Midterm Skills Exam: Data Wrangling and Analysis

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In this activity, you are expected to demonstrate skills learned from concluded modules. Specifically:

Analyze data using tools such as numpy and pandas for data wrangling tasks; Visualize data using pandas and seaborn; Perform exploratory data analysis on a complex dataset. Resources:

Jupyter Lab / Notebook Dataset: https://archive-beta.ics.uci.edu/dataset/20/census+incomeLinks to an external site. Submission Requirements:

Perform data wrangling on the given dataset. Visualize the given dataset. Submit pdf of exploratory data analysis. Submit pdf of EDA presentation. Sample: https://aseandse.org/asean-dse-storyboard/Links to an external site.

```
pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.10/dist-packages (0.0.6)
```

```
from ucimlrepo import fetch_ucirepo

# fetch dataset
census_income = fetch_ucirepo(id=20)

# data (as pandas dataframes)
X = census_income.data.features
y = census_income.data.targets

# metadata
print(census_income.metadata)

# variable information
print(census_income.variables)
```

```
{'uci_id': 20, 'name': 'Census Income', 'repository_url': 'https://archive.ics.uci.edu/dataset/20/census+income', 'data_url': 'https:/
              name     role         type      demographic  \
0              age  Feature      Integer              Age
1        workclass  Feature  Categorical           Income
2           fnlwgt  Feature      Integer             None
3        education  Feature  Categorical  Education Level
4    education-num  Feature      Integer  Education Level
5   marital-status  Feature  Categorical            Other
6       occupation  Feature  Categorical            Other
7     relationship  Feature  Categorical            Other
8             race  Feature  Categorical             Race
9              sex  Feature       Binary              Sex
10    capital-gain  Feature      Integer             None
11    capital-loss  Feature      Integer             None
12  hours-per-week  Feature      Integer             None
13  native-country  Feature  Categorical            Other
14          income   Target       Binary           Income

                                          description units missing_values
0                                                 N/A  None             no
1   Private, Self-emp-not-inc, Self-emp-inc, Feder...  None            yes
2                                                None  None             no
3    Bachelors, Some-college, 11th, HS-grad, Prof-...  None             no
4                                                None  None             no
5   Married-civ-spouse, Divorced, Never-married, S...  None             no
6   Tech-support, Craft-repair, Other-service, Sal...  None            yes
7   Wife, Own-child, Husband, Not-in-family, Other...  None             no
8   White, Asian-Pac-Islander, Amer-Indian-Eskimo,...  None             no
9                                       Female, Male.  None             no
10                                               None  None             no
11                                               None  None             no
12                                               None  None             no
13  United-States, Cambodia, England, Puerto-Rico,...  None            yes
14                                       >50K, <=50K.  None             no
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
ci = pd.concat([X,y], axis=1)
ci
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	n c
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-relative	Black	Male	0	0	40	
48839	38	Private	374983	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	
48840	44	Private	83891	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	
48841	35	Self-emp-inc	182148	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	

48842 rows × 15 columns

Next steps: View recommended plots

```
ci.dtypes
```

```
age                int64
workclass         object
fnlwgt             int64
education         object
education-num      int64
marital-status    object
occupation        object
relationship      object
race              object
sex               object
capital-gain       int64
capital-loss       int64
hours-per-week     int64
native-country    object
income            object
dtype: object
```

Data type conversion

```
# Convert categorical variables to category data type
ci['workclass'] = ci['workclass'].astype('category')
ci['education'] = ci['education'].astype('category')
ci['marital-status'] = ci['marital-status'].astype('category')
ci['occupation'] = ci['occupation'].astype('category')
ci['relationship'] = ci['relationship'].astype('category')
ci['race'] = ci['race'].astype('category')
ci['sex'] = ci['sex'].astype('category')
ci['native-country'] = ci['native-country'].astype('category')
ci['income'] = ci['income'].astype('category')
ci.dtypes
```

```
age                  int64
workclass         category
fnlwgt               int64
education         category
education-num        int64
marital-status    category
occupation        category
relationship      category
race              category
sex               category
capital-gain         int64
capital-loss         int64
hours-per-week       int64
native-country    category
income            category
dtype: object
```

Check for missing values

```
ci_null=ci.isnull().sum()
ci_null
```

```
age                 0
workclass         963
fnlwgt              0
education           0
education-num       0
marital-status      0
occupation        966
relationship        0
race                0
sex                 0
capital-gain        0
capital-loss        0
hours-per-week      0
native-country    274
income              0
dtype: int64
```

since every row have missing record we will not drop it

```
ci.describe()
```

	age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week
count	48842.000000	4.884200e+04	48842.000000	48842.000000	48842.000000	48842.000000
mean	38.643585	1.896641e+05	10.078089	1079.067626	87.502314	40.422382
std	13.710510	1.056040e+05	2.570973	7452.019058	403.004552	12.391444
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.175505e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.781445e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.376420e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.490400e+06	16.000000	99999.000000	4356.000000	99.000000

Remove duplicates

```
# Check for duplicates
duplicate_rows = ci.duplicated()

# Count the number of duplicate rows
num_duplicates = duplicate_rows.sum()
print("Number of duplicate rows:", num_duplicates)
```

```
Number of duplicate rows: 29
```

```
ci.drop_duplicates(inplace=True)
ci
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	n c
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-relative	Black	Male	0	0	40	
48839	38	Private	374983	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	
48840	44	Private	83891	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	
48841	35	Self-emp-inc	182148	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	

48813 rows × 15 columns

Next steps: View recommended plots

Sorting

```
# Sort the DataFrame by 'age' in ascending order
ci_sorted_age = ci.sort_values(by='age', ascending=True)
ci_sorted_age
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	na co
48098	17	Federal-gov	29078	11th	7	Never-married	Adm-clerical	Own-child	Amer-Indian-Eskimo	Female	0	0	15	
1389	17	Private	46496	11th	7	Never-married	Other-service	Own-child	White	Male	0	0	5	
35107	17	Private	36801	10th	6	Never-married	Other-service	Own-child	White	Female	0	0	18	
6820	17	Private	130795	10th	6	Never-married	Other-service	Own-child	White	Male	0	0	20	
38099	17	Private	23856	11th	7	Never-married	Exec-managerial	Own-child	White	Female	0	0	20	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
4109	90	?	256514	Bachelors	13	Widowed	?	Other-relative	White	Female	991	0	10	
18725	90	Local-gov	153602	HS-grad	9	Married-civ-spouse	Other-service	Husband	White	Male	6767	0	40	
19489	90	Private	84553	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	
18413	90	Private	313749	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Female	0	0	10	
33460	90	Private	149069	Assoc-acdm	12	Married-civ-spouse	Sales	Husband	White	Male	0	1825	50	

48813 rows × 15 columns

Next steps: View recommended plots

New column 'continent' in the DataFrame, where each country is mapped to its corresponding continent based on the description native-country

```
continent_dict = {
    'United-States': 'North America',
    'Cambodia': 'Asia',
    'England': 'Europe',
    'Puerto-Rico': 'North America',
    'Canada': 'North America',
    'Germany': 'Europe',
    'Outlying-US(Guam-USVI-etc)': 'Oceania',
    'India': 'Asia',
    'Japan': 'Asia',
    'Greece': 'Europe',
    'South': 'Other',
    'China': 'Asia',
    'Cuba': 'North America',
    'Iran': 'Asia',
    'Honduras': 'North America',
    'Philippines': 'Asia',
    'Italy': 'Europe',
    'Poland': 'Europe',
    'Jamaica': 'North America',
    'Vietnam': 'Asia',
    'Mexico': 'North America',
    'Portugal': 'Europe',
    'Ireland': 'Europe',
    'France': 'Europe',
    'Dominican-Republic': 'North America',
    'Laos': 'Asia',
    'Ecuador': 'South America',
    'Taiwan': 'Asia',
    'Haiti': 'North America',
    'Columbia': 'South America',
```

```
    'Hungary': 'Europe',
    'Guatemala': 'North America',
    'Nicaragua': 'North America',
    'Scotland': 'Europe',
    'Thailand': 'Asia',
    'Yugoslavia': 'Europe',
    'El-Salvador': 'North America',
    'Trinadad&Tobago': 'North America',
    'Peru': 'South America',
    'Hong': 'Asia',
    'Holand-Netherlands': 'Europe'
}

# Map countries to continents and create 'continent' column
ci['continent'] = ci['native-country'].map(continent_dict)
continent_table = pd.concat([ci['native-country'], ci['continent']], axis=1)
continent_table
```

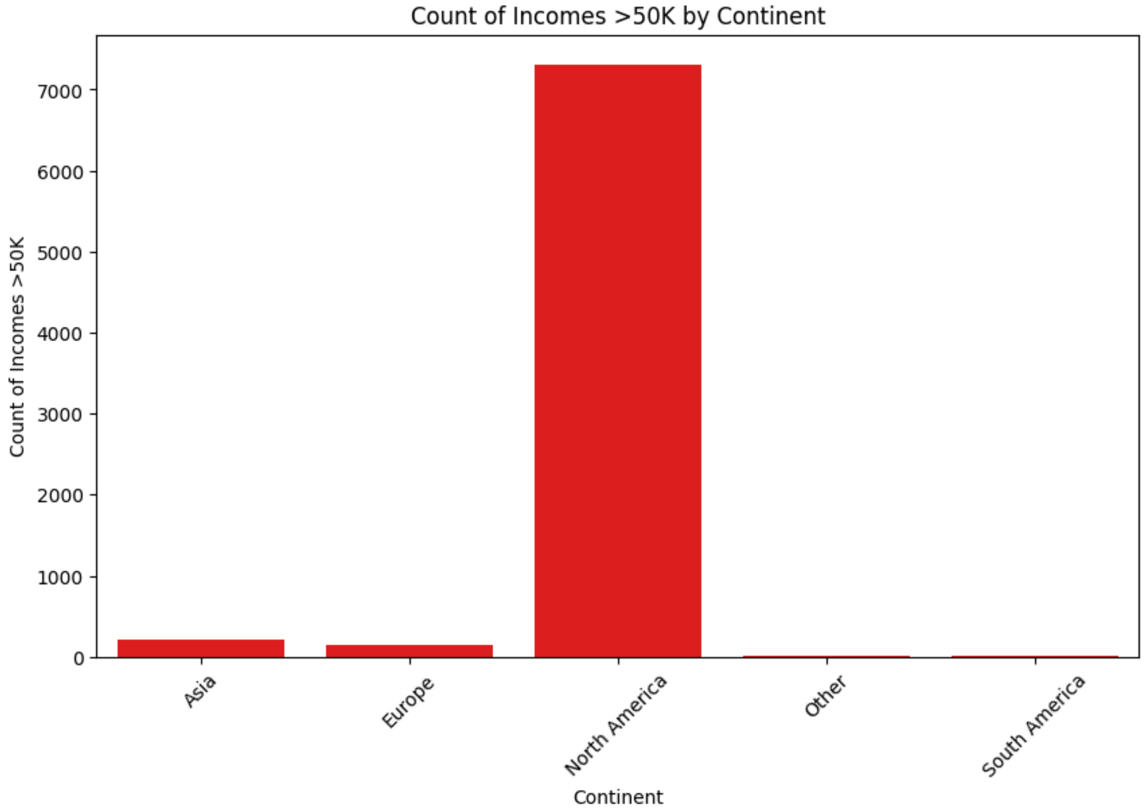
	native-country	continent
0	United-States	North America
1	United-States	North America
2	United-States	North America
3	United-States	North America
4	Cuba	North America
...	...	...
48837	United-States	North America
48838	United-States	North America
48839	United-States	North America
48840	United-States	North America
48841	United-States	North America

48813 rows × 2 columns

Next steps: View recommended plots

This shows the count of incomes greater than 50K for each continent

```
# Filter the dataset for incomes greater than $50K
high_income = ci[ci['income'] == '>50K']

# Group by continent and count the number of high incomes
continent_income_counts = high_income.groupby('continent')['income'].count().reset_index()

# Plot bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x='continent', y='income', data=continent_income_counts,color='red')
plt.title('Count of Incomes >50K by Continent')
plt.xlabel('Continent')
plt.ylabel('Count of Incomes >50K')
plt.xticks(rotation=45)
plt.show()
```



The results indicating that North America has the most people with the highest income this means have stronger economies compared to other continents, leading to higher average incomes and more people earning incomes greater than 50K

'education_level'

New column 'education_level' in the DataFrame, where 'High Education' corresponds to 'Bachelors', 'Masters', and 'Doctorate', and 'Low Education' corresponds to the rest of the education levels.*

```
education_mapping = {
    'Bachelors': 'High Education',
    'Masters': 'High Education',
    'Doctorate': 'High Education',
    'Some-college': 'Low Education',
    '11th': 'Low Education',
    'HS-grad': 'Low Education',
    'Prof-school': 'High Education',
    'Assoc-acdm': 'Low Education',
    'Assoc-voc': 'Low Education',
    '9th': 'Low Education',
    '7th-8th': 'Low Education',
    '12th': 'Low Education',
    '1st-4th': 'Low Education',
    '10th': 'Low Education',
    '5th-6th': 'Low Education',
    'Preschool': 'Low Education'
}

# Map education levels to 'education_level' column
ci['education_level'] = ci['education'].map(education_mapping)
education_level_table = pd.concat([ci['education'], ci['education_level']], axis=1)
education_level_table
```

	education	education_level
0	Bachelors	High Education
1	Bachelors	High Education
2	HS-grad	Low Education
3	11th	Low Education
4	Bachelors	High Education
...	...	...
48837	Bachelors	High Education
48838	HS-grad	Low Education
48839	Bachelors	High Education
48840	Bachelors	High Education
48841	Bachelors	High Education

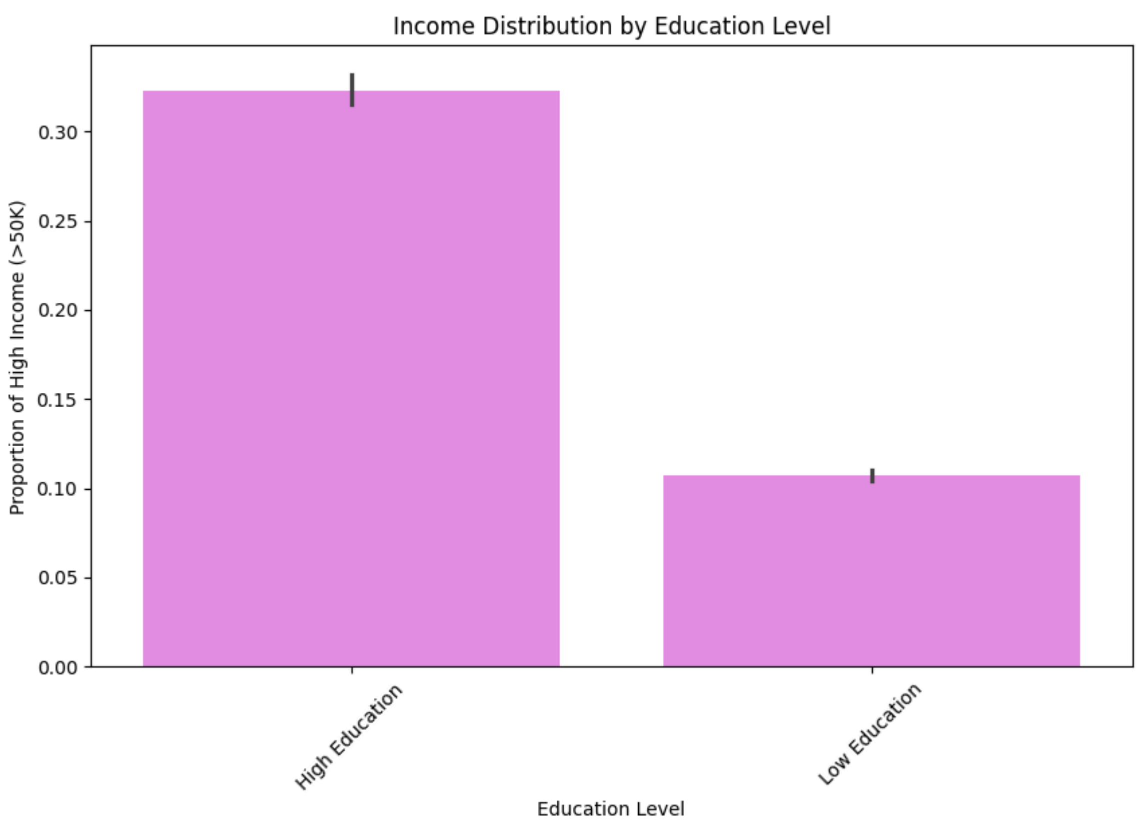
48813 rows × 2 columns

Next steps: View recommended plots

Income distribution by education level

this shows if there is a connection in education level to their income

```
# Plot bar plot of income distribution by education level
plt.figure(figsize=(10, 6))
sns.barplot(x='education_level', y=ci['income'] == '>50K', data=ci, color='violet')
plt.title('Income Distribution by Education Level')
plt.xlabel('Education Level')
plt.ylabel('Proportion of High Income (>50K)')
plt.xticks(rotation=45)
plt.show()
```



The result indicates that the higher education level have higher proportions of individuals with income greater than 50K.

'work_hours_category'

Instead of using hours-per-week as a continuous variable, we can categorize it into groups such as part-time, full-time, or overtime.

```
ci['work_hours_category'] = pd.cut(ci['hours-per-week'], bins=[0, 20, 40, np.inf], labels=['Part-time', 'Full-time', 'Overtime'])
hours_table = pd.concat([ci['work_hours_category'], ci['hours-per-week']], axis=1)
hours_table
```

	work_hours_category	hours-per-week
0	Full-time	40
1	Part-time	13
2	Full-time	40
3	Full-time	40
4	Full-time	40
...	...	...
48837	Full-time	36
48838	Full-time	40
48839	Overtime	50
48840	Full-time	40
48841	Overtime	60

48813 rows × 2 columns

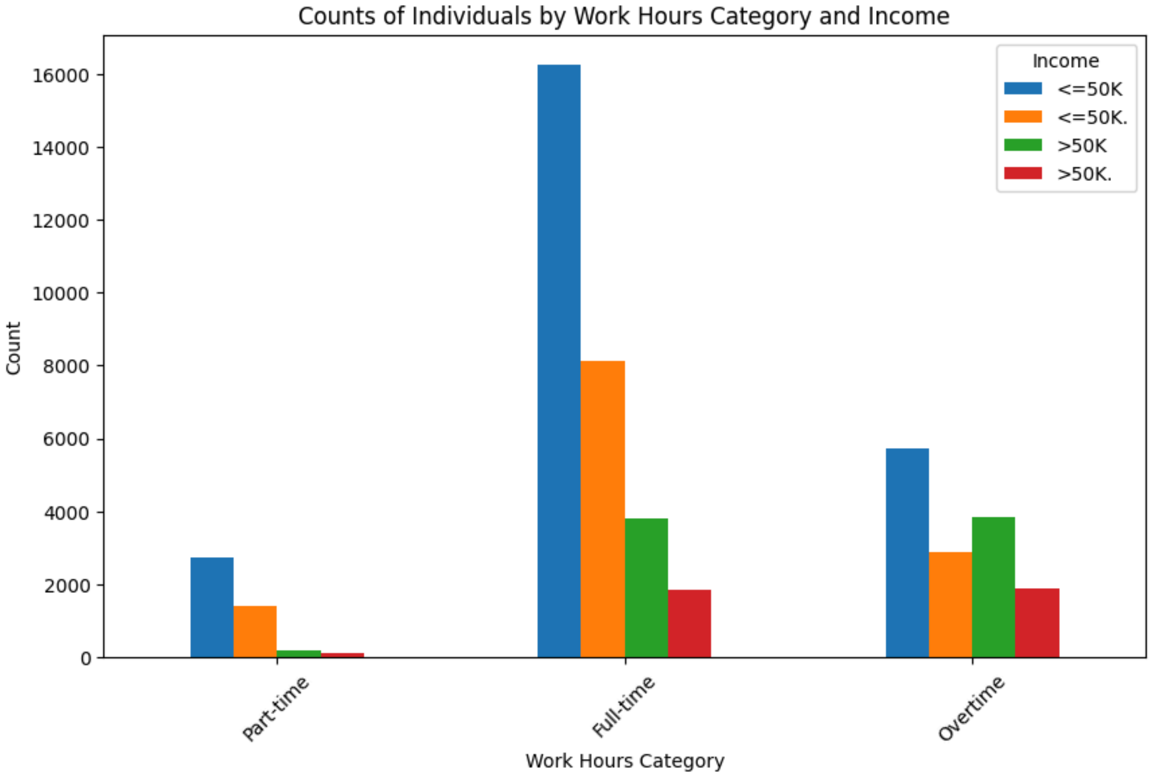
Next steps: View recommended plots

```
# Count the number of individuals in each income category for each work_hours_category
income_counts = ci.groupby(['work_hours_category', 'income'])['income'].count()

# Print the counts
print(income_counts)
```

```
work_hours_category  income
Part-time            <=50K      2729
                     <=50K.     1418
                     >50K        195
                     >50K.       106
Full-time            <=50K     16248
                     <=50K.     8127
                     >50K       3789
                     >50K.      1854
Overtime             <=50K      5721
                     <=50K.     2885
                     >50K       3855
                     >50K.      1886
Name: income, dtype: int64
```

To know the distribution of individuals across different work hours categories, segmented by income levels.

```
# Create a pivot table to reshape the data for plotting
pivot_table = ci.pivot_table(index='work_hours_category', columns='income', aggfunc='size', fill_value=0)

# Plot the counts of individuals in each income category for each work_hours_category
pivot_table.plot(kind='bar', figsize=(10, 6))
plt.title('Counts of Individuals by Work Hours Category and Income')
plt.xlabel('Work Hours Category')
plt.ylabel('Count')
plt.legend(title='Income')
plt.xticks(rotation=45)
plt.show()
```



The Full-time category has the highest count of individuals for both income levels. In all categories, there are more individuals earning <=50K than those earning >50K.

```
ci['work_hours_per_year'] = ci['hours-per-week'] * 52
ci['work_hours_per_year']
```

```
0        2080
1         676
2        2080
3        2080
4        2080
         ...
48837    1872
48838    2080
48839    2600
48840    2080
48841    3120
Name: work_hours_per_year, Length: 48813, dtype: int64
```

```
# Calculate average age by occupation
avg_age_by_occupation = ci.groupby('occupation')['age'].mean()
avg_age_by_occupation
```

```
occupation
?                    40.882800
Adm-clerical         37.196148
Armed-Forces         31.466667
Craft-repair         39.006550
Exec-managerial      42.203156
Farming-fishing      41.324815
Handlers-cleaners    32.659102
Machine-op-inspct    37.742299
Other-service        35.101850
Priv-house-serv      43.554167
Prof-specialty       40.566888
Protective-serv      38.899288
Sales                37.408612
Tech-support         37.161938
Transport-moving     40.651380
Name: age, dtype: float64
```

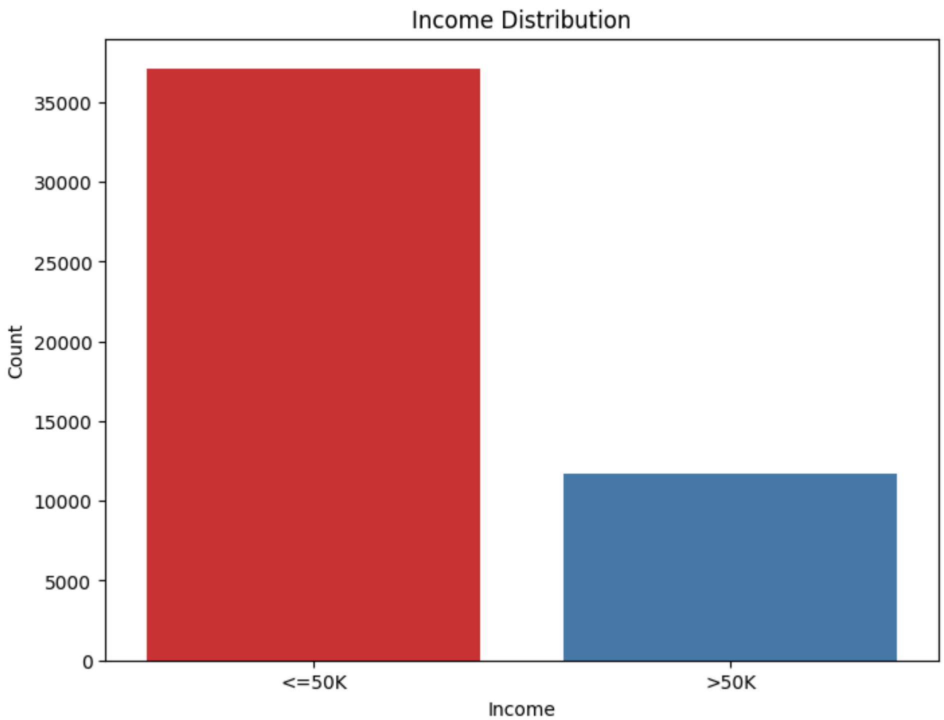
```
# Replace inconsistent values in the 'income' column
ci['income'] = ci['income'].replace({'<=50K.': '<=50K',
                                     '>50K.': '>50K'})
```

```
income_counts = ci['income'].value_counts()
income_counts
```

```
income
<=50K    37128
>50K     11685
Name: count, dtype: int64
```

```
# Plot the distribution of income
plt.figure(figsize=(8, 6))
sns.countplot(x='income', data=ci,palette='Set1')
plt.title('Income Distribution')
plt.xlabel('Income')
plt.ylabel('Count')
plt.show()
```

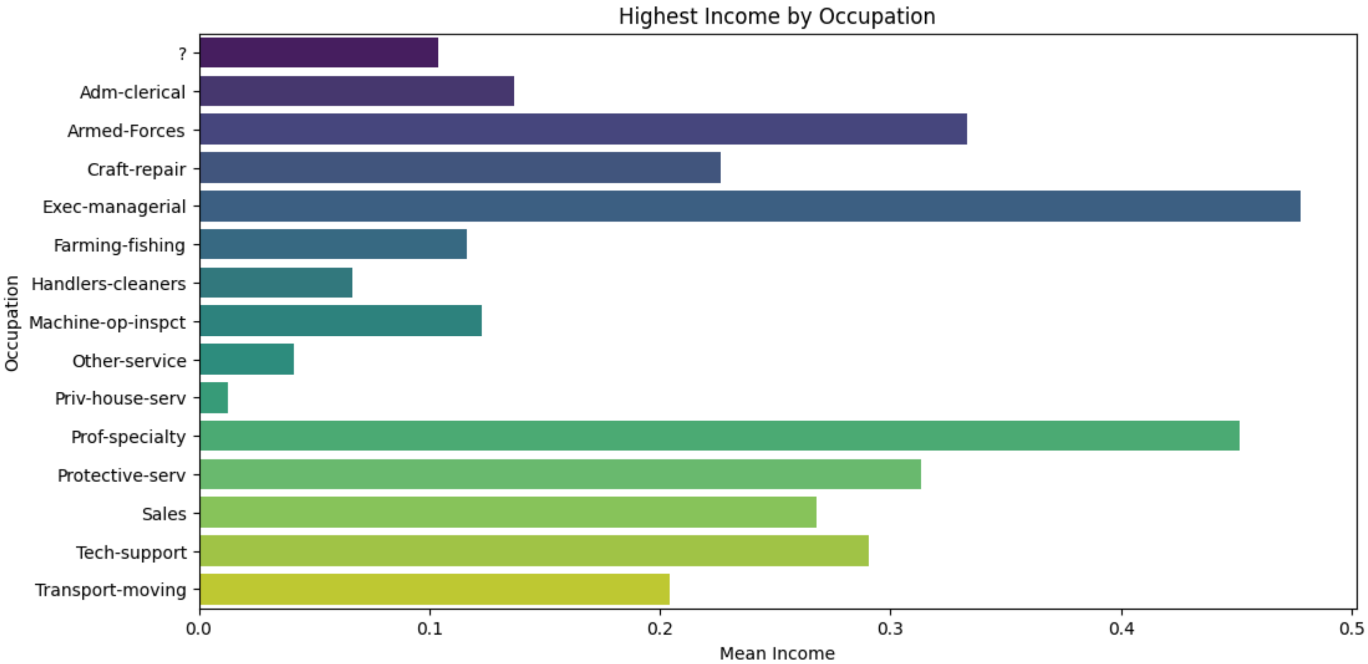
```
<ipython-input-22-6f4b1cb8d7da>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `lege

  sns.countplot(x='income', data=ci,palette='Set1')
```



This indicates that a lot of individuals in the dataset (37,128 out of 48,813) earn less than or equal to 50K. This means that the dataset contains a large proportion of individuals with lower income

```
# Calculate the mean income for each occupation
mean_inc_occ = ci.groupby('occupation')['income'].apply(lambda x: (x == '>50K').mean()).reset_index()
mean_inc_occ.columns = ['occupation', 'mean_income']

# Sort the occupations by mean income
mean_inc_occ_sorted = mean_inc_occ.sort_values(by='mean_income', ascending=False)

# Plot the bar plot
plt.figure(figsize=(12, 6))
sns.barplot(x='mean_income', y='occupation', data=mean_inc_occ_sorted, palette='viridis')
plt.title('Highest Income by Occupation')
plt.xlabel('Mean Income')
plt.ylabel('Occupation')
plt.show()
```

```
<ipython-input-23-0ff5f4796957>:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `lege

  sns.barplot(x='mean_income', y='occupation', data=mean_inc_occ_sorted, palette='viridis')
```



The 'Exec-managerial' occupation has the highest mean income among all the occupations in the dataset.

This insight is valuable for understanding the income distribution across different occupations and identifying which occupations tend to have higher average incomes.

'capital-net'

'capital-net' represents the net capital gain or loss for each individual. By subtracting the 'capital-loss' from the 'capital-gain', this encapsulates the overall financial gain or loss from investments or other financial activities.

```
ci['capital-net'] = ci['capital-gain'] - ci['capital-loss']
ci
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	n c
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-relative	Black	Male	0	0	40	
48839	38	Private	374983	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	
48840	44	Private	83891	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	
48841	35	Self-emp-inc	182148	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	

48813 rows × 20 columns

Next steps: View recommended plots

Capital Gain/Loss Ratio

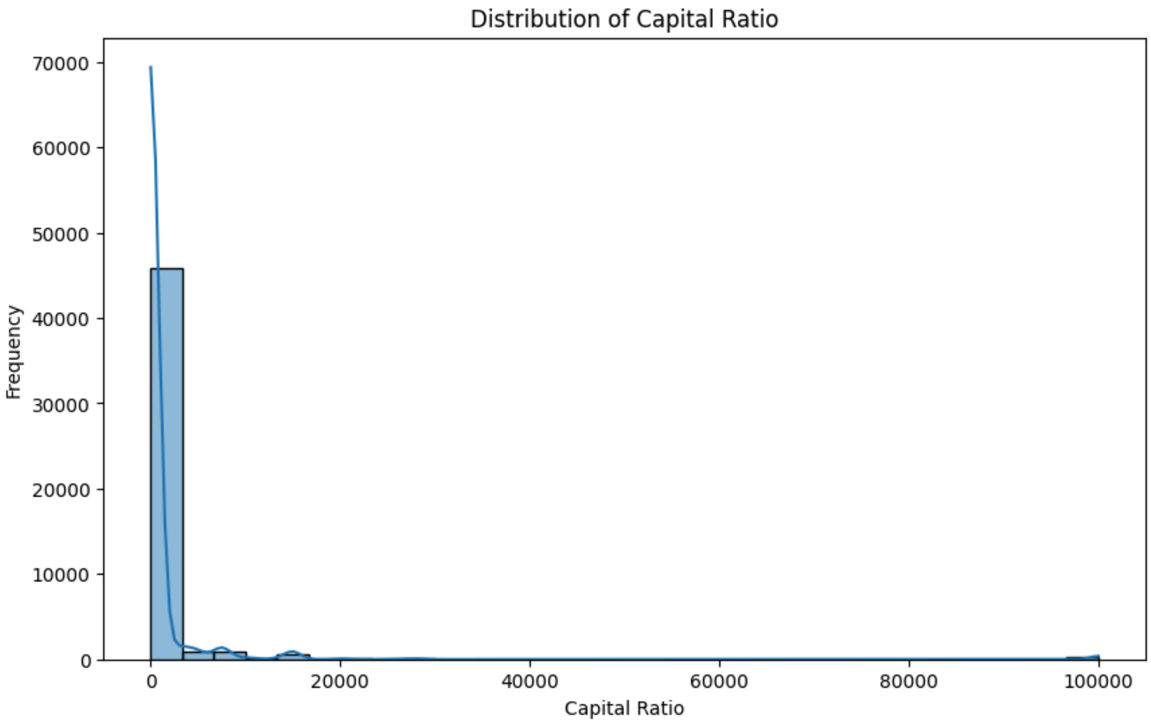
```
ci['capital_ratio'] = ci['capital-gain'] / (ci['capital-loss'] + 1)  # Adding 1 to avoid division by zero
capital_ratio_table = pd.concat([ci['capital-gain'], ci['capital-loss'], ci['capital_ratio']], axis=1)
capital_ratio_table
```

	capital-gain	capital-loss	capital_ratio
0	2174	0	2174.0
1	0	0	0.0
2	0	0	0.0
3	0	0	0.0
4	0	0	0.0
...	...	...	...
48837	0	0	0.0
48838	0	0	0.0
48839	0	0	0.0
48840	5455	0	5455.0
48841	0	0	0.0

48813 rows × 3 columns

Next steps: View recommended plots

```
import seaborn as sns
import matplotlib.pyplot as plt

# Plot histogram of capital_ratio
plt.figure(figsize=(10, 6))
sns.histplot(ci['capital_ratio'], bins=30, kde=True)
plt.title('Distribution of Capital Ratio')
plt.xlabel('Capital Ratio')
plt.ylabel('Frequency')
plt.show()
```



The 'capital_ratio' column in the dataset presents insights into the relative balance of capital gains and losses among sampled individuals. Analysis for the first row illustrates a substantial capital gain, indicative of potentially financial activities. For the row that have 0.0, suggesting financial inactivity or unreported information. This offers valuable insights into financial behaviors and outcomes, emphasizing varying levels of financial success and activity.

```
# Calculate average hours worked per week by education level
avg_hours_per_week_education = ci.groupby('education')['hours-per-week'].mean()
avg_hours_per_week_education
```

```
education
10th            36.986321
11th            33.952539
12th            35.413110
1st-4th         38.751020
5th-6th         38.891732
7th-8th         39.002096
9th             38.359788
Assoc-acdm      40.809494
Assoc-voc       41.659223
Bachelors       42.484040
Doctorate       46.582492
HS-grad         40.640553
Masters         43.573419
Preschool       36.402439
Prof-school     47.579137
Some-college    38.876898
Name: hours-per-week, dtype: float64
```

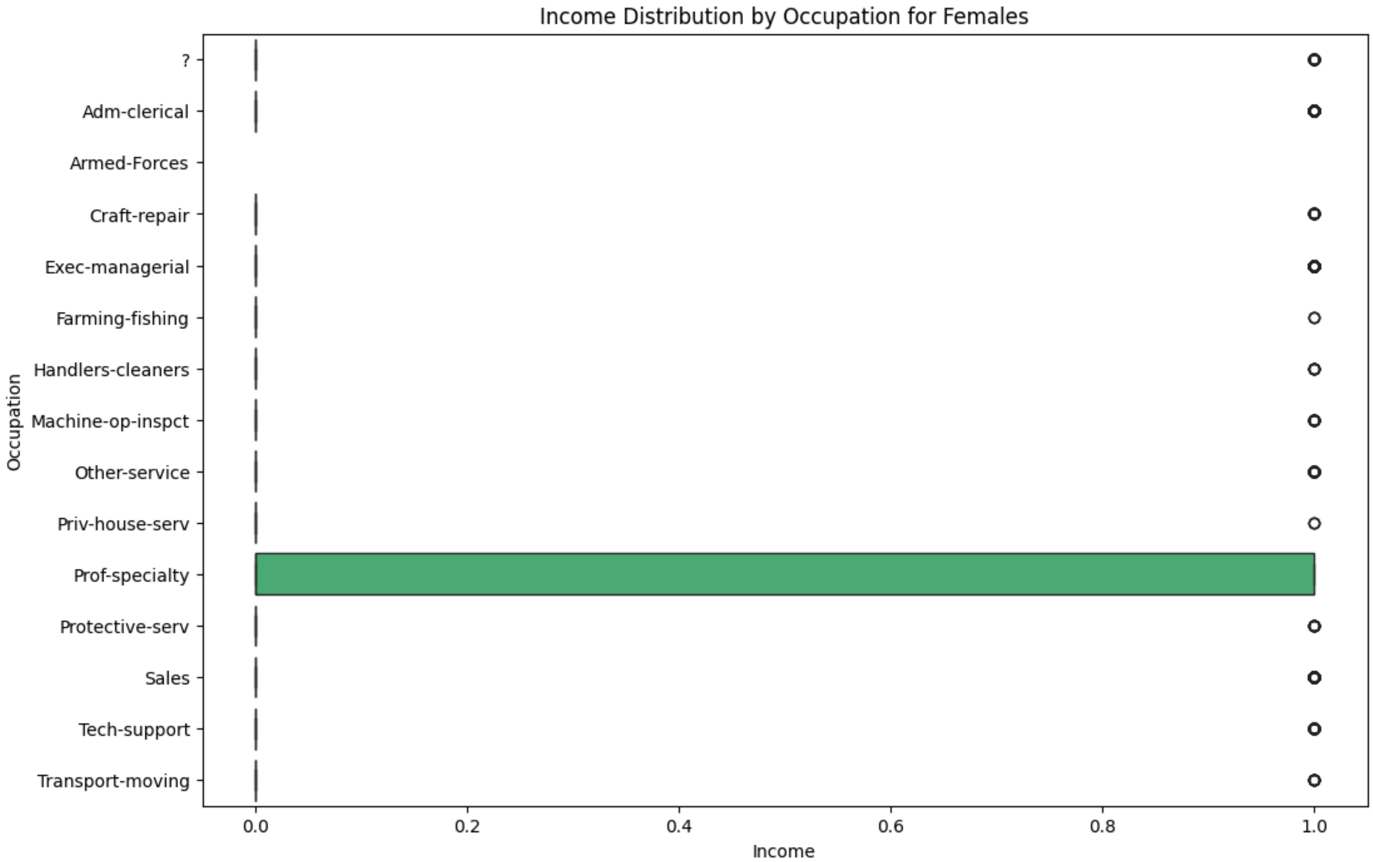
```
# Calculate median age by occupation and gender
median_age_occupation_gender = ci.groupby(['occupation', 'sex'])['age'].median()
median_age_occupation_gender
```

```
occupation         sex
?                  Female    29.0
                   Male      46.5
Adm-clerical       Female    35.0
                   Male      36.0
Armed-Forces       Female     NaN
                   Male      29.0
Craft-repair       Female    39.0
                   Male      38.0
Exec-managerial    Female    39.0
                   Male      42.0
Farming-fishing    Female    36.0
                   Male      39.0
Handlers-cleaners  Female    32.0
                   Male      29.0
Machine-op-inspct  Female    37.0
                   Male      36.0
Other-service      Female    33.0
                   Male      31.0
Priv-house-serv    Female    44.5
                   Male      23.0
Prof-specialty     Female    38.0
                   Male      41.0
Protective-serv    Female    33.0
                   Male      37.0
Sales              Female    29.0
                   Male      38.0
Tech-support       Female    34.0
                   Male      37.0
Transport-moving   Female    37.0
                   Male      40.0
Name: age, dtype: float64
```

What occupation has a higher income for females

```
# Filter data for females
female_data = ci[ci['sex'] == 'Female']

# Create a swarm plot of income by occupation for females
plt.figure(figsize=(12, 8))
sns.boxplot(x=ci['income'] == '>50K', y='occupation', data=female_data, palette='viridis')
plt.title('Income Distribution by Occupation for Females')
plt.xlabel('Income')
plt.ylabel('Occupation')
plt.show()
```

```
<ipython-input-29-d8a96d31c475>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `lege

  sns.boxplot(x=ci['income'] == '>50K', y='occupation', data=female_data, palette='viridis')
```

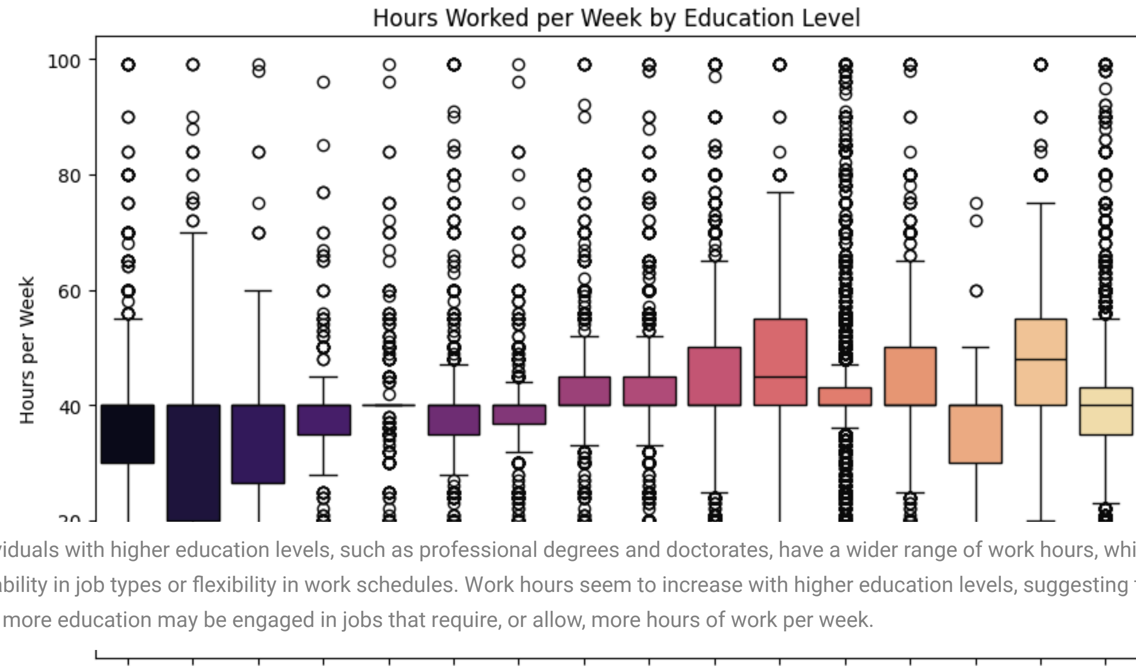


Prof-specialty have the highest income in the occupation for females. It also implies that there is a correlation between high education level and higher income, as professions requiring advanced education ('Prof-specialty') have a higher income

To know the comparison of the distribution of hours worked per week across various education levels.

```
plt.figure(figsize=(10, 6))
sns.boxplot(x='education', y='hours-per-week', data=ci,palette='magma')
plt.title('Hours Worked per Week by Education Level')
plt.xlabel('Education Level')
plt.ylabel('Hours per Week')
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-30-5a689d20326e>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `lege

  sns.boxplot(x='education', y='hours-per-week', data=ci,palette='magma')
```



Individuals with higher education levels, such as professional degrees and doctorates, have a wider range of work hours, which could indicate variability in job types or flexibility in work schedules. Work hours seem to increase with higher education levels, suggesting that individuals with more education may be engaged in jobs that require, or allow, more hours of work per week.

Reorder columns

```
# Define the desired order of columns
desired_order = ['age',
                 'workclass',
                 'fnlwgt',
                 'education',
                 'education-num',
                 'education_level',
                 'marital-status',
                 'occupation',
                 'relationship',
                 'race',
                 'sex',
                 'capital-gain',
```