Income evaluation

September 18, 2020

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪the files in the input directory
# import warnings
import warnings
# ignore warnings
warnings.filterwarnings("ignore")
from subprocess import check_output
# print(check_output(["ls", "../input"]).decode("utf8"))
```

[2]:
```
data = pd.read_csv('income_evaluation.csv')
print(plt.style.available) # look at available plot styles
plt.style.use('ggplot')
```

```
['bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot',
'grayscale', 'seaborn-bright', 'seaborn-colorblind', 'seaborn-dark-palette',
'seaborn-dark', 'seaborn-darkgrid', 'seaborn-deep', 'seaborn-muted', 'seaborn-
notebook', 'seaborn-paper', 'seaborn-pastel', 'seaborn-poster', 'seaborn-talk',
'seaborn-ticks', 'seaborn-white', 'seaborn-whitegrid', 'seaborn',
'Solarize_Light2', 'tableau-colorblind10', '_classic_test']
```

[3]:
```
data.shape
```

[3]:
```
(32561, 15)
```

[4]:
```
data.describe()
```

[4]:
```
                age        fnlwgt  education-num  capital-gain  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000
mean      38.581647  1.897784e+05      10.080679   1077.648844
std       13.640433  1.055500e+05       2.572720   7385.292085
min       17.000000  1.228500e+04       1.000000      0.000000
25%       28.000000  1.178270e+05       9.000000      0.000000
50%       37.000000  1.783560e+05      10.000000      0.000000
```

```
75%        48.000000  2.370510e+05       12.000000       0.000000
max        90.000000  1.484705e+06       16.000000   99999.000000

         capital-loss   hours-per-week
count    32561.000000     32561.000000
mean        87.303830        40.437456
std        402.960219        12.347429
min          0.000000         1.000000
25%          0.000000        40.000000
50%          0.000000        40.000000
75%          0.000000        45.000000
max       4356.000000        99.000000
```

[5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
age                   32561 non-null int64
 workclass            32561 non-null object
 fnlwgt               32561 non-null int64
 education            32561 non-null object
 education-num        32561 non-null int64
 marital-status       32561 non-null object
 occupation           32561 non-null object
 relationship         32561 non-null object
 race                 32561 non-null object
 sex                  32561 non-null object
 capital-gain         32561 non-null int64
 capital-loss         32561 non-null int64
 hours-per-week       32561 non-null int64
 native-country       32561 non-null object
 income               32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

[6]:
```
data.isnull().sum()
```

[6]:
```
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
```

No null data , that makes work a bit easier !!!

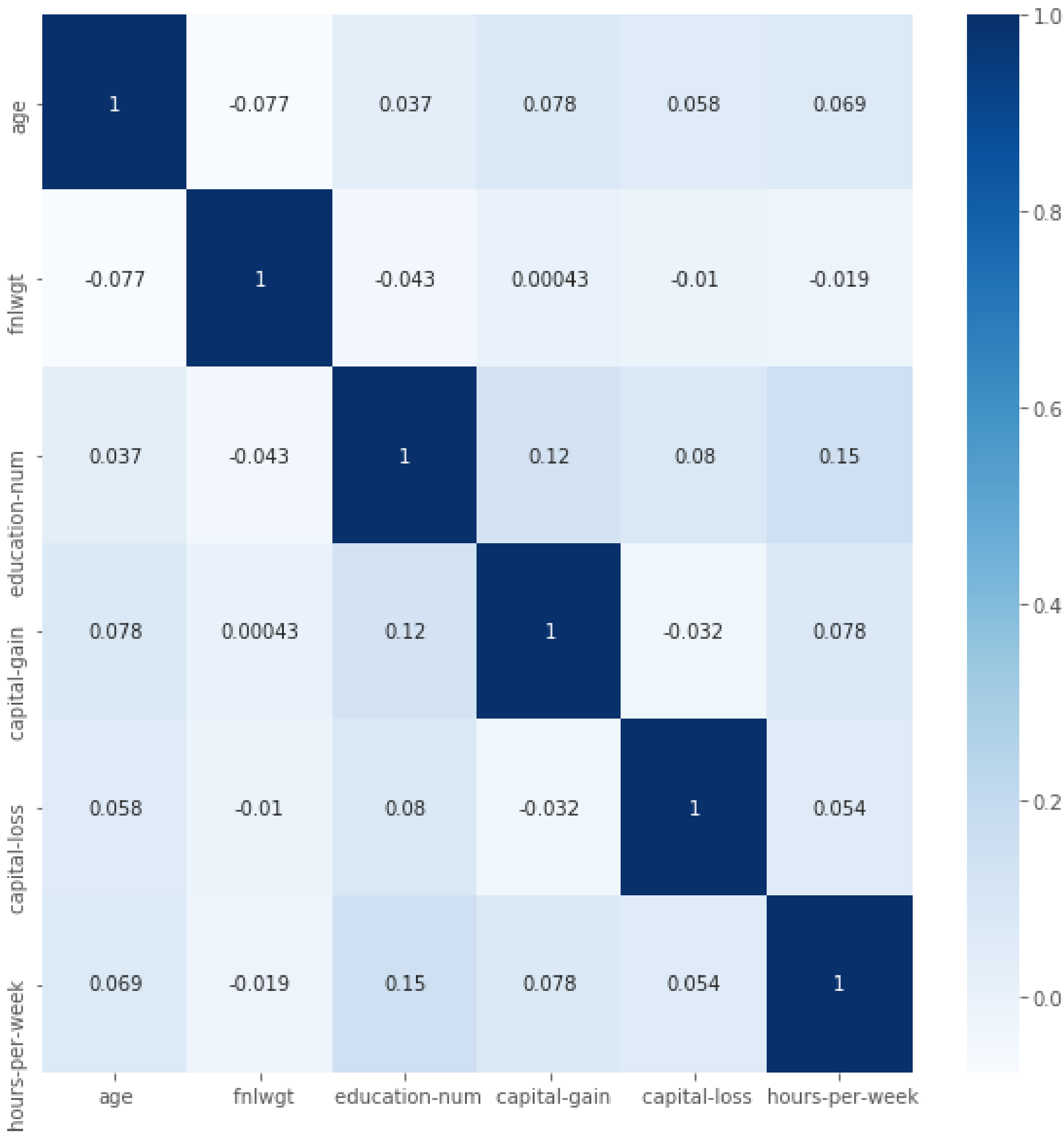
[7]:
```python
data.head()
```

[7]:
```
   age         workclass  fnlwgt  education  education-num  \
0   39         State-gov   77516  Bachelors             13
1   50  Self-emp-not-inc   83311  Bachelors             13
2   38           Private  215646    HS-grad              9
3   53           Private  234721       11th              7
4   28           Private  338409  Bachelors             13

       marital-status         occupation   relationship   race     sex  \
0       Never-married       Adm-clerical  Not-in-family  White    Male
1  Married-civ-spouse    Exec-managerial        Husband  White    Male
2            Divorced  Handlers-cleaners  Not-in-family  White    Male
3  Married-civ-spouse  Handlers-cleaners        Husband  Black    Male
4  Married-civ-spouse     Prof-specialty           Wife  Black  Female

   capital-gain  capital-loss  hours-per-week native-country income
0          2174             0              40  United-States  <=50K
1             0             0              13  United-States  <=50K
2             0             0              40  United-States  <=50K
3             0             0              40  United-States  <=50K
4             0             0              40           Cuba  <=50K
```

If we understand the data, income needs to be changed from object to integer. After which further tools can be used to understand the behavior of this data. Later can be used to classify the data under cateogorial data of 0's and 1's. The target column can be income and rest can be the features for the moment. Let's analyze the correlation among the features and check which is important enough to effect data.

[8]:
```python
fig,ax=plt.subplots(figsize=(10,10))
sns.heatmap(data.corr(), cmap='Blues', annot = True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

[8]:
```
(6.0, 0.0)
```



The values obtained do not have a strong relation among themselves. education num and hours per week.

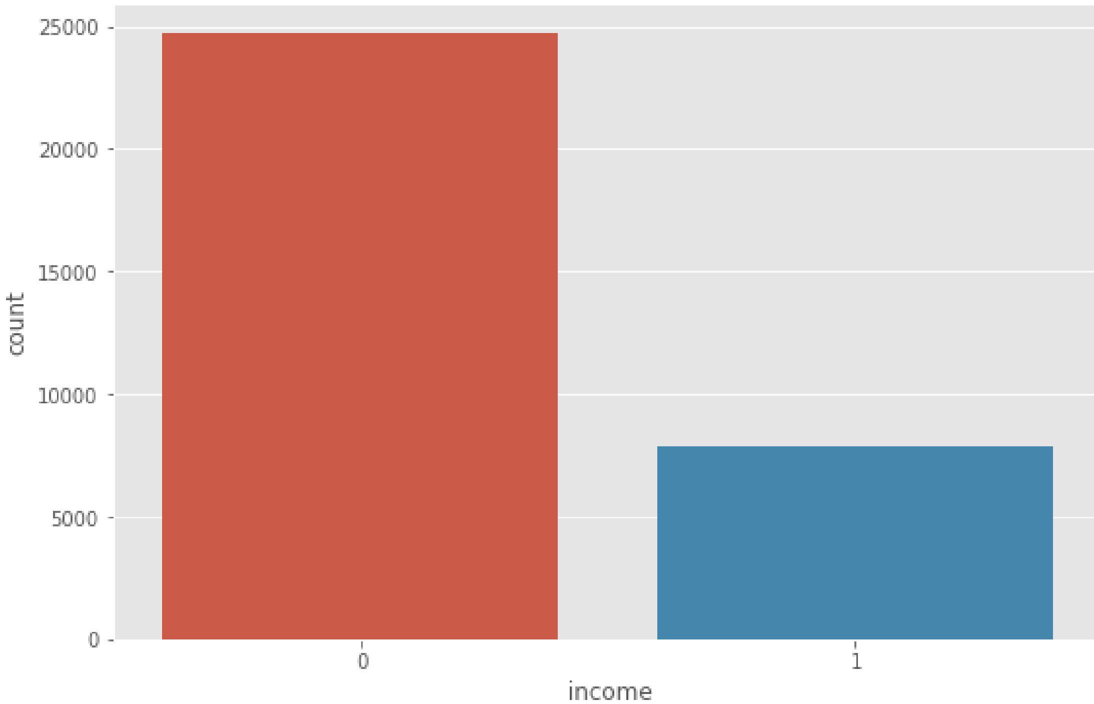
[9]:
```
data[' income'] = data[' income'].str.replace('K','')
```

[10]:
```
data[' income']= data[' income'].str.replace('<=50', '0')
data[' income']= data[' income'].str.replace('>50', '1' )
```

[11]:
```
data[' income'].value_counts()
```

[11]: 0   24720
 1   7841
Name: income, dtype: int64

[12]:
```
plt.figure(figsize = (20, 6))
plt.subplot(1,2,1)
chart=sns.countplot(data = data ,x=' income')
```

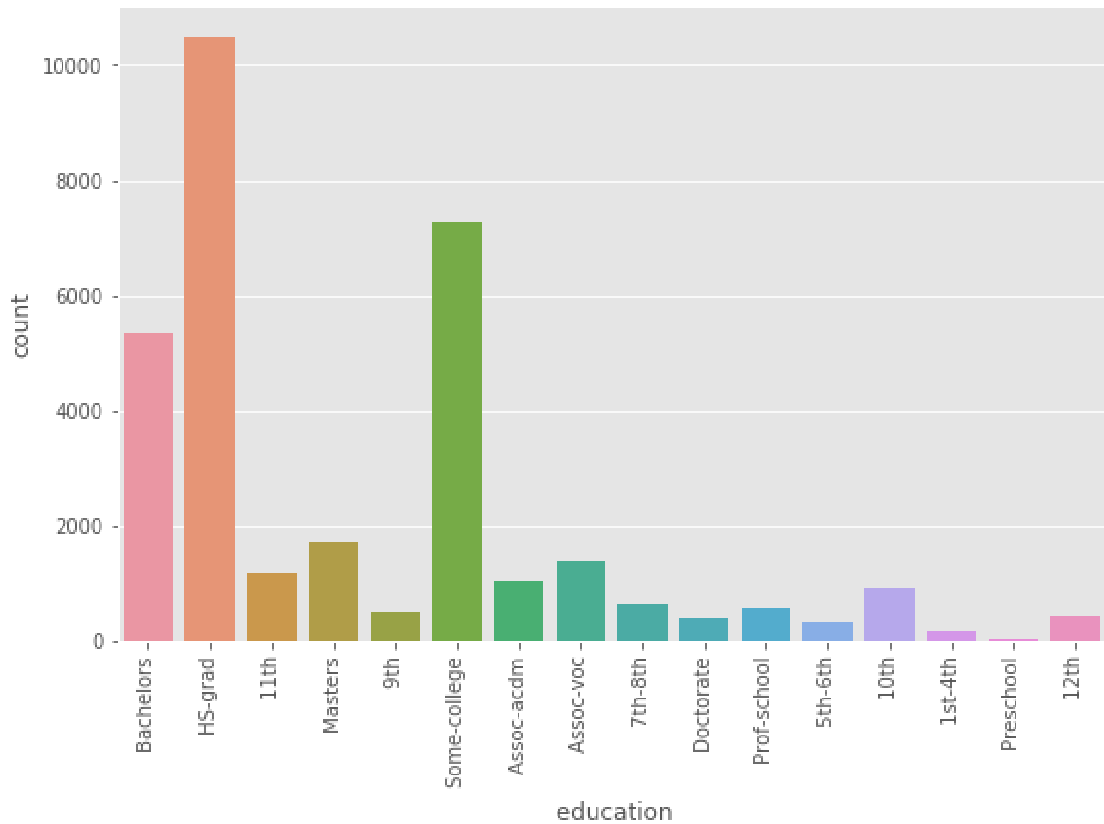


Let's use the countplots in order to understand the cateogorial classification of data.

[13]:
```
plt.figure(figsize = (20, 6))
plt.subplot(1,2,1)
chart=sns.countplot(data = data ,x=' education')
chart.set_xticklabels(chart.get_xticklabels(),rotation=90)
```

[13]:
```
[Text(0, 0, ' Bachelors'),
 Text(0, 0, ' HS-grad'),
 Text(0, 0, ' 11th'),
 Text(0, 0, ' Masters'),
 Text(0, 0, ' 9th'),
 Text(0, 0, ' Some-college'),
 Text(0, 0, ' Assoc-acdm'),
 Text(0, 0, ' Assoc-voc'),
 Text(0, 0, ' 7th-8th'),
```

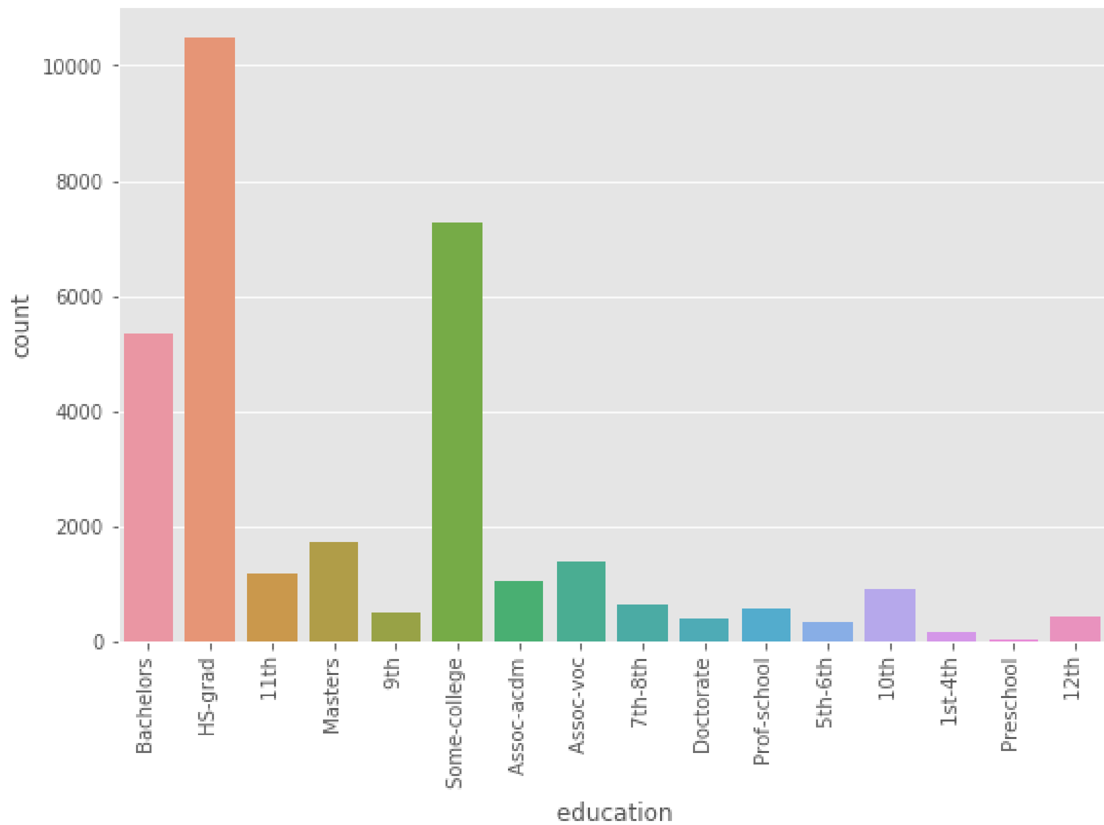
```
 Text(0, 0, ' Doctorate'),
 Text(0, 0, ' Prof-school'),
 Text(0, 0, ' 5th-6th'),
 Text(0, 0, ' 10th'),
 Text(0, 0, ' 1st-4th'),
 Text(0, 0, ' Preschool'),
 Text(0, 0, ' 12th')]
```



[14]:
```
plt.figure(figsize = (20, 6))
plt.subplot(1,2,1)
chart=sns.countplot(data = data ,x=' education')
chart.set_xticklabels(chart.get_xticklabels(),rotation=90)
```

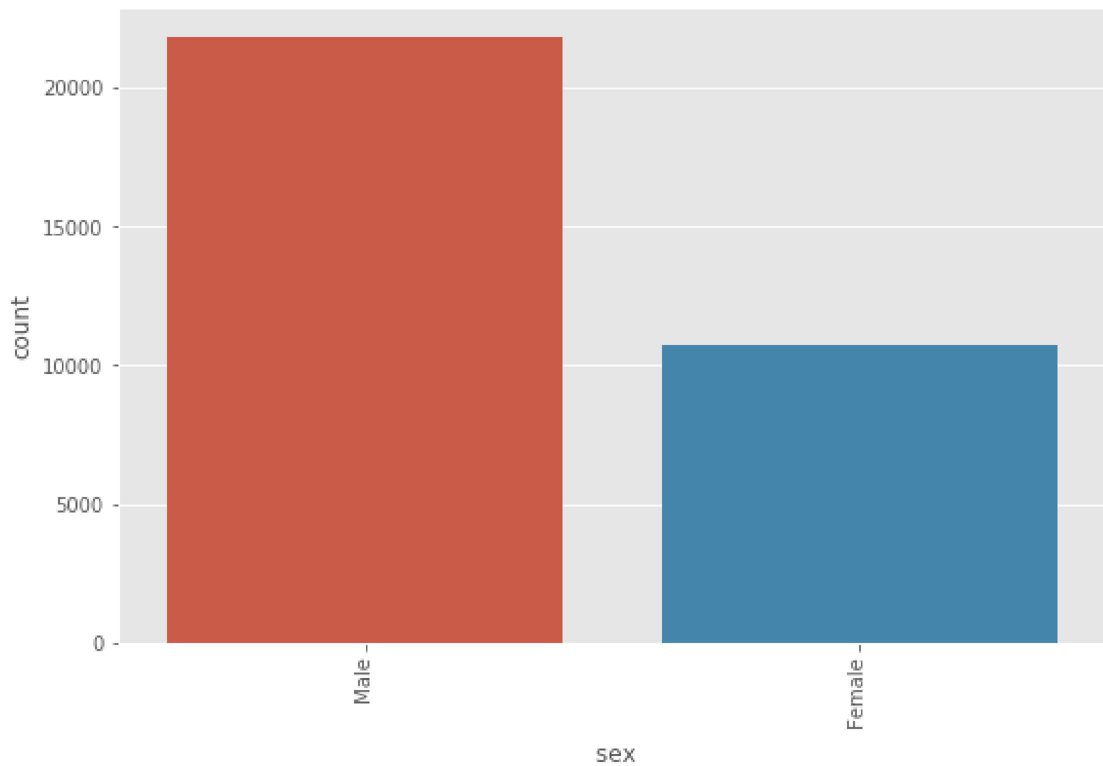
[14]:
```
[Text(0, 0, ' Bachelors'),
 Text(0, 0, ' HS-grad'),
 Text(0, 0, ' 11th'),
 Text(0, 0, ' Masters'),
 Text(0, 0, ' 9th'),
 Text(0, 0, ' Some-college'),
 Text(0, 0, ' Assoc-acdm'),
```

```
 Text(0, 0, ' Assoc-voc'),
 Text(0, 0, ' 7th-8th'),
 Text(0, 0, ' Doctorate'),
 Text(0, 0, ' Prof-school'),
 Text(0, 0, ' 5th-6th'),
 Text(0, 0, ' 10th'),
 Text(0, 0, ' 1st-4th'),
 Text(0, 0, ' Preschool'),
 Text(0, 0, ' 12th')]
```



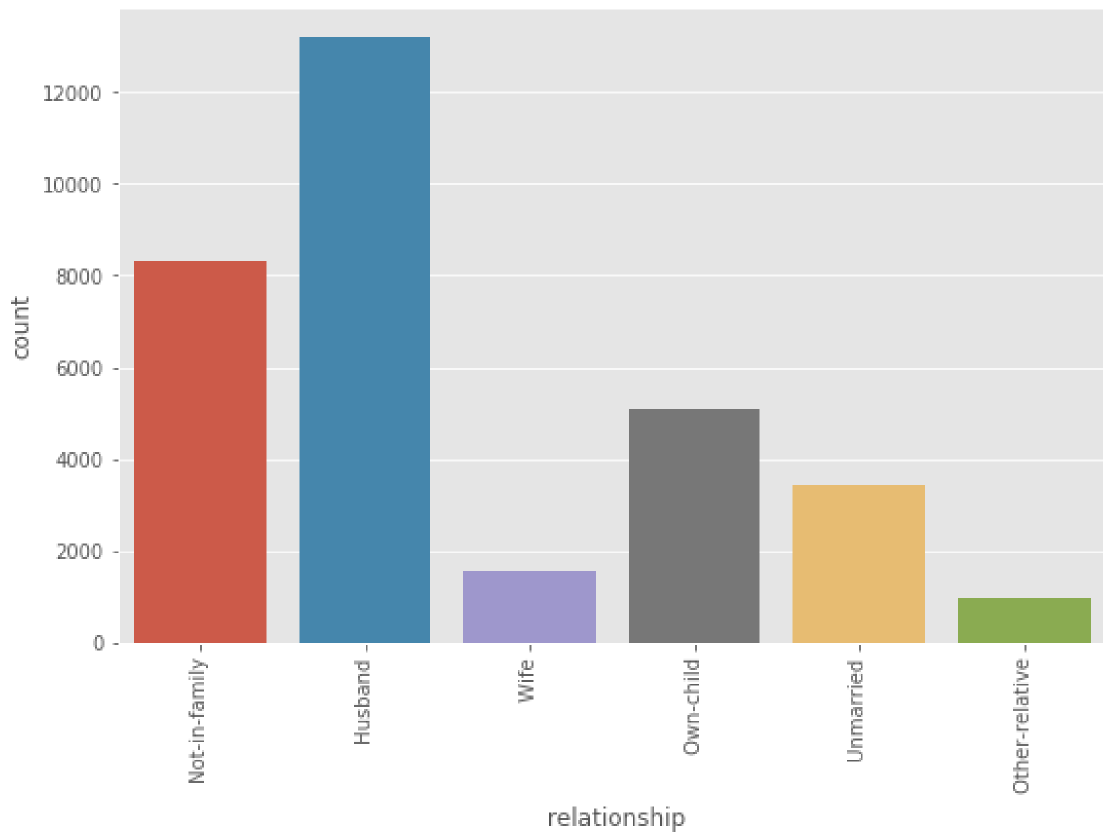
[15]:
```
plt.figure(figsize = (20, 6))
plt.subplot(1,2,1)
chart=sns.countplot(data = data ,x=' sex')
chart.set_xticklabels(chart.get_xticklabels(),rotation=90)
```

[15]:
```
[Text(0, 0, ' Male'), Text(0, 0, ' Female')]
```



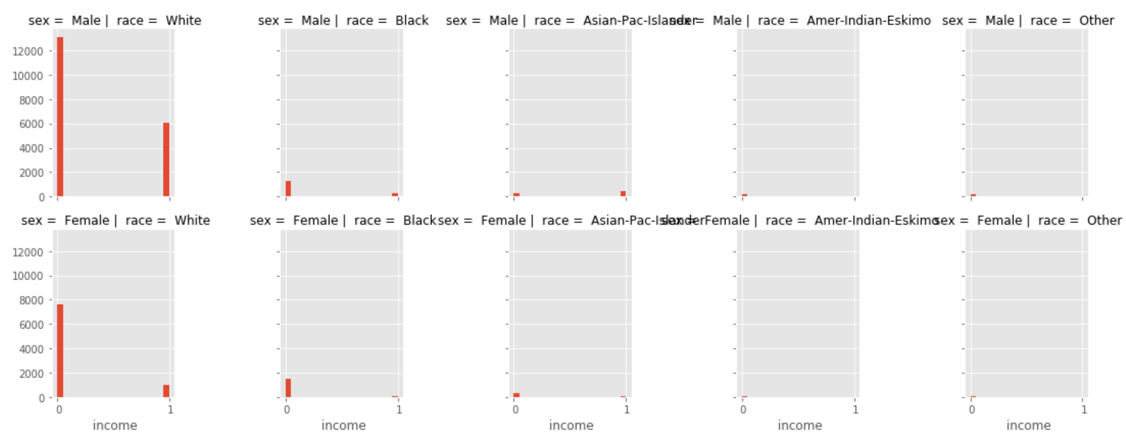
[16]:
```
plt.figure(figsize = (20, 6))
plt.subplot(1,2,1)
chart=sns.countplot(data = data ,x=' relationship')
chart.set_xticklabels(chart.get_xticklabels(),rotation=90)
```

[16]:
```
[Text(0, 0, ' Not-in-family'),
 Text(0, 0, ' Husband'),
 Text(0, 0, ' Wife'),
 Text(0, 0, ' Own-child'),
 Text(0, 0, ' Unmarried'),
 Text(0, 0, ' Other-relative')]
```



[17]:
```
g=sns.FacetGrid(data, col = ' race', row= ' sex')
# g = g.map(sns.distplot, ' income', color = 'r')
g.map(plt.hist, ' income', bins=20)
```

[17]: <seaborn.axisgrid.FacetGrid at 0x23bd2bcec48>



Facet grid plots are amazing for visulization as two 2-3 data can be simuntaneously visualised. For example column talks about race, so it will plot all cateogorial data in race under n cateogories. Second cateogory is in row, which explains about the second feature. Here as we compare both white male and female has higher income compared to other race.

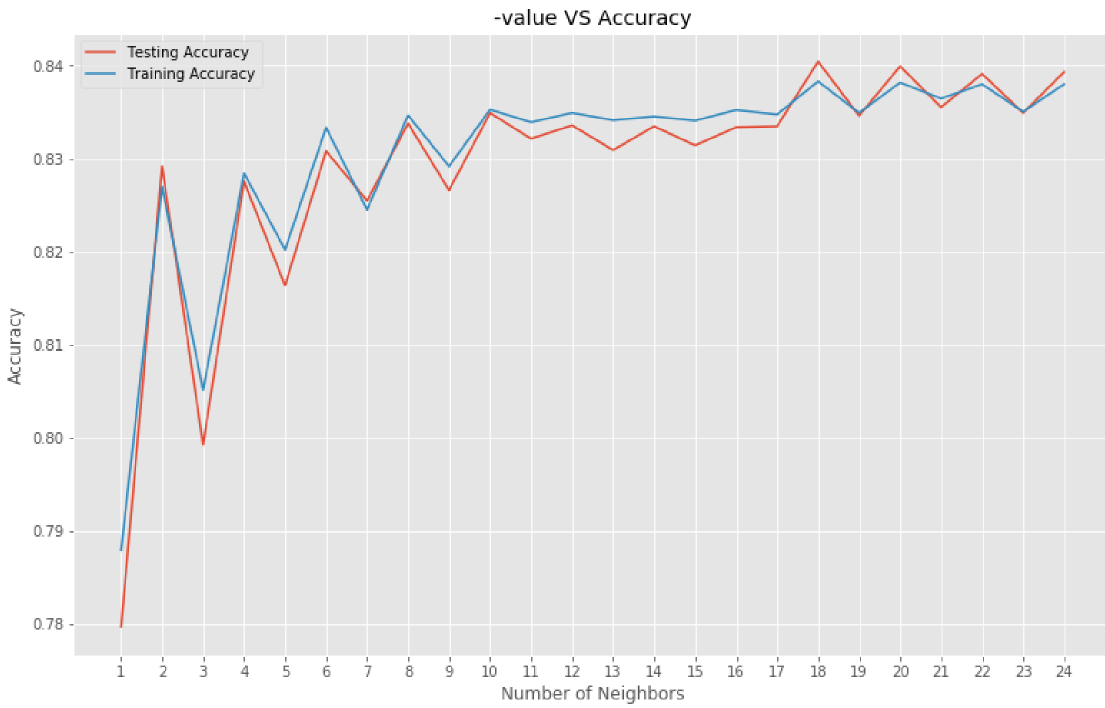
[18]:
```
# KNN
from sklearn.neighbors import KNeighborsClassifier

# x,y = data.loc[:,data.columns != 'class'], data.loc[:,'class']
x = data[[ 'age', ' education-num',' capital-loss', ' capital-gain']]
y = data[' income']
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.
↪3,random_state = 1)
knn = KNeighborsClassifier(n_neighbors = 4)
x,y = data.loc[:,data.columns != ' income'], data.loc[:,' income']
knn.fit(x_train,y_train)
prediction = knn.predict(x_test)
print('Prediction: {}'.format(prediction))
print('With KNN (K=3) accuracy is: ',knn.score(x_test,y_test)) # accuracy
```

```
Prediction: [' 0' ' 0' ' 1' … ' 0' ' 0' ' 0']
With KNN (K=3) accuracy is:  0.8275156106049749
```

Accuracy obtained with model is 79 % . For the features column we have selected (age, education-num, capital-loss, capital-gain) and rest income is for target!! We have divided data into 30 % ratio of traning and testing !!! Nieghbours are 4 as a not too high and not too low are expected. K should be wisely chosen ? Why K are the nearest nieghbours. If value of K is very large , both the test and train data will be underfitted , implies high bias and high variance!! And if the data is overfitted it implies low bias and high variance !! (k value small) means the traning data is a good fit but testing data is poorly fit.

[19]:
```
neig = np.arange(1, 25)
train_accuracy = []
test_accuracy = []
# Loop over different values of k
for i, k in enumerate(neig):
    # k from 1 to 25(exclude)
    knn = KNeighborsClassifier(n_neighbors=k)
    # Fit with knn
    knn.fit(x_train,y_train)
    #train accuracy
    train_accuracy.append(knn.score(x_train, y_train))
    # test accuracy
    test_accuracy.append(knn.score(x_test, y_test))

# Plot
plt.figure(figsize=[13,8])
```

```
plt.plot(neig, test_accuracy, label = 'Testing Accuracy')
plt.plot(neig, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.title('-value VS Accuracy')
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.xticks(neig)
plt.savefig('graph.png')
plt.show()
print("Best accuracy is {} with K = {}".format(np.
 ↪max(test_accuracy),1+test_accuracy.index(np.max(test_accuracy))))
```




```
Best accuracy is 0.8404135530760569 with K = 18
```

Again if we understand the model of KNN, the best accuracy is obtained at 84% with K= 18

```
[ ]:
```