Homework 7

Jasmine Nakayama

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Link to repository: (https://github.com/jynakay/Assignments (https://github.com/jynakay/Assignments))
[https://github.com/jynakay/Assignments (https://github.com/jynakay/Assignments)]

```
# load libraries and dataset
library(tidyverse)
library(haven)
library(car)
library(ROCR)
library(rpart)
library(partykit)
library(reshape2)
library(party)
library(randomForestSRC)
library(ggRandomForests)
```

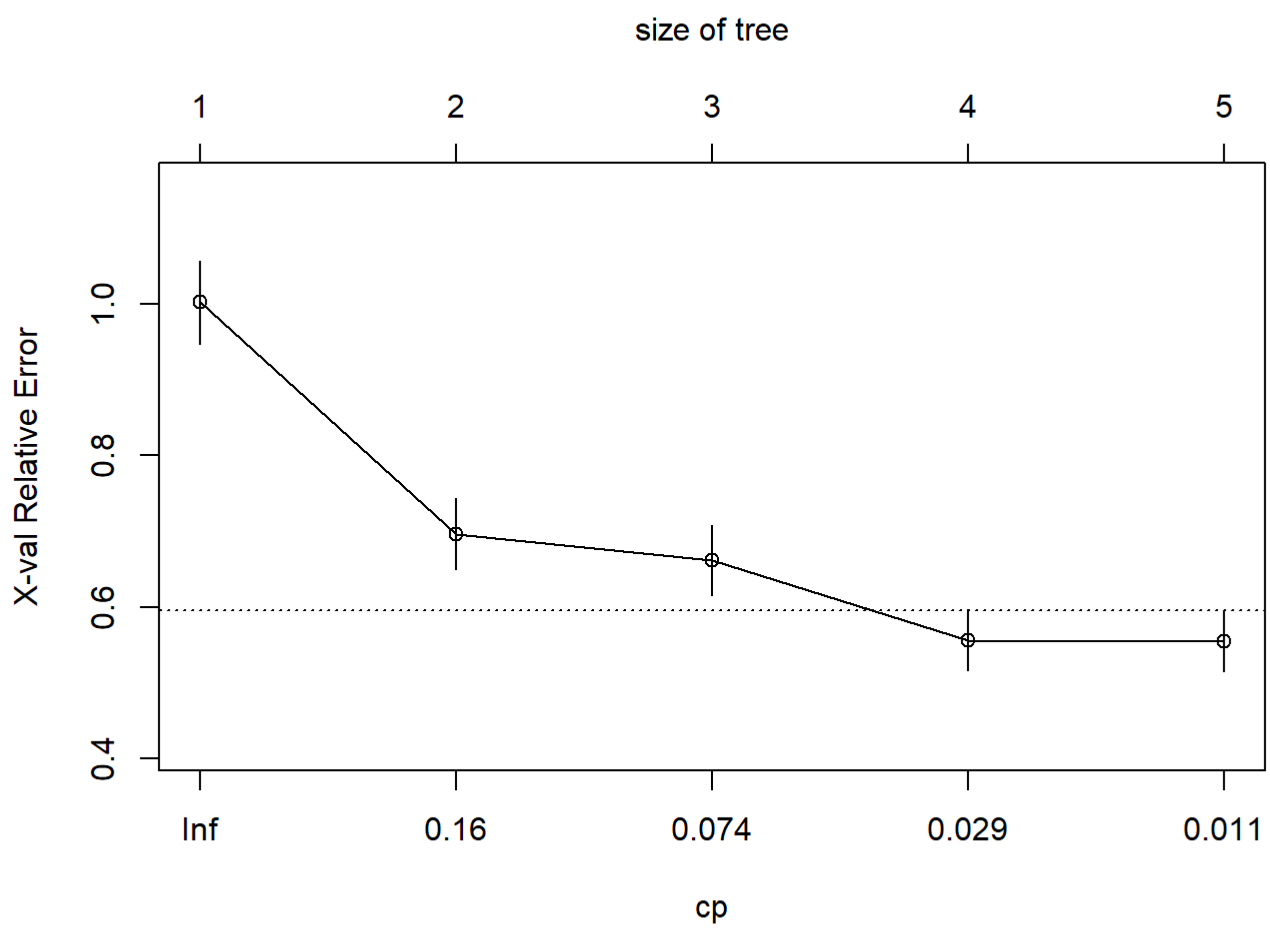
```
helpdata <- haven::read_spss("helpmkh.sav")

h1 <- helpdata %>%
  select(age, female, pss_fr, homeless,
         pcs, mcs, cesd)

# add dichotomous variable
# to indicate depression for
# people with CESD scores >= 16
# and people with mcs scores < 45

h1 <- h1 %>%
  mutate(cesd_gte16 = cesd >= 16) %>%
  mutate(mcs_lt45 = mcs < 45)

# change cesd_gte16 and mcs_lt45 LOGIC variable type
# to numeric coded 1=TRUE and 0=FALSE

h1$cesd_gte16 <- as.numeric(h1$cesd_gte16)
h1$mcs_lt45 <- as.numeric(h1$mcs_lt45)

# add a label for these 2 new variables
attributes(h1$cesd_gte16)$label <- "Indicator of Depression"
attributes(h1$mcs_lt45)$label <- "Indicator of Poor Mental Health"
```

PROBLEM 1: Regression Tree for MCS

```
# fit a regression tree model to the mcs as the outcome
# and using the cesd as the only predictor
fitmcs <- rpart::rpart(mcs ~ cesd, data = h1)
rpart::printcp(fitmcs) # Display the results
```

```
##
## Regression tree:
## rpart::rpart(formula = mcs ~ cesd, data = h1)
##
## Variables actually used in tree construction:
## [1] cesd
##
## Root node error: 74512/453 = 164.48
##
## n= 453
##
##         CP nsplit rel error  xerror     xstd
## 1 0.325298      0   1.00000 1.00215 0.054461
## 2 0.081349      1   0.67470 0.69619 0.046929
## 3 0.066496      2   0.59335 0.66177 0.046268
## 4 0.012496      3   0.52686 0.55661 0.040155
## 5 0.010000      4   0.51436 0.55516 0.040680
```

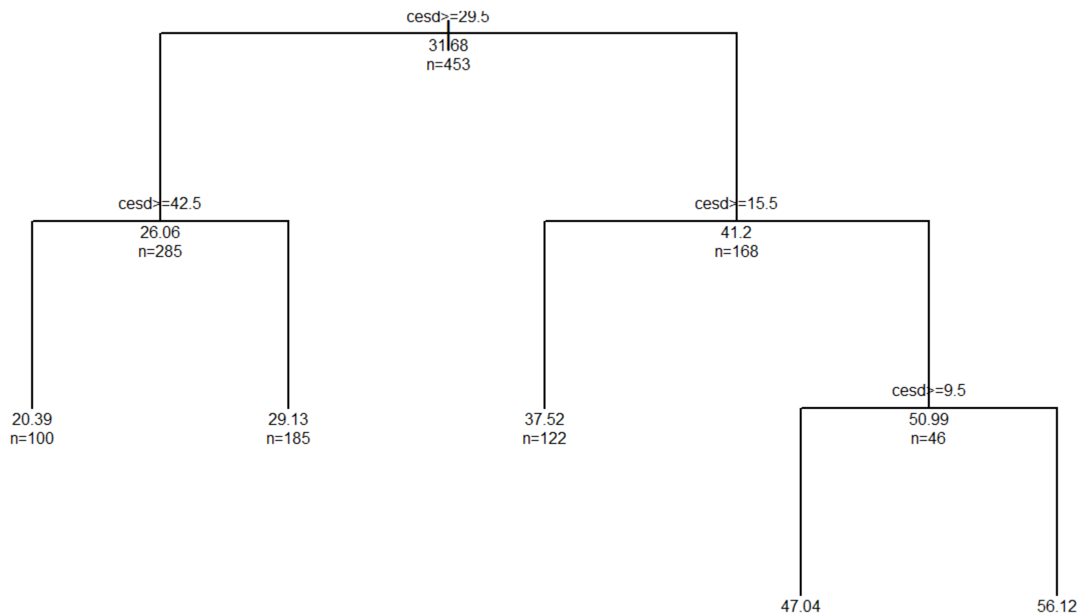
```
rpart::plotcp(fitmcs) # Visualize cross-validation results
```



```
summary(fitmcs) # Detailed summary of fit
```

```
## Call:
## rpart::rpart(formula = mcs ~ cesd, data = h1)
##   n= 453
##
##           CP nsplit rel error    xerror       xstd
## 1 0.32529813      0 1.0000000 1.0021466 0.05446069
## 2 0.08134904      1 0.6747019 0.6961924 0.04692943
## 3 0.06649553      2 0.5933528 0.6617703 0.04626769
## 4 0.01249609      3 0.5268573 0.5566115 0.04015486
## 5 0.01000000      4 0.5143612 0.5551561 0.04068024
##
## Variable importance
## cesd
##  100
##
## Node number 1: 453 observations,    complexity param=0.3252981
##   mean=31.67668, MSE=164.4847
##   left son=2 (285 obs) right son=3 (168 obs)
##   Primary splits:
##       cesd < 29.5 to the right, improve=0.3252981, (0 missing)
##
## Node number 2: 285 observations,    complexity param=0.06649553
##   mean=26.06057, MSE=100.1894
##   left son=4 (100 obs) right son=5 (185 obs)
##   Primary splits:
##       cesd < 42.5 to the right, improve=0.17352, (0 missing)
##
## Node number 3: 168 observations,    complexity param=0.08134904
##   mean=41.20401, MSE=129.2805
##   left son=6 (122 obs) right son=7 (46 obs)
##   Primary splits:
##       cesd < 15.5 to the right, improve=0.2790834, (0 missing)
##
## Node number 4: 100 observations
##   mean=20.38941, MSE=43.95751
##
## Node number 5: 185 observations
##   mean=29.12606, MSE=103.8029
##
## Node number 6: 122 observations
##   mean=37.51566, MSE=103.6988
##
## Node number 7: 46 observations,    complexity param=0.01249609
##   mean=50.98616, MSE=65.35702
##   left son=14 (26 obs) right son=15 (20 obs)
##   Primary splits:
##       cesd < 9.5  to the right, improve=0.3097046, (0 missing)
##
## Node number 14: 26 observations
##   mean=47.04024, MSE=67.29195
##
## Node number 15: 20 observations
##   mean=56.11586, MSE=16.28645
```

```
# plot tree
plot(fitmcs, uniform = TRUE, compress = FALSE)
text(fitmcs, use.n = TRUE, all = TRUE, cex = 0.5)
```

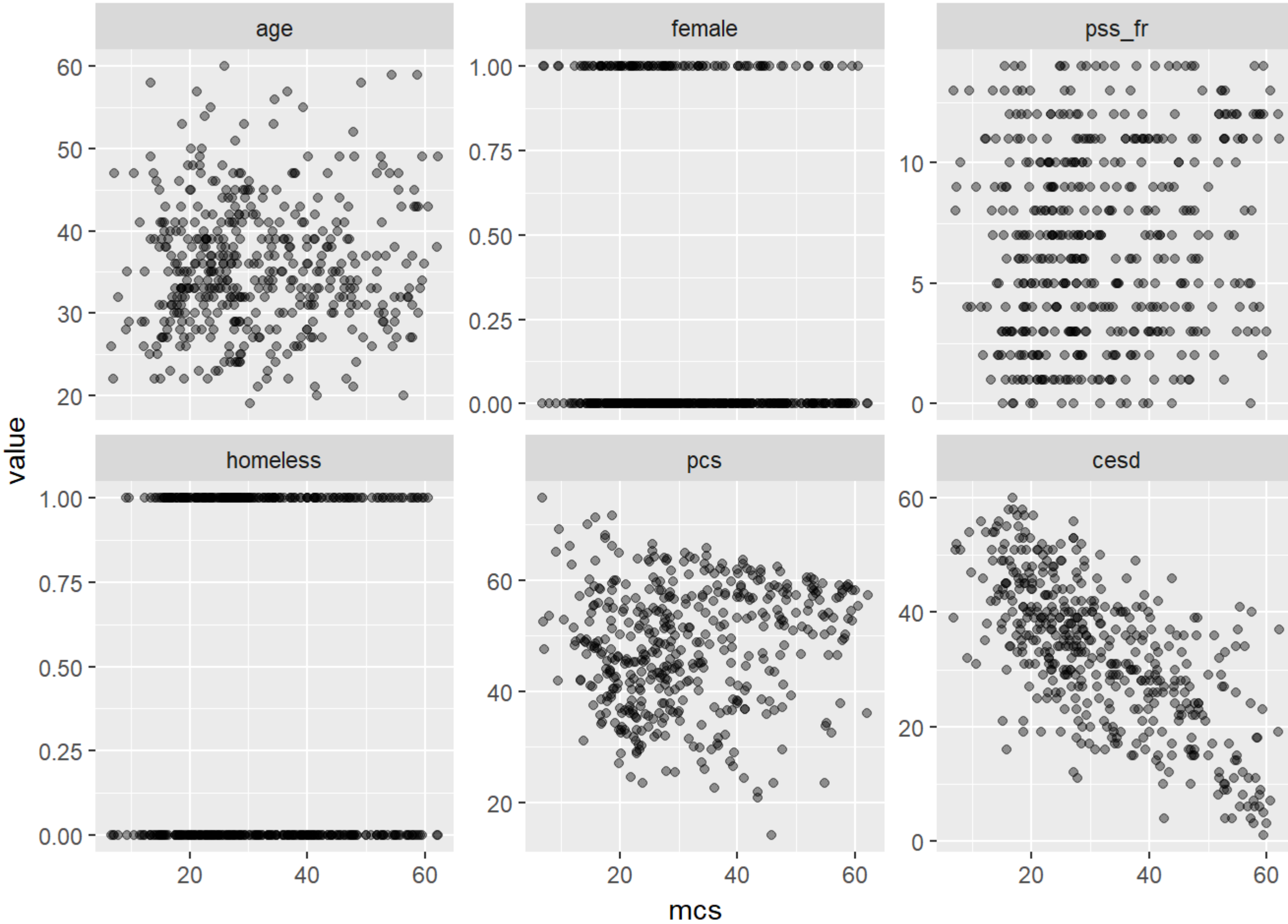


PROBLEM 2: Matrix Scatterplot of Other Variables with MCS

```
# all vars except the dichotomous cesd_gte16 and mcs_lt45
h1a <- h1[,1:7]

# Melt the other variables down and link to mcs
h1m <- reshape2::melt(h1a, id.vars = "mcs")
```

```
## Warning: attributes are not identical across measure variables; they will
## be dropped
```

```
# Plot panels for each covariate
ggplot(h1m, aes(x=mcs, y=value)) +
  geom_point(alpha=0.4)+
  scale_color_brewer(palette="Set2")+
  facet_wrap(~variable, scales="free_y", ncol=3)
```

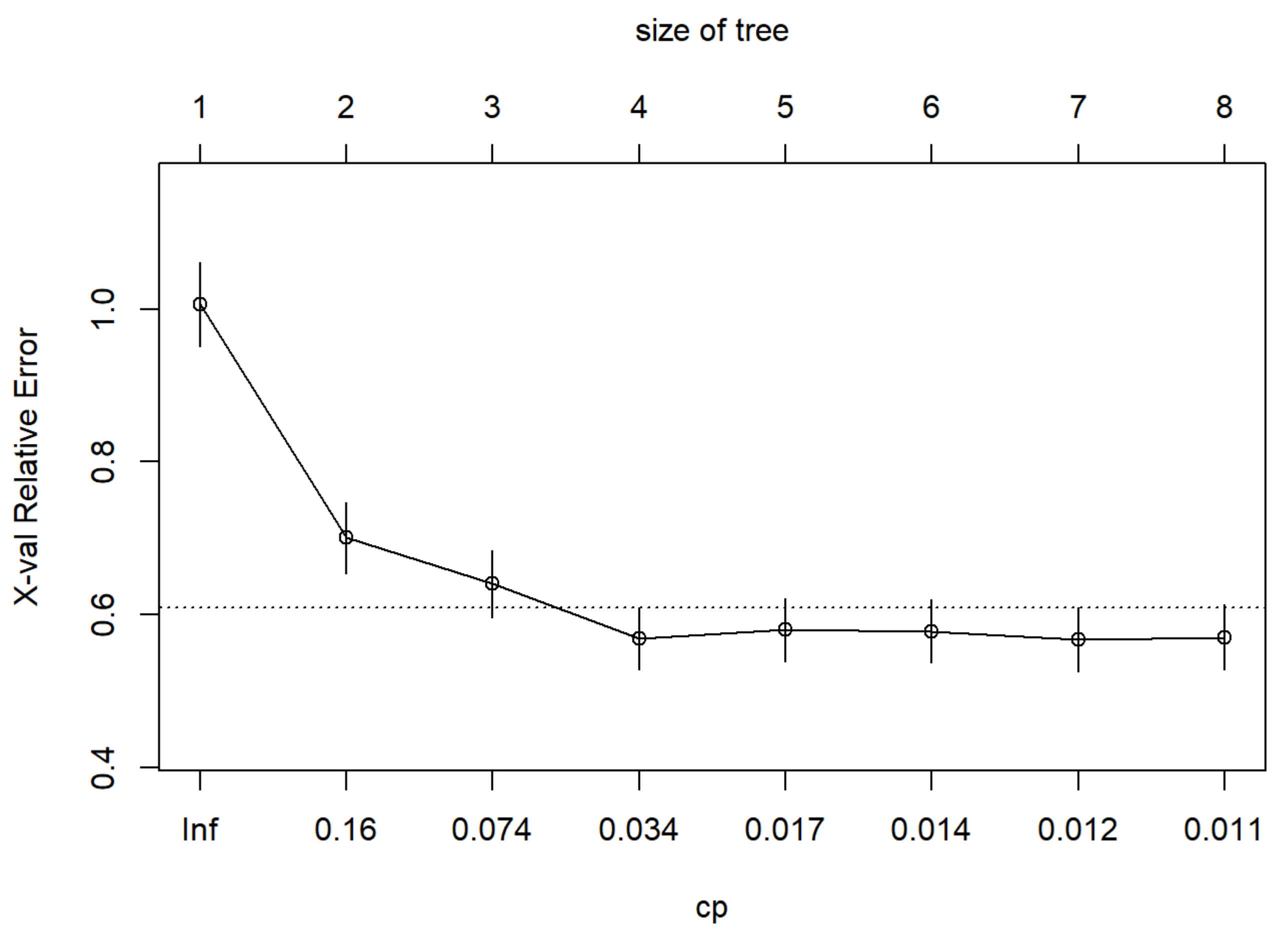


PROBLEM 3: Regression Tree for MCS Using Rest of Variables

```
# fit a regression tree with all vars
fitall <- rpart::rpart(mcs ~ ., data = h1a)

# equivalent code statement without the shorthand
# using the period for the "rest of the variables"
# this time each variable to be included is listed
# individually putting a plus + in between each
# variable added to the model

fitall <- rpart::rpart(mcs ~ age + female + pss_fr +
                              homeless + pcs + cesd,
                              data = h1a)

# Now let's look at fitall
rpart::printcp(fitall) # Display the results
```

```
##
## Regression tree:
## rpart::rpart(formula = mcs ~ age + female + pss_fr + homeless +
##     pcs + cesd, data = h1a)
##
## Variables actually used in tree construction:
## [1] cesd pcs
##
## Root node error: 74512/453 = 164.48
##
## n= 453
##
##          CP nsplit rel error  xerror     xstd
## 1 0.325298      0   1.00000 1.00641 0.054843
## 2 0.081349      1   0.67470 0.70015 0.046829
## 3 0.066496      2   0.59335 0.64047 0.043897
## 4 0.017717      3   0.52686 0.56846 0.040187
## 5 0.015767      4   0.50914 0.57972 0.041104
## 6 0.012496      5   0.49337 0.57789 0.041325
## 7 0.012258      6   0.48088 0.56708 0.041548
## 8 0.010000      7   0.46862 0.57046 0.041955
```

```
rpart::plotcp(fitall) # Visualize cross-validation results
```



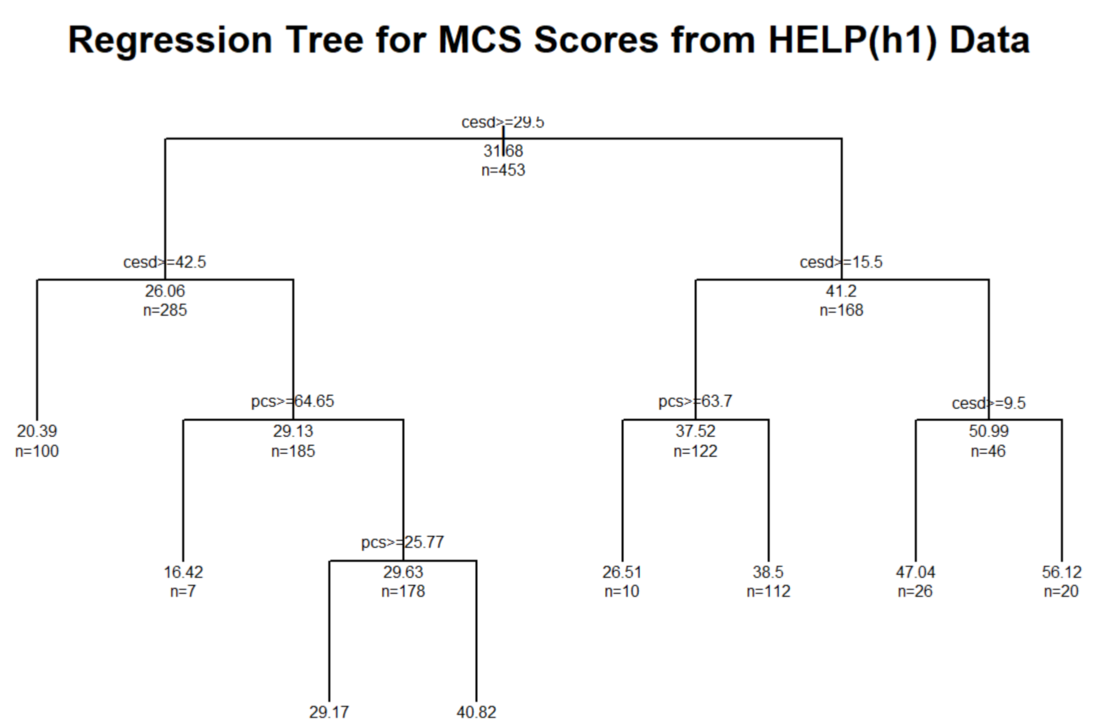
```
summary(fitall) # Detailed summary of fit
```

```
## Call:
## rpart::rpart(formula = mcs ~ age + female + pss_fr + homeless +
##     pcs + cesd, data = h1a)
##   n= 453
##
##           CP nsplit rel error    xerror       xstd
## 1 0.32529813      0 1.0000000 1.0064090 0.05484298
## 2 0.08134904      1 0.6747019 0.7001475 0.04682921
## 3 0.06649553      2 0.5933528 0.6404681 0.04389675
## 4 0.01771736      3 0.5268573 0.5684580 0.04018699
## 5 0.01576737      4 0.5091399 0.5797248 0.04110393
## 6 0.01249609      5 0.4933726 0.5778941 0.04132472
## 7 0.01225792      6 0.4808765 0.5670800 0.04154758
## 8 0.01000000      7 0.4686186 0.5704585 0.04195470
##
## Variable importance
##   cesd    pcs    age pss_fr
##     83     14      1      1
##
## Node number 1: 453 observations,    complexity param=0.3252981
##   mean=31.67668, MSE=164.4847
##   left son=2 (285 obs) right son=3 (168 obs)
##   Primary splits:
##       cesd   < 29.5     to the right, improve=0.325298100, (0 missing)
##       pcs    < 49.46132 to the left,  improve=0.064711670, (0 missing)
##       pss_fr < 10.5     to the left,  improve=0.039318510, (0 missing)
##       female < 0.5      to the right, improve=0.014091560, (0 missing)
##       age    < 42.5     to the left,  improve=0.005473724, (0 missing)
##   Surrogate splits:
##       pcs < 56.34591 to the left,  agree=0.669, adj=0.107, (0 split)
##       age < 57.5     to the left,  agree=0.631, adj=0.006, (0 split)
##
## Node number 2: 285 observations,    complexity param=0.06649553
##   mean=26.06057, MSE=100.1894
##   left son=4 (100 obs) right son=5 (185 obs)
##   Primary splits:
##       cesd   < 42.5     to the right, improve=0.173520000, (0 missing)
##       pcs    < 24.47511 to the right, improve=0.057879990, (0 missing)
##       pss_fr < 10.5     to the left,  improve=0.015219690, (0 missing)
##       age    < 22.5     to the right, improve=0.005742931, (0 missing)
##       female < 0.5      to the right, improve=0.001903900, (0 missing)
##   Surrogate splits:
##       pss_fr < 0.5      to the left,  agree=0.660, adj=0.03, (0 split)
##       pcs    < 68.64778 to the right, agree=0.653, adj=0.01, (0 split)
##
## Node number 3: 168 observations,    complexity param=0.08134904
##   mean=41.20401, MSE=129.2805
##   left son=6 (122 obs) right son=7 (46 obs)
##   Primary splits:
##       cesd   < 15.5     to the right, improve=0.279083400, (0 missing)
##       pcs    < 62.7532  to the right, improve=0.113215200, (0 missing)
##       pss_fr < 10.5     to the left,  improve=0.053187210, (0 missing)
##       age    < 48.5     to the left,  improve=0.036737610, (0 missing)
```

```
##       female < 0.5      to the right, improve=0.007177787, (0 missing)
##   Surrogate splits:
##       age < 58.5     to the left,  agree=0.738, adj=0.043, (0 split)
##
## Node number 4: 100 observations
##   mean=20.38941, MSE=43.95751
##
## Node number 5: 185 observations,    complexity param=0.01576737
##   mean=29.12606, MSE=103.8029
##   left son=10 (7 obs) right son=11 (178 obs)
##   Primary splits:
##       pcs    < 64.65134 to the right, improve=0.061178900, (0 missing)
##       age    < 22.5     to the right, improve=0.031248410, (0 missing)
##       cesd   < 37.5     to the right, improve=0.020833690, (0 missing)
##       pss_fr < 10.5     to the left,  improve=0.015175680, (0 missing)
##       female < 0.5      to the left,  improve=0.004355548, (0 missing)
##
## Node number 6: 122 observations,    complexity param=0.01771736
##   mean=37.51566, MSE=103.6988
##   left son=12 (10 obs) right son=13 (112 obs)
##   Primary splits:
##       pcs    < 63.69606 to the right, improve=0.10434930, (0 missing)
##       age    < 47.5     to the left,  improve=0.02626159, (0 missing)
##       cesd   < 24.5     to the right, improve=0.02348926, (0 missing)
##       female < 0.5      to the right, improve=0.02256241, (0 missing)
##       pss_fr < 2.5      to the right, improve=0.01295167, (0 missing)
##
## Node number 7: 46 observations,    complexity param=0.01249609
##   mean=50.98616, MSE=65.35702
##   left son=14 (26 obs) right son=15 (20 obs)
##   Primary splits:
##       cesd     < 9.5      to the right, improve=0.30970460, (0 missing)
##       pcs      < 59.57495 to the right, improve=0.16249370, (0 missing)
##       pss_fr   < 11.5     to the left,  improve=0.13099300, (0 missing)
##       age      < 40       to the left,  improve=0.06604375, (0 missing)
##       homeless < 0.5      to the left,  improve=0.00873942, (0 missing)
##   Surrogate splits:
##       pss_fr   < 11.5     to the left,  agree=0.674, adj=0.25, (0 split)
##       pcs      < 54.5861  to the left,  agree=0.652, adj=0.20, (0 split)
##       age      < 46       to the left,  agree=0.609, adj=0.10, (0 split)
##       homeless < 0.5      to the left,  agree=0.609, adj=0.10, (0 split)
##
## Node number 10: 7 observations
##   mean=16.41837, MSE=35.31025
##
## Node number 11: 178 observations,    complexity param=0.01225792
##   mean=29.6258, MSE=99.89614
##   left son=22 (171 obs) right son=23 (7 obs)
##   Primary splits:
##       pcs      < 25.77119 to the right, improve=0.051365510, (0 missing)
##       age      < 22.5     to the right, improve=0.029936490, (0 missing)
##       pss_fr   < 10.5     to the left,  improve=0.022699840, (0 missing)
##       cesd     < 37.5     to the right, improve=0.020642200, (0 missing)
##       homeless < 0.5      to the right, improve=0.002448012, (0 missing)
```

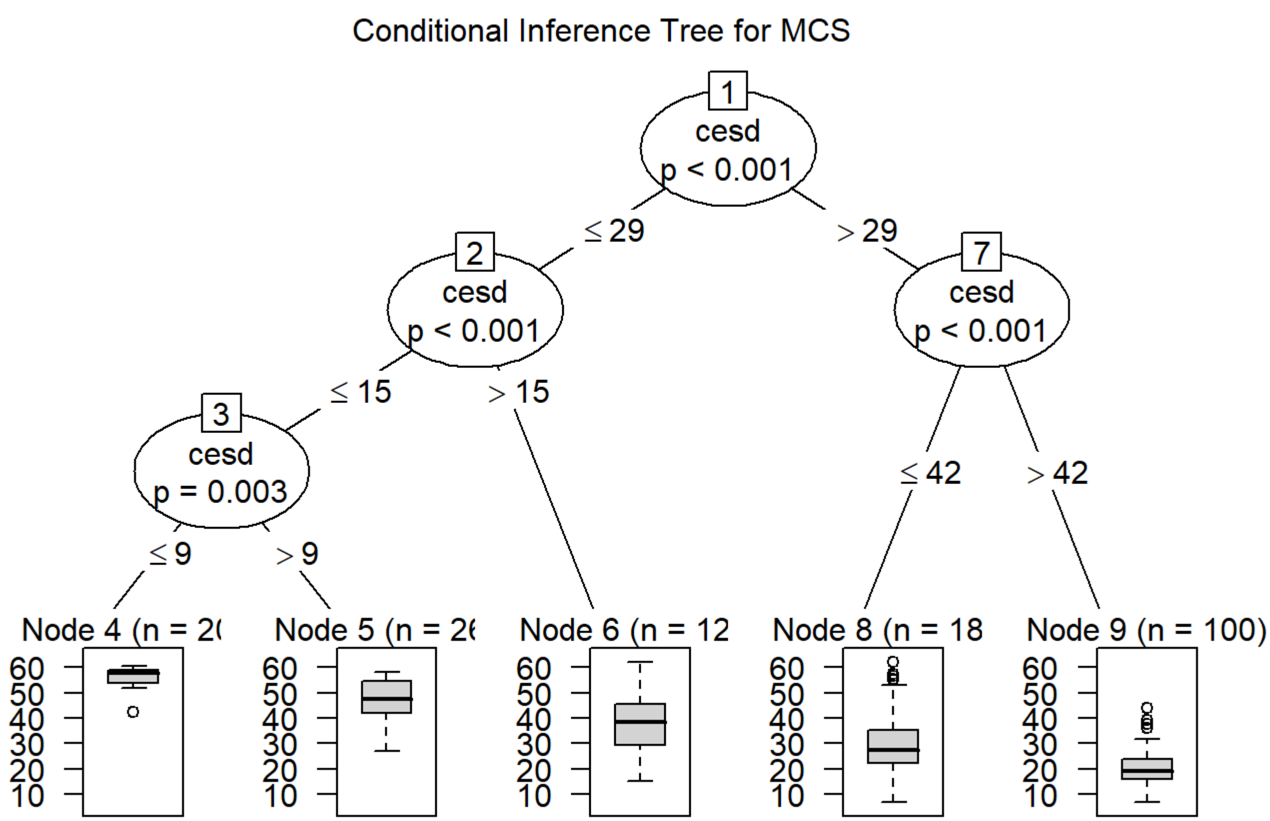
```
##
## Node number 12: 10 observations
##   mean=26.50685, MSE=30.97799
##
## Node number 13: 112 observations
##   mean=38.49859, MSE=98.40465
##
## Node number 14: 26 observations
##   mean=47.04024, MSE=67.29195
##
## Node number 15: 20 observations
##   mean=56.11586, MSE=16.28645
##
## Node number 22: 171 observations
##   mean=29.16748, MSE=95.51594
##
## Node number 23: 7 observations
##   mean=40.8217, MSE=76.41866
```

```
plot(fitall, uniform = TRUE, compress = FALSE, main = "Regression Tree for MCS Scores from HELP
(h1) Data")
text(fitall, use.n = TRUE, all = TRUE, cex = 0.5)
```



PROBLEM 4: Fit a Conditional Regression Tree for MCS

```
fitallp <- party::ctree(mcs ~ ., data = h1a)
plot(fitallp, main = "Conditional Inference Tree for MCS")
```



PROBLEM 5: Fit a Logistic Regression Model for MCS < 45

```
# begin with a logistic regression - poor mental health or not
glm1 <- glm(mcs_lt45 ~ age + female + pss_fr + homeless +
              pcs + cesd, data = h1)
summary(glm1)
```

```
##
## Call:
## glm(formula = mcs_lt45 ~ age + female + pss_fr + homeless + pcs +
##     cesd, data = h1)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -0.96035  -0.10332   0.08078   0.21806   0.62498
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.3611168  0.1386939   2.604  0.00953 **
## age         -0.0023080  0.0021130  -1.092  0.27529
## female       0.0202380  0.0382212   0.529  0.59672
## pss_fr      -0.0036606  0.0040882  -0.895  0.37104
## homeless     0.0172706  0.0323939   0.533  0.59420
## pcs          0.0005446  0.0015809   0.344  0.73064
## cesd         0.0158725  0.0013519  11.741  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1114291)
##
##     Null deviance: 68.424  on 452  degrees of freedom
## Residual deviance: 49.697  on 446  degrees of freedom
## AIC: 300.46
##
## Number of Fisher Scoring iterations: 2
```

This model is different from the model for cesd_gte16. This model shows that `cesd` is significant, whereas the cesd_gte16 model has `pcs` and `mcs` as significant variables. Additionally, all the variables had negative estimates in the cesd_gte16 model, whereas this model shows `age` and `pss_fr` as positive.

PROBLEM 6: Fit a Classification Tree for MCS < 45

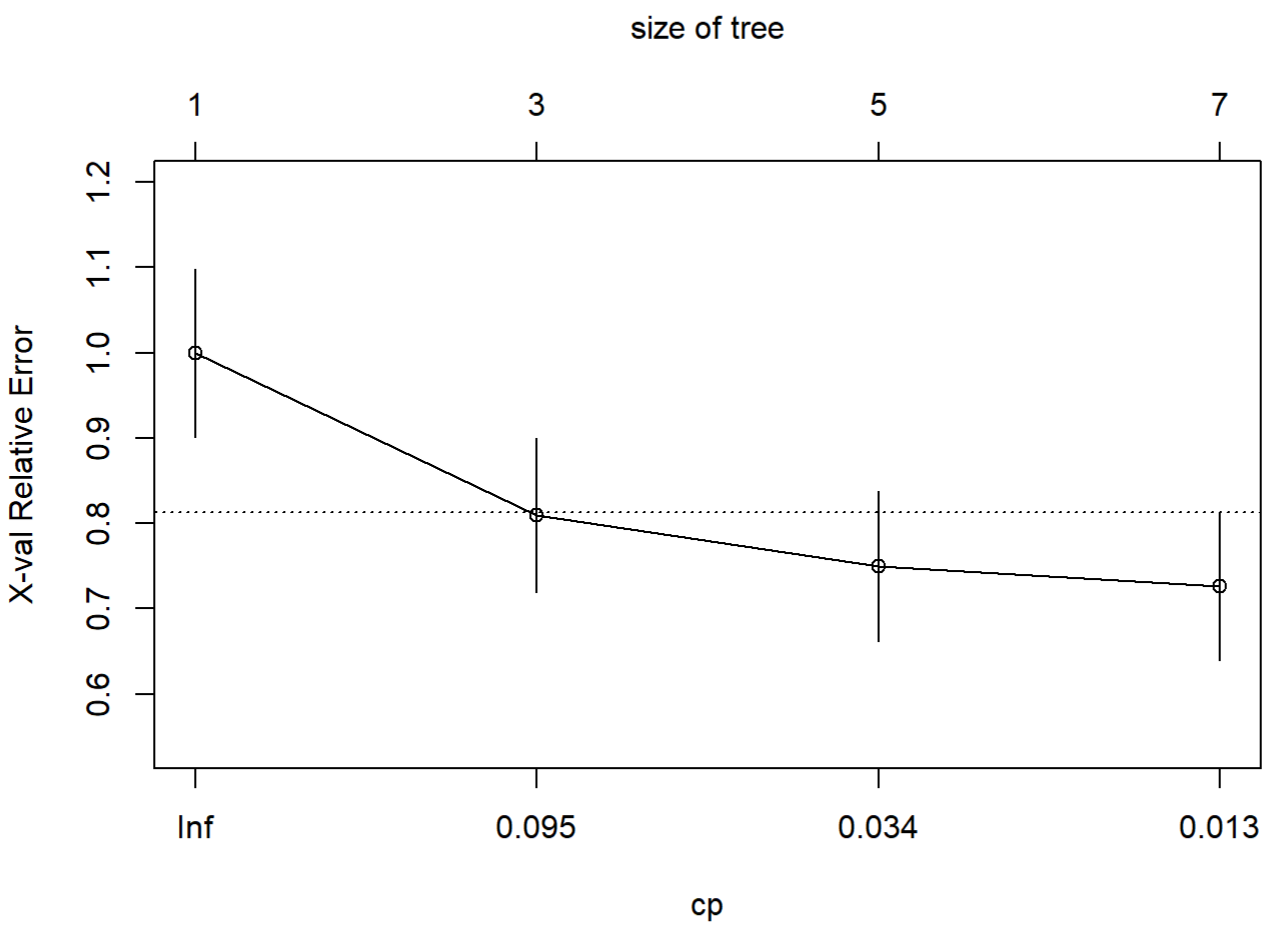
```
fitk <- rpart::rpart(mcs_lt45 ~ age + female + pss_fr +
                       homeless + pcs + cesd,
                     method = "class", data = h1)
class(fitk)
```

```
## [1] "rpart"
```

```
# Display the results
rpart::printcp(fitk)
```

```
##
## Classification tree:
## rpart::rpart(formula = mcs_lt45 ~ age + female + pss_fr + homeless +
##     pcs + cesd, data = h1, method = "class")
##
## Variables actually used in tree construction:
## [1] age  cesd pcs
##
## Root node error: 84/453 = 0.18543
##
## n= 453
##
##         CP nsplit rel error  xerror     xstd
## 1 0.136905      0   1.00000 1.00000 0.098475
## 2 0.065476      2   0.72619 0.80952 0.090502
## 3 0.017857      4   0.59524 0.75000 0.087675
## 4 0.010000      6   0.55952 0.72619 0.086493
```

```
#Visualize the cross-validation results
rpart::plotcp(fitk)
```



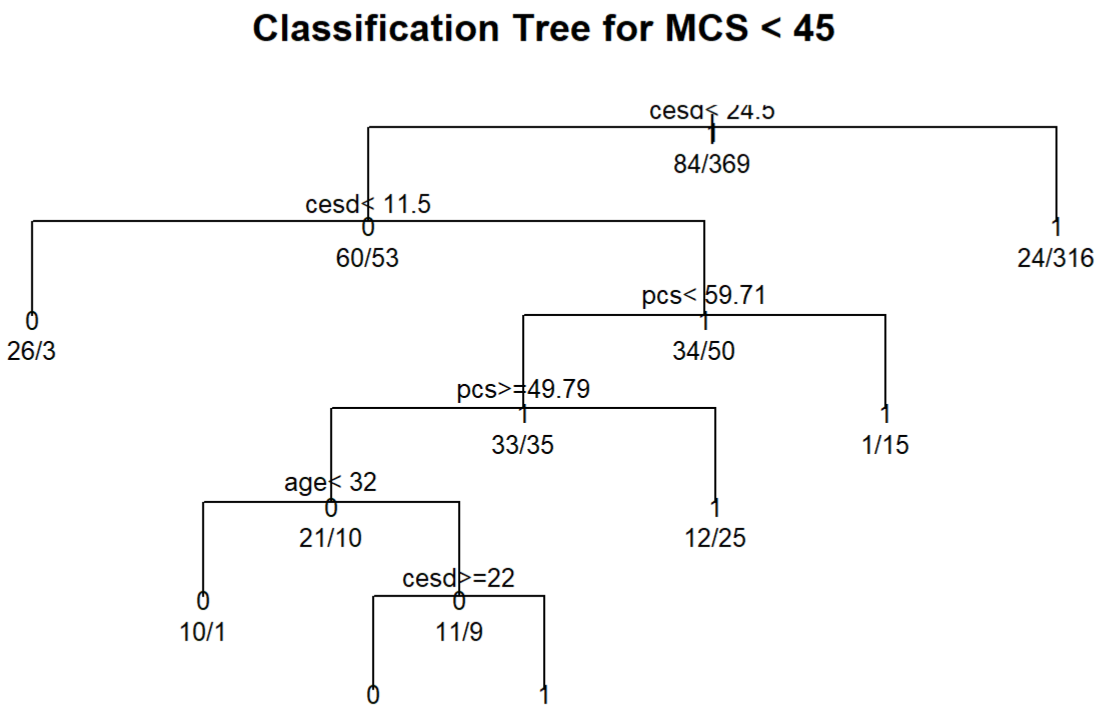

```
# Get a detailed summary of the splits
summary(fitk)
```

```
## Call:
## rpart::rpart(formula = mcs_lt45 ~ age + female + pss_fr + homeless +
##     pcs + cesd, data = h1, method = "class")
##   n= 453
##
##           CP nsplit rel error    xerror       xstd
## 1 0.13690476      0 1.0000000 1.0000000 0.09847465
## 2 0.06547619      2 0.7261905 0.8095238 0.09050164
## 3 0.01785714      4 0.5952381 0.7500000 0.08767468
## 4 0.01000000      6 0.5595238 0.7261905 0.08649272
##
## Variable importance
##   cesd    pcs    age pss_fr
##     76     16      6      2
##
## Node number 1: 453 observations,    complexity param=0.1369048
##   predicted class=1  expected loss=0.1854305  P(node) =1
##     class counts:    84   369
##    probabilities: 0.185 0.815
##   left son=2 (113 obs) right son=3 (340 obs)
##   Primary splits:
##       cesd   < 24.5     to the left,  improve=35.952730, (0 missing)
##       pcs    < 49.46132 to the right, improve= 7.907014, (0 missing)
##       pss_fr < 10.5     to the right, improve= 4.386206, (0 missing)
##       female < 0.5      to the left,  improve= 1.504589, (0 missing)
##       age    < 48.5     to the right, improve= 1.425056, (0 missing)
##   Surrogate splits:
##       age < 57.5     to the right, agree=0.753, adj=0.009, (0 split)
##       pcs < 70.77019 to the right, agree=0.753, adj=0.009, (0 split)
##
## Node number 2: 113 observations,    complexity param=0.1369048
##   predicted class=0  expected loss=0.4690265  P(node) =0.2494481
##     class counts:    60    53
##    probabilities: 0.531 0.469
##   left son=4 (29 obs) right son=5 (84 obs)
##   Primary splits:
##       cesd   < 11.5     to the left,  improve=10.427690, (0 missing)
##       pcs    < 60.7539  to the left,  improve= 8.921666, (0 missing)
##       pss_fr < 11.5     to the right, improve= 2.105364, (0 missing)
##       female < 0.5      to the left,  improve= 1.591788, (0 missing)
##       age    < 47.5     to the right, improve= 1.587768, (0 missing)
##   Surrogate splits:
##       age < 58.5     to the right, agree=0.761, adj=0.069, (0 split)
##
## Node number 3: 340 observations
##   predicted class=1  expected loss=0.07058824  P(node) =0.7505519
##     class counts:    24   316
##    probabilities: 0.071 0.929
##
## Node number 4: 29 observations
##   predicted class=0  expected loss=0.1034483  P(node) =0.06401766
##     class counts:    26     3
##    probabilities: 0.897 0.103
```

```
##
## Node number 5: 84 observations,    complexity param=0.06547619
##   predicted class=1  expected loss=0.4047619  P(node) =0.1854305
##     class counts:    34    50
##    probabilities: 0.405 0.595
##   left son=10 (68 obs) right son=11 (16 obs)
##   Primary splits:
##       pcs    < 59.71077 to the left,  improve=4.6306020, (0 missing)
##       female < 0.5      to the left,  improve=1.8658960, (0 missing)
##       cesd   < 21.5     to the right, improve=1.7155130, (0 missing)
##       age    < 38.5     to the left,  improve=0.2586838, (0 missing)
##       pss_fr < 11.5     to the right, improve=0.2539683, (0 missing)
##
## Node number 10: 68 observations,    complexity param=0.06547619
##   predicted class=1  expected loss=0.4852941  P(node) =0.1501104
##     class counts:    33    35
##    probabilities: 0.485 0.515
##   left son=20 (31 obs) right son=21 (37 obs)
##   Primary splits:
##       pcs    < 49.7901  to the right, improve=4.2059850, (0 missing)
##       female < 0.5      to the left,  improve=2.0824760, (0 missing)
##       cesd   < 16.5     to the left,  improve=1.1284830, (0 missing)
##       age    < 43.5     to the left,  improve=0.4790628, (0 missing)
##       pss_fr < 7.5      to the left,  improve=0.2761438, (0 missing)
##   Surrogate splits:
##       age      < 27.5     to the left,  agree=0.588, adj=0.097, (0 split)
##       pss_fr   < 13.5     to the right, agree=0.588, adj=0.097, (0 split)
##       homeless < 0.5      to the right, agree=0.559, adj=0.032, (0 split)
##       cesd     < 12.5     to the left,  agree=0.559, adj=0.032, (0 split)
##
## Node number 11: 16 observations
##   predicted class=1  expected loss=0.0625  P(node) =0.03532009
##     class counts:     1    15
##    probabilities: 0.062 0.938
##
## Node number 20: 31 observations,    complexity param=0.01785714
##   predicted class=0  expected loss=0.3225806  P(node) =0.06843267
##     class counts:    21    10
##    probabilities: 0.677 0.323
##   left son=40 (11 obs) right son=41 (20 obs)
##   Primary splits:
##       age      < 32       to the left,  improve=1.830205000, (0 missing)
##       pss_fr   < 8.5      to the left,  improve=1.607211000, (0 missing)
##       cesd     < 21.5     to the right, improve=1.462673000, (0 missing)
##       pcs      < 57.31713 to the right, improve=1.274883000, (0 missing)
##       homeless < 0.5      to the left,  improve=0.004527448, (0 missing)
##   Surrogate splits:
##       pcs  < 59.00035 to the right, agree=0.710, adj=0.182, (0 split)
##       cesd < 16.5     to the left,  agree=0.677, adj=0.091, (0 split)
##
## Node number 21: 37 observations
##   predicted class=1  expected loss=0.3243243  P(node) =0.0816777
##     class counts:    12    25
##    probabilities: 0.324 0.676
```

```
##
## Node number 40: 11 observations
##   predicted class=0  expected loss=0.09090909  P(node) =0.02428256
##     class counts:    10     1
##    probabilities: 0.909 0.091
##
## Node number 41: 20 observations,    complexity param=0.01785714
##   predicted class=0  expected loss=0.45  P(node) =0.04415011
##     class counts:    11     9
##    probabilities: 0.550 0.450
##   left son=82 (7 obs) right son=83 (13 obs)
##   Primary splits:
##       cesd     < 22       to the right, improve=2.0318680, (0 missing)
##       age      < 39.5     to the right, improve=0.5813187, (0 missing)
##       pcs      < 57.14784 to the right, improve=0.5813187, (0 missing)
##       pss_fr   < 7        to the left,  improve=0.4454545, (0 missing)
##       homeless < 0.5      to the right, improve=0.1000000, (0 missing)
##   Surrogate splits:
##       pss_fr < 7        to the left,  agree=0.80, adj=0.429, (0 split)
##       age    < 45       to the right, agree=0.75, adj=0.286, (0 split)
##       pcs    < 57.34769 to the right, agree=0.75, adj=0.286, (0 split)
##
## Node number 82: 7 observations
##   predicted class=0  expected loss=0.1428571  P(node) =0.01545254
##     class counts:     6     1
##    probabilities: 0.857 0.143
##
## Node number 83: 13 observations
##   predicted class=1  expected loss=0.3846154  P(node) =0.02869757
##     class counts:     5     8
##    probabilities: 0.385 0.615
```

```
# Plot the tree
plot(fitk, uniform = TRUE,
     main = "Classification Tree for MCS < 45")
text(fitk, use.n = TRUE, all = TRUE, cex = 0.8)
```

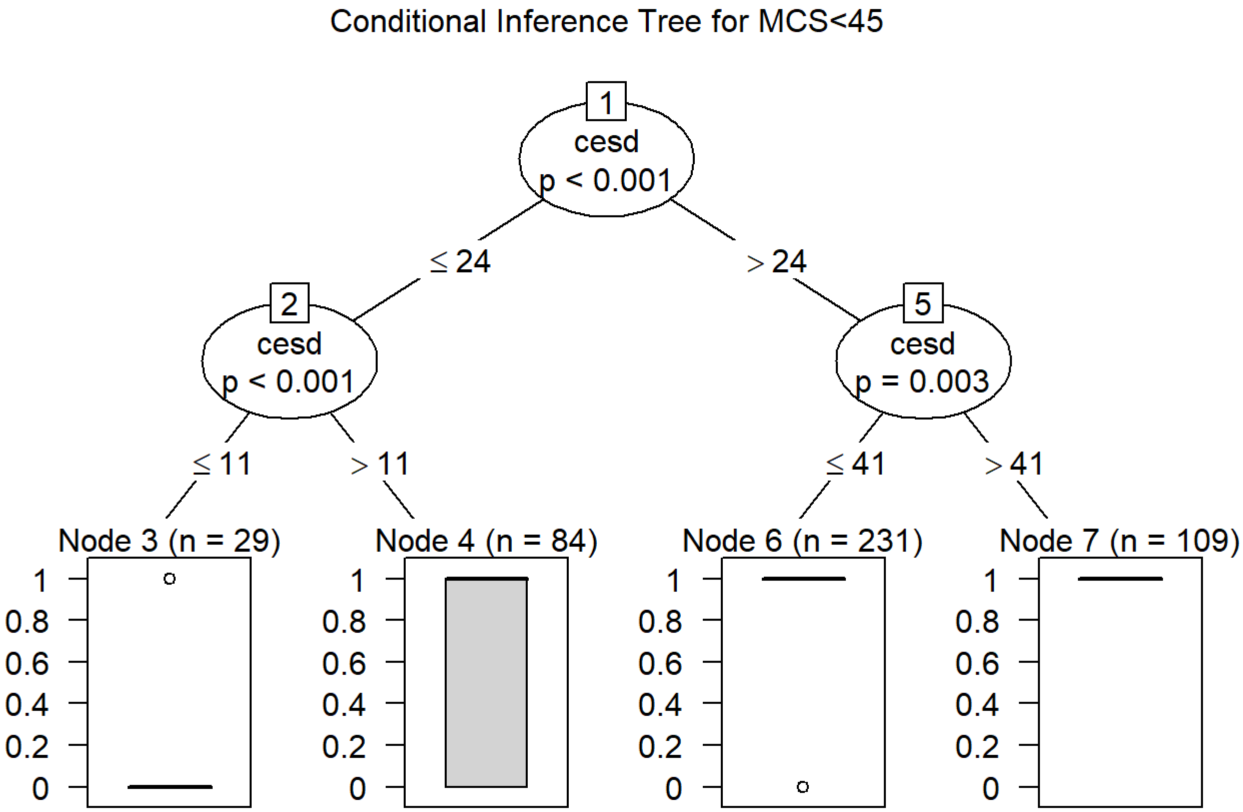


PROBLEM 7: Fit a Conditional Classification Tree for MCS < 45

```
# look at mcs_lt45 with ctree from party
fitallpk <- party::ctree(mcs_lt45 ~ age + female + pss_fr +
                          homeless + pcs + cesd, data = h1)
class(fitallpk)
```

```
## [1] "BinaryTree"
## attr(,"package")
## [1] "party"
```

```
plot(fitallpk, main = "Conditional Inference Tree for MCS<45")
```

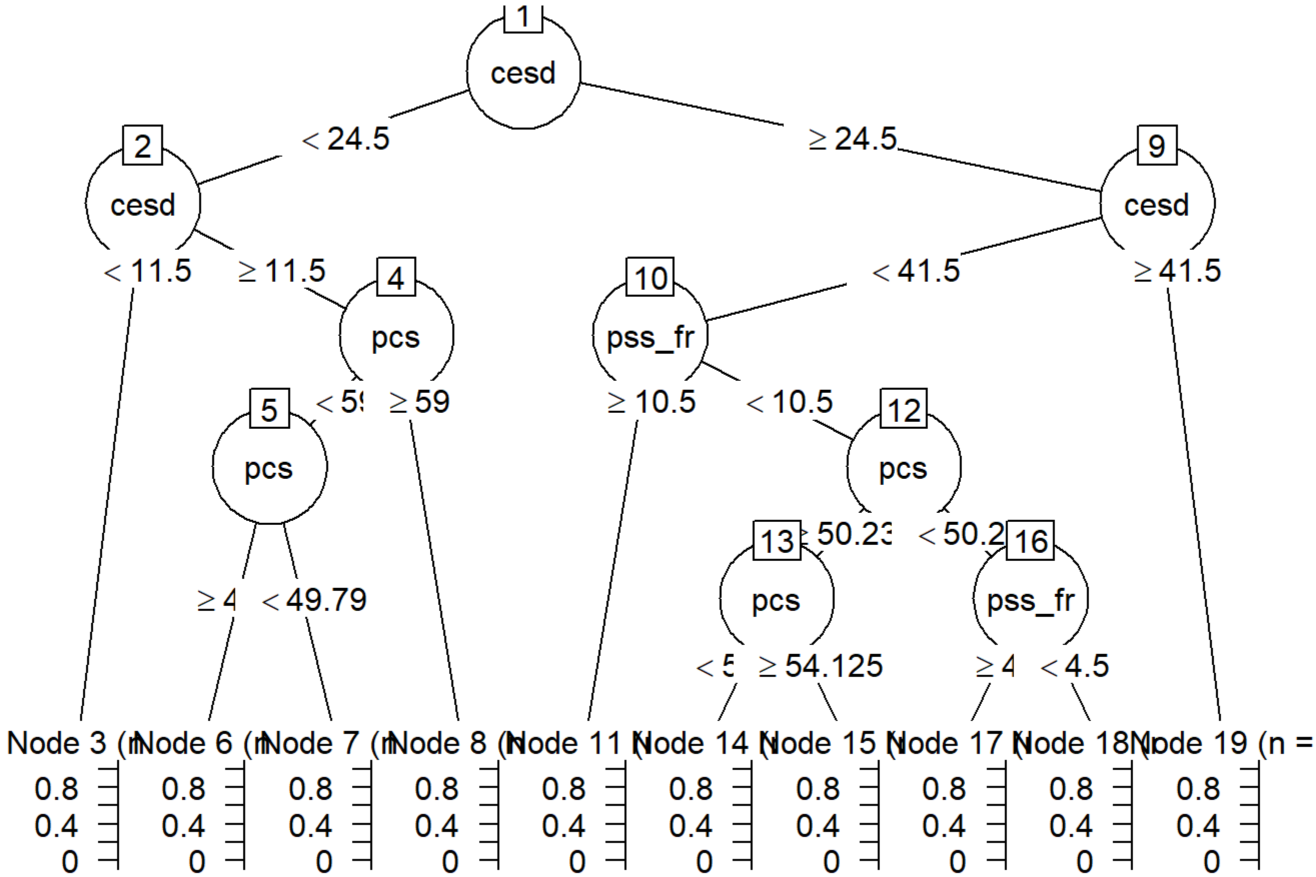


PROBLEM 8: Recursive Partitioning of Classification Tree for MCS < 45

```
# Recursive partitioning of MCS<45 on age,
# female, pss_fr, homeless, pcs, cesd
whoIsDepressed <- rpart::rpart(mcs_lt45 ~ age + female +
                                 pss_fr + homeless + pcs + cesd,
                               data = h1,
                               control = rpart.control(cp = 0.001,
                                                       minbucket = 20))

whoIsDepressed
```

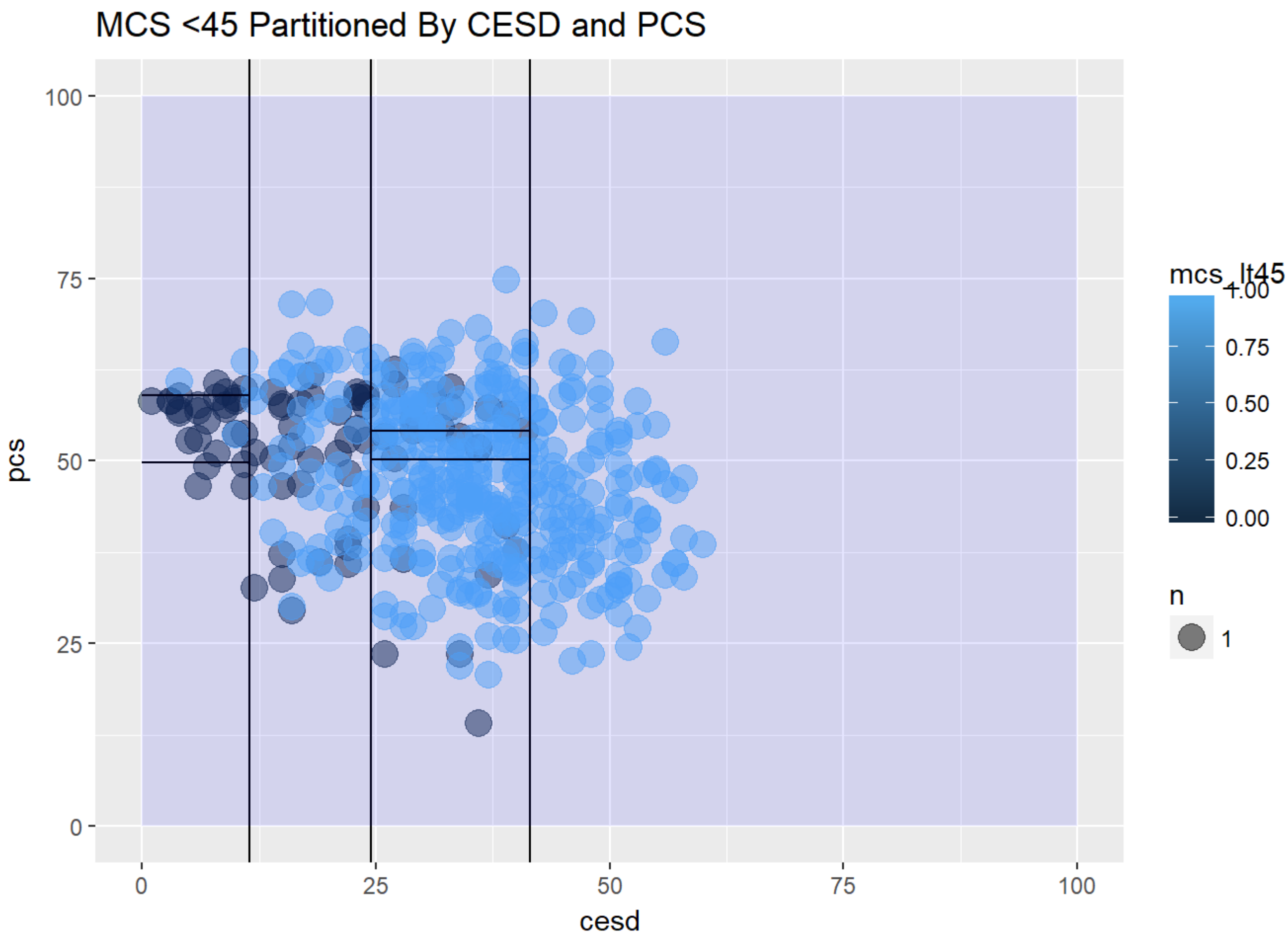
```
## n= 453
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
##  1) root 453 68.423840 0.8145695
##    2) cesd< 24.5 113 28.141590 0.4690265
##      4) cesd< 11.5 29  2.689655 0.1034483 *
##      5) cesd>=11.5 84 20.238100 0.5952381
##       10) pcs< 59.00035 64 15.937500 0.5312500
##         20) pcs>=49.7901 27  6.000000 0.3333333 *
##         21) pcs< 49.7901 37  8.108108 0.6756757 *
##       11) pcs>=59.00035 20  3.200000 0.8000000 *
##    3) cesd>=24.5 340 22.305880 0.9294118
##      6) cesd< 41.5 231 21.506490 0.8961039
##       12) pss_fr>=10.5 52  8.076923 0.8076923 *
##       13) pss_fr< 10.5 179 12.905030 0.9217877
##         26) pcs>=50.23704 80  8.750000 0.8750000
##           52) pcs< 54.12466 25  4.560000 0.7600000 *
##           53) pcs>=54.12466 55  3.709091 0.9272727 *
##         27) pcs< 50.23704 99  3.838384 0.9595960
##           54) pss_fr>=4.5 55  3.709091 0.9272727 *
##           55) pss_fr< 4.5 44  0.000000 1.0000000 *
##      7) cesd>=41.5 109  0.000000 1.0000000 *
```

```
library(partykit)
# Plot the tree
plot(partykit::as.party(whoIsDepressed))
```



EXTRA CREDIT Scatterplot of recursive partitions for MCS < 45 for PCS and CESD

```
# EXTRA CREDIT
# Graph as partition
# using the break points shown from the
# conditional tree
ggplot(data = h1, aes(x = cesd, y = pcs)) +
  geom_count(aes(color = mcs_lt45), alpha = 0.5) +
  geom_vline(xintercept = 24.5) +
  geom_vline(xintercept = 11.5) +
  geom_segment(x = 11.5, xend = 0, y = 59.00035, yend = 59.00035) +
  geom_segment(x = 11.5, xend = 0, y = 49.7901, yend = 49.7901) +
  geom_vline(xintercept = 41.5) +
  geom_segment(x = 41.5, xend = 24.5, y = 50.23704, yend = 50.23704) +
  geom_segment(x = 41.5, xend = 24.5, y = 54.12466, yend = 54.12466) +
  annotate("rect", xmin = 0, xmax = 100, ymin = 0, ymax = 100, fill = "blue", alpha = 0.1) +
  ggtitle("MCS <45 Partitioned By CESD and PCS")
```

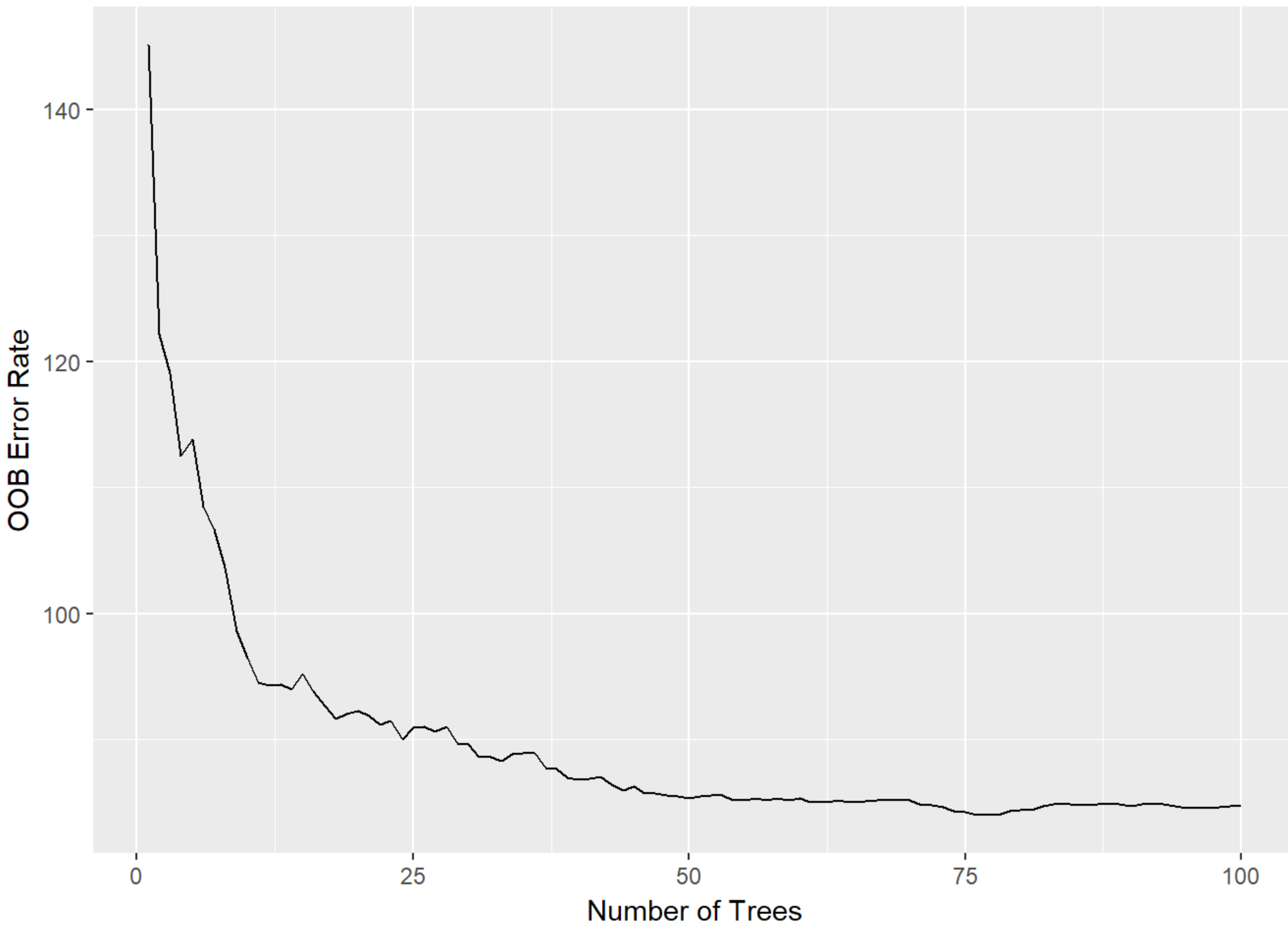


PROBLEM 9: Fit a Random Forest Model for MCS

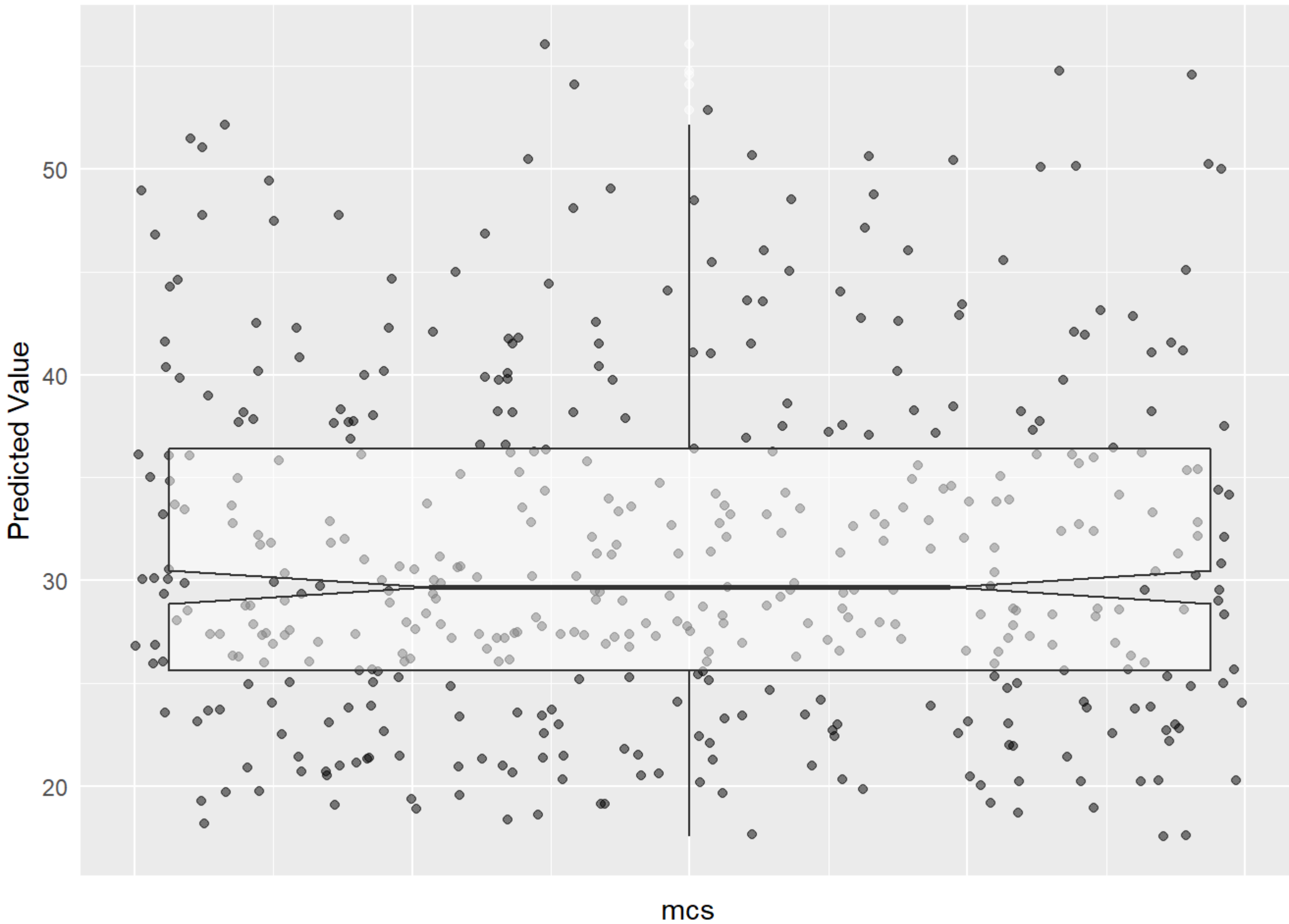
```
h1 <- as.data.frame(h1)
set.seed(131)
# Random Forest for the h1 dataset
fitallrf <- randomForestSRC::rfsrc(mcs ~ age + female +
                                     pss_fr + homeless + pcs + cesd,
                                   data = h1, ntree = 100,
                                   tree.err=TRUE)
# view the results
fitallrf
```

```
##                          Sample size: 453
##                      Number of trees: 100
##            Forest terminal node size: 5
##        Average no. of terminal nodes: 90.85
## No. of variables tried at each split: 2
##               Total no. of variables: 6
##                             Analysis: RF-R
##                               Family: regr
##                       Splitting rule: mse
##              % variance explained: 48.6
##                           Error rate: 84.74
```

```
gg_e <- ggRandomForests::gg_error(fitallrf)
plot(gg_e)
```

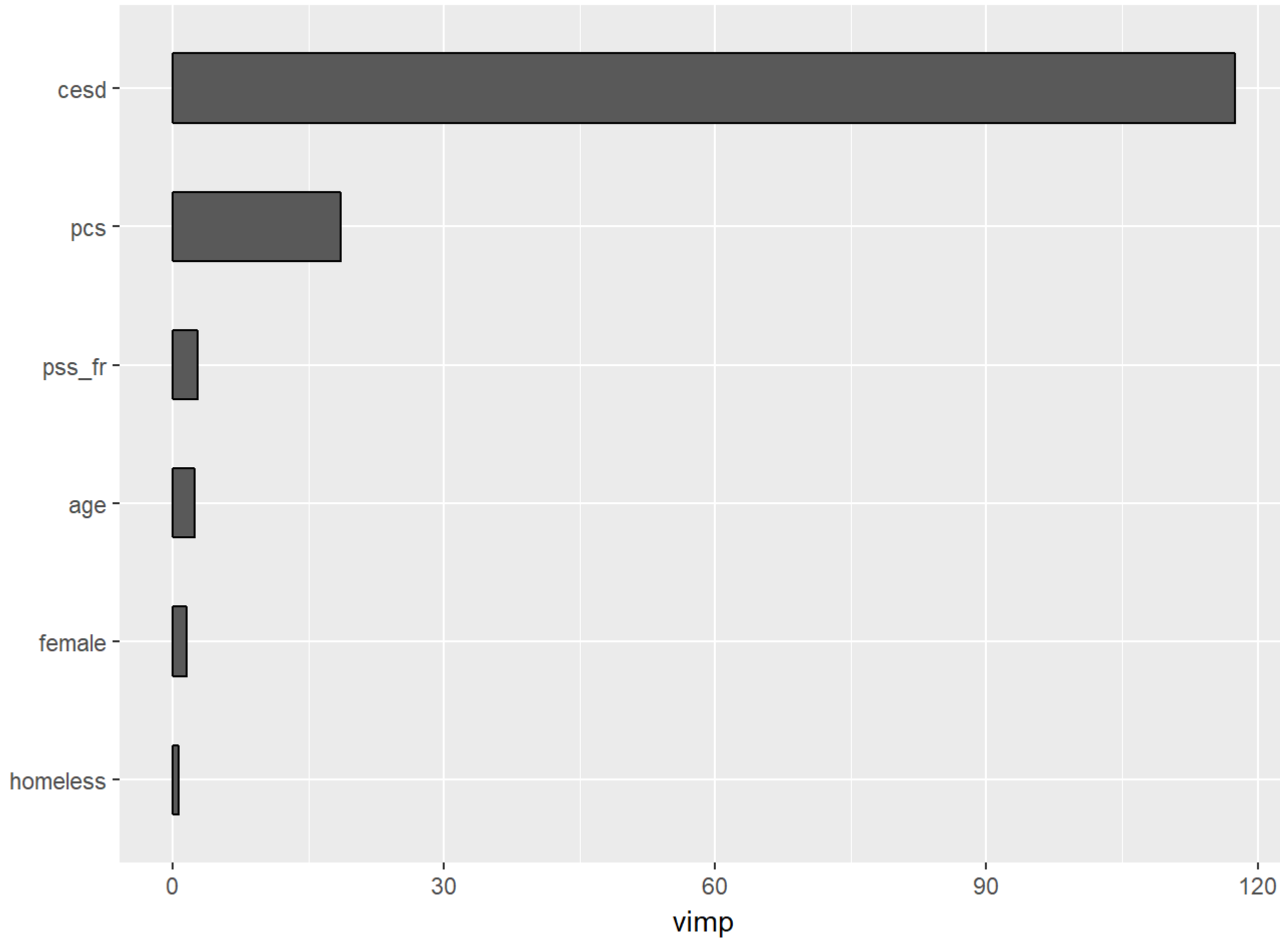



```
# Plot the predicted cesd values
plot(ggRandomForests::gg_rfsrc(fitallrf), alpha = 0.5)
```




```
# Plot the VIMP rankins of independent variables
plot(ggRandomForests::gg_vimp(fitallrf))
```

```
## Warning in gg_vimp.rfsrc(fitallrf): rfsrc object does not contain VIMP
## information. Calculating...
```



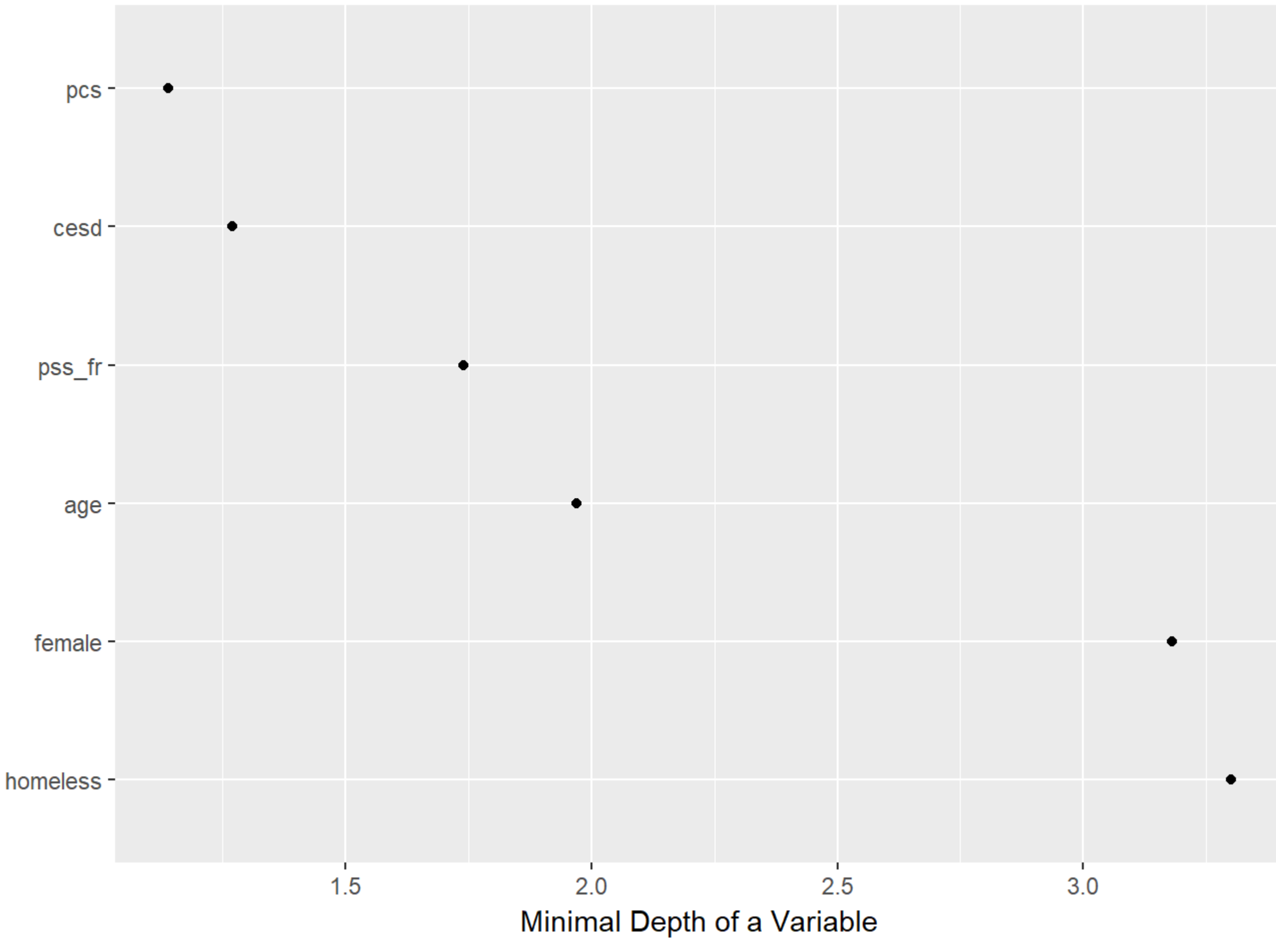

```
# Select the variables
varsel_mcs <- randomForestSRC::var.select(fitallrf)
```

```
## minimal depth variable selection ...
##
##
## -----------------------------------------------------------
## family             : regr
## var. selection     : Minimal Depth
## conservativeness   : medium
## x-weighting used?  : TRUE
## dimension          : 6
## sample size        : 453
## ntree              : 100
## nsplit             : 0
## mtry               : 2
## nodesize           : 5
## refitted forest    : FALSE
## model size         : 6
## depth threshold    : 5.9024
## PE (true OOB)      : 84.7368
##
##
## Top variables:
##          depth vimp
## pcs       1.14   NA
## cesd      1.27   NA
## pss_fr    1.74   NA
## age       1.97   NA
## female    3.18   NA
## homeless  3.30   NA
## -----------------------------------------------------------
```

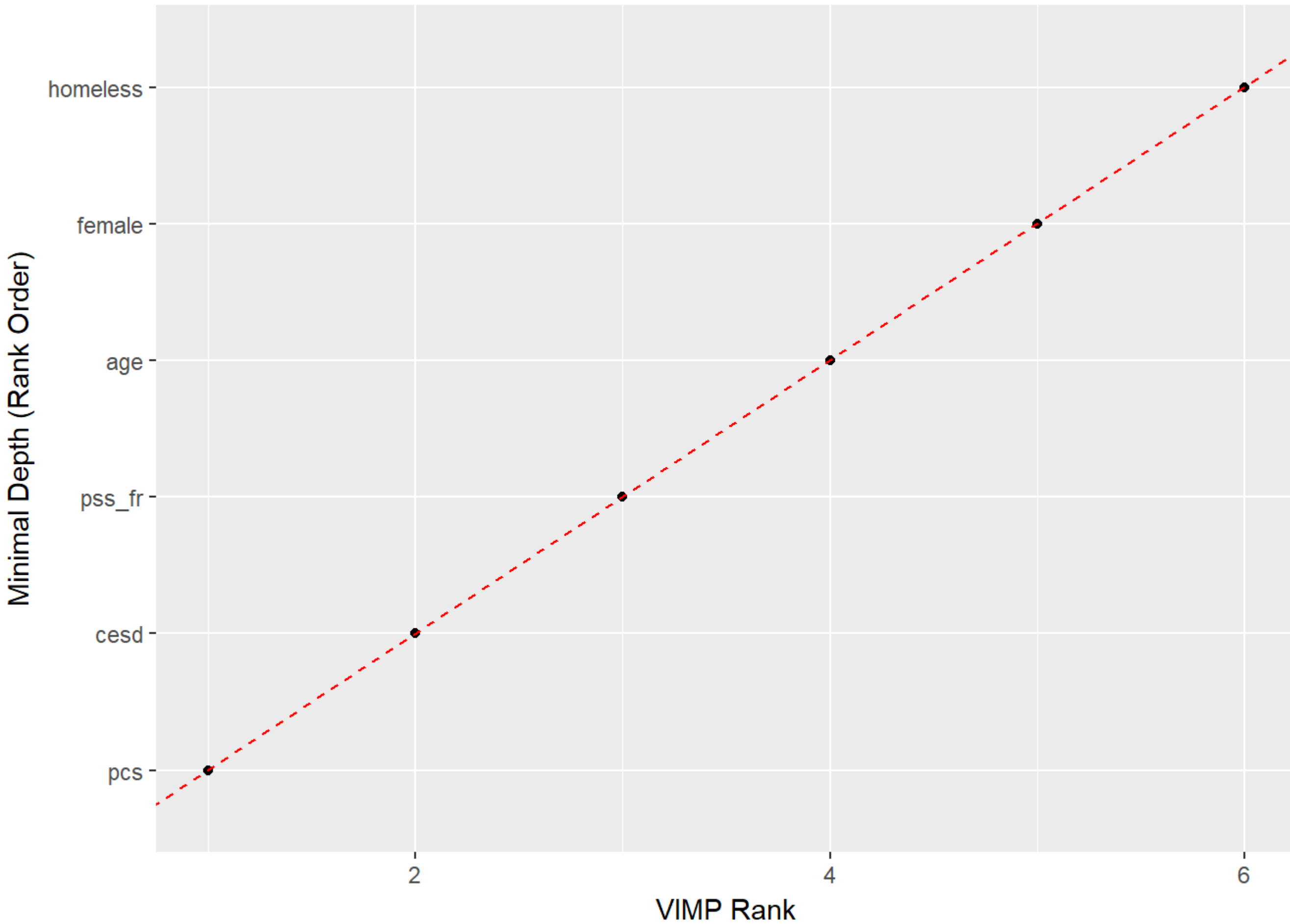
```
glimpse(varsel_mcs)
```

```
## List of 6
##  $ err.rate       : num 84.7
##  $ modelsize      : int 6
##  $ topvars        : chr [1:6] "pcs" "cesd" "pss_fr" "age" ...
##  $ varselect      :'data.frame': 6 obs. of  2 variables:
##   ..$ depth: num [1:6] 1.14 1.27 1.74 1.97 3.18 3.3
##   ..$ vimp : num [1:6] NA NA NA NA NA NA
##  $ rfsrc.refit.obj: NULL
##  $ md.obj         :List of 11
##   ..$ order                : num [1:6, 1:2] 1.97 3.18 1.74 3.3 1.14 1.27 4.04 5.38 5.76 4.64
...
##   .. ..- attr(*, "dimnames")=List of 2
##   ..$ count                : Named num [1:6] 0.1396 0.0918 0.1192 0.0993 0.092 ...
##   .. ..- attr(*, "names")= chr [1:6] "age" "female" "pss_fr" "homeless" ...
##   ..$ nodes.at.depth       : num [1:10000, 1:100] 2 4 5 9 10 13 13 13 7 3 ...
##   ..$ sub.order            : NULL
##   ..$ threshold            : num 5.9
##   ..$ threshold.1se        : num 6.1
##   ..$ topvars              : chr [1:6] "age" "female" "pss_fr" "homeless" ...
##   ..$ topvars.1se          : chr [1:6] "age" "female" "pss_fr" "homeless" ...
##   ..$ percentile           : Named num [1:6] 0.172 0.299 0.161 0.303 0.104 ...
##   .. ..- attr(*, "names")= chr [1:6] "age" "female" "pss_fr" "homeless" ...
##   ..$ density              : Named num [1:23] 0.0612 0.0906 0.1222 0.1232 0.0981 ...
##   .. ..- attr(*, "names")= chr [1:23] "0" "1" "2" "3" ...
##   ..$ second.order.threshold: num 10.4
```

```
# Save the gg_minimal_depth object for later use
gg_md <- ggRandomForests::gg_minimal_depth(varsel_mcs)
# Plot the object
plot(gg_md)
```




```
# Plot minimal depth v VIMP
gg_mdVIMP <- ggRandomForests::gg_minimal_vimp(gg_md)
plot(gg_mdVIMP)
```



PROBLEM 10: Create Plots of How Well Each Variable Predicts CESD

```
#Create the variable dependence object from the random forest
gg_v <- ggRandomForests::gg_variable(fitallrf)

# Use the top ranked minimal depth variables only, plotted in minimal depth rank order
xvar <- gg_md$topvars

# Plot the variable list in a single panel plot
plot(gg_v, xvar = xvar, panel = TRUE, alpha = 0.4) +
  labs(y="Predicted MCS reading", x="")
```

```
## Warning in plot.gg_variable(gg_v, xvar = xvar, panel = TRUE, alpha = 0.4):
## Mismatched variable types... assuming these are all factor variables.
```

```
## `geom_smooth()` using method = 'loess'
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : at -0.005
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : radius 2.5e-005
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : all data on boundary of neighborhood. make span bigger
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : pseudoinverse used at -0.005
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : neighborhood radius 0.005
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : reciprocal condition number 1
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : There are other near singularities as well. 1.01
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : zero-width neighborhood. make span bigger
```

```
## Warning: Computation failed in `stat_smooth()`:
## NA/NaN/Inf in foreign function call (arg 5)
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : pseudoinverse used at -0.005
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : neighborhood radius 1.005
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : reciprocal condition number 1.1006e-029
```

```
## Warning in simpleLoess(y, x, w, span, degree = degree, parametric =
## parametric, : There are other near singularities as well. 1.01
```

```
## Warning in predLoess(object$y, object$x, newx = if
## (is.null(newdata)) object$x else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : pseudoinverse used
## at -0.005
```

```
## Warning in predLoess(object$y, object$x, newx = if
## (is.null(newdata)) object$x else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : neighborhood radius
## 1.005
```

```
## Warning in predLoess(object$y, object$x, newx = if
## (is.null(newdata)) object$x else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : reciprocal
## condition number 1.1006e-029
```

```
## Warning in predLoess(object$y, object$x, newx = if
## (is.null(newdata)) object$x else if (is.data.frame(newdata))
## as.matrix(model.frame(delete.response(terms(object)), : There are other
## near singularities as well. 1.01
```