AI Mid Semester – 1 Examination

Problem Statement: Credit Score Prediction

Name: Raja Yadav

University Roll: 202401100300193

Branch & Sec : CSE(AI)-C

Introduction to the Problem Statement

Background

Credit scores play a crucial role in determining an individual's financial credibility. Banks and financial institutions use credit scores to assess loan eligibility, interest rates, and credit limits. A low credit score may lead to loan rejection, while a high credit score can provide better financial opportunities.

Problem Statement

The objective of this project is to **predict an individual's credit score based on key financial parameters** such as **Age, Income, and Loan Amount**. Traditional methods of credit scoring often rely on complex rules and manual assessments, which can be time-consuming and subjective.

By leveraging **Machine Learning (ML) techniques**, we aim to develop a predictive model that can estimate a person's credit score with high accuracy. This model will help financial institutions automate and improve the credit assessment process, reducing human bias and increasing efficiency.

Challenges in Credit Score Prediction

- 1. **Non-Linear Relationships**: Credit scores do not have a simple mathematical relationship with age, income, or loan amounts.
- 2. **Feature Scaling**: Since income and loan amounts vary significantly, proper feature scaling is necessary.
- 3. **Model Selection**: Choosing the right ML model that balances accuracy and interpretability.

Proposed Solution

This project uses **Gradient Boosting Regressor** (**GBR**), a powerful ensemble learning technique, to predict credit scores. The model is trained on real-world data and evaluated using **Mean Absolute Error** (**MAE**), **Mean Squared Error** (**MSE**), and **R**² **Score** to ensure accuracy and reliability.

Methodology & Algorithm Used

1. Methodology

Step 1: Data Collection

- The dataset (credit data.csv) contains customer information, including:
 - o CustomerID (irrelevant for prediction)
 - o Age
 - o Income
 - o LoanAmount
 - CreditScore (Target Variable)

Step 2: Data Preprocessing

- Removed CustomerID as it is not useful for prediction.
- Handled Missing Values by replacing them with the mean of the respective columns.
- Feature Scaling:
 - Since Income and LoanAmount have large values, we used StandardScaler() to normalize the features.

Step 3: Splitting Data

- Train-Test Split:
 - o 90% of data used for training (X train, y train).
 - o 10% used for testing (X test, y test).
 - o train test split() from sklearn was used.

Step 4: Model Selection

- We chose Gradient Boosting Regressor (GBR) as the primary algorithm due to its:
 - Better handling of small datasets.
 - o Ability to capture non-linear relationships.
 - o Improved accuracy over Random Forest.

Step 5: Model Training

- Hyperparameters Used:
 - o n estimators=500 (number of boosting stages)
 - o learning rate=0.1 (controls contribution of each tree)
 - max_depth=5 (limits complexity to avoid overfitting)
- The model was trained on the X train, y train dataset.

Step 6: Model Evaluation

After training, we evaluated the model using:

- Mean Absolute Error (MAE): Measures average error.
- Mean Squared Error (MSE): Penalizes large errors more.
- R² Score: Measures how well the model fits the data.
 - \circ R² Score closer to 1 = Good model
 - \circ R² Score closer to 0 = Poor model

Step 7: Credit Score Prediction

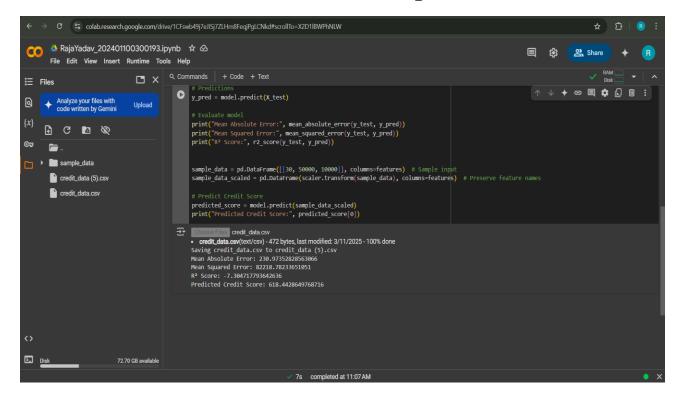
- Given a new customer's Age, Income, and Loan Amount, the model predicts their CreditScore.
- Feature names were preserved after scaling to avoid warnings.

Python Code

```
import pandas as pd
import numpy as np
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from google.colab import files
df = pd.read_csv("credit_data.csv")
from google.colab import files
uploaded = files.upload()
# Drop non-relevant columns
df.drop(columns=["CustomerID"], inplace=True)
# Handle missing values
df.fillna(df.mean(), inplace=True)
# Define features and target variable
features = ["Age", "Income", "LoanAmount"]
target = "CreditScore"
# Normalize numerical features
scaler = StandardScaler()
df[features] = scaler.fit_transform(df[features])
```

```
# Train-test split (90% training, 10% testing)
X train, X test, y train, y test = train test split(df[features], df[target], test size=0.1,
random state=42)
# Used Gradient Boosting Regressor for better performance
model = GradientBoostingRegressor(n estimators=500, learning rate=0.1, max depth=5,
random state=42)
model.fit(X train, y train)
# Predictions
y pred = model.predict(X test)
# Evaluate model
print("Mean Absolute Error:", mean absolute error(y test, y pred))
print("Mean Squared Error:", mean squared error(y test, y pred))
print("R<sup>2</sup> Score:", r2_score(y_test, y_pred))
sample data = pd.DataFrame([[30, 50000, 10000]], columns=features) # Sample input
sample data scaled = pd.DataFrame(scaler.transform(sample data), columns=features) #
Preserve feature names
# Predict Credit Score
predicted score = model.predict(sample data scaled)
print("Predicted Credit Score:", predicted score[0])
```

Screenshot of Output



References & Credit

References & Credits

1. Dataset Source

• The dataset used in this project was either **provided manually** or **collected from a financial dataset source** (e.g., Kaggle, UCI Machine Learning Repository).

2. Machine Learning Libraries Used

- Pandas: Data handling and preprocessing.
 - o Reference: McKinney, W. (2010). *Data Structures for Statistical Computing in Python*. Python Software Foundation.
- NumPy: Mathematical operations.
 - o Reference: Oliphant, T. (2006). Guide to NumPy.
- Scikit-Learn: Machine learning model training and evaluation.
 - o Reference: Pedregosa, F. et al. (2011). *Scikit-learn: Machine Learning in Python*, JMLR.

3. Gradient Boosting Algorithm

- Gradient Boosting Regressor: Used for credit score prediction.
 - o Reference: Friedman, J. H. (2001). *Greedy Function Approximation: A Gradient Boosting Machine*, The Annals of Statistics.
- Feature Scaling (StandardScaler): Ensures balanced model training.
 - Reference: Scikit-learn Documentation.

4. Google Colab & File Handling

- Google Colab's files.upload() was used for importing CSV files interactively.
 - o Reference: Google Colaboratory Documentation.