** Customer Segmentation Analysis**

1. problem statement

Customer segmentation is the problem of uncovering information about a firm's customer base, based on their interactions with the business.In most cases this interaction is in terms of their purchase behaviour and patterns. We explore some of the ways in which this can be used.

You own the mall and want to understand the customers like who can be easily converge(Target Customers)so that the sense can be given to marketing team and plan the strategy accordingly.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
import xgboost as xgb
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.preprocessing import LabelEncoder, StandardScaler
from yellowbrick.cluster import KElbowVisualizer
from yellowbrick.classifier import ConfusionMatrix,
ClassificationReport
import warnings
# Ignore warnings
warnings.filterwarnings("ignore")

df = pd.read_csv("Mall_Customers.csv")
df
```

```
     CustomerID   Genre  Age  Annual Income (k$)  Spending Score (1-
100)
0             1    Male   19                  15
39
1             2    Male   21                  15
81
2             3  Female   20                  16
6
3             4  Female   23                  16
77
4             5  Female   31                  17
40
..          ...     ...  ...                 ...                    .
..
195         196  Female   35                 120
```

```
79
196         197  Female   45                  126
28
197         198    Male   32                  126
74
198         199    Male   32                  137
18
199         200    Male   30                  137
83

[200 rows x 5 columns]
```

```
df.head()
```

```
   CustomerID   Genre  Age  Annual Income (k$)  Spending Score (1-100)
0           1    Male   19                  15                      39
1           2    Male   21                  15                      81
2           3  Female   20                  16                       6
3           4  Female   23                  16                      77
4           5  Female   31                  17                      40
```

```
df.shape
```

```
(200, 5)
```

```
df.describe()
```

```
       CustomerID         Age  Annual Income (k$)  Spending Score (1-
100)
count  200.000000  200.000000          200.000000
200.000000
mean   100.500000   38.850000           60.560000
50.200000
std     57.879185   13.969007           26.264721
25.823522
min      1.000000   18.000000           15.000000
1.000000
25%     50.750000   28.750000           41.500000
34.750000
50%    100.500000   36.000000           61.500000
50.000000
75%    150.250000   49.000000           78.000000
73.000000
max    200.000000   70.000000          137.000000
99.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
```

```
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Genre                   200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

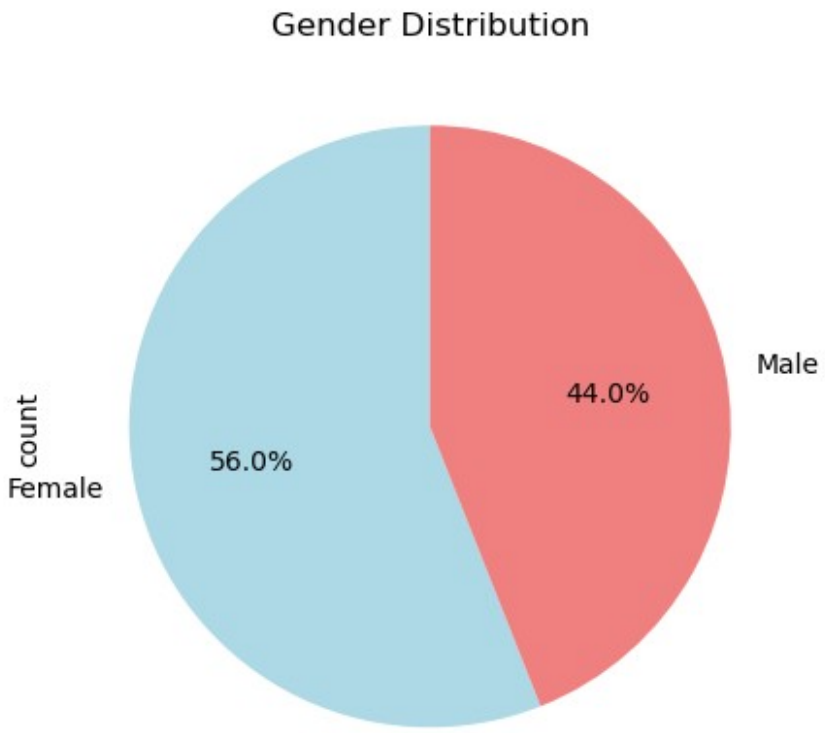
```
df.isnull().sum()
```

```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

```
df.columns
```

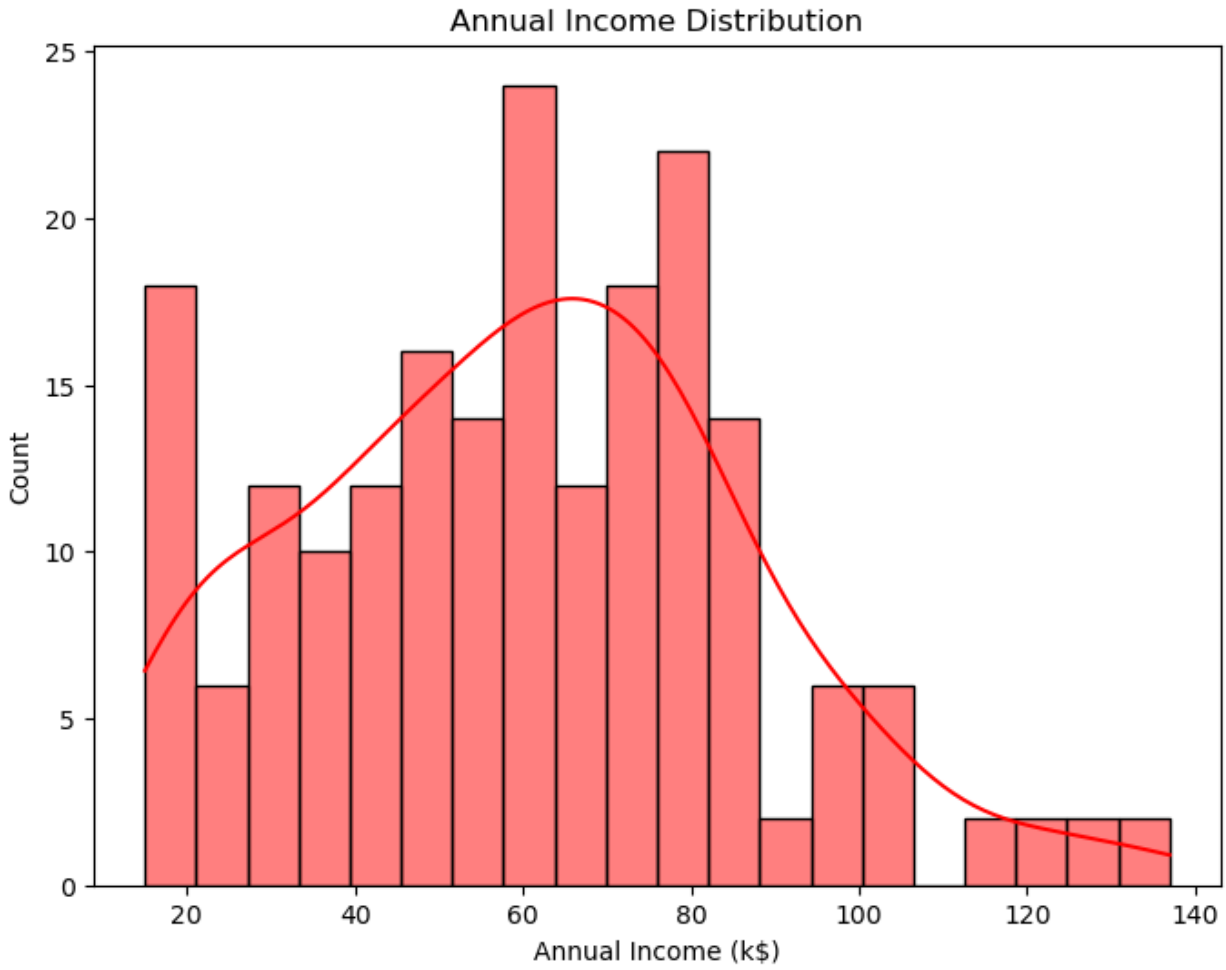
```
Index(['CustomerID', 'Genre', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

```
plt.figure(figsize=(5, 6))
df['Genre'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90,
colors=['lightblue', 'lightcoral'])
plt.title('Gender Distribution')
plt.show()
```

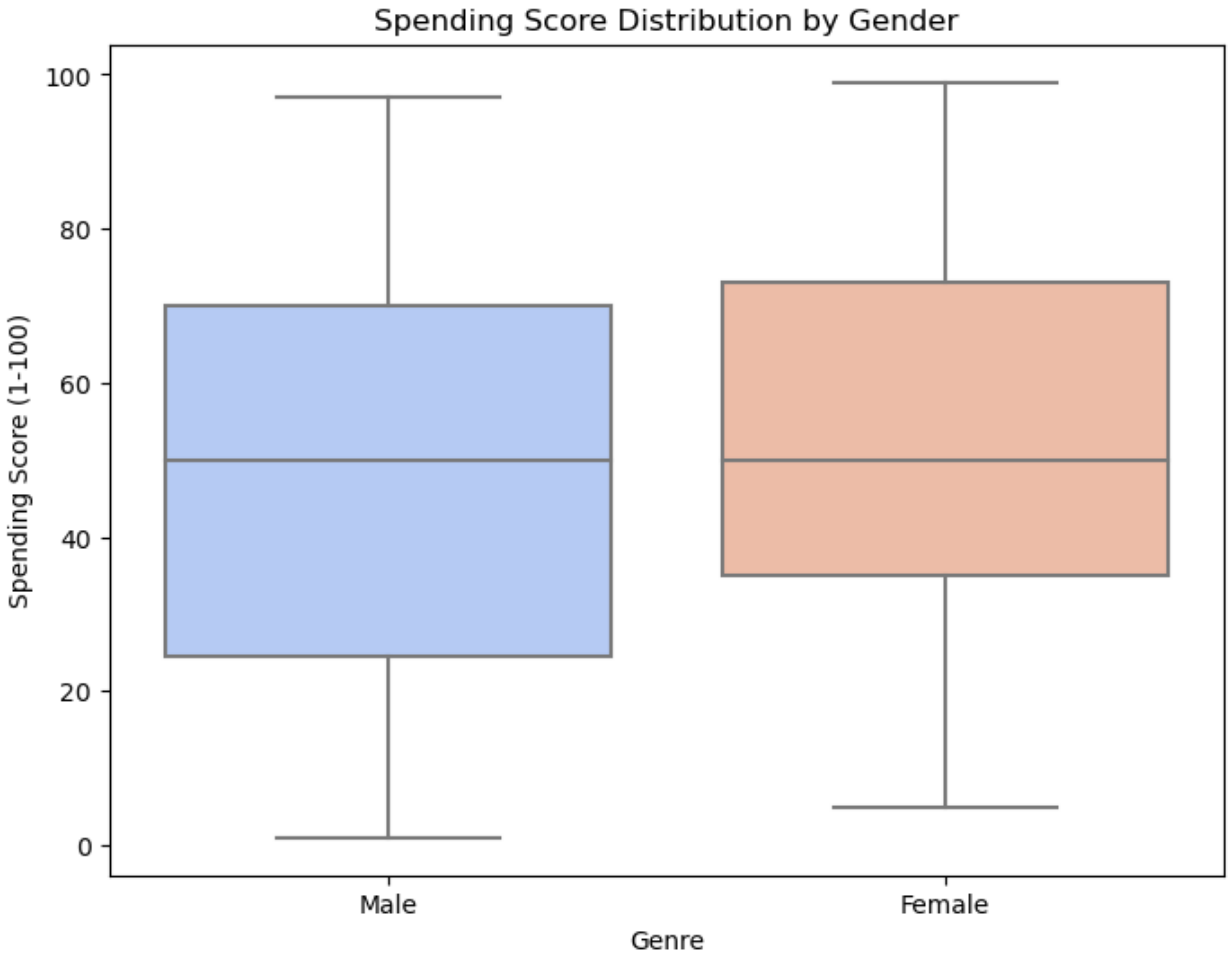



```
plt.figure(figsize=(8, 6))
sns.violinplot(x='Genre', y='Age', data=df, palette='pastel')
plt.title('Age Distribution by Gender')
plt.show()
```


```
plt.figure(figsize=(8, 6))
sns.histplot(df['Annual Income (k$)'], bins=20, kde=True, color='red')
plt.title('Annual Income Distribution')
plt.xlabel('Annual Income (k$)')
plt.show()
```



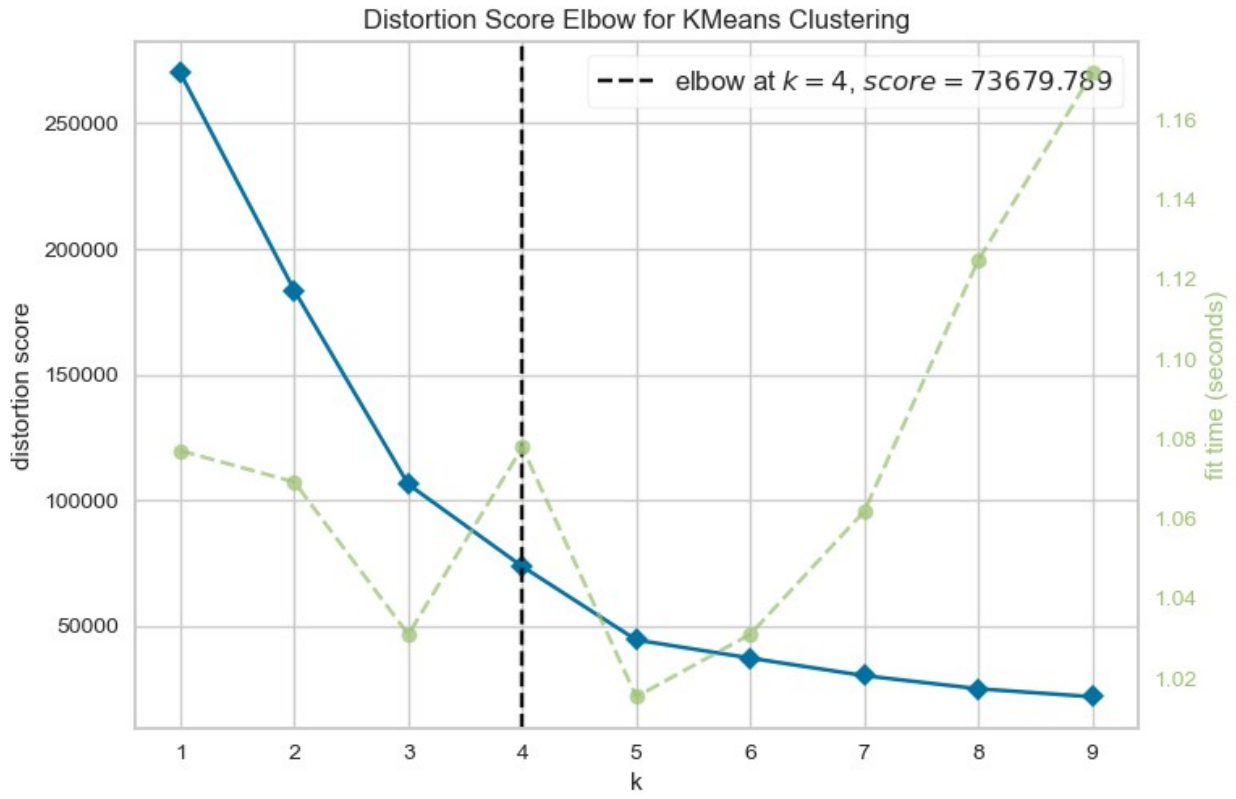

```
plt.figure(figsize=(8, 6))
sns.boxplot(x='Genre', y='Spending Score (1-100)', data=df,
palette='coolwarm')
plt.title('Spending Score Distribution by Gender')
plt.show()
```



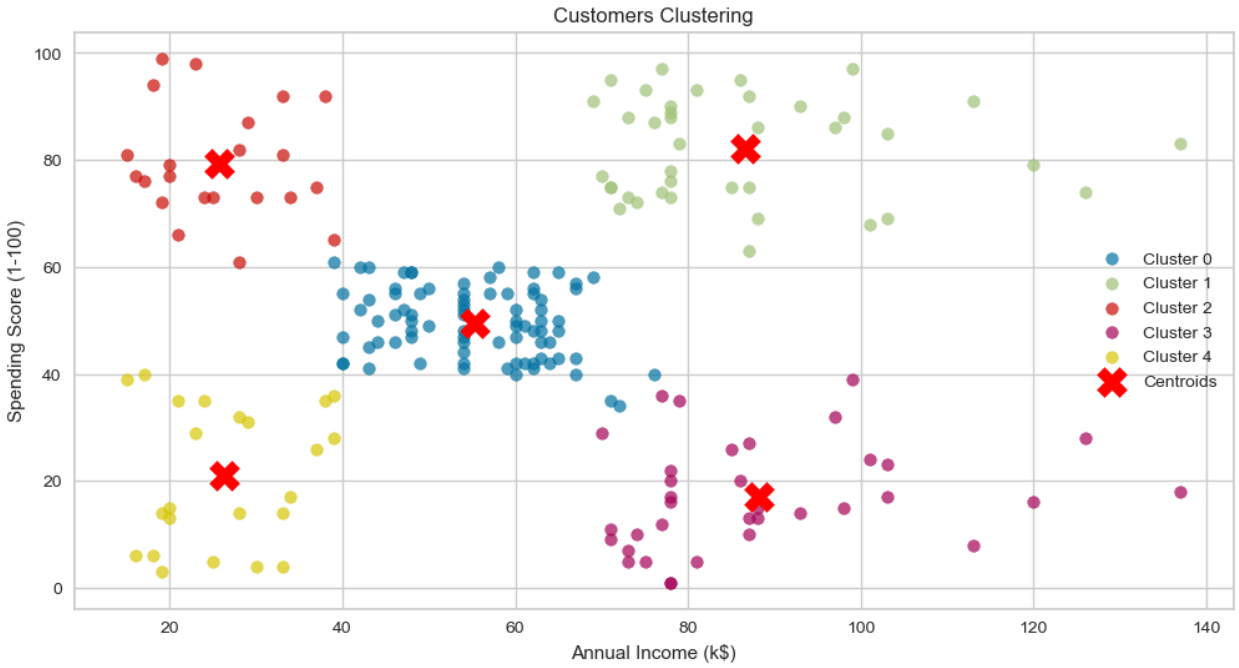

```
duplicates = df.duplicated().sum()
print("Number of Duplicates:", duplicates)

Number of Duplicates: 0
```

Perform K-means Clustering

```
X = df[['Annual Income (k$)', 'Spending Score (1-100)']]
visualizer = KElbowVisualizer(KMeans(), k=(1, 10))
visualizer.fit(X)
visualizer.show()
```




```
<Axes: title={'center': 'Distortion Score Elbow for KMeans
Clustering'}, xlabel='k', ylabel='distortion score'>

k_clusters = 5
km = KMeans(n_clusters=k_clusters, random_state=42)
df['Clusters'] = km.fit_predict(X)

plt.figure(figsize=(12, 6))
for cluster in range(k_clusters):
    plt.scatter(X[df['Clusters'] == cluster]['Annual Income (k$)'],
                X[df['Clusters'] == cluster]['Spending Score (1-
100)'],
                label=f'Cluster {cluster}', alpha=0.7)

plt.scatter(km.cluster_centers_[:, 0], km.cluster_centers_[:, 1],
s=300, c='red', marker='X', label='Centroids')
plt.title('Customers Clustering')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



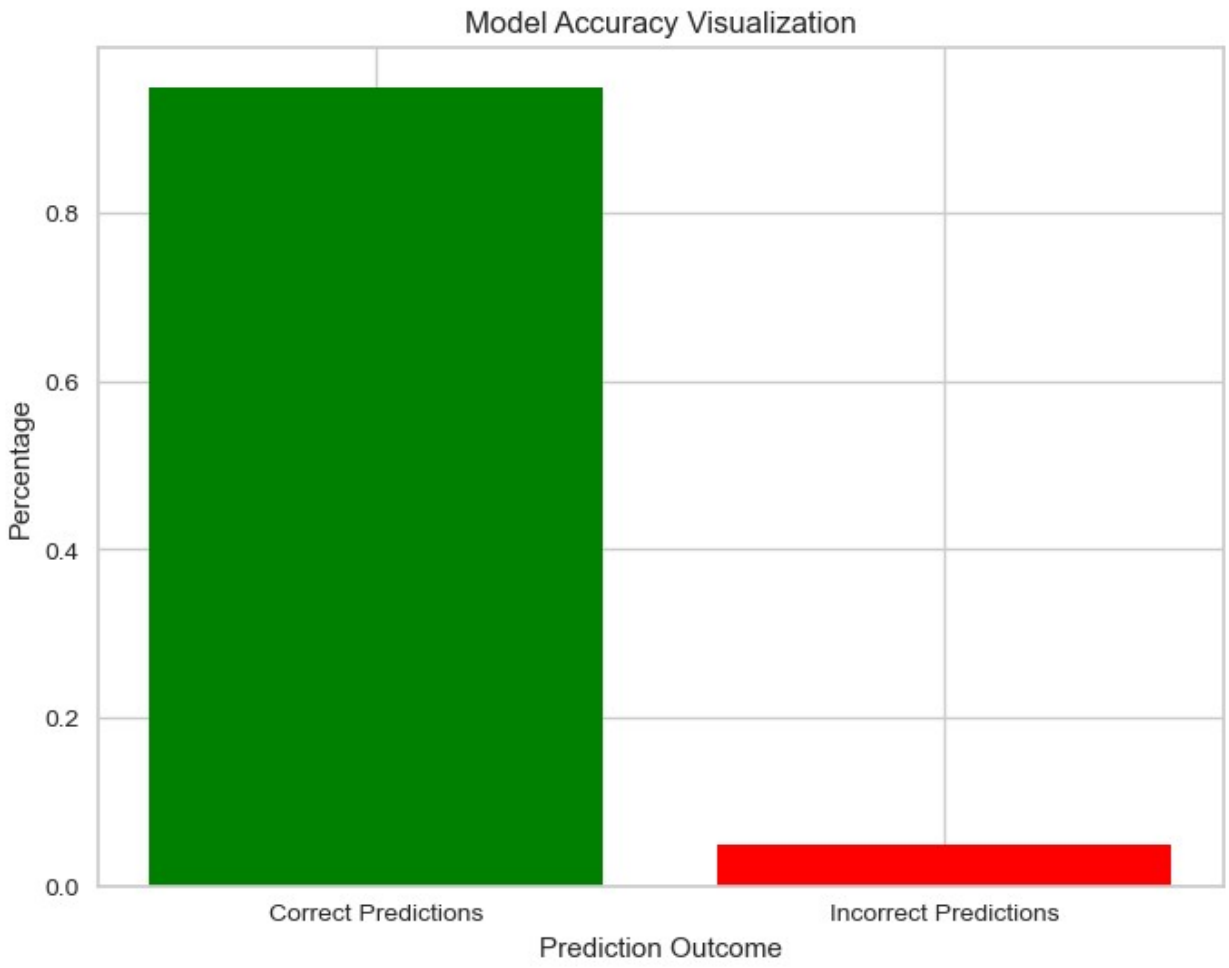
Model and Evaluation

```
X = df[['Genre', 'Age', 'Annual Income (k$)', 'Spending Score (1-
100)']]
y = df['Clusters']

LE = LabelEncoder()
X['Genre'] = LE.fit_transform(X['Genre'])

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

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

XGBoost model

```
model = xgb.XGBClassifier(objective='multi:softmax',
num_class=k_clusters, random_state=42)
model.fit(X_train, y_train)

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None,
early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None,
```

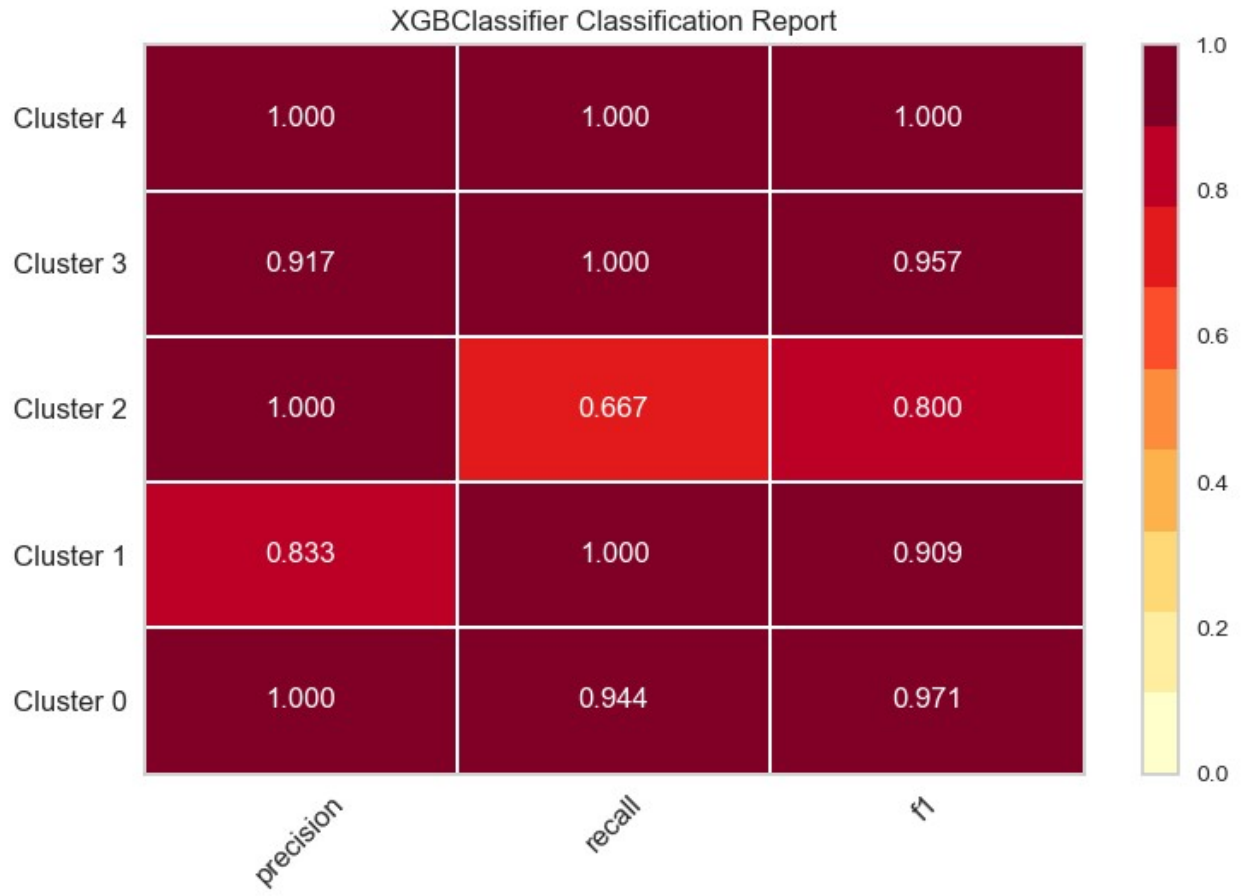
```
feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None,
max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan,
monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
num_class=5,
              num_parallel_tree=None, ...)

y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print(f'Accuracy: {accuracy * 100:.2f}%')

Accuracy: 95.00%

plt.figure(figsize=(8, 6))
accuracies = [accuracy, 1 - accuracy]  # Accuracy and error
labels = ['Correct Predictions', 'Incorrect Predictions']

plt.bar(labels, accuracies, color=['green', 'red'])
plt.title('Model Accuracy Visualization')
plt.xlabel('Prediction Outcome')
plt.ylabel('Percentage')
plt.show()
```




```
cm = confusion_matrix(y_test, y_pred)
cm
```

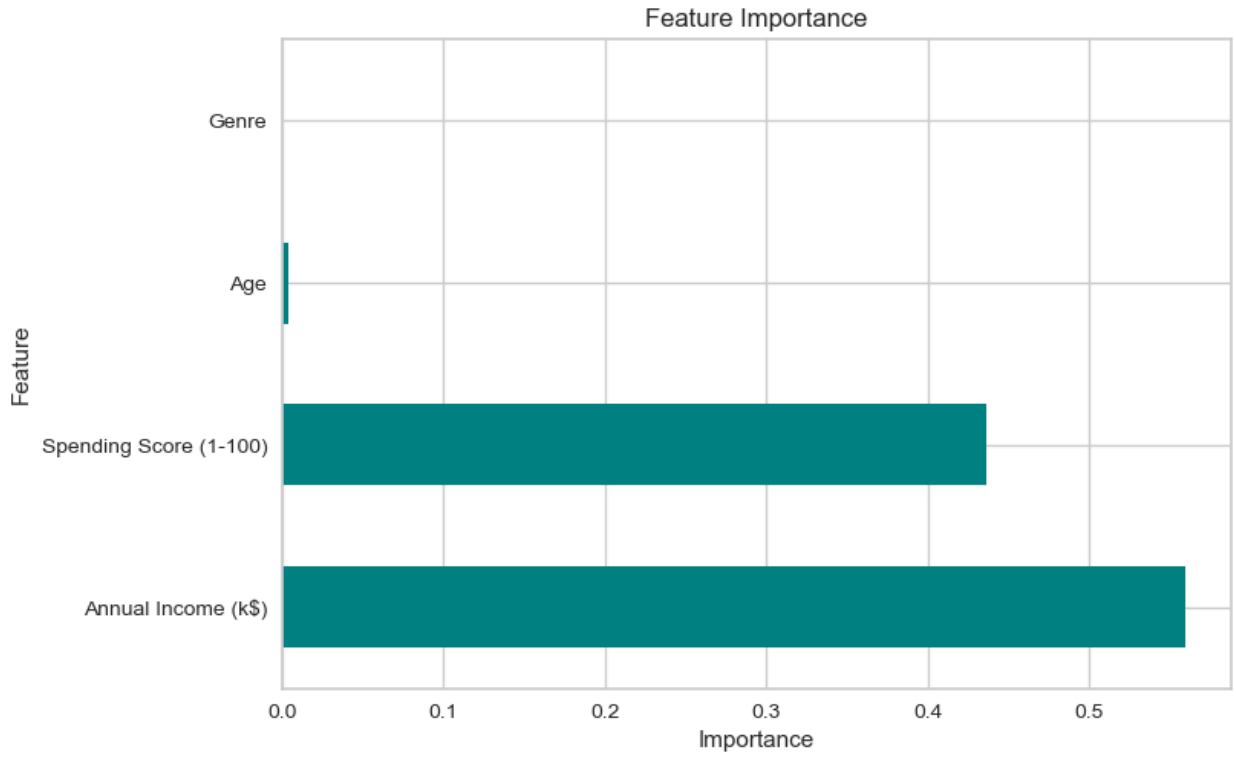
```
array([[17,  0,  0,  1,  0],
       [ 0,  5,  0,  0,  0],
       [ 0,  1,  2,  0,  0],
       [ 0,  0,  0, 11,  0],
       [ 0,  0,  0,  0,  3]], dtype=int64)
```

```
cr = ClassificationReport(model, classes=[f'Cluster {i}' for i in
range(k_clusters)])
cr.fit(X_train, y_train)
cr.score(X_test, y_test)
cr.show()
```




```
<Axes: title={'center': 'XGBClassifier Classification Report'}>
```

```
feature_importance = pd.Series(model.feature_importances_,
index=X.columns)
feature_importance.sort_values(ascending=False).plot(kind='barh',
color='teal')
plt.title('Feature Importance')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```


Feature Importance
Genre
Age
Spending Score (1-100)
Annual Income (k$)
Feature
0.0
0.1
0.2
0.3
0.4
0.5
Importance