incomeprediction

March 24, 2023

1 Importing all necessary libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

2 Data Ingestion

[2]:
```
df=pd.read_csv(r'C:\Users\PS4Z\Downloads\archive\income_evaluation.csv')
```

[3]:
```
#seeing how the looks like
df.head()
```

[3]:
```
   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
```

3 Understanding data

[4]:
```
#seeing the shape of data
print('Data Shape: ',df.shape)
```

```
Data Shape:  (32561, 15)
```

[5]:
```
#understanding about null values in data
df.isnull().sum()
```

[5]:
```
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
```

[6]:
```
#Getting information about data; null counts and data types of data columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              32561 non-null  int64
 1    workclass       32561 non-null  object
 2    fnlwgt          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   capital-gain    32561 non-null  int64
 11   capital-loss    32561 non-null  int64
 12   hours-per-week  32561 non-null  int64
```

```
 13   native-country  32561 non-null  object
 14   income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

Observations:There are total 32537 rows and 15 columns in the dataset Categorical features = 9 and Numerical features = 6

[7]:
```
#list od column names
df.columns
```

[7]:
```
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')
```

[8]:
```
#getting rid of all spaces in the column names
df.columns= df.columns.str.strip()
```

[9]:
```
df.columns
```

[9]:
```
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')
```

[10]:
```
#getting data types of each column header
df.dtypes
```

[10]:
```
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
```

[11]:
```
#getting a closer look on our targe variable
df['income'].value_counts()
```

[11]:
```
 <=50K    24720
 >50K      7841
Name: income, dtype: int64
```

Observation:Most employees fall in <=50K income category

[12]:
```
#classifying our target variable in binary notations for ease of understanding
df['income']=df['income'].map({' <=50K':0, ' >50K':1})
```

[13]:
```
#seeing the data type of target variable change from object to int
df.dtypes
```

[13]:
```
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             int64
dtype: object
```

[14]:
```
#duplicate entries in data
df.duplicated().sum()
```

[14]: 24

[15]:
```
#dropping all duplicate entries
df.drop_duplicates(inplace=True)
```

[16]:
```
df.head()
```

[16]:
```
   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       0
1             0             0              13   United-States       0
2             0             0              40   United-States       0
3             0             0              40   United-States       0
4             0             0              40            Cuba       0
```

[17]:
```
#getting value counts for workclass column
df['workclass'].value_counts()
```

[17]:
```
 Private             22673
 Self-emp-not-inc     2540
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
```

[18]:
```
#getting value counts for native-country column
df['native-country'].value_counts()
```

[18]:
```
 United-States                 29153
 Mexico                          639
 ?                               582
 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
Japan                            62
Guatemala                        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
```

[19]:
```
#getting value counts for occupation column
df['occupation'].value_counts()
```

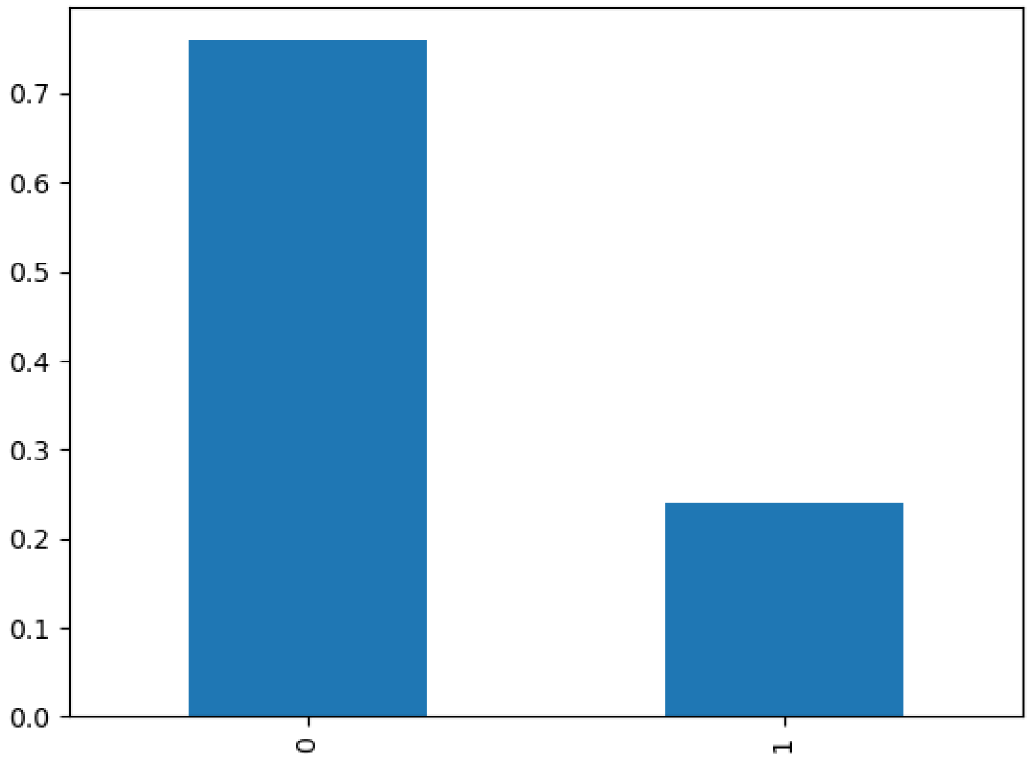
[19]:
```
Prof-specialty       4136
Craft-repair         4094
Exec-managerial      4065
Adm-clerical         3768
Sales                3650
Other-service        3291
Machine-op-inspct    2000
?                    1843
Transport-moving     1597
Handlers-cleaners    1369
Farming-fishing       992
Tech-support          927
Protective-serv       649
Priv-house-serv       147
```

```
 Armed-Forces           9
Name: occupation, dtype: int64
```

Observation:workclass, occupation and native_country has missing values

4 Understanding Imbalanced Data

[20]:
```
#Plotting Bar Plot for target variable
df['income'].value_counts(normalize=True).plot(kind='bar');
```



Observation:we can see above data is imbalanced, more class belongs to less than or equal to 50k

[21]:
```
#getting a sample from data
df.sample(7)
```

[21]:
```
       age        workclass  fnlwgt     education  education-num  \
15765   29          Private   94892  Some-college             10
29330   37          Private  212437  Some-college             10
19533   26          Private   86483  Some-college             10
20227   40                ?   65545       Masters             14
14230   62        Local-gov   33365       HS-grad              9
13385   54     Self-emp-inc  383365     Bachelors             13
```

```
20389   50   Self-emp-not-inc   30731      Assoc-voc            11

            marital-status         occupation    relationship    race  \
15765   Married-civ-spouse     Prof-specialty         Husband   White
29330              Widowed  Machine-op-inspct       Unmarried   Black
19533        Never-married    Exec-managerial   Not-in-family   White
20227             Divorced                  ?       Own-child   White
14230              Widowed      Other-service   Not-in-family   White
13385   Married-civ-spouse              Sales         Husband   White
20389        Never-married      Other-service   Not-in-family   White

           sex  capital-gain  capital-loss  hours-per-week  native-country  \
15765     Male             0             0              40   United-States
29330   Female             0             0              48   United-States
19533   Female             0             0              40   United-States
20227   Female             0             0              55   United-States
14230   Female             0             0              40          Canada
13385     Male             0             0              70   United-States
20389     Male             0             0              50   United-States

       income
15765       0
29330       0
19533       0
20227       0
14230       0
13385       1
20389       0
```

[22]:
```python
#Getting 5 point summary for all numercial features
df.describe()
```

[22]:
```
                age        fnlwgt  education-num  capital-gain  capital-loss  \
count  32537.000000  3.253700e+04   32537.000000  32537.000000  32537.000000
mean      38.585549  1.897808e+05      10.081815   1078.443741     87.368227
std       13.637984  1.055565e+05       2.571633   7387.957424    403.101833
min       17.000000  1.228500e+04       1.000000      0.000000      0.000000
25%       28.000000  1.178270e+05       9.000000      0.000000      0.000000
50%       37.000000  1.783560e+05      10.000000      0.000000      0.000000
75%       48.000000  2.369930e+05      12.000000      0.000000      0.000000
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000

       hours-per-week        income
count    32537.000000  32537.000000
mean        40.440329      0.240926
std         12.346889      0.427652
min          1.000000      0.000000
```

```
25%          40.000000      0.000000
50%          40.000000      0.000000
75%          45.000000      0.000000
max          99.000000      1.000000
```

5 Separating numerical features from categorical features

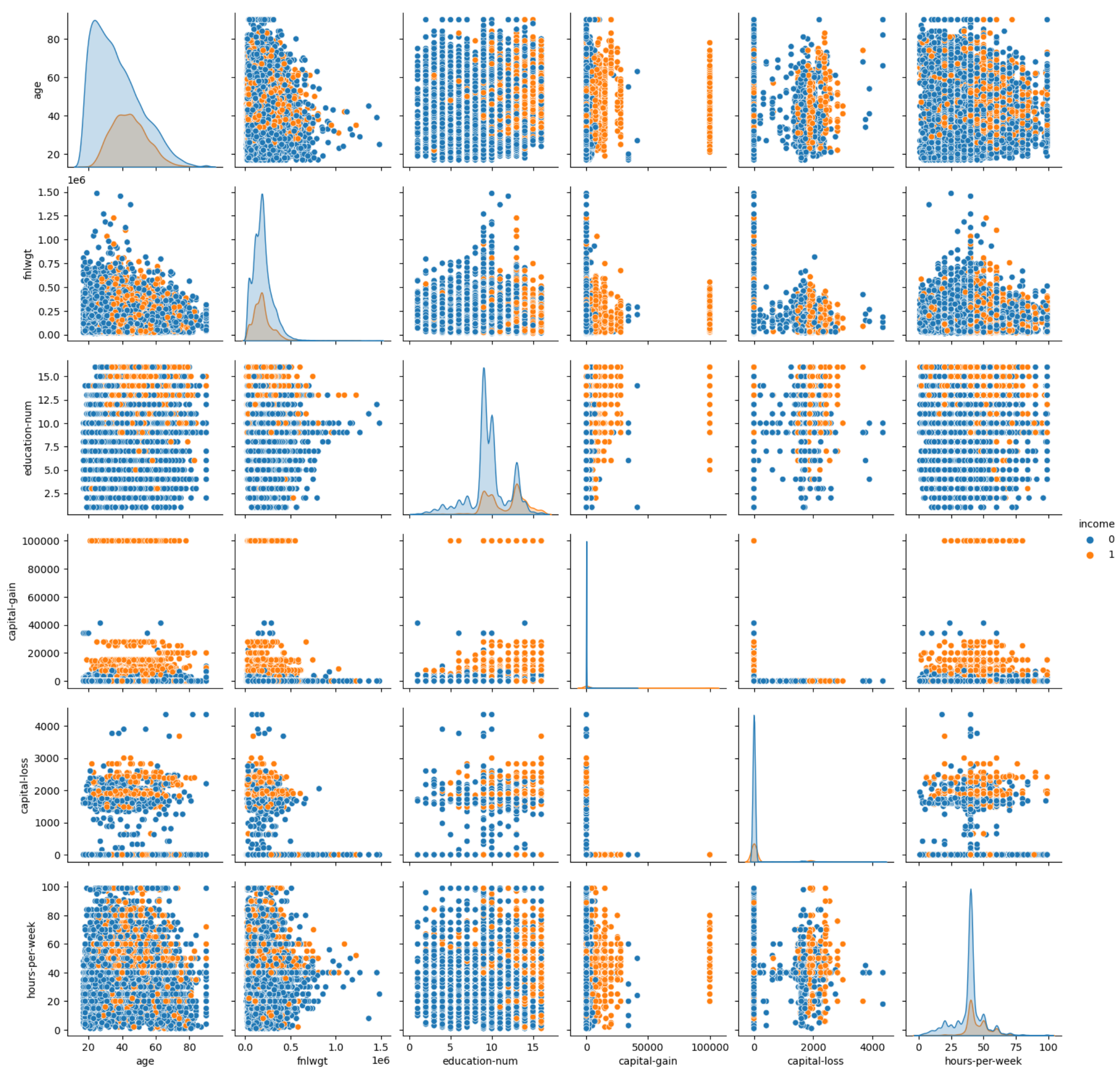
[23]:
```
#categorizing numericl and categorical features based on the data type
num_feat=[i for i in df.columns if df[i].dtypes!='O']
cat_feat=[j for j in df.columns if df[j].dtypes=='O']
```

[24]:
```
num_feat, cat_feat
```

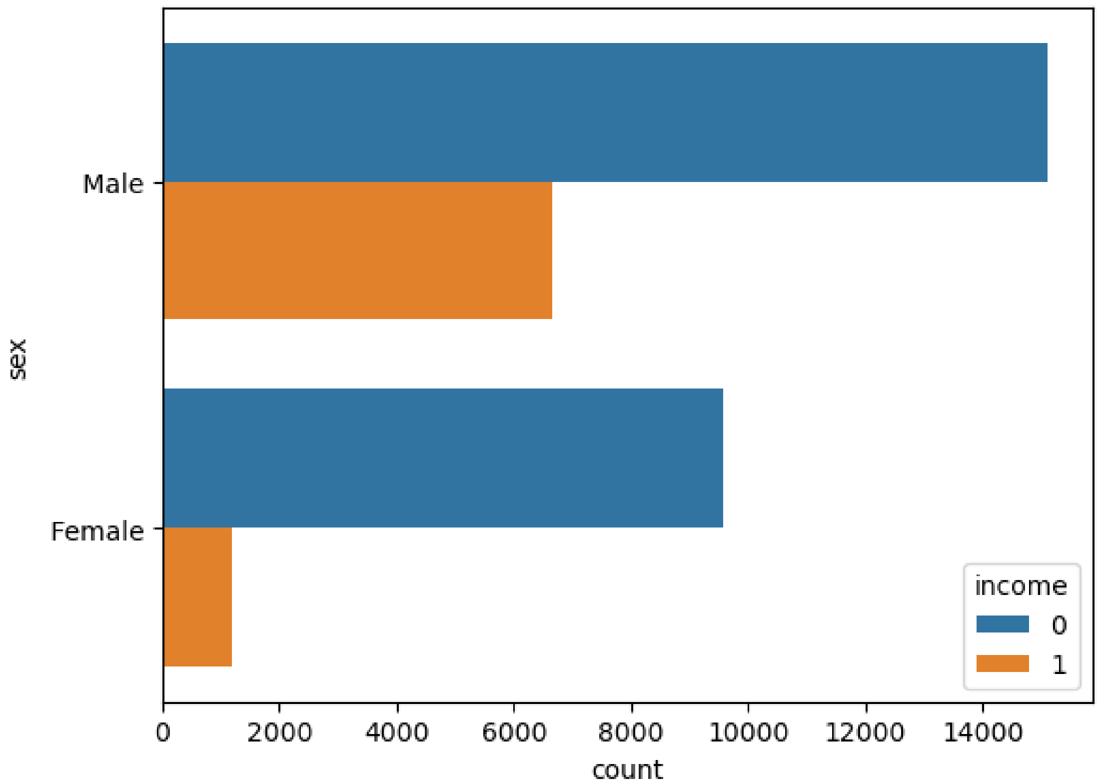
[24]:
```
(['age',
  'fnlwgt',
  'education-num',
  'capital-gain',
  'capital-loss',
  'hours-per-week',
  'income'],
 ['workclass',
  'education',
  'marital-status',
  'occupation',
  'relationship',
  'race',
  'sex',
  'native-country'])
```

6 Visualizing the data

[25]:
```
#pairplot shows graphical representation of all numerical features with one␣
 ↪another with target variable in legend
sns.pairplot(data=df,hue='income');
```

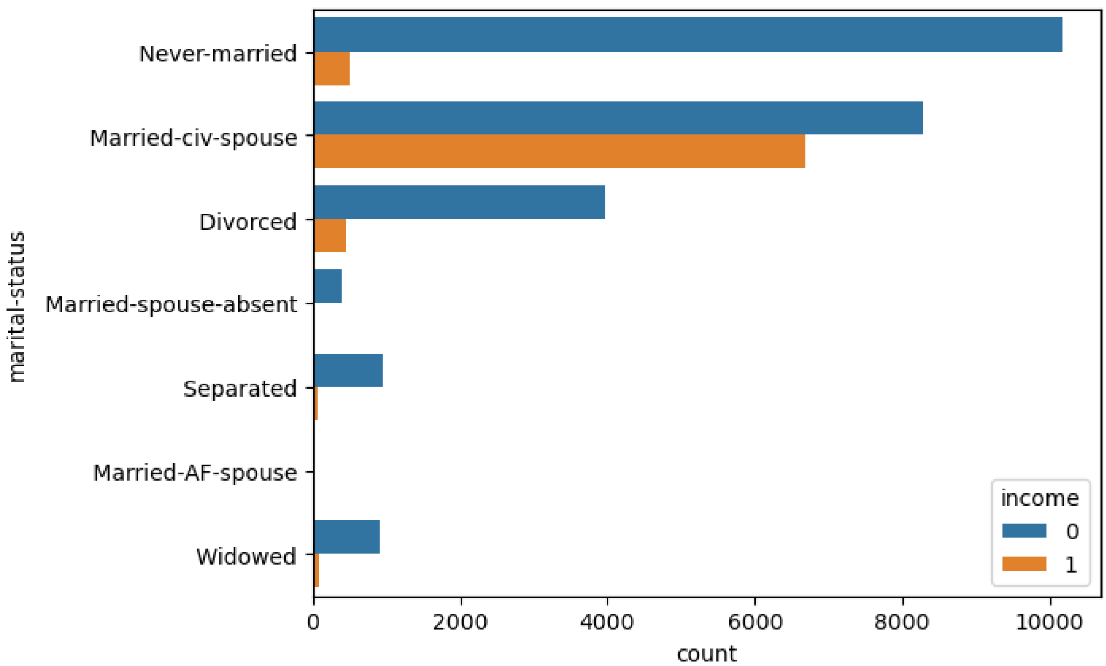


[26]:
```
#countplot of sex of employees with legend
sns.countplot(y=df['sex'],hue=df['income']);
```



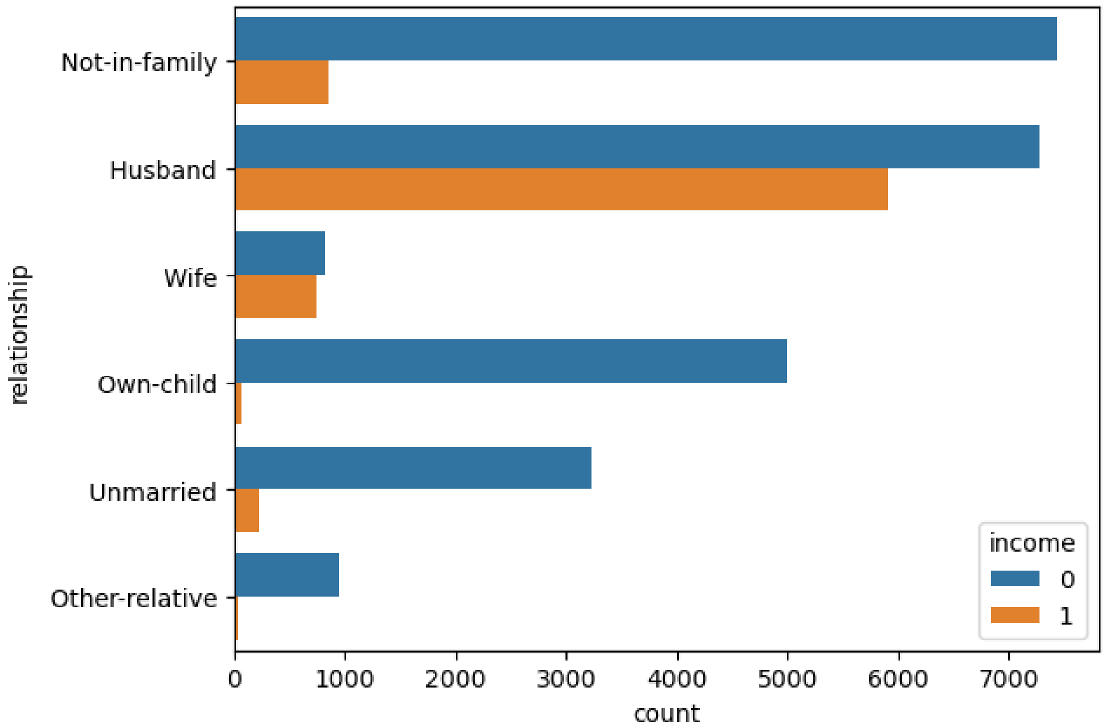
Observation:from above plot, we can say that male are earning more than female

[27]:
```
#countplot of marital Status of employees with legend
sns.countplot(y=df['marital-status'],hue=df['income']);
```



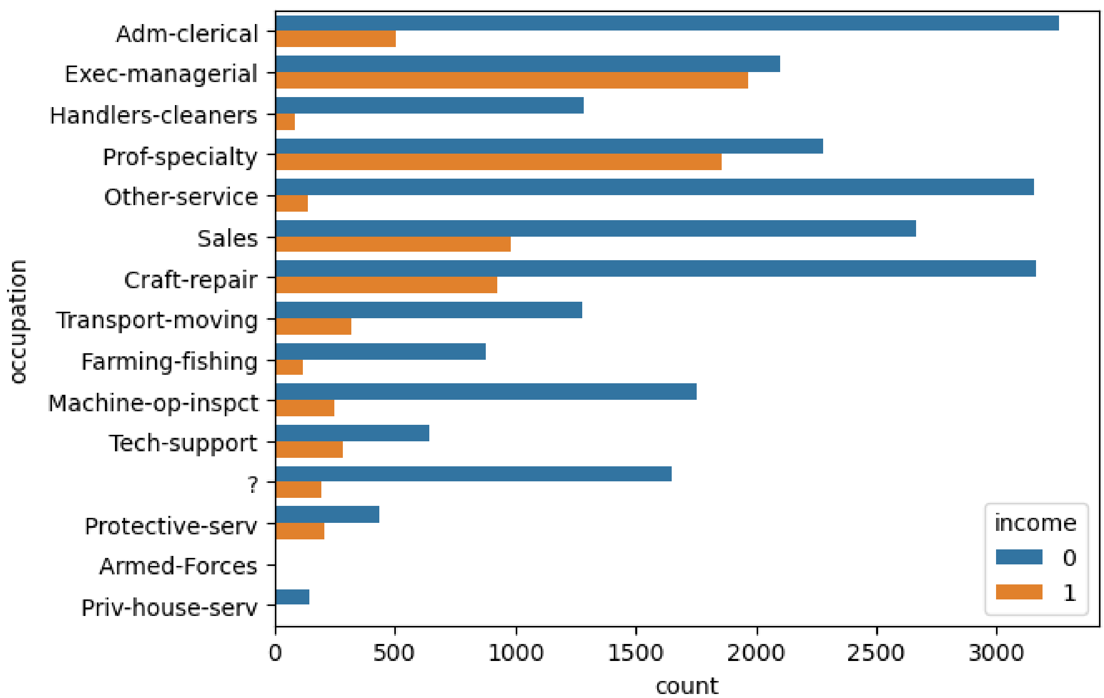
Observation:people belonging to 'never married' status, are earning more than that of people belonging to other marital status

[28]:
```
#countplot of relationship of employees with legend
sns.countplot(y=df['relationship'],hue=df['income']);
```



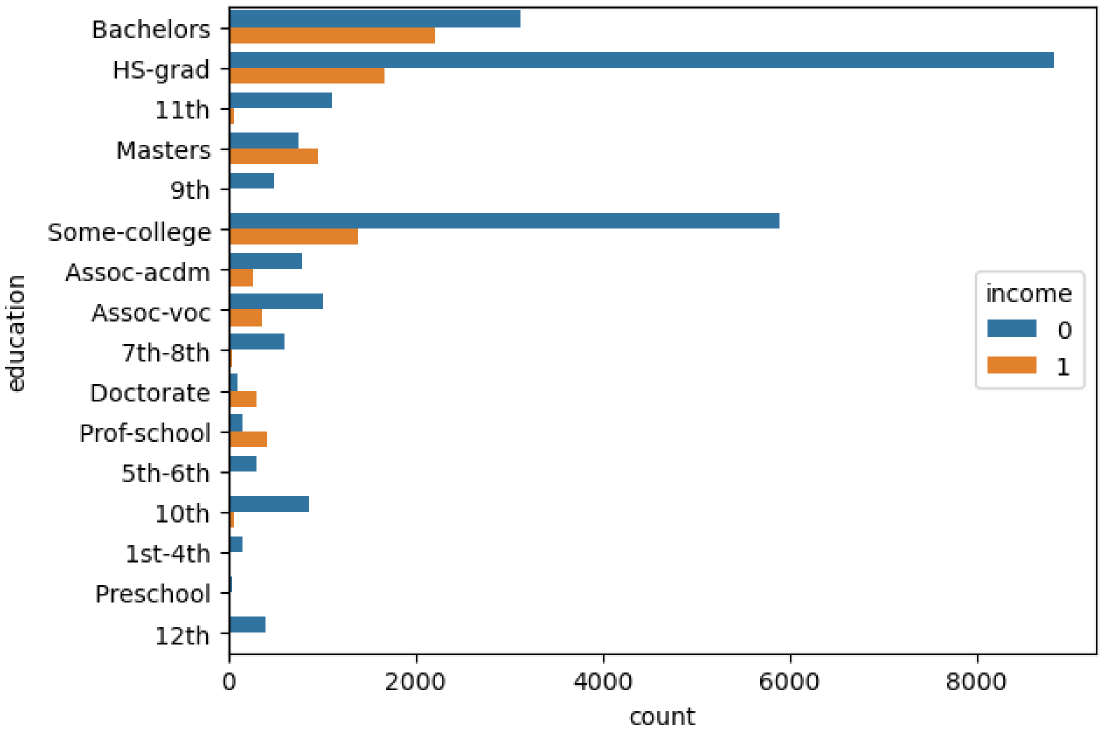
Observation:people belonging to 'Not-in-family' and 'Husband' status, are earning more than that of people belonging to other relationship status.

[29]:
```
#countplot of occupation of employees with legend
sns.countplot(y=df['occupation'],hue=df['income']);
```



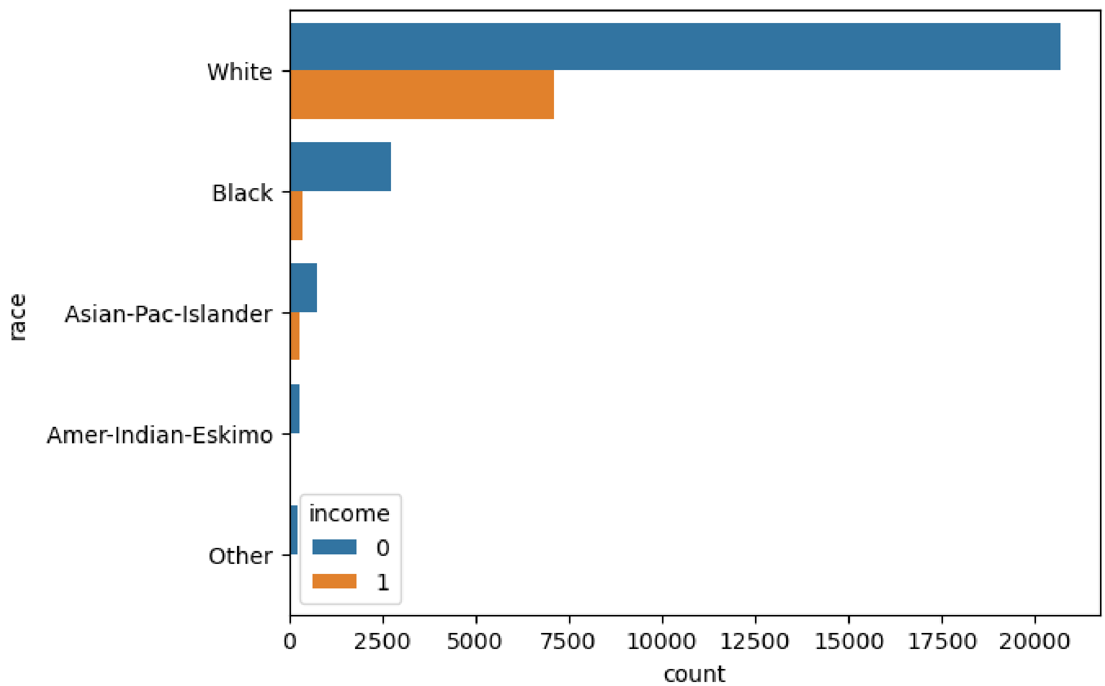
Observation:people belonging to 'Adm-clerical' occupation, are earning more than that of people belonging to other occupations.

[30]:
```
#countplot of education of employees with legend
sns.countplot(y=df['education'],hue=df['income']);
```



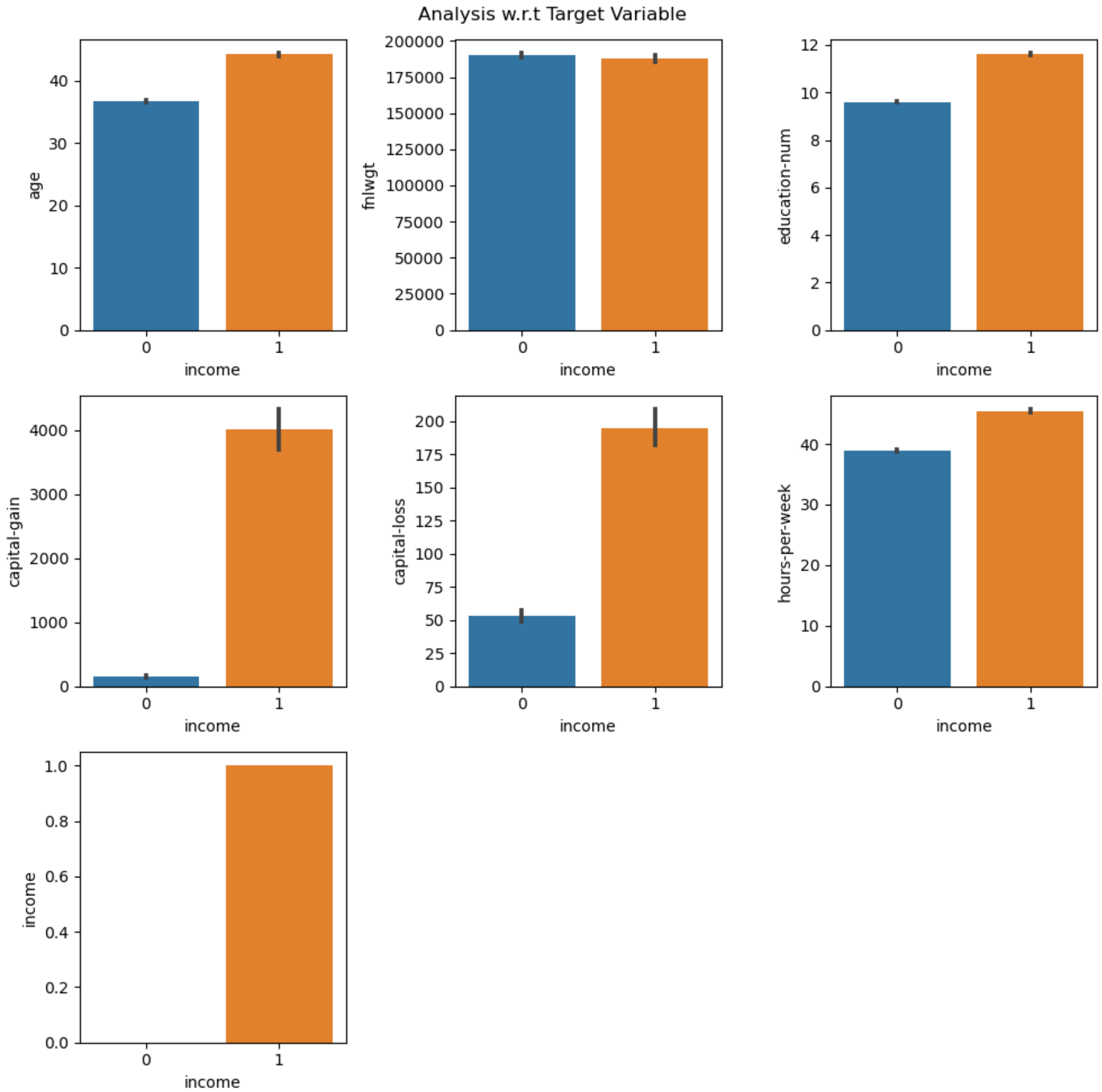
Observation:people belonging to 'HS-grad' status, are earning more than that of people belonging to other education qualification

[31]:
```
#countplot of race of employees with legend
sns.countplot(y=df['race'],hue=df['income']);
```



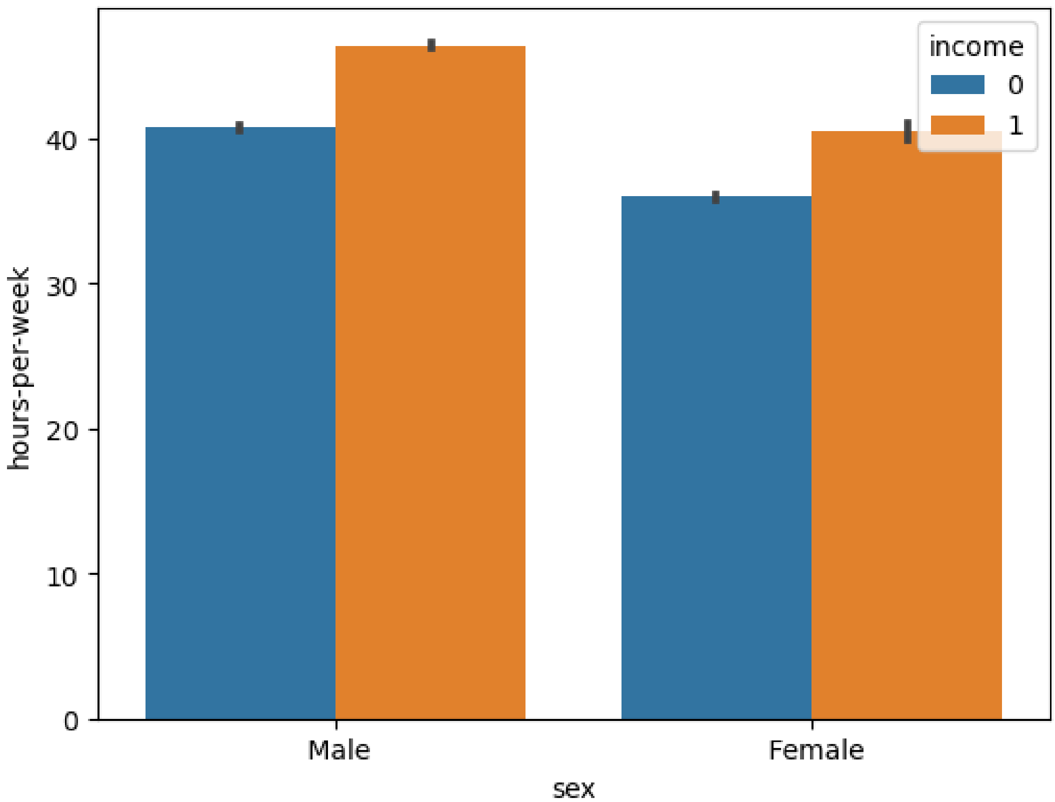
Observation:people belonging to 'white' race, are earning more than that of people belonging to other races

[32]:
```
#Bivariate analysis of numerical features w.r.t Target Variable
plt.figure(figsize=(10,10))
plt.suptitle('Analysis w.r.t Target Variable')
for a in range(0,len(num_feat)):
    plt.subplot(3,3,a+1)
    sns.barplot(x='income',y=num_feat[a],data=df)
    plt.tight_layout()
```



Observations: The bar plot above are bivariate plots. In terms of Age, older the person, more is the probability of income getting higher. Capital gain, and capital loss are more experienced by people having higher income.

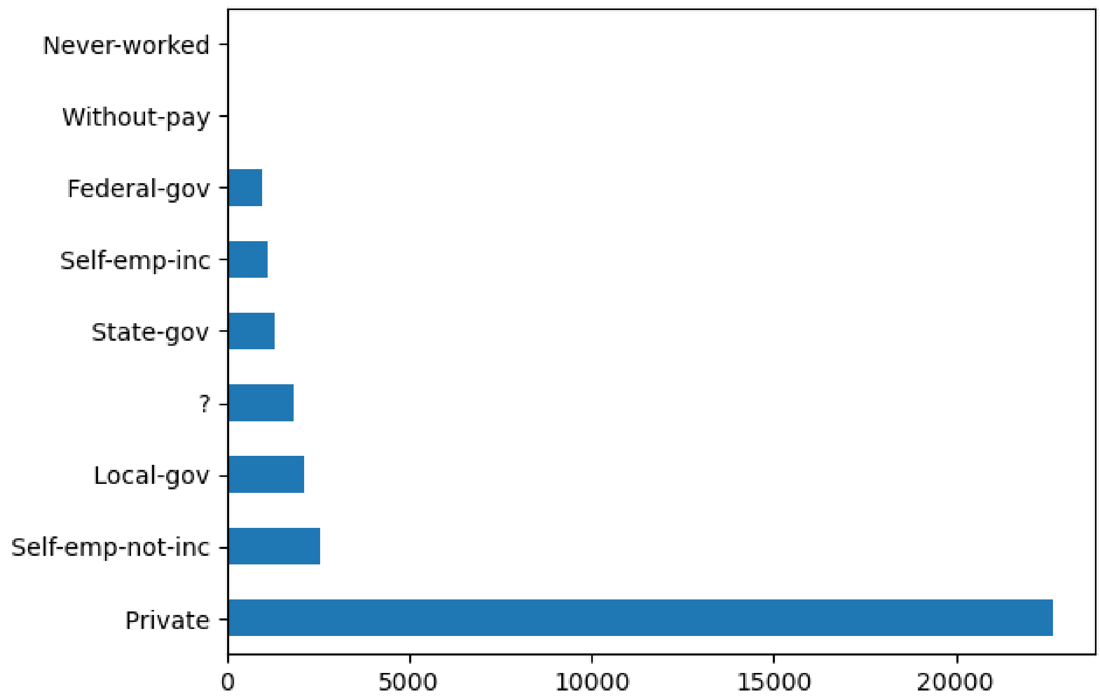
[33]:
```
#barplot of sex with legend of Target Variable
sns.barplot(x=df['sex'],y=df['hours-per-week'],hue=df['income'],data=df);
```



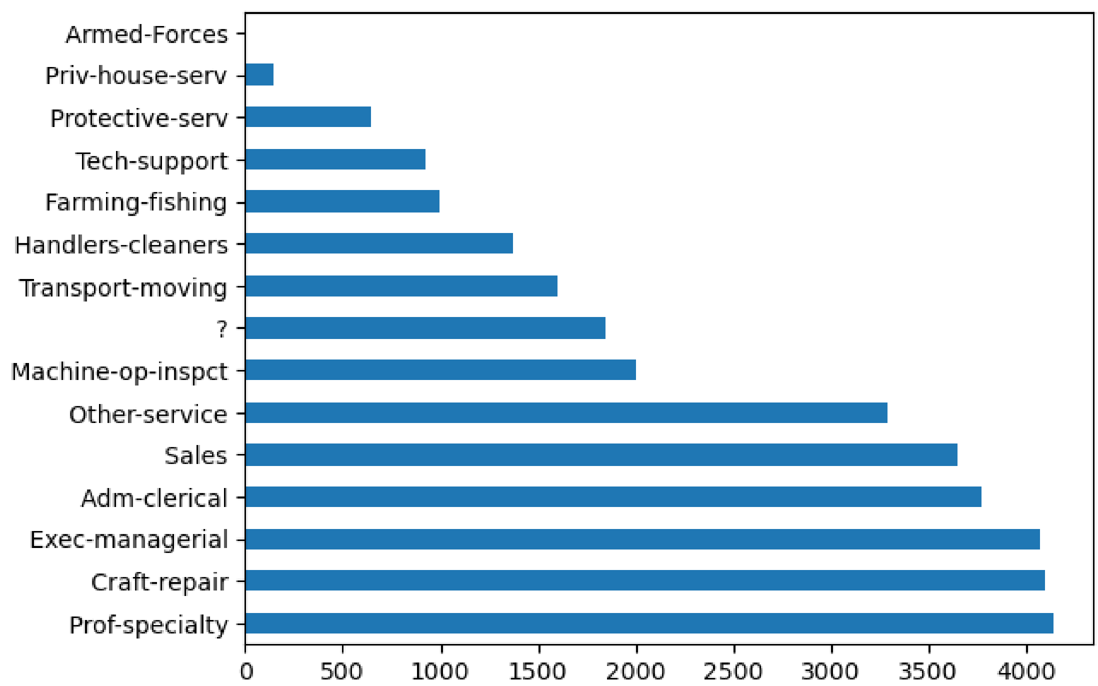
Observations:male works more hours than female

7 Checking for Special Symbol

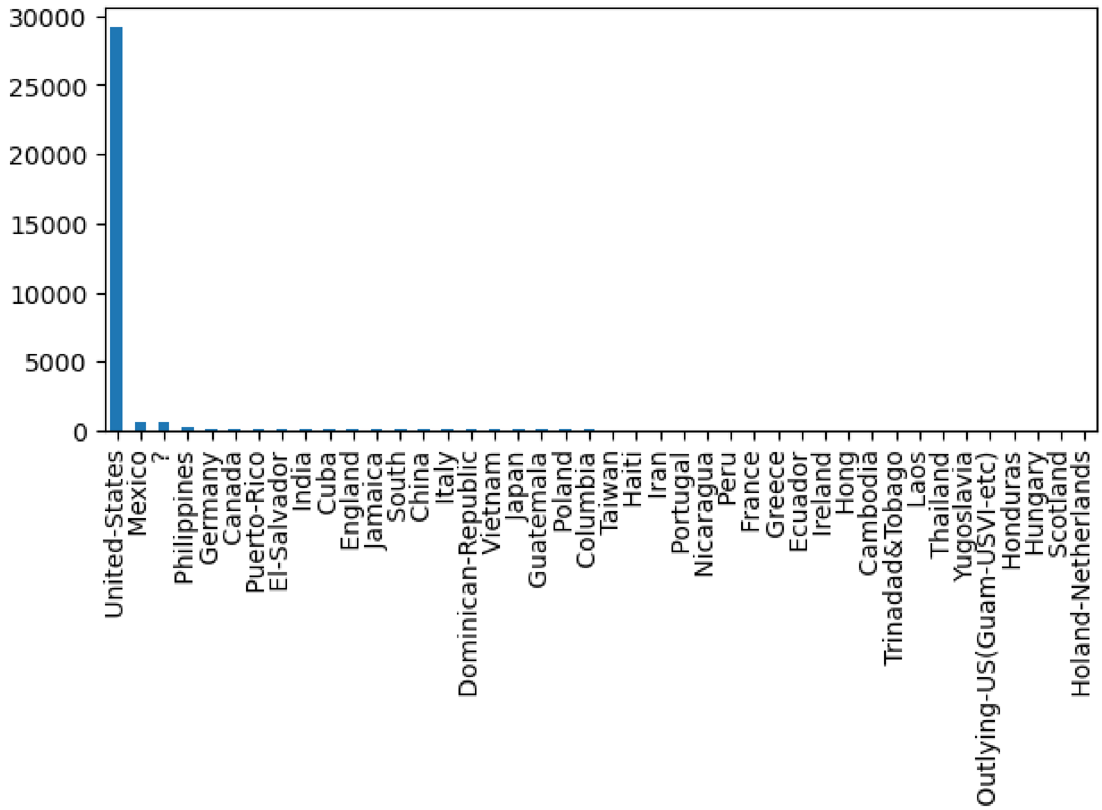
[34]:
```
df['workclass'].value_counts().plot(kind='barh');
```



[35]:
```
df['occupation'].value_counts().plot(kind='barh');
```



[36]:
```
df['native-country'].value_counts().plot(kind='bar')
plt.tight_layout();
```



Observations: ' ?' symbon in workclass, occupation and native-country are most possibly NaN values

8 Replacing the Special Symbol

[37]:
```
df.replace(' ?',np.NAN,inplace=True)
```

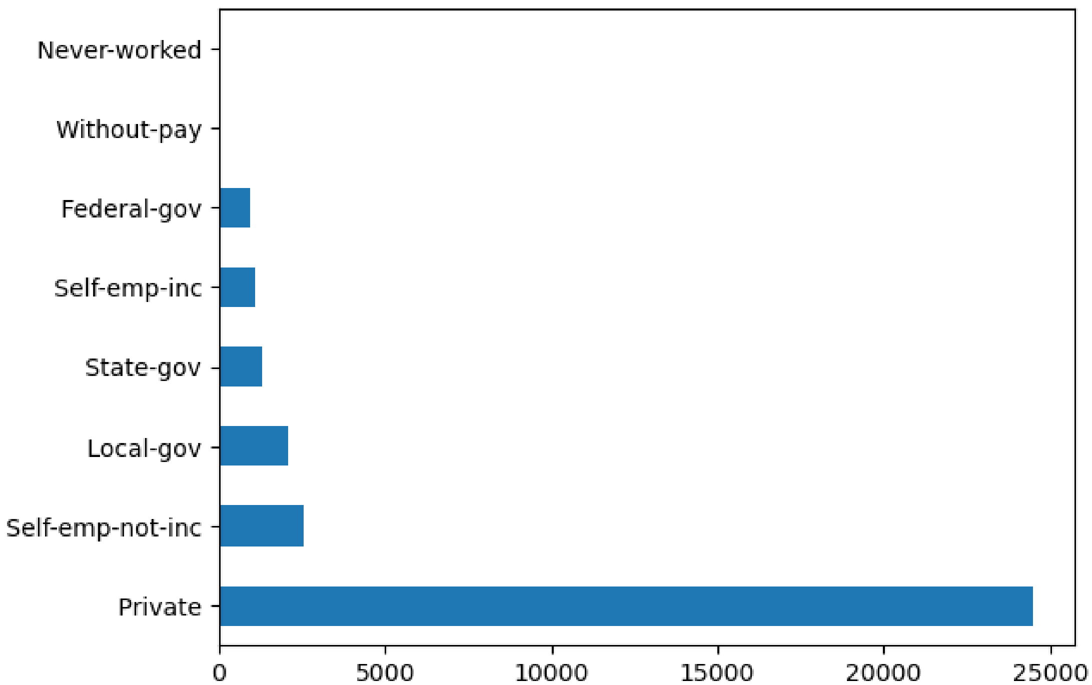
[38]:
```
df.isna().sum()
```

[38]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education-num        0
marital-status       0
occupation        1843
relationship         0
```

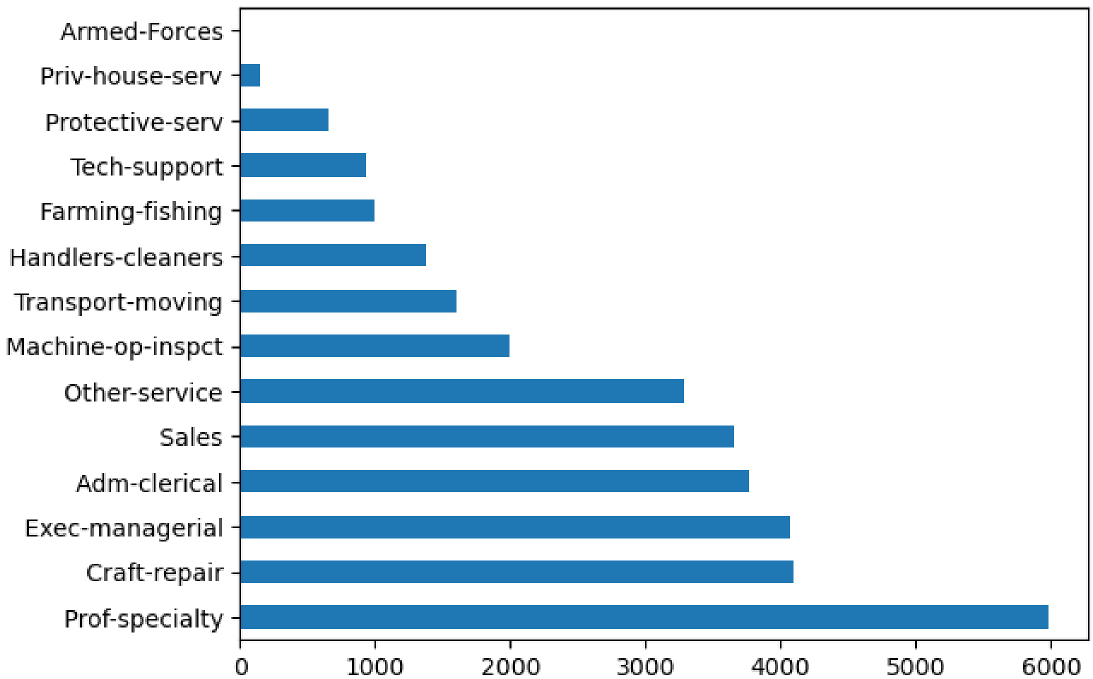
```
race                0
sex                 0
capital-gain        0
capital-loss        0
hours-per-week      0
native-country    582
income              0
dtype: int64
```

[39]:
```python
for col in ['workclass','occupation','native-country']:
    df[col].fillna(df[col].mode()[0],inplace=True)
```

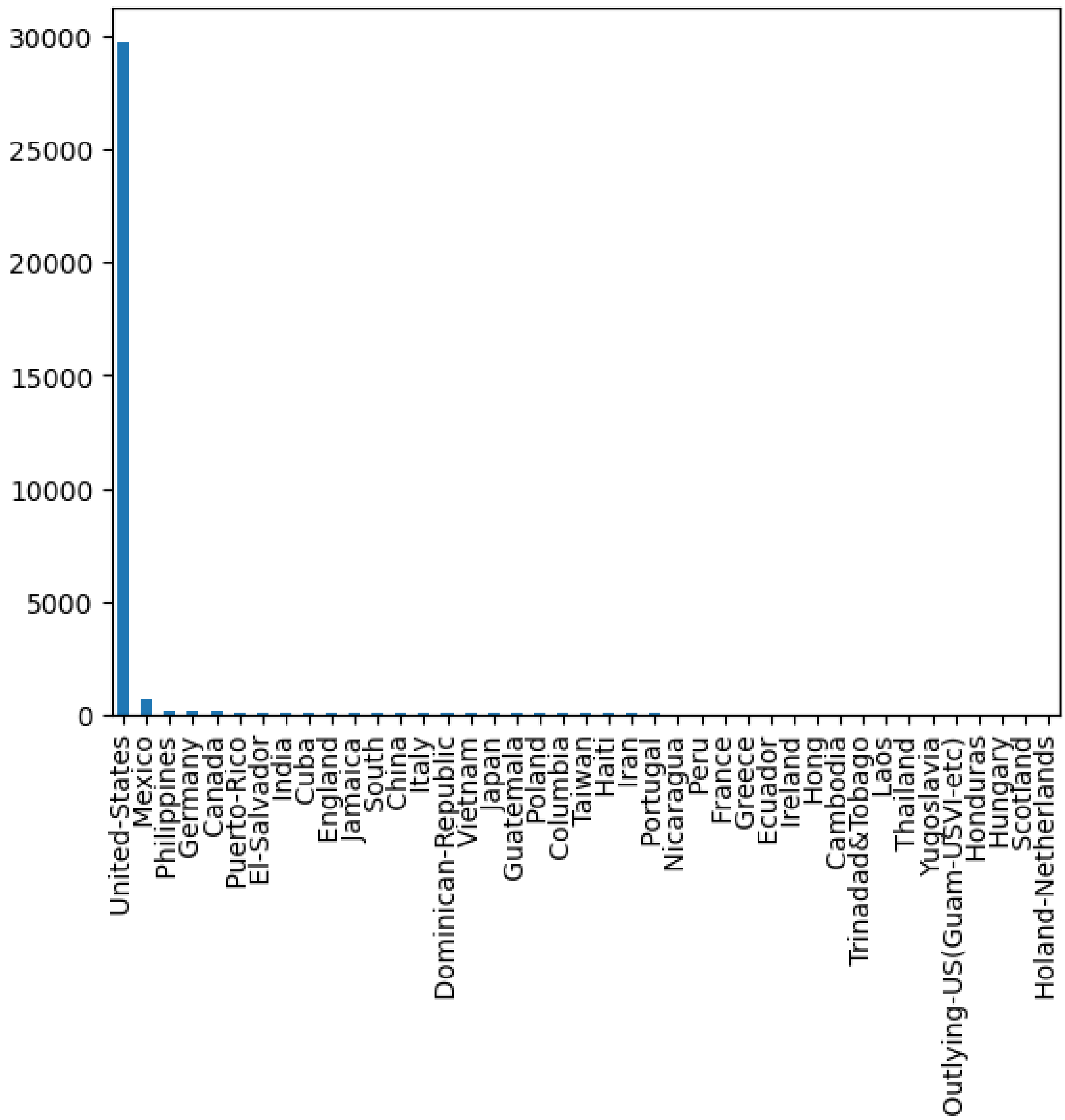
[40]:
```python
df['workclass'].value_counts().plot(kind='barh');
```



[41]:
```python
df['occupation'].value_counts().plot(kind='barh');
```



[42]:
```
df['native-country'].value_counts().plot(kind='bar');
```



Observations: NaN values are replaced and we can see in above three plot the value is increased as compared to the previous plots

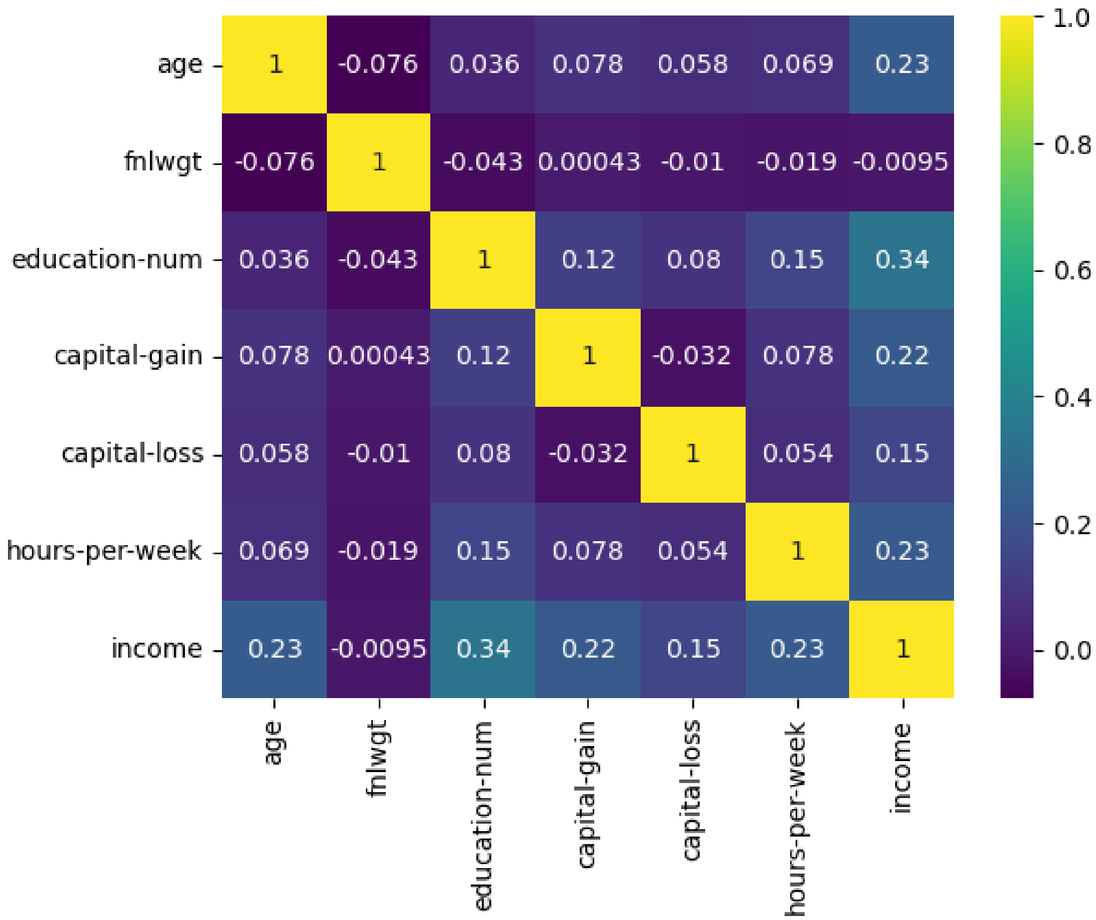
[43]:
```
df.corr()
```

[43]:

	age	fnlwgt	education-num	capital-gain	capital-loss	\
age	1.000000	-0.076447	0.036224	0.077676	0.057745	
fnlwgt	-0.076447	1.000000	-0.043388	0.000429	-0.010260	
education-num	0.036224	-0.043388	1.000000	0.122664	0.079892	
capital-gain	0.077676	0.000429	0.122664	1.000000	-0.031639	
capital-loss	0.057745	-0.010260	0.079892	-0.031639	1.000000	
hours-per-week	0.068515	-0.018898	0.148422	0.078408	0.054229	

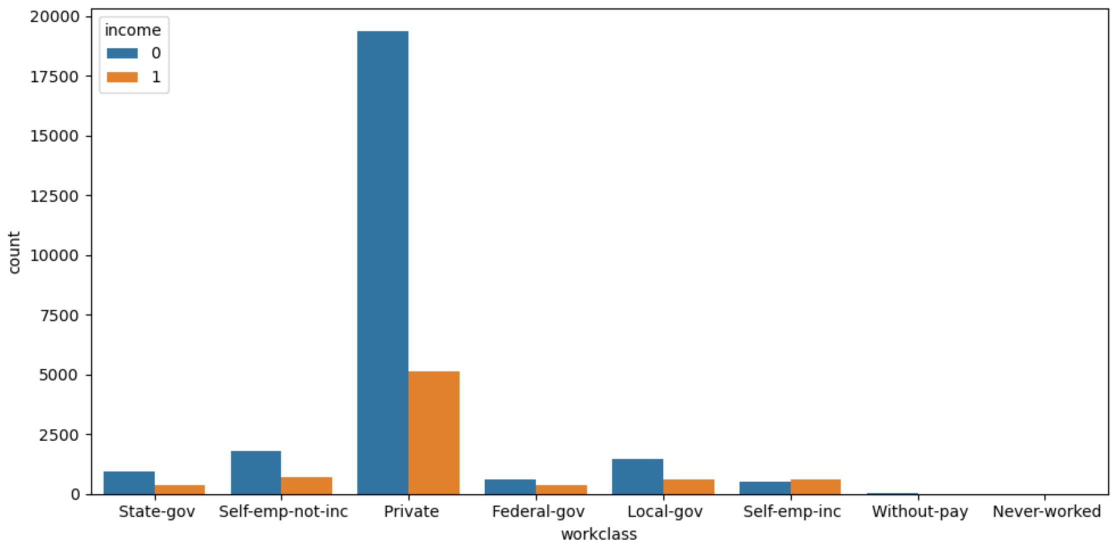
```
income           0.234037 -0.009502        0.335272       0.223336       0.150501

                hours-per-week    income
age                   0.068515  0.234037
fnlwgt               -0.018898 -0.009502
education-num         0.148422  0.335272
capital-gain          0.078408  0.223336
capital-loss          0.054229  0.150501
hours-per-week        1.000000  0.229658
income                0.229658  1.000000
```

[44]:
```python
sns.heatmap(data=df.corr(),annot=True,cmap='viridis');
```



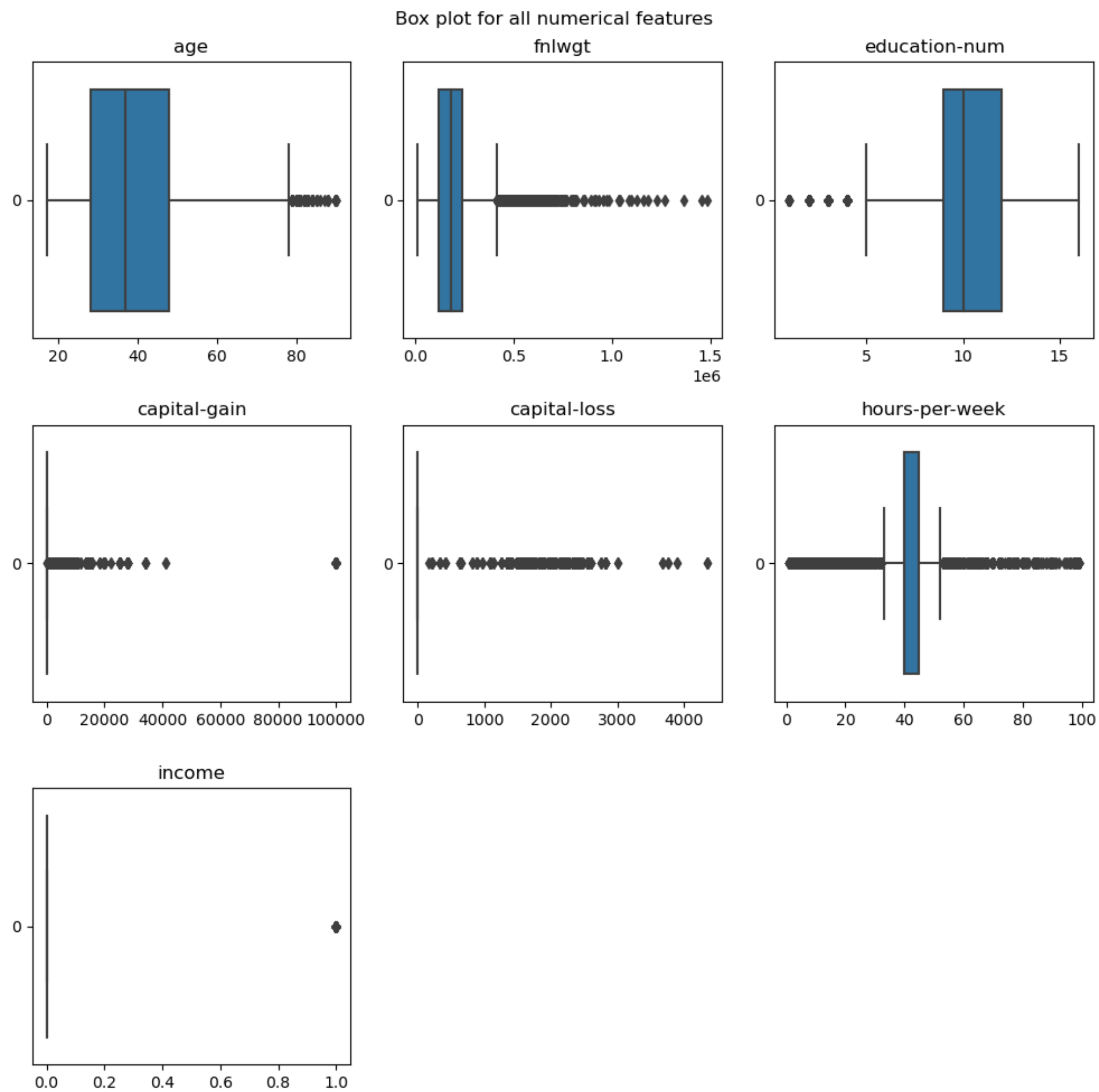
Observations:there is very less correlation between features, which shows the there is no to multicollinearity and fnlwgt has lowest correlation with rest of featurees; the highest correlation is in between eduaction and income.

[45]:
```
plt.figure(figsize=(10,5))
sns.countplot(x=df['workclass'],hue=df['income'])
plt.tight_layout();
```



Observations:employees in 'Private' workclass get paid the most and within those, most of them falls in <=50K pay scale

[46]:
```
#Bivariate analysis of numerical features w.r.t Target Variable
plt.figure(figsize=(10,10))
plt.suptitle('Box plot for all numerical features')
for a in range(0,len(num_feat)):
    plt.subplot(3,3,a+1)
    sns.boxplot(data=df[num_feat[a]],orient='h')
    plt.title(label=num_feat[a])
    plt.tight_layout()
```



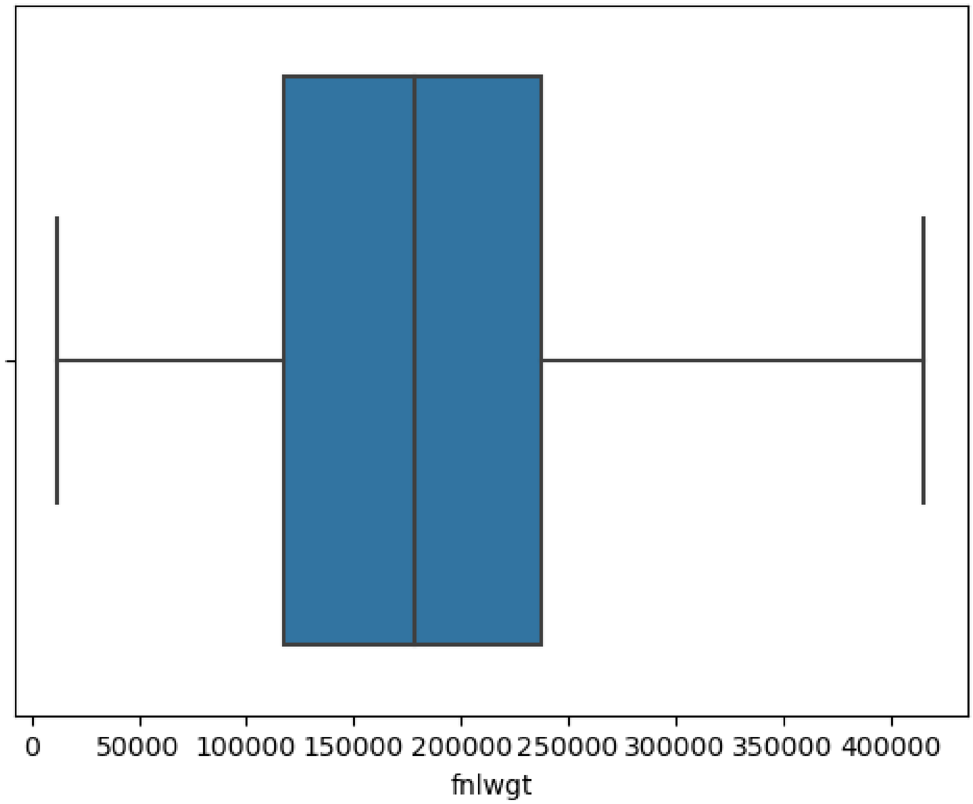
9 Handeling Outliers

[47]:
```
#deriving upperlimit and lowerlimit for 'fnlwgt'
IQR= df['fnlwgt'].quantile(0.75)-df['fnlwgt'].quantile(0.25)
Lower=df['fnlwgt'].quantile(0.25)-1.5*IQR
Upper=df['fnlwgt'].quantile(0.75)+1.5*IQR
print('Lower_limt:',Lower)
print('Upper_limit:',Upper)
```

```
Lower_limt: -60922.0
Upper_limit: 415742.0
```

[48]:
```
#getting rid of outliers
df['fnlwgt']=np.where(df['fnlwgt']>Upper,Upper,np.
 ↪where(df['fnlwgt']<Lower,Lower,df['fnlwgt']))
```

[49]:
```
#boxplot must not show outliers now
sns.boxplot(x='fnlwgt', data=df);
```

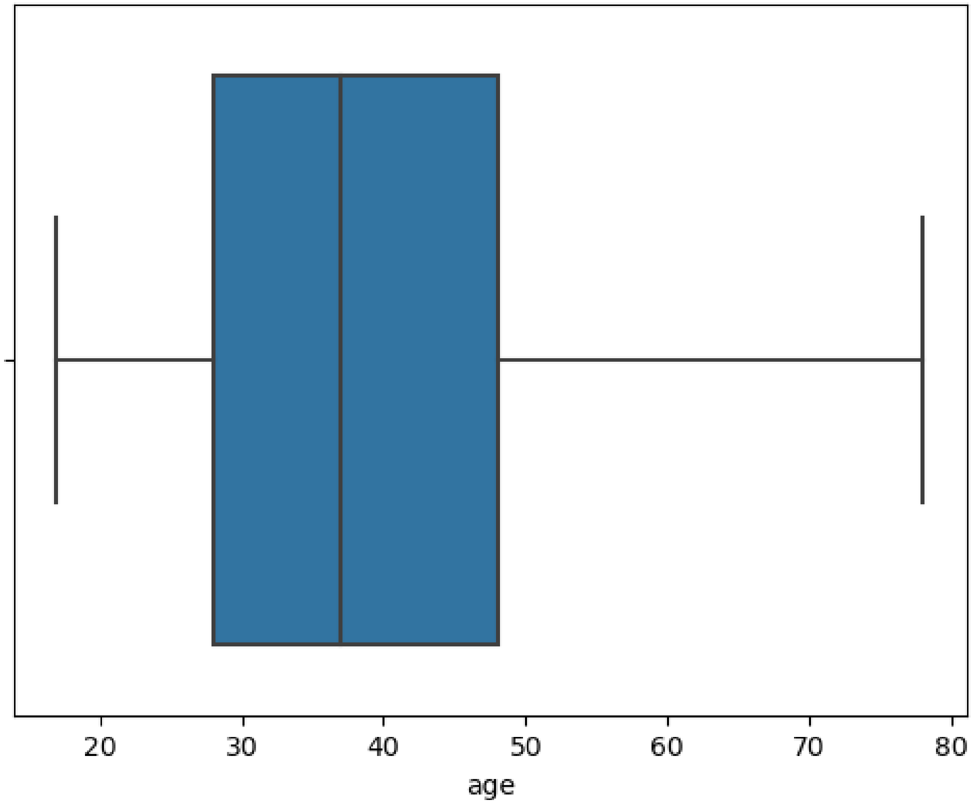


[50]:
```
#deriving upperlimit and lowerlimit for 'age'
IQR= df['age'].quantile(0.75)-df['age'].quantile(0.25)
Lower=df['age'].quantile(0.25)-1.5*IQR
Upper=df['age'].quantile(0.75)+1.5*IQR
print('Lower_limt:',Lower)
print('Upper_limit:',Upper)
```

```
Lower_limt: -2.0
Upper_limit: 78.0
```

[51]:
```
#getting rid of outliers
df['age']=np.where(df['age']>Upper,Upper,np.
 ↪where(df['age']<Lower,Lower,df['age']))
```

[52]:
```
#boxplot must not show outliers now
sns.boxplot(x='age', data=df);
```

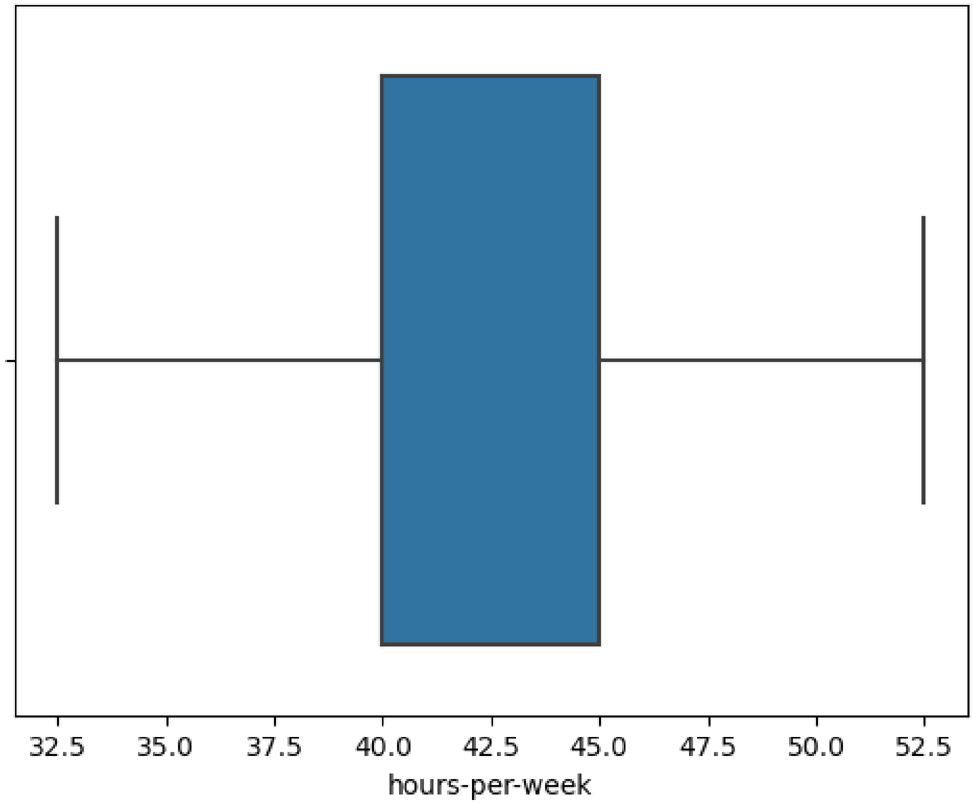


[53]:
```
#deriving upperlimit and lowerlimit for 'hours-per-week'
IQR= df['hours-per-week'].quantile(0.75)-df['hours-per-week'].quantile(0.25)
Lower=df['hours-per-week'].quantile(0.25)-1.5*IQR
Upper=df['hours-per-week'].quantile(0.75)+1.5*IQR
print('Lower_limt:',Lower)
print('Upper_limit:',Upper)
```

```
Lower_limt: 32.5
Upper_limit: 52.5
```

[54]:
```
#getting rid of outliers
df['hours-per-week']=np.where(df['hours-per-week']>Upper,Upper,np.
 ↪where(df['hours-per-week']<Lower,Lower,df['hours-per-week']))
```

[55]:
```
#boxplot must not show outliers now
sns.boxplot(x='hours-per-week', data=df);
```



10 Separating target variable(Dependent) from Indeendent variables

[56]:
```
x=df.iloc[:,:-1]
y=df['income']
```

[57]:
```
# We have Imbalanced Data and we have to do sampling to avoid this problem
# we have two method so for 1] Under Sampling, 2] Oversampling
# We will go for Oversampling.
!pip install -U imbalanced-learn
from imblearn.over_sampling import RandomOverSampler
ros=RandomOverSampler()
x_sample,y_sample=ros.fit_resample(x,y)
```

```
Requirement already satisfied: imbalanced-learn in
c:\users\ps4z\anaconda3\lib\site-packages (0.10.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\ps4z\anaconda3\lib\site-packages (from imbalanced-learn) (2.2.0)
Requirement already satisfied: scipy>=1.3.2 in c:\users\ps4z\anaconda3\lib\site-
packages (from imbalanced-learn) (1.9.1)
```

```
Requirement already satisfied: joblib>=1.1.1 in
c:\users\ps4z\anaconda3\lib\site-packages (from imbalanced-learn) (1.2.0)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\ps4z\anaconda3\lib\site-packages (from imbalanced-learn) (1.21.5)
Requirement already satisfied: scikit-learn>=1.0.2 in
c:\users\ps4z\anaconda3\lib\site-packages (from imbalanced-learn) (1.0.2)
```

[58]:
```
#checking our independent variable data
x.head()
```

[58]:
```
    age          workclass    fnlwgt  education  education-num  \
0  39.0          State-gov   77516.0  Bachelors             13
1  50.0   Self-emp-not-inc   83311.0  Bachelors             13
2  38.0            Private  215646.0    HS-grad              9
3  53.0            Private  234721.0       11th              7
4  28.0            Private  338409.0  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
0          2174             0            40.0   United-States
1             0             0            32.5   United-States
2             0             0            40.0   United-States
3             0             0            40.0   United-States
4             0             0            40.0            Cuba
```

[59]:
```
#checking oit dependent variable data
y.head()
```

[59]:
```
0    0
1    0
2    0
3    0
4    0
Name: income, dtype: int64
```

11 Label encoding on the categorical features

[60]:
```
#Feature Engineering
from sklearn.preprocessing import LabelEncoder
labelEncoder=LabelEncoder()
```

[61]:
```
#fit and transform
x[cat_feat]=x[cat_feat].apply(LabelEncoder().fit_transform)
```

[62]:
```
#checking independent variable data
x.head()
```

[62]:
```
    age  workclass    fnlwgt  education  education-num  marital-status  \
0  39.0          6   77516.0          9             13               4
1  50.0          5   83311.0          9             13               2
2  38.0          3  215646.0         11              9               0
3  53.0          3  234721.0          1              7               2
4  28.0          3  338409.0          9             13               2

   occupation  relationship  race  sex  capital-gain  capital-loss  \
0           0             1     4    1          2174             0
1           3             0     4    1             0             0
2           5             1     4    1             0             0
3           5             0     2    1             0             0
4           9             5     2    0             0             0

   hours-per-week  native-country
0            40.0              38
1            32.5              38
2            40.0              38
3            40.0              38
4            40.0               4
```

[63]:
```
#checking target variable data
y.head()
```

[63]:
```
0    0
1    0
2    0
3    0
4    0
Name: income, dtype: int64
```

[64]:
```
#Hyperparameter Tuning
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.33,␣
↪random_state=10)
```

[65]:
```
#getting shape of training data of independent variables
x_train.shape
```

[65]:
```
(21799, 14)
```

[66]:
```
#getting shape of training data of target variable
y_train.shape
```

[66]: (21799,)

[67]:
```
#getting shape of testing data of independent variables
x_test.shape
```

[67]: (10738, 14)

[68]:
```
#getting shape of testing data of target variable
y_test.shape
```

[68]: (10738,)

12 Decision Tree Classifier

[69]:
```
#Decision Tree Model
from sklearn.tree import DecisionTreeClassifier
DT=DecisionTreeClassifier()
```

[70]:
```
#fitting the model
DT.fit(x_train,y_train)
```

[70]: DecisionTreeClassifier()

[71]:
```
#learning the scores
DT.score(x_test,y_test)
```

[71]: 0.8097411063512758

[72]:
```
#predecting target variable
DTpred=DT.predict(x_test)
```

[73]:
```
#Model Evaluation
from sklearn.metrics import accuracy_score
DTacc=accuracy_score(y_test,DTpred)
report=[]
report.append(['Decision Tree', DTacc])
DTacc
```

[73]: 0.8097411063512758

13 Hyperparameter Tuning

[74]:
```
#Hyper-Tuning
from sklearn.model_selection import GridSearchCV
grid_parameter={
    'criterion':['gini', 'entropy'],
    'max_depth':range(2,32,1),
    'min_samples_leaf':range(1,10,1),
    'min_samples_split':range(2,10,1),
    'splitter':['best','random']
    }
```

[75]:
```
DTgrid=GridSearchCV(estimator=DT, param_grid=grid_parameter, cv=3, n_jobs=-1)
```

[76]:
```
DTgrid.fit(x_train, y_train)
```

[76]:
```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(2, 32),
                         'min_samples_leaf': range(1, 10),
                         'min_samples_split': range(2, 10),
                         'splitter': ['best', 'random']})
```

[77]:
```
DTgrid.best_params_
```

[77]:
```
{'criterion': 'gini',
 'max_depth': 6,
 'min_samples_leaf': 9,
 'min_samples_split': 2,
 'splitter': 'best'}
```

[78]:
```
DTbest_para=DecisionTreeClassifier(criterion = "gini", max_depth= 8 ,␣
 ↪min_samples_leaf= 9, min_samples_split= 2 ,
                                   splitter= "best")
```

[79]:
```
DTbest_para.fit(x_train,y_train)
```

[79]:
```
DecisionTreeClassifier(max_depth=8, min_samples_leaf=9)
```

[80]:
```
DTbest_para_pred2 = DTbest_para.predict(x_test)
```

[81]:
```
print("Accuracy Before Hyper-parameter tunning:",accuracy_score(y_test,DTpred))
print("Accuracy after Hyper-parameter tunning:
 ↪",accuracy_score(y_test,DTbest_para_pred2))
```

```
Accuracy Before Hyper-parameter tunning: 0.8097411063512758
Accuracy after Hyper-parameter tunning: 0.8573291115663997
```

[82]:
```python
import pickle
filename='income_pred_model'
pickle.dump(DT, open(filename,'wb'))
```

[83]:
```python
loaded_model=pickle.load(open(filename,'rb'))
```

[84]:
```python
loaded_model.predict(x_test)
```

[84]:
```
array([0, 0, 1, …, 1, 0, 1], dtype=int64)
```

[85]:
```python
df
```

[85]:
```
        age          workclass    fnlwgt    education  education-num  \
0      39.0          State-gov   77516.0    Bachelors             13
1      50.0   Self-emp-not-inc   83311.0    Bachelors             13
2      38.0            Private  215646.0      HS-grad              9
3      53.0            Private  234721.0         11th              7
4      28.0            Private  338409.0    Bachelors             13
…       …                 …        …          …           …
32556  27.0            Private  257302.0   Assoc-acdm             12
32557  40.0            Private  154374.0      HS-grad              9
32558  58.0            Private  151910.0      HS-grad              9
32559  22.0            Private  201490.0      HS-grad              9
32560  52.0       Self-emp-inc  287927.0      HS-grad              9

            marital-status         occupation   relationship   race  \
0            Never-married       Adm-clerical  Not-in-family  White
1       Married-civ-spouse    Exec-managerial        Husband  White
2                 Divorced  Handlers-cleaners  Not-in-family  White
3       Married-civ-spouse  Handlers-cleaners        Husband  Black
4       Married-civ-spouse     Prof-specialty           Wife  Black
…                      …                  …             …     …
32556   Married-civ-spouse       Tech-support           Wife  White
32557   Married-civ-spouse  Machine-op-inspct        Husband  White
32558              Widowed       Adm-clerical      Unmarried  White
32559        Never-married       Adm-clerical      Own-child  White
32560   Married-civ-spouse    Exec-managerial           Wife  White

           sex  capital-gain  capital-loss  hours-per-week  native-country  \
0         Male          2174             0            40.0   United-States
1         Male             0             0            32.5   United-States
2         Male             0             0            40.0   United-States
3         Male             0             0            40.0   United-States
4       Female             0             0            40.0            Cuba
…         …            …             …              …              …
32556   Female             0             0            38.0   United-States
32557     Male             0             0            40.0   United-States
```

```
32558   Female         0          0          40.0  United-States
32559     Male         0          0          32.5  United-States
32560   Female     15024          0          40.0  United-States

       income
0           0
1           0
2           0
3           0
4           0
…       …
32556       0
32557       1
32558       0
32559       0
32560       1

[32537 rows x 15 columns]
```

[86]:

```
x
```

[86]:

```
        age  workclass    fnlwgt  education  education-num  marital-status  \
0      39.0          6   77516.0          9             13               4
1      50.0          5   83311.0          9             13               2
2      38.0          3  215646.0         11              9               0
3      53.0          3  234721.0          1              7               2
4      28.0          3  338409.0          9             13               2
…       …         …         …        …              …              …
32556  27.0          3  257302.0          7             12               2
32557  40.0          3  154374.0         11              9               2
32558  58.0          3  151910.0         11              9               6
32559  22.0          3  201490.0         11              9               4
32560  52.0          4  287927.0         11              9               2

       occupation  relationship  race  sex  capital-gain  capital-loss  \
0               0             1     4    1          2174             0
1               3             0     4    1             0             0
2               5             1     4    1             0             0
3               5             0     2    1             0             0
4               9             5     2    0             0             0
…            …             …   …   …           …             …
32556          12             5     4    0             0             0
32557           6             0     4    1             0             0
32558           0             4     4    0             0             0
32559           0             3     4    1             0             0
32560           3             5     4    0         15024             0
```

```
       hours-per-week  native-country
0                40.0              38
1                32.5              38
2                40.0              38
3                40.0              38
4                40.0               4
…                 …              …
32556            38.0              38
32557            40.0              38
32558            40.0              38
32559            32.5              38
32560            40.0              38

[32537 rows x 14 columns]
```