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

from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from sklearn.naive_bayes import GaussianNB

df = pd.read_csv('adult_dataset.csv')

df.head()
```

```
   age  workclass  fnlwgt     education  educational-num      marital-
status  \
0   25    Private  226802          11th                7       Never-
married
1   38    Private   89814       HS-grad                9  Married-civ-
spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-
spouse
3   44    Private  160323  Some-college               10  Married-civ-
spouse
4   18          ?  103497  Some-college               10       Never-
married

          occupation relationship   race  gender  capital-gain
capital-loss  \
0  Machine-op-inspct    Own-child  Black    Male             0
0
1    Farming-fishing      Husband  White    Male             0
0
2    Protective-serv      Husband  White    Male             0
0
3  Machine-op-inspct      Husband  Black    Male          7688
0
4                  ?    Own-child  White  Female             0
0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K
```

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

```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

```
df.replace('?', pd.NA, inplace=True)
```

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

```
age                   0
workclass          2799
fnlwgt                0
education             0
educational-num       0
marital-status        0
occupation         2809
relationship          0
race                  0
gender                0
capital-gain          0
capital-loss          0
hours-per-week        0
native-country      857
income                0
dtype: int64
```

```
df.dropna(inplace=True)
```

```
df.shape
```

```
(45222, 15)
```

```
df = df[df['age'] >= 0]
df = df[df['fnlwgt'] >= 0]
df = df[df['capital-gain'] >= 0]
df = df[df['capital-loss'] >= 0]
df = df[df['hours-per-week'] >= 0]
```

```
df.shape
```

```
(45222, 15)
```

```
print(df['income'].unique())
```

```
['<=50K' '>50K']
```

```
def remove_outliers(df, cols):
    for col in cols:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
    return df

# Remove outliers from numeric columns
numeric_cols = ['age', 'fnlwgt', 'capital-gain', 'capital-loss',
'hours-per-week']
df = remove_outliers(df, numeric_cols)
```

```
df.shape
```

```
(27897, 15)
```

```
print(df['income'].unique())
```

```
['<=50K' '>50K']
```

```
df = pd.get_dummies(df, columns=['workclass', 'education', 'marital-
status',
                                 'occupation', 'relationship', 'race',

                                 'gender', 'native-country'],
drop_first=True)
```

```
print(df['income'].unique())
```

```
['<=50K' '>50K']
```

```
df['income'] = df['income'].apply(lambda x: 1 if x == '>50K' else (0
if x == '<=50K' else x))

# Check if the transformation worked properly
print(df['income'].unique())
print(df['income'].value_counts())
```

```
[0 1]
income
0    22041
1     5856
Name: count, dtype: int64
```

```
scaler = StandardScaler()
df[numeric_cols] = scaler.fit_transform(df[numeric_cols])

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

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

lr_model = LogisticRegression(max_iter=500)
lr_model.fit(X_train, y_train)

# Predictions
y_pred_lr = lr_model.predict(X_test)

# Accuracy
accuracy_lr = accuracy_score(y_test, y_pred_lr)
print(f'Logistic Regression Accuracy: {accuracy_lr:.4f}')
```

```
Logistic Regression Accuracy: 0.8444
```

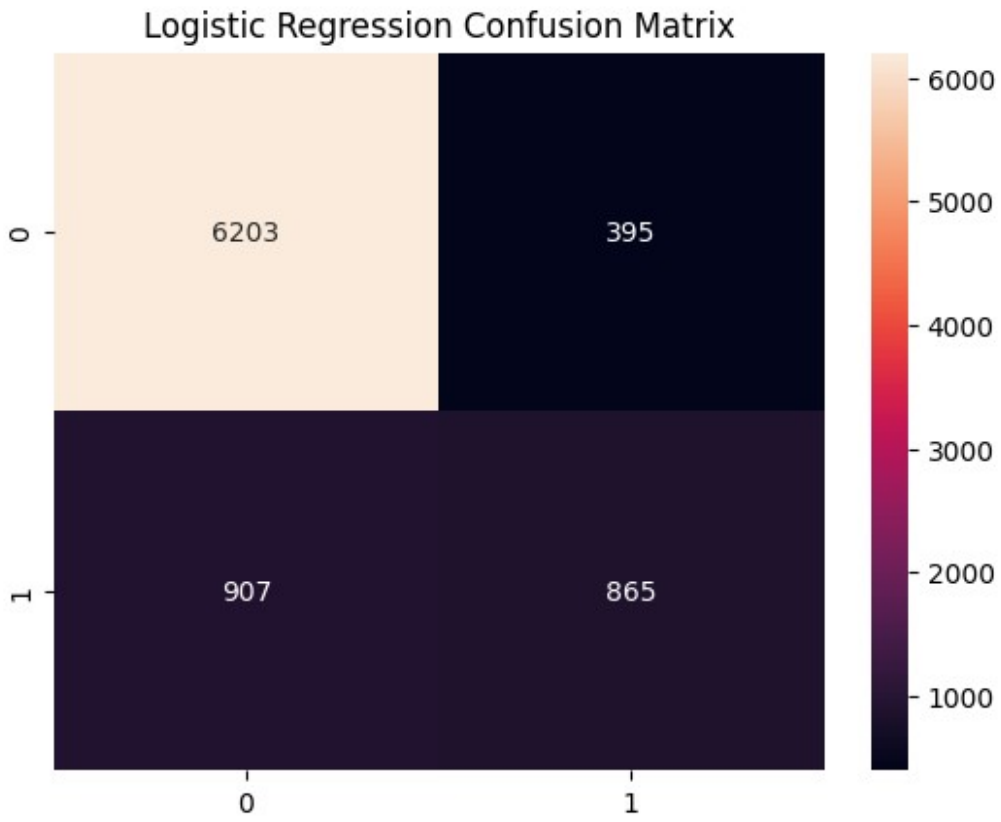
```
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

# Predictions
y_pred_nb = nb_model.predict(X_test)

# Accuracy
accuracy_nb = accuracy_score(y_test, y_pred_nb)
print(f'Naive Bayes Accuracy: {accuracy_nb:.4f}')
```

```
Naive Bayes Accuracy: 0.5219
```

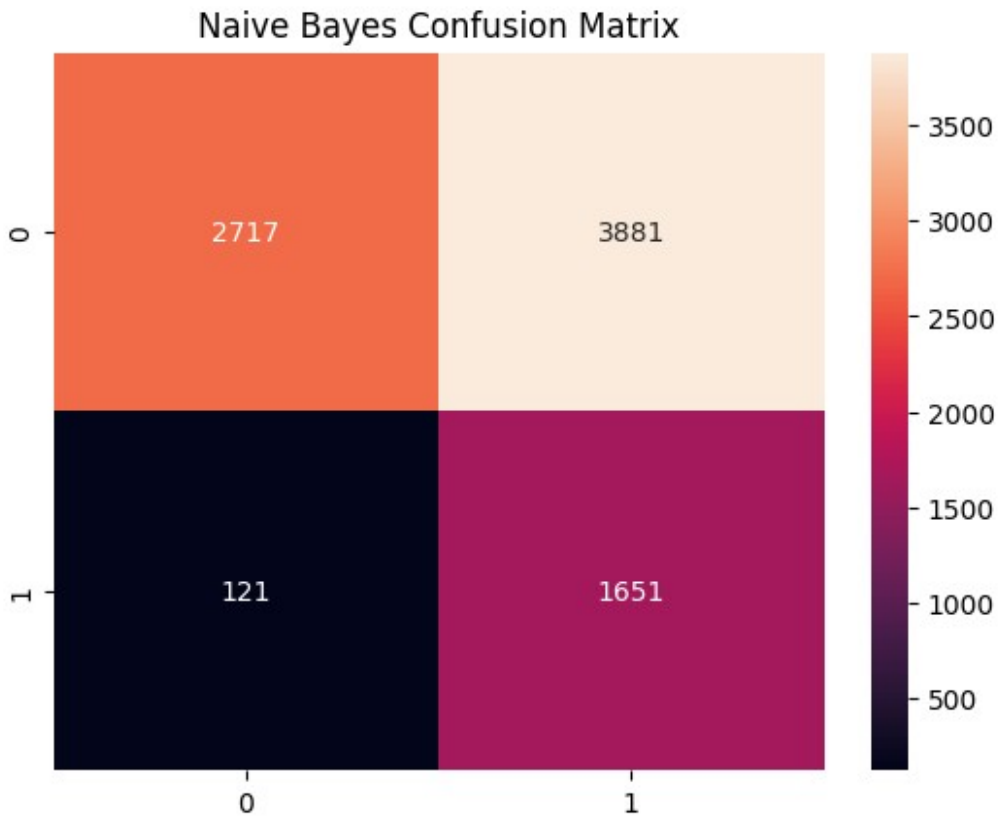
```
print(f'Logistic Regression Accuracy: {accuracy_lr:.4f}')
print(f'Naive Bayes Accuracy: {accuracy_nb:.4f}')
```

```
Logistic Regression Accuracy: 0.8444
Naive Bayes Accuracy: 0.5219
```

```
sns.heatmap(confusion_matrix(y_test, y_pred_lr), annot=True, fmt='d')
plt.title("Logistic Regression Confusion Matrix")
plt.show()
```




```
sns.heatmap(confusion_matrix(y_test, y_pred_nb), annot=True, fmt='d')
plt.title("Naive Bayes Confusion Matrix")
plt.show()
```


Naive Bayes Confusion Matrix
2717
3881
121
1651
0
1
0
1
3500
3000
2500
2000
1500
1000
500