Week 7 Homework

Question 10.1

Using the same crime data set uscrime.txt as in Questions 8.2 and 9.1, find the best model you can using:
(a) a regression tree model, and
(b) a random forest model.
In R, you can use the tree package or the rpart package, and the randomForest package.
For each model, describe one or two qualitative takeaways you get from analyzing the results (i.e., don't just stop when you have a good model, but interpret it too).

In [1]:

```
# loading the dataset
# READ DATASET as DataFrame
df <- read.table("uscrime.txt", header = TRUE, sep = "\t")
# Display Data
head(df)
cat("No. of cols:", ncol(df), "\n")
cat("No. of rows:", nrow(df))
```

A data.frame: 6 × 16

	M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob
	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>	<dbl>	<int>	<dbl>	<dbl>
1	15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602
2	14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599
3	14.2	1	8.9	4.5	4.4	0.533	96.9	18	21.9	0.094	3.3	3180	25.0	0.083401
4	13.6	0	12.1	14.9	14.1	0.577	99.4	157	8.0	0.102	3.9	6730	16.7	0.015801
5	14.1	0	12.1	10.9	10.1	0.591	98.5	18	3.0	0.091	2.0	5780	17.4	0.041399
6	12.1	0	11.0	11.8	11.5	0.547	96.4	25	4.4	0.084	2.9	6890	12.6	0.034201

```
No. of cols: 16
No. of rows: 47
```

Regression tree model

In [2]:

```
# install.packages("tree")
library(tree)
```

```
Warning message:
"package 'tree' was built under R version 3.6.3"
```

In [3]:

```
tree_model <- tree(Crime~., data=df, model=TRUE)
summary(tree_model)
```

```
Regression tree:
tree(formula = Crime ~ ., data = df, model = TRUE)
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 [4]:

```
# review Leaves data
tree_model$frame
```

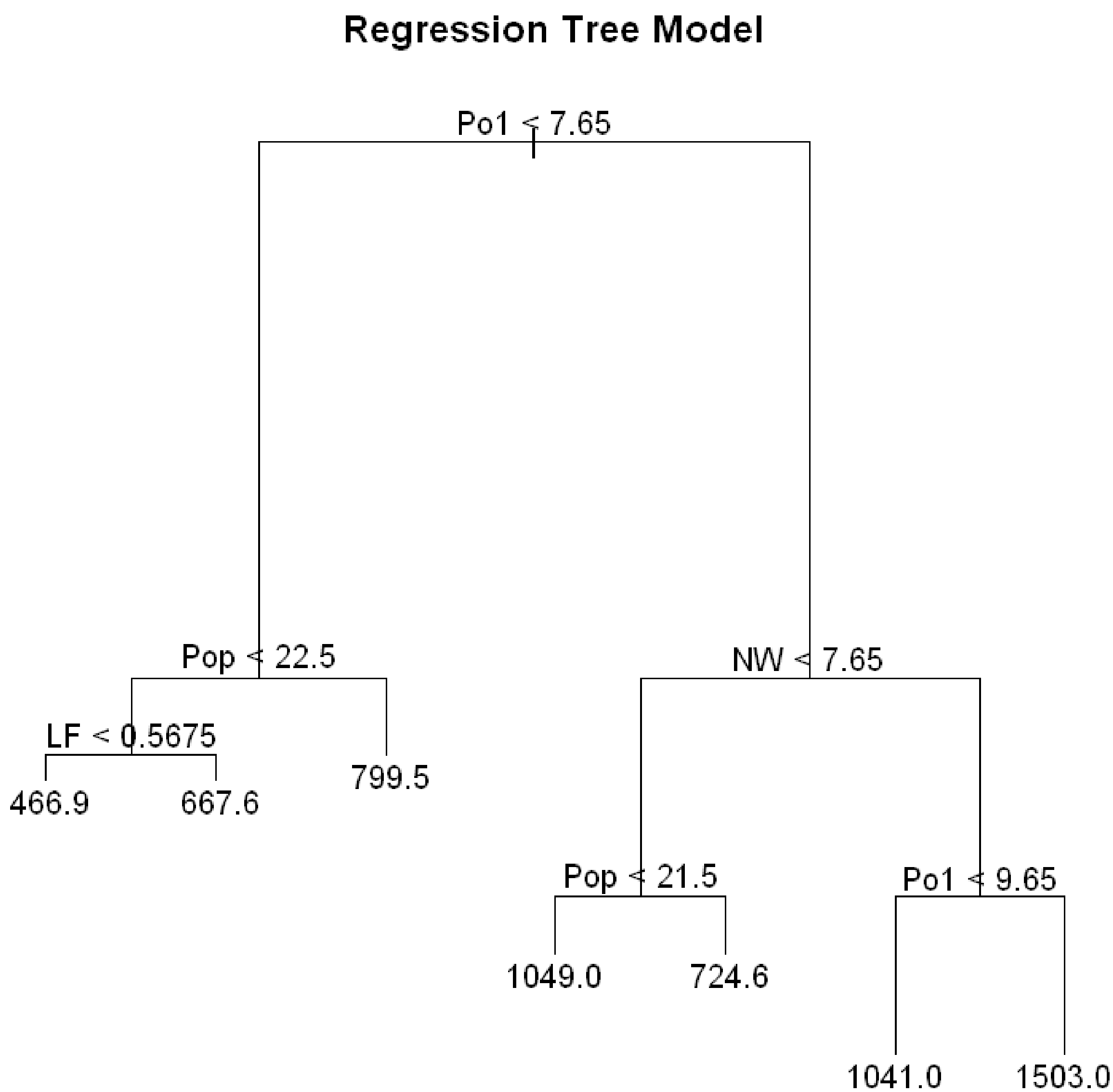
A data.frame: 13 × 5

	var	n	dev	yval	splits
	<fct>	<dbl>	<dbl>	<dbl>	<chr[,2]>
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	,

From the Data above, the minimum number of data points per leaf (\<leaf> in Var column) is 5 points (n==5).
Assuming the rule of thumb: minimum number of data points per leaf >= 5% data points (3 points).
Conclusion: The minimum number of data points per leaf is greater than the allowed minimum.

In [5]:

```
plot(tree_model)
text(tree_model)
title("Regression Tree Model")
```

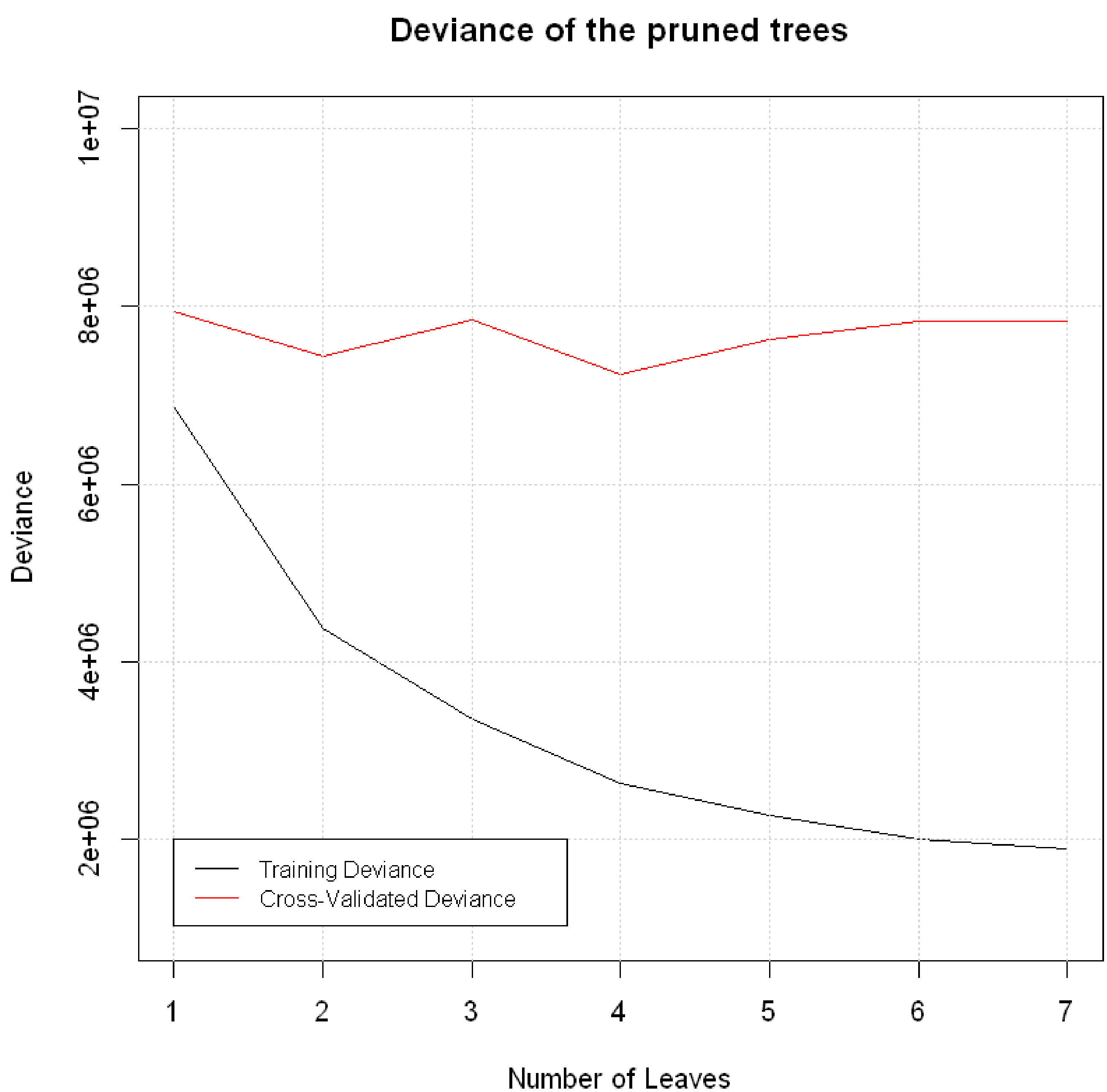


We can see that the basic tree model has 7 terminal nodes (leaves). Each terminal node shows the predicted Crime rate/ 100,000 population in that node.
Variables used in tree construction: Po1, POP, LF, NW
Note that instead of having a model for each leaf, the model uses average of points in each leaf to predict leaf value directly

Cross Validating and testing pruning the tree.

In [6]:
```
set.seed(10)
# testing pruning the tree
pruned_trees_dev <- prune.tree(tree_model)$dev
# 5 fold cross validating for each of the pruned trees
CV_pruned_trees_dev <- cv.tree(tree_model, K=5)$dev
# storing size of the trees
size_trees <- prune.tree(tree_model)$size
```

In [7]:
```
plot(size_trees, pruned_trees_dev, ylim=c(1e6,10e6), type="l", col="black", xlab="Number
lines(size_trees, CV_pruned_trees_dev, col="red")
grid()
title("Deviance of the pruned trees")
legend(1, 2e6, legend=c("Training Deviance", "Cross-Validated Deviance"), col=c("black",
```



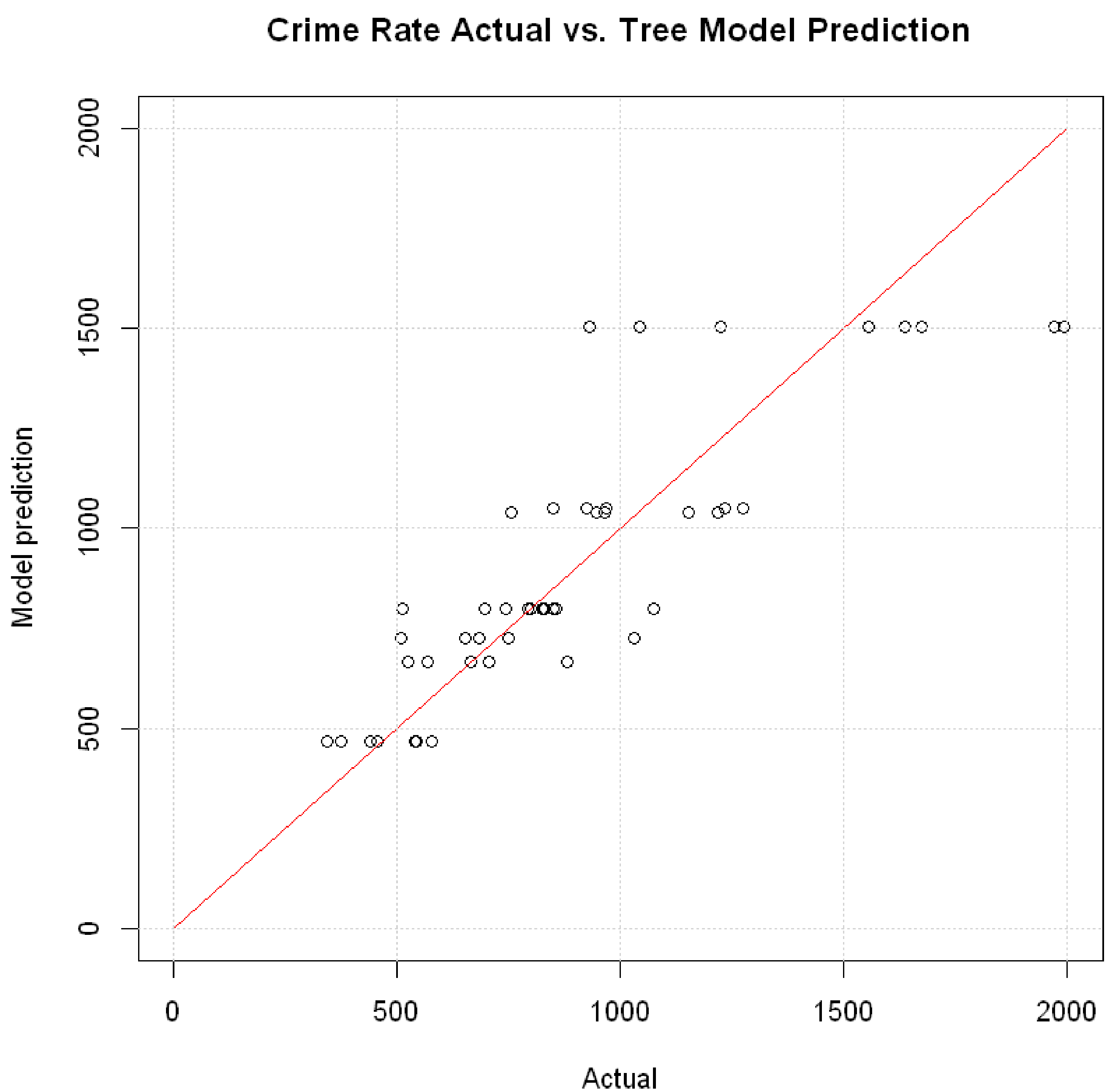
Judging by the deviance plot above, although training Deviance decreases with increasing Number of leafs, 5 Fold cross-validation indicates no imporvement with increasing number of leafs almost constant Deviance. This indicates significant over-fitting by the model.

Note: Deviance of a model can be computed as the node residual sums of squares, summed over all nodes. In other words, the sum of squared differences between predicted and observed values. The higher the deviance, the worse the model is.

Refrence: https://stats.stackexchange.com/questions/6581/what-is-deviance-specifically-in-cart-rpart

In [8]:

```
# plot results for Visual QAQC
tree_model_results <- predict(tree_model)
plot(df$Crime, tree_model_results, xlim=c(0,2000), ylim=c(0,2000), xlab="Actual", ylab='
lines(c(0,2000), c(0,2000), col="red")
title("Crime Rate Actual vs. Tree Model Prediction")
grid()
```



In [9]:

```
# Calculating TRAINING R2 for Tree model
rss <- sum((tree_model_results - df$Crime) ^ 2)  ## residual sum of squares
tss <- sum((df$Crime - mean(df$Crime)) ^ 2)  ## total sum of squares
r2 <- 1 - rss/tss
cat("Training R2 for Tree Model:", round(r2, 3))
```

```
Training R2 for Tree Model: 0.724
```

Note that significant over-fitting is expected from the Deviance analysis Cross-validation

Random forest model

In [10]:

```
# install.packages("randomForest")
library(randomForest)
```

```
randomForest 4.6-14
Type rfNews() to see new features/changes/bug fixes.
```

Assumptions

1. Minimum size of terminal node (nodesize= 5% data points i.e. 3 points)
2. Number of variables randomly sampled as candidates at each split (mtry= 1+log(m) i.e. 3 Variables)

In [11]:

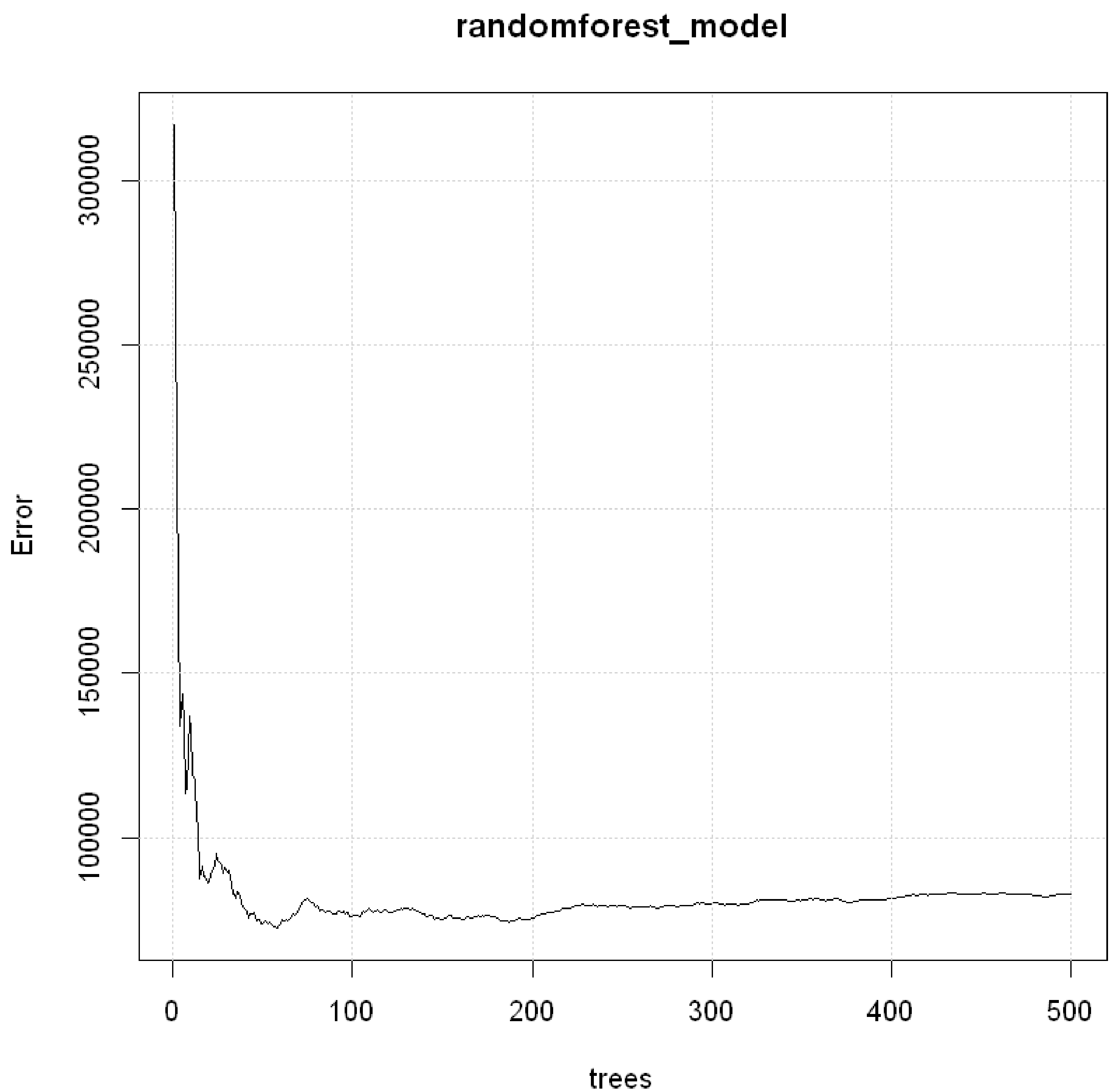
```
# Build the Model
set.seed(0)
randomforest_model <- randomForest(Crime~., data=df, importance = TRUE, nodesize=3, mtry
randomforest_model
```

```
Call:
 randomForest(formula = Crime ~ ., data = df, importance = TRUE,      nodesize = 3, mtry
= 3)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 3

          Mean of squared residuals: 82738.35
                    % Var explained: 43.49
```

In [12]:

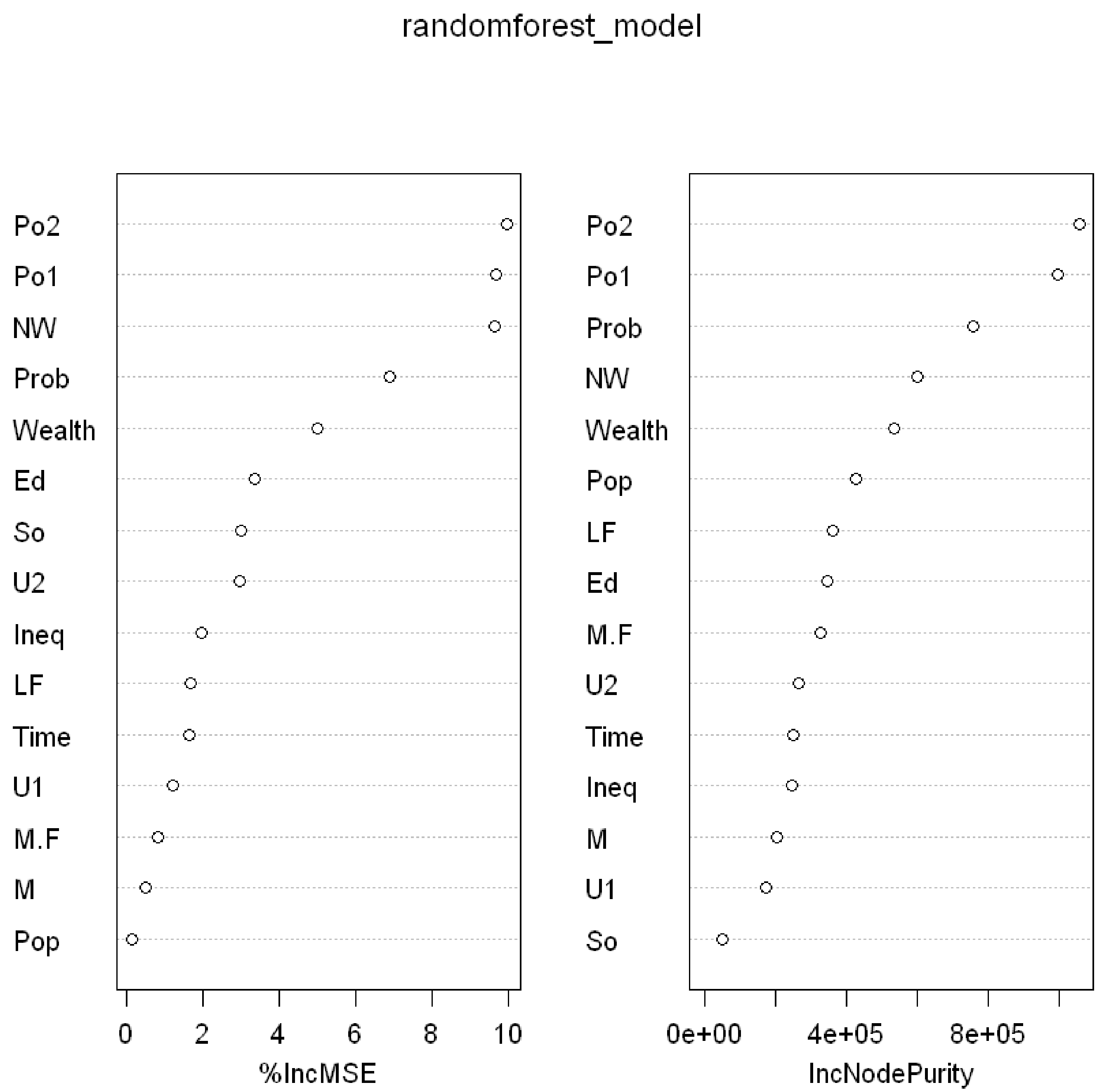
```
# plot Random Forest results
plot(randomforest_model)
grid()
```



From the chart, it is clear that when using 50 trees or more, the Mean of squared residuals (Error) roughly stabilizes.

In [13]:

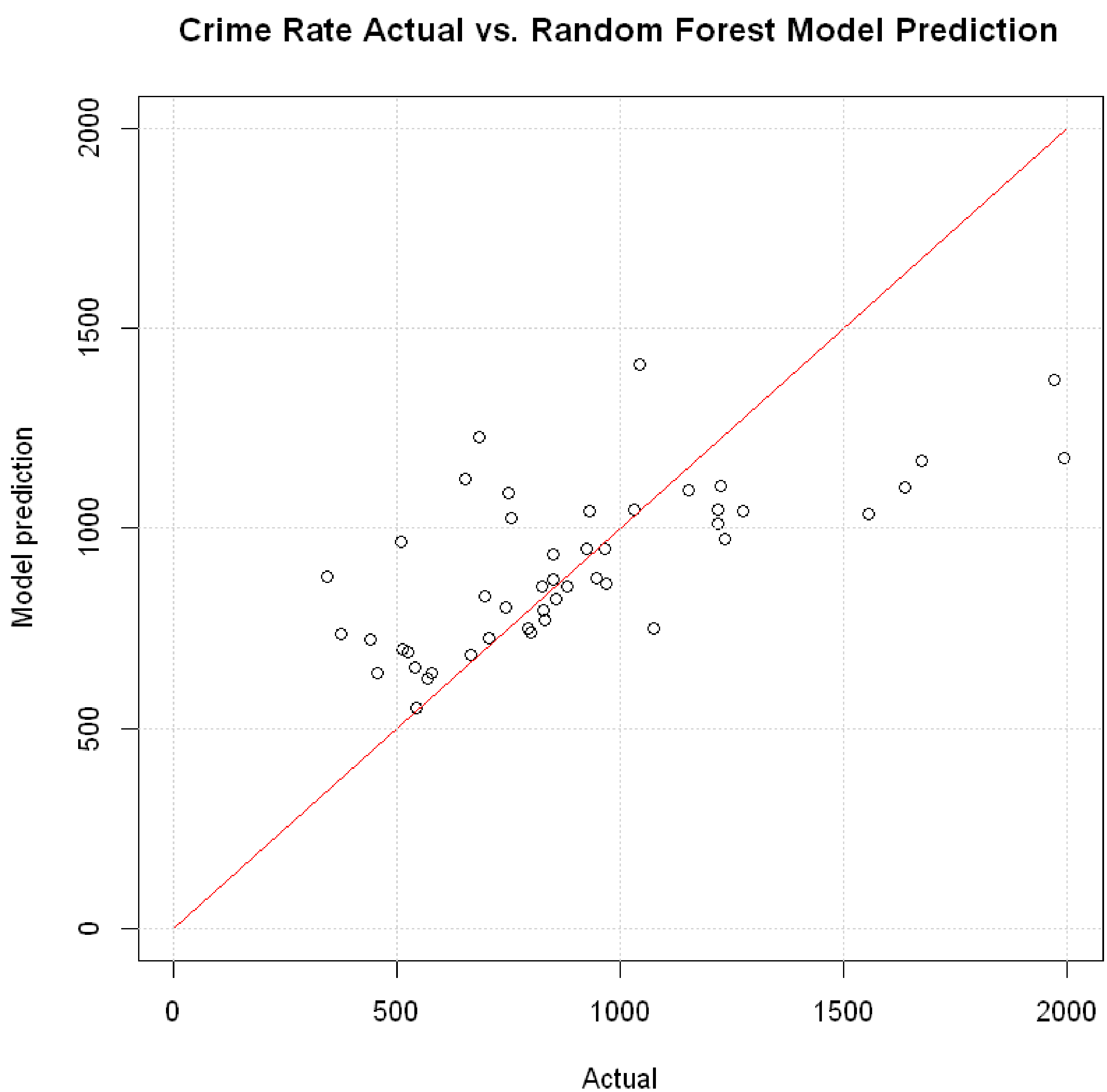
```
# Plot parameters importance
varImpPlot(randomforest_model, sort=TRUE)
```



The most important parameters for the random forest model are Po1/Po2, followed by NW, Prob and Wealth.

In [14]:

```
# plot results for visual QAQC
randomforest_results <- predict(randomforest_model)
plot(df$Crime, randomforest_results, xlim=c(0,2000), ylim=c(0,2000), xlab="Actual", ylab
lines(c(0,2000), c(0,2000), col="red")
title("Crime Rate Actual vs. Random Forest Model Prediction")
grid()
```



In [15]:

```
# Calculating TRAINING R2 for Tree model
rss <- sum((randomforest_results - df$Crime) ^ 2)  ## residual sum of squares
tss <- sum((df$Crime - mean(df$Crime)) ^ 2)  ## total sum of squares
r2 <- 1 - rss/tss
cat("Training R2 for Random Forest Model:", round(r2, 3))
```

```
Training R2 for Random Forest Model: 0.435
```

The Random forest model R2 on training data (0.435) is lower than the Tree model R2 on training data (0.72). However, Random forest is less susceptible to over-fitting while analysis of the tree model showed strong evidence of over-fitting when cross-validated.

New City Prediction for quality checking...

In [16]:
```
# creating required test city data
test_city <- data.frame("M"=14.0, "So"=0, "Ed"=10.0, "Po1"=12.0, "Po2"=15.5, "LF"=0.64,
                        "U1"=0.12, "U2"=3.6, "Wealth"=3200, "Ineq"=20.1, "Prob"=0.04, "T
test_city
```

A data.frame: 1 × 15

M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	T
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<(
14	0	10	12	15.5	0.64	94	150	1.1	0.12	3.6	3200	20.1	0.04	

In [17]:
```
cat("Tree Model Prediction",round(predict(tree_model, test_city),0), "\n")
cat("Random Forest Model Prediction",round(predict(randomforest_model, test_city),0))
```

```
Tree Model Prediction 725
Random Forest Model Prediction 1184
```

Comparison between Different models results for new city prediction (in Crime/100,000 population):

1. 6 Factor linear regression model: 1,304
2. First 5 Principal Components linear regression model: 1,389
3. Random Forest Model Prediction: 1,184
4. Tree Model Prediction: 725

From the data, its clear that the optimized linear regression model, the model based on the First 5 Principal Components and the random Forest Model has very close prediction results for the test city crime rate.

On the other hand, The tree model prediction is significantly different at 725 Crime/ 100,000 population confirming its possible over-fitting and low prediction capabilities.

Question 10.2

Describe a situation or problem from your job, everyday life, current events, etc., for which a logistic regression model would be appropriate. List some (up to 5) predictors that you might use.

Answer 10.2

The early diagnosis and prognosis of cancer can facilitate the subsequent early treatment and clinical management of patients.
Logistic regression can be used to predict the risk of cancer thus flagging high risk persons for further check up.
Examples of predictors:

1. Age
2. Life Habits (e.g. Obesity, smoking etc.)
3. Family medical history (Number of first-degree relatives who have had cancer)
4. Patient medical history (e.g. diabetes, asthma, etc.)

Question 10.3

1. Using the GermanCredit data set germancredit.txt from http://archive.ics.uci.edu/ml/machinelearning-databases/statlog/german / (description at http://archive.ics.uci.edu/ml/datasets/Statlog+%28German+Credit+Data%29),
   Use logistic regression to find a good predictive model for whether credit applicants are good credit risks or not.
   Show your model (factors used and their coefficients), the software output, and the quality of fit.
   You can use the glm function in R. To get a logistic regression (logit) model on data where the response is either zero or one, use family=binomial(link="logit") in your glm function call.

1. Because the model gives a result between 0 and 1, it requires setting a threshold probability to separate between "good" and "bad" answers. In this data set, they estimate that incorrectly identifying a bad customer as good, is 5 times worse than incorrectly classifying a good customer as bad. Determine a good threshold probability based on your model.

In [18]:

```
# loading the dataset
# READ DATASET as DataFrame
german_df <- read.table("german.txt", header = FALSE, sep = " ")
# Display Data
head(german_df)
cat("No. of cols:", ncol(german_df), "\n")
cat("No. of rows:", nrow(german_df))
```

A data.frame: 6 × 21

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

```
No. of cols: 21
No. of rows: 1000
```

Replacing the target Column (V21) with binary (0 and 1) values

Note 1 = Good and 2 = Bad based on Description file

In [19]:

```
german_df$V21[german_df$V21==1] <- 1
german_df$V21[german_df$V21==2] <- 0
head(german_df)
```

A data.frame: 6 × 21

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

Dividing the data into training and validation_datasets 70% training and 30% validation

In [20]:

```
# install.packages("caret", dependencies=TRUE)
library(caret)
# Fix Seed Number
set.seed(1)
# Find indexes
training_idx <- createDataPartition(german_df$V21, times = 1, p = 0.7, list=FALSE)
train_df <- german_df[training_idx,]
valid_df <- german_df[-training_idx,]
```

```
Loading required package: lattice
Loading required package: ggplot2
Registered S3 methods overwritten by 'ggplot2':
  method         from
  [.quosures     rlang
  c.quosures     rlang
  print.quosures rlang

Attaching package: 'ggplot2'

The following object is masked from 'package:randomForest':

    margin
```

In [21]:

```
"Summary of Database Response values"
table(german_df$V21)
cat("Ratio of 0 to 1 responses:", round(table(german_df$V21)[1]/nrow(german_df),3), "\n'
```

'Summary of Database Response values'

```
  0   1 
300 700 
Ratio of 0 to 1 responses: 0.3
```

In [22]:

```
"Summary of Training Response values"
table(train_df$V21)
cat("Ratio of 0 to 1 responses:", round(table(train_df$V21)[1]/nrow(train_df),3), "\n")
```

'Summary of Training Response values'

```
  0   1 
208 492 
Ratio of 0 to 1 responses: 0.297
```

In [23]:

```
"Summary of Validation Response values"
table(valid_df$V21)
cat("Ratio of 0 to 1 responses:", round(table(valid_df$V21)[1]/nrow(valid_df),3), "\n")
```

'Summary of Validation Response values'

```
  0   1 
 92 208 
Ratio of 0 to 1 responses: 0.307
```

From the data, The original dataframe and the subsets (training and Validation) has the same non-creditable ratio 30% (response=0)

Building the basic logistic Model using all input variables

In [24]:
```
# building the intial model
set.seed(0)
base_logit_model <- glm(V21 ~ ., data = train_df, family=binomial(link="logit"))
summary(base_logit_model)
```

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

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.4540  -0.6750   0.3608   0.6861   2.4438

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.823e-01  1.332e+00  -0.287 0.774162
V1A12        5.201e-01  2.681e-01   1.940 0.052408 .
V1A13        1.150e+00  4.473e-01   2.570 0.010173 *
V1A14        1.675e+00  2.750e-01   6.091 1.12e-09 ***
V2          -2.570e-02  1.159e-02  -2.217 0.026647 *
V3A31       -8.440e-02  6.580e-01  -0.128 0.897943
V3A32        8.078e-01  4.996e-01   1.617 0.105907
V3A33        7.683e-01  5.372e-01   1.430 0.152634
V3A34        1.446e+00  5.127e-01   2.821 0.004784 **
V4A41        1.513e+00  4.479e-01   3.379 0.000728 ***
V4A410       2.412e+00  1.160e+00   2.080 0.037543 *
V4A42        5.496e-01  3.195e-01   1.720 0.085354 .
V4A43        9.142e-01  3.024e-01   3.023 0.002503 **
V4A44        4.163e-01  9.455e-01   0.440 0.659751
V4A45        1.562e-01  6.742e-01   0.232 0.816732
V4A46        2.569e-01  5.085e-01   0.505 0.613382
V4A48        1.531e+01  4.556e+02   0.034 0.973202
V4A49        5.397e-01  4.017e-01   1.344 0.179086
V5          -1.076e-04  5.600e-05  -1.922 0.054633 .
V6A62        3.474e-01  3.579e-01   0.971 0.331777
V6A63        2.440e-01  4.761e-01   0.513 0.608232
V6A64        1.379e+00  6.535e-01   2.110 0.034823 *
V6A65        8.106e-01  3.223e-01   2.515 0.011910 *
V7A72        1.814e-01  5.243e-01   0.346 0.729300
V7A73        5.253e-01  5.001e-01   1.050 0.293529
V7A74        1.129e+00  5.455e-01   2.070 0.038431 *
V7A75        5.927e-01  5.052e-01   1.173 0.240705
V8          -3.523e-01  1.094e-01  -3.219 0.001284 **
V9A92       -4.849e-02  4.760e-01  -0.102 0.918863
V9A93        4.446e-01  4.691e-01   0.948 0.343279
V9A94        4.288e-01  5.837e-01   0.735 0.462524
V10A102     -3.052e-01  5.338e-01  -0.572 0.567472
V10A103      3.086e-01  5.237e-01   0.589 0.555669
V11          1.080e-01  1.073e-01   1.007 0.314147
V12A122     -2.219e-01  3.161e-01  -0.702 0.482767
V12A123     -3.274e-01  2.922e-01  -1.120 0.262504
V12A124     -1.156e+00  5.656e-01  -2.044 0.040944 *
V13          2.257e-02  1.140e-02   1.980 0.047667 *
V14A142      5.214e-01  4.925e-01   1.059 0.289757
V14A143      7.780e-01  2.848e-01   2.732 0.006299 **
V15A152      6.323e-01  2.870e-01   2.203 0.027579 *
V15A153      6.674e-01  6.202e-01   1.076 0.281931
V16         -2.866e-01  2.236e-01  -1.282 0.199939
V17A172     -1.565e+00  8.891e-01  -1.760 0.078442 .
V17A173     -1.564e+00  8.582e-01  -1.823 0.068370 .
V17A174     -1.400e+00  8.772e-01  -1.596 0.110563
V18         -1.645e-01  3.004e-01  -0.548 0.583871
V19A192      3.319e-01  2.413e-01   1.376 0.168942
V20A202      2.137e+00  8.573e-01   2.493 0.012665 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 851.79  on 699  degrees of freedom
Residual deviance: 613.21  on 651  degrees of freedom
AIC: 711.21
```

```
Number of Fisher Scoring iterations: 14
```

Convert Factorial columns into Binary columns e.g. Column V1 Factor A13 into V1A13 Column with binary inputs (0,1)

In [25]:

```r
# copy initial Dataframe
train_df_edit <- train_df
# Convert Factorial columns into Binary columns e.g. Column V1 Factor A13 into V1A13 Co
train_df_edit$V1A12 <- ifelse(train_df_edit$V1 == "A12", 1, 0)
train_df_edit$V1A13 <- ifelse(train_df_edit$V1 == "A13", 1, 0)
train_df_edit$V1A14 <- ifelse(train_df_edit$V1 == "A14", 1, 0)
train_df_edit$V3A34 <- ifelse(train_df_edit$V3 == "A34", 1, 0)
train_df_edit$V4A41 <- ifelse(train_df_edit$V4 == "A41", 1, 0)
train_df_edit$V4A410 <- ifelse(train_df_edit$V4 == "A410", 1, 0)
train_df_edit$V4A42 <- ifelse(train_df_edit$V4 == "A42", 1, 0)
train_df_edit$V4A43 <- ifelse(train_df_edit$V4 == "A43", 1, 0)
train_df_edit$V6A64 <- ifelse(train_df_edit$V6 == "A64", 1, 0)
train_df_edit$V6A65 <- ifelse(train_df_edit$V6 == "A65", 1, 0)
train_df_edit$V7A74 <- ifelse(train_df_edit$V7 == "A74", 1, 0)
train_df_edit$V12A124 <- ifelse(train_df_edit$V12 == "A124", 1, 0)
train_df_edit$V14A143 <- ifelse(train_df_edit$V14 == "A143", 1, 0)
train_df_edit$V15A152 <- ifelse(train_df_edit$V15 == "A152", 1, 0)
train_df_edit$V17A172 <- ifelse(train_df_edit$V17 == "A172", 1, 0)
train_df_edit$V17A173 <- ifelse(train_df_edit$V17 == "A173", 1, 0)
train_df_edit$V20A202 <- ifelse(train_df_edit$V20 == "A202", 1, 0)
head(train_df_edit)
```

A data.frame: 6 × 38

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V4A43	V6A64	V6A65	V7A74
	<fct>	<int>	<fct>	<fct>	<int>	<fct>	<fct>	<int>	<fct>	<fct>	...	<dbl>	<dbl>	<dbl>	<dbl>
1	A11	6	A34	A43	1169	A65	A75	4	A93	A101	...	1	0	1	0
3	A14	12	A34	A46	2096	A61	A74	2	A93	A101	...	0	0	0	1
4	A11	42	A32	A42	7882	A61	A74	2	A93	A103	...	0	0	0	1
5	A11	24	A33	A40	4870	A61	A73	3	A93	A101	...	0	0	0	0
6	A14	36	A32	A46	9055	A65	A73	2	A93	A101	...	0	0	1	0
7	A14	24	A32	A42	2835	A63	A75	3	A93	A101	...	0	0	0	0

Optimized models will be created based on using the p-values of each Coefficient, where p-value <=0.10

1st Optimized Model

In [26]:
```
# building the optimized model
set.seed(0)
opt_logit_model_1 <- glm(V21~V1A12+V1A13+V1A14+V2+
                         V3A34+V4A41+V4A410+V4A42+V4A43+
                         V5+V6A64+V6A65+V7A74+V8+
                         V12A124+V13+V14A143+V15A152+V20A202,
                         data = train_df_edit, family=binomial(link="logit"))
summary(opt_logit_model_1)
```

```
Call:
glm(formula = V21 ~ V1A12 + V1A13 + V1A14 + V2 + V3A34 + V4A41 + 
    V4A410 + V4A42 + V4A43 + V5 + V6A64 + V6A65 + V7A74 + V8 + 
    V12A124 + V13 + V14A143 + V15A152 + V20A202, family = binomial(link = "logit"), 
    data = train_df_edit)

Deviance Residuals: 
    Min       1Q   Median       3Q      Max  
-2.6489  -0.8057   0.3919   0.7396   2.0341  

Coefficients:
              Estimate Std. Error z value Pr(>|z|)    
(Intercept) -9.534e-01  5.669e-01  -1.682 0.092640 .  
V1A12        5.588e-01  2.439e-01   2.291 0.021937 *  
V1A13        1.118e+00  4.163e-01   2.686 0.007236 ** 
V1A14        1.764e+00  2.588e-01   6.816 9.37e-12 ***
V2          -2.322e-02  1.069e-02  -2.172 0.029845 *  
V3A34        6.137e-01  2.448e-01   2.507 0.012189 *  
V4A41        1.436e+00  4.063e-01   3.535 0.000408 ***
V4A410       2.329e+00  9.793e-01   2.378 0.017404 *  
V4A42        2.566e-01  2.677e-01   0.958 0.337867    
V4A43        7.834e-01  2.478e-01   3.162 0.001568 ** 
V5          -1.159e-04  4.993e-05  -2.322 0.020221 *  
V6A64        1.106e+00  6.012e-01   1.840 0.065701 .  
V6A65        8.257e-01  2.981e-01   2.770 0.005610 ** 
V7A74        7.824e-01  2.906e-01   2.692 0.007097 ** 
V8          -3.056e-01  9.993e-02  -3.058 0.002231 ** 
V12A124     -4.117e-01  3.330e-01  -1.237 0.216233    
V13          3.118e-02  9.849e-03   3.166 0.001544 ** 
V14A143      6.719e-01  2.347e-01   2.863 0.004197 ** 
V15A152      5.663e-01  2.436e-01   2.325 0.020068 *  
V20A202      1.740e+00  7.963e-01   2.185 0.028876 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 851.79  on 699  degrees of freedom
Residual deviance: 645.60  on 680  degrees of freedom
AIC: 685.6

Number of Fisher Scoring iterations: 5
```

Using the p-values of each Coefficient, a second optimized model will be created where p-value <=0.10

2nd Optimized Model

In [27]:

```r
# building the 2nd optimized model
opt_logit_model_2 <- glm(V21~V1A12+V1A13+V1A14+V2+
                         V3A34+V4A41+V4A410+V4A43+
                         V5+V6A64+V6A65+V7A74+V8+
                         V13+V14A143+V15A152+V20A202,
                         data = train_df_edit, family=binomial(link="logit"))
summary(opt_logit_model_2)
```

```
Call:
glm(formula = V21 ~ V1A12 + V1A13 + V1A14 + V2 + V3A34 + V4A41 +
    V4A410 + V4A43 + V5 + V6A64 + V6A65 + V7A74 + V8 + V13 +
    V14A143 + V15A152 + V20A202, family = binomial(link = "logit"),
    data = train_df_edit)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.6374  -0.8241   0.3956   0.7478   1.9601

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -7.769e-01  5.430e-01  -1.431 0.152522
V1A12        5.121e-01  2.404e-01   2.130 0.033165 *
V1A13        1.079e+00  4.145e-01   2.604 0.009213 **
V1A14        1.741e+00  2.572e-01   6.770 1.28e-11 ***
V2          -2.478e-02  1.056e-02  -2.347 0.018927 *
V3A34        6.001e-01  2.432e-01   2.467 0.013612 *
V4A41        1.349e+00  3.947e-01   3.418 0.000632 ***
V4A410       2.217e+00  9.795e-01   2.264 0.023603 *
V4A43        7.163e-01  2.337e-01   3.065 0.002173 **
V5          -1.212e-04  4.911e-05  -2.467 0.013616 *
V6A64        1.164e+00  6.043e-01   1.927 0.053982 .
V6A65        8.053e-01  2.950e-01   2.730 0.006341 **
V7A74        7.752e-01  2.880e-01   2.692 0.007104 **
V8          -3.252e-01  9.888e-02  -3.289 0.001006 **
V13          2.685e-02  9.335e-03   2.877 0.004021 **
V14A143      6.945e-01  2.336e-01   2.973 0.002944 **
V15A152      7.243e-01  2.110e-01   3.432 0.000598 ***
V20A202      1.761e+00  8.026e-01   2.194 0.028267 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 851.79  on 699  degrees of freedom
Residual deviance: 648.22  on 682  degrees of freedom
AIC: 684.22

Number of Fisher Scoring iterations: 5
```

Selecting the Optimal Model

In [28]:

```
delta_AIC <- opt_logit_model_1$aic - opt_logit_model_2$aic
cat("The Delta AIC between the 2 optimized models is", delta_AIC)
```

```
The Delta AIC between the 2 optimized models is 1.380515
```

Following the rule of thumb, since Δ AIC < 2, there is substantial support for the 1st optimized model. (i.e. the extra dimension reduction of the second optimized model is not supported)

In [29]:

```
delta_AIC <- base_logit_model$aic - opt_logit_model_1$aic
cat("The Delta AIC between the 2 models is", delta_AIC)
```

```
The Delta AIC between the 2 models is 25.61516
```

Following the rule of thumb since Δ AIC >10, The 1st optimized model is significantly better than the base model with all the variables.

Reference:
https://stats.stackexchange.com/questions/232465/how-to-compare-models-on-the-basis-of-aic

Evaluating the selected model using Confusion Matrix and Model Accuracy on Training Data

In [30]:

```
train_predict <- predict(opt_logit_model_1, newdata=train_df_edit, type="response")
confusionMatrix(as.factor(train_df_edit$V21), as.factor(round(train_predict)))
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0 108 100
         1  49 443

               Accuracy : 0.7871
                 95% CI : (0.7549, 0.8169)
    No Information Rate : 0.7757
    P-Value [Acc > NIR] : 0.2498

                  Kappa : 0.4516

 Mcnemar's Test P-Value : 4.201e-05

            Sensitivity : 0.6879
            Specificity : 0.8158
         Pos Pred Value : 0.5192
         Neg Pred Value : 0.9004
             Prevalence : 0.2243
         Detection Rate : 0.1543
   Detection Prevalence : 0.2971
      Balanced Accuracy : 0.7519

       'Positive' Class : 0
```

Evaluating the selected model using Confusion Matrix and Model Accuracy on Validation Data

In [31]:

```
# copy initial Dataframe
valid_df_edit <- valid_df
# Convert Factorial columns into Binary columns e.g. Column V1 Factor A13 into V1A13 Co
valid_df_edit$V1A12 <- ifelse(valid_df_edit$V1 == "A12", 1, 0)
valid_df_edit$V1A13 <- ifelse(valid_df_edit$V1 == "A13", 1, 0)
valid_df_edit$V1A14 <- ifelse(valid_df_edit$V1 == "A14", 1, 0)
valid_df_edit$V3A34 <- ifelse(valid_df_edit$V3 == "A34", 1, 0)
valid_df_edit$V4A41 <- ifelse(valid_df_edit$V4 == "A41", 1, 0)
valid_df_edit$V4A410 <- ifelse(valid_df_edit$V4 == "A410", 1, 0)
valid_df_edit$V4A42 <- ifelse(valid_df_edit$V4 == "A42", 1, 0)
valid_df_edit$V4A43 <- ifelse(valid_df_edit$V4 == "A43", 1, 0)
valid_df_edit$V6A64 <- ifelse(valid_df_edit$V6 == "A64", 1, 0)
valid_df_edit$V6A65 <- ifelse(valid_df_edit$V6 == "A65", 1, 0)
valid_df_edit$V7A74 <- ifelse(valid_df_edit$V7 == "A74", 1, 0)
valid_df_edit$V12A124 <- ifelse(valid_df_edit$V12 == "A124", 1, 0)
valid_df_edit$V14A143 <- ifelse(valid_df_edit$V14 == "A143", 1, 0)
valid_df_edit$V15A152 <- ifelse(valid_df_edit$V15 == "A152", 1, 0)
valid_df_edit$V17A172 <- ifelse(valid_df_edit$V17 == "A172", 1, 0)
valid_df_edit$V17A173 <- ifelse(valid_df_edit$V17 == "A173", 1, 0)
valid_df_edit$V20A202 <- ifelse(valid_df_edit$V20 == "A202", 1, 0)
head(valid_df_edit)
```

A data.frame: 6 × 38

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V4A43	V6A64	V6A65	V7A74
	<fct>	<int>	<fct>	<fct>	<int>	<fct>	<fct>	<int>	<fct>	<fct>	...	<dbl>	<dbl>	<dbl>	<dbl>
2	A12	48	A32	A43	5951	A61	A73	2	A92	A101	...	1	0	0	0
10	A12	30	A34	A40	5234	A61	A71	4	A94	A101	...	0	0	0	0
14	A11	24	A34	A40	1199	A61	A75	4	A93	A101	...	0	0	0	0
18	A11	30	A30	A49	8072	A65	A72	2	A93	A101	...	0	0	1	0
21	A14	9	A34	A40	2134	A61	A73	4	A93	A101	...	0	0	0	0
23	A11	10	A34	A40	2241	A61	A72	1	A93	A101	...	0	0	0	0

In [32]:

```
valid_predict <- predict(opt_logit_model_1, newdata=valid_df_edit, type="response")
confusionMatrix(as.factor(valid_df_edit$V21), as.factor(round(valid_predict)))
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0  44  48
         1  35 173

               Accuracy : 0.7233
                 95% CI : (0.669, 0.7732)
    No Information Rate : 0.7367
    P-Value [Acc > NIR] : 0.7246

                  Kappa : 0.3227

 Mcnemar's Test P-Value : 0.1878

            Sensitivity : 0.5570
            Specificity : 0.7828
         Pos Pred Value : 0.4783
         Neg Pred Value : 0.8317
             Prevalence : 0.2633
         Detection Rate : 0.1467
   Detection Prevalence : 0.3067
      Balanced Accuracy : 0.6699

       'Positive' Class : 0
```

From the data above,

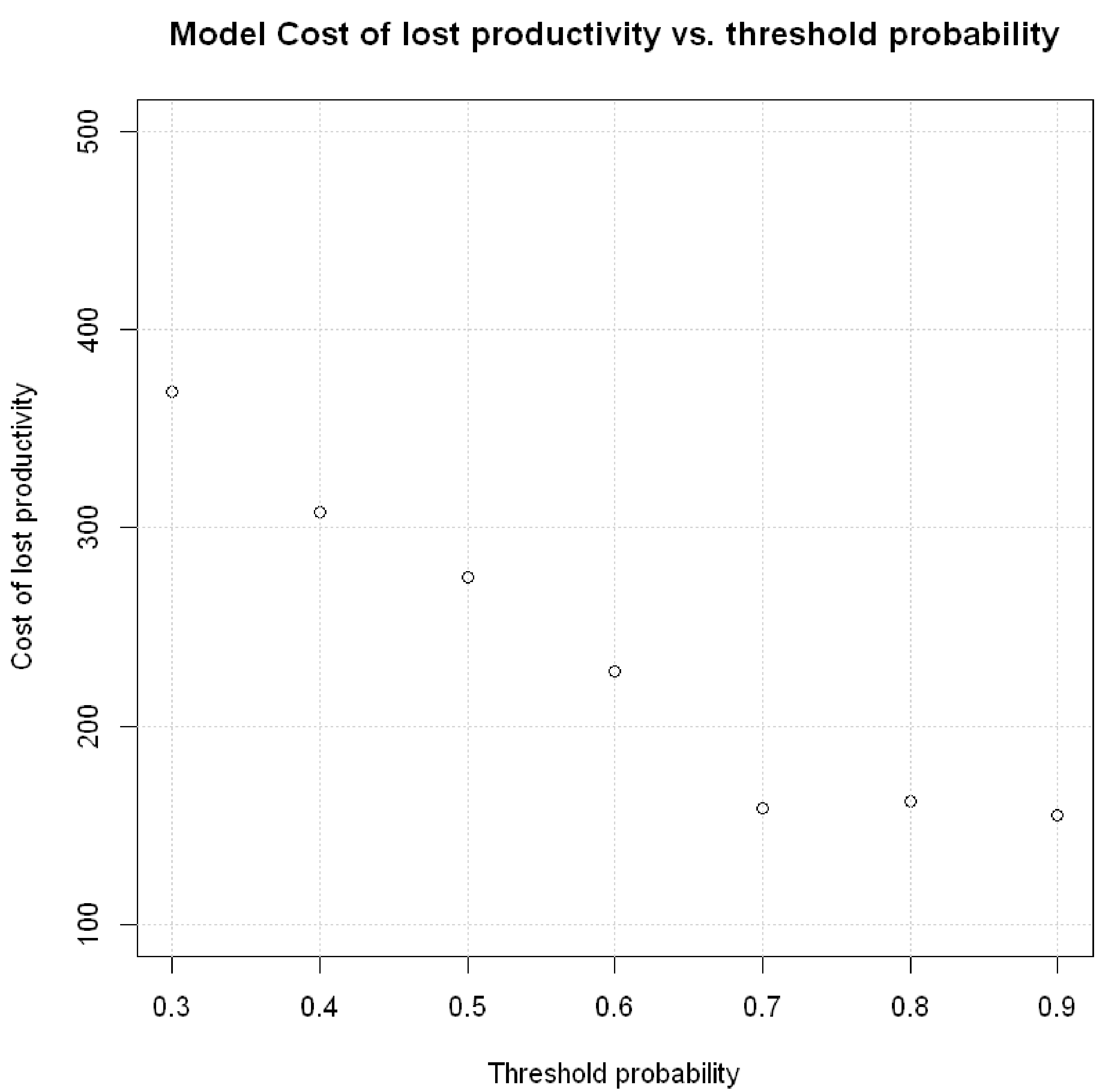
1. The model Accuracy on the Validation set is slightly lower than the training set (indicating some overfitting) however overall it is still acceptable (72%)
2. The model still suffers from high confusion in class 0 (50% of the points are mis-classified)

Finding Optimal Threshold

Assuming that incorrectly identifying a bad customer as good, is 5 times worse than incorrectly classifying a good customer as bad, A sensitivity run was made to find the optimal threshold.

In [33]:

```
cost_list <- seq(1,7)
threshold_list <- seq(3,9)/10
for (i in seq(1,7)){
    result_matrix <- table(valid_df_edit$V21, as.numeric(valid_predict>threshold_list[i]
    model_cost <- result_matrix[1,1]*0 + result_matrix[1,2]*5 + result_matrix[2,1]*1 + r
    cost_list[i] <- model_cost
}
plot(threshold_list, cost_list, ylim=c(100,500), xlab="Threshold probability", ylab="Cos
title("Model Cost of lost productivity vs. threshold probability")
grid()
```



In [34]:

```r
# Final Model Confusion Matrix on Validation data
confusionMatrix(as.factor(valid_df_edit$V21), as.factor(round(valid_predict>=0.7)))
```

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0  73  19
         1  64 144

               Accuracy : 0.7233
                 95% CI : (0.669, 0.7732)
    No Information Rate : 0.5433
    P-Value [Acc > NIR] : 1.164e-10

                  Kappa : 0.4275

 Mcnemar's Test P-Value : 1.368e-06

            Sensitivity : 0.5328
            Specificity : 0.8834
         Pos Pred Value : 0.7935
         Neg Pred Value : 0.6923
             Prevalence : 0.4567
         Detection Rate : 0.2433
   Detection Prevalence : 0.3067
      Balanced Accuracy : 0.7081

       'Positive' Class : 0
```

Conclusion:

Based on the sensitivity analysis, a threshold of 0.7 should be used (when incorrectly identifying a bad customer as good, is 5 times worse than incorrectly classifying a good customer)