A 4-Level Analysis of E-Commerce Consumer Behavior

1. **Descriptive Analysis:** KMeans Clustering for Customer Segmentation
2. **Diagnostic Analysis:** Explaining Customer Satisfaction
3. **Predictive Analysis:** Predicting Purchase Level of a Customer
4. **Prescriptive Analysis:** Recommending action based on Customer Satisfaction

```
from google.colab import files
file = files.upload()
```

Choose Files ecommerce dataset.csv

- **ecommerce dataset.csv**(text/csv) - 194153 bytes, last modified: 5/21/2025 - 100% done

Saving ecommerce dataset.csv to ecommerce dataset (1).csv

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

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, ConfusionMatrixDisplay
from sklearn.preprocessing import LabelEncoder
```

```
df = pd.read_csv('ecommerce dataset.csv')
df.head()
```

	Customer_ID	Age	Gender	Income_Level	Marital_Status	Education_Level	Occupation	Location	Purcha
0	37-611-6911	22	Female	Middle	Married	Bachelor's	Middle	Évry	
1	29-392-9296	49	Male	High	Married	High School	High	Huocheng	Fooc
2	84-649-5117	24	Female	Middle	Single	Master's	High	Huzhen	C
3	48-980-6078	29	Female	Middle	Single	Master's	Middle	Wiwilí	Hor
4	91-170-9072	33	Female	Middle	Widowed	High School	Middle	Nara	

5 rows × 28 columns

Data Cleaning

```
df['Purchase_Amount'] = df['Purchase_Amount'].replace('[\$,]', '', regex=True).astype(float)
```

1. Descriptive Analysis: KMeans Clustering for Customer Segmentation

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

Features Selection

```
features = [
    'Age', 'Purchase_Amount', 'Frequency_of_Purchase',
    'Brand_Loyalty', 'Product_Rating', 'Time_Spent_on_Product_Research(hours)',
    'Return_Rate', 'Customer_Satisfaction', 'Time_to_Decision'
]
X = df[features]
```

```
print("Missing values:\n", X.isnull().sum())
```

```
Missing values:
 Age                                     0
Purchase_Amount                         0
Frequency_of_Purchase                   0
Brand_Loyalty                           0
Product_Rating                          0
Time_Spent_on_Product_Research(hours)   0
Return_Rate                             0
Customer_Satisfaction                   0
Time_to_Decision                        0
dtype: int64
```

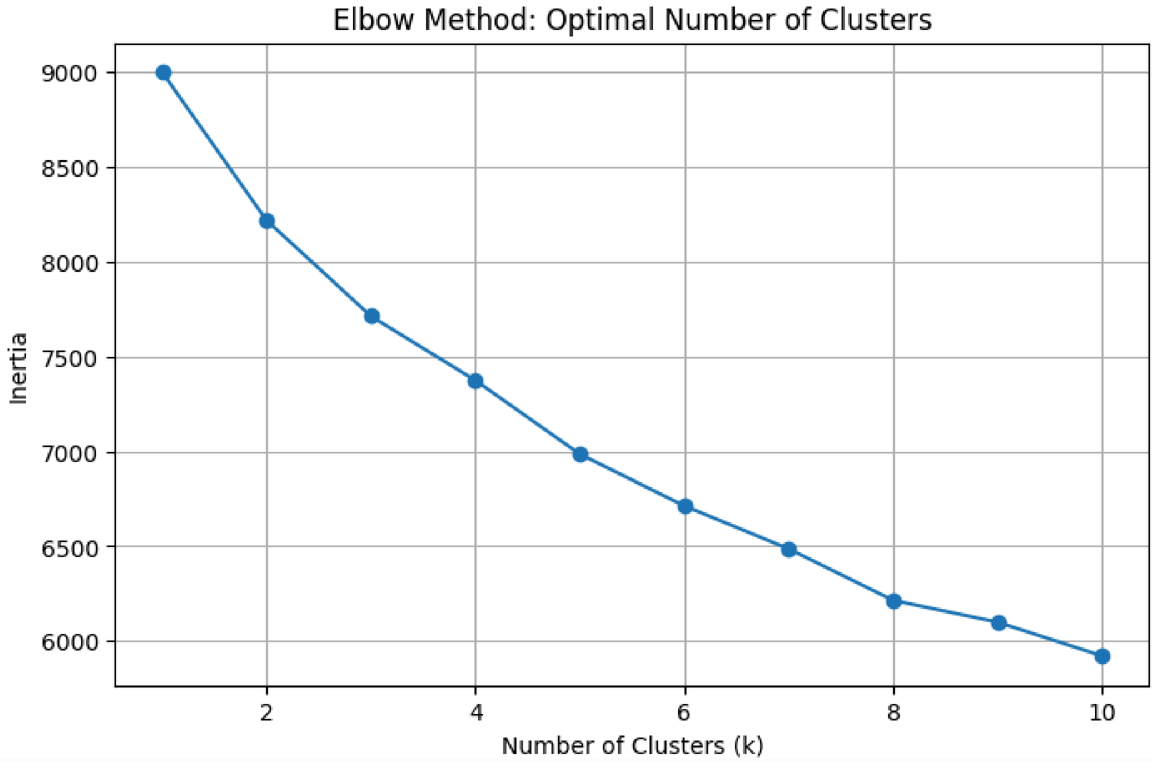
Feature Standardization

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Elbow Curve

```
inertia = []
k_range = range(1, 11)

for k in k_range:
    km = KMeans(n_clusters=k, random_state=42)
    km.fit(X_scaled)
    inertia.append(km.inertia_)
```

```
plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia, marker='o')
plt.title("Elbow Method: Optimal Number of Clusters")
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Inertia")
plt.grid(True)
plt.show()
```




```
kmeans = KMeans(n_clusters=4, random_state=42)
df['Customer_Segment'] = kmeans.fit_predict(X_scaled)
```

Cluster Characteristics

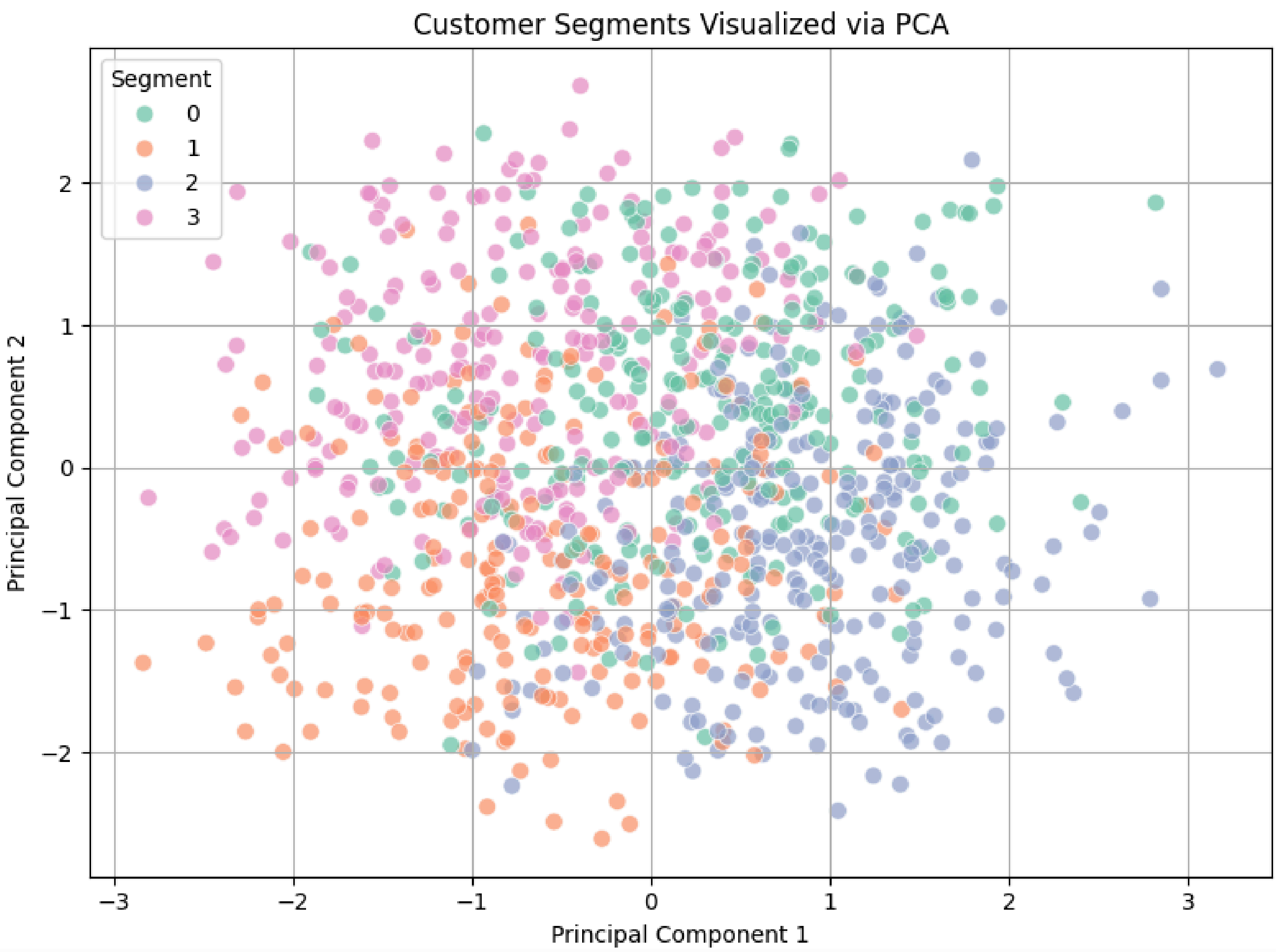
```
cluster_summary = df.groupby('Customer_Segment')[features].mean().round(2)
print("Cluster Summary:\n")
print(cluster_summary)
```

```
Cluster Summary:

                    Age  Purchase_Amount  Frequency_of_Purchase  \
Customer_Segment
0                 32.76           338.72                   5.05
1                 33.73           233.87                   9.80
2                 35.22           213.40                   5.30
3                 35.51           315.35                   8.19

                  Brand_Loyalty  Product_Rating  \
Customer_Segment
0                          3.10            3.13
1                          3.52            2.97
2                          3.26            3.72
3                          2.20            2.20

                  Time_Spent_on_Product_Research(hours)  Return_Rate  \
Customer_Segment
0                                                  1.12         0.53
1                                                  1.63         1.15
2                                                  0.65         1.50
3                                                  0.73         0.61

                  Customer_Satisfaction  Time_to_Decision
Customer_Segment
0                                  3.77              5.29
1                                  5.17              7.24
2                                  5.75              8.49
3                                  7.01              9.25
```

PCA for 2D Visualization

```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
df['PCA1'] = X_pca[:, 0]
df['PCA2'] = X_pca[:, 1]
```

```
plt.figure(figsize=(8, 6))
sns.scatterplot(
    x='PCA1', y='PCA2',
    hue='Customer_Segment',
    data=df,
    palette='Set2',
    s=60, alpha=0.7
)
plt.title("Customer Segments Visualized via PCA")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title='Segment')
plt.grid(True)
plt.tight_layout()
plt.show()
```



2. Diagnostic Analysis: Explaining Customer Satisfaction

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeRegressor, plot_tree
```

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
```

```
df = df.dropna(subset=['Customer_Satisfaction'])
```

Features and Target

```
features = [
    'Age', 'Purchase_Amount', 'Frequency_of_Purchase',
    'Brand_Loyalty', 'Product_Rating', 'Time_Spent_on_Product_Research(hours)',
    'Return_Rate', 'Time_to_Decision'
]
target = 'Customer_Satisfaction'

X = df[features]
y = df[target]
```

Train-Test Split

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=25)
```

```
tree_model = DecisionTreeRegressor(max_depth=4, random_state=19)
tree_model.fit(X_train, y_train)
```

```
DecisionTreeRegressor
DecisionTreeRegressor(max_depth=4, random_state=19)
```

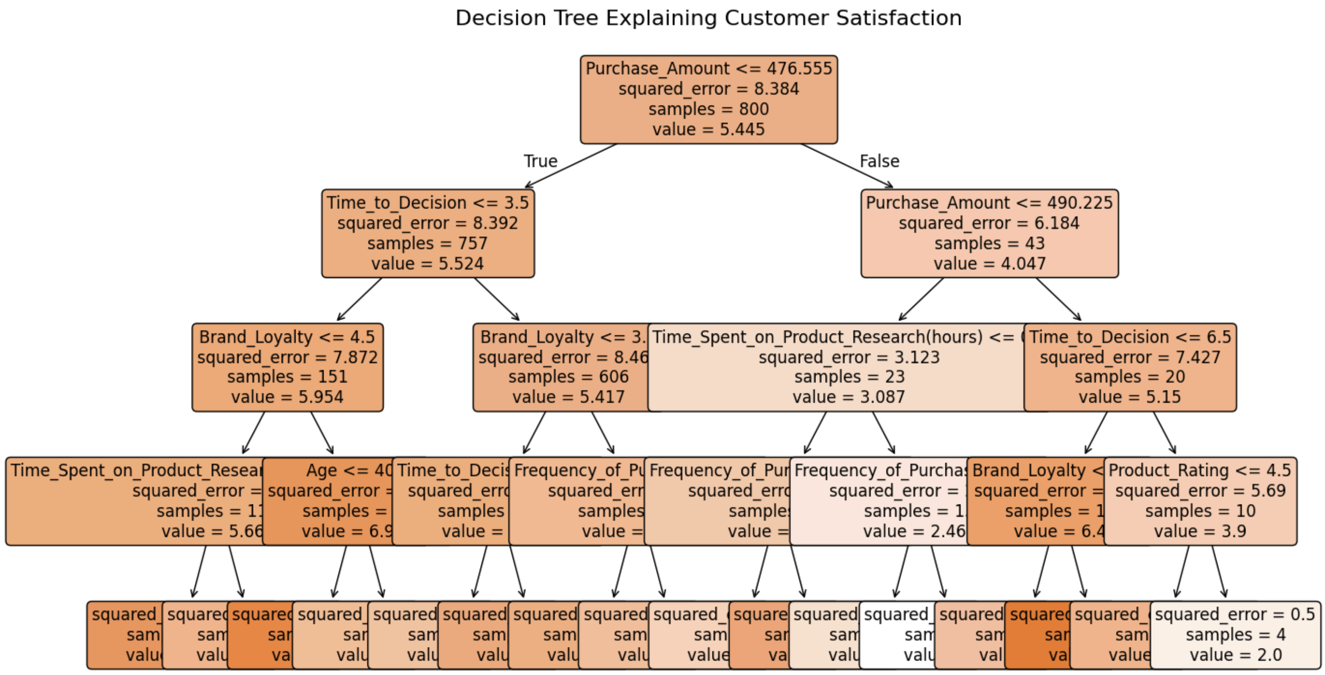
Model Score

```
X_test_for_prediction = X_test[features]

y_pred = tree_model.predict(X_test_for_prediction)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse:.2f}")
print(f"R² Score: {r2:.2f}")
```

```
Mean Squared Error: 8.56
R² Score: -0.14
```

Plot the Decision Tree

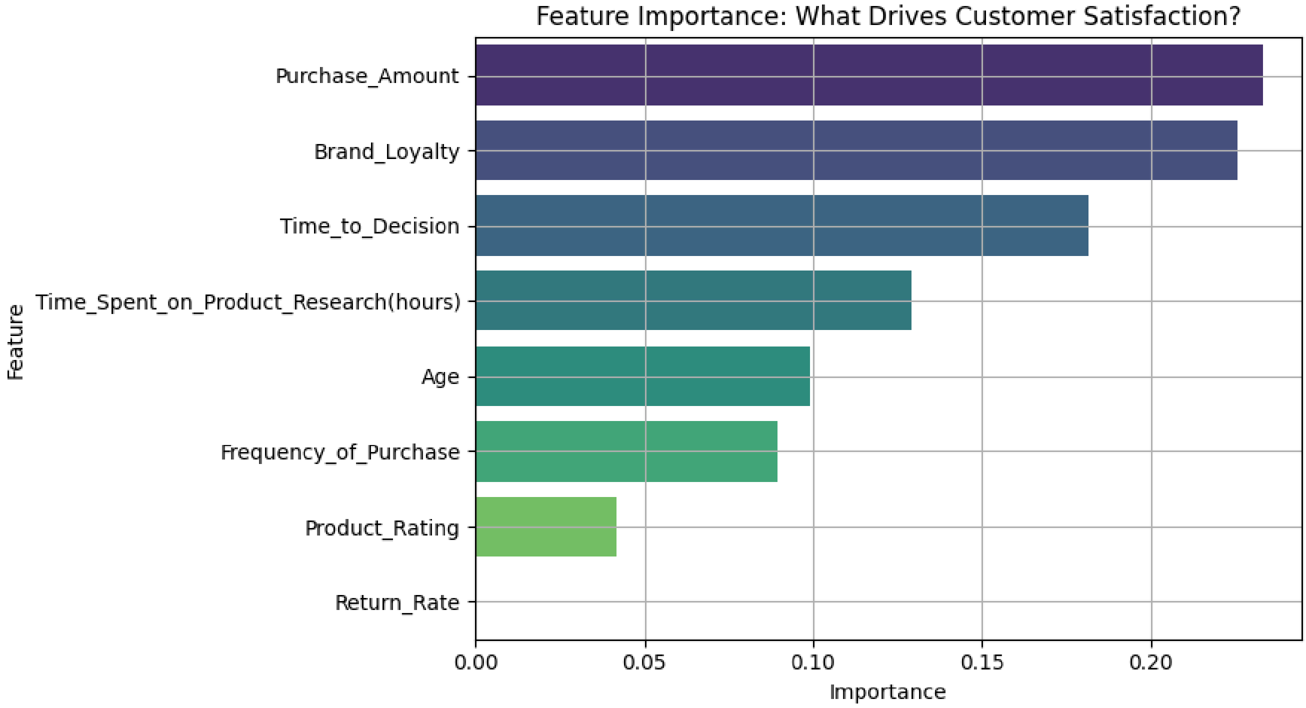
```
plt.figure(figsize=(15, 9))

plot_tree(
    tree_model,
    feature_names=features,
    filled=True,
    rounded=True,
    fontsize=12
)
plt.title("Decision Tree Explaining Customer Satisfaction", fontsize=16)
plt.show()
```



Feature Importance Plot

```
importances = tree_model.feature_importances_
importance_df = pd.DataFrame({
    'Feature': features,
    'Importance': importances
}).sort_values(by='Importance', ascending=False)

plt.figure(figsize=(9, 5))
sns.barplot(data=importance_df, x='Importance', y='Feature', palette='viridis')
plt.title("Feature Importance: What Drives Customer Satisfaction?")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-135-443601718.py:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` 

  sns.barplot(data=importance_df, x='Importance', y='Feature', palette='viridis')
```



3. **Predictive Analysis:** Predicting Purchase Level of a Customer

Creating Purchase Level

```
def classify_purchase_level(amount):
    if amount < 200:
        return "Low"
    elif amount <= 400:
        return "Medium"
    else:
        return "High"

df['Purchase_Level'] = df['Purchase_Amount'].apply(classify_purchase_level)
```

Features Selection

```
features = [
    'Age', 'Purchase_Amount', 'Frequency_of_Purchase',
    'Brand_Loyalty', 'Product_Rating', 'Time_Spent_on_Product_Research(hours)',
    'Return_Rate', 'Time_to_Decision'
]
```

```
X = df[features]
y = df['Purchase_Level']
```

```
le = LabelEncoder()
y_encoded = le.fit_transform(y)
```

Train-Test Split and Model Training

```
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.3, random_state=5)
```

```
clf = RandomForestClassifier(random_state=25)
clf.fit(X_train, y_train)
```

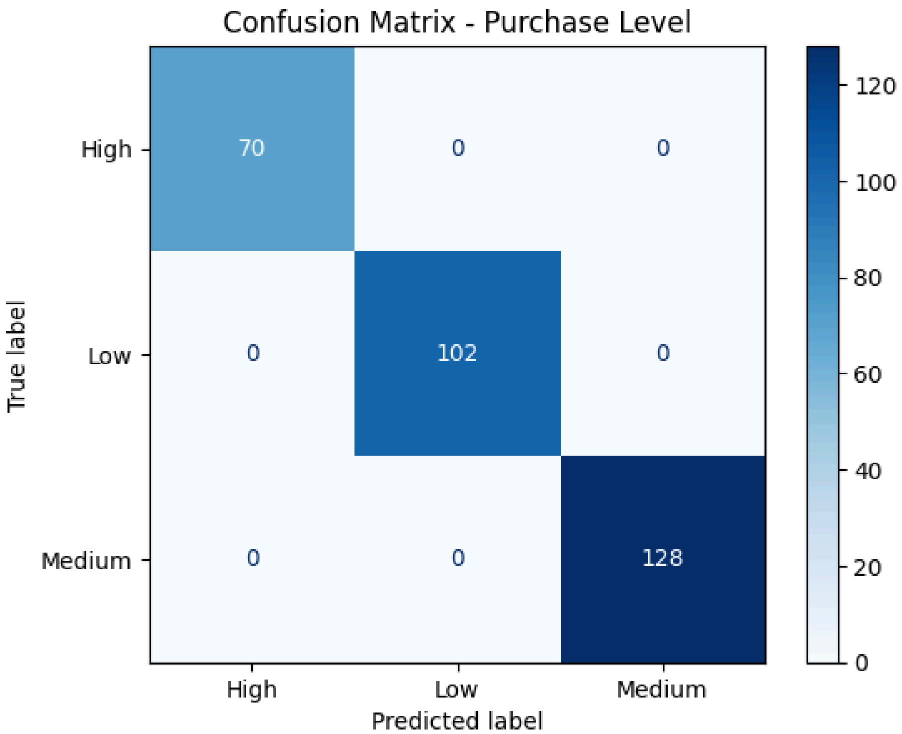
```
RandomForestClassifier
RandomForestClassifier(random_state=25)
```

```
y_pred = clf.predict(X_test)
print("Classification Report:\n")
print(classification_report(y_test, y_pred, target_names=le.classes_))
```

```
Classification Report:

              precision    recall  f1-score   support

        High       1.00      1.00      1.00        70
         Low       1.00      1.00      1.00       102
      Medium       1.00      1.00      1.00       128

    accuracy                           1.00       300
   macro avg       1.00      1.00      1.00       300
weighted avg       1.00      1.00      1.00       300
```

Confusion Matrix

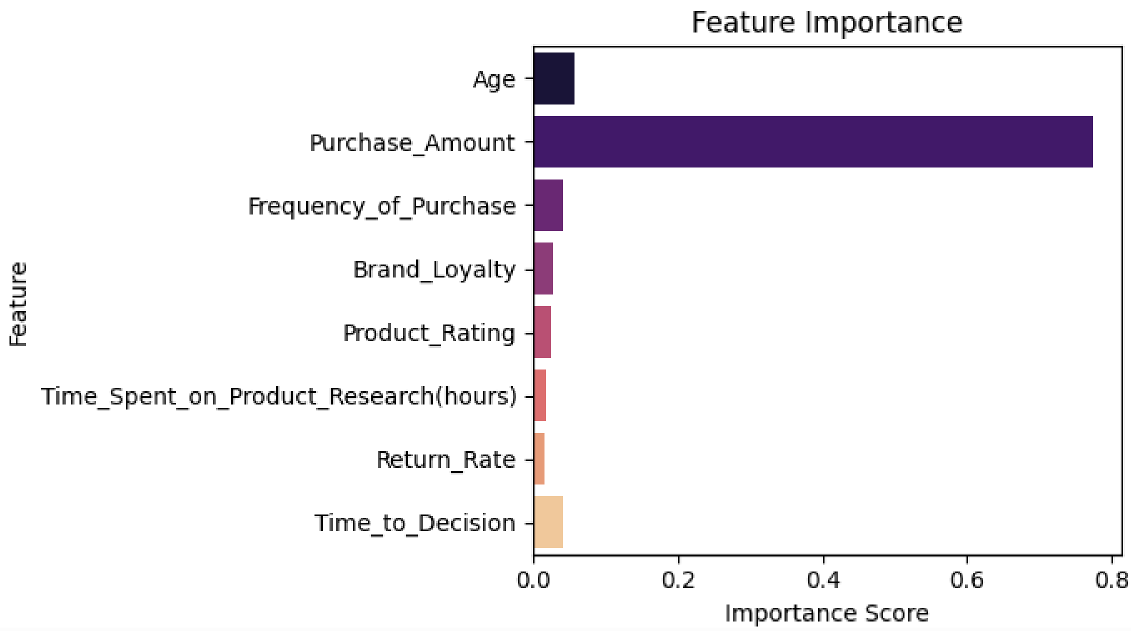
```
ConfusionMatrixDisplay.from_estimator(clf, X_test, y_test, display_labels=le.classes_, cmap="Blues")
plt.title("Confusion Matrix - Purchase Level")
plt.show()
```




```
importances = clf.feature_importances_
plt.figure(figsize=(7, 4))
```

```
sns.barplot(x=importances, y=features, palette='magma')
plt.title('Feature Importance')
plt.xlabel('Importance Score')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-86-1550391081.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` v

  sns.barplot(x=importances, y=features, palette='magma')
```




```
def recommend_action(purchase_level):
    if purchase_level == "Low":
        return "Offer first-time discount or retarget via ads."
    elif purchase_level == "Medium":
        return "Send loyalty rewards or cross-sell with bundles."
    else:  # High
        return "Promote premium products or VIP membership."
```

```
new_customers = df[features].sample(5, random_state=25)
new_preds_encoded = clf.predict(new_customers)
new_preds = le.inverse_transform(new_preds_encoded)
```

```
results = new_customers.copy()
results['Predicted_Level'] = new_preds
results['Recommended_Action'] = results['Predicted_Level'].apply(recommend_action)
```

```
print("Prescriptive Recommendations:\n")
print(results[['Age', 'Brand_Loyalty', 'Predicted_Level', 'Recommended_Action']])
```

```
Prescriptive Recommendations:

     Age  Brand_Loyalty Predicted_Level  \
688   50              5             Low
49    46              1          Medium
288   29              5            High
698   23              4          Medium
775   33              5             Low

                                  Recommended_Action
688   Offer first-time discount or retarget via ads.
49   Send loyalty rewards or cross-sell with bundles.
```

```
288       Promote premium products or VIP membership.
698  Send loyalty rewards or cross-sell with bundles.
775    Offer first-time discount or retarget via ads.
```

4. Prescriptive Analysis

```
X_test_for_prediction = X_test[features]

predicted_satisfaction = tree_model.predict(X_test_for_prediction)
```

```
X_test['Predicted_Satisfaction'] = predicted_satisfaction
```

```
#Customers with low satisfaction (<5)
low_satisfaction = X_test[X_test['Predicted_Satisfaction'] < 5].copy()
```

Logic: if Brand_Loyalty < 3, suggest boosting loyalty

```
low_satisfaction['Recommended_Action'] = low_satisfaction['Brand_Loyalty'].apply(
    lambda x: 'Increase Brand Loyalty' if x < 3 else 'Improve Product Info')
```

Results

```
result = low_satisfaction[['Predicted_Satisfaction', 'Brand_Loyalty', 'Recommended_Action']].head(15)
print(result)
```

```
     Predicted_Satisfaction  Brand_Loyalty      Recommended_Action
544                     2.0              2  Increase Brand Loyalty
515                     2.0              3    Improve Product Info
193                     0.0              2  Increase Brand Loyalty
11                      2.0              4    Improve Product Info
279                     0.0              4    Improve Product Info
653                     1.0              5    Improve Product Info
643                     2.0              5    Improve Product Info
763                     2.0              3    Improve Product Info
```