# 10.0 Validation and Governance

## 10.1 Introduction

In the rapidly evolving landscape of financial services, ensuring the stability and performance of machine learning models is crucial for effective decision-making and risk management. This report focuses on the development and governance of a predictive model for loan approval. The model's objective is to enhance the efficiency and accuracy of loan approval processes, thereby improving operational performance and reducing financial risks. Effective model validation and governance are integral to this process, ensuring that the model continues to perform optimally over time and adapting to any changes in the input data distribution or business environment.

## 10.2 Variable Level Monitoring

Variable Level Monitoring is a critical component of model governance, focusing on the consistent performance of key features used in the loan approval model. This involves tracking the statistical properties of features over time to detect any shifts or drifts that could impact the model's predictions.

A screenshot of a computer screen

Description automatically generated

### 10.2.1 Variable Drift Monitoring

### Monitoring the drift of key variables like Dependents, ApplicantIncome, LoanAmount, and Loan\_Amount\_Term is essential to maintaining the accuracy and relevance of the loan approval model. Variable drift refers to changes in the statistical properties of these features over time, which could affect the model's predictions if not properly monitored and addressed.

### Dependents: This variable has a mean of 0.68 and a standard deviation of 0.99, with values ranging from 0 to 3. A significant change in the distribution of Dependents might suggest demographic shifts in the applicant pool. For instance, an increase in dependents could imply more family-based applications, potentially altering the risk profile of loan applicants.

### ApplicantIncome: With a mean of 3579.85 and a standard deviation of 1419.81, ApplicantIncome varies significantly, ranging from 150 to 9703. Any observable drift, such as a shift towards higher or lower incomes, could impact the model's ability to accurately assess credit risk. For example, an increase in average income might require recalibrating the model to avoid overestimating the risk for lower-income applicants.

### LoanAmount: This feature has a mean of 104.99 and a standard deviation of 28.36, with values ranging from 9 to 150. Changes in this variable might reflect shifts in borrowing behavior, such as applicants requesting higher loan amounts due to economic factors like inflation. Monitoring this variable ensures that the model remains aligned with current lending trends.

### Loan\_Amount\_Term: With a mean of 331.02 months and a standard deviation of 88.48, this variable typically ranges from 0 to 480 months. Any drift in Loan\_Amount\_Term could indicate changes in loan products or borrower preferences, which might necessitate adjustments in the model's predictions.

### The acceptable range for each feature is defined by the minimum and maximum values observed in the training dataset. If future values fall outside this range, they may be flagged as outliers. In such cases, Caps and Floors will be applied to ensure all values remain within the acceptable range. If the data exhibits drift, these thresholds may need to be updated to reflect new trends.

### Missing values in future datasets will be imputed using the K-Nearest Neighbors (KNN) technique, which estimates missing values based on the nearest observations in the data. For categorical variables, bar charts can be generated to track changes in the distribution of categories over time. Missing values in categorical features will first be encoded numerically before undergoing KNN imputation.

### 10.2.2 Tolerance for Drift of Each Variable

Drift tolerance for each variable is determined by the importance of the feature and its statistical properties:

**Dependents**: Given its moderate variability, a drift tolerance of 10% of the mean (approximately 0.07) is set. This allows for small fluctuations in the distribution of dependents without necessitating immediate model recalibration.

**ApplicantIncome**: Due to its significant range, a drift tolerance of 5% of the mean (about 178.99) is recommended. This stricter tolerance ensures that significant shifts in applicant income levels are quickly identified and addressed.

**LoanAmount**: With a relatively narrow distribution, a drift tolerance of 5% of the mean (around 5.25) is applied. This helps detect and respond to changes in loan amounts requested by applicants.

**Loan\_Amount\_Term**: Considering its wide variability, a drift tolerance of 7% of the mean (approximately 23.17 months) is appropriate. This tolerance level allows for minor shifts in loan term preferences while still flagging significant changes for review.

## 10.3 Model Health & Stability

As businesses increasingly rely on data-driven decision-making, ensuring the stability and accuracy of predictive models is critical. Variable drift monitoring plays a key role in maintaining model health by detecting shifts in data that could undermine the model's performance. When a feature exhibits drift beyond the established tolerance, the following steps will be taken:

**Initial Assessment**: The model's health will first be assessed by examining key performance metrics such as AUC-ROC and Accuracy. If these metrics indicate potential issues, further investigation into the source of the drift will be conducted.

**Model Adjustment**: Depending on the severity of the drift, different strategies may be employed. For minor drifts (within the tolerance), hyperparameter tuning or reweighting of features may suffice. For more significant drifts, the model may need to be retrained with updated data to ensure it continues to provide accurate predictions.

**Risk Management**: If the drift indicates a substantial change in the underlying data, such as a structural shift in applicant behavior or economic conditions, a more comprehensive risk management approach may be required. This could include updating the model to reflect new data distributions or even redesigning the model if necessary.