Homework 1 for Data Science II

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2/12/2022

Setup and import data

```
library(tidyverse)
library(caret)
library(corrplot)
library(leaps)
```

```
train_df =
  read_csv("data/housing_training.csv") %>%
  janitor::clean_names() %>%
  na.omit()

test_df =
  read_csv("data/housing_test.csv") %>%
  janitor::clean_names() %>%
  na.omit()

dim(train_df)
```

```
## [1] 1440   26
```

```
table(sapply(train_df[ , -1], class)) %>%
  knitr::kable()
```

Var1	Freq
character	4
numeric	21

```
dim(test_df)
```

```
## [1] 959  26
```

```
table(sapply(test_df[ , -1], class)) %>%
  knitr::kable()
```

Var1	Freq
character	4
numeric	21

- We want to predict outcome variable `sale_price` by selecting predictors from 25 variables, among which there are 4 categorical variables and 21 continuous variables.
- There are 1440 data in training data and 959 in test data.

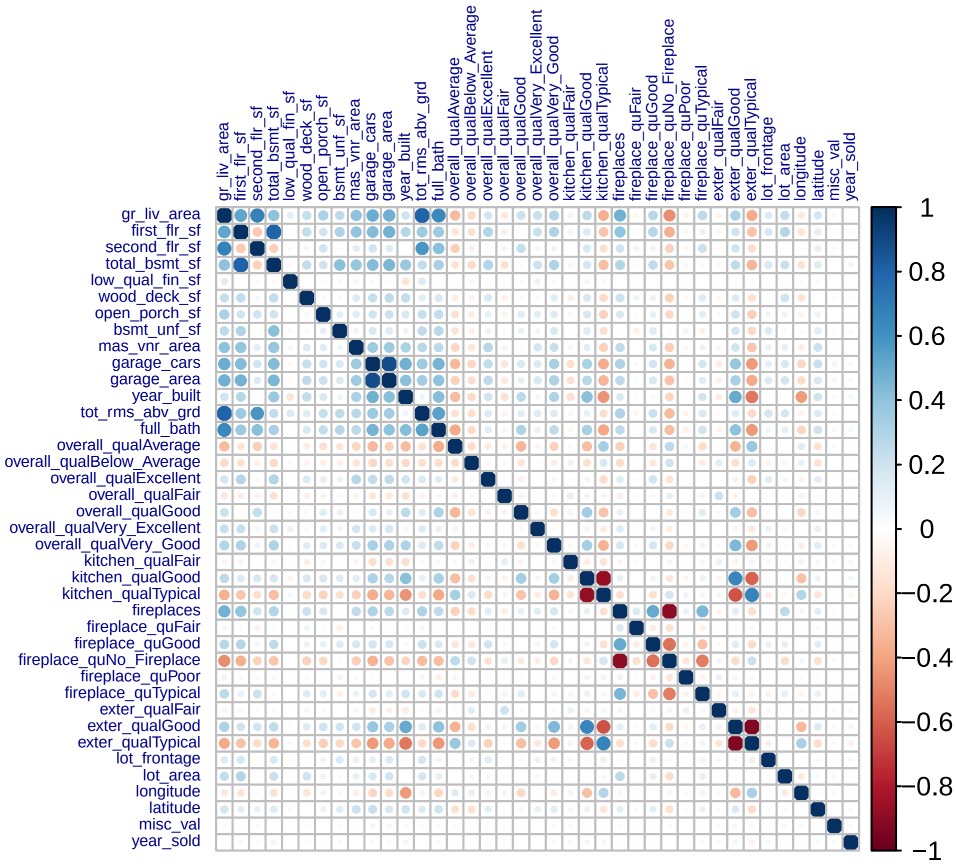
Data preparation

For the convenience of fitting models, we want to create vectors and matrices in advance:

```
train_x <- model.matrix(sale_price ~ ., train_df)[ ,-1]
train_y <- train_df$sale_price
test_x <- model.matrix(sale_price ~ ., test_df)[ , -1]
test_y <- test_df$sale_price
test_all <- model.matrix(sale_price ~ ., test_df)
```

In linear regression, correlation among variables can cause large variance and make interpretation harder. So we want to have a look and the potential correlation among predictors:

```
corrplot(
  cor(train_x),
  method = "circle",
  type = "full",
  tl.cex = .5,
  tl.col = "darkblue")
```



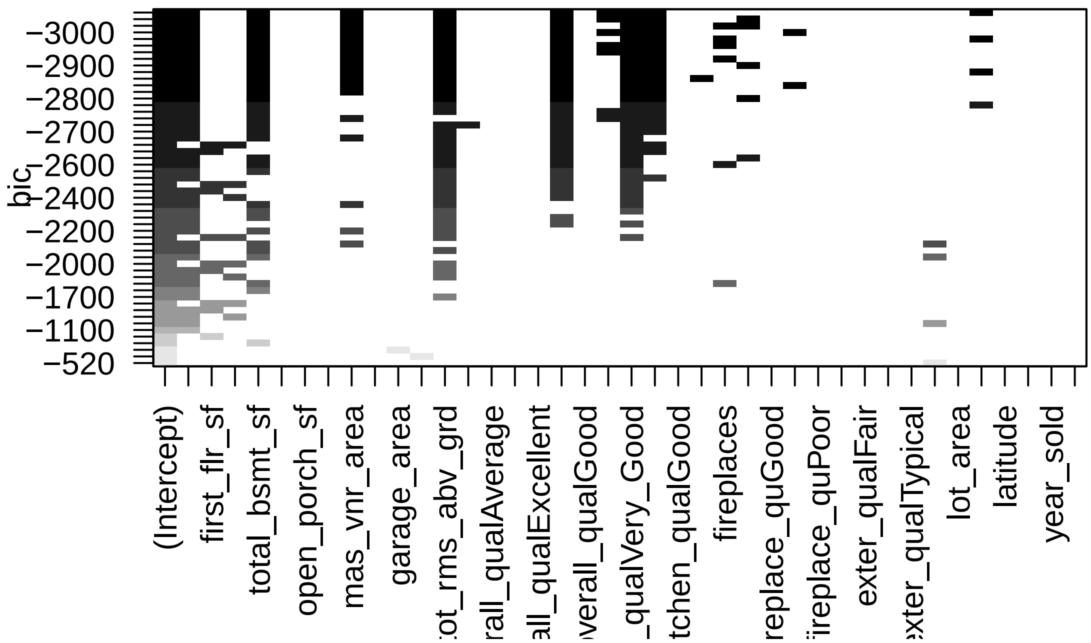
- From the plot above, we can see some positive correlations in the upright corner among some area-related predictors such as `gr_liv_area` and `second_flr_sf`, and also negative correlations among categorical variables such as `exter_qualTypical` and `kitchen_qualTypical`.
- To reduce the influence of correlation, we may want to reduce the number of predictors using best subset model selection.

```
lm_subsets <- regsubsets(sale_price ~ .,
                         data = train_df,
                         method = "exhaustive",
                         nbest = 6)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax, force.in =
## force.in, : 1 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
plot(lm_subsets, scale = "bic")
```




```
# Look at actual numbers of predictors
# summary(lm_subsets)
```

- The plot above gives us a sense of model selsction. Hoever, we will stick to using all the predictors in this assignment.

Least Squares

Fit a linear model using least squares on the training data. Is there any potential disadvantage of this model?

Model fitting

```
set.seed(2570)

# Specify resampling method
ctrl <- trainControl(method = "repeatedcv", number = 10, repeats = 5)

# Fit a linear model using caret
lm_fit <- train(sale_price ~ .,
                data = train_df,
                method = "lm",
                preProcess = c("center", "scale"),
```

```r
                 trControl = ctrl)

# Extract coefficiencts
round(lm_fit$finalModel$coefficients, 3) %>%
  knitr::kable()
```

	x
(Intercept)	177568.502
gr_liv_area	11918.089
first_flr_sf	15645.580
second_flr_sf	17658.087
total_bsmt_sf	14564.164
low_qual_fin_sf	NA
wood_deck_sf	1609.235
open_porch_sf	1027.166
bsmt_unf_sf	-8661.325
mas_vnr_area	1756.926
garage_cars	3056.314
garage_area	1566.065
year_built	9546.428
tot_rms_abv_grd	-5883.709
full_bath	-2344.038
overall_qualAverage	-2287.250
overall_qualBelow_Average	-3314.296
overall_qualExcellent	12221.926
overall_qualFair	-1367.698
overall_qualGood	4994.161
overall_qualVery_Excellent	12335.966
overall_qualVery_Good	11604.560
kitchen_qualFair	-3410.143
kitchen_qualGood	-9158.701
kitchen_qualTypical	-13332.542
fireplaces	7400.044
fireplace_quFair	-1198.986
fireplace_quGood	258.914
fireplace_quNo_Fireplace	1697.355
fireplace_quPoor	-677.410
fireplace_quTypical	-2624.348
exter_qualFair	-3914.380
exter_qualGood	-9346.023
exter_qualTypical	-11719.787
lot_frontage	3327.997
lot_area	5015.883
longitude	-923.258
latitude	1071.879
misc_val	541.446
year_sold	-831.994

```r
# Calculate mean training RMSE
mean(lm_fit$resample$RMSE)
```

```
## [1] 23004.66
```

Make prediction

```r
# Make prediction on test data
lm_predict <- predict(lm_fit, newdata = test_df)
```

```
## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading
```

```r
# Calculate test RMSE
RMSE(lm_predict, test_df$sale_price)
```

```
## [1] 21149.18
```

Potential disadvantage

1. The model contains too many predictors, which is hard for interpretation.

2. As seen above, there are correlations among predictors, which may lead to: 1. higher variance and RMSE 2. less prediction accuracy 3. difficulty for interpretation

3. Due to the nature of its modeling method, Least Squares is sensitive to outliers.

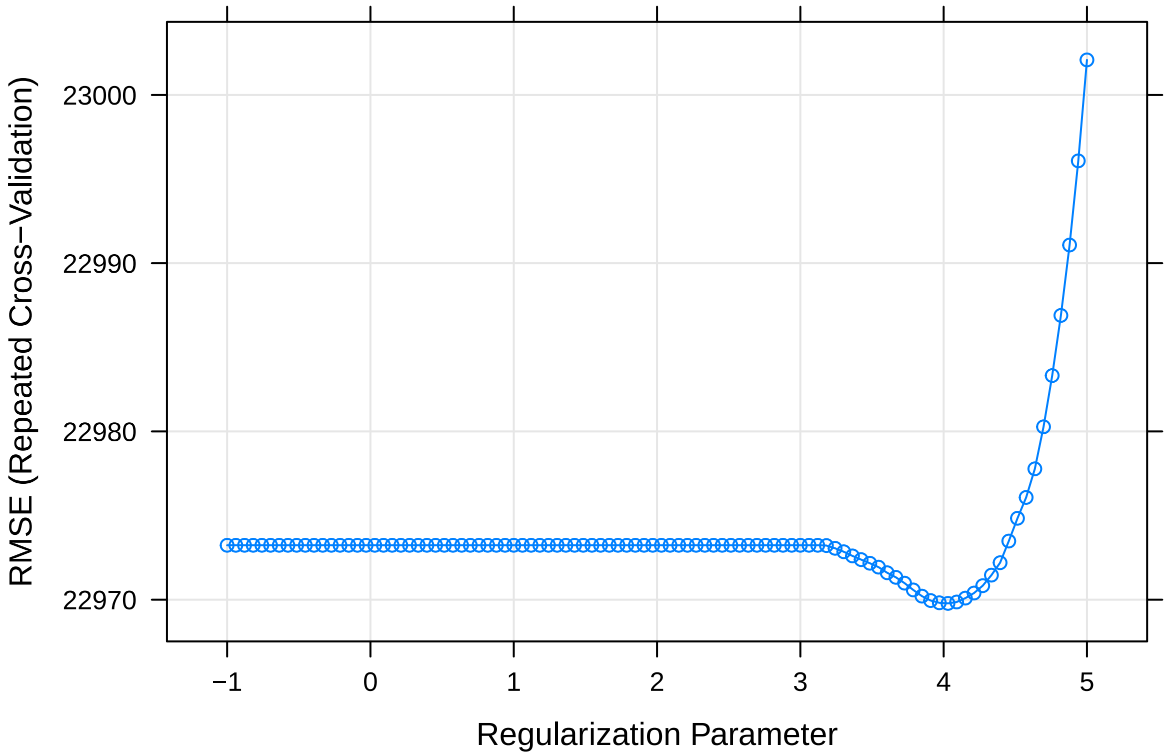
4. Large data set is necessary in order to obtain reliable results. Our sample in this case might not be large enough.

Lasso

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

Model fitting

```r
set.seed(2570)

# Specify resampling method for 1SE
ctrl_1se <- trainControl(method = "repeatedcv", number = 10, repeats = 5, selectionFunction = "oneSE")

# Fit a lasso model using caret
# The fitted model is a glemnet object, so we need to use matrix as input
lasso_fit <- train(x = train_x,
                   y = train_y,
                   method = "glmnet",
                   preProcess = c("center", "scale"),
                   tuneGrid = expand.grid(alpha = 1,
                                          lambda = exp(seq(5, -1, length = 100))),
                   trControl = ctrl_1se)

# Plot RMSE against lambda
plot(lasso_fit, xTrans = log)
```




```
# Extract optimum lambda
lasso_fit$bestTune
```

```
##     alpha   lambda
## 100     1 148.4132
```

```
# Extract coefficiencts
as.matrix(round(coef(lasso_fit$finalModel, lasso_fit$bestTune$lambda), 3)) %>%
  knitr::kable()
```

	s1
(Intercept)	177568.502
gr_liv_area	31177.974
first_flr_sf	312.809
second_flr_sf	0.000
total_bsmt_sf	14771.156
low_qual_fin_sf	-1761.842
wood_deck_sf	1497.382
open_porch_sf	923.948
bsmt_unf_sf	-8659.929
mas_vnr_area	1919.024
garage_cars	2884.238
garage_area	1693.861

	s1
year_built	9426.789
tot_rms_abv_grd	-5137.676
full_bath	-1759.334
overall_qualAverage	-2110.979
overall_qualBelow_Average	-3109.903
overall_qualExcellent	13217.628
overall_qualFair	-1252.728
overall_qualGood	4840.638
overall_qualVery_Excellent	13371.602
overall_qualVery_Good	11519.159
kitchen_qualFair	-2897.028
kitchen_qualGood	-7433.618
kitchen_qualTypical	-11708.623
fireplaces	6269.475
fireplace_quFair	-1229.132
fireplace_quGood	0.000
fireplace_quNo_Fireplace	0.000
fireplace_quPoor	-699.184
fireplace_quTypical	-2854.099
exter_qualFair	-2850.018
exter_qualGood	-4763.756
exter_qualTypical	-7061.312
lot_frontage	3129.665
lot_area	5002.484
longitude	-811.926
latitude	920.239
misc_val	419.839
year_sold	-590.579

- From the fitted lasso model, we can see that the optimum lambda chosen is 148.41

Make prediction

```r
set.seed(2570)

# Make prediction on test data
lasso_predict <- predict(lasso_fit, newdata = test_all)

# Calculate test RMSE
RMSE(lasso_predict, test_df$sale_price)
```

```
## [1] 20806.29
```

Test error and number of predictors

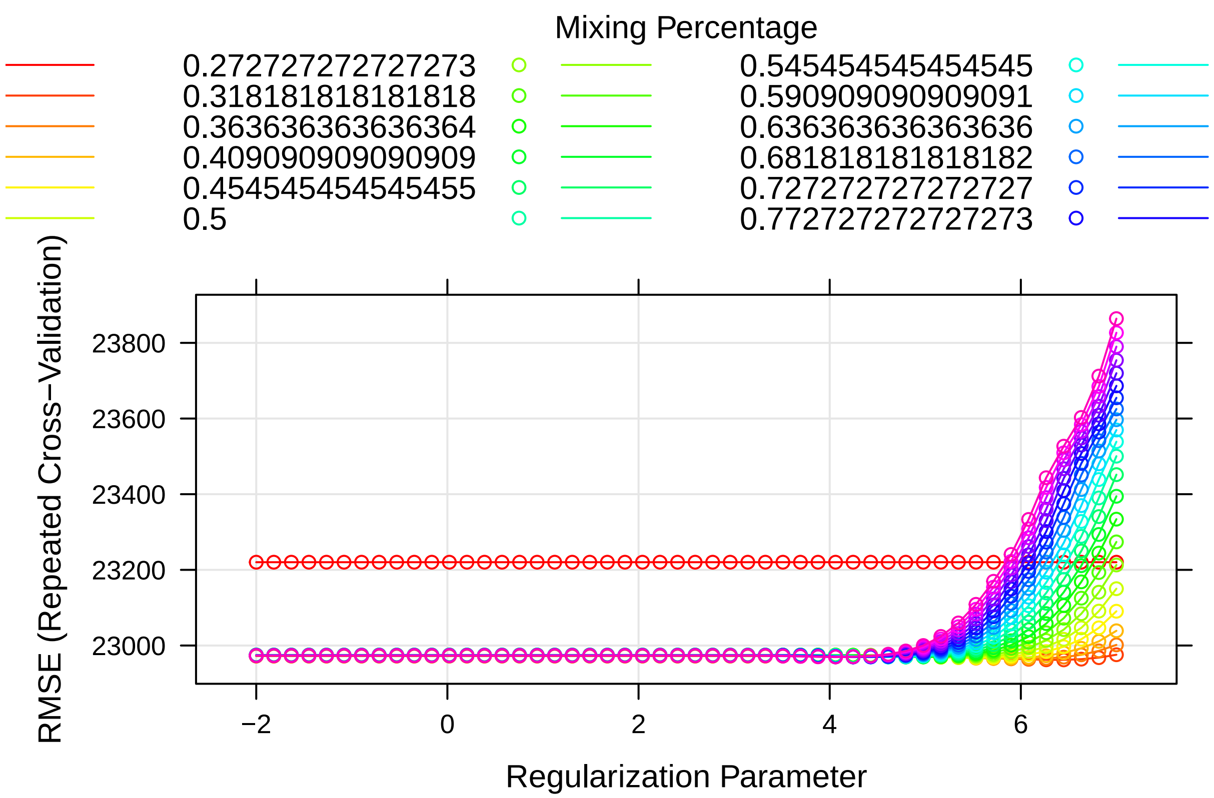
- The test RMSE is 2.08×10^4.
- When the 1SE rule is applied, there are 37 predictors included in the model.

Elastic Net

Fit an elastic net model on the training data. Report the selected tuning parameters and the test error.

Model fitting

```
set.seed(2570)

# Fit a elastic net model
enet_fit <- train(x = train_x,
                  y = train_y,
                  method = "glmnet",
                  preProcess = c("center", "scale"),
                  tuneGrid = expand.grid(alpha = seq(0, 1, length = 23),
                                         lambda = exp(seq(-2, 7, length = 50))),
                  trControl = ctrl)

# Plot RMSE against lambda
myCol = rainbow(25)
myPar = list(superpose.symbol = list(col = myCol),
             superpose.line = list(col = myCol))
plot(enet_fit, par.settings = myPar, xTrans = log)
```



```r
# Extract optimum lambda
enet_fit$bestTune
```

```
##         alpha  lambda
## 97 0.04545455 632.057
```

```r
# Extract coefficiencts
as.matrix(round(coef(enet_fit$finalModel, enet_fit$bestTune$lambda), 3)) %>%
  knitr::kable()
```

	s1
(Intercept)	177568.502
gr_liv_area	18684.332
first_flr_sf	9866.358
second_flr_sf	10797.626
total_bsmt_sf	14445.433
low_qual_fin_sf	-698.348
wood_deck_sf	1655.071
open_porch_sf	1076.647
bsmt_unf_sf	-8594.472
mas_vnr_area	1971.988
garage_cars	2918.671
garage_area	1807.314
year_built	9355.046
tot_rms_abv_grd	-5235.645
full_bath	-1974.020
overall_qualAverage	-2338.884
overall_qualBelow_Average	-3291.158
overall_qualExcellent	12777.215
overall_qualFair	-1413.279
overall_qualGood	4872.483
overall_qualVery_Excellent	12919.649
overall_qualVery_Good	11500.201
kitchen_qualFair	-3019.089
kitchen_qualGood	-7796.754
kitchen_qualTypical	-11979.554
fireplaces	7045.435
fireplace_quFair	-1311.070
fireplace_quGood	62.986
fireplace_quNo_Fireplace	897.342
fireplace_quPoor	-761.123
fireplace_quTypical	-2857.834
exter_qualFair	-3333.062
exter_qualGood	-6753.521
exter_qualTypical	-9150.162
lot_frontage	3253.583
lot_area	5006.949
longitude	-936.908
latitude	1055.915
misc_val	512.614
year_sold	-738.814

- From the fitted elastic net model, we can see that the optimum alpha chosen is 0.05, and the optimum lambda chosen is 632.06.

Make prediction

```
set.seed(2570)

# Make prediction on test data
enet_predict <- predict(enet_fit, newdata = test_all)

# Calculate test RMSE
RMSE(enet_predict, test_df$sale_price)
```

```
## [1] 20934.66
```

Selected tuning parameters and test error

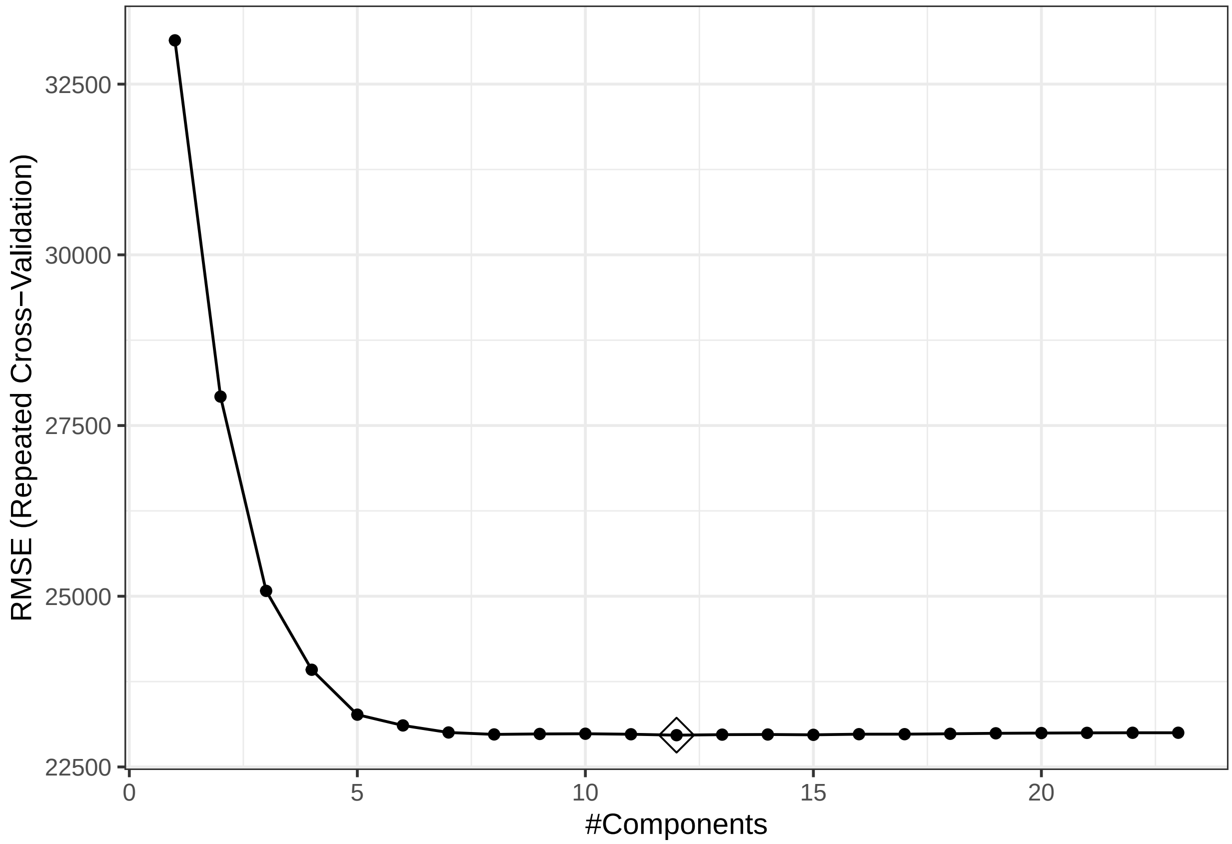
- The selected tuning parameter lambda is 632.06.
- The test RMSE is 2.09×10^4.

Partial Least Squares

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

Model fitting

```
set.seed(2570)

# Fit a partial least squares model
pls_fit <- train(x = train_x,
                 y = train_y,
                 method = "pls",
                 preProcess = c("center", "scale"),
                 tuneGrid = data.frame(ncomp = 1:23),
                 trControl = ctrl)

# Plot RMSE against number of components
ggplot(pls_fit, highlight = TRUE) +
  theme_bw()
```




```r
# Extract best tuning parameter
pls_fit$bestTune
```

```
##    ncomp
## 12    12
```

- From the fitted partial least squares model, we can see that the number of components is 12.
- The highlighted dot in the plot also shows the same result.

Make prediction

```r
set.seed(2570)

# Make prediction on test data
pls_predict <- predict(pls_fit, newdata = test_all)

# Calculate test RMSE
RMSE(pls_predict, test_df$sale_price)
```

```
## [1] 21204.31
```

Number of components and test error

- The number of components is 12,
- The test RMSE is 2.12×10^4.

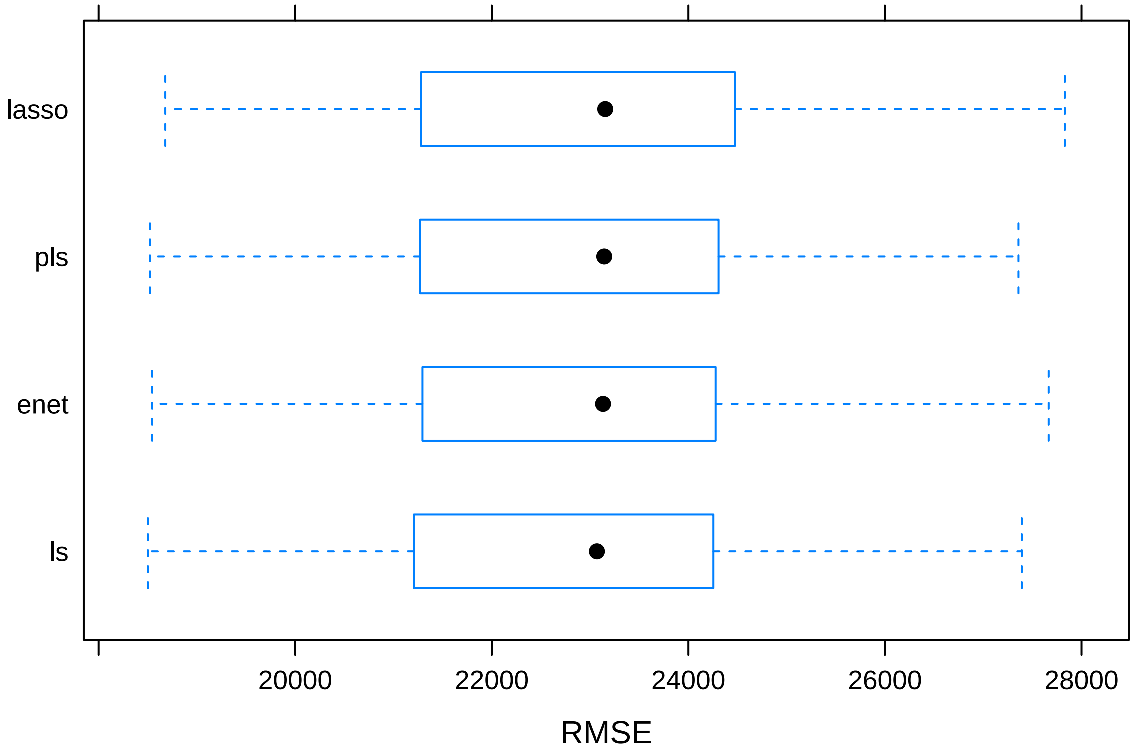
Model selection

Which model will you choose for predicting the response? Why?

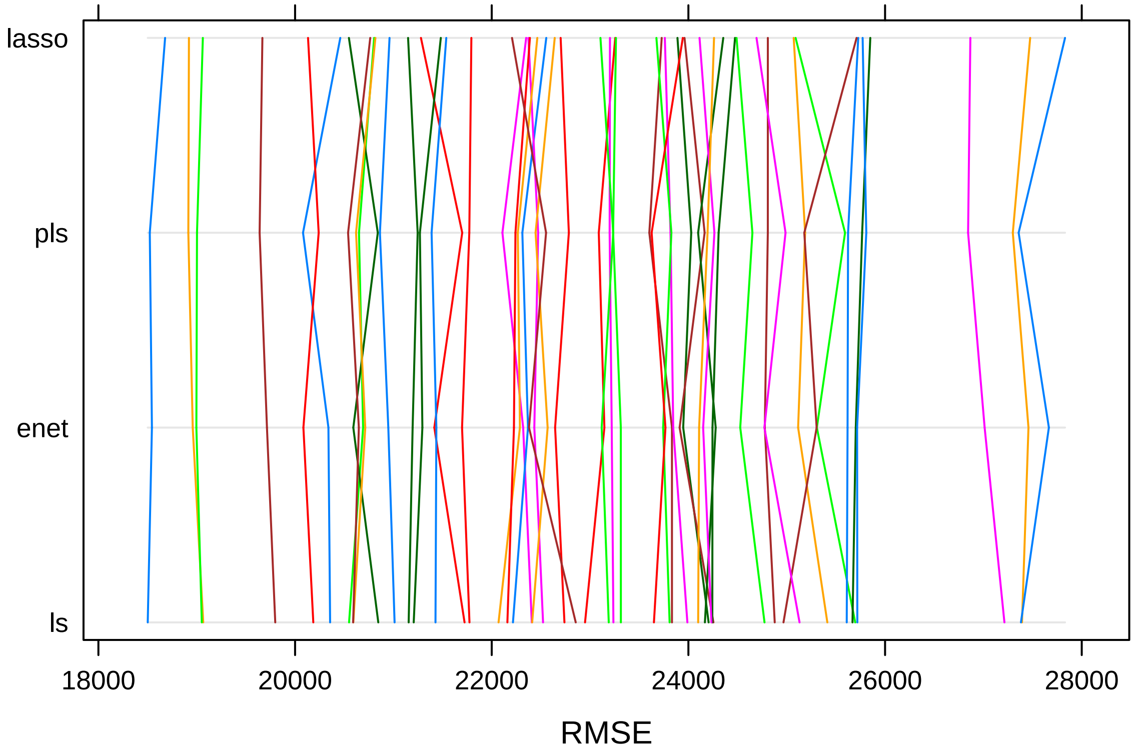
```r
# Compare the models based on resampling results
resamp<- resamples(list(ls = lm_fit,
                        lasso = lasso_fit,
                        enet = enet_fit,
                        pls = pls_fit))

summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
## Models: ls, lasso, enet, pls
## Number of resamples: 50
##
## MAE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## ls    14090.94 15801.89 16831.57 16728.33 17773.66 19634.15    0
## lasso 13989.94 15765.16 16498.30 16634.89 17612.42 19502.48    0
## enet  14049.49 15761.51 16619.83 16639.03 17622.10 19555.85    0
## pls   14081.67 15860.56 16773.07 16728.38 17824.76 19573.13    0
##
## RMSE
##           Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## ls    18501.59 21261.93 23069.48 23004.66 24251.76 27392.47    0
## lasso 18678.33 21330.67 23153.88 23002.08 24444.28 27830.31    0
## enet  18544.30 21325.08 23131.87 22961.99 24269.45 27665.80    0
## pls   18522.50 21299.13 23143.86 22965.37 24296.63 27358.46    0
##
## Rsquared
##            Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
## ls    0.8508070 0.8900840 0.9057787 0.9029181 0.9156418 0.9332064    0
## lasso 0.8547969 0.8900067 0.9051182 0.9028911 0.9160773 0.9340001    0
## enet  0.8541008 0.8897702 0.9056619 0.9032550 0.9160787 0.9337732    0
## pls   0.8522521 0.8895366 0.9058105 0.9031715 0.9150440 0.9342464    0
```

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




```
parallelplot(resamp, metric = "RMSE")
```



- Based on the summary and plots above, we would likely to choose the **least squares** model, since it has the lowest RMSE compared to other models. We have to admit that sometimes "Simplicity is the ultimate sophistication" :)