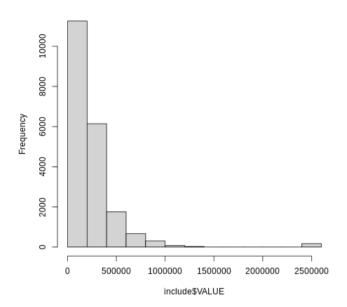
```
%load ext rpy2.ipython
from google.colab import files
uploaded = files.upload()
for fn in uploaded.keys():
  print('User uploaded file "{name}" with length {length} bytes'.format(
      name=fn, length=len(uploaded[fn])))
     选择文件 include_sum_numeric.txt
    • include sum numeric.txt(text/plain) - 4639780 bytes, last modified: 2021/12/11 - 100% done
    Saving include sum numeric.txt to include sum numeric.txt
    User uploaded file "include sum numeric.txt" with length 4639780 bytes
%%R
include = read.table('include sum numeric.txt')
%%R
install.packages('fastDummies')
library('fastDummies')
88R
include = dummy_cols(include, select_columns = c('METRO3','SMSA','CMSA','REGION','DIVISION','NUNIT2','BATHS','BEDRMS','BUILT','TENURE','KITCHEN','HHCITSHP','HHRACE','CELLAR','HHGRAD','TYPE
include = subset(include, select = -c(METRO3,SMSA,CMSA,REGION,DIVISION,NUNIT2,BATHS,BEDRMS,BUILT,TENURE,KITCHEN,HHCITSHP,HHRACE,CELLAR,HHGRAD,TYPE,WATER))
%%R
dim(include)
     [1] 20415 317
%%R
include = subset(include, select = -CONTROL)
for(i in 1:20415){
    for (j in list('PORCH','IFFEE','TXRE','WATERS','BSINK','SHARPF','TOILET','TUB','GARAGE','DRSHOP','DRSHOP','OTBUP','EBAR','HDSB','HHSPAN','NEWC','HOTPIP')){
        if (include[i,j]==2){
            include[i,j] = 0
        }
for(i in 1:20415){
    if (include[i,'CONDO']==3){
            include[i,'CONDO'] = 0
```

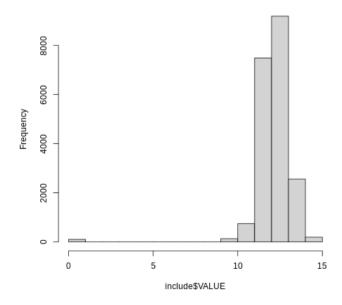
hist(include\$VALUE)

Histogram of include\$VALUE



%%R
include\$VALUE = log(include\$VALUE)
hist(include\$VALUE)

Histogram of include\$VALUE

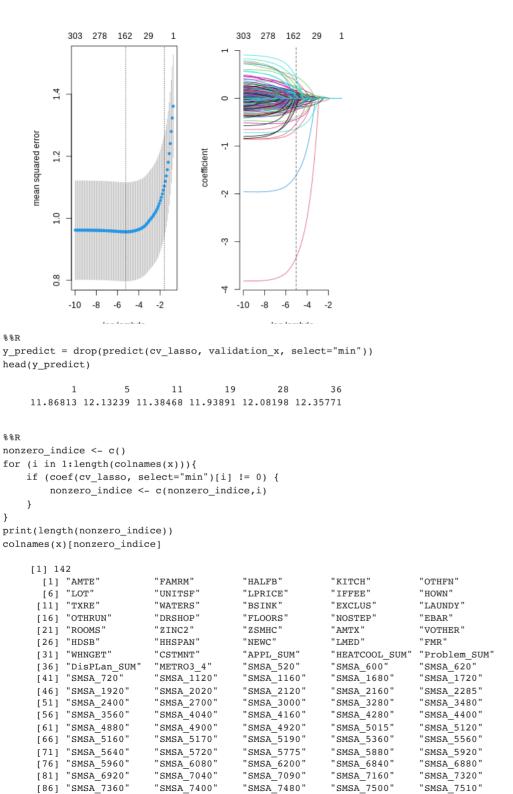


```
# 1/5 of sample for prediction in the test
set.seed(0)
n = 20415/5
test index = sample(c(1:20415), size=n)
sample test = include[test index,]
sample train = include[-test index,]
88R
dim(sample train)
    [1] 16332 310
%%R
# linear regression
OLS model <- glm(VALUE ~., data=sample train)
summary(OLS model)
    BUILT 2011
                  1.409e-01 2.553e-01 0.552 0.580964
    BUILT 2012
                  2.045e-01 2.552e-01
                                       0.801 0.422989
    BUILT 2013
                 4.101e-01 4.912e-01
                                       0.835 0.403774
    KITCHEN 2
                  2.337e-01 1.564e-01 1.494 0.135158
    HHCITSHP 2
                 1.812e-02 9.105e-02
                                      0.199 0.842232
    HHCITSHP 3
                 -2.149e-01 9.194e-02 -2.338 0.019407 *
    \mathtt{HHCITSHP}_4
                 2.747e-02 3.602e-02
                                       0.763 0.445755
                  2.119e-03 4.558e-02
                                      0.046 0.962915
    HHCITSHP 5
                 -2.011e-01 3.113e-02 -6.458 1.09e-10 ***
    HHRACE 2
    HHRACE 3
                  2.564e-02 1.184e-01 0.217 0.828568
    HHRACE 4
                 -6.330e-03 4.786e-02 -0.132 0.894773
    HHRACE 5
                 -1.881e-02 1.687e-01 -0.111 0.911222
                 -4.079e-01 1.903e-01 -2.143 0.032124 *
    HHRACE 6
    HHRACE 7
                 -2.552e-01 1.218e-01 -2.095 0.036205
                 1.174e-01 2.405e-01 0.488 0.625336
    HHRACE 8
                 -7.933e-01 6.969e-01 -1.138 0.254993
    HHRACE 9
    HHRACE 10
                 2.010e-01 4.920e-01 0.409 0.682848
    HHRACE 11
                 -1.343e-01 5.683e-01 -0.236 0.813137
    HHRACE 13
                 1.478e-01 9.884e-01 0.149 0.881165
    HHRACE 14
                 -4.067e-01 4.233e-01 -0.961 0.336737
    HHRACE_15
                 -5.270e-02 4.025e-01 -0.131 0.895841
    HHRACE 17
                         NA
                                   NA
                                           NA
    HHRACE 18
                  6.118e-01 1.012e+00
                                       0.605 0.545414
    HHRACE 19
                 -6.397e-01 9.876e-01 -0.648 0.517156
    HHRACE 21
                  7.548e-01 9.960e-01
                                       0.758 0.448565
    CELLAR 2
                  4.052e-02 2.513e-02
                                       1.613 0.106848
                 -1.447e-02 2.845e-02 -0.509 0.610988
    CELLAR 3
    CELLAR 4
                 -1.177e-01 3.040e-02 -3.872 0.000108 ***
    CELLAR 5
                 -2.568e-02 8.229e-02 -0.312 0.755013
    HHGRAD 32
                 -2.254e-02 2.828e-01 -0.080 0.936472
                  2.707e-01 2.624e-01
    HHGRAD 33
                                       1.031 0.302382
    HHGRAD 34
                  1.235e-01 2.593e-01
                                       0.476 0.633835
    HHGRAD 35
                  8.527e-02 2.626e-01 0.325 0.745402
    HHGRAD 36
                  1.896e-01 2.603e-01 0.728 0.466534
    HHGRAD 37
                  1.194e-01 2.601e-01
                                      0.459 0.646293
    HHGRAD 38
                  2.820e-01 2.557e-01
                                      1.103 0.270120
    HHGRAD 39
                  2.691e-01 2.506e-01 1.074 0.282918
    HHGRAD 40
                  2.954e-01 2.510e-01 1.177 0.239276
    HHGRAD 41
                  2.437e-01 2.538e-01
                                        0.960 0.336843
    HHGRAD 42
                  2.571e-01 2.527e-01
                                       1.018 0.308930
    HHGRAD 43
                  3.640e-01 2.531e-01
                                       1.438 0.150434
                  3.399e-01 2.509e-01
    HHGRAD 44
                                       1.355 0.175537
    HHGRAD 45
                  4.012e-01 2.515e-01
                                      1.595 0.110719
```

```
HHGRAD 47
                  4.376e-01 2.559e-01 1.710 0.087288 .
    WATER 2
                  5.932e-02 8.868e-02 0.669 0.503566
    WATER 3
                  1.526e-01 2.742e-01 0.556 0.577909
    WATER 4
                  1.130e-01 3.396e-01 0.333 0.739213
    WATER 5
                  9.459e-01 5.682e-01 1.665 0.096014 .
    Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
     (Dispersion parameter for gaussian family taken to be 0.9573114)
        Null deviance: 22577 on 16331 degrees of freedom
    Residual deviance: 15349 on 16033 degrees of freedom
    AIC: 45934
    Number of Fisher Scoring iterations: 2
%%R
# 9/10 of sample for estimation, 1/10 of sample for test
set.seed(0)
n est sample <- round(9*length(sample_train[,1])/10)</pre>
est sample ind <- sample.int(n = length(sample train[,1]), size = n est sample, replace = FALSE)
training sample = sample train[est sample ind,]
training true y = training sample['VALUE']
validation sample = sample_train[-est_sample_ind,]
validation x = subset(validation sample, select = -VALUE)
validation true y = validation sample['VALUE']
OLS model <- glm(VALUE ~ ., data=training sample)
in sample predictions = predict(OLS model, newdata = training sample)
out sample predictions = predict(OLS model, newdata = validation x)
is mse = sum((training true y - in sample predictions)^2)/length(training true y)
is rmse = is mse^{(0.5)}
cat(is mse,' ', is rmse)
    13564.91 116.4685
oos mse = sum((validation true y - out sample predictions)^2)/length(validation true y)
oos rmse = oos_mse^(0.5)
cat(oos mse,' ', oos_rmse)
    1836.477 42.85414
%%R
#lasso
install.packages('gamlr')
library(gamlr)
%%R
set.seed(0)
training x = subset(training sample, select = -VALUE)
par(mfrow=c(1,2))
plot(cv_lasso <- cv.gamlr(x=training_x, y=training_sample['VALUE'], lmr=1e-4, nford = 10)</pre>
plot(cv_lasso$gamlr)
```

2.435e-01 2.558e-01 0.952 0.340980

HHGRAD 46



```
[91] "SMSA 7600"
                           "SMSA 7840"
                                          "SMSA 8000"
                                                          "SMSA 8120"
                                          "SMSA 9320"
     [96] "SMSA 8520"
                          "SMSA 9240"
                                                          "SMSA 9992"
     [101] "CMSA 10"
                           "CMSA 34"
                                          "CMSA 41"
                                                          "CMSA 47"
     [106] "CMSA_78"
                           "CMSA_82"
                                          "CMSA 91"
                                                          "REGION 2"
     [111] "DIVISION 4"
                          "DIVISION 89"
                                          "BATHS 1"
                                                          "BATHS 3"
     [116] "BEDRMS 1"
                          "BEDRMS 3"
                                          "BEDRMS 4"
                                                          "BUILT 1920"
     [121] "BUILT 1985"
                          "BUILT 2000"
                                          "BUILT 2002"
                                                          "BUILT 2004"
     [126] "BUILT 2010"
                          "HHCITSHP 2"
                                          "HHCITSHP 3"
                                                          "HHCITSHP 4"
     [131] "HHRACE_9"
                          "HHRACE_11"
                                          "HHRACE_15"
                                                          "HHGRAD_32"
                                          "HHGRAD_42"
                          "HHGRAD 41"
                                                          "HHGRAD_44"
     [136] "HHGRAD_39"
     [141] "WATER 3"
                          "WATER 4"
%%R
rmse = (sum((validation sample['VALUE'] - y predict)^2))^0.5
rmse
     [1] 42.79308
%%R
#regression tree
install.packages('tree')
library(tree)
%%R
set.seed(0)
tree <- tree(VALUE ~ ., data=training_sample)</pre>
plot(tree, col = 8)
text(tree,cex=.75, font=2)
```

"SMSA 8280"

"SMSA 9993"

"DIVISION 3"

"BUILT 1980"

"BUILT 2008"

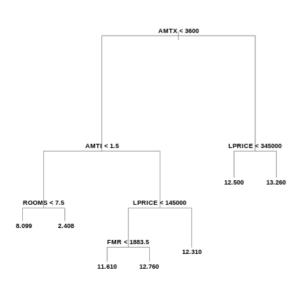
"HHRACE 4"

"HHGRAD_36"

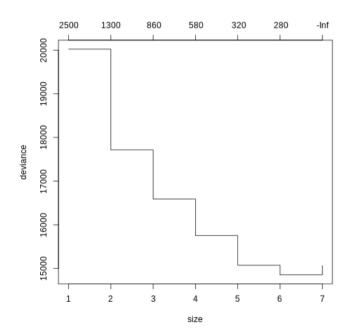
"HHGRAD_46"

"CMSA 49"

"BATHS 4"



set.seed(0) cv_tree <- cv.tree(tree) plot(cv_tree)</pre>



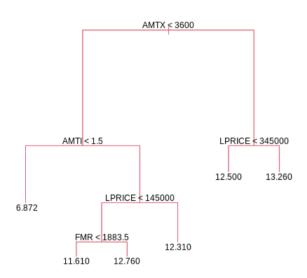
%%R cv_tree\$dev

[1] 15062.43 14851.41 15072.18 15751.60 16588.82 17712.77 20022.96

```
cv_tree$size
    [1] 7 6 5 4 3 2 1

%%R
( cv_tree_best_size <- cv_tree$size[which.min(cv_tree$dev)] )
    [1] 6

%%R
pr_tree <- prune.tree(tree, best=cv_tree_best_size)
plot(pr_tree, col=2)
text(pr_tree)</pre>
```



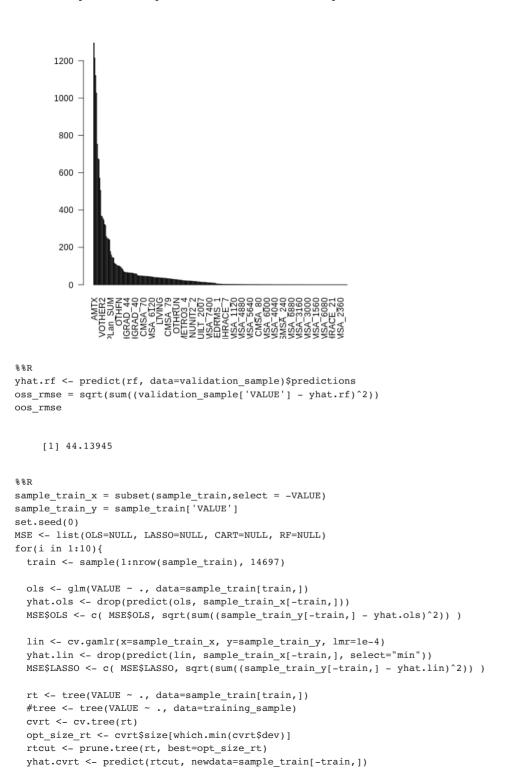
```
yhat.cvrt <- predict(pr_tree, newdata = validation_x)
oos_rmse = sqrt(sum((validation_sample['VALUE'] - yhat.cvrt)^2))
oos_rmse

[1] 44.13945

%%R
#random forest
set.seed(0)
install.packages('ranger')
library(ranger)

%%R
rf <- ranger(VALUE ~ ., data=training_sample, write.forest=TRUE, num.tree=200, min.node.size=5, importance="impurity")
barplot(sort(importance(rf), decreasing=TRUE), las=2)</pre>
```

Growing trees.. Progress: 93%. Estimated remaining time: 2 seconds.



```
rf <- ranger(VALUE ~ ., data=sample train[train,],</pre>
               num.tree=200, min.node.size=5, write.forest=TRUE)
 yhat.rf <- predict(rf, data=sample train[-train,])$predictions</pre>
 MSE$RF <- c( MSE$RF, sqrt(sum((sample_train_y[-train,] - yhat.rf)^2)) )</pre>
par(mai=c(.8,.8,.1,.1))
boxplot(as.data.frame(MSE), col="dodgerblue", xlab="model", ylab="root-MSE")
    Growing trees.. Progress: 99%. Estimated remaining time: 0 seconds.
    Growing trees.. Progress: 100%. Estimated remaining time: 0 seconds.
        45
        40
        35
        30
                  OLS
                             LASSO
                                         CART
                                                      RF
```

MSE\$CART <- c(MSE\$CART, sqrt(sum((sample_train_y[-train,] - yhat.cvrt)^2)))</pre>

%%R #predict predict_value = predict(rf, data=sample_test)\$predictions accuracy = 1-abs(exp(sample_test['VALUE']) - exp(predict_value))/exp(sample_test['VALUE']) summary(accuracy)

model

VALUE
Min. :-253614.51
1st Qu.: 0.64
Median : 0.79
Mean : -447.79
3rd Qu.: 0.90
Max. : 1.00

✓ 0秒 完成时间: 20:20