Midterm Skill Exam

Name: Jann Moises Nyll B. De los Reyes

Section: CPE22S3

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Submitted to: Engr. Roman M. Richard

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

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/

About Data

Setup

We need to install the following package to install the dataset using API

In [113…
```
pip install ucimlrepo
```

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

Import the dataset into your code

In [114…
```
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://archive.ics.uci.edu/static/public/20/data.csv', 'abstract': 'Predict whether income exceeds $50K/yr based on census da
ta.  Also known as Adult dataset.', 'area': 'Social Science', 'tasks': ['Classification'], 'characteristics': ['Multivariate'],
'num_instances': 48842, 'num_features': 14, 'feature_types': ['Categorical', 'Integer'], 'demographics': ['Age', 'Income', 'Edu
cation Level', 'Other', 'Race', 'Sex'], 'target_col': ['income'], 'index_col': None, 'has_missing_values': 'yes', 'missing_valu
es_symbol': 'NaN', 'year_of_dataset_creation': 1996, 'last_updated': 'Thu Aug 10 2023', 'dataset_doi': '10.24432/C5GP7S', 'crea
tors': ['Ron Kohavi'], 'intro_paper': None, 'additional_info': {'summary': 'Extraction was done by Barry Becker from the 1994 C
ensus database.  A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AF
NLWGT>1)&& (HRSWK>0))\r\n\r\nPrediction task is to determine whether a person makes over 50K a year.', 'purpose': None, 'funded
_by': None, 'instances_represent': None, 'recommended_data_splits': None, 'sensitive_data': None, 'preprocessing_description':
None, 'variable_info': 'Listing of attributes:\r\n\r\n>50K, <=50K.\r\n\r\nage: continuous.\r\nworkclass: Private, Self-emp-not-
inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.\r\nfnlwgt: continuous.\r\neducation: Bachelor
s, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-
6th, Preschool.\r\neducation-num: continuous.\r\nmarital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowe
d, Married-spouse-absent, Married-AF-spouse.\r\noccupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial,
Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protect
ive-serv, Armed-Forces.\r\nrelationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.\r\nrace: White, As
ian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.\r\nsex: Female, Male.\r\ncapital-gain: continuous.\r\ncapital-loss: continu
ous.\r\nhours-per-week: continuous.\r\nnative-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying
-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mex
ico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scot
land, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.', 'citation': None}}
```

	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

By importing the dataframes, we can access the metadata were we will be able to know the information such as missing values

Importing the necessary package to be used on Data Wrangling

In [115…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Accessing each dataframe columns

In [116…
```
#Accessing  the X dataframe
X.columns
```

Out[116…
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'marital-status', 'occupation', 'relationship', 'race', 'sex',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country'],
      dtype='object')
```

In [117…
```
#Accessing the y dataframe
```

```
y.columns
```

Out[117… `Index(['income'], dtype='object')`

Merging the two separate dataframe

We will use the .concat() to merge the X and y dataframe with an axis = 1 to make a new dataframe called `census_df` with a dataset containing X and y columns.

In [ ]:
```
census_df = pd.concat([X,y],axis = 1)
census_df
```

Out[ ]:

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

48842 rows × 15 columns

Identifying the Dataframe Characteristics

It is important for us to know the characteristics of our dataframe. By knowing the size, missing values and etc. We can use `shape()`, `describe()`, and `info` to know more information about our dataframe. We can make a list of all changes we need before we proceed in data cleaning.

In [ ]:
```
# Identify the size of our dataframe
print('Rows:{} Columns:{}'.format(census_df.shape[0],census_df.shape[1]))
```

```
Rows:48842 Columns:15
```

In [ ]:
```
#Statistical Summary of  our dataframe
census_df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
age	48842.0	38.643585	13.710510	17.0	28.0	37.0	48.0	90.0
fnlwgt	48842.0	189664.134597	105604.025423	12285.0	117550.5	178144.5	237642.0	1490400.0
education-num	48842.0	10.078089	2.570973	1.0	9.0	10.0	12.0	16.0
capital-gain	48842.0	1079.067626	7452.019058	0.0	0.0	0.0	0.0	99999.0
capital-loss	48842.0	87.502314	403.004552	0.0	0.0	0.0	0.0	4356.0
hours-per-week	48842.0	40.422382	12.391444	1.0	40.0	40.0	45.0	99.0

In [ ]:
```
census_df.info()
```

```
<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       47879 non-null  object
 2   fnlwgt          48842 non-null  int64 
 3   education       48842 non-null  object
 4   education-num   48842 non-null  int64 
 5   marital-status  48842 non-null  object
 6   occupation      47876 non-null  object
 7   relationship    48842 non-null  object
 8   race            48842 non-null  object
 9   sex             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  48568 non-null  object
 14  income          48842 non-null  object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
```

On our first exploration on our data we found that we have missing data in **workclass**, **occupation**, and **native-country** column. We need to explore more about the data entered in each columns. We will use the `unique()` to extract unique data entries.

In [ ]:
```
# to access workclass column entries
census_df['workclass'].unique()
```

Out[ ]:
```
array(['State-gov', 'Self-emp-not-inc', 'Private', 'Federal-gov',
       'Local-gov', '?', 'Self-emp-inc', 'Without-pay', 'Never-worked',
       nan], dtype=object)
```

In [ ]:
```
# to accesse education column entries
census_df['education'].unique()
```

Out[ ]:
```
array(['Bachelors', 'HS-grad', '11th', 'Masters', '9th', 'Some-college',
       'Assoc-acdm', 'Assoc-voc', '7th-8th', 'Doctorate', 'Prof-school',
       '5th-6th', '10th', '1st-4th', 'Preschool', '12th'], dtype=object)
```

In [ ]:
```
# to access marital-status column entries
census_df['marital-status'].unique()
```

Out[ ]:
```
array(['Never-married', 'Married-civ-spouse', 'Divorced',
       'Married-spouse-absent', 'Separated', 'Married-AF-spouse',
       'Widowed'], dtype=object)
```

In [ ]:
```
# to access occupation column entries
census_df['occupation'].unique()
```

Out[ ]:
```
array(['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', nan], dtype=object)
```

In [ ]:
```
# to access relationship column entries
census_df['relationship'].unique()
```

Out[ ]:
```
array(['Not-in-family', 'Husband', 'Wife', 'Own-child', 'Unmarried',
       'Other-relative'], dtype=object)
```

In [ ]:
```
# to access race column entries
```

```
census_df['race'].unique()
```

```
Out[ ]: array(['White', 'Black', 'Asian-Pac-Islander', 'Amer-Indian-Eskimo',
       'Other'], dtype=object)
```

```
In [ ]: # to access native country column entries
census_df['native-country'].unique()
```

```
Out[ ]: array(['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', nan], dtype=object)
```

```
In [ ]: census_df['income'].unique()
```

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

- As we can see in the above summary of our dataframe, we have NaN values as `nan` and unknown values denoted as `?` in `workclass`, `ocupation`, `native-country` column.
- Meanwhile, `education` column has a a data entries of *`9th`*, *`10th`*, *`11th`*, and *`12th`* grade is part of a `Highschool undergrad` but it was mentioned separately.We need to also make an object called `Elementary` for `1st-4th`, `5th-6th` and `7th-8th` since we need a formality in the dataset.
- In workclass, we can simple join the `self-emp-not-inc` and `self-emp-income` under `self employed` category. We can also join `local-gov`, `State-gov`, `Federal-gov` under government employees.
- We can also simplfy the category of marital status by making married-civ-spouse, married-spous-absent, married-AF-spouse into `married`. We can also simplfy the Divorced, separated into `separated` category.
- Lastly the income can be simplify by joining `>50k` where it includes `>50k` and `50k.` and `<=50k` from `<=50k` and `<=50k.`

Note that simplifying some category would make our analysis substandard since some profitability is different from one another.

Missing Values

The following procedures allow us to change the missing and unknown values in our dataframe. First we need to know the number of missing and unknown values of our dataset

```
In [ ]: census_df.isnull().sum()  #Count the missing value of each columns using .isnull()
```

```
Out[ ]: 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
```

```
In [ ]: census_df.isin(['?']).sum() #Count the unknown value (denoted as '?' ) in each columns
```

Out[ ]:
```
age                0
workclass       1836
fnlwgt             0
education          0
education-num      0
marital-status     0
occupation      1843
relationship       0
race               0
sex                0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country   583
income             0
dtype: int64
```

Dealing with missing values

In our data, we found several missing value in our dataset.

In [ ]:
```
census_df[census_df['workclass'].isna()]
# We can change  the  columns to the above code to see  the nan values
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	nati coun
32565	18	NaN	103497	Some-college	10	Never-married	NaN	Own-child	White	Female	0	0	30	Unit Sta
32567	29	NaN	227026	HS-grad	9	Never-married	NaN	Unmarried	Black	Male	0	0	40	Unit Sta
32574	58	NaN	299831	HS-grad	9	Married-civ-spouse	NaN	Husband	White	Male	0	0	35	Unit Sta
32583	72	NaN	132015	7th-8th	4	Divorced	NaN	Not-in-family	White	Female	0	0	6	Unit Sta
32596	65	NaN	191846	HS-grad	9	Married-civ-spouse	NaN	Husband	White	Male	0	0	40	Unit Sta
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
48682	61	NaN	265201	Some-college	10	Married-civ-spouse	NaN	Husband	White	Male	0	0	14	Unit Sta
48769	21	NaN	212661	Some-college	10	Never-married	NaN	Own-child	White	Female	0	0	30	Unit Sta
48800	73	NaN	144872	HS-grad	9	Married-civ-spouse	NaN	Husband	White	Male	0	0	25	Cana
48812	81	NaN	26711	Assoc-voc	11	Married-civ-spouse	NaN	Husband	White	Male	2936	0	20	Unit Sta
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-relative	Black	Male	0	0	40	Unit Sta

963 rows × 15 columns

We use the `.apply()` to fill the nan values with the most common class in the dataset using `.fillna()`. We can do this by taking the index of the most common class which can be determined by using `value_counts()` method.

In [ ]:
```
# filling with most common class
census_df = census_df.apply(lambda x: x.fillna(x.value_counts().index[0]))
#Check the following by locating some nan value in the previous code.
census_df.head()
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	i
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	

In [ ]:
```
census_df.isnull().sum()  #To check if we have any missing value of each columns using .isnull()
```

Out[ ]:
```
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
```

Dealing with unknown value

We can use .replace() to change the ? with a class of `unknown`

In [118…
```
census_df.loc[census_df['native-country'] == '?']
# We can change  the  columns to the above code to see  the missing values
```

Out[118…

	age	workclass	fnlwgt	education	education-num	marital_status	occupation	relationship	race	sex	capital_gain	capital-loss	hours-per-week	native countr

In [119…
```
unknown_cols = ['native-country','occupation','workclass']
# Replace ? with Unknown
for col in unknown_cols:
    census_df.loc[census_df[col] == '?', col] = 'unknown'
```

In [120…
```
# Check if ? is present
for col in unknown_cols:
    print(f"? in {col}: {census_df[(census_df[col] == '?')].any().sum()}")
```

```
? in native-country: 0
? in occupation: 0
? in workclass: 0
```

In [ ]:
```
for col in unknown_cols:
    print(f"? in {col}: {census_df[(census_df[col] == '?')].any().sum()}")
```

```
? in native-country: 0
? in occupation: 0
? in workclass: 0
```

We can check the following columnn if theres any '?' value in the dataset.

In [121…
```
census_df.isin(['?']).sum() #Count the unknown value (denoted as '?' ) in each columns
```

Out[121…
```
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
```

In [122…
```
#rename column
census_df = census_df.rename(columns={'marital-status': 'marital_status'})
census_df
```

Out[122…

	age	workclass	fnlwgt	education	education-num	marital_status	occupation	relationship	race	sex	capital_gain	capital-loss
0	39	govt_employee	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0
1	50	self_employed	83311	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0
2	38	Private	215646	HS-grad	9	Separated	Handlers-cleaners	Not-in-family	White	Male	0	0
3	53	Private	234721	HS-grad	7	Married	Handlers-cleaners	Husband	Black	Male	0	0
4	28	Private	338409	Bachelors	13	Married	Prof-specialty	Wife	Black	Female	0	0
…	…	…	…	…	…	…	…	…	…	…	…	…
48837	39	Private	215419	Bachelors	13	Separated	Prof-specialty	Not-in-family	White	Female	0	0
48838	64	Private	321403	HS-grad	9	Widowed	Prof-specialty	Other-relative	Black	Male	0	0
48839	38	Private	374983	Bachelors	13	Married	Prof-specialty	Husband	White	Male	0	0
48840	44	Private	83891	Bachelors	13	Separated	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0
48841	35	self_employed	182148	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0

48842 rows × 15 columns

Correcting and Simplfying data

Now that we already clean and fill up the missing value we can now normalize the data by simplifying some class in the following columns (`education`, `marital-status`, `workclass` and `income`).

Education columns

In [ ]:
```
#simplify the class of each columns
HS_grad = ['HS-grad','11th','9th','12th','10th']
elementary = ['1st-4th','5th-6th','7th-8th']
associate = ['Assoc-acdm','Assoc-voc']
bachelor = ['Bachelors','Some-college']
post_grad = ['Prof-school','Masters','Doctorate']
#replace elements in  list
```

```
census_df['education'].replace(to_replace = HS_grad,value = 'HS-grad',inplace =True)
census_df['education'].replace(to_replace = elementary,value = 'Elementary',inplace =True)
census_df['education'].replace(to_replace = associate,value = 'Associate',inplace =True)
census_df['education'].replace(to_replace = bachelor,value = 'Bachelors',inplace =True)
census_df['education'].replace(to_replace = post_grad,value = 'Post-Graduate',inplace =True)
#count the number of class in education  columns
census_df['education'].value_counts()
```

Out[ ]:
```
education
HS-grad          20398
Bachelors        18903
Post-Graduate     4085
Associate         3662
Elementary        1711
Preschool           83
Name: count, dtype: int64
```

In [ ]:
```
census_df['education'].unique()
```

Out[ ]:
```
array(['Bachelors', 'HS-grad', 'Post-Graduate', 'Associate', 'Elementary',
       'Preschool'], dtype=object)
```

Marital status columns

In [ ]:
```
married = ['Married-civ-spouse','Married-spouse-absent','Married-AF-spouse']
separated = ['Divorced','Separated']

#replace elements in list
census_df['marital_status'].replace(to_replace = married, value = 'Married',inplace =True)
census_df['marital_status'].replace(to_replace = separated,value = 'Separated',inplace =True)

#count the number of class in marital-status  columns
census_df['marital_status'].value_counts()
```

Out[ ]:
```
marital_status
Married          23044
Never-married    16117
Separated         8163
Widowed           1518
Name: count, dtype: int64
```

In [ ]:
```
census_df['marital_status'].unique()
```

Out[ ]:
```
array(['Never-married', 'Married', 'Separated', 'Widowed'], dtype=object)
```

Workclass

In [ ]:
```
self_employees = ['Self-emp-not-inc','Self-emp-inc']
govt_employees = ['State-gov','Federal-gov','Local-gov']

#replace elements in list
census_df['workclass'].replace(to_replace = self_employees, value = 'self_employed',inplace =True)
census_df['workclass'].replace(to_replace = govt_employees,value = 'govt_employee',inplace =True)

#count the number of class in marital-status  columns
census_df['workclass'].value_counts()
```

Out[ ]:
```
workclass
Private          34869
govt_employee     6549
self_employed     5557
unknown           1836
Without-pay         21
Never-worked        10
Name: count, dtype: int64
```

In [ ]:
```
census_df['workclass'].unique()
```

Out[ ]:
```
array(['govt_employee', 'self_employed', 'Private', 'unknown',
       'Without-pay', 'Never-worked'], dtype=object)
```

Income

In [ ]:
```
less50 = ['<=50K','<=50K.']
greater50 = ['>50K','>50K.']

#replace elements in list
```

```
census_df['income'].replace(to_replace = less50, value = '<=50k',inplace =True)
census_df['income'].replace(to_replace = greater50,value = '>50k',inplace =True)

#count the number of class in marital-status  columns
census_df['income'].value_counts()
```

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

In [ ]:
```
census_df['income'].unique()
```

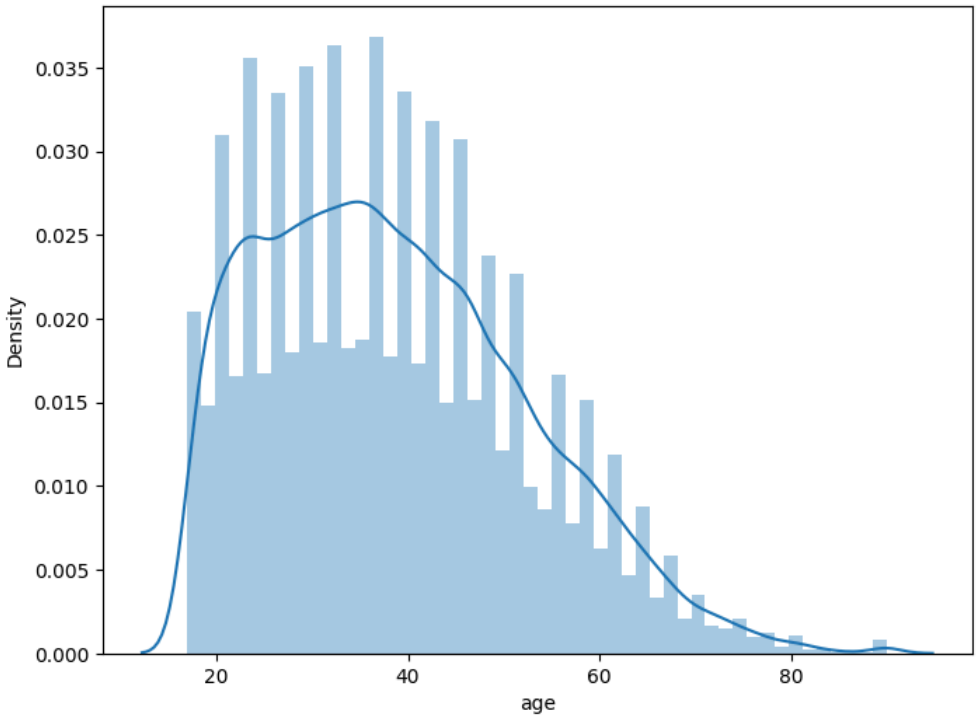
Out[ ]:
```
array(['<=50k', '>50k'], dtype=object)
```

Data visualization

In [ ]:
```
#Distribution of  Age in  Income  Census
sns.distplot(census_df.age)
```

```
<ipython-input-93-8f9664b7e8e6>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(census_df.age)
```

Out[ ]:
```
<Axes: xlabel='age', ylabel='Density'>
```

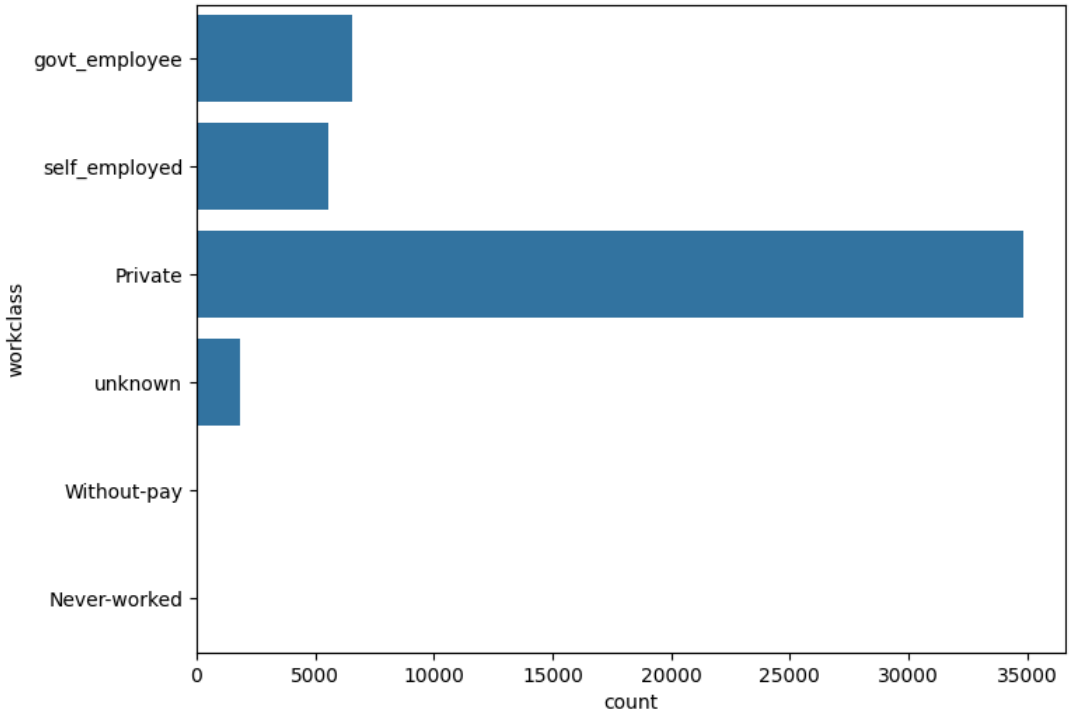


In [ ]:
```
census_df['workclass'].value_counts()
```

Out[ ]:
```
workclass
Private          34869
govt_employee     6549
self_employed     5557
unknown           1836
Without-pay         21
Never-worked        10
Name: count, dtype: int64
```

In [ ]:
```
sns.countplot(census_df.workclass)
```

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

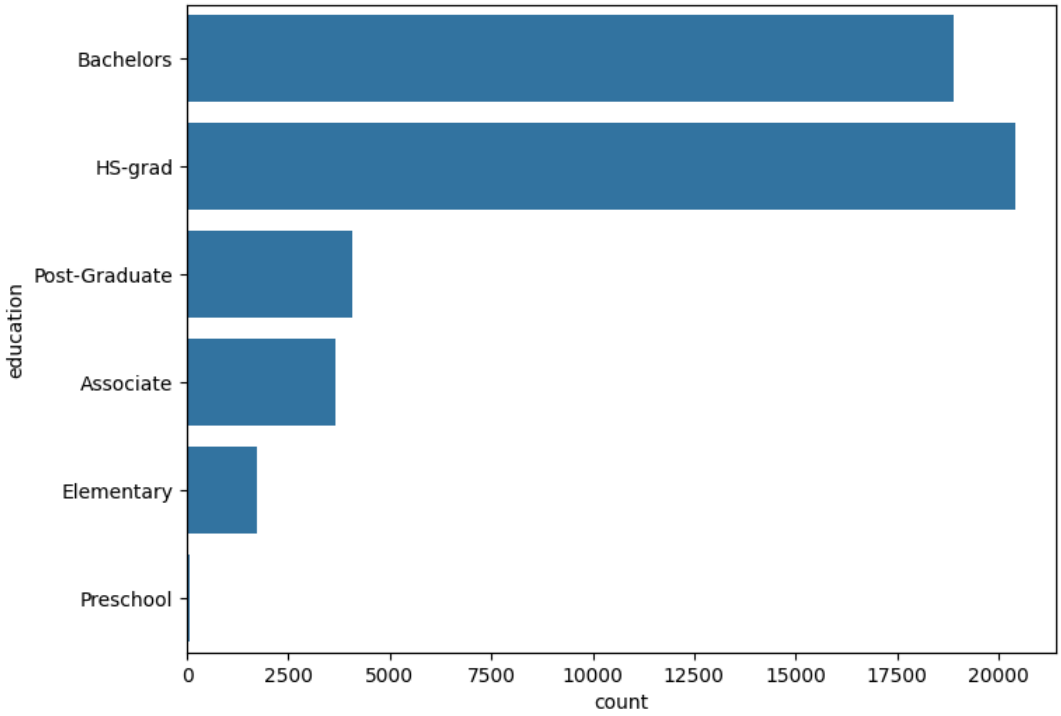


In [ ]:
```
census_df['education'].value_counts()
```

Out[ ]:
```
education
HS-grad          20398
Bachelors        18903
Post-Graduate     4085
Associate         3662
Elementary        1711
Preschool           83
Name: count, dtype: int64
```

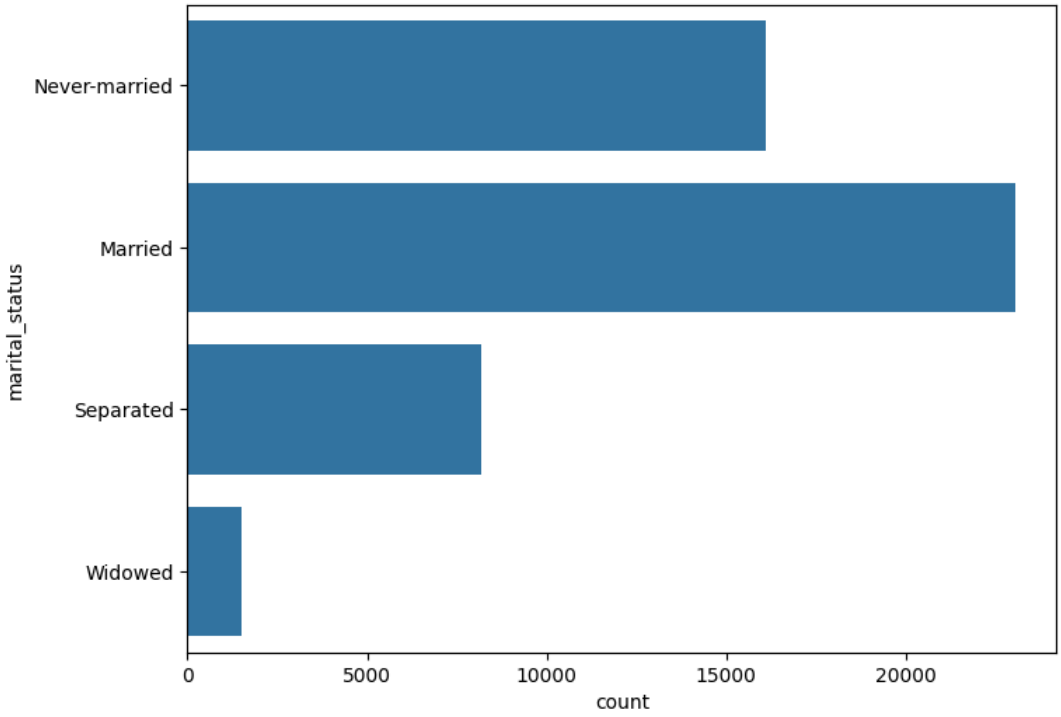
In [ ]:
```
sns.countplot(census_df.education)
```

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



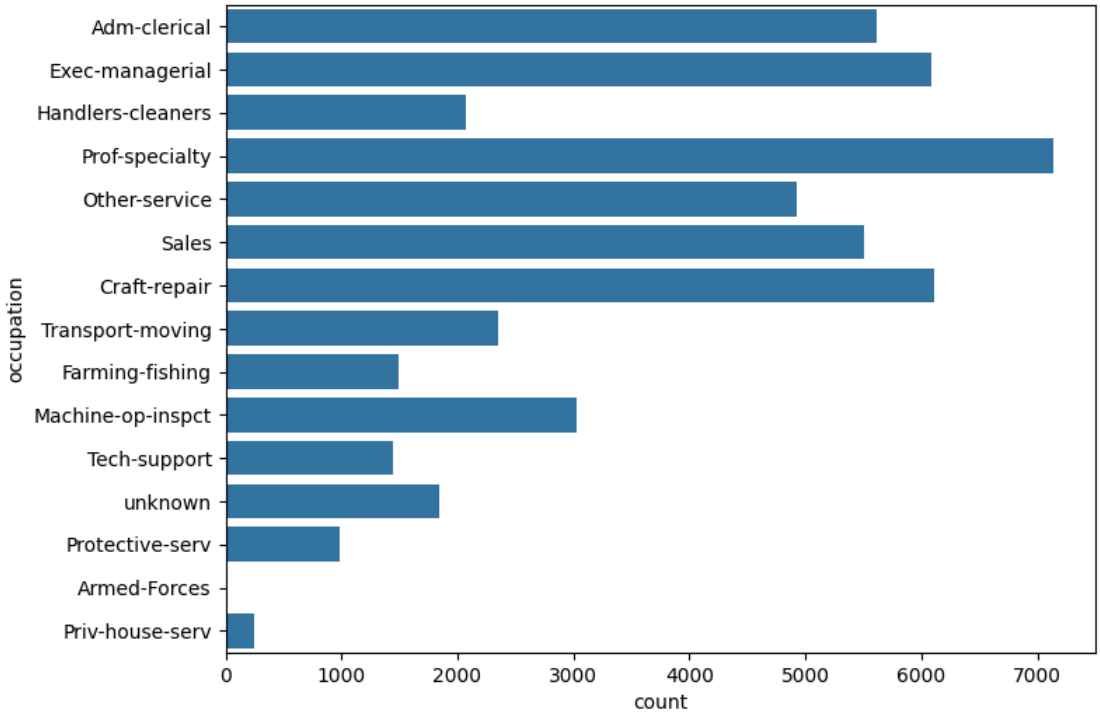
In [ ]:
```
sns.countplot(census_df.marital_status)
```

Out[ ]: <Axes: xlabel='count', ylabel='marital_status'>



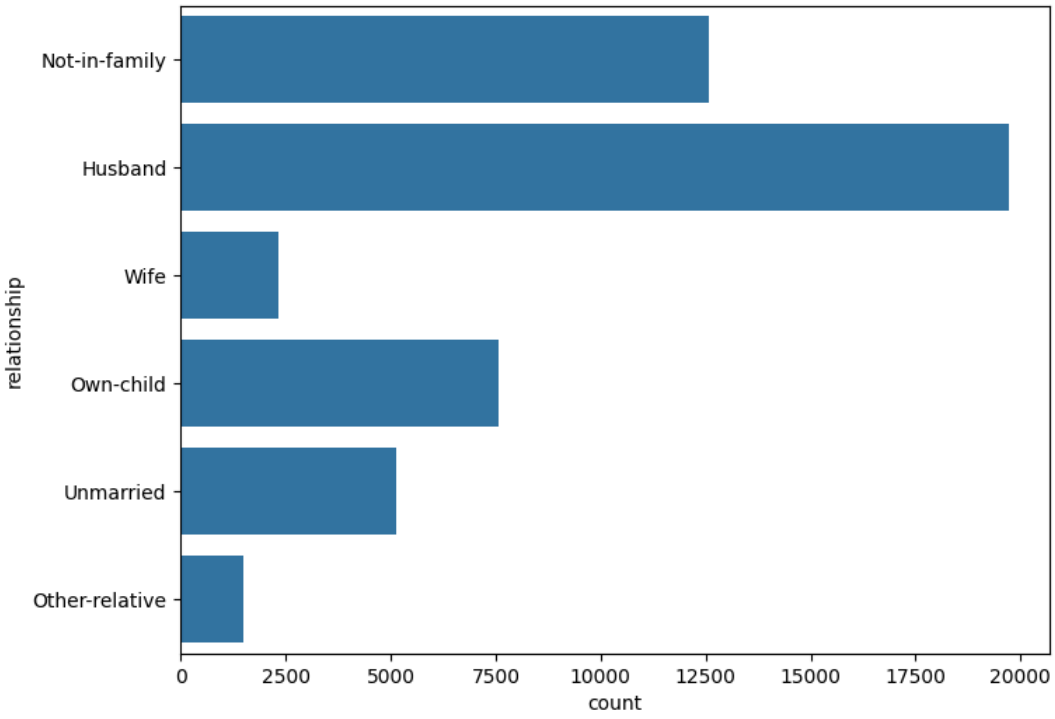
In [ ]:
```
sns.countplot(census_df.occupation)
```

Out[ ]: <Axes: xlabel='count', ylabel='occupation'>



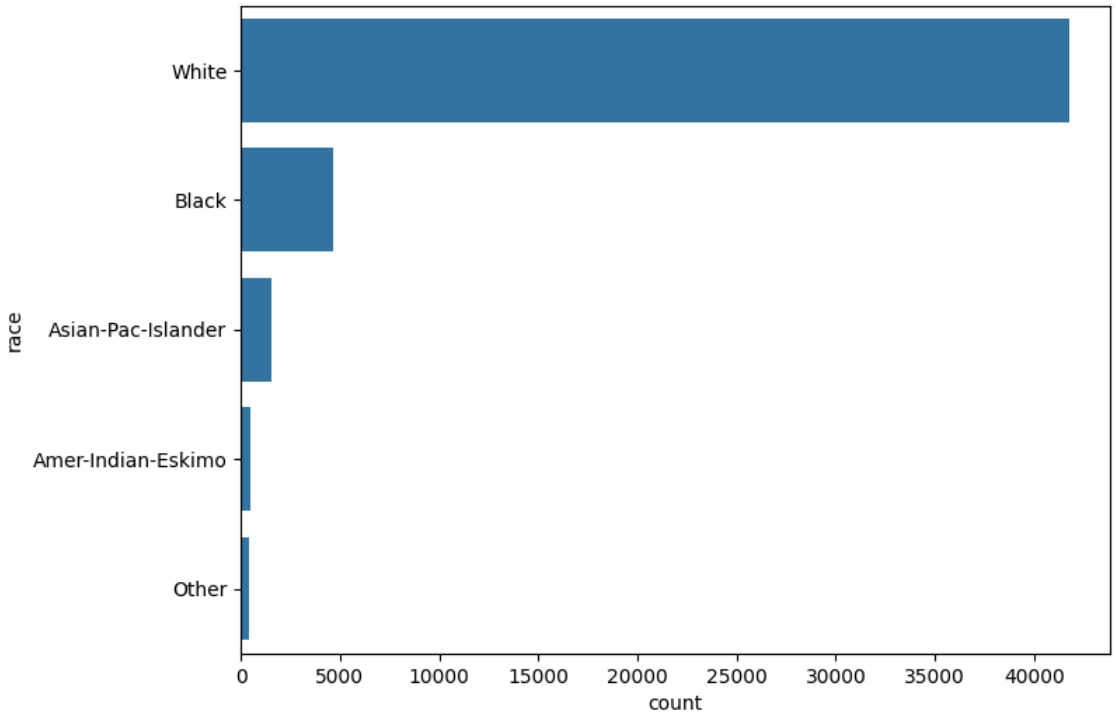
In [ ]:
```
sns.countplot(census_df.relationship)
```

Out[ ]: <Axes: xlabel='count', ylabel='relationship'>



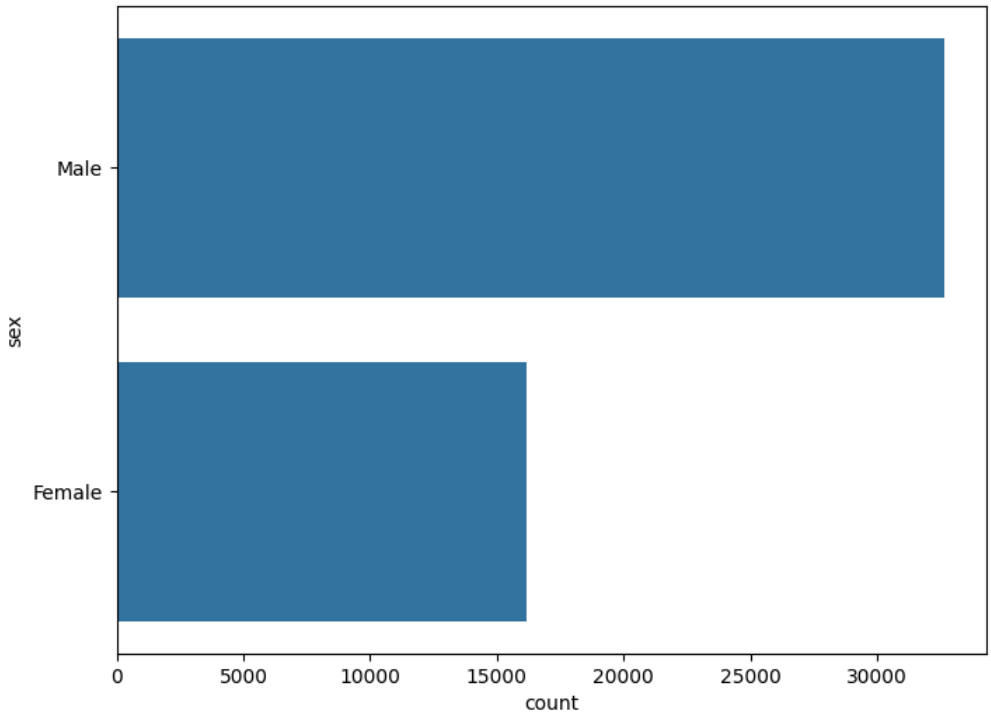
In [ ]:
```
sns.countplot(census_df.race)
```

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



In [ ]:
```
sns.countplot(census_df.sex)
```

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



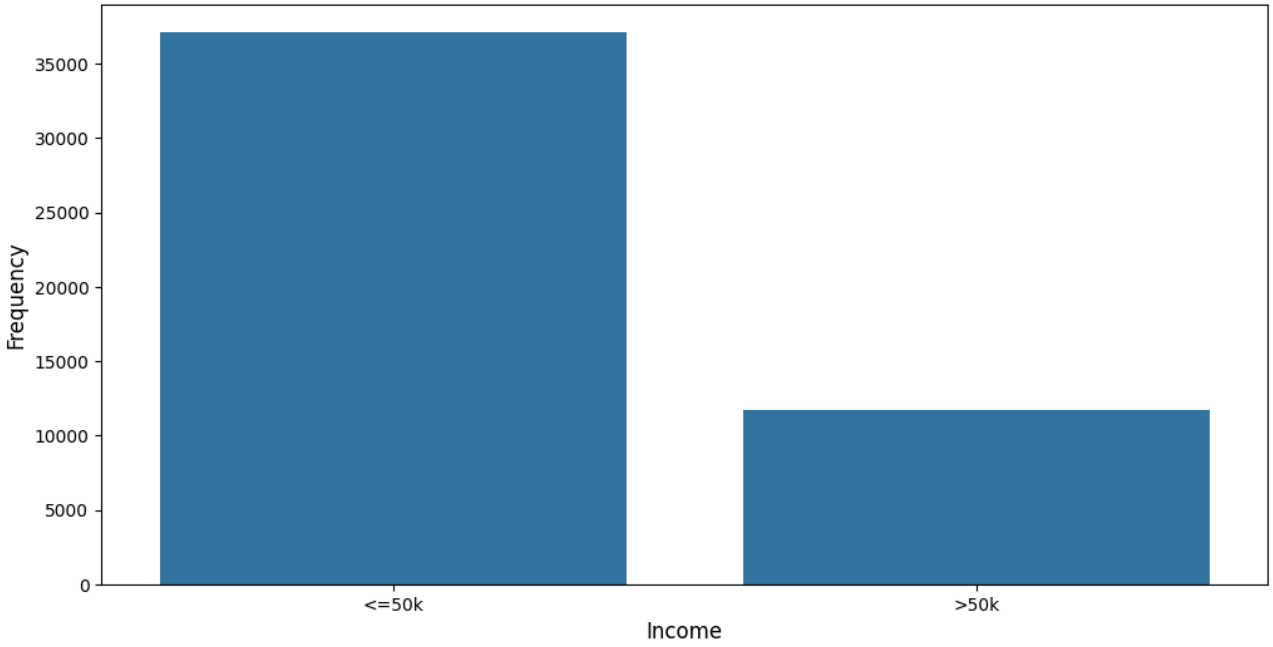
In [ ]:
```
census_df = census_df.rename(columns={'capital-gain': 'capital_gain'})
census_df
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital_status	occupation	relationship	race	sex	capital_gain	capital-loss
0	39	govt_employee	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0
1	50	self_employed	83311	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0
2	38	Private	215646	HS-grad	9	Separated	Handlers-cleaners	Not-in-family	White	Male	0	0
3	53	Private	234721	HS-grad	7	Married	Handlers-cleaners	Husband	Black	Male	0	0
4	28	Private	338409	Bachelors	13	Married	Prof-specialty	Wife	Black	Female	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	215419	Bachelors	13	Separated	Prof-specialty	Not-in-family	White	Female	0	0
48838	64	Private	321403	HS-grad	9	Widowed	Prof-specialty	Other-relative	Black	Male	0	0
48839	38	Private	374983	Bachelors	13	Married	Prof-specialty	Husband	White	Male	0	0
48840	44	Private	83891	Bachelors	13	Separated	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0
48841	35	self_employed	182148	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0

48842 rows × 15 columns

In [ ]:
```
plt.figure(figsize =(12,6));
sns.countplot(x = 'income', data = census_df);
plt.xlabel("Income",fontsize = 12);
plt.ylabel("Frequency",fontsize = 12);
```



- Our dataset has 35000 people earning <=50K i.e. 75% and remainng 30% earns more than 50K.

Data Visualization and Analysis

The followig

In [ ]:
```
census_df
```

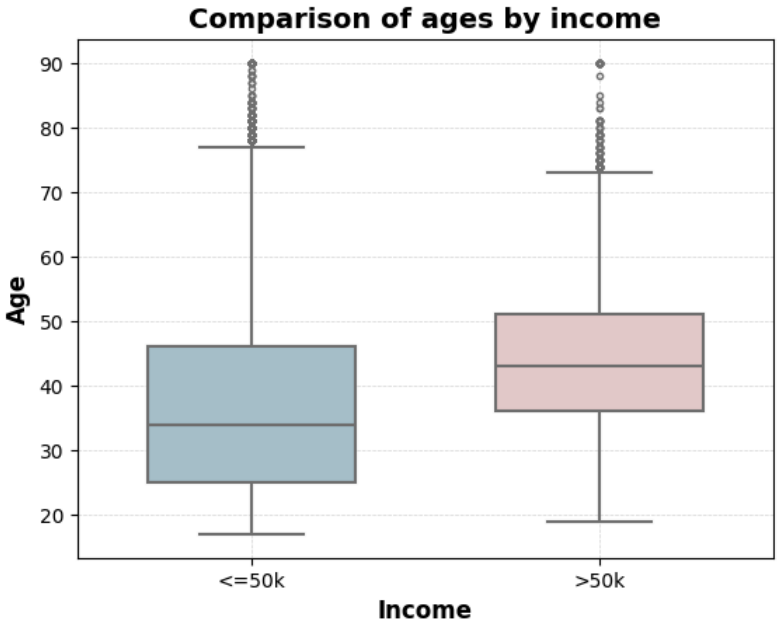
Out[ ]:

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

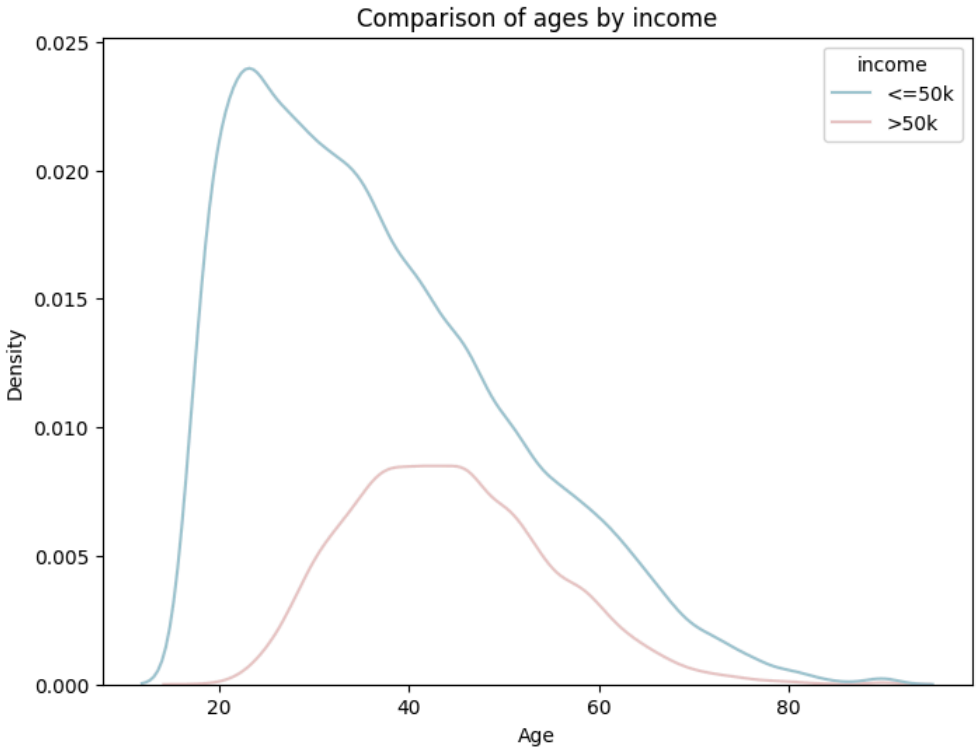
48842 rows × 15 columns

In [ ]:
```
sns.boxplot(x='income', y='age', data=census_df, width=0.6, fliersize=3, linewidth=1.5, palette=['#9FC3D0', '#E9C7C6'])
plt.title('Comparison of ages by income', fontsize=14, fontweight='bold')
plt.xlabel('Income', fontsize=12, fontweight='bold')
plt.ylabel('Age', fontsize=12, fontweight='bold')
plt.rcParams['figure.figsize'] = (8, 6)
plt.grid(True, linestyle='--', linewidth=0.5, alpha=0.5)
plt.tick_params(axis='both', which='major', labelsize=10)
plt.show()
```

```
<ipython-input-38-ea806d25165e>:1: FutureWarning:

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

  sns.boxplot(x='income', y='age', data=census_df, width=0.6, fliersize=3, linewidth=1.5, palette=['#9FC3D0', '#E9C7C6'])
```



In [ ]:
```
sns.kdeplot(data=census_df, x='age', hue='income', palette=['#9FC3D0', '#E9C7C6'])
plt.title('Comparison of ages by income')
plt.xlabel('Age')
plt.ylabel('Density')
plt.show()
```



In [ ]:
```
maledf = census_df[census_df['sex']=='Male']
maledf
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week
0	39	govt_employee	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40
1	50	self_employed	83311	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0	13
2	38	Private	215646	HS-grad	9	Separated	Handlers-cleaners	Not-in-family	White	Male	0	0	40
3	53	Private	234721	HS-grad	7	Married	Handlers-cleaners	Husband	Black	Male	0	0	40
7	52	self_employed	209642	HS-grad	9	Married	Exec-managerial	Husband	White	Male	0	0	45
...	...	...	...	...	...	...	...	...	...	...	...	...	...
48836	33	Private	245211	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Male	0	0	40
48838	64	Private	321403	HS-grad	9	Widowed	Prof-specialty	Other-relative	Black	Male	0	0	40
48839	38	Private	374983	Bachelors	13	Married	Prof-specialty	Husband	White	Male	0	0	50
48840	44	Private	83891	Bachelors	13	Separated	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40
48841	35	self_employed	182148	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0	60

32650 rows × 15 columns

In [ ]:
```
fmaledf = census_df[census_df['sex']=='Female']
fmaledf
```

Out[ ]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week
4	28	Private	338409	Bachelors	13	Married	Prof-specialty	Wife	Black	Female	0	0	40
5	37	Private	284582	Masters	14	Married	Exec-managerial	Wife	White	Female	0	0	40
6	49	Private	160187	HS-grad	5	Married	Other-service	Not-in-family	Black	Female	0	0	16
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50
12	23	Private	122272	Bachelors	13	Never-married	Adm-clerical	Own-child	White	Female	0	0	30
...	...	...	...	...	...	...	...	...	...	...	...	...	...
48826	50	govt_employee	139347	Masters	14	Married	Prof-specialty	Wife	White	Female	0	0	40
48827	55	Private	224655	HS-grad	9	Separated	Priv-house-serv	Not-in-family	White	Female	0	0	32
48828	38	Private	247547	Assoc-voc	11	Never-married	Adm-clerical	Unmarried	Black	Female	0	0	40
48834	25	Private	350977	HS-grad	9	Never-married	Other-service	Own-child	White	Female	0	0	40
48837	39	Private	215419	Bachelors	13	Separated	Prof-specialty	Not-in-family	White	Female	0	0	36

16192 rows × 15 columns

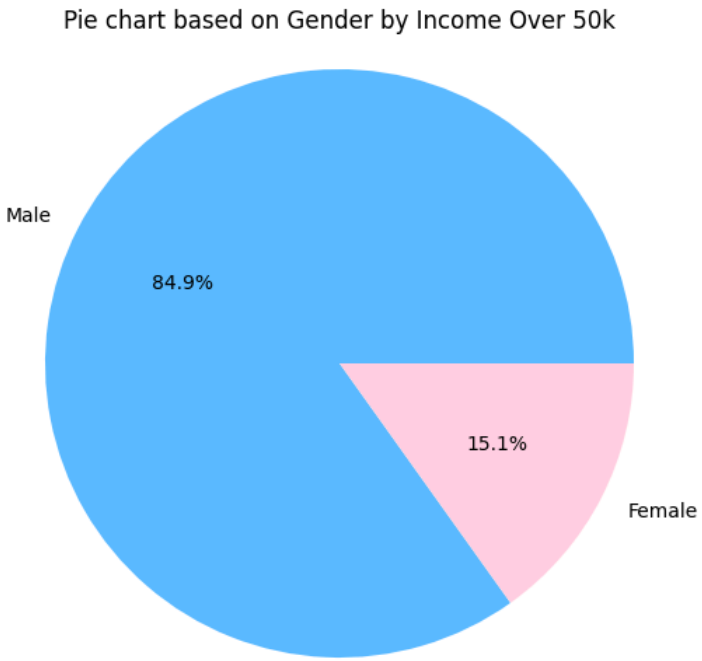
In [ ]:
```
above50df = census_df[census_df['income']=='>50k']
above50df
```

Out[ ]:

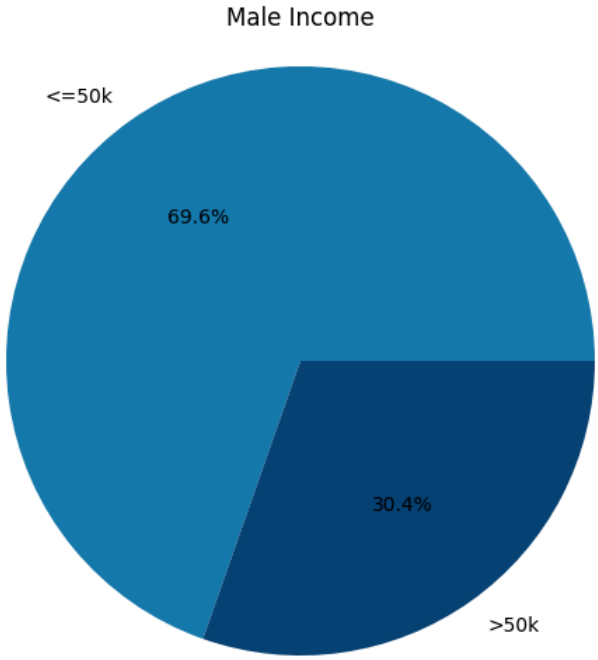
	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week
7	52	self_employed	209642	HS-grad	9	Married	Exec-managerial	Husband	White	Male	0	0	45
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50
9	42	Private	159449	Bachelors	13	Married	Exec-managerial	Husband	White	Male	5178	0	40
10	37	Private	280464	Some-college	10	Married	Exec-managerial	Husband	Black	Male	0	0	80
11	30	govt_employee	141297	Bachelors	13	Married	Prof-specialty	Husband	Asian-Pac-Islander	Male	0	0	40
...	...	...	...	...	...	...	...	...	...	...	...	...	...
48815	38	Private	149347	Masters	14	Married	Prof-specialty	Husband	White	Male	0	0	50
48816	43	govt_employee	23157	Masters	14	Married	Exec-managerial	Husband	White	Male	0	1902	50
48822	40	Private	202168	Prof-school	15	Married	Prof-specialty	Husband	White	Male	15024	0	55
48826	50	govt_employee	139347	Masters	14	Married	Prof-specialty	Wife	White	Female	0	0	40
48841	35	self_employed	182148	Bachelors	13	Married	Exec-managerial	Husband	White	Male	0	0	60

11687 rows × 15 columns

In [ ]:
```
# Create a pie chart of the number of cars by cyl
labels = above50df['sex'].value_counts().index
sizes = above50df['sex'].value_counts().values
colors = ['#5BBCFF', '#FFD1E3']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%')
plt.axis('equal')
plt.title('Pie chart based on Gender by Income Over 50k')
plt.show()
```

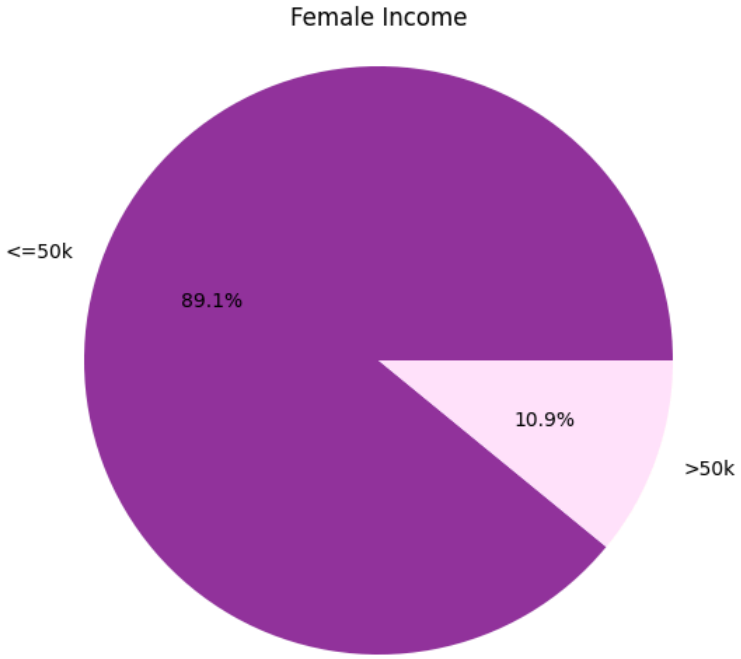


In [ ]:
```
labels = maledf['income'].value_counts().index
sizes = maledf['income'].value_counts().values
colors = ['#1679AB', '#074173']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%')
plt.axis('equal')
plt.title('Male Income')
plt.show()
```



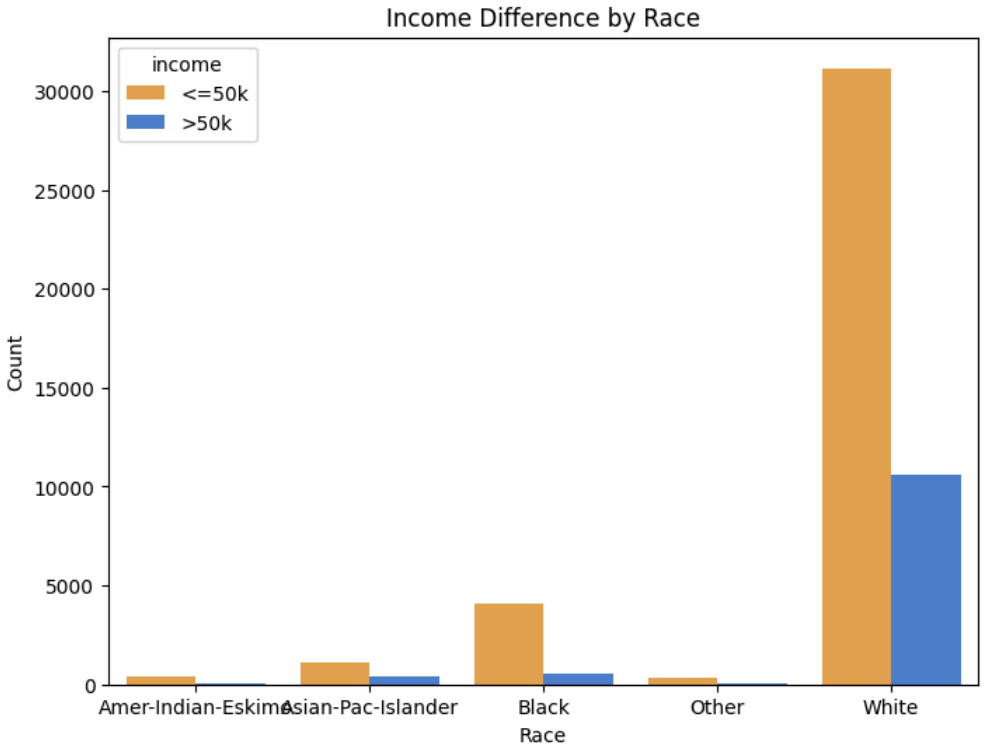
In [131…

```
labels = fmaledf['income'].value_counts().index
sizes = fmaledf['income'].value_counts().values
colors = ['#93329E', '#FFE3FE']

plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%')
plt.axis('equal')
plt.title('Female Income')
plt.show()
```



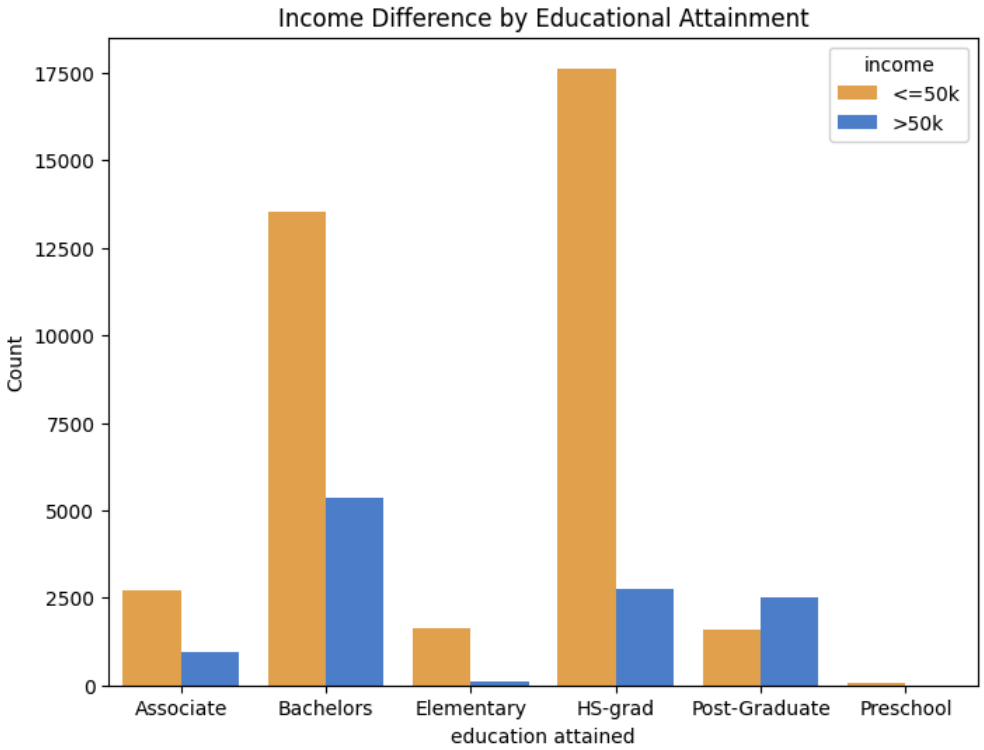
In [130…

```
grouped_data = census_df.groupby(['income', 'race']).size().reset_index(name='counts')
sns.barplot(x='race', y='counts', hue='income', data=grouped_data, palette=['#FBA834', '#387ADF'])
plt.title('Income Difference by Race')
plt.xlabel('Race')
plt.ylabel('Count')
plt.show()
```



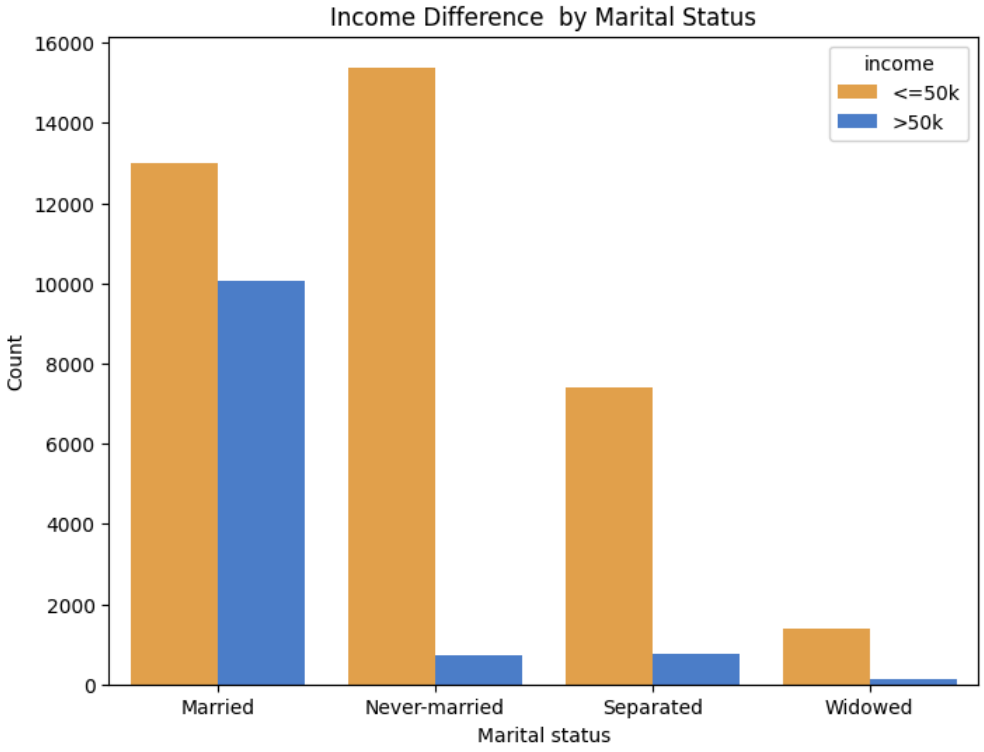
In [129…

```
grouped_data = census_df.groupby(['income', 'education']).size().reset_index(name='counts')
sns.barplot(x='education', y='counts', hue='income', data=grouped_data, palette=['#FBA834', '#387ADF'])
plt.title('Income Difference by Educational Attainment')
plt.xlabel('education attained')
plt.ylabel('Count')
plt.show()
```



In [128…

```
grouped_data = census_df.groupby(['income', 'marital_status']).size().reset_index(name='counts')
sns.barplot(x='marital_status', y='counts', hue='income', data=grouped_data, palette=['#FBA834', '#387ADF'])
plt.title('Income Difference  by Marital Status')
plt.xlabel('Marital status')
plt.ylabel('Count')
plt.show()
```



In [125…

```
grouped_data = census_df.groupby(['income', 'relationship']).size().reset_index(name='counts')
sns.barplot(x='relationship', y='counts', hue='income', data=grouped_data, palette=['#FBA834', '#387ADF'])
plt.title('Income Difference By Relationship ')
plt.xlabel('Relationship')
plt.ylabel('Count')
plt.show()
```