Machine Learning in Production

Agenda

00. Course Introduction & workspace set up

01. Experimentation

02. Model Management

03. Deployment Paradigms

04. Production

05. Pipeline Example

Introductions

- Name/Role
- Experience with:
  - MLflow?
  - Deploy/productionize models?
- Expectations?

00 Course Introduction

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

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

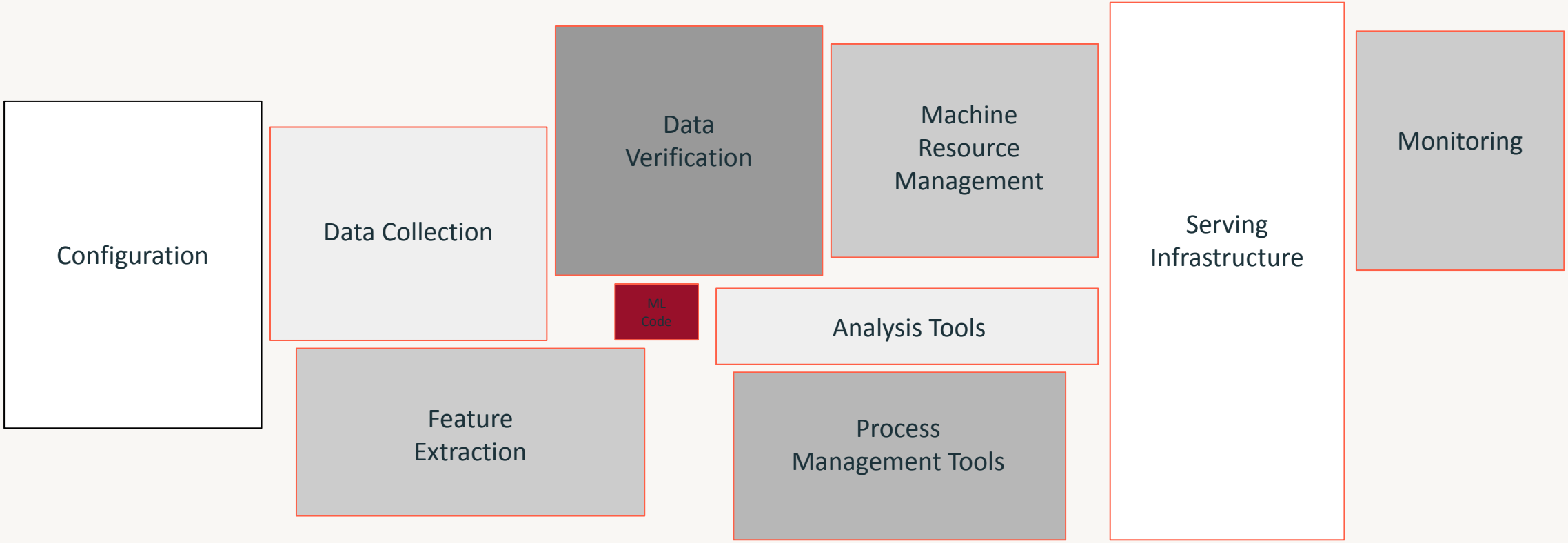
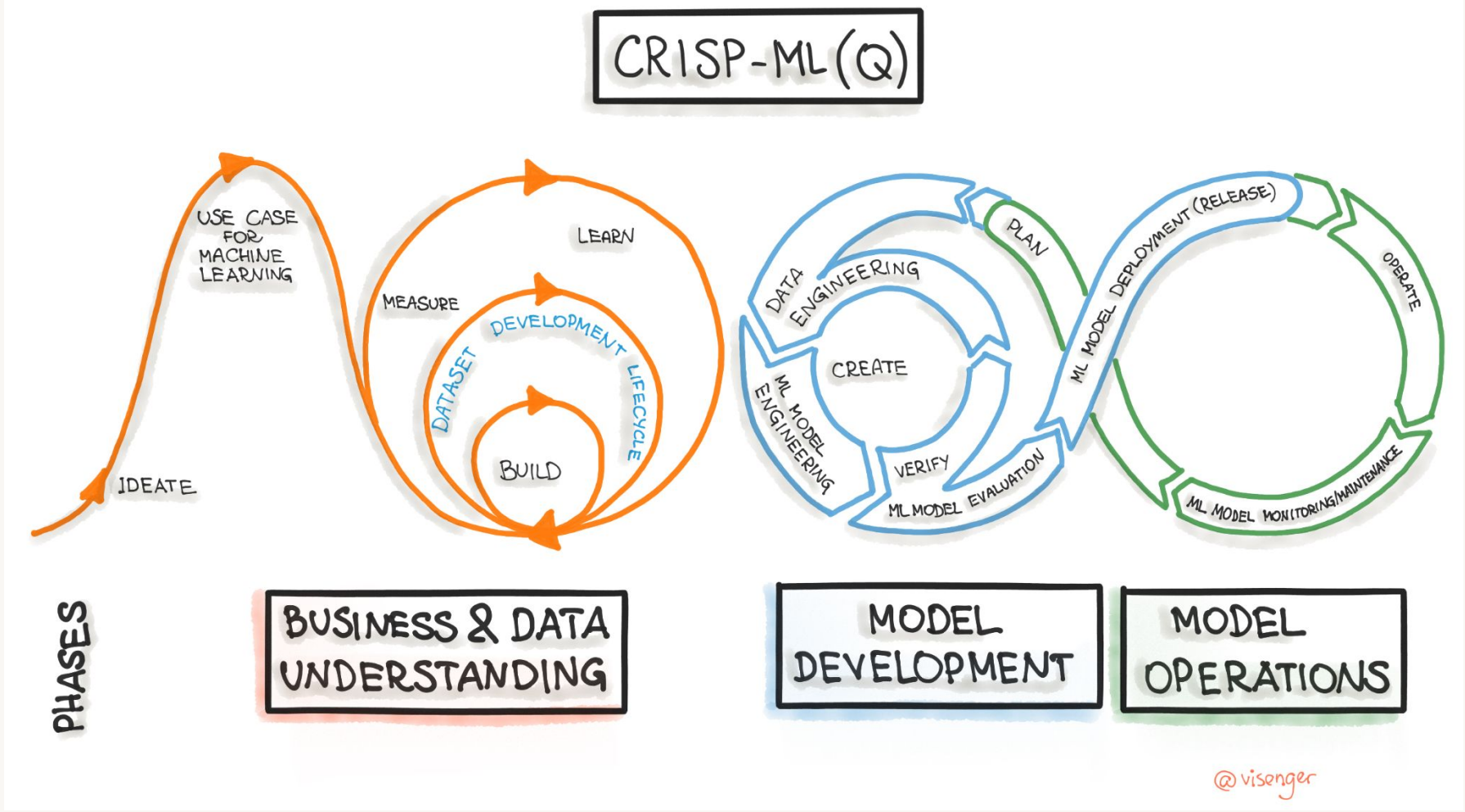


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small green box in the middle. The required surrounding infrastructure is vast and complex.

MLops Lifecycle



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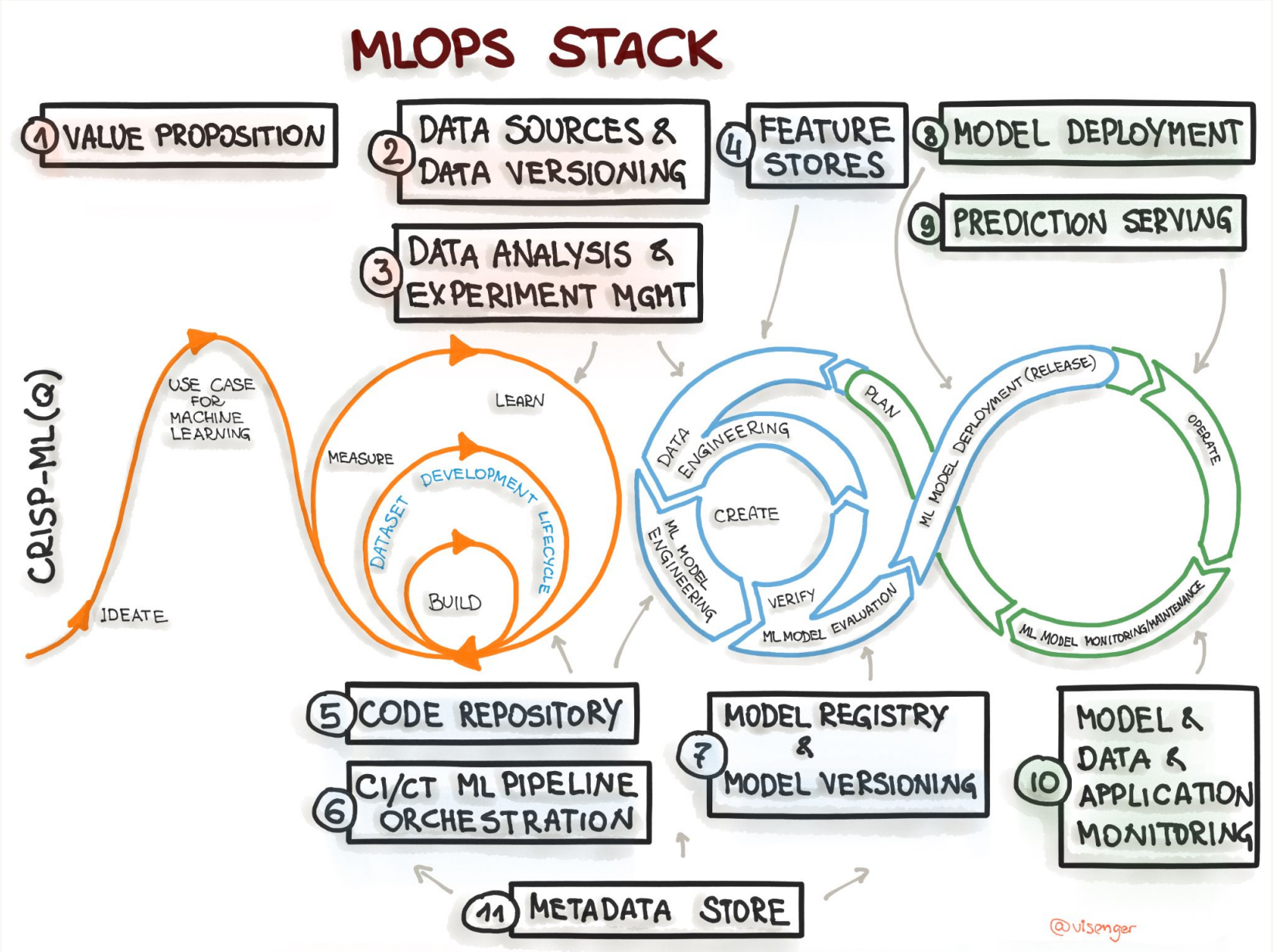

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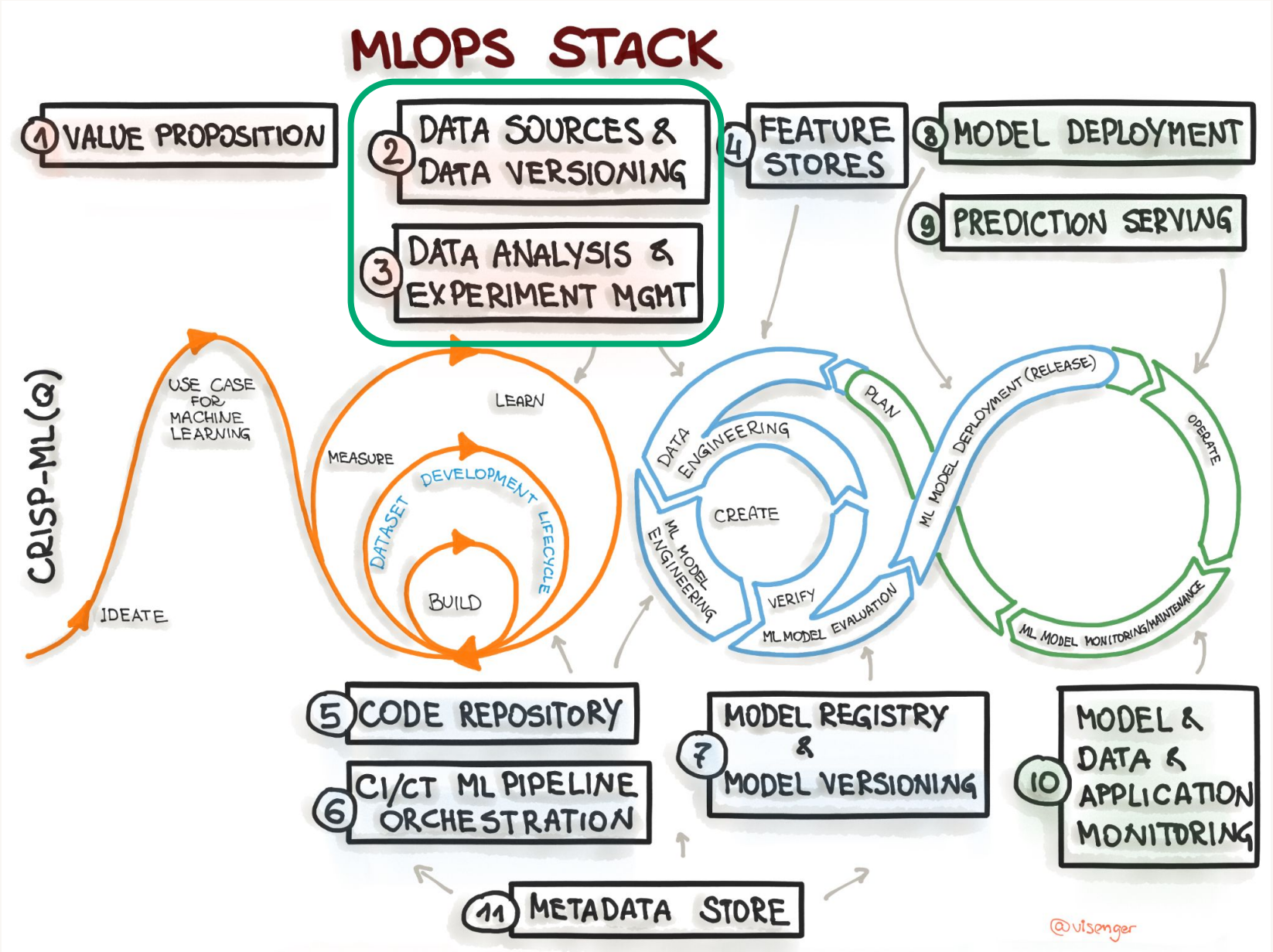

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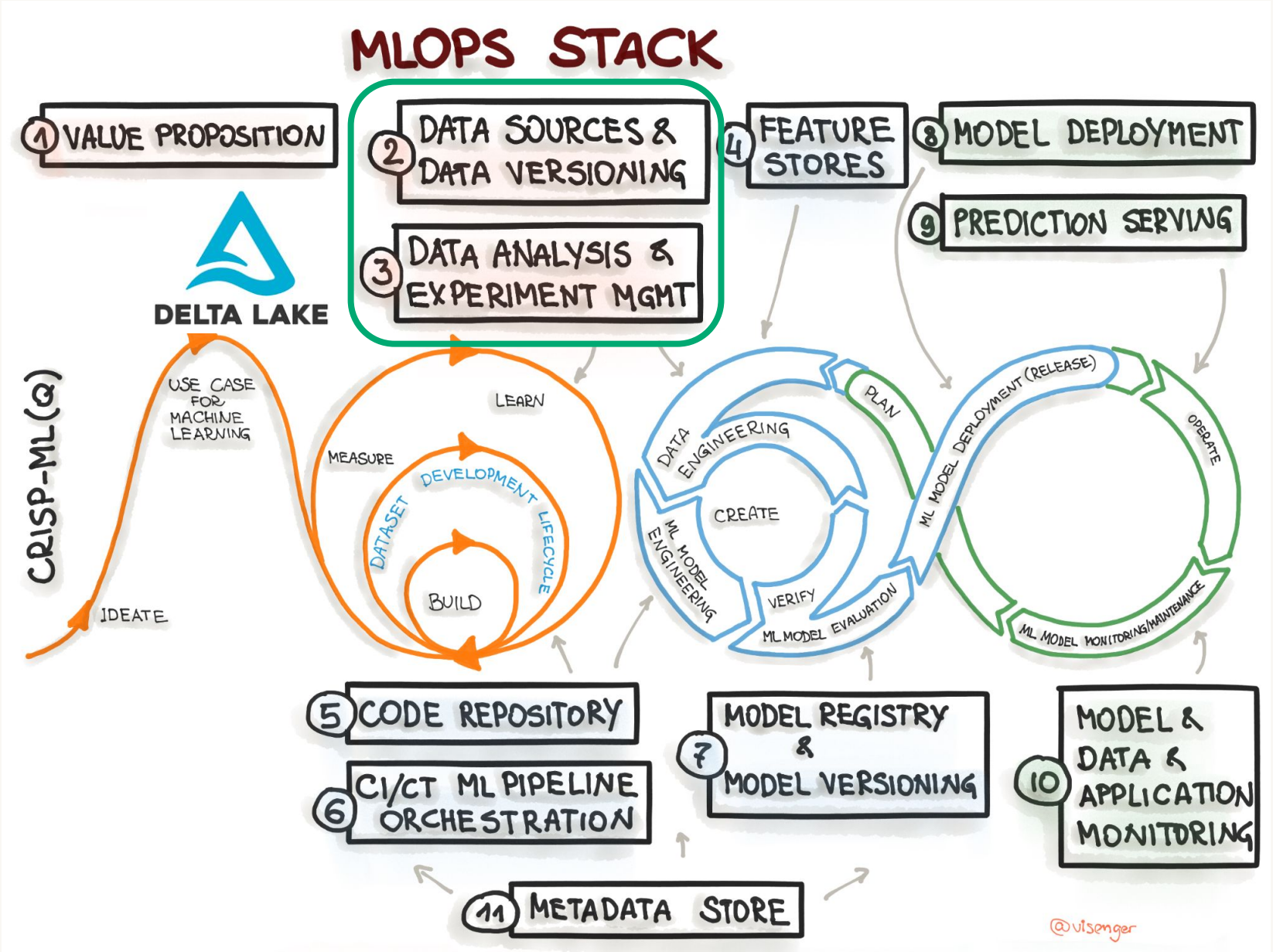

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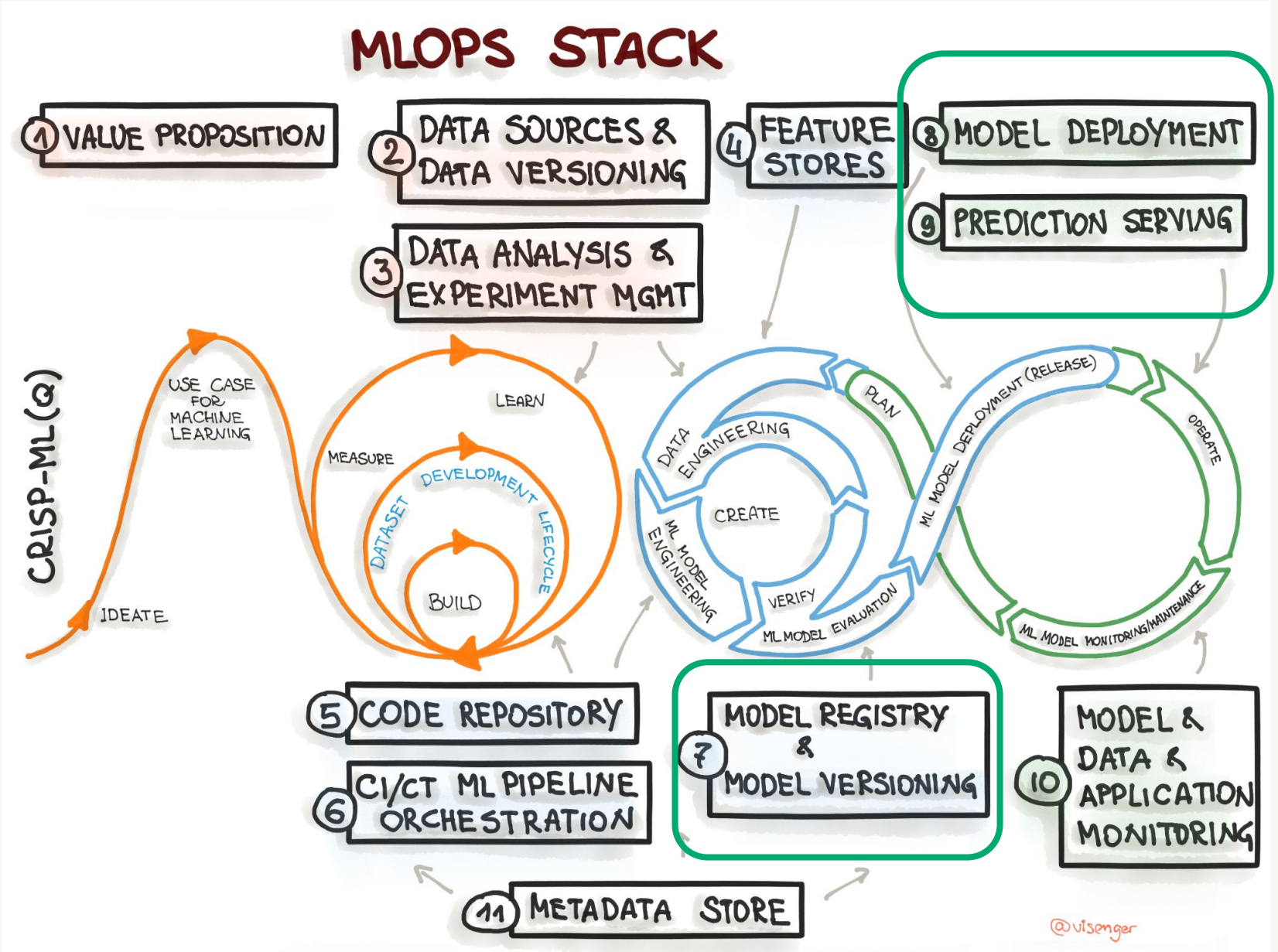

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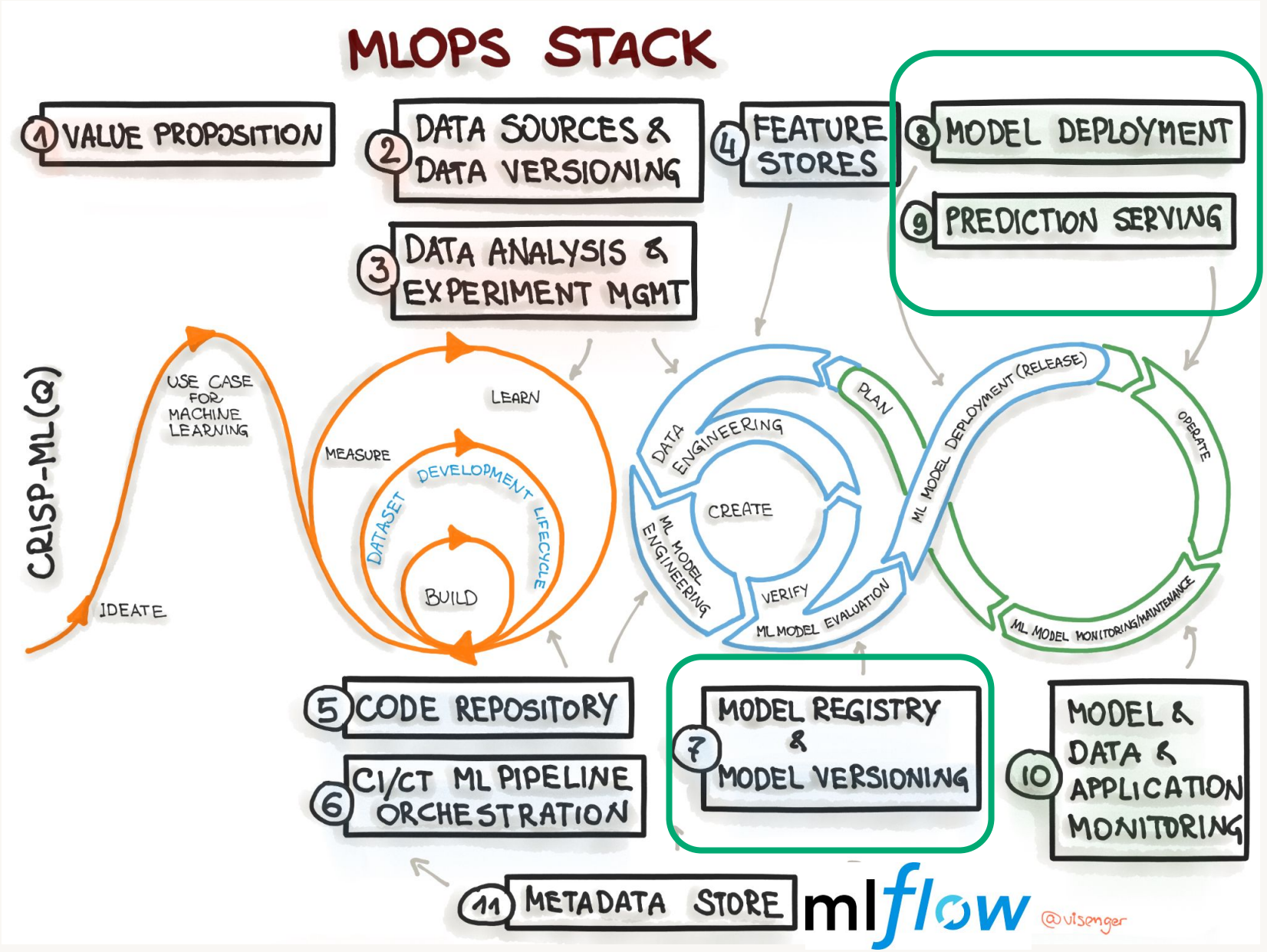

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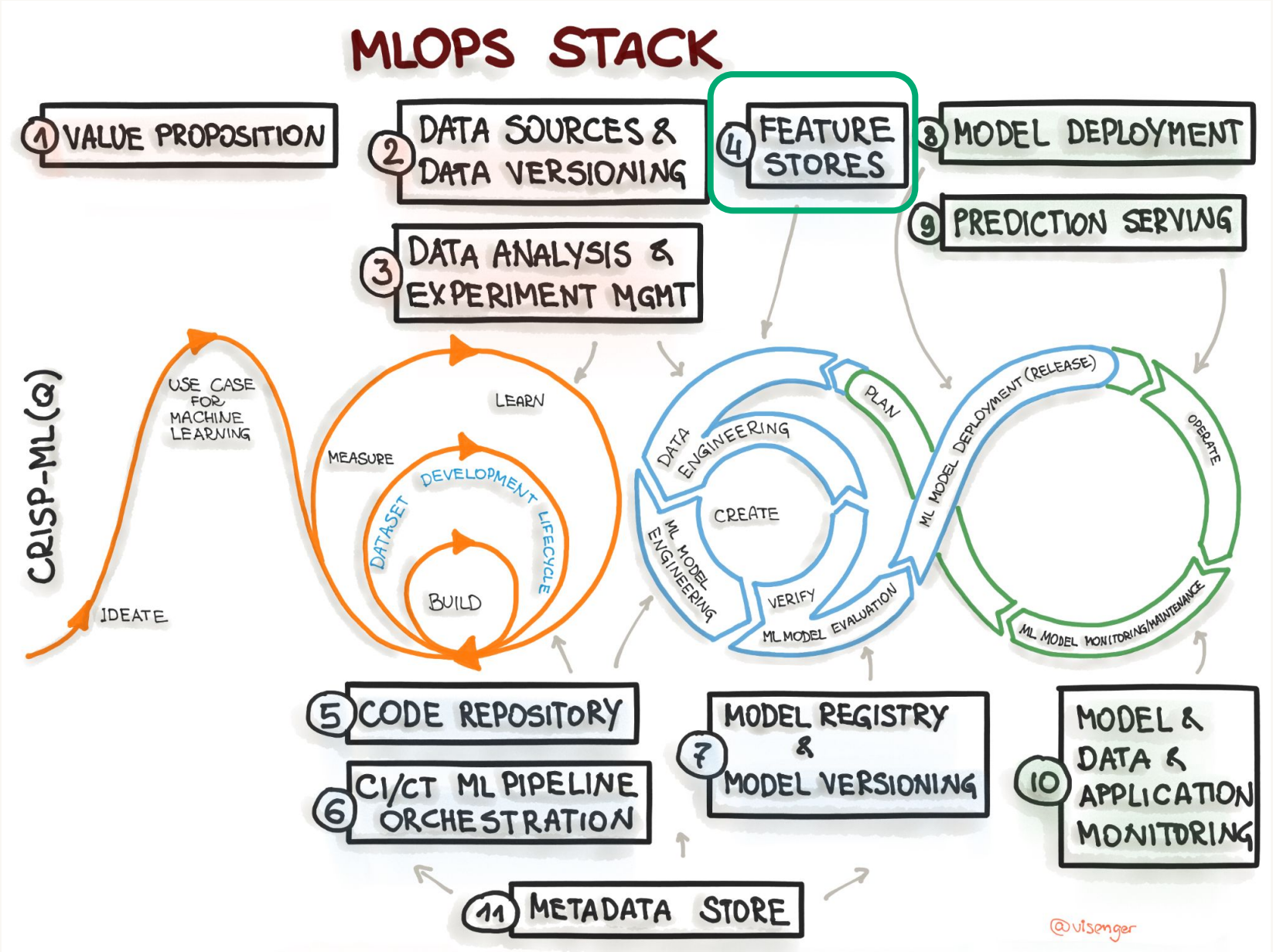

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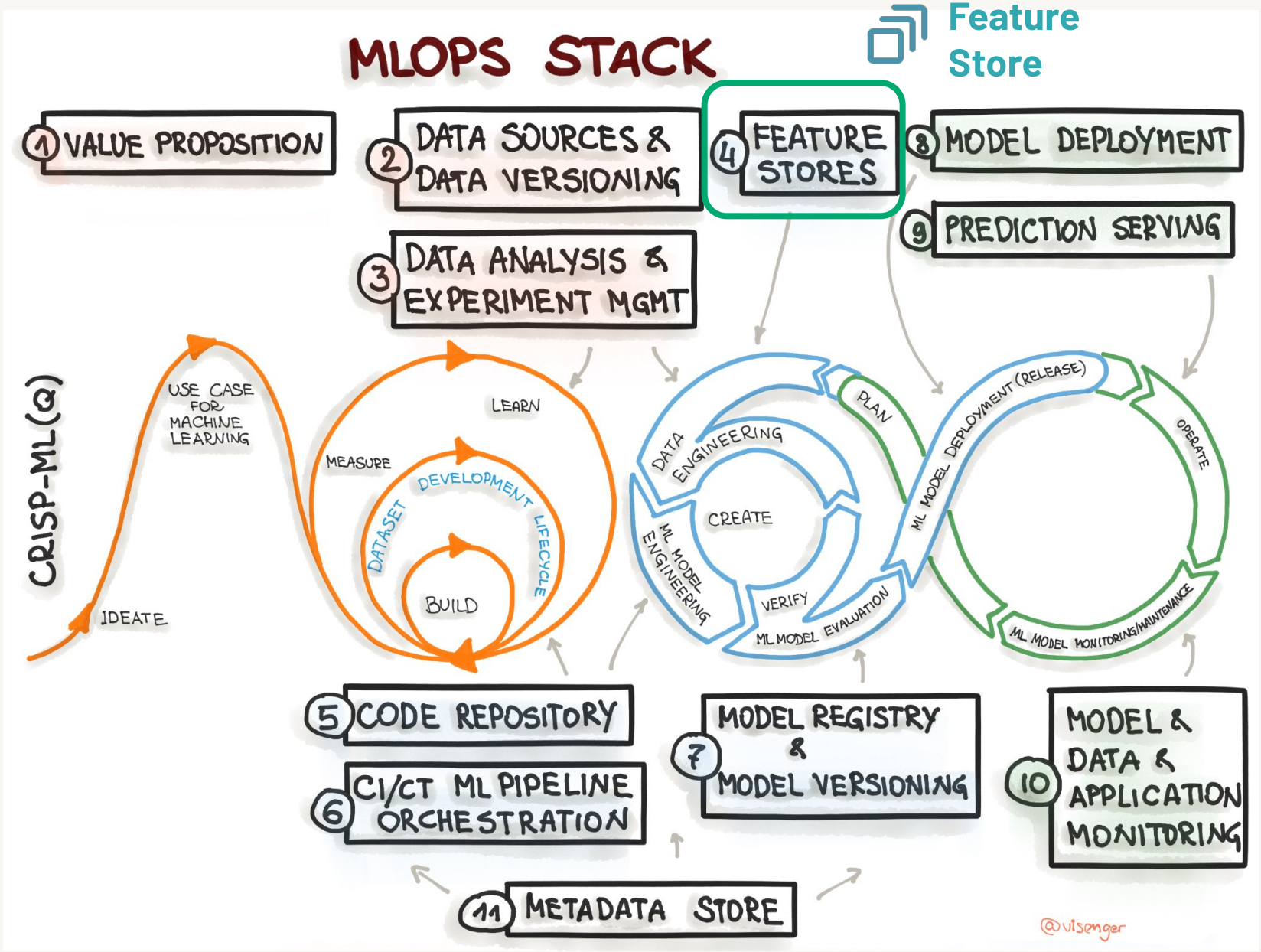
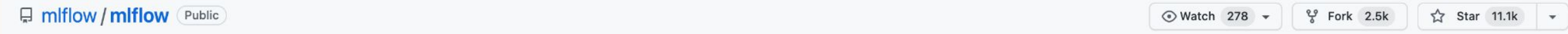


Source

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



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

MLflow Components

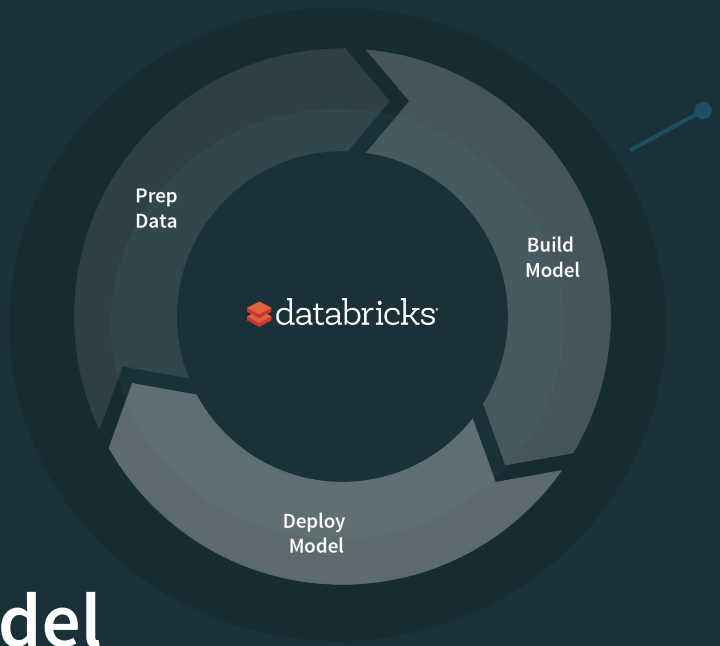
- APIs: CLI, Python, R, Java, REST

Standardizing the ML Lifecycle

Prep Data

Feed data to Models
Enrich data in experiments

Delta Lake



Build Model

Track Experiments
Reproduce experiments

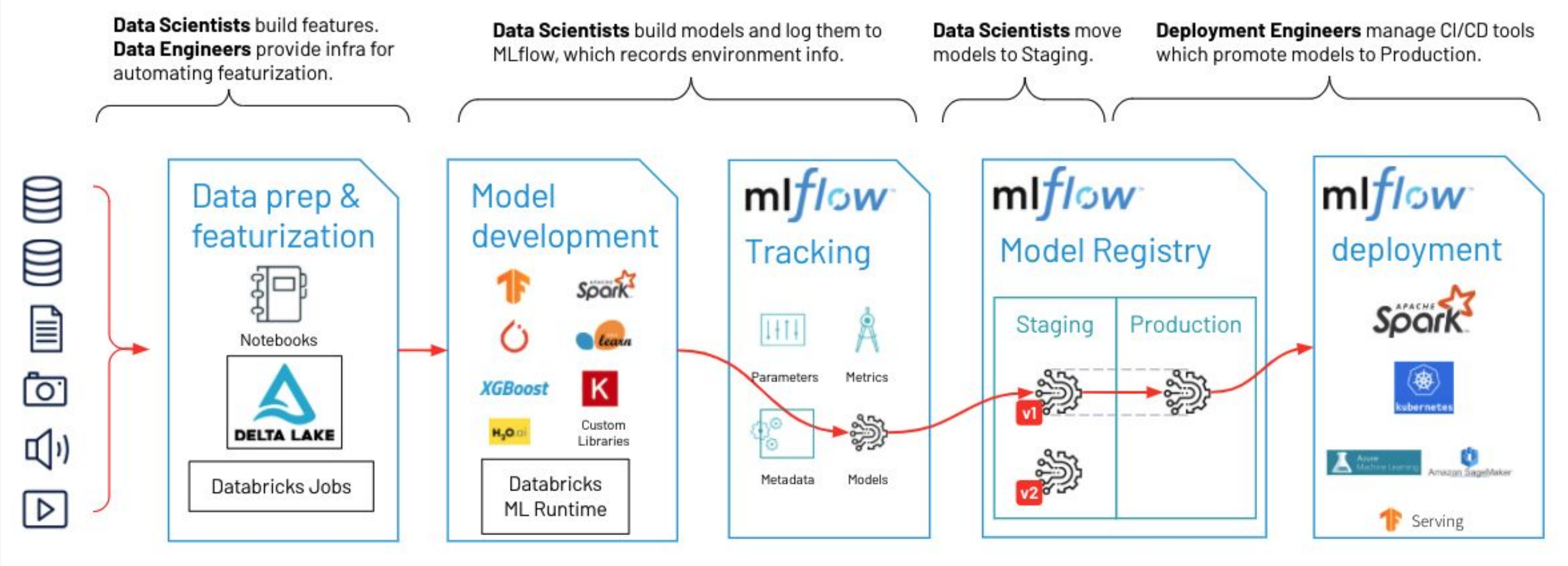
Machine Learning Runtime
MLflow Project & Tracking
MLflow Model Registry

Deploy Model

Integrate with multiple clouds
Manage and monitor models

MLflow Models
MLflow Model Registry

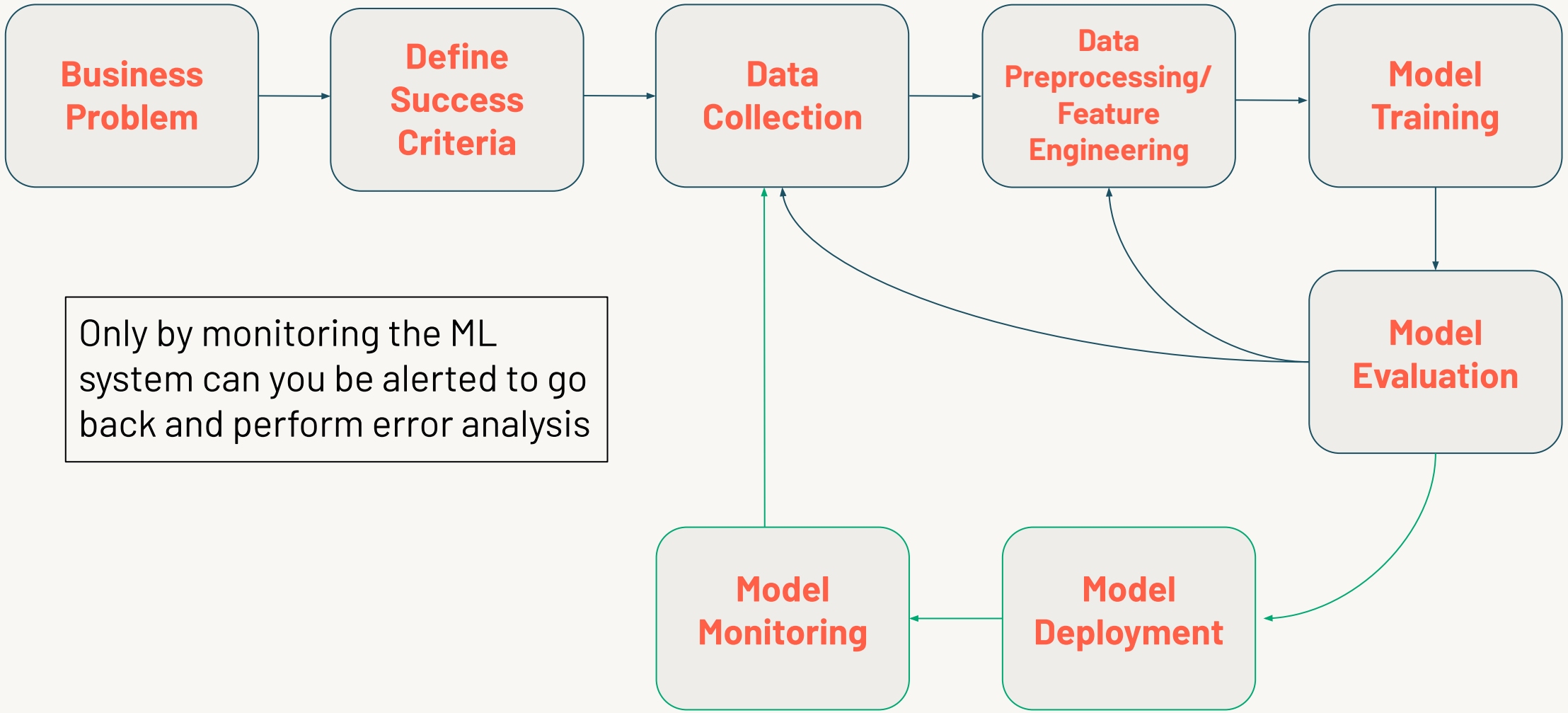
The Full ML Lifecycle



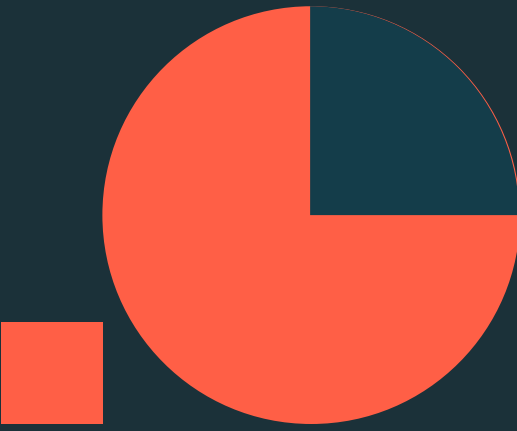
Data is never static, how to deal with drift?

Model Centric → Data Centric Machine Learning

How to action monitoring metrics



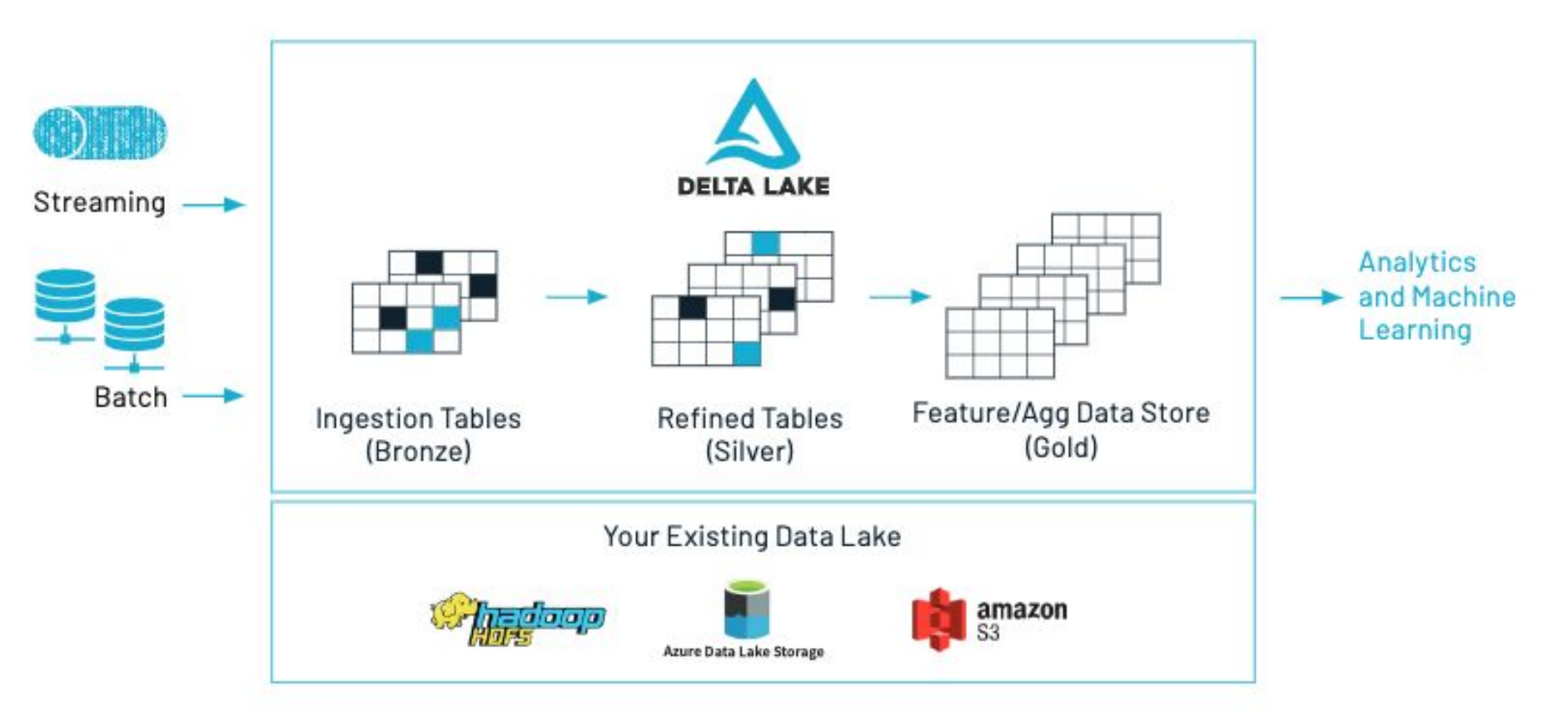
Workspace Setup



01 Experimentation

Delta Lake

Open-source Storage Layer



Delta Lake's 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

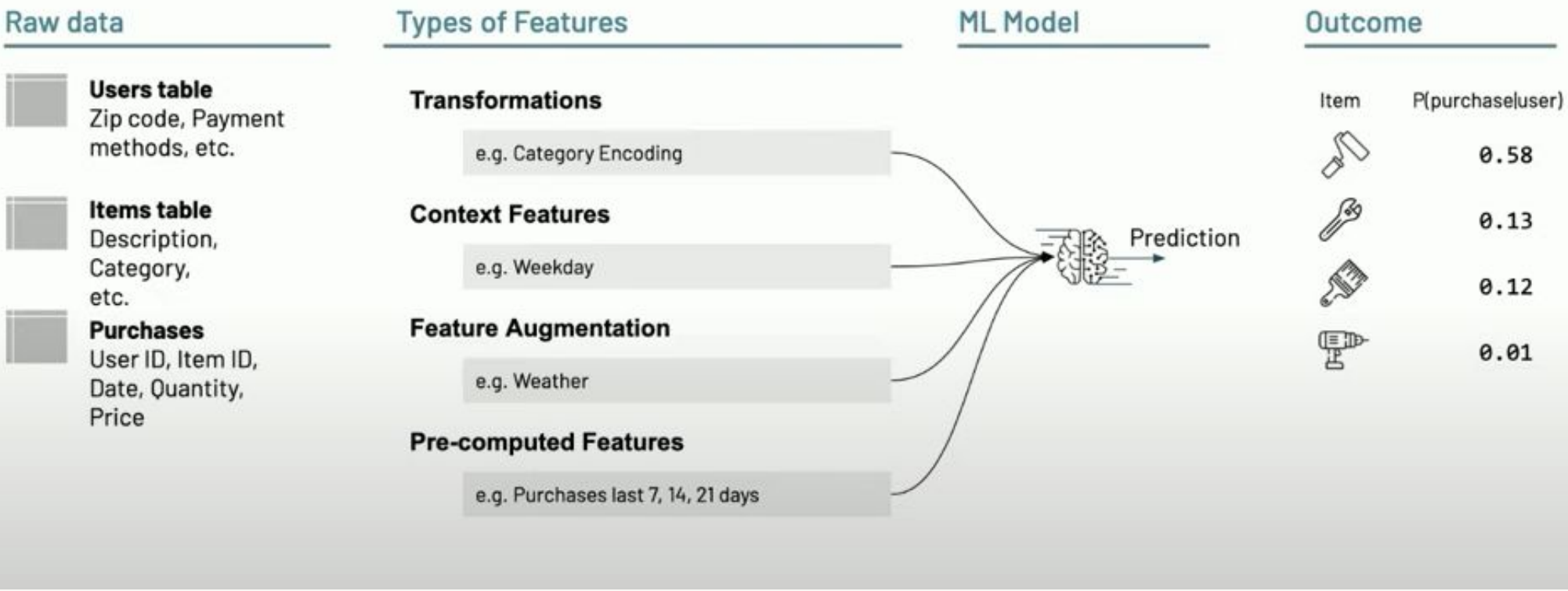
Delta Lake Optimize

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

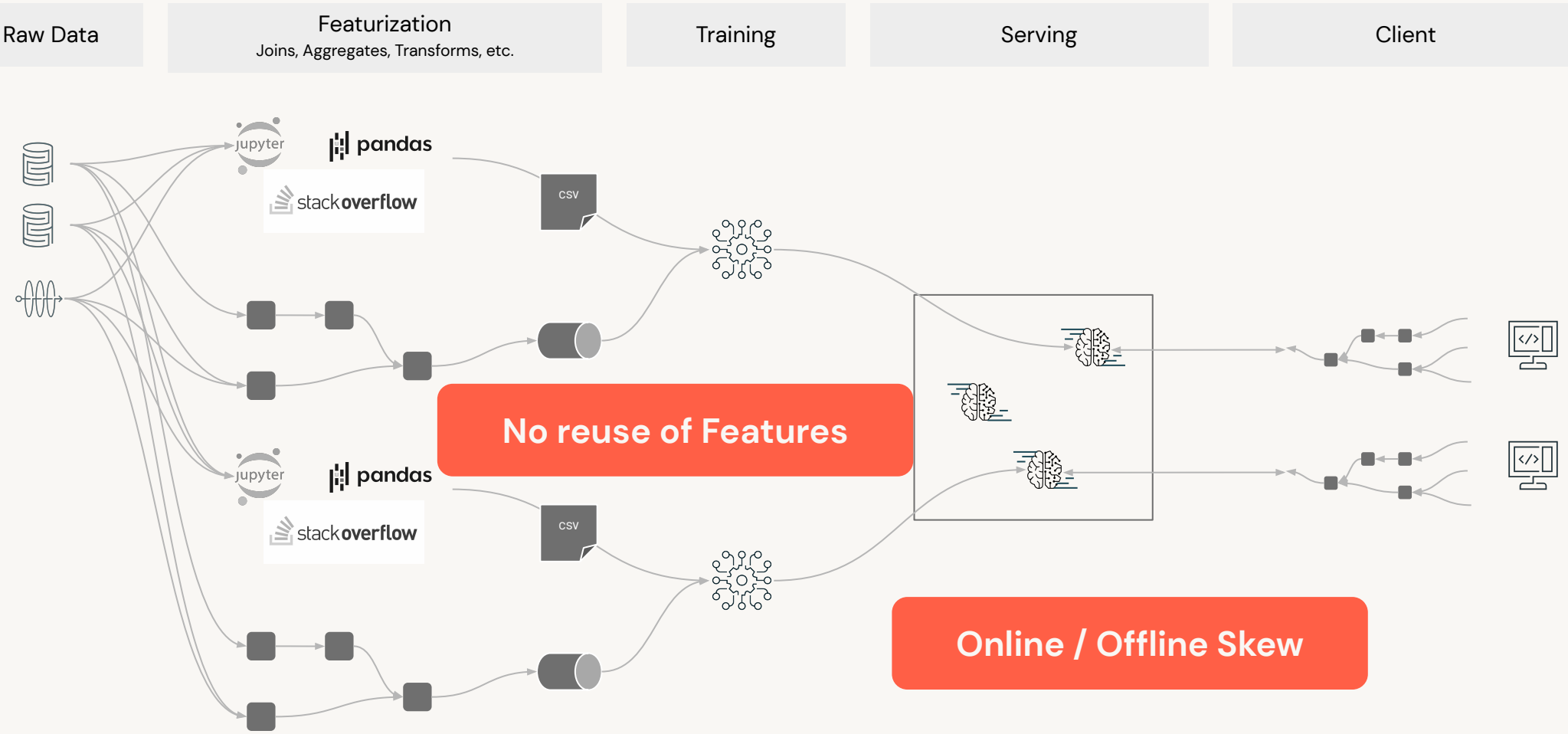
Feature Store

First things first: What is a feature?

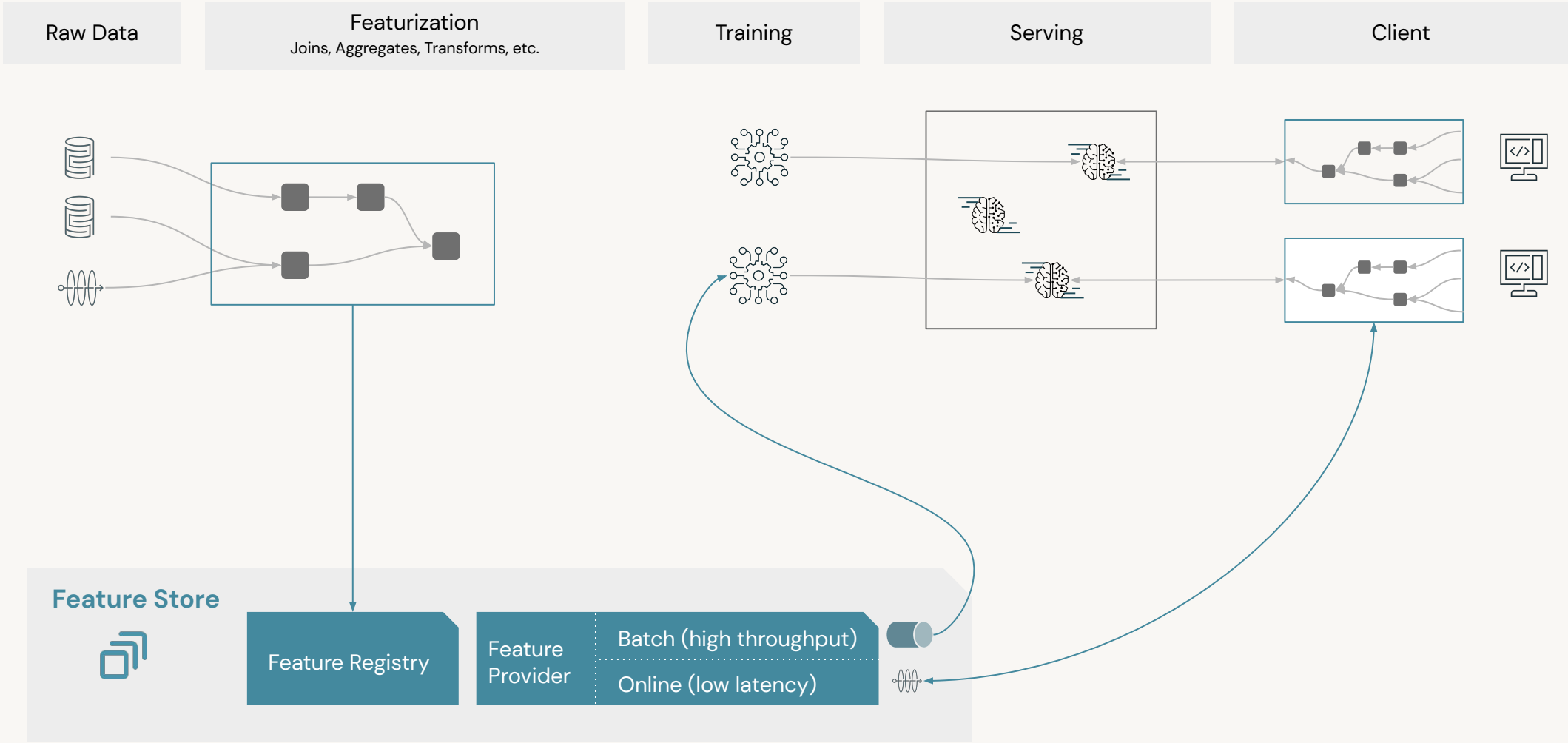
On the example of a recommendation system



A day (or 6 months) in the life of an ML model

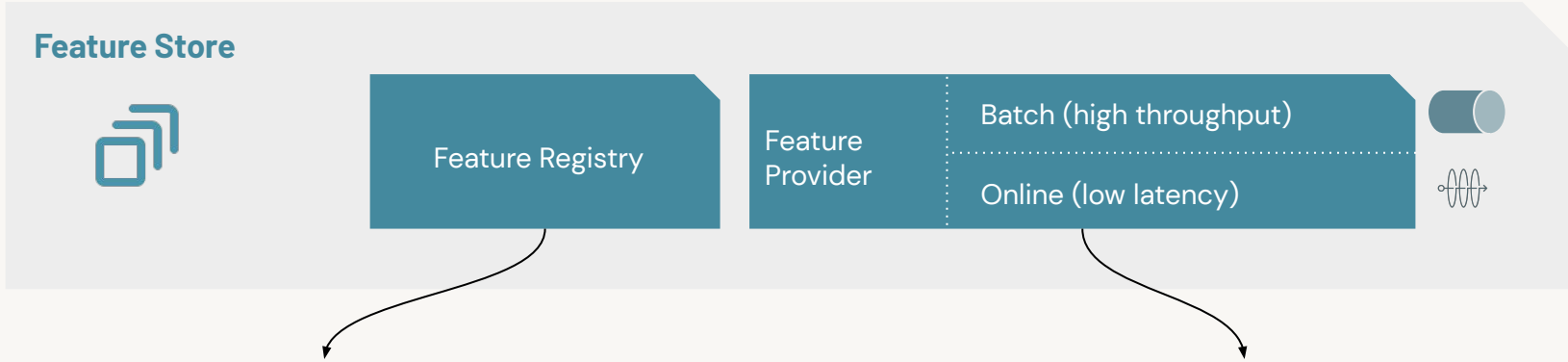


Solving the Feature Store Problem



Feature Store

The first Feature Store codesigned with a Data and MLOps Platform



Feature Registry

- Discoverability and Reusability
- Versioning
- Upstream and downstream Lineage

Feature Provider

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

Co-designed with DELTA LAKE

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

Co-designed with mlflow

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

MLflow Tracking

Experiment Tracking

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

Provides:

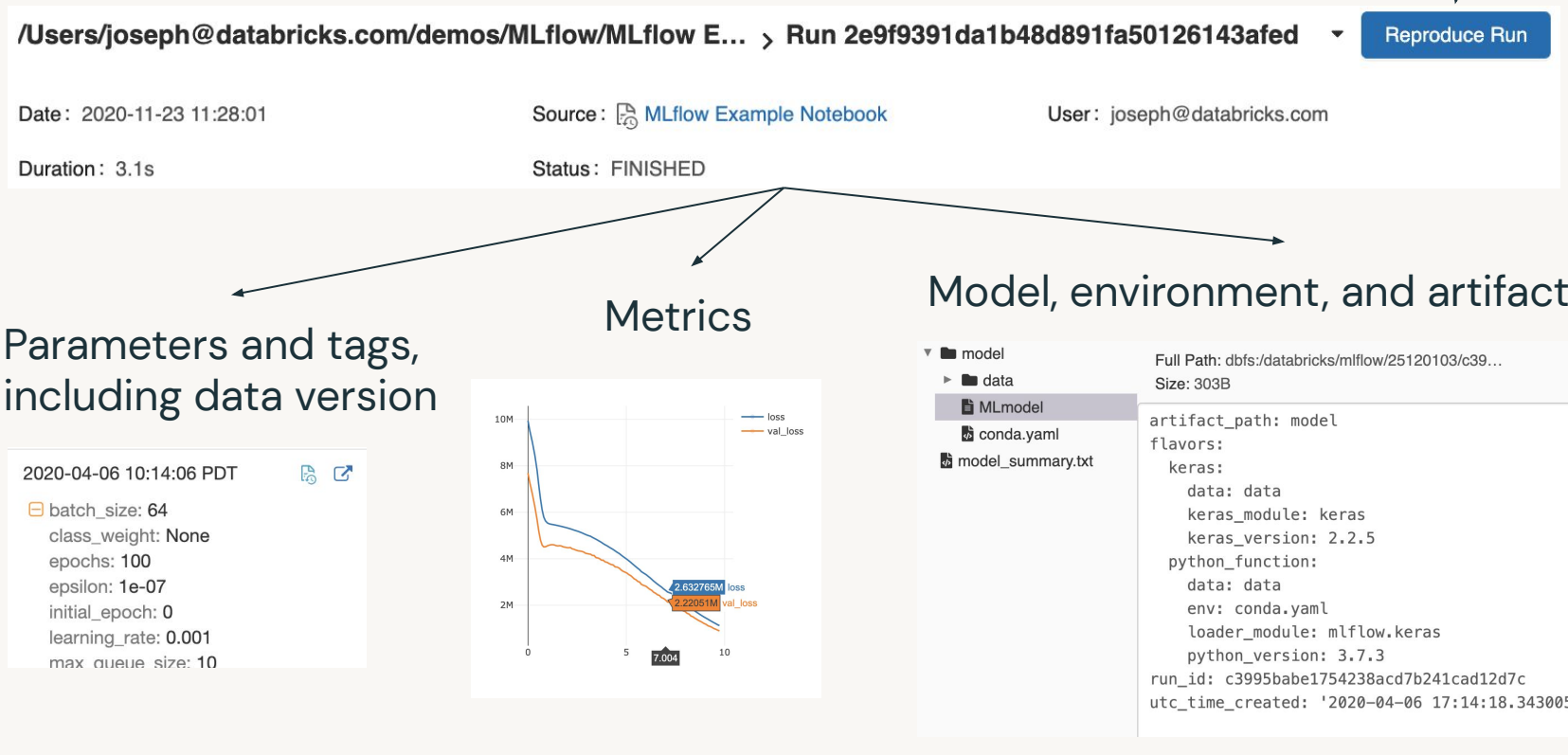
- Pre-configured MLflow tracking server
- Databricks Workspace & Notebooks UI integration
- S3, Azure Blob Storage, Google Cloud for artifacts storage
- Experiments management via role based Access Control Lists (ACLs)

MLflow tracking and autologging

Ensure reproducibility

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

```
mlflow.autolog()
```



Analyze results in UI or programmatically

- How does tuning parameter X affect my metric?
- What is the best model?
- Did I run training for long enough?

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

02 Model Management

End to End Model Management

Setup MLflow Model webhook
Slack notifications, Trigger Testing Jobs

Schedule Monthly Retrain Job
Databricks Job

Data Prep & Featurization
ETL + EDA, Feature Engineering

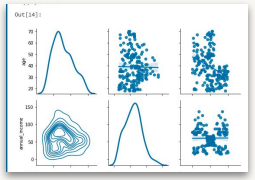
Build baseline Model with AutoML
MLflow autologging, Hyperopt +Spark

Promote Best Run to Registry
Annotate model. Request transition to staging

Automated Model testing
Schema, Demographic accuracy, Docs & artifacts...
Approve/reject request

Run inferences
Load model
Batch or real-time

Feature Store



XGBoost · scikit-learn · Keras · Spark · ...

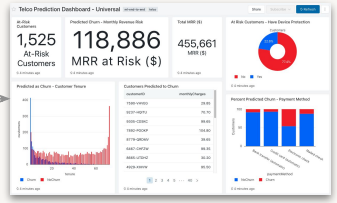
mlflow Tracking

STAGING Request
Model Registry
Webhook triggers test

Approved.
Move to STAGING

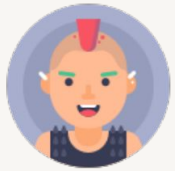
Rejected

mlflow STAGING



{ api }
Realtime HTTP inference


Data Scientist


ML Engineer


Data Engineer

Data Transformation

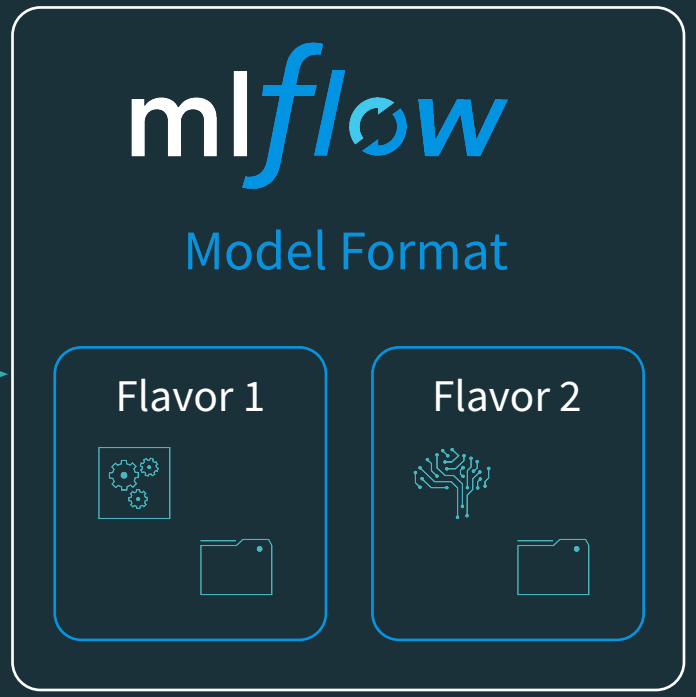
Within the model or prior to model training? It depends!

	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

ML Libraries

scikit learn
TensorFlow
Spark
H2O.ai
PyTorch
Keras
mleap
ONNX



Simple model flavors usable by many tools

In-Line Code

docker
kubernetes

Containers

SELDON
mleap
Spark

Batch & Stream Scoring

Azure Machine Learning
Amazon SageMaker

Cloud Inference Services

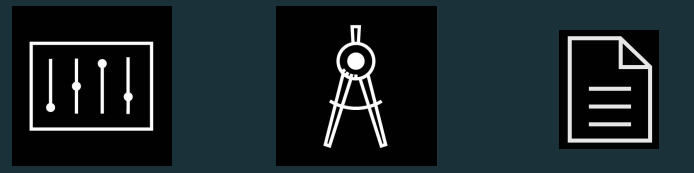
databricks

mlflow Model Registry

VISION: Centralized and collaborative model lifecycle management

mlflow

Tracking Server

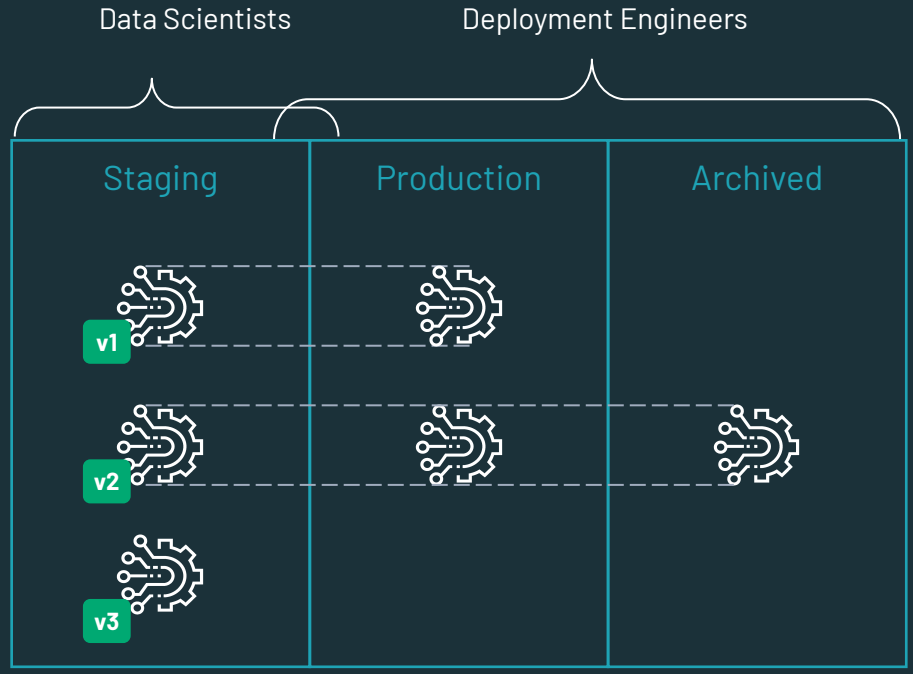


Parameters Metrics Artifacts

Metadata Models

mlflow

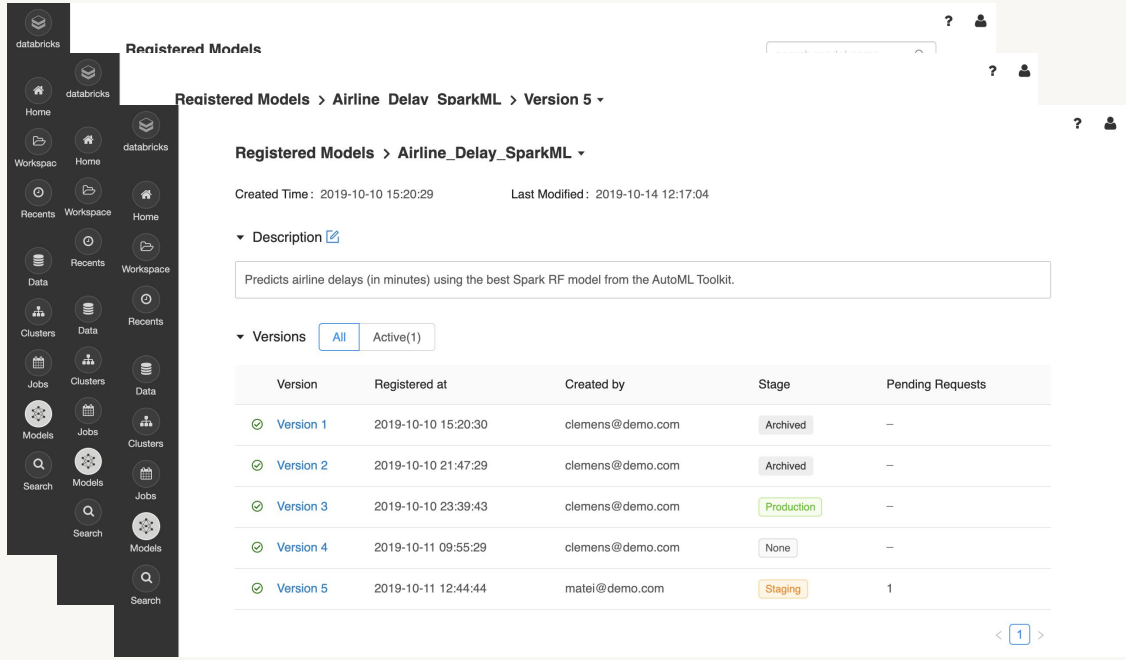
Model Registry



databricks

Model Management

Use one central place to collaboratively manage ML models, from experimentation to online testing and production.



Provides:

- Automatic models versioning
- Integration with governance workflows
- Automatic/manual approval of stage transition
- Full visibility into model lifecycle from experimentation to production

Model Registry Benefits

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.

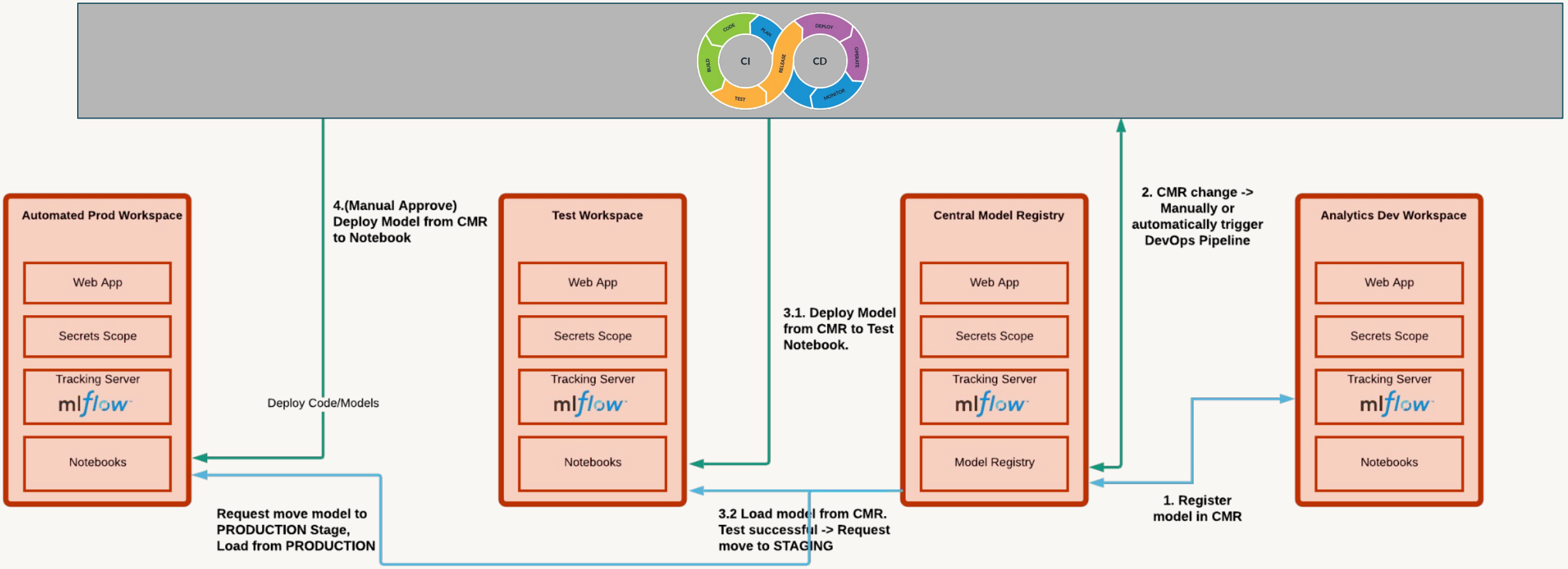
Model Registry Workflow Options

1. **Central Model Registry**: Dedicated workspace(s) to store models, feature tables, and experiments (optional)

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

Central Model Registry

Dedicated workspace(s) to store models, feature tables, and experiments



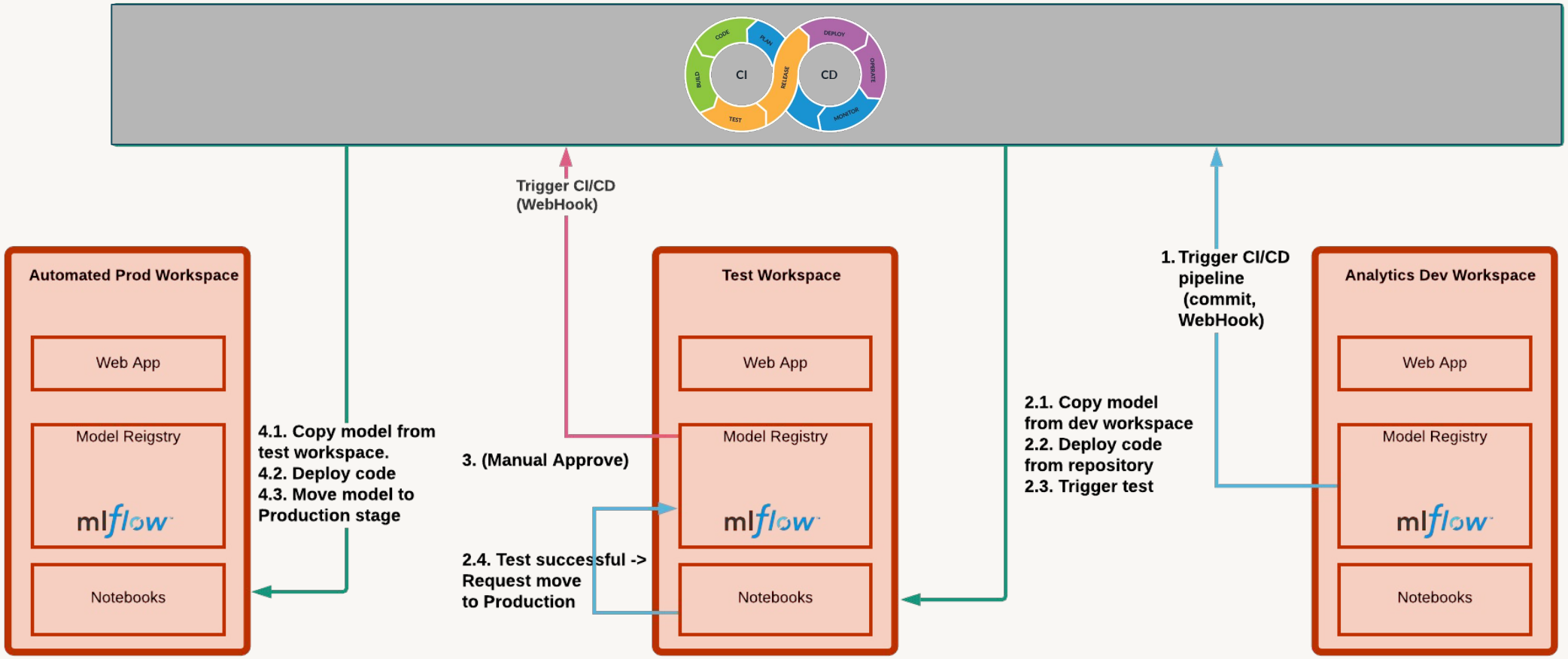
Central Model Registry

Dedicated workspace(s) to store models, feature tables, 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



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

03 Deployment Paradigms

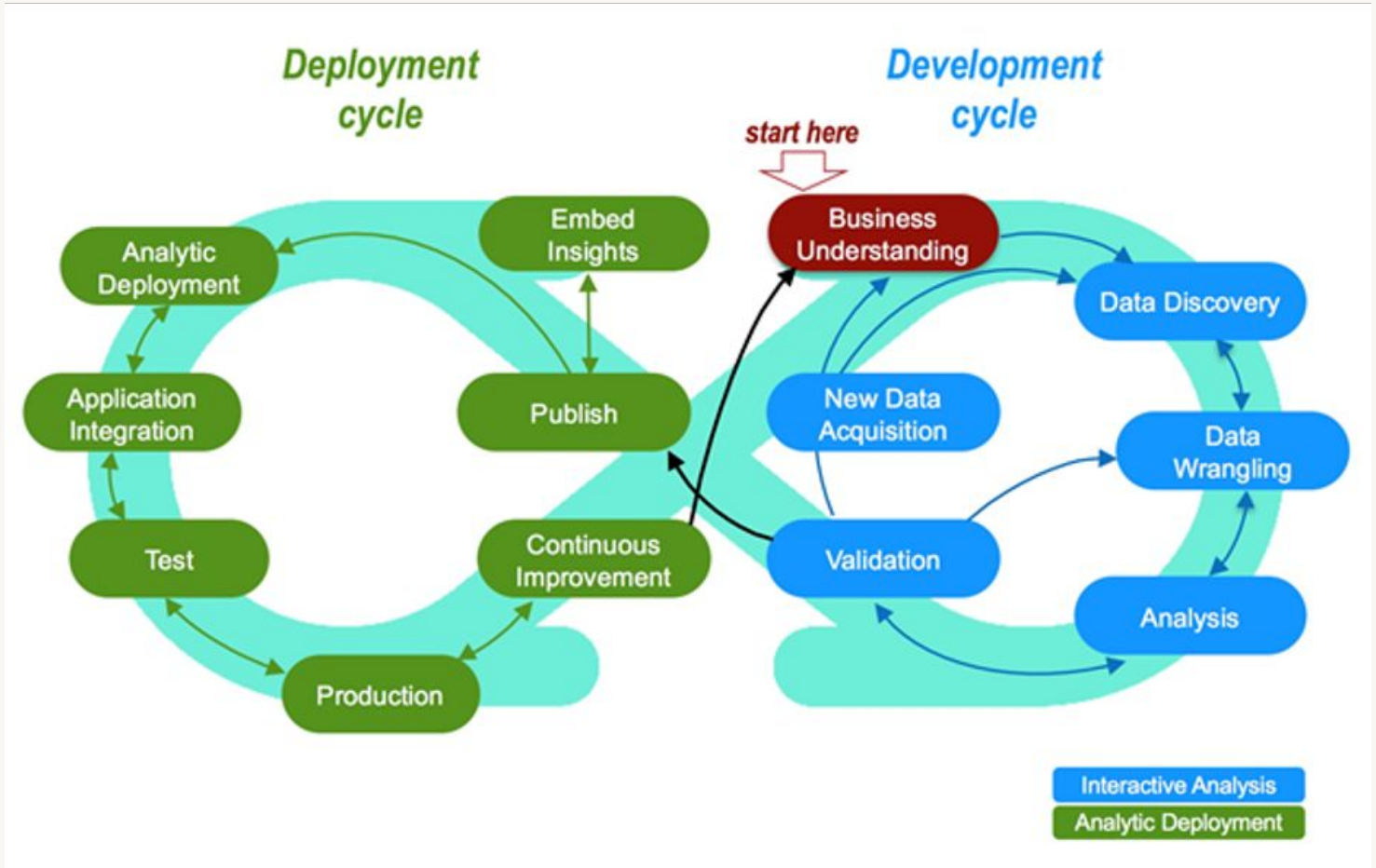
Machine Learning Deployment

- What is ML deployment?
- The Four Deployment Paradigms
- Deployment Requirements
- Deployment Architectures
- Other Issues

What is ML Deployment?

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

Closed Loop Systems



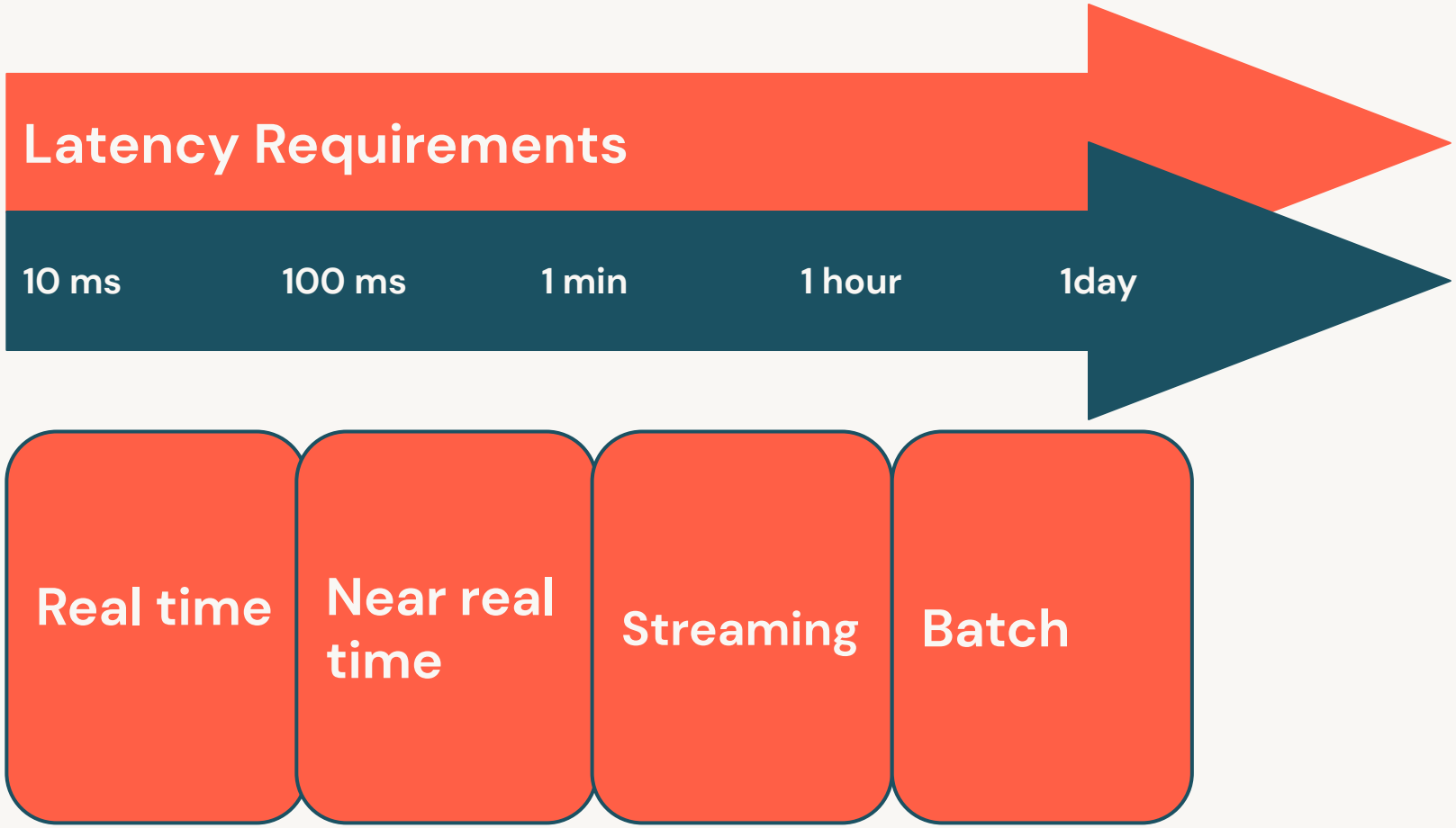
DevOps vs. ModelOps

- DevOps = software development + IT operations
  - Manages deployments
  - CI/CD of features, patches, updates, rollbacks
- ModelOps = data modeling + deployment operations
  - Java, containers, C/C++ and legacy environments
  - Artifact management (Continuous Training)
  - Model performance monitoring (Continuous Monitoring)

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

04 Production

Production Requirements

Core Requirements

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

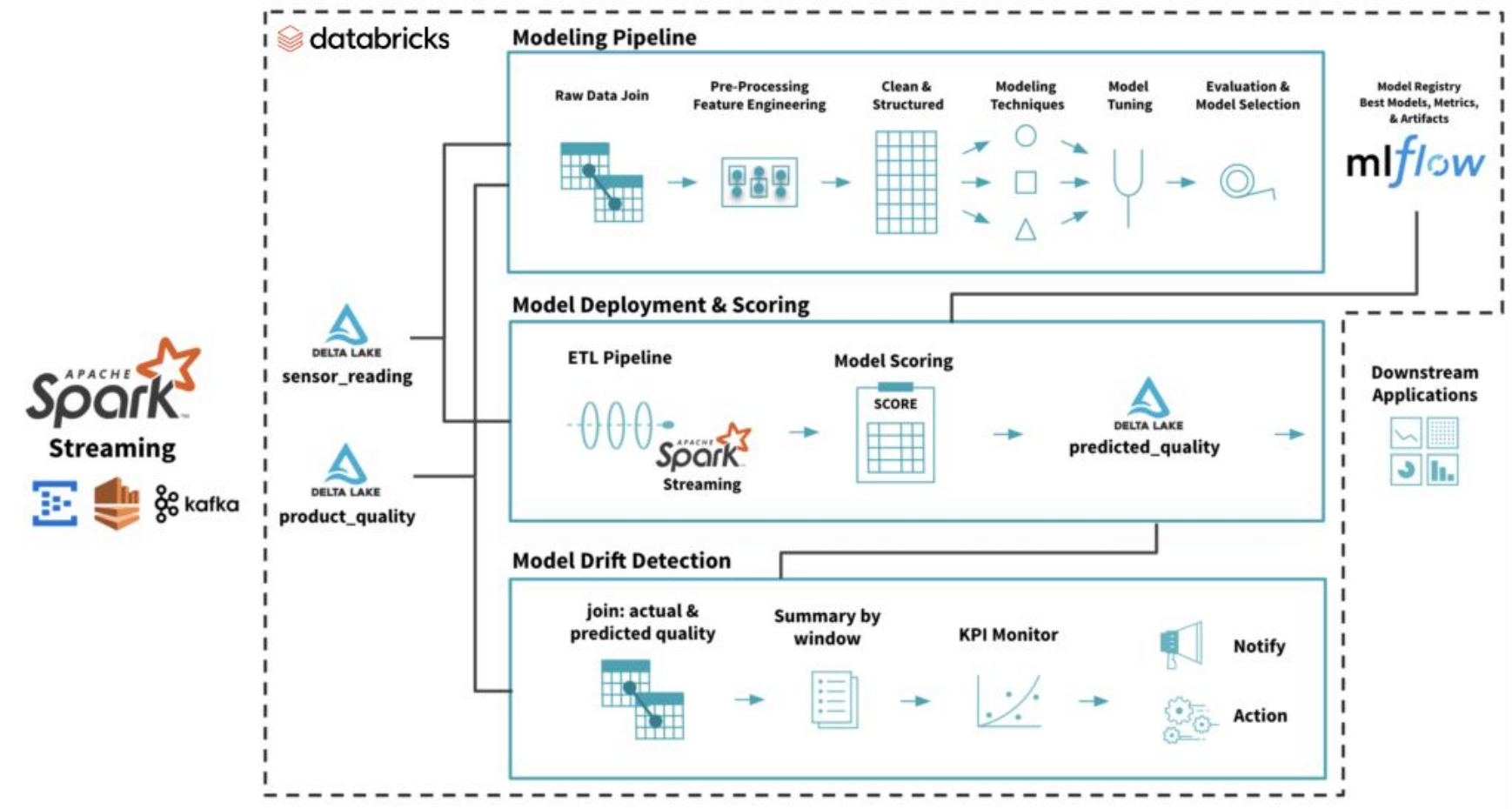
Core +

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

Specialized

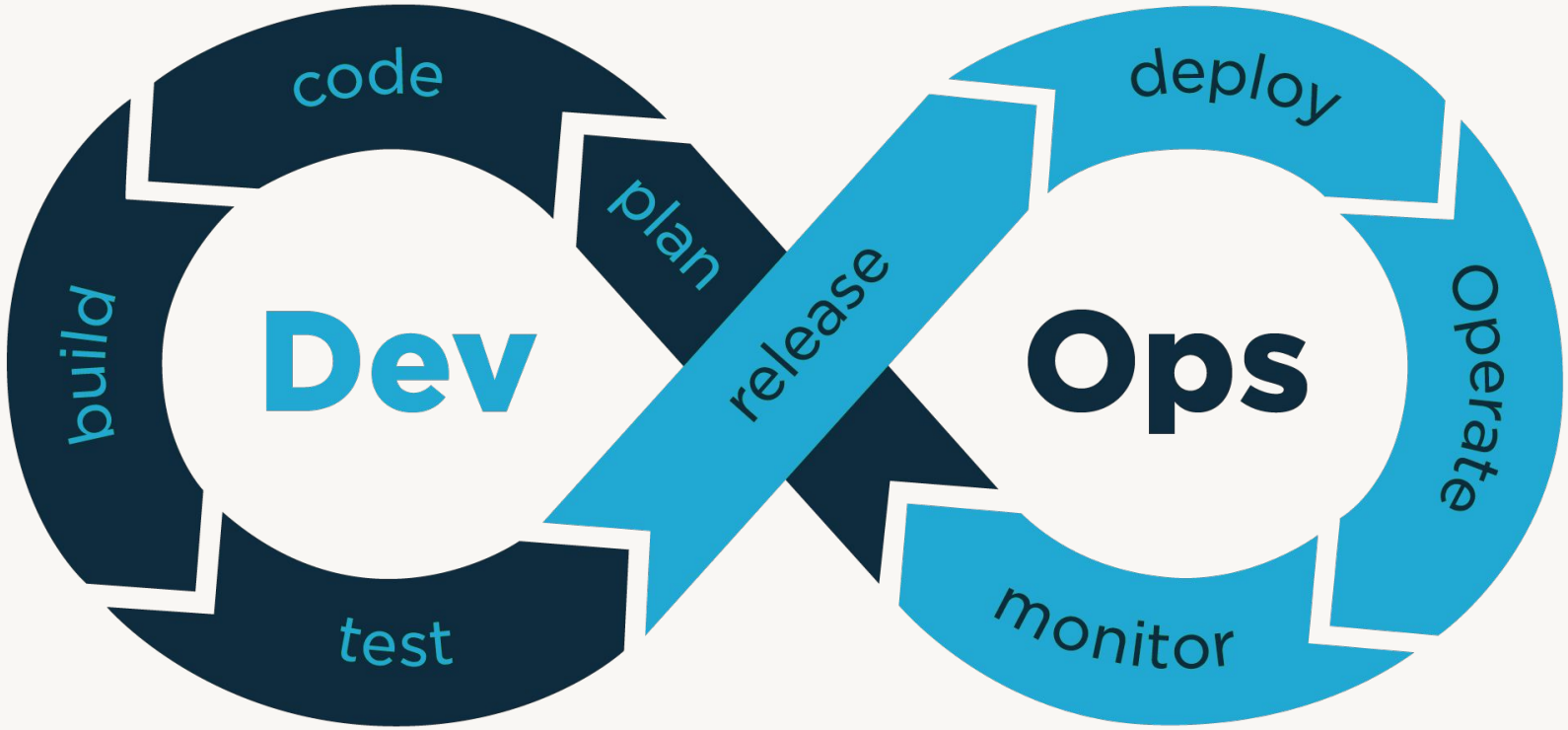
- Feature dictionary
- Cost management
- A/B testing
- Performance optimization

Architecture Example

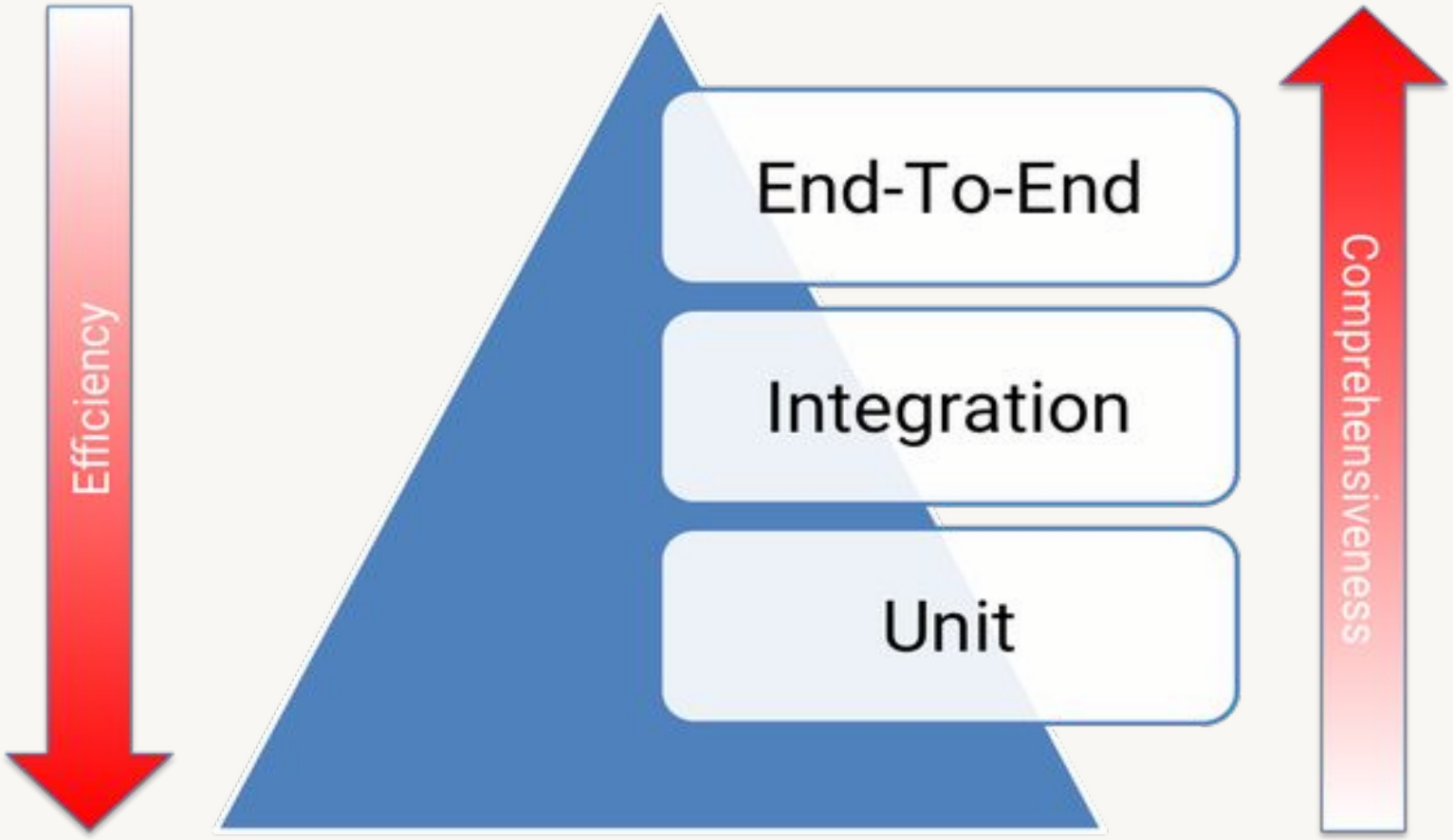


CI/CD

DevOps...



… And the Test Pyramid…



Overview of a typical Databricks CI/CD pipeline

Continuous integration

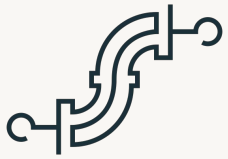
Continuous delivery

Code

Build

Release

Deploy



Test

Operate

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

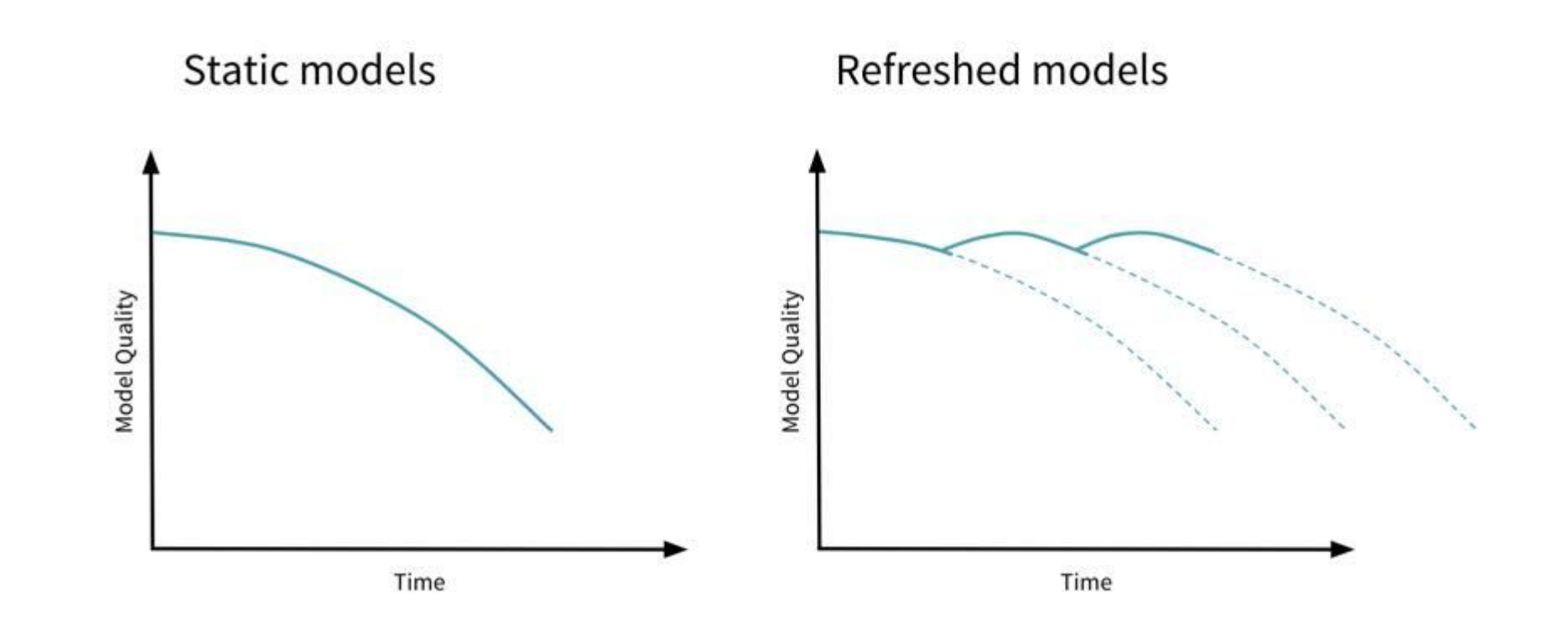
Big Data & AI Present new challenges…

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!

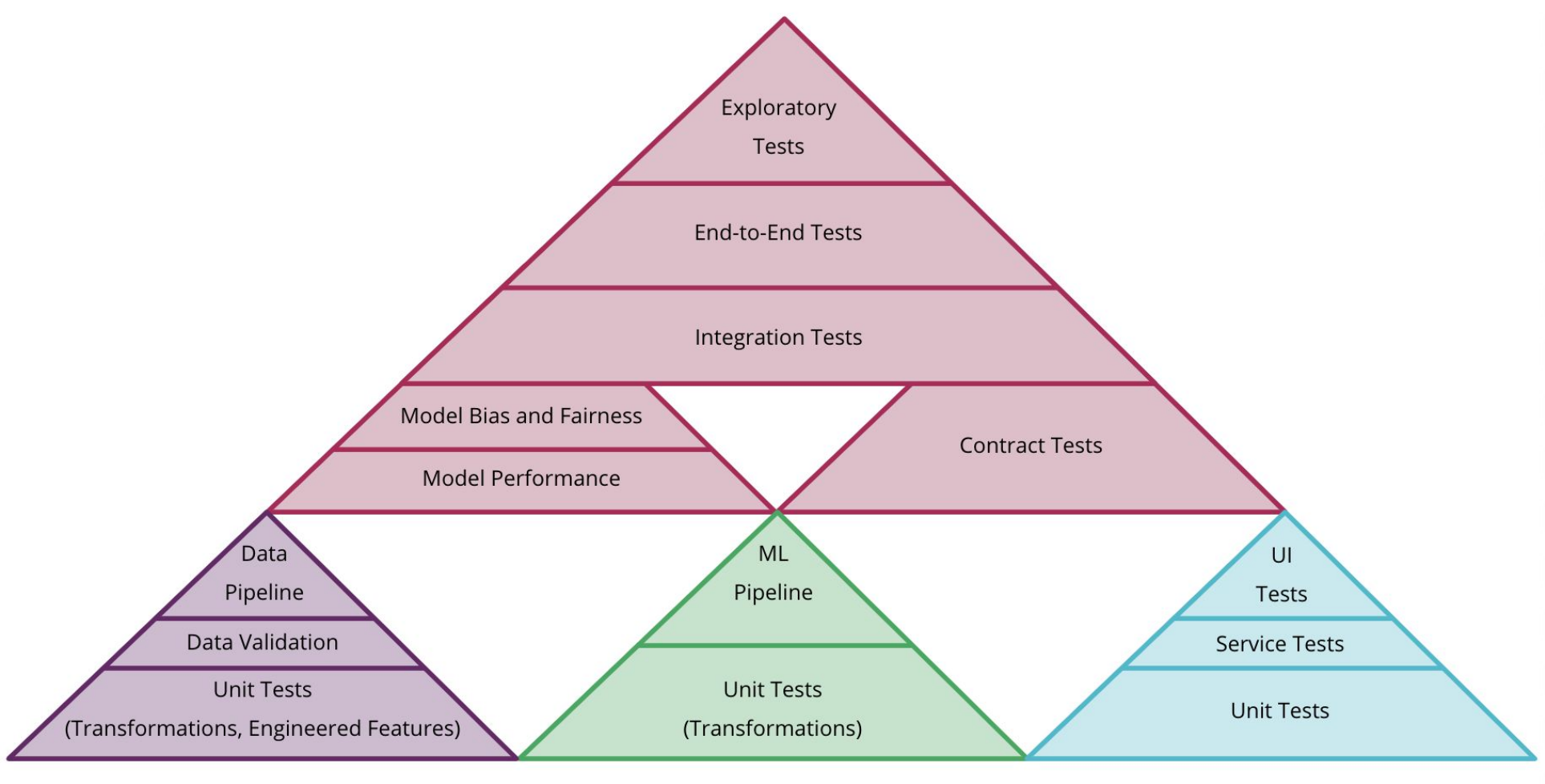
Why do ML projects fail in production?

Neglect maintenance: Lack of re-training and testing



Source

And these make for one complicated test pyramid...



MLOps: Continuous …

- 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

Feature Drift

Input feature(s) distributions deviate

Label Drift

Label distribution deviates

Prediction Drift

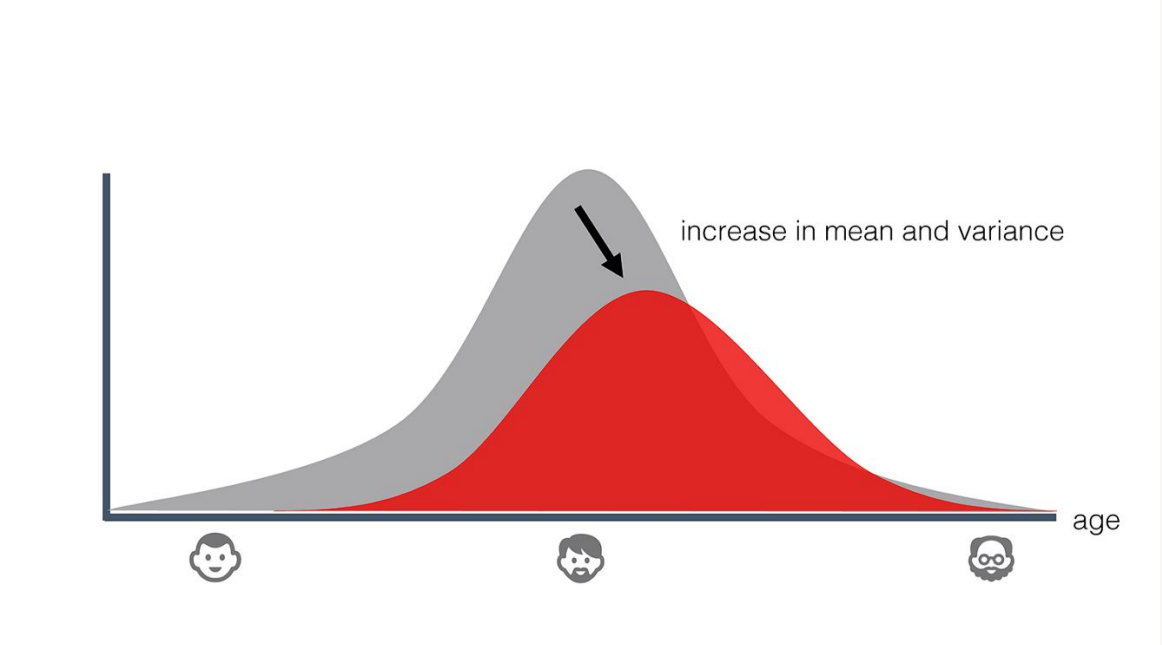
Model prediction distribution deviates

Concept Drift

External factors cause the label to evolve

Feature, Label, and Prediction Drift

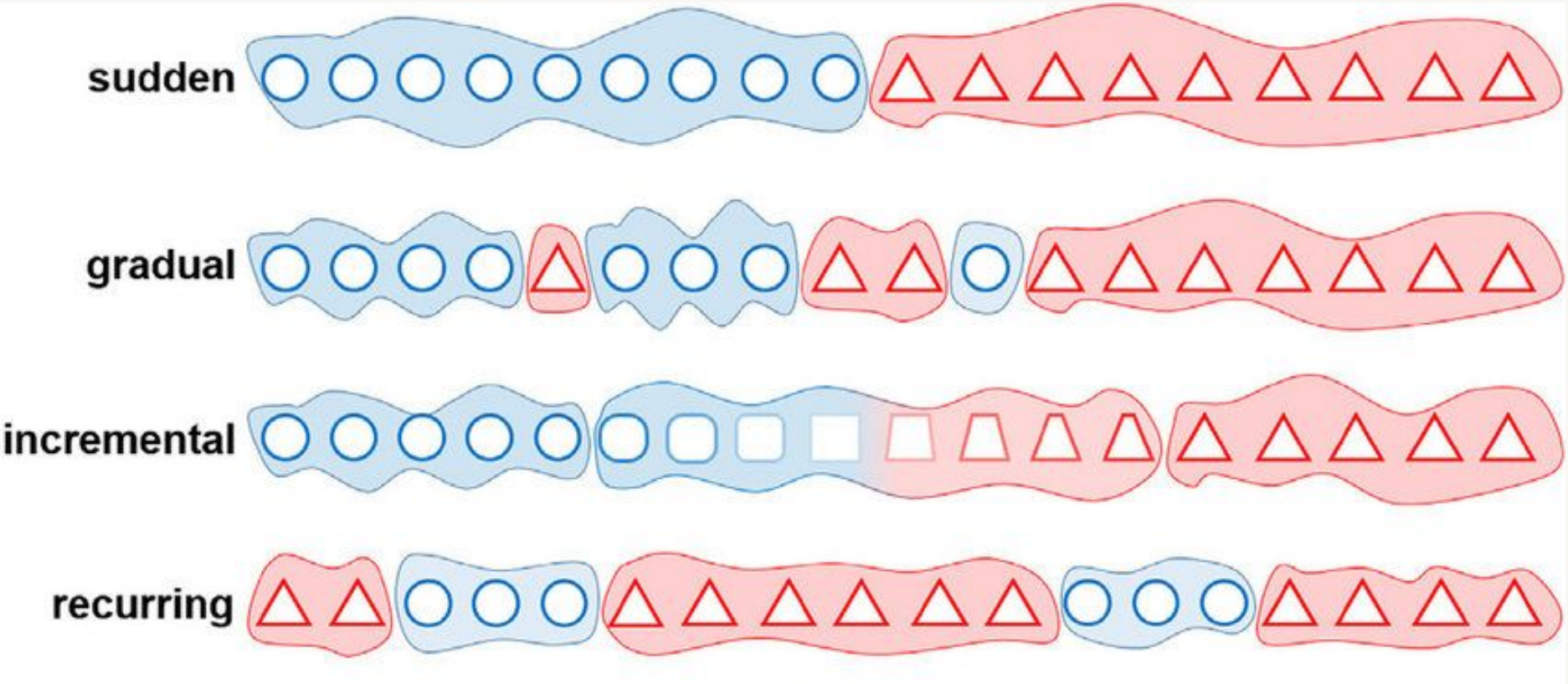
Categories	Expected	Observed	Total
A	25	35	60
B	25	20	56
C	25	25	50
D	25	20	45
Total	100	100	100



Source 1

Source 2

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

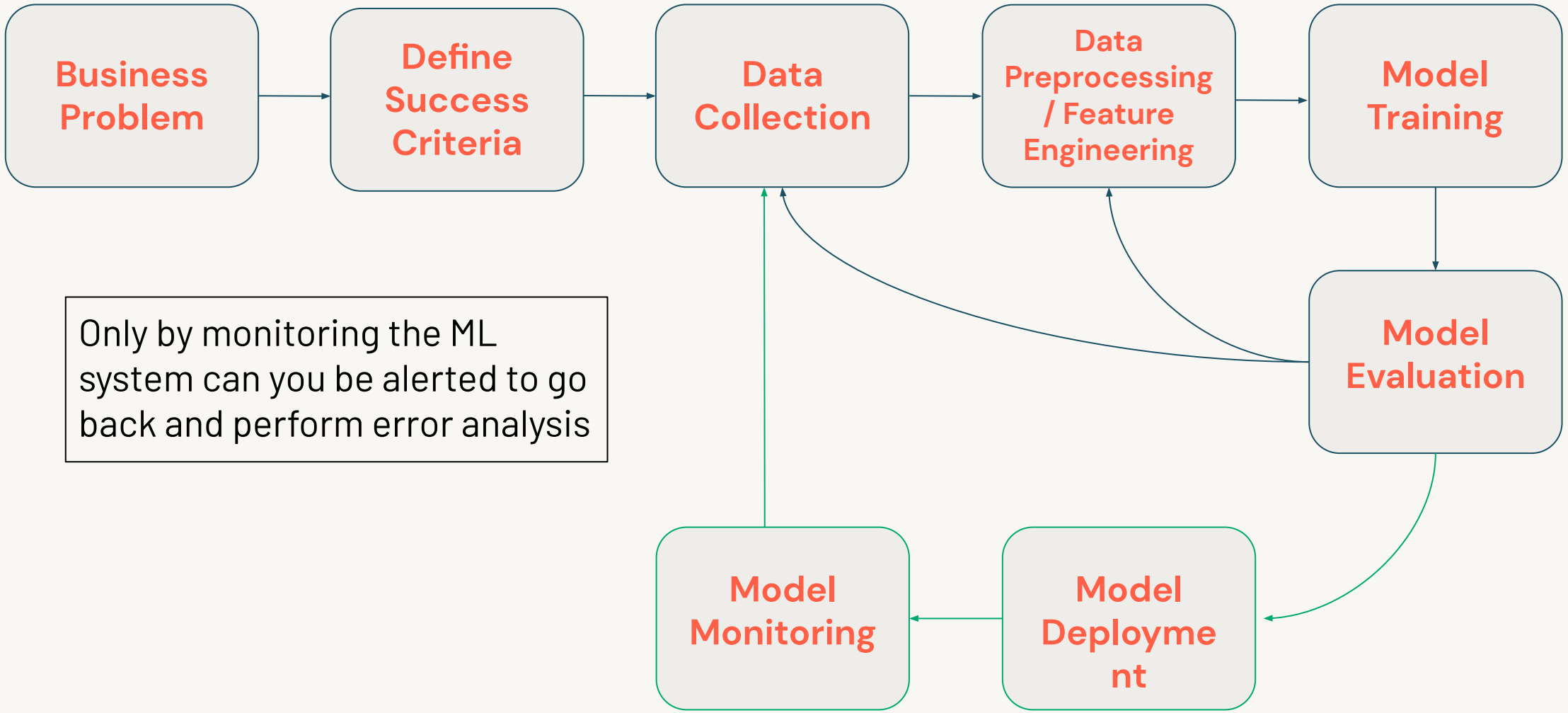
Output Metrics

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

Monitoring tests on models

- Relationship between target and features
  - Numeric Target: Pearson Coefficient
  - Categorical Target: Contingency tables
- Model Performance
  - Regression models: MSE, error distribution plots etc
  - Classification models: ROC, confusion matrix, F1-score etc
  - Performance on data slices
- Time taken to train

How to action monitoring metrics



Deployment Strategies

Deployment Strategies

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

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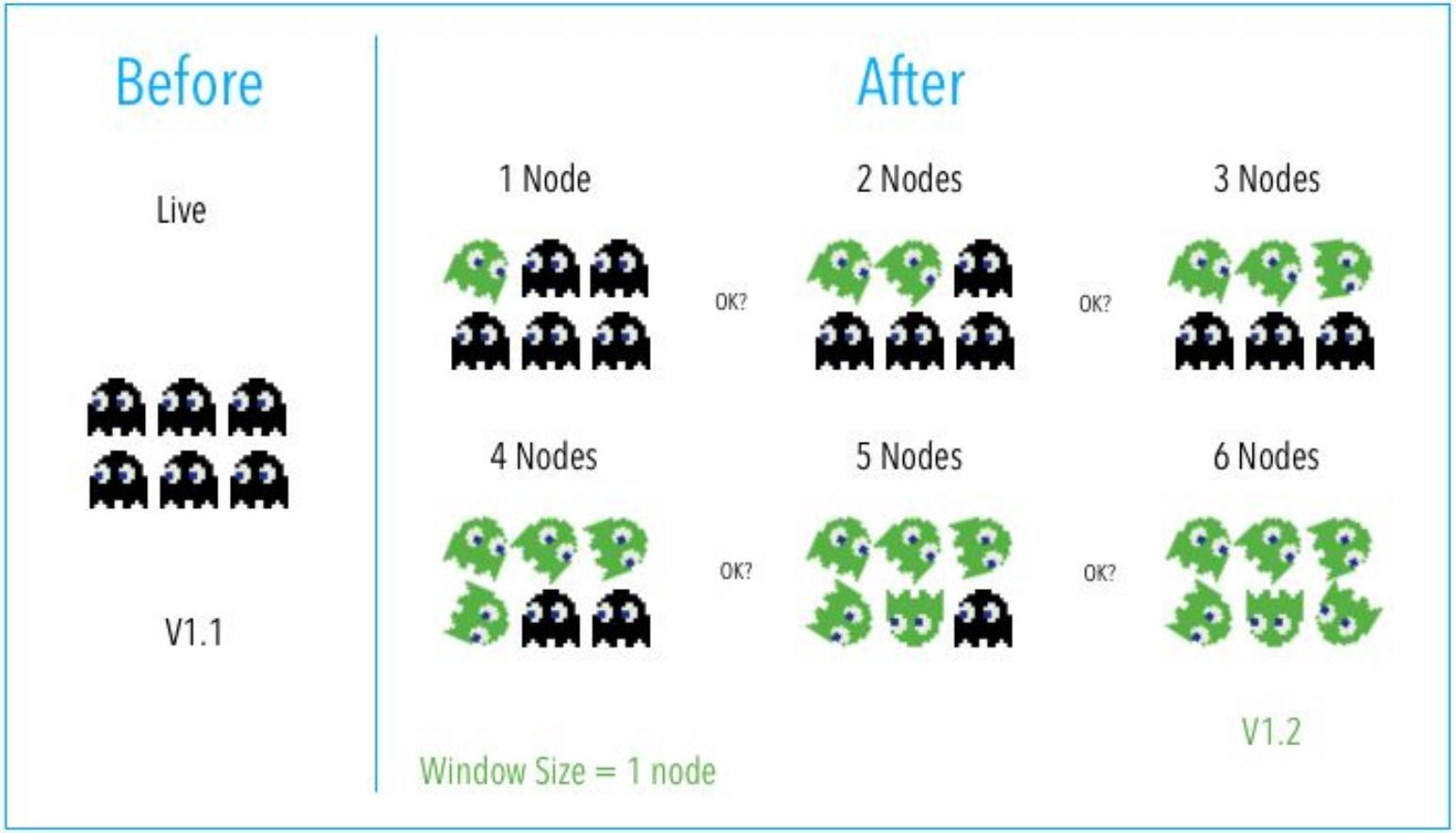
Deployment Strategies

- 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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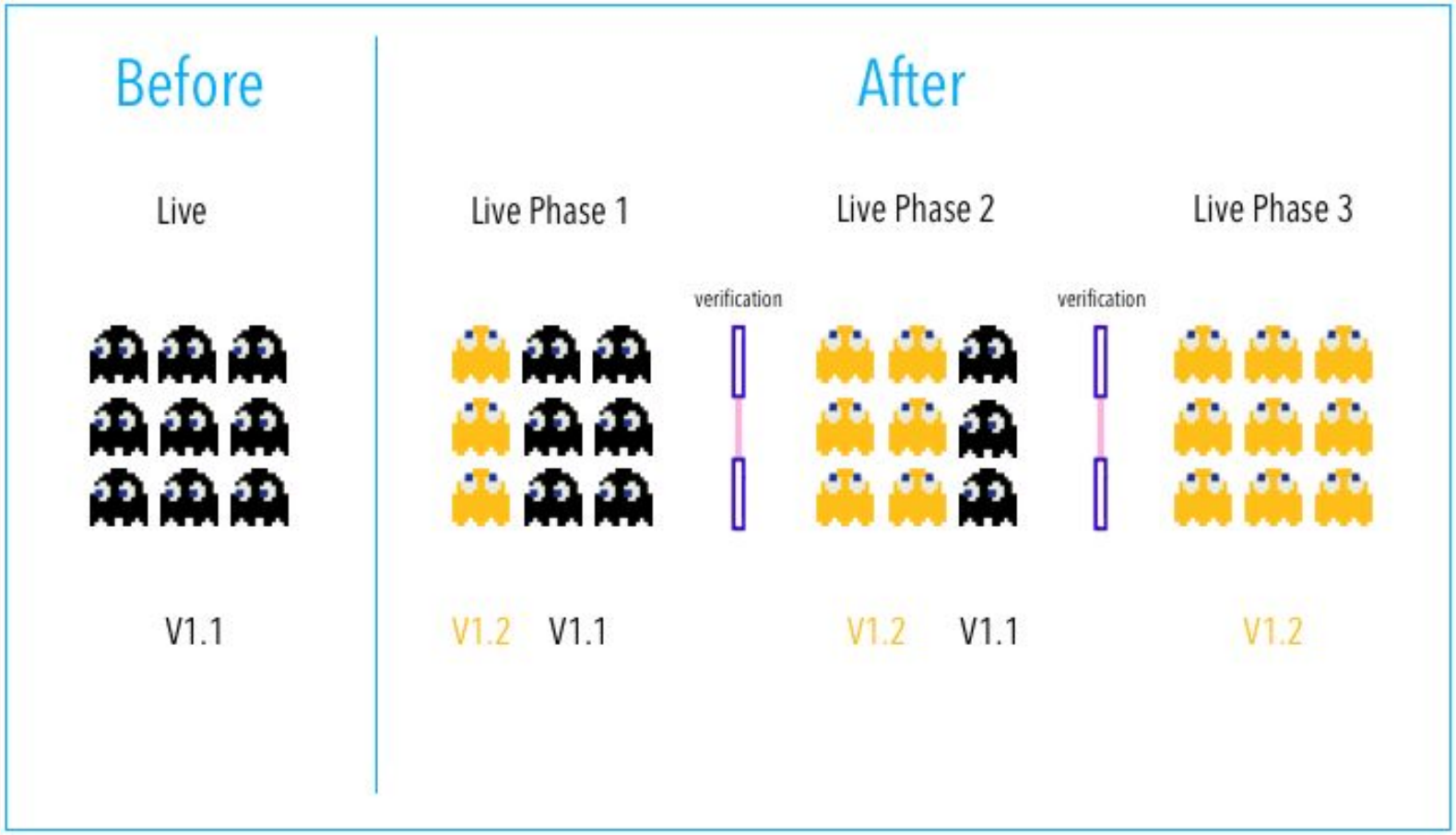
Deployment Strategies

- 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

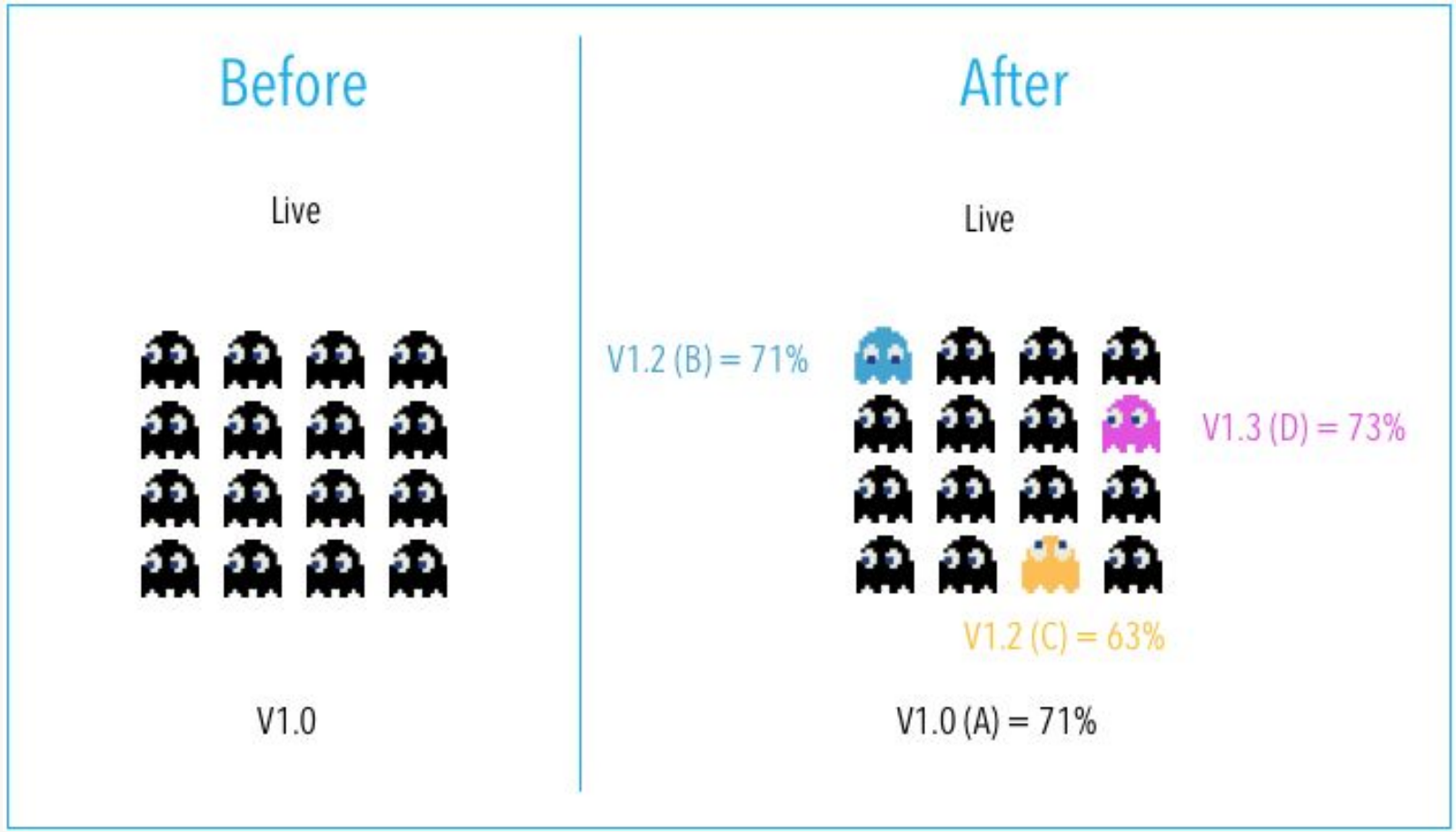
Deployment Strategies

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



Deployment Strategies

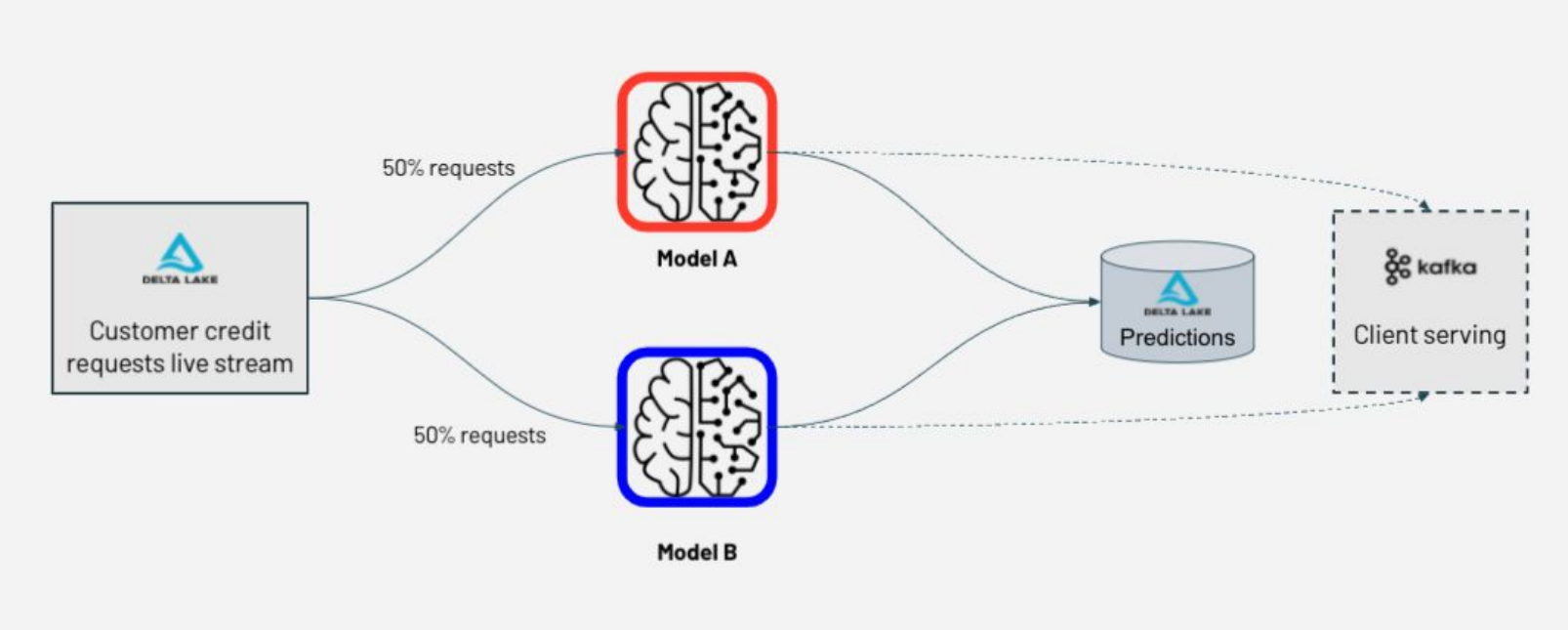
- Shadow
- Rolling
- Blue-Green
- Canary
- **A/B Testing**
  - Different versions of the same service run simultaneously in the same environment for a period of time.



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

Thank you!