HW2

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If document rendering becomes time consuming due to long computations or plots that are expensive to generate you can use knitr caching to improve performance. The documentation knitr chunk and package options describe how caching works and the cache examples provide additional details.

If you want to enable caching globally for a document you can include a code chunk like this at the top of the document:

```
# ```{r setup, include=FALSE}
# knitr::opts_chunk$set(cache=TRUE)
# ```
#Set working directory and latter, I don't need to type the full directory
#The results between chunk will remain
#The working directory will also remain
setwd("/Users/kungangzhang/Documents/OneDrive/Northwestern/Study/Courses/MSiA
-420-0/HW2")
rm(list = ls())
require(gdata)
```

```
## Loading required package: gdata
```

```
## gdata: read.xls support for 'XLS' (Excel 97-2004) files ENABLED.
```

```
##
```

```
## gdata: read.xls support for 'XLSX' (Excel 2007+) files ENABLED.
```

```
##
## Attaching package: 'gdata'
```

```
## The following object is masked from 'package:stats':
##
##     nobs
```

```
## The following object is masked from 'package:utils':
##
##     object.size
```

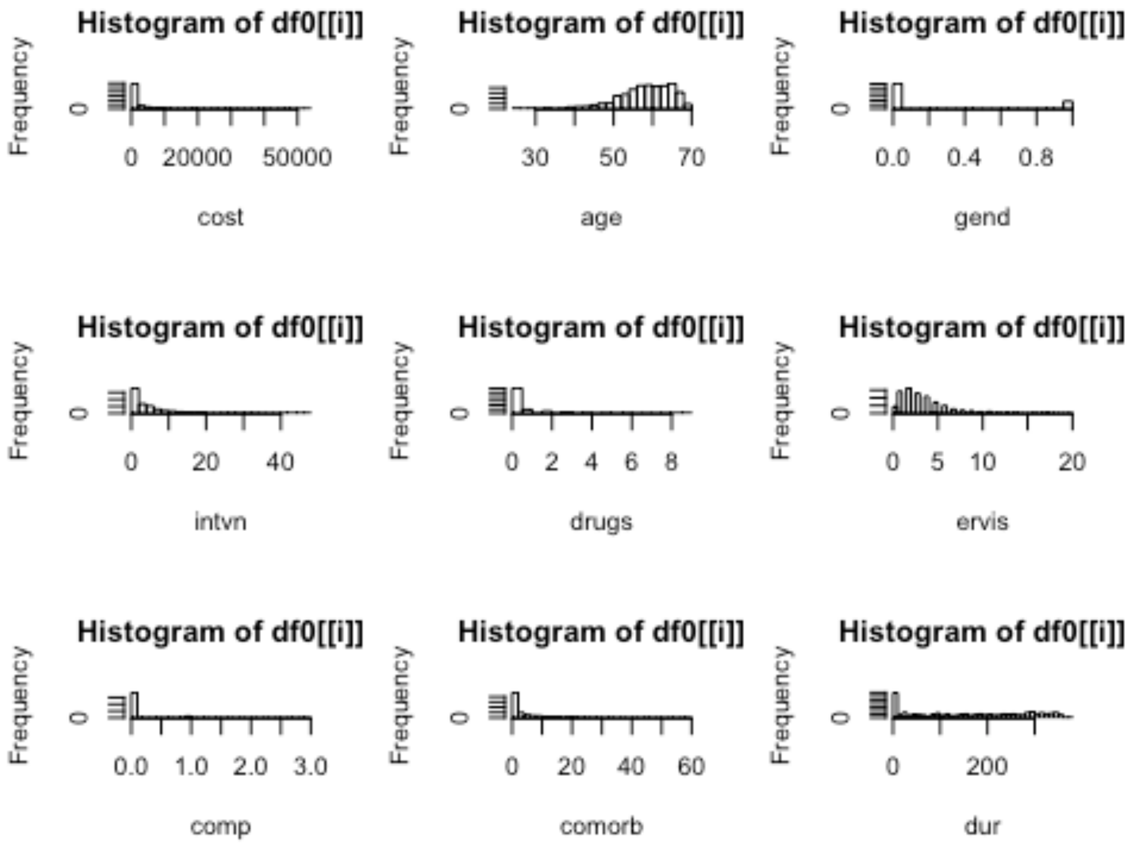
```
set.seed(111)
```

Prob 1)

(a)Fit a linear model and discuss the predictive power.

Answer: First I take log transform to the cost, the response variable, and then fit the model with all predictors unchanged. The R^2 is 0.5831. Then, I tried to standardize everything and the R^2 is 0.5527. I saw some of predictors also have skewed distribution or long tail problem, so that I try log transform (or some special log transform depending on whether it is left-skewed and right-skewed), and the histograms look more symmetric. For the rest of predictors, I just let them be. The R^2 increases to 0.658. Generally, those predictors significant before transform are also significant afterwards.

```
##The histogram of each columns
df0<-read.xls("./HW2_data.xls",sheet=1,header=TRUE)
par(mfrow=c(3,3))
df<-df0
df$gend <- as.factor(df$gend)
par(mfrow=c(3,3))
for (i in seq(2,10)) hist(df0[[i]],breaks=30,xlab=names(df0)[i])
```




```
df$cost <- log10(df$cost)
mod1<-lm(cost~.,data = df[-1])
summary(mod1)
```

```
##
## Call:
## lm(formula = cost ~ ., data = df[-1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.44852 -0.30093  0.01049  0.28276  1.72581
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.2228290  0.1698975  13.083  < 2e-16 ***
## age         -0.0044135  0.0028817  -1.532   0.1260
## gend1       -0.0669173  0.0460024  -1.455   0.1462
## intvn        0.0878065  0.0038090  23.053  < 2e-16 ***
## drugs       -0.0257198  0.0213709  -1.203   0.2291
## ervis        0.0224358  0.0090588   2.477   0.0135 *
## comp         0.3270883  0.0794497   4.117 4.25e-05 ***
## comorb       0.0228849  0.0037393   6.120 1.48e-09 ***
## dur          0.0012181  0.0001874   6.501 1.43e-10 ***
```

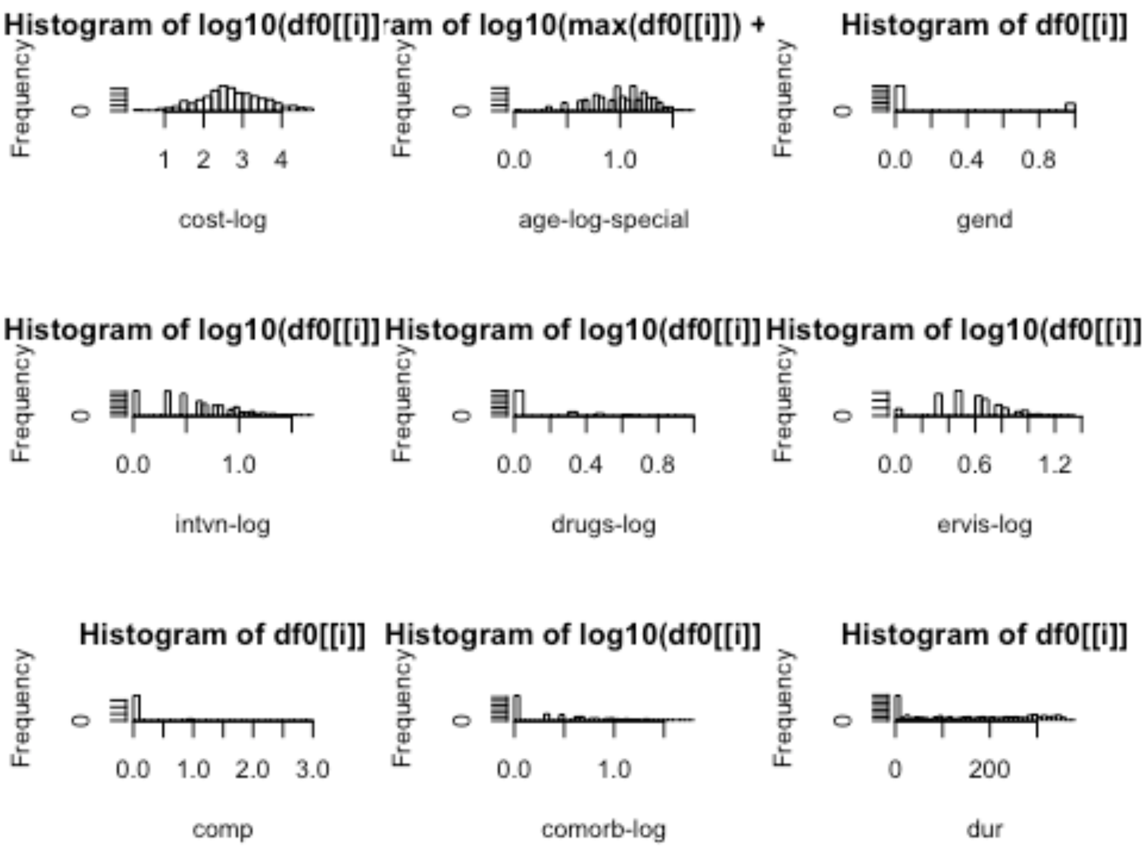
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5373 on 779 degrees of freedom
## Multiple R-squared:  0.5831, Adjusted R-squared:  0.5789
## F-statistic: 136.2 on 8 and 779 DF,  p-value: < 2.2e-16
```

```
##Also, I tried to standardize each variable to see effect.
df_std<-df
df_std[c(2,3,5:10)]<-sapply(df_std[c(2,3,5:10)], function(x) (x-
mean(x))/sd(x))
mod2<-lm(cost~.,data = df_std[-1])
summary(mod2)
```

```
##
## Call:
## lm(formula = cost ~ ., data = df_std[-1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.95741 -0.36347  0.01268  0.34153  2.08450
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.01846    0.02637   0.700   0.4841
## age         -0.03600    0.02351  -1.532   0.1260
## gend1       -0.08083    0.05556  -1.455   0.1462
## intvn        0.59335    0.02574  23.053  < 2e-16 ***
## drugs       -0.03305    0.02746  -1.203   0.2291
## ervis        0.07147    0.02886   2.477   0.0135 *
## comp         0.09800    0.02381   4.117 4.25e-05 ***
## comorb       0.16449    0.02688   6.120 1.48e-09 ***
## dur          0.17790    0.02737   6.501 1.43e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.649 on 779 degrees of freedom
## Multiple R-squared:  0.5831, Adjusted R-squared:  0.5789
## F-statistic: 136.2 on 8 and 779 DF,  p-value: < 2.2e-16
```

```
##Except the intercept, the other aspects of the linear model would not be
changed by standardization, given the full-rank design matrix.

##As shown in the histogram plots the columns of cost, num of interventions,
num of drugs, num of emergency, num of complication, num of other diseaes are
left-skewed, while the age is right-skewed. So I need to do a log transform
to those columns left-skewed and do a special log transform to those columns
right-skewed.
par(mfrow=c(3,3))
for (i in seq(2,10)) {
  if (i %in% c(2,5,6,7,9)){
```

```
    hist(log10(df0[[i]]+1),breaks=30,xlab=paste(names(df0)[i],'log',sep='-'))
  }
  if (i==3){
    hist(log10(max(df0[[i]])+1-df0[[i]]),breaks=30,xlab =
paste(names(df0)[i],'log','special',sep='-'))
  }
  if (i %in% c(4,8,10)){
    hist(df0[[i]],breaks=30,xlab=names(df0)[i])
  }

}
```




```
df_trans_std <- df
df_trans_std$age <- log10(max(df_trans_std$age)+1-df_trans_std$age)
df_trans_std$intvn <- log10(df_trans_std$intvn+1)
df_trans_std$drugs <- log10(df_trans_std$drugs+1)
df_trans_std$ervis <- log10(df_trans_std$ervis+1)
df_trans_std$comorb <- log10(df_trans_std$comorb+1)
df_trans_std[c(2,3,5:10)]<-sapply(df_trans_std[c(2,3,5:10)], function(x) (x-
mean(x))/sd(x))
mod3<-lm(cost~.,data = df_trans_std[-1])#no matter use log10(age+1) or
log10(I(age+1)), the result is the same.
summary(mod3)
```

```
##
## Call:
## lm(formula = cost ~ ., data = df_trans_std[-1])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.41656 -0.35471  0.00511  0.32302  1.90417
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.016807   0.023884   0.704  0.48184
## age          0.036743   0.021232   1.731  0.08393 .
## gend1       -0.073577   0.050303  -1.463  0.14396
## intvn        0.642449   0.022936  28.010  < 2e-16 ***
## drugs       -0.008038   0.023799  -0.338  0.73563
## ervis        0.075082   0.024177   3.105  0.00197 **
## comp         0.090160   0.021528   4.188 3.13e-05 ***
## comorb       0.269192   0.026498  10.159  < 2e-16 ***
## dur          0.062558   0.026960   2.320  0.02058 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5878 on 779 degrees of freedom
## Multiple R-squared:  0.658,  Adjusted R-squared:  0.6545
## F-statistic: 187.4 on 8 and 779 DF,  p-value: < 2.2e-16

##After the log transform, we see the $R^2$ increases from $0.5831$ to
$0.658$ and the influential predictors don't change much.

##(From website by searching 'long tail distribution log transform') You
don't need to assume a lognormal distribution; there's no requirement that an
independent variable in linear regression itself has a normal distribution.
The hope is that, with log transformation of the independent variable, the
other requirements for interpreting linear regression results will better be
met, such as having normally distributed residual errors independent of
fitted values. If the regression against the log-transformed independent
variable meets those requirements, there are no problems with interpreting p-
values, etc. Regression coefficients will now mean the change in the
dependent variable per log change in the independent variable. So if you use
log10, the regression coefficient will be "change per 10-fold change in GDP"
for your example; for log2, "change per doubling of GDP."
```

(b)Which variables appear to have the most influence on the cost.

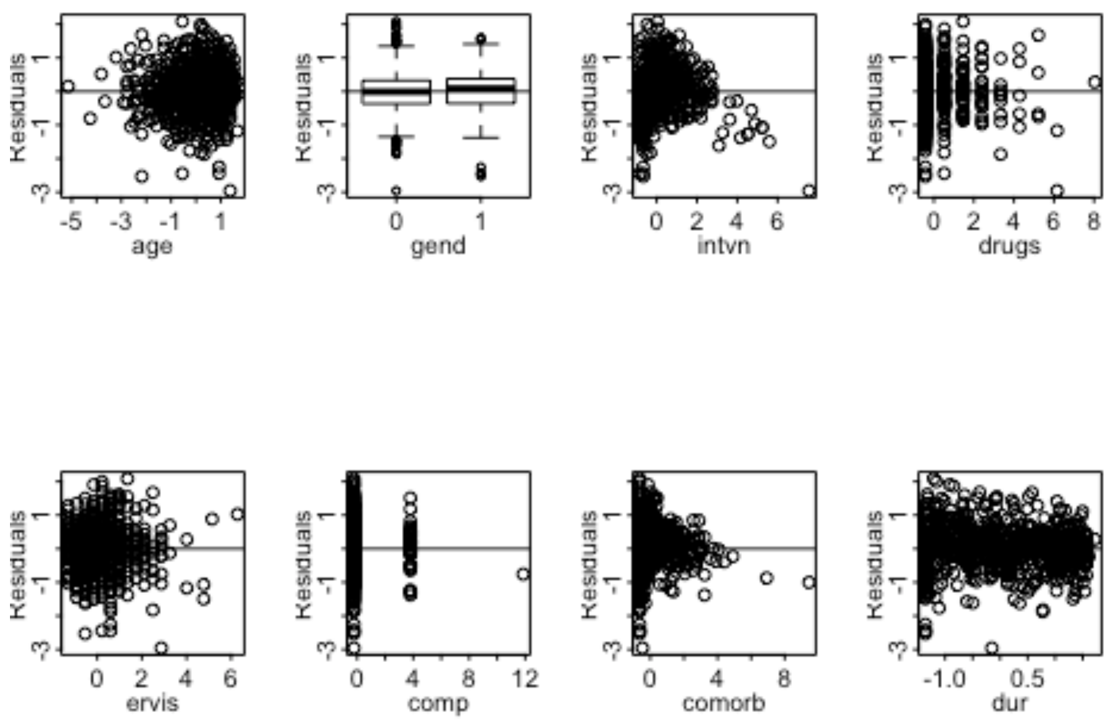
Answer: From the mod2 (the standardized model without log tranforming predictors), we have the biggest coefficient of number of interventions (0.59335), so that this predictor would have the most influence on the cost. Similarily, in the mod3 (standardized model with log tranforming predictors) the number of intervention also has the biggest influence (0.642449).

(c)Construct appropriate diagnostics and residual plots to assess (related to nonlinearity in the relation b/w the response and the predictors.)

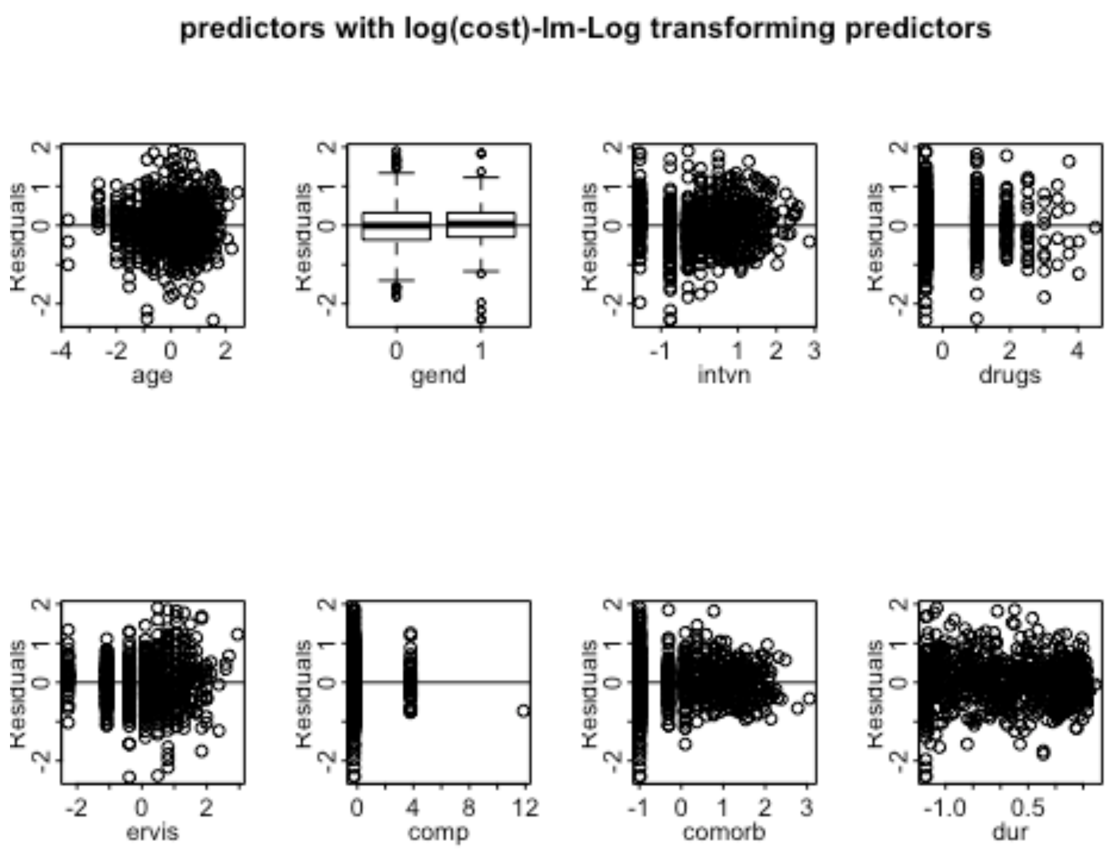
Answer: From both of the plots below, we saw the residuals have little correlation with predictors, so that we don't need to change the model. If there were any nonlinear correlation, we probably need to design better predictors to capture this nonlinearity.

```
##For linear model without log transforming predictors
par(mfrow=c(2,4),pin=c(0.8,0.8),tcl=-0.15,mgp=c(1,0.2,0))
for (i in seq(3:10)) {

plot(df_std[[i+2]],resid(mod2),ylab="Residuals",xlab=names(df_std)[i+2],main=
"")
  abline(0, 0)}
title(main="Ischemic heart disease-standardized \n predictors with log(cost)-
lm",outer = T)
```

predictors with log(cost)-lm




```
##For linear model with log transforming skewed predictors
par(mfrow=c(2,4),pin=c(0.8,0.8),tcl=-0.15,mgp=c(1,0.2,0))
for (i in seq(3:10)) {

plot(df_trans_std[[i+2]],resid(mod3),ylab="Residuals",xlab=names(df_trans_std
)[i+2],main="")
  abline(0, 0)}
title(main="Ischemic heart disease-standardized \n predictors with log(cost)-
lm-Log transforming predictors",outer = T)
```



Prob 2)Find the best neural network model for the ischemic heart disease data set, using linear output activation func, and do not rescale the response.

(a)Use 10-fold CV to find the best combination of shrinkage param and the number of hidden nodes.

Answer: The neural network with the smallest MSE has $= $ and number of hidden nodes , and the MSE is . It has R^2.

```
##CV index random generator
CVInd <- function(n,K) {  #n is sample size; K is number of parts; returns K-length list of indices for each part
  m<-floor(n/K)  #approximate size of each part
  r<-n-m*K
  I<-sample(n,n)  #random reordering of the indices
  Ind<-list()  #will be list of indices for all K parts
  length(Ind)<-K
```

```
  for (k in 1:K) {
    if (k <= r) kpart <- ((m+1)*(k-1)+1):((m+1)*k)
    else kpart<-((m+1)*r+m*(k-r-1)+1):((m+1)*r+m*(k-r))
    Ind[[k]] <- I[kpart]  #indices for kth part of data
  }
  Ind
}
```

Now use multiple reps of CV to compare Neural Nets and linear reg models

```
library(nnet)
CVfunc_nnet <- function(data, lam_seq, num_hidnode_seq,Nrep,K,y) {
  n=nrow(data)
  n.models = n.lam*n.num_hidnode #number of different models to fit
  yhat=matrix(0,n,n.models)

  ##Each column of mod_par corresponds to a set of lambda and number of
hidden nodes of a trail model

mod_par=matrix(c(rep(lam_seq,times=1,each=n.num_hidnode),rep(num_hidnode_seq,
times=n.lam,each=1)),2,n.models,byrow = T)#Store the model parameters: lambda
and the number of nodes in hidden layer
  MSE<-matrix(0,Nrep,n.models)
  for (j in 1:Nrep) {
    print(c(0,0,0,j))#Print out the index of replicates of CV
    Ind<-CVInd(n,K)
    for (k in 1:K) {
      print(k)#Print out the index of different fold of CV
      for (m in 1:n.models) {
        out<-nnet(cost~.,data[-Ind[[k]],],linout = T,
skip=F,size=as.integer(mod_par[2,m]),decay=mod_par[1,m],maxit=1000,trace=F)
        yhat[Ind[[k]],m]<-as.numeric(predict(out,data[Ind[[k]],]))
      }
    } #end of k loop
    MSE[j,]=apply(yhat,2,function(x) sum((y-x)^2))/n
  } #end of j loop
  MSE
  MSEAve<- apply(MSE,2,mean); MSEAve #averaged mean square CV error
  MSEsd <- apply(MSE,2,sd); MSEsd   #SD of mean square CV error
  r2<-1-MSEAve/var(y); r2  #CV r^2
  ##The best model in terms of the minimum MSEAve or the maximum r2.
  min(MSEAve)
  max(r2)
  ##Return the index of the minimum MSEAve or the maximum r2.
  which(MSEAve==min(MSEAve))
  which(r2==max(r2))
  ##The optimal lambda and number of hidden nodes
```

```
  mod_par[,which(MSEAve==min(MSEAve))]
}
```

Do a CV in crude interval of lambda and number of hidden nodes.

```
ptm <- proc.time()
Nrep<-2 #number of replicates of CV
K<-10  #K-fold CV on each replicate
n.lam = 4 #number of lambda
n.num_hidnode = 2 #number of different numbers of hidden nodes
y<-df_std$cost #observed responses
lam_seq = 10^seq(-as.integer(n.lam/2),as.integer(n.lam/2)-1) #seq of penalty
parameters
num_hidnode_seq = 5*seq(1,n.num_hidnode) #seq of number of hidden nodes

par_best_crude <- CVfunc_nnet(df_std, lam_seq, num_hidnode_seq,Nrep,K,y)

## [1] 0 0 0 1
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
## [1] 0 0 0 2
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10

proc.time() - ptm

##    user  system elapsed
##  25.085   0.108  25.325
```

Do a CV in smaller interval of lambda and number of hidden nodes again.

```
ptm <- proc.time()
Nrep <- 2 #number of replicates of CV
```

```r
K<-10  #K-fold CV on each replicate
n.lam = 2 #number of lambda
n.num_hidnode = 2 #number of different numbers of hidden nodes
y<-df_std$cost #observed responses
lam_seq = c(seq(4,4),seq(10,10,10))
num_hidnode_seq = seq(15,17,2)

par_best <- CVfunc_nnet(df_std, lam_seq, num_hidnode_seq,Nrep,K,y) #Best
parameter
```

```
## [1] 0 0 0 1
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
## [1] 0 0 0 2
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
```

```r
proc.time() - ptm
```

```
##    user  system elapsed
##  31.810   0.109  32.018
```

(b)Fit the best model and discuss how good the predictive power is.

Answer: The cross-validation R^2 of the best model is , with the penalization and number of hidden nodes as .

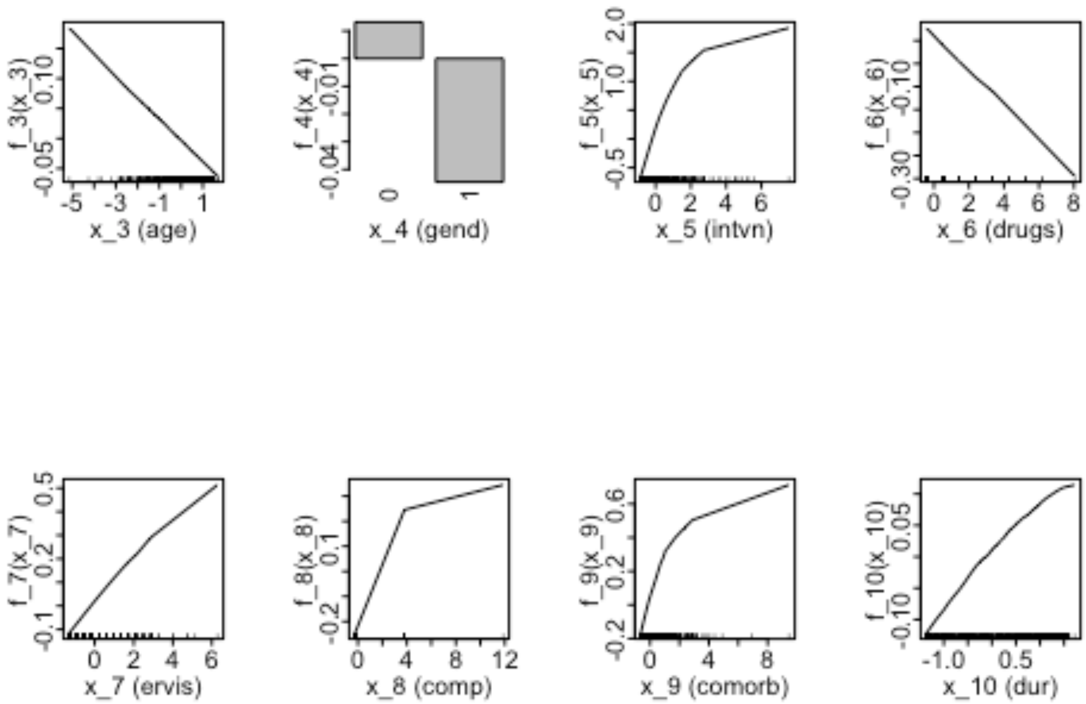
```r
nnet_mod<-nnet(cost~.,df_std,linout = T,
skip=F,size=as.integer(par_best[2]),decay=par_best[1],maxit=1000,trace=F)
summary(nnet_mod)
```

```
## a 9-15-1 network with 166 weights
## options were - linear output units  decay=4
##  b->h1 i1->h1 i2->h1 i3->h1 i4->h1 i5->h1 i6->h1 i7->h1 i8->h1 i9->h1
```

```
##  -0.04   0.00   0.04   0.13  -0.56  -0.01  -0.13   0.08   0.00   0.06 
##  b->h2 i1->h2 i2->h2 i3->h2 i4->h2 i5->h2 i6->h2 i7->h2 i8->h2 i9->h2 
##   0.00  -0.04  -0.03   0.00  -0.02   0.00   0.01   0.00  -0.02  -0.03 
##  b->h3 i1->h3 i2->h3 i3->h3 i4->h3 i5->h3 i6->h3 i7->h3 i8->h3 i9->h3 
##   0.00  -0.04  -0.04   0.00  -0.02   0.00   0.01   0.00  -0.02  -0.03 
##  b->h4 i1->h4 i2->h4 i3->h4 i4->h4 i5->h4 i6->h4 i7->h4 i8->h4 i9->h4 
##  -0.08   0.00   0.01   0.12  -0.62  -0.04  -0.14  -0.21  -0.06   0.04 
##  b->h5 i1->h5 i2->h5 i3->h5 i4->h5 i5->h5 i6->h5 i7->h5 i8->h5 i9->h5 
##  -0.01   0.04   0.07   0.00   0.03   0.00  -0.02   0.01   0.03   0.06 
##  b->h6 i1->h6 i2->h6 i3->h6 i4->h6 i5->h6 i6->h6 i7->h6 i8->h6 i9->h6 
##  -0.08   0.00   0.01   0.12  -0.62  -0.04  -0.14  -0.21  -0.06   0.04 
##  b->h7 i1->h7 i2->h7 i3->h7 i4->h7 i5->h7 i6->h7 i7->h7 i8->h7 i9->h7 
##   0.00  -0.04  -0.03   0.00  -0.02   0.00   0.01   0.00  -0.02  -0.03 
##  b->h8 i1->h8 i2->h8 i3->h8 i4->h8 i5->h8 i6->h8 i7->h8 i8->h8 i9->h8 
##   0.00  -0.04  -0.03   0.00  -0.02   0.00   0.01   0.00  -0.02  -0.03 
##  b->h9 i1->h9 i2->h9 i3->h9 i4->h9 i5->h9 i6->h9 i7->h9 i8->h9 i9->h9 
##  -0.01   0.04   0.07   0.00   0.03   0.00  -0.02   0.01   0.03   0.06 
##  b->h10 i1->h10 i2->h10 i3->h10 i4->h10 i5->h10 i6->h10 i7->h10 i8->h10 
##    0.02   -0.02    0.11    0.02    0.08    0.09   -0.04    0.05    0.07 
## i9->h10 
##    0.12 
##  b->h11 i1->h11 i2->h11 i3->h11 i4->h11 i5->h11 i6->h11 i7->h11 i8->h11 
##    0.92    0.00   -0.06    0.04    1.51   -0.17    0.05    0.15    0.84 
## i9->h11 
##    0.31 
##  b->h12 i1->h12 i2->h12 i3->h12 i4->h12 i5->h12 i6->h12 i7->h12 i8->h12 
##    0.04    0.00   -0.03   -0.09    0.47    0.04    0.13    0.11    0.05 
## i9->h12 
##    0.00 
##  b->h13 i1->h13 i2->h13 i3->h13 i4->h13 i5->h13 i6->h13 i7->h13 i8->h13 
##    0.00   -0.04   -0.03    0.00   -0.02    0.00    0.01    0.00   -0.02 
## i9->h13 
##   -0.03 
##  b->h14 i1->h14 i2->h14 i3->h14 i4->h14 i5->h14 i6->h14 i7->h14 i8->h14 
##    0.00   -0.04   -0.03    0.00   -0.02    0.00    0.01    0.00   -0.02 
## i9->h14 
##   -0.03 
##  b->h15 i1->h15 i2->h15 i3->h15 i4->h15 i5->h15 i6->h15 i7->h15 i8->h15 
##    0.00   -0.04   -0.03    0.00   -0.02    0.00    0.01    0.00   -0.02 
## i9->h15 
##   -0.03 
##   b->o  h1->o  h2->o  h3->o  h4->o  h5->o  h6->o  h7->o  h8->o  h9->o 
##  -0.04  -0.66   0.08   0.08  -0.75  -0.16  -0.75   0.08   0.08  -0.16 
## h10->o h11->o h12->o h13->o h14->o h15->o 
##  -0.26   1.98   0.55   0.08   0.08   0.08

##(c)The variables having the most influence on cost (Use the ALEPlot package for this).
##Answer:
library(ALEPlot)
```

```
## Loading required package: yaImpute
```

```
yhat <- function(X.model, newdata) as.numeric(predict(X.model, newdata))
par(mfrow=c(2,4),pin=c(0.7,0.7),tcl=-0.2,mgp = c(1,0.15,0))
for (j in 3:10)  {ALEPlot(df_std, nnet_mod, pred.fun=yhat, J=j, K=50, NA.plot
= TRUE)
  rug(df_std[,j]) }  ## This creates main effect ALE plots for all 8
predictors
```




```
par(mfrow=c(1,1))

par(mfrow=c(2,2),pin=c(1.3,1.3),mgp = c(1,0.15,0),tcl=-0.15)
## This creates 2nd-order interaction ALE plots for x3, x7, x6, x8, x5, x10
ALEPlot(df_std, nnet_mod, pred.fun=yhat, J=c(3,7), K=50, NA.plot = TRUE)
```

```
## $K
## [1] 25 11
##
## $x.values
## $x.values[[1]]
##  [1] -5.14031174 -2.47527110 -2.03109766 -1.73498204 -1.43886641
##  [6] -1.29080860 -1.14275079 -0.99469297 -0.84663516 -0.69857735
## [11] -0.55051953 -0.40246172 -0.25440391 -0.10634609  0.04171172
```

```
## [16]  0.18976953  0.33782734  0.48588516  0.63394297  0.78200078
## [21]  0.93005860  1.07811641  1.22617422  1.37423204  1.52228985
## [26]  1.67034766
##
## $x.values[[2]]
##  [1] -1.2986393 -0.9194886 -0.5403379 -0.1611872  0.2179635  0.5971142
##  [7]  0.9762649  1.3554156  1.7345663  2.1137170  2.8720185  6.2843748
##
##
## $f.values
##                          1             2             3             4
##     -6.428006e-04 -3.606228e-04 -2.808563e-04 -1.959205e-04  8.293719e-04
## 1   -2.079620e-04 -8.030519e-05  2.693103e-04  2.666655e-04  3.237156e-04
## 2   -2.816257e-04 -6.448674e-05  1.701832e-04  2.640947e-04  4.177013e-04
## 3   -1.831639e-04 -2.728806e-05  1.290957e-04  1.779766e-04  3.326541e-04
## 4   -1.334922e-04 -4.449034e-05  1.005730e-04  1.925952e-04  2.815117e-04
## 5   -1.286524e-04 -3.969405e-05  8.362988e-05  2.128789e-04  2.477966e-04
## 6   -1.045551e-04 -1.143455e-05  8.422791e-05  1.852492e-04  2.098194e-04
## 7   -1.171003e-04 -4.356791e-05  4.748723e-05  1.739079e-04  1.986741e-04
## 8   -1.207789e-04 -5.610210e-05  3.958052e-05  1.449167e-04  1.733634e-04
## 9   -8.551478e-05 -3.982606e-05  3.802173e-05  1.284807e-04  1.229496e-04
## 10 -8.500270e-05 -4.645550e-05  2.506367e-05  1.195629e-04  8.782678e-05
## 11 -4.428142e-05 -3.253012e-05  3.095382e-06  6.367518e-05  6.671889e-05
## 12 -7.743107e-06 -7.091140e-06 -8.193537e-06  2.718712e-05  3.540246e-05
## 13 -2.746901e-05 -2.142038e-05 -2.421052e-05 -2.783379e-06  1.599812e-05
## 14 -9.730431e-06  1.271554e-05 -2.511871e-05 -1.617943e-05 -1.410498e-07
## 15  9.149961e-06  2.106970e-05 -2.316685e-05 -2.230074e-05 -3.264521e-05
## 16  3.251068e-05  2.205871e-05 -2.601808e-05 -4.006971e-05 -5.512289e-05
## 17  6.816875e-05  2.648832e-05 -3.958990e-05 -6.491691e-05 -8.475713e-05
## 18  1.212779e-04  4.021486e-05 -5.953896e-05 -1.046071e-04 -1.249307e-04
## 19  1.450489e-04  5.166729e-05 -6.397043e-05 -1.230440e-04 -1.463457e-04
## 20  1.757585e-04  6.040052e-05 -5.857725e-05 -1.270226e-04 -1.611756e-04
## 21  2.386077e-04  7.737904e-05 -5.161344e-05 -1.297448e-04 -2.035358e-04
## 22  2.577888e-04  8.231070e-05 -4.875997e-05 -1.523500e-04 -2.478824e-04
## 23  2.744127e-04  7.695069e-05 -7.691828e-05 -1.861956e-04 -2.802545e-04
## 24  3.078836e-04  7.836064e-05 -1.041371e-04 -2.042126e-04 -2.888288e-04
## 25  3.545254e-04  9.294138e-05 -1.539403e-04 -2.448139e-04 -3.199873e-04
##                 5             6             7             8             9
##      1.565893e-03  1.975827e-03  2.580409e-03  1.808616e-03  8.224781e-04
## 1    9.199410e-05 -3.247911e-04 -5.469283e-04 -7.910327e-04 -1.249482e-03
## 2    2.560193e-04 -9.072627e-05 -2.775029e-04 -4.862468e-04 -8.667267e-04
## 3    2.505884e-04 -2.671985e-05 -1.781360e-04 -3.089102e-04 -6.114203e-04
## 4    2.261409e-04  1.826991e-05 -1.464804e-04 -1.992849e-04 -4.238254e-04
## 5    2.191206e-04  3.697184e-05 -1.411128e-04 -1.303895e-04 -2.914022e-04
## 6    1.782470e-04  1.892703e-05 -1.495365e-04 -1.863372e-04 -3.201830e-04
## 7    1.642053e-04  5.018128e-05 -1.086612e-04 -1.929857e-04 -2.996646e-04
## 8    1.442822e-04  4.591053e-05 -8.846626e-05 -1.673557e-04 -2.468677e-04
## 9    9.925599e-05  1.860550e-05 -9.130557e-05 -1.647599e-04 -2.171050e-04
## 10   7.660010e-05  4.098294e-05 -5.393400e-05 -7.854988e-05 -1.373820e-04
## 11   6.129291e-05  3.589354e-05 -3.649948e-05 -1.102037e-04 -1.755228e-04
```

```
## 12  6.119694e-06 -1.573806e-06 -2.995061e-05 -1.527431e-04 -2.245493e-04
## 13  2.004281e-05  5.216376e-05  6.780316e-05 -1.157543e-05 -5.744539e-05
## 14 -2.651528e-06  3.733679e-05  7.103979e-05 -1.642114e-05 -3.635484e-05
## 15 -3.198373e-05  6.910740e-06  5.867733e-05 -1.046195e-05 -4.459397e-06
## 16 -4.377688e-05  1.783602e-05  9.992484e-05  5.880064e-05  9.213478e-05
## 17 -5.135651e-05  3.150863e-05  1.580733e-04  1.449642e-04  2.056299e-04
## 18 -8.432969e-05  4.676030e-05  2.178008e-04  2.327067e-04  3.001699e-04
## 19 -1.112081e-04 -2.740847e-05  1.743502e-04  2.299552e-04  3.360252e-04
## 20 -1.544709e-04 -5.631510e-05  1.723396e-04  2.686437e-04  4.133206e-04
## 21 -1.828350e-04 -9.278495e-05  1.140089e-04  2.510121e-04  4.170078e-04
## 22 -1.828922e-04 -9.899498e-05  8.593804e-05  2.728752e-04  4.858017e-04
## 23 -1.789903e-04 -7.382244e-05  1.440275e-04  3.808986e-04  6.140711e-04
## 24 -1.512906e-04 -7.887020e-05  1.718966e-04  4.587017e-04  7.121203e-04
## 25 -1.461751e-04 -1.065022e-04  1.771815e-04  4.710280e-04  7.446927e-04
##               10            11
##    -5.282915e-04 -0.0043862199
## 1  -2.072563e-03 -0.0054028033
## 2  -1.611105e-03 -0.0048230012
## 3  -1.277095e-03 -0.0043706483
## 4  -1.010797e-03 -0.0039860069
## 5  -7.996707e-04 -0.0036565372
## 6  -7.497482e-04 -0.0034882715
## 7  -6.505267e-04 -0.0029219352
## 8  -5.022854e-04 -0.0023065791
## 9  -3.770783e-04 -0.0017142572
## 10 -2.440444e-04 -0.0012193239
## 11 -1.767625e-04 -0.0007901426
## 12 -2.153926e-04 -0.0004668733
## 13  3.892341e-05 -0.0002798484
## 14  1.472260e-04  0.0003240055
## 15  1.406914e-04  0.0008130221
## 16  1.988556e-04  0.0013667375
## 17  2.553819e-04  0.0016762002
## 18  5.060452e-04  0.0021798000
## 19  4.664262e-04  0.0023931175
## 20  4.682473e-04  0.0025319886
## 21  5.421931e-04  0.0027429845
## 22  6.812457e-04  0.0030190871
## 23  8.060005e-04  0.0032808921
## 24  9.005351e-04  0.0035124767
## 25  9.295929e-04  0.0036785846
```

```
ALEPlot(df_std, nnet_mod, pred.fun=yhat, J=c(3,6), K=50, NA.plot = TRUE)
```

```
## $K
## [1] 25  5
## 
## $x.values
## $x.values[[1]]
##  [1] -5.14031174 -2.47527110 -2.03109766 -1.73498204 -1.43886641
```

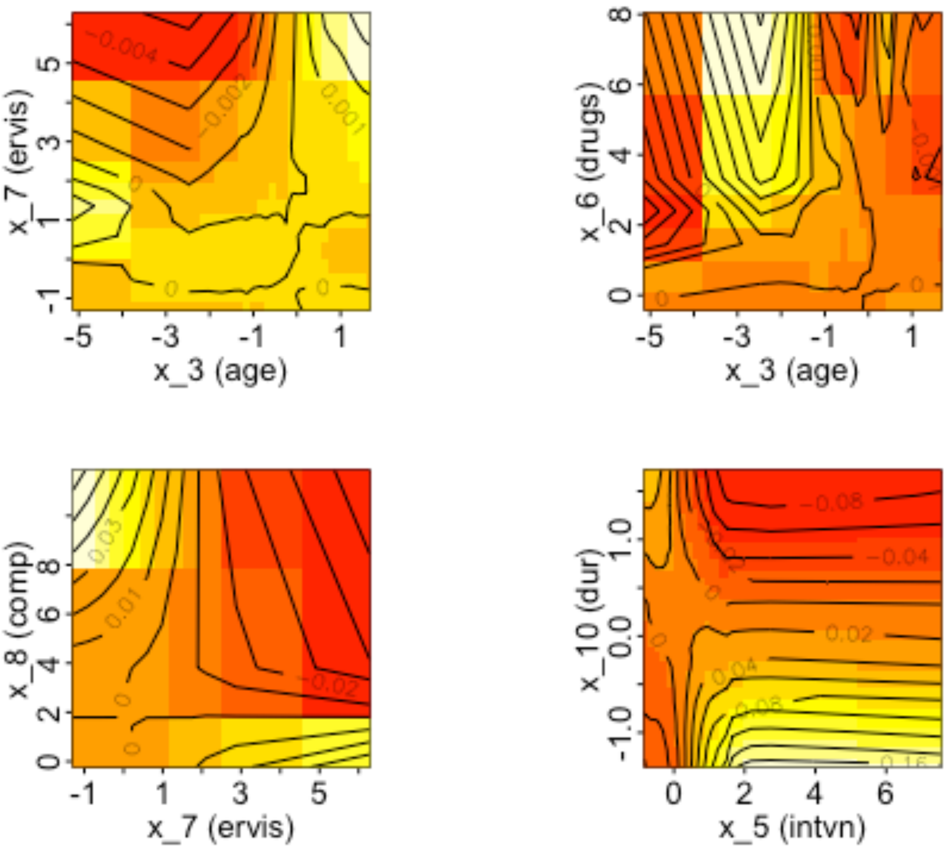
```
##  [6] -1.29080860 -1.14275079 -0.99469297 -0.84663516 -0.69857735
## [11] -0.55051953 -0.40246172 -0.25440391 -0.10634609  0.04171172
## [16]  0.18976953  0.33782734  0.48588516  0.63394297  0.78200078
## [21]  0.93005860  1.07811641  1.22617422  1.37423204  1.52228985
## [26]  1.67034766
##
## $x.values[[2]]
## [1] -0.4198780  0.5200762  1.4600303  2.3999844  3.3399386  8.0397093
##
##
## $f.values
##                            1             2             3             4
##    -3.639280e-04  9.985034e-04 -0.0026170348 -4.926082e-03 -2.872470e-03
## 1  -4.620949e-04  1.209531e-04  0.0004998031  2.185144e-03  4.364209e-03
## 2  -4.266677e-04  8.552589e-05  0.0006388952  1.827607e-03  3.831363e-03
## 3  -4.595096e-04  1.063577e-04  0.0008342463  1.526329e-03  3.354776e-03
## 4  -3.920794e-04  1.313829e-04  0.0005529551  7.484094e-04  2.401546e-03
## 5  -3.350426e-04  1.565054e-04  0.0003651097  5.066294e-04  1.984457e-03
## 6  -3.163938e-04  1.677642e-04  0.0002084721  2.960572e-04  1.598576e-03
## 7  -2.337119e-04  1.384865e-04  0.0002694259  3.030764e-04  1.430285e-03
## 8  -1.674770e-04  9.901176e-05  0.0002623118  3.402749e-04  1.292175e-03
## 9  -1.392074e-04  6.517640e-05  0.0002608372  5.142901e-04  1.211220e-03
## 10 -7.589645e-05  6.080335e-05  0.0001291570  3.075561e-04  7.495165e-04
## 11 -8.213419e-05  4.652966e-05  0.0002724145  3.757598e-04  5.627504e-04
## 12 -5.995769e-05  2.964687e-05  0.0002724186  1.448278e-04  7.684874e-05
## 13  1.180742e-05 -1.491919e-05  0.0001687455  2.548575e-05 -2.974630e-04
## 14  2.783640e-05 -2.927637e-05  0.0001179025  1.879473e-05 -3.046589e-04
## 15  7.495605e-05 -5.156078e-05 -0.0000684681 -1.234239e-04 -4.473824e-04
## 16  1.169198e-04 -8.498917e-05 -0.0001463389 -1.571427e-04 -4.816061e-04
## 17  1.371257e-04 -9.154163e-05 -0.0002033082 -3.443998e-04 -8.980528e-04
## 18  1.737095e-04 -5.266686e-05 -0.0002148502 -4.862296e-04 -1.269072e-03
## 19  2.309107e-04 -6.929822e-05 -0.0002184896 -5.719602e-04 -1.583993e-03
## 20  2.557385e-04 -8.465250e-05 -0.0001872419 -5.862408e-04 -1.874407e-03
## 21  2.691201e-04 -8.388379e-05 -0.0002567787 -5.097338e-04 -2.074034e-03
## 22  2.828073e-04 -1.054191e-04 -0.0002808844 -3.877958e-04 -1.959233e-03
## 23  3.469433e-04 -1.066604e-04 -0.0004905700 -4.514377e-04 -2.030011e-03
## 24  3.711086e-04 -1.136807e-04 -0.0007235797 -5.384037e-04 -2.124114e-03
## 25  3.743743e-04 -1.169464e-04 -0.0009528348 -6.216151e-04 -2.214462e-03
##                5
##    -1.387169e-04
## 1   7.223415e-03
## 2   5.820579e-03
## 3   4.474002e-03
## 4   2.650783e-03
## 5   1.363703e-03
## 6   1.078315e-04
## 7  -9.304487e-04
## 8  -1.241011e-03
## 9  -1.494417e-03
## 10 -2.002710e-03
```

```
## 11 -2.046777e-03
## 12 -2.389980e-03
## 13 -1.701537e-03
## 14 -6.459785e-04
## 15  2.740525e-04
## 16  1.302583e-03
## 17  1.715958e-03
## 18 -2.042986e-05
## 19 -5.635107e-04
## 20 -8.303671e-04
## 21 -1.006436e-03
## 22 -8.831540e-04
## 23 -9.454520e-04
## 24 -1.031074e-03
## 25 -1.112942e-03
```

```
ALEPlot(df_std, nnet_mod, pred.fun=yhat, J=c(7,8), K=50, NA.plot = TRUE)
```

```
## $K
## [1] 11  2
##
## $x.values
## $x.values[[1]]
##  [1] -1.2986393 -0.9194886 -0.5403379 -0.1611872  0.2179635  0.5971142
##  [7]  0.9762649  1.3554156  1.7345663  2.1137170  2.8720185  6.2843748
##
## $x.values[[2]]
## [1] -0.2302054  3.8009470 11.8632519
##
##
## $f.values
##                             1            2
##    -2.849681e-03  2.839745e-03  0.066742957
## 1  -2.516128e-03  2.506191e-03  0.058891379
## 2  -2.030454e-03  2.020518e-03  0.050887681
## 3  -1.138223e-03  1.128287e-03  0.042477425
## 4   2.476283e-05 -3.469892e-05  0.033796414
## 5   1.964085e-03 -1.974022e-03  0.024339066
## 6   4.075781e-03 -4.085717e-03  0.014709346
## 7   6.591437e-03 -6.601373e-03  0.004675664
## 8   9.058872e-03 -9.068808e-03 -0.005309795
## 9   1.213011e-02 -1.128626e-02 -0.015045274
## 10  1.731731e-02 -1.647346e-02 -0.027750499
## 11  4.006290e-02 -3.921906e-02 -0.058014121
```

```
ALEPlot(df_std, nnet_mod, pred.fun=yhat, J=c(5,10), K=50, NA.plot = TRUE)
```




```
## $K
## [1] 16 44
##
## $x.values
## $x.values[[1]]
##  [1] -0.84131152 -0.66256968 -0.48382784 -0.30508600 -0.12634417
##  [6]  0.05239767  0.23113951  0.40988135  0.58862318  0.76736502
## [11]  0.94610686  1.12484870  1.48233237  1.66107421  2.19729972
## [16]  2.73352523  7.55955484
##
## $x.values[[2]]
##  [1] -1.356566133 -1.331755507 -1.298674671 -1.265593836 -1.182891748
##  [6] -1.125000286 -1.050568406 -0.992676945 -0.909974856 -0.810732350
## [11] -0.678409009 -0.620517547 -0.554355876 -0.488194206 -0.405492117
## [16] -0.322790029 -0.215277314 -0.132575226 -0.074683764  0.008018324
## [21]  0.123801248  0.189962919  0.256124589  0.330556469  0.413258557
## [26]  0.504230854  0.570392525  0.653094613  0.710986075  0.768877537
## [31]  0.835039208  0.934281714  0.983902967  1.033524220  1.074875264
## [36]  1.124496517  1.182387979  1.232009232  1.281630485  1.347792155
## [41]  1.413953826  1.455304870  1.496655914  1.546277167  1.719951553
##
##
## $f.values
```

```
##                         1           2           3           4
##     -0.018819989 -0.019096034 -0.019635929 -0.020096658 -0.021686585
## 1   -0.023578049 -0.023516288 -0.023621621 -0.023602117 -0.024006082
## 2   -0.027333823 -0.026996365 -0.026710640 -0.026388319 -0.025980839
## 3   -0.027165223 -0.026669835 -0.026114257 -0.025585399 -0.025128850
## 4   -0.019638280 -0.019069311 -0.018390708 -0.017835254 -0.016966771
## 5   -0.007737575 -0.007101212 -0.006628715 -0.006282985 -0.005467176
## 6    0.008926179  0.009391184  0.009692321  0.009754224  0.010184360
## 7    0.028899386  0.028949978  0.028836704  0.028484195  0.028528659
## 8    0.051409780  0.051092558  0.050611468  0.049745091  0.049275688
## 9    0.070972082  0.070135360  0.069134771  0.067748895  0.066765624
## 10   0.089029722  0.087673502  0.086153414  0.084437418  0.082655331
## 11   0.102978539  0.101292198  0.099441991  0.097395875  0.094814972
## 12   0.126674323  0.124657863  0.120988797  0.117123824  0.112724062
## 13   0.156030635  0.152195316  0.146707392  0.141023561  0.134804941
## 14   0.174590164  0.168935987  0.161629205  0.154126515  0.146089037
## 15   0.179515787  0.172042752  0.162917112  0.155286199  0.147120497
## 16   0.166921031  0.159853524  0.151133412  0.143908027  0.136147853
##                5            6            7             8             9
##     -0.021791979 -0.021532630 -0.021751992 -0.0211411811 -0.0200682488
## 1   -0.023463302 -0.022351263 -0.021853990 -0.0208744607 -0.0190794724
## 2   -0.024777028 -0.023005606 -0.022106848 -0.0207270120 -0.0188155698
## 3   -0.023432401 -0.021373064 -0.020107355 -0.0190151510 -0.0161990811
## 4   -0.015426013 -0.013078762 -0.011694472 -0.0108776888 -0.0094044820
## 5   -0.004135427 -0.002501838 -0.001339134 -0.0009788537  0.0003244427
## 6    0.010943853  0.011863778  0.012185627  0.0119858672  0.0117391598
## 7    0.028492270  0.028698532  0.028179526  0.0273132384  0.0255165272
## 8    0.048443416  0.047473322  0.046092205  0.0445593903  0.0413862643
## 9    0.065068494  0.062922044  0.060803630  0.0580206433  0.0534711027
## 10   0.080093342  0.076830874  0.074321611  0.0702884524  0.0644887402
## 11   0.091451764  0.087073278  0.084173165  0.0788898356  0.0718399520
## 12   0.107780549  0.102038366  0.097952740  0.0906471713  0.0815750481
## 13   0.128281121  0.121175243  0.115904104  0.1065762953  0.0967259837
## 14   0.137984912  0.130100845  0.124051518  0.1139455206  0.1033170206
## 15   0.138888148  0.130875858  0.124698307  0.1144640861  0.1037073626
## 16   0.128321032  0.120714270  0.114942247  0.1051135547  0.0947623593
##               10           11           12           13           14
##     -0.019654580 -0.019060600 -0.018612328 -0.018913414 -0.018689916
## 1   -0.017622123 -0.017137835 -0.016347187 -0.016030962 -0.015354052
## 2   -0.016704387 -0.015949564 -0.014888380 -0.014355682 -0.013260762
## 3   -0.013622558 -0.012329124 -0.011207671 -0.009931540 -0.008857519
## 4   -0.006362618 -0.005973028 -0.005394063 -0.004221326 -0.003168202
## 5    0.001973683  0.002066251  0.002348194  0.002983260  0.003738355
## 6    0.012105419  0.011686869  0.011186254  0.011283650  0.010933592
## 7    0.023814851  0.022885183  0.021602009  0.020594253  0.019139044
## 8    0.038111654  0.035609053  0.033543321  0.031729182  0.029467591
## 9    0.048623559  0.044548025  0.041675910  0.039055389  0.035987415
## 10   0.058068264  0.053510812  0.050156780  0.046729877  0.042855520
## 11   0.064937558  0.059898189  0.056062240  0.051430694  0.046015091
## 12   0.072065784  0.065821772  0.060781180  0.054944990  0.047988141
```

```
## 13  0.084609848  0.077161193  0.070915959  0.063875126  0.055377030
## 14  0.090422697  0.082195854  0.074745976  0.066500500  0.056461157
## 15  0.090684815  0.082329748  0.074751647  0.066746435  0.056947355
## 16  0.082145340  0.074195801  0.067023228  0.059509840  0.050202583
##              15           16           17            18           19
##    -0.017971638 -0.016406136 -0.012014932 -0.0095455524 -0.008999603
## 1  -0.014388687 -0.011957765 -0.006990853 -0.0044591971 -0.003890073
## 2  -0.011790896 -0.008180650 -0.002834595 -0.0009188969 -0.000213883
## 3  -0.007497682 -0.003596220  0.001436953  0.0029790959  0.003310166
## 4  -0.001918394  0.001952187  0.006672477  0.0073983278  0.007355455
## 5   0.003744967  0.006095044  0.010293892  0.0104983006  0.009280258
## 6   0.009666362  0.010415977  0.013370926  0.0126696713  0.011225784
## 7   0.016643036  0.016419858  0.018130910  0.0165239912  0.014854259
## 8   0.025742806  0.023883603  0.024373743  0.0221822173  0.020286640
## 9   0.031456248  0.027957254  0.027226482  0.0249220136  0.022913493
## 10  0.037131083  0.032438819  0.030737312  0.0277792509  0.025221978
## 11  0.038965419  0.032947920  0.030121740  0.0265100856  0.023404060
## 12  0.039434142  0.031912317  0.028142024  0.0235862576  0.019931479
## 13  0.045318705  0.036292553  0.031578148  0.0260782691  0.022388517
## 14  0.046643095  0.037581970  0.032832592  0.0272977400  0.023573015
## 15  0.047369556  0.038548694  0.033542385  0.0277440103  0.023755762
## 16  0.041116608  0.032453127  0.027604200  0.0219632058  0.018132338
##               20           21           22            23            24
##    -0.0057420220 -0.004348121 -0.003590824 -0.0033568648  0.0007831891
## 1  -0.0003960318  0.001286212  0.002032487  0.0026220307  0.0066072856
## 2   0.0035166176  0.005093963  0.005447629  0.0061748164  0.0100052723
## 3   0.0057151244  0.006860549  0.007940934  0.0082556661  0.0118084078
## 4   0.0084348702  0.009148374  0.010955478  0.0114397372  0.0141828072
## 5   0.0098163358  0.010097919  0.010875061  0.0106015709  0.0120522063
## 6   0.0105894633  0.010053855  0.009870820  0.0085825621  0.0091987081
## 7   0.0130455401  0.011731224  0.010588011  0.0082849862  0.0080666427
## 8   0.0168634807  0.014770456  0.012848535  0.0095307429  0.0079974772
## 9   0.0178758939  0.014168429  0.012219555  0.0078953590  0.0051172386
## 10  0.0185699379  0.014835520  0.012859693  0.0075290931  0.0035061181
## 11  0.0162032670  0.012441895  0.010439115  0.0041021123 -0.0017537333
## 12  0.0126034177  0.008608823  0.006372819 -0.0001974077 -0.0078861240
## 13  0.0149331875  0.010811324  0.008448052  0.0015044474 -0.0065576465
## 14  0.0158699393  0.011527393  0.008943439  0.0017791517 -0.0062209163
## 15  0.0161268010  0.011858369  0.009348529  0.0022583569 -0.0061760078
## 16  0.0112964866  0.007821164  0.006104433 -0.0001926302 -0.0082869735
##               25           26            27           28            29
##     0.0030563558  0.007697841  0.0099618761  0.013695611  0.0165922179
## 1   0.0081957588  0.012154340  0.0143777923  0.017662026  0.0200343630
## 2   0.0116017530  0.015077510  0.0173476598  0.020227948  0.0221819921
## 3   0.0134249342  0.016417868  0.0178346778  0.020025029  0.0212274167
## 4   0.0147693325  0.016799985  0.0174953315  0.018792376  0.0191014574
## 5   0.0117168997  0.012785270  0.0128265434  0.013524301  0.0130912793
## 6   0.0079415695  0.008284488  0.0072805378  0.007037192  0.0056630671
## 7   0.0060840522  0.005701519  0.0036523452  0.002870831  0.0009585361
## 8   0.0048115204  0.003428249  0.0003338513 -0.001364005 -0.0041699684
```

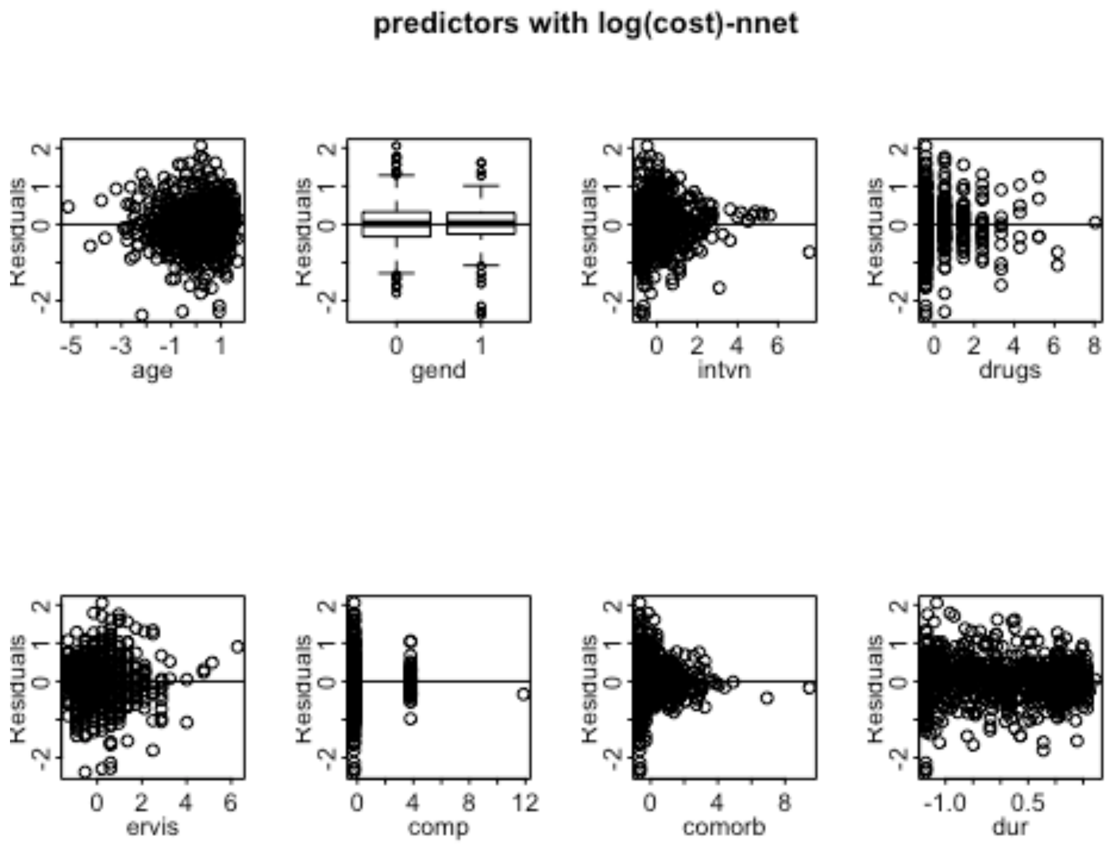
```
## 9   0.0007279155 -0.001656095 -0.0054828143 -0.007912993 -0.0111542538
## 10 -0.0021286477 -0.005758101 -0.0108221400 -0.013773658 -0.0172973841
## 11 -0.0086339418 -0.013500715 -0.0198020737 -0.023274932 -0.0271855992
## 12 -0.0156394967 -0.021379434 -0.0285539571 -0.032548155 -0.0368457641
## 13 -0.0144565683 -0.020342055 -0.0276621270 -0.031920460 -0.0364822036
## 14 -0.0140578123 -0.020088848 -0.0275473430 -0.031944099 -0.0366442656
## 15 -0.0144472004 -0.020351439 -0.0278253290 -0.032137756 -0.0367535944
## 16 -0.0158112695 -0.020968612 -0.0279094242 -0.031641424 -0.0356768345
##              30           31           32            33            34
##     0.018527403  0.023990102  0.025279527  0.0271946042  0.0291291937
## 1   0.021551385  0.026986147  0.028047620  0.0296092990  0.0311766369
## 2   0.023395466  0.028414884  0.028962548  0.0299226087  0.0310879140
## 3   0.022065658  0.025829437  0.026466338  0.0267173912  0.0272187212
## 4   0.019046392  0.021214029  0.021178420  0.0208775857  0.0208111179
## 5   0.012294111  0.012865606  0.012149913  0.0111526924  0.0104624713
## 6   0.003799927  0.002931229  0.001824280  0.0003297069 -0.0008578668
## 7  -0.001970576 -0.004144480 -0.005642684 -0.0073762230 -0.0088027621
## 8  -0.007992749 -0.011471859 -0.013708024 -0.0156455442 -0.0172227587
## 9  -0.015412333 -0.019536268 -0.022510393 -0.0246518942 -0.0263797841
## 10 -0.021837928 -0.026606688 -0.030225638 -0.0326845332 -0.0347298171
## 11 -0.032113084 -0.037526669 -0.041463014 -0.0442393029 -0.0466019808
## 12 -0.041993953 -0.047628241 -0.051785289 -0.0548789717 -0.0575590437
## 13 -0.041894527 -0.047669526 -0.051967284 -0.0552016780 -0.0577922935
## 14 -0.042195012 -0.048377370 -0.052599094 -0.0557440318 -0.0582451908
## 15 -0.042261761 -0.048703916 -0.053185438 -0.0565901726 -0.0593511288
## 16 -0.040604574 -0.046354763 -0.050144319 -0.0528570872 -0.0549260773
##              35           36           37           38           39
##     0.029998963  0.033414967  0.035392575  0.037775579  0.040875545
## 1   0.031902002  0.035188106  0.036660503  0.038599064  0.041121190
## 2   0.031654134  0.034004742  0.034862553  0.035981015  0.037469562
## 3   0.027495697  0.029210512  0.029278698  0.029605061  0.029998663
## 4   0.020609649  0.021460774  0.020999525  0.020535009  0.019968701
## 5   0.009637249  0.009624683  0.008392398  0.007156845  0.005816142
## 6  -0.002240885 -0.003101812 -0.004663740 -0.005886104 -0.007758126
## 7  -0.010424746 -0.012154465 -0.014203724 -0.015913421 -0.018139835
## 8  -0.019014283 -0.021280615 -0.024033939 -0.026447701 -0.028958323
## 9  -0.028340849 -0.031143794 -0.034601183 -0.037299153 -0.040093985
## 10 -0.037008276 -0.039974181 -0.043594529 -0.046455460 -0.049852537
## 11 -0.049197834 -0.052597528 -0.056476316 -0.059595686 -0.063251203
## 12 -0.060588685 -0.064422169 -0.068734746 -0.072112556 -0.076026513
## 13 -0.061255724 -0.065522997 -0.070269363 -0.073790200 -0.077847184
## 14 -0.061752412 -0.066063474 -0.070806859 -0.074583971 -0.078913548
## 15 -0.062902140 -0.067256993 -0.071997396 -0.076030784 -0.080632953
## 16 -0.057785123 -0.061448009 -0.065723227 -0.069291428 -0.073428411
##              40           41           42           43           44
##     0.043893407  0.045516856  0.048327220  0.050463104  0.060225642
## 1   0.043496630  0.044744420  0.046964228  0.048990260  0.056022193
## 2   0.039327041  0.040056868  0.041758714  0.043078350  0.047871222
## 3   0.031226704  0.031282145  0.032695854  0.033300573  0.036537329
## 4   0.020634242  0.020127183  0.020897234  0.020772533  0.023248031
```

```
## 5   0.005595491  0.004789316  0.005260252  0.004984859  0.004916723
## 6  -0.009013979 -0.010227874 -0.010098607 -0.010360948 -0.011157823
## 7  -0.020249365 -0.022109582 -0.022539037 -0.023360101 -0.026050227
## 8  -0.031923939 -0.033818467 -0.034282233 -0.035137608 -0.039720986
## 9  -0.043787915 -0.045938538 -0.046772260 -0.048038615 -0.053032974
## 10 -0.053540736 -0.055685629 -0.056879397 -0.058150051 -0.063148709
## 11 -0.066933672 -0.069072833 -0.070259501 -0.071523056 -0.076514613
## 12 -0.079747269 -0.081924718 -0.083339445 -0.085003001 -0.090221020
## 13 -0.081710967 -0.084031443 -0.085589197 -0.087652755 -0.093097235
## 14 -0.083049923 -0.085513305 -0.087213965 -0.089420429 -0.095360511
## 15 -0.084770135 -0.087234323 -0.088935790 -0.091143061 -0.097083950
## 16 -0.076920988 -0.078740572 -0.080043563 -0.081852358 -0.087394771
```

(d)Construct appropriate residual plots to assess the nonlinearity not captured by the nnet.

Answer: From the residual plts, there is no nonlinearity not captured by neural network.

```
par(mfrow=c(2,4),pin=c(0.8,0.8),tcl=-0.15,mgp=c(1,0.2,0))
for (i in seq(3:10)) {

plot(df_std[[i+2]],resid(nnet_mod),ylab="Residuals",xlab=names(df)[i+2],main=
"")
  abline(0, 0)}
title(main="Ischemic heart disease-standardized \n predictors with log(cost)-
nnet",outer = T)
```

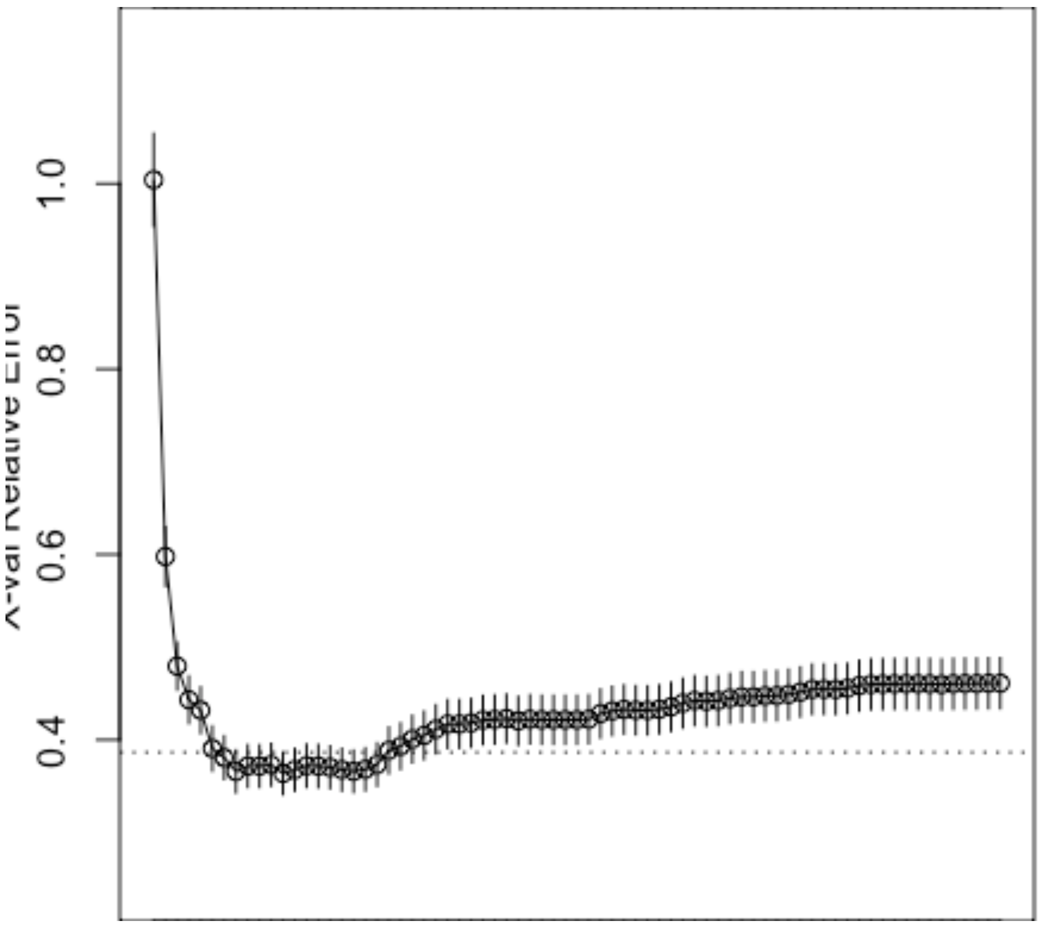


Prob 3)Repeat Prob 2) but for a regression tree.

(a)Use 10-fold CV to find the best tree size or complexity parameter value

Answer: The cross-validation R^2 of the best model is , with the penalization and number of hidden nodes as .

```
#do not have to standardize or transform predictors to fit trees
# the CV shell is not correct in tree?
# cp is \lambda, the complex parameter; with small cp we will grow a big
tree(overfit)
# xval: fold of cross validation
library(rpart)
control <- rpart.control(minbucket = 5, cp = 0.0001, maxsurrogate = 0,
usesurrogate = 0, xval = 10)
par(mfrow=c(1,1),pin=c(4,4),mgp=c(2,1,0))
df_std.tr <- rpart(cost ~ .,df_std, method = "anova", control = control)
plotcp(df_std.tr)  #plot of CV r^2 vs. size
```




```
printcp(df_std.tr)  #same info is in df_std.tr$cptable

##
## Regression tree:
## rpart(formula = cost ~ ., data = df_std, method = "anova", control =
control)
##
## Variables actually used in tree construction:
## [1] age    comorb comp   dur    ervis  gend   intvn  X
##
## Root node error: 787/788 = 0.99873
##
## n= 788
##
##            CP nsplit rel error  xerror     xstd
## 1  0.43938070      0   1.00000 1.00418 0.049875
## 2  0.09581897      1   0.56062 0.59773 0.031942
## 3  0.05828524      2   0.46480 0.47955 0.025505
## 4  0.03070183      3   0.40652 0.44327 0.025352
## 5  0.02475265      4   0.37581 0.43202 0.025008
## 6  0.01166647      5   0.35106 0.39063 0.024038
## 7  0.00991235      6   0.33939 0.38080 0.023348
## 8  0.00664712      7   0.32948 0.36589 0.022869
```

```
## 9  0.00622922      8   0.32283 0.37176 0.022742
## 10 0.00607735      9   0.31661 0.37168 0.022716
## 11 0.00577605     10   0.31053 0.37310 0.022817
## 12 0.00543282     11   0.30475 0.36386 0.022735
## 13 0.00468591     12   0.29932 0.36769 0.022781
## 14 0.00409089     14   0.28995 0.37211 0.023163
## 15 0.00399151     15   0.28586 0.37170 0.023141
## 16 0.00367634     16   0.28187 0.37038 0.022880
## 17 0.00351925     17   0.27819 0.36778 0.022885
## 18 0.00325939     18   0.27467 0.36605 0.022590
## 19 0.00314084     19   0.27141 0.36817 0.023029
## 20 0.00239211     21   0.26513 0.37331 0.023182
## 21 0.00218520     22   0.26274 0.38859 0.025057
## 22 0.00201994     23   0.26055 0.39313 0.024958
## 23 0.00198681     24   0.25853 0.40083 0.025465
## 24 0.00191879     25   0.25654 0.40479 0.025943
## 25 0.00172807     26   0.25463 0.41144 0.026129
## 26 0.00171146     27   0.25290 0.41702 0.026068
## 27 0.00169081     28   0.25119 0.41707 0.026067
## 28 0.00165318     29   0.24950 0.41831 0.026033
## 29 0.00159386     32   0.24454 0.42138 0.026206
## 30 0.00154465     33   0.24294 0.42194 0.026227
## 31 0.00148975     34   0.24140 0.42296 0.026236
## 32 0.00145187     35   0.23991 0.42048 0.026212
## 33 0.00137539     36   0.23846 0.42216 0.026248
## 34 0.00137445     37   0.23708 0.42164 0.026154
## 35 0.00137418     38   0.23571 0.42164 0.026154
## 36 0.00136847     40   0.23296 0.42164 0.026154
## 37 0.00135649     41   0.23159 0.42164 0.026154
## 38 0.00131296     42   0.23023 0.42222 0.026174
## 39 0.00121457     43   0.22892 0.42837 0.026276
## 40 0.00120267     44   0.22770 0.43123 0.026306
## 41 0.00118913     45   0.22650 0.43280 0.026317
## 42 0.00116990     47   0.22412 0.43197 0.026192
## 43 0.00114827     50   0.22061 0.43183 0.026117
## 44 0.00110054     51   0.21947 0.43291 0.026239
## 45 0.00103407     53   0.21726 0.43561 0.026276
## 46 0.00095212     54   0.21623 0.43960 0.026549
## 47 0.00091540     56   0.21433 0.44232 0.026658
## 48 0.00091359     57   0.21341 0.44162 0.026508
## 49 0.00089511     58   0.21250 0.44235 0.026512
## 50 0.00084125     59   0.21160 0.44471 0.026650
## 51 0.00083257     60   0.21076 0.44640 0.026837
## 52 0.00079518     62   0.20910 0.44635 0.026837
## 53 0.00075828     65   0.20671 0.44742 0.026840
## 54 0.00075577     66   0.20595 0.44776 0.026834
## 55 0.00065863     67   0.20520 0.44908 0.026845
## 56 0.00058355     68   0.20454 0.45163 0.026801
## 57 0.00054158     69   0.20395 0.45457 0.026906
## 58 0.00049403     71   0.20287 0.45461 0.026908
```

```
## 59 0.00047174     72   0.20238 0.45442 0.026882
## 60 0.00044834     73   0.20191 0.45557 0.026836
## 61 0.00037554     74   0.20146 0.45843 0.027161
## 62 0.00036051     75   0.20108 0.45986 0.027268
## 63 0.00034685     76   0.20072 0.46013 0.027259
## 64 0.00029060     77   0.20037 0.46031 0.027271
## 65 0.00027881     78   0.20008 0.46050 0.027273
## 66 0.00027063     79   0.19980 0.46048 0.027274
## 67 0.00025437     80   0.19953 0.46034 0.027272
## 68 0.00024858     82   0.19903 0.45980 0.027219
## 69 0.00021032     83   0.19878 0.46051 0.027217
## 70 0.00020138     84   0.19857 0.46078 0.027213
## 71 0.00019722     85   0.19837 0.46078 0.027213
## 72 0.00013895     86   0.19817 0.46112 0.027218
## 73 0.00010000     87   0.19803 0.46113 0.027217
```

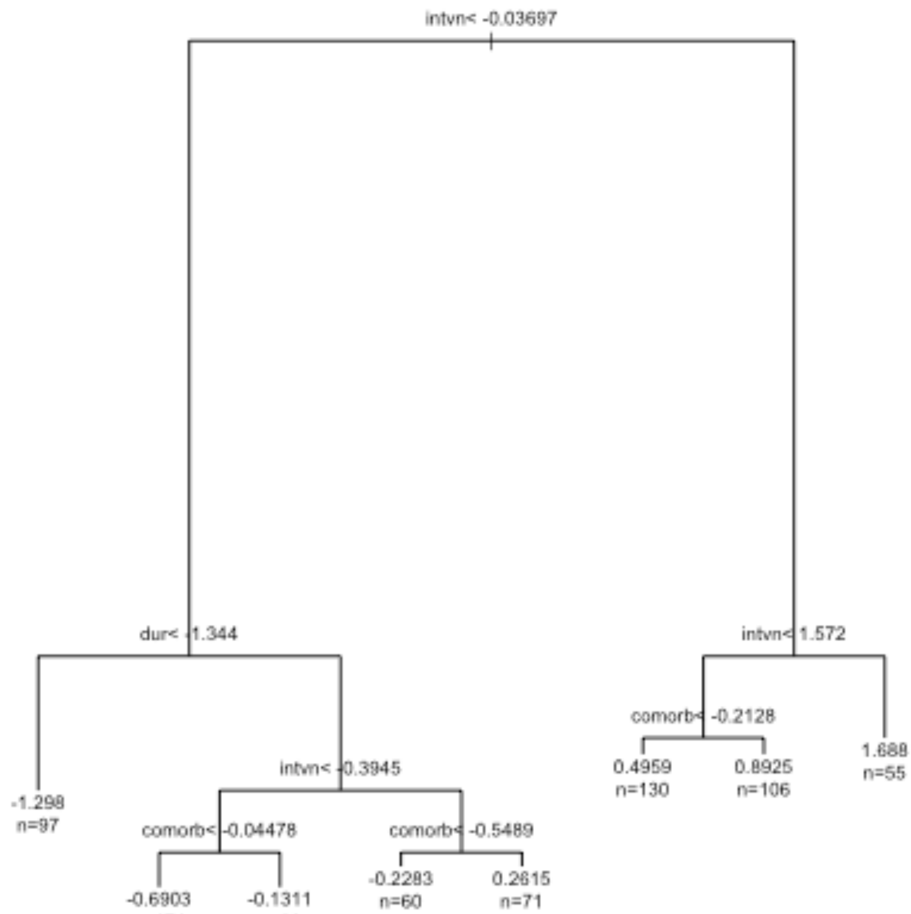
```
#prune back to optimal size, according to plot of CV 1-r^2
df_std.tr1 <- prune(df_std.tr, cp=0.00991235)  #approximately the best size
pruned tree
df_std.tr1$variable.importance#The importance of each predictors
```

```
##     intvn       dur    comorb
## 415.82543  75.40953  36.46287
```

```
df_std.tr1$cptable[nrow(df_std.tr1$cptable),] #shows training and CV 1-r^2,
and other things
```

```
##         CP     nsplit  rel error     xerror       xstd
## 0.00991235 7.00000000 0.32948180 0.36589363 0.02286890
```

```
# #prune and plot a little smaller tree than the optimal one, just for
display
# df_std.tr2 <- prune(df_std.tr, cp=0.00631770)  #bigger cp gives smaller
size tree
# df_std.tr2
par(cex=.5); plot(df_std.tr1, uniform=F); text(df_std.tr1, use.n = T);
par(cex=1)
```




```
##
yhat<-predict(df_std.tr1); e<-df_std$cost-yhat
c(1-var(e)/var(df_std$cost), 1-
df_std.tr1$cptable[nrow(df_std.tr1$cptable),3]) #check to see training r^2
agrees with what is in cptable

## [1] 0.6705182 0.6705182
```

(b)Fit the best model and discuss how good the predictive power of model is.

Answer: The R^2 of the best model is .

```
control_best <- rpart.control(minbucket = 5, cp = 0.00991235, maxsurrogate =
0, usesurrogate = 0)
df_std.tr_best <- rpart(cost ~ .,df_std, method = "anova", control = control)
summary(df_std.tr_best)

## Call:
## rpart(formula = cost ~ ., data = df_std, method = "anova", control =
control)
##   n= 788
```

```
##
##              CP nsplit rel error    xerror       xstd
## 1  0.4393806980      0 1.0000000 1.0012859 0.04969062
## 2  0.0958189687      1 0.5606193 0.5786511 0.03041456
## 3  0.0582852400      2 0.4648003 0.4876924 0.02518666
## 4  0.0307018259      3 0.4065151 0.4234470 0.02370008
## 5  0.0247526454      4 0.3758133 0.4103806 0.02318566
## 6  0.0116664748      5 0.3510606 0.3711441 0.02212699
## 7  0.0099123516      6 0.3393941 0.3651516 0.02175201
## 8  0.0066471212      7 0.3294818 0.3557923 0.02119254
## 9  0.0062292206      8 0.3228347 0.3524980 0.02084895
## 10 0.0060773511      9 0.3166055 0.3538237 0.02115414
## 11 0.0057760514     10 0.3105281 0.3488309 0.02113143
## 12 0.0054328169     11 0.3047521 0.3569755 0.02194587
## 13 0.0046859091     12 0.2993192 0.3551443 0.02162683
## 14 0.0040908932     14 0.2899474 0.3519707 0.02132498
## 15 0.0039915125     15 0.2858565 0.3531667 0.02120588
## 16 0.0036763410     16 0.2818650 0.3526794 0.02115299
## 17 0.0035192504     17 0.2781887 0.3521567 0.02102946
## 18 0.0032593908     18 0.2746694 0.3495872 0.02075046
## 19 0.0031408351     19 0.2714100 0.3496215 0.02096043
## 20 0.0023921101     21 0.2651284 0.3555114 0.02146275
## 21 0.0021851965     22 0.2627362 0.3541340 0.02196686
## 22 0.0020199429     23 0.2605511 0.3542153 0.02183583
## 23 0.0019868052     24 0.2585311 0.3555504 0.02206639
## 24 0.0019187941     25 0.2565443 0.3637513 0.02279507
## 25 0.0017280675     26 0.2546255 0.3692774 0.02294902
## 26 0.0017114612     27 0.2528974 0.3722436 0.02310999
## 27 0.0016908144     28 0.2511860 0.3751710 0.02313302
## 28 0.0016531753     29 0.2494952 0.3774764 0.02316394
## 29 0.0015938622     32 0.2445356 0.3775323 0.02316220
## 30 0.0015446491     33 0.2429418 0.3815622 0.02368391
## 31 0.0014897502     34 0.2413971 0.3823339 0.02371365
## 32 0.0014518749     35 0.2399074 0.3859007 0.02394141
## 33 0.0013753869     36 0.2384555 0.3891178 0.02393746
## 34 0.0013744505     37 0.2370801 0.3923620 0.02402686
## 35 0.0013741820     38 0.2357057 0.3923620 0.02402686
## 36 0.0013684667     40 0.2329573 0.3923620 0.02402686
## 37 0.0013564880     41 0.2315888 0.3941048 0.02405453
## 38 0.0013129566     42 0.2302323 0.3950325 0.02410118
## 39 0.0012145663     43 0.2289194 0.3961811 0.02416805
## 40 0.0012026706     44 0.2277048 0.3968755 0.02424335
## 41 0.0011891268     45 0.2265022 0.3964759 0.02423941
## 42 0.0011699030     47 0.2241239 0.3969063 0.02424304
## 43 0.0011482663     50 0.2206142 0.3975923 0.02428895
## 44 0.0011005356     51 0.2194659 0.4031947 0.02453942
## 45 0.0010340717     53 0.2172649 0.4068800 0.02473075
## 46 0.0009521186     54 0.2162308 0.4100927 0.02476712
## 47 0.0009153973     56 0.2143265 0.4132673 0.02475891
## 48 0.0009135854     57 0.2134111 0.4140330 0.02478324
```

```
## 49 0.0008951054     58 0.2124976 0.4140330 0.02478324
## 50 0.0008412472     59 0.2116025 0.4160754 0.02487156
## 51 0.0008325706     60 0.2107612 0.4166382 0.02494894
## 52 0.0007951798     62 0.2090961 0.4165106 0.02494249
## 53 0.0007582752     65 0.2067105 0.4181090 0.02493675
## 54 0.0007557695     66 0.2059523 0.4169767 0.02488438
## 55 0.0006586300     67 0.2051965 0.4162883 0.02475721
## 56 0.0005835501     68 0.2045379 0.4153512 0.02474075
## 57 0.0005415793     69 0.2039543 0.4174531 0.02480829
## 58 0.0004940284     71 0.2028711 0.4183426 0.02475713
## 59 0.0004717407     72 0.2023771 0.4176996 0.02472919
## 60 0.0004483399     73 0.2019054 0.4186287 0.02476807
## 61 0.0003755365     74 0.2014570 0.4199849 0.02484124
## 62 0.0003605072     75 0.2010815 0.4198727 0.02483015
## 63 0.0003468544     76 0.2007210 0.4191001 0.02478548
## 64 0.0002906009     77 0.2003741 0.4193551 0.02475935
## 65 0.0002788063     78 0.2000835 0.4206516 0.02475723
## 66 0.0002706308     79 0.1998047 0.4209884 0.02478058
## 67 0.0002543666     80 0.1995341 0.4209884 0.02478058
## 68 0.0002485771     82 0.1990254 0.4209884 0.02478058
## 69 0.0002103247     83 0.1987768 0.4215253 0.02479106
## 70 0.0002013780     84 0.1985665 0.4214592 0.02479099
## 71 0.0001972181     85 0.1983651 0.4215459 0.02478939
## 72 0.0001389504     86 0.1981679 0.4219656 0.02479055
## 73 0.0001000000     87 0.1980289 0.4228664 0.02484757
## 
## Variable importance
##  intvn    dur comorb  ervis    age      X   comp 
##     70     13      8      3      3      2      1 
## 
## Node number 1: 788 observations,    complexity param=0.4393807
##   mean=4.990192e-17, MSE=0.998731 
##   left son=2 (497 obs) right son=3 (291 obs)
##   Primary splits:
##       intvn  < -0.03697325 to the left,  improve=0.43938070, (0 missing)
##       dur    < -1.344161   to the left,  improve=0.22953210, (0 missing)
##       comorb < -0.2128213  to the left,  improve=0.14947230, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.08468142, (0 missing)
##       comp   < 1.785371    to the left,  improve=0.06102652, (0 missing)
## 
## Node number 2: 497 observations,    complexity param=0.09581897
##   mean=-0.5068892, MSE=0.5936514 
##   left son=4 (97 obs) right son=5 (400 obs)
##   Primary splits:
##       dur    < -1.344161   to the left,  improve=0.25558670, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.19056300, (0 missing)
##       intvn  < -0.3944569  to the left,  improve=0.18556480, (0 missing)
##       comp   < 1.785371    to the left,  improve=0.04626715, (0 missing)
##       X      < 81.5        to the right, improve=0.00946294, (0 missing)
## 
```

```
## Node number 3: 291 observations,    complexity param=0.05828524
##   mean=0.865718, MSE=0.5022771
##   left son=6 (236 obs) right son=7 (55 obs)
##   Primary splits:
##       intvn  < 1.571703    to the left,  improve=0.31383180, (0 missing)
##       ervis  < -0.3507625  to the left,  improve=0.12641140, (0 missing)
##       comorb < -0.2128213  to the left,  improve=0.09684730, (0 missing)
##       comp   < 1.785371    to the left,  improve=0.04126791, (0 missing)
##       dur    < -0.4137623  to the left,  improve=0.03181452, (0 missing)
##
## Node number 4: 97 observations,    complexity param=0.005776051
##   mean=-1.297894, MSE=0.4423941
##   left son=8 (80 obs) right son=9 (17 obs)
##   Primary splits:
##       intvn < -0.5731988  to the left,  improve=0.10593140, (0 missing)
##       gend  splits as  RL, improve=0.06391250, (0 missing)
##       age   < -1.809011   to the left,  improve=0.03172130, (0 missing)
##       ervis < 0.4075389   to the right, improve=0.02278604, (0 missing)
##       X     < 42.5        to the right, improve=0.01857077, (0 missing)
##
## Node number 5: 400 observations,    complexity param=0.03070183
##   mean=-0.3150706, MSE=0.4418075
##   left son=10 (269 obs) right son=11 (131 obs)
##   Primary splits:
##       intvn  < -0.3944569  to the left,  improve=0.13672430, (0 missing)
##       comorb < 0.4593358   to the left,  improve=0.12631820, (0 missing)
##       dur    < 1.0542      to the left,  improve=0.07286293, (0 missing)
##       comp   < 1.785371    to the left,  improve=0.04958728, (0 missing)
##       X      < 81.5        to the right, improve=0.01470129, (0 missing)
##
## Node number 6: 236 observations,    complexity param=0.01166647
##   mean=0.6740518, MSE=0.3684249
##   left son=12 (130 obs) right son=13 (106 obs)
##   Primary splits:
##       comorb < -0.2128213  to the left,  improve=0.10559740, (0 missing)
##       intvn  < 0.4992523   to the left,  improve=0.08040409, (0 missing)
##       ervis  < -0.3507625  to the left,  improve=0.07371652, (0 missing)
##       comp   < 1.785371    to the left,  improve=0.02288521, (0 missing)
##       dur    < 1.492521    to the left,  improve=0.01794721, (0 missing)
##
## Node number 7: 55 observations,    complexity param=0.00351925
##   mean=1.68814, MSE=0.2426159
##   left son=14 (45 obs) right son=15 (10 obs)
##   Primary splits:
##       intvn < 3.805976    to the left,  improve=0.20755970, (0 missing)
##       ervis < 1.16584     to the left,  improve=0.10447630, (0 missing)
##       dur   < 0.194098    to the left,  improve=0.08316169, (0 missing)
##       X     < 64.5        to the left,  improve=0.06211012, (0 missing)
##       age   < -1.809011   to the right, improve=0.06004955, (0 missing)
##
```

```
## Node number 8: 80 observations,    complexity param=0.001544649
##   mean=-1.397686, MSE=0.3949815
##   left son=16 (20 obs) right son=17 (60 obs)
##   Primary splits:
##       gend  splits as  RL, improve=0.038471390, (0 missing)
##       age   < -1.809011   to the left,  improve=0.024535370, (0 missing)
##       X     < 489.5       to the left,  improve=0.022957860, (0 missing)
##       ervis < 0.7866896   to the left,  improve=0.019549280, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.001351071, (0 missing)
##
## Node number 9: 17 observations,    complexity param=0.00148975
##   mean=-0.8282836, MSE=0.3981151
##   left son=18 (12 obs) right son=19 (5 obs)
##   Primary splits:
##       age   < 0.1897695   to the left,  improve=0.17323300, (0 missing)
##       X     < 404.5       to the right, improve=0.17294750, (0 missing)
##       ervis < -0.7299132  to the right, improve=0.02013875, (0 missing)
##
## Node number 10: 269 observations,    complexity param=0.02475265
##   mean=-0.4865843, MSE=0.3824584
##   left son=20 (171 obs) right son=21 (98 obs)
##   Primary splits:
##       comorb < -0.04478204 to the left,  improve=0.18934760, (0 missing)
##       dur    < 0.2023682   to the left,  improve=0.07974283, (0 missing)
##       ervis  < 0.7866896   to the left,  improve=0.03083300, (0 missing)
##       drugs  < 1.930007    to the right, improve=0.02464214, (0 missing)
##       X      < 762         to the right, improve=0.01123997, (0 missing)
##
## Node number 11: 131 observations,    complexity param=0.009912352
##   mean=0.03712181, MSE=0.3792317
##   left son=22 (60 obs) right son=23 (71 obs)
##   Primary splits:
##       comorb < -0.5488999  to the left,  improve=0.15702740, (0 missing)
##       dur    < 1.083145    to the left,  improve=0.09381864, (0 missing)
##       comp   < 1.785371    to the left,  improve=0.05937084, (0 missing)
##       ervis  < 2.303292    to the right, improve=0.03666887, (0 missing)
##       X      < 58          to the right, improve=0.03383980, (0 missing)
##
## Node number 12: 130 observations,    complexity param=0.006229221
##   mean=0.4959442, MSE=0.3883622
##   left son=24 (96 obs) right son=25 (34 obs)
##   Primary splits:
##       intvn < 0.8567359   to the left,  improve=0.09710199, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.06682977, (0 missing)
##       comp  < 1.785371    to the left,  improve=0.06246507, (0 missing)
##       age   < 0.8560297   to the right, improve=0.02531820, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.02265002, (0 missing)
##
## Node number 13: 106 observations,    complexity param=0.006647121
##   mean=0.8924857, MSE=0.2573555
```

```
##   left son=26 (63 obs) right son=27 (43 obs)
##   Primary splits:
##       intvn  < 0.4992523   to the left,  improve=0.19176490, (0 missing)
##       dur    < 0.02869385  to the right, improve=0.03153982, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.02757362, (0 missing)
##       comorb < 0.4593358   to the right, improve=0.02016753, (0 missing)
##       X      < 673.5       to the left,  improve=0.02005670, (0 missing)
##
## Node number 14: 45 observations,    complexity param=0.001374182
##   mean=1.582355, MSE=0.2172972
##   left son=28 (38 obs) right son=29 (7 obs)
##   Primary splits:
##       age   < 0.7079719   to the left,  improve=0.10189360, (0 missing)
##       X     < 619.5       to the left,  improve=0.06367864, (0 missing)
##       ervis < 1.16584     to the left,  improve=0.06206714, (0 missing)
##       dur   < 0.194098    to the left,  improve=0.05755897, (0 missing)
##       intvn < 2.286671    to the left,  improve=0.03695674, (0 missing)
##
## Node number 15: 10 observations
##   mean=2.164174, MSE=0.0795848
##
## Node number 16: 20 observations,    complexity param=0.001375387
##   mean=-1.611196, MSE=0.7822615
##   left son=32 (6 obs) right son=33 (14 obs)
##   Primary splits:
##       ervis < 0.4075389   to the right, improve=0.06918591, (0 missing)
##       X     < 403.5       to the left,  improve=0.05426015, (0 missing)
##       intvn < -0.7519406  to the right, improve=0.04088996, (0 missing)
##       age   < -1.586924   to the left,  improve=0.03911049, (0 missing)
##
## Node number 17: 60 observations,    complexity param=0.0008325706
##   mean=-1.326516, MSE=0.2456275
##   left son=34 (12 obs) right son=35 (48 obs)
##   Primary splits:
##       X     < 636.5       to the right, improve=0.031237200, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.028561650, (0 missing)
##       ervis < 0.02838819  to the left,  improve=0.011923470, (0 missing)
##       intvn < -0.7519406  to the left,  improve=0.010331530, (0 missing)
##       age   < 0.5599141   to the left,  improve=0.007843768, (0 missing)
##
## Node number 18: 12 observations
##   mean=-0.9978009, MSE=0.2800886
##
## Node number 19: 5 observations
##   mean=-0.4214421, MSE=0.4468919
##
## Node number 20: 171 observations,    complexity param=0.005432817
##   mean=-0.6903059, MSE=0.4157082
##   left son=40 (154 obs) right son=41 (17 obs)
##   Primary splits:
```

```
##       ervis  < 0.7866896   to the left,  improve=0.06014716, (0 missing)
##       X      < 84          to the right, improve=0.03594703, (0 missing)
##       intvn  < -0.5731988  to the left,  improve=0.03573340, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.03216706, (0 missing)
##       drugs  < 1.930007    to the right, improve=0.01823729, (0 missing)
##
## Node number 21: 98 observations,    complexity param=0.003259391
##   mean=-0.131111, MSE=0.1256621
##   left son=42 (77 obs) right son=43 (21 obs)
##   Primary splits:
##       comorb < 1.299532    to the left,  improve=0.20829600, (0 missing)
##       dur    < -0.2276826  to the left,  improve=0.09581209, (0 missing)
##       ervis  < 0.7866896   to the left,  improve=0.04381983, (0 missing)
##       X      < 170.5       to the left,  improve=0.02533905, (0 missing)
##       age    < 1.448261    to the right, improve=0.02445647, (0 missing)
##
## Node number 22: 60 observations,    complexity param=0.006077351
##   mean=-0.2283348, MSE=0.3726663
##   left son=44 (39 obs) right son=45 (21 obs)
##   Primary splits:
##       age   < -0.3284328  to the right, improve=0.21390340, (0 missing)
##       X     < 132.5       to the right, improve=0.07888370, (0 missing)
##       dur   < 0.3181512   to the right, improve=0.03303060, (0 missing)
##       comp  < 1.785371    to the left,  improve=0.03015901, (0 missing)
##       ervis < 0.7866896   to the right, improve=0.02865753, (0 missing)
##
## Node number 23: 71 observations,    complexity param=0.003676341
##   mean=0.2614514, MSE=0.2749064
##   left son=46 (66 obs) right son=47 (5 obs)
##   Primary splits:
##       comp   < 1.785371    to the left,  improve=0.14823380, (0 missing)
##       comorb < 0.7954144   to the left,  improve=0.11798930, (0 missing)
##       ervis  < 0.02838819  to the left,  improve=0.07963678, (0 missing)
##       X      < 66.5        to the right, improve=0.04915741, (0 missing)
##       dur    < 1.07901     to the left,  improve=0.03078364, (0 missing)
##
## Node number 24: 96 observations,    complexity param=0.004090893
##   mean=0.3803765, MSE=0.3485705
##   left son=48 (87 obs) right son=49 (9 obs)
##   Primary splits:
##       comp  < 1.785371    to the left,  improve=0.09621239, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.09599961, (0 missing)
##       age   < -0.6245484  to the left,  improve=0.02468846, (0 missing)
##       dur   < -0.6205175  to the right, improve=0.01943866, (0 missing)
##       X     < 51.5        to the right, improve=0.01645515, (0 missing)
##
## Node number 25: 34 observations,    complexity param=0.001711461
##   mean=0.8222529, MSE=0.3565271
##   left son=50 (29 obs) right son=51 (5 obs)
##   Primary splits:
```

```
##       ervis < 0.7866896   to the left,  improve=0.11111440, (0 missing)
##       age   < -0.03231719 to the left,  improve=0.08202016, (0 missing)
##       drugs < 0.9900532   to the left,  improve=0.06417642, (0 missing)
##       gend  splits as  RL, improve=0.04642856, (0 missing)
##       dur   < -0.2318177  to the right, improve=0.03547546, (0 missing)
##
## Node number 26: 63 observations,    complexity param=0.001169903
##   mean=0.7089522, MSE=0.2079169
##   left son=52 (38 obs) right son=53 (25 obs)
##   Primary splits:
##       age   < 0.4118563   to the left,  improve=0.05560168, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.03908651, (0 missing)
##       X     < 673.5       to the left,  improve=0.03725504, (0 missing)
##       intvn < 0.1417686   to the left,  improve=0.03634097, (0 missing)
##       dur   < 1.016984    to the left,  improve=0.03045981, (0 missing)
##
## Node number 27: 43 observations,    complexity param=0.002185197
##   mean=1.161383, MSE=0.2081309
##   left son=54 (16 obs) right son=55 (27 obs)
##   Primary splits:
##       comorb < 1.131493    to the right, improve=0.19215880, (0 missing)
##       dur    < 0.8226339   to the right, improve=0.12748010, (0 missing)
##       age    < 0.8560297   to the right, improve=0.10568630, (0 missing)
##       intvn  < 1.21422     to the right, improve=0.06893980, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.02044871, (0 missing)
##
## Node number 28: 38 observations,    complexity param=0.001374182
##   mean=1.518491, MSE=0.2236022
##   left son=56 (16 obs) right son=57 (22 obs)
##   Primary splits:
##       age    < -0.03231719 to the right, improve=0.13729850, (0 missing)
##       comorb < 0.1232572   to the left,  improve=0.05227259, (0 missing)
##       ervis  < 0.7866896   to the left,  improve=0.04656738, (0 missing)
##       X      < 628.5       to the left,  improve=0.04380298, (0 missing)
##       intvn  < 2.107929    to the left,  improve=0.03738194, (0 missing)
##
## Node number 29: 7 observations
##   mean=1.929047, MSE=0.04073398
##
## Node number 32: 6 observations
##   mean=-1.96656, MSE=0.8252277
##
## Node number 33: 14 observations
##   mean=-1.458897, MSE=0.686531
##
## Node number 34: 12 observations
##   mean=-1.501704, MSE=0.232573
##
## Node number 35: 48 observations,    complexity param=0.0008325706
##   mean=-1.282719, MSE=0.2393002
```

```
##   left son=70 (35 obs) right son=71 (13 obs)
##   Primary splits:
##       X     < 496         to the left,  improve=0.07400948, (0 missing)
##       age   < 0.1157406   to the right, improve=0.03296519, (0 missing)
##       ervis < 0.02838819  to the left,  improve=0.02996235, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.02408183, (0 missing)
##       intvn < -0.7519406  to the left,  improve=0.01192502, (0 missing)
##
## Node number 40: 154 observations,    complexity param=0.004685909
##   mean=-0.742843, MSE=0.3612642
##   left son=80 (75 obs) right son=81 (79 obs)
##   Primary splits:
##       comorb < -0.5488999  to the left,  improve=0.05660563, (0 missing)
##       intvn  < -0.5731988  to the left,  improve=0.04917607, (0 missing)
##       X      < 84          to the right, improve=0.04221382, (0 missing)
##       dur    < 1.050065    to the left,  improve=0.02818956, (0 missing)
##       ervis  < 0.4075389   to the right, improve=0.01774486, (0 missing)
##
## Node number 41: 17 observations,    complexity param=0.001593862
##   mean=-0.2143818, MSE=0.6573995
##   left son=82 (7 obs) right son=83 (10 obs)
##   Primary splits:
##       age   < 0.1157406   to the right, improve=0.11223990, (0 missing)
##       dur   < -0.07468376 to the left,  improve=0.07571241, (0 missing)
##       X     < 259.5       to the right, improve=0.06922836, (0 missing)
##       ervis < 1.544991    to the right, improve=0.04754902, (0 missing)
##       drugs < 0.05009908  to the right, improve=0.03055514, (0 missing)
##
## Node number 42: 77 observations,    complexity param=0.001202671
##   mean=-0.2156013, MSE=0.1054947
##   left son=84 (40 obs) right son=85 (37 obs)
##   Primary splits:
##       comorb < 0.4593358   to the left,  improve=0.11651990, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.11160690, (0 missing)
##       dur    < -0.2276826  to the left,  improve=0.06680239, (0 missing)
##       X      < 472.5       to the right, improve=0.06022436, (0 missing)
##       age    < 0.2637984   to the right, improve=0.02358988, (0 missing)
##
## Node number 43: 21 observations,    complexity param=0.0003605072
##   mean=0.1786868, MSE=0.07745963
##   left son=86 (12 obs) right son=87 (9 obs)
##   Primary splits:
##       intvn  < -0.7519406  to the left,  improve=0.1744191, (0 missing)
##       comorb < 2.811886    to the left,  improve=0.1620935, (0 missing)
##       age    < 0.4118563   to the left,  improve=0.1566595, (0 missing)
##       ervis  < -0.3507625  to the left,  improve=0.1046579, (0 missing)
##       X      < 581         to the left,  improve=0.1038960, (0 missing)
##
## Node number 44: 39 observations,    complexity param=0.002019943
##   mean=-0.4355141, MSE=0.3048099
```

```
##   left son=88 (13 obs) right son=89 (26 obs)
##   Primary splits:
##       age   < 0.7079719   to the right, improve=0.13372730, (0 missing)
##       ervis < -0.7299132  to the right, improve=0.11413300, (0 missing)
##       X     < 579         to the left,  improve=0.07164840, (0 missing)
##       dur   < 0.272665    to the right, improve=0.05499074, (0 missing)
##       drugs < 0.05009908  to the right, improve=0.04125141, (0 missing)
##
## Node number 45: 21 observations,    complexity param=0.001034072
##   mean=0.1564266, MSE=0.2709294
##   left son=90 (5 obs) right son=91 (16 obs)
##   Primary splits:
##       gend  splits as  RL, improve=0.14303750, (0 missing)
##       ervis < 0.02838819  to the left,  improve=0.13015920, (0 missing)
##       X     < 266         to the right, improve=0.09795595, (0 missing)
##       dur   < -0.6660037  to the left,  improve=0.02535338, (0 missing)
##       drugs < 0.05009908  to the right, improve=0.01466328, (0 missing)
##
## Node number 46: 66 observations,    complexity param=0.00239211
##   mean=0.2058892, MSE=0.2484325
##   left son=92 (39 obs) right son=93 (27 obs)
##   Primary splits:
##       comorb < 0.2912965   to the left,  improve=0.11481630, (0 missing)
##       X      < 66.5        to the right, improve=0.07728612, (0 missing)
##       ervis  < 0.02838819  to the left,  improve=0.04453639, (0 missing)
##       intvn  < -0.2157151  to the left,  improve=0.03452760, (0 missing)
##       age    < 0.1157406   to the left,  improve=0.03088927, (0 missing)
##
## Node number 47: 5 observations
##   mean=0.9948719, MSE=0.04570561
##
## Node number 48: 87 observations,    complexity param=0.003140835
##   mean=0.3214756, MSE=0.3140433
##   left son=96 (41 obs) right son=97 (46 obs)
##   Primary splits:
##       ervis < -0.3507625  to the left,  improve=0.07399046, (0 missing)
##       dur   < 0.9714977   to the right, improve=0.04592374, (0 missing)
##       age   < 1.300203    to the left,  improve=0.04057243, (0 missing)
##       X     < 539         to the right, improve=0.03506547, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.03019103, (0 missing)
##
## Node number 49: 9 observations
##   mean=0.9497526, MSE=0.3246076
##
## Node number 50: 29 observations,    complexity param=0.001100536
##   mean=0.7396078, MSE=0.292288
##   left son=100 (13 obs) right son=101 (16 obs)
##   Primary splits:
##       dur    < -0.2318177  to the right, improve=0.09456307, (0 missing)
##       X      < 447         to the left,  improve=0.07842554, (0 missing)
```

```
##       age    < -0.03231719 to the left,  improve=0.04664487, (0 missing)
##       ervis  < 0.02838819  to the left,  improve=0.04512998, (0 missing)
##       comorb < -0.5488999  to the left,  improve=0.02787724, (0 missing)
##
## Node number 51: 5 observations
##   mean=1.301595, MSE=0.4597301
##
## Node number 52: 38 observations,    complexity param=0.0005415793
##   mean=0.6217421, MSE=0.1853497
##   left son=104 (32 obs) right son=105 (6 obs)
##   Primary splits:
##       X      < 672.5       to the left,  improve=0.05435871, (0 missing)
##       age    < -1.068722   to the right, improve=0.04400341, (0 missing)
##       ervis  < 1.16584     to the right, improve=0.04115982, (0 missing)
##       dur    < 0.946687    to the left,  improve=0.03659770, (0 missing)
##       comorb < -0.04478204 to the right, improve=0.02155456, (0 missing)
##
## Node number 53: 25 observations,    complexity param=0.001169903
##   mean=0.8415117, MSE=0.2130866
##   left son=106 (5 obs) right son=107 (20 obs)
##   Primary splits:
##       X      < 160         to the left,  improve=0.17230680, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.16451140, (0 missing)
##       intvn  < 0.1417686   to the left,  improve=0.08331400, (0 missing)
##       drugs  < 0.05009908  to the left,  improve=0.06418527, (0 missing)
##       comorb < 0.4593358   to the right, improve=0.05714859, (0 missing)
##
## Node number 54: 16 observations,    complexity param=0.0003468544
##   mean=0.9015948, MSE=0.1440944
##   left son=108 (5 obs) right son=109 (11 obs)
##   Primary splits:
##       X      < 256         to the left,  improve=0.11840080, (0 missing)
##       comorb < 2.811886    to the left,  improve=0.09034923, (0 missing)
##       intvn  < 1.035478    to the right, improve=0.05590831, (0 missing)
##       age    < 1.004088    to the right, improve=0.03145365, (0 missing)
##       dur    < 1.294036    to the left,  improve=0.01521802, (0 missing)
##
## Node number 55: 27 observations,    complexity param=0.001451875
##   mean=1.315332, MSE=0.182384
##   left son=110 (22 obs) right son=111 (5 obs)
##   Primary splits:
##       intvn < 0.6779941   to the right, improve=0.23203490, (0 missing)
##       dur   < 1.269225    to the right, improve=0.10848350, (0 missing)
##       age   < 0.8560297   to the right, improve=0.08583497, (0 missing)
##       X     < 230         to the right, improve=0.08369517, (0 missing)
##       gend  splits as  RL, improve=0.07471168, (0 missing)
##
## Node number 56: 16 observations,    complexity param=0.0004483399
##   mean=1.313033, MSE=0.2495448
##   left son=112 (5 obs) right son=113 (11 obs)
```

```
##   Primary splits:
##       X      < 467         to the right, improve=0.08837178, (0 missing)
##       dur    < 0.8019584   to the right, improve=0.05701744, (0 missing)
##       ervis  < 0.02838819  to the right, improve=0.05490333, (0 missing)
##       intvn  < 2.286671    to the left,  improve=0.04005110, (0 missing)
##       comorb < 0.1232572   to the left,  improve=0.02891695, (0 missing)
##
## Node number 57: 22 observations,    complexity param=0.0004717407
##   mean=1.667914, MSE=0.1517071
##   left son=114 (11 obs) right son=115 (11 obs)
##   Primary splits:
##       intvn < 2.107929    to the left,  improve=0.11123700, (0 missing)
##       dur   < 0.194098    to the left,  improve=0.10343920, (0 missing)
##       ervis < 0.7866896   to the left,  improve=0.09097616, (0 missing)
##       gend  splits as  RL, improve=0.08430905, (0 missing)
##       X     < 332.5       to the right, improve=0.07350113, (0 missing)
##
## Node number 70: 35 observations,    complexity param=0.0002906009
##   mean=-1.363825, MSE=0.1490721
##   left son=140 (29 obs) right son=141 (6 obs)
##   Primary splits:
##       age    < 1.004088    to the left,  improve=0.043833620, (0 missing)
##       intvn  < -0.7519406  to the left,  improve=0.041505760, (0 missing)
##       X      < 422.5       to the right, improve=0.018340160, (0 missing)
##       comorb < -0.5488999  to the right, improve=0.013175120, (0 missing)
##       ervis  < -0.7299132  to the left,  improve=0.001690954, (0 missing)
##
## Node number 71: 13 observations
##   mean=-1.064357, MSE=0.4168296
##
## Node number 80: 75 observations,    complexity param=0.004685909
##   mean=-0.8896089, MSE=0.4504312
##   left son=160 (7 obs) right son=161 (68 obs)
##   Primary splits:
##       ervis < 0.4075389   to the right, improve=0.12510630, (0 missing)
##       intvn < -0.5731988  to the left,  improve=0.10673890, (0 missing)
##       X     < 84          to the right, improve=0.10671580, (0 missing)
##       age   < -1.364838   to the right, improve=0.04757302, (0 missing)
##       dur   < 1.004578    to the left,  improve=0.03090843, (0 missing)
##
## Node number 81: 79 observations,    complexity param=0.001368467
##   mean=-0.6035083, MSE=0.2367482
##   left son=162 (27 obs) right son=163 (52 obs)
##   Primary splits:
##       intvn  < -0.7519406  to the left,  improve=0.05758313, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.02918951, (0 missing)
##       drugs  < 0.05009908  to the right, improve=0.02637457, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.02383657, (0 missing)
##       dur    < 1.050065    to the left,  improve=0.01701144, (0 missing)
##
```

```
## Node number 82: 7 observations
##   mean=-0.5390496, MSE=0.673527
##
## Node number 83: 10 observations
##   mean=0.01288572, MSE=0.5206734
##
## Node number 84: 40 observations,    complexity param=0.0009135854
##   mean=-0.322233, MSE=0.1264226
##   left son=168 (33 obs) right son=169 (7 obs)
##   Primary splits:
##       ervis < 0.02838819  to the left,  improve=0.14218020, (0 missing)
##       X     < 453         to the right, improve=0.08627539, (0 missing)
##       dur   < -0.2276826  to the left,  improve=0.07154348, (0 missing)
##       gend  splits as  LR, improve=0.07108591, (0 missing)
##       age   < -0.03231719 to the right, improve=0.03656625, (0 missing)
##
## Node number 85: 37 observations,    complexity param=0.0002543666
##   mean=-0.1003238, MSE=0.05728872
##   left son=170 (16 obs) right son=171 (21 obs)
##   Primary splits:
##       dur    < 1.103821    to the right, improve=0.09360318, (0 missing)
##       intvn  < -0.5731988  to the right, improve=0.06956834, (0 missing)
##       age    < 0.7079719   to the right, improve=0.05956940, (0 missing)
##       X      < 369         to the right, improve=0.05833095, (0 missing)
##       comorb < 0.7954144   to the right, improve=0.01834478, (0 missing)
##
## Node number 86: 12 observations
##   mean=0.07802482, MSE=0.07262581
##
## Node number 87: 9 observations
##   mean=0.3129027, MSE=0.05238037
##
## Node number 88: 13 observations
##   mean=-0.7210361, MSE=0.242639
##
## Node number 89: 26 observations,    complexity param=0.00137445
##   mean=-0.2927531, MSE=0.2747532
##   left son=178 (16 obs) right son=179 (10 obs)
##   Primary splits:
##       intvn < -0.2157151  to the left,  improve=0.15142160, (0 missing)
##       ervis < -0.7299132  to the right, improve=0.12591760, (0 missing)
##       drugs < 0.05009908  to the right, improve=0.10777980, (0 missing)
##       X     < 235.5       to the left,  improve=0.05835144, (0 missing)
##       age   < 0.4118563   to the left,  improve=0.05222621, (0 missing)
##
## Node number 90: 5 observations
##   mean=-0.1957237, MSE=0.09622386
##
## Node number 91: 16 observations,    complexity param=0.0007582752
##   mean=0.2664736, MSE=0.2746615
```

```
##   left son=182 (9 obs) right son=183 (7 obs)
##   Primary splits:
##       ervis < 0.02838819  to the left,  improve=0.13579500, (0 missing)
##       age   < -1.364838   to the left,  improve=0.06760745, (0 missing)
##       X     < 299         to the right, improve=0.04721696, (0 missing)
##       drugs < 0.05009908  to the right, improve=0.04353354, (0 missing)
##       dur   < -0.5088697  to the right, improve=0.01657195, (0 missing)
##
## Node number 92: 39 observations,    complexity param=0.001728067
##   mean=0.06536358, MSE=0.2654394
##   left son=184 (29 obs) right son=185 (10 obs)
##   Primary splits:
##       dur    < -0.4964644  to the right, improve=0.13137280, (0 missing)
##       X      < 328.5       to the right, improve=0.08219991, (0 missing)
##       age    < 0.5599141   to the right, improve=0.06824538, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.02799128, (0 missing)
##       drugs  < 0.05009908  to the right, improve=0.01759428, (0 missing)
##
## Node number 93: 27 observations,    complexity param=0.001918794
##   mean=0.4088707, MSE=0.1541413
##   left son=186 (17 obs) right son=187 (10 obs)
##   Primary splits:
##       ervis  < 0.02838819  to the left,  improve=0.36284430, (0 missing)
##       age    < 0.4118563   to the left,  improve=0.07565637, (0 missing)
##       dur    < 1.455305    to the right, improve=0.07312091, (0 missing)
##       comorb < 1.971689    to the left,  improve=0.06339109, (0 missing)
##       X      < 171         to the left,  improve=0.03154854, (0 missing)
##
## Node number 96: 41 observations,    complexity param=0.001189127
##   mean=0.1600138, MSE=0.2261795
##   left son=192 (34 obs) right son=193 (7 obs)
##   Primary splits:
##       ervis  < -1.109064   to the right, improve=0.09907769, (0 missing)
##       age    < 0.8560297   to the right, improve=0.09741340, (0 missing)
##       dur    < 0.4339341   to the left,  improve=0.06929544, (0 missing)
##       X      < 682.5       to the left,  improve=0.03832117, (0 missing)
##       comorb < -0.3808606  to the right, improve=0.01129648, (0 missing)
##
## Node number 97: 46 observations,    complexity param=0.003140835
##   mean=0.4653871, MSE=0.3484099
##   left son=194 (18 obs) right son=195 (28 obs)
##   Primary splits:
##       dur   < 0.115531    to the right, improve=0.18232670, (0 missing)
##       ervis < 1.924142    to the right, improve=0.11887350, (0 missing)
##       X     < 612         to the right, improve=0.11615000, (0 missing)
##       age   < -0.4764906  to the right, improve=0.03468014, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.02667370, (0 missing)
##
## Node number 100: 13 observations
##   mean=0.555168, MSE=0.2953872
```

```
##
## Node number 101: 16 observations,    complexity param=0.001100536
##   mean=0.8894651, MSE=0.239673
##   left son=202 (10 obs) right son=203 (6 obs)
##   Primary splits:
##       ervis < -0.7299132  to the left,  improve=0.24269880, (0 missing)
##       dur   < -0.9885418  to the left,  improve=0.15550700, (0 missing)
##       age   < -0.03231719 to the left,  improve=0.12326820, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.06255544, (0 missing)
##       X     < 260         to the left,  improve=0.04376938, (0 missing)
##
## Node number 104: 32 observations,    complexity param=0.0005415793
##   mean=0.5782779, MSE=0.1903667
##   left son=208 (14 obs) right son=209 (18 obs)
##   Primary splits:
##       dur   < 0.6489595   to the left,  improve=0.07708507, (0 missing)
##       age   < -1.068722   to the right, improve=0.06921209, (0 missing)
##       intvn < 0.3205104   to the left,  improve=0.06653473, (0 missing)
##       X     < 459.5       to the right, improve=0.06273523, (0 missing)
##       gend  splits as  LR, improve=0.04047772, (0 missing)
##
## Node number 105: 6 observations
##   mean=0.8535508, MSE=0.09478151
##
## Node number 106: 5 observations
##   mean=0.4582819, MSE=0.05979883
##
## Node number 107: 20 observations,    complexity param=0.001169903
##   mean=0.9373191, MSE=0.2055132
##   left son=214 (14 obs) right son=215 (6 obs)
##   Primary splits:
##       X      < 332         to the right, improve=0.27149620, (0 missing)
##       dur    < 0.2850703   to the left,  improve=0.15245640, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.06899738, (0 missing)
##       comorb < 0.4593358   to the right, improve=0.05221294, (0 missing)
##       age    < 1.152145    to the right, improve=0.01866991, (0 missing)
##
## Node number 108: 5 observations
##   mean=0.7078579, MSE=0.1191009
##
## Node number 109: 11 observations
##   mean=0.989657, MSE=0.1306393
##
## Node number 110: 22 observations,    complexity param=0.0009153973
##   mean=1.217261, MSE=0.1641226
##   left son=220 (8 obs) right son=221 (14 obs)
##   Primary splits:
##       age   < 0.4118563   to the right, improve=0.19952310, (0 missing)
##       gend  splits as  RL, improve=0.10905120, (0 missing)
##       X     < 545.5       to the right, improve=0.09979841, (0 missing)
```

```
##       dur   < -0.3517358  to the right, improve=0.05222840, (0 missing)
##       ervis < 0.7866896   to the right, improve=0.04520298, (0 missing)
## 
## Node number 111: 5 observations
##   mean=1.746848, MSE=0.03420911 
## 
## Node number 112: 5 observations
##   mean=1.09277, MSE=0.3877943 
## 
## Node number 113: 11 observations
##   mean=1.413153, MSE=0.1546274 
## 
## Node number 114: 11 observations
##   mean=1.538009, MSE=0.2035506 
## 
## Node number 115: 11 observations
##   mean=1.79782, MSE=0.0661127 
## 
## Node number 140: 29 observations,    complexity param=0.0002706308
##   mean=-1.400594, MSE=0.169683 
##   left son=280 (18 obs) right son=281 (11 obs)
##   Primary splits:
##       intvn  < -0.7519406  to the left,  improve=0.043282830, (0 missing)
##       age    < 0.1157406   to the right, improve=0.037674640, (0 missing)
##       X      < 168.5       to the right, improve=0.013645510, (0 missing)
##       comorb < -0.5488999  to the right, improve=0.006327138, (0 missing)
##       ervis  < -0.3507625  to the right, improve=0.002756803, (0 missing)
## 
## Node number 141: 6 observations
##   mean=-1.18611, MSE=0.01133558 
## 
## Node number 160: 7 observations
##   mean=-1.629486, MSE=0.3270255 
## 
## Node number 161: 68 observations,    complexity param=0.003991512
##   mean=-0.8134451, MSE=0.400982 
##   left son=322 (35 obs) right son=323 (33 obs)
##   Primary splits:
##       intvn < -0.5731988  to the left,  improve=0.11520690, (0 missing)
##       X     < 84          to the right, improve=0.10550340, (0 missing)
##       age   < -1.364838   to the right, improve=0.03793938, (0 missing)
##       dur   < 1.004578    to the left,  improve=0.02641534, (0 missing)
##       ervis < 0.02838819  to the left,  improve=0.02109461, (0 missing)
## 
## Node number 162: 27 observations,    complexity param=0.001312957
##   mean=-0.765544, MSE=0.2803853 
##   left son=324 (9 obs) right son=325 (18 obs)
##   Primary splits:
##       dur    < -0.5708963  to the left,  improve=0.13649170, (0 missing)
##       ervis  < 0.02838819  to the left,  improve=0.09776928, (0 missing)
```

```
##       age    < 0.7079719   to the left,  improve=0.09283472, (0 missing)
##       X      < 540.5       to the left,  improve=0.07563882, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.02736853, (0 missing)
##
## Node number 163: 52 observations,    complexity param=0.0007951798
##   mean=-0.5193743, MSE=0.1933792
##   left son=326 (20 obs) right son=327 (32 obs)
##   Primary splits:
##       comorb < -0.3808606  to the left,  improve=0.04181459, (0 missing)
##       dur    < 0.6448244   to the left,  improve=0.04107682, (0 missing)
##       age    < -0.180375   to the right, improve=0.04004286, (0 missing)
##       X      < 144.5       to the left,  improve=0.02530745, (0 missing)
##       drugs  < 0.05009908  to the right, improve=0.02027467, (0 missing)
##
## Node number 168: 33 observations,    complexity param=0.0002788063
##   mean=-0.3839811, MSE=0.05606277
##   left son=336 (22 obs) right son=337 (11 obs)
##   Primary splits:
##       dur    < 0.9714977   to the left,  improve=0.11860110, (0 missing)
##       comorb < 0.2912965   to the right, improve=0.09280048, (0 missing)
##       intvn  < -0.7519406  to the left,  improve=0.08430351, (0 missing)
##       age    < -0.6245484  to the left,  improve=0.08375077, (0 missing)
##       X      < 598         to the right, improve=0.04967185, (0 missing)
##
## Node number 169: 7 observations
##   mean=-0.0311345, MSE=0.3554058
##
## Node number 170: 16 observations,    complexity param=0.0002543666
##   mean=-0.1842175, MSE=0.03494047
##   left son=340 (9 obs) right son=341 (7 obs)
##   Primary splits:
##       age    < -0.03231719 to the right, improve=0.361264600, (0 missing)
##       dur    < 1.28163     to the left,  improve=0.134869400, (0 missing)
##       X      < 540.5       to the left,  improve=0.058258510, (0 missing)
##       intvn  < -0.5731988  to the right, improve=0.049449400, (0 missing)
##       comorb < 0.7954144   to the right, improve=0.008783127, (0 missing)
##
## Node number 171: 21 observations,    complexity param=0.0001389504
##   mean=-0.03640476, MSE=0.06486791
##   left son=342 (14 obs) right son=343 (7 obs)
##   Primary splits:
##       comorb < 0.6273751   to the right, improve=0.08027590, (0 missing)
##       X      < 369         to the right, improve=0.07685477, (0 missing)
##       dur    < 0.2809352   to the left,  improve=0.07326069, (0 missing)
##       ervis  < -0.3507625  to the right, improve=0.01700568, (0 missing)
##       intvn  < -0.7519406  to the left,  improve=0.01069074, (0 missing)
##
## Node number 178: 16 observations,    complexity param=0.0008412472
##   mean=-0.4540051, MSE=0.2903912
##   left son=356 (10 obs) right son=357 (6 obs)
```

```
##   Primary splits:
##       age   < 0.2637984   to the left,  improve=0.14249350, (0 missing)
##       X     < 576.5       to the left,  improve=0.11077350, (0 missing)
##       dur   < -0.6866792  to the right, improve=0.03943537, (0 missing)
##       ervis < 0.2179635   to the right, improve=0.03368417, (0 missing)
##
## Node number 179: 10 observations
##   mean=-0.0347498, MSE=0.1415631
##
## Node number 182: 9 observations
##   mean=0.09615243, MSE=0.2326087
##
## Node number 183: 7 observations
##   mean=0.4854579, MSE=0.2434776
##
## Node number 184: 29 observations,    complexity param=0.0007557695
##   mean=-0.04429343, MSE=0.1669351
##   left son=368 (17 obs) right son=369 (12 obs)
##   Primary splits:
##       intvn  < -0.2157151  to the left,  improve=0.12286220, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.10830150, (0 missing)
##       dur    < 0.2602597   to the left,  improve=0.08909159, (0 missing)
##       age    < 0.4858852   to the right, improve=0.04147986, (0 missing)
##       ervis  < 0.4075389   to the left,  improve=0.03593895, (0 missing)
##
## Node number 185: 10 observations
##   mean=0.3833689, MSE=0.4151029
##
## Node number 186: 17 observations,    complexity param=0.000201378
##   mean=0.2274883, MSE=0.06970879
##   left son=372 (8 obs) right son=373 (9 obs)
##   Primary splits:
##       X      < 199.5       to the left,  improve=0.13373660, (0 missing)
##       ervis  < -0.3507625  to the right, improve=0.11718990, (0 missing)
##       dur    < 1.24855     to the right, improve=0.07143137, (0 missing)
##       comorb < 0.9634536   to the right, improve=0.06828797, (0 missing)
##       age    < 0.633943    to the right, improve=0.05964198, (0 missing)
##
## Node number 187: 10 observations
##   mean=0.7172208, MSE=0.1466675
##
## Node number 192: 34 observations,    complexity param=0.001189127
##   mean=0.09208969, MSE=0.1940952
##   left son=384 (12 obs) right son=385 (22 obs)
##   Primary splits:
##       ervis < -0.7299132  to the left,  improve=0.14439590, (0 missing)
##       dur   < 0.4339341   to the left,  improve=0.06743822, (0 missing)
##       X     < 76.5        to the left,  improve=0.04214739, (0 missing)
##       age   < -0.6245484  to the left,  improve=0.03346771, (0 missing)
##       intvn < 0.1417686   to the left,  improve=0.01853122, (0 missing)
```

```
##
## Node number 193: 7 observations
##   mean=0.489931, MSE=0.2507628
##
## Node number 194: 18 observations,    complexity param=0.001690814
##   mean=0.1510373, MSE=0.2937364
##   left son=388 (6 obs) right son=389 (12 obs)
##   Primary splits:
##       X     < 620         to the right, improve=0.25167520, (0 missing)
##       age   < -0.180375   to the left,  improve=0.12371510, (0 missing)
##       intvn < 0.3205104   to the left,  improve=0.07330974, (0 missing)
##       dur   < 0.6158787   to the right, improve=0.06547892, (0 missing)
##       ervis < 1.16584     to the right, improve=0.06466393, (0 missing)
##
## Node number 195: 28 observations,    complexity param=0.001986805
##   mean=0.6674691, MSE=0.2791956
##   left son=390 (20 obs) right son=391 (8 obs)
##   Primary splits:
##       X     < 218         to the right, improve=0.20001540, (0 missing)
##       intvn < 0.1417686   to the right, improve=0.12949880, (0 missing)
##       ervis < 0.7866896   to the right, improve=0.04820343, (0 missing)
##       drugs < 0.05009908  to the left,  improve=0.04398700, (0 missing)
##       dur   < -0.876894   to the left,  improve=0.03914327, (0 missing)
##
## Node number 202: 10 observations
##   mean=0.702647, MSE=0.203822
##
## Node number 203: 6 observations
##   mean=1.200829, MSE=0.144309
##
## Node number 208: 14 observations
##   mean=0.4409203, MSE=0.2612511
##
## Node number 209: 18 observations,    complexity param=0.0004940284
##   mean=0.6851117, MSE=0.1091465
##   left son=418 (12 obs) right son=419 (6 obs)
##   Primary splits:
##       X      < 316.5       to the left,  improve=0.19789940, (0 missing)
##       age    < 0.1157406   to the right, improve=0.09921979, (0 missing)
##       dur    < 1.041794    to the right, improve=0.09102804, (0 missing)
##       comorb < 0.1232572   to the right, improve=0.06168906, (0 missing)
##       gend   splits as  LR, improve=0.03357727, (0 missing)
##
## Node number 214: 14 observations
##   mean=0.7826821, MSE=0.1831875
##
## Node number 215: 6 observations
##   mean=1.298139, MSE=0.07161962
##
## Node number 220: 8 observations
```

```
##   mean=0.977874, MSE=0.08837788
##
## Node number 221: 14 observations
##   mean=1.354053, MSE=0.1559469
##
## Node number 280: 18 observations,    complexity param=0.0002103247
##   mean=-1.467588, MSE=0.1142321
##   left son=560 (5 obs) right son=561 (13 obs)
##   Primary splits:
##       X     < 146.5       to the left,  improve=0.08050155, (0 missing)
##       age   < -0.03231719 to the right, improve=0.07428325, (0 missing)
##       ervis < -0.7299132  to the left,  improve=0.01437987, (0 missing)
##
## Node number 281: 11 observations
##   mean=-1.290967, MSE=0.2410583
##
## Node number 322: 35 observations,    complexity param=0.001653175
##   mean=-1.022146, MSE=0.3323596
##   left son=644 (5 obs) right son=645 (30 obs)
##   Primary splits:
##       dur   < -1.162216   to the left,  improve=0.10790040, (0 missing)
##       X     < 697.5       to the right, improve=0.08666097, (0 missing)
##       age   < -0.4764906  to the right, improve=0.08663404, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.03008663, (0 missing)
##       gend  splits as  LR, improve=0.02191865, (0 missing)
##
## Node number 323: 33 observations,    complexity param=0.001356488
##   mean=-0.5920955, MSE=0.3785719
##   left son=646 (28 obs) right son=647 (5 obs)
##   Primary splits:
##       age   < -1.290809   to the right, improve=0.08545322, (0 missing)
##       X     < 97.5        to the right, improve=0.07253317, (0 missing)
##       dur   < -1.112595   to the right, improve=0.05412884, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.01654424, (0 missing)
##       gend  splits as  RL, improve=0.01395576, (0 missing)
##
## Node number 324: 9 observations
##   mean=-1.042204, MSE=0.0367601
##
## Node number 325: 18 observations,    complexity param=0.001148266
##   mean=-0.6272142, MSE=0.3447925
##   left son=650 (13 obs) right son=651 (5 obs)
##   Primary splits:
##       ervis  < 0.02838819  to the left,  improve=0.14560860, (0 missing)
##       X      < 540.5       to the left,  improve=0.12550060, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.06693848, (0 missing)
##       dur    < 0.2850703   to the right, improve=0.06055252, (0 missing)
##       age    < 0.7079719   to the left,  improve=0.05271006, (0 missing)
##
## Node number 326: 20 observations,    complexity param=0.00065863
```

```
##   mean=-0.6331184, MSE=0.1391463
##   left son=652 (9 obs) right son=653 (11 obs)
##   Primary splits:
##       X     < 493        to the right, improve=0.186257800, (0 missing)
##       age   < 0.1897695  to the right, improve=0.176115500, (0 missing)
##       dur   < -0.7445707  to the right, improve=0.142289000, (0 missing)
##       ervis < -0.3507625  to the right, improve=0.073518900, (0 missing)
##       intvn < -0.5731988  to the right, improve=0.004969151, (0 missing)
##
## Node number 327: 32 observations,    complexity param=0.0007951798
##   mean=-0.4482843, MSE=0.2141349
##   left son=654 (6 obs) right son=655 (26 obs)
##   Primary splits:
##       X     < 144.5      to the left,  improve=0.10157680, (0 missing)
##       intvn < -0.5731988  to the left,  improve=0.05353456, (0 missing)
##       age   < 0.7079719   to the right, improve=0.04496460, (0 missing)
##       dur   < 0.7027159   to the left,  improve=0.04150807, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.02518043, (0 missing)
##
## Node number 336: 22 observations,    complexity param=0.0001972181
##   mean=-0.4416401, MSE=0.0578959
##   left son=672 (8 obs) right son=673 (14 obs)
##   Primary splits:
##       comorb < 0.2912965   to the right, improve=0.12185720, (0 missing)
##       age    < -0.6245484  to the left,  improve=0.07749122, (0 missing)
##       dur    < -0.6039771  to the right, improve=0.05257631, (0 missing)
##       intvn  < -0.5731988  to the left,  improve=0.03168148, (0 missing)
##       X      < 465.5       to the left,  improve=0.02660603, (0 missing)
##
## Node number 337: 11 observations
##   mean=-0.2686632, MSE=0.03244919
##
## Node number 340: 9 observations
##   mean=-0.2833018, MSE=0.02125358
##
## Node number 341: 7 observations
##   mean=-0.05682344, MSE=0.02368588
##
## Node number 342: 14 observations
##   mean=-0.08743088, MSE=0.03787926
##
## Node number 343: 7 observations
##   mean=0.06564748, MSE=0.1032232
##
## Node number 356: 10 observations
##   mean=-0.611572, MSE=0.288099
##
## Node number 357: 6 observations
##   mean=-0.1913937, MSE=0.183868
##
```

```
## Node number 368: 17 observations,    complexity param=0.0002485771
##   mean=-0.1646166, MSE=0.114006
##   left son=736 (11 obs) right son=737 (6 obs)
##   Primary splits:
##       ervis  < -0.3507625  to the right, improve=0.10093910, (0 missing)
##       age    < 0.1157406   to the right, improve=0.09514170, (0 missing)
##       X      < 318         to the right, improve=0.06422201, (0 missing)
##       gend   splits as  LR, improve=0.05556417, (0 missing)
##       comorb < -0.3808606  to the left,  improve=0.04236504, (0 missing)
##
## Node number 369: 12 observations
##   mean=0.1261644, MSE=0.1923522
##
## Node number 372: 8 observations
##   mean=0.1250776, MSE=0.0543313
##
## Node number 373: 9 observations
##   mean=0.31852, MSE=0.06576827
##
## Node number 384: 12 observations
##   mean=-0.1345863, MSE=0.1931774
##
## Node number 385: 22 observations,    complexity param=0.0003755365
##   mean=0.2157311, MSE=0.151282
##   left son=770 (11 obs) right son=771 (11 obs)
##   Primary splits:
##       dur    < -0.4840591  to the right, improve=0.08880081, (0 missing)
##       X      < 279.5       to the right, improve=0.08548585, (0 missing)
##       intvn  < 0.1417686   to the left,  improve=0.07477387, (0 missing)
##       comorb < -0.5488999  to the left,  improve=0.04664731, (0 missing)
##       age    < -0.6985773  to the left,  improve=0.02705166, (0 missing)
##
## Node number 388: 6 observations
##   mean=-0.2334784, MSE=0.03025144
##
## Node number 389: 12 observations
##   mean=0.3432951, MSE=0.3145896
##
## Node number 390: 20 observations,    complexity param=0.001214566
##   mean=0.5180122, MSE=0.2010572
##   left son=780 (6 obs) right son=781 (14 obs)
##   Primary splits:
##       X     < 349.5       to the left,  improve=0.2377094, (0 missing)
##       dur   < -0.876894   to the left,  improve=0.1978829, (0 missing)
##       drugs < 0.9900532   to the right, improve=0.1368225, (0 missing)
##       ervis < 0.7866896   to the right, improve=0.1278937, (0 missing)
##       intvn < 0.1417686   to the right, improve=0.1093300, (0 missing)
##
## Node number 391: 8 observations
##   mean=1.041111, MSE=0.2790898
```

```
##
## Node number 418: 12 observations
##   mean=0.5811886, MSE=0.05397554
##
## Node number 419: 6 observations
##   mean=0.8929578, MSE=0.1546883
##
## Node number 560: 5 observations
##   mean=-1.622214, MSE=0.07395438
##
## Node number 561: 13 observations
##   mean=-1.408116, MSE=0.1169908
##
## Node number 644: 5 observations
##   mean=-1.486011, MSE=0.3040113
##
## Node number 645: 30 observations,    complexity param=0.001653175
##   mean=-0.9448354, MSE=0.2952456
##   left son=1290 (24 obs) right son=1291 (6 obs)
##   Primary splits:
##       ervis < 0.02838819  to the left,  improve=0.14227880, (0 missing)
##       X     < 477         to the right, improve=0.11686980, (0 missing)
##       age   < -0.4764906  to the right, improve=0.10835110, (0 missing)
##       dur   < 0.7688775   to the left,  improve=0.01947408, (0 missing)
##       intvn < -0.7519406  to the left,  improve=0.01794481, (0 missing)
##
## Node number 646: 28 observations,    complexity param=0.0009521186
##   mean=-0.6681009, MSE=0.4005724
##   left son=1292 (15 obs) right son=1293 (13 obs)
##   Primary splits:
##       ervis < -0.3507625  to the left,  improve=0.06562993, (0 missing)
##       X     < 204         to the right, improve=0.06191728, (0 missing)
##       dur   < 0.5662574   to the left,  improve=0.05468035, (0 missing)
##       age   < -0.4764906  to the left,  improve=0.04802425, (0 missing)
##       gend  splits as  RL, improve=0.02818121, (0 missing)
##
## Node number 647: 5 observations
##   mean=-0.1664654, MSE=0.04185773
##
## Node number 650: 13 observations
##   mean=-0.7661729, MSE=0.2936071
##
## Node number 651: 5 observations
##   mean=-0.2659216, MSE=0.2971375
##
## Node number 652: 9 observations
##   mean=-0.8110972, MSE=0.1171051
##
## Node number 653: 11 observations
##   mean=-0.4874994, MSE=0.1100581
```

```
##
## Node number 654: 6 observations
##   mean=-0.7552939, MSE=0.3628807
##
## Node number 655: 26 observations,    complexity param=0.0007951798
##   mean=-0.3774359, MSE=0.1530383
##   left son=1310 (10 obs) right son=1311 (16 obs)
##   Primary splits:
##       age   < 0.7079719   to the right, improve=0.19123110, (0 missing)
##       X     < 288.5       to the right, improve=0.11622730, (0 missing)
##       dur   < -0.8024621  to the left,  improve=0.08812371, (0 missing)
##       intvn < -0.5731988  to the left,  improve=0.07110992, (0 missing)
##       ervis < -0.3507625  to the left,  improve=0.01443268, (0 missing)
##
## Node number 672: 8 observations
##   mean=-0.552754, MSE=0.02526336
##
## Node number 673: 14 observations
##   mean=-0.3781464, MSE=0.06545659
##
## Node number 736: 11 observations
##   mean=-0.2438435, MSE=0.1418592
##
## Node number 737: 6 observations
##   mean=-0.01936723, MSE=0.03033672
##
## Node number 770: 11 observations
##   mean=0.09982617, MSE=0.2099931
##
## Node number 771: 11 observations
##   mean=0.3316361, MSE=0.06570294
##
## Node number 780: 6 observations
##   mean=0.18407, MSE=0.150911
##
## Node number 781: 14 observations
##   mean=0.6611303, MSE=0.1542724
##
## Node number 1290: 24 observations,    complexity param=0.001653175
##   mean=-1.047314, MSE=0.2395569
##   left son=2580 (16 obs) right son=2581 (8 obs)
##   Primary splits:
##       age   < -0.4764906  to the right, improve=0.24137810, (0 missing)
##       X     < 498         to the right, improve=0.14073170, (0 missing)
##       dur   < -0.6825441  to the left,  improve=0.08028015, (0 missing)
##       ervis < -0.7299132  to the right, improve=0.02643623, (0 missing)
##       gend  splits as  LR, improve=0.00522808, (0 missing)
##
## Node number 1291: 6 observations
##   mean=-0.5349223, MSE=0.3079646
```

```
##
## Node number 1292: 15 observations,    complexity param=0.0009521186
##   mean=-0.8190455, MSE=0.2388639
##   left son=2584 (8 obs) right son=2585 (7 obs)
##   Primary splits:
##       dur   < -0.4096272  to the left,  improve=0.21282070, (0 missing)
##       age   < -0.5505195  to the left,  improve=0.06477352, (0 missing)
##       X     < 375.5       to the left,  improve=0.05065016, (0 missing)
##       ervis < -0.7299132  to the right, improve=0.02239685, (0 missing)
##
## Node number 1293: 13 observations
##   mean=-0.4939341, MSE=0.5305355
##
## Node number 1310: 10 observations
##   mean=-0.593827, MSE=0.1754965
##
## Node number 1311: 16 observations,    complexity param=0.0005835501
##   mean=-0.2421915, MSE=0.09144514
##   left son=2622 (10 obs) right son=2623 (6 obs)
##   Primary splits:
##       age   < 0.2637984   to the left,  improve=0.31388620, (0 missing)
##       ervis < -0.3507625  to the right, improve=0.13055160, (0 missing)
##       dur   < -0.5667612  to the right, improve=0.07526464, (0 missing)
##       X     < 404         to the right, improve=0.04887992, (0 missing)
##       intvn < -0.5731988  to the left,  improve=0.02278307, (0 missing)
##
## Node number 2580: 16 observations,    complexity param=0.0008951054
##   mean=-1.217349, MSE=0.1809823
##   left son=5160 (7 obs) right son=5161 (9 obs)
##   Primary splits:
##       X     < 498         to the right, improve=0.243272400, (0 missing)
##       ervis < -0.3507625  to the right, improve=0.171675600, (0 missing)
##       age   < 0.2637984   to the left,  improve=0.068778840, (0 missing)
##       dur   < 0.2354491   to the right, improve=0.028218950, (0 missing)
##       gend  splits as  LR, improve=0.002970729, (0 missing)
##
## Node number 2581: 8 observations
##   mean=-0.7072437, MSE=0.1832347
##
## Node number 2584: 8 observations
##   mean=-1.02995, MSE=0.2783213
##
## Node number 2585: 7 observations
##   mean=-0.5780116, MSE=0.08483716
##
## Node number 2622: 10 observations
##   mean=-0.3734242, MSE=0.0444054
##
## Node number 2623: 6 observations
##   mean=-0.02347035, MSE=0.09330239
```

```
##
## Node number 5160: 7 observations
##   mean=-1.455272, MSE=0.1378365
##
## Node number 5161: 9 observations
##   mean=-1.032297, MSE=0.1362682
```

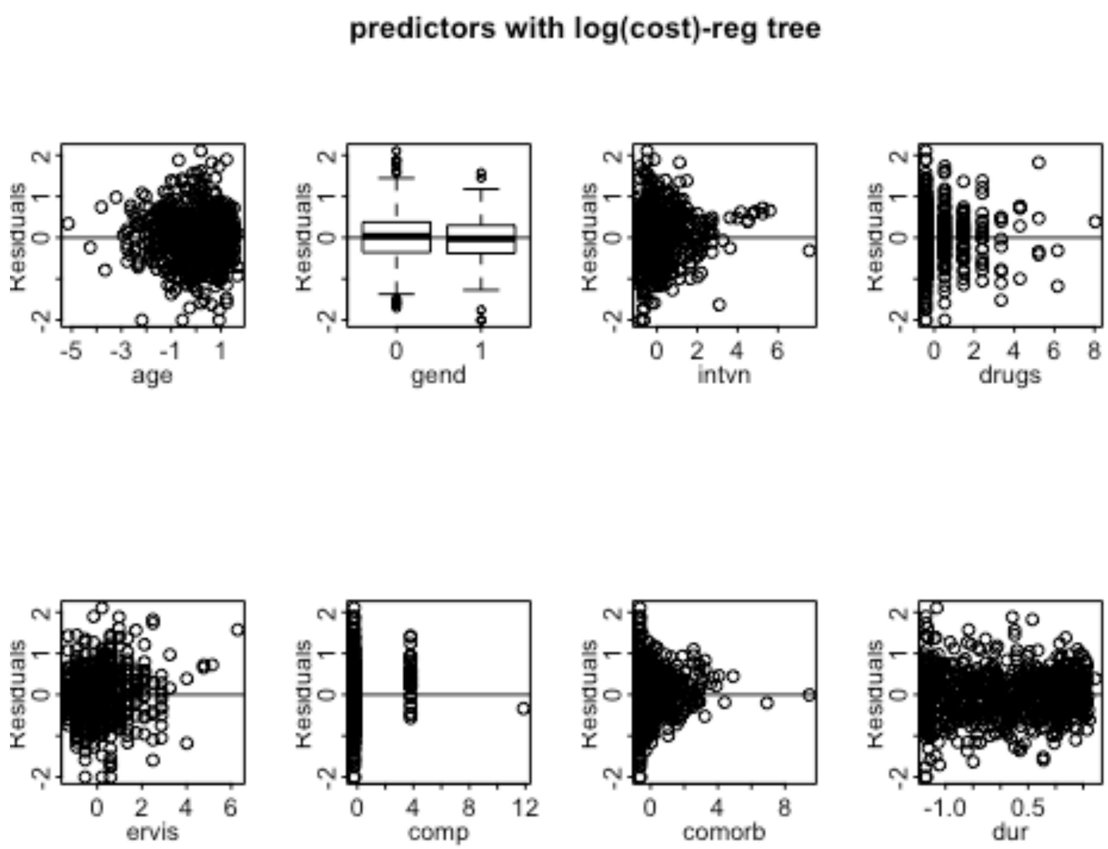
(c)The most influencing variable on the cost and the effect.

Answer: From the above result, the intvn has the most influence on the cost, and the effect is the larger intvn, the more of final cost.

(d)Construct appropriate residual plots to assess whether there remains any linearity not captured by the regression tree model.

Answer: From the residual plts, there is no nonlinearity not captured by regression tree.

```
par(mfrow=c(2,4),pin=c(0.8,0.8),tcl=-0.15,mgp=c(1,0.2,0))
for (i in seq(3:10)) {

plot(df_std[[i+2]],resid(df_std.tr1),ylab="Residuals",xlab=names(df_std)[i+2]
,main="")
  abline(0, 0)}
title(main="Ischemic heart disease-standardized \n predictors with log(cost)-
reg tree",outer = T)
```



(e)Linear reg, nnet,reg tree, which you recommand for this data set and why?

Answer:

Prob 4)Forensic example, keep all 6-category to do classification

```
##Prepare dataset
FGL<-read.table("../Data_for_Lecture_Examples/fgl.txt",sep="\t")
FGL1<-FGL
k<-ncol(FGL1)-1;
FGL1[1:k]<-sapply(FGL1[1:k], function(x) (x-mean(x))/sd(x))
FGL1<-data.frame(FGL1,"type_ind"=as.numeric(factor(FGL1$type)))#add a column
of categories with index, instead of strings
##Or use: as.numeric(factor(FGL1$type, levels=levels(FGL1$type)))
```

(a)10-fold CV to find the best nnet for classifying the class type

Answer: The neural network with the smallest misclassification rate has $= $ and number of hidden nodes as . The misclassification rate is .

```
##CV function for classification
CVfunc_nnet_clf <- function(data, lam_seq, num_hidnode_seq,Nrep,K,y) {
  n=nrow(data)
  n.models = n.lam*n.num_hidnode #number of different models to fit
  yhat=matrix(0,n,n.models)

  ##Each column of mod_par corresponds to a set of lambda and number of
hidden nodes of a trail model

mod_par=matrix(c(rep(lam_seq,times=1,each=n.num_hidnode),rep(num_hidnode_seq,
times=n.lam,each=1)),2,n.models,byrow = T)#Store the model parameters: lambda
and the number of nodes in hidden layer
  MSE<-matrix(0,Nrep,n.models)
  for (j in 1:Nrep) {
    print(c(0,0,0,j))#Print out the index of replicates of CV
    Ind<-CVInd(n,K)
    for (k in 1:K) {
      print(k)#Print out the index of different fold of CV
      for (m in 1:n.models) {
        out<-nnet(type~.,data[-Ind[[k]],],linout = F,
skip=F,size=as.integer(mod_par[2,m]),decay=mod_par[1,m],maxit=1000,trace=F)
        phat<-predict(out,data[Ind[[k]],])
        yhat[Ind[[k]],m]<-apply(phat,1,function(x) which(x==max(x)))
      }
    } #end of k loop
    MSE[j,]=apply(yhat,2,function(x) sum(y != x)/n)
  } #end of j loopE
  MSEAve<- apply(MSE,2,mean); MSEAve #averaged mean square CV error
  MSEsd <- apply(MSE,2,sd); MSEsd   #SD of mean square CV error
  r2<-1-MSEAve/var(y); r2  #CV r^2
  ##The best model in terms of the minimum MSEAve or the maximum r2.
  min(MSEAve)
  max(r2)
  ##Return the index of the minimum MSEAve or the maximum r2.
  which(MSEAve==min(MSEAve))
  which(r2==max(r2))
  ##The optimal lambda and number of hidden nodes
  mod_par[,which(MSEAve==min(MSEAve))]
}

##Do a CV on crude interval of lambda and number of hidden nodes again.
library(nnet)
```

```r
ptm <- proc.time()
Nrep<-2 #number of replicates of CV
K<-10  #K-fold CV on each replicate
n.lam = 4 #number of lambda
n.num_hidnode = 2 #number of different numbers of hidden nodes
y<-FGL1$type_ind
lam_seq = 10^seq(-as.integer(n.lam/2),as.integer(n.lam/2)-1)
num_hidnode_seq = 5*seq(1,n.num_hidnode)

par_best_crude <- CVfunc_nnet_clf(FGL1[,c(1:10)], lam_seq,
num_hidnode_seq,Nrep,K,y)

## [1] 0 0 0 1
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
## [1] 0 0 0 2
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10

proc.time() - ptm

##    user  system elapsed
##   6.538   0.026   6.585

##Do a CV in smaller interval of lambda and number of hidden nodes again.
ptm <- proc.time()
Nrep<-2 #number of replicates of CV
K<-10  #K-fold CV on each replicate
n.lam = 2 #number of lambda
n.num_hidnode = 2 #number of different numbers of hidden nodes
y<-FGL1$type_ind
lam_seq = c(seq(0.05,0.05,0.01),seq(0.1,0.1,0.1))
num_hidnode_seq = seq(24,26,2)
```

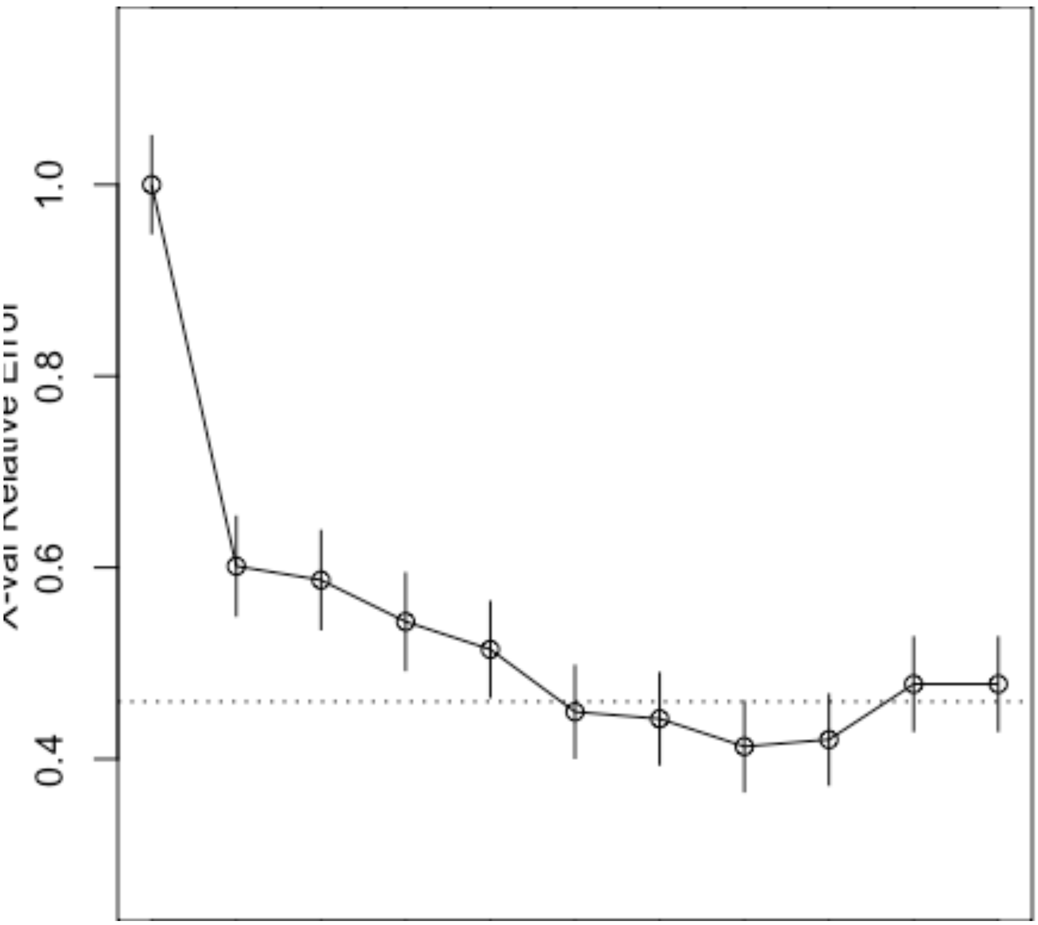
```
par_best <- CVfunc_nnet_clf(FGL1[,c(1:10)], lam_seq,
num_hidnode_seq,Nrep,K,y)

## [1] 0 0 0 1
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10
## [1] 0 0 0 2
## [1] 1
## [1] 2
## [1] 3
## [1] 4
## [1] 5
## [1] 6
## [1] 7
## [1] 8
## [1] 9
## [1] 10

proc.time() - ptm

##    user  system elapsed
##  27.869   0.099  28.125

##Fit the best nnet model
out<-nnet(type~.,FGL1[,c(1:10)],linout = F,
skip=F,size=as.integer(par_best[2]),decay=par_best[1],maxit=1000,trace=F)##ty
pe is a factor
phat<-predict(out,FGL1)
yhat<-apply(phat,1,function(x) which(x==max(x)))
e.nnet<-sum(yhat!=y)*1.0/length(y)
```

(b)10-fold CV to find the best tree model for classifying the class type.

Answer: The classification tree with the smallest misclassification rate has complexity parameter $\text{cp} = 0.0326087$, and the misclassification rate is 0.1495327.

```
library(rpart)
control <- rpart.control(minbucket = 1, cp = 0.0001, maxsurrogate = 0,
usesurrogate = 0, xval = 10)
par(mfrow=c(1,1),pin=c(4,4),mgp=c(2,1,0))
FGL1.tr <- rpart(type ~ .,FGL1[,c(1:10)], method = "class", control =
```

```
control)
plotcp(FGL1.tr)  #plot of CV r^2 vs. size
```




```
printcp(FGL1.tr)  #same info is in df_std.tr$cptable
```

```
##
## Classification tree:
## rpart(formula = type ~ ., data = FGL1[, c(1:10)], method = "class",
##     control = control)
##
## Variables actually used in tree construction:
## [1] Al Ba Ca Fe K  Mg Na RI Si
##
## Root node error: 138/214 = 0.64486
##
## n= 214
##
##            CP nsplit rel error  xerror     xstd
## 1  0.2065217      0  1.000000 1.00000 0.050729
## 2  0.0724638      2  0.586957 0.60145 0.051652
## 3  0.0579710      3  0.514493 0.58696 0.051414
## 4  0.0362319      4  0.456522 0.54348 0.050577
## 5  0.0326087      5  0.420290 0.51449 0.049913
```

```
## 6  0.0217391      7  0.355072 0.44928 0.048087
## 7  0.0144928      8  0.333333 0.44203 0.047855
## 8  0.0108696     15  0.231884 0.41304 0.046860
## 9  0.0072464     18  0.195652 0.42029 0.047118
## 10 0.0036232     38  0.050725 0.47826 0.048957
## 11 0.0001000     44  0.028986 0.47826 0.048957
```

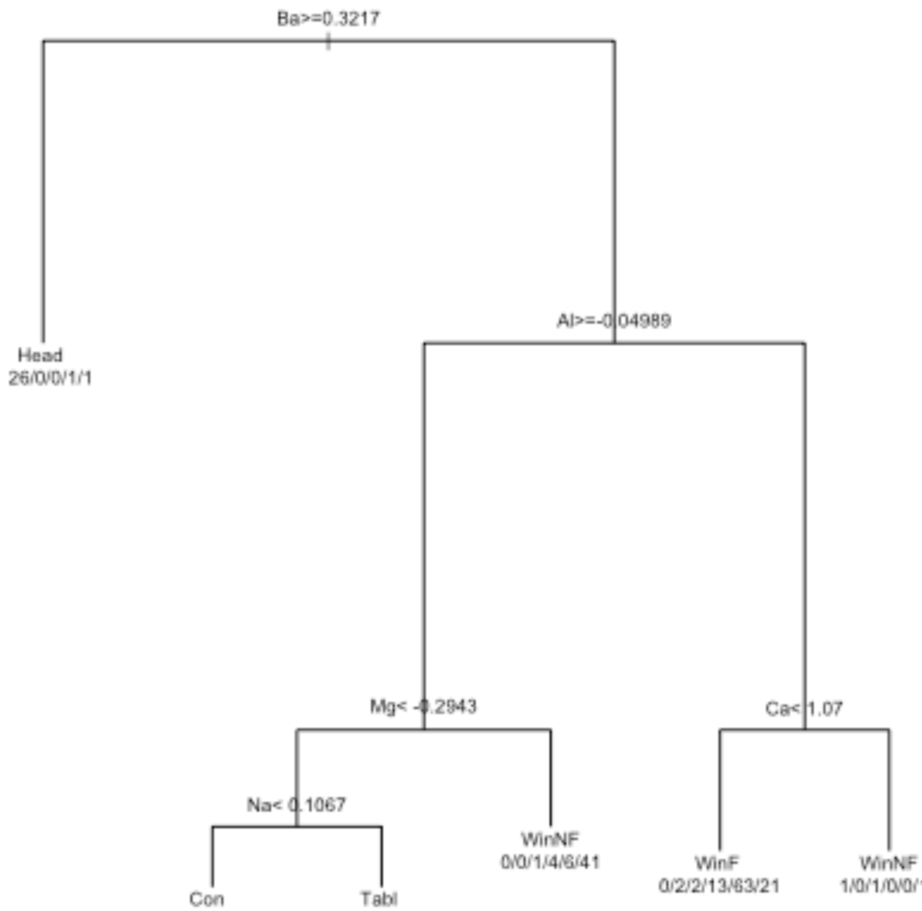
```
#prune back to optimal size, according to plot of CV 1-r^2
FGL1.tr1 <- prune(FGL1.tr, cp=0.0326087)  #approximately the best size pruned tree
FGL1.tr1$variable.importance#The importance of each predictors
```

```
##        Ba        Al        Mg        Ca        Na
## 26.044912 16.085776 11.340598  8.668054  6.116667
```

```
FGL1.tr1$cptable[nrow(FGL1.tr1$cptable),] #shows training and CV 1-r^2, and other things
```

```
##         CP     nsplit  rel error     xerror       xstd
## 0.03260870 5.00000000 0.42028986 0.51449275 0.04991272
```

```
# #prune and plot a little smaller tree than the optimal one, just for display
# FGL1.tr2 <- prune(FGL1.tr, cp=0.0108696)  #bigger cp gives smaller size tree
# FGL1.tr2
par(cex=.5); plot(FGL1.tr1, uniform=F); text(FGL1.tr1, use.n = T); par(cex=1)
```




```
##
yhat<-apply(predict(FGL1.tr1),1,function(x) which(x==max(x)))
e.tr<-sum(FGL1$type_ind!=yhat)/length(yhat)
```

(c)Fit multinomial results and discuss it

Answer: The misclassification rate is 0.2616822.

```
FGL1.multinom<-multinom(type~.,FGL1[,c(1:10)])

## # weights:  66 (50 variable)
## initial  value 383.436526
## iter  10 value 177.590797
## iter  20 value 138.457855
## iter  30 value 131.091430
## iter  40 value 126.200258
## iter  50 value 124.021003
## iter  60 value 122.318924
## iter  70 value 121.792280
## iter  80 value 121.490672
## iter  90 value 121.385524
## iter 100 value 121.347733
```

```
## final  value 121.347733
## stopped after 100 iterations
```

```
yhat<-predict(FGL1.multinom,FGL1[,c(1:10)])
e.multi<-sum(FGL1$type!=yhat)/length(yhat)
```

(d)Compare the three models from parts (a)-(c).

Answer: The neural network has the best predictive ability but not very interpretable. Classification tree has very good interpretability, but the predictive ability is not as good as that of neural network. The multinomial regression has the worse predictive ability and the interpretability is better than neural network, but it can only capture the linear relation between predictors and response. For simple predicting purpose, I think neural network is the best for this problem.