HW 10.1 (a)

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Read in Data and Packages

```
library("tree")
crimedata <- read.table("uscrime.txt", header = TRUE)

crimedata
```

```
##       M So   Ed  Po1  Po2    LF   M.F Pop   NW    U1  U2 Wealth Ineq     Prob
## 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
## 7  12.7  1 11.1  8.2  7.9 0.519  98.2   4 13.9 0.097 3.8   6200 16.8 0.042100
## 8  13.1  1 10.9 11.5 10.9 0.542  96.9  50 17.9 0.079 3.5   4720 20.6 0.040099
## 9  15.7  1  9.0  6.5  6.2 0.553  95.5  39 28.6 0.081 2.8   4210 23.9 0.071697
## 10 14.0  0 11.8  7.1  6.8 0.632 102.9   7  1.5 0.100 2.4   5260 17.4 0.044498
## 11 12.4  0 10.5 12.1 11.6 0.580  96.6 101 10.6 0.077 3.5   6570 17.0 0.016201
## 12 13.4  0 10.8  7.5  7.1 0.595  97.2  47  5.9 0.083 3.1   5800 17.2 0.031201
## 13 12.8  0 11.3  6.7  6.0 0.624  97.2  28  1.0 0.077 2.5   5070 20.6 0.045302
## 14 13.5  0 11.7  6.2  6.1 0.595  98.6  22  4.6 0.077 2.7   5290 19.0 0.053200
## 15 15.2  1  8.7  5.7  5.3 0.530  98.6  30  7.2 0.092 4.3   4050 26.4 0.069100
## 16 14.2  1  8.8  8.1  7.7 0.497  95.6  33 32.1 0.116 4.7   4270 24.7 0.052099
## 17 14.3  0 11.0  6.6  6.3 0.537  97.7  10  0.6 0.114 3.5   4870 16.6 0.076299
## 18 13.5  1 10.4 12.3 11.5 0.537  97.8  31 17.0 0.089 3.4   6310 16.5 0.119804
## 19 13.0  0 11.6 12.8 12.8 0.536  93.4  51  2.4 0.078 3.4   6270 13.5 0.019099
## 20 12.5  0 10.8 11.3 10.5 0.567  98.5  78  9.4 0.130 5.8   6260 16.6 0.034801
## 21 12.6  0 10.8  7.4  6.7 0.602  98.4  34  1.2 0.102 3.3   5570 19.5 0.022800
## 22 15.7  1  8.9  4.7  4.4 0.512  96.2  22 42.3 0.097 3.4   2880 27.6 0.089502
## 23 13.2  0  9.6  8.7  8.3 0.564  95.3  43  9.2 0.083 3.2   5130 22.7 0.030700
## 24 13.1  0 11.6  7.8  7.3 0.574 103.8   7  3.6 0.142 4.2   5400 17.6 0.041598
## 25 13.0  0 11.6  6.3  5.7 0.641  98.4  14  2.6 0.070 2.1   4860 19.6 0.069197
## 26 13.1  0 12.1 16.0 14.3 0.631 107.1   3  7.7 0.102 4.1   6740 15.2 0.041698
## 27 13.5  0 10.9  6.9  7.1 0.540  96.5   6  0.4 0.080 2.2   5640 13.9 0.036099
## 28 15.2  0 11.2  8.2  7.6 0.571 101.8  10  7.9 0.103 2.8   5370 21.5 0.038201
## 29 11.9  0 10.7 16.6 15.7 0.521  93.8 168  8.9 0.092 3.6   6370 15.4 0.023400
## 30 16.6  1  8.9  5.8  5.4 0.521  97.3  46 25.4 0.072 2.6   3960 23.7 0.075298
## 31 14.0  0  9.3  5.5  5.4 0.535 104.5   6  2.0 0.135 4.0   4530 20.0 0.041999
## 32 12.5  0 10.9  9.0  8.1 0.586  96.4  97  8.2 0.105 4.3   6170 16.3 0.042698
## 33 14.7  1 10.4  6.3  6.4 0.560  97.2  23  9.5 0.076 2.4   4620 23.3 0.049499
## 34 12.6  0 11.8  9.7  9.7 0.542  99.0  18  2.1 0.102 3.5   5890 16.6 0.040799
## 35 12.3  0 10.2  9.7  8.7 0.526  94.8 113  7.6 0.124 5.0   5720 15.8 0.020700
## 36 15.0  0 10.0 10.9  9.8 0.531  96.4   9  2.4 0.087 3.8   5590 15.3 0.006900
```

```
## 37 17.7  1  8.7  5.8  5.6 0.638  97.4  24 34.9 0.076 2.8   3820 25.4 0.045198
## 38 13.3  0 10.4  5.1  4.7 0.599 102.4   7  4.0 0.099 2.7   4250 22.5 0.053998
## 39 14.9  1  8.8  6.1  5.4 0.515  95.3  36 16.5 0.086 3.5   3950 25.1 0.047099
## 40 14.5  1 10.4  8.2  7.4 0.560  98.1  96 12.6 0.088 3.1   4880 22.8 0.038801
## 41 14.8  0 12.2  7.2  6.6 0.601  99.8   9  1.9 0.084 2.0   5900 14.4 0.025100
## 42 14.1  0 10.9  5.6  5.4 0.523  96.8   4  0.2 0.107 3.7   4890 17.0 0.088904
## 43 16.2  1  9.9  7.5  7.0 0.522  99.6  40 20.8 0.073 2.7   4960 22.4 0.054902
## 44 13.6  0 12.1  9.5  9.6 0.574 101.2  29  3.6 0.111 3.7   6220 16.2 0.028100
## 45 13.9  1  8.8  4.6  4.1 0.480  96.8  19  4.9 0.135 5.3   4570 24.9 0.056202
## 46 12.6  0 10.4 10.6  9.7 0.599  98.9  40  2.4 0.078 2.5   5930 17.1 0.046598
## 47 13.0  0 12.1  9.0  9.1 0.623 104.9   3  2.2 0.113 4.0   5880 16.0 0.052802
##       Time Crime
## 1  26.2011   791
## 2  25.2999  1635
## 3  24.3006   578
## 4  29.9012  1969
## 5  21.2998  1234
## 6  20.9995   682
## 7  20.6993   963
## 8  24.5988  1555
## 9  29.4001   856
## 10 19.5994   705
## 11 41.6000  1674
## 12 34.2984   849
## 13 36.2993   511
## 14 21.5010   664
## 15 22.7008   798
## 16 26.0991   946
## 17 19.1002   539
## 18 18.1996   929
## 19 24.9008   750
## 20 26.4010  1225
## 21 37.5998   742
## 22 37.0994   439
## 23 25.1989  1216
## 24 17.6000   968
## 25 21.9003   523
## 26 22.1005  1993
## 27 28.4999   342
## 28 25.8006  1216
## 29 36.7009  1043
## 30 28.3011   696
## 31 21.7998   373
## 32 30.9014   754
## 33 25.5005  1072
## 34 21.6997   923
## 35 37.4011   653
## 36 44.0004  1272
## 37 31.6995   831
## 38 16.6999   566
## 39 27.3004   826
## 40 29.3004  1151
## 41 30.0001   880
## 42 12.1996   542
```

```
## 43 31.9989   823
## 44 30.0001  1030
## 45 32.5996   455
## 46 16.6999   508
## 47 16.0997   849
```

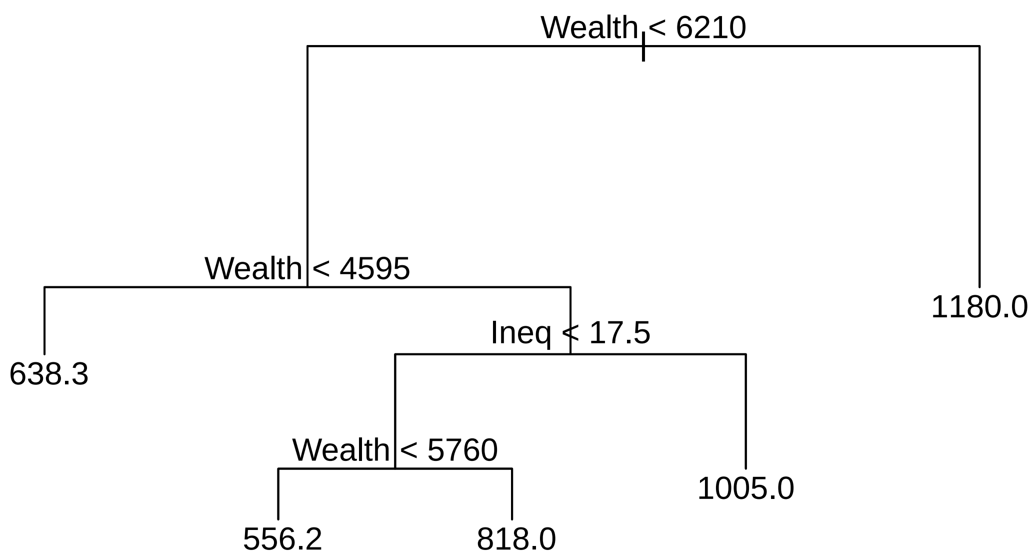
```
set.seed(1234)
```

Split Data into Train, Validation, and Test

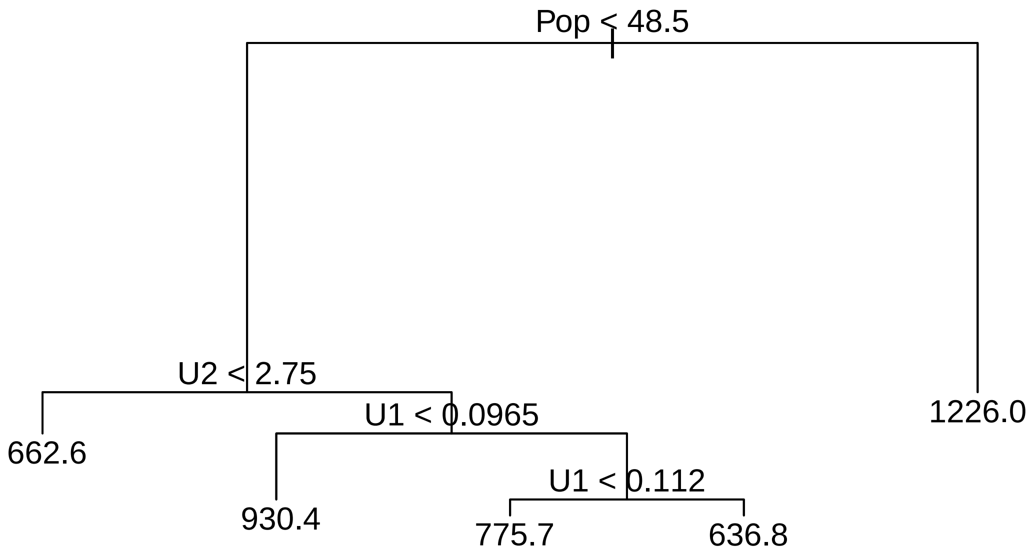
```
splitSample <- sample(1:3, size = nrow(crimedata), prob = c(0.7, 0.15, 0.15), replace = TRUE)

crimedata.train <- crimedata[splitSample == 1,]
crimedata.val <- crimedata[splitSample == 2,]
crimedata.test <- crimedata[splitSample ==3,]
```

Training the Regression Decision Tree

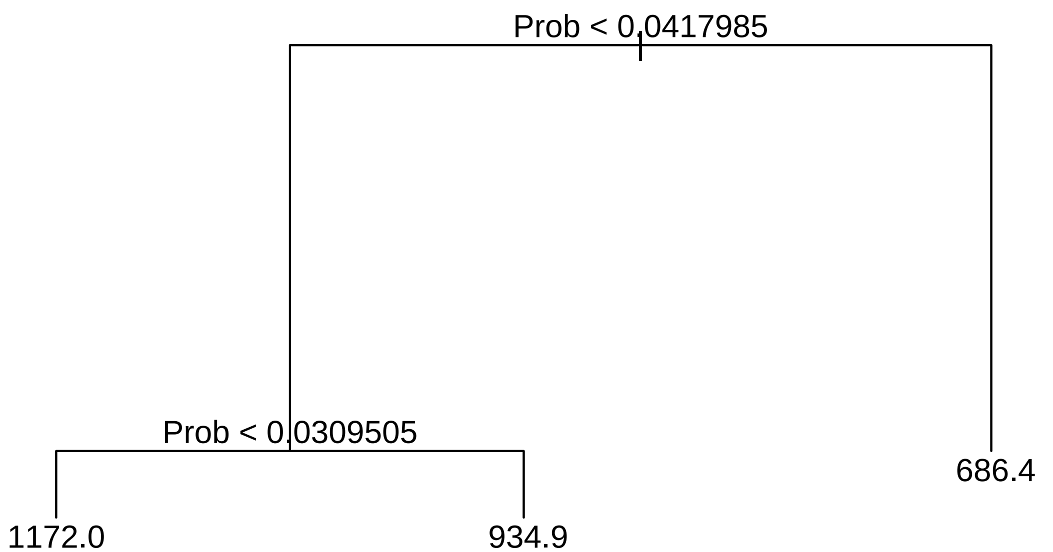
```
# Predicting Crime Rates

# Model 1: Crime Rate Based on Income Inequality and Wealth
reg_tree1 <- tree(Crime~Ineq+Wealth, crimedata.train)
plot(reg_tree1)
text(reg_tree1, pretty = 0)
```



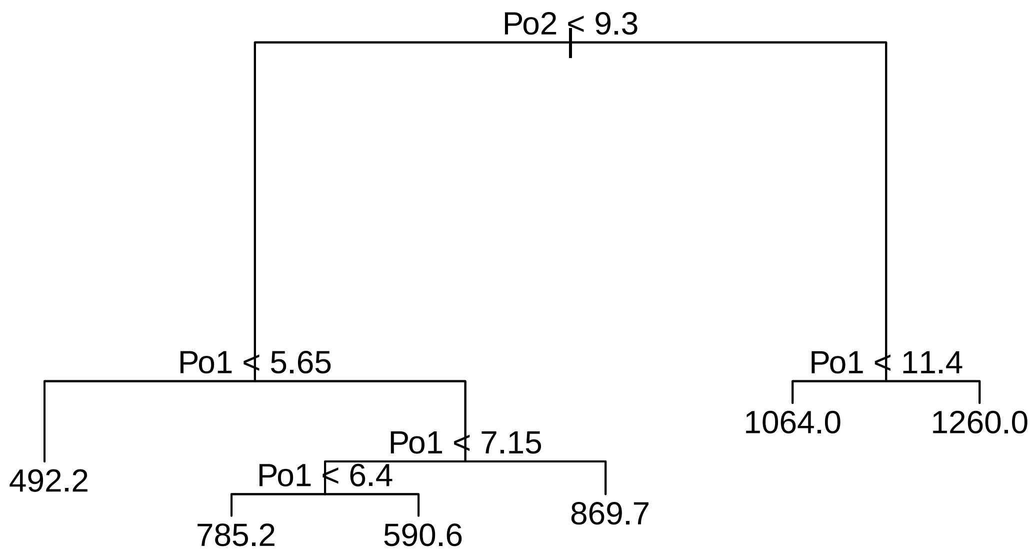

```
# Model 2: Crime Rate Based on Unemployment Rates and Population
reg_tree2 <- tree(Crime~U1+U2+Pop, crimedata.train)
plot(reg_tree2)
text(reg_tree2, pretty = 0)
```



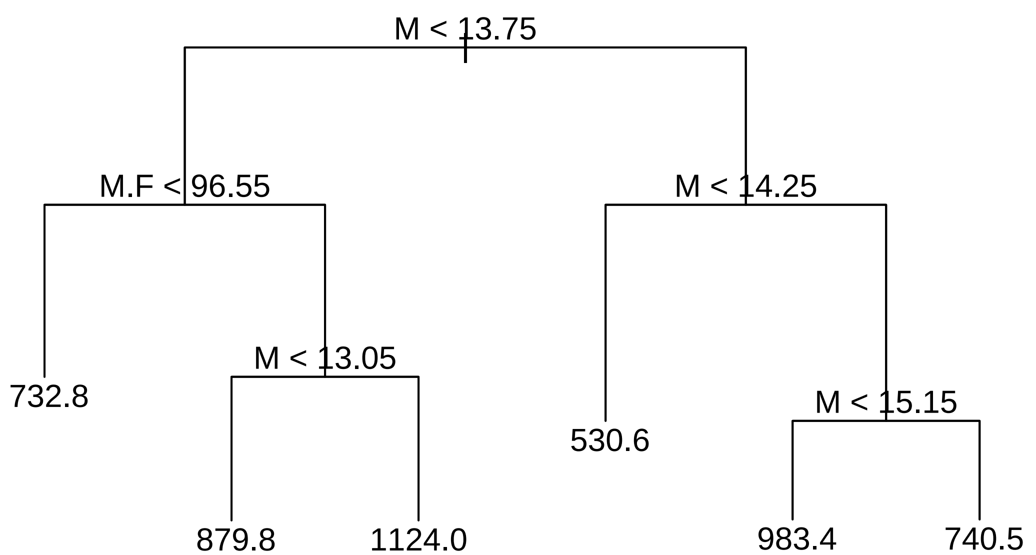

```r
# Model 3: Crime Rate Based on Previous Crime History (Prob of Imprisonment)
reg_tree3 <- tree(Crime~Prob, crimedata.train)
plot(reg_tree3)
text(reg_tree3, pretty = 0)
```



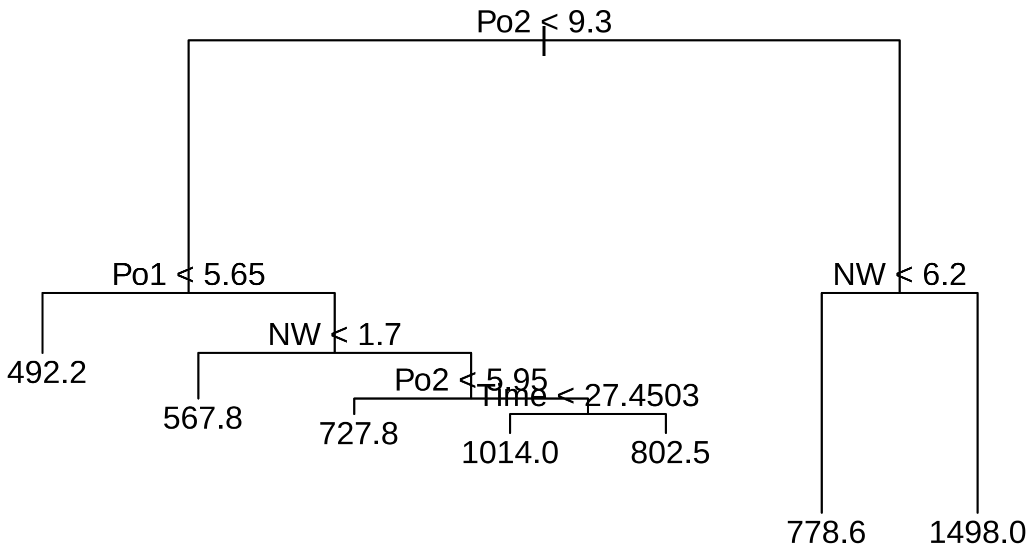

```r
# Model 4: Crime Rate Based on Expenditure on Police Protection
reg_tree4 <- tree(Crime~Po1+Po2, crimedata.train)
plot(reg_tree4)
text(reg_tree4, pretty = 0)
```




```
# Model 5: Crime Rate Based on Presence of Males
reg_tree5 <- tree(Crime~M+M.F, crimedata.train)
plot(reg_tree5)
text(reg_tree5, pretty = 0)
```




```
# Model Baseline: ALL to Predict Crime Rate (use this as a baseline)
reg_treeB <- tree(Crime~., crimedata.train)
plot(reg_treeB)
text(reg_treeB, pretty = 0)
```



Validating Tree

Models

```r
# MSE scores for evaluation (Mean Squared Error)
# Model 1
val_tree1 <- predict(reg_tree1, crimedata.val)
val_tree1_MSE <- mean((crimedata.val$Crime - val_tree1)^2)

paste("Model 1: Income Inequality/Wealth", val_tree1_MSE)
```

```
## [1] "Model 1: Income Inequality/Wealth 92272.3225"
```

```r
# Model 2
val_tree2 <- predict(reg_tree2, crimedata.val)
val_tree2_MSE <- mean((crimedata.val$Crime - val_tree2)^2)

paste("Model 2: Unemployment Rate/Population", val_tree2_MSE)
```

```
## [1] "Model 2: Unemployment Rate/Population 132815.018044848"
```

```r
# Model 3
val_tree3 <- predict(reg_tree3, crimedata.val)
val_tree3_MSE <- mean((crimedata.val$Crime - val_tree3)^2)

paste("Model 3: Previous Crime History", val_tree3_MSE)
```

```
## [1] "Model 3: Previous Crime History 47128.8860895598"
```

```r
# Model 4
val_tree4 <- predict(reg_tree4, crimedata.val)
val_tree4_MSE <- mean((crimedata.val$Crime - val_tree4)^2)

paste("Model 4: Police Expenditure", val_tree4_MSE)
```

```
## [1] "Model 4: Police Expenditure 41276.1130555555"
```

```r
# Model 5
val_tree5 <- predict(reg_tree5, crimedata.val)
val_tree5_MSE <- mean((crimedata.val$Crime - val_tree5)^2)

paste("Model 5: Presence of Males", val_tree5_MSE)
```

```
## [1] "Model 5: Presence of Males 239245.948622449"
```

```r
# Model Baseline
val_treeB <- predict(reg_treeB, crimedata.val)
val_treeB_MSE <- mean((crimedata.val$Crime - val_treeB)^2)

paste("Baseline Model: All Features", val_treeB_MSE)
```

```
## [1] "Baseline Model: All Features 95054.58"
```

From the looks of it, even though the MSE for all models are high, when compared to the baseline of all factors in the regression, the model of Crime Rate Based on Previous Per Capita Expenditure on Police Protection seems to have performed the most optimally. Henceforth, we will get the performance (MSE) of the model (reg_tree4) on the test set.

```r
# Model 4 (Previous Crime History)
crime_model_test <- predict(reg_tree4, crimedata.test)
crime_model_MSE <- mean((crimedata.val$Crime - crime_model_test)^2)
```

```
## Warning in crimedata.val$Crime - crime_model_test: longer object length is not
## a multiple of shorter object length
```

```r
paste("Final Model Score in MSE:", crime_model_MSE)
```

```
## [1] "Final Model Score in MSE: 135821.388444444"
```

The reason why Previous Per Capita Expenditure on Police Protection Model performed the best may be because it provides a historical estimate of a feature that is closely related to crime rates: police spending. It makes sense that the more spent on police protection, the more dangerous/vulnerable to crime a area is.

The per capita expenditure is the total expenditure divided by the total population of a given economy, hence the higher the number, it means that individuals of the population are spending more on police protection. By spending more on police protection, it is because civilians most likely suspect a higher rate of crime in the area.