# MODEL MONITORING AND GOVERNANCE

Predictive models' ongoing performance and reliability in a dynamic environment like Ikeja Electric’s operations are critical to ensuring consistent business outcomes. This section outlines the rigorous model monitoring and governance framework that guarantees model stability, data integrity, and continuous improvement while mitigating the risks associated with model degradation or drift.

## 1.0 Introduction

In the fast-paced and data-intensive environment of Ikeja Electric, maintaining the reliability and performance of predictive models is essential to achieving consistent business outcomes. As the operational landscape evolves, so must the models that drive critical decisions. This document outlines a comprehensive monitoring and governance framework designed to ensure model stability, data integrity, and continuous improvement while mitigating risks such as model degradation or data drift. By systematically tracking variable behavior, detecting shifts, and automating responses, this framework helps safeguard the accuracy and effectiveness of predictive models, ensuring they remain aligned with real-world conditions and business objectives.

### 1.1 Variable Level Monitoring

To maintain the relevance and accuracy of the model, continuous monitoring of key variables is essential. The governance framework implements regular checks on the statistical properties of these variables:

#### 1.1.1 Descriptive Statistics Monitoring

Key metrics such as mean, median, standard deviation, minimum, and maximum values are tracked for critical features like Current Payment, Feeder No, and Billing Adjustment. The monitoring process helps to detect early signs of data drift or anomalies, ensuring that the model’s inputs remain aligned with real-world conditions. The acceptable range for each feature is represented by the range between min and max. Impute zero for null values found in actual closing balance (these customers do not have any outstanding payments which is why they have a corresponding null data in actual closing balance column, that is: they are on credit or not owing the organization).

A screenshot of a computer

Description automatically generated

#### 1.1.2 Categorical Distribution Analysis

For features like Account Type 2, bar charts are generated to visualize the distribution of categories over time. This allows stakeholders to quickly identify shifts in customer segments, tariff groups, or other significant categorical data that might impact model performance.

1.1.3 Monitoring Frequency

Depending on operational requirements, these checks are performed daily, weekly, or monthly, with results logged for historical analysis and trend detection.

A graph of different colored squares

Description automatically generated with medium confidence

**Categorical distribution analysis**

### 1.2 Variable Drift Monitoring and Detection

Model performance can deteriorate if the underlying data distribution changes significantly, a phenomenon known as data drift. Drift monitoring focuses on detecting shifts in both feature distributions and model predictions:

#### 1.2.1 Feature Drift Monitoring

Drift is quantitatively measured using statistical tests (e.g., Kullback-Leibler divergence, population stability index) to compare current distributions with the training set distributions. Drift is flagged if it exceeds pre-defined thresholds:

#### 1.2.2 Critical Features

A 7% drift threshold of the mean of features such as Current Payment, which have a direct impact on model outcomes is to be adhered.

#### 1.2.3 Secondary Features

A 10% drift threshold is applied to less critical features that might still influence model stability.

#### 1.2.4 Actions upon Drift Detection

When drift is detected, the model’s health is reassessed by analyzing predictive performance metrics such as the MSE, RMSE, and MAE. If necessary, corrective actions are initiated to maintain the model’s integrity.

## 2.0 Model Health & Stability

Ensuring the health and stability of machine learning models is crucial for their reliability and performance over time. Key aspects to consider for better model health and stability:

### 2.1 Model Stability

This refers to the consistency of a model’s performance when exposed to different datasets or slight variations in the data. A stable model should provide comparable results even when the input data changes slightly. Techniques to assess and improve model stability include:

#### 2.1.1 Stability Index

This is a quantitative measure used to assess how consistent a model’s performance is across different datasets. Methods like cross-validation can help calculate this index by introducing variations in the data and measuring the model’s performance.

#### 2.1.2 Model Health

Model health involves monitoring and maintaining the model’s performance over time. Key practices include:

2.1.3 Regular Validation

Continuously validating the model with new data helps in identifying any performance degradation early. This can involve retraining the model periodically to adapt to new patterns in the data.

#### 2.1.4 Error Analysis

Analyzing the errors made by the model can provide insights into areas where the model might be struggling, allowing for targeted improvements.

#### 2.1.4 Robustness to Data Changes

Models should be robust to changes in the data distribution. This can be achieved by:

#### 2.1.5 Data Augmentation

Introducing variations in the training data to make the model more adaptable to different scenarios.

#### 2.1.6 Continuous Monitoring

Implementing a system for continuous monitoring of the model in production ensures that any issues are detected and addressed promptly. This includes setting up alerts for significant deviations in performance metrics.

### 2.2 Initial Model Fit Statistics

To better evaluate the health of algorithms and monitor the stability of the model over time, Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are selected as the model diagnostics and performance indicators and benchmarks.

#### 2.2.1 Mean Squared Error (MSE)

measures the average of the squared differences between the predicted values and the actual values. A lower MSE indicates a better fit of the model to the data.

The selected model in this project, the Random Forest has an MSE of 33239447903.410583

#### 2.2.2 Root Mean Squared Error (RMSE)

RMSE is the square root of the MSE. It represents the average magnitude of the errors in the same units as the target variable (in this case, 'Current Payment').

The selected model in this project, the Random Forest has an RMSE of 182316.88869496042

#### 2.2.3 Mean Absolute Error (MAE)

MAE calculates the average of the absolute differences between predicted and actual values. It treats all errors equally, regardless of their direction. MAE is less sensitive to outliers compared to MSE and RMSE.

The selected model in this project, the Random Forest has an MAE of 54649.63194734574

#### 2.2.4 Hyperparameter Tracking and Tuning

The model governance framework emphasizes not just the monitoring of data but also the continuous review of model configuration:

##### 2.2.4.1 Hyperparameter Monitoring

For decision tree-based models like Random Forest and Decision Trees, key hyperparameters (e.g., max\_depth, min\_samples\_split, n\_estimators) are logged and monitored. Over time, adjustments are made based on evolving data patterns and model performance.

##### 2.2.4.2 Automated Hyperparameter Optimization

The model is subjected to automated tuning processes such as grid search and random search at regular intervals or when drift thresholds are breached. These optimizations focus on striking the right balance between model complexity and performance.

## 3.0 Risk Tiering and Escalation Procedures

Model risk tiering is a structured approach to managing the various levels of drift and associated risks:

In this project, we have chosen MSE, RMSE and MAE as our key performance benchmarks. To maintain the model’s effectiveness, we will closely monitor these metrics. Should we observe a drift of 1% to 10% from the current values, we will promptly act based on our risk tiering strategy to ensure the model continues to perform optimally.

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| --- | --- | --- |
|  | **Current Value** | **Acceptable** |
| **MSE** | 33,239,447,903.410583 | 31,577,475,508.24 |
| **RMSE** | 182,316.88869496042 | 173,201.04 |
| **MAE** | 54,649.63194734574 | 51,917.15 |

### 3.0.1 Low Risk (0%-2% Drift)

This range indicates minimal changes, where no immediate action is required. Routine monitoring continues, and no model adjustments are made.

### 3.0.2 Moderate Risk (2%-5% Drift)

If drift falls within this range, optimization techniques such as hyperparameter tuning, feature selection, or minor data adjustments are implemented. The goal is to recalibrate the model without major structural changes.

### 3.0.3 High Risk (6%-10% Drift)

Significant drift in this range indicates that the model may no longer be performing optimally. A full model refit is performed, incorporating recent data, to realign the model with current trends and conditions.

Unacceptable Risk (>10% Drift): Drift beyond this threshold suggests that the data structure has fundamentally changed. The model is outdated and will be redeveloped from scratch. A new model development cycle is triggered, including updated feature engineering, retraining, and validation.

### 3.1 Monitoring Automation and Reporting

The governance framework integrates automation tools to enhance the efficiency of monitoring and reporting:

#### 3.1.1 Automated Alerts and Dashboards

Real-time dashboards display key metrics like drift percentages, model performance scores, and feature importance rankings. Alerts are generated when thresholds are breached, ensuring timely interventions.

#### 3.1.2 Quarterly Performance Reviews

Detailed reports are generated quarterly, summarizing the model’s health, drift trends, performance metrics, and any corrective actions taken. These reports provide clear insights for stakeholders, enabling proactive decision-making and model governance.