

DADS7305: MLOPs

Northeastern University

Instructor: Ramin Mohammadi

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These materials have been prepared and sourced for the course **MLOPs** at Northeastern University. Every effort has been made to provide proper citations and credit for all referenced works.

If you believe any material has been inadequately cited or requires correction, please contact me at:

`r.mohammadi@northeastern.edu`

Thank you for your understanding and collaboration.

About Me



Dr. Ramin Mohammadi

- ▶ **iBase-t** - Enterprise AI, Applied Machine Learning, Intelligent Automation
- ▶ **Tausight** - Healthcare AI, Federated Learning, Privacy-Aware ML
- ▶ **Partners HealthCare** - Predictive Modeling, Clinical AI, Healthcare Analytics
- ▶ **MGH Institute of Technology Assessment** - Statistical Modeling, Medical Imaging, Health Economics
- ▶ **Northeastern University** - Generative AI, MLOps, NLP, ML
- ▶ **Philips** - Computer Vision, Sensor Fusion, Deep Learning
- ▶ **Mitsubishi Electric Research Labs (MERL)** - Reinforcement Learning, Anomaly Detection

Why This Course? A Hiring Manager's Perspective

The Observation

- ▶ As an ML hiring manager, I interviewed many smart, motivated candidates from top-tier programs.
- ▶ Most candidates understood deep learning theory but struggled to build or ship end-to-end systems.

The Problem

- ▶ The industry expects engineers to build production-ready systems on day one.
- ▶ There is a significant gap between "Model Accuracy" and "System Reliability."

The Solution

Students need a place to practice the full lifecycle before hitting the job market. This course is designed to bridge that gap by focusing on shipping, not just theory.

The Machine Learning Project Lifecycle

Deployment Example

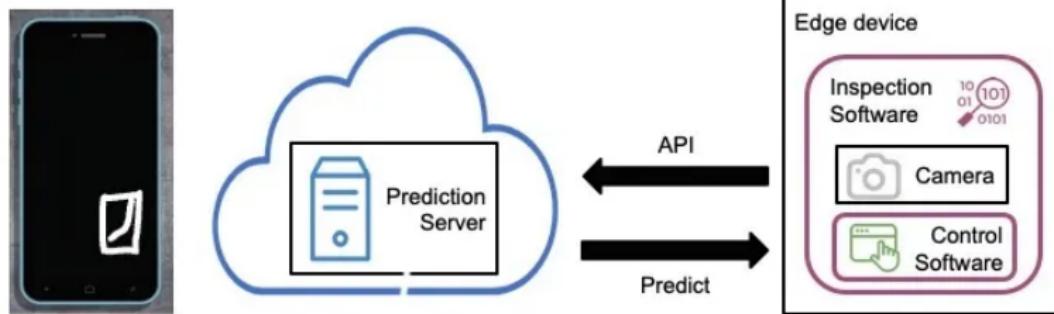


Photo from camera

Visual inspection example



Figure: Visual inspection example

ML In Production

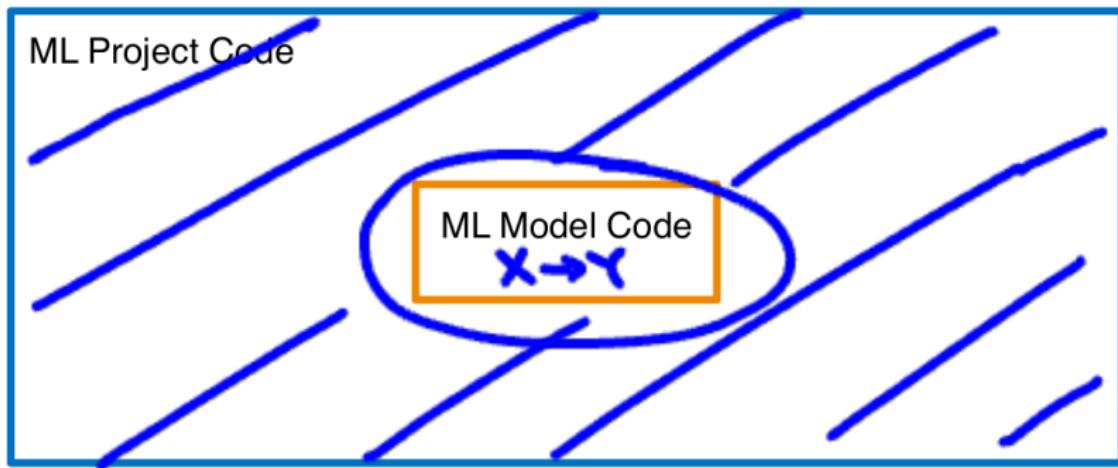


Figure: POC to Production Gap

The requirements surrounding ML infrastructure

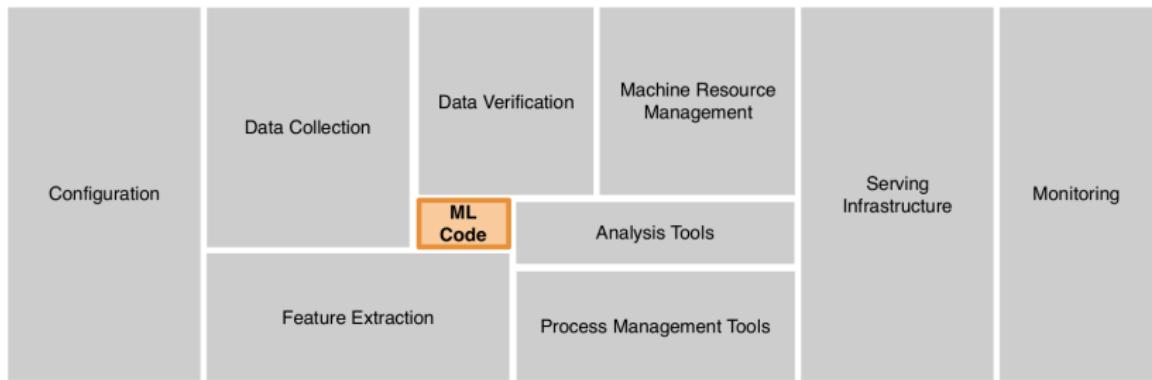


Figure: D. Sculley et. al. NIPS 2015: Hidden Technical Debt in Machine Learning Systems

MLOps structures the ML system lifecycle into four main stages, each addressing critical engineering and operational challenges:

- ▶ **Data management** – Collection, preprocessing, and augmentation of data to ensure consistency and quality.
- ▶ **Model learning** – Model selection, training, and hyperparameter tuning within compute, interpretability, and resource constraints.
- ▶ **Model verification** – Validation against functional, regulatory, and business requirements through formal or test-based methods.
- ▶ **Model deployment** – Integration into production systems with support for monitoring, feedback, and continuous updates.

Cross-cutting aspects influence every stage of the pipeline:

- ▶ **Ethics** – Fairness, accountability, and decision transparency.
- ▶ **Law** – Adherence to regional regulations and compliance standards.
- ▶ **End users' trust** – Usability, explainability, and user involvement.
- ▶ **Security** – Protection against threats like model stealing, data poisoning, and inversion attacks.

This structure is not strictly linear-stages often run in parallel and inform each other through feedback loops. The following slides summarize common challenges at each step.

Data Management

Deployment Stage	Deployment Step	Considerations, Issues and Concerns
Data management	Data collection	Data discovery
	Data preprocessing	Data dispersion, Data cleaning
	Data augmentation	Labeling of large volumes of data Access to experts, Lack of high-variance data
	Data analysis	Data profiling

Model Learning

Deployment Stage	Deployment Step	Considerations, Issues and Concerns
Model learning	Model selection	Model complexity, Resource-constrained environments, Interpretability of the model
	Training	Computational cost, Environmental impact, Privacy-aware training
	Hyper-parameter selection	Resource-heavy techniques, Unknown search space, Hardware-aware optimization

Model Verification

Deployment Stage	Deployment Step	Considerations, Issues and Concerns
Model verification	Requirement encoding	Performance metrics, Business driven metrics
	Formal verification	Regulatory frameworks
	Test-based verification	Simulation-based testing, Data validation routines, Edge case testing

Model Deployment

Deployment Stage	Deployment Step	Considerations, Issues and Concerns
Model deployment	Integration	Operational support, Reuse of code and models, Software engineering anti-patterns, Mixed team dynamics
	Monitoring	Feedback loops, Outlier detection, Custom design tooling
	Updating	Concept drift, Continuous delivery

Cross-cutting Aspects

Deployment Stage	Deployment Step	Considerations, Issues and Concerns
Cross-cutting aspects	Ethics	Aggravation of biases, Fairness and accountability, Authorship, Decision making
	Law	Country-level regulations, Abiding by existing legislation, Focus on technical solution only
	End users' trust	Involvement of end users, User experience, Explainability score
	Security	Data poisoning, Model stealing, Model inversion

Data Issues

- ▶ Missing or incomplete data
- ▶ Data drift over time
- ▶ Labeling errors or inconsistencies
- ▶ Leakage between train/test splits

Model Issues

- ▶ Overfitting or underfitting
- ▶ Poor generalization to unseen data
- ▶ Lack of interpretability
- ▶ Biases embedded in the model

Training Issues

- ▶ Insufficient computational resources
- ▶ Hyperparameter misconfiguration
- ▶ Unstable training dynamics
- ▶ Incomplete convergence or premature stopping

Deployment Issues

- ▶ Mismatch between training and production environments
- ▶ Inference latency or memory bottlenecks
- ▶ Integration failures with existing systems
- ▶ Lack of rollback or CI/CD support

Monitoring and Maintenance Issues

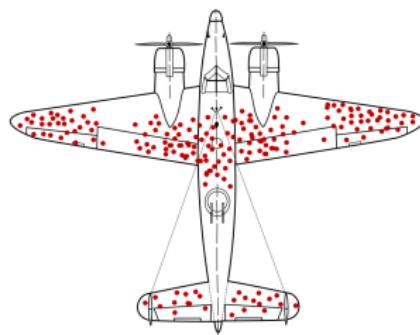
- ▶ No alerting for model degradation
- ▶ Failure to detect concept drift
- ▶ Lack of A/B testing or shadow deployment
- ▶ Manual, error-prone update process

Cross-cutting Issues

- ▶ Security vulnerabilities (e.g., model stealing)
- ▶ Legal non-compliance (e.g., data privacy)
- ▶ Lack of user trust and transparency
- ▶ Ethical concerns (e.g., fairness violations)

WWII - Survivorship Bias

During WWII, a study of bullet hole patterns on returning aircraft led to a counterintuitive insight about survivorship bias. The military planned to reinforce areas with the most bullet holes (fuselage, wings, tail).



What could go wrong?

The Machine Learning Project Lifecycle

Steps of an ML project

The ML project lifecycle

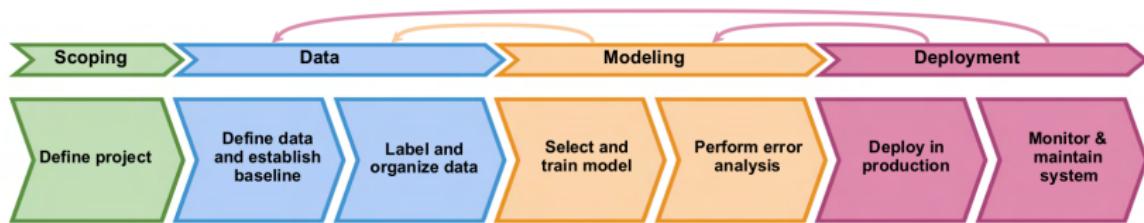


Figure: The ML project lifecycle

- ▶ Scoping
- ▶ Data
- ▶ Modeling
- ▶ Deployment

The Machine Learning Project Lifecycle

Case study: speech recognition

Speech recognition: Scoping stage

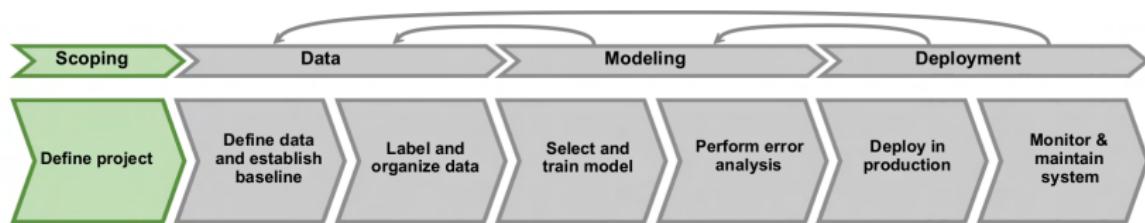


Figure: The ML project lifecycle

- ▶ Decide to work on speech recognition for voice search.
- ▶ Decide on key metrics:
 - ▶ Accuracy, latency, throughput
- ▶ Estimate resources and timeline

Speech recognition: Data stage

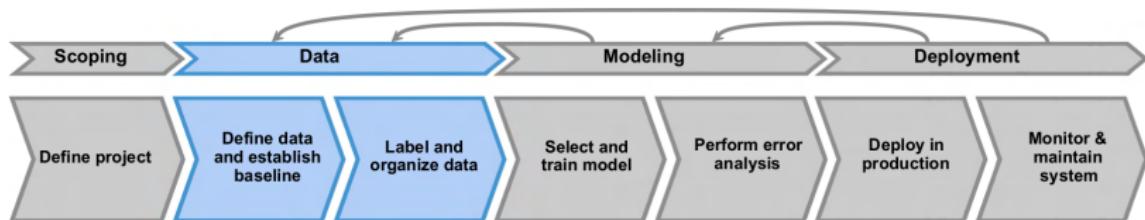


Figure: The ML project lifecycle

Define data:

- ▶ Is the data labeled consistently?
- ▶ How much silence before/after each clip?
- ▶ How to perform volume normalization?

Examples:

- ▶ "Um, today's weather"
- ▶ "Um... today's weather"
- ▶ "Today's weather"

Speech recognition: Modeling stage

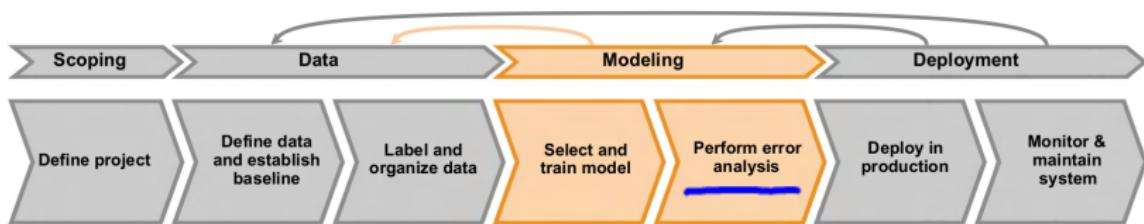
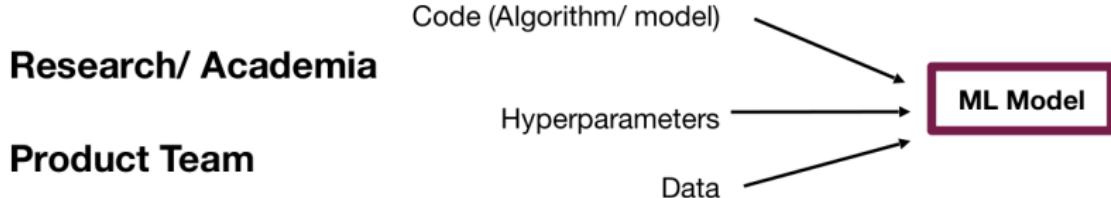


Figure: The ML project lifecycle



Speech recognition: Deployment stage

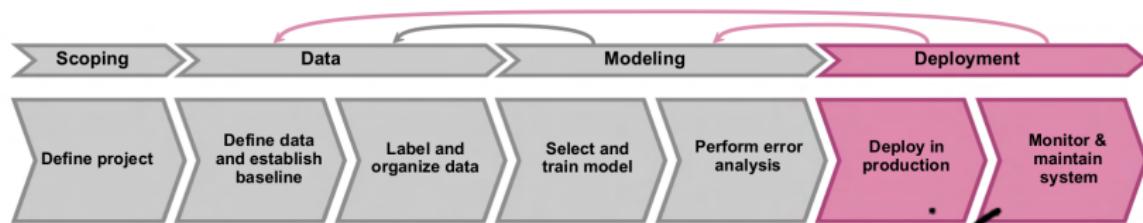
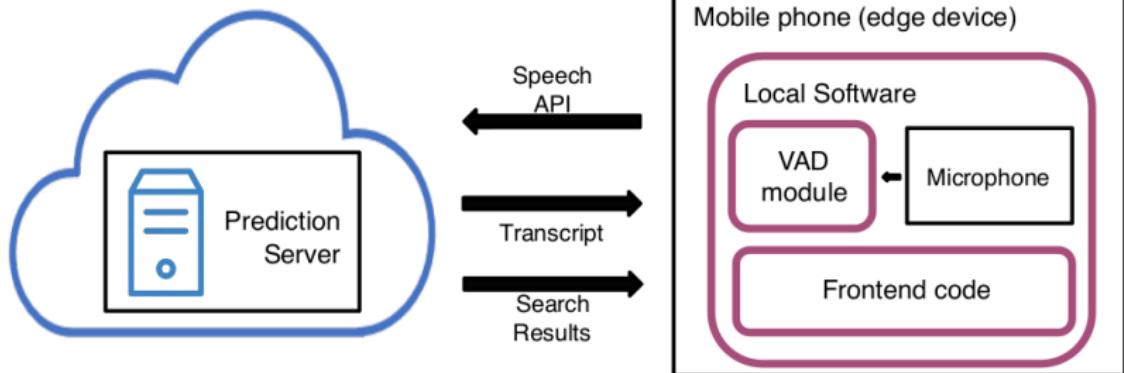


Figure: The ML project lifecycle



Key requirements for an MLOps foundation

AI-driven organizations are transforming industries:

- ▶ Leverage data and machine learning to tackle their hardest problems.
- ▶ According to McKinsey, companies that adopt AI across workflows by 2025 may see **+120% cash flow growth by 2030.**

But operationalizing ML is not easy:

- ▶ ML systems incur significant technical debt if unmanaged.
- ▶ Combine traditional software issues *plus* ML-specific challenges:
 - ▶ Complex hardware/software dependencies
 - ▶ Data needs to be validated, not just code
 - ▶ Models degrade over time due to changing environments
 - ▶ Fail silently; harder to debug and monitor
- ▶ **Building a model is easy; managing its lifecycle is hard.**

Bridging ML and IT: MLOps Meets DevOps

DevOps: Proven practice for large-scale software systems

- ▶ Evolved over decades of software engineering experience.
- ▶ Benefits:
 - ▶ Shorter development cycles
 - ▶ Faster deployment velocity
 - ▶ Reliable, high-quality releases

MLOps: Extending DevOps to Machine Learning

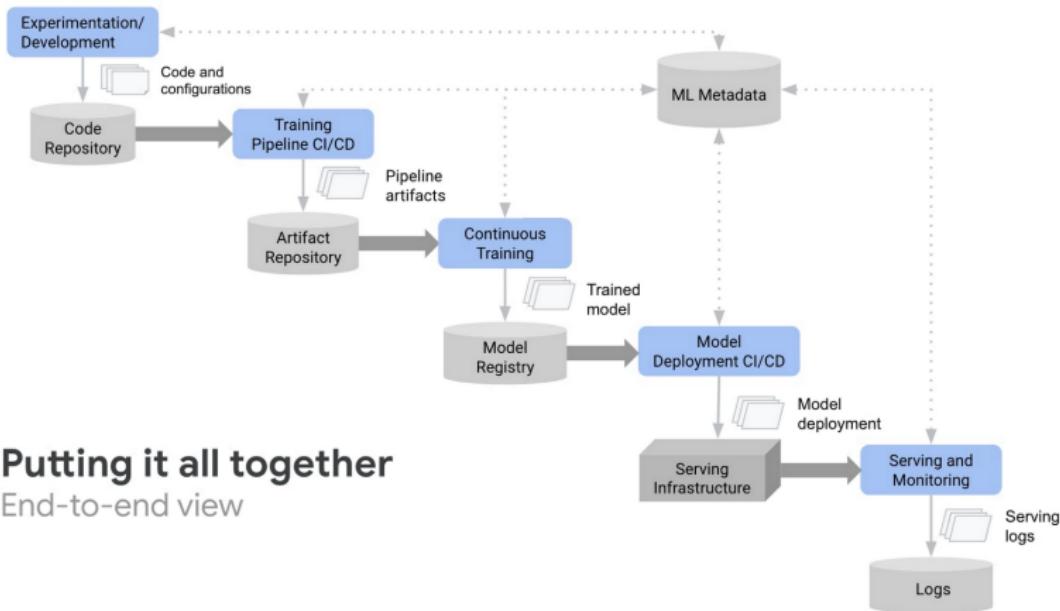
- ▶ MLOps = ML system development (Dev) + ML system operation (Ops)
- ▶ Inspired by DevOps, but adapted for the ML lifecycle.
- ▶ Challenges:
 - ▶ Continuous Integration / Delivery (CI/CD) is harder in ML
 - ▶ ML systems involve data, models, code, and environments

CI/CD in ML Systems: Beyond Traditional Software

ML systems redefine CI/CD and introduce new requirements:

- ▶ **Continuous Integration (CI):**
 - ▶ Validate not just code and components
 - ▶ Also validate data, data schemas, and trained models
- ▶ **Continuous Delivery (CD):**
 - ▶ Not just deploying software
 - ▶ Deliver end-to-end ML pipelines that deploy model services
- ▶ **Continuous Training (CT):**
 - ▶ Unique to ML systems
 - ▶ Automate retraining of models for testing and deployment
- ▶ **Continuous Monitoring (CM):**
 - ▶ Monitor more than just system errors
 - ▶ Track live inference data and model performance degradation

End-to-End ML Pipeline



Putting it all together

End-to-end view

The Machine Learning Project Lifecycle

LLMOps

LLMOps vs MLOps

LLMOps is a specialized extension of MLOps:

- ▶ **MLOps:** General practices for managing ML models ; includes data pipelines, training, deployment, monitoring, and CI/CD.
- ▶ **LLMOps:** Focused on large language models (LLMs), addressing unique challenges:
 - ▶ Extremely large model sizes
 - ▶ Complex multi-stage training
 - ▶ High compute and storage demands

What is LLMOps and Why is it Needed?

LLMOps = Practices, tools, and workflows for managing the lifecycle of Large Language Models (LLMs) from development to deployment.

- ▶ Sub-discipline of MLOps tailored to the unique challenges of LLMs.
- ▶ Traditional ML: produces a single prediction/score.
- ▶ LLMs: generate complex language outputs ; harder to evaluate and control.
- ▶ Challenges: unpredictable behavior, hallucinations, inappropriate responses.
- ▶ Goal: Ensure LLM-powered applications are reliable and scalable in production.

Why LLMOps Matters

- ▶ LLMs are larger, more complex, and often pre-trained by third parties.
- ▶ Without LLMOps:
 - ▶ Unpredictable outputs
 - ▶ High computational costs
 - ▶ Ethical risks
- ▶ LLM performance judged by human feedback for factuality and helpfulness.
- ▶ Practices include:
 - ▶ Human-in-the-loop evaluations
 - ▶ Prompt management
 - ▶ Safety checks

LLMOps vs Traditional MLOps (Part 1)

Shared Aspects:

- ▶ Dataset management
- ▶ Version control
- ▶ CI/CD deployment pipelines

Key Differences:

- ▶ **Evaluation:** Harder to quantify, often requires human evaluation.
- ▶ Custom evaluation sets, RLHF, monitoring hallucinations/toxicity.

LLMOps vs Traditional MLOps (Part 2)

- ▶ **Model Adaptation:** Start from pre-trained models (GPT, LLaMA).
- ▶ Adaptation techniques:
 - ▶ Prompt engineering
 - ▶ Fine-tuning on domain data
 - ▶ Retrieval Augmented Generation (RAG)
- ▶ **Infrastructure:** LLMs require GPUs, optimization, cost control.
- ▶ Techniques:
 - ▶ Request batching
 - ▶ Response caching
 - ▶ Routing to smaller models

LLMOps vs Traditional MLOps (Part 3)

- ▶ **Monitoring Focus:**
 - ▶ Traditional ML: Accuracy, data drift.
 - ▶ LLMOps: Output content, hallucinations, bias, prompt injection.
- ▶ Summary: “MLOps for LLMs” + workflows for prompt management, feedback, ethical guardrails.

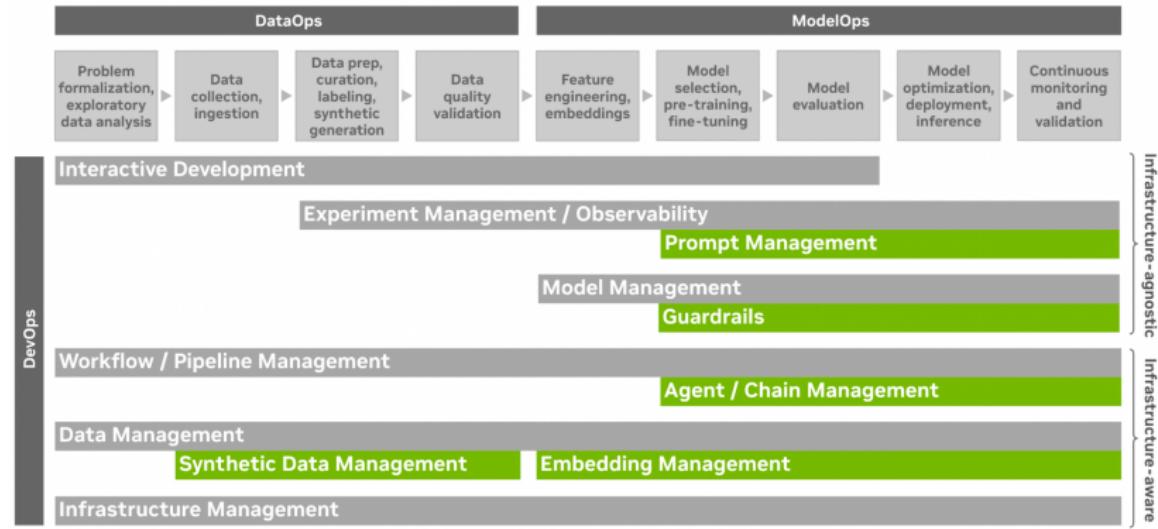


Figure: An end-2-end machine learning lifecycle showcasing core MLOps (gray) and GenAIOps capabilities (green)

Core Components of the LLMOps Lifecycle

1. Data Collection and Preparation
2. Prompt Engineering and Embeddings
3. Fine-Tuning and Adaptation
4. LLM Chains and Agents
5. Evaluation and Testing
6. Deployment, Serving, and Monitoring
7. Governance and Security

1. Data Collection and Preparation

- ▶ Collect large text corpora from multiple sources.
- ▶ Clean, preprocess, normalize formats.
- ▶ Remove duplicates, irrelevant content.
- ▶ Ensure diversity and domain-representative coverage.

2. Prompt Engineering and Embeddings

- ▶ Iteratively design prompts to elicit desired outputs.
- ▶ Use instruction templates or few-shot examples.
- ▶ Manage embeddings for semantic search or RAG.
- ▶ Store and update embeddings in vector databases.

3. Fine-Tuning and Adaptation

- ▶ Fine-tune on domain-specific data.
- ▶ Use parameter-efficient methods (e.g., LoRA).
- ▶ Tailor vocabulary, tone, and style to application needs.
- ▶ Improves relevance, accuracy, and user satisfaction.

4. LLM Chains and Agents

- ▶ Go beyond single prompt→response.
- ▶ Chain multiple calls and tools.
- ▶ Agents can plan, retrieve info, and execute multi-step solutions.
- ▶ Use orchestration frameworks (e.g., LangChain).

5. Evaluation and Testing

- ▶ Continuous evaluation with structured rubrics.
- ▶ Human review and automated checks.
- ▶ Compare model versions side-by-side.
- ▶ Detect toxic, biased, or factually incorrect outputs.

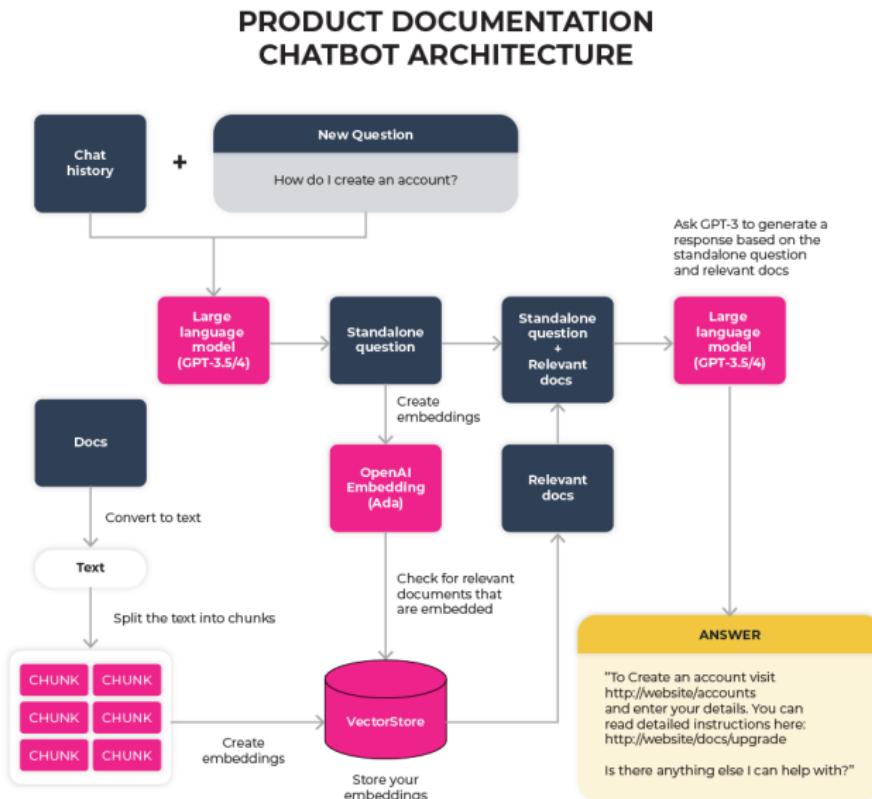
6. Deployment, Serving, and Monitoring

- ▶ Deploy as API, containerized service, or backend integration.
- ▶ Monitor latency, throughput, cost per request.
- ▶ Track output quality, drift, and anomalies.
- ▶ Feed failures back into improvement cycles.

7. Governance and Security

- ▶ Control access to models and data.
- ▶ Enforce compliance with privacy and safety standards.
- ▶ Manage sensitive data flows and logs.
- ▶ Add content moderation and safety filters.

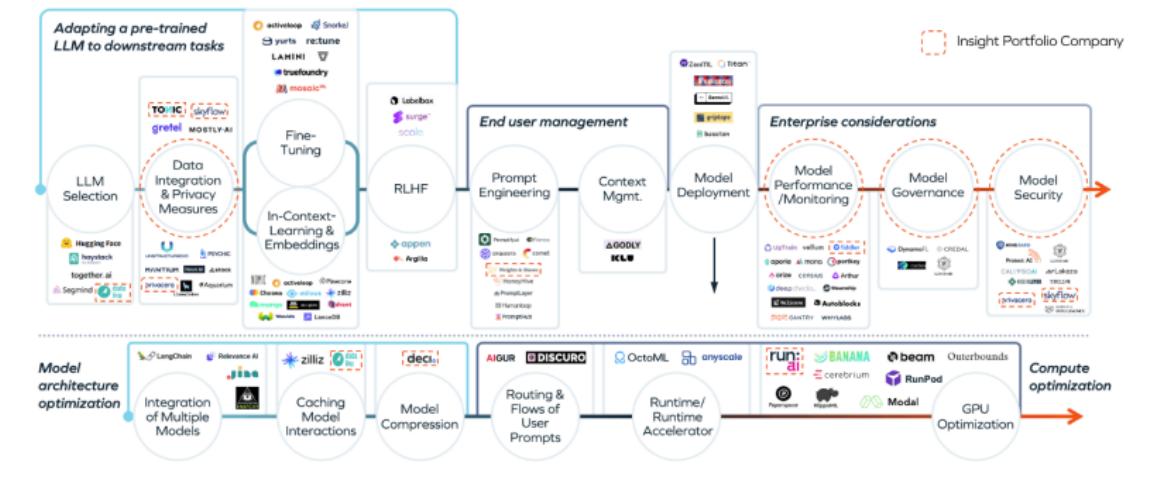
LLOMops Example:



LLOMops Steps:

LLOMops adapts the Mlops tech stack for generative AI use cases

**INSIGHT
PARTNERS**



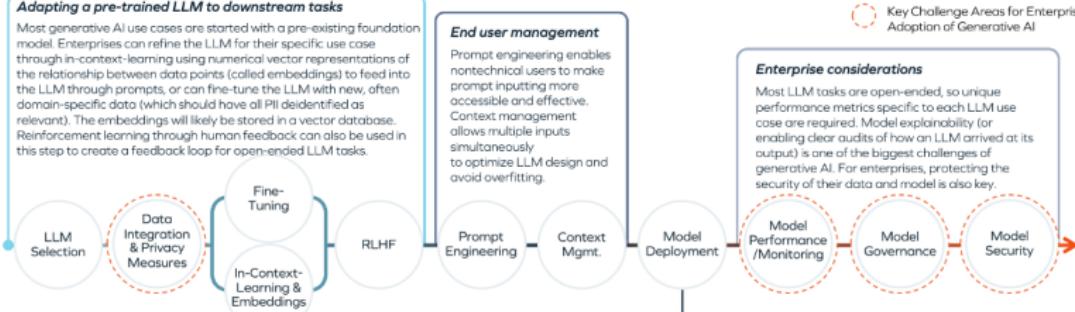
LLOMops Steps:

LLOMops adapts the MLops tech stack for generative AI use cases

**INSIGHT
PARTNERS**

Adapting a pre-trained LLM to downstream tasks

Most generative AI use cases are started with a pre-existing foundation model. Enterprises can refine the LLM for their specific use case through in-context-learning using numerical vector representations of the relationship between data points (called embeddings) to feed into the LLM through prompts, or can fine-tune the LLM with new, often domain-specific data (which should have all PII deidentified as relevant). The embeddings will likely be stored in a vector database. Reinforcement learning through human feedback can also be used in this step to create a feedback loop for open-ended LLM tasks.



The Machine Learning Project Lifecycle

Course outline

Course outline

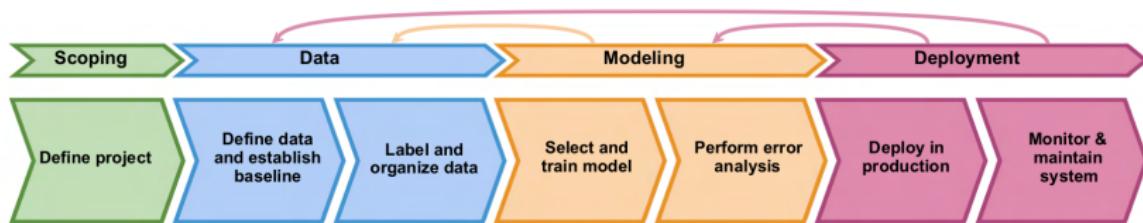


Figure: The ML project lifecycle

1. Scoping
2. Data
3. Modeling
4. Deployment

MLOps (Machine Learning Operations) is an emerging discipline, and comprises a set of tools and principles to support progress through the ML project lifecycle.

Labs for This Week

Objective

Learn how to setup GitHub Action/workflows.

Lab Activities:

- ▶ Lab 1: [Github] ; [Github Workflow]

Submission Deadline: [Before the next class]

- ▶ Assignment 1: [Github] ; [Github Workflow]

Reading Materials

This Week's Theme

Topic focus: [Hidden Technical Debt in Machine Learning Systems]

Required Readings:

- ▶ [Hidden Technical Debt in Machine Learning Systems]

Be prepared to discuss highlights and open questions in class.

Sources



[DeepLearning.AI](#)