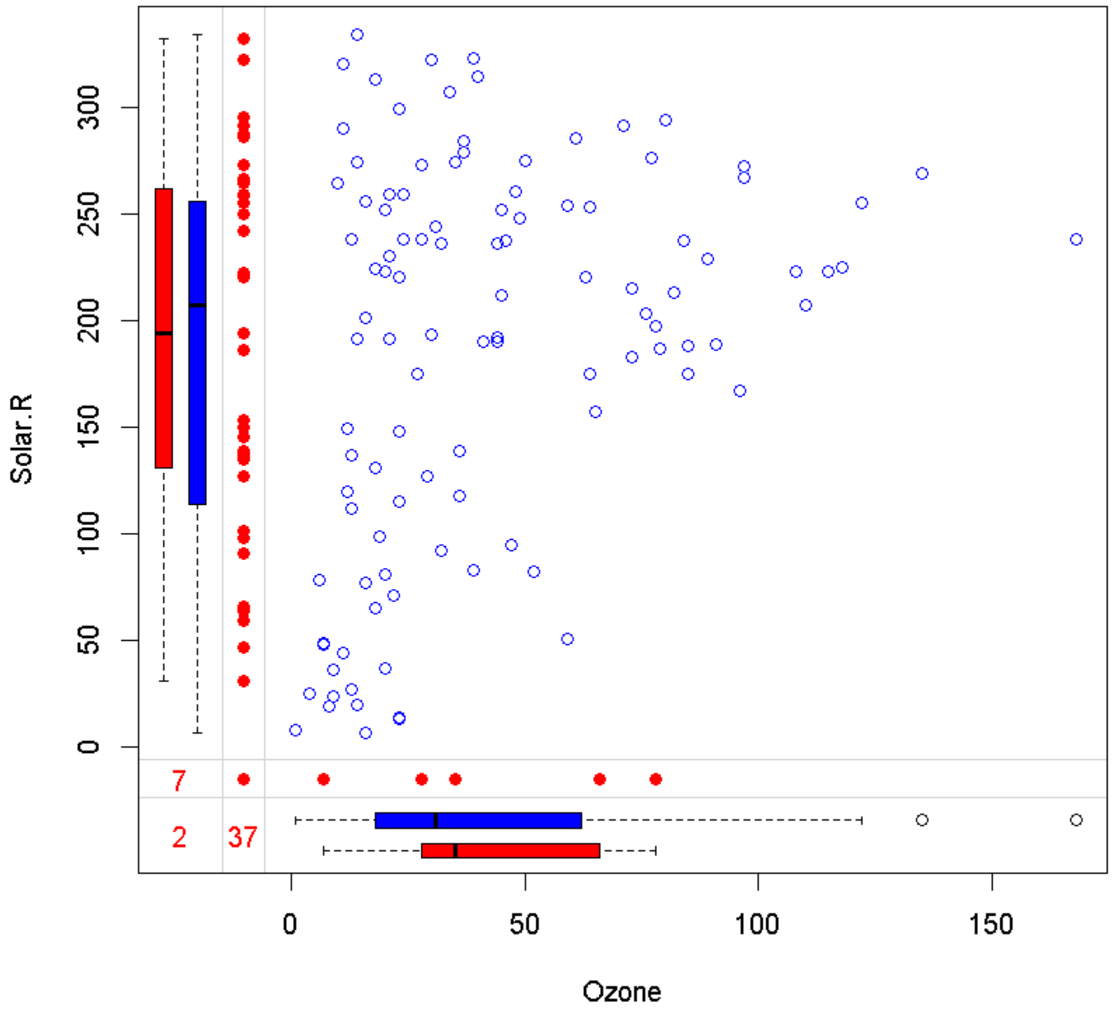
```
> md.pairs(mydata)
$rr
        Ozone Solar.R Wind Temp Month Day
Ozone     116     111  111  112   116 116
Solar.R   111     146  141  142   146 146
Wind      111     141  146  143   146 146
Temp      112     142  143  148   148 148
Month     116     146  146  148   153 153
Day       116     146  146  148   153 153

$rm
        Ozone Solar.R Wind Temp Month Day
Ozone       0       5    5    4     0   0
Solar.R    35       0    5    4     0   0
Wind       35       5    0    3     0   0
Temp       36       6    5    0     0   0
Month      37       7    7    5     0   0
Day        37       7    7    5     0   0
```

- **rr**: response-response, both variables are observed
- **rm**: response-missing, row observed, column missing
- **mr**: missing-response, row missing, column observed
- **mm**: missing-missing, both variables are missing

```
$mr
        Ozone Solar.R Wind Temp Month Day
Ozone       0      35   35   36    37  37
Solar.R     5       0    5    6     7   7
Wind        5       5    0    5     7   7
Temp        4       4    3    0     5   5
Month       0       0    0    0     0   0
Day         0       0    0    0     0   0

$mm
        Ozone Solar.R Wind Temp Month Day
Ozone      37       2    2    1     0   0
Solar.R     2       7    2    1     0   0
Wind        2       2    7    2     0   0
Temp        1       1    2    5     0   0
Month       0       0    0    0     0   0
Day         0       0    0    0     0   0
```

Marginplot

```
> marginplot(mydata[,c("Ozone", "Solar.R")], col = c("blue", "red"))
```



- The blue box plot located on the left and bottom margins shows the distribution of the non-missing datapoints.
- The red box plot on the left shows the distribution of Solar.R with Ozone missing while
- Likewhise for the Ozone box plots at the bottom of the graph.
- If our assumption of MCAR data is correct, then we expect the red and blue box plots to be very similar.

Generates Multivariate Imputations by Chained Equations (MICE)

```
mice(data, m = 5, method = vector("character", length = ncol(data)),
  predictorMatrix = (1 - diag(1, ncol(data))),
  visitSequence = (1:ncol(data))[apply(is.na(data), 2, any)],
  form = vector("character", length = ncol(data)),
  post = vector("character", length = ncol(data)), defaultMethod = c("pmm",
  "logreg", "polyreg", "polr"), maxit = 5, diagnostics = TRUE,
  printFlag = TRUE, seed = NA, imputationMethod = NULL,
  defaultImputationMethod = NULL, data.init = NULL, ...)
```

```
> methods(mice)
 [1] mice.impute.2l.norm      mice.impute.2l.pan       mice.impute.2lonly.mean
 [4] mice.impute.2lonly.norm  mice.impute.2lonly.pmm   mice.impute.cart
 [7] mice.impute.fastpmm      mice.impute.lda          mice.impute.logreg
[10] mice.impute.logreg.boot  mice.impute.mean         mice.impute.norm
[13] mice.impute.norm.boot    mice.impute.norm.nob     mice.impute.norm.predict
[16] mice.impute.passive      mice.impute.pmm          mice.impute.polr
[19] mice.impute.polyreg      mice.impute.quadratic    mice.impute.rf
[22] mice.impute.ri           mice.impute.sample       mice.mids
[25] mice.theme
see '?methods' for accessing help and source
Warning message:
In .S3methods(generic.function, class, paren
  function 'mice' appears not to be S3 generic; fou
```

Method	Description	Scale type	Default
pmm	Predictive mean matching	numeric	Y
norm	Bayesian linear regression	numeric	
norm.nob	Linear regression, non-Bayesian	numeric	
mean	Unconditional mean imputation	numeric	
2L.norm	Two-level linear model	numeric	
logreg	Logistic regression	factor, 2 levels	Y
polyreg	Multinomial logit model	factor, >2 levels	Y
polr	Ordered logit model	ordered, >2 levels	Y
lda	Linear discriminant analysis	factor	
sample	Random sample from the observed data	any	

PMM (Predictive Mean Matching) – For numeric v

Impute Missing Values

```
> mydata.ip <- mice(mydata, m = 5, maxit = 50, meth = 'pmm', seed = 500)

 iter imp variable
  1   1  Ozone  Solar.R  Wind  Temp
  1   2  Ozone  Solar.R  Wind  Temp
...
  50   4  Ozone  Solar.R  Wind  Temp
  50   5  Ozone  Solar.R  Wind  Temp
> summary(mydata.ip)
Multiply imputed data set
Call:
mice(data = mydata, m = 5, method = "pmm", maxit = 50, seed = 500)
Number of multiple imputations:  5
Missing cells per column:
  Ozone Solar.R    Wind    Temp   Month     Day
     37       7       7       5       0       0
Imputation methods:
  Ozone Solar.R    Wind    Temp   Month     Day
  "pmm"   "pmm"   "pmm"   "pmm"   "pmm"   "pmm"
VisitSequence:
  Ozone Solar.R    Wind    Temp
      1       2       3       4
PredictorMatrix:
        Ozone Solar.R Wind Temp Month Day
Ozone       0       1    1    1     1   1
Solar.R     1       0    1    1     1   1
Wind        1       1    0    1     1   1
Temp        1       1    1    0     1   1
Month       0       0    0    0     0   0
Day         0       0    0    0     0   0
Random generator seed value:  500
```

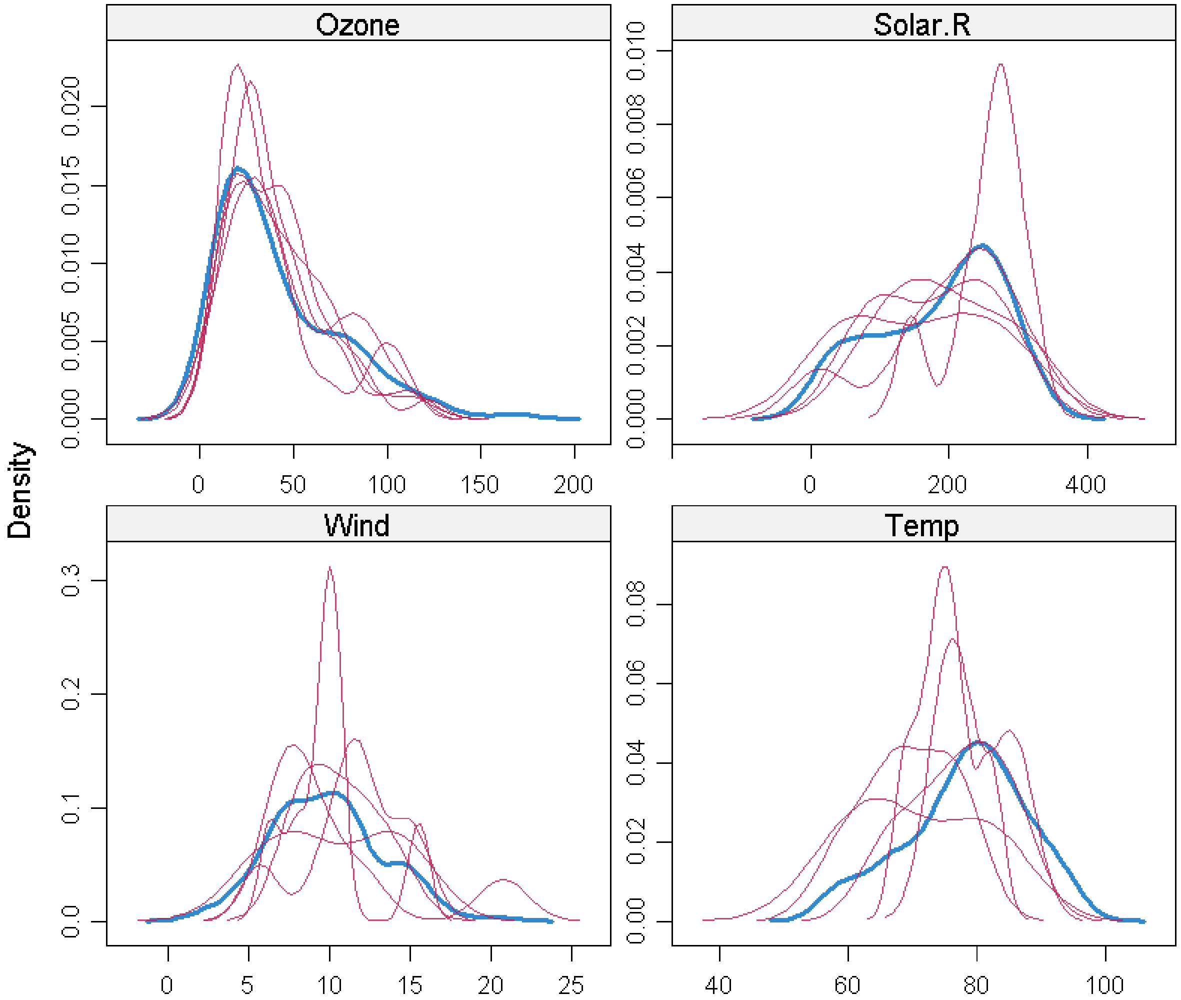
```
> mydata.ip$imp$Ozone
>  1   2   3   4   5
5      59  85  20 108  18
10     11   7  27  14  21
...
150     9  34  27  12  22
```

The output shows the imputed data for each observation (first column left) within each imputed dataset (first row at the top).

```
> # get back the first completed dataset out of 5
> mydata.completed <- complete(mydata.ip, 1)
```

Density Plot

```
> densityplot(mydata.ip)
```



The density of the imputed data for each imputed dataset is showed in magenta while the density of the observed data is showed in blue. Under MCAR, we expect the distributions to be similar.

Pooling

- Next step: fit a linear model to the data.
- **mice** fit a model to each of the imputed dataset and then pool the results together.

```
> # linear regression for each imputed data set - 5 regression are run
> modelFit1 <- with(mydata.ip, lm(Temp ~ Ozone + Solar.R + Wind))
> # pool coefficients and standard errors across all 5 regression models
> summary(pool(modelFit1))
                    est          se          t       df     Pr(>|t|)        lo 95
(Intercept) 71.11418579 2.840129171 25.0390674 85.04465 0.000000e+00 65.467290906
Ozone        0.17412083 0.025108183  6.9348239 72.90551 1.383136e-09  0.124079199
Solar.R      0.01004273 0.007163085  1.4020115 87.03503 1.644683e-01 -0.004194599
Wind        -0.21504110 0.222484210 -0.9665454 61.98616 3.375274e-01 -0.659782671
                  hi 95 nmis       fmi    lambda
(Intercept) 76.76108067   NA 0.1459648 0.1261138
Ozone        0.22416246   37 0.1734348 0.1510666
Solar.R      0.02428005    7 0.1418215 0.1223252
Wind         0.22970047    7 0.2026905 0.1773735
```

To reduce the effect of the random seed initialization, we can impute a higher number of dataset, by changing the default **m = 5** parameter in the **mice()** function.

```
mydata.ip2 <- mice(mydata, m = 50, seed = 245435)
modelFit2 <- with(mydata.ip2,lm(Temp ~ Ozone + Solar.R + Wind))
summary(pool(modelFit2))
```

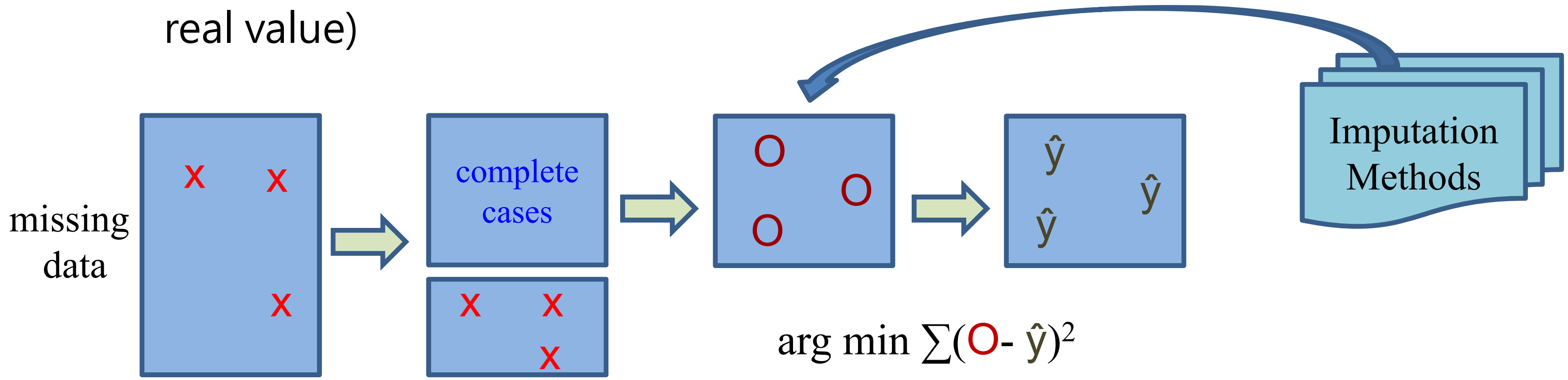
Quick Tutorial on MICE Package

```
> # Generate 10% missing values at Random
> iris.mis <- prodNA(iris, noNA = 0.1)  # library(missForest)
> # Check missing values introduced in the data
> summary(iris.mis)
> iris.mis <- subset(iris.mis, select = -c(Species))
> summary(iris.mis)
>
> #  A tabular form of missing value present in each variable
> library(mice)
> md.pattern(iris.mis)
> # Visualization
> library(VIM)
> mice_plot <- aggr(iris.mis, col=c('navyblue','yellow'), numbers=TRUE, sortVars=TRUE,
                    labels=names(iris.mis), cex.axis=.7,
                    gap=3, ylab=c("Missing data","Pattern"))

> #  Imputation
> imputed_Data <- mice(iris.mis, m=5, maxit = 50, method = 'pmm', seed = 500)
> summary(imputed_Data)
> # Check imputed values
> imputed_Data$imp$Sepal.Width
> # Get complete data ( 2nd out of 5)
> completeData <- complete(imputed_Data,2)
> #  Build predictive model
> fit <- with(data = imputed_Data, exp = lm(Sepal.Width ~ Sepal.Length + Petal.Width))
> #  Combine results of all 5 models
> combine <- pool(fit)
> summary(combine)
```

Source: http://www.analyticsvidhya.com/blog/2016/03/tutorial-powerful-packages-imputing-missing-values/

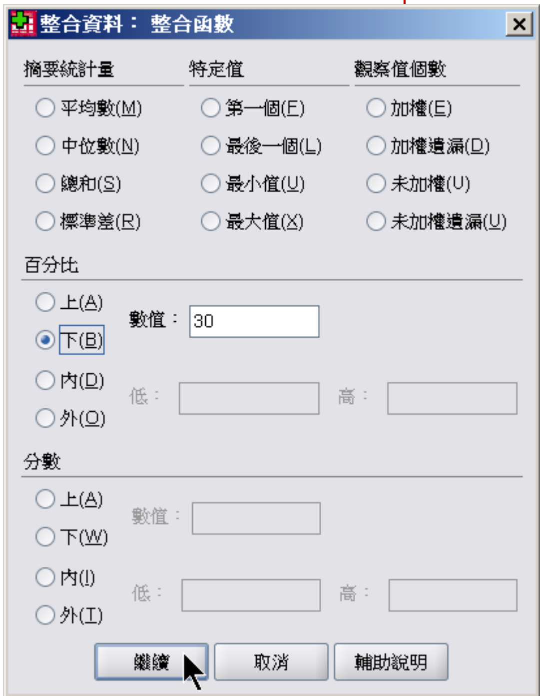
哪一種補值方法較好?

- KNN is the most widely-used.
- Characteristics of data **that may affect choice of imputation method:**
  - dimensionality.
  - percentage of values missing.
  - experimental design (time series, case/control, etc.)
  - patterns of correlation in data.
- 建議:
  - add (**same percentage**) artificial missing values to your (**complete cases**) data set.
  - impute them with various methods, see which is best (since you know the real value)



資料整合

```
> aggre_data <- read.csv("data/整合資料.csv")
> head(aggre_data)
  性別 學校規模 年齡 工作壓力 工作滿意 組織承諾
1    1        1   32       24       12       24
2    1        1   28       26       14       40
...
6    1        1   29       25       30       54
> str(aggre_data)
'data.frame':           90 obs. of  6 variables:
 $ 性別    : int  1 1 1 1 1 1 1 1 1 1 ...
 $ 學校規模: int  1 1 1 1 1 1 1 1 1 1 ...
 $ 年齡    : int  32 28 25 31 28 29 27 28 28 26 ...
 $ 工作壓力: int  24 26 30 31 24 25 34 40 20 24 ...
 $ 工作滿意: int  12 14 15 21 23 30 29 28 12 21 ...
 $ 組織承諾: int  24 40 54 52 53 54 52 51 32 64 ...
> aggre_data$性別 <- as.factor(aggre_data$性別)
> aggre_data$學校規模 <- as.factor(aggre_data$學校規模)
> str(aggre_data)
'data.frame':           90 obs. of  6 variables:
 $ 性別    : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...
 $ 學校規模: Factor w/ 3 levels "1","2","3": 1 1 1 1 1 1 1 1 1 1 ...
 $ 年齡    : int  32 28 25 31 28 29 27 28 28 26 ...
 $ 工作壓力: int  24 26 30 31 24 25 34 40 20 24 ...
 $ 工作滿意: int  12 14 15 21 23 30 29 28 12 21 ...
 $ 組織承諾: int  24 40 54 52 53 54 52 51 32 64 ...
>
> aggregate(aggre_data[, 3:6], by = list(性別 = aggre_data$性別,
+                                        學校規模 = aggre_data$學校規模),
+           FUN = function(x){round(mean(x), 2)})
  性別 學校規模  年齡 工作壓力 工作滿意 組織承諾
1    1        1 29.93    27.20    20.13    48.73
2    2        1 35.82    40.35    22.53    48.24
3    1        2 41.47    32.40    19.87    51.27
4    2        2 39.00    28.93    19.36    48.43
5    1        3 37.36    34.93    26.71    56.00
6    2        3 40.47    32.00    25.80    49.07
```




```
mean, median, sum, sd
x[1], x[length(x)], min, max
length(which(x > 0)) / length(x)
```

資料檢核與轉換
知識管理調查問卷

企業組織知識管理調查問卷

一、基本資料

1. 我的性別：□男生　□女生
2. 我的教育程度：□國小　□國中　□高中職　□專科大學　□研究所
3. 我的服務年資：□5 年以下　□6-10 年　□11-15 年　□16-20 年　□21 年以上

二、知識管理

	非常不同意	←		→	非常同意
1. 我覺得公司常請專家學者來授課或派員到外界接受訓練。	□	□	□	□	□
2. 我覺得公司有設置各種知識庫或書面資料等供員工學習。	□	□	□	□	□
3. 我覺得公司常透過教育訓練方式傳授工作的知能與技術。	□	□	□	□	□
4. 我覺得公司員工常會把經驗心得用口語、書面、實做表達。	□	□	□	□	□
5. 我覺得公司會注重資料的蒐集、分析與分類並加予儲存。	□	□	□	□	□
6. 我覺得公司員工不善用資訊科技尋找工作相關知識。	□	□	□	□	□
7. 我覺得公司員工常會將所獲得的知識在工作中嘗試。	□	□	□	□	□
8. 我覺得公司員工常用電腦設備與網路系統傳遞內部資訊。	□	□	□	□	□
9. 我覺得公司未建置多元溝通管道來與員工或外界傳遞資訊。	□	□	□	□	□
10. 我覺得公司經常採用各種不同的方法改善工作的流程。	□	□	□	□	□

- 知識管理量表經**預試效度分析**，建構效度包含二個層面(構念)。
  - 因素一包含題項1至題項6，命名為**知識獲取**。
  - 因素二包含題項7至題項10，命名為**知識流通**。
- 題項1至題項10所測量的特質，共同因素為「**知識管理**」。
- 第6題，第9題是反向題。

次數分配表

```
> trans_data_orig <- read.csv("data/資料轉換_1.csv")
> head(trans_data_orig)
  編號 性別 教育程度 服務年資 a1 a2 a3 a4 a5 a6 a7 a8 a9 a10
1    1    1        1        5  5  1  5  2  1  5  3  3  1   5
2    2    1        1        5  5  2  5  2  2  4  4  2  3   5
...
6    6    1        2        4  4  2  5  2  2  4  3  6  5   1
> str(trans_data_orig)
'data.frame':         55 obs. of  14 variables:
 $ 編號    : int  1 2 3 4 5 6 7 8 9 10 ...
 $ 性別    : int  1 1 1 1 1 1 1 1 1 1 ...
 $ 教育程度: int  1 1 2 2 2 2 2 2 2 2 ...
 $ 服務年資: int  5 5 4 4 4 4 4 4 4 4 ...
 $ a1      : int  5 5 5 5 1 4 4 4 1 4 ...
 ...
 $ a10     : int  5 5 4 3 2 1 2 3 5 4 ...
> summary(trans_data_orig[, c("性別", "教育程度", "服務年資")])
      性別            教育程度          服務年資
 Min.   :1.000   Min.   :1.000   Min.   :1.000
 1st Qu.:1.000   1st Qu.:2.000   1st Qu.:2.000
 Median :1.000   Median :3.000   Median :3.000
 Mean   :1.436   Mean   :3.091   Mean   :2.636
 3rd Qu.:2.000   3rd Qu.:4.000   3rd Qu.:4.000
 Max.   :3.000   Max.   :5.000   Max.   :5.000
```

有資料輸入錯誤　　　　要轉換成正確的類別

次數分配表

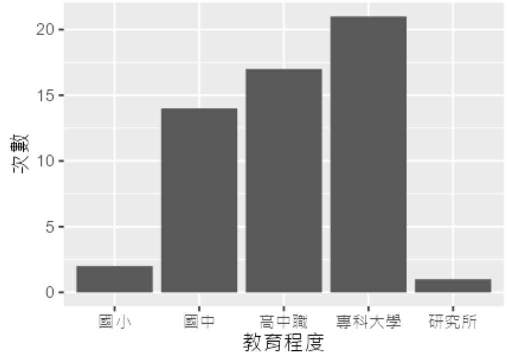
更正各背景變項鍵入錯誤數值。

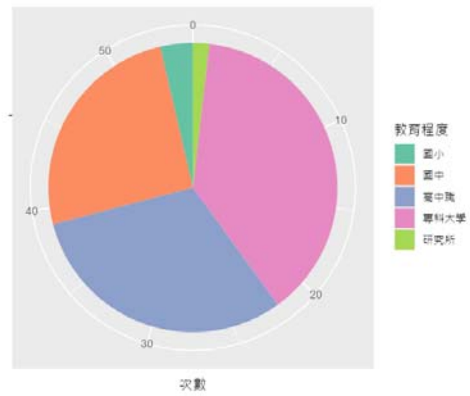
```
> trans_data <- trans_data_orig
> gender <- c("男生", "女生", NA)
> edu <- c("國小", "國中", "高中職", "專科大學", "研究所")
> work_year <- c("5年以下", "6-10年", "11-15年", "16-20年", "21年以上")
>
> trans_data$性別 <- factor(gender[trans_data_orig$性別], levels = gender)
> trans_data$教育程度 <- factor(edu[trans_data_orig$教育程度], levels = edu, ordered = T)
> trans_data$服務年資 <- factor(work_year[trans_data_orig$服務年資], levels = work_year, ordered = T)
> summary(trans_data[, c("性別", "教育程度", "服務年資")])
       性別          教育程度        服務年資
 男生     :33     國小     : 2    5年以下   :12
 女生     :20     國中     :14    6-10年   :13
 NA's    : 2     高中職    :17    11-15年 :15
                 專科大學 :21    16-20年 :13
                 研究所    : 1    21年以上: 2
>
> tbl_edu <- table(trans_data$教育程度)
> n <- length(trans_data$教育程度)
> freq_data <- data.frame(次數 = tbl_edu, 百分比 = round(tbl_edu/n, 2),
+               累積次數 = cumsum(tbl_edu),   累積百分比 = round(cumsum(tbl_edu/n), 2))
> freq_data$次數.Var1 <- NULL
> freq_data$百分比.Var1 <- NULL
> freq_data
         次數.Freq  百分比.Freq  累積次數   累積百分比
國小             2        0.04         2        0.04
國中            14        0.25        16        0.29
高中職          17        0.31        33        0.60
專科大學        21        0.38        54        0.98
研究所           1        0.02        55        1.00
```

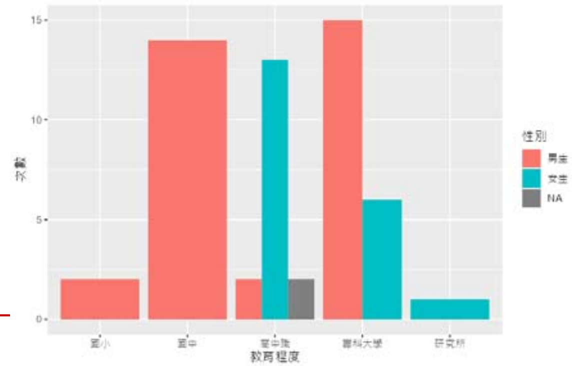
需組別合併

長條圖、圓餅圖

```
library(ggplot2)
ggplot(trans_data, aes(x = 教育程度)) +
  geom_bar() +
  labs(x = "教育程度", y = "次數")

trans_df <- data.frame(table(trans_data$教育程度))
names(trans_df) <- c("教育程度", "次數")
trans_df
教育程度 次數
1     國小    2
2     國中   14
3   高中職   17
4 專科大學   21
5   研究所    1

ggplot(trans_df, aes(x = "", y = 次數, fill = 教育程度)) +
  geom_bar(width = 1, stat = "identity") +
  labs(x = "", fill = "教育程度") +
  coord_polar("y", start=0) +
  scale_fill_brewer(palette="Set2")


table(trans_data$性別, trans_data$教育程度)
       國小 國中 高中職 專科大學 研究所
  男生    2   14      2       15      0
  女生    0    0     13        6      1
ggplot(trans_data, aes(x = 教育程度, fill = 性別)) +
  geom_bar(position = "dodge") +
  labs(x = "教育程度", y = "次數")
```







組別合併: 重新編碼 (合併過少觀察值之組別)

```
> edu2 <- c("國中以下", "國中以下", "高中職", "專科大學以上", "專科大學以上")
> trans_data$教育程度 <- factor(edu2[trans_data_orig$教育程度], levels = unique(edu2),
ordered = T)
> table(trans_data$教育程度)

    國中以下        高中職      專科大學以上
          16            17            22
>
> work_year2 <- c("5年以下", "6-10年", "11-15年", "16年以上", "16年以上")
> trans_data$服務年資 <- factor(work_year2[trans_data_orig$服務年資], levels =
unique(work_year2), ordered = T)
> table(trans_data$服務年資)

 5年以下   6-10年   11-15年   16年以上
     12       13        15        15
>
> str(trans_data)
'data.frame':      55 obs. of  14 variables:
 $ 編號    : int  1 2 3 4 5 6 7 8 9 10 ...
 $ 性別    : Factor w/ 2 levels "男生","女生": 1 1 1 1 1 1 1 1 1 1 ...
 $ 教育程度: Ord.factor w/ 3 levels "國中以下"<"高中職"<..: 1 1 1 1 1 1 1 1 1 1 ...
 $ 服務年資: Ord.factor w/ 4 levels "5年以下"<"6-10年"<..: 4 4 4 4 4 4 4 4 4 4 ...
 $ a1      : int  5 5 5 5 1 4 4 4 1 4 ...
 ...
 $ a10     : int  5 5 4 3 2 1 2 3 5 4 ...
> trans_data$服務年資
 [1] 16年以上 16年以上 16年以上 16年以上 16年以上 16年以上 16年以上 ...
Levels: 5年以下 < 6-10年 < 11-15年 < 16年以上
> as.integer(trans_data$服務年資)
 [1] 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2 2 2
[36] 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1 1
```

教育程度重新編碼
1 => 1，2 => 1，3 => 2，4 => 3，5 => 3
國小、國中 => 國中以下
專科大學、研究所 => 專科大學以上

服務年資重新編碼
5 => 4
16-20年、21年以上 => 16年以上

題項檢核: 描述性統計量 (針對單一題項修正錯誤值)

```
> summary(trans_data[, 5:14])
       a1              a2              a3              a4              a5       
 Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
 1st Qu.:2.000   1st Qu.:1.000   1st Qu.:3.000   1st Qu.:1.000   1st Qu.:2.000  
 Median :4.000   Median :2.000   Median :4.000   Median :2.000   Median :2.000  
 Mean   :3.527   Mean   :2.109   Mean   :3.564   Mean   :2.255   Mean   :2.727  
 3rd Qu.:5.000   3rd Qu.:2.000   3rd Qu.:4.000   3rd Qu.:3.000   3rd Qu.:3.500  
 Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000  
       a6              a7              a8              a9            a10       
 Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.0   Min.   :1.000  
 1st Qu.:3.000   1st Qu.:3.000   1st Qu.:3.000   1st Qu.:2.0   1st Qu.:2.000  
 Median :4.000   Median :3.000   Median :5.000   Median :3.0   Median :3.000  
 Mean   :3.818   Mean   :3.236   Mean   :4.073   Mean   :3.2   Mean   :3.164  
 3rd Qu.:5.000   3rd Qu.:4.000   3rd Qu.:5.000   3rd Qu.:4.5   3rd Qu.:5.000  
 Max.   :5.000   Max.   :5.000   Max.   :6.000   Max.   :5.0   Max.   :5.000  
> sapply(trans_data[, 5:14], table)
$a1

 1  2  3  4  5 
 3 12 10 13 17 
...
$a8

 1  2  3  4  5  6 
 2  6  9  9 27  2 

...
> trans_data$a8[trans_data_orig$a8 == 6] <- 5 # NA
> table(trans_data$a8)

 1  2  3  4  5 
 2  6  9  9 29 
```

各題數值介於1-5。
最小值有可能大於1
最大值不能超過5

反向題的反向計分

- 問句範例:「不善用」「未建置」
- 李克特五點量表:
  「非常不同意」<= =>「非常同意」
- 進行層面加總與總分計算，須反向計分。
- 「1 -> 5」「2 -> 4」...「5 -> 1」

```
> trans_data <- trans_data_orig
> table(trans_data$a6)
 1  2  3  4  5
 1  3 16 20 15
> trans_data$a6 <- 6 - trans_data$a6
> table(trans_data$a6)
 1  2  3  4  5
15 20 16  3  1
>
> table(trans_data$a9)
> trans_data$a9 <- 6 - trans_data$a9
> table(trans_data$a9)
```

```
> likert_5 <- c("非常不同意", "不同意", "普通", "同意", "非常同意")
> trans_data$a1 <- factor(likert_5[trans_data_orig$a1], levels = likert_5, ordered = T)
> trans_data$a1
 [1] 非常同意   非常同意   非常同意   非常同意   非常不同意 同意       同意
...
Levels: 非常不同意 < 不同意 < 普通 < 同意 < 非常同意
> table(trans_data$a1)
非常不同意     不同意       普通       同意   非常同意
         3         12         10         13         17
> trans_data_a1_to_a10 <- sapply(5:14, function(x){
+   factor(likert_5[trans_data[, x]], levels = likert_5, ordered = T)
+ })
> colnames(trans_data_a1_to_a10) <- paste0("a", 1:10)
> head(trans_data_a1_to_a10)
          a1             a2           a3         a4         a5             a6        a7
[1,] "非常同意"   "非常不同意" "非常同意" "不同意" "非常不同意" "非常不同意" "普通"
...
```

層面加總

- 問卷調查中，某種特質，態度，行為等潛在構念，不能逐題分析。
- 單一題項所測量的不足以代表某一潛在特質或構念。
- 潛在特質或構念通常包含數個題項。
- 屬性相似的題項所要測量的共同特質稱為「建構效度」。
- 「建構效度」中的層面測量是數個題項的加總分數。
- 例如:
  - 「知識獲取」層面: 包含六個題項。
  - 「知識流通」層面: 包含四個題項。

各層面的加總及計算層面單題平均

```
> score_sum <- data.frame(知識獲取層面加總 = rowSums(trans_data[, 5:10]),
+                         知識流通層面加總 = rowSums(trans_data[, 11:14]),
+                         知識管理層面加總 = rowSums(trans_data[, 5:14]))
>
> head(score_sum)
  知識獲取層面加總 知識流通層面加總 知識管理層面加總
1               15               16               31
2               18               14               32
3               19               10               29
4               18               11               29
5               13               10               23
6               17               10               27
>
> score_average <- data.frame(知識獲取層面平均 = rowMeans(trans_data[, 5:10]),
+                             知識流通層面平均 = rowMeans(trans_data[, 11:14]),
+                             知識管理層面平均 = rowMeans(trans_data[, 5:14]))
>
> head(score_average)
  知識獲取層面平均 知識流通層面平均 知識管理層面平均
1         2.500000             4.00              3.1
2         3.000000             3.50              3.2
3         3.166667             2.50              2.9
4         3.000000             2.75              2.9
5         2.166667             2.50              2.3
6         2.833333             2.50              2.7
```

「知識獲取」各層面的加總: a1 ~ a6
「知識流通」層面的加總: a7 ~a10
「知識管理」層面的加總: a1 ~a10

層面單題平均得分可以看出觀察值對構念特質的知覺感受到何種程度。

層面間之比較

- 層面包含題項數不同，無法從層面的平均數比較。
- 如何進行層面間的比較: 求出樣本觀察值在層面或總量表得分之單題平均的描述性統計量。
  - 「知識獲取層面單題平均」的平均=2.7273
  - 「知識流通層面單題平均」的平均=3.3182
  - 樣本觀察值在「知識流通」層面單題平均得分高於「知識獲取」層面單題平均得分。
- 此差異是否顯著，須加以檢定。

```
> apply(score_average, 2, mean)
知識獲取層面平均    知識流通層面平均    知識管理層面平均
      2.727273          3.309091          2.960000
> apply(score_average, 2, sd)
知識獲取層面平均    知識流通層面平均    知識管理層面平均
     0.5926189         0.5610086         0.4724248
```

求測驗成績百分等級

- 百分等級 (PR, percentile rank): 指觀察值在某個測量變項上的測量值(分數)，在團體中所占的等為多少。PR最高為99。
  - 例如: PR=80，表示100人的群體中，樣本觀察值的分數可以贏過80個人。
- 百分位數 (Pp, percentile point): 在群體中居某一個百分等級時的分數。
  - 例如: P80=75。百分等級為PR=80，數學測成績為75分。

```
> score_data <- read.csv("data/成績_1.csv")
> head(score_data)
  班級 性別 數學 英文 測驗平均
1    1    1   60   66      63.0
...
> dim(score_data)
[1] 50  5
> score_data$數學
 [1]  60  42  78  65  68  57  55  97  87  92  75  55  64  71  78  84  85  76  71
...
> rank(score_data$數學) # rank(- score_data$數學)
 [1]  9.0  1.0 29.5 12.5 15.0  7.0  3.0 47.0 38.5 43.5 24.0  3.0 11.0 18.5 29.5
...
> rank(score_data$數學, ties.method = "first")
 [1]  9  1 28 12 15  6  2 47 37 43 23  3 11 17 29 33 35 26 18 30 32 19 16 22  5  7
...
> library(dplyr)
> round(percent_rank(score_data$數學) * 100)
 [1]  16   0  55  22  29  10   2  94  73  86  45   2  20  33  55  65  69  51  33
...
> quantile(score_data$數學, probs = seq(0, 1, 0.1))
   0%   10%   20%   30%   40%   50%   60%   70%   80%   90%  100% 
 42.0  56.9  63.6  69.4  71.6  75.5  78.0  85.0  87.4  94.1 100.0
```

求出數學成績的百分等級

等級觀察值

等級觀察值、次數分配表

```
> scores <- c(75, 82, 90, 65, 88, 72, 95, 60, 78, 85)
> percentile_75 <- quantile(scores, 0.75)
> percentile_rank_80 <- sum(scores <= 80) / length(scores) * 100
> cat("75th Percentile:", percentile_75, "\n")
75th Percentile: 87.25
> cat("Percentile Rank of 80:", percentile_rank_80, "%\n")
Percentile Rank of 80: 50 %
```

- 求出數學成績五個等第各組人數，並以長條圖及直方圖表示。
  - 等第一: >=90; 等第二: 80-89; 等第三: 70-79; 等第四: 60-69; 等第五: <=59

```
> rank_table <- c(">= 90", "80-89", "70-79", "60-69", "<= 60")
> score_to_rank <- function(x){
+   group_id <- ifelse(x >= 90, 1,
+                      ifelse(x >= 80, 2,
+                             ifelse(x >= 70, 3,
+                                    ifelse(x >= 60, 4, 5))))
+   data.frame(score = x,
+              rank = factor(rank_table[group_id], levels = rank_table, ordered = T),
+              row.names = NULL)
+ }
>
> math_data <- score_to_rank(score_data$數學)
> table(math_data$rank)

>= 90 80-89 70-79 60-69 <= 60
    9    10    16     7     8
>
> library(psych)
> describe(math_data$score)
   vars  n  mean    sd median trimmed   mad min max range  skew kurtosis   se
X1    1 50 75.78 13.96   75.5   75.92 16.31  42 100    58 -0.16     -0.8 1.97
```

Junk, Noisy Data, or Outlier

- As in a physics or statistics test, noise is a random error that occurs during the test process to seize the measured data. No matter what means you apply to the data gathering process, noise inevitably exists.

- **Deal with noisy data using smoothing**:
  - **Binning**: This is a local scope smoothing method in which the neighborhood values are used to compute the final value for the certain bin. The sorted data is distributed into a number of bins and each value in that bin will be replaced by a value depending on some certain computation of the neighboring values. The computation can be bin median, bin boundary, which is the boundary data of that bin.
  - **Regression**: The target of regression is to find the best curve or something similar to one in a multidimensional space; as a result, the other values will be used to predict the value of the target attribute or variable. In other aspects, it is a popular means for smoothing.

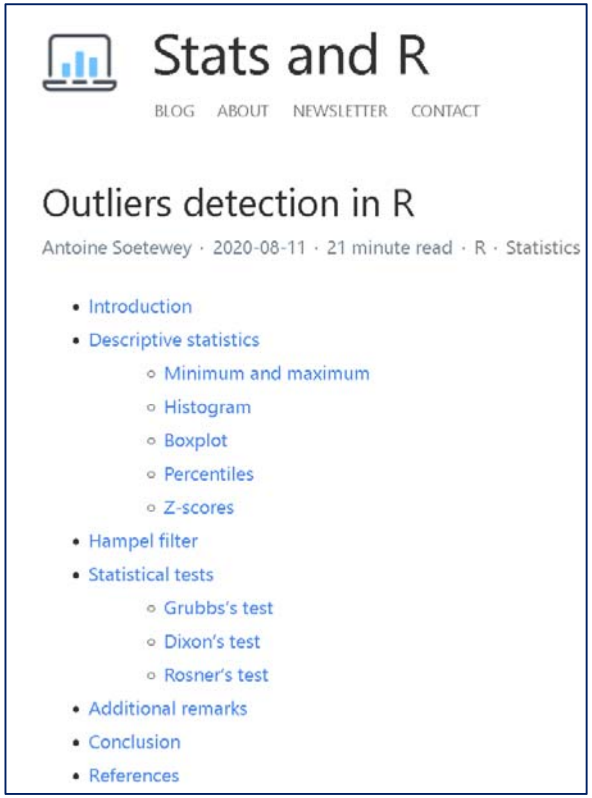
- Classification or outlier: The classifier is another inherent way to find the noise or outlier. During the process of classifying, most of the source data is grouped into couples of groups, except the outliers.

異常檢測的統計方法
(Outliers Detection in R)

- **Graphical techniques**: index plot, Boxplot side-by-side, scatterplot, heatmap and so on.
- **R packages:**
  - **`outliers`**: Tests for outliers，a collection of some tests commonly used for identifying outliers.
  - **`extRemes`**: Extreme Value Analysis.
  - **`in2extRemes`**: Into the extRemes Package, GUI to some of the functions in the package extRemes. (http://www.assessment.ucar.edu/toolkit/)
  - **`extremevalues`**: Univariate Outlier Detection
  - Extreme Value Analysis(EVA) packages in R: **`evd, evdbayes, evir, fExtremes, lmom, SpatialExtremes, texmex, extRemes, ismev, texmex, ismev`**

- **Robust approaches to data with outliers:** Robustify the classical algorithm by replacing the sample mean vector and covariance matrix with the robust location and scatter estimators.

Outliers detection in R: https://statsandr.com/blog/outliers-detection-in-r/



See also: Chapter 7, Outlier Detection, RDataMining-book-2015

Outliers Detection

- **Graphical techniques**: index plot, Boxplot side-by-side, scatterplot, heatmap and so on.
- R packages:
  - **`outliers`**: Tests for outliers
    - A collection of some tests commonly used for identifying outliers.
    https://cran.r-project.org/web/packages/outliers/index.html
    - Grubbs' test (Grubbs 1969 and Stefansky 1972) is used to detect outliers in a univariate data set. It is based on the assumption of normality. That is, you should first verify that your data can be reasonably approximated by a normal distribution before applying the Grubbs' test.
  - **`extRemes`**: Extreme Value Analysis.
  - **`in2extRemes`**: Into the extRemes Package, GUI to some of the functions in the package extRemes. (http://www.assessment.ucar.edu/toolkit/)
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- Robust approaches to data with outliers
  - Robustify the classical algorithm by replacing the sample mean vector and covariance matrix with the robust location and scatter estimators.

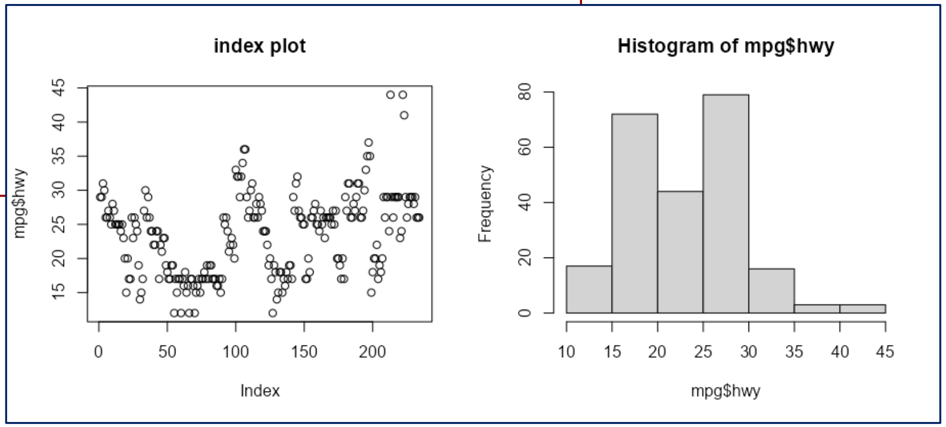
See also: Chapter 7, Outlier Detection, RDataMining-book-2015

R package: ou1tliers StatistIcal Tests

- **`chisq.out.test`**: Chi-squared test for outlier
- **`cochran.test`**: Test for outlying or inlying variance
- **`dixon.test`**: Dixon tests for outlier
- **`grubbs.test`**: Grubbs tests for one or two outliers in data sample.

- Dixon, W.J. (1950). Analysis of extreme values. Ann. Math. Stat. 21, 4, 488-506.
- Dixon, W.J. (1951). Ratios involving extreme values. Ann. Math. Stat. 22, 1, 68-78.
- Snedecor, G.W., Cochran, W.G. (1980). Statistical Methods (seventh edition). Iowa State University Press, Ames, Iowa.
- Grubbs, F.E. (1950). Sample Criteria for testing outlying observations. Ann. Math. Stat. 21, 1, 27-58.


```
> library(outliers)
> dim(mpg)
[1] 234  11
> head(mpg, 3)
# A tibble: 3 x 11
  manufacturer model displ  year   cyl trans      drv     cty   hwy fl    class
  <chr>        <chr> <dbl> <int> <int> <chr>      <chr> <int> <int> <chr> <chr>
1 audi         a4      1.8  1999     4 auto(l5)   f        18    29 p     compact
2 audi         a4      1.8  1999     4 manual(m5) f        21    29 p     compact
3 audi         a4      2    2008     4 manual(m6) f        20    31 p     compact
>
> summary(mpg$hwy)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  12.00   18.00   24.00   23.44   27.00   44.00
> par(mfrow = c(1, 2))
> plot(mpg$hwy, main = "index plot")
> hist(mpg$hwy)
```



`mpg {ggplot2}`
Fuel economy data from 1999 to 2008 for 38 popular models of cars
`hwy`: highway miles per gallon

Grubbs' Test for a Single Outlier

- **Assumption**: the data (without any outliers) are approximately normally distributed.
- **Hypothesis**:
  - H_0: There are no outliers in the data set
  - H_1: There is exactly one outlier in the data set
- **Test Statistic**: ESD (extreme studentized deviate)

$$ESD = max_{i=1,\ldots,n} \frac{|X_i - \bar{X}|}{s}$$

- **Critical Region**: For the two-sided test, the hypothesis of no outliers is rejected if

The Grubbs test detects one outlier at a time (highest or lowest value), so the null and alternative hypotheses are as follows:

if we want to test the highest value

- H_0: The highest value is not an outlier
- H_1: The highest value is an outlier

if we want to test the lowest value.

- H_0: The lowest value is not an outlier
- H_1: The lowest value is an outlier

$$ESD > \frac{n-1}{\sqrt{n}} \sqrt{\frac{t^2}{n-2+t^2}}$$

where t is short for $t_{n-2,p}$ and $p = 1 - \alpha/(2n)$.

Grubbs, Frank (February 1969), Procedures for Detecting Outlying Observations in Samples, Technometrics, 11(1), pp. 1-21.

R package: outliers
StatistIcal Tests

```
> test <- grubbs.test(mpg$hwy)
> test

         Grubbs test for one outlier

data:  mpg$hwy
G = 3.45274, U = 0.94862, p-value = 0.05555
alternative hypothesis: highest value 44 is an outlier
>
>
> test <- grubbs.test(mpg$hwy, opposite = TRUE)
> test

         Grubbs test for one outlier

data:  mpg$hwy
G = 1.92122, U = 0.98409, p-value = 1
alternative hypothesis: lowest value 12 is an outlier

>
>
> dixon.test(mpg$hwy)
Error in dixon.test(mpg$hwy) : Sample size must be in range 3-30
>
```

> # The p-value is 0.056. At the 5% significance level, we do not reject the hypothesis that the highest value 44 is not an outlier.

> # At the 5% significance level, we do not reject the hypothesis that the lowest value 12 is not an outlier.

Robust Statistical Methods

CRAN Task View: Robust Statistical Methods

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

- Robust Location and Scatter Estimators
  - Median, MAD (median of the absolute deviations from the median)
  - M-estimator (Huber, 1964; Maronna, 1976)
  - Stahel-Donoho estimator (Stahel, 1981; Donoho, 1982)
  - MVE (minimum volume ellipsoid), MCD (minimum covariance determinant) (Rousseeuw, 1983, 1984, 1985)
  - S-estimator (Davis, 1987)
  - Depth weighted and maximum depth estimators (Zuo, Cui and He, 2004)

MVE (minimum volume ellipsoid)

- Affine equivariant with high breakdown points.
- The existing efficient algorithm for computation.
- Readily available implementations.
- Ability to Identify extreme values.

$$\text{Outlier values} \sim 2 \times \sqrt{\chi^2_{0.975,p}} + N(0,1)$$

```
> qchisq(0.975,5)
[1] 12.83250
```

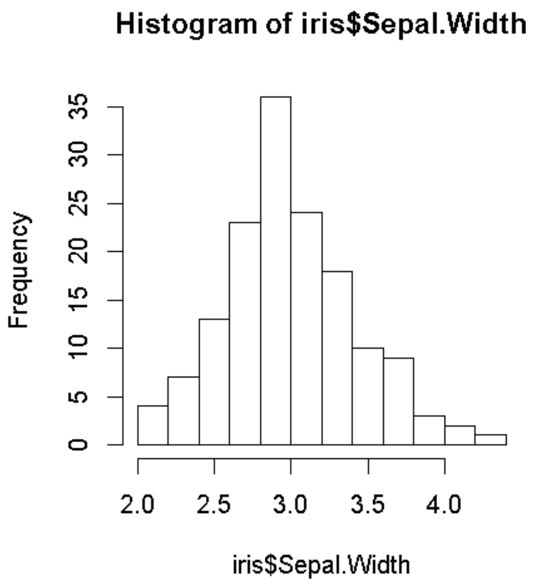
預檢資料:檢定變項是否符合常態分配
Formal Tests for Normality

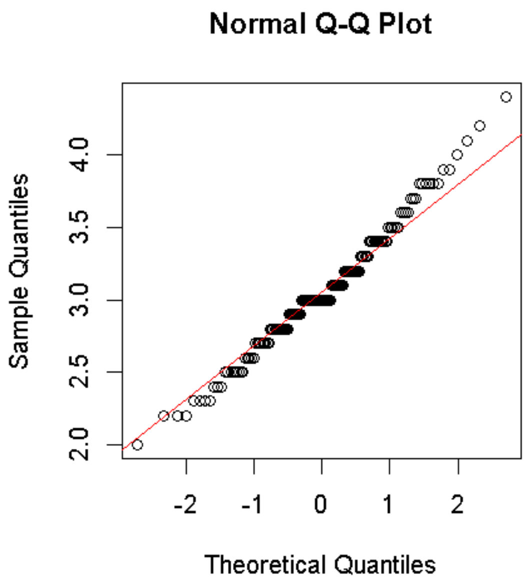
- The hypotheses used are:

H_0: The sample data are not significantly different than a normal population.

H_a: The sample data are significantly different than a normal population

```
> par(mfrow=c(1, 2))
> hist(iris$Sepal.Width)
> qqnorm(iris$Sepal.Width)
> qqline(iris$Sepal.Width, col="red")
```





Packages: `nortest`
Five omnibus tests for testing the composite hypothesis of normality:
`ad.test`, `cvm.test`, `lillie.test`, `pearson.test`, `sf.test`

ks.test, ad.test, shapiro.test

- Kolmogorov-Smirnov (K-S) test (Chakravarti et al., 1967).
- The Anderson-Darling test (Stephens, 1974).
- The Shapiro-Wilk normality test (Shapiro and Wilk, 1965).
- A large *p*-value (larger than, say, 0.05) indicates that the sample is not different from normal with the sample's mean and standard deviation.

```
> x <- iris$Sepal.Width
> ks.test(x, 'pnorm', mean(x), sd(x))

        One-sample Kolmogorov-Smirnov test

data:  x
D = 0.10566, p-value = 0.07023
alternative hypothesis: two-sided

Warning message:
In ks.test(x, "pnorm", mean(x), sd(x)) :
  ties should not be present for the Kolmogorov-Smirnov test
```

```
> library(nortest)
> ad.test(iris$Sepal.Width)

        Anderson-Darling normality test

data:  iris$Sepal.Width
A = 0.90796, p-value = 0.02023
```

```
> shapiro.test(iris$Sepal.Width)

        Shapiro-Wilk normality test

data:  iris$Sepal.Width
W = 0.98492, p-value = 0.1012
```

Which Normality Test Should I Use?

- **Kolmogorov-Smirnov test**:
  - The test applies to continuous densities only.
  - It is more sensitive near the center of the density than at the tails than other tests;
  - For data sets n > 50.
- **The Anderson-Darling test**:
  - A-D test is a modification of the K-S test and gives more weight to the tails of the density than does the K-S test. It is generally preferable to the K-S test.
- **Shapiro-Wilks test**:
  - Doesn't work well if several values in the data set are the same.
  - Works best for data sets with n < 50, but can be used with larger data sets.
- **W/S test (range(x)/sd(x))**: simple, but effective.
- **Jarque-Bera test** (`jarque.test {moments}`): tests for skewness and kurtosis, very effective.
- **D'Agostino test** (`agostino.test{moments}`) : powerful omnibus (skewness, kurtosis, centrality) test.

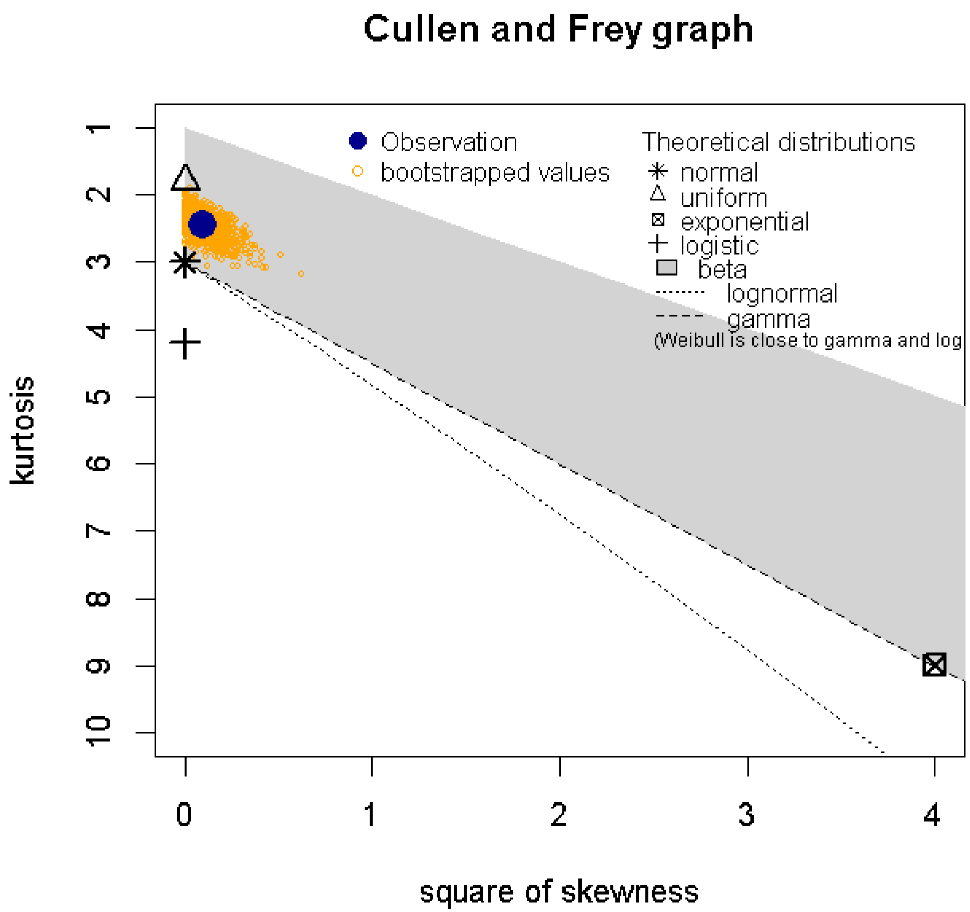
Which Normality Test Should I Use?

- Asghar Ghasemi and Saleh Zahediasl, Normality Tests for Statistical Analysis: A Guide for Non-Statisticians, Int J Endocrinol Metab. 2012 Spring; 10(2): 486–489.
  - assessing the normality assumption should be taken into account for using parametric statistical tests.
  - The K-S test, should no longer be used owing to its low power.
  - It is preferable that normality be assessed both visually and through normality tests, of which the **Shapiro-Wilk test** is highly recommended.

- NOTE:
  - If the data are not normal, use non-parametric tests.
  - If the data are normal, use parametric tests.
  - If you have groups of data, you MUST test each group for normality.
  - It's common seen that a model is built from the training data and is then applied to the testing data. Did these two data sets follow the same distribution?

fitdistrplus: An R Package for Fitting Distributions

```
> install.packages("fitdistrplus")
> library(fitdistrplus)
> x <-  iris$Sepal.Length
> descdist(x, boot=1000)
summary statistics
------
min:  4.3   max:  7.9
median:  5.8
mean:  5.843333
estimated sd:  0.8280661
estimated skewness:  0.314911
estimated kurtosis:  2.447936
> fit.n  <- fitdist(x, "norm")
> summary(fit.n)
Fitting of the distribution ' norm '
by maximum likelihood
Parameters :
      estimate Std. Error
mean 5.8433333 0.06738557
sd   0.8253013 0.04764848
Loglikelihood:  -184.0398
AIC:  372.0795   BIC:  378.1008
Correlation matrix:
     mean sd
mean    1  0
sd      0  1
```



rapidFitFun {qAnalyst}: Function to obtain rapid fitting of multiple distributions

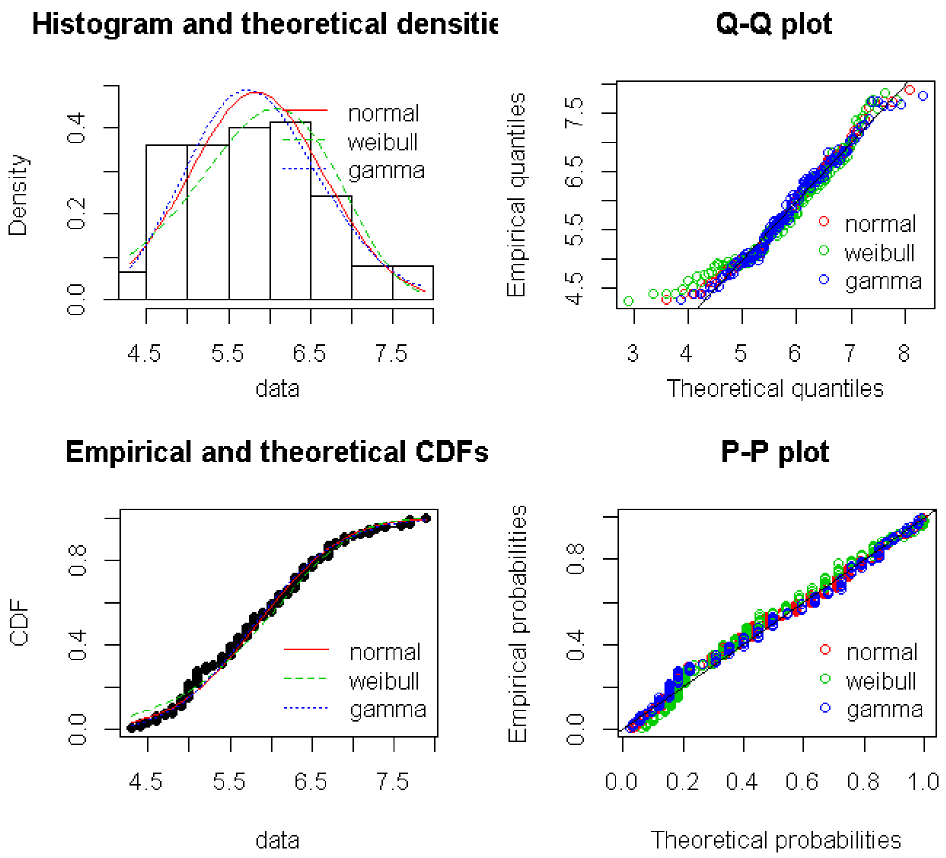
https://cran.r-project.org/web/packages/qAnalyst/index.html

Package 'qAnalyst' **was removed** from the CRAN repository.

Formerly available versions can be obtained from the archive.

fitdistrplus: An R Package for Fitting Distributions

```
> fit.w <- fitdist(x, "weibull")
> fit.g  <- fitdist(x, "gamma")
> par(mfrow=c(1 ,4))
> plot.legend <- c("normal", "weibull", "gamma")
> denscomp(list(fit.n,  fit.w, fit.g),  legendtext=plot.legend)
> qqcomp(list(fit.n,  fit.w, fit.g),  legendtext=plot.legend)
> cdfcomp(list(fit.n,  fit.w, fit.g),  legendtext=plot.legend)
> ppcomp(list(fit.n,  fit.w, fit.g),  legendtext=plot.legend)
```




```
> summary(fit.w)
Fitting of the distribution
'weibull' by maximum likelihood
Parameters :
      estimate Std. Error
shape 7.454379 0.45168136
scale 6.208005 0.07209406
Loglikelihood:   -190.7689
AIC:   385.5377    BIC:   391.559
Correlation matrix:
          shape     scale
shape 1.0000000 0.3323758
scale 0.3323758 1.0000000

> summary(fit.g)
Fitting of the distribution
'gamma' by maximum likelihood
Parameters :
       estimate Std. Error
shape 50.634073   5.827566
rate   8.665336   1.002253
Loglikelihood:   -182.3061
AIC:   368.6122   BIC:   374.6335
Correlation matrix:
          shape      rate
shape 1.0000000 0.9950669
rate  0.9950669 1.0000000
```