In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
df = pd.read_csv("../../CSV/salary.csv",index_col=0)
```

In [6]:

```
df.head()
```

Out[6]:

	age	Workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black Fe

In [7]:

```
df.describe(include="all")
```

Out[7]:

	age	Workclass	fnlwgt	education	education-num	marital-status	occupation	re
count	1032.000000	1032	1.032000e+03	1032	1032.000000	1032	1032	
unique	NaN	6	NaN	16	NaN	7	14	
top	NaN	Private	NaN	HS-grad	NaN	Married-civ-spouse	Prof-specialty	
freq	NaN	766	NaN	338	NaN	472	143	
mean	37.954457	NaN	1.918318e+05	NaN	10.221899	NaN	NaN	
std	12.825353	NaN	1.074243e+05	NaN	2.501636	NaN	NaN	
min	17.000000	NaN	2.117400e+04	NaN	1.000000	NaN	NaN	
25%	28.000000	NaN	1.155792e+05	NaN	9.000000	NaN	NaN	
50%	37.000000	NaN	1.807065e+05	NaN	10.000000	NaN	NaN	
75%	46.000000	NaN	2.461932e+05	NaN	13.000000	NaN	NaN	
max	90.000000	NaN	1.033222e+06	NaN	16.000000	NaN	NaN	

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1032 entries, 0 to 1119
Data columns (total 15 columns):
age               1032 non-null int64
Workclass         1032 non-null object
fnlwgt            1032 non-null int64
education         1032 non-null object
education-num     1032 non-null int64
marital-status    1032 non-null object
occupation        1032 non-null object
relationship      1032 non-null object
race              1032 non-null object
sex               1032 non-null object
capital-gain      1032 non-null int64
capital-loss      1032 non-null int64
hours-per-week    1032 non-null int64
native-country    1032 non-null object
Income            1032 non-null int64
dtypes: int64(7), object(8)
memory usage: 129.0+ KB
```

In [9]:

```
df.isnull().sum()
```

Out[9]:

```
age               0
Workclass         0
fnlwgt            0
education         0
education-num     0
marital-status    0
occupation        0
relationship      0
race              0
sex               0
capital-gain      0
capital-loss      0
hours-per-week    0
native-country    0
Income            0
dtype: int64
```

In [13]:

```
df["Income"].value_counts()
```

Out[13]:

```
0    778
1    254
Name: Income, dtype: int64
```

In [9]:

```
cat_df = df.select_dtypes("object")
num_df = df.select_dtypes("int64")
```

In [11]:

```
from sklearn.preprocessing import LabelEncoder
```

In [13]:

```
for col in cat_df:
    le = LabelEncoder()
    cat_df[col] = le.fit_transform(cat_df[col])
```

In [15]:

```
cat_df.head()
```

Out[15]:

	Workclass	education	marital-status	occupation	relationship	race	sex	native-country
0	5	9	4	0	1	4	1	28
1	4	9	2	3	0	4	1	28
2	2	11	0	5	1	4	1	28
3	2	1	2	5	0	2	1	28
4	2	9	2	9	5	2	0	4

In [22]:

```
df = pd.concat([cat_df,num_df],axis=1)
```

In [23]:

```
df.head()
```

Out[23]:

	Workclass	education	marital-status	occupation	relationship	race	sex	native-country	age	fnlwgt
0	5	9	4	0	1	4	1	28	39	77516
1	4	9	2	3	0	4	1	28	50	83311
2	2	11	0	5	1	4	1	28	38	215646
3	2	1	2	5	0	2	1	28	53	234721
4	2	9	2	9	5	2	0	4	28	338409

Some visualization

In [24]:

```
cat_col = ("Workclass,education,marital-status,occupation,relationship,race,sex,native-cour
```

In [25]:

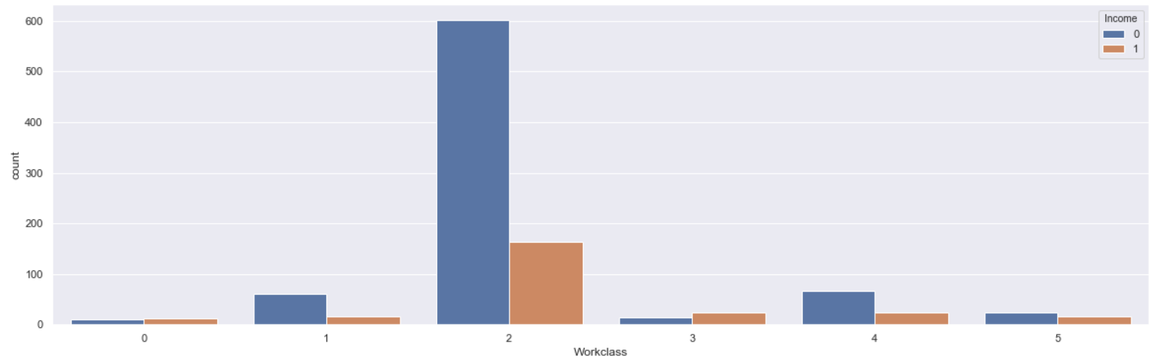
```
cat_col
```

Out[25]:

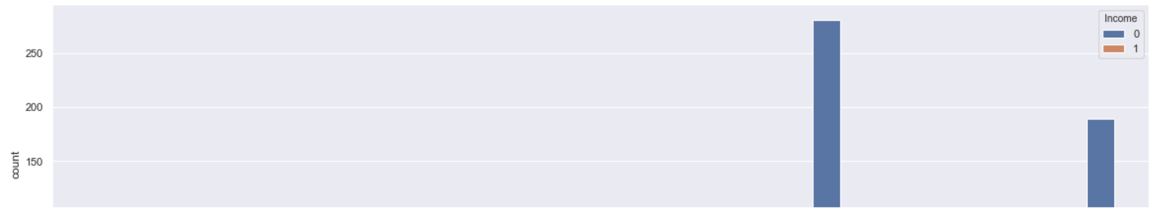
```
['Workclass',
 'education',
 'marital-status',
 'occupation',
 'relationship',
 'race',
 'sex',
 'native-country']
```

In [26]:

```
for col in cat_col:
    plt.figure(figsize=(20,6))
    sns.countplot(data=df,x=col,hue="Income")
    plt.show()
    print("------------------------------------------------------------------------")
```




```
------------------------------------------------------------------------
```

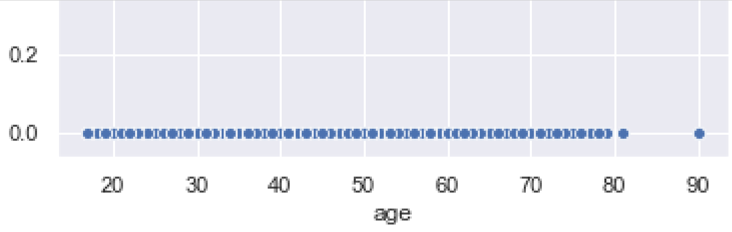


In [27]:

```
num_col = ("age,fnlwgt,education-num,capital-gain,capital-loss,hours-per-week").split(",")
```

In [28]:

```
for col in num_col:
    plt.figure()
    sns.scatterplot(data=df,x=col,y="Income")
    plt.show()
    print("-------------------------------------------------------------------------------"
```



Train Test Split

In [29]:

```
X = df.iloc[:,:-1]
y = df.iloc[:,-1]
```

In [33]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report,confusion_matrix
```

In [34]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

In [35]:

```
log  = LogisticRegression()
log.fit(X_train,y_train)
```

Out[35]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [36]:

```
log.score(X_test,y_test)
```

Out[36]:

```
0.8064516129032258
```

In [39]:

```
y_pred = log.predict(X_test)
y_pred
```

Out[39]:

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

In [40]:

```
log.predict_proba(X_test)
```

Out[40]:

```
array([[0.78289909, 0.21710091],
       [0.85198354, 0.14801646],
       [0.4454658 , 0.5545342 ],
       [0.75771233, 0.24228767],
       [0.83252627, 0.16747373],
       [0.89213857, 0.10786143],
       [0.80077115, 0.19922885],
       [0.78079358, 0.21920642],
       [0.70564887, 0.29435113],
       [0.76828643, 0.23171357],
       [0.82301475, 0.17698525],
       [0.47687899, 0.52312101],
       [0.79644364, 0.20355636],
       [0.80810884, 0.19189116],
       [0.76485285, 0.23514715],
       [0.81625166, 0.18374834],
       [0.91743654, 0.08256346],
       [0.76957656, 0.23042344],
```

Evaluation metrics

In [41]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.98      0.89       238
           1       0.77      0.24      0.36        72

    accuracy                           0.81       310
   macro avg       0.79      0.61      0.62       310
weighted avg       0.80      0.81      0.76       310
```

In [42]:

```
tn, fp, fn, tp = confusion_matrix(y_test,y_pred).ravel()
```

In [43]:

```
print(tp,fp,"\n",fn,tn)
```

```
17 5
 55 233
```

In [44]:

```
print("Accuracy:",(tp+tn)/(tp+tn+fp+fn))
```

```
Accuracy: 0.8064516129032258
```

In [ ]: