DATA+AI SUMMIT 2022

MLOps at DoorDash

Hien Luu

Head of ML Platform, DoorDash

ORGANIZED BY databricks

Agenda

- Motivation: Objective Function
- MLOps Blueprint
- MLOps Strategy
- DoorDash MLOps Journey
- Summary

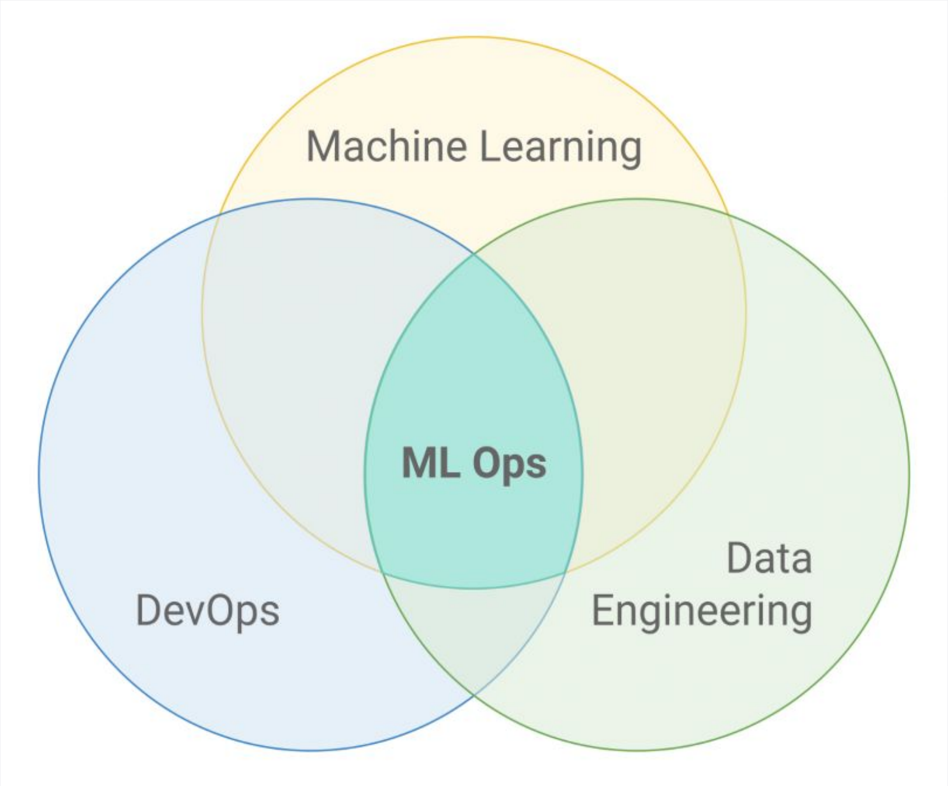
Motivation: Objective Function

- Optimize for a successful strategy of applying MLOps @ your company
  - Use DoorDash as a case study

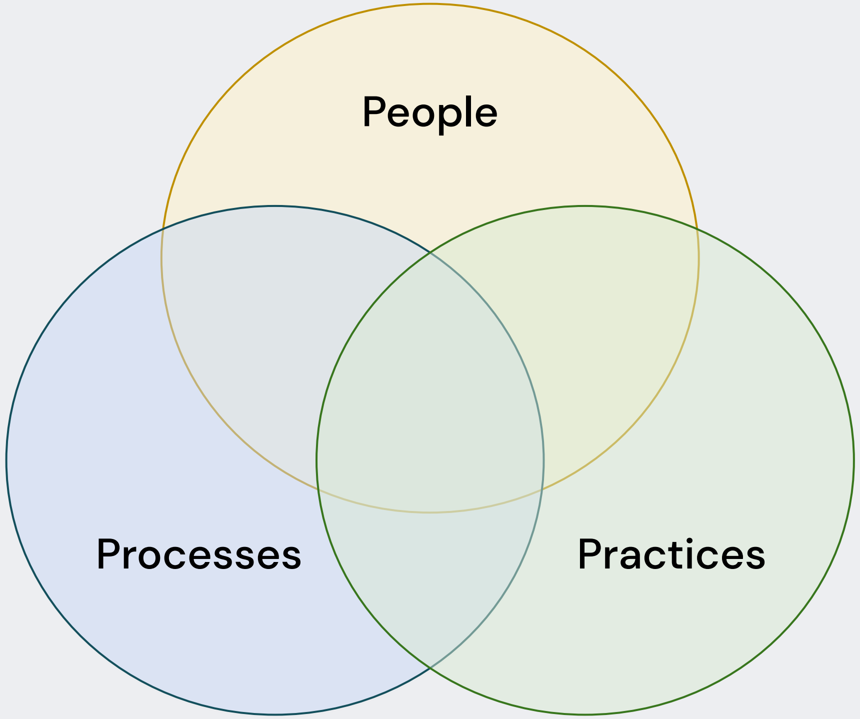
MLOps Blueprint

MLOps Blueprint

MLOps: ML as an Engineering Discipline



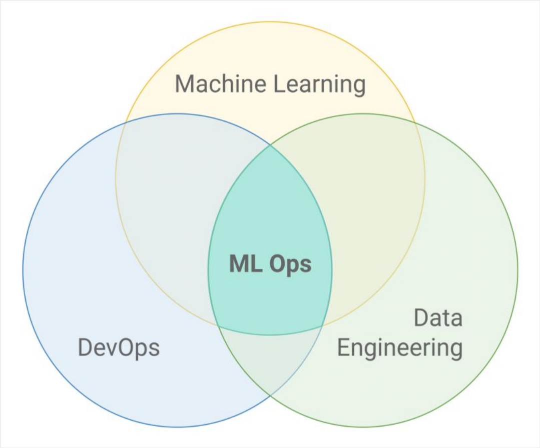
Automation & Infrastructure

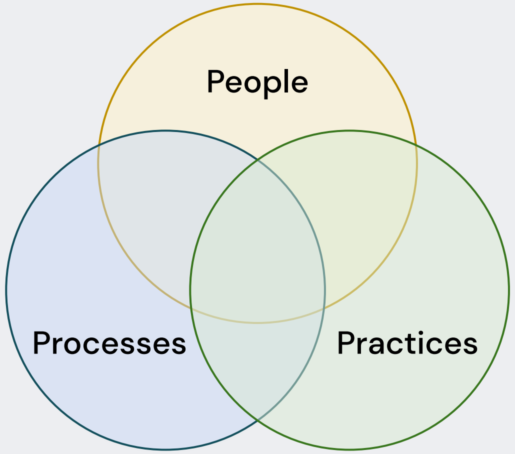


Effective Discipline

MLOps is important & needed

MLOps Blueprint





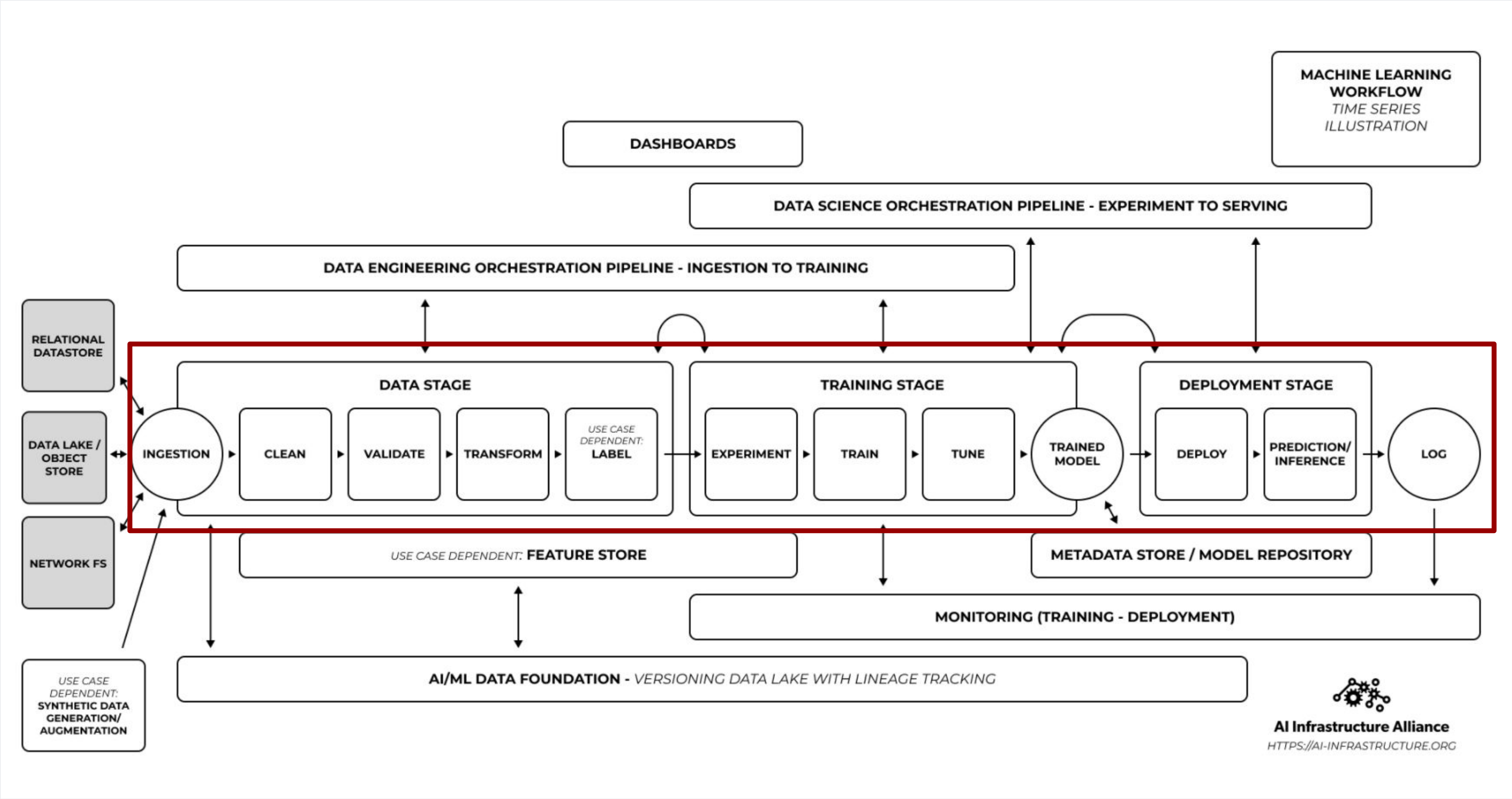
Similar Journey & Needs

Strategy + Starting Point

Specific ML Needs

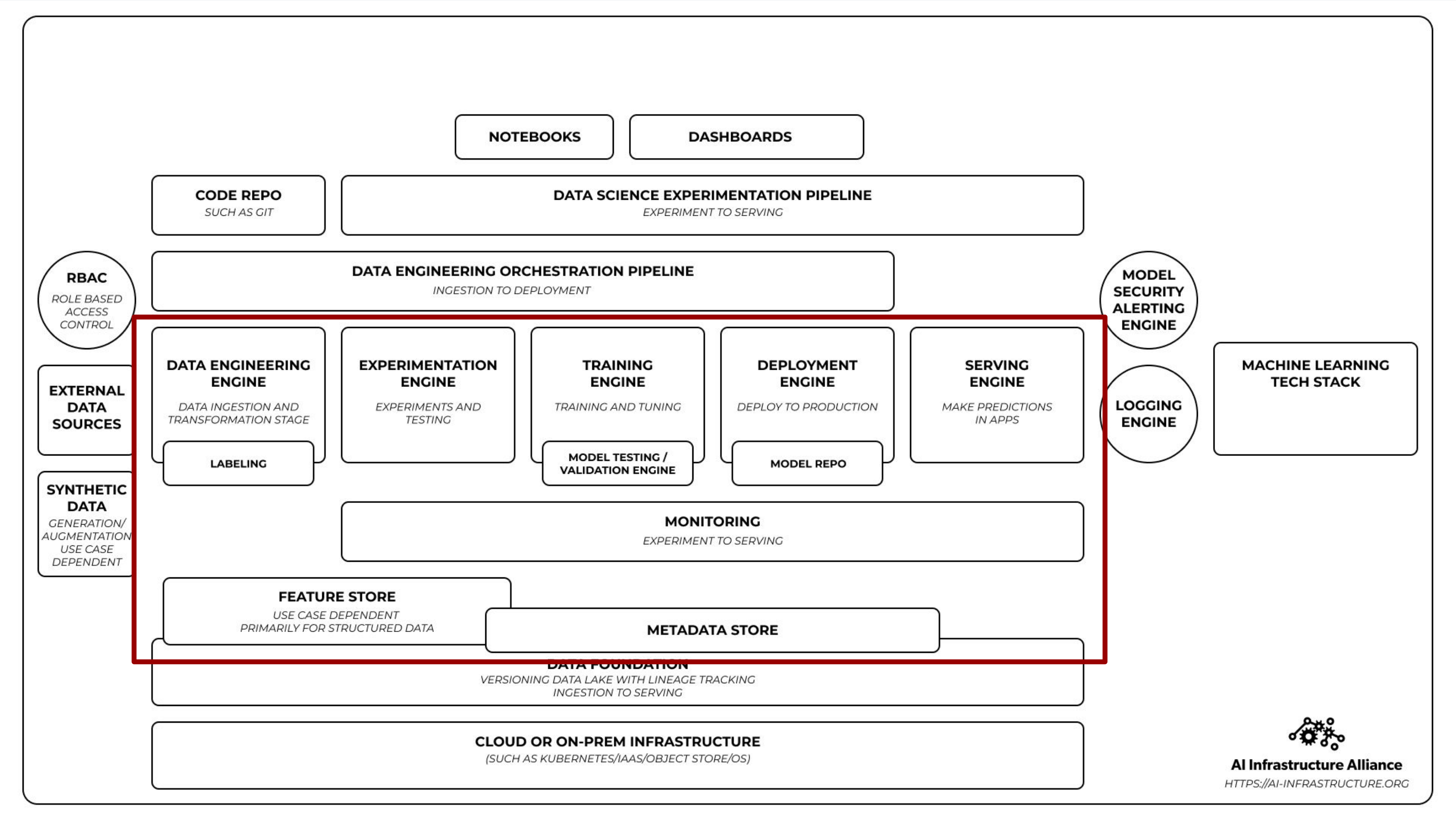
MLOps Blueprint

AI Infrastructure Alliance - AI/ML Workflow



MLOps Blueprint

AI Infrastructure Alliance - AI/ML Tech. Stack



MLOps Blueprint

Maturity Level

- Level 4 – Full MLOps Automation
- Level 3 – Automated Model Deployment
- Level 2 – Automated Training
- Level 1 – DevOps Only
- Level 0 – No MLOps

- Level 2 – CI/CD Pipeline Automation
- Level 1 – ML Pipeline Automation
- Level 0 – Manual

Which maturity level?

MLOps Blueprint

Maturity Level

	Low / Medium / High
Organizational Alignment	M
Data	H
Training	M
Deployment	M
Management	L
Governance	L

Based on what factors?

MLOps Strategy

successful_mlops(use_case, culture, technology, people)

Large influence on the outcome

MLOps Strategy

Use Case - identify the game you are playing

Governance

- Banking
- Insurance
- Health care
- Financial
- Self-driving cars

Velocity

- Customer experience
- Personalized marketing
- Voice assistance
- IoT
- Transportation optimization

successful_mlops(**use_case**, culture, technology, people)

MLOps Strategy

Culture

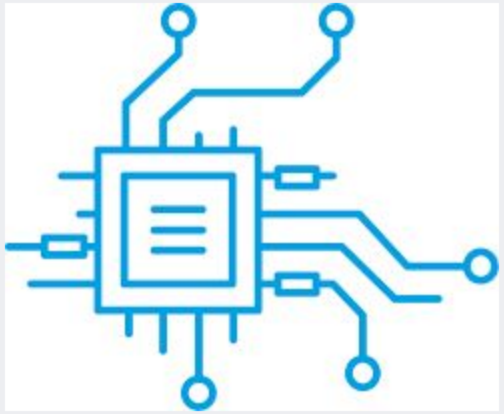
MLOps Adoption Pace

- Risk tolerance
  - Effort
- Velocity
  - Customer's pace
- Decision making process
  - Time & effort
- Collaborative
  - Effort

successful_mlops(use_case, **culture**, technology, people)

MLOps Blueprint & Best Practices

Technology



MLOps Dependencies

Maturity

- Data infrastructure
- Experimentation infrastructure
- CI/CD
- Compute infrastructure

MLOps Strategy

People

- Customers (alignment)
  - Data Scientists, ML Engineers, Data Analysts
- Business teams – PM, product owners (impact)
- Your team
  - MLOps experience
  - Size

Align on their needs and MLOps Infra. impact

MLOps @ DoorDash

MLOps @ DoorDash

- Use cases
  - Logistics, search & recommendation, ads & promotion, fraud, forecasting
- Culture
  - Impact driven, fast moving, favor iterations, collaborative
- Technology
  - Early adult phase - data warehouse, data lake
- People
  - Young Data Scientist teams, a mixed of MLOps experience

MLOps @ DoorDash

- Use cases
  - Logistics, search & recommendation, ads & promotion, fraud, forecasting
- Culture
  - Impact driven, fast moving, favor iterations, collaborative
- Technology
  - Early adult phase – data warehouse, data lake
- People
  - Young Data Scientist teams, a mixed of MLOps experience

MLOps @ DoorDash

- Use cases
  - Logistics, search & recommendation, ads & promotion, fraud, forecasting
- Culture
  - Impact driven, fast moving, favor iterations, collaborative
- Technology
  - Early adult phase - data warehouse, data lake
- People
  - Young Data Scientist teams, a mixed of MLOps experience

MLOps @ DoorDash

- Use cases
  - Logistics, search & recommendation, ads & promotion, fraud, forecasting
- Culture
  - Impact driven, fast moving, favor iterations, collaborative
- Technology
  - Early adult phase – data warehouse, data lake
- People
  - Young Data Scientist teams, a mixed of MLOps experience

MLOps @ DoorDash

Journey

- Prediction service w/ fast model deployment (use case, people, culture)
- Model training infrastructure (people, use case)
- ML Observability (people, use case)
  - feature and model prediction quality
- Feature engineering (use case, technology)

MLOps @ DoorDash

Journey

- Prediction service w/ fast model deployment (use case, people, culture)
- Model training infrastructure (people, use case)
- ML Observability (people, use case)
  - feature and model prediction quality
- Feature engineering (use case, technology)

MLOps @ DoorDash

Journey

- Prediction service w/ fast model deployment (use case, people, culture)
- Model training infrastructure (people, use case)
- ML Observability (people, use case)
  - feature and model prediction quality
- Feature engineering (use case, technology)

MLOps @ DoorDash

Journey

- Prediction service w/ fast model deployment (use case, people, culture)
- Model training infrastructure (people, use case)
- ML Observability (people, use case)
  - feature and model prediction quality
- Feature engineering (use case, technology)

MLOps @ DoorDash

Journey

- Prediction service w/ fast model deployment (use case, people, culture)
- Model training infrastructure (people, use case)
- ML Observability (people, use case)
    - feature and model prediction quality
- Feature engineering (use case, technology)

MLOps @ DoorDash

Tech. Stack

snowflake

APACHE Spark

DATA LAKE

mlflow

Sibyl Prediction Service

PyTorch

LightGBM

Summary

- Successful MLOps strategy
  - Use case, culture, technology, people
- Adopt MLOps as a team sport
  - Pay attention to organizational alignment upfront
  - Necessary to be successful
- Start small and iterate

DATA+AI SUMMIT 2022

Thank you