In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.set_style('darkgrid')
```

In [4]:
```
## read the dataset

df = pd.read_csv('income_evaluation.csv')
```

In [5]:
```
df.head()
```

Out[5]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

In [6]:
```
## check null values in dataset

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

Out[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
```

In [7]:
```
df.shape
```

Out[7]:
```
(32561, 15)
```

In [8]:
```
df.columns = ['age', 'workclass', 'final_weight', 'education', 'education_num', 'martial_status', 'occupation', 'relationship', 'race', 'sex',
             'capital_gain', 'capital_loss', 'hrs_per_week', 'native_country', 'income']
```

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

Out[9]:
```
Index(['age', 'workclass', 'final_weight', 'education', 'education_num',
       'martial_status', 'occupation', 'relationship', 'race', 'sex',
       'capital_gain', 'capital_loss', 'hrs_per_week', 'native_country',
       'income'],
      dtype='object')
```

In [10]:
```
df.income.unique()
```

Out[10]:
```
array([' <=50K', ' >50K'], dtype=object)
```

In [11]:
```
## converting income columns to 0's and 1's {0 for salary <=50K and 1 for salary >50K}
df['income'] = [1 if value == ' >50K' else 0 for value in df['income'].values]
```

In [12]:
```
## last 5 rows in dataset

df.tail()
```

Out[12]:

	age	workclass	final_weight	education	education_num	martial_status	occupation	relationship	race	sex	capital_gain	capital_loss	hrs_per_week	native_country	income
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	0
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	1
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	0
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	0
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	1

In [13]:
```
df.workclass.unique()
```

Out[13]:
```
array([' State-gov', ' Self-emp-not-inc', ' Private', ' Federal-gov',
       ' Local-gov', ' ?', ' Self-emp-inc', ' Without-pay',
       ' Never-worked'], dtype=object)
```

In [14]:
```
## removing ? from column workclass
df['workclass'] = np.where(df.workclass == ' ?', np.nan, df['workclass'])
```

In [15]:
```
df.dropna(axis=0, inplace=True)
```

In [16]:
```
workclass_label = {v:k for k, v in enumerate(df.workclass.unique())}
```

In [17]:
```
workclass_label
```

Out[17]:
```
{' State-gov': 0,
 ' Self-emp-not-inc': 1,
 ' Private': 2,
 ' Federal-gov': 3,
 ' Local-gov': 4,
 ' Self-emp-inc': 5,
 ' Without-pay': 6,
 ' Never-worked': 7}
```

In [22]:
```
df.workclass = df.workclass.map(workclass_label)
```

In [23]:
```
df.education.unique()
```

Out[23]:
```
array([' Bachelors', ' HS-grad', ' 11th', ' Masters', ' 9th',
       ' Some-college', ' Assoc-acdm', ' Assoc-voc', ' 7th-8th',
       ' Doctorate', ' Prof-school', ' 5th-6th', ' 10th', ' Preschool',
       ' 12th', ' 1st-4th'], dtype=object)
```

In [24]:
```
education_label = {v:k for k, v in enumerate(df.education.unique())}
```

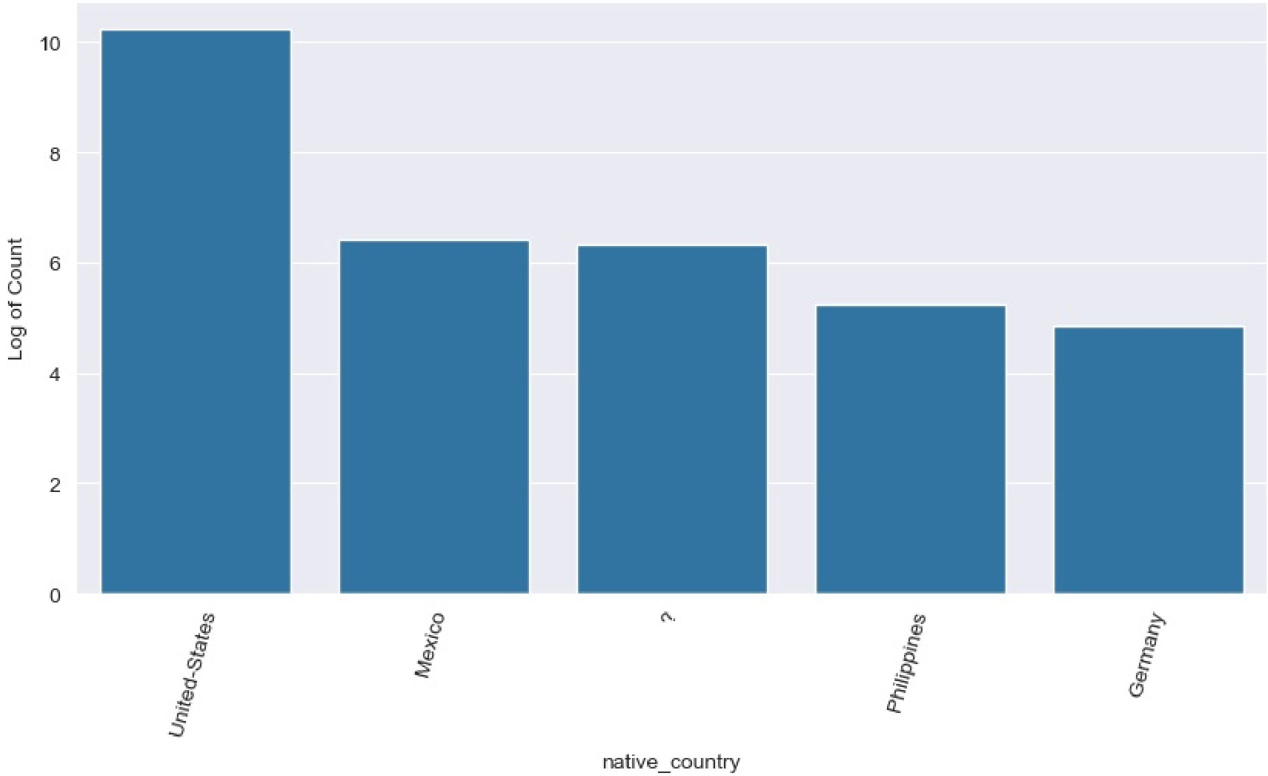
In [25]:
```
education_label
```

Out[25]:
```
{' Bachelors': 0,
 ' HS-grad': 1,
 ' 11th': 2,
 ' Masters': 3,
 ' 9th': 4,
 ' Some-college': 5,
 ' Assoc-acdm': 6,
 ' Assoc-voc': 7,
 ' 7th-8th': 8,
 ' Doctorate': 9,
 ' Prof-school': 10,
 ' 5th-6th': 11,
 ' 10th': 12,
 ' Preschool': 13,
 ' 12th': 14,
 ' 1st-4th': 15}
```

In [26]:
```
df.education = df.education.map(education_label)
```

In [27]:
```
plt.figure(figsize=(10, 4))
sns.countplot(x='income', data=df, hue='sex');
```

In [31]:
```
plt.figure(figsize=(10, 5))
plt.xticks(rotation=75)
sns.barplot(x=native_country.index, y=np.log(native_country))
plt.ylabel('Log of Count')
plt.show()
```



In [32]:
```
df.native_country = np.where(df.native_country == ' ?', np.nan, df['native_country'])
```

In [33]:
```
df.dropna(axis=0, inplace=True)
```

In [34]:
```
native_country = {v:k for k, v in enumerate(df.native_country.unique())}
```

In [35]:
```
df.native_country = df.native_country.map(native_country)
```

In [36]:
```
df.head()
```

Out[36]:

	age	workclass	final_weight	education	education_num	martial_status	occupation	relationship	race	sex	capital_gain	capital_loss	hrs_per_week	native_country	income
0	39	0	77516	0	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	0	0
1	50	1	83311	0	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	0	0
2	38	2	215646	1	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	0	0
3	53	2	234721	2	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	0	0
4	28	2	338409	0	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	1	0

In [37]:
```
df.martial_status.unique()
```

Out[37]:
```
array([' Never-married', ' Married-civ-spouse', ' Divorced',
       ' Married-spouse-absent', ' Separated', ' Married-AF-spouse',
       ' Widowed'], dtype=object)
```

In [38]:
```
marital_label = {v:k for k, v in enumerate(df.martial_status.unique())}
```

In [39]:
```
df.martial_status = df.martial_status.map(marital_label)
```

In [40]:
```
df.occupation.unique()
```

Out[40]:
```
array([' Adm-clerical', ' Exec-managerial', ' Handlers-cleaners',
       ' Prof-specialty', ' Other-service', ' Sales', ' Transport-moving',
       ' Farming-fishing', ' Machine-op-inspct', ' Tech-support',
       ' Craft-repair', ' Protective-serv', ' Armed-Forces',
       ' Priv-house-serv', ' ?'], dtype=object)
```

In [41]:
```
df.occupation = np.where(df.occupation == ' ?', np.nan, df['occupation'])
```

In [42]:
```
df.dropna(axis=0, inplace=True)
```

In [43]:
```
occ_label = {v:k for k, v in enumerate(df.occupation.unique())}
```

In [44]:
```
df.occupation = df.occupation.map(occ_label)
```

In [45]:
```
df.relationship.unique()
```

Out[45]:
```
array([' Not-in-family', ' Husband', ' Wife', ' Own-child', ' Unmarried',
       ' Other-relative'], dtype=object)
```

In [46]:
```
relationship_label = {v:k for k, v in enumerate(df.relationship.unique())}
```

In [47]:
```
df.relationship = df.relationship.map(relationship_label)
```

In [48]:
```
df.head()
```

Out[48]:

	age	workclass	final_weight	education	education_num	martial_status	occupation	relationship	race	sex	capital_gain	capital_loss	hrs_per_week	native_country	income
0	39	0	77516	0	13	0	0	0	White	Male	2174	0	40	0	0
1	50	1	83311	0	13	1	1	1	White	Male	0	0	13	0	0
2	38	2	215646	1	9	2	2	0	White	Male	0	0	40	0	0
3	53	2	234721	2	7	1	2	1	Black	Male	0	0	40	0	0
4	28	2	338409	0	13	1	3	2	Black	Female	0	0	40	1	0

In [49]:
```
df.sex = np.where(df.sex == ' Male', 1, 0)
```

In [50]:
```
df.race.unique()
```

Out[50]:
```
array([' White', ' Black', ' Asian-Pac-Islander', ' Amer-Indian-Eskimo',
       ' Other'], dtype=object)
```

In [51]:
```
race_label = {v:k for k, v in enumerate(df.race.unique())}
```

In [52]:
```python
race_label
```

Out[52]:
```
{' White': 0,
 ' Black': 1,
 ' Asian-Pac-Islander': 2,
 ' Amer-Indian-Eskimo': 3,
 ' Other': 4}
```

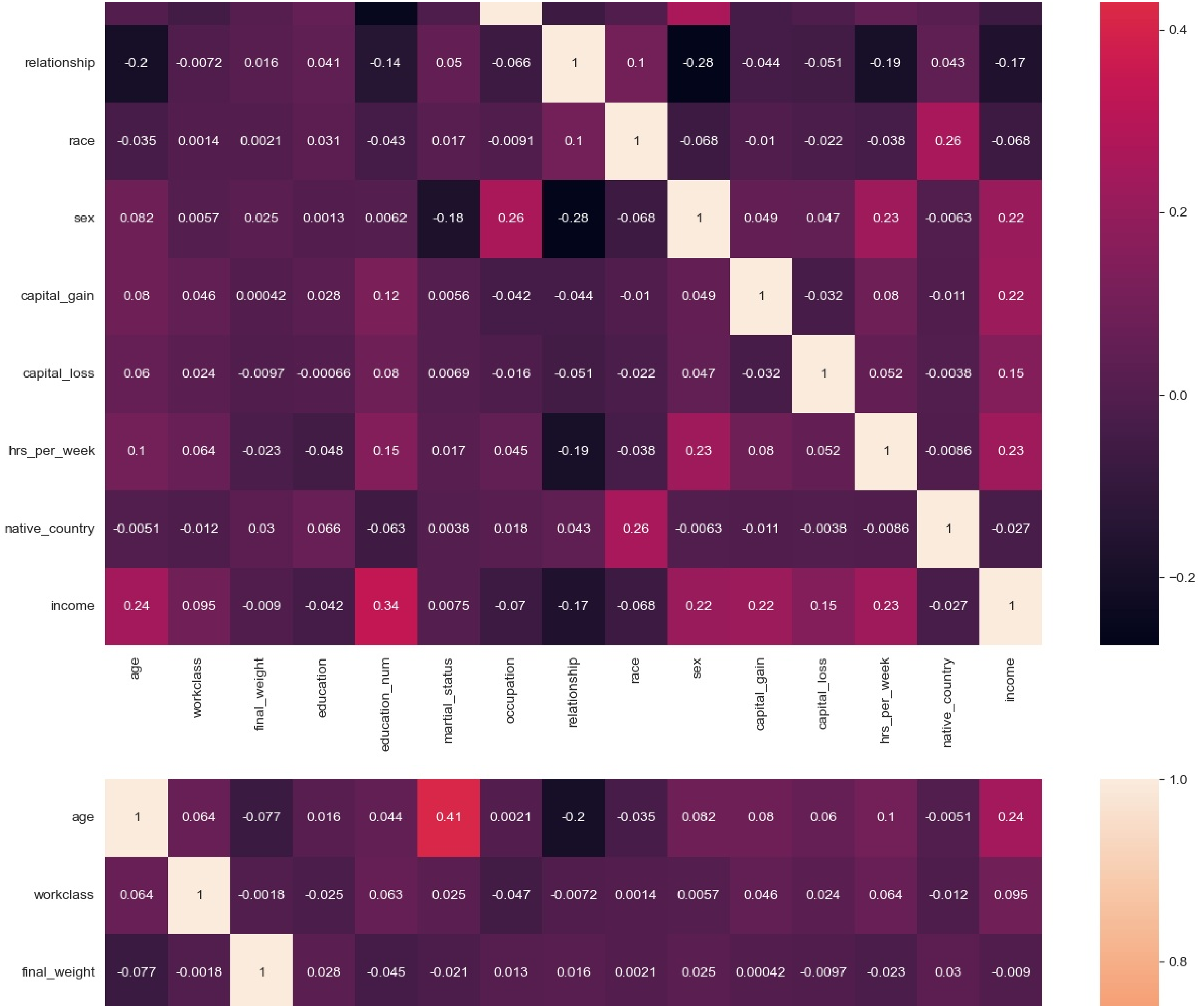
In [53]:
```python
df.race = df.race.map(race_label)
```

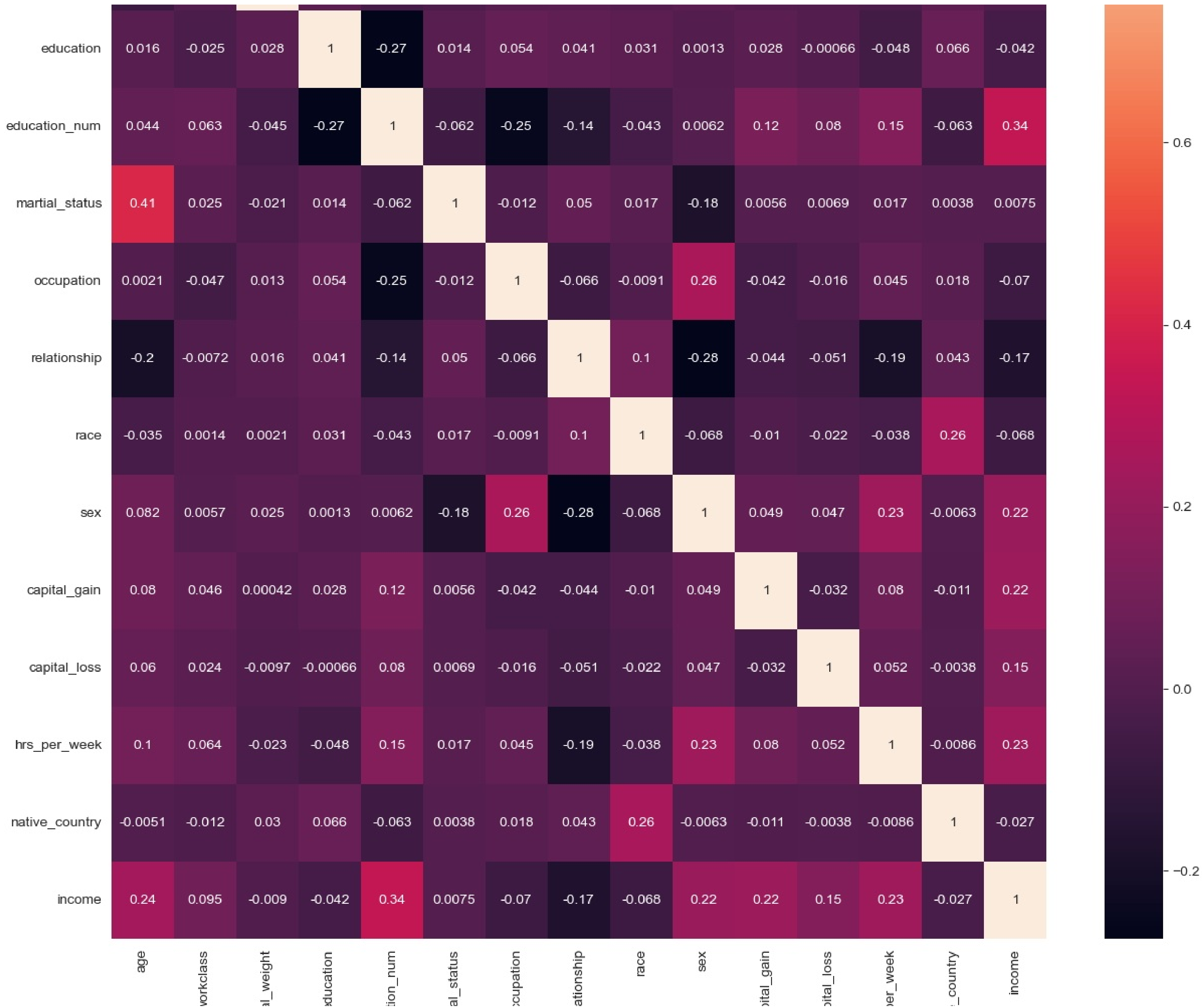
In [54]:
```python
df.head()
```

Out[54]:

	age	workclass	final_weight	education	education_num	martial_status	occupation	relationship	race	sex	capital_gain	capital_loss	hrs_per_week	native_country	income
0	39	0	77516	0	13	0	0	0	0	1	2174	0	40	0	0
1	50	1	83311	0	13	1	1	1	0	1	0	0	13	0	0
2	38	2	215646	1	9	2	2	0	0	1	0	0	40	0	0
3	53	2	234721	2	7	1	2	1	1	1	0	0	40	0	0
4	28	2	338409	0	13	1	3	2	1	0	0	0	40	1	0

In [56]:
```python
plt.figure(figsize=(15, 15))
sns.heatmap(df.corr(), annot=True)
plt.show()
```


relationship -0.2 -0.0072 0.016 0.041 -0.14 0.05 -0.066 1 0.1 -0.28 -0.044 -0.051 -0.19 0.043 -0.17
race -0.035 0.0014 0.0021 0.031 -0.043 0.017 -0.0091 0.1 1 -0.068 -0.01 -0.022 -0.038 0.26 -0.068
sex 0.082 0.0057 0.025 0.0013 0.0062 -0.18 0.26 -0.28 -0.068 1 0.049 0.047 0.23 -0.0063 0.22
capital_gain 0.08 0.046 0.00042 0.028 0.12 0.0056 -0.042 -0.044 -0.01 0.049 1 -0.032 0.08 -0.011 0.22
capital_loss 0.06 0.024 -0.0097 -0.00066 0.08 0.0069 -0.016 -0.051 -0.022 0.047 -0.032 1 0.052 -0.0038 0.15
hrs_per_week 0.1 0.064 -0.023 -0.048 0.15 0.017 0.045 -0.19 -0.038 0.23 0.08 0.052 1 -0.0086 0.23
native_country -0.0051 -0.012 0.03 0.066 -0.063 0.0038 0.018 0.043 0.26 -0.0063 -0.011 -0.0038 -0.0086 1 -0.027
income 0.24 0.095 -0.009 -0.042 0.34 0.0075 -0.07 -0.17 -0.068 0.22 0.22 0.15 0.23 -0.027 1
age workclass final_weight education education_num martial_status occupation relationship race sex capital_gain capital_loss hrs_per_week native_country income
0.4
0.2
0.0
−0.2
age 1 0.064 -0.077 0.016 0.044 0.41 0.0021 -0.2 -0.035 0.082 0.08 0.06 0.1 -0.0051 0.24
workclass 0.064 1 -0.0018 -0.025 0.063 0.025 -0.047 -0.0072 0.0014 0.0057 0.046 0.024 0.064 -0.012 0.095
final_weight -0.077 -0.0018 1 0.028 -0.045 -0.021 0.013 0.016 0.0021 0.025 0.00042 -0.0097 -0.023 0.03 -0.009
1.0
0.8

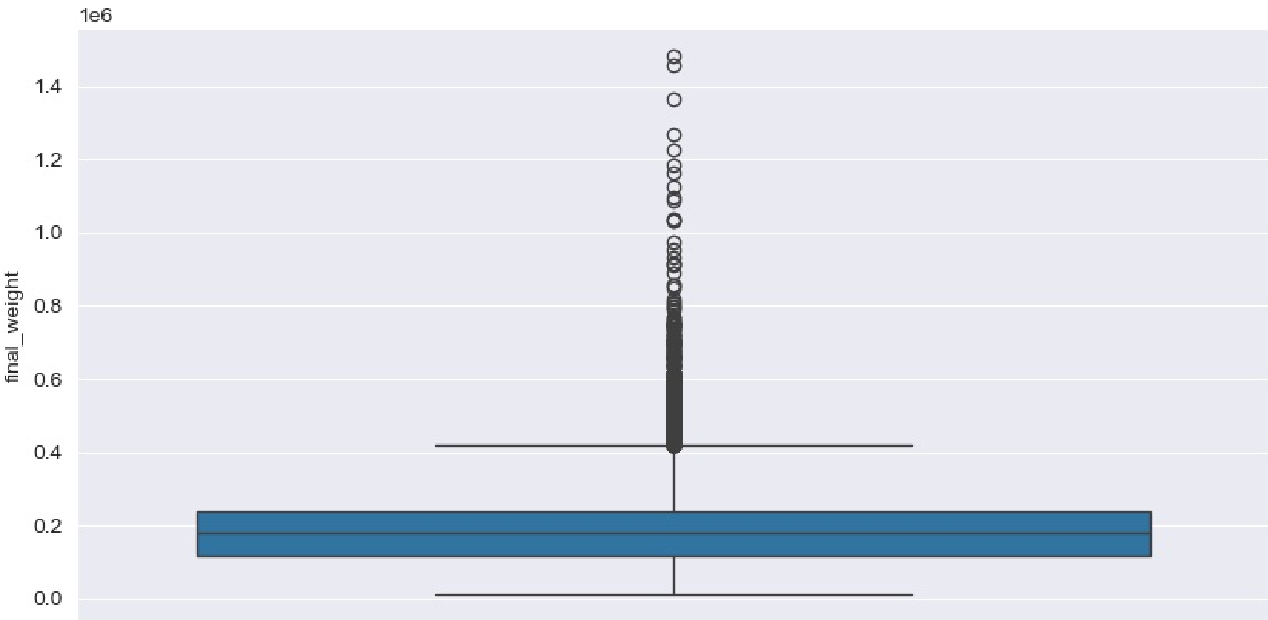

education 0.016 -0.025 0.028 1 -0.27 0.014 0.054 0.041 0.031 0.0013 0.028 -0.00066 -0.048 0.066 -0.042
education_num 0.044 0.063 -0.045 -0.27 1 -0.062 -0.25 -0.14 -0.043 0.0062 0.12 0.08 0.15 -0.063 0.34
martial_status 0.41 0.025 -0.021 0.014 -0.062 1 -0.012 0.05 0.017 -0.18 0.0056 0.0069 0.017 0.0038 0.0075
occupation 0.0021 -0.047 0.013 0.054 -0.25 -0.012 1 -0.066 -0.0091 0.26 -0.042 -0.016 0.045 0.018 -0.07
relationship -0.2 -0.0072 0.016 0.041 -0.14 0.05 -0.066 1 0.1 -0.28 -0.044 -0.051 -0.19 0.043 -0.17
race -0.035 0.0014 0.0021 0.031 -0.043 0.017 -0.0091 0.1 1 -0.068 -0.01 -0.022 -0.038 0.26 -0.068
sex 0.082 0.0057 0.025 0.0013 0.0062 -0.18 0.26 -0.28 -0.068 1 0.049 0.047 0.23 -0.0063 0.22
capital_gain 0.08 0.046 0.00042 0.028 0.12 0.0056 -0.042 -0.044 -0.01 0.049 1 -0.032 0.08 -0.011 0.22
capital_loss 0.06 0.024 -0.0097 -0.00066 0.08 0.0069 -0.016 -0.051 -0.022 0.047 -0.032 1 0.052 -0.0038 0.15
hrs_per_week 0.1 0.064 -0.023 -0.048 0.15 0.017 0.045 -0.19 -0.038 0.23 0.08 0.052 1 -0.0086 0.23
native_country -0.0051 -0.012 0.03 0.066 -0.063 0.0038 0.018 0.043 0.26 -0.0063 -0.011 -0.0038 -0.0086 1 -0.027
income 0.24 0.095 -0.009 -0.042 0.34 0.0075 -0.07 -0.17 -0.068 0.22 0.22 0.15 0.23 -0.027 1
age
vorkclass
al_weight
education
tion_num
al_status
ccupation
ationship
race
sex
pital_gain
pital_loss
per_week
_country
income
0.6
0.4
0.2
0.0
−0.2

In [57]:
```python
df.head()
```

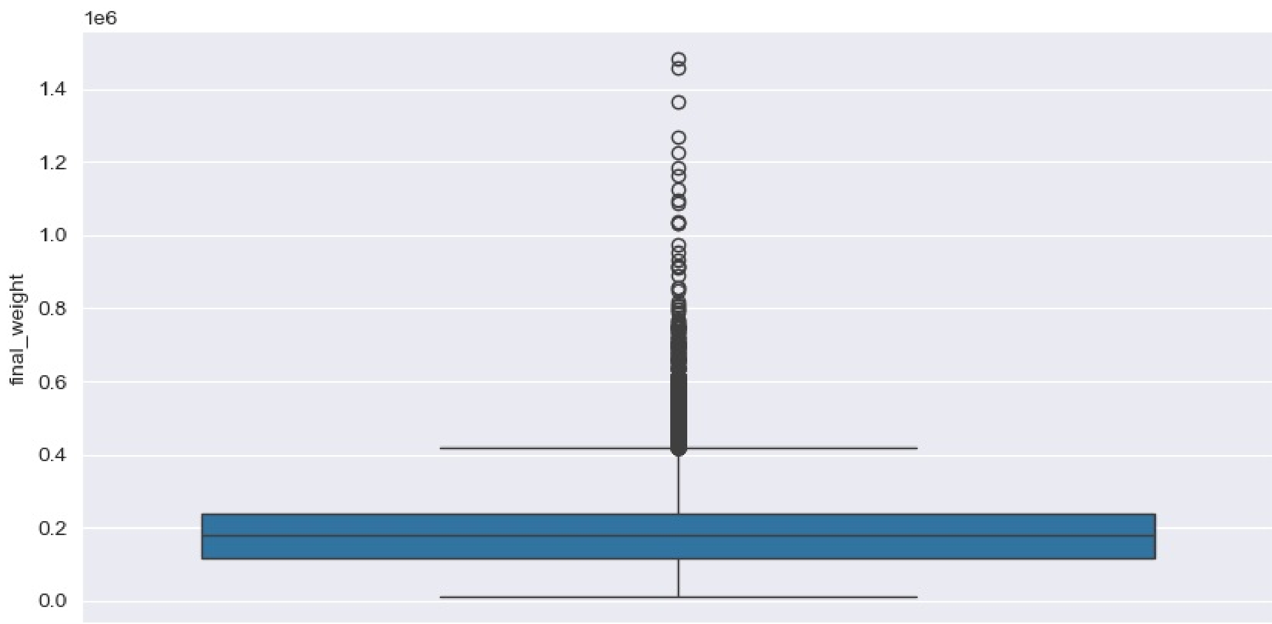
Out[57]:

	age	workclass	final_weight	education	education_num	martial_status	occupation	relationship	race	sex	capital_gain	capital_loss	hrs_per_week	native_country	income
0	39	0	77516	0	13	0	0	0	0	1	2174	0	40	0	0
1	50	1	83311	0	13	1	1	1	0	1	0	0	13	0	0
2	38	2	215646	1	9	2	2	0	0	1	0	0	40	0	0
3	53	2	234721	2	7	1	2	1	1	1	0	0	40	0	0
4	28	2	338409	0	13	1	3	2	1	0	0	0	40	1	0

In [59]:
```python
for feature in ['final_weight', 'capital_gain']:
    plt.figure(figsize=(10, 5))
    sns.boxplot(df[feature])
    plt.show()
```



100000
80000
60000
40000
20000
0
capital_gain


1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
final_weight

In [60]:

```
df.describe()
```

Out[60]:

	age	workclass	final_weight	education	education_num	martial_status	occupation	relationship	race	sex	capital_gain	capital_loss	hrs_per_wee
count	30162.000000	30162.000000	3.016200e+04	30162.000000	30162.000000	30162.000000	30162.000000	30162.000000	30162.000000	30162.000000	30162.000000	30162.000000	30162.00000
mean	38.437902	2.109343	1.897938e+05	3.368842	10.121312	1.075061	4.615609	1.523971	0.211823	0.675685	1092.007858	88.372489	40.93123
std	13.134665	0.934785	1.056530e+05	3.404320	2.549995	1.217557	3.432195	1.431980	0.612461	0.468126	7406.346497	404.298370	11.97998
min	17.000000	0.000000	1.376900e+04	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.00000
25%	28.000000	2.000000	1.176272e+05	1.000000	9.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	40.00000
50%	37.000000	2.000000	1.784250e+05	2.000000	10.000000	1.000000	4.000000	1.000000	0.000000	1.000000	0.000000	0.000000	40.00000
75%	47.000000	2.000000	2.376285e+05	5.000000	13.000000	1.000000	8.000000	3.000000	0.000000	1.000000	0.000000	0.000000	45.00000
max	90.000000	6.000000	1.484705e+06	15.000000	16.000000	6.000000	13.000000	5.000000	4.000000	1.000000	99999.000000	4356.000000	99.00000

In [61]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [62]:
```python
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
```

In [63]:
```python
X = X.values
y = y.values

sc = StandardScaler()
sc.fit_transform(X)
```

Out[63]:
```
array([[ 0.04279571, -2.25653747, -1.0627216 , ..., -0.21858598,
        -0.07773411, -0.23923831],
       [ 0.88028814, -1.18675527, -1.00787131, ..., -0.21858598,
        -2.3315307 , -0.23923831],
       [-0.03333996, -0.11697307,  0.24469349, ..., -0.21858598,
        -0.07773411, -0.23923831],
       ...,
       [ 1.48937355, -0.11697307, -0.3585745 , ..., -0.21858598,
        -0.07773411, -0.23923831],
       [-1.25151078, -0.11697307,  0.11070545, ..., -0.21858598,
        -1.74721307, -0.23923831],
       [ 1.0325595 ,  3.09237353,  0.92884082, ..., -0.21858598,
        -0.07773411, -0.23923831]])
```

In [64]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [65]:
```python
from sklearn.linear_model import LogisticRegression
```

In [66]:
```python
lg = LogisticRegression()
```

In [67]:
```python
lg.fit(X_train, y_train)
```

```
C:\Users\amiglani\AppData\Local\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[67]:
```
▾ LogisticRegression
LogisticRegression()
```

In [68]:
```python
pred = lg.predict(X_test)
```

In [69]:
```python
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

In [70]:
```python
print("--------------------------------------------Classification Report---------------------------------------------")
print(classification_report(y_test, pred))

print("------------------------------------------Accuracy Score----------------------------------------------------------")
print(accuracy_score(y_test, pred))

print("--------------------------------------------Confustion Matrix----------------------------------------------------")
plt.figure(figsize=(10,5))
```

```
sns.heatmap(confusion_matrix(y_test, pred), annot=True);
```

```
--------------------------------------------Classification Report--------------------------------------------
              precision    recall  f1-score   support

           0       0.79      0.97      0.87      6767
           1       0.70      0.23      0.35      2282

    accuracy                           0.78      9049
   macro avg       0.74      0.60      0.61      9049
weighted avg       0.77      0.78      0.74      9049

------------------------------------------Accuracy Score--------------------------------------------------------
0.780970272958338
--------------------------------------------Confustion Matrix--------------------------------------------------
```

In [72]:

```
from sklearn.metrics import accuracy_score

# Fit a basic model and check accuracy
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)

# Evaluate on training and test sets
train_accuracy = accuracy_score(y_train, model.predict(X_train))
test_accuracy = accuracy_score(y_test, model.predict(X_test))

print(f"Training Accuracy: {train_accuracy}")
print(f"Test Accuracy: {test_accuracy}")
```

```
Training Accuracy: 1.0
Test Accuracy: 0.8060559177809703
```

In [74]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

models = {
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "SVM": SVC(),
    "XGBoost": XGBClassifier()
}

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"{name} Accuracy: {accuracy}")
```

```
Decision Tree Accuracy: 0.8081555973035695
Random Forest Accuracy: 0.8541275279036358
SVM Accuracy: 0.7810807824068958
XGBoost Accuracy: 0.8697093601502929
```

In [82]:

```
from sklearn.model_selection import cross_val_score
```

```python
from sklearn.ensemble import RandomForestClassifier

# Initialize the RandomForestClassifier
rf_classifier = RandomForestClassifier()

# Perform cross-validation
cv_scores = cross_val_score(rf_classifier, X_train, y_train, cv=5)

# Output the results
print(f'Cross-validation scores: {cv_scores}')
print(f'Mean CV score: {cv_scores.mean()}')
```

```
Cross-validation scores: [0.85578972 0.8598153  0.84915937 0.85054477 0.85315017]
Mean CV score: 0.8536918633640213
```

In [ ]:

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