DSA-5103-001 Homework #5 Group 09

Students Names Redacted

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Import data

```
data <- read.csv("housingData.csv")
data$Id <- NULL
data$SalePrice <- log(data$SalePrice)
```

Data Preparation

Drop variables with more than 30% missing observations

```
data <- data[colSums(is.na(data))/nrow(data) < .3]

paste("Number of remaining variables:",length(names(data)))
```

```
## [1] "Number of remaining variables: 68"
```

```
#get character variables
char_variables <- unlist(lapply(data, is.character), use.names = FALSE)

data <- as.data.frame(unclass(data),stringsAsFactors=TRUE)
#convert categorical to numeric
data[sapply(data, is.factor)] <- data.matrix(data[sapply(data, is.factor)])

data[,char_variables] <- lapply(data[,char_variables] , factor)



var_mode <- function(x) {
    ij <- unique(x)
    ij[which.max(tabulate(match(x, ij)))]
}
```

```r
data<- data %>% mutate_if(is.numeric, funs(replace(.,is.na(.), mean(., na.rm = TRUE)))) %>%
  mutate_if(is.factor, funs(replace(.,is.na(.), var_mode(na.omit(.)))))

colSums(is.na(data))
```

```
##   MSSubClass     MSZoning  LotFrontage      LotArea     LotShape  LandContour
##            0            0            0            0            0            0
##    LotConfig    LandSlope Neighborhood   Condition1     BldgType   HouseStyle
##            0            0            0            0            0            0
##  OverallQual  OverallCond    YearBuilt YearRemodAdd    RoofStyle  Exterior1st
##            0            0            0            0            0            0
##  Exterior2nd   MasVnrType   MasVnrArea    ExterQual    ExterCond   Foundation
##            0            0            0            0            0            0
##     BsmtQual     BsmtCond BsmtExposure BsmtFinType1   BsmtFinSF1 BsmtFinType2
##            0            0            0            0            0            0
##   BsmtFinSF2    BsmtUnfSF  TotalBsmtSF      Heating    HeatingQC   CentralAir
##            0            0            0            0            0            0
##   Electrical    X1stFlrSF    X2ndFlrSF LowQualFinSF    GrLivArea BsmtFullBath
##            0            0            0            0            0            0
## BsmtHalfBath     FullBath     HalfBath BedroomAbvGr KitchenAbvGr  KitchenQual
##            0            0            0            0            0            0
## TotRmsAbvGrd   Functional   Fireplaces   GarageType  GarageYrBlt GarageFinish
##            0            0            0            0            0            0
##   GarageCars   GarageArea   GarageQual   GarageCond   PavedDrive   WoodDeckSF
##            0            0            0            0            0            0
##  OpenPorchSF   EncPorchSF     PoolArea      MiscVal       MoSold       YrSold
##            0            0            0            0            0            0
##     SaleType    SalePrice
##            0            0
```

(a) OLS Model

```r
#hold data
hold <- data[1:100,]
#train data
train <- data[101:nrow(data),]
paste("Observations in train data:", nrow(train),"with", ncol(train),"columns")
```

```
## [1] "Observations in train data: 900 with 68 columns"
```

```r
paste("Observations in hold data:", nrow(hold),"with", ncol(hold),"columns")
```

```
## [1] "Observations in hold data: 100 with 68 columns"
```

We began by loading the dataset and partitioning it into a training set (900 observations) and a hold-out validation set (100 observations). The training set served as the basis for model development, while the validation set was used to assess the model's generalization performance.

Stepwise regression model

```r
model <- lm(SalePrice ~. ,data = train)
# Performing regression model
```

```r
step.model <- stepAIC(model, direction = "both",
                      trace = FALSE)

#summary of the step model
summ(step.model)
```

Observations	900
Dependent variable	SalePrice
Type	OLS linear regression

F(89,810)	165.84
R^2	0.95
Adj. R^2	0.94

We initiated the analysis by constructing a multiple linear regression model using the training set. This model aimed to predict sale prices based on a set of predictor variables. All available features were considered initially.To enhance the model's relevance and accuracy, we employed a stepwise regression technique. This process involved iteratively adding and removing predictors based on their significance, as determined by the Akaike Information Criterion (AIC).

```r
# Bayesian Information Criterion (BIC)
BIC(step.model)
```

BIC

```
## [1] -1314.297
```

The Bayesian Information Criterion (BIC) penalizes the number of parameters in the model, aiming to strike a balance between model fit and complexity. In this case, the BIC value for the selected stepwise regression model is approximately -1314.297. A lower BIC value suggests a better-fitting and less complex model, making it a useful metric for model comparison.

```r
#Root Mean Squared Error (RMSE)
rmse_lm <- sqrt(mean(step.model$residuals^2))
rmse_lm
```

RMSE

```
## [1] 0.08266142
```

The Root Mean Squared Error (RMSE) measures the square root of the average of the squared differences between predicted and actual values. For this stepwise regression model, the calculated RMSE is approximately

0.08266142. A lower RMSE indicates a better fit of the model to the actual data, implying that the model's predictions are closer to the true values.

VIF

```r
#Variance Inflation Factor (VIF)
VIF(step.model)
```

```
##                    GVIF Df GVIF^(1/(2*Df))
## MSZoning       23.737712  3        1.695274
## LotArea         2.420379  1        1.555757
## LotConfig       1.447094  3        1.063529
## Neighborhood 1864.794439 17        1.247944
## Condition1      2.218190  5        1.082929
## BldgType       14.115677  4        1.392236
## OverallQual     3.849691  1        1.962063
## OverallCond     1.923266  1        1.386819
## YearBuilt       8.363010  1        2.891887
## RoofStyle       1.588499  2        1.122656
## Exterior1st    10.330287  7        1.181508
## ExterQual       3.805491  2        1.396699
## ExterCond       1.977169  2        1.185799
## Foundation      9.642107  3        1.458911
## BsmtCond        1.616542  2        1.127578
## BsmtExposure    2.248349  3        1.144574
## BsmtFinSF1      5.643927  1        2.375695
## BsmtFinSF2      1.639739  1        1.280523
## BsmtUnfSF       4.856965  1        2.203852
## HeatingQC       2.052702  2        1.196965
## CentralAir      2.023201  1        1.422393
## Electrical      2.257429  3        1.145343
## X1stFlrSF       5.798951  1        2.408101
## X2ndFlrSF       3.876825  1        1.968965
## LowQualFinSF    1.253629  1        1.119656
## BsmtFullBath    2.073398  1        1.439930
## FullBath        3.149348  1        1.774640
## BedroomAbvGr    2.397242  1        1.548303
## KitchenAbvGr    3.745382  1        1.935299
## Functional      2.544402  5        1.097889
## Fireplaces      1.768861  1        1.329985
## GarageCars      5.837521  1        2.416096
## GarageArea      5.594452  1        2.365259
## GarageCond      1.501465  2        1.106952
## WoodDeckSF      1.383779  1        1.176341
## OpenPorchSF     1.322793  1        1.150128
## EncPorchSF      1.312488  1        1.145639
## PoolArea        1.076190  1        1.037396
## LandSlope       2.805385  2        1.294190
```

The Variance Inflation Factor (VIF) helps to identify problematic multi collinearity, which can adversely affect the model's stability and interpretability. The VIF values for each predictor were computed, and most of the predictors exhibit VIF values well below 10, indicating acceptable levels of collinearity.

```
#R-squared value
lm_rsq <- round(summary(step.model)$r.squared, 5)
paste("R-Squared:", lm_rsq)
```

```
## [1] "R-Squared: 0.94798"
```

The R-squared value, approximately 0.94798, represents the proportion of variance in the dependent variable (SalePrice) that is predictable from the independent variables included in the model. In this case, the R-squared value suggests that approximately 94.80% of the variability in the SalePrice can be explained by the predictors in the model. A higher R-squared value signifies a better fit of the model to the data.

Stepwise regression model after removing collinear variables

```
#convert categorical to numeric
data[sapply(data, is.factor)] <- data.matrix(data[sapply(data, is.factor)])

correl <- cor(data)
correl[!lower.tri(correl)] <- 0

data.new <-
  data[, !apply(correl, 2, function(x) any(abs(x) > 0.7, na.rm = TRUE))]

#hold data
hold1 <- data.new[1:100,]
#train datas
train1 <- data.new[101:nrow(data.new),]
paste("Observations in train data:", nrow(train1),"with", ncol(train1),"columns" )
```

```
## [1] "Observations in train data: 900 with 58 columns"
```

```
paste("Observations in test data:", nrow(hold1),"with", ncol(hold1),"columns" )
```

```
## [1] "Observations in test data: 100 with 58 columns"
```

Stepwise regression model with interaction effects

```
#convert categorical to numeric
data[sapply(data, is.factor)] <- data.matrix(data[sapply(data, is.factor)])
```

```r
datax <- data
datax$`GarageArea:PoolArea` <- datax$GarageArea*datax$PoolArea
datax$`YearBuilt:YearRemodAdd` <- datax$YearBuilt*datax$YearRemodAdd
datax$`BedroomAbvGr:KitchenAbvGr` <- datax$BedroomAbvGr*datax$KitchenAbvGr
datax$`OverallQual:OverallCond` <- datax$OverallQual*datax$OverallCond
#hold data
hold2 <- datax[1:100,]
#train data
train2 <- datax[101:nrow(data),]
paste("Observations in train data:", nrow(train2),"with", ncol(train2),"columns" )
```

```
## [1] "Observations in train data: 900 with 72 columns"
```

```r
paste("Observations in test data:", nrow(hold2),"with", ncol(hold2),"columns" )
```

```
## [1] "Observations in test data: 100 with 72 columns"
```

```r
model2 <- lm(SalePrice ~. ,data = train2)

# Performing Stepwise regression model2
step.model2 <- stepAIC(model2, direction = "both",
                      trace = FALSE)

#summary
summ(step.model2)
```

Report coefficient estimates, p-values, and adjusted R2 for the best model, AIC

```r
paste("AIC- Stepwise:" ,round(extractAIC(step.model)[2], 4))
```

```
## [1] "AIC- Stepwise: -4307.4041"
```

```r
paste("AIC- Interaction Effects:" ,round(extractAIC(step.model2)[2], 4))
```

```
## [1] "AIC- Interaction Effects: -4180.7299"
```

```r
BIC(step.model2)
```

BIC

```
## [1] -1403.73
```

RMSE

```r
rmse_lm2 <- sqrt(mean(step.model2$residuals^2))
rmse_lm2
```

```
## [1] 0.09323541
```

```r
VIF(step.model2)
```

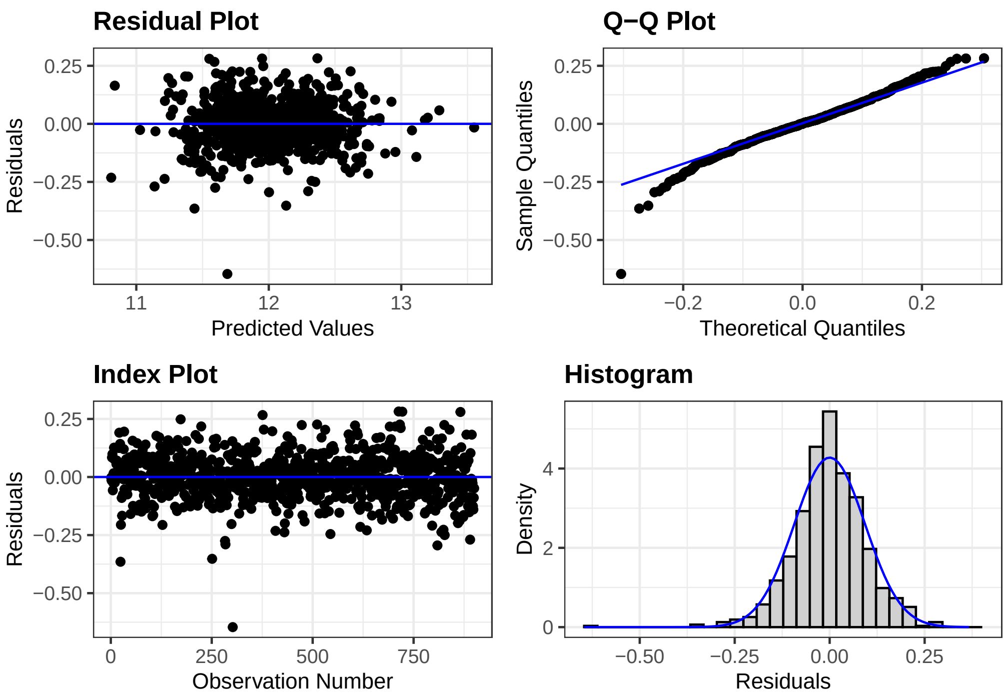
VIF

```
##                    MSZoning                LotFrontage                    LotArea
##                    1.306216                   1.595231                   1.266480
##                    LotShape               Neighborhood                 Condition1
##                    1.219197                   1.229411                   1.097026
##                    BldgType                OverallQual                OverallCond
##                    1.797310                  37.309777                  27.034811
##                YearRemodAdd                  RoofStyle                Exterior1st
##                    6.397126                   1.171822                   3.426345
##                 Exterior2nd                 MasVnrType                  ExterQual
##                    3.309035                   1.115040                   2.772420
##                   ExterCond                 Foundation                   BsmtCond
##                    1.232235                   2.587254                   1.187280
##                BsmtExposure                 BsmtFinSF1                 BsmtFinSF2
##                    1.320666                   4.431384                   1.379183
##                   BsmtUnfSF                  HeatingQC                 CentralAir
##                    3.546428                   1.566956                   1.562963
##                   X1stFlrSF                  X2ndFlrSF               LowQualFinSF
##                    5.275174                   4.236770                   1.150247
##                BsmtFullBath               BedroomAbvGr               KitchenAbvGr
##                    1.933157                   2.521240                   1.676046
##                 KitchenQual               TotRmsAbvGrd                 Functional
##                    2.485059                   5.293264                   1.249885
##                  Fireplaces                GarageYrBlt               GarageFinish
##                    1.639889                   3.451448                   1.804948
##                  GarageCars                 GarageArea                 WoodDeckSF
##                    5.311613                   5.054878                   1.268350
##                 OpenPorchSF                EncPorchSF                   PoolArea
##                    1.201710                   1.227207                   1.042685
##    `YearBuilt:YearRemodAdd` `OverallQual:OverallCond`
##                   13.570155                  51.949618
```

```r
lm_rsq2 <- round(summary(step.model2)$r.squared, 5)
paste("R-Squared:", lm_rsq2)
```

```
## [1] "R-Squared: 0.93381"
```

Analysis of the residuals



The histogram suggests that the residuals approximately follow a normal distribution, which is a positive indication. A normal distribution of residuals is a fundamental assumption in many statistical models, including linear regression.The presence of extreme values or outliers in the index plot (Q-Q plot) is significant. Outliers in the residuals can impact the model's assumptions and performance. They may lead to biased parameter estimates, affect the model's accuracy, and violate assumptions like normality.

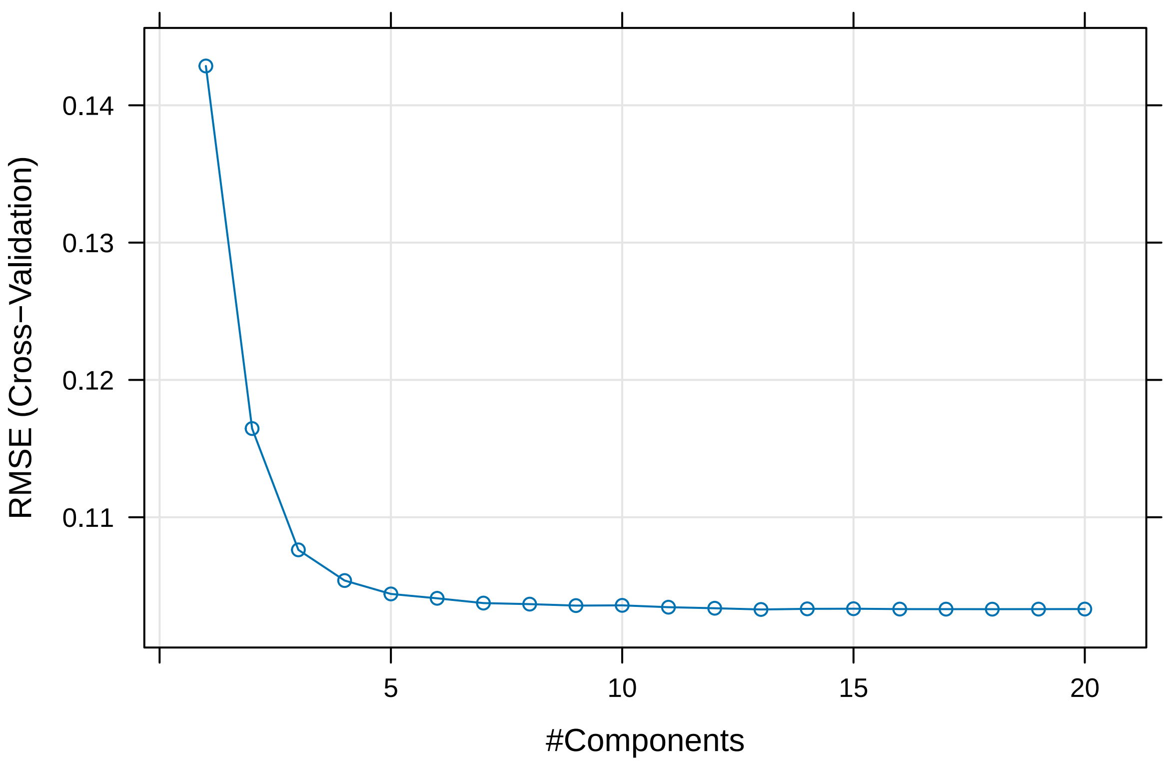
(b) PLS model to predict the log of the sale price.

```r
set.seed(1)
plsFit1 <- train(SalePrice~., data=data, method = "pls",
                 tuneLength=20, metric="RMSE",
                 trControl=(trainControl(method="cv", number=5
                 )),
                 preProc=c("center","scale"))
plsFit1
```

```
## Partial Least Squares
##
## 1000 samples
##   67 predictor
##
## Pre-processing: centered (67), scaled (67)
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 801, 801, 800, 799, 799
## Resampling results across tuning parameters:
```

```
##
##   ncomp  RMSE       Rsquared   MAE
##    1     0.1428624  0.8467598  0.10702737
##    2     0.1164585  0.8986846  0.08660085
##    3     0.1076250  0.9136403  0.08125174
##    4     0.1053908  0.9174558  0.08058844
##    5     0.1044146  0.9190081  0.07943962
##    6     0.1040965  0.9194974  0.07880601
##    7     0.1037492  0.9201753  0.07838806
##    8     0.1036735  0.9203394  0.07810993
##    9     0.1035663  0.9205130  0.07809902
##   10     0.1035844  0.9204837  0.07809258
##   11     0.1034502  0.9207373  0.07802095
##   12     0.1033734  0.9208533  0.07795069
##   13     0.1032844  0.9210037  0.07788218
##   14     0.1033284  0.9209129  0.07786214
##   15     0.1033378  0.9208938  0.07787140
##   16     0.1033121  0.9209255  0.07785808
##   17     0.1033078  0.9209335  0.07785178
##   18     0.1033058  0.9209373  0.07784547
##   19     0.1033102  0.9209304  0.07784807
##   20     0.1033133  0.9209249  0.07785008
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was ncomp = 13.
```

```r
plot(plsFit1)
```



Number of components and the CV RMSE estimate for the final model

```
res <- plsFit1$results
best_perf <- subset(res, res$RMSE == min(res$RMSE) )

pls_perf <- best_perf[,1:3]

pls_perf
```

```
##    ncomp      RMSE  Rsquared
## 13    13 0.1032844 0.9210037
```

The PLS model was trained using the train function from the caret package in R. Hyperparameter tuning was conducted by varying the number of components (ncomp) from 1 to 20. The RMSE was used as the performance metric for model evaluation. The dataset was split into 5 folds for cross-validation.

The optimal number of components chosen for the final model was 13, yielding an RMSE of approximately 0.1033 and an R-squared of approximately 0.9210.

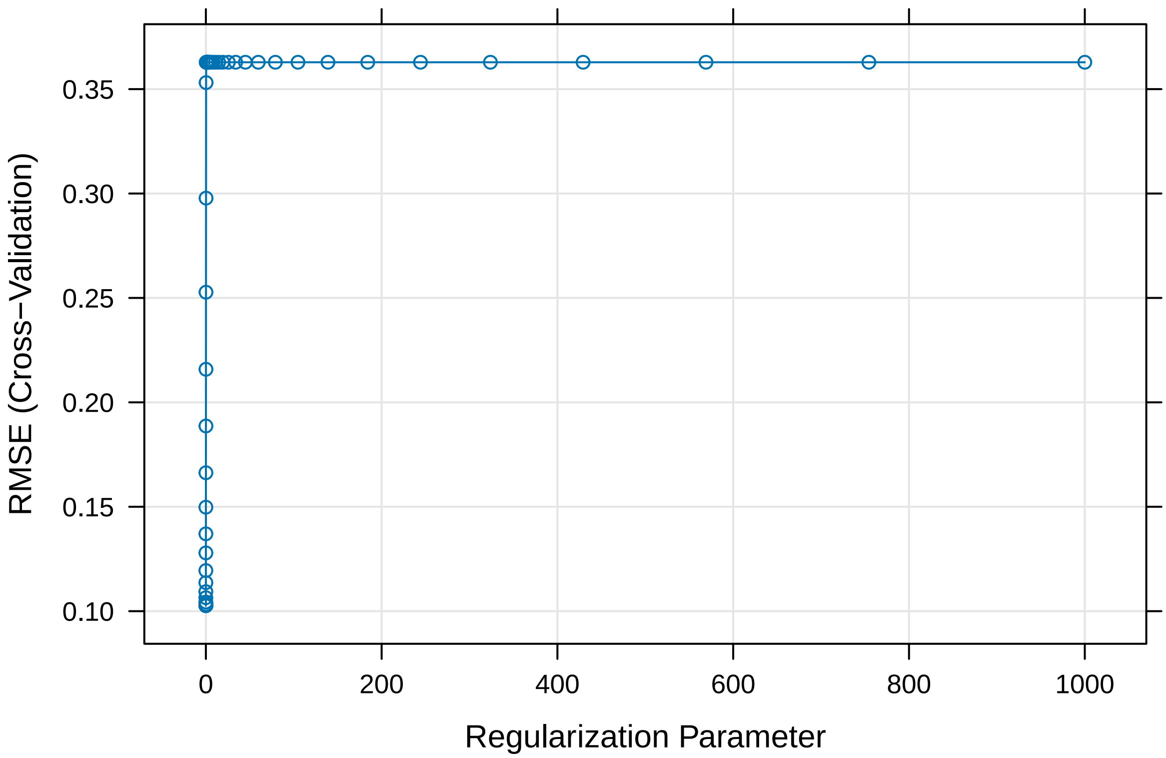
Summary of Model Performance: The performance of the final PLS model is as follows:

Number of Components (ncomp): 13 Cross-validated RMSE: 0.1032844 Cross-validated R-squared: 0.9210037

This indicates that the PLS model with 13 components achieved a good fit to the data, explaining approximately 92.10% of the variance in the log of the sale prices.

(c) LASSO model to predict the log of the sale price

```
data$SalePrice[is.na(data$SalePrice)] <- mean(data$SalePrice, na.rm = TRUE)

# Build the LASSO model
set.seed(1)
lambda <- 10^seq(-3, 3, length = 50)
lasso_caret <- train(
  SalePrice ~ ., data = data, method = "glmnet",
  trControl = trainControl(method = "cv", number = 5),
  tuneGrid = expand.grid(alpha = 1, lambda = lambda)
)

# Plot the LASSO model
plot(lasso_caret)
```




```r
# Extract the best performance and parameters
res_lasso <- lasso_caret$results
best_perf_lasso <- subset(res_lasso, res_lasso$RMSE == min(res_lasso$RMSE))
lasso_perf <- best_perf_lasso[, 1:4]


# Display the best performance
cat("Best fraction and the CV RMSE estimate for the final model:\n")
```

```
## Best fraction and the CV RMSE estimate for the final model:
```

```r
print(lasso_perf)
```

```
##   alpha lambda      RMSE  Rsquared
## 1     1  0.001 0.1026033 0.9220277
```

```r
cat("\nVariables with non-zero coefficients and their values:\n")
```

```
##
## Variables with non-zero coefficients and their values:
```

```r
non_zero_coefs <- coef(lasso_caret$finalModel, lasso_caret$bestTune$lambda)
print(non_zero_coefs[non_zero_coefs != 0])
```

```
##  [1]  9.562309e+00 -5.259451e-05 -4.504714e-02  1.927082e-04  2.306189e-06
##  [6] -3.628933e-03 -3.644229e-03  3.216202e-03 -3.085258e-03  3.277983e-03
## [11] -6.511714e-03  5.799571e-02  4.286935e-02  1.801703e-03  5.853094e-04
## [16]  1.715898e-02 -4.668259e-03  4.223985e-03  7.984307e-03  9.364124e-06
## [21] -1.430859e-02  1.141894e-02  1.242744e-02 -3.178249e-03 -2.717721e-02
## [26] -6.228190e-03 -1.175198e-03  7.212014e-05  8.954021e-04  3.131128e-05
## [31]  1.131167e-04  2.083362e-02 -1.371025e-02  4.525208e-02  3.356214e-06
## [36] -7.509337e-05  2.640349e-04  1.842829e-02  5.951212e-03  6.189700e-03
```

```
## [41]  4.504353e-03 -1.190067e-02 -4.979870e-02 -2.170358e-02  5.109794e-03
## [46]  2.427497e-02  3.588392e-02 -2.899040e-04 -9.613169e-03  3.865621e-02
## [51]  8.052745e-05 -1.580944e-02 -4.312281e-03  1.613583e-02  5.474086e-05
## [56]  9.826977e-05  1.588360e-04  1.094606e-04 -1.320953e-05 -2.437550e-04
## [61] -1.472328e-03
```

(d) combination of techniques (PCA, LDA, missing value imputation, etc.) find the log sale price.

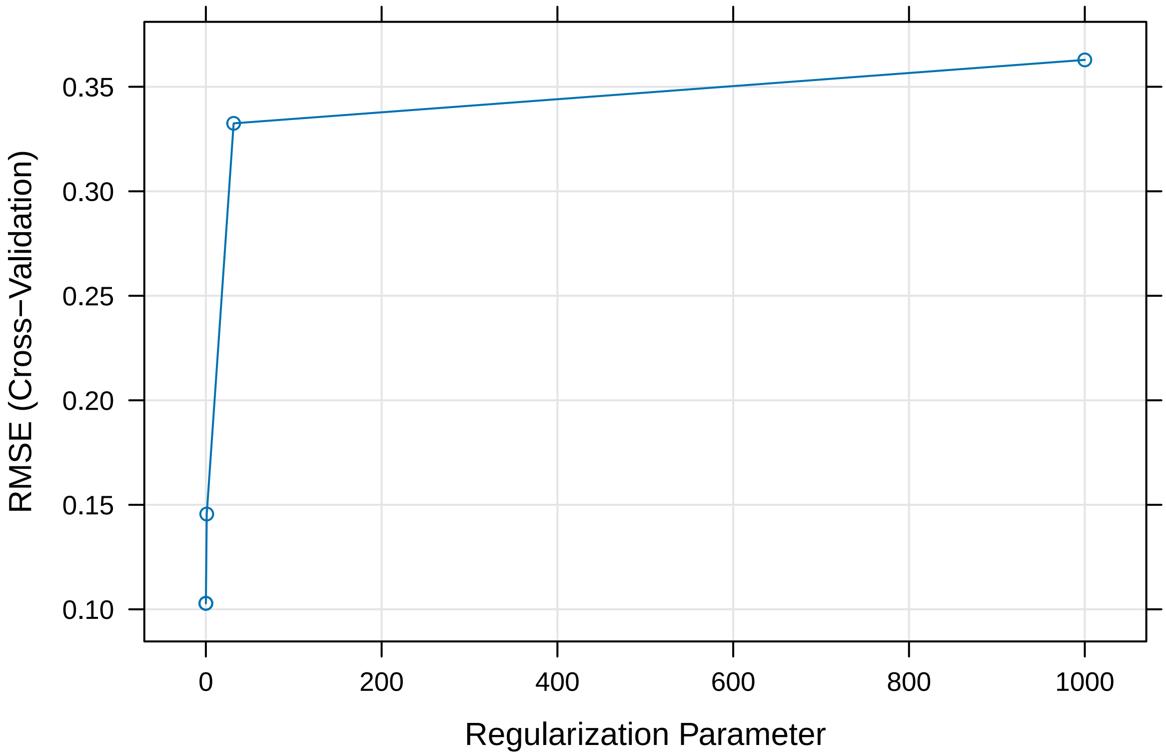
```
### (d) Combination of regression models with missing value imputation

#### Ridge regression

set.seed(1)

# Define lambda values
lambda_ridge <- 10^seq(-3, 3, length = 5)

ridge_model <- train(
  SalePrice ~ ., data = data, method = "glmnet",
  trControl = trainControl(method = "cv", number = 5),
  tuneGrid = expand.grid(alpha = 0, lambda = lambda_ridge)
)

ridge_model
```

```
## glmnet
##
## 1000 samples
##   67 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 801, 801, 800, 799, 799
## Resampling results across tuning parameters:
##
##   lambda        RMSE       Rsquared   MAE
##   1.000000e-03  0.1028405  0.9215242  0.07745862
##   3.162278e-02  0.1028799  0.9214755  0.07748555
##   1.000000e+00  0.1455800  0.8929743  0.10462020
##   3.162278e+01  0.3325026  0.8505105  0.25795690
##   1.000000e+03  0.3628687        NaN  0.28398051
##
## Tuning parameter 'alpha' was held constant at a value of 0
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were alpha = 0 and lambda = 0.001.
```

```r
# Extract results for Ridge
ridge_results <- ridge_model$results
best_ridge_perf <- subset(ridge_results, ridge_results$RMSE == min(ridge_results$RMSE))
ridge_perf <- best_ridge_perf[, 1:4]
ridge_perf
```

```
##   alpha lambda      RMSE  Rsquared
## 1     0  0.001 0.1028405 0.9215242
```

```r
plot(ridge_model)
```



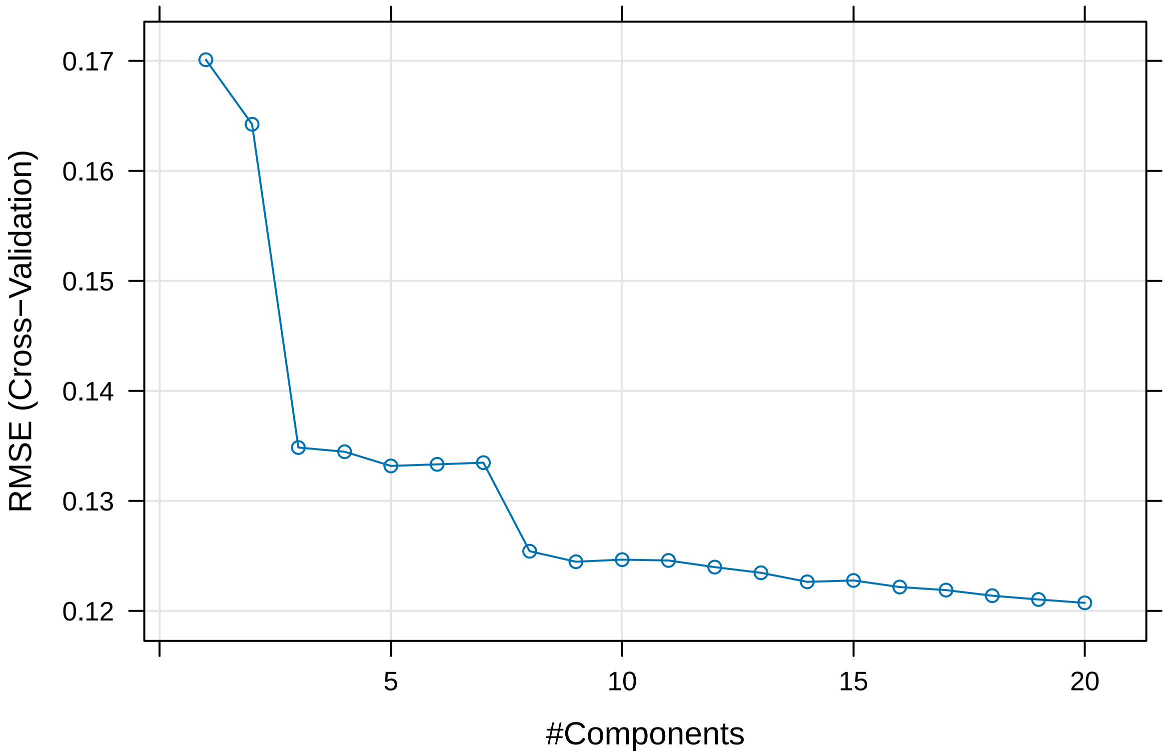

```r
# Build the ElasticNet model
set.seed(123)
elastic_model <- train(
  SalePrice ~ ., data = data, method = "glmnet",
  trControl = trainControl(method = "cv", number = 5),
  tuneLength = 10
)

elastic_results <- elastic_model$results
best_elastic_perf <- subset(elastic_results,
                            elastic_results$RMSE == min(elastic_results$RMSE))
elastic_perf <- best_elastic_perf[, 1:4]

elastic_perf
```

```
##    alpha      lambda     RMSE  Rsquared
## 65   0.7 0.003859544 0.101711 0.9193239
```

```r
# Build the PCR model
set.seed(1)
pcr_model <- train(SalePrice ~ ., data = data, method = "pcr",
                   tuneLength = 20, metric = "RMSE",
                   trControl = (trainControl(method = "cv", number = 5)),
                   preProc = c("center", "scale"))

pcr_model
```

```
## Principal Component Analysis
##
## 1000 samples
##   67 predictor
##
## Pre-processing: centered (67), scaled (67)
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 801, 801, 800, 799, 799
## Resampling results across tuning parameters:
##
##   ncomp  RMSE       Rsquared   MAE
##    1     0.1701037  0.7819618  0.12746462
##    2     0.1642354  0.7972012  0.12384750
##    3     0.1348489  0.8638040  0.10024819
##    4     0.1344690  0.8646946  0.09968538
##    5     0.1331776  0.8672175  0.09883725
##    6     0.1333219  0.8668801  0.09889975
##    7     0.1334738  0.8666219  0.09882253
##    8     0.1254227  0.8823501  0.09349766
##    9     0.1244691  0.8841165  0.09272263
##   10     0.1246582  0.8835870  0.09292842
##   11     0.1245832  0.8838489  0.09277726
##   12     0.1239785  0.8853334  0.09257153
##   13     0.1234621  0.8862226  0.09236980
##   14     0.1226404  0.8878841  0.09166850
##   15     0.1227633  0.8876754  0.09184973
##   16     0.1221681  0.8887609  0.09141195
##   17     0.1218901  0.8893217  0.09131148
##   18     0.1213793  0.8901707  0.09108105
##   19     0.1210364  0.8908090  0.09084028
##   20     0.1207309  0.8914422  0.09070347
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was ncomp = 20.
```

```r
plot(pcr_model)
```




```r
# Extract PCR model performance
pcr_results <- pcr_model$results
best_pcr_perf <- subset(pcr_results, pcr_results$RMSE == min(pcr_results$RMSE))
pcr_perf <- best_pcr_perf[, 1:3]

pcr_perf
```

```
##    ncomp      RMSE  Rsquared
## 20    20 0.1207309 0.8914422
```

```r
# Model
Model <- c("OLS", "OLS", "PLS", "LASSO", "Ridge", "ElasticNet", "PCR")
# Notes
notes <- c("lm - Stepwise", "lm + 2-way interactions", "caret",
           "caret and elasticnet", "caret and elasticnet", "caret
           and elasticnet", "caret")

hyps <- c("N/A", "N/A", paste("ncomp =", pls_perf$ncomp),
          paste("alpha =", lasso_perf$alpha, "and lambda =",
                round(lasso_perf$lambda, 4)),
          paste("alpha =", ridge_perf$alpha, "and lambda =",
                round(ridge_perf$lambda, 4)),
          paste("alpha =", elastic_perf$alpha, "and lambda =",
```

```
                 round(elastic_perf$lambda, 4)),
           paste("ncomp =", pcr_perf$ncomp))
# RMSE
rmses <- c(rmse_lm, rmse_lm2, pls_perf$RMSE,
            lasso_perf$RMSE, ridge_perf$RMSE,
            elastic_perf$RMSE, pcr_perf$RMSE)
# R-squared
rsqs <- c(lm_rsq, lm_rsq2, pls_perf$Rsquared,
           lasso_perf$Rsquared, ridge_perf$Rsquared,
           elastic_perf$Rsquared, pcr_perf$Rsquared)


perf <- data.frame(Model)
perf$Notes <- notes
perf$Hyperparameters <- hyps
# RMSE
perf$`CV RMSE` <- rmses
# R-Squared
perf$`CV R2` <- rsqs
# Sort by RMSE
perf <- perf[order(perf$`CV RMSE`),]
row.names(perf) <- NULL
perf <- data.frame(lapply(perf, function(y) if(is.numeric(y)) round(y, 4) else y))

knitr::kable(perf,
             caption = "Table 1: Summary of Model Performance with 5-fold CV")
```

Table 1: Table 1: Summary of Model Performance with 5-fold CV

Model	Notes	Hyperparameters	CV.RMSE	CV.R2
OLS	lm - Stepwise	N/A	0.0827	0.9480
OLS	lm + 2-way interactions	N/A	0.0932	0.9338
ElasticNet	caret			
and	alpha = 0.7 and lambda = 0.0039	0.1017	0.9193	
elasticnet				
LASSO	caret and elasticnet	alpha = 1 and lambda = 0.001	0.1026	0.9220
Ridge	caret and elasticnet	alpha = 0 and lambda = 0.001	0.1028	0.9215
PLS	caret	ncomp = 13	0.1033	0.9210
PCR	caret	ncomp = 20	0.1207	0.8914

	Est.	S.E.	t val.	p
(Intercept)	5.37	0.57	9.38	0.00
MSZoning2	-0.03	0.05	-0.61	0.54
MSZoning3	0.01	0.04	0.30	0.76
MSZoning4	-0.07	0.04	-1.73	0.08
LotArea	0.00	0.00	5.72	0.00
LotConfig2	0.02	0.01	1.70	0.09
LotConfig3	-0.01	0.01	-1.08	0.28
LotConfig4	-0.02	0.02	-0.91	0.36
Neighborhood2	-0.02	0.03	-0.75	0.45
Neighborhood3	-0.07	0.02	-2.80	0.01
Neighborhood4	0.09	0.03	3.46	0.00
Neighborhood5	-0.09	0.02	-4.35	0.00
Neighborhood6	-0.08	0.03	-3.16	0.00
Neighborhood7	0.05	0.03	1.55	0.12
Neighborhood8	-0.10	0.03	-3.86	0.00
Neighborhood9	-0.07	0.02	-3.31	0.00
Neighborhood10	-0.06	0.03	-1.86	0.06
Neighborhood11	0.01	0.03	0.40	0.69
Neighborhood12	-0.07	0.02	-2.95	0.00
Neighborhood13	-0.07	0.02	-3.43	0.00
Neighborhood14	-0.06	0.02	-2.45	0.01
Neighborhood15	-0.08	0.02	-3.39	0.00
Neighborhood16	-0.08	0.03	-3.26	0.00
Neighborhood17	0.01	0.04	0.13	0.90
Neighborhood18	-0.04	0.03	-1.24	0.22
Condition12	0.01	0.02	0.30	0.76
Condition13	0.04	0.02	2.27	0.02
Condition14	-0.02	0.05	-0.42	0.68
Condition15	-0.00	0.03	-0.01	0.99
Condition16	-0.01	0.03	-0.20	0.84
BldgType2	0.03	0.03	0.98	0.33
BldgType3	-0.02	0.03	-0.83	0.41
BldgType4	-0.10	0.02	-4.74	0.00
BldgType5	-0.04	0.02	-2.51	0.01
OverallQual	0.05	0.00	11.40	0.00
OverallCond	0.05	0.00	13.78	0.00
YearBuilt	0.00	0.00	9.36	0.00
RoofStyle2	0.02	0.01	1.75	0.08
RoofStyle3	0.09	0.02	4.06	0.00
Exterior1st2	-0.07	0.02	-2.94	0.00
Exterior1st3	-0.07	0.02	-3.85	0.00
Exterior1st4	-0.06	0.02	-3.30	0.00
Exterior1st5	-0.04	0.02	-2.05	0.04
Exterior1st6	-0.07	0.02	-3.75	0.00
Exterior1st7	-0.05	0.02	-2.73	0.01
Exterior1st8	-0.07	0.02	-3.95	0.00
ExterQual2	-0.01	0.01	-0.97	0.33
ExterQual3	-0.14	0.04	-3.15	0.00
ExterCond2	0.03	0.01	2.55	0.01
ExterCond3	0.05	0.03	1.60	0.11
Foundation2	0.01	0.01	0.94	0.35
Foundation3	-0.02	0.03	-0.76	0.45
Foundation4	0.04	0.02	2.56	0.01
BsmtCond2	-0.02	0.02	-1.17	0.24
BsmtCond3	0.06	0.03	2.34	0.02

Observations	900
Dependent variable	SalePrice
Type	OLS linear regression

$F(44,855)$	274.16
R^2	0.93
Adj. R^2	0.93

	Est.	S.E.	t val.	p
(Intercept)	10.72	0.63	16.99	0.00
MSZoning	-0.05	0.01	-7.18	0.00
LotFrontage	0.00	0.00	1.46	0.14
LotArea	0.00	0.00	6.68	0.00
LotShape	-0.00	0.00	-1.92	0.06
Neighborhood	-0.00	0.00	-5.04	0.00
Condition1	0.01	0.00	1.40	0.16
BldgType	-0.01	0.00	-1.94	0.05
OverallQual	0.08	0.01	5.12	0.00
OverallCond	0.07	0.01	4.57	0.00
YearRemodAdd	-0.00	0.00	-4.39	0.00
RoofStyle	0.02	0.01	2.80	0.01
Exterior1st	-0.01	0.00	-2.84	0.00
Exterior2nd	0.01	0.00	2.42	0.02
MasVnrType	0.01	0.01	1.77	0.08
ExterQual	-0.02	0.01	-1.54	0.12
ExterCond	0.02	0.01	2.11	0.03
Foundation	0.01	0.00	2.87	0.00
BsmtCond	-0.04	0.01	-2.69	0.01
BsmtExposure	-0.01	0.00	-1.95	0.05
BsmtFinSF1	0.00	0.00	11.18	0.00
BsmtFinSF2	0.00	0.00	5.92	0.00
BsmtUnfSF	0.00	0.00	7.07	0.00
HeatingQC	-0.01	0.01	-1.89	0.06
CentralAir	0.04	0.02	2.42	0.02
X1stFlrSF	0.00	0.00	13.46	0.00
X2ndFlrSF	0.00	0.00	18.04	0.00
LowQualFinSF	0.00	0.00	2.08	0.04
BsmtFullBath	0.01	0.01	1.61	0.11
BedroomAbvGr	-0.02	0.01	-3.47	0.00
KitchenAbvGr	-0.06	0.02	-3.24	0.00
KitchenQual	-0.02	0.01	-2.32	0.02
TotRmsAbvGrd	0.01	0.00	2.07	0.04
Functional	0.02	0.00	5.47	0.00
Fireplaces	0.03	0.01	5.44	0.00
GarageYrBlt	-0.00	0.00	-1.87	0.06
GarageFinish	-0.01	0.01	-1.47	0.14
GarageCars	0.04	0.01	3.36	0.00
GarageArea	0.00	0.00	2.27	0.02
WoodDeckSF	0.00	0.00	1.91	0.06
OpenPorchSF	0.00	0.00	2.20	0.03
EncPorchSF	0.00	0.00	3.95	0.00
PoolArea	0.00	0.00	1.45	0.15
‘YearBuilt:YearRemodAdd‘	0.00	0.00	8.17	0.00
‘OverallQual:OverallCond‘	-0.00	0.00	-1.49	0.14

Standard errors: OLS