P8106 Homework1

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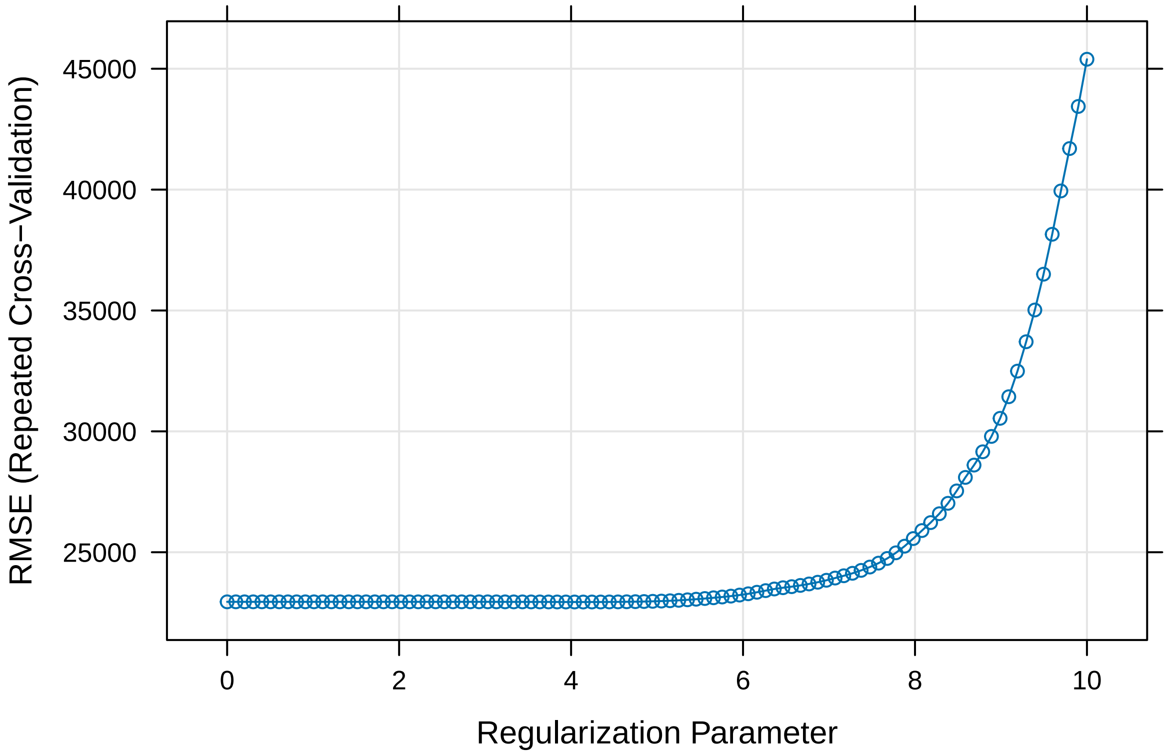
```r
# load libraries
library(tidyverse)
library(caret)
library(tidymodels)
library(plotmo)
library(kknn)
library(FNN)
library(pls)

# read csv files
df_test = read_csv("./data/housing_test.csv") |>
  janitor::clean_names()

df_train = read_csv("./data/housing_training.csv") |>
  janitor::clean_names()
```

(a) Lasso model on the training data

I will use caret to fit a lasso model.

```r
# set up 10-fold CV
ctrl1 <- trainControl(
  method = "repeatedcv",
  number = 10,
  repeats = 5,
  selectionFunction = "best"
)

set.seed(1)

# find lambda by CV
lasso.fit <-
  train(
    sale_price ~ .,
    data = df_train,
    method = "glmnet",
    tuneGrid = expand.grid(
      alpha = 1,
      lambda = exp(seq(10, 0, length = 100))
    ),
    trControl = ctrl1
```

```r
)

# plot RMSE and lambda
plot(lasso.fit, xTrans = log)
```




```r
# print the best tuning parameter
lasso.fit$bestTune
```

```
##    alpha  lambda
## 42     1 62.8917
```

```r
# Obtain the test error
lasso.pred <- predict(lasso.fit, newdata = df_test)
mean((lasso.pred - pull(df_test, "sale_price"))^2) # test error
```

```
## [1] 440215066
```

The selected tuning parameter is $\lambda = 62.89$ $(\alpha = 1)$
The test error is 440215066

Now, I will apply 1SE rule to obtain the most regularized model.

```r
# apply 1SE rule
ctrl2 <- trainControl(
  method = "repeatedcv",
  number = 10,
  repeats = 5,
  selectionFunction = "oneSE"
)

set.seed(1)

lasso.fit_oneSE <-
  train(
    sale_price ~ .,
    data = df_train,
    method = "glmnet",
    tuneGrid = expand.grid(
      alpha = 1,
      lambda = exp(seq(10, 0, length = 100))
    ),
    trControl = ctrl2
  )

# coefficients in the final model
coef(lasso.fit_oneSE$finalModel, s = lasso.fit_oneSE$bestTune$lambda)
```

```
## 40 x 1 sparse Matrix of class "dgCMatrix"
##                                    s1
## (Intercept)                -3.967225e+06
## gr_liv_area                 6.116858e+01
## first_flr_sf                9.422068e-01
## second_flr_sf               .
## total_bsmt_sf               3.624249e+01
## low_qual_fin_sf            -3.564387e+01
## wood_deck_sf                1.008785e+01
## open_porch_sf               1.221931e+01
## bsmt_unf_sf                -2.061856e+01
## mas_vnr_area                1.290135e+01
## garage_cars                 3.516368e+03
## garage_area                 9.683597e+00
## year_built                  3.154577e+02
## tot_rms_abv_grd            -2.564604e+03
## full_bath                  -1.521328e+03
## overall_qualAverage        -4.050185e+03
## overall_qualBelow_Average  -1.091854e+04
## overall_qualExcellent       8.683918e+04
## overall_qualFair           -8.861656e+03
## overall_qualGood            1.116048e+04
## overall_qualVery_Excellent  1.555241e+05
## overall_qualVery_Good       3.733021e+04
## kitchen_qualFair           -1.484041e+04
## kitchen_qualGood           -8.241031e+03
## kitchen_qualTypical        -1.699737e+04
## fireplaces                  8.310271e+03
```

```
## fireplace_quFair           -4.071334e+03
## fireplace_quGood            2.028562e+03
## fireplace_quNo_Fireplace    .
## fireplace_quPoor           -1.756346e+03
## fireplace_quTypical        -4.345175e+03
## exter_qualFair             -1.703686e+04
## exter_qualGood              .
## exter_qualTypical          -4.789024e+03
## lot_frontage                8.725771e+01
## lot_area                    5.924384e-01
## longitude                  -2.295215e+04
## latitude                    3.846862e+04
## misc_val                    3.376656e-01
## year_sold                  -1.809022e+02
```

```
# Obtain the test error
lasso.pred_oneSE <- predict(lasso.fit_oneSE, newdata = df_test)
mean((lasso.pred_oneSE - pull(df_test, "sale_price"))^2) # test error
```

```
## [1] 421099983
```

36 predictors are included in the model.

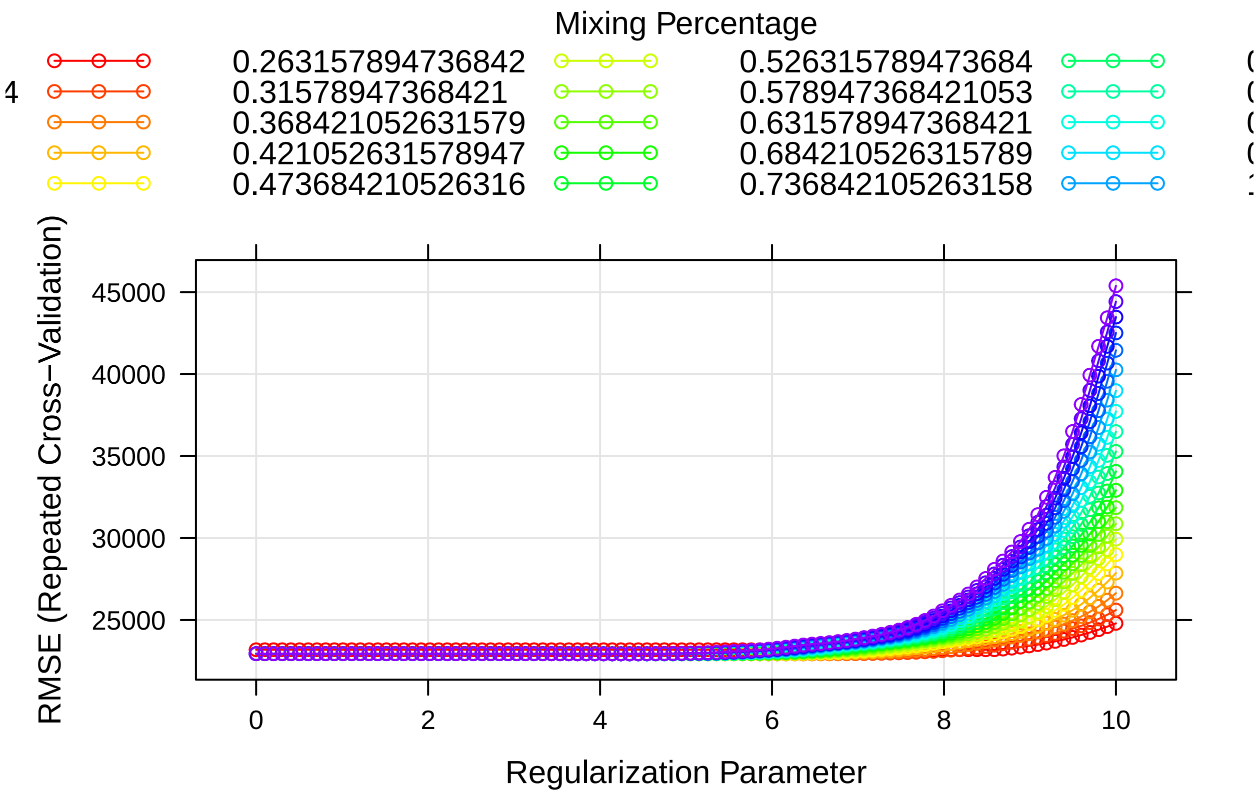
(b) Elastic net model on the training data

```
# fit the model
set.seed(1)

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

# check the best tuning parameter
enet.fit$bestTune
```

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

```
# plot RMSE, lambda and alpha
myCol <- rainbow(25)
myPar <- list(
  superpose.symbol = list(col = myCol),
```

```r
  superpose.line = list(col = myCol)
)

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




```r
# coefficients in the final model
coef(enet.fit$finalModel, s = enet.fit$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
# obtain predicted values
enet.pred <- predict(enet.fit, newdata = df_test)

# test error
mean((enet.pred - pull(df_test, "sale_price"))^2)
```

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

The selected tuning parameters are $\lambda = 580.35$ and $\alpha = 0.0526$ The test error is 438502352

1SE rule can be applied in λs for each α.

```r
# apply 1SE rule
set.seed(1)

enet.fit_oneSE <-
  train(
    sale_price ~ .,
    data = df_train,
    method = "glmnet",
    tuneGrid = expand.grid(
      alpha = seq(0, 1, length = 20),
      lambda = exp(seq(10, 0, length = 100))
    ),
    trControl = ctrl2
  )
```

```r
# check the tuning parameters
enet.fit_oneSE$bestTune
```

```
##    alpha   lambda
## 87     0 5924.601
```

```r
# Obtain the test error
enet.pred_oneSE <- predict(enet.fit_oneSE, newdata = df_test)
mean((enet.pred_oneSE - pull(df_test, "sale_price"))^2) # test error
```

```
## [1] 426417643
```

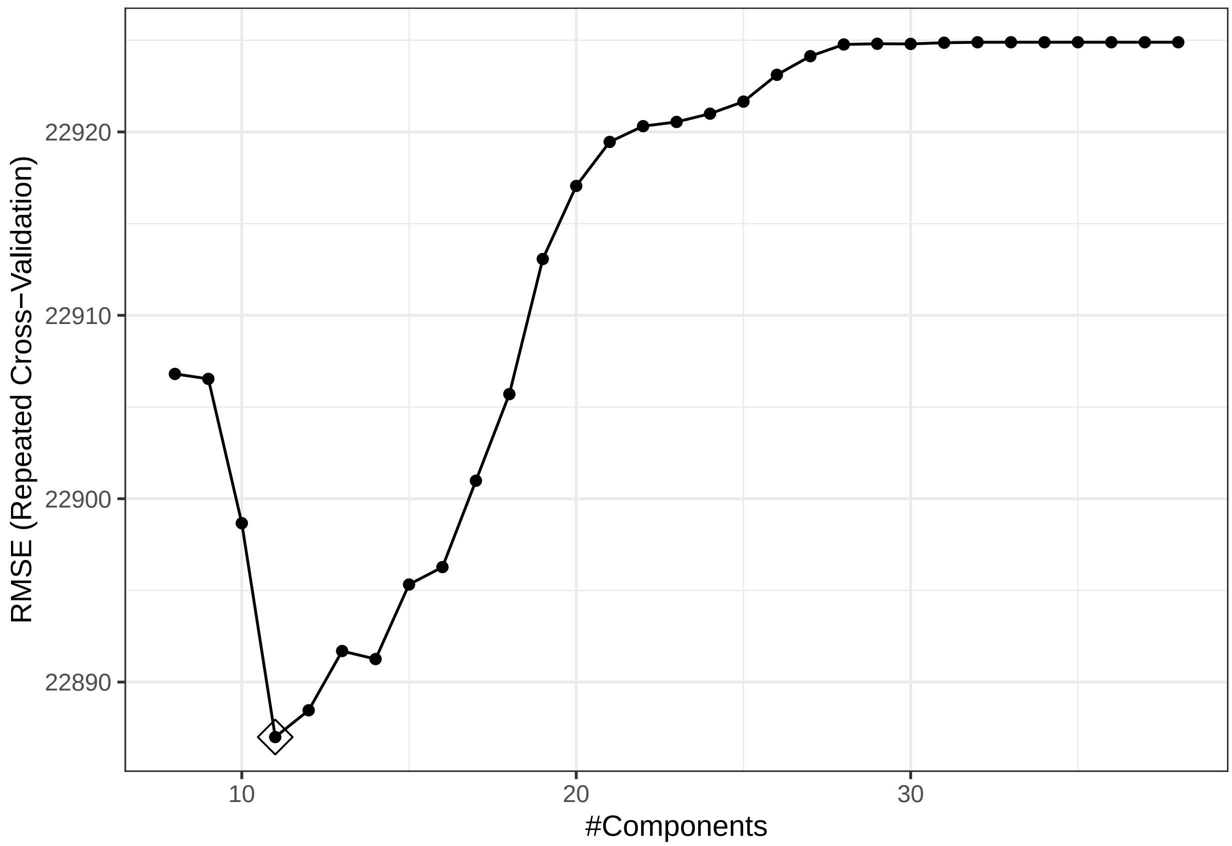
Now, the optimal tuning parameters are $\lambda = 5924.60$ and $\alpha = 0$

(c) Partial least squares model on the training data

```r
# using caret

# prepare x and y
# training
x <- model.matrix(sale_price ~ ., df_train)[, -1]
y <- df_train$sale_price

# test
x2 <- model.matrix(sale_price ~ ., df_test)[, -1]
y2 <- df_test$sale_price

# fit a partial least squares model on the training data
set.seed(2)

pls.fit <- train(
  x, y,
  method = "pls",
  tuneGrid = data.frame(ncomp = 8:38),
  trControl = ctrl1,
  preProcess = c("center", "scale")
)

summary(pls.fit)
```

```
## Data:    X dimension: 1440 39
##  Y dimension: 1440 1
## Fit method: oscorespls
## Number of components considered: 11
## TRAINING: % variance explained
##           1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps
## X           20.02    25.93    29.67    33.59    37.01    40.03    42.49
## .outcome    79.73    86.35    89.36    90.37    90.87    90.99    91.06
##           8 comps  9 comps  10 comps  11 comps
## X           45.53    47.97     50.15     52.01
## .outcome    91.08    91.10     91.13     91.15
```

```r
# obtain predicted values
pred.pls <- predict(
  pls.fit,
  newdata = x2
)

# visualize RMSE and the number of components
ggplot(pls.fit, highlight = T) + theme_bw()
```




```r
# test MSE
mean((pred.pls - y2)^2)
```

```
## [1] 451276530
```

11 components are included in the partial least squares model on the training data.
The test error is 451276530

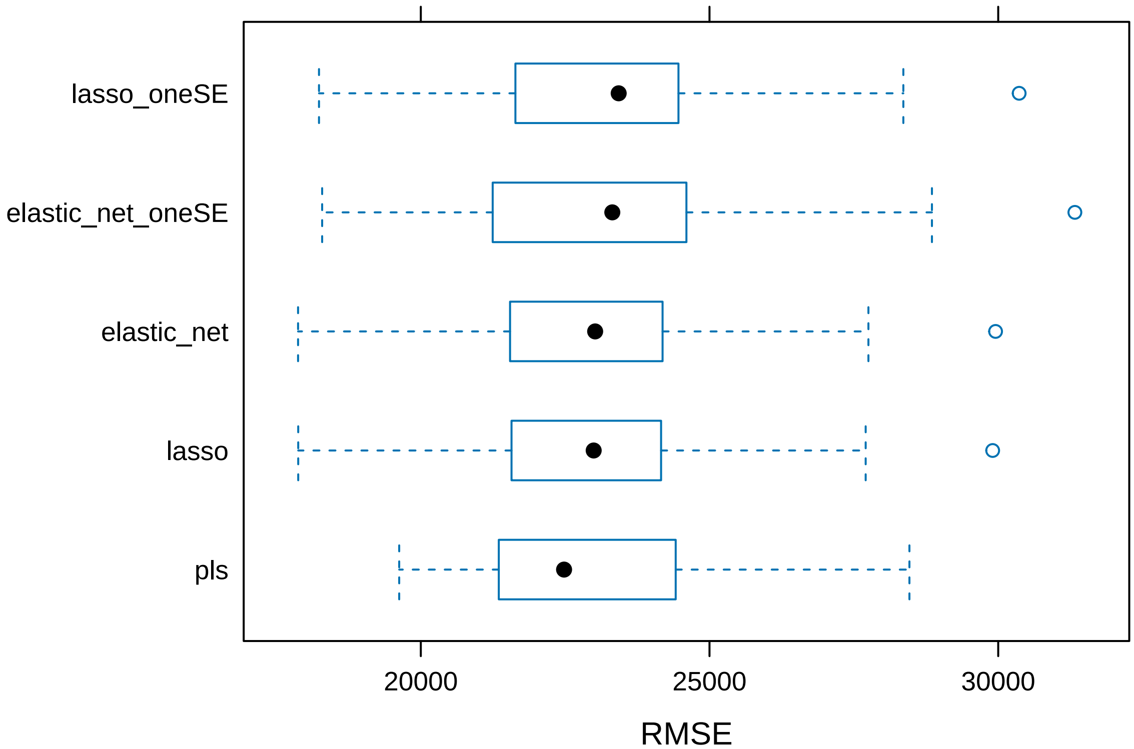
(d) The best model for response prediction

```r
# compare models

# resampling
```

```r
resamp <- resamples(list(
  lasso = lasso.fit,
  lasso_oneSE = lasso.fit_oneSE,
  elastic_net = enet.fit,
  elastic_net_oneSE = enet.fit_oneSE,
  pls = pls.fit
))

summary(resamp)
```

```
##
## Call:
## summary.resamples(object = resamp)
##
## Models: lasso, lasso_oneSE, elastic_net, elastic_net_oneSE, pls
## Number of resamples: 50
##
## MAE
##                       Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## lasso             13538.32 15959.78 16652.47 16657.11 17452.75 19127.21    0
## lasso_oneSE       13606.88 16028.59 16825.09 16650.35 17418.16 19208.65    0
## elastic_net       13491.26 15931.74 16567.00 16626.04 17391.32 19166.57    0
## elastic_net_oneSE 13198.39 16034.65 16689.20 16607.47 17394.40 19493.07    0
## pls               14022.76 15696.11 16734.02 16686.61 17486.46 20931.03    0
##
## RMSE
##                       Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
## lasso             17877.16 21592.59 22994.31 22941.14 24142.02 29904.32    0
## lasso_oneSE       18237.15 21713.36 23427.26 23228.85 24447.39 30363.08    0
## elastic_net       17874.28 21565.57 23019.54 22936.41 24167.06 29954.34    0
## elastic_net_oneSE 18291.48 21318.48 23316.47 23232.16 24593.61 31328.11    0
## pls               19625.67 21393.49 22481.30 22887.00 24395.86 28462.45    0
##
## Rsquared
##                        Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## lasso             0.8605656 0.8924796 0.9073985 0.9031727 0.9149599 0.9394451
## lasso_oneSE       0.8593829 0.8916811 0.9038715 0.9010143 0.9118504 0.9365696
## elastic_net       0.8603663 0.8931082 0.9069821 0.9032425 0.9146348 0.9393994
## elastic_net_oneSE 0.8553709 0.8942059 0.9035794 0.9013262 0.9123490 0.9362294
## pls               0.8553670 0.8909901 0.9036199 0.9037282 0.9180389 0.9399278
##                   NA's
## lasso                0
## lasso_oneSE          0
## elastic_net          0
## elastic_net_oneSE    0
## pls                  0
```

```r
# visualize RMSEs
bwplot(resamp, metric = "RMSE")
```



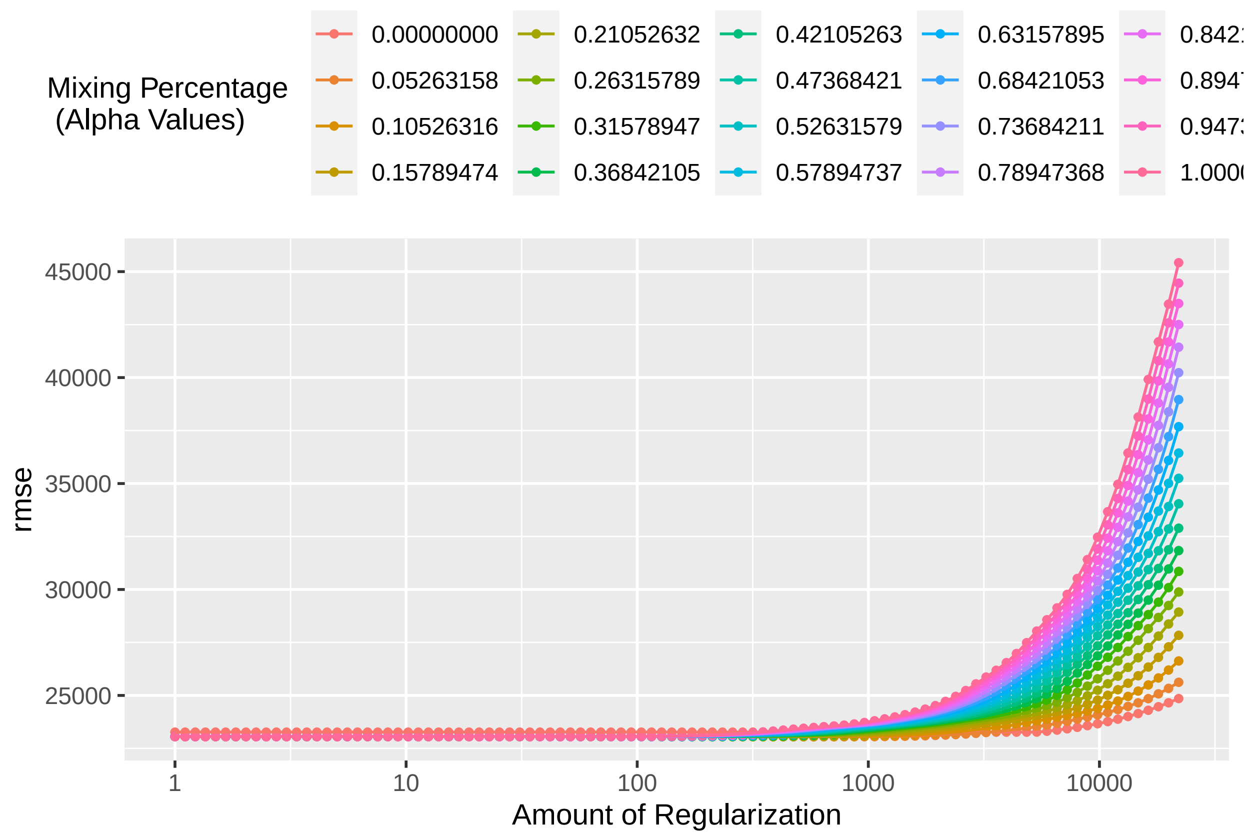
I choose the partial least square model as the best model in this practice because it has the smallest mean of RMSE among five models.

(e) Alternative meta-engine

I used caret in (b), so I will retrain the model with tidymodels.

```
# set up cv (10 fold)
set.seed(2)
cv_folds <- vfold_cv(df_train, v = 10)

# using tidymodels
enet_spec <- linear_reg(penalty = tune(), mixture = tune()) |>
  set_engine("glmnet") |>
  set_mode("regression")

# set the grid for lambda and alpha
enet_grid_set <- parameters(
  penalty(range = c(0, 10), trans = log_trans()), # lambda exp(0)-exp(10)
  mixture(range = c(0, 1)) # alpha 0 - 1
)

# set levels for lambda and alpha
enet_grid <- grid_regular(enet_grid_set, levels = c(100, 20))
```

```r
enet_workflow <- workflow() |>
  add_model(enet_spec) |>
  add_formula(sale_price ~ .)

# use cv to fit the elastic net model
enet_tune <- tune_grid(
  enet_workflow,
  resamples = cv_folds,
  grid = enet_grid
)

# visualize RMSE and tuning parameters
autoplot(enet_tune, metric = "rmse") +
  theme(legend.position = "top") +
  labs(color = "Mixing Percentage \n (Alpha Values)")
```




```r
# select the best tuning parameters
enet_best <- select_best(enet_tune, metric = "rmse")
enet_best
```

```
## # A tibble: 1 x 3
##   penalty mixture .config
##     <dbl>   <dbl> <chr>
## 1    642.  0.0526 Preprocessor1_Model0165
```

```r
# final model
final_enet_spec <- enet_spec |>
  update(penalty = enet_best$penalty, mixture = enet_best$mixture)

enet_fit <- fit(final_enet_spec, formula = sale_price ~ ., data = df_train)

# get coefficients
enet_model <- extract_fit_engine(enet_fit)
coef(enet_model, s = enet_best$penalty)
```

```
## 40 x 1 sparse Matrix of class "dgCMatrix"
##                                     s1
## (Intercept)               -5.117750e+06
## gr_liv_area                3.875965e+01
## first_flr_sf               2.652197e+01
## second_flr_sf              2.522278e+01
## total_bsmt_sf              3.491296e+01
## low_qual_fin_sf           -1.600666e+01
## wood_deck_sf               1.234578e+01
## open_porch_sf              1.692256e+01
## bsmt_unf_sf               -2.070535e+01
## mas_vnr_area               1.177486e+01
## garage_cars                4.027765e+03
## garage_area                9.004748e+00
## year_built                 3.185051e+02
## tot_rms_abv_grd           -3.394479e+03
## full_bath                 -3.617682e+03
## overall_qualAverage       -5.120434e+03
## overall_qualBelow_Average -1.268867e+04
## overall_qualExcellent      7.608294e+04
## overall_qualFair          -1.149660e+04
## overall_qualGood           1.194644e+04
## overall_qualVery_Excellent  1.368943e+05
## overall_qualVery_Good      3.761252e+04
## kitchen_qualFair          -2.344583e+04
## kitchen_qualGood          -1.588577e+04
## kitchen_qualTypical       -2.394984e+04
## fireplaces                 1.077050e+04
## fireplace_quFair          -7.944517e+03
## fireplace_quGood           6.866081e+01
## fireplace_quNo_Fireplace   1.616524e+03
## fireplace_quPoor          -5.887859e+03
## fireplace_quTypical       -7.040612e+03
## exter_qualFair            -3.244018e+04
## exter_qualGood            -1.405155e+04
## exter_qualTypical         -1.867531e+04
## lot_frontage               9.988078e+01
## lot_area                   6.030622e-01
## longitude                 -3.513064e+04
## latitude                   5.756778e+04
## misc_val                   8.609877e-01
## year_sold                 -5.667994e+02
```

```r
# obtain test RMSE
enet.pred_tidy <- predict(enet_fit, new_data = df_test)
# RMSE
sqrt(mean((enet.pred_tidy[[1]] - pull(df_test, "sale_price"))^2))
```

```
## [1] 20922.95
```

The selected tuning parameters in this model are $\lambda = 642.04$ and $\alpha = 0.0526$

Although the α is the same, the selected λ is different 580.35 in caret. This may be due to the different calclation methods used in each package.