P8106_HW1

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Contents

Loading libraries

```
library(ISLR)
library(glmnet)
library(caret)
library(tidymodels)
library(corrplot)
library(ggplot2)
library(plotmo)
library(ggrepel)
```

Question (a): Lasso Model

To start, we load the training and testing data and subsequently set a seed for reproducibility.

Next, we initialise 10-fold cross-validation to partition the training data into 10 equal subsets. This allows training the model on 9 folds while validating on the final fold. This ensures we evaluate the performance of the model, while avoiding overfitting.

```
# Load training and testing data

training_data <- read.csv("housing_training.csv")
testing_data <- read.csv("housing_test.csv")

set.seed(29)  # Ensure results are reproducible

# Using 10 fold cross-validation

ctrl1 <- trainControl(method = "cv", number = 10)
```

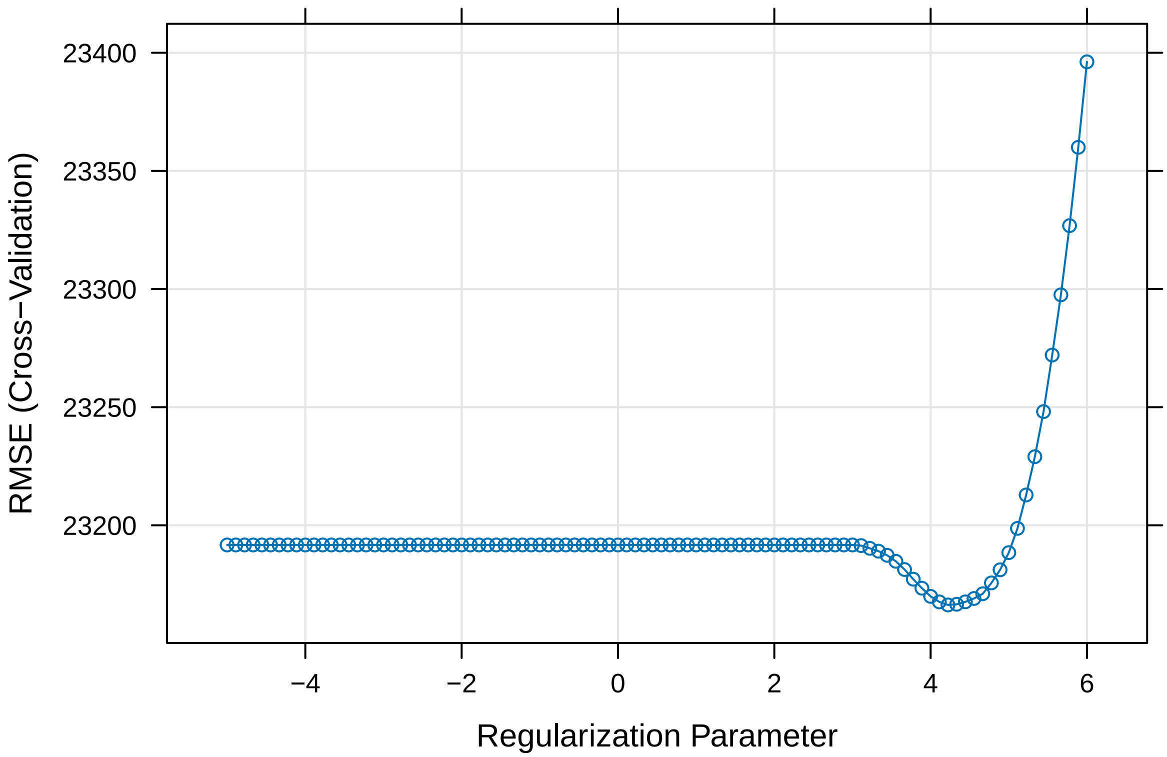
Next, we proceed to fit a lasso regression model using the training data. Sale_Price is the outcome variable, with all other variables as predictors. The lasso model is tuned over a sequence of 100 lambda values ranging from exp(6) to exp(-5).

```r
# Fit the Lasso model

lasso.fit  <- train(
  Sale_Price ~ .,
  data = training_data,
  method = "glmnet",
  tuneGrid = expand.grid(alpha = 1, lambda = exp(seq(6, -5, length = 100))),
  trControl = ctrl1
)

# Plot

plot(lasso.fit, xTrans = log)
```



Based on the plot, it appears as though the optimal lambda value is around exp(4), as this is where the RMSE is minimised. Higher lambda values (i.e., greater penalisation) appear to result in poorer model performance, likely due to excessive shrinkage forcing too many coefficients to zero, leading to underfitting.

```r
# Find optimal tuning parameter

lasso.fit$bestTune
```

```
##    alpha   lambda
## 84     1 68.18484
```

```r
# Extracting coefficients for each predictor, at the optimal lambda

coef(lasso.fit$finalModel, lasso.fit$bestTune$lambda)
```

```
## 40 x 1 sparse Matrix of class "dgCMatrix"
##                                      s1
## (Intercept)                -4.820791e+06
## Gr_Liv_Area                 6.534680e+01
## First_Flr_SF                8.043483e-01
## Second_Flr_SF               .
## Total_Bsmt_SF               3.542591e+01
## Low_Qual_Fin_SF            -4.089879e+01
## Wood_Deck_SF                1.161853e+01
## Open_Porch_SF               1.539927e+01
## Bsmt_Unf_SF                -2.088675e+01
## Mas_Vnr_Area                1.091770e+01
## Garage_Cars                 4.078354e+03
## Garage_Area                 8.182394e+00
## Year_Built                  3.232484e+02
## TotRms_AbvGrd              -3.607362e+03
## Full_Bath                  -3.820746e+03
## Overall_QualAverage        -4.845814e+03
## Overall_QualBelow_Average  -1.244202e+04
## Overall_QualExcellent       7.559703e+04
## Overall_QualFair           -1.073410e+04
## Overall_QualGood            1.211373e+04
## Overall_QualVery_Excellent  1.358907e+05
## Overall_QualVery_Good       3.788544e+04
## Kitchen_QualFair           -2.476713e+04
## Kitchen_QualGood           -1.713660e+04
## Kitchen_QualTypical        -2.525278e+04
## Fireplaces                  1.051146e+04
## Fireplace_QuFair           -7.657866e+03
## Fireplace_QuGood            .
## Fireplace_QuNo_Fireplace    1.385656e+03
## Fireplace_QuPoor           -5.632703e+03
## Fireplace_QuTypical        -7.010013e+03
## Exter_QualFair             -3.316061e+04
## Exter_QualGood             -1.492745e+04
## Exter_QualTypical          -1.936658e+04
## Lot_Frontage                9.952901e+01
## Lot_Area                    6.042265e-01
## Longitude                  -3.285809e+04
## Latitude                    5.492284e+04
## Misc_Val                    8.240622e-01
## Year_Sold                  -5.568142e+02
```

Note that at the optimal lambda value, most of the predictors remain in the model. However, some are shrunk to zero (i.e., Second_Flr_SF, Fireplace_QuGood) during the variable selection process, and removed from the model. Therefore, this final model includes 37 predictors.

```r
# Finding RMSE

lasso_preds <- predict(lasso.fit, newdata = testing_data)
rmse <- sqrt(mean((lasso_preds - testing_data$Sale_Price)^2))
print(rmse)
```

```
## [1] 20969.2
```

For the lasso model, the optimal tuning parameter lambda is **68.18484**, representing where RMSE is minimised. The test error (RMSE) at this lambda is **20969.2**.

```r
# Using 1se cross-validation

ctrl_1se <- trainControl(
  method = "cv",
  selectionFunction = "oneSE"
)

# Fit the lasso model using 1se

lasso_1se_fit <- train(
  Sale_Price ~ .,
  data = training_data,
  method = "glmnet",
  tuneGrid = expand.grid(
    alpha = 1,
    lambda = exp(seq(6, -5, length = 100))
  ),
  trControl = ctrl_1se
)

# Optimal lambda using 1SE

lasso_lambda_1se <- lasso_1se_fit$bestTune$lambda
print(lasso_lambda_1se)
```

```
## [1] 403.4288
```

```r
# Extracting coefficients for each predictor, at the optimal lambda

coef(lasso_1se_fit$finalModel, s = lasso_lambda_1se)
```

```
## 40 x 1 sparse Matrix of class "dgCMatrix"
##                                        s1
## (Intercept)                 -3.919159e+06
## Gr_Liv_Area                  6.099153e+01
## First_Flr_SF                 9.477449e-01
## Second_Flr_SF                .
## Total_Bsmt_SF                3.627699e+01
## Low_Qual_Fin_SF             -3.523480e+01
## Wood_Deck_SF                 1.000632e+01
## Open_Porch_SF                1.203918e+01
```

```
## Bsmt_Unf_SF                 -2.059528e+01
## Mas_Vnr_Area                 1.297320e+01
## Garage_Cars                  3.491107e+03
## Garage_Area                  9.740129e+00
## Year_Built                   3.150805e+02
## TotRms_AbvGrd               -2.518326e+03
## Full_Bath                   -1.415647e+03
## Overall_QualAverage         -4.006722e+03
## Overall_QualBelow_Average   -1.084480e+04
## Overall_QualExcellent        8.719850e+04
## Overall_QualFair            -8.763236e+03
## Overall_QualGood             1.111389e+04
## Overall_QualVery_Excellent   1.559964e+05
## Overall_QualVery_Good        3.730815e+04
## Kitchen_QualFair            -1.420320e+04
## Kitchen_QualGood            -7.639239e+03
## Kitchen_QualTypical         -1.644274e+04
## Fireplaces                   8.190689e+03
## Fireplace_QuFair            -3.809974e+03
## Fireplace_QuGood             2.196176e+03
## Fireplace_QuNo_Fireplace     .
## Fireplace_QuPoor            -1.484163e+03
## Fireplace_QuTypical         -4.125304e+03
## Exter_QualFair              -1.695505e+04
## Exter_QualGood               .
## Exter_QualTypical           -4.790664e+03
## Lot_Frontage                 8.663344e+01
## Lot_Area                     5.915806e-01
## Longitude                   -2.246220e+04
## Latitude                     3.767830e+04
## Misc_Val                     3.093854e-01
## Year_Sold                   -1.654627e+02
```

Using the 1SE rule, the optimal lambda is 403.4288. During the variable selection process, variables Second_Flr_SF, Fireplace_QuNo_Fireplace, and Exter_QualGood are removed from the model. When the 1SE rule is applied, there are 36 predictors included in the model, which is 1 fewer than the original lasso model.