## Project Title: Food Demand Prediction using Machine Learning on AWS

### Introduction

The project focuses on developing a system that predicts food demand using AWS Machine Learning services. The main objective is to address the common challenges faced by restaurants and food delivery services — either preparing insufficient food, which leads to shortages, or preparing excess food, which results in wastage. By forecasting demand in advance, this project aims to optimize food preparation, reduce wastage, and improve cost efficiency.

### Problem Statement

In the food industry, accurate demand estimation is often difficult. Businesses frequently face situations where the supply does not match the actual demand. If too little food is prepared, customer satisfaction decreases due to shortages. If too much food is prepared, it leads to wastage and financial losses. To overcome these issues, a predictive model based on past sales data was developed to provide reliable demand forecasts.

### Dataset and Preprocessing

The dataset used consisted of one year of historical food demand records. Data preprocessing was carried out in Jupyter Notebook on AWS. The data was converted into JSONL format, as this is the accepted format for training models on AWS Machine Learning platforms. The preprocessing step ensured that the data was clean, structured, and ready for training.

### Model Training

Amazon SageMaker was used to build and train the predictive model. Several hyperparameters were configured to enhance model performance:

- **Cardinality:** Defined categorical variables such as day-of-week, weather conditions, and menu items.
- **Context Length (12):** Determined how many previous time steps the model should consider for learning.
- **Dropout Rate (0.1):** Reduced overfitting by ignoring a fraction of neurons during training.
- **Early Stopping (40):** Prevented unnecessary training when no further improvement was observed.

- **Embedding Dimension (10):** Converted categorical variables into numerical representations for better learning.
- **Epochs (400) and Learning Rate (0.001):** Ensured stable and effective training.
- **Likelihood (Student-t):** Chosen to handle outliers better than a normal distribution.
- **Batch Size (128), Num Layers (2), Num Cells (40):** Controlled model depth and learning efficiency.
- **Prediction Length (5):** Enabled the model to forecast demand for five days in advance.

These hyperparameters were selected after experimentation to balance accuracy and training efficiency.

**Model Deployment and Predictions**

After successful training, Amazon SageMaker automatically provided an endpoint for deployment. This endpoint enabled real-time predictions directly from Jupyter Notebook. Input data could be sent to the endpoint, and the predicted food demand was retrieved instantly. This verified that the model worked as expected and could generate accurate forecasts.

**User Interface and Chatbot Integration**

To make the system user-friendly, a simple interface was developed with an integrated chatbot. The chatbot allows users to ask natural language queries such as *"What will be the demand for the next 5 days?"* and instantly receive predictions. This feature enhances accessibility and demonstrates how the model can be applied in real-world scenarios.

**Use of Amazon Q**

Amazon Q was utilized to support the coding process by providing real-time code suggestions and improvements. This reduced development time and minimized errors during implementation.

**Why AWS?**

AWS was chosen for its simplicity, scalability, and integrated environment. The entire process — from data preprocessing and training to deployment and real-time prediction — was carried out on a single platform. Automatic endpoint creation simplified integration, while the scalable infrastructure ensured that the model pipeline could handle large datasets and workloads efficiently.

**Conclusion**

The project successfully implemented a demand prediction system using AWS Machine Learning services. By leveraging past sales data, the model provided accurate forecasts that

can help restaurants and food services optimize food preparation. This approach reduces wastage, prevents shortages, and improves cost efficiency. The combination of AWS SageMaker, automated deployment, and a user-friendly interface demonstrates a practical solution for real-world food demand prediction.