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Section: CPE22S3

source: https://archive.ics.uci.edu/dataset/20/census+income

Setup

```
pip install ucimlrepo
```

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

```
import pandas as pd
import numpy as np

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)
```

```
'Other', 'Race', 'Sex'], 'target_col': ['income'], 'index_col': None, 'has_missing_values': 'yes', 'missing_values_symbol': 'NaN', 'yea
```

```
X
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationshir
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husbanc
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husbanc
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife
...	...	...	...	...	...	...	...	..
48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-family
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-relative
48839	38	Private	374983	Bachelors	13	Married-civ-	Prof-specialty	Husbanc

Next steps: View recommended plots

y

	income
0	<=50K
1	<=50K
2	<=50K
3	<=50K
4	<=50K
...	...
48837	<=50K.
48838	<=50K.
48839	<=50K.
48840	<=50K.
48841	>50K.

48842 rows × 1 columns

Next steps: View recommended plots

We concatenate the two dataframes

```
dataFrames = [X,y]
df = pd.concat(dataFrames, axis = 1)
df
```

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

Next steps: View recommended plots

We check the datatypes of the columns.

```
df.dtypes
```

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

After checking the datatypes, we attempt to change some of them to the preferred datatypes.

This copying of dataframe is for the purpose of having separate dataframes with different datatypes

```
census_df = df.copy()
```

Check null values

```
census_df.isnull().sum()
```

```
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
```

function for checking duplicates...

```
def check_duplicates(df):
  if df[df.duplicated()].shape[0] != 0:
    print(df[df.duplicated()].shape[0])
  else:
    print("No existing duplicates")
check_duplicates(census_df)
```

```
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```

We use .info() to check if there are null values, three columns could does not meet the total value of 48842 meaning they have null values.

```
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
```

```
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
```

drop duplicates for both dataframes

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

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

```
df.rename(columns={'native-country': 'native_country'}, inplace=True) # rename column
```

code block for removing the null values

```
df.workclass.replace('?', 'Private', inplace = True)
df.workclass.fillna('Private', inplace = True)
df.occupation.replace('?', 'Prof-specialty', inplace = True)
df.occupation.fillna('Prof-specialty', inplace = True)
df.native_country.replace('?', 'United-States', inplace = True)
df.native_country.fillna('United-States', inplace = True)
```

```
census_df.isnull().sum()
```

```
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
```

this copying of dataframe will enable me to recycle the dataframe in which the datatypes don't have all numerical values

```
category_df = df.copy()
```

Let's create a function for checking value counts of a column in a certain dataframe for the three columns with duplicates

```
def check_value_counts(column):
  print(df.value_counts(column))
```

```
check_value_counts(census_df['workclass'])
```

```
workclass
Private             33879
Self-emp-not-inc     3861
Local-gov            3136
State-gov            1981
?                    1836
Self-emp-inc         1694
Federal-gov          1432
Without-pay            21
Never-worked           10
Name: count, dtype: int64
```

```
check_value_counts(census_df['occupation'])
```

```
occupation
Prof-specialty       6167
Craft-repair         6107
Exec-managerial      6084
Adm-clerical         5608
Sales                5504
Other-service        4919
Machine-op-inspct    3019
Transport-moving     2355
Handlers-cleaners    2071
```

```
?                   1843
Farming-fishing     1487
Tech-support        1445
Protective-serv      983
Priv-house-serv      240
Armed-Forces          15
Name: count, dtype: int64
```

```
check_value_counts(census_df['native-country'])
```

```
native-country
United-States                 43810
Mexico                          947
?                               582
Philippines                     295
Germany                         206
Puerto-Rico                     184
Canada                          182
El-Salvador                     155
India                           151
Cuba                            138
England                         127
China                           122
South                           115
Jamaica                         106
Italy                           105
Dominican-Republic              103
Japan                            92
Poland                           87
Vietnam                          86
Guatemala                        86
Columbia                         85
Haiti                            75
Portugal                         67
Taiwan                           65
Iran                             59
Greece                           49
Nicaragua                        49
Peru                             46
Ecuador                          45
France                           38
Ireland                          37
Hong                             30
Thailand                         30
Cambodia                         28
Trinadad&Tobago                  27
Outlying-US(Guam-USVI-etc)       23
Laos                             23
Yugoslavia                       23
Scotland                         21
Honduras                         20
Hungary                          19
Holand-Netherlands                1
Name: count, dtype: int64
```

convert to list before changing it to numeric datatype1

```
workclass_type = list(census_df['workclass'].unique())
education_type = list(census_df['education'].unique())
marital_status_type = list(census_df['marital-status'].unique())
occupation_type = list(census_df['occupation'].unique())
relationship_type = list(census_df['relationship'].unique())
race_type = list(census_df['race'].unique())
sex_type = list(census_df['sex'].unique())
native_country_type = list(census_df['native-country'].unique())
income_type = list(census_df['income'].unique())
```

using .apply and lambda for enabling the categorical datatypes to have a numerical value

```
# in this case, we use the categorical columns, we apply lambda to the dataframes in which we get their indices using the x variable and .in
census_df['workclass'] = census_df.apply(lambda x: workclass_type.index(x['workclass']) + 1, axis=1)
census_df['education'] = census_df.apply(lambda x: education_type.index(x['education']) + 1, axis=1)
census_df['marital-status'] = census_df.apply(lambda x: marital_status_type.index(x['marital-status']) + 1, axis=1)
census_df['occupation'] = census_df.apply(lambda x: occupation_type.index(x['occupation']) + 1, axis=1)
census_df['relationship'] = census_df.apply(lambda x: relationship_type.index(x['relationship']) + 1, axis=1)
census_df['race'] = census_df.apply(lambda x: race_type.index(x['race']) + 1, axis=1)
census_df['sex'] = census_df.apply(lambda x: sex_type.index(x['sex']) + 1, axis=1)
census_df['native-country'] = census_df.apply(lambda x: native_country_type.index(x['native-country']) + 1, axis=1)
census_df['income'] = census_df.apply(lambda x: income_type.index(x['income']) + 1, axis=1)
```

remove the duplicated column of income in which it has a period

```
category_df.income.replace('<=50K.', '<=50K', inplace = True)
category_df.income.replace('>50K.', '>50K', inplace = True)
census_df.income.replace('<=50K.', '<=50K', inplace = True)
census_df.income.replace('>50K.', '>50K', inplace = True)
```

time to replace null values for the other dataframe and fill it with the most frequent value in the column

```
census_df.workclass.replace(np.nan, 'Private', inplace = True)
census_df.workclass.fillna('Private', inplace = True)
census_df.occupation.replace(np.nan, 'Prof-specialty', inplace = True)
census_df.occupation.fillna('Prof-specialty', inplace = True)
census_df.native_country.replace( np.nan, 'United-States', inplace = True)
census_df.native_country.fillna('United-States', inplace = True)
```

no more null values...

```
census_df.isnull().sum()
```

```
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
```

.info() for double checking

```
census_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 48813 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             48813 non-null  int64
 1   workclass       48813 non-null  int64
 2   fnlwgt          48813 non-null  int64
 3   education       48813 non-null  int64
 4   education-num   48813 non-null  int64
 5   marital-status  48813 non-null  int64
 6   occupation      48813 non-null  int64
 7   relationship    48813 non-null  int64
 8   race            48813 non-null  int64
 9   sex             48813 non-null  int64
 10  capital-gain    48813 non-null  int64
 11  capital-loss    48813 non-null  int64
 12  hours-per-week  48813 non-null  int64
 13  native_country  48813 non-null  int64
 14  income          48813 non-null  int64
dtypes: int64(15)
memory usage: 6.0 MB
```

```
category_df
```

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

Next steps: View recommended plots

```
category_df.isnull().sum()
```

```
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
```

double check unique values

```
category_df['income'].unique()
```

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

now the unique values of the categorical datatype is numerical

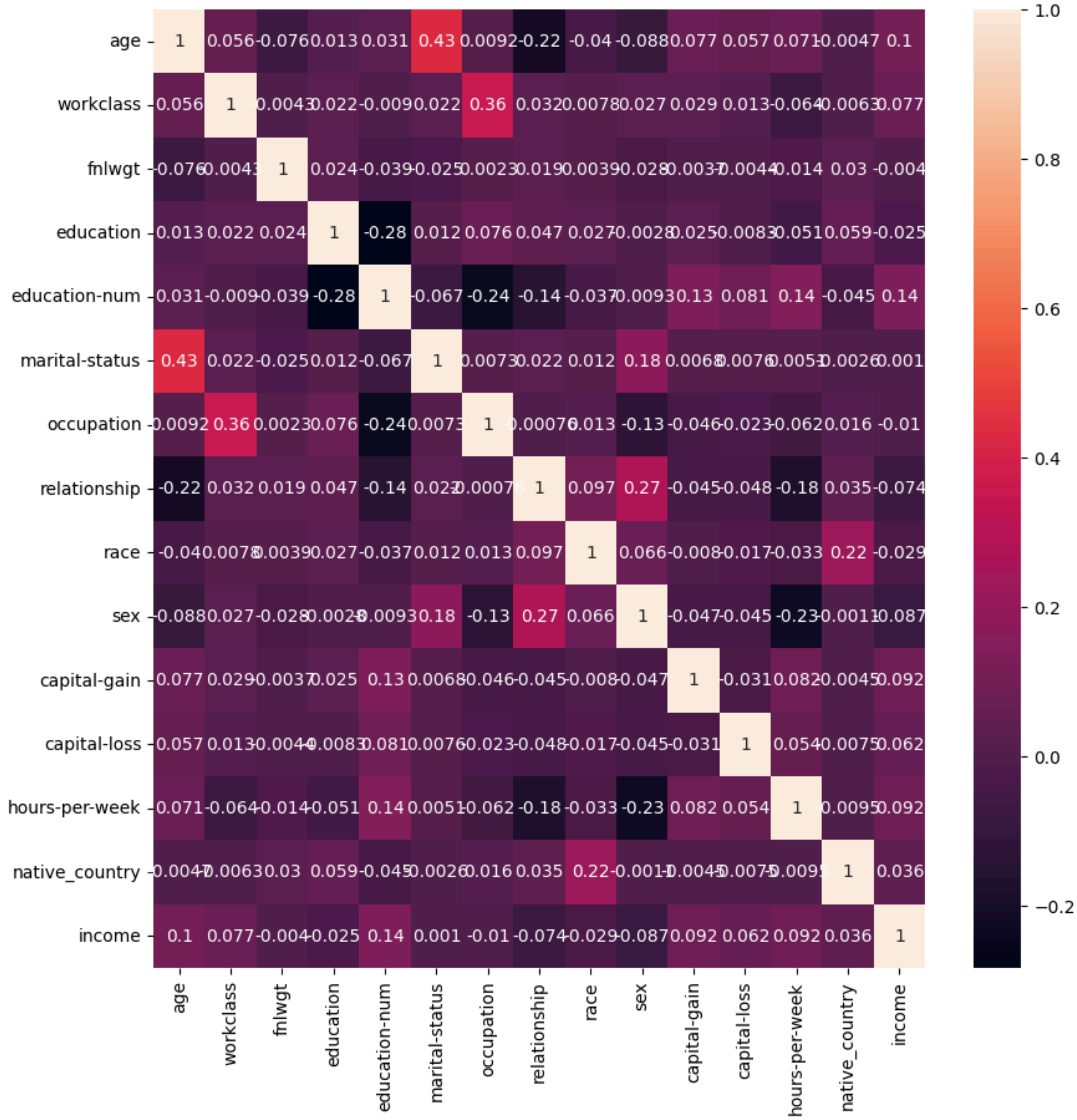
```
census_df['workclass'].unique()
```

```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10])
```

i used heatmaps to check their correlation and to determine which columns i'd like to combine

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

plt.figure(figsize=(10, 10))
sns.heatmap(census_df.corr(), annot=True)
```

```
<Axes: >
```



Data Aggregation

Age

```
age_agg = category_df.groupby('age').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
age_agg
```

age	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
17	179157.852101	10	34095	1721	21.137815	595
18	193206.656214	14	34095	1721	25.764228	861
19	205094.159199	13	34095	2129	30.587226	1049
20	198157.824640	14	34095	2258	32.452338	1112
21	200142.544790	14	99999	2603	34.260512	1094
...	...	...	...	...	...	...
86	149912.000000	14	0	0	40.000000	1
87	110402.333333	9	0	0	7.000000	3
88	149540.666667	15	6418	1816	35.833333	6
89	90972.500000	13	0	0	30.000000	2
90	172530.629630	15	20051	4356	37.703704	54

74 rows × 6 columns

Next steps: View recommended plots

Workclass

```
workclass_agg = category_df.groupby('workclass').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
workclass_agg
```

workclass	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
Federal-gov	183590.028631	16	99999	3683	41.513268	1432
Local-gov	190161.134885	16	99999	2467	40.847258	3136
Never-worked	215033.300000	10	0	0	28.900000	10
Private	192264.401767	16	99999	4356	39.630078	36678
Self-emp-inc	178872.700118	16	99999	2824	48.593270	1694
Self-emp-not-inc	175613.219373	16	99999	2824	44.396270	3861
State-gov	181933.464917	16	99999	3683	39.090863	1981
Without-pay	167902.666667	12	4416	1887	33.952381	21

Next steps: View recommended plots

Education

```
education_agg = category_df.groupby('education').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
education_agg
```

education	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
10th	196532.558675	6	99999	3770	36.986321	1389
11th	195102.272627	7	15024	2824	33.952539	1812
12th	197263.035061	8	18481	2258	35.413110	656
1st-4th	235339.110204	2	7688	2603	38.751020	245
5th-6th	229838.559055	3	99999	2603	38.891732	508
7th-8th	187752.355346	4	10566	3900	39.002096	954
9th	199006.851852	5	99999	2231	38.359788	756
Assoc-acdm	193700.075578	12	99999	2824	40.809494	1601
Assoc-voc	179420.665534	11	99999	3004	41.659223	2060
Bachelors	188359.298753	13	99999	3770	42.484040	8020
Doctorate	184090.478114	16	99999	3683	46.582492	594
HS-grad	188628.420929	9	99999	4356	40.640553	15777
Masters	181444.984940	14	99999	2824	43.573419	2656
Preschool	238888.292683	1	41310	1719	36.402439	82
Prof-school	186585.876499	15	99999	2824	47.579137	834
Some-college	190039.856933	10	99999	4356	38.876898	10869

Next steps: View recommended plots

Marital Status

```
marital_status_agg = category_df.groupby('marital-status').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
marital_status_agg
```

marital-status	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
Divorced	184728.631674	16	99999	3900	41.115988	6630
Married-AF-spouse	184132.675676	16	99999	1651	39.810811	37
Married-civ-spouse	186815.806991	16	99999	2603	43.307661	22372
Married-spouse-absent	197523.157643	16	99999	3004	39.684713	628
Never-married	195440.619207	16	99999	3770	36.895515	16098
Separated	202974.111111	16	99999	3900	39.667974	1530
Widowed	175529.942688	16	99999	4356	33.438076	1518

Next steps: View recommended plots

Occupation

```
occupation_agg = category_df.groupby('occupation').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
occupation_agg
```

occupation	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
Adm-clerical	191904.265335	16	99999	3770	37.712197	5608
Armed-Forces	216972.600000	15	7298	1887	41.600000	15
Craft-repair	192320.266252	16	99999	3004	42.271164	6107
Exec-managerial	186153.437541	16	99999	4356	44.978632	6084
Farming-fishing	172524.914593	16	99999	2457	46.844654	1487
Handlers-cleaners	202034.153549	14	99999	3175	37.902945	2071
Machine-op-inspct	193190.163962	16	99999	3900	40.776747	3019
Other-service	187912.713560	16	99999	3770	34.754015	4919
Priv-house-serv	194470.341667	16	25236	3175	32.966667	240
Prof-specialty	186009.327540	16	99999	4356	39.006462	8976
Protective-serv	201530.266531	16	99999	2444	42.789420	983
Sales	190483.155887	16	99999	2824	40.749273	5504
Tech-support	190511.809689	16	99999	2472	39.741176	1445
Transport-moving	191550.581741	16	99999	2824	44.727389	2355

Next steps: View recommended plots

Relationship

```
relationship_agg = category_df.groupby('relationship').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
relationship_agg
```

relationship	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
Husband	187222.099853	16	99999	2603	44.167183	19709
Not-in-family	190334.002387	16	99999	4356	40.530516	12567
Other-relative	203524.602258	16	41310	3683	37.128154	1506
Own-child	193756.483105	16	99999	3900	33.154567	7576
Unmarried	191381.556206	16	99999	4356	39.172326	5124
Wife	180748.781639	16	99999	2457	36.729730	2331

Next steps: View recommended plots

Sex

```
sex_agg = category_df.groupby('sex').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
sex_agg
```

sex	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
Female	185491.732172	16	99999	4356	36.403720	16182
Male	191738.905795	16	99999	3770	42.419264	32631

Next steps: View recommended plots

Native Country

```
native_country_agg = category_df.groupby('native_country').agg({
  'fnlwgt': 'mean',
  'education-num': 'max',
  'capital-gain': 'max',
  'capital-loss': 'max',
  'hours-per-week': 'mean',
  'income': 'count'
})
native_country_agg
```

native_country	fnlwgt	education-num	capital-gain	capital-loss	hours-per-week	income
Cambodia	200296.142857	13	13550	1977	42.035714	28
Canada	181262.406593	16	99999	2467	40.406593	182
China	172780.385246	16	99999	2415	38.262295	122
Columbia	217853.647059	16	3781	2042	39.929412	85
Cuba	240603.449275	16	15024	2001	40.101449	138
Dominican-Republic	203678.854369	14	99999	2258	41.621359	103
Ecuador	178576.777778	14	9386	0	39.266667	45
El-Salvador	250671.741935	16	20051	2339	36.361290	155
England	183573.094488	16	20051	2559	41.937008	127
France	186503.605263	16	8614	1408	42.789474	38
Germany	192997.485437	16	27828	1977	40.815534	206
Greece	150477.959184	15	15024	2603	46.897959	49
Guatemala	257758.953488	13	7688	1594	38.686047	86
Haiti	217718.386667	15	15024	1740	36.920000	75
Holand-Netherlands	27882.000000	10	0	2205	40.000000	1
Honduras	239431.250000	15	1506	1902	35.650000	20
Hong	212912.100000	16	15024	2377	40.266667	30
Hungary	198379.684211	15	5178	1668	37.947368	19
India	165606.046358	16	99999	2415	41.423841	151
Iran	193843.983051	16	27828	2002	42.949153	59
Ireland	146093.675676	14	10520	1887	42.432432	37
Italy	179078.790476	16	20051	1977	40.942857	105
Jamaica	211369.537736	16	20051	1887	39.160377	106
Japan	194803.195652	16	99999	1977	42.282609	92
Laos	204812.869565	15	2885	1740	39.391304	23
Mexico	284506.927138	16	99999	2603	40.182682	947
Nicaragua	284620.244898	16	3887	1848	36.938776	49
Outlying-US(Guam-USVI-etc)	185348.521739	13	0	1762	41.347826	23
Peru	271642.565217	14	1831	1848	36.543478	46
Philippines	163534.484746	15	99999	2415	39.620339	295
Poland	183844.701149	16	20051	2129	37.689655	87
Portugal	150979.582090	14	5178	0	42.238806	67
Puerto-Rico	204617.646739	14	15024	3770	39.016304	184
Scotland	156451.380952	14	5178	0	41.666667	21
South	167183.269565	16	99999	2258	42.852174	115
Taiwan	184651.384615	16	99999	2415	39.400000	65
Thailand	183225.600000	16	7298	1485	44.700000	30
Trinadad&Tobago	208312.814815	14	3137	2339	38.888889	27
United-States	187277.769803	16	99999	4356	40.455671	44666
Vietnam	170859.441860	16	15024	2457	37.976744	86
Yugoslavia	212527.739130	13	7688	0	40.217391	23

Next steps: View recommended plots

```
category_df.columns
```

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

```
category_df['income'].unique()
```

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

```
category_df
```

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

Next steps: View recommended plots

creation of two dataframes for income

```
less = category_df.query('income == "<=50K"')
greater = category_df.query('income == ">50K"')
```

```
less[['income']]
```

	income
0	<=50K
1	<=50K
2	<=50K
3	<=50K
4	<=50K
...	...
48836	<=50K
48837	<=50K
48838	<=50K
48839	<=50K
48840	<=50K

37128 rows × 1 columns

```
greater
```

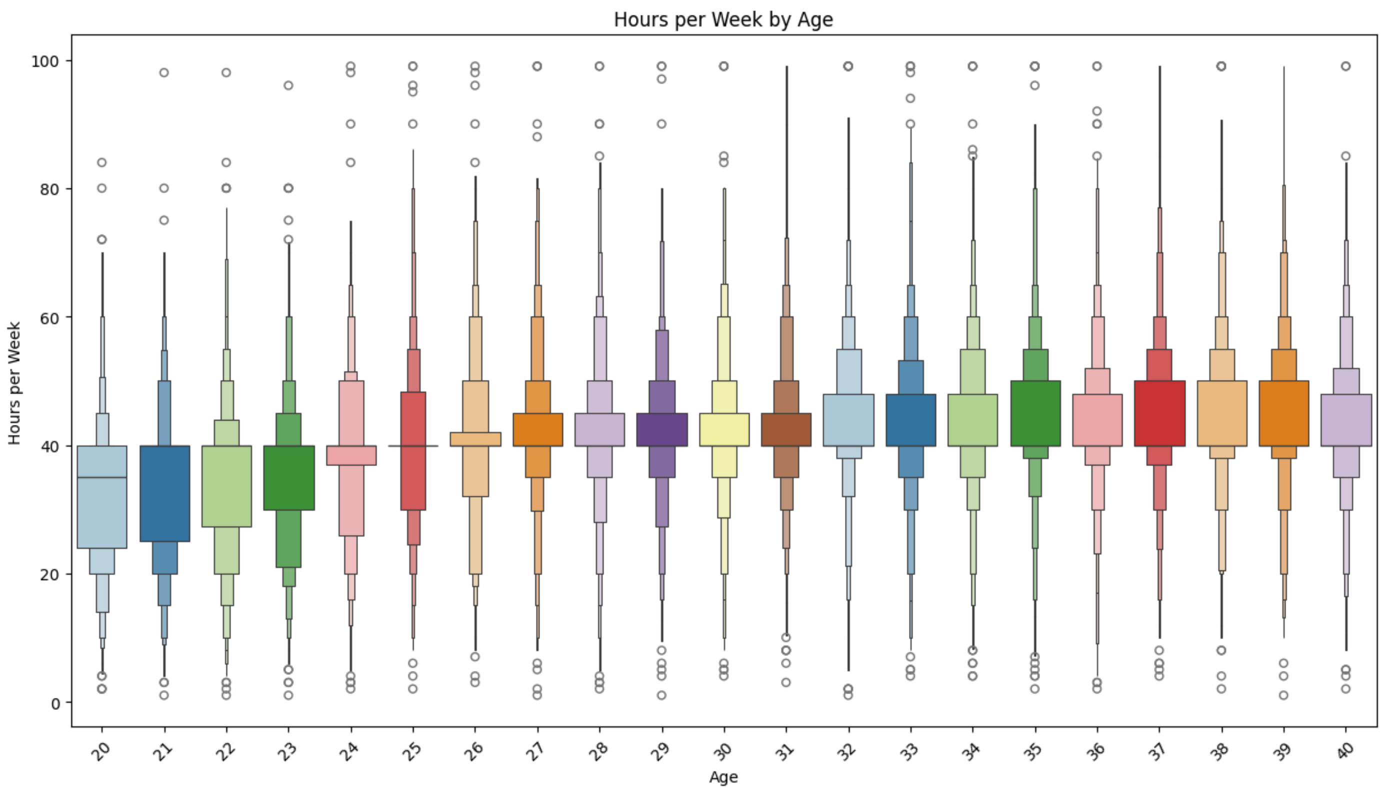
	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	na
7	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	45	
8	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family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

Next steps: View recommended plots

Usage of Seaborn Boxenplotting

```
selected_age_df = category_df.query('age >= 20 and age <= 40')
plt.figure(figsize=(15, 8))
sns.boxenplot(x='age', y='hours-per-week', data=selected_age_df, palette = 'Paired')
plt.xlabel('Age')
plt.ylabel('Hours per Week')
plt.title('Hours per Week by Age')
plt.xticks(rotation=45)
```

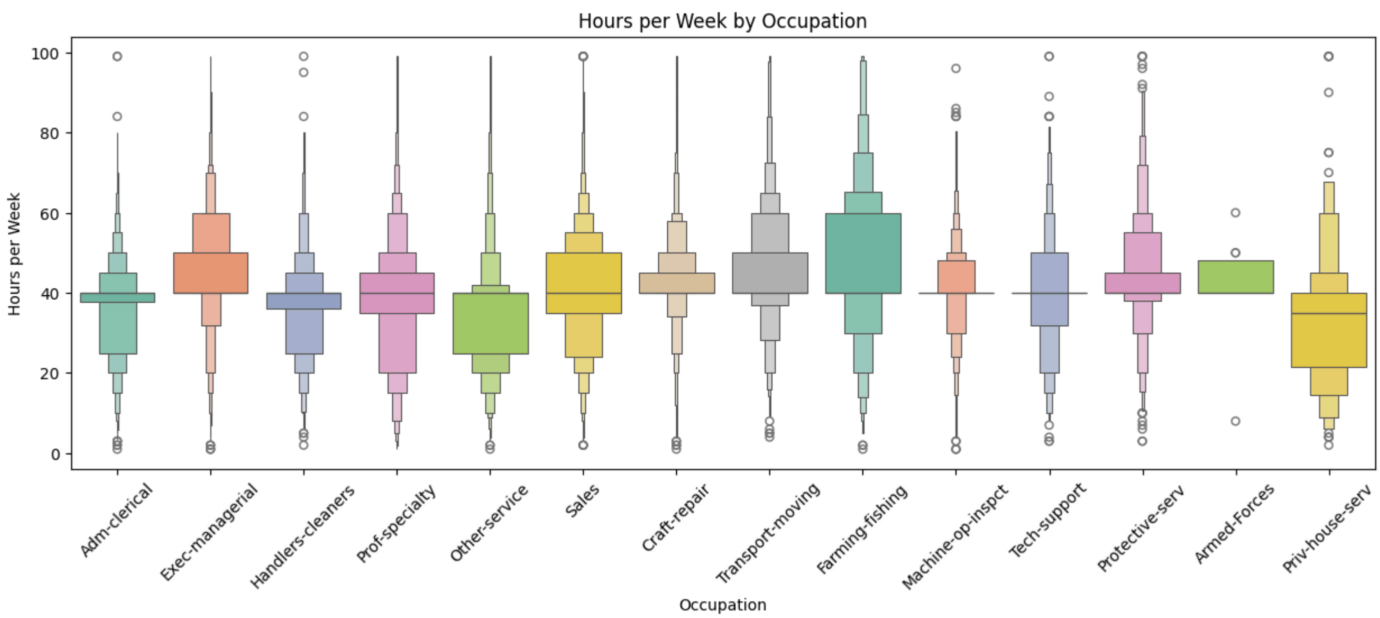
```
<ipython-input-372-46834607748d>:3: FutureWarning:

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

  sns.boxenplot(x='age', y='hours-per-week', data=selected_age_df, palette = 'Paired')
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20],
 [Text(0, 0, '20'),
  Text(1, 0, '21'),
  Text(2, 0, '22'),
  Text(3, 0, '23'),
  Text(4, 0, '24'),
  Text(5, 0, '25'),
  Text(6, 0, '26'),
  Text(7, 0, '27'),
  Text(8, 0, '28'),
  Text(9, 0, '29'),
  Text(10, 0, '30'),
  Text(11, 0, '31'),
  Text(12, 0, '32'),
  Text(13, 0, '33'),
  Text(14, 0, '34'),
  Text(15, 0, '35'),
  Text(16, 0, '36'),
  Text(17, 0, '37'),
  Text(18, 0, '38'),
  Text(19, 0, '39'),
  Text(20, 0, '40')])
```




```
selected_occupation_df = category_df[category_df['occupation'].isin(['Prof-specialty',
                                                                      'Craft-repair',
                                                                      'Exec-managerial',
                                                                      'Adm-clerical',
                                                                      'Sales',
                                                                      'Other-service',
                                                                      'Machine-op-inspct',
                                                                      'Transport-moving',
                                                                      'Handlers-cleaners',
                                                                      'Farming-fishing',
                                                                      'Tech-support',
                                                                      'Protective-serv',
```

```
                                                                    'Priv-house-serv',
                                                                    'Armed-Forces'])]
plt.figure(figsize=(15, 5))
sns.boxenplot(x='occupation', y='hours-per-week', data=selected_occupation_df, palette = 'Set2')
plt.suptitle('')
plt.xlabel('Occupation')
plt.ylabel('Hours per Week')
plt.title('Hours per Week by Occupation')
plt.xticks(rotation=45)
```

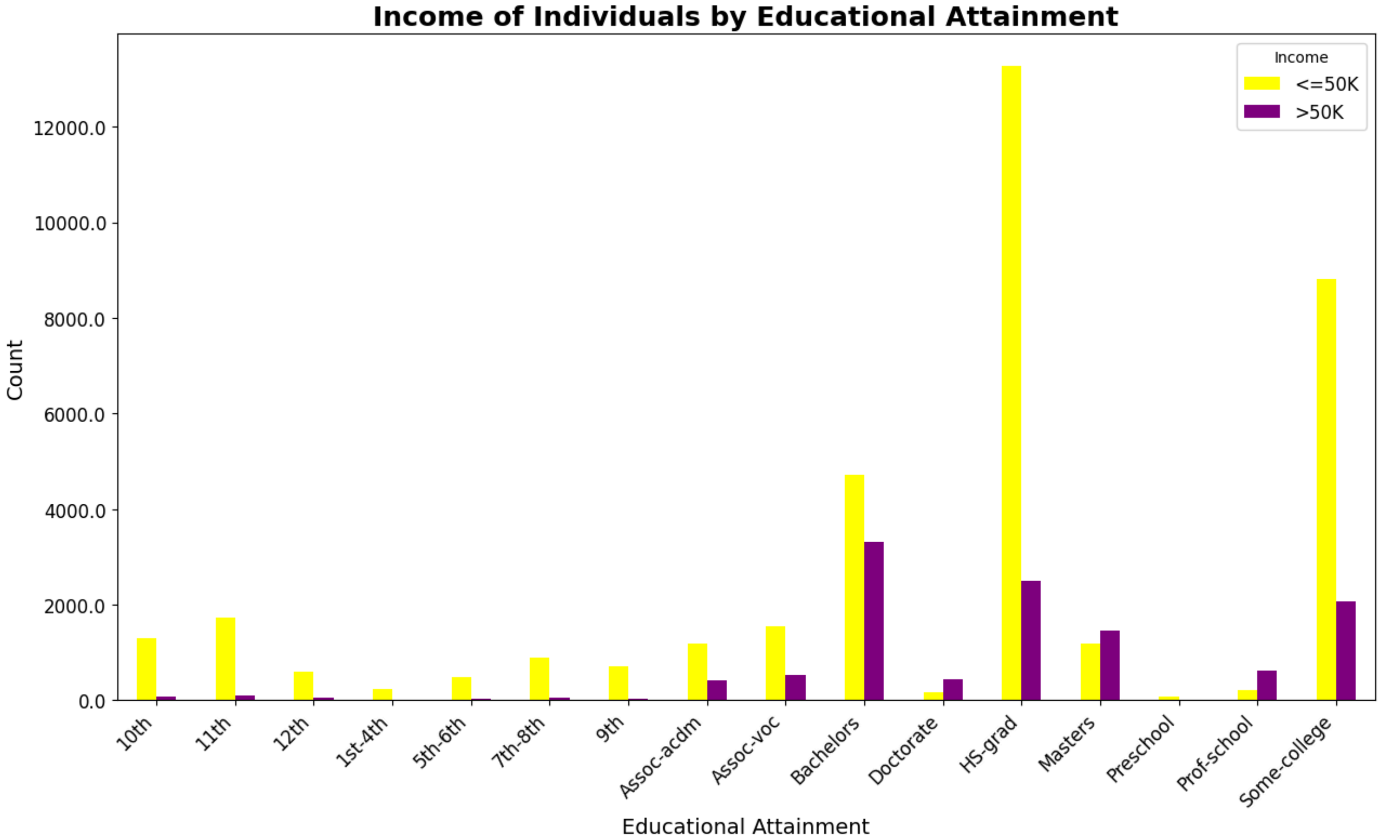
```
<ipython-input-451-ae948e49debe>:16: FutureWarning:

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

  sns.boxenplot(x='occupation', y='hours-per-week', data=selected_occupation_df, palette = 'Set2')
([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13],
 [Text(0, 0, 'Adm-clerical'),
  Text(1, 0, 'Exec-managerial'),
  Text(2, 0, 'Handlers-cleaners'),
  Text(3, 0, 'Prof-specialty'),
  Text(4, 0, 'Other-service'),
  Text(5, 0, 'Sales'),
  Text(6, 0, 'Craft-repair'),
  Text(7, 0, 'Transport-moving'),
  Text(8, 0, 'Farming-fishing'),
  Text(9, 0, 'Machine-op-inspct'),
  Text(10, 0, 'Tech-support'),
  Text(11, 0, 'Protective-serv'),
  Text(12, 0, 'Armed-Forces'),
  Text(13, 0, 'Priv-house-serv')])
```



Usage of pivot table to merge the two columns and onwards creating a bar graph for data visualization

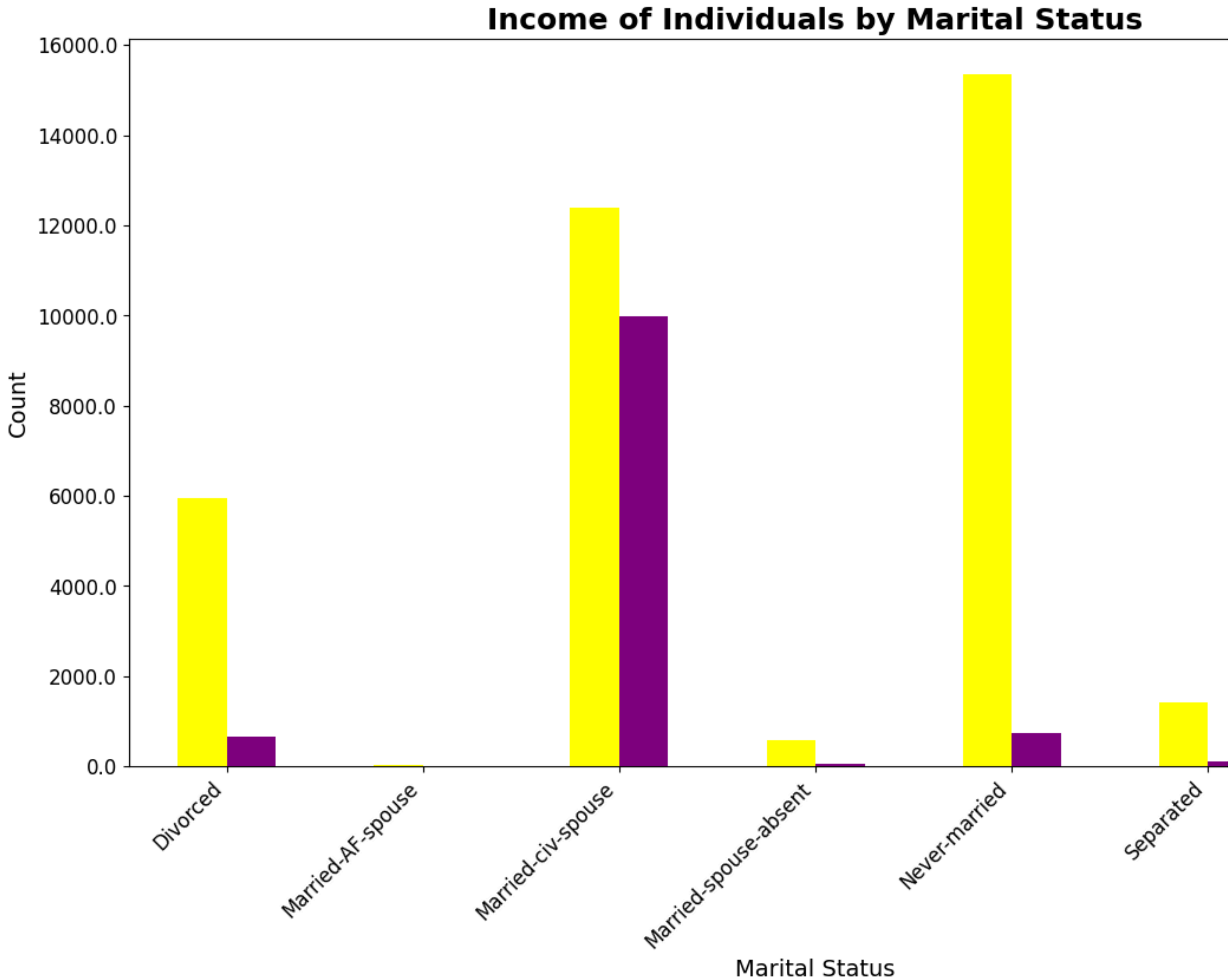
```
pivot_table = category_df.pivot_table(index='education', columns='income', aggfunc='size', fill_value=0)
fig, ax = plt.subplots(figsize=(15, 8))
pivot_table.plot(kind='bar', ax=ax, color = ['yellow', 'purple'])
ax.set_title('Income of Individuals by Educational Attainment', fontsize=18, fontweight='bold')
ax.set_xlabel('Educational Attainment', fontsize=14)
ax.set_ylabel('Count', fontsize=14)
ax.set_xticklabels(ax.get_xticklabels(), fontsize=12, rotation=45, ha='right')
ax.set_yticklabels(ax.get_yticks(), fontsize=12)
ax.legend(title='Income', fontsize=12)
```

```
<ipython-input-446-88e71c0452a4>:8: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ax.get_yticks(), fontsize=12)
<matplotlib.legend.Legend at 0x78fe71be6500>
```



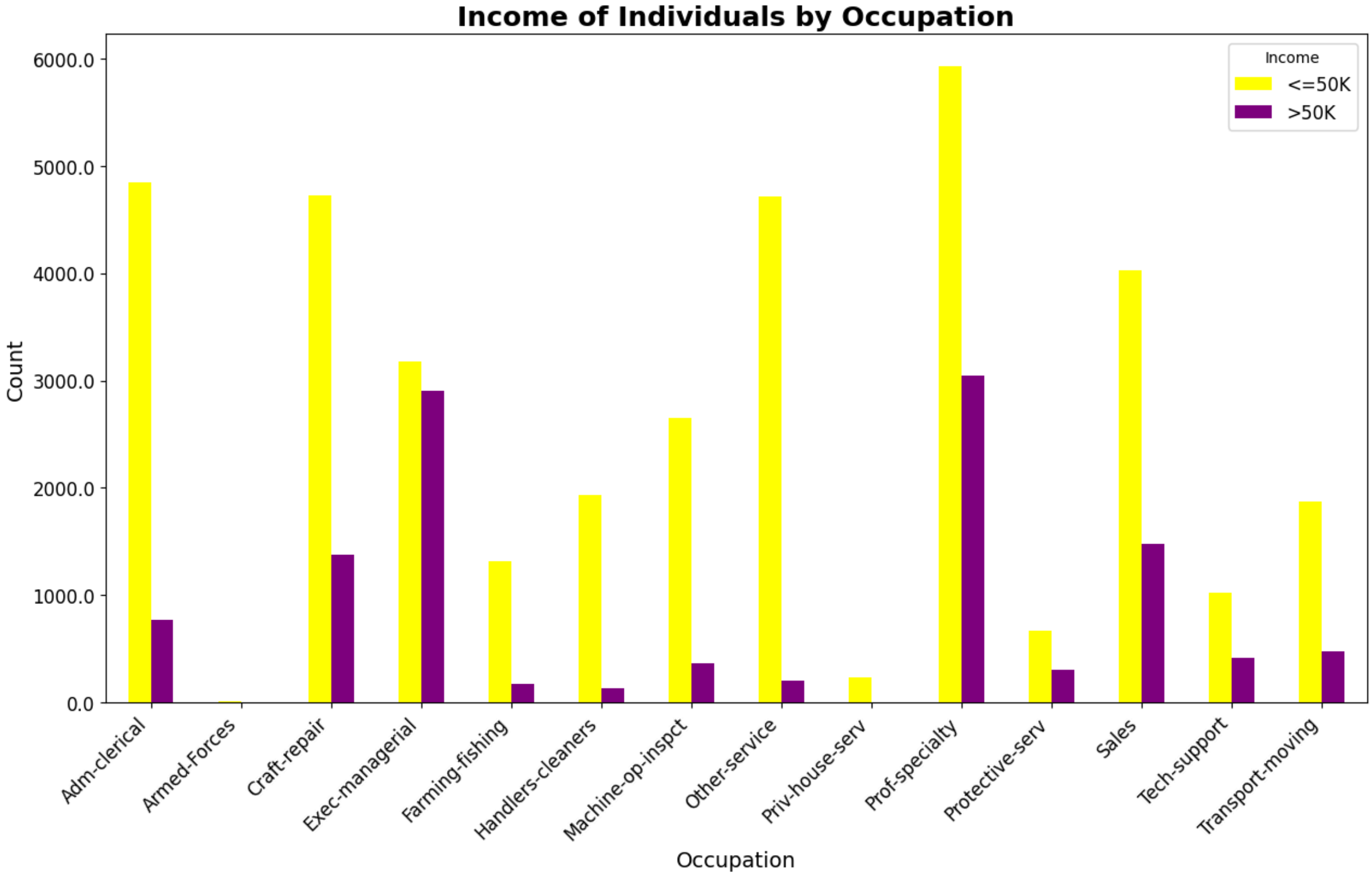

```
pivot_table = category_df.pivot_table(index='marital-status', columns='income', aggfunc='size', fill_value=0)
fig, ax = plt.subplots(figsize=(15, 8))
pivot_table.plot(kind='bar', ax=ax, color = ['yellow', 'purple'])
ax.set_title('Income of Individuals by Marital Status', fontsize=18, fontweight='bold')
ax.set_xlabel('Marital Status', fontsize=14)
ax.set_ylabel('Count', fontsize=14)
ax.set_xticklabels(ax.get_xticklabels(), fontsize=12, rotation=45, ha='right')
ax.set_yticklabels(ax.get_yticks(), fontsize=12)
ax.legend(title='Income', fontsize=12)
```

```
<ipython-input-441-8492ce2c9264>:8: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ax.get_yticks(), fontsize=12)
<matplotlib.legend.Legend at 0x78fe71b97130>
```




```
pivot_table = category_df.pivot_table(index='occupation', columns='income', aggfunc='size', fill_value=0)
fig, ax = plt.subplots(figsize=(15, 8))
pivot_table.plot(kind='bar', ax=ax, color = ['yellow', 'purple'])
ax.set_title('Income of Individuals by Occupation', fontsize=18, fontweight='bold')
ax.set_xlabel('Occupation', fontsize=14)
ax.set_ylabel('Count', fontsize=14)
ax.set_xticklabels(ax.get_xticklabels(), fontsize=12, rotation=45, ha='right')
ax.set_yticklabels(ax.get_yticks(), fontsize=12)
ax.legend(title='Income', fontsize=12)
```

```
<ipython-input-447-6107974bf15f>:8: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_yticklabels(ax.get_yticks(), fontsize=12)
<matplotlib.legend.Legend at 0x78fe71725930>
```



+ Code + Text