

Assignment 04 Trees

BQOM 2578 | Data Mining

Theresa Wohlever

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Executive Summary

Predicting Pennsylvania County Suicide Rates from Hospital Data: A Comparative Analysis

This analysis investigates how effectively county suicide rates in Pennsylvania can be predicted using hospital-level data through three distinct modeling approaches: logistic regression, regression trees, and classification trees. The *dependent variable* is county suicide rate, with county hospital characteristics serving as predictors after extensive data preparation including feature reduction, categorical variable encoding, and dataset joining.

discharges1864 (hospital patient discharges ages 18-64) emerges as the dominant predictor across all three modeling approaches, though each method reveals distinct patterns in variable importance and predictive performance.

Model Performance

Logistic Regression Insights

The presence of a children's hospital shows the strongest effect ($\beta = 2.865$, $p < 0.001$), translating to 17.6 times higher odds of elevated suicide rates. Patient discharge volume demonstrates a small but statistically significant effect ($\beta = 0.0001$, $p = 0.022$). Notably, `type_of_organization` shows marginal significance ($\beta = -0.302$, $p = 0.070$), while variables including `psychiatrists`, `clinic_psychiatric`, and `comprehensive_rehab` demonstrate no significant impact.

Regression Tree Performance

The model relies heavily on `discharges1864` as the primary split variable (initial threshold: 2,228), with subsequent splits at 153, 254, 338, 349, and 523. Secondary variables include `clinic_psychiatric` (threshold: 1.5-2), `psychiatrists` (thresholds: 7.5, 15.5, 35.5), and `comprehensive_rehab` (threshold: 2). The model achieves an out-of-sample R^2 of 0.039 with MAE of 48.32, indicating modest predictive capability.

Classification Tree Results

The classification approach shows the most parsimonious structure, using only `discharges1864` (primary split at 8,431) and `psychiatrists` (splits at 15 and 21) in the features-of-interest model. The simpler all-features tree (Tree 1) achieves 72.73% accuracy using only `discharges1864`, while

the expanded trees incorporating psychiatrist staffing levels (Trees 2 & 3) reach 77.27% accuracy. However, this still underperforms logistic regression, which achieves 84.09% accuracy.

Clinical Implications

The finding that specialized psychiatric resources (`psychiatrists`, `clinic_psychiatric`, `psych_over17`) show minimal direct predictive value is counterintuitive. The strong signal from general hospital discharge volume suggests that overall healthcare access and utilization may be more informative proxies for community suicide risk than specialized mental health resources alone. The marginal significance of `type_of_organization` hints that organizational structure may influence outcomes in ways not fully captured by facility-level service indicators.

Model Features Impact Comparison

Feature	<i>Logistic Regression</i>	Regression Tree	Classification Tree
<code>children_hospital</code>	Very large effect ($\beta = 2.849$)	Not Used	Not Used
<code>psych_over17</code>	Small effect, but not significant ($\beta = 0.184$)	Not Used	Not Used
<code>discharges1864</code>	Very small but significant effect ($\beta = 0.0001$)	Primary split variable First split at 2,228 Subsequent splits: 153, 254, 349, 523, 8431, etc. Most important predictor $OSR^2 = 0.088$, MAE = 48.32	Primary and only split variable - Main split at 8,431 discharges - Tree 1 accuracy: 72.73% - Trees 2 & 3 accuracy: 65.91%
<code>psych_over17_beds_lic</code>	Negligible effect ($\beta = 0.001$)	Not Used	Not Used
<code>psychiatrists</code>	Negligible effect ($\beta = 0.000794$, $p = 0.880$) - Not statistically significant	Secondary split variable - Used at multiple thresholds: 7.5, 15.5, 35.5 - Appears in deeper tree nodes	Secondary split variable - Used at thresholds: 15, 21 - Splits high-discharge facilities

Feature	<i>Logistic Regression</i>	Regression Tree	Classification Tree
clinic_psychiatric	Small positive effect ($\beta = 0.120$, $p = 0.554$) - Not statistically significant	Secondary split variable - Split threshold at 1.5 and 2 - Distinguishes facilities with/without psychiatric clinics	Not Used
comprehensive_rehab	Negative effect ($\beta = -0.318$, $p = 0.104$) - Marginally non-significant	Terminal split variable - Threshold at 2 - Used only in deepest nodes	Not Used
type_of_organization	Negative effect ($\beta = -0.302$, $p = 0.070$) - Marginally significant - Certain organization types associated with lower suicide rates	Not Used	Not Used

Tree accuracy figures reflect the features-of-interest (FOI) model. The simpler all-features classification tree using only `discharges1864` achieved higher accuracy (72.73%). Logistic regression outperformed both tree approaches with 84.09% accuracy.

Data Preparation

Importing Data, Cleaning, & Wrangling

Set the cut-off value for 1 or 0 (binary) for Logistic regression is the local minimum of county Suicide Rates.

Split Dataset into Training and Test

We will leave 80% of observations in the training set and 20% in the test set.

```
#set.seed keeps results random but constant for all using the same seed (so we all will have the same results)
set.seed(1760, sample.kind = "Rejection")
spl = sample(nrow(df), 0.8*nrow(df))
head(spl)
```

```
[1] 193  59 139 177 122  20
```

```
# Split into train and test:
train.df = df[spl,]
test.df = df[-spl,]
```

Preliminary Analysis

Evaluate Correlation Matrix

```
## Prep for correlation
df_cor <- df_clean

cor_mat <- cor(df)
cor_threshold <- 0
cor_threshold_count <- 2

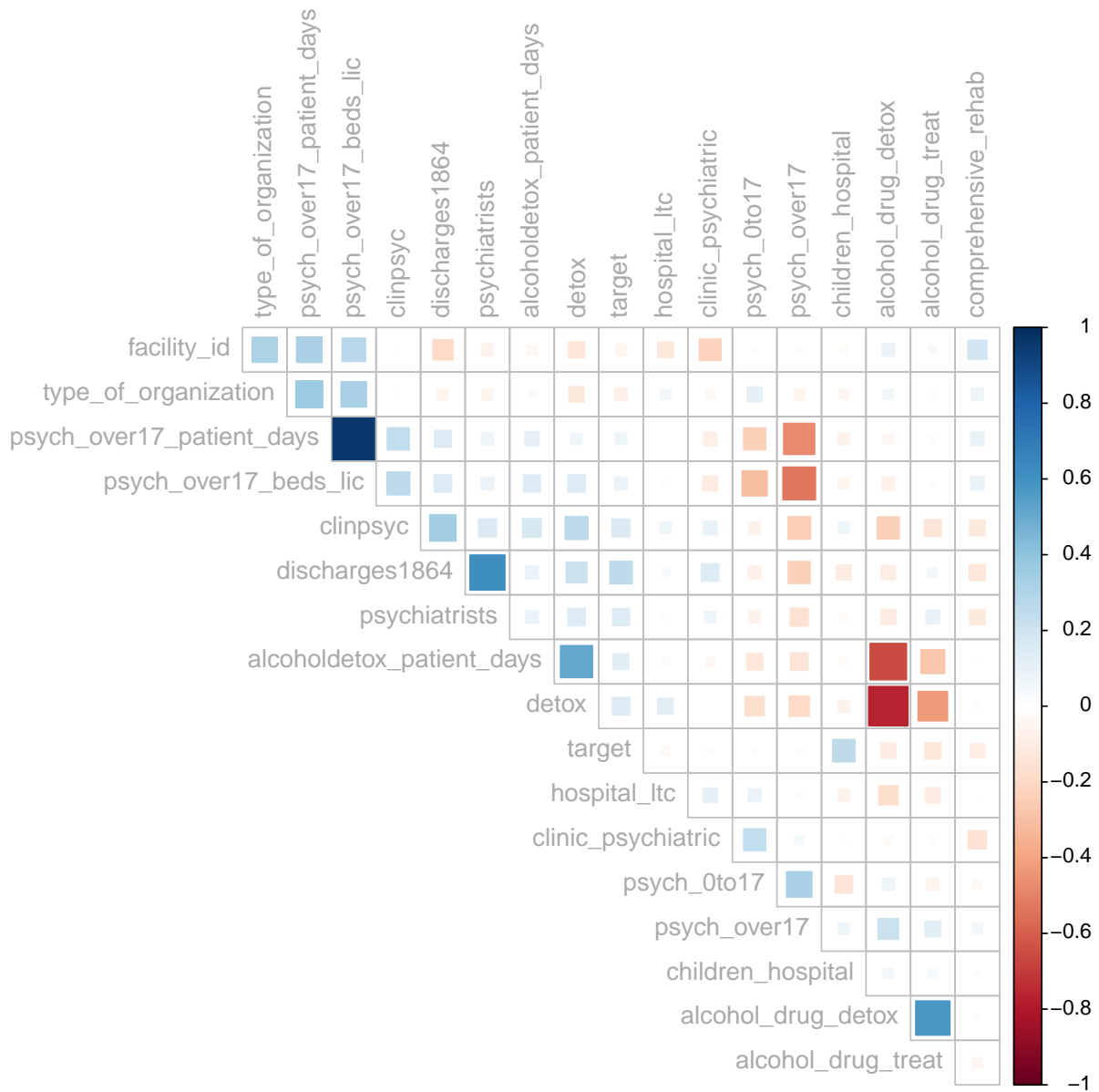
cols_above_threshold <- which( colSums(abs(cor_mat) > cor_threshold, na.rm = TRUE) >= cor_threshold_count)
df <- subset(df, select = colnames(cor_mat)[cols_above_threshold] )
cor_mat <- cor(df)

cor_mat_plot <- round(cor_mat, 2)
cor_mat_plot[is.na(cor_mat_plot)] <- 0 # Replace all NA values with zero
cat(paste(colnames(cor_mat_plot), collapse = "\n"))
```

```
facility_id
type_of_organization
children_hospital
hospital_ltc
discharges1864
alcohol_drug_detox
alcoholdetox_patient_days
alcohol_drug_treat
comprehensive_rehab
psych_0to17
psych_over17
psych_over17_beds_lic
psych_over17_patient_days
detox
clinpsyc
```

```
clinic_psychiatric  
psychiatrists  
target
```

```
corrplot(cor_mat_plot,  
  method="square",  
  type="upper",  
  order="AOE",  
  tl.col="darkgrey",  
  cl.align.text = "r",  
  diag=FALSE,  
  number.cex=0.6)
```



Regression

Stepwise Linear Regression

```
model <- lm(target ~ ., data = df)
summary(model)
```

Call:

```
lm(formula = target ~ ., data = df)
```

Residuals:

Min	1Q	Median	3Q	Max
-98.80	-40.27	-14.39	26.85	132.00

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	9.837e+01	5.475e+01	1.797	0.073863	.
facility_id	5.033e-09	2.712e-07	0.019	0.985212	
type_of_organization	-4.438e+00	3.035e+00	-1.462	0.145204	
children_hospital	9.625e+01	2.053e+01	4.688	5.1e-06	***
hospital_ltc	-8.800e+00	1.261e+01	-0.698	0.485998	
discharges1864	4.268e-03	1.134e-03	3.763	0.000221	***
alcohol_drug_detox	6.592e+00	1.572e+01	0.419	0.675419	
alcoholdetox_patient_days	3.616e-03	3.944e-03	0.917	0.360344	
alcohol_drug_treat	-2.762e+01	1.356e+01	-2.037	0.042938	*
comprehensive_rehab	-7.007e+00	4.397e+00	-1.594	0.112576	
psych_0to17	1.157e+01	6.609e+00	1.750	0.081633	.
psych_over17	1.091e+01	4.858e+00	2.245	0.025842	*
psych_over17_beds_lic	3.940e-01	2.758e-01	1.429	0.154690	
psych_over17_patient_days	-5.272e-04	8.691e-04	-0.607	0.544840	
detox	8.600e+00	2.020e+01	0.426	0.670717	
clinpsyc	-8.861e-01	8.850e+00	-0.100	0.920344	
clinic_psychiatric	-5.928e+00	4.407e+00	-1.345	0.180073	
psychiatrists	-6.321e-02	1.256e-01	-0.503	0.615476	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 54.57 on 200 degrees of freedom

Multiple R-squared: 0.229, Adjusted R-squared: 0.1634

F-statistic: 3.494 on 17 and 200 DF, p-value: 1.028e-05

```
# Perform stepwise regression
step_model_back <- step(model, direction = "backward", trace=0)
summary(step_model_back)
```

Call:

```
lm(formula = target ~ type_of_organization + children_hospital +
```



```
discharges1864 + alcohol_drug_treat + comprehensive_rehab +
psych_0to17 + psych_over17 + psych_over17_beds_lic + clinic_psychiatric,
data = df)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-106.02	-40.33	-10.98	28.88	134.42

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.295e+02	3.853e+01	3.361	0.000924 ***
type_of_organization	-5.079e+00	2.881e+00	-1.763	0.079397 .
children_hospital	9.551e+01	1.995e+01	4.788	3.20e-06 ***
discharges1864	4.001e-03	8.419e-04	4.753	3.74e-06 ***
alcohol_drug_treat	-2.928e+01	1.057e+01	-2.772	0.006083 **
comprehensive_rehab	-6.924e+00	4.281e+00	-1.617	0.107307
psych_0to17	9.837e+00	6.380e+00	1.542	0.124614
psych_over17	1.085e+01	4.695e+00	2.312	0.021772 *
psych_over17_beds_lic	2.496e-01	9.096e-02	2.744	0.006595 **
clinic_psychiatric	-6.337e+00	4.253e+00	-1.490	0.137781

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 53.87 on 208 degrees of freedom

Multiple R-squared: 0.2186, Adjusted R-squared: 0.1848

F-statistic: 6.466 on 9 and 208 DF, p-value: 4.224e-08

```
step_model_forward <- step(model, direction = "forward", trace=0)
summary(step_model_forward)
```

Call:

```
lm(formula = target ~ facility_id + type_of_organization + children_hospital +
hospital_ltc + discharges1864 + alcohol_drug_detox + alcoholdetox_patient_days +
alcohol_drug_treat + comprehensive_rehab + psych_0to17 +
psych_over17 + psych_over17_beds_lic + psych_over17_patient_days +
detox + clinpsyc + clinic_psychiatric + psychiatrists, data = df)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-98.80	-40.27	-14.39	26.85	132.00

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	9.837e+01	5.475e+01	1.797	0.073863 .
facility_id	5.033e-09	2.712e-07	0.019	0.985212
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discharges1864	4.268e-03	1.134e-03	3.763	0.000221 ***
alcohol_drug_detox	6.592e+00	1.572e+01	0.419	0.675419
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detox	8.600e+00	2.020e+01	0.426	0.670717
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clinic_psychiatric	-5.928e+00	4.407e+00	-1.345	0.180073
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Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 54.57 on 200 degrees of freedom

Multiple R-squared: 0.229, Adjusted R-squared: 0.1634

F-statistic: 3.494 on 17 and 200 DF, p-value: 1.028e-05

Logistic Regression

```
df <- df_clean
# Update target to be binomial
df$target <- ifelse(df$target < target_bin_cutoff, 0, 1)
train.df = df[spl,]
test.df = df[-spl,]

# Logistic Regression with FOI
logreg <- glm(model_feature_input, data=df, family="binomial")
summary(logreg)
```

Call:

```
glm(formula = model_feature_input, family = "binomial", data = df)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-1.288e+00	8.774e-01	-1.468	0.142029
children_hospital	2.865e+00	8.650e-01	3.313	0.000925 ***
psych_over17	3.007e-01	2.305e-01	1.305	0.192016
discharges1864	1.023e-04	4.452e-05	2.298	0.021540 *
psych_over17_beds_lic	5.740e-03	4.584e-03	1.252	0.210548
psychiatrists	7.944e-04	5.246e-03	0.151	0.879633
clinic_psychiatric	1.199e-01	2.028e-01	0.591	0.554350
comprehensive_rehab	-3.175e-01	1.955e-01	-1.624	0.104344
type_of_organization	-3.022e-01	1.666e-01	-1.814	0.069601 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 229.83 on 217 degrees of freedom
Residual deviance: 199.78 on 209 degrees of freedom
AIC: 217.78

Number of Fisher Scoring iterations: 5

```
coeftable <- data.frame(col1=coef(logreg),col2=exp(coef(logreg)))  
colnames(coeftable)<-c('Coefficient (log-odds)', 'e^coefficient (odds)')  
coeftable
```

	Coefficient (log-odds)	e^coefficient (odds)
(Intercept)	-1.2882266421	0.2757594
children_hospital	2.8654745262	17.5573827
psych_over17	0.3007478757	1.3508687
discharges1864	0.0001023188	1.0001023
psych_over17_beds_lic	0.0057395644	1.0057561
psychiatrists	0.0007943842	1.0007947
clinic_psychiatric	0.1198965844	1.1273803
comprehensive_rehab	-0.3175226706	0.7279502
type_of_organization	-0.3022347150	0.7391646

```
#
# Confusion Matrix
#
df$PredLogOdds <- df$PredProbs <- predict(logreg, newdata=df)
df$PredProbs <- predict(logreg, newdata=df, type="response")
# type="response" gives the probability
summary(df$PredProbs)
```

```
      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.01934 0.12504 0.17154 0.22018 0.25243 0.87779
```

Trees: Regression

```
df <- df_clean
train.df = df[spl,]
test.df = df[-spl,]

rpart(model_feature_input, data=train.df)
```

n= 174

```
node), split, n, deviance, yval
      * denotes terminal node
```

```
1) root 174 611057.600  73.31609
  2) discharges1864< 2228 110 348748.300  61.28182
    4) clinic_psychiatric>=1.5 45 127295.800  45.22222
      8) discharges1864< 337.5 21  28082.670  26.66667 *
      9) discharges1864>=337.5 24  85655.960  61.45833 *
    5) clinic_psychiatric< 1.5 65 201811.600  72.40000
      10) psychiatrists>=35.5 8   703.875  30.62500 *
      11) psychiatrists< 35.5 57 185187.100  78.26316
        22) psychiatrists< 15.5 49 143652.000  71.79592
          44) discharges1864< 153 20  46627.800  52.90000
            88) discharges1864>=68 10   8729.600  32.20000 *
            89) discharges1864< 68 10  29328.400  73.60000 *
          45) discharges1864>=153 29  84958.140  84.82759
            90) discharges1864>=254 21  54546.950  75.38095 *
```

```

91) discharges1864< 254 8 23617.880 109.62500 *
23) psychiatrists>=15.5 8 26932.880 117.87500 *
3) discharges1864>=2228 64 218998.000 94.00000
6) psych_over17_beds_lic< 62 57 194989.700 88.59649
12) psychiatrists< 7.5 11 13195.640 45.81818 *
13) psychiatrists>=7.5 46 156850.600 98.82609
26) psych_over17_beds_lic>=27 16 43872.000 72.00000 *
27) psych_over17_beds_lic< 27 30 95323.470 113.13330
54) comprehensive_rehab>=2 18 49460.940 96.05556 *
55) comprehensive_rehab< 2 12 32738.250 138.75000 *
7) psych_over17_beds_lic>=62 7 8792.000 138.00000 *

```

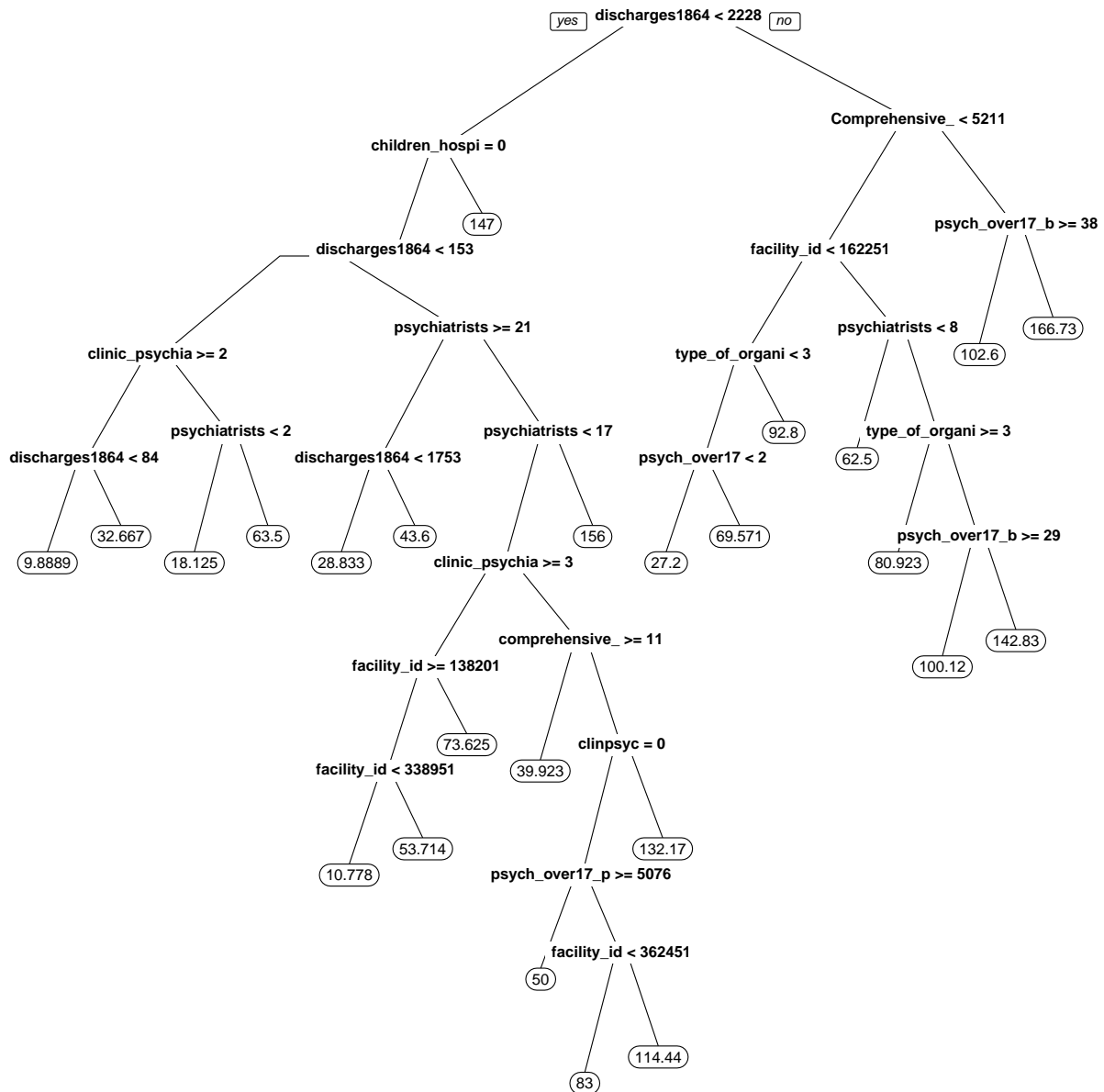
```
(train.df%>%filter(children_hospital==1))$target%>%mean()
```

```
[1] 134.6
```

```
(train.df%>%filter(children_hospital==0))$target%>%mean()
```

```
[1] 71.50296
```

```
prp(rpart(target ~ .,data=df, method="anova",minbucket=5,cp=0.0001),digits=-5)
```



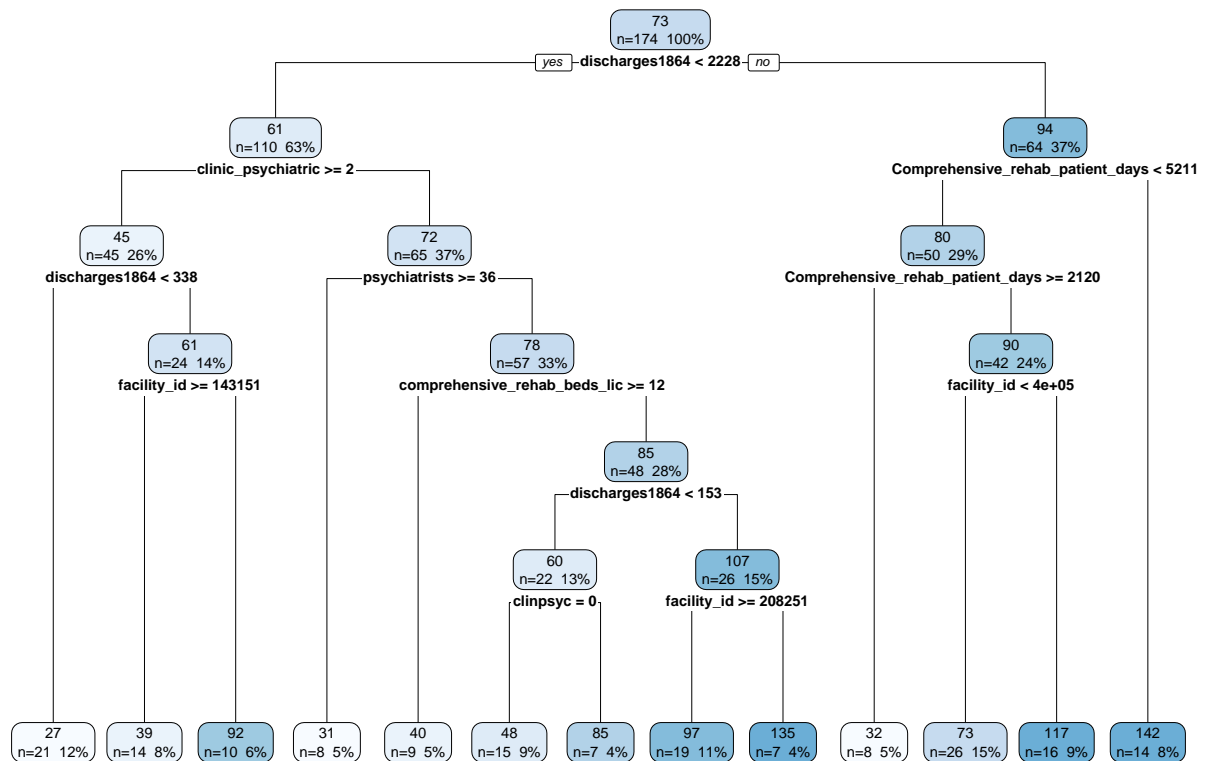
Cross Validation

```

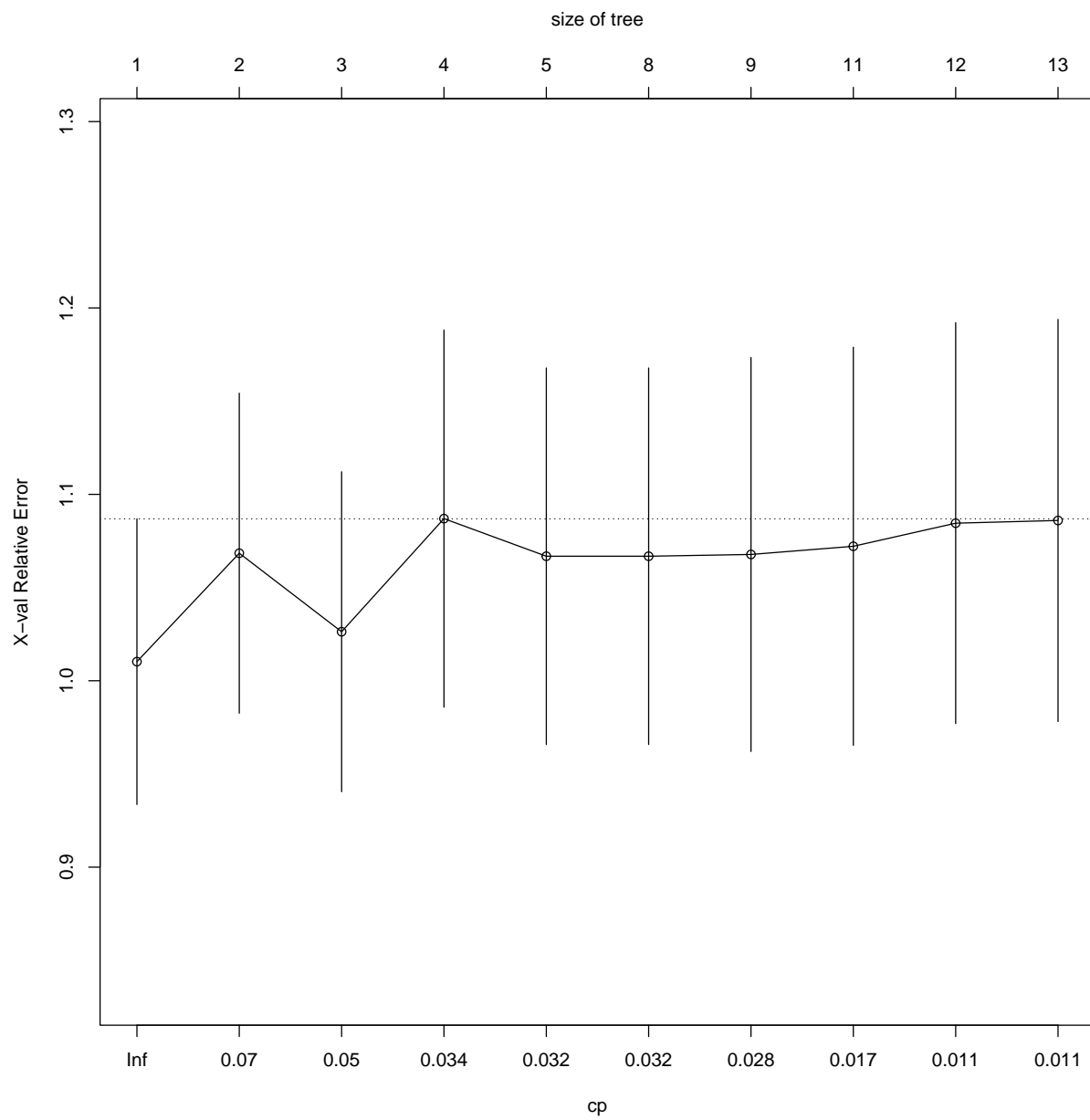
set.seed(1760, sample.kind = "Rejection")

tree_cv_all <- rpart(target ~ ., data=train.df, method="anova")
rpart.plot(tree_cv_all, digits=-2, extra=101)

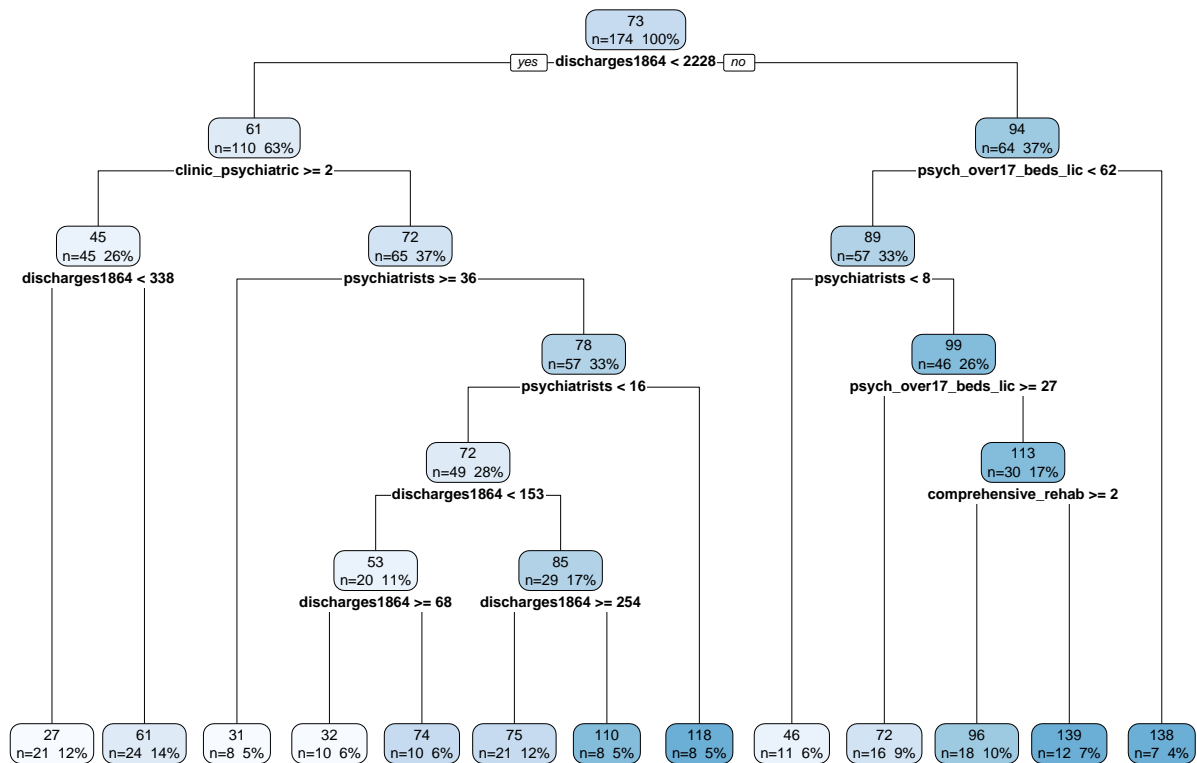
```



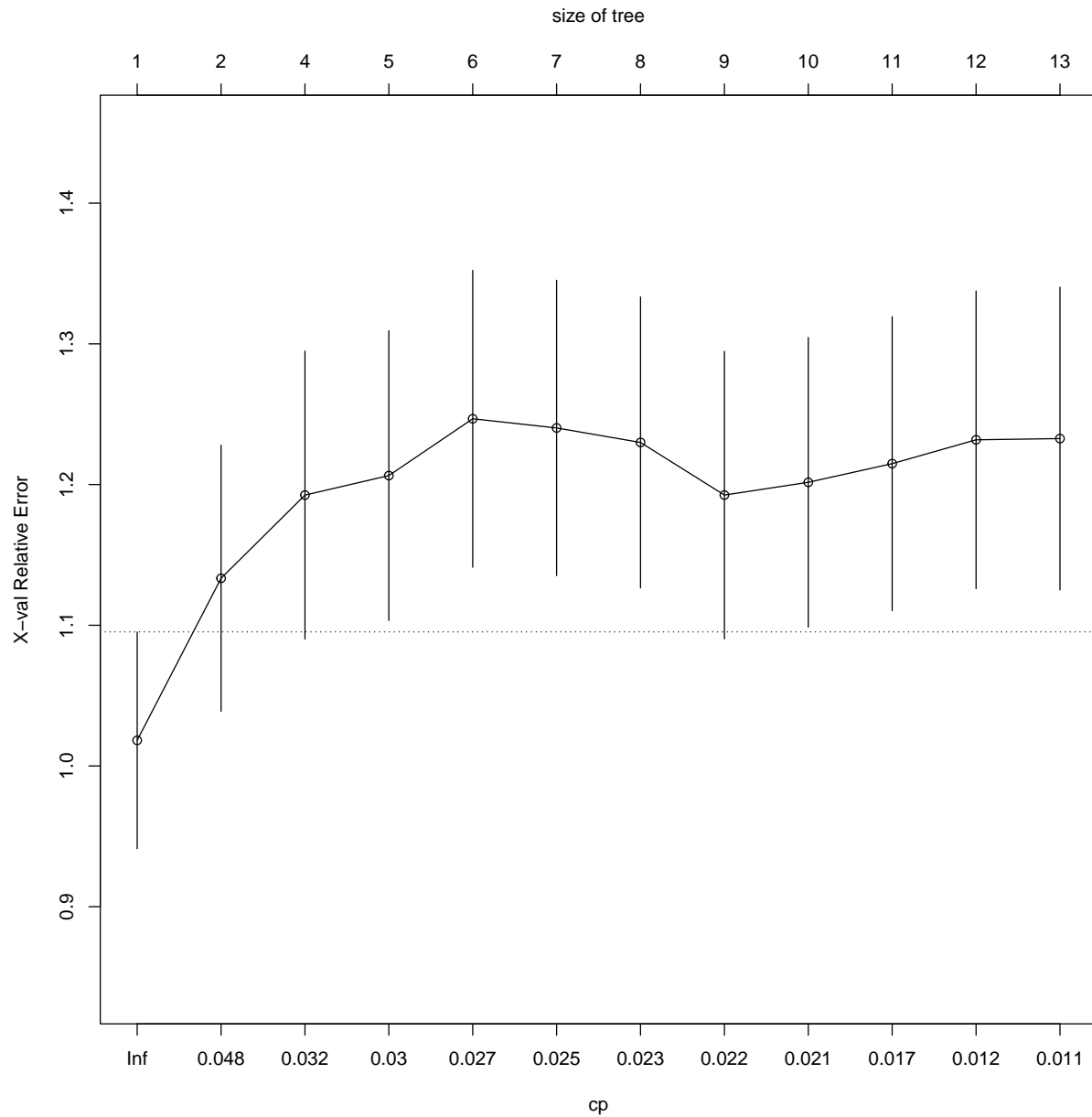
`plotcp(tree_cv_all)`



```
tree_cv_foi <- rpart(model_feature_input, data=train.df, method="anova")
rpart.plot(tree_cv_foi, digits=-2, extra=101)
```

plotcp(tree_cv_foi)



```
mean_train = mean(train.df$target)
SST = sum((test.df$target - mean_train)^2)

## Predictions
test.df$pred_cv_all = predict(tree_cv_all, newdata=test.df)
test.df$pred_cv_foi = predict(tree_cv_foi, newdata=test.df)

# Compute the sum of squared errors (SSE) using our tree:
```

```
SSE_all = sum((test.df$target - test.df$pred_cv_all)^2)
print(paste("Tree All has a SSE of", SSE_all))
```

```
[1] "Tree All has a SSE of 186610.784586498"
```

```
OSR2_all = 1 - SSE_all/SST
OSR2_all
```

```
[1] -0.1561529
```

```
# Compute the sum of squared errors (SSE) using our tree:
SSE_foi = sum((test.df$target - test.df$pred_cv_foi)^2)
print(paste("Tree FOI has a SSE of", SSE_foi))
```

```
[1] "Tree FOI has a SSE of 155112.10444095"
```

```
OSR2_foi = 1 - SSE_foi/SST
OSR2_foi
```

```
[1] 0.03899819
```

Let's see the MAE for comparisons:

```
MAE = mean(abs(test.df$target - test.df$pred01))
```

```
MAE
```

```
[1] NaN
```

Trees: Classification

```
df <- df_clean
# Update target to be binomial
df$target <- ifelse(df$target < target_bin_cutoff, 0, 1)
train.df = df[spl,]
test.df = df[-spl,]

#It is always a good practice to see the proportion of observations we have for each case
table(df$target)
```

```
0 1
170 48
```

```
prop.table(table(df$target)) # prop is "proportion"
```

```
0 1
0.7798165 0.2201835
```

```
cat("\n For the train dataset: ") # \n is a "new line" printing control
```

For the train dataset:

```
prop.table(table(train.df$target))
```

```
0 1
0.7816092 0.2183908
```

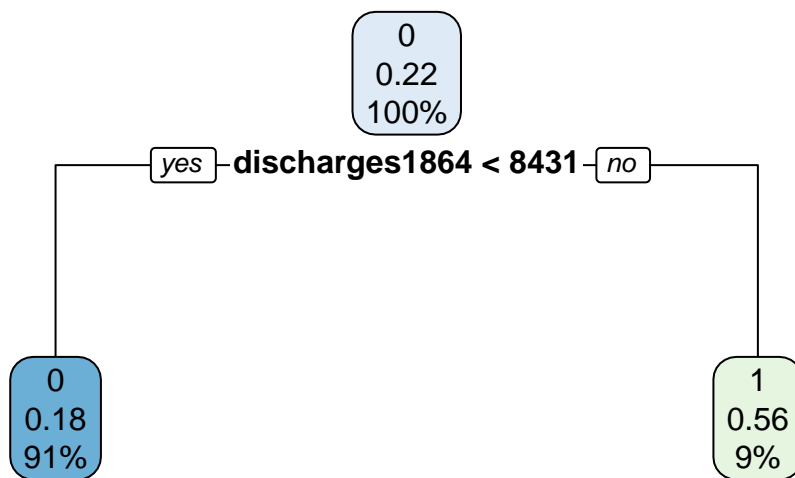
```
cat("\n For the test dataset: ")
```

For the test dataset:

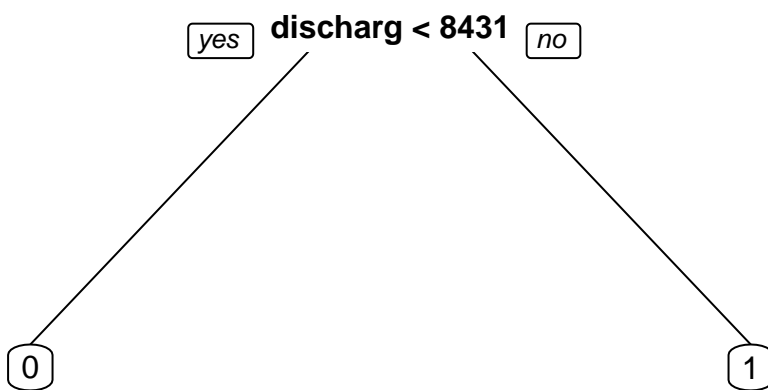
```
prop.table(table(test.df$target))
```

```
0 1
0.7727273 0.2272727
```

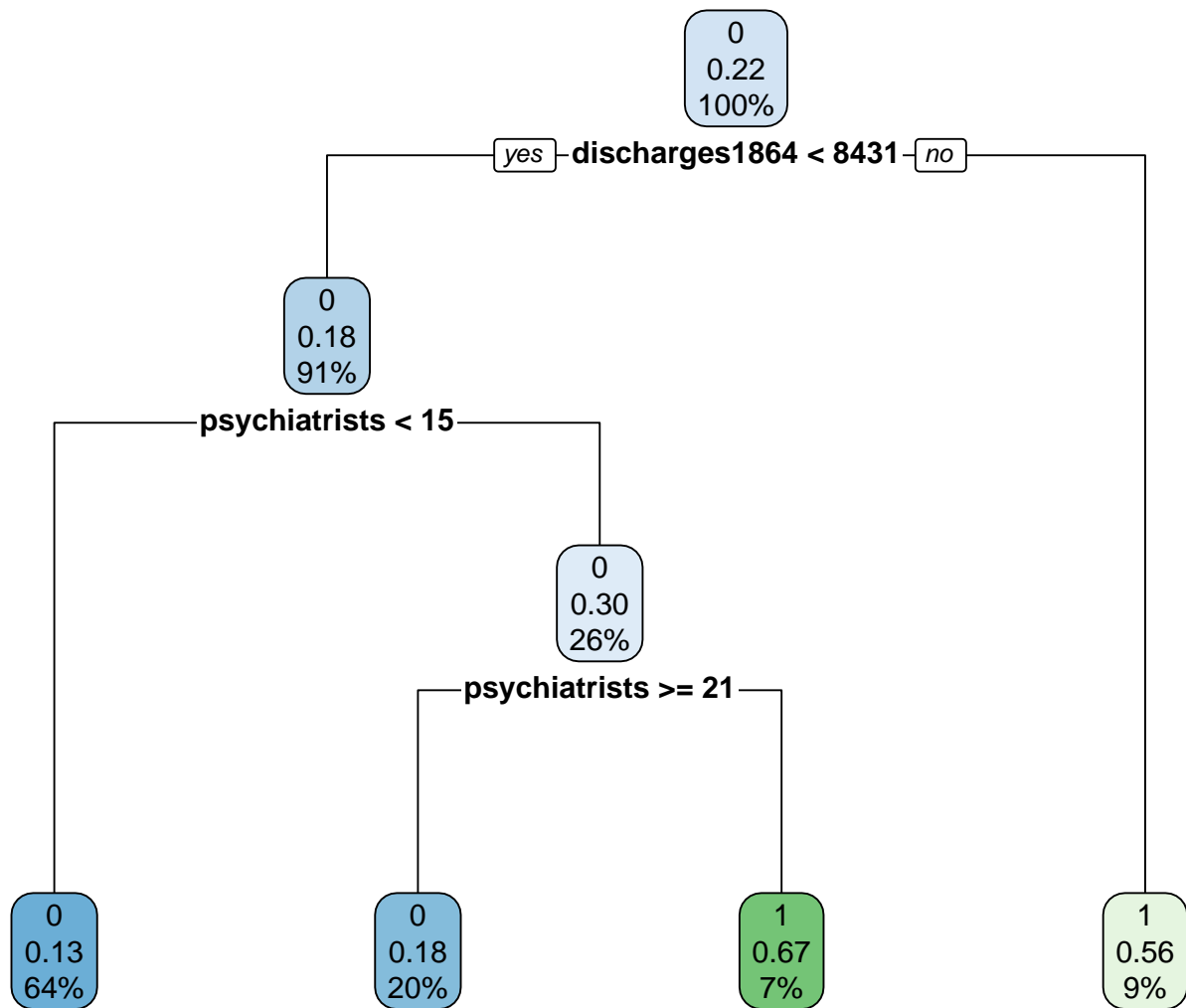
```
tree_all <-rpart(target ~ ., data=train.df, method="class",cp=0.05)
rpart.plot(tree_all, digits=-2)
```



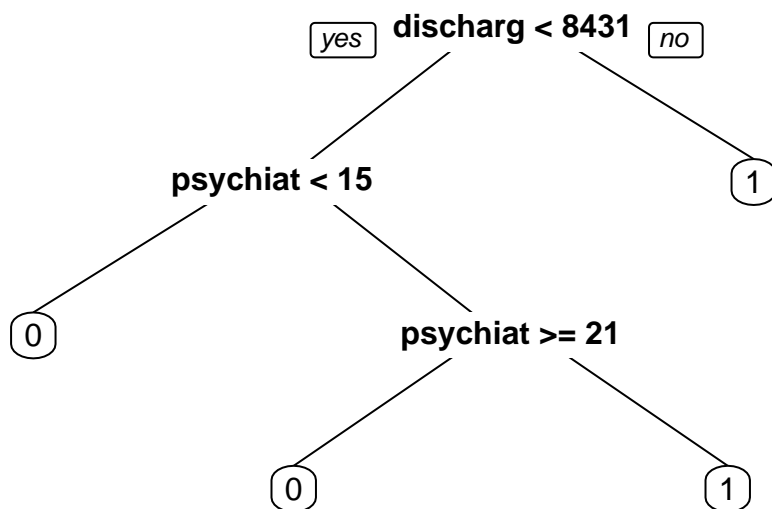
```
prp(tree_all)
```



```
tree_foi<-rpart(model_feature_input, data=train.df, method="class", cp=0.05)
rpart.plot(tree_foi,digits=-2)
```



`prp(tree_foi)`



Cross-Validation

```
cat("All Features Tree:")
```

All Features Tree:

```
test.df$pred_all = predict(tree_all, newdata = test.df, type="class")
confusionMatrix(test.df$pred_all, as.factor(test.df$target), positive="1")
```

Confusion Matrix and Statistics

```

      Reference
Prediction 0  1
      0 30  8
      1  4  2

```

```

Accuracy : 0.7273
95% CI : (0.5721, 0.8504)
No Information Rate : 0.7727
P-Value [Acc > NIR] : 0.8176

```

```
Kappa : 0.0959
```

```
McNemar's Test P-Value : 0.3865
```

Sensitivity : 0.20000
Specificity : 0.88235
Pos Pred Value : 0.33333
Neg Pred Value : 0.78947
Prevalence : 0.22727
Detection Rate : 0.04545
Detection Prevalence : 0.13636
Balanced Accuracy : 0.54118

'Positive' Class : 1

```
acc_tree_all <- sum(test.df$pred_all == test.df$target) / nrow(test.df)
print(paste("Accuracy for All Features Tree", round(acc_tree_all * 100, 2), "%"))
```

```
[1] "Accuracy for All Features Tree 72.73 %"
```

```
cat("FOI Tree:")
```

FOI Tree:

```
test.df$pred_foi = predict(tree_foi, newdata = test.df, type="class")
confusionMatrix(test.df$pred_foi, as.factor(test.df$target), positive="1")
```

Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	27	8
1	7	2

Accuracy : 0.6591
95% CI : (0.5008, 0.7951)
No Information Rate : 0.7727
P-Value [Acc > NIR] : 0.9717

Kappa : -0.0061

Mcnemar's Test P-Value : 1.0000

Sensitivity : 0.20000


```

        Specificity : 0.79412
        Pos Pred Value : 0.22222
        Neg Pred Value : 0.77143
        Prevalence : 0.22727
        Detection Rate : 0.04545
        Detection Prevalence : 0.20455
        Balanced Accuracy : 0.49706

        'Positive' Class : 1

```

```

acc_tree_foi <- sum(test.df$pred_foi == test.df$target) / nrow(test.df)
print(paste("Accuracy for FOI Tree:", round(acc_tree_foi * 100, 2), "%"))

```

```
[1] "Accuracy for FOI Tree: 65.91 %"
```

Compare Classification Tree with Logistic regressions

```

## Logistic Regression
test.df$predregprobs_foi = predict(logreg, newdata = test.df, type="response")
test.df$predreg1<-ifelse(test.df$predregprobs_foi>0.5,1,0)
acc_reg <- sum(test.df$predregprobs_foi == test.df$target) / nrow(test.df)
print(paste("Accuracy for Logistic Regression 1:", round(acc_reg * 100, 2), "%"))

```

```
[1] "Accuracy for Logistic Regression 1: 0 %"
```

```

ConfMatReg <- confusionMatrix(data=as.factor(test.df$predreg1),reference=as.factor(test.df$target), positive = "1")
ConfMatReg

```

Confusion Matrix and Statistics

```

          Reference
Prediction 0  1
0      33  6
1       1  4

      Accuracy : 0.8409
      95% CI   : (0.6993, 0.9336)
No Information Rate : 0.7727

```

P-Value [Acc > NIR] : 0.1859

Kappa : 0.45

McNemar's Test P-Value : 0.1306

Sensitivity : 0.40000

Specificity : 0.97059

Pos Pred Value : 0.80000

Neg Pred Value : 0.84615

Prevalence : 0.22727

Detection Rate : 0.09091

Detection Prevalence : 0.11364

Balanced Accuracy : 0.68529

'Positive' Class : 1

```
# Classification Tree
test.df$predregtreeprobs_foi = predict(tree_foi, newdata = test.df, type="class")
test.df$predreg2 <- ifelse(test.df$predregtreeprobs_foi > 0.5, 1, 0)
acc_reg_tree <- sum(test.df$predregtreeprobs_foi == test.df$target) / nrow(test.df)
print(paste("Accuracy for Classification Tree:", round(acc_reg_tree * 100, 2), "%"))
```

```
[1] "Accuracy for Classification Tree: 65.91 %"
```

```
ConfMatTreeReg <- confusionMatrix(data=as.factor(test.df$predregtreeprobs_foi), reference=as.factor(test.df$target), positive = "1")
ConfMatTreeReg
```

Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	27	8
1	7	2

Accuracy : 0.6591

95% CI : (0.5008, 0.7951)

No Information Rate : 0.7727

P-Value [Acc > NIR] : 0.9717

Kappa : -0.0061

McNemar's Test P-Value : 1.0000

Sensitivity : 0.20000

Specificity : 0.79412

Pos Pred Value : 0.22222

Neg Pred Value : 0.77143

Prevalence : 0.22727

Detection Rate : 0.04545

Detection Prevalence : 0.20455

Balanced Accuracy : 0.49706

'Positive' Class : 1

References

Hospital Data: https://www.pa.gov/psych_over17ncies/health/health-statistics/health-facilities/hospital-reports

Suicide by County Data: <https://www.phaim.health.pa.gov/EDD/WebForms/DeathCntySt.aspx>