Experiment results

QUESTION ONE:

Reasonable Data Baseline for Prophet Model in Production

For a Prophet model used in a real-time monitoring system, a reasonable data baseline would typically span many hours or even days. This extended training period helps stabilize the model's performance metrics, such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), which tend to fluctuate with shorter training windows. Since the model processes minute-level data, a longer training window allows it to detect daily or weekly seasonality patterns more accurately. Generally, using several weeks to a month of historical data ensures that the Prophet model captures recurring trends effectively, improving its predictive power in a production environment.

Challenges of Long Training Lengths

However, training the Prophet model continuously or with large datasets introduces operational challenges, including increased computational demands, latency, and data storage management issues. These challenges can impact system performance, particularly when handling high-frequency updates like those seen in real-time monitoring applications. To mitigate these challenges, strategies such as batch retraining at defined intervals and optimizing the data window for training can balance performance and accuracy. This approach reduces computational overhead while maintaining model accuracy, making it more feasible for real-time applications.

QUESTION TWO:

Allowing a Prophet model to retrain continuously in a production environment can offer the advantage of quickly adapting to changes in data, potentially enhancing prediction accuracy over time. However, there is a risk of the model overfitting to short-term fluctuations, leading to false positives in anomaly detection. Introducing manual review or validation steps before retraining can help mitigate this risk. For example, setting thresholds for Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), or anomaly counts before retraining can prevent the model from learning from noise. Incorporating human-in-the-loop systems can also enhance trust in the model's predictions and improve the identification of genuine anomalies.

Pitfalls of Fully Automatic Retraining

A fully automated retraining system can lead to several pitfalls:

- Overfitting to Noise: The model may start detecting false anomalies due to small, sporadic fluctuations in the data. This could cause the model to misinterpret minor changes as significant patterns, resulting in misleading forecasts.
- Alert Fatigue: Continuous flagging of minor errors or anomalies could overwhelm users, leading to desensitization to alerts and missing critical issues that require immediate attention.

- Model Drift: Without manual oversight, the model could gradually drift if the underlying data characteristics change, producing inaccurate forecasts and anomaly detections that go unnoticed.

To prevent these pitfalls, combining automated retraining with manual checks or defined thresholds can help maintain the model's accuracy and reliability in production settings.