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Operationalizing Intelligence: A Unified Approach to MLOps and Scalable AI Workflows in Hybrid Cloud Environments

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Abstract

Artificial intelligence (AI) is poised to play an increasingly significant role in most organizations, enabling them to offer innovative new products and services, delivering value through automation, and maximizing returns through advanced predictive and prescriptive insights. However, deploying and operating AI at scale is often hindered by complexity, confusion, and operational inertia. Multiple definitions and perspectives of MLOps and other related concepts, such as DataOps, DevSecOps, GitOps, AI Engineering, and AI Lifecycle Management, have created a patchwork of standards and best practices, focused on only certain aspects of the broader challenge of developing and operationalizing AI capabilities. This has made it difficult for enterprise decision-makers to understand the complexity of AI operations, how different roles and teams fit together, and how to establish company-wide systems and processes to manage the development and deployment of AI technologies at scale. As organizations enter into the next phase of AI maturity, these challenges need to be addressed, so that the initial experimentation with pilot AI projects can be scaled into large-scale production-grade AI systems that deliver the benefits of AI capabilities to enterprises more efficiently and effectively. In this chapter, we first provide an overview of AI and its business value. The overview is followed by a high-level look into the machine learning (ML) lifecycle, where we introduce the concept of operationalizing intelligence, AI system parts, and the need for AI-enabled business infrastructures, before delving into the operationalizing of the ML lifecycle with MLOps. Next, we highlight key themes that form the basis of the subsequent chapters in this book. We then introduce the audience and structure of the book. Finally, we conclude with a summary that recaps the key lessons shared in this chapter. This helps set the foundation for a deep-dive exploration of the various aspects of MLOps, as an instantiation of the broader concept of operationalizing intelligence, in the rest of the book.

Keywords: AI Business Value, AI Operationalization, Enterprise AI Scaling, MLOps Lifecycle, AI Lifecycle Management, DevSecOps Integration, DataOps Practices, GitOps for AI, AI Engineering Standards, Production-Grade AI, AI System Infrastructure, Cross-Team Collaboration, AI Deployment Pipelines, Operationalizing Intelligence, ML System Complexity, AI Maturity Phases, Best Practices for MLOps, Scalable AI Systems, AI Governance Models, Strategic AI Enablement.

1. Introduction

The importance of Artificial Intelligence (AI) in harnessing the power of data to support critical decision-making is omnipresent, and it's for this very reason that organizations are racing at heightened speed to operationalize Intelligence Services at scale. Intelligent Data Serve Services based on Machine Learning (ML) and powered by generative AI techniques are becoming ever more crucial because they are enhancing so many aspects of our lives, allowing us to leverage data for applications such as Medical Diagnostics, Computer Vision, Speech Recognition, Predictive Maintenance, Fraud Protection, Generative Image and Text Synthesis, Chatbots, Recommender Systems, and Smart Assistants, to name just a few. Plans to invest over $100 billion to build the most advanced semiconductor manufacturing capacity in the US are largely premised on unlocking the immense potential of AI, and the incredible advances that we're seeing in generative AI over the past two years, which have made it possible for virtually anyone with an internet connection to create realistic content spanning text, audio, images, and video, accelerates this move towards hyper-scale Intelligent Data Services. In this document, we aim to share the lessons learned from deploying and scaling AI services that are arguably among the most complex ever built using the public cloud. Focusing primarily on Natural Language Services, we share our architectural, developer, and operational experiences and the problems we faced along the way. We intend to provide help and guidance to other teams passionate about AI, solve these problems earlier in the lifecycle of product development, or better prepare for the challenge of deploying and operating them at scale.

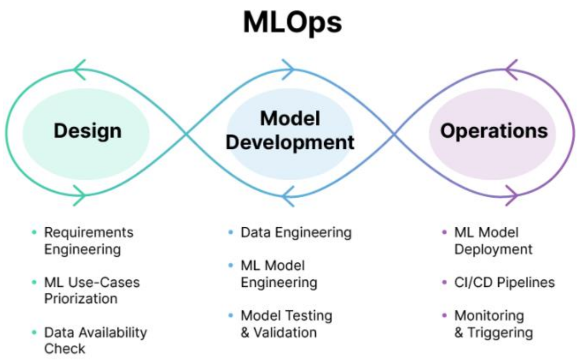

MLOps
Design
Model Development
Operations
• Requirements Engineering
• ML Use-Cases Priorization
• Data Availability Check
• Data Engineering
• ML Model Engineering
• Model Testing & Validation
• ML Model Deployment
• CI/CD Pipelines
• Monitoring & Triggering

Fig 1 : MLOps

1.1. Overview of the Document's Structure and Objectives

Operationalizing Artificial Intelligence (AI) has become of paramount importance for organizations of all kinds and sizes. The term AI Operationalization denotes the full spectrum of activities spanning the entire lifecycle of AI, from the creation of techniques and algorithms to the workflow management of training, validation, and testing of those techniques, onto their deployment into Artificial Intelligence Applications (AI Apps), observing and monitoring their behavior in production, curating them by adding more knowledge and/or improving them, and finally retiring them when no longer useful. AI Operationalization implies the existence of mature AI capabilities and expertise within the organization; however, it is not possible to deploy an effective AI Operationalization strategy and program without Enterprise AI, whose aim is to unify the management of the AI lifecycle and integrate it into the wider Enterprise Data Operations environment.

Real AI enterprise-scale deployments at the moment tend to occur in larger organizations or startups with deep pockets, or organizations that are within the orbit of the sponsors of AI Projects and Centers of Expertise. We aim to provide a guide to best practices in the AI journey, recognizing that organizations will be at different stages of their particular journeys. We describe what we call an AI Workflow, the AI counterpart to Data Pipelines in Data Operations, building scale and trust in the AI App; an Enterprise AI Platform, which is an Enterprise-grade MLOps Platform that assists in the governing of all AI Workflows and how they relate to one another; and, finally, a set of recommendations for organizations on the critical success factors and guidelines for being able to safely take the AI journey in a scalable manner that is responsible, ethical, sustainable, and good for the planet.

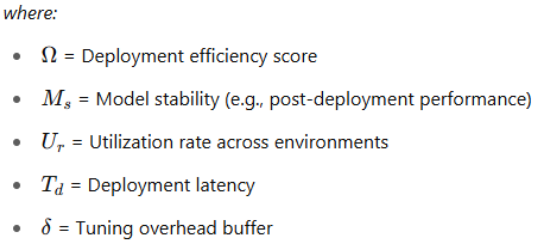
2. Understanding MLOps

Machine Learning Operations (MLOps) refers to the set of practices integrating machine learning system development and machine learning system operations. MLOps aims to decrease the cycle time of machine learning and artificial intelligence. For early-stage products, this tight feedback loop is critical so that the lessons from practice are rapidly learned. This is particularly important in domains where the environment is dynamic and prone to change. MLOps disciplines define and govern the productivity of a collaborative development environment and the performance of deployed systems.

MLOps is inspired by DevOps, and it borrows several of its practices. MLOps enables model versioning, collaborating using notebooks, CI/CD and rollout of trained models, collaborative and organized model publishing, A/B testing of model performance in production, monitoring, and management of model performance, handling of retraining and model deprecation, and versioning, management, and organization of datasets. Unlike DevOps, MLOps is new – there is an enthusiastic and growing community around it, but the approaches are only beginning to mature and are yet to become best practices. MLOps is also more specialized – it focuses on the problems particular to machine learning and AI system development and deployment. Such specialist knowledge in particular domains is vital since the same set of tools and practices cannot be applied without modification to every industry. At the same time, MLOps cannot afford to reinvent all the tools for every industry, and a proper balance between domain-specific people, practices, and tools, and industry-agnostic ones is the goal of MLOps.

Equation 1 : Model Deployment Efficiency (MDE):

$$\Omega = \frac{M_s \cdot U_r}{T_d + \delta}$$



where:

- Ω = Deployment efficiency score
- M_s = Model stability (e.g., post-deployment performance)
- U_r = Utilization rate across environments
- T_d = Deployment latency
- δ = Tuning overhead buffer

2.1. Definition and Importance

Machine Learning Operations (MLOps), a cross-disciplinary set of practices, is designed to deploy and maintain machine learning and artificial intelligence models in production reliably and efficiently. Similar to the concepts of DevOps and DataOps, which combine Development, Operations, and Data functions in a synergistic collaboration throughout the software and data lifecycle, MLOps builds a bridge between data scientists and operations professionals, integrating model development and operations to formalize the full lifecycle from building models to running them in production. These models are securely and efficiently hosted on production infrastructure, scaled up and down to serve online analytics and recommendations, reserved for batch processing and reports, retrained when necessary, monitored for health and performance, and retired when necessary.

Business leaders across multiple sectors are betting on machine learning and AI, and are seeking that

ML and AI models can enhance decision-making in their functions, from enterprise strategy to fraud detection, from machine diagnostics to product-enhancing recommendations to customers. There is high promise and the payoffs are attractive, but achieving success with mission-critical ML and AI applications is difficult. Enterprises need a unified approach to operating ML and AI applications, integrating people and technology across their business functions. If implemented right, MLOps standardizes the deployment of ML and AI applications, making the process less risky and more efficient, enabling collaboration among technical and operational people, and freeing data scientists to do what they do best: building better models at a higher velocity. All of these aspects of MLOps are critical to the success of any ML or AI application at scale.

2.2. Key Components of MLOps

The broad area of MLOps tasks can be summarized as the implementation of software infrastructure and platforming required for a successful deployment of machine learning technologies. The main areas of MLOps research are pipelines, modularization and versioning, monitoring, and orchestration. Machine learning pipelines are at the heart of most MLOps activities. The operationalization of ML solutions follows the standard path of code-defined automation made popular by DevOps in general and CI/CD systems in particular. This is the ML area of continuous integration. Once your ML pipeline has been defined, you move from an experimentation cycle to a production ML cycle.

Modularization and versioning are another component of MLOps. Large ML solutions are large because of the size of the models that must be trained. The ML experimentation and production cycles proceed by continuously playing with these models - retraining and/or fine-tuning them. In particular, there is a need to separate the training and fine-tuning of an ML model from running production endpoint inference through a well-defined API. At the same time, when moving from experiments to production endpoint deployments, we want to engage in control versioning of the models we produce and are deploying.

There is an additional subtlety to model architectures and versioning. Given the LLM revolution and the goals around reducing the cost and the time associated with building new 'foundation' models, another component of MLOps is monitoring the evolution of the demand for LLMs and the foundation models that are being built to answer — and drive — that demand.

2.3. Challenges in MLOps Implementation

Due to the rapid evolution of MLOps, there lacks a unifying theory or clear methodology on how to operationalize or implement it. As such, enterprises are faced with a significant amount of complexity and challenges when attempting to generate business value from the production of their AI models or products. One thing is clear – MLOps is not the same as DevOps for enterprise ML pipelines, although there are a lot of overlapping technical enablers. Instead, MLOps is an orchestration of a heterogeneous set of workflows, processes, tools, and technology focused on building, deploying, managing, and governing enterprise AI products, spanning many disciplines other than just engineering. Because of this, there are a myriad of challenges that make MLOps hard, but these can generically be classified into business and technology challenges.

On the business side, ML pipelines are very different than traditional software engineering processes, from the data dependencies that are controlled by data scientists, to the less-structured open-ended nature of building models using AI algorithms. Business leaders often have unrealistic expectations of how quickly AI models can be built or how accurate they should perform, leading to project scope bloating, headcount surprises, or creating production models that are based on guessing and trial-and-error instead of the concept of a statistically validated, generalized model. Tech-savvy leaders who understand models built using MLOps are still surprised about how long AI pipelines take to mature and often do not consider the fact that poorly defined initial projects generate unforeseen costs and delays. MLOps is at the intersection of business and technology. Most AI products are either poorly designed or poorly utilized, with a high percentage of AI projects failing.

3. AI Workflows in Hybrid Cloud Environments

1. Overview of Hybrid Cloud Architecture

A plethora of components are captured by the MLOps stack. Collectively, they enable the management of automated ML pipelines and their associated service components for the data analytics lifecycle from inception to completion, across multidisciplinary environments that span multiple clouds, data sources, and resources. A unified MLOps architecture follows a simple but potent premise: “Doing AI is hard, but we can make it easier.” By architecting and tool-bunding AI workflows against the surface area of disparate cloud services, the goal is to help data scientists and other domain experts onboard and deliver data and models faster, with fewer resources and a lower risk of error. These AI workflows provide a set of recommended services and tools that domain experts can apply to their domain analytic problems. Such recommendations take the burden of composing target-specific data operations workflows – a complex problem for even seasoned experts!

In this section, we go into additional detail into how hybrid cloud comes to life specifically for running AI workloads. We discuss how operationalizing data analytics workflows with specific solutions enables domain experts to carry out highly-productive model development without needing to invoke specialized internal tools.

2. Benefits of Hybrid Cloud for AI Workflows

The recent enthusiasm for AI has not escaped the enterprise. From an infrastructure perspective, these workloads fall broadly into three types. Storage and processing of the terabytes of unstructured and semi-structured data owned by enterprises continue to burgeon in scale, complexity, and diversity. Intelligent models need to be built upon this foundation of data, frequently using very specialized and talented external data science teams. Finally, enterprises need to be able to deploy, access, and budget these models to provide production services to their customers and business units. These service APIs also need to be able to be retrained, monitored, and updated based on feedback from the production phase.

The good news is that the recent acceleration in the development of cloud-based services makes the execution of any of these three functions both easier and faster. It is possible to scale these services on demand and de-burden the engineering and product management teams, allowing these internal teams to apply themselves to other enterprise-specific problems. Accelerating business impact with AI is a compelling business goal for any enterprise, with advertising, marketing, and entertainment leading the charge.

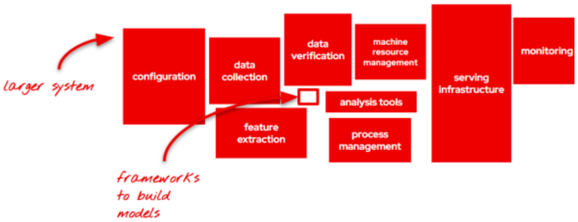


Fig 2 : Hybrid MLOps platform

3.1. Overview of Hybrid Cloud Architecture

An information technology infrastructure that incorporates both on-premises deployments that are dedicated to a single organization and shared resources hosted in the cloud today is known as a hybrid cloud infrastructure. The appeal of hybrid cloud computing lies in its ability to balance the burdens of compute-intensive workloads involving very large datasets that have traditionally been the domain of on-premises solutions along with the economies of scale and agility associated with outsourcing a variety of less intensive workloads to public cloud-based offerings. A key goal of hybrid cloud computing is to create a coordinated technology stack across clouds that allows workloads that are part of the overall process to transfer workloads to and from both types of deployment in a seamless manner. Common forms of hybrid solutions emphasize either the on-premises or the cloud elements. For AI workflows, a hybrid cloud infrastructure allows organizations to bring together the best of both worlds while implementing widely differential security and compliance requirements, enabling the use of high-performance computing and enterprise storage sanctioned for proprietary data to run large AI models but also the flexibility to operate a variety of workflows related to production model inference, retraining, and parameter tuning over federated datasets and share them among multiple model sponsors and operators. Such commonly deployed workloads include feature extractions, model point-inference and batch processing, transfer and tuning of model parameters, processing of model data for use in enterprise applications, and final deployment of models for enterprise applications, such as enterprise resource planning, workforce management, and regulatory compliance—backed by collaborations among teams of data scientists, IT, and the business for annual or semiannual cycles of digital transformation.

3.2. Benefits of Hybrid Cloud for AI Workflows

Hybrid cloud is not new: many organizations have been using multiple public clouds along with their private resources—their data centers or their edge devices—for many years, in an attempt to benefit from the best of each. But with the advent of Artificial Intelligence (AI), the hybrid cloud takes on a more prominent role because AI demands both specialized resources that can be found in the public clouds and a reduced cost for the deployment of mission-critical AI-based applications that require large data movement across many pipelines, a desirable feature in a data center or an edge location. The reality of operating AI solutions “at scale,” that is, the ingestion, persistence, processing of, and inference based on huge amounts of data, kernelizes the AI “life cycle” in a deployment that, thanks to hybrid cloud, uses the appropriate infrastructure for each step according to its peculiar needs. In that sense, hybrid clouds can help organizations at different levels of maturity: they facilitate the adoption of AI technologies that demand infrastructure enablement while allowing the transition into a cost-efficient deployment of scalable and mission-critical systems that incorporate AI solutions.

Remote public infrastructures contain technology accelerators that can support the AI workflow. In turn, local private infrastructures allow multi-stage AI workflows required for a scalable solution. Public clouds provide options for the necessary additional capacity at peak demand times. Federated learning, a novel AI solution against data consolidation due to privacy or legal reasons, is also an enabler of more agile hybrid clouds.

3.3. Common Use Cases in Hybrid Cloud

And, while we have mentioned a few potential use cases for running AI workloads in hybrid cloud, they can still be covered and better explained. We will describe each use case briefly without going in-depth at this point to keep the flow of the rest of the chapter coherent, focusing on use cases specific to the hybrid cloud environment.

1. ML Development Workflow

Typically, the resources for the development of MLOps workflows are mostly CPU-bound, without the need for GPUs. In addition, proper experimentation management and probably better tools and resource entropy control mechanisms are needed. This phase of the development may happen in both data scientist's laptops and smaller CPU-based scalable compute clusters on-premises and cloud, making sure budgets are being adhered to. In this case, the hybrid cloud serves as a temporary, on-demand extension of on-premises resource pools for experimentation and validation quotas.

2. Model Training Workflow

Model training usually leverages large GPU-equipped clusters, accelerating processing and helping cover demanding timelines for repetitive task execution. If the model evaluation fails, then the team may go back to the previous phase, experimenting further and adding more evaluations for optimization and hyper-parameter tuning, until satisfied. While some training workloads may run entirely in the on-premises infrastructure, allocation may come closer to the so-called "80-20" rule, trending 80% in the cloud and 20% on-premises for data security and performance reasons.

4. Unified Framework for MLOps

The large-scale adoption of ML technologies across different industries has made it imperative to implement a streamlined pipeline, governed by a unified framework for MLOps, and consisting of a set of structured processes utilizing appropriate tools and technology stacks, which can be executed repetitively across different ML workloads to ensure operational efficiency, reliability, and scalability. A unified model for MLOps would essentially facilitate the orchestration of different workloads and associated efforts in the entire MLOps pipeline – from management of data, ML model training, configuration, experimentation, validation, and security to that of deployment, monitoring, scaling, cost optimization, and governance for different workloads. The MLOps lifecycle would thus help tie in the multiple activities that need to be implemented cohesively within every stage of the MLOps funnel and implement the appropriate feedback mechanisms.

Different parameters must also be taken care of throughout the MLOps lifecycle – automation of tasks across different degrees as per the business requirements, risk tolerance, and model accuracy; building a collaborative culture and infrastructure between the team implementing different workloads and DevOps team; clear identification of responsibilities across the MLOps lifecycle; extensibility of existing tools and technologies being used for model deployment and monitoring; sensitivity and security of data and ML assets being processed/created, and quality and performance of the ML models being created, deployed, and monitored; process-driven approach to different roles being involved in the MLOps lifecycle, and so on.

Core Principles of a Unified Framework: To achieve our goals, we propose the implementation of best practices and a set of key principles controlling different parameters across tools and technologies, specific to each type of workload throughout the pipeline. These principles are control of different MLOps pipeline parameters by the modeled process and collaboration of tools and technologies being used through seamless flexibility and extensibility, focus on automation, sensitivity, and security associated with models, support for a unified approach by a single vendor at each stage across the data life cycle, continuous feedback-driven, template-based design with appropriate real-time monitoring and governance enabling reliable performance, and finally, best practices across the board for implementing different operations associated with various workloads within the pipeline.

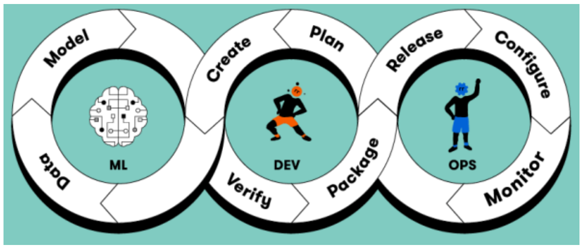


Fig 3 : MLOps Explained

4.1. Core Principles of a Unified Framework

The benefits of AI and machine learning for processes and activities have been recognized at enterprise and public organization levels. But while there are many enablers for creating, training, testing, and validating ML models, the desired scaling effect has not happened. Workflows and pipelines have been constructed and operated in a standalone mode using different tools for different workflows, not allowing easy reuse. This leads to a lot of redundancy and non-optimal operations. We present a holistic framework for removing the current impediments towards efficient and maximum intelligent operations. The main components of the framework support the optimization of model engineering, model lifecycle management, data management, and orchestration of hybrid cloud execution environments. The key principle is to consider all of these components simultaneously, combining the strengths of public clouds, private clouds, and on-premise infrastructures, allowing for the most flexible, dependable, scalable, and cost-efficient operations of ML models for inference.

Machine learning model failure is a natural part of the life of a specific ML model. However, entities decide to invest to reach measurable and profitable results. To increase the probability of reaching and maintaining success, we define a set of principles for a unified framework supporting MLOps. These are: Horizontal Support of Vertical Process Steps Supporting Model Inference Performance and Quality Goals; Combined and Joint Operations of All Model Stages and Qualified Models Without Silos; Seamless Operations of All Infrastructure Types and Sizes; A Strong Abstraction of Complexity; Intelligent Recommendations Generated by the Framework; Role-Sensitive User Interfaces Supporting Collaboration; International Compliance of Requirements for Model Design, Performance, and Verification.

4.2. Integration of Tools and Technologies

Strategically list, define and prioritize the most commonly used tools and underlying technologies in what is now known as MLOps. Acknowledge some of the other frameworks in current usage in more detail. Given the rise of hybrid deployment options increasingly being taken by enterprise IT departments, and the need to operate in a secure environment taking into account enterprise security policies and compliance, specifically IT infrastructure security and data governance, provide a detailed discussion on the technologies and options for tool deployment both on-premise and in the cloud. Describe in some detail the role played by other enterprise tools not specifically designed for AI/ML but which do provide relevant and useful capabilities, such as logging tools, work management tools, pipelines, and others.

Necessarily all enterprise production ML service operations will be associated with a need for some level of application management, given that ML Services deployed in production will invariably be deployed as microservices and/or part of a microservices architecture structure. Various wrappers around popular open-source projects perform, at least in part, an application management function. Cloud providers also make available application management tools designed specifically for ML-enabled applications. Given that IT service teams and backend engineers own the application management function, those designing and implementing ML Services need to know and understand the capabilities already offered by the enterprise application management tools, and as a result, to design the ML Services Public APIs and service contracts to be in alignment with what is already offered in this domain, whether this be a cloud provider tool or enterprise owned and operated tool.

4.3. Best Practices for Implementation

More than just these technical principles, practitioners also need to follow best practices for implementation. These are also driven by our years of practical experience and feedback from customers and partners. Each organization is likely to have a commonly followed practice that has worked well for specific projects, but the goal of the following guiding principles is to ensure that these are followed, or characteristically adapted to suit the organization's needs. Although these guidelines can be used independently or in combination, we discuss these pillars in the context of our previous sections or general data and compute stacks.

1. Build Modular Pipelines

In its simplest form, a pipeline is a directed acyclic graph of a series of steps, whose output from one step is consumed as the input to the next step. Each of these steps typically deals with particular units of work, which could be creating the data assets used for training, training, and evaluating the model, or deploying and monitoring the model in production. Each of these steps can utilize frameworks of its choice and can run in any environment of choice, utilizing a loosely coupled microservices architecture. This modular architecture can help speed up the development of several models simultaneously, test pieces of the pipeline independently, and concurrently work on improving various steps of the workflow.

2. Use Proven Frameworks

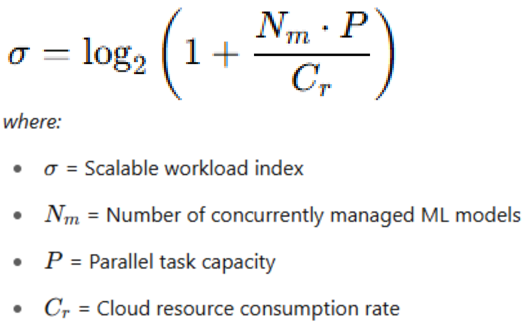
Machine learning is currently in a phase of rapid experimentation and innovation. It is often not unusual for different teams within the same organization to be using different frameworks. Despite the need for agility and flexibility, however, there is value to the scaled deployment of a limited vector of commonly used frameworks. For example, for model training, many customers follow the guidelines of using popular frameworks and standardizing on specific model architectures. A similar standardized approach is possible for key tasks such as CV and NLP.

5. Scalability in AI Workflows

Data and Artificial Intelligence (AI) workloads have emerged as critical players in the Digital Transformer model for large corporations, both from an operational efficiency perspective and from a revenue generation viewpoint. Operational scalability in data and AI workflows goes beyond just focusing on performance improvements but includes costs and personnel optimizations. In this chapter, we explore how organizations can achieve operational scalability through a hybrid cloud approach and MLOps best practices. Scalability is a requirement of a deployed solution that cannot be neglected. It generates hidden costs that no one wants to be responsible for, as they often deteriorate service level agreements (SLAs) negotiated with customers. Scalability is not just solving a problem efficiently but being able to be seen as the default go-to tool. Thus it is always a balancing act between the quality of the solution, the efficiency of solving the problem, and the scalability of the solution.

The main advantage one gets from becoming the default function is that more users will rely on the solution. At this point, we assume there will always be a workload, and this is not affected by economy of scales accentuated by hybrid cloud strategies. Models exposed to users become more powerful and improve in quality because the loss function has now morphed into multi-armed bandit problems. User behavior is more unpredictable, and finding the best parameter policy that the user is satisfying is not always obvious.

Equation 2 : Workflow Scalability Function (WSF):



$$\sigma = \log_2 \left(1 + \frac{N_m \cdot P}{C_r}\right)$$

where:

- σ = Scalable workload index
- N_m = Number of concurrently managed ML models
- P = Parallel task capacity
- C_r = Cloud resource consumption rate

5.1. Defining Scalability in AI

As described in the earlier chapters of this book, a wide range of technologies and operational techniques are required to successfully build and deploy AI projects at scale. This has led to an equally wide range of definitions of what ‘scalability’ truly means concerning AI and ML. It is also widely known that the degree of success with a project, and the barriers to that success, can vary significantly across AI project types and phases. For example, the NLP work underway at various organizations has monopolized computational budgets and cycles across the industry, while the production rush has already come and gone for image recognition. So does scaling mean growing more efficient with model and data resource budgets? Or does scaling mean fractalizing technology paths to quickly optimize microtransactions or personalized recommendations associated with a preferred MLOps partner? Or both?

To set some specific guidelines to keep this discussion talking about the right things, we feel there is a really simple approach to defining scale in conversational and constrained budgetary terms. With these criteria make it clear what part of AI overall we are talking about, the replies from industry visitors who have just undergone the move ‘from Technical Proof of Concepts to Business Proof of Solutions’ with Generative AI Maturity Models. If a success factor has been raised in importance due to AI tech cycles then indeed it is more of a nontechnical project constraint now, namely, building systems to increase the ‘Scale of Linear Effectiveness’ or ‘Scale of Human Decisioning or Creativity’ in Manufacturing and Knowledge Work business processes. Most of these applied process changes result in marginal improvement because there’s no secret sauce or secret AI model that is transformationally better (or worse).

5.2. Techniques for Achieving Scalability

Scalability is largely an issue of software. Achieving the scaling promised by hardware solutions is often thwarted by the limiting assumptions of AI algorithms and the software frameworks that implement them. Here, we discuss the primary techniques available for improving scaling. The solutions we discuss can be categorized into two major classes, functional and architectural. Like the operant conditioning box of pigeons, AI models express natural preferences for particular types of data, and scaling thus often requires aligning models with those preferences to achieve better SNR.

Functional techniques are directly applied to the inputs and outputs of AI models and the algorithms that train them. The most obvious way to scale is to increase the quantity of data a model is trained on, and so improve the model's generalization to new inputs. Input-output scaling has increasingly been achieved through procedures such as meta-learning, autoregression, and contrastive learning. Meta-learning allows models to leverage the common patterns inherent to large collections of tasks, extending the amount of data they can learn and generalize from far beyond the size of the individual task's dataset. Such methods have been shown to enable the transfer of knowledge between vastly heterogeneous inputs, and many attribute the success of pre-trained models in NLP and CV to the architected diversity of tasks and datasets, held together by a simple training algorithm, designed to model natural phenomena as different as human language understanding, text style transfer, and the prediction of the next word in a sequence.

5.3. Monitoring and Optimization Strategies

Monitoring pipelines is much more complex than monitoring traditional software operations. Proprietary MLOps solution typically has the monitoring covered, but open-source efforts don't yet have a reliable solution. Since machine learning models aren't deterministic, subtle inaccuracies will almost necessarily slip through on the first execution. These small deterministic errors may only grow to be significant when the model is being executed on an edge case or for a long period. Luckily, data scientists know where they have errors in their pipelines and the criteria required to identify the acceleration/deceleration of error over time.

For monitoring, we recommend keeping a rolling sum/count of the number of events passing through each major point in your pipeline, collecting execution times of major stages of your pipelines, and tracking the number of active users for each model system. These metrics are a good suite of metrics for finding unusual performance issues. Luckily, MLOps solutions have been covered from a monitoring perspective. Pipelines that are started frequently (or 1 off) are a tricky situation to monitor. In those situations, actively checking the performance of your models and their performance over time/degradation over time in your other product systems may be the most reliable. In the case of historical or batch systems, detection of data distributional shift can be readily detected with outlier detection algorithms enabling easy initiations of retrains.

6. Security and Compliance in Hybrid Environments

Organizations across various industries must comply with an expanding array of laws, regulations, standards, and guidelines. Such regulatory and compliance regimes exist to protect sensitive data from breaches and data leaks and are responsible for the emergence of security and compliance silos across organizations. This has posed challenges for enterprises operationalizing AI workflows, given the sensitive and proprietary data leveraged by machine learning pipelines. In this chapter, we outline the multifaceted security considerations and compliance challenges facing the hybrid deployment of machine learning, before presenting best practices for addressing these challenges.

With hybrid AI deployments, organizations are faced with the possibility that proprietary and sensitive internal data, such as confidential customer information, is moved to public cloud resources. Concerns arise over whether organizations can adequately protect against insiders at the public cloud provider from accessing proprietary and sensitive internal data stored in virtual machines, databases, or object stores. This concern may be amplified as the quality of machine learning models improves with access to more and more data, including proprietary and sensitive data, such that it may also be infeasible to protect against inadvertent leakage by model developers of sensitive or proprietary information from the model. Companies also want to prevent adversaries from using models hosted in the public cloud for illicit purposes, such as adversarial attacks, especially when models are hosted by competitive organizations.

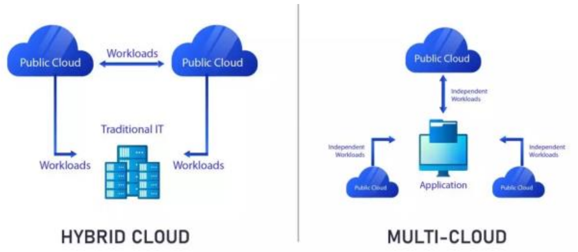


Fig 4 : Multi-Cloud vs Hybrid Cloud

6.1. Data Privacy Concerns

Privacy risks arise whenever sensitive data is stored, processed, or transmitted electronically, and are especially prevalent in hybrid cloud environments, in which sensitive information may move between an enterprise data center and an external cloud environment operated by a third party. Privacy risks are related to security vulnerabilities, such as inadequate data protection, in that lapses in security protections can create privacy risks. However, privacy is a distinct legal and compliance area with its own rules, requirements, and risks. Privacy concerns revolve around the use of personal data. The collection, storage, use, transfer, and destruction of personal data is governed by a variety of federal and state laws, as well as industry regulations. Hybrid cloud environments can create personal data privacy risks if organizations do not take sufficient steps to comply with the myriad laws governing sensitive data that is being shared among and between different organizations and environments.

For example, a company might be at risk of violating the privacy of personal data such as social security numbers or healthcare data if it hires a third-party cloud provider without taking the necessary steps to ensure that its security protections are by privacy guidelines. If personal data is improperly hosted, accessed, or moved between jurisdictions by internal employees or third-party cloud providers, the organization could face legal consequences, fines, sanctions, or serious reputational harm. Privacy is a major consideration in implementing hybrid cloud systems because organizations that employ hybrid cloud strategies must deal with complex privacy compliance requirements based on the industries that they are part of and the geographies where they do business. They also have to make use of a complex technology environment that includes third-party vendors and service providers.

6.2. Regulatory Compliance Challenges

From a regulatory compliance perspective, the challenges with hybrid environments relate to the interconnectivity of on-premise and cloud environments with the usage of core services like cloud storage, sharing data across services, and access management in the cloud. The most prominent regulatory compliance requirements are those surrounding how data can be collected and processed and how it should be stored. Adhering to these regulations can be especially hard for organizations that are trying to modernize their IT environments and embrace a hybrid model. But also, this is where hybrid environments can be especially valuable. With intelligent tools in place that can automatically detect and manage sensitive data, organizations can use their hybrid environment for exactly the use cases they envision while remaining compliant and secure.

Many organizations desire to use the public cloud for sensitive workloads because of the scale, speed, and capabilities that it can provide. To do that effectively, sensitive data must be detected and managed. Detecting sensitive data is often daunting, let alone applying the appropriate policies around access, protection, and monitoring. Organizations tend to treat sensitive data differently depending on where it lives, whether it's in a repository on an end-user computer or if it's in a cloud service. Organizations today struggle to manage sensitive data across hybrid and multi-cloud environments, especially as the costs and consequences of breaches continue to rise. Yet this challenge is often due to a lack of visibility that organizations have into sensitive data discovery, classification, monitoring, and first-party protection across endpoints, on-premises systems, and multi-cloud environments.

6.3. Implementing Security Best Practices

Having scalable AI orchestration capabilities comes at a cost, especially in terms of security, data privacy, and compliance considerations. While there are many security and compliance considerations across hybrid environments, there are some best practices that can assist with implementing data protection and maintaining the principle of least privilege. Enabling audit logging of usage details enables monitoring for credential and cache usage, critical to maintaining a secure enterprise environment. Providing integration with identity providers allows avoiding the use of API keys for authentication and makes it possible to automatically export users and groups. Importantly, requiring authentication for using a connection helps enforce user security.

Supporting the OAuth 2.0 protocol helps securely connect and transfer data to and from cloud services. In some cases, connections need to use the service role identity of a serverless architecture component or microservice to enable access. Using temporary credentials ensures the service role key is not exposed. Whenever possible, account linking should leverage a shared services architecture. Furthermore, document libraries should use separate service accounts by organization and disable long-lived credentials. APIs should use HTTPS to protect sensitive connection information in transit and use signed requests with a short expiration time.

To fully address the principle of least privilege, organizations should restrict the use of privileged connections to the most trusted users and pre-scheduled access. Data handling guidelines need to specify that only hashed fields and anonymized datasets that cannot be reversed into sensitive data may be used in public pipeline stores. Some implementations allow organizations to restrict their pipelines to only use internal stores.

7. Case Studies

In this section, we present two case studies that demonstrate the effectiveness of the approaches described in the previous sections. While our first case study describes a successful implementation of MLOps lifecycle in a life science organization, the second one focuses on a hybrid cloud AI workflow with focus on scaling the operationalization of AI in multiple regions.

1. Case Study 1: Successful MLOps Implementation

The data science group has approximately 150 data scientists who construct various types of ML models for different use cases such as predictive maintenance, quality control, demand forecasting, etc. Projects are distributed to remote offices in multiple countries. The group supports numerous data sources, including internal, external, structured, and unstructured data. There is a centralized data science platform with multiple shared model-serving and data preparation and validation services. The platform is deployed in a private cloud using on-premises infrastructure with a few edge components. However, the group has been facing several AI operationalization challenges.

The data scientists are using notebooks for running their experiments. Due to the data size and test duration, the experiments are run very infrequently. When an experiment is run, it is often started with a different version or subset of data. Models are created using many different tools suitable for various use cases and deployment and validation requirements. The low-code/no-code development environment is available for a limited number of pipelines. Data discovery and collaboration are often difficult and time-consuming. There are multiple versions of the same ML model, some of which could be out of date. Not all models have been monitored. Such concerns caused the group to look for MLOps lifecycle tooling before they could scale their operations further.

2. Case Study 2: Hybrid Cloud AI Workflow

A large international retail company is at an early stage of using AI for business needs. The company's initial use cases are exploratory and include product recommendation, customer churn forecasting, demand forecasting, and shopping cart data understanding. Although the business department is test-driving a few use cases with their respective data science teams, they quickly realized that testing and deploying many different models will no longer be sustainable. Meanwhile, the data and IT organizations have been working together to build a big-data infrastructure, focused on data preparation and data validation capabilities. As the data science teams are becoming increasingly enterprise-centric, with established collaboration among them, the need for deploying a full-featured hybrid cloud environment in data centers around the world is gaining ground. With a plan to create an enterprise data lake and handle AI model development and deployment, MLOps and AI workflows are becoming essential business capabilities.

In this section, we present a case study on how and why the company has made a successful investment to scale its activity to operationalize AI in a hybrid cloud environment, including how we standardized the MLOps lifecycle architecture in the various clouds in the hybrid cloud environment to facilitate a common experience for template- and use-case driven AI for different business objectives.

7.1. Case Study 1: Successful MLOps Implementation

After development, AI models must be successfully deployed and continuously retrained based on new data in production for the models to yield business value. The entire machine learning process requires collaboration between data scientists and traditional DevOps engineers. Although this process has traditionally been managed privately, it is becoming increasingly common for companies to look for a true enterprise solution that has governances in place, allowing the organizations to transfer some aspects of the machine learning process to third parties or providing tools for managing the machine learning process. As companies look for MLOps solutions that offer collaborative tools for managing machine learning processes, one company has emerged at the top of the food chain response a holistic enterprise focus, a strong product suite, and a vision that aligns closely with how best to make machine learning work. This AI platform company was the first to operationalize AI with a model management solution for MLOps and has pioneered the machine learning operationalization market, establishing enterprise capabilities in ML model governance, compliance, and collaboration. Built the first extensive enterprise-grade ML model governance and management capabilities, reinforcing how organizations must govern machine learning models and decision systems the same way they do for traditional business processes – from data to application. These capabilities allow enterprise DevOps teams to create guardrails around data science and MLOps so that data scientists have the autonomy they need to do their jobs without putting the organization at risk, while at the same time allowing the enterprise to get to market quickly without compromising on governance or security. Most importantly, these capabilities support the growing desire by organizations to infuse AI and machine learning worldwide into their mission and business strategy, empowering developers and lines of business to leverage the best technology, while maintaining the MLOps visibility and control needed for mission-critical operations.

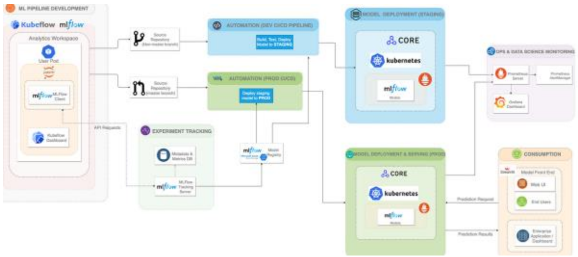


Fig 5 : MLOps Platform Implementation

7.2. Case Study 2: Hybrid Cloud AI Workflow

AI has become a core competitive advantage in many of the public cloud companies, and the public cloud itself has made this business model possible for companies across a wide variety of industries. Companies may not want to engage cloud providers directly, but for them to take advantage of the scale, AI capabilities, and lower costs possible through the pipelines and workflow data management pioneered by these cloud companies, they may have to move some of their workloads to a cloud. It makes sense in many use cases, but hybrid cloud architectures, models, and security become incredibly important in these workflows, as well as completing the model management across the end-to-end lifecycle, from model training, to model performance monitoring, to model retraining and redeployment. Each cloud has its best-of-breed offerings. There is the level of core scalable storage and processing capabilities needed to maximize the amount of data available to the training, fast, efficient training on GPUs, TPUs, custom silicon, or clusters of such accelerators, possibly leveraging open source accelerators. Then the actual training, monitoring, and orchestration services, with parameters and hyperparameters, need to be as easy to use as the most user-friendly, successful mature ML or AI products. These cloud capabilities need to be tightly synchronized with the on-premises capabilities, in terms of data access and other shared resources, or the value of the run models in production cannot be maximized by leveraging the cloud. At the same time, cloud-based costs need to be carefully modeled, predicting and avoiding spikes, while providing a tightly controlled and preferably automated way of navigating the trade-offs.

7.3. Lessons Learned from Case Studies

The two case studies highlight practical aspects related to operationalizing ML and deploying AI workflows with production quality. We summarize them into four key items.

Unified models in MLserve. Our clients often develop and deploy different types of models in production to satisfy various business needs. For example, in today's hospitality industry, search-based experiences constitute a common use case. At the same time, it is essential to leverage user-generated images, video content, and reviews to generate content. The models dealing with the two types of tasks can be different but also can be unified. The same key inputs can be used to build different types of models with different types of desirable outcomes. Leveraging a unified architecture for the models allows for several benefits: (1) improved generalization, as we leverage common input signals, (2) the ability to avail of common services such as model serving, and (3) faster experimentation and model retraining.

Support for hybrid cloud infrastructure. Many organizations began adopting a multi-cloud strategy to avoid vendor lock-in, mitigate risk, balance regulatory requirements, and reduce latency. By using and switching between private and public clouds to deploy various workloads, they can leverage the right cloud for the right workload at the right time, dynamically change application placement according to business needs, and optimize their IT expenses. Our second case study highlights how to support the deployment of various components in a hybrid cloud infrastructure, linking services running in different clouds and externalizing the dependencies on the cloud with the workflow definitions. A hybrid workflow example would consist of the data ingestion and model training components running in a public cloud, model serving running in a private cloud, and an external API consuming model predictions. The users appreciate the flexibility. They can dynamically compose the cloud service deployment strategy without being locked in a particular cloud platform stack.

8. Future Trends in MLOps and AI Workflows

In this chapter, we explore the future of MLOps from a thought leader perspective. We summarize the opinions of a dozen experts in the fields of AI and MLOps. What are their expectations for the next fifteen years in the field of AI operationalization? What key ideas and messages do they share that make sense for every data professional, CTO, or CDO? What will the industry look like at the end of 2035?

But first, what do we mean by MLOps? After all, the operationalization of intelligence can be a wide area. Isn't MLOps simply about connecting and deploying ML pipelines? Well, many think that MLOps is applied to only a fraction of industries that use AI services. Others have a more vertical vision that imagines MLOps as operating any AI service within the technology domain. This would reduce MLOps to a single architecture element around a service supporting all applications. Others have expressed similar opinions and suggested the semantics of the term AI Workflows to get over the limitations of the current demarcation visually drawn using the Operations term. Yet, others think that enterprise AI is simply about producing analytics at scale using MLOps; and therefore use the term AI Workflows when evaluating AI-based companies.

8.1. Emerging Technologies and Innovations

Artificial intelligence (AI) is increasingly becoming the de facto technology whose acceleration will solve many of human's pressing problems. The ever-growing computational capabilities and massive amounts of data are driving rapid advancements in AI. Meanwhile, the AI industry and applications are rapidly evolving and maturing. There is a multitude of AI frameworks and libraries that are being released, in particular domain-specific models or derivatives, open AI foundation models, and the ecosystem around these models. MLOps definitions and the associated tools portfolios are rapidly expanding. Businesses are adopting AI to improve existing products and services, create new products and business models, automate processes, and make data-driven decision-making. They are also leveraging MLOps to optimize the operationalization of AI.

The acceleration of innovation in AI and the expanding adoption of MLOps by organizations of different scales and industries are driving new premises, principles, and challenges for the next decade. The emergence of innovative technologies such as foundation models is disrupting the AI landscape. Foundation models are rapidly driving an increasing amount of interest around a new set of capabilities such as few-shot or zero-shot learning. They are also radically driving new AI opportunities and use cases as well as new adoption challenges. They present empirical challenges, including bias, toxicity, and other ethical challenges such as environmental concerns due to the carbon footprint created when training massive-size models. They also present technical challenges in adapting the model for effectively solving specific tasks and domains.

8.2. Predictions for the Next Decade

Part of being successful in business is being able to predict the future. The following is a collection of predicted future events relating to MLOps and AI workflows. They are all written in the future tense, but rather than being proposed predictions, they are presented as predictions from the perspective of the current date. The intent is to quickly communicate them rather than explore them in more detail. We will note that they are all expected ten years in the future.

MLOps as a discipline has taken its place alongside the established mature disciplines of DevOps and DataOps and is an integral part of any modern data-driven organization. The century-long march of special-purpose machines taking the place of more generic machines like the mainframe continues, with AI and ML as the new general-purpose technology of the century. Global economic productivity has increased by 20% due to broad AI adoption efficiencies in almost every sector of the economy and society. Cloud vendor infrastructure services have specialized to the point where deploying and running workloads in hybrid cloud environments that include both public cloud and on-premise components are trivialized and the cost of consumption equalized.

For AI, innovation around General-Purpose AI has led to commercialized “AI agents” that can engage in conversation with people, interpret their intent, offer advice about specific tasks, and execute those tasks automatically or with minimal human involvement. AI and ML are being increasingly used to decide what are the best tasks for these AI agents to be working on, determine the location and visibility exposure of resources, script workflows, and monitor AI-assisted execution. Hybrid cloud environments have led to on-demand access to AI-assisted analysis and operational execution of logistics problems on a global scale, allowing businesses, agencies, and NGOs to offload operational execution of those problems to the AI agents and to dynamically provide context and oversight for best action outcomes.

Equation 3 : MLOps Pipeline Reliability (MPR):

$$\Gamma = 1 - \prod_{i=1}^{k}(1 - r_i)$$

Γ = Overall pipeline reliability

r_i = Reliability of stage i (data ingest, train, test, deploy)

k = Number of pipeline stages

8.3. Impact on Industry Practices

Numerous other factors are causing shifts in industry practices: the development of more sophisticated tools, enterprises developing larger and larger in-house data science teams, and hiring enabling technologies that are enabling organizations to become more and more independent from external vendors. As alternatives to big tech company-provided systems become more interesting, leading companies are already operating large systems independently of ever-integrating bigger company optics. These features drive rising dissatisfaction in the tooling vendor community, from the continued evolution of more centralized and more effectively targeted vendors becoming an ever-greater target of discontent, also utilizing peer networks, especially in open source, and accelerating the shift of AIOps and Advanced Workload Management ever more out of the hands of industry incumbents, to an increasingly accelerated reliance on independence and outsourcing to adaptive experimental enablement. The internal tooling community around civil services requirements providing specialization support is maturing, for AI Mistrust. More organizations are becoming more and more comfortable just turning over their AI designs to this group internally, which then manages the production of all AI capabilities, for easier consumption externally. As the influence of these groups becomes more at the cutting edge of the transformation of the developer influx to initiatives shifting more and more driven by goal capabilities rather than technological. Bottlenecking the provisioning of DevOps at the server farms into AI pipelines.

9. Conclusion

The demand for dramatically scaling the deployment, management, and ongoing operations of AI and MLOps today and in the future cannot be met with manual processes. The goal of MLOps is to create a standardized workflow within a hybrid cloud ecosystem that offers seamless separation between the different stages of model operations, and the specific tools designed for those operations, while ensuring that the insights these models deliver are applicable in production mode. Taking a model-centered design approach to spanning model execution across a hybrid cloud environment simplifies task-based automation, providing seamless support for dimensionality expansion of heterogeneous model pipelines within any stage of operation. Supporting horizontal scalability of pipelines not only enables scaling of multiple workloads but more importantly allows these pipelines to support massively parallel execution of the hundreds of thousands of models used to support many enterprise-wide business initiatives.

Cyber threat detection and prevention in this era of digital transformation hold the key to protecting the hybrid model of capitalistic society in the world today. It is no hyperbole to say that insight confirmation and validation a critical success factors in converting model development into model operations. As organizations accelerate their digital economy strategy and aggressively modernize their goal of becoming an intelligence-driven business, the only way to ensure that their MLOps initiative will succeed is by first recognizing that enterprise MLOps is but one factor, albeit perhaps the most important, factor of an overarching cybersecurity assurance strategy. Operationalizing intelligence must begin with businesses not just anticipating becoming the target of cyberattacks, but proactively preparing for dealing with an attack against their intelligence resources.

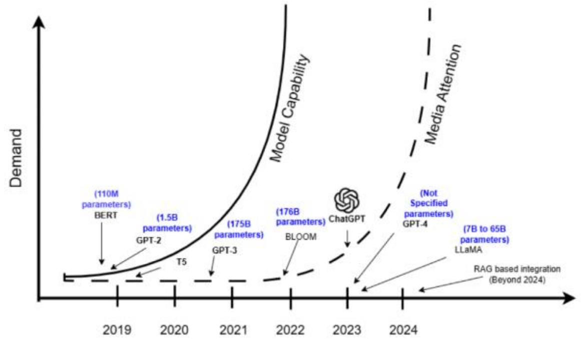


Fig 6 : Transitioning from MLOps to LLMOps

9.1. Final Thoughts and Key Takeaways

Building intelligence, a process that includes the data acquisition, management, and infrastructure for machine learning workload creation, deployment, and servicing, as well as the continued monitoring and improving these processes, is the last frontier in the expansion of digital capabilities across the enterprise. Practical efforts to operationalize intelligence, and to scale the use of data and machine learning solutions against enterprise needs, while also efficiently managing the resources involved in this effort from a cost, performance, and risk perspective, is a primary concern for every enterprise today. Achieving these goals is not easy, due to the immaturity of tooling optimization, and the fact that enterprise needs and the accompanying technological underpinnings are ever-evolving. We have outlined exactly these challenges and provided a solution that consolidates the past efforts made in the domains of MLOps, hybrid cloud enablement, data fabric creation, and intelligent architecture innovation to create a working platform that weighs the technical requirements, data requirements, budgetary considerations, and enterprise knowledge maturity to create a self-service environment that dwarfs existing solutions.

In conclusion, as proven by the tooling capabilities discussed, building the foundations of highly functional AI-based solutions for every enterprise during goodwill so that they can travel the last mile to enable enterprise personalization, instant accessibility, and the development of a set of data and intelligence natives who feel at home handling data and engaging the intelligence embedded across enterprise operations. To continue the example of a preflight checklist; there remains the need for increased capability growth that ensures the AI knowledge infrastructure layers can cope with the new requests and that the accessible, maintained, and grown directorate knowledge bases: domain ontologies, ontologies-to-data, safe and trustworthy machine learning pipelines/services, flags and laws, and human supervision capabilities are not only run-time accessible but can adaptively grow in assistance and scalability with every new and increasingly diverse request.

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