

Predicting Labour Wages using Ridge and Lasso Regression

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Ridge and Lasso Regression

$$RSS(\beta) + \lambda \sum_{j=1}^p \beta_j^2$$

$$RSS(\beta) + \lambda \sum_{j=1}^p |\beta_j|$$

Read and Understand the data

```
getwd()
```

```
## [1] "/Users/hasifa/Programming"
```

```
labour_data <- read.csv("labour_income.csv")
```

```
str(labour_data)
```

```
## 'data.frame': 3987 obs. of 5 variables:
## $ wages : num 10.6 11 17.8 14 8.2 ...
## $ education: num 15 13.2 14 16 15 13.5 12 14 18 11 ...
## $ age : int 40 19 46 50 31 30 61 46 43 17 ...
## $ sex : chr "Male" "Male" "Male" "Female" ...
## $ language : chr "English" "English" "Other" "English" ...
```

```
summary(labour_data)
```

```
##      wages      education      age      sex
## Min.   : 2.30   Min.    : 0.00   Min.   :16.0   Length:3987
## 1st Qu.: 9.25   1st Qu.:12.00   1st Qu.:28.0   Class :character
## Median :14.13   Median :13.00   Median :36.0   Mode  :character
## Mean   :15.54   Mean    :13.34   Mean    :37.1
## 3rd Qu.:19.72   3rd Qu.:15.10   3rd Qu.:46.0
## Max.   :49.92   Max.    :20.00   Max.    :69.0
## language
## Length:3987
## Class :character
## Mode  :character
##
##
##
```

Data Pre-processing

Train-Test Split

- Split the data into train and test

```
set.seed(007)
train_row <- sample(x=seq(1,nrow(labour_data),1),size = 0.7*nrow(labour_data))

train_data <- labour_data[train_row,]
test_data <- labour_data[-train_row,]
```

Standardize the Data

- Standardize the continuous independent variables

```
library(caret)
```

```
## Warning: package 'caret' was built under R version 4.0.2
```

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

```
## Loading required package: ggplot2
```

```
## Warning: package 'ggplot2' was built under R version 4.0.2
```

```
library(ggplot2)
```

```
library(lattice)
```

```
std_obj <- preProcess(x=train_data[,!colnames(train_data) %in% c("wages")],  
train_std_data <- predict(std_obj , train_data)  
  
test_std_data <- predict(std_obj,test_data)
```

Dummify the Data

- Use the dummyVars() function from caret to convert sex and age into dummy variables

```
dummy_oj <- dummyVars(~., train_std_data)  
train_dummy_data <- as.data.frame(predict(dummy_oj,train_std_data))  
test_dummy_data <- as.data.frame(predict(dummy_oj,test_std_data))
```

Get the data into a compatible format

- The functions we will be using today from the glmnet package expect a matrix as an input and not our familiar formula structure, so we need to convert our dataframes into a matrix

```
x_train <- as.matrix(train_dummy_data[,-1])  
y_train <- as.matrix(train_dummy_data[,1])  
x_test <- as.matrix(train_dummy_data[,-1])  
y_test <- as.matrix(train_dummy_data[,1])
```

Hyper-parameter Tuning

- Choose an optimal lambda value for the ridge and lasso regression models by using cross validation

Choosing a lambda for Lasso Regression

- The alpha value is 1 for lasso regression

```
library(glmnet)
```

```
## Warning: package 'glmnet' was built under R version 4.0.2
```

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

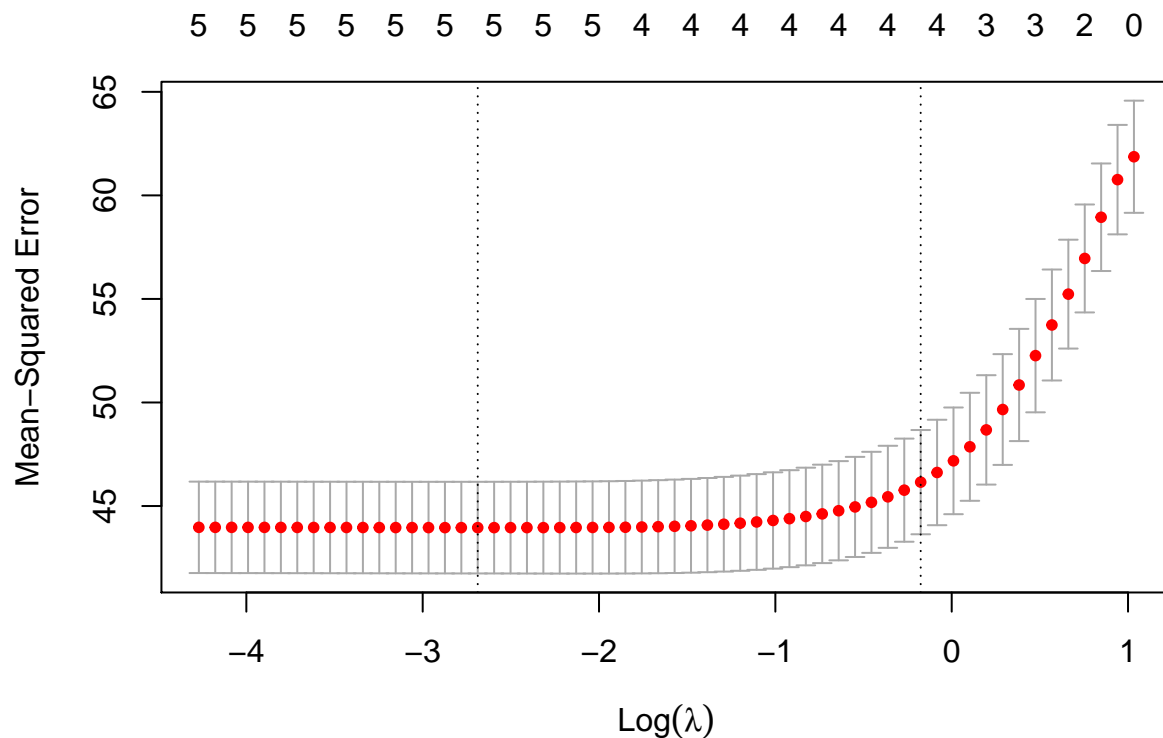
```
## Loaded glmnet 4.0-2
```

```
library(foreach)
```

```
## Warning: package 'foreach' was built under R version 4.0.2
```

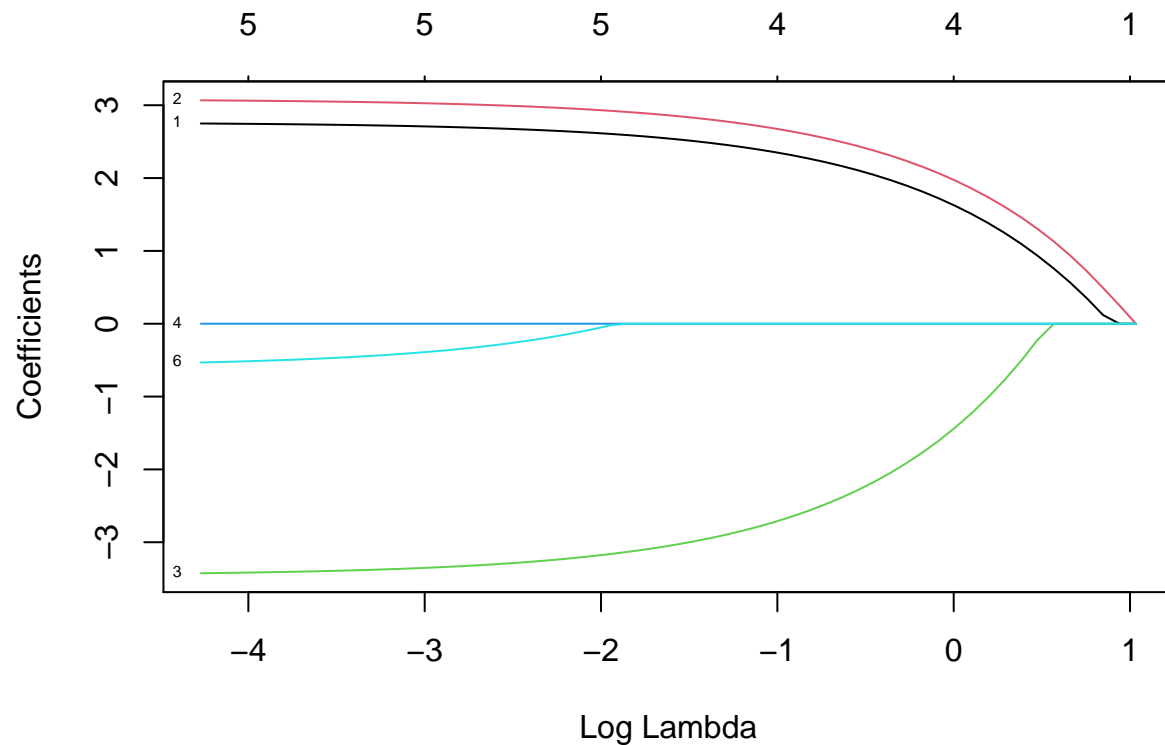
```
library(Matrix)
```

```
cv_lasso <- cv.glmnet(x_train, y_train, alpha = 1, type.measure = "mse", nfolds = 4)  
plot(cv_lasso)
```



- The object returned from the call to `cv.glmnet()` function, contains the lambda values of importance
- The coefficients are accessible calling the `coef()` function on the `cv_lasso` object

```
plot(cv_lasso$glmnet.fit,xvar="lambda",label = TRUE)
```



```
print(cv_lasso$lambda.min)
```

```
## [1] 0.06803175
```

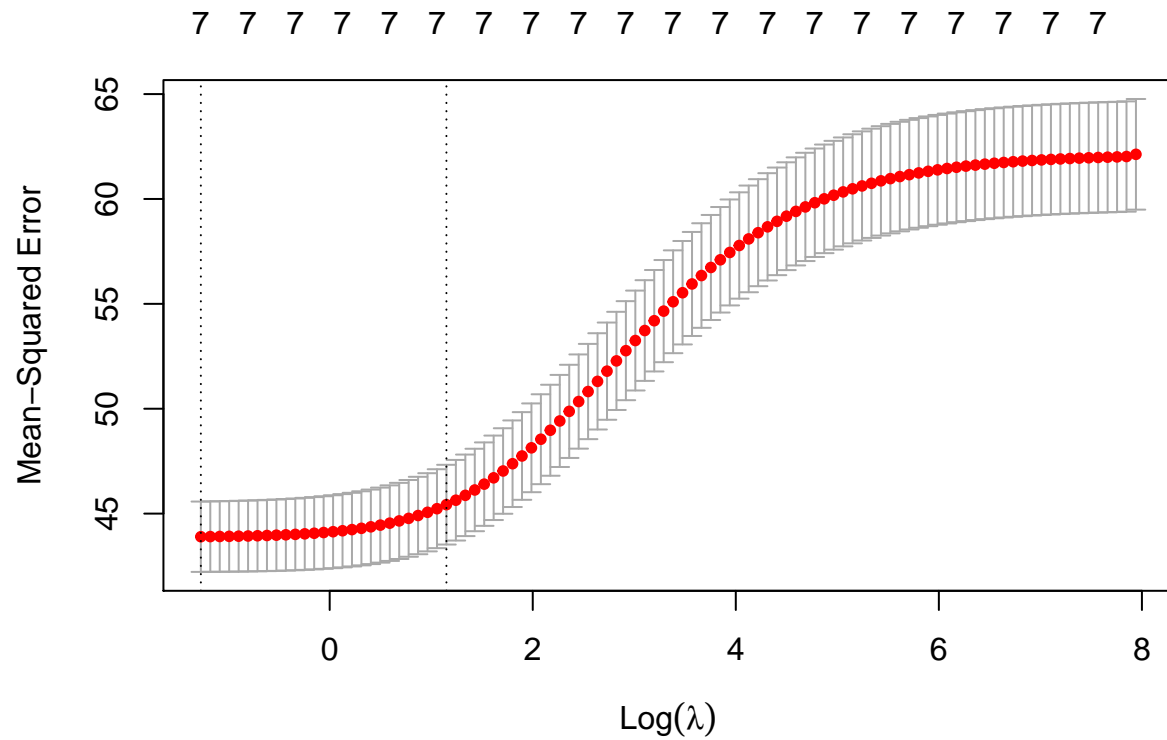
```
coef(cv_lasso)
```

```
## 8 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept)  1.640412e+01
## education    1.812587e+00
## age          2.153717e+00
## sexFemale    -1.766271e+00
## sexMale      8.259089e-14
## languageEnglish .
## languageFrench .
## languageOther .
```

Choosing a lambda for Ridge Regression

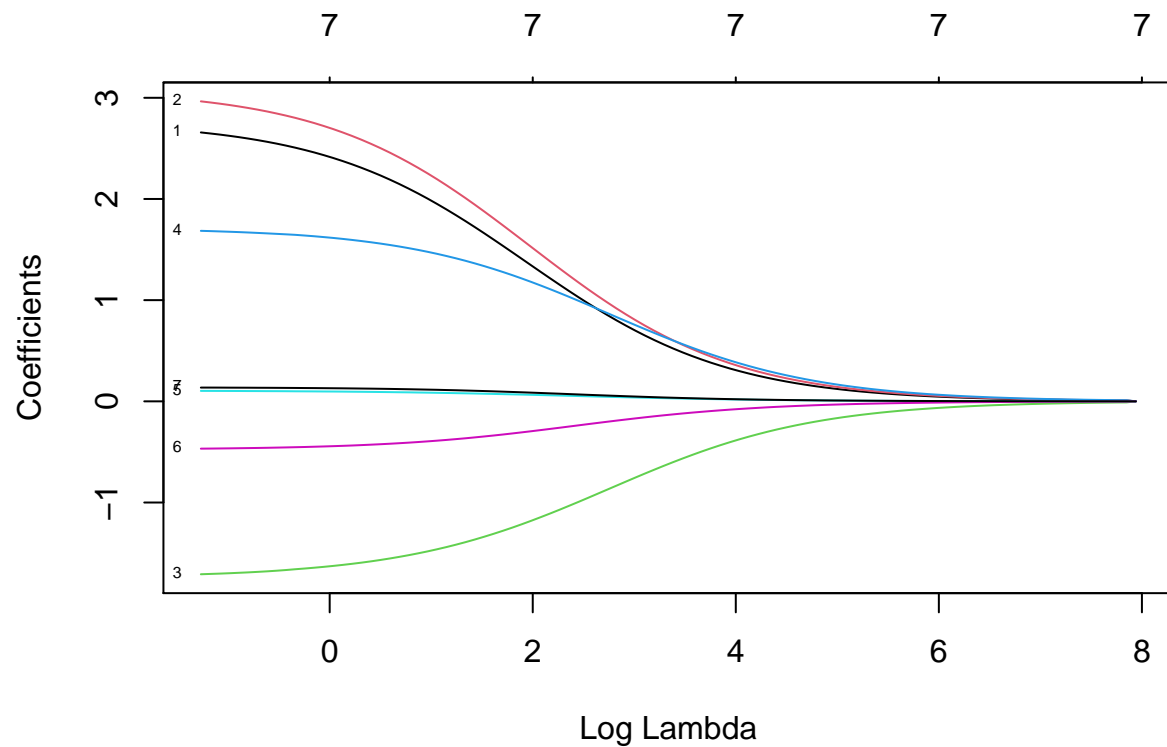
- The alpha value is 0 for ridge regression

```
cv_ridge<- cv.glmnet(x_train, y_train, alpha =0, type.measure = "mse",nfolds = 4)
plot(cv_ridge)
```



- We can access the lambda and the coefficients as we did before

```
plot(cv_ridge$glmnet.fit,xvar="lambda",label = TRUE)
```



```
print(cv_ride$lambda.min)
```

```
## [1] 0.281108
```

```
coef(cv_ride)
```

```
## 8 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept)  15.46625297
## education    1.89683861
## age          2.13566648
## sexFemale    -1.44034175
## sexMale      1.43636353
## languageEnglish 0.08263341
## languageFrench -0.38150197
## languageOther 0.11172119
```

Building The Final Model

- By using the optimal lambda values obtained above, we can build our ridge and lasso models

Building the Final Lasso Regression Model

```
lasso_model <-glmnet(x_train, y_train, lambda = cv_lasso$lambda.min,alpha = 1)
coef(lasso_model)
```

```
## 8 x 1 sparse Matrix of class "dgCMatrix"
##              s0
## (Intercept)  1.719687e+01
## education    2.689314e+00
## age          3.006946e+00
## sexFemale    -3.314947e+00
## sexMale      2.811204e-13
## languageEnglish .
## languageFrench -3.176708e-01
## languageOther .
```

- Use the model to predict on test data

```
preds_lasso <- predict(lasso_model,x_test)
```

Building the Final Ridge Regression Model

```
ridge_model <-glmnet(x_train, y_train, lambda = cv_ridge$lambda.min,alpha = 0)
coef(ridge_model)
```

```
## 8 x 1 sparse Matrix of class "dgCMatrix"
##              s0
## (Intercept)  15.5071089
## education    2.6575550
## age          2.9648092
## sexFemale    -1.7573840
## sexMale      1.6383518
## languageEnglish 0.1050676
## languageFrench -0.4659695
## languageOther  0.1378338
```

- Use the model to predict on test data

```
preds_ridge <- predict(ridge_model,x_test)
```

Model Performance Evaluation

Lasso Regression Model Metrics


```
library(DMwR)
```

```
## Warning: package 'DMwR' was built under R version 4.0.2
```

```
## Loading required package: grid
```

```
## Registered S3 method overwritten by 'quantmod':  
##   method      from  
##   as.zoo.data.frame zoo
```

```
regr.eval(trues = y_test , preds = preds_lasso)
```

```
##           mae           mse           rmse           mape  
##  5.0051579 43.6905282  6.6098811  0.4058685
```

Ridge Regression Model Metrics

```
regr.eval(trues = y_test , preds = preds_ridge)
```

```
##           mae           mse           rmse           mape  
##  5.0084714 43.6942827  6.6101651  0.4062369
```