

810_Team_8

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```
df <- fread("adult_revised.csv",stringsAsFactors = TRUE)

#Creating dummy variables, removing the first column and selected columns
dd <- dummy_cols(df, select_columns = c('Employment', 'Education', 'Marital_status','Occupation', 'Relationship', 'Race', 'Sex'),
                  remove_first_dummy = TRUE, remove_selected_columns = TRUE)

#Setting US as 1 and others as 0
dd$US<-ifelse(dd$Country == 'United-States',1,0)
dd$Country <- NULL

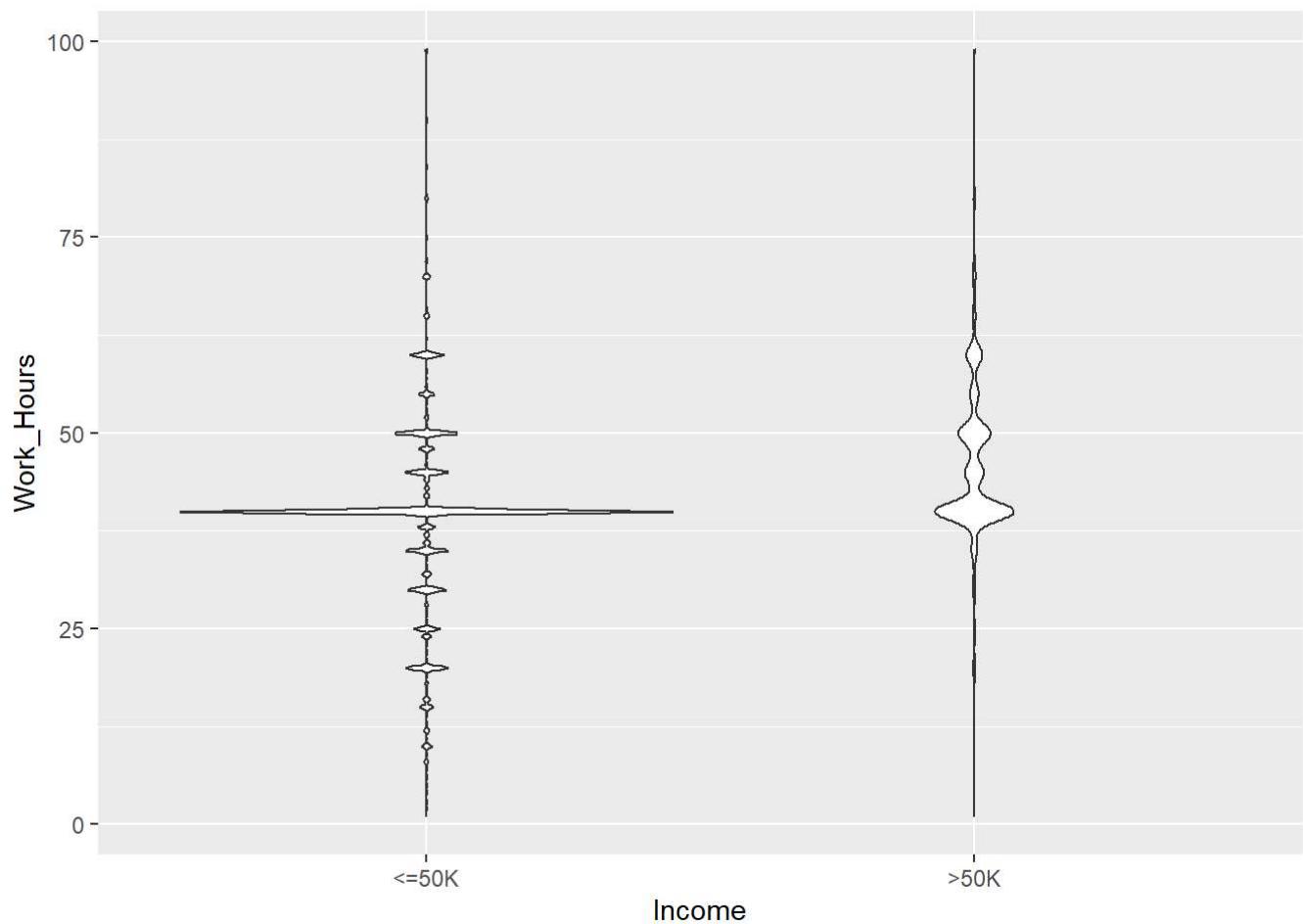
#rearranges column order so that income is placed in the last row
dd <- dd[,c(1,2,3,4,5,6,8:58,7)]
names(dd) <- make.names(names(dd))

#Creating train and test set and defining formula
id <- createDataPartition(dd$Income, p = 0.8, list = FALSE)
train<-dd[id, ]
test<-dd[-id, ]
formula <- as.formula(Income ~ .)

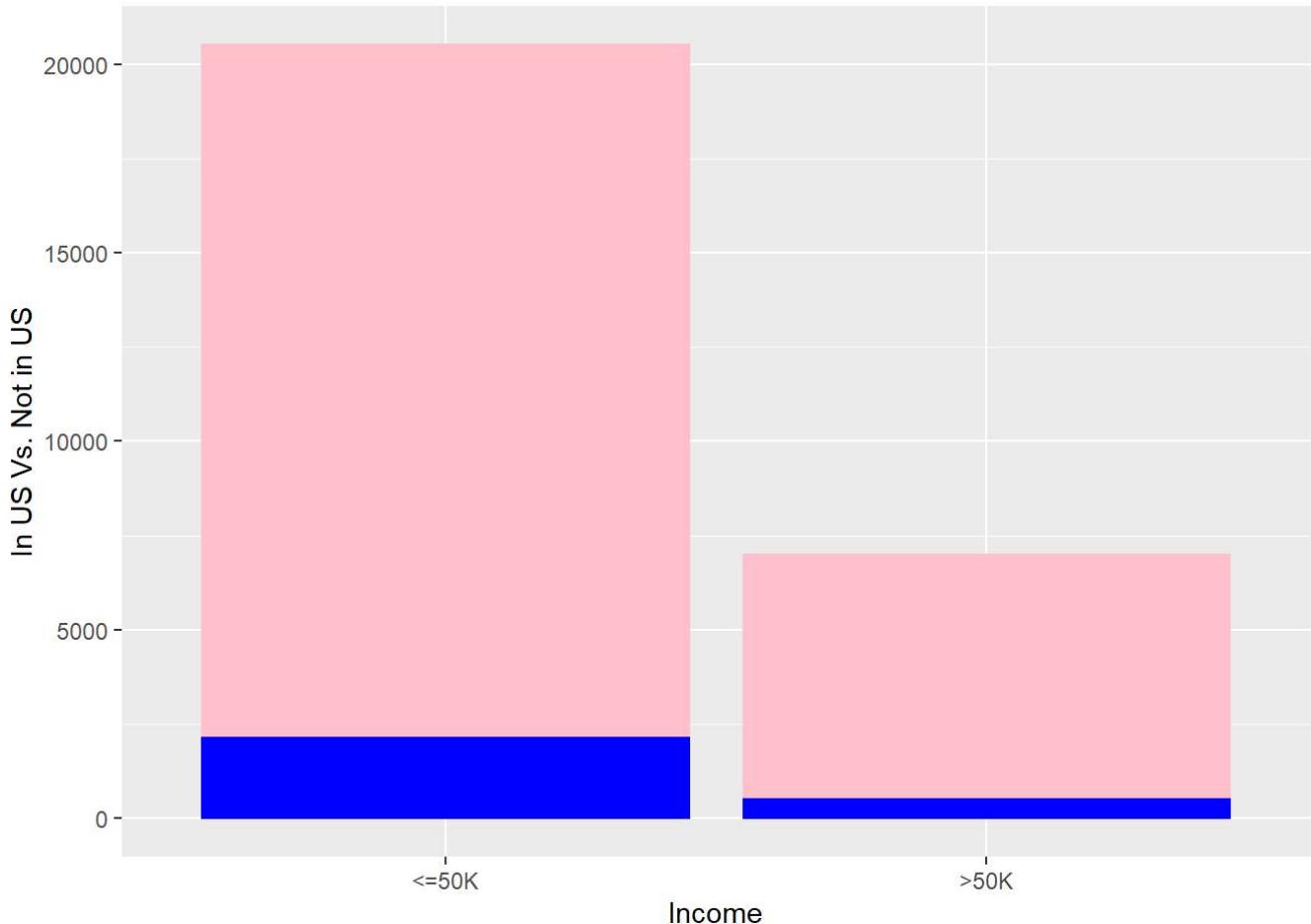
train2 <- train
test2 <- test
test2$Income <- ifelse(test2$Income == "<=50K", 0, 1)
train2$Income <- ifelse(train2$Income == "<=50K", 0, 1)
y_train <- train2$Income
y_test <- test2$Income
X_train <- model.matrix(as.formula(Income~.),train)[,-1]
X_test <- model.matrix(as.formula(Income~.),test)[,-1]

#Exploring with the Data

#Violin Graph of Income vs Work Hours
ggplot(data=dd ,mapping=aes(y=Work_Hours,x=Income))+  
  geom_violin()
```



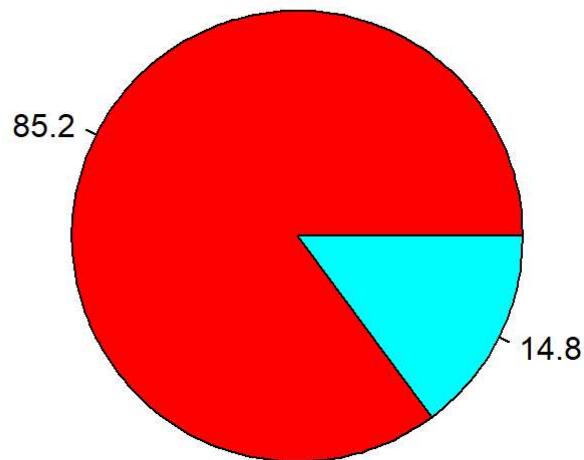
```
#Bar Graph of US vs non-US citizens
dd2 <- dd
dd2$INUS<-ifelse(dd2$US == '1',1,0)
dd2$NOTUS<-ifelse(dd2$US == '0',1,0)
ggplot(data=dd2)+  
  geom_col(mapping=aes(y=INUS,x=Income),color="pink")+
  geom_col(mapping=aes(y=NOTUS,x=Income),color="blue")+
  ylab("In US Vs. Not in US")
```



#Pie Chart 1

```
dd2$MFIVEK<-ifelse(dd2$Sex_Male=='1'&dd2$Income=='>50K',1,0)
dd2$FFIVEK<-ifelse(dd2$Sex_Male=='0'&dd2$Income=='>50K',1,0)
dd2$MFIVEK2<-ifelse(dd2$Sex_Male=='1'&dd2$Income=='<=50K',1,0)
dd2$FFIVEK2<-ifelse(dd2$Sex_Male=='0'&dd2$Income=='<=50K',1,0)

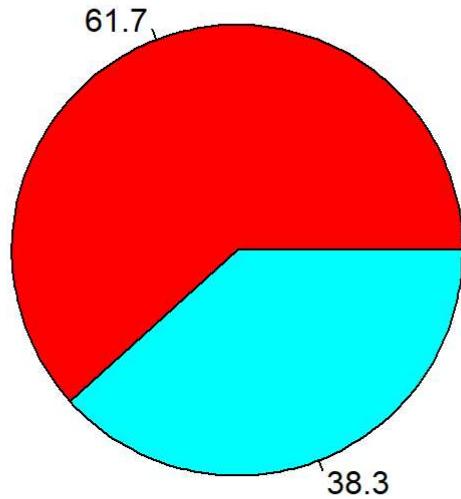
greater_50k <- c(sum(dd2$MFIVEK),sum(dd2$FFIVEK))
piepercent <- round(100*greater_50k/sum(greater_50k), 1)
labels <- c('Male > 50k','Female > 50k')
print(pie(greater_50k, labels = piepercent, main = 'Male Vs. Female > 50k', col = rainbow(length(greater_50k))))
```

Male Vs. Female > 50k

```
## NULL
```

```
#Pie Chart 2
under_50k <- c(sum(dd2$MFIVEK2),sum(dd2$FFIVEK2))
piepercent <- round(100*under_50k/sum(under_50k), 1)
labels <- c('Male <= 50k','Female <= 50k')
print(pie(under_50k, labels = piepercent, main = 'Male Vs. Female under 50k', col = rainbow(length(under_50k))))
```

Male Vs. Female under 50k



```
## NULL
```

```
#Point Plot with Education on Age
print(ggplot(dd, aes(x = Age, y = Years_of_education, color = Income))+geom_point(position =
"jitter")+
  labs(x = "Age", y = "Years of Education", color = "Income"))
```

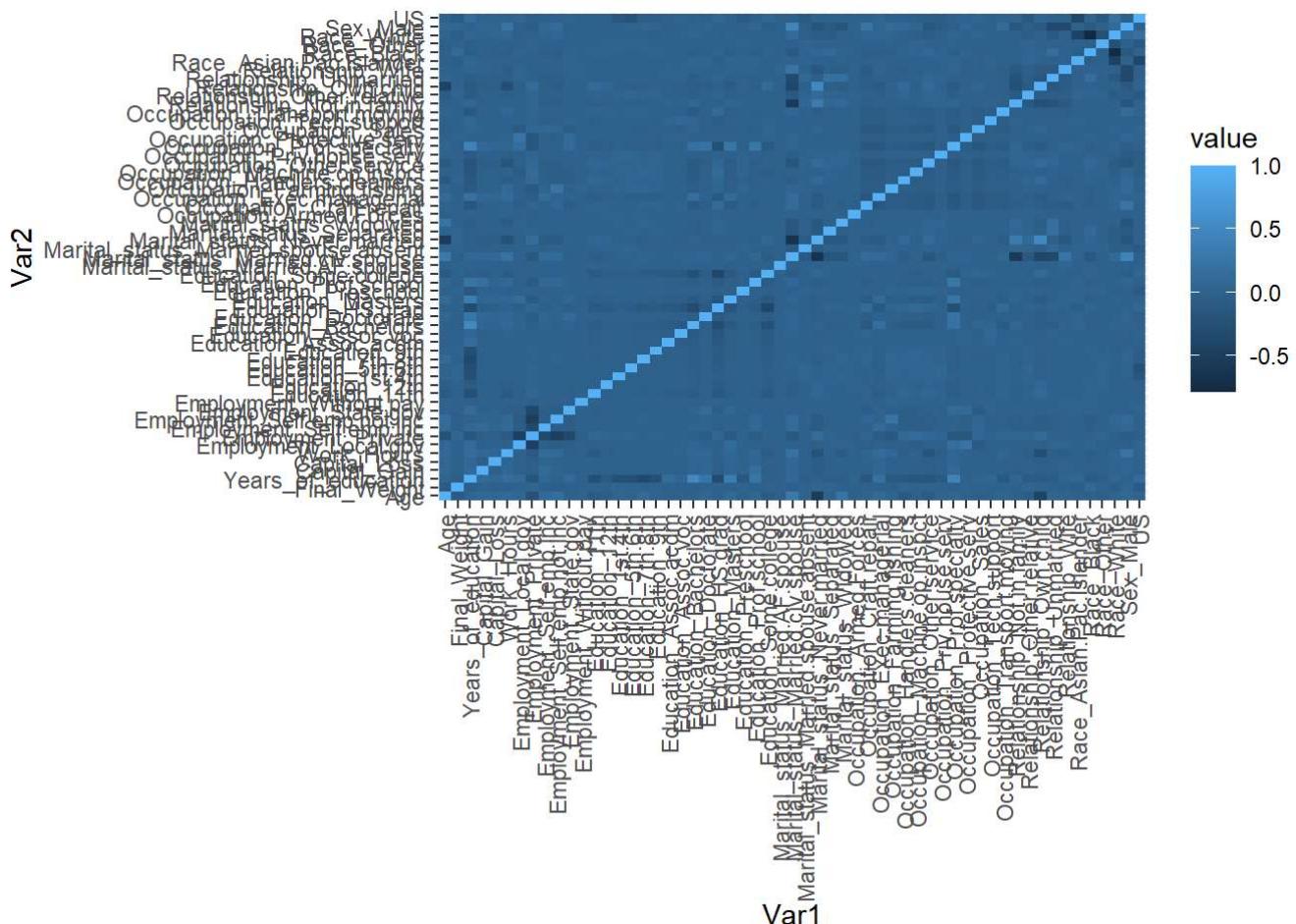


```
#Correlation Heatmap
```

```
ddf <- dd
ddf$Income <- NULL
cormat <- round(cor(ddf),2)
melted_cormat <- melt(cormat)
```

```
## Warning in melt(cormat): The melt generic in data.table has been passed a matrix
## and will attempt to redirect to the relevant reshape2 method; please note that
## reshape2 is deprecated, and this redirection is now deprecated as well. To
## continue using melt methods from reshape2 while both libraries are attached,
## e.g. melt.list, you can prepend the namespace like reshape2::melt(cormat). In
## the next version, this warning will become an error.
```

```
print(ggplot(data = melted_cormat, aes(x=Var1, y=Var2, fill=value)) +
  geom_tile() + theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1)))
```



```
#Simple Linear Regression
fit.lm <- lm(formula, train2)
yhat.train.lm <- predict(fit.lm)
mse.train.lm <- mean((y_train - yhat.train.lm)^2)
print(mse.train.lm)
```

```
## [1] 0.1179064
```

```
#Lasso
fit_lasso <- cv.glmnet(X_train, y_train, family = "binomial", alpha = 1, nfolds = 10)
## Predict responses
y_train_hat <- predict(fit_lasso,newx=X_train,type='response')
y_test_hat <- predict(fit_lasso,newx=X_test,type='response')
mse.min <- fit_lasso$cvm[which(fit_lasso$lambda == fit_lasso$lambda.min)]
print(mse.min)
```

```
## [1] 0.6505893
```

```
## Compute MSEs

#ridge
fit_ridge <- cv.glmnet(X_train, y_train, family = "binomial", alpha = 0, nfolds = 10)
## Predict responses
y_train_rid <- predict(fit_ridge,newx=X_train,type='response')
y_test_rid <- predict(fit_ridge,newx=X_test,type='response')
mse.min_rid <- fit_ridge$cvm[which(fit_ridge$lambda == fit_ridge$lambda.min)]
print(mse.min_rid)
```

```
## [1] 0.6759002
```

```
#mse_rid <- data.table(Lambda = fit_ridge$Lambda,mse = mse_train_rid,dataset = "Train")
#mse_rid <- rbind(mse_rid, data.table(Lambda = fit_ridge$Lambda,mse = mse_test_rid,dataset =
"Test"))

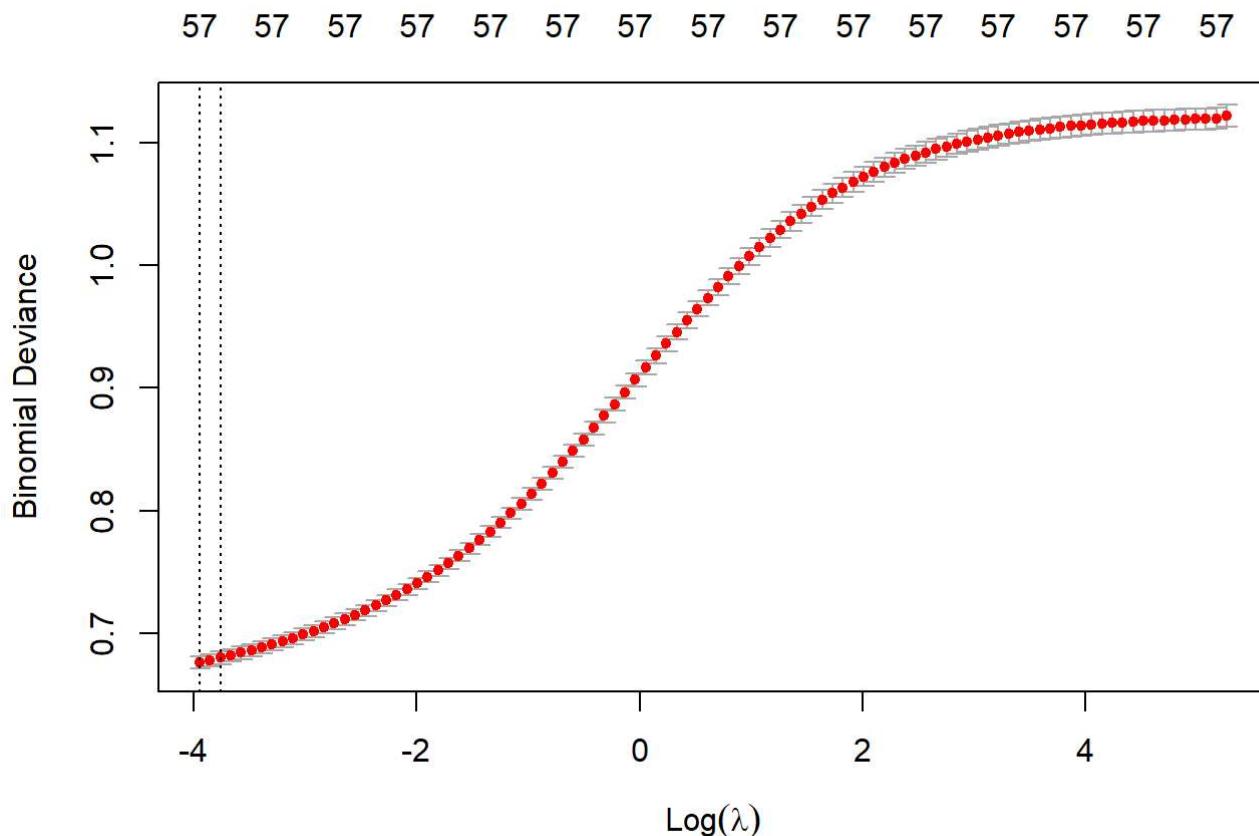
min_mse_rid<-fit_ridge$lambda.min
print(min_mse_rid)
```

```
## [1] 0.01933403
```

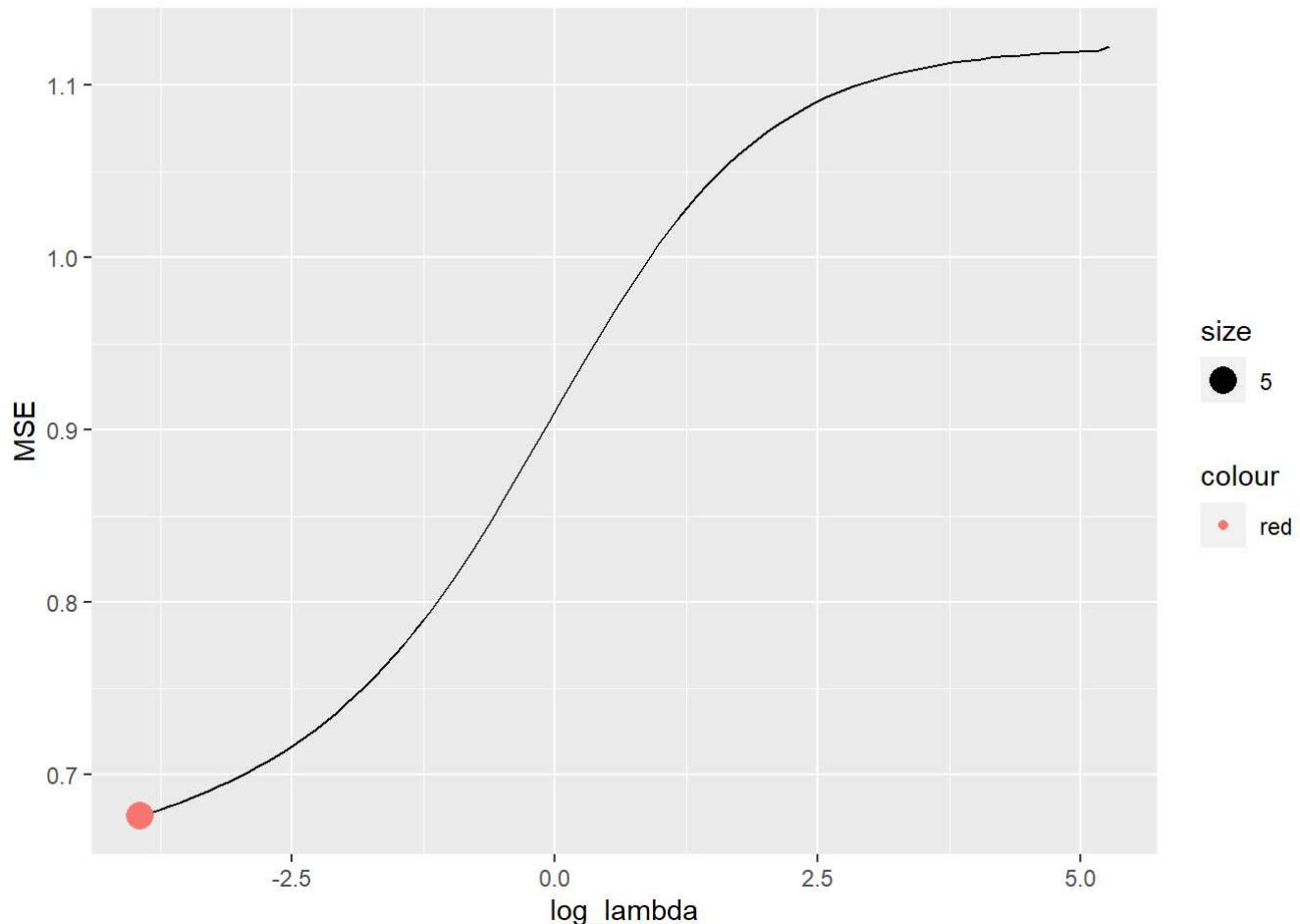
```
print(log(min_mse_rid))
```

```
## [1] -3.945889
```

```
plot(fit_ridge)
```



```
dd_mse_rid <- data.table(log_lambda = log(fit_ridge$lambda), mse = fit_ridge$cvm)
ggplot(dd_mse_rid, aes(log_lambda, mse)) + geom_line() + geom_point(aes(x=log(fit_ridge$lambda.min),y=fit_ridge$cvm[which(fit_ridge$lambda == fit_ridge$lambda.min)]),colour='red',size=5)
+ scale_y_continuous("MSE")
```



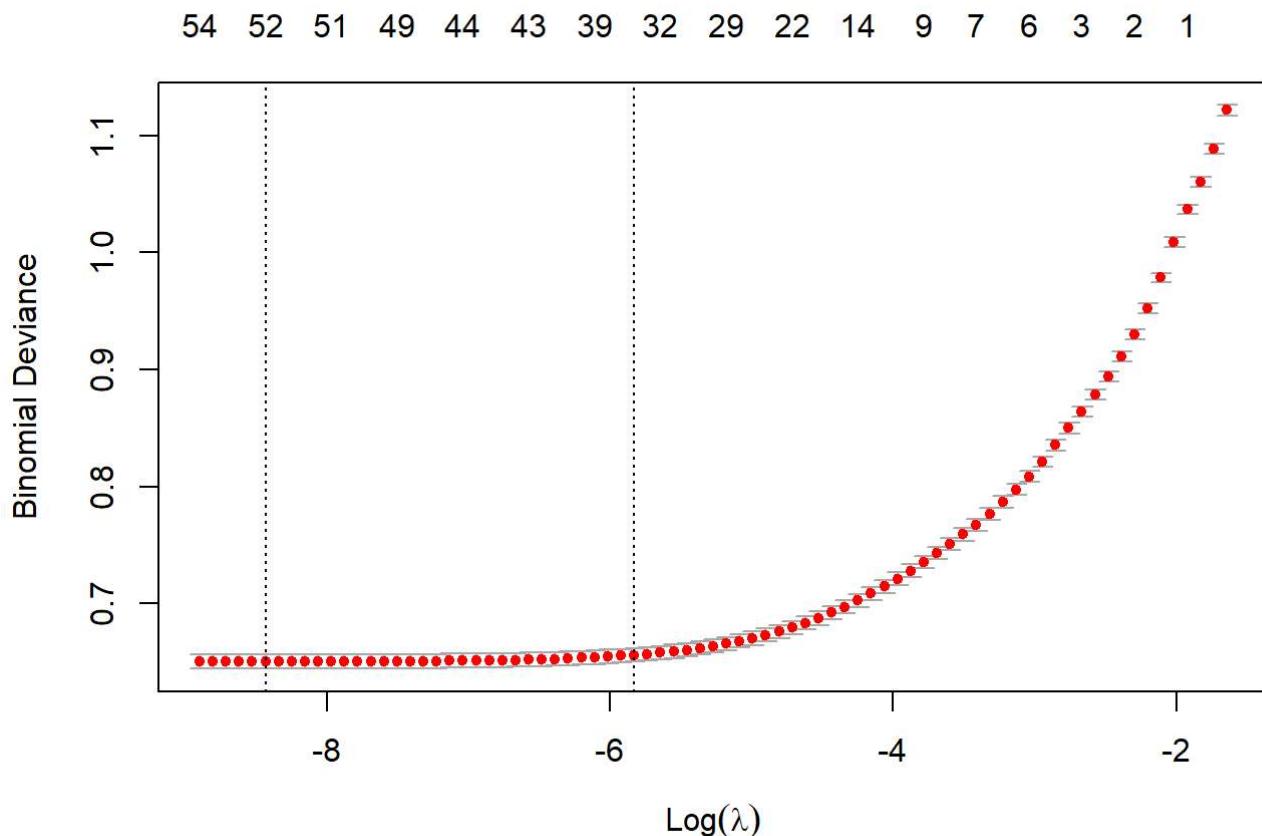
```
####Lasso  
min_mse_las<-fit_lasso$lambda.min  
print(min_mse_las)
```

```
## [1] 0.0002171838
```

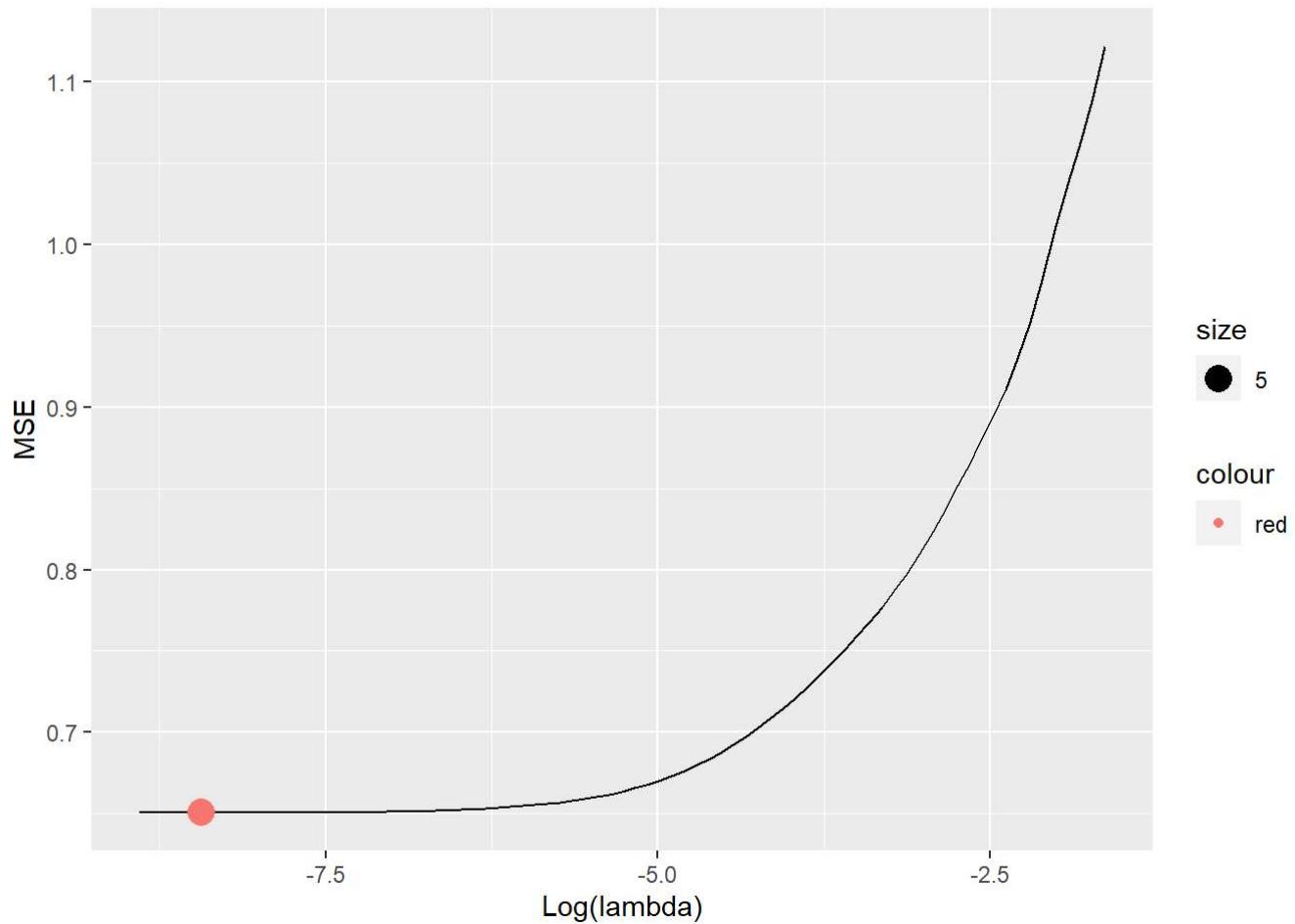
```
print(log(min_mse_las))
```

```
## [1] -8.434767
```

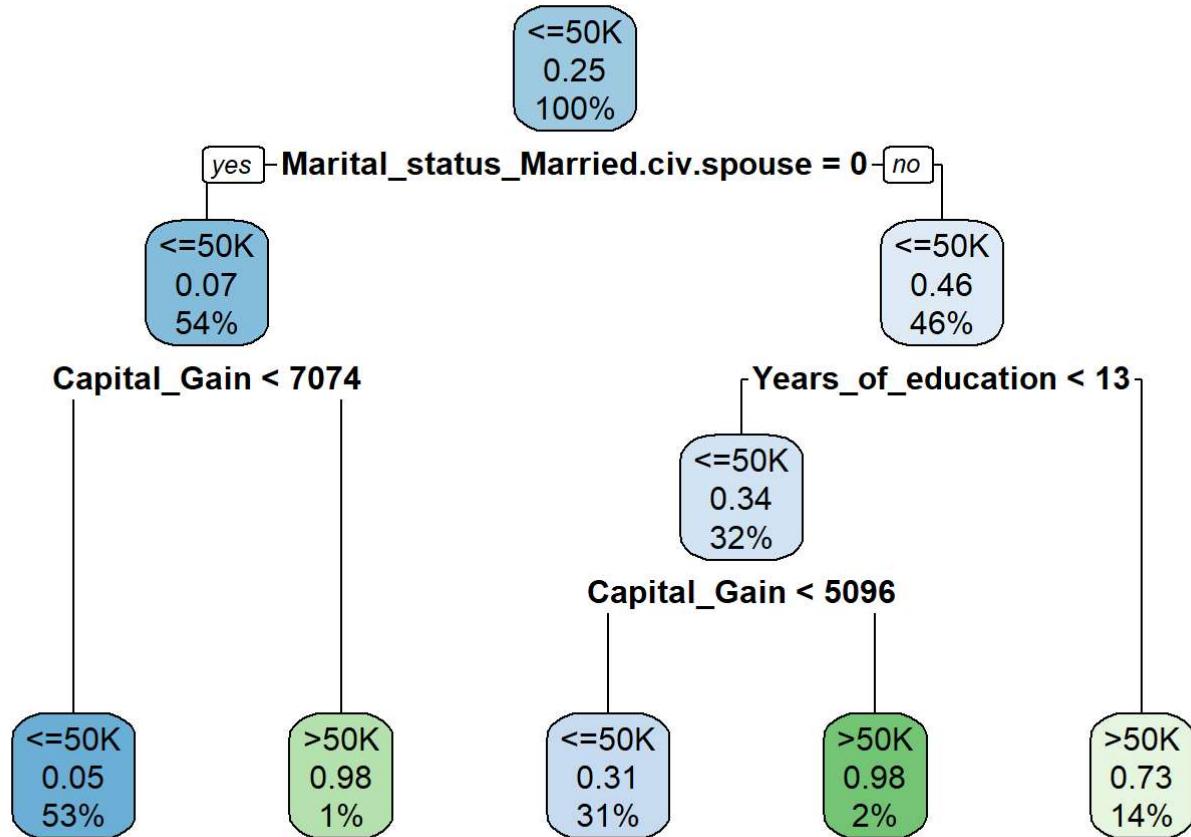
```
#mse_Las <- data.table(Lambda = fit_Lasso$Lambda,mse = mse_train_Las,dataset = "Train")  
#mse_Las <- rbind(mse_Las, data.table(Lambda = fit_Lasso$Lambda,mse = mse_test_Las,dataset =  
#"Test"))  
plot(fit_lasso)
```



```
#plotting
dd_mse <- data.table(lambda = log(fit_lasso$lambda), mse = fit_lasso$cvm)
ggplot(dd_mse, aes(lambda, mse)) + geom_line() + geom_point(aes(x=log(fit_lasso$lambda.min),y=fit_lasso$cvm[which(fit_lasso$lambda == fit_lasso$lambda.min)]),colour='red',size=5)) + scale_y_continuous("MSE") + scale_x_continuous("Log(lambda)")
```



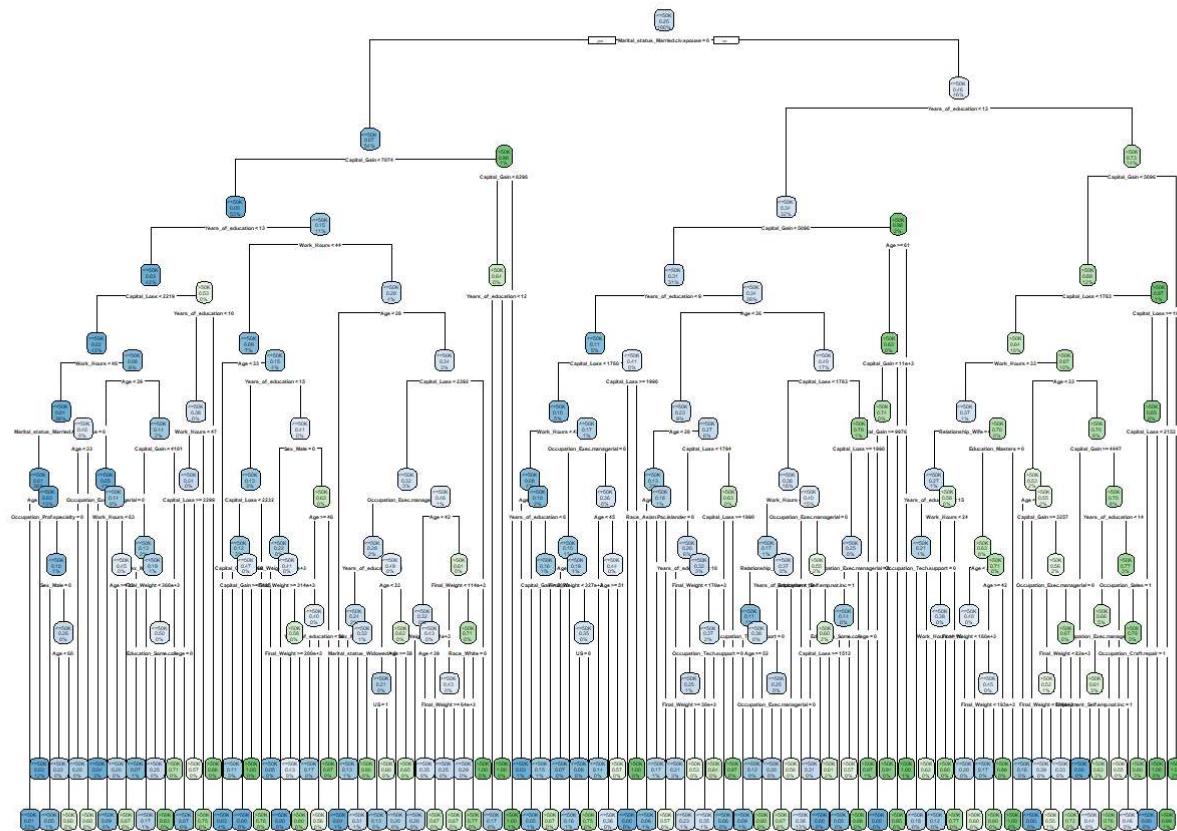
```
#Classification Tree  
#making a decision tree  
dtm <- rpart(formula, train, method="class", control=rpart.control(cp=0.01,minsplit =0.01, mi  
nbucket = 5, maxdepth = 10 ))  
rpart.plot(dtm)
```



```

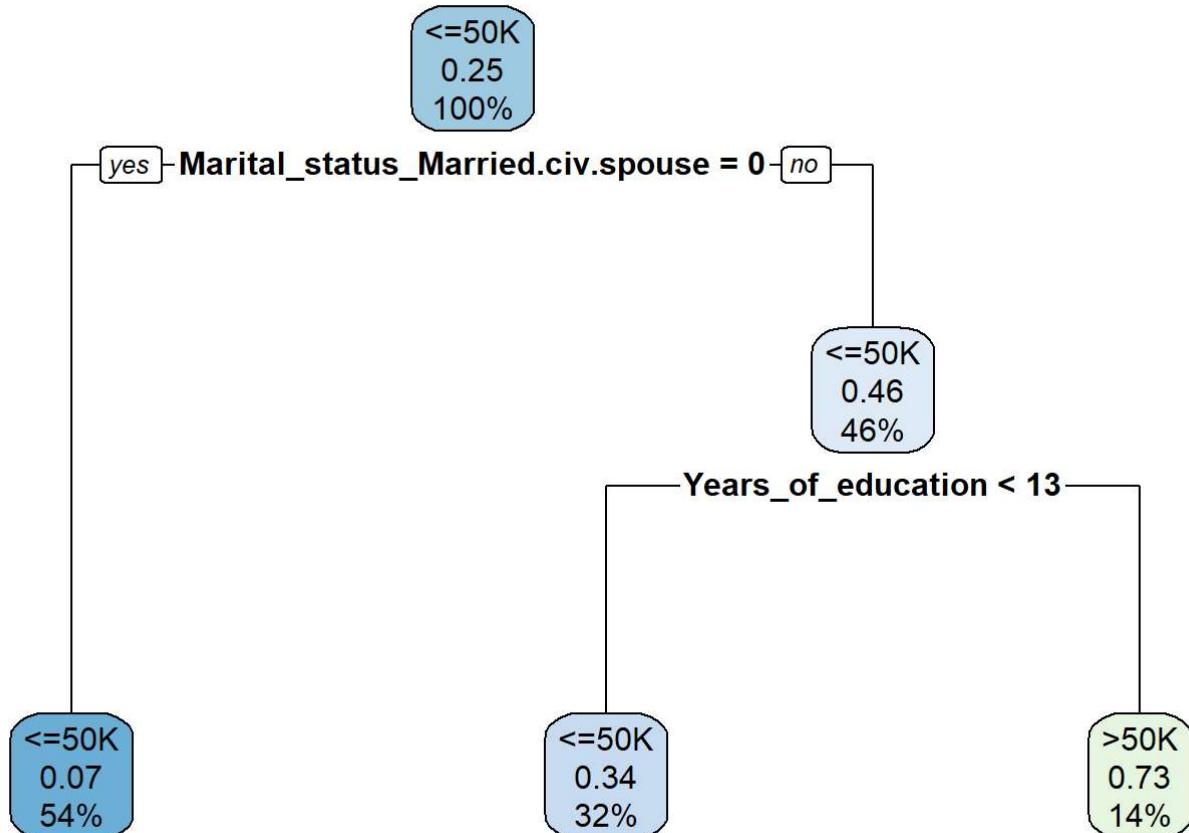
#adjustment in cp
#Overfitting
dtm_2 <- rpart(formula, train, method="class",control=rpart.control(cp=0,minsplit =0.01, minbucket = 5, maxdepth = 10 ))
rpart.plot(dtm_2)
  
```

```
## Warning: labs do not fit even at cex 0.15, there may be some overplotting
```



#Underfitting

```
dtm_3 <- rpart(formula, train, method="class",control=rpart.control(cp=0.1,minsplit =0.1, minbucket = 5, maxdepth = 10 ))
rpart.plot(dtm_3)
```



```
#predicting a result and printing MSE
yhat4.tree <- predict(dtm, train2)
print(mse.tree <- mean((yhat4.tree - y_train) ^ 2))
```

```
## [1] 0.3806214
```

```
#Initialize instance of random forest
#Base Model
randomForest(formula, data = train, do.trace=T, mtry=10, keep.inbag=TRUE)
```

```
## ntree      OOB      1      2
## 1: 18.33% 12.07% 37.17%
## 2: 17.89% 10.99% 38.74%
## 3: 17.75% 10.57% 39.58%
## 4: 17.58% 9.84% 40.97%
## 5: 17.25% 9.52% 40.65%
## 6: 17.16% 9.51% 40.37%
## 7: 16.65% 9.02% 39.79%
## 8: 16.35% 8.76% 39.33%
## 9: 16.26% 8.62% 39.31%
## 10: 16.22% 8.55% 39.37%
## 11: 16.20% 8.53% 39.37%
## 12: 15.90% 8.23% 39.04%
## 13: 15.76% 8.01% 39.13%
## 14: 15.49% 7.78% 38.75%
## 15: 15.36% 7.75% 38.35%
## 16: 15.20% 7.57% 38.27%
## 17: 15.06% 7.53% 37.79%
## 18: 15.14% 7.48% 38.23%
## 19: 15.08% 7.48% 37.99%
## 20: 14.94% 7.33% 37.92%
## 21: 14.80% 7.15% 37.87%
## 22: 14.70% 7.06% 37.76%
## 23: 14.75% 7.02% 38.07%
## 24: 14.77% 6.91% 38.49%
## 25: 14.70% 6.91% 38.19%
## 26: 14.57% 6.79% 38.04%
## 27: 14.61% 6.86% 37.99%
## 28: 14.68% 6.87% 38.24%
## 29: 14.67% 6.89% 38.16%
## 30: 14.61% 6.78% 38.26%
## 31: 14.67% 6.83% 38.32%
## 32: 14.60% 6.79% 38.17%
## 33: 14.56% 6.76% 38.09%
## 34: 14.51% 6.70% 38.07%
## 35: 14.55% 6.74% 38.11%
## 36: 14.54% 6.70% 38.17%
## 37: 14.60% 6.75% 38.29%
## 38: 14.67% 6.80% 38.41%
## 39: 14.70% 6.89% 38.26%
## 40: 14.57% 6.80% 38.04%
## 41: 14.67% 6.80% 38.41%
## 42: 14.59% 6.79% 38.12%
## 43: 14.54% 6.70% 38.21%
## 44: 14.44% 6.64% 37.96%
## 45: 14.40% 6.67% 37.71%
## 46: 14.50% 6.72% 37.96%
## 47: 14.40% 6.64% 37.84%
## 48: 14.39% 6.57% 37.99%
## 49: 14.41% 6.62% 37.92%
## 50: 14.45% 6.64% 38.04%
## 51: 14.45% 6.66% 37.97%
## 52: 14.34% 6.54% 37.87%
## 53: 14.36% 6.62% 37.72%
## 54: 14.40% 6.71% 37.62%
## 55: 14.46% 6.75% 37.72%
## 56: 14.42% 6.65% 37.87%
```

```
## 57: 14.39% 6.63% 37.81%
## 58: 14.41% 6.65% 37.82%
## 59: 14.39% 6.67% 37.67%
## 60: 14.36% 6.62% 37.72%
## 61: 14.33% 6.58% 37.71%
## 62: 14.38% 6.66% 37.69%
## 63: 14.34% 6.59% 37.71%
## 64: 14.34% 6.64% 37.59%
## 65: 14.33% 6.60% 37.67%
## 66: 14.29% 6.51% 37.79%
## 67: 14.19% 6.42% 37.61%
## 68: 14.22% 6.44% 37.69%
## 69: 14.18% 6.50% 37.36%
## 70: 14.22% 6.51% 37.51%
## 71: 14.24% 6.51% 37.57%
## 72: 14.28% 6.53% 37.69%
## 73: 14.28% 6.51% 37.72%
## 74: 14.36% 6.57% 37.86%
## 75: 14.29% 6.57% 37.61%
## 76: 14.28% 6.55% 37.59%
## 77: 14.27% 6.48% 37.79%
## 78: 14.32% 6.54% 37.77%
## 79: 14.35% 6.58% 37.81%
## 80: 14.33% 6.61% 37.62%
## 81: 14.33% 6.55% 37.77%
## 82: 14.30% 6.53% 37.74%
## 83: 14.26% 6.47% 37.77%
## 84: 14.31% 6.54% 37.77%
## 85: 14.31% 6.54% 37.72%
## 86: 14.33% 6.59% 37.69%
## 87: 14.32% 6.56% 37.72%
## 88: 14.30% 6.55% 37.67%
## 89: 14.24% 6.50% 37.61%
## 90: 14.27% 6.53% 37.62%
## 91: 14.21% 6.46% 37.57%
## 92: 14.28% 6.58% 37.52%
## 93: 14.28% 6.60% 37.46%
## 94: 14.29% 6.59% 37.52%
## 95: 14.28% 6.56% 37.57%
## 96: 14.23% 6.55% 37.41%
## 97: 14.25% 6.57% 37.42%
## 98: 14.26% 6.58% 37.41%
## 99: 14.21% 6.51% 37.47%
## 100: 14.19% 6.51% 37.36%
## 101: 14.20% 6.48% 37.47%
## 102: 14.21% 6.52% 37.42%
## 103: 14.17% 6.49% 37.36%
## 104: 14.17% 6.49% 37.36%
## 105: 14.18% 6.54% 37.22%
## 106: 14.17% 6.54% 37.19%
## 107: 14.20% 6.58% 37.17%
## 108: 14.16% 6.57% 37.09%
## 109: 14.18% 6.59% 37.06%
## 110: 14.15% 6.59% 36.96%
## 111: 14.21% 6.62% 37.11%
## 112: 14.17% 6.62% 36.97%
## 113: 14.19% 6.59% 37.12%
## 114: 14.19% 6.60% 37.06%
```

```
## 115: 14.24% 6.65% 37.14%
## 116: 14.22% 6.62% 37.14%
## 117: 14.19% 6.59% 37.09%
## 118: 14.21% 6.63% 37.07%
## 119: 14.22% 6.66% 37.04%
## 120: 14.21% 6.63% 37.07%
## 121: 14.19% 6.62% 37.02%
## 122: 14.15% 6.59% 36.96%
## 123: 14.11% 6.59% 36.81%
## 124: 14.17% 6.63% 36.91%
## 125: 14.17% 6.63% 36.91%
## 126: 14.14% 6.57% 36.99%
## 127: 14.13% 6.55% 36.99%
## 128: 14.14% 6.55% 37.04%
## 129: 14.15% 6.57% 37.01%
## 130: 14.12% 6.55% 36.97%
## 131: 14.13% 6.54% 37.02%
## 132: 14.18% 6.57% 37.12%
## 133: 14.14% 6.55% 37.04%
## 134: 14.09% 6.51% 36.96%
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## 140: 14.16% 6.53% 37.19%
## 141: 14.14% 6.52% 37.14%
## 142: 14.19% 6.53% 37.27%
## 143: 14.14% 6.49% 37.19%
## 144: 14.11% 6.46% 37.21%
## 145: 14.11% 6.50% 37.09%
## 146: 14.12% 6.48% 37.17%
## 147: 14.09% 6.46% 37.09%
## 148: 14.10% 6.46% 37.17%
## 149: 14.07% 6.46% 37.04%
## 150: 14.05% 6.42% 37.07%
## 151: 14.10% 6.49% 37.04%
## 152: 14.04% 6.43% 36.99%
## 153: 14.06% 6.48% 36.94%
## 154: 14.05% 6.47% 36.92%
## 155: 14.03% 6.47% 36.84%
## 156: 14.04% 6.49% 36.81%
## 157: 14.04% 6.48% 36.84%
## 158: 14.00% 6.46% 36.76%
## 159: 14.03% 6.49% 36.77%
## 160: 14.02% 6.44% 36.86%
## 161: 14.05% 6.48% 36.89%
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## 163: 14.03% 6.47% 36.84%
## 164: 13.99% 6.43% 36.79%
## 165: 14.02% 6.44% 36.87%
## 166: 14.04% 6.46% 36.91%
## 167: 14.04% 6.47% 36.87%
## 168: 14.02% 6.44% 36.89%
## 169: 14.07% 6.48% 36.96%
## 170: 14.06% 6.46% 36.97%
## 171: 14.03% 6.46% 36.87%
## 172: 14.06% 6.49% 36.87%
```

```
## 173: 14.05% 6.48% 36.91%
## 174: 14.05% 6.48% 36.91%
## 175: 14.05% 6.46% 36.96%
## 176: 14.07% 6.49% 36.94%
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## 178: 14.04% 6.46% 36.89%
## 179: 14.03% 6.46% 36.89%
## 180: 14.03% 6.49% 36.77%
## 181: 14.05% 6.50% 36.84%
## 182: 14.07% 6.47% 37.01%
## 183: 14.05% 6.47% 36.92%
## 184: 14.05% 6.46% 36.97%
## 185: 14.04% 6.42% 37.01%
## 186: 14.05% 6.47% 36.94%
## 187: 14.06% 6.47% 36.96%
## 188: 14.07% 6.46% 37.02%
## 189: 14.04% 6.43% 37.01%
## 190: 14.03% 6.43% 36.97%
## 191: 14.06% 6.46% 37.01%
## 192: 14.05% 6.44% 37.01%
## 193: 14.05% 6.45% 36.97%
## 194: 14.03% 6.47% 36.84%
## 195: 14.06% 6.48% 36.91%
## 196: 14.04% 6.49% 36.82%
## 197: 14.05% 6.50% 36.84%
## 198: 14.04% 6.50% 36.79%
## 199: 14.02% 6.51% 36.67%
## 200: 14.01% 6.49% 36.71%
## 201: 14.03% 6.52% 36.71%
## 202: 14.02% 6.49% 36.74%
## 203: 14.04% 6.51% 36.79%
## 204: 14.05% 6.50% 36.84%
## 205: 14.07% 6.53% 36.82%
## 206: 14.07% 6.52% 36.87%
## 207: 14.06% 6.54% 36.77%
## 208: 14.05% 6.53% 36.72%
## 209: 14.02% 6.52% 36.67%
## 210: 14.03% 6.49% 36.77%
## 211: 14.05% 6.49% 36.86%
## 212: 14.02% 6.49% 36.76%
## 213: 14.06% 6.51% 36.82%
## 214: 14.06% 6.51% 36.84%
## 215: 14.04% 6.52% 36.74%
## 216: 14.06% 6.53% 36.77%
## 217: 14.09% 6.57% 36.77%
## 218: 14.07% 6.55% 36.76%
## 219: 14.09% 6.56% 36.81%
## 220: 14.06% 6.55% 36.74%
## 221: 14.08% 6.55% 36.79%
## 222: 14.06% 6.54% 36.74%
## 223: 14.06% 6.54% 36.72%
## 224: 14.04% 6.54% 36.66%
## 225: 14.03% 6.53% 36.64%
## 226: 14.02% 6.52% 36.66%
## 227: 14.06% 6.54% 36.74%
## 228: 14.06% 6.52% 36.81%
## 229: 14.06% 6.53% 36.76%
## 230: 14.04% 6.51% 36.76%
```

```
## 231: 14.02% 6.48% 36.76%
## 232: 14.04% 6.52% 36.71%
## 233: 14.04% 6.51% 36.77%
## 234: 14.03% 6.50% 36.76%
## 235: 14.04% 6.50% 36.77%
## 236: 14.00% 6.52% 36.57%
## 237: 14.06% 6.55% 36.72%
## 238: 14.03% 6.51% 36.72%
## 239: 14.02% 6.48% 36.76%
## 240: 13.98% 6.47% 36.64%
## 241: 13.99% 6.47% 36.66%
## 242: 14.00% 6.47% 36.72%
## 243: 13.98% 6.48% 36.59%
## 244: 14.02% 6.48% 36.77%
## 245: 14.00% 6.46% 36.76%
## 246: 14.02% 6.47% 36.79%
## 247: 13.99% 6.46% 36.71%
## 248: 13.98% 6.46% 36.69%
## 249: 13.99% 6.46% 36.69%
## 250: 13.99% 6.46% 36.69%
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## 305: 14.07% 6.55% 36.77%
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## 321: 14.03% 6.51% 36.72%
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## 474: 13.94% 6.45% 36.52%
## 475: 13.96% 6.47% 36.56%
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## 478: 13.95% 6.47% 36.51%
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## 497: 13.90% 6.44% 36.41%
## 498: 13.92% 6.44% 36.51%
## 499: 13.92% 6.44% 36.47%
## 500: 13.91% 6.44% 36.44%

```

```

##
## Call:
## randomForest(formula = formula, data = train, do.trace = T, mtry = 10,      keep.inbag =
TRUE)
##           Type of random forest: classification
##                   Number of trees: 500
## No. of variables tried at each split: 10
##
##       OOB estimate of error rate: 13.91%
## Confusion matrix:
##       <=50K >50K class.error
## <=50K 16957 1167  0.06438976
## >50K    2189 3818  0.36440819

```

#Bagging Model, mtry = 57 because the last one is Income
randomForest(formula, data = train2, do.trace=T, mtry=57, keep.inbag=TRUE)

```
## Warning in randomForest.default(m, y, ...): The response has five or fewer  
## unique values. Are you sure you want to do regression?
```

##		Out-of-bag
## Tree		MSE %Var(y)
## 1		0.1773 94.81
## 2		0.1711 91.49
## 3		0.1621 86.68
## 4		0.155 82.89
## 5		0.1491 79.75
## 6		0.1437 76.87
## 7		0.1391 74.42
## 8		0.1349 72.17
## 9		0.1312 70.18
## 10		0.128 68.45
## 11		0.1256 67.15
## 12		0.123 65.79
## 13		0.1213 64.89
## 14		0.1196 63.95
## 15		0.1182 63.21
## 16		0.117 62.59
## 17		0.1161 62.11
## 18		0.1151 61.57
## 19		0.1142 61.10
## 20		0.1137 60.83
## 21		0.1128 60.35
## 22		0.1123 60.07
## 23		0.1118 59.79
## 24		0.1112 59.45
## 25		0.1107 59.23
## 26		0.1103 58.98
## 27		0.1099 58.80
## 28		0.1096 58.64
## 29		0.1093 58.47
## 30		0.1093 58.45
## 31		0.109 58.33
## 32		0.1087 58.16
## 33		0.1086 58.08
## 34		0.1084 57.95
## 35		0.1082 57.88
## 36		0.108 57.77
## 37		0.1079 57.71
## 38		0.1078 57.64
## 39		0.1077 57.58
## 40		0.1075 57.48
## 41		0.1074 57.45
## 42		0.1072 57.35
## 43		0.1072 57.33
## 44		0.107 57.24
## 45		0.1069 57.20
## 46		0.1069 57.15
## 47		0.1068 57.11
## 48		0.1067 57.09
## 49		0.1066 57.01
## 50		0.1064 56.93
## 51		0.1063 56.84
## 52		0.1062 56.79
## 53		0.106 56.71
## 54		0.1059 56.64
## 55		0.1057 56.56

##	56		0.1057	56.54	
##	57		0.1056	56.48	
##	58		0.1054	56.40	
##	59		0.1053	56.34	
##	60		0.1053	56.31	
##	61		0.1052	56.27	
##	62		0.1051	56.23	
##	63		0.1051	56.20	
##	64		0.1051	56.19	
##	65		0.105	56.18	
##	66		0.105	56.15	
##	67		0.105	56.16	
##	68		0.105	56.16	
##	69		0.1049	56.13	
##	70		0.1049	56.11	
##	71		0.1049	56.11	
##	72		0.1048	56.03	
##	73		0.1047	56.00	
##	74		0.1047	55.98	
##	75		0.1047	55.98	
##	76		0.1046	55.95	
##	77		0.1047	55.98	
##	78		0.1046	55.96	
##	79		0.1046	55.95	
##	80		0.1046	55.95	
##	81		0.1046	55.95	
##	82		0.1046	55.92	
##	83		0.1045	55.91	
##	84		0.1045	55.92	
##	85		0.1045	55.90	
##	86		0.1045	55.88	
##	87		0.1044	55.85	
##	88		0.1044	55.86	
##	89		0.1044	55.83	
##	90		0.1044	55.82	
##	91		0.1044	55.83	
##	92		0.1043	55.80	
##	93		0.1043	55.78	
##	94		0.1042	55.75	
##	95		0.1042	55.73	
##	96		0.1042	55.72	
##	97		0.1041	55.69	
##	98		0.1041	55.69	
##	99		0.1041	55.69	
##	100		0.1041	55.67	
##	101		0.1041	55.66	
##	102		0.1041	55.67	
##	103		0.1041	55.67	
##	104		0.1041	55.65	
##	105		0.104	55.61	
##	106		0.1039	55.59	
##	107		0.1039	55.58	
##	108		0.1039	55.59	
##	109		0.1039	55.57	
##	110		0.1039	55.55	
##	111		0.1039	55.55	
##	112		0.1038	55.53	
##	113		0.1038	55.52	

## 114	0.1038	55.53
## 115	0.1039	55.55
## 116	0.1039	55.56
## 117	0.1039	55.55
## 118	0.1038	55.54
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## 120	0.1039	55.55
## 121	0.1038	55.52
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## 126	0.1037	55.47
## 127	0.1037	55.45
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## 265	0.1031	55.16
## 266	0.1031	55.16
## 267	0.1031	55.16
## 268	0.1031	55.15
## 269	0.1031	55.15
## 270	0.1031	55.15
## 271	0.1031	55.14
## 272	0.1031	55.15
## 273	0.1031	55.14
## 274	0.1031	55.15
## 275	0.1031	55.15
## 276	0.1031	55.16
## 277	0.1031	55.15
## 278	0.1031	55.16
## 279	0.1031	55.17
## 280	0.1031	55.17
## 281	0.1032	55.17
## 282	0.1032	55.17
## 283	0.1032	55.17
## 284	0.1031	55.17
## 285	0.1032	55.17
## 286	0.1032	55.18
## 287	0.1031	55.16

## 288	0.1032	55.17
## 289	0.1032	55.17
## 290	0.1031	55.16
## 291	0.1031	55.16
## 292	0.1031	55.16
## 293	0.1031	55.16
## 294	0.1031	55.15
## 295	0.1031	55.15
## 296	0.1031	55.16
## 297	0.1031	55.15
## 298	0.1031	55.15
## 299	0.1031	55.14
## 300	0.1031	55.14
## 301	0.1031	55.14
## 302	0.1031	55.15
## 303	0.1031	55.16
## 304	0.1031	55.15
## 305	0.1031	55.14
## 306	0.1031	55.13
## 307	0.1031	55.14
## 308	0.1031	55.14
## 309	0.1031	55.14
## 310	0.1031	55.14
## 311	0.1031	55.14
## 312	0.1031	55.14
## 313	0.1031	55.14
## 314	0.1031	55.14
## 315	0.1031	55.13
## 316	0.1031	55.14
## 317	0.1031	55.14
## 318	0.1031	55.13
## 319	0.1031	55.13
## 320	0.1031	55.13
## 321	0.1031	55.12
## 322	0.1031	55.13
## 323	0.1031	55.14
## 324	0.1031	55.14
## 325	0.1031	55.14
## 326	0.1031	55.14
## 327	0.1031	55.13
## 328	0.1031	55.14
## 329	0.1031	55.14
## 330	0.1031	55.13
## 331	0.1031	55.13
## 332	0.1031	55.13
## 333	0.1031	55.12
## 334	0.103	55.12
## 335	0.1031	55.12
## 336	0.1031	55.13
## 337	0.1031	55.13
## 338	0.1031	55.13
## 339	0.1031	55.13
## 340	0.1031	55.13
## 341	0.1031	55.13
## 342	0.1031	55.14
## 343	0.1031	55.14
## 344	0.1031	55.13
## 345	0.1031	55.13

## 346	0.1031	55.13
## 347	0.1031	55.12
## 348	0.103	55.11
## 349	0.103	55.12
## 350	0.103	55.11
## 351	0.103	55.11
## 352	0.103	55.11
## 353	0.103	55.11
## 354	0.103	55.10
## 355	0.103	55.10
## 356	0.103	55.10
## 357	0.103	55.09
## 358	0.103	55.09
## 359	0.103	55.09
## 360	0.103	55.09
## 361	0.103	55.08
## 362	0.103	55.08
## 363	0.103	55.08
## 364	0.103	55.08
## 365	0.103	55.07
## 366	0.103	55.07
## 367	0.103	55.07
## 368	0.103	55.07
## 369	0.103	55.07
## 370	0.103	55.08
## 371	0.103	55.08
## 372	0.103	55.07
## 373	0.103	55.07
## 374	0.103	55.07
## 375	0.103	55.07
## 376	0.103	55.07
## 377	0.103	55.07
## 378	0.103	55.07
## 379	0.103	55.08
## 380	0.103	55.08
## 381	0.103	55.08
## 382	0.103	55.07
## 383	0.103	55.07
## 384	0.103	55.07
## 385	0.103	55.08
## 386	0.103	55.08
## 387	0.103	55.07
## 388	0.103	55.08
## 389	0.103	55.07
## 390	0.103	55.07
## 391	0.103	55.07
## 392	0.103	55.08
## 393	0.103	55.08
## 394	0.103	55.09
## 395	0.103	55.09
## 396	0.103	55.09
## 397	0.103	55.09
## 398	0.103	55.08
## 399	0.103	55.08
## 400	0.103	55.08
## 401	0.103	55.09
## 402	0.103	55.08
## 403	0.103	55.08

## 404	0.103	55.07
## 405	0.103	55.07
## 406	0.103	55.07
## 407	0.103	55.07
## 408	0.103	55.07
## 409	0.103	55.08
## 410	0.103	55.08
## 411	0.103	55.08
## 412	0.103	55.08
## 413	0.103	55.08
## 414	0.103	55.08
## 415	0.103	55.08
## 416	0.103	55.07
## 417	0.103	55.07
## 418	0.103	55.07
## 419	0.103	55.07
## 420	0.103	55.07
## 421	0.103	55.07
## 422	0.1029	55.06
## 423	0.103	55.06
## 424	0.1029	55.06
## 425	0.1029	55.06
## 426	0.1029	55.06
## 427	0.1029	55.06
## 428	0.1029	55.06
## 429	0.1029	55.06
## 430	0.1029	55.06
## 431	0.103	55.07
## 432	0.103	55.07
## 433	0.103	55.06
## 434	0.103	55.07
## 435	0.1029	55.06
## 436	0.1029	55.06
## 437	0.1029	55.06
## 438	0.1029	55.06
## 439	0.1029	55.05
## 440	0.1029	55.06
## 441	0.1029	55.06
## 442	0.1029	55.06
## 443	0.1029	55.05
## 444	0.1029	55.05
## 445	0.1029	55.05
## 446	0.1029	55.05
## 447	0.1029	55.05
## 448	0.1029	55.05
## 449	0.1029	55.05
## 450	0.1029	55.05
## 451	0.1029	55.05
## 452	0.1029	55.05
## 453	0.1029	55.05
## 454	0.1029	55.05
## 455	0.1029	55.05
## 456	0.1029	55.05
## 457	0.1029	55.04
## 458	0.1029	55.04
## 459	0.1029	55.03
## 460	0.1029	55.02
## 461	0.1029	55.02

```

## 462 | 0.1029 55.02 |
## 463 | 0.1029 55.01 |
## 464 | 0.1029 55.01 |
## 465 | 0.1029 55.01 |
## 466 | 0.1028 55.01 |
## 467 | 0.1029 55.02 |
## 468 | 0.1029 55.02 |
## 469 | 0.1029 55.02 |
## 470 | 0.1029 55.02 |
## 471 | 0.1029 55.02 |
## 472 | 0.1029 55.02 |
## 473 | 0.1029 55.02 |
## 474 | 0.1028 55.01 |
## 475 | 0.1028 55.01 |
## 476 | 0.1028 55.01 |
## 477 | 0.1028 55.01 |
## 478 | 0.1028 55.01 |
## 479 | 0.1028 55.01 |
## 480 | 0.1029 55.01 |
## 481 | 0.1028 55.01 |
## 482 | 0.1028 55.01 |
## 483 | 0.1028 55.01 |
## 484 | 0.1028 55.00 |
## 485 | 0.1028 55.00 |
## 486 | 0.1028 55.00 |
## 487 | 0.1028 55.00 |
## 488 | 0.1028 55.00 |
## 489 | 0.1028 54.99 |
## 490 | 0.1028 54.99 |
## 491 | 0.1028 54.99 |
## 492 | 0.1028 54.99 |
## 493 | 0.1028 55.00 |
## 494 | 0.1028 55.00 |
## 495 | 0.1028 55.00 |
## 496 | 0.1028 55.00 |
## 497 | 0.1028 55.00 |
## 498 | 0.1028 54.99 |
## 499 | 0.1028 55.00 |
## 500 | 0.1028 54.99 |

```

```

##
## Call:
## randomForest(formula = formula, data = train2, do.trace = T,      mtry = 57, keep.inbag =
TRUE)
##           Type of random forest: regression
##           Number of trees: 500
## No. of variables tried at each split: 57
##
##           Mean of squared residuals: 0.1028199
##           % Var explained: 45.01

```

```

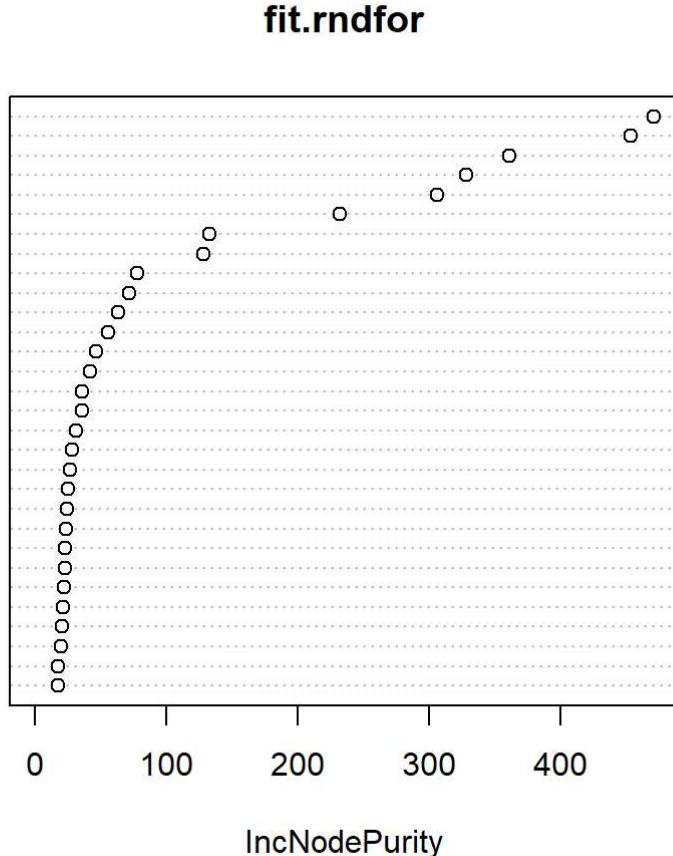
#Fitting the model and plotting the varImpPlot
fit.rndfor <- randomForest(formula, data = train2, mtry=10, do.trace=F)

```

```
## Warning in randomForest.default(m, y, ...): The response has five or fewer  
## unique values. Are you sure you want to do regression?
```

```
print(varImpPlot(fit.rndfor))
```

Capital_Gain
Marital_status_Married.civ.spouse
Age
Years_of_education
Final_Weight
Work_Hours
Marital_status_Never.married
Capital_Loss
Occupation_Exec.managerial
Sex_Male
Relationship_Not.in.family
Occupation_Prof.specialty
Education_Bachelors
Relationship_Own.child
Employment_Private
Relationship_Wife
Employment_Self.emp.not.inc
Relationship_Unmarried
Education_Masters
Occupation_Sales
Occupation_Other.service
Education_HS.grad
EDS
Race_White
Occupation_Craft.repair
Occupation_Tech.support
Employment_Self.emp.inc
Employment_Local.gov
Occupation_Farming.fishing
Education_Some.college



	IncNodePurity
##	3.617307e+02
## Age	3.066685e+02
## Final_Weight	3.284605e+02
## Years_of_education	4.714479e+02
## Capital_Gain	1.284757e+02
## Capital_Loss	2.321549e+02
## Work_Hours	2.014484e+01
## Employment_Local.gov	3.578570e+01
## Employment_Private	2.105498e+01
## Employment_Self.emp.inc	3.169223e+01
## Employment_Self.emp.not.inc	1.635410e+01
## Employment_State.gov	1.920413e-01
## Employment_Without.pay	4.895572e+00
## Education_11th	2.465664e+00
## Education_12th	5.191785e-01
## Education_1st.4th	1.419470e+00
## Education_5th.6th	5.467591e+00
## Education_7th.8th	2.809688e+00
## Education_9th	8.105621e+00
## Education_Assoc.acdm	9.961570e+00
## Education_Assoc.voc	4.661084e+01
## Education_Bachelors	1.088214e+01
## Education_Doctorate	2.401448e+01
## Education_HS.grad	2.656794e+01
## Education_Masters	2.523108e-01
## Education_Preschool	1.554456e+01
## Education_Prof.school	1.744635e+01
## Education_Some.college	2.044273e+00
## Marital_status_Married.AF.spouse	4.540250e+02
## Marital_status_Married.civ.spouse	3.168091e+00
## Marital_status_Married.spouse.absent	1.327596e+02
## Marital_status_Never.married	5.756307e+00
## Marital_status_Separated	5.052245e+00
## Marital_status_Widowed	6.818373e-04
## Occupation_Armed.Forces	2.228452e+01
## Occupation_Craft.repair	7.808279e+01
## Occupation_Exec.managerial	1.746278e+01
## Occupation_Farming.fishing	1.217100e+01
## Occupation_Handlers.cleaners	1.443226e+01
## Occupation_Machine.op.inspct	2.438119e+01
## Occupation_Other.service	3.328196e-01
## Occupation_Priv.house.serv	5.585062e+01
## Occupation_Prof.specialty	1.294748e+01
## Occupation_Protective.serv	2.522474e+01
## Occupation_Sales	2.143473e+01
## Occupation_Tech.support	1.696974e+01
## Occupation_Transport.moving	6.326625e+01
## Relationship_Not.in.family	6.975224e+00
## Relationship_Other.relative	4.183853e+01
## Relationship_Own.child	2.859783e+01
## Relationship_Unmarried	3.566675e+01
## Relationship_Wife	1.158793e+01
## Race_Asian.Pac.Islander	1.526600e+01
## Race_Black	3.588875e+00
## Race_Other	2.266579e+01

```
## Sex_Male          7.155483e+01  
## US              2.311997e+01
```

```
yhat.rndfor <- predict(fit.rndfor, test)  
mse.tree <- mean((yhat.rndfor - y_test) ^ 2)  
print(mse.tree)
```

```
## [1] 0.096711
```

```
#Boosting Model  
fit.btree <- gbm(formula, data = train2,  
                   distribution = "gaussian",  
                   n.trees = 100,  
                   interaction.depth = 2,  
                   shrinkage = 0.001)  
relative.influence(fit.btree)
```

```
## n.trees not given. Using 100 trees.
```

##	Age	Final_Weight
##	0.0000	0.0000
##	Years_of_education	Capital_Gain
##	15491.9513	564.7292
##	Capital_Loss	Work_Hours
##	0.0000	0.0000
##	Employment_Local.gov	Employment_Private
##	0.0000	0.0000
##	Employment_Self.emp.inc	Employment_Self.emp.not.inc
##	0.0000	0.0000
##	Employment_State.gov	Employment_Without.pay
##	0.0000	0.0000
##	Education_11th	Education_12th
##	0.0000	0.0000
##	Education_1st.4th	Education_5th.6th
##	0.0000	0.0000
##	Education_7th.8th	Education_9th
##	0.0000	0.0000
##	Education_Assoc.acdm	Education_Assoc.voc
##	0.0000	0.0000
##	Education_Bachelors	Education_Doctorate
##	0.0000	0.0000
##	Education_HS.grad	Education_Masters
##	0.0000	0.0000
##	Education_Preschool	Education_Prof.school
##	0.0000	0.0000
##	Education_Some.college	Marital_status_Married.AF.spouse
##	0.0000	0.0000
##	Marital_status_Married.civ.spouse	Marital_status_Married.spouse.absent
##	41124.3867	0.0000
##	Marital_status_Never.married	Marital_status_Separated
##	0.0000	0.0000
##	Marital_status_Widowed	Occupation_Armed.Forces
##	0.0000	0.0000
##	Occupation_Craft.repair	Occupation_Exec.managerial
##	0.0000	0.0000
##	Occupation_Farming.fishing	Occupation_Handlers.cleaners
##	0.0000	0.0000
##	Occupation_Machine.op.inspct	Occupation_Other.service
##	0.0000	0.0000
##	Occupation_Priv.house.serv	Occupation_Prof.specialty
##	0.0000	0.0000
##	Occupation_Protective.serv	Occupation_Sales
##	0.0000	0.0000
##	Occupation_Tech.support	Occupation_Transport.moving
##	0.0000	0.0000
##	Relationship_Not.in.family	Relationship_Other.relative
##	0.0000	0.0000
##	Relationship_Own.child	Relationship_Unmarried
##	0.0000	0.0000
##	Relationship_Wife	Race_Asian.Pac.Islander
##	0.0000	0.0000
##	Race_Black	Race_Other
##	0.0000	0.0000
##	Race_White	Sex_Male
##	0.0000	0.0000

```
## US  
## 0.0000
```

```
yhat.btree <- predict(fit.btree, train, n.trees = 100)  
mse.btree <- mean((yhat.btree - y_train) ^ 2)  
print(mse.btree)
```

```
## [1] 0.1775245
```