R Notebook

Mitali Yadav (3034158469)

Q4.

```
install.packages("fda.usc")
install.packages("pls")
```

```
library("fda.usc")
```

```
## Warning: package 'fda.usc' was built under R version 4.0.4

## Loading required package: fda

## Warning: package 'fda' was built under R version 4.0.4

## Loading required package: splines

## Loading required package: Matrix

## Loading required package: fds

## Warning: package 'fds' was built under R version 4.0.4

## Loading required package: rainbow

## Warning: package 'rainbow' was built under R version 4.0.4

## Loading required package: MASS

## Loading required package: pcaPP

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

## Loading required package: RCurl

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

##
## Attaching package: 'fda'
```

```
## The following object is masked from 'package:graphics':
##
##     matplot
```

```
## Loading required package: mgcv
```

```
## Loading required package: nlme
```

```
## This is mgcv 1.8-31. For overview type 'help("mgcv-package")'.
```

```
## ------------------------------------------------------------------------------
##  Functional Data Analysis and Utilities for Statistical Computing
##  fda.usc version 2.0.2 (built on 2020-02-17) is now loaded
##  fda.usc is running sequentially usign foreach package
##  Please, execute ops.fda.usc() once to run in local parallel mode
##  Deprecated functions: min.basis, min.np, anova.hetero, anova.onefactor, anova.RPm
##  New functions: optim.basis, optim.np, fanova.hetero, fanova.onefactor, fanova.RPm
## ------------------------------------------------------------------------------
```

```
library("pls")
```

```
## Warning: package 'pls' was built under R version 4.0.4
```

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

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

```
library("ggplot2")
```

```
#importing the CSV files (as an alternate method)
X_data = read.csv("tecator_X.csv")
Y_data = read.csv("tecator_Y.csv")

#combining them using cbind into a matrix
data = cbind(X_data, Y_data)
data = as.data.frame(data)
typeof(data)
```

```
## [1] "list"
```

```
dim(data)
```

```
## [1] 215 101
```

```r
#splitting into training and testing
tec_train = data[1:172,]
tec_test = data[173:215,]

head(tec_train)
```

```
##        X1      X2      X3      X4      X5      X6      X7      X8      X9
## 1 2.61776 2.61814 2.61859 2.61912 2.61981 2.62071 2.62186 2.62334 2.62511
## 2 2.83454 2.83871 2.84283 2.84705 2.85138 2.85587 2.86060 2.86566 2.87093
## 3 2.58284 2.58458 2.58629 2.58808 2.58996 2.59192 2.59401 2.59627 2.59873
## 4 2.82286 2.82460 2.82630 2.82814 2.83001 2.83192 2.83392 2.83606 2.83842
## 5 2.78813 2.78989 2.79167 2.79350 2.79538 2.79746 2.79984 2.80254 2.80553
## 6 3.00993 3.01540 3.02086 3.02634 3.03190 3.03756 3.04341 3.04955 3.05599
##       X10     X11     X12     X13     X14     X15     X16     X17     X18
## 1 2.62722 2.62964 2.63245 2.63565 2.63933 2.64353 2.64825 2.65350 2.65937
## 2 2.87661 2.88264 2.88898 2.89577 2.90308 2.91097 2.91953 2.92873 2.93863
## 3 2.60131 2.60414 2.60714 2.61029 2.61361 2.61714 2.62089 2.62486 2.62909
## 4 2.84097 2.84374 2.84664 2.84975 2.85307 2.85661 2.86038 2.86437 2.86860
## 5 2.80890 2.81272 2.81704 2.82184 2.82710 2.83294 2.83945 2.84664 2.85458
## 6 3.06274 3.06982 3.07724 3.08511 3.09343 3.10231 3.11185 3.12205 3.13294
##       X19     X20     X21     X22     X23     X24     X25     X26     X27
## 1 2.66585 2.67281 2.68008 2.68733 2.69427 2.70073 2.70684 2.71281 2.71914
## 2 2.94929 2.96072 2.97272 2.98493 2.99690 3.00833 3.01920 3.02990 3.04101
## 3 2.63361 2.63835 2.64330 2.64838 2.65354 2.65870 2.66375 2.66880 2.67383
## 4 2.87308 2.87789 2.88301 2.88832 2.89374 2.89917 2.90457 2.90991 2.91521
## 5 2.86331 2.87280 2.88291 2.89335 2.90374 2.91371 2.92305 2.93187 2.94060
## 6 3.14457 3.15703 3.17038 3.18429 3.19840 3.21225 3.22552 3.23827 3.25084
##       X28     X29     X30     X31     X32     X33     X34     X35     X36
## 1 2.72628 2.73462 2.74416 2.75466 2.76568 2.77679 2.78790 2.79949 2.81225
## 2 3.05345 3.06777 3.08416 3.10221 3.12106 3.13983 3.15810 3.17623 3.19519
## 3 2.67892 2.68411 2.68937 2.69470 2.70012 2.70563 2.71141 2.71775 2.72490
## 4 2.92043 2.92565 2.93082 2.93604 2.94128 2.94658 2.95202 2.95777 2.96419
## 5 2.94986 2.96035 2.97241 2.98606 3.00097 3.01652 3.03220 3.04793 3.06413
## 6 3.26393 3.27851 3.29514 3.31401 3.33458 3.35591 3.37709 3.39772 3.41828
##       X37     X38     X39     X40     X41     X42     X43     X44     X45
## 1 2.82706 2.84356 2.86106 2.87857 2.89497 2.90924 2.92085 2.93015 2.93846
## 2 3.21584 3.23747 3.25889 3.27835 3.29384 3.30362 3.30681 3.30393 3.29700
## 3 2.73344 2.74327 2.75433 2.76642 2.77931 2.79272 2.80649 2.82064 2.83541
## 4 2.97159 2.98045 2.99090 3.00284 3.01611 3.03048 3.04579 3.06194 3.07889
## 5 3.08153 3.10078 3.12185 3.14371 3.16510 3.18470 3.20140 3.21477 3.22544
## 6 3.43974 3.46266 3.48663 3.51002 3.53087 3.54711 3.55699 3.55986 3.55656
##       X46     X47     X48     X49     X50     X51     X52     X53     X54
## 1 2.94771 2.96019 2.97831 3.00306 3.03506 3.07428 3.11963 3.16868 3.21771
## 2 3.28925 3.28409 3.28505 3.29326 3.30923 3.33267 3.36251 3.39661 3.43188
## 3 2.85121 2.86872 2.88905 2.91289 2.94088 2.97325 3.00946 3.04780 3.08554
## 4 3.09686 3.11629 3.13775 3.16217 3.19068 3.22376 3.26172 3.30379 3.34793
## 5 3.23505 3.24586 3.26027 3.28063 3.30889 3.34543 3.39019 3.44198 3.49800
## 6 3.54937 3.54169 3.53692 3.53823 3.54760 3.56512 3.59043 3.62229 3.65830
##       X55     X56     X57     X58     X59     X60     X61     X62     X63
## 1 3.26254 3.29988 3.32847 3.34899 3.36342 3.37379 3.38152 3.38741 3.39164
## 2 3.46492 3.49295 3.51458 3.53004 3.54067 3.54797 3.55306 3.55675 3.55921
## 3 3.11947 3.14696 3.16677 3.17938 3.18631 3.18924 3.18950 3.18801 3.18498
## 4 3.39093 3.42920 3.45998 3.48227 3.49687 3.50558 3.51026 3.51221 3.51215
```

```
## 5 3.55407 3.60534 3.64789 3.68011 3.70272 3.71815 3.72863 3.73574 3.74059
## 6 3.69515 3.72932 3.75803 3.78003 3.79560 3.80614 3.81313 3.81774 3.82079
##       X64     X65     X66     X67     X68     X69     X70     X71     X72
## 1 3.39418 3.39490 3.39366 3.39045 3.38541 3.37869 3.37041 3.36073 3.34979
## 2 3.56045 3.56034 3.55876 3.55571 3.55132 3.54585 3.53950 3.53235 3.52442
## 3 3.18039 3.17411 3.16611 3.15641 3.14512 3.13241 3.11843 3.10329 3.08714
## 4 3.51036 3.50682 3.50140 3.49398 3.48457 3.47333 3.46041 3.44595 3.43005
## 5 3.74357 3.74453 3.74336 3.73991 3.73418 3.72638 3.71676 3.70553 3.69289
## 6 3.82258 3.82301 3.82206 3.81959 3.81557 3.81021 3.80375 3.79642 3.78835
##       X73     X74     X75     X76     X77     X78     X79     X80     X81
## 1 3.33769 3.32443 3.31013 3.29487 3.27891 3.26232 3.24542 3.22828 3.21080
## 2 3.51583 3.50668 3.49700 3.48683 3.47626 3.46552 3.45501 3.44481 3.43477
## 3 3.07014 3.05237 3.03393 3.01504 2.99569 2.97612 2.95642 2.93660 2.91667
## 4 3.41285 3.39450 3.37511 3.35482 3.33376 3.31204 3.28986 3.26730 3.24442
## 5 3.67900 3.66396 3.64785 3.63085 3.61305 3.59463 3.57582 3.55695 3.53796
## 6 3.77958 3.77024 3.76040 3.75005 3.73929 3.72831 3.71738 3.70681 3.69664
##       X82     X83     X84     X85     X86     X87     X88     X89     X90
## 1 3.19287 3.17433 3.15503 3.13475 3.11339 3.09116 3.06850 3.04596 3.02393
## 2 3.42465 3.41419 3.40303 3.39082 3.37731 3.36265 3.34745 3.33245 3.31818
## 3 2.89655 2.87622 2.85563 2.83474 2.81361 2.79235 2.77113 2.75015 2.72956
## 4 3.22117 3.19757 3.17357 3.14915 3.12429 3.09908 3.07366 3.04825 3.02308
## 5 3.51880 3.49936 3.47938 3.45869 3.43711 3.41458 3.39129 3.36772 3.34450
## 6 3.68659 3.67649 3.66611 3.65503 3.64283 3.62938 3.61483 3.59990 3.58535
##       X91     X92     X93     X94     X95     X96     X97     X98     X99
## 1 3.00247 2.98145 2.96072 2.94013 2.91978 2.89966 2.87964 2.85960 2.83940
## 2 3.30473 3.29186 3.27921 3.26655 3.25369 3.24045 3.22659 3.21181 3.19600
## 3 2.70934 2.68951 2.67009 2.65112 2.63262 2.61461 2.59718 2.58034 2.56404
## 4 2.99820 2.97367 2.94951 2.92576 2.90251 2.87988 2.85794 2.83672 2.81617
## 5 3.32201 3.30025 3.27907 3.25831 3.23784 3.21765 3.19766 3.17770 3.15770
## 6 3.57163 3.55877 3.54651 3.53442 3.52221 3.50972 3.49682 3.48325 3.46870
##      X100    y
## 1 2.81920 22.5
## 2 3.17942 40.1
## 3 2.54816  8.4
## 4 2.79622  5.9
## 5 3.13753 25.5
## 6 3.45307 42.7
```

1. PC Regression

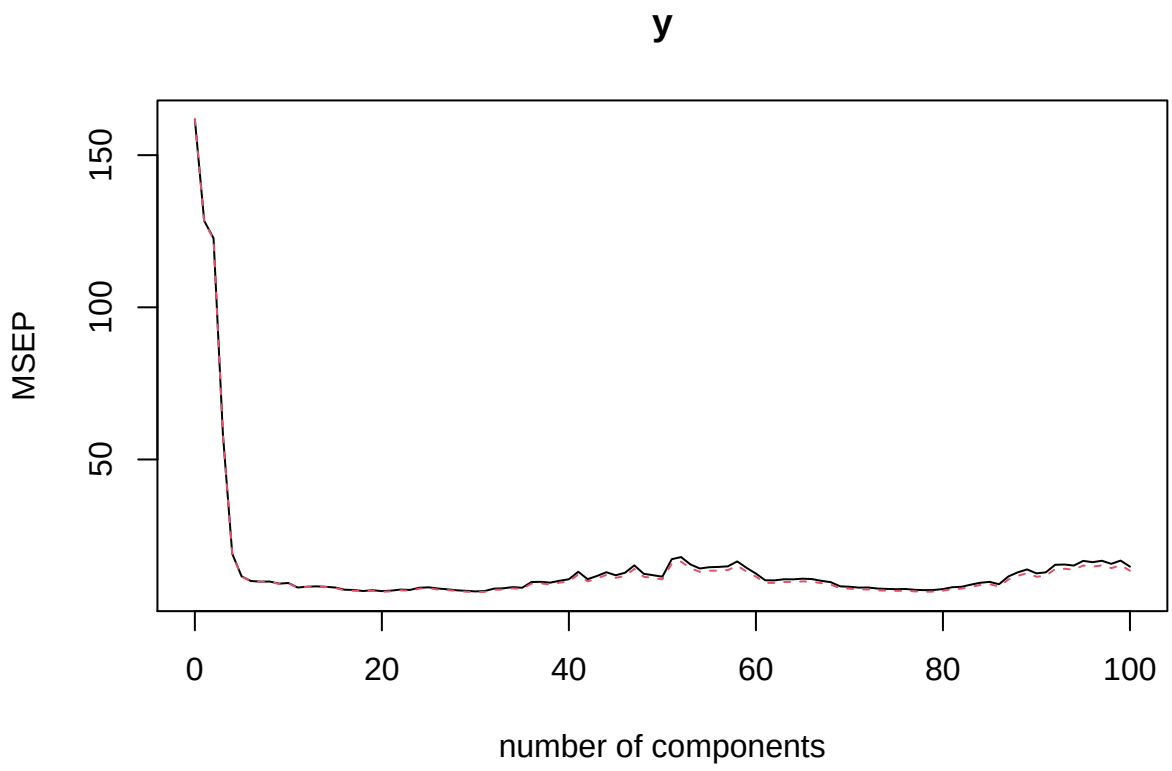
```r
#using the PLS package to perform pc regression
set.seed(18)
pcr_fit <- pcr(y ~., data= tec_train, scale=TRUE, validation="CV")

summary(pcr_fit)
```

```
## Data:    X dimension: 172 100
##  Y dimension: 172 1
## Fit method: svdpc
## Number of components considered: 100
##
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
```

```
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           12.72    11.33    11.08    7.638    4.363    3.403    3.172
## adjCV        12.72    11.32    11.07    7.626    4.355    3.393    3.163
##        7 comps  8 comps  9 comps  10 comps  11 comps  12 comps  13 comps
## CV       3.140    3.146    3.034     3.066     2.815     2.862     2.883
## adjCV    3.129    3.134    3.020     3.050     2.798     2.844     2.864
##        14 comps  15 comps  16 comps  17 comps  18 comps  19 comps  20 comps
## CV        2.856     2.817     2.686     2.666     2.604     2.653     2.597
## adjCV     2.838     2.792     2.646     2.620     2.595     2.616     2.550
##        21 comps  22 comps  23 comps  24 comps  25 comps  26 comps  27 comps
## CV        2.628     2.692     2.670     2.802     2.826     2.758     2.708
## adjCV     2.582     2.649     2.617     2.747     2.772     2.694     2.670
##        28 comps  29 comps  30 comps  31 comps  32 comps  33 comps  34 comps
## CV        2.648     2.617     2.578     2.604     2.753     2.770     2.840
## adjCV     2.602     2.559     2.525     2.549     2.678     2.698     2.765
##        35 comps  36 comps  37 comps  38 comps  39 comps  40 comps  41 comps
## CV        2.802     3.119     3.131     3.086     3.184     3.263     3.619
## adjCV     2.732     3.032     3.051     2.982     3.089     3.152     3.496
##        42 comps  43 comps  44 comps  45 comps  46 comps  47 comps  48 comps
## CV        3.267     3.422     3.599     3.458     3.574     3.900     3.527
## adjCV     3.153     3.304     3.473     3.331     3.429     3.747     3.387
##        49 comps  50 comps  51 comps  52 comps  53 comps  54 comps  55 comps
## CV        3.460     3.390     4.152     4.234     3.937     3.766      3.82
## adjCV     3.325     3.259     3.975     4.055     3.778     3.617      3.67
##        56 comps  57 comps  58 comps  59 comps  60 comps  61 comps  62 comps
## CV        3.834     3.858     4.064     3.793     3.536     3.209     3.205
## adjCV     3.670     3.695     3.886     3.629     3.389     3.078     3.070
##        63 comps  64 comps  65 comps  66 comps  67 comps  68 comps  69 comps
## CV        3.262     3.258     3.290     3.271     3.182     3.112     2.884
## adjCV     3.124     3.122     3.152     3.136     3.056     2.983     2.770
##        70 comps  71 comps  72 comps  73 comps  74 comps  75 comps  76 comps
## CV        2.860     2.811     2.817     2.755     2.733     2.717     2.728
## adjCV     2.748     2.704     2.700     2.644     2.625     2.613     2.622
##        77 comps  78 comps  79 comps  80 comps  81 comps  82 comps  83 comps
## CV        2.679     2.658     2.667     2.723     2.833     2.858     2.979
## adjCV     2.577     2.555     2.565     2.621     2.725     2.749     2.863
##        84 comps  85 comps  86 comps  87 comps  88 comps  89 comps  90 comps
## CV        3.081     3.128     3.000     3.401     3.593     3.725     3.546
## adjCV     2.958     3.006     2.873     3.251     3.430     3.555     3.385
##        91 comps  92 comps  93 comps  94 comps  95 comps  96 comps  97 comps
## CV        3.594     3.924     3.936     3.892     4.084     4.031     4.089
## adjCV     3.430     3.743     3.754     3.712     3.894     3.844     3.901
##        98 comps  99 comps  100 comps
## CV        3.965     4.096      3.847
## adjCV     3.780     3.904      3.668
##
## TRAINING: % variance explained
##    1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X    98.50    99.59    99.88    99.99   100.00   100.00   100.00   100.00
## y    22.32    26.16    65.31    88.91    93.51    94.38    94.58    94.67
##    9 comps  10 comps  11 comps  12 comps  13 comps  14 comps  15 comps
## X   100.00    100.00       100    100.00    100.00    100.00     100.0
## y    95.19     95.29        96     96.01     96.01     96.13      96.5
##    16 comps  17 comps  18 comps  19 comps  20 comps  21 comps  22 comps
```

```
## X    100.00       100    100.00    100.00    100.00    100.00    100.00
## y     96.83        97     97.04     97.42     97.59     97.62     97.66
##    23 comps  24 comps  25 comps  26 comps  27 comps  28 comps  29 comps
## X    100.00    100.00     100.0     100.0    100.00    100.00    100.00
## y     97.75     97.76      97.8      97.9     97.91     98.09     98.17
##    30 comps  31 comps  32 comps  33 comps  34 comps  35 comps  36 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00     100.0
## y     98.19     98.22     98.27     98.28     98.29     98.29      98.3
##    37 comps  38 comps  39 comps  40 comps  41 comps  42 comps  43 comps
## X    100.00    100.00    100.00    100.00    100.00     100.0     100.0
## y     98.31     98.46     98.48     98.57     98.57      98.7      98.7
##    44 comps  45 comps  46 comps  47 comps  48 comps  49 comps  50 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00    100.00
## y     98.74     98.83     98.91     98.91     98.98     98.98     98.98
##    51 comps  52 comps  53 comps  54 comps  55 comps  56 comps  57 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00    100.00
## y     99.01     99.02     99.02     99.04     99.07     99.14     99.14
##    58 comps  59 comps  60 comps  61 comps  62 comps  63 comps  64 comps
## X    100.00    100.00    100.00     100.0    100.00    100.00    100.00
## y     99.21     99.25     99.28      99.3     99.33     99.34     99.34
##    65 comps  66 comps  67 comps  68 comps  69 comps  70 comps  71 comps
## X    100.00    100.00    100.00    100.00    100.00     100.0     100.0
## y     99.34     99.34     99.34     99.38     99.38      99.4      99.4
##    72 comps  73 comps  74 comps  75 comps  76 comps  77 comps  78 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00    100.00
## y     99.44     99.44     99.45     99.45     99.45     99.45     99.46
##    79 comps  80 comps  81 comps  82 comps  83 comps  84 comps  85 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00    100.00
## y     99.46     99.46     99.47     99.47     99.48     99.49     99.49
##    86 comps  87 comps  88 comps  89 comps  90 comps  91 comps  92 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00    100.00
## y     99.58     99.59     99.61     99.62     99.63     99.63     99.64
##    93 comps  94 comps  95 comps  96 comps  97 comps  98 comps  99 comps
## X    100.00    100.00    100.00    100.00    100.00    100.00    100.00
## y     99.65     99.65     99.65     99.66     99.66     99.68     99.69
##    100 comps
## X      100.0
## y       99.7
```

```r
validationplot(pcr_fit, val.type = "MSEP")
```



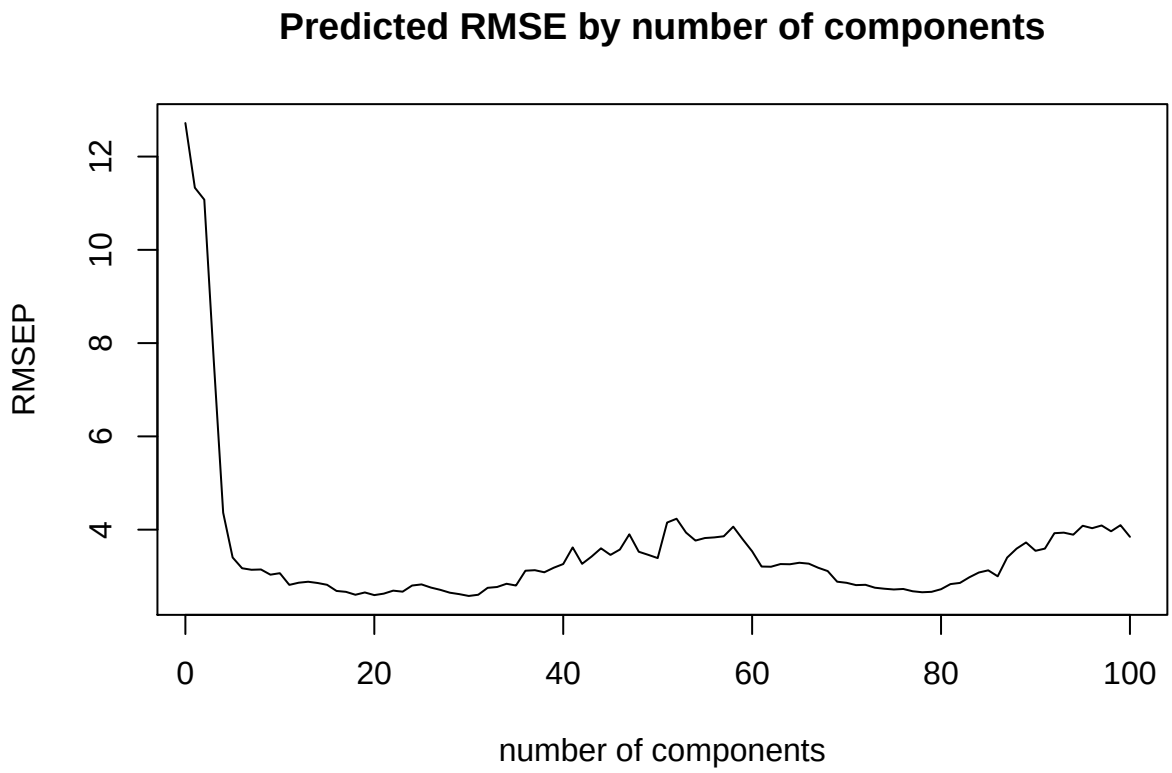

```
#Number of components to be used should be 8 according to the validation plot
#this has been calculated using the validation plot shown below as well as the variance explained by nu
```

```
#root mean squared error
rmse = function(x,y) {sqrt(mean((x-y)^2))}

#calcualte r^2
ss_res = function(yi,y_hat) {sum((yi-y_hat) ^2)}
ss_tot = function(yi) {sum((yi - mean(yi)) ^2)}
r2 = function(ss_res, ss_tot) {1 - (ss_res/ss_tot)}
rmseCV = RMSEP(pcr_fit, estimate ='CV');
rmseCV
```

```
## (Intercept)      1 comps      2 comps      3 comps      4 comps      5 comps
##      12.719       11.333       11.076        7.638        4.363        3.403
##     6 comps      7 comps      8 comps      9 comps     10 comps     11 comps
##       3.172        3.140        3.146        3.034        3.066        2.815
##    12 comps     13 comps     14 comps     15 comps     16 comps     17 comps
##       2.862        2.883        2.856        2.817        2.686        2.666
##    18 comps     19 comps     20 comps     21 comps     22 comps     23 comps
##       2.604        2.653        2.597        2.628        2.692        2.670
##    24 comps     25 comps     26 comps     27 comps     28 comps     29 comps
##       2.802        2.826        2.758        2.708        2.648        2.617
##    30 comps     31 comps     32 comps     33 comps     34 comps     35 comps
##       2.578        2.604        2.753        2.770        2.840        2.802
```

```
##    36 comps     37 comps     38 comps     39 comps     40 comps     41 comps
##       3.119        3.131        3.086        3.184        3.263        3.619
##    42 comps     43 comps     44 comps     45 comps     46 comps     47 comps
##       3.267        3.422        3.599        3.458        3.574        3.900
##    48 comps     49 comps     50 comps     51 comps     52 comps     53 comps
##       3.527        3.460        3.390        4.152        4.234        3.937
##    54 comps     55 comps     56 comps     57 comps     58 comps     59 comps
##       3.766        3.820        3.834        3.858        4.064        3.793
##    60 comps     61 comps     62 comps     63 comps     64 comps     65 comps
##       3.536        3.209        3.205        3.262        3.258        3.290
##    66 comps     67 comps     68 comps     69 comps     70 comps     71 comps
##       3.271        3.182        3.112        2.884        2.860        2.811
##    72 comps     73 comps     74 comps     75 comps     76 comps     77 comps
##       2.817        2.755        2.733        2.717        2.728        2.679
##    78 comps     79 comps     80 comps     81 comps     82 comps     83 comps
##       2.658        2.667        2.723        2.833        2.858        2.979
##    84 comps     85 comps     86 comps     87 comps     88 comps     89 comps
##       3.081        3.128        3.000        3.401        3.593        3.725
##    90 comps     91 comps     92 comps     93 comps     94 comps     95 comps
##       3.546        3.594        3.924        3.936        3.892        4.084
##    96 comps     97 comps     98 comps     99 comps    100 comps
##       4.031        4.089        3.965        4.096        3.847
```

```
plot(rmseCV, main='Predicted RMSE by number of components', xlim=c(1,100),xlab = "number of components")
```



```r
#predicting the values using 8 principal components
yhat = predict(pcr_fit, tec_test, ncomp=8)

# calculating the mse
mse_pred <- rmse(tec_test$y, yhat)^2
ss_res_pcr = ss_res(tec_test$y, yhat)
ss_tot_pcr = ss_tot(yhat)
r2_pcr = r2(ss_res_pcr, ss_tot_pcr)
r2_pcr
```

```
## [1] 0.9506282
```

```r
rmse(tec_test$y, yhat)
```

```
## [1] 2.833257
```

2. Ridge Regression

```r
#installing the packages
install.packages("glmnet")
```

```r
library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 4.0.4
```

```
## Loaded glmnet 4.1-1
```

```r
#using the pre-split data from training and testing tec_train and tec_test
train_X = tec_train[,1:100]
test_X = tec_test[,1:100]
#scaling training and testing X
train_X = scale(train_X, center = T, scale = T)
test_X = scale(test_X, center = T, scale = T)
#convert into matrix
temp_train_X = as.matrix(train_X)
temp_test_X = as.matrix(test_X)

train_Y = tec_train[,101]
test_Y = tec_test[,101]

#fitting the ridge regression model
lambdas = 10^seq(2, -3, by = -.1)
ridge_reg = glmnet(temp_train_X, train_Y, nlambda = 25, alpha = 0, family = 'gaussian', lambda = lambdas

summary(ridge_reg)
```

```
##           Length Class     Mode
## a0          51   -none-    numeric
## beta      5100   dgCMatrix S4
## df          51   -none-    numeric
```

```
## dim          2   -none-    numeric
## lambda      51   -none-    numeric
## dev.ratio   51   -none-    numeric
## nulldev      1   -none-    numeric
## npasses      1   -none-    numeric
## jerr         1   -none-    numeric
## offset       1   -none-    logical
## call         7   -none-    call
## nobs         1   -none-    numeric
```

```
#performing cross validation
ridge_crossval <- cv.glmnet(temp_train_X, train_Y, alpha = 0, lambda = lambdas)

#thus we used the functions provided by the glmnet package to figure out the most optimal lambda
optimal_lambda <- ridge_crossval$lambda.min
optimal_lambda
```

```
## [1] 0.001
```

We were able to calculate the optimal lambda using cross-validation

```
#use the optimal lambda to predict the y_fat values and calculate MSE
rmse = function(x,y) {sqrt(mean((x-y)^2))}
mse = function(x,y) {mean((x-y)^2)}


y_hat_ridge = predict(ridge_reg, s = optimal_lambda, newx = temp_test_X)
mse_pred_ridge = mse(y_hat_ridge, test_Y)

ss_res_ridge = ss_res(test_Y, y_hat_ridge)
ss_tot_ridge = ss_tot(y_hat_ridge)
r2_ridge = r2(ss_res = ss_res_ridge,ss_tot = ss_tot_ridge)


mse_pred_ridge
```

```
## [1] 10.87534
```

```
r2_ridge
```

```
## [1] 0.9317082
```

3. Lasso Regression

```
lambdas <- 10^seq(2, -3, by = -.1)

#alpha=1 for lasso regression
lasso_reg = cv.glmnet(temp_train_X, train_Y, alpha =1, lambda = lambdas, standardize=T)

optimal_lambda_lasso = lasso_reg$lambda.min
optimal_lambda_lasso
```

```
## [1] 0.001
```

```
#using the optimal lambda to predict the values of y_fat
y_hat_lasso = predict(lasso_reg, s = optimal_lambda_lasso, newx = temp_test_X)

#calculating the r2 for this method
ss_res_lasso = ss_res(test_Y, y_hat_lasso)
ss_tot_lasso = ss_tot(y_hat_lasso)
r2_lasso = r2(ss_res = ss_res_lasso,ss_tot = ss_tot_lasso)

#mean squared error being calcualted over the testing dataset
mse_pred_lasso = mse(y_hat_lasso, test_Y)
mse_pred_lasso
```

```
## [1] 11.02909
```

```
r2_lasso
```

```
## [1] 0.9315608
```

The best method so far has been the PCA Regression technique that had the lowest value of mean squared error on the same testing dataset.

Q5.

```
install.packages("plsr")
install.packages("faraway")
install.packages("spls")
install.packages("caret")
```

```
library("plsr")
```

```
## Warning: package 'plsr' was built under R version 4.0.4

## Be aware that plsr 0.0.1 contains experimental and partly untested code.
## Use cautiously.

##
## Attaching package: 'plsr'

## The following object is masked from 'package:pls':
##
##     loadings

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

```r
library("spls")
```

```
## Warning: package 'spls' was built under R version 4.0.4
```

```
## Sparse Partial Least Squares (SPLS) Regression and
## Classification (version 2.2-3)
```

```r
library("tidyverse")
```

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

```
## v tibble  3.0.3     v dplyr   1.0.2
## v tidyr   1.1.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
## v purrr   0.3.4
```

```
## Warning: package 'dplyr' was built under R version 4.0.3
```

```
## Warning: package 'stringr' was built under R version 4.0.3
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::collapse() masks nlme::collapse()
## x tidyr::complete() masks RCurl::complete()
## x tidyr::expand()   masks Matrix::expand()
## x dplyr::filter()   masks stats::filter()
## x dplyr::lag()      masks stats::lag()
## x tidyr::pack()     masks Matrix::pack()
## x dplyr::select()   masks MASS::select()
## x tidyr::unpack()   masks Matrix::unpack()
```

```r
library("caret")
```

```
## Warning: package 'caret' was built under R version 4.0.4
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'lattice'
```

```
## The following object is masked from 'package:fda':
##
##     melanoma
```

```
## Registered S3 methods overwritten by 'caret':
##   method         from
##   predict.splsda spls
##   print.splsda   spls
```

```
##
## Attaching package: 'caret'
```

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

## The following object is masked from 'package:spls':
##
##     splsda

## The following object is masked from 'package:pls':
##
##     R2
```

```
#load the prostate dataset
data("prostate")
X = prostate$x
prostate$x[1:5,1:5]
```

```
##            [,1]       [,2]       [,3]       [,4]       [,5]
## [1,] -0.9271777 -0.7400391 -0.5320164 -1.0978915 -0.9866733
## [2,] -0.8358990 -0.8358990 -0.5856470 -0.8358990 -0.3297677
## [3,]  0.2360733  0.2526450 -1.1543512 -0.3723715 -0.3388998
## [4,] -0.7486226 -0.4391652  0.7909530 -1.0338757  0.2411153
## [5,]  0.1012387 -0.2982854 -1.1215187 -0.9577135  0.3422581
```

```
prostate$y[1:45]
```

```
##  [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
## [39] 0 0 0 0 0 0 0
```

```
#preparing the data
prostate = na.omit(prostate)
set.seed(18)
train_pros_idx = sample(seq_len(nrow(prostate$x)), size = 70)
train_pros_idx
```

```
##  [1]  42  80  65  32  60  50  70  41  98  75  20  57  30  44   4  17  97  29  85
## [20]  40  13  11  82  76  96  90  95  55  91  26   1  84   8  47  62  23  31  12
## [39]  77   5  58  86  81  87 100  25  63  33  83  73  14  52  78  88  68  21  10
## [58]  35  71 101  15  38  72  48  64  79  27  36  59  24
```

```
pros_trainX = prostate$x[train_pros_idx,]
pros_testX = prostate$x[-train_pros_idx,]

pros_trainY = prostate$y[train_pros_idx]
pros_testY = prostate$y[-train_pros_idx]
```

```
#trying out the sparse model (without the lambda)
slg_model_cv = cv.glmnet(pros_trainX, pros_trainY, family="binomial",alpha=1)


#using this cross-validation to find the optimal lambda
optimal_lambda_slgr = slg_model_cv$lambda.min
optimal_lambda_slgr
```

```
## [1] 0.03158691
```

```
#using the optimal value of lambda to build the classifier
slgr_model = glmnet(pros_trainX, pros_trainY, alpha = 1, family = "binomial",
                lambda = optimal_lambda_slgr)
```

Now that we have built the model, we can use it to predict the values for the test set as well as the training set

```
#coef(slgr_model)

#type="response" gives the probability
yhat_slgr_prob = predict(slgr_model, newx = pros_testX, type="response")
yhat_slgr = as.numeric((yhat_slgr_prob>0.5))
yhat_slgr
```

```
##  [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1
```

```
#testing the accuracy of the model by diving the number of correct predictions by number of rows
corr_pred_slgr = sum(yhat_slgr == pros_testY)
corr_pred_slgr/32
```

```
## [1] 0.96875
```

Part2. Building another classifier - Logistic Regression Model with L2 regularization

```
#using the same dataset and partitions created for the sparse logistic regression and use for ridge reg
lg_model_cv = cv.glmnet(pros_trainX, pros_trainY, family="binomial", alpha=0)

#calculating optimal lambda
optimal_lambda_lgr = lg_model_cv$lambda.min
optimal_lambda_lgr
```

```
## [1] 4.079606
```

```
#building the classifier with the optimal lambda
lgr_model = glmnet(pros_trainX, pros_trainY, alpha = 0, family = "binomial",
                lambda = optimal_lambda_lgr)
```

```
#predicting values using this model
yhat_lgr_prob = predict(lgr_model, newx = pros_testX, type="response")
yhat_lgr = as.numeric((yhat_lgr_prob > 0.5))
yhat_lgr
```

```
##  [1] 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1
```

```
#testing the accuracy of this model
corr_pred_lgr = sum(yhat_lgr == pros_testY)
corr_pred_lgr/32
```

```
## [1] 0.9375
```

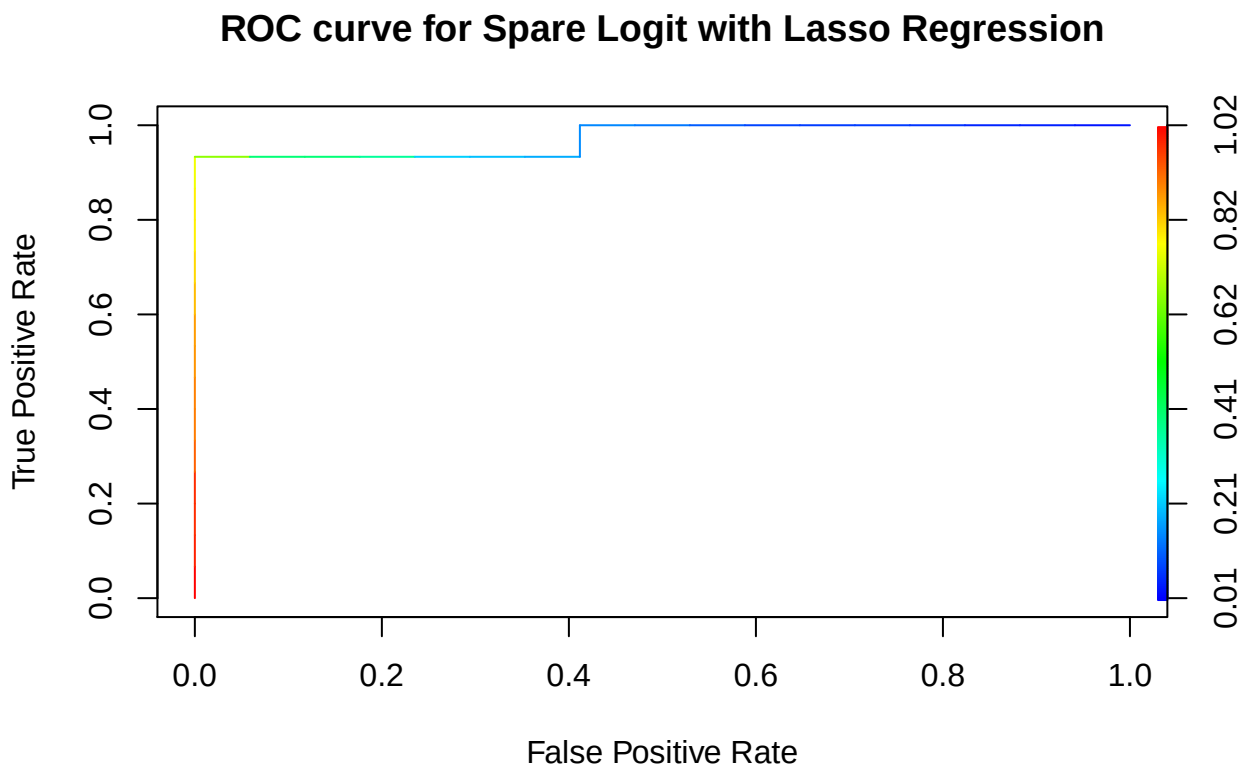
Comparing the 2 models We can say that based on the accuracy of the 2 models, the SLR with L1 regularization is more accurate. However, we can take a look at the ROC curve to further understand which model has a more accurate prediction.

```
install.packages("ROCR")
```

```
library(ROCR)
```

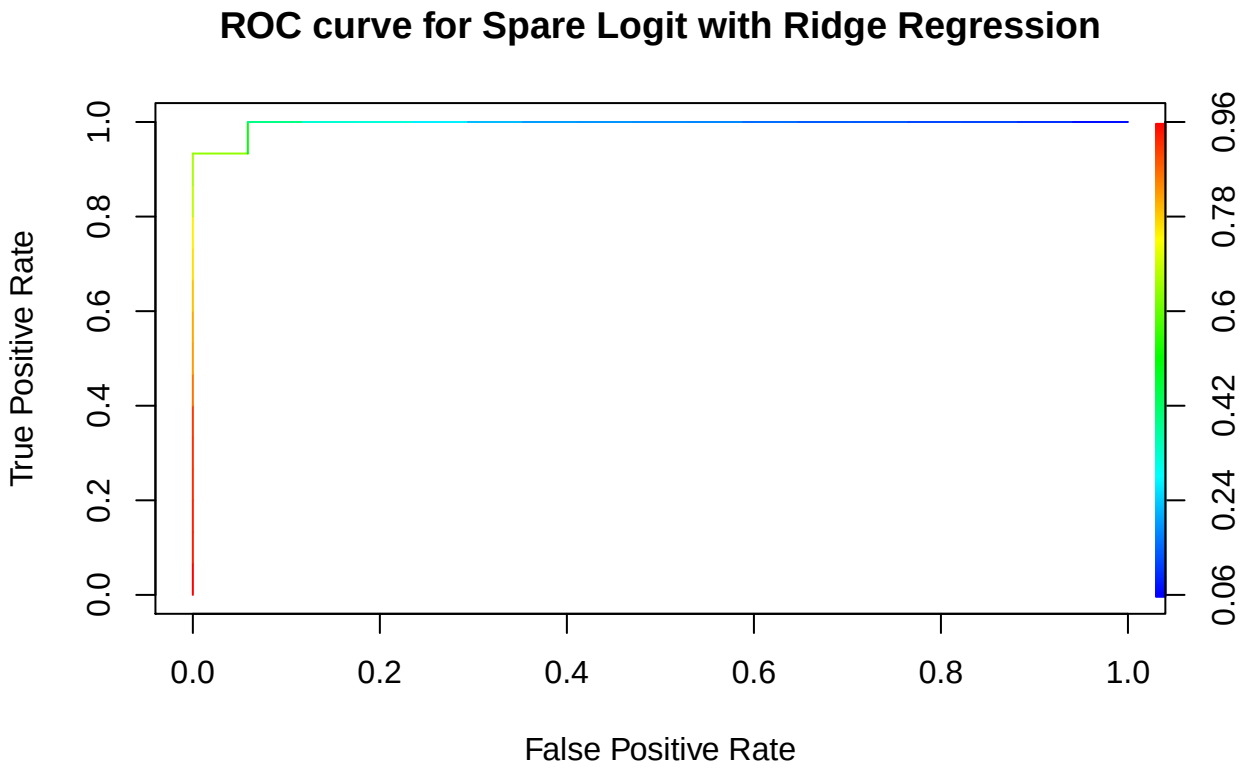
```
## Warning: package 'ROCR' was built under R version 4.0.4
```

```
thesePredictions<-yhat_slgr_prob
theseLabels<-pros_testY

pred <- prediction(thesePredictions, theseLabels)
perf <- performance(pred,"tpr","fpr")
plot(perf,colorize=TRUE, main="ROC curve for Spare Logit with Lasso Regression", xlab="False Positive Ra
```



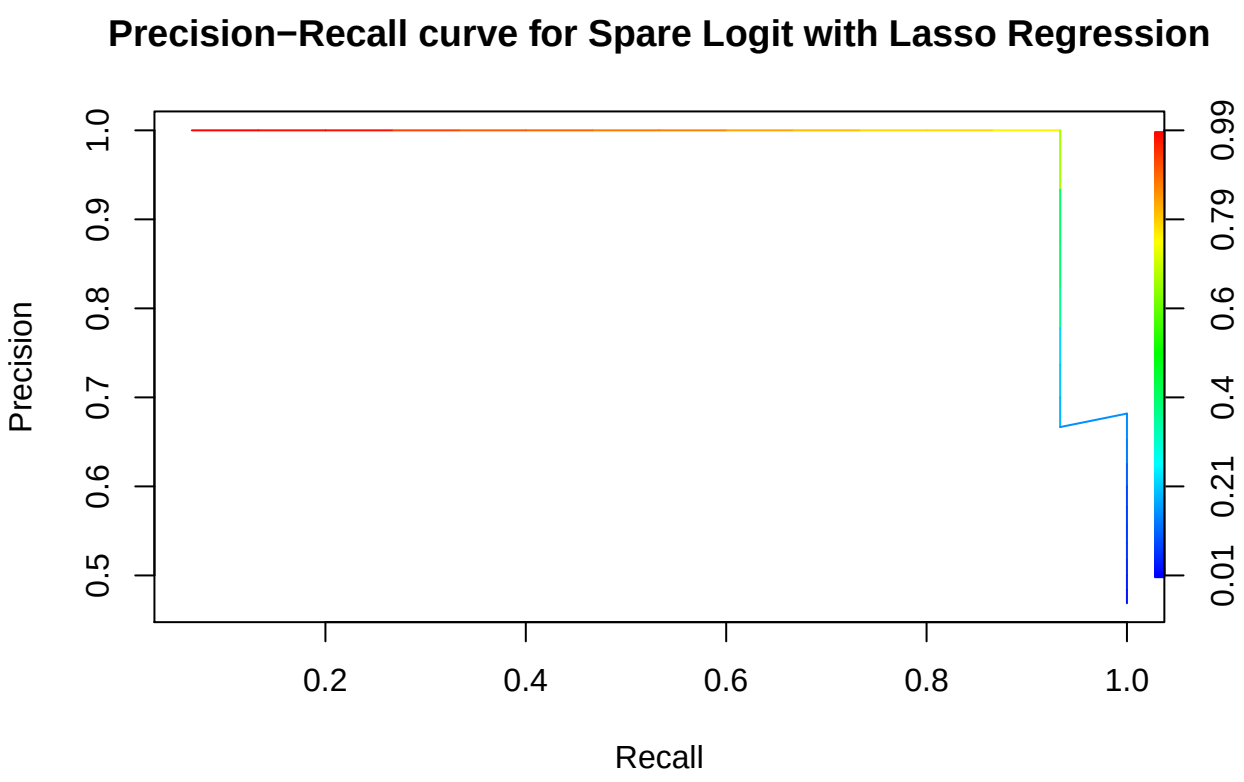

```
#doing the same for L2
thesePredictions2<-yhat_lgr_prob
theseLabels2<-pros_testY

pred2 <- prediction(thesePredictions2, theseLabels2)
```

```
perf2 <- performance(pred2,"tpr","fpr")
plot(perf2,colorize=TRUE, main="ROC curve for Spare Logit with Ridge Regression", xlab="False Positive R
```

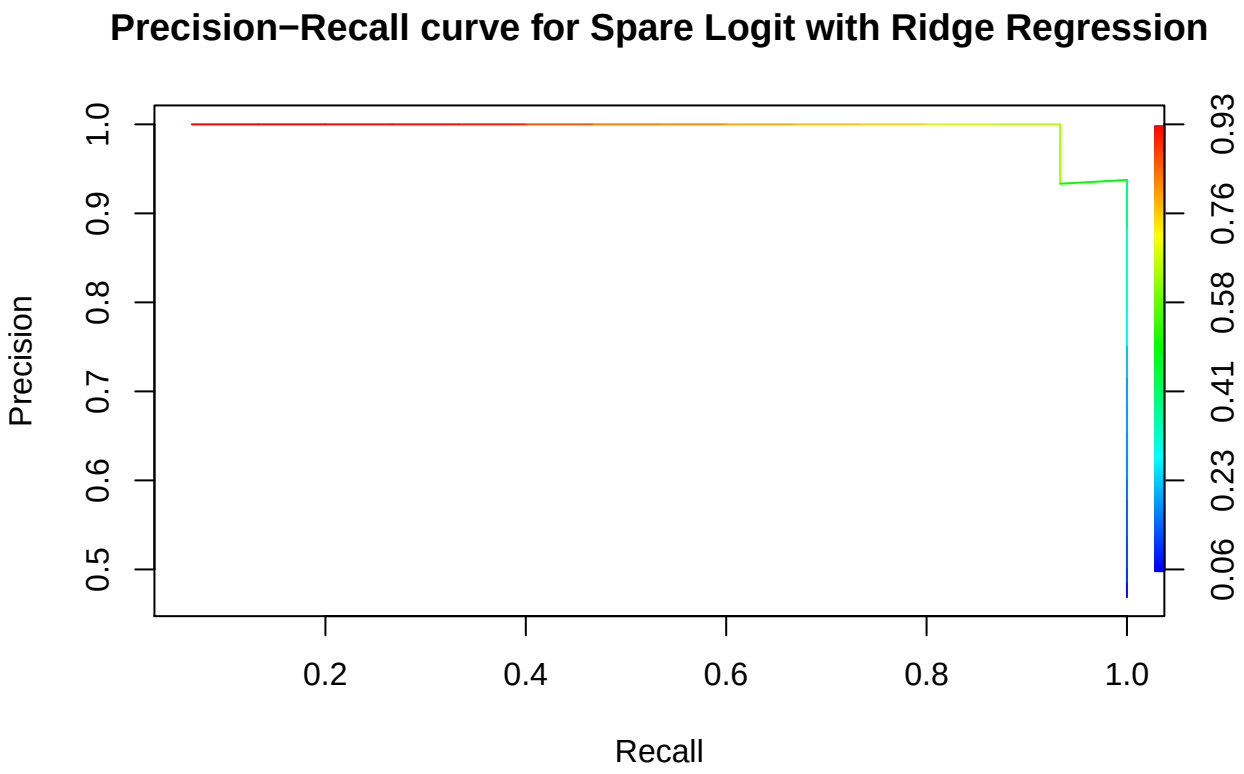


Also plotting the Precision vs. recall curves for both regressions

```
perfPR <- performance(pred, "prec", "rec")
plot(perfPR,colorize=TRUE,main="Precision-Recall curve for Spare Logit with Lasso Regression", xlab="Re
```




```
#for l2
perfPR2 <- performance(pred2, "prec", "rec")
plot(perfPR2,colorize=TRUE,main="Precision-Recall curve for Spare Logit with Ridge Regression", xlab="R
```



Based on both, the ROC curve and the precision-recall curve, we can confirm that the Lasso Regularization yields more accurate results compared to Ridge Regularization. In the ridge, the coefficients of the linear transformation are normal distributed and in the lasso they are Laplace distributed. In the lasso, this makes it easier for the coefficients to be zero and therefore easier to eliminate some of your input variable as not contributing to the output. Since we are using all the variables, this makes the model extremely specific and reduces the ability of the model to accurately predict on an unknown dataset. It increases variance and bias.