Predicting Income with Census Data

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I. Introduction

The goal of this project is to predict an individual's income level with machine learning models using the 14 attributes provided by the census income dataset. Specifically, I implement classification tree and random forest algorithmns to predict whether a person's annual income is more than $50,000.

The "Census Income" dataset, also know as the "Adult" dataset, was extracted by Barry Becker from the 1994 US Census database for a prediction task on income level. The dataset consists of 48,842 observations and 15 variables, six numerical and nine categorical, and is archived at the UC Irvine Machine Learning Repository. The following is a list of variable names by their types.

Categorical Variable	Numerical Variable
income	age
workclass	fnlwgt
education	education.num
occupation	capital.gain
marital.status	capital.loss
relationship	hours.per.week
race	
sex	
native.country	

The `income` variable identifies whether a person makes over $50,000 annually, and is used as the dependent variable. The dataset is divided into a `train` set with 32,561 observations, and a `test` set with 16,281 observations. After removing the missing values denoted by question marks, there are 45,222 rows left in the dataset with 30,162 rows in the `train` set, and 15,060 rows in the `test` set.

The variable names are mostly self-explanatory with a few exceptions. The variable `education` is a categorical representation of the numerical `education.num`, which stands for the number of years of education. The variable `relationship` indicates the respondant's role in the family. The variable `fnlwgt` specifies the final weight, which is the number of people the census believes the entry represents. Gain and loss from investments are stored in `capital.gain` and `capital.loss`. The variable `hours.per.week` indicates the number of working hours per week.

```
# Download the Adult Dataset (Census Income Dataset)

# Census Income Data Set:
# https://archive.ics.uci.edu/ml/datasets/Adult

url_train <- 'http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data'
url_test <- 'http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.test'
```

```
url_names <- 'http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.names'

train <- read.table(url_train, sep = ',', stringsAsFactors = FALSE)
test <- readLines(url_test)[-1]
test <- read.table(textConnection(test), sep = ',', stringsAsFactors = FALSE)

names <- readLines(url_names)[97:110]
names <- as.character(lapply(strsplit(names,':'), function(x) x[1]))
names <- c(names, 'income')
colnames(train) <- names
colnames(test) <- names

# Remove the missing values (denoted by question marks)

no.question.mark <- apply(train, 1, function(r) !any(r %in% ' ?'))
train <- train[no.question.mark,]
no.question.mark <- apply(test, 1, function(r) !any(r %in% ' ?'))
test <- test[no.question.mark,]

train <- as.data.frame(unclass(train),stringsAsFactors = T)
test <- as.data.frame(unclass(test),stringsAsFactors = T)

# Create adult set (combine train, test set)

adult <- rbind(train, test)

# Remove the "." from "<=50K." and ">50K." in adult set

adult$income <- gsub(".", "", as.character(adult$income), fixed = TRUE)

str(adult)
```

```
## 'data.frame':    45222 obs. of  15 variables:
##  $ age           : int  39 50 38 53 28 37 49 52 31 42 ...
##  $ workclass     : Factor w/ 7 levels " Federal-gov",..: 6 5 3 3 3 3 3 5 3 3 ...
##  $ fnlwgt        : int  77516 83311 215646 234721 338409 284582 160187 209642 45781 159449 ...
##  $ education     : Factor w/ 16 levels " 10th"," 11th",..: 10 10 12 2 10 13 7 12 13 10 ...
##  $ education.num : int  13 13 9 7 13 14 5 9 14 13 ...
##  $ marital.status: Factor w/ 7 levels " Divorced"," Married-AF-spouse",..: 5 3 1 3 3 3 4 3 5 3 ...
##  $ occupation    : Factor w/ 14 levels " Adm-clerical",..: 1 4 6 6 10 4 8 4 10 4 ...
##  $ relationship  : Factor w/ 6 levels " Husband"," Not-in-family",..: 2 1 2 1 6 6 2 1 2 1 ...
##  $ race          : Factor w/ 5 levels " Amer-Indian-Eskimo",..: 5 5 5 3 3 5 3 5 5 5 ...
##  $ sex           : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 1 1 2 1 2 ...
##  $ capital.gain  : int  2174 0 0 0 0 0 0 0 14084 5178 ...
##  $ capital.loss  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ hours.per.week: int  40 13 40 40 40 40 16 45 50 40 ...
##  $ native.country: Factor w/ 41 levels " Cambodia"," Canada",..: 39 39 39 39 5 39 23 39 39 39 ...
##  $ income        : chr  " <=50K" " <=50K" " <=50K" " <=50K" ...
```

```
dim(train)
```

```
## [1] 30162    15
```

```r
dim(test)
```

```
## [1] 15060    15
```

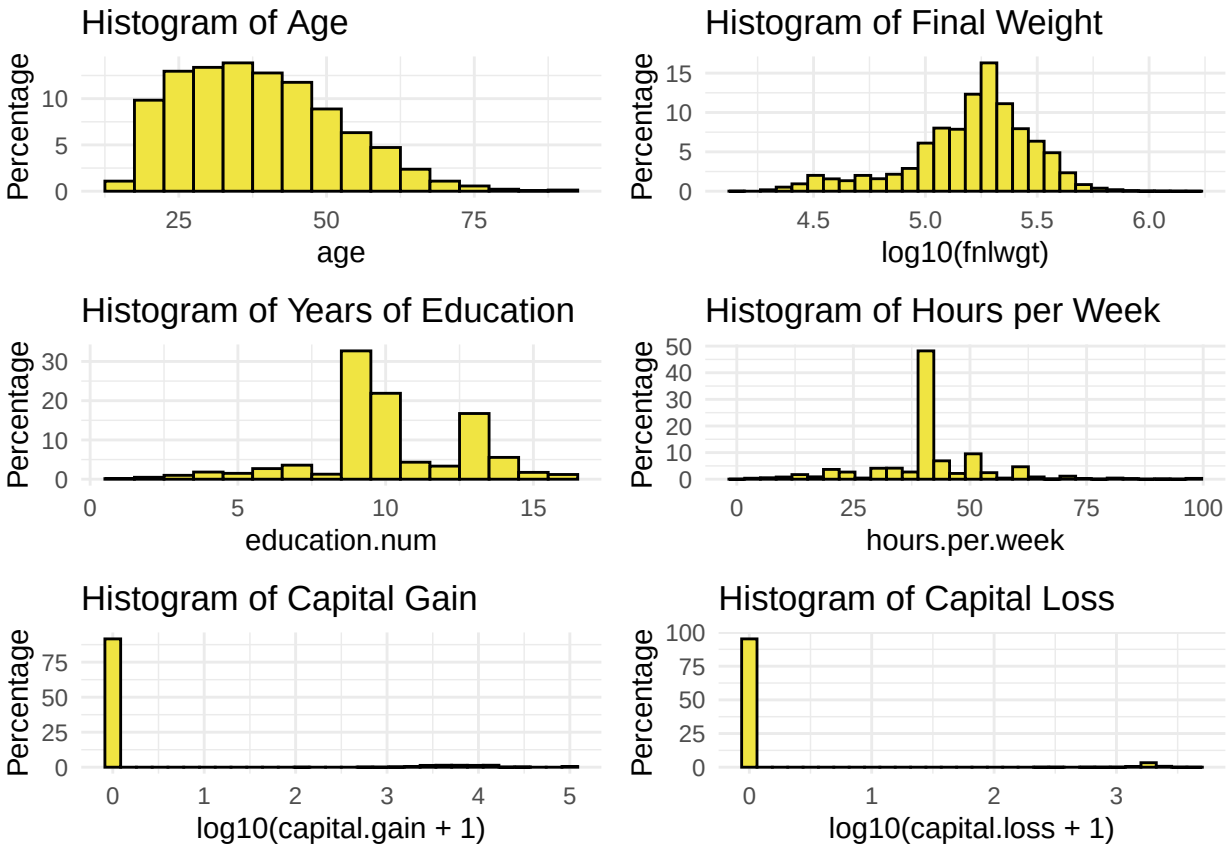
II. Analysis

2.1 Data Exploration

From the histograms of the numerical variables, I find that the distributions of `capital.gain` and `capital.loss` are very narrow and concentrated at zero. The zeros constitute 91.61912% of `capital.gain` entries and 95.26779% of `capital.loss` entries. In the modeling section, I combine these two columns into a single variable called `capital.change` for a more efficient representation.

```r
# Visualize numerical variables

# Histogram of Age

p1 <- ggplot(train, aes(x = age)) +
  ggtitle("Histogram of Age") +
  geom_histogram(aes(y = 100*(..count..)/sum(..count..)), binwidth = 5, colour = "black", fill = "#F0E4
  ylab("Percentage") +
  theme_minimal()

# Histogram of Final Weight

p2 <- ggplot(adult, aes(x = log10(fnlwgt))) +
  ggtitle("Histogram of Final Weight") +
  geom_histogram(aes(y = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  ylab("Percentage") +
  theme_minimal()

# Histogram of Years of Education

p3 <- ggplot(adult, aes(x = education.num)) +
  ggtitle("Histogram of Years of Education") +
  geom_histogram(aes(y = 100*(..count..)/sum(..count..)), binwidth = 1, colour = "black", fill = "#F0E4
  ylab("Percentage") +
  theme_minimal()

# Histogram of Hours per Week

p4 <- ggplot(adult, aes(x = hours.per.week)) +
  ggtitle("Histogram of Hours per Week") +
  geom_histogram(aes(y = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  ylab("Percentage") +
  theme_minimal()

# Histogram of Capital Gain

p5 <- ggplot(adult, aes(x = log10(capital.gain+1))) +
  ggtitle("Histogram of Capital Gain") +
  geom_histogram(aes(y = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
```

```
  ylab("Percentage") +
  theme_minimal()

# Histogram of Capital Loss

p6 <- ggplot(adult, aes(x = log10(capital.loss+1))) +
  ggtitle("Histogram of Capital Loss") +
  geom_histogram(aes(y = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  ylab("Percentage") +
  theme_minimal()

grid.arrange(p1,p2,p3,p4,p5,p6)
```




```
# Percentage of data with zero capital gain

sum(adult$capital.gain==0)/length(adult$capital.gain)*100
```

```
## [1] 91.61912
```

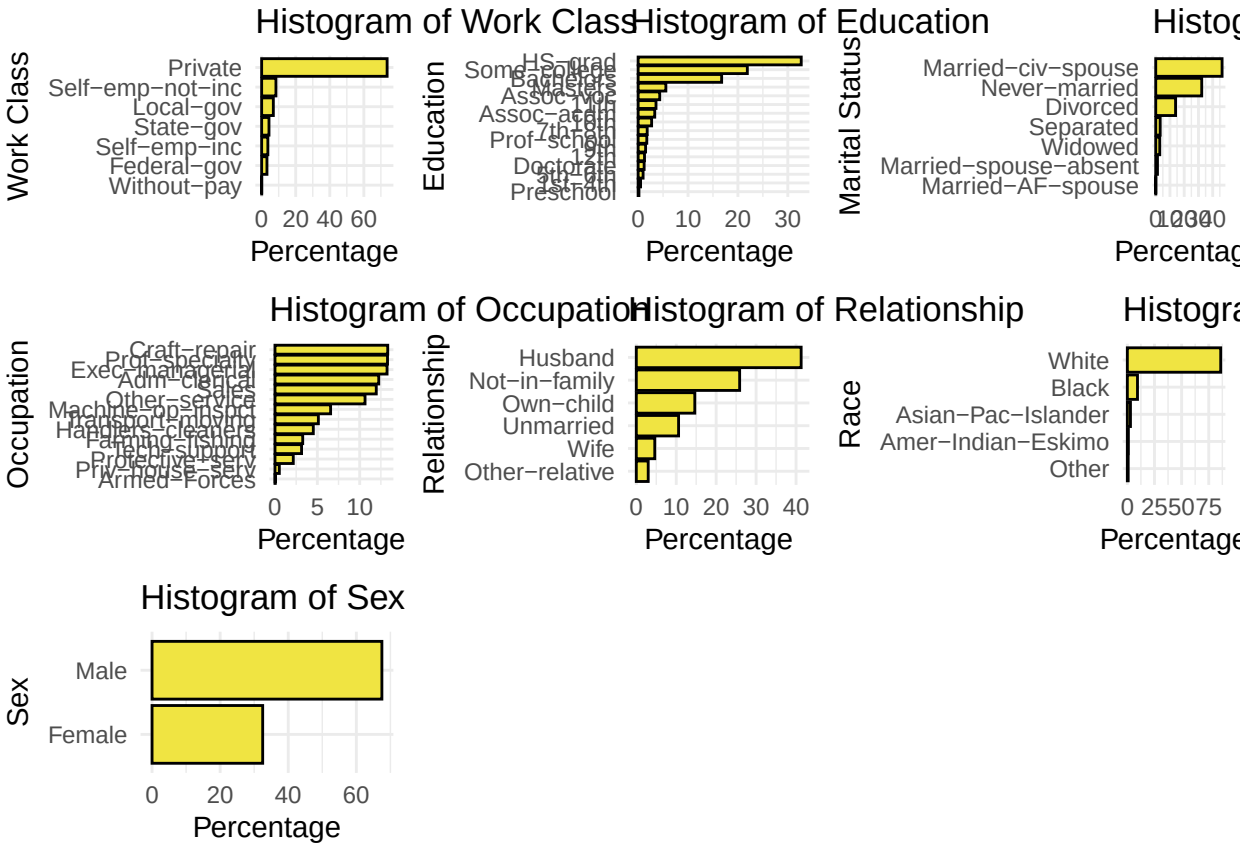
```
# Percentage of data with zero capital loss

sum(adult$capital.loss==0)/length(adult$capital.loss)*100
```

```
## [1] 95.26779
```

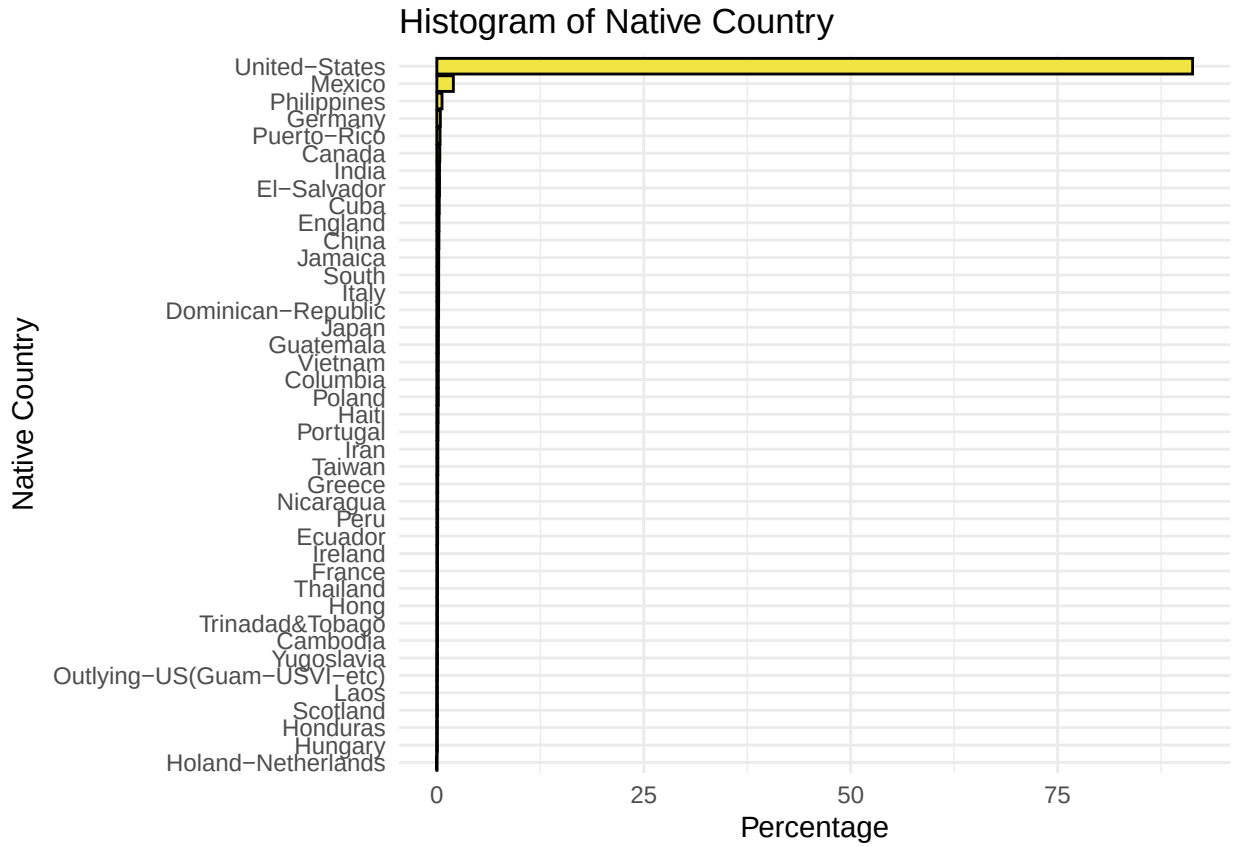
The histograms of the categorical variables are plotted as follows.

```
# Sort categorical variables in descending order

sort.categ <- function(x){reorder(x,x,function(y){length(y)})}
var.categ <- which(sapply(adult, is.factor))
for (c in var.categ){adult[,c] <- sort.categ(adult[,c])}
attach(adult)

# Histogram of Work Class

c1 <- ggplot(adult, aes(y = workclass)) +
  ggtitle("Histogram of Work Class") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(workclass)) +
  xlab("Percentage") +
  ylab("Work Class") +
  theme_minimal()

# Histogram of Education

c2 <- ggplot(adult, aes(y = education)) +
  ggtitle("Histogram of Education") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(education)) +
  xlab("Percentage") +
  ylab("Education") +
  theme_minimal()

# Histogram of Marital Status

c3 <- ggplot(adult, aes(y = marital.status)) +
  ggtitle("Histogram of Marital Status") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(marital.status)) +
  xlab("Percentage") +
  ylab("Marital Status") +
  theme_minimal()

# Histogram of Occupation

c4 <- ggplot(adult, aes(y = occupation)) +
  ggtitle("Histogram of Occupation") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(occupation)) +
  xlab("Percentage") +
  ylab("Occupation") +
  theme_minimal()

# Histogram of Relationship

c5 <- ggplot(adult, aes(y = relationship)) +
  ggtitle("Histogram of Relationship") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
```

```
  scale_y_discrete(limits = levels(relationship)) +
  xlab("Percentage") +
  ylab("Relationship") +
  theme_minimal()

# Histogram of Race

c6 <- ggplot(adult, aes(y = race)) +
  ggtitle("Histogram of Race") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(race)) +
  xlab("Percentage") +
  ylab("Race") +
  theme_minimal()

# Histogram of Sex

c7 <- ggplot(adult, aes(y = sex)) +
  ggtitle("Histogram of Sex") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(sex)) +
  xlab("Percentage") +
  ylab("Sex") +
  theme_minimal()

# Histogram of Native Country

c8 <- ggplot(adult, aes(y = native.country)) +
  ggtitle("Histogram of Native Country") +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), colour = "black", fill = "#F0E442") +
  scale_y_discrete(limits = levels(native.country)) +
  xlab("Percentage") +
  ylab("Native Country") +
  theme_minimal()

grid.arrange(c1,c2,c3,c4,c5,c6,c7)
```


Histogram of Work Class
Work Class
Private
Self−emp−not−inc
Local−gov
State−gov
Self−emp−inc
Federal−gov
Without−pay
0 20 40 60
Percentage
Histogram of Education
Education
HS−grad
Some−college
Bachelors
Masters
Assoc−voc
Assoc−acdm
11th
7th−8th
Prof−school
10th
9th
Doctorate
5th−6th
1st−4th
Preschool
0 10 20 30
Percentage
Histog
Marital Status
Married−civ−spouse
Never−married
Divorced
Separated
Widowed
Married−spouse−absent
Married−AF−spouse
Percentag
Histogram of Occupation
Occupation
Craft−repair
Prof−specialty
Exec−managerial
Adm−clerical
Sales
Other−service
Machine−op−inspct
Transport−moving
Handlers−cleaners
Farming−fishing
Tech−support
Protective−serv
Priv−house−serv
Armed−Forces
0 5 10
Percentage
Histogram of Relationship
Relationship
Husband
Not−in−family
Own−child
Unmarried
Wife
Other−relative
0 10 20 30 40
Percentage
Histogra
Race
White
Black
Asian−Pac−Islander
Amer−Indian−Eskimo
Other
0 255075
Percentage
Histogram of Sex
Sex
Male
Female
0 20 40 60
Percentage

```
c8
```



The variable `native.country` shows a narrow distribution with 91.30954% of the respondents coming from the Unites States.

```
summary(adult$native.country)
```

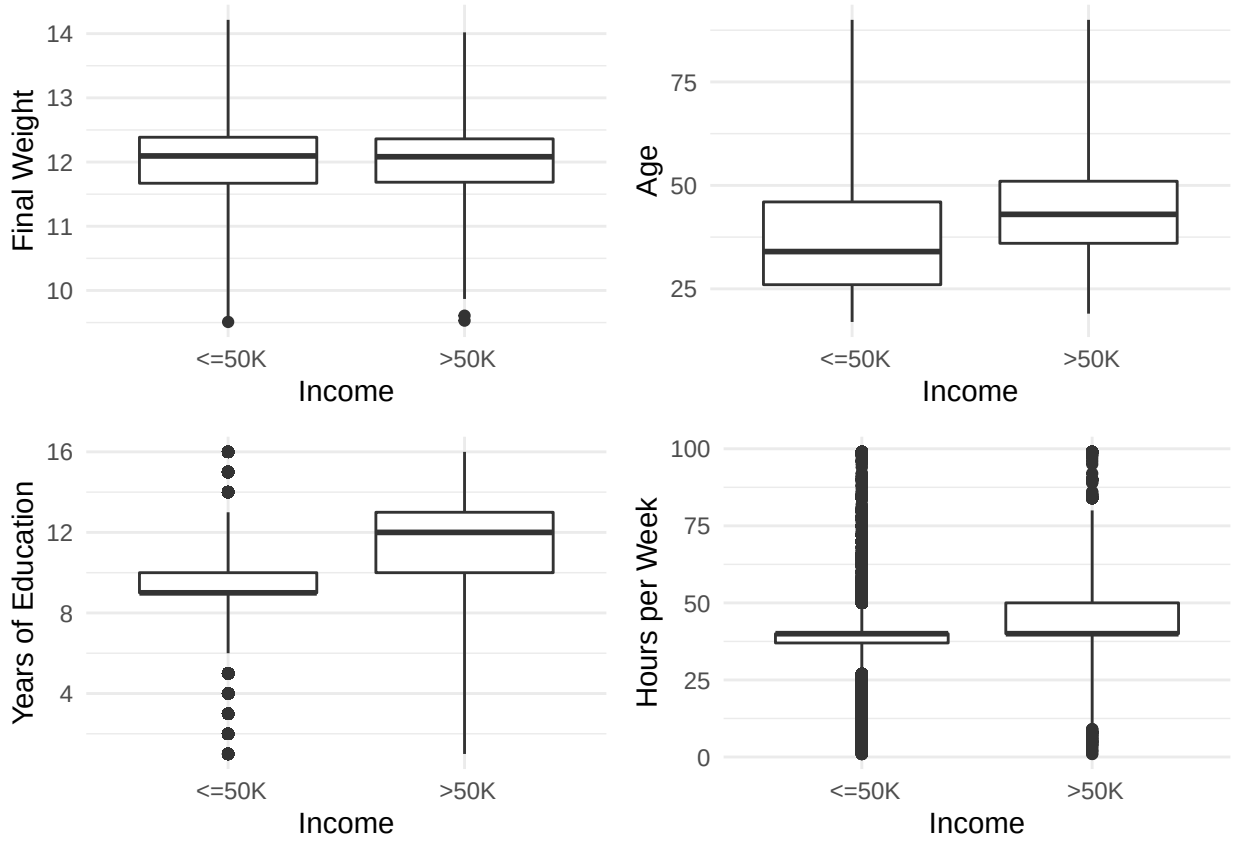
```
##          Holand-Netherlands                      Hungary
##                           1                           18
##                    Honduras                     Scotland
##                          19                           20
##                        Laos   Outlying-US(Guam-USVI-etc)
##                          21                           22
##                  Yugoslavia                     Cambodia
##                          23                           26
##             Trinadad&Tobago                         Hong
##                          26                           28
##                    Thailand                       France
##                          29                           36
##                     Ireland                      Ecuador
##                          36                           43
##                        Peru                    Nicaragua
##                          45                           48
##                      Greece                       Taiwan
##                          49                           55
##                        Iran                     Portugal
##                          56                           62
##                       Haiti                       Poland
```

```
##                         69                         81
##                   Columbia                    Vietnam
##                         82                         83
##                  Guatemala                      Japan
##                         86                         89
##          Dominican-Republic                      Italy
##                         97                        100
##                      South                    Jamaica
##                        101                        103
##                      China                    England
##                        113                        119
##                       Cuba                El-Salvador
##                        133                        147
##                      India                     Canada
##                        147                        163
##                Puerto-Rico                    Germany
##                        175                        193
##                Philippines                     Mexico
##                        283                        903
##              United-States
##                      41292
```

To identify the potential variable that impacts the income level, I plot the attributes against income to examine correlations. The boxplots shows that the numeric variables `age`, `education`, and `hours.per.week` are correlatted with income.

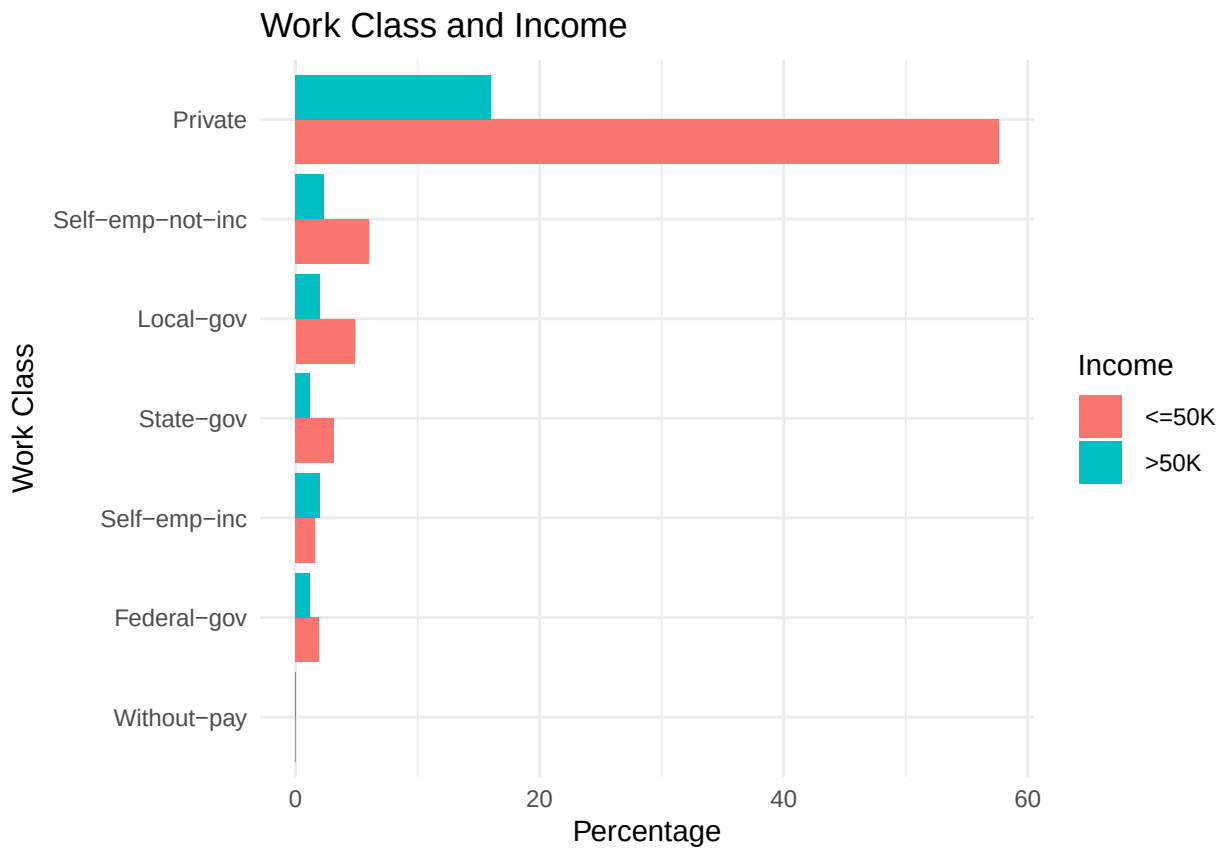
```
# Final weight and income

b1 <- ggplot(adult, aes(income, log(fnlwgt))) +
  geom_boxplot(coef=3) +
  xlab("Income") +
  ylab("Final Weight") +
  theme_minimal()

# Age and income

b2 <- ggplot(adult, aes(income, age)) +
  geom_boxplot(coef=3) +
  xlab("Income") +
  ylab("Age") +
  theme_minimal()

# Education and income

b3 <- ggplot(adult, aes(income, education.num)) +
  geom_boxplot(coef=3) +
  xlab("Income") +
  ylab("Years of Education") +
  theme_minimal()

# Hours per week and income

b4 <- ggplot(adult, aes(income, hours.per.week)) +
  geom_boxplot(coef=3) +
```

```
  xlab("Income") +
  ylab("Hours per Week") +
  theme_minimal()

grid.arrange(b1, b2, b3, b4)
```



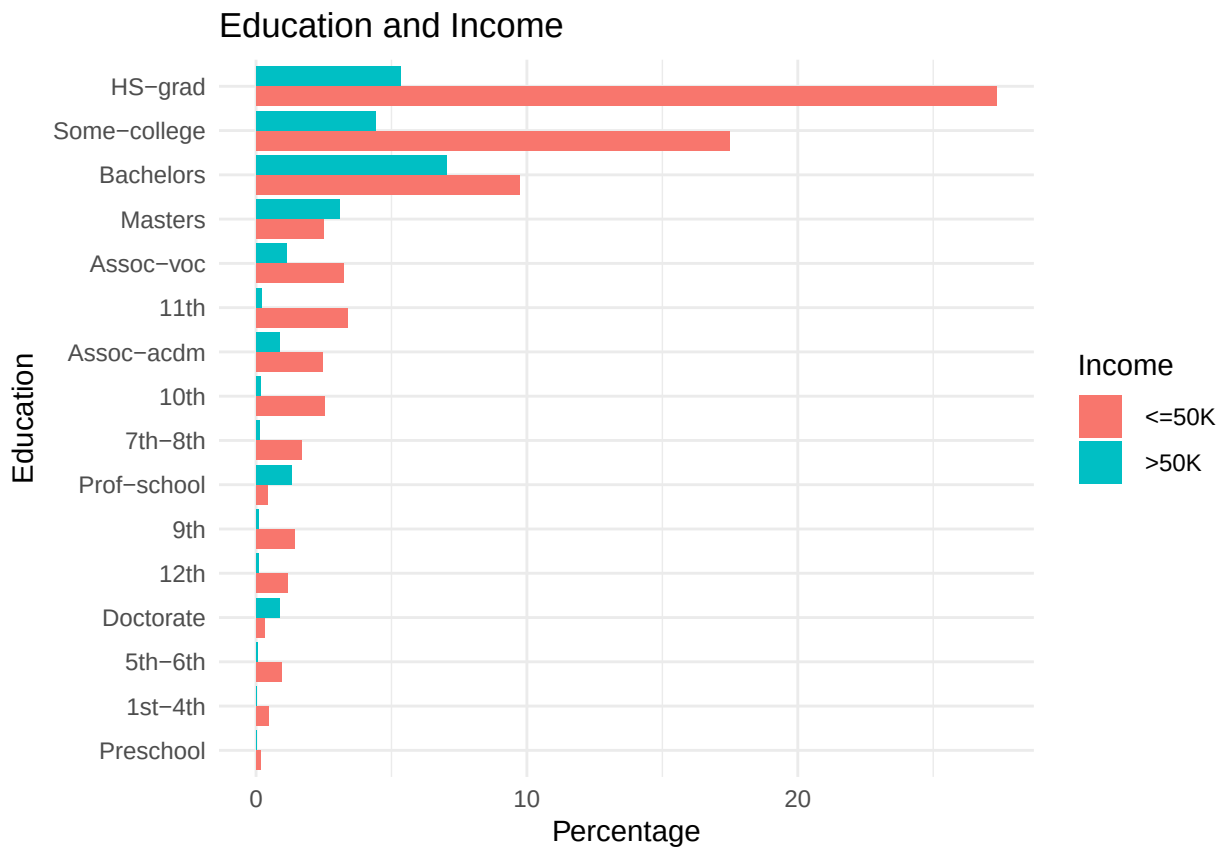
I use bar charts to show the correlation between categorical variables and income.

```
# Work class and income

ggplot(adult, aes(y = workclass, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Work Class and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Work Class") +
  theme_minimal()
```

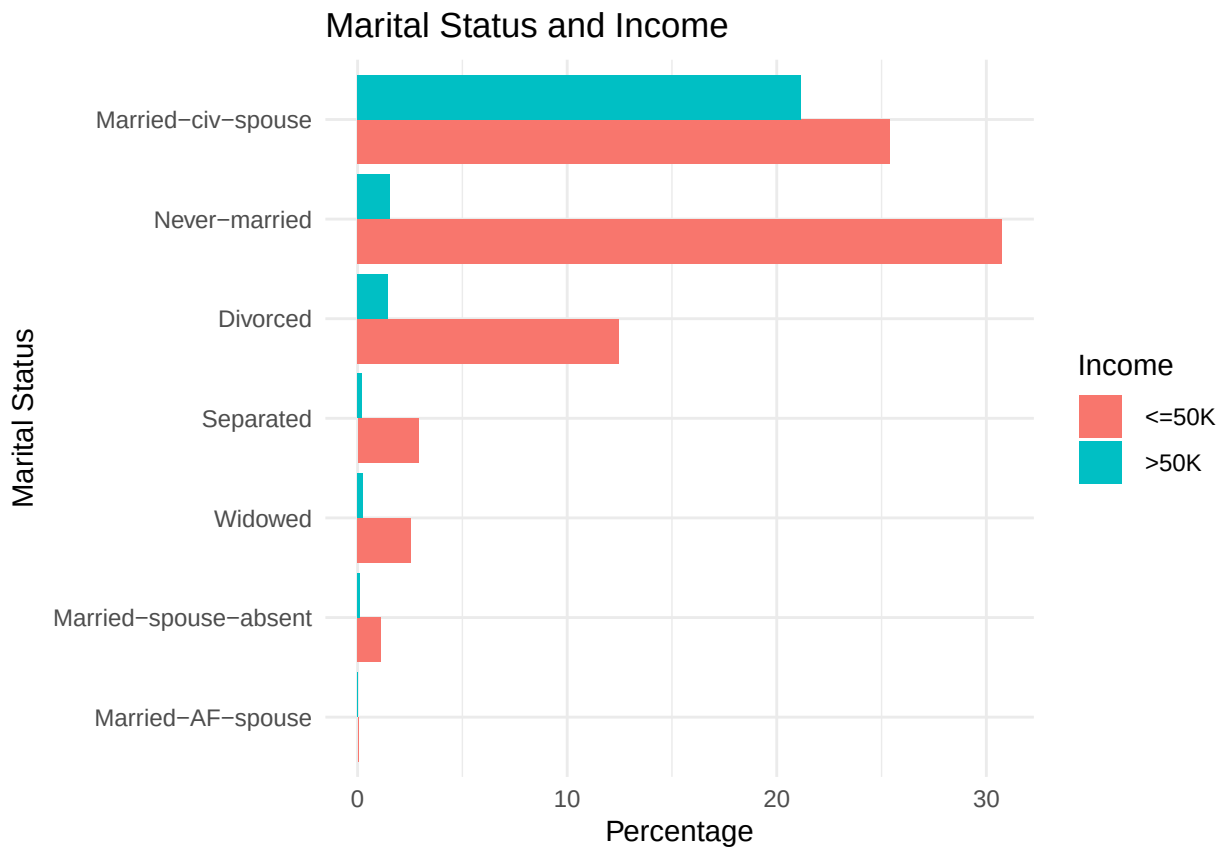



```r
# Occupation and income

ggplot(adult, aes(y = occupation, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Occupation and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Occupation") +
  theme_minimal()
```

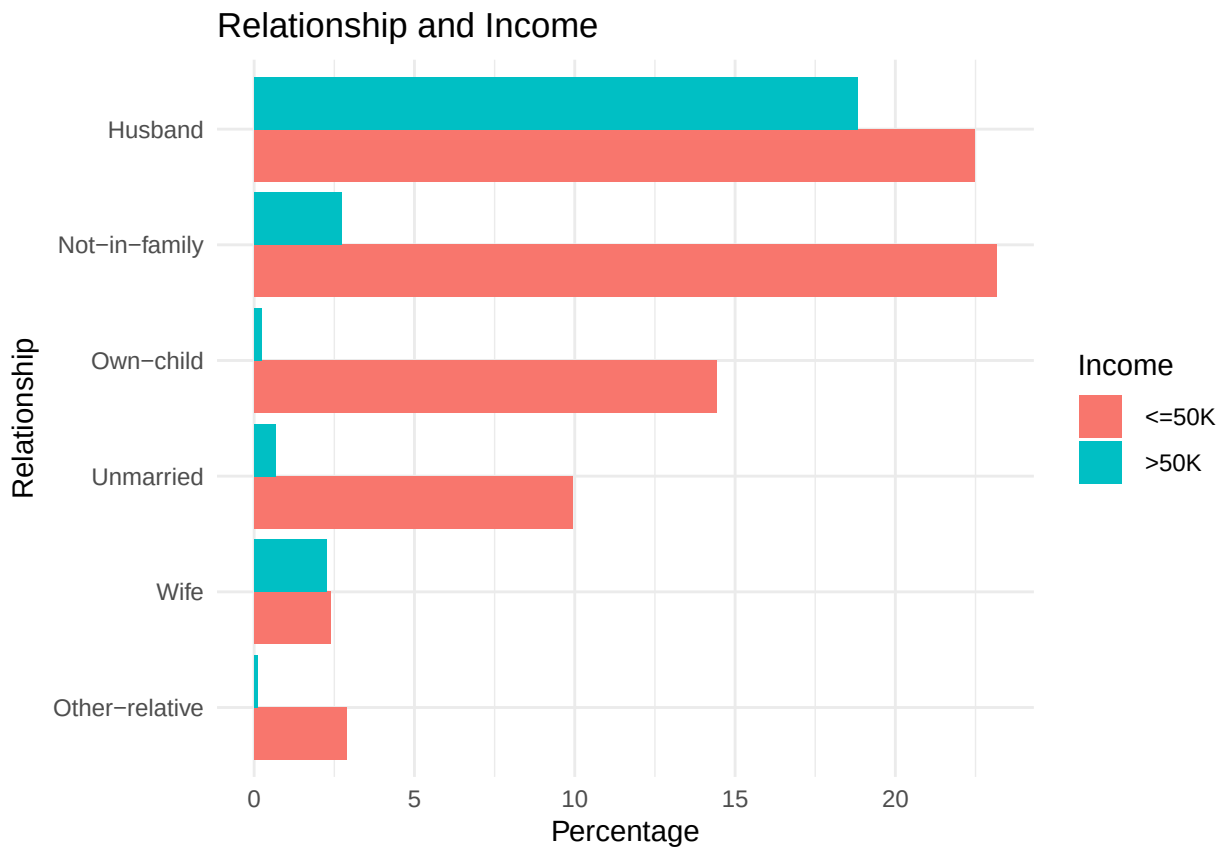

```r
# Education and income

ggplot(adult, aes(y = education, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Education and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Education") +
  theme_minimal()
```



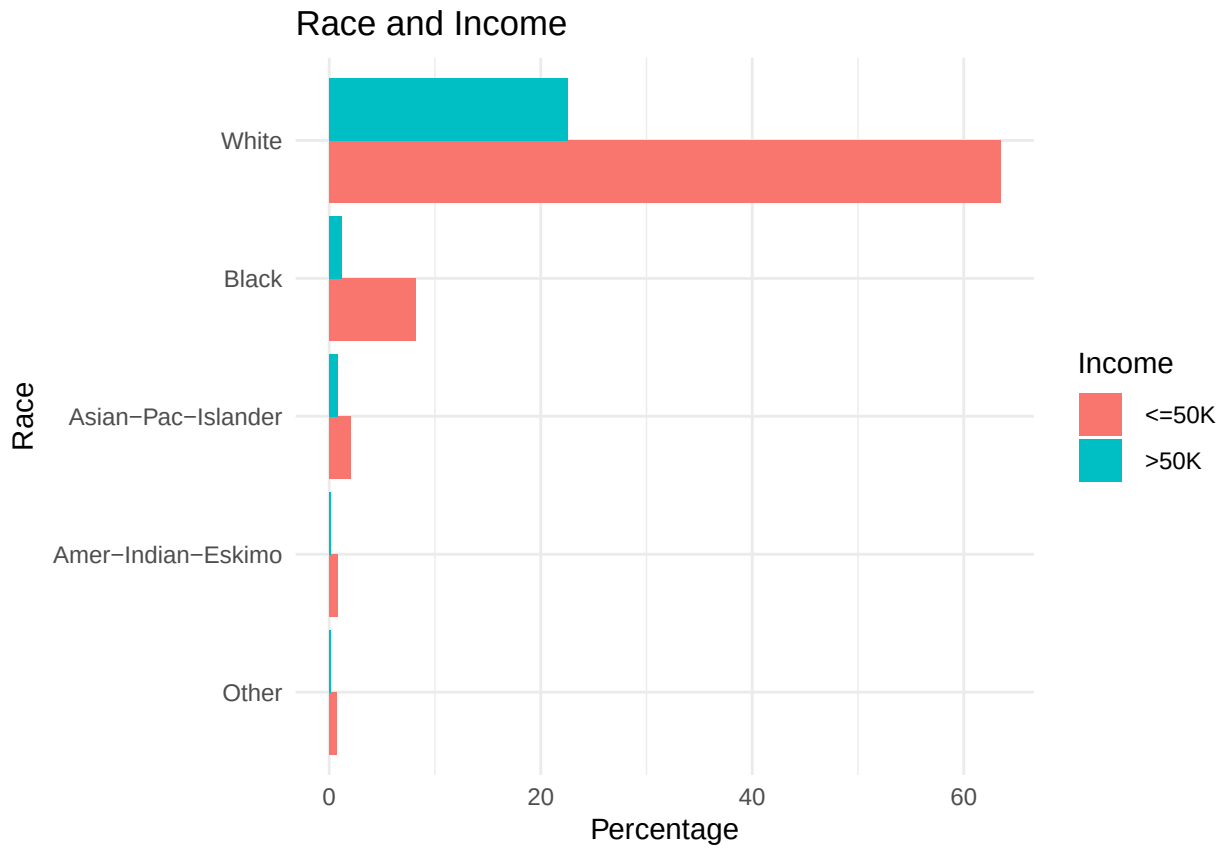

```r
# Marital status and income

ggplot(adult, aes(y = marital.status, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Marital Status and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Marital Status") +
  theme_minimal()
```



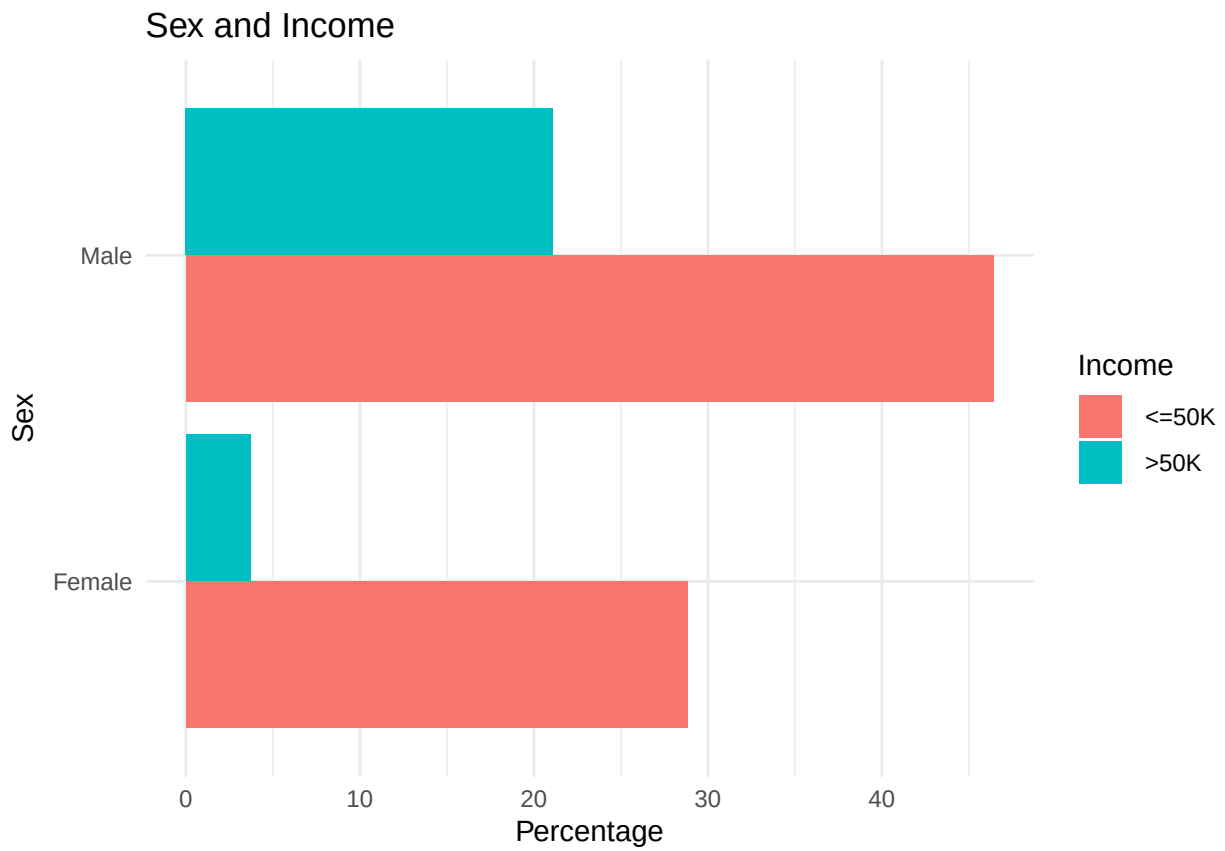

```
# Relationship and income

ggplot(adult, aes(y = relationship, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Relationship and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Relationship") +
  theme_minimal()
```




```r
# Race and income

ggplot(adult, aes(y = race, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Race and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Race") +
  theme_minimal()
```




```
# Sex and income

ggplot(adult, aes(y = sex, fill = income)) +
  geom_bar(aes(x = 100*(..count..)/sum(..count..)), position='dodge') +
  ggtitle("Sex and Income") +
  labs(fill = "Income") +
  xlab("Percentage") +
  ylab("Sex") +
  theme_minimal()
```



As we see from the above graphs, all categorical variables shows influence on income level.

2.2 Data Cleaning

In this section, I clean the dataset for modeling.

```
# Combine capital.gain and capital.loss into a single capital.change variable in train and test set

train$capital.change <- train$capital.gain - train$capital.loss
test$capital.change <- test$capital.gain - test$capital.loss

train$capital.gain <- NULL
train$capital.loss <- NULL
test$capital.gain <- NULL
test$capital.loss<-NULL

# Switch income and capital.change columns (let income be the last column)

train[c(11,12)] <- train[c(12,11)]
colnames(train)[11:12] <- colnames(train)[12:11]
test[c(11,12)] <- test[c(12,11)]
colnames(test)[11:12] <- colnames(test)[12:11]


# Delete education variable in train and test set
```

```r
train$education <- NULL
test$education <- NULL

# Delete native.country variable in train and test set

train$native.country <- NULL
test$native.country <- NULL

# Convert income to dummy variable

train$income <- as.factor(ifelse(train$income == ' <=50K', 0, 1))
test$income <- as.factor(ifelse(test$income == ' <=50K.', 0, 1))
```

2.3 Classification Tree

In the classification tree model, we achieve the prediction accuracy of 83.89774%.

```r
set.seed(1, sample.kind = "Rounding")
tree <- rpart(income ~ ., data = train, method = 'class')
tree.hat <- predict(tree, newdata = test, type = 'class')
confusionMatrix(tree.hat, test$income)$overall["Accuracy"]
```

```
##  Accuracy
## 0.8389774
```

2.3 Random Forest

With the random forest model, we achieve the OOB error rate of 13.92% and prediction accuracy of 85.73705%.

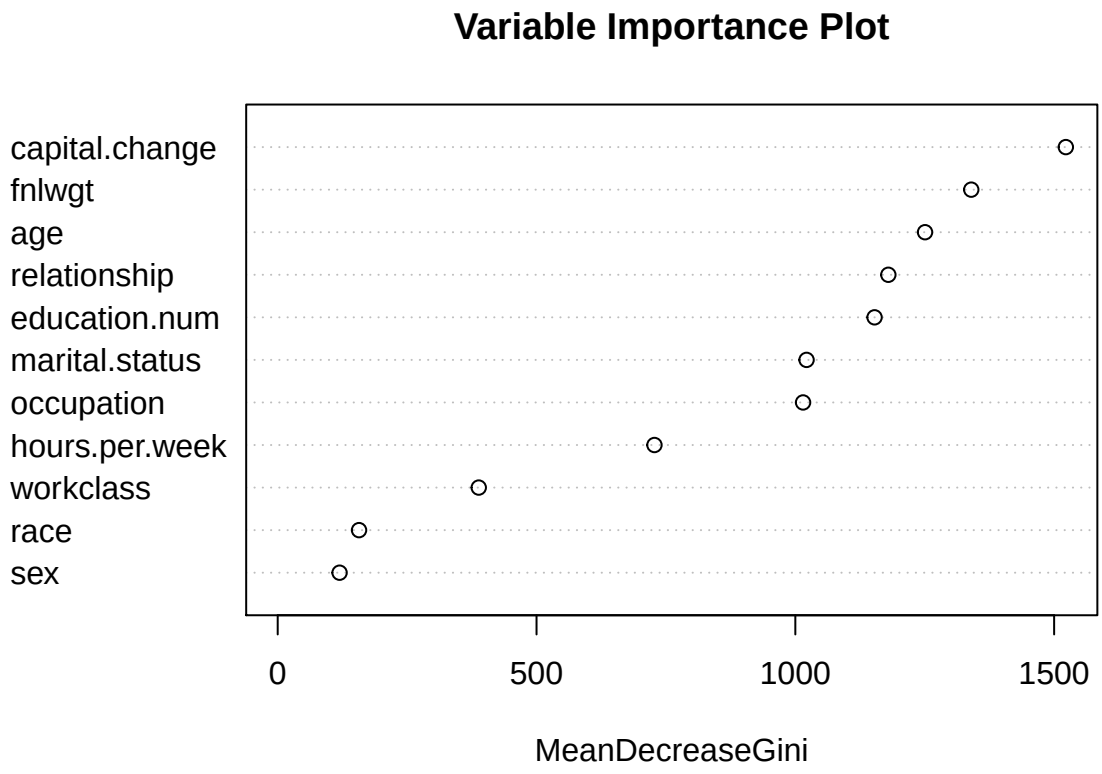
```r
set.seed(1, sample.kind="Rounding")
forest <- randomForest(train$income ~ ., data = train, mtry = sqrt(10), importance = TRUE)
forest
```

```
##
## Call:
##  randomForest(formula = train$income ~ ., data = train, mtry = sqrt(10),      importance = TRUE)
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 3
##
##         OOB estimate of  error rate: 13.92%
## Confusion matrix:
##       0    1 class.error
## 0 21140 1514  0.06683146
## 1  2684 4824  0.35748535
```

```r
forest.hat <- predict(forest, newdata = test, type = "class")
confusionMatrix(forest.hat, test$income)$overall["Accuracy"]
```

```
##  Accuracy
## 0.8573705
```

```
varImpPlot(forest, type = 2, main = "Variable Importance Plot")
```



III. Conclusion

In this project, I built classification tree and random forest models to predict a person's income level with the Census Income dataset. The randome forest model achieved the accuracy of 85.73705%, higher than the 83.89774% accuracy provided by the initial classification tree model. The future work would focus on building other machine learning models such as logistic regression, KNN, naive Bayes, and neural network to increase the accuracy and predictive power.