# **Customer Purchase Prediction Project**

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**Course:** - BUSN5101 Programing for Business

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## 1. Project Goal

I aim to predict whether a customer will return (make a repeat purchase) based on their transaction data.

### 2. Data Preparation

- Dropped missing CustomerID s
- Created TotalPrice = Quantity × UnitPrice
- Created target label IsRepeat based on repeat customer behavior

## 3. Modeling

- Logistic Regression: strong on class 1, poor recall on class 0
- Random Forest: improved accuracy, still biased
- Balanced RF: fairer model, better macro average

### 4. Results

- TotalPrice was the most important feature
- Balancing improved detection of one-time customers
- Macro F1-score went from ~0.5 → ~0.7+

### 5. Conclusion

Simple models like Random Forest + class balancing can power real business decisions like churn prediction or loyalty program targeting.

```
In [7]: # Import Libraries
  import pandas as pd
  import numpy as np
  import matplotlib.pyplot as plt
  import seaborn as sns
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.utils import resample
# Load dataset
df = pd.read_csv(r'C:\Users\13707\anaconda3\Brandon\data.csv', encoding='ISO-885
df = df.copy()
# Drop rows with missing CustomerID
df_clean = df.dropna(subset=['CustomerID']).copy()
# Create TotalPrice column
df_clean['TotalPrice'] = df_clean['Quantity'] * df_clean['UnitPrice']
# Mark customers as repeat (1) or not (0)
customer_counts = df_clean['CustomerID'].value_counts()
df_clean['IsRepeat'] = df_clean['CustomerID'].apply(lambda x: 1 if customer_coun
# Group data by CustomerID
customer_df = df_clean.groupby('CustomerID').agg({
    'Quantity': 'sum',
    'UnitPrice': 'mean',
    'TotalPrice': 'sum',
    'IsRepeat': 'max' # Target variable
}).reset_index()
# Define features and target
X = customer_df[['Quantity', 'UnitPrice', 'TotalPrice']]
y = customer_df['IsRepeat']
# Split into train/test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_
# Train Logistic Regression
lr_model = LogisticRegression(max_iter=1000)
lr_model.fit(X_train, y_train)
# Predict and evaluate
y_pred_lr = lr_model.predict(X_test)
print("Logistic Regression - Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_lr))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_lr))
# Train Random Forest
rf model = RandomForestClassifier(random state=42)
rf_model.fit(X_train, y_train)
# Predict and evaluate
y pred rf = rf model.predict(X test)
print("Random Forest - Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
# Plot feature importance
importances = rf_model.feature_importances_
feature_names = X.columns
plt.figure(figsize=(8, 5))
sns.barplot(x=importances, y=feature_names)
plt.title("Feature Importance - Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
# Separate majority and minority classes
majority = customer_df[customer_df['IsRepeat'] == 1]
minority = customer_df[customer_df['IsRepeat'] == 0]
# Downsample majority
majority_downsampled = resample(majority,
                                replace=False,
                                n_samples=len(minority),
                                random_state=42)
# Combine
balanced_df = pd.concat([majority_downsampled, minority])
# Features and Labels
X_bal = balanced_df[['Quantity', 'UnitPrice', 'TotalPrice']]
y_bal = balanced_df['IsRepeat']
# Split again
X_train_bal, X_test_bal, y_train_bal, y_test_bal = train_test_split(X_bal, y_bal
# Train and evaluate RF
rf_bal = RandomForestClassifier(random_state=42)
rf_bal.fit(X_train_bal, y_train_bal)
y_pred_bal = rf_bal.predict(X_test_bal)
print("Balanced Random Forest - Confusion Matrix:")
print(confusion_matrix(y_test_bal, y_pred_bal))
print("\nClassification Report:")
print(classification_report(y_test_bal, y_pred_bal))
```

#### Logistic Regression - Confusion Matrix:

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#### Classification Report:

|                       | precision    | recall       | f1-score     | support      |
|-----------------------|--------------|--------------|--------------|--------------|
| 0<br>1                | 0.50<br>0.98 | 0.04<br>1.00 | 0.08<br>0.99 | 24<br>1288   |
| accuracy<br>macro avg | 0.74         | 0.52         | 0.98<br>0.53 | 1312<br>1312 |
| weighted avg          | 0.97         | 0.98         | 0.97         | 1312         |

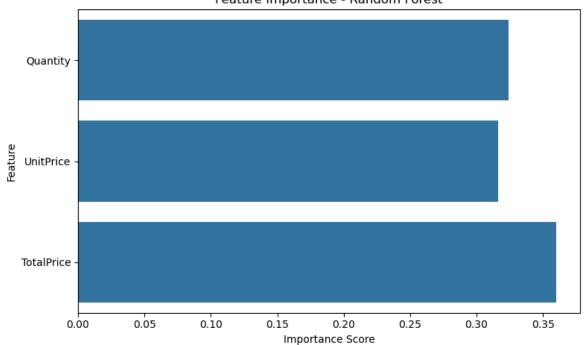
#### Random Forest - Confusion Matrix:

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#### Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.57      | 0.33   | 0.42     | 24      |
| 1            | 0.99      | 1.00   | 0.99     | 1288    |
| accuracy     |           |        | 0.98     | 1312    |
| macro avg    | 0.78      | 0.66   | 0.71     | 1312    |
| weighted avg | 0.98      | 0.98   | 0.98     | 1312    |

#### Feature Importance - Random Forest



Balanced Random Forest - Confusion Matrix:

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#### Classification Report:

|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0            | 0.82      | 0.92   | 0.87     | 25      |
| 1            | 0.90      | 0.78   | 0.84     | 23      |
| accuracy     |           |        | 0.85     | 48      |
| macro avg    | 0.86      | 0.85   | 0.85     | 48      |
| weighted avg | 0.86      | 0.85   | 0.85     | 48      |