The Emergence of the MLOps Engineer

From MLE/DevOps to AI Platform Engineering

by Gourav Shah

Who does MLOps Afterall?

1

AI Application Lifecycle

Understanding the complete lifecycle from data engineering to deployment and iteration.

2

Evolution of MLOps Roles

Tracing how roles have developed from manual processes to fully automated systems.

3

MLOps Practitioners

ML Engineers and Data Scientists with operational knowledge, and DevOps Engineers with ML expertise.

4

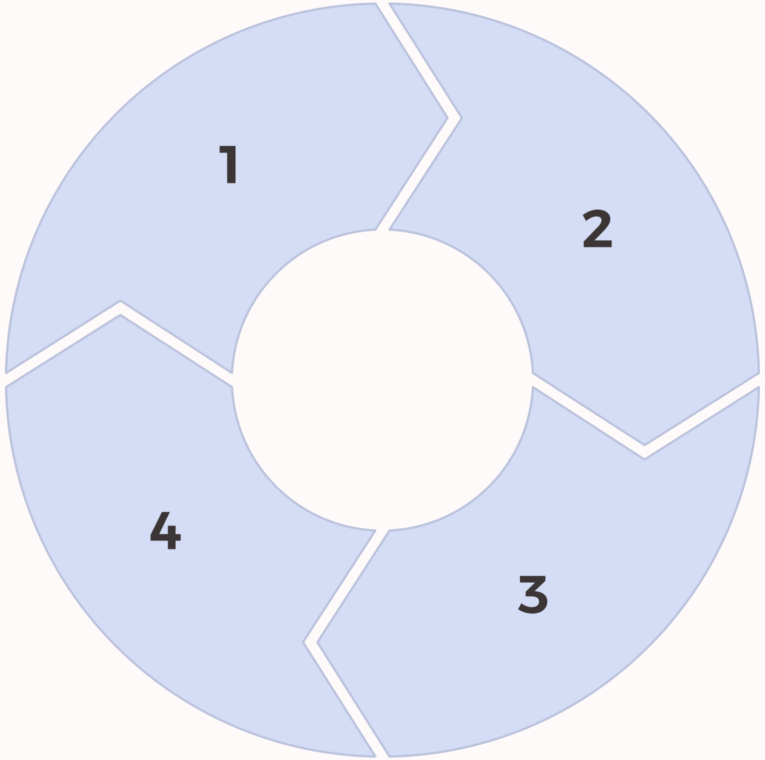
Future Trajectory

From traditional ML to Large Language Models (LLMs) and eventually to Agentic AI systems.

The AI Application Lifecycle

Data Engineering

Collection, preparation, and validation of data



Experimentation

Model development and training

Operationalization

Deployment, monitoring, and governance

Iteration

Retraining, optimization, and adaptation

The AI application lifecycle represents a continuous process where models are developed, deployed, monitored, and improved. Each phase requires specific expertise and tools, creating the need for specialized roles within organizations.

Traditional ML Pipeline vs. Production ML System

Research Pipeline

- Jupyter notebooks
- Local development
- Ad-hoc evaluation
- Manual processes

Production System

- Automated pipelines
- Scalable infrastructure
- Continuous monitoring
- Governance & compliance

The transition from research to production represents one of the biggest challenges in machine learning. Research environments prioritize exploration and model accuracy, while production systems require reliability, scalability, and maintainability—creating the need for MLOps practices.

The MLOps Gap

87% Failure Rate

A staggering 87% of ML projects never make it to production, highlighting the critical need for better operationalization practices.

Skills Mismatch

Data scientists typically lack infrastructure expertise, while DevOps teams often don't possess the specialized ML knowledge needed.

Missing Standards

The industry lacks standardized practices for operationalizing ML, creating inconsistent approaches across organizations.

This gap between development and production represents both a challenge and an opportunity for organizations and professionals looking to specialize in MLOps.

Evolution of MLOps Roles

MLOps Level 0: Manual Processes

No automation, characterized by the "It works on my machine!" approach. Models are developed and deployed manually with minimal reproducibility.

MLOps Level 1: Pipeline Automation

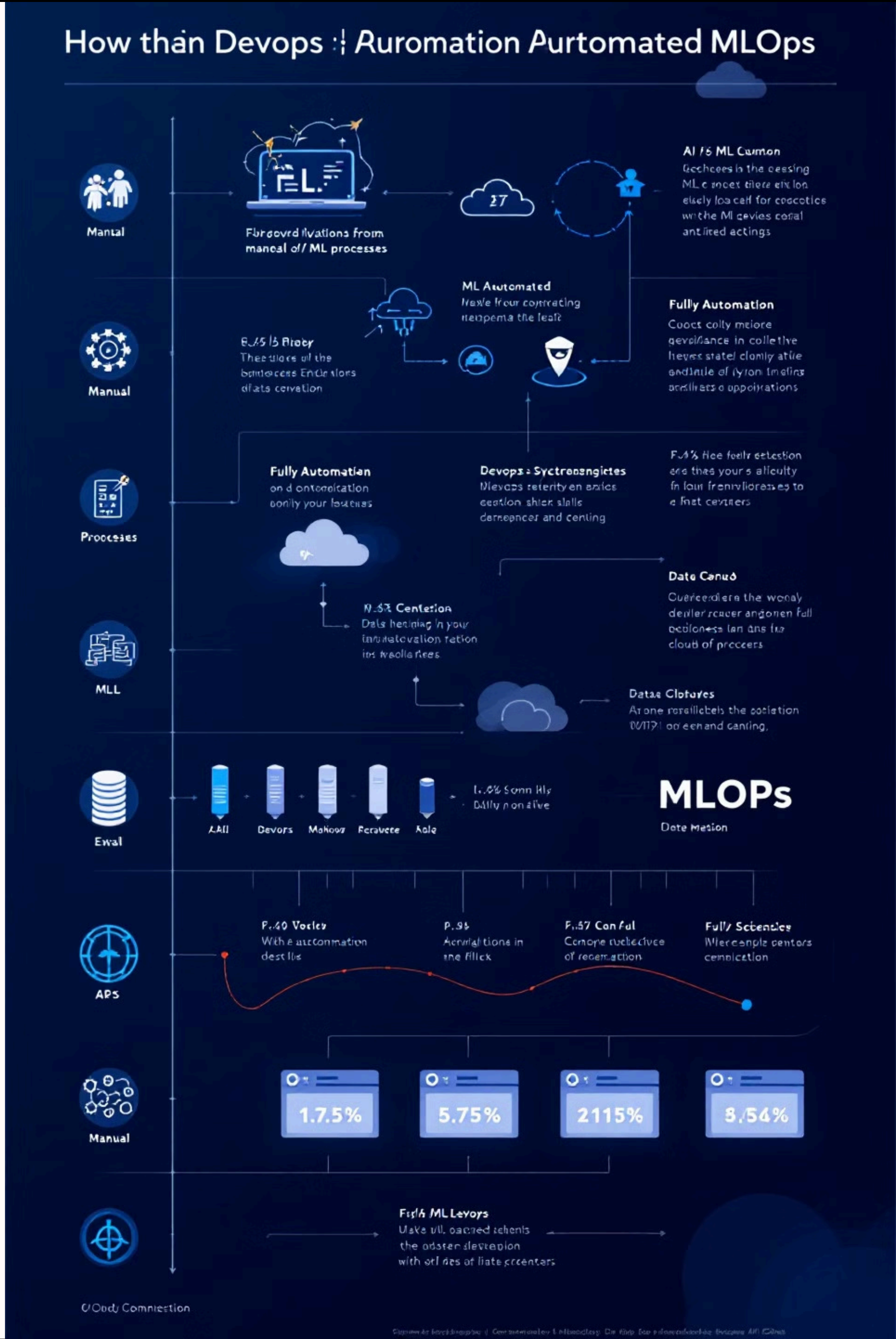
Automated training and data pipelines, but deployment remains a manual process. This introduces some consistency to model development.

MLOps Level 2: Automated CI/CD

Full automation of ML deployments through continuous integration and deployment pipelines, enabling faster and more reliable releases.

MLOps Level 3: Automated Retraining

Complete automation of the ML lifecycle, including automated retraining based on performance metrics or data drift detection.



Who Does MLOps?

End-to-End Data Scientists

Single individuals handling the entire ML lifecycle from data to deployment to monitoring. These "renaissance" professionals possess broad skillsets across multiple domains.

They own the complete process, reducing handoffs between teams and enabling faster iteration cycles.

Cross-Functional Teams

Specialized roles collaborating on ML systems with clear ownership boundaries. Team members focus on their areas of expertise while sharing responsibility for production success.

This approach leverages specialized knowledge at each stage of the ML lifecycle, creating more scalable and standardized implementations.

The End-to-End Data Scientist Approach

Advantages

No handoffs between teams, faster iteration cycles, full context on model development and operation, and complete ownership of the entire ML lifecycle.

Challenges

Requires rare skill combinations (unicorn hunting), time spent on infrastructure versus core modeling, difficult to scale across multiple projects, risk of non-standard implementations.

Burnout Risk

Constant context switching between different domains and responsibilities can lead to burnout, reducing long-term effectiveness and sustainability.

While the end-to-end approach works well for smaller organizations or initial ML projects, it becomes increasingly difficult to maintain as ML initiatives grow in number and complexity.

Cross-Functional Team Approach

Data Scientists

Focus on model development and evaluation, leveraging their expertise in statistics and machine learning algorithms.

ML Engineers

Specialize in model optimization and pipeline development, bridging the gap between research and production.

Data Engineers

Build and maintain data pipelines and feature stores, ensuring high-quality data is available for training and inference.

MLOps/Platform Engineers

Manage infrastructure, CI/CD pipelines, and monitoring systems, enabling reliable and scalable ML operations.

This specialized approach offers benefits including expertise at each stage, scalability across multiple ML initiatives, standardized practices, and reduced single-person dependencies.

The Buy vs. Build Decision

When to Buy a Platform

- End-to-End Data Scientists need comprehensive tooling
- Limited infrastructure expertise in-house
- Early ML maturity stages
- Focus on rapid time-to-market
- Standard ML workflows with common patterns

When to Build

- Cross-Functional Teams can create tailored solutions
- Sufficient scale to justify investment
- Unique requirements not met by vendors
- Data security/compliance requires custom solutions
- Advanced ML maturity with specialized workflows

The decision between buying an existing MLOps platform or building custom solutions depends on organizational maturity, available expertise, and specific requirements. Many organizations adopt a hybrid approach, starting with purchased platforms and gradually developing custom components.

Roles in Cross-Functional Teams

1

MLOps Practitioners

Data Scientists with operational knowledge and ML Engineers who productionize models. They focus on model quality, experiment tracking, and evaluation.

2

MLOps Engineers

DevOps Engineers specialized in ML infrastructure who build and maintain the systems that support model development and deployment.

3

AI Platform Engineers

Platform Engineers building reusable components and focusing on scalable infrastructure, automation, and governance across all AI workloads.

These two operational tracks—practitioners and platform builders—represent different career paths within the MLOps ecosystem. Organizations need both to successfully operationalize machine learning at scale.

The Rise of the AI Platform Engineer

1

Traditional ML Workflows

Managing basic ML model deployment

2

Large Language Models

Supporting LLM infrastructure

3

Generative AI

Enabling creative AI applications

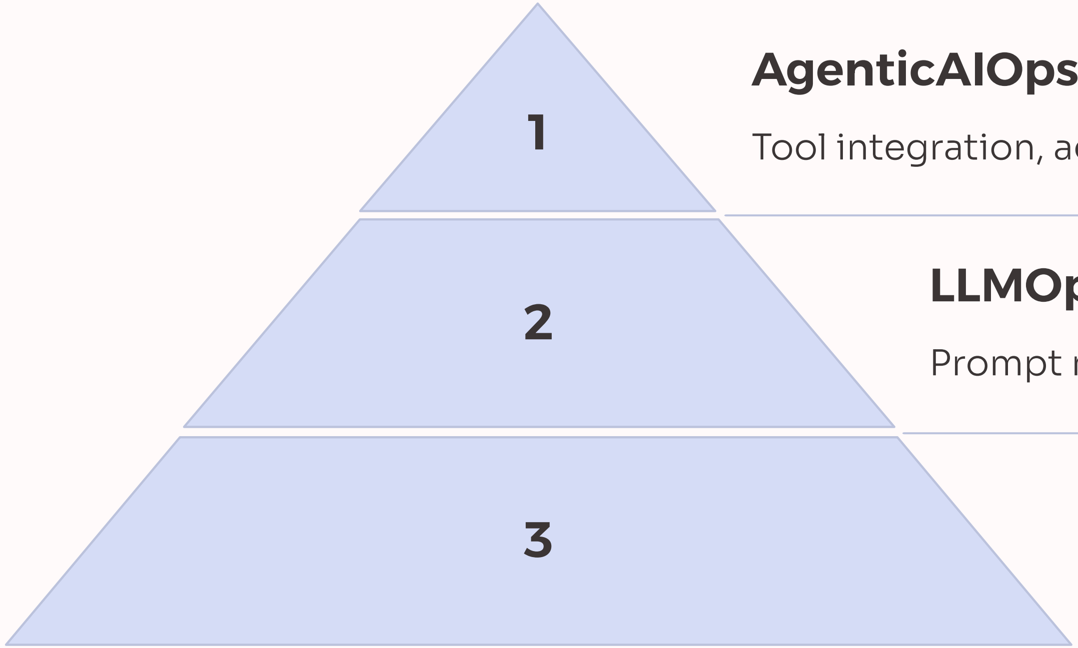
4

Agentic AI Systems

Building platforms for autonomous agents

AI Platform Engineers design unified platforms for all AI workloads, create standardized deployment patterns, establish governance frameworks, and enable self-service capabilities for data scientists and ML engineers. This role represents the evolution of MLOps engineering to support increasingly complex AI systems.

MLOps to LLMOps to AgenticAIOps



AgenticAIOps

Tool integration, agent orchestration, feedback systems

LLMOps

Prompt management, vector databases, RAG architectures

Traditional MLOps

Data/model versioning, automated pipelines, monitoring

As AI systems evolve from traditional machine learning models to large language models and eventually to agentic systems, the operational requirements grow in complexity. Each layer builds upon the previous one, requiring additional capabilities and expertise while still maintaining the foundational elements.

Skills Matrix

Role	Technical Skills	Domain Knowledge
MLOps Practitioner	Python, ML frameworks, basic Docker	Strong ML, statistics
MLOps Engineer	Kubernetes, Terraform, CI/CD, monitoring	Basic ML understanding
AI Platform Engineer	Advanced K8s, cloud platforms, security	Broad AI knowledge

Different roles within the MLOps ecosystem require different skill combinations. MLOps Practitioners need strong ML knowledge with basic operational skills, while MLOps Engineers and AI Platform Engineers need stronger infrastructure expertise with varying levels of AI domain knowledge.

Evolution of Team Structures

Stage 1: Single Expert (Startup Phase)

End-to-end data scientist handling everything from data preparation to model deployment. Organizations at this stage typically buy off-the-shelf ML platforms to support limited-scale, focused use cases.

Stage 2: Specialized Team (Growth Phase)

Dedicated ML/AI team with specialized roles emerges as complexity increases. Organizations adopt a mix of bought platforms and custom components to support multiple ML use cases in production.

Stage 3: Platform Team (Enterprise Scale)

Central AI Platform team supporting multiple ML teams across the organization. Custom platforms with reusable components enable dozens or hundreds of models in production.

As organizations mature in their ML capabilities, team structures evolve to support increasing complexity and scale. This progression reflects the natural development of ML operations from individual efforts to enterprise-wide platforms.

The AI/ML Dream Team 2025

Data Engineer

Responsible for data pipelines, quality assurance, and storage solutions that feed the ML systems.

Data Scientist

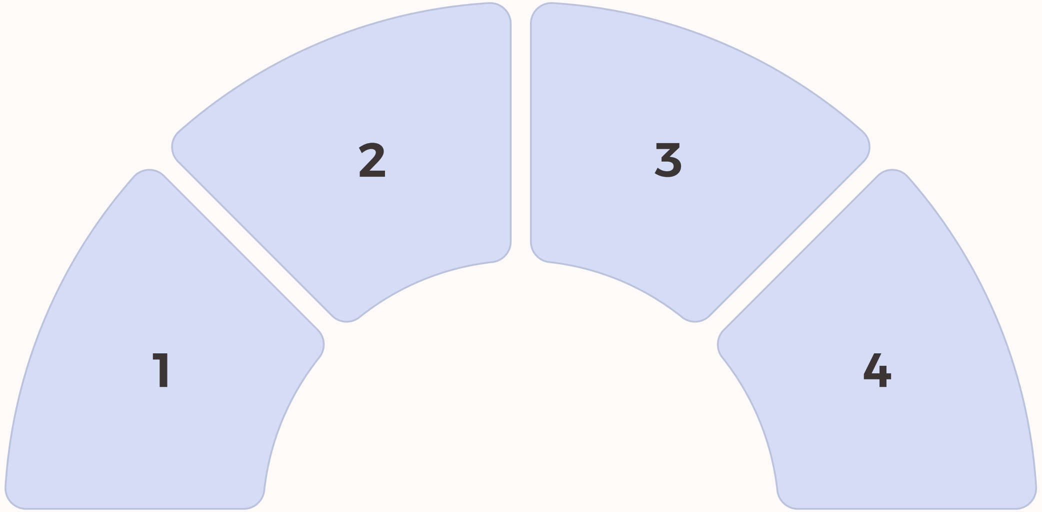
Focuses on analysis, model development, and evaluation to create effective ML solutions.

ML/AI Engineer

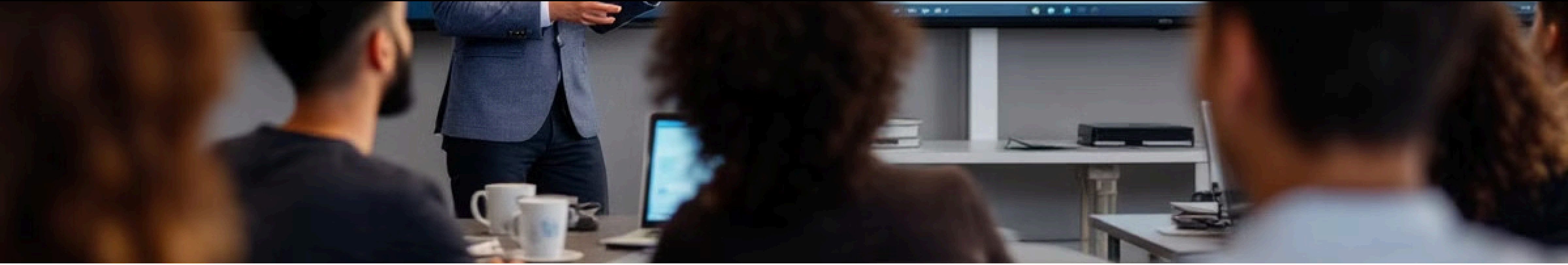
Specializes in model architectures, optimization techniques, and embedding models into applications.

MLOps/AI Platform Engineer

Builds and maintains infrastructure, CI/CD pipelines, and monitoring systems for all AI workloads.



Career paths typically follow two trajectories: Data Scientists/Software Engineers/Data Engineers evolving into ML Engineers and then MLOps Practitioners, or DevOps Engineers becoming MLOps Engineers and eventually AI Platform Engineers. These complementary paths create teams capable of delivering reliable, scalable AI systems.



School of DevOps AI Education Tracks

Track 1: MLOps Practitioner

Designed for Data Scientists, ML Engineers, Software Engineers, and Data Engineers who want to expand their operational capabilities. This track focuses on the skills needed to operationalize models and monitor their performance in production environments.

Track 2: AI Platform Engineer

Tailored for DevOps Engineers and Infrastructure Specialists looking to specialize in AI systems. This track emphasizes building robust platforms that can support all types of AI workloads, from traditional ML to cutting-edge agentic systems.

School of DevOps offers comprehensive training programs to help professionals navigate the evolving MLOps landscape. Our specialized tracks provide the knowledge and skills needed to excel in these emerging roles.

Key Takeaways

1

Bridge the Gap

MLOps bridges the critical gap between ML research and production environments.

2

Converging Paths

Two career paths converge in MLOps: ML professionals learning operations and DevOps engineers learning ML.

3

Emerging Role

AI Platform Engineering is emerging as ML evolves to include LLMs and Agentic AI systems.

4

Dual Needs

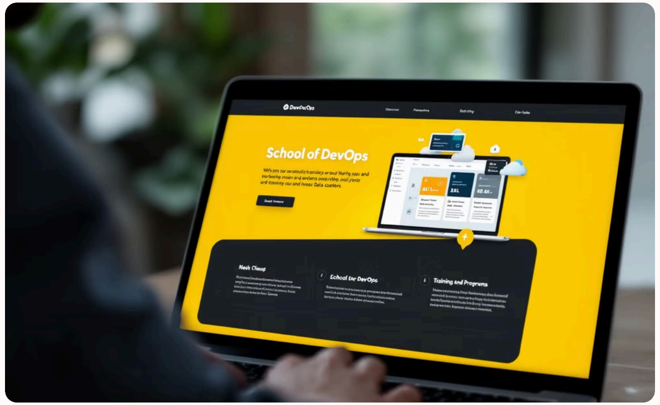
Organizations need both MLOps practitioners and platform builders to succeed.

School of DevOps offers specialized training for both career paths, helping professionals develop the skills needed to thrive in this rapidly evolving field. Our programs prepare you for the future of AI operations.

Questions?

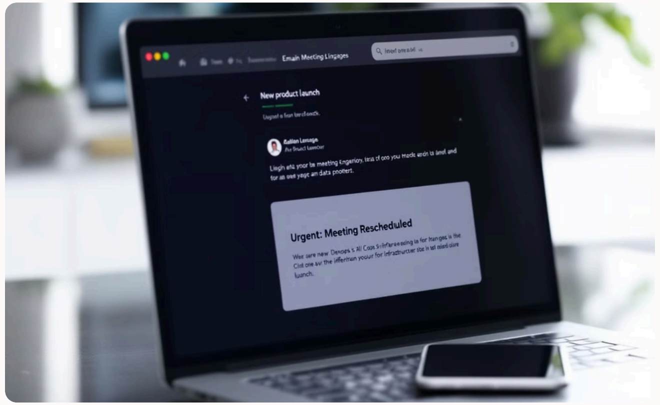
Contact Us

We're here to answer your questions and help you navigate your MLOps career journey. Reach out through any of our channels to learn more about our programs.



Website

Visit schoolofdevops.com for complete program details, upcoming course schedules, and registration information.



Email

Contact us directly at contact@schoolofdevops.com with specific questions about our MLOps training programs.

Connect with us on LinkedIn at linkedin.com/company/schoolofdevops to stay updated on the latest developments in MLOps and AI platform engineering.

Thank You for Attending

We hope this presentation has provided valuable insights into the emerging field of MLOps engineering and the evolution toward AI platform engineering. As organizations continue to operationalize AI at scale, these roles will become increasingly critical to success.

School of DevOps is committed to providing the education and resources needed to help professionals navigate this exciting career path. Whether you're coming from a data science background or a DevOps background, we have programs designed to help you develop the specialized skills needed in MLOps.

We look forward to being part of your journey in this rapidly evolving field.