Qualitative Takeways:

It can be seen that the first split is on Po1. This hints towards the fact that higher crime areas have higher police expenditure. Please remember the difference between correlation and causation.

And since it is a decision tree, it is a weak learner and highly overfits the data.

Also note that Pop is used at two places. Even Po1 is used in two places.

In [1]:
```
suppressWarnings(suppressMessages(library("tree")))
suppressWarnings(suppressMessages(library("randomForest")))
suppressWarnings(suppressMessages(require(pROC)))
```

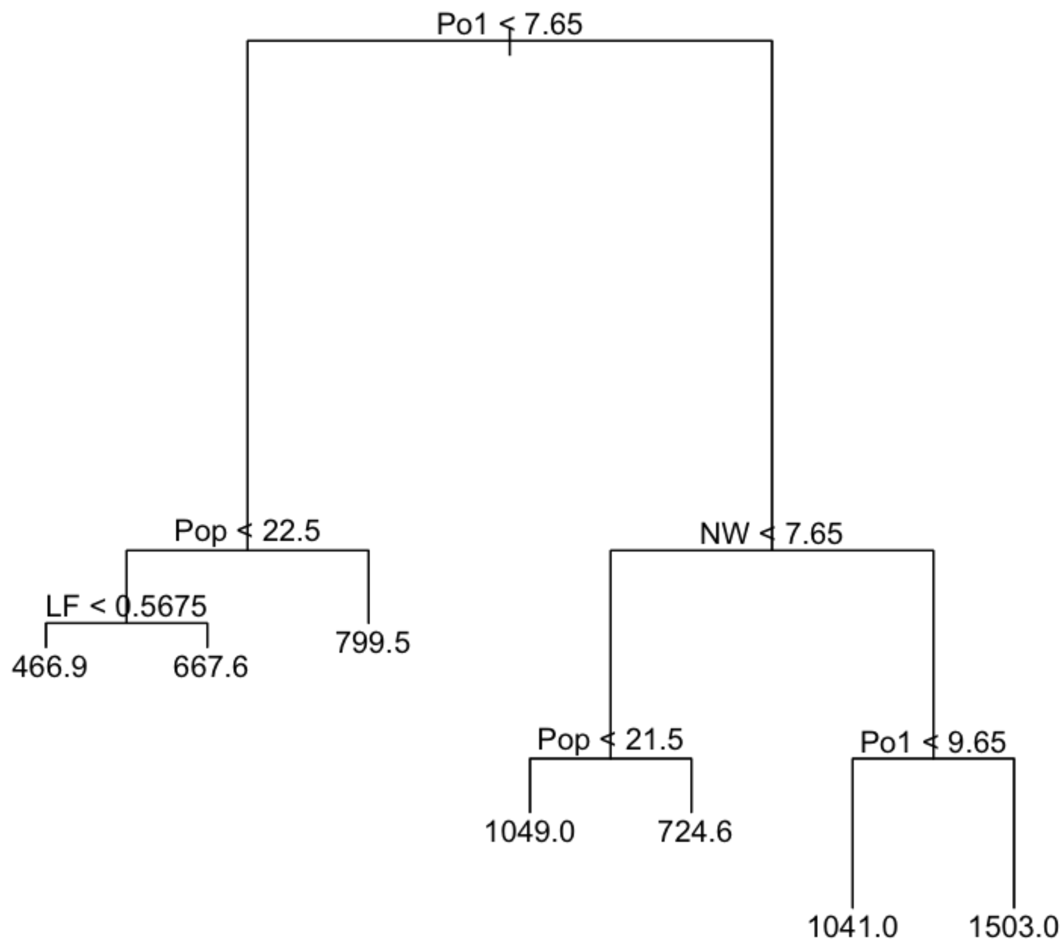
In [2]:
```
#reading the US crime dataset
us_crime <- read.table("uscrime.txt", header = T)
```

In [3]:
```
#building a full decision tree without any kind of pruning
model_tree <- tree(Crime ~., us_crime)
```

In [4]:
```
summary(model_tree)
```

```
Regression tree:
tree(formula = Crime ~ ., data = us_crime)
Variables actually used in tree construction:
[1] "Po1" "Pop" "LF"  "NW"
Number of terminal nodes:  7
Residual mean deviance:  47390 = 1896000 / 40
Distribution of residuals:
    Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
-573.900  -98.300   -1.545    0.000  110.600  490.100
```

In [5]:
```
plot(model_tree)
text(model_tree)
```



In [6]:
```
#Function to calculate R2
compute_rsquared <- function(y_hat, y){
    SSR <- sum((y_hat - y)^2)
    SST <- sum((y - mean(y))^2)
    rsquared <- 1 - SSR/SST
    return (rsquared)
}
```

In [7]:
```
#getting the prediction from our tree model
y_hat_tree <- predict(model_tree)
```

In [8]:
```
y <- us_crime$Crime
```

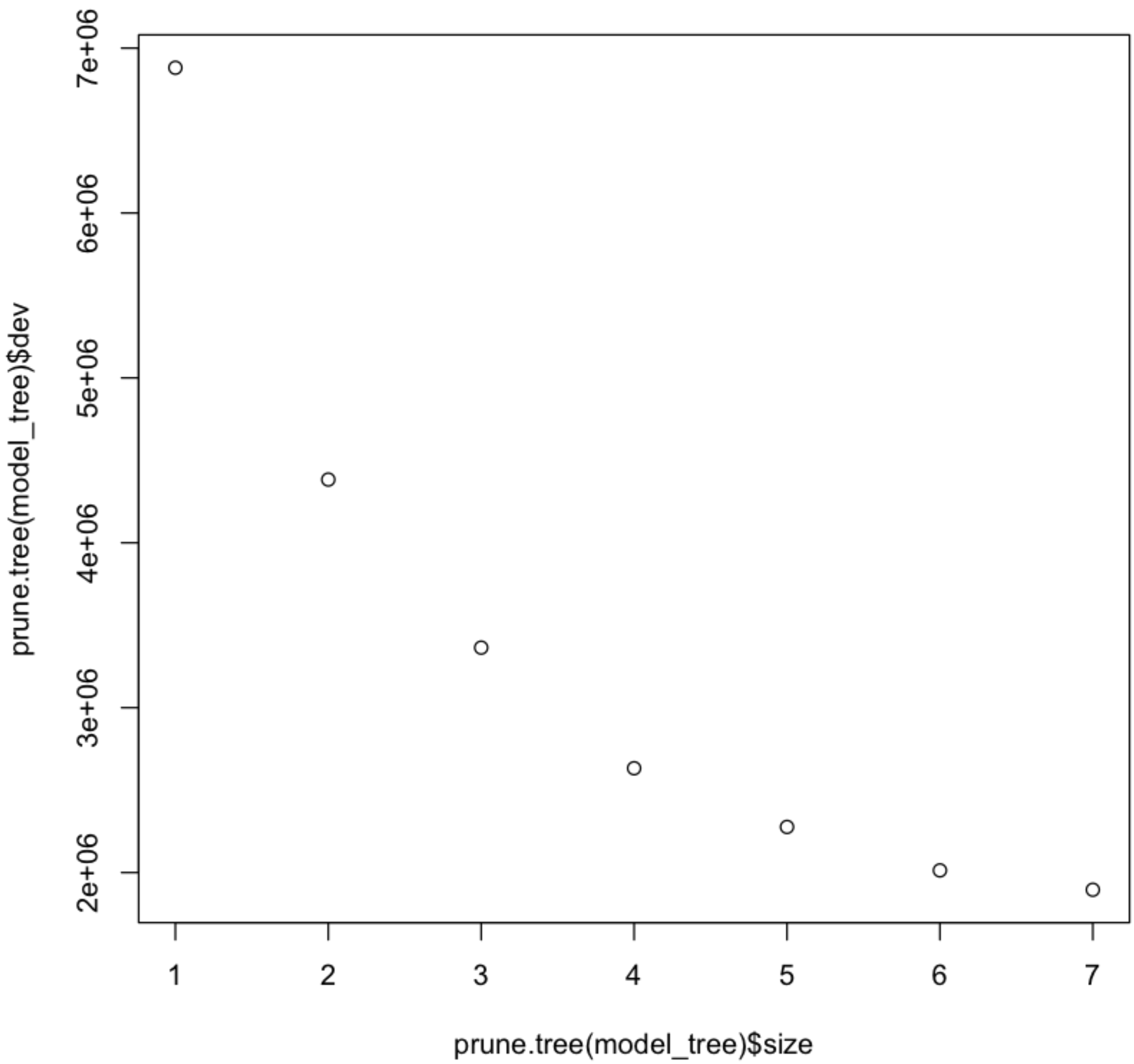
In [9]:
```
#getting the rsquared for the whole decision tree in general
compute_rsquared(y_hat_tree, y)
```

0.724496208475934

In [10]:
```
print(model_tree$frame)
```

```
       var  n         dev      yval splits.cutleft splits.cutright
1      Po1 47 6880927.66  905.0851          <7.65           >7.65
2      Pop 23  779243.48  669.6087          <22.5           >22.5
4       LF 12  243811.00  550.5000        <0.5675         >0.5675
8   <leaf>  7   48518.86  466.8571
9   <leaf>  5   77757.20  667.6000
5   <leaf> 11  179470.73  799.5455
3       NW 24 3604162.50 1130.7500          <7.65           >7.65
6      Pop 10  557574.90  886.9000          <21.5           >21.5
12  <leaf>  5  146390.80 1049.2000
13  <leaf>  5  147771.20  724.6000
7      Po1 14 2027224.93 1304.9286          <9.65           >9.65
14  <leaf>  6  170828.00 1041.0000
15  <leaf>  8 1124984.88 1502.8750
```

In [11]:
```
plot(prune.tree(model_tree)$size, prune.tree(model_tree)$dev)
```



In [12]:
```
#From the above plot it can be seen that the tree can be pruned at 4
tree_pruned <- prune.tree(model_tree, best = 4)
```

In [13]:
```
summary(tree_pruned)
```

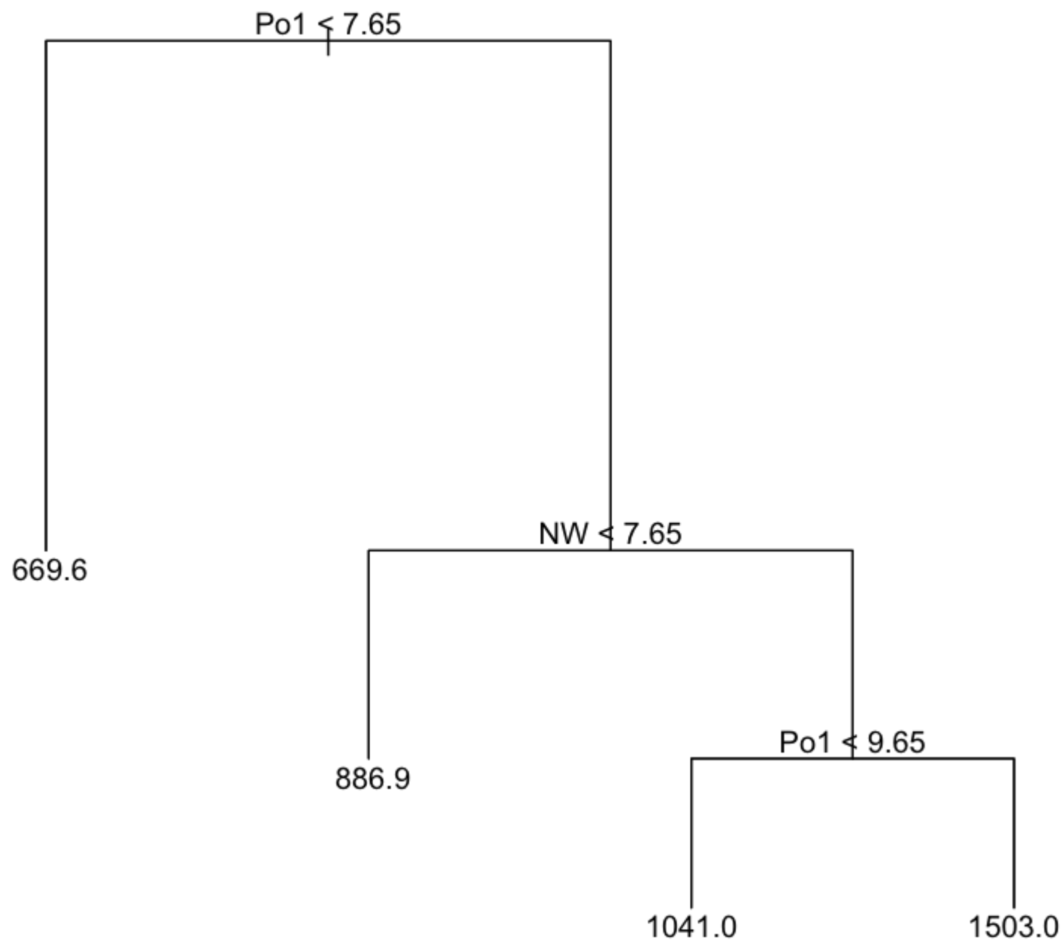
```
Regression tree:
snip.tree(tree = model_tree, nodes = c(6L, 2L))
Variables actually used in tree construction:
[1] "Po1" "NW"
Number of terminal nodes:  4
Residual mean deviance:  61220 = 2633000 / 43
Distribution of residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
-573.90 -152.60   35.39    0.00  158.90  490.10
```

In [14]:
```
y_hat_pruned <- predict(tree_pruned)
```

In [15]:
```
compute_rsquared(y_hat_pruned, y)
```

0.617401695889406

In [16]:
```
plot(tree_pruned)
text(tree_pruned)
```



In [17]:
```
#Let's do a regression on the first leaf data from the left for decision
leaf1 <- us_crime[us_crime$Po1 <7.65,]

#performing linear regression on the this data
linear_model <- lm(Crime~., data = leaf1)
summary(linear_model)
```

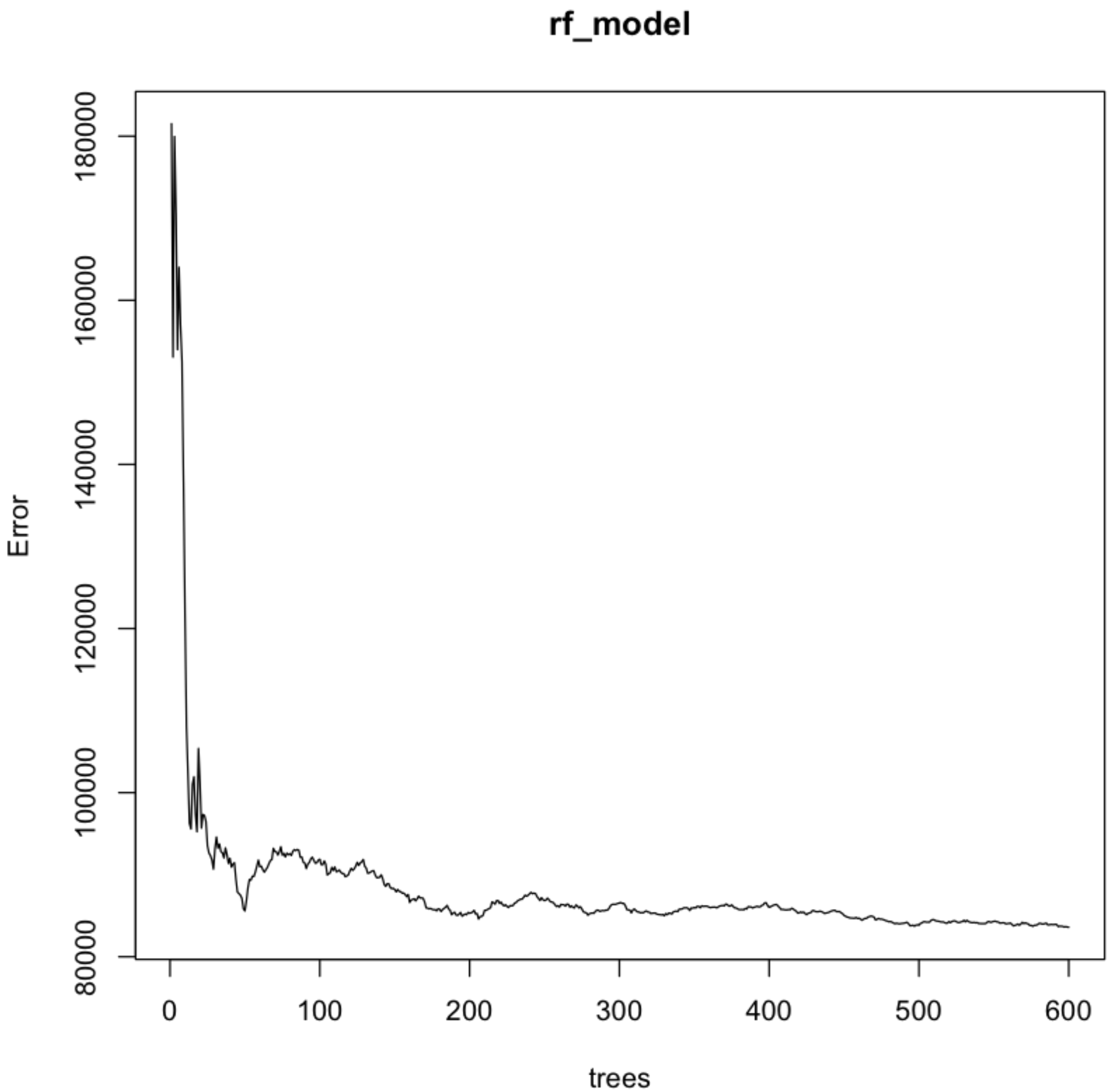
```
Call:
lm(formula = Crime ~ ., data = leaf1)

Residuals:
     Min       1Q   Median       3Q      Max
-109.147  -52.803   -6.495   53.784  127.196

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   -48.5477  2044.9766  -0.024   0.9817
M              45.8622    58.6256   0.782   0.4597
So            380.4815   223.1072   1.705   0.1319
Ed            187.9074    89.5799   2.098   0.0741 .
Po1            -3.5138   157.7513  -0.022   0.9829
Po2            44.6382   148.5528   0.300   0.7725
LF           1059.3652  1187.9722   0.892   0.4021
M.F           -22.5521    21.4677  -1.051   0.3284
Pop            10.6413     5.0929   2.089   0.0750 .
NW              0.1010     7.9019   0.013   0.9902
U1           4878.2802  4874.8165   1.001   0.3503
U2             -5.5126   133.5094  -0.041   0.9682
Wealth         -0.1022     0.1752  -0.583   0.5779
Ineq            4.7779    35.5290   0.134   0.8968
Prob        -7317.4407  3280.7511  -2.230   0.0609 .
Time          -20.0603     7.7287  -2.596   0.0357 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 115.9 on 7 degrees of freedom
Multiple R-squared:  0.8794,    Adjusted R-squared:  0.6209
F-statistic: 3.403 on 15 and 7 DF,  p-value: 0.0541
```

In [18]:
```
#We are getting rsquared of 0.8794... quite good.
```

In [19]:
```
### moving on to randomforest

#professor mentioned we generally use 1+log(n) features

num_features <- 1 + log(ncol(us_crime))
rf_model <- randomForest(Crime~., data = us_crime, mtry = num_features, i
rf_model
```

```
Call:
 randomForest(formula = Crime ~ ., data = us_crime, mtry = num_feature
s,      importance = T, ntree = 600)
               Type of random forest: regression
                     Number of trees: 600
No. of variables tried at each split: 4

          Mean of squared residuals: 83595.78
                    % Var explained: 42.9
```

In [20]:
```
plot(rf_model)
```



In [21]:
```
##it can seen that the error flattens out at nearly 250 trees.
```

In [22]:
```
y_rf <- predict(rf_model)
compute_rsquared(y_rf, y)
```

0.429001200204716

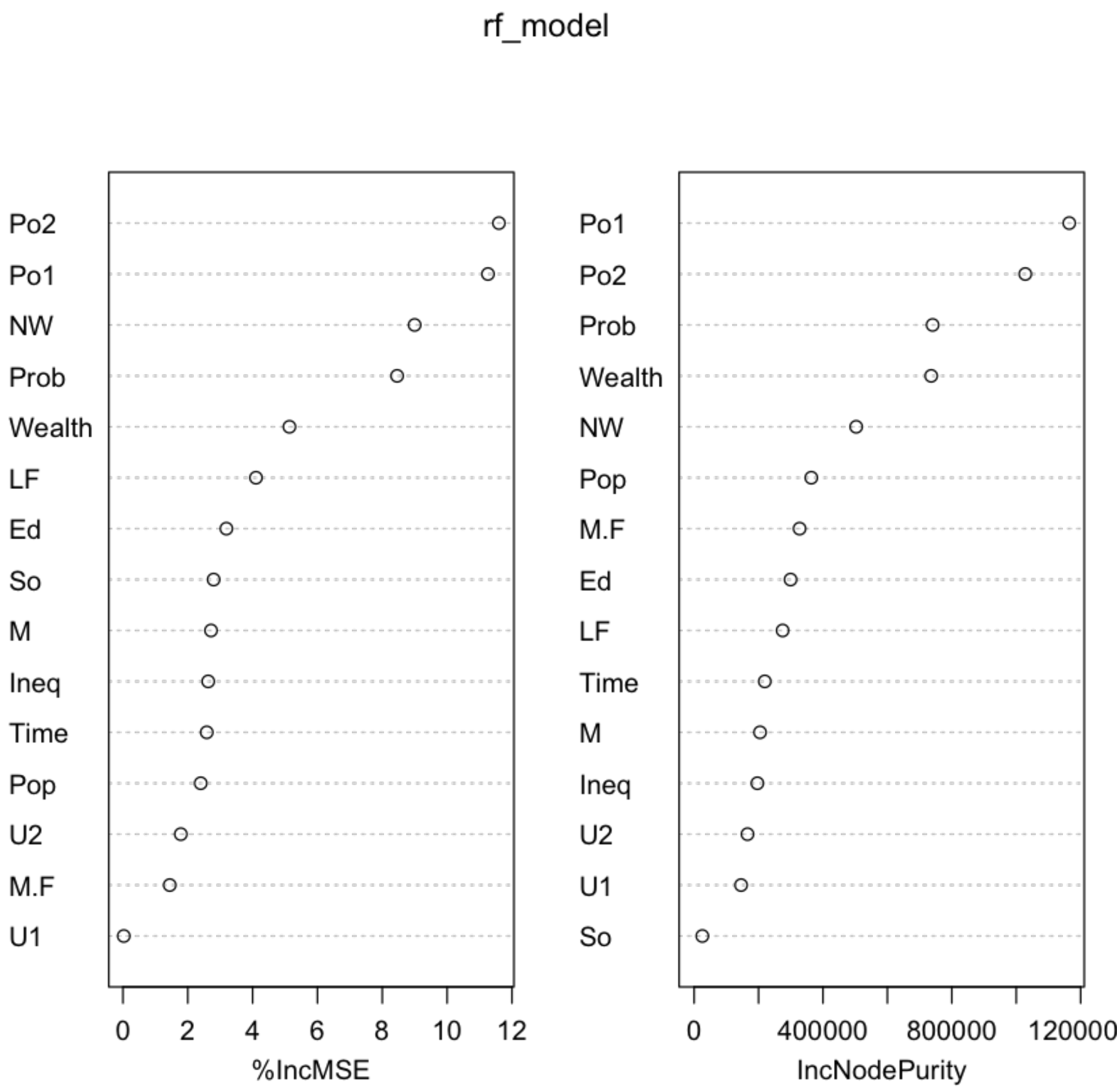
In [23]:
```
##we are not getting a very high rsquared value. I'm assuming this would
##of random forest. We though we are getting low rsqured value, it may be
```

In [24]:
```
importance(rf_model)
```

	%IncMSE	IncNodePurity
M	2.71718885	204654.60
So	2.79747368	25524.24
Ed	3.19063979	299459.44
Po1	11.26052677	1164577.61
Po2	11.59805130	1028113.22
LF	4.10407505	274845.70
M.F	1.44406694	327424.98
Pop	2.39911736	363768.27
NW	8.99770627	503117.25
U1	0.02594937	145775.67
U2	1.78538116	165738.71
Wealth	5.13609225	735944.62
Ineq	2.63007537	196384.06
Prob	8.45735899	740392.31
Time	2.58490286	219383.26

In [25]:
```
###We have the features ranked as per feature importance scores professor
```

In [26]:
```
varImpPlot(rf_model)
```



10.2

I work as a Data Scientist for a small business lender. We mainly use logistic regression to predict the probability of default and price the loan accordingly. Main features that go into our model -- FICO, Company FICO score, Length of credit history, % utilization, Time in business, Commercial Email ID flag (which is either 0 or 1), home based business, risky industry, etc.

In [27]:
```r
#reading the german credit data

german <- read.table("germancredit.txt", header = F)
```

In [28]:
```r
head(german)
```

V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	⋯	V12	V13	V14	V15	V16	V17	V1
A11	6	A34	A43	1169	A65	A75	4	A93	A101	⋯	A121	67	A143	A152	2	A173	[illegible]
A12	48	A32	A43	5951	A61	A73	2	A92	A101	⋯	A121	22	A143	A152	1	A173	[illegible]
A14	12	A34	A46	2096	A61	A74	2	A93	A101	⋯	A121	49	A143	A152	1	A172	[illegible]
A11	42	A32	A42	7882	A61	A74	2	A93	A103	⋯	A122	45	A143	A153	1	A173	[illegible]
A11	24	A33	A40	4870	A61	A73	3	A93	A101	⋯	A124	53	A143	A153	2	A173	[illegible]
A14	36	A32	A46	9055	A65	A73	2	A93	A101	⋯	A124	35	A143	A153	1	A172	[illegible]

In [29]:
```r
### 1 -> good
### 0 -> bad
german$V21[german$V21 == 2] <- 0
```

In [46]:
```r
#splitting the data into train and test

mask <- sample(1:nrow(german), size = round(0.8*nrow(german)))
train <- german[mask,]
test <- german[-mask,]
```

In [47]:
```r
#building a logistic regression using all features
logistic_full <- glm(V21 ~., family = binomial(link="logit"), train)
summary(logistic_full)
```

```
Call:
glm(formula = V21 ~ ., family = binomial(link = "logit"), data = train
)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.7251  -0.6673   0.3393   0.6834   2.5424

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.287815   1.253466   0.230 0.818391
V1A12        0.218067   0.249399   0.874 0.381918
V1A13        1.069835   0.425221   2.516 0.011871 *
```

```
V1A14        1.760467   0.264063   6.667 2.61e-11 ***
V2          -0.025282   0.010574  -2.391 0.016804 *
V3A31       -0.689345   0.629710  -1.095 0.273647
V3A32        0.152510   0.509832   0.299 0.764835
V3A33        0.201200   0.545822   0.369 0.712412
V3A34        0.877855   0.510166   1.721 0.085301 .
V4A41        1.976494   0.440298   4.489 7.16e-06 ***
V4A410       1.667881   0.879396   1.897 0.057878 .
V4A42        0.947220   0.296466   3.195 0.001398 **
V4A43        0.990205   0.279431   3.544 0.000395 ***
V4A44        1.338258   0.980102   1.365 0.172119
V4A45        0.801775   0.690890   1.160 0.245847
V4A46       -0.301838   0.450318  -0.670 0.502681
V4A48        2.180152   1.254357   1.738 0.082200 .
V4A49        0.993894   0.391595   2.538 0.011147 *
V5          -0.000154   0.000053  -2.906 0.003656 **
V6A62        0.272612   0.321787   0.847 0.396895
V6A63        0.472101   0.466952   1.011 0.312003
V6A64        1.245899   0.593979   2.098 0.035945 *
V6A65        0.827102   0.305311   2.709 0.006748 **
V7A72        0.372243   0.493213   0.755 0.450410
V7A73        0.410877   0.472441   0.870 0.384469
V7A74        1.155937   0.515103   2.244 0.024827 *
V7A75        0.421359   0.478386   0.881 0.378430
V8          -0.342885   0.101098  -3.392 0.000695 ***
V9A92        0.627890   0.432649   1.451 0.146705
V9A93        1.475678   0.430629   3.427 0.000611 ***
V9A94        0.849102   0.516235   1.645 0.100011
V10A102     -0.762951   0.450818  -1.692 0.090576 .
V10A103      0.923850   0.458831   2.013 0.044063 *
V11         -0.017331   0.099204  -0.175 0.861312
V12A122     -0.289269   0.291082  -0.994 0.320334
V12A123     -0.374919   0.269435  -1.392 0.164073
V12A124     -0.565752   0.477805  -1.184 0.236387
V13          0.007386   0.011190   0.660 0.509205
V14A142      0.206814   0.470116   0.440 0.659995
V14A143      0.580312   0.269778   2.151 0.031471 *
V15A152      0.459578   0.276737   1.661 0.096773 .
V15A153      0.727896   0.544462   1.337 0.181252
V16         -0.354491   0.216245  -1.639 0.101150
V17A172     -0.808112   0.762971  -1.059 0.289525
V17A173     -0.796558   0.732182  -1.088 0.276629
V17A174     -0.597054   0.750988  -0.795 0.426599
V18         -0.490905   0.288385  -1.702 0.088708 .
V19A192      0.414972   0.232686   1.783 0.074522 .
V20A202      0.912202   0.684954   1.332 0.182936
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```

```
    Null deviance: 972.25  on 799  degrees of freedom
Residual deviance: 697.58  on 751  degrees of freedom
AIC: 795.58

Number of Fisher Scoring iterations: 5
```

In [48]:

```
yhat_logit <- predict(logistic_full, test, type = "response")
yhat1 <- as.integer(yhat_logit > 0.5)
```

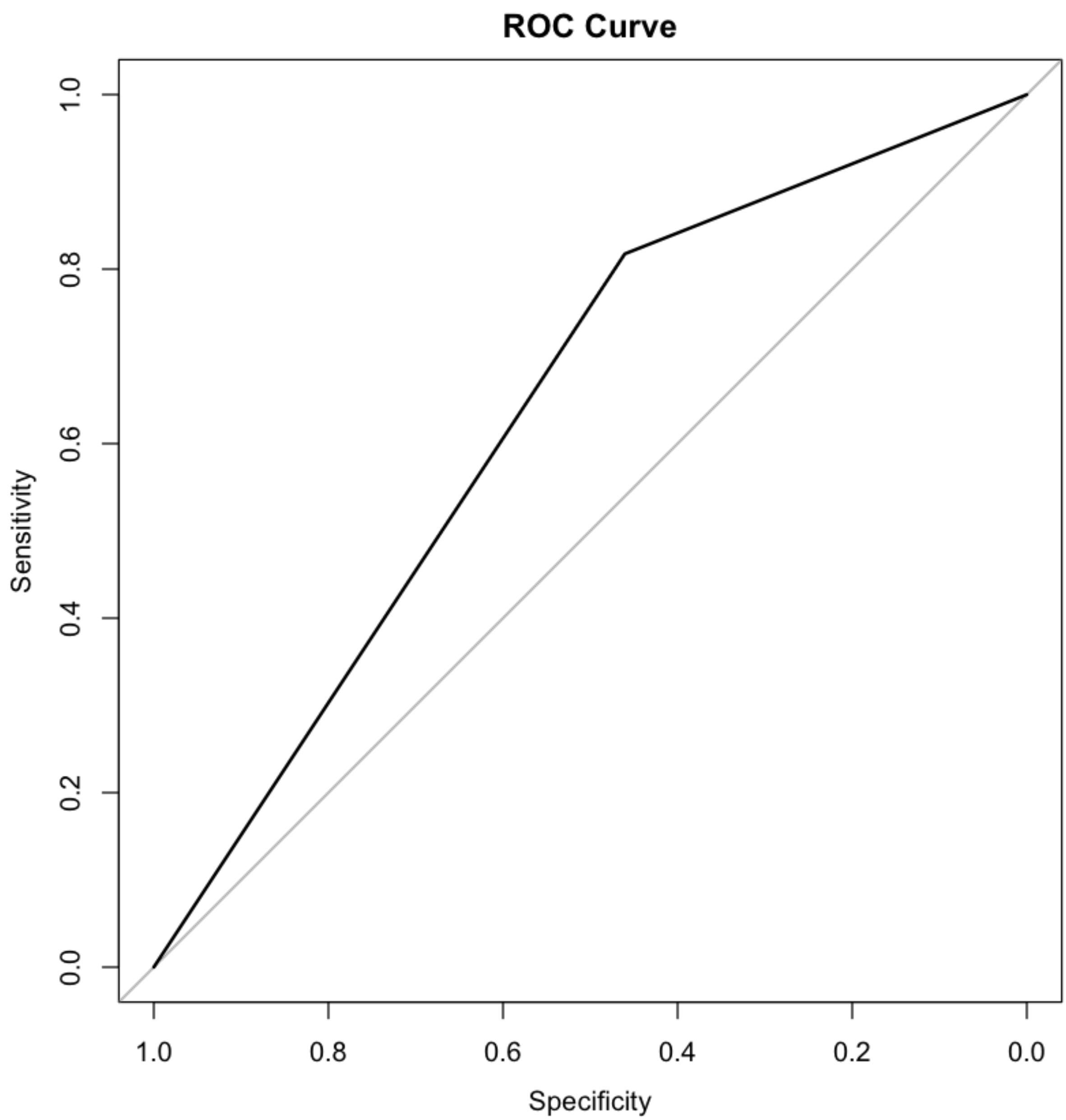
In [49]:

```
table(yhat1, test$V21)
```

```
yhat1   0   1
    0  29  25
    1  34 112
```

In [50]:
```
AUC <- roc(test$V21, yhat1)
plot(AUC, main = "ROC Curve")
AUC
```

```
Call:
roc.default(response = test$V21, predictor = yhat1)

Data: yhat1 in 63 controls (test$V21 0) < 137 cases (test$V21 1).
Area under the curve: 0.6389
```



In [51]:
```
#getting AUC of 0.6795
```

In [52]:
```
#Lets perform stepwise feature selection
```

In [53]:
```
step_selection <- step(logistic_full)
step_selection
```

```
- V3     4   710.50 800.50
- V5     1   706.17 802.17
- V8     1   709.51 805.51
- V9     3   717.33 809.33
- V4     9   737.22 817.22
- V1     3   756.71 848.71

Step:  AIC=791.02
V21 ~ V1 + V2 + V3 + V4 + V5 + V6 + V7 + V8 + V9 + V10 + V11 +
    V12 + V13 + V14 + V15 + V16 + V18 + V19 + V20

       Df Deviance    AIC
- V12   3   701.46 787.46
- V11   1   699.12 789.12
- V13   1   699.51 789.51
- V15   2   701.99 789.99
- V7    4   706.65 790.65
<none>      699.02 791.02
- V20   1   701.05 791.05
```

In [54]:
```
logistic_feature_selection <- glm(formula = V21 ~ V1 + V2 + V3 + V4 + V5
    V14 + V20, family = binomial(link = "logit"), data = train)
```

In [55]:
```
summary(logistic_feature_selection)
```

```
Call:
glm(formula = V21 ~ V1 + V2 + V3 + V4 + V5 + V6 + V8 + V9 + V13 +
    V14 + V20, family = binomial(link = "logit"), data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.8165  -0.7443   0.3860   0.7205   2.1132

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.329e+00  8.081e-01  -1.645 0.100069
V1A12        3.517e-01  2.361e-01   1.490 0.136235
V1A13        1.176e+00  4.099e-01   2.869 0.004121 **
V1A14        1.810e+00  2.536e-01   7.138 9.48e-13 ***
V2          -2.088e-02  9.824e-03  -2.125 0.033562 *
V3A31       -3.316e-01  5.781e-01  -0.574 0.566171
V3A32        5.244e-01  4.661e-01   1.125 0.260527
```

```
V3A33        2.893e-01  5.225e-01   0.554 0.579810
V3A34        1.023e+00  4.856e-01   2.107 0.035086 *
V4A41        1.872e+00  4.190e-01   4.467 7.92e-06 ***
V4A410       1.527e+00  8.157e-01   1.872 0.061272 .
V4A42        8.547e-01  2.792e-01   3.061 0.002206 **
V4A43        1.069e+00  2.686e-01   3.981 6.87e-05 ***
V4A44        1.368e+00  9.407e-01   1.454 0.145924
V4A45        6.204e-01  6.474e-01   0.958 0.337931
V4A46       -3.554e-01  4.370e-01  -0.813 0.415981
V4A48        2.078e+00  1.216e+00   1.709 0.087395 .
V4A49        1.053e+00  3.687e-01   2.856 0.004296 **
V5          -1.369e-04  4.748e-05  -2.884 0.003933 **
V6A62        1.538e-01  3.017e-01   0.510 0.610226
V6A63        4.888e-01  4.650e-01   1.051 0.293212
V6A64        1.175e+00  5.598e-01   2.098 0.035887 *
V6A65        8.474e-01  2.916e-01   2.906 0.003656 **
V8          -3.117e-01  9.438e-02  -3.303 0.000958 ***
V9A92        5.236e-01  4.148e-01   1.262 0.206896
V9A93        1.346e+00  4.102e-01   3.281 0.001034 **
V9A94        8.647e-01  4.991e-01   1.733 0.083137 .
V13          1.049e-02  9.474e-03   1.107 0.268200
V14A142      1.132e-01  4.542e-01   0.249 0.803175
V14A143      5.553e-01  2.564e-01   2.166 0.030324 *
V20A202      1.043e+00  6.778e-01   1.538 0.123954
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 972.25  on 799  degrees of freedom
Residual deviance: 731.12  on 769  degrees of freedom
AIC: 793.12

Number of Fisher Scoring iterations: 5
```

In [56]:

```r
yhat_logit_feature_selection <- predict(logistic_feature_selection, test,
yhat2 <- as.integer(yhat_logit_feature_selection > 0.5)
```

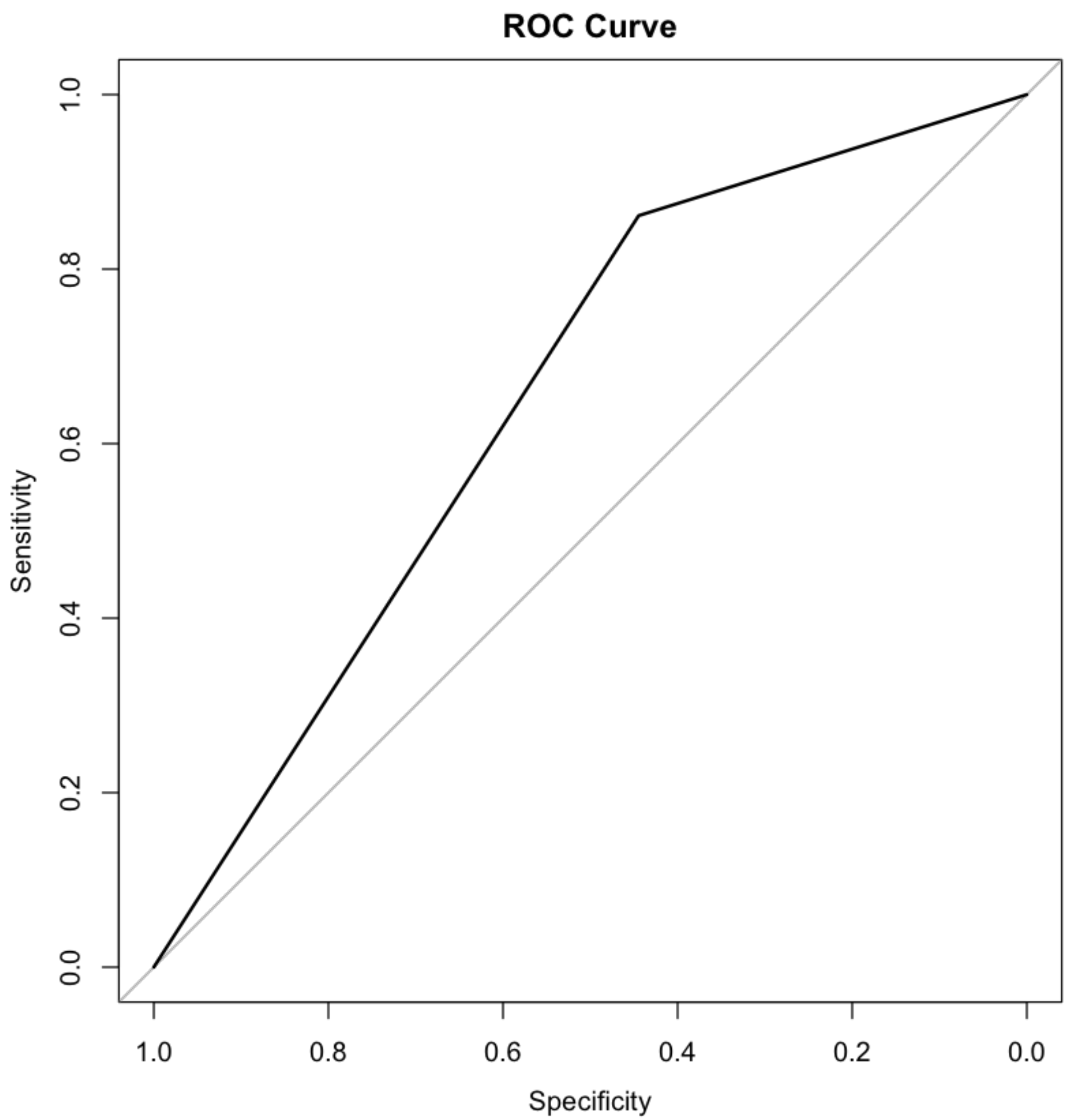
In [57]:

```r
table(yhat2, test$V21)
```

```
yhat2   0   1
    0  28  19
    1  35 118
```

In [58]:
```
AUC <- roc(test$V21, yhat2)
plot(AUC, main = "ROC Curve")
AUC
```

```
Call:
roc.default(response = test$V21, predictor = yhat2)

Data: yhat2 in 63 controls (test$V21 0) < 137 cases (test$V21 1).
Area under the curve: 0.6529
```



In [59]:
```
##it can be seen that we have slight improvement in AUC 0.6884
```

In [69]:

```
### finding the threshold
results <- vector("list",92)


#reason for using 8 to 95 is at values close to zero or one, we get only
# see link
#https://stackoverflow.com/questions/32940593/subscript-out-of-bounds-err
for (i in seq(8,95, by=1)){
    thresh <- i/100
    yhat <- as.integer(yhat_logit_feature_selection > thresh)
    table <- as.matrix(table(yhat, test$V21))
    cost <- table[2,1] + 5*table[1,2]
    results[i] <- cost
}
```

In [70]:

```
results
```

8. 61
9. 61
10. 61
11. 60
12. 60
13. 59
14. 63
15. 63
16. 63
17. 62
18. 62
19. 62
20. 67
21. 67
22. 66
23. 66

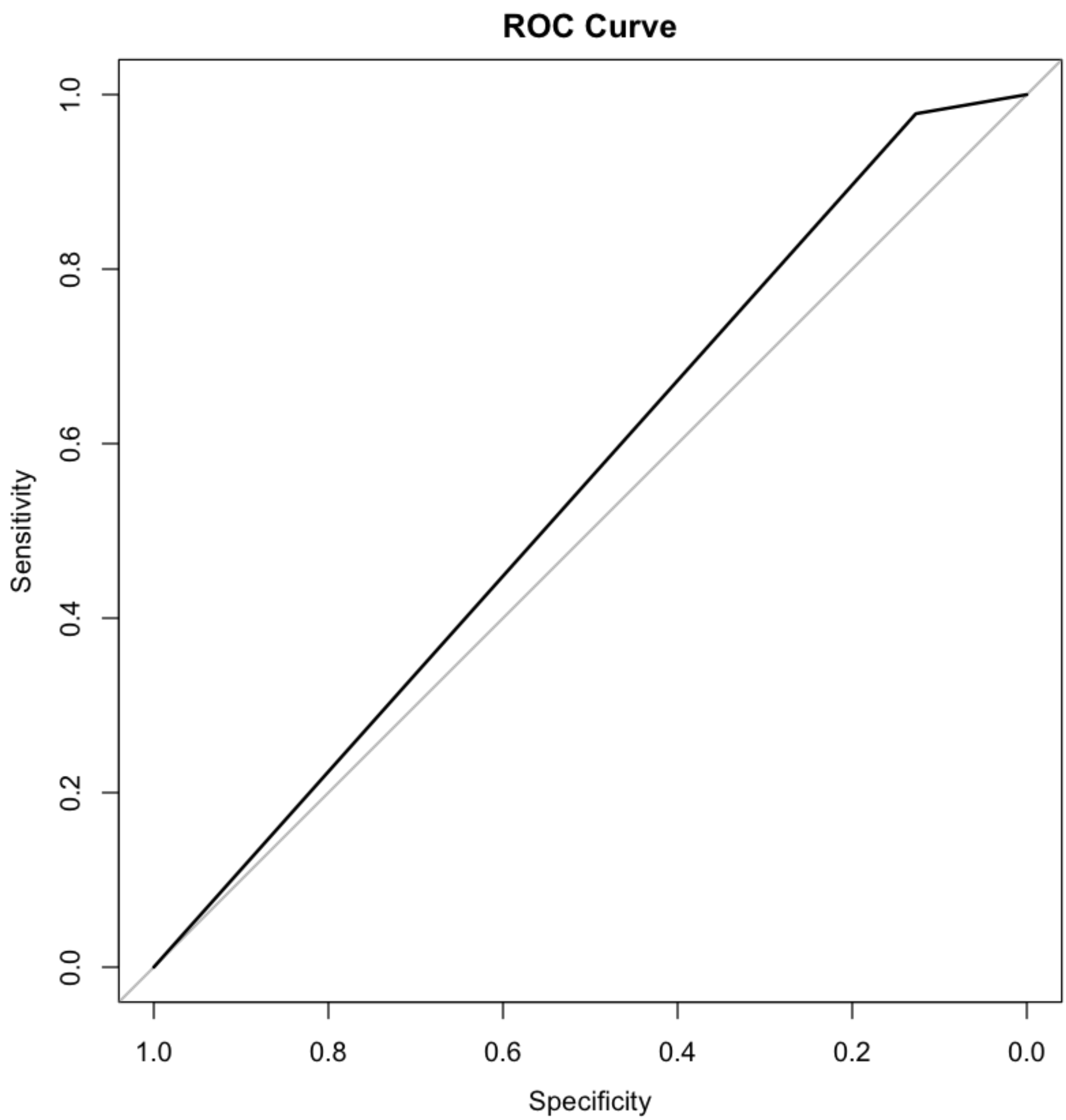
In [62]:

```
##The minimum cost is obtained at threshold of cutoff of 0.25
yhat_logit_feature_selection <- predict(logistic_feature_selection, test,
yhat3 <- as.integer(yhat_logit_feature_selection > 0.25)
table(yhat3, test$V21)
```

```
yhat3   0   1
    0   8   3
    1  55 134
```

In [63]:
```
AUC <- roc(test$V21, yhat3)
plot(AUC, main = "ROC Curve")
AUC
```

```
Call:
roc.default(response = test$V21, predictor = yhat3)

Data: yhat3 in 63 controls (test$V21 0) < 137 cases (test$V21 1).
Area under the curve: 0.5525
```



In [71]:
```
#please note that each run of the program gives different results for thr
```

```
In [ ]:
```