

136_Liz_Project_Step5_Regularized Linear Regression

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```
#install.packages("glmnet")
#install.packages("mlbench")
#install.packages("Boruta")
library(caret)

## Loading required package: lattice

## Loading required package: ggplot2

library(tidyverse)

## -- Attaching packages -----
----- tidyverse 1.2.1 --

## v tibble 1.4.2      v purrr 0.2.5
## v tidyr 0.8.1      v dplyr 0.7.7
## v readr 1.1.1      v stringr 1.3.1
## v tibble 1.4.2      v forcats 0.3.0

## -- Conflicts -----
----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## x purrr::lift()    masks caret::lift()

library(psych)

##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##   %+%, alpha

library(glmnet)

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following object is masked from 'package:tidyr':
##
##   expand
```

```
## Loading required package: foreach

##
## Attaching package: 'foreach'

## The following objects are masked from 'package:purrr':
##
##   accumulate, when

## Loaded glmnet 2.0-16

library(mlbench)
library(Boruta)

## Loading required package: ranger

library(MASS) # stepwise regression

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##   select

library(leaps) # all subsets regression
library(randomForest)

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ranger':
##
##   importance

## The following object is masked from 'package:psych':
##
##   outlier

## The following object is masked from 'package:dplyr':
##
##   combine

## The following object is masked from 'package:ggplot2':
##
##   margin
```

Import Clean Data

```
H_Clean<-read.csv( file = "C:\\Users\\Hyunkyung Kim\\Desktop\\CKME999\\136\\dataset\\all\\H_clean.csv")
#H_Clean$MSSubClass<-as.factor(H_Clean$MSSubClass)
#Train<-H_Clean[!is.na(H_Clean$SalePrice),]
#Test<-H_Clean[is.na(H_Clean$SalePrice),]
act<-read.csv( file = "C:\\Users\\Hyunkyung Kim\\Desktop\\CKME999\\136\\dataset\\all\\AMES_test.csv")
# Test Price
H_clean_Combined<-merge(H_Clean[, -81], act, by = 'Id')
actual<-act[1461:2919, 2]
```

Divide as Train/Validate/Test set - give indexes.- Possibly for future.

Train - 1:1460 (50%) Validate - Random from 1460 to 2919 (20%) Test - Random from 1460 to 2919 (30%)

```
set.seed(100)

IndexTrain<-1:1460
IV<-NULL
IV[1:1460]<-0
IV[1461:2919]<-sample(2,1459, replace=T, prob=c(0.4,0.6))
#IV<-
## IV==1 is Validate, IV=2 is Test

#HTrain<-H_clean_Combined[IV==0,]
#HValid<-H_clean_Combined[IV==1,]
#HTest<-H_clean_Combined[IV==2,]

#
H_Eng<-H_clean_Combined
```

Remove Utilities - among 2919 observations there are only 1 exception and there is no point of keeping it. This is in the training set but since the test set does not contain any of level 1 and one observation will give too much variance. This is also causing issues when tuning.

```
H_Eng<-H_Eng[, names(H_Eng)!="Utilities"]
```

Function to predict and shoot out RMSE(log)

```
PdRMSE<-function(x,y=H_Clean[1461:2919, -81], z=actual){
Pdfun<-predict(x, newdata=y)
#return(Pdfun)
return(RMSE(log(Pdfun), log(z)))
}
```

```
f2<-SalePrice ~ OverallQual + GrLivArea + Neighborhood + BsmtFinSF1 +
  RoofMatl + MSSubClass + BsmtExposure + KitchenQual + Condition2 +
  SaleCondition + LotArea + YearBuilt + OverallCond + MasVnrArea +
  PoolQC + BedroomAbvGr + GarageCars + MasVnrType + TotalBsmtSF +
  BldgType + Functional + ExterQual + BsmtCond + Condition1 +
  Exterior1st + MoSold + GarageCond + ScreenPorch + LandContour +
  LowQualFinSF + LotConfig + LotFrontage + TotRmsAbvGrd + KitchenAbvGr +
  WoodDeckSF + Street + GarageArea + LotShape + BsmtQual +
  Fireplaces + FireplaceQu + PoolArea + RoofStyle + BsmtFinSF2 +      Exter
Cond #Removed Utilities.
f3<- SalePrice ~ LotFrontage + LotArea + Street + LotShape + LandContour +
  Utilities + LotConfig + Neighborhood + Condition1 + Condition2 +
  BldgType + HouseStyle + OverallQual + OverallCond + YearBuilt +
  RoofMatl + Exterior1st + MasVnrType + MasVnrArea + ExterQual +
  ExterCond + Foundation + BsmtQual + BsmtCond + BsmtExposure +
  BsmtFinSF1 + BsmtFinSF2 + BsmtUnfSF + X1stFlrSF + X2ndFlrSF +
  HalfBath + BedroomAbvGr + KitchenAbvGr + KitchenQual + TotRmsAbvGrd +
  Functional + Fireplaces + FireplaceQu + GarageType + GarageCars +
  GarageArea + WoodDeckSF + X3SsnPorch + ScreenPorch + PoolQC +
  Fence + MiscFeature + MoSold + SaleCondition
```

```
f4<-SalePrice ~MSSubClass+MSZoning+LotFrontage+LotArea+Alley+LotShape+LandCon
tour+LandSlope+Neighborhood+
BldgType+HouseStyle+OverallQual+OverallCond+YearBuilt+YearRemodAdd+RoofStyle+
Exterior1st+Exterior2nd+
MasVnrType+MasVnrArea+ExterQual+Foundation+BsmQual+BsmCond+BsmExposure+Bsm
tFinType1+BsmFinSF1+
BsmtFinType2+BsmUnfSF+TotalBsmtSF+HeatingQC+CentralAir+X1stFlrSF+X2ndFlrSF+G
rLivArea+BsmFullBath+
FullBath+HalfBath+BedroomAbvGr+KitchenAbvGr+KitchenQual+TotRmsAbvGrd+Fireplac
es+FireplaceQu+GarageType+
GarageYrBlt+GarageFinish+GarageCars+GarageArea+GarageQual+GarageCond+PavedDri
ve+WoodDeckSF+OpenPorchSF
```

Divide into numeric and categorical.

```
HC_numeric<-unlist(lapply(H_Clean,is.numeric))
HC_cat<-unlist(lapply(H_Clean,is.factor))
```

Need to update factors into numerics for glmnet - otherwise do not work. x_train <- model.matrix(~ .-1, train[,features]) best_lambda <- lmlambda[which.min(lmcvm)]
H_cat_dummy

Lasso

```
tc<-trainControl(method="repeatedcv", number=10, repeats=5)
#Trainset -DummyVariables
H_Dummy_Train<- as.data.frame(model.matrix(~.-1,data=H_Eng[IV==0,-1], na.act
ion = na.pass)) # Remove ID

#TestSet -DummyVariables
```

```

H_Dummy_Test<- as.data.frame(model.matrix(~.-1,data=H_Eng[1461:2919,-c(1,80)
])) # RemoveID, salePrice
      #as.data.frame

dim(H_Dummy_Train)

## [1] 1460 218

set.seed(12334)

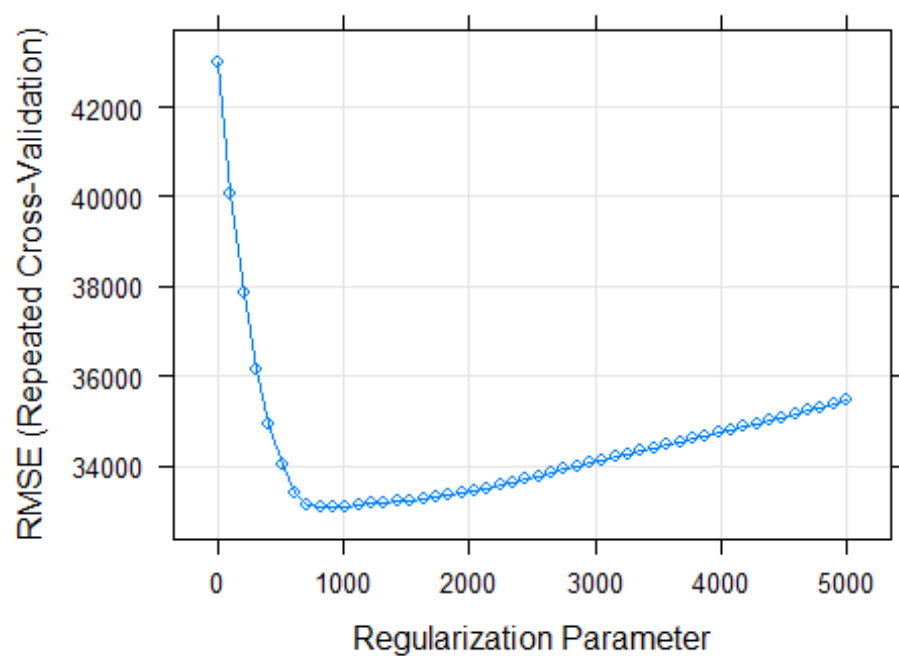
myLasso1<-train(SalePrice~.,
                data = H_Dummy_Train
                ,method='glmnet',
                tuneGrid=expand.grid(alpha=1,lambda=seq(0.001,5000,length=50
)), trControl=tc)
myLasso2<-train(SalePrice~., data = H_Dummy_Train[-c(524,1299),]
                ,method='glmnet',tuneGrid=expand.grid(alpha=1,lambda=seq(0.001,5000,length=
50)), trControl=tc)
#myLasso3 <-train(f3, data = H_Dummy_Train
# ,method='glmnet',tuneGrid=expand.grid(alpha=1,Lambda=seq(500,1500,Length=5
0)), trControl=tc)
#myLasso4 <-train(f4, data = H_Dummy_Train
# ,method='glmnet',tuneGrid=expand.grid(alpha=1,Lambda=seq(500,1500,Length=5
0)), trControl=tc)

set.seed(12334)

plot(myLasso1, main='model11')

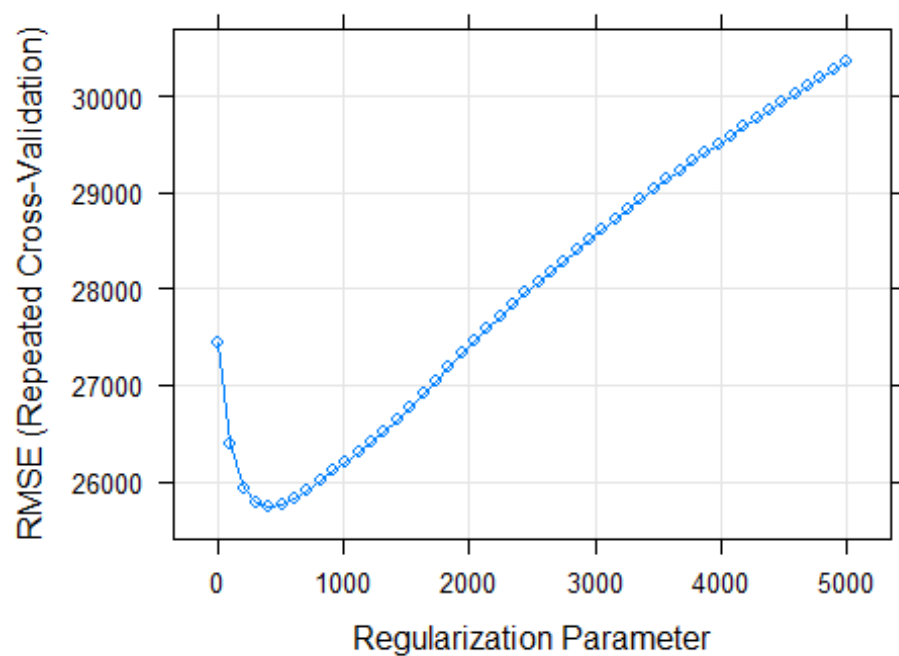
```

model1



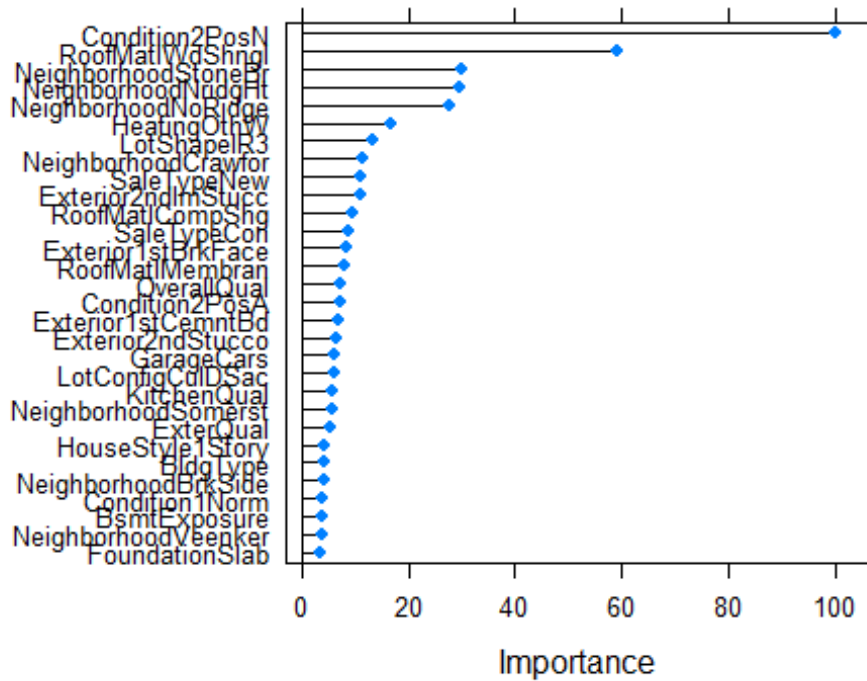
```
plot(myLasso2, main='model2')
```

model2

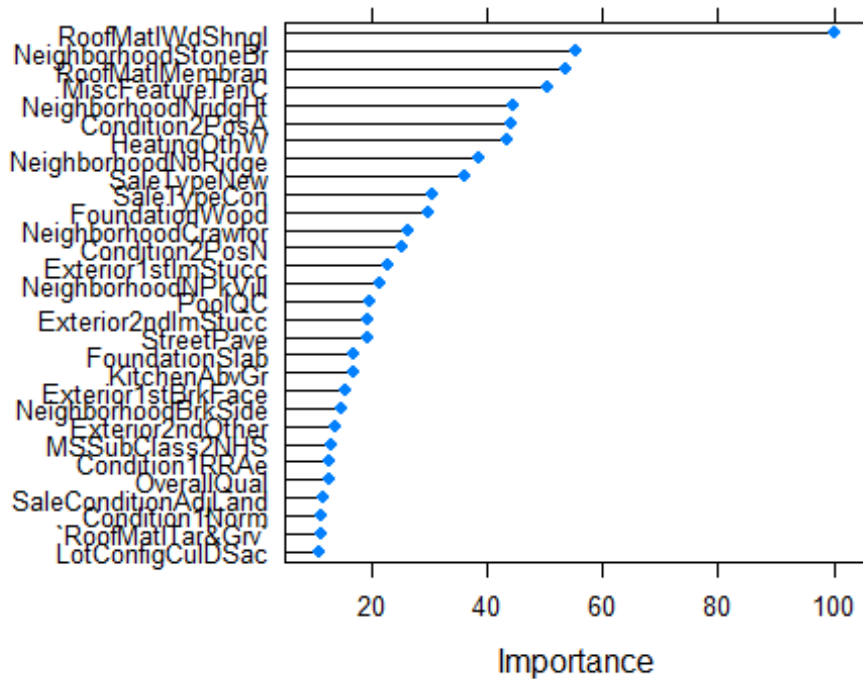


```
#plot(myLasso3,main='model3')
#plot(myLasso4,main='model4')
```

```
plot(varImp(myLasso1), Scale=F, top=30)
```



```
plot(varImp(myLasso2), Scale=F ,top=30)
```



```
#plot(varImp(myLasso3), Scale=F, top=25)
#plot(varImp(myLasso4), Scale=F ,top=25)
```

```
varImp(myLasso1)
```

```
## glmnet variable importance
##
## only 20 most important variables shown (out of 217)
##
## Overall
## Condition2PosN 100.000
## RoofMatlWdShngl 59.138
## NeighborhoodStoneBr 29.849
## NeighborhoodNridgHt 29.735
## NeighborhoodNoRidge 27.677
## HeatingOthW 16.673
## LotShapeIR3 13.449
## NeighborhoodCrawfor 11.482
## SaleTypeNew 11.246
## Exterior2ndImStucc 11.068
## RoofMatlCompShg 9.446
## SaleTypeCon 8.942
## Exterior1stBrkFace 8.549
## RoofMatlMembran 7.930
## OverallQual 7.379
## Condition2PosA 7.239
## Exterior1stCemntBd 6.787
```



```

## Exterior2ndStucco      6.576
## GarageCars            6.321
## LotConfigCulDSac      6.023

varImp(myLasso2)

## glmnet variable importance
##
##   only 20 most important variables shown (out of 217)
##
##               Overall
## RoofMatlWdShngl    100.00
## NeighborhoodStoneBr 55.45
## RoofMatlMembran     53.59
## MiscFeatureTenC     50.47
## NeighborhoodNridgHt 44.53
## Condition2PosA      44.21
## HeatingOthW         43.41
## NeighborhoodNoRidge 38.69
## SaleTypeNew         36.26
## SaleTypeCon         30.68
## FoundationWood      29.92
## NeighborhoodCrawfor 26.56
## Condition2PosN      25.40
## Exterior1stImStucc  22.90
## NeighborhoodNPkVill 21.33
## PoolQC              19.71
## Exterior2ndImStucc  19.52
## StreetPave          19.29
## FoundationSlab      17.01
## KitchenAbvGr        16.95

#varImp(myLasso3)
#varImp(myLasso4)

coef(myLasso1)

## NULL

coef(myLasso2    )

## NULL

#coef(myLasso3)
#coef(myLasso4)

myLasso1$bestTune

##   alpha   lambda
## 10      1 918.3682

```

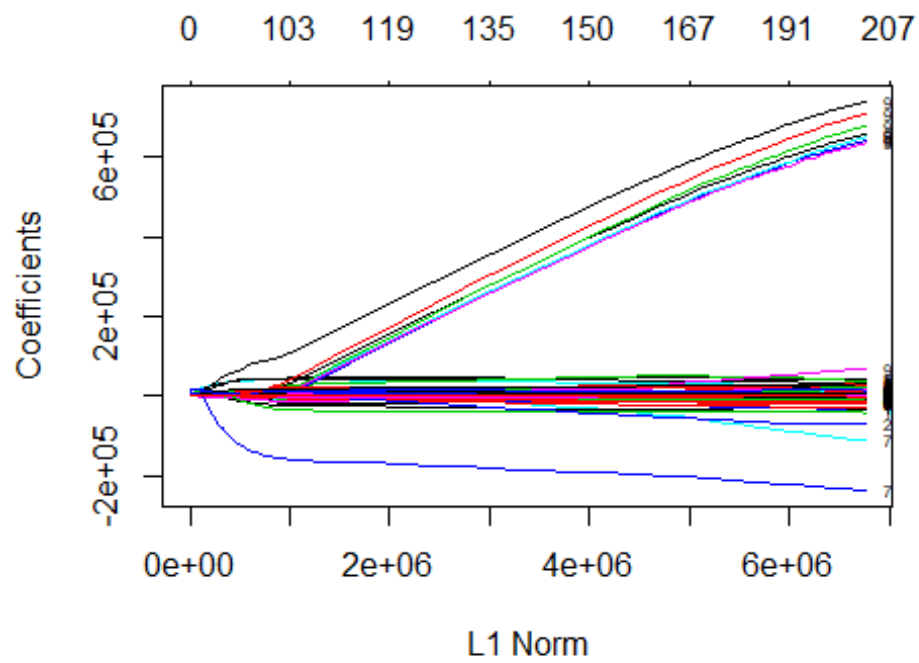
```
myLasso2$bestTune
```

```
##   alpha  lambda  
## 5      1 408.1642
```

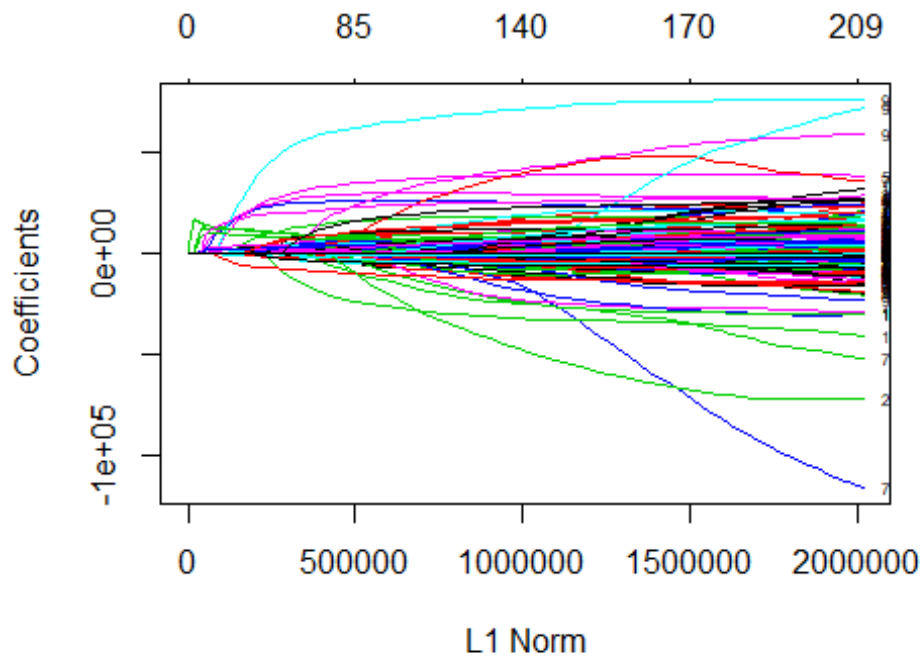
```
#myLasso3$bestTune
```

```
#myLasso4$bestTune
```

```
plot(myLasso1$finalModel, label=T)
```



```
plot(myLasso2$finalModel ,label=T)
```



```
#plot(myLasso3$finalModel)
#plot(myLasso4$finalModel)
```

Example of Coeff

```
coef(myLasso1$finalModel, s=myLasso1$bestTune$lambda)

## 218 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept)  -4.539657e+05
## `MSSubClass1N+PUD`      .
## MSSubClass1NHFin        .
## MSSubClass1NHUnf        .
## MSSubClass1SFA          .
## MSSubClass1SNEW         3.324209e+03
## MSSubClass1SOLD         .
## MSSubClass1SPUD         .
## MSSubClass2FCONV        .
## MSSubClass2NHS          .
## MSSubClass2SNEW         .
## MSSubClass2SOLD         .
## MSSubClassDUPL          .
## MSSubClassMLPUD         .
## MSSubClassSPL           .
## MSSubClassSPLF          .
## MSZoningFV              .
## MSZoningRH              .
```

## MSZoningRL	.
## MSZoningRM	-1.320008e+03
## LotFrontage	.
## LotArea	2.883250e-01
## StreetPave	9.064636e+02
## AlleyNoAlley	.
## AlleyPave	.
## LotShapeIR2	4.803337e+03
## LotShapeIR3	-1.930629e+04
## LotShapeReg	.
## LandContourHLS	5.082823e+03
## LandContourLow	.
## LandContourLvl	.
## LotConfigCulDSac	8.645689e+03
## LotConfigFR2	-7.405997e+01
## LotConfigFR3	-1.786943e+03
## LotConfigInside	.
## LandSlope	.
## NeighborhoodBlueste	.
## NeighborhoodBrDale	.
## NeighborhoodBrkSide	6.082094e+03
## NeighborhoodClearCr	.
## NeighborhoodCollgCr	.
## NeighborhoodCrawfor	1.648233e+04
## NeighborhoodEdwards	-2.066387e+03
## NeighborhoodGilbert	.
## NeighborhoodIDOTRR	.
## NeighborhoodMeadowV	.
## NeighborhoodMitchel	.
## NeighborhoodNames	.
## NeighborhoodNoRidge	3.972892e+04
## NeighborhoodNPkVill	.
## NeighborhoodNridgHt	4.268321e+04
## NeighborhoodNWAmes	-1.668130e+03
## NeighborhoodOldTown	-3.074045e+03
## NeighborhoodSawyer	.
## NeighborhoodSawyerW	.
## NeighborhoodSomerst	8.055050e+03
## NeighborhoodStoneBr	4.284677e+04
## NeighborhoodSWISU	.
## NeighborhoodTimber	.
## NeighborhoodVeenker	5.446138e+03
## Condition1Feedr	-2.546385e+03
## Condition1Norm	5.640058e+03
## Condition1PosA	.
## Condition1PosN	.
## Condition1RR Ae	-1.742488e+03
## Condition1RRAn	.
## Condition1RRNe	.
## Condition1RRNn	.

## Condition2Feedr	.
## Condition2Norm	.
## Condition2PosA	1.039167e+04
## Condition2PosN	-1.435469e+05
## Condition2RR Ae	.
## Condition2RR An	.
## Condition2RR Nn	.
## BldgType	6.336518e+03
## HouseStyle1.5Unf	.
## HouseStyle1Story	6.371419e+03
## HouseStyle2.5Fin	-1.913174e+03
## HouseStyle2.5Unf	.
## HouseStyle2Story	.
## HouseStyleSFoyer	.
## HouseStyleSLvl	.
## OverallQual	1.059280e+04
## OverallCond	2.917256e+03
## YearBuilt	1.251559e+02
## YearRemodAdd	2.071373e+01
## RoofStyleGable	-4.890518e+03
## RoofStyleGambrel	.
## RoofStyleHip	.
## RoofStyleMansard	.
## RoofStyleShed	.
## RoofMatlCompShg	1.355943e+04
## RoofMatlMembran	1.138374e+04
## RoofMatlMetal	.
## RoofMatlRoll	.
## `RoofMatlTar&Grv`	.
## RoofMatlWdShake	.
## RoofMatlWdShngl	8.489081e+04
## Exterior1stAsphShn	.
## Exterior1stBrkComm	.
## Exterior1stBrkFace	1.227188e+04
## Exterior1stCBlock	.
## Exterior1stCemntBd	9.742071e+03
## Exterior1stHdBoard	-1.622847e+03
## Exterior1stImStucc	-4.960084e+02
## Exterior1stMetalSd	.
## Exterior1stPlywood	.
## Exterior1stStone	.
## Exterior1stStucco	.
## Exterior1stVinylSd	.
## `Exterior1stWd Sdng`	-4.264067e+02
## Exterior1stWdShing	.
## Exterior2ndAsphShn	.
## `Exterior2ndBrk Cmn`	.
## Exterior2ndBrkFace	.
## Exterior2ndCBlock	.
## Exterior2ndCmentBd	.

## Exterior2ndHdBoard	.
## Exterior2ndImStucc	1.588788e+04
## Exterior2ndMetalSd	.
## Exterior2ndOther	.
## Exterior2ndPlywood	.
## Exterior2ndStone	.
## Exterior2ndStucco	-9.439429e+03
## Exterior2ndVinylSd	.
## `Exterior2ndWd Sdng`	.
## `Exterior2ndWd Shng`	-3.744145e+03
## MasVnrTypeBrkFace	-1.402610e+03
## MasVnrTypeNone	.
## MasVnrTypeStone	.
## MasVnrArea	1.973263e+01
## ExterQual	7.905622e+03
## ExterCond	.
## FoundationCBlock	.
## FoundationPConc	.
## FoundationSlab	5.251551e+03
## FoundationStone	.
## FoundationWood	.
## BsmtQual	3.274180e+03
## BsmtCond	-9.214782e+01
## BsmtExposure	5.513707e+03
## BsmtFinType1	1.071152e+03
## BsmtFinSF1	7.588560e+00
## BsmtFinType2	.
## BsmtFinSF2	.
## BsmtUnfSF	.
## TotalBsmtSF	.
## HeatingGasA	.
## HeatingGasW	.
## HeatingGrav	.
## HeatingOthW	-2.393407e+04
## HeatingWall	.
## HeatingQC	5.769865e+02
## CentralAirY	.
## ElectricalFuseF	.
## ElectricalFuseP	.
## ElectricalMix	.
## ElectricalSBrkr	.
## X1stFlrSF	.
## X2ndFlrSF	.
## LowQualFinSF	-2.162492e+00
## GrLivArea	4.852910e+01
## BsmtFullBath	3.776391e+03
## BsmtHalfBath	.
## FullBath	3.728424e+03
## HalfBath	8.072234e+02
## BedroomAbvGr	-1.688012e+03

## KitchenAbvGr	-3.294560e+03
## KitchenQual	8.104659e+03
## TotRmsAbvGrd	1.087187e+03
## Functional	3.129704e+03
## Fireplaces	3.584246e+03
## FireplaceQu	9.321132e+01
## GarageTypeAttchd	.
## GarageTypeBasment	-9.226457e+01
## GarageTypeBuiltIn	9.694822e+02
## GarageTypeCarPort	.
## GarageTypeDetchd	.
## GarageTypeNoGarage	3.992096e+03
## GarageYrBlt	.
## GarageFinish	.
## GarageCars	9.073116e+03
## GarageArea	.
## GarageQual	.
## GarageCond	.
## PavedDrive	.
## WoodDeckSF	9.939889e+00
## OpenPorchSF	.
## EnclosedPorch	.
## X3SsnPorch	.
## ScreenPorch	2.585779e+01
## PoolArea	.
## PoolQC	.
## FenceGdWo	.
## FenceMnPrv	.
## FenceMnWw	.
## FenceNoFence	.
## MiscFeatureNoMiscFeature	.
## MiscFeatureOthr	.
## MiscFeatureShed	.
## MiscFeatureTenC	.
## MiscVal	.
## MoSold	-1.214922e+02
## YrSold	.
## SaleTypeCon	1.283538e+04
## SaleTypeConLD	.
## SaleTypeConLI	.
## SaleTypeConLw	.
## SaleTypeCWD	.
## SaleTypeNew	1.614275e+04
## SaleTypeOth	.
## SaleTypeWD	.
## SaleConditionAdjLand	.
## SaleConditionAlloca	.
## SaleConditionFamily	-1.783551e+02
## SaleConditionNormal	.
## SaleConditionPartial	.

```
abcde<-predict(myLasso1, newdata=H_Dummy_Test)
#RMSE(abcde, actual)
```

```
PdRMSE(myLasso1,H_Dummy_Test,H_Eng$SalePrice[1461:2919])
```

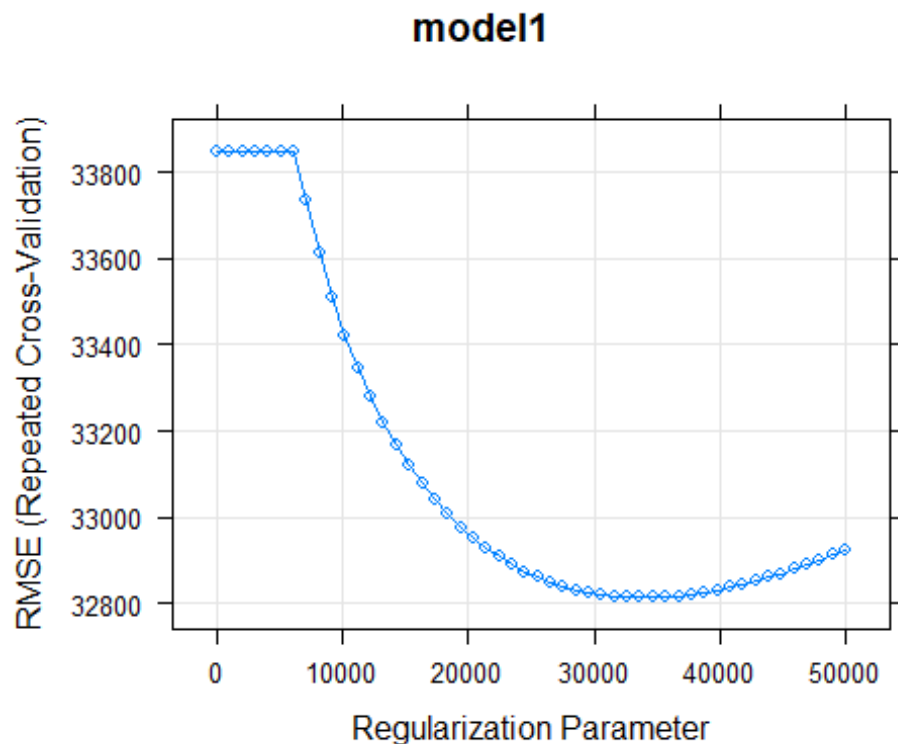
```
## [1] 0.1530179
```

```
PdRMSE(myLasso2,H_Dummy_Test,H_Eng$SalePrice[1461:2919])
```

```
## [1] 0.154825
```

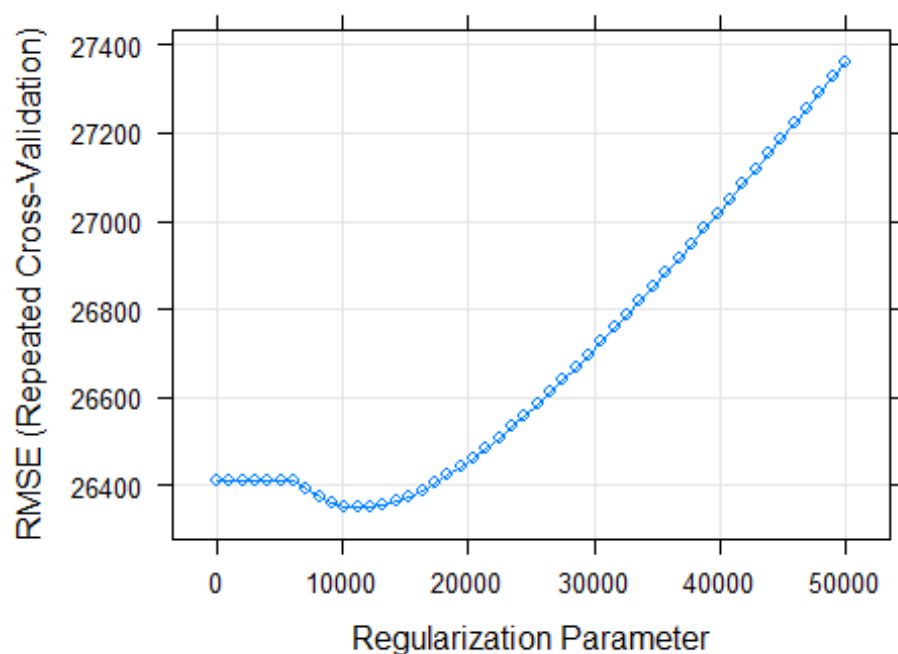
Ridge

```
set.seed(12334)
myRidge1 <-train(SalePrice~.,
                 data = H_Dummy_Train
                 ,method='glmnet',
                 tuneGrid=expand.grid(alpha=0,lambda=seq(0.001,50000,length=5
0)), trControl=tc)
set.seed(12334)
myRidge2 <-train(SalePrice~., data = H_Dummy_Train[-c(524,1299),]
                 ,method='glmnet',tuneGrid=expand.grid(alpha=0,lambda=seq(0.001,50000,length
=50)), trControl=tc) # without outlier
plot(myRidge1, main='model1')
```

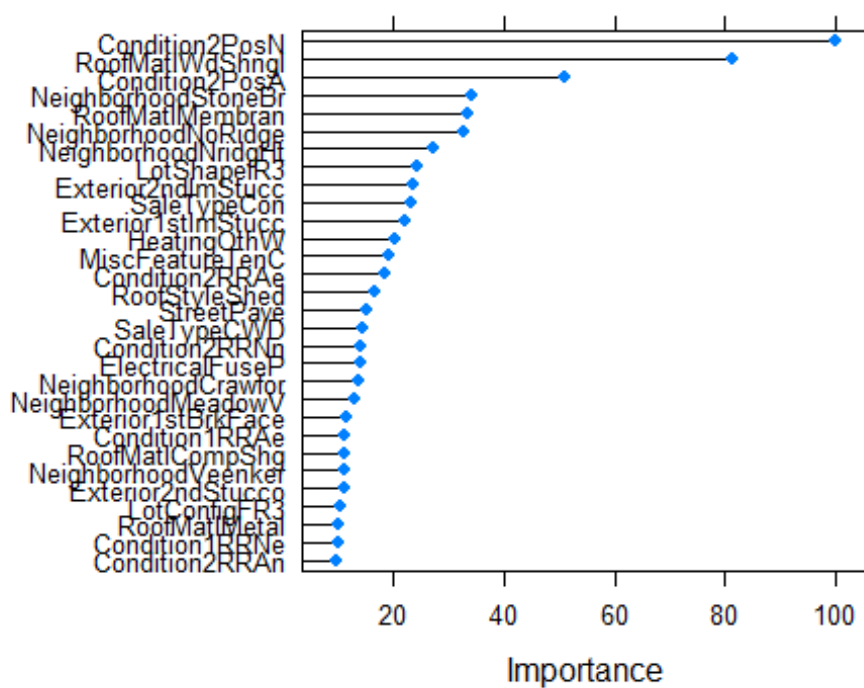


```
plot(myRidge2, main='model2')
```

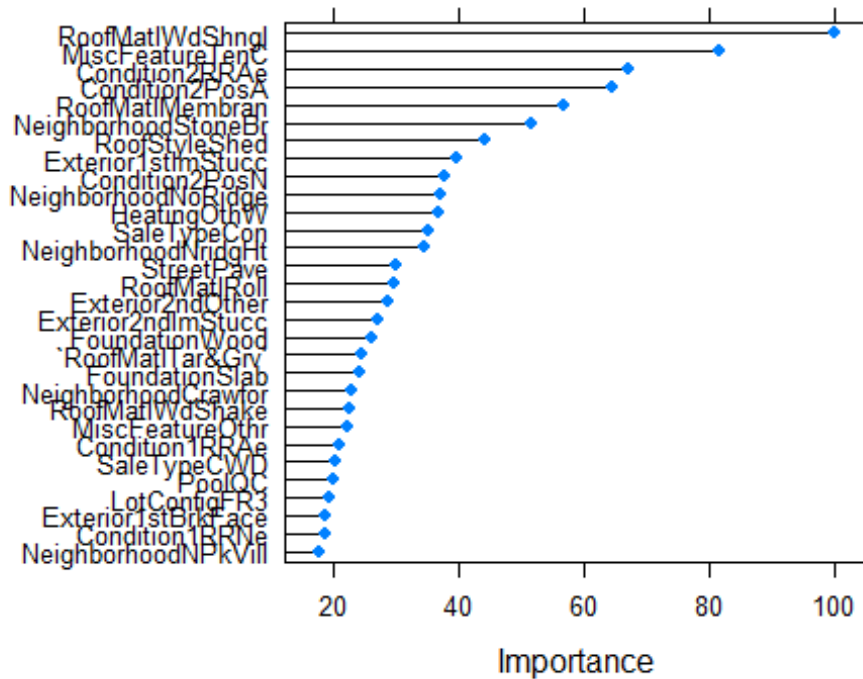

model2



```
plot(varImp(myRidge1), Scale=F, top=30)
```



```
plot(varImp(myRidge2), Scale=F ,top=30)
```



```
varImp(myRidge1)

## glmnet variable importance
##
##   only 20 most important variables shown (out of 217)
##
##               Overall
## Condition2PosN    100.00
## RoofMatlWdShngl   81.32
## Condition2PosA    51.01
## NeighborhoodStoneBr 34.28
## RoofMatlMembran   33.52
## NeighborhoodNoRidge 32.76
## NeighborhoodNridgHt 27.18
## LotShapeIR3       24.51
## Exterior2ndImStucc 23.81
## SaleTypeCon        23.32
## Exterior1stImStucc 22.02
## HeatingOthW        20.42
## MiscFeatureTenC    19.28
## Condition2RRAe     18.43
## RoofStyleShed      16.74
## StreetPave         15.28
## SaleTypeCWD        14.58
## Condition2RRNn     14.22
## ElectricalFuseP    14.14
## NeighborhoodCrawfor 13.89
```

```

varImp(myRidge2)

## glmnet variable importance
##
##   only 20 most important variables shown (out of 217)
##
##               Overall
## RoofMatlWdShngl    100.00
## MiscFeatureTenC     81.82
## Condition2RRAe      67.22
## Condition2PosA      64.38
## RoofMatlMembran     56.91
## NeighborhoodStoneBr 51.42
## RoofStyleShed       44.23
## Exterior1stImStucc  39.65
## Condition2PosN      37.52
## NeighborhoodNoRidge 37.15
## HeatingOthW         36.83
## SaleTypeCon         35.16
## NeighborhoodNridgHt 34.37
## StreetPave          29.90
## RoofMatlRoll        29.52
## Exterior2ndOther    28.65
## Exterior2ndImStucc  27.00
## FoundationWood      25.92
## `RoofMatlTar&Grv`   24.53
## FoundationSlab      23.95

myRidge1$bestTune

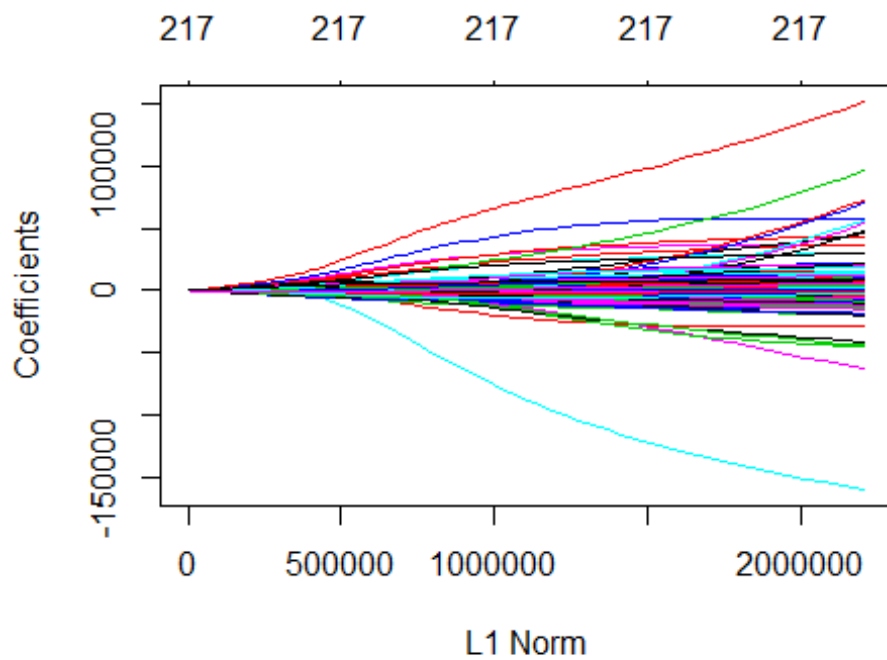
##   alpha  lambda
## 34      0 33673.47

myRidge2$bestTune

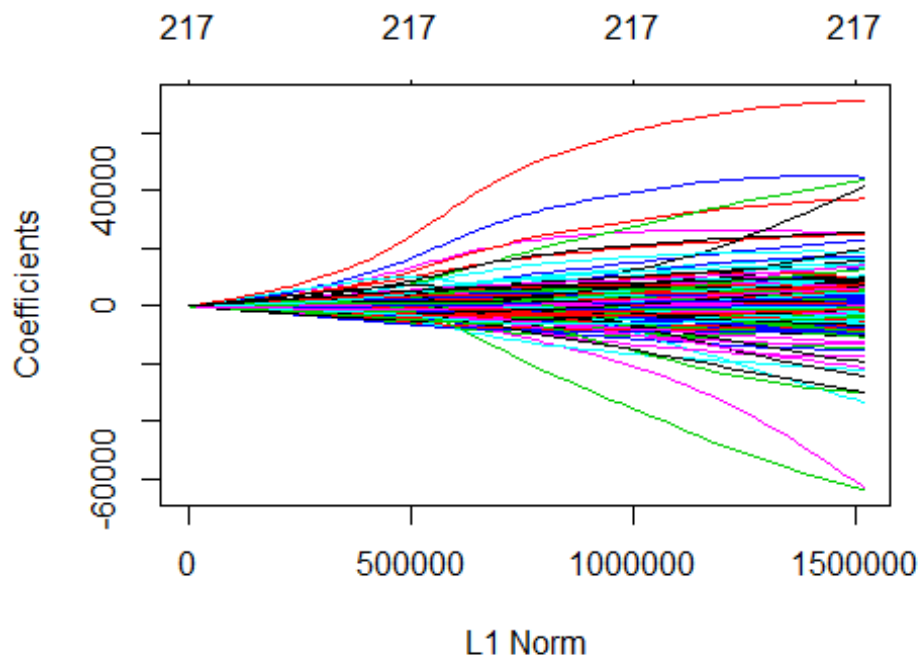
##   alpha  lambda
## 12      0 11224.49

plot(myRidge1$finalModel)

```



```
plot(myRidge2$finalModel)
```



Elasticnet

```
PdRMSE(myRidge1,H_Dummy_Test)
```

```
## [1] 0.1521245
```

```
PdRMSE(myRidge2,H_Dummy_Test)
```

```
## [1] 0.156761
```

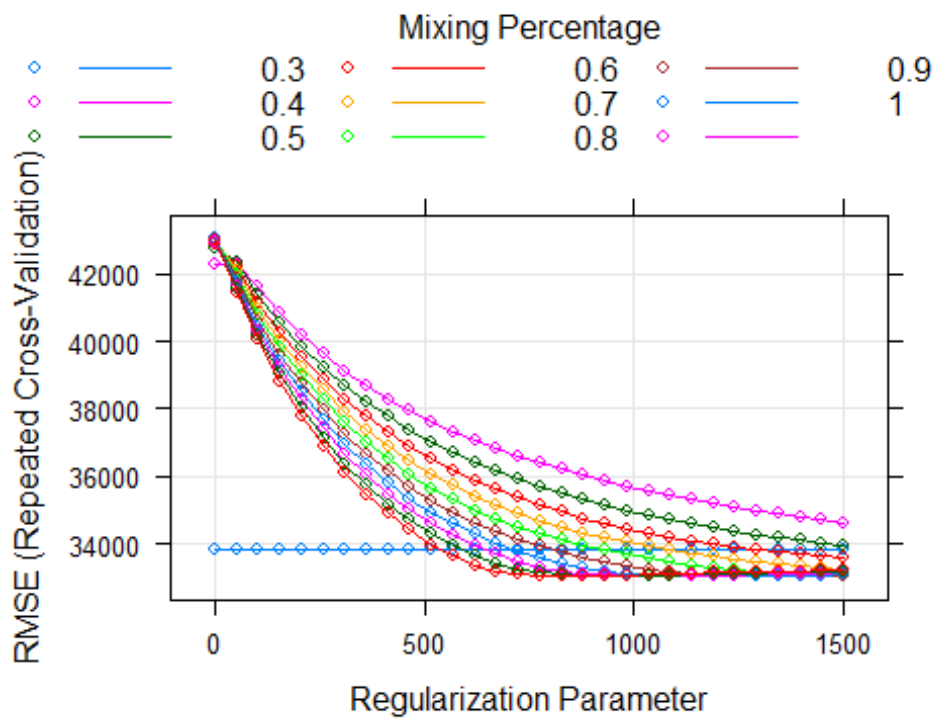
```
set.seed(12334)
```

```
myEla1<-train(SalePrice~.,data=H_Dummy_Train,method='glmnet',tuneGrid=expand.grid(alpha=seq(0, 1,length=11),lambda=seq(0.0001,1500,length=30)), trControl=tc)
```

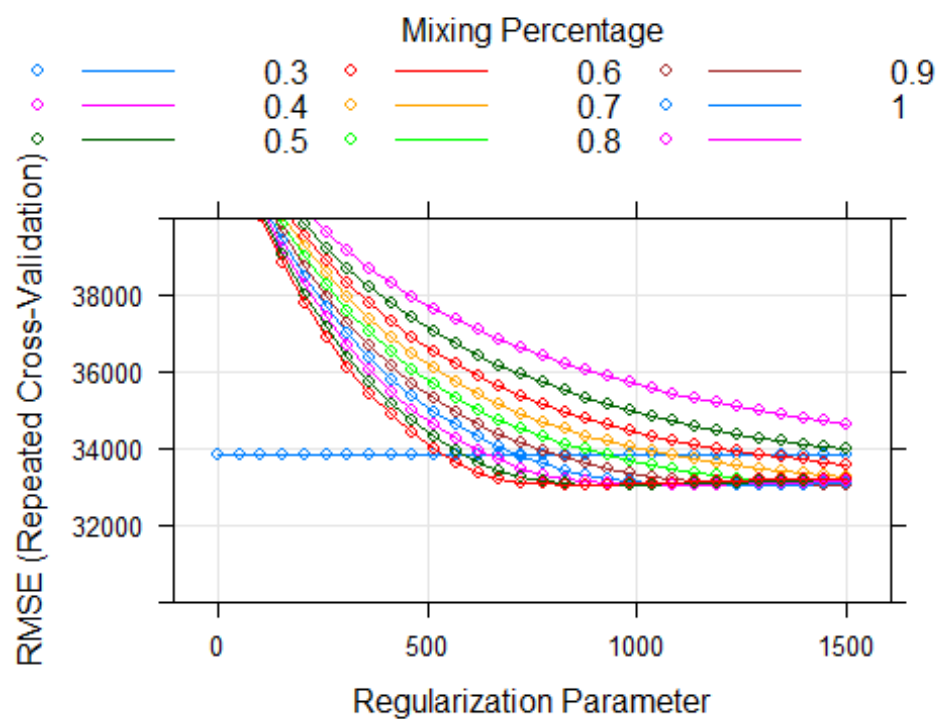
```
min(myEla1$result$RMSE)
```

```
## [1] 33040.03
```

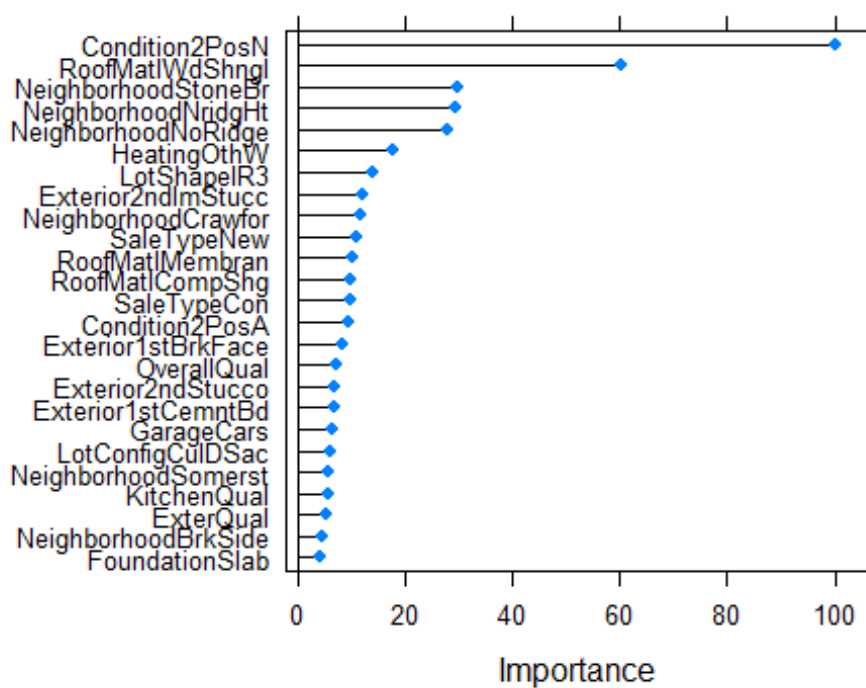
```
plot(myEla1, cex=0.8)
```



```
plot(myEla1, ylim=c(30000,40000))
```



```
plot(varImp(myEla1), top=25)
```



```
varImp(myEla1)
```

```
## glmnet variable importance
##
##   only 20 most important variables shown (out of 217)
##
##               Overall
## Condition2PosN    100.000
## RoofMatlWdShngl   60.404
## NeighborhoodStoneBr 29.976
## NeighborhoodNridgHt 29.489
## NeighborhoodNoRidge 28.100
## HeatingOthW       17.753
## LotShapeIR3        14.026
## Exterior2ndImStucc 12.103
## NeighborhoodCrawfor 11.760
## SaleTypeNew        11.186
## RoofMatlMembran    10.417
## RoofMatlCompShg    10.006
## SaleTypeCon         9.934
## Condition2PosA      9.478
## Exterior1stBrkFace  8.561
## OverallQual         7.251
## Exterior2ndStucco   6.862
## Exterior1stCemntBd  6.786
## GarageCars          6.389
## LotConfigCulDSac   6.089

myEla1$bestTune

##      alpha  lambda
## 208    0.6 1396.552

myEla1

## glmnet
##
## 1460 samples
## 217 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 5 times)
## Summary of sample sizes: 1314, 1314, 1313, 1316, 1315, 1313, ...
## Resampling results across tuning parameters:
##
##   alpha  lambda      RMSE      Rsquared    MAE
##   0.0     0.00010  33849.39  0.8236609 19442.43
##   0.0     51.72423  33849.39  0.8236609 19442.43
##   0.0    103.44837  33849.39  0.8236609 19442.43
##   0.0    155.17250  33849.39  0.8236609 19442.43
##   0.0    206.89664  33849.39  0.8236609 19442.43
##   0.0    258.62077  33849.39  0.8236609 19442.43
##   0.0    310.34491  33849.39  0.8236609 19442.43
```

##	0.0	362.06904	33849.39	0.8236609	19442.43
##	0.0	413.79318	33849.39	0.8236609	19442.43
##	0.0	465.51731	33849.39	0.8236609	19442.43
##	0.0	517.24144	33849.39	0.8236609	19442.43
##	0.0	568.96558	33849.39	0.8236609	19442.43
##	0.0	620.68971	33849.39	0.8236609	19442.43
##	0.0	672.41385	33849.39	0.8236609	19442.43
##	0.0	724.13798	33849.39	0.8236609	19442.43
##	0.0	775.86212	33849.39	0.8236609	19442.43
##	0.0	827.58625	33849.39	0.8236609	19442.43
##	0.0	879.31039	33849.39	0.8236609	19442.43
##	0.0	931.03452	33849.39	0.8236609	19442.43
##	0.0	982.75866	33849.39	0.8236609	19442.43
##	0.0	1034.48279	33849.39	0.8236609	19442.43
##	0.0	1086.20692	33849.39	0.8236609	19442.43
##	0.0	1137.93106	33849.39	0.8236609	19442.43
##	0.0	1189.65519	33849.39	0.8236609	19442.43
##	0.0	1241.37933	33849.39	0.8236609	19442.43
##	0.0	1293.10346	33849.39	0.8236609	19442.43
##	0.0	1344.82760	33849.39	0.8236609	19442.43
##	0.0	1396.55173	33849.39	0.8236609	19442.43
##	0.0	1448.27587	33849.39	0.8236609	19442.43
##	0.0	1500.00000	33849.39	0.8236609	19442.43
##	0.1	0.00010	42266.77	0.7493704	20801.35
##	0.1	51.72423	42266.77	0.7493704	20801.35
##	0.1	103.44837	41607.06	0.7544213	20663.02
##	0.1	155.17250	40862.51	0.7602992	20509.61
##	0.1	206.89664	40210.20	0.7656094	20377.76
##	0.1	258.62077	39640.22	0.7703653	20270.28
##	0.1	310.34491	39137.35	0.7746480	20180.30
##	0.1	362.06904	38694.63	0.7784909	20102.19
##	0.1	413.79318	38298.65	0.7819837	20033.56
##	0.1	465.51731	37945.27	0.7851397	19971.71
##	0.1	517.24144	37624.78	0.7880350	19915.94
##	0.1	568.96558	37332.95	0.7906963	19866.14
##	0.1	620.68971	37066.74	0.7931421	19820.31
##	0.1	672.41385	36822.49	0.7954019	19779.57
##	0.1	724.13798	36597.02	0.7975000	19741.21
##	0.1	775.86212	36388.11	0.7994498	19704.94
##	0.1	827.58625	36200.09	0.8012147	19670.87
##	0.1	879.31039	36022.81	0.8028799	19638.23
##	0.1	931.03452	35857.98	0.8044250	19607.31
##	0.1	982.75866	35706.90	0.8058444	19578.80
##	0.1	1034.48279	35561.80	0.8072096	19551.62
##	0.1	1086.20692	35432.68	0.8084241	19526.33
##	0.1	1137.93106	35306.64	0.8096129	19501.21
##	0.1	1189.65519	35191.68	0.8106952	19476.02
##	0.1	1241.37933	35079.27	0.8117548	19451.76
##	0.1	1293.10346	34979.31	0.8126973	19428.82
##	0.1	1344.82760	34882.19	0.8136128	19406.91

##	0.1	1396.55173	34792.78	0.8144539	19386.29
##	0.1	1448.27587	34709.37	0.8152354	19366.47
##	0.1	1500.00000	34627.73	0.8160009	19346.64
##	0.2	0.00010	42753.43	0.7457785	20863.57
##	0.2	51.72423	42333.56	0.7489153	20759.95
##	0.2	103.44837	41364.76	0.7563657	20519.67
##	0.2	155.17250	40532.39	0.7629930	20317.19
##	0.2	206.89664	39822.68	0.7688007	20154.92
##	0.2	258.62077	39209.86	0.7739601	20028.50
##	0.2	310.34491	38673.13	0.7785926	19925.61
##	0.2	362.06904	38197.96	0.7827711	19839.70
##	0.2	413.79318	37771.85	0.7865585	19763.71
##	0.2	465.51731	37383.98	0.7900652	19695.77
##	0.2	517.24144	37032.70	0.7932585	19633.86
##	0.2	568.96558	36710.32	0.7962063	19576.83
##	0.2	620.68971	36420.07	0.7988885	19525.66
##	0.2	672.41385	36155.95	0.8013461	19479.13
##	0.2	724.13798	35917.19	0.8035787	19436.54
##	0.2	775.86212	35697.85	0.8056356	19396.53
##	0.2	827.58625	35494.46	0.8075470	19358.71
##	0.2	879.31039	35310.48	0.8092786	19324.40
##	0.2	931.03452	35141.02	0.8108724	19292.04
##	0.2	982.75866	34983.92	0.8123498	19262.02
##	0.2	1034.48279	34841.13	0.8136922	19233.33
##	0.2	1086.20692	34705.83	0.8149646	19206.23
##	0.2	1137.93106	34587.06	0.8160803	19180.81
##	0.2	1189.65519	34472.15	0.8171625	19155.70
##	0.2	1241.37933	34370.65	0.8181179	19131.58
##	0.2	1293.10346	34273.92	0.8190276	19108.04
##	0.2	1344.82760	34188.56	0.8198298	19086.29
##	0.2	1396.55173	34109.57	0.8205720	19066.10
##	0.2	1448.27587	34035.11	0.8212734	19046.67
##	0.2	1500.00000	33970.21	0.8218817	19028.71
##	0.3	0.00010	42915.80	0.7446177	20882.34
##	0.3	51.72423	42205.71	0.7499201	20683.84
##	0.3	103.44837	41145.75	0.7581227	20391.36
##	0.3	155.17250	40259.69	0.7651983	20161.03
##	0.3	206.89664	39511.48	0.7713970	19986.22
##	0.3	258.62077	38863.51	0.7769084	19857.06
##	0.3	310.34491	38290.33	0.7819009	19749.65
##	0.3	362.06904	37776.16	0.7864273	19657.94
##	0.3	413.79318	37308.12	0.7906039	19574.93
##	0.3	465.51731	36892.68	0.7943672	19499.91
##	0.3	517.24144	36523.21	0.7977606	19434.82
##	0.3	568.96558	36188.72	0.8008583	19375.86
##	0.3	620.68971	35886.26	0.8036697	19322.99
##	0.3	672.41385	35613.22	0.8062211	19275.92
##	0.3	724.13798	35366.39	0.8085362	19233.46
##	0.3	775.86212	35144.24	0.8106217	19195.33
##	0.3	827.58625	34941.76	0.8125280	19158.58

##	0.3	879.31039	34756.62	0.8142754	19124.29
##	0.3	931.03452	34594.82	0.8158072	19093.83
##	0.3	982.75866	34447.17	0.8172084	19067.02
##	0.3	1034.48279	34315.65	0.8184539	19043.07
##	0.3	1086.20692	34200.20	0.8195489	19020.51
##	0.3	1137.93106	34095.14	0.8205459	18998.98
##	0.3	1189.65519	34001.53	0.8214372	18978.04
##	0.3	1241.37933	33916.51	0.8222494	18959.25
##	0.3	1293.10346	33839.16	0.8229934	18941.04
##	0.3	1344.82760	33771.33	0.8236472	18924.76
##	0.3	1396.55173	33703.74	0.8243077	18907.54
##	0.3	1448.27587	33643.11	0.8249022	18890.39
##	0.3	1500.00000	33585.94	0.8254674	18875.48
##	0.4	0.00010	42988.02	0.7441182	20889.42
##	0.4	51.72423	42083.68	0.7508868	20610.75
##	0.4	103.44837	40947.32	0.7596990	20278.91
##	0.4	155.17250	40022.35	0.7671621	20031.52
##	0.4	206.89664	39241.63	0.7736656	19855.86
##	0.4	258.62077	38545.35	0.7796285	19721.81
##	0.4	310.34491	37925.99	0.7850156	19607.61
##	0.4	362.06904	37373.96	0.7899081	19507.60
##	0.4	413.79318	36887.75	0.7942985	19419.79
##	0.4	465.51731	36458.07	0.7982244	19343.45
##	0.4	517.24144	36074.21	0.8017699	19280.07
##	0.4	568.96558	35728.69	0.8049858	19224.31
##	0.4	620.68971	35417.24	0.8079022	19174.19
##	0.4	672.41385	35139.30	0.8105186	19127.92
##	0.4	724.13798	34893.59	0.8128410	19087.13
##	0.4	775.86212	34678.06	0.8148857	19053.51
##	0.4	827.58625	34488.70	0.8166888	19024.70
##	0.4	879.31039	34320.54	0.8182946	18998.04
##	0.4	931.03452	34175.11	0.8196847	18973.89
##	0.4	982.75866	34048.19	0.8209001	18951.71
##	0.4	1034.48279	33931.72	0.8220279	18932.36
##	0.4	1086.20692	33825.32	0.8230704	18912.10
##	0.4	1137.93106	33724.57	0.8240694	18893.38
##	0.4	1189.65519	33632.57	0.8249937	18873.08
##	0.4	1241.37933	33550.43	0.8258231	18854.63
##	0.4	1293.10346	33476.47	0.8265720	18834.57
##	0.4	1344.82760	33412.50	0.8272232	18816.25
##	0.4	1396.55173	33350.56	0.8278433	18793.06
##	0.4	1448.27587	33291.69	0.8284294	18768.15
##	0.4	1500.00000	33240.36	0.8289432	18744.40
##	0.5	0.00010	43025.96	0.7438296	20889.53
##	0.5	51.72423	41971.23	0.7517741	20542.57
##	0.5	103.44837	40771.68	0.7611056	20181.89
##	0.5	155.17250	39816.89	0.7688579	19927.93
##	0.5	206.89664	38984.47	0.7758365	19749.04
##	0.5	258.62077	38245.09	0.7821531	19607.63
##	0.5	310.34491	37586.95	0.7879251	19486.07

##	0.5	362.06904	37014.34	0.7930502	19380.80
##	0.5	413.79318	36513.48	0.7976027	19294.74
##	0.5	465.51731	36064.07	0.8017462	19224.20
##	0.5	517.24144	35659.02	0.8055240	19160.82
##	0.5	568.96558	35305.60	0.8088415	19107.37
##	0.5	620.68971	34996.88	0.8117585	19059.14
##	0.5	672.41385	34729.30	0.8143056	19020.53
##	0.5	724.13798	34498.80	0.8165058	18988.34
##	0.5	775.86212	34296.44	0.8184452	18959.73
##	0.5	827.58625	34118.98	0.8201587	18935.14
##	0.5	879.31039	33962.39	0.8216867	18912.33
##	0.5	931.03452	33810.41	0.8232010	18888.68
##	0.5	982.75866	33680.79	0.8245039	18867.61
##	0.5	1034.48279	33565.10	0.8256746	18844.17
##	0.5	1086.20692	33467.34	0.8266675	18822.52
##	0.5	1137.93106	33372.56	0.8276135	18790.85
##	0.5	1189.65519	33292.26	0.8284181	18760.48
##	0.5	1241.37933	33224.62	0.8290937	18728.51
##	0.5	1293.10346	33168.05	0.8296537	18698.76
##	0.5	1344.82760	33124.83	0.8300830	18673.51
##	0.5	1396.55173	33094.27	0.8303838	18654.62
##	0.5	1448.27587	33071.24	0.8306087	18638.44
##	0.5	1500.00000	33054.50	0.8307732	18625.64
##	0.6	0.00010	43028.04	0.7438177	20877.69
##	0.6	51.72423	41856.20	0.7526869	20477.45
##	0.6	103.44837	40607.42	0.7624444	20093.47
##	0.6	155.17250	39612.76	0.7705512	19838.09
##	0.6	206.89664	38731.69	0.7779305	19653.11
##	0.6	258.62077	37948.94	0.7846714	19504.17
##	0.6	310.34491	37268.89	0.7906801	19377.81
##	0.6	362.06904	36676.90	0.7960170	19276.59
##	0.6	413.79318	36150.55	0.8008508	19193.64
##	0.6	465.51731	35681.97	0.8052120	19124.14
##	0.6	517.24144	35278.02	0.8090078	19066.23
##	0.6	568.96558	34930.10	0.8123133	19016.44
##	0.6	620.68971	34632.52	0.8151563	18977.64
##	0.6	672.41385	34377.71	0.8175985	18945.77
##	0.6	724.13798	34153.75	0.8197726	18920.36
##	0.6	775.86212	33943.49	0.8218598	18894.88
##	0.6	827.58625	33761.68	0.8236867	18870.62
##	0.6	879.31039	33606.46	0.8252591	18845.05
##	0.6	931.03452	33469.30	0.8266404	18814.49
##	0.6	982.75866	33348.99	0.8278466	18776.61
##	0.6	1034.48279	33253.54	0.8288028	18736.50
##	0.6	1086.20692	33176.87	0.8295647	18698.25
##	0.6	1137.93106	33126.00	0.8300686	18668.28
##	0.6	1189.65519	33090.15	0.8304188	18645.45
##	0.6	1241.37933	33065.14	0.8306644	18627.42
##	0.6	1293.10346	33048.06	0.8308309	18614.01
##	0.6	1344.82760	33041.97	0.8308860	18606.15

##	0.6	1396.55173	33040.03	0.8309037	18601.19
##	0.6	1448.27587	33041.08	0.8308952	18598.65
##	0.6	1500.00000	33044.60	0.8308650	18598.71
##	0.7	0.00010	43048.78	0.7437185	20875.10
##	0.7	51.72423	41749.91	0.7535238	20417.03
##	0.7	103.44837	40460.35	0.7636400	20017.13
##	0.7	155.17250	39416.24	0.7721671	19757.55
##	0.7	206.89664	38484.13	0.7799952	19566.04
##	0.7	258.62077	37667.52	0.7870827	19409.08
##	0.7	310.34491	36967.72	0.7933064	19286.59
##	0.7	362.06904	36347.75	0.7989473	19188.91
##	0.7	413.79318	35798.84	0.8040380	19108.73
##	0.7	465.51731	35330.21	0.8084395	19044.24
##	0.7	517.24144	34929.76	0.8122504	18990.84
##	0.7	568.96558	34595.22	0.8154456	18952.04
##	0.7	620.68971	34306.79	0.8182317	18924.56
##	0.7	672.41385	34034.09	0.8209429	18896.62
##	0.7	724.13798	33798.97	0.8233116	18869.30
##	0.7	775.86212	33604.86	0.8252768	18841.65
##	0.7	827.58625	33432.80	0.8270030	18798.72
##	0.7	879.31039	33298.62	0.8283527	18751.87
##	0.7	931.03452	33194.38	0.8293899	18702.98
##	0.7	982.75866	33132.01	0.8300092	18666.71
##	0.7	1034.48279	33089.76	0.8304223	18639.79
##	0.7	1086.20692	33061.39	0.8306993	18619.49
##	0.7	1137.93106	33047.81	0.8308249	18606.39
##	0.7	1189.65519	33044.01	0.8308564	18598.66
##	0.7	1241.37933	33044.73	0.8308474	18594.22
##	0.7	1293.10346	33048.56	0.8308134	18593.84
##	0.7	1344.82760	33055.47	0.8307539	18597.39
##	0.7	1396.55173	33065.15	0.8306703	18605.70
##	0.7	1448.27587	33078.80	0.8305532	18618.23
##	0.7	1500.00000	33093.82	0.8304248	18633.94
##	0.8	0.00010	42968.85	0.7443102	20854.87
##	0.8	51.72423	41651.90	0.7542840	20361.66
##	0.8	103.44837	40320.68	0.7647750	19949.04
##	0.8	155.17250	39220.68	0.7737571	19682.45
##	0.8	206.89664	38243.53	0.7820186	19483.87
##	0.8	258.62077	37405.38	0.7893318	19328.80
##	0.8	310.34491	36669.62	0.7959389	19208.46
##	0.8	362.06904	36026.53	0.8018534	19114.59
##	0.8	413.79318	35475.08	0.8070082	19039.97
##	0.8	465.51731	35006.87	0.8114543	18980.81
##	0.8	517.24144	34617.44	0.8151762	18942.33
##	0.8	568.96558	34275.52	0.8185100	18914.80
##	0.8	620.68971	33960.07	0.8216825	18884.67
##	0.8	672.41385	33700.15	0.8243142	18854.35
##	0.8	724.13798	33479.14	0.8265366	18808.09
##	0.8	775.86212	33311.22	0.8282255	18752.64
##	0.8	827.58625	33186.74	0.8294665	18694.62

##	0.8	879.31039	33123.02	0.8300962	18656.97
##	0.8	931.03452	33080.26	0.8305135	18628.89
##	0.8	982.75866	33056.51	0.8307385	18609.52
##	0.8	1034.48279	33049.60	0.8307964	18598.63
##	0.8	1086.20692	33048.77	0.8307993	18591.88
##	0.8	1137.93106	33052.06	0.8307687	18589.92
##	0.8	1189.65519	33059.62	0.8307030	18593.80
##	0.8	1241.37933	33071.77	0.8305981	18604.70
##	0.8	1293.10346	33087.79	0.8304608	18620.52
##	0.8	1344.82760	33102.45	0.8303430	18639.71
##	0.8	1396.55173	33117.96	0.8302222	18660.89
##	0.8	1448.27587	33133.47	0.8301071	18683.85
##	0.8	1500.00000	33145.60	0.8300257	18704.30
##	0.9	0.00010	42992.55	0.7441108	20846.34
##	0.9	51.72423	41552.49	0.7550684	20308.92
##	0.9	103.44837	40180.59	0.7659105	19887.40
##	0.9	155.17250	39025.94	0.7753546	19611.52
##	0.9	206.89664	38010.32	0.7839865	19409.57
##	0.9	258.62077	37142.04	0.7916197	19256.73
##	0.9	310.34491	36378.36	0.7985457	19141.09
##	0.9	362.06904	35721.92	0.8046331	19051.63
##	0.9	413.79318	35167.31	0.8098736	18983.32
##	0.9	465.51731	34713.03	0.8142051	18942.61
##	0.9	517.24144	34301.86	0.8182377	18911.38
##	0.9	568.96558	33934.91	0.8219348	18878.96
##	0.9	620.68971	33637.58	0.8249409	18840.90
##	0.9	672.41385	33402.52	0.8273107	18784.72
##	0.9	724.13798	33229.21	0.8290444	18713.55
##	0.9	775.86212	33140.23	0.8299278	18664.12
##	0.9	827.58625	33086.62	0.8304503	18630.11
##	0.9	879.31039	33060.06	0.8306987	18608.05
##	0.9	931.03452	33053.18	0.8307553	18595.65
##	0.9	982.75866	33053.02	0.8307510	18588.79
##	0.9	1034.48279	33057.58	0.8307099	18588.46
##	0.9	1086.20692	33067.81	0.8306200	18596.57
##	0.9	1137.93106	33084.51	0.8304750	18612.26
##	0.9	1189.65519	33100.91	0.8303399	18632.98
##	0.9	1241.37933	33117.16	0.8302130	18656.24
##	0.9	1293.10346	33133.32	0.8300943	18681.32
##	0.9	1344.82760	33147.28	0.8300009	18704.63
##	0.9	1396.55173	33163.85	0.8298872	18732.06
##	0.9	1448.27587	33173.89	0.8298373	18755.70
##	0.9	1500.00000	33183.63	0.8297905	18779.61
##	1.0	0.00010	43012.73	0.7439951	20852.08
##	1.0	51.72423	41457.59	0.7558252	20257.95
##	1.0	103.44837	40043.14	0.7670198	19829.41
##	1.0	155.17250	38834.70	0.7769281	19544.75
##	1.0	206.89664	37788.00	0.7858705	19343.53
##	1.0	258.62077	36881.94	0.7939073	19194.83
##	1.0	310.34491	36097.33	0.8010872	19083.50

```
## 1.0      362.06904 35431.66 0.8073168 18999.85
## 1.0      413.79318 34890.68 0.8124535 18950.36
## 1.0      465.51731 34404.90 0.8171951 18916.70
## 1.0      517.24144 33972.28 0.8215560 18881.46
## 1.0      568.96558 33623.54 0.8250768 18835.94
## 1.0      620.68971 33361.40 0.8277180 18767.02
## 1.0      672.41385 33192.23 0.8294144 18692.15
## 1.0      724.13798 33113.95 0.8301817 18645.49
## 1.0      775.86212 33070.48 0.8306008 18615.17
## 1.0      827.58625 33058.27 0.8307032 18598.50
## 1.0      879.31039 33056.75 0.8307080 18588.98
## 1.0      931.03452 33061.20 0.8306661 18587.23
## 1.0      982.75866 33072.55 0.8305672 18596.07
## 1.0     1034.48279 33091.26 0.8304071 18613.90
## 1.0     1086.20692 33107.38 0.8302771 18637.49
## 1.0     1137.93106 33124.92 0.8301398 18664.30
## 1.0     1189.65519 33140.61 0.8300305 18690.61
## 1.0     1241.37933 33159.29 0.8298964 18719.08
## 1.0     1293.10346 33173.32 0.8298126 18746.73
## 1.0     1344.82760 33183.27 0.8297686 18772.97
## 1.0     1396.55173 33194.21 0.8297190 18799.18
## 1.0     1448.27587 33203.09 0.8296895 18823.06
## 1.0     1500.00000 33215.09 0.8296323 18849.75
##
## RMSE was used to select the optimal model using the smallest value.
## The final values used for the model were alpha = 0.6 and lambda = 1396.552
.

PdEla1<-predict(myEla1, newdata=H_Dummy_Test)
RMSE(log(PdEla1), log(actual))

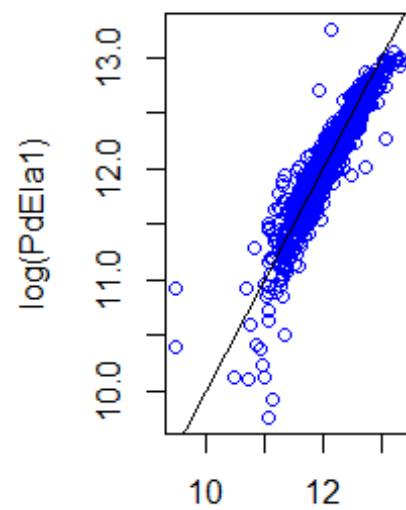
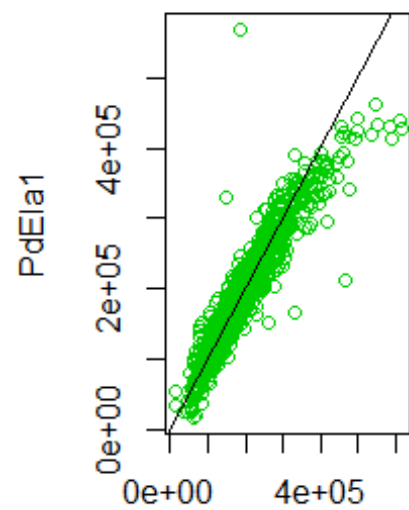
## [1] 0.1527468

PdRMSE(myEla1,H_Dummy_Test,H_Eng$SalePrice[1461:2919])

## [1] 0.1527468
```

Plot Elasticnet Result

```
par(mfrow=c(1,2))
plot(H_Eng$SalePrice[1461:2919], PdEla1, col=203)
abline(a=0,b=1)
plot(log(H_Eng$SalePrice[1461:2919]), log(PdEla1), col=204)
abline(a=0,b=1)
```



$H_Eng\$SalePrice[1461:2919]$ $\log(H_Eng\$SalePrice[1461:2919])$