eda-2

November 26, 2024

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('dark_background')
```

[ ]:
```
df = pd.read_csv('adult_with_headers.csv')
df.head()
```

[ ]:

	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

[ ]:
```
df.shape
```

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

[ ]:
```
df.describe()
```

[ ]:
```
                age        fnlwgt  education_num  capital_gain  capital_loss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.000000
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.303830
std       13.640433  1.055500e+05       2.572720   7385.292085    402.960219
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  2.370510e+05      12.000000      0.000000      0.000000
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000

       hours_per_week
count    32561.000000
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

[ ]:
```
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
```

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

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

[ ]:
```
df['sex'].value_counts()
```

[ ]:
```
Male      21790
Female    10771
Name: sex, dtype: int64
```

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

[ ]:
```
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
```

[ ]:
```
df['workclass'].value_counts()
```

[ ]:
```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
```

[ ]:
```
df['occupation'].value_counts()
```

[ ]:
```
 Prof-specialty       4140
 Craft-repair         4099
 Exec-managerial      4066
 Adm-clerical         3770
 Sales                3650
 Other-service        3295
 Machine-op-inspct    2002
 ?                    1843
 Transport-moving     1597
 Handlers-cleaners    1370
 Farming-fishing       994
 Tech-support          928
 Protective-serv       649
 Priv-house-serv       149
 Armed-Forces            9
Name: occupation, dtype: int64
```

[ ]:
```
#Dropping Education - Education No. is enough, Dropping Final Weight - Highly␣
 ↪Discrete Data so not useful.
```

[ ]:
```
df = df.drop(['education', 'fnlwgt'], axis = 1)
df.head()
```

[ ]:

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	income
0	39	State-gov	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

[ ]:
```
#Replacing "?" with NaN
```

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

[ ]:

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	income
0	39	State-gov	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

1 Replacing NaN with Forward Fill

[ ]:
```
df.fillna(method = 'ffill', inplace = True)
```

2 Label Encoding

[ ]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['workclass'] = le.fit_transform(df['workclass'])
df['marital.status'] = le.fit_transform(df['marital_status'])
df['occupation'] = le.fit_transform(df['occupation'])
df['relationship'] = le.fit_transform(df['relationship'])
df['race'] = le.fit_transform(df['race'])
df['sex'] = le.fit_transform(df['sex'])
df['native_country'] = le.fit_transform(df['native_country'])
df['income'] = le.fit_transform(df['income'])
df.head()
```

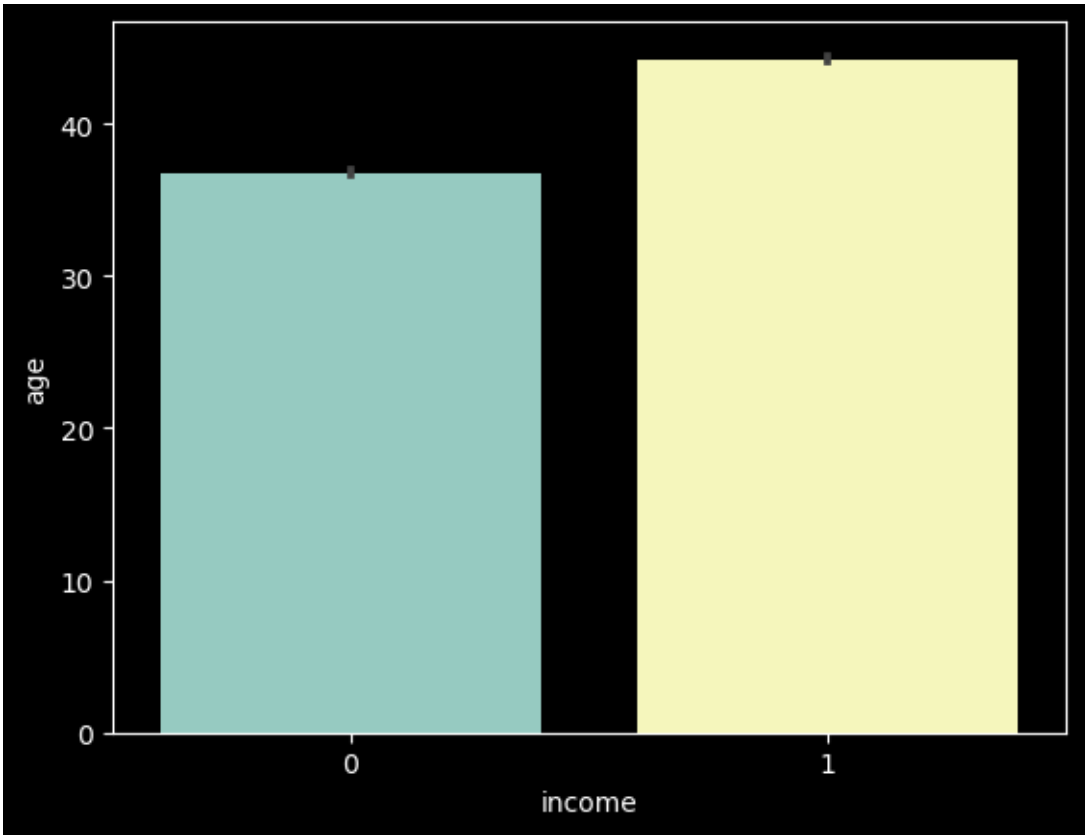
[ ]:

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	income	marital.status
0	39	7	13	Never-married	1	1	4	1	2174	0	40	39	0	4
1	50	6	13	Married-civ-spouse	4	0	4	1	0	0	13	39	0	2
2	38	4	9	Divorced	6	1	4	1	0	0	40	39	0	0
3	53	4	7	Married-civ-spouse	6	0	2	1	0	0	40	39	0	2
4	28	4	13	Married-civ-spouse	10	5	2	0	0	0	40	5	0	2

3 People with more age earn more

[ ]:
```
sns.barplot(x = 'income', y = 'age', data = df)
```

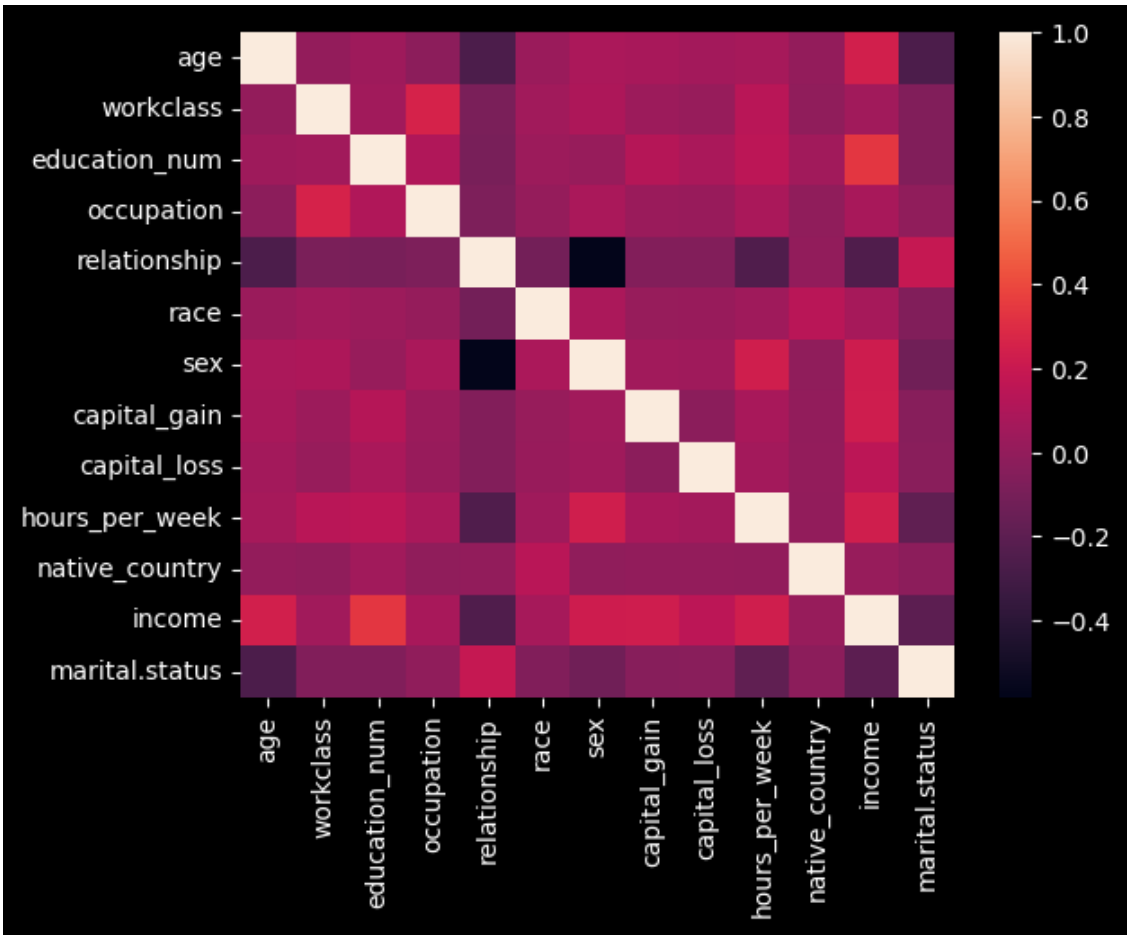
[ ]:
```
<Axes: xlabel='income', ylabel='age'>
```



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

```
C:\Users\excel\AppData\Local\Temp\ipykernel_25540\58359773.py:1: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  sns.heatmap(df.corr())
```

[ ]:
```
<Axes: >
```



[ ]:
```
X = df.drop(['income'],axis = 1)
y = df['income']
```

[ ]:
```
print('Shape of X =', X.shape)
print('Shape of y =', y.shape)
```

```
Shape of X = (32561, 13)
Shape of y = (32561,)
```

4 Train Test Split

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.
↪2,random_state=42)
```

[ ]:
```
# Instantiate Gaussian Naive Bayes model
gnb = GaussianNB()
```

```
# Fit the model
gnb.fit(X_train, y_train)
```

[ ]:
```
GaussianNB()
```

[ ]:
```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

[ ]:
```
y_pred = gnb.predict(X_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(accuracy_score(y_test, y_pred)*100)
```

```
              precision    recall  f1-score   support

           0       0.82      0.95      0.88      4942
           1       0.67      0.32      0.44      1571

    accuracy                           0.80      6513
   macro avg       0.74      0.64      0.66      6513
weighted avg       0.78      0.80      0.77      6513

[[4698  244]
 [1065  506]]
79.90173499155534
```

[ ]:
```

```