

Ridge and Lasso(101C)

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Data

```
data <- fivethirtyeight::hate_crimes
data2 <- na.omit(data)
x = model.matrix(avg_hatecrimes_per_100k_fbi~., data = data2)
y = data2$avg_hatecrimes_per_100k_fbi
```

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-18
```

Ridge

```
set.seed(1)
grid=10^seq(10,-2,length=100)
ridge.mod=glmnet(x,y,alpha=0,lambda=grid)
dim(coef(ridge.mod))
```

```
## [1] 100 100
```

```
ridge.mod$lambda [50]
```

```
## [1] 11497.57
```

```
# When lamda = 11498
```

```
coef(ridge.mod)[,50]
```

##	(Intercept)	(Intercept)
##	2.369628e+00	0.000000e+00
##	stateAlaska	stateArizona
##	-1.083680e-04	1.571791e-04
##	stateArkansas	stateCalifornia
##	-2.273161e-04	3.587598e-06
##	stateColorado	stateConnecticut
##	6.509133e-05	2.113427e-04
##	stateDelaware	stateDistrict of Columbia
##	-1.366018e-04	1.296322e-03
##	stateFlorida	stateGeorgia
##	-2.532533e-04	-2.964739e-04
##	stateIdaho	stateIllinois
##	-7.284709e-05	-2.009928e-04
##	stateIndiana	stateIowa
##	-9.310507e-05	-2.738737e-04
##	stateKansas	stateKentucky
##	-3.467657e-05	2.772508e-04
##	stateLouisiana	stateMaryland
##	-1.560126e-04	-1.585933e-04

##	stateMassachusetts	stateMichigan
##	3.668585e-04	1.249248e-04
##	stateMinnesota	stateMissouri
##	1.871467e-04	-7.022271e-05
##	stateMontana	stateNebraska
##	8.787902e-05	4.727435e-05
##	stateNevada	stateNew Hampshire
##	-3.927237e-05	-4.044599e-05
##	stateNew Jersey	stateNew Mexico
##	3.081650e-04	-7.366936e-05
##	stateNew York	stateNorth Carolina
##	1.100091e-04	-1.679054e-04
##	stateOhio	stateOklahoma
##	1.310069e-04	-1.952089e-04
##	stateOregon	statePennsylvania
##	1.542440e-04	-2.936169e-04
##	stateRhode Island	stateSouth Carolina
##	-1.649348e-04	-6.596990e-05
##	stateTennessee	stateTexas
##	1.152415e-04	-2.449918e-04
##	stateUtah	stateVermont
##	1.585954e-06	-7.111904e-05
##	stateVirginia	stateWashington
##	-9.812036e-05	2.181599e-04
##	stateWest Virginia	stateWisconsin
##	-5.081058e-05	-1.891548e-04
##	state_abbrevAL	state_abbrevAR
##	-8.569621e-05	-2.273078e-04
##	state_abbrevAZ	state_abbrevCA
##	1.571732e-04	3.587557e-06
##	state_abbrevCO	state_abbrevCT
##	6.508902e-05	2.113350e-04
##	state_abbrevDC	state_abbrevDE
##	1.296275e-03	-1.365956e-04
##	state_abbrevFL	state_abbrevGA
##	-2.532438e-04	-2.964629e-04
##	state_abbrevIA	state_abbrevID
##	-2.738632e-04	-7.284455e-05
##	state_abbrevIL	state_abbrevIN
##	-2.009855e-04	-9.310178e-05
##	state_abbrevKS	state_abbrevKY
##	-3.467521e-05	2.772406e-04
##	state_abbrevLA	state_abbrevMA
##	-1.560068e-04	3.668452e-04
##	state_abbrevMD	state_abbrevMI
##	-1.585871e-04	1.249203e-04
##	state_abbrevMN	state_abbrevMO
##	1.871399e-04	-7.022004e-05
##	state_abbrevMT	state_abbrevNC
##	8.787588e-05	-1.678994e-04
##	state_abbrevNE	state_abbrevNH
##	4.727256e-05	-4.044452e-05
##	state_abbrevNJ	state_abbrevNM
##	3.081536e-04	-7.366666e-05

```
##          state_abbrevNV          state_abbrevNY
##          -3.927081e-05          1.100050e-04
##          state_abbrevOH          state_abbrevOK
##          1.310022e-04          -1.952017e-04
##          state_abbrevOR          state_abbrevPA
##          1.542384e-04          -2.936060e-04
##          state_abbrevRI          state_abbrevSC
##          -1.649287e-04          -6.596738e-05
##          state_abbrevTN          state_abbrevTX
##          1.152374e-04          -2.449827e-04
##          state_abbrevUT          state_abbrevVA
##          1.585984e-06          -9.811660e-05
##          state_abbrevVT          state_abbrevWA
##          -7.111642e-05          2.181519e-04
##          state_abbrevWI          state_abbrevWV
##          -1.891478e-04          -5.080878e-05
##          median_house_inc        share_unemp_seas
##          8.214471e-09          4.330809e-03
##          share_pop_metro          share_pop_hs
##          3.386042e-04          1.092815e-03
##          share_non_citizen        share_white_poverty
##          2.539813e-03          -2.496585e-03
##          gini_index              share_non_white
##          5.866340e-03          2.294301e-04
##          share_vote_trump hate_crimes_per_100k_splc
##          -1.241740e-03          7.695299e-04
```

```
sqrt(sum(coef(ridge.mod)[-1,50]^2))
```

```
## [1] 0.008675493
```

```
ridge.mod$lambda [60]
```

```
## [1] 705.4802
```

```
# when lambda = 705
coef(ridge.mod)[,60]
```

```
##          (Intercept)          (Intercept)
##          2.306360e+00          0.000000e+00
##          stateAlaska          stateArizona
##          -1.755878e-03          2.546724e-03
##          stateArkansas          stateCalifornia
##          -3.664979e-03          3.673349e-05
##          stateColorado          stateConnecticut
##          1.047622e-03          3.406758e-03
##          stateDelaware stateDistrict of Columbia
##          -2.218951e-03          2.093385e-02
##          stateFlorida          stateGeorgia
##          -4.110238e-03          -4.807917e-03
##          stateIdaho            stateIllinois
##          -1.159433e-03          -3.269166e-03
##          stateIndiana          stateIowa
##          -1.491614e-03          -4.433163e-03
##          stateKansas          stateKentucky
##          -5.441306e-04          4.521749e-03
```

##	stateLouisiana	stateMaryland
##	-2.515596e-03	-2.594463e-03
##	stateMassachusetts	stateMichigan
##	5.921966e-03	2.026223e-03
##	stateMinnesota	stateMissouri
##	3.023224e-03	-1.129707e-03
##	stateMontana	stateNebraska
##	1.442574e-03	7.854590e-04
##	stateNevada	stateNew Hampshire
##	-6.393535e-04	-6.467394e-04
##	stateNew Jersey	stateNew Mexico
##	4.985764e-03	-1.199918e-03
##	stateNew York	stateNorth Carolina
##	1.763306e-03	-2.718906e-03
##	stateOhio	stateOklahoma
##	2.138037e-03	-3.144898e-03
##	stateOregon	statePennsylvania
##	2.479890e-03	-4.762134e-03
##	stateRhode Island	stateSouth Carolina
##	-2.682272e-03	-1.060007e-03
##	stateTennessee	stateTexas
##	1.884882e-03	-3.977577e-03
##	stateUtah	stateVermont
##	3.766151e-05	-1.147070e-03
##	stateVirginia	stateWashington
##	-1.601885e-03	3.520748e-03
##	stateWest Virginia	stateWisconsin
##	-7.973323e-04	-3.057065e-03
##	state_abbrevAL	state_abbrevAR
##	-1.372778e-03	-3.664979e-03
##	state_abbrevAZ	state_abbrevCA
##	2.546724e-03	3.673340e-05
##	state_abbrevCO	state_abbrevCT
##	1.047622e-03	3.406758e-03
##	state_abbrevDC	state_abbrevDE
##	2.093385e-02	-2.218951e-03
##	state_abbrevFL	state_abbrevGA
##	-4.110238e-03	-4.807917e-03
##	state_abbrevIA	state_abbrevID
##	-4.433163e-03	-1.159433e-03
##	state_abbrevIL	state_abbrevIN
##	-3.269166e-03	-1.491614e-03
##	state_abbrevKS	state_abbrevKY
##	-5.441305e-04	4.521749e-03
##	state_abbrevLA	state_abbrevMA
##	-2.515596e-03	5.921966e-03
##	state_abbrevMD	state_abbrevMI
##	-2.594463e-03	2.026223e-03
##	state_abbrevMN	state_abbrevMO
##	3.023224e-03	-1.129707e-03
##	state_abbrevMT	state_abbrevNC
##	1.442574e-03	-2.718906e-03
##	state_abbrevNE	state_abbrevNH
##	7.854591e-04	-6.467393e-04

```
##          state_abbrevNJ          state_abbrevNM
##          4.985764e-03          -1.199918e-03
##          state_abbrevNV          state_abbrevNY
##          -6.393536e-04          1.763306e-03
##          state_abbrevOH          state_abbrevOK
##          2.138037e-03          -3.144898e-03
##          state_abbrevOR          state_abbrevPA
##          2.479890e-03          -4.762134e-03
##          state_abbrevRI          state_abbrevSC
##          -2.682272e-03          -1.060007e-03
##          state_abbrevTN          state_abbrevTX
##          1.884882e-03          -3.977577e-03
##          state_abbrevUT          state_abbrevVA
##          3.766152e-05          -1.601885e-03
##          state_abbrevVT          state_abbrevWA
##          -1.147070e-03          3.520748e-03
##          state_abbrevWI          state_abbrevWV
##          -3.057065e-03          -7.973322e-04
##          median_house_inc        share_unemp_seas
##          1.319772e-07          6.970554e-02
##          share_pop_metro          share_pop_hs
##          5.413916e-03          1.766453e-02
##          share_non_citizen        share_white_poverty
##          4.075425e-02          -4.000019e-02
##          gini_index              share_non_white
##          9.458950e-02          3.647184e-03
##          share_vote_trump hate_crimes_per_100k_splc
##          -1.998286e-02          1.242298e-02
```

```
sqrt(sum(coef(ridge.mod)[-1,60]^2))
```

```
## [1] 0.1397194
```

```
predict(ridge.mod,s=50,type="coefficients")[1:20,]
```

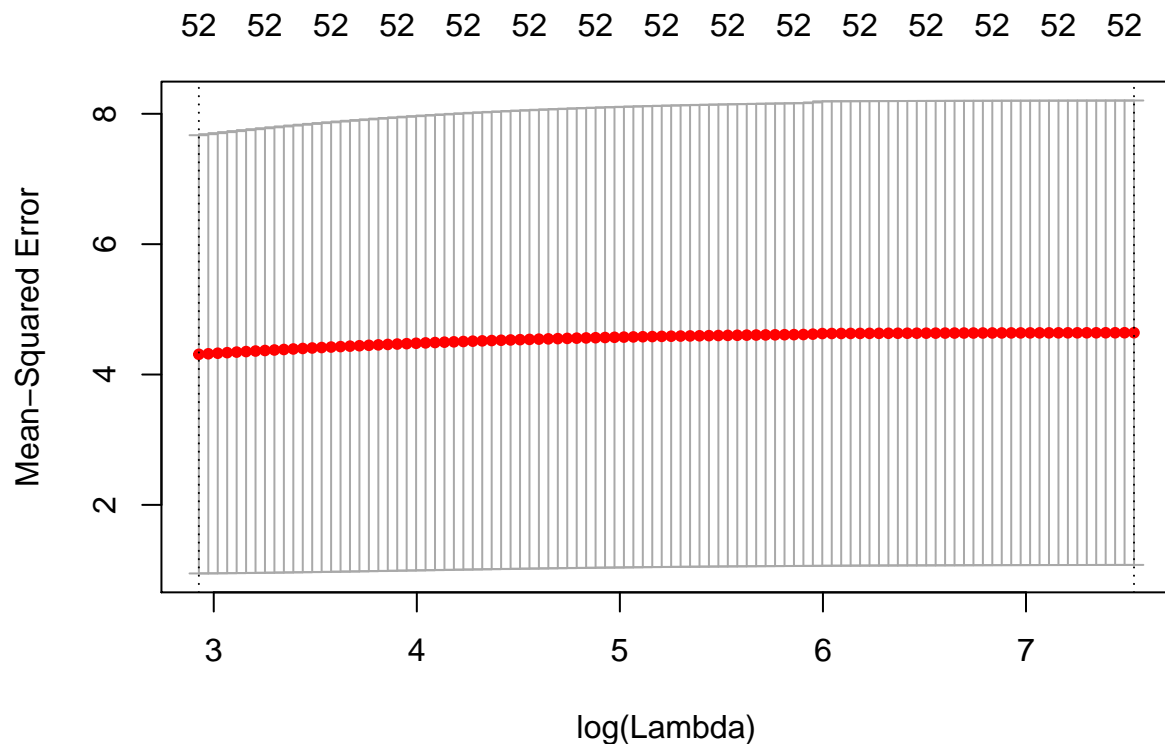
```
##          (Intercept)          (Intercept)
##          1.532861427          0.000000000
##          stateAlaska          stateArizona
##          -0.023333329          0.033963005
##          stateArkansas          stateCalifornia
##          -0.045812501          -0.002783144
##          stateColorado          stateConnecticut
##          0.012796094          0.042488126
##          stateDelaware stateDistrict of Columbia
##          -0.030350812          0.266878224
##          stateFlorida          stateGeorgia
##          -0.055669875          -0.064503440
##          stateIdaho          stateIllinois
##          -0.012075860          -0.045399714
##          stateIndiana          stateIowa
##          -0.017148926          -0.058337421
##          stateKansas          stateKentucky
##          -0.004410140          0.064686168
##          stateLouisiana          stateMaryland
##          -0.031467522          -0.038349695
```

```
# split the samples into a training and a test in order to estimate the test error of ridge and lasso
train=sample(1:nrow(x), nrow(x)/2)
test=(-train)
y.test=y[test]
```

```
cv.out=cv.glmnet(x[train,],y[train],alpha=0)
```

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations
## per fold
```

```
plot(cv.out)
```



```
bestlam=cv.out$lambda.min
```

```
bestlam # lambda that results in the smallest cv error is 1745
```

```
## [1] 18.66568
```

```
# what is the MSE with this lambda?
```

```
ridge.pred=predict(ridge.mod,s=bestlam ,newx=x[test,])
```

```
mean((ridge.pred-y.test)^2)
```

```
## [1] 1.029258
```

```
# refit our ridge regression model on the full data set, using the lambda chosen by cv, and examine the
```

```
out=glmnet(x,y,alpha=0)
```

```
predict(out,type="coefficients",s=bestlam)[1:20,]
```

```
##           (Intercept)           (Intercept)
##      0.564425852      0.000000000
##      stateAlaska      stateArizona
##     -0.054406549      0.080265456
##      stateArkansas      stateCalifornia
##     -0.099061034     -0.014563616
```

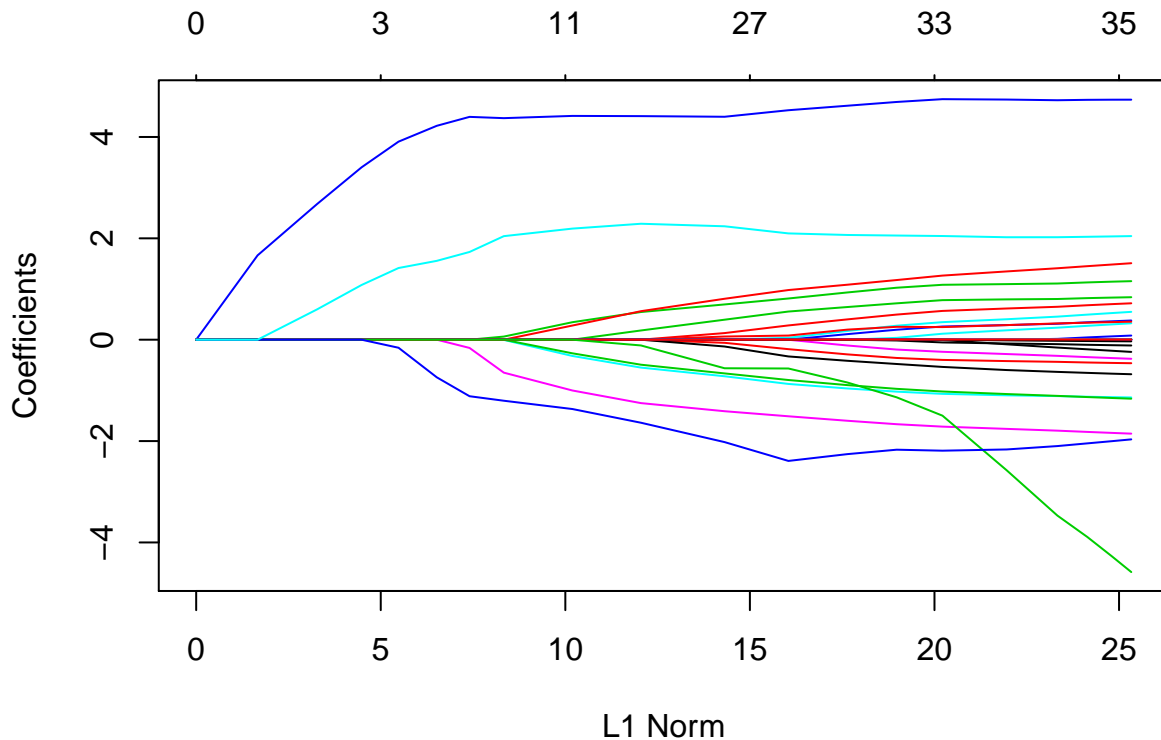
```
##          stateColorado          stateConnecticut
##          0.026782394            0.091660630
##          stateDelaware stateDistrict of Columbia
##          -0.072930474            0.591021612
##          stateFlorida          stateGeorgia
##          -0.132507839            -0.151787213
##          stateIdaho            stateIllinois
##          -0.019105970            -0.110977733
##          stateIndiana          stateIowa
##          -0.032914945            -0.135211179
##          stateKansas          stateKentucky
##          -0.002643702            0.162691724
##          stateLouisiana        stateMaryland
##          -0.068033787            -0.099454259
```

None of the coefficients are zero; ridge regression does not perform variable selection.

Lasso

```
lasso.mod=glmnet(x[train ],y[train],alpha=1,lambda=grid)
plot(lasso.mod)
```

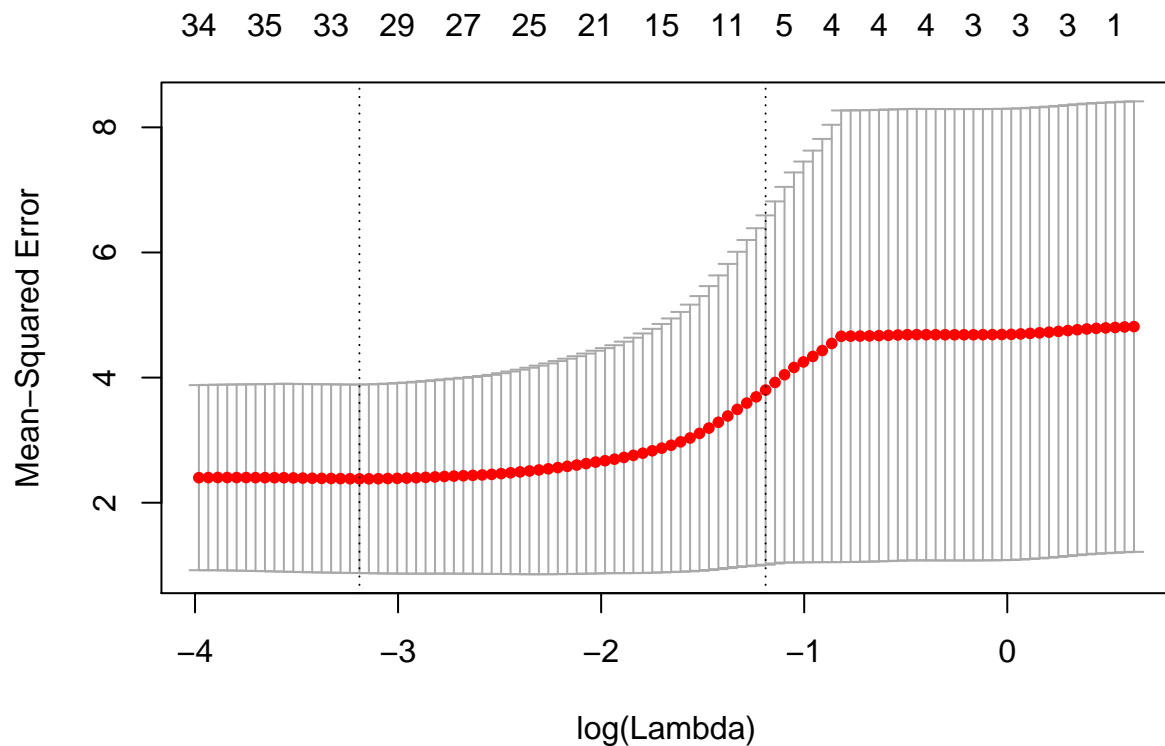
```
## Warning in regularize.values(x, y, ties, missing(ties)): collapsing to
## unique 'x' values
```



```
set.seed (1)
cv.out=cv.glmnet(x[train ],y[train],alpha=1)
```

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations
## per fold
```

```
plot(cv.out)
```



```
bestlam=cv.out$lambda.min
lasso.pred=predict(lasso.mod,s=bestlam ,newx=x[test,])
mean((lasso.pred-y.test)^2)
```

```
## [1] 1.366457
```

```
out=glmnet(x,y,alpha=1,lambda=grid)
lasso.coef=predict(out,type="coefficients",s=bestlam)[1:20,]
lasso.coef
```

##	(Intercept)	(Intercept)
##	0.59259566	0.00000000
##	stateAlaska	stateArizona
##	0.00000000	1.05190096
##	stateArkansas	stateCalifornia
##	-0.32196182	0.00000000
##	stateColorado	stateConnecticut
##	0.00000000	1.06221941
##	stateDelaware	stateDistrict of Columbia
##	-0.59401179	4.49283542
##	stateFlorida	stateGeorgia
##	-0.95824359	-1.01887614
##	stateIdaho	stateIllinois
##	0.00000000	-0.64831686
##	stateIndiana	stateIowa
##	-0.03195501	-1.91500154
##	stateKansas	stateKentucky
##	0.20397193	1.67484458
##	stateLouisiana	stateMaryland
##	0.00000000	-0.98113228

Lasso Regression has a advantage over Ridge Regression in that the resulting coefficient estimates are sparse.

We can see 4 coefficient estimates are exactly zero. So the lasso model with λ chosen by cv contains only 4 variables.