Loan Application Risk Classification Guide

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1 Introduction

This document provides a comprehensive technical overview of the loan screening process implemented in the backend application via the `loan_screening.py` script. The primary objective of this process is to automate the assessment of loan applications by assigning a risk category to each applicant. This is achieved through a combination of a rules-based risk index score and a predictive machine learning model. The system is designed to be transparent and interpretable, utilizing modern explainability techniques like SHAP and LIME to provide clear justifications for each decision.

2 Data Preprocessing and Feature Engineering

The initial step in our pipeline is to load and preprocess the applicant data from a CSV file. This involves several key transformations to prepare the data for modeling.

2.1 Data Loading and Cleaning

The data is loaded using the pandas library. Categorical features are explicitly converted to string types to ensure proper handling by the label encoders. Any missing numerical values are imputed using the median of their respective columns to avoid data loss and maintain the integrity of the dataset.

2.2 Categorical Feature Encoding

All categorical columns that are not personally identifiable information (PII) are transformed into numerical representations using `sklearn.preprocessing.LabelEncoder`. Each encoder is stored in a global dictionary, `ENCODER_STORE`, keyed by the column name. This allows us to invert the transformation later to interpret the model's output with the original labels.

3 Risk Index Score Calculation

A key component of our system is the proprietary **Risk Index Score**, a continuous variable that quantifies the creditworthiness of an applicant. This score is calculated as a weighted sum of several normalized financial and behavioral metrics.

3.1 Feature Normalization

The features used in the risk index score are first normalized to a scale of 0 to 1 to ensure that no single feature dominates the calculation due to its scale. The normalization formula is:

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{1}$$

3.2 Weighted Score Formula

The base score is calculated using the following weights:

- `credit_limit`: 10%
- `gross_monthly_income`: 20%
- `bpi_loans_taken`: 30%
- `bpi_successful_loans`: 20%
- `gcash_avg_monthly_deposits`: 10%
- `data_usage_patterns`: 10%

3.3 Alternative Data Boost

To reward applicants with a good history but limited traditional credit data, we introduce an **Alternative Data Boost**. This boost adjusts the weights for applicants in the bottom quartile of BPI loans taken. The adjustment is 15% and is applied as follows:

$$\text{alternative\_data\_boost} = \begin{cases} 0.15 & \text{if bpi\_loans\_taken} \leq Q_1(\text{bpi\_loans\_taken}) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

This boost dynamically re-weights the formula to give more importance to alternative data sources for these specific applicants.

3.4 Final Risk Index Score

The final score is calculated and then inverted (1 - score) so that a higher score indicates higher risk. The complete formula is:

$$\begin{aligned} \text{risk\_index\_score} = 1 - \Big(&\text{credit\_limit} \times (w_1 - \frac{\text{boost}}{2}) + \\ &\text{gross\_monthly\_income} \times w_2 + \\ &\text{bpi\_loans\_taken} \times (w_3 - \text{boost}) + \\ &\text{bpi\_successful\_loans} \times w_4 + \\ &\text{gcash\_avg\_monthly\_deposits} \times (w_5 + \text{boost}) + \\ &\text{data\_usage\_patterns} \times (w_6 + \frac{\text{boost}}{2})\Big) \end{aligned}$$

4 Risk Categorization

The continuous `risk_index_score` is then mapped to one of five discrete risk categories. To ensure a balanced distribution of applicants across these categories, we employ a method that approximates a bell curve distribution.

4.1 Bell Curve Binning

The categories are determined by binning the scores based on their standard deviation from the mean. The bin edges are defined as:

- **Default (4)**: Score $> \mu + 1.5\sigma$
- **Critical (3)**: $\mu + 0.5\sigma <$ Score $\leq \mu + 1.5\sigma$
- **Risky (2)**: $\mu - 0.5\sigma <$ Score $\leq \mu + 0.5\sigma$
- **Unstable (1)**: $\mu - 1.5\sigma <$ Score $\leq \mu - 0.5\sigma$
- **Secure (0)**: Score $\leq \mu - 1.5\sigma$

where μ is the mean and σ is the standard deviation of the `risk_index_score`.

5 Machine Learning Model

We use a **LightGBM (LGBM) Classifier** to predict the risk category based on the applicant's features. LGBM is a gradient boosting framework that is known for its speed and efficiency.

5.1 Model Training

The dataset is split into training (75%) and testing (25%) sets. The split is stratified by the `risk_category` to ensure that the distribution of categories is the same in both sets. The model is then trained on the training data.

5.2 Model Evaluation

The model's performance is evaluated on the test set using a classification report and a confusion matrix. The classification report provides metrics such as precision, recall, and F1-score for each risk category. The confusion matrix visualizes the model's performance by showing the actual versus predicted classifications.

6 Prediction and Explainability

For each new loan application, the model predicts a risk category and provides a detailed explanation for its decision using SHAP and LIME.

6.1 LIME (Local Interpretable Model-agnostic Explanations)

LIME explains the prediction for a single instance by creating a local, interpretable model around that prediction. It shows which features contributed most to the prediction, and in which direction (positive or negative).

6.2 SHAP (SHapley Additive exPlanations)

SHAP provides a unified measure of feature importance by assigning each feature a SHAP value. This value represents the impact of that feature on the model's output for a specific prediction. We generate waterfall and force plots to visualize these values.

6.3 The 5 Cs of Credit

To provide a more intuitive explanation for business users, the LIME feature importances are aggregated into the traditional **5 Cs of Credit**:

- **Character**: The applicant's financial history and reputation.
- **Capacity**: The applicant's ability to repay the loan.
- **Capital**: The applicant's own financial resources.
- **Collateral**: Assets pledged as security for the loan.
- **Conditions**: The purpose of the loan and external economic factors.

A bar chart is generated to show the aggregated impact of each of the 5 Cs on the loan application's risk assessment.

7 Conclusion

The loan screening process is a robust and transparent system that combines a rules-based scoring mechanism with a powerful machine learning model. The integration of explainability tools like LIME and SHAP, along with the aggregation into the 5 Cs of Credit, ensures that every decision is not only accurate but also easily understandable by all stakeholders.