EDA Adult Data Set

Python Librarys

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Add column names to adult csv data set

```
column_names =
['Age','Workclass','Fnlgwt','Education','Education_num','Marital_statu
s',

'Occupation','Relationship','Race','Sex','Capital_gain','Capital_loss'
,
           'Hours_per_week','Native_country','Income']
df = pd.read_csv('adult.csv', names=column_names)
df.head()
```

```
   Age         Workclass  Fnlgwt   Education  Education_num  \
0   39         State-gov   77516   Bachelors             13
1   50  Self-emp-not-inc   83311   Bachelors             13
2   38           Private  215646     HS-grad              9
3   53           Private  234721        11th              7
4   28           Private  338409   Bachelors             13

        Marital_status          Occupation    Relationship    Race
Sex  \
0        Never-married        Adm-clerical   Not-in-family   White
Male
1   Married-civ-spouse     Exec-managerial         Husband   White
Male
2             Divorced   Handlers-cleaners   Not-in-family   White
Male
3   Married-civ-spouse   Handlers-cleaners         Husband   Black
Male
4   Married-civ-spouse      Prof-specialty            Wife   Black
Female

   Capital_gain  Capital_loss  Hours_per_week  Native_country  Income

0          2174             0              40   United-States   <=50K

1             0             0              13   United-States   <=50K
```

2	0	0	40	United-States	<=50K
3	0	0	40	United-States	<=50K
4	0	0	40	Cuba	<=50K

Handling missing values

```
df[df == ' ?'] = np.nan
df.isna().any()
```

```
Age                False
Workclass           True
Fnlgwt             False
Education          False
Education_num      False
Marital_status     False
Occupation          True
Relationship       False
Race               False
Sex                False
Capital_gain       False
Capital_loss       False
Hours_per_week     False
Native_country      True
Income             False
dtype: bool
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             32561 non-null  int64
 1   Workclass       30725 non-null  object
 2   Fnlgwt          32561 non-null  int64
 3   Education       32561 non-null  object
 4   Education_num   32561 non-null  int64
 5   Marital_status  32561 non-null  object
 6   Occupation      30718 non-null  object
 7   Relationship    32561 non-null  object
 8   Race            32561 non-null  object
 9   Sex             32561 non-null  object
 10  Capital_gain    32561 non-null  int64
 11  Capital_loss    32561 non-null  int64
 12  Hours_per_week  32561 non-null  int64
```

```
 13  Native_country  31978 non-null  object
 14  Income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

Recoding ? as a Mode value of Categorial Variables

```
for col in ['Workclass', 'Occupation', 'Native_country']:
    df[col].fillna(df[col].mode()[0], inplace=True)

df.isna().any()
```

```
Age                  False
Workclass            False
Fnlgwt               False
Education            False
Education_num        False
Marital_status       False
Occupation           False
Relationship         False
Race                 False
Sex                  False
Capital_gain         False
Capital_loss         False
Hours_per_week       False
Native_country       False
Income               False
dtype: bool
```

Checking the duplicates

```
df.duplicated() # True for duplicated in rows
```

```
0        False
1        False
2        False
3        False
4        False
         ...
32556    False
32557    False
32558    False
32559    False
32560    False
Length: 32561, dtype: bool
```

```
df.duplicated().sum() # Number of duplicated rows
```

```
24
```

```
len(df)
```

```
32561
```

```
df.drop_duplicates(inplace=True) # Dropping duplicated rows
```

```
len(df)
```

```
32537
```

```
df.duplicated().sum()
```

```
0
```

Search unique values in Variables

```
print(df.Workclass.unique())
```

```
[' State-gov' ' Self-emp-not-inc' ' Private' ' Federal-gov' ' Local-
gov'
 ' Self-emp-inc' ' Without-pay' ' Never-worked']
```

```
print(df.Education.unique())
```

```
[' Bachelors' ' HS-grad' ' 11th' ' Masters' ' 9th' ' Some-college'
 ' Assoc-acdm' ' Assoc-voc' ' 7th-8th' ' Doctorate' ' Prof-school'
 ' 5th-6th' ' 10th' ' 1st-4th' ' Preschool' ' 12th']
```

```
print(df.Marital_status.unique())
```

```
[' Never-married' ' Married-civ-spouse' ' Divorced'
 ' Married-spouse-absent' ' Separated' ' Married-AF-spouse' '
Widowed']
```

```
print(df.Occupation.unique())
```

```
[' Adm-clerical' ' Exec-managerial' ' Handlers-cleaners' ' Prof-
specialty'
 ' Other-service' ' Sales' ' Craft-repair' ' Transport-moving'
 ' Farming-fishing' ' Machine-op-inspct' ' Tech-support'
 ' Protective-serv' ' Armed-Forces' ' Priv-house-serv']
```

```
print(df.Relationship.unique())
```

```
[' Not-in-family' ' Husband' ' Wife' ' Own-child' ' Unmarried'
 ' Other-relative']
```

```
print(df.Native_country.unique())
```

```
[' United-States' ' Cuba' ' Jamaica' ' India' ' Mexico' ' South'
 ' Puerto-Rico' ' Honduras' ' England' ' Canada' ' Germany' ' Iran'
 ' Philippines' ' Italy' ' Poland' ' Columbia' ' Cambodia' ' Thailand'
 ' Ecuador' ' Laos' ' Taiwan' ' Haiti' ' Portugal' ' Dominican-
```

```
Republic'
 ' El-Salvador' ' France' ' Guatemala' ' China' ' Japan' ' Yugoslavia'
 ' Peru' ' Outlying-US(Guam-USVI-etc)' ' Scotland' ' Trinadad&Tobago'
 ' Greece' ' Nicaragua' ' Vietnam' ' Hong' ' Ireland' ' Hungary'
 ' Holand-Netherlands']
```

```
print(df.Income.unique())
```

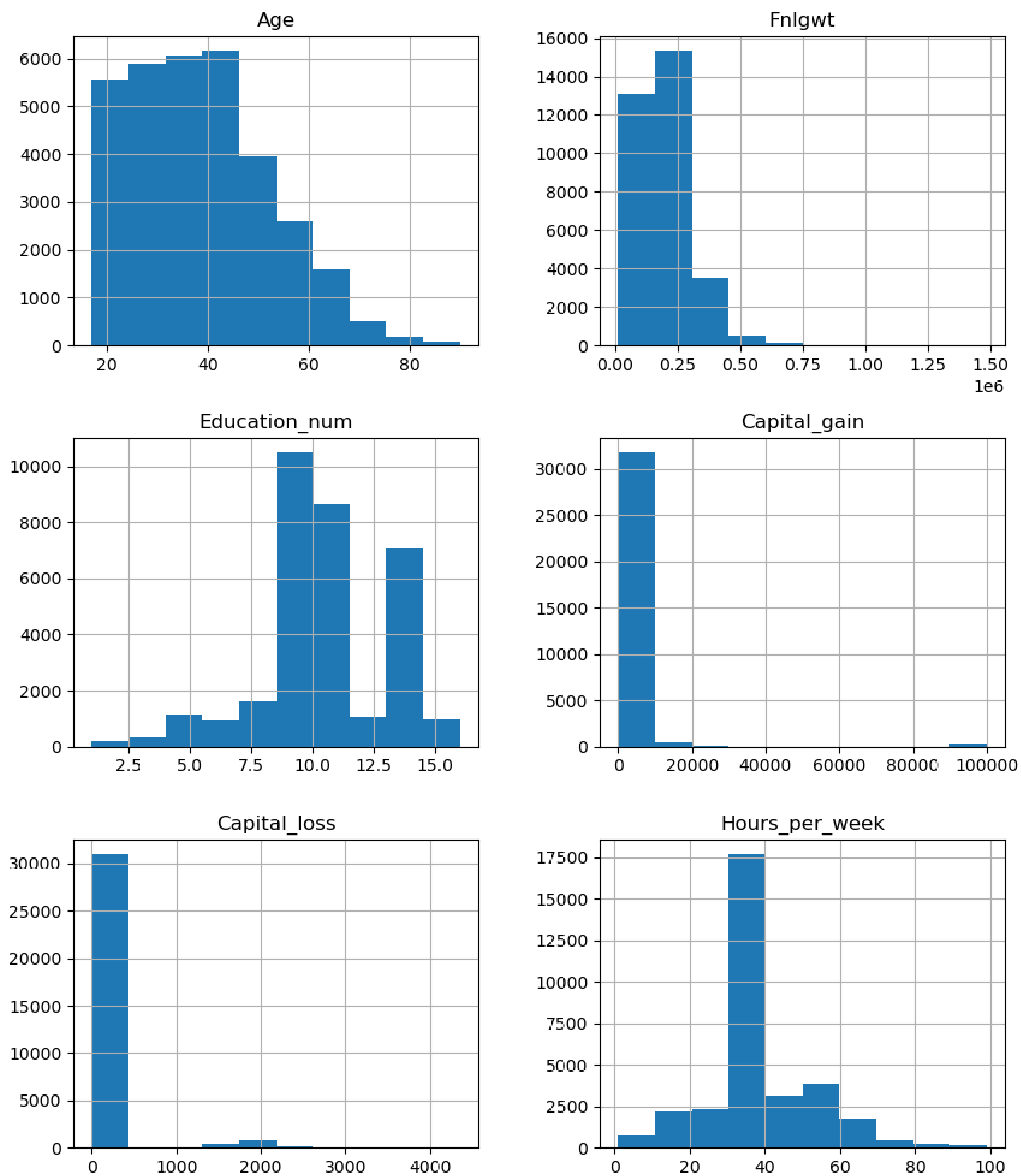
```
[' <=50K' ' >50K']
```

Exploratory Data Analysis

Univariate Analysis

Histograms for Continuous Data

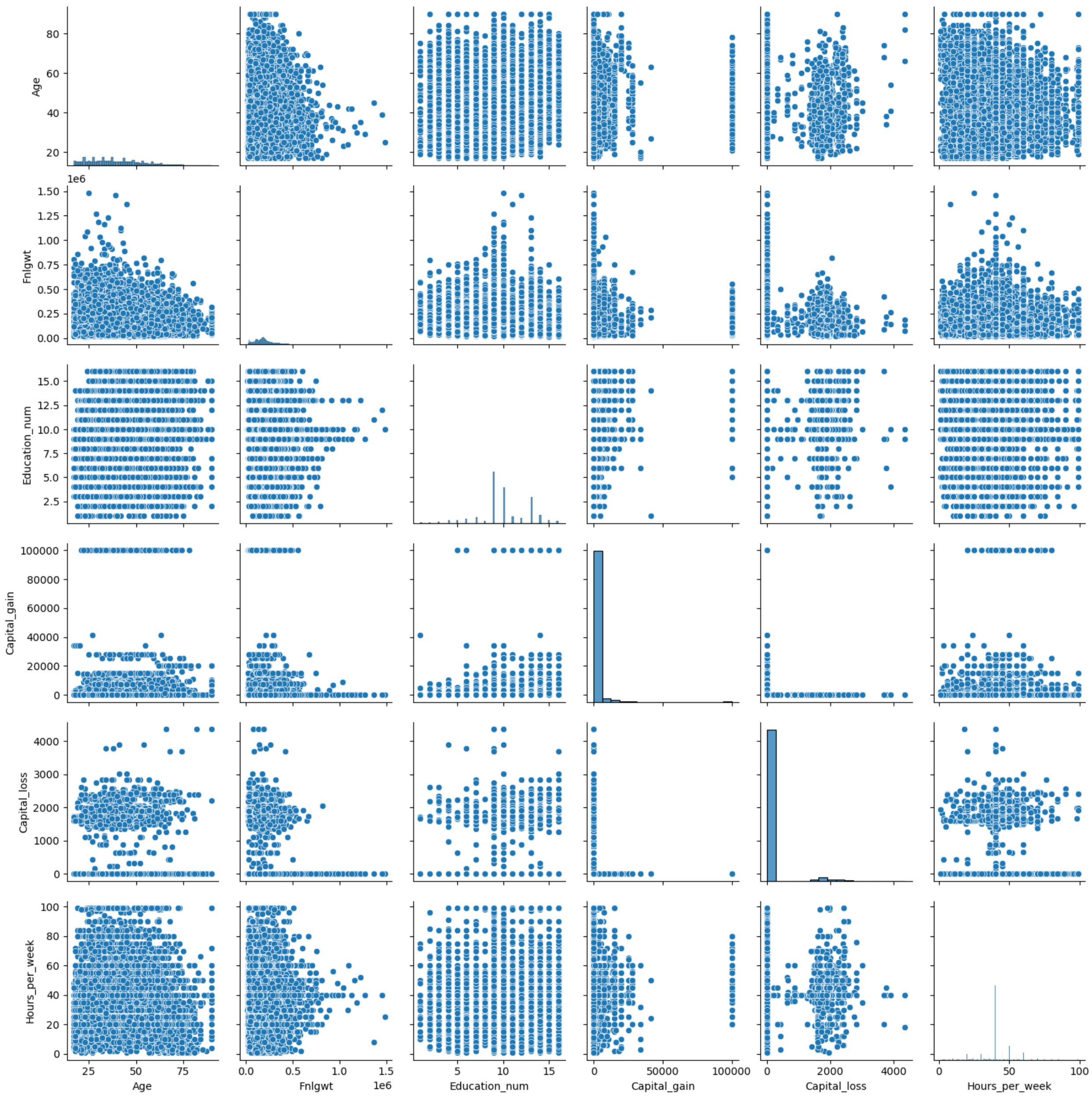
```
Histogram_graphs=df.select_dtypes(include=['int'])
Histogram_graphs.hist(figsize=(10,12))
plt.show()
```



Draw a pair plot for dataset

```
sns.pairplot(df)
plt.show()
```

```
C:\Users\sanda\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

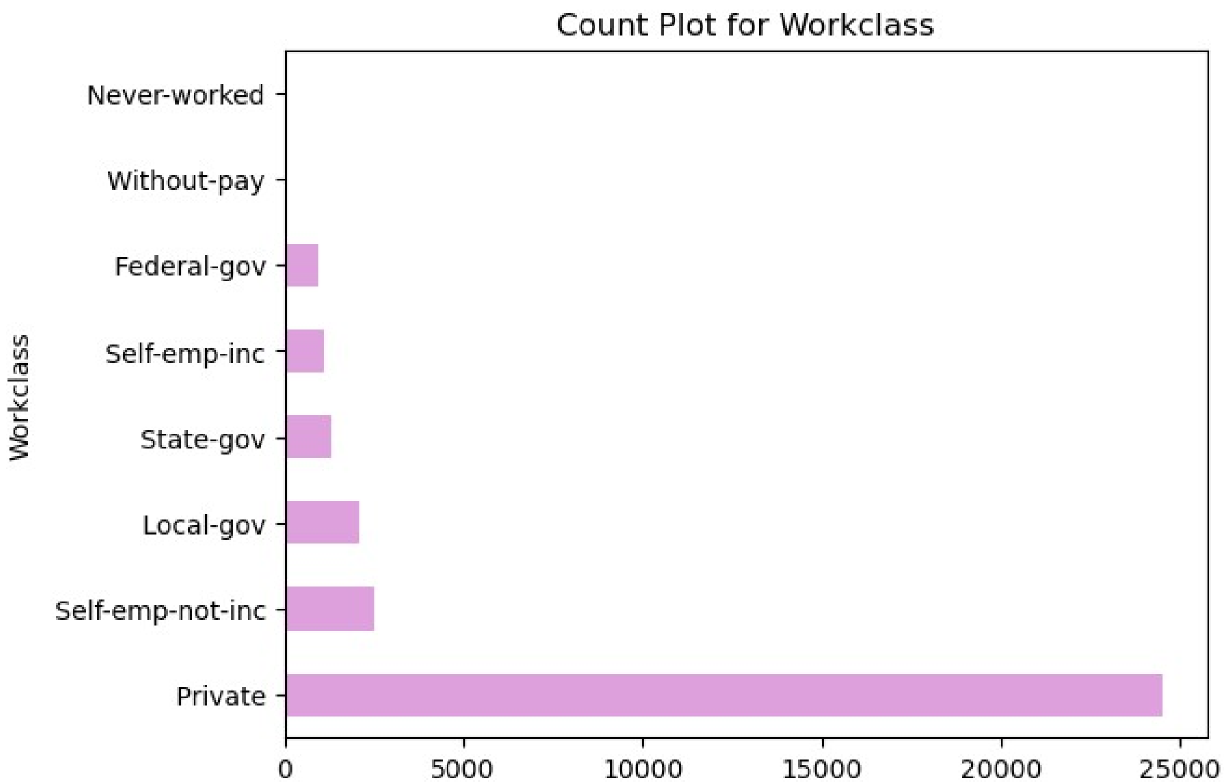


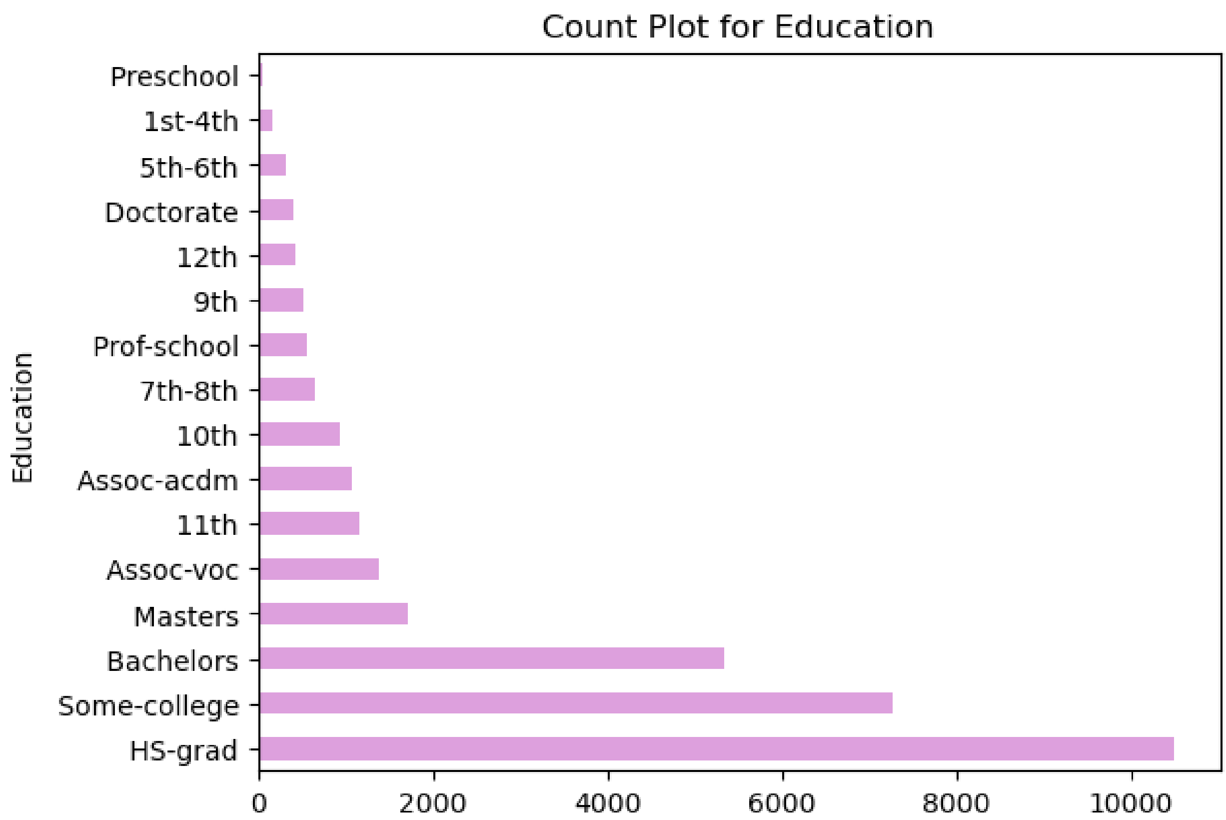
Counts plots for variables

Workclass, Education, Marital_status, Occupation, Relationship, Race

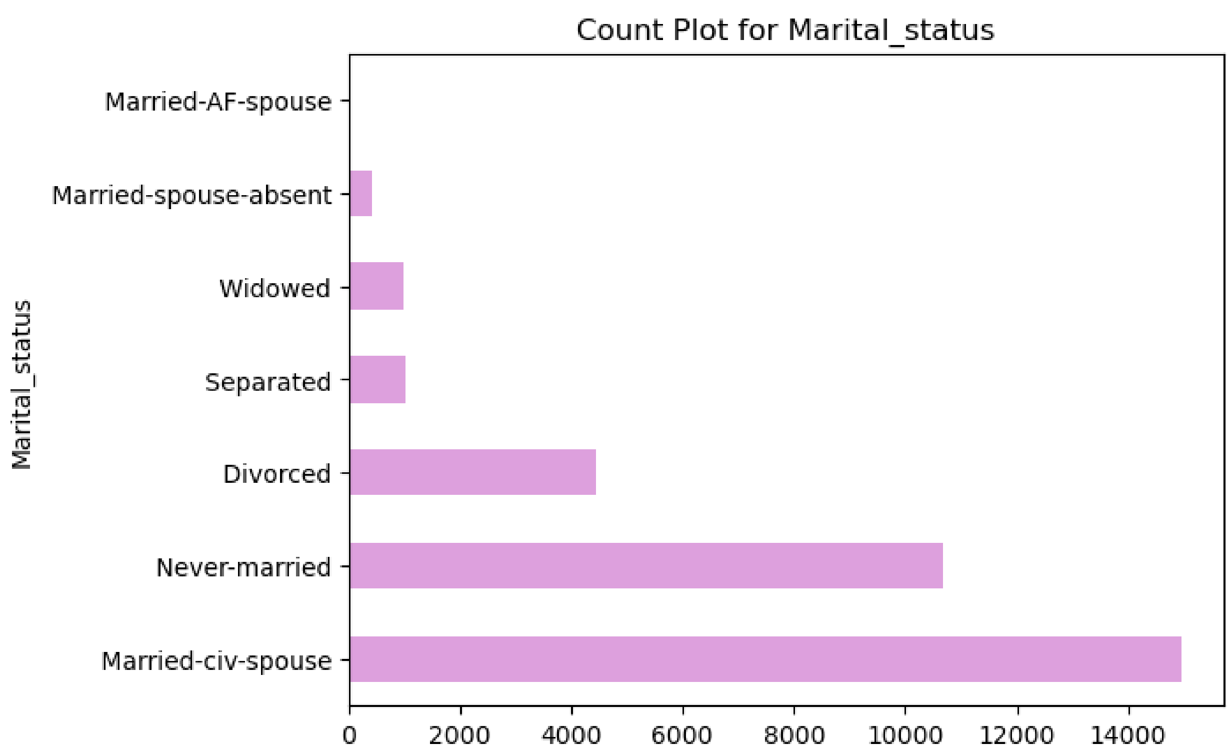
```python
categorical_columns = ['Workclass', 'Education', 'Marital_status',
'Occupation', 'Relationship', 'Race']

for colname in categorical_columns:
```

```
    plt.title('Count Plot for ' + colname)

    (df[colname].value_counts().head(20).plot(kind='barh',
color='plum'))
    plt.show()
```

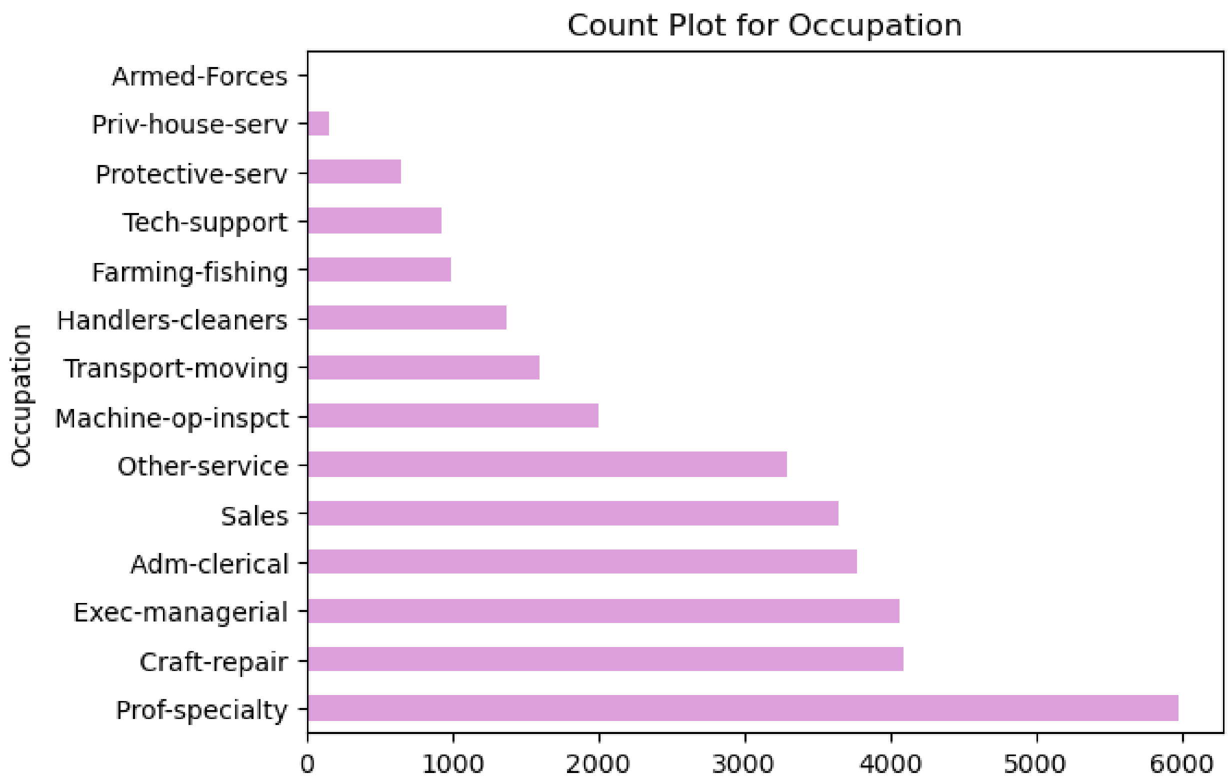


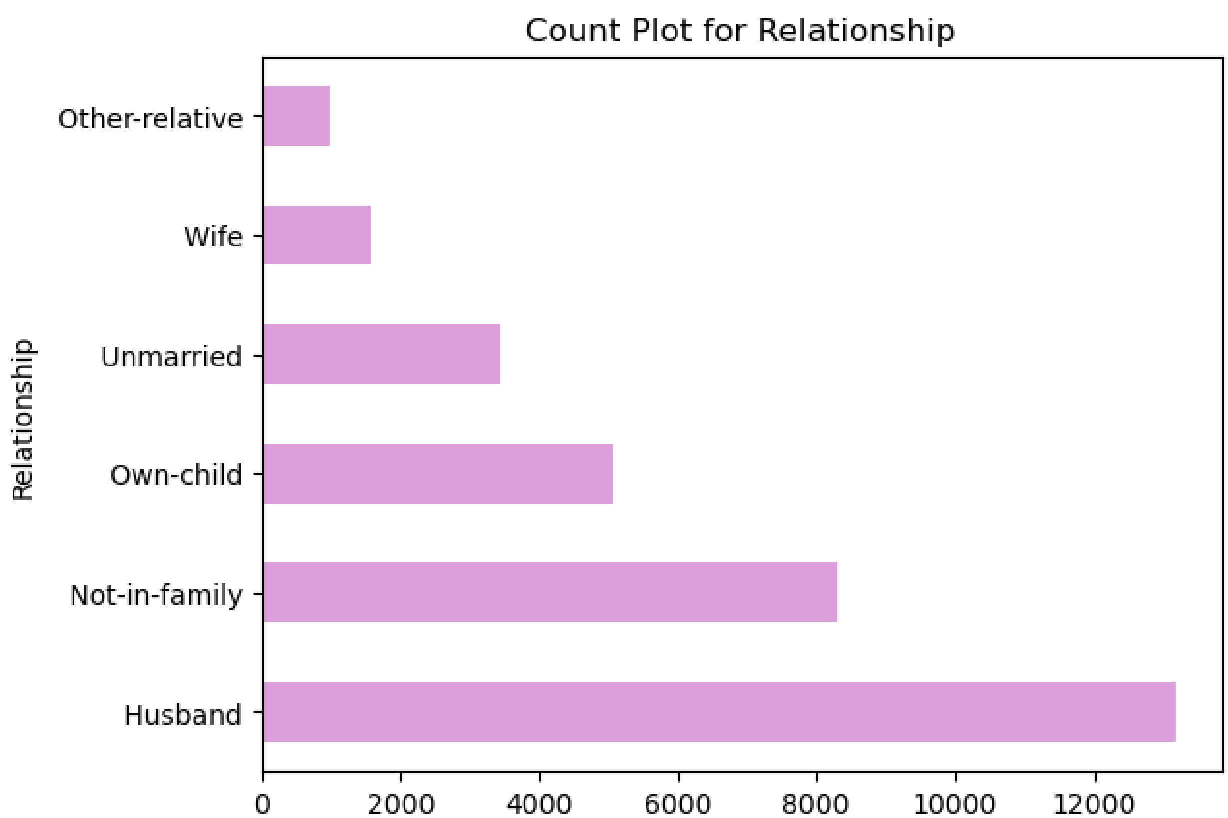


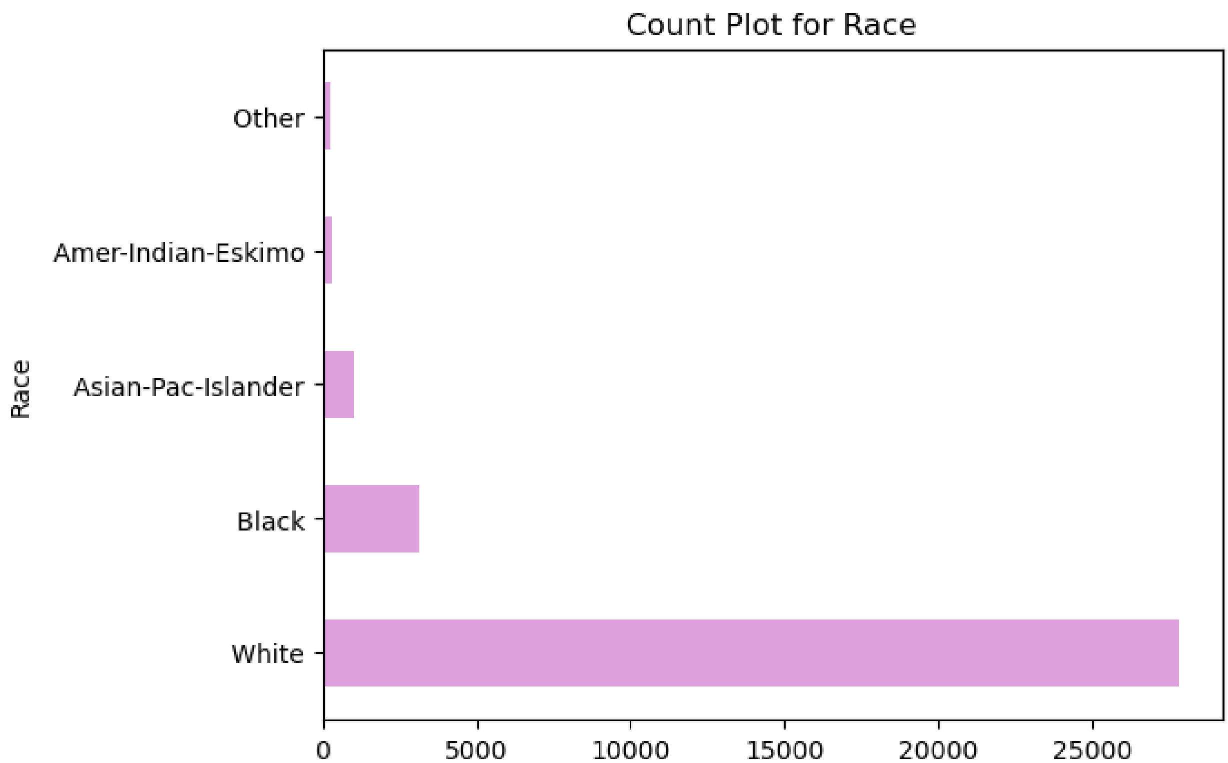
Count Plot for Education
Education
Preschool
1st-4th
5th-6th
Doctorate
12th
9th
Prof-school
7th-8th
10th
Assoc-acdm
11th
Assoc-voc
Masters
Bachelors
Some-college
HS-grad
0
2000
4000
6000
8000
10000



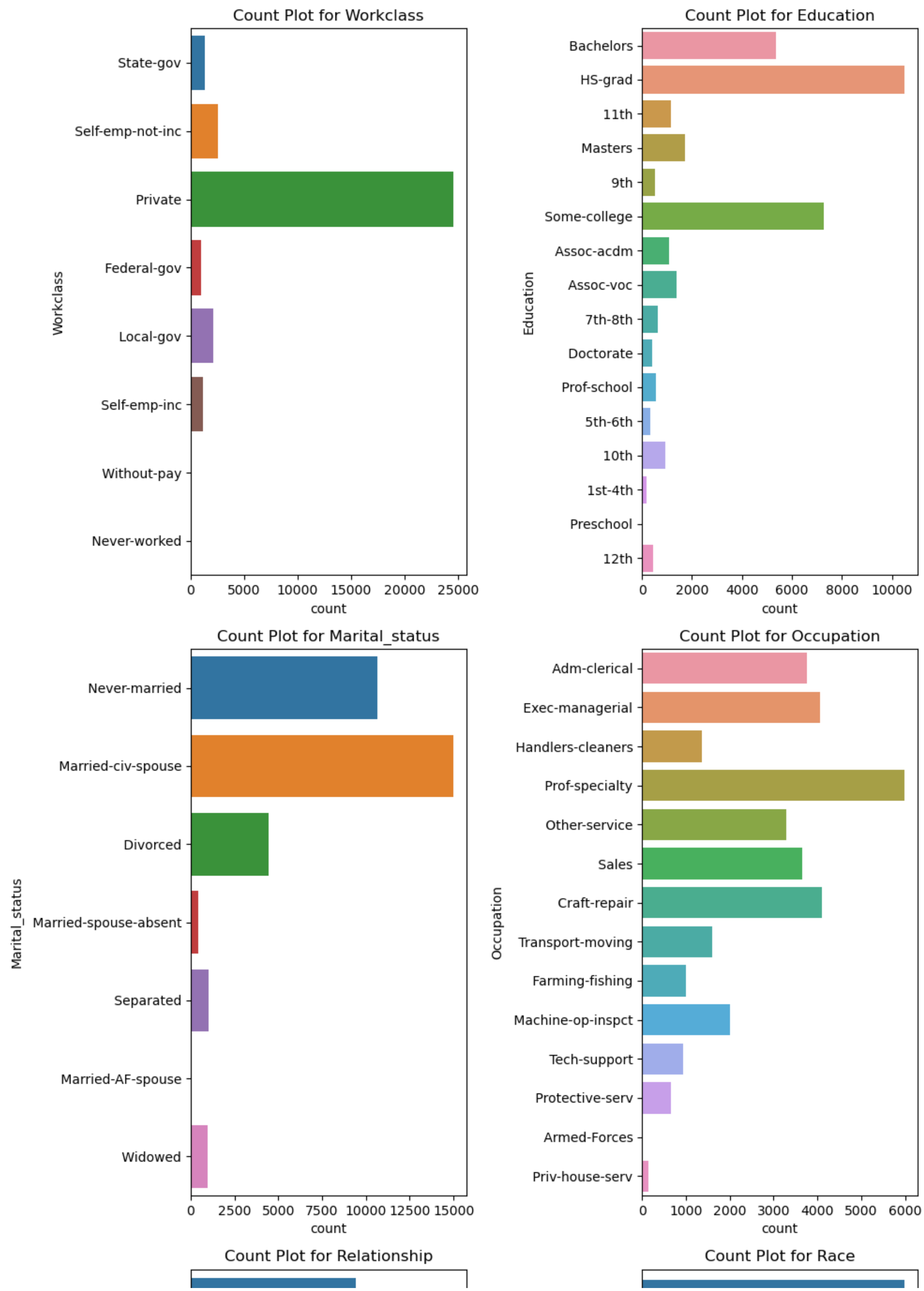
Count Plot for Marital_status
Marital_status
Married-AF-spouse
Married-spouse-absent
Widowed
Separated
Divorced
Never-married
Married-civ-spouse
0
2000
4000
6000
8000
10000
12000
14000


Count Plot for Occupation
Occupation
Armed-Forces
Priv-house-serv
Protective-serv
Tech-support
Farming-fishing
Handlers-cleaners
Transport-moving
Machine-op-inspct
Other-service
Sales
Adm-clerical
Exec-managerial
Craft-repair
Prof-specialty
0
1000
2000
3000
4000
5000
6000


Count Plot for Relationship
Relationship
Other-relative
Wife
Unmarried
Own-child
Not-in-family
Husband
0
2000
4000
6000
8000
10000
12000



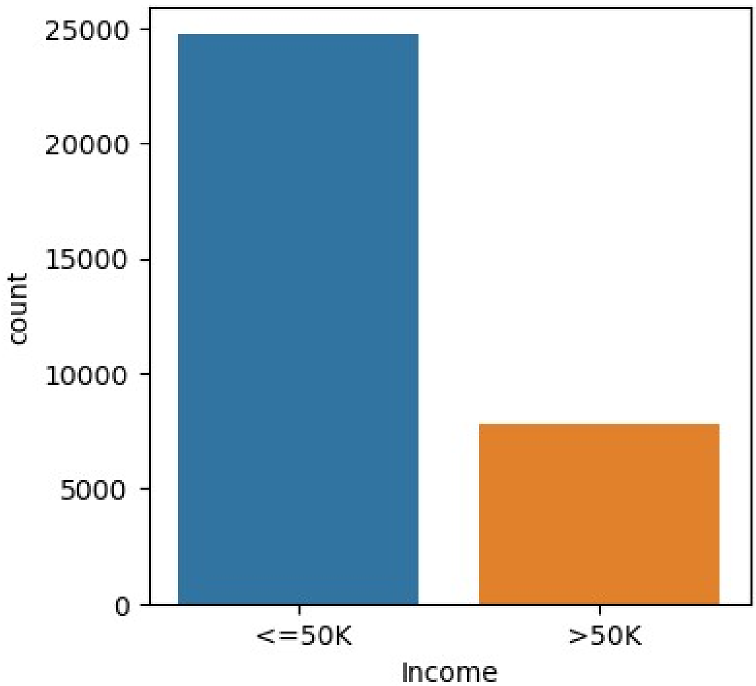

```python
categorical_columns = ['Workclass', 'Education', 'Marital_status',
'Occupation', 'Relationship', 'Race']

# Set up the matplotlib figure with subplots
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(10, 20))

# Flatten the axes for easier iteration
axes = axes.flatten()

# Loop through the categorical columns and create count plots
for i, column in enumerate(categorical_columns):
    sns.countplot(y=column, data=df, ax=axes[i])
    axes[i].set_title(f'Count Plot for {column}')

# Adjust layout to prevent overlapping
plt.tight_layout()

# Show the plot
plt.show()
```


Count Plot for Workclass
State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
Self-emp-inc
Without-pay
Never-worked
Workclass
0 5000 10000 15000 20000 25000
count
Count Plot for Education
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
Education
0 2000 4000 6000 8000 10000
count
Count Plot for Marital_status
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
Marital_status
0 2500 5000 7500 10000 12500 15000
count
Count Plot for Occupation
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
Occupation
0 1000 2000 3000 4000 5000 6000
count
Count Plot for Relationship
Count Plot for Race

Income

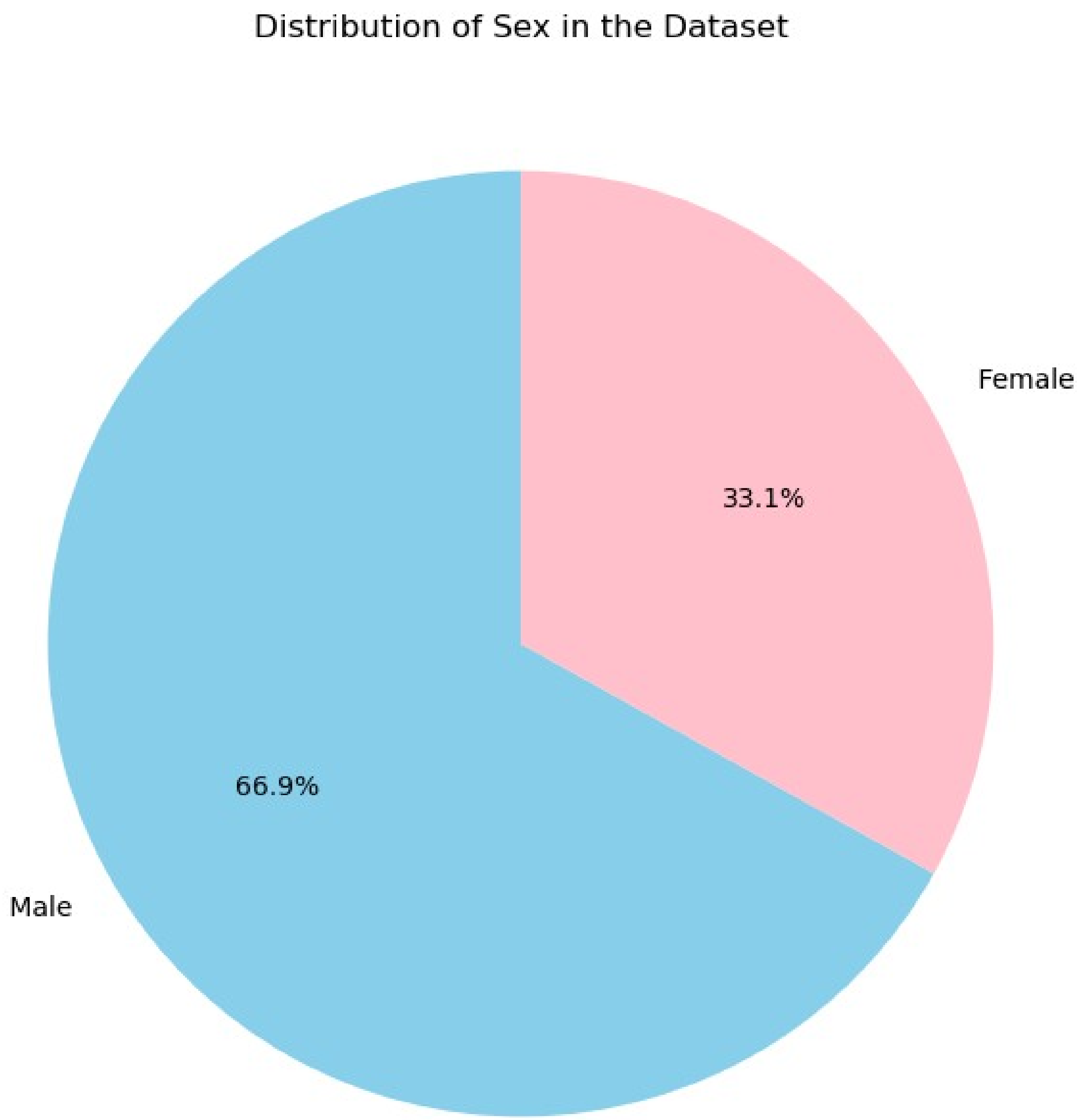
```
plt.figure(figsize=(4,4))
sns.countplot(x="Income", data=df)
```

```
<Axes: xlabel='Income', ylabel='count'>
```



Pie Chart for Gender

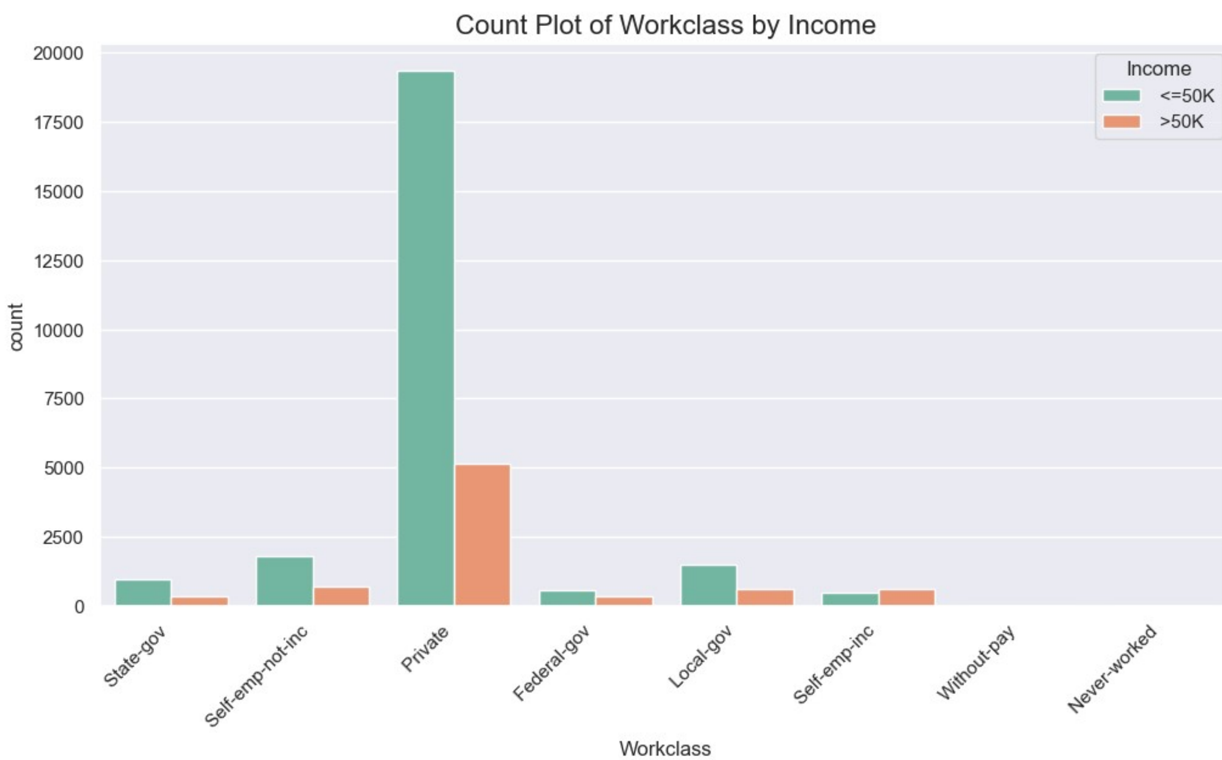
```
sex_counts = df['Sex'].value_counts()

# Plotting the pie chart
plt.figure(figsize=(8, 8))
plt.pie(sex_counts, labels=sex_counts.index, autopct='%1.1f%%',
startangle=90, colors=['skyblue', 'pink'])
plt.title('Distribution of Sex in the Dataset')
plt.show()
```

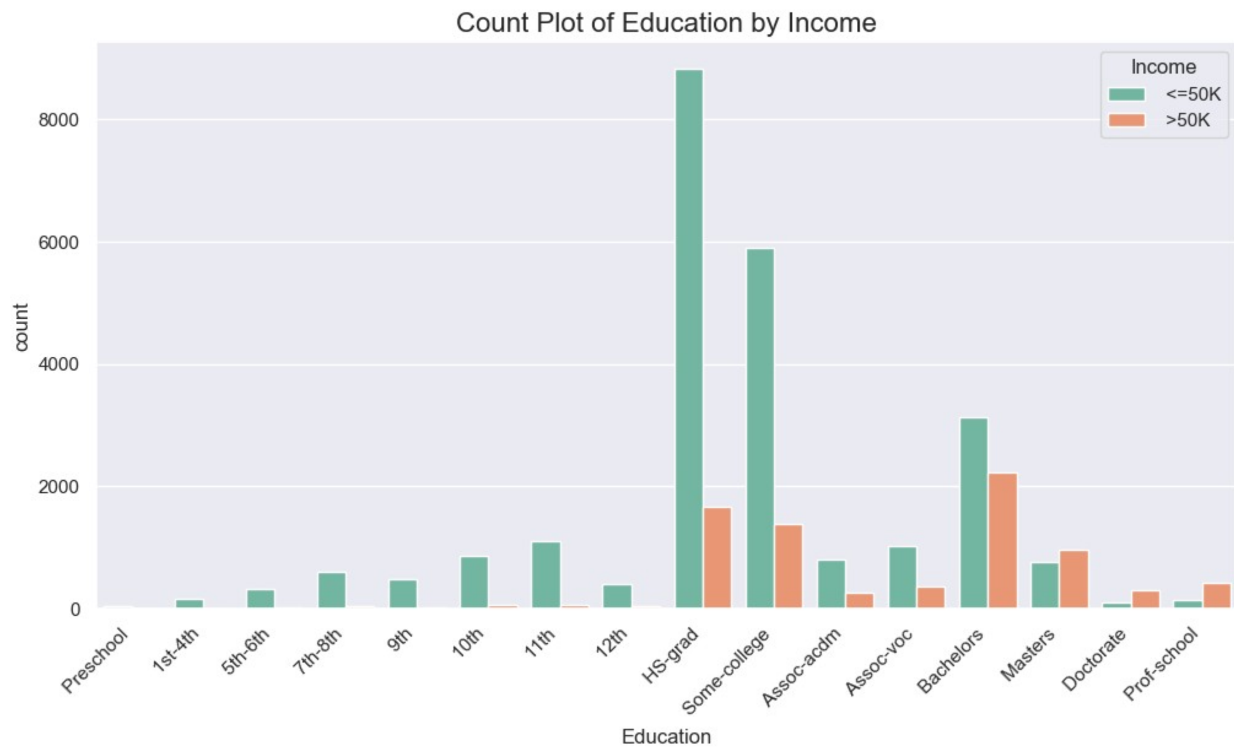


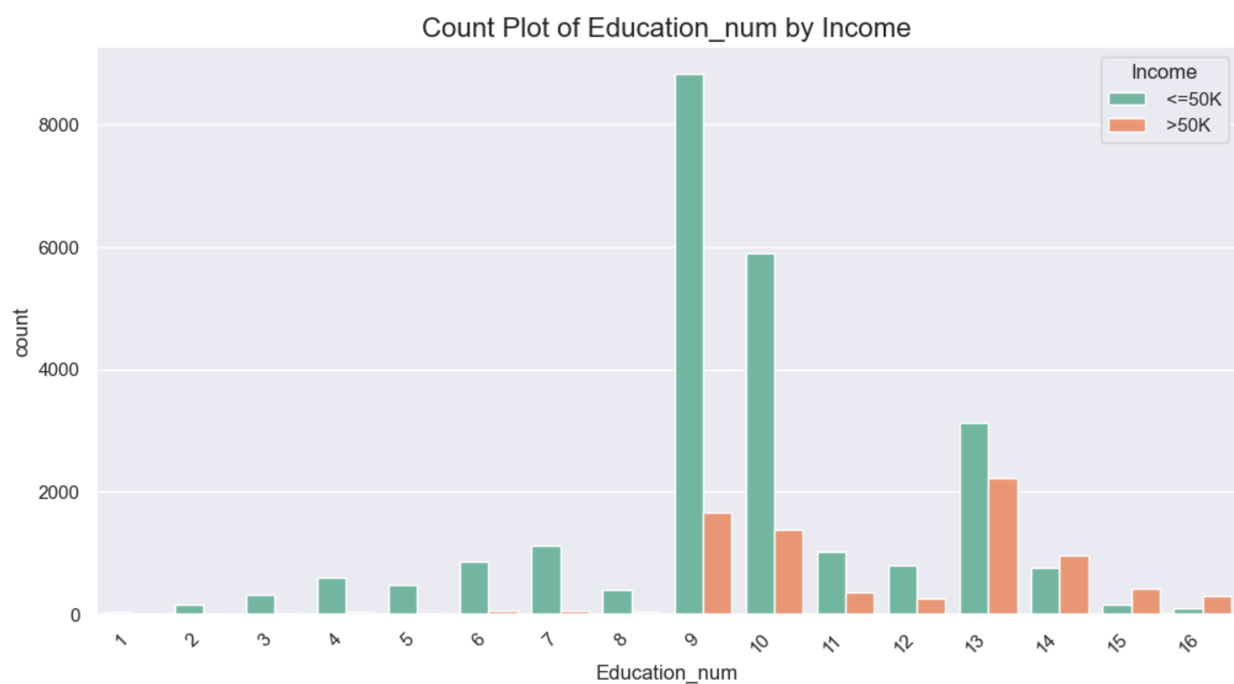
Count Plots Based on Income

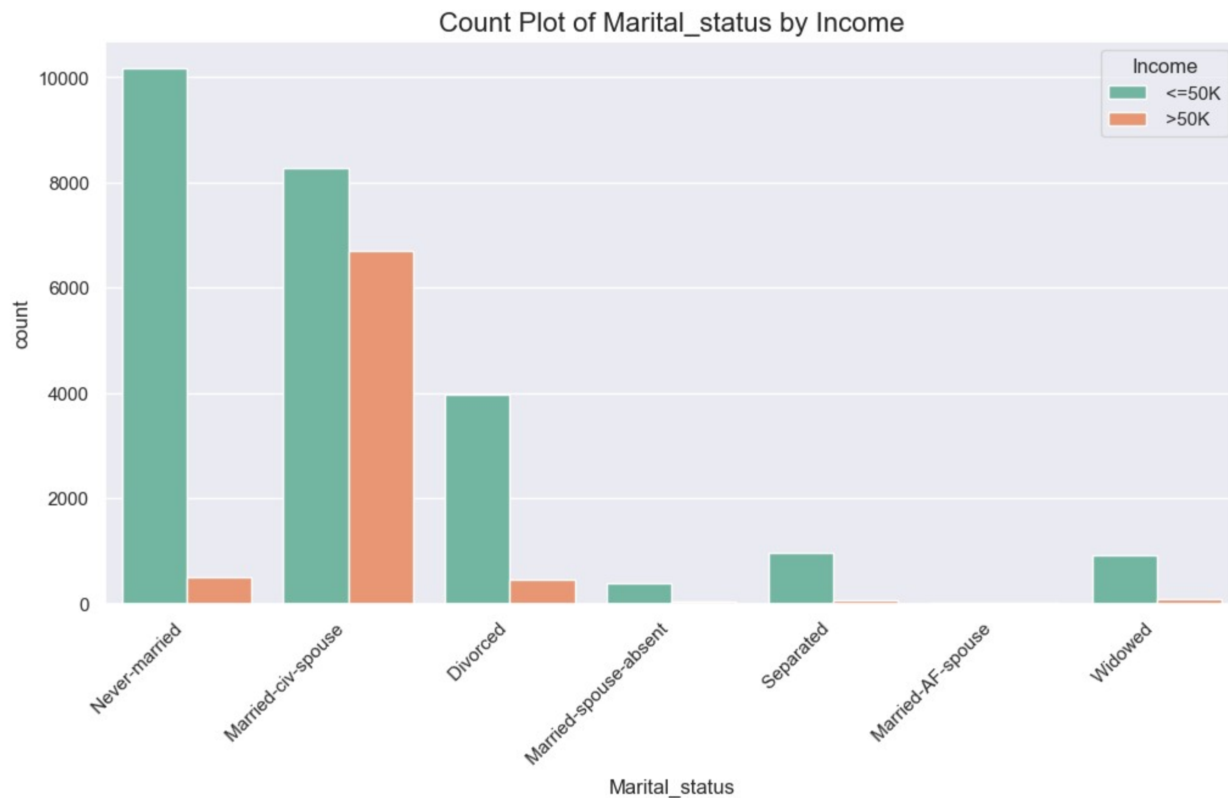
```
# Categorical columns in the dataset
categorical_columns = ['Workclass', 'Education', 'Education_num',
'Marital_status', 'Occupation', 'Relationship', 'Race', 'Sex',
'Native_country', 'Income']

# Set the style of seaborn for better visualization
sns.set(style="darkgrid")

# Plot count plots for each categorical variable
for column in categorical_columns:
```

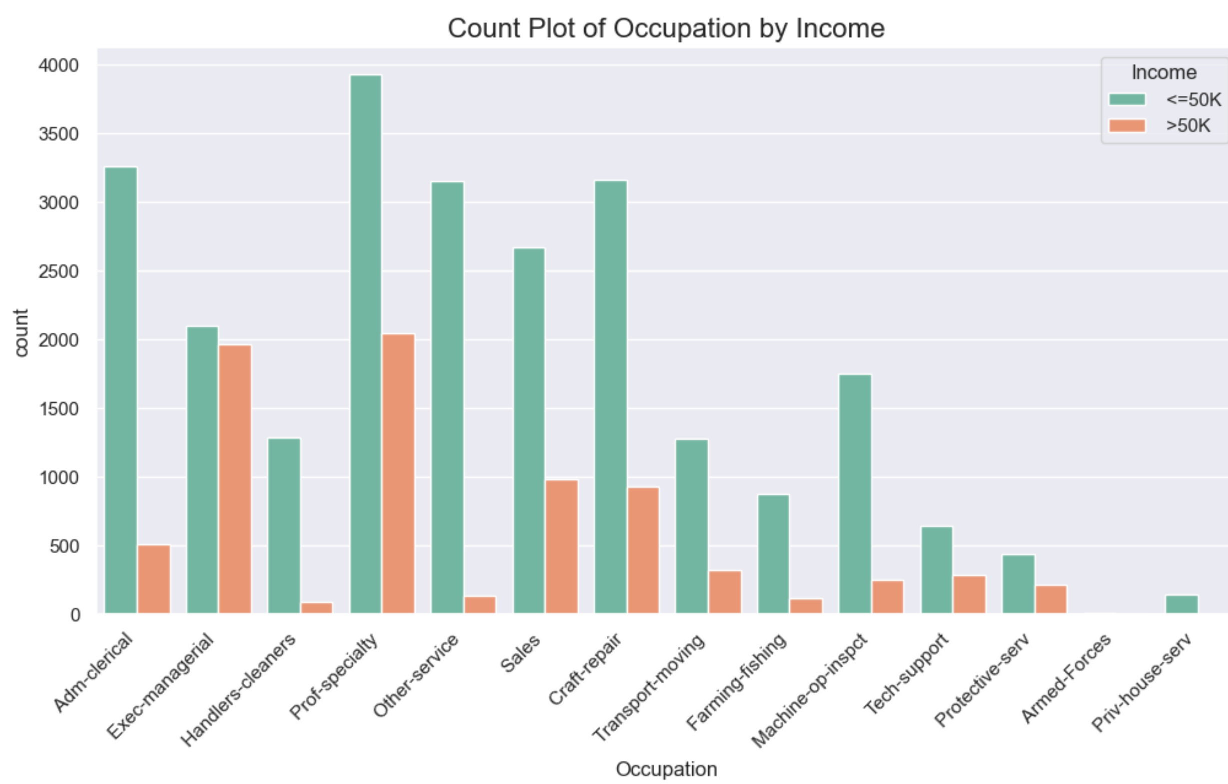
```
    plt.figure(figsize=(12, 6))

    # Set the order for 'Education' variable
    if column == 'Education':
        order = sorted(df['Education'].unique(), key=lambda x: ['
Preschool', ' 1st-4th', ' 5th-6th', ' 7th-8th', ' 9th', ' 10th', '
11th', ' 12th',
                        ' HS-grad', ' Some-college', ' Assoc-acdm', ' Assoc-
voc', ' Bachelors', ' Masters', ' Doctorate', ' Prof-
school'].index(x))
        sns.countplot(x=column, hue='Income', data=df, palette='Set2',
order=order)
    else:
        sns.countplot(x=column, hue='Income', data=df, palette='Set2')

    plt.title(f'Count Plot of {column} by Income', fontsize=16)
    plt.xticks(rotation=45, ha='right')
    plt.show()
```

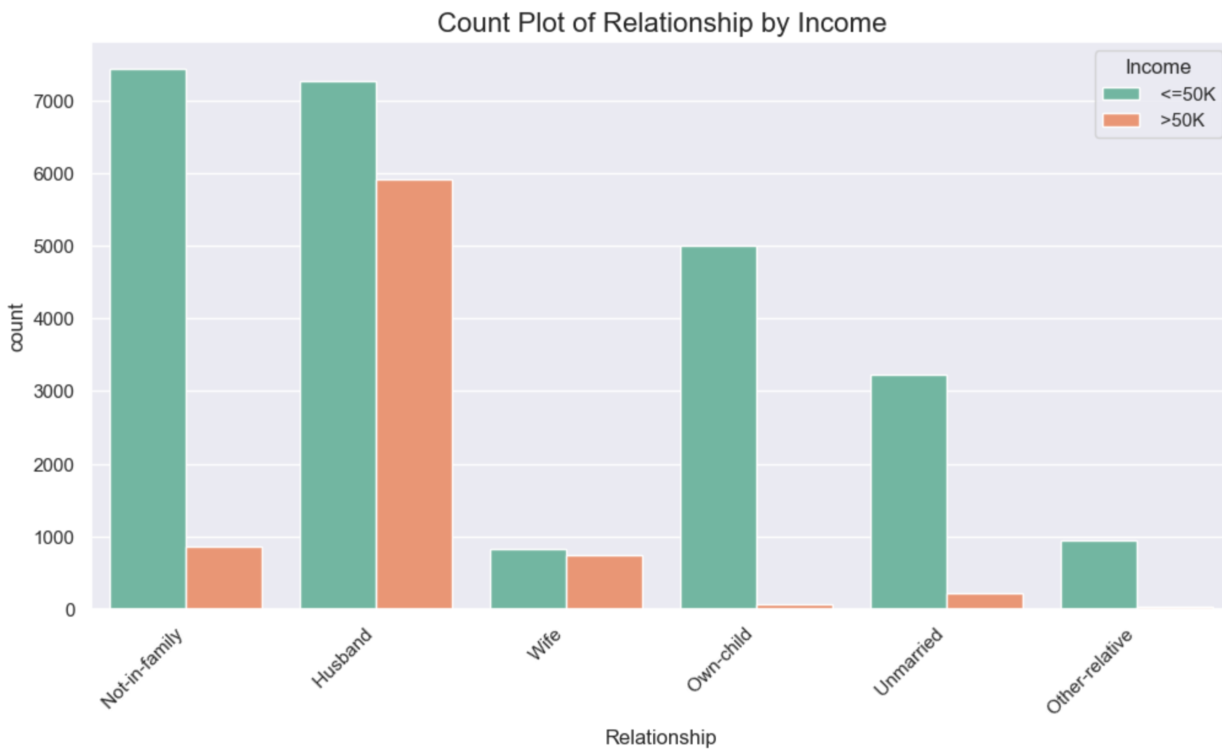


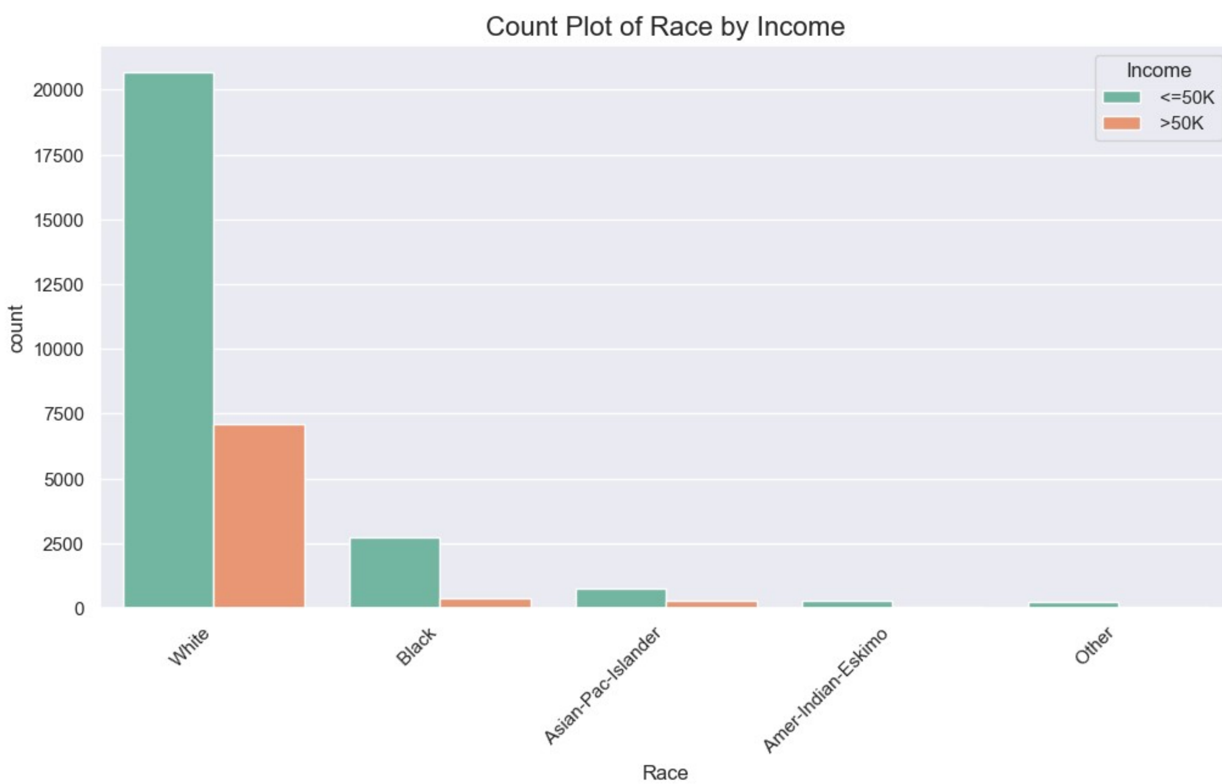

Count Plot of Education by Income
Income
<=50K
>50K
count
0
2000
4000
6000
8000
Preschool
1st-4th
5th-6th
7th-8th
9th
10th
11th
12th
HS-grad
Some-college
Assoc-acdm
Assoc-voc
Bachelors
Masters
Doctorate
Prof-school
Education

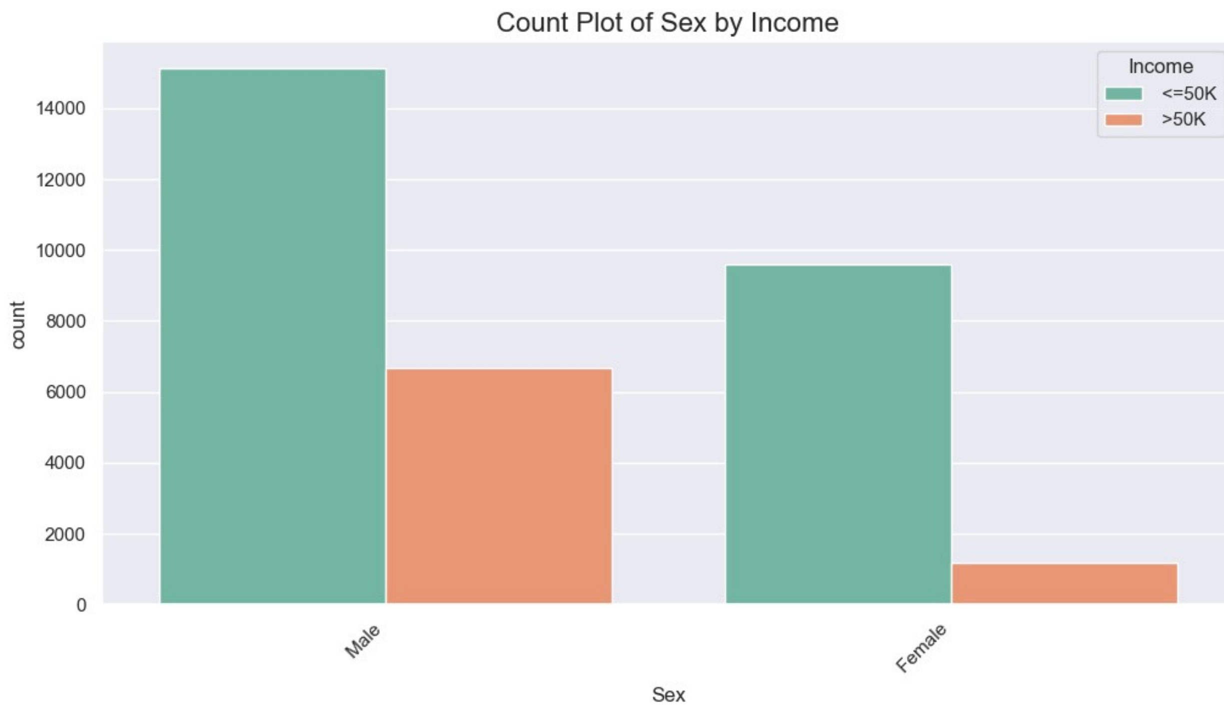

Count Plot of Education_num by Income
Income
<=50K
>50K
count
0
2000
4000
6000
8000
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Education_num

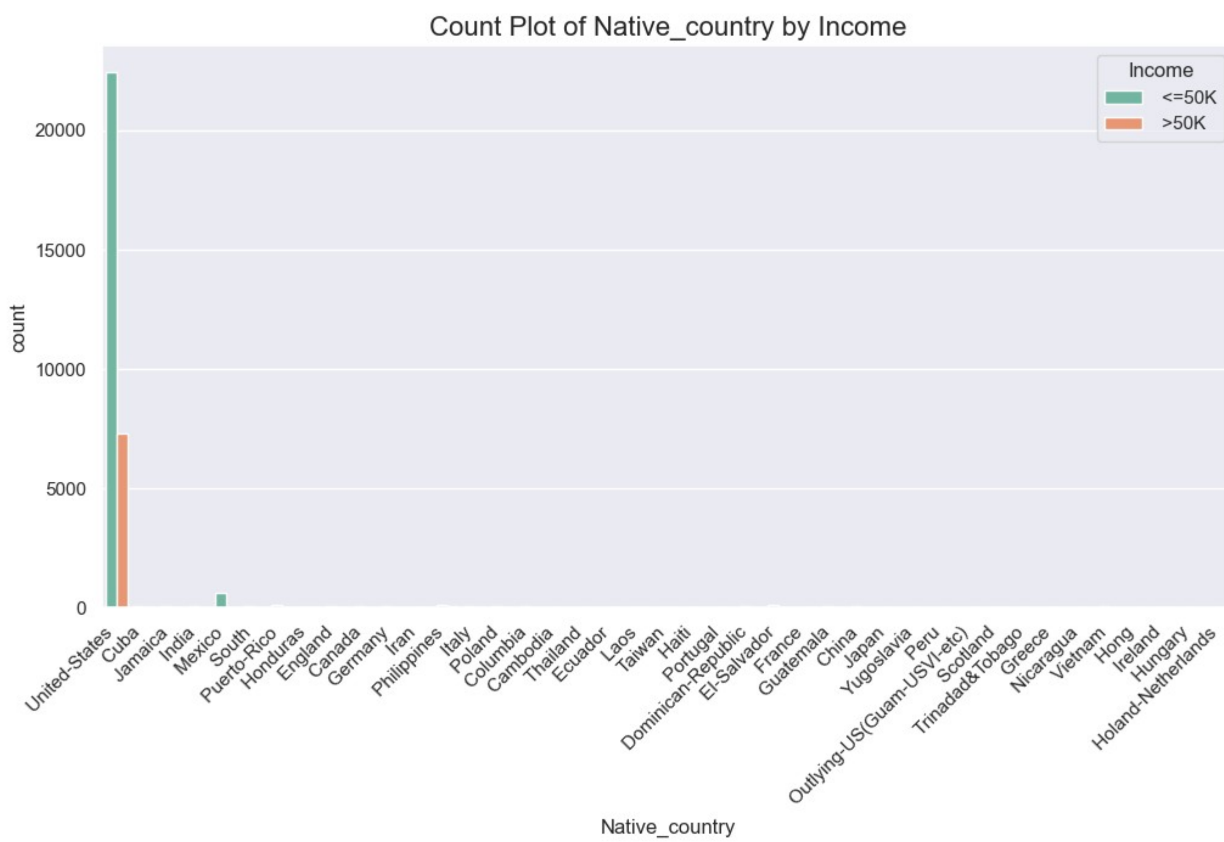

Count Plot of Marital_status by Income
Income
<=50K
>50K
count
10000
8000
6000
4000
2000
0
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
Marital_status

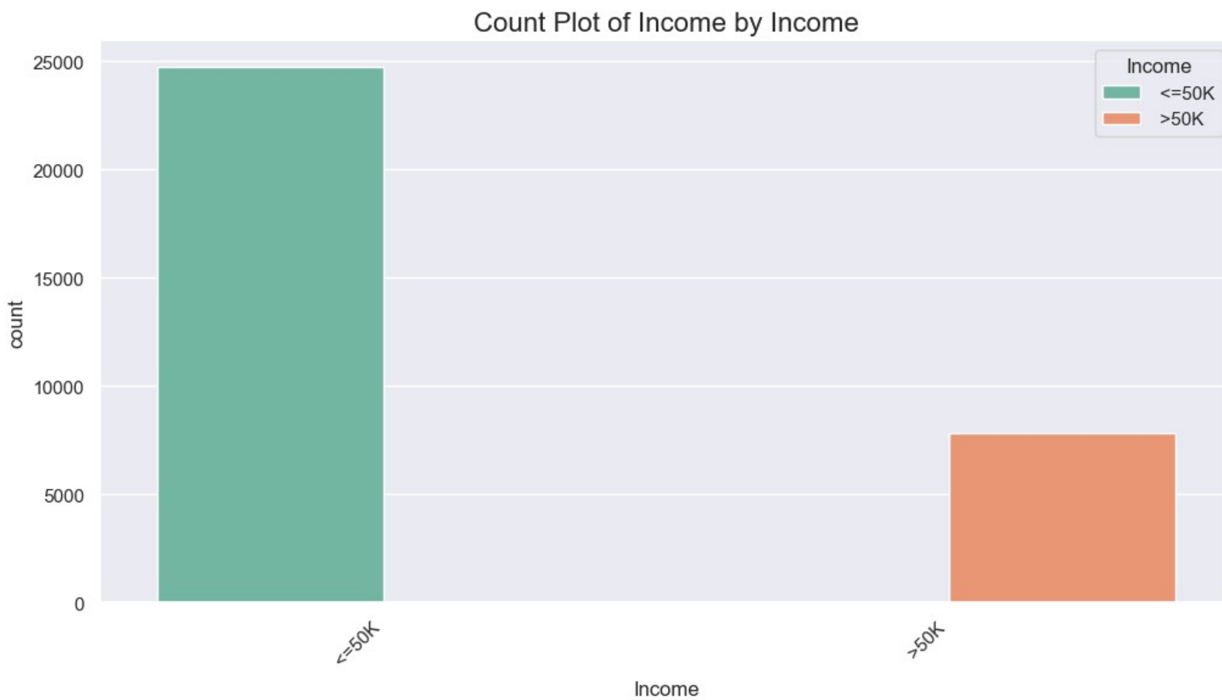

Count Plot of Occupation by Income
Income
<=50K
>50K
count
4000
3500
3000
2500
2000
1500
1000
500
0
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
Occupation


Count Plot of Relationship by Income
Income
<=50K
>50K
count
7000
6000
5000
4000
3000
2000
1000
0
Not-in-family
Husband
Wife
Own-child
Unmarried
Other-relative
Relationship


Count Plot of Race by Income
Income
<=50K
>50K
count
20000
17500
15000
12500
10000
7500
5000
2500
0
White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
Race

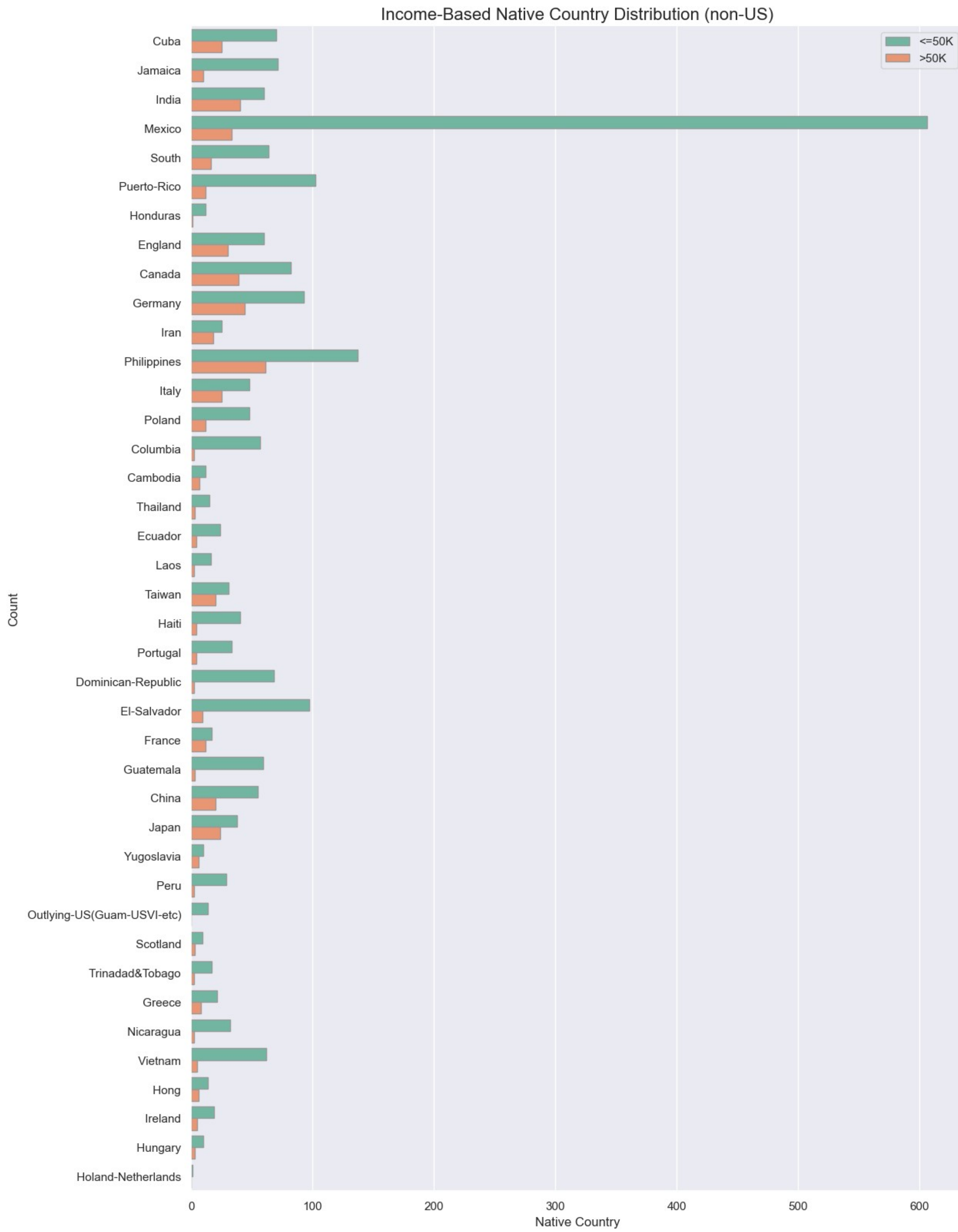

Count Plot of Sex by Income
Income
<=50K
>50K
count
14000
12000
10000
8000
6000
4000
2000
0
Male
Female
Sex


Count Plot of Native_country by Income
Income
<=50K
>50K
count
20000
15000
10000
5000
0
United-States
Cuba
Jamaica
India
Mexico
South
Puerto-Rico
Honduras
England
Canada
Germany
Iran
Philippines
Italy
Poland
Columbia
Cambodia
Thailand
Ecuador
Laos
Taiwan
Haiti
Portugal
Dominican-Republic
El-Salvador
France
Guatemala
China
Japan
Yugoslavia
Peru
Outlying-US(Guam-USVI-etc)
Scotland
Trinadad&Tobago
Greece
Nicaragua
Vietnam
Hong
Ireland
Hungary
Holand-Netherlands
Native_country




```
plot = sns.catplot(data=df.query('Native_country != " United-States"'), y='Native_country', hue="Income", kind="count",
                   palette="Set2", edgecolor=".6", legend=False,
                   height=16, aspect=.8, orient='v');
plot.set_xlabels('Native Country');
plot.set_ylabels('Count');
plt.legend(loc='upper right', labels=['<=50K', '>50K']);
plt.title('Income-Based Native Country Distribution (non-US)', fontsize=16);
```

```
C:\Users\sanda\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Income-Based Native Country Distribution (non-US)
<=50K
>50K
Count
Native Country
0
100
200
300
400
500
600
Cuba
Jamaica
India
Mexico
South
Puerto-Rico
Honduras
England
Canada
Germany
Iran
Philippines
Italy
Poland
Columbia
Cambodia
Thailand
Ecuador
Laos
Taiwan
Haiti
Portugal
Dominican-Republic
El-Salvador
France
Guatemala
China
Japan
Yugoslavia
Peru
Outlying-US(Guam-USVI-etc)
Scotland
Trinadad&Tobago
Greece
Nicaragua
Vietnam
Hong
Ireland
Hungary
Holand-Netherlands

Cross Table Based on Sex

```
column_name=["Age", "Workclass", "Education", "Education_num",
"Marital_status", "Occupation", "Relationship", "Race", "Sex",
"Native_country"]
for column in column_name:
    if column != 'Income':
        print(pd.crosstab(df[column], df['Income'], margins=True,
margins_name='Total'))
        print("\n")
```

```
Income   <=50K   >50K   Total
Age
17         395      0     395
18         550      0     550
19         706      2     708
20         752      0     752
21         715      3     718
...        ...    ...     ...
86           1      0       1
87           1      0       1
88           3      0       3
90          34      8      42
Total    24698   7839   32537

[74 rows x 3 columns]


Income              <=50K   >50K   Total
Workclass
 Federal-gov          589    371     960
 Local-gov           1476    617    2093
 Never-worked           7      0       7
 Private            19357   5152   24509
 Self-emp-inc         494    622    1116
 Self-emp-not-inc    1816    724    2540
 State-gov            945    353    1298
 Without-pay           14      0      14
Total               24698   7839   32537


Income          <=50K   >50K   Total
Education
 10th             871     62     933
 11th            1115     60    1175
 12th             400     33     433
 1st-4th          160      6     166
 5th-6th          316     16     332
 7th-8th          605     40     645
 9th              487     27     514
```

```
 Assoc-acdm        802    265   1067
 Assoc-voc        1021    361   1382
 Bachelors        3132   2221   5353
 Doctorate         107    306    413
 HS-grad          8820   1674  10494
 Masters           763    959   1722
 Preschool          50      0     50
 Prof-school       153    423    576
 Some-college     5896   1386   7282
Total            24698   7839  32537


Income           <=50K   >50K  Total
Education_num
1                   50      0     50
2                  160      6    166
3                  316     16    332
4                  605     40    645
5                  487     27    514
6                  871     62    933
7                 1115     60   1175
8                  400     33    433
9                 8820   1674  10494
10                5896   1386   7282
11                1021    361   1382
12                 802    265   1067
13                3132   2221   5353
14                 763    959   1722
15                 153    423    576
16                 107    306    413
Total            24698   7839  32537


Income                        <=50K   >50K  Total
Marital_status
 Divorced                      3978    463   4441
 Married-AF-spouse               13     10     23
 Married-civ-spouse            8280   6690  14970
 Married-spouse-absent          384     34    418
 Never-married                10176    491  10667
 Separated                      959     66   1025
 Widowed                        908     85    993
Total                         24698   7839  32537


Income                    <=50K   >50K  Total
Occupation
 Adm-clerical              3261    507   3768
 Armed-Forces                 8      1      9
 Craft-repair              3165    929   4094
```

Exec-managerial	2097	1968	4065
Farming-fishing	877	115	992
Handlers-cleaners	1283	86	1369
Machine-op-inspct	1751	249	2000
Other-service	3154	137	3291
Priv-house-serv	146	1	147
Prof-specialty	3930	2049	5979
Protective-serv	438	211	649
Sales	2667	983	3650
Tech-support	644	283	927
Transport-moving	1277	320	1597
Total	24698	7839	32537

Income	<=50K	>50K	Total
Relationship			
Husband	7271	5916	13187
Not-in-family	7436	856	8292
Other-relative	944	37	981
Own-child	4997	67	5064
Unmarried	3227	218	3445
Wife	823	745	1568
Total	24698	7839	32537

Income	<=50K	>50K	Total
Race			
Amer-Indian-Eskimo	275	36	311
Asian-Pac-Islander	762	276	1038
Black	2735	387	3122
Other	246	25	271
White	20680	7115	27795
Total	24698	7839	32537

Income	<=50K	>50K	Total
Sex			
Female	9583	1179	10762
Male	15115	6660	21775
Total	24698	7839	32537

Income	<=50K	>50K	Total
Native_country			
Cambodia	12	7	19
Canada	82	39	121
China	55	20	75
Columbia	57	2	59
Cuba	70	25	95
Dominican-Republic	68	2	70

```
 Ecuador                          24     4     28
 El-Salvador                      97     9    106
 England                          60    30     90
 France                           17    12     29
 Germany                          93    44    137
 Greece                           21     8     29
 Guatemala                        59     3     62
 Haiti                            40     4     44
 Holand-Netherlands                1     0      1
 Honduras                         12     1     13
 Hong                             14     6     20
 Hungary                          10     3     13
 India                            60    40    100
 Iran                             25    18     43
 Ireland                          19     5     24
 Italy                            48    25     73
 Jamaica                          71    10     81
 Japan                            38    24     62
 Laos                             16     2     18
 Mexico                          606    33    639
 Nicaragua                        32     2     34
 Outlying-US(Guam-USVI-etc)       14     0     14
 Peru                             29     2     31
 Philippines                     137    61    198
 Poland                           48    12     60
 Portugal                         33     4     37
 Puerto-Rico                     102    12    114
 Scotland                          9     3     12
 South                            64    16     80
 Taiwan                           31    20     51
 Thailand                         15     3     18
 Trinadad&Tobago                  17     2     19
 United-States                 22420  7315  29735
 Vietnam                          62     5     67
 Yugoslavia                       10     6     16
Total                          24698  7839  32537
```

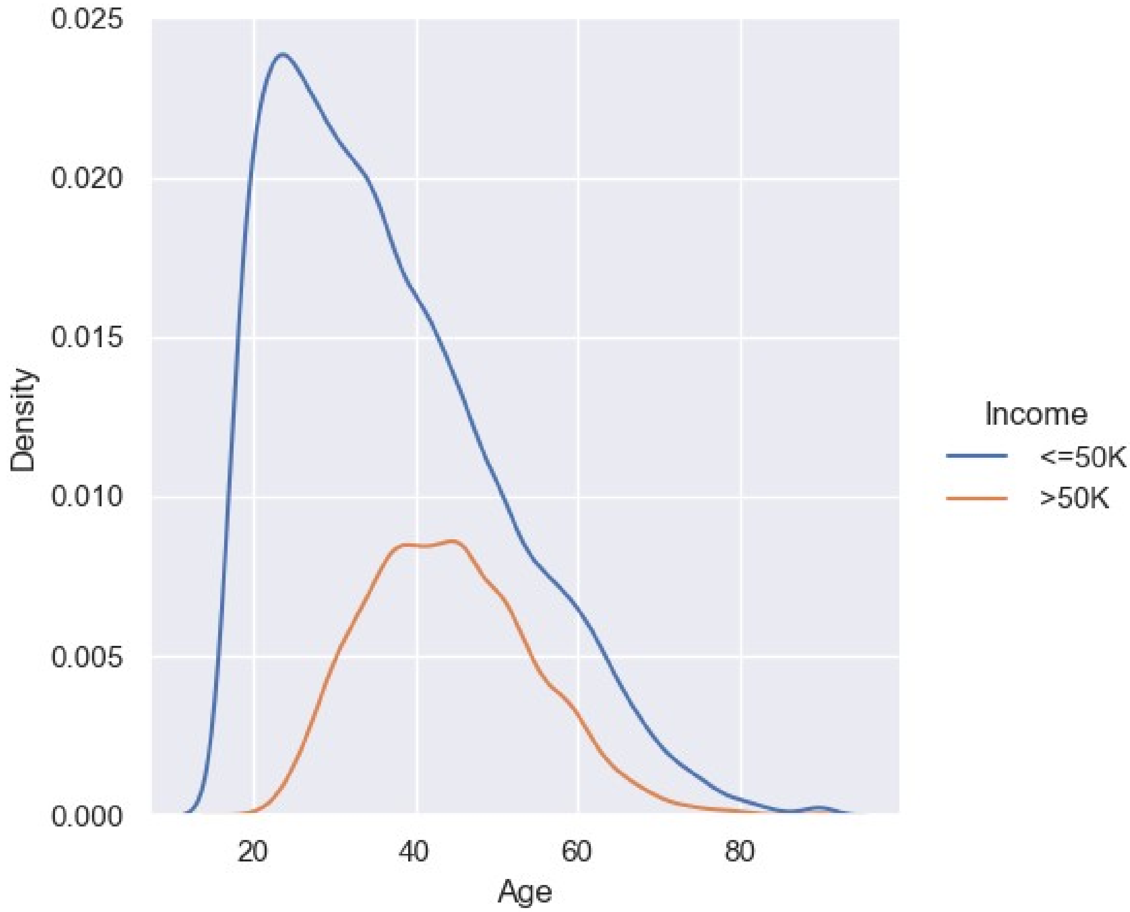
Bivariate Analysis

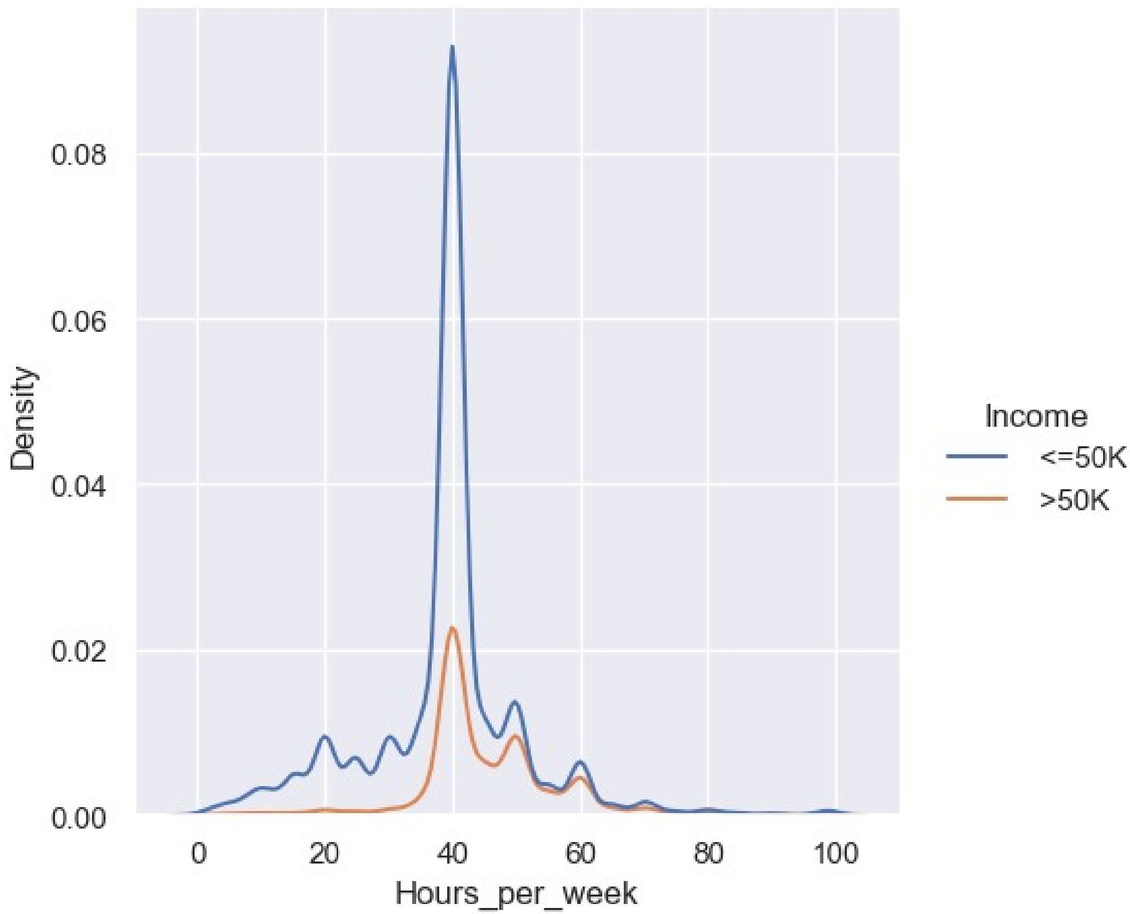
Density Plots Hours_per_week and Age Based on Income

```python
sns.displot(x='Age', hue='Income', data=df, kind='kde')
sns.displot(x='Hours_per_week', hue='Income', data=df, kind='kde')
```

```
C:\Users\sanda\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

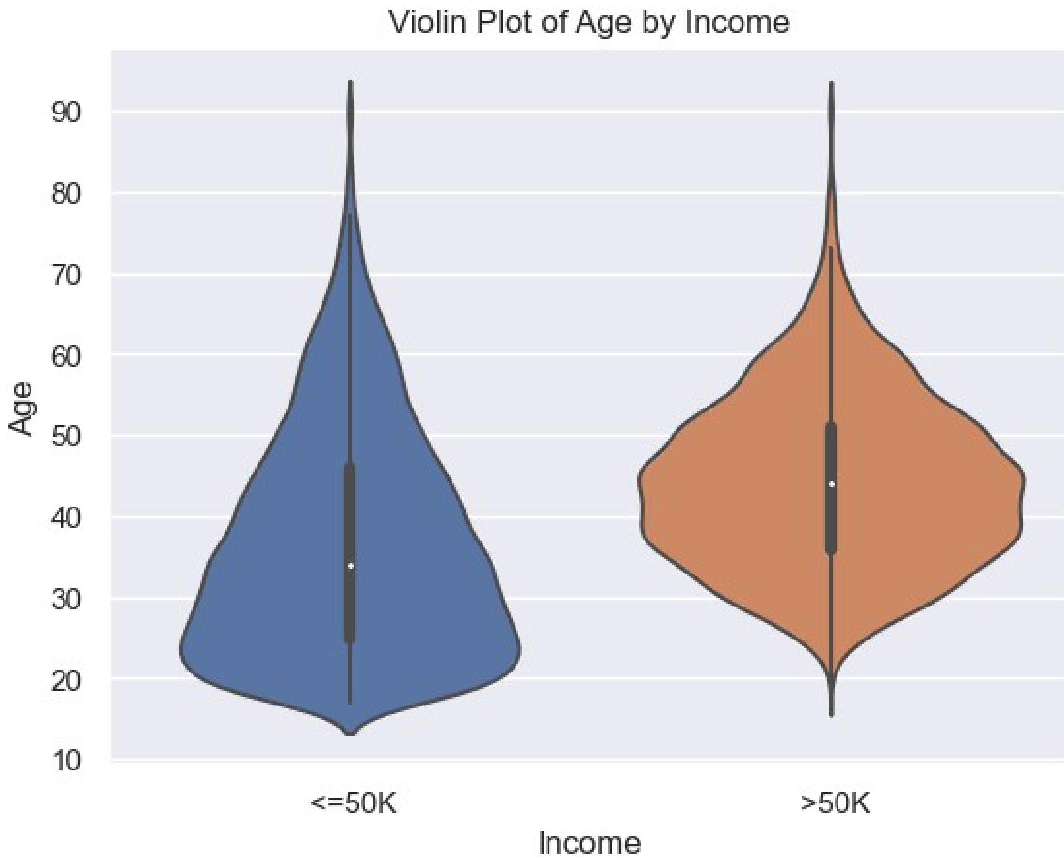
```
C:\Users\sanda\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)

<seaborn.axisgrid.FacetGrid at 0x207eb0c9290>
```





Violine Plot for Age Based on Income

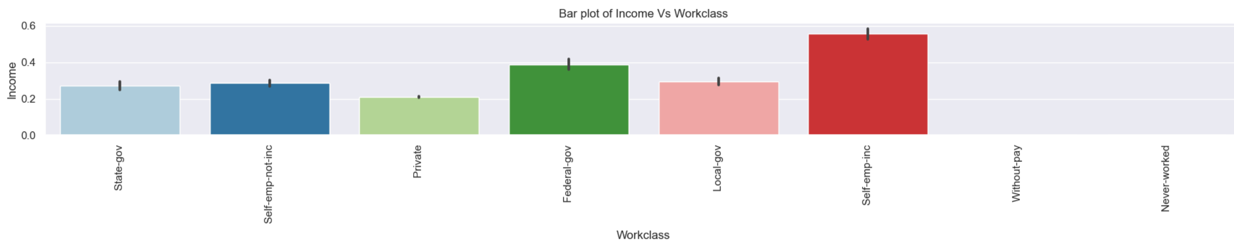
```
sns.violinplot(x = 'Income', y = 'Age', data = df, size = 6)
plt.title('Violin Plot of Age by Income')

Text(0.5, 1.0, 'Violin Plot of Age by Income')
```

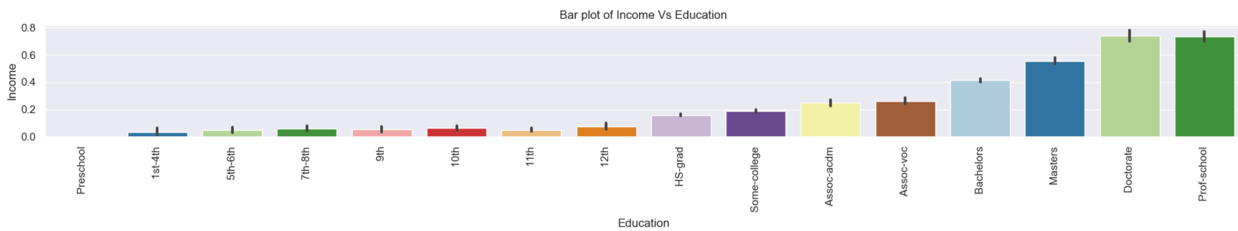


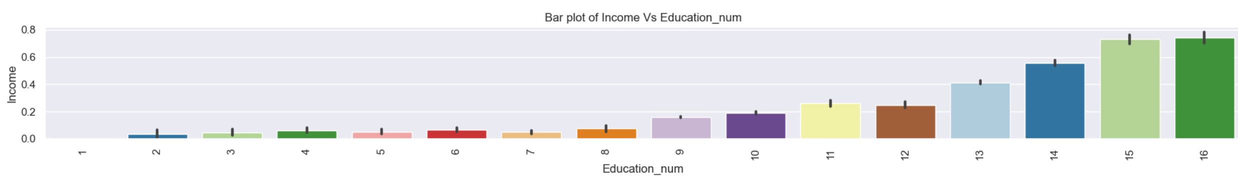
Bar Plot For Income Vs Categoriacal Variables

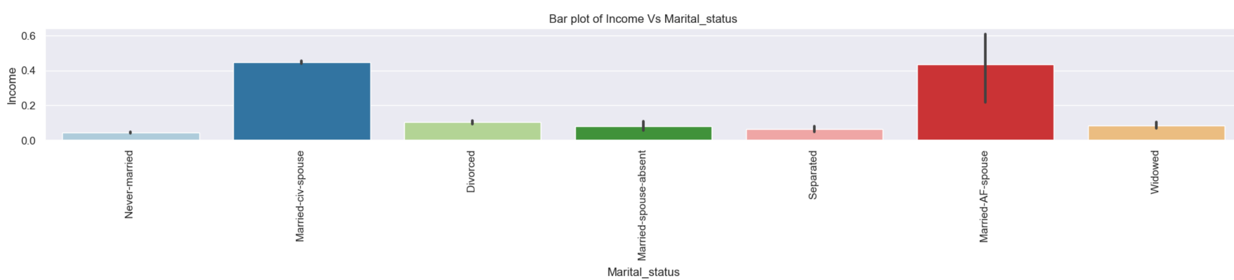
```
df1 = df.copy()
# Convert 'Income' column to binary values (1 if '>50K', 0 otherwise)
df1['Income'] = df['Income'].apply(lambda x: 1 if x == ' >50K' else 0)
education_order = [' Preschool', ' 1st-4th', ' 5th-6th', ' 7th-8th', ' 
9th', ' 10th', ' 11th', ' 12th', ' HS-grad', ' Some-college', ' Assoc-
acdm', ' Assoc-voc', ' Bachelors', ' Masters', ' Doctorate', ' Prof-
school']
# List of categorical variables to include in the plot
categorical_vars = ['Workclass', 'Education', 'Education_num', 
'Marital_status', 'Occupation', 'Relationship', 'Race', 'Sex', 
'Native_country']

# Determine the number of rows and columns dynamically
num_plots = len(categorical_vars)
num_cols = min(1, num_plots)
num_rows = (num_plots - 1) // num_cols + 1

# Create a grouped bar plot for each categorical variable
plt.figure(figsize=(18, 4 * num_rows))
for i, var in enumerate(categorical_vars, 1):
    plt.subplot(num_rows, num_cols, i)
```

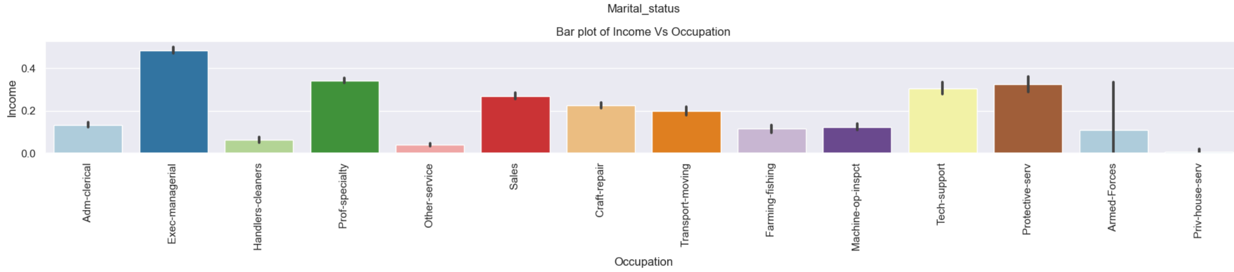
```
    sns.barplot(x=var, y="Income", data=df1, order=education_order if
var == 'Education' else None, palette="Paired")
    plt.xticks(rotation=90)
    plt.title(f"Bar plot of Income Vs {var}")

plt.tight_layout()
plt.show()
```

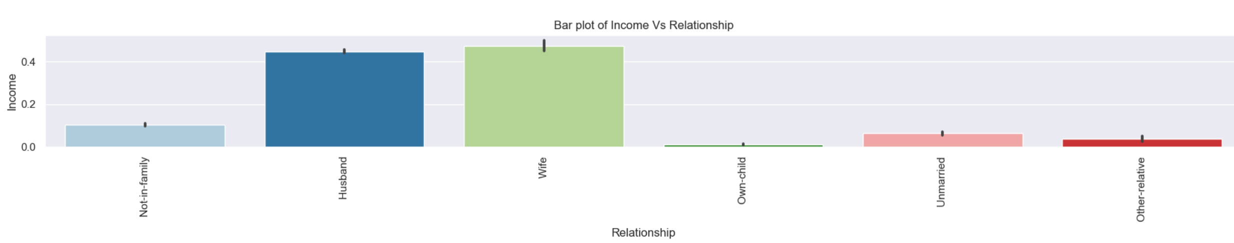

Bar plot of Income Vs Workclass
Income
0.0
0.2
0.4
0.6
State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
Self-emp-inc
Without-pay
Never-worked
Workclass

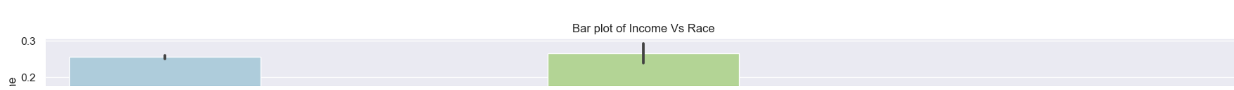

Bar plot of Income Vs Education
Income
0.0
0.2
0.4
0.6
0.8
Preschool
1st-4th
5th-6th
7th-8th
9th
10th
11th
12th
HS-grad
Some-college
Assoc-acdm
Assoc-voc
Bachelors
Masters
Doctorate
Prof-school
Education


Bar plot of Income Vs Education_num
Income
0.0
0.2
0.4
0.6
0.8
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Education_num

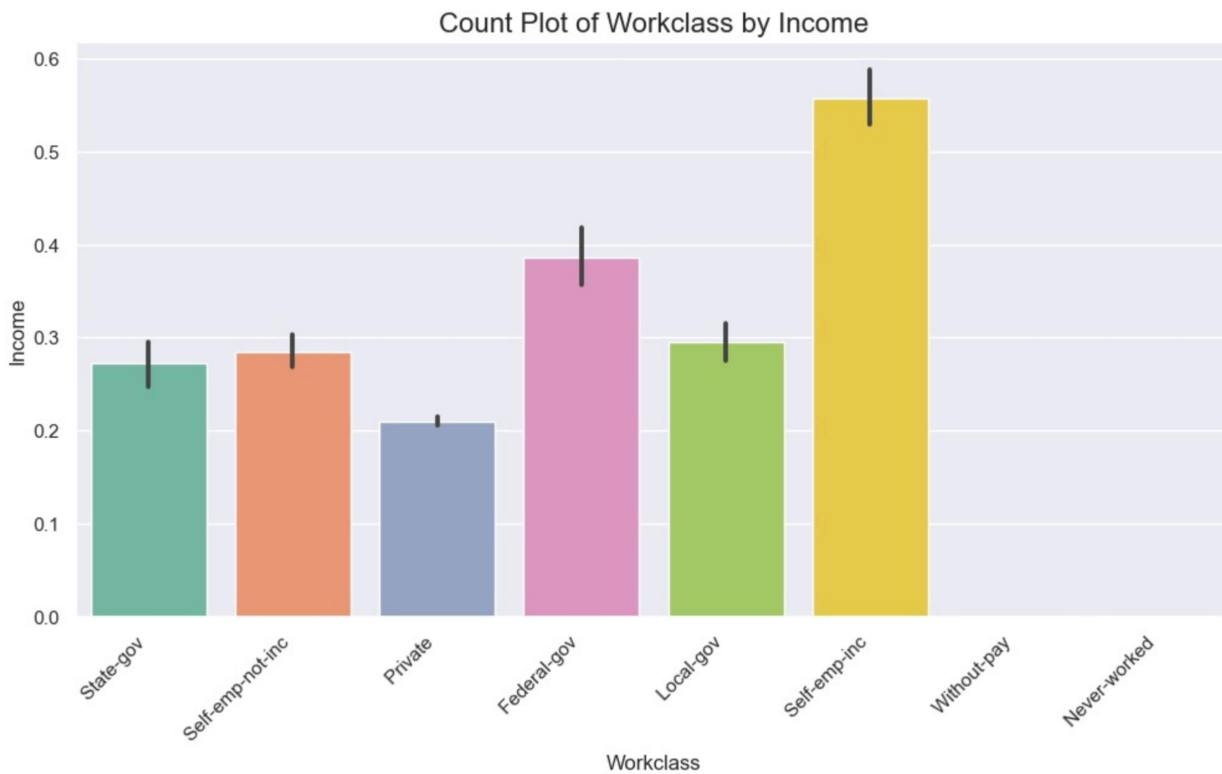

Bar plot of Income Vs Marital_status
Income
0.0
0.2
0.4
0.6
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed
Marital_status

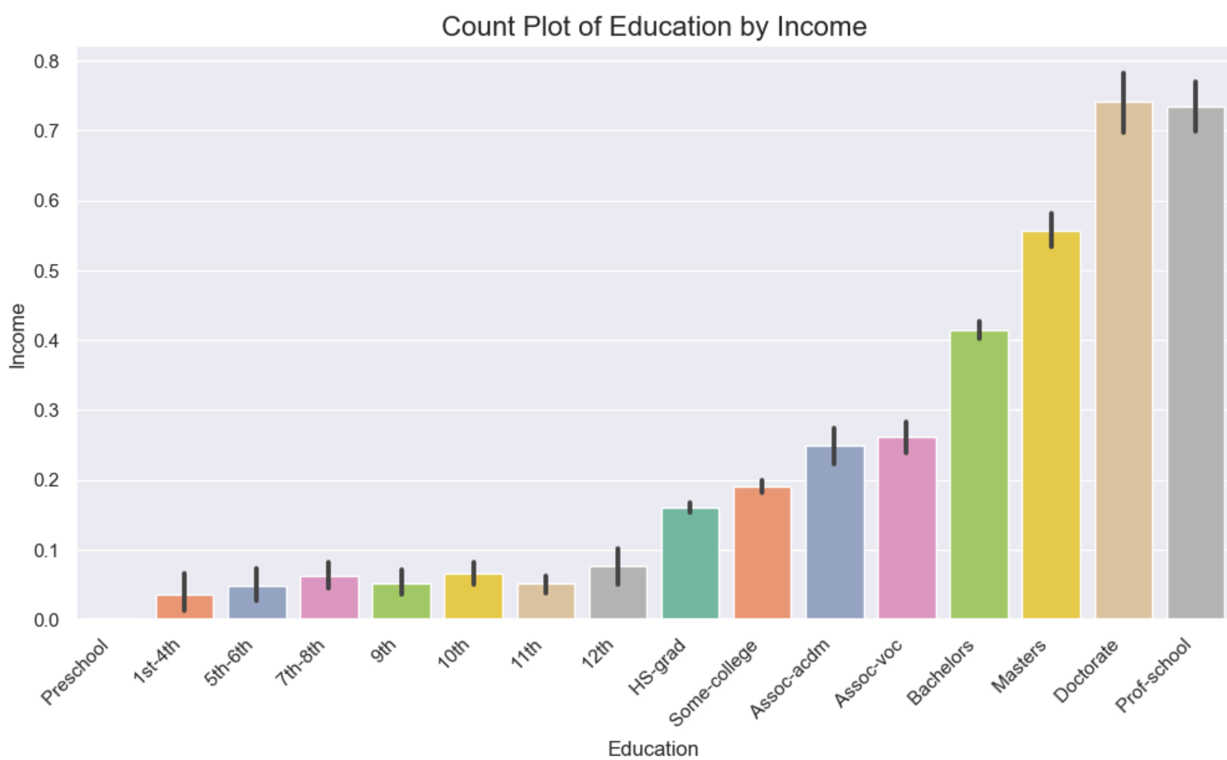

Bar plot of Income Vs Occupation
Income
0.0
0.2
0.4
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
Occupation

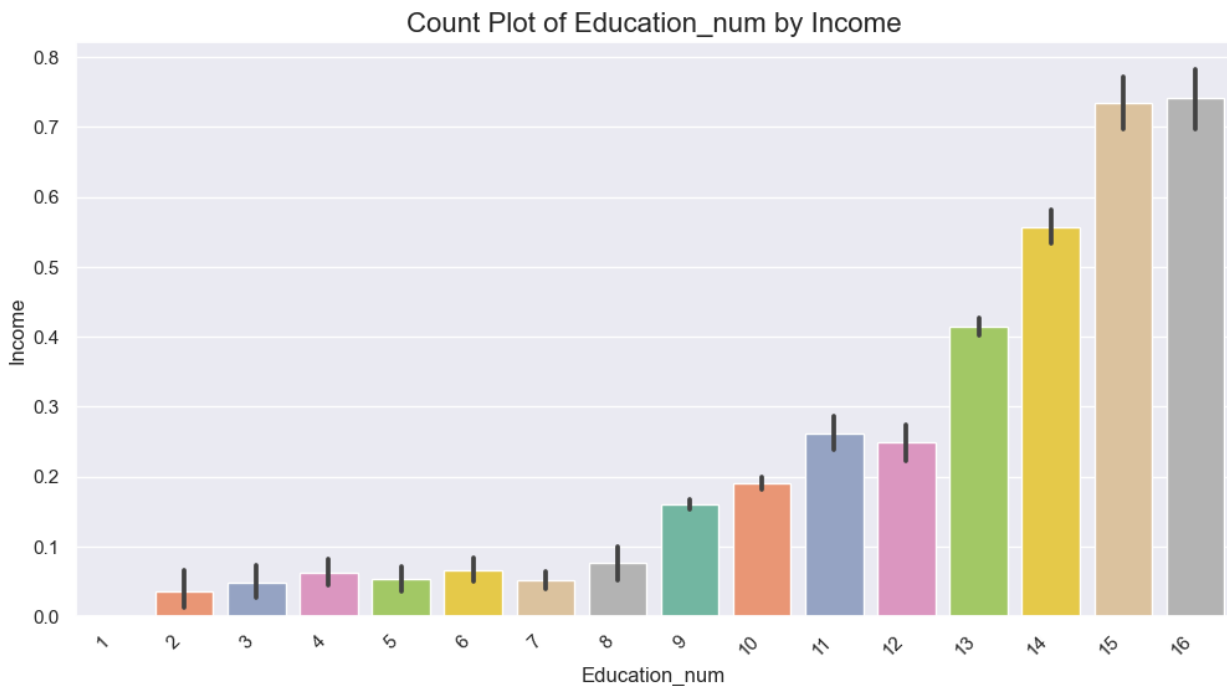

Bar plot of Income Vs Relationship
Income
0.0
0.2
0.4
Not-in-family
Husband
Wife
Own-child
Unmarried
Other-relative
Relationship

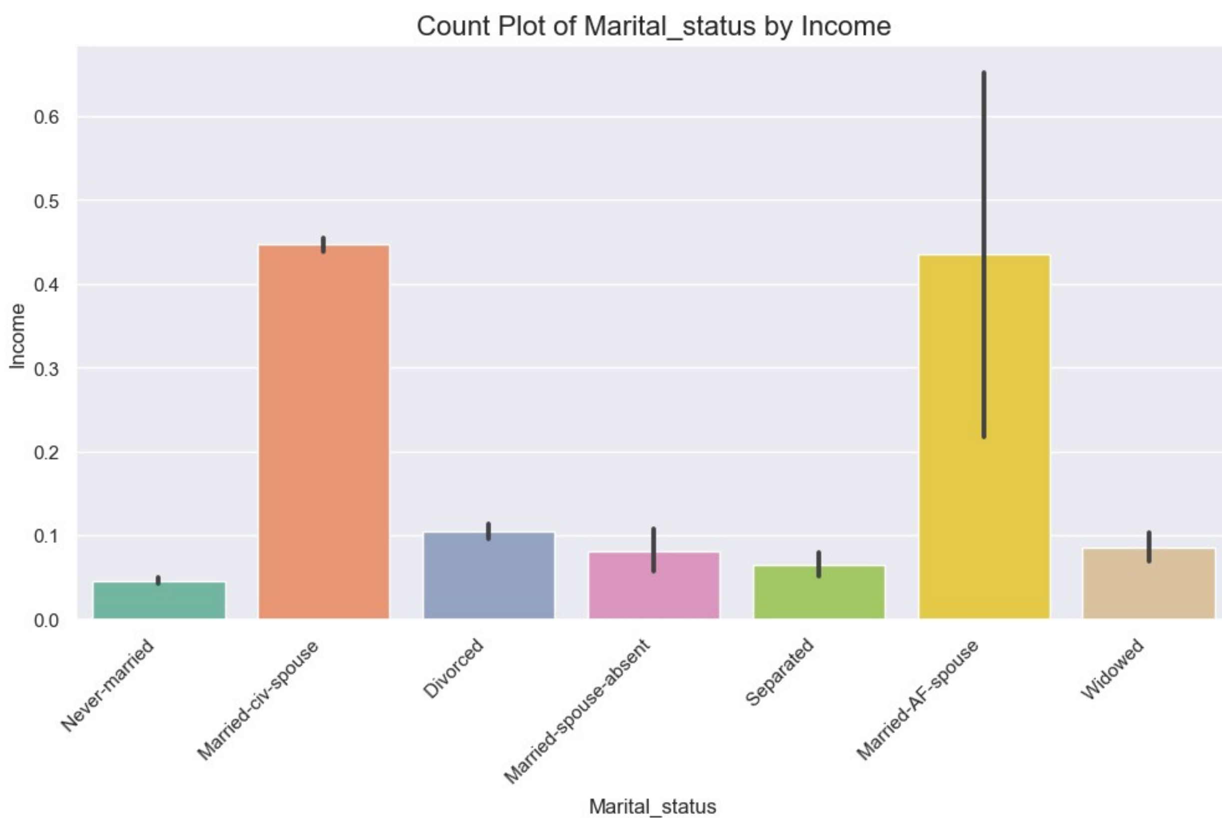

Bar plot of Income Vs Race
0.2
0.3

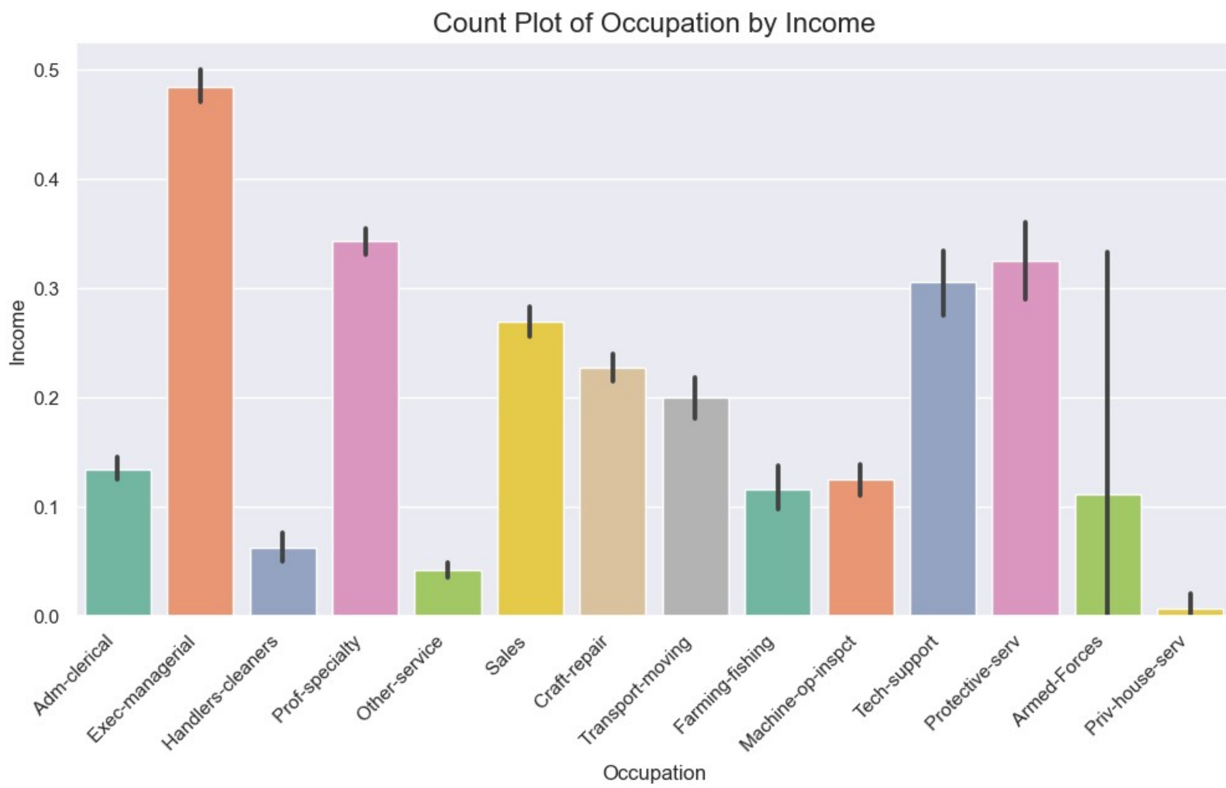
```python
# Categorical columns in the dataset
categorical_columns = ['Workclass', 'Education', 'Education_num',
'Marital_status', 'Occupation', 'Relationship', 'Race', 'Sex',
'Native_country']

# Set the style of seaborn for better visualization
sns.set(style="darkgrid")

# Plot count plots for each categorical variable
for column in categorical_columns:
    plt.figure(figsize=(12, 6))

    # Set the order for 'Education' variable
    if column == 'Education':
        order = sorted(df['Education'].unique(), key=lambda x: ['
Preschool', ' 1st-4th', ' 5th-6th', ' 7th-8th', ' 9th', ' 10th', '
11th', ' 12th',
                ' HS-grad', ' Some-college', ' Assoc-acdm', ' Assoc-
voc', ' Bachelors', ' Masters', ' Doctorate', ' Prof-
school'].index(x))
        sns.barplot(x=column, y='Income', data=df1, palette='Set2',
order=order)
    else:
        sns.barplot(x=column, y='Income', data=df1, palette='Set2')

    plt.title(f'Count Plot of {column} by Income', fontsize=16)
    plt.xticks(rotation=45, ha='right')
    plt.show()
```


Count Plot of Workclass by Income
Income
0.0
0.1
0.2
0.3
0.4
0.5
0.6
State-gov
Self-emp-not-inc
Private
Federal-gov
Local-gov
Self-emp-inc
Without-pay
Never-worked
Workclass

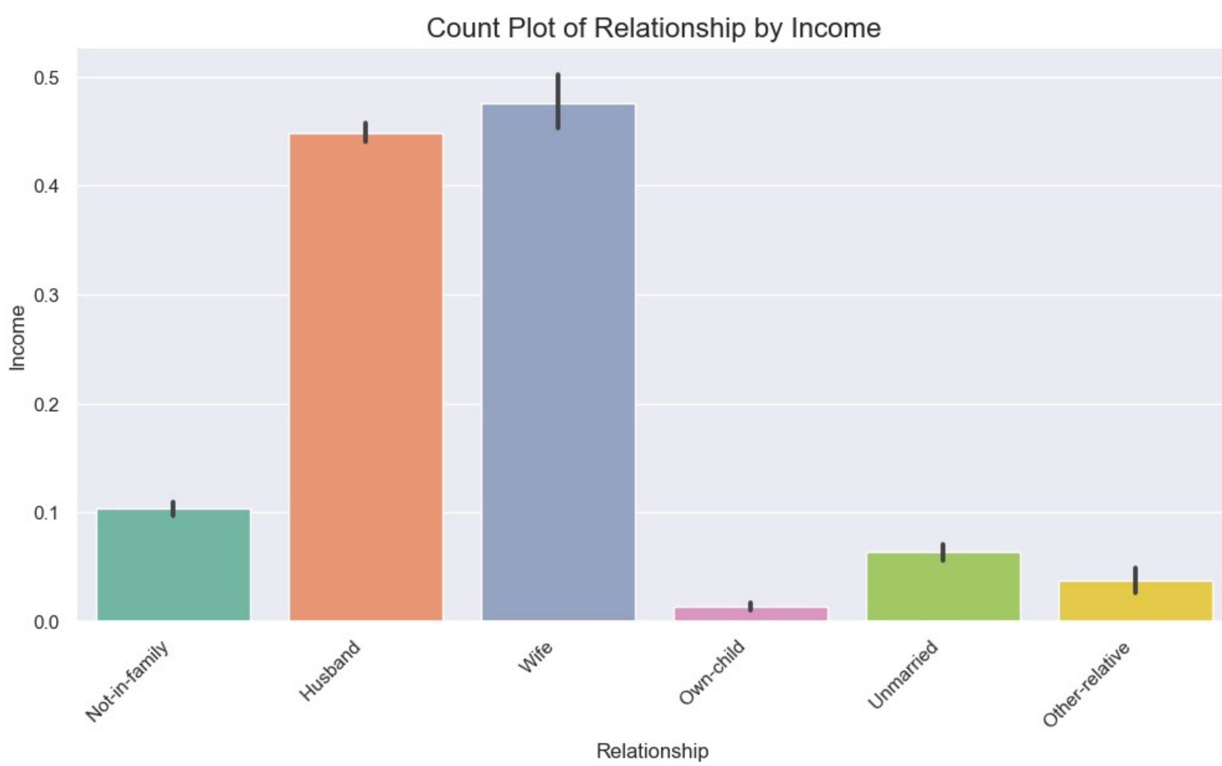

Count Plot of Education by Income
Income
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Preschool
1st-4th
5th-6th
7th-8th
9th
10th
11th
12th
HS-grad
Some-college
Assoc-acdm
Assoc-voc
Bachelors
Masters
Doctorate
Prof-school
Education


Count Plot of Education_num by Income
Income
Education_num
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16

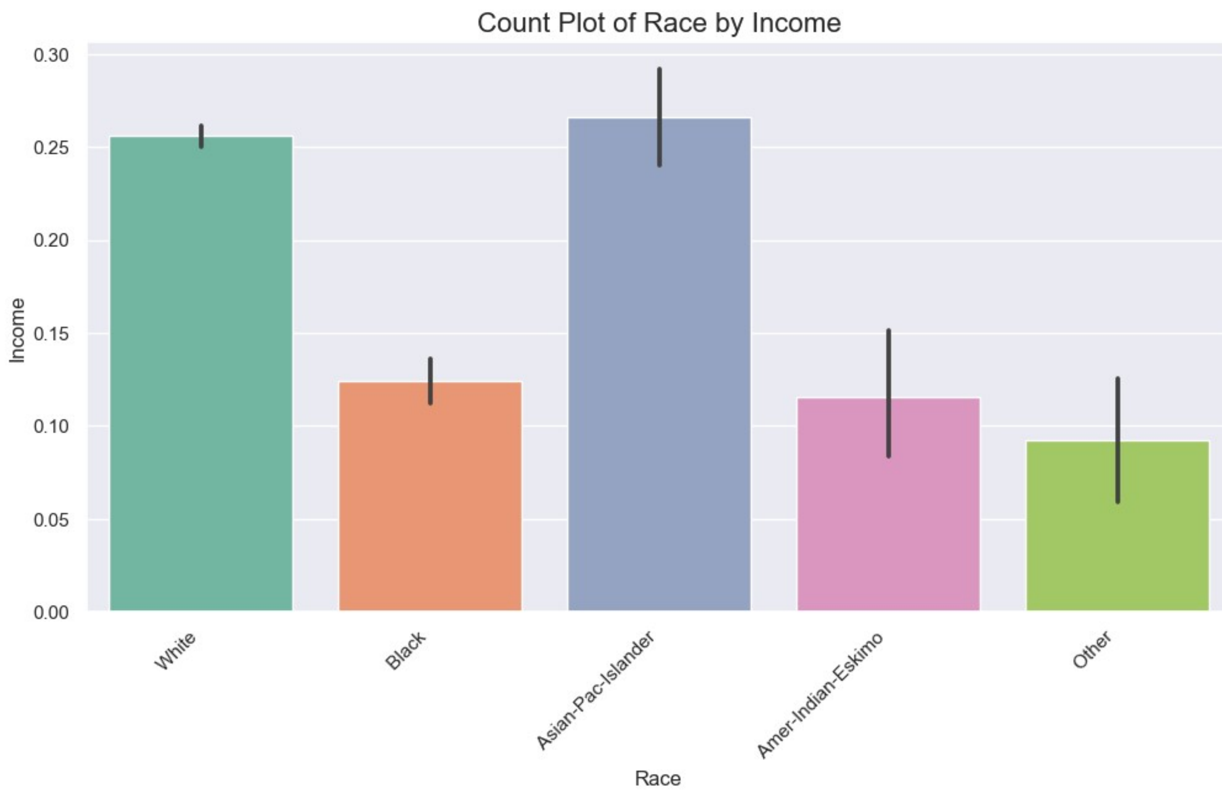

Count Plot of Marital_status by Income
Income
Marital_status
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Never-married
Married-civ-spouse
Divorced
Married-spouse-absent
Separated
Married-AF-spouse
Widowed

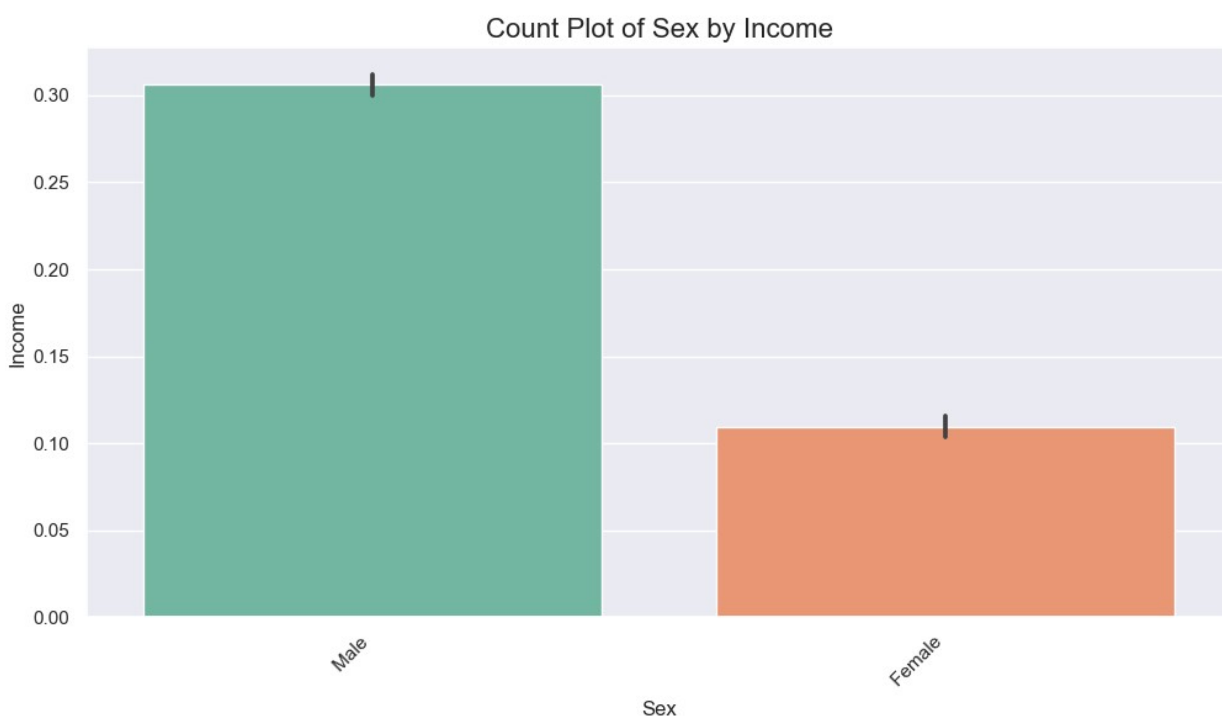


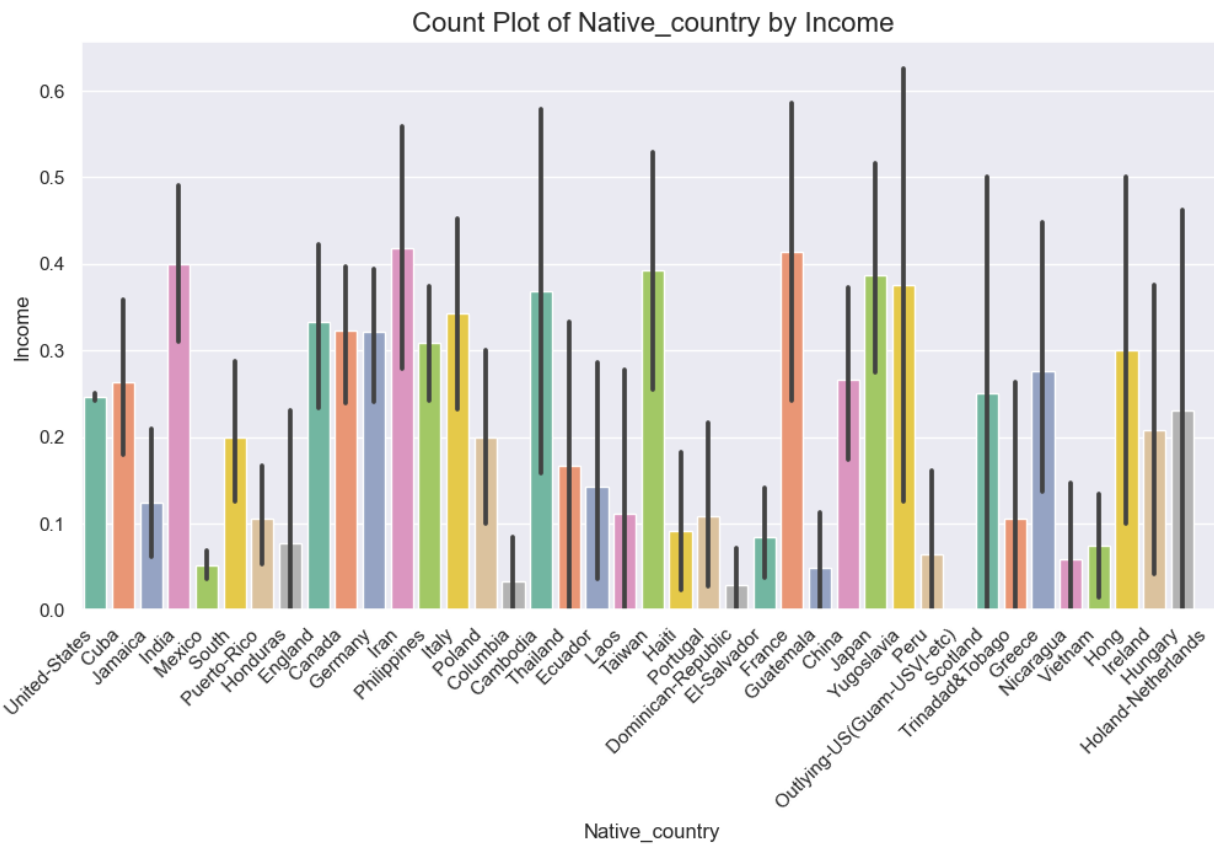
Count Plot of Occupation by Income
Income
0.0
0.1
0.2
0.3
0.4
0.5
Adm-clerical
Exec-managerial
Handlers-cleaners
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Machine-op-inspct
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv
Occupation



Count Plot of Relationship by Income
Income
0.0
0.1
0.2
0.3
0.4
0.5
Not-in-family
Husband
Wife
Own-child
Unmarried
Other-relative
Relationship


Count Plot of Race by Income
Income
0.00
0.05
0.10
0.15
0.20
0.25
0.30
White
Black
Asian-Pac-Islander
Amer-Indian-Eskimo
Other
Race


Count Plot of Sex by Income
Income
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Male
Female
Sex



Heat Map

```
numerical_columns = df.select_dtypes(include=['int64', 'float64'])

# Create a correlation matrix
correlation_matrix = numerical_columns.corr()

# Set up the matplotlib figure
plt.figure(figsize=(12, 10))

# Create a heatmap using seaborn to visualize the correlation matrix
sns.heatmap(correlation_matrix, annot=True, cmap="YlGn", fmt=".2f",
linewidths=.5)

# Show the plot
plt.title("Correlation Plot of Numerical Features")
plt.show()
```

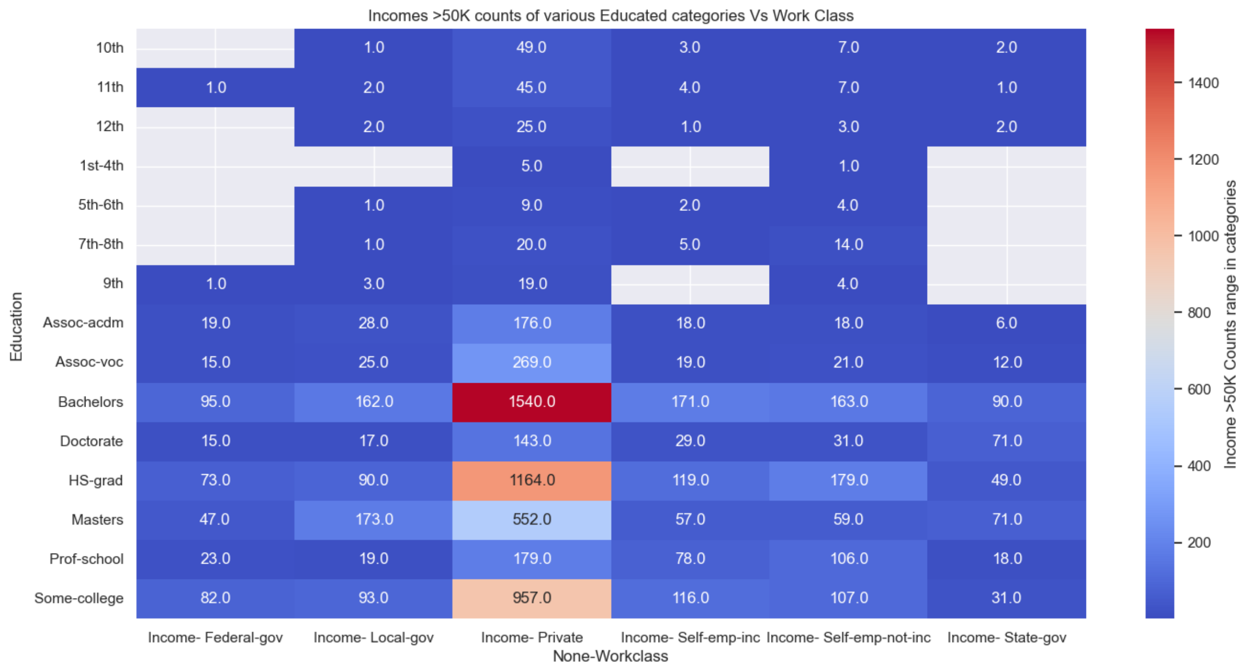
Multivariate Analysis

```
mult_df = df.where(df.Income == "
>50K").pivot_table(values=['Income'],

index='Education',

columns='Workclass',

aggfunc='count')

mult_df.sort_index()

                        Income                                         \
Workclass       Federal-gov  Local-gov  Private  Self-emp-inc
Education
```

```
 10th                     NaN         1.0     49.0            3.0
 11th                     1.0         2.0     45.0            4.0
 12th                     NaN         2.0     25.0            1.0
 1st-4th                  NaN         NaN      5.0            NaN
 5th-6th                  NaN         1.0      9.0            2.0
 7th-8th                  NaN         1.0     20.0            5.0
 9th                      1.0         3.0     19.0            NaN
 Assoc-acdm              19.0        28.0    176.0           18.0
 Assoc-voc               15.0        25.0    269.0           19.0
 Bachelors               95.0       162.0   1540.0          171.0
 Doctorate               15.0        17.0    143.0           29.0
 HS-grad                 73.0        90.0   1164.0          119.0
 Masters                 47.0       173.0    552.0           57.0
 Prof-school             23.0        19.0    179.0           78.0
 Some-college            82.0        93.0    957.0          116.0


Workclass      Self-emp-not-inc  State-gov
Education
 10th                       7.0        2.0
 11th                       7.0        1.0
 12th                       3.0        2.0
 1st-4th                    1.0        NaN
 5th-6th                    4.0        NaN
 7th-8th                   14.0        NaN
 9th                        4.0        NaN
 Assoc-acdm                18.0        6.0
 Assoc-voc                 21.0       12.0
 Bachelors                163.0       90.0
 Doctorate                 31.0       71.0
 HS-grad                  179.0       49.0
 Masters                   59.0       71.0
 Prof-school              106.0       18.0
 Some-college             107.0       31.0
```

```python
plt.figure(figsize=(16, 8))
sns.heatmap(mult_df.sort_index(), annot=True, fmt='.1f', cbar_kws=
{'label':'Income >50K Counts range in categories'}, cmap='coolwarm')
plt.title('Incomes >50K counts of various Educated categories Vs Work
Class')
```

```
Text(0.5, 1.0, 'Incomes >50K counts of various Educated categories Vs
Work Class')
```



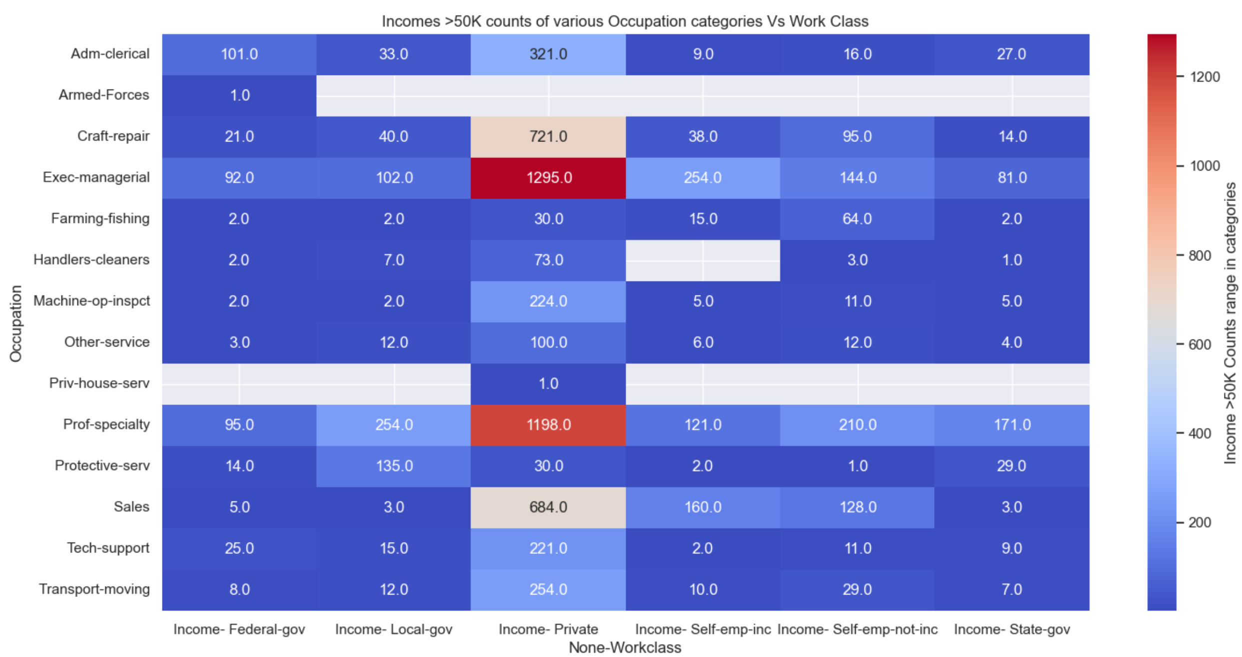

```
mult_df1 = df.where(df.Income == "
>50K").pivot_table(values=['Income'],

index='Occupation',

columns='Workclass',

aggfunc='count')

mult_df1.sort_index()
```

```
                         Income                                          \
Workclass           Federal-gov  Local-gov  Private  Self-emp-inc
Occupation
 Adm-clerical             101.0       33.0    321.0           9.0
 Armed-Forces               1.0        NaN      NaN           NaN
 Craft-repair              21.0       40.0    721.0          38.0
 Exec-managerial           92.0      102.0   1295.0         254.0
 Farming-fishing            2.0        2.0     30.0          15.0
 Handlers-cleaners          2.0        7.0     73.0           NaN
 Machine-op-inspct          2.0        2.0    224.0           5.0
 Other-service              3.0       12.0    100.0           6.0
 Priv-house-serv            NaN        NaN      1.0           NaN
 Prof-specialty            95.0      254.0   1198.0         121.0
 Protective-serv           14.0      135.0     30.0           2.0
 Sales                      5.0        3.0    684.0         160.0
 Tech-support              25.0       15.0    221.0           2.0
 Transport-moving           8.0       12.0    254.0          10.0
```

```
Workclass            Self-emp-not-inc  State-gov
Occupation
 Adm-clerical                    16.0       27.0
 Armed-Forces                     NaN        NaN
 Craft-repair                    95.0       14.0
 Exec-managerial                144.0       81.0
 Farming-fishing                 64.0        2.0
 Handlers-cleaners                3.0        1.0
 Machine-op-inspct               11.0        5.0
 Other-service                   12.0        4.0
 Priv-house-serv                  NaN        NaN
 Prof-specialty                 210.0      171.0
 Protective-serv                  1.0       29.0
 Sales                          128.0        3.0
 Tech-support                    11.0        9.0
 Transport-moving                29.0        7.0
```

```
plt.figure(figsize=(16, 8))
sns.heatmap(mult_df1.sort_index(), annot=True, fmt='.1f', cbar_kws=
{'label':'Income >50K Counts range in categories'}, cmap='coolwarm')
plt.title('Incomes >50K counts of various Occupation categories Vs
Work Class')
```

```
Text(0.5, 1.0, 'Incomes >50K counts of various Occupation categories
Vs Work Class')
```




```
mult_df2 = df.where(df.Income == "
>50K").pivot_table(values=['Income'],
```

```
index='Race',

columns='Education',

aggfunc='count')

mult_df2.sort_index()

                        Income
\
Education                 10th  11th  12th  1st-4th  5th-6th  7th-8th
9th
Race

 Amer-Indian-Eskimo        NaN   2.0   NaN      NaN      NaN      NaN
NaN
 Asian-Pac-Islander        1.0   1.0   1.0      NaN      3.0      NaN
1.0
 Black                     6.0   7.0   5.0      1.0      NaN      2.0
4.0
 Other                     1.0   NaN   NaN      NaN      1.0      NaN
NaN
 White                    54.0  50.0  27.0      5.0     12.0     38.0
22.0


\
Education                Assoc-acdm  Assoc-voc  Bachelors  Doctorate  HS-
grad
Race

 Amer-Indian-Eskimo             1.0        1.0        8.0        2.0
11.0
 Asian-Pac-Islander             8.0        9.0       97.0       18.0
34.0
 Black                         19.0       18.0       96.0        9.0
86.0
 Other                          2.0        NaN        5.0        1.0
2.0
 White                        235.0      333.0     2015.0      276.0
1541.0


Education                Masters  Prof-school  Some-college
Race
 Amer-Indian-Eskimo          3.0          2.0           6.0
 Asian-Pac-Islander         43.0         27.0          33.0
 Black                      40.0          8.0          86.0
 Other                       2.0          4.0           7.0
 White                     871.0        382.0        1254.0
```

```
plt.figure(figsize=(16, 8))
sns.heatmap(mult_df2.sort_index(), annot=True, fmt='.1f', cbar_kws=
{'label':'Income >50K Counts range in categories'}, cmap='coolwarm')
plt.title('Incomes >50K counts of various Race categories Vs Education
categories')
```

```
Text(0.5, 1.0, 'Incomes >50K counts of various Race categories Vs
Education categories')
```