Towards Automating the AI Operations Lifecycle

Matthew Arnold, Jeffrey Boston, Michael Desmond, Evelyn Duesterwald, Benjamin Elder, Anupama Murthi, Jiri Navrátil, and Darrell Reimer*

IBM Research AI
Yorktown Heights, NY, USA

Abstract

Today’s AI deployments often require significant human involvement and skill in the operational stages of the model lifecycle, including pre-release testing, monitoring, problem diagnosis and model improvements. We present a set of enabling technologies that can be used to increase the level of automation in AI operations, thus lowering the human effort required. Since a common source of human involvement is the need to assess the performance of deployed models, we focus on technologies for performance prediction and KPI analysis and show how they can be used to improve automation in the key stages of a typical AI operations pipeline.

1 Introduction

The end-to-end AI lifecycle consists of many often complex stages, including data preparation, modeling, and operations. While the details may vary from instance to instance, the overall flow often follows that depicted in Figure 1. A lot of attention in both academia and industry has been focused on the earlier data science stages of the lifecycle. The remaining stages in AI operations are often neglected, or even overlooked entirely, despite being critical to the successful use of AI models in real-world applications.

It is not uncommon in today’s AI deployments for AI operations to require significant human involvement and skill. For example, pre-release testing generally relies on static hold-out test sets, which are expensive to create and nearly impossible to keep aligned with continually evolving production traffic [8, 18]. Monitoring a model post-deployment is often achieved by performing periodic manual assessments of the log data. The cost of manual labeling during the evaluation can sometimes be reduced through crowd sourcing, but crowd sourcing may not be a viable option for enterprise customers with confidential data. Furthermore, once a model has been identified as performing poorly, diagnosing and improving the model is a challenging, often manual, task that requires significant expertise.

We are working on addressing these operations challenges by developing a set of enabling technologies that can be used to increase the level of automation in the AI operations lifecycle, thus lowering the human effort required. A common source of human involvement across AI operations is

*Authors listed in alphabetical order.
the need to assess the performance of models deployed into production, so we focus on technologies that capture aspects of production performance:

1. **Performance Prediction** - AI-based approaches for estimating accuracy-related model metrics on unlabeled data, such as the data in production traffic.

2. **KPI Analytics** - Techniques for capturing and analyzing application-level key performance indicators (KPIs) and feedback signals to monitor, analyze, and improve AI models.

This paper describes these technologies and shows how they can be used to improve four key stages of a typical AI operations pipeline: pre-deploy test, deploy, monitor, and improve.

## 2 Enabling Technologies

This section describes enabling performance technologies developed to support the AI operations pipeline stages.

### 2.1 Performance Prediction

Performance prediction is a technique to estimate how a model will perform on a new, unlabeled data set, in terms of an accuracy-related metric (e.g., classification accuracy, regression error, or ranking precision). Although performance prediction closely relates to the problem of uncertainty estimation (or confidence scoring), virtually all research attention in this area \[6, 9, 10\] aims at solving the task of filtering model predictions to improve its output precision. For example, one class of such algorithms is based on calibration, i.e., producing probabilities that reflect the expected proportion of accurately classified samples \[11, 19\]. Another is a model-based approach via meta-modeling \[10\] offering a good degree of flexibility in capturing the various sources of uncertainty. All of these algorithms can be applied to predict a model’s performance on unlabeled production (operational) data in a rather straightforward way: convert well-calibrated point-wise confidences generated by a model based on the above-mentioned methods into a batch accuracy prediction, thus providing insight into potential risks associated with a new version of a model, or a new operational environment.
However, despite the clear application to production model risk management, performance prediction is rarely talked about in this context. We believe there is significant opportunity for applying performance predictors as part of AI operations, especially for new predictors that are specifically designed for this purpose.

2.2 KPI Analytics

There are many metrics available for evaluating the quality of a model, such as precision, recall, F1, and accuracy. However, these metrics evaluate a model in isolation, independent of the context of how the model is being used. In a production setting, machine learning models are rarely exposed directly to end users; typically, models are embedded within an application, where the application leverages the model to help make key decisions, such as whether to approve a loan or whether to tag an image.

End users of such an application generally do not care about model performance metrics. In fact, they may not even be aware that the application is using a model in the first place. What ultimately matters is how well the application is performing as visible to the end user. User-visible application performance is generally tracked with business metrics, or key performance indicators (KPI), e.g. sales rate, click rate, customer satisfaction, and time on page.

Thus, when evaluating models in the context of an application, model performance metrics are not sufficient. Instead, it is critical to understand how the model behavior is impacting the application’s KPIs. Failure to do so can result in wasting resources to improve model metrics that in fact had little or no impact on what matters to end users. The most basic step towards supporting such KPI-based analyses is to ensure that KPIs and model metrics are being stored with a common correlation ID to identify which model operations contributed to transactions with a particular KPI score.

3 Enabled AI-Operations Stages

This section describes how the above enabling technologies can be leveraged within a typical AI Operations pipeline.

3.1 Pre-deploy Test

The objective of the pre-deploy test stage is to assess a model’s level of readiness for deployment into production [20]. This is traditionally performed with static test sets [12], which are laborious to setup, expensive to maintain, and notorious for being out of date, since data in production is continually changing over time. Relying on static test sets to assess model quality, therefore, often leads to poor results in real world deployments.

Our AI enabled pre-deploy testing approach augments traditional test sets with performance prediction. Instead of evaluating a model against a test set and using that test set score as an indicator of model quality, the test set is used to train a performance predictor, and the predictor is run on a recent window of production traffic. The resulting scores from the predictor provide a performance estimate of the model on actual production traffic.

While this approach still requires some amount of labeled data, it has many advantages over a traditional static test set based approach:
- It does not require production data to be labeled in order to get an indication of production performance of the model.
- It is less fragile, thus remains a better indicator of accuracy as production data changes over time.
- It enables assessing risk of deploying a model into different deployment zones or usage scenarios, such as deploying a model into different geographic regions.

3.2 Deploy

The goal of the deployment stage is to enable a seamless rollout of new models, with as little risk as possible. Best practices in the continuous delivery of software services is to use safe deployment techniques, such as A/B tests, and canary releases [1]. Various techniques can be used to automate the rollback decision process, significantly reducing the risk of deploying a new model. Multi-armed bandits are one such example [2].

However, these techniques require a meaningful signal of quality in order to detect problems and trigger rollback reliably, and such signals are often not readily available in a typical model deployment. Our AI enabled deploy stage leverages both performance prediction and KPI analytics as the metrics for driving safe deployment. These metrics provide reliable and automated indicators of model quality with respect to the application, and therefore are both effective and efficient for identifying potential problems and triggering rollback in production.

3.3 Monitor

The main objective during the monitoring stage is to manage the risks of in-production models by checking for performance drift [14, 3] and alerting an operator that model accuracy has dropped. Traditionally, this is achieved by performing periodic manual assessments of the log data. This is labor intensive, and thus expensive and tedious to perform on a regular basis. Feature drift (also referred to as covariate shift) [4, 7] and prior shift [5], are relatively straightforward to detect, neither of these necessarily implies that model accuracy has decreased and can produce many false positives [13, 17, 21].

Our AI enabled monitoring approach is focused on detecting drift that actually impacts model performance. It does so by leveraging performance prediction and KPI analytics. Performance prediction is run periodically on production traffic. If the predicted accuracy of the model drops, or if a KPI metric drops, an alert is triggered pulling in human assistance to perform an analysis of the relevant models.

3.4 Diagnose and Improve

Model improvement is typically an iterative, continuous process, and is known to be a challenging task that requires skill and expertise. There are many ways of improving AI models, such as feature engineering, model architecture selection, hyperparameter tuning, and the addition of more training data using techniques such as active learning [16].

Our diagnosis and improve stage is driven by a KPI analysis, which strives to reduce the time and expertise needed to identify root causes and improve performance. First, KPI analysis can be used to narrow down the scope of the problem, by focusing diagnosis efforts on data points that
were involved in low-KPI transactions. This reduces the volume of data that needs to be examined and focuses the human analysis on the problematic cases.

But even more importantly, KPI analysis allows comparing and contrasting model metrics across the good versus bad transactions. Simple correlation analysis can identify model trends that correlate with KPI drops, and thus are worthy of human investigation. More advanced causal analyses may also be possible, depending on the available information about the relevant models [15].

4 Conclusions

Today’s AI operations pipelines require significant human intervention and effort. This paper described a set of enabling technologies that help increase the level of automation during AI operations, thus reducing the human effort and cost required. We showed how these technologies can be used to drive automation within four common operations pipeline stages - pre-deploy test, deploy, monitoring, and improvement. We believe there is significant opportunity remaining for improving AI operations automation and hope to encourage more research in this area.

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