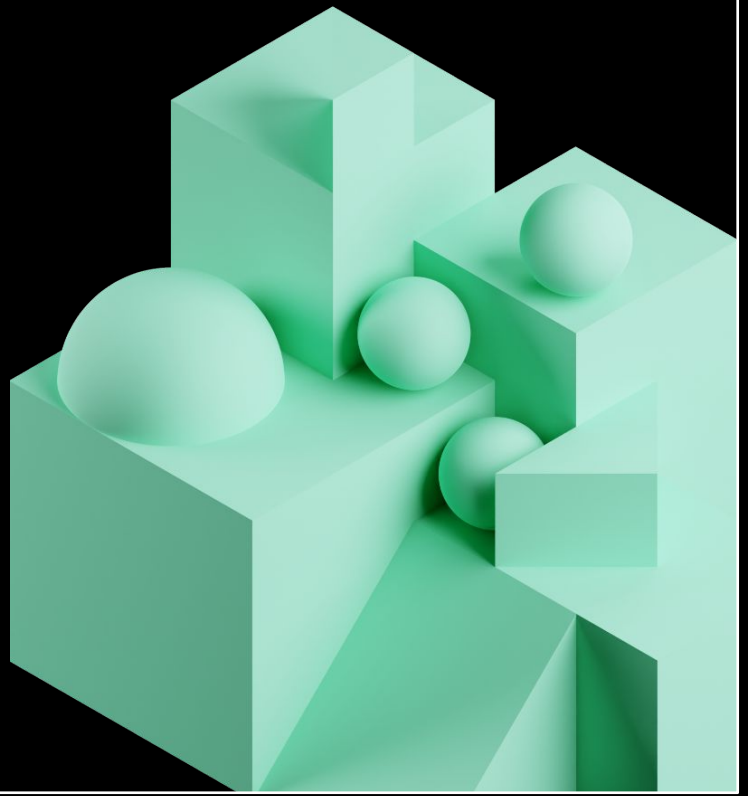
DATA+AI SUMMIT
BY databricks

Machine Learning in Production



Databricks
2023

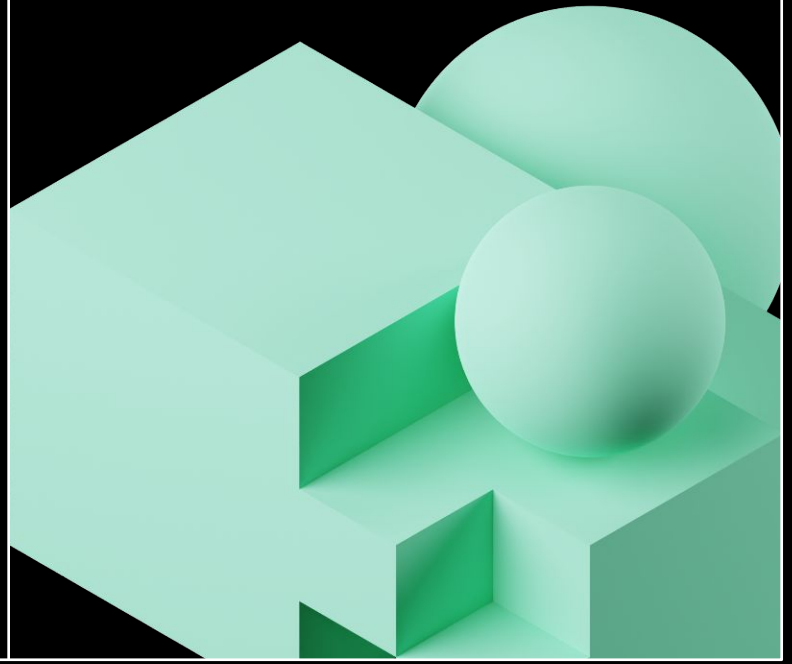
Agenda

MORNING		
	Demo	Lab
Introduction		
01. Experimentation		
Delta Lake		
Feature Store	✔	
ML*flow* Experiment Tracking	✔	✔
02. Model Management		
ML*flow* Model Management	✔	✔
ML*flow* Model Registry	✔	

AFTERNOON		
	Demo	Lab
03. Deployment Paradigms		
DevOps vs. ModelOps		
Deployment Patterns	✔	
Deployment Paradigms	✔	✔
04. Production		
CI/CD		
Monitoring	✔	✔
Model Rollout Strategies		

LET’S GET STARTED

Course Introduction



Hardest Part of ML isn't ML, it's Data

"Hidden Technical Debt in Machine Learning Systems," Google NIPS 2015

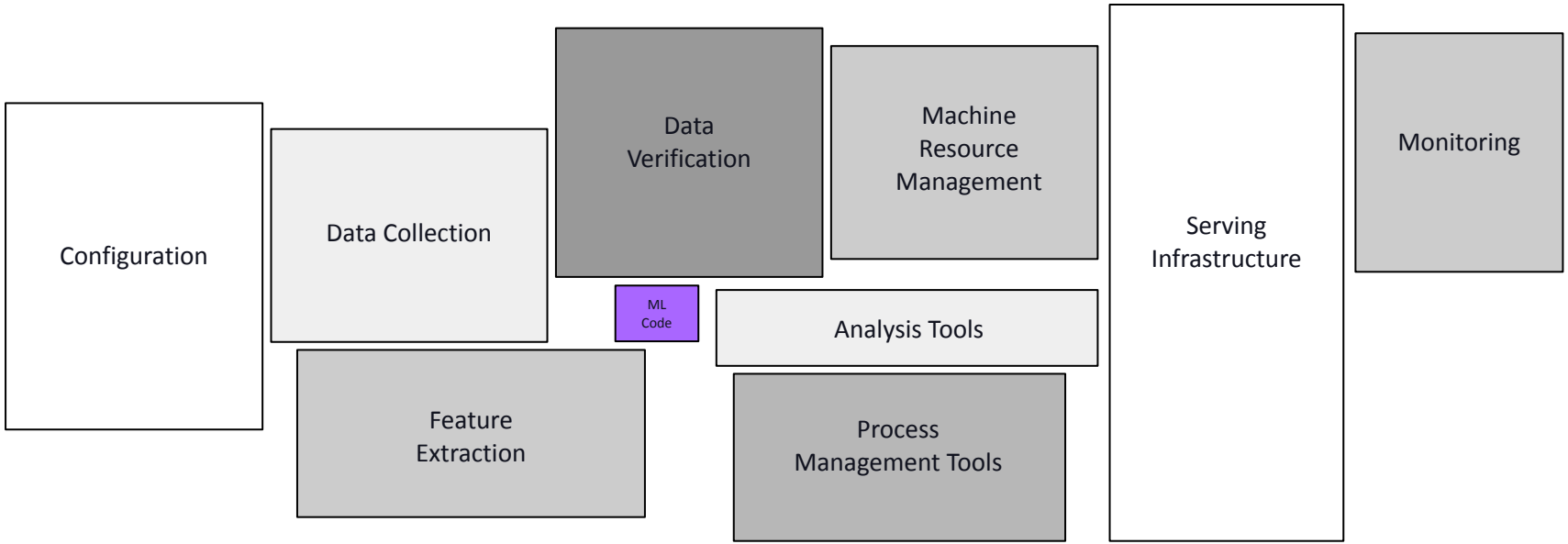


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small green box in the middle. The required surrounding infrastructure is vast and complex.

What is MLOps and why should we care about it?

What is MLOps?

MLOps is a set of **processes and automation** for **managing code, data, and models** to **improve performance, stability and long-term efficiency** of ML systems

MLOps = **Dev**Ops + **Data**Ops + **Model**Ops

Why Should We Care About MLOps?

MLOps helps you **reduce risk**

- **Technical risk** - poorly performing models, fragile infrastructure
- **Compliance risk** - violating regulatory or corporate policies

MLOps improves **long-term efficiency** through **automation**

- Catch errors before they hit production
- Avoid slow, manual processes

People and Process

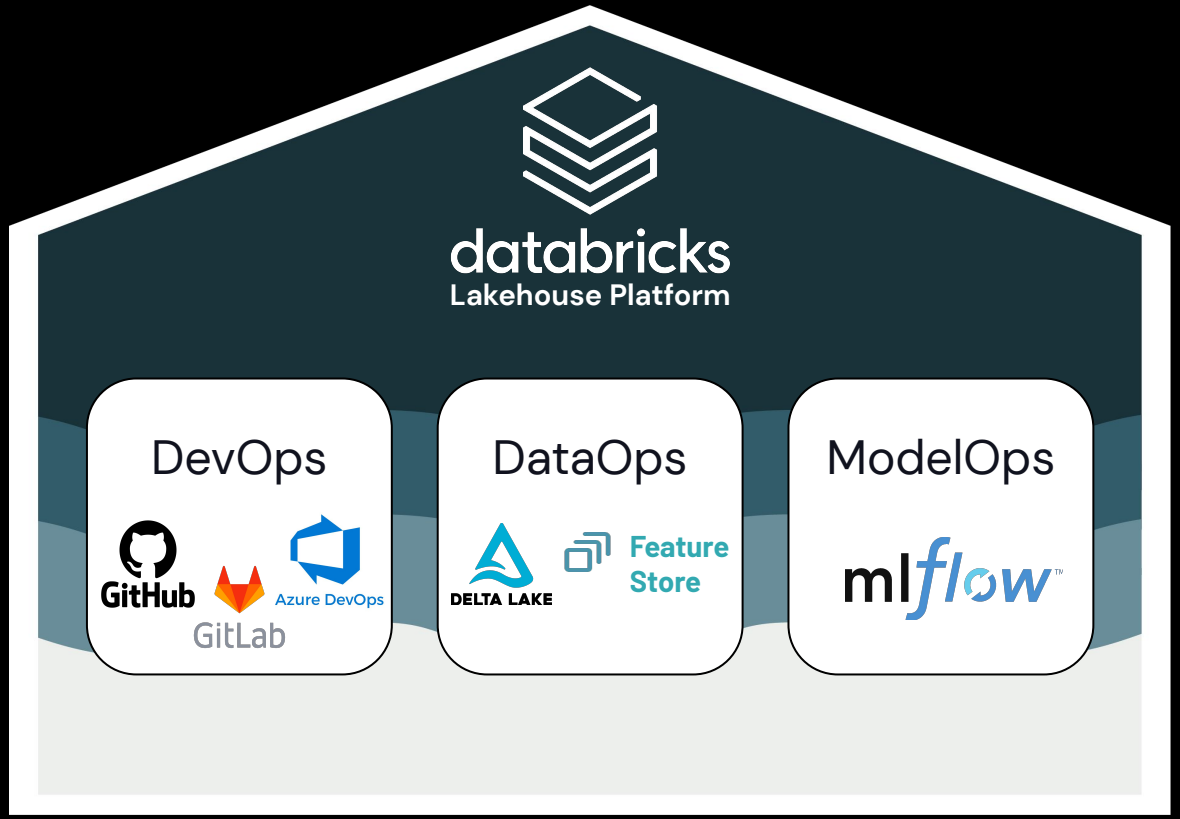
Business Stakeholder → Responsible for business value of the ML solution

Data Engineer → Builds data pipelines

Data Scientist → Translates business problem; trains, tunes model

ML Engineer → Deploys ML model to production

Data Governance Officer → Responsible for data governance and compliance



Data-Centric ML Platform

Guiding Principles

Always keep your business goals in mind

Take a data-centric approach to machine learning

Implement MLOps in a modular fashion

Process should guide automation

Data & Model Management and Reproducibility

Managing the machine learning lifecycle means:

- **Reproducibility of data** -- data management
- **Reproducibility of code** -- version control, source tracking
- **Reproducibility of models** -- model management
- **Automated integration** with production systems -- CI/CD, testing

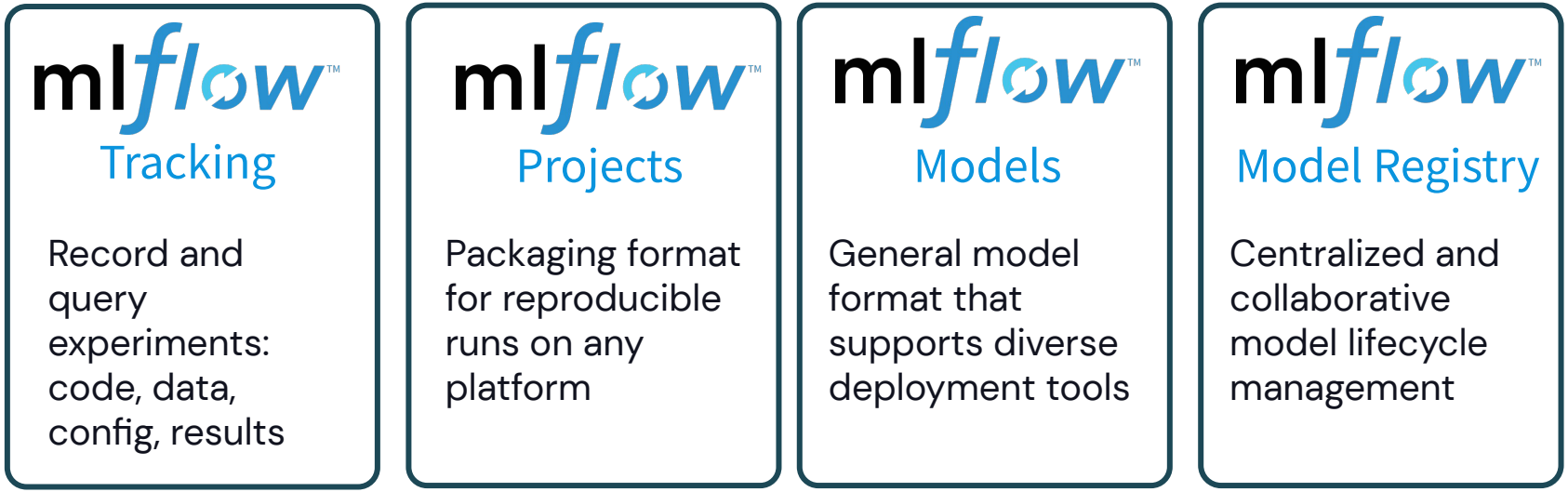
MLflow

An open-source platform for managing end-to-end ML lifecycle

- Open-source platform for machine learning lifecycle
- Operationalizing machine learning
- Developed by Databricks
- Pre-installed on the Databricks Runtime for ML

MLflow Components

The four components of MLflow



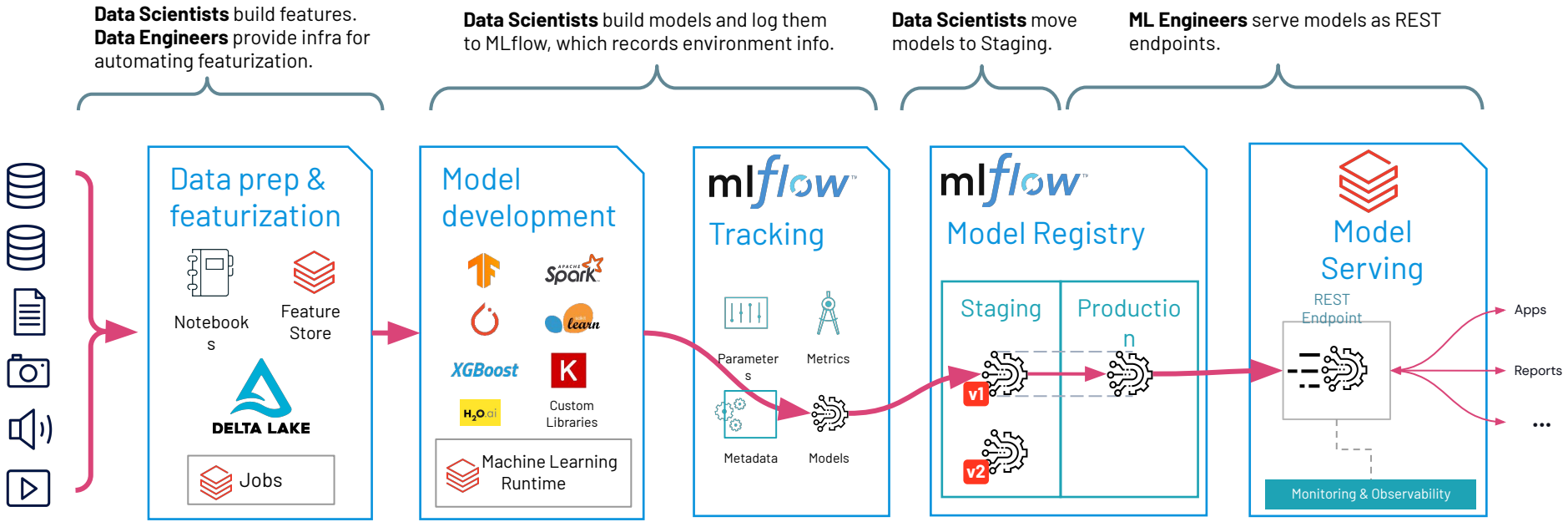
APIs: CLI, Python, R, Java, REST

Data is never static!

Model Centric → Data Centric Machine Learning

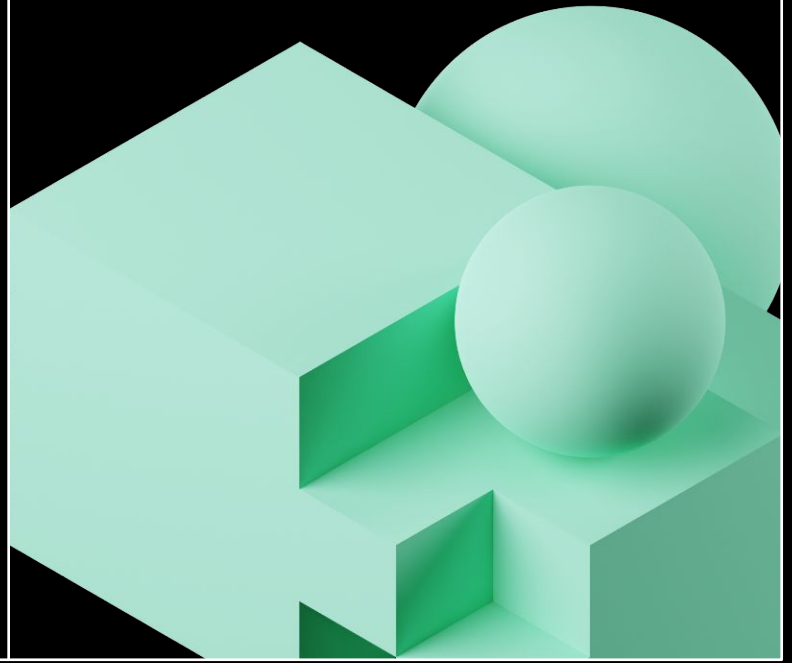
The Full ML Lifecycle

Build, train, test, deploy and monitor machine learning models with ease

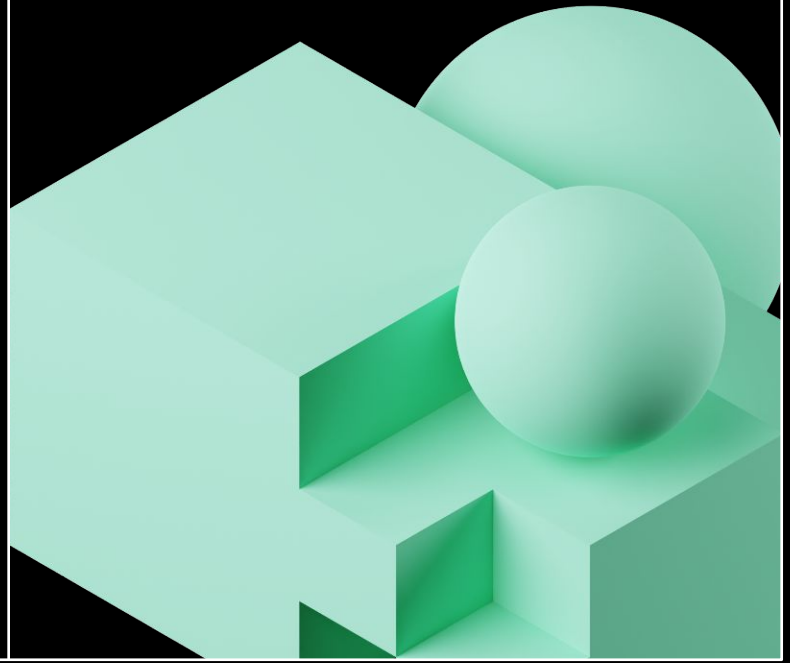


WORKSPACE SETUP

01. Experimentation

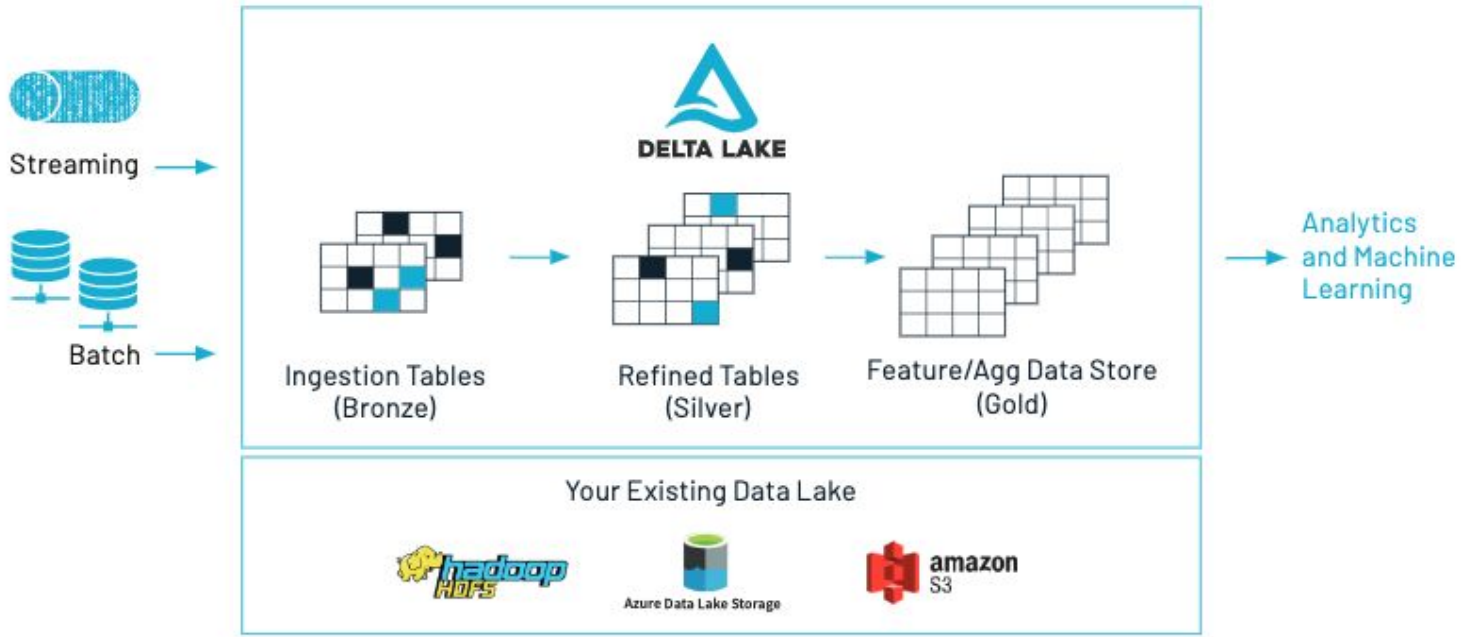


Delta Lake



Delta Lake Overview

An open-source storage framework for building a modern Lakehouse



Delta Lake Overview

Key Features

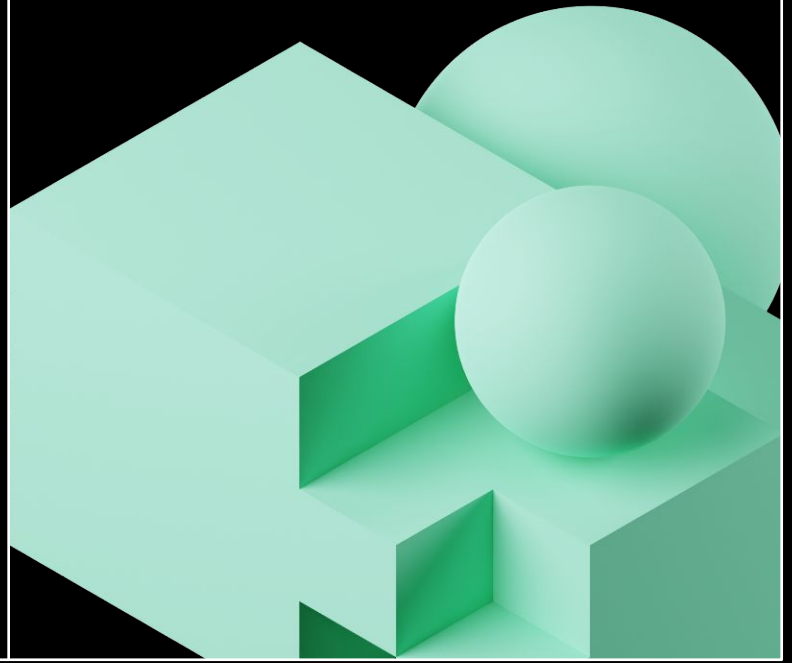
- ACID transactions → reliability
- Time travel (data versioning) → reliability, error recovery, synchronization
- Schema enforcement and evolution → reliability
- Audit history → data governance and compliance
- Parquet format + transaction log
- Compatible with Apache Spark API

Delta Lake Overview

Optimization features

- Compaction
- Data Skipping
- Z-ordering
- FAQs on “OPTIMIZE”

Feature Store



Production Machine Learning

= Production Software + Data

What is a Feature?

An example feature in a recommendation system

Raw data

User profile
Zip code
Payment methods
...

User history
Last 6 months of purchases

Web session
User ID
Shopping cart
Item view in last hour
...

Types of Features

Feature Augmentation

e.g. Weather in region

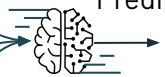
Pre-computed Features

e.g. Purchases last 7, 14, 21 days

Transformations of real-time data

e.g. Category Encoding

ML Model

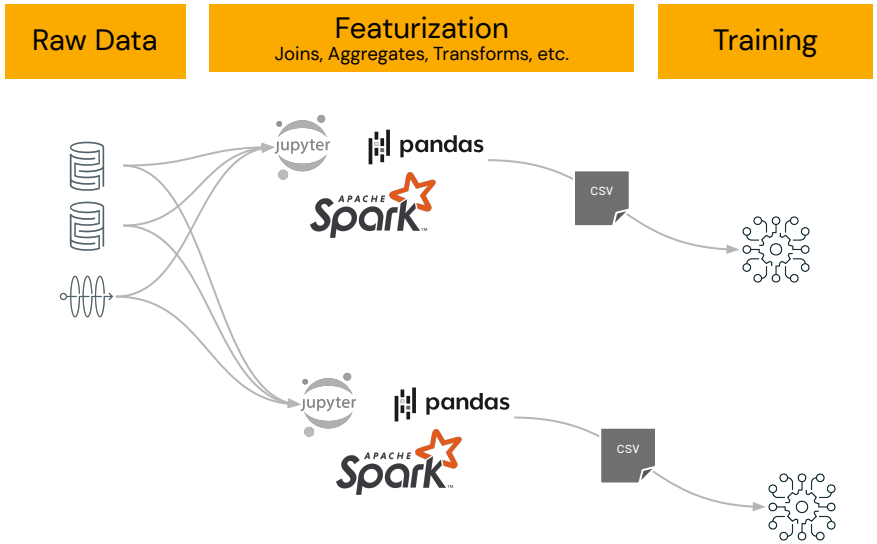


Prediction

Outcome

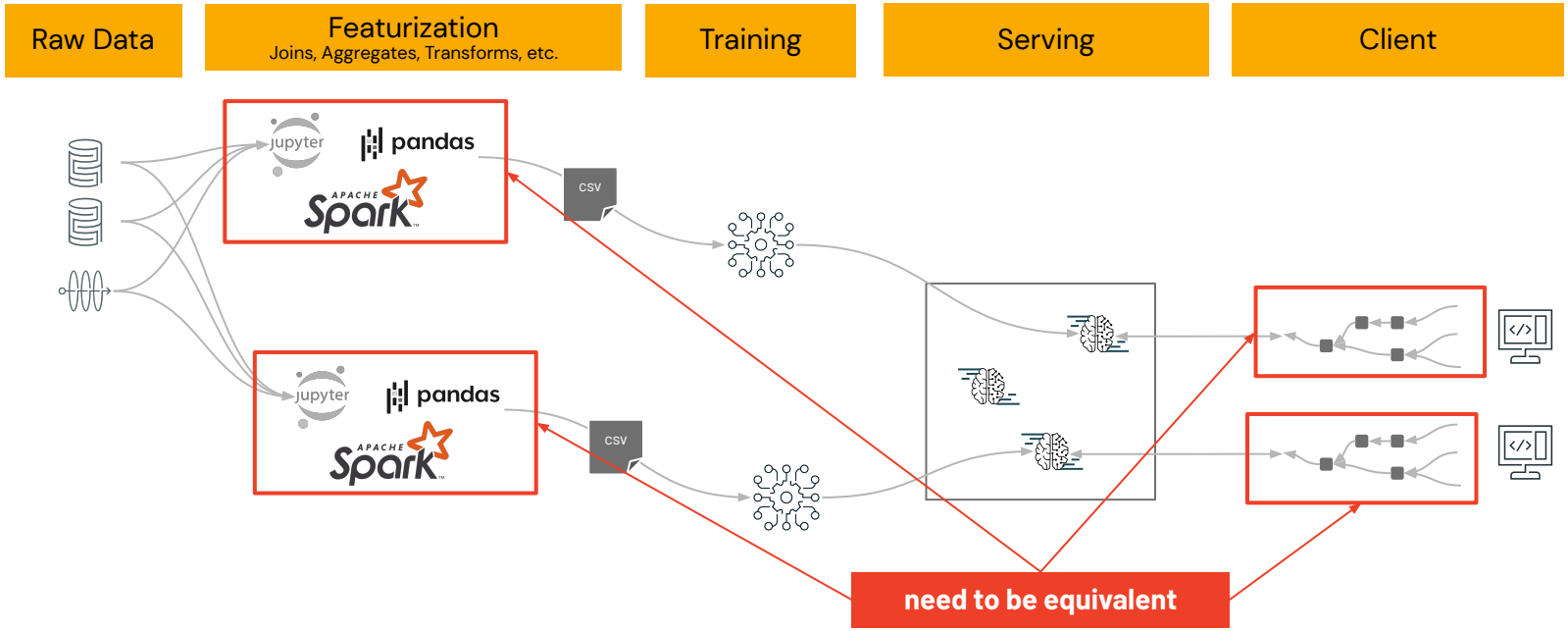
Item	P(purchase|user)
	0.58
	0.13
	0.12
	0.01

Data Challenges in ML



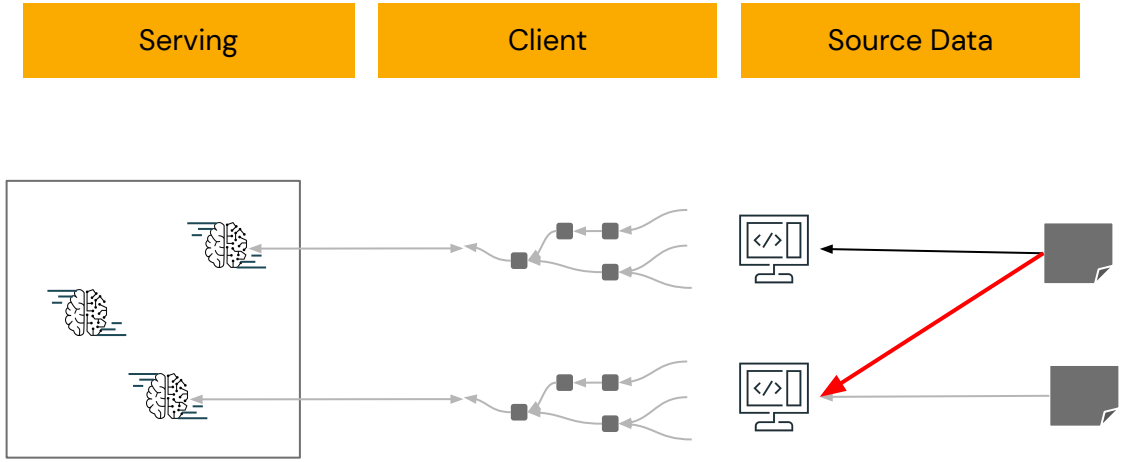
Challenge 1: Data silos

Data Challenges in ML



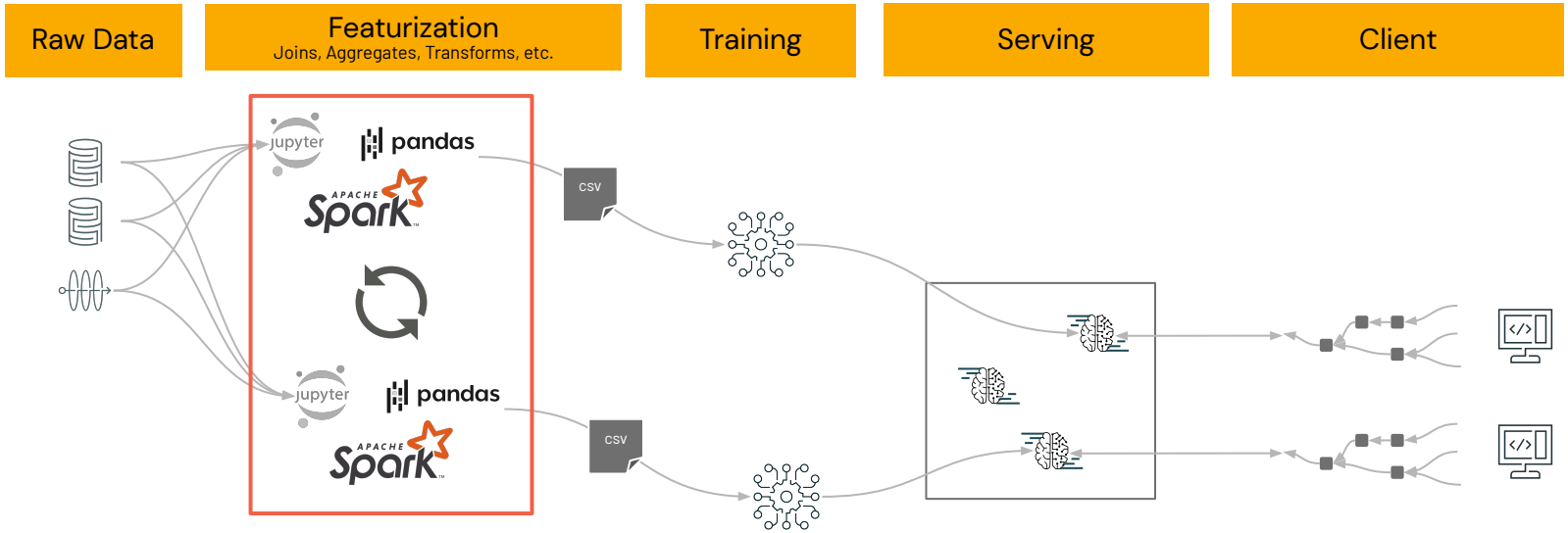
Challenge 2: Online/offline skew

Data Challenges in ML



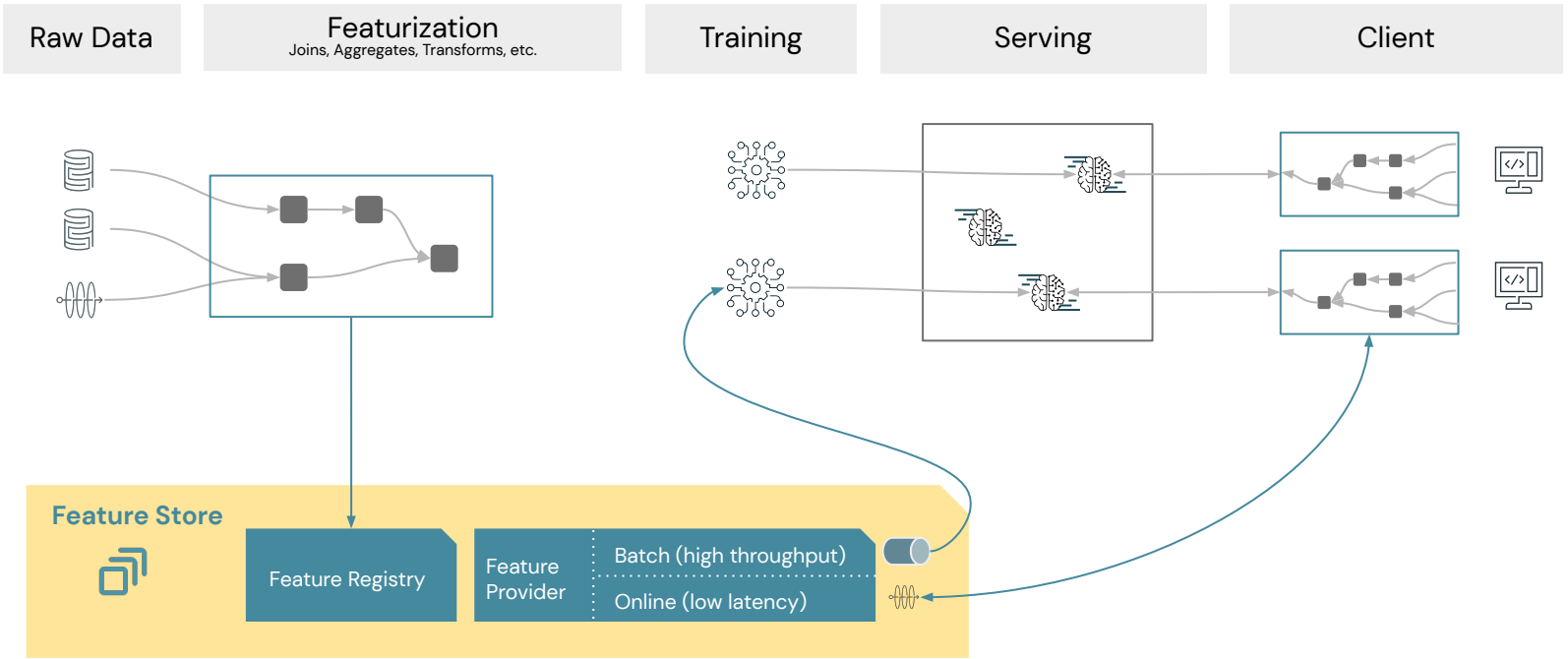
Challenge 3: Client Configuration

Data Challenges in ML



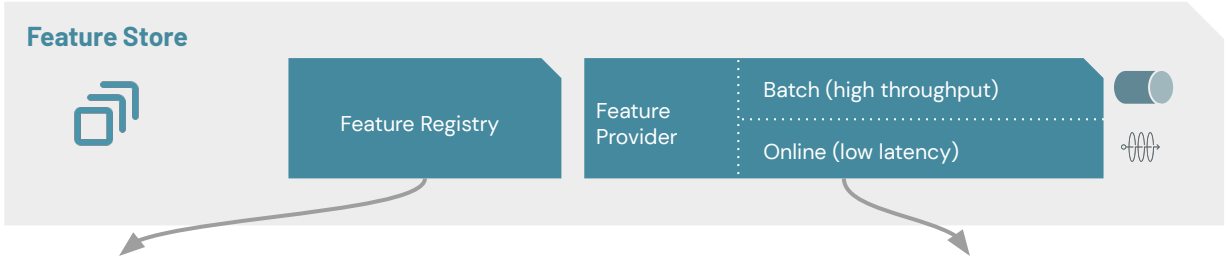
Challenge 4: Data Freshness

Solving the Feature Store Problem



Feature Store

The first Feature Store codesigned with a Data and MLOps Platform



Feature Registry

- Discoverability and Reusability
- Versioning
- Upstream and downstream Lineage

Co-designed with DELTA LAKE

- Open format
- Built-in data versioning and governance
- Native access through PySpark, SQL, etc.

Feature Provider

- Batch and online access to Features
- Feature lookup packaged with Models
- Simplified deployment process

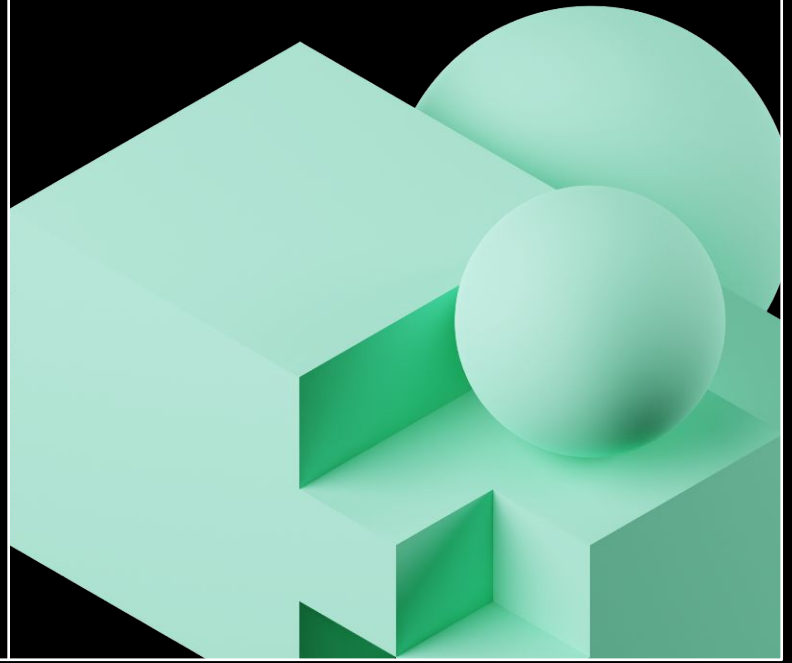
Co-designed with mlflow

- Open model format that supports all ML frameworks
- Feature version and lookup logic hermetically logged with Model

DEMO:
FEATURE STORE

Notebook: 01-Experimentation → 01-Feature-Store

MLflow Tracking



Experiment Tracking

Record runs, and keep track of models parameters, results, code, and data from each experiment and in one place.

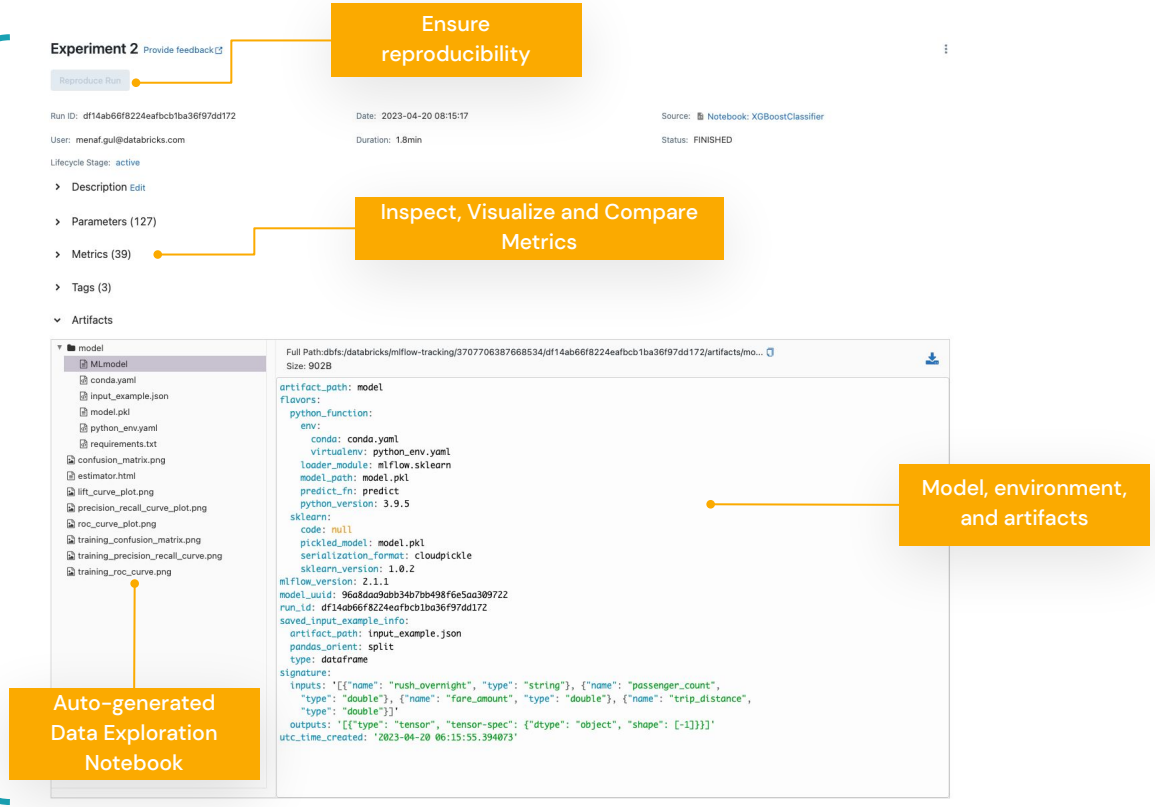
Provides:

- Pre-configured MLflow tracking server
- Databricks Workspace & Notebooks UI integration
- S3, Azure Blob Storage, Google Cloud for artifacts storage
- Experiments management via role based Access Control Lists (ACLs)

MLflow Tracking and Auto-logging

```
mlflow.autolog()
```

Track ML development with one line of code: parameters, metrics, data lineage, model, and environment.



Workflow Overview

- Write code to convert raw data into features and create a Spark DataFrame
- Write the DataFrame as a feature table in Feature Store
- Create a training set based on features from feature tables
- Train model and log it with MLflow
- Perform batch inference on new data. The model automatically retrieves the features it needs from Feature Store.
- (Optional) Publish the features to an online store for batch or real-time inference

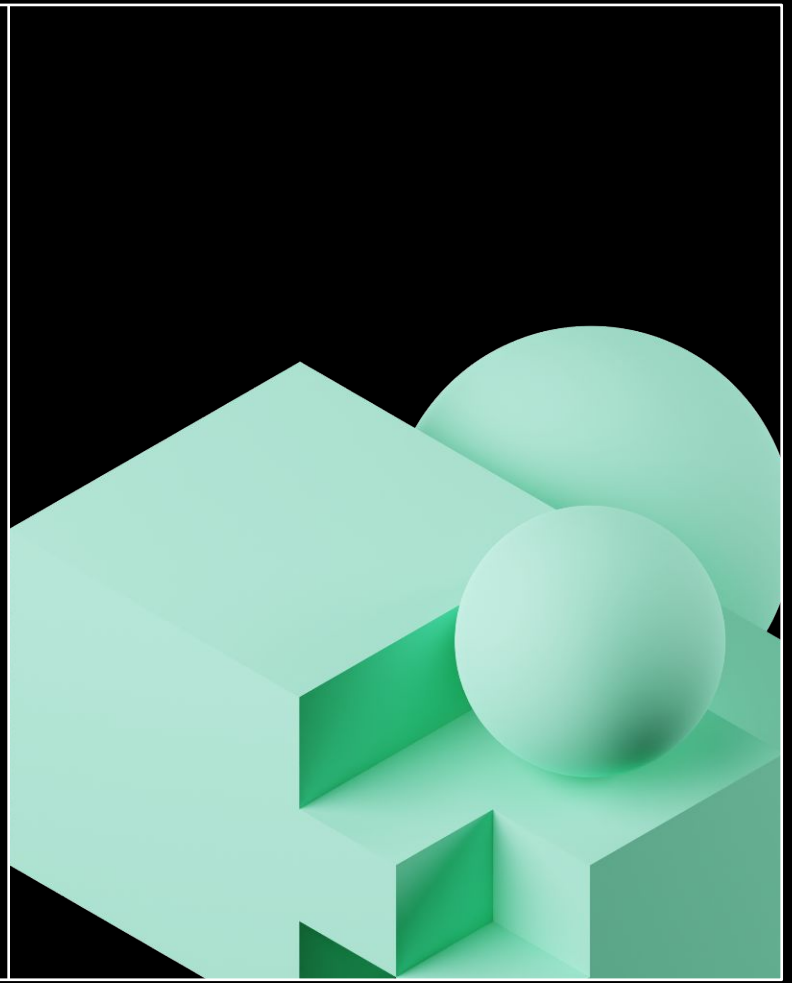
DEMO:
EXPERIMENT TRACKING

Notebook: 01-Experimentation → 02-Experiment-Tracking

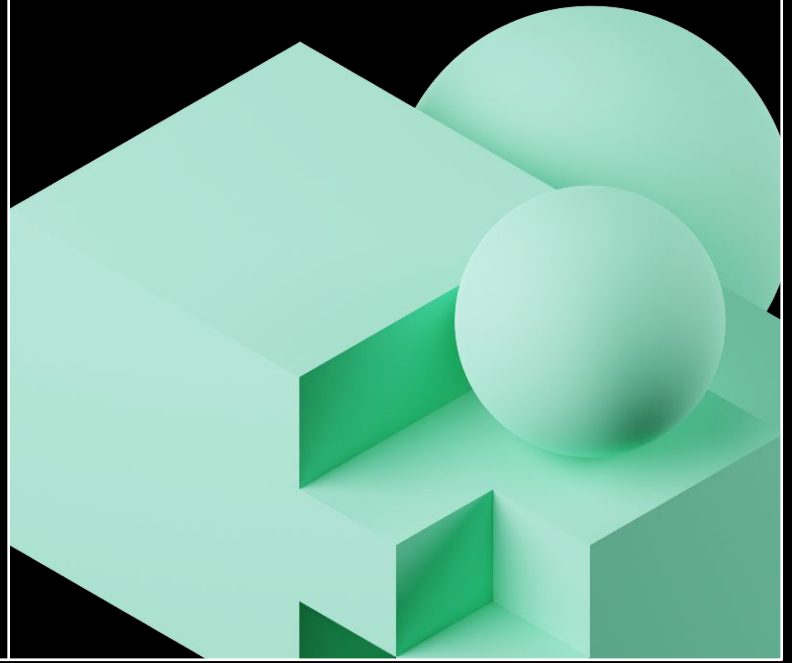
LAB:
EXPERIMENT TRACKING

Notebook: 01-Experimentation → Labs → 02-Experiment-Tracking-Lab

02.
Model Management



MLflow Models

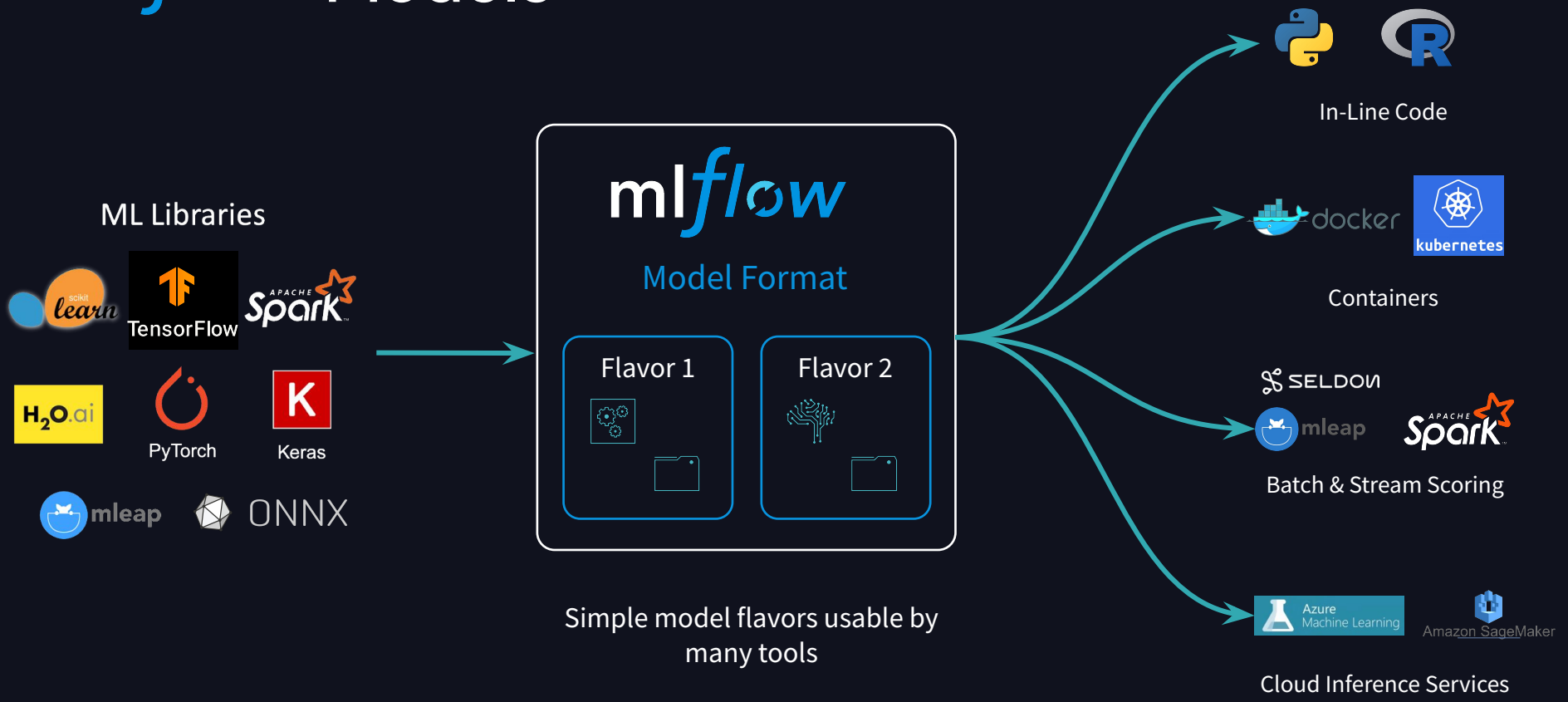


Data Transformation

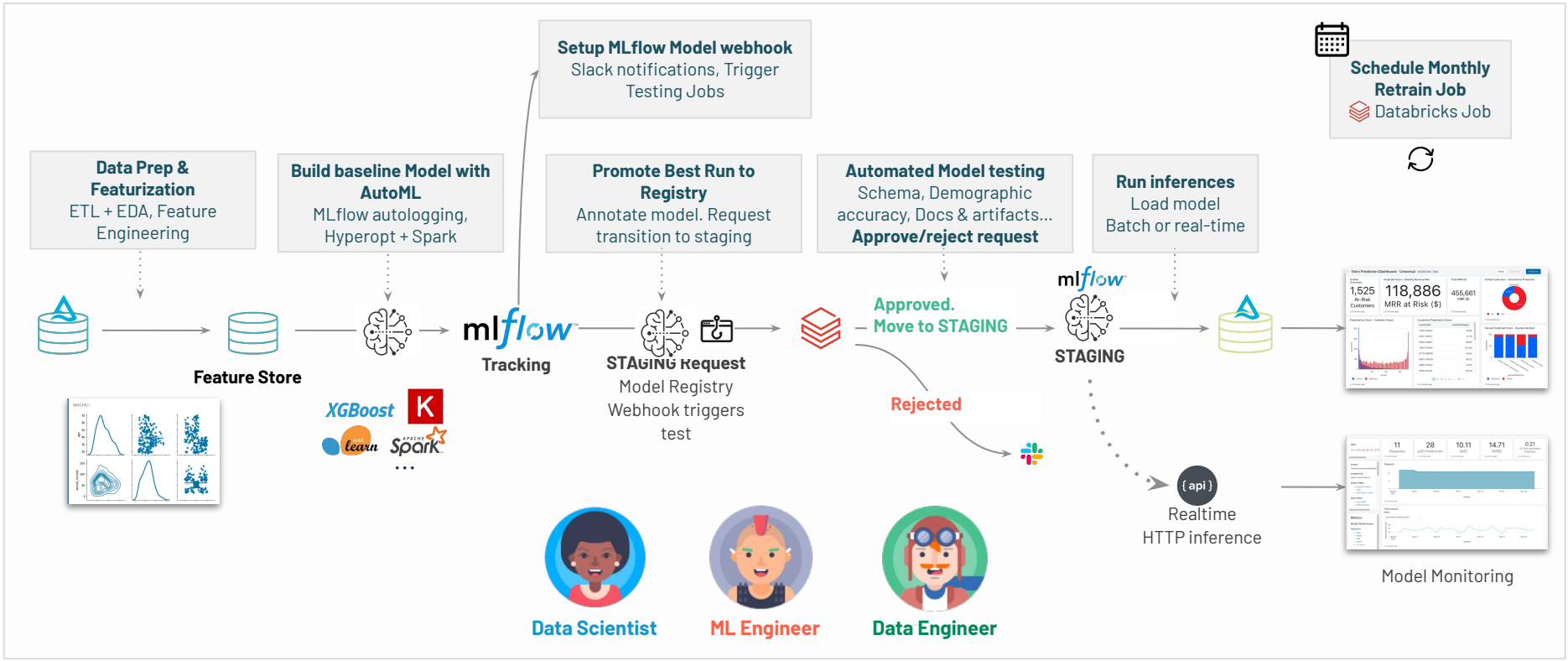
Within the model or prior to model training? It depends!

	Pros	Cons
Prior to Model Training	- Compute once and reuse - Leverages full dataset	- Increases production footprint - Slower to iterate
Within the Model	- Easier to iterate - Smaller production footprint	- Model latency depends upon transformation overheads - Data visibility

mlflow Models



End to End Model Management



Model Management with Model Registry

Use one central place to collaboratively manage ML models

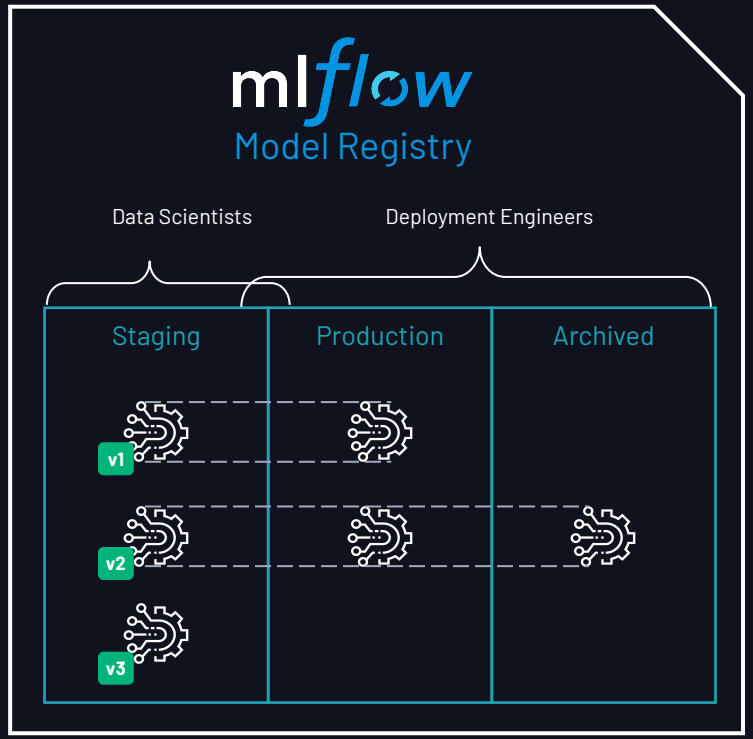
One Collaborative Hub: The Model Registry provides a central hub for making models discoverable, improving **collaboration** and **knowledge sharing** across the organization.

Manage the entire Model Lifecycle (MLOps): The Model Registry provides lifecycle management for models from experimentation to deployment, improving **reliability** and robustness of the model deployment process.

Visibility and Governance: The Model Registry provides full visibility into the deployment stage of all models, who requested and approved changes, allowing for full governance and auditability.

mlflow Model Registry

VISION: Centralized and collaborative model lifecycle management



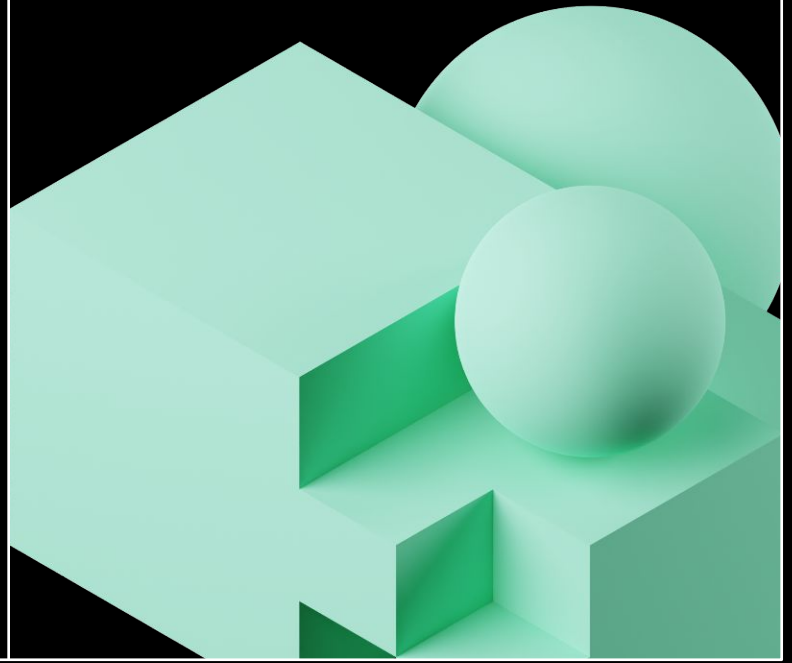
DEMO:
MODEL MANAGEMENT

Notebook: 02-Model-Management → 01-Model-Management

LAB:
MODEL MANAGEMENT

Notebook: 02-Model-Management → Labs → 01-Model-Management-Lab

Model Registry



Model Registry Workflow Options

Central Model Registry – Model Access Management

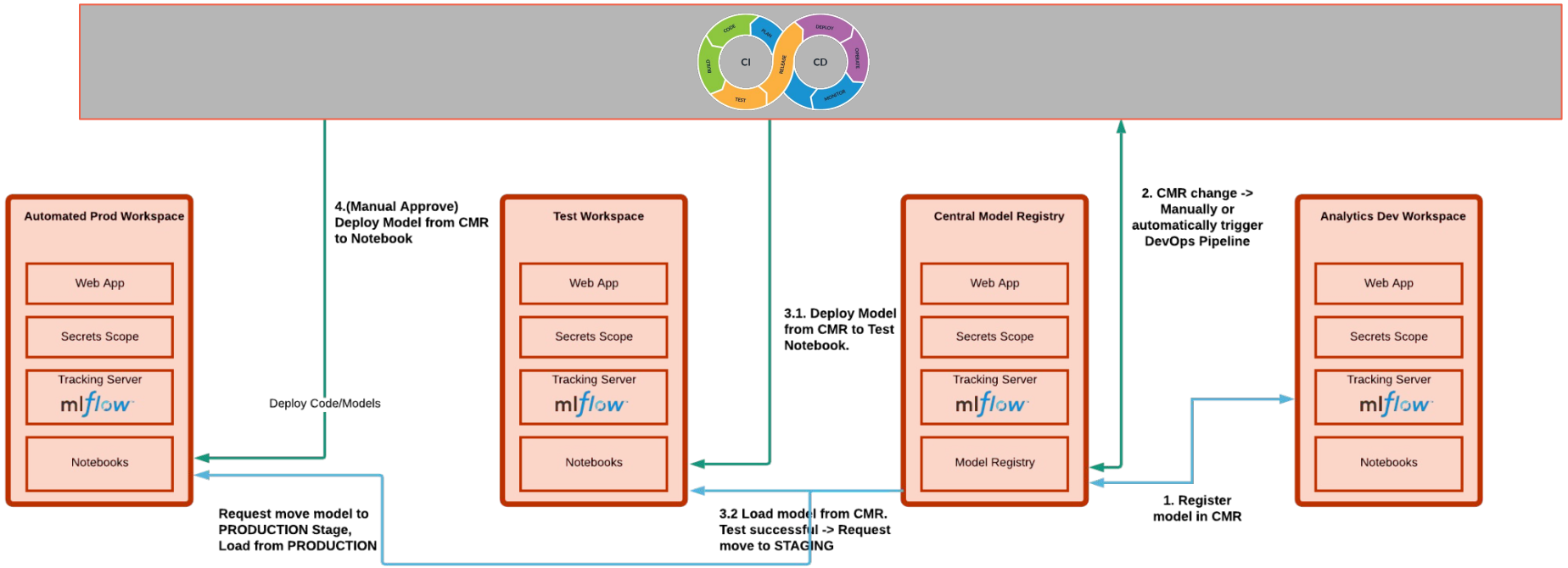
- **Central Model Registry**: Dedicated workspace(s) to store models and experiments
  - Refer to this documentation

- **Per-workspace Model Registries**: Each workspace has its own model registry, model transition is made via CI/CD

- **Model Registry - *Unity Catalog* Integration**: Centrally govern model access permissions, share models across workspaces, model lineage

Central Model Registry

Dedicated workspace(s) to store models and experiments



Central Model Registry

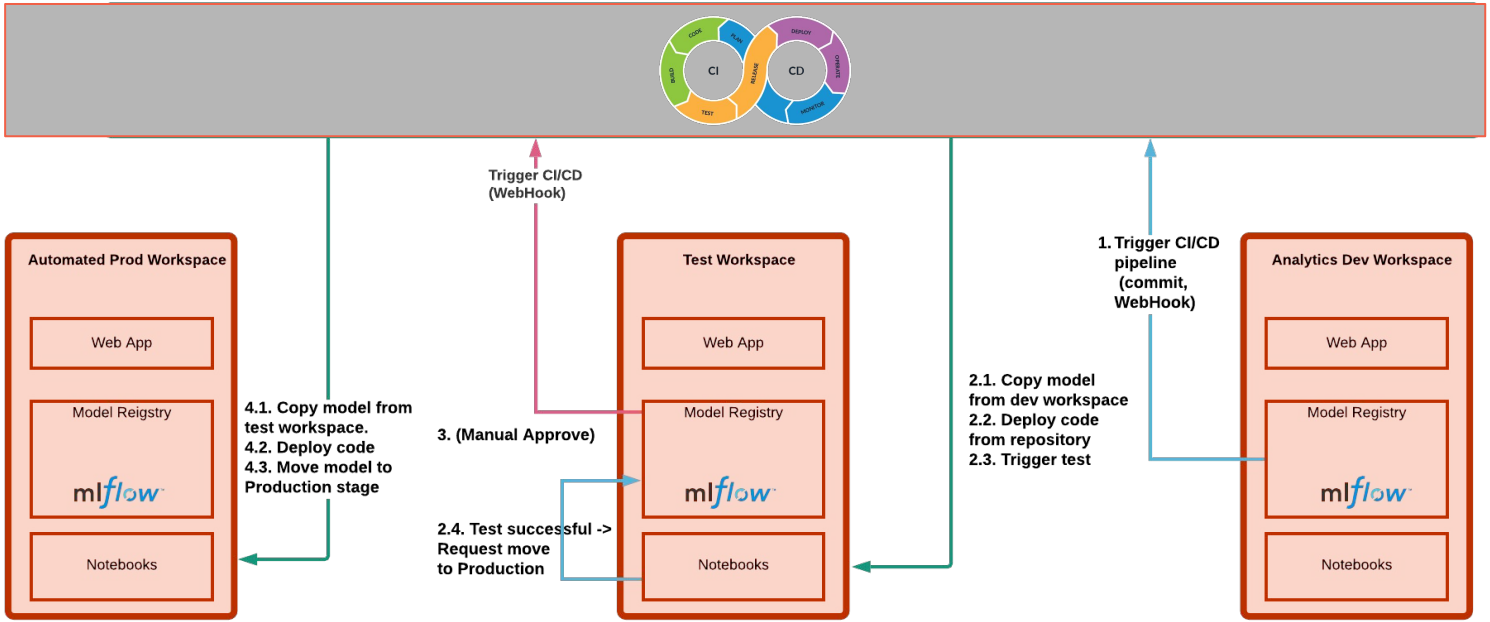
Dedicated workspace(s) to store models and experiments

- Pros:
  - Visibility into current state of all models
  - Central management of models
  - Cross cloud

- Cons:
  - Setup is a bit complicated:
    - We need PAT & other configuration in a secret scope
    - We can have max 100 secret scopes per workspace
    - Using shared PATs isn't good from compliance point of view
  - Could be cluttered, especially if we'll use it for tracking of experiments
  - Control of permissions could be complex if we have many teams

Per-workspace Model Registries

Each workspace has its own model registry, model transitions via CI/CD



With Model Registry - Unity Catalog Integration, you can manage model access permissions in single location and share models across workspaces.

Per-workspace Model Registries

Each workspace has its own model registry, model transitions via CI/CD

- Pros:
  - Narrowed access to staging/production workspace
  - PAT is required only for a system account (service principals, for example)
- Cons:
  - Limited observability - you need to visit staging/production workspaces to get information about model state
  - Approvals needs to be done in relevant workspaces
  - There are no built-in tools for transitioning of models/experiments between workspaces, although there is some tooling
  - Requires implementation as part of CI/CD pipeline

DEMO:
MODEL REGISTRY

Notebook: 02-Model-Management → 02-Model-Registry

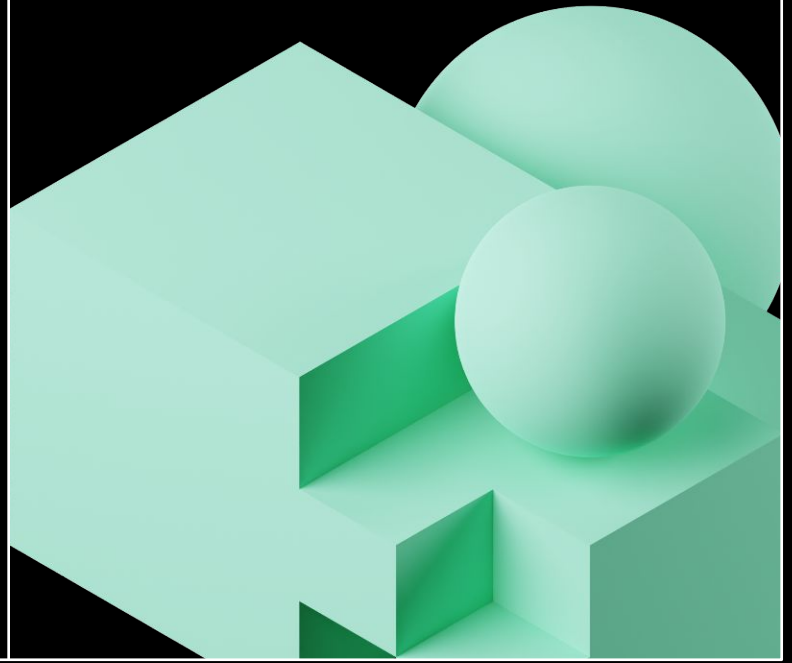
DEMO:
WEB HOOKS & TESTING

Notebook: 02-Model-Management → 03a-Webhooks-and-Testing

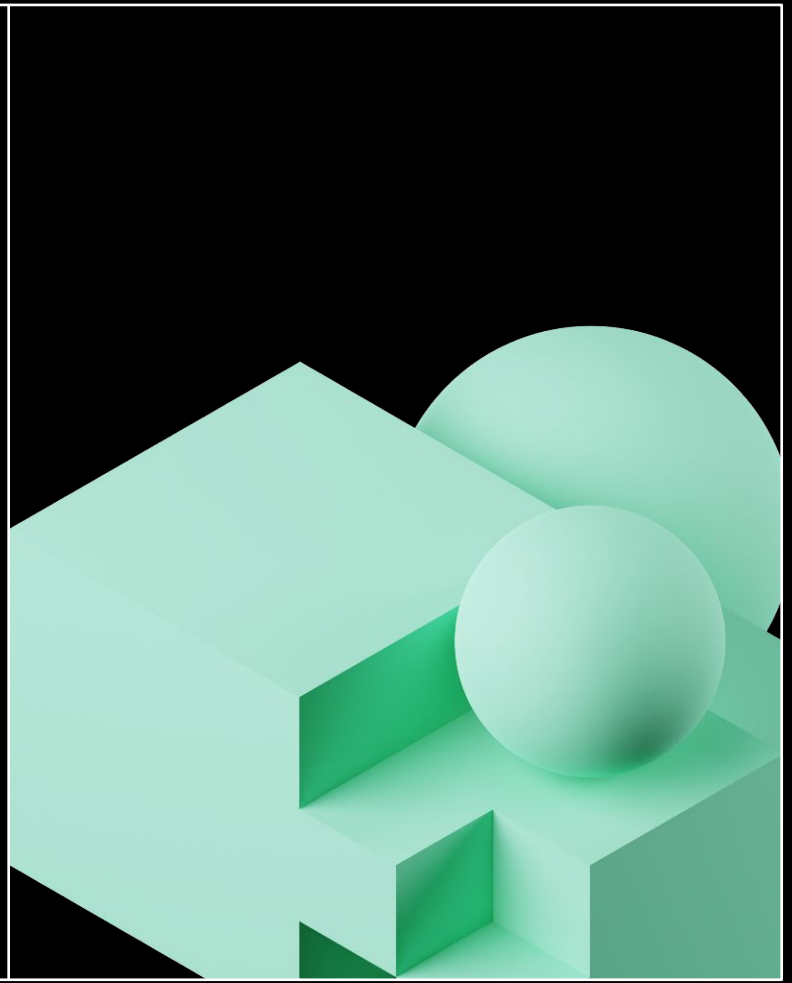
DEMO:
AUTOMATED TESTING

Notebook: 02-Model-Management → 03b-Webhooks-Job-Demo

03. Deployment Paradigms



DevOps vs. ModelOps



What is ML Deployment?

- Data Science != ML Engineering
- Data science is scientific
  - Business problems → data problems
  - Model mathematically
  - Optimize performance
- ML engineers are concerned with
  - Reliability
  - Scalability
  - Maintainability
  - SLAs
  - ...

DevOps vs. ModelOps

DevOps

Software development + IT operations

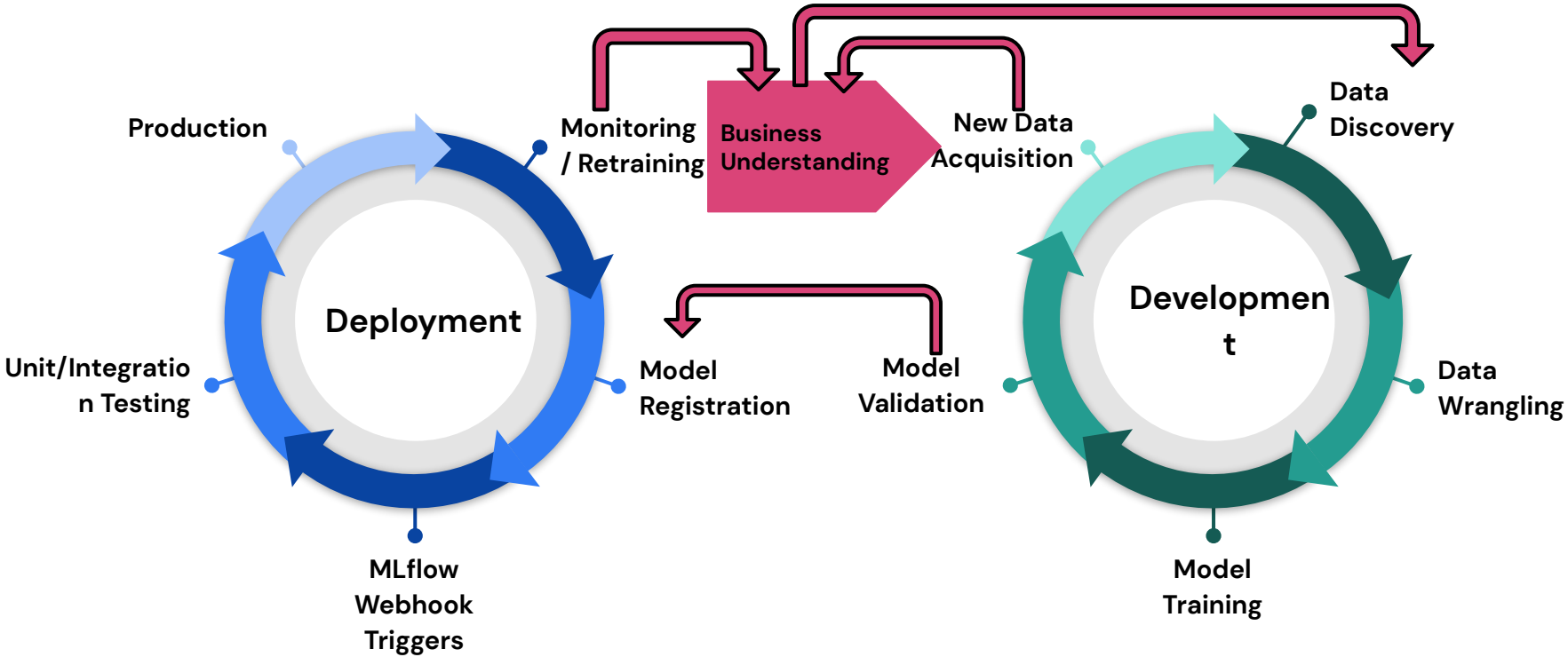
- Manages deployments
- CI/CD of features, patches, updates, rollbacks

ModelOps

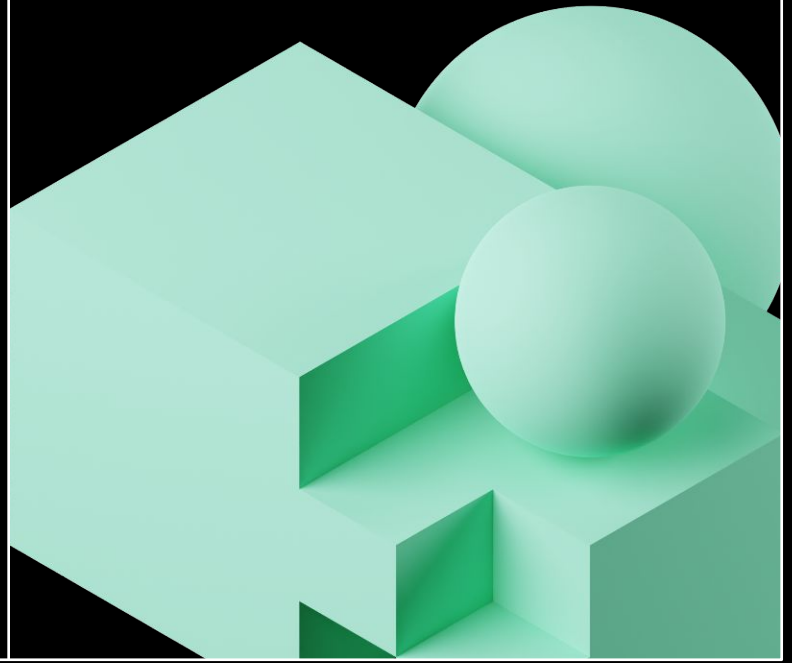
Data modeling + deployment operations

- Artifact management (Continuous Training)
- Model performance monitoring (Continuous Monitoring)
- Data management
- Use of containers and managed services

Closed Loop Systems



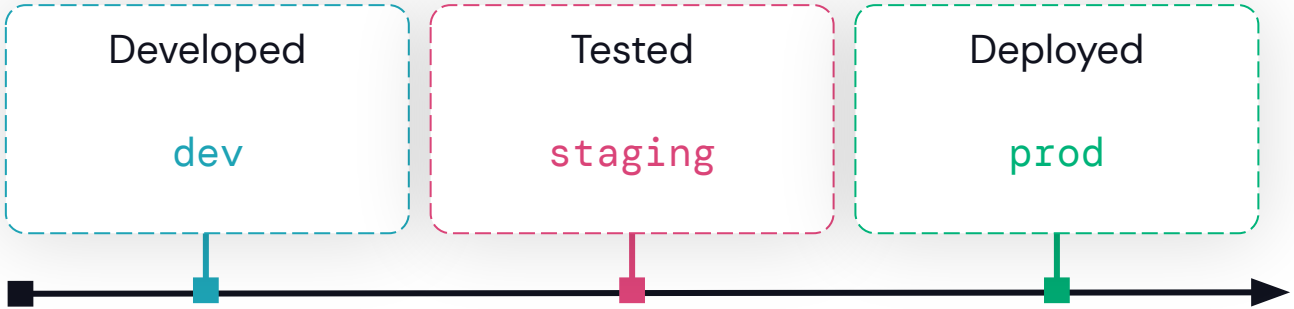
Deployment Patterns



Semantics of Dev, Staging, and Production

ML Workflow Assets:

Assets need to be:

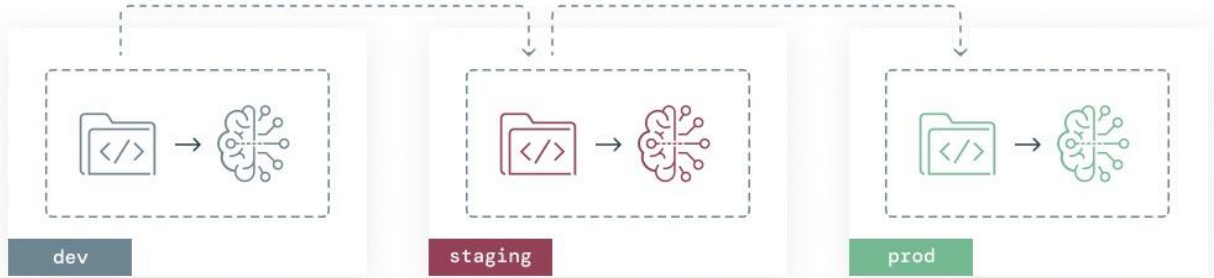


Dev vs. Staging vs. Production

Level of trust, quality, testing and openness

Level of trust, quality and testing:

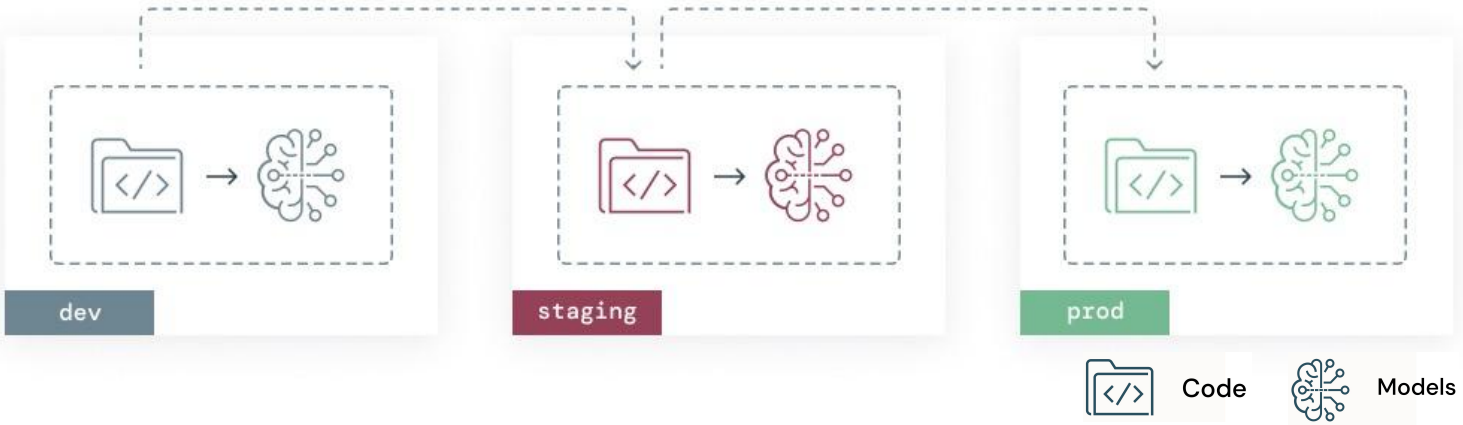
Low ⟷ High



Openness of access:

Open ⟷ Locked-down

Model vs. Code Lifecycles



Model and code lifecycles often operate asynchronously

- Weekly fraud detection model
  - Model update; no code change
- Computer vision model, large language model
  - No model update; code change

→ mlflow

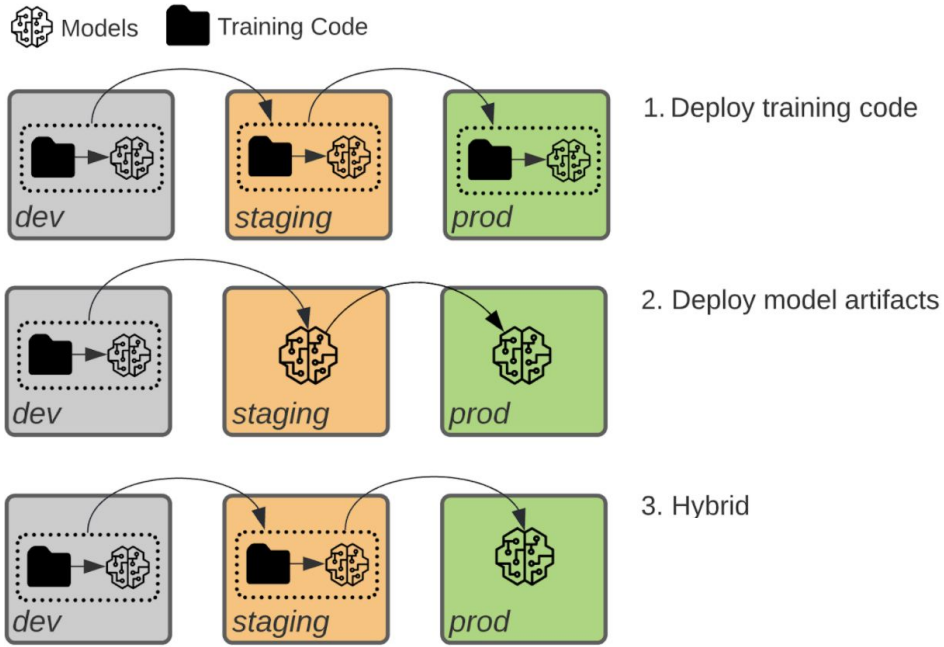
Dev vs. Staging vs. Production

Managing Assets

ASSET	SEMANTICS	SEPARATED BY
Execution environments	Labeled according to where development, testing and connections with production systems happen	Cloud provider and Databricks Workspace access controls
Models	Labeled according to model lifecycle phase	MLflow access controls or cloud storage permissions
Data	Labeled according to its origin in dev, staging or prod execution environments	Table access controls or cloud storage permissions
Code	Labeled according to software development lifecycle phase	Git repository branches

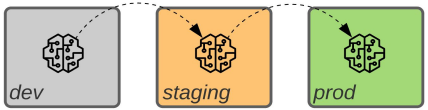
Three Model Deployment Patterns

More information on The Big Book of MLOps published by Databricks



What Moves Towards Production?

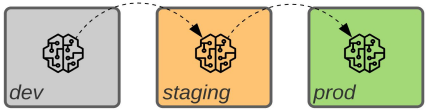
Pattern 1: Deploy models

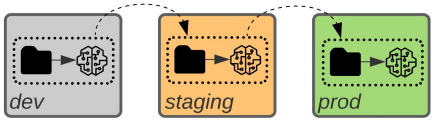


	Deploy models
Process	1. Models are trained in dev and promoted to staging 2. Models are tested in staging 3. Models are promoted to prod
Trade-offs	↑ Simplicity ↑ DS familiarity ↑ Computational cost ↓ Automation ↓ Scalability ↓ Reproducibility

What Moves Towards Production?

Pattern 1: Deploy code

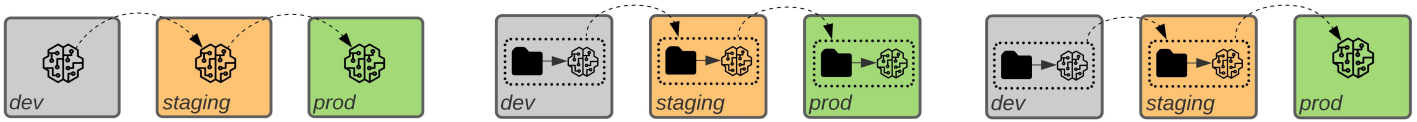




	Deploy models	Deploy code
Process	1. Models are trained in dev and promoted to staging 2. Models are tested in staging 3. Models are promoted to prod	1. Code is promoted from dev to staging 2. Models are retrained and tested in staging 3. Code is promoted to prod 4. Models are retrained in prod
Trade-offs	↑ Simplicity ↑ DS familiarity ↑ Computational cost ↓ Automation ↓ Scalability ↓ Reproducibility	↑ Scalability ↑ Automation ↑ Reproducibility ↑ ML Eng familiarity ↓ Simplicity ↓ DS familiarity ↓ Computational cost

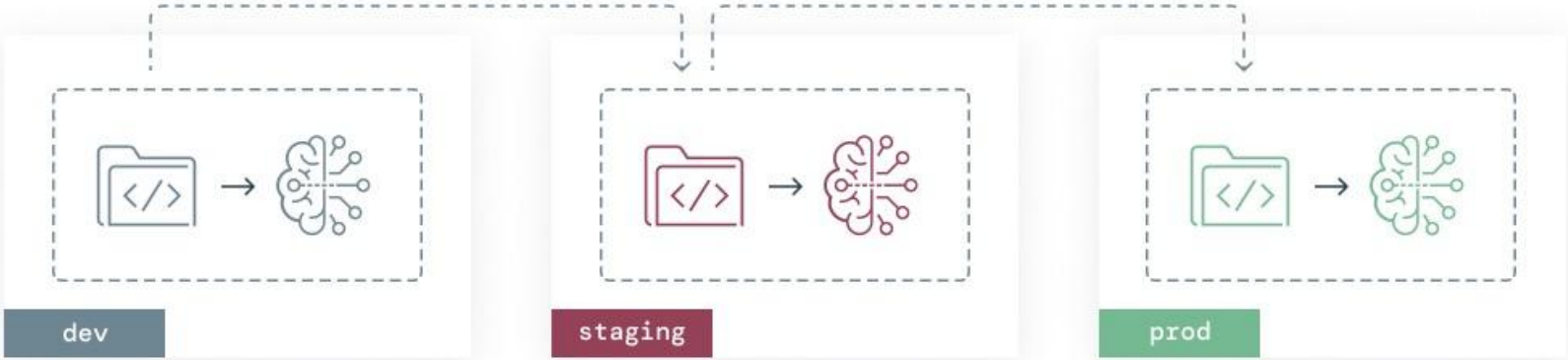
What Moves Towards Production?

Pattern 1: Hybrid



	Deploy models	Deploy code	Hybrid
Process	1. Models are trained in dev and promoted to staging 2. Models are tested in staging 3. Models are promoted to prod	1. Code is promoted from dev to staging 2. Models are retrained and tested in staging 3. Code is promoted to prod 4. Models are retrained in prod	1. Code is promoted from dev to staging 2. Models are retrained and tested in staging 3. Models are promoted to prod
Trade-offs	↑ Simplicity ↑ DS familiarity ↑ Computational cost ↓ Automation ↓ Scalability ↓ Reproducibility	↑ Scalability ↑ Automation ↑ Reproducibility ↑ ML Eng familiarity ↓ Simplicity ↓ DS familiarity ↓ Computational cost	↑ Scalability ↑ Automation ↑ Reproducibility ↑ ML Eng familiarity ↑ Computational cost ↓ Simplicity ↓ DS familiarity

Recommended Deploy Code Pattern



Develop training code

Develop ancillary code

→ Promote code

✔ Test model training code on subset of data

✔ Test ancillary code

→ Promote code

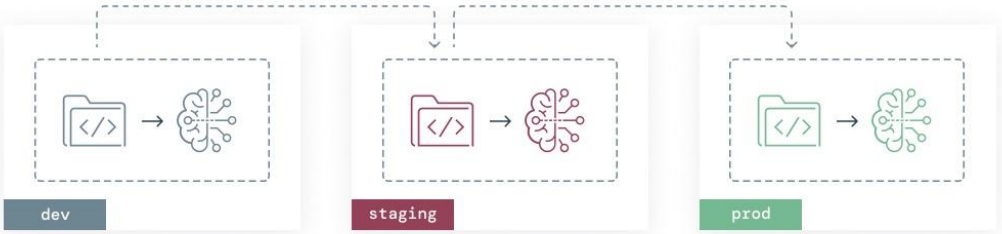
✔ Train model on production data

✔ Test model

→ Deploy model

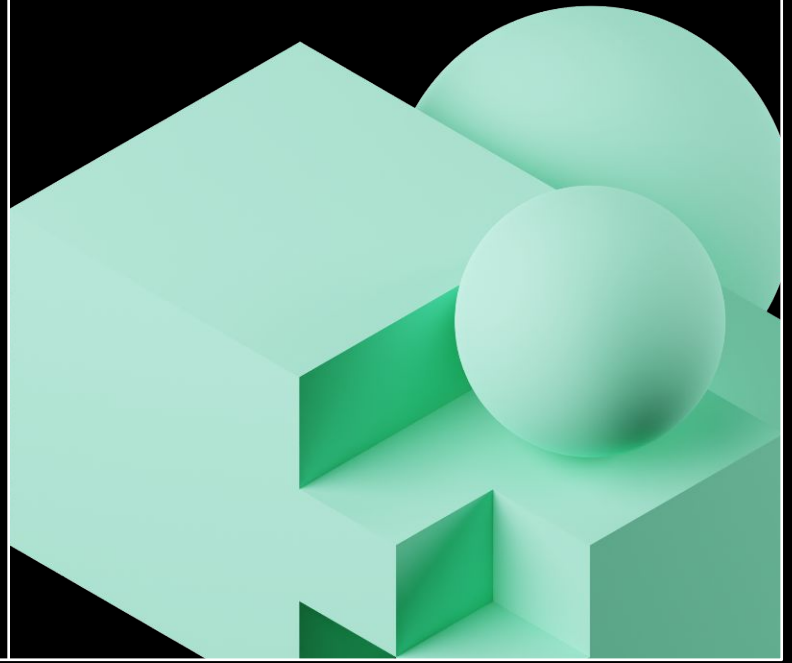
→ Deploy ancillary code

Deeper Dive into Benefits of “Deploy Code”



Automation	↑ Supports automated retraining in locked-down env.
Data access control	↑ Only prod env needs read access to prod training data.
Reproducible models	↑ Eng control over training env, which helps to simplify reproducibility.
Support for large projects	↑ This pattern forces the DS team to use modular code and iterative testing, which helps with coordination and development in larger projects.
Data science familiarity	↓ DS team must learn to write & hand off modular code to Eng.
Eng setup & maintenance	↓ Requires CI/CD infra for unit and integration tests, even for one-off models.

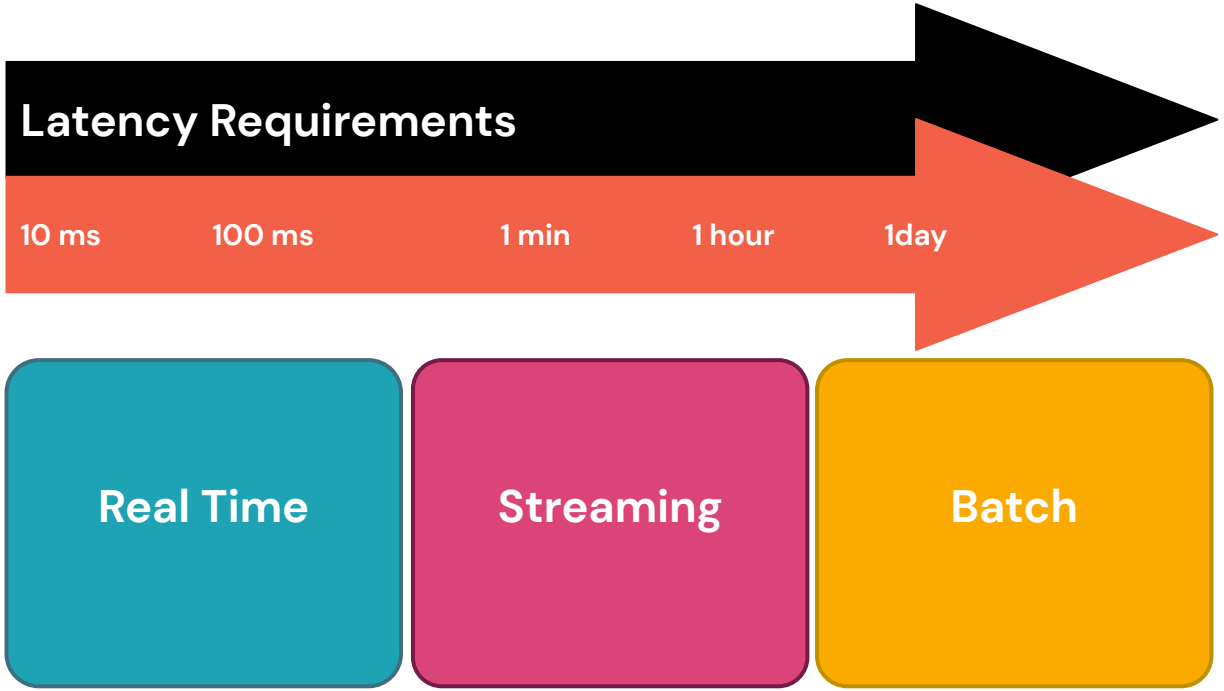
Deployment Paradigms



The Four Deployment Paradigms

1. **Batch**
   - 80-90% of deployments
   - Leverages databases and object storage
   - Fast retrieval of stored predictions
2. **Streaming (continuous)**
   - 10-15% of deployments
   - Moderately fast scoring on new data
3. **Real Time**
   - 5-10% of deployments
   - Usually using REST (Azure ML, SageMaker, containers)
4. **On-device (edge)**

Latency Requirements (roughly)



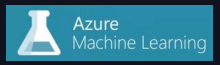
mlflow Model Deployment Options

In-Line Code

Containers

Batch & Stream Scoring

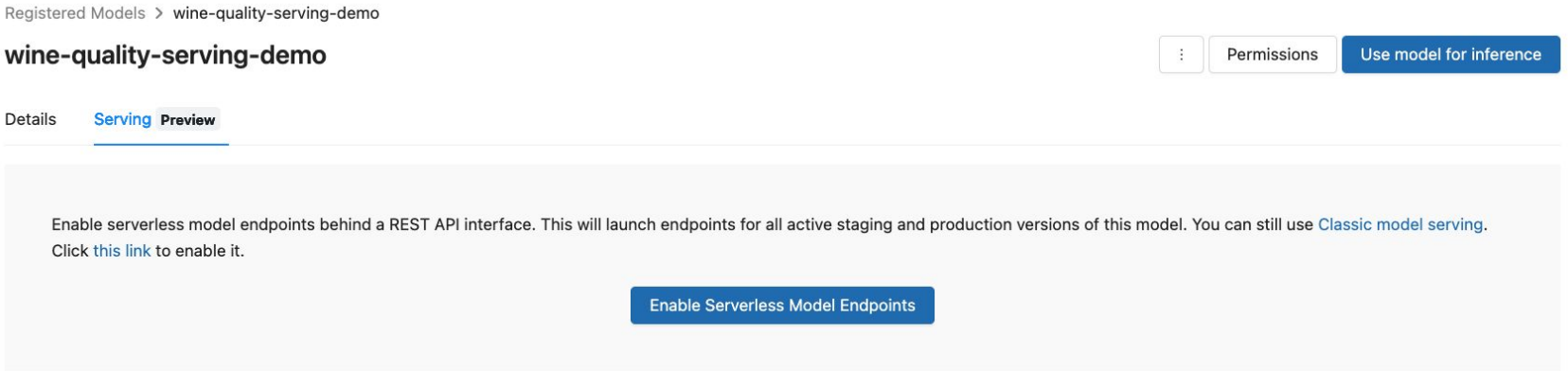
OSS Inference Solutions



Cloud Inference Services

Databricks Model Serving

Enable Model Serving with 1 Click

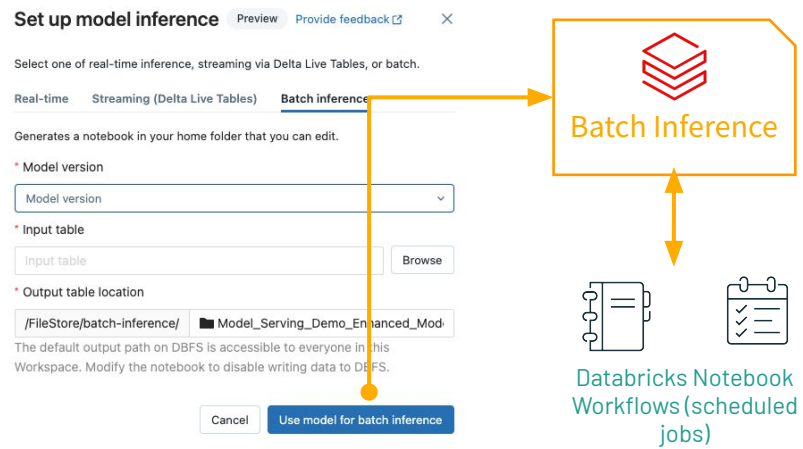


Use model for inference — One click model deployment directly from the Model Registry

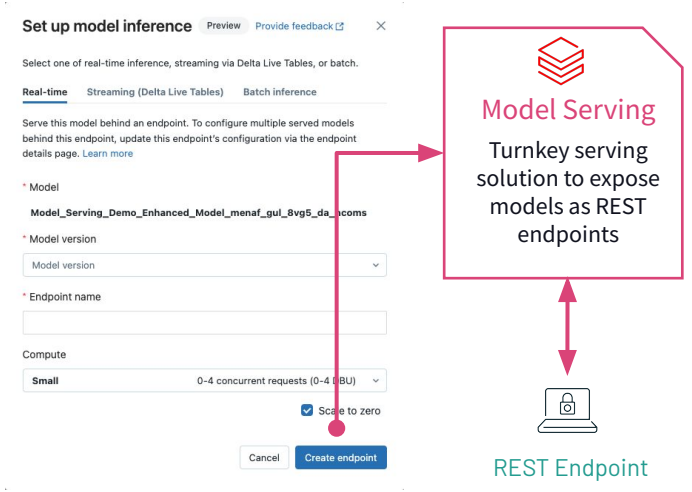
Online/Offline Model Serving with Databricks

Deploy any ML model at large scale AND low latency

Large-scale batch scoring



Low-latency online serving

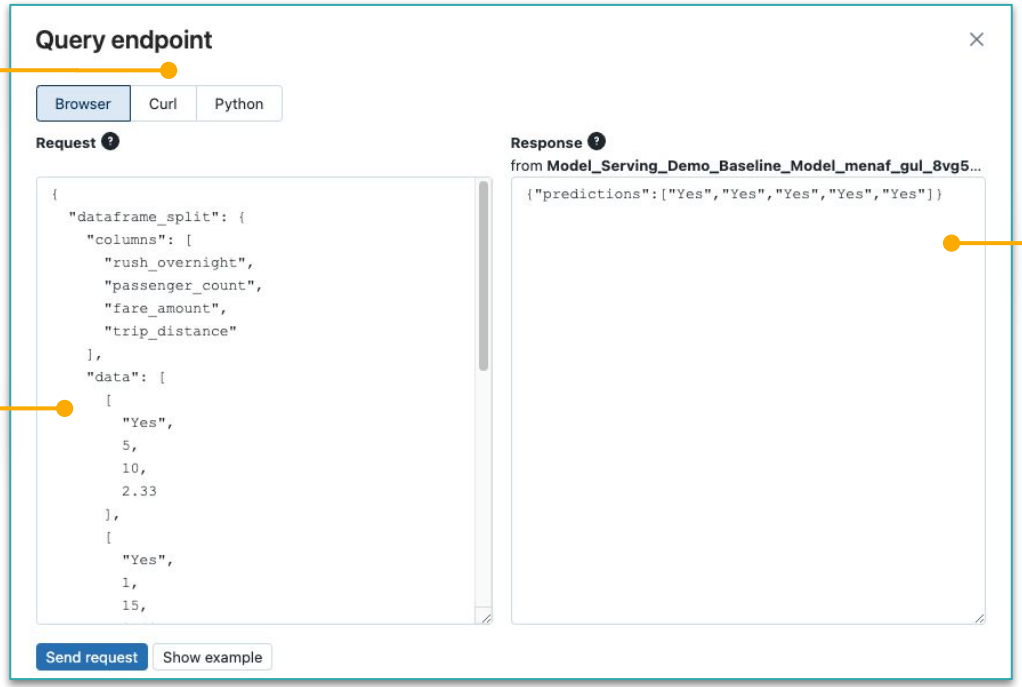


Validate Model Serving with Input Examples

In-browser testing with auto-populated example

Code snippets for CURL and Python

Sample request based on model definition



Model response

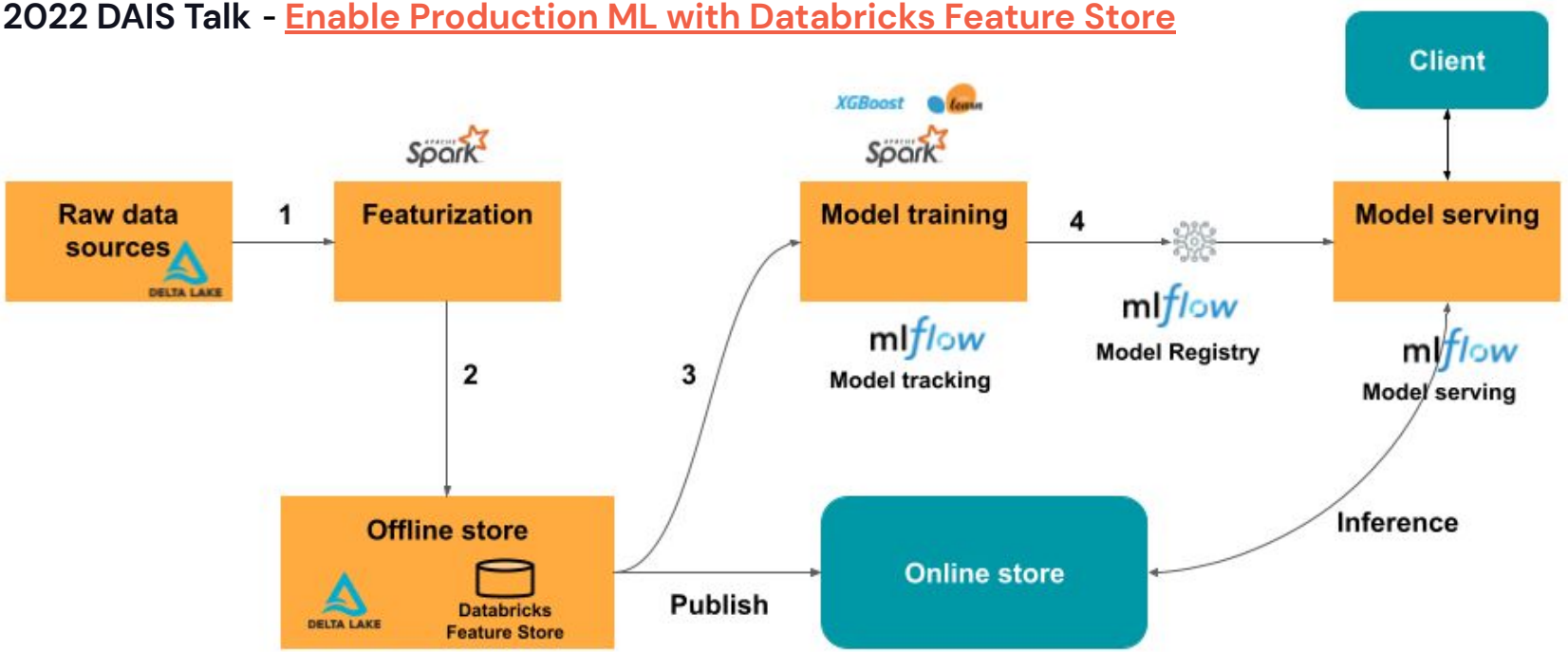
Serving Models on Databricks

Serverless Model Endpoint - Preview in AWS & Azure

- Production-grade serving
- Low latency, high availability and scalable
- HTTP endpoints accessible with Databricks authentication
- Scoring validation from the UI (same UI across clouds)
- 1-click enable serving
- Autoscaling clusters
- Endpoint latency & QPS monitoring

Serve Feature Store Models Online

2022 DAIS Talk - Enable Production ML with Databricks Feature Store



DEMO:
BATCH INFERENCE

Notebook: 03-Deployment-Paradigms → 01-Batch

DEMO:
REAL-TIME INFERENCE

Notebook: 03-Deployment-Paradigms → 02-Real-Time

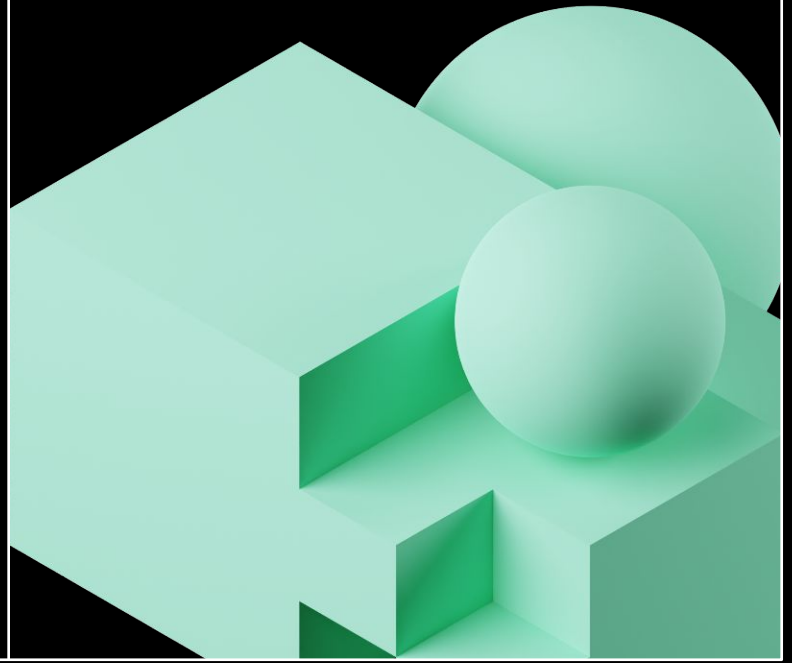
LAB:
BATCH INFERENCE

Notebook: 03-Deployment-Paradigms → Labs → 01-Batch-Lab

LAB:
REAL-TIME INFERENCE

Notebook: 03-Deployment-Paradigms → Labs → 02-Real-Time-Lab

04.
Production



Production Requirements

Core Requirements

- Model registry
- Data and model drift
- Interpretability
- Reproducibility
- Security
- Environment management

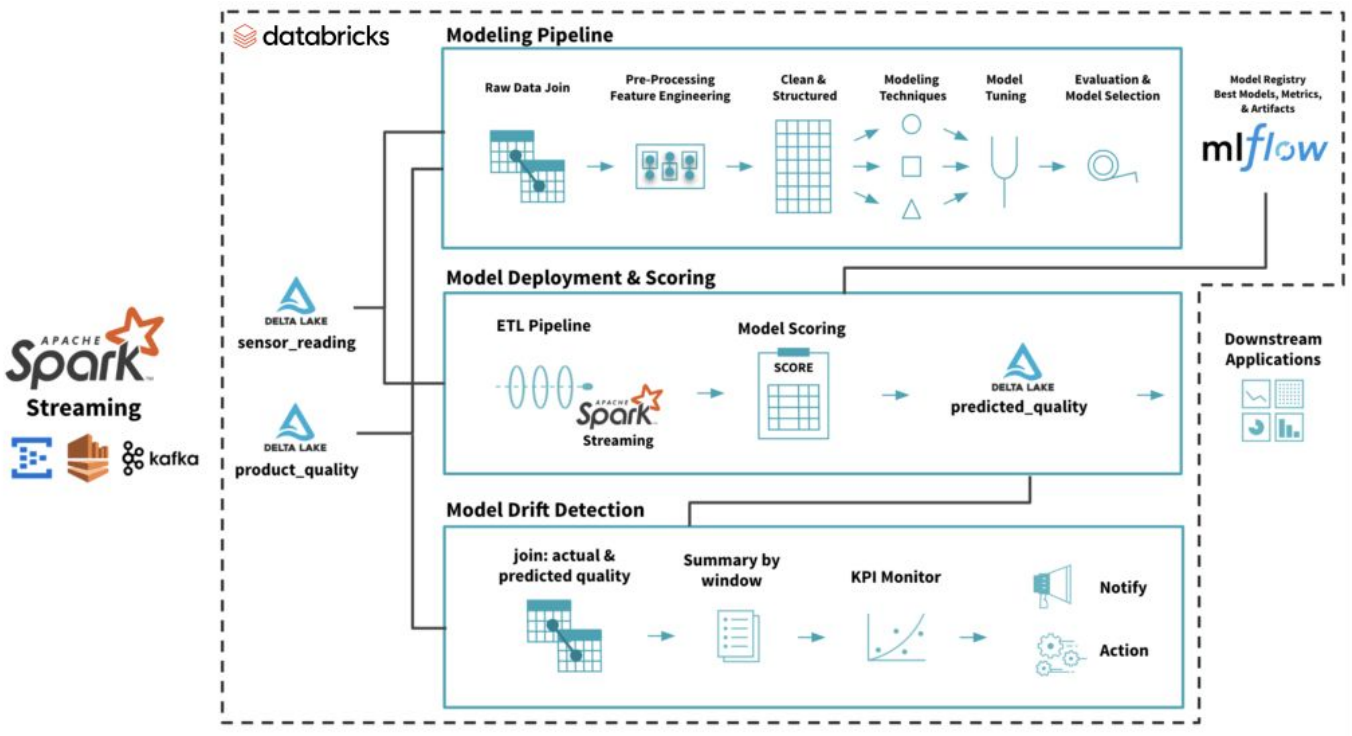
Core +

- ML pipeline with featurization logic
- CI/CD pipeline for automation
- Monitoring and alerting
- Testing framework
- Version control

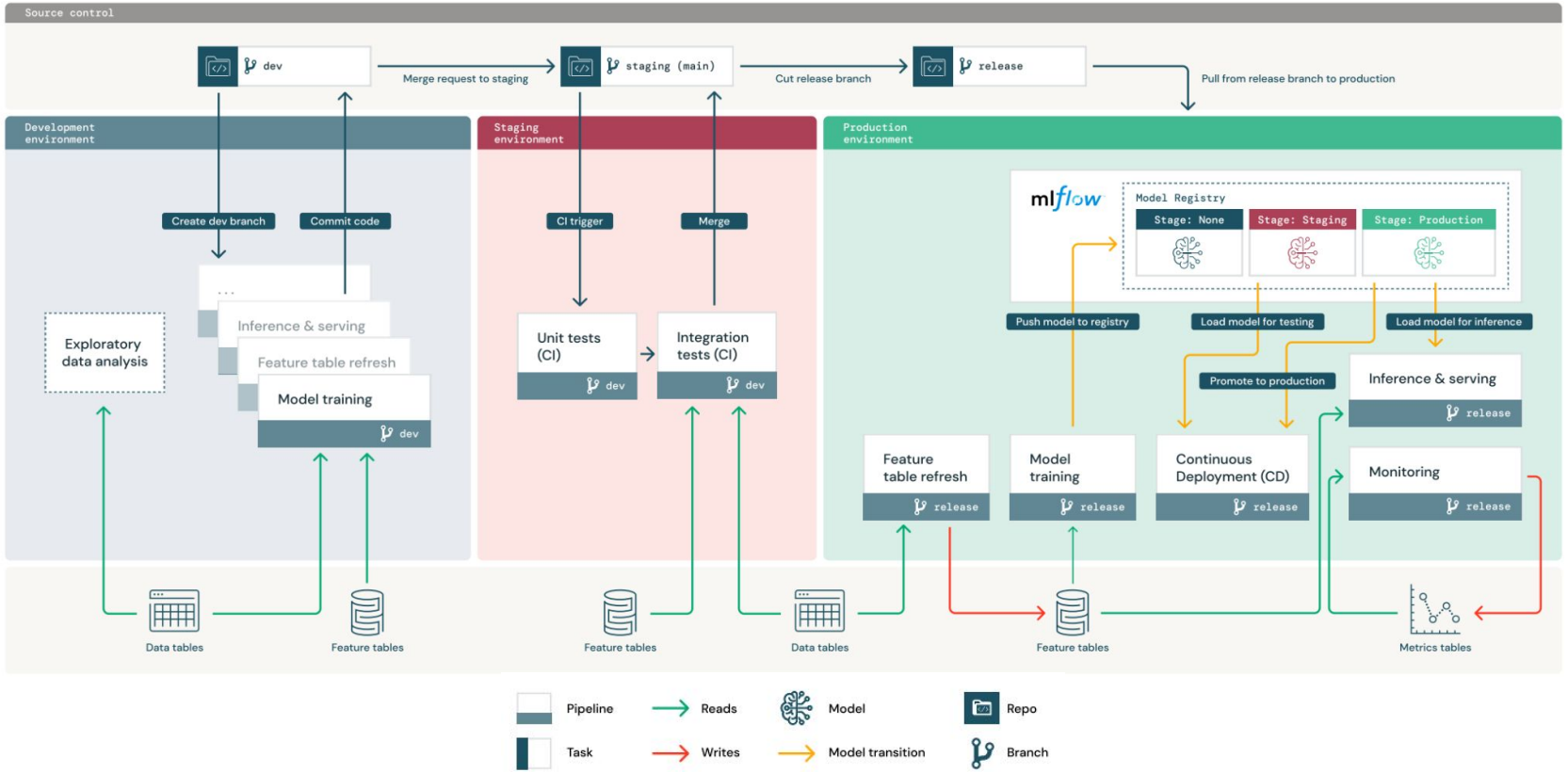
Specialized

- Feature dictionary
- Cost management
- A/B testing
- Performance optimization

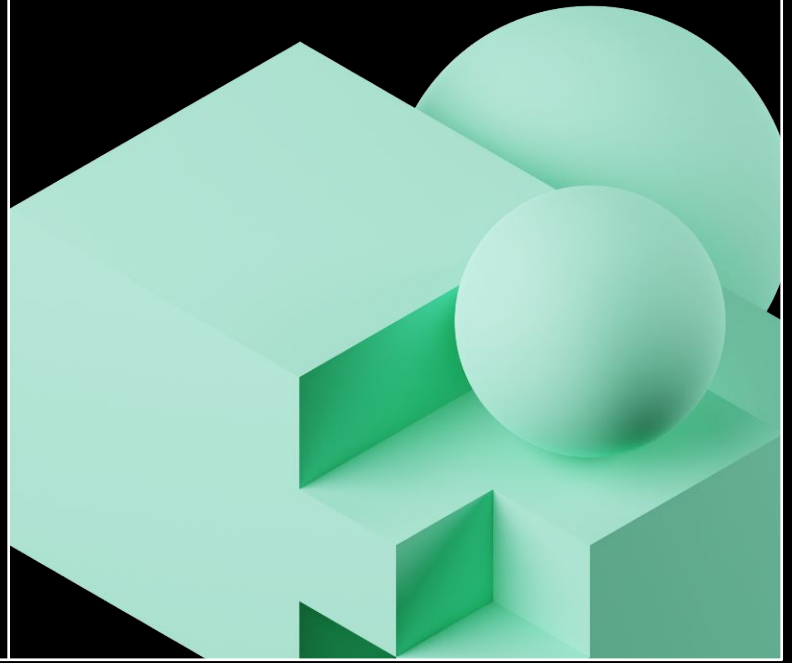
Architecture Example



Architecture Perspective

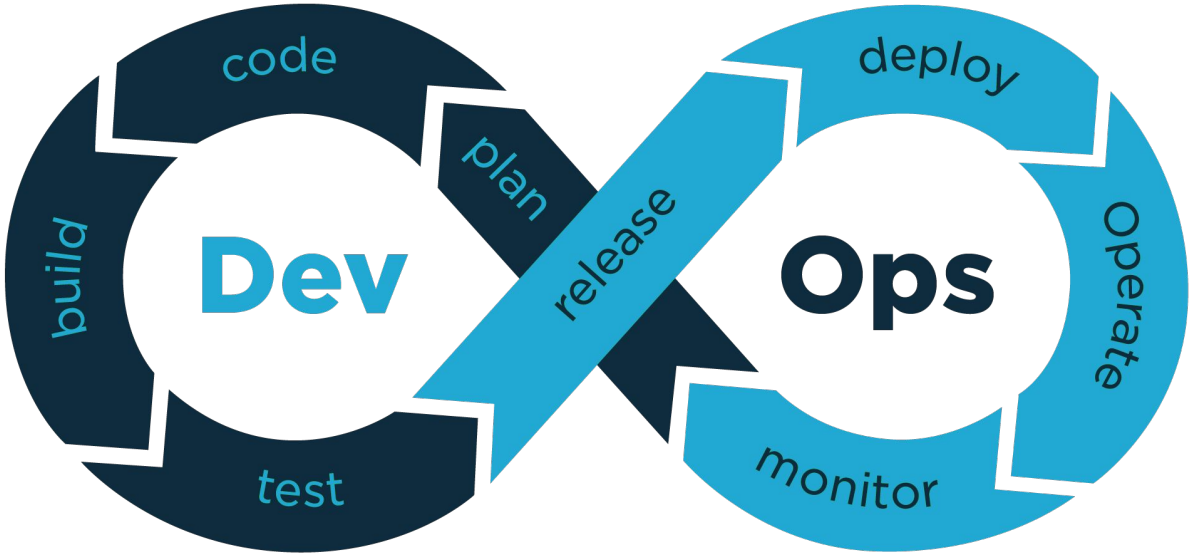


CI/CD

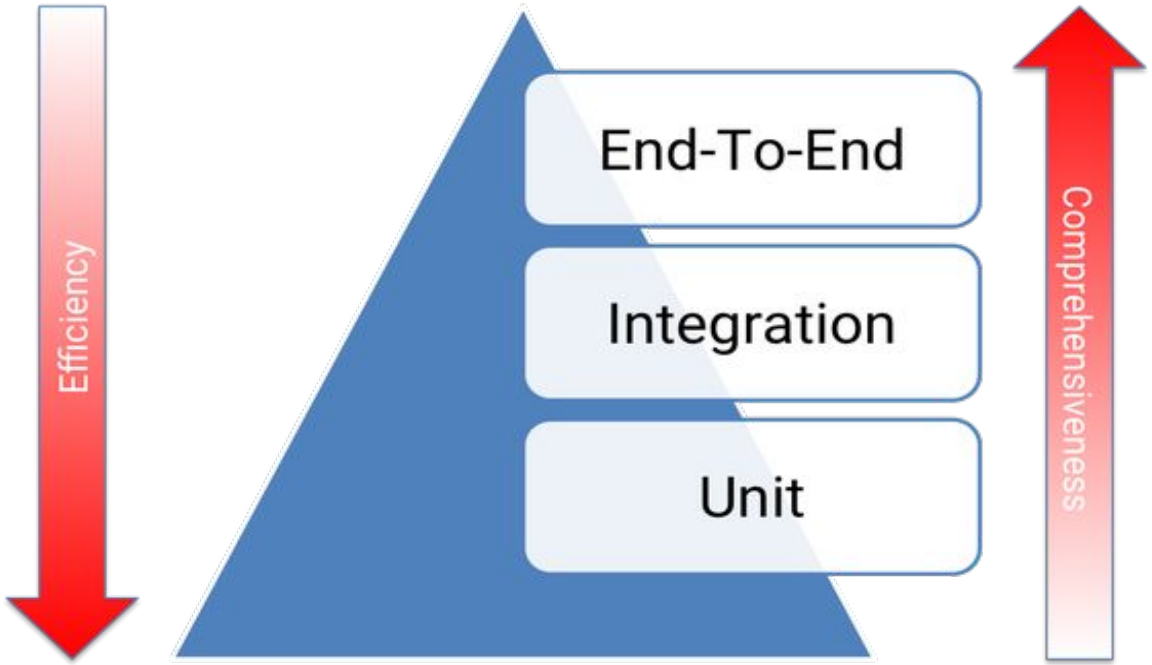


DevOps...

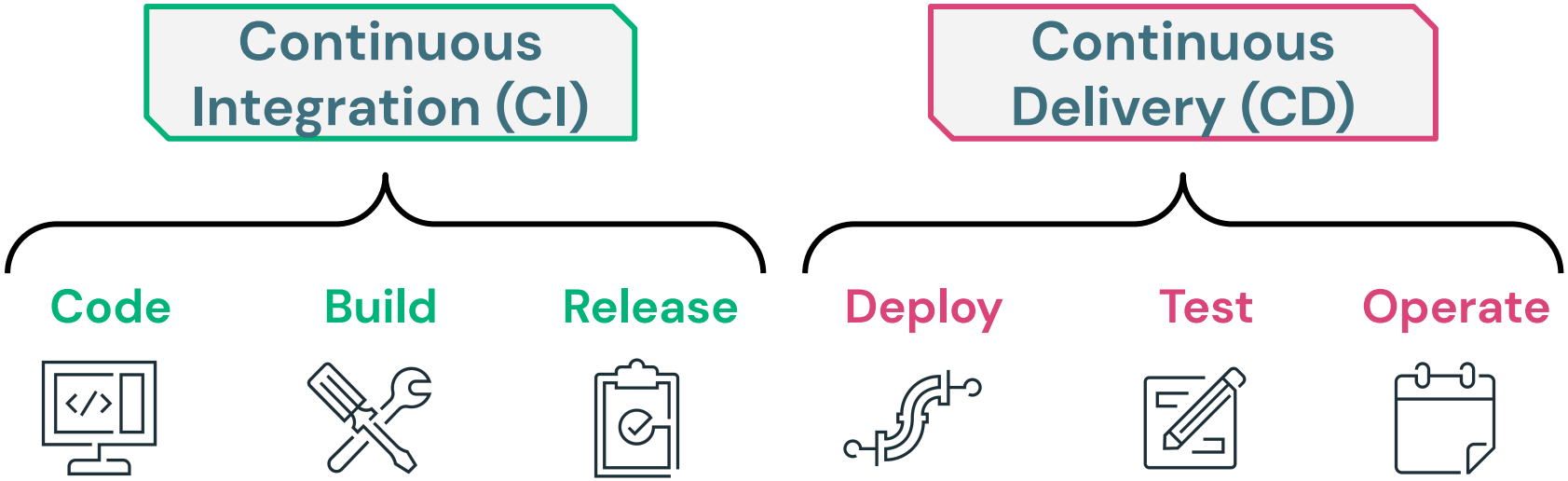
A process for continuously integrating, testing and deploying your code



The Test Pyramid



A Typical Databricks CI/CD Pipeline



Types of Pipelines

- Scheduled by a workflow manager
- Types of pipelines
  - **ETL:** heavy lifting data transformation
  - **Featurization:** Generate features for model development
  - **Training:** Produce models for deployment
  - **Scoring:** Inference pipeline post deployment
  - **Monitoring:** recurring jobs post deployment with alerts set up

Key Benefits of Continuous Integration

- Regressions are captured early by the automated tests
- Building the release is easy as all integration issues have been solved early
- Your QA team spends less time testing and can focus on significant improvements to the quality culture

Key Benefits of Continuous Delivery

- The complexity of deploying software has been taken away
- You can release more often, thus accelerating the feedback loop with your customers
- There is much less pressure on decisions for small changes, hence encouraging iterating faster

CI/CD Terminology

- **Build pipeline** - set of steps that build, test (usually only unit tests) & package code or notebooks
- **Release pipeline** - set of steps that performing deployment of the assets
- **Trigger** - event or action that initiates the execution of pipeline. It could be a commit to repository, or explicit execution of the pipeline
- **Asset / Artifact** - deliverable produced by build pipeline, or some other process (model training)
- **Environment** - typically:
  - Development - where development happens
  - Staging - for integration & E2E testing
  - Production - actual work

CI/CD Technologies

	OSS Standard	Databricks	AWS	Azure	Third Party
Orchestration	Airflow, Jenkins	Jobs, notebook workflows	CodePipeline, CodeBuild, CodeDeploy	DevOps, Data Factor	
Git Hooks		MLflow Webhooks			Github Actions, Gitlab, Travis CI
Artifact Management	PyPi, Maven	MLflow Model Registry			Nexus
Environment Management	Docker, Kubernetes, Conda, pyenv		Elastic Container Repository	Container Registry	DockerHub
Testing	pytest				Sonar
Alerting		Jobs	CloudWatch	Monitor	PagerDuty, Slack integrations

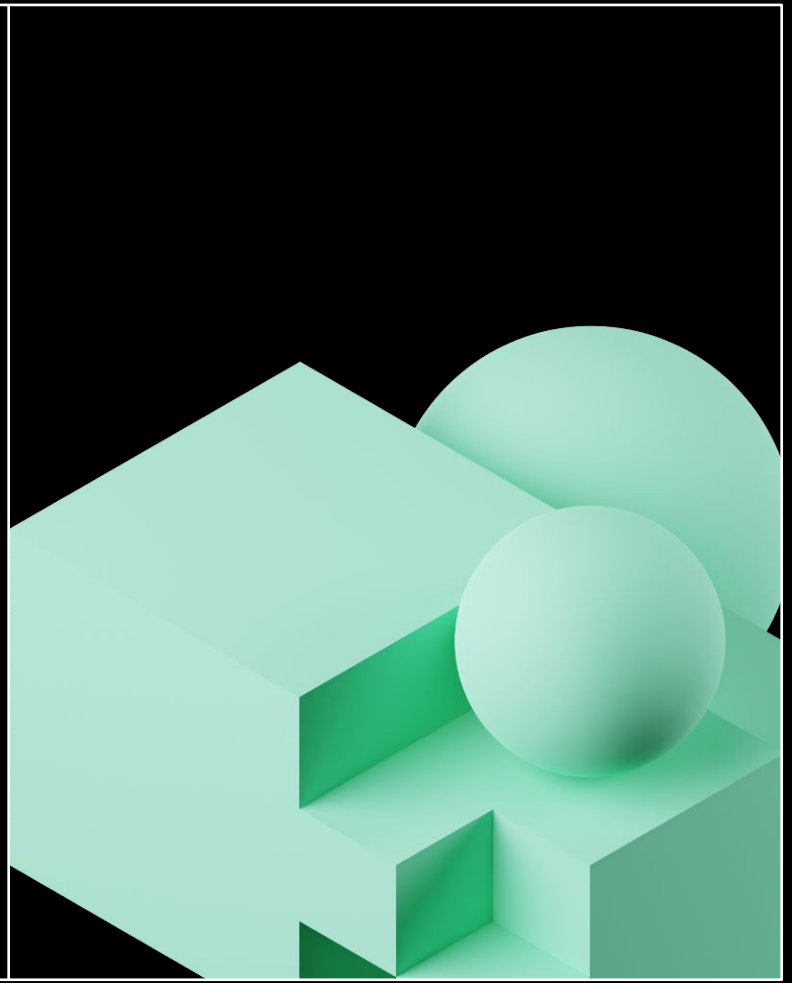
Databricks Resources

- Implementing CI/CD on Databricks Using Databricks Notebooks and Azure DevOps Part 1, Part 2 (blog)
- Continuous Integration and Delivery on Databricks using Jenkins (blog)
- Automate Continuous Integration and Continuous Delivery on Databricks using Databricks Labs CI/CD Templates (blog)

Recommended Books

- Machine Learning Engineering in Action by Ben Wilson
- Designing Data-Intensive Applications by Martin Kleppmann
- Clean Code: A Handbook of Agile Software Craftsmanship by Robert C. Martin
- Refactoring: Improving the Design of Existing Code by Martin Fowler, Kent Beck, Don Roberts
- Test-Driven Development: By Example by Kent Beck
- Code Complete, 2nd ed. by Steve McConnell
- The Pragmatic Programmer: From Journeyman to Master by Andy Hunt, Dave Thomas

Monitoring



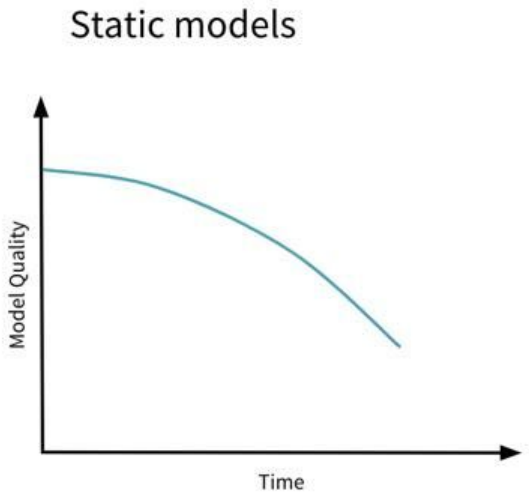
Big Data & AI Present New Challenges…

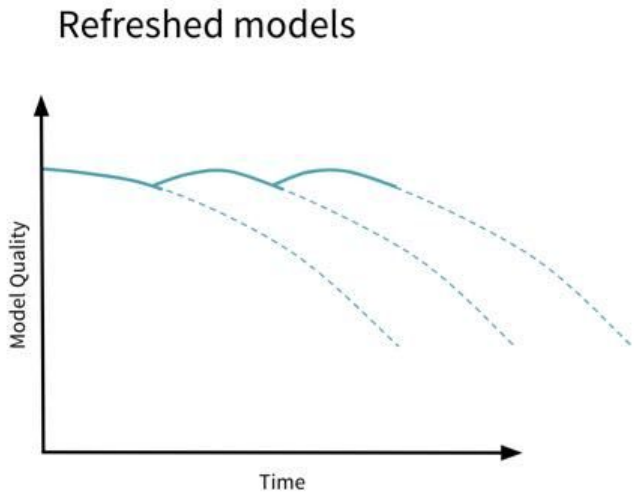
3 changeable ingredients go into training an ML model…

Ingredient	Frequency of change	Well defined process/tools for managing change?
 Code	 ~Daily?	Yes!
 Configuration	 ~Daily/Weekly?	Emerging
 Data	 ~Every second?	No!

Why Do ML Projects Fail in Production?

Neglect maintenance: Lack of re-training and testing





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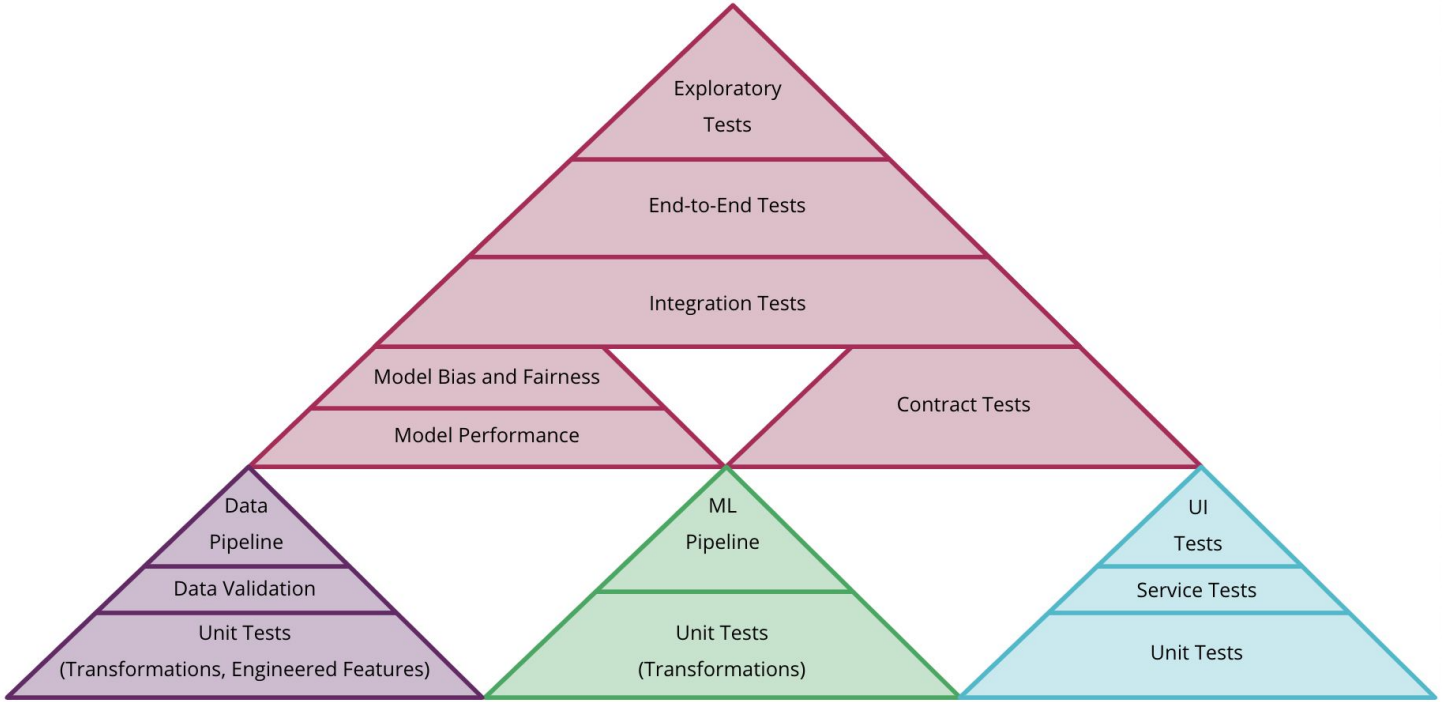
This Leads One Complicated Test Pyramid...



MLOps: Continuous …

CT and CM are unique to ML systems

- Continuous Integration (CI) extends the testing and validating code and components by adding testing and validating data and models
- Continuous Delivery (CD) concerns with delivery of an ML training pipeline that automatically deploys another the ML model prediction service.
- **Continuous Training** (CT) automatically retrains ML models for redeployment
- **Continuous Monitoring** (CM) concerns with monitoring production data and model performance metrics, which are bound to business metrics

Types of Drift

Four main reasons of model degradation

Feature Drift

Input feature(s) distributions deviate

Label Drift

Label distribution deviates

Prediction Drift

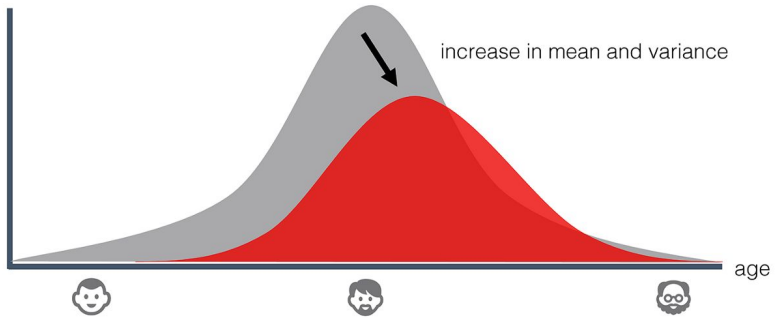
Model prediction distribution deviates

Concept Drift

External factors cause the label to evolve

Feature, Label, and Prediction Drift

Categories	Expected	Observed	Total
A	25	35	60
B	25	20	45
C	25	25	50
D	25	20	45
Total	100	100	200



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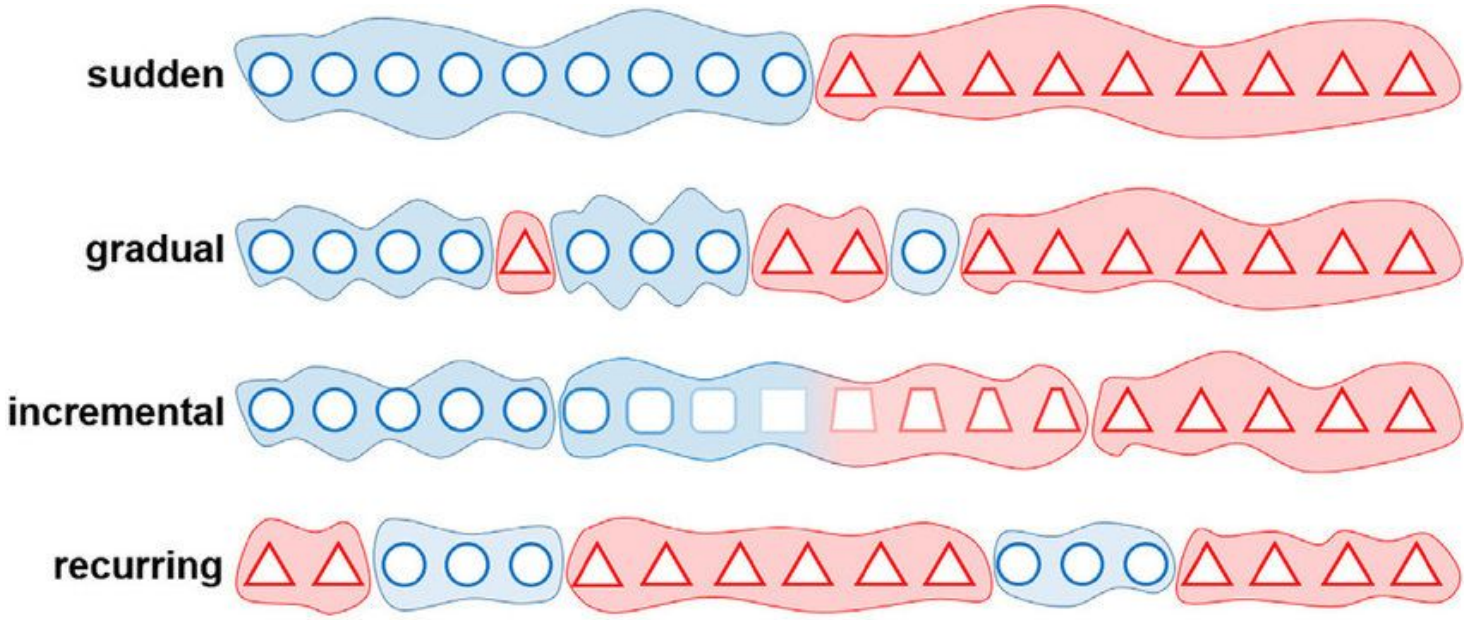
Concept Drift



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Drift Types and Actions to Take

Drift Type Identified	Action
Feature Drift	• Investigate feature generation process • Retrain using new data
Label Drift	• Investigate label generation process • Retrain using new data
Prediction Drift	• Investigate model training process • Assess business impact of change in predictions
Concept Drift	• Investigate additional feature engineering • Consider alternative approach/solution • Retrain/tune using new data

What to Monitor?

Software Metrics

- Memory
- Compute
- Latency
- Throughput
- Server load

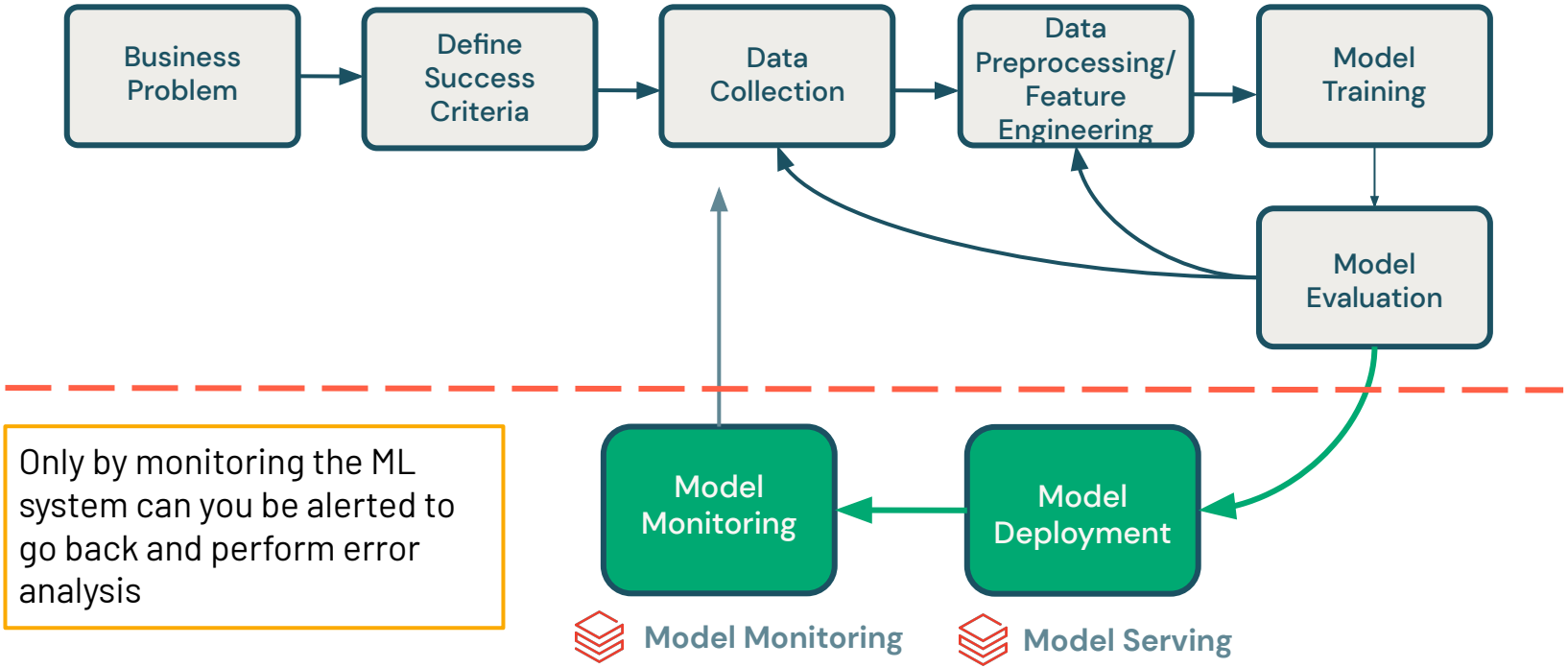
Input Metrics

- Feature summary stats
  - Mean/Median/Min/Max
  - Num missing vals
- Statistical tests
  - KS test/Mann Whitney
  - Jensen Shannon Distance
  - Levene

Output Metrics

- Prediction summary stats
  - Mean/Med/Min/Max
- Business metrics

How to Action Monitoring Metrics



Only by monitoring the ML system can you be alerted to go back and perform error analysis

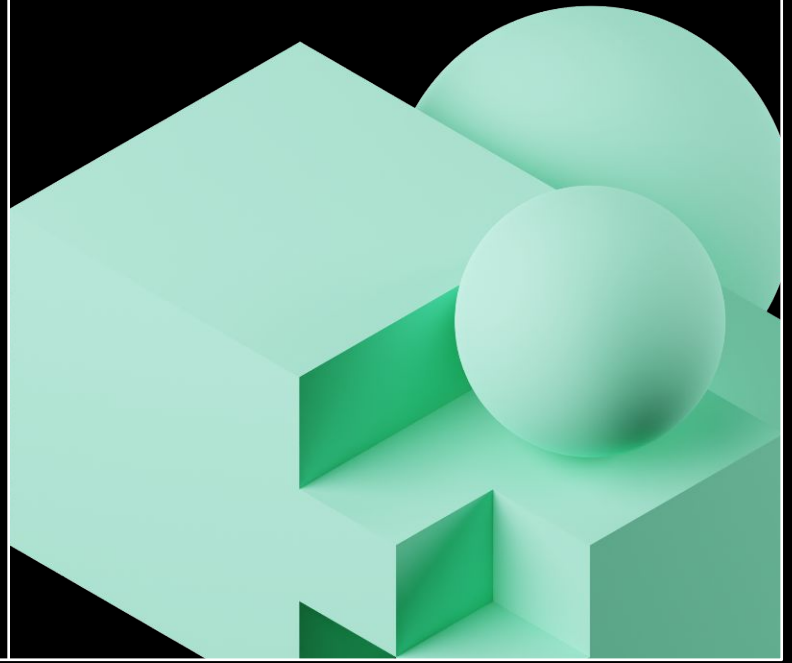
DEMO:
MODEL MONITORING

Notebook: 04-Production → 01-Monitoring

LAB:
MODEL MONITORING

Notebook: 04-Production → Labs → 01-Monitoring-Lab

Model Rollout Strategies



Model Rollout Strategies

- **Shadow**
  - New deployment shows existing system but not used for decision making
- Rolling
- Blue-Green
- Canary
- A/B Testing

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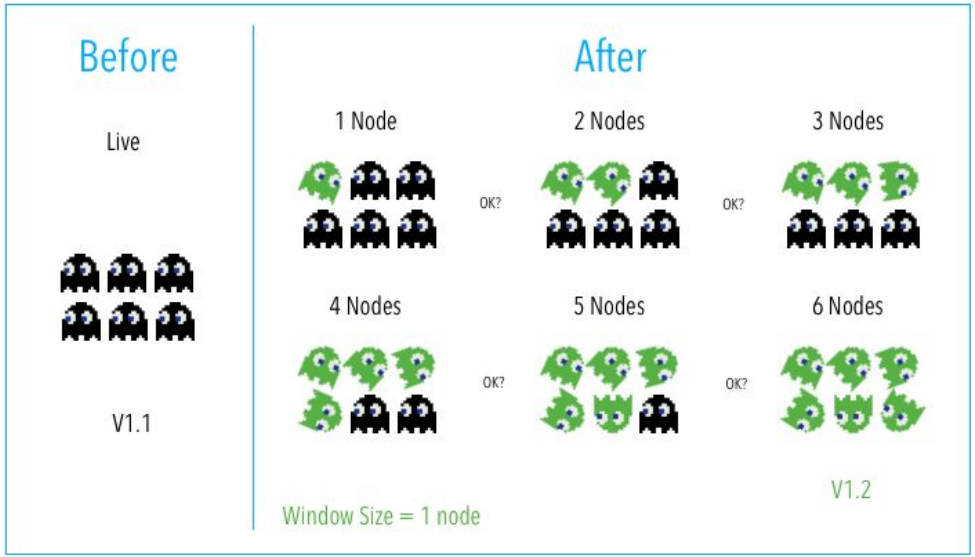
Model Rollout Strategies

- Shadow
- **Rolling**
  - Updates nodes in a target environment incrementally in batches with the new service version.
- Blue-Green
- Canary
- A/B Testing



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Model Rollout Strategies

- Shadow
- Rolling
- **Blue-Green**
  - Utilizes two identical environments, a “blue” and a “green” environment with different versions of an application or service
- Canary
- A/B Testing

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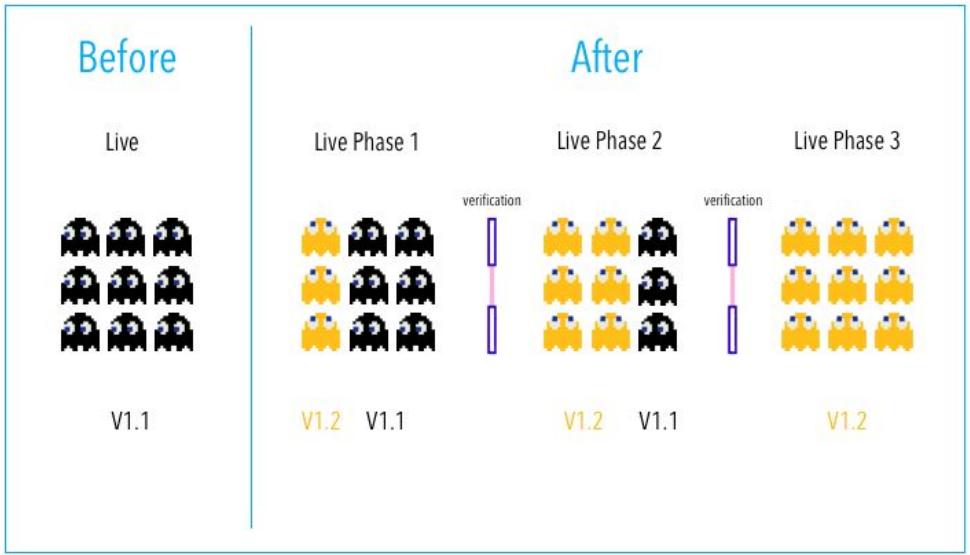
Model Rollout Strategies

- Shadow
- Rolling
- Blue-Green
- **Canary**
  - Releases an application or service incrementally to a subset of users
- A/B Testing



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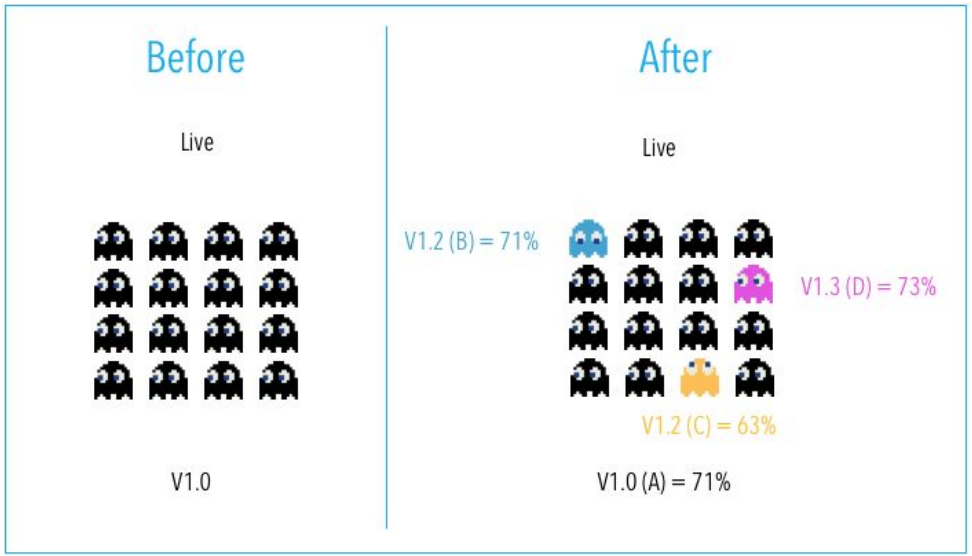
Model Rollout Strategies

- Shadow
- Rolling
- Blue-Green
- Canary
- **A/B Testing**
  - Different versions of the same service run simultaneously in the same environment for a period of time.



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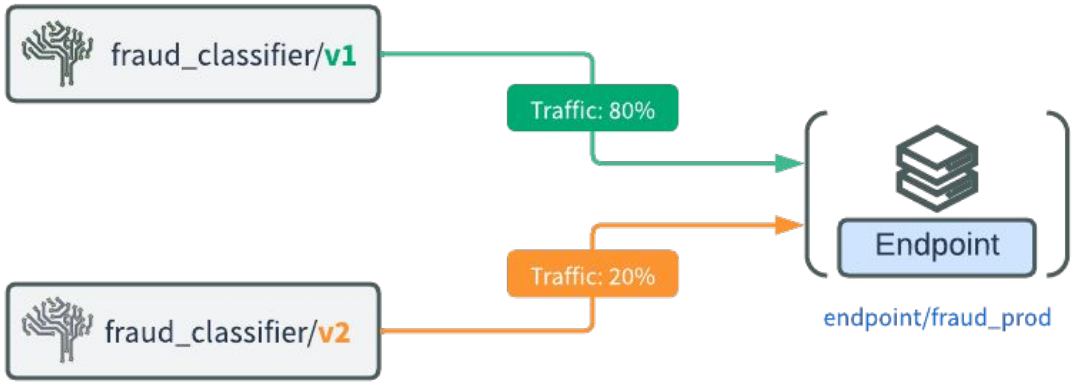
A/B Testing Framework

A/B testing is essentially an experiment where two or more variants of a deployment are shown to users at random, and statistical analysis is used to determine which variation performs better for a given conversion goal.

- Collect data
- Identify goals
- Generate hypothesis
- Create variations
- Run experiment
- Analyze results

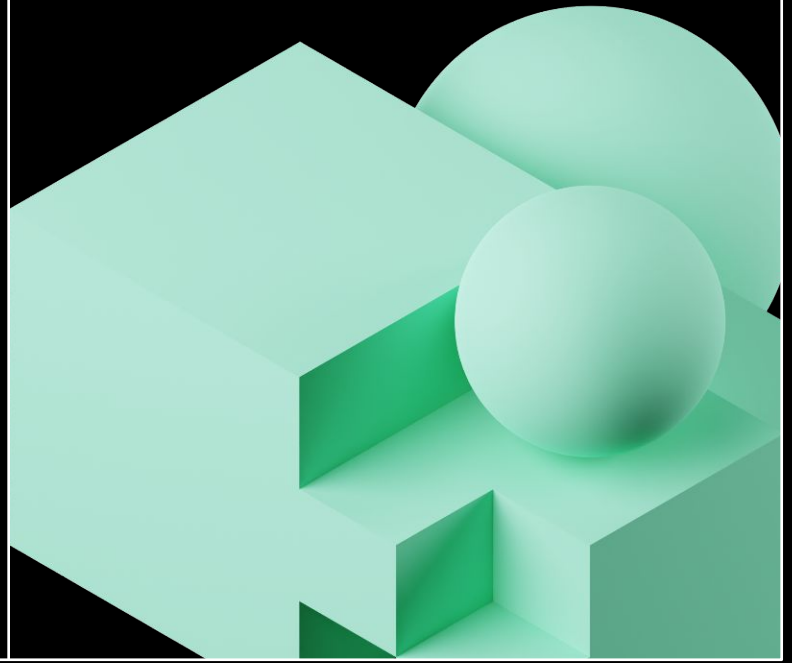


A/B Testing Metrics

Project	ML metric	Business Metric
Fraud Detection	Area Under PR, Area Under ROC, f1	Fraud Loss $, # Fraud Investigations
Churn Prediction	Area Under PR, Area Under ROC, f1	Recency of purchases Login events for high churn risk
Sales Forecasting	AIC, BIC, RMSE, et al.	Revenue
Sentiment Analysis	bleurt, bertscore	Number of users of tool, engagement rate
Ice Cream Coupons	MAE, MSE, RMSE	Revenue, Coupon usage

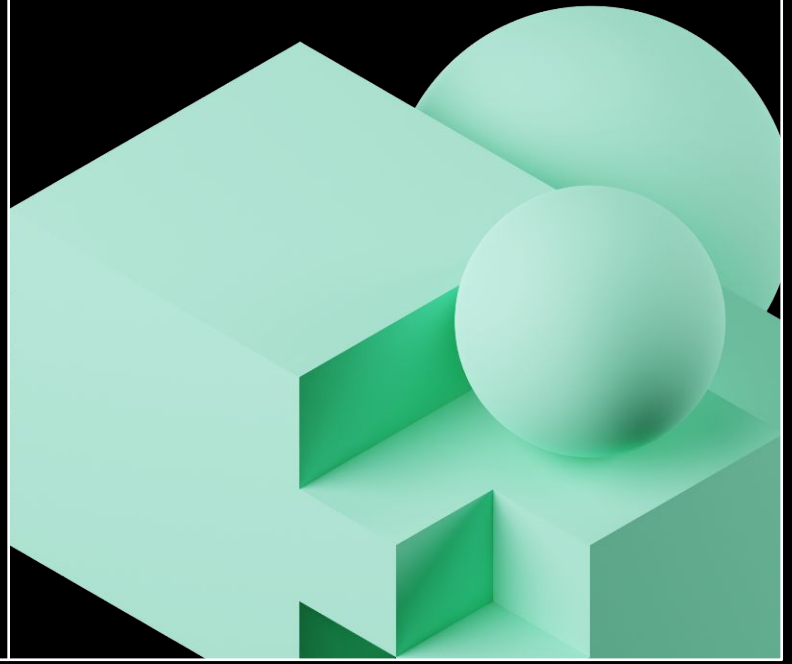
Source

Questions?



Summary and Next Steps

DAWD 00-1



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THANK YOU!