Adult Income Analysis

Python Data Analyst Project

1. Project Overview This project performs an in-depth analysis of the Adult Income dataset, originally from the UCI Machine Learning Repository and hosted on Kaggle. The dataset includes demographic and employment information of individuals, categorizing their income levels into two classes: <=50K and >50K. Through this analysis, we aim to uncover socio-economic patterns and key factors that contribute to higher income levels, providing insights that could benefit sectors like policy-making, human resources, and socio-economic research.

2. Problem Statement The main objective of this project is to identify the factors associated with higher income among adults. Specifically, we aim to answer questions such as: - Which demographic factors, like age, gender, and work class, are linked to higher income levels? - Does education level significantly impact income potential? - Are certain occupations associated with higher earnings?

By answering these questions, we aim to deliver valuable insights into the socio-economic determinants of income distribution.

3. Dataset

- **Source**: Adult Income Dataset on Kaggle
- **Description**: The dataset includes variables such as age, work class, education level, marital status, occupation, race, and gender, along with an income label indicating whether the individual earns more or less than 50K.

4. Libraries Used The following Python libraries are utilized for data manipulation, analysis, and visualization:

- **Pandas**: For data handling and cleaning.
- **NumPy**: For numerical computations and handling missing values.
- **Matplotlib** and **Seaborn**: For creating plots and visualizing data trends.
- **Scikit-learn**: For encoding categorical variables and data transformations.

5. Data Visualization Various visualization techniques are applied to understand the relationships between income and demographic factors: - **Histograms** for examining age distribution and income categories. - **Bar charts** to analyze work class, education, and gender distributions. **Box plots** to observe age variation across income classes. - **Count plots** to visualize frequency distributions in categorical data.

Visualizing these relationships enables us to easily identify patterns and trends related to income.

6. Analysis Queries To align with the project objectives, the analysis addresses several queries: 1. **What are the age, education, and work class distributions among individuals with high income?** 2. **How does gender impact income levels, and is there a noticeable gender disparity?** 3. **Does higher education correlate with a higher income, and to what degree?** 4. **Are there certain work classes that are significantly linked with higher income?**

This project provides insights that can support career guidance, socio-economic policy formulation, and research on income disparities.

Author This project was created by Shaun Mia, a data analyst and AI enthusiast with a passion for uncovering insights through data analysis and visualization.

[ ]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

1 1. Setup and Import Libraries

[ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix

# Configuring plot settings
sns.set(style='whitegrid')
plt.style.use('seaborn')
```

```
<ipython-input-3-c0d2e5020696>:13: MatplotlibDeprecationWarning: The
seaborn styles shipped by Matplotlib are deprecated since 3.6, as they
no longer correspond to the styles shipped by seaborn. However, they
will remain available as 'seaborn-v0_8-<style>'. Alternatively,
directly use the seaborn API instead. plt.style.use('seaborn')
```

2 2. Load Dataset and Initial Exploration

```
[ ]: # Load the dataset
data = pd.read_csv('/content/drive/MyDrive/Data Analysis/Python Project/Adult␣
 ↪Income Analysis/adult.csv')

# Display the first 5 rows
print("Top 5 Rows of the Dataset: ")
display(data.head())

# Display the last 5 rows
print("Last 5 Rows of the Dataset: ")
display(data.tail())

# Check dataset shape (number of rows and columns)
print("Dataset Shape (Rows, Columns):", data.shape)

# Get dataset info
print("Dataset Information:")
data.info()
```

```
Top 5 Rows of the Dataset:

  age workclass fnlwgt   education educational-num    marital-status \
0 25    Private 226802   11th  7     Never-married 1  38    Private
 89814 HS-grad    9 Married-civ-spouse 2 28 Local-gov 336951
 Assoc-acdm 12 Married-civ-spouse
3   44  Private 160323 Some-college 10 Married-civ-spouse
4   18  ? 103497 Some-college 10    Never-married

        occupation relationship race gender capital-gain capital-loss \
0 Machine-op-inspct  Own-child Black  Male           0            0
1   Farming-fishing  Husband White    Male           0            0
2   Protective-serv  Husband White    Male           0            0
3 Machine-op-inspct  Husband Black    Male        7688            0
4                 ?  Own-child White Female          0            0
  hours-per-week native-country income
0             40 United-States <=50K
1             50 United-States <=50K
2             40 United-States  >50K
3             40 United-States  >50K
4             30 United-States <=50K

Last 5 Rows of the Dataset:

       age    workclass fnlwgt education educational-num \
48837  27    Private 257302 Assoc-acdm   12
48838  40    Private 154374   HS-grad    9
```

```
48839  58    Private 151910   HS-grad    9
48840  22    Private 201490   HS-grad    9
48841  52 Self-emp-inc 287927     HS-grad    9

         marital-status     occupation relationship race gender \
48837 Married-civ-spouse   Tech-support      Wife White Female
48838 Married-civ-spouse Machine-op-       Husband White   Male
inspct
48839          Widowed     Adm-clerical   Unmarried       White
                                          Female
48840     Never-married    Adm-clerical   Own-child White  Male
48841 Married-civ-spouseExec-managerial      Wife White Female
      capital-gain capital-loss hours-per-week native-country income
48837          0           0            38      United-States
                                        <=50K
48838          0           0            40 United-States >50K
48839          0           0            40      United-States
                                        <=50K
48840          0           0            20      United-States
                                        <=50K
48841      15024           0            40 United-States >50K

Dataset Shape (Rows, Columns): (48842,
15) Dataset Information:
<class
'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to
48841 Data columns (total 15
columns):
#   Column         Non-Null Count Dtype
--- ------         -------------- -----
 0    age   48842 non-null int64
 1    workclass  48842 non-null object
 2    fnlwgt     48842 non-null int64
 3    education  48842 non-null object
 4    educational-num 48842 non-null
 int64
 5    marital-status   48842 non-null
 object 6  occupation 48842 non-null
 object
 7    relationship    48842 non-null
 object
 8    race  48842 non-null object
 9    gender     48842 non-null object
 10   capital-gain    48842 non-null
 int64
```

```
 11   capital-loss     48842 non-null
 int64
 12   hours-per-week   48842 non-null
 int64
 13   native-country   48842 non-null
 object 14 income      48842 non-null
 object
```

```
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
```

3 3. Fetch a Random Sample (50%) of the Dataset

[ ]:
```
# Fetch random 50% sample sample_data =
data.sample(frac=0.5, random_state=42)
print("Random 50% Sample of the Dataset:")
display(sample_data.head())
```

```
Random 50% Sample of the Dataset:

    age workclass fnlwgt education educational-num   marital-status \
7762   56  Private  33115   HS-grad               9          Divorced
23881  25  Private 112847   HS-grad              9 Married-civ-spouse
 30507    43    Private 170525 Bachelors    13    Divorced 28911   32
              Private 186788   HS-grad     9 Married-civ-spouse
19484  39  Private 277886 Bachelors           13 Married-civ-spouse

             occupation relationship  race gender capital-gain \
7762    Other-service    Unmarried White Female            0
23881 Transport-moving   Own-child Other   Male            0
30507  Prof-specialty Not-in-family White Female       14344
```

```
28911 Transport-moving     Husband White    Male             0
19484            Sales         Wife White  Female            0

      capital-loss hours-per-week native-country
      income
7762             0             40 United-States <=50K
23881            0             40 United-States <=50K
30507            0             40 United-States  >50K
28911            0             40 United-States <=50K
19484            0             30 United-States <=50K
```

#4. Check and Handle Missing Values

[ ]:
```python
# Replace '?' with NaN
data.replace(' ?', np.nan, inplace=True)

# Check for missing values
print("Missing Values in Each Column: ")
print(data.isnull().sum())

# Drop missing values
data.dropna(inplace=True)
```

```
Missing Values in Each Column:
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype:
int64
```

4 5. Check for and Drop Duplicates

[ ]:
```
# Check for duplicates
duplicate_rows = data.duplicated().sum()
print(f"Number of Duplicate Rows: {duplicate_rows}")

# Drop duplicates if any
data = data.drop_duplicates()
```

```
Number of Duplicate Rows: 52
```

#6. Statistical Summary and Drop Unnecessary Columns

[ ]:
```
# Check which columns are available in the dataset
columns_to_drop = ['education-num', 'capital-
loss'] existing_columns = [col for col in columns_to_drop if col
in data.columns]

# Drop only the columns that exist in the
dataset data =
data.drop(columns=existing_columns)

# Display the first few rows after dropping the columns
data.head()
```

[ ]:
```
   age workclass fnlwgt   education educational-num   marital-status \
0 25 Private 226802 11th 7 Never-married 1 38 Private 89814 HS-grad
9 Married-civ-spouse 2 28 Local-gov 336951 Assoc-acdm 12 Married-
civ-spouse
3   44  Private 160323 Some-college 10 Married-civ-spouse
4   18  ? 103497 Some-college 10    Never-married

          occupation relationship race gender hours-per-week \
0    Machine-op-inspct   Own-child Black  Male  40
1    Farming-fishing     Husband White    Male  50
2   Protective-serv     Husband White   Male             40
3 Machine-op-inspct    Husband Black   Male             40
4                 ?   Own-child White Female            30

  native-country
income    0    United-
States <=50K
1  United-States <=50K
2  United-States >50K
3  United-States >50K
4  United-States <=50K
```

[ ]:
```
# Correct column names based on the dataset columns_to_drop =
['educational-num', 'capital-gain', 'capital-loss']
```

```
existing_columns = [col for col in columns_to_drop if col in
data.columns]

# Drop only the columns that exist in the
dataset data =
data.drop(columns=existing_columns)

# Display the first few rows after dropping the columns
data.head()
```

[ ]:
```
   age workclass fnlwgt   education    marital-status \
0   25  Private 226802   11th  Never-married
1   38  Private    89814 HS-grad Married-civ-spouse
2   28 Local-gov 336951 Assoc-acdm Married-civ-spouse
3   44  Private 160323 Some-college Married-civ-spouse
4   18  ? 103497 Some-college Never-married

        occupation relationship race gender hours-per-week \
 0 Machine-op-inspct  Own-child Black  Male            40
 1  Farming-fishing    Husband White   Male            50
 2  Protective-serv    Husband White   Male            40
 3 Machine-op-inspct   Husband Black   Male            40
 4                ?    Own-child White Female          30
  native-country
income 0 United-
States <=50K
1  United-States <=50K
2  United-States   >50K
3  United-States   >50K
4  United-States <=50K
```

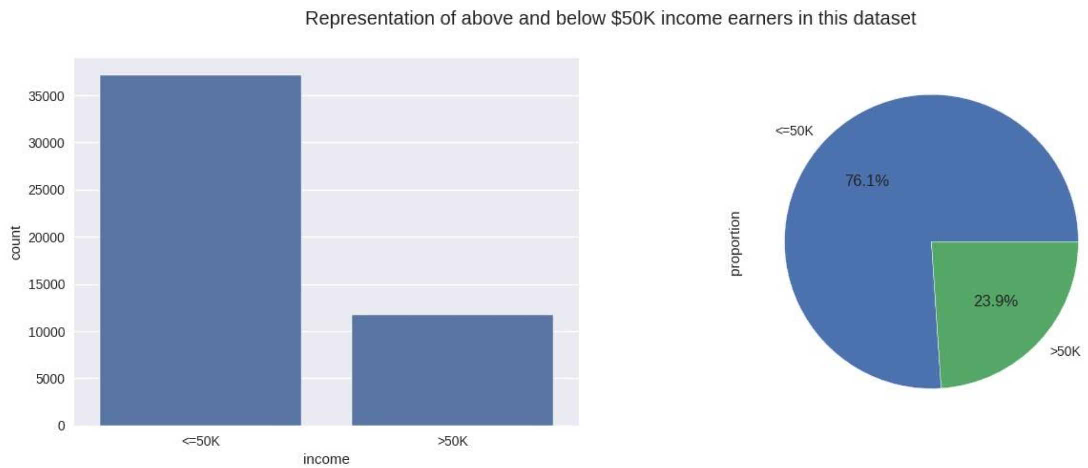
[ ]:
```
# Get a statistical summary of the dataset
print("Overall Statistics of the Dataset:")
print(data.describe())
```

```
Overall Statistics of the Dataset:
                age      fnlwgt hours-per-week
count 48790.000000            48790.000000
4.879000e+04
mean      38.652798 1.896690e+05    40.425886
std       13.708493 1.056172e+05    12.392729
min       17.000000 1.228500e+04     1.000000
25%       28.000000 1.175550e+05    40.000000
50%       37.000000 1.781385e+05    40.000000
75%       48.000000 2.376062e+05    45.000000
max       90.000000 1.490400e+06    99.000000
```

5 7. Univariate Analysis

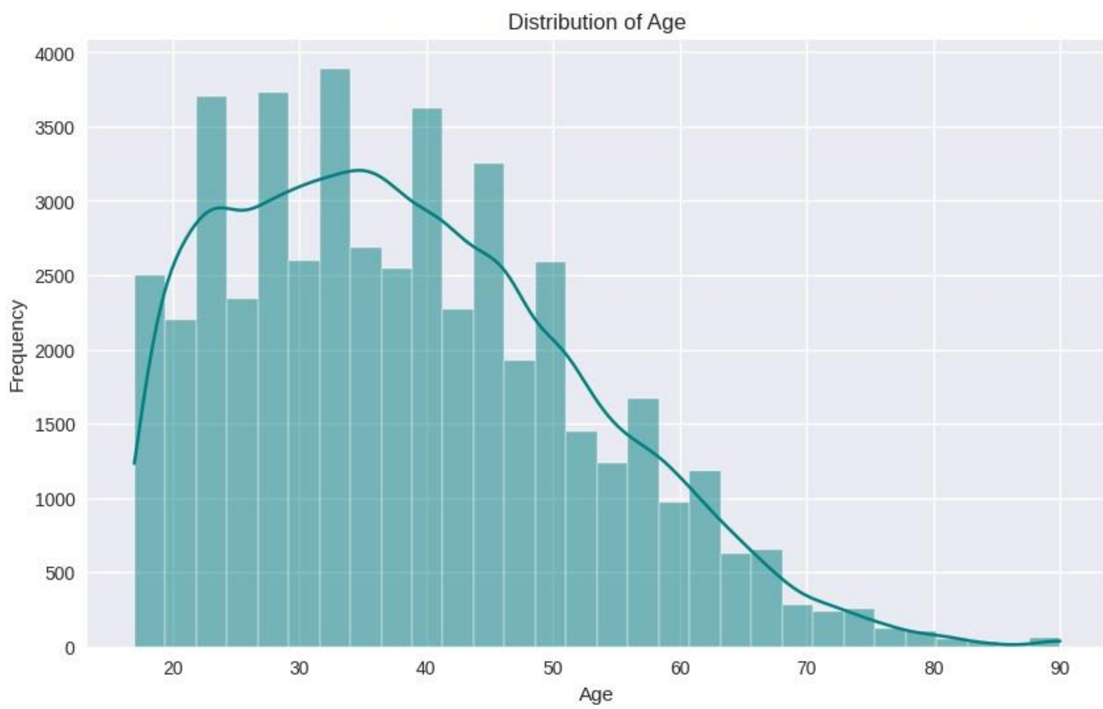
Income

[ ]:
```
_, axes = plt.subplots(1, 2, figsize=(15, 5))

sns.countplot(x='income', data=data, ax=axes[0])
data.income.value_counts(normalize=True).plot.pie(ax=axes[1], autopct='%1.1f%%')
plt.suptitle('Representation of above and below $50K income earners in this ␣
↪dataset');
```



Distribution of Age Column

[ ]:
```
# Plot age distribution
plt.figure(figsize=(10, 6))
sns.histplot(data['age'], kde=True, bins=30, color='teal')
plt.title("Distribution of Age")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



Find Total Number of Persons with Age Between 17 and 48

[ ]:
```
# Count persons between ages 17 and 48
age_between_17_48 = data[data['age'].between(17, 48)].shape[0]
print(f"Number of Persons Between Ages 17 and 48:
{age_between_17_48}")
```

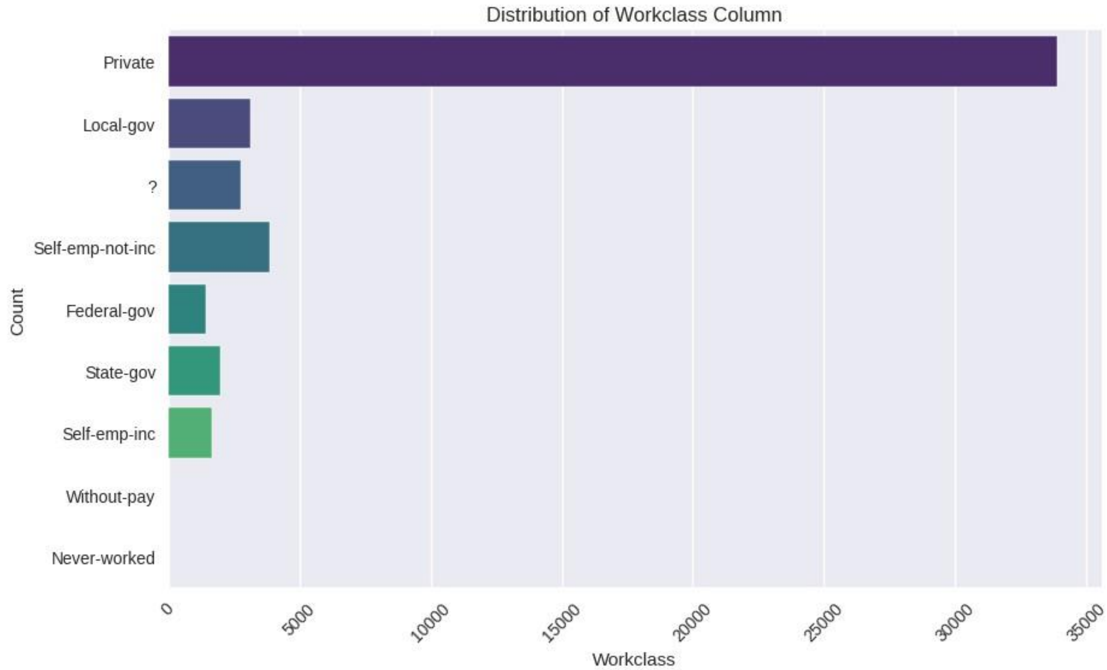
```
Number of Persons Between Ages 17 and 48: 37272
```

Distribution of Workclass Column

[ ]:
```
# Plot workclass distribution
plt.figure(figsize=(10, 6))
sns.countplot(data['workclass'], palette='viridis')
plt.title("Distribution of Workclass Column")
plt.xlabel("Workclass")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.show()
```

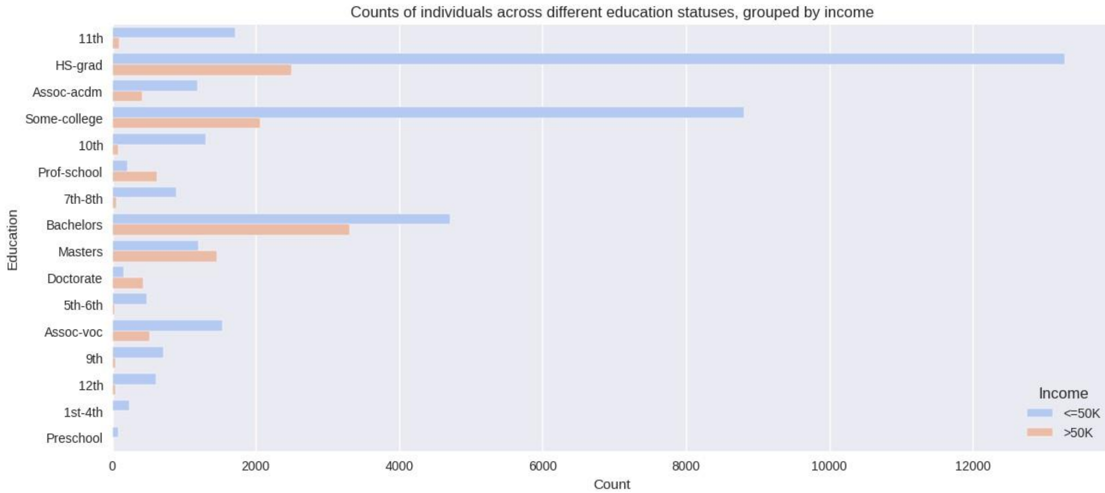
```
<ipython-input-14-bdd7693a1bca>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.
```

```
sns.countplot(data['workclass'], palette='viridis')
```



Higher Education Increase Income

[ ]:
```
# Assuming your DataFrame is named `data` and has 'education' and 'income' ␣
↪columns
plt.figure(figsize=(14, 6))

# Create a count plot with hue for income
sns.countplot(data=data, y='education', hue='income', palette='coolwarm')

# Set titles and labels
plt.title("Counts of individuals across different education statuses, grouped ␣
↪by income")
plt.xlabel("Count")
plt.ylabel("Education")

plt.legend(title="Income")
plt.show()
```

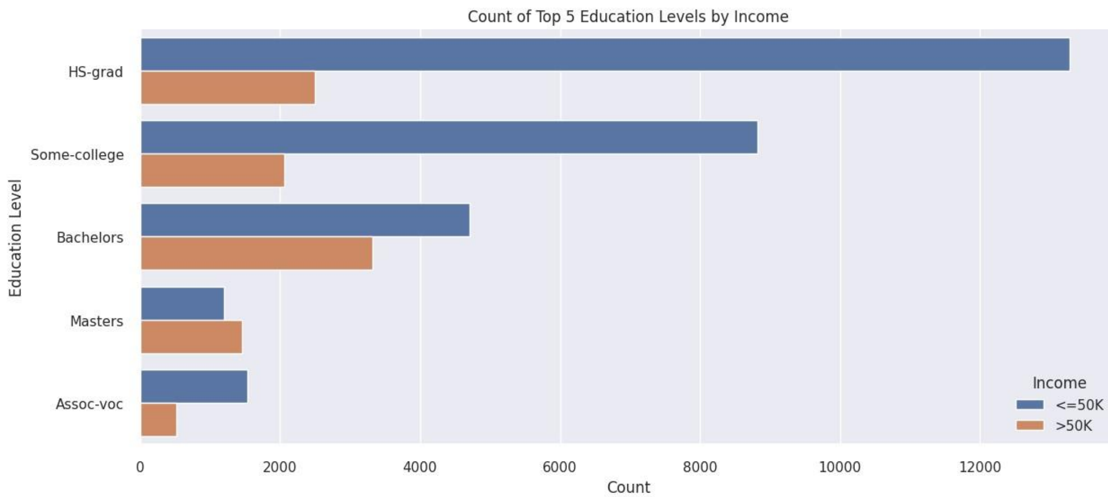


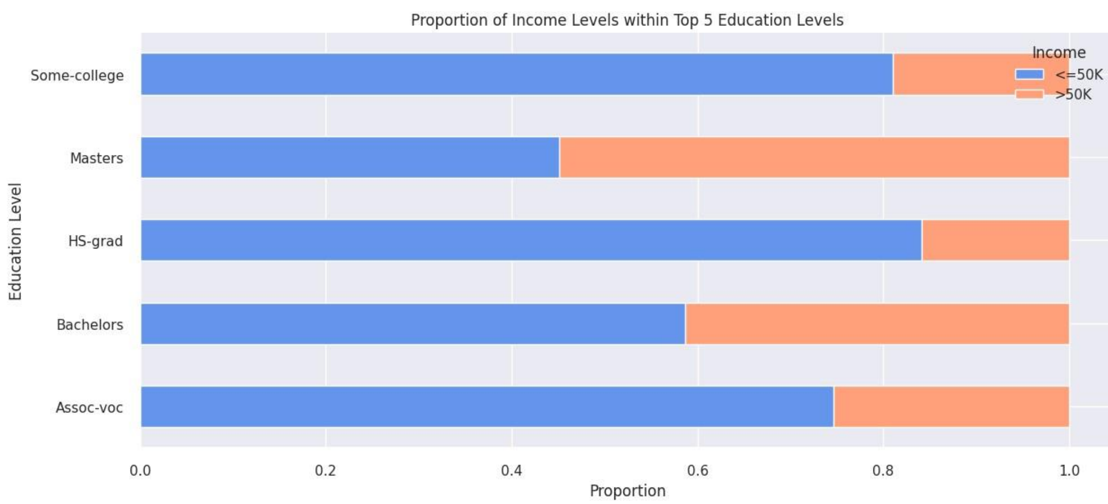
Top 5 top 5 education levels by count and income

```
[ ]: # Set the style
sns.set(style="darkgrid")

# Get the top 5 education levels by count
top_5_education_levels =
data['education'].value_counts().nlargest(5).index top_5_data =
data[data['education'].isin(top_5_education_levels)]

# Plot the count of individuals by top 5 education levels
and income plt.figure(figsize=(14, 6))
sns.countplot(data=top_5_data, y='education',
hue='income',␣
↪order=top_5_education_levels)
plt.title("Count of Top 5 Education Levels by
Income") plt.xlabel("Count")
plt.ylabel("Education Level")
plt.legend(title="Income") plt.show()

# Calculate the proportion of individuals in each of the top 5
education levels␣
↪who earn above/below $50K edu_income_proportion_top5 =
top_5_data.groupby('education')['income'].
↪value_counts(normalize=True).unstack()

# Plot the proportion for top 5 education levels
edu_income_proportion_top5.plot(kind='barh', stacked=True,
figsize=(14, 6),␣
```

```
↪color=["#6495ED", "#FFA07A"]) plt.title("Proportion of
Income Levels within Top 5 Education Levels")
plt.xlabel("Proportion") plt.ylabel("Education Level")
```

```
plt.legend(title="Income")
plt.show()
```



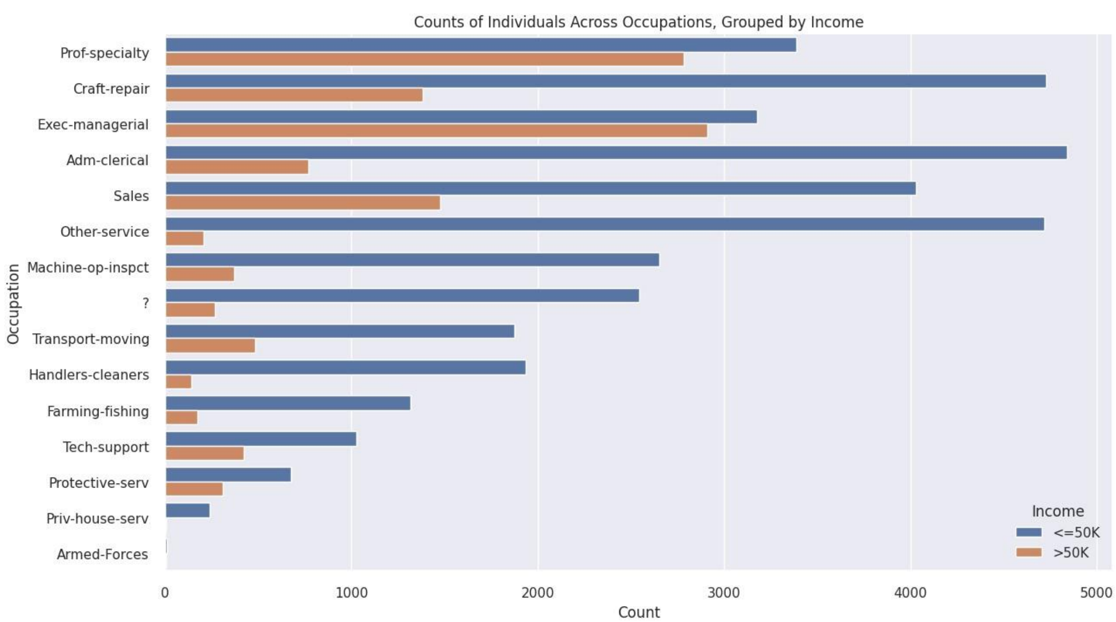


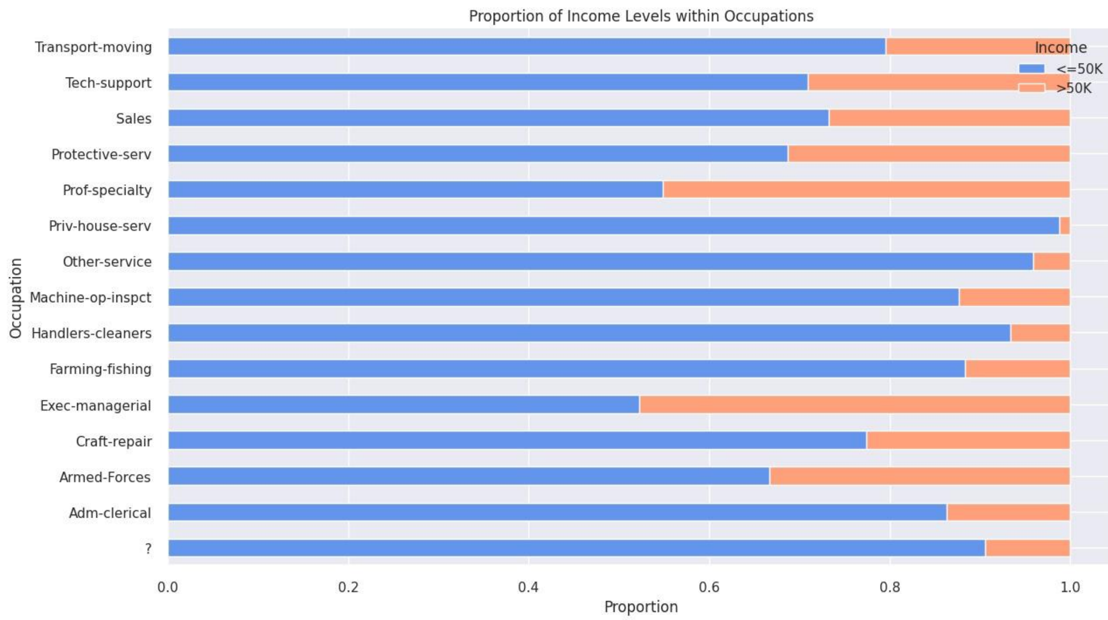
Income by Occupation

```
[ ]: # Set the style
sns.set(style="darkgrid")

# Plot the count of individuals by occupation and income
```

```
plt.figure(figsize=(14, 8)) sns.countplot(data=data, y='occupation',
hue='income', order=data['occupation'].
↪value_counts().index) plt.title("Counts of Individuals
Across Occupations, Grouped by Income")
```

```
plt.xlabel("Count")
plt.ylabel("Occupation")
plt.legend(title="Income")
plt.show()

# Calculate the proportion of individuals in each occupation who earn above/
↪below $50K
occupation_income_proportion = data.groupby('occupation')['income'].
↪value_counts(normalize=True).unstack()

# Plot the proportion for each occupation
occupation_income_proportion.plot(kind='barh', stacked=True, figsize=(14, 8),␣
↪color=["#6495ED", "#FFA07A"])
plt.title("Proportion of Income Levels within Occupations ")
plt.xlabel("Proportion")
plt.ylabel("Occupation")
plt.legend(title="Income")
plt.show()
```



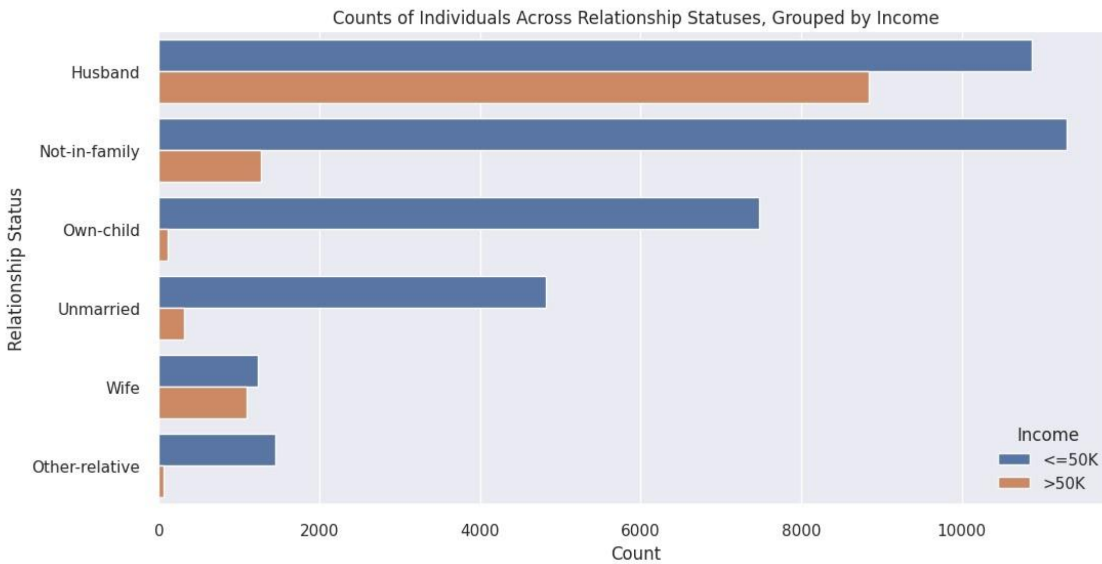


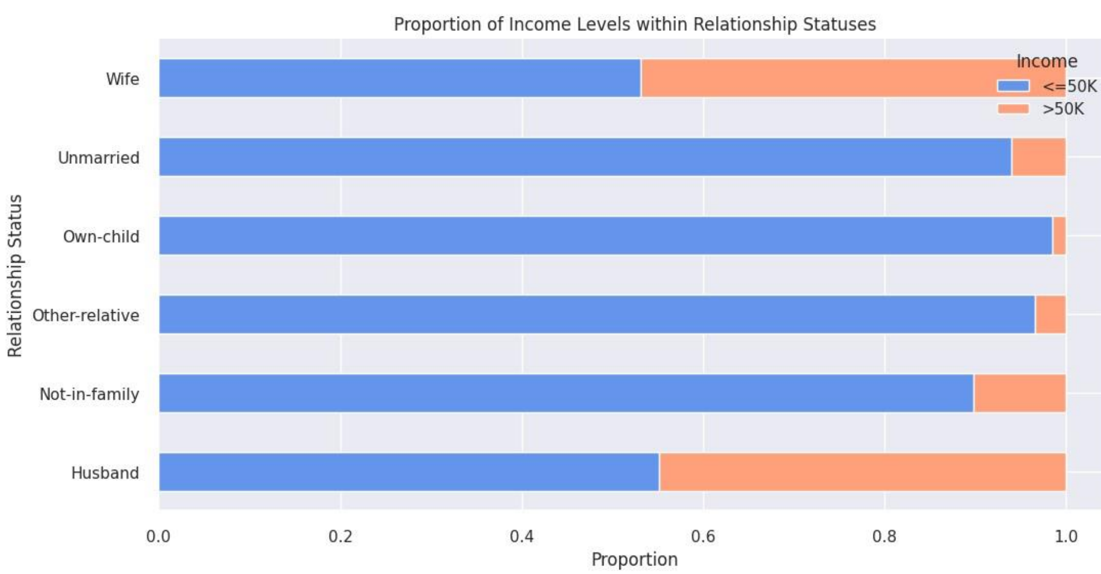
relationship status and income

```
[ ]: # Set the style
sns.set(style="darkgrid")

# Plot the count of individuals by relationship status and income
plt.figure(figsize=(12, 6))
sns.countplot(data=data, y='relationship', hue='income',␣
 ↪order=data['relationship'].value_counts().index)
plt.title("Counts of Individuals Across Relationship Statuses,
Grouped by␣
 ↪Income")
plt.xlabel("Count")
plt.ylabel("Relationship
Status")
plt.legend(title="Income")
plt.show()

# Calculate the proportion of individuals in each relationship status
who earn␣
 ↪above/below $50K relationship_income_proportion =
data.groupby('relationship')['income'].
↪value_counts(normalize=True).unstack()
```

```
# Plot the proportion for each relationship status
relationship_income_proportion.plot(kind='barh', stacked=True,
figsize=(12, 6),␣
 ↪color=["#6495ED", "#FFA07A"]) plt.title("Proportion of
Income Levels within Relationship Statuses")
plt.xlabel("Proportion") plt.ylabel("Relationship Status")
```

```
plt.legend(title="Income")
plt.show()
```

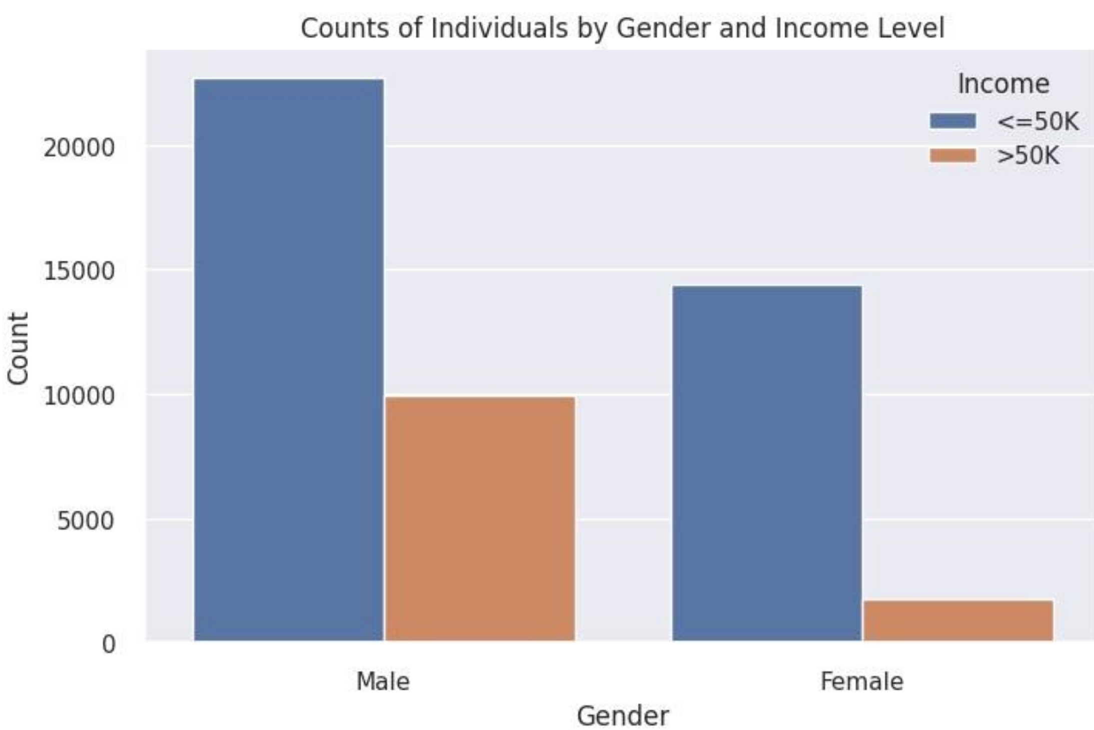


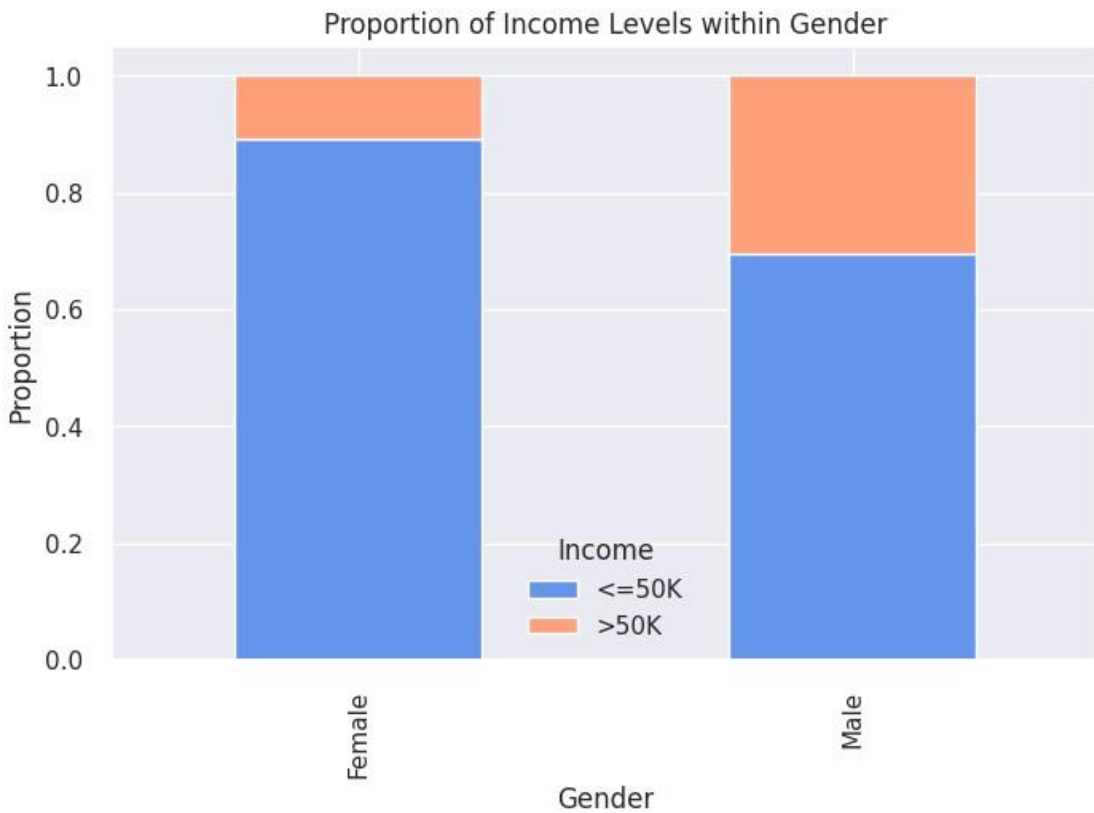


Income by Gender

```
[ ]: # Set the style
sns.set(style="darkgrid")

# Plot the count of individuals by gender and income
```

```
plt.figure(figsize=(8, 5))
sns.countplot(data=data, x='gender', hue='income', order=data['gender'].
 ↪value_counts().index)
plt.title("Counts of Individuals by Gender and Income Level ")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.legend(title="Income")
plt.show()

# Calculate the proportion of income levels within each gender
gender_income_proportion = data.groupby('gender')['income'].
 ↪value_counts(normalize=True).unstack()

# Plot the proportion for each gender
gender_income_proportion.plot(kind='bar', stacked=True, figsize=(8, 5),␣
 ↪color=["#6495ED", "#FFA07A"])
plt.title("Proportion of Income Levels within Gender ")
plt.xlabel("Gender")
plt.ylabel("Proportion")
plt.legend(title="Income")
plt.show()
```





Persons with Bachelors or Masters Degree

[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Filter the data for individuals with Bachelors or Masters degree
bachelors_masters_data = data[data['education'].isin(['Bachelors',
'Masters'])]

# Set the style
sns.set(style="darkgrid")

# Plot the count of individuals with Bachelors or Masters degree by
income plt.figure(figsize=(8, 5))
sns.countplot(data=bachelors_masters_data, x='education',
hue='income') plt.title("Income Levels for Individuals with
Bachelor's or Master's Degree") plt.xlabel("Education Level")
plt.ylabel("Count") plt.legend(title="Income") plt.show()
```

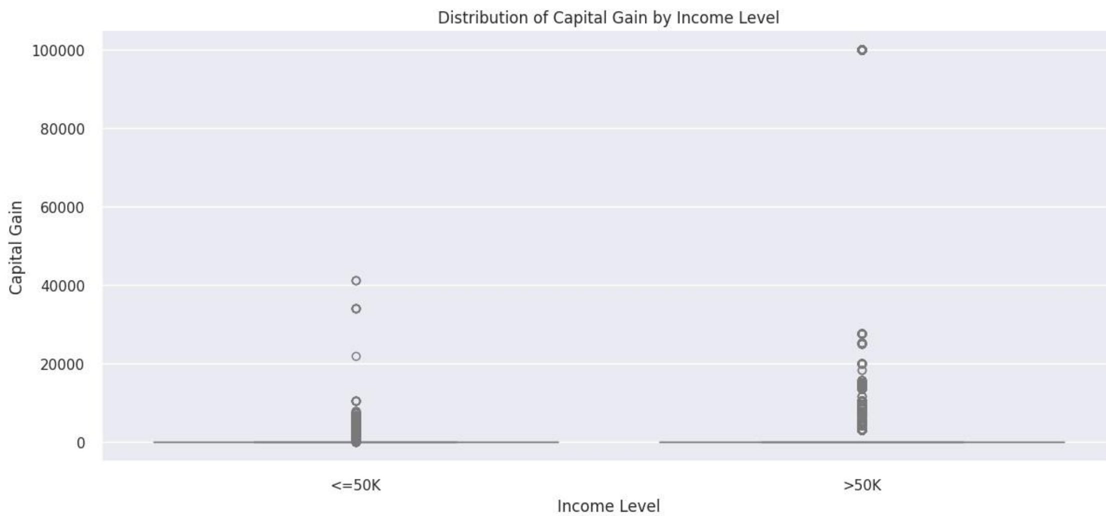
Capital Gain and Income Analysis

```
[ ]: # Set the style
sns.set(style="darkgrid")

# Plot the distribution of capital gain by income level
plt.figure(figsize=(14, 6)) sns.boxplot(data=data, x='income',
y='capital-gain', palette='coolwarm')
plt.title("Distribution of Capital Gain by Income Level")
plt.xlabel("Income Level")
plt.ylabel("Capital Gain")
plt.show()

# Calculate the mean capital gain by income level
mean_capital_gain = data.groupby('income')['capital-gain'].mean()
print("Mean Capital Gain by Income Level:")
print(mean_capital_gain)

# Plot the mean capital gain by income level
mean_capital_gain.plot(kind='bar', color=['#6495ED', '#FFA07A'])
plt.title("Mean Capital Gain by Income Level")
plt.xlabel("Income Level")
plt.ylabel("Mean Capital Gain")
```

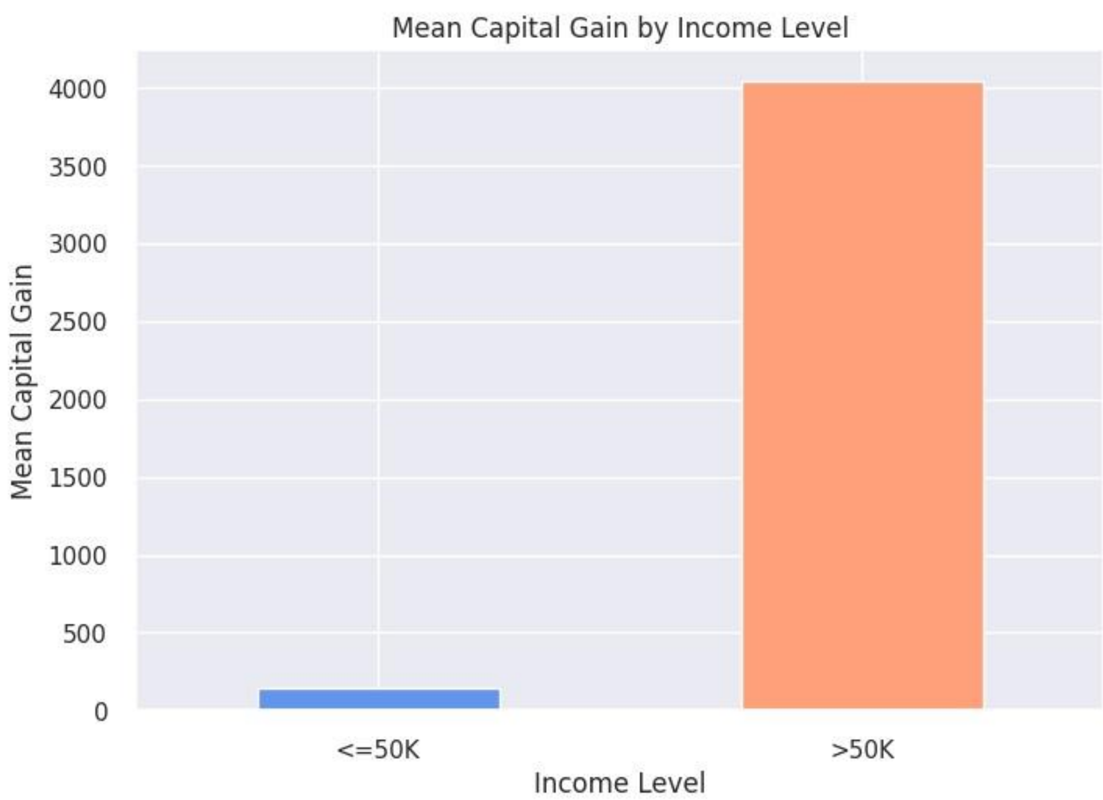
```
plt.xticks(rotation=0)
plt.show()
```

<ipython-input-35-9f9ef435ccab>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect. sns.boxplot(data=data, x='income', y='capital-gain', palette='coolwarm')




```
Mean Capital Gain by Income Level:
income
<=50K     147.010308
>50K     4042.239497
Name: capital-gain, dtype: float64
```



Capital Loss and Income Analysis

[ ]:
```
# Set the style
plt.figure(figsize=(14, 6))

# Plot the distribution of capital loss by income level
sns.boxplot(data=data, x='income', y='capital-loss',
palette='coolwarm')
plt.title("Distribution of Capital Loss by Income Level")
plt.xlabel("Income Level")
plt.ylabel("Capital Loss")
plt.show()

# Calculate the mean capital loss by income level
mean_capital_loss = data.groupby('income')['capital-loss'].mean()
print("Mean Capital Loss by Income Level:")
print(mean_capital_loss)

# Plot the mean capital loss by income level
mean_capital_loss.plot(kind='bar', color=['#6495ED', '#FFA07A'])
plt.title("Mean Capital Loss by Income Level")
```

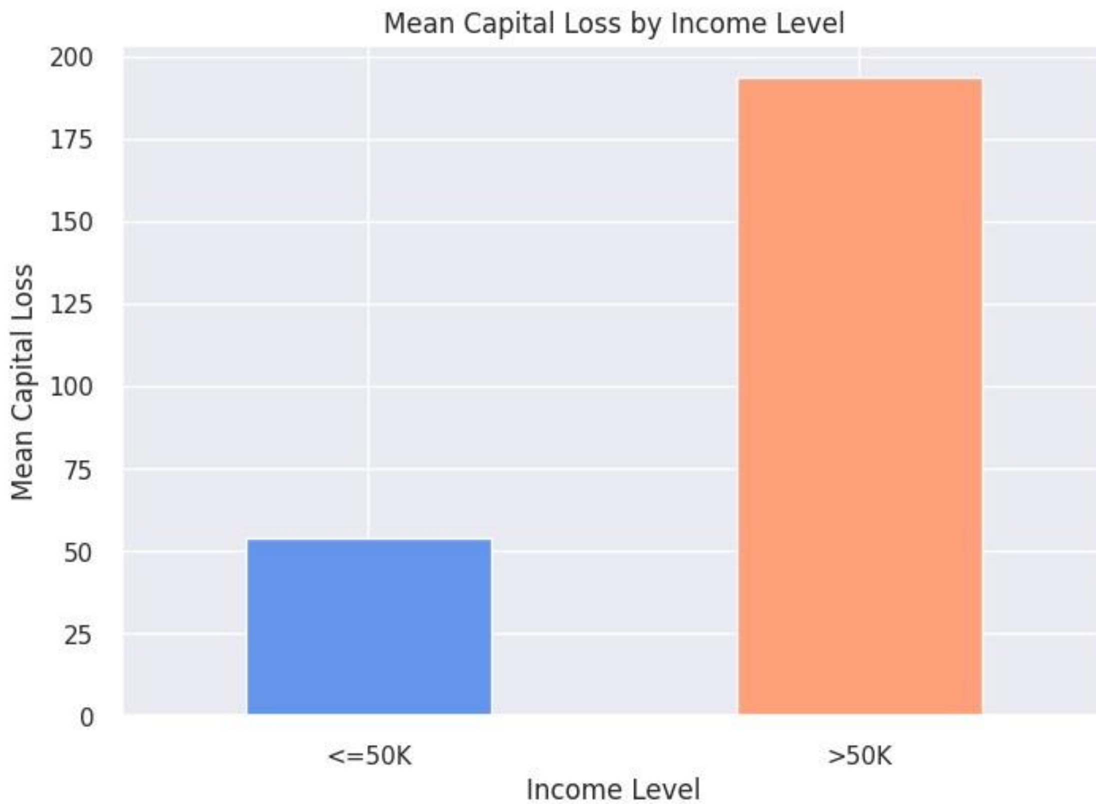
```
plt.xlabel("Income Level")
plt.ylabel("Mean Capital Loss")
```

```
plt.xticks(rotation=0)
plt.show()
```

```
<ipython-input-36-cee0e63c7276>:5: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect. sns.boxplot(data=data,
x='income', y='capital-loss', palette='coolwarm')
```


```
Mean Capital Loss by Income Level:
income
<=50K    54.151931
>50K    193.528964
Name: capital-loss, dtype: float64
```

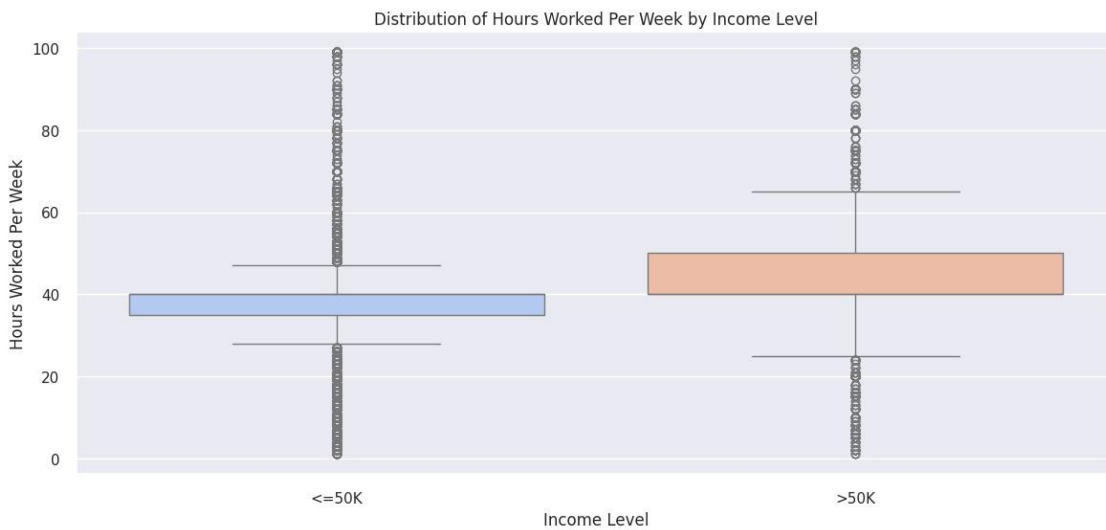


Hours Per Week and Income Analysis

```
[ ]: # Set the style
plt.figure(figsize=(14, 6))

# Plot the distribution of hours worked per week by income level
sns.boxplot(data=data, x='income', y='hours-per-week',
palette='coolwarm') plt.title("Distribution of Hours Worked Per
Week by Income Level") plt.xlabel("Income Level")
plt.ylabel("Hours Worked Per Week") plt.show()

# Calculate the mean hours worked per week by income level
mean_hours_per_week = data.groupby('income')['hours-per-
week'].mean()
print("Mean Hours Worked Per Week by Income Level:")
print(mean_hours_per_week)

# Plot the mean hours worked per week by income level
mean_hours_per_week.plot(kind='bar', color=['#6495ED',
'#FFA07A']) plt.title("Mean Hours Worked Per Week by
Income Level") plt.xlabel("Income Level")
```

```
plt.ylabel("Mean Hours Worked Per Week")
plt.xticks(rotation=0)
plt.show()
```

```
<ipython-input-37-3bf228be006b>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect. sns.boxplot(data=data,
x='income', y='hours-per-week', palette='coolwarm')
```




```
Mean Hours Worked Per Week by Income Level:
income
<=50K    38.840048
>50K     45.452896
Name: hours-per-week, dtype: float64
```


```
[ ]: sum(data['education'].isin(['Bachelors','Masters']))
```

```
[ ]: 10669
```

6 8. Bivariate Analysis

Replace Income Values with 0 and 1

```
[ ]: data.columns
```

```
[ ]: Index(['age', 'workclass', 'fnlwgt', 'education', 'marital-status',
  'occupation', 'relationship', 'race', 'gender', 'hours-per-week',
         'native-country', 'income'],
        dtype='object')
```

```
[ ]: data.head()
```

```
[ ]:   age workclass fnlwgt    education    marital-status \
    0   25  Private 226802   11th  Never-married
    1   38  Private    89814 HS-grad Married-civ-spouse
    2   28 Local-gov 336951 Assoc-acdm Married-civ-spouse
```

```
3   44  Private 160323 Some-college Married-civ-spouse
4   18  ? 103497 Some-college Never-married

        occupation relationship race gender hours-per-week \
 0 Machine-op-inspct  Own-child Black   Male            40
 1   Farming-fishing    Husband White   Male            50
 2   Protective-serv    Husband White   Male            40
 3 Machine-op-inspct    Husband Black   Male            40
 4                 ?    Own-child White Female          30
  native-country
income 0 United-
States <=50K
1  United-States <=50K
2  United-States   >50K
3  United-States   >50K
 4  United-States  <=50K
```

[ ]:
```
data = pd.read_csv('/content/drive/MyDrive/Data Analysis/Python Project/Adult␣
↪Income Analysis/adult.csv', skipinitialspace=True)
```

[ ]:
```
data.columns = data.columns.str.strip()
```

[ ]:
```
data['income'].unique()
```

[ ]:
```
array(['<=50K', '>50K'], dtype=object)
```

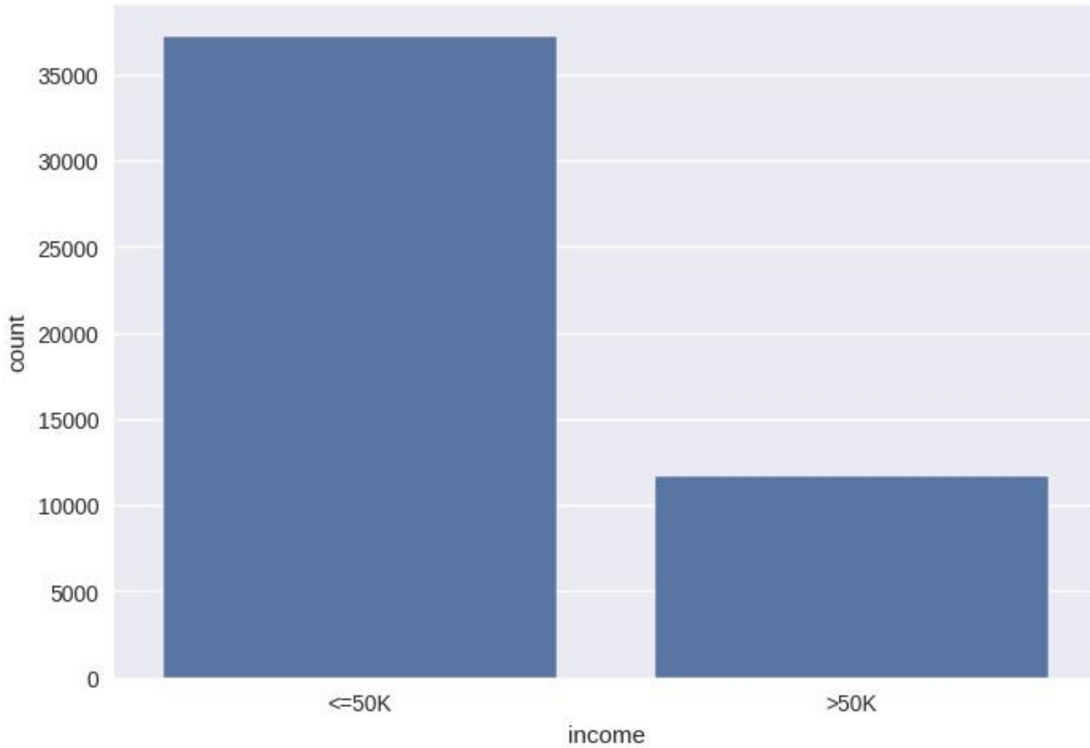
[ ]:
```
# lets find number of records for each category in this salary
column.
# for that we can use "value_counts" method of Pandas
```

[ ]:
```
data['income'].value_counts()
```

[ ]:
```
income
<=50K   37155
>50K    11687
Name: count, dtype: int64
```

[ ]:
```
sns.countplot(x='income',data = data)
```

[ ]:
```
<Axes: xlabel='income', ylabel='count'>
```




```
[ ]: def income_data(inc):
         if inc=='<=50K':
             return 0
         else:
             return 1
     data['enconded_salary'] = data['income'].apply(income_data)
     data.head(1)
```

```
[ ]:age workclass fnlwgt education educational-num marital-status \
    0   25   Private 226802     11th               7 Never-married

          occupation relationshiprace gender capital-gain capital-loss \
   0 Machine-op-inspct   Own-child Black   Male            0            0

     hours-per-week native-country income enconded_salary
    0             40 United-States <=50K                0
```

Display the updated unique values in the income column

Highest Salary by Workclass Gender Comparison for Higher Salary Probability Convert Workclass Column Data Type to Category

[ ]:
```
# Convert workclass to categorical data type
data['workclass'] =
data['workclass'].astype('category')
print("Updated Data Types:\n", data.dtypes)
```

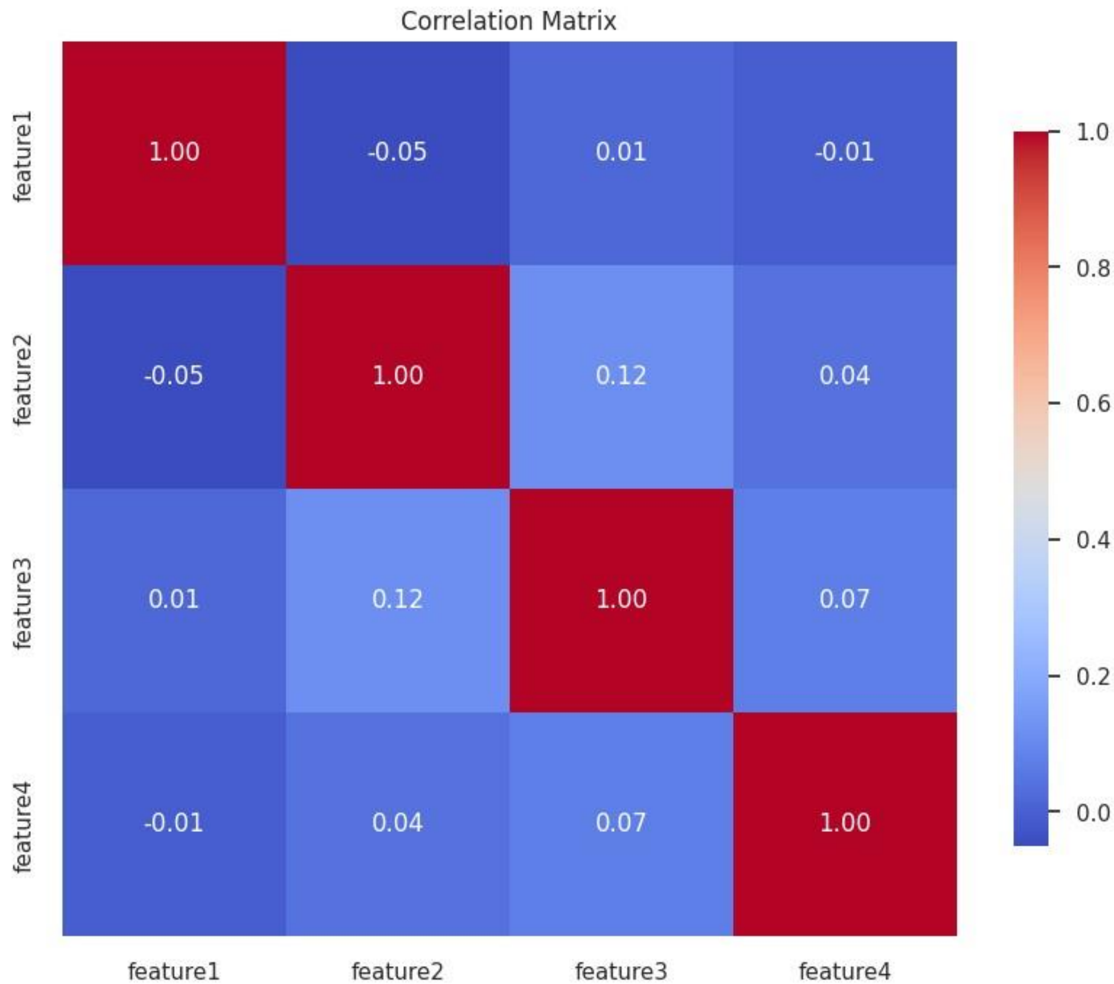
```
Updated Data Types:
 age                  int64
workclass         category
fnlwgt               int64
education           object
educational-num      int64
marital-status      object
occupation          object
relationship        object
race                object
gender              object
capital-gain         int64
capital-loss         int64
hours-per-week       int64
native-country      object
income              object
enconded_salary      int64
dtype: object
```

[ ]:
```
pip install pandas numpy seaborn matplotlib
```

```
Requirement already satisfied: pandas in
/usr/local/lib/python3.10/dist-packages (2.2.2)
Requirement already satisfied: numpy in
/usr/local/lib/python3.10/dist-packages (1.26.4)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/distpackages (0.13.2)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/distpackages (3.7.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/distpackages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.10/distpackages (from pandas) (2024.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/distpackages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
```

```
/usr/local/lib/python3.10/dist-packages (from matplotlib) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (24.1)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/distpackages (from matplotlib) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (3.2.0)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/distpackages (from python-
dateutil>=2.8.2->pandas) (1.16.0)
```

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Sample dataset creation (you can replace this with your own dataset)
data = {
    'feature1': np.random.rand(100),
    'feature2': np.random.rand(100),
    'feature3': np.random.rand(100),
    'feature4': np.random.rand(100)
}
df = pd.DataFrame(data)

# Calculate the correlation matrix
correlation_matrix = df.corr()

# Set up the matplotlib figure
plt.figure(figsize=(10, 8))

# Generate a heatmap
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm',␣
 ↪square=True, cbar_kws={"shrink": .8})

# Set the title
plt.title("Correlation Matrix")
plt.show()
```



6.1 7. Conclusion

The analysis of the Adult Income dataset reveals significant socio-economic patterns that influence income levels among adults. Key findings include:

- **Demographic Factors:** Age, education, and work class are strong indicators of income. Older individuals and those with higher education levels tend to earn more, highlighting the importance of education and experience in income potential.
- **Gender Disparity:** A noticeable gender disparity exists, with men being more likely to earn over 50K compared to women. This points to ongoing issues of inequality in the workforce.
- **Occupation Influence:** Certain occupations are consistently associated with higher earnings, suggesting that career choice plays a crucial role in income distribution.
- **Socio-Economic Insights:** The data provides valuable insights for policymakers, educators, and career counselors to address income inequality and support individuals in achieving higher income potential through targeted education and training programs.

Overall, this analysis serves as a foundation for further research into income distribution and socioeconomic factors, encouraging data-driven decision-making in various sectors.

Shaun Mia | LinkedIn