Exploratory Data Analysis (EDA)

Census Income DataSet

Abstract: Predict whether income exceeds $50K/yr based on census data. Also known as "Adult" dataset.

Details of dataset: (https://archive.ics.uci.edu/ml/machine-learning-databases/adult/)

In [1]:
```
#import necesary library and tools
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Data ingestion from github
datalink="https://raw.githubusercontent.com/ayan-zz/adult_census_income/main/adult.csv"
data=pd.read_csv(datalink,header=None, sep=',\s')
```

In [3]:
```
header=['age','workclass','fnl-wgt','education','education-num','marital status','occupation','relationship','r
df=pd.DataFrame(data)
df.columns=header
df.head()
```

Out[3]:

	age	workclass	fnl-wgt	education	education-num	marital status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native_country
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 [4]:
```
df_cat=[feature for feature in df.columns if df[feature].dtype=='O']
df_num=[feature for feature in df.columns if df[feature].dtype!='O']
print("Categorical features include:\n",df_cat)
print("Numerical features include:\n",df_num)
```

```
Categorical features include:
 ['workclass', 'education', 'marital status', 'occupation', 'relationship', 'race', 'sex', 'native_country', 'i
ncome']
Numerical features include:
 ['age', 'fnl-wgt', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week']
```

Initial Observation:

1. Total categorical features: 08 total numerical features: 06 Target/output feature: Income
2. Many datapoints are having '?' values in categorical features: workclass, occupation, native_country
3. Income is in categorical form '<=50k' and '>=50k'
4. Total gain or loss of capital is separated by capital gain and capital loss

Initial Tasks:

1. Modify the categorical features
2. Replace the '?' datapoints
3. Income field can be replaced by 0 and 1 values
4. Combining total gain and loss into Capital_gain/loss
5. Numerical feature 'age' can be replaced by binned age for better understanding off data
6. Categorical feature 'capital_gain/loss' can be binned as no-gain,gain,high-gain
7. Check for datatypes and nan/null values
8. Taking action on null/nan values
9. Dropping the duplicates
10. Bringing insights on numerical datas by correlation and heatmap
11. Comparing numerical data with cateorical features

12. Observing the distribution of target features with rest of data

In [5]:
```
#Data Transformation
df['workclass']=df['workclass'].replace({'?': 'Private'})
df['occupation']=df['occupation'].replace({'?': 'Prof-specialty'})
df['income']=df['income'].replace({'<=50K': 0,'<50K':0,'>=50K': 1,'>50K': 1})
```

In [6]:
```
df['income'].value_counts()
```

Out[6]:
```
0    24720
1     7841
Name: income, dtype: int64
```

In [7]:
```
df['capital gain/loss']=df['capital-gain']-df['capital-loss']
df=df.drop(columns=['capital-gain','capital-loss'])
```

In [8]:
```
df.head()
```

Out[8]:

	age	workclass	fnl-wgt	education	education-num	marital status	occupation	relationship	race	sex	hours-per-week	native_country	income	capita gain/los
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	40	United-States	0	217
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	13	United-States	0	
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	40	United-States	0	
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40	United-States	0	
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40	Cuba	0	

In [9]:
```
d=np.sort(df['hours-per-week'].unique())
d
```

Out[9]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
       35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51,
       52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68,
       70, 72, 73, 74, 75, 76, 77, 78, 80, 81, 82, 84, 85, 86, 87, 88, 89,
       90, 91, 92, 94, 95, 96, 97, 98, 99], dtype=int64)
```

In [10]:
```
#we convert the hours per week into bins of size 0-20,20-40,40-60,60-80,80-100.
bins = [0, 20,  40, 60, 80, 100]
labels=['0-20','20-40','40-60','60-80','80-100']
df['binned_hours'] = pd.cut(df['hours-per-week'], bins, labels=labels)
```

In [11]:
```
df['binned_hours'].value_counts()
```

Out[11]:
```
20-40     20052
40-60      8471
0-20       2928
60-80       902
80-100      208
Name: binned_hours, dtype: int64
```

In [12]:
```
bins = [0, 20,  40, 60, 80, 100]
labels=['0-20','20-40','40-60','60-80','80-100']
df['binned_age'] = pd.cut(df['age'], bins, labels=labels)
```

In [13]:
```
df['binned_age'].value_counts()
```

Out[13]:
```
20-40     16708
40-60     11111
0-20       2410
60-80      2233
80-100       99
Name: binned_age, dtype: int64
```

In [14]:
```
bins = [-10000,0,10000,1000000]
labels =['no-gain','gain','high-gain']
df['capital_gain/loss'] = pd.cut(df['capital gain/loss'], bins,labels=labels)
```

In [15]:
```
df['capital_gain/loss'].value_counts()
```

Out[15]:
```
no-gain      29849
gain          1942
high-gain      770
Name: capital_gain/loss, dtype: int64
```

In [16]:
```
df.isna().sum()
```

Out[16]:
```
age                0
workclass          0
fnl-wgt            0
education          0
education-num      0
marital status     0
occupation         0
relationship       0
race               0
sex                0
hours-per-week     0
native_country     0
income             0
capital gain/loss  0
binned_hours       0
binned_age         0
capital_gain/loss  0
dtype: int64
```

In [17]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   age                32561 non-null  int64
 1   workclass          32561 non-null  object
 2   fnl-wgt            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         32561 non-null  object
 7   relationship       32561 non-null  object
 8   race               32561 non-null  object
 9   sex                32561 non-null  object
 10  hours-per-week     32561 non-null  int64
 11  native_country     32561 non-null  object
 12  income             32561 non-null  int64
 13  capital gain/loss  32561 non-null  int64
 14  binned_hours       32561 non-null  category
 15  binned_age         32561 non-null  category
 16  capital_gain/loss  32561 non-null  category
dtypes: category(3), int64(6), object(8)
memory usage: 3.6+ MB
```

In [18]:
```
df_cat=[feature for feature in df.columns if df[feature].dtype=='object']
df_num=[feature for feature in df.columns if df[feature].dtype=='int64']
print("Categorical features include:\n",df_cat)
print("Numerical features include:\n",df_num)
```

```
Categorical features include:
 ['workclass', 'education', 'marital status', 'occupation', 'relationship', 'race', 'sex', 'native_country']
Numerical features include:
 ['age', 'fnl-wgt', 'education-num', 'hours-per-week', 'income', 'capital gain/loss']
```

In [19]:
```
df[df_num].describe()
```

Out[19]:

	age	fnl-wgt	education-num	hours-per-week	income	capital gain/loss
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561.000000
mean	38.581647	1.897784e+05	10.080679	40.437456	0.240810	990.345014
std	13.640433	1.055500e+05	2.572720	12.347429	0.427581	7408.986951
min	17.000000	1.228500e+04	1.000000	1.000000	0.000000	-4356.000000
25%	28.000000	1.178270e+05	9.000000	40.000000	0.000000	0.000000
50%	37.000000	1.783560e+05	10.000000	40.000000	0.000000	0.000000
75%	48.000000	2.370510e+05	12.000000	45.000000	0.000000	0.000000
max	90.000000	1.484705e+06	16.000000	99.000000	1.000000	99999.000000

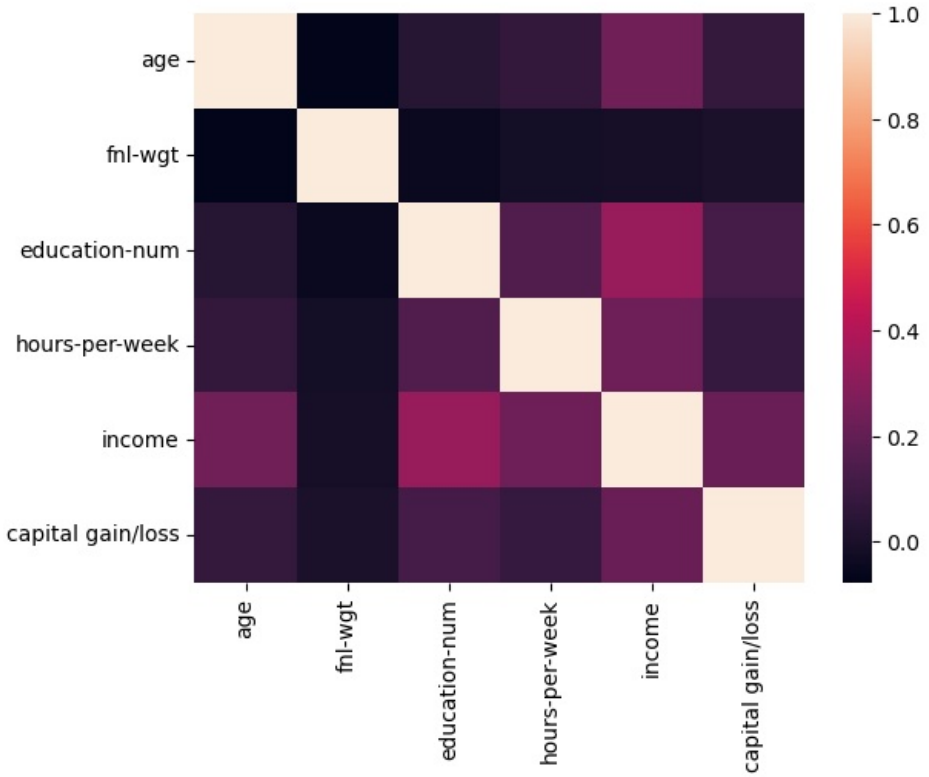
In [20]:
```
df.corr()
```

Out[20]:

	age	fnl-wgt	education-num	hours-per-week	income	capital gain/loss
age	1.000000	-0.076646	0.036527	0.068756	0.234037	0.074284
fnl-wgt	-0.076646	1.000000	-0.043195	-0.018768	-0.009463	0.000988
education-num	0.036527	-0.043195	1.000000	0.148123	0.335154	0.117891
hours-per-week	0.068756	-0.018768	0.148123	1.000000	0.229689	0.075207
income	0.234037	-0.009463	0.335154	0.229689	1.000000	0.214428
capital gain/loss	0.074284	0.000988	0.117891	0.075207	0.214428	1.000000

In [21]:
```
sns.heatmap(df.corr())
```

Out[21]:
```
<AxesSubplot:>
```



Final-weight is having high correlation. The following assumption made from research paper and analysis: The weights on the CPS files are controlled to independent estimates of the civilian noninstitutional population of the US. These are prepared monthly for us by Population Division here at the Census Bureau. We use 3 sets of controls. These are:

1. A single cell estimate of the population 16+ for each state.
2. Controls for Hispanic Origin by age and sex.
3. Controls by Race, age and sex.

Hence dropping the feature

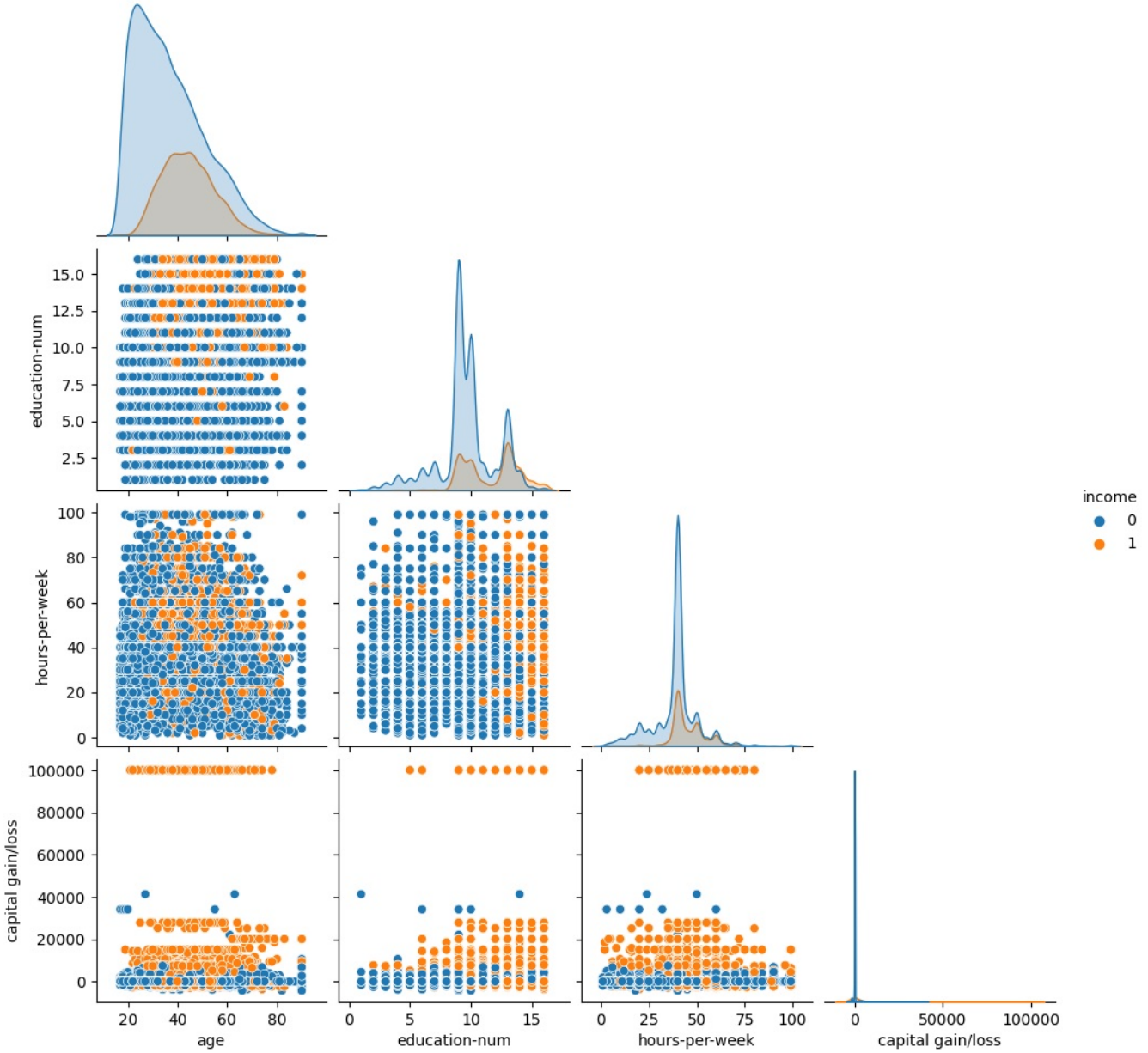
In [22]:
```
df.drop(columns=['fnl-wgt'],inplace=True)
```

In [23]:
```
df.head()
```

Out[23]:

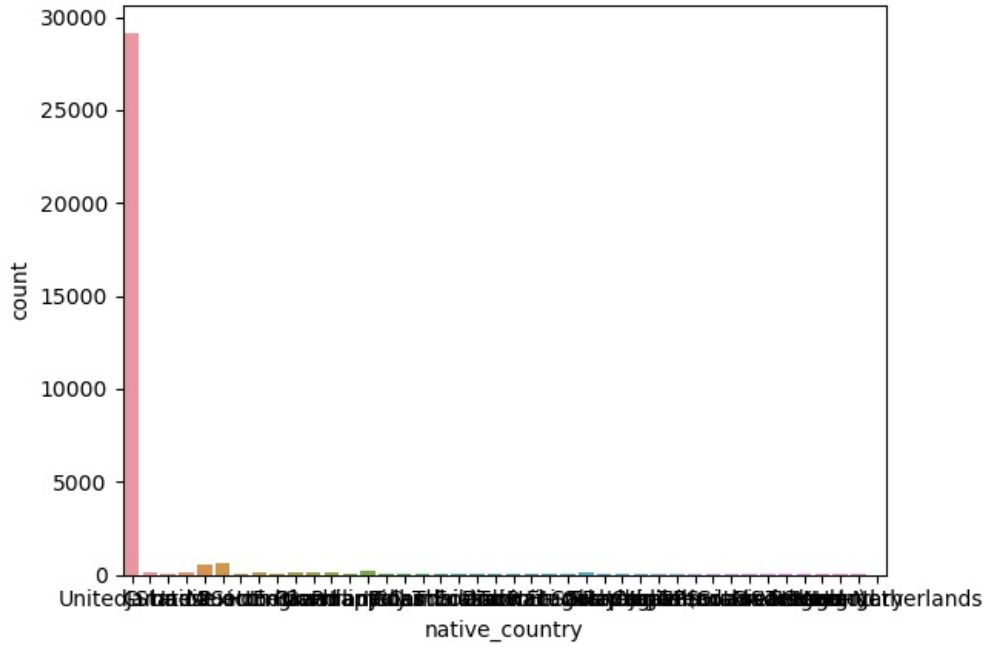
	age	workclass	education	education-num	marital status	occupation	relationship	race	sex	hours-per-week	native_country	income	capital gain/loss	binne
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	40	United-States	0	2174	
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse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

In [24]:
```
sns.pairplot(df,hue='income',corner=True)
plt.show()
```



In [25]:
```
sns.countplot(data=df,x='native_country')
```

Out[25]:
```
<AxesSubplot:xlabel='native_country', ylabel='count'>
```



In [26]:
```
df['native_country'].value_counts()
```

Out[26]:
```
United-States                 29170
Mexico                          643
?                               583
Philippines                     198
Germany                         137
Canada                          121
Puerto-Rico                     114
El-Salvador                     106
India                           100
Cuba                             95
England                          90
Jamaica                          81
South                            80
China                            75
Italy                            73
Dominican-Republic               70
Vietnam                          67
Guatemala                        64
Japan                            62
Poland                           60
Columbia                         59
Taiwan                           51
Haiti                            44
Iran                             43
Portugal                         37
Nicaragua                        34
Peru                             31
France                           29
Greece                           29
Ecuador                          28
Ireland                          24
Hong                             20
Cambodia                         19
Trinadad&Tobago                  19
Laos                             18
Thailand                         18
Yugoslavia                       16
Outlying-US(Guam-USVI-etc)       14
Honduras                         13
Hungary                          13
Scotland                         12
Holand-Netherlands                1
Name: native_country, dtype: int64
```

In [27]:
```
df['native_country'].unique()
```

Out[27]:
```
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'], dtype=object)
```

In [28]:
```
dd=df[df['native_country']=='?']
dd['race'].value_counts()
```

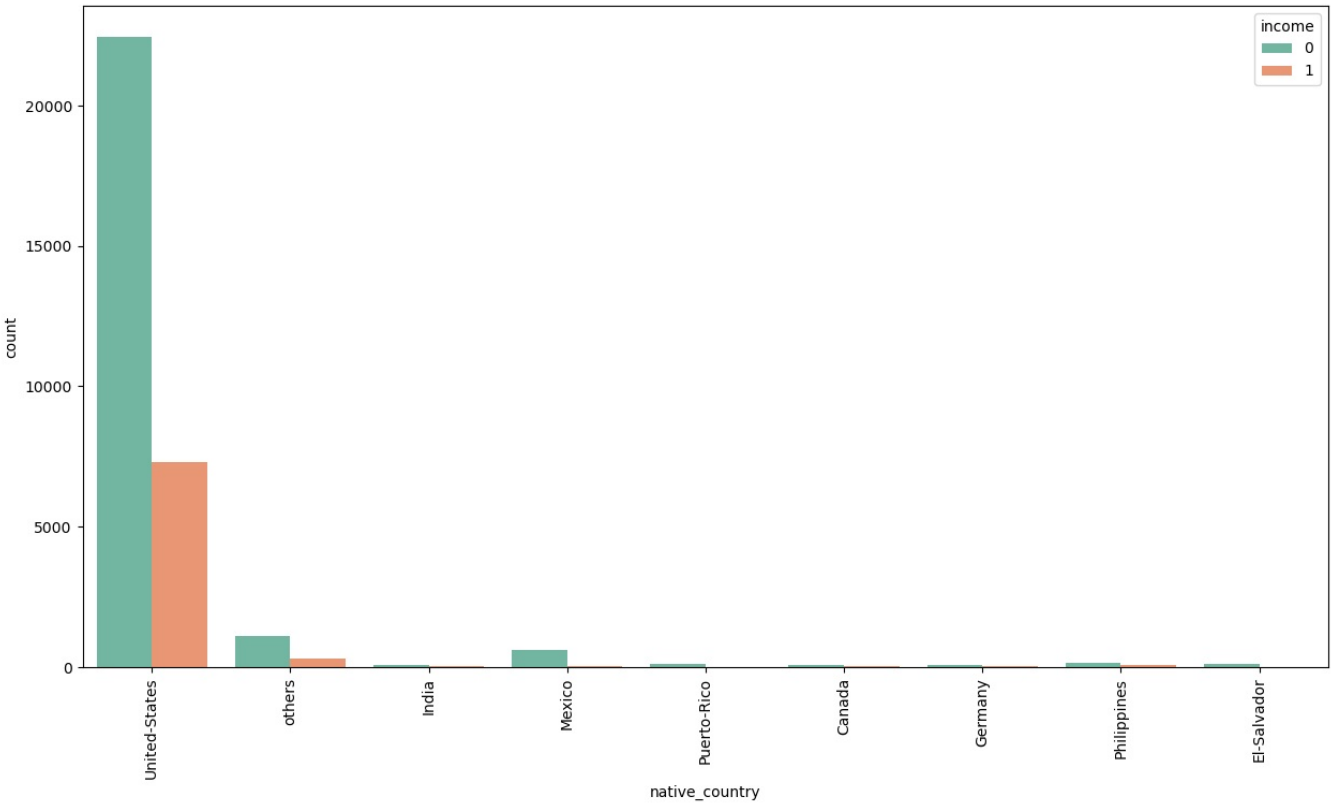
Out[28]:
```
White                 386
Black                  96
Asian-Pac-Islander     83
Other                  18
Name: race, dtype: int64
```

From the above observation its affirmed that United States data is in high number where as other country'scontribution is very less. A large number of data are narked as '?'. We see that out of these data all people has a race of White/ Black/Asia Pac Islander which belongs nearly the American region. Hence we can consider them as 'United States'. We will re-group other contries on separate bins and United States as is.

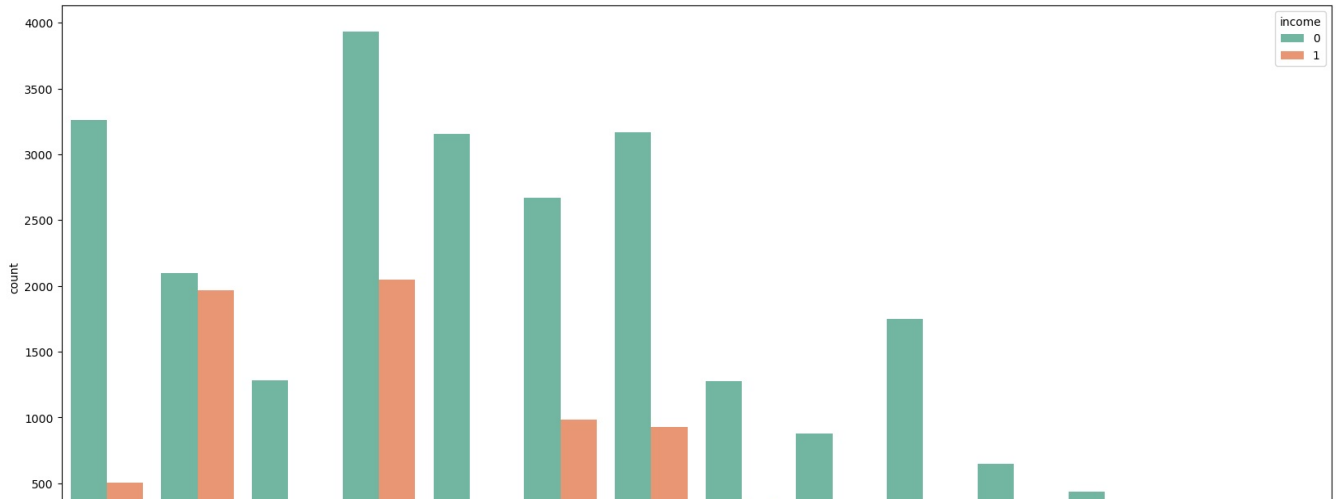
In [29]:
```
othrs=[ 'Cuba', 'Jamaica', 'South', 'Honduras', 'England', 'Iran', 'Italy', 'Poland', 'Columbia', 'Cambodia','T
'Ecuador', 'Laos', 'Taiwan', 'Haiti', 'Portugal','Dominican-Republic',  'France', 'Guatemala','China', 'Japan',
'Yugoslavia', 'Peru','Outlying-US(Guam-USVI-etc)', 'Scotland', 'Trinadad&Tobago','Greece', 'Nicaragua', 'Vietna
'Ireland', 'Hungary','Holand-Netherlands']


df["native_country"] = np.where(df["native_country"]=='?','United-States',df["native_country"])
df['native_country']=df['native_country'].replace(to_replace=othrs,value='others')
df['native_country'].value_counts()
```

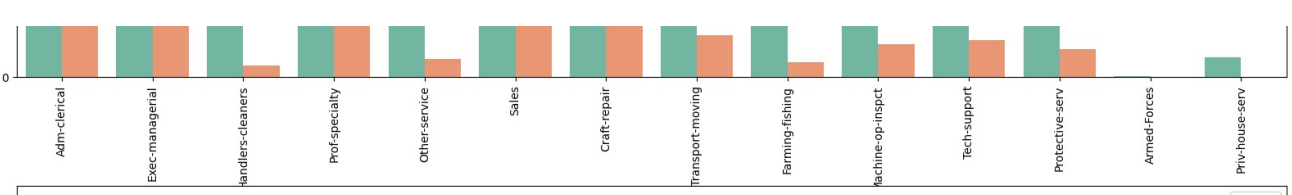
Out[29]:
```
United-States    29753
others            1389
Mexico             643
Philippines        198
Germany            137
Canada             121
Puerto-Rico        114
El-Salvador        106
India              100
Name: native_country, dtype: int64
```

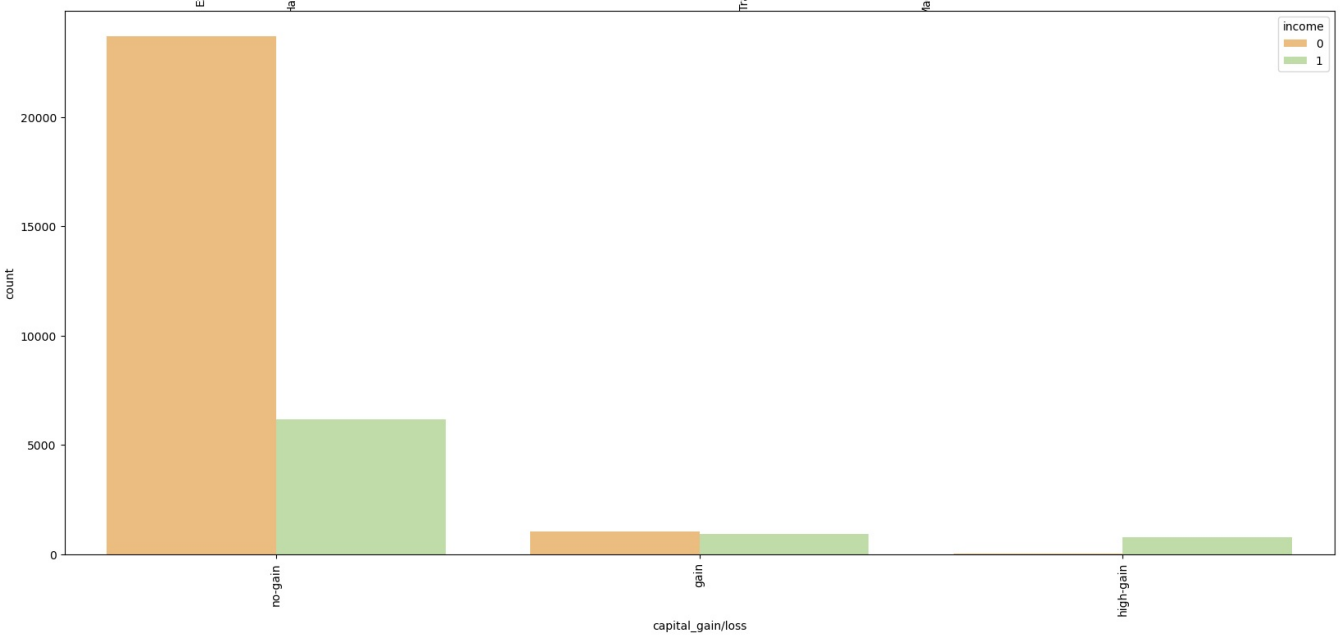
In [30]:
```
fig, axs = plt.subplots(1, 1, figsize=(15,8))
plt.subplot(111)
sns.countplot(data=df,x='native_country',hue='income',palette='Set2')
plt.xticks(rotation=90)
plt.show()
```

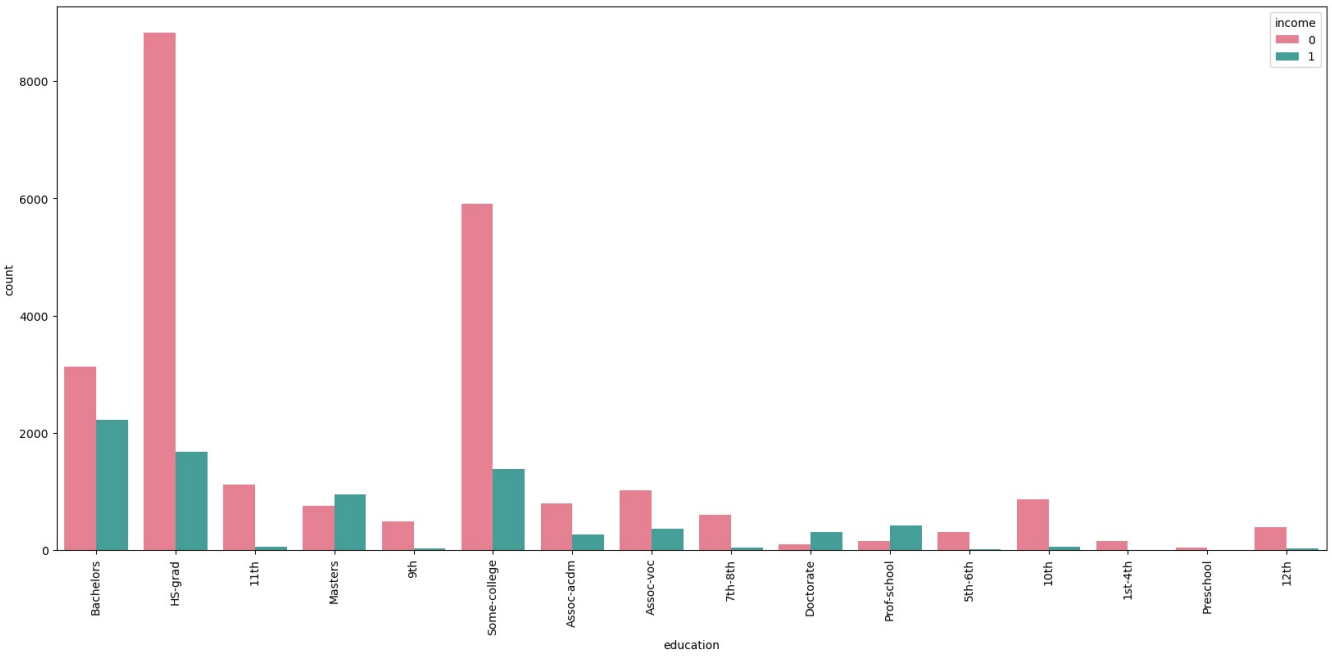


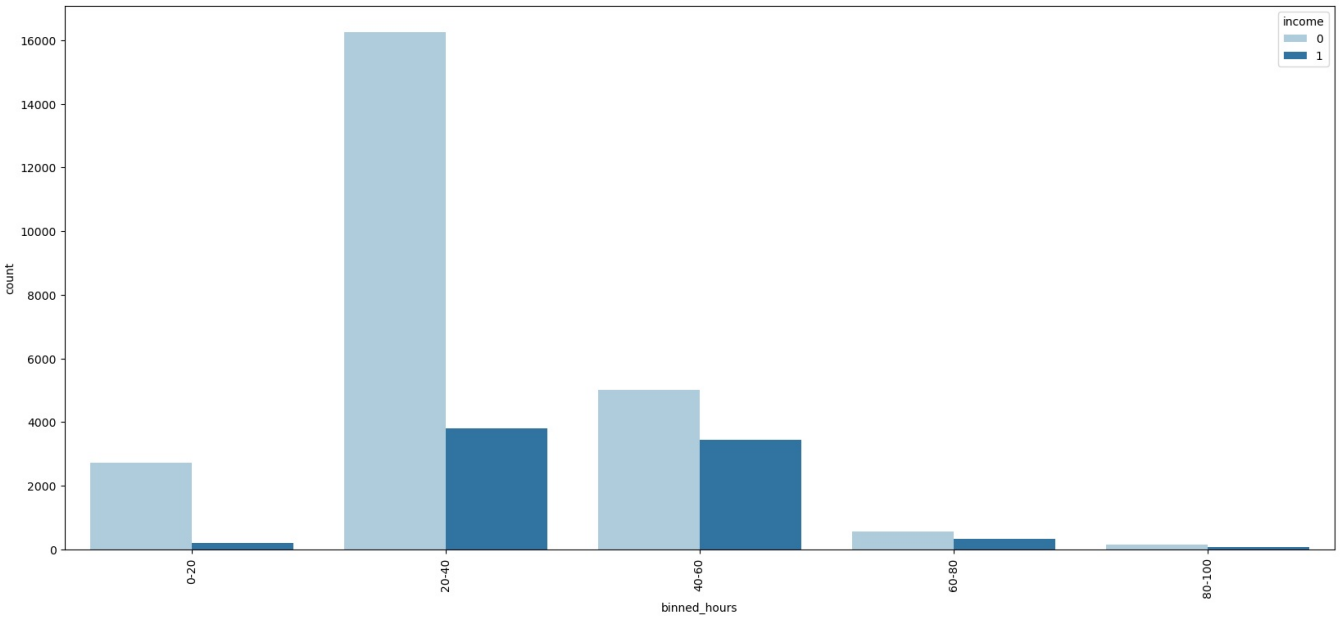
In [31]:
```
fig, axs = plt.subplots(1, 1, figsize=(20,50))
plt.subplot(511)
sns.countplot(data=df,x='occupation',hue='income',palette='Set2')
plt.xticks(rotation=90)
plt.subplot(512)
sns.countplot(data=df,x='capital_gain/loss',hue='income',palette='Spectral')
plt.xticks(rotation=90)
plt.subplot(513)
sns.countplot(data=df,x='education',hue='income',palette='husl')
plt.xticks(rotation=90)
plt.subplot(514)
sns.countplot(data=df,x='binned_hours',hue='income',palette='Paired')
plt.xticks(rotation=90)
plt.subplot(515)
sns.countplot(data=df,x='binned_age',hue='income',palette='rocket')
plt.xticks(rotation=90)
plt.show()
```



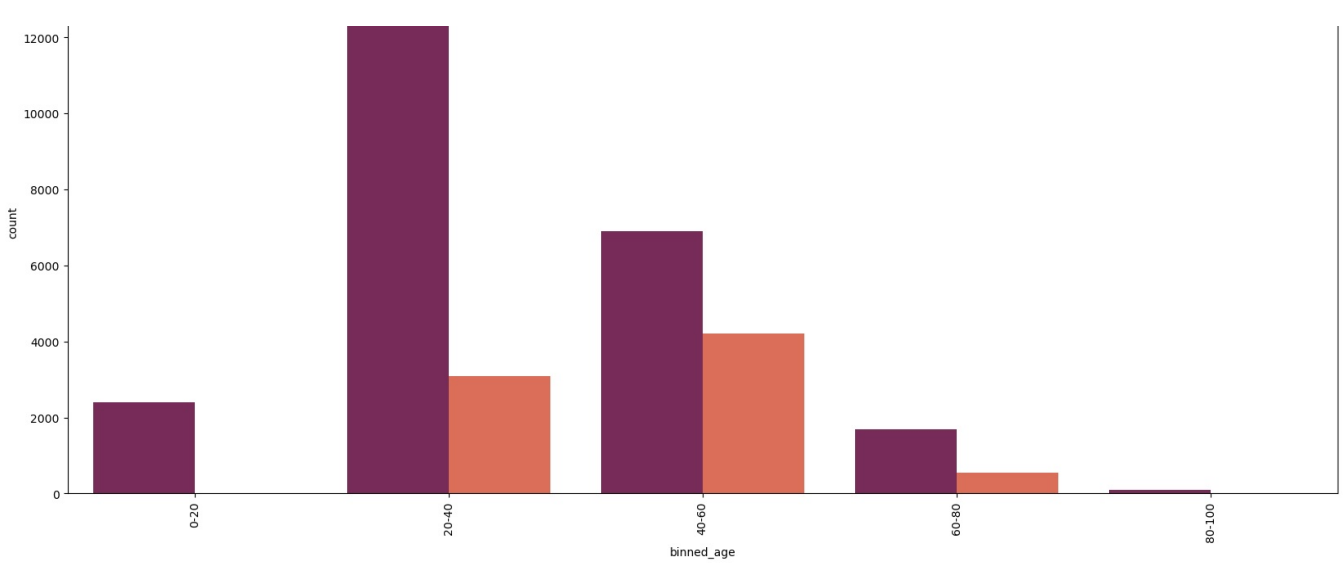

0
Adm-clerical
Exec-managerial
Prof-specialty
Other-service
Sales
Craft-repair
Transport-moving
Farming-fishing
Tech-support
Protective-serv
Armed-Forces
Priv-house-serv


income
0
1
count
20000
15000
10000
5000
0
no-gain
gain
high-gain
capital_gain/loss

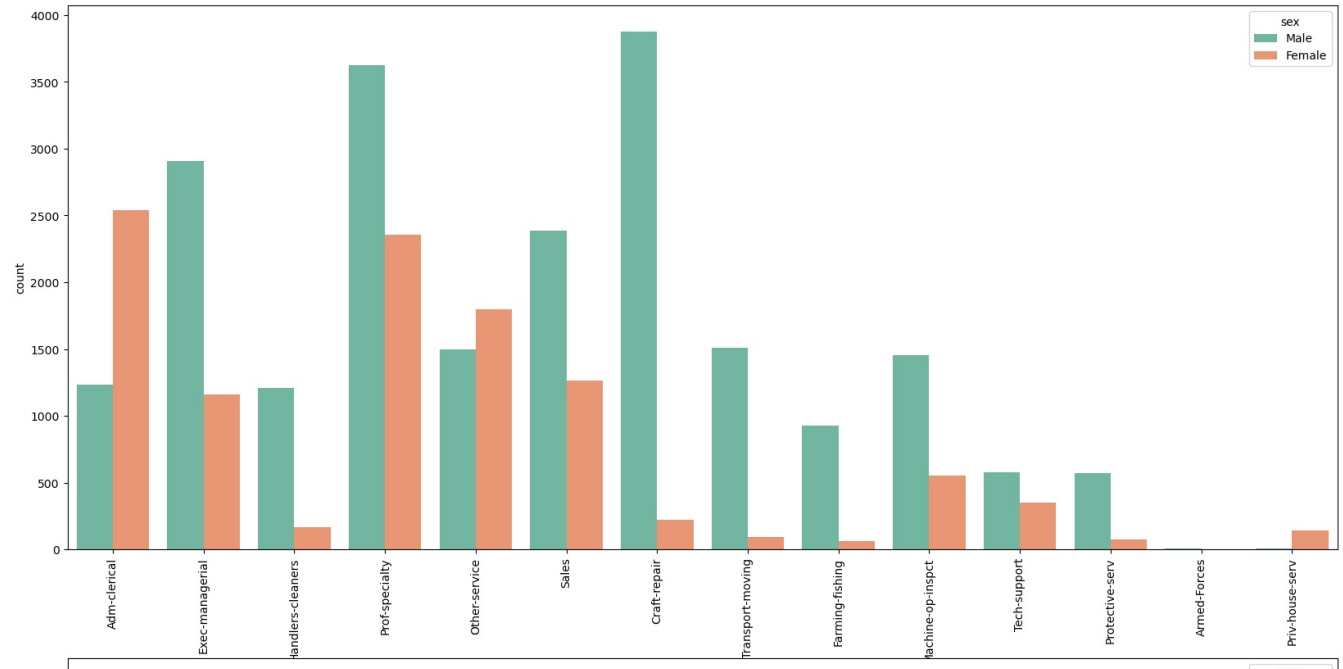

income
0
1
count
8000
6000
4000
2000
0
Bachelors
HS-grad
11th
Masters
9th
Some-college
Assoc-acdm
Assoc-voc
7th-8th
Doctorate
Prof-school
5th-6th
10th
1st-4th
Preschool
12th
education

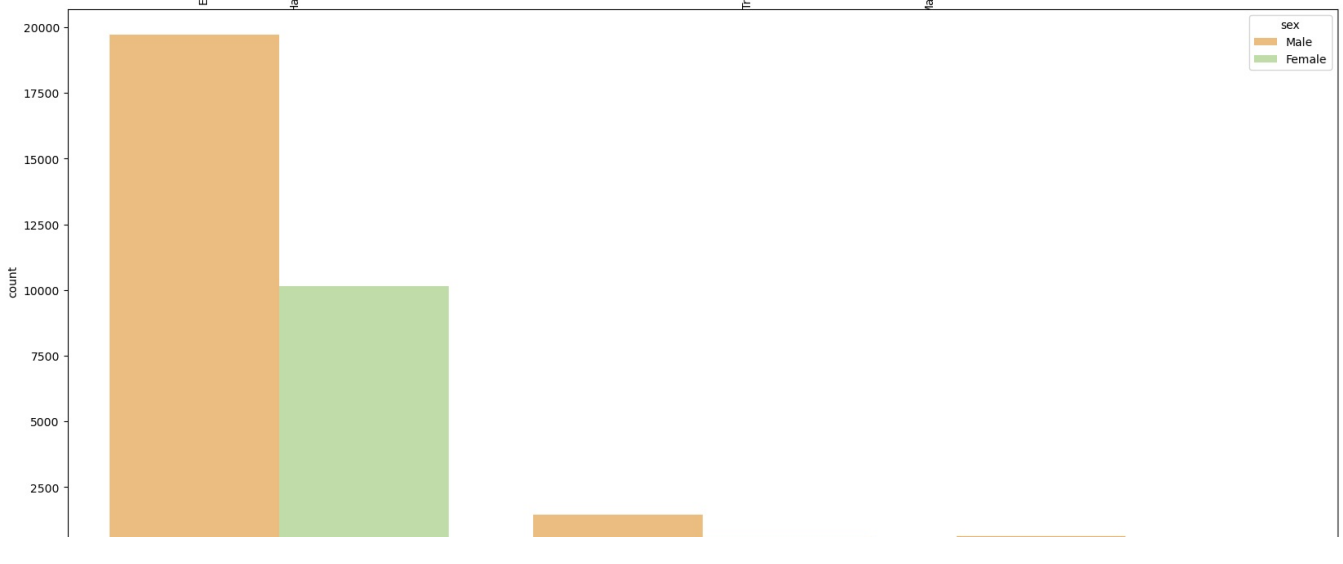

income
0
1
count
16000
14000
12000
10000
8000
6000
4000
2000
0
0-20
20-40
40-60
60-80
80-100
binned_hours

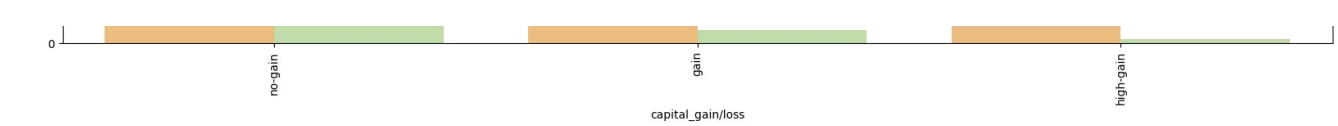

14000
income
0
1

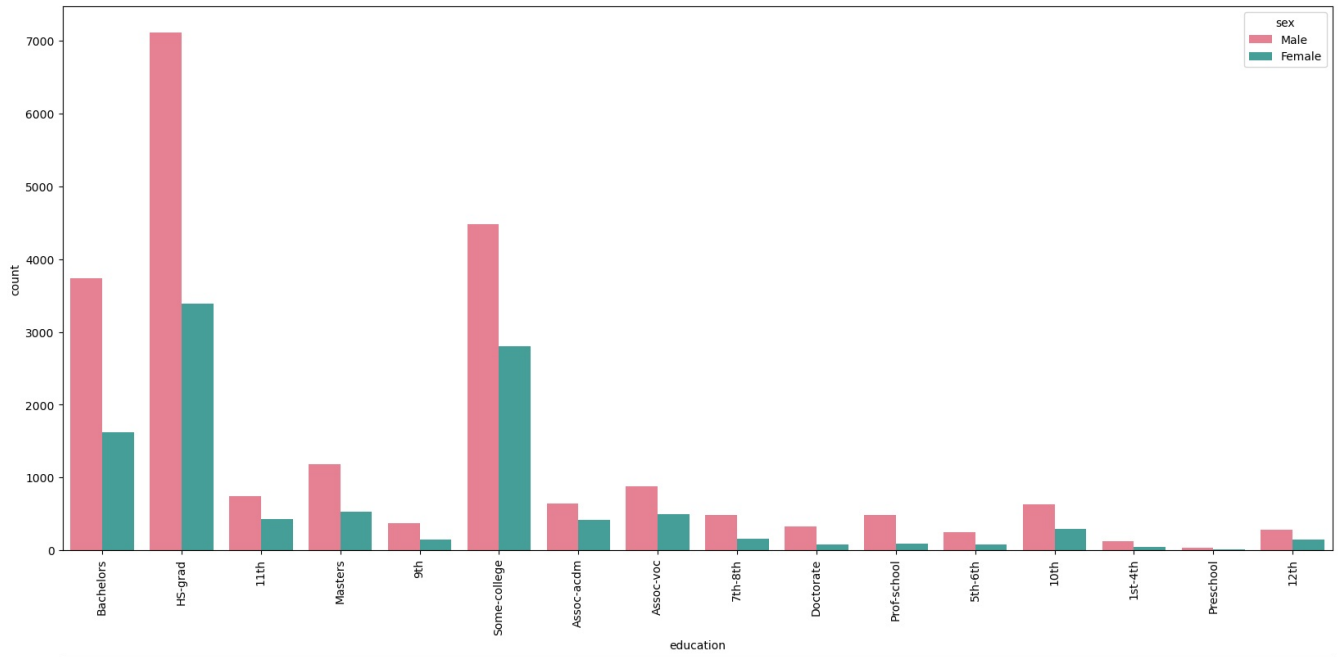


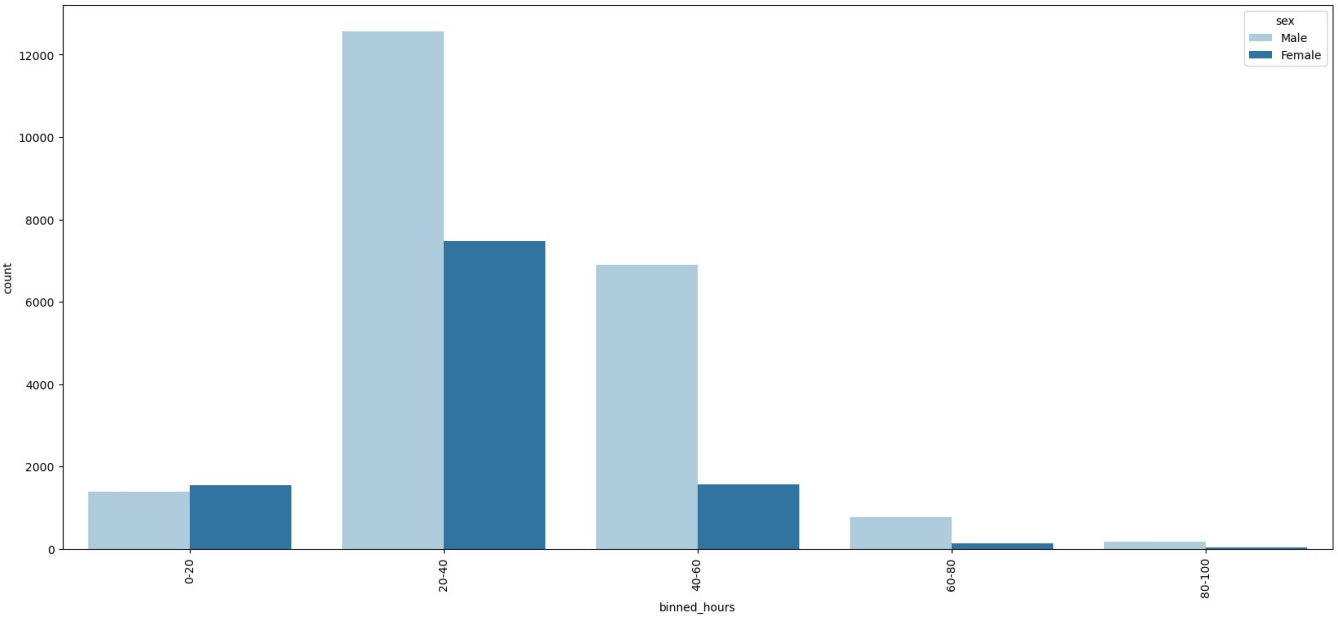
In [32]:
```
fig, axs = plt.subplots(1, 1, figsize=(20,50))
plt.subplot(511)
sns.countplot(data=df,x='occupation',hue='sex',palette='Set2')
plt.xticks(rotation=90)
plt.subplot(512)
sns.countplot(data=df,x='capital_gain/loss',hue='sex',palette='Spectral')
plt.xticks(rotation=90)
plt.subplot(513)
sns.countplot(data=df,x='education',hue='sex',palette='husl')
plt.xticks(rotation=90)
plt.subplot(514)
sns.countplot(data=df,x='binned_hours',hue='sex',palette='Paired')
plt.xticks(rotation=90)
plt.subplot(515)
sns.countplot(data=df,x='binned_age',hue='sex',palette='rocket')
plt.xticks(rotation=90)
plt.show()
```

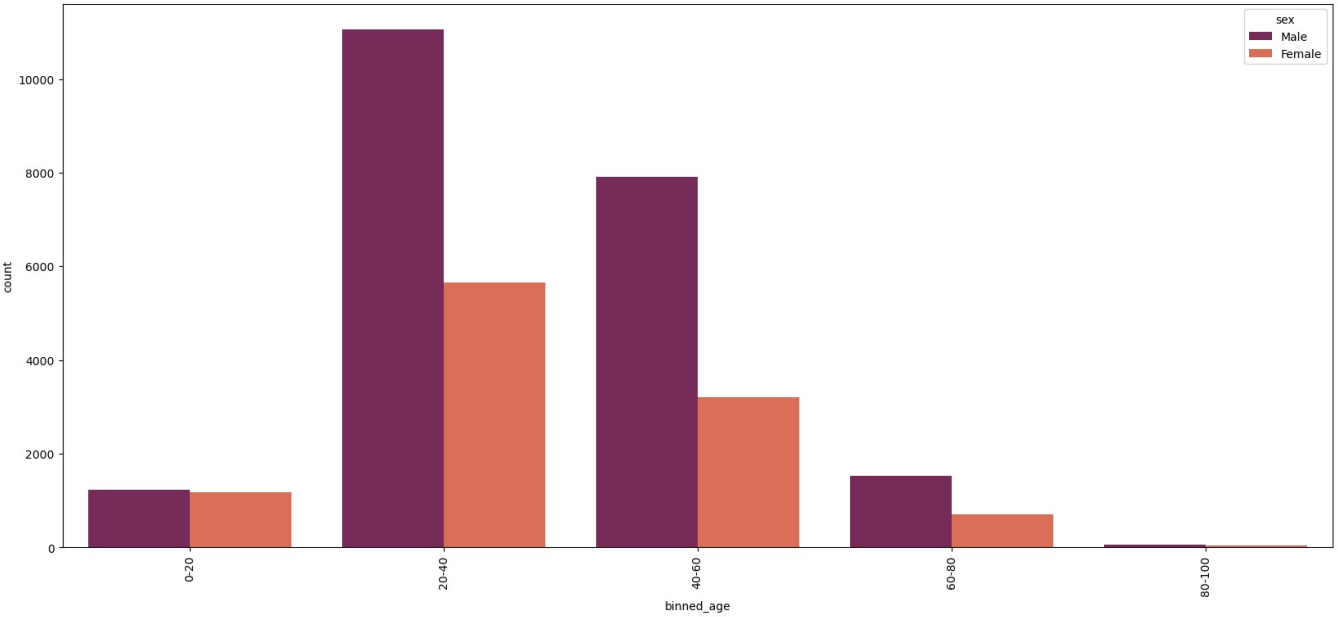












Observations

1. Income Generation:

i) Occupation of people having 'Exec-managerial' and 'Prof-speciality' are having higher income generation (>=50k) whereas Armed forces and Pri-House Serv are having minimal income(<=50).

ii) People completed their bachelorate degree have more chance of getting an income generation of >=50k.

iii) Higher income is found in the 40-60 yrs age group of people.

iv) Maximum number of people in <=50k range of income are of 20-40 years age group and are working more hours per week than others.

v) Neutral/ No-gain/ loss of capital is observed in the people having <=50k income generation and high gain is only observed in >=50 k zone.

2. Sex Ratio:

i) Male have dominated in almost every field

ii) Admin Clerical an Other services have higher female count than men in occupation section.

3. Ethinicity/Native Country:

Maximum of population is from United States with race as white. Mostly of them generate <=50k income, approximating about 26-30% people have higher income.

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