Technological Institute of the Philippines
Computer Engineering Department
Quezon city Campus

Midterm Skills Exam: Data Wrangling and Analysis

Course: CPE 311	Program: BSCpE
Course Title: Computational Thinking with Python	**Date Performed:** April 13 , 2024
Section: BSCPE22S3	**Date Submitted:** April 13, 2024
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Data Import

```
pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.6-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.6
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from ucimlrepo import fetch_ucirepo
```

```
census_income = fetch_ucirepo(id=20)
```

```
X = census_income.data.features
y = census_income.data.targets
```

Initial Exploration

```
X.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week
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

Handlers-

Next steps: View recommended plots

```
1 y.head()
```

	income
0	<=50K
1	<=50K
2	<=50K
3	<=50K
4	<=50K

Next steps: View recommended plots

Data Concatenation

```
1 df = pd.concat([X, pd.DataFrame(y, columns=['income'])], axis=1)
```

```
1 print("Data Imported. Shape of DataFrame:", df.shape)
```

```
Data Imported. Shape of DataFrame: (48842, 15)
```

```
1 # Save DataFrame to CSV file
2 df.to_csv('Census.csv', index=False)
```

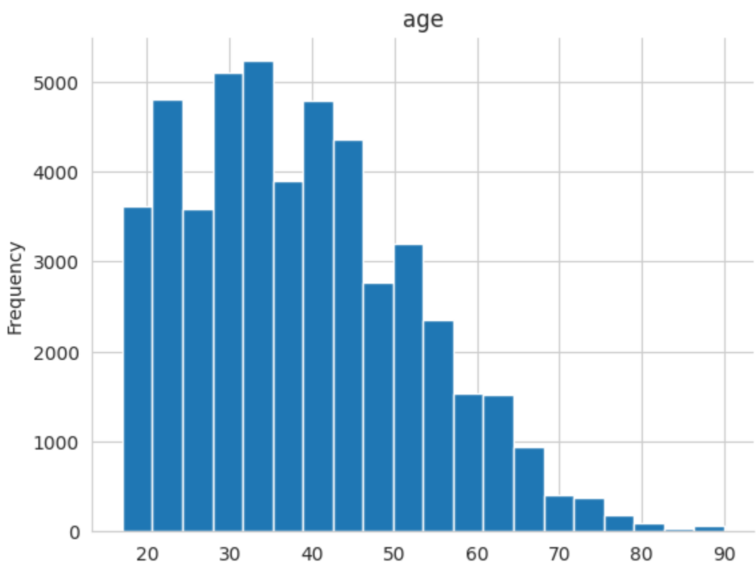
```
1 df.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week
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

Next steps: View recommended plots

age

Show code



Summary of the repondents age.

Check or missing values

```
# Check for missing values
missing_values = df.isnull().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 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
```

```
# Fill missing values
df.fillna(method='ffill', inplace=True)  # Forward fill missing values
```

```
#Recheck for missing values
missing_values = df.isnull().sum()
print("Missing Values:\n", missing_values)
```

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

Check for Outliers

```
df.income.replace({'<=50K.': '<=50K','>50K.' : '>50K'},  inplace = True)
df.income.unique()
```

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

Check for duplicate values

```
# Checking for duplicate values
duplicates = df.duplicated().sum()
print("\nNumber of Duplicate Rows:", duplicates)
```

```
Number of Duplicate Rows: 20
```

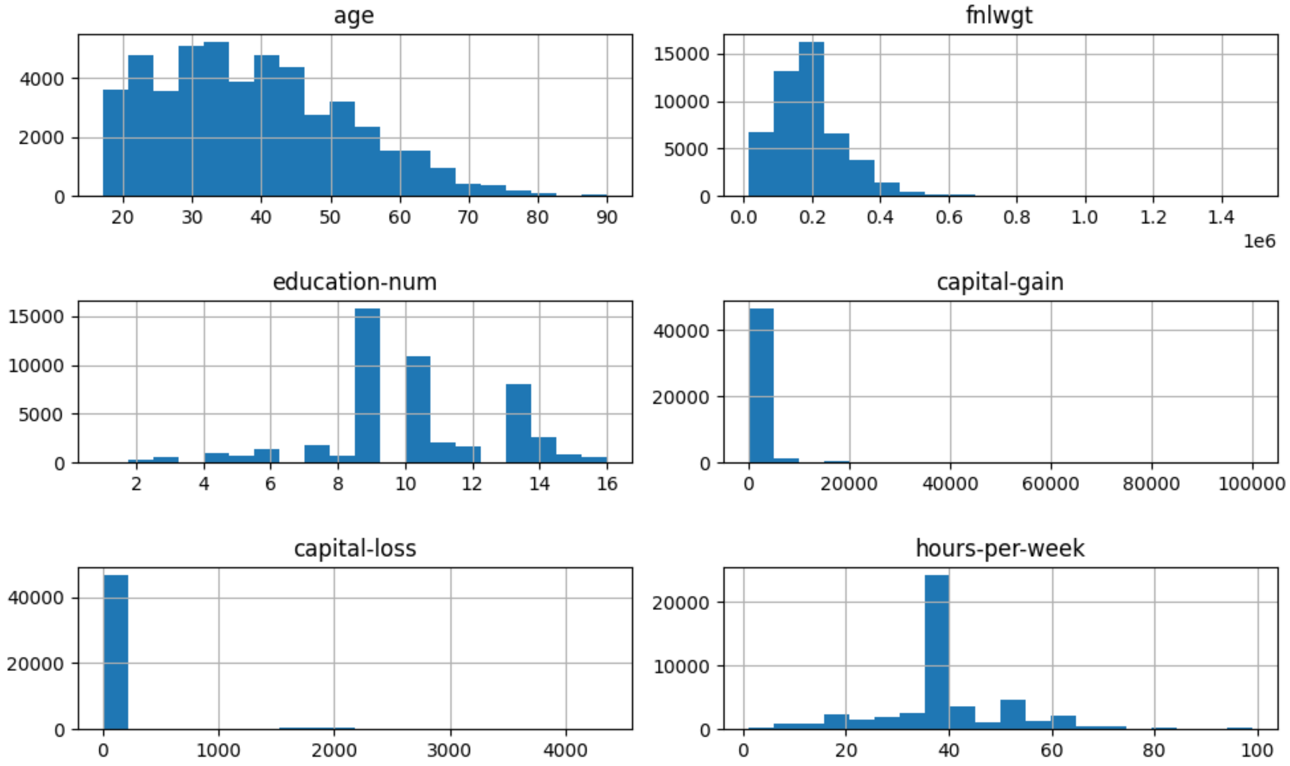
```
# Drop duplicate rows
df.drop_duplicates(inplace=True)
```

```
#Rechecking for duplicate values
duplicates = df.duplicated().sum()
print("\nNumber of Duplicate Rows:", duplicates)
```

```
Number of Duplicate Rows: 0
```

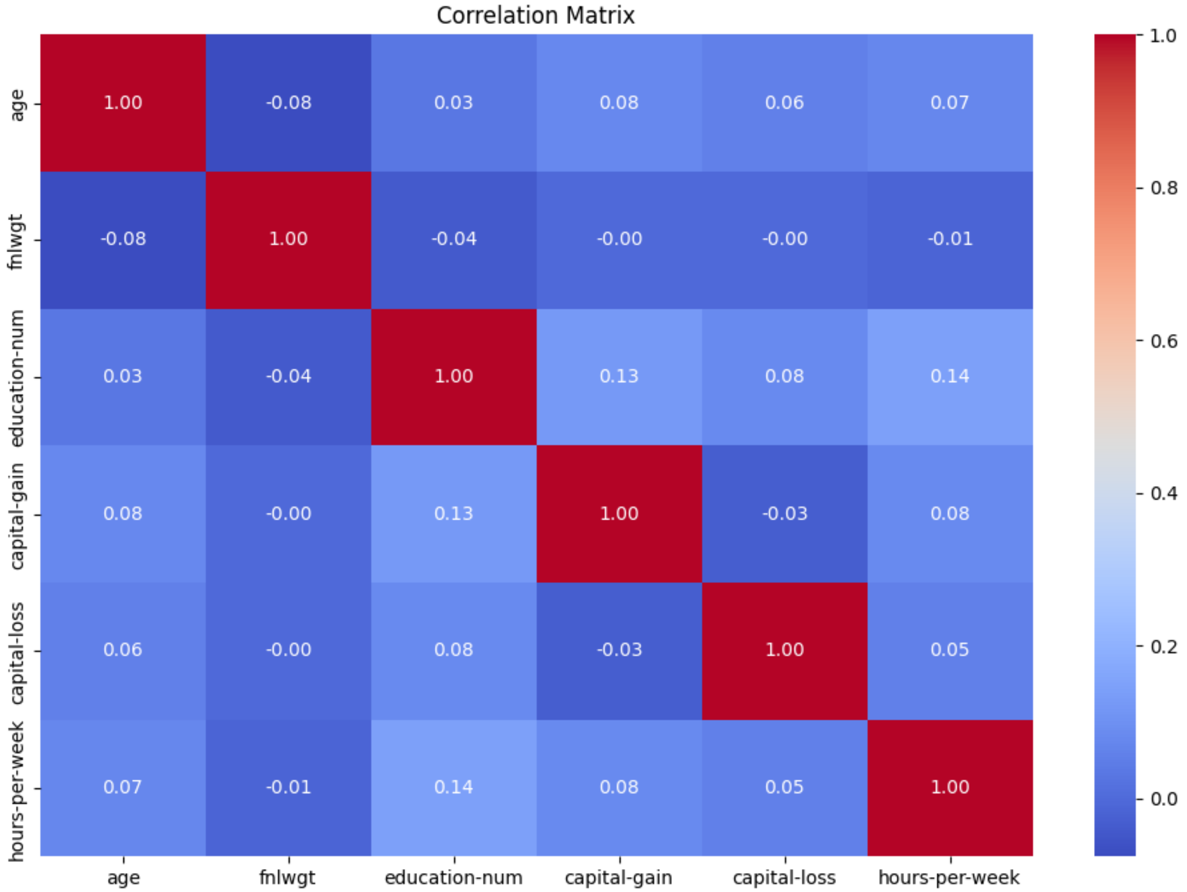
Initial Plot

```
import matplotlib.pyplot as plt

df.hist(bins=20, figsize=(10, 6))
plt.tight_layout()
plt.show()
```



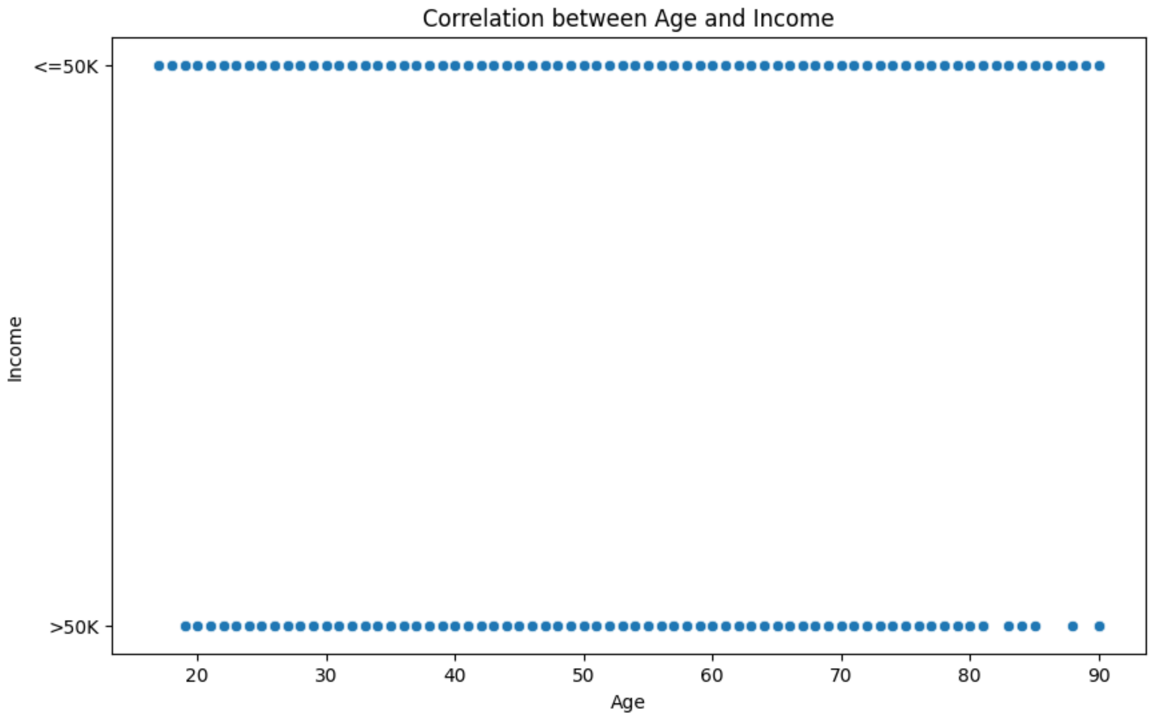
Correlation Matrix

```
# Correlation matrix (excluding non-numeric columns)
correlation_matrix = df.select_dtypes(include=np.number).corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



Data Correlation/Comparions Plotting

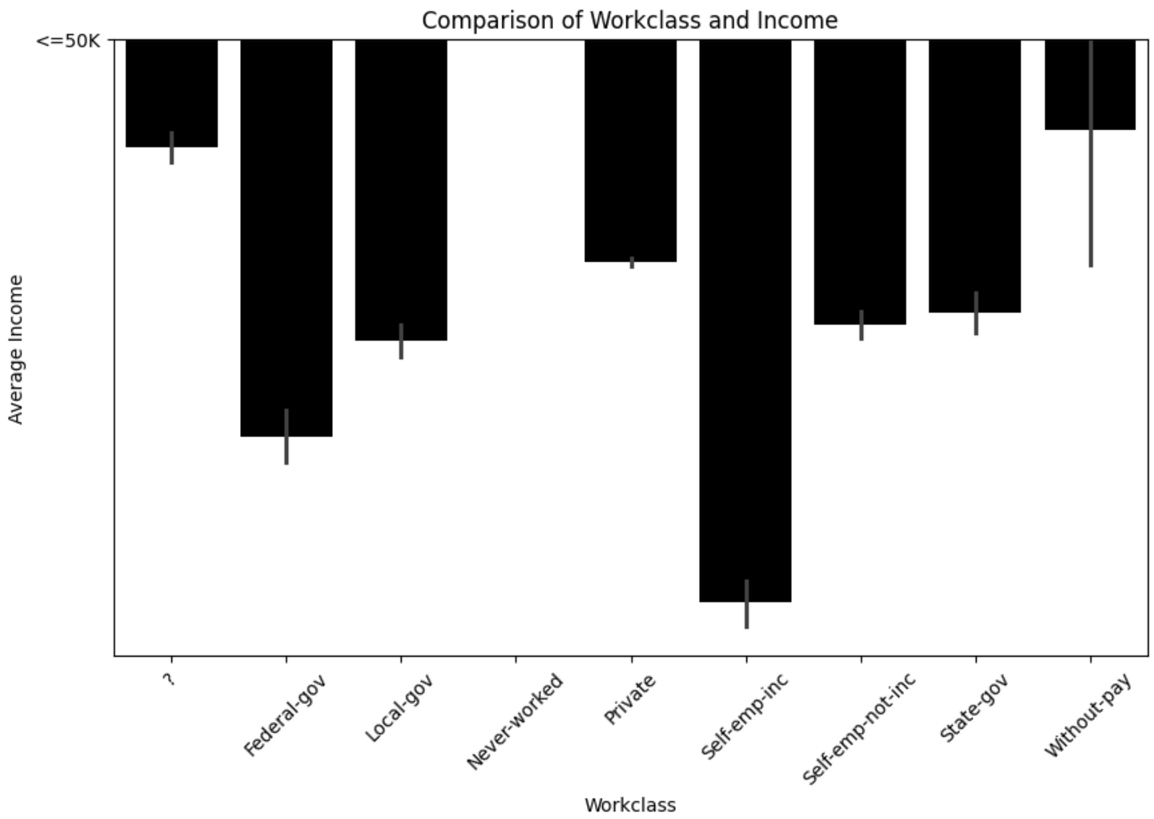
```
plt.figure(figsize=(10, 6))

sns.scatterplot(x='age', y='income', data=df)
plt.title('Correlation between Age and Income')
plt.xlabel('Age')
plt.ylabel('Income')
plt.show()
```



Correlation between Age and Income:

Description: This comparison explores how age correlates with income levels. It can reveal whether there is a trend of increasing or decreasing income with age, which is important for understanding age-related income dynamics, workforce participation, and retirement planning.

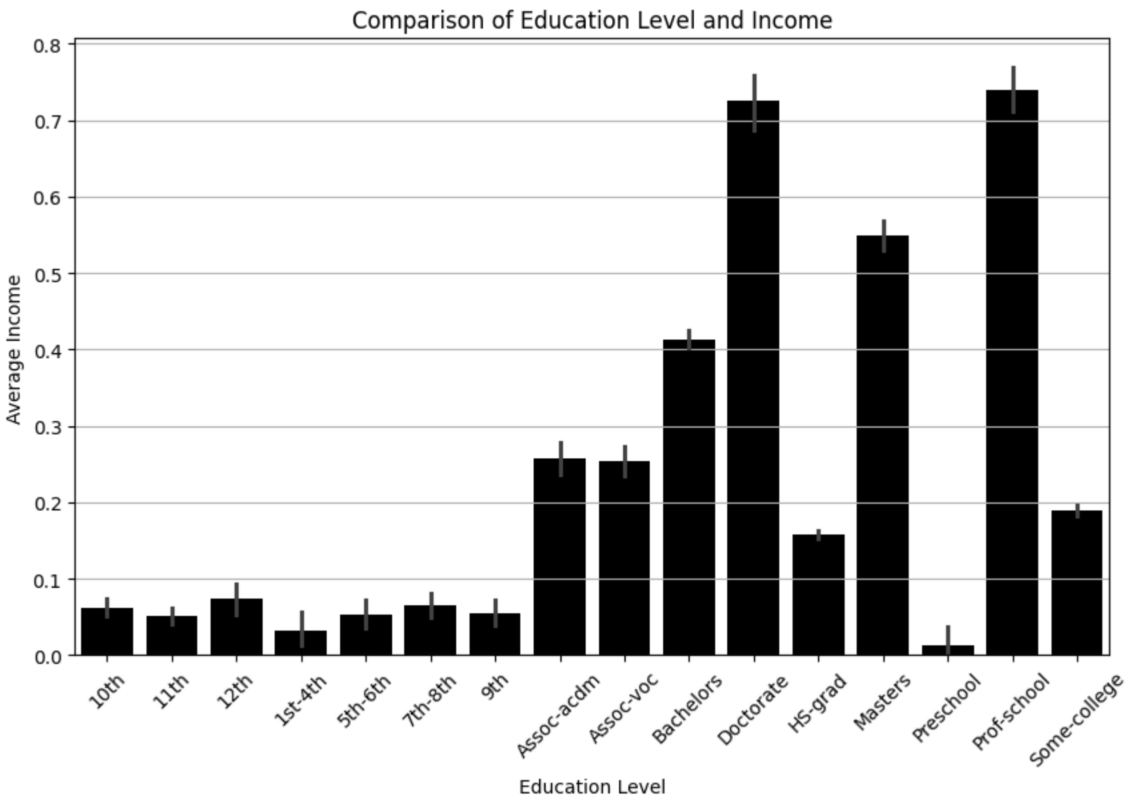
```
plt.figure(figsize=(10, 6))

sns.barplot(x='workclass', y='income', data=df, order=df['workclass'].value_counts().index.sort_values(), color='black')
plt.title('Comparison of Workclass and Income')
plt.xlabel('Workclass')
plt.ylabel('Average Income')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()

```



Comparison of Workclass and Income

Description: between workclass categories and income levels. It helps to understand how different types of employment, such as private sector, government, or self-employment, influence income.

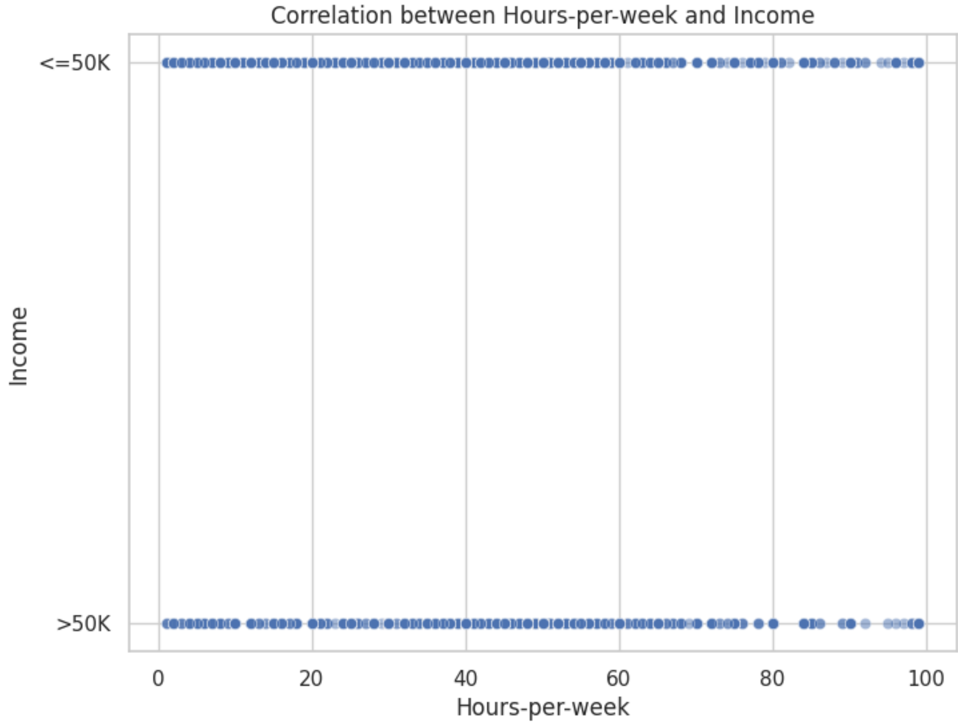
```
df['income_numeric'] = df['income'].map({'<=50K': 0, '>50K': 1})

plt.figure(figsize=(10, 6))

sns.barplot(x='education', y='income_numeric', data=df, order=df['education'].value_counts().index.sort_values(), color='black')
plt.title('Comparison of Education Level and Income')
plt.xlabel('Education Level')
plt.ylabel('Average Income')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



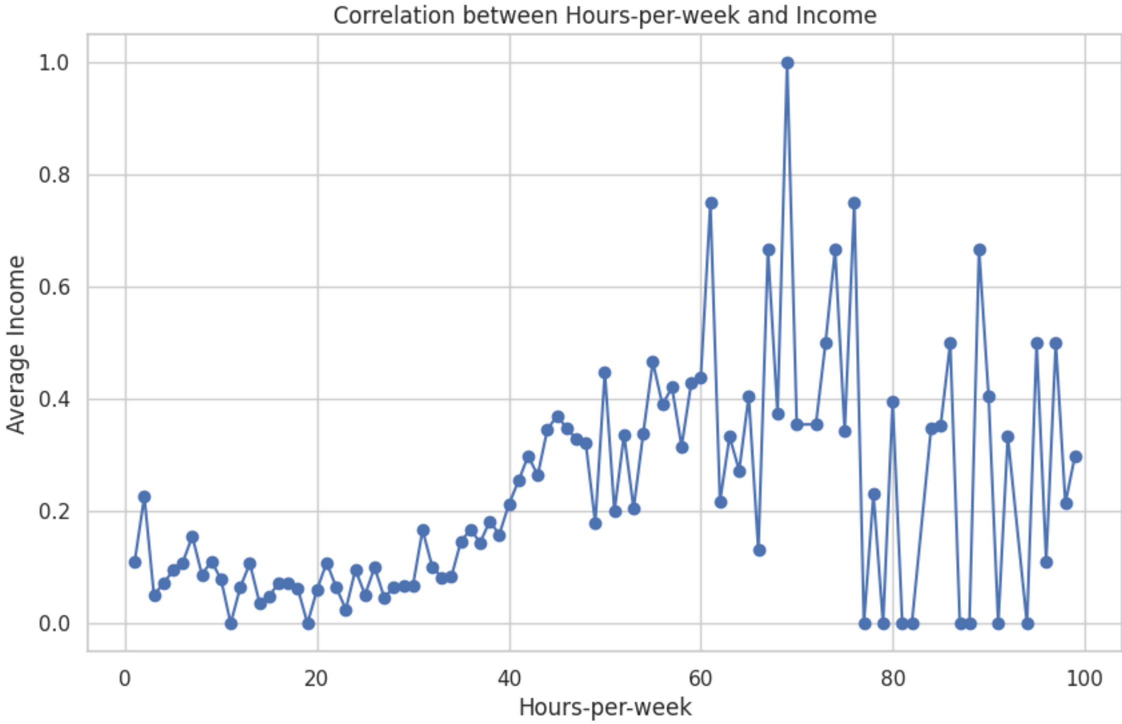
Comparison of Education Level and Income:

Description: This comparison helps to understand the relationship between education level and income. It can reveal whether higher education attainment generally leads to higher income levels, which has implications for policy-making, career choices, and socioeconomic mobility.

```
sns.set_theme(style="whitegrid")

plt.figure(figsize=(8, 6))
sns.scatterplot(x=df['hours-per-week'], y=df['income'], alpha=0.5)
plt.title('Correlation between Hours-per-week and Income')
plt.xlabel('Hours-per-week')
plt.ylabel('Income')
plt.grid(True)
plt.show()
```



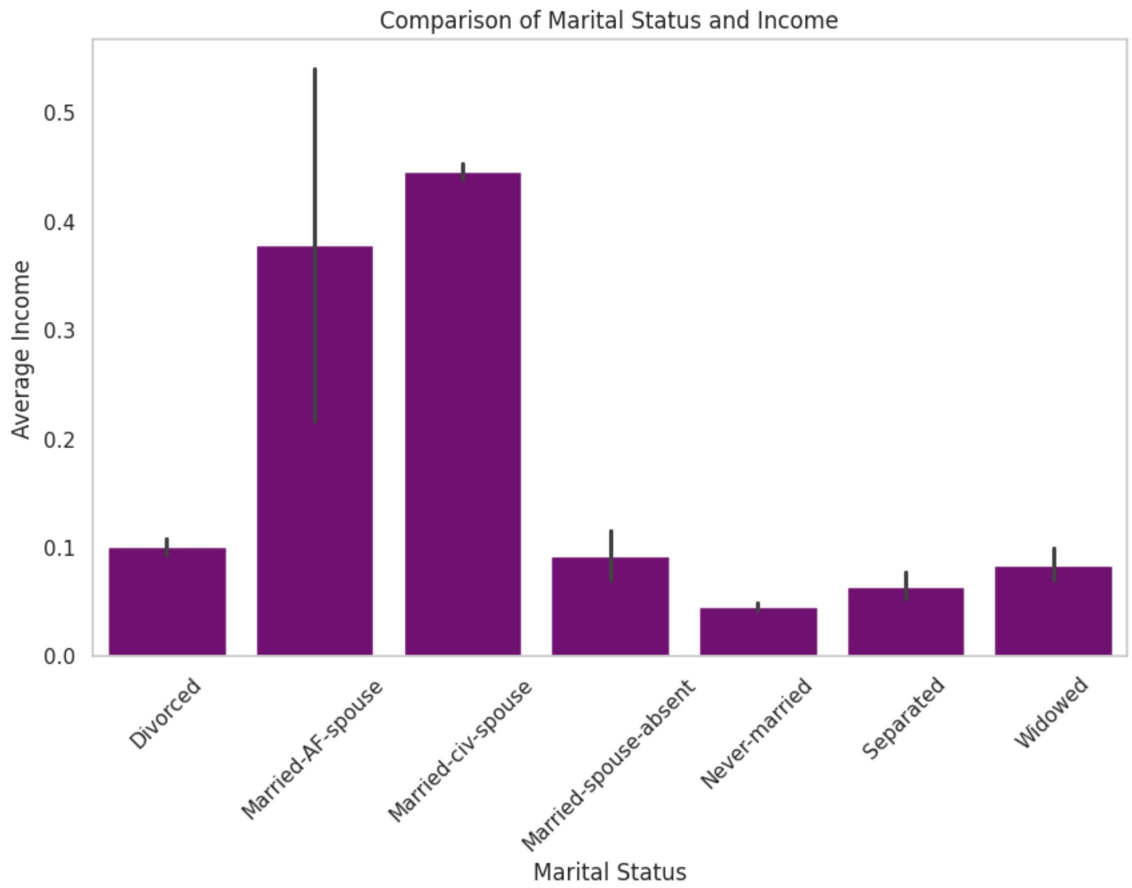

```
plt.figure(figsize=(10, 6))
plt.plot(df.groupby('hours-per-week')['income_numeric'].mean(), marker='o', linestyle='-')
plt.title('Correlation between Hours-per-week and Income')
plt.xlabel('Hours-per-week')
plt.ylabel('Average Income')
plt.grid(True)
plt.show()
```



Correlation between Hours-per-week and Income:

Description: This comparison examines how the number of hours worked per week correlates with income levels. It helps to understand whether working longer hours is associated with higher income and provides insights into labor market dynamics and wage structures.

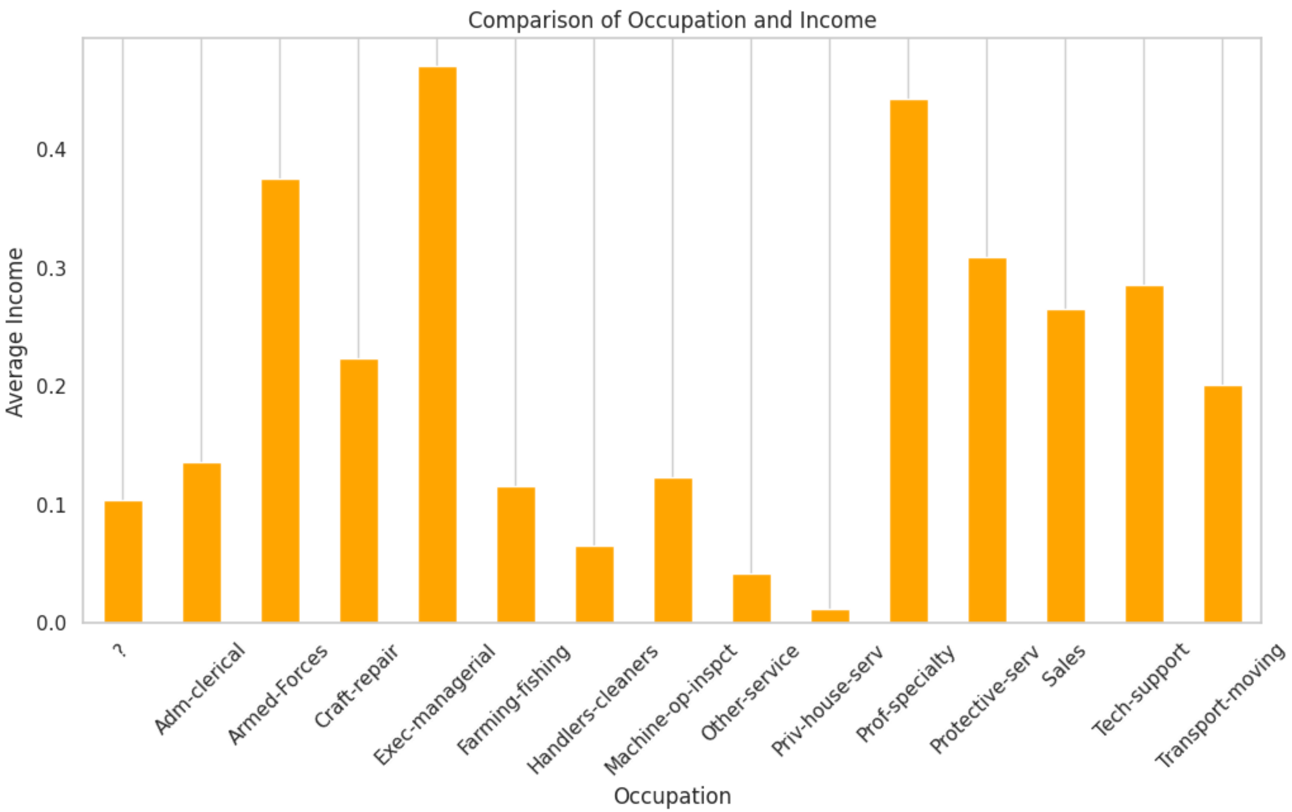
```
df['marital_numeric'] = df['marital-status'].map({'Married-civ-spouse': 1, 'Never-married': 0})

sns.set_theme(style="whitegrid")

plt.figure(figsize=(10, 6))
sns.barplot(x='marital-status', y='income_numeric', data=df, order=df['marital-status'].value_counts().index.sort_values(), color='purple')
plt.title('Comparison of Marital Status and Income')
plt.xlabel('Marital Status')
plt.ylabel('Average Income')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



Comparison of Marital Status and Income:

Description: This comparison explores how marital status correlates with income levels. It can shed light on whether married individuals tend to have higher incomes compared to unmarried individuals, and it may highlight potential socioeconomic factors influencing income disparities between marital statuses.

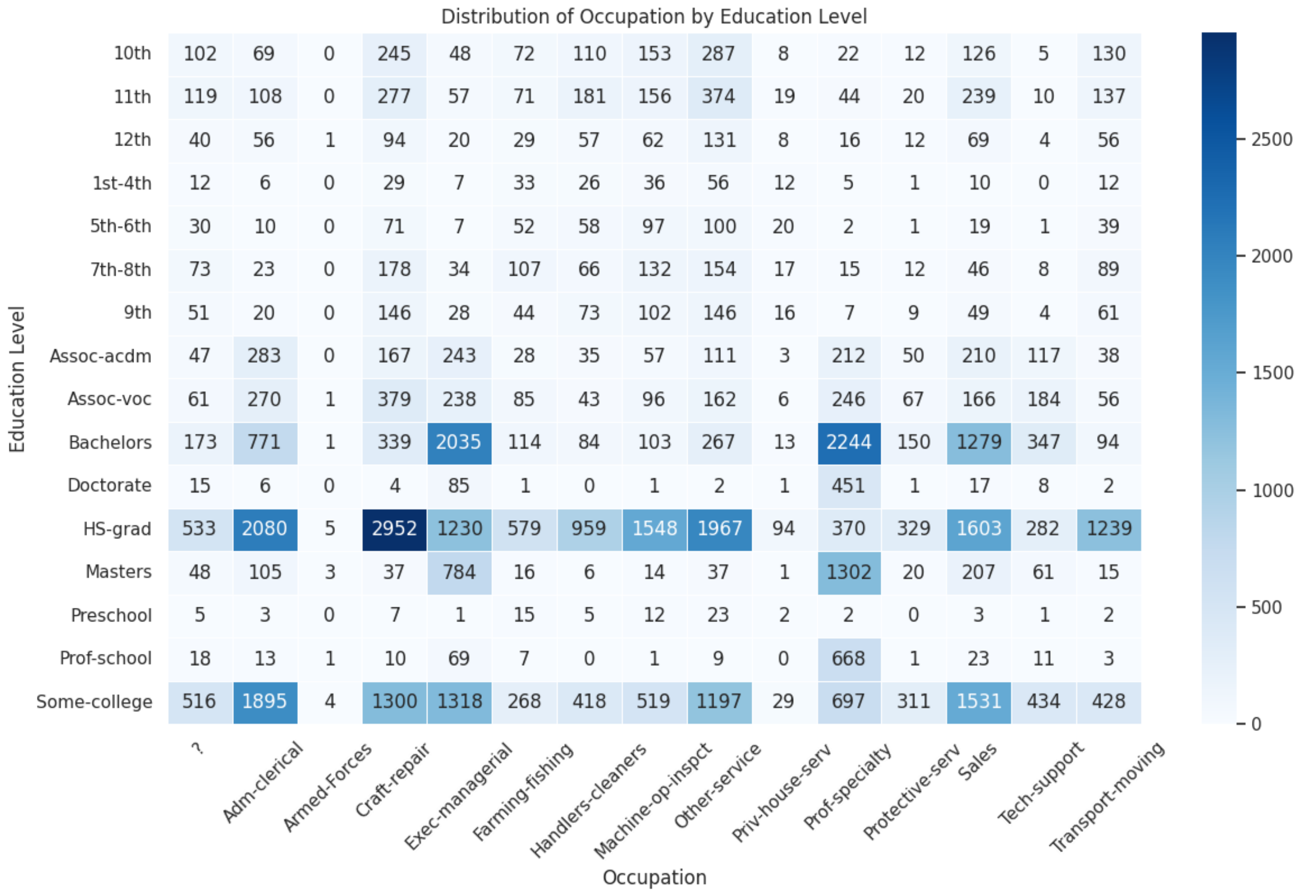
```
df['occupation_numeric'] = df['occupation'].map({'Prof-specialty': 1, 'Craft-repair': 2, 'Exec-managerial': 3,
                                                 'Adm-clerical': 4, 'Sales': 5, 'Other-service': 6,
                                                 'Machine-op-inspct': 7, 'Transport-moving': 8, 'Handlers-cleaners': 9,
                                                 'Farming-fishing': 10, 'Tech-support': 11, 'Protective-serv': 12,
                                                 'Priv-house-serv': 13, 'Armed-Forces': 14})

plt.figure(figsize=(12, 6))
occupation_order = df['occupation'].value_counts().index.sort_values()
occupation_counts = df.groupby('occupation')['income_numeric'].mean().loc[occupation_order]
occupation_counts.plot(kind='bar', color='orange')
plt.title('Comparison of Occupation and Income')
plt.xlabel('Occupation')
plt.ylabel('Average Income')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



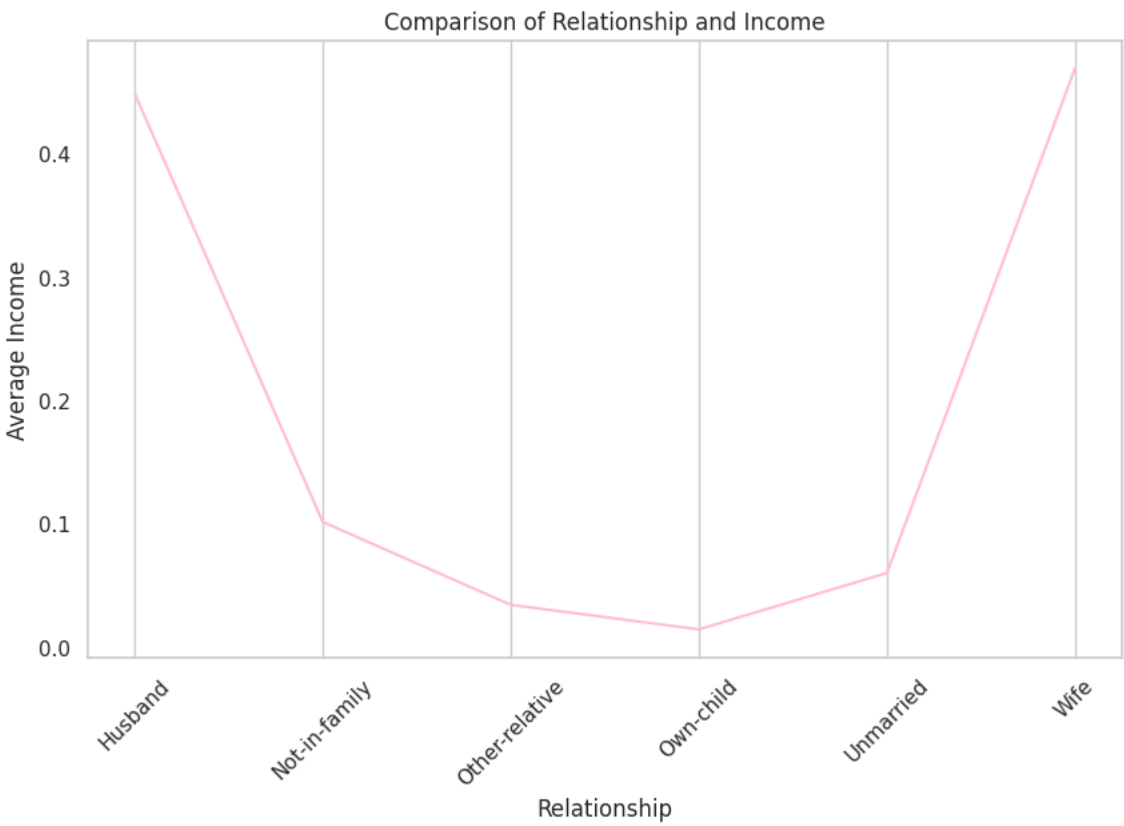
Comparison of Occupation and Income:

Description: This comparison examines the income disparities across various occupations. It helps to identify occupations that typically offer higher salaries and those that may have lower income levels. Understanding these income differences can inform career choices, workforce development strategies, and policies aimed at reducing income inequality.

```
occupation_education_pivot = df.pivot_table(index='education', columns='occupation', aggfunc='size', fill_value=0)

plt.figure(figsize=(14, 8))
sns.heatmap(occupation_education_pivot, cmap='Blues', annot=True, fmt='g', linewidths=.5)
plt.title('Distribution of Occupation by Education Level')
plt.xlabel('Occupation')
plt.ylabel('Education Level')
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.show()
```


Distribution of Occupation by Education Level
Education Level
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
10th 102 69 0 245 48 72 110 153 287 8 22 12 126 5 130
11th 119 108 0 277 57 71 181 156 374 19 44 20 239 10 137
12th 40 56 1 94 20 29 57 62 131 8 16 12 69 4 56
1st-4th 12 6 0 29 7 33 26 36 56 12 5 1 10 0 12
5th-6th 30 10 0 71 7 52 58 97 100 20 2 1 19 1 39
7th-8th 73 23 0 178 34 107 66 132 154 17 15 12 46 8 89
9th 51 20 0 146 28 44 73 102 146 16 7 9 49 4 61
Assoc-acdm 47 283 0 167 243 28 35 57 111 3 212 50 210 117 38
Assoc-voc 61 270 1 379 238 85 43 96 162 6 246 67 166 184 56
Bachelors 173 771 1 339 2035 114 84 103 267 13 2244 150 1279 347 94
Doctorate 15 6 0 4 85 1 0 1 2 1 451 1 17 8 2
HS-grad 533 2080 5 2952 1230 579 959 1548 1967 94 370 329 1603 282 1239
Masters 48 105 3 37 784 16 6 14 37 1 1302 20 207 61 15
Preschool 5 3 0 7 1 15 5 12 23 2 2 0 3 1 2
Prof-school 18 13 1 10 69 7 0 1 9 0 668 1 23 11 3
Some-college 516 1895 4 1300 1318 268 418 519 1197 29 697 311 1531 434 428
2500
2000
1500
1000
500
0

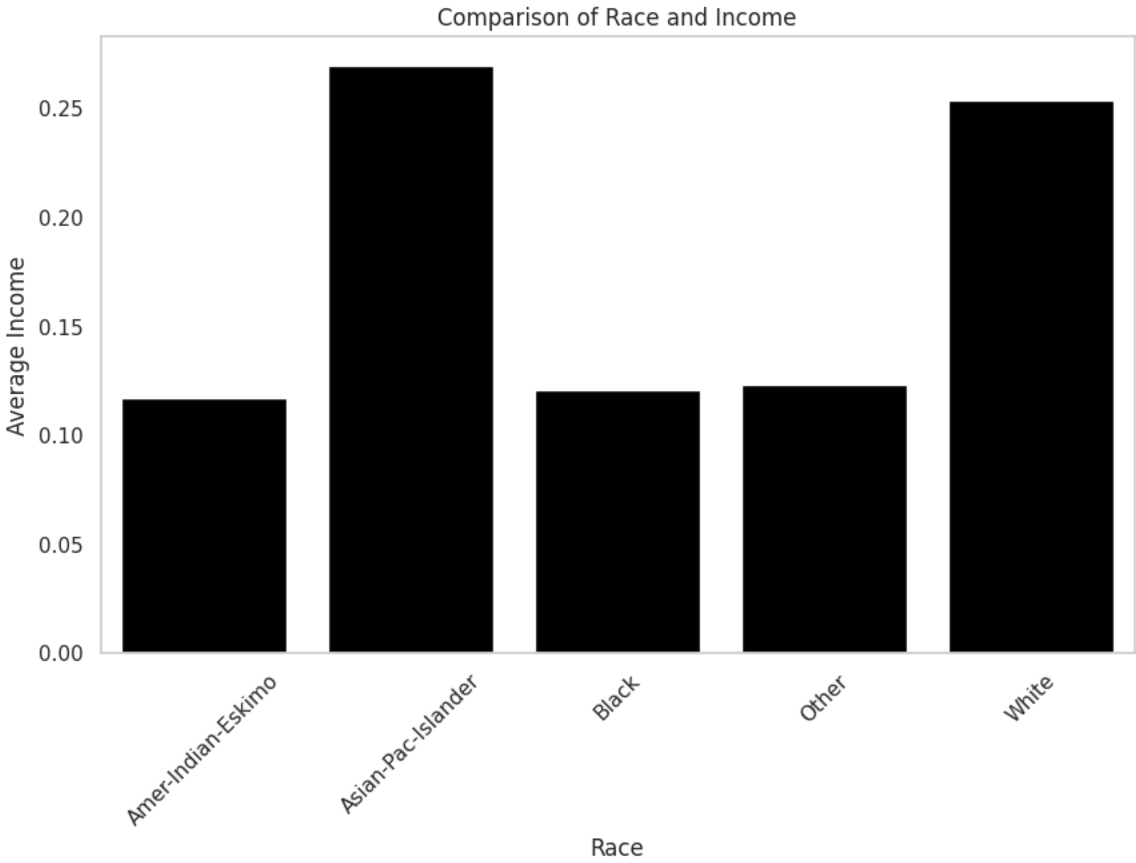
```python
sns.set_theme(style="whitegrid")

plt.figure(figsize=(10, 6))
relationship_order = df['relationship'].value_counts().index.sort_values()
relationship_counts = df.groupby('relationship')['income_numeric'].mean().loc[relationship_order]
sns.lineplot(x=relationship_counts.index, y=relationship_counts.values, color='pink')
plt.title('Comparison of Relationship and Income')
plt.xlabel('Relationship')
plt.ylabel('Average Income')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



Comparison o Relationship and Income

Description: This comparison examines the correlation between relationship status and income levels. It helps to understand whether factors such as being married, single, or in other relationship statuses impact income, providing insights into household dynamics and financial well-being.

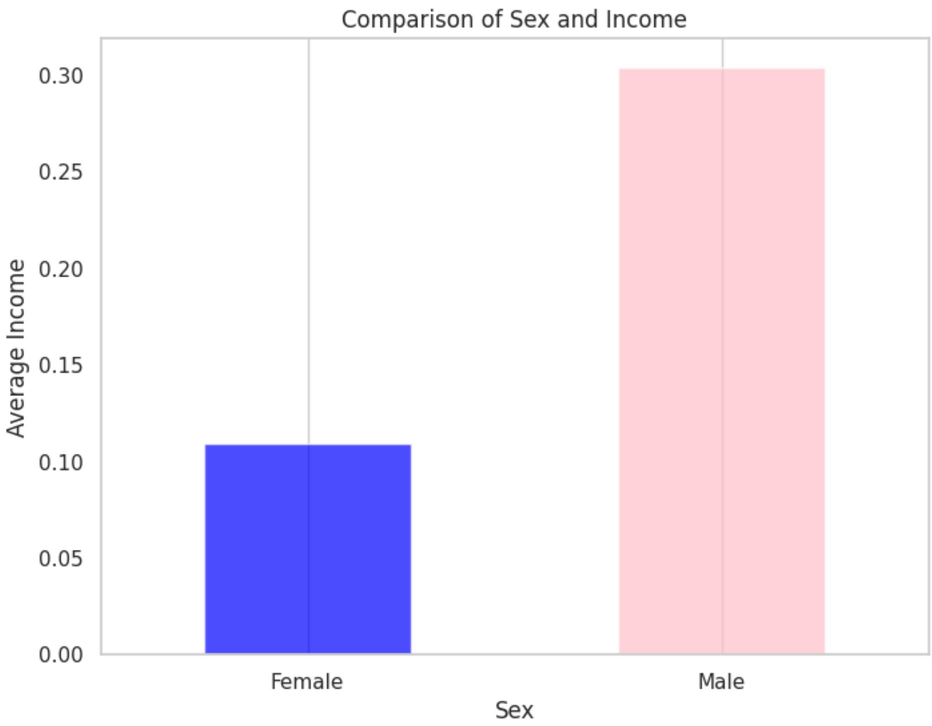
```
sns.set_theme(style="whitegrid")

plt.figure(figsize=(10, 6))
race_order = df['race'].value_counts().index.sort_values()
race_counts = df.groupby('race')['income_numeric'].mean().loc[race_order]
sns.barplot(x=race_counts.index, y=race_counts.values, color='black')
plt.title('Comparison of Race and Income')
plt.xlabel('Race')
plt.ylabel('Average Income')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



Comparison of Race and Income

Description: This comparison explores income disparities across different racial groups. It helps to identify whether certain racial demographics tend to have higher or lower incomes, highlighting potential disparities and informing efforts to promote equity and inclusion.

```python
plt.figure(figsize=(8, 6))
sex_counts = df.groupby('sex')['income_numeric'].mean()
sex_counts.plot(kind='bar', color=['blue', 'pink'], alpha=0.7)
plt.title('Comparison of Sex and Income')
plt.xlabel('Sex')
plt.ylabel('Average Income')
plt.xticks(rotation=0)
plt.grid(axis='y')
plt.show()
```

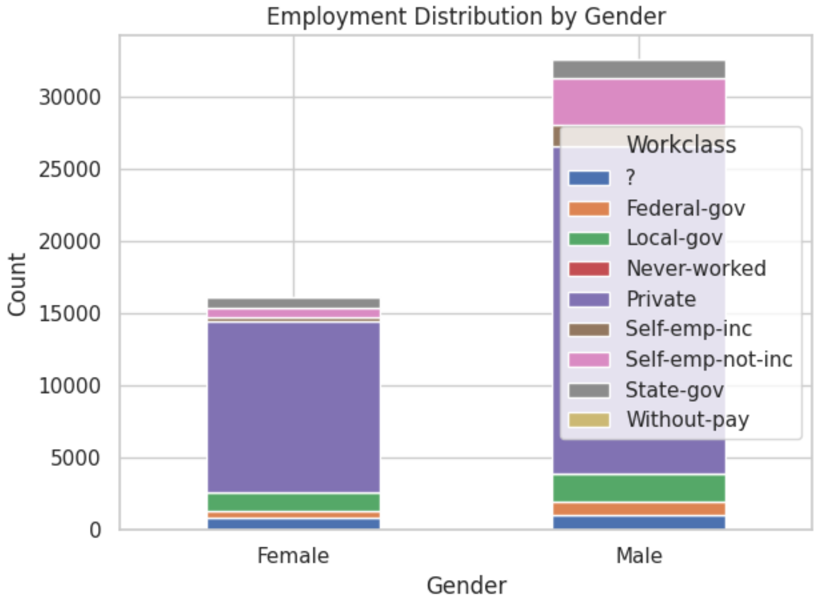



```python
gender_workclass_pivot = df.pivot_table(index='sex', columns='workclass', aggfunc='size', fill_value=0)

print("Employment Distribution by Gender:")
print(gender_workclass_pivot)
```

```
Employment Distribution by Gender:
workclass    ?  Federal-gov  Local-gov  Never-worked  Private  Self-emp-inc  \
sex
Female     839          465       1282             3    11910           225
Male       997         1004       1908             7    22668          1506

workclass  Self-emp-not-inc  State-gov  Without-pay
sex
Female                  665        779            8
Male                   3271       1241           15
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))

gender_workclass_pivot.plot(kind='bar', stacked=True)

plt.title('Employment Distribution by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.xticks(rotation=0)

plt.legend(title='Workclass')

plt.tight_layout()
plt.show()

```

```
<Figure size 1000x600 with 0 Axes>
```




```
total_employment = gender_workclass_pivot.sum(axis=1)

print("Total Employment Count for Each Gender:")
print(total_employment)
```

```
Total Employment Count for Each Gender:
sex
Female    16176
Male      32617
dtype: int64
```

Comparison o Sex and Income:

Description: This comparison investigates income differences between genders. It helps to understand whether there is a gender wage gap and how gender identity influences income levels, providing insights into gender equality and workplace diversity.

In addition it also examines the total employment count for each gender, revealing 16,182 females and 32,631 males. With a total difference of 16,449, it sheds light on potential income disparities between genders, offering insights into the presence of a gender wage gap and the influence of gender identity on income levels. This data contributes to discussions on gender equality and workplace diversity by highlighting the significant difference in employment numbers between males and females.