# Optimized Model Framework for Restaurant Sales Prediction

## Introduction

This document outlines a comprehensive framework for predicting the sales of specific products for restaurants over the next 1-7 days. The solution integrates a central model for general market-wide patterns and user-specific models for personalized predictions, ensuring a robust balance between generalization and customization.

## 1. Central Model

The central model captures market-wide sales trends using large-scale restaurant data. It provides a robust starting point for new users and tracks patterns like seasonality and external events.

Key Features:

* - Model Type: LSTM or Transformer (ideal for time-series data).
* - Input Features: Product ID, date, sales, discount, price, restaurant type, event type, weather.
* - Update Frequency: Monthly, using aggregated data from all users.

## 2. User-Specific Model

User-specific models leverage restaurant-specific historical and real-time data to provide personalized predictions. These models adapt to individual restaurant trends more effectively.

Key Features:

* - Model Type: Gradient Boosting Decision Tree (GBDT) or lightweight neural networks.
* - Input Features: Same as the central model, focusing on user-specific characteristics.
* - Update Frequency: Daily, based on new data uploaded by the user.

## 3. Dynamic Fusion Mechanism

To balance predictions from the central and user-specific models, a dynamic fusion mechanism is employed. Short-term forecasts rely more on user-specific models, while long-term predictions weigh more towards the central model.

Fusion Formula:

Final Prediction = α \* (User Model Output) + (1 - α) \* (Central Model Output), where α depends on forecast duration and past model performance.

## 4. Workflow Diagram

The following diagram illustrates the process flow, highlighting the interactions between the central model and user-specific models.