Ridge Lasso Elastic-net - Demo

Comparisons of model coefficient estimate

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Regularized linear regressions

Comparisons of Ridge, Lasso, and Elastic-net

Goal: Parameter estimation in linear regression

$$Y = \beta_o + \mathbf{X}\beta + \epsilon$$

```
library(MASS) # use lm.ridge
library(glmnet)
```

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Estimators

$$\hat{\beta}_{LS} = \operatorname{argmin}_{\beta} \left\{ \| Y - \beta_0 - \mathbf{X}\beta \|_2^2 \right\}$$

$$\hat{\beta}_{\textit{Ridge}} = \operatorname{argmin}_{\beta} \left\{ \| \mathbf{Y} - \beta_0 - \mathbf{X}\beta \|_2^2 + \lambda_{\textit{ridge}} \|\beta\|_2^2 \right\}$$

$$\hat{\beta}_{\textit{Lasso}} = \operatorname{argmin}_{\beta} \left\{ \| \mathbf{Y} - \beta_0 - \mathbf{X}\beta \|_2^2 + \lambda_{\textit{lasso}} \|\beta\|_1 \right\}$$

$$\hat{\beta}_{\textit{E-net}} = \operatorname{argmin}_{\beta} \left\{ \| Y - \beta_0 - \mathbf{X}\beta \|_2^2 + \lambda \left[\alpha \| \beta \|_2^2 + (1 - \alpha) \| \beta \|_1 \right] \right\}$$

Example 1: Explanatory variables X

```
p = 30 input X variables
```

n = 50 observations

```
set.seed(246329)
n=50
p1=10  # "signals"
p2=20  # "noise"
X = matrix(rnorm(n*(p1+p2)),n, p1+p2)
dim(X)
```

[1] 50 30

Example 1: Response variable Y

10 signal, 20 uniform noise input variables

```
c1 = 0.5 + (runif(10))/2 # "signals" 0.5 + U(0,1)/2

c2 = (runif(20))*3/10 # "noise" U(0,1)*3/10

Y = X[,1:10]%*%c1 + X[,11:30]%*%c2 + rnorm(n)
```

To fit the model

$$Y = \beta_o + \mathbf{X}\beta + \epsilon$$

In expanded form,

$$Y = \beta_0 + \beta_1 X_1 + \dots + \beta_{10} X_{10} + \beta_{11} X_{11} + \dots + \beta_{30} X_{30} + \epsilon$$

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Least Squares for $Y = \beta_o + \mathbf{X}\beta + \epsilon$

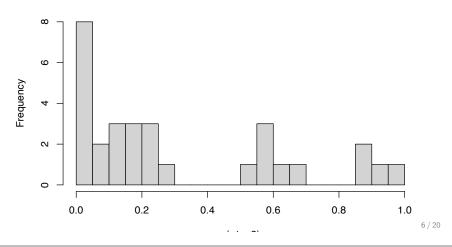
```
Y = X[,1:10]%*%c1 + X[,11:30]%*%c2 + rnorm(n)
LSfit = lm(Y~X)
round(LSfit$coeff,2)
```

##	(Intercept)	X1	Х2	ХЗ	
##	-0.18	0.35	0.92	0.28	(
##	Х6	Х7	Х8	Х9	
##	0.68	0.87	0.83	0.28	(
##	X12	X13	X14	X15	
##	0.03	0.14	-0.24	0.35	(
##	X18	X19	X20	X21	
##	0.12	-0.12	0.19	0.23	(
##	X24	X25	X26	X27	
##	-0.35	-0.11	0.22	0.47	(
##	X30				
##	0.29				

```
True \beta values in Y = \beta_o + \mathbf{X}\beta + \epsilon
```

```
#range(c1)
#range(c2)
hist(c(c1,c2),nclass=15)
```

Histogram of c(c1, c2)

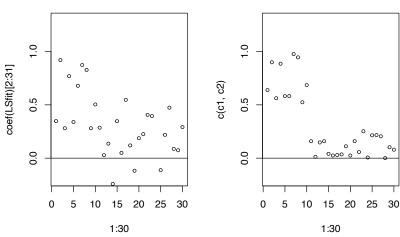


Compare model fitted $\hat{\beta}$ with true β (code)

$\hat{\beta}_{LS}$ values for $Y = \beta_o + \mathbf{X}\beta + \epsilon$

LS estimates

True coefficients



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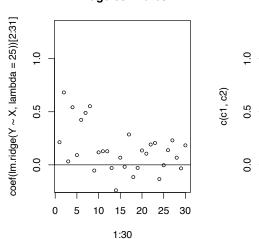
$\hat{\beta}_{Lasso}$ values for $Y = \beta_o + \mathbf{X}\beta + \epsilon$

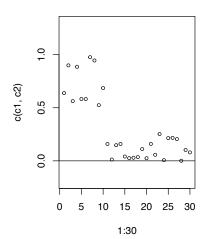


$\hat{\beta}_{Ridge}$ values for $Y = \beta_o + \mathbf{X}\beta + \epsilon$

Ridge estimates

True coefficients



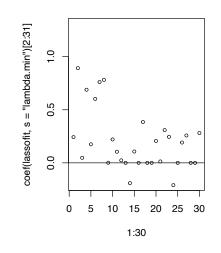


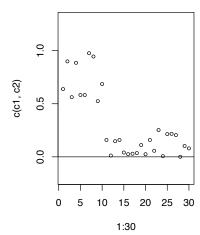
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\hat{eta}_{Lasso} values when $\lambda = \texttt{lambda.min}$

LASSO lambda.min

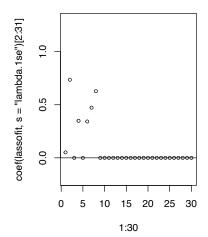
True coefficients



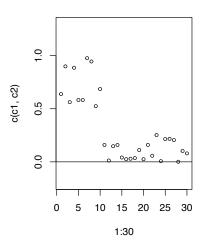


$\hat{eta}_{ extsf{Lasso}}$ values when $\lambda = extsf{lambda.1se}$

LASSO lambda.1se



True coefficients



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Model parameter estimates comparison

$$Y = \beta_o + \mathbf{X}\beta + \epsilon$$

We compare value and range of the true coefficients

$$\beta = (\beta_1, \cdots, \beta_{30})$$

with estimated $\hat{\beta}$ values

$$\hat{\beta} = (\hat{\beta}_1, \cdots, \hat{\beta}_{30})$$

Using the method

- Least Squares
- Ridge
- Lasso
- Elastic-net

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Viusualize model parameter estimates $\hat{\beta}$

Fit linear regression model $Y = \beta_o + \mathbf{X}\beta + \epsilon$ by

- Least Squares
- Ridge
- Lasso
- Elastic-net

(Code)

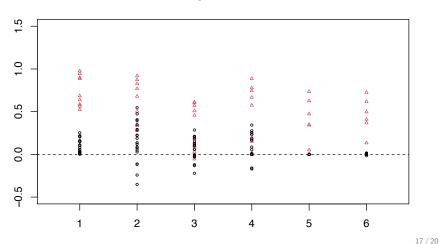
```
points(rep(2,30),lm(Y~X)$coef[2:31],cex=.5,
    col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(3,30),lm.ridge(Y~X,lambda=25)$coef,cex=.5,
    col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(4,30),coef(lassofit,s="lambda.min")[2:31],cex=.{
    col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(5,30),coef(lassofit,s="lambda.1se")[2:31],cex=.{
    col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(6,30),coef(netfit,s="lambda.1se")[2:31],cex=.5,
    col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
title("True coefficients, LS, Ridge,
    Lasso.min, Lasso.1se, Net.1se")
```

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Input variables: **Signal** (triangles) + uniform **Noise**

 β , $\hat{\beta}_{LS}$ $\hat{\beta}_{Ridge}$ $\hat{\beta}_{Lasso.min}$ $\hat{\beta}_{Lasso.1se}$ $\hat{\beta}_{E-net}$

True coefficients, LS, Ridge, Lasso.min, Lasso.1se, Net.1se



Example 2: Signal + white noise

```
X: 10 Singal + 20 normal noise input variables n=50; p1=10; p2=20 set.seed(19) X = matrix(rnorm(n*(p1+p2)),n, p1+p2) dim(X) ## [1] 50 30 c1 = 0.5 + runif(10)/2 # "signals" c2 = (rnorm(20))*3/40 # "noise" ~ N(0,sigma^2) Y = X[,1:10]%*%c1 + X[,11:30]%*%c2 + rnorm(n) lassofit = cv.glmnet(X,Y); par(mfrow=c(1,2))
```

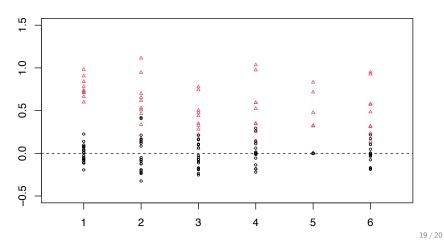
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Example 2: Parameter estimates $\hat{\beta}$ comparison

Input variables: $\textbf{Signal} \; (\text{triangles}) + \textbf{Noise} \; (\text{normal})$

 β , $\hat{\beta}_{LS}$ $\hat{\beta}_{Ridge}$ $\hat{\beta}_{Lasso,min}$ $\hat{\beta}_{Lasso,1se}$ $\hat{\beta}_{E-net}$

True coefficients, LS, Ridge, Lasso.min, Lasso.1se, Net.1se



(Code)

```
netfit = cv.glmnet(X,Y,alpha=0.5)
plot(rep(1,30),c(c1,c2),cex=.5,col=c(rep(2,10),rep(1,20)),
     xlim=c(0.5,6.5), ylim=c(-.5,1.5), xlab="", ylab="")
abline(h=0,lty=2)
points(rep(2,30),lm(Y~X)$coef[2:31],cex=.5,
  col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(3,30),lm.ridge(Y~X,lambda=25)$coef,cex=.5,
  col=c(rep(2,10), rep(1,20)), pch=c(rep(2,10), rep(1,20)))
points(rep(4,30),coef(lassofit,s="lambda.min")[2:31],cex=.
  col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(5,30),coef(lassofit,s="lambda.1se")[2:31],cex=.
 col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
points(rep(6,30),coef(netfit,s="lambda.1se")[2:31],cex=.5,
  col=c(rep(2,10),rep(1,20)), pch=c(rep(2,10),rep(1,20)))
title("True coefficients, LS, Ridge,
      Lasso.min, Lasso.1se, Net.1se")
```