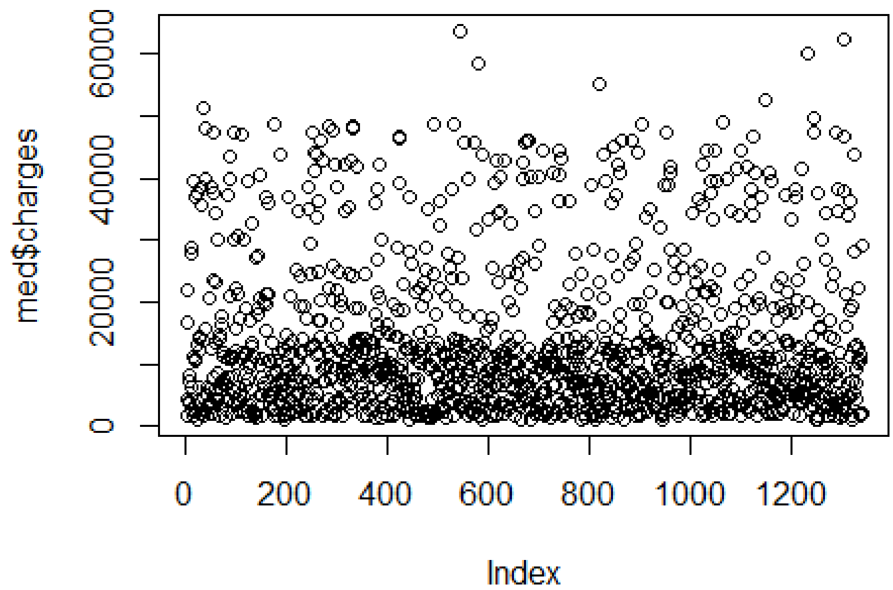
Final Project

Bert

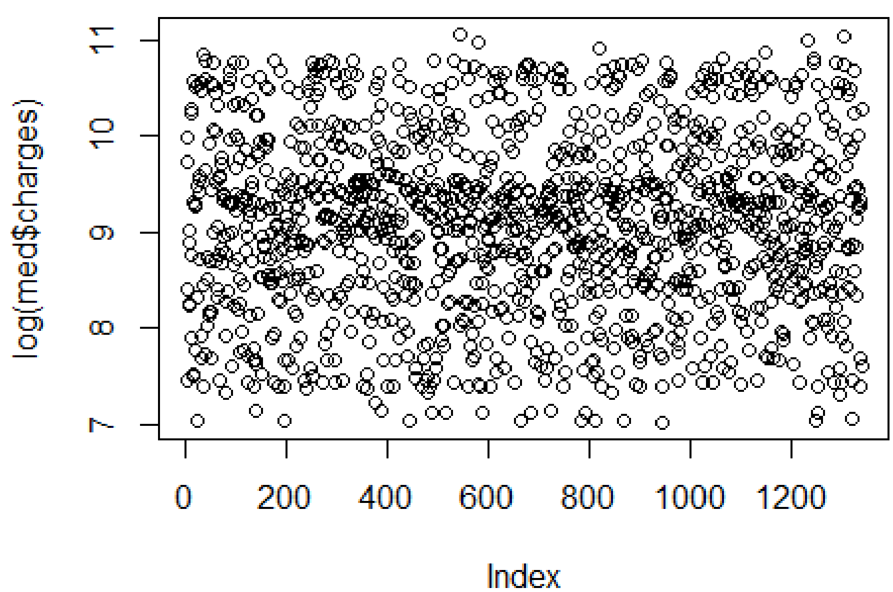
2022-04-14

```
library(readr)
library(corrplot)

## corrplot 0.92 loaded

library(ggplot2)
library(leaps)
library(glmnet)

## Loading required package: Matrix

## Loaded glmnet 4.1-8

library(tree)
library(randomForest)

## randomForest 4.7-1.1

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

##
## Attaching package: 'randomForest'

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

library(gbm)

## Loaded gbm 2.1.8.1

library(reshape2)

#import data
med = read.csv("C:/Users/bert0/Documents/Bert-school/Columbia University/Spri
ng 2022/PM/insurance.csv", header=TRUE)
df = read.csv("C:/Users/bert0/Documents/Bert-school/Columbia University/Sprin
g 2022/PM/insurance.csv", header=TRUE)

#check missing data
which(is.na(med))

## integer(0)
```

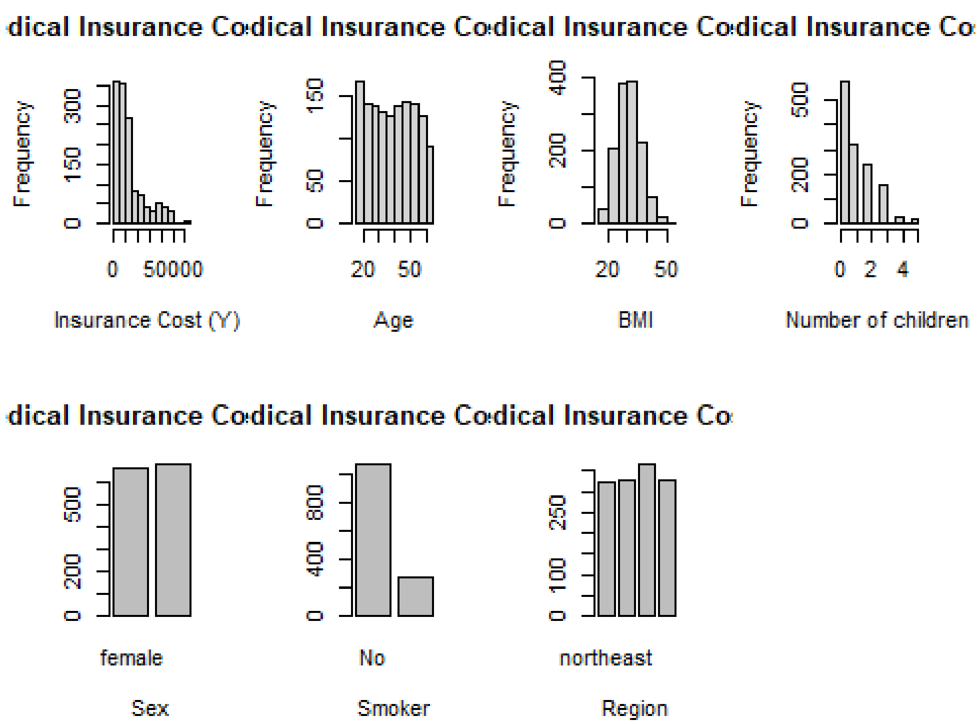
```r
#change data structure
med$sex <- as.factor(med$sex)
med$smoker <- as.factor(med$smoker)
med$region <- as.factor(med$region)

levels(med$sex) <- c("female", "male")
levels(med$smoker) <- c("No", "Yes")
levels(med$region) <- c("northeast", "northwest", "southwest","southeast")

#data visualization
summary(med)

##       age            sex           bmi            children      smoker
##  Min.   :18.00   female:662   Min.   :15.96   Min.   :0.000   No :1064
##  1st Qu.:27.00   male  :676   1st Qu.:26.30   1st Qu.:0.000   Yes: 274
##  Median :39.00                Median :30.40   Median :1.000
##  Mean   :39.21                Mean   :30.66   Mean   :1.095
##  3rd Qu.:51.00                3rd Qu.:34.69   3rd Qu.:2.000
##  Max.   :64.00                Max.   :53.13   Max.   :5.000
##        region       charges
##  northeast:324   Min.   : 1122
##  northwest:325   1st Qu.: 4740
##  southwest:364   Median : 9382
##  southeast:325   Mean   :13270
##                  3rd Qu.:16640
##                  Max.   :63770

plot(med$charges)
```



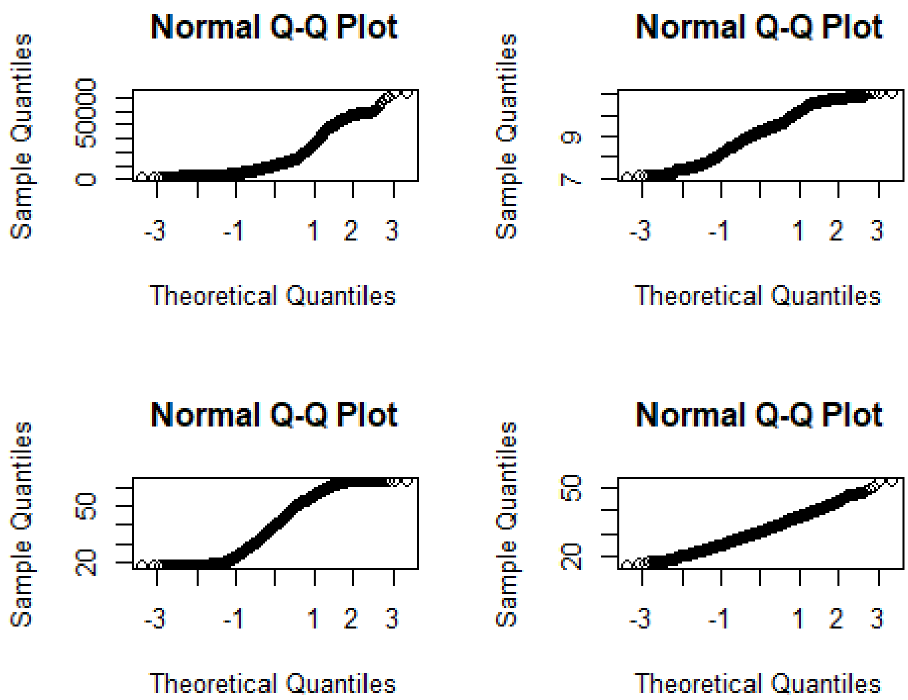

```
plot(log(med$charges))
```



```r
par(mfrow = c(2,4))
#4 numerical data
hist(med$charges,xlab = "Insurance Cost (Y) ", main="Medical Insurance Cost D
ata")
hist(med$age,xlab = "Age", main="Medical Insurance Cost Data")
hist(med$bmi,xlab = "BMI", main="Medical Insurance Cost Data")
hist(med$children,xlab = "Number of children", main="Medical Insurance Cost D
ata")
#3 categorical data
barplot(table(med$sex),xlab="Sex",
main = "Medical Insurance Cost Data")
barplot(table(med$smoker),xlab="Smoker",
main = "Medical Insurance Cost Data")
barplot(table(med$region),xlab="Region",
main = "Medical Insurance Cost Data")
```




```r
par(mfrow = c(2,2))
qqnorm(med$charges)
qqnorm(log(med$charges))
qqnorm(med$age)
qqnorm(med$bmi)
```




```
#Charts :1.charges, 2.ln(charge) 3.age 4.bmi

#Change charges into ln()
med$charges<-log(med$charges)

#Validation Set
set.seed(1)
train=sample(c(TRUE,FALSE), nrow(med),rep=TRUE)
#sum(train==TRUE);sum(train==FALSE)
test=(!train)

#full regression model
y=med$charges
res=lm(y~age+sex+bmi+children+smoker+region,data=med)
summary(res)

##
## Call:
## lm(formula = y ~ age + sex + bmi + children + smoker + region,
##     data = med)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.07186 -0.19835 -0.04917  0.06598  2.16636
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)      7.0305581  0.0723960  97.112  < 2e-16 ***
## age              0.0345816  0.0008721  39.655  < 2e-16 ***
## sexmale         -0.0754164  0.0244012  -3.091 0.002038 **
## bmi              0.0133748  0.0020960   6.381 2.42e-10 ***
## children         0.1018568  0.0100995  10.085  < 2e-16 ***
## smokerYes        1.5543228  0.0302795  51.333  < 2e-16 ***
## regionnorthwest -0.0637876  0.0349057  -1.827 0.067860 .
## regionsouthwest -0.1571967  0.0350828  -4.481 8.08e-06 ***
## regionsoutheast -0.1289522  0.0350271  -3.681 0.000241 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4443 on 1329 degrees of freedom
## Multiple R-squared:  0.7679, Adjusted R-squared:  0.7666
## F-statistic: 549.8 on 8 and 1329 DF,  p-value: < 2.2e-16
```

We are going to select models, we use MSE and other values to compare models and following part have three methods to measure MSE: #1.using all data 2.validation set 3.Cross Validation

```
reg.best=regsubsets(charges~ . ,data=med,nvmax=8)
summary(reg.best)
```

```
## Subset selection object
## Call: regsubsets.formula(charges ~ ., data = med, nvmax = 8)
## 8 Variables  (and intercept)
##                 Forced in Forced out
## age                 FALSE      FALSE
## sexmale             FALSE      FALSE
## bmi                 FALSE      FALSE
## children            FALSE      FALSE
## smokerYes           FALSE      FALSE
## regionnorthwest     FALSE      FALSE
## regionsouthwest     FALSE      FALSE
## regionsoutheast     FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##          age sexmale bmi children smokerYes regionnorthwest regionsouthwes
t
## 1  ( 1 ) " " " "     " " " "      "*"       " "             " "
## 2  ( 1 ) "*" " "     " " " "      "*"       " "             " "
## 3  ( 1 ) "*" " "     " " "*"      "*"       " "             " "
## 4  ( 1 ) "*" " "     "*" "*"      "*"       " "             " "
## 5  ( 1 ) "*" " "     "*" "*"      "*"       " "             "*"
## 6  ( 1 ) "*" " "     "*" "*"      "*"       " "             "*"
## 7  ( 1 ) "*" "*"     "*" "*"      "*"       " "             "*"
## 8  ( 1 ) "*" "*"     "*" "*"      "*"       "*"             "*"
##          regionsoutheast
## 1  ( 1 ) " "
## 2  ( 1 ) " "
```

```
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) "*"
## 7  ( 1 ) "*"
## 8  ( 1 ) "*"
```

```
#using whole data to train
reg.Med.summary=summary(reg.best)
reg.Med.summary$outmat
```

```
##          age sexmale bmi children smokerYes regionnorthwest regionsouthwes
t
## 1  ( 1 ) " " " "     " " " "      "*"       " "             " "
## 2  ( 1 ) "*" " "     " " " "      "*"       " "             " "
## 3  ( 1 ) "*" " "     " " "*"      "*"       " "             " "
## 4  ( 1 ) "*" " "     "*" "*"      "*"       " "             " "
## 5  ( 1 ) "*" " "     "*" "*"      "*"       " "             "*"
## 6  ( 1 ) "*" " "     "*" "*"      "*"       " "             "*"
## 7  ( 1 ) "*" "*"     "*" "*"      "*"       " "             "*"
## 8  ( 1 ) "*" "*"     "*" "*"      "*"       "*"             "*"
##          regionsoutheast
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) "*"
## 7  ( 1 ) "*"
## 8  ( 1 ) "*"
```

```
r2=reg.Med.summary$rsq
adjr2=reg.Med.summary$adjr2
cp=reg.Med.summary$cp
bic=reg.Med.summary$bic
table_best=data.frame(model=c(1:8),r2,adjr2,cp,bic)
table_best
```

```
##   model        r2     adjr2          cp       bic
## 1     1 0.4428978 0.4424809 1856.61244  -768.341
## 2     2 0.7395465 0.7391564  159.65828 -1778.456
## 3     3 0.7572654 0.7567195   60.17950 -1865.527
## 4     4 0.7621566 0.7614429   34.16713 -1885.564
## 5     5 0.7639274 0.7630413   26.02496 -1888.365
## 6     6 0.7657049 0.7646487   17.84507 -1891.278
## 7     7 0.7673647 0.7661403   10.33949 -1893.591
## 8     8 0.7679478 0.7665509    9.00000 -1889.750
```

```
#looking for coef
coef(reg.best,3)
```

```
## (Intercept)         age    children   smokerYes
##  7.28772342  0.03528491  0.10163109  1.54427238
```

```
coef(reg.best,4)
```

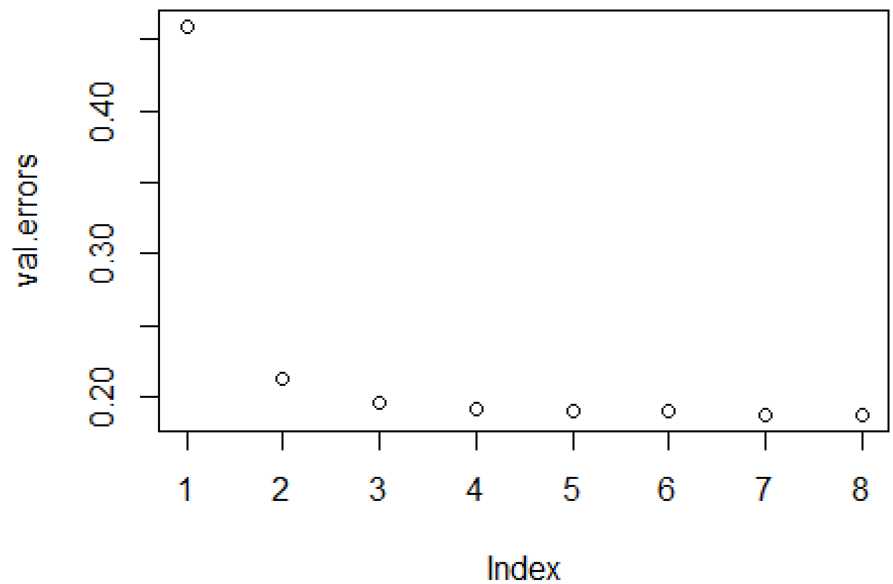
```
## (Intercept)         age         bmi    children   smokerYes
##  6.98277656  0.03478256  0.01060965  0.10119760  1.54324382
```

prefer 3 or 4 model

```
#Validation Set
regfit.full=regsubsets(charges~.,data=med[train,],nvmax=8)
#summary(regfit.full)
test.mat=model.matrix(charges~.,data=med[test,])
val.errors=rep(NA,8)
for (i in 1:8)
{
  coefi=coef(regfit.full,id=i)
  pred=test.mat[,names(coefi)]%*%coefi
  val.errors[i]=mean((med$charges[test]-pred)^2)

}
data.frame(model=c(1:8),val.errors)
```

```
##   model val.errors
## 1     1  0.4586110
## 2     2  0.2126700
## 3     3  0.1962058
## 4     4  0.1916911
## 5     5  0.1911752
## 6     6  0.1905866
## 7     7  0.1886521
## 8     8  0.1881355
```

```
plot(val.errors)
```




```
#minimum errors' model
#coef(regfit.full, which(val.errors==min(val.errors)))
```

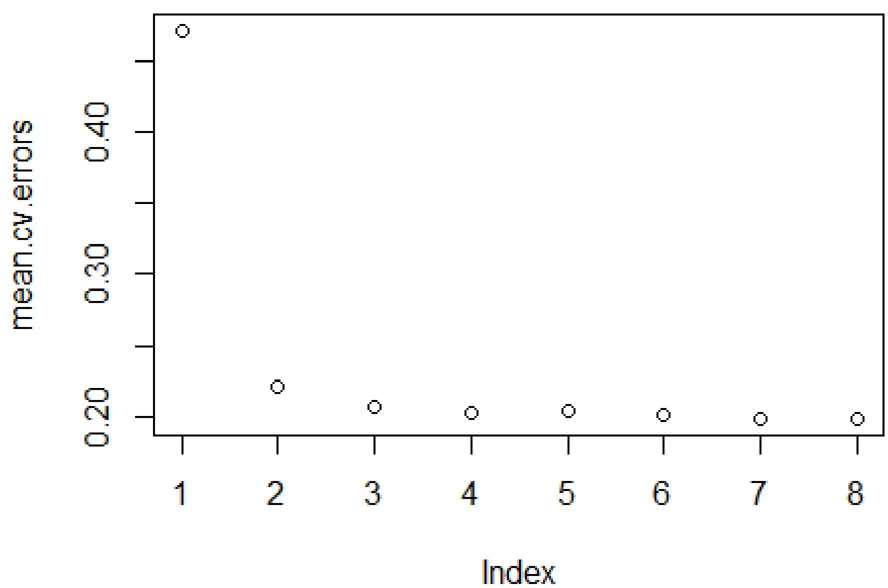
validation test show…

```
#prediction
predict.regsubsets=function(object,newdata,id,...)
{
form=as.formula(object$call[[2]])
mat=model.matrix(form,newdata)
coefi=coef(object,id=id)
xvars=names(coefi)
mat[,xvars]%*%coefi
}
#Cross validation
k=10
set.seed(1)
folds=sample(1:k,nrow(med),replace=TRUE)
#folds
cv.errors=matrix(NA,k,8, dimnames=list(NULL, paste(1:8)))
for(j in 1:k){
  best.fit=regsubsets(charges~.,data=med[folds!=j,],nvmax=8)
  for(i in 1:8){
    pred=predict.regsubsets(best.fit,med[folds==j,],id=i)
    cv.errors[j,i]=mean( (med$charges[folds==j]-pred)^2)
    }
}
```

```
mean.cv.errors=apply(cv.errors,2,mean)
#draw plot
data.frame(model=c(1:8),mean.cv.errors)
```

```
##   model mean.cv.errors
## 1     1      0.4711180
## 2     2      0.2209773
## 3     3      0.2061846
## 4     4      0.2021111
## 5     5      0.2033770
## 6     6      0.2013673
## 7     7      0.1986568
## 8     8      0.1982912
```

```
plot(mean.cv.errors)
```




```
#minimum errors' model#coef(regfit.full, which(mean.cv.errors==min(mean.cv.er
rors)))
```

CV shows ....

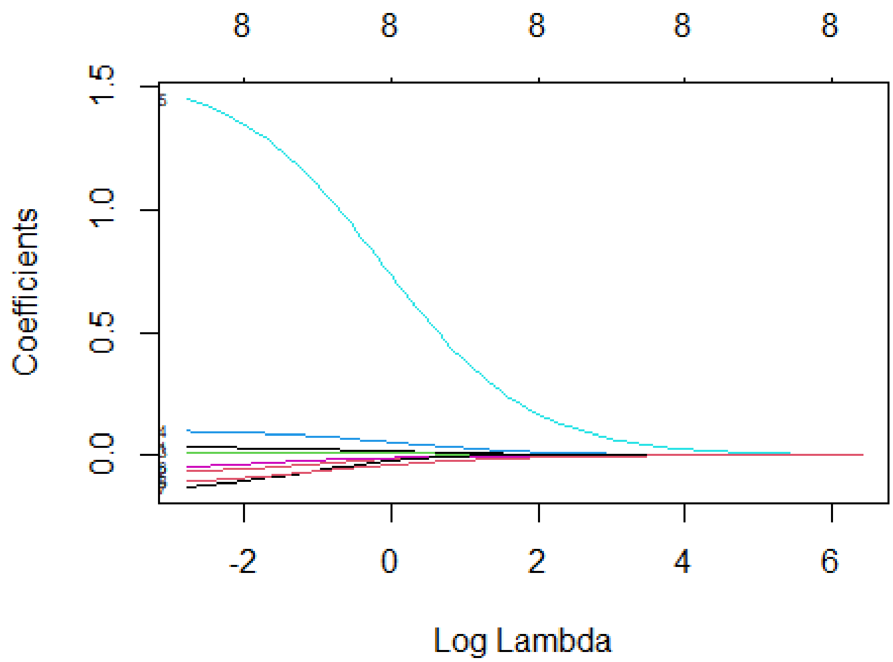
CONCLUSION could be: Although we have model 6 with lowest MSE, we prefer 3 factor model is the best, because it is not complicated and the accuracy is ratively high.

```
#3 factor model is the best, because it is not complicated and the accuracy i
s ratively high.
res2=lm(y~age+children+smoker,data=med)
summary(res2)
```

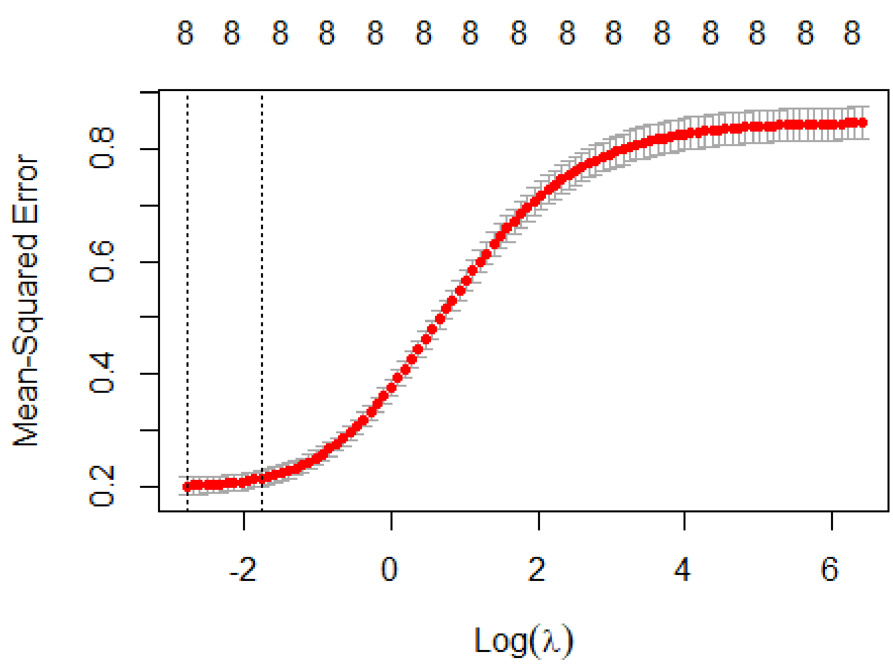
```
##
## Call:
## lm(formula = y ~ age + children + smoker, data = med)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.94939 -0.17632 -0.04368  0.04252  2.13501
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 7.2877234  0.0387040 188.294   <2e-16 ***
## age         0.0352849  0.0008839  39.919   <2e-16 ***
## children    0.1016311  0.0102990   9.868   <2e-16 ***
## smokerYes   1.5442724  0.0307364  50.242   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4535 on 1334 degrees of freedom
## Multiple R-squared:  0.7573, Adjusted R-squared:  0.7567
## F-statistic:  1387 on 3 and 1334 DF,  p-value: < 2.2e-16
```

Also, we can try to do Ridge and Lasso to reduce Variance

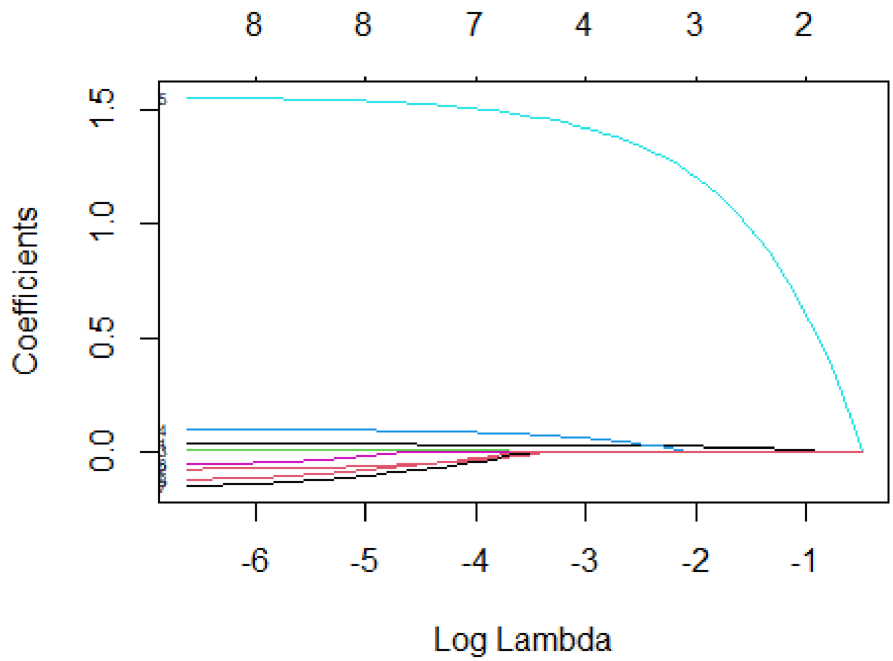
```
#Ridge & Lasso
# make design matrix x and response y=charges
x=model.matrix(charges~.,med)[,-1]
y=med$charges
fit.ridge = glmnet(x,y,alpha=0)
plot(fit.ridge, xvar="lambda", label=TRUE)
```



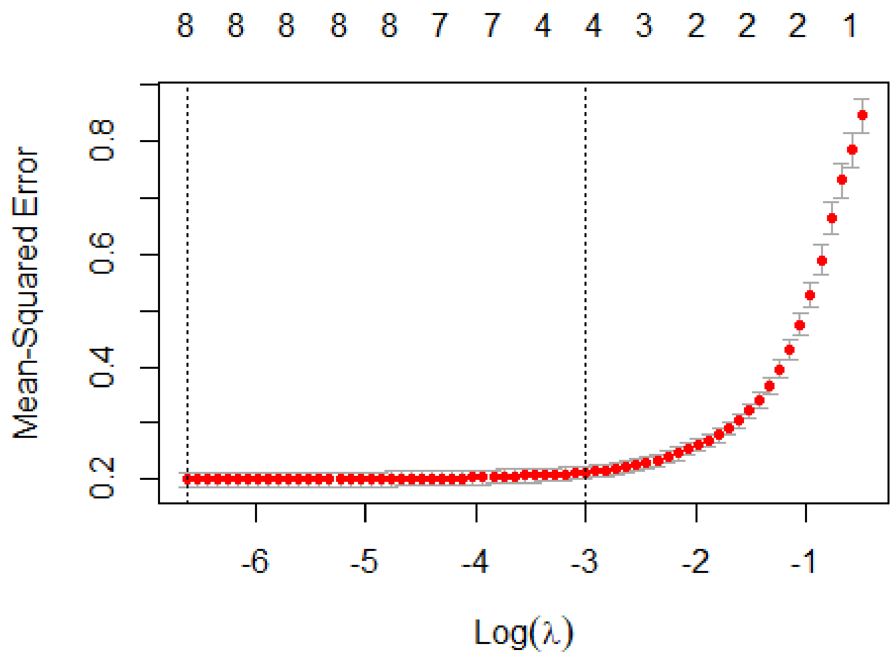

```
cv.ridge = cv.glmnet(x,y,alpha =0);plot(cv.ridge)
```



```r
fit.lasso = glmnet(x,y,alpha=1)
plot(fit.lasso, xvar="lambda", label=TRUE)
```




```r
cv.lasso = cv.glmnet(x,y,alpha =1);plot(cv.lasso)
```



We can see which proportion of training set have best performance Both Ridge and Lasso.
Table1:Ridge;Table2:Lasso

```
#decide training set
set.seed(1)
tp=rep(0,9)
mse=rep(0,9)
a=c(0.5,0.5625,0.625,0.6875,0.75,0.8125,0.875,0.9375,1)
for (i in 1:9) {
    if (i<1) {
    train=sample(1:nrow(x), a[i]*nrow(x))
    test=(-train)
    y.test = y[-train]
    alpha0.fit =cv.glmnet(x[train,],y[train], alpha=0, type.measure="mse",fam
ily="gaussian")
    alpha0.predicted = predict(alpha0.fit, s=alpha0.fit$lambda.1se,newx=x[-tr
ain,])
    tp[i]=alpha0.fit$lambda.1se
    mse[i]=mean((y.test-alpha0.predicted)^2)
    }
    else {
    train=sample(1:nrow(x), a[i]*nrow(x))
    test=(train)
    y.test = y[train]
    alpha0.fit =cv.glmnet(x[train,],y[train], alpha=0, type.measure="mse",fam
ily="gaussian")
    alpha0.predicted = predict(alpha0.fit, s=alpha0.fit$lambda.1se,newx=x[tra
```

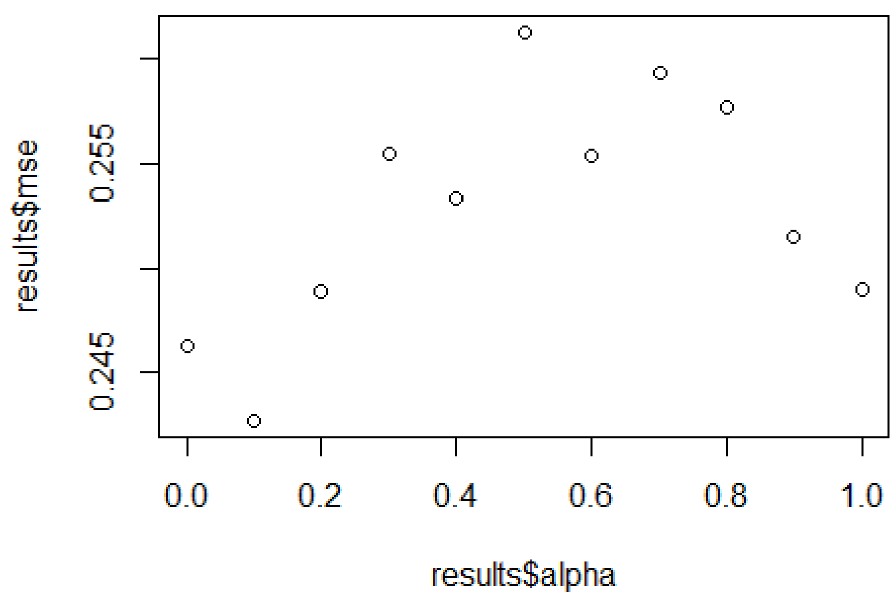
```
in,])
    tp[i]=alpha0.fit$lambda.1se
    mse[i]=mean((y.test-alpha0.predicted)^2)
    }

}

table_Ridge=data.frame(RatioOfTrainingSet = a, tp=tp,MSE=mse)
table_Ridge

##   RatioOfTrainingSet        tp       MSE
## 1             0.5000 0.1867904 0.2029582
## 2             0.5625 0.2037921 0.2294636
## 3             0.6250 0.1635435 0.1942499
## 4             0.6875 0.1896704 0.2163271
## 5             0.7500 0.1725343 0.2206320
## 6             0.8125 0.1875701 0.2154752
## 7             0.8750 0.1429752 0.2069787
## 8             0.9375 0.1517741 0.2087969
## 9             1.0000 0.1868110 0.2152947

#Lasso
for (i in 1:9) {
    if (i<1) {
    train=sample(1:nrow(x), a[i]*nrow(x))
    test=(-train)
    y.test = y[-train]
    alpha1.fit =cv.glmnet(x[train,],y[train], alpha=1, type.measure="mse",fam
ily="gaussian")
    alpha1.predicted = predict(alpha1.fit, s=alpha1.fit$lambda.1se,newx=x[-tr
ain,])
    tp[i]=alpha1.fit$lambda.1se
    mse[i]=mean((y.test-alpha1.predicted)^2)
    }
    else {
    train=sample(1:nrow(x), a[i]*nrow(x))
    test=(train)
    y.test = y[train]
    alpha1.fit =cv.glmnet(x[train,],y[train], alpha=1, type.measure="mse",fam
ily="gaussian")
    alpha1.predicted = predict(alpha1.fit, s=alpha1.fit$lambda.1se,newx=x[tra
in,])
    tp[i]=alpha1.fit$lambda.1se
    mse[i]=mean((y.test-alpha1.predicted)^2)
    }

}

table_Lasso=data.frame(RatioOfTrainingSet = a, tp=tp,MSE=mse)
table_Lasso
```

```
##   RatioOfTrainingSet         tp       MSE
## 1             0.5000 0.05541572 0.2192705
## 2             0.5625 0.07042788 0.2347370
## 3             0.6250 0.04659242 0.2043661
## 4             0.6875 0.06036091 0.2075990
## 5             0.7500 0.06036840 0.2022688
## 6             0.8125 0.05063202 0.2036441
## 7             0.8750 0.04950568 0.2046174
## 8             0.9375 0.05522830 0.2120856
## 9             1.0000 0.06559293 0.2170027
```

conclude that ratio between 0.625-0.75 is better ratio Using Elastic_Net Regression and using 0.6875 times of data as training data

```
#Elastic_Net Regression
set.seed(1)
train=sample(1:nrow(x), 0.6875*nrow(x))
test=(-train)
y.test = y[-train]

list.of.fits = list()
for (i in 0:10) {
  fit.name = paste0("alpha",i/10)
  list.of.fits[[fit.name]] = cv.glmnet(x[train,], y[train],alpha=i/10,type.me
asure="mse", family="gaussian")
}
results= data.frame()

for (i in 0:10) {
  fit.name = paste0("alpha",i/10)
  predicted =
predict(list.of.fits[[fit.name]],s=list.of.fits[[fit.name]]$lambda.1se,newx=x
[-train,])

  mse = mean((y.test - predicted)^2)
  temp = data.frame(alpha = i/10, mse=mse, fit.name = fit.name)
  results = rbind(results,temp)
}
results

##    alpha       mse fit.name
## 1    0.0 0.2463103   alpha0
## 2    0.1 0.2426991 alpha0.1
## 3    0.2 0.2488905 alpha0.2
## 4    0.3 0.2554663 alpha0.3
## 5    0.4 0.2533036 alpha0.4
## 6    0.5 0.2613081 alpha0.5
## 7    0.6 0.2553572 alpha0.6
## 8    0.7 0.2593479 alpha0.7
## 9    0.8 0.2576691 alpha0.8
```

```
## 10   0.9 0.2514805 alpha0.9
## 11   1.0 0.2489712   alpha1

results[match(min(results$mse),results$mse),]

##   alpha       mse fit.name
## 2   0.1 0.2426991 alpha0.1

plot(results$alpha,results$mse)
```




```
alpha1=results[match(min(results$mse),results$mse),][1,1]
alpha1

## [1] 0.1

list.of.fits = list()
for (i in 0:10) {
  fit.name = paste0("alpha",i/100 +alpha1)
  list.of.fits[[fit.name]] = cv.glmnet(x[train,], y[train],alpha=i/100 +alpha
1,type.measure="mse", family="gaussian")
}
results= data.frame()

for (i in 0:10) {
  fit.name = paste0("alpha",i/100 +alpha1)
  predicted =
predict(list.of.fits[[fit.name]],s=list.of.fits[[fit.name]]$lambda.1se,newx=x
[-train,])
```

```
  mse = mean((y.test - predicted)^2)
  temp = data.frame(alpha = i/100+alpha1, mse=mse, fit.name = fit.name)
  results = rbind(results,temp)
}
results[match(min(results$mse),results$mse),][1,1]
```

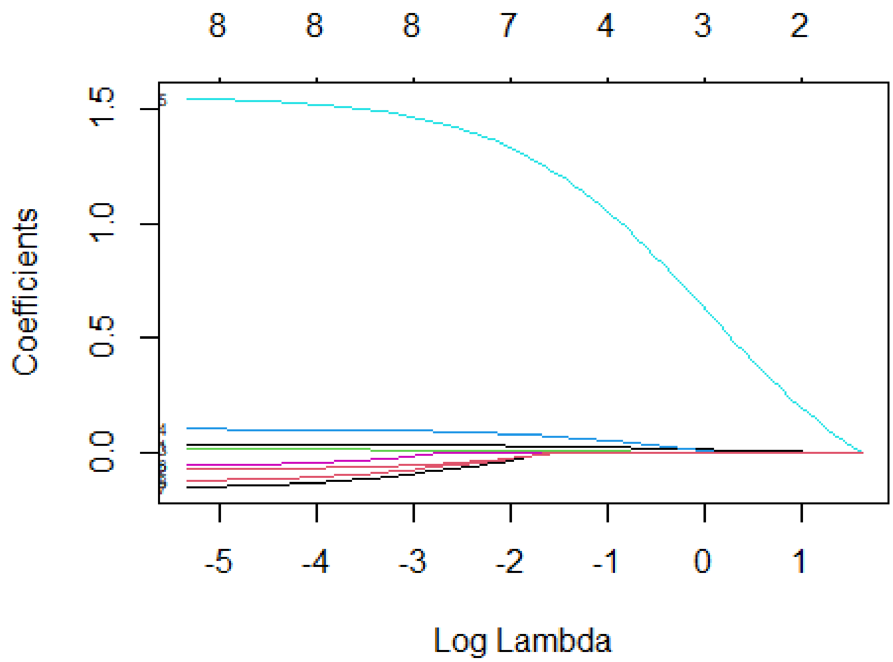
```
## [1] 0.11
```

```
results
```

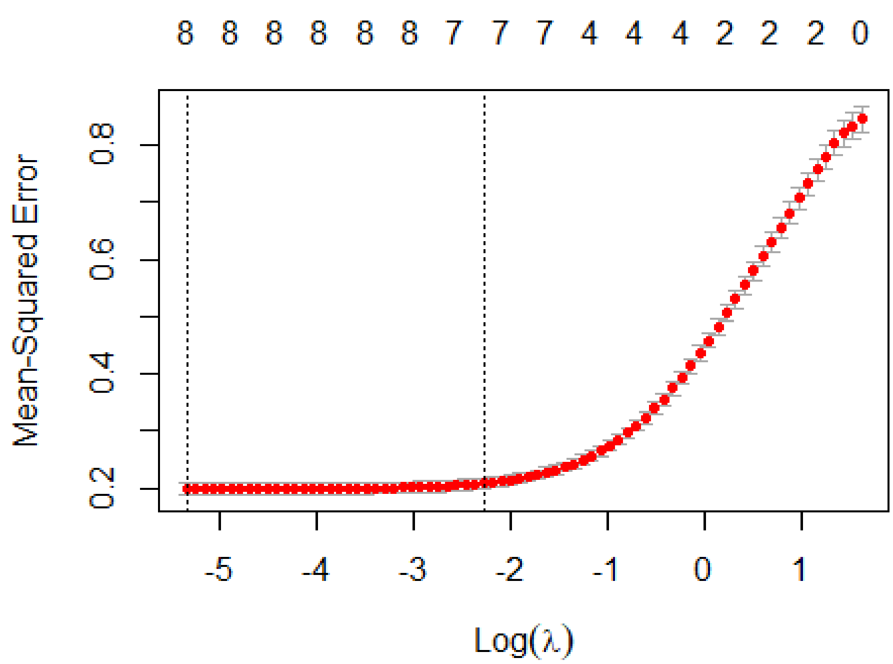
```
##    alpha       mse  fit.name
## 1   0.10 0.2511796  alpha0.1
## 2   0.11 0.2430825 alpha0.11
## 3   0.12 0.2454672 alpha0.12
## 4   0.13 0.2462956 alpha0.13
## 5   0.14 0.2525605 alpha0.14
## 6   0.15 0.2511881 alpha0.15
## 7   0.16 0.2525787 alpha0.16
## 8   0.17 0.2490182 alpha0.17
## 9   0.18 0.2505073 alpha0.18
## 10  0.19 0.2541204 alpha0.19
## 11  0.20 0.2584083  alpha0.2
```

get the result that alpha=0.12 in EN regression has lowest MSE

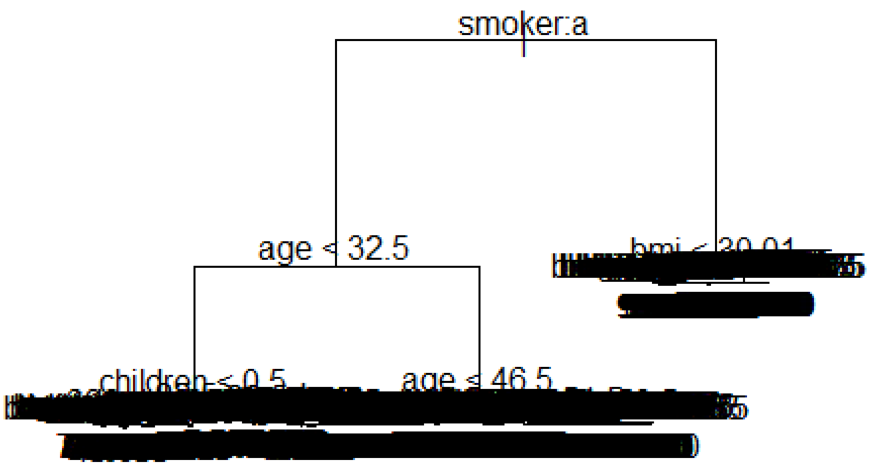
```
x=model.matrix(charges~.,med)[,-1]
y=med$charges
fit.model = glmnet(x,y,alpha=0.12)
plot(fit.model, xvar="lambda", label=TRUE)
```



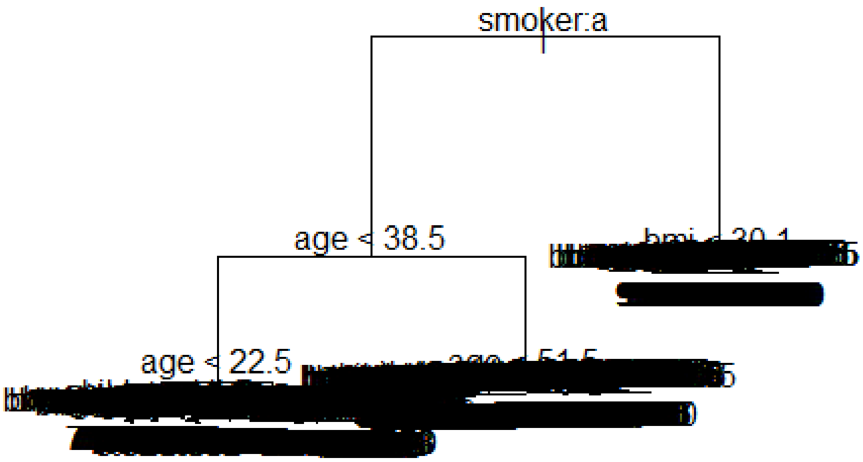

```
cv.model = cv.glmnet(x,y,alpha =0.12);plot(cv.model)
```



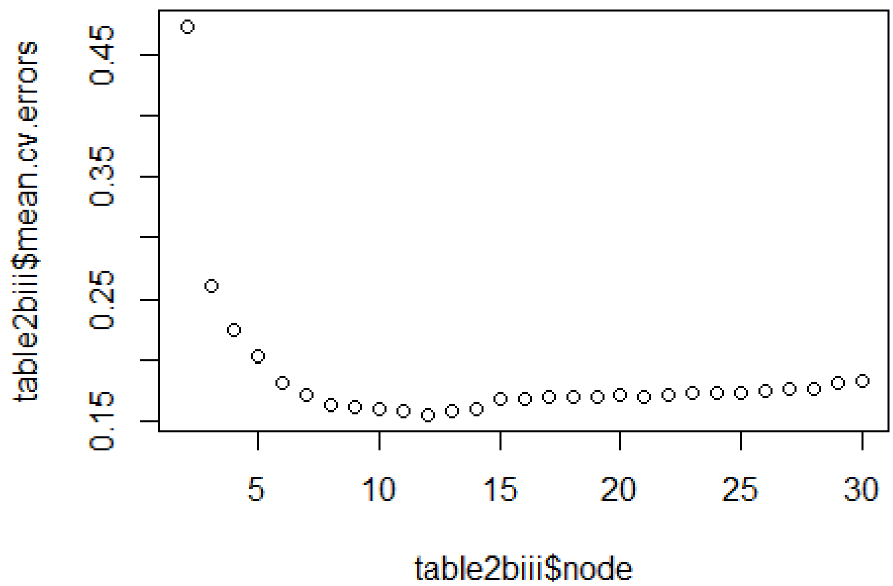
```r
#Decision Tree- whole tree
tree.M=tree(charges~. ,data=med,control= tree.control(nrow(med), mincut = 0,m
insize = 2,mindev = 0))
plot(tree.M)
text(tree.M)
```



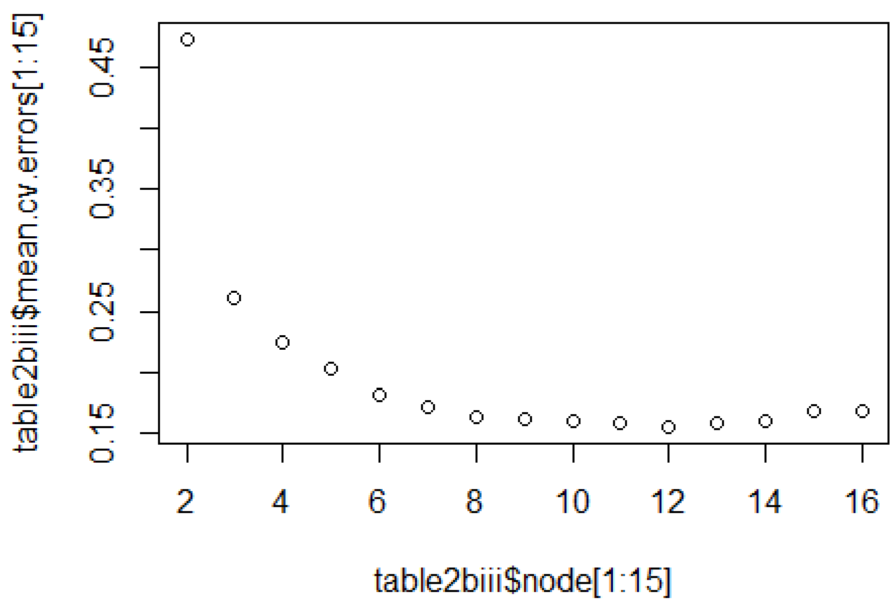

```r
#using training set to build tree
tree.M=tree(charges~. ,data=med[train,],control= tree.control(nrow(med[train,
]), mincut = 1,minsize = 2,mindev = 0))
plot(tree.M)
text(tree.M)
```



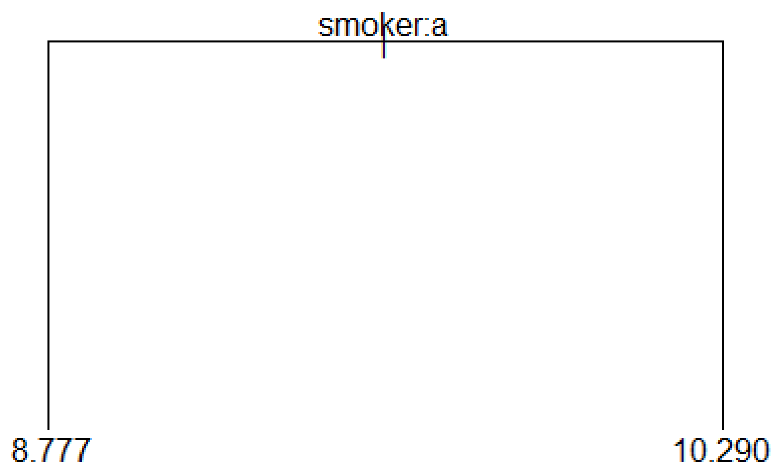

```
#MSE
mean((med[test,"charges"]-predict(tree.M,med[test,]))^2)

## [1] 0.2845708

#Cross validation:Find the best pruned tree n=13
k=10

folds=sample(1:k,nrow(med),replace=TRUE)
#folds
cv.errors=matrix(NA,k,29, dimnames=list(NULL, paste(1:29)))
for(j in 1:k){
  set.seed(1)
  tree.M2=tree(charges~. ,data=med[folds!=j,],control= tree.control(nrow(med[
folds!=j,]), mincut = 1,minsize = 2,mindev = 0))
  for(i in 1:29){
    set.seed(1)
    prune.M2=prune.tree(tree.M2,best=i+1)
    pred=predict(prune.M2,med[folds==j,])
    cv.errors[j,i]=mean((med[folds==j,"charges"]-pred)^2)
    }
}
mean.cv.errors=apply(cv.errors,2,mean)
#draw plot
table2biii=data.frame(node=c(2:30),mean.cv.errors)
plot(table2biii$node,table2biii$mean.cv.errors)
```

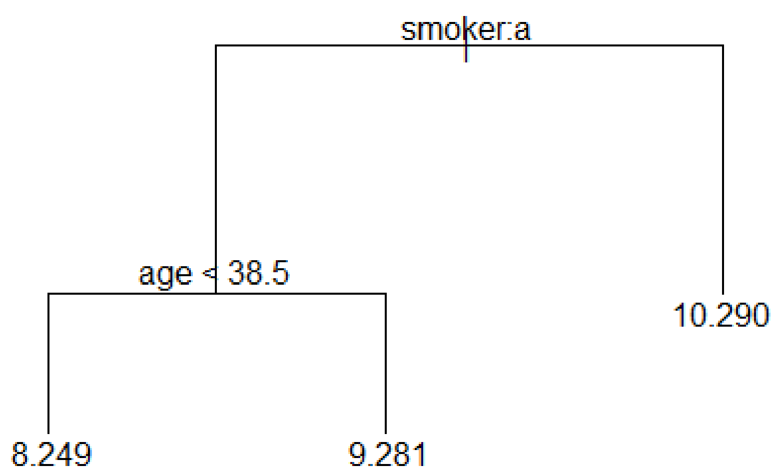


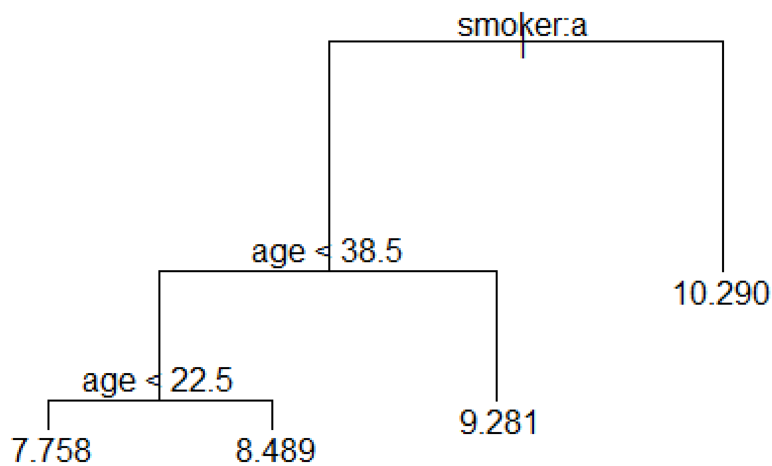

```
plot(table2biii$node[1:15],table2biii$mean.cv.errors[1:15])
```

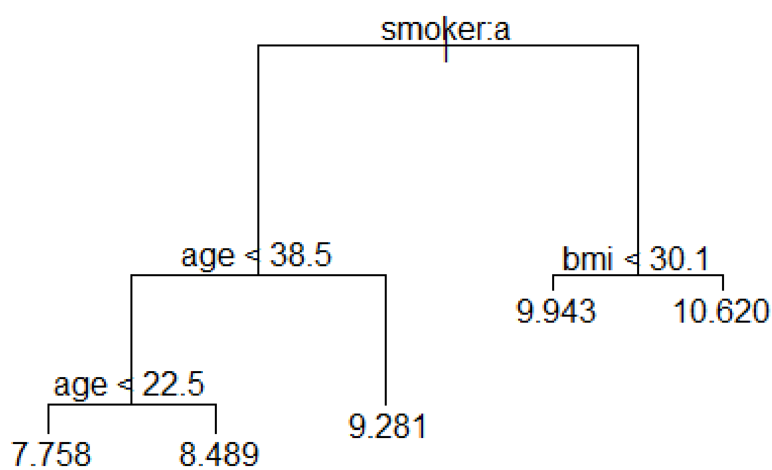


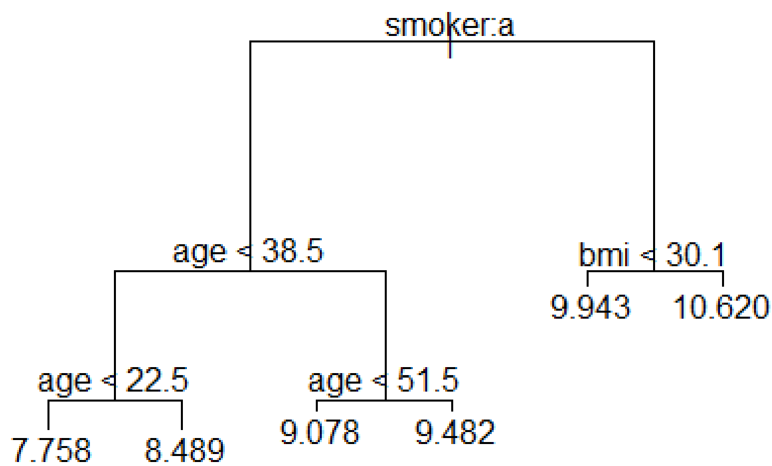
```r
n=which(table2biii$mean.cv.errors==min(table2biii$mean.cv.errors))+1
n

## [1] 12

prune.M3=prune.tree(tree.M,best=n)
mean((med[test,"charges"]-predict(prune.M3,med[test,]))^2)

## [1] 0.1915374

branchs=c(1:20)
MSE.tr=c(rep(NA,20))

for(j in 2:20){
  prune.test=prune.tree(tree.M,best=j)
  MSE.tr[j]=mean((med[test,"charges"]-predict(prune.test,med[test,]))^2)
}
MSE.tr[1]=mean((med[test,"charges"]-mean(med[train,"charges"]))^2)



table.tr=data.frame(branchs,MSE.tr)
table.tr

##    branchs    MSE.tr
## 1        1 0.8721997
## 2        2 0.5020904
## 3        3 0.2915389
## 4        4 0.2442833
## 5        5 0.2207118
## 6        6 0.2029762
## 7        7 0.2043064
## 8        8 0.1908290
## 9        9 0.1904854
## 10      10 0.1907478
## 11      11 0.1890266
## 12      12 0.1915374
## 13      13 0.1919413
## 14      14 0.1914564
## 15      15 0.1957887
## 16      16 0.1957887
## 17      17 0.1957887
## 18      18 0.2308279
## 19      19 0.2308279
## 20      20 0.2308279

for(j in 2:12){
  prune.test=prune.tree(tree.M,best=j)
  plot(prune.test)
  text(prune.test)
}
```

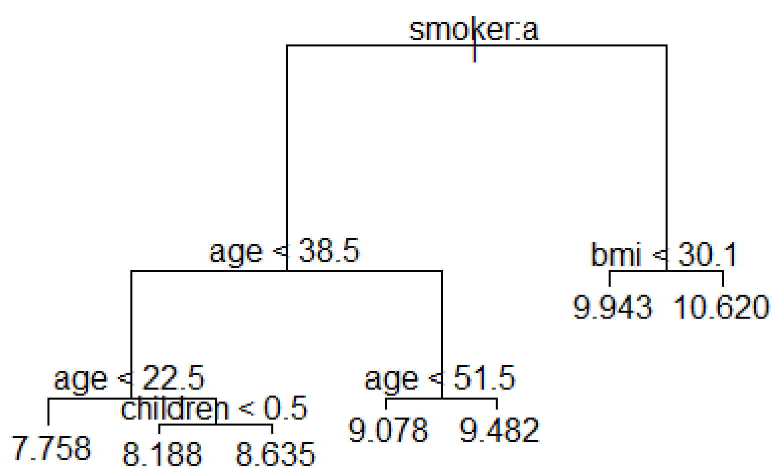

smoker:a
8.777
10.290

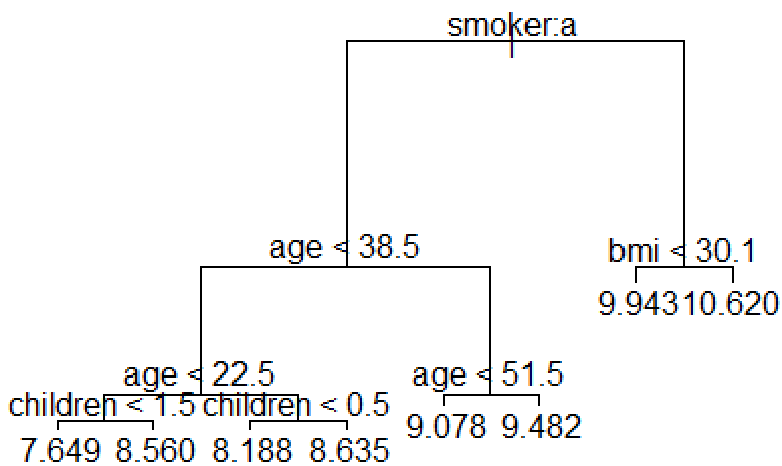

smoker:a
age < 38.5
10.290
8.249
9.281

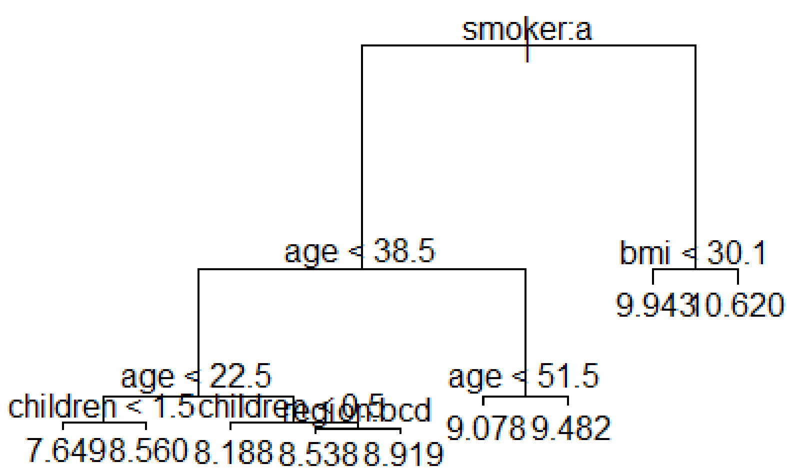

smoker:a
age < 38.5
10.290
age < 22.5
9.281
7.758
8.489

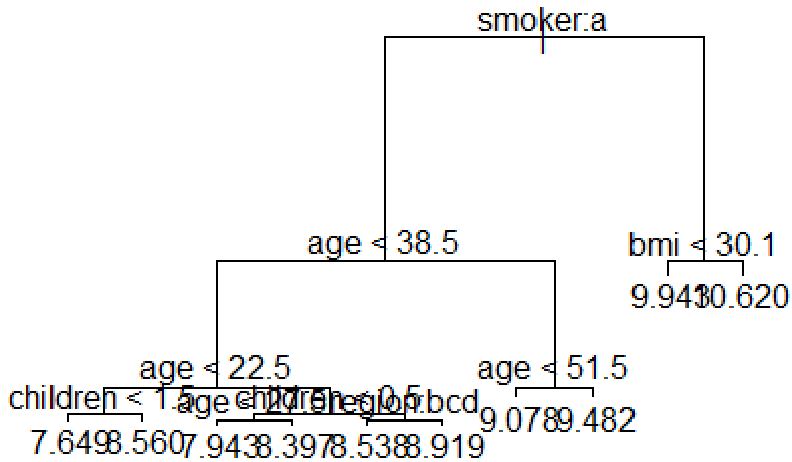

smoker:a
age < 38.5
bmi < 30.1
9.943
10.620
age < 22.5
9.281
7.758
8.489

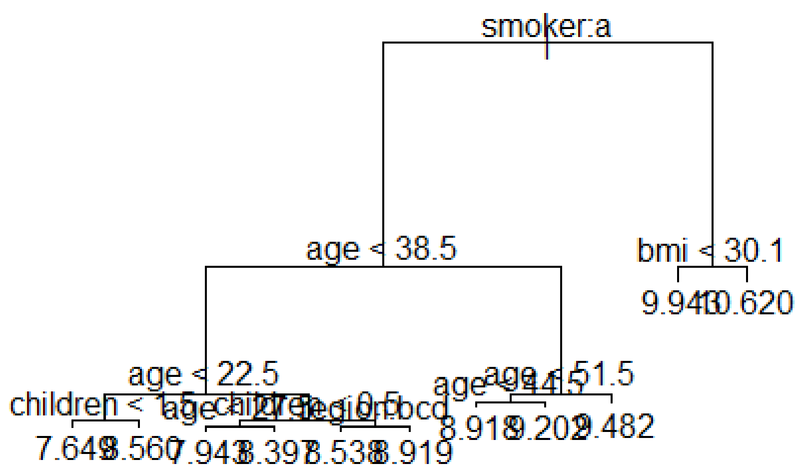

smoker:a
age < 38.5
bmi < 30.1
9.943
10.620
age < 22.5
age < 51.5
7.758
8.489
9.078
9.482

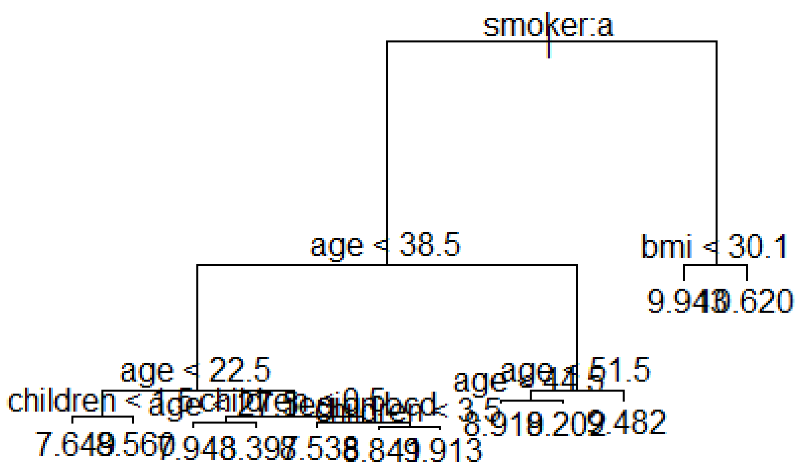

smoker:a
age < 38.5
bmi < 30.1
9.943
10.620
age < 22.5
children < 0.5
age < 51.5
7.758
8.188
8.635
9.078
9.482


smoker:a
age < 38.5
bmi < 30.1
9.943
10.620
age < 22.5
age < 51.5
children < 1.5
children < 0.5
7.649
8.560
8.188
8.635
9.078
9.482


smoker:a
age < 38.5
bmi < 30.1
9.943
10.620
age < 22.5
age < 51.5
children < 1.5
children < 0.5
region:bcd
7.649
8.560
8.188
8.538
8.919
9.078
9.482


smoker:a
age < 38.5
bmi < 30.1
9.941
10.620
age < 22.5
age < 51.5
children < 1.5
region:bcd
9.078
9.482
7.649
8.560
7.943
8.397
8.538
8.919


smoker:a
age < 38.5
bmi < 30.1
9.941
10.620
age < 22.5
age < 51.5
children < 1.5
region:bcd
9.482
7.649
8.560
7.943
8.397
8.538
8.919

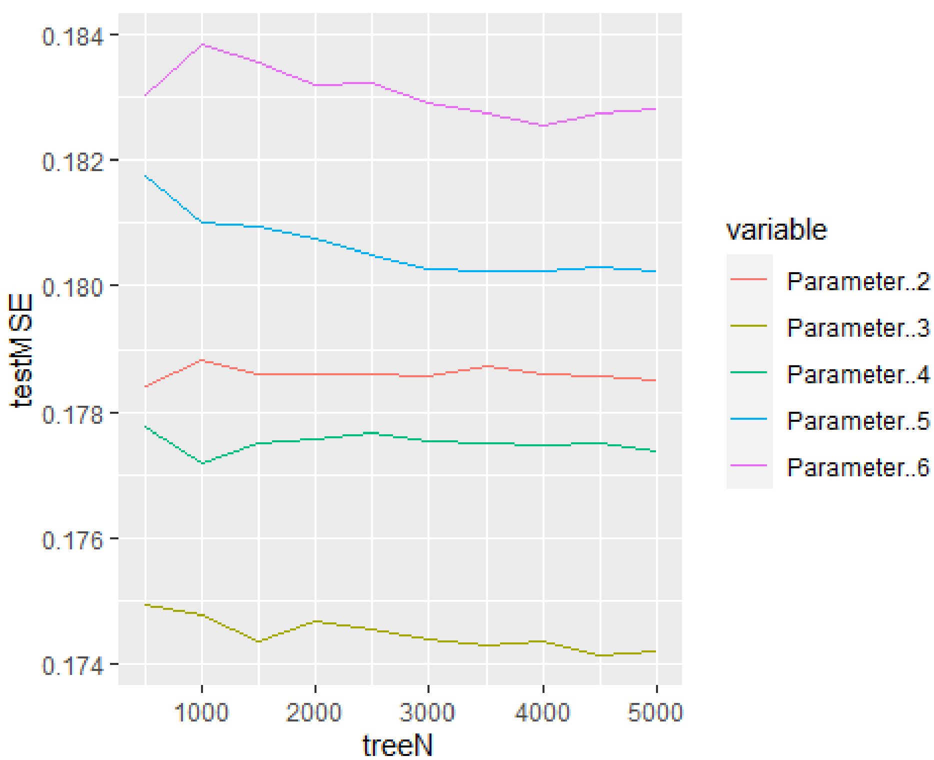



```
#test MSE
MSE.lm=val.errors
table.lm=data.frame(model=c(1:8),MSE.lm)
table.compare=data.frame(table.lm,table.tr[5:12,])
table.compare

##    model    MSE.lm branchs    MSE.tr
## 5      1 0.4586110       5 0.2207118
## 6      2 0.2126700       6 0.2029762
## 7      3 0.1962058       7 0.2043064
## 8      4 0.1916911       8 0.1908290
## 9      5 0.1911752       9 0.1904854
## 10     6 0.1905866      10 0.1907478
## 11     7 0.1886521      11 0.1890266
## 12     8 0.1881355      12 0.1915374

p_number=c(1:6)
treeN=c(1:10)*500
error.mat=matrix(NA,length(treeN),length(p_number))
er.df=data.frame(error.mat)
colnames(er.df) = paste0("Parameter#:",c(1:6))
for(i in c(1:6)){

  for(j in c(1:10)){
    set.seed(1)
    rf.med=randomForest(formula = charges ~ ., data = med[train,] , ntree = j
*500,mtry=i,proximity = TRUE)
```

```
    yhat.rf.med=predict(rf.med, newdata = med[test,],n.trees =j*500,mtry=i,pr
oximity = TRUE)
    er.df[j,i]=mean((yhat.rf.med$predicted-med[test,"charges"])^2)
  }
  print(i)
}
```

```
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
```

```
er.df2=data.frame(treeN,er.df[,2:6])
data_long <- melt(er.df2, id = "treeN")
colnames(data_long)[3]="testMSE"
randomforest_plot <- ggplot(data_long,
               aes(x = treeN,
                   y = testMSE,
                   color = variable)) +  geom_line()

randomforest_plot
```




```
#using 3 parameter's rf has lowest MSE
table.rf=er.df2[,c(1,3)]
```

```r
colnames(table.rf)[2]="MSE.rf_p3"
table.compare2=data.frame(table.compare,table.rf[3:10,])

d=c(1:10)
lamda=c(1:30)/100
error.mat.boost=matrix(NA,length(lamda),length(d))
er.boost=data.frame(error.mat.boost)
colnames(er.boost) = paste0("Depth",c(1:10))
for(i in c(1:10)){
  print(i)
  for(j in c(1:30)){
    set.seed(1)
    boost.med=gbm(charges~.,data=med[train,],distribution = "gaussian",n.trees = 5000,interaction.depth = i,shrinkage = lamda[j])
    yhat.boost=predict(boost.med,newdata = med[test,],n.trees = 5000,interaction.depth = i,shrinkage = lamda[j])
    er.boost[j,i]=mean((yhat.boost-med[test,"charges"])^2)
  }
}
```

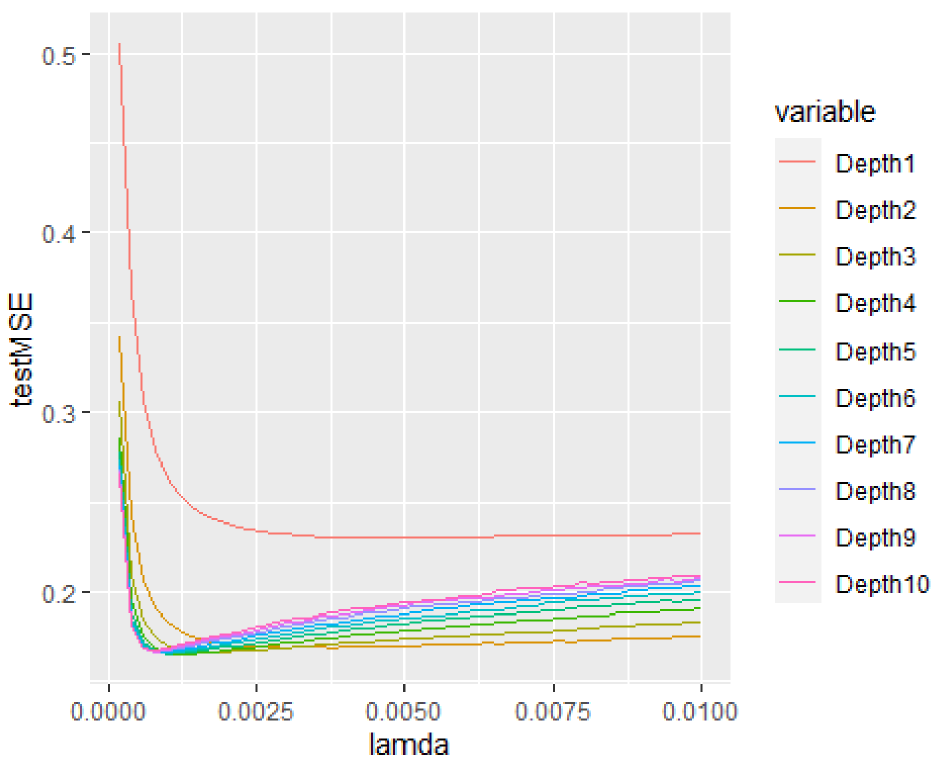
```
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
```

```r
er.boost2=data.frame(lamda,er.boost)
#colnames(er.df2)[1]="lamda"


boost_long <- melt(er.boost2, id = "lamda")
colnames(boost_long)[3]="testMSE"
gfg_plot <- ggplot(boost_long,
               aes(x = lamda,
                   y = testMSE,
                   color = variable)) +  geom_line()

gfg_plot
```


```
#lamda for 0.0002 ~0.01
d.2=c(1:10)
lamda.2=c(1:50)/5000
error.mat.boost.2=matrix(NA,length(lamda.2),length(d.2))
er.boost.2=data.frame(error.mat.boost.2)
colnames(er.boost.2) = paste0("Depth",c(1:10))
for(i in c(1:10)){
  print(i)
  for(j in c(1:50)){
    set.seed(1)
    boost.med.2=gbm(charges~.,data=med[train,],distribution = "gaussian",n.tr
ees = 5000,interaction.depth = i,shrinkage = lamda.2[j])
    yhat.boost.2=predict(boost.med.2,newdata = med[test,],n.trees = 5000,inte
raction.depth = i,shrinkage = lamda.2[j])
    er.boost.2[j,i]=mean((yhat.boost.2-med[test,"charges"])^2)
  }
}
```

```
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
```

```
## [1] 9
## [1] 10

er.boost2.2=data.frame(lamda.2,er.boost.2)
#colnames(er.df2)[1]="lamda"


boost_long.2 <- melt(er.boost2.2, id = "lamda.2")
colnames(boost_long.2)[3]="testMSE"
colnames(boost_long.2)[1]="lamda"
gfg_plot.2 <- ggplot(boost_long.2,
               aes(x = lamda,
                   y = testMSE,
                   color = variable)) +  geom_line()

gfg_plot.2
```




```
er.boost2.2[which(er.boost2.2==min(er.boost2.2[,2:11]))%%50,1]

## [1] 0.0012

colnames(er.boost2.2)[which(er.boost2.2==min(er.boost2.2[,2:11]))%/%50+1]

## [1] "Depth4"

Depth=colnames(er.boost2.2)[2:11]
MSE.bo_l0.0012=t(er.boost2.2[6,2:11])[1:10]
```

```
table.bo=data.frame(Depth,MSE.bo_l0.0012)
table.compare3=data.frame(table.compare2,table.bo[3:10,])

table.compare3

##    model    MSE.lm branchs    MSE.tr treeN MSE.rf_p3   Depth MSE.bo_l0.001
2
## 5      1 0.4586110       5 0.2207118  1500 0.1743677  Depth3      0.167360
5
## 6      2 0.2126700       6 0.2029762  2000 0.1746719  Depth4      0.165211
8
## 7      3 0.1962058       7 0.2043064  2500 0.1745387  Depth5      0.165687
5
## 8      4 0.1916911       8 0.1908290  3000 0.1743732  Depth6      0.166741
3
## 9      5 0.1911752       9 0.1904854  3500 0.1742815  Depth7      0.167547
8
## 10     6 0.1905866      10 0.1907478  4000 0.1743549  Depth8      0.168480
4
## 11     7 0.1886521      11 0.1890266  4500 0.1741359  Depth9      0.169268
7
## 12     8 0.1881355      12 0.1915374  5000 0.1741971 Depth10      0.170205
4
```