Predict Income Level from Census Data

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Contents

Summary of the data

This data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1) && (HRSWK>0)). The prediction task is to determine whether a person makes over $50K a year.

The data contains 32561 observations (people) and 15 variables. A high level summary of the data is below.

```
income <- read.csv('adult.csv', na.strings = c('','?'))
str(income)
```

```
## 'data.frame':    32561 obs. of  15 variables:
##  $ age           : int  90 82 66 54 41 34 38 74 68 41 ...
##  $ workclass     : chr  NA "Private" NA "Private" ...
##  $ fnlwgt        : int  77053 132870 186061 140359 264663 216864 150601 88638 422013 70037 ...
##  $ education     : chr  "HS-grad" "HS-grad" "Some-college" "7th-8th" ...
##  $ education.num : int  9 9 10 4 10 9 6 16 9 10 ...
##  $ marital.status: chr  "Widowed" "Widowed" "Widowed" "Divorced" ...
##  $ occupation    : chr  NA "Exec-managerial" NA "Machine-op-inspct" ...
##  $ relationship  : chr  "Not-in-family" "Not-in-family" "Unmarried" "Unmarried" ...
##  $ race          : chr  "White" "White" "Black" "White" ...
##  $ sex           : chr  "Female" "Female" "Female" "Female" ...
##  $ capital.gain  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ capital.loss  : int  4356 4356 4356 3900 3900 3770 3770 3683 3683 3004 ...
##  $ hours.per.week: int  40 18 40 40 40 45 40 20 40 60 ...
##  $ native.country: chr  "United-States" "United-States" "United-States" "United-States" ...
##  $ income        : chr  "<=50K" "<=50K" "<=50K" "<=50K" ...
```

Statistics summary after changing missing values to 'NA'.

```
summary(income)
```

```
##       age         workclass             fnlwgt         education
##  Min.   :17.00   Length:32561       Min.   :  12285   Length:32561
##  1st Qu.:28.00   Class :character   1st Qu.: 117827   Class :character
##  Median :37.00   Mode  :character   Median : 178356   Mode  :character
##  Mean   :38.58                      Mean   : 189778
##  3rd Qu.:48.00                      3rd Qu.: 237051
##  Max.   :90.00                      Max.   :1484705
##  education.num   marital.status      occupation        relationship
##  Min.   : 1.00   Length:32561       Length:32561       Length:32561
##  1st Qu.: 9.00   Class :character   Class :character   Class :character
##  Median :10.00   Mode  :character   Mode  :character   Mode  :character
##  Mean   :10.08
##  3rd Qu.:12.00
##  Max.   :16.00
##      race               sex             capital.gain    capital.loss
##  Length:32561       Length:32561       Min.   :    0   Min.   :   0.0
##  Class :character   Class :character   1st Qu.:    0   1st Qu.:   0.0
##  Mode  :character   Mode  :character   Median :    0   Median :   0.0
##                                        Mean   : 1078   Mean   :  87.3
##                                        3rd Qu.:    0   3rd Qu.:   0.0
```

```
##                                          Max.   :99999   Max.   :4356.0
##   hours.per.week  native.country        income
##   Min.   : 1.00   Length:32561       Length:32561
##   1st Qu.:40.00   Class :character   Class :character
##   Median :40.00   Mode  :character   Mode  :character
##   Mean   :40.44
##   3rd Qu.:45.00
##   Max.   :99.00
```

Data Cleaning Process

Check for 'NA' values and look how many unique values there are for each variable.

```
sapply(income,function(x) sum(is.na(x)))
```

```
##            age      workclass         fnlwgt      education  education.num
##              0           1836              0              0              0
## marital.status     occupation   relationship           race            sex
##              0           1843              0              0              0
##   capital.gain   capital.loss hours.per.week native.country         income
##              0              0              0            583              0
```

```
sapply(income, function(x) length(unique(x)))
```

```
##            age      workclass         fnlwgt      education  education.num
##             73              9          21648             16             16
## marital.status     occupation   relationship           race            sex
##              7             15              6              5              2
##   capital.gain   capital.loss hours.per.week native.country         income
##            119             92             94             42              2
```

```
table(complete.cases (income))
```

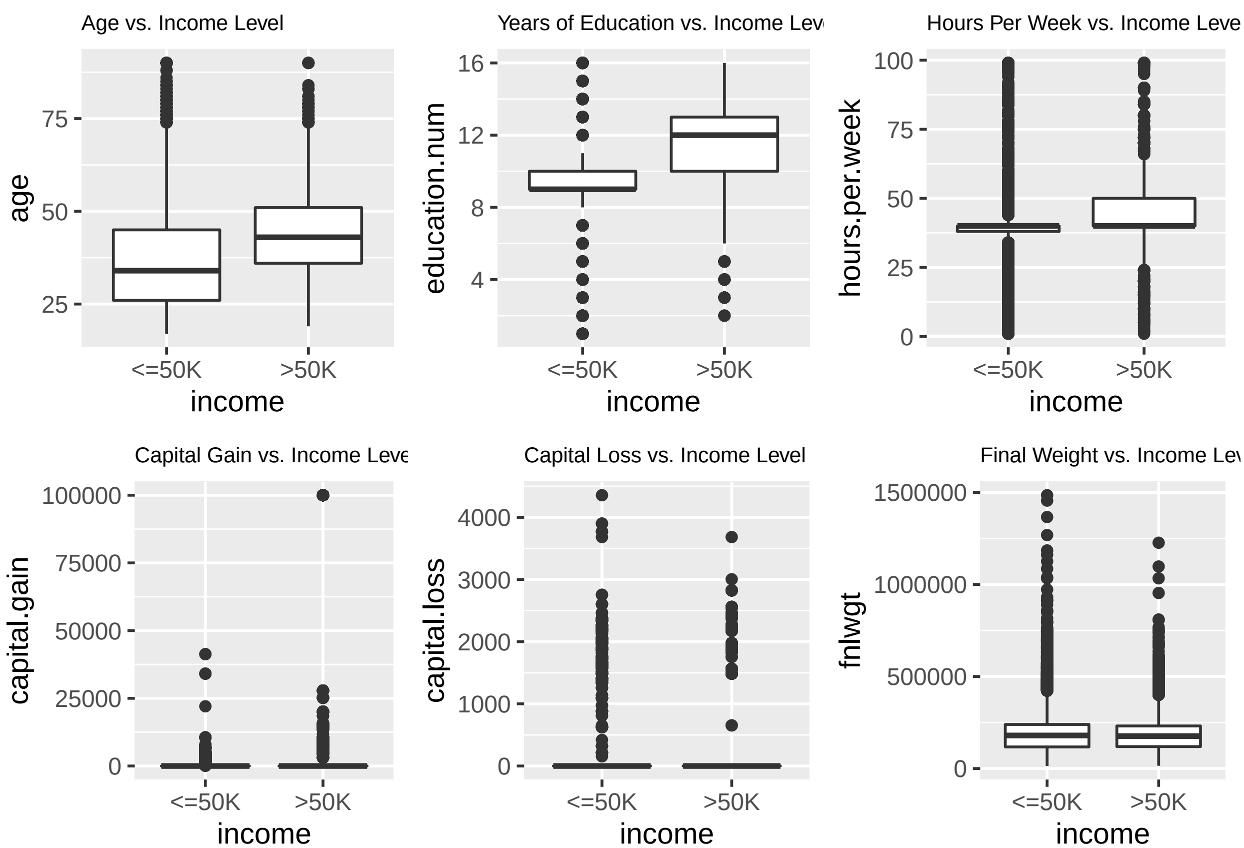
```
##
## FALSE  TRUE
##  2399 30162
```

Approximate 7%(2399/32561) of the total data has missing value. They are mainly in variables 'occupation', 'workclass' and 'native country'. I decided to remove those missing values because I don't think its a good idea to replace categorical values by imputing.

Explore Numeric Variables With Income Levels

```
income <- income[complete.cases(income),]
p1 <- ggplot(aes(x=income, y=age), data = income) + geom_boxplot() +
  ggtitle('Age vs. Income Level')+
  theme(plot.title = element_text(size = 8))
```

```r
p2 <- ggplot(aes(x=income, y=education.num), data = income) + geom_boxplot() +
  ggtitle('Years of Education vs. Income Level')+
  theme(plot.title = element_text(size = 8))
p3 <- ggplot(aes(x=income, y=hours.per.week), data = income) + geom_boxplot()+
  ggtitle('Hours Per Week vs. Income Level')+
  theme(plot.title = element_text(size = 8))
p4 <- ggplot(aes(x=income, y=capital.gain), data=income) + geom_boxplot() +
  ggtitle('Capital Gain vs. Income Level')+
  theme(plot.title = element_text(size = 8))
p5 <- ggplot(aes(x=income, y=capital.loss), data=income) + geom_boxplot() +
  ggtitle('Capital Loss vs. Income Level')+
  theme(plot.title = element_text(size = 8))
p6 <- ggplot(aes(x=income, y=fnlwgt), data=income) + geom_boxplot() +
  ggtitle('Final Weight vs. Income Level')+
  theme(plot.title = element_text(size = 8))
grid.arrange(p1, p2, p3, p4, p5, p6, ncol=3)
```



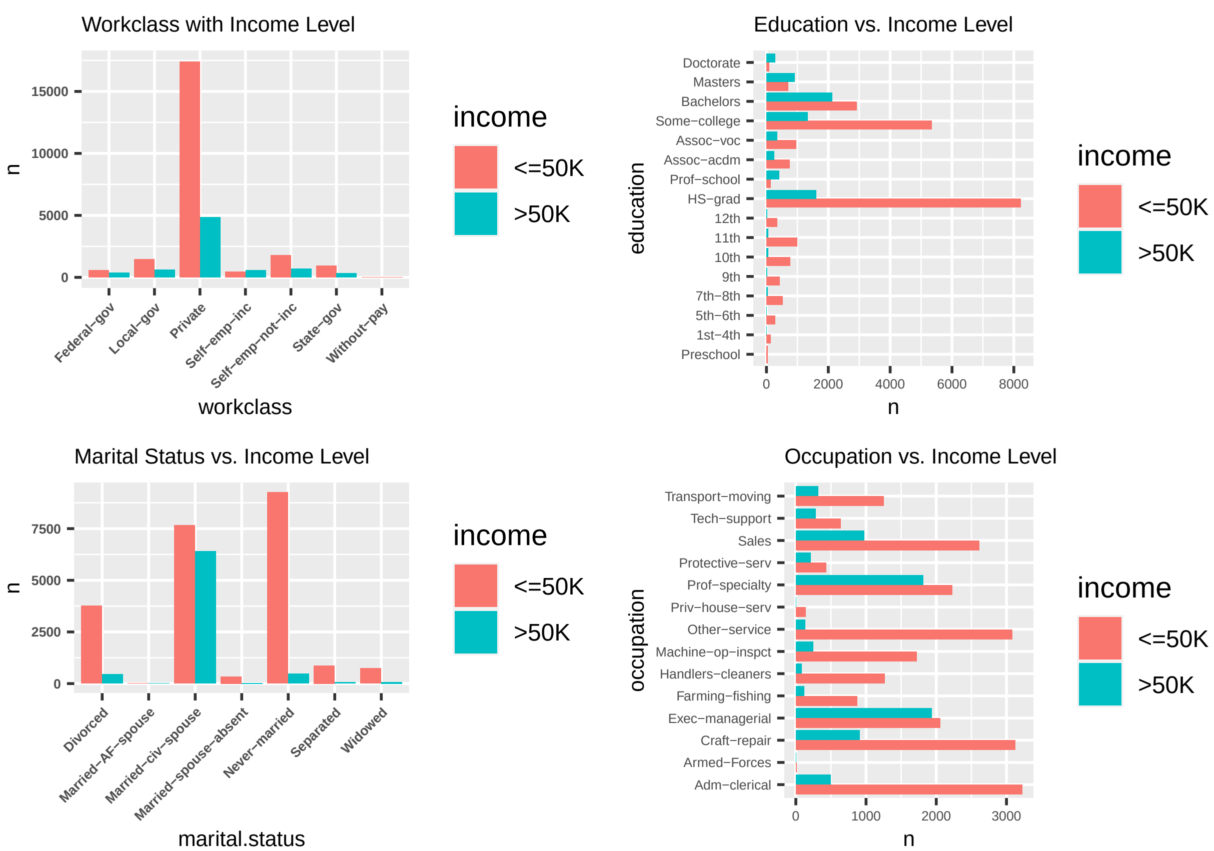
"Age", "Years of education" and "hours per week" all show significant variations with income level. Therefore, they will be kept for the regression analysis. "Final Weight" does not show any variation with income level, therefore, it will be excluded from the analysis. Its hard to see whether "Capital gain" and "Capital loss" have variation with Income level from the above plot, so I will keep them for now.

Explore Categorical Variables With Income Levels

```
income$fnlwgt <- NULL
by_workclass <- income %>% group_by(workclass, income) %>% summarise(n=n())
by_education <- income %>% group_by(education, income) %>% summarise(n=n())
by_education$education <- ordered(by_education$education,
                                   levels = c('Preschool', '1st-4th', '5th-6th', '7th-8th', '9th', '10t
by_marital <- income %>% group_by(marital.status, income) %>% summarise(n=n())
by_occupation <- income %>% group_by(occupation, income) %>% summarise(n=n())
by_relationship <- income %>% group_by(relationship, income) %>% summarise(n=n())
by_race <- income %>% group_by(race, income) %>% summarise(n=n())
by_sex <- income %>% group_by(sex, income) %>% summarise(n=n())
by_country <- income %>% group_by(native.country, income) %>% summarise(n=n())

p7 <- ggplot(aes(x=workclass, y=n, fill=income), data=by_workclass)+
  geom_bar(stat = 'identity', position = position_dodge())+
  ggtitle('Workclass with Income Level') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8)) +
  theme(axis.text = element_text(face = "bold"))
p8 <- ggplot(aes(x=education, y=n, fill=income), data=by_education) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  ggtitle('Education vs. Income Level') +
  coord_flip()+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8))
p9 <- ggplot(aes(x=marital.status, y=n, fill=income), data=by_marital) +
  geom_bar(stat = 'identity', position=position_dodge()) +
  ggtitle('Marital Status vs. Income Level') +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8))+
  theme(axis.text = element_text(face = "bold"))
p10 <- ggplot(aes(x=occupation, y=n, fill=income), data=by_occupation) +
  geom_bar(stat = 'identity', position=position_dodge()) +
  ggtitle('Occupation vs. Income Level') +
  coord_flip()+
  theme(plot.title = element_text(size = 8))+
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8))
p11 <- ggplot(aes(x=relationship, y=n, fill=income), data=by_relationship) +
  geom_bar(stat = 'identity', position=position_dodge()) +
  ggtitle('Relationship vs. Income Level') +
  coord_flip()+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8))
p12 <- ggplot(aes(x=race, y=n, fill=income), data=by_race) +
  geom_bar(stat = 'identity', position = position_dodge()) +
```

```r
  ggtitle('Race vs. Income Level') +
  coord_flip()+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8))
p13 <- ggplot(aes(x=sex, y=n, fill=income), data=by_sex) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  ggtitle('Sex vs. Income Level')+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5))+
  theme(axis.title = element_text(size = 8))
p14 <- ggplot(aes(x=native.country, y=n, fill=income), data=by_country) +
  geom_bar(stat = 'identity', position = position_dodge()) +
  ggtitle('Native Country vs. Income Level') +
  coord_flip()+
  theme(plot.title = element_text(size = 8)) +
  theme(axis.text = element_text(size = 5)) +
  theme(axis.text.x = element_text(size = 5),
    axis.text.y = element_text(size = 3)) +
  theme(axis.title = element_text(size = 8))
grid.arrange(p7, p8, p9, p10, ncol=2)
```



```r
grid.arrange(p11,p12,p13, p14, ncol=2)
```

Most of the data was collected from the United States, so variable “native country” does not have effect on my analysis, I will exclude it from regression model. And all the other categorial variables seem to have reasonable variation, so will be kept.

```r
income$native.country <- NULL
income$income = as.factor(ifelse(income$income==income$income[1],0,1))
```

Convert income level to 0’s and 1’s,“<=50K” will be 0 and “>50K”" will be 1(binary outcome).

Model Fitting

split the data into two chunks: training and testing set.

```r
train <- income[1:24000,]
test <- income[24001:30162,]
```

Fit the model

```r
model <-glm(income ~.,family=binomial(link='logit'),data=train)
summary(model)
```

```
##
## Call:
## glm(formula = income ~ ., family = binomial(link = "logit"),
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -5.1023  -0.5221  -0.1872   0.0581   3.3415
##
## Coefficients: (1 not defined because of singularities)
##                                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)                         -6.946e+00  4.711e-01 -14.743  < 2e-16 ***
## age                                  2.436e-02  1.888e-03  12.899  < 2e-16 ***
## workclassLocal-gov                  -6.826e-01  1.259e-01  -5.420 5.97e-08 ***
## workclassPrivate                    -4.959e-01  1.049e-01  -4.727 2.28e-06 ***
## workclassSelf-emp-inc               -3.309e-01  1.383e-01  -2.392 0.016734 *
## workclassSelf-emp-not-inc           -1.004e+00  1.228e-01  -8.181 2.82e-16 ***
## workclassState-gov                  -7.998e-01  1.401e-01  -5.708 1.15e-08 ***
## workclassWithout-pay                -1.306e+01  2.386e+02  -0.055 0.956366
## education11th                       -7.654e-03  2.285e-01  -0.034 0.973272
## education12th                        2.253e-01  3.101e-01   0.727 0.467456
## education1st-4th                    -6.456e-01  5.343e-01  -1.208 0.226955
## education5th-6th                    -7.638e-01  3.970e-01  -1.924 0.054348 .
## education7th-8th                    -7.297e-01  2.656e-01  -2.748 0.006003 **
## education9th                        -6.099e-01  3.093e-01  -1.972 0.048662 *
## educationAssoc-acdm                  1.165e+00  1.941e-01   6.003 1.94e-09 ***
## educationAssoc-voc                   1.088e+00  1.863e-01   5.840 5.23e-09 ***
## educationBachelors                   1.784e+00  1.721e-01  10.366  < 2e-16 ***
## educationDoctorate                   2.773e+00  2.433e-01  11.397  < 2e-16 ***
## educationHS-grad                     6.298e-01  1.671e-01   3.769 0.000164 ***
## educationMasters                     2.116e+00  1.851e-01  11.433  < 2e-16 ***
## educationPreschool                  -2.026e+01  1.422e+02  -0.142 0.886719
## educationProf-school                 2.641e+00  2.266e-01  11.654  < 2e-16 ***
## educationSome-college                9.415e-01  1.698e-01   5.544 2.96e-08 ***
## education.num                               NA         NA      NA       NA
## marital.statusMarried-AF-spouse      3.113e+00  6.846e-01   4.548 5.43e-06 ***
## marital.statusMarried-civ-spouse     2.071e+00  3.025e-01   6.846 7.57e-12 ***
## marital.statusMarried-spouse-absent -9.842e-02  2.684e-01  -0.367 0.713876
## marital.statusNever-married         -4.215e-01  9.933e-02  -4.243 2.20e-05 ***
## marital.statusSeparated              4.981e-02  1.795e-01   0.277 0.781443
## marital.statusWidowed                1.641e-01  1.811e-01   0.906 0.364857
## occupationArmed-Forces              -1.030e+00  1.519e+00  -0.678 0.497620
## occupationCraft-repair               1.312e-01  8.996e-02   1.458 0.144763
## occupationExec-managerial            8.642e-01  8.719e-02   9.912  < 2e-16 ***
## occupationFarming-fishing           -9.219e-01  1.556e-01  -5.927 3.09e-09 ***
## occupationHandlers-cleaners         -6.340e-01  1.624e-01  -3.903 9.50e-05 ***
## occupationMachine-op-inspct         -2.581e-01  1.148e-01  -2.248 0.024571 *
## occupationOther-service             -7.466e-01  1.302e-01  -5.735 9.74e-09 ***
## occupationPriv-house-serv           -4.065e+00  1.761e+00  -2.309 0.020966 *
## occupationProf-specialty             5.969e-01  9.185e-02   6.499 8.11e-11 ***
## occupationProtective-serv            6.089e-01  1.401e-01   4.345 1.39e-05 ***
## occupationSales                      3.265e-01  9.278e-02   3.519 0.000434 ***
## occupationTech-support               7.090e-01  1.247e-01   5.684 1.31e-08 ***
## occupationTransport-moving           6.729e-03  1.104e-01   0.061 0.951385
```

```
## relationshipNot-in-family           3.903e-01  2.989e-01   1.306 0.191598
## relationshipOther-relative         -4.501e-01  2.736e-01  -1.645 0.100029
## relationshipOwn-child              -7.227e-01  2.971e-01  -2.433 0.014990 *
## relationshipUnmarried               2.333e-01  3.171e-01   0.736 0.461827
## relationshipWife                    1.344e+00  1.176e-01  11.424  < 2e-16 ***
## raceAsian-Pac-Islander              2.932e-01  2.811e-01   1.043 0.296968
## raceBlack                           4.212e-01  2.667e-01   1.579 0.114232
## raceOther                          -5.576e-01  4.370e-01  -1.276 0.201988
## raceWhite                           4.978e-01  2.549e-01   1.953 0.050844 .
## sexMale                             8.690e-01  8.981e-02   9.677  < 2e-16 ***
## capital.gain                        3.239e-04  1.083e-05  29.899  < 2e-16 ***
## capital.loss                        6.432e-04  3.870e-05  16.622  < 2e-16 ***
## hours.per.week                      2.840e-02  1.912e-03  14.854  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 27607  on 23999  degrees of freedom
## Residual deviance: 15626  on 23945  degrees of freedom
## AIC: 15736
##
## Number of Fisher Scoring iterations: 13
```

Interpreting the results of the logistic regression model:

1. "Age", "Hours per week", "sex", "capital gain" and "capital loss" are the most statistically significant variables. Their lowest p-values suggesting a strong association with the probability of wage>50K from the data.
2. "Workclass", "education", "marital status", "occupation" and "relationship" are all across the table. so cannot be eliminated from the model.
3. "Race" category is not statistically significant and can be eliminated from the model.

Run the anova() function on the model to analyze the table of deviance.

```r
anova(model, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: income
##
## Terms added sequentially (first to last)
##
##
##                Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
## NULL                           23999      27607
## age             1   1390.0     23998      26217 < 2.2e-16 ***
## workclass       6    357.4     23992      25859 < 2.2e-16 ***
## education      15   3009.1     23977      22850 < 2.2e-16 ***
## education.num   0      0.0     23977      22850
## marital.status  6   4121.0     23971      18729 < 2.2e-16 ***
```

```
## occupation     13    634.8     23958      18094 < 2.2e-16 ***
## relationship    5    167.8     23953      17926 < 2.2e-16 ***
## race            4     19.9     23949      17907 0.0005157 ***
## sex             1    136.3     23948      17770 < 2.2e-16 ***
## capital.gain    1   1625.5     23947      16145 < 2.2e-16 ***
## capital.loss    1    293.2     23946      15852 < 2.2e-16 ***
## hours.per.week  1    225.6     23945      15626 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference between the null deviance and the residual deviance indicates how the model is doing against the null model. The bigger difference, the better. From the above table we can see the drop in deviance when adding each variable one at a time. Adding age, workclass, education, marital status, occupation, relationship, race, sex, capital gain, capital loss and hours per week significantly reduces the residual deviance. education.num seem to have no effect.

Apply model to the test set

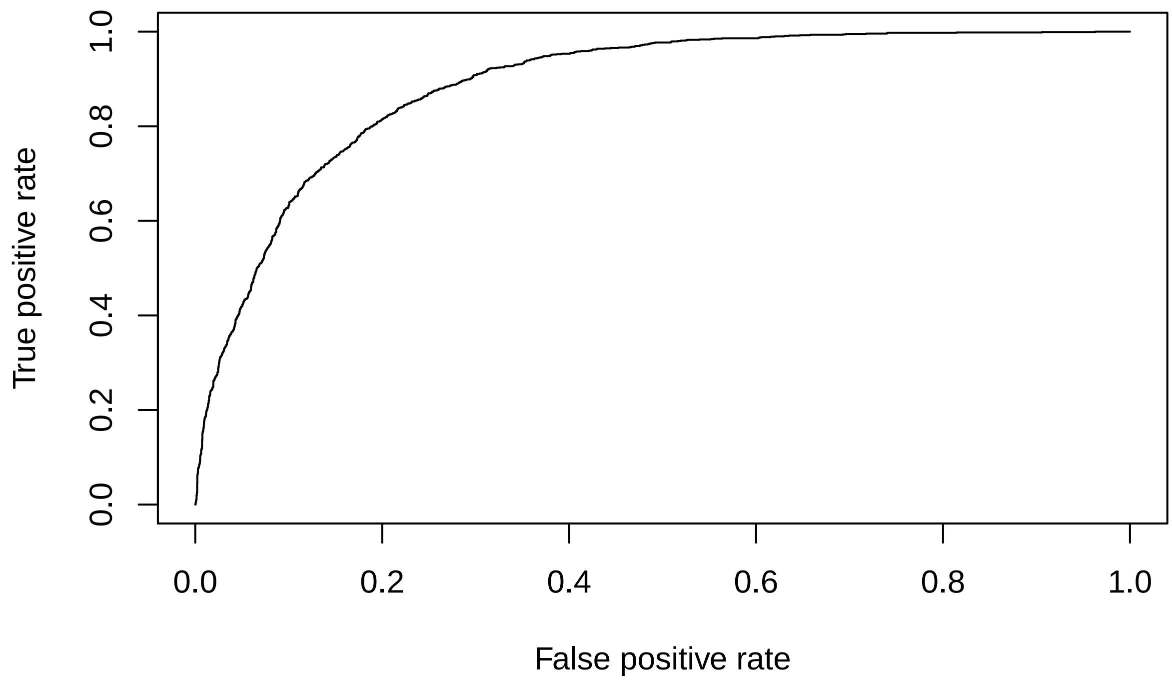
```
fitted.results <- predict(model,newdata=test,type='response')
fitted.results <- ifelse(fitted.results > 0.5,1,0)
misClasificError <- mean(fitted.results != test$income)
print(paste('Accuracy',1-misClasificError))
```

```
## [1] "Accuracy 0.844368711457319"
```

The 0.84 accuracy on the test set is a very encouraging result.

At last, plot the ROC curve and calculate the AUC (area under the curve). The closer AUC for a model comes to 1, the better predictive ability.

```
p <- predict(model, newdata=test, type="response")
pr <- prediction(p, test$income)
prf <- performance(pr, measure = "tpr", x.measure = "fpr")
plot(prf)
```




```
auc <- performance(pr, measure = "auc")
auc <- auc@y.values[[1]]
auc
```

```
## [1] 0.8868877
```

The area under the curve corresponds the AUC.

The End

I have been very cautious on removing variables because I don't want to compromise the data as I may end up removing valid information. As a result, I may have kept variables that I should have removed such as "education.num".