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Chapter 8: Model Deployment, Monitoring, and Continuous Optimization

8.1. Introduction

The journey of every machine learning model reaches a momentous milestone when the model is deployed for public use. However, this accomplishment is merely an intermediary step in what is, in actuality, a dynamic continuous process. The production stage requires the model to operate reliably in an environment populated by users and competing models. Such an operational environment is rife with challenges that demand considerable technical investments using knowledge and techniques that transcend issues of mere performance. Deployment decisions can determine whether the platform will smoothly provide services for months or whether constant firefighting and regime change will compromise reliability and quality of service and lead to eventual abandonment or deprecation of the model. Both the definition of an automated monitoring framework and the establishment of a continuous optimization feedback loop are critical in determining the need for constant firefighting, burnout of scarce technical resources, and the ultimate operational success of the model.

A careful consideration of monitoring practices for machine learning systems in production reveals a sizable body of literature recommending the adoption of research and practices used in the operation of traditional IT systems. Indeed, many of the recommendations are both useful and appropriate. However, IT systems are not deployed to showcase intelligence and prove better orquestration decisions, risk aversion, and resource allocation compared to human users. Such tasks are, among other qualities, precisely where ML models are expected to succeed and usually employed. They are therefore used in a comparatively more competitive environment than standard IT systems. In addition, aspects of quality and fairness are ever-present ingredients of business communication for AI solutions and must be actively pursued in production. Monitoring approaches devised specifically for machine learning-driven systems thus also have to adopt an SRE perspective, yet with the added dimension of quality and fairness.

8.1.1. Background and Significance

Operationalizing machine learning (ML) systems is a multidisciplinary engineering challenge, going beyond simply putting a solution into production. Successful deployment and monitoring require a pragmatic understanding of the system's operational environment and its objectives during its lifecycle. A carefully developed monitoring strategy enables the operation team to respond suitably to incidents when the system eventually fails to perform as required. Continuous optimization establishes feedback loops that guide the entire ML team in improving system performance and avoiding unnoticed performance degradation.

There is currently no universal guide to complete the engineering work of deploying, monitoring, and continuously optimizing a machine learning model in production. However, there is a wealth of resources detailing the separate steps and areas involved, and some emerging literature focuses on assembling these pieces into a single view or process. One such resource classifies the fundamental concepts and strategies outlined in the following sections. This classification is not unique; rather, it represents one way of organizing the practical details from the underlying literature. The proposed terminology is a simple extension of the operationalization definition and serves to develop the accompanying framework more formally. The definitions are brief and focus on the model's operational environment and objectives, rather than its ML properties.

Fig 8.1: Model Deployment, Monitoring, and Continuous Optimization

8.1.2. Research design

Monitoring and optimization are crucial for ensuring the sustainable quality of deployed ML models; and are best considered under the umbrella of operationalization. Given the broad nature of the topics, the discussion on monitoring encompasses performance, reliability, and fairness considerations, while continuous optimization focuses the feedback loop to increasing performance metrics, based on user or agent feedback.

The approach to operationalization is based on strategies from traditional software engineering (e.g., logging, alerting, A/B testing) and Site Reliability Engineering (SRE), as well as recent literature on operationalizing ML models (on SRE, see also the chapter by C. Z. R. Sarmento). There are several specifics that need to be considered for monitoring and optimization. An additional subtlety in improving the overall system performance (ML systems are rarely if ever isolated anymore) is presented and expanded upon by applying an SRE-like approach to ML models.

8.2. Model Deployment: Principles and Architectures

Mention model deployment and the word "production" rapid evocation of software engineering systems and procedures, but machine learning (ML) systems present unique challenges for productization, affecting both the technical implementation and the business case. Deployment involves four different environments — development, staging, testing, and production — and the introduction of intensive training pipelines, with continuous second-generation data-collection and labelling pipelines required for performance maintenance when concept drift occurs. Production-mode characteristics such as containerization, orchestration, model-library management, and elaborate logging and tracing infrastructures all play a central role in operationalization.

The basic principles, roles, and entities involved in deploying, refining, continuously monitoring, and optimizing an ML-powered offering are detailed in the following sections. The descriptions cover the tasks of deployment and continuous optimization throughout the architecture of the overall application and supporting systems, with an SRE-style perspective focusing on principles and questions that apply to every system and component, and specific technologies covered in subsequent sections.

8.2.1. Deployment Environments and Pipelines

Available options to deploy machine learning models in production environments and release them include development, staging, UAT (user acceptance testing), and production environments. A commented reaction between a model tested in staging and the next UAT environment is depicted in Figure 8.4. A model meets the dashboard

requirements defined by business users during the development phase. It may have implemented reprocessing of the model previously deployed in production, model retraining, or hyper-parameter tuning in production. Deployment of a model from a test environment to a staging environment is done by the data science team using data science tools and dashboards. Upon passing the tests defined during the development phase, the model is deployed in the UAT environment. Validations are executed by business users. They evaluate the model according to the documented STONE TEST criteria predefined during the project kick-off and with help of a STONE TEST cybersecurity checklist recognized by both parties.

If approved, the model is deployed in production. Alerts to the production and UAT teams are generated to inform them about the new model available for usage, all through a machine learning monitoring tool (third party or developed) that may implement timestamp tagging of the model. Deployment in production can be done via public clouds (for private or hybrid clouds), on-premises using virtualization (virtual machines) and/or orchestrators (containing technology such as Kubernetes), or in a hybrid architecture. For cloud implementations, model deployments can also make use of model serving or artificial hosting solutions focused on machine learning and artificial intelligence models, such as Amazon Sagemaker.

8.2.2. Containerization, Orchestration, and Reproducibility

Containerization and orchestration support deployment studies by simplifying publishing infrastructure and addressing environmental issues. The encapsulation of software via tools such as Docker and Singularity allows for the implementation of machine learning solutions on multiple operating systems with a minimal set of dependencies. Container orchestration tools such as Kubernetes allow for automatic scaling and handling of multiple concurrent requests. Because deployed systems are generally used for a long period of time, the latent need for experimentation becomes critical and cannot constantly rely on online HTTP services. Continual learning techniques that update a model for a sequentially updating environment with changing conditions are actively pursued; update frequency may be sped up through the use of time-sensitive alternative hyperparameter sets. ML solutions that do not change in structure but in weights can be more easily monitored for changes in data distributions over time. Comparison against both old models and simpler proxies addresses concept drift, one form of model failure, without the need for constant retraining from scratch.

For ML models that do change structure during best model selection or latency-aware regular training, maintaining retrievability is also necessary. Popularized in deep learning, hyperparameter tuning has a wide-ranging impact on systems but can also take a long time. Such tuning can therefore be placed in production, where sensing via set-

based generalization gives estimates of the effect of removing a hyperparameter and suitable response surfaces permit faster convergence to good hyperparameter settings. This creates a relation between predictive logic and system response surfaces.

8.3. Operationalization Metrics and Monitoring Frameworks

Model performance can degrade after deployment for several reasons, including data drift within the underlying feature set of the machine learning (ML) model, changes to the data distribution with respect to the prediction target, and the introduction of unanticipated prediction use cases. A framework that encompasses bias, drift, and performance monitoring, with extensive logging and tooling, offers development and engineering teams a mechanism to identify these issues rapidly. A diverse application of operational monitoring metrics is combined with a monitoring and alerting strategy directed at Site Reliability Engineering (SRE) teams so they can support production systems at Big Tech companies. Such a framework is built upon established principles from the software engineering community while also addressing the unique operational characteristics and data challenges of ML workloads.

Fig 8.2: Operationalization Metrics and Monitoring Frameworks

The operationalization of an ML model can be extended beyond performance metrics to include reliability and fairness aspects. ML pipelines, from the raw feature transformations to the prediction outputs, must be inherently instrumented to log the necessary data for understanding their reliability during production operation. In addition to classic logging, observability principles can be applied to ML workloads

using tracing. By augmenting the standard prediction-path telemetry with the SRE principles of tracing, Infra-as-Code, and Chaos Engineering, the identification and remediation of problems can be accelerated. These principles are then distilled into a set of alerts, defining behavioral shifts that fall outside defined bounds, and presented in the context of Hypothesis-Driven Development (HDD) within a collaborative R&D and SRE design environment.

8.3.1. Performance, Reliability, and Fairness Metrics

To ensure high-quality performance over time, it is crucial to define reliable, reproducible, and well-designed performance metrics. Consequently, the design of the operational performance metric must consider non-functional attributes of the system, such as: service call latency, availability, response correctness, information security, data protection, and fairness. Moreover, many ML applications can be viewed as a black box system, where the ML component conducts only a small part of the complete flow.

In these situations, the ML team is often held accountable for metrics that are linked or copied from the non-ML components, leading to a possible blame game in production. Therefore, ML operational metrics should have an in-depth analysis of how the ML component feeds into the larger system and probe possible leakage into the performance metric, especially if SLOs of other components are being considered.

8.3.2. Logging, Tracing, and Alerting Strategies

ML systems are generally designed for high availability and reliability, as are the underlying infrastructure and dependency services. Detecting issues when they happen so that there are no or minimal interruptions is of paramount importance. Consequently, ML systems must all include logging and/or tracing in areas of interest. Mechanisms should also be built into services that automatically raise alerts when key metrics deviate from expected ranges so that on-call DevOps or SRE engineers can respond to incidents.

For ML systems, tracking signals related to data or concept drift is important, as is monitoring latency, both for inference and for data prep. User-facing services should also monitor user behavior patterns (e.g., traffic load, patterns of incoming abusive content) through external A/B tests, user research, or other similar means, as shifts in user behavior can affect even the most stable models. As bugs or anomalies are observed, these conditions can then become input signals for business, product, or engineering leadership to take action. Often these situations point toward longer-term work, adjustments to business strategy, or changes in product strategy. Even if the signals are clean, the model can still perform poorly, so dedicated system-level code paths for

detecting increases in prediction error, along with model debug and check-in behavior, should be in place.

8.4. Continuous Evaluation and Model Drift Management

The distribution and characteristics of the underlying data may change over time, causing the trained ML model's performance to degrade. The phenomenon is termed concept drift when the data manager properties change, resulting in the model's predictions no longer matching the true target. Alternately, data drift occurs when the properties of the data flowing into the model evolve, although the underlying concept remains stable. Monitoring these shifts' onset, pace, and intensity through statistical and machine-learning-based processes helps detect drift in advance empowers fast automated feedback, operationalizes a continuous evaluation culture during production deployment, and sustains a feedback loop for new dataset collection and model refinement.

A comprehensive evaluation protocol actively tests the overall ML system in production through periodic monitoring with different evaluation methodologies and automation of the setup, including but not confined to, chaos engineering, benchmark testing, stress testing, shadow deployment, dark launching, and canary releasing. Such careful management operations can proactively anticipate incidents before they slip into users' vision and break the product. The ML system can be treated like a commercial product, and any business-challenging features can be actively invalidated without due testing using human experts only by continuously maintaining a collection of known hypothesis tests that must be satisfied in production.

8.4.1. Concept Drift vs. Data Drift

Many papers on continuous learning introduce the notion of concept drift, which occurs when the relationship between inputs and outputs changes over time. This entails a change in the underlying function or mapping that the model is attempting to learn. Other papers refer to data drift or covariate shift, meaning that the input distributions have changed, which can lead to degraded predictions even if the relationship remains constant. In the context of supervised learning, these two types of drifts are clearly distinct and necessitate different responses, but in an online learning context, the distinction narrows.

Reinforcement learning with an environment built from real-world data may introduce a third notion of drift: policy drift, where the policy being learned has impacted the underlying environment, which can consequently generate samples from a different

distribution. Again, sample-based methods must still consider when and how to respond to such drift, but other aspects of modifying or monitoring the model have greater priority for these methods.

8.4.2. Evaluation Protocols and Benchmarking in Production

Models present a moving target due to dynamic data distributions, and careful consideration must therefore be given to how and when they are evaluated during live operation. Although evaluation procedures developed during training remain crucial, they may be complemented or supplanted by protocols that are more attuned to production realities, such as joint testing with a surrogate model or comparison against a challenger deployed within the same environment. A rigorous post-mortem examination of prediction failures can also yield valuable insights.

Promoting confidence in the performance of production ML systems is typically achieved through an extensive repertoire of monitoring protocols rather than a single, grand evaluation. Such protocols encompass logging, tracing, and alerting strategies, as detailed in the section on operational metrics and monitoring. Markov chain models can also be harnessed to formulate how performance differences change over time, indicating when a recently deployed ML model is anticipated to exhibit higher predictive quality than an incumbent.

8.5. Automated Monitoring, Alarms, and Incident Response

To mitigate the adverse consequences of service disruptions, automated monitoring that triggers alerts remains essential. Despite the inherent unpredictability of the production environment, appropriate monitoring can foresee the majority of problems. These monitoring tools, combined with incident playbooks that define alert types, expected corrective measures, and responsible personnel, are crucial to reestablishing normal service as quickly as possible.

To realize these benefits for ML systems, an SRE-inspired incident response approach is valuable. SRE offers a solid foundation for developing best practices for maintaining the reliability of ML systems in production—such reliable systems both minimize the probability of failure and ensure fast recovery when failures occur. Like SRE, this approach is also based on the concept of service-level objectives (SLOs) as a means of defining reliability targets for products and systems; these support a trust-based model between service supplier and consumer and can take many forms. SLOs for ML products need to reflect the whole system, including components such as data quality, latency, and availability whose impact may not arise until some time after service delivery.

8.5.1. SRE-inspired Practices for ML Systems

Many techniques and practices pioneered by the SRE community can be adapted for ML systems, addressing the question of how DevOps principles apply to ML. Increased scale leads to monitoring architecture that accepts large-scale, potentially noisy inputs from various points in the system, handles them in a scalable way, and answers questions of interest. Examples of ML-specific activity at the SRE level include defining what the monitoring system can or cannot give a usable answer for, identifying how to retrain the model continuously, scaling incident response, and discovering where the latest model really is.

A more detailed distillation of ML monitoring principles takes the form of a monitoring tasks table, where columns indicate whether alerts on the task are automated and if alarms are specified in runbooks. An alert for a safety-related event can be very simple but requires an associated incident playbook. If an event is complex to monitor or responds to speedily, it should be the subject of an event-tracing mechanism. The presumably costly steps of triggering an incident or alarm for a safety event should ideally be captured in an incident playbook even if largely left out of the alarm.

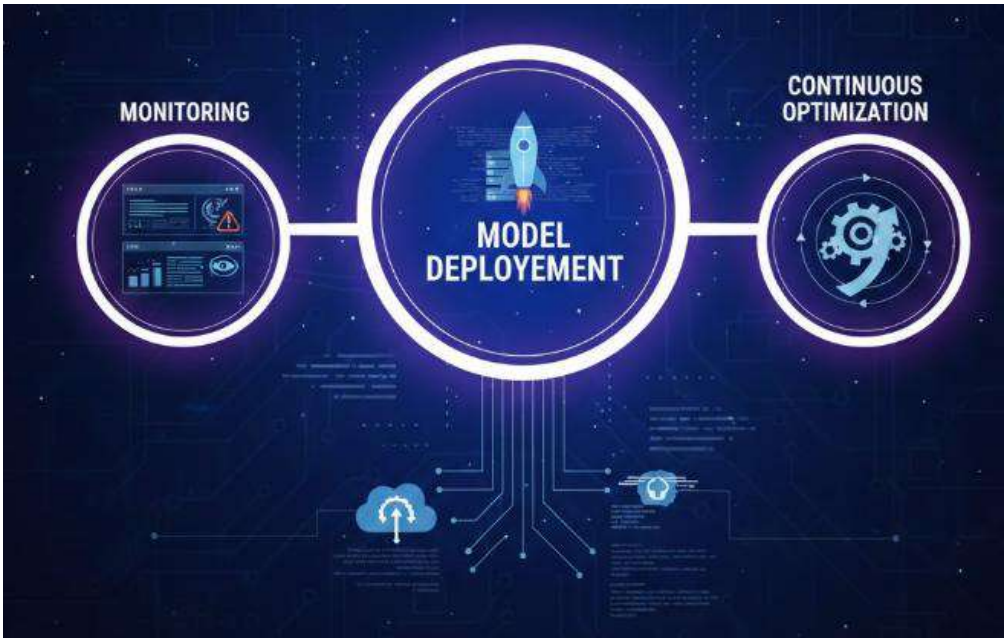

Fig 8.3: SRE-inspired Practices for ML Systems

8.5.2. Incident Playbooks and Runbooks

Incident playbooks and runbooks define what to do when things go wrong. They are based on observations from previous incidents as well as on anticipated problems. Playbooks answer the question "What do we do now?" and may have information about the situation already established. For example, if a problem happens regularly, a playbook could define the steps for resolving it and for deploying a quick fix that should prevent it from happening again. Other examples include specific actions that need to be taken for certain error patterns detected in the logs or alerts raised by external monitoring services.

Runbooks answer the more general question "How do we do this?" They are especially valuable when an incident involves more than one person or team. Runbooks provide a place to sequence actions, minimize errors, and make sure that all the steps get done. An important principle of runbooks is to use a checklist-format, with each item clearly stated and specific enough so that even a junior engineer unfamiliar with the topic can follow it successfully. Runbooks are also a good way to share knowledge with less experienced engineers and distributed teams, as they standardize the response to a type of event.

8.6. Continuous Optimization: Feedback Loops and Lifecycle Management

Logical feedback loops are necessary for continuous optimization of ML systems, both for model and data. Incorporating automatic retraining in the model pipeline, coupled with resource-efficient online learning, simplifies the query-response time trade-off for environments that require periodic model updates with minimal latency. Incorporating automatic retraining in the model pipeline – taking place either entirely offline or in an online manner – combined with a responsive architecture that prepares the model for rapid query-response with minimum latency – very likely reduces TCO. Continuous feedback management and tiered storage for different data types (hot/warm/cold) suitable for online and offline learning contribute equally.

Ensuring smooth transitioning between different layers of optimized storage and enabling resource-efficient online learning during critical periods, while completely offloading the entire model retraining, reduces expensive model retraining costs when the data changes are significant. Online learning together with minimum resource allocation for automatic retraining achieves a fine balance between query latency and retraining TCO. Fitting models to the nature of the business problem, achieving an SLO-driven business strategy while handling DR traffic efficiently, and resource-efficiently performing hyperparameter tuning during production further drive down the TCO.

8.6.1. Online Learning, Offline Retraining, and Model Retrievability

Not all deployed ML systems require retraining; while it is essential to address model obsolescence, retraining may not be the right approach. Online learning algorithms adapt based on new data, bypassing the need for retraining. However, for most other deployed systems, a retraining path is essential to avoid obsolescence and support continuous optimization. An effective offline retraining path demands the definition of a set of conditions that trigger retraining. Once a need is determined, the next challenge is ensuring adequate computational resources and up-to-date data to perform effective retraining within the stipulated timeline.

A special case of obsolescence is that of data unavailability. You can often retrain a model without up-to-date data labels, either because it is costly to acquire ground truth or because it is simply infeasible to do so, as in the case of societal events. During such intervals of low data availability, it would be useful to be able to access and utilize deprecated models, provided their performance meets the necessary criteria and supports the proposed use case. Thus, a retrievability mechanism should accompany the continuous optimization processes.

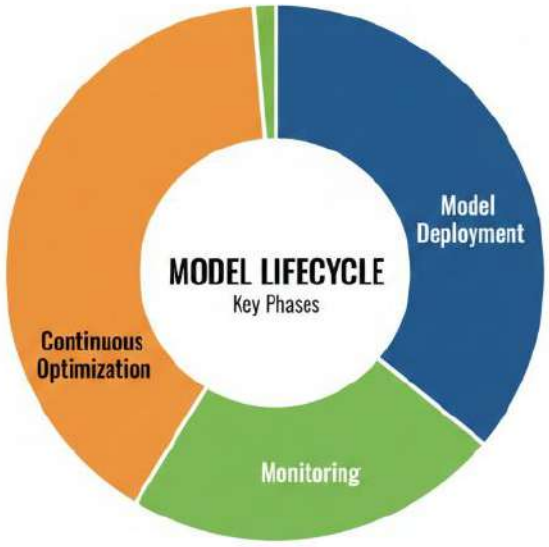

Fig 8.4: Model Deployment, Monitoring, and Continuous Optimization

8.6.2. Hyperparameter Tuning in Production

Deploying a model into production is just the beginning of an ongoing lifecycle that requires maintenance, monitoring, support, and iteration. One area that often entices ML teams is the continuous tuning of the model's hyperparameters. (Re-)tuning a model's

hyperparameters in production is quite different from traditional settings, where researchers perform tuning in controlled, offline evaluations. Tuning must be done carefully to minimize degradation of the live service and to design for reproducibility—new models and/or hyperparameters should not be selected based solely on the live feedback loop, as this will likely result in significant drift and overfitting. Instead, a balance should be found that accepts automating the influence of the feedback loop while still using offline evaluation as the primary guide for tuning.

To support reproducible tuning, periodic retraining should be performed: periodically, data should be ingested, cleansed, and formed into a training set, and new models and hyperparameters should be selected from the updated dataset. In such a setup, because a new model is being selected, quality checks can also be performed to ensure that predicted performance is acceptable before replacing the currently running model. Hyperparameter tuning may also be performed as a part of this periodic retraining, though careful attention is required to guard against issues noted previously with tuning in live settings. Providing teams with a clear direction on how to best use offline evaluations will aid hyperparameter tuning efforts in a production setting.

8.7. Conclusion

The research and development are typically bifurcated into two development lines. One focuses on designing robust, accurate models through the formal training stage. The other focuses on equipping these models with production readiness through the operationalization and deployment stage of the machine learning lifecycle. Operationalization aims to guarantee that the model works as intended and reliably over time in real-life usage conditions. This process employees the technical SRE principles commonly applied in managing production services for large-scale software systems and leverages enhanced monitoring and alarm logic.

Large-scale ML systems, however, also adjust themselves based on feedback from the first train-and-retest cycle. Feedback codecs to retrain and tip models online; periodically reoptimize hyperparameters and policies, or pursue RERouting. Such capability-scoped continuous optimization reduces the cost of unguarded operations and fortifies service features. The objective behind this cost is to gradually—ideally goal-caught the risk and uncertainty not demonstratively evident during training. In this rest, two major categories of feedback appear: operational drifts drifting outside detection boundary conditions, estimation of-yield variables for which production is unfaceted-given by the training-time operating context.

8.7.1. Emerging Trends

Availability of model deployment pipelines and monitoring frameworks is a prerequisite for operationalizing machine learning systems in production. However, deploying machine learning models to production is merely the first step towards a long-term operational strategy. Several operational aspects must be properly attended to ensure the smooth functioning of machine-learning models in production. Some of the operational aspects, such as logging, tracing, alerting and incident-response strategies, are essential to guarantee high performance and availability of the model. Monitoring performance, reliability, fairness and other operationalization metrics keep the model in good shape and help to identify when a retraining is necessary. Such frameworks, however, must move beyond merely detecting performance deterioration: they should also link to an automated feedback loop that efficiently closes the gap between specification and deployed implementation. Finally, an incident-response strategy – including runbooks for service-recovery processes and playbooks for managing errors, such as data and model drift – is paramount to restoring the expected machine-learning behavior.

To ensure that ML systems deployed to production keep providing value, a proper lifecycle management should be defined. Solutions such as online learning and retraining have been extensively discussed in literature. Recently, attention has also been paid to continuously tuning model hyperparameters while in production, further closing the gap between specification and practical implementation..

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