1. 從外部匯入資料

```
getData <- function(){
  csvFile <- file.path("D:/R/insurance.csv")
  data <- read.csv(csvFile,sep=",")
}</pre>
```

Dataset (Medical Cost Personal Datasets Insurance Forecast by using Linear Regression) 此 data 在研究不同地區的健保費與年紀、性別、BMI、是否有孩子以及是否抽菸等資料是否相關。

2.敘述統計

#觀察 dataset 前五筆資料 head(data,5)

```
bmi children smoker
                                   region
                                           charges
 age
        sex
  19 female 27.900
                            yes southwest 16884.924
                        0
  18 male 33.770
                             no southeast 1725.552
                       1
 28
       male 33.000
                       3
                             no southeast 4449.462
                      0
  33 male 22.705
                             no northwest 21984.471
      male 28.880
5
  32
                       0
                             no northwest 3866.855
```

#了解資料的統計特徵

查看 data summary summary(data)

> summary(data)

bmi children age sex Min. :18.00 Length:1338 Min. :15.96 Min. :0.000 1st Qu.:27.00 Class :character 1st Qu.:26.30 1st Qu.:0.000 Median :39.00 Mode :character Median :30.40 Median :1.000 Mean :39.21 Mean :30.66 Mean :1.095 3rd Qu.:51.00 3rd Qu.:34.69 3rd Qu.:2.000 :64.00 :53.13 Max. :5.000 Max. Max. smoker region charges Length:1338 Length: 1338 Min. : 1122 Class :character Class :character 1st Qu.: 4740

Mode :character Median : 9382 Mode :character Mean :13270

3rd Qu.:16640 Max. :63770

經過此步驟我觀察出:

1. age:年齡介在 18~64 之間 2.BMI :BMI 介於 15.96~53.13

3.children:有幾個小孩介在 0~5 個

4.charges:醫療保險費用介於 1122~6370

5.平均保險花費是 13270

6.各項欄位的極端值都蠻大的

使用 Hmisc 了解資料的統計特徵

library(Hmisc) #使用 Hmisc library

describe(data) #使用 Hmisc 的內建函數來查看 data summary

> describe(data)

data

7	Variables		1338	Observations	5			
age	n 1338 .25 27	missing 0 .50 39	distinct 47 .79	7 0.999 5 .90	Mean 39.21 .95 62	Gmd 16.21	.05 18	.10 19

lowest : 18 19 20 21 22, highest: 60 61 62 63 64

```
n missing distinct
    1338 0 2
Value female male
Frequency 662 676
Proportion 0.495 0.505
   n missing distinct Info Mean Gmd .05 .10
1338 0 548 1 30.66 6.893 21.26 22.99
.25 .50 .75 .90 .95
26.30 30.40 34.69 38.62 41.11
lowest: 15.960 16.815 17.195 17.290 17.385, highest: 48.070 49.060 50.380
 52.580 53.130
children
    n missing distinct Info Mean Gmd
1338 0 6 0.899 1.095 1.275
lowest: 0 1 2 3 4, highest: 1 2 3 4 5
Value 0 1 2 3 4 5 Frequency 574 324 240 157 25 18
Proportion 0.429 0.242 0.179 0.117 0.019 0.013
    n missing distinct
          0 2
    1338
Value no yes
Frequency 1064 274
Proportion 0.795 0.205
region
     n missing distinct
Value northeast northwest southeast southwest
Frequency 324 325 364 325
Proportion 0.242 0.243 0.272 0.243
charges
     n missing distinct Info Mean Gmd .05 .10
1338 0 1337 1 13270 12301 1758 2347
.25 .50 .75 .90 .95
4740 9382 16640 34832 41182
lowest: 1121.874 1131.507 1135.941 1136.399 1137.011
highest: 55135.402 58571.074 60021.399 62592.873 63770.428
```

經過此步驟我觀察出:

- 1.此資料在收集四個不同的地區的醫療保險費
- 2. 男女比接近 1:1

- 3.年齡、BMI 差距頗大
- 4.有接近八成的受試者不抽菸

#用視覺化的方式列出欄位資訊

(只針對 BMI,charges,children 這三欄做分析,因為只有這三欄是數字資料)

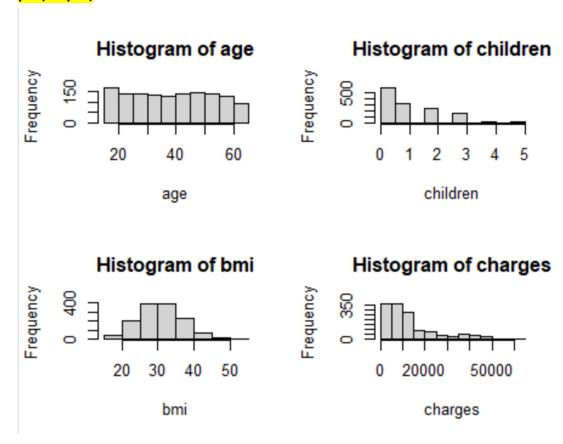
oldpar <- par(mfcol=c(2,2)) #讓圖表顯示成兩列兩欄

titles <- names(data) #取得欄位名稱

for(i in c(1,3,4,7)){ #1,3,4,7 的欄位是我們想要取得的三個欄位

hist(x=data[,i],main=paste("Histogram of",titles[i]),xlab=titles[i])

par(oldpar)



由此可觀察出:

- 1.BMI 大多介在 20-40
- 2.大多數沒有小孩
- 3.醫療保險費大多小於 20000

觀察在不同性別底下, Ages, BMI, children, charges 三個變數的關係

cor.all <- by(data[,c(1,3,4,7)],INDICES = data\$sex,cor) print(cor.all)</pre>

> print(cor.all)

data\$sex: female

age bmi children charges age 1.00000000 0.09721409 0.07849989 0.3245748 bmi 0.09721409 1.00000000 0.02215070 0.1614187 children 0.07849989 0.02215070 1.00000000 0.0584917 charges 0.32457479 0.16141865 0.05849170 1.0000000

data\$sex: male

age bmi children age 1.00000000 0.123088412 0.008689940 bmi 0.12308841 1.000000000 0.002385175 children 0.00868994 0.002385175 1.000000000 charges 0.28236853 0.225847080 0.074496435

charges age 0.28236853 bmi 0.22584708 children 0.07449643

charges 1.00000000

>

由此可觀察出:

不管男性或是女性醫療保險花費都和年齡以及 BMI 成正相關,與 children 成微弱正相關,因為相關性趨近於 0 表示花費跟有幾個小孩沒什麼關連性。

3.常態檢定

檢測 age,BMI,children,charges 是否是常態分布

#age

qqnorm(data\$age,main="age") # 常態機率圖 qqline(data\$age,col = "Red") #畫出最佳斜線 print(shapiro.test(data\$age[0:5000])) #shapiro-wilk 檢定

BMI

qqnorm(data\$bmi,main="BMI") qqline(data\$bmi= "Blue") print(shapiro.test(data\$bmi[0:5000]))

children

qqnorm(data\$ children,main="children")

qqline(data\$ children = "Green")

print(shapiro.test(data\$ children [0:5000]))

charges

qqnorm(data\$ charges,main="charges")

qqline(data\$ charges = "Yellow")

print(shapiro.test(data\$ charges [0:5000]))

- > qqnorm(data\$age,main="age")
- > qqline(data\$age,col = "Red")
- > print(shapiro.test(data\$age[0:5000]))

Shapiro-Wilk normality test

data: data\$age[0:5000] W = 0.9447, p-value < 2.2e-16

- Sample Quantiles 8 20
 - Theoretical Quantiles

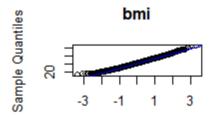
age

- qqnorm(data\$bmi,main="bmi")
- qqline(data\$bmi,col = "Blue")
- print(shapiro.test(data\$bmi[0:5000]))

Shapiro-Wilk normality test

data\$bmi[0:5000]

W = 0.99389, p-value = 2.605e-05

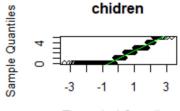


Theoretical Quantiles

- > qqnorm(data\$children,main="chidren")
- > qqline(data\$children,col = "Green")
- > print(shapiro.test(data\$children[0:5000]))

Shapiro-Wilk normality test

data: data\$children[0:5000] W = 0.82318, p-value < 2.2e-16

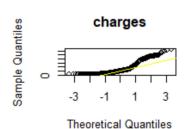


Theoretical Quantiles

- > qqnorm(data\$charges,main="charges")
- > qqline(data\$charges,col = "Yellow")
- > print(shapiro.test(data\$charges[0:5000]))

Shapiro-Wilk normality test

data: data\$charges[0:5000]
W = 0.81469, p-value < 2.2e-16</pre>



透過此步驟我觀察到

- 1.在 Shapiro-Wilk 檢定中得出的 Age,bmi,children,charges 的 p-value 都小於 0.05
- 2. charges 的常態機率圖中斜線與真實分布圖存在較大的差異;而 age,bmi,chidren 的常態機率圖中斜線與真實分布圖存在較小的差異
- 3.由前面兩個敘述可以得知前三欄資料為"常態性分布",而最後一欄資料則為"非 常態性分布"

4. 簡單線性回歸分析

#使用 ggplot2 package

install.packages("ggplot2")

library(ggplot2)

#建立模型

bmi <- data\$bmi

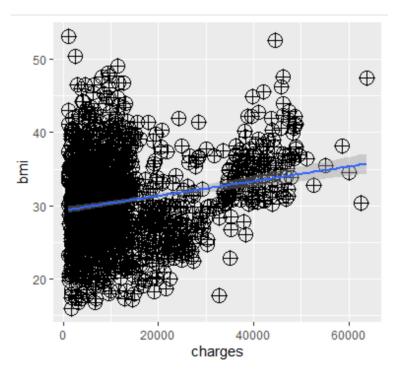
charges<- data\$charges

LM<-lm(bmi ~charges,data=data)

dev.off()#避免錯誤發生

畫出分布加預測圖

ggplot(data, aes(x=data\$charges, y=data\$bmi)) + geom_point(shape = 10, size = 5) + geom_smooth(method = lm) + labs(x = "charges", y = "bmi")



#取得方程式參數

summary(LM)

```
> summary(LM)
```

call:

lm(formula = bmi ~ charges, data = data)

Residuals:

Min 1Q Median 3Q Max -14.8424 -4.1030 -0.2401 3.8467 23.6758

Coefficients:

Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.934e+01 2.426e-01 120.956 < 2e-16 ***
charges 9.988e-05 1.350e-05 7.397 2.46e-13 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.979 on 1336 degrees of freedom Multiple R-squared: 0.03934, Adjusted R-squared: 0.03862 F-statistic: 54.71 on 1 and 1336 DF, p-value: 2.459e-13

由此觀察出:

- 1.此回歸模型公式可寫成 bmi = (2.934e+01)+(9.988e-05)*charges+e
- 2.Adjusted R-squared 偏小,表示此模型的預測能力偏低

#殘差性常態性檢定

shapiro.test(LM\$residual[0:5000])

由此觀察出:p-value 極低,故殘差值的常態性假設是不成立的

5. 利用預測函數取得結果

由此可知,醫療保險花費在 40000 時,模型預測出的 BMI 為 33.33