Import necessary libraries

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
```

Load the dataset

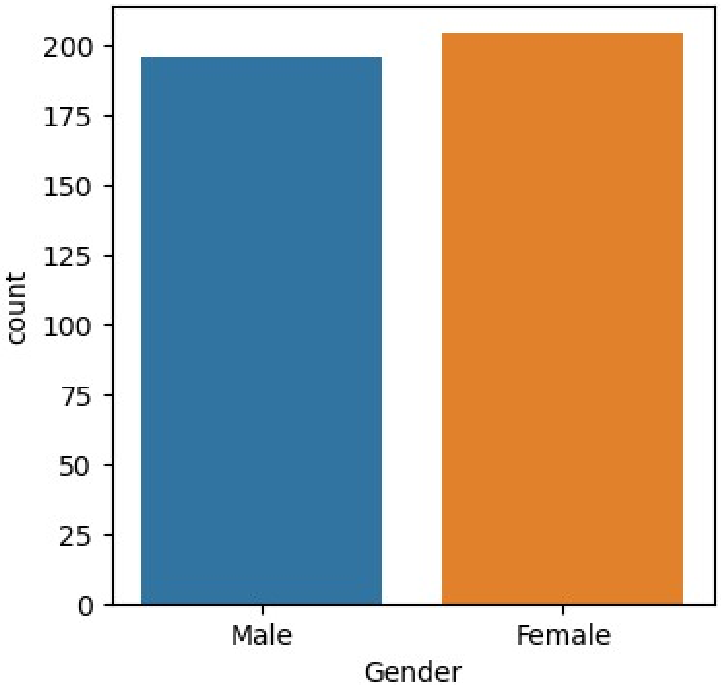
```
# Assuming the dataset is in a CSV file named 'Social_Network_Ads.csv'
df = pd.read_csv('Social_Network_Ads.csv')
```

Dataset Visualization

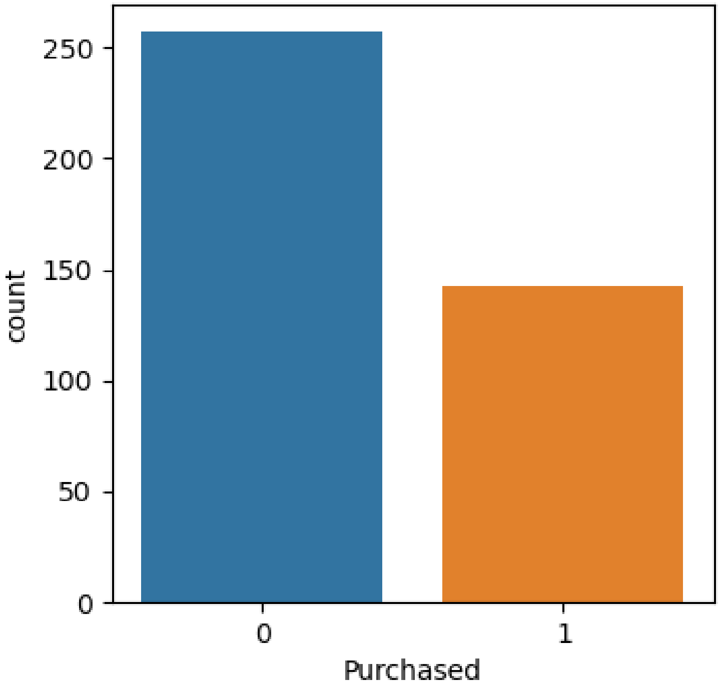
```
df.head()

    User ID  Gender  Age  EstimatedSalary  Purchased
0  15624510    Male   19            19000          0
1  15810944    Male   35            20000          0
2  15668575  Female   26            43000          0
3  15603246  Female   27            57000          0
4  15804002    Male   19            76000          0

df.shape

(400, 5)
```

EDA

```
ax = plt.subplots(figsize = (4,4))
ax = sns.countplot(x=df['Gender'])
plt.show()
```



```
ax = plt.subplots(figsize = (4,4))
ax = sns.countplot(x=df['Purchased'])
plt.show()
```



Feature Extraction

```
# Separate features (X) and target variable (y)
X = df.iloc[:, [1, 2, 3]].values  # Considering Gender, Age, and
Estimated Salary as features
y = df.iloc[:, 4].values  # Assuming 'Purchased' is the target
variable
```

Use LabelEncoder for 'Gender' as 'Gender' is non-numeric

```
label_encoder = LabelEncoder()
X[:, 0] = label_encoder.fit_transform(X[:, 0])
```

Split the dataset into training and testing sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Feature scaling

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Create a Gaussian Naive Bayes classifier

```
g_nb_classifier = GaussianNB()
```

Fit the model to the training data

```
g_nb_classifier.fit(X_train, y_train)
```

```
GaussianNB()
```

Make predictions on the test set

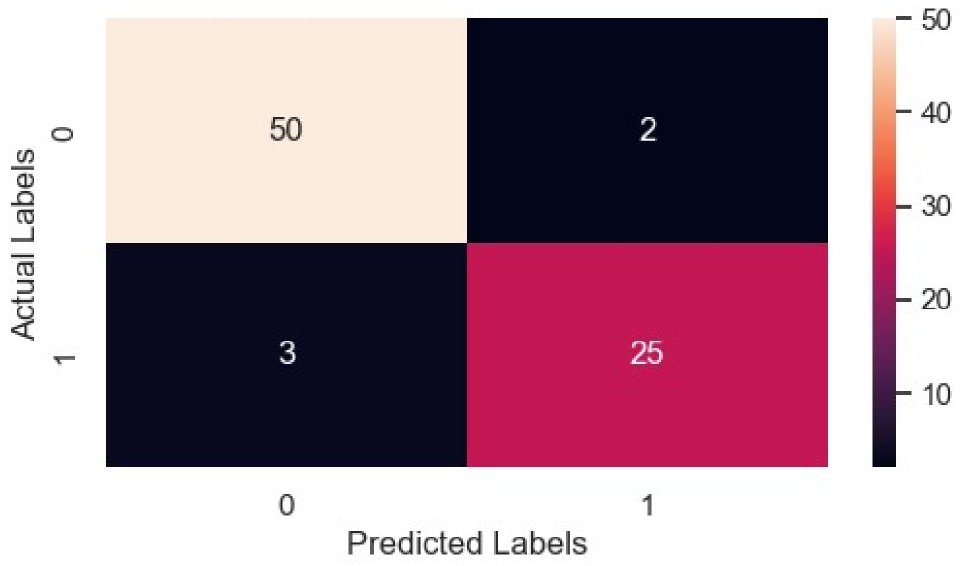
```
y_pred = g_nb_classifier.predict(X_test)
```

Evaluate the performance of the classifier

```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_report_str = classification_report(y_test, y_pred)
```

Print the results

```
print(f'Gaussian NB Accuracy: {accuracy}')
print(f'Gaussian NB Confusion Matrix:\n{conf_matrix}')
sns.set(rc={'figure.figsize':(6,3)})
sns.heatmap(confusion_matrix(y_test,y_pred),annot = True,fmt = 'd')
plt.xlabel('Predicted Labels')
plt.ylabel('Actual Labels')
print(f'Gaussian NB Classification Report:\
n{classification_report_str}')

Gaussian NB Accuracy: 0.9375
Gaussian NB Confusion Matrix:
[[50  2]
 [ 3 25]]
Gaussian NB Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.96      0.95        52
           1       0.93      0.89      0.91        28

    accuracy                           0.94        80
   macro avg       0.93      0.93      0.93        80
weighted avg       0.94      0.94      0.94        80
```

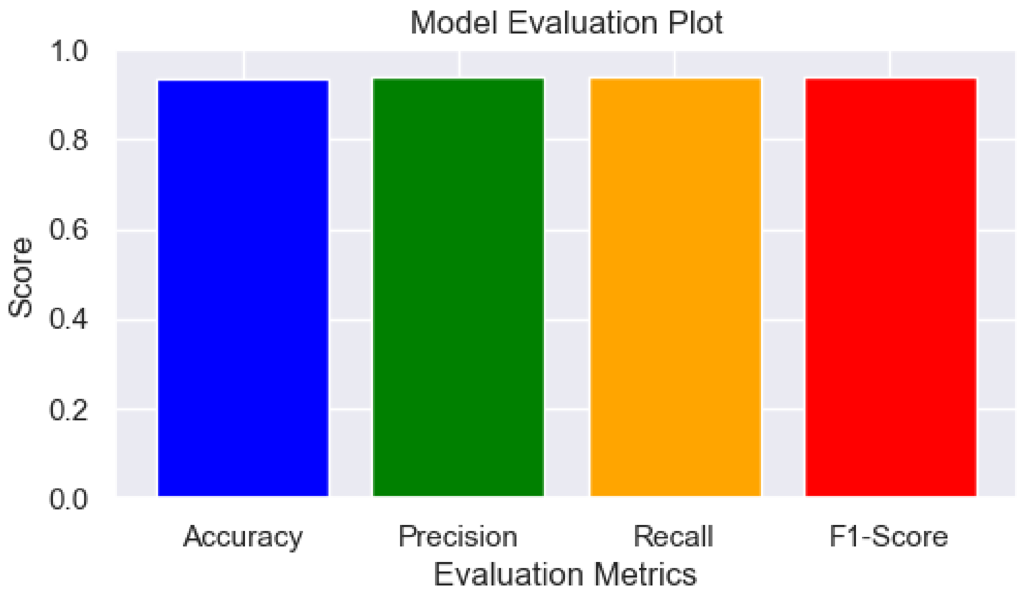


Predict whether a targeted audience or person will purchase the product or not

```
# Assuming we have a new set of feature values for prediction
new_data = np.array([[0, 30, 50000]])  # Example: Gender (0 for
Female, 1 for Male), Age, Estimated Salary

# Use the trained Gaussian NB model to make predictions
predicted_purchase = g_nb_classifier.predict(new_data)

# Print the predicted outcome
if predicted_purchase[0] == 1:
    print("The targeted audience is predicted to purchase the
product.")
else:
    print("The targeted audience is predicted not to purchase the
product.")

The targeted audience is predicted to purchase the product.
```

Output Visualization using Bar Plot

```
# Assuming we have already evaluated the model and obtained these
metrics, hence plotting the same in a bar plot
accuracy = 0.9375
precision = 0.94
recall = 0.94
f1_score = 0.94

# Plotting the bar plot
metrics_names = ['Accuracy', 'Precision', 'Recall', 'F1-Score']
metrics_values = [accuracy, precision, recall, f1_score]

plt.bar(metrics_names, metrics_values, color=['blue', 'green',
'orange', 'red'])
plt.ylim([0, 1])  # Set the y-axis limit between 0 and 1
plt.title('Model Evaluation Plot')
plt.xlabel('Evaluation Metrics')
plt.ylabel('Score')
plt.show()
```



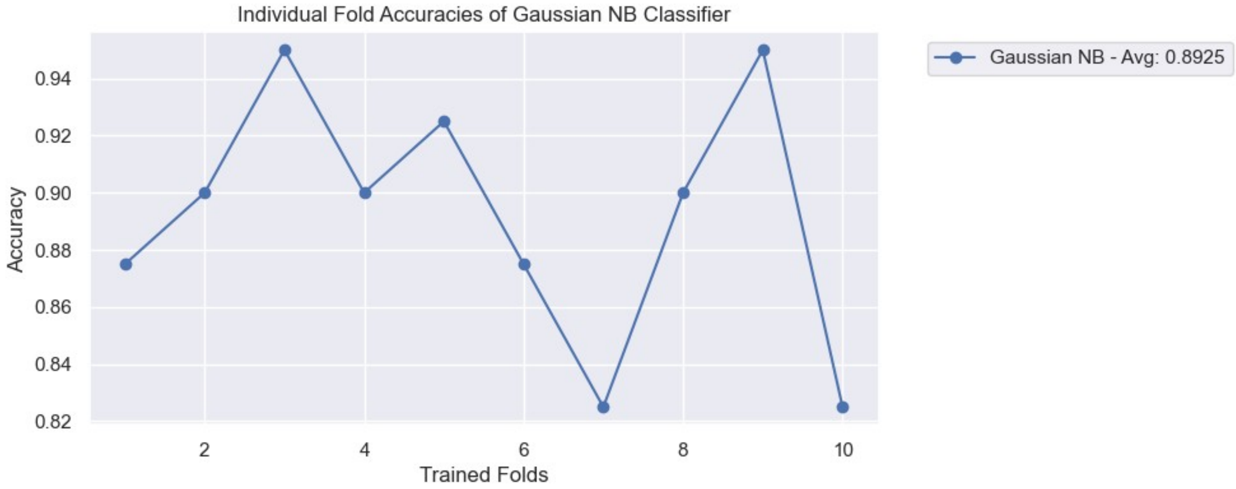
10-fold Cross-Validation

```python
from sklearn.model_selection import cross_val_score, StratifiedKFold
from sklearn.metrics import make_scorer

# Define stratified 10-fold cross-validation
cross_val = StratifiedKFold(n_splits=10, shuffle=True,
random_state=42)

# Define accuracy as the evaluation metric
scoring = make_scorer(accuracy_score)

# Perform cross-validation on Gaussian NB
cv_results = cross_val_score(g_nb_classifier, X, y, cv=cross_val,
scoring=scoring)

# Display results
print("Cross-Validation Results:")
print("Individual Accuracies:", cv_results)
print("Average Accuracy:", np.mean(cv_results))
```

```
Cross-Validation Results:
Individual Accuracies: [0.875 0.9   0.95  0.9   0.925 0.875 0.825 0.9
0.95  0.825]
Average Accuracy: 0.8924999999999998
```

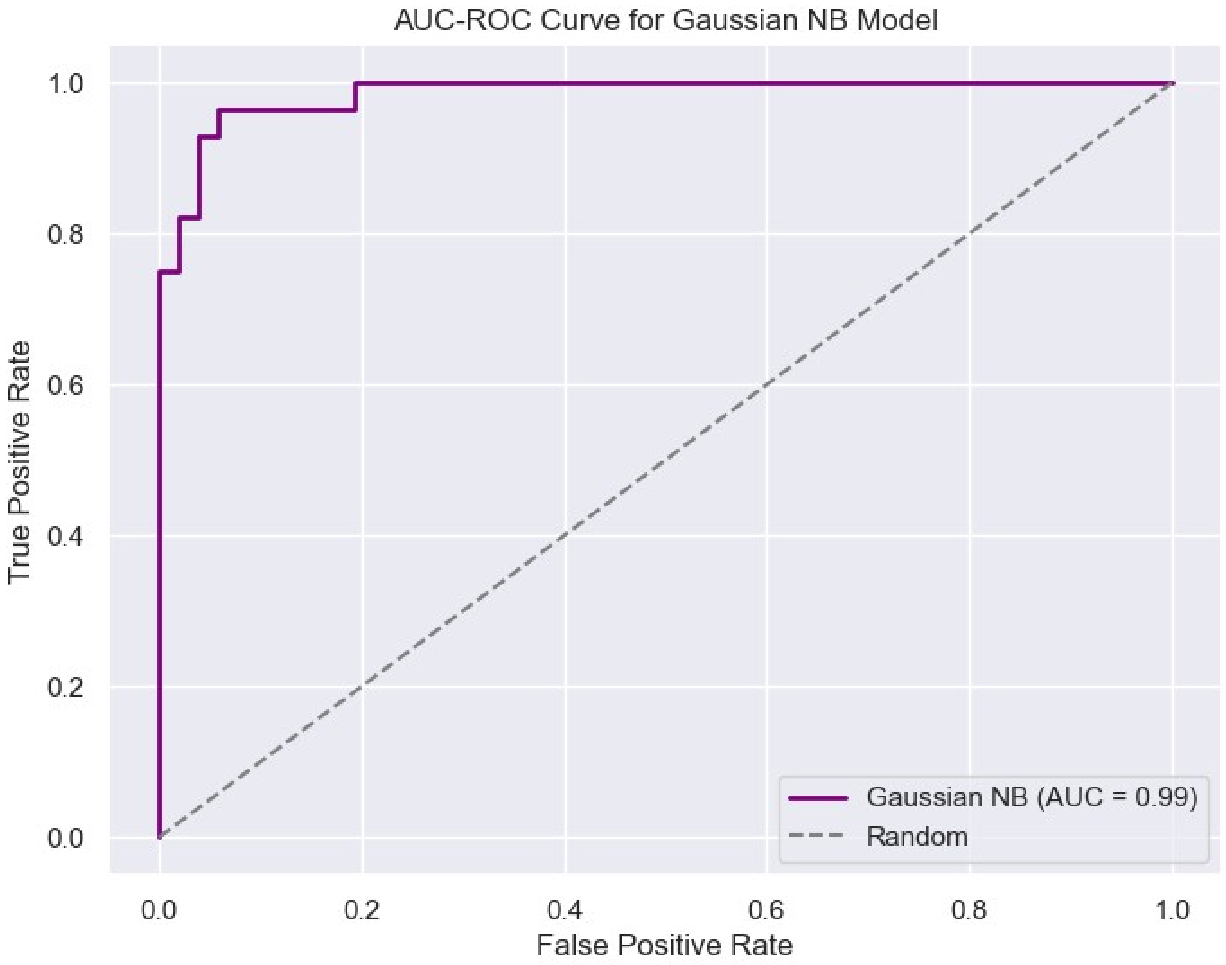
Cross-Validation Result Visualization using Bar Plot

```python
# Cross-Validation Result
model = ['Gaussian NB']
accuracies = {
    'Gaussian NB': [0.875, 0.9, 0.95, 0.9, 0.925, 0.875, 0.825, 0.9,
0.95, 0.825],
}

# Plotting
plt.figure(figsize=(8, 4))

for model in model:
    plt.plot(range(1, 11), accuracies[model], marker='o',
label=f'{model} - Avg: {sum(accuracies[model])/10:.4f}')

plt.title('Individual Fold Accuracies of Gaussian NB Classifier')
plt.xlabel('Trained Folds')
plt.ylabel('Accuracy')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')  # Placing the
legend outside the plot area
plt.show()
```



ROC Curve Plotting for the above Gaussian NB Model

```
from sklearn.metrics import roc_curve, auc

# Assuming y_test is the actual labels
label_encoder = LabelEncoder()
y_test_binary = label_encoder.fit_transform(y_test)

# Get predicted probabilities for the positive class
g_nb_predicted_scores = g_nb_classifier.predict_proba(X_test)[:, 1]

# Compute ROC curve and AUC for Gaussian NB model
g_nb_fpr, g_nb_tpr, _ = roc_curve(y_test_binary,
g_nb_predicted_scores)

# Compute AUC for Gaussian NB model
g_nb_roc_auc = auc(g_nb_fpr, g_nb_tpr)

# Plot ROC curve for Gaussian NB model
plt.figure(figsize=(8, 6))
sns.set(style='darkgrid')

plt.plot(g_nb_fpr, g_nb_tpr, color='purple', lw=2, label=f'Gaussian NB
(AUC = {g_nb_roc_auc:.2f})')

plt.plot([0, 1], [0, 1], linestyle='--', color='gray', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('AUC-ROC Curve for Gaussian NB Model')
plt.legend(loc='lower right')
plt.show()
```


AUC-ROC Curve for Gaussian NB Model
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
Gaussian NB (AUC = 0.99)
Random