Data Science II HW 1

Maya Krishnamoorthy

2025-02-22

Contents

Read and prep CSV files.

```r
train_df = read_csv("housing_training.csv") %>% janitor::clean_names()
```

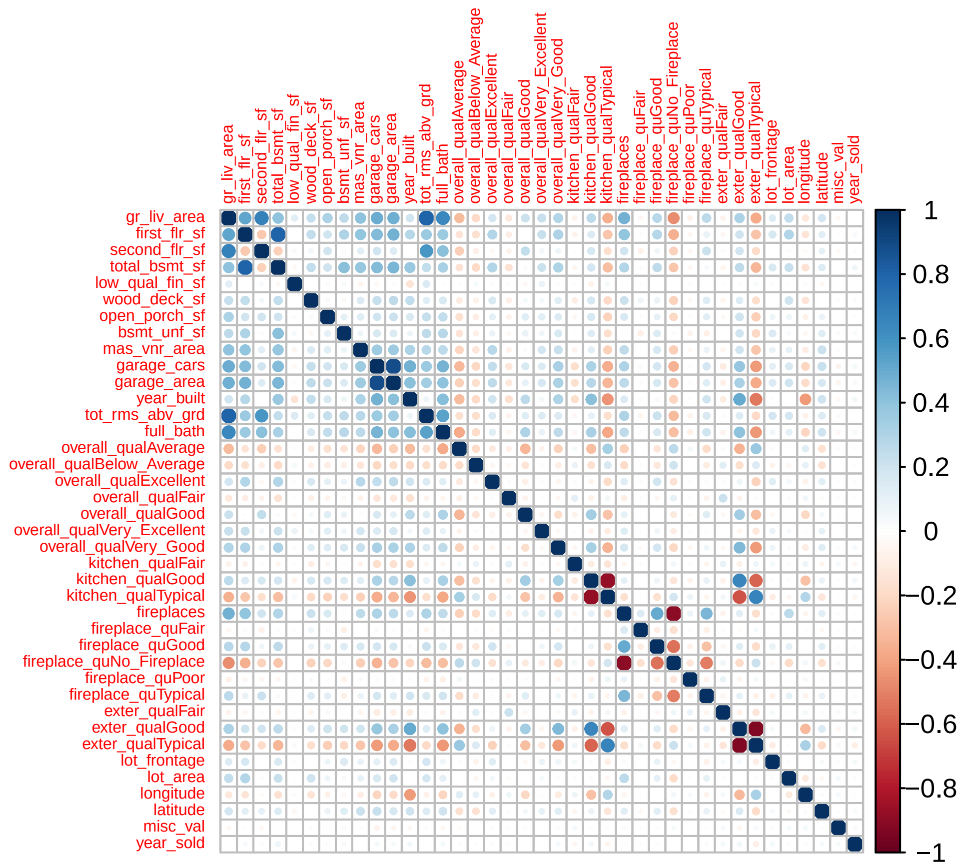
```
## Rows: 1440 Columns: 26
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (4): Overall_Qual, Kitchen_Qual, Fireplace_Qu, Exter_Qual
## dbl (22): Gr_Liv_Area, First_Flr_SF, Second_Flr_SF, Total_Bsmt_SF, Low_Qual_...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
test_df = read_csv("housing_test.csv") %>% janitor::clean_names()
```

```
## Rows: 959 Columns: 26
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (4): Overall_Qual, Kitchen_Qual, Fireplace_Qu, Exter_Qual
## dbl (22): Gr_Liv_Area, First_Flr_SF, Second_Flr_SF, Total_Bsmt_SF, Low_Qual_...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Response variable: `sale_price`

```r
x <- model.matrix(sale_price ~ ., train_df)[,-1] # convert into a binary indicator variable
# vector of response
y <- train_df[, "sale_price"]

corrplot(cor(x), method = "circle", type = "full", tl.cex = 0.5)
```



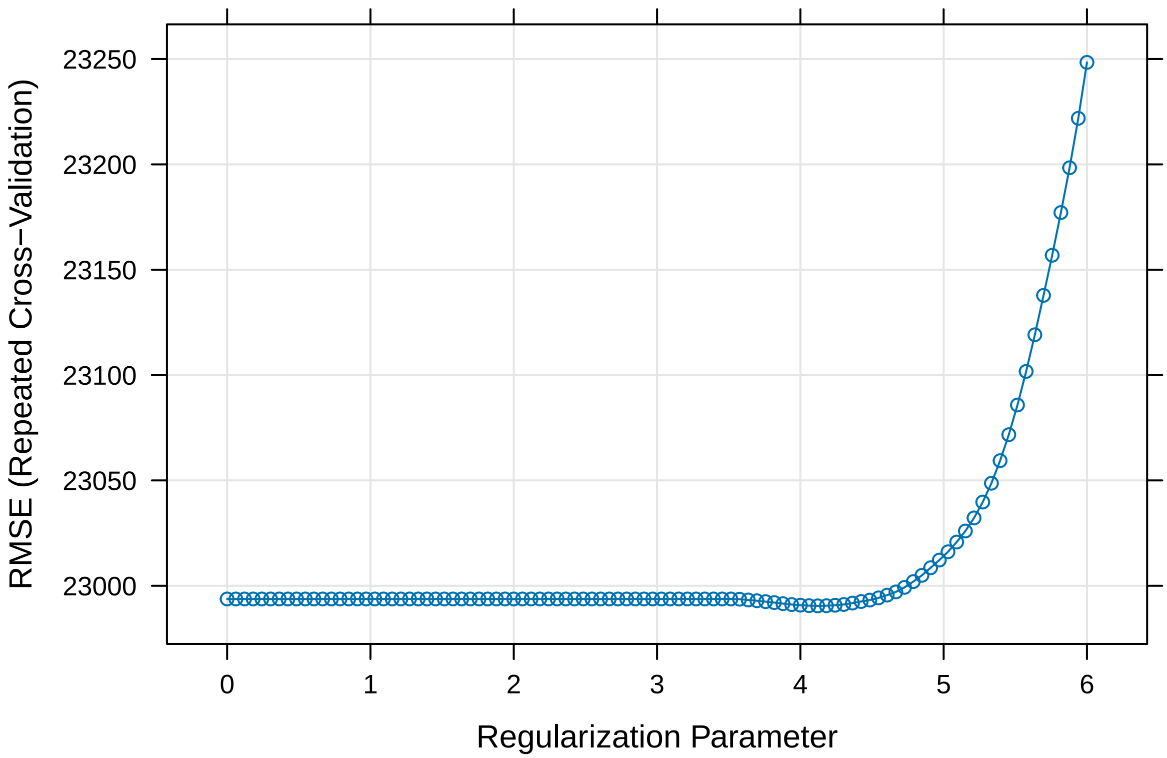
0.1 Part a)

Fit a lasso model on the training data. Report the selected tuning parameter and the test error. When the 1SE rule is applied, how many predictors are included in the model?

0.1.1 Minimizing CV error

```r
# Using glmnet
ctrl1 = trainControl(method = "repeatedcv",
                     number = 10,
                     repeats = 5,
                     selectionFunction = "best")
```

```r
set.seed(2025)
lasso.fit =
  train(sale_price ~ .,
        data = train_df,
        method = "glmnet",
        tuneGrid = expand.grid(alpha = 1, lambda = exp(seq(6, 0, length = 100))),
        trControl = ctrl1)

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




```r
lasso.fit$bestTune
```

```
##    alpha  lambda
## 69     1 61.6339
```

```r
# coefficients in the final model
coef(lasso.fit$finalModel, lasso.fit$bestTune$lambda)
```

```
## 40 x 1 sparse Matrix of class "dgCMatrix"
##                                     s1
## (Intercept)              -4.836395e+06
```

```
## gr_liv_area                  6.543755e+01
## first_flr_sf                 7.999642e-01
## second_flr_sf                .
## total_bsmt_sf                3.540696e+01
## low_qual_fin_sf             -4.099739e+01
## wood_deck_sf                 1.165602e+01
## open_porch_sf                1.547641e+01
## bsmt_unf_sf                 -2.088888e+01
## mas_vnr_area                 1.087575e+01
## garage_cars                  4.091188e+03
## garage_area                  8.148299e+00
## year_built                   3.234411e+02
## tot_rms_abv_grd             -3.629012e+03
## full_bath                   -3.867530e+03
## overall_qualAverage         -4.863474e+03
## overall_qualBelow_Average   -1.247712e+04
## overall_qualExcellent        7.536386e+04
## overall_qualFair            -1.077495e+04
## overall_qualGood             1.213092e+04
## overall_qualVery_Excellent   1.354555e+05
## overall_qualVery_Good        3.789907e+04
## kitchen_qualFair            -2.493652e+04
## kitchen_qualGood            -1.728827e+04
## kitchen_qualTypical         -2.539112e+04
## fireplaces                   1.058861e+04
## fireplace_quFair            -7.677808e+03
## fireplace_quGood             .
## fireplace_quNo_Fireplace     1.511070e+03
## fireplace_quPoor            -5.651580e+03
## fireplace_quTypical         -7.012976e+03
## exter_qualFair              -3.356377e+04
## exter_qualGood              -1.530384e+04
## exter_qualTypical           -1.973755e+04
## lot_frontage                 9.979682e+01
## lot_area                     6.043028e-01
## longitude                   -3.303322e+04
## latitude                     5.529084e+04
## misc_val                     8.333497e-01
## year_sold                   -5.648620e+02
```

```r
# test error
predictions = predict(lasso.fit, newdata = test_df)
mse = mean((predictions - pull(test_df, "sale_price"))^2)
```

The tuning parameter that minimizes CV error is 61.6339. The MSE associated with this model is 440335429.

0.1.2 Minimizing for 1SE

```
ctrl2 =
  trainControl(method = "repeatedcv",
               number = 10,
               repeats = 5,
               selectionFunction = "oneSE")

set.seed(2025)

lasso.fit_1se =
  train(sale_price ~ .,
        data = train_df,
        method = "glmnet",
        tuneGrid = expand.grid(alpha = 1, lambda = exp(seq(6, 0, length = 100))),
        trControl = ctrl2)

# Best lambda for 1SE
lasso.fit_1se$bestTune
```

```
##     alpha   lambda
## 100     1 403.4288
```

```
# Getting number of predictors
coeff = coef(lasso.fit_1se$finalModel, lasso.fit_1se$bestTune$lambda)
length(which(coeff != 0)) - 1
```

```
## [1] 36
```

```
# MSE
predictions = predict(lasso.fit_1se, newdata = test_df)
mse = mean((predictions - pull(test_df, "sale_price"))^2); mse
```

```
## [1] 420726548
```

Using the 1SE rule, the optimal tuning parameter is 403.4288. The MSE is 420726548. There are 36 (non-zero) predictors in this model. Since this model has a lower MSE than the first model, we can conclude that this 1SE model may be better for prediction purposes than the former.

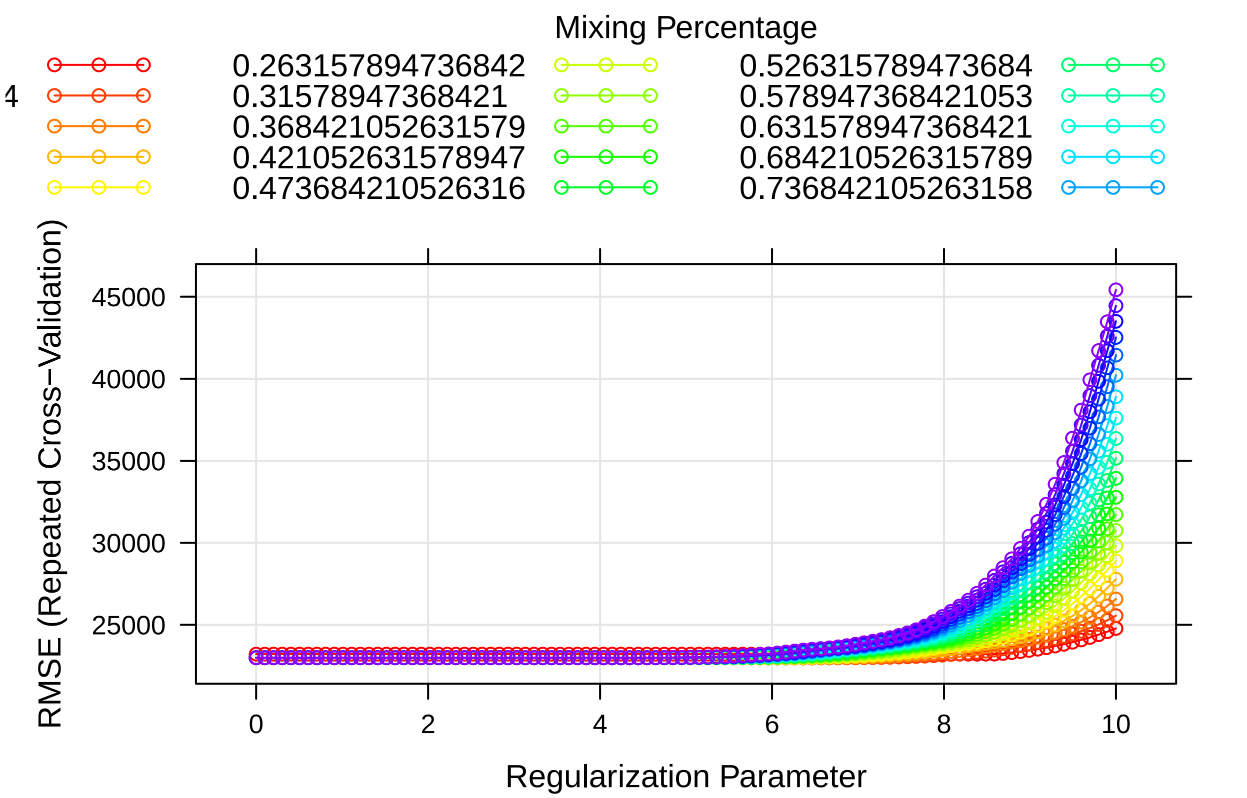
0.2 Part b)

Fit an elastic net model on the training data. Report the selected tuning parameters and the test error. Is it possible to apply the 1SE rule to select the tuning parameters for elastic net? If the 1SE rule is applicable, implement it to select the tuning parameters. If not, explain why.

```r
set.seed(2025)

enet.fit <- train(sale_price ~ .,
                  data = train_df,
                  method = "glmnet",
                  tuneGrid = expand.grid(alpha = seq(0, 1, length = 20),
                                         lambda = exp(seq(10, 0, length = 100))),
                  trControl = ctrl1)
enet.fit$bestTune
```

```
##          alpha   lambda
## 164 0.05263158 580.3529
```

```r
myCol <- rainbow(25)
myPar <- list(superpose.symbol = list(col = myCol),
              superpose.line = list(col = myCol))

plot(enet.fit, par.settings = myPar, xTrans = log)
```




```r
# coefficients in the final model
coef(enet.fit$finalModel, enet.fit$bestTune$lambda)
```

```
## 40 x 1 sparse Matrix of class "dgCMatrix"
##                                       s1
## (Intercept)                 -5.113316e+06
## gr_liv_area                  3.888606e+01
## first_flr_sf                 2.659339e+01
## second_flr_sf                2.534167e+01
## total_bsmt_sf                3.495196e+01
## low_qual_fin_sf             -1.596905e+01
## wood_deck_sf                 1.231770e+01
## open_porch_sf                1.686371e+01
## bsmt_unf_sf                 -2.072999e+01
## mas_vnr_area                 1.165591e+01
## garage_cars                  4.046669e+03
## garage_area                  8.894532e+00
## year_built                   3.191010e+02
## tot_rms_abv_grd             -3.439303e+03
## full_bath                   -3.693423e+03
## overall_qualAverage         -5.113423e+03
## overall_qualBelow_Average   -1.269944e+04
## overall_qualExcellent        7.586249e+04
## overall_qualFair            -1.145724e+04
## overall_qualGood             1.197943e+04
## overall_qualVery_Excellent   1.364598e+05
## overall_qualVery_Good        3.765074e+04
## kitchen_qualFair            -2.367794e+04
## kitchen_qualGood            -1.610305e+04
## kitchen_qualTypical         -2.415426e+04
## fireplaces                   1.080415e+04
## fireplace_quFair            -7.895400e+03
## fireplace_quGood             1.050416e+02
## fireplace_quNo_Fireplace     1.745086e+03
## fireplace_quPoor            -5.840965e+03
## fireplace_quTypical         -7.003111e+03
## exter_qualFair              -3.285657e+04
## exter_qualGood              -1.445844e+04
## exter_qualTypical           -1.905526e+04
## lot_frontage                 1.001013e+02
## lot_area                     6.031323e-01
## longitude                   -3.514521e+04
## latitude                     5.771438e+04
## misc_val                     8.665642e-01
## year_sold                   -5.730607e+02
```

```r
# MSE
enet.pred = predict(enet.fit, newdata = test_df)
mean((enet.pred - pull(test_df, "sale_price"))^2)
```

```
## [1] 438502352
```

The optimal tuning parameters for the elastic net model are lambda = 580.3529 and alpha = 0.05263158. The test error is 438502352.

```
# Trying 1SE method
set.seed(2025)
enet.fit_1se <- train(sale_price ~ .,
                  data = train_df,
                  method = "glmnet",
                  tuneGrid = expand.grid(alpha = seq(0, 1, length = 20),
                                         lambda = exp(seq(10, 0, length = 100))),
                  trControl = ctrl2)
enet.fit_1se$bestTune
```

```
##    alpha   lambda
## 88     0 6554.314
```

```
# MSE
enet.pred_1se = predict(enet.fit_1se, newdata = test_df)
mean((enet.pred_1se - pull(test_df, "sale_price"))^2)
```

```
## [1] 426591709
```

Using 1SE, the resulting tuning parameters are alpha = 0 and lambda = 6554.314. The resulting test error is 426591709. Since the test errors are similar for both 1SE and CV methods, we can go ahead and use the 1SE method as well. **CHECK THIS**

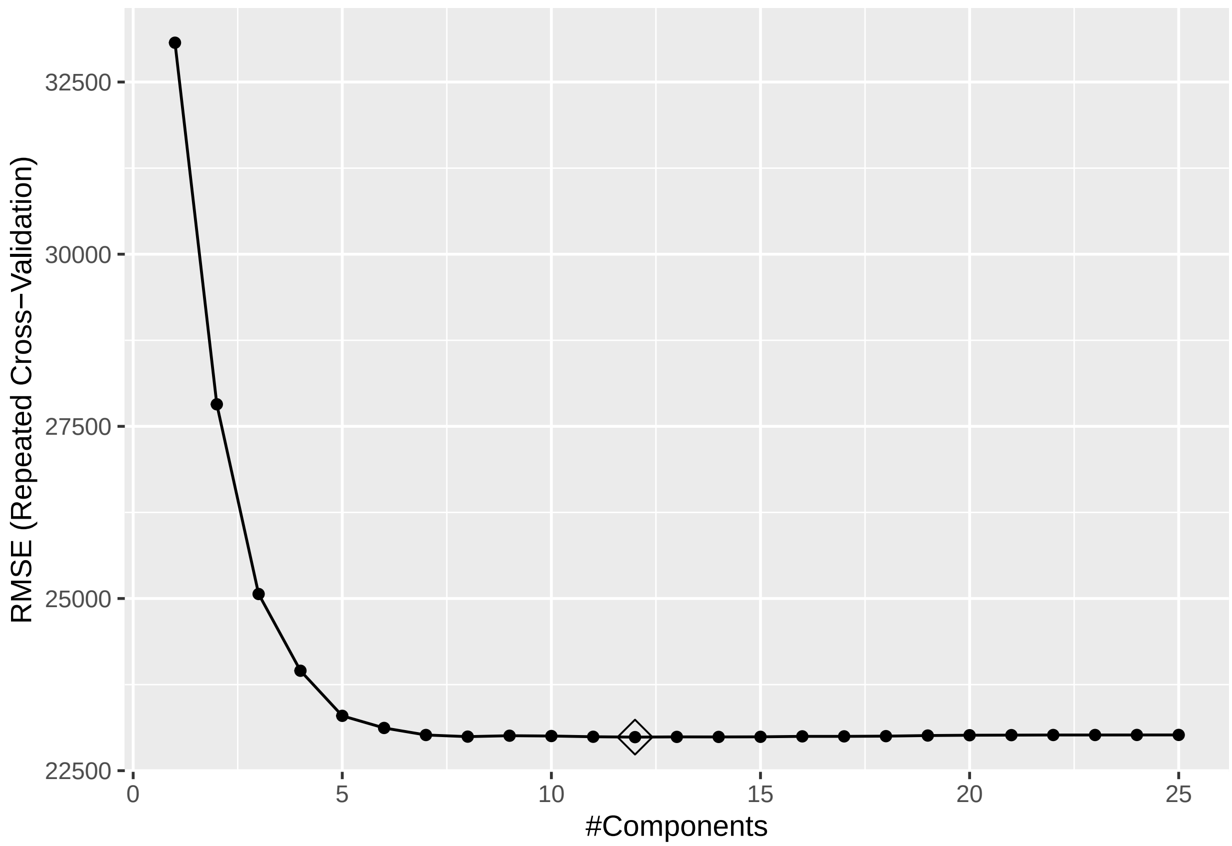
0.3 Part c)

Fit a partial least squares model on the training data and report the test error. How many components are included in your model?

```
set.seed(2025)

pls_fit = train(sale_price ~ .,
                data = train_df,
                method = "pls",
                tuneGrid = data.frame(ncomp = 1:(ncol(train_df)-1)),
                trControl = ctrl1,
                preProcess = c("center", "scale"))

pred.pls = predict(pls_fit, newdata = test_df)
mean((pred.pls - pull(test_df, "sale_price"))^2)
```

```
## [1] 449622718
```

```r
ggplot(pls_fit, highlight = TRUE)
```



The final model used 12 components.

0.4 Part d)

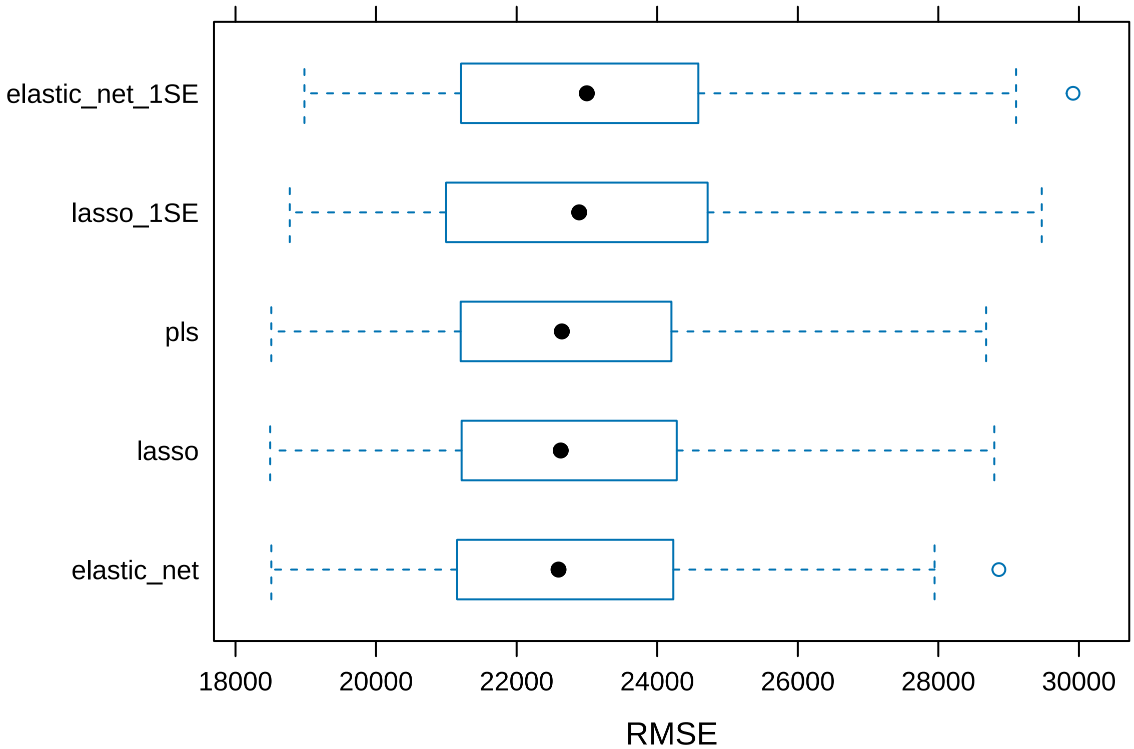
Choose the best model for predicting the response and explain your choice.

```r
resamp = resamples(list(
  lasso = lasso.fit,
  lasso_1SE = lasso.fit_1se,
  elastic_net = enet.fit,
  elastic_net_1SE = enet.fit_1se,
  pls = pls_fit))

summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
```

```
## Models: lasso, lasso_1SE, elastic_net, elastic_net_1SE, pls
## Number of resamples: 50
##
## MAE
##                     Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## lasso           13537.09 15652.66 16706.03 16683.64 17460.55 20389.90    0
## lasso_1SE       13741.05 15488.04 16760.51 16675.72 17582.44 20329.70    0
## elastic_net     13538.68 15621.61 16685.48 16653.81 17464.58 20380.78    0
## elastic_net_1SE 13923.44 15537.41 16736.04 16665.25 17662.25 20403.12    0
## pls             13541.05 15705.61 16801.97 16743.35 17425.24 20449.02    0
##
## RMSE
##                     Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## lasso           18494.38 21261.73 22627.67 22990.46 24204.20 28796.33    0
## lasso_1SE       18772.02 21086.26 22889.89 23248.40 24683.32 29471.25    0
## elastic_net     18510.31 21196.91 22596.01 22978.75 24164.42 28861.39    0
## elastic_net_1SE 18980.70 21253.63 22998.71 23305.37 24567.25 29916.65    0
## pls             18509.98 21294.47 22643.58 22987.04 24135.51 28679.31    0
##
## Rsquared
##                      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## lasso           0.8630327 0.8935367 0.9037721 0.9027869 0.9126593 0.9360194
## lasso_1SE       0.8571894 0.8902468 0.9004985 0.9007136 0.9114975 0.9382990
## elastic_net     0.8624895 0.8934559 0.9033690 0.9029035 0.9131980 0.9367516
## elastic_net_1SE 0.8537071 0.8918571 0.8991045 0.9007256 0.9098063 0.9350768
## pls             0.8639320 0.8933068 0.9036110 0.9028056 0.9128070 0.9361768
##                 NA's
## lasso              0
## lasso_1SE          0
## elastic_net        0
## elastic_net_1SE    0
## pls                0
```

```r
bwplot(resamp, metric = "RMSE")
```



Elastic net (minimizing CV error) performs the best out of the 5 models with regards to all measures of test error, as seen in the graph above and the list of resamples. Based on RMSE, I would conclude that the elastic net model is the best-performing for prediction.

0.5 Part e)

If R package `caret` was used for the lasso in (a), retrain this model using R package `glmnet`, and vice versa. Compare the selected tuning parameters between the two software approaches. Should there be discrepancies in the chosen parameters, discuss potential reasons for these differences.

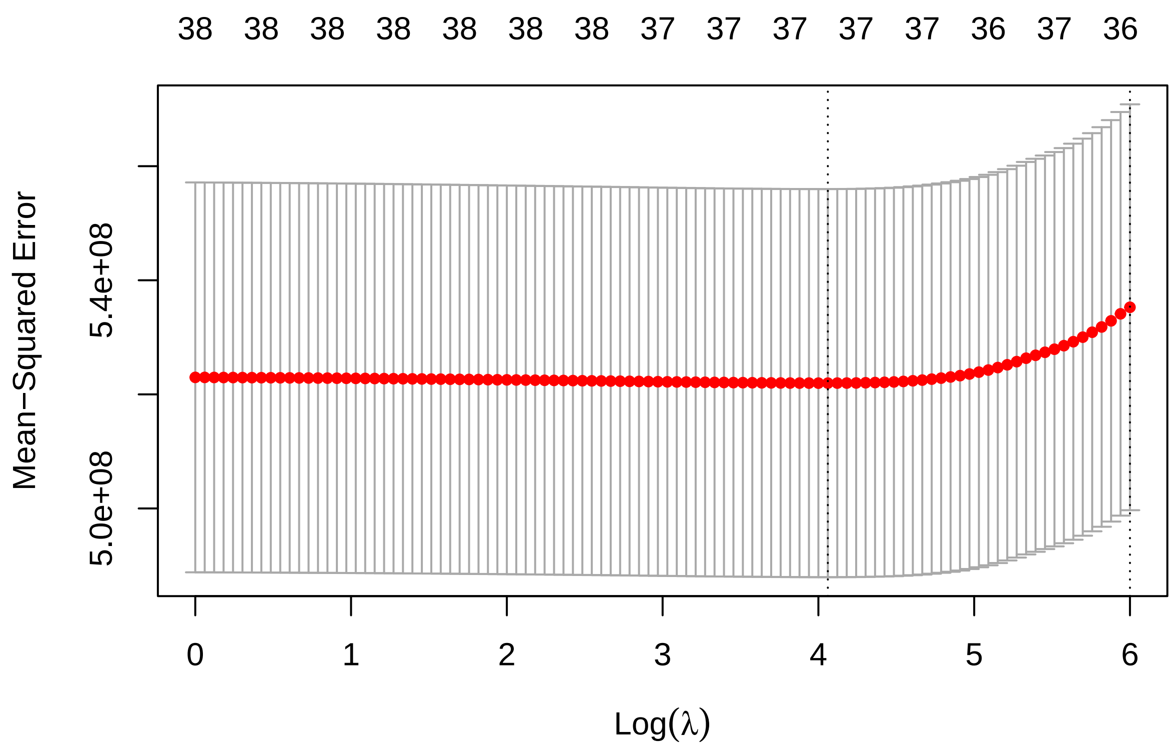
```
x = model.matrix(sale_price ~ ., train_df)[,-1] # convert into a binary indicator variable
# vector of response
y = pull(train_df, "sale_price")

set.seed(2025)
cv.lasso = cv.glmnet(x, y,
                     alpha = 1,
                     lambda = exp(seq(6, 0, length = 100)))

cv.lasso$lambda.min
```

```
## [1] 58.00946
```

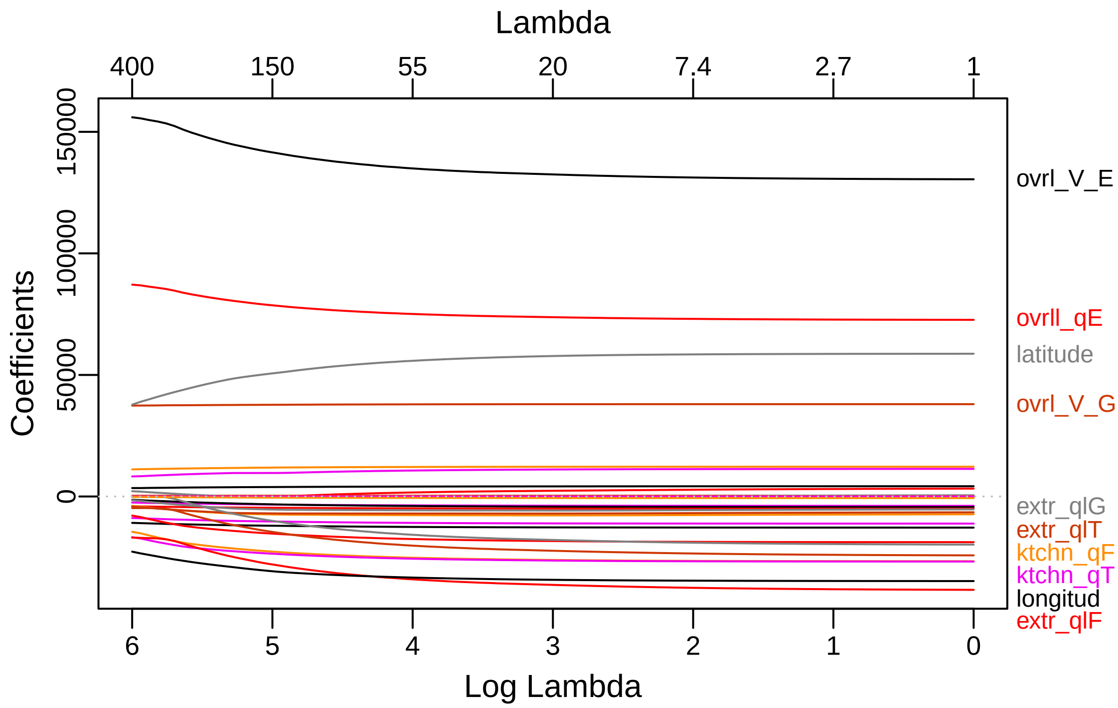
```r
cv.lasso$lambda.1se
```

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

```r
plot(cv.lasso)
```




```r
plot_glmnet(cv.lasso$glmnet.fit)
```



The tuning parameter using `glmnet` is 58.00946, and 403.4288 when the 1SE method is used. The lambda value for the 1SE method is the same for both tests, but slightly different for the minimum method. Potential reasons for this can include:

1) `glmnet` automatically standardizes the predictors, whereas `caret` does not. Since I did not include a preProcess argument in my `train()` function, the predictors were not standardized in that model.

2) `glmnet` automatically does a single round of 10-fold CV, whereas in the `train()` function in `caret`, I manually required a 10-fold CV repeated 5 times.