MATH 9102 - Probability and Statistical Inference Assignment
Final Assignment

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Method

Participants

The dataset~[1] for this study originates from the 1994 U.S. Census, which involved a diverse range of participants to provide a comprehensive snapshot of the U.S. population. This extensive coverage makes the findings relevant to the adult population of the United States during that period.

The data captures key demographic details critical for examining income disparities, including age, gender, race/ethnicity, education level, marital status, and employment status. Specifically, it categorizes gender into male or female; race/ethnicity includes White, Black, Asian, Hispanic, among others; and education levels vary from none to advanced degrees.

The census participants were not specifically recruited like in targeted research studies but were included through a national initiative aimed at documenting the demographic attributes of the U.S. population. Participation was solicited from households nationwide, covering both urban and rural areas to ensure a representative sample.

Although the census gathered data from millions, this study analyzes a subset of 32,561 complete records, chosen for their comprehensive demographic details needed to study income variations. No power analysis was conducted as the census was designed to encompass as broad a population segment as possible, not to meet specific sample size calculations for statistical power.

The data was gathered specifically to analyze the earned income of the population, and the collection was conducted according to the following criteria:

AAGE > 16 Keep only working-age adults;

AGI > 100 Adjusted Gross Income;

AFNLWGT > 1 Final Weight meaning the number of people that is believed that this entry represents;

HRSWK > 0 Participants with working hours reported.

The dataset comes in comma-separated values (CSV) format has *14 features* and has 0.9% missing values. The target variable is the *income* that can be either *more* or *less or equal* than $50000.

Due to the census's scope, there was no allocation of participants into experimental groups or need for randomization typical of controlled experiments. The dataset naturally includes a broad demographic diversity reflective of the national census effort.

Procedure

Hypothesis

As an initial analysis, we aim to explore how social factors such as gender and race affect income levels. We want to understand if a specific gender is more likely to earn more.

We also intend to investigate how other factors interact with gender. One interesting analysis could be to examine how ethnic groups might experience advantages or disadvantages combined with gender in terms of income disparity.

Another intriguing hypothesis would consider the income progression influenced by combinations of age and gender.

Exploration

Features Description

First, we need to conduct a thorough exploration of the dataset to understand the underlying structure and quality of the data. This will involve assessing various features for their relevance and potential impact on the study's outcomes, particularly how they relate to income levels. We will also present a summary in Table X.

```r
census <- read.csv("../adult.csv", na.strings =  c("?"))
head(census)
```

```
##   age workclass fnlwgt    education education.num marital.status
## 1  90      <NA>  77053      HS-grad             9        Widowed
## 2  82   Private 132870      HS-grad             9        Widowed
## 3  66      <NA> 186061 Some-college            10        Widowed
## 4  54   Private 140359      7th-8th             4       Divorced
## 5  41   Private 264663 Some-college            10      Separated
## 6  34   Private 216864      HS-grad             9       Divorced
##          occupation  relationship  race    sex capital.gain capital.loss
## 1              <NA> Not-in-family White Female            0         4356
## 2   Exec-managerial Not-in-family White Female            0         4356
## 3              <NA>     Unmarried Black Female            0         4356
## 4 Machine-op-inspct     Unmarried White Female            0         3900
## 5    Prof-specialty     Own-child White Female            0         3900
## 6     Other-service     Unmarried White Female            0         3770
##   hours.per.week native.country income
## 1             40  United-States  <=50K
## 2             18  United-States  <=50K
## 3             40  United-States  <=50K
## 4             40  United-States  <=50K
## 5             40  United-States  <=50K
## 6             45  United-States  <=50K
```

```r
missing_values <- census %>% summarise(across(everything(), ~sum(is.na(.))))
missing_values_ft <- missing_values %>%
  pivot_longer(cols = everything(), names_to = "Feature", values_to = "MissingValues")

ggplot(missing_values_ft, aes(x = Feature, y = MissingValues, fill = Feature)) +
  geom_bar(stat = "identity") +
  theme_minimal() +
  labs(title = "Missing Values Per Feature", x = "Feature", y = "Missing Values") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1), legend.position = "none") +
  theme(plot.title = element_text(hjust = 0.5))
```

We get the following resume for the categories:

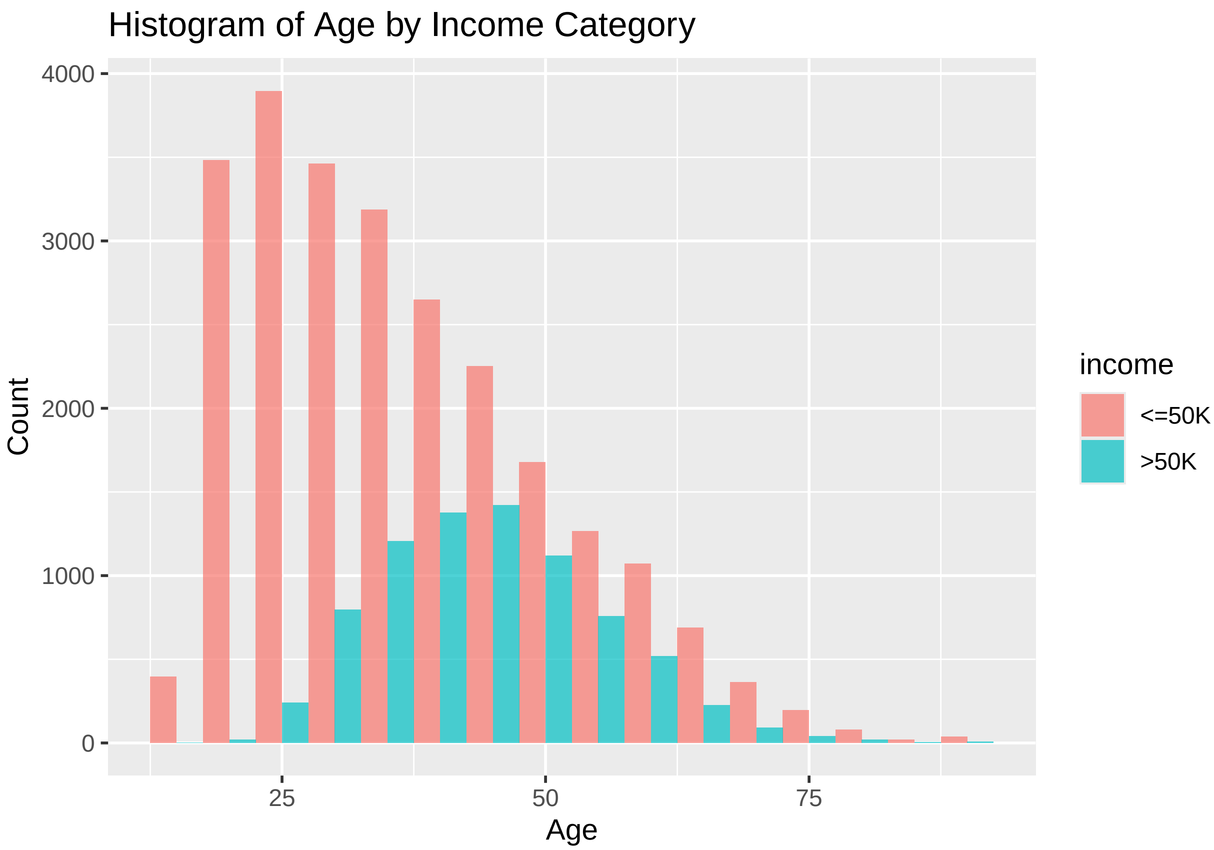
Scoring (Optional)

Appendix

Statistics Description

```r
feat_desc_cat <- function(variable_name, render_table = TRUE) {
  summary_stats <- census %>%
    group_by(!!sym(variable_name), income) %>%
    summarise(count = n(), .groups = "drop") %>%
    mutate(proportion = count / sum(count)) %>%
    ungroup()  %>%
    mutate(percent = scales::percent(proportion, 1))

  g <- ggplot(summary_stats, aes(x = !!sym(variable_name), y = proportion, fill = income)) +
    geom_bar(stat = "identity", position = position_dodge()) +
    theme_minimal() +
    labs(title = paste("Proportion of income by ", variable_name)) +
    theme(plot.title = element_text(hjust = 0.5)) +
    theme(axis.text.x = element_text(angle = 90, hjust = 1))

  grid.draw(g)
  if (render_table) {
    kable(summary_stats, "latex")
  }
}
```

```r
feat_desc_num <- function(variable_name, render_table = TRUE) {
  summary_stats <- census %>%
    group_by(income) %>%
    summarise(count = n(),
              mean = mean(age, na.rm = TRUE),
              median = median(age, na.rm = TRUE),
              min = min(age, na.rm = TRUE),
              max = max(age, na.rm = TRUE),
              kurtosis = kurtosis(age, na.rm = TRUE),
              skewness = skewness(age, na.rm = TRUE),
              .groups = "drop") %>%
    ungroup()

  g <- ggplot(census, aes(x = age, fill = income)) +
      geom_histogram(binwidth = 5, position = "dodge", alpha = 0.7) +
      labs(title = "Histogram of Age by Income Category",
      x = "Age",
      y = "Count")

  grid.draw(g)
  if (render_table) {
    kable(summary_stats, "latex")
  }
}

feat_desc_num('age')
```

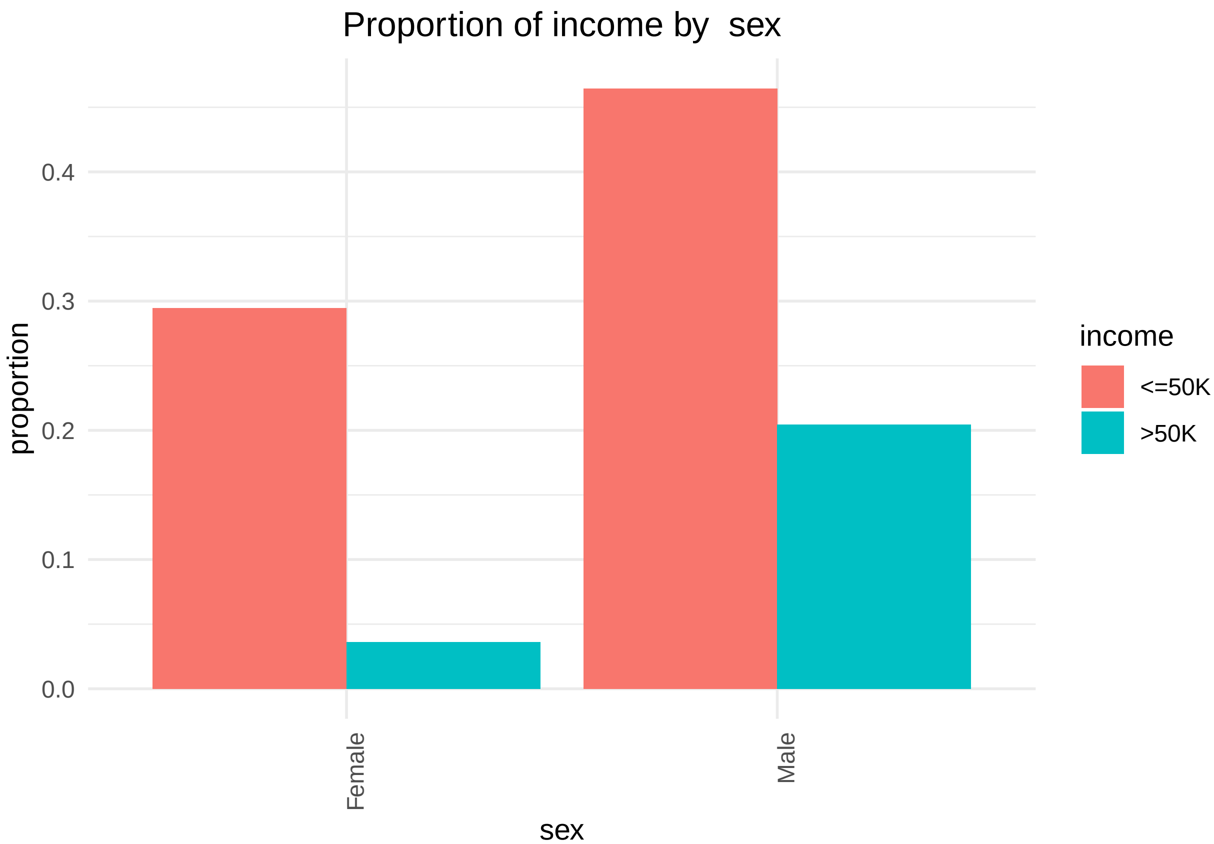


income	count	mean	median	min	max	kurtosis	skewness
<=50K	24720	36.78374	34	17	90	3.032914	0.7631435
>50K	7841	44.24984	44	19	90	3.154975	0.4773580

age fnlwgt education-num capital-gain capital-loss hours-per-week

sex

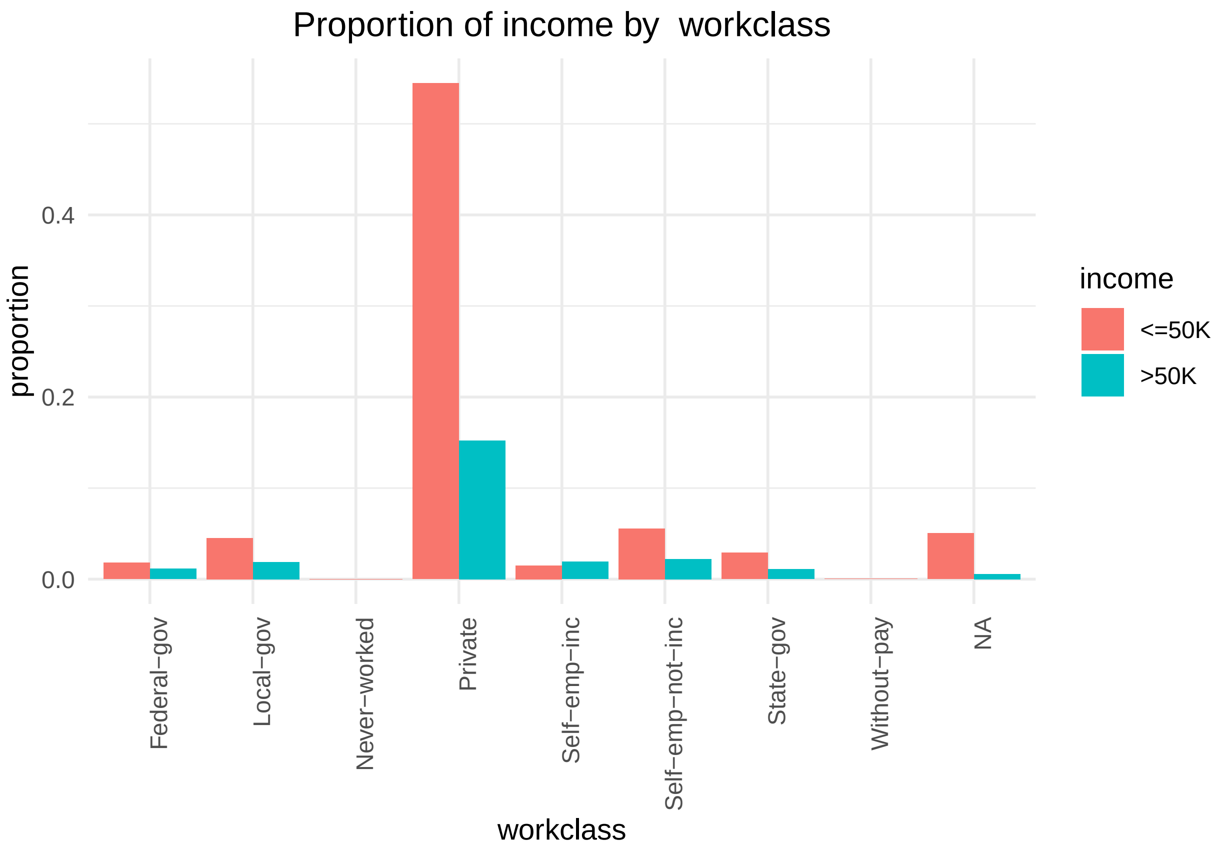
```
feat_desc_cat('sex')
```



sex	income	count	proportion	percent
Female	<=50K	9592	0.2945855	29%
Female	>50K	1179	0.0362090	4%
Male	<=50K	15128	0.4646049	46%
Male	>50K	6662	0.2046006	20%

workclass

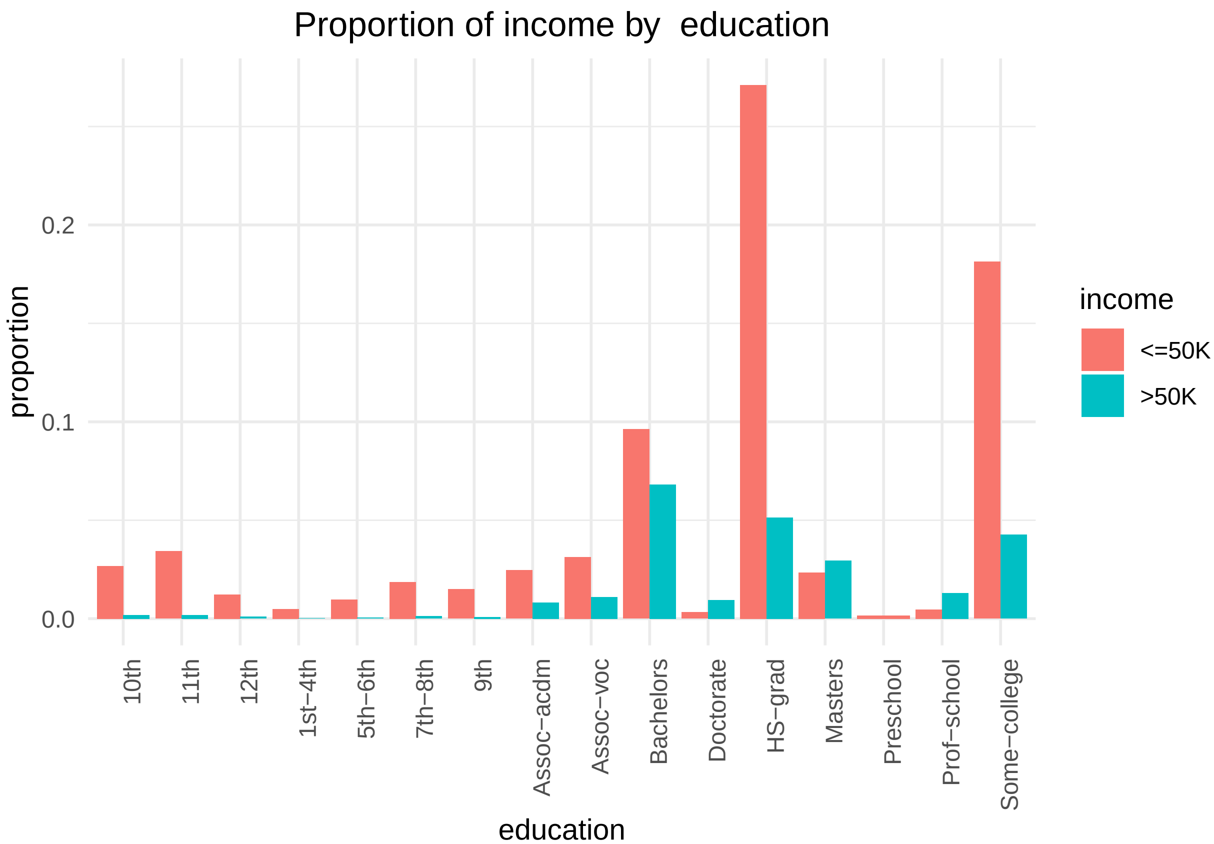
```
feat_desc_cat('workclass')
```



workclass	income	count	proportion	percent
Federal-gov	<=50K	589	0.0180891	2%
Federal-gov	>50K	371	0.0113940	1%
Local-gov	<=50K	1476	0.0453303	5%
Local-gov	>50K	617	0.0189490	2%
Never-worked	<=50K	7	0.0002150	0%
Private	<=50K	17733	0.5446086	54%
Private	>50K	4963	0.1524216	15%
Self-emp-inc	<=50K	494	0.0151715	2%
Self-emp-inc	>50K	622	0.0191026	2%
Self-emp-not-inc	<=50K	1817	0.0558030	6%
Self-emp-not-inc	>50K	724	0.0222352	2%
State-gov	<=50K	945	0.0290225	3%
State-gov	>50K	353	0.0108412	1%
Without-pay	<=50K	14	0.0004300	0%
NA	<=50K	1645	0.0505206	5%
NA	>50K	191	0.0058659	1%

education

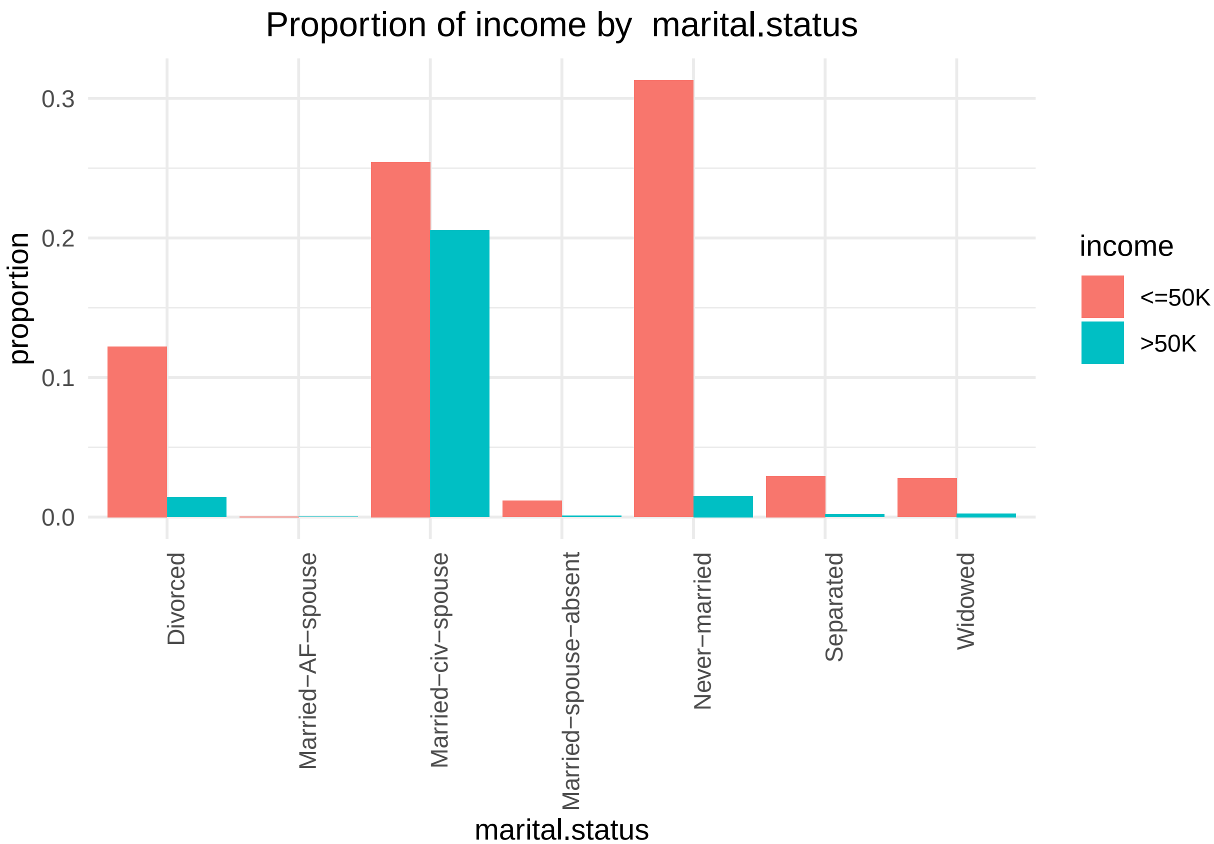
```
feat_desc_cat('education')
```



Proportion of income by education
proportion
0.2
0.1
0.0
10th
11th
12th
1st−4th
5th−6th
7th−8th
9th
Assoc−acdm
Assoc−voc
Bachelors
Doctorate
HS−grad
Masters
Preschool
Prof−school
Some−college
education
income
<=50K
>50K

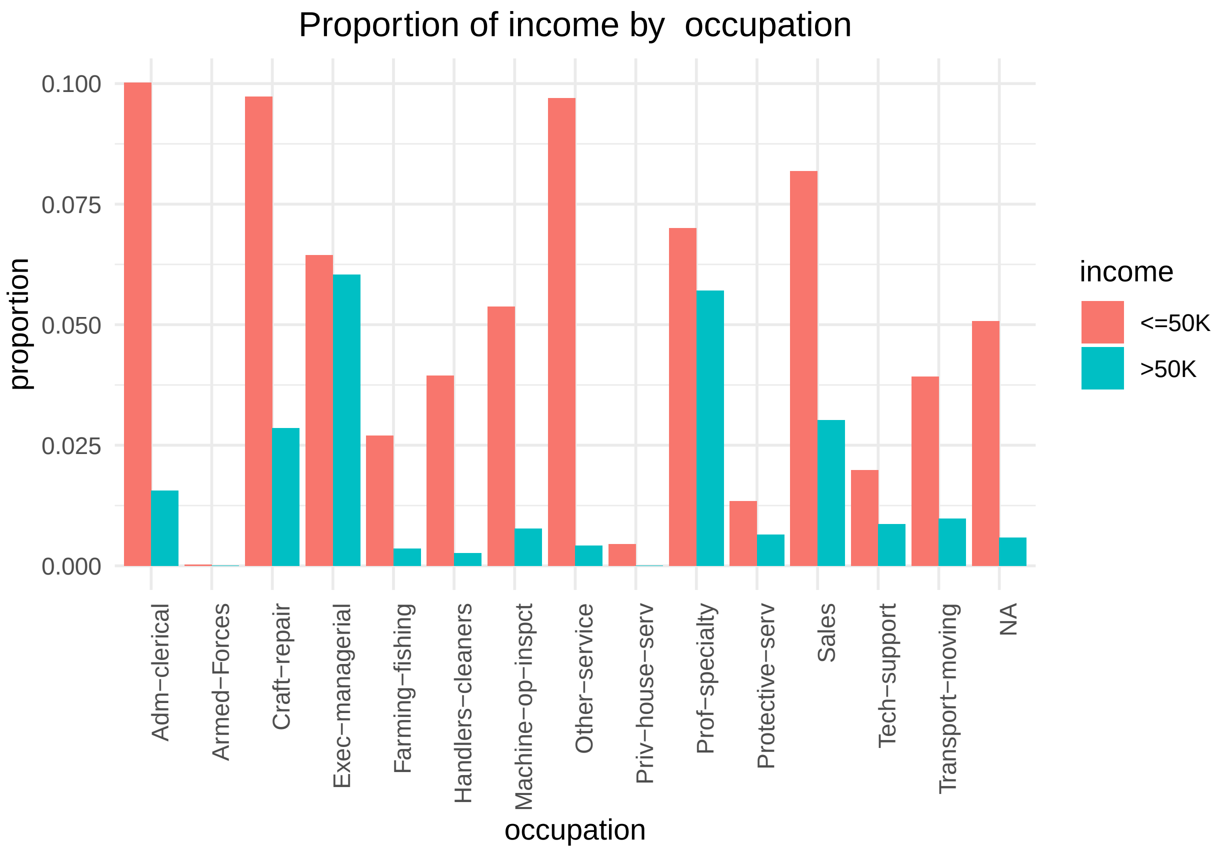
education	income	count	proportion	percent
10th	<=50K	871	0.0267498	3%
10th	>50K	62	0.0019041	0%
11th	<=50K	1115	0.0342434	3%
11th	>50K	60	0.0018427	0%
12th	<=50K	400	0.0122846	1%
12th	>50K	33	0.0010135	0%
1st-4th	<=50K	162	0.0049753	0%
1st-4th	>50K	6	0.0001843	0%
5th-6th	<=50K	317	0.0097356	1%
5th-6th	>50K	16	0.0004914	0%
7th-8th	<=50K	606	0.0186112	2%
7th-8th	>50K	40	0.0012285	0%
9th	<=50K	487	0.0149565	1%
9th	>50K	27	0.0008292	0%
Assoc-acdm	<=50K	802	0.0246307	2%
Assoc-acdm	>50K	265	0.0081386	1%
Assoc-voc	<=50K	1021	0.0313565	3%
Assoc-voc	>50K	361	0.0110869	1%
Bachelors	<=50K	3134	0.0962501	10%
Bachelors	>50K	2221	0.0682104	7%
Doctorate	<=50K	107	0.0032861	0%
Doctorate	>50K	306	0.0093977	1%
HS-grad	<=50K	8826	0.2710605	27%
HS-grad	>50K	1675	0.0514419	5%
Masters	<=50K	764	0.0234637	2%
Masters	>50K	959	0.0294524	3%
Preschool	<=50K	51	0.0015663	0%
Prof-school	<=50K	153	0.0046989	0%
Prof-school	>50K	423	0.0129910	1%
Some-college	<=50K	5904	0.1813212	18%
Some-college	>50K	1387	0.0425970	4%

```
feat_desc_cat('marital.status')
```



marital.status	income	count	proportion	percent
Divorced	<=50K	3980	0.1222321	12%
Divorced	>50K	463	0.0142195	1%
Married-AF-spouse	<=50K	13	0.0003993	0%
Married-AF-spouse	>50K	10	0.0003071	0%
Married-civ-spouse	<=50K	8284	0.2544148	25%
Married-civ-spouse	>50K	6692	0.2055219	21%
Married-spouse-absent	<=50K	384	0.0117932	1%
Married-spouse-absent	>50K	34	0.0010442	0%
Never-married	<=50K	10192	0.3130125	31%
Never-married	>50K	491	0.0150794	2%
Separated	<=50K	959	0.0294524	3%
Separated	>50K	66	0.0020270	0%
Widowed	<=50K	908	0.0278861	3%
Widowed	>50K	85	0.0026105	0%

```
feat_desc_cat('occupation')
```

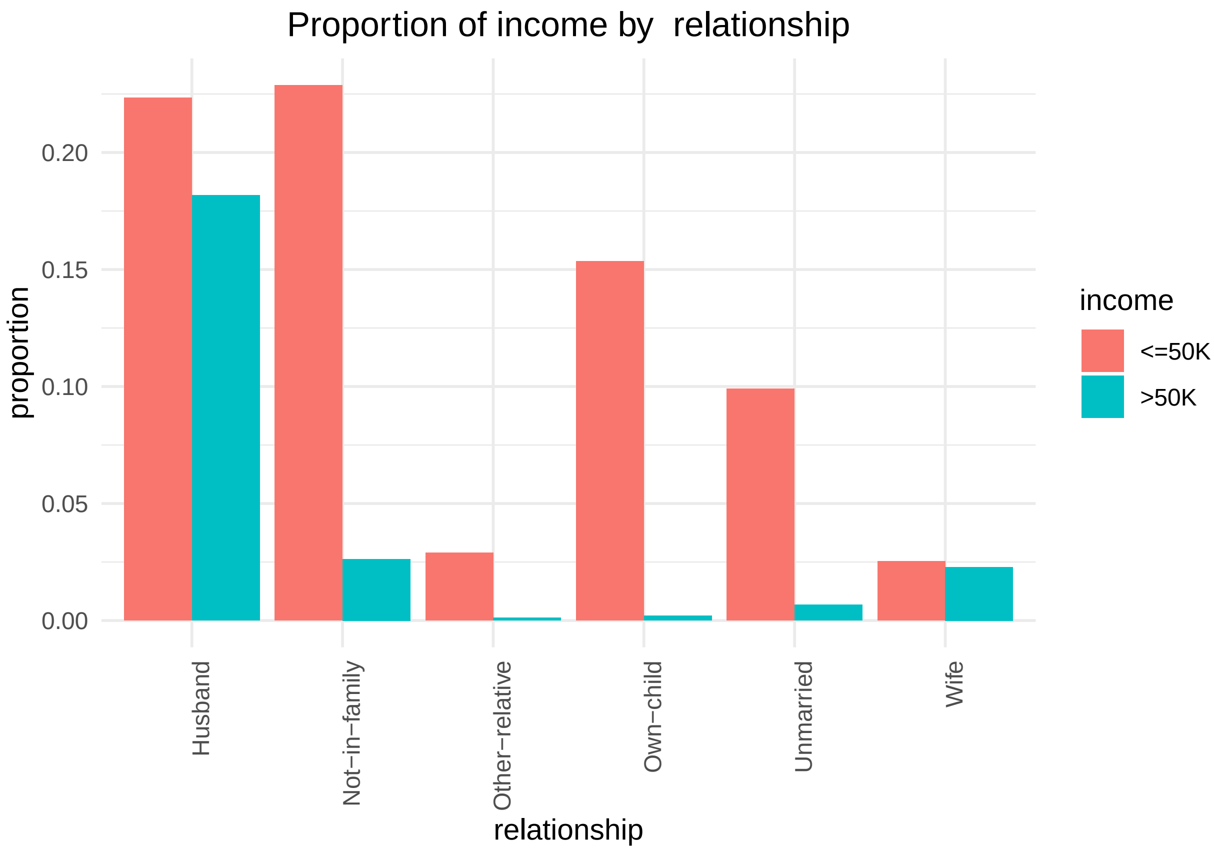


Proportion of income by occupation
proportion
0.100
0.075
0.050
0.025
0.000
occupation
Adm−clerical
Armed−Forces
Craft−repair
Exec−managerial
Farming−fishing
Handlers−cleaners
Machine−op−inspct
Other−service
Priv−house−serv
Prof−specialty
Protective−serv
Sales
Tech−support
Transport−moving
NA
income
<=50K
>50K

occupation	income	count	proportion	percent
Adm-clerical	<=50K	3263	0.1002119	10%
Adm-clerical	>50K	507	0.0155708	2%
Armed-Forces	<=50K	8	0.0002457	0%
Armed-Forces	>50K	1	0.0000307	0%
Craft-repair	<=50K	3170	0.0973557	10%
Craft-repair	>50K	929	0.0285311	3%
Exec-managerial	<=50K	2098	0.0644329	6%
Exec-managerial	>50K	1968	0.0604404	6%
Farming-fishing	<=50K	879	0.0269955	3%
Farming-fishing	>50K	115	0.0035318	0%
Handlers-cleaners	<=50K	1284	0.0394337	4%
Handlers-cleaners	>50K	86	0.0026412	0%
Machine-op-inspct	<=50K	1752	0.0538067	5%
Machine-op-inspct	>50K	250	0.0076779	1%
Other-service	<=50K	3158	0.0969872	10%
Other-service	>50K	137	0.0042075	0%
Priv-house-serv	<=50K	148	0.0045453	0%
Priv-house-serv	>50K	1	0.0000307	0%
Prof-specialty	<=50K	2281	0.0700531	7%
Prof-specialty	>50K	1859	0.0570928	6%
Protective-serv	<=50K	438	0.0134517	1%
Protective-serv	>50K	211	0.0064801	1%
Sales	<=50K	2667	0.0819078	8%
Sales	>50K	983	0.0301895	3%
Tech-support	<=50K	645	0.0198090	2%
Tech-support	>50K	283	0.0086914	1%
Transport-moving	<=50K	1277	0.0392187	4%
Transport-moving	>50K	320	0.0098277	1%
NA	<=50K	1652	0.0507355	5%
NA	>50K	191	0.0058659	1%

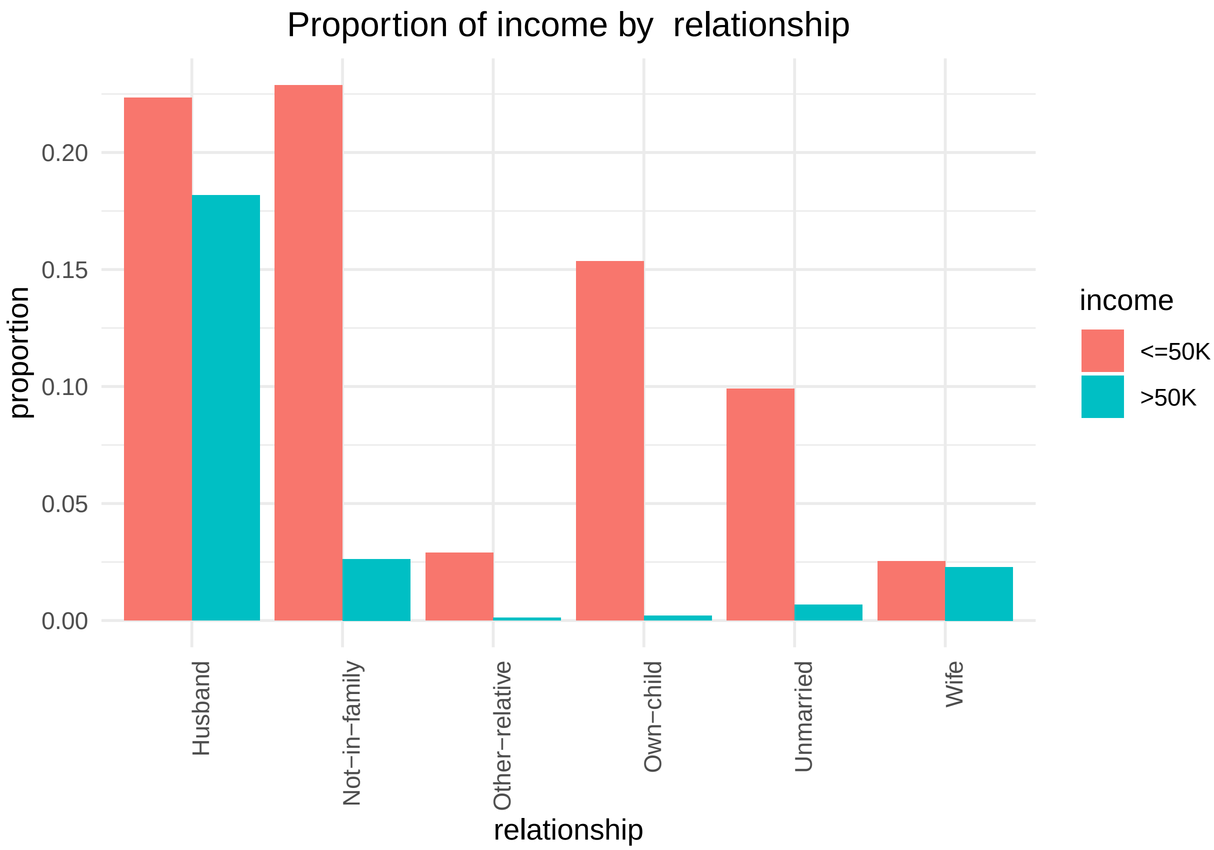
relationship

```
feat_desc_cat('relationship')
```



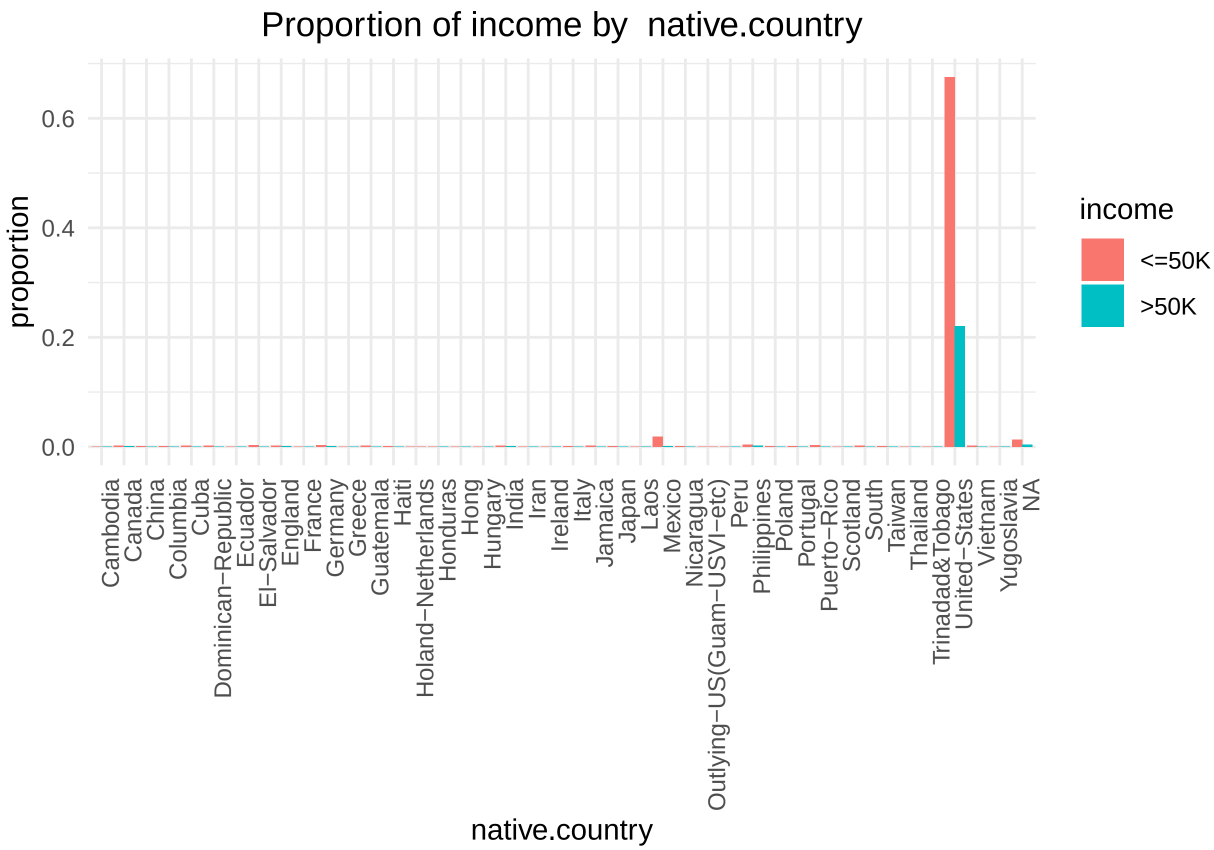
relationship	income	count	proportion	percent
Husband	<=50K	7275	0.2234268	22%
Husband	>50K	5918	0.1817512	18%
Not-in-family	<=50K	7449	0.2287706	23%
Not-in-family	>50K	856	0.0262891	3%
Other-relative	<=50K	944	0.0289917	3%
Other-relative	>50K	37	0.0011363	0%
Own-child	<=50K	5001	0.1535886	15%
Own-child	>50K	67	0.0020577	0%
Unmarried	<=50K	3228	0.0991370	10%
Unmarried	>50K	218	0.0066951	1%
Wife	<=50K	823	0.0252756	3%
Wife	>50K	745	0.0228801	2%

```
feat_desc_cat('relationship')
```



relationship	income	count	proportion	percent
Husband	<=50K	7275	0.2234268	22%
Husband	>50K	5918	0.1817512	18%
Not-in-family	<=50K	7449	0.2287706	23%
Not-in-family	>50K	856	0.0262891	3%
Other-relative	<=50K	944	0.0289917	3%
Other-relative	>50K	37	0.0011363	0%
Own-child	<=50K	5001	0.1535886	15%
Own-child	>50K	67	0.0020577	0%
Unmarried	<=50K	3228	0.0991370	10%
Unmarried	>50K	218	0.0066951	1%
Wife	<=50K	823	0.0252756	3%
Wife	>50K	745	0.0228801	2%

```
feat_desc_cat('native.country', FALSE)
```



References

[1] UCI UC Irvine Machine Learning Repository. *Census Income*. 1996. URL: https://archive.ics.uci.edu/dataset/20/census+income (visited on 05/11/2024).