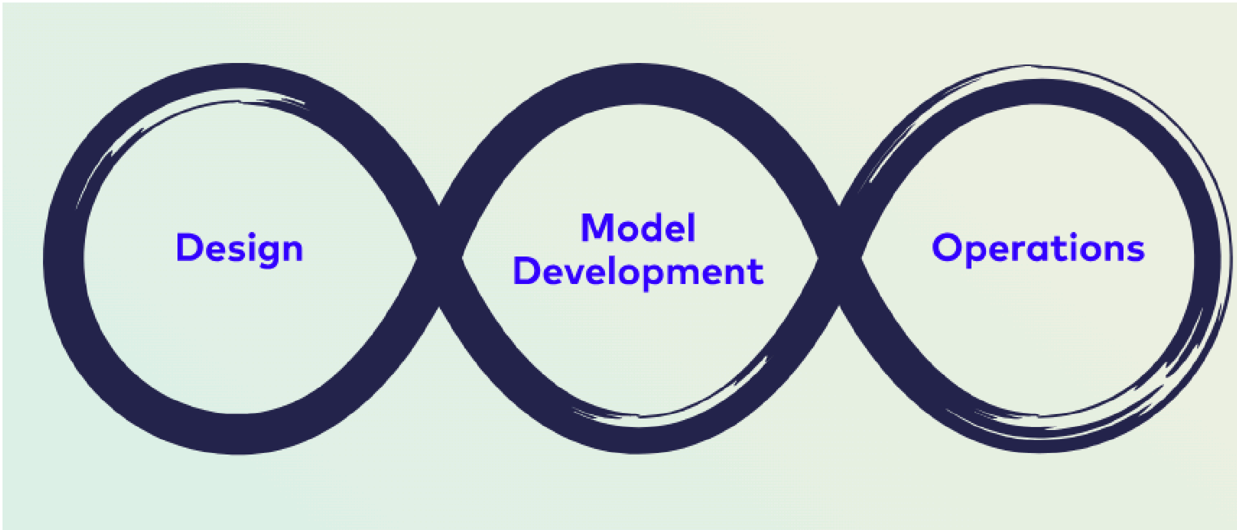
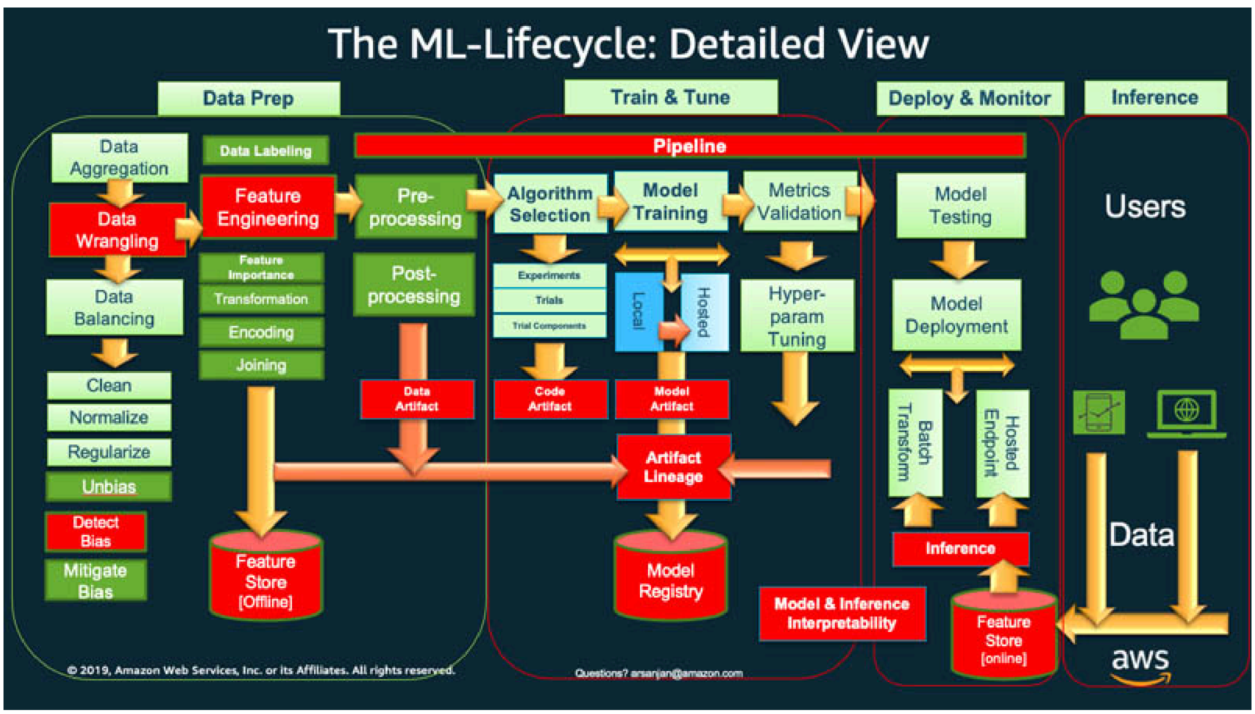
- **Official site**: https://ml-ops.org/ .
- 



- **Machine learning operations (MLOps) are a set of practices that automate and simplify [machine learning (ML)] workflows and deployments. Machine learning and [artificial intelligence (AI)] are core capabilities that you can implement to solve complex real-world problems and deliver value to your customers. MLOps is an ML culture and practice that unifies ML application development (Dev) with ML system deployment and operations (Ops). Your organization can use MLOps to automate and standardize processes across the ML lifecycle. These processes include model development, testing, integration, release, and infrastructure management.**

four key principles of MLOps.

Version control

This process involves tracking changes in the machine learning assets so you can reproduce results and roll back to previous versions if necessary. Every ML training code or model specification goes through a code review phase. Each is versioned to make the training of ML models reproducible and auditable.

Reproducibility in an ML workflow is important at every phase, from data processing to ML model deployment. It means that each phase should produce identical results given the same input.

Automation

Automate various stages in the machine learning pipeline to ensure repeatability, consistency, and scalability. This includes stages from data ingestion, preprocessing, model training, and validation to deployment.

These are some factors that can trigger automated model training and deployment:

- **Messaging**
- **Monitoring or calendar events**
- **Data changes**
- **Model training code changes**
- **Application code changes.**

Automated testing helps you discover problems early for fast error fixes and learnings. Automation is more efficient with infrastructure as code (IaC). You can use tools to define and manage infrastructure. This helps ensure it's reproducible and can be consistently deployed across various environments.

Read about IaC »

Continuous X

Through automation, you can continuously run tests and deploy code across your ML pipeline.

In MLOps, *continuous* refers to four activities that happen continuously if any change is made anywhere in the system:

- ***Continuous integration* extends the validation and testing of code to data and models in the pipeline**
- ***Continuous delivery* automatically deploys the newly trained model or model prediction service**
- ***Continuous training* automatically retrains ML models for redeployment**
- ***Continuous monitoring* concerns data monitoring and model monitoring using metrics related to business**

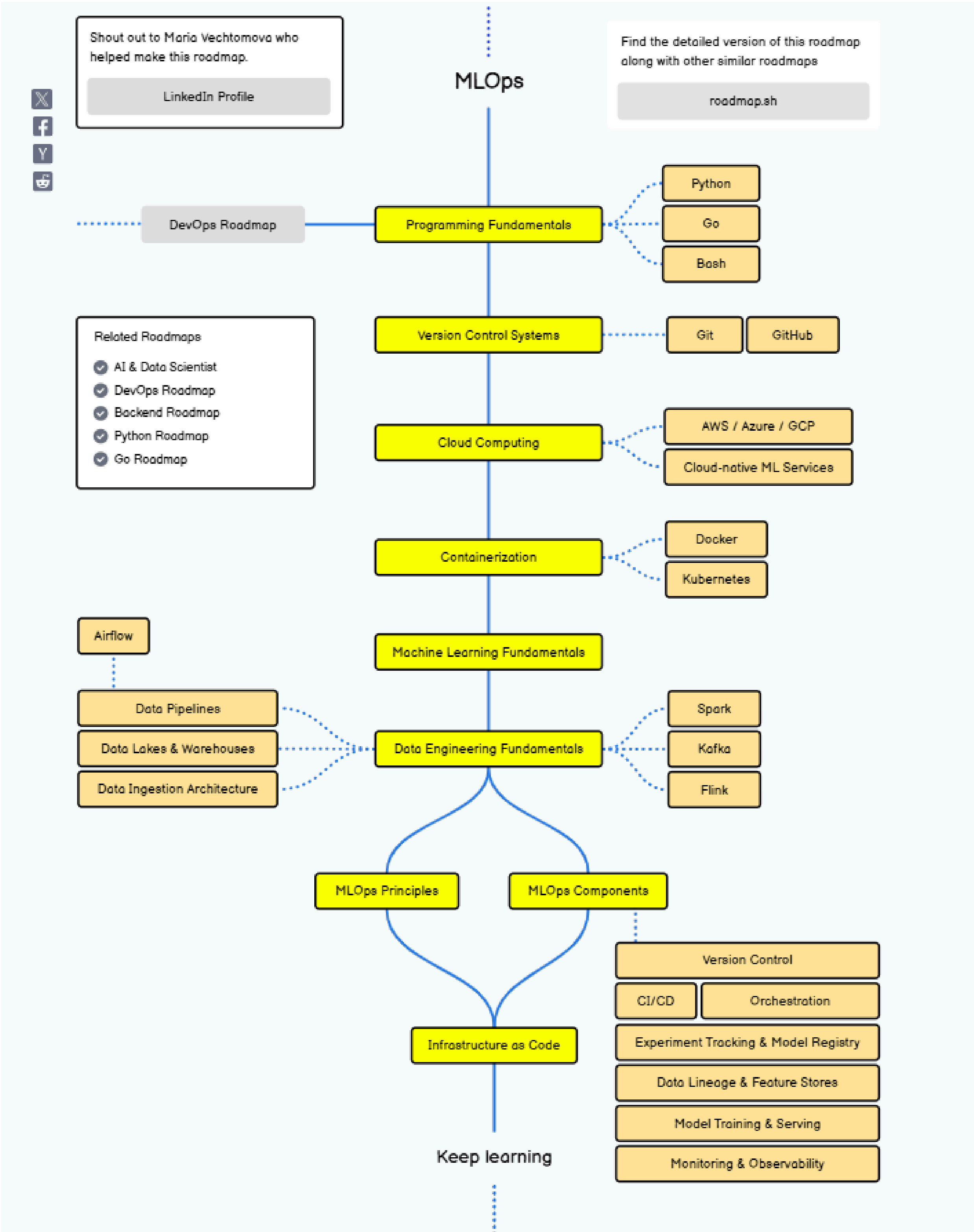
Model governance

Governance involves managing all aspects of ML systems for efficiency. You should do many activities for governance:

- **Foster close collaboration between data scientists, engineers, and business stakeholders**
- **Use clear documentation and effective communication channels to ensure everyone is aligned**
- **Establish mechanisms to collect feedback about model predictions and retrain models further**
- **Ensure that sensitive data is protected, access to models and infrastructure is secure, and compliance requirements are met**

It’s also essential to have a structured process to review, validate, and approve models before they go live. This can involve checking for fairness, bias, and ethical considerations.

ROADMAP:


Shout out to Maria Vechtomova who helped make this roadmap.
LinkedIn Profile
MLOps
Find the detailed version of this roadmap along with other similar roadmaps
roadmap.sh
DevOps Roadmap
Programming Fundamentals
Python
Go
Bash
Related Roadmaps
AI & Data Scientist
DevOps Roadmap
Backend Roadmap
Python Roadmap
Go Roadmap
Version Control Systems
Git
GitHub
Cloud Computing
AWS / Azure / GCP
Cloud-native ML Services
Containerization
Docker
Kubernetes
Airflow
Machine Learning Fundamentals
Data Pipelines
Data Lakes & Warehouses
Data Ingestion Architecture
Data Engineering Fundamentals
Spark
Kafka
Flink
MLOps Principles
MLOps Components
Version Control
CI/CD
Orchestration
Experiment Tracking & Model Registry
Data Lineage & Feature Stores
Model Training & Serving
Monitoring & Observability
Infrastructure as Code
Keep learning

What is the use of MLOps?

MLOps is a useful approach for the creation and quality of machine learning and AI solutions. By adopting an MLOps approach, data scientists and machine learning engineers can collaborate and increase the pace of model development and production, by implementing continuous integration and deployment (CI/CD) practices with proper monitoring, validation, and governance of ML models.

Why do we need MLOps?

Productionizing machine learning is difficult. The machine learning lifecycle consists of many complex components such as data ingest, data prep, model training, model tuning, model deployment, model monitoring, explainability, and much more. It also requires collaboration and hand-offs across teams, from Data Engineering to Data Science to ML Engineering. Naturally, it requires stringent operational rigor to keep all these processes synchronous and working in tandem. MLOps encompasses the experimentation, iteration, and continuous improvement of the machine learning lifecycle.

What are the benefits of MLOps?

The primary benefits of MLOps are efficiency, scalability, and risk reduction. Efficiency: MLOps allows data teams to achieve faster model development, deliver higher quality ML models, and faster deployment and production. Scalability: MLOps also enables vast scalability and management where thousands of models can be overseen, controlled, managed, and monitored for continuous integration, continuous delivery, and continuous deployment. Specifically, MLOps provides reproducibility of ML pipelines, enabling more tightly-coupled collaboration across data teams, reducing conflict with devops and IT, and accelerating release velocity. Risk reduction: Machine learning models often need regulatory scrutiny and drift-check, and MLOps enables greater transparency and faster response to such requests and ensures greater compliance with an organization's or industry's policies.