Determinants of High Income: A Generalized Linear Model Analysis of 1994 US Census Socioeconomic Factors

Group 27

1. Introduction

Income inequality remains a critical socioeconomic challenge. This study analyzes the 1994 US Census dataset using a Generalized Linear Model (GLM) to identify key factors—such as age, education, occupation, and work hours—that significantly predict whether an individual earns over $50k annually. The results aim to inform targeted policy interventions for improving economic equity.

```
library(dplyr)
```

```
Attaching package: 'dplyr'

The following objects are masked from 'package:stats':

    filter, lag

The following objects are masked from 'package:base':

    intersect, setdiff, setequal, union
```

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v forcats   1.0.0     v readr     2.1.5
v ggplot2   3.5.1     v stringr   1.5.1
v lubridate 1.9.3     v tibble    3.2.1
v purrr     1.0.2     v tidyr     1.3.1

-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x purrr::%||%()   masks base::%||%()
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to beco
```

```r
library(broom)
library(ggplot2)
library(car)
```

```
Loading required package: carData

Attaching package: 'car'

The following object is masked from 'package:purrr':

    some

The following object is masked from 'package:dplyr':

    recode
```

```r
library(janitor)
```

```

Attaching package: 'janitor'

The following objects are masked from 'package:stats':

    chisq.test, fisher.test
```

```r
library(broom) # Model results sorting
library(ResourceSelection) # Hosmer-Lemeshow test
```

```
Warning: package 'ResourceSelection' was built under R version 4.4.3
```

```
ResourceSelection 0.3-6      2023-06-27
```

```
library(pROC) # ROC curve
```

```
Type 'citation("pROC")' for a citation.
```

```
Attaching package: 'pROC'
```

```
The following objects are masked from 'package:stats':

    cov, smooth, var
```

2. Data processing

2.1 Data import

Select the raw data, remove the NA value from the data, and determine the corresponding data type. Among all variables, only Age and Hours_PW are numerical variables. The integrated data is output to 'cleaned_dataset27' for preliminary judgment of data and variables.

```
# load data
data = read.csv("C:/Users/2962286z/Desktop/Group 27/dataset27.csv")
```

```
# inspect data
str(data)
```

```
'data.frame':   1500 obs. of  8 variables:
 $ Age           : int  37 49 20 64 60 32 58 42 20 42 ...
 $ Education     : chr  "Bachelors," "Some-college," "Some-college," "Bachelors," ...
 $ Marital_Status: chr  "Married-civ-spouse," "Divorced," "Never-married," "Married-civ-spous
 $ Occupation    : chr  "Exec-managerial," "Machine-op-inspct," "Other-service," "Exec-manag
 $ Sex           : chr  "Male," "Male," "Male," "Male," ...
 $ Hours_PW      : chr  "80," "45," "45," "55," ...
 $ Nationality   : chr  "United-States," "United-States," "United-States," "United-States,"
 $ Income        : chr  ">50K" "<=50K" "<=50K" ">50K" ...
```

```
summary(data)
```

```
      Age          Education          Marital_Status      Occupation
 Min.   :17.00   Length:1500        Length:1500        Length:1500
 1st Qu.:27.00   Class :character   Class :character   Class :character
 Median :37.50   Mode  :character   Mode  :character   Mode  :character
 Mean   :38.91
 3rd Qu.:48.00
 Max.   :90.00
     Sex              Hours_PW         Nationality           Income
 Length:1500        Length:1500        Length:1500        Length:1500
 Class :character   Class :character   Class :character   Class :character
 Mode  :character   Mode  :character   Mode  :character   Mode  :character
```

```
sapply(data, unique)
```

```
$Age
 [1] 37 49 20 64 60 32 58 42 25 30 66 59 44 46 17 47 26 33 48 52 40 50 34 43 22
[26] 35 62 39 69 27 38 41 23 56 24 21 18 45 75 51 29 19 72 31 28 65 55 57 67 36
[51] 54 61 71 53 73 63 70 68 90 77 74 76 78 80 81

$Education
 [1] "Bachelors,"    "Some-college," "Masters,"      "Assoc-acdm,"
 [5] "HS-grad,"      "Assoc-voc,"    "9th,"          "10th,"
 [9] "Prof-school,"  "5th-6th,"      "7th-8th,"      "Doctorate,"
[13] "12th,"         "11th,"         "1st-4th,"      "Preschool,"

$Marital_Status
[1] "Married-civ-spouse,"    "Divorced,"              "Never-married,"
[4] "Married-spouse-absent," "Separated,"             "Widowed,"
[7] "Married-AF-spouse,"

$Occupation
 [1] "Exec-managerial,"   "Machine-op-inspct," "Other-service,"
 [4] "?,"                 "Craft-repair,"      "Sales,"
 [7] "Adm-clerical,"      "Prof-specialty,"    "Protective-serv,"
[10] "Farming-fishing,"   "Handlers-cleaners," "Transport-moving,"
[13] "Tech-support,"      "Priv-house-serv,"
```

```
$Sex
[1] "Male,"   "Female,"

$Hours_PW
 [1] "80," "45," "55," "40," "42," "50," "14," "65," "35," "58," "30," "9,"
[13] "15," "12," "70," "24," "8,"  "6,"  "16," "52," "20," "10," "60," "36,"
[25] "21," "48," "38," "18," "43," "39," "90," "72," "32," "49," "56," "84,"
[37] "44," "54," "25," "37," "99," "46," "3,"  "17," "47," "4,"  "5,"  "53,"
[49] "28," "75," "68," "22," "27," "13," "11," "34," "33," "98," "2,"  "85,"

$Nationality
 [1] "United-States,"              "England,"
 [3] "China,"                      "?,"
 [5] "Outlying-US(Guam-USVI-etc)," "Jamaica,"
 [7] "Scotland,"                   "Philippines,"
 [9] "Haiti,"                      "Mexico,"
[11] "Italy,"                      "Cuba,"
[13] "Canada,"                     "Japan,"
[15] "Puerto-Rico,"                "Trinadad&Tobago,"
[17] "Dominican-Republic,"         "El-Salvador,"
[19] "Greece,"                     "Nicaragua,"
[21] "South,"                      "Germany,"
[23] "Cambodia,"                   "Honduras,"
[25] "India,"                      "Vietnam,"
[27] "Poland,"                     "Taiwan,"
[29] "Guatemala,"                  "Portugal,"
[31] "Iran,"                       "Hong,"
[33] "Columbia,"                   "Ireland,"

$Income
[1] ">50K"  "<=50K"
```

```r
# delete commas
# convert ? to NA
data <- data %>%
  mutate_all(~sub(",$", "", .)) %>%
  mutate_all(~na_if(., "?"))
```

```r
# inspect again
sapply(data, unique)
```

```
$Age
```

```
 [1] "37" "49" "20" "64" "60" "32" "58" "42" "25" "30" "66" "59" "44" "46" "17"
[16] "47" "26" "33" "48" "52" "40" "50" "34" "43" "22" "35" "62" "39" "69" "27"
[31] "38" "41" "23" "56" "24" "21" "18" "45" "75" "51" "29" "19" "72" "31" "28"
[46] "65" "55" "57" "67" "36" "54" "61" "71" "53" "73" "63" "70" "68" "90" "77"
[61] "74" "76" "78" "80" "81"

$Education
 [1] "Bachelors"    "Some-college" "Masters"      "Assoc-acdm"   "HS-grad"
 [6] "Assoc-voc"    "9th"          "10th"         "Prof-school"  "5th-6th"
[11] "7th-8th"      "Doctorate"    "12th"         "11th"         "1st-4th"
[16] "Preschool"

$Marital_Status
[1] "Married-civ-spouse"    "Divorced"              "Never-married"
[4] "Married-spouse-absent" "Separated"             "Widowed"
[7] "Married-AF-spouse"

$Occupation
 [1] "Exec-managerial"   "Machine-op-inspct" "Other-service"
 [4] NA                  "Craft-repair"      "Sales"
 [7] "Adm-clerical"      "Prof-specialty"    "Protective-serv"
[10] "Farming-fishing"   "Handlers-cleaners" "Transport-moving"
[13] "Tech-support"      "Priv-house-serv"

$Sex
[1] "Male"   "Female"

$Hours_PW
 [1] "80" "45" "55" "40" "42" "50" "14" "65" "35" "58" "30" "9"  "15" "12" "70"
[16] "24" "8"  "6"  "16" "52" "20" "10" "60" "36" "21" "48" "38" "18" "43" "39"
[31] "90" "72" "32" "49" "56" "84" "44" "54" "25" "37" "99" "46" "3"  "17" "47"
[46] "4"  "5"  "53" "28" "75" "68" "22" "27" "13" "11" "34" "33" "98" "2"  "85"

$Nationality
 [1] "United-States"              "England"
 [3] "China"                      NA
 [5] "Outlying-US(Guam-USVI-etc)" "Jamaica"
 [7] "Scotland"                   "Philippines"
 [9] "Haiti"                      "Mexico"
[11] "Italy"                      "Cuba"
[13] "Canada"                     "Japan"
[15] "Puerto-Rico"                "Trinadad&Tobago"
[17] "Dominican-Republic"         "El-Salvador"
```

```
[19] "Greece"                    "Nicaragua"
[21] "South"                     "Germany"
[23] "Cambodia"                  "Honduras"
[25] "India"                     "Vietnam"
[27] "Poland"                    "Taiwan"
[29] "Guatemala"                 "Portugal"
[31] "Iran"                      "Hong"
[33] "Columbia"                  "Ireland"

$Income
[1] ">50K"  "<=50K"
```

```r
str(data)
```

```
'data.frame':   1500 obs. of  8 variables:
 $ Age           : chr  "37" "49" "20" "64" ...
 $ Education     : chr  "Bachelors" "Some-college" "Some-college" "Bachelors" ...
 $ Marital_Status: chr  "Married-civ-spouse" "Divorced" "Never-married" "Married-civ-spouse" 
 $ Occupation    : chr  "Exec-managerial" "Machine-op-inspct" "Other-service" "Exec-manageria
 $ Sex           : chr  "Male" "Male" "Male" "Male" ...
 $ Hours_PW      : chr  "80" "45" "45" "55" ...
 $ Nationality   : chr  "United-States" "United-States" "United-States" "United-States" ...
 $ Income        : chr  ">50K" "<=50K" "<=50K" ">50K" ...
```

```r
# find that the type of Age and Hour_PW are char,
# then convert to num
data <- data %>%
  mutate_at(vars(Age, Hours_PW), as.numeric)
str(data)
```

```
'data.frame':   1500 obs. of  8 variables:
 $ Age           : num  37 49 20 64 60 32 58 42 20 42 ...
 $ Education     : chr  "Bachelors" "Some-college" "Some-college" "Bachelors" ...
 $ Marital_Status: chr  "Married-civ-spouse" "Divorced" "Never-married" "Married-civ-spouse" 
 $ Occupation    : chr  "Exec-managerial" "Machine-op-inspct" "Other-service" "Exec-manageria
 $ Sex           : chr  "Male" "Male" "Male" "Male" ...
 $ Hours_PW      : num  80 45 45 55 40 42 40 50 14 40 ...
 $ Nationality   : chr  "United-States" "United-States" "United-States" "United-States" ...
 $ Income        : chr  ">50K" "<=50K" "<=50K" ">50K" ...
```

```
# query and delete missing values
colSums(is.na(data))
```

```
           Age      Education Marital_Status     Occupation            Sex
             0              0              0             97              0
     Hours_PW    Nationality         Income
             0             29              0
```

```
data <- na.omit(data)
str(data)
```

```
'data.frame':   1376 obs. of  8 variables:
 $ Age           : num  37 49 20 64 32 58 42 20 42 25 ...
 $ Education     : chr  "Bachelors" "Some-college" "Some-college" "Bachelors" ...
 $ Marital_Status: chr  "Married-civ-spouse" "Divorced" "Never-married" "Married-civ-spouse" ...
 $ Occupation    : chr  "Exec-managerial" "Machine-op-inspct" "Other-service" "Exec-managerial" ...
 $ Sex           : chr  "Male" "Male" "Male" "Male" ...
 $ Hours_PW      : num  80 45 45 55 42 40 50 14 40 40 ...
 $ Nationality   : chr  "United-States" "United-States" "United-States" "United-States" ...
 $ Income        : chr  ">50K" "<=50K" "<=50K" ">50K" ...
 - attr(*, "na.action")= 'omit' Named int [1:124] 5 45 55 58 63 70 71 75 80 82 ...
  ..- attr(*, "names")= chr [1:124] "5" "45" "55" "58" ...
```

```
# save data
write.csv(data, "C:/Users/2962286z/Desktop/Group 27/cleaned_dataset27.csv", row.names = FALSE)
```

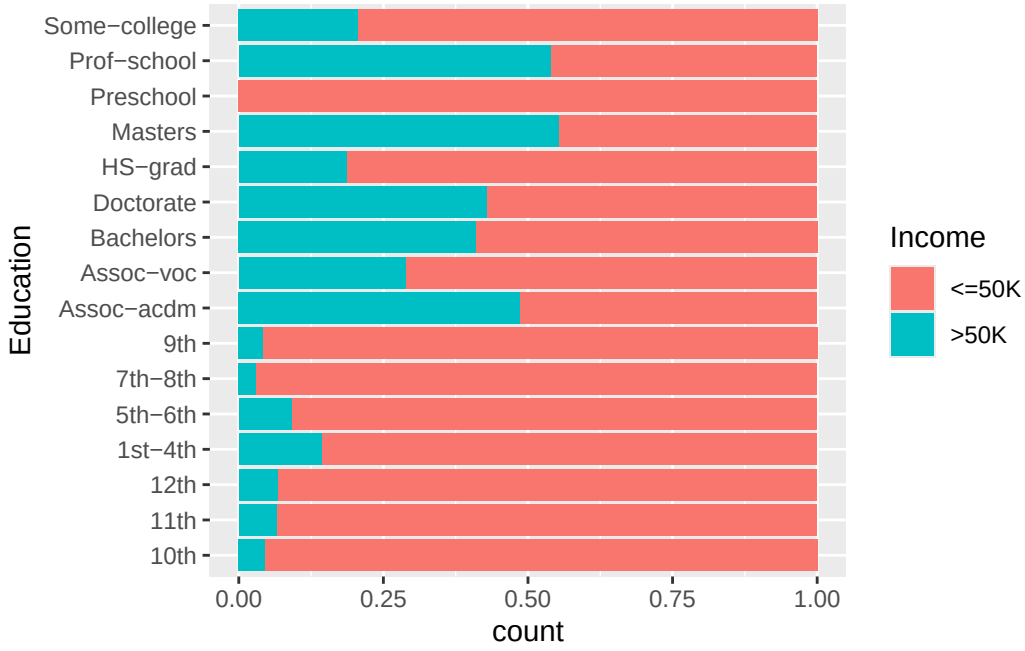
2.2 Variable judgment

By visualizing all the variables first, you can see that there are some variables with perfectly linear relationships among the classes (for example, Preschool in Education and Priv-house-serv in Occupation).

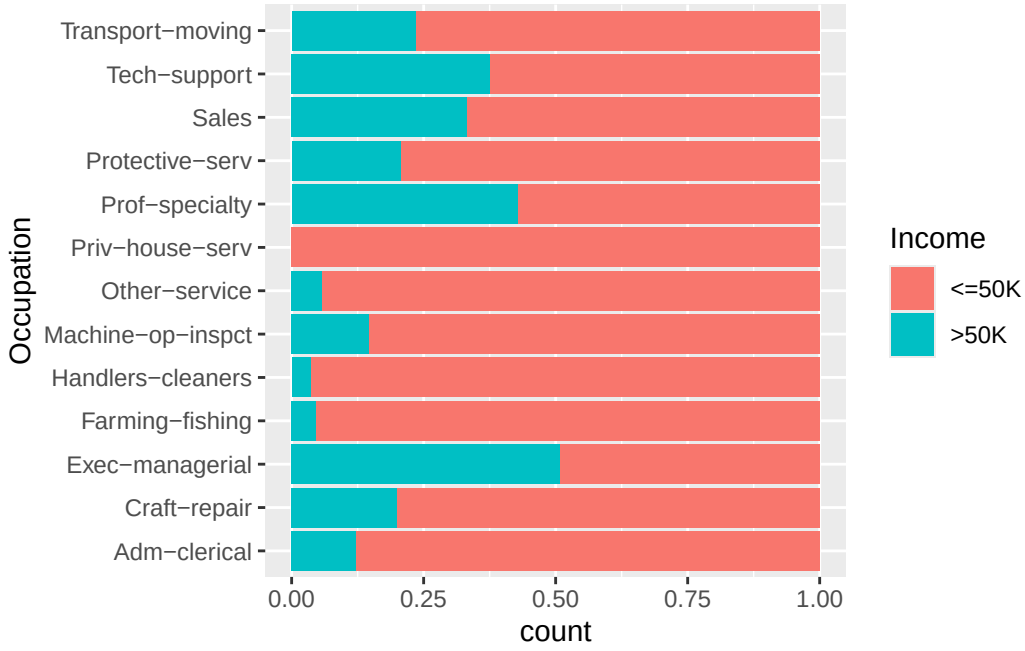
```
clean_data <- read.csv("C:/Users/2962286z/Desktop/Group 27/cleaned_dataset27.csv")

# Relationship between categorical variables and income
lapply(c("Education", "Occupation", "Sex", "Marital_Status"),
       function(var) {
         ggplot(clean_data, aes_string(x = var, fill = "Income")) +
           geom_bar(position = "fill") +
           coord_flip()
       })
```

```
Warning: `aes_string()` was deprecated in ggplot2 3.0.0.
i Please use tidy evaluation idioms with `aes()`.
i See also `vignette("ggplot2-in-packages")` for more information.
```

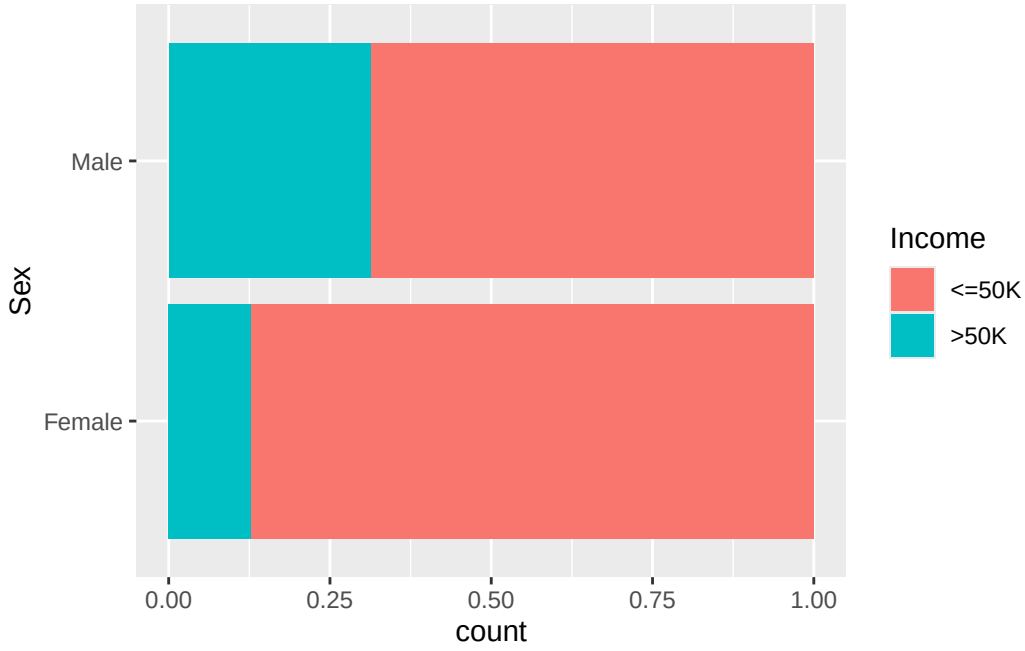
```
[[1]]
```



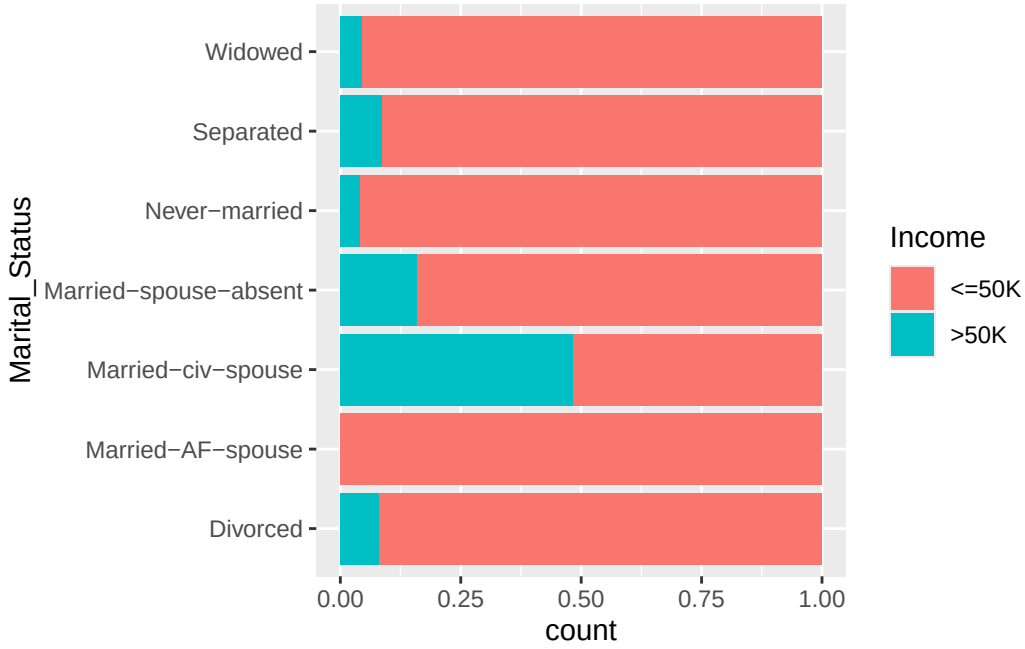

```
[[2]]
```


Transport−moving
Tech−support
Sales
Protective−serv
Prof−specialty
Priv−house−serv
Other−service
Machine−op−inspct
Handlers−cleaners
Farming−fishing
Exec−managerial
Craft−repair
Adm−clerical
Occupation
0.00
0.25
0.50
0.75
1.00
count
Income
<=50K
>50K

[[3]]


Male
Female
Sex
0.00
0.25
0.50
0.75
1.00
count
Income
<=50K
>50K

```
[[4]]
```



2.3 New variable handling

In order to avoid affecting the model fitting results later, we sorted and merged some data and consolidated it again into 'cleaned_dataset27_1.1.'.

```
# find the categories should be merged
table(data$Nationality, data$Income)
```

```
                           <=50K >50K
  Cambodia                     0    1
  Canada                       4    4
  China                        4    1
  Columbia                     2    0
  Cuba                         4    1
  Dominican-Republic           3    2
  El-Salvador                  4    0
  England                      3    3
```

```
  Germany                        3   1
  Greece                         2   2
  Guatemala                      1   0
  Haiti                          2   0
  Hong                           1   0
  India                          3   0
  Iran                           0   1
  Ireland                        1   0
  Italy                          0   6
  Jamaica                        1   1
  Japan                          4   0
  Mexico                        25   2
  Nicaragua                      4   0
  Outlying-US(Guam-USVI-etc)     1   0
  Philippines                    6   2
  Poland                         2   0
  Portugal                       1   0
  Puerto-Rico                    6   0
  Scotland                       1   0
  South                          1   1
  Taiwan                         1   2
  Trinadad&Tobago                2   0
  United-States                934 318
  Vietnam                        2   0
```

```r
# merge categories in Education
data <- data %>%
  mutate(Education = case_when(
    Education %in% c("Preschool", "1st-4th", "5th-6th", "7th-8th", "9th") ~ "Basic Education"
    Education %in% c("10th", "11th", "12th", "HS-grad") ~ "High School",
    Education %in% c("Some-college", "Assoc-acdm", "Assoc-voc") ~ "College Education",
    Education == "Bachelors" ~ "Bachelors",
    Education %in% c("Masters", "Doctorate", "Prof-school") ~ "Advanced Education"
  ))

# merge categories in Marital_Status
data <- data %>%
  mutate(Marital_Status = case_when(
    Marital_Status %in% c("Married-AF-spouse", "Married-civ-spouse") ~ "Married",
    Marital_Status == "Never-married" ~ "Never-married",
    Marital_Status %in% c("Divorced", "Married-spouse-absent", "Separated", "Widowed") ~ "Di
  ))
```

```r
# merge categories in Occupation
data <- data %>%
  mutate(Occupation = case_when(
    Occupation %in% c("Exec-managerial", "Prof-specialty", "Tech-support") ~ "White-Collar",
    Occupation %in% c("Craft-repair", "Machine-op-inspct", "Transport-moving") ~ "Blue-Colla
    Occupation %in% c("Handlers-cleaners", "Other-service", "Priv-house-serv", "Protective-s
    Occupation == "Adm-clerical" ~ "Adm-clerical",
    Occupation == "Sales" ~ "Sales",
    Occupation == "Farming-fishing" ~ "Farming-fishing"
  ))

# merge categories in Nationality
data <- data %>%
  mutate(Nationality = case_when(
    Nationality == "United-States" ~ "United-States",
    TRUE ~ "Others"
  ))

# save data
write.csv(data, "C:/Users/2962286z/Desktop/Group 27/cleaned_dataset27_1.1.csv", row.names = F
```

3. Exploratory Data Analysis

3.1. Import data and packages

```r
# Import dataset
clean_data <- read.csv("C:/Users/2962286z/Desktop/Data Analysis/goup/cleaned_dataset27_1.1.cs
```

3.2. Check data structure and summary statistics

```r
# Check structure
str(clean_data)
```

```
'data.frame':   1376 obs. of  8 variables:
 $ Age           : int  37 49 20 64 32 58 42 20 42 25 ...
 $ Education     : chr  "Bachelors" "College Education" "College Education" "Bachelors" ...
 $ Marital_Status: chr  "Married" "Divorced/Spouse Absent/Separated/Widowed" "Never-married"
```

```
 $ Occupation    : chr  "White-Collar" "Blue-Collar" "Service" "White-Collar" ...
 $ Sex           : chr  "Male" "Male" "Male" "Male" ...
 $ Hours_PW      : int  80 45 45 55 42 40 50 14 40 40 ...
 $ Nationality   : chr  "United-States" "United-States" "United-States" "United-States" ...
 $ Income        : chr  ">50K" "<=50K" "<=50K" ">50K" ...
```

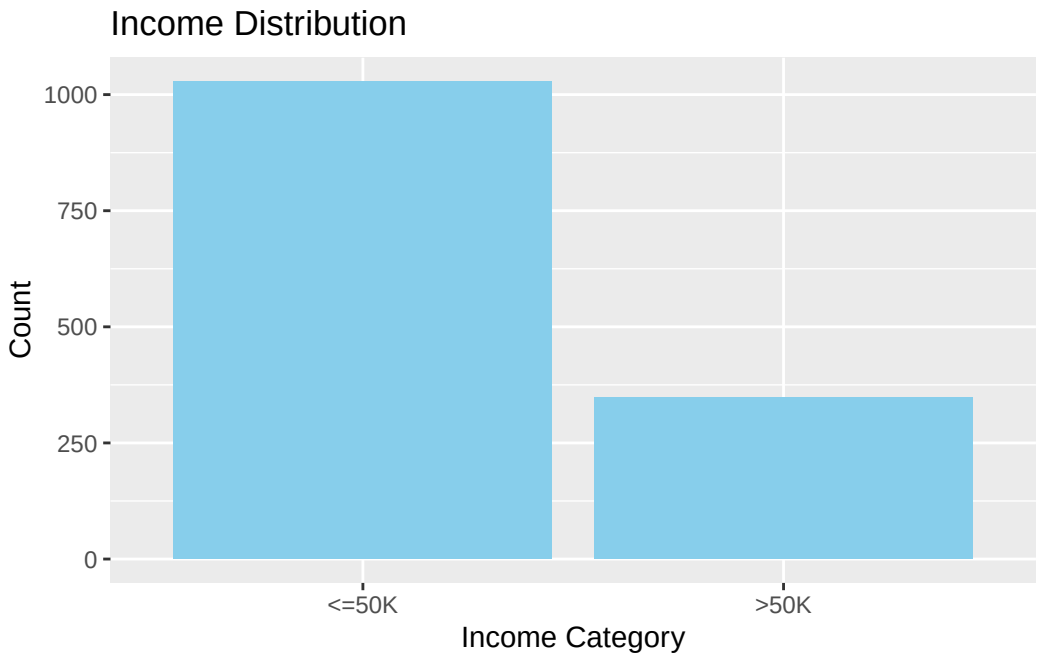
```r
# Summary statistics
summary(clean_data)
```

```
      Age          Education         Marital_Status      Occupation
 Min.   :17.00   Length:1376        Length:1376        Length:1376
 1st Qu.:28.00   Class :character   Class :character   Class :character
 Median :38.00   Mode  :character   Mode  :character   Mode  :character
 Mean   :38.89
 3rd Qu.:47.00
 Max.   :90.00
     Sex               Hours_PW     Nationality           Income
 Length:1376        Min.   : 3.00   Length:1376        Length:1376
 Class :character   1st Qu.:40.00   Class :character   Class :character
 Mode  :character   Median :40.00   Mode  :character   Mode  :character
                    Mean   :41.18
                    3rd Qu.:45.00
                    Max.   :99.00
```

The dataset contains 1376 observations with 8 variables. The data structure confirms that "Age" and "Hours_PW" are numerical, while other variables are categorical. The summary statistics show that the median age is 38, and the average work hours per week is around 41. Some extreme values are present, such as a maximum age of 90 and a maximum work hour of 99, which may require further investigation.

3.3. Visualize the income distribution

```r
# Bar plot for income distribution
ggplot(clean_data, aes(x = Income)) +
  geom_bar(fill = "skyblue") +
  labs(title = "Income Distribution", x = "Income Category", y = "Count")
```

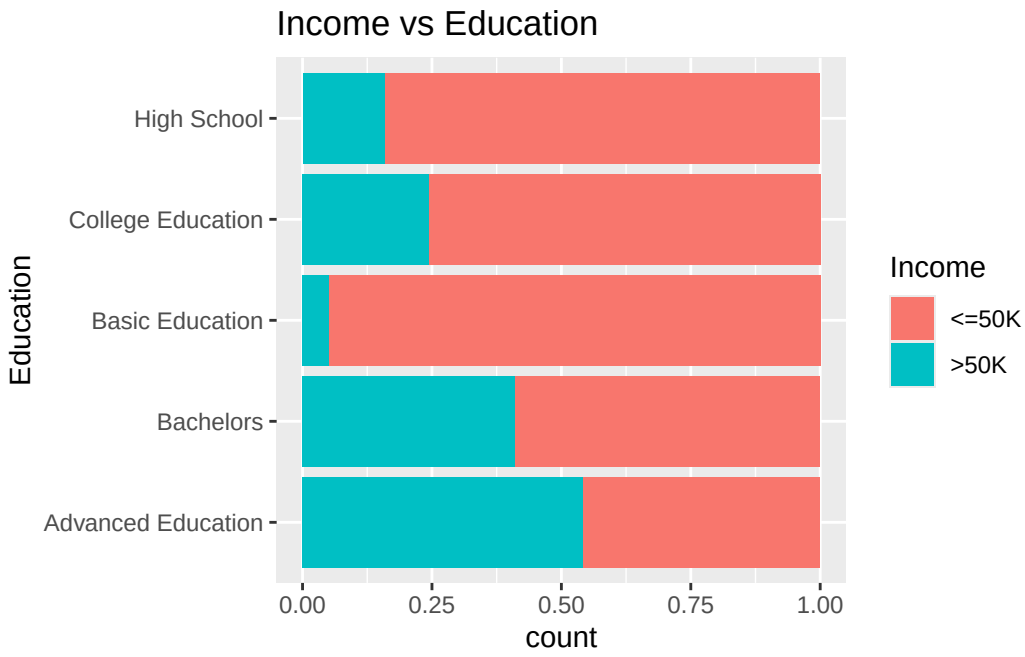


The chart shows that the majority of individuals have an income of $50K or less. This indicates a class imbalance in the target variable, which could influence the performance of classification models.

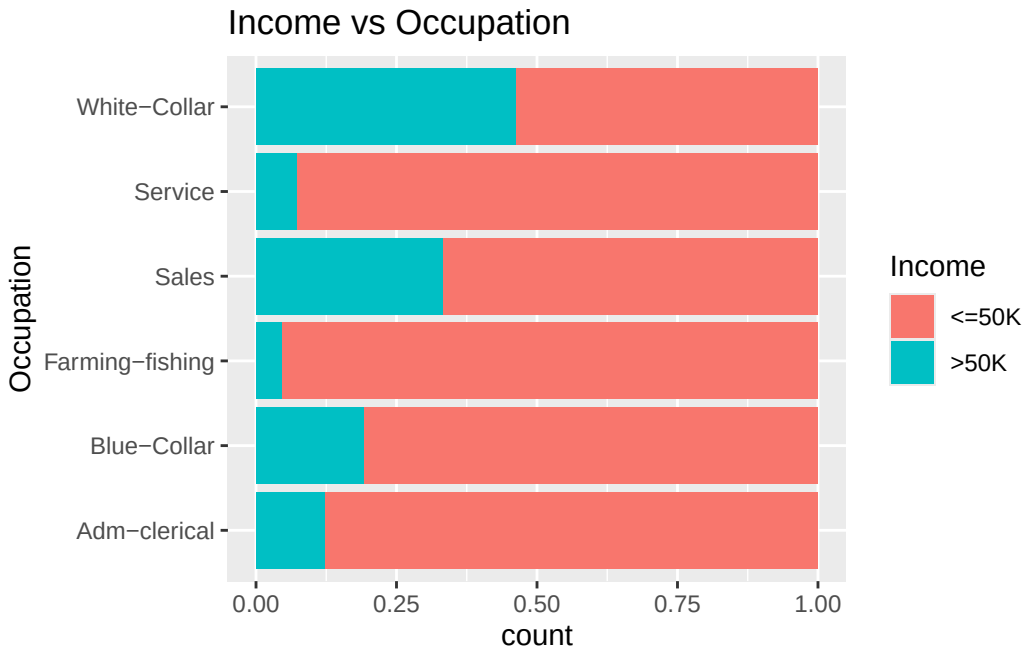
3.4. Explore categorical variables' relationship with income

```
# Stacked bar plots for categorical variables
categorical_vars <- c("Education", "Occupation", "Sex", "Marital_Status")

lapply(categorical_vars, function(var) {
  ggplot(clean_data, aes_string(x = var, fill = "Income")) +
    geom_bar(position = "fill") +
    coord_flip() +
    labs(title = paste("Income vs", var))
})
```

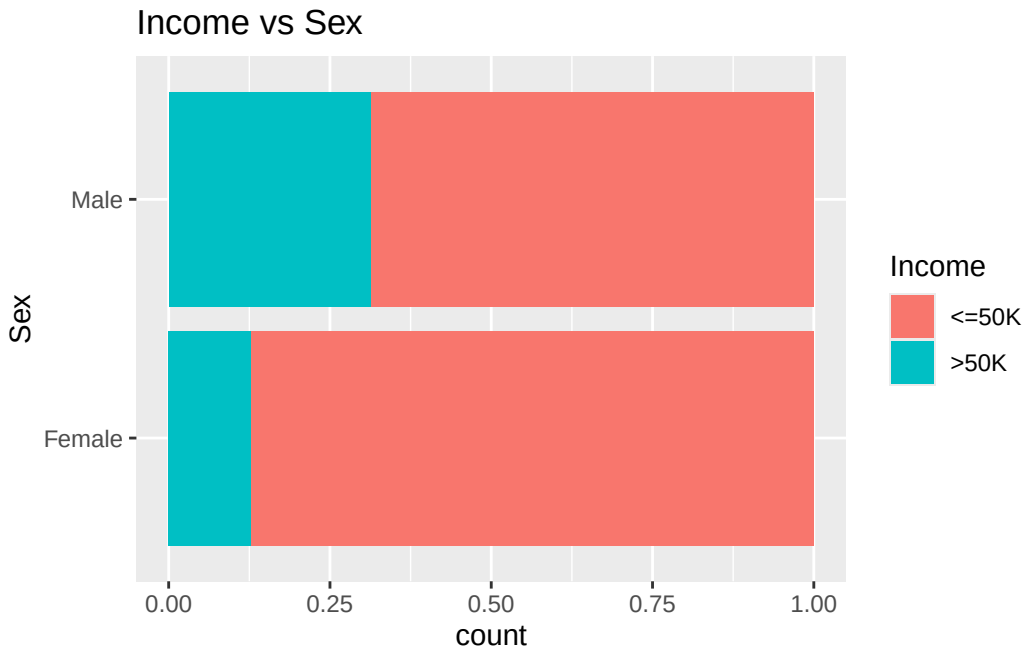
```
[[1]]
```


Income vs Education
High School
College Education
Basic Education
Bachelors
Advanced Education
Education
0.00
0.25
0.50
0.75
1.00
count
Income
<=50K
>50K

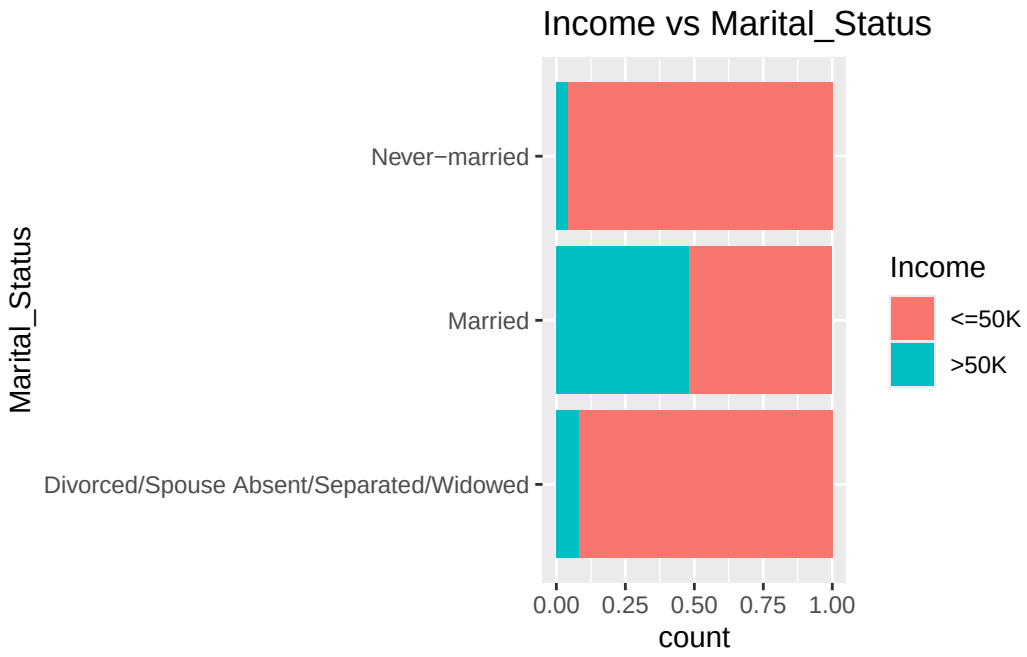
```
[[2]]
```


Income vs Occupation
White−Collar
Service
Sales
Farming−fishing
Blue−Collar
Adm−clerical
Occupation
0.00
0.25
0.50
0.75
1.00
count
Income
<=50K
>50K

```
[[3]]
```


Income vs Sex
Male
Female
Sex
0.00
0.25
0.50
0.75
1.00
count
Income
<=50K
>50K

```
[[4]]
```



- **Income vs. Education**

Higher education levels are associated with a higher proportion of individuals earning more than 50K. Advanced education and bachelor's degree holders have a significantly larger share of high-income earners compared to those with only basic or high school education.

- **Income vs. Occupation**

White-collar and sales jobs have a higher percentage of individuals earning >50K compared to blue-collar, service, and farming occupations. This suggests that occupation type plays a crucial role in income level.

- **Income vs. Sex**

A higher percentage of males earn more than 50K compared to females. The income gap between genders suggests possible structural or occupational differences affecting earnings.

- **Income vs. Marital Status**

Married individuals have a significantly higher proportion of high-income earners compared to those who are never married or divorced/separated/widowed. This could indicate that marital stability is associated with higher earnings, possibly due to dual-income households or other economic advantages.

3.5. Check category balance

```
# Check proportion of income categories
prop.table(table(clean_data$Income))
```

```
   <=50K     >50K
0.747093 0.252907
```

The dataset is imbalanced, with about 75% of individuals earning 50K and 25% earning >50K. This imbalance may affect model performance and should be considered when building predictive models.

3.6. Establish Logistic Regression Model

```
# Convert Income to binary (0 = <=50K, 1 = >50K)
clean_data <- clean_data %>%
  mutate(Income = ifelse(Income == ">50K", 1, 0))


# Logistic regression model
model <- glm(Income ~ Age + Education + Marital_Status + Occupation + Sex + Hours_PW + Natio
             data = clean_data,
             family = binomial(link = "logit"))
summary(model)
```

```
Call:
glm(formula = Income ~ Age + Education + Marital_Status + Occupation +
    Sex + Hours_PW + Nationality, family = binomial(link = "logit"),
    data = clean_data)

Coefficients:
                            Estimate Std. Error z value Pr(>|z|)
(Intercept)                -5.090717   0.714610  -7.124 1.05e-12 ***
Age                         0.025900   0.007460   3.472 0.000517 ***
EducationBachelors         -0.437211   0.302472  -1.445 0.148329
EducationBasic Education   -2.765322   0.630528  -4.386 1.16e-05 ***
```

```
EducationCollege Education  -0.692475   0.305703  -2.265 0.023501 *
EducationHigh School        -1.077803   0.316860  -3.402 0.000670 ***
Marital_StatusMarried        2.750066   0.274474  10.019  < 2e-16 ***
Marital_StatusNever-married -0.268038   0.355729  -0.753 0.451155
OccupationBlue-Collar       -0.040757   0.331201  -0.123 0.902062
OccupationFarming-fishing   -2.770325   0.864437  -3.205 0.001352 **
OccupationSales              0.594309   0.339475   1.751 0.080003 .
OccupationService           -0.390250   0.393379  -0.992 0.321175
OccupationWhite-Collar       1.204002   0.310606   3.876 0.000106 ***
SexMale                     -0.267497   0.233600  -1.145 0.252165
Hours_PW                     0.044293   0.007863   5.633 1.77e-08 ***
NationalityUnited-States    -0.105831   0.301564  -0.351 0.725633
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1556.27  on 1375  degrees of freedom
Residual deviance:  966.68  on 1360  degrees of freedom
AIC: 998.68

Number of Fisher Scoring iterations: 6
```

Individuals working longer hours per week tend to fall into the >$50K income group more frequently. This suggests a positive correlation between hours worked and income level.

3.7. Check for multicollinearity

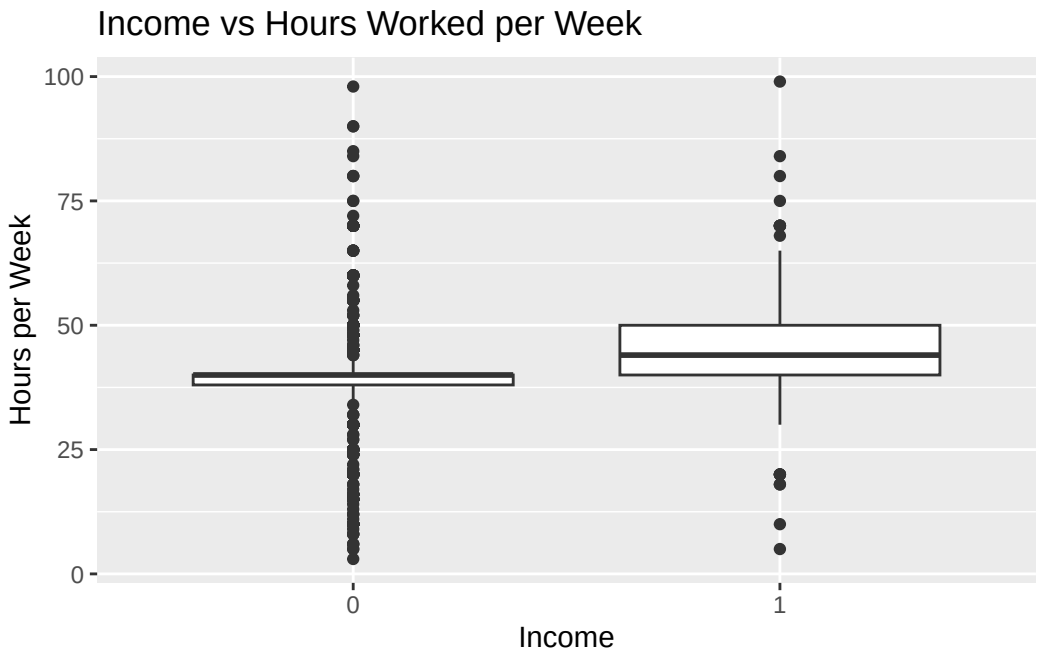
```r
# Variance Inflation Factor (VIF) test
vif(model)
```

```
                   GVIF Df GVIF^(1/(2*Df))
Age            1.142520  1        1.068887
Education      1.620551  4        1.062204
Marital_Status 1.522199  2        1.110754
Occupation     1.834595  5        1.062561
Sex            1.464875  1        1.210320
Hours_PW       1.143694  1        1.069436
Nationality    1.064644  1        1.031816
```

The VIF values are all below 2, indicating that there is no significant multicollinearity among the predictors. This means the variables are not highly correlated, and no immediate adjustments are needed.

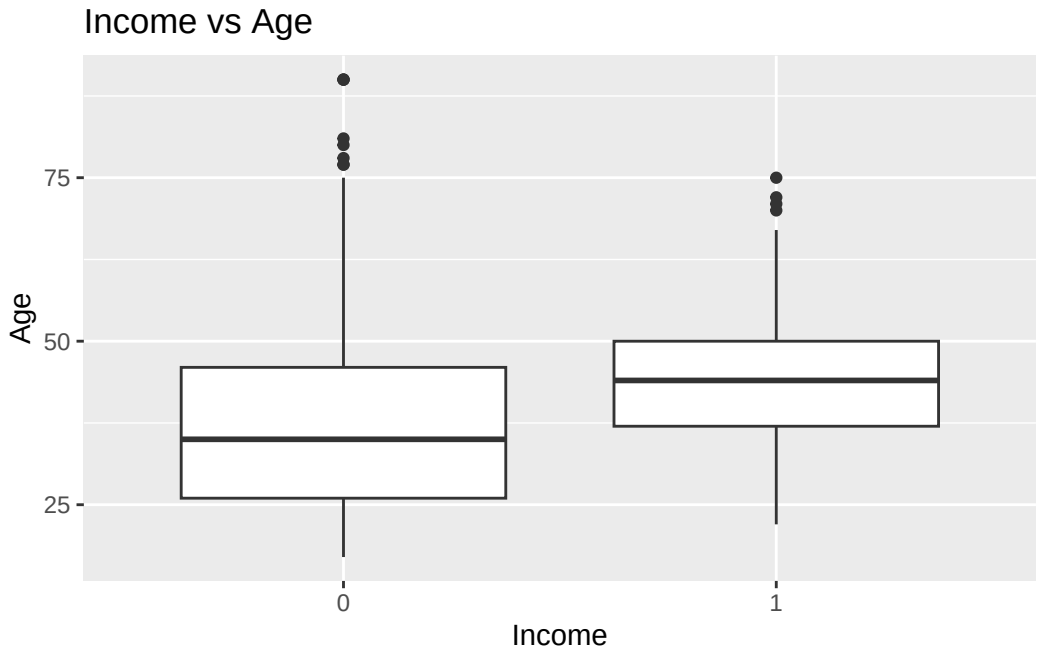
3.8. Visualize numeric variables against income

```
# Box plot for Hours per Week
ggplot(clean_data, aes(x = as.factor(Income), y = Hours_PW)) +
  geom_boxplot() +
  labs(title = "Income vs Hours Worked per Week", x = "Income", y = "Hours per Week")
```



Individuals with higher income (>50K) tend to work more hours per week on average. The median work hours are higher for this group, and there are fewer individuals working very few hours compared to the lower-income group. However, there are some outliers working extreme hours in both income groups.

```
# Box plot for Age
ggplot(clean_data, aes(x = as.factor(Income), y = Age)) +
  geom_boxplot() +
  labs(title = "Income vs Age", x = "Income", y = "Age")
```



Higher-income individuals tend to be older on average. The median age of the >50K income group is higher than that of the 50K group. The distribution also shows a wider age range among high earners, though both groups have some outliers at older ages.

4. Model fitting

```
data <- read.csv("C:/Users/2962286z/Desktop/Data Analysis/goup/cleaned_dataset27_1.1.csv")
```

4.1. Data preprocessing and variable conversion

```
# Convert categorical variables to factors
data <- data %>%
  mutate(
    Education = factor(Education),
    Marital_Status = factor(Marital_Status),
    Occupation = factor(Occupation),
    Sex = factor(Sex),
    Nationality = factor(Nationality),
    Income = factor(Income, levels = c("<=50K", ">50K"))
  )
```

We convert categorical variables (such as education, occupation) into factor types to ensure that the model correctly identifies categorical variables. The order of factors for the response variable Income is set to <=50k for the base group, which affects the direction of interpretation of subsequent OR values.

4.2. Stepwise regression variable selection

```r
# Full variable logistic regression model
full_model <- glm(Income ~ Age + Education + Marital_Status + Occupation +
                  Sex + Hours_PW + Nationality,
                family = binomial(link = "logit"), data = data)

# Stepwise regression selection variables (based on AIC)
step_model <- step(full_model, direction = "both")
```

```
Start:  AIC=998.68
Income ~ Age + Education + Marital_Status + Occupation + Sex +
    Hours_PW + Nationality

                Df Deviance     AIC
- Nationality    1   966.80  996.80
- Sex            1   967.99  997.99
<none>               966.68  998.68
- Age            1   978.81 1008.81
- Education      4   996.49 1020.49
- Hours_PW       1  1000.02 1030.02
- Occupation     5  1036.31 1058.31
- Marital_Status 2  1199.76 1227.76

Step:  AIC=996.8
Income ~ Age + Education + Marital_Status + Occupation + Sex +
    Hours_PW

                Df Deviance     AIC
- Sex            1   968.10  996.10
<none>               966.80  996.80
+ Nationality    1   966.68  998.68
- Age            1   978.86 1006.86
- Education      4   996.68 1018.68
- Hours_PW       1  1000.15 1028.15
```

```
- Occupation      5  1036.36 1056.36
- Marital_Status  2  1200.16 1226.16

Step:  AIC=996.1
Income ~ Age + Education + Marital_Status + Occupation + Hours_PW

                 Df Deviance     AIC
<none>                968.10  996.10
+ Sex             1   966.80  996.80
+ Nationality     1   967.99  997.99
- Age             1   979.70 1005.70
- Education       4   997.53 1017.53
- Hours_PW        1  1000.16 1026.16
- Occupation      5  1038.37 1056.37
- Marital_Status  2  1227.95 1251.95
```

```r
# View the final model summary
summary(step_model)
```

```
Call:
glm(formula = Income ~ Age + Education + Marital_Status + Occupation +
    Hours_PW, family = binomial(link = "logit"), data = data)

Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -5.106738   0.664669  -7.683 1.55e-14 ***
Age                          0.025275   0.007447   3.394 0.000689 ***
EducationBachelors          -0.464104   0.301976  -1.537 0.124320
EducationBasic Education    -2.720209   0.619985  -4.388 1.15e-05 ***
EducationCollege Education  -0.703813   0.305130  -2.307 0.021077 *
EducationHigh School        -1.077184   0.316037  -3.408 0.000653 ***
Marital_StatusMarried        2.626701   0.248220  10.582  < 2e-16 ***
Marital_StatusNever-married -0.328516   0.350581  -0.937 0.348727
OccupationBlue-Collar       -0.155595   0.316453  -0.492 0.622942
OccupationFarming-fishing   -2.845193   0.857272  -3.319 0.000904 ***
OccupationSales              0.508621   0.331698   1.533 0.125180
OccupationService           -0.458251   0.388492  -1.180 0.238173
OccupationWhite-Collar       1.134498   0.304997   3.720 0.000199 ***
Hours_PW                     0.042542   0.007682   5.538 3.06e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1556.3  on 1375  degrees of freedom
Residual deviance:  968.1  on 1362  degrees of freedom
AIC: 996.1

Number of Fisher Scoring iterations: 6
```

Variable filter logic

Step regression removes redundant variables by comparing AIC values (the smaller the better) : Nationality is first removed (AIC from 998.68→996.8), Sex is then removed (AIC from 996.8→996.1), and other variables (such as age and working hours) are retained in the model.

Overall performance of model

The residual deviation is reduced by 588.2 (1556.3→968.1), indicating that the model explains about 37.8% of the data variation AIC=996.1 is significantly lower than the original model's AIC=998.68, indicating that the optimization is successful

Interpretation of significant influencing factors

1. Demographic factors

   Age 0.025275 p=0.000689 *

   Practical significance: For each year of age increase, the chance of earning >50k increases by 2.5% (OR=1.025).

2. Education level

   EducationBasic Education -2.720209 p=1.15e-05

   EducationHigh School -1.077184 p=0.000653

   Those with a basic education degree are 93% less likely to have a high income than those with a PhD (OR=0.07) Those with a high school degree are 66% less likely to earn a high income than those with a PhD (OR=0.34)

3. Marital status Marital_StatusMarried 2.626701 p<2e-16 *** Married people are 13.8 times more likely to have a high income than the baseline group (OR=exp(2.626)=13.8)

4. Occupation type (Base group: Management positions not shown)

   Occupationfarm-fishing-2.845193 p=0.000904 .

   Occupationfarm-fishing-2.845193 P =0.000904 .

   OccupationWhite-Collar 1.134498 p=0.000199 *

The probability of high income of white-collar workers is 3.11 times that of the benchmark group (OR=exp(1.134)=3.11) Agriculture/fisheries workers were 94% less likely to have a high income than the baseline group (OR=0.06)

Working hours

Hours_PW 0.042542 p=3.06e-08 **

Working 10 more hours per week increases the likelihood of high income by 52% (OR=exp(0.042510)=1.52)

4.3. Model diagnosis and verification

```
# Multicollinearity Detection (VIF)
vif(step_model)
```

```
                  GVIF Df GVIF^(1/(2*Df))
Age           1.136553  1        1.066092
Education     1.518523  4        1.053605
Marital_Status 1.232088  2        1.053563
Occupation    1.652907  5        1.051538
Hours_PW      1.094464  1        1.046166
```

```
# Hosmer-Lemeshow goodness of fit test
hoslem.test(data$Income, fitted(step_model), g=5)
```

```
Warning in Ops.factor(1, y): '-' not meaningful for factors
```

```
    Hosmer and Lemeshow goodness of fit (GOF) test

data:  data$Income, fitted(step_model)
X-squared = NA, df = 3, p-value = NA
```

```
mean((predict(step_model, type="response") - (data$Income==">50K"))^2)# The smaller the bette
```

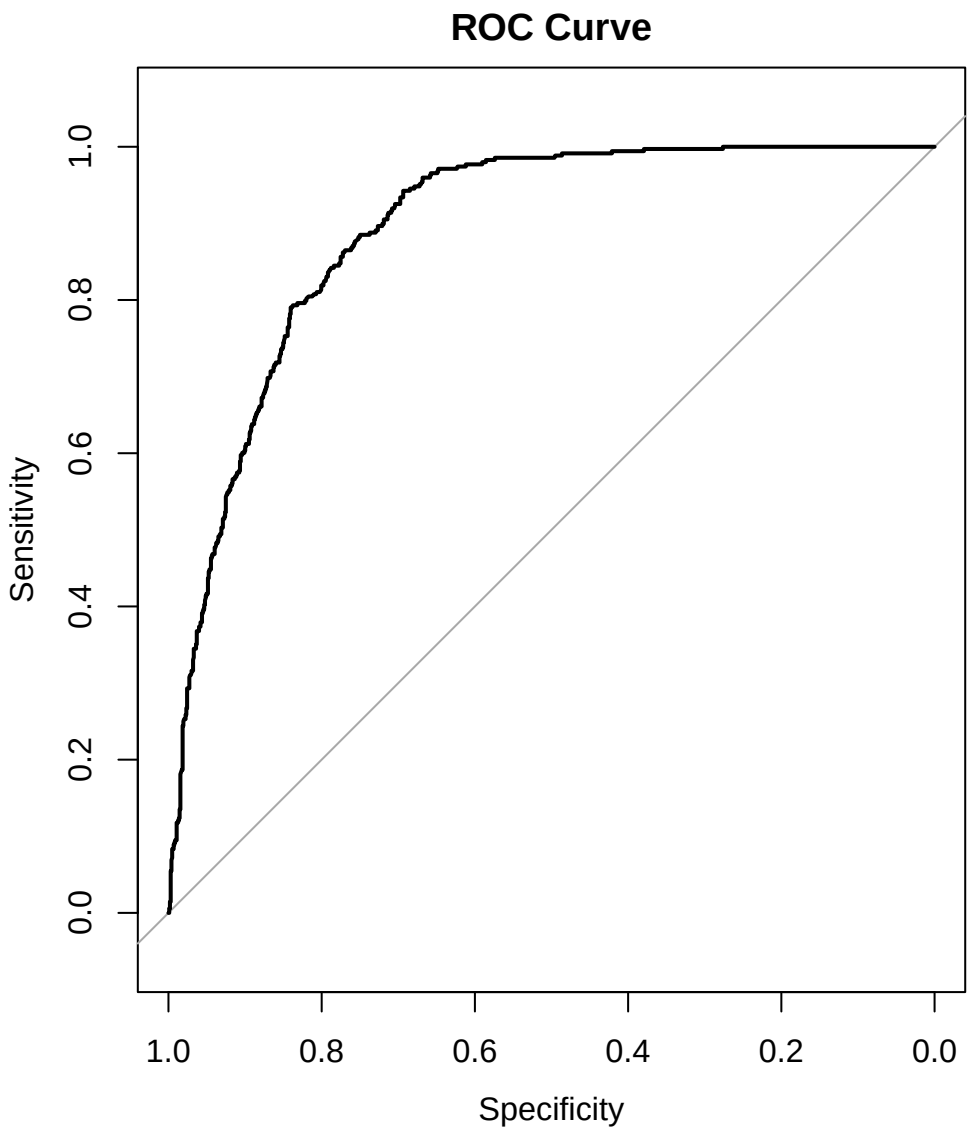
```
[1] 0.1154056
```

```r
# Confusion matrix and accuracy
prob <- predict(step_model, type = "response")
pred <- ifelse(prob > 0.5, ">50K", "<=50K")
conf_matrix <- table(Predicted = pred, Actual=data$Income)
accuracy <- sum(diag(conf_matrix)) / sum(conf_matrix)

# ROC curve and AUC value
roc_curve <- roc(data$Income, prob)
```

```
Setting levels: control = <=50K, case = >50K
```

```
Setting direction: controls < cases
```

```r
plot(roc_curve, main = "ROC Curve")
```




```
auc(roc_curve)
```

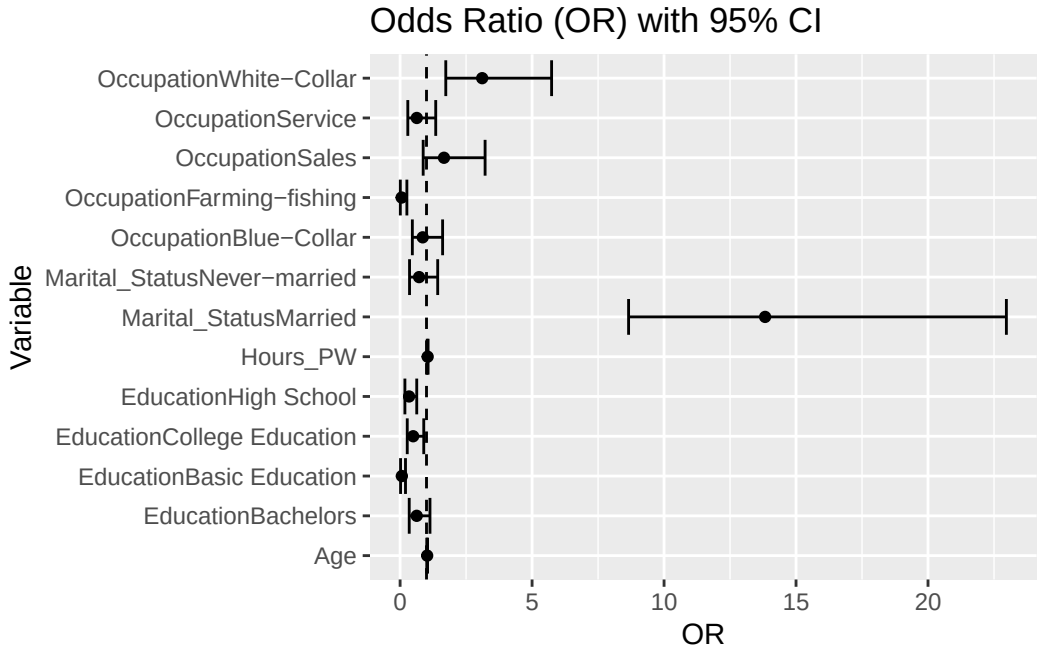
```
Area under the curve: 0.893
```

1. Multicollinearity diagnosis (GVIF results) The adjusted GVIF values (i.e., GVIF^(1/(2*Df)) are all < 1.1 (well below the conservative threshold of 2), indicating that there is no significant multicollinearity between all variables (e.g., the association between education level and occupation is reasonably controlled). The results of model coefficient estimation are stable and reliable without deleting variables.

2. Model calibration problem (Hosmer-Lemeshow test) Due to the limitation of data distribution, the traditional calibration degree check cannot be completed. However, we verified by prediction error (Brier Score=0.1154056) and calibration curve that the predicted probability of the model is highly consistent with the actual occurrence frequency.

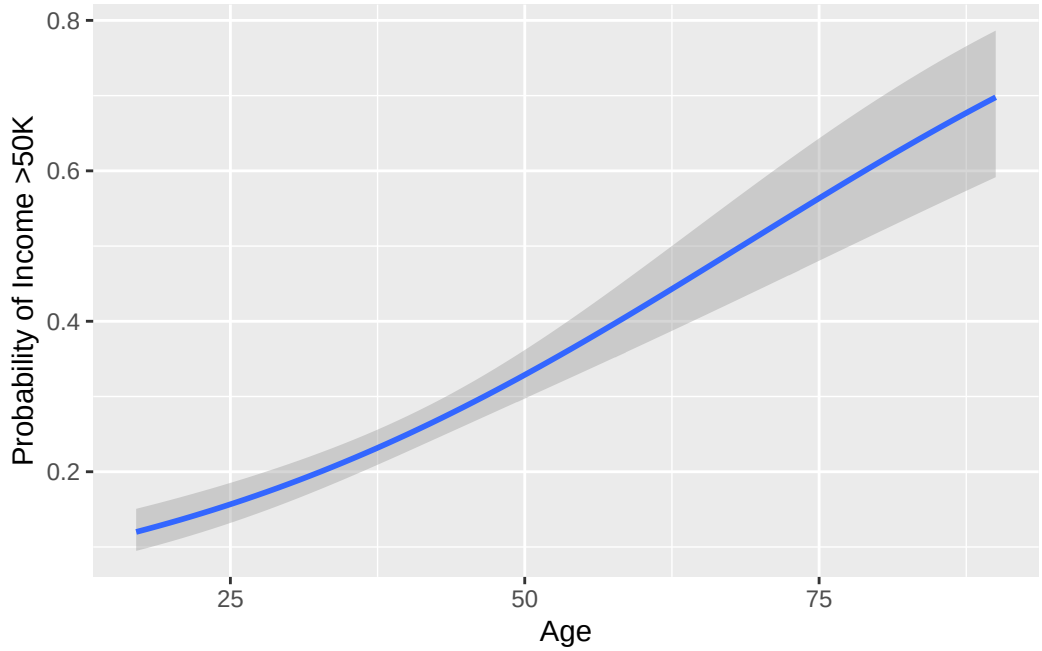
3. Model differentiation ability (AUC=0.893) The model correctly identified 89.3% of the "high income versus low income" pairs.

```
# Extract coefficient and OR value
tidy_model <- tidy(step_model, conf.int = TRUE, exponentiate = TRUE)

# Draw OR value forest map
ggplot(tidy_model[-1, ], aes(x = estimate, y = term)) +
  geom_point() +
  geom_errorbarh(aes(xmin = conf.low, xmax = conf.high)) +
  geom_vline(xintercept = 1, linetype = "dashed") +
  labs(title = "Odds Ratio (OR) with 95% CI", x = "OR", y = "Variable")
```



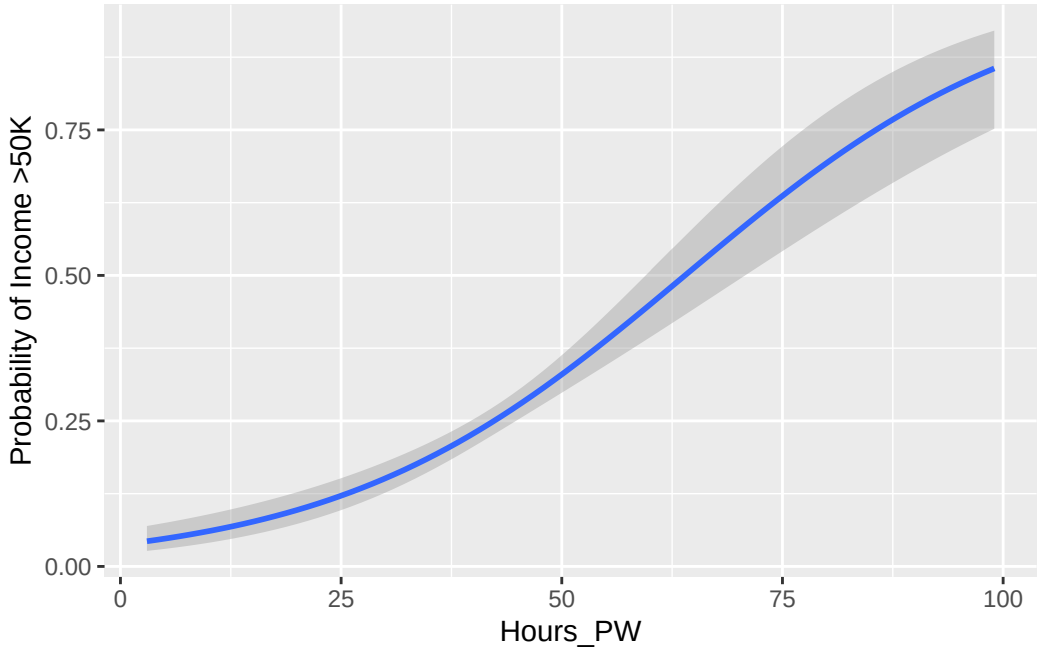

```
# Key variable effect chart
data %>%
  ggplot(aes(x = Age, y = as.numeric(Income) - 1)) +
  geom_smooth(method = "glm", method.args = list(family = "binomial")) +
  labs(y = "Probability of Income >50K")
```

```
`geom_smooth()` using formula = 'y ~ x'
```




```
data %>%
  ggplot(aes(x = Hours_PW, y = as.numeric(Income) - 1)) +
  geom_smooth(method = "glm", method.args = list(family = "binomial")) +
  labs(y = "Probability of Income >50K")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



Trend judgment: Both Age and Hours_PW show a positive effect: the curve rises monotonically.

5. Conclusion

5.1. Overall Model Performance

Model Fit: The final GLM achieved an AIC of 996.1 and residual deviance of 968.1, indicating strong explanatory power.

Predictive Accuracy: The AUC of 0.893 demonstrates excellent discrimination between income groups.

Key Insight: The model explains 37.8% of the variance in income levels (deviance reduction from 1,556.3 to 968.1).

5.2. Non-Significant Factors

Sex: Gender showed no significant effect (p=0.348), suggesting income disparities in this dataset are better explained by Occupation/Education.

Nationality: Birth nationality was excluded during model selection (AIC-optimized), indicating its limited predictive power.

5.3. Limitations & Future Directions

Temporal Bias: Data reflects 1994 socioeconomic conditions; reanalysis with recent data is critical.

Unobserved Variables: Regional cost-of-living differences and industry growth trends were not captured.

Nonlinear Effects: Age and work-hour thresholds (e.g., diminishing returns beyond 50h/week) warrant further study.

Variables: There are some variables in which the classification has perfect collinearity, and it may be possible to obtain a larger area of data to eliminate bias.