HW4

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```
library(tidyverse)

## ─ Attaching packages ──────────────────── tidyverse 1.3.0 ─

## ✓ ggplot2 3.2.1     ✓ purrr   0.3.3
## ✓ tibble  3.0.3     ✓ dplyr   1.0.2
## ✓ tidyr   1.0.0     ✓ stringr 1.4.0
## ✓ readr   1.3.1     ✓ forcats 0.4.0

## Warning: package 'tibble' was built under R version 3.6.2

## Warning: package 'dplyr' was built under R version 3.6.2

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

library(glmnet)

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loaded glmnet 3.0-1
```

Analyze all the spam data using variable selection methods including (a) forward stepwise regression and backward stepwise regression. (12%) (b) Randomly select two thirds of the data as the training dataset and the remaining one third as the test data. (set.seed(1001)) (i) Use the training data to identify the lambda value that gives minimum cross-validated error for lasso regression, ridge regression, and elastic net regression with different alpha values. (20%) (ii) Apply the lambda with minimum cross-validated error to the test data and evaluate their mean square errors. (20%)

(a)

```
p1 <- read.table("/Users/linyuxiang/R/MSA/Data/spam.dat", header = T)
p1.fwd <- step(lm(Y ~ 1, data=p1),~X.1+X.2+X.3+X.4+X.5+X.6+X.7+X.8+X.9+
X.10+X.11+X.12+X.13+X.14+X.15+X.16+X.17+X.18+X.19+X.20+X.21+X.22+X.23+X
.24+X.25+X.26+X.27+X.28+X.29+X.30+X.31+X.32+X.33+X.34+X.35+X.36+X.37+X.
38+X.39+X.40+X.41+X.42+X.43+X.44+X.45+X.46+X.47+X.48+X.49+X.50+X.51+X.5
2+X.53+X.54+X.55+X.56+X.57, data=p1, direction="forward")
fw_res <- p1.fwd$model %>% names()
# backward
p1.lrs <- lm(Y~., data = p1)
pr.bwd <- step(p1.lrs, direction = "backward")
bw_res <- pr.bwd %>% names()

intersect(fw_res, bw_res)

## character(0)

setdiff(fw_res, bw_res)

##  [1] "Y"    "X.21" "X.23" "X.7"  "X.57" "X.16" "X.52" "X.25" "X.5" 
"X.53"
## [11] "X.8"  "X.24" "X.6"  "X.20" "X.22" "X.42" "X.18" "X.27" "X.46"
"X.49"
## [21] "X.45" "X.19" "X.33" "X.9"  "X.26" "X.12" "X.17" "X.37" "X.44"
"X.3" 
## [31] "X.4"  "X.48" "X.47" "X.43" "X.1"  "X.2"  "X.35" "X.55" "X.40"
"X.30"
## [41] "X.11" "X.54" "X.38" "X.10" "X.50" "X.56" "X.34" "X.39"

setdiff(bw_res, fw_res)

##  [1] "coefficients"  "residuals"     "effects"       "rank"         
##  [5] "fitted.values" "assign"        "qr"            "df.residual"  
##  [9] "xlevels"       "call"          "terms"         "model"        
## [13] "anova"
```

- Ans: Forward 和 Backward 方法篩選出來的變數大致相同，有 X.21, X.23, X.7, X.57, X.16, X.52, X.25, X.5, X.53, X.8, X.24, X.6, X.20, X.22, X.42, X.18, X.27, X.46, X.49, X.45, X.19, X.33, X.9, X.26, X.12, X.17, X.37, X.44, X.3, X.4, X.48, X.47, X.43, X.1, X.2, X.35, X.40, X.30, X.11, X.54, X.38, X.10, X.50, X.56, X.34, X.39，唯一不同的是 Forward 方法有選出 X.55，Backward 方法沒有

(b)

```
set.seed(1001)
indx <- sample(1:nrow(p1) ,nrow(p1)*.67)
train.p1 <- p1[indx,]
test.p1 <- p1[-indx,]
nrow(train.p1)+nrow(test.p1) == nrow(p1)
```

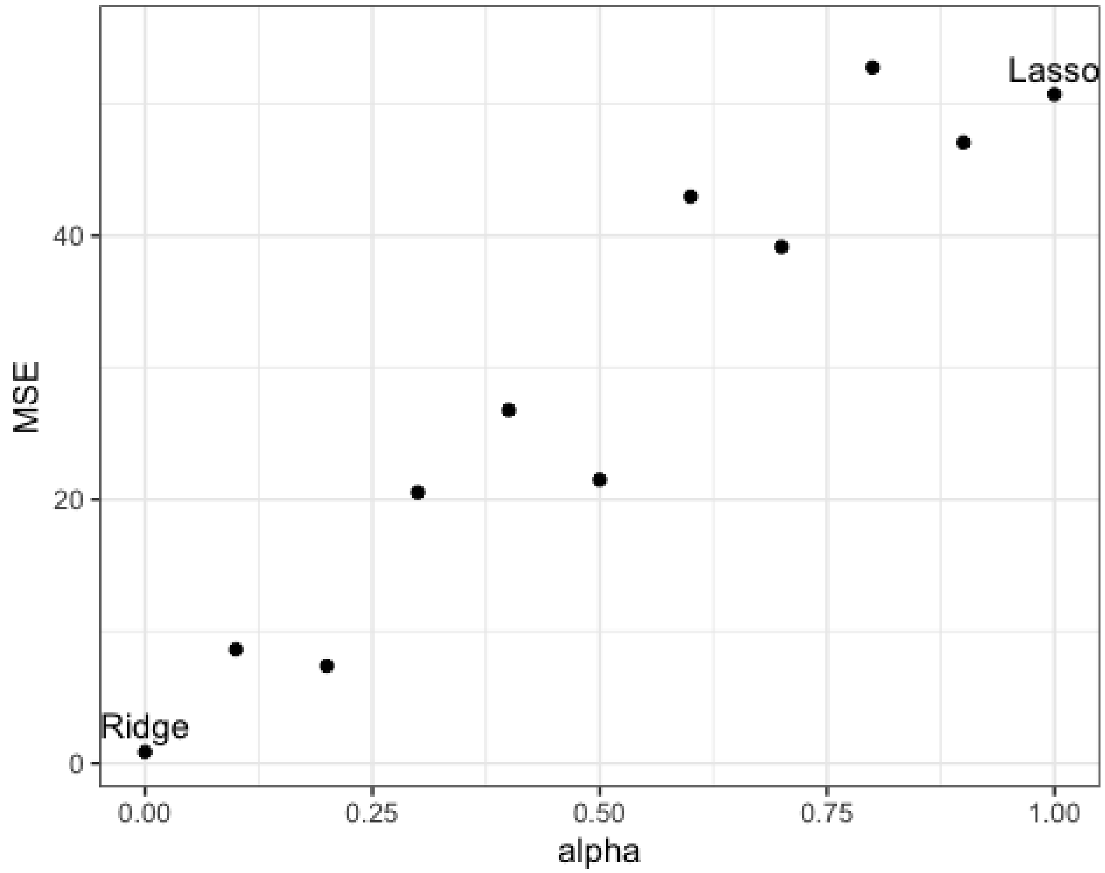
```
## [1] TRUE
```

```
df <- data_frame(alpha = rep(NA,11), MSE = NA)
```

```
## Warning: `data_frame()` is deprecated as of tibble 1.1.0.
## Please use `tibble()` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_warnings()` to see where this warning was gene
rated.
```

```
for (i in 0:10){
cv_fit <-  cv.glmnet(train.p1[,-58] %>% as.matrix, train.p1[,58] %>% as
.matrix, type.measure="mse", alpha=i/10,family="gaussian")

fit <- glmnet(train.p1[,-58] %>% as.matrix, train.p1[,58] %>% as.matrix
, family="binomial", alpha=1, lambda = cv_fit$lambda.min)

fit_pred <- predict(fit, newx = test.p1[,-58] %>% as.matrix)
# MSE lasso
df$MSE[i+1] <- sum((fit_pred - test.p1$Y)^2) / nrow(fit_pred)
df$alpha[i+1] <- (i/10)
message(i)
}
```

```
## 0

## 1

## 2

## 3

## 4

## 5

## 6
## 7

## 8

## 9

## 10

df$label[1] <- "Ridge"

## Warning: Unknown or uninitialised column: `label`.

df$label[2:10] <- NA
df$label[11] <- "Lasso"
df %>%
  ggplot(aes(x = alpha, y = MSE))+
  geom_point()+
  geom_text(aes(label = label, y = MSE+2))+
  theme_bw()

## Warning: Removed 9 rows containing missing values (geom_text).
```



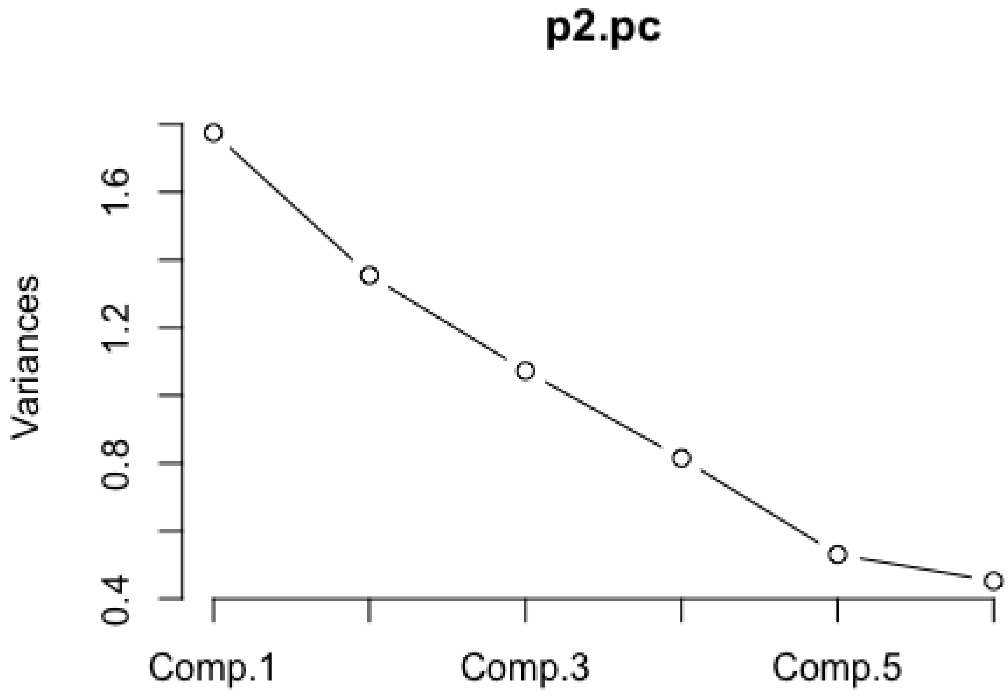
- Ans: 從圖中可以看出選擇 Alpha = 0，也就是使用 Ridge Regression 時 MSE 為最低，當選擇的 Alpha 值上升，也就是 Lasso 方法的比例提升時，模型 MSE

數值會提高，在使用 Lasso Regression，即 Alpha = 1 時，MSE 為最高。由此得知該資料可能較適合使用 Ridge Regression 進行變數篩選。

Problem 2

Carry out a principal component analysis on the engineer data as follows. Ignore groups and use a correlation matrix based on all 40 observations. (48%)(pilots.dat)
Table. Comparison of Six Tests on Engineer Apprentices and Pilots

```
p2 <- read.table("/Users/linyuxiang/R/MSA/Data/pilots.dat", header = F)

p2 <- p2[,-1]
eigen(cor(p2))

## eigen() decomposition
## $values
## [1] 1.7751277 1.3544159 1.0726505 0.8147958 0.5306128 0.4523973
##
## $vectors
##             [,1]       [,2]       [,3]       [,4]       [,5]       [
,6]
## [1,] -0.40239072  0.3964661  0.4617841 -0.3928149 -0.2103062  0.5187
674
## [2,]  0.09715877  0.7472294 -0.1752970 -0.1315611 -0.2801896 -0.5528
697
## [3,] -0.38541311 -0.2181560 -0.4329575 -0.7177525  0.2585104 -0.1855
163
## [4,] -0.54333623 -0.3144601 -0.1065065  0.2453920 -0.7066663 -0.1869
825
## [5,]  0.31188931 -0.3559400  0.6268314 -0.3992852 -0.2012981 -0.4279
773
## [6,] -0.53629229  0.1062657  0.4053555  0.3058981  0.5201339 -0.4155
385

p2.pc <- princomp(p2,cor=TRUE)
plot(p2.pc, type = "l")
```



- Ans: 從圖中可以看出第六個 Component 幾乎沒有變異，此資料若要進一步分析，最後可能只會選擇五個主成分。