

A model monitoring pipeline should offer various components, monitoring from different aspects to assure the team that the deployed model's performance is maintained and outputs are still reliable.

Firstly, I will monitor the collection and logging of data. All models are being fed heavily with data for training, which will cause a direct impact on the quality and reliability of outputs. It is hence important that we have to monitor these features used by models for training and making inferences. Logging the data not only helps the team backtrack and understand what type of data affected the prior performance, it also helps to catch any potential data drift through anomalies or by comparing data distribution with those observed during model training. Logging frameworks like Elasticsearch enables team to configure how they wish to roll their logs and capture the data.

Next to monitor is the performance of the model. In order to track for model drift proactively before it causes major implications to the end users, determining a baseline performance metric to measure the model's performance can help detect degradation in model accuracy or its effectiveness, alerting the team the need for model retraining/tuning. Tracking of model's performance with a metric and a validation dataset that represents the current production data can help the team to identify or even forecast performance degradation over time. Some of the metrics we can consider using to calculate and assess the model's performance are accuracy and precision, which can be monitored through dashboards like Kibana (an open-source data visualization and exploration tool designed for Elasticsearch) updated at specific intervals or in real time, if required. We can also monitor confidence scores against model predictions and actual outcomes to detect for prediction drift.

Last but not the least, I will also include statistical methods like probability distributions, paired with automated alerting functions to alert the team whenever a change or drift is detected, such as feature drift or concept drift. With automated monitoring and alerting, the team would have to define thresholds for acceptable drift levels based on factors like historical performance and/or subject matter experts' advice on the risk tolerance. A real-time monitoring system that continuously checks for drift indicators such as AWS Kinesis can be utilised by the team to process data in real-time and apply drift detection algorithms.

By consistently monitoring input features, predictions, performance metrics, and putting in place automated drift detection methods, the team can detect and manage model drift effectively. This proactive strategy helps maintain the accuracy and relevance of models. For a product team, these practices can streamline decision-making processes, enhance product performance over time, and foster greater confidence in the reliability of the models used. This, in turn, can lead to quicker adaptation to the everchanging needs of the users, ultimately bolstering the team's ability to deliver impactful solutions.

(472 words)