Gartner

Use Gartner's 3-Stage MLOps Framework to Successfully Operationalize Machine Learning Projects

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Initiatives: Artificial Intelligence

Organizations struggle to integrate AI solutions with existing production applications, wasting time and money on data science projects that are never put in production. Data and analytics leaders can greatly reduce the risk of such failures with three stages that create a framework for MLOps.

Overview

Key Challenges

- Organizations often plan machine learning (ML) initiatives focusing on the use of interesting technology rather than the creation of critical business value.

- Most ML and DS projects fail because operationalization is only addressed after the fact, as a DevOps consideration. A Gartner survey indicates that one of the top three barriers to AI implementation is the complexity of AI solution integration with existing infrastructure.

- ML efforts face significant maintainability, scalability and governance challenges once in production.

Recommendations

To achieve long-term data science (DS) and machine learning project success, data and analytics leaders responsible for artificial intelligence (AI) strategy should:

- Establish a systematic machine learning operationalization (MLOps) process through Gartner's MLOps framework.

- Review and revalidate ML model operational performance by ensuring that deployed models meet the goals of integrity (technical and economic), transparency and sustainability.
- Minimize the technical debt and complex maintenance procedures to operationalize machine learning models by reviewing and revalidating their business value on an ongoing basis.

Strategic Planning Assumption

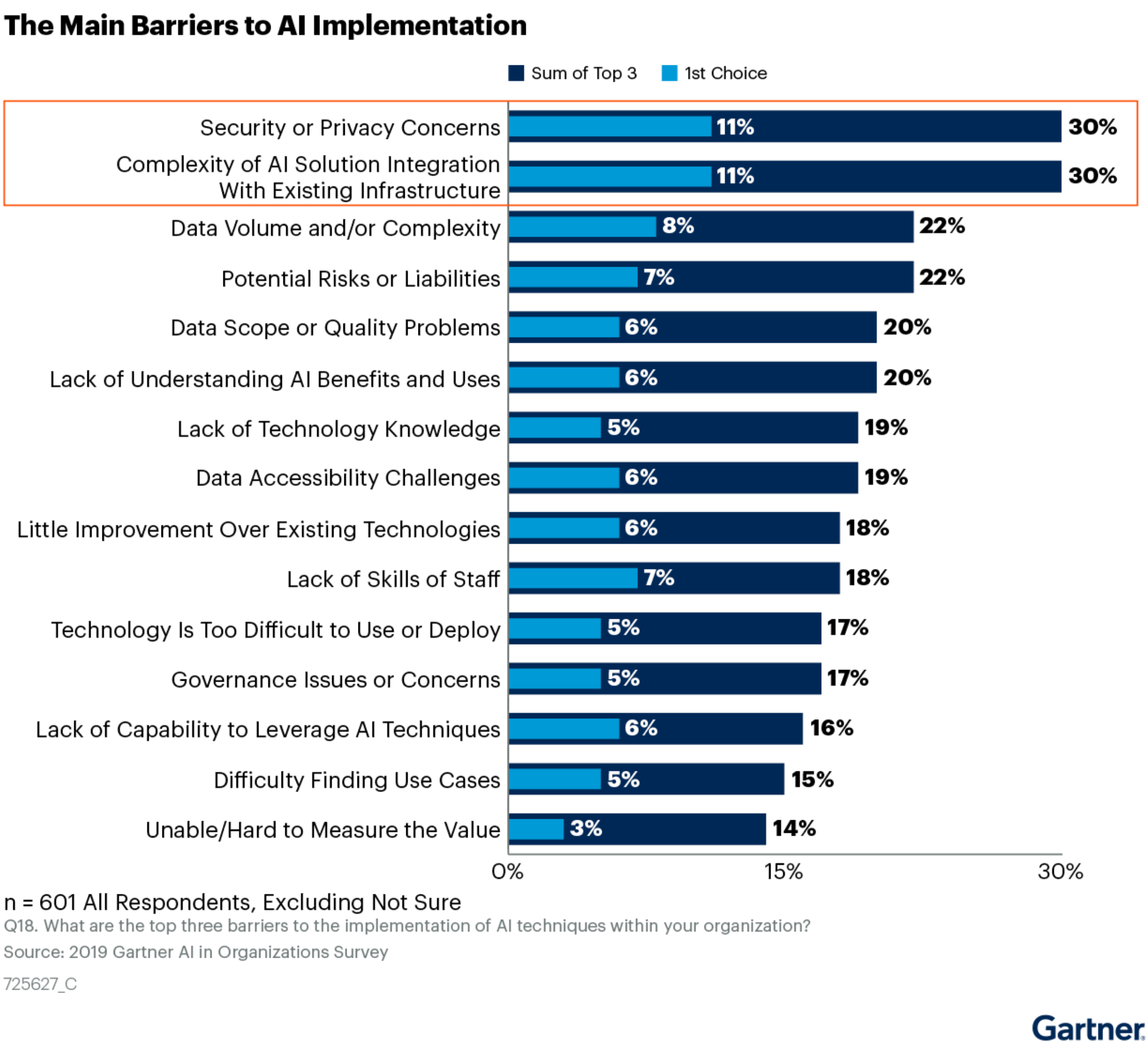
By 2021, 80% of data science labs that have failed to establish measurable operationalization practices will be outsourced.

Introduction

> This research is the first part of a two-part series on MLOps. For a comprehensive overview of organizational best practices accompanying MLOps, please refer to the companion piece, "Use 3 MLOps Organizational Practices to Successfully Deliver Machine Learning Results."

According to the Gartner AI in Organizations Survey, [1] conducted at the end of 2019, the challenges related to security, privacy, integration and data complexity are the top most important barriers to the implementation of AI techniques (see Figure 1).

Figure 1. The Main Barriers to AI Implementation



In the last decade, organizations have often learned that publishing a model is not enough. That "publish moment" is followed by many steps that make the analytical model operationalization cycle as important as the analytical model development cycle.

> **The focus of data science teams has traditionally been on developing analytical assets (see Note 1), while dealing with the operationalization of these assets has been an afterthought.**

Many reasons underlie that afterthought:

- Lack of a formal operationalization methodology
- Lack of data science teams' understanding and interest in the engineering discipline of production
- Deficit of formal communication channels among the data science team, the IT operational team and the line-of-business stakeholders
- Unwillingness to deal with the operational aspect of advanced analytics, along with a misunderstanding of the practical business impact of operationalization

Machine learning operationalization is a critical step in aligning analytics investments with strategic business objectives — the "last mile" toward business value. Establishing best practices beyond the analytical asset development process starts with understanding the organization's business priorities and then systematically applying a model management life cycle discipline. ModelOps (see Note 2) refers to the operationalization of all AI models and includes MLOps that deals with the operationalization of ML models. This research specifically refers to the end-to-end life cycle of ML models, that we define as MLOps below.

MLOps (machine learning operationalization): *MLOps enables the operationalization of the end-to-end pipeline that supports the continuous delivery and continuous integration of models in a production environment. Core capabilities include feature curation, feature management (store), model governance (in some cases through ModelOps), model release, activation, monitoring, performance tracking, management, logging, reuse and maintenance.*

However, from an AI perspective (i.e., dealing with the wide variety of AI models beyond ML), consider a ModelOps approach.

The current analytical open-source movement is producing a wide range of analytical assets that will eventually have to be consumed — but current open-source deployment techniques provide "dissemination means" not "managed production means." From that perspective, techniques such as containerization or serverless deployment (see "A CIO's Guide to Serverless Computing") are efficient and effective in pushing (deploying) models into production, but they do not relieve the organization from adopting a formal operationalization process.

Analysis

Establish a Systematic Operationalization Process

The model development cycle shown in Figure 2 is a variation on the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology that has been used for two decades. That methodology, simple and powerful, imposes a development discipline that promotes the integrity and robustness of the resulting analytical models.

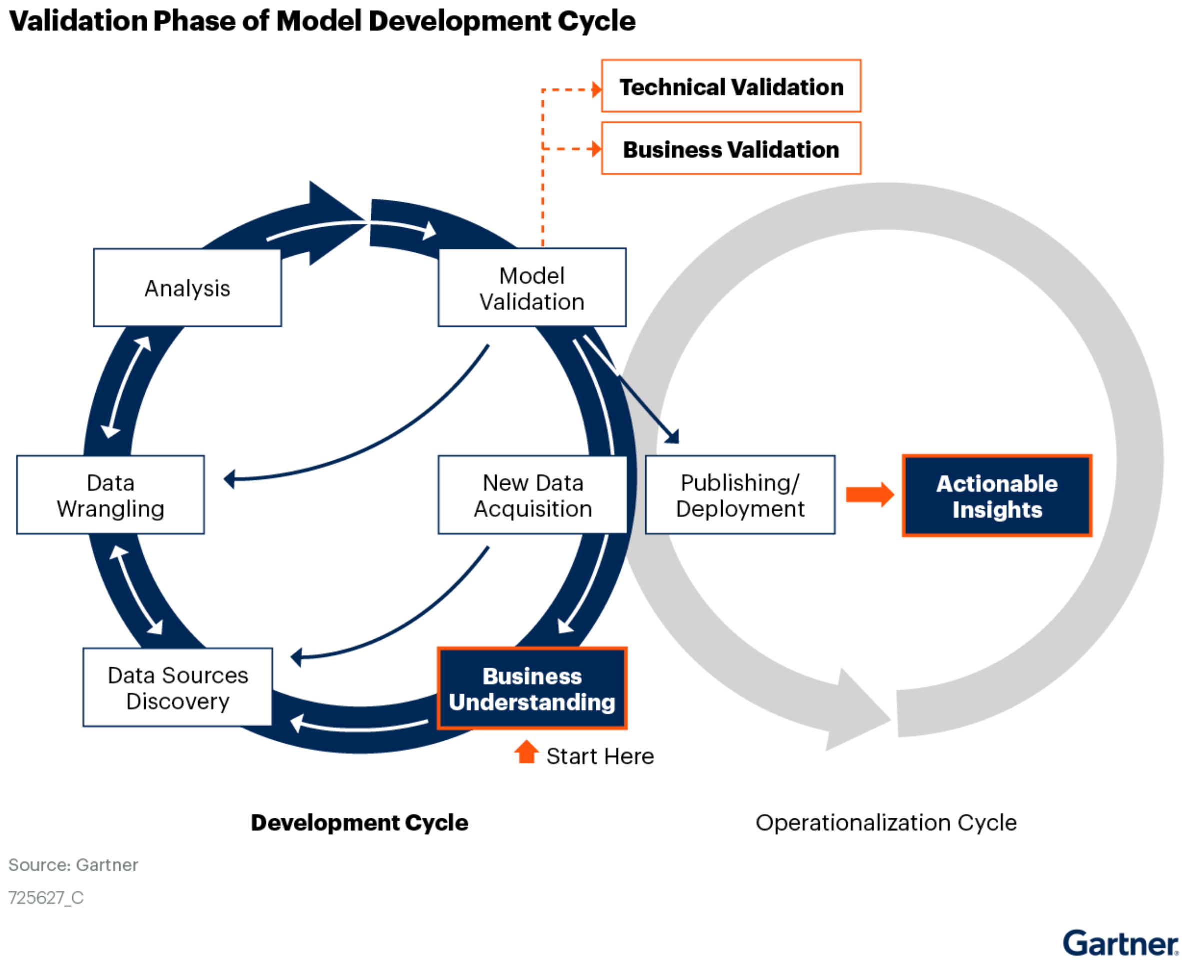
Validation Phase of Model Development Cycle Process

For successful ModelOps, it is important to introduce validation checkpoints throughout the development and operationalization cycles of a project workflow. Collaboration among all team members and the ability to reproduce results with the model are key aspects to ensure successful validation. The *model validation* step in the development cycle (see Figure 2) includes:

- **Business Validation.** The model is developed on the basis of specific desired business outcomes and needs to operate within specified business thresholds. Business validation will ensure that the model actually delivers the value determined in the *business understanding* step.

- **Technical Validation.** The model is technically sound while tested against the dataset, set apart at the beginning of the model development process. Model engineering should also satisfy any interpretability requirements.

Figure 2. Validation Phase of Model Development Cycle



Gartner sees a new role coming up, that of a model validator — a data scientist who did not participate in the development of the model.

Model Operationalization Cycle Process

Once a model has been published out of the development cycle, its introduction into the operationalization cycle takes place in two main phases: the release phase and the activation phase, depicted in Figures 3 and 4.

Depending on their project size and complexity, not all organizations undergo those two phases. It is also possible that some organizations (especially while implementing real-time model operationalizations) might integrate the release phase as part of their development cycle, but a large majority of analytically mature organizations productionize models through those two phases.

It is also important to note at this point that models in production are often part of an ensemble of models working together to provide insights within a particular process.

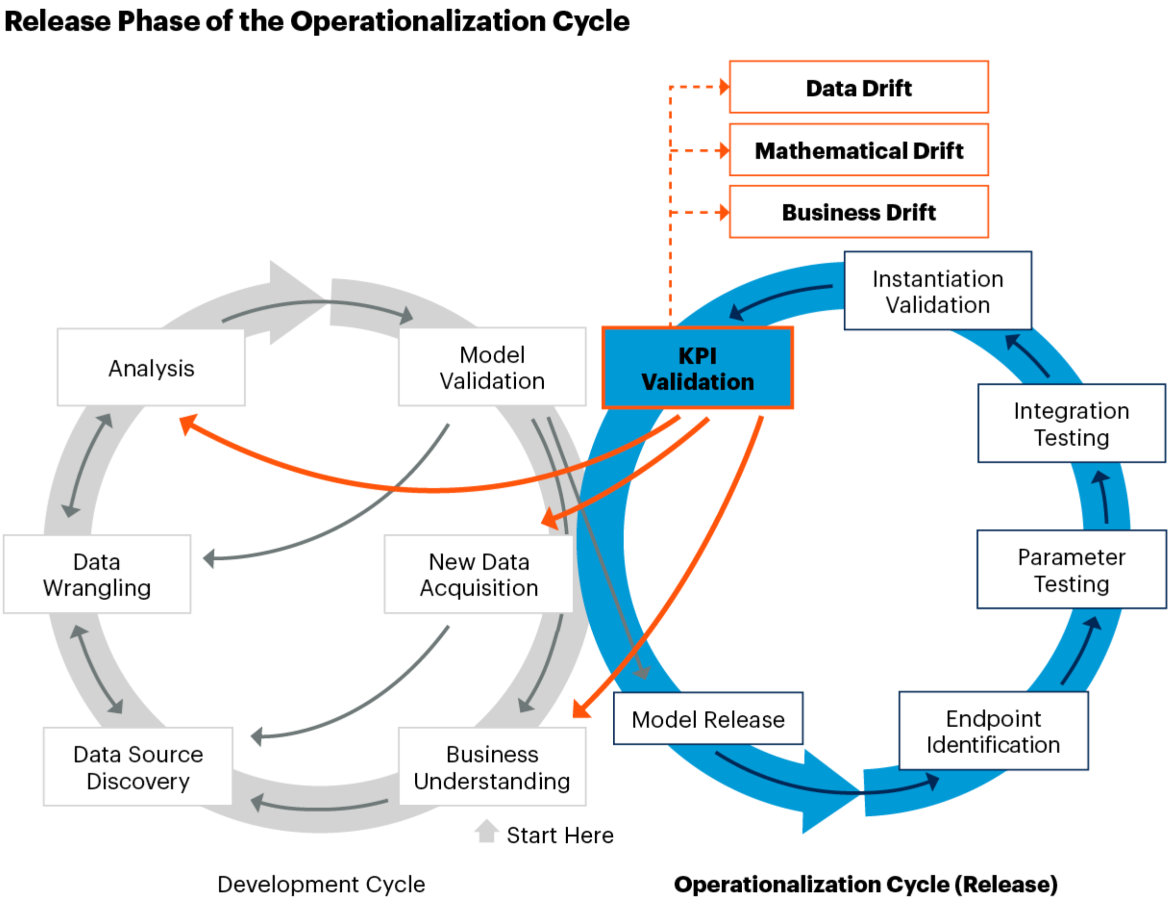
Release Phase: Testing Models in Business Conditions

The goal of the release phase is to set the published model free inside a guarded perimeter to verify that the assumptions made while developing the model still hold true in the real world of the actual business process. We have identified six steps in this process (see Figure 3):

- **Model release.** The model is promoted to the release phase, ready to be undertaken by the operationalization team and labeled as a candidate model (that is, development-vetted, but not yet fully production-ready).
- **Endpoint identification.** This step refers to validation of the decision points where the model will be delivering its insight. Those analytics endpoints could be within an existing application, within a business process, as part of an ensemble of models, as an input to another decision-modeling mechanism (like a business rule) or on the edge devices.
- **Parameter testing.** Target business processes might be subject to technical constraints where the velocity, shape, volume and quality of the input data might not exactly align with the data in sandboxes used to develop the models. This step aims at testing that alignment.
- **Integration testing.** Provided that the expected data matches the development assumptions, integration assumptions (that is, REST APIs, microservices call, code integration) also have to be tested to ensure proper performance.
- **Instantiation validation.** As models in production are often part of model ensembles, even slight variations in those elemental models (such as a propensity to buy models instantiated across multiple states or regions in the same country) can produce radically different results.

- **KPI validation.** Model performance should not only be measured against technical parameters (such as precision) but also against the agreed-on KPIs. Validate models for:
  - **Business drift.** This includes the deviations in business KPIs (measurable business outcomes) set forth as early as the *business understanding* step in the development process. The model could be drifting due to new market conditions that do not necessarily affect the data directly.
  - **Mathematical drift.** Deviations in technical parameters (such as precision) result in degraded model performance. The model drift could be due to a radical change in the pattern being monitored.
  - **Data drift.** Any shift between the data that has been used to build the model and the actual data in production could render the model inefficient or incompetent.

Figure 3. Release Phase of the Operationalization Cycle



Source: Gartner
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Depending on the outcome of the *KPI validation* step, four paths are possible:

- The model fails due to data drift. In this case, the process can proceed back to the *new data acquisition* step in the development process.
- The model fails due to business drift. In this case, it might be wise to reevaluate the original business assumptions through the *business understanding* step back at the beginning of the development cycle.
- The model fails due to mathematical drift. In this case, proceed back to the *analysis step* in the development cycle.
- The model delivers as promised and is ready to move to the activation phase of the operationalization cycle.

Activation Phase: Operating Models in Real Business Conditions

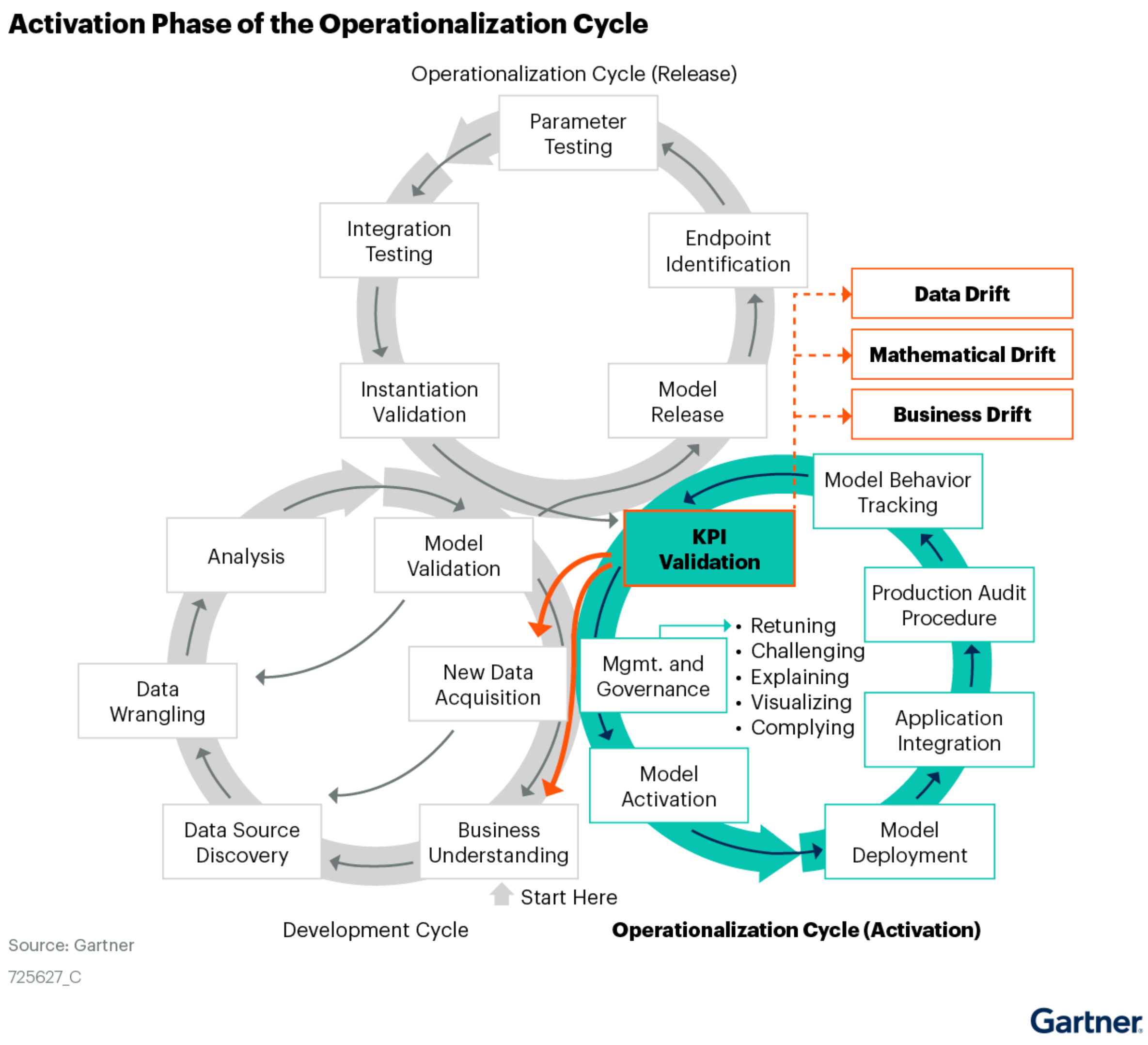
Now that the model has been tested in the real world and is performing as intended, it is ready for prime time. The goal is to activate that model within existing business processes across the organization at the endpoints identified (and validated) in the release phase of the operationalization process. We have identified seven steps in this process (see Figure 4):

- **Management and governance.** Once a model is ready for activation, it should be cataloged, documented and versioned (including the original set of variables that has been used to develop it). That model should also be submitted to the governance rules adopted by the data science team and the *production committee* (and in particular, application product managers).
- **Model activation.** This step is the hand-off of the operationalization-process-validated models to the production team as activated models. At this point, the models are *production-ready*, fully documented and compliant with the governance rules.
- **Model deployment.** Depending on how those models will be executed (on-premises, in the cloud or both, leveraging streaming infrastructures and parallel processing mechanisms like Spark), measures need to be taken to guarantee the smooth processing of the transactions leveraging the model (or the ensemble the activated model is part of).
- **Application integration.** Insights are delivered through decision endpoints, the large majority of which are part of existing applications. Extra coding is sometimes necessary to properly embed a model, or its input, within an application, a business process or another set of insights, to enhance a business outcome. This is where the model will finally deliver its business value.
- **Production audit procedures.** Model telemetry, along with various performance metrics in terms of accuracy, response time, input data variations and infrastructure performance instrumentation, including possible implementation of software agents, have to be implemented to gather the necessary data to monitor models in production. Various instruments (see Note 3), such A/B testing methods, multivariate testing, multiarmed bandits (MABs; see Note 4) and shadow models, can be implemented to judiciously appreciate the performance of models.

- **Model tracking behavior.** Alerts and monitoring methods have to be established to track the performance of models in production. Performance thresholds and notification mechanisms are implemented in this step to systematically flag any divergence or suspicious behavior.

- **KPI validation.** Extended from the release phase and fed by the two previous steps, the *KPI validation* step consistently measures the business contribution of the models (or ensemble models) in production. The idea is to get, as precisely as possible, the business value that can be attributed to the model. To determine that value, data from the *production audit procedures* step should prove invaluable.

Figure 4. Activation Phase of the Operationalization Cycle



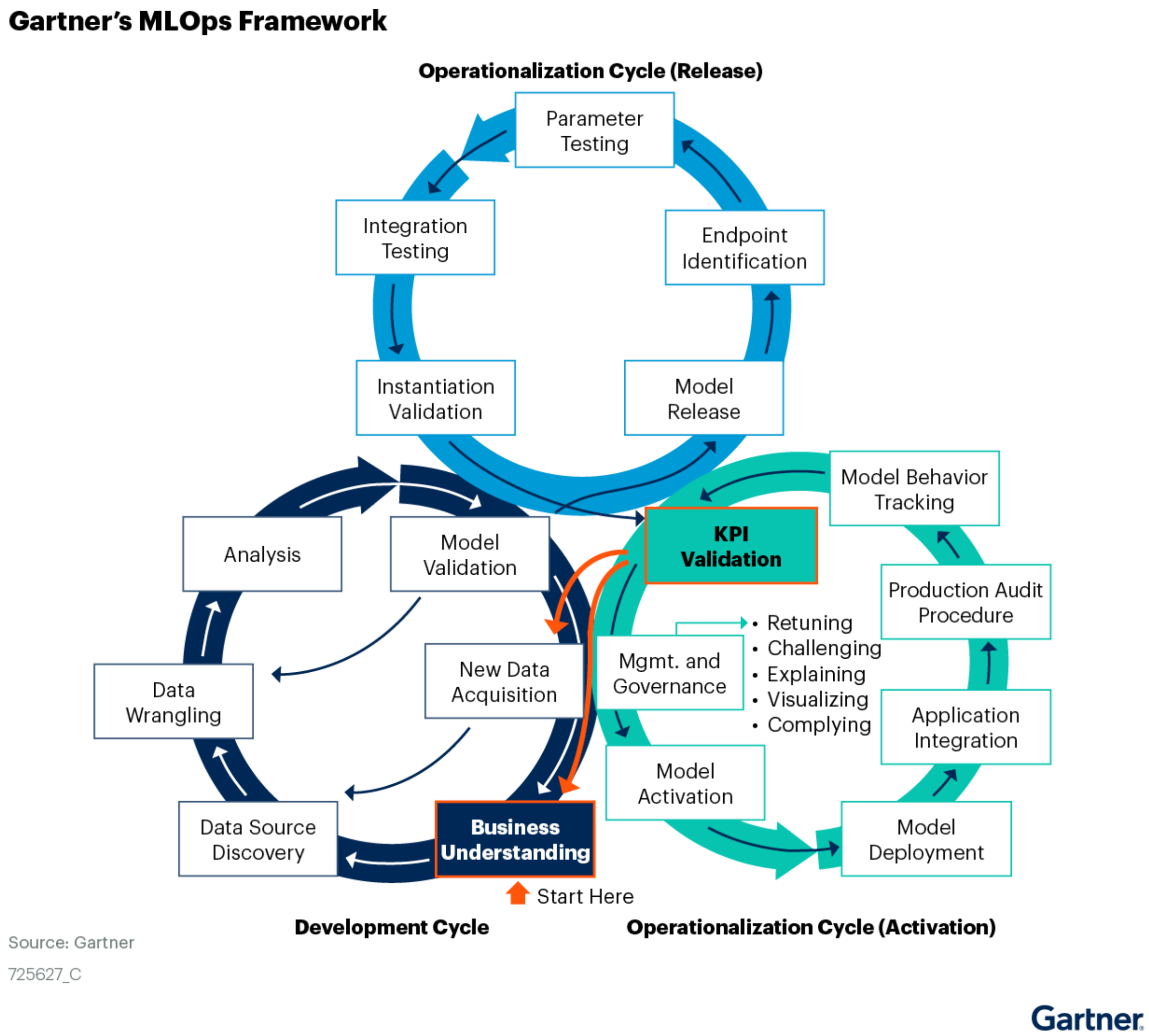
Review and Revalidate ML Model Operational Performance

From this point, the models remain in the operationalization cycle as long as they are performant, meet attribution thresholds and deliver business value derived from the models in production. As long as models are performing, they keep their place in the production cycle. Otherwise, management rules are in place in the *management and governance* step to reevaluate those models in the light of changing circumstances captured in the three previous operationalization steps. Those models are then sent back into the development cycle process. Successful organizations have adopted various technologies to provide the foundation to manage operational decision services in a reliable, repeatable, scalable and secure way. That governance (see Note 5) foundation should provide:

- **Catalog.** A *centralized* way to store and secure analytical assets to make it easier for analysts to collaborate and to allow them to reuse or exchange models or other assets as needed. (It could be a secured community or a collaboration space.)
- **Governance.** Protocols to ensure adherence to all internal and external standards, procedures and regulations, not just for compliance reasons, but as an increasing amount of data gets aggregated, for example, to address potential privacy issues.
- **Capabilities.** Automated versioning, fine-grained traceable model scoring and change management capabilities (including champion/challenger features) to closely test, monitor and audit analytical asset life cycles from a technical as well as a business performance perspective (through KPIs).
- **Coherence.** Simple protocols established to:
  - Provide functional bridges between the development and operationalization cycles
  - Enhance cooperation and consultations between development and operationalization teams
  - Provide efficient liaison services between data science and lines of business
  - Improve the transparency of deployed analytical assets
  - Control the exchanges between the production and the development teams (such as when to retune models, expose challenger models and levels of model explanations)

The combined processes are illustrated in Figure 5.

Figure 5. Gartner's MLOps Framework



Recommendations

Machine learning systems carry a significant technical debt [2] that has to be addressed upfront. To confront the problem early, data and analytics leaders should:

- Start as early as the development process to address the KPIs and detect operationalization risks. Most successful organizations balance risk and ROI.
- Establish a well-instrumented and disciplined model operationalization process to scrupulously track the behavior and performance of ML models deployed across business processes.

- Heed the management and governance step in the operationalization process as its rules and procedures will eventually define the success or failure of your deployed analytical assets.

Review and Revalidate ML Model Business Value

The KPI validation step of the operationalization process needs to be constantly revalidated while the model is in production. Beyond the organization's changes of business strategy and tactics, market conditions can shift, and customer behaviors or competitive pressure can evolve, impacting the business performance of models. While all of those factors can contribute to models' degradation, others to watch for include:

- Concept drift (where seasonality, decision impacts, local data particularities, dynamic data transitions and so on can induce a change in class distribution)
- Bias reinforcements (where decisions are increasingly subjective through models' self-fulfilling recommendations)
- Feedback loops (where models influence their own behavior as they evolve over time)

KPIs should also be subjected to a higher level of scrutiny that allows them to track not only the business process context of the active model, but across the business processes that are impacted by the decisions influenced by models (or collection of models). This will avoid the local optimum problem where a few decisions are optimized for local decisions, eventually leading to global issues. By auditing the development, refinement and usage of models and other assets throughout their life cycle, the formalization of the operationalization cycle provides a bigger-picture advantage: more consistent organizational decisions. For a list of sample vendors that offer niche capabilities in MLOps, refer to Note 6.

Recommendations

- Secure the commitment of the business stakeholders at the business understanding step for the continuous validation of the business KPIs while the model is in production.
- Track the models' (or model ensembles') degradation signals by constantly monitoring the business indicators influenced by productized models.

- Continuously measure and harmonize the overall business impact and collective contribution, within or across processes, of integrated model collections.

Evidence

[1] 2019 Gartner AI in Organizations Survey. The research was conducted online during November and December 2019 among 607 respondents from organizations in the U.S., Germany and the U.K. Quotas were established for company size and for industries to ensure the sample provided a good representation across industries and company sizes. Organizations were required to have developed AI or intended to deploy AI within the next three years.

Respondents were screened to be part of the organization's corporate leadership or report into corporate leadership roles, have a high level of involvement with at least one AI initiative and have one of the following roles when related to AI in their organizations:

- Determine AI business objectives
- Measure the value derived from AI initiatives
- Manage AI initiatives development and implementation

The survey was developed collaboratively by Gartner analysts and the Primary Research Team.

Artificial intelligence (AI): Gartner defines "artificial intelligence" as applying advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions.

[2] D. Sculley and others, "Hidden Technical Debt in Machine Learning Systems," Advances in Neural Information Processing Systems, 28 — Proceedings (NIPS 2015).

[3] "Staffing Data Science Teams: Mapping Capabilities to Key Roles"

Note 1: Analytical Assets

Analytical assets include machine learning (predictive) and mathematical models, and precalculated propensities (such as predictive scores).

Note 2: ModelOps

ModelOps (AI Model Operationalization): ModelOps is focused primarily on the governance and life cycle management of a wide range of operationalized AI and decision models (including machine learning, knowledge graphs, rules, optimization, linguistic and agent-based models). Core capabilities include CI/CD integration, model development environments, champion-challenger testing, model versioning, model store and rollback. ModelOps also enables the governance (see Note 5) and procedures for retuning, reusing, retraining or rebuilding AI models, aimed at providing an uninterrupted flow between the development, operationalization and full maintenance of AI models. Adopting a ModelOps strategy should facilitate the performance, scalability and reliability of AI models.

Note 3: Model Evaluation Techniques

An often-preferred online model evaluation and selection technique is to use a multiarmed bandit algorithm. A/B testing has one major drawback. The number of test results in each group, A and B, needed to find the value of the A/B test is high.This means that a significant part of the users routed to the suboptimal model would experience suboptimal behavior of the product for a long time. Ideally, user exposure to a suboptimal model should be as few times as possible.

At the same time, users should be exposed to each of the two models several times to get reliable estimates of both models' performance. This is known as the exploration-exploitation dilemma. The performance of the models should be explored enough to be able to reliably choose the best one. However, at the same time, the performance of the best model should be exploited as much as possible to reduce the negative effect of exposing the users to a suboptimal model.

Note 4: Multiarmed Bandits

Multiarmed bandits (MABs) are a way to compare one or more versions of the model and select the best-performing one in the production environment. MABs have an interesting property. After an initial exploration period, during which the MAB algorithm gathers enough evidence to evaluate the performance of each model (arm), eventually, the best-performing arm is played all the time. This means that, after the convergence of the MAB algorithm, all users are routed to the version of the software running the best model.

This property of the MAB algorithm allows users to deploy the new model while keeping the old one and waiting for the MAB algorithm to converge. This gives users the information on whether the new model performs better than the old one. At the same time, it lets the MAB algorithm replace the old model with the new one once it is certain that the new model performs better.

Note 5: Gartner's Definition of Governance

- Setting decision rights and accountability, as well as establishing policies that are aligned to business objectives (preservation and growth of shareholder value)
- Balancing investments in accordance with policies and in support of business objectives (coherent strategy realization)
- Establishing measures to monitor adherence to decisions and policies (compliance and assurance)
- Ensuring that processes, behaviors, and procedures are in accordance with policies and within tolerances to support decisions (risk management)

Note 6: Operationalization at Scale

Sample vendors that support operationalization at scale include Algorithmia, DataRobot (ParallelM), Datatron, Iguazio, ModelOp, Saagie and Seldon.

Document Revision History

How to Operationalize Machine Learning and Data Science Projects - 3 July 2018

Recommended by the Authors

Some documents may not be available as part of your current Gartner subscription.

A Guidance Framework for Operationalizing Machine Learning

Accelerate Your Machine Learning and Artificial Intelligence Journey Using These DevOps Best Practices

Integrating Machine Learning Into Your Application Architecture

Gartner Analytics Evolution Framework

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