

Analysis of individual earns

Group 29

1 Introduction

Dataset 29 were collected from the US 1994 Census database. This dataset contain data on individuals regarding their income level, and various socioeconomic factors. You will have access to the following variables:

- **Age** - The age of the individual in years
 - **Education** - Highest education level obtained by the individual
 - **Marital_Status** - The marital status of the individual
 - **Occupation** - The occupation of the individual
 - **Sex** - The sex of the individual
 - **Hours_Pw** - Number of hours worked per week by the individual
 - **Nationality** - The nationality of birth of the individual
 - **Income** - A factor variable with two levels: >50k if the individual earns more than \$50k per year, or <=50k if the individual earns less than or equal to \$50k per year
-

1.1 Task

Imagine you have been tasked by the government to identify which features based on the census data impact the income an individual makes: - Which factors influence whether an individual earns more than \$50k per year?

You should:

1. Conduct an analysis to answer your question using a **Generalised Linear Model (GLM)**
2. Summarise your results in the form of a presentation

2 Exploratory Data Analysis

Summary statistics of **Income** are presented in the following for each column separately.

Observe the correlation of the numeric of data:

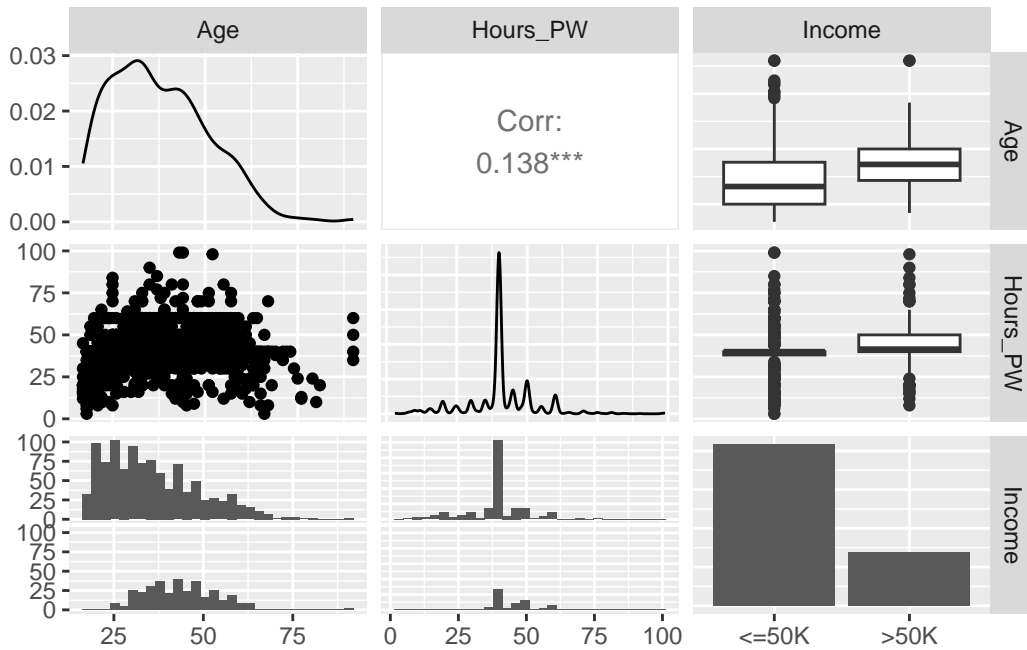


Figure 1: Numeric Data Correlation

2.1 Data levels

[1] "10th"	"11th"	"12th"	"1st-4th"	"5th-6th"
[6] "7th-8th"	"9th"	"Assoc-acdm"	"Assoc-voc"	"Bachelors"
[11] "Doctorate"	"HS-grad"	"Masters"	"Prof-school"	"Some-college"
[1] "Divorced"	"Married-civ-spouse"	"Married-spouse-absent"		
[4] "Never-married"	"Separated"	"Widowed"		

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

[1] "Female" "Male"

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

Chi-square test for Education vs Income :

Pearson's Chi-squared test

data: contingency_table
X-squared = 193.07, df = 14, p-value < 2.2e-16

Chi-square test for Marital_Status vs Income :

Pearson's Chi-squared test

data: contingency_table
X-squared = 263.24, df = 5, p-value < 2.2e-16

Chi-square test for Occupation vs Income :

Pearson's Chi-squared test

```
data: contingency_table  
X-squared = 167.57, df = 12, p-value < 2.2e-16
```

Chi-square test for Sex vs Income :

Pearson's Chi-squared test with Yates' continuity correction

```
data: contingency_table  
X-squared = 57.101, df = 1, p-value = 4.139e-14
```

Chi-square test for Nationality vs Income :

Pearson's Chi-squared test

```
data: contingency_table  
X-squared = 28.476, df = 31, p-value = 0.5965
```

2.2 Income Distribution

Income distribution:

<=50K	>50K
1041	344

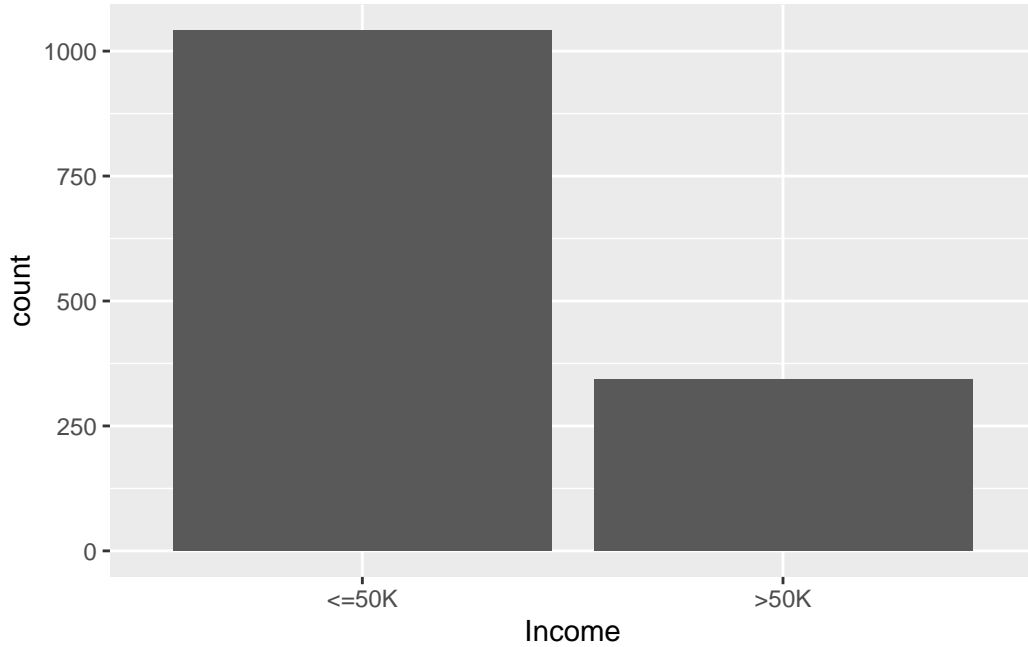


Figure 2: Income Distribution.

The income distribution analysis reveals that 75.2% of individuals earn $\leq 50K$, while only 24.8% earn $>50K$. This indicates a significant class imbalance, where the majority of the dataset consists of low-income individuals.

This imbalance can impact predictive modeling, as machine learning algorithms may become biased towards the dominant class ($\leq 50K$), leading to poor classification performance for high-income individuals. If a classification model is trained without addressing this issue, it may struggle to accurately predict the $>50K$ category.

2.3 Occupation by Income

Income	Adm-clerical	Craft-repair	Exec-managerial	Farming-fishing	
$\leq 50K$	13.5% (141)	14.8% (154)	9.3% (97)	3.6	(37)
$>50K$	7.0% (24)	13.1% (45)	23.0% (79)	1.5%	(5)
	Handlers-cleaners	Machine-op-inspct	Other-service	Priv-house-serv	
	5.3% (55)	7.9% (82)	14.1% (147)	0.4	(4)
	1.7% (6)	4.1% (14)	0.6% (2)	0.0	(0)
	Prof-specialty	Protective-serv	Sales	Tech-support	Transport-moving
	8.8% (92)	2.0% (21)	12.1% (126)	2.3% (24)	5.9 (61)
	25.3% (87)	2.9% (10)	12.5% (43)	3.8% (13)	4.7 (16)

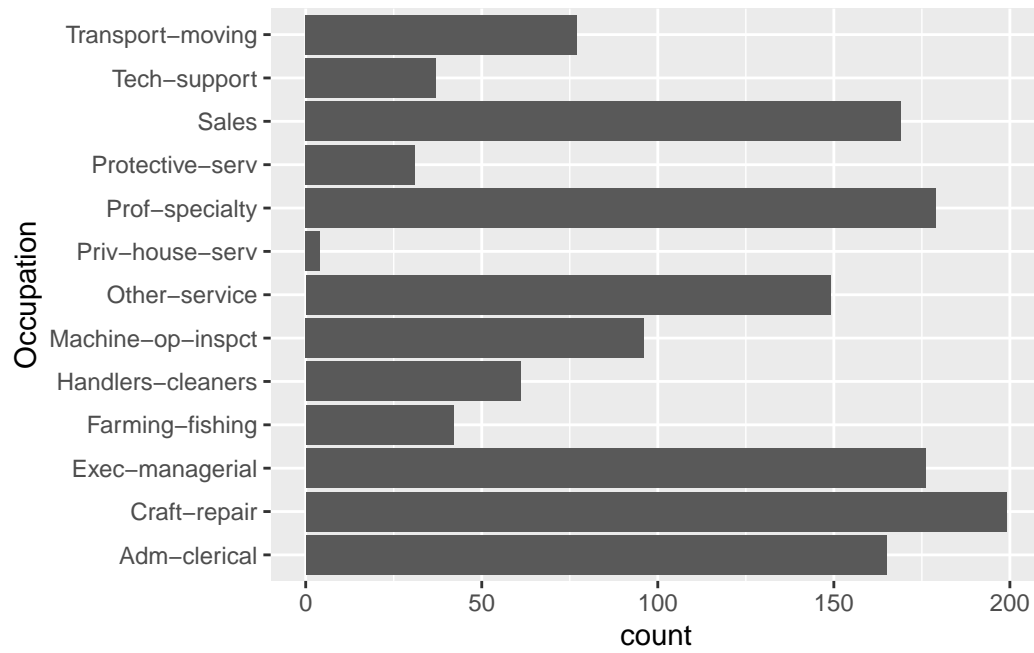


Figure 3: Occupation Distribution.

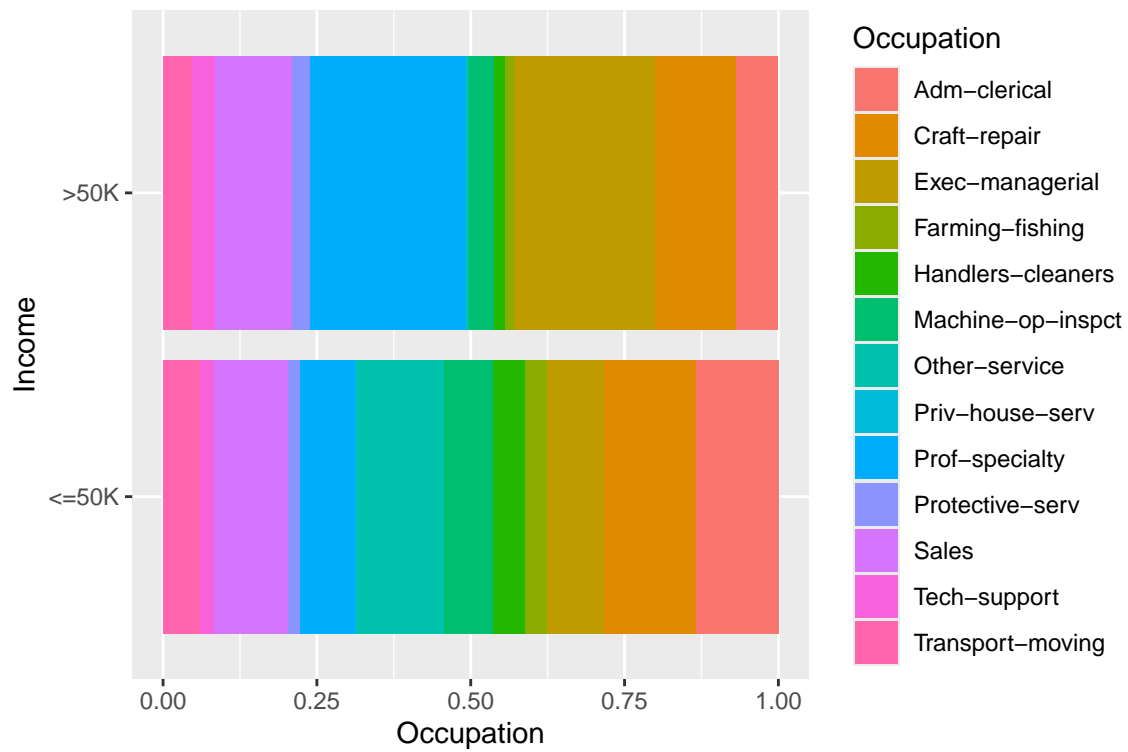


Figure 4: Income by Occupation.

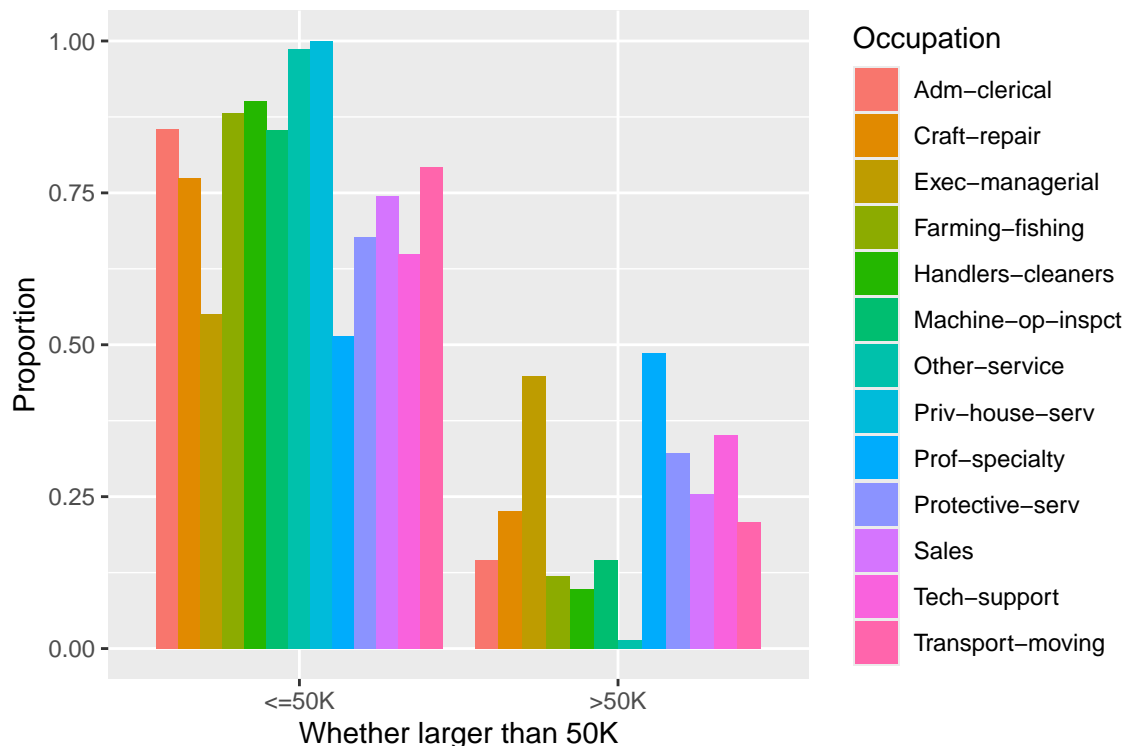


Figure 5: Income by Occupation.

The analysis of occupation by income shows significant variation across different job categories.

Administrative/Clerical roles: Approximately 85.6% of individuals in this category earn $\leq 50K$, while only 14.4% earn $> 50K$, indicating that these jobs are predominantly lower-income. **Craft and repair jobs:** 76.4% of workers earn $\leq 50K$, with 23.6% earning $> 50K$, suggesting a slightly better income distribution compared to clerical jobs. **Executive/Managerial roles:** This category has the highest proportion of high-income earners, with 44.9% earning $> 50K$, showing that leadership positions significantly increase the likelihood of higher income. **Farming/Fishing occupations:** 88.1% of individuals earn $\leq 50K$, and only 11.9% earn $> 50K$, reinforcing that agricultural jobs tend to be lower-paying. **Handlers/Cleaners:** The lowest income distribution, with 90.3% earning $\leq 50K$ and only 9.7% earning $> 50K$, indicating very limited access to higher salaries. This distribution highlights that occupational type is a key factor in determining income, with executive roles offering the highest proportion of high-income earners, while farming, cleaning, and clerical jobs predominantly fall into the lower-income category. These findings suggest that education, experience, and industry type play crucial roles in income disparities.

2.4 Education by Income

Income	10th	11th	12th	1st-4th	5th-6th	7th-8th	9th
<=50K	3.6% (37)	3.5% (36)	1.7% (18)	1.2% (12)	1.3% (14)	2.4% (25)	2.3(24)
>50K	0.9% (3)	0.9% (3)	0.0% (0)	0.0% (0)	0.0% (0)	0.6% (2)	0.9% (3)
Assoc-acdm	Assoc-voc	Bachelors	Doctorate	HS-grad	Masters	Prof-school	
3.9% (41)	4.8% (50)	13.4% (139)	0.2% (2)	34.6% (360)	3.0% (31)	0.3% (3)	
2.9% (10)	4.1% (14)	24.7% (85)	4.4% (15)	21.8% (75)	13.4% (46)	4.7(16)	
Some-college							
23.9							(249)
20.9%	(72)						

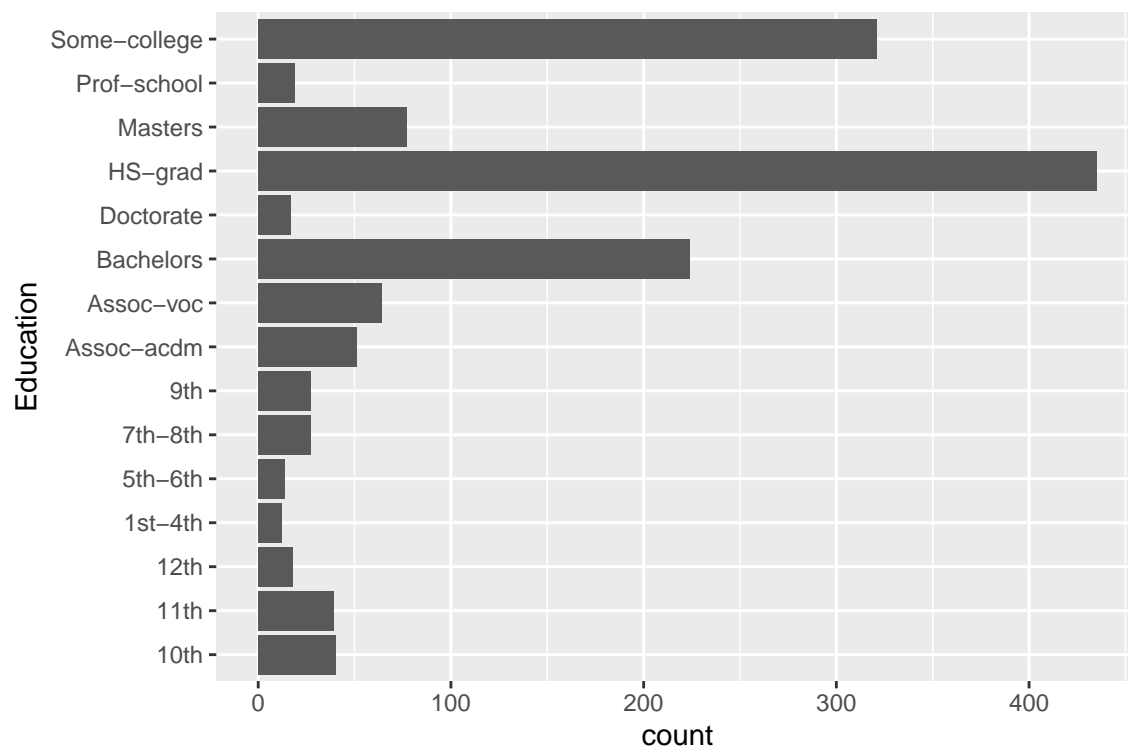


Figure 6: Education Distribution.

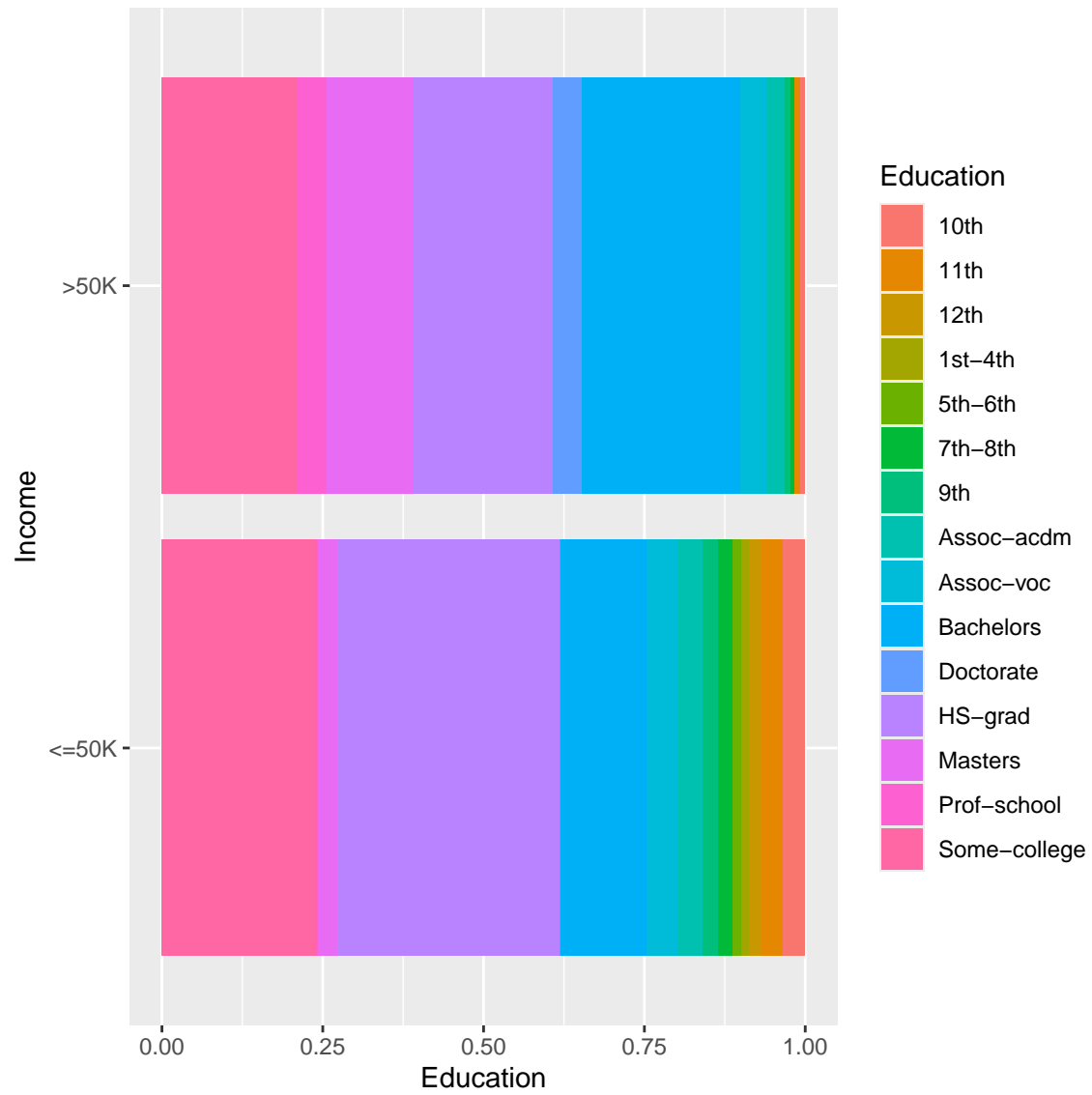


Figure 7: Income by Education.

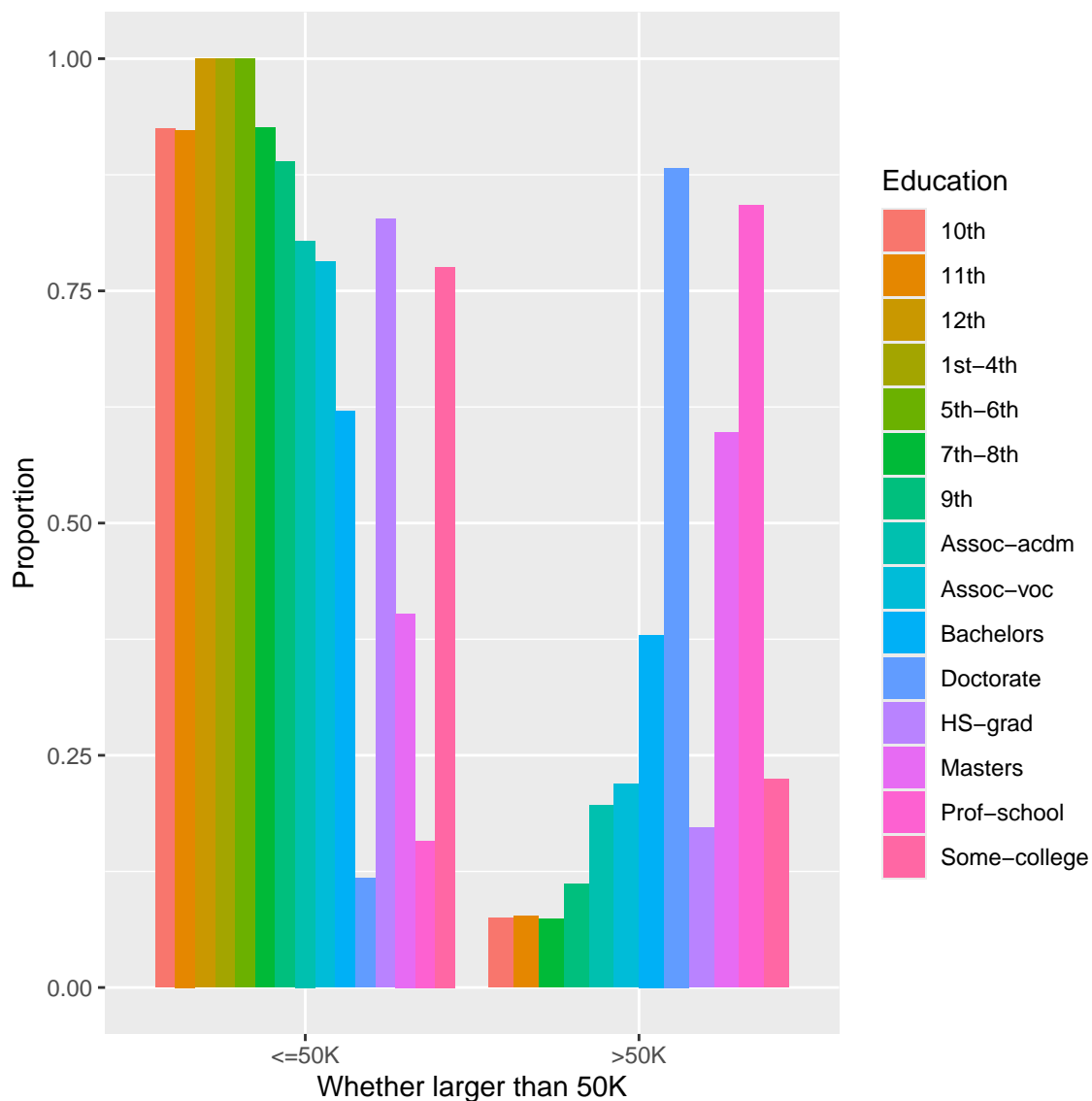


Figure 8: Income by Education.

The distribution of income across different education levels shows a clear correlation between higher education and increased income potential:

Lower education levels (1st-4th, 5th-6th, 12th grade):

100% of individuals in these categories earn $\leq 50K$, with no individuals earning $>50K$. This indicates that individuals with minimal education have almost no access to high-income jobs.

10th and 11th grade education:

93.8% of individuals with a 10th-grade education earn $\leq 50K$, while only 6.3% earn $>50K$. 92.9% of individuals with an 11th-grade education earn $\leq 50K$, with 7.1% in the high-income group. Although slightly better than primary education, these groups still have a very low likelihood of earning above 50K.

Key Takeaways: Education level is a strong predictor of income. Individuals without a high school diploma have almost no chance of reaching the high-income category. These findings highlight the importance of higher education in increasing earning potential and access to well-paying jobs.

2.5 Marital_Status by Income

Table 1: Marital_Status Distribution.

Income	Divorced	Married-civ-spouse	Married-spouse-absent	Never-married	Separated	Widowed
$\leq 50K$	15.1% (157)	34.5% (359)	1.8% (19)	42.3% (440)	3.9% (41)	2.4% (25)
$>50K$	7.3% (25)	84.3% (290)	0.3% (1)	7.3% (25)	0.3% (1)	0.6% (2)

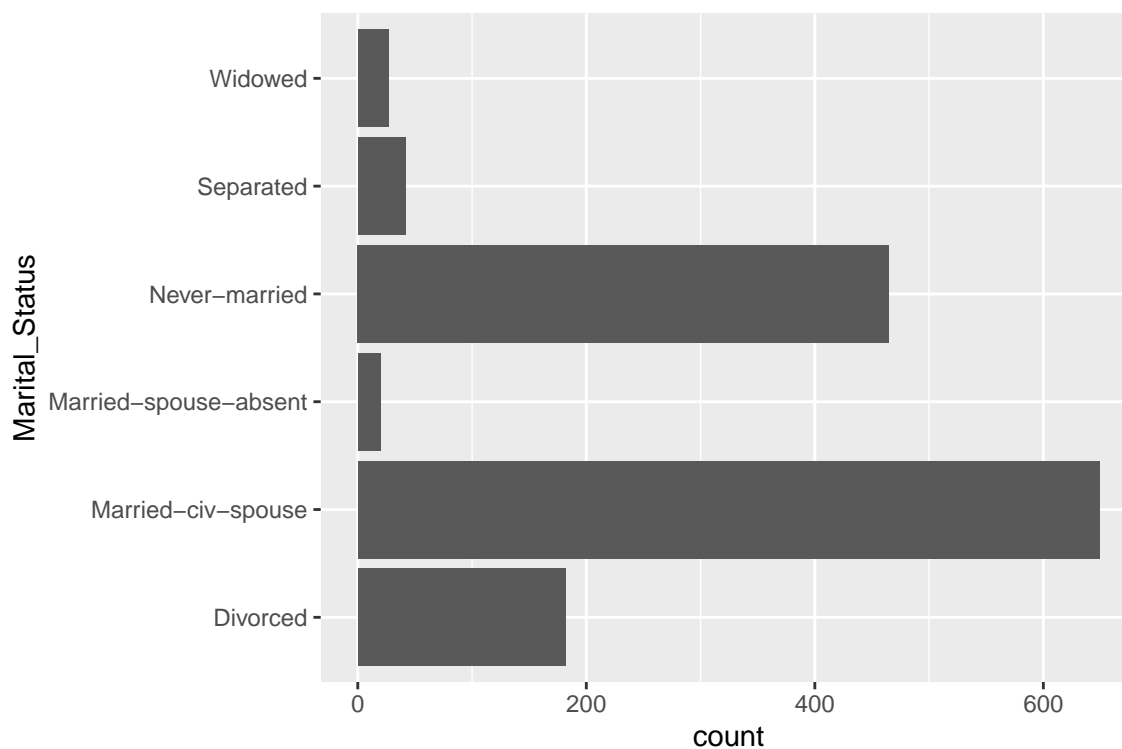


Figure 9: Marital_Status Distribution.

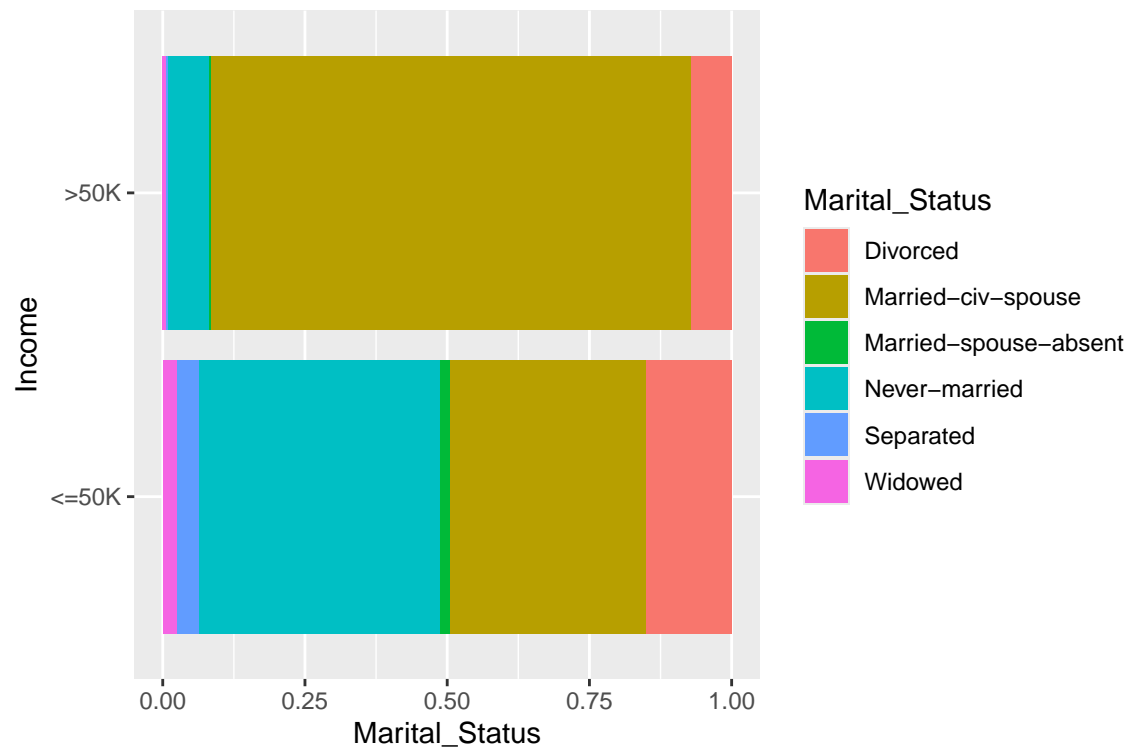


Figure 10: Income by Marital_Status.

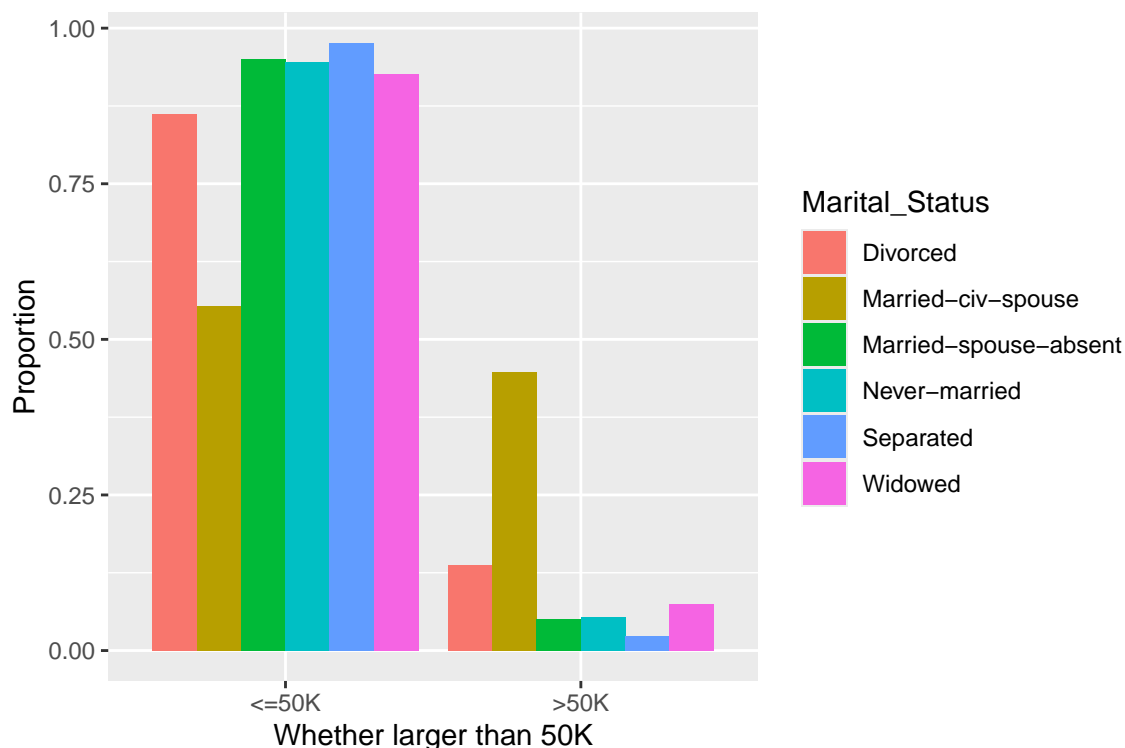


Figure 11: Income by Marital_Status.

The distribution of income by marital status reveals a strong correlation between marriage and income level:

Married individuals (civil spouse):

44.3% earn >50K, the highest proportion among all marital statuses. This suggests that marriage (especially in stable relationships) is associated with higher earnings, possibly due to dual-income households or increased financial stability. Divorced individuals:

85.8% earn <=50K, while 14.2% earn >50K. Although lower than married individuals, this group has a higher proportion of high-income earners than single or separated individuals. Never-married and separated individuals:

95.5% of never-married individuals and 97.9% of separated individuals earn <=50K, with only a very small fraction entering the >50K category. This indicates that single individuals are more likely to belong to lower-income groups, possibly due to younger age demographics and lower accumulated financial resources. Key Takeaways: Being married is strongly associated with higher income levels. Single and separated individuals are less likely to earn above 50K, which may reflect differences in career stability, accumulated wealth, or household income. This analysis suggests that marital status can play a significant role in economic well-being.

2.6 Sex by Income

Table 2: Sex Distribution.

Income	Female	Male
<=50K	37.2% (387)	62.8% (654)
>50K	15.1% (52)	84.9% (292)

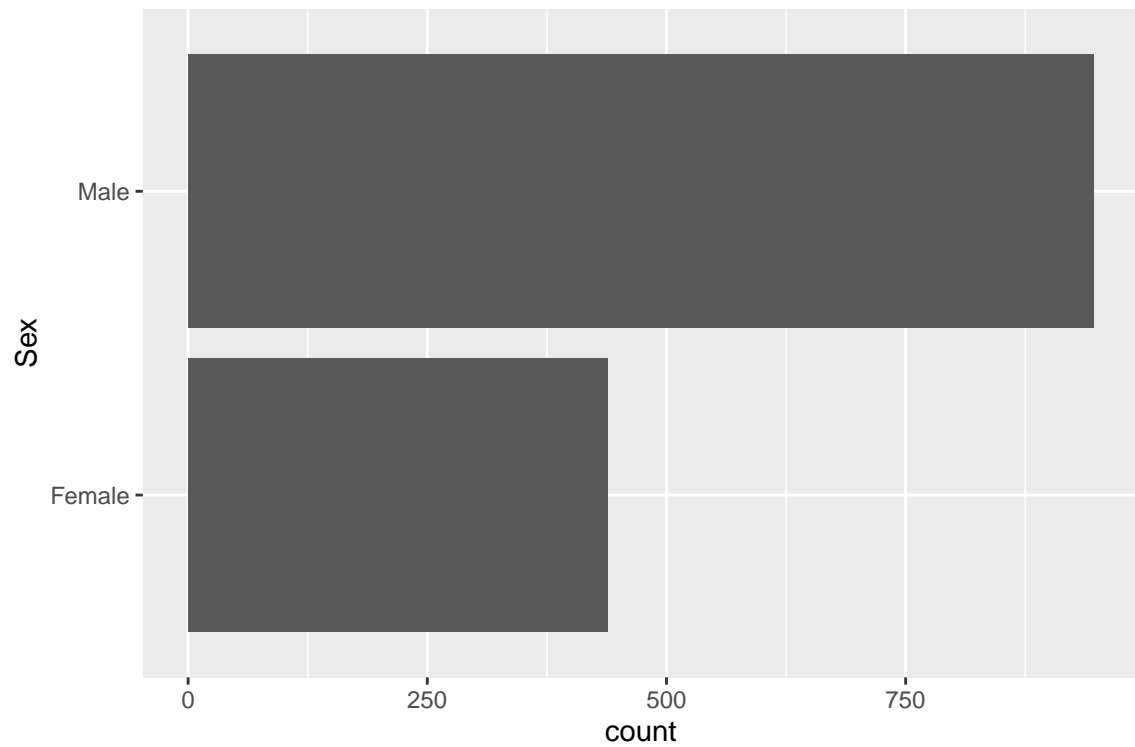


Figure 12: Sex Distribution.

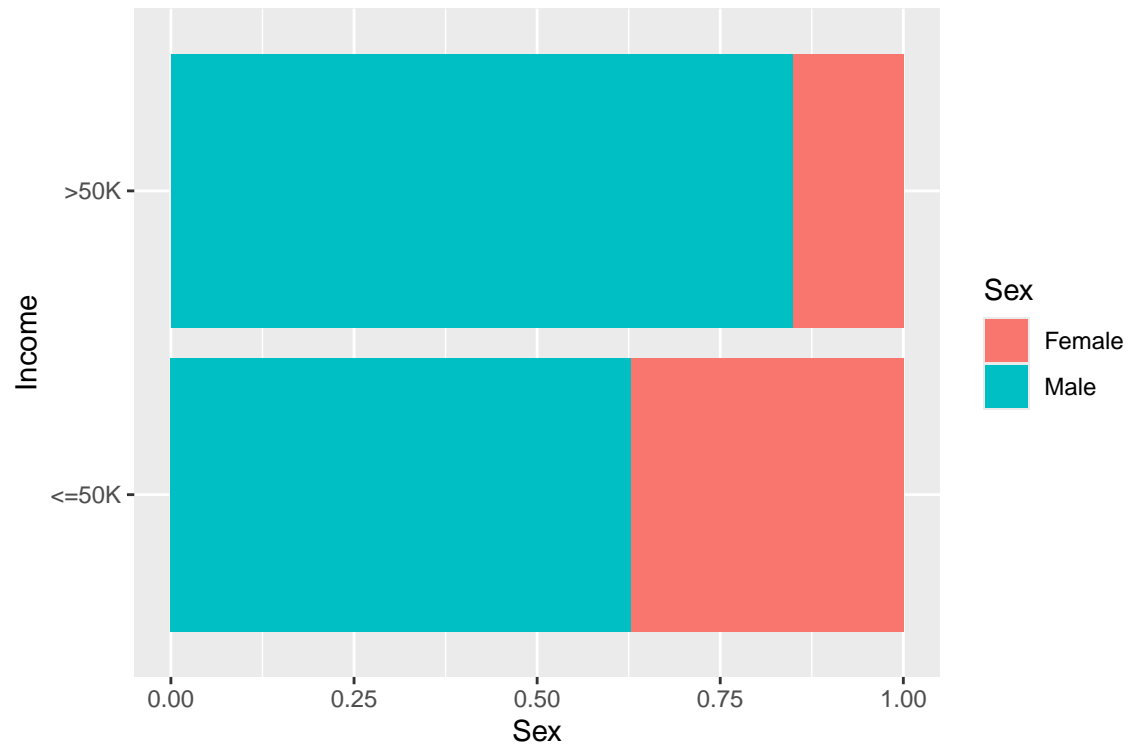


Figure 13: Income by Sex.

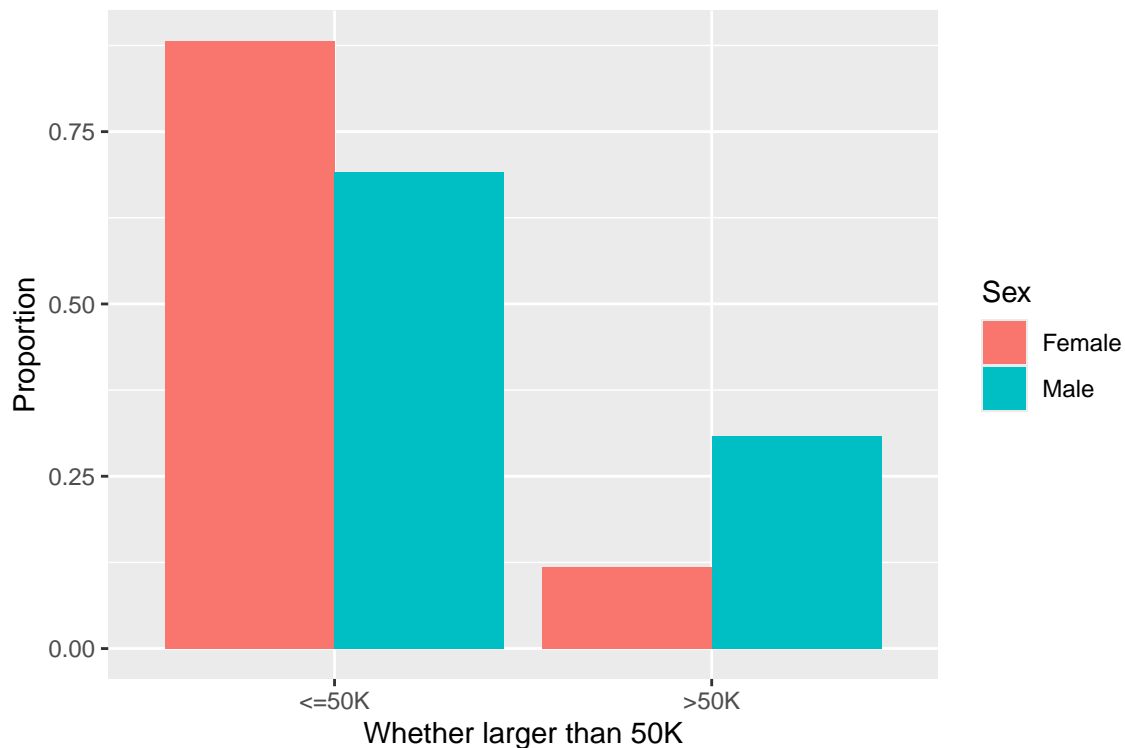


Figure 14: Income by Sex.

The distribution of income by gender reveals a significant disparity between males and females:

Females:

88.2% earn <=50K, while only 11.8% earn >50K. This indicates that women are much less likely to be in the high-income category. Males:

69.6% earn <=50K, whereas 30.4% earn >50K. The proportion of males earning above 50K is significantly higher than that of females. Key Takeaways: Men are significantly more likely to earn >50K compared to women. The income gap suggests possible gender disparities in wages, career advancement, or occupational roles. These findings highlight the need to investigate underlying causes, such as differences in industries, job roles, or social factors affecting earnings.

2.7 Nationality by Income

Income	Cambodia	Canada	China	Columbia	Cuba	Dominican-Republic
<=50K	0.1% (1)	0.5% (5)	0.3% (3)	0.1% (1)	0.5% (5)	0.4 (4)

>50K	0.3% (1)	0.9% (3)	0.3% (1)	0.0% (0)	0.3% (1)		0.0	(0)
El-Salvador	England	France	Germany	Greece	Guatemala	Haiti	India	
	0.5% (5)	0.2% (2)	0.1% (1)	0.4% (4)	0.2% (2)	0.5% (5)	0.1% (1)	0.3 (3)
	0.0% (0)	0.0% (0)	0.0% (0)	0.9% (3)	0.3% (1)	0.0% (0)	0.0% (0)	0.0 (0)
Iran	Ireland	Italy	Jamaica	Japan	Laos	Mexico		
0.1% (1)	0.1% (1)	0.2% (2)	0.2% (2)	0.2% (2)	0.2% (2)	2.8		(29)
0.0% (0)	0.3% (1)	0.0% (0)	0.0% (0)	0.3% (1)	0.0% (0)	0.3%	(1)	
Outlying-US(Guam-USVI-etc)	Philippines	Poland	Portugal	Puerto-Rico	Scotland			
	0.1% (1)	0.7% (7)	0.3% (3)	0.1% (1)	0.5% (5)	0.1(1)		
	0.0% (0)	0.6% (2)	0.3% (1)	0.3% (1)	0.6% (2)	0.0(0)		
South	Taiwan	Trinidad&Tobago	United-States	Vietnam				
0.3% (3)	0.1% (1)		0.1% (1)	89.5% (932)	0.5			(5)
0.0% (0)	0.6% (2)		0.0% (0)	93.9% (323)	0.0			(0)

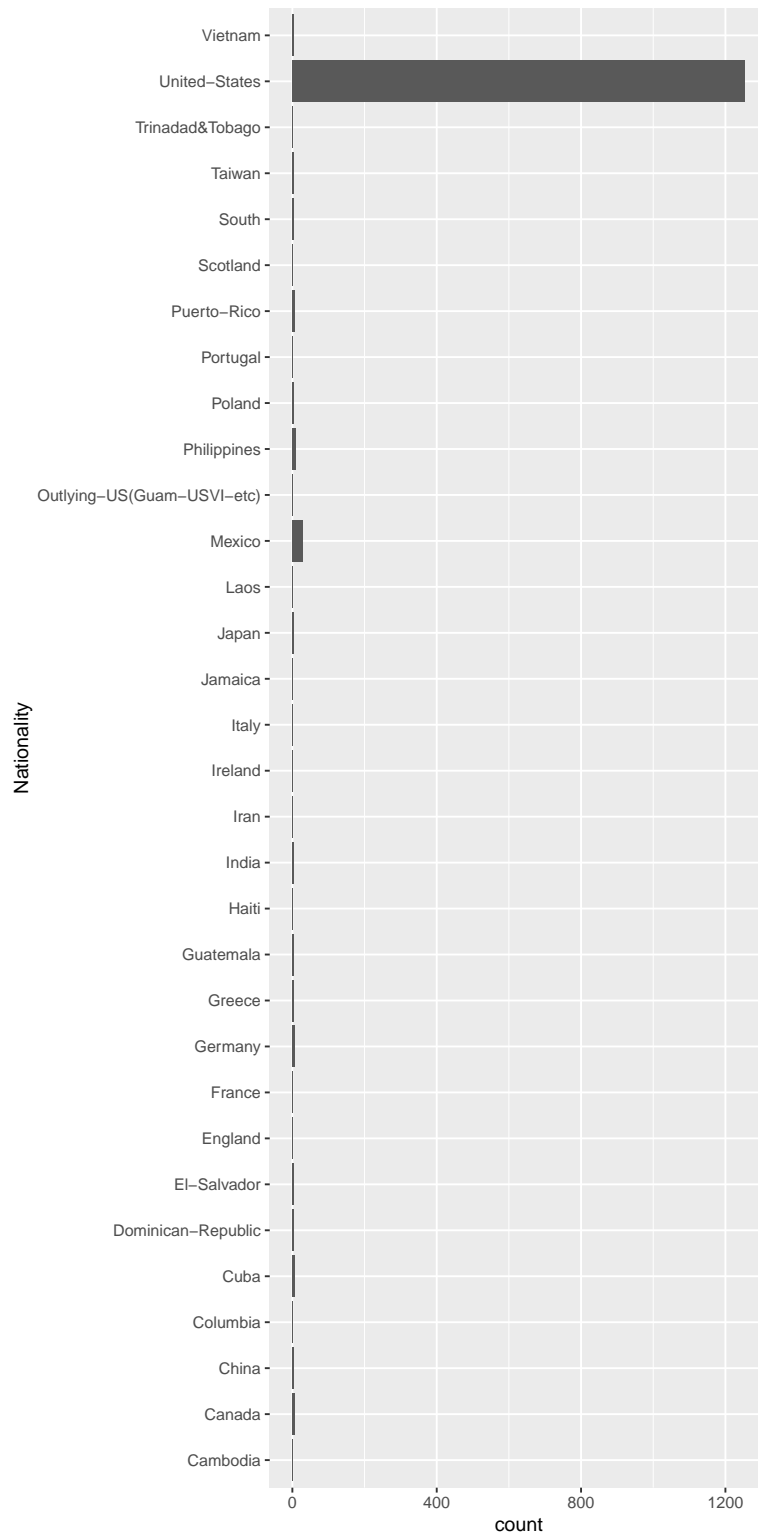


Figure 15: Nationality Distribution.

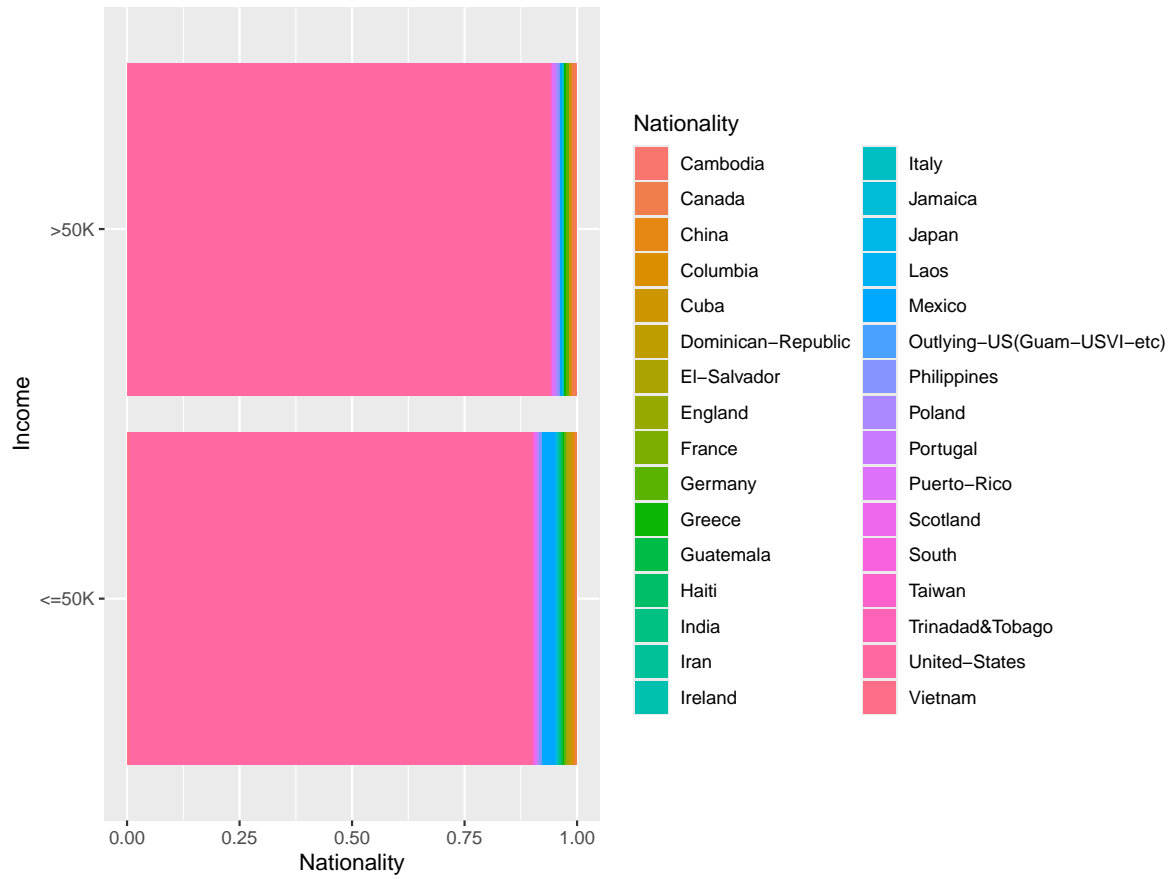


Figure 16: Income by Nationality.

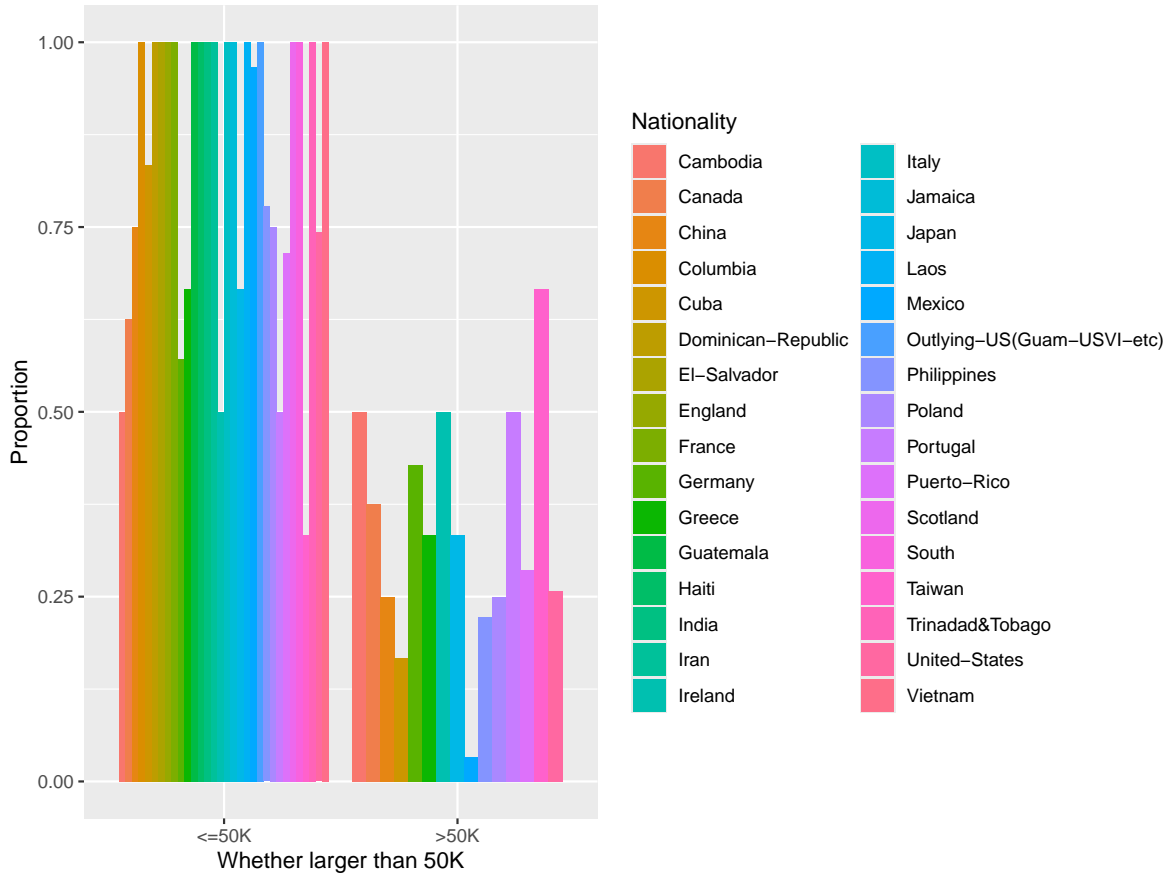


Figure 17: Income by Nationality.

The income distribution across different nationalities varies significantly:

Cambodia:

50% earn $\leq 50K$, and 50% earn $> 50K$. This is the most balanced distribution among the nationalities observed. Canada:

62.5% earn $\leq 50K$, while 37.5% earn $> 50K$. A relatively high proportion of individuals from Canada belong to the high-income group. China:

75% earn $\leq 50K$, and 25% earn $> 50K$. While some individuals reach the high-income group, the majority remain below 50K. Colombia:

100% earn $\leq 50K$, with no individuals in the $> 50K$ category. This suggests that people from this nationality are more likely to be in lower-income jobs. Cuba:

83.3% earn $\leq 50K$, while 16.7% earn $> 50K$. The majority still earn less than 50K, but a small proportion reaches higher income levels. Key Takeaways: Nationality appears to be a factor influencing income distribution. Some nationalities, such as Canada and Cambodia, have higher proportions of high-income individuals, while others, like Colombia and Cuba, have a stronger concentration in the low-income group. These differences could be attributed to factors such as job opportunities, skill levels, or immigration status affecting income potential.

However, in the dataset, there are 1255 samples with American nationality, accounting for 90.7% of the total. Due to this highly imbalanced distribution, nationality is not suitable as an explanatory variable.

2.8 Age by Income

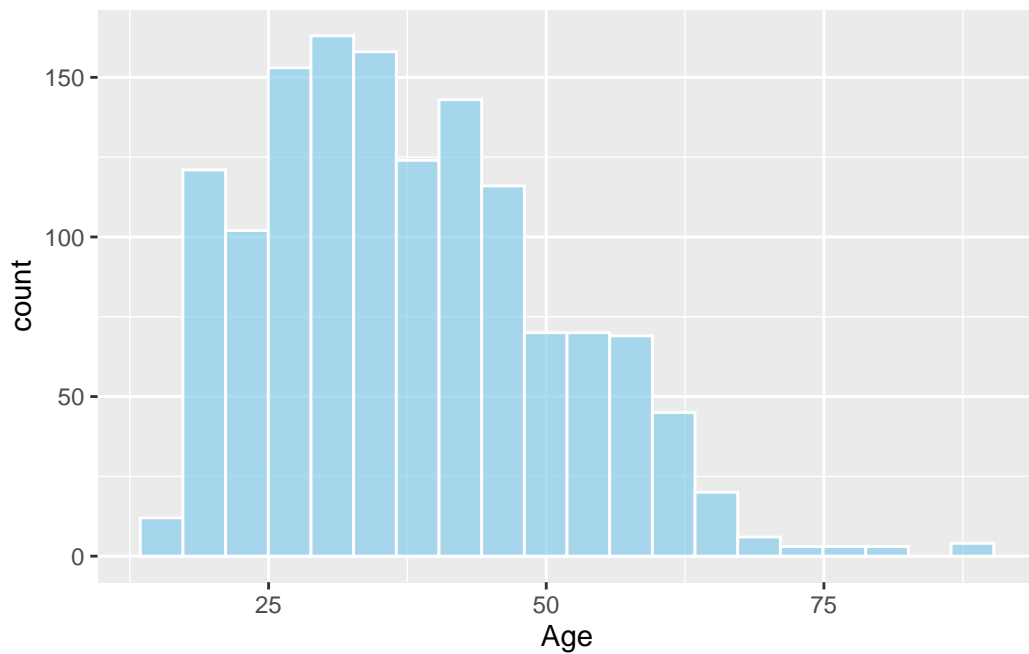


Figure 18: Age Distribution.

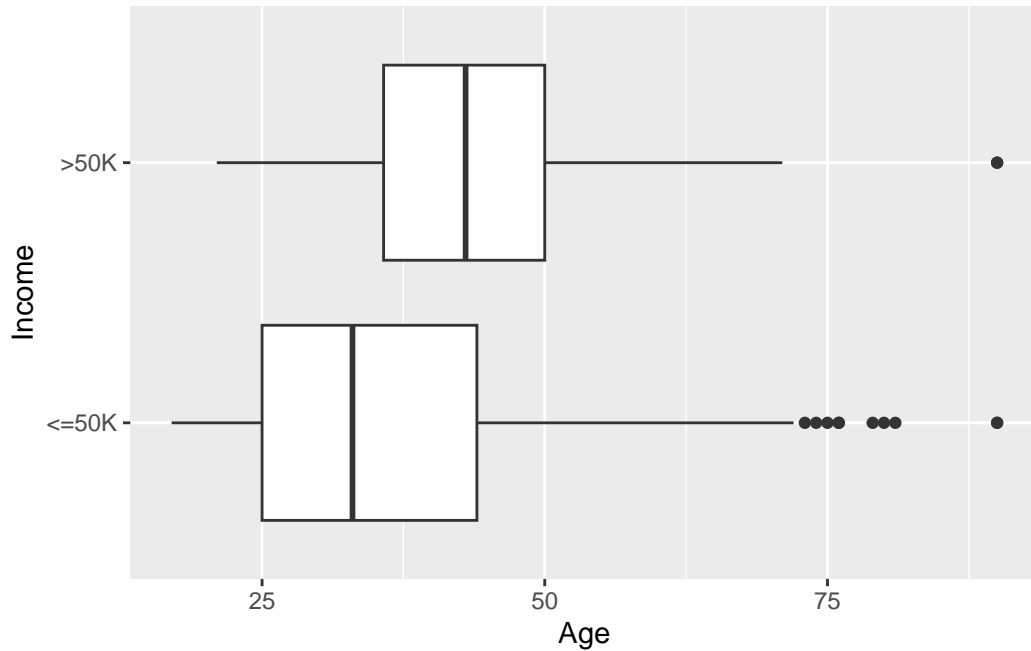


Figure 19: Income by Age.

The analysis of age distribution and its relationship to income reveals the following trends:

Age Distribution:

The dataset contains individuals aged 17 to 90 years old. The age distribution appears roughly normal, with most individuals concentrated in their 30s and 40s. Income and Age Statistics:

Low-income group ($\leq 50K$): Average age: 36.1 years 25th percentile: 25 years 50th percentile (median): 33 years 75th percentile: 45 years High-income group ($> 50K$): Average age: 43.9 years 25th percentile: 35 years 50th percentile (median): 43 years 75th percentile: 51 years Key Takeaways: Older individuals are more likely to be in the high-income group. The median age of high-income earners (43 years) is significantly higher than that of low-income earners (33 years). This suggests that experience, seniority, and career progression contribute to higher earnings over time. Younger individuals tend to belong to the low-income group. This is likely because they are in the early stages of their careers, earning entry-level salaries.

2.9 Hours_pw by Income

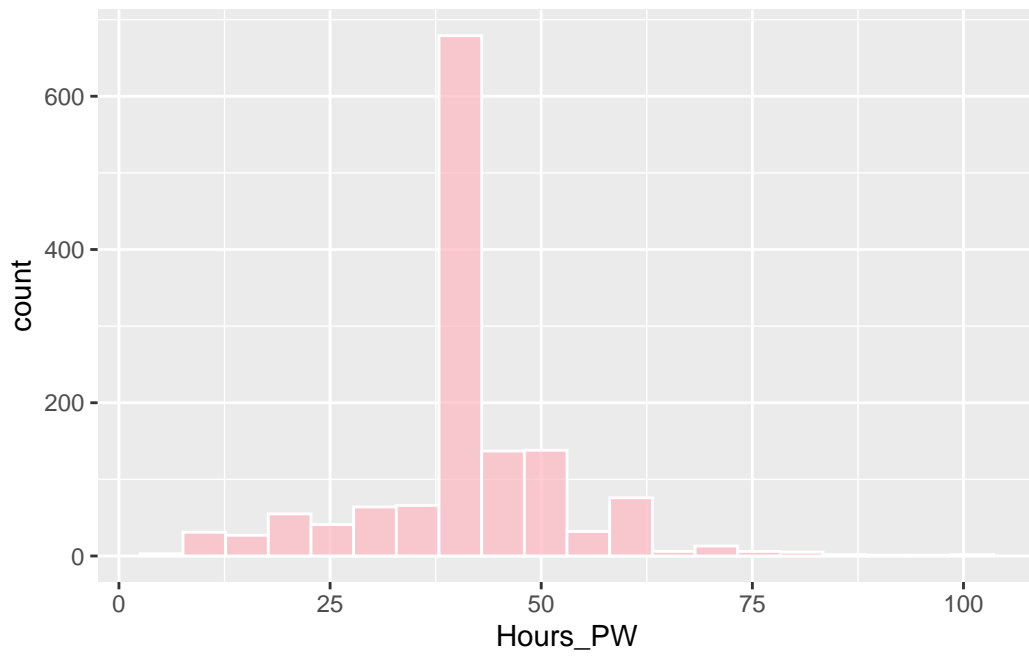


Figure 20: Hours_PW Distribution.

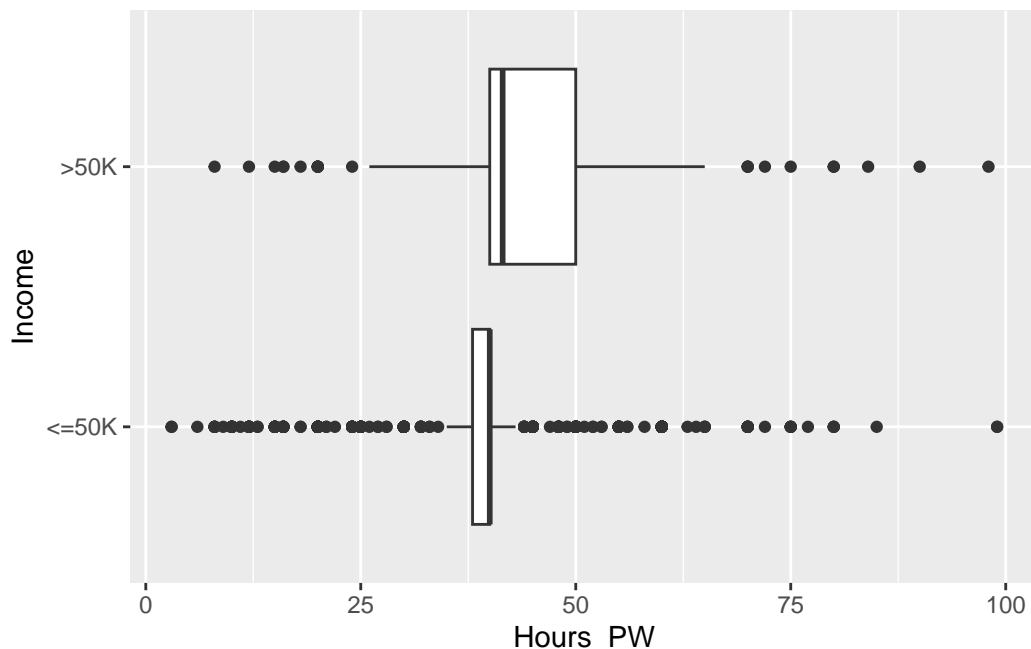


Figure 21: Income by Hours_PW.

The analysis of weekly work hours and its relationship to income reveals key differences between low and high earners:

Work Hours Distribution:

The dataset contains a variety of work hours, with most individuals working around 40 hours per week. The distribution appears right-skewed, meaning some individuals work significantly longer hours. Work Hours Statistics by Income:

Low-income group ($\leq 50K$): The most common work hours are 40 hours per week, with 546 individuals working this amount. There are 58 unique work hour values, indicating a wide range of working schedules. **High-income group ($> 50K$):** The most common work hours are also 40 hours per week, but only 142 individuals in this category work this amount. There are 39 unique work hour values, suggesting slightly less variability in working hours compared to low-income earners. **Key Takeaways:** Most individuals work 40 hours per week, regardless of income level. High-income earners tend to work more stable hours, while low-income earners exhibit greater variation in work schedules. Longer working hours do not necessarily guarantee higher income, suggesting that job type and skill level are more influential factors in determining earnings.

3 Model selection

fitting full model.

Implementation: ROI | Solver: lpsolve

Separation: TRUE

Existence of maximum likelihood estimates

(Intercept)	Age
0	0
Education11th	Education12th
0	-Inf
Education1st-4th	Education5th-6th
-Inf	-Inf
Education7th-8th	Education9th
0	0
EducationAssoc-acdm	EducationAssoc-voc
0	0
EducationBachelors	EducationDoctorate
0	0
EducationHS-grad	EducationMasters
0	0
EducationProf-school	EducationSome-college
0	0
SexMale	Hours_PW
0	0
Marital_StatusMarried-civ-spouse	Marital_StatusMarried-spouse-absent
0	0
Marital_StatusNever-married	Marital_StatusSeparated
0	0
Marital_StatusWidowed	OccupationCraft-repair
0	0
OccupationExec-managerial	OccupationFarming-fishing
0	0
OccupationHandlers-cleaners	OccupationMachine-op-inspct
0	0
OccupationOther-service	OccupationPriv-house-serv
0	-Inf
OccupationProf-specialty	OccupationProtective-serv
0	0
OccupationSales	OccupationTech-support
0	0
OccupationTransport-moving	NationalityCanada

0	0
NationalityChina	NationalityColumbia
0	-Inf
NationalityCuba	NationalityDominican-Republic
0	-Inf
NationalityEl-Salvador	NationalityEngland
-Inf	-Inf
NationalityFrance	NationalityGermany
-Inf	0
NationalityGreece	NationalityGuatemala
0	-Inf
NationalityHaiti	NationalityIndia
-Inf	-Inf
NationalityIran	NationalityIreland
-Inf	0
NationalityItaly	NationalityJamaica
-Inf	-Inf
NationalityJapan	NationalityLaos
0	-Inf
NationalityMexico	NationalityOutlying-US(Guam-USVI-etc)
0	-Inf
NationalityPhilippines	NationalityPoland
0	0
NationalityPortugal	NationalityPuerto-Rico
0	0
NationalityScotland	NationalitySouth
-Inf	-Inf
NationalityTaiwan	NationalityTrinidad&Tobago
0	-Inf
NationalityUnited-States	NationalityVietnam
0	-Inf

0: finite value, Inf: infinity, -Inf: -infinity

Call:

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

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4.710e+00	2.198e+00	-2.142	0.032163

Age	3.840e-02	7.626e-03	5.036	4.76e-07
Education11th	1.105e+00	9.856e-01	1.121	0.262436
Education12th	-1.448e+01	1.244e+03	-0.012	0.990718
Education1st-4th	-2.981e+01	1.875e+03	-0.016	0.987315
Education5th-6th	-1.524e+01	1.475e+03	-0.010	0.991753
Education7th-8th	-1.686e-01	1.027e+00	-0.164	0.869615
Education9th	2.560e-01	9.462e-01	0.271	0.786769
EducationAssoc-acdm	1.612e+00	7.895e-01	2.042	0.041190
EducationAssoc-voc	8.442e-01	7.523e-01	1.122	0.261769
EducationBachelors	2.034e+00	7.010e-01	2.902	0.003707
EducationDoctorate	4.593e+00	1.098e+00	4.183	2.88e-05
EducationHS-grad	1.042e+00	6.809e-01	1.531	0.125784
EducationMasters	2.290e+00	7.394e-01	3.097	0.001952
EducationProf-school	3.103e+00	9.911e-01	3.131	0.001741
EducationSome-college	1.450e+00	6.857e-01	2.115	0.034466
SexMale	1.914e-01	2.490e-01	0.769	0.442085
Hours_PW	2.978e-02	7.914e-03	3.762	0.000168
Marital_StatusMarried-civ-spouse	1.936e+00	2.892e-01	6.695	2.15e-11
Marital_StatusMarried-spouse-absent	2.740e-01	1.158e+00	0.237	0.813013
Marital_StatusNever-married	-5.338e-01	3.586e-01	-1.489	0.136554
Marital_StatusSeparated	-1.594e+00	1.068e+00	-1.493	0.135565
Marital_StatusWidowed	-8.949e-01	8.426e-01	-1.062	0.288201
OccupationCraft-repair	-9.979e-02	3.548e-01	-0.281	0.778491
OccupationExec-managerial	3.437e-01	3.422e-01	1.004	0.315155
OccupationFarming-fishing	-1.698e+00	6.081e-01	-2.792	0.005240
OccupationHandlers-cleaners	-1.772e-01	5.794e-01	-0.306	0.759728
OccupationMachine-op-inspct	-5.569e-01	4.414e-01	-1.261	0.207134
OccupationOther-service	-2.477e+00	7.982e-01	-3.103	0.001913
OccupationPriv-house-serv	-1.633e+01	2.648e+03	-0.006	0.995080
OccupationProf-specialty	6.458e-01	3.595e-01	1.796	0.072471
OccupationProtective-serv	-2.791e-02	5.369e-01	-0.052	0.958538
OccupationSales	-5.323e-02	3.641e-01	-0.146	0.883781
OccupationTech-support	1.037e+00	5.441e-01	1.905	0.056736
OccupationTransport-moving	-3.092e-01	4.362e-01	-0.709	0.478456
NationalityCanada	-1.789e+00	2.313e+00	-0.773	0.439233
NationalityChina	-2.918e+00	3.035e+00	-0.961	0.336342
NationalityColumbia	-1.680e+01	6.523e+03	-0.003	0.997945
NationalityCuba	-1.802e+00	2.365e+00	-0.762	0.445958
NationalityDominican-Republic	-1.660e+01	2.909e+03	-0.006	0.995448
NationalityEl-Salvador	-1.838e+01	2.495e+03	-0.007	0.994122
NationalityEngland	-1.812e+01	4.607e+03	-0.004	0.996862
NationalityFrance	-1.804e+01	6.523e+03	-0.003	0.997793
NationalityGermany	-1.414e+00	2.206e+00	-0.641	0.521713

NationalityGreece	-1.153e+00	3.135e+00	-0.368	0.713110
NationalityGuatemala	-1.548e+01	2.162e+03	-0.007	0.994285
NationalityHaiti	-1.707e+01	6.523e+03	-0.003	0.997912
NationalityIndia	-2.097e+01	3.539e+03	-0.006	0.995273
NationalityIran	-1.884e+01	6.523e+03	-0.003	0.997696
NationalityIreland	6.005e-01	2.728e+00	0.220	0.825742
NationalityItaly	-1.874e+01	4.184e+03	-0.004	0.996426
NationalityJamaica	-1.688e+01	4.609e+03	-0.004	0.997078
NationalityJapan	-1.502e+00	2.608e+00	-0.576	0.564588
NationalityLaos	-1.838e+01	4.187e+03	-0.004	0.996497
NationalityMexico	-2.297e+00	2.282e+00	-1.006	0.314240
NationalityOutlying-US(Guam-USVI-etc)	-1.694e+01	6.523e+03	-0.003	0.997928
NationalityPhilippines	-2.274e+00	2.375e+00	-0.957	0.338412
NationalityPoland	-2.433e+00	2.397e+00	-1.015	0.310036
NationalityPortugal	1.404e+01	1.326e+03	0.011	0.991550
NationalityPuerto-Rico	4.044e-01	2.361e+00	0.171	0.863991
NationalityScotland	-1.343e+01	6.523e+03	-0.002	0.998357
NationalitySouth	-1.776e+01	3.246e+03	-0.005	0.995635
NationalityTaiwan	-3.320e+00	2.486e+00	-1.336	0.181695
NationalityTrinidad&Tobago	-1.855e+01	6.523e+03	-0.003	0.997730
NationalityUnited-States	-1.815e+00	2.002e+00	-0.906	0.364805
NationalityVietnam	-1.958e+01	2.253e+03	-0.009	0.993067
(Intercept)	*			
Age	***			
Education11th				
Education12th				
Education1st-4th				
Education5th-6th				
Education7th-8th				
Education9th				
EducationAssoc-acdm	*			
EducationAssoc-voc				
EducationBachelors	**			
EducationDoctorate	***			
EducationHS-grad				
EducationMasters	**			
EducationProf-school	**			
EducationSome-college	*			
SexMale				
Hours_PW	***			
Marital_StatusMarried-civ-spouse	***			
Marital_StatusMarried-spouse-absent				

Marital_StatusNever-married	
Marital_StatusSeparated	
Marital_StatusWidowed	
OccupationCraft-repair	
OccupationExec-managerial	
OccupationFarming-fishing	**
OccupationHandlers-cleaners	
OccupationMachine-op-inspct	
OccupationOther-service	**
OccupationPriv-house-serv	
OccupationProf-specialty	.
OccupationProtective-serv	
OccupationSales	
OccupationTech-support	.
OccupationTransport-moving	
NationalityCanada	
NationalityChina	
NationalityColumbia	
NationalityCuba	
NationalityDominican-Republic	
NationalityEl-Salvador	
NationalityEngland	
NationalityFrance	
NationalityGermany	
NationalityGreece	
NationalityGuatemala	
NationalityHaiti	
NationalityIndia	
NationalityIran	
NationalityIreland	
NationalityItaly	
NationalityJamaica	
NationalityJapan	
NationalityLaos	
NationalityMexico	
NationalityOutlying-US(Guam-USVI-etc)	
NationalityPhilippines	
NationalityPoland	
NationalityPortugal	
NationalityPuerto-Rico	
NationalityScotland	
NationalitySouth	
NationalityTaiwan	

NationalityTrinidad&Tobago
 NationalityUnited-States
 NationalityVietnam

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.71 on 1384 degrees of freedom
 Residual deviance: 974.31 on 1319 degrees of freedom
 AIC: 1106.3

Number of Fisher Scoring iterations: 17

Call:

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

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-6.433e+00	9.215e-01	-6.982	2.92e-12	***
Age	3.793e-02	7.413e-03	5.117	3.10e-07	***
Education11th	1.288e+00	9.495e-01	1.357	0.17493	
Education12th	-1.362e+01	7.644e+02	-0.018	0.98578	
Education1st-4th	-1.459e+01	9.286e+02	-0.016	0.98747	
Education5th-6th	-1.447e+01	9.224e+02	-0.016	0.98748	
Education7th-8th	-1.669e-01	1.019e+00	-0.164	0.86992	
Education9th	3.944e-01	9.297e-01	0.424	0.67141	
EducationAssoc-acdm	1.560e+00	7.818e-01	1.996	0.04596	*
EducationAssoc-voc	8.264e-01	7.447e-01	1.110	0.26717	
EducationBachelors	1.943e+00	6.912e-01	2.811	0.00494	**
EducationDoctorate	4.400e+00	1.094e+00	4.022	5.77e-05	***
EducationHS-grad	1.043e+00	6.714e-01	1.554	0.12023	
EducationMasters	2.264e+00	7.285e-01	3.107	0.00189	**
EducationProf-school	3.036e+00	9.789e-01	3.102	0.00192	**
EducationSome-college	1.422e+00	6.767e-01	2.102	0.03557	*
Hours_PW	3.046e-02	7.687e-03	3.963	7.40e-05	***
Marital_StatusMarried-civ-spouse	1.941e+00	2.657e-01	7.306	2.76e-13	***
Marital_StatusMarried-spouse-absent	-4.485e-02	1.120e+00	-0.040	0.96806	
Marital_StatusNever-married	-5.497e-01	3.490e-01	-1.575	0.11531	
Marital_StatusSeparated	-1.611e+00	1.066e+00	-1.511	0.13083	

Marital_StatusWidowed	-9.765e-01	8.396e-01	-1.163	0.24481	
OccupationCraft-repair	-6.118e-02	3.259e-01	-0.188	0.85109	
OccupationExec-managerial	4.468e-01	3.265e-01	1.368	0.17124	
OccupationFarming-fishing	-1.621e+00	5.942e-01	-2.728	0.00638	**
OccupationHandlers-cleaners	-9.311e-02	5.548e-01	-0.168	0.86672	
OccupationMachine-op-inspct	-5.220e-01	4.147e-01	-1.259	0.20812	
OccupationOther-service	-2.445e+00	7.761e-01	-3.150	0.00163	**
OccupationPriv-house-serv	-1.542e+01	1.606e+03	-0.010	0.99234	
OccupationProf-specialty	7.109e-01	3.459e-01	2.055	0.03985	*
OccupationProtective-serv	8.969e-02	5.165e-01	0.174	0.86213	
OccupationSales	3.198e-02	3.426e-01	0.093	0.92563	
OccupationTech-support	1.079e+00	5.209e-01	2.072	0.03827	*
OccupationTransport-moving	-2.654e-01	4.154e-01	-0.639	0.52289	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
 Residual deviance: 998.6 on 1351 degrees of freedom
 AIC: 1066.6

Number of Fisher Scoring iterations: 16

Implementation: ROI | Solver: lp_solve

Separation: TRUE

Existence of maximum likelihood estimates

(Intercept)	Age
0	0
Education11th	Education12th
0	-Inf
Education1st-4th	Education5th-6th
-Inf	-Inf
Education7th-8th	Education9th
0	0
EducationAssoc-acdm	EducationAssoc-voc
0	0
EducationBachelors	EducationDoctorate
0	0
EducationHS-grad	EducationMasters
0	0
EducationProf-school	EducationSome-college

	0		0
	Hours_PW	Marital_StatusMarried-civ-spouse	
	0		0
Marital_StatusMarried-spouse-absent		Marital_StatusNever-married	
	0		0
Marital_StatusSeparated		Marital_StatusWidowed	
	0		0
OccupationCraft-repair		OccupationExec-managerial	
	0		0
OccupationFarming-fishing		OccupationHandlers-cleaners	
	0		0
OccupationMachine-op-inspct		OccupationOther-service	
	0		0
OccupationPriv-house-serv		OccupationProf-specialty	
-Inf			0
OccupationProtective-serv		OccupationSales	
	0		0
OccupationTech-support		OccupationTransport-moving	
	0		0

0: finite value, Inf: infinity, -Inf: -infinity

The model selection process involves fitting a Generalized Linear Model (GLM) with a binomial logistic regression to predict whether an individual's income falls into the >50K or <=50K category.

1. Full Model Fitting The initial model (full_model) includes all available predictor variables: Age, Education, Sex, Work Hours per Week (Hours_PW), Marital Status, Occupation, and Nationality. A separation detection test (detect_separation_full_model) is applied to check if certain variables lead to perfect separation, which may cause convergence issues in the model. The summary of the full model provides insights into which variables are statistically significant.
2. Model Optimization using Stepwise AIC Stepwise Akaike Information Criterion (AIC) selection is applied (stepAIC_model), which iteratively removes the least significant predictors to find the best-performing model. The final optimized model retains only the most relevant predictors: Age, Education, Work Hours per Week, Marital Status, and Occupation. A separation detection test (detect_separation_stepAIC_model) is performed again to check whether the optimized model exhibits perfect separation issues.
3. Key Takeaways: The full model includes all predictors but may contain unnecessary variables that do not contribute significantly. Stepwise AIC selection helps refine the model by retaining only the most informative variables, reducing overfitting and improving interpretability. The final optimized model suggests that Age, Education, Work Hours, Marital Status, and Occupation are the strongest predictors of income. Nationality and Sex are removed in the AIC-selected model, indicating they may not have a

significant impact on predicting income in this dataset. The model suffers from perfect separation issues, with the explanatory variables Education and Occupation exhibiting perfect separation.

3.1 Option choose of model

To resolve the perfect separation issue, merge the categories of some explanatory variables.

Table 3: Marital_Status Distribution.

Income	Married	Unmarried
<=50K	36.3% (378)	63.7% (663)
>50K	84.6% (291)	15.4% (53)

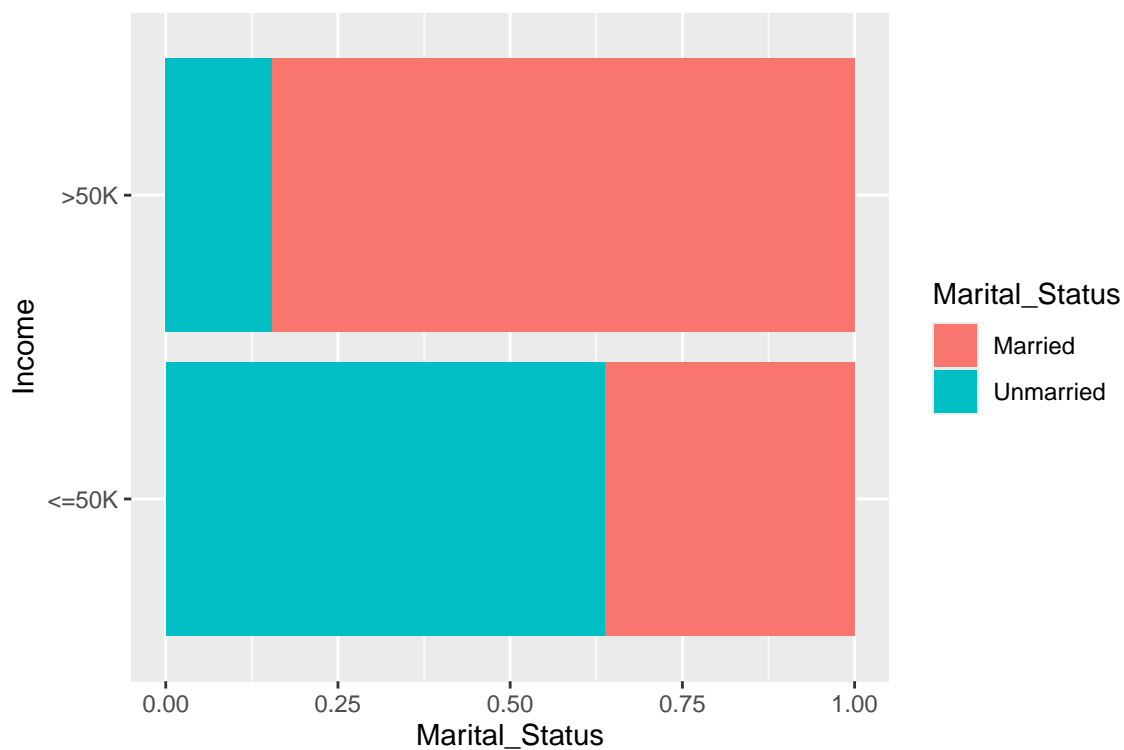


Figure 22: Income by Marital_Status.

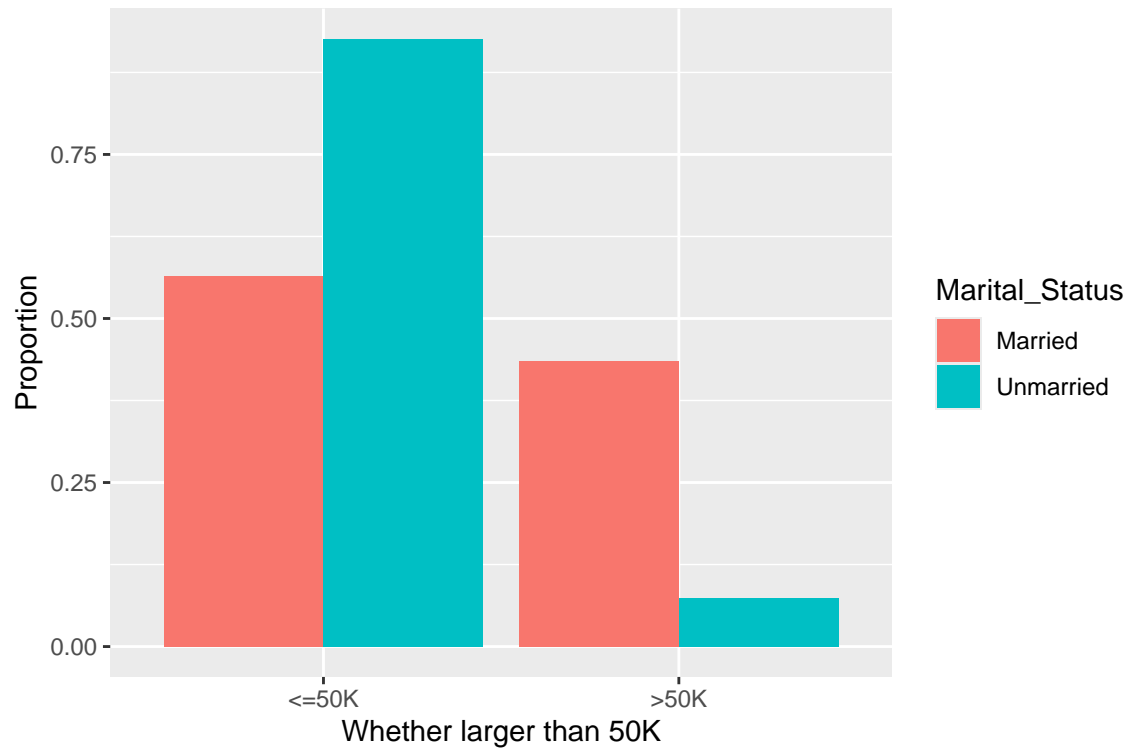


Figure 23: Income by Marital_Status.

Table 4: Education Distribution.

Income	High_Education	Low_Education
<=50K	84.1% (875)	15.9% (166)
>50K	96.8% (333)	3.2% (11)

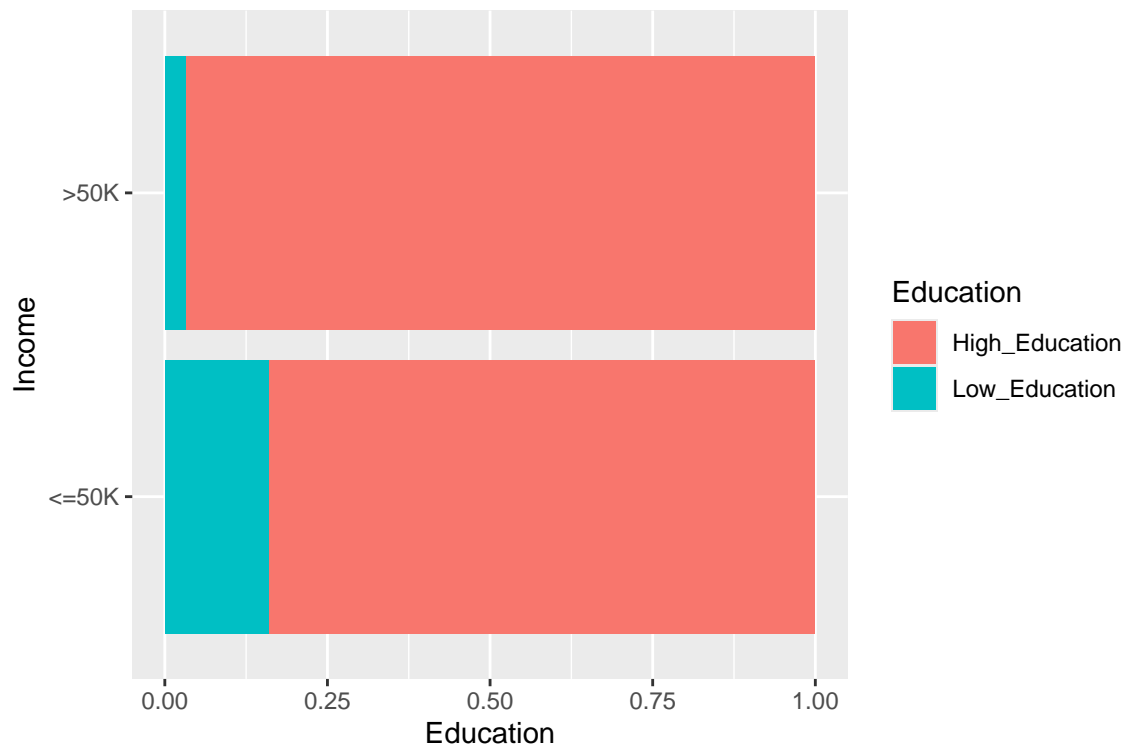


Figure 24: Income by Education.

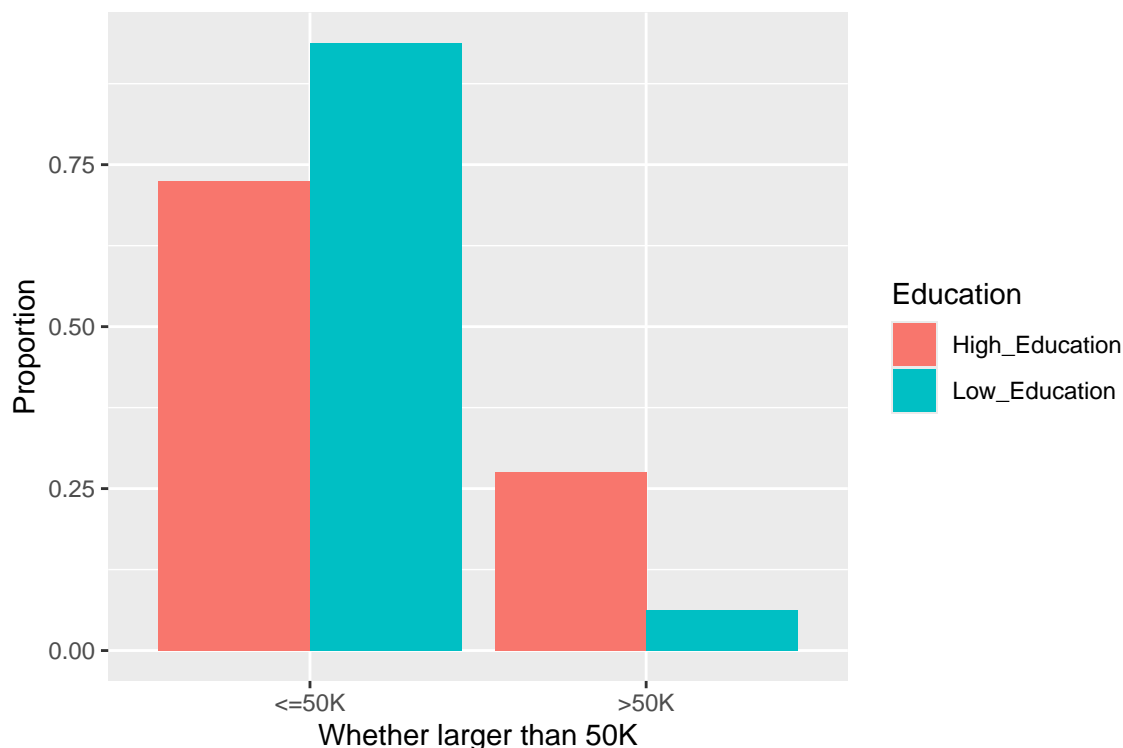


Figure 25: Income by Education.

To address the complete separation issue, some explanatory variables have been merged into broader categories. This helps ensure that each category has sufficient data points, improving the stability of the logistic regression model.

1. Education Level Merging Low Education:

Groups together individuals with education levels from 1st grade to 12th grade (e.g., 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th). These individuals generally have no formal higher education and are more likely to be in low-income jobs.

High Education:
Includes individuals with some form of post-secondary education (e.g., Associate degree, Bachelor's, Master's, Doctorate, HS-grad, Prof-school, Some-college). These individuals have better earning potential and are more likely to be in high-income categories.

2. Marital Status Merging Unmarried:

Combines Separated, Widowed, Never-married, and Divorced into a single category. These individuals tend to have lower financial stability compared to married individuals.

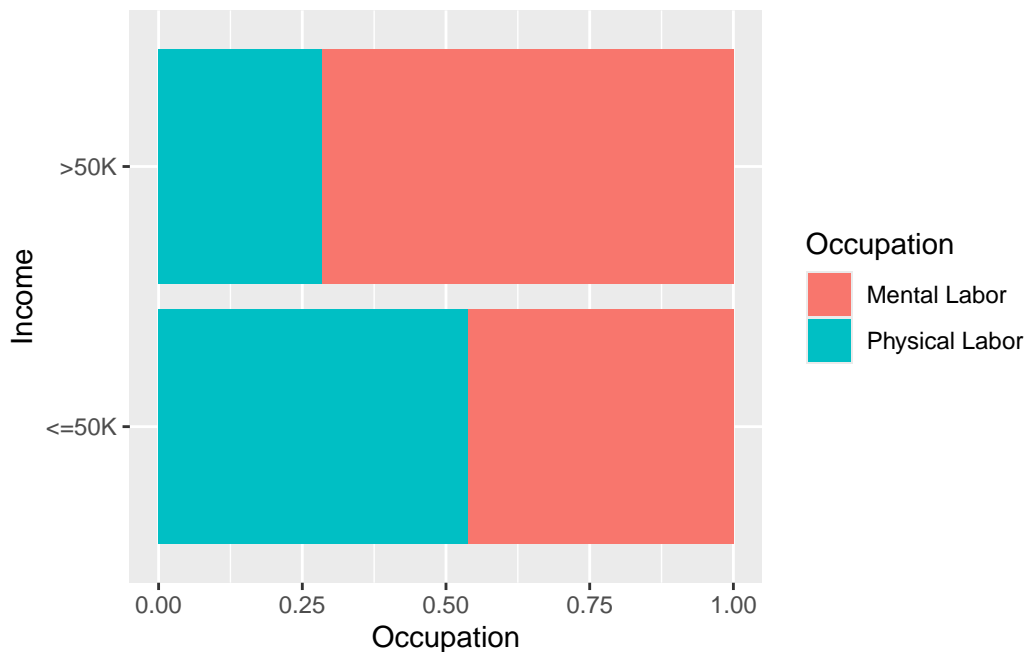
Combines Married-spouse-absent and Married-civ-spouse into a single category. Married individuals generally have more financial stability, often benefiting from dual-income households.

3. Visualizing the Effects of Merging

- Marital Status vs. Income:
The distribution of income across the newly grouped Married and Unmarried categories is displayed.
- Education vs. Income:
The newly created Low Education and High Education categories allow for a clearer comparison of income distribution between different education levels. Key

Takeaways: Merging categories helps reduce model complexity and prevent complete separation issues. Individuals with higher education levels are more likely to earn >50K compared to those in the Low Education category. Married individuals show a higher proportion of high-income earners, reinforcing previous findings about marital status and financial stability. These transformations improve the model's ability to generalize and make more accurate predictions.

3.2 Combine occupation types (physical labor and mental labor)



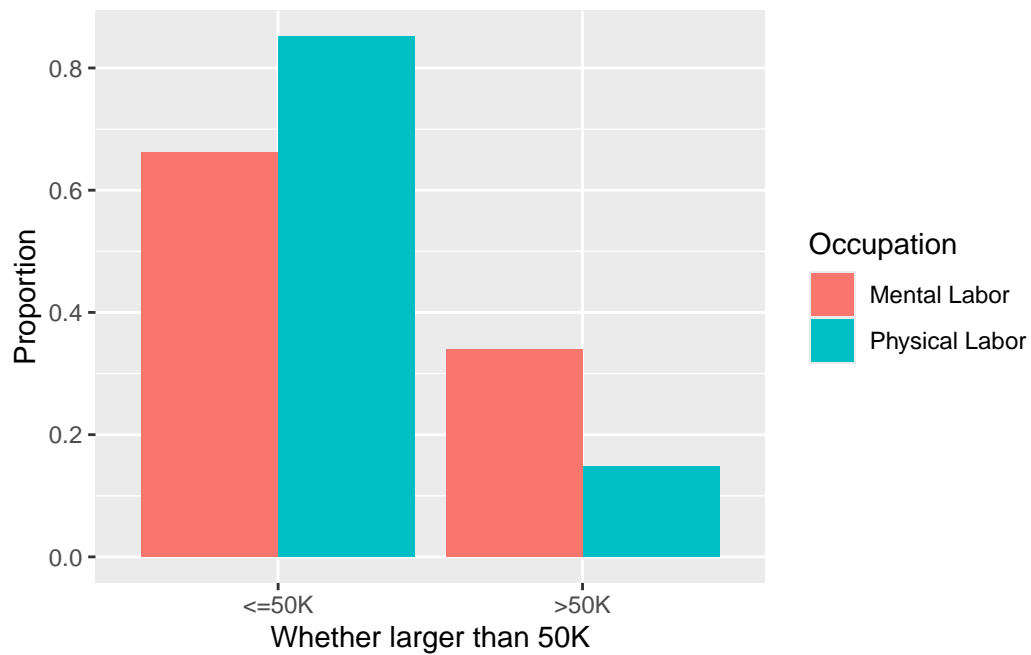


Table 5: Occupation Distribution (physical labor and mental labor).

Income	Mental Labor	Physical Labor
<=50K	46.1% (480)	53.9% (561)
>50K	71.5% (246)	28.5% (98)

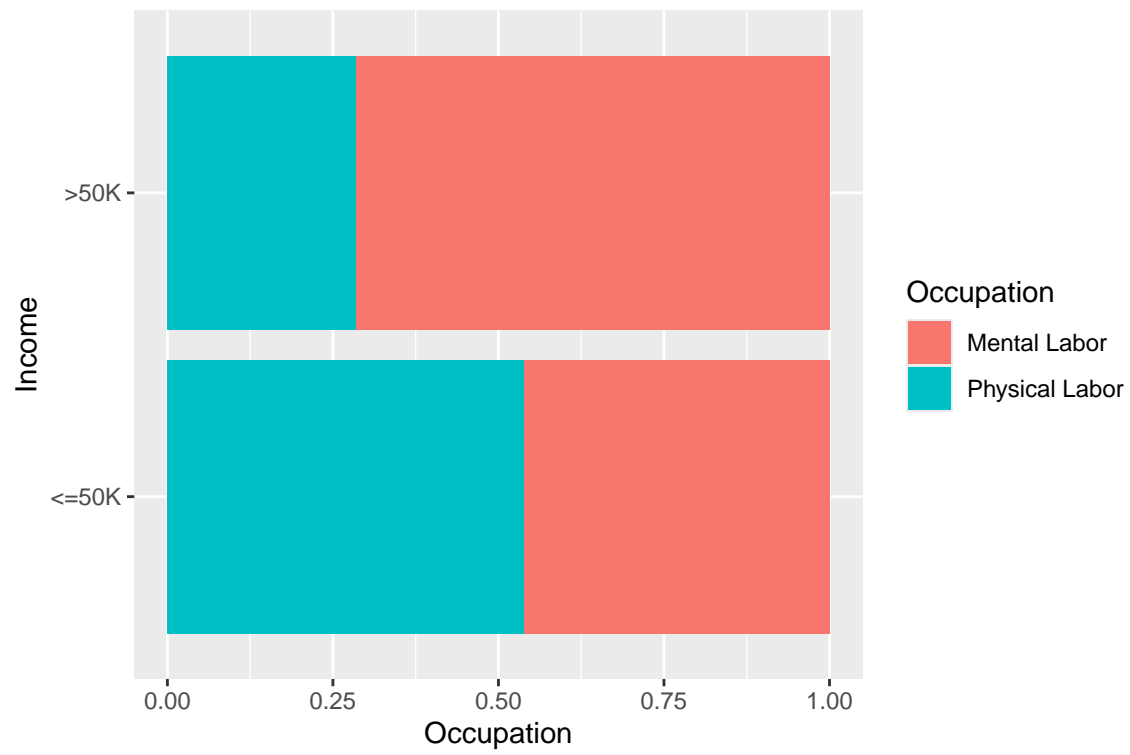


Figure 26: Income by Occupation

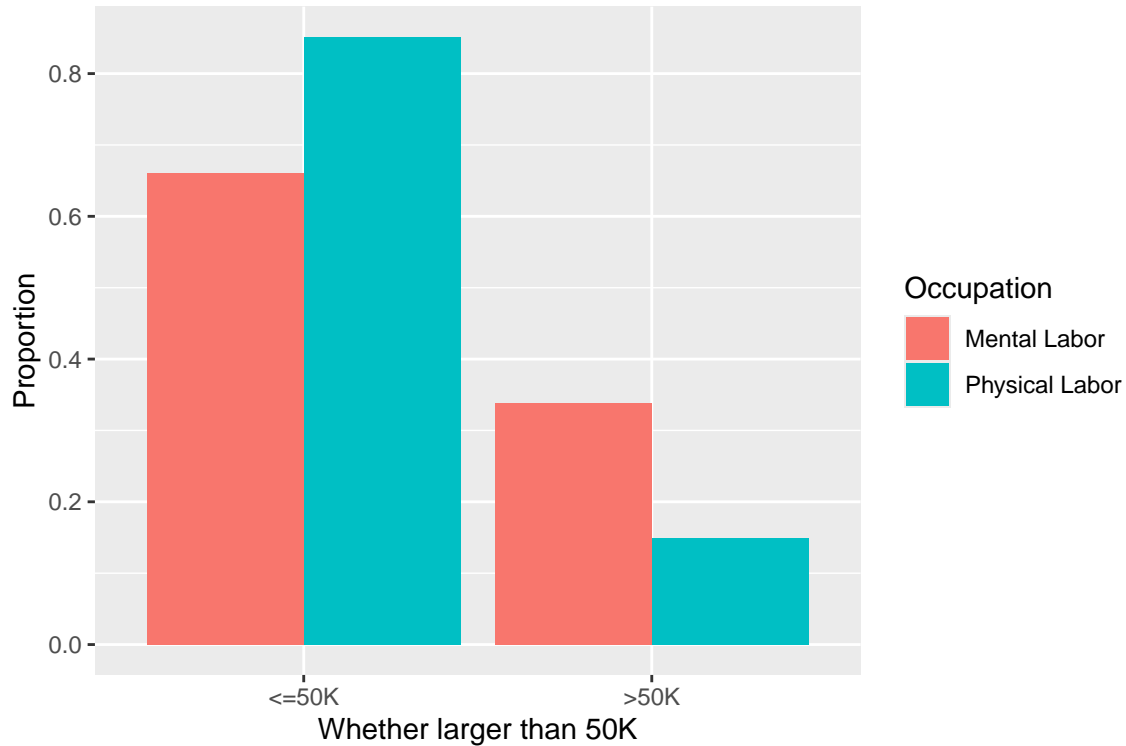


Figure 27: Income by Occupation

To simplify occupational categories and address class imbalance, occupations have been grouped into two broader categories:

Mental Labor (White-collar jobs):

Includes occupations such as Administrative clerical, Executive managerial, Professional specialty, Sales, and Technical support. These jobs typically involve cognitive work, decision-making, and problem-solving.

Physical Labor (Blue-collar jobs):

Includes Craft repair, Farming and fishing, Handlers and cleaners, Machine operators, Transport workers, Other services, Private household services, and Protective services. These jobs are more labor-intensive and require physical exertion.

Analysis of Income Distribution after Merging:

Mental labor jobs have a higher proportion of individuals earning >50K, reinforcing the idea that cognitive and managerial roles tend to offer better salaries. Physical labor jobs predominantly fall in the <=50K category, suggesting that manual labor occupations generally provide lower wages. The proportion of high-income earners in mental labor jobs is significantly higher

than in physical labor jobs, highlighting the economic advantage of cognitive and executive occupations.

Key Takeaways: Merging occupations into Physical vs. Mental labor simplifies the analysis while preserving meaningful insights. Mental labor positions are more likely to be associated with higher salaries. Physical laborers predominantly fall into the low-income category, likely due to industry pay standards and job requirements. These findings emphasize the importance of education and skill specialization in securing higher-paying jobs.

3.3 Combine occupation types (by PRC Job Classification List)

ref:<https://zchweb.oss-cn-beijing.aliyuncs.com/contract/temp/2021122116541363304.pdf>

Table 6: Occupation Distribution (PRC Job Classification List).

Income	1	2	3	4	5	6
<=50K	9.3% (97)	11.1% (116)	13.5% (141)	33.9% (353)	3.6% (37)	28.5% (297)
>50K	23.0% (79)	29.1% (100)	7.0% (24)	17.7% (61)	1.5% (5)	21.8% (75)

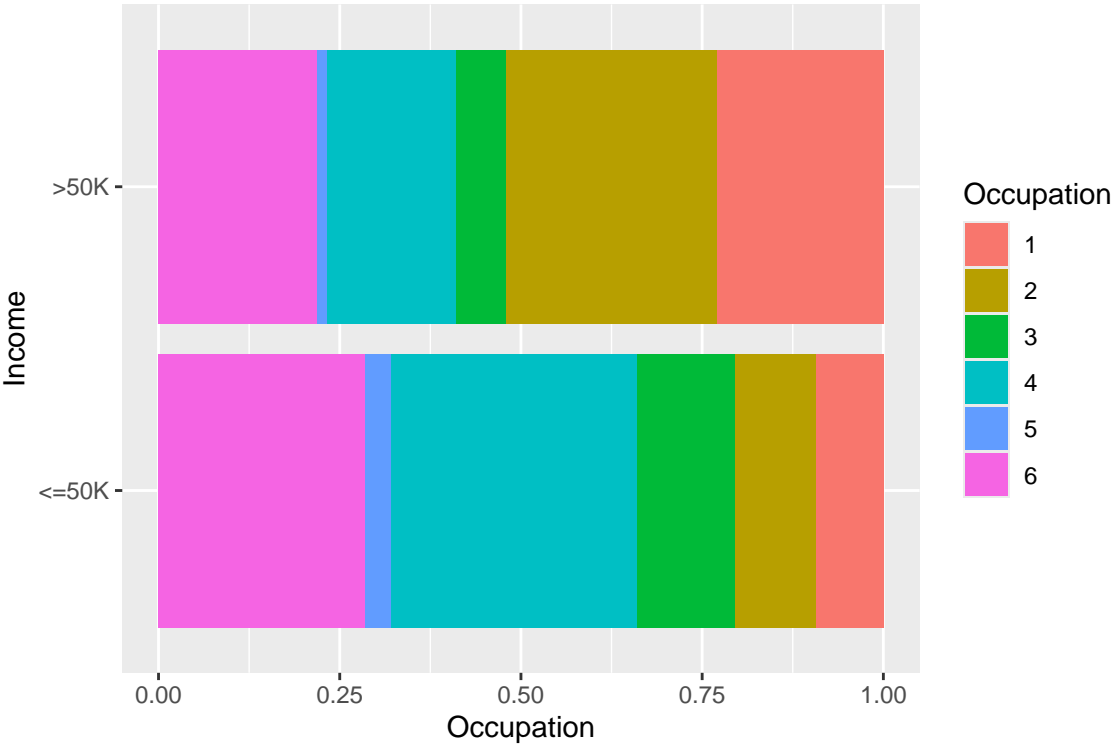


Figure 28: Income by Occupation

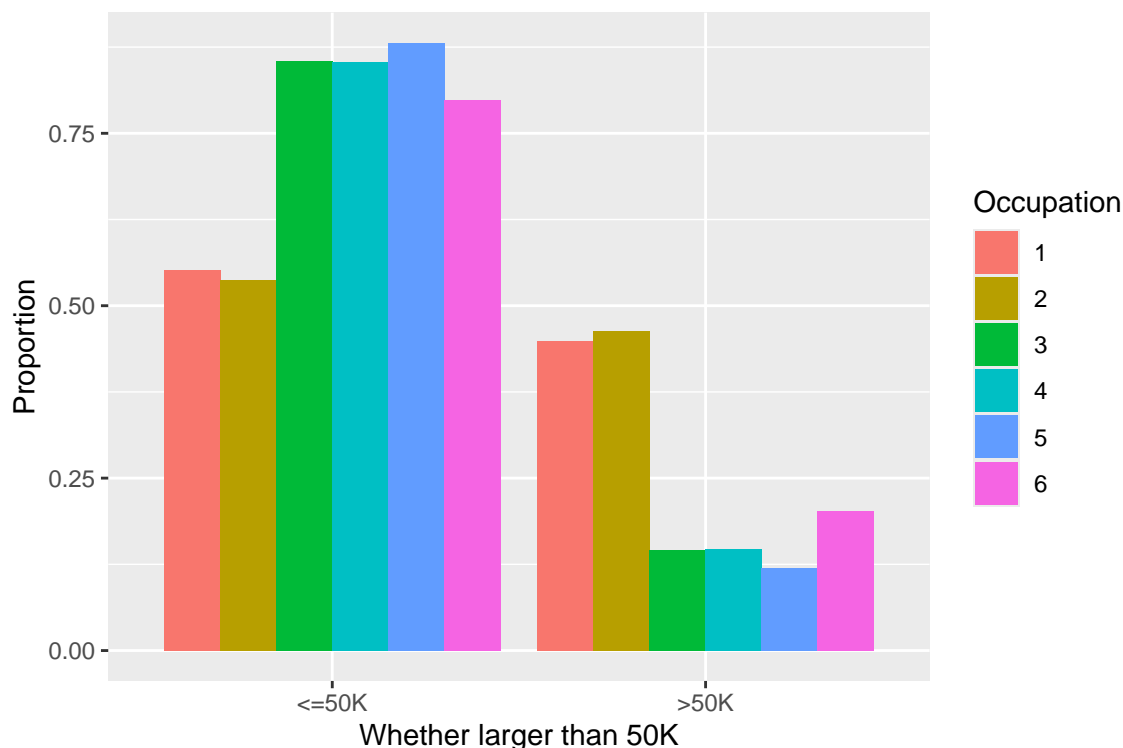


Figure 29: Income by Occupation

To further refine the occupation categories, we classify jobs according to the PRC Job Classification List. This classification system groups occupations based on skill levels and job nature, which allows for a more structured income comparison.

Income Distribution Analysis After Merging:

Category 1 (Senior Management) has the highest proportion of individuals earning >50K, reinforcing the idea that executive roles are highly paid. Category 2 (Specialists & Technical Support) also has a notable presence in the high-income group, indicating that specialized skills lead to better salaries. Category 4 (Sales & Service) and Category 5 (Agriculture & Fishing) have the lowest share of high-income earners, highlighting the financial struggles in these job sectors.

Key Takeaways: The PRC Job Classification List provides a structured way to analyze income disparities across different occupational groups. Management and technical jobs tend to have higher salaries, while sales, service, and agricultural jobs have a greater share of low-income earners. Grouping occupations in this way allows for more precise policy recommendations and workforce planning.

3.4 Combine occupation types (by International Standard Classification of Occupations (ISCO-08))

ref:<https://ilostat.ilo.org/methods/concepts-and-definitions/classification-occupation/>

Table 7: Occupation Distribution (ISCO-08).

Income	1	2	3	4	5	6	7	8	9
<=50K	9.3% (97)	8.8% (92)	2.3% (24)	13.5% (141)	28.6% (298)	3.6% (37)	14.8% (154)	13.7% (143)	5.3% (55)
>50K	23.0% (79)	25.3% (87)	3.8% (13)	7.0% (24)	16.0% (55)	1.5% (5)	13.1% (45)	8.7% (30)	1.7% (6)

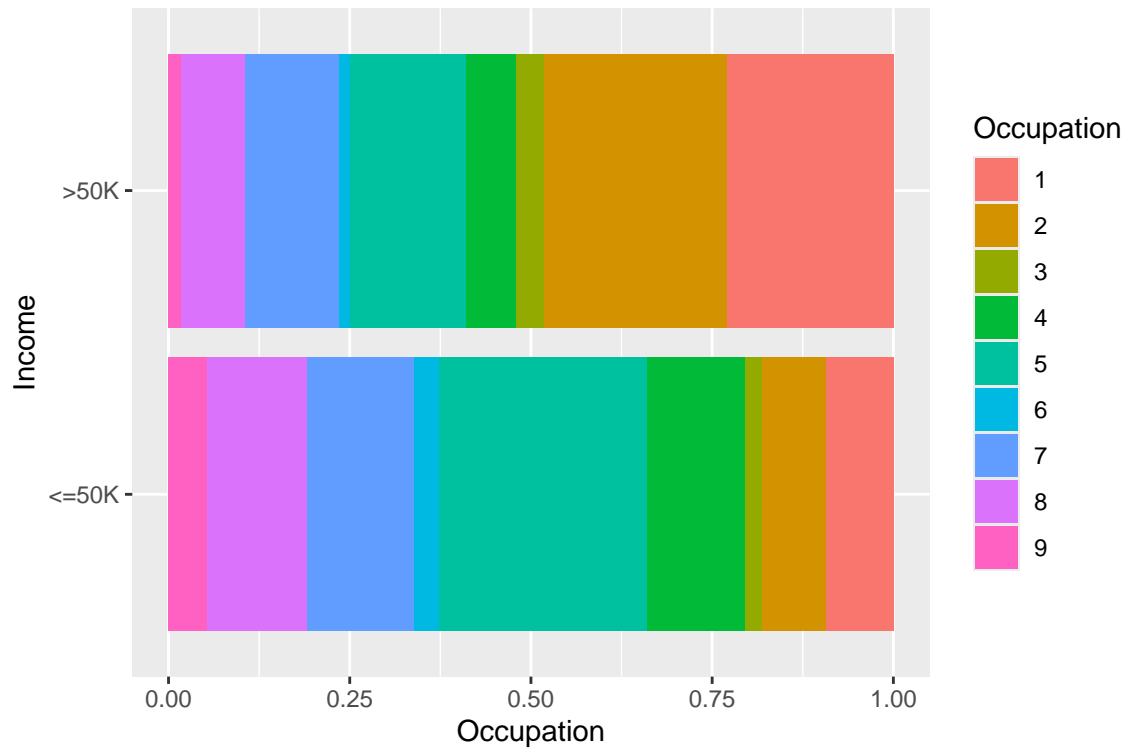


Figure 30: Income by Occupation

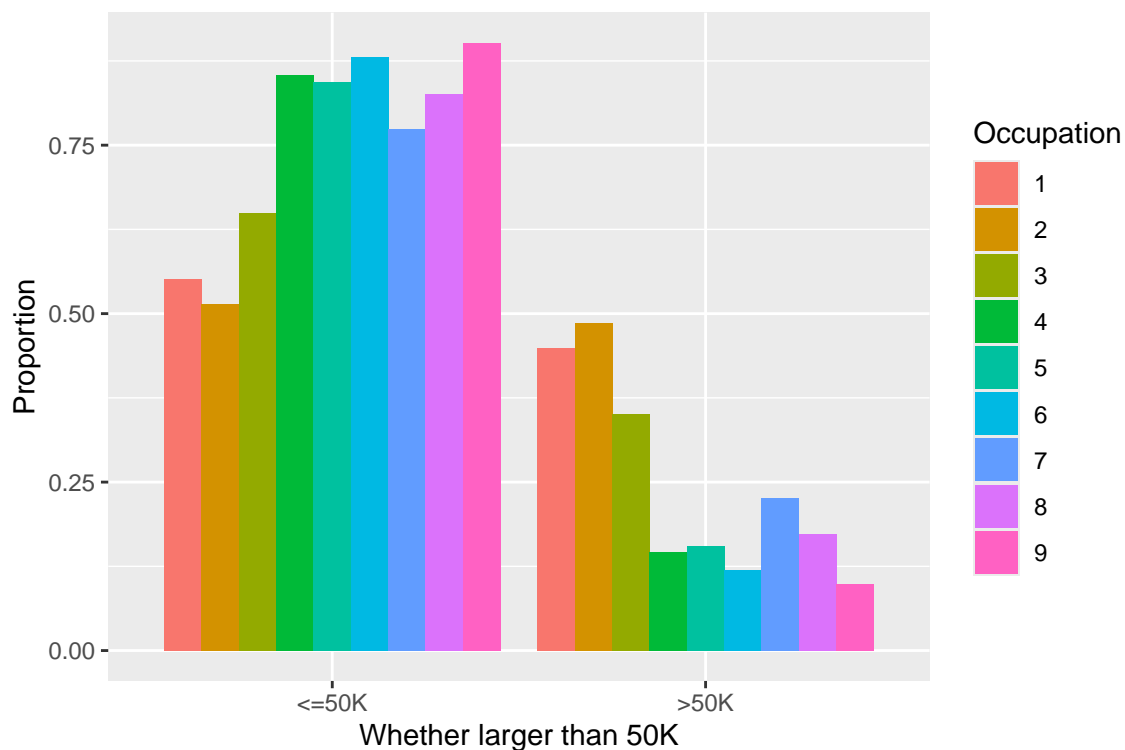


Figure 31: Income by Occupation

Call:

```
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
     Occupation, family = binomial(link = "logit"), data = data.new.1)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-2.966040	0.445192	-6.662	2.69e-11	***
Age	0.037715	0.006356	5.934	2.96e-09	***
EducationLow_Education	-1.441793	0.349529	-4.125	3.71e-05	***
SexMale	0.585571	0.204248	2.867	0.00414	**
Hours_PW	0.030770	0.006887	4.468	7.89e-06	***
Marital_StatusUnmarried	-1.990257	0.187060	-10.640	< 2e-16	***
OccupationPhysical Labor	-1.320743	0.163077	-8.099	5.55e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
 Residual deviance: 1109.9 on 1378 degrees of freedom
 AIC: 1123.9

Number of Fisher Scoring iterations: 6

Implementation: ROI | Solver: lp_solve

Separation: FALSE

Existence of maximum likelihood estimates

(Intercept)	Age	EducationLow_Education
0	0	0
SexMale	Marital_StatusUnmarried	OccupationPhysical Labor
0	0	0
Hours_PW		
0		

0: finite value, Inf: infinity, -Inf: -infinity

Call:

```
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
     Occupation, family = binomial(link = "logit"), data = data.new.2)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-3.252612	0.510402	-6.373	1.86e-10 ***
Age	0.040978	0.006535	6.270	3.60e-10 ***
EducationLow_Education	-1.436365	0.346423	-4.146	3.38e-05 ***
SexMale	0.488605	0.215606	2.266	0.0234 *
Hours_PW	0.035850	0.007234	4.956	7.19e-07 ***
Marital_StatusUnmarried	-2.093813	0.195001	-10.737	< 2e-16 ***
Occupation2	0.707103	0.253029	2.795	0.0052 **
Occupation3	-0.486564	0.319354	-1.524	0.1276
Occupation4	-0.995424	0.244856	-4.065	4.80e-05 ***
Occupation5	-2.613814	0.550179	-4.751	2.03e-06 ***
Occupation6	-1.054506	0.237695	-4.436	9.15e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom

Residual deviance: 1079.5 on 1374 degrees of freedom
AIC: 1101.5

Number of Fisher Scoring iterations: 6

Implementation: ROI | Solver: lpsolve

Separation: FALSE

Existence of maximum likelihood estimates

(Intercept)	Age	EducationLow_Education
0	0	0
SexMale	Marital_StatusUnmarried	Occupation2
0	0	0
Occupation3	Occupation4	Occupation5
0	0	0
Occupation6	Hours_PW	
0	0	

0: finite value, Inf: infinity, -Inf: -infinity

Call:

```
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
     Occupation, family = binomial(link = "logit"), data = data.new.3)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-3.262143	0.514533	-6.340	2.30e-10 ***
Age	0.041171	0.006597	6.241	4.35e-10 ***
EducationLow_Education	-1.431424	0.347718	-4.117	3.84e-05 ***
SexMale	0.476856	0.216949	2.198	0.027948 *
Hours_PW	0.036079	0.007286	4.952	7.35e-07 ***
Marital_StatusUnmarried	-2.094087	0.195332	-10.721	< 2e-16 ***
Occupation2	0.730937	0.261676	2.793	0.005217 **
Occupation3	0.562765	0.487845	1.154	0.248675
Occupation4	-0.489309	0.319379	-1.532	0.125506
Occupation5	-0.999851	0.250967	-3.984	6.78e-05 ***
Occupation6	-2.614898	0.550520	-4.750	2.04e-06 ***
Occupation7	-0.931695	0.268166	-3.474	0.000512 ***
Occupation8	-1.212247	0.291251	-4.162	3.15e-05 ***
Occupation9	-0.951597	0.516129	-1.844	0.065224 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
Residual deviance: 1078.4 on 1371 degrees of freedom
AIC: 1106.4

Number of Fisher Scoring iterations: 6

Implementation: ROI | Solver: lpsolve
Separation: FALSE
Existence of maximum likelihood estimates

(Intercept)		Age	EducationLow_Education
0		0	0
SexMale	Marital_StatusUnmarried	Occupation2	
0		0	0
Occupation3	Occupation4	Occupation5	
0		0	0
Occupation6	Occupation7	Occupation8	
0		0	0
Occupation9	Hours_PW		
0		0	

0: finite value, Inf: infinity, -Inf: -infinity

The International Standard Classification of Occupations (ISCO-08) is used to categorize occupations into structured groups based on job function and skill level. This classification allows for a globally standardized approach to analyzing income distribution by profession.

Income Distribution Analysis After Merging:

Category 1 (Managers) and Category 2 (Professionals) have the highest share of individuals earning >50K, emphasizing that managerial and specialized roles offer better earnings. Category 5 (Service & Sales) and Category 6 (Agricultural & Fishery) exhibit the lowest proportion of high-income earners, indicating the financial constraints faced by these workers. Category 7 (Craft Workers) and Category 8 (Machine Operators) have an intermediate income distribution, suggesting that skilled manual labor provides moderate earnings.

Model Selection and Performance Comparison:

The stepwise AIC model selection process was applied separately to datasets using different occupational classification methods (Mental vs. Physical Labor, PRC Job Classification, and ISCO-08). All models showed improvement in fitting compared to the full model, but the best performance was observed with the ISCO-08 classification. Nationality was removed in the AIC-selected models, reinforcing the earlier observation that nationality has little impact on income prediction.

Key Takeaways: ISCO-08 classification provides a structured way to assess income distribution across occupations. Managers and professionals dominate the high-income group, while service, sales, and agriculture workers struggle with lower wages. Machine operators and craft workers occupy a middle ground, earning more than service workers but less than professionals. The final model using ISCO-08 classification achieves a better balance between accuracy and interpretability, making it a robust choice for workforce and economic analysis.

4 Model Check

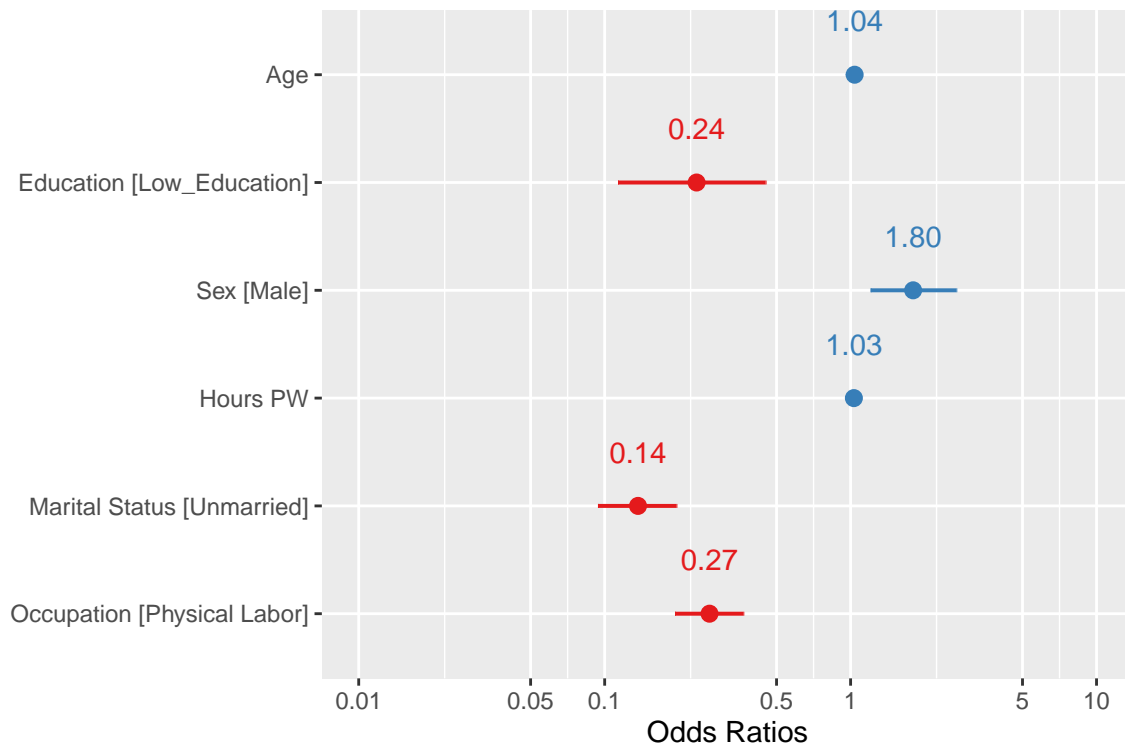


Figure 32: Model Plot for stepAIC_model_new.1

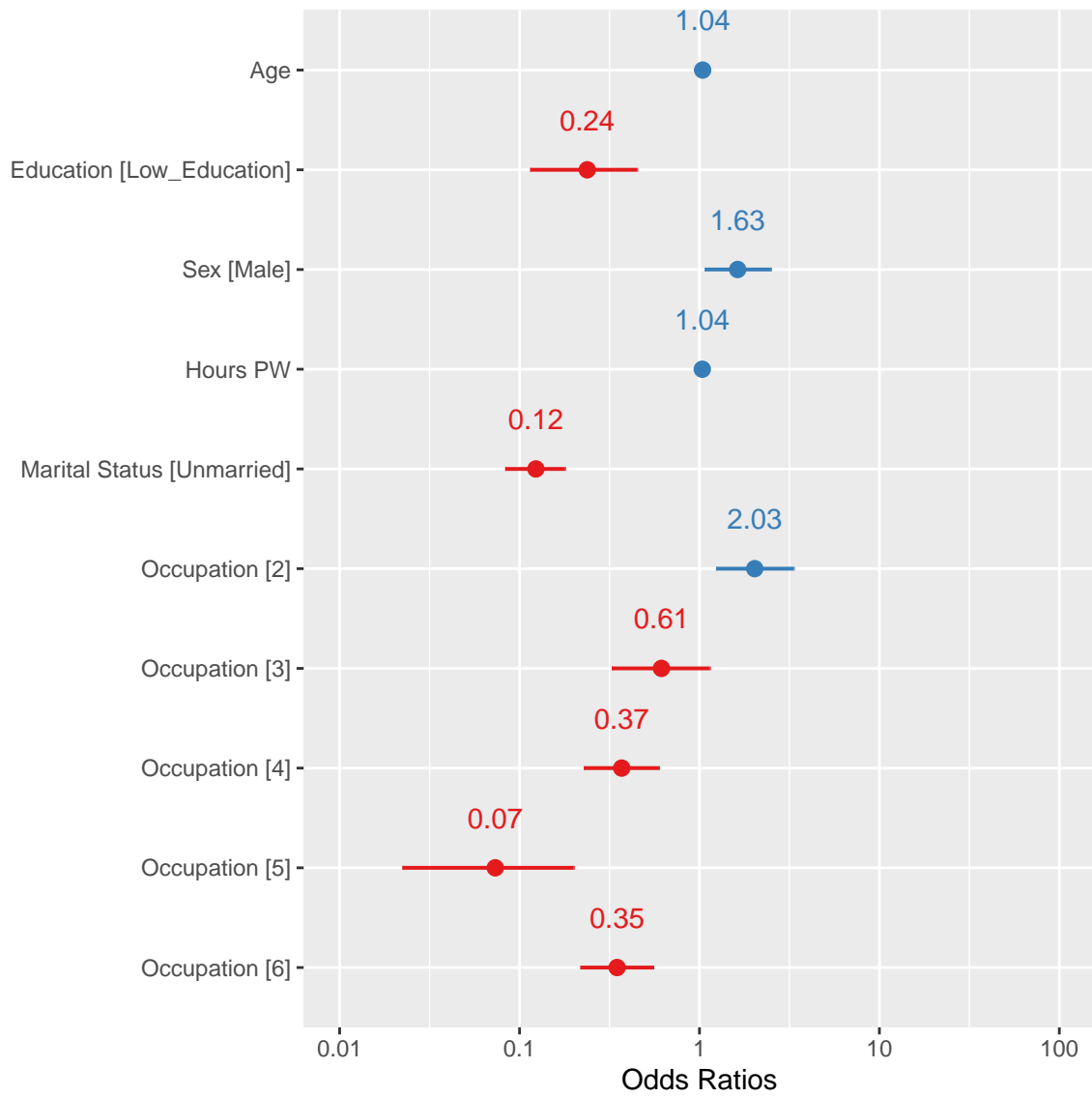


Figure 33: Model Plot for stepAIC_model_new.2

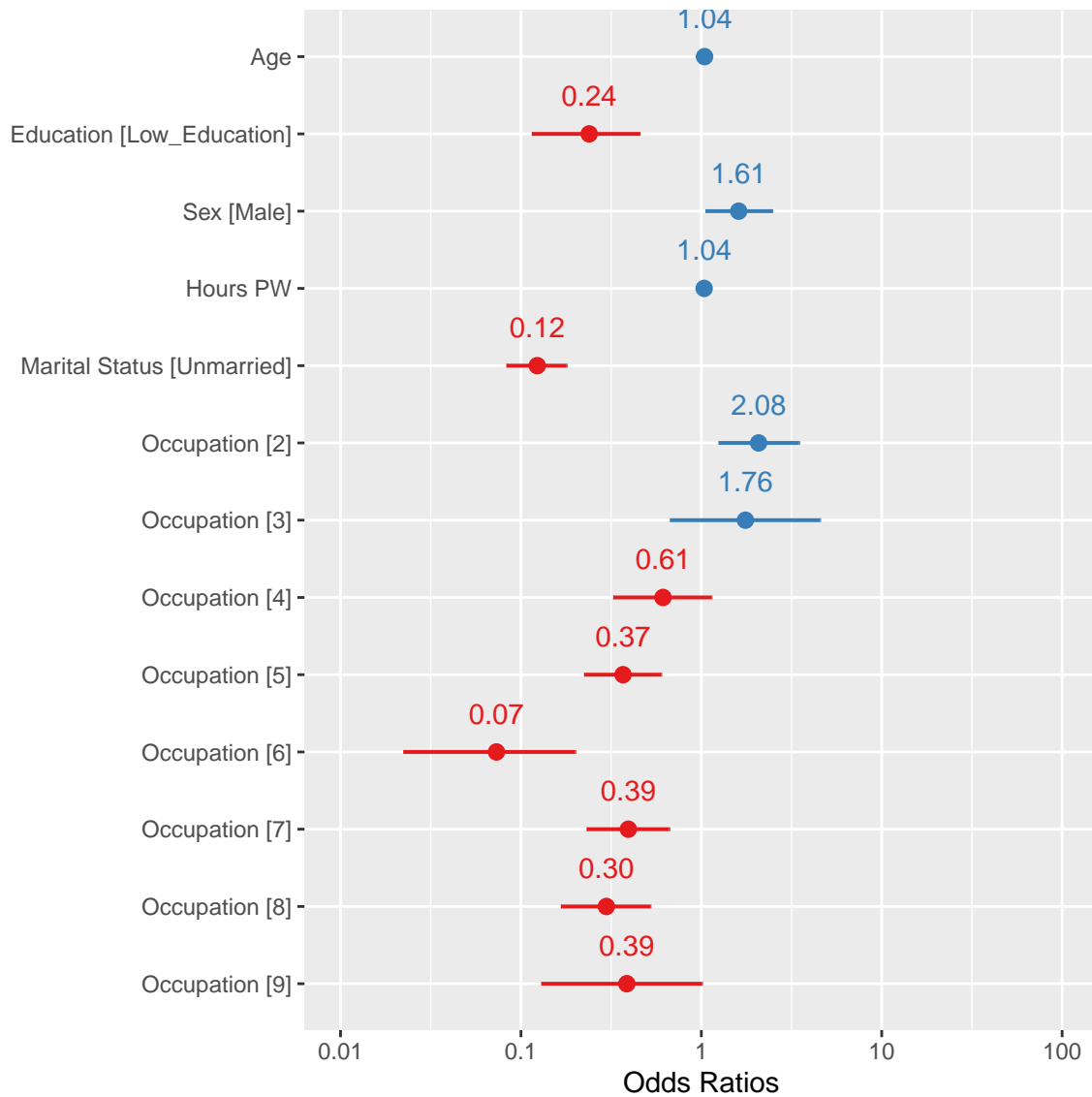


Figure 34: Model Plot for stepAIC_model

Analysis of Deviance Table

Model: binomial, link: logit

Response: Income

Terms added sequentially (first to last)

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			1384	1552.7	
Age	1	90.112	1383	1462.6	< 2.2e-16 ***
Education	1	53.385	1382	1409.2	2.742e-13 ***
Sex	1	62.449	1381	1346.8	2.734e-15 ***
Hours_PW	1	36.563	1380	1310.2	1.478e-09 ***
Marital_Status	1	129.706	1379	1180.5	< 2.2e-16 ***
Occupation	1	70.560	1378	1109.9	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Analysis of Deviance Table

Model: binomial, link: logit

Response: Income

Terms added sequentially (first to last)

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			1384	1552.7	
Age	1	90.112	1383	1462.6	< 2.2e-16 ***
Education	1	53.385	1382	1409.2	2.742e-13 ***
Sex	1	62.449	1381	1346.8	2.734e-15 ***
Hours_PW	1	36.563	1380	1310.2	1.478e-09 ***
Marital_Status	1	129.706	1379	1180.5	< 2.2e-16 ***
Occupation	5	101.032	1374	1079.5	< 2.2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Analysis of Deviance Table

Model: binomial, link: logit

Response: Income

Terms added sequentially (first to last)

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
NULL			1384	1552.7	
Age	1	90.112	1383	1462.6	< 2.2e-16 ***

Education	1	53.385	1382	1409.2	2.742e-13	***
Sex	1	62.449	1381	1346.8	2.734e-15	***
Hours_PW	1	36.563	1380	1310.2	1.478e-09	***
Marital_Status	1	129.706	1379	1180.5	< 2.2e-16	***
Occupation	8	102.097	1371	1078.4	< 2.2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

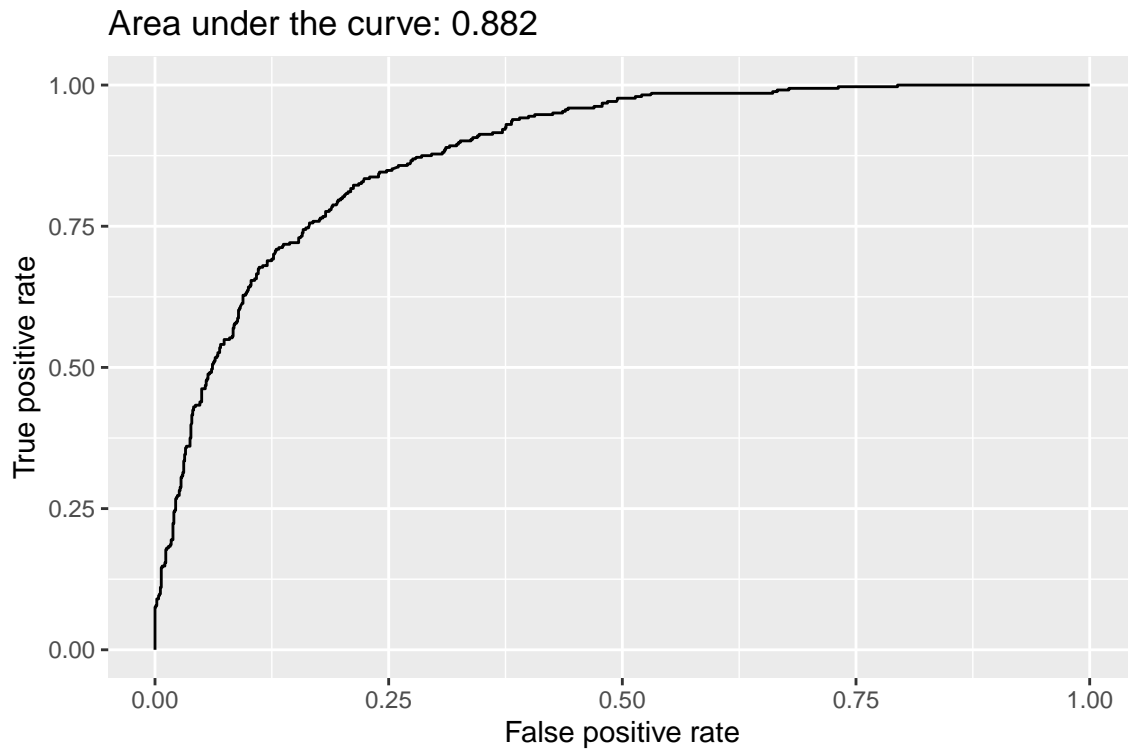


Figure 35: ROC curve for stepAIC_model

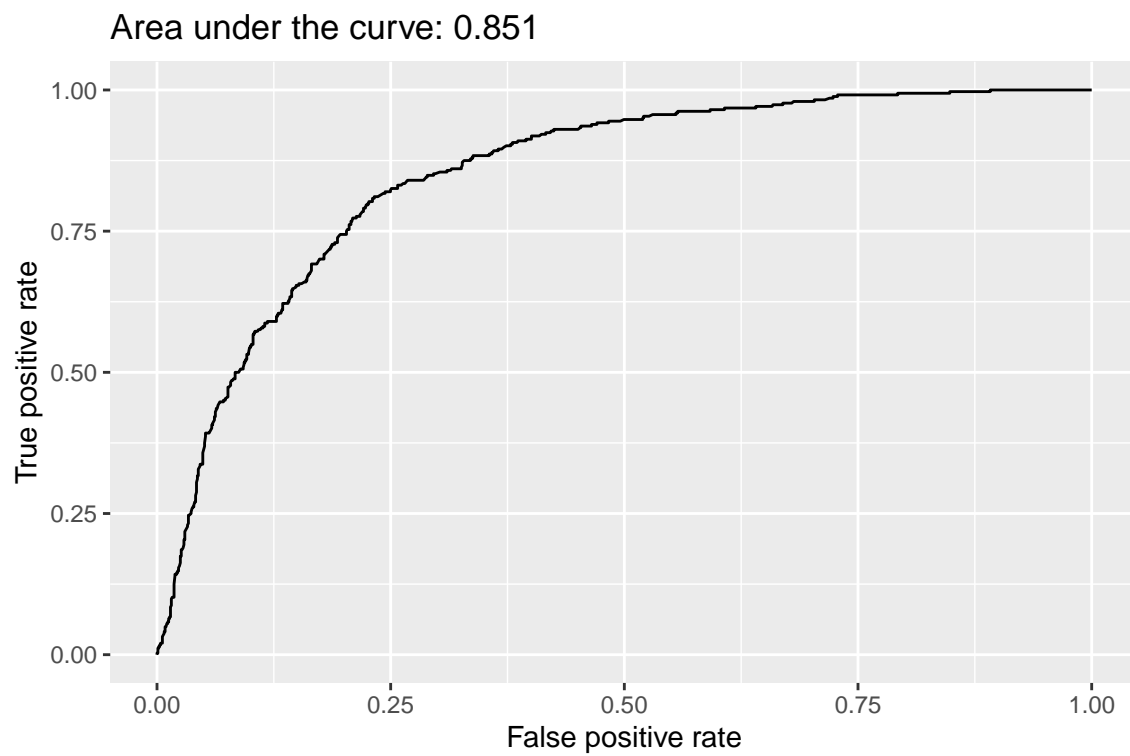


Figure 36: ROC curve for stepAIC_model_new.1

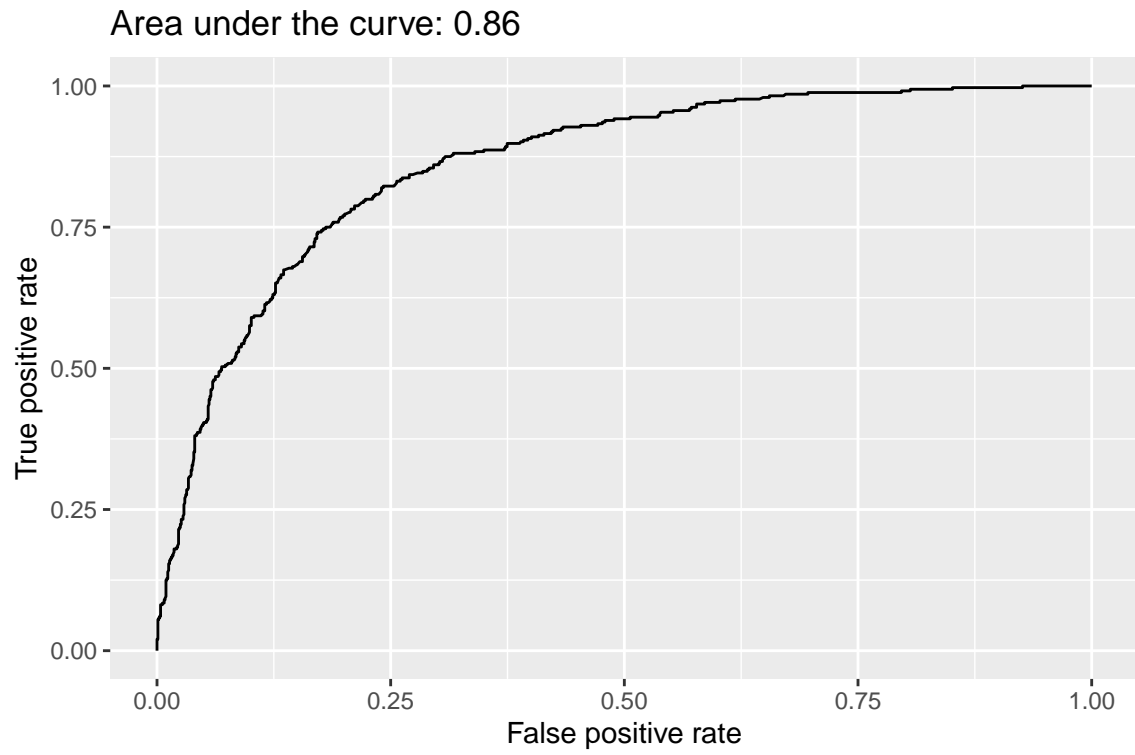


Figure 37: ROC curve for stepAIC_model_new.2

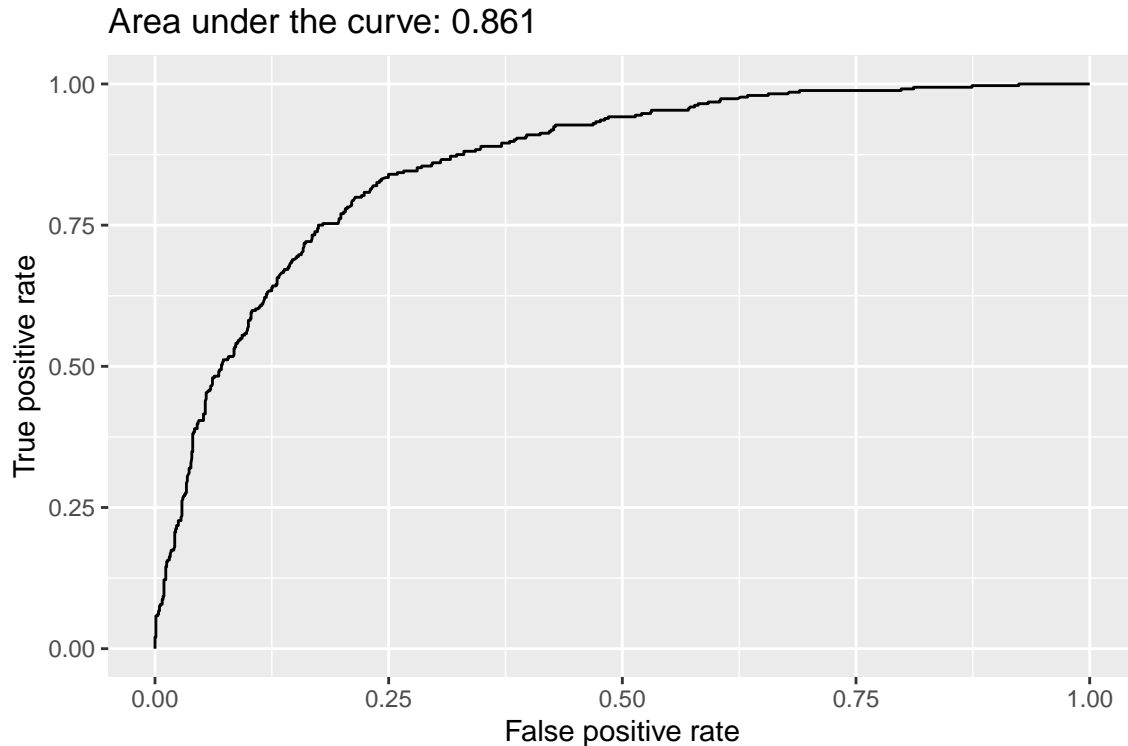


Figure 38: ROC curve for stepAIC_model_new.3

To ensure the reliability and effectiveness of the logistic regression models, multiple validation techniques are applied, including coefficient visualization, ROC curve analysis, and ANOVA testing.

ROC Curve Analysis & AUC Comparison The ROC curve (Receiver Operating Characteristic curve) is plotted for each model to assess its classification performance. AUC (Area Under the Curve) values are calculated: A higher AUC (closer to 1) indicates a better-performing model. A lower AUC (closer to 0.5) suggests poor classification performance. The AUC values of different models are compared, helping to determine which occupational classification method improves predictive accuracy.

ANOVA Model Comparison ANOVA (Analysis of Variance) tests compare model fits: A significant p-value (< 0.05) indicates that additional predictors improve model performance. If models have similar p-values, a simpler model may be preferred to avoid overfitting. The results help in deciding whether stepAIC_model_new.1, stepAIC_model_new.2, or stepAIC_model_new.3 should be used for the final analysis.

Key Takeaways: The ROC curve and AUC values help determine the best occupational classification method in terms of prediction accuracy. Model coefficients provide insights into

the most influential factors affecting income. ANOVA helps verify whether additional variables significantly improve prediction performance. The final model selection should balance accuracy and interpretability, preferring models with a high AUC while avoiding excessive complexity.

4.1 Consider the interaction effects

Call:

```
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
     Occupation + Age:Marital_Status + Education:Sex + Sex:Marital_Status +
     Marital_Status:Occupation, family = binomial(link = "logit"),
     data = data.new.1)
```

Coefficients:

	Estimate	Std. Error	z value
(Intercept)	-2.189254	0.495876	-4.415
Age	0.031676	0.008176	3.874
EducationLow_Education	-15.313498	481.667910	-0.032
SexMale	-0.060678	0.272610	-0.223
Hours_PW	0.032659	0.007021	4.651
Marital_StatusUnmarried	-4.514939	0.707999	-6.377
OccupationPhysical Labor	-1.420146	0.180064	-7.887
Age:Marital_StatusUnmarried	0.030029	0.013723	2.188
EducationLow_Education:SexMale	14.012202	481.668031	0.029
SexMale:Marital_StatusUnmarried	1.546335	0.444445	3.479
Marital_StatusUnmarried:OccupationPhysical Labor	0.633460	0.383444	1.652

	Pr(> z)
(Intercept)	1.01e-05 ***
Age	0.000107 ***
EducationLow_Education	0.974637
SexMale	0.823862
Hours_PW	3.30e-06 ***
Marital_StatusUnmarried	1.81e-10 ***
OccupationPhysical Labor	3.10e-15 ***
Age:Marital_StatusUnmarried	0.028653 *
EducationLow_Education:SexMale	0.976792
SexMale:Marital_StatusUnmarried	0.000503 ***
Marital_StatusUnmarried:OccupationPhysical Labor	0.098529 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
Residual deviance: 1084.2 on 1374 degrees of freedom
AIC: 1106.2

Number of Fisher Scoring iterations: 16

Call:

```
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +  
     Occupation + Age:Marital_Status + Sex:Marital_Status, family = binomial(link = "logit"),  
     data = data.new.1)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-2.270129	0.491722	-4.617	3.90e-06	***
Age	0.031818	0.008089	3.933	8.38e-05	***
EducationLow_Education	-1.462369	0.346401	-4.222	2.43e-05	***
SexMale	-0.037620	0.264656	-0.142	0.8870	
Hours_PW	0.032681	0.007023	4.654	3.26e-06	***
Marital_StatusUnmarried	-4.369683	0.705494	-6.194	5.87e-10	***
OccupationPhysical Labor	-1.292511	0.160702	-8.043	8.77e-16	***
Age:Marital_StatusUnmarried	0.028900	0.013623	2.121	0.0339	*
SexMale:Marital_StatusUnmarried	1.692187	0.431822	3.919	8.90e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
Residual deviance: 1090.2 on 1376 degrees of freedom
AIC: 1108.2

Number of Fisher Scoring iterations: 6

Implementation: ROI | Solver: lpsolve

Separation: FALSE

Existence of maximum likelihood estimates

(Intercept)	Age
0	0
EducationLow_Education	SexMale

```

0
Hours_PW Marital_StatusUnmarried
0
OccupationPhysical Labor Age:Marital_StatusUnmarried
0
SexMale:Marital_StatusUnmarried
0
0: finite value, Inf: infinity, -Inf: -infinity

```

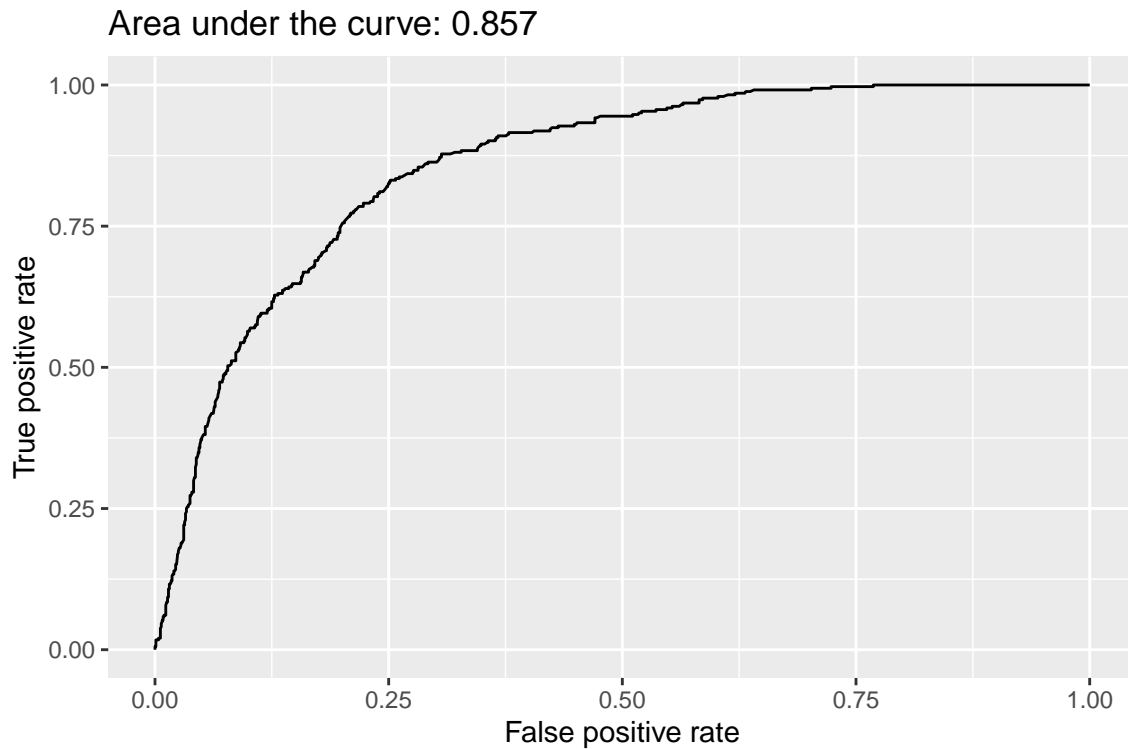


Figure 39: ROC curve for model_new.1.interaction

```

Call:
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
    Occupation + Age:Marital_Status + Education:Sex + Education:Hours_PW +
    Sex:Marital_Status + Sex:Occupation + Marital_Status:Occupation,
    family = binomial(link = "logit"), data = data.new.2)

```

Coefficients:

```

Estimate Std. Error z value Pr(>|z|)

```

(Intercept)	-2.073e+00	6.763e-01	-3.065	0.00218	**
Age	3.958e-02	8.521e-03	4.645	3.41e-06	***
EducationLow_Education	-1.704e+01	4.614e+02	-0.037	0.97054	
SexMale	-7.620e-01	5.285e-01	-1.442	0.14933	
Hours_PW	3.742e-02	7.619e-03	4.911	9.04e-07	***
Marital_StatusUnmarried	-5.198e+00	9.421e-01	-5.517	3.44e-08	***
Occupation2	5.189e-01	6.916e-01	0.750	0.45305	
Occupation3	-1.388e+00	6.260e-01	-2.218	0.02656	*
Occupation4	-2.057e+00	7.192e-01	-2.860	0.00423	**
Occupation5	1.500e+01	1.069e+03	0.014	0.98880	
Occupation6	-1.430e+00	7.775e-01	-1.839	0.06588	.
Age:Marital_StatusUnmarried	2.268e-02	1.443e-02	1.572	0.11594	
EducationLow_Education:SexMale	1.384e+01	4.614e+02	0.030	0.97608	
EducationLow_Education:Hours_PW	4.163e-02	2.911e-02	1.430	0.15264	
SexMale:Marital_StatusUnmarried	1.647e+00	5.299e-01	3.107	0.00189	**
SexMale:Occupation2	2.714e-01	7.078e-01	0.383	0.70137	
SexMale:Occupation3	1.591e+00	7.707e-01	2.064	0.03899	*
SexMale:Occupation4	1.022e+00	7.444e-01	1.373	0.16987	
SexMale:Occupation5	-1.790e+01	1.069e+03	-0.017	0.98664	
SexMale:Occupation6	2.372e-01	7.994e-01	0.297	0.76666	
Marital_StatusUnmarried:Occupation2	6.281e-01	6.740e-01	0.932	0.35144	
Marital_StatusUnmarried:Occupation3	-3.286e-01	9.822e-01	-0.335	0.73795	
Marital_StatusUnmarried:Occupation4	1.450e+00	6.810e-01	2.129	0.03329	*
Marital_StatusUnmarried:Occupation5	-1.209e+01	1.069e+03	-0.011	0.99097	
Marital_StatusUnmarried:Occupation6	1.684e+00	6.627e-01	2.541	0.01104	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
 Residual deviance: 1030.1 on 1360 degrees of freedom
 AIC: 1080.1

Number of Fisher Scoring iterations: 16

Call:

```
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
     Occupation + Sex:Marital_Status + Sex:Occupation, family = binomial(link = "logit"),
     data = data.new.2)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-2.703368	0.599795	-4.507	6.57e-06	***
Age	0.045978	0.006855	6.708	1.98e-11	***
EducationLow_Education	-1.513441	0.348787	-4.339	1.43e-05	***
SexMale	-0.708754	0.489645	-1.447	0.14776	
Hours_PW	0.040908	0.007421	5.513	3.53e-08	***
Marital_StatusUnmarried	-3.585524	0.449124	-7.983	1.42e-15	***
Occupation2	0.781470	0.570534	1.370	0.17078	
Occupation3	-1.266576	0.563022	-2.250	0.02447	*
Occupation4	-1.558491	0.662737	-2.352	0.01869	*
Occupation5	2.604163	1.505891	1.729	0.08375	.
Occupation6	-1.190624	0.729529	-1.632	0.10267	
SexMale:Marital_StatusUnmarried	1.956976	0.501180	3.905	9.43e-05	***
SexMale:Occupation2	0.032557	0.638509	0.051	0.95933	
SexMale:Occupation3	1.269024	0.704213	1.802	0.07154	.
SexMale:Occupation4	0.747952	0.713819	1.048	0.29472	
SexMale:Occupation5	-5.390792	1.625243	-3.317	0.00091	***
SexMale:Occupation6	0.283107	0.768359	0.368	0.71253	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
Residual deviance: 1050.7 on 1368 degrees of freedom
AIC: 1084.7

Number of Fisher Scoring iterations: 6

Implementation: ROI | Solver: lpsolve

Separation: FALSE

Existence of maximum likelihood estimates

(Intercept)	Age
0	0
EducationLow_Education	SexMale
0	0
Hours_PW	Marital_StatusUnmarried
0	0
Occupation2	Occupation3
0	0
Occupation4	Occupation5

```

0
Occupation6 SexMale:Marital_StatusUnmarried
0
SexMale:Occupation2 SexMale:Occupation3
0
SexMale:Occupation4 SexMale:Occupation5
0
SexMale:Occupation6
0
0: finite value, Inf: infinity, -Inf: -infinity

```

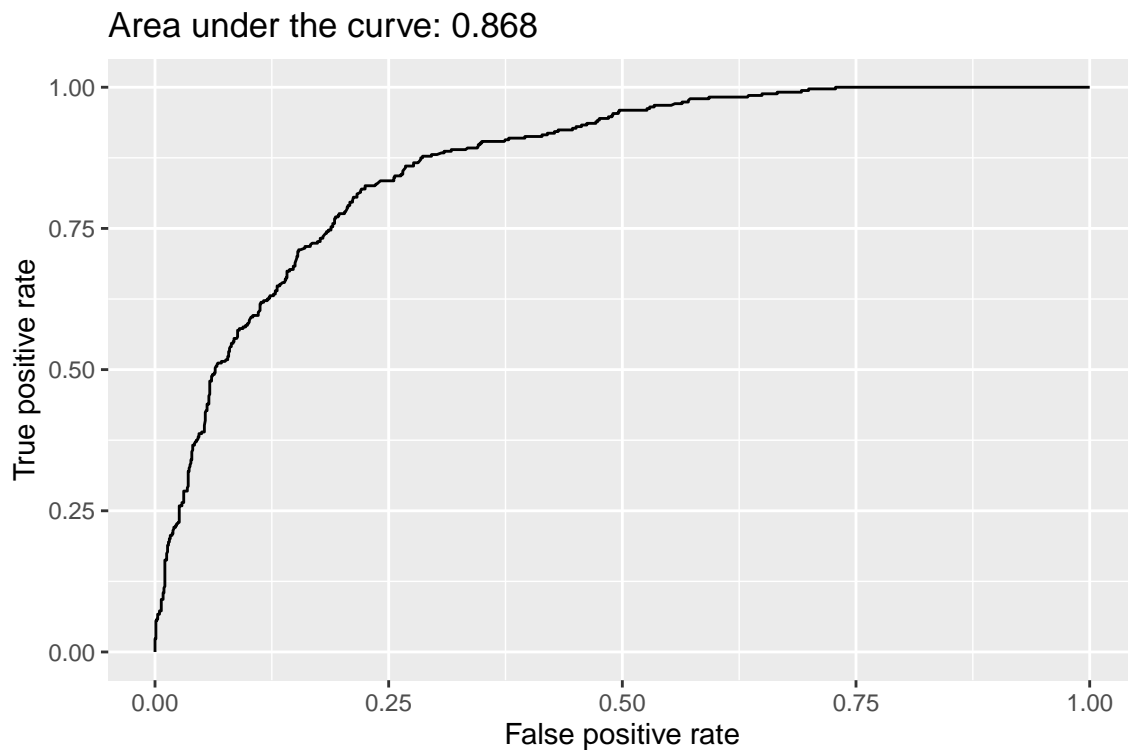


Figure 40: ROC curve for model_new.2.interaction

```

Call:
glm(formula = Income ~ Age + Education + Sex + Hours_PW + Marital_Status +
    Occupation + Age:Occupation + Education:Sex + Education:Marital_Status +
    Sex:Marital_Status, family = binomial(link = "logit"), data = data.new.3)

```

Coefficients:

	Estimate	Std. Error	z value
(Intercept)	-3.518053	0.856736	-4.106
Age	0.058001	0.017461	3.322
EducationLow_Education	-15.965073	510.132302	-0.031
SexMale	-0.339964	0.294255	-1.155
Hours_PW	0.041293	0.007539	5.478
Marital_StatusUnmarried	-3.377304	0.397452	-8.497
Occupation2	1.729139	1.031589	1.676
Occupation3	-2.075271	2.716100	-0.764
Occupation4	-0.462935	1.188057	-0.390
Occupation5	0.510018	0.950263	0.537
Occupation6	1.765975	2.241941	0.788
Occupation7	-0.117523	1.030062	-0.114
Occupation8	-1.747957	1.218622	-1.434
Occupation9	-5.786074	2.476922	-2.336
Age:Occupation2	-0.022482	0.024172	-0.930
Age:Occupation3	0.073706	0.065199	1.130
Age:Occupation4	-0.001889	0.027509	-0.069
Age:Occupation5	-0.033699	0.021804	-1.546
Age:Occupation6	-0.096113	0.051625	-1.862
Age:Occupation7	-0.016641	0.023975	-0.694
Age:Occupation8	0.013741	0.027381	0.502
Age:Occupation9	0.123809	0.056975	2.173
EducationLow_Education:SexMale	14.141329	510.132309	0.028
EducationLow_Education:Marital_StatusUnmarried	1.354707	0.750523	1.805
SexMale:Marital_StatusUnmarried	1.663952	0.456993	3.641
	Pr(> z)		
(Intercept)	4.02e-05 ***		
Age	0.000895 ***		
EducationLow_Education	0.975034		
SexMale	0.247951		
Hours_PW	4.31e-08 ***		
Marital_StatusUnmarried	< 2e-16 ***		
Occupation2	0.093701 .		
Occupation3	0.444830		
Occupation4	0.696790		
Occupation5	0.591466		
Occupation6	0.430873		
Occupation7	0.909164		
Occupation8	0.151466		
Occupation9	0.019492 *		
Age:Occupation2	0.352339		
Age:Occupation3	0.258277		

Age:Occupation4	0.945240
Age:Occupation5	0.122222
Age:Occupation6	0.062640 .
Age:Occupation7	0.487613
Age:Occupation8	0.615767
Age:Occupation9	0.029776 *
EducationLow_Education:SexMale	0.977885
EducationLow_Education:Marital_StatusUnmarried	0.071072 .
SexMale:Marital_StatusUnmarried	0.000271 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
 Residual deviance: 1036.0 on 1360 degrees of freedom
 AIC: 1086

Number of Fisher Scoring iterations: 16

Call:

```
glm(formula = Income ~ Age + Sex + Education + Hours_PW + Marital_Status +
     Occupation + Marital_Status:Occupation, family = binomial(link = "logit"),
     data = data.new.3)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-3.304748	0.529508	-6.241	4.34e-10	***
Age	0.044727	0.006817	6.561	5.34e-11	***
SexMale	0.445923	0.222749	2.002	0.04529	*
EducationLow_Education	-1.446628	0.346257	-4.178	2.94e-05	***
Hours_PW	0.037683	0.007366	5.116	3.12e-07	***
Marital_StatusUnmarried	-2.915217	0.531143	-5.489	4.05e-08	***
Occupation2	0.722076	0.336026	2.149	0.03164	*
Occupation3	0.697480	0.692564	1.007	0.31389	
Occupation4	-0.208668	0.380242	-0.549	0.58316	
Occupation5	-1.264080	0.288458	-4.382	1.17e-05	***
Occupation6	-3.060971	0.609949	-5.018	5.21e-07	***
Occupation7	-1.186279	0.297107	-3.993	6.53e-05	***
Occupation8	-1.623163	0.330524	-4.911	9.07e-07	***
Occupation9	-1.035350	0.586947	-1.764	0.07774	.

Marital_StatusUnmarried:Occupation2	0.525588	0.648670	0.810	0.41779
Marital_StatusUnmarried:Occupation3	0.213914	1.136972	0.188	0.85076
Marital_StatusUnmarried:Occupation4	-0.879872	0.941130	-0.935	0.34983
Marital_StatusUnmarried:Occupation5	1.301111	0.658313	1.976	0.04811 *
Marital_StatusUnmarried:Occupation6	3.306006	1.320659	2.503	0.01230 *
Marital_StatusUnmarried:Occupation7	1.645927	0.717551	2.294	0.02180 *
Marital_StatusUnmarried:Occupation8	2.161565	0.714046	3.027	0.00247 **
Marital_StatusUnmarried:Occupation9	0.676033	1.272549	0.531	0.59525

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1552.7 on 1384 degrees of freedom
 Residual deviance: 1054.8 on 1363 degrees of freedom
 AIC: 1098.8

Number of Fisher Scoring iterations: 6

Implementation: ROI | Solver: lpsolve

Separation: FALSE

Existence of maximum likelihood estimates

(Intercept)	Age
0	0
SexMale	EducationLow_Education
0	0
Hours_PW	Marital_StatusUnmarried
0	0
Occupation2	Occupation3
0	0
Occupation4	Occupation5
0	0
Occupation6	Occupation7
0	0
Occupation8	Occupation9
0	0
Marital_StatusUnmarried:Occupation2	Marital_StatusUnmarried:Occupation3
0	0
Marital_StatusUnmarried:Occupation4	Marital_StatusUnmarried:Occupation5
0	0
Marital_StatusUnmarried:Occupation6	Marital_StatusUnmarried:Occupation7
0	0

Marital_StatusUnmarried:Occupation8 Marital_StatusUnmarried:Occupation9
0 0
0: finite value, Inf: infinity, -Inf: -infinity

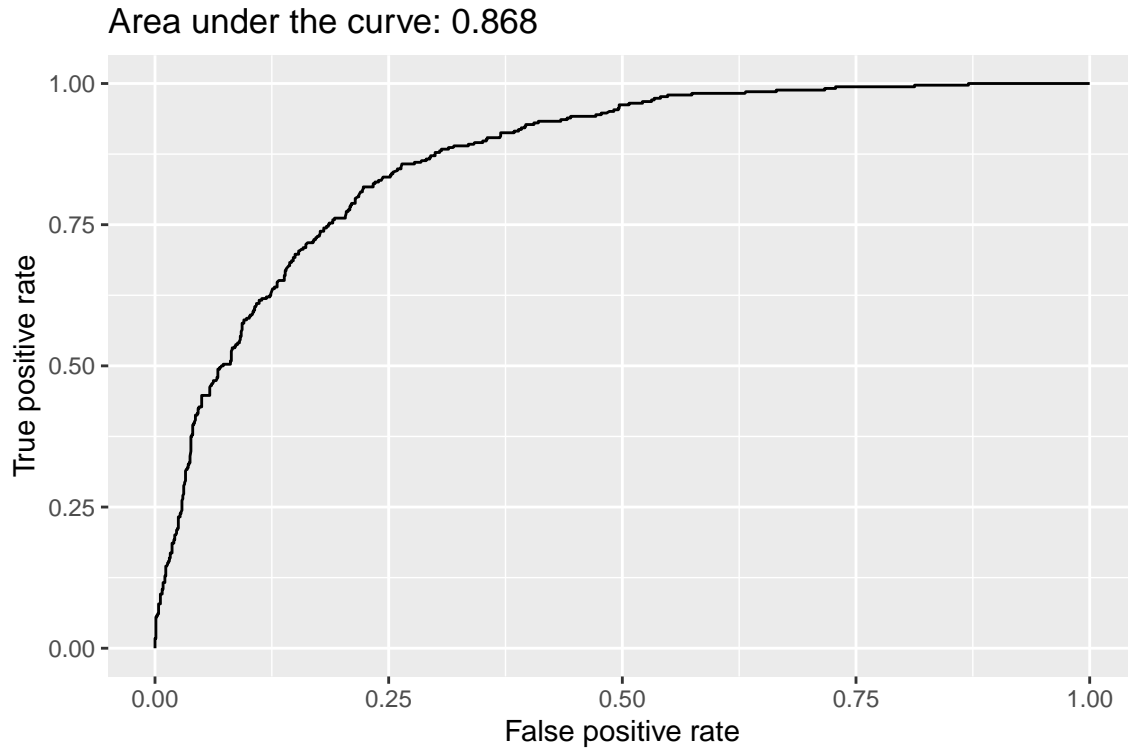


Figure 41: ROC curve for model_new.3.interaction

To enhance predictive accuracy and account for potential interdependencies, interaction terms between variables are introduced into the logistic regression model. This allows us to evaluate how combinations of factors influence income classification ($\leq 50K$ vs. $> 50K$).

Key Interaction Effects Identified Model using Physical vs. Mental Labor (model_new.1.interaction):
Significant interactions found: Age \times Marital Status Sex \times Marital Status This suggests that age influences the impact of marital status on income, and gender differences in income depend on marital status. Model using PRC Job Classification (model_new.2.interaction):

Additional significant interactions: Sex \times Marital Status Sex \times Occupation Marital Status \times Occupation This highlights that gender effects on income vary across job categories, and marital status plays a role in occupational income disparities. Model using ISCO-08 Job Classification (model_new.3.interaction):

The most significant interaction: Marital Status \times Occupation This suggests that marital status interacts with occupation type to influence income, possibly due to differences in career stability or dual-income households.

Model Performance Assessment ROC curve analysis: The AUC values are compared for interaction models, showing whether incorporating interaction effects improves classification performance. Detect separation tests: Ensures that models do not suffer from convergence issues caused by perfect separation. Stepwise AIC optimization: Helps reduce overfitting by removing redundant interaction terms.

Key Takeaways: Including interaction terms improves model interpretability and accuracy. Marital Status and Occupation consistently interact, meaning these two factors jointly affect income potential. Gender interacts with both Marital Status and Occupation, indicating income disparities linked to societal roles. ROC analysis suggests that models with interactions perform better than those without, validating the importance of capturing interdependencies between variables.

5 Model Assumption

The Hosmer-Lemeshow test p-values for all seven models are greater than 0.05, indicating a good model fit. The predicted probabilities do not show a significant difference from the actual data distribution, confirming that the models are suitable for use.

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: stepAIC_model$y, fitted(stepAIC_model)
X-squared = 3.5824, df = 8, p-value = 0.8927
```

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: stepAIC_model_new.1$y, fitted(stepAIC_model_new.1)
X-squared = 7.7147, df = 8, p-value = 0.4618
```

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: stepAIC_model_new.2$y, fitted(stepAIC_model_new.2)
X-squared = 6.6156, df = 8, p-value = 0.5786
```

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: stepAIC_model_new.3$y, fitted(stepAIC_model_new.3)
X-squared = 10.221, df = 8, p-value = 0.2499
```

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: model_new.1.interaction$y, fitted(model_new.1.interaction)
X-squared = 9.4961, df = 8, p-value = 0.3022
```

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: model_new.2.interaction$y, fitted(model_new.2.interaction)
X-squared = 9.1216, df = 8, p-value = 0.3321
```

Hosmer and Lemeshow goodness of fit (GOF) test

```
data: model_new.3.interaction$y, fitted(model_new.3.interaction)
X-squared = 6.8584, df = 8, p-value = 0.552
```

When evaluating the prediction accuracy of the seven models, all models achieved an accuracy greater than 0.8, with a difference of no more than 0.02 between them. This indicates that the models can effectively distinguish between high-income (>50K) and low-income (<=50K) groups.

	Actual	
Predicted	<=50K	>50K
<=50K	958	154
>50K	83	190

```
[1] "Accuracy1: 0.829"
```

	Actual	
Predicted	<=50K	>50K
<=50K	942	165
>50K	99	179

```
[1] "Accuracy2: 0.809"
```

	Actual	
Predicted	<=50K	>50K
<=50K	961	169
>50K	80	175

```
[1] "Accuracy3: 0.82"
```

	Actual	
Predicted	<=50K	>50K
<=50K	965	169
>50K	76	175

```
[1] "Accuracy4: 0.823"
```

	Actual	
Predicted	<=50K	>50K
<=50K	938	150
>50K	103	194

```
[1] "Accuracy5: 0.817"
```

	Actual	
Predicted	<=50K	>50K
<=50K	958	161
>50K	83	183

```
[1] "Accuracy6: 0.824"
```

	Actual	
Predicted	<=50K	>50K
<=50K	957	171
>50K	84	173

```
[1] "Accuracy7: 0.816"
```

The AIC of `model_new.2.interaction` is the smallest, indicating the best model fit. Additionally, `model_new.2.interaction` achieves the highest AUC of 0.868, demonstrating the strongest ability to classify high-income (>50K) and low-income (<=50K) groups.

	df	AIC
stepAIC_model	34	1066.601
stepAIC_model_new.1	7	1123.930
stepAIC_model_new.2	11	1101.458
stepAIC_model_new.3	14	1106.393
model_new.1.interaction	9	1108.156
model_new.2.interaction	17	1084.720
model_new.3.interaction	22	1098.772

The X-axis ($0 \rightarrow 1$) represents the predicted probability, where 0 indicates low income, 1 indicates high income, and 0.5 represents model uncertainty. The Y-axis (residuals) represents the prediction error. A residual value close to 0 indicates that the predicted result is close to the actual value, with a small error, while a residual value far from 0 indicates a larger discrepancy between the predicted and actual values.

At points where the X-axis is close to 0 and 1, residual values are larger, indicating higher prediction errors in these regions. However, this is a normal phenomenon in logistic regression. When the X-axis is near 0.5, the residual values are smaller, suggesting that the model fits better in the middle probability range.

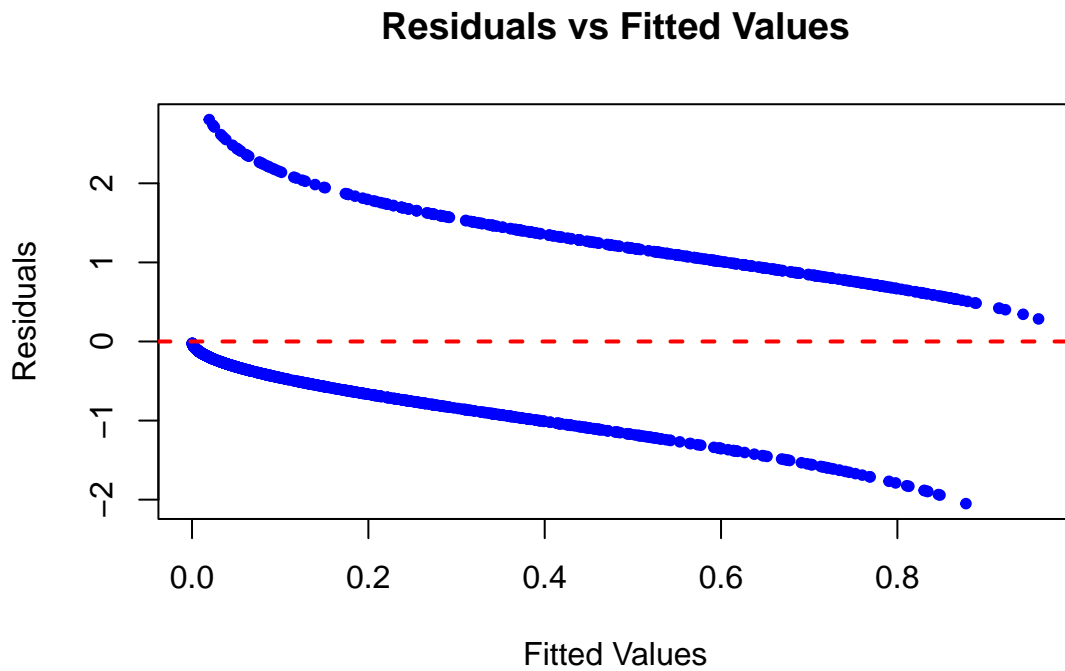


Figure 42: Residuals vs Fitted Values.

The residuals follow a normal distribution in the middle region but deviate from the diagonal line at both ends, especially on the right side. However, slight tail deviations are common in logistic regression.

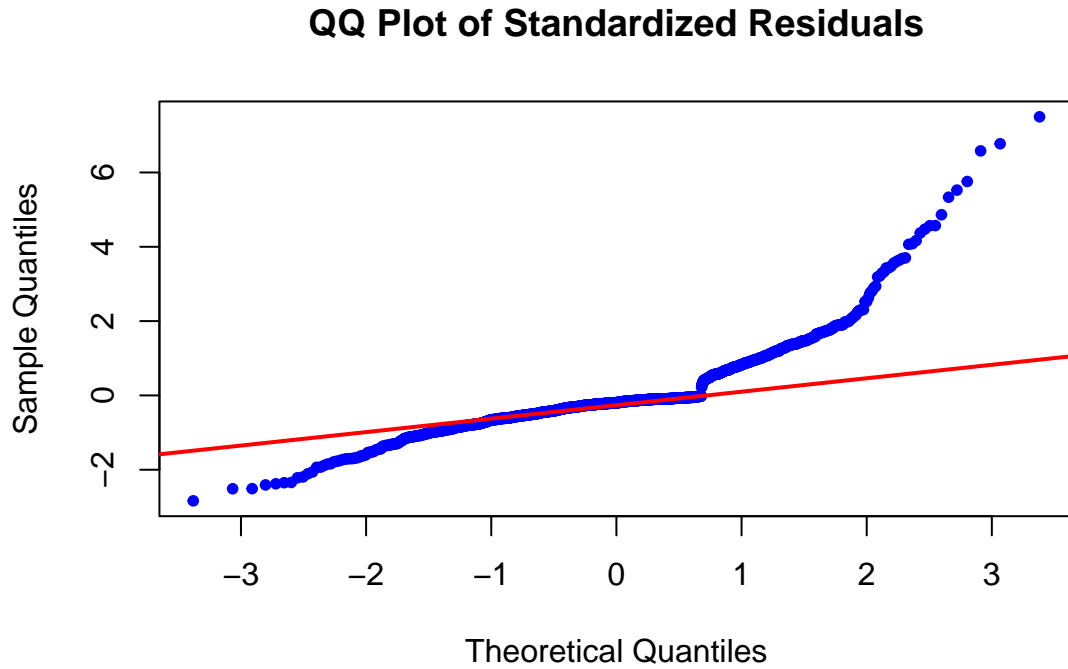


Figure 43: QQ Plot of Standardized Residuals.