HW4

賴冠維

2020/11/16

Question 10

```
## Loading required package: ISLR

## Loading required package: tidyverse

## -- Attaching packages ----------------------------------------------------------------
--------------- tidyverse 1.3.0 --

## √ ggplot2 3.3.2     √ purrr   0.3.4
## √ tibble  3.0.3     √ dplyr   1.0.2
## √ tidyr   1.1.2     √ stringr 1.4.0
## √ readr   1.3.1     √ forcats 0.5.0

## -- Conflicts -------------------------------------------------------------------------
--------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

## Loading required package: ggthemes

## Warning: package 'ggthemes' was built under R version 4.0.3

## Loading required package: GGally

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2
```

(a)

Weekly 為 S&P500 指數從 1990 到 2010 的周報酬率資料， 資料組成有:
1. $Year$ (年份)
2. $Lag1-5$ (滯後 1-5 期的報酬率資料)

3. $Volume$ (成交量)

4. $Today$ (當日報酬率)

5. $Direction$ (當天是漲/跌)

```
## 'data.frame':    1089 obs. of  9 variables:
##  $ Year     : num  1990 1990 1990 1990 1990 1990 1990 1990 1990 1990 ...
##  $ Lag1     : num  0.816 -0.27 -2.576 3.514 0.712 ...
##  $ Lag2     : num  1.572 0.816 -0.27 -2.576 3.514 ...
##  $ Lag3     : num  -3.936 1.572 0.816 -0.27 -2.576 ...
##  $ Lag4     : num  -0.229 -3.936 1.572 0.816 -0.27 ...
##  $ Lag5     : num  -3.484 -0.229 -3.936 1.572 0.816 ...
##  $ Volume   : num  0.155 0.149 0.16 0.162 0.154 ...
```

```
##  $ Today    : num  -0.27 -2.576 3.514 0.712 1.178 ...
##  $ Direction: Factor w/ 2 levels "Down","Up": 1 1 2 2 2 1 2 2 2 1 ...
```

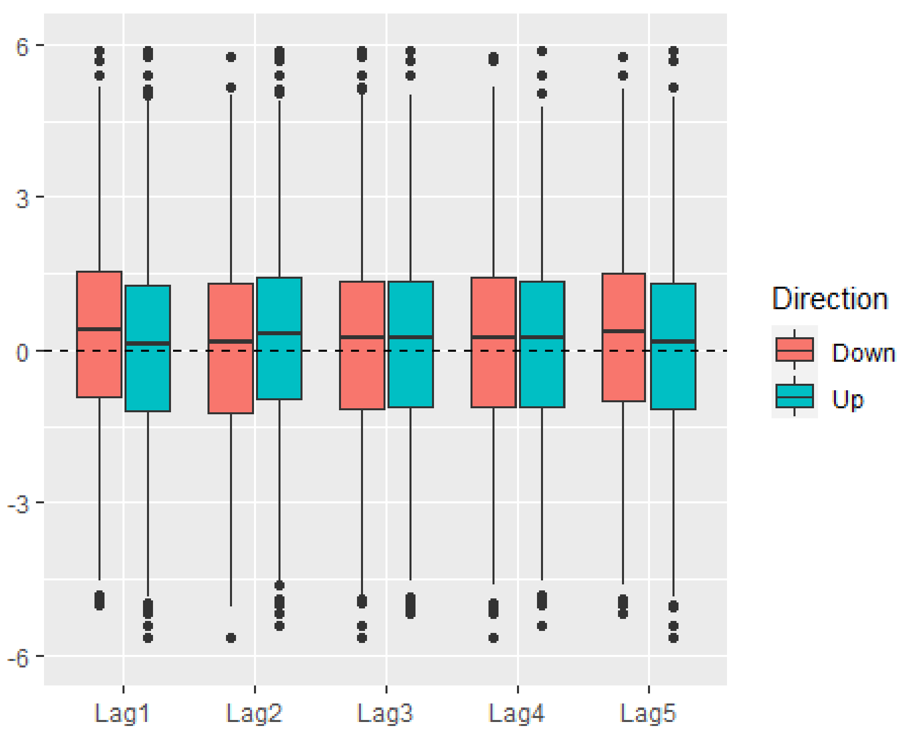
列出不同 Lag 期之下對應本日漲跌的幅度，單純從數字上看不太出有什麼關係

```
## `summarise()` regrouping output by 'Variable' (override with `.groups` argument)

## # A tibble: 12 x 6
## # Groups:   Variable [6]
##    Variable Direction    Q25 median    mean    Q75
##    <chr>    <fct>      <dbl>  <dbl>   <dbl>  <dbl>
##  1 Lag1     Down      -0.937  0.382  0.282   1.59
##  2 Lag1     Up        -1.24   0.099  0.0452  1.31
##  3 Lag2     Down      -1.31   0.154 -0.0404  1.30
##  4 Lag2     Up        -1.00   0.299  0.304   1.46
##  5 Lag3     Down      -1.15   0.250  0.208   1.41
##  6 Lag3     Up        -1.17   0.224  0.0989  1.42
##  7 Lag4     Down      -1.15   0.224  0.200   1.44
##  8 Lag4     Up        -1.16   0.241  0.102   1.35
##  9 Lag5     Down      -1.09   0.328  0.188   1.50
## 10 Lag5     Up        -1.20   0.128  0.102   1.34
## 11 Today    Down      -2.29  -1.33  -1.75   -0.592
## 12 Today    Up         0.63   1.25   1.67    2.22
```

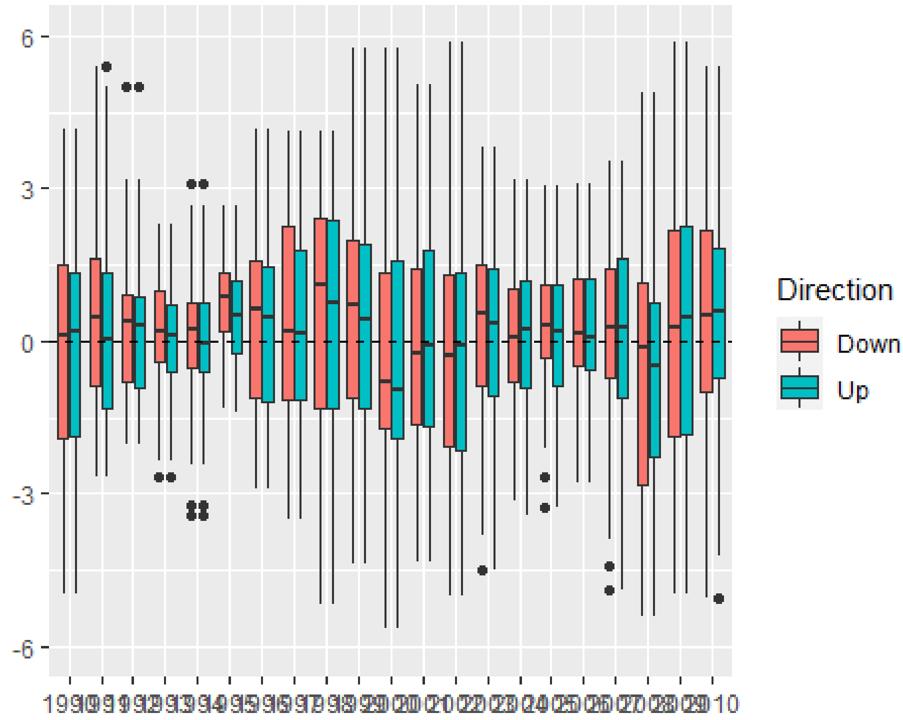
畫出 Box Plot 之後可以觀察到 Lag1、Lag2、Lag5 之下，Down 跟 Up 之間盒狀圖有顯著的差異

```
## Warning: Removed 125 rows containing non-finite values (stat_boxplot).
```



若是對 Year 畫出盒狀圖，可以看到 S&P500 報酬的波動有群聚的現象， 1992-1995 為波動較小的時期，而 1996 到 2002 波動較大，對應到當時正面臨網際網路泡沫的衝擊。

```
## Warning: Removed 125 rows containing non-finite values (stat_boxplot).
```



分別對 Lag1、Lag2 進行 Two Sample t-test， 在 90%信心水準下，拒絕虛無假設，代表不同 Direction 之下的 Lag1、Lag2 間存在差異。

```
##
##  Welch Two Sample t-test
##
## data:  Lag1 by Direction
## t = 1.6563, df = 1047.9, p-value = 0.09795
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.04378476  0.51794261
## sample estimates:
## mean in group Down   mean in group Up
##         0.28229545         0.04521653

##
##  Welch Two Sample t-test
##
## data:  Lag2 by Direction
## t = -2.4154, df = 1053.6, p-value = 0.01589
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.62473558 -0.06467351
## sample estimates:
## mean in group Down   mean in group Up
##        -0.04042355         0.30428099
```

(b)

去掉 Year,Today 變數後，因 Outcome 有兩個結果，family 使用 binomial，為 Logistic Regression。 由配飾結果可見，僅 Lag2 與截距項顯著拒絕虛無假設，通過個別 t 檢定，故在此認為僅 Lag2 為較有解釋力之變數。

```
##
## Call:
## glm(formula = Direction ~ . - Year - Today, family = "binomial",
##     data = Weekly)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6949  -1.2565   0.9913   1.0849   1.4579
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.26686    0.08593   3.106   0.0019 **
## Lag1        -0.04127    0.02641  -1.563   0.1181
## Lag2         0.05844    0.02686   2.175   0.0296 *
## Lag3        -0.01606    0.02666  -0.602   0.5469
## Lag4        -0.02779    0.02646  -1.050   0.2937
## Lag5        -0.01447    0.02638  -0.549   0.5833
## Volume      -0.02274    0.03690  -0.616   0.5377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1496.2  on 1088  degrees of freedom
## Residual deviance: 1486.4  on 1082  degrees of freedom
## AIC: 1500.4
##
## Number of Fisher Scoring iterations: 4
```

(c)

由下表可見準確率(Accuracy)僅 56.11%，下表視Up為$Positive$的情況下，Sensitivity 雖高達 92%， 但 Specificity 僅 11.16%，代表配飾的模型將絕大部分的資料都判斷為Up，並不能有效區別Up及$Down$。

```
## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift

## Confusion Matrix and Statistics
##
##
## pred_values  Up Down
##        Up   557  430
##        Down  48   54
##
```

```
##                Accuracy : 0.5611
##                  95% CI : (0.531, 0.5908)
##     No Information Rate : 0.5556
##     P-Value [Acc > NIR] : 0.369
##
##                   Kappa : 0.035
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9207
##             Specificity : 0.1116
##          Pos Pred Value : 0.5643
##          Neg Pred Value : 0.5294
##              Prevalence : 0.5556
##          Detection Rate : 0.5115
##    Detection Prevalence : 0.9063
##       Balanced Accuracy : 0.5161
##
##        'Positive' Class : Up
##
```

此處試驗全部都猜Up準確率也有 55.56%，代表上述模型配飾結果很差，跟全部猜Up差不多。

```
## [1] 0.5555556
```

(d)

因為此資料為時間序列的資料，因此在拆分 Train、Test 時不能像一般 Cross-Section 的資料隨機抽樣， 因此按照資料在 2008 年之前/後分為 Train、Test，並且只放入通過個別 t 檢定的變數:$Lag\ 2$。以 Train 資料配飾的 Logistic Regression 在配飾 Test 資料所得到的 Confusion Matrix 來看， 看似準確率有提升至 62.5%，但若是全部猜Up之下也有 58%的準確度，該模型依舊無顯著的預測能力。

```
## Confusion Matrix and Statistics
##
##
## pred_values Up Down
##        Up   56   34
##        Down  5    9
##
##                Accuracy : 0.625
##                  95% CI : (0.5247, 0.718)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.2439
##
##                   Kappa : 0.1414
##
##  Mcnemar's Test P-Value : 7.34e-06
##
##             Sensitivity : 0.9180
##             Specificity : 0.2093
##          Pos Pred Value : 0.6222
##          Neg Pred Value : 0.6429
##              Prevalence : 0.5865
##          Detection Rate : 0.5385
##    Detection Prevalence : 0.8654
##       Balanced Accuracy : 0.5637
```

```
##
##        'Positive' Class : Up
##

## [1] 0.5865385
```

(e)

使用 LDA 方法配飾預測模型，同樣僅放入Lag 2，發現準確率與 Logisitc 相同,並無提升。

```
## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

## Confusion Matrix and Statistics
##
##
## pred_values Up Down
##        Up   56   34
##        Down  5    9
##
##                Accuracy : 0.625
##                  95% CI : (0.5247, 0.718)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.2439
##
##                   Kappa : 0.1414
##
##  Mcnemar's Test P-Value : 7.34e-06
##
##             Sensitivity : 0.9180
##             Specificity : 0.2093
##          Pos Pred Value : 0.6222
##          Neg Pred Value : 0.6429
##              Prevalence : 0.5865
##          Detection Rate : 0.5385
##    Detection Prevalence : 0.8654
##       Balanced Accuracy : 0.5637
##
##        'Positive' Class : Up
##
```

(f)

使用 QDA 來預測之 Confusion Matrix，可得模型判所有的 Test 資料皆為Up，無預測能力。

```
## Confusion Matrix and Statistics
##
##
## pred_values Up Down
##        Up   61   43
##        Down  0    0
```

```
##
##                Accuracy : 0.5865
##                  95% CI : (0.4858, 0.6823)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.5419
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : 1.504e-10
##
##             Sensitivity : 1.0000
##             Specificity : 0.0000
##          Pos Pred Value : 0.5865
##          Neg Pred Value :    NaN
##              Prevalence : 0.5865
##          Detection Rate : 0.5865
##    Detection Prevalence : 1.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : Up
##
```

(g)

使用 KNN 演算法預測 Test 資料，我們需要先給定 center 有幾個，若我們設定 center=1，以 Train 進行配飾，並對 Test 資料預測所建立的 Confusion Matrix，準確率僅 50.82%，比全部猜Up還要更低。

```
## Loading required package: class

## Confusion Matrix and Statistics
##
##
## knn_pred Up Down
##     Up   31   22
##     Down 30   21
##
##                Accuracy : 0.5
##                  95% CI : (0.4003, 0.5997)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.9700
##
##                   Kappa : -0.0033
##
##  Mcnemar's Test P-Value : 0.3317
##
##             Sensitivity : 0.5082
##             Specificity : 0.4884
##          Pos Pred Value : 0.5849
##          Neg Pred Value : 0.4118
##              Prevalence : 0.5865
##          Detection Rate : 0.2981
##    Detection Prevalence : 0.5096
##       Balanced Accuracy : 0.4983
##
##        'Positive' Class : Up
##
```

使用 Naive Bayes 來預測之 Confusion Matrix，可得模型判所有的 Test 資料皆為Up，無預測能力。

```
## Loading required package: e1071

## Confusion Matrix and Statistics
##
##
## pred   Up Down
##   Up   61   43
##   Down  0    0
##
##                Accuracy : 0.5865
##                  95% CI : (0.4858, 0.6823)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.5419
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : 1.504e-10
##
##             Sensitivity : 1.0000
##             Specificity : 0.0000
##          Pos Pred Value : 0.5865
##          Neg Pred Value :    NaN
##              Prevalence : 0.5865
##          Detection Rate : 0.5865
##    Detection Prevalence : 1.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : Up
##
```

(h)

若是僅看 Accuracy 之下，可能會選擇 Logistic Regression 或是 LDA，但是我們可觀察到 KNN 在 Center=1 時，模型預測 Test 資料為$Down$大量出現，也讓 Specificity 明顯提升，故我們可試試看藉由調整 Center，優化 KNN 的結果。

(i)

將 Lag1、I(Volume^2)加進自變數進行 Logistic Regression，可發現 Accuracy 略下降，但是 Specificity 大幅提升，因此認為是較佳的模型。

```
## Confusion Matrix and Statistics
##
##
## pred_values Up Down
##        Up   30   16
##        Down 31   27
##
##                Accuracy : 0.5481
##                  95% CI : (0.4474, 0.6459)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.81516
##
##                   Kappa : 0.1139
```

```
##
##  Mcnemar's Test P-Value : 0.04114
##
##             Sensitivity : 0.4918
##             Specificity : 0.6279
##          Pos Pred Value : 0.6522
##          Neg Pred Value : 0.4655
##              Prevalence : 0.5865
##          Detection Rate : 0.2885
##    Detection Prevalence : 0.4423
##       Balanced Accuracy : 0.5599
##
##        'Positive' Class : Up
##
```

接著以相同的自變數帶入 LDA 模型，兩者結果相近。

```
## Confusion Matrix and Statistics
##
##
## pred_values Up Down
##        Up   32   17
##        Down 29   26
##
##                Accuracy : 0.5577
##                  95% CI : (0.457, 0.655)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.7579
##
##                   Kappa : 0.1241
##
##  Mcnemar's Test P-Value : 0.1048
##
##             Sensitivity : 0.5246
##             Specificity : 0.6047
##          Pos Pred Value : 0.6531
##          Neg Pred Value : 0.4727
##              Prevalence : 0.5865
##          Detection Rate : 0.3077
##    Detection Prevalence : 0.4712
##       Balanced Accuracy : 0.5646
##
##        'Positive' Class : Up
##
```

藉由測試 Center:1-14 之下的模型表現，選出 Accuracy 最高者，可發現在 k=13 之下有最高的 Accuracy。

```
##  [1] 0.5096154 0.5576923 0.5480769 0.5576923 0.5384615 0.5288462 0.5384615
##  [8] 0.5288462 0.5480769 0.5480769 0.5673077 0.5961538 0.5961538 0.5673077
## [15] 0.5865385 0.5384615
```

發現 KNN 在 k=13 之下，Accuracy 比上面兩模型表現更佳。

```
## Confusion Matrix and Statistics
##
```

```
##
## knn_pred Up Down
##     Up   40   23
##     Down 21   20
##
##                Accuracy : 0.5769
##                  95% CI : (0.4761, 0.6732)
##     No Information Rate : 0.5865
##     P-Value [Acc > NIR] : 0.6193
##
##                   Kappa : 0.1217
##
##  Mcnemar's Test P-Value : 0.8802
##
##             Sensitivity : 0.6557
##             Specificity : 0.4651
##          Pos Pred Value : 0.6349
##          Neg Pred Value : 0.4878
##              Prevalence : 0.5865
##          Detection Rate : 0.3846
##    Detection Prevalence : 0.6058
##       Balanced Accuracy : 0.5604
##
##        'Positive' Class : Up
##
```

Question 11

mpg 資料變數介紹：

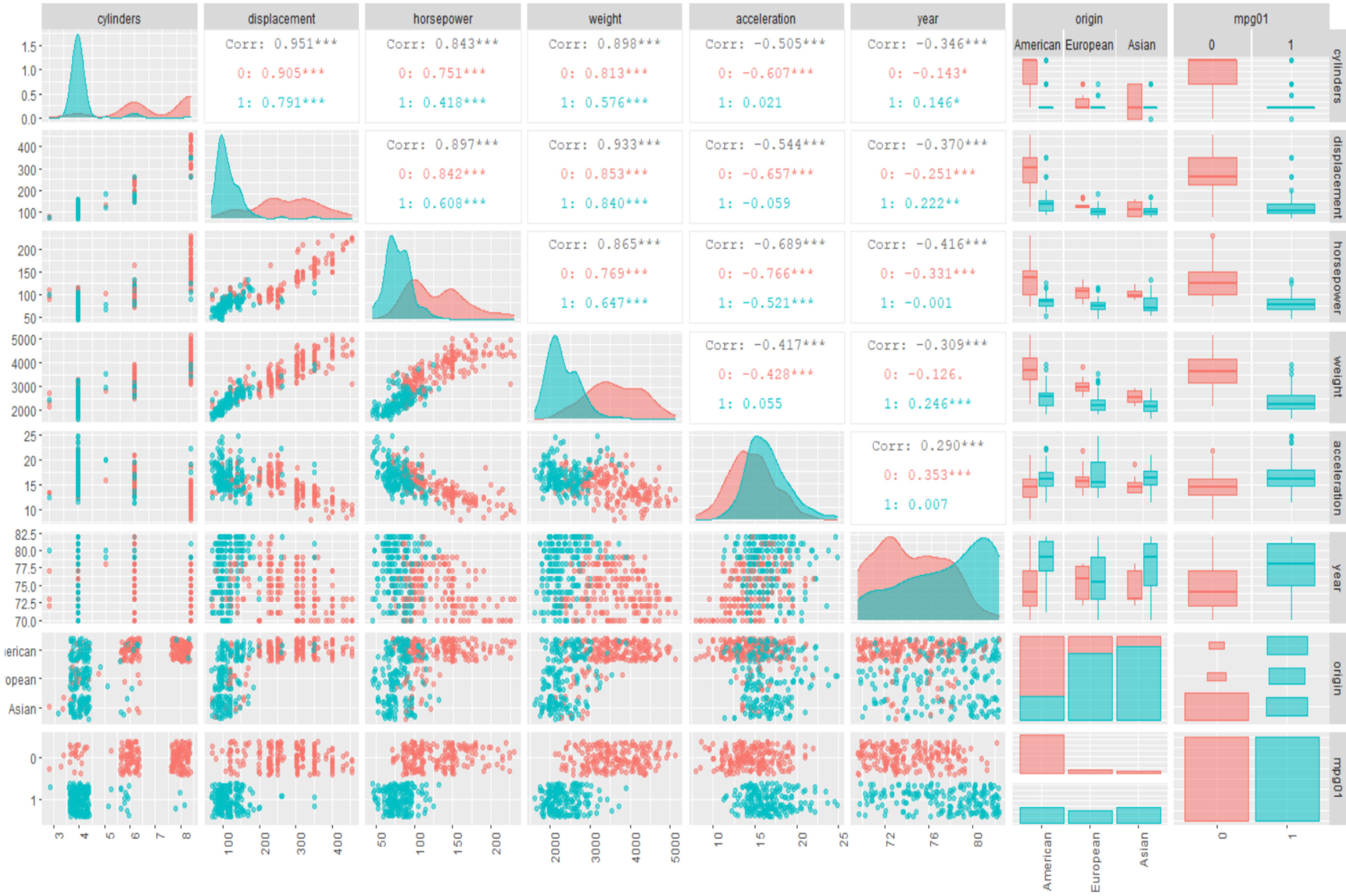
- mpg:miles per gallon
- cylinders:Number of cylinders between 4 and 8
- displacement:Engine displacement (cu. inches)
- horsepower:Engine horsepower
- weight:Vehicle weight (lbs.)
- acceleration:Time to accelerate from 0 to 60 mph (sec.)
- year:Model year (modulo 100)
- origin:Origin of car (1. American, 2. European, 3. Japanese)
- name:Vehicle name

(a)

建立 mpg01，將 mpg 大於中位數令為 1，否則為 0，並且將 origin 的 Outcome 改為 $[American, European, Asian]$

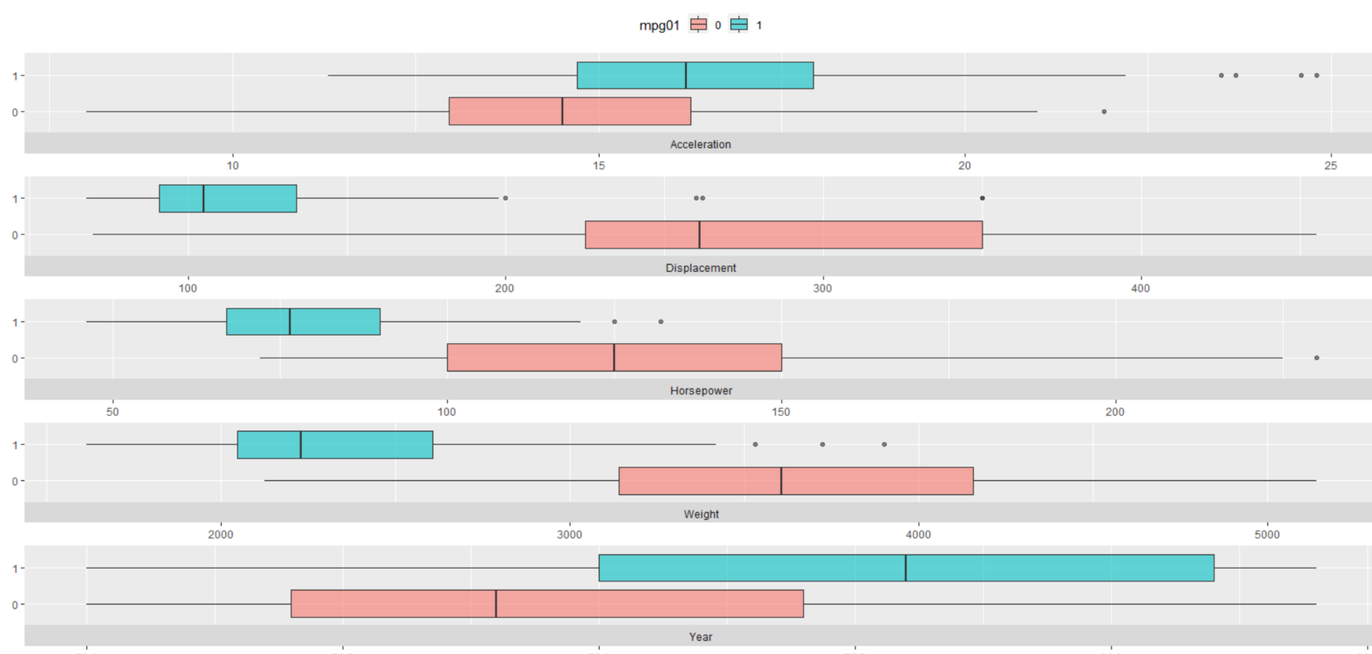
(b)

從下圖觀察，發現有以下這些變數對 mpg01 有較顯著的變化，可能代表著較有解釋力，變數如下：cylinders 、displacement 、 horsepower 、 weight 、 year



個別將這些變數對 mpg1 做 Box Plot，更可以觀察到這些變數對 mpg01 有顯著的不一樣，可能代表著具有較佳的解釋力。

```
## Warning: 'switch' is deprecated.
## Use 'strip.position' instead.
## See help("Deprecated")
```



(c)

以 80:20，將資料分成 Train、Test

```
set.seed(1234)

num_train <- nrow(Auto) * 0.8

inTrain <- sample(nrow(Auto), size = num_train)

train <- Auto[inTrain,]

test <- Auto[-inTrain,]
```

(d)

使用 LDA 模型，以 Train 資料配飾，預測 Test 資料，觀察所得之 Confusion Matrix，準確率為 88.61%，代表模型表現不錯。

```
## Confusion Matrix and Statistics
##
##
## pred_values  1  0
##           1 38  7
##           0  2 32
##
##                Accuracy : 0.8861
##                  95% CI : (0.7947, 0.9466)
##     No Information Rate : 0.5063
##     P-Value [Acc > NIR] : 8.396e-13
##
##                   Kappa : 0.7717
##
##  Mcnemar's Test P-Value : 0.1824
##
##             Sensitivity : 0.9500
##             Specificity : 0.8205
##          Pos Pred Value : 0.8444
##          Neg Pred Value : 0.9412
##              Prevalence : 0.5063
##          Detection Rate : 0.4810
##    Detection Prevalence : 0.5696
##       Balanced Accuracy : 0.8853
##
##        'Positive' Class : 1
##
```

我們可以發現在 4 缸的歐洲車以及六缸的美國車佔錯誤的大宗，若以廠牌來看，Ford 判斷錯誤出現次數最多，並且大部分都是 mpg01 為 0 代表實際是油耗較差的那群，可能顯示出 Ford 的造車可能存在與其他車廠之間的落差。

```
##      mpg cylinders displacement horsepower weight acceleration year   origin
## 21  25.0         4          110         87   2672         17.5   70 European
## 119 20.0         4          114         91   2582         14.0   73 European
## 120 19.0         4          121        112   2868         15.5   73 European
## 192 24.0         6          200         81   3012         17.6   76 American
## 269 21.1         4          134         95   2515         14.8   78    Asian
## 281 22.3         4          140         88   2890         17.3   79 American
## 359 22.4         6          231        110   3415         15.8   81 American
## 361 20.2         6          200         88   3060         17.1   81 American
## 384 22.0         6          232        112   2835         14.7   82 American
##                          name mpg01
## 21                peugeot 504     1
## 119                audi 100ls     0
## 120               volvo 144ea     0
## 192             ford maverick     1
## 269 toyota celica gt liftback     0
## 281           ford fairmont 4     0
## 359             buick century     0
## 361           ford granada gl     0
## 384            ford granada l     0
```

(e)

使用 QDA 模型，以 Train 資料配飾，預測 Test 資料，觀察所得之 Confusion Matrix，準確率為 87.34%，表現略差於 LDA。

```
## Confusion Matrix and Statistics
##
##
## pred_values  1  0
##           1 36  6
##           0  4 33
##
##                Accuracy : 0.8734
##                  95% CI : (0.7795, 0.9376)
##     No Information Rate : 0.5063
##     P-Value [Acc > NIR] : 5.838e-12
##
##                   Kappa : 0.7466
##
##  Mcnemar's Test P-Value : 0.7518
##
##             Sensitivity : 0.9000
##             Specificity : 0.8462
##          Pos Pred Value : 0.8571
##          Neg Pred Value : 0.8919
##              Prevalence : 0.5063
##          Detection Rate : 0.4557
##    Detection Prevalence : 0.5316
##       Balanced Accuracy : 0.8731
##
```

```
##        'Positive' Class : 1
##
```

使用 QDA 也有相似於 LDA 的結果，判斷錯誤的汽缸數皆是 4,6 缸，而不同的是此結果亞洲地區的車判斷錯誤比例上升。

```
##      mpg cylinders displacement horsepower weight acceleration year   origin
## 119 20.0         4          114         91   2582         14.0   73 European
## 192 24.0         6          200         81   3012         17.6   76 American
## 269 21.1         4          134         95   2515         14.8   78    Asian
## 281 22.3         4          140         88   2890         17.3   79 American
## 331 32.7         6          168        132   2910         11.4   80    Asian
## 357 25.4         6          168        116   2900         12.6   81    Asian
## 358 24.2         6          146        120   2930         13.8   81    Asian
## 359 22.4         6          231        110   3415         15.8   81 American
## 361 20.2         6          200         88   3060         17.1   81 American
## 384 22.0         6          232        112   2835         14.7   82 American
##                          name mpg01
## 119                 audi 100ls     0
## 192              ford maverick     1
## 269 toyota celica gt liftback     0
## 281            ford fairmont 4     0
## 331              datsun 280-zx     1
## 357            toyota cressida     1
## 358          datsun 810 maxima     1
## 359              buick century     0
## 361            ford granada gl     0
## 384             ford granada l     0
```

(f)

使用 Logistic Regression 模型，以 Train 資料配飾，預測 Test 資料，觀察所得之 Confusion Matrix，準確率為 87.34%，模型表現略差於 LDA。

```
## Confusion Matrix and Statistics
##
##
## pred_values  1  0
##           1 36  6
##           0  4 33
##
##                Accuracy : 0.8734
##                  95% CI : (0.7795, 0.9376)
##     No Information Rate : 0.5063
##     P-Value [Acc > NIR] : 5.838e-12
##
##                   Kappa : 0.7466
##
##  Mcnemar's Test P-Value : 0.7518
##
##             Sensitivity : 0.9000
##             Specificity : 0.8462
##          Pos Pred Value : 0.8571
##          Neg Pred Value : 0.8919
##              Prevalence : 0.5063
##          Detection Rate : 0.4557
```

```
##    Detection Prevalence : 0.5316
##       Balanced Accuracy : 0.8731
##
##        'Positive' Class : 1
##
```

使用 Logistic Regression 也有相似於 QDA 的結果，判斷錯誤的汽缸數皆是 4,6 缸，亞洲地區的車判斷錯誤比例上升。

```
##      mpg cylinders displacement horsepower weight acceleration year   origin
## 119 20.0         4          114         91   2582         14.0   73 European
## 192 24.0         6          200         81   3012         17.6   76 American
## 269 21.1         4          134         95   2515         14.8   78    Asian
## 281 22.3         4          140         88   2890         17.3   79 American
## 331 32.7         6          168        132   2910         11.4   80    Asian
## 357 25.4         6          168        116   2900         12.6   81    Asian
## 358 24.2         6          146        120   2930         13.8   81    Asian
## 359 22.4         6          231        110   3415         15.8   81 American
## 361 20.2         6          200         88   3060         17.1   81 American
## 384 22.0         6          232        112   2835         14.7   82 American
##                          name mpg01
## 119                 audi 100ls     0
## 192              ford maverick     1
## 269 toyota celica gt liftback     0
## 281            ford fairmont 4     0
## 331              datsun 280-zx     1
## 357            toyota cressida     1
## 358          datsun 810 maxima     1
## 359              buick century     0
## 361             ford granada gl     0
## 384              ford granada l     0
```

(g)

將(b)裡所提出較可能較有解釋力的變數帶進 KNN，並測試 KNN 的 Center 從 1-15，可得到在 c1=5,7 的地方有最佳的 Accuracy。

```
##  [1] 0.8101266 0.8101266 0.8860759 0.8734177 0.9113924 0.8987342 0.9113924
##  [8] 0.8860759 0.8734177 0.8734177 0.8734177 0.8860759 0.8860759 0.8860759
## [15] 0.8734177
```

最後使用 k=5，為所有模型裡面表現最佳

```
## Confusion Matrix and Statistics
##
##
## knn_pred  1  0
##        1 37  4
##        0  3 35
##
##                Accuracy : 0.9114
##                  95% CI : (0.8259, 0.9636)
##     No Information Rate : 0.5063
##     P-Value [Acc > NIR] : 1.201e-14
##
##                   Kappa : 0.8227
```

```
##
##  Mcnemar's Test P-Value : 1
##
##             Sensitivity : 0.9250
##             Specificity : 0.8974
##          Pos Pred Value : 0.9024
##          Neg Pred Value : 0.9211
##              Prevalence : 0.5063
##          Detection Rate : 0.4684
##    Detection Prevalence : 0.5190
##       Balanced Accuracy : 0.9112
##
##        'Positive' Class : 1
##
```

在判斷錯誤的車裡面，大多屬於美國車，並且同樣為 4,6 缸。

```
##      mpg cylinders displacement horsepower weight acceleration year   origin
## 18  21.0         6          200         85   2587         16.0   70 American
## 113 21.0         6          155        107   2472         14.0   73 American
## 119 20.0         4          114         91   2582         14.0   73 European
## 192 24.0         6          200         81   3012         17.6   76 American
## 269 21.1         4          134         95   2515         14.8   78    Asian
## 271 23.8         4          151         85   2855         17.6   78 American
## 358 24.2         6          146        120   2930         13.8   81    Asian
##                          name mpg01
## 18              ford maverick     0
## 113           mercury capri v6     0
## 119                audi 100ls     0
## 192             ford maverick     1
## 269 toyota celica gt liftback     0
## 271    oldsmobile starfire sx     1
## 358          datsun 810 maxima     1
```

附錄(程式碼)：

```
 #### Question 10

require(ISLR); require(tidyverse); require(ggthemes);

require(GGally);

#### (a)

set.seed(1)

data('Weekly')

str(Weekly)

Weekly %>%

  gather(Variable, value, starts_with('Lag'), Today) %>%

  group_by(Variable, Direction) %>%
```

```
  summarise(Q25 = quantile(value, 0.25),
            median = median(value),
            mean = mean(value),
            Q75 = quantile(value, 0.75))
Weekly %>%
  gather(value_type, value, starts_with('Lag')) %>%
  ggplot(aes(value_type, value, fill = Direction)) +
  geom_boxplot(notch = F) +
  labs(x = '', y = '') +
  ylim(c(-6, 6)) +
  geom_hline(yintercept = 0, linetype = 2)
Weekly %>%
  gather(value_type, value, starts_with('Lag')) %>%
  ggplot(aes(as.factor(Year), value, fill = Direction)) +
  geom_boxplot(notch = F) +
  labs(x = '', y = '') +
  ylim(c(-6,6)) +
  geom_hline(yintercept = 0, linetype = 2)
t.test(Lag1 ~ Direction, data = Weekly)
t.test(Lag2 ~ Direction, data = Weekly)
#### (b)
Log_ful <- glm(Direction ~ . - Year - Today, data = Weekly, family = 'binomial')
summary(Log_ful)
#### (c)
pred <- predict(Log_ful, type = 'response')
pred_values <- ifelse(pred >= 0.5, 'Up', 'Down')
library(caret)
xtab <- table(pred_values,Weekly$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
mean(Weekly$Direction == 'Up')
```

```
#### (d)
train <- Weekly[Weekly$Year <= 2008,]
test <- Weekly[Weekly$Year > 2008,]
lag2_logreg <- glm(Direction ~ Lag2, data = train, family = 'binomial')
pred <- predict(lag2_logreg, newdata = test, type = 'response')
pred_values <- ifelse(pred >= 0.5, 'Up', 'Down')
xtab <- table(pred_values,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
mean(test$Direction == 'Up')
#### (e)
require(MASS)
lda_model <- lda(Direction ~ Lag2, data = train)
pred <- predict(lda_model, newdata = test)
pred_values <- pred$class
xtab <- table(pred_values,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
#### (f)
qda_model <- qda(Direction ~ Lag2, data = train)
pred <- predict(qda_model, newdata = test)
pred_values <- pred$class
xtab <- table(pred_values,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
#### (g)
require(class)
knn_pred <- knn(train = data.frame(train$Lag2),
        test = data.frame(test$Lag2),
        cl = train$Direction, k = 1)
xtab <- table(knn_pred,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
require(e1071)
```

```r
NB = naiveBayes(Direction ~Lag2, data = train)
pred <- predict(NB, newdata = test)
xtab <- table(pred,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
#### (h)
#### (i)
lag2_logreg <- glm(Direction~Lag1+Lag2+I(Volume^2), data = train,family = 'binomial')
pred <- predict(lag2_logreg, newdata = test, type = 'response')
pred_values <- ifelse(pred >= 0.5, 'Up', 'Down')
xtab <- table(pred_values,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
require(MASS)
lda_model <- lda(Direction ~Lag1+Lag2+I(Volume^2), data = train)
pred <- predict(lda_model, newdata = test)
pred_values <- pred$class
xtab <- table(pred_values,test$Direction)
print(confusionMatrix(xtab[2:1,2:1]))
acc <- list()
set.seed(12345)
acc = sapply(1:16, function(x){
  knn_pred <- knn(train = data.frame(train$Lag2),
                  test = data.frame(test$Lag2),
                  cl = train$Direction, k = x)
  acc[as.character(x)] = mean(knn_pred == test$Direction)
})
unlist(acc)
knn_pred <- knn(train = data.frame(train$Lag2),
                test = data.frame(test$Lag2),
                cl = train$Direction, k = 13)
xtab <- table(knn_pred,test$Direction)
```

```
print(confusionMatrix(xtab[2:1,2:1]))


### Question 11
#### (a)
data(Auto)
Auto <- Auto %>%
  mutate(mpg01 = factor(ifelse(mpg > median(mpg), 1, 0)),
         origin = factor(origin,
                         levels = c(1,2,3),
                         labels = c('American', 'European', 'Asian')))


#### (b)
Auto %>%
  dplyr::select(-name, -mpg) %>%
  ggpairs(aes(col = mpg01, fill = mpg01, alpha = 0.6),
          upper = list(combo = 'box'),
          diag = list(discrete = wrap('barDiag', position = 'fill')),
          lower = list(combo = 'dot_no_facet')) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
Auto %>%
  dplyr::select(-name, -mpg, - origin, -cylinders) %>%
  gather(Variable, value, -mpg01) %>%
  mutate(Variable = str_to_title(Variable)) %>%
  ggplot(aes(mpg01, value, fill = mpg01)) +
  geom_boxplot(alpha = 0.6) +
  facet_wrap(~ Variable, scales = 'free', ncol = 1, switch = 'x') +
  coord_flip() +
  theme(legend.position = 'top') +
  labs(x = '', y = '', title = 'Variable Boxplots by mpg01')
```

```
#### (c)

set.seed(1234)

num_train <- nrow(Auto) * 0.8

inTrain <- sample(nrow(Auto), size = num_train)

train <- Auto[inTrain,]

test <- Auto[-inTrain,]


#### (d)

require(MASS)

fmla <- as.formula('mpg01 ~ displacement + horsepower + weight + year + cylinders')

lda_model <- lda(fmla, data = train)

pred <- predict(lda_model, newdata = test)

pred_values <- pred$class

xtab <- table(pred_values,test$mpg01)

print(confusionMatrix(xtab[2:1,2:1]))

err =  test[which(pred_values!=test$mpg01),]

print(err)


#### (e)

qda_model <- qda(fmla, data = train)

pred <- predict(qda_model, newdata = test)

pred_values <- pred$class

xtab <- table(pred_values,test$mpg01)

print(confusionMatrix(xtab[2:1,2:1]))

err =  test[which(pred_values!=test$mpg01),]

print(err)


#### (f)

log_reg <- glm(fmla, data = train, family = binomial)

pred <- predict(qda_model, newdata = test)
```

```
pred_values <- pred$class
xtab <- table(pred_values,test$mpg01)
print(confusionMatrix(xtab[2:1,2:1]))
err =  test[which(pred_values!=test$mpg01),]
print(err)


#### (g)
set.seed(1234)
acc <- list()
x_train <- train[,c('cylinders', 'displacement', 'horsepower', 'weight', 'year')]
y_train <- train$mpg0
x_test <- test[,c('cylinders', 'displacement', 'horsepower', 'weight', 'year')]
acc =  sapply(1:15, function(x){
  knn_pred <- knn(train = x_train, test = x_test, cl = y_train, k = x)
  acc[as.character(x)] = mean(knn_pred == test$mpg01)
})
unlist(acc)
knn_pred <- knn(train = x_train,
                test = x_test,
                cl = y_train, k = 5)
xtab <- table(knn_pred,test$mpg01)
print(confusionMatrix(xtab[2:1,2:1]))
err =  test[which(knn_pred!=test$mpg01),]
print(err)
```