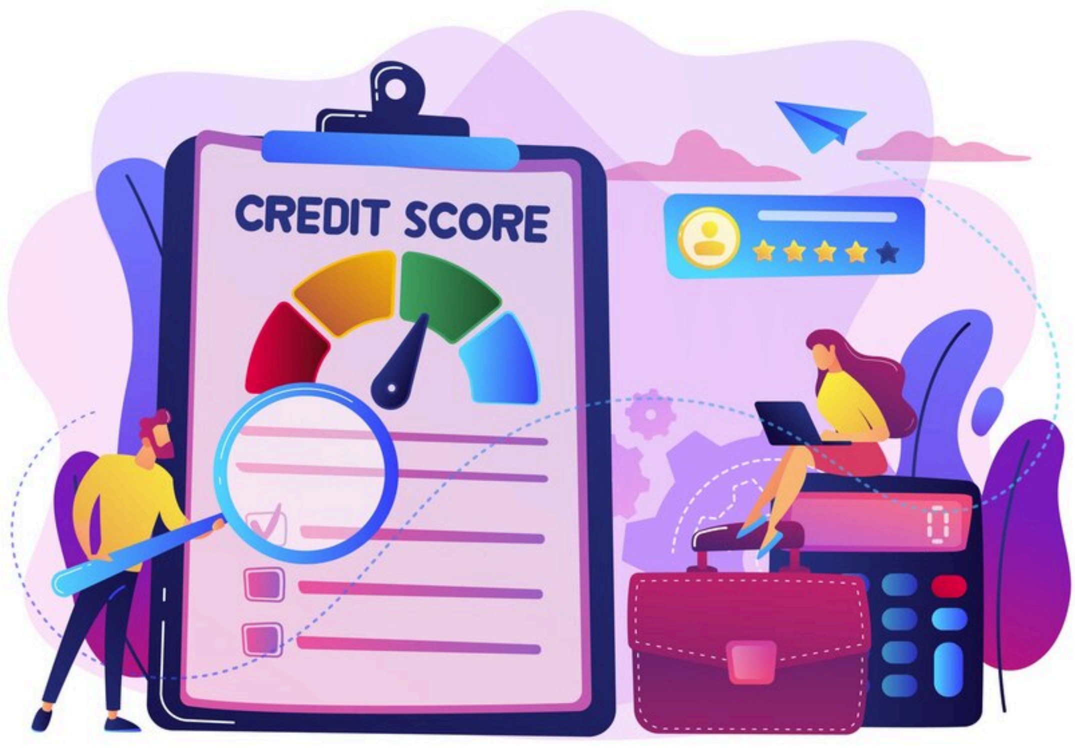
CREDIT SCORE CLASSIFICATION

MACHINE LEARNING PROJECT



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INTRODUCTION

There are three credit scores that banks and credit card companies use to label their customers:

- Good
- Standard
- Poor

A person with a good credit score will get loans from any bank and financial institution. For the task of Credit Score Classification, we need a labeled dataset with credit scores. I found an ideal dataset for this task labeled according to the credit history of credit card customers. You can download the dataset **here**.

OBJECTIVE

Banks and credit card companies calculate your credit score to determine your creditworthiness. It helps banks and credit card companies immediately to issue loans to customers with good creditworthiness. Today banks and credit card companies use Machine Learning **algorithms** to classify all the customers in their database based on their credit history.

DATA UNDERSTANDING

The credit score of a person determines the creditworthiness of the person. It helps financial companies determine if you can repay the loan or credit you are applying for. Here is a dataset based on the credit score classification submitted by **Rohan Paris** on Kaggle. Below are all the features in the dataset:

- ID: Unique ID of the record
- Customer_ID: Unique ID of the customer
- Month: Month of the year
- Name: The name of the person
- Age: The age of the person
- SSN: Social Security Number of the person
- Occupation: The occupation of the person
- Annual_Income: The Annual Income of the person
- Monthly_Inhand_Salary: Monthly in-hand salary of the person
- Num_Bank_Accounts: The number of bank accounts of the person
- Num_Credit_Card: Number of credit cards the person is having

- Interest_Rate: The interest rate on the credit card of the person
- Num_of_Loan: The number of loans taken by the person from the bank
- Type_of_Loan: The types of loans taken by the person from the bank
- Delay_from_due_date: The average number of days delayed by the person from the date of payment
- Num_of_Delayed_Payment: Number of payments delayed by the person
- Changed_Credit_Card: The percentage change in the credit card limit of the person
- Num_Credit_Inquiries: The number of credit card inquiries by the person
- Credit_Mix: Classification of Credit Mix of the customer
- Outstanding_Debt: The outstanding balance of the person
- Credit_Utilization_Ratio: The credit utilization ratio of the credit card of the customer
- Credit_History_Age: The age of the credit history of the person
- Payment_of_Min_Amount: Yes if the person paid the minimum amount to be paid only, otherwise no.
- Total_EMI_per_month: The total EMI per month of the person
- Amount_invested_monthly: The monthly amount invested by the person
- Payment_Behaviour: The payment behavior of the person
- Monthly_Balance: The monthly balance left in the account of the person
- Credit_Score: The credit score of the person

The Credit_Score column is the target variable in this problem. We are required to find relationships based on how banks classify credit scores and train a model to classify the credit score of a person.

DATA PREPARATION

In the data preparation phase of our credit score classification project, we focused on ensuring that our dataset was clean, structured, and suitable for training machine learning models. Here's an overview of the key steps we undertook:

- Handling Missing Values:

We began by identifying and addressing missing values in the dataset. Using techniques such as imputation and deletion, we handled missing data points while striving to preserve the integrity of the dataset.

- Encoding Categorical Variables:

Since many machine learning algorithms require numerical input, we encoded categorical variables into a numerical format. This involved techniques like one-hot encoding or label encoding to transform categorical attributes into numerical equivalents while retaining their categorical information.

- Scaling Numerical Features:

To ensure uniformity in feature scales and prevent bias in model training, we applied feature scaling techniques to standardize or normalize numerical features. By scaling the features, we aimed to enhance the convergence of our machine learning models.

- Feature Engineering:

Leveraging domain knowledge and intuition, we engineered new features from existing ones to capture additional information or improve model performance. Feature engineering techniques such as polynomial features, interaction terms, and domain-specific transformations were explored to extract valuable insights from the data.

- Feature Selection:

Not all features in the dataset may contribute equally to the predictive task. Hence, we employed feature selection techniques to identify and retain the most important features while discarding redundant or irrelevant ones. Methods such as correlation analysis, feature importance ranking, and model-based selection were used to select the subset of features that significantly impacted the predictive performance of our models.

Through these data preparation steps, we ensured that our dataset was well-prepared for training machine learning models to predict credit scores accurately. This foundational phase set the stage for building robust and effective classification models.

DATA MODELLING

In the data modeling phase of our credit score classification project, we implemented and evaluated multiple machine learning models to predict credit scores based on the prepared dataset. Here's an overview of the modeling process:

- Exploration of Different Models:

We conducted research to identify suitable machine learning models for our project. Commonly considered models included linear regression, decision trees, random forests, support vector machines, and gradient boosting models. Each model was evaluated based on its ability to handle the characteristics of our dataset and its potential for accurate credit score classification.

- Feature Selection Techniques:

Prior to model implementation, we considered feature selection techniques to choose relevant features for training our models. Feature selection helps in improving model performance by focusing on the most informative features while discarding irrelevant ones. We explained our choice of feature selection method, if applicable, and justified its relevance to our project.

- Implementation and Evaluation of Models:

Using libraries like scikit-learn, we implemented multiple machine learning models on our prepared dataset. We split the dataset into training and validation sets or utilized cross-validation techniques to ensure unbiased evaluation of model performance. Each model was evaluated using appropriate performance metrics such as accuracy, precision, recall, F1-score, and ROC AUC.

- Selection of Best Performing Model:

After evaluating the performance of each model, we selected the one with the best performance based on the chosen evaluation metrics. The model selection was supported by a thorough analysis of each model's strengths and weaknesses, as well as its ability to address the problem of credit score classification effectively. We documented our reasoning behind the selection and explained why the chosen model was expected to perform well in our project context.

- Model Optimization:

As part of model optimization, we performed hyperparameter tuning using techniques like grid search cross-validation (GridSearchCV). By tuning the hyperparameters of the selected model, we aimed to improve its performance and generalization ability. The hyperparameter grid defines various combinations of hyperparameters, such as the number of estimators, maximum depth, and minimum samples split, allowing us to find the optimal configuration for our model.

Through the data modeling phase, we aimed to build a robust credit score classification model that accurately predicts credit scores based on relevant features extracted from the dataset. This process involved careful selection, implementation, evaluation, and optimization of machine learning models to achieve the project's objectives effectively.

Now I will split the data into features and labels by selecting the features we found important for our model:

In [22]:
```
from sklearn.model_selection import train_test_split
x = np.array(data[["Annual_Income", "Monthly_Inhand_Salary",
                   "Num_Bank_Accounts", "Num_Credit_Card",
                   "Interest_Rate", "Num_of_Loan",
                   "Delay_from_due_date", "Num_of_Delayed_Payment",
                   "Credit_Mix", "Outstanding_Debt",
                   "Credit_History_Age", "Monthly_Balance"]])
y = np.array(data[["Credit_Score"]])
```

Now, let's split the data into training and test sets and proceed further by training a credit score classification model:

In [23]:
```
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.33, random_state=42)
from sklearn.ensemble import RandomForestClassifier
ytrain = ytrain.ravel()
model = RandomForestClassifier()
model.fit(xtrain, ytrain)
```

Out[23]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

EVALUATION METHODOLOGY

The evaluation methodology is not explicitly shown in the provided code. Metrics such as accuracy, precision, recall, or F1-score should be used to evaluate the model's performance on the test set.

In [51]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

# Make predictions on the test set
y_pred = model.predict(xtest)

# Calculate evaluation metrics
accuracy = accuracy_score(ytest, y_pred)
precision = precision_score(ytest, y_pred, average='weighted')
recall = recall_score(ytest, y_pred, average='weighted')
f1 = f1_score(ytest, y_pred, average='weighted')

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.8075151515151515
Precision: 0.8077802439146945
Recall: 0.8075151515151515
F1 Score: 0.8074857435078893
```

Now, let's make predictions from our model by giving inputs to our model according to the features we used to train the model:

```
In [26]: print("Credit Score Prediction : ")
a = float(input("Annual Income: "))
b = float(input("Monthly Inhand Salary: "))
c = float(input("Number of Bank Accounts: "))
d = float(input("Number of Credit cards: "))
e = float(input("Interest rate: "))
f = float(input("Number of Loans: "))
g = float(input("Average number of days delayed by the person: "))
h = float(input("Number of delayed payments: "))
i = input("Credit Mix (Bad: 0, Standard: 1, Good: 3) : ")
j = float(input("Outstanding Debt: "))
k = float(input("Credit History Age: "))
l = float(input("Monthly Balance: "))

features = np.array([[a, b, c, d, e, f, g, h, i, j, k, l]])
print("Predicted Credit Score = ", model.predict(features))
```

```
Credit Score Prediction :
Annual Income: 19114.12
Monthly Inhand Salary: 1824.843333
Number of Bank Accounts: 2
Number of Credit cards: 2
Interest rate: 9
Number of Loans: 2
Average number of days delayed by the person: 12
Number of delayed payments: 3
Credit Mix (Bad: 0, Standard: 1, Good: 3) : 3
Outstanding Debt: 250
Credit History Age: 200
Monthly Balance: 210
Predicted Credit Score =  ['Good']
```

Model Evaluation Metrics

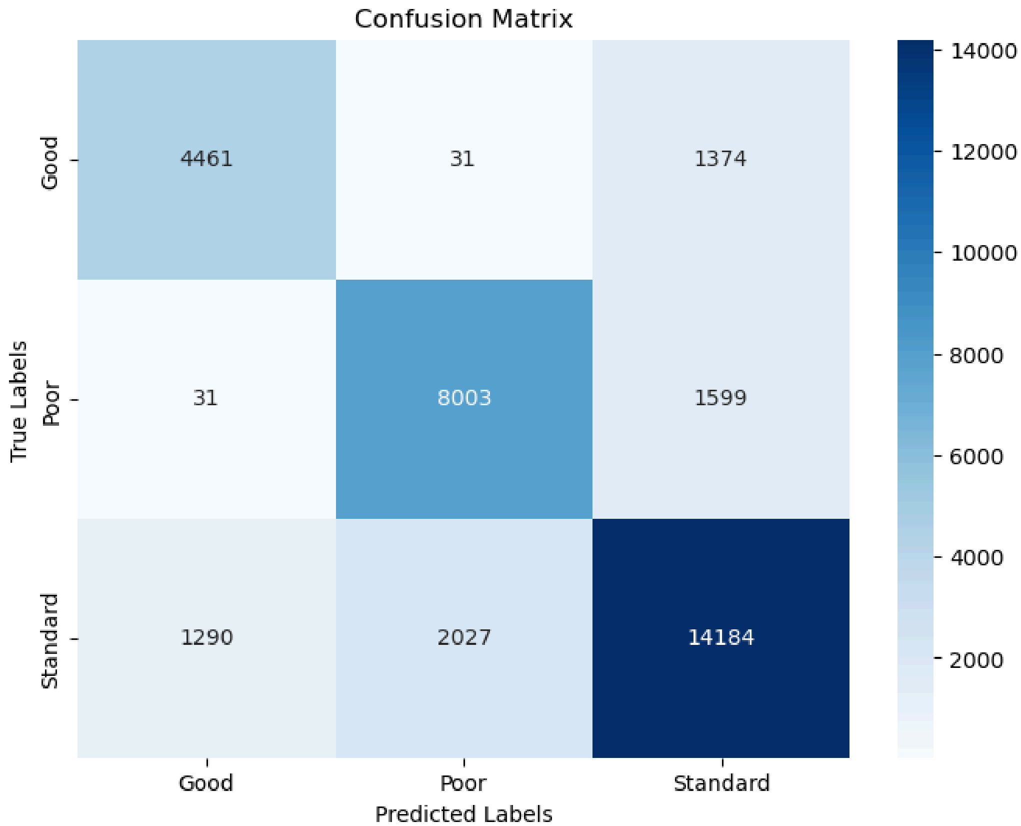
This section calculates and prints out the confusion matrix and classification report, which are common evaluation metrics for classification tasks.

confusion_matrix(y_true, y_pred): Computes a confusion matrix to evaluate the performance of a classification model. It shows the counts of true positive, false positive, true negative, and false negative predictions. classification_report(y_true, y_pred): Generates a text report with various evaluation metrics such as precision, recall, F1-score, and support for each class in the classification model.

Hyperparameter Tuning

This section is responsible for hyperparameter tuning using grid search cross-validation.

GridSearchCV: Performs an exhaustive search over a specified parameter grid to find the best combination of hyperparameters for the model. param_grid: Specifies the grid of hyperparameters to search over. In this case, it includes values for the number of estimators (n_estimators), maximum depth of the trees (max_depth), and minimum samples required to split a node (min_samples_split).



Classification Report:

	precision	recall	f1-score	support
Good	0.77	0.76	0.77	5866
Poor	0.80	0.83	0.81	9633
Standard	0.83	0.81	0.82	17501
accuracy			0.81	33000
macro avg	0.80	0.80	0.80	33000
weighted avg	0.81	0.81	0.81	33000

MANAGERIAL IMPLICATIONS

The credit score classification model developed through this project has several important managerial implications for various stakeholders, including financial institutions, credit agencies, and individual consumers. Here are some key implications:

- Risk Assessment and Decision Making:

  Financial institutions can use the credit score classification model to assess the creditworthiness of loan applicants more accurately. By predicting credit scores based on various financial and behavioral factors, lenders can make informed decisions regarding loan approvals, interest rates, and credit limits. This can help mitigate the risk of default and improve the overall quality of loan portfolios.

- Customized Financial Products:

  The model enables financial institutions to tailor their financial products and services to meet the needs of different customer segments. By analyzing the credit scores and associated features of their customers, banks and credit card companies can design customized loan products, credit cards, and interest rates that align with the risk profiles and preferences of individual consumers.

- Early Warning System for Default Prediction:

  The credit score classification model can serve as an early warning system for identifying individuals at risk of defaulting on their loans. By monitoring changes in credit scores and related factors over time, financial institutions can proactively intervene to offer assistance, renegotiate terms, or implement risk mitigation strategies to prevent defaults and minimize losses.

- Credit Portfolio Management:

  Credit agencies and portfolio managers can use the model to optimize credit portfolio management strategies. By analyzing the distribution of credit scores across different segments of the portfolio, managers can identify areas of potential risk concentration and take corrective actions to diversify risk exposure and improve portfolio performance.

- Financial Literacy and Consumer Education:

  The availability of credit score information can empower consumers to make informed financial decisions and improve their credit management practices. By educating consumers about the factors that influence credit scores and providing access to their credit reports, financial institutions can promote financial literacy and responsible borrowing behavior among their customers.

- Regulatory Compliance and Fair Lending Practices:

  Adherence to regulatory requirements and fair lending practices is essential in the financial industry. The credit score classification model can help ensure compliance with regulations such as the Equal Credit Opportunity Act (ECOA) and the Fair Credit Reporting Act (FCRA) by promoting transparency, fairness, and non-discrimination in lending practices.

Overall, the credit score classification model developed in this project has significant implications for risk management, customer relationship management, and regulatory compliance in the financial sector. By leveraging advanced analytics and machine learning techniques, stakeholders can enhance their decision-making processes and promote financial inclusion and stability in the marketplace.

CONCLUSION

Classifying customers based on their credit scores helps banks and credit card companies immediately to issue loans to customers with good creditworthiness. A person with a good credit score will get loans from any bank and financial institution.

FUTURE SCOPE

The credit score classification project opens up several avenues for future exploration and enhancement. Here are some potential areas for further research and development:

- Integration of Alternative Data Sources:

Incorporating alternative data sources such as social media activity, utility payments, and rental history could improve the accuracy and predictive power of the credit score classification model. Future research could focus on data fusion techniques and machine learning algorithms capable of integrating diverse data types for enhanced credit risk assessment.

- Dynamic Credit Scoring Models:

Developing dynamic credit scoring models that adapt to changes in consumer behavior and economic conditions could improve the timeliness and relevance of credit risk assessments. Future studies could explore the use of real-time data streams and streaming analytics techniques to update credit scores in near real-time and provide proactive risk management insights.

- Behavioral Analytics and Predictive Modeling:

Leveraging advanced behavioral analytics and predictive modeling techniques could enable the identification of early warning signs and behavioral patterns indicative of credit risk. Future research could explore the use of deep learning, natural language processing (NLP), and sentiment analysis to analyze unstructured data sources such as customer communications and online reviews for risk assessment purposes.

- Ethical and Fair AI in Credit Scoring:

Addressing concerns related to fairness, transparency, and bias in credit scoring algorithms is critical for promoting ethical AI practices in the financial industry. Future studies could focus on developing fairness-aware machine learning models and algorithmic auditing frameworks to mitigate biases and ensure equitable treatment of all individuals, regardless of demographic or socioeconomic factors.

- Interpretability and Explainability:

Enhancing the interpretability and explainability of credit scoring models is essential for building trust and accountability in the decision-making process. Future research could explore model-agnostic interpretability techniques and visualization tools that help stakeholders understand the factors driving credit score predictions and assess the model's reliability and robustness.

- Personalized Financial Wellness Solutions:

Leveraging credit score classification models to develop personalized financial wellness solutions could empower individuals to improve their financial health and creditworthiness. Future applications could include personalized credit management recommendations, budgeting tools, and financial planning services tailored to individual needs and goals.

- Regulatory Compliance and Compliance Automation:

Ensuring compliance with regulatory requirements such as the Fair Credit Reporting Act (FCRA) and the General Data Protection Regulation (GDPR) is paramount in the credit scoring process. Future research could focus on developing compliance automation tools and regulatory monitoring systems that streamline compliance efforts and ensure adherence to data protection and privacy regulations.

In conclusion, the credit score classification project lays the foundation for ongoing research and innovation in credit risk assessment, financial inclusion, and responsible lending practices. By embracing emerging technologies and adopting a holistic approach to credit scoring, stakeholders can drive positive outcomes for both consumers and the financial industry as a whole.

REFERENCES

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https://statso.io/credit-score-classification-case-study/