

# HW2\_DataMining

Yaniv Bronshtein

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import libraries

```
library(tidyverse)
```

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

```
## v ggplot2 3.3.3      v purrr  0.3.4
## v tibble  3.0.5      v dplyr  1.0.3
## v tidyr   1.1.2      v stringr 1.4.0
## v readr   1.4.0      v forcats 0.5.0
```

```
## -- 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 4.1
```

```
library(Matrix)
library(rsample)
library(ISLR)
library(pls)
```

```
##
```

```
## Attaching package: 'pls'
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
##      loadings
```

### Question 3

*Bootstrap with Least squares, Ridge and Lasso* Let  $\beta = (\beta_1, \beta_2, \dots, \beta_p)$  and let  $x, y$  be random variables such that the entries of  $x$  are i.i.d standard normal variables (i.e, with mean zero and variance one) and  $y = \beta^T x + \epsilon$  where  $\epsilon \sim N(0, 1)$ . (a). Simulate a dataset  $(x_1, y_1), \dots, (x_n, y_n)$  as  $n$  i.i.d copies of the random variables  $x, y$  defined above, with  $n = 800$ ,  $p = 200$ , and  $\beta_j = j^{-1}$ .

```
#Define n and p
p <- 200
n <- 800
#Construct x by create p copies of rnorm() which will generate n numbers. Each column represents a random variable
x <- replicate(p, rnorm(n = n, mean = 0, sd = 1))
#Create the j vector
j = 1:p
#Beta is j inverted
beta <- j^-1
#Transform beta
beta_t <- beta %>% as.matrix()
#epsilon is a column vector nX1
epsilon <- rnorm(n = n, mean = 0, sd = 1) %>% as.matrix()
#Construct matrix y according to the formula in the question
y = x %*% beta_t + epsilon

#Create a data frame from y and x
df <- data.frame("y"= y, x)
```

(b) The goal of this problem is to construct confidence intervals for  $\beta_1$  using Bootstrap method.

**Specify a 95% confidence interval.** Use  $\psi$  to avoid confusion with alpha in glmnet()

```
psi = 0.05
```

**Generate the bootstraps to be used for all the models**

```
set.seed(1)
samples <- df %>% bootstraps(1000)
```

(i). Construct confidence intervals for  $\beta_1$  by bootstrapping the data and applying Least Squares to the bootstrapped data set. **Create a function to return the coefficients of the linear model**

```
get_beta1_lm <- function(data){
  x_mat <- model.matrix(y~.,data)[-1]
  y <- as.matrix(data['y'])
  lm_model <- lm(y ~ x_mat)
  beta_1_estim <- coef(lm_model)[2]
  return(beta_1_estim)
}
```

**Create a vector of 1000 bootstrap estimates of beta 1 for least square**

```

estim_lm <- samples$splits %>%
  map(., ~as.data.frame(.)) %>%
  map(., ~get_beta1_lm(.)) %>%
  simplify()

```

```
estim_lm
```

```

##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9198947 0.9786692 1.0156690 1.0458242 1.0760794 1.0131668 0.8911744 0.9711342
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9678475 1.0213258 0.9937837 0.8931286 0.9403398 1.0231839 0.9306646 0.9438314
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9739355 1.0196414 0.9151550 1.0583078 0.9765379 0.9689989 1.0548590 1.0341454
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9720323 0.9241653 1.0570991 0.9490265 0.8600840 1.0898541 0.9056544 0.9745879
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9642519 1.0502443 1.1072987 1.0166539 1.1099852 1.0315581 1.0320642 1.0339638
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0196268 0.9681221 0.9987922 1.0298655 1.0013170 1.0558315 0.9612283 0.9519157
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9338356 0.9942892 0.9811803 1.0256725 1.0509844 0.9399390 0.9512246 1.0676239
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0113035 0.9648494 1.0283646 1.0375995 1.0034919 1.0458048 1.0193061 1.0733394
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9614978 1.0177641 0.9741181 0.9477524 1.0009987 1.0020269 1.0124911 0.9561293
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0279186 1.0365276 1.0425889 1.0496619 1.0320294 1.0543084 1.0518831 0.8887751
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.8798863 0.9982975 1.0729815 0.9989488 0.9386808 1.0490345 1.0022620 1.0385067
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9975377 0.9273037 0.9575338 0.9958526 0.8886100 0.9631446 1.0139194 0.9639169
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9832154 1.0150638 0.9464973 0.9762201 0.9759765 1.0052108 0.9635617 0.9473460
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0102224 1.0132266 1.0499850 1.0162747 0.9592215 0.9999271 1.0584122 0.9738106
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0572437 1.0672817 0.9111970 1.0496229 0.9032576 0.9526896 1.0284540 1.0276221
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.8893982 1.0239462 1.0089273 0.9548201 1.0511459 1.0074496 1.0212367 1.0864375
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0394440 0.9620582 0.9487107 1.0350930 1.0404489 0.9597783 0.9751477 0.9629864
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0145551 1.0020142 1.0492624 1.0140154 0.9905807 1.0253498 0.9878853 0.9332883
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0848748 0.9884597 0.9545988 0.9557274 0.9779127 0.9834163 1.0032455 1.1074624
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0855759 1.0076888 1.0414008 0.9698381 0.9968597 1.0263921 1.0546542 1.0105672
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 0.9601930 0.9636028 1.0864052 1.0344336 1.0241582 1.0748722 0.9570658 1.0250436
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0083599 0.9744628 1.0020109 0.9251354 0.9094637 0.9248985 0.9951025 1.0494659
##   x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1  x_matX1
## 1.0736551 0.9333748 0.9896772 1.0372710 0.9960045 1.0568946 0.9710753 0.9807220

```

##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9784021	1.0122495	0.9585275	1.0795563	0.9813089	1.0249847	0.9724334	0.9651843
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9818387	1.0185284	1.0228870	0.9679080	1.0093621	0.9638427	0.9343023	1.0210490
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0242613	1.0334996	1.0540815	0.9632900	0.9479806	0.9334249	1.0875427	0.9684958
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0464284	0.9520619	0.9515980	0.9435644	1.0267710	0.9794059	0.9244876	0.9287340
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9497247	1.0037994	1.0425150	1.0487849	0.9828232	0.9626040	0.9537726	0.9798339
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9662414	1.0195409	0.9971579	0.9243153	1.0028242	0.9791771	0.9625319	0.8821420
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9232935	0.9943758	1.0691520	0.9910427	1.0229763	0.8951269	1.0761666	0.9934374
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0150844	0.8341990	1.0475569	1.0635977	0.9799951	1.0049584	0.9260274	1.0503732
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0097795	0.8904975	0.9342607	0.9912580	1.0127379	0.9958113	0.9202575	0.9624243
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9342328	1.0424202	1.0246135	1.0456124	1.0105457	1.0215931	0.9488350	0.9068206
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0076574	0.9133780	1.0287347	1.0764292	0.9985598	0.9785774	0.9339965	0.9154130
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9767432	1.0229045	1.0269412	1.0633537	1.0445864	0.9977654	0.9779324	0.9485023
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9764459	1.0145993	0.9086280	0.9905611	1.0384079	0.9653729	0.9710351	1.0177884
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9522261	0.9927985	0.9496147	0.9598676	1.0132632	0.9475689	1.0119673	1.0738431
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0011266	1.0503475	1.0304129	1.0226183	0.9528920	1.0378564	1.0129812	1.0192174
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9241491	0.9887877	0.9366591	1.0530886	0.9826103	0.9422098	0.9005180	1.0232565
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9081222	1.0302755	0.9152258	0.9524972	1.0489665	1.0319952	1.0333879	0.9662192
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9574447	1.0269621	1.0225189	0.9929998	1.0330632	0.9838714	1.0629970	1.0817117
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0405276	0.9861349	1.0039630	0.9940203	0.9861131	0.9441590	0.9867795	0.9373021
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0437247	0.9770879	1.0078018	0.9971368	1.1008363	1.0509842	0.9520789	1.0227216
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0301348	0.9477487	1.0620227	1.0349867	0.9063626	1.0237830	0.9972308	0.9823694
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0145841	0.9869689	1.0414538	1.0132268	1.0237223	0.9845674	1.0767852	0.9980984
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9456004	1.0424701	1.0268175	0.9900264	0.9954535	1.0693083	0.9884517	0.9705501
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	0.9570614	0.9700292	0.9710956	0.9583065	0.9606046	0.9395316	1.0329075	1.0126627
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0691616	0.9539271	1.0257187	0.9869830	0.9666469	0.9327526	1.0030623	0.9998625
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0106294	0.9267039	0.8877596	1.0036918	0.9095863	1.0816621	1.0185402	1.0020580
##	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1	x_matX1
##	1.0001161	0.9581982	1.0246167	0.9412208	1.0177996	1.0029916	1.0310539	0.9220063

```

## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9796296 1.0391503 1.0938147 1.0217783 0.9535952 0.9426859 0.9799765 0.9982980
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9955421 0.9948887 0.9776098 1.0405606 1.0156920 0.9917367 1.0272228 1.0716395
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.8766995 1.0556697 0.9852289 0.9694291 1.0516120 0.9806091 0.9628718 1.1053335
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0249155 1.0179028 0.9766770 0.8864963 0.9655074 1.0238217 0.9612055 1.0164119
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9781061 0.9954311 0.9925768 0.9972625 0.9755829 1.0045905 0.9880040 1.0900249
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9265634 0.9954194 0.9230058 1.0520386 1.0354745 1.0101128 1.0898633 1.0141580
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9265133 1.0204116 1.0500035 0.9630580 0.9911423 1.0406082 1.0155915 1.0294068
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0853703 0.9676933 0.9631054 1.0229940 0.9582459 1.0166378 1.0292647 0.9639793
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9954665 0.9663809 1.0946169 0.9075531 0.9658719 0.9151069 0.9625784 1.0061609
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0427209 0.9954236 0.9936099 1.0130083 1.0459145 1.0262712 0.9572908 1.0356357
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9779514 1.0226078 1.0594543 1.0300157 1.0703748 1.0170745 1.0455704 0.9947855
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9876327 0.8885033 0.9596444 1.0091180 1.0079374 1.0063500 1.0078268 1.0371378
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0021207 1.0372033 1.1149432 0.9865899 0.9905592 0.9630380 0.9194118 0.8833411
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0008034 1.0052205 0.9543905 1.0606851 1.0020223 0.9596290 0.9942491 1.0017267
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0869545 1.0023012 1.0360228 0.8917000 0.9541829 1.0154291 1.0332189 0.9743751
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0009020 1.0409807 0.9696967 0.9083316 0.9515143 0.9803010 0.9539481 0.9691387
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9886653 0.9861861 0.9491991 1.0279549 1.0420720 1.0521232 0.9962758 0.9997138
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9890617 0.9448175 1.0092044 0.9275262 0.9818877 1.0458290 1.0820439 1.0251156
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0232302 1.0314866 1.0316533 1.0245384 0.9331168 1.0569764 0.9419619 1.0615734
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0263318 0.9471860 1.0192736 1.0366561 0.9194088 1.0305972 0.9966190 1.0265806
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9742424 1.0521756 0.9844927 0.9805152 1.0286272 1.0134838 1.0320326 0.9734771
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0357675 1.0095465 1.0206727 1.0194645 1.0112973 1.0050470 1.0245748 1.0016489
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0265058 1.0251117 0.8872741 1.1165488 0.9928213 1.0238229 1.0117414 0.9734900
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0392448 0.9914664 0.9428528 0.9539791 1.0097614 0.9589860 1.0047060 0.9647388
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0632959 0.9299326 0.9508690 0.9741759 1.0133988 0.9583345 0.9764993 0.9780540
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9345610 1.0500132 0.9518282 1.0201744 0.9293902 1.0105311 0.9698785 1.0537628
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0124679 0.9761560 1.0004173 0.9839735 1.0264126 1.0781989 0.8995902 1.0026680

```

```

## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9862048 0.9486174 1.0245011 1.0377305 0.9851592 0.9813818 0.9897931 0.9972467
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0290009 1.0287190 0.9975577 0.9917136 0.9377211 0.9895274 1.0429694 1.0060400
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.1071904 0.9668809 0.9460837 1.0730427 1.0069356 0.9296926 0.9933641 0.9801744
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0034317 0.9340553 0.9739997 0.9793247 1.1222979 1.0095372 0.9781989 0.9533980
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9890538 0.9882338 0.9860329 0.9434437 0.9277253 1.0262789 0.9139467 1.0379330
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0067856 1.0027502 1.0247727 0.9659297 0.9955808 0.9851412 1.0576272 1.0068194
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9679356 0.9739452 1.0427578 0.9966072 1.0408772 0.9767807 0.9884497 1.0294630
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9939010 0.9496163 0.9992926 1.0250294 0.9628703 1.0243225 0.9622338 1.0309822
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0336219 0.9959452 1.0510831 0.9999705 0.9366851 1.0242429 0.9961332 0.9583154
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9285697 0.9505965 1.0288405 0.9535355 0.9256597 1.0044224 0.9971810 0.9389225
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0468110 0.9648289 0.9381886 1.0060417 0.9811304 1.0818845 1.0441552 1.0247566
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9787934 1.0232679 0.9689720 0.9701929 1.0249431 1.0046446 0.9504088 0.9725746
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0270122 0.9676728 1.0553297 0.9755483 1.0584560 1.0020032 0.9708451 1.0613370
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0814580 0.9444859 0.9862882 0.9508051 0.9836599 0.9625821 1.0357592 1.0180692
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9623491 0.9804979 1.0162162 0.9654607 1.0381891 1.0656816 1.0125973 1.0593711
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0053229 1.0659910 0.9615151 1.0033519 1.0304715 0.9503345 0.9589905 0.9149634
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.8961051 0.9652091 0.9856552 1.0250545 0.9606064 1.0080408 1.0569807 0.9507197
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9842999 1.0565412 1.0098300 0.9638092 1.0038317 0.9119774 0.9589941 1.0346690
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0030086 0.9414487 1.0070078 1.0043016 1.0680164 1.0096902 1.0209148 0.9134212
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0153167 1.0296054 0.8664424 0.9647438 0.9858585 1.0243345 1.0062961 1.0099822
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9648660 1.1073495 0.9950626 0.9236892 0.9679534 0.9994973 1.0129287 0.9859358
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0534142 1.0474483 0.9913526 1.0161071 0.9655156 0.9660394 1.0647183 0.9796698
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9659897 0.9937891 1.0098357 1.0394305 0.9640827 1.0273612 0.9829232 1.0426499
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9990075 0.9147371 1.0693006 0.9905609 0.9909176 1.0562756 0.9834951 1.0407299
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0699743 0.9227365 1.0031370 0.9052164 1.0402731 0.9735231 1.0719420 0.9819743
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9953251 0.9652544 0.9904909 1.0120996 0.9863178 0.9919137 0.9837995 0.9921276
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9802121 0.9521174 1.0319118 1.0105381 0.9489376 0.9780002 0.9265885 0.9794099

```

```
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9668309 0.9581089 1.0155393 1.0066032 0.9368677 1.0068993 0.9944453 0.9614527
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9645243 0.9889811 1.0024713 0.9200306 0.9627901 0.9833683 0.9792891 0.9761990
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9074045 0.9282546 1.0485030 0.9460663 0.9450125 0.9754917 1.0114060 1.0678821
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9936269 0.9896551 1.0332804 1.0408454 0.9975460 0.8968997 0.9063927 1.0612425
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9341073 0.9467477 0.9376071 1.0104275 0.9803537 0.9878755 0.9973880 1.0135220
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0350569 1.0020078 0.9990109 0.9642229 0.9724353 0.9768769 1.0384327 1.0067318
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0015202 0.8844905 0.9279512 1.0246801 0.9731415 0.9515739 1.0370910 0.9844573
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9473984 0.9548493 1.0178420 1.0510811 0.9293358 1.0169315 0.9827815 1.0347438
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9587153 0.9712059 1.0267707 1.0267899 1.0516450 0.9621788 1.0996896 1.0481467
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9717446 0.9392353 0.9552818 0.9628091 1.0067333 1.0458453 0.9887961 1.0245239
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9150036 1.0026744 0.9805006 0.9505085 1.0252100 1.0012170 1.0335829 1.0531080
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0554487 1.0404811 1.0688584 1.0474394 1.0540501 1.0562356 0.8986464 0.9428480
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0399277 0.9586207 1.0006316 1.0506873 0.9673024 1.0401208 1.0079508 0.8996452
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9758642 1.0053933 0.9551616 0.9568309 0.9676261 1.0235171 0.9749138 1.0195205
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9376173 0.9633816 1.0284842 0.9758496 0.9509036 0.9682979 1.0188714 0.9346805
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0082968 1.0401229 0.9859845 1.0384567 0.9673877 0.9605891 1.0427459 0.9742667
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0472991 0.9656051 0.9838263 1.0746011 0.9594095 0.9709409 0.9436661 1.0278385
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0373878 1.0518851 0.9821714 0.9729706 0.9298226 1.0046148 0.9758360 1.0034662
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 1.0244752 0.9835934 0.9533373 0.9715194 0.9758628 1.0439805 0.9678169 0.9495575
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9845194 0.9431443 1.0377010 1.0352064 0.9351620 1.0193471 0.9819925 1.0630688
## x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1 x_matX1
## 0.9987477 0.9423180 1.0281257 1.0296351 0.9476046 1.1142084 0.9719002 1.0439778
```

Display the confidence interval for the bootstrap estimates by applying the `quantile()` function to get the lower and upper bounds and `median()` to get the estimate

```
lm_confint <- estim_lm %>%
  as.data.frame()
colnames(lm_confint)[1] = "estimate"
lm_confint <- lm_confint %>%
  summarise(conf.low = quantile(estimate, psi / 2),
            median = median(estimate),
            conf.high = quantile(estimate, 1 - psi / 2))
lm_confint
```

```
##      conf.low      median conf.high
## 1 0.9004962 0.9964415 1.081889
```

- ii. Construct confidence intervals for  $\beta_1$  by bootstrapping the data and applying Ridge to the bootstrapped data set. Define `x_mat_cv` and `y_cv` to be used for `cv.glmnet()` for both ridge and lasso

```
x_mat_cv = model.matrix(y~.,df)[-1]
y_cv = as.matrix(df['y'])
```

Use `cv.glmnet()` to perform cross validation for ridge to extract the optimal(minimal) `lambda` to be used in `glmnet()`

```
best_lambda_ridge <- (cv.glmnet(x_mat_cv, y_cv, alpha = 0))$lambda.min
```

Create a function to return the coefficients of the Ridge model

```
get_beta1_ridge = function(data){
  x_mat = model.matrix(y~.,data)[-1]
  y = as.matrix(data['y'])
  ridge_model = glmnet(x_mat, y, alpha = 0, lambda = best_lambda_ridge)
  coef_ridge <- coef(ridge_model)
  beta_1_estim <- coef_ridge[2, 1]
  return(beta_1_estim)
}
```

Create a vector of 1000 bootstrap estimates of beta 1 for ridge

```
estim_ridge <- samples$splits %>%
  map(.,~as.data.frame(.)) %>%
  map(.,~get_beta1_ridge(.)) %>%
  simplify()

estim_ridge
```

```
##      [1] 0.7097176 0.7445196 0.7714905 0.7787428 0.7923692 0.7782389 0.6957261
##      [8] 0.7594222 0.7358038 0.7792644 0.7573250 0.6939873 0.7479135 0.7827265
##     [15] 0.7213151 0.7386054 0.7369787 0.7724025 0.7011172 0.8167422 0.7465947
##     [22] 0.7604086 0.7958661 0.8050109 0.7317098 0.6951037 0.8238828 0.7287042
##     [29] 0.6599533 0.8284938 0.6838492 0.7464226 0.7135441 0.7978399 0.7980748
##     [36] 0.7664522 0.8258698 0.7680932 0.7519327 0.8009131 0.7585040 0.7386098
##     [43] 0.7772201 0.7452146 0.7508061 0.7990401 0.7473985 0.7578202 0.7311751
##     [50] 0.7297944 0.7180124 0.7937719 0.7807356 0.7270569 0.7241785 0.8020031
##     [57] 0.7762751 0.7288494 0.7819297 0.7861039 0.7891623 0.7911025 0.7693903
##     [64] 0.8069206 0.7645307 0.7727808 0.7802573 0.7218666 0.7601952 0.7730647
##     [71] 0.7651433 0.7300846 0.7776865 0.7751960 0.7902243 0.7969392 0.7571641
##     [78] 0.7973073 0.7938214 0.6889560 0.6896220 0.7616942 0.8148593 0.7433733
##     [85] 0.7248862 0.7985370 0.7734775 0.7946140 0.7434004 0.7174536 0.7267286
##     [92] 0.7727373 0.7063185 0.7502314 0.7769451 0.7218164 0.7460744 0.7824586
##     [99] 0.7265576 0.7338202 0.7587752 0.7889481 0.7674774 0.7185510 0.8053014
##    [106] 0.7708317 0.8091550 0.7889674 0.7395048 0.7574946 0.7979135 0.7481547
##    [113] 0.7838699 0.7911026 0.7046881 0.8006087 0.6830706 0.7640539 0.7798347
##    [120] 0.7967030 0.6695028 0.7819089 0.7789580 0.7281855 0.7953795 0.7808871
```



##	[127]	0.7898206	0.8051974	0.7992139	0.7240514	0.7428429	0.7926884	0.7943105
##	[134]	0.7413032	0.7474622	0.7376180	0.7889143	0.7602737	0.8171497	0.7808483
##	[141]	0.7618910	0.7954293	0.7757222	0.7022213	0.8008767	0.7689037	0.7549544
##	[148]	0.7364487	0.7535600	0.7372698	0.7549883	0.8601659	0.8177538	0.7510477
##	[155]	0.7951937	0.7357499	0.7633083	0.7767061	0.8156750	0.7451277	0.7450715
##	[162]	0.7527099	0.8150727	0.7855672	0.7718950	0.8149486	0.7251206	0.7934454
##	[169]	0.7471314	0.7528225	0.7520146	0.7222922	0.6779255	0.7207259	0.7197297
##	[176]	0.7691013	0.8449649	0.7320536	0.7554997	0.7985872	0.7795602	0.7930994
##	[183]	0.7415957	0.7608608	0.7378618	0.7774668	0.7356658	0.7999217	0.7417687
##	[190]	0.7759793	0.7452051	0.7327038	0.7480114	0.7852465	0.7776302	0.7377749
##	[197]	0.7715552	0.7545905	0.7197125	0.7765360	0.7718110	0.7827341	0.8137529
##	[204]	0.7421285	0.7143915	0.7106810	0.8425367	0.7441481	0.8117139	0.7437224
##	[211]	0.7427385	0.7088623	0.7603480	0.7575295	0.6992575	0.6870935	0.7392695
##	[218]	0.7770561	0.7811901	0.7904581	0.7573385	0.7406791	0.7078041	0.7533992
##	[225]	0.7265085	0.7846565	0.7542615	0.7049146	0.7595367	0.7349457	0.7468969
##	[232]	0.6863485	0.6960311	0.7409287	0.8092361	0.7318471	0.7878724	0.6775576
##	[239]	0.8116021	0.7244805	0.7778419	0.6469124	0.8068277	0.8031002	0.7515035
##	[246]	0.7799974	0.7050617	0.8095600	0.7768901	0.6939549	0.7362192	0.7548875
##	[253]	0.7699461	0.7703982	0.7012211	0.7428939	0.7210711	0.7882435	0.7988014
##	[260]	0.7781047	0.7691159	0.7809858	0.7361348	0.7086043	0.7635100	0.6959352
##	[267]	0.7830189	0.8112004	0.7766608	0.7476133	0.7006352	0.6951825	0.7370439
##	[274]	0.7565240	0.7703847	0.8108358	0.7900504	0.7616386	0.7735282	0.7383459
##	[281]	0.7701028	0.7456687	0.7060310	0.7468749	0.7862308	0.7475704	0.7386600
##	[288]	0.7924289	0.7306495	0.7557731	0.7381370	0.7339678	0.7843271	0.7367506
##	[295]	0.7720199	0.8176789	0.7638613	0.7572934	0.7572932	0.7735786	0.7290114
##	[302]	0.7619875	0.7730341	0.7690902	0.7135374	0.7364904	0.7146498	0.7892280
##	[309]	0.7672202	0.7345109	0.6858267	0.7476967	0.6850172	0.7501022	0.7317778
##	[316]	0.7549400	0.7821506	0.7753397	0.7795530	0.7588050	0.7238428	0.7709579
##	[323]	0.7861103	0.7633756	0.7874541	0.7751759	0.8114995	0.8216292	0.7715249
##	[330]	0.7363183	0.7560442	0.7510116	0.7547421	0.7231771	0.7544025	0.7418099
##	[337]	0.7694342	0.7242777	0.7684125	0.7772745	0.8173440	0.8365975	0.7192787
##	[344]	0.7757309	0.7752063	0.7032879	0.7950761	0.8021546	0.7107581	0.7631285
##	[351]	0.7778836	0.7791999	0.7901445	0.7642313	0.7964979	0.7857416	0.7661779
##	[358]	0.7549131	0.8145135	0.7612992	0.7194277	0.7887460	0.7864489	0.7610941
##	[365]	0.7570200	0.8253470	0.7464123	0.7508252	0.7407733	0.7564472	0.7471730
##	[372]	0.7368950	0.7348487	0.7215540	0.7783964	0.7828364	0.8024278	0.7095538
##	[379]	0.7970126	0.7671227	0.7419712	0.7098767	0.7577754	0.7663527	0.7468424
##	[386]	0.7168323	0.7005595	0.7424421	0.7074310	0.8047293	0.7679581	0.7595712
##	[393]	0.7652986	0.7480108	0.7672823	0.7322590	0.7804416	0.7731963	0.7963475
##	[400]	0.7106855	0.7683639	0.7853027	0.8248033	0.7367410	0.7408710	0.7381330
##	[407]	0.7238854	0.7660995	0.7845773	0.7511353	0.7660659	0.7979913	0.7916460
##	[414]	0.7812328	0.7717177	0.8019255	0.6697820	0.8130005	0.7549317	0.7572629
##	[421]	0.7936881	0.7638536	0.7791103	0.8196490	0.7947665	0.7742734	0.7629127
##	[428]	0.6777188	0.7540567	0.7728792	0.7273836	0.7541639	0.7327987	0.7604712
##	[435]	0.7452571	0.7512687	0.7595014	0.7624224	0.7458503	0.8305900	0.7149168
##	[442]	0.7547369	0.7231186	0.8079475	0.7832152	0.7639900	0.8102649	0.7805384
##	[449]	0.7191559	0.7832159	0.7842970	0.7284506	0.7433402	0.7837665	0.7678254
##	[456]	0.7855148	0.8195710	0.7437230	0.7380321	0.7811874	0.7595103	0.7595085
##	[463]	0.7798696	0.7314806	0.7625771	0.7362997	0.8343001	0.7070793	0.7498922
##	[470]	0.7107318	0.7508251	0.7649803	0.8025812	0.7741666	0.7808625	0.7606939
##	[477]	0.7766998	0.7906052	0.7339892	0.7754406	0.7513138	0.7968455	0.7755948
##	[484]	0.7439476	0.8141716	0.7912462	0.7592575	0.7578330	0.7574911	0.6790819
##	[491]	0.7481432	0.7316896	0.7688730	0.7741761	0.7884836	0.7757666	0.7642496
##	[498]	0.7809706	0.8198417	0.7593918	0.7719383	0.7322211	0.7346099	0.6930967

##	[505]	0.7621863	0.7618844	0.7325877	0.7702570	0.7660062	0.7331280	0.7400238
##	[512]	0.7527823	0.8097231	0.7643873	0.7827824	0.6728654	0.7383619	0.7646211
##	[519]	0.7815219	0.7684025	0.7489344	0.7799688	0.7544311	0.7103718	0.7103173
##	[526]	0.7575945	0.7324794	0.7275563	0.7370850	0.7507998	0.7380905	0.8034782
##	[533]	0.7944511	0.7876981	0.7639128	0.7588500	0.7629149	0.7197824	0.7865061
##	[540]	0.7167282	0.7433368	0.7581316	0.8045285	0.7604060	0.7679702	0.8055961
##	[547]	0.7941208	0.7610057	0.7237212	0.7818208	0.7151214	0.7925691	0.7824176
##	[554]	0.7310375	0.7877092	0.8019362	0.7017412	0.7658456	0.7640428	0.7867915
##	[561]	0.7481731	0.8048671	0.7594008	0.7432810	0.7796324	0.7734923	0.7716872
##	[568]	0.7552097	0.7938998	0.7332623	0.7738276	0.7662496	0.7654629	0.7515155
##	[575]	0.7834108	0.7583199	0.7686469	0.7741013	0.6720262	0.8317202	0.7547630
##	[582]	0.7908994	0.7578089	0.7539210	0.7804128	0.7429877	0.7173809	0.7003543
##	[589]	0.7472377	0.7340865	0.7555046	0.7449298	0.7871542	0.7167109	0.7302139
##	[596]	0.7478731	0.7704538	0.7373981	0.7434166	0.7379777	0.7138844	0.8197764
##	[603]	0.7234499	0.7730975	0.7146831	0.7843648	0.7580857	0.7896640	0.7705150
##	[610]	0.7640991	0.7651008	0.7683909	0.7608487	0.8188121	0.6859476	0.7663132
##	[617]	0.7663199	0.7177644	0.7818596	0.8037115	0.7456440	0.7609530	0.7448636
##	[624]	0.7765114	0.7756016	0.7995925	0.7693231	0.7382889	0.7249796	0.7663714
##	[631]	0.7829138	0.7564638	0.8361472	0.7259572	0.7096493	0.8058101	0.7550947
##	[638]	0.7108840	0.7506040	0.7865525	0.7655187	0.7121616	0.7314727	0.7534783
##	[645]	0.8392904	0.7987876	0.7362875	0.7207819	0.7531336	0.7751723	0.7796229
##	[652]	0.7061945	0.7051802	0.7710498	0.7160704	0.7871573	0.7761228	0.7734939
##	[659]	0.8027999	0.7329060	0.7677719	0.7381065	0.7972752	0.7640089	0.7476565
##	[666]	0.7567894	0.7922771	0.7638907	0.7762012	0.7694710	0.7393224	0.7966868
##	[673]	0.7500533	0.7377243	0.7553378	0.7942636	0.7356740	0.7830284	0.7137869
##	[680]	0.7760154	0.7804262	0.7689830	0.8085716	0.7836000	0.7011377	0.7810696
##	[687]	0.7722431	0.7468239	0.7131480	0.7446722	0.7942309	0.7209722	0.7097414
##	[694]	0.7580007	0.7565439	0.7295744	0.8001474	0.7222959	0.7019543	0.7421976
##	[701]	0.7487925	0.8096339	0.7984880	0.7610823	0.7355186	0.7762745	0.7433679
##	[708]	0.7503059	0.7988963	0.7270844	0.7431145	0.7526247	0.7929404	0.7503846
##	[715]	0.7895025	0.7375688	0.7955349	0.7625262	0.7259245	0.7946503	0.8327328
##	[722]	0.7034930	0.7506833	0.7176934	0.7526820	0.7406013	0.8127844	0.7638394
##	[729]	0.7371841	0.7555121	0.7913393	0.7291205	0.7740573	0.7913644	0.7677698
##	[736]	0.7865419	0.7677646	0.8215546	0.7415451	0.7699418	0.7984056	0.7181179
##	[743]	0.7264955	0.7018749	0.6965446	0.7370281	0.7392357	0.7704490	0.7528796
##	[750]	0.7640266	0.7879673	0.7433790	0.7321303	0.8216673	0.7499268	0.7096615
##	[757]	0.7463737	0.6972008	0.7266166	0.8093551	0.7617726	0.7083978	0.7763628
##	[764]	0.7714957	0.7998181	0.7679219	0.7835073	0.6979469	0.7876820	0.7876157
##	[771]	0.6942559	0.7237274	0.7373187	0.7743651	0.7880079	0.7742051	0.7306328
##	[778]	0.8493174	0.7752680	0.7283702	0.7464663	0.7459073	0.7442638	0.7523335
##	[785]	0.7974775	0.7694005	0.7613752	0.7659485	0.7575711	0.7332705	0.7843000
##	[792]	0.7693880	0.7582131	0.7522422	0.7635245	0.7937395	0.7579158	0.7932399
##	[799]	0.7513301	0.7942216	0.7512858	0.7154570	0.7747557	0.7485355	0.7555953
##	[806]	0.7848658	0.7490410	0.8148709	0.8093258	0.7350039	0.7610974	0.7257832
##	[813]	0.8068983	0.7245355	0.8224420	0.7527587	0.7454078	0.7289901	0.7841109
##	[820]	0.7638379	0.7516077	0.7476620	0.7535752	0.7720954	0.7590873	0.7121733
##	[827]	0.7972156	0.7673343	0.7209848	0.7527451	0.7121147	0.7459590	0.7293050
##	[834]	0.7356005	0.7570230	0.7854624	0.7106302	0.7778324	0.7795340	0.7447704
##	[841]	0.7264073	0.7718415	0.7843854	0.7207865	0.7548043	0.7490838	0.7630751
##	[848]	0.7573036	0.6943022	0.7183966	0.7938692	0.7369656	0.7350734	0.7161560
##	[855]	0.7937013	0.8132343	0.7597536	0.7408224	0.7667556	0.8024384	0.7472141
##	[862]	0.7108751	0.7064760	0.7870626	0.7180252	0.7304149	0.7094265	0.7610742
##	[869]	0.7231457	0.7545931	0.7689343	0.7853897	0.7811566	0.7438201	0.7670147
##	[876]	0.7380250	0.7287908	0.7473960	0.7693339	0.7647018	0.7736287	0.6992859

```
## [883] 0.6916131 0.7861045 0.7436295 0.7014249 0.7778297 0.7686290 0.7298030
## [890] 0.7277556 0.7663882 0.7841627 0.6807730 0.7546451 0.7401919 0.7884830
## [897] 0.7299611 0.7371765 0.7453238 0.7749179 0.7911399 0.7584592 0.8105124
## [904] 0.7987124 0.7537020 0.7273182 0.6899221 0.7432251 0.7729911 0.7882767
## [911] 0.7533967 0.7634334 0.6943599 0.7540386 0.7674488 0.7162514 0.7855322
## [918] 0.7808445 0.8012213 0.7984689 0.8047773 0.7620774 0.7971858 0.7877581
## [925] 0.8074601 0.7949674 0.7053898 0.7145091 0.7846863 0.7289324 0.7587493
## [932] 0.7870515 0.7547258 0.8029106 0.7556521 0.6989972 0.7476167 0.7574723
## [939] 0.7405180 0.7253315 0.7218436 0.7708241 0.7564524 0.7813669 0.7204354
## [946] 0.7367840 0.7626278 0.7539889 0.7426674 0.7391746 0.7770520 0.7039320
## [953] 0.7823384 0.7912773 0.7854495 0.7940831 0.7431181 0.7453755 0.7980380
## [960] 0.7663854 0.7944726 0.7378449 0.7742843 0.8121794 0.7385644 0.7351148
## [967] 0.7364993 0.7707877 0.8021556 0.8088461 0.7556215 0.7719632 0.7422482
## [974] 0.7687719 0.7366197 0.7583285 0.7792891 0.7508156 0.7257168 0.7504903
## [981] 0.7404687 0.7868759 0.7454054 0.7397834 0.7414770 0.7272082 0.7946580
## [988] 0.8125782 0.7194974 0.7723783 0.7628173 0.7962465 0.7639691 0.7253625
## [995] 0.7991080 0.7642114 0.7397696 0.8099999 0.7453567 0.7944218
```

Display the confidence interval for the bootstrap estimates by applying the `quantile()` function to get the lower and upper bounds and `median()` to get the estimate

```
ridge_confint <- estim_ridge %>%
  as.data.frame()
colnames(ridge_confint)[1] = "estimate"
ridge_confint <- ridge_confint %>%
  summarise(conf.low = quantile(estimate, psi / 2),
            median = median(estimate),
            conf.high = quantile(estimate, 1 - psi / 2))

ridge_confint
```

```
##   conf.low   median conf.high
## 1 0.6942491 0.7595539 0.8177802
```

(iii). Construct confidence intervals for  $\beta_1$  by bootstrapping the data and applying Lasso to the bootstrapped data set.

Use `cv.glmnet()` to perform cross validation for lasso to extract the optimal(minimal) `lambda` to be used in `glmnet()`

```
best_lambda_lasso <- (cv.glmnet(x_mat_cv, y_cv, alpha = 1))$lambda.min
```

Create a function to return the coefficients of the Lasso model

```
get_beta1_lasso = function(data){
  x_mat = model.matrix(y~.,data)[,-1]
  y = as.matrix(data['y'])
  lasso_model = glmnet(x_mat, y, alpha = 1, lambda = best_lambda_lasso)
  coef_lasso <- coef(lasso_model)
  beta_1_estim <- coef_lasso[2, 1]
  return(beta_1_estim)
}
```

Create a vector of 1000 bootstrap estimates of beta 1 for lasso

```
estim_lasso <- samples$splits %>%  
  map(., ~as.data.frame(.)) %>%  
  map(., ~get_beta1_lasso(.)) %>%  
  simplify()  
  
estim_lasso
```

```
##      [1] 0.8866644 0.8985255 0.9242725 0.9276995 0.9444668 0.9588975 0.8451853  
##      [8] 0.9685211 0.8828291 0.9695218 0.9179477 0.8466190 0.9453458 0.9591695  
##     [15] 0.9070580 0.9405312 0.9109404 0.9459126 0.8728344 0.9832534 0.9481791  
##     [22] 0.9221063 0.9767601 0.9782987 0.9139078 0.8230130 0.9839861 0.8906673  
##     [29] 0.8222634 1.0125764 0.8500391 0.9036113 0.9040392 0.9362062 0.9641979  
##     [36] 0.9397687 1.0315318 0.9499756 0.9458378 0.9884270 0.9271215 0.8784637  
##     [43] 0.9294682 0.9095834 0.9086202 0.9986124 0.9135295 0.9273830 0.9089430  
##     [50] 0.9104951 0.8653036 0.9758097 0.9529394 0.8828750 0.8982052 0.9616433  
##     [57] 0.9667523 0.8925547 0.9533790 0.9416007 0.9736191 0.9516655 0.9467800  
##     [64] 0.9602473 0.9771661 0.9415753 0.9713124 0.9155157 0.8914027 0.9580916  
##     [71] 0.9517025 0.8936908 0.9302457 0.9513721 0.9829752 0.9733080 0.9259420  
##     [78] 0.9617770 1.0102212 0.8696085 0.8574328 0.9398746 0.9870652 0.8998634  
##     [85] 0.8803742 0.9753343 0.9514251 0.9511127 0.9267590 0.9324064 0.8633897  
##     [92] 0.9520876 0.8629779 0.9260873 0.9420001 0.8877811 0.9212558 0.9318625  
##     [99] 0.8902473 0.8719358 0.9470212 0.9681946 0.9395341 0.8557472 0.9669304  
##    [106] 0.9253206 0.9867080 0.9515093 0.8979274 0.9184626 0.9686145 0.9114991  
##    [113] 0.9690648 0.9838493 0.8648765 0.9783980 0.8598395 0.9491019 0.9294148  
##    [120] 0.9875992 0.8568638 0.9476656 0.9546155 0.9026445 0.9783159 0.9572546  
##    [127] 0.9510655 0.9849803 0.9580782 0.8967775 0.8938675 0.9846444 0.9700814  
##    [134] 0.8978489 0.9219558 0.9122594 0.9490374 0.9509542 0.9990840 0.9677496  
##    [141] 0.9065593 0.9718334 0.9428539 0.8886073 0.9499756 0.9492699 0.9298228  
##    [148] 0.9165874 0.9392285 0.9054387 0.9341410 1.0421854 1.0169062 0.9316233  
##    [155] 0.9708052 0.9136841 0.9307772 0.9403303 0.9885627 0.9165400 0.9209717  
##    [162] 0.9215720 1.0148325 0.9538789 0.9620842 0.9917551 0.9045457 0.9710063  
##    [169] 0.8899936 0.8990656 0.9254089 0.8985601 0.8311603 0.8959058 0.8865723  
##    [176] 0.9141958 1.0216179 0.9082475 0.9321217 0.9830749 0.9509241 0.9434456  
##    [183] 0.9193370 0.9437260 0.8969349 0.9681287 0.8833780 0.9733986 0.8911919  
##    [190] 0.9618219 0.9243516 0.8838296 0.9361712 0.9737420 0.9439583 0.8917888  
##    [197] 0.9318855 0.9621731 0.9067167 0.9640811 0.9307029 0.9488687 0.9739263  
##    [204] 0.8900583 0.8761258 0.9042318 1.0263563 0.9370366 0.9896724 0.9185603  
##    [211] 0.9361371 0.8570320 0.8956238 0.9165398 0.8515741 0.8517502 0.9026755  
##    [218] 0.9429912 0.9592920 0.9510306 0.9393869 0.9222988 0.8868377 0.9299533  
##    [225] 0.8845944 0.9521581 0.9259703 0.8615563 0.9515886 0.8910442 0.9453006  
##    [232] 0.8799167 0.8812506 0.9374611 0.9758763 0.8881374 0.9631494 0.8569769  
##    [239] 0.9895383 0.9055557 0.9276039 0.8200130 0.9594868 0.9690657 0.9519035  
##    [246] 0.9586939 0.8982767 0.9925048 0.9102716 0.8876119 0.9242961 0.9001998  
##    [253] 0.9483803 0.9454428 0.8621033 0.9172735 0.9026592 0.9867498 0.9535515  
##    [260] 0.9098192 0.9426451 0.9468557 0.9082065 0.8692055 0.9170538 0.8461652  
##    [267] 0.9530598 0.9792622 0.9563348 0.9137164 0.8691390 0.8877322 0.9379656  
##    [274] 0.9530166 0.9417752 0.9640225 0.9629021 0.9345061 0.9944415 0.9600937  
##    [281] 0.9610732 0.9202189 0.8805679 0.8781146 0.9263370 0.9111285 0.9206605  
##    [288] 0.9624451 0.8991046 0.9338518 0.8972598 0.9097565 0.9925934 0.8999039  
##    [295] 0.8982250 1.0262274 0.9444289 0.9044345 0.9224141 0.9595652 0.9087727  
##    [302] 0.9130903 0.9461421 0.9271604 0.8736601 0.9124153 0.9233584 0.9519133  
##    [309] 0.9618227 0.8916857 0.8798648 0.9088922 0.8739441 0.9173379 0.9237045
```

##	[316]	0.9382833	0.9654414	0.9317185	0.9512035	0.9522639	0.8936655	0.9497259
##	[323]	0.9694224	0.9635932	0.9783170	0.9876113	0.9806181	0.9937135	0.9158193
##	[330]	0.8947092	0.9223355	0.9220797	0.9273547	0.8765571	0.9435266	0.9188782
##	[337]	0.9377335	0.8922068	0.9298727	0.9676217	0.9780848	1.0435483	0.9069473
##	[344]	0.9307395	0.9744894	0.8621080	0.9684136	0.9723867	0.8977981	0.9509037
##	[351]	0.9216552	0.9688464	0.9798631	0.9360583	0.9666594	0.9550947	0.9188485
##	[358]	0.9014406	0.9792581	0.9350031	0.9009371	0.9642318	0.9534072	0.9470833
##	[365]	0.9485706	1.0004734	0.9020469	0.9067655	0.9026468	0.9446484	0.9070012
##	[372]	0.8760680	0.8670577	0.8796168	0.9642046	0.9332871	1.0084645	0.8866684
##	[379]	0.9759188	0.9378454	0.9125887	0.8723202	0.9372468	0.9506056	0.9003314
##	[386]	0.8913659	0.8692945	0.9209380	0.8779876	0.9440423	0.9443209	0.9361099
##	[393]	0.9526900	0.9174495	0.9402769	0.9011420	0.9705029	1.0042196	0.9750606
##	[400]	0.8801731	0.9589637	0.9576255	0.9854596	0.9008702	0.9042897	0.9221151
##	[407]	0.8907855	0.9416375	0.9591653	0.9130747	0.9651485	0.9519591	0.9870198
##	[414]	0.9831067	0.9490494	0.9789145	0.8495590	0.9814351	0.9288278	0.9516465
##	[421]	0.9769981	0.9170088	0.9788284	0.9852910	0.9713214	0.9304622	0.9133804
##	[428]	0.8483685	0.9505148	0.9273458	0.9002192	0.9027701	0.8968946	0.9228471
##	[435]	0.9614104	0.9246483	0.9340204	0.9558707	0.8949437	1.0065415	0.9025513
##	[442]	0.9602958	0.9059914	0.9995737	0.9663029	0.9335824	0.9863118	0.9505091
##	[449]	0.9115006	0.9690425	0.9787149	0.8905684	0.9349397	0.9672669	0.9454125
##	[456]	0.9845726	1.0075539	0.9148866	0.9057964	0.9257944	0.9457807	0.9420082
##	[463]	0.9241650	0.9089932	0.9620919	0.9005941	0.9995585	0.8712128	0.9369516
##	[470]	0.8732645	0.9226638	0.9534720	1.0018015	0.9468630	0.9634924	0.9027596
##	[477]	0.9647279	0.9576303	0.9284995	0.9311921	0.9324603	0.9823110	0.9580949
##	[484]	0.8882159	0.9895329	0.9659656	0.9513654	0.9369393	0.9104691	0.8518139
##	[491]	0.9078652	0.8811713	0.9197790	0.9345732	0.9770401	0.9535744	0.9248660
##	[498]	0.9447733	0.9992565	0.9461078	0.9566259	0.9236143	0.9088534	0.8830453
##	[505]	0.9783057	0.9308610	0.9095528	0.9411041	0.9404197	0.8842071	0.8951187
##	[512]	0.8837429	0.9726079	0.9162542	0.9399184	0.7955815	0.8939660	0.9107874
##	[519]	0.9435764	0.9884149	0.9087844	0.9393128	0.9333108	0.9107384	0.8581953
##	[526]	0.9373549	0.9063806	0.8872081	0.8982553	0.9239925	0.8986625	0.9951444
##	[533]	0.9623525	0.9641764	0.9492742	0.9376193	0.9251601	0.8911874	0.9856384
##	[540]	0.8904433	0.9105990	0.9249443	0.9823329	0.9218468	0.9434050	0.9558703
##	[547]	0.9743601	0.9447398	0.9157164	0.9620428	0.9057118	0.9592745	0.9718097
##	[554]	0.8856001	0.9628420	0.9557460	0.8811211	0.9569168	0.9382922	1.0049189
##	[561]	0.9217286	0.9879093	0.9212269	0.9308166	0.9622571	0.9452699	0.9666980
##	[568]	0.9081755	0.9902459	0.8943485	0.9367541	0.9436589	0.9331485	0.9257579
##	[575]	0.9356795	0.9190294	0.9281084	0.9580137	0.8464440	1.0092268	0.9189857
##	[582]	0.9506337	0.9282524	0.9321918	0.9294667	0.9314024	0.9109988	0.8713535
##	[589]	0.9275105	0.9359836	0.9486917	0.8998948	0.9325894	0.9115309	0.9171521
##	[596]	0.9435213	0.9567113	0.9102142	0.9074259	0.9083162	0.8816563	1.0008049
##	[603]	0.8773306	0.9369637	0.8665796	0.9686827	0.9143324	0.9515226	0.9380244
##	[610]	0.9396287	0.9278115	0.9326262	0.9103974	0.9876507	0.8496464	0.9295589
##	[617]	0.9299233	0.8693104	0.9445426	0.9495715	0.9153985	0.9388286	0.9092283
##	[624]	0.9718196	0.9542364	0.9708383	0.9211981	0.8953992	0.8842211	0.9336912
##	[631]	0.9457765	0.9487786	1.0447112	0.9001316	0.8803392	0.9854424	0.9040696
##	[638]	0.8748309	0.9482077	0.9893531	0.9745078	0.8657095	0.9065751	0.9624518
##	[645]	1.0290546	0.9712131	0.8943905	0.8677562	0.9424910	0.9323225	0.9592605
##	[652]	0.8578565	0.8904409	0.9182194	0.9045339	0.9660344	0.9774270	0.9279601
##	[659]	0.9833361	0.8998064	0.9448223	0.9048127	0.9533589	0.9355986	0.9215257
##	[666]	0.9276309	0.9636859	0.9345018	0.9651786	0.9680817	0.9401477	1.0104849
##	[673]	0.8523572	0.9057358	0.9324831	0.9727885	0.8900941	0.9448230	0.8829993
##	[680]	0.9407559	0.9379378	0.9604633	0.9859476	0.9380876	0.8574344	0.9436663
##	[687]	0.9572460	0.9238615	0.8753180	0.9283253	0.9820996	0.8914759	0.8937371

```
## [694] 0.9374554 0.9210139 0.8876993 0.9596984 0.8961654 0.8970571 0.9144826
## [701] 0.9071671 0.9789637 0.9686429 0.9540766 0.9228848 0.9414327 0.9253510
## [708] 0.9384899 0.9868870 0.8683542 0.9179274 0.9117385 0.9626102 0.9193853
## [715] 0.9793735 0.9406260 0.9751693 0.9297479 0.8569206 0.9577573 1.0286614
## [722] 0.8892711 0.9104528 0.8961753 0.9249526 0.9103764 1.0036500 0.9193341
## [729] 0.9164189 0.9549762 0.9758549 0.8939863 0.9546693 0.9807017 0.9056936
## [736] 0.9680070 0.9712677 1.0216583 0.9069216 0.9399154 0.9766730 0.8454296
## [743] 0.9110339 0.8750734 0.8963494 0.9242699 0.9194636 0.9148462 0.9221658
## [750] 0.9270006 0.9809607 0.9214238 0.8887594 0.9977908 0.9331726 0.8996824
## [757] 0.9270204 0.8496010 0.8763421 1.0044351 0.9311213 0.8517576 0.9371484
## [764] 0.9392324 0.9807213 0.9587610 0.9590912 0.8522558 0.9656227 0.9643888
## [771] 0.8597593 0.8990989 0.9151626 0.9514713 0.9773499 0.9358680 0.9217786
## [778] 1.0105848 0.9859097 0.8949263 0.9261717 0.9077551 0.9246400 0.9048629
## [785] 0.9611311 0.9539389 0.9386465 0.9489694 0.9256297 0.9092482 0.9600399
## [792] 0.9476788 0.9155018 0.9136217 0.9376709 0.9766098 0.9470553 0.9486325
## [799] 0.9296047 0.9677817 0.9367750 0.9136920 0.9563303 0.9552591 0.9164872
## [806] 0.9679249 0.9343103 1.0152978 0.9605367 0.9412048 0.9336704 0.9444096
## [813] 0.9965777 0.8731299 0.9901314 0.9257516 0.9116948 0.8931713 0.9694283
## [820] 0.9267795 0.9741094 0.8916320 0.9300911 0.9661125 0.9174317 0.9046186
## [827] 0.9753166 0.9054280 0.9031615 0.9206182 0.8683808 0.9230620 0.8960727
## [834] 0.9176075 0.8960054 0.9628376 0.8802459 0.9598903 0.9850366 0.8959338
## [841] 0.9661284 0.9821680 0.9345171 0.8992460 0.9338311 0.9412226 0.9409629
## [848] 0.9131058 0.8941911 0.9070923 0.9574283 0.9425502 0.9114247 0.8907186
## [855] 0.9656708 0.9742025 0.9597091 0.9196423 0.9454393 0.9716225 0.9236624
## [862] 0.8887601 0.8490858 0.9499420 0.8928048 0.9076606 0.8709874 0.9133311
## [869] 0.9020108 0.9090331 0.9350471 0.9646367 0.9922725 0.9148800 0.9318201
## [876] 0.8952693 0.9096098 0.9339558 0.9282400 0.9129124 0.9388362 0.8897677
## [883] 0.8785407 0.9922907 0.9034501 0.8656308 0.9409620 0.9758169 0.9283276
## [890] 0.8789611 0.9414521 0.9457248 0.8670255 0.9004152 0.9172234 0.9741263
## [897] 0.8833637 0.9090982 0.8852771 0.9673446 0.9583805 0.9102225 0.9378227
## [904] 0.9748980 0.9350438 0.9427443 0.8468758 0.9347754 0.9320504 0.9694287
## [911] 0.9534614 0.9578739 0.8367737 0.9186027 0.9615586 0.8818722 0.9804749
## [918] 0.9884936 0.9929520 0.9567397 0.9899265 0.8901431 1.0018319 0.9681582
## [925] 0.9801150 0.9562148 0.9027278 0.8708203 0.9616410 0.9154818 0.9339876
## [932] 0.9619435 0.9089991 0.9847698 0.9121370 0.8682660 0.9309232 0.9441279
## [939] 0.9101988 0.9084480 0.8812352 0.9479253 0.9495053 0.9362900 0.8917249
## [946] 0.9218943 0.9006198 0.9273403 0.9327713 0.8891859 0.9505138 0.8671086
## [953] 0.9498452 0.9614892 0.9488980 0.9849925 0.8665598 0.9568795 0.9467416
## [960] 0.9390410 0.9792772 0.9163278 0.9278371 0.9921725 0.9341025 0.9392010
## [967] 0.9173451 0.9698551 0.9648440 1.0186835 0.9347241 0.9448899 0.9377759
## [974] 0.9498827 0.9107805 0.9165861 0.9694012 0.9231000 0.9062803 0.9063814
## [981] 0.9256209 0.9492561 0.9343131 0.8778119 0.9242609 0.8966138 0.9995873
## [988] 1.0217461 0.8768014 0.9777821 0.9450588 0.9638950 0.9458049 0.8789258
## [995] 0.9858269 0.9485212 0.9412506 0.9843307 0.9111920 0.9766610
```

Display the confidence interval for the bootstrap estimates by applying the `quantile()` function to get the lower and upper bounds and `median()` to get the estimate

```
lasso_confint <- estim_lasso %>%
  as.data.frame()
colnames(lasso_confint)[1] = "estimate"
lasso_confint <- lasso_confint %>%
  summarise(conf.low = quantile(estimate, psi / 2),
            median = median(estimate),
```

```

      conf.high = quantile(estimate, 1 - psi / 2))
lasso_confint

```

```

##      conf.low      median conf.high
## 1 0.8568359 0.9338414 1.004225

```

(c). Comment on the obtained results **From the results, we ascertain that lasso and least squares produce similar estimates for  $\beta_1$  with lasso providing the tightest bound of all 3. Ridge produces a significantly lower estimate than both lasso and least squares with a bound that is not as tight as lasso but significantly tighter than least squares**

## Problem 4(Question 9 in ISL Pg. 263 )

9.In this exercise, we will predict the number of applications received using the other variables in the College data set.

```
data(College)
```

(a). Split the data set into a training set and a test set. set.seed(1)

```

data(College)
set.seed(1)
smp_siz <- dim(College)[1] / 2

train <- sample(seq_len(nrow(College)),size = smp_siz)
test <- -train
data_train <- College[train,]
data_test <- College[test,]

```

(b). Fit a linear model using least squares on the training set, and report the test error obtained.

```

lm_model <- lm(Apps ~ ., data = data_train)
lm_predict <- predict(lm_model, data_test)
lm_predict

```

```

##              Agnes Scott College
##              2054.898055
##              Albertson College
##              673.657532
##              Albertus Magnus College
##              -149.929987
##              Albion College
##              2722.169420
##              Albright College
##              847.596822
##              Alderson-Broaddus College
##              564.067517
##              Alfred University
##              1876.762135
##              Allegheny College

```

##		3021.916028
##	Allentown Coll. of St. Francis de Sales	
##		2103.586449
##	Alma College	
##		2089.054859
##	Amherst College	
##		4021.813888
##	Aquinas College	
##		279.238899
##	Arizona State University Main campus	
##		15388.046640
##	Arkansas Tech University	
##		1739.892865
##	Assumption College	
##		2200.024338
##	Augustana College IL	
##		2404.481987
##	Barat College	
##		189.927754
##	Barnard College	
##		3064.308673
##	Bellarmino College	
##		1582.064502
##	Bemidji State University	
##		1127.599072
##	Benedictine College	
##		643.902085
##	Berry College	
##		2198.723251
##	Bethel College KS	
##		48.483671
##	Bethel College	
##		39.979913
##	Bethune Cookman College	
##		1498.360522
##	Birmingham-Southern College	
##		2616.612399
##	Bloomsburg Univ. of Pennsylvania	
##		4096.048123
##	Bluffton College	
##		173.140508
##	Bowdoin College	
##		3906.766362
##	Bradford College	
##		-227.930183
##	Bradley University	
##		5625.391819
##	Brenau University	
##		-116.347870
##	Brewton-Parker College	
##		-166.425775
##	Briar Cliff College	
##		279.516939
##	Bridgewater College	



##		873.392683
##	Brigham Young University at Provo	
##		6871.083493
##	Buena Vista College	
##		549.788656
##	Butler University	
##		3302.882740
##	Cabrini College	
##		602.669882
##	California Lutheran University	
##		-61.762048
##	California State University at Fresno	
##		3911.210406
##	Campbell University	
##		1198.215103
##	Capital University	
##		2088.526232
##	Carleton College	
##		4209.193690
##	Carnegie Mellon University	
##		9474.711129
##	Carson-Newman College	
##		1011.182444
##	Case Western Reserve University	
##		6580.419320
##	Catawba College	
##		809.468312
##	Catholic University of America	
##		2143.807971
##	Cazenovia College	
##		5902.705647
##	Cedar Crest College	
##		895.012915
##	Cedarville College	
##		1653.297911
##	Centenary College of Louisiana	
##		1012.055042
##	Center for Creative Studies	
##		1247.389412
##	Central College	
##		1474.177755
##	Centre College	
##		2471.491235
##	Chatham College	
##		132.570559
##	Christian Brothers University	
##		7.187550
##	Christopher Newport University	
##		296.797058
##	Claremont McKenna College	
##		3187.364649
##	Clarkson University	
##		2935.944391
##	Clinch Valley Coll. of the Univ. of Virginia	

##	845.718438
##	Colby College
##	3072.535064
##	College Misericordia
##	1962.389804
##	College of Mount St. Vincent
##	1221.043263
##	College of Saint Benedict
##	894.473493
##	College of Saint Catherine
##	485.387588
##	College of Saint Rose
##	1072.339197
##	College of St. Joseph
##	314.233474
##	College of St. Scholastica
##	845.541600
##	College of William and Mary
##	6506.186190
##	Colorado State University
##	9785.996455
##	Columbia College
##	419.459649
##	Concordia College at St. Paul
##	-315.803498
##	Concordia University
##	436.799538
##	Converse College
##	744.953424
##	Cornell College
##	1606.377657
##	Creighton University
##	4821.067906
##	Culver-Stockton College
##	1539.813629
##	Cumberland College
##	1524.315585
##	D'Youville College
##	624.205205
##	Dana College
##	15.243377
##	Daniel Webster College
##	545.769532
##	Dartmouth College
##	6142.651321
##	Davidson College
##	3499.495954
##	Dickinson College
##	3525.354608
##	Dickinson State University
##	365.992449
##	Dordt College
##	470.691569
##	Dowling College

##	38.087731
##	Drake University
##	3750.312779
##	Drury College
##	991.742535
##	Duke University
##	8686.745839
##	East Carolina University
##	8744.087198
##	East Tennessee State University
##	3663.271944
##	Eastern Illinois University
##	6078.761481
##	Eastern Nazarene College
##	344.188401
##	Elizabethtown College
##	2913.551837
##	Elms College
##	240.239278
##	Elon College
##	3367.212879
##	Emory & Henry College
##	1397.852166
##	Eureka College
##	1121.887686
##	Evergreen State College
##	1788.516051
##	Ferrum College
##	898.727067
##	Flagler College
##	834.507749
##	Florida International University
##	3772.520809
##	Florida State University
##	14306.970264
##	Fordham University
##	4740.359992
##	Fort Lewis College
##	3660.644249
##	Francis Marion University
##	1758.816865
##	Franklin College
##	923.464024
##	Franklin Pierce College
##	6655.980696
##	Fresno Pacific College
##	1120.473048
##	Gannon University
##	2542.881259
##	Gardner Webb University
##	1004.118394
##	Georgetown College
##	1180.335191
##	Georgia Institute of Technology

##	9636.161174
##	Georgia State University
##	2785.003681
##	Georgian Court College
##	-292.832076
##	Gettysburg College
##	3393.017864
##	Goldey Beacom College
##	575.519112
##	Gonzaga University
##	2096.601990
##	Goshen College
##	802.267907
##	Goucher College
##	2078.320275
##	Grace College and Seminary
##	443.411485
##	Greensboro College
##	157.612168
##	Greenville College
##	351.385386
##	Grove City College
##	3156.209768
##	Guilford College
##	1092.634160
##	Hamilton College
##	2465.101862
##	Hamline University
##	781.747466
##	Hampden - Sydney College
##	528.429036
##	Hampton University
##	4996.896686
##	Harding University
##	1633.674287
##	Hartwick College
##	1943.881807
##	Harvard University
##	6280.605273
##	Hastings College
##	589.512413
##	Hendrix College
##	1859.077906
##	Hiram College
##	1407.651272
##	Hobart and William Smith Colleges
##	2520.582855
##	Hofstra University
##	9112.390541
##	Hollins College
##	747.509831
##	Hope College
##	2244.431479
##	Houghton College

##	764.110944
##	Huntingdon College
##	945.801856
##	Huntington College
##	105.274392
##	Huron University
##	-189.330820
##	Husson College
##	837.223549
##	Illinois Benedictine College
##	612.135829
##	Illinois Institute of Technology
##	2118.522576
##	Immaculata College
##	256.966834
##	Indiana State University
##	4473.360944
##	Indiana University at Bloomington
##	17312.797489
##	Indiana Wesleyan University
##	694.469286
##	Iowa State University
##	10259.734800
##	John Brown University
##	588.226618
##	Johnson State College
##	608.598608
##	Juniata College
##	1374.466108
##	Kansas State University
##	4753.934201
##	Kentucky Wesleyan College
##	634.535842
##	King College
##	681.577317
##	Knox College
##	1643.936858
##	La Roche College
##	-85.903902
##	Lake Forest College
##	322.099903
##	Lakeland College
##	704.795958
##	Lander University
##	1112.916990
##	Le Moyne College
##	887.076489
##	Lehigh University
##	6407.165106
##	Lenoir-Rhyne College
##	905.967781
##	Lesley College
##	303.170639
##	LeTourneau University

##	1145.423001
##	Lewis and Clark College
##	3006.462513
##	Lincoln University
##	1703.651271
##	Lindenwood College
##	459.437196
##	Linfield College
##	2365.996377
##	Loras College
##	1514.046220
##	Louisiana State University at Baton Rouge
##	6204.643802
##	Loyola Marymount University
##	4982.879359
##	Luther College
##	1937.689335
##	Lycoming College
##	724.854019
##	Lynchburg College
##	1566.295688
##	Macalester College
##	3163.460193
##	Malone College
##	704.801359
##	Manhattanville College
##	605.523658
##	Mankato State University
##	3580.443374
##	Marian College of Fond du Lac
##	234.517418
##	Marist College
##	4771.274014
##	Mary Baldwin College
##	1482.906336
##	Mary Washington College
##	4342.770107
##	Marymount Manhattan College
##	1645.981908
##	Marymount University
##	539.584739
##	Maryville College
##	1117.461420
##	Maryville University
##	816.756892
##	Mercer University
##	2439.346157
##	Meredith College
##	998.992783
##	Merrimack College
##	2330.138872
##	Mesa State College
##	2116.792932
##	Messiah College

##	2185.691759
##	Miami University at Oxford
##	11756.600121
##	Michigan State University
##	20084.836678
##	Millersville University of Penn.
##	4668.576280
##	Millikin University
##	1778.684436
##	Milwaukee School of Engineering
##	1900.186869
##	Mississippi State University
##	3674.828707
##	Missouri Valley College
##	819.687391
##	Monmouth College IL
##	181.684941
##	Montana State University
##	3247.375032
##	Moorhead State University
##	2577.501430
##	Moravian College
##	717.826170
##	Morehouse College
##	3639.959396
##	Morningside College
##	484.111603
##	Mount Holyoke College
##	2499.552386
##	Mount Mary College
##	-117.677318
##	Mount Mercy College
##	64.392998
##	Mount Saint Mary's College
##	1562.481707
##	Mount Saint Mary College
##	715.718603
##	Mount St. Mary's College
##	1277.736381
##	Mount Union College
##	827.223804
##	Mount Vernon Nazarene College
##	572.699606
##	Muhlenberg College
##	2456.788542
##	Newberry College
##	469.654341
##	Niagara University
##	4546.825442
##	North Adams State College
##	1422.980349
##	North Carolina A. & T. State University
##	3486.103705
##	North Central College

##	2003.026668
##	North Dakota State University
##	1923.875657
##	North Park College
##	185.404050
##	Northern Arizona University
##	7302.293866
##	Northwestern University
##	10466.636291
##	Norwich University
##	1289.681926
##	Notre Dame College
##	34.604359
##	Occidental College
##	2827.852011
##	Oglethorpe University
##	1823.638014
##	Ohio University
##	11818.950859
##	Otterbein College
##	1619.783352
##	Pacific Union College
##	695.735628
##	Pembroke State University
##	709.122502
##	Pennsylvania State Univ. Main Campus
##	17009.683053
##	Pepperdine University
##	5689.277531
##	Pfeiffer College
##	502.228103
##	Philadelphia Coll. of Textiles and Sci.
##	1919.870975
##	Piedmont College
##	653.524947
##	Pitzer College
##	746.576495
##	Point Park College
##	847.234268
##	Prairie View A. and M. University
##	3429.537256
##	Presbyterian College
##	1264.822112
##	Providence College
##	4806.981192
##	Queens College
##	834.608133
##	Radford University
##	7126.060635
##	Randolph-Macon College
##	1398.773253
##	Randolph-Macon Woman's College
##	1367.901344
##	Rhodes College



##	4032.701634
##	Ripon College
##	172.936602
##	Rivier College
##	63.611233
##	Roanoke College
##	2377.364539
##	Rocky Mountain College
##	2.544508
##	Rosary College
##	654.023346
##	Rutgers State University at Newark
##	5061.277715
##	Saint Ambrose University
##	224.024154
##	Saint Anselm College
##	1929.869642
##	Saint Francis College IN
##	38.781269
##	Saint Joseph's University
##	3371.248392
##	Saint Joseph College
##	-218.249751
##	Salem-Teikyo University
##	577.502623
##	Samford University
##	1897.046050
##	Schreiner College
##	726.623181
##	Scripps College
##	2738.223533
##	Seattle Pacific University
##	1769.951086
##	Seattle University
##	1837.257016
##	Seton Hall University
##	5327.961524
##	Shippensburg University of Penn.
##	4286.677710
##	Siena College
##	2780.943741
##	Siena Heights College
##	245.004280
##	Sioux Falls College
##	-292.972074
##	Skidmore College
##	3669.871085
##	Smith College
##	3247.461319
##	South Dakota State University
##	2806.536174
##	Southeast Missouri State University
##	1991.875790
##	Southern Illinois University at Edwardsville

##	2876.676285
##	Southwest State University
##	1458.376895
##	Southwestern College
##	193.404734
##	Southwestern University
##	1938.780201
##	Spring Arbor College
##	470.610059
##	St. Mary's College of Maryland
##	2329.908498
##	St. Mary's University of San Antonio
##	1817.943297
##	St. Thomas Aquinas College
##	873.100832
##	Stevens Institute of Technology
##	2397.779348
##	Stockton College of New Jersey
##	2864.333555
##	SUNY at Albany
##	14539.680463
##	SUNY College at Cortland
##	4764.509318
##	SUNY College at Fredonia
##	4087.129733
##	SUNY College at Geneseo
##	8757.857436
##	Susquehanna University
##	1713.112191
##	Tabor College
##	46.153986
##	Taylor University
##	2074.804588
##	Texas A&M University at Galveston
##	572.855789
##	Texas Christian University
##	4491.871376
##	Texas Lutheran College
##	573.366543
##	Texas Southern University
##	1015.378237
##	Trinity College DC
##	319.052141
##	Trinity College VT
##	292.335285
##	Tuskegee University
##	2401.441948
##	Univ. of Wisconsin at OshKosh
##	3194.273054
##	University of California at Irvine
##	20201.965743
##	University of Charleston
##	819.402531
##	University of Cincinnati

##		7821.671230
##	University of Connecticut at Storrs	
##		10934.529378
##	University of Dallas	
##		1788.519062
##	University of Detroit Mercy	
##		754.121188
##	University of Dubuque	
##		-144.898111
##	University of Illinois - Urbana	
##		16398.738475
##	University of Illinois at Chicago	
##		7978.940150
##	University of Indianapolis	
##		1797.820037
##	University of Louisville	
##		3792.154325
##	University of Maine at Machias	
##		746.091677
##	University of Maine at Presque Isle	
##		-82.713679
##	University of Maryland at College Park	
##		15530.655642
##	University of Massachusetts at Amherst	
##		17832.246271
##	University of Massachusetts at Dartmouth	
##		3575.763968
##	University of Miami	
##		8629.660503
##	University of Minnesota at Duluth	
##		3420.304221
##	University of Minnesota Twin Cities	
##		8358.198297
##	University of Missouri at Saint Louis	
##		1608.809258
##	University of Mobile	
##		-33.480505
##	University of Nebraska at Lincoln	
##		7662.509796
##	University of North Carolina at Asheville	
##		1578.767924
##	University of North Carolina at Chapel Hill	
##		10282.073664
##	University of North Carolina at Wilmington	
##		4619.806033
##	University of North Dakota	
##		2125.203655
##	University of North Texas	
##		3600.272200
##	University of Northern Iowa	
##		4233.009902
##	University of Oregon	
##		9244.189110
##	University of Portland	

##	1863.686370
##	University of Rhode Island
##	11648.410396
##	University of Scranton
##	4695.592718
##	University of Southern California
##	13552.994621
##	University of Southern Indiana
##	2356.486269
##	University of Southern Mississippi
##	3071.849835
##	University of St. Thomas TX
##	1037.272234
##	University of Texas at Austin
##	13454.168424
##	University of Texas at San Antonio
##	4459.459346
##	University of the South
##	1840.520656
##	University of Tulsa
##	2472.922724
##	University of Virginia
##	9159.403622
##	University of Wisconsin-Stout
##	2170.083543
##	University of Wisconsin-Superior
##	520.797110
##	University of Wisconsin-Whitewater
##	4758.448014
##	University of Wisconsin at Green Bay
##	2379.650528
##	University of Wisconsin at Milwaukee
##	4457.057911
##	Upper Iowa University
##	-101.923829
##	Ursuline College
##	600.524869
##	Valley City State University
##	157.806288
##	Valparaiso University
##	3225.510183
##	Vassar College
##	3473.172153
##	Virginia State University
##	3179.644109
##	Virginia Tech
##	16612.020525
##	Virginia Union University
##	1784.693906
##	Virginia Wesleyan College
##	1177.889754
##	Wabash College
##	1275.490453
##	Wake Forest University

##	6760.832103
##	Walsh University
##	522.118368
##	Wartburg College
##	1617.162144
##	Washington and Lee University
##	3600.513472
##	Washington College
##	1327.508245
##	Washington State University
##	8749.758530
##	Wayne State College
##	1832.050800
##	Waynesburg College
##	1058.023796
##	Webster University
##	362.340633
##	Wellesley College
##	4300.701940
##	Wentworth Institute of Technology
##	3051.807327
##	Wesley College
##	928.679849
##	Wesleyan University
##	4240.993141
##	West Chester University of Penn.
##	4361.885015
##	Western Carolina University
##	3040.814028
##	Western State College of Colorado
##	2059.419051
##	Western Washington University
##	5340.463086
##	Westfield State College
##	2658.548865
##	Westminster College MO
##	518.351648
##	Westminster College of Salt Lake City
##	600.338167
##	Westminster College PA
##	1676.912512
##	Whitworth College
##	1910.057624
##	Widener University
##	1605.005506
##	Wilkes University
##	1857.012219
##	Willamette University
##	2385.468953
##	William Woods University
##	535.184986
##	Wilson College
##	-295.074534
##	Winona State University

```
##                2765.598209
##                Wittenberg University
##                2702.474799
##                Wofford College
##                2026.872540
##                York College of Pennsylvania
##                3035.206068
```

```
test_error_least_square = mean((data_test[, 'Apps'] - lm_predict)^2)
test_error_least_square
```

```
## [1] 1135758
```

For the next series of questions, we need our feature data to be in matrix form because `glmnet()` requires it. Thus we create a train and test matrix containing only feature values from our respectful train and test data

```
x_mat_train <- model.matrix(Apps ~ ., data = data_train)[, -1]
x_mat_test  <- model.matrix(Apps ~ ., data = data_test)[, -1]
```

(c). Fit a ridge regression model on the training set, with  $\lambda$  chosen by cross-validation. Report the test error obtained. **Extract the optimal lambda for lasso using `cv.glmnet()`**

```
lambda_min_ridge <- cv.glmnet(x_mat_train, data_train[, 'Apps'], alpha = 0)$lambda.min
lambda_min_ridge
```

```
## [1] 405.8404
```

Fit a `ridge_model` using `glmnet()` with the optimal lambda Then, call `predict()` to get the prediction values to ultimately compute the test error

```
ridge_model <- glmnet(x_mat_train, data_train[, 'Apps'], lambda = lambda_min_ridge, alpha = 0)
ridge_predict <- predict(ridge_model, newx = x_mat_test, s = lambda_min_ridge)

test_error_ridge = mean((data_test[, 'Apps'] - ridge_predict)^2)
test_error_ridge
```

```
## [1] 976897.6
```

(d). Fit a lasso model on the training set, with  $\lambda$  chosen by cross-validation. Report the test error obtained, along with the number of non-zero coefficient estimates.

**Extract the optimal lambda for lasso using `cv.glmnet()`**

```
lambda_min_lasso <- cv.glmnet(x_mat_train, data_train[, 'Apps'], alpha = 1)$lambda.min
lambda_min_lasso
```

```
## [1] 1.97344
```

Fit a `ridge_model` using `glmnet()` with the optimal lambda Then, call `predict()` to get the prediction values to ultimately compute the test error

```
lasso_model <- glmnet(x_mat_train, data_train[, 'Apps'], lambda = lambda_min_lasso, alpha = 1)
lasso_predict <- predict(lasso_model, newx = x_mat_test, s = lambda_min_lasso)

test_error_lasso = mean((data_test[, 'Apps'] - lasso_predict)^2)
test_error_lasso
```

```
## [1] 1116402
```

Extract the coefficients from the lasso model

```
coef_lasso <- coef(lasso_model)
coef_lasso
```

```
## 18 x 1 sparse Matrix of class "dgCMatrix"
##              s0
## (Intercept) -763.46736132
## PrivateYes  -313.76789130
## Accept      1.76295802
## Enroll      -1.32011619
## Top10perc    64.98040139
## Top25perc   -20.93406827
## F.Undergrad  0.07157355
## P.Undergrad  0.01197052
## Outstate    -0.10493165
## Room.Board   0.20915417
## Books        0.29265420
## Personal     0.00351509
## PhD         -14.48803558
## Terminal     5.33334391
## S.F.Ratio    21.67584609
## perc.alumni  0.51564913
## Expend       0.04812700
## Grad.Rate    7.01799292
```

Filter out the coefficients equal to zero. Note this process removes the names

```
coef_lasso_vec <- coef_lasso %>% as.vector()
coef_lasso_vec
```

```
## [1] -763.46736132 -313.76789130  1.76295802 -1.32011619  64.98040139
## [6] -20.93406827  0.07157355  0.01197052 -0.10493165  0.20915417
## [11]  0.29265420  0.00351509 -14.48803558  5.33334391  21.67584609
## [16]  0.51564913  0.04812700  7.01799292
```

```
coef_lasso_non_zero <- subset(coef_lasso_vec, !(coef_lasso_vec %in% 0.0))
coef_lasso_non_zero
```

```
## [1] -763.46736132 -313.76789130  1.76295802 -1.32011619  64.98040139
## [6] -20.93406827  0.07157355  0.01197052 -0.10493165  0.20915417
## [11]  0.29265420  0.00351509 -14.48803558  5.33334391  21.67584609
## [16]  0.51564913  0.04812700  7.01799292
```

(e). Fit a PCR model on the training set, with M chosen by cross validation. Report the test error obtained, along with the value of M selected by cross-validation.

### Fit a PCR model using Cross Validation

```
set.seed(1)
pcr_model <- pcr(Apps ~., data = data_train, scale = TRUE,
                 validation = "CV")

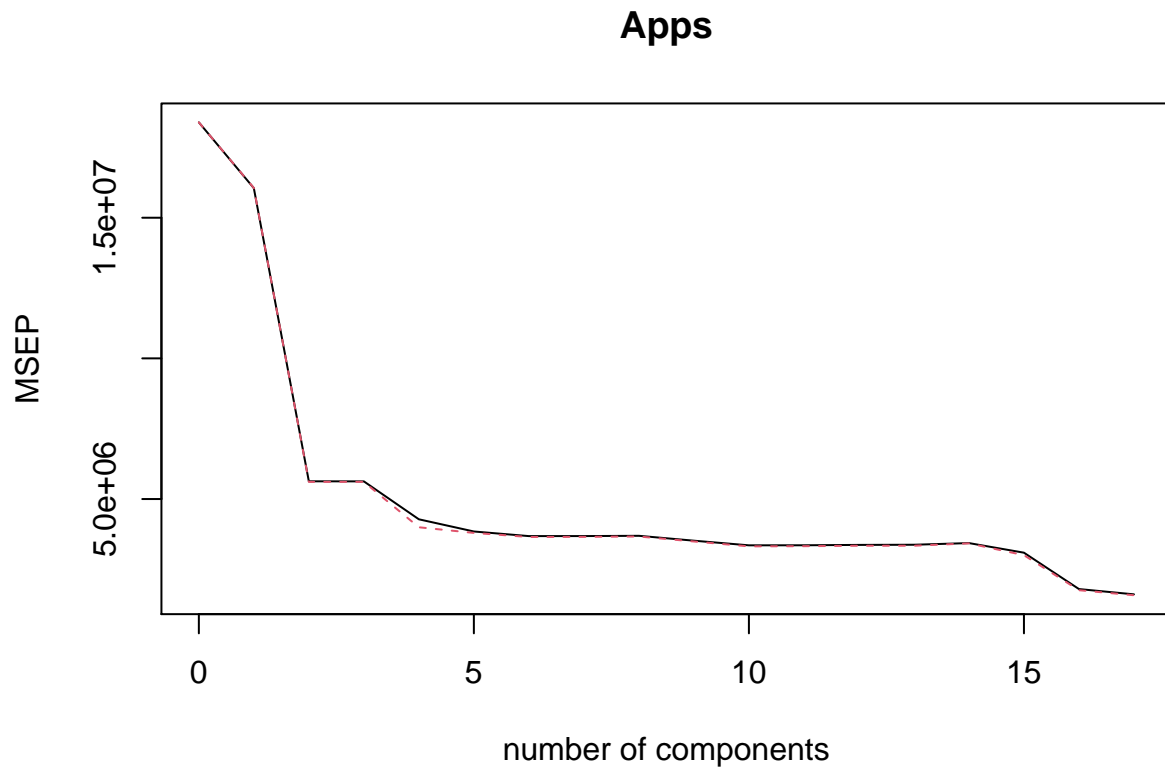
summary(pcr_model)
```

```
## Data:      X dimension: 388 17
## Y dimension: 388 1
## Fit method: svdpc
## Number of components considered: 17
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##      (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV              4288    4006    2373    2372    2069    1961    1919
## adjCV           4288    4007    2368    2369    1999    1948    1911
##      7 comps  8 comps  9 comps 10 comps 11 comps 12 comps 13 comps
## CV           1919    1921    1876    1832    1832    1836    1837
## adjCV        1912    1915    1868    1821    1823    1827    1827
##      14 comps 15 comps 16 comps 17 comps
## CV           1853    1759    1341    1270
## adjCV        1850    1733    1326    1257
##
## TRAINING: % variance explained
##      1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X          32.20   57.78   65.31   70.99   76.37   81.27   84.8    87.85
## Apps       13.44   70.93   71.07   79.87   81.15   82.25   82.3    82.33
##      9 comps 10 comps 11 comps 12 comps 13 comps 14 comps 15 comps
## X          90.62   92.91   94.98   96.74   97.79   98.72   99.42
## Apps       83.38   84.76   84.80   84.84   85.11   85.14   90.55
##      16 comps 17 comps
## X          99.88   100.00
## Apps       93.42   93.89
```

Generate a validation plot to determine the optimal value of M for pcr Based on the plot, M is either 5 or 6. We shall go with 6

```
validationplot(pcr_model, val.type = "MSEP")
```





Report the test error obtained for pcr

```
pcr_predict <- predict(pcr_model, x_mat_test, ncomp = 6)
test_error_pcr <- mean((data_test[, 'Apps'] - pcr_predict)^2)
test_error_pcr
```

```
## [1] 1966028
```

(f). Fit a PLS model on the training set, with  $M$  chosen by cross-validation. Report the test error obtained, along with the value of  $M$  selected by cross-validation.

**Fit a PLS model using Cross Validation**

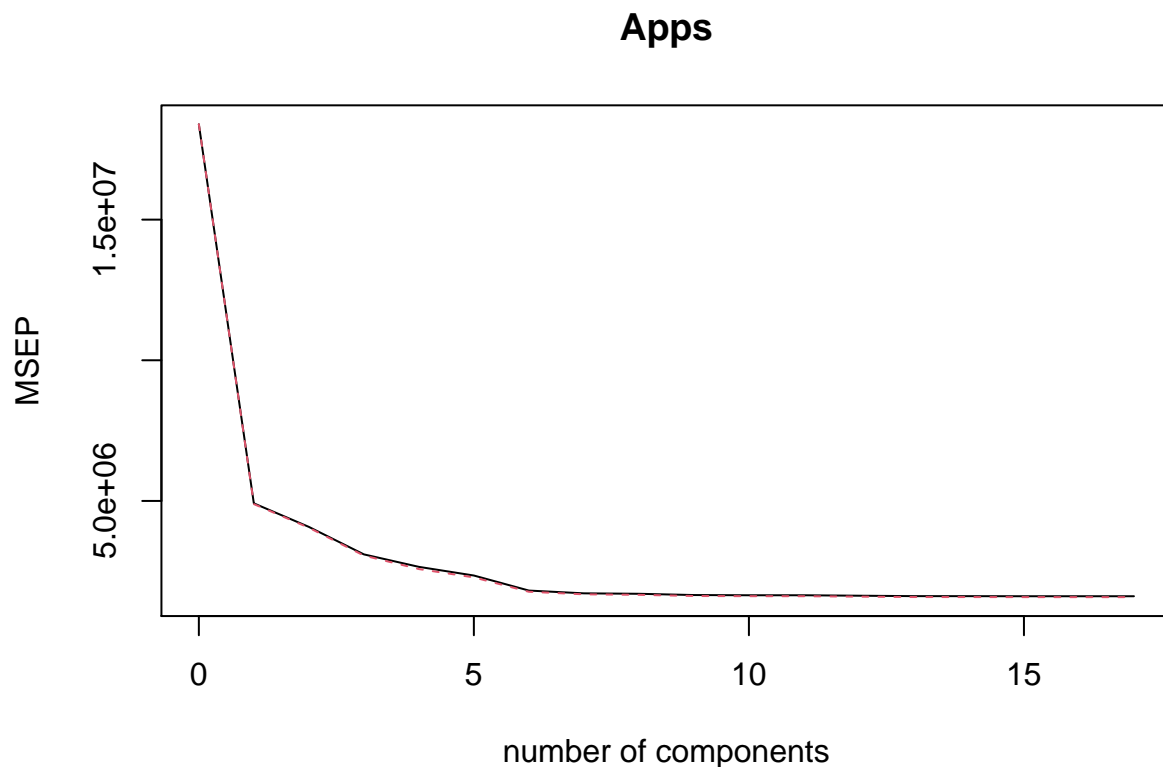
```
set.seed(1)
pls_model <- plsr(Apps ~ ., data = data_train, scale = TRUE, validation = "CV")
summary(pls_model)
```

```
## Data:      X dimension: 388 17
## Y dimension: 388 1
## Fit method: kernelpls
## Number of components considered: 17
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
```

```
##      (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV             4288    2217    2019    1761    1630    1533    1347
## adjCV          4288    2211    2012    1749    1605    1510    1331
##      7 comps  8 comps  9 comps 10 comps 11 comps 12 comps 13 comps
## CV             1309    1303    1286    1283    1283    1277    1271
## adjCV          1296    1289    1273    1270    1270    1264    1258
##      14 comps 15 comps 16 comps 17 comps
## CV             1270    1270    1270    1270
## adjCV          1258    1257    1257    1257
##
## TRAINING: % variance explained
##      1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X          27.21   50.73   63.06   65.52   70.20   74.20   78.62   80.81
## Apps       75.39   81.24   86.97   91.14   92.62   93.43   93.56   93.68
##      9 comps 10 comps 11 comps 12 comps 13 comps 14 comps 15 comps
## X          83.29   87.17   89.15   91.37   92.58   94.42   96.98
## Apps       93.76   93.79   93.83   93.86   93.88   93.89   93.89
##      16 comps 17 comps
## X          98.78   100.00
## Apps       93.89   93.89
```

Generate a validation plot to determine the optimal value of M for pls Based on the plot, M is either 6 or 7. We shall go with 6

```
validationplot(pls_model, val.type = "MSEP")
```



Report the test error obtained for pcr

```
pls_predict <- predict(pls_model, x_mat_test, ncomp = 6)
test_error_pls <- mean((data_test[, 'Apps'] - pls_predict)^2)
test_error_pls
```

```
## [1] 1066991
```

(g). Comment on the results obtained. How accurately can we predict the number of college applications received? Is there much difference among the test errors resulting from these five approaches?

```
lm_test_r2 <- 1 - test_error_least_square / mean((data_test[, 'Apps'] - mean(data_test[, 'Apps']))^2)
ridge_test_r2 <- 1 - test_error_ridge / mean((data_test[, 'Apps'] - mean(data_test[, 'Apps']))^2)
lasso_test_r2 <- 1 - test_error_lasso / mean((data_test[, 'Apps'] - mean(data_test[, 'Apps']))^2)
pcr_test_r2 <- 1 - test_error_pcr / mean((data_test[, 'Apps'] - mean(data_test[, 'Apps']))^2)
pls_test_r2 <- 1 - test_error_pls / mean((data_test[, 'Apps'] - mean(data_test[, 'Apps']))^2)
```

## OLS

```
cat("Test Error:", test_error_least_square, "\n")
```

```
## Test Error: 1135758
```

```
cat("R squared:", lm_test_r2)
```

```
## R squared: 0.9015413
```

## Ridge

```
cat("Test Error:", test_error_ridge, "\n")
```

```
## Test Error: 976897.6
```

```
cat("R squared:", ridge_test_r2)
```

```
## R squared: 0.9153129
```

## Lasso

```
cat("Test Error:", test_error_lasso, "\n")
```

```
## Test Error: 1116402
```

```
cat("R squared:", lasso_test_r2)
```

```
## R squared: 0.9032193
```

## PCR

```
cat("Test Error:", test_error_pcr, "\n")
```

```
## Test Error: 1966028
```

```
cat("R squared:", pcr_test_r2)
```

```
## R squared: 0.8295654
```

**PLS**

```
cat("Test Error:", test_error_pls, "\n")
```

```
## Test Error: 1066991
```

```
cat("R squared:", pls_test_r2)
```

```
## R squared: 0.9075028
```

**Discussion:** All the models have similar test error. With regards to R squared, all the models produced similar values close to 1. Surprisingly, PCR had significantly lower R\_squared then the rest and unsurprisingly, Ridge had the highest All models could be used to accurately predict college applications