ML Project: Credit Score

Project to analyse and get the best model for Credit Score prediction of unknown data.

Areen Vaghasiya
IMT2022048
areen.vaghasiya@iiitb.ac.in

Aryan Vaghasiya
IMT2022046
aryan.vaghasiya@iiitb.ac.in

Shreyank Gopalkrishna Bhat
IMT2022516
shreyank.bhat@iiitb.ac.in

I. Introduction

This project focuses on building machine learning models to predict the **Credit Score** of individuals based on various financial and behavioral features. By leveraging historical data, the goal is to create a robust and accurate model that can assist in evaluating the risk associated with extending credit. Credit scoring is a critical aspect of financial decision-making, providing institutions with a quantitative measure of an individual's creditworthiness.

The dataset used for this project includes two parts:

- *train.csv* - A labeled dataset used to train the machine learning models.
- *test.csv* - An unlabeled dataset(doesn't have the column 'Credit_Score') to evaluate the model's final performance and predict credit scores for unseen data.

The columns of the dataset(train.csv) are:

1) 'ID'
2) 'Customer_ID'
3) 'Month'
4) 'Name'
5) 'Age'
6) 'Number'
7) 'Profession'
8) 'Income_Annual'
9) 'Base_Salary_PerMonth'
10) 'Total_Bank_Accounts'
11) 'Total_Credit_Cards'
12) 'Rate_Of_Interest'
13) 'Total_Current_Loans'
14) 'Loan_Type'
15) 'Delay_from_due_date'
16) 'Total_Delayed_Payments'
17) 'Credit_Limit'
18) 'Total_Credit_Enquiries'
19) 'Credit_Mix'
20) 'Current_Debt_Outstanding'
21) 'Ratio_Credit_Utilization'
22) 'Credit_History_Age'
23) 'Payment_of_Min_Amount'
24) 'Per_Month_EMI'
25) 'Monthly_Investment'
26) 'Payment_Behaviour'
27) 'Monthly_Balance'
28) 'Credit_Score'

	ID	Customer_ID	Month	Name	Age	Number	Profession	Income_Annual	Base_Salary_PerMonth	Total_Bank_Accounts	...
0	0x522a	CUS_0x2dbf	May	Abhishek Vishnoiw	51	370-51-2390	Musician	101583.48	NaN	5	...
1	0x6091	CUS_0x8167	August	Freifeldu	23	721-85-0529	Writer	101926.95	8635.9125	4	...
2	0xcb5f	CUS_0x3a0b	February	NaN	49	618-96-2558	Writer	158871.12	NaN	0	...
3	0x17dbc	CUS_0x9a4b	March	Alex Dobuzinskiso	40	817-31-4270	Doctor	60379.28	NaN	5	...
4	0x225b3	CUS_0x253a	June	NaN	17	580-53-4920	Accountant	50050.83	4085.9025	9	...

5 rows × 28 columns

Fig. 1. Shows the result of $print(train\_data.head())$

A sample data of what the dataset looks like is shown in Fig 1.

II. Exploratory Data Analysis & Preprocessing

The dataset underwent various preprocessing steps to prepare it for modeling. Key steps included:

- Handling mistyped numerical values.(eg - '_4_')
- Handling missing values in columns with specific data transformations to avoid bias.
- Removing irrelevant columns
- Handling miscellaneous values
- Encoding categorical variables using one-hot encoding and label encoding where necessary.
- Normalizing or scaling numerical features to improve model convergence and performance.

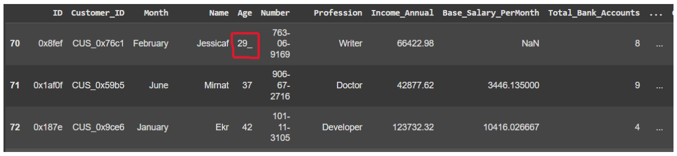
A. Handling Mistyped Values:

There are many columns in the dataset that are supposed to have numerical type data (integer,float) but have the datatype defined for them as 'object' after storing them in python's Panda data frame. Fig 2 is such an example.

certain columns expected to have numerical values may be of type 'object' in Panda's Dataframe due to errors such as **improper formatting**, **inclusion of non-numeric characters**, or **missing values** represented as strings.

The columns susceptible to this error are :

- 'Age'
- 'Income_Annual'
- 'Total_Current_Loans'
- 'Total_Delayed_Payments'



	ID	Customer_ID	Month	Name	Age	Number	Profession	Income_Annual	Base_Salary_PerMonth	Total_Bank_Accounts	...
70	0x8fef	CUS_0x76c1	February	Jessicaf	29_	763-06-9169	Writer	66422.98	NaN	8	...
71	0x1af0f	CUS_0x59b5	June	Mimat	37	906-67-2716	Doctor	42877.62	3446.135000	9	...
72	0x187e	CUS_0x9ce6	January	Ekr	42	101-11-3105	Developer	123732.32	10416.026667	4	...

Fig. 2. Shows the result of $print(train\_data[70:80])$

- 'Credit_Limit'
- 'Credit_Mix'
- 'Current_Debt_Outstanding'
- 'Monthly_Investment'
- 'Monthly_Balance'

Correcting these columns involve 2 steps:

→ Stripping '_'s from the column

→ Manually converting the *object* dtypes to *float* or *integer* dtypes.

Correcting these errors is essential for the following reasons:

- **Facilitating Numerical Operations**
- **Ensuring Consistency in Data Representation:** Incorrect data types can lead to inconsistencies when processing or visualizing data.
- **Avoiding Bias or Skew in Analysis:** Numerical values incorrectly stored as strings may be excluded or misinterpreted by algorithms, reducing the model's ability to learn relationships in the data.

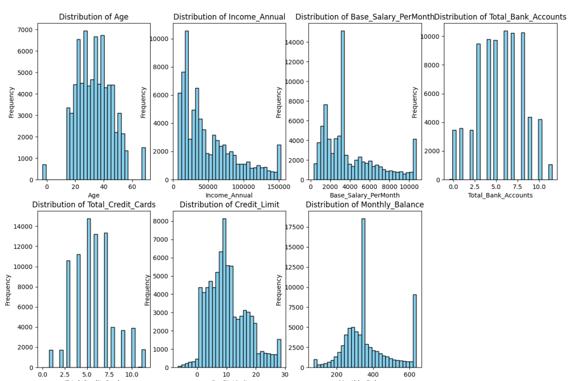


Fig. 3. Univariate Data Analysis

Fig 3 shows the missing data pattern.

B. Handling Outliers:

There are many columns that are wrongly predicted due to the presence of outliers. Columns like Age, BaseSalaryPerMonth, IncomeAnnual, TotalBankAccounts, CreditLimit, PerMonthEMI, etc have large outliers in them as shown in fig 5 .

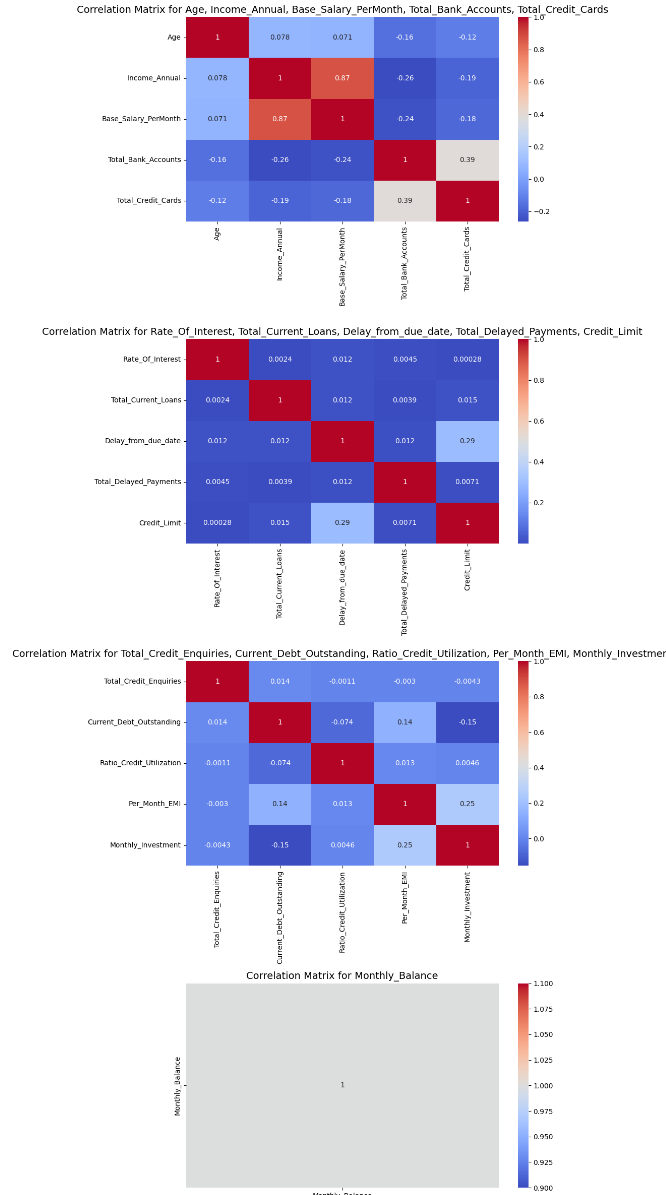


Fig. 4. Enter Caption

However, this can be easily solved as for the columns with outliers have numerical values so we can simply replace these values with the upper and lower whisker values. Defining the quartiles from 0.25 to 0.75 and adding or subtracting 1.5(inter quartile-range) will give an appropriate values to replace the outliers as in fig 6.

Having corrected the outlier values, we can also do analysis like distribution of CreditScore by age 8.
We can see which age values contribute more to the creditScores and which don't. We can see that for the age range between age 50 to 60, there are more people that maintain a good CreditScore as compared to those having Standard or Poor CreditScore.

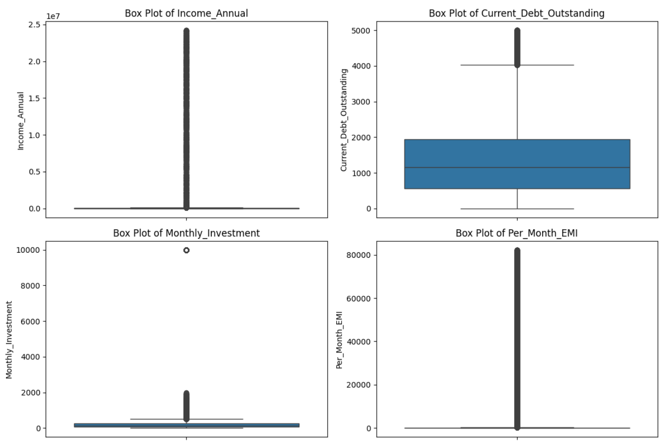


Fig. 5. Columns with Outliers present

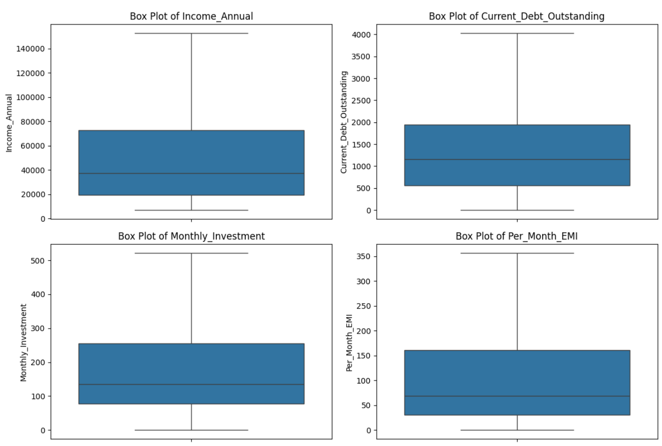


Fig. 6. Columns with outliers removed

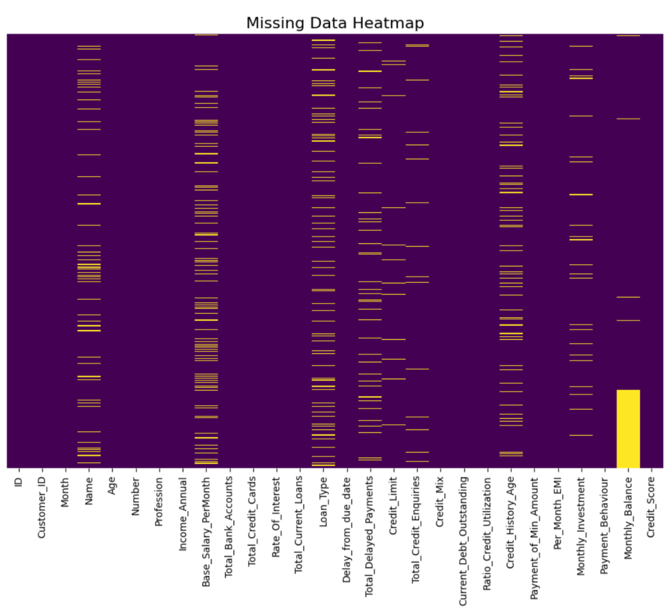


Fig. 7. Shows the Missing Data(null) in various columns

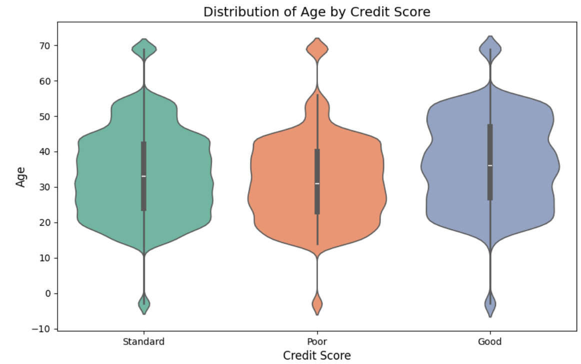


Fig. 8. Age Distribution by CreditScore

We can also do scatterPlots to identify trends and try to correlate between the different variables and see how they affect each other. We can have a Age vs. Income_Annual or Age vs. Monthly Balance to identify potential trends with age. A shown in 10, 11, 9

Fig. 9. Scatter Plot of Annual Income vs Age

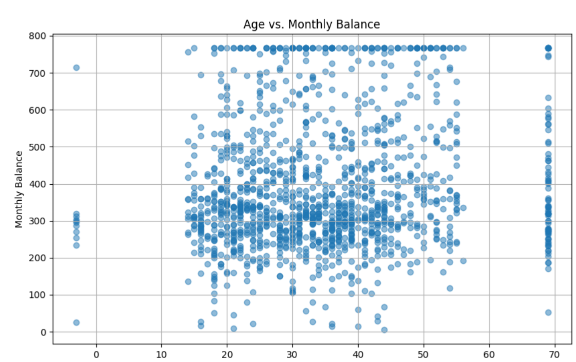


Fig. 10. Scatter Plot of Monthly_Balance vs Age

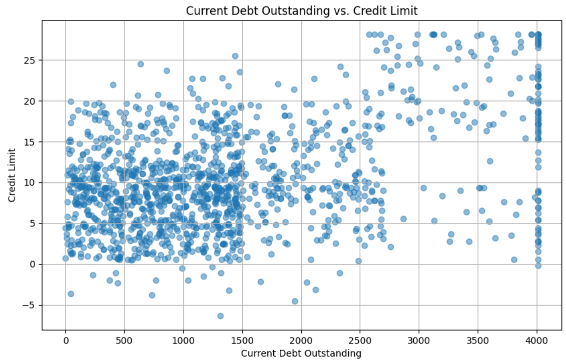


Fig. 11. Scatter Plot of Current_Debt_Outstanding vs CreditLimit

C. *Correcting Miscellaneous Variables*

There are a few columns in the dataset that have data in an inaccessible/unreadable format.
For ex- columns such as 'Profession' has value '_______', which doesn't make sense.

There is another column 'Credit_History_Age' which contains the information about how long is the credit history of the corresponding customer. This is stored in the dataset as strings, e.g '1 year and 5 months'. This has been changed to integer values representing number of months. The code updating this column is:

```
import numpy as np

def calc_total_months(history):
   if pd.isna(history): # Check for NaN values
       directly using pandas
      return np.nan
   histlist = history.split() # Split by whitespace
   years = int(histlist[0]) if
       histlist[0].isdigit() else 0
   months = int(histlist[3]) if len(histlist) > 3
       and histlist[3].isdigit() else 0
   return years * 12 + months

train['Credit_History_Age'] =
train['Credit_History_Age'].apply(calc_total_months)
test['Credit_History_Age'] =
    test['Credit_History_Age'].apply(calc_total_months)
```

Similarly, column 'Loan_Type' has string values such as *'Payday Loan, Student Loan, Payday Loan, and Debt Consolidation Loan '* as a single string. This has been handled by adding corresponding 'loan' columns. The following columns have been added:

- Loan_Type_Mortgage Loan
- Loan_Type_Debt Consolidation Loan
- Loan_Type_Auto Loan
- Loan_Type_Student Loan
- Loan_Type_Payday Loan
- Loan_Type_Personal Loan
- Loan_Type_Not Specified
- Loan_Type_Home Equity Loan
- Loan_Type_Credit-Builder Loan

Columns such as 'Payment_Behaviour' have garbage values '!@9#%8' have also been replaced with value 'Not Specified'.

D. *Removing Irrevelant columns*

Columns such as 'Name', 'Customer_ID', 'Number' have no significance in the Credit Score of the customer. Hence, these columns are not used for training models.

E. *Filling null / missing values*

Numerical columns identified with missing values are:

- Income_Annual
- Total_Delayed_Payments
- Monthly_Investment
- Monthly_Balance
- Total_Credit_Enquiries
- Credit_Limit
- Base_Salary_PerMonth

Imputation Approach:
The missing values were imputed with the median of the respective columns.

```
numeric_columns2 = ['Income_Annual',
    'Total_Delayed_Payments', 'Monthly_Investment',
              'Monthly_Balance',
                  'Total_Credit_Enquiries',
                  'Credit_Limit',
              'Base_Salary_PerMonth']
for col in numeric_columns2:
   train_data[col].fillna(train_data[col].median(),
       inplace=True)
   test_data[col].fillna(test_data[col].median(),
       inplace=True)
```

Why Median?
The median is a robust measure of central tendency and is less affected by outliers compared to the mean. This choice suggests an awareness of potential skewness in the data distribution.

F. *Encoding techniques*

Since multiple kinds of models have been experimented on the dataset, the categorical columns of have been both label encoded and one-hot encoded for different model*(one-hot encoded for models such as Bayesian classifier and label encoded for models such as decision trees)*.Categorical columns identified are:

- Profession
- Credit_Mix
- Payment_of_Min_Amount
- Payment _Behaviour

1) Label Encoding: Label encoding is done to convert categorical data into a numerical format. Certain algorithms can leverage the ordinal relationship between encoded values (if applicable) to make better predictions.

2) One-Hot Encoding: Converts categories into binary columns. This is done to avoid bias in independent non-hierarchical data values.

III. Training Models

A. Decision Tree

Description:
A Decision Tree is a supervised learning model used for classification and regression tasks. It splits the dataset into subsets based on the value of input features, creating a tree structure that represents the decision-making process. While simple and interpretable, decision trees are prone to overfitting, which can be mitigated with proper hyperparameter tuning.

- **Best Hyperparameters** (from *RandomizedSearchCV*):
  - *min_samples_split*: 5 (minimum number of samples required to split an internal node)
  - *min_samples_leaf*: 4 (minimum number of samples required to be at a leaf node)
  - *max_depth*: 10 (maximum depth of the tree)
- **Performance Metrics:**
  - *Test Accuracy*: 0.6985
  - *Test Precision (weighted)*: 0.704114
  - *Test Recall (weighted)*: 0.6985
  - *Test F1 Score (weighted)*: 0.699378
- **Insights and Observations**:
  1) *Model Performance*:
     The Decision Tree model achieved an accuracy of approximately 69.85%, with similar values for precision, recall, and F1-score. The metrics suggest moderately good performance, though the model may benefit from further refinement.
  2) *Evaluation of Hyperparameters*:
     - Max Depth (10): Restricting the tree depth helps reduce overfitting by limiting the complexity of the tree.
     - Min Samples Split (5): Ensures that nodes are not split unless there are at least 5 samples, preventing overly granular splits.
     - Min Samples Leaf (4): Forces each leaf node to contain at least 4 samples, promoting generalization and robustness.
  3) *Possible Reasons for Limited Accuracy*:
     - Feature Complexity: Features in the dataset may not provide sufficient predictive power, leading to limited performance.
     - Class Imbalance: If target classes are imbalanced, the tree might be biased towards the majority class.
     - Limited Tree Depth: While reducing overfitting, the restriction on tree depth may have prevented the model from capturing complex patterns.

While the Decision Tree provides interpretable results, its performance may improve with additional feature engineering, balancing the dataset, or exploring advanced ensemble methods such as Gradient Boosting or Random Forest. A deeper hyperparameter search and fine-tuning might also yield better results.

B. Random Forest

Description:
Random Forest is an ensemble learning method that constructs multiple decision trees and merges their results for more accurate predictions. It's robust to overfitting due to the averaging of trees and often performs well on structured data.

- **Best Hyperparameters** (from *RandomizedSearchCV*):
  - *n_estimators*: 150 (number of trees)
  - *min_samples_split*: 2 (minimum number of samples required to split an internal node)
  - *min_samples_leaf*: 2 (minimum number of samples required to be at a leaf node)
  - *max_depth*: None (trees are expanded fully unless limited by other parameters)
  - *bootstrap*: False (does not use bootstrapping, which may improve accuracy but increases overfitting risk slightly)
- **Performance Metrics:**
  - *Test Accuracy*: 0.79225
  - *Test Precision (weighted)*: 0.79201
  - *Test Recall (weighted)*: 0.79225
  - *Test F1 Score (weighted)*: 0.79211
- **Insights and Observations**:
  1) *Model Performance*:
     The Random Forest model has achieved an accuracy of approximately 79%, with similar values for precision, recall, and F1-score. This consistency across metrics indicates a balanced performance on both positive and negative samples within the classes.
  2) *Evaluation of Hyper parameters*:
     - Number of Estimators (150): Using a higher number of trees increases the model's stability and ability to generalize, while 150 trees are typically enough to balance performance and computational efficiency.
     - Max Depth (None): Allowing trees to grow to full depth can help capture complex patterns but may increase overfitting. With the selected settings, the effect seems well-balanced.
     - Bootstrap (False): The lack of bootstrapping may have contributed to a slight overfitting but generally increased the model's accuracy.
  3) *Possible Reasons for Limited Accuracy*:
     - Feature Complexity: Some features in the dataset (e.g., *Credit_Mix*, *Payment_Behaviour*) may not have straightforward relationships with the *Credit_Score*, causing a reduction in model accuracy.
     - Class Imbalance: If the *Credit_Score* categories are imbalanced, the model might favor the majority class, reducing overall performance.
     - Non-linear Relationships: The data may contain non-linear patterns that the Random Forest model captures well to an extent but could be

improved by trying other ensemble or boosting models.

Perhaps we can improve accuracy by doing a more intensive hyperparameter search to using finer parameters around the best parameters found. We can also create additional features or remove highly correlated features to reduce noise in the model. We could also try scaling or transforming some features differently from how we have done, particularly if they contain outliers or non-normal distributions.

C. Naive Bayes Classifier

Description:
Gaussian Naive Bayes is a probabilistic classification technique based on Bayes' Theorem, assuming independence among features. It is particularly effective for high-dimensional data and is known for its simplicity and speed. The Gaussian variant assumes that the likelihood of the features is normally distributed.

- **Assumptions and Key Features**:
  - Assumes that all features are independent given the class label, which might not hold true for all datasets.
  - Uses the Gaussian distribution to model the likelihood of continuous data, making it suitable for numerical datasets.
- **Performance Metrics**:
  - *Training Accuracy*: 0.5745 (approximately 57.45%)
  - *Test Accuracy*: 0.5796 (approximately 57.96%)
  - *Test Precision (weighted)*: 0.643 (indicates alignment of predictions with actual positive instances across classes)
  - *Test Recall (weighted)*: 0.580 (proportion of true positives correctly identified by the model)
  - *Test F1 Score (weighted)*: 0.583 (harmonic mean of precision and recall, providing a balanced metric)
- **Insights and Observations**:
  1) *Model Performance*:
     - The training and test accuracies are very close, indicating that the model generalizes well without overfitting to the training data.
     - Despite its simplicity, Naive Bayes achieves a weighted F1 score of approximately 58.3%, showing its potential for tasks with moderately complex data.
  2) *Advantages of the Naive Bayes Classifier*:
     - **Simplicity**: The model is computationally efficient and requires minimal parameter tuning, making it suitable for quick prototyping.
     - **Robustness to Small Datasets**: Performs well even with limited data due to its probabilistic nature.
     - **Handling Continuous Features**: Gaussian assumption allows effective handling of numerical data without the need for extensive preprocessing.
  3) *Challenges and Potential Issues*:
     - **Feature Independence Assumption**: The assumption of feature independence might oversimplify the data, reducing its ability to capture feature interactions.
     - **Sensitivity to Distribution Assumptions**: The Gaussian assumption might not hold true for all features, leading to suboptimal results in some cases.
- **Suggestions for Improvement**:
  1) *Feature Engineering*: Incorporating additional features or transforming existing ones (e.g., scaling or normalizing) might improve model performance.
  2) *Handling Dependencies*: Employing models that can handle feature dependencies, like Bayesian Networks or ensemble methods, could provide better results.
  3) *Alternative Distributions*: For features that do not follow a Gaussian distribution, consider using other variants like Multinomial Naive Bayes or Kernel Density Estimation.

D. XG Boosting

Description:
XGBoost (Extreme Gradient Boosting) is a powerful ensemble learning technique that combines multiple decision trees in a boosting manner. It is known for its scalability and efficiency in handling large datasets and complex feature interactions. The model iteratively improves by focusing on previously misclassified instances, making it robust for tasks like classification and regression.

- **Best Hyperparameters** (from *RandomizedSearchCV*):
  - *subsample*: 1.0 (uses the full dataset for each boosting round, which can capture maximum information from the data)
  - *reg_lambda*: 1 (ridge regularization to control overfitting by penalizing large weights)
  - *reg_alpha*: 0 (no lasso regularization applied)
  - *n_estimators*: 100 (number of boosting rounds)
  - *min_child_weight*: 1 (minimum sum of instance weight in a child, a regularization parameter to avoid overfitting)
  - *max_depth*: 15 (maximum depth of each tree, allowing for deeper trees to capture complex relationships)
  - *learning_rate*: 0.3 (controls the contribution of each tree to the final model, with a moderately high rate here for faster convergence)
  - *gamma*: 0 (no minimum loss reduction for splits, allowing for unrestricted splitting)
  - *colsample_bytree*: 0.6 (60% of features are used to build each tree, adding diversity to each tree in the ensemble)
- **Performance Metrics**:
  - *Training Accuracy*: 1.0 (100%)
  - *Test Accuracy*: 0.796 (approximately 79.56%)

- *Test Precision (weighted)*: 0.795 (alignment of predictions with actual positive instances across classes)
- *Test Recall (weighted)*: 0.796 (indicates the proportion of true positives correctly classified by the model)
- *Test F1 Score (weighted)*: 0.795 (harmonic mean of precision and recall, providing a balanced metric)

- **Insights and Observations**
  1) *Model Performance*:
     - The model achieved a high training accuracy, suggesting it fit the training data well. However, test accuracy of 79.56% indicates a potential risk of overfitting since the model might be memorizing rather than generalizing.
     - XGBoost performed well across metrics, showing balanced precision, recall, and F1 scores. This suggests that the model is consistently accurate across the ‘Credit_Score‘ classes.
  2) *Advantages of Hyperparameters*:
     - ‘max_depth=15‘: Allows the model to capture complex patterns in the data.
     - ‘learning_rate=0.3‘ and ‘n_estimators=100‘: A moderately high learning rate with a sufficient number of estimators allowed quick convergence without needing a larger model.
     - ‘colsample_bytree=0.6‘: Using only 60% of features per tree likely mitigates overfitting and enhances the model’s generalizability.
  3) *Challenges and Potential Issues*:
     - Risk of Overfitting: The high training accuracy indicates that the model might have overfit to the training set. Reducing *max_depth* or adding regularization could be tested to improve generalization.
     - Complexity of the Model: XGBoost’s ability to capture nuanced patterns means it might also be sensitive to noise in the dataset.

We can try experimenting with strong regularization (higher *reg_alpha* and *reg_lambda*) could help reduce overfitting, making the model less sensitive to noise. Perhaps we could also try lowering *max_depth* (e.g., 10 or 12) in order to reduce the model’s sensitivity to noise while still capturing the primary patterns in the data. We improve on the feature engineering and selection part also.

E. ADA Boosting

Description: AdaBoost (Adaptive Boosting) is a robust ensemble learning method that combines multiple weak learners (typically shallow decision trees) to create a strong predictive model. By iteratively focusing on misclassified instances, AdaBoost assigns higher weights to difficult examples, improving overall model accuracy and robustness. It is particularly effective for classification tasks and is simple to implement.

- **Best Hyperparameters** (from *RandomizedSearchCV*):
  - **n_estimators**: 200 (Higher number of estimators allows the model to iteratively improve accuracy over more rounds).
  - *learning_rate*: 0.5 (Moderates the contribution of each weak learner, balancing between underfitting and overfitting).
- **Performance Metrics**:
  - *Test Accuracy*: 65.61
  - *Test Precision (weighted)*: 65.50% (Indicates how closely predictions align with actual classes).
  - *Test Recall (weighted)*: 65.61% Represents the proportion of true positives captured).
  - *Test F1 Score (weighted)*: 65.12% (Balances precision and recall, showing consistent performance across classes).
- **Insights and Observations**:
  1) *Model Performance:*
     - AdaBoost achieved moderate test accuracy (65.61%) compared to XGBoost (79.56%). The lower accuracy reflects AdaBoost’s tendency to struggle with very complex datasets compared to gradient boosting methods.
     - Balanced precision, recall , and F1 scores indicate that the model performs consistently across the ’Credit Score’ classes but may fail to capture the most complex patterns.
  2) *Advantages of Hyperparameters*:
     - *n_estimators* = 200 (A larger number of boosting rounds ensures the model can iteratively focus on challenging examples).
     - *learning_rate* = 0.5 (Provides a middle ground to ensure weak learners contribute meaningfully without dominating the ensemble).
  3) *Challenges and Potential Issues*:
     - *Risk of Underfitting:*
       The model, while consistent, has lower accuracy compared to XGBoost. AdaBoost’s reliance on shallow weak learners may limit its capacity to capture highly non-linear relationships.
     - *Sensitivity to Noise:*
       Assigning higher weights to misclassified samples may amplify noise in the data, reducing overall performance.

F. K Nearest Neighbours

K-Nearest Neighbors (KNN) is a simple, non-parametric, and instance-based machine learning algorithm commonly used for classification and regression tasks. It works by identifying the `k` nearest data points (neighbors) to a query point and making predictions based on the majority class (for classification) or averaging the values (for regression) of these neighbors.

Selecting the Value of K: Scatter plots were created to identify an optimal value of k for achieving the best accuracy. In these plots, blue represents the 'Standard' class of the credit score, while red and green represent the 'Poor' and 'Good' classes, respectively.

The figure 13 shows the scatter plot for the variables Credit History Age (Y-axis) and Current Debt Outstanding (X-axis).

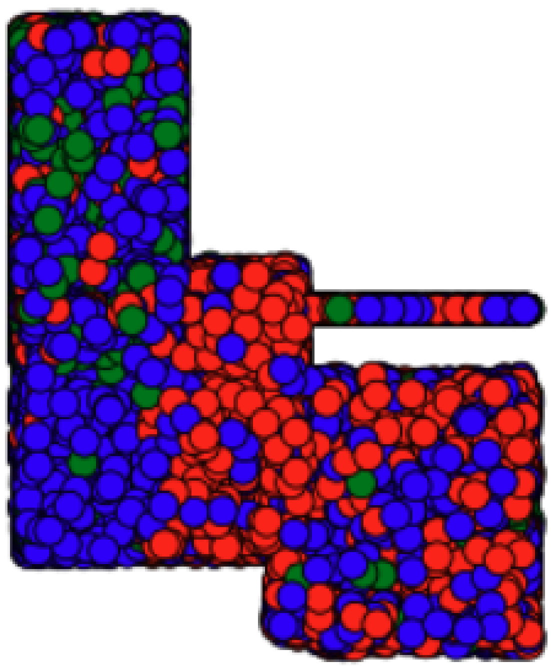


Fig. 12. Scatter Plot of Credit History Age vs Current Debt Outstanding

A similar approach was followed for multiple pairs of variables plotted against the categorical 'Credit Score' variable. These scatter plots helped visualize the degree of separation between clusters corresponding to the credit score classes. Better separation among the clusters is crucial for improving the accuracy of the K-Nearest Neighbor (KNN) algorithm. However, some variables exhibited poor separation of the red, green, and blue clusters.

For example, Figure 13 illustrates a scatter plot where the classes are not well-separated. This plot was generated with Credit History Age on the Y-axis and Rate of Interest on the X-axis. Poorly separated clusters like these posed challenges in achieving high accuracy with KNN.

Training the model: The model has been trained for k values between 2 and 21. The training score and testing score has been printed out. The test data taken here is based on the train_test_split from the Scikit learn's preprocessing library. The accuracy is based on the formula

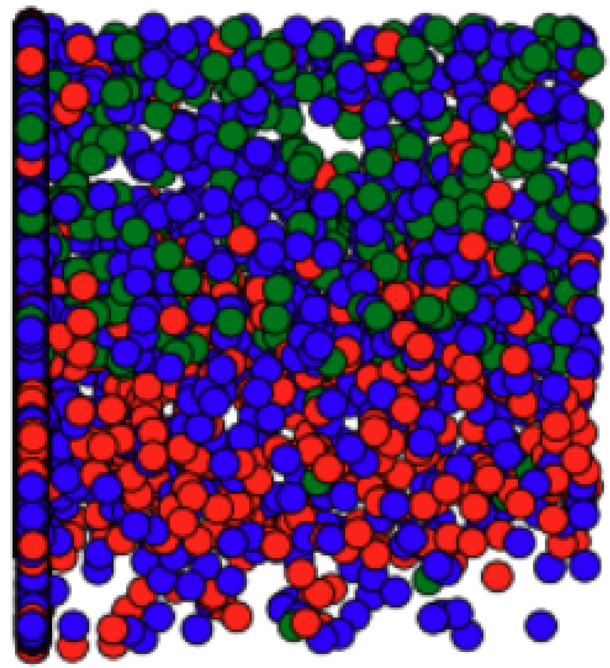


Fig. 13. Scatter Plot of Credit History Age vs Rate of Interest

Accuracy=Total Number of Predictions/Number of Correct Predictions

The training and testing accuracies were as follows: {2: [0.83865625, 0.641], 3: [0.82884375, 0.657625], 4: [0.792515625, 0.647], 5: [0.776109375, 0.64325], 6: [0.755765625, 0.6405], 7: [0.7408125, 0.636], 8: [0.726953125, 0.6321875], 9: [0.715453125, 0.6271875], 10: [0.70509375, 0.625125], 11: [0.69603125, 0.6239375], 12: [0.688921875, 0.6219375], 13: [0.68378125, 0.62025], 14: [0.677734375, 0.62025], 15: [0.675203125, 0.6229375], 16: [0.66965625, 0.6214375], 17: [0.666984375, 0.620625], 18: [0.663640625, 0.619125], 19: [0.66046875, 0.618], 20: [0.65771875, 0.618625]} The keys represent the values of k. The 1st element in the value array is the train accuracy, and the 2nd element in the value array is the test accuracy. The test accuracy was poor showing a maximum of 65.7625% where the k value is 3. So this model was not used for the final prediction as the other models performed a lot more better.