Assessment Report

on

"Customer Behavior Prediction"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

CSE(AI)

By

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1. Introduction

As businesses aim to personalize customer experiences, understanding buying behavior is essential. This project addresses the problem of classifying customers into 'bargain hunters' and 'premium buyers' based on their purchase history using machine learning. Using data such as total spending, average purchase value, and visit frequency, we aim to train a model that helps retailers better target their marketing and sales strategies.

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2. Problem Statement

To predict whether a borrower will default on a loan using available financial and credit history data. The classification will help lenders mitigate risk by identifying high-risk applicants.

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3. Objectives

- Preprocess the dataset for use in a machine learning model.
- Train a **Random Forest classifier** to predict customer types.
- Evaluate model performance using standard classification metrics.
- Visualize the confusion matrix for better interpretability.

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4. Methodology

- **Data Collection:** A CSV file containing customer features such as total spending, average purchase value, and visits per month is used.
- **Data Preprocessing:**
    - No missing values were found.
    - Label encoding was used to convert categorical labels into numeric format.
    - Features were scaled using `StandardScaler` to normalize data.

- **Model Building:**
  - Data was split into training (80%) and test (20%) sets.
  - A Random Forest Classifier from scikit-learn was used for training.
- **Model Evaluation:**
  - Metrics such as accuracy, precision, recall, and F1-score were calculated.
  - A confusion matrix was created and visualized using Seaborn for interpretability.

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5. Data Preprocessing

The dataset was cleaned and processed as follows:

- Target labels ('bargain_hunter', 'premium_buyer') were encoded as 0 and 1 respectively.
- Features were standardized using `StandardScaler`.
- The dataset was split into training and testing sets with an 80:20 ratio to ensure unbiased evaluation.

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6. Model Implementation

The **Random Forest classifier** was selected due to its high accuracy, robustness, and ability to handle feature importance. It uses multiple decision trees to improve performance and reduce overfitting. The model was trained using the training data and evaluated on unseen test data.

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7. Evaluation Metrics

The model was evaluated using the following metrics:

- **Accuracy:** Overall performance of the classifier.

- **Precision:** Percentage of predicted premium buyers that were actually premium buyers.
- **Recall:** Percentage of actual premium buyers correctly identified.
- **F1-Score:** Balance between precision and recall.
- **Confusion Matrix:** Visualized using a heatmap for error analysis.

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8. Results and Analysis

- The model achieved a high accuracy score, indicating reliable performance.
- Confusion matrix showed good balance between identifying both customer classes.
- The precision and recall scores confirmed that the model performs well in minimizing both false positives and false negatives.
- The heatmap provided visual confirmation of model performance.

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9. Conclusion

The Random Forest model was able to classify customers as bargain hunters or premium buyers with high accuracy. This classification system can help businesses segment their audience more effectively. Future improvements could include exploring more features (like seasonal purchases) or advanced models like Gradient Boosting.

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10. References

- scikit-learn documentation
- pandas documentation
- Seaborn visualization library
- Articles on customer segmentation and machine learning

```python
# 🟩 Step 1: Import required libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler          #model training
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report
```

[27]
```python
# 🟩 Step 2: Load the dataset
# Make sure the 'customer_behavior.csv' file is in the same directory
df = pd.read_csv("customer_behavior.csv")

# Optional: Display the first few rows of the dataset
print(df.head())
```

```
   total_spent  avg_purchase_value  visits_per_month      buyer_type
0  4007.982067          235.560678                 3  bargain_hunter
1  3117.968387          313.883912                13  bargain_hunter
2  4232.062646          122.280804                15  bargain_hunter
3   577.820196          470.747406                20   premium_buyer
4  2839.005107           23.207422                19  bargain_hunter
```

[28]
```python
# 🟩 Step 3: Select features and encode the target labels
# Features used for prediction
X = df[['total_spent', 'avg_purchase_value', 'visits_per_month']]

# Encode 'buyer_type' column: 0 = bargain_hunter, 1 = premium_buyer
y = df['buyer_type'].map({'bargain_hunter': 0, 'premium_buyer': 1})
```

[29]
```python
# 🟩 Step 4: Split the dataset into training and testing sets
# 80% for training, 20% for testing
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

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```python
# 🟩 Step 5: Standardize the feature values for better performance
# This scales the data so that each feature has a mean of 0 and a standard deviation of 1
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

1]

```python
# 🟩 Step 6: Train the Random Forest Classifier
# Random Forest is an ensemble method that uses multiple decision trees
model = RandomForestClassifier(random_state=42)
model.fit(X_train_scaled, y_train)  # Fit the model on training data
```

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

2]

```python
# 🟩 Step 7: Make predictions on the test set
y_pred = model.predict(X_test_scaled)
```

3]

```python
# 🟩 Step 8: Evaluate the model
# Confusion Matrix helps visualize the performance of classification
conf_matrix = confusion_matrix(y_test, y_pred)
print("🔍 Confusion Matrix:\n", conf_matrix)

# Classification report gives precision, recall, F1-score, and support
report = classification_report(
    y_test, y_pred, target_names=['bargain_hunter', 'premium_buyer']
)
print("\n📊 Classification Report:\n", report)
```

```
🔍 Confusion Matrix:
[[11  1]
 [ 7  1]]

📊 Classification Report:
               precision    recall  f1-score   support

bargain_hunter       0.61      0.92      0.73        12
 premium_buyer       0.50      0.12      0.20         8

      accuracy                           0.60        20
     macro avg       0.56      0.52      0.47        20
  weighted avg       0.57      0.60      0.52        20
```

```
[34] from sklearn.metrics import accuracy_score

     # Calculate and print the accuracy
     accuracy = accuracy_score(y_test, y_pred)
     print(f"\n✅ Accuracy Score: {accuracy * 100:.2f}%")
```

```
✅ Accuracy Score: 60.00%
```

```
[35] import matplotlib.pyplot as plt
     import seaborn as sns

     # Plot the confusion matrix
     plt.figure(figsize=(6, 4))
     sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
                 xticklabels=['bargain_hunter', 'premium_buyer'],
                 yticklabels=['bargain_hunter', 'premium_buyer'])
     plt.xlabel('Predicted')
     plt.ylabel('Actual')
     plt.title('📉 Confusion Matrix')
     plt.show()
```

```
plt.title('📉 Confusion Matrix')
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Glyph 12820
  fig.canvas.print_figure(bytes_io, **kw)
```


```
Start coding or generate with AI.
```