

Credit Score Prediction

Introduction

Credit score prediction is crucial for financial institutions to assess the creditworthiness of customers.

A high credit score indicates a responsible borrower, while a low score suggests higher risk.

This report explores a logistic regression model applied to predict whether a customer has a good or bad credit score based on financial attributes.

Methodology

1. **Data Preprocessing:**

- Loaded dataset from 'credit_data 1.csv'.
- Removed unnecessary columns (CustomerID).
- Transformed CreditScore into a binary classification:
 - Good Credit Score (1) if >600, otherwise Bad Credit Score (0).

2. **Feature Engineering and Splitting:**

- Features such as Income and Loan Amount were used.
- The dataset was split into 80% training and 20% testing.

3. **Model Selection and Training:**

- Logistic Regression was chosen as the classification model.
- StandardScaler was used to normalize the features.
- The model was trained and evaluated using accuracy and classification metrics.

4. **Visualization and Insights:**

- Distribution of Credit Scores.
- Correlation Heatmap to analyze relationships between features.
- Loan Amount vs. Income Scatter Plot to understand financial trends.

Code Implementation

```
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.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Load dataset from uploaded file
file_path = "/mnt/data/credit_data 1.csv"
data = pd.read_csv(file_path)

# Drop CustomerID as it is not needed
data.drop(columns=["CustomerID"], inplace=True)

# Convert CreditScore into binary classification (Good: >600, Bad: <=600)
data["CreditScore"] = data["CreditScore"].apply(lambda x: 1 if x > 600 else 0)

# Splitting into features and target
X = data.drop(columns=["CreditScore"], axis=1)
y = data["CreditScore"]

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardizing features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train the Logistic Regression Model
model = LogisticRegression()
model.fit(X_train, y_train)

# Predictions
y_pred = model.predict(X_test)

# Model Evaluation
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Visualization - Credit Score Distribution
plt.figure(figsize=(8, 5))
sns.countplot(x=data["CreditScore"], palette="coolwarm")
plt.title("Distribution of Credit Scores")
plt.xlabel("Credit Score Category (0 = Bad, 1 = Good)")
plt.ylabel("Count")
plt.show()
```

```
# Visualization - Correlation Heatmap
```

```
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(data.corr(), annot=True, cmap="coolwarm", fmt=".2f", linewidths=0.5)
```

```
plt.title("Feature Correlation Heatmap")
```

```
plt.show()
```

```
# Visualization - Loan Amount vs. Income
```

```
plt.figure(figsize=(8, 5))
```

```
sns.scatterplot(x=data["Income"], y=data["LoanAmount"], hue=data["CreditScore"], palette="coolwarm")
```

```
plt.title("Loan Amount vs. Income")
```

```
plt.xlabel("Income")
```

```
plt.ylabel("Loan Amount")
```

```
plt.show()
```

Results

- **Accuracy Score:** The model's performance is measured using accuracy.
- **Classification Report:** Evaluates precision, recall, and F1-score for both good and bad credit scores.
- **Key Insights:**
 - The correlation heatmap shows relationships between income, loan amount, and credit scores.
 - Credit score distribution helps understand class balance.
 - Financial trends indicate how income impacts loan amount and creditworthiness.



