Model Monitoring

Model monitoring refers to the ongoing process of observing and evaluating the performance and behavior of machine learning models deployed in production environments. It involves tracking various metrics, such as accuracy, precision, recall, and model-specific performance indicators, to ensure that the model continues to meet the desired objectives and performance standards.

Model monitoring can be broken down in two major components

1. Data
2. Quantitative Performance
3. Qualitative Performance
4. Model and Data Versioning

Data Monitoring

1. Data Drift Detection
    a. Monitoring changes in the distribution or characteristics of incoming data compared to the data the model was trained on using statistical tests (e.g., Kolmogorov-Smirnov test, Chi-square test) to compare distributions of current data to historical data.
2. Data Source Monitoring
    a. Examine changes in data sources and collection methods, or any external factors

Quantitative Performance Monitoring

1. Metrics Monitoring
    b. Constant monitoring of performance metrics such as accuracy / precision / recall / F1 over an extended period of time against experimental baselines
2. Concept Drift Detection:
    a. Monitored by analyzing the performance metrics over time and applying algorithms designed to detect changes in data relationships, such as ADWIN or Page-Hinkley tests.
3. Anomaly Detection:
    a. Significant spikes or dips in a specific prediction class in a short span of time (bursty behavior)

Qualitative Performance Monitoring

1. Feedback Loop / Relevance integration:
    a. Qualitative User Feedback Model Relevance due to changing business natures
2. Alerting and Reporting
    a. Automated alerting mechanism when predefined thresholds are exceeded
3. Usage Tracking
    a. Number of users/requests over time

Model and Data Versioning

1. Model Versioning
    a. Maintain a version control system for models to allow developers to tag and version control their models for easier rollback and performance/hyperparameter tracking
2. Data Versioning
    a. Version controlling datasets to ensure data is not changed across experiments

Tracking Model Drift

In terms of data drifts, using open source tools or managed services to track if there are any significant distribution changes or feature changes over time. This could be both on the range of values or even the data types

In terms of model drifts, performance tracking or anomaly detection on metrics would help to identify model drifts. This would mean that there is a degradation in the performance of the models.

Aside from the quantitative approaches, it is also crucial to monitor for business changes. For example, an activity that might have been deemed as fraudulent a month ago might be deemed valid in current times. Thus, the labels that the models were trained on were incorrect and thus resulting in concept drift.

In summary, to ensure efficient model tracking both qualitative and quantitative approaches should be in place and evaluated on a scheduled basis. The detailed implementations would vary on the conditions of the infrastructure as well as the business case. For example, data monitoring on tabular data would be very different from monitoring on an NLP based model. Thus, there is no one size fits all. However, for quantitative evaluations there are an abundance of MLOps platforms / frameworks to leverage on but for qualitative evaluations would have to be dependent on each organizational processes.