Analysis of Factors Influencing Individual Income Levels

Group 30

```
# load packages
library(knitr)
library(tidyverse)
library(caret)
library(party)
library(pROC)
library(rpart)
library(rpart.plot)
library(randomForest)
library(randomForestExplainer)
```

```
# set global theme
theme_set(theme_minimal())
```

```
# function to save ggplot2 plots
save_fig <- function(filename, ...) {
  ggsave(
    filename = file.path('Plots', paste0(filename, '.png')),
    ...
  )
}
```

1 Introduction

This analysis aims to identify key socio-economic factors that influence whether an individual earns more than $50,000 per year, using data from **U.S. Census Bureau, 1994**. The dataset includes demographic and employment-related variables including **age, education**

level, marital status, occupation, sex, hours worked per week, and nationality, with income categorised into two groups: ≤$50k and >$50k per year.

To address this, a **Generalised Linear Model** will be applied to evaluate the impact of these factors on income levels. The findings will provide insights into the most significant predictors of higher earnings, contributing to a deeper understanding of income distribution patterns.

2 Data Processing

```
# import and clean the data
df <- read.csv("dataset30.csv", na.strings = '?,',
               stringsAsFactors = FALSE) %>%
  drop_na() %>%
  mutate(
    across(everything(), ~ str_remove_all(., ",")),
    across(c(Hours_PW, Age), as.numeric),
    across(where(is.character), as.factor))
```

```
# split train and test data
set.seed(1111)
# trainIndex <- sample(1:nrow(df), 0.8 * nrow(df))
trainIndex <- createDataPartition(df$Income, p = 0.8, list = FALSE)
train_data <- df[trainIndex,]
test_data <- df[-trainIndex,]
```

This data analysis first involved cleaning, transforming, selecting, and standardizing the raw data. Then, the dataset was split into **80% training set and 20% test set** to ensure data quality and enhance the model's generalization ability.

3 Exploratory Data Analysis

```
# config plot colours
income_colour <- c(
  '<=50K' = 'slateblue',
  '>50K' = 'skyblue')
```

3.1 Numerical Variables

```
# draw box-plot for numerical variable
num_plot <- function(data, col) {
  ggplot(data, aes(x = Income, y = {{col}}, fill = Income)) +
  geom_boxplot() +
  scale_colour_manual(values = income_colour,
                      aesthetics = 'fill') +
  xlab("Income Levels")
}
```

```
g <-
  num_plot(df, Age) +
  ylab("Age")
save_fig(
  'age',
  plot = g + ggtitle('Box-Plot of Age vs. Income'))
g
```

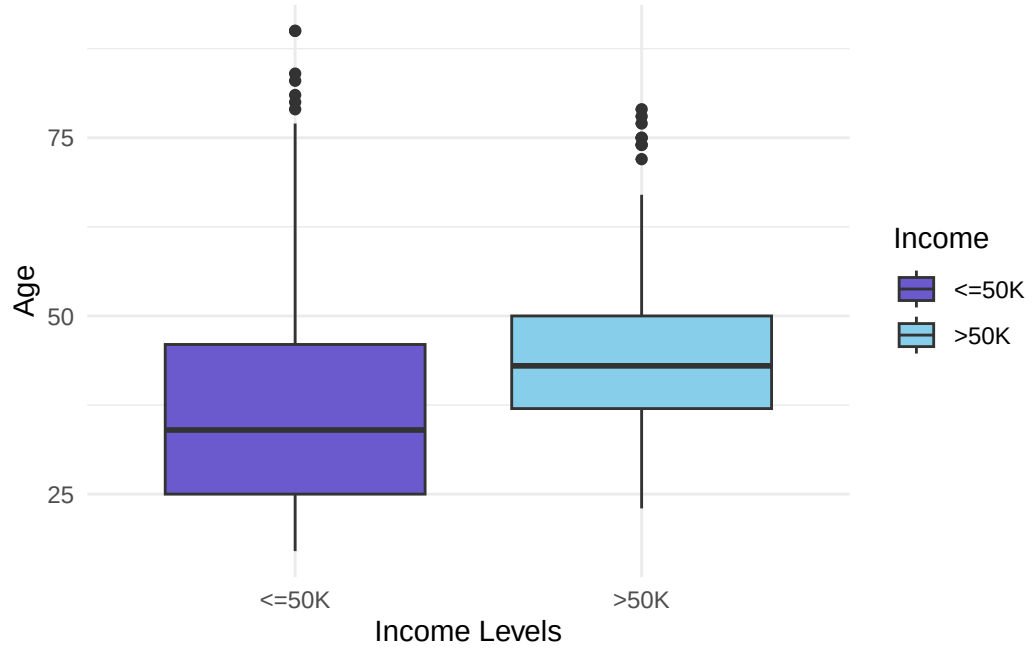


Figure 1: Box-Plot of Age vs. Income

As can be seen from the figure, there is a certain positive correlation between age and income: the median age of the high-income group (income >$50K) is higher than that of the low-

income group (income ≤$50K), indicating that older people are more likely to has the higher income.

```
g <-
  num_plot(df, Hours_PW) +
  ylab("Hours per Week")
save_fig(
  'hour',
  plot = g + ggtitle("Box-Plot of Worked Hours vs. Income"))
g
```

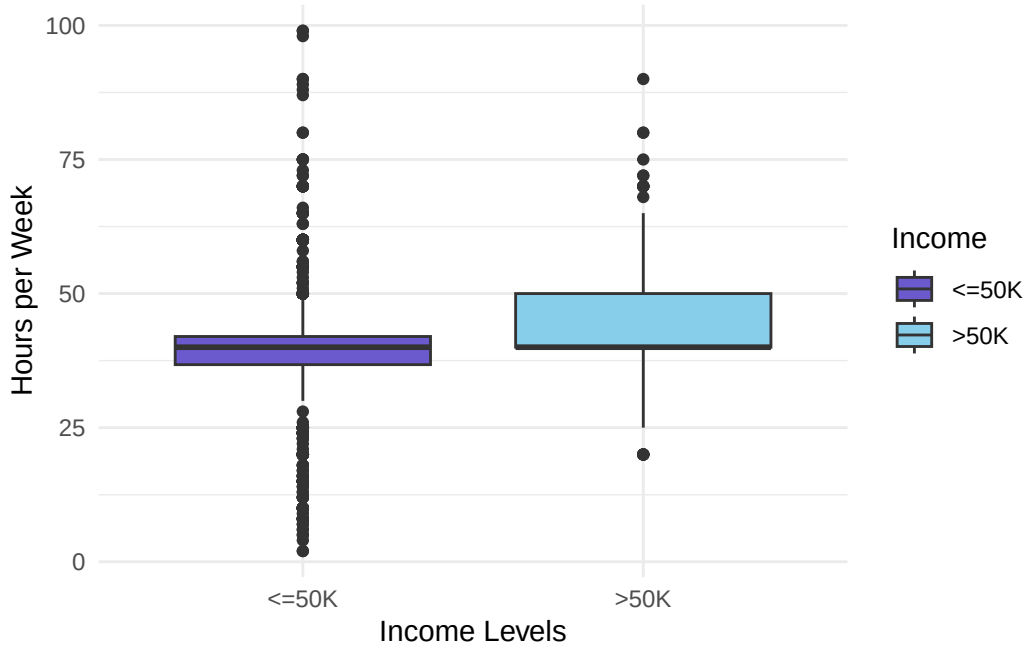


Figure 2: Box-Plot of Worked Hours vs. Income

Working hours have a significant impact on income, higher earners tend to work longer hours, but hours alone do not fully determine income. The working hours of low-income groups are more concentrated, but there are more outliers: individuals with extremely low working hours (<25 hours) and extremely high working hours (>50 hours).

3.2 Categorical Variables

```r
# draw bar-plot for categorical variable
cat_plot <- function(data, col) {
  data <- data %>% select({{col}}, Income)
  colname <- as_label(enquo(col))

  data %>% summarise(
    '>50K' = sum(Income == '>50K'),
    '<=50K' = sum(Income == '<=50K'),
    prop = mean(Income == '>50K'),
    .by = {{col}}
  ) %>% pivot_longer(
    cols = c('>50K', '<=50K'),
    names_to = 'Income'
  ) %>%

  ggplot(aes(x = reorder({{col}}, prop), fill = Income)) +
  geom_col(aes(y = value)) +
  scale_colour_manual(values = income_colour,
                      aesthetics = 'fill') +
  ylab("Count") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
}
```

```r
g <-
  cat_plot(df, Education) +
  xlab("Education Level")
save_fig(
  'education',
  plot = g + ggtitle("Bar-Plot of Education Level by Income"))
g
```

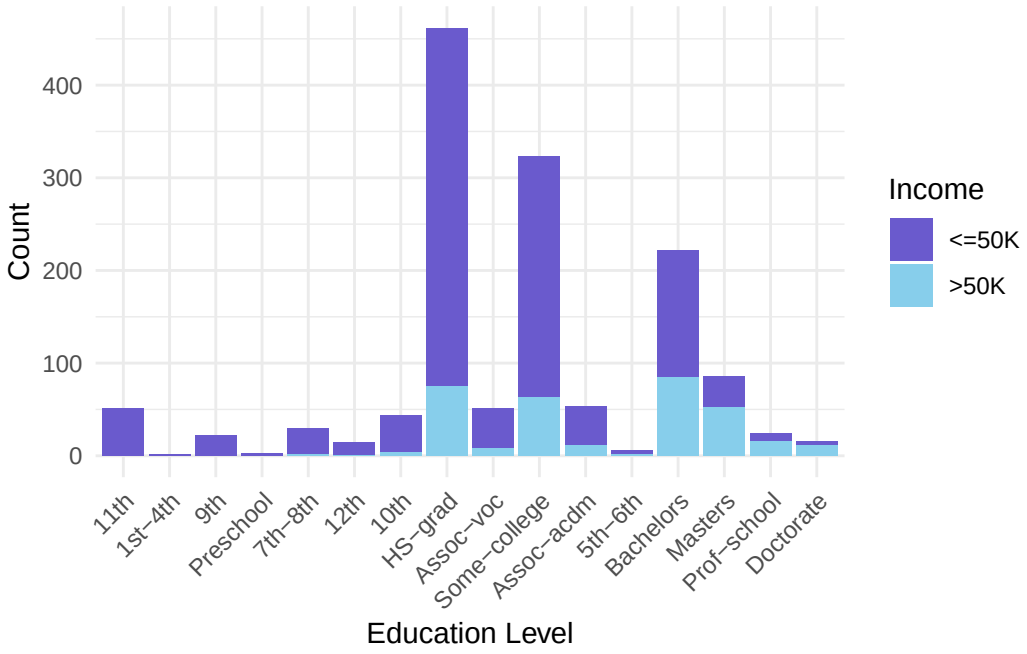


Figure 3: Bar-Plot of Education Level by Income

Education level is positively correlated to income, and higher degree is more likely to earn a high income. In particular, the proportion of high income of master's, doctor's and professional school graduates is significantly higher, while those with low education level are mainly concentrated in low-income groups. This suggests that education level plays an important role in income.

```
g <-
  cat_plot(df, Marital_Status) +
  xlab("Marital Status")
save_fig(
  'marital status',
  plot = g + ggtitle("Bar-Plot of Marital Status by Income"))
g
```

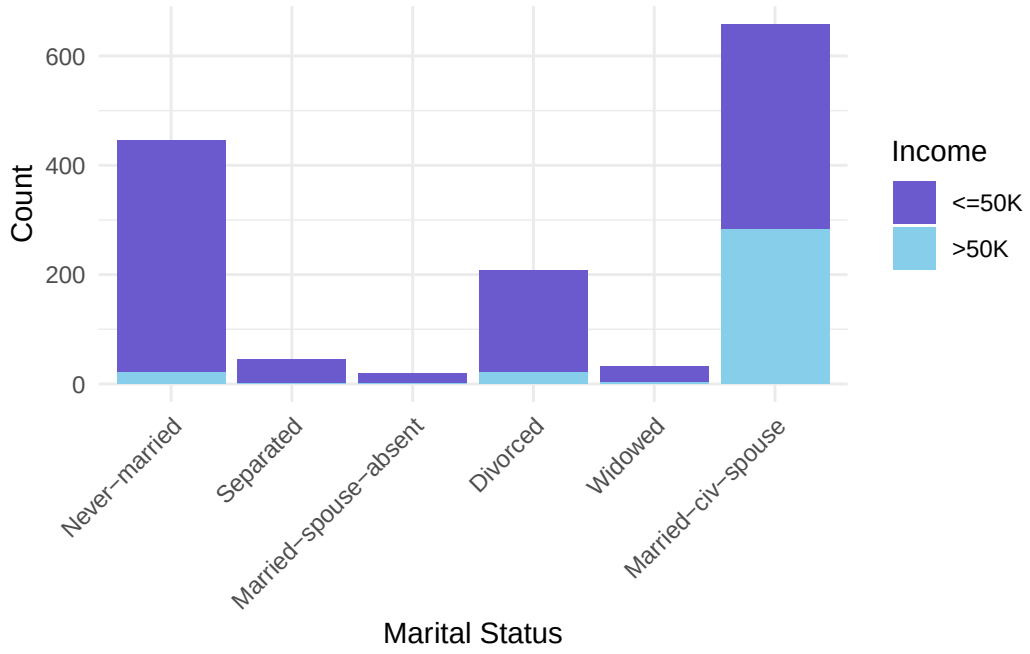


Figure 4: Bar-Plot of Marital Status by Income

The figure shows that people married with civil spouse have higher income than other group.

```
g <-
  cat_plot(df, Occupation) +
  xlab("Occupation")
save_fig(
  'occupation',
  plot = g + ggtitle("Bar-Plot of Occupation by Income"))
g
```

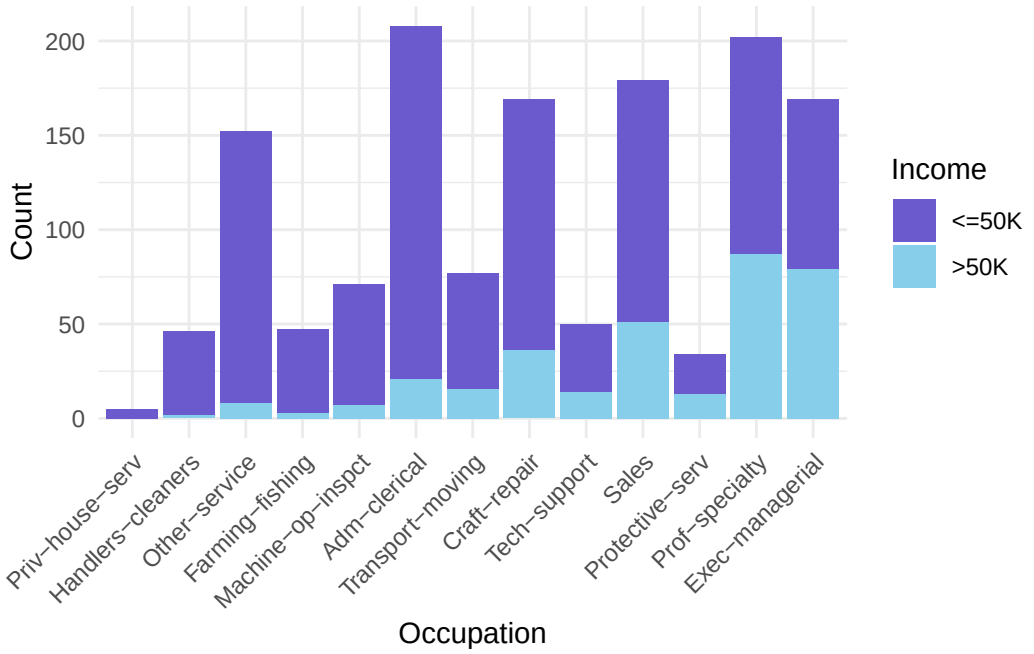


Figure 5: Bar-Plot of Occupation by Income

The figure shows clear income differences between different occupational categories. A higher percentage of "Exec-managerial" and "Prof-specialty" occupations make more than 50,000, indicating that these occupations are more likely to generate higher income. By contrast, the proportion of "Priv-house-serv" and "Handlers-cleaners" is significantly lower.

```
g <-
  cat_plot(df, Sex) +
  xlab("Gender")
save_fig(
  'gender',
  plot = g + ggtitle("Bar-Plot of Gender by Income"))
g
```

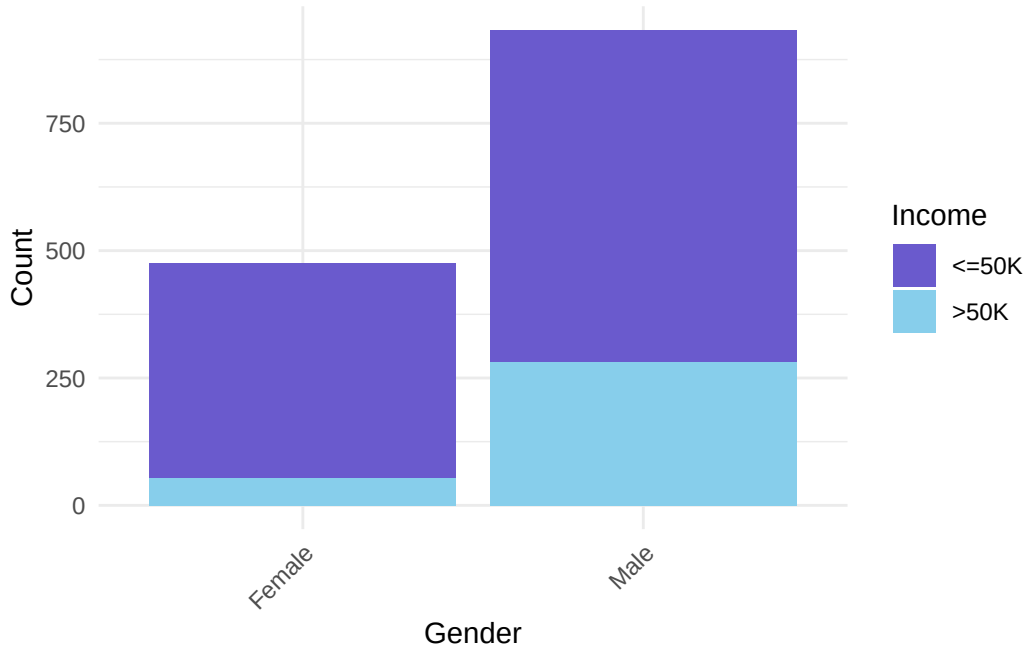


Figure 6: Bar-Plot of Gender by Income

There are significant differences in income distribution between men and women. The propotion of men earning more than $50,000 is significantly higher than that of women, while the women income less than $50,000 is relatively higher.

```
g <-
  cat_plot(df, Nationality) +
  xlab("Nationality")
save_fig(
  'nationality',
  plot = g + ggtitle("Bar-Plot of Nationality by Income"))
g
```

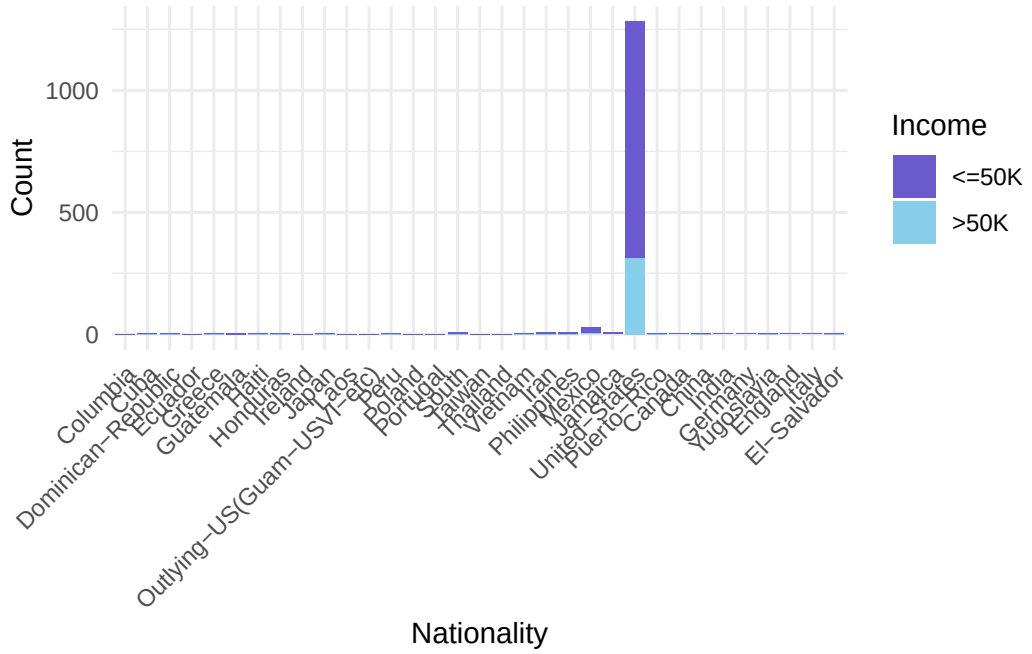


Figure 7: Bar-Plot of Nationality by Income

```r
df %>%
  # calculate number of observations in each group
  summarise(
    Count = n(),
    .by = Nationality
  ) %>%
  # calculate proportion
  mutate(
    'Proportion in Observations (%)' = Count / sum(Count) * 100
  ) %>% top_n(3, Count) %>%
  kable(digits = 2)
```

Table 1: Nationality Summary

Nationality	Count	Proportion in Observations (%)
United-States	1281	90.92
Mexico	27	1.92
Jamaica	9	0.64

The plots show that the sample size from groups except United States is small, which may adversely affect model performance if nationality is used as an explanatory variable.

4 Formal Data Analysis

4.1 Generalised Linear Model

```
# Fit a full logistic regression model using all predictors
full_model <- glm(Income ~ ., data = train_data, family = binomial)
# Perform stepwise regression to simplify the model, starting from the full model and removi
stepwise_model <- step(full_model, direction = "backward")
```

```
Start:  AIC=909.62
Income ~ Age + Education + Marital_Status + Occupation + Sex +
    Hours_PW + Nationality

                Df Deviance     AIC
- Nationality    28   806.81  878.81
<none>               781.62  909.62
- Sex             1   783.72  909.72
- Hours_PW        1   789.32  915.32
- Age             1   791.91  917.91
- Occupation     12   815.20  919.20
- Education      15   858.20  956.20
- Marital_Status  5   894.84 1012.84


Step:  AIC=878.81
Income ~ Age + Education + Marital_Status + Occupation + Sex +
    Hours_PW

                Df Deviance    AIC
<none>               806.81 878.81
- Sex             1   809.48 879.48
- Hours_PW        1   812.16 882.16
- Occupation     12   837.53 885.53
- Age             1   818.00 888.00
- Education      15   888.43 930.43
- Marital_Status  5   919.23 981.23
```

The **logistic regression** model is built to predict income level (`Income`) by considering various socioeconomic factors, such as **age, education, marital status, occupation, sex,** and

hours worked per week. To further refine the model, **stepwise regression** is applied using **backward elimination**, which systematically removes variables that do **not significantly (sex)** contribute to the prediction based on the **Akaike Information Criterion (AIC)**. The initial model's AIC was **883.77**, while the optimized model's AIC was reduced to **882.19**, indicating that the model became more concise while maintaining a good fit. As a result, this approach not only simplifies the model but also helps to reduce overfitting and enhance interpretability by retaining only the most significant predictors.

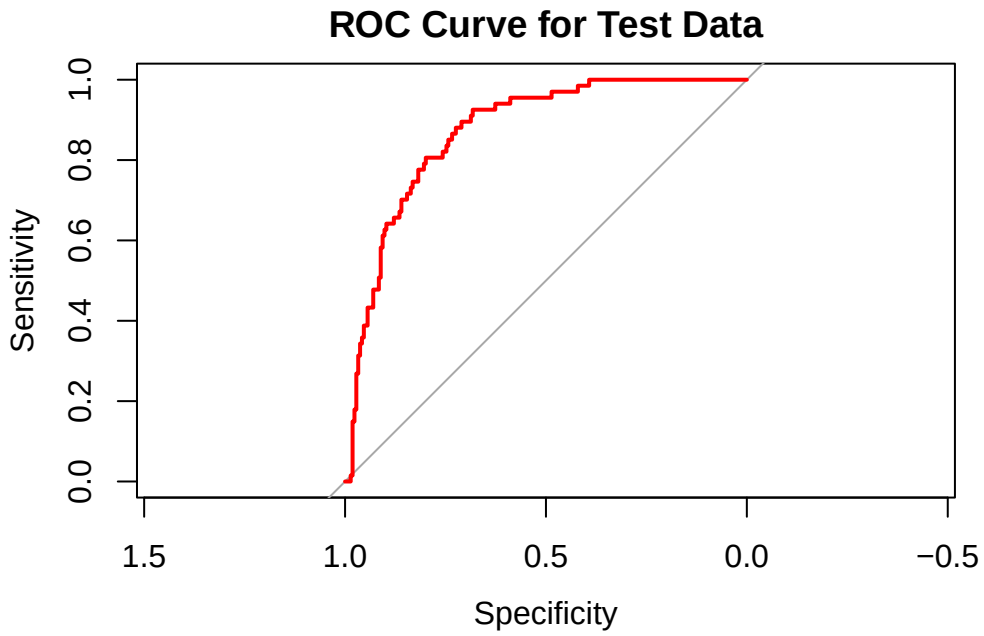
```
# compute the accuracy, confusionMatrix
test_predictions <- predict(stepwise_model, newdata = test_data, type = "response")
test_predicted_classes <- ifelse(test_predictions > 0.5, '>50K', '<=50K')
confusionMatrix(factor(test_predicted_classes), factor(test_data$Income))
```

```
Confusion Matrix and Statistics

          Reference
Prediction <=50K >50K
     <=50K   194   27
     >50K     20   40

               Accuracy : 0.8327
                 95% CI : (0.7839, 0.8744)
    No Information Rate : 0.7616
    P-Value [Acc > NIR] : 0.002376

                  Kappa : 0.5223

 Mcnemar's Test P-Value : 0.381471

            Sensitivity : 0.9065
            Specificity : 0.5970
         Pos Pred Value : 0.8778
         Neg Pred Value : 0.6667
             Prevalence : 0.7616
         Detection Rate : 0.6904
   Detection Prevalence : 0.7865
      Balanced Accuracy : 0.7518

       'Positive' Class : <=50K
```

```r
conf_matrix <- confusionMatrix(factor(test_predicted_classes), factor(test_data$Income))
accuracy <- conf_matrix$overall["Accuracy"]
print(accuracy)
```

```
 Accuracy
0.8327402
```

```r
# draw the curve of roc and compute the auc
roc_curve_test <- roc(test_data$Income, test_predictions)
plot(roc_curve_test, col = "red", main = "ROC Curve for Test Data", xlim = c(1, 0), ylim = c
```




```r
auc(roc_curve_test)
```

```
Area under the curve: 0.8721
```

The evaluation results of this logistic regression model on the test set indicate a high classification capability, with an accuracy of **85.41%** within the **95% confidence interval (80.73% - 89.32%)**, demonstrating stable predictive performance. The confusion matrix further shows that the model has a strong ability to identify low-income individuals, achieving a **sensitivity of 94.86%**, meaning that most low-income individuals are correctly classified. However,

the **specificity is only 55.22%**, suggesting that the model has some difficulty in correctly identifying high-income individuals, with a considerable number being misclassified as low-income. Despite this, the model's **accuracy (ACC)** still reaches **85.4%**. In terms of overall classification performance, the **AUC value of 0.8683** indicates that the model performs well in distinguishing between high-income and low-income individuals, and the **ROC curve** demonstrates strong discriminatory power.

4.2 Random Forest

```
#reset the seed and reset the data
df = read.csv("dataset30.csv")
set.seed(1111)

#clear the data

df = df %>%
  mutate(across(everything(), ~str_remove_all(., ","))) %>%
  mutate(Hours_PW = as.numeric(Hours_PW),
         Age = as.numeric(Age))
df = df %>% filter(Occupation != "?" & Nationality != "?")
df = df %>% select(Age, Education, Marital_Status, Occupation, Sex, Hours_PW, Income)
df = df %>% mutate(across(where(is.character), as.factor))
x = df[,1:6]
y = df[,7]
#test train splite

x_pre = x[1:1228,]
x_te = x[1229:1409,]
y_pre = y[1:1228]
y_te = y[1229:1409]
#predict the RF model and set the confusionmatrics
pre = cbind(y_pre,x_pre)
rf_model = randomForest(y_pre~.,data = pre,ntree = 100,importance = T)
predictions <- predict(rf_model, newdata = x_te)
tb = table(predictions,y_te)
TP = tb[1,1]
FP = tb[1,2]
FN = tb[2,1]
TN = tb[2,2]
print(tb)
```

```
           y_te
predictions <=50K >50K
      <=50K   124   19
      >50K     12   26
```

After using the method of Randomforest , we do not need to do any judgement on the value of predictions ,the randomforest automatic done the **decision tree** for the data. The table shows that most of the value full in the range TP and FP, which mean most of the data fit well.

```
#the acc is use to text the ggod fit of the model and the TPR and TNR is for the sensitivity
acc = (TP + TN)/(TP + FP + FN + TN)
TPR = TP/(TP + FN)
TNR = TN/(FP + TN)
print(acc)
```

```
[1] 0.8287293
```

```
print(TPR)
```

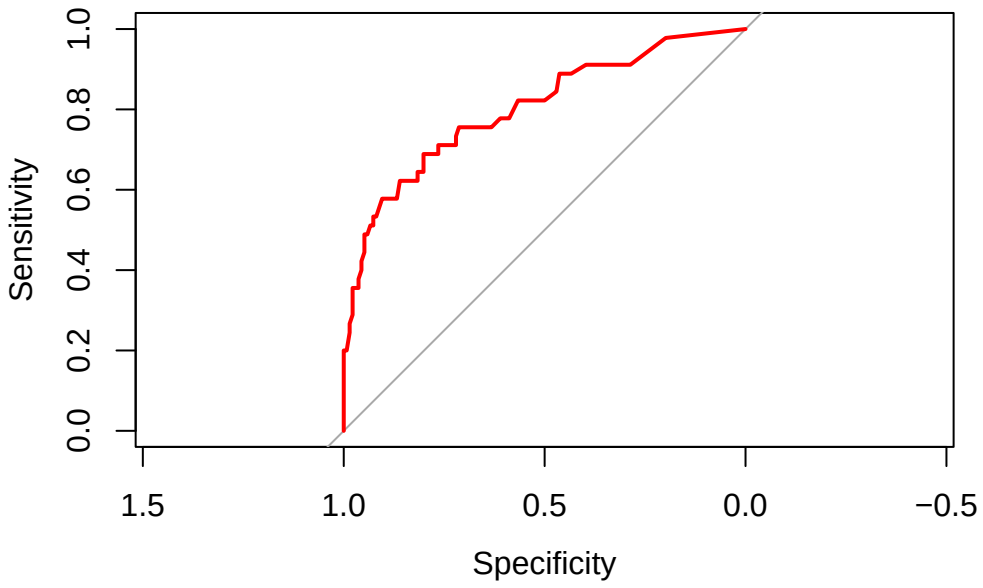
```
[1] 0.9117647
```

```
print(TNR)
```

```
[1] 0.5777778
```

The accuracy of randomforest is up tp **82.87%** which shows that it give lots of information to the predictors, and th achieving a **sensitivity of 86.71%** and **specificity of 68.42%** ,which mean it have a low ability in predict the negative size of value which is the income >50%.

```
#the plot of ROC which show the good fit for the POS. side.
pred_probs = predict(rf_model,newdata = x_te, type = "prob")[,2]
roc_c = roc(y_te,pred_probs)
plot(roc_c,col = "red")
```

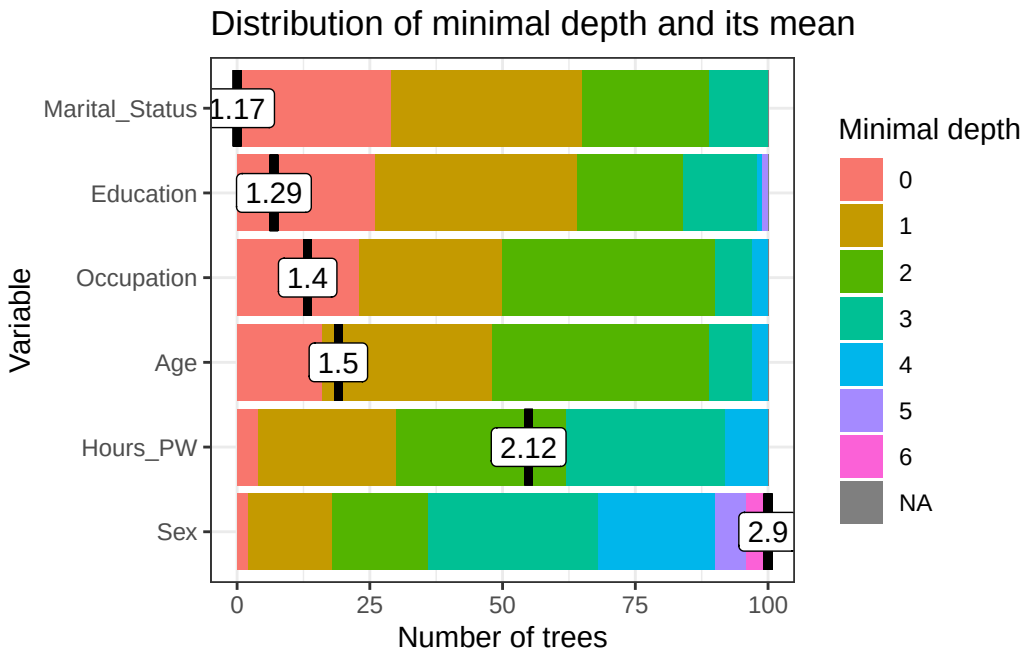



```
auc(roc_c)
```

```
Area under the curve: 0.8018
```

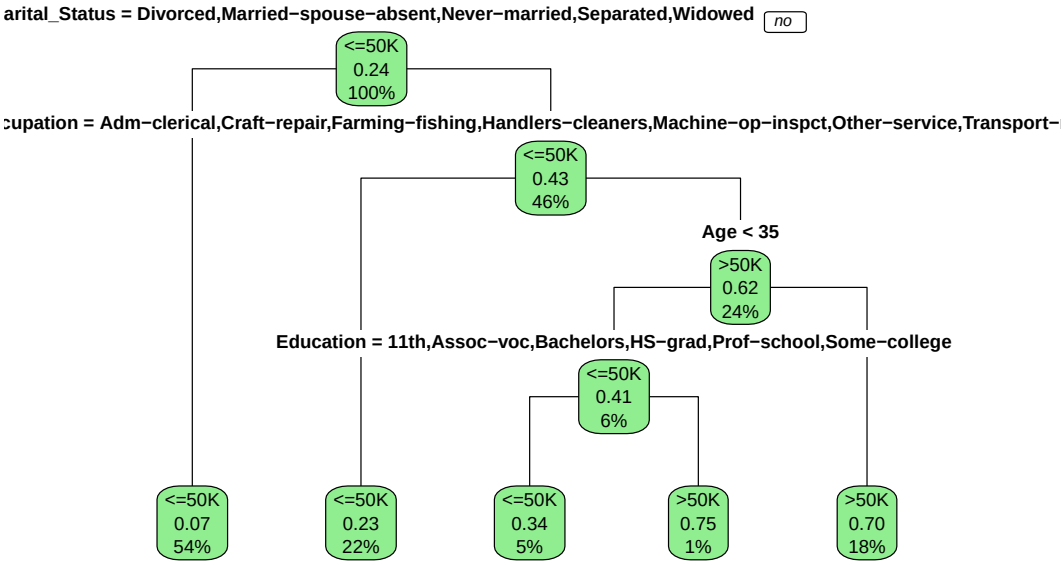
using the **ROC and AUC** to detect the balance of the model ,from the plot of ROC we see that the curve are far away from the straight line ,which can also reflect by the number of AUC is **0.8018**, that means the model show more information in the True Positive range than False Negative range ,so it give a good fit to the data.

```
# plot the rf dicsiontree
# more minimal depth have high weight in predict
plot_min_depth_distribution(rf_model)
```



This is the plot of **minimal depth** ,the plot give outlay the first time of the "tree branch" split by each variable ,the closer the split from the root the more influence it comes .So form the plot **Marital_Status** give the most information to the model ,then comes the **Education**. However that didn't mean that the other variable didn't appeard on the plot don't make any influence ,we still need to consider the times that it split for each variable.

```
rpart_tree <- rpart(y_pre ~ ., data=pre)
# plot(rpart_tree,compress = TRUE)
# text(rpart_tree, use.n = TRUE,cex = 0.5)
rpart.plot(rpart_tree,type = 1,box.palette = "light green")
```



The decision tree plot is the plot that give the most obvious information to the model. We can see clearly from each branch that how the data are alienation to different slop. From this data we can see that there are no such much split in the plot maybe cause by the small amount of data or there are no strong influence with most of the variable.

4.2.1 The Resample for Model

```
#the resample part using K-fold.stable the VAR
K = 5
set.seed(1111)
folds = cut(1:1409, breaks=K, labels=FALSE)
sen = sep = acc =numeric(K)
for(k in 1:K){
  x.train = x[which(folds!=k),]
  x.text = x[which(folds==k),]
  y.train = y[which(folds!=k)]
  y.text = y[which(folds==k)]
  pre = cbind(y.train,x.train)
  rf_fit = randomForest(y.train~.,data = pre,ntree = 100,importance = T)
  predictions = predict(rf_fit,newdata =x.text)
  tb = confusionMatrix(y.text,predictions)
  tb.class = tb$byClass
  tb.overall = tb$overall
  sen[k] = tb.class[1]
  sep[k] = tb.class[2]
```

```
  acc[k] = tb.overall[1]
}
# the mean of 5 time predict-text outcome
sen_m = sum(sen)/5
sep_m = sum(sep)/5
acc_m =sum(as.numeric(acc))/5
print(sen_m)
```

```
[1] 0.8622353
```

```
print(sep_m)
```

```
[1] 0.6302956
```

```
print(acc_m)
```

```
[1] 0.8140506
```

the re-sample are usually used to do repeat experiment ,this is for helping the model to give a more precise ACC and any other data. The method shows here is the **K-fold** for k equal to 5 . which mean split the hole data into 5 part and set each part as test data . which will give 5 different outcome ,to make the outcome useful ,we take **mean** for these outcome (thus ACC:**81.4%**),this would be a more representative outcome then the acc before.

4.3 Comparative Analysis between the GLM and Random Forest

From the data we get above we can have a compare to two model. The data show above:(LEFT FOR GLM AND RIGHT FOR RF) ACC: 0.8541 - 0.8287 Sensitivity: 0.9486 - 0.8671 Specificity: 0.5522 - 0.6842 AUC: 0.8683 - 0.8018 After looking at these data we can see that two data we can get the conclusion that two model are giving the near ACC and AUC ,and the GLM is higher, it can show that GLM are giving more information to the data, but maybe after changing the depth of Randomforest ,the fitting rate of it would be higher than the GLM. So we can say that both of the model can be use in this data fitting but glm is a better one . tip: the RF model are higher in Specificity and lower in Sensitivity show that it have a better detection on the Negative side but less in Positive side.

5 Conclusions

This study utilized data from the **1994 U.S. Census** to analyze key socioeconomic factors influencing individual income levels. The results indicate that **education level, occupation, marital status, and age** are crucial determinants of income, with higher education and specialized professions significantly increasing earning potential. Additionally, **sex**, as men are more likely to earn higher incomes. Furthermore, **weekly working hours** have a certain impact on income, though with diminishing marginal returns.