50 Crystal you did a good job with the layout. Your lasso and ridge regression models a

Crystal Mosley
Predict 422
Project #1

Introduction

MSE: mean((y_actual - y_predicted)^2)SE: s

This report examines the diabetes data in Efran et al (2003) to review the effects of ten predictor variables on a quantitate measure of disease progression on year after the baseline. The predictor variables are: age, sex, bmi (body mass index), map (avg blood pressure), and six blood serum measurements – tc, ldl, hdl, tch, ltg, and glu. There are 442 diabetes patients within this dataset. This set has been broken down into training data (75%) and test data (25%). The machine learning techniques that were used are: least squares regression, best subset selection using BIC (bayesian information criterion), ridge regression using 10-fold cross-validation, and lasso using 10-fold cross validation.

Analysis

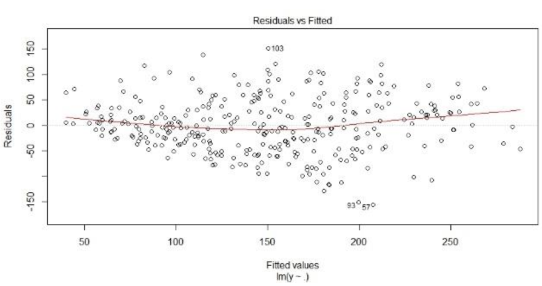
Model 1 – Least Squares Regression using all 10 predictors

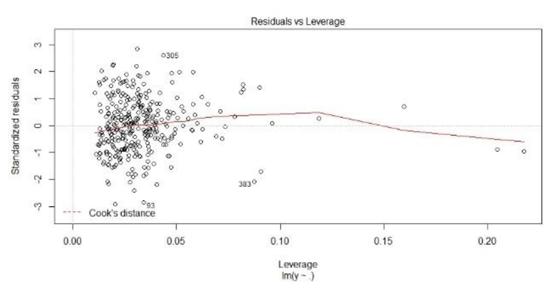
Coefficients

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  149.920      2.976  50.382  < 2e-16 ***
age          -66.758     68.946  -0.968  0.33364
sex         -304.651     69.847  -4.362 1.74e-05 ***
bmi          518.663     76.573   6.773 6.01e-11 ***
map          388.111     72.755   5.335 1.81e-07 ***
tc          -815.268    537.549  -1.517  0.13034
ldl          387.604    439.162   0.883  0.37811
hdl          162.903    269.117   0.605  0.54539
tch          323.832    186.803   1.734  0.08396 .
ltg          673.620    206.888   3.256  0.00125 **
glu           94.219     79.590   1.184  0.23737
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 54.05 on 321 degrees of freedom
Multiple R-squared:  0.5213,    Adjusted R-squared:  0.5064
F-statistic: 34.96 on 10 and 321 DF,  p-value: < 2.2e-16
```

The highlighted predictors are the only significant using 0.05 as alpha.

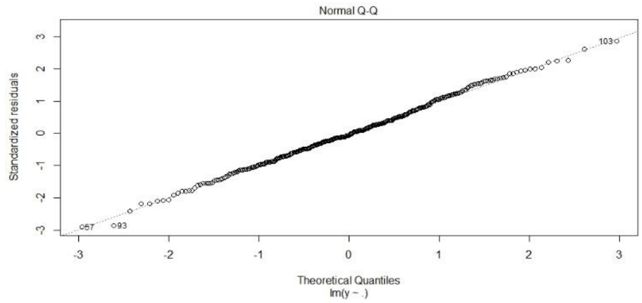




The first plot shows the residuals vs fitted values. There looks to be no pattern, and all the values flowing are showing homoscedasticity.

The second plot shows the residuals vs leverage. There are 3 values to the far right that are outliers and may need to be examined more to see if they're relevant.

The next plot is a QQ normal plot of the residuals. All the points show a straight line, and nothing else.

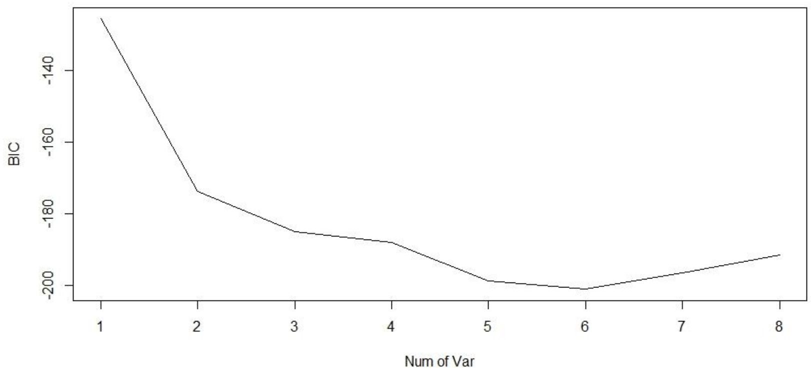


Mean Prediction Error for Test	Standard Error of the Prediction Error
31851.8	2581.989

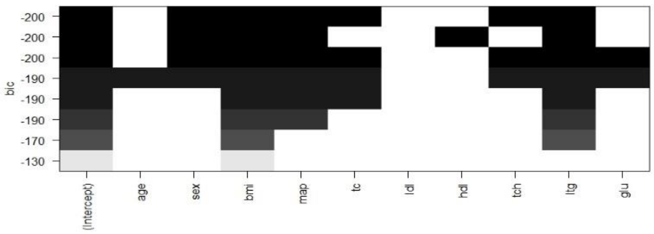
Model 2 - Best subset selection using BIC to select the number of predictors -2 MSE and SE incorrect

```
Subset selection object
Call: regsubsets.formula(y ~ ., data.train)
10 Variables  (and intercept)
    Forced in Forced out
age     FALSE      FALSE
sex     FALSE      FALSE
bmi     FALSE      FALSE
map     FALSE      FALSE
tc      FALSE      FALSE
ldl     FALSE      FALSE
hdl     FALSE      FALSE
tch     FALSE      FALSE
ltg     FALSE      FALSE
glu     FALSE      FALSE
```

```
1 subsets of each size up to 8
Selection Algorithm: exhaustive
         age sex bmi map tc  ldl hdl tch ltg glu
1  ( 1 ) " " " " "*" " " " " " " " " " " " " " "
2  ( 1 ) " " " " "*" " " " " " " " " " "*" " "
3  ( 1 ) " " " " "*" "*" " " " " " " " "*" " "
4  ( 1 ) " " " " "*" "*" "*" " " " " " "*" " "
5  ( 1 ) " " "*" "*" "*" " " " " "*" " " "*" " "
6  ( 1 ) " " "*" "*" "*" "*" " " " " "*" "*" " "
7  ( 1 ) " " "*" "*" "*" "*" " " " " "*" "*" "*"
8  ( 1 ) "*" "*" "*" "*" "*" " " " " "*" "*" "*"
```



The summary of the regsubsets fit shows the best 2-variable model contains bmi/ltg; the best 3-variable model contains bmi/map/ltg; the best 4-variable model contains bmi/map/tc/ltg ...and so on.



The model with the lowest BIC is the 6-variable model, -200; so, we use the coefficient associated with this 6-variable model.

Coefficients

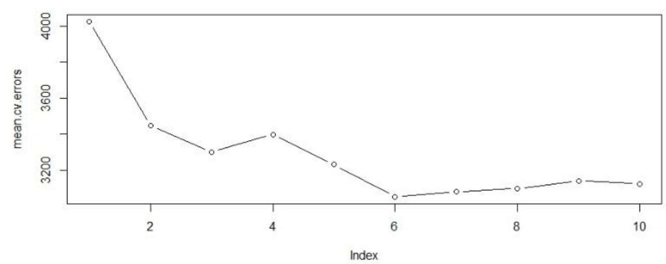
(Intercept)	Sex	Bmi	Map	Tc	Tch	Ltg
150.1166	-306.0420	538.8274	389.0673	-379.0379	332.6735	527.5658

Mean Prediction Error for Test	Standard Error of the Prediction Error
31851.8	2581.989

-2 MSE and SE incorrec

Model 3 - Best subset selection using 10-fold cross-validation to select the number of predictors

The 6 variables utilized from the best subset shows the lowest mean cross-validation error.



Coefficients

(Intercept)	Sex	Bmi	Map	Tc	Tch	Ltg
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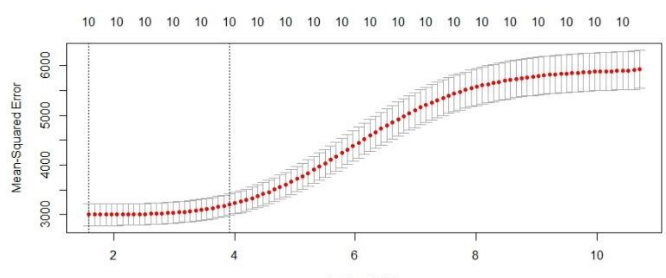
Mean Prediction Error for Test	Standard Error of the Prediction Error
31851.8	2581.989

-2 MSE and SE incorrect

Model 4 - Ridge regression modeling using 10-fold cross-validation to select the largest value of lambda

We used *lambda.1se* to find the largest value of lambda with the cv error being within 1 std. error of the minimum. This value is **50.19418**.



Coefficients

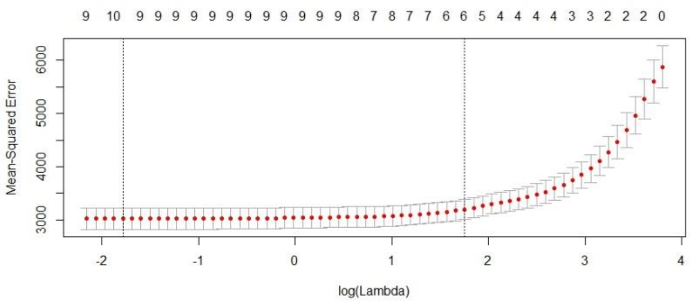
(Intercept)	149.977557
age	-8.557134
sex	-149.136379
bmi	364.867848
map	257.973377
tc	-28.362552
ldl	-62.483558
hdl	-171.383585
tch	122.170756
ltg	299.972608
glu	134.577219

Mean Prediction Error for Test	Standard Error of the Prediction Error
31851.8	2581.989

-2 MSE and SE incorrect

Your coefficients are close, my guess is that you did not set the seed befor

Model 5 - Lasso model using 10-fold cross-validation to select the largest value of lambda



We used *lambda.1se* to find the largest value of lambda with the cv error being within 1 std. error of the minimum. This value is **5.771111**.

Coefficients

(Intercept)	149.926939
age	.
sex	-82.459870
bmi	500.664831
map	251.759713
tc	.
ldl	.
hdl	-153.214079
tch	.
ltg	388.281077
glu	5.506856

Mean Prediction Error for Test	Standard Error of the Prediction Error
31851.8	2581.989

-2 MSE and SE incorrect

Your coefficients are close, my guess is that you did not set the seed before yo

Results

Model	Mean Prediction Error for Test	Standard Error of the Prediction Error
Model 1	31851.8	2581.989
Model 2	31851.8	2581.989
Model 3	31851.8	2581.989
Model 4	31851.8	2581.989
Model 5	31851.8	2581.989

Conclusion

All the model results came out the same, which could mean I did something wrong within the code, but in the case I did not, this means that any model using the 6 predictor variables (sex, bmi, map, hdl, ltg, and glu) can be used for further investigation in predicting the quantitative measure of disease progression one year after the baseline.

Reference

Hastie, T., James, G., Tibshirani, R., Witten, D. *An Introduction to Statistical Learning, with Applications in R* (2013). Springer New York Heidelberg Dordrecht London. http://www-bcf.usc.edu/~gareth/ISL/ISLR%20Seventh%20Printing.pdf Accessed 29 July 2018.

Appendix

R Code

```
# Load the diabetes data
library(lars)
data(diabetes)
data.all <- data.frame(cbind(diabetes$x, y = diabetes$y))

# Partition the patients into two groups: training (75%) and test (25%)
n <- dim(data.all)[1] # sample size = 442
set.seed(1306) # set random number generator seed to enable

# repeatability of results
test <- sample(n, round(n/4)) # randomly sample 25% test
data.train <- data.all[-test,]
data.test <- data.all[test,]
x <- model.matrix(y ~ ., data = data.all)[,-1] # define predictor matrix

# excl intercept col of 1s
x.train <- x[-test,] # define training predictor matrix
x.test <- x[test,] # define test predictor matrix
y <- data.all$y # define response variable
y.train <- y[-test] # define training response variable
y.test <- y[test] # define test response variable
n.train <- dim(data.train)[1] # training sample size = 332
n.test <- dim(data.test)[1] # test sample size = 110

# load library's for lm and glmnet procedures
library(leaps)
library(glmnet)

# perform least squares regression using all variables
lm.fit=lm(y~.,data.train)
lm.fit

# model coeff est's
summary(lm.fit)
confint(lm.fit) #conf interval for coeff

# predict responses for test set
lm.fitpredict=predict(lm.fit, data.test)

# plot diag's
plot(lm.fit)

# mean predict error for Test
```

```
mean((lm.fitpredict=y.test)^2)

# std error of predict error
sd((lm.fitpredict=y.test)^2)/sqrt(n.test)

# use predict function to product confidence and prediction intervals for response, given predictor
predict(lm.fit, data.frame(data.train), interval = "confidence")
predict(lm.fit, data.frame(data.train), interval = "prediction")

plot(data.train, y)
abline(lm.fit)

# plot residuals
plot(predict(lm.fit), residuals(lm.fit))

# perform best subset selection using BIC to select # of predictors
lm.subset.bic=regsubsets(y~., data.train)

regfit.full=regsubsets(y~., data.train)
summary(regfit.full)
  # best 2-variable model contains bmi/ltg
  # best 3-variable model contains bmi/map/ltg
  # best 4-variable model contains bmi/map/tc/ltg  ...and so on.

# summaries of BIC
reg.summary=summary(lm.subset.bic)
reg.summary$bic

# plot BIC
plot(reg.summary$bic, xlab = "Num of Var", ylab = "BIC", type = "l")

# plot regsubsets
plot(regfit.full, scale = "bic")
  # model with the lowest BIC is the 6-variable model, -200; so
  # we use coef associated with this 6-variable model.

# plot coeff of BIC
coef(lm.subset.bic,6)

# use predict function for regsubsets, per book page 249
predict.regsubsets=function(object, newdata, id,...)
{
  form=as.formula(object$call[[2]])
  mat=model.matrix(form, newdata)
  coefi=coef(object, id=id)
  xvars=names(coefi)
  mat[,xvars]%*%coefi
}

# predict test set with BIC subset
lm.subset.bic.pred = predict(lm.subset.bic, data.test, id=6)

# mean predict error for Test
mean((lm.subset.bic.pred=y.test)^2)

# std error of predict error
```

```
sd((lm.subset.bic.pred=y.test)^2)/sqrt(n.test)

# perform best subset using 10-fold cross-validation
k=10
folds <- sample(1:k, nrow(data.train), replace = TRUE)
cv.errors=matrix(NA, k, 10, dimnames = list(NULL, paste(1:10)))

for(j in 1:k){
  lm.subset.cv=regsubsets(y~., data.train[folds!=j,],
                          nvmax = 10)
  for(i in 1:10){
    pred=predict(lm.subset.cv, data.train[folds==j,], id=i)
    cv.errors[j,i]=mean((data.train$y[folds==j]-pred)^2)
  }
}

mean.cv.errors=apply(cv.errors, 2, mean)
mean.cv.errors
par(mfrow=c(1,1))
plot(mean.cv.errors, type = "b")

# model cv for best subset, 6
lm.subset.cv.best=regsubsets(y~., data.train, nvmax = 6)

# model coeff est's for cv best subset, 6
coef(lm.subset.cv.best, 6)

# predict test set for cv
lm.subset.cv.best.pred=predict(lm.subset.cv.best, data.test, id=6)

# mean predict error for Test
mean((lm.subset.cv.best.pred=y.test)^2)

# std error of predict error
sd((lm.subset.cv.best.pred=y.test)^2/sqrt(n.test))

# perform ridge regression using 10-fold cv
cv.out <- cv.glmnet(x.train, y.train, alpha = 0)
plot(cv.out)

biglam.ridge <- cv.out$lambda.1se
  #lambda.1se - the most regularized model such that error is within one standard error of the
minimum
biglam.ridge
bestlam=cv.out$lambda.min
  #lambda.min - the value of \(\lambda\) that gives minimum mean cross-validated error
bestlam

# model coeff est's for cv ridge regression
ridge.model=glmnet(x.train, y.train, alpha = 0, lambda = 45.73507)
coef(ridge.model)

# predict test set for ridge regression
ridge.model.pred=predict(ridge.model, newx = x.test)

# mean predict error for Test
```

```
mean((ridge.model.pred=y.test)^2)

# std error of predict error
sd((ridge.model.pred=y.test)^2)/sqrt(n.test)

# perform lasso using 10-fold cv
cv.out <- cv.glmnet(x.train, y.train, alpha = 1)
plot(cv.out)

bestlam2=cv.out$lambda.min
bestlam2
biglam.lasso <- cv.out$lambda.1se
biglam.lasso

# model coeff est's for lasso
lasso.model=glmnet(x.train, y.train, alpha = 1, lambda = 5.771111)
coef(lasso.model)

# predict test set for lasso
lasso.model.pred=predict(lasso.model, newx = x.test)

# mean predict error for Test
mean((lasso.model.pred=y.test)^2)

# std error of predict error
sd((lasso.model.pred=y.test)^2)/sqrt(n.test)
```