Key Factors Influencing Income Level

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1 Introductions

This study aims to identify the key socioeconomic determinants influencing whether an individual earns more than $50k annually, utilizing data from the 1994 U.S. Census. The dataset comprises a diverse set of socioeconomic attributes, including age, education level, marital status, occupation, sex, hours worked per week, and nationality. The outcome variable, Income, is a binary classification indicating whether an individual's earnings exceed the $50k threshold.

To achieve this objective, a Generalized Linear Model (GLM) is employed to examine the relationship between income levels and various socioeconomic predictors. In this framework, income serves as the dependent variable, while the remaining attributes function as independent variables, enabling a systematic evaluation of their respective contributions to income disparity.

2 Libraries and reading

First, we load all the necessary packages required for the analysis.

```
# Load the necessary package
library(ggplot2)
library(glmnet)
library(tidyverse)
library(gt)
library(patchwork)
library(gridExtra)
```

```r
library(moderndive)
library(skimr)
library(sjPlot)
```

Then we import the CSV file from the specified source.

```r
# Read CSV data
data <- read.csv('dataset26.csv', na.strings = '?,')
```

3 Initial Model

3.1 Data Tidying

Initially, we delete the null data, and treat only hours and age as numeric variables.

```r
data <- na.omit(data)
data <- data %>%
  mutate(across(2:ncol(data), ~ substr(.x, 1, nchar(.x) - 1)))
write.csv(data, 'cleaned_data.csv', row.names = FALSE)
```

```r
data$Income <- ifelse(data$Income == "<=50", 0, 1)
data$Education <- as.factor(data$Education)
data$Marital_Status <- as.factor(data$Marital_Status)
data$Occupation <- as.factor(data$Occupation)
data$Sex <- as.factor(data$Sex)
data$Hours_PW <- as.numeric(data$Hours_PW)
data$Nationality <- as.factor(data$Nationality)

str(data)
```

```
'data.frame':	1379 obs. of  8 variables:
 $ Age           : int  39 50 38 53 28 37 49 52 31 42 ...
 $ Education     : Factor w/ 16 levels "10th","11th",..: 10 10 12 2 10 13 7 12 13 10 ...
 $ 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 ...
 $ Sex           : Factor w/ 2 levels "Female","Male": 2 2 2 2 1 1 1 2 1 2 ...
 $ Hours_PW      : num  40 13 40 40 40 40 16 45 50 40 ...
 $ Nationality   : Factor w/ 31 levels "Cambodia","Canada",..: 30 30 30 30 5 30 18 30 30 30 ...
 $ Income        : num  0 0 0 0 0 0 0 1 1 1 ...
 - attr(*, "na.action")= 'omit' Named int [1:121] 15 28 39 52 62 70 78 94 107 129 ...
  ..- attr(*, "names")= chr [1:121] "15" "28" "39" "52" ...
```

3.2 Full Modeling

After fitting the model, we observed that the large number of coefficients makes it difficult to identify the most influential variables.

```r
model <- glm(Income ~ Age + Education + Marital_Status + Occupation + Sex + Hours_PW + Nationality,
             data = data,
             family = binomial)
summary(model)
```

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

Coefficients:
                                      Estimate Std. Error z value Pr(>|z|)    
(Intercept)                          1.374e+01  6.523e+03   0.002 0.998320    
Age                                  2.612e-02  7.848e-03   3.329 0.000872 ***
Education11th                        7.994e-01  1.052e+00   0.760 0.447236    
Education12th                        1.757e+00  1.269e+00   1.385 0.166017    
Education1st-4th                    -1.476e+01  2.950e+03  -0.005 0.996008    
```

Education5th-6th	-1.487e+01	1.795e+03	-0.008	0.993391	
Education7th-8th	2.012e+00	1.104e+00	1.822	0.068515	.
Education9th	-1.507e+01	1.339e+03	-0.011	0.991025	
EducationAssoc-acdm	2.142e+00	9.024e-01	2.374	0.017610	*
EducationAssoc-voc	1.948e+00	8.754e-01	2.225	0.026060	*
EducationBachelors	2.404e+00	8.333e-01	2.885	0.003912	**
EducationDoctorate	5.071e+00	1.225e+00	4.141	3.46e-05	***
EducationHS-grad	1.128e+00	8.111e-01	1.391	0.164286	
EducationMasters	2.361e+00	8.684e-01	2.719	0.006552	**
EducationPreschool	-1.546e+01	4.117e+03	-0.004	0.997004	
EducationProf-school	2.816e+00	1.011e+00	2.786	0.005334	**
EducationSome-college	1.150e+00	8.275e-01	1.390	0.164471	
Marital_StatusMarried-AF-spouse	-1.439e+01	6.523e+03	-0.002	0.998240	
Marital_StatusMarried-civ-spouse	2.431e+00	3.112e-01	7.810	5.72e-15	***
Marital_StatusMarried-spouse-absent	-3.034e+01	1.629e+03	-0.019	0.985139	
Marital_StatusNever-married	-2.927e-01	3.702e-01	-0.791	0.429122	
Marital_StatusSeparated	-1.259e+00	1.217e+00	-1.035	0.300880	
Marital_StatusWidowed	6.237e-01	6.081e-01	1.026	0.305052	
OccupationArmed-Forces	-1.486e+01	4.572e+03	-0.003	0.997407	
OccupationCraft-repair	1.557e-01	3.418e-01	0.456	0.648713	
OccupationExec-managerial	1.053e+00	3.371e-01	3.123	0.001793	**
OccupationFarming-fishing	-7.481e-01	6.188e-01	-1.209	0.226683	
OccupationHandlers-cleaners	-1.379e+00	8.829e-01	-1.562	0.118294	
OccupationMachine-op-inspct	-1.705e-01	4.592e-01	-0.371	0.710489	
OccupationOther-service	-4.829e-01	4.868e-01	-0.992	0.321139	
OccupationPriv-house-serv	-1.314e+01	2.688e+03	-0.005	0.996100	
OccupationProf-specialty	3.560e-01	3.575e-01	0.996	0.319396	
OccupationProtective-serv	5.170e-01	5.929e-01	0.872	0.383186	
OccupationSales	4.660e-01	3.567e-01	1.306	0.191405	
OccupationTech-support	-6.100e-02	4.542e-01	-0.134	0.893168	
OccupationTransport-moving	-2.207e-01	4.111e-01	-0.537	0.591322	
SexMale	-1.601e-01	2.332e-01	-0.686	0.492417	
Hours_PW	2.707e-02	7.864e-03	3.442	0.000577	***
NationalityCanada	-1.794e+01	6.523e+03	-0.003	0.997806	

```
NationalityChina                    -6.193e+00  6.624e+03  -0.001 0.999254
NationalityColumbia                 -3.737e+01  9.224e+03  -0.004 0.996767
NationalityCuba                     -3.838e+01  7.057e+03  -0.005 0.995660
NationalityDominican-Republic       -3.599e+01  7.289e+03  -0.005 0.996060
NationalityEcuador                  -3.913e+01  9.224e+03  -0.004 0.996616
NationalityEl-Salvador              -1.888e+01  7.739e+03  -0.002 0.998054
NationalityEngland                  -2.067e+01  6.523e+03  -0.003 0.997472
NationalityFrance                   -3.562e+01  9.224e+03  -0.004 0.996919
NationalityGermany                  -2.162e+01  6.523e+03  -0.003 0.997355
NationalityGuatemala                -1.609e+01  7.829e+03  -0.002 0.998360
NationalityHaiti                    -3.470e+01  7.986e+03  -0.004 0.996533
NationalityHonduras                 -2.011e+01  6.523e+03  -0.003 0.997540
NationalityIndia                    -1.870e+01  6.523e+03  -0.003 0.997712
NationalityIran                     -1.770e+01  6.523e+03  -0.003 0.997835
NationalityItaly                    -3.782e+01  7.725e+03  -0.005 0.996094
NationalityJamaica                  -1.989e+01  6.523e+03  -0.003 0.997567
NationalityJapan                    -2.098e+01  6.523e+03  -0.003 0.997433
NationalityLaos                     -3.759e+01  9.224e+03  -0.004 0.996748
NationalityMexico                   -2.123e+01  6.523e+03  -0.003 0.997403
NationalityPeru                     -3.887e+01  9.224e+03  -0.004 0.996638
NationalityPhilippines              -1.868e+01  6.523e+03  -0.003 0.997715
NationalityPoland                   -3.798e+01  7.007e+03  -0.005 0.995675
NationalityPortugal                 -2.035e+01  6.523e+03  -0.003 0.997510
NationalityPuerto-Rico              -3.679e+01  7.131e+03  -0.005 0.995884
NationalitySouth                    -3.993e+01  9.224e+03  -0.004 0.996547
NationalityTaiwan                   -1.959e+01  6.523e+03  -0.003 0.997603
NationalityThailand                 -2.055e+01  6.523e+03  -0.003 0.997487
NationalityUnited-States            -2.022e+01  6.523e+03  -0.003 0.997527
NationalityYugoslavia               -3.803e+01  9.224e+03  -0.004 0.996710
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

```
    Null deviance: 1566.65  on 1378  degrees of freedom
Residual deviance:  974.94  on 1311  degrees of freedom
AIC: 1110.9

Number of Fisher Scoring iterations: 17
```

Therefore, we selected variables with p-values below 0.05 for further analysis.

```r
coef_table <- summary(model)$coefficients
coef_df <- as.data.frame(coef_table)

significant_vars <- coef_df[coef_df$`Pr(>|z|)` < 0.05, ]
significant_vars
```

```
                                Estimate  Std. Error  z value     Pr(>|z|)
Age                           0.02612374 0.007847890 3.328760 8.723351e-04
EducationAssoc-acdm           2.14195202 0.902365218 2.373709 1.761045e-02
EducationAssoc-voc            1.94813351 0.875442554 2.225313 2.606025e-02
EducationBachelors            2.40412690 0.833276942 2.885148 3.912303e-03
EducationDoctorate            5.07122829 1.224671598 4.140888 3.459634e-05
EducationMasters              2.36089013 0.868359955 2.718792 6.552079e-03
EducationProf-school          2.81560422 1.010576503 2.786137 5.334038e-03
Marital_StatusMarried-civ-spouse 2.43054424 0.311214660 7.809864 5.724962e-15
OccupationExec-managerial     1.05263979 0.337111865 3.122524 1.793077e-03
Hours_PW                      0.02707194 0.007864248 3.442407 5.765620e-04
```

As observed, **Age**, **Education**, **Marital Status**, **Occupation**, and **Hours Worked per Week** appear to be the most significant variables in this model.

4 Refined Model

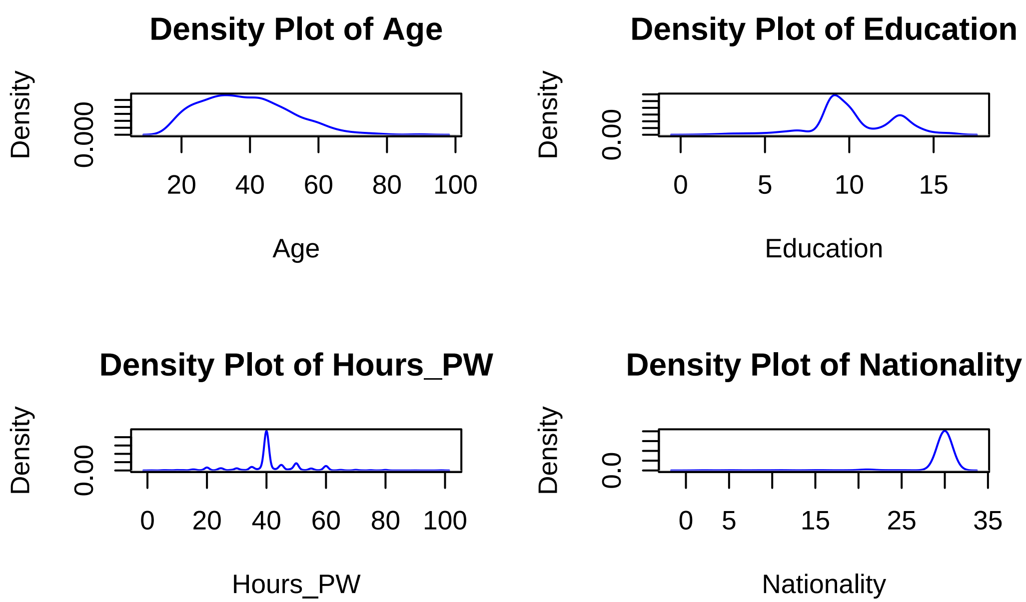
4.1 Data wrangling

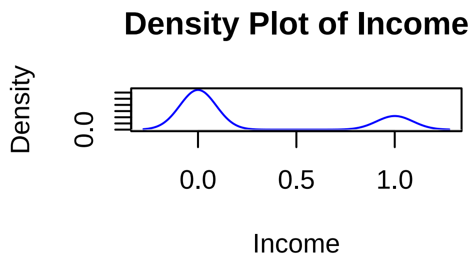
Based on the previous p-value selection, we made adjustments to the variables: the education levels were reclassified, converted into a factor variable in ascending order, and then transformed into continuous numerical values. A similar transformation was applied to nationality. Significant job positions were treated as a separate variable, while other positions were consolidated into a general “Other” category to reduce overfitting in the model. A similar approach was applied to marital status.

```r
# Order education level
edu_levels <- c(
  "Preschool", "1st-4th", "5th-6th", "7th-8th", "9th", "10th",
  "11th", "12th", "HS-grad", "Some-college", "Assoc-acdm",
  "Assoc-voc", "Bachelors", "Masters", "Prof-school", "Doctorate"
)
data$Education <- factor(data$Education, levels = edu_levels, ordered = TRUE)
data$Education <- as.numeric(data$Education)

# Order nationality level
data$Nationality <- as.factor(data$Nationality)
data$Nationality <- as.numeric(data$Nationality)

# Merge Occupation
levels(data$Occupation) <- ifelse(levels(data$Occupation) %in% c("Exec-managerial"),
                                      levels(data$Occupation), "Other")
data$Occupation <- factor(data$Occupation)
data$Occupation <- relevel(data$Occupation, ref = "Other") # Set "Other" as the base group

# Merge Marital Status
levels(data$Marital_Status) <- ifelse(levels(data$Marital_Status) %in% c("Married-civ-spouse"),
                                      levels(data$Marital_Status), "Other")
data$Marital_Status <- factor(data$Marital_Status)
data$Marital_Status <- relevel(data$Marital_Status, ref = "Other") # Set "Other" as the base group
```

4.2 Data Visualization

```r
# Select numerical variables for density plotting.
numeric_vars <- sapply(data, is.numeric)
data_numeric <- data[, numeric_vars]

# Plot the density graph
par(mfrow=c(2,2))  # 2x2
for (var in names(data_numeric)) {
  plot(density(data_numeric[[var]]),
       col = "blue",
       main = paste("Density Plot of", var),
       xlab = var)
}
```



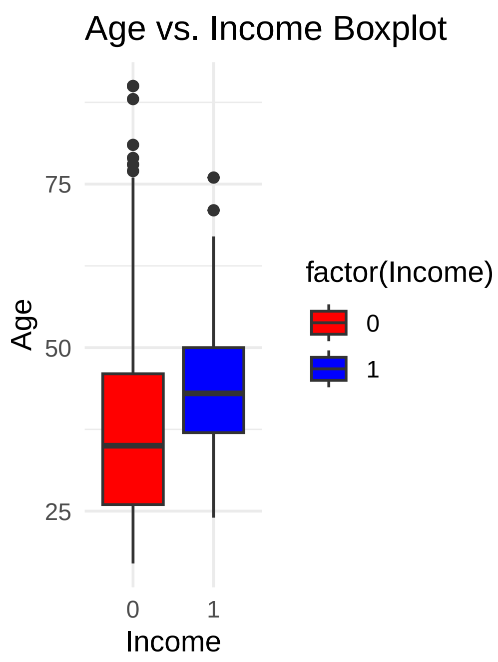


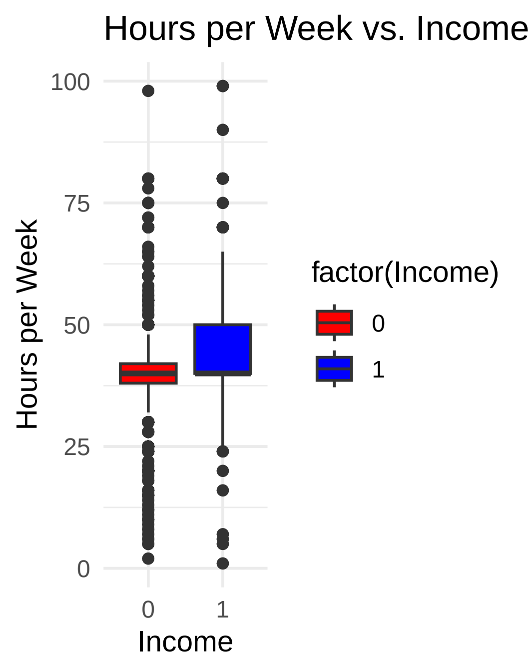
The Density Plots show the distribution of the data, but in GLM, whether the data follows a normal distribution is not a concern for our analysis. Therefore, we only present the distribution of the data here.

Based on the practical context, only age and hours worked are continuous variables in a meaningful sense. Therefore, we only plot the boxplot for these two variables.

```
# Define colors
colors <- c("red", "blue")

# Generate Age vs. Income boxplot
plot_age <- ggplot(data, aes(x = factor(Income), y = Age, fill = factor(Income))) +
  geom_boxplot() +
  scale_fill_manual(values = colors) +
  xlab('Income') +
  ylab('Age') +
```

```
  ggtitle('Age vs. Income Boxplot') +
  theme_minimal()

# Generate Hours per Week vs. Income boxplot
plot_hours <- ggplot(data, aes(x = factor(Income), y = Hours_PW, fill = factor(Income))) +
  geom_boxplot() +
  scale_fill_manual(values = colors) +
  xlab('Income') +
  ylab('Hours per Week') +
  ggtitle('Hours per Week vs. Income Boxplot') +
  theme_minimal()

# Arrange all boxplots in a grid layout
grid.arrange(plot_age, plot_hours, ncol = 2)
```





From the chart, it can be observed that higher age seems to be helpful for earning >50K, while the distribution of hours worked is more scattered.

4.3 New Modeling

```
model_new <- glm(Income ~ Age + Education + Marital_Status + Occupation + Sex + Hours_PW + Nationality,
             data = data,
             family = binomial)
summary(model_new)
```

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

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)    
(Intercept)                      -8.920565   0.814705 -10.949  < 2e-16 ***
Age                               0.029694   0.006862   4.327 1.51e-05 ***
Education                         0.350798   0.036069   9.726  < 2e-16 ***
Marital_StatusMarried-civ-spouse  2.474452   0.203712  12.147  < 2e-16 ***
OccupationExec-managerial         0.967995   0.207100   4.674 2.95e-06 ***
SexMale                          -0.116492   0.206619  -0.564 0.572888    
Hours_PW                          0.027992   0.007223   3.875 0.000106 ***
Nationality                       0.002565   0.017611   0.146 0.884198    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1566.6  on 1378  degrees of freedom
Residual deviance: 1049.8  on 1371  degrees of freedom
```

```
AIC: 1065.8

Number of Fisher Scoring iterations: 6
```

The model is now more concise, and the results of variable selection align with our initial expectations.

5 Stepwise

```r
stepwise_model <- step(model_new, direction = "both", trace = 0)
summary(stepwise_model)
```

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

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                      -8.875728   0.639862 -13.871  < 2e-16 ***
Age                               0.029576   0.006850   4.318 1.58e-05 ***
Education                         0.350616   0.036009   9.737  < 2e-16 ***
Marital_StatusMarried-civ-spouse  2.430059   0.186893  13.002  < 2e-16 ***
OccupationExec-managerial         0.965227   0.207038   4.662 3.13e-06 ***
Hours_PW                          0.027512   0.007167   3.839 0.000124 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1566.6  on 1378  degrees of freedom
Residual deviance: 1050.1  on 1373  degrees of freedom
```

```
AIC: 1062.1

Number of Fisher Scoring iterations: 6
```

```r
stepwise_aic <- AIC(stepwise_model)
print(paste("Stepwise AIC: ", stepwise_aic))
```

```
[1] "Stepwise AIC:  1062.08865027124"
```

As can be seen, our new model also performs well under AIC, showing the same selection results as the p-value approach.

6 Data Correlation

```r
num_data <- data[, sapply(data, is.numeric)]
cor_matrix <- cor(num_data)
print(cor_matrix)
```

```
                    Age  Education     Hours_PW  Nationality      Income
Age          1.00000000 0.02315912  0.101108879 -0.008046100 0.233332257
Education    0.02315912 1.00000000  0.178761432  0.063284814 0.315397938
Hours_PW     0.10110888 0.17876143  1.000000000 -0.005931541 0.230447516
Nationality -0.00804610 0.06328481 -0.005931541  1.000000000 0.005067934
Income       0.23333226 0.31539794  0.230447516  0.005067934 1.000000000
```

```r
data_encoded <- model.matrix(~ Marital_Status + Occupation + Sex- 1, data = data)
cor_matrix_encoded <- cor(data_encoded)
print(cor_matrix_encoded)
```

```
                                  Marital_StatusOther
Marital_StatusOther                         1.0000000
Marital_StatusMarried-civ-spouse           -1.0000000
OccupationExec-managerial                  -0.1075835
SexMale                                    -0.3876342
                                  Marital_StatusMarried-civ-spouse
Marital_StatusOther                                     -1.0000000
Marital_StatusMarried-civ-spouse                         1.0000000
OccupationExec-managerial                                0.1075835
SexMale                                                  0.3876342
                                  OccupationExec-managerial     SexMale
Marital_StatusOther                             -0.10758352 -0.38763421
Marital_StatusMarried-civ-spouse                 0.10758352  0.38763421
OccupationExec-managerial                        1.00000000  0.04762762
SexMale                                          0.04762762  1.00000000
```

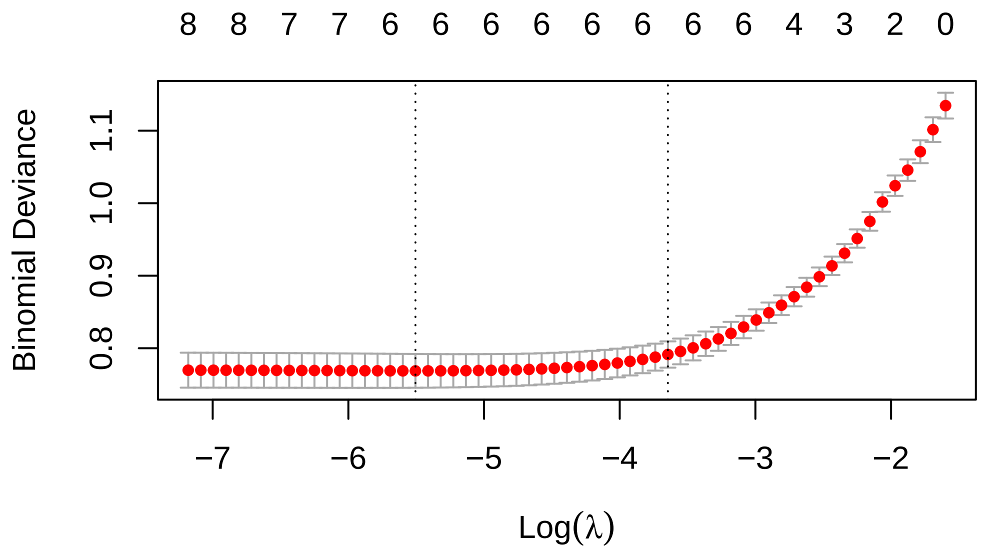
The correlation matrix reveals some degree of correlation within the data. While multicollinearity is present, its impact on the overall model is minimal. Additionally, Lasso regression effectively mitigates these issues by performing variable selection and regularization.

7 Lasso Regression

```r
x <- model.matrix(Income ~ Age + Education + Marital_Status + Occupation + Sex + Hours_PW + Nationality - 1, data = data)
y <- data$Income

cv_lasso <- cv.glmnet(x, y, alpha = 1, family = "binomial")
print(paste("Best lambda for Lasso: ", cv_lasso$lambda.min))
```

```
[1] "Best lambda for Lasso:  0.00406380980208752"
```

```r
plot(cv_lasso)
```




```r
final_lasso_model <- glmnet(x, y, alpha = 1, lambda = cv_lasso$lambda.min)
coef(final_lasso_model)
```

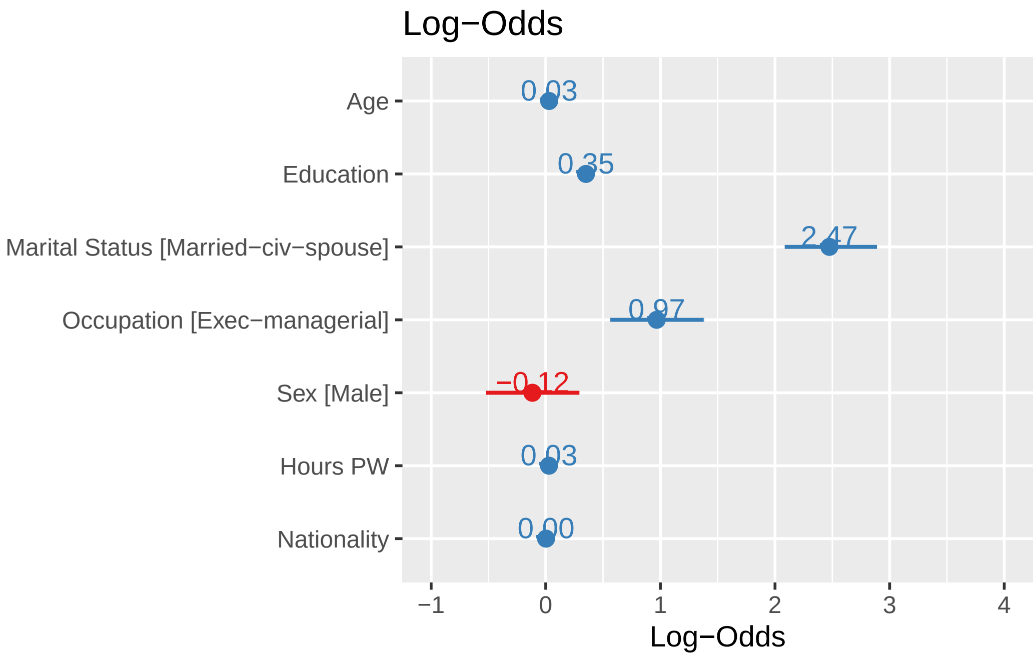
```
9 x 1 sparse Matrix of class "dgCMatrix"
                                        s0
(Intercept)                  -2.177903e-01
Age                           2.693547e-03
Education                     4.223099e-02
Marital_StatusOther          -3.325071e-01
Marital_StatusMarried-civ-spouse  2.717515e-14
OccupationExec-managerial     1.586751e-01
```

```
SexMale                            .
Hours_PW                           2.305034e-03
Nationality                        .
```

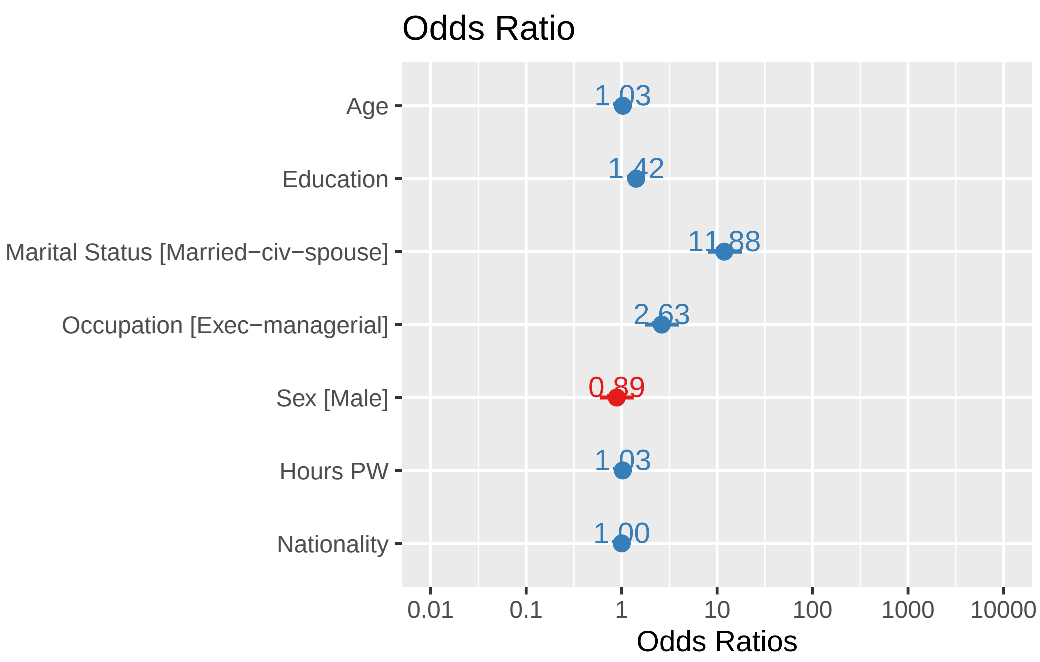
Based on the analysis, we identified Age, Education, Marital Status (specifically "Married-civ-spouse"), Occupation (specifically "Exec-managerial"), and Hours Worked per Week as the most significant variables influencing income.

8 Log-Odds and Odds Ratios

```r
mod.coed.logodds<- model_new %>%
                   summary() %>%
                   coef()
plot_model(model_new, show.values = TRUE, transform = NULL,
           title = "Log-Odds", show.p = FALSE)
```




```
plot_model(model_new, show.values = TRUE, axis.lim = c(0, 10000),
           title = "Odds Ratio", show.p = FALSE, transform = "exp")
```



The bar chart above illustrates the Log-Odds and Odds Ratios from model_new for the selected variables that have the strongest influence on income.

8.1 Explanation of Variables' Impact on Income:

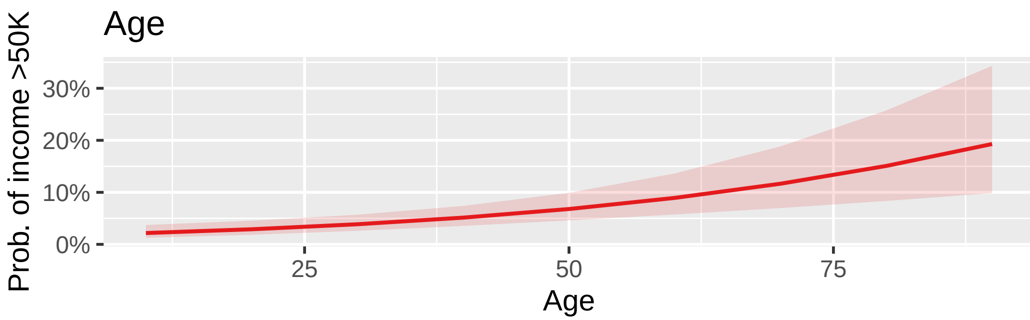
- **Marital_StatusMarried-civ-spouse**: Being married to a civilian spouse has the highest Odds Ratio(11.88), indicating that individuals in this marital status are much more likely to earn over $50k compared to others.
- **OccupationExec-managerial**: Holding an executive or managerial position significantly increases the odds of earning more than $50k(2.63).
- **Education**: Higher levels of education are associated with a higher likelihood of earning more than $50k, with the Odds Ratio being moderately high(1.42).
- **Age**: Older individuals are slightly more likely to earn more than $50k, although the impact is relatively smaller compared to other variables(1.03).

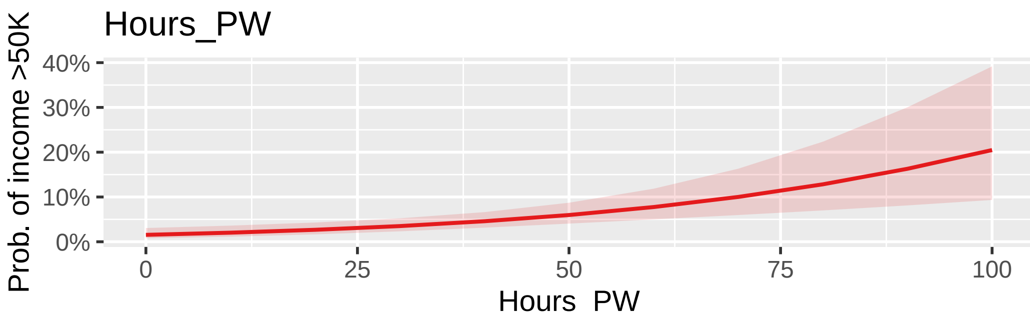
- **Hours_PW**: Working more hours per week increases the odds of earning more than $50k, showing a positive relationship(1.03).
- **Nationality**: The coefficient for nationality in the chart is 1, indicating that the different values of this variable have no impact on the probability of the outcome.
- **Sex**: The coefficient for gender is 0.89 (highlighted in red), which also indicates that the coefficient is not significant.

This chart highlights that **marital status**, **occupation**, and **education** have the most significant impact on income, whereas **sex** and **nationality** have a relatively minor effect.

9 Probability continuous

```
p1 <- plot_model(model_new, type = "pred", terms="Age" ,title = "Age",
           axis.title = c("Age", "Prob. of income >50K"))
p2 <- plot_model(model_new, type = "pred", terms="Hours_PW" ,title = "Hours_PW",
           axis.title = c("Hours_PW", "Prob. of income >50K"))
grid.arrange(p1,p2,nrow=2)
```





As we metioned before, only age and hours worked are continuous variables in a meaningful sense. Therefore, we only plot these two variables.

10 Conclusions

In summary, the p-value, AIC, and Lasso regression all yield consistent results: gender and nationality have an insignificant impact on whether an individual earns more than $50K, while marital status and holding an executive position exert a stronger influence. Additionally, while factors such as education, age, and hours worked do play a role, they are not decisive in determining high income.

This finding is intriguing, as it suggests that marital status has a significant impact on income levels. However, the opposite conclusion seems more plausible: individuals with higher incomes tend to have more stable marital statuses. Moreover, the primary determinant of an employee's salary within a company appears to be their position. Without a managerial role, factors such as age, working hours, or education have little bearing on income.