# MLOPS

By: Ashish Pal

# MODEL DEPLOYMENT

When designing an ML system architecture, the following should be borne in mind.

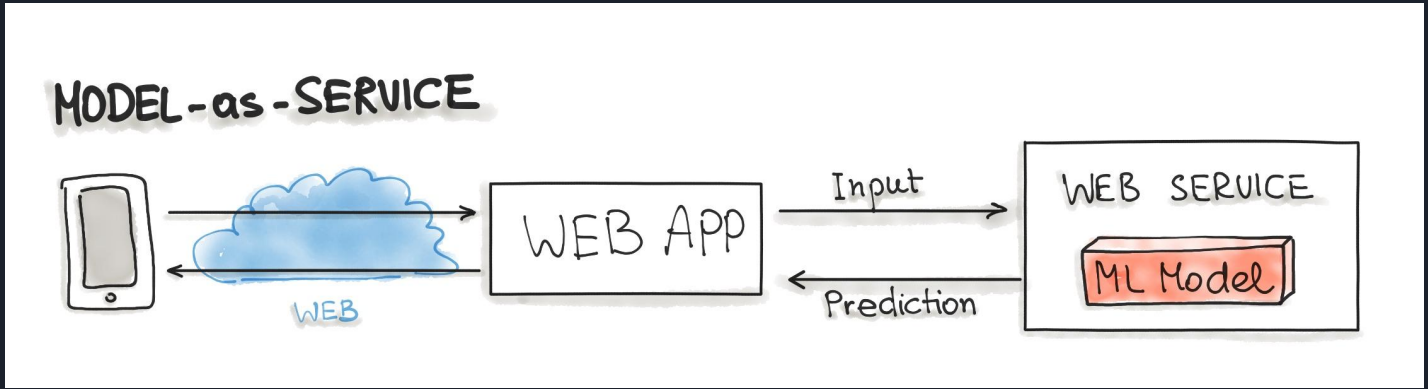
- **Modularity**: the code used in preprocessing/feature engineering should be arranged in comprehensive pipelines.
- **Reproducibility**: the output of each component must be replicable for any version in time.
- **Scalability**: the model must be serveable to a large number of customers with minimal response time.
- **Extensibility**: it should be easy to modify for future tasks.
- **Testing**: the ability to test variation between model versions.
- **Automation**: eliminating manual steps wherever possible to reduce error chances.

| Deployment Type | Training Approach | Prediction Approach - Batch | Prediction Approach - Live |
|---|---|---|---|
| On-Premises | Training is done locally on dedicated hardware or servers. | Batch predictions are run periodically on the same infrastructure. | Live predictions are served from the on-premises infrastructure. |
| Cloud | Training is performed on cloud-based resources. | Batch predictions can be scheduled using cloud services (e.g., AWS Batch). | Live predictions are served via cloud-based APIs or services (e.g., AWS Lambda). |
| Hybrid | A combination of local and cloud training resources. | Batch predictions can use cloud services for scalability (e.g., Azure Data Factory). | Live predictions can be a mix of on-premises and cloud APIs. |
| Edge | Training can occur on edge devices or remote servers. | Batch predictions might not be common due to limited resources. | Live predictions are executed directly on edge devices with optimized models. |
| Serverless | Training might involve serverless functions for specific tasks. | Batch predictions can be triggered by events using serverless functions. | Live predictions are served through serverless functions or APIs. |
| Containerized | Training is done within Docker containers for consistency. | Batch predictions can be executed within containerized environments. | Live predictions are served using containerized applications or microservices. |

# DEPLOYMENT PIPELINES

# Model as a Service

- Model-as-Service is a common pattern for wrapping an ML model as an independent service. We can wrap the ML model and the interpreter within a dedicated web service that applications can request through a REST API or consume as a gRPC service.
- This pattern can be used for various ML workflows, such as Forecast, Web Service, Online Learning.

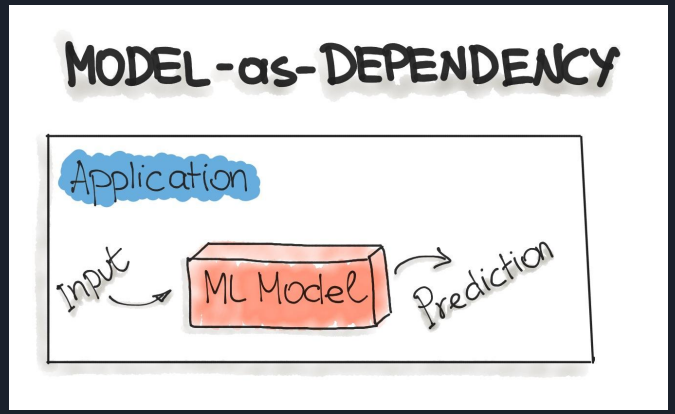


# Model as a Dependency

Model-as-Dependency is probably the most straightforward way to package an ML model. A packaged ML model is considered as a dependency within the software application.

For example, the application consumes the ML model like a conventional jar dependency by invoking the prediction method and passing the values. The return value of such method execution is some prediction that is performed by the previously trained ML model.

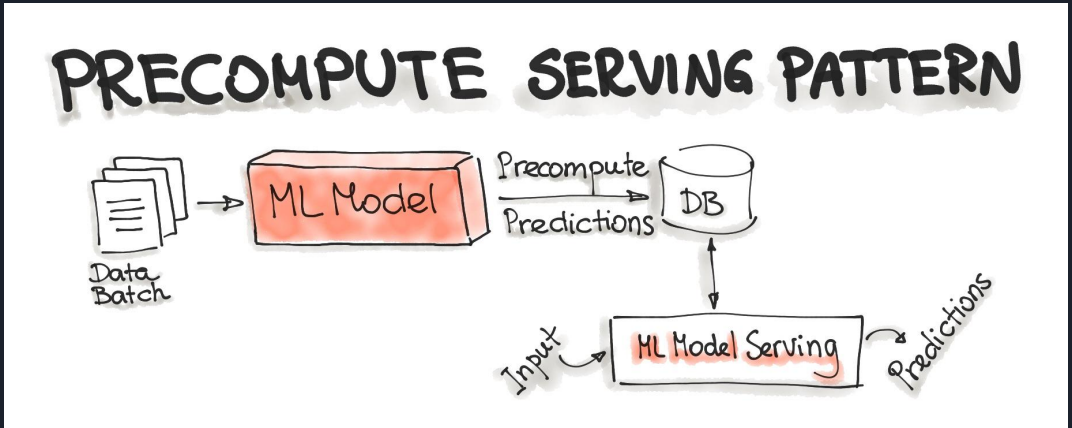
The Model-as-Dependency approach is mostly used for implementing the Forecast pattern.



# Precompute Serving Pattern

This type of ML model serving is tightly related to the Forecast ML workflow. With the Precompute serving pattern, we use an already trained ML model and precompute the predictions for the incoming batch of data.

The resulting predictions are persisted in the database. Therefore, for any input request, we query the database to get the prediction result.



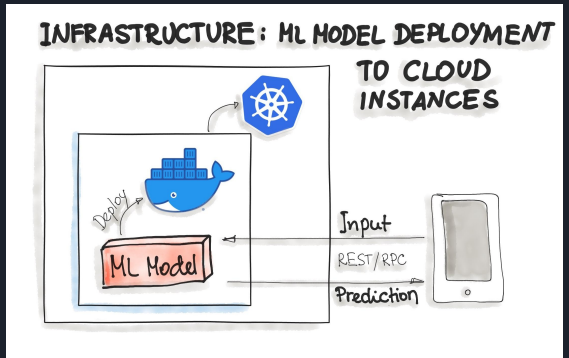
# Deploying ML Models as Docker Containers

As of now, there is no standard, open solution to ML model deployment. As ML model inference being considered stateless, lightweight, and idempotent, containerization becomes the de-facto standard for delivery.

This means we deploy a container that wraps an ML model inference code. For on-premise, cloud, or hybrid deployments, Docker is considered to be de-facto standard containerization technology.

One ubiquitous way is to package the whole ML tech stack (dependencies) and the code for ML model prediction into a Docker container. Then Kubernetes or an alternative (e.g. AWS Fargate) does the orchestration.

The ML model functionality, such as prediction, is then available through a REST API (e.g. implemented as Flask application)



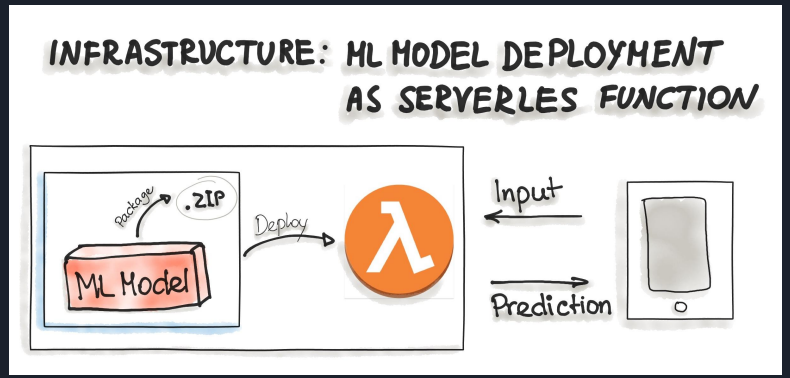
# Deploying ML Models as Serverless Functions

Various cloud vendors already provide machine-learning platforms, and you can deploy your model with their services. Examples are Amazon AWS Sagemaker, Google Cloud AI Platform, Azure Machine Learning Studio, and IBM Watson Machine Learning, to name a few.

Commercial cloud services also provide containerization of ML models such as AWS Lambda and Google App Engine servlet host.

In order to deploy an ML model as a serverless function, the application code and dependencies are packaged into .zip files, with a single entry point function.

This function then could be managed by major cloud providers such as Azure Functions, AWS Lambda, or Google Cloud Functions.

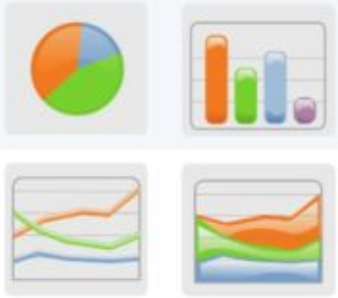


# MODEL MONITORING

# ML Monitoring

*Operational - Is it working?*

- Latencies
- Memory size
- CPU usage



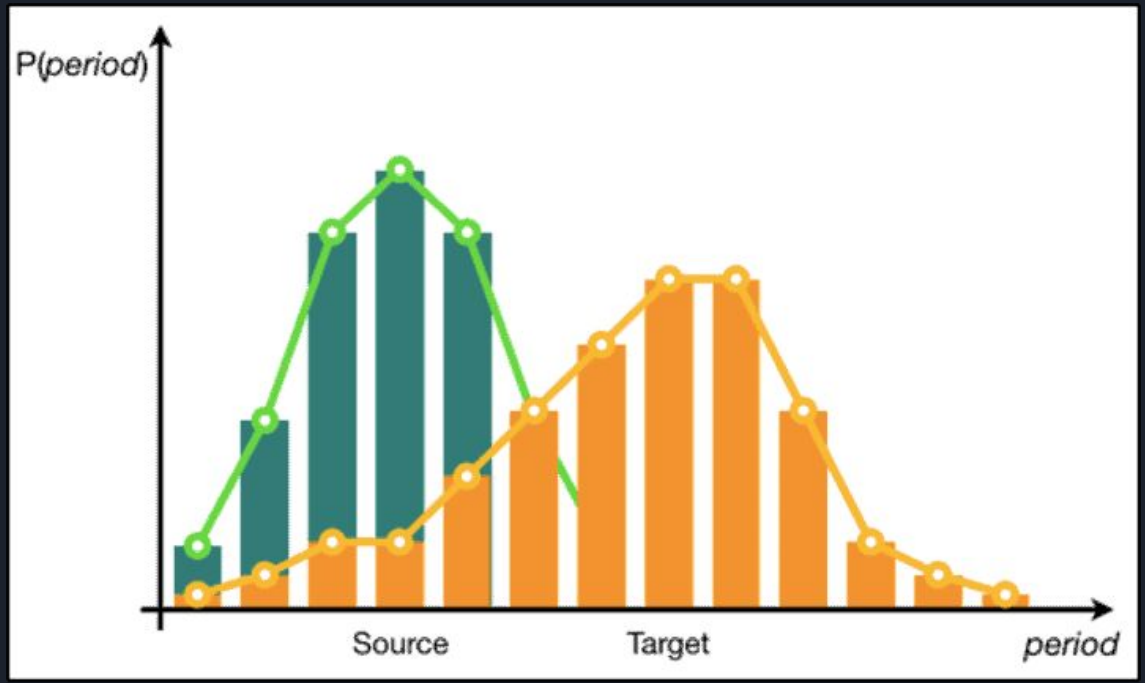
*Are the predictions accurate?*

- Model Outputs

*Is the data what is expected?*

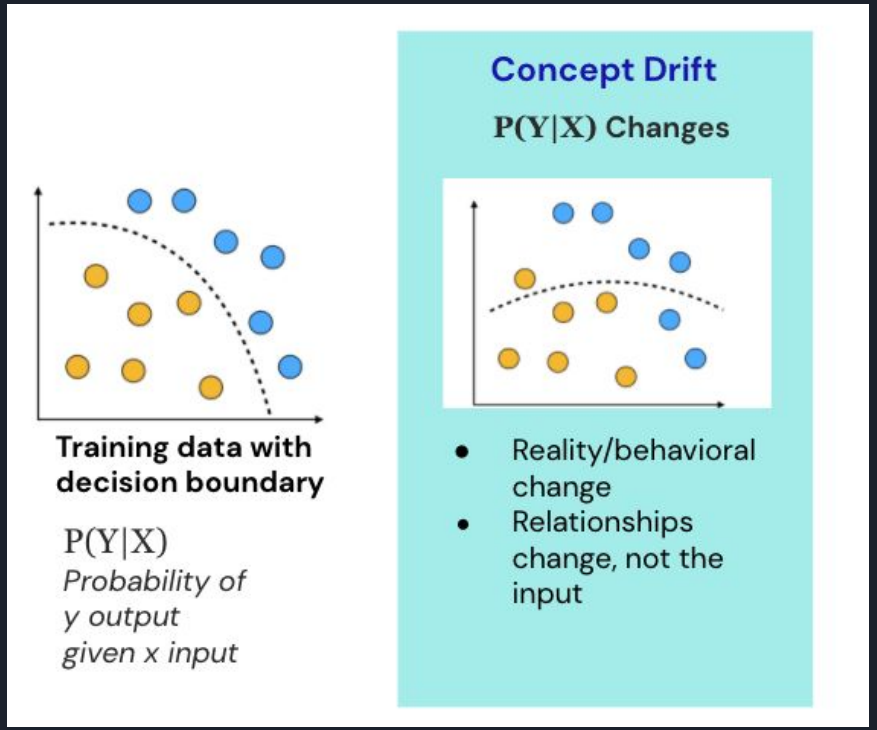
- Model Inputs

# Data Drift




**Data drift** refers to the situation where the statistical properties of the incoming data used for model prediction change over time.
This change can be due to various factors such as shifts in the data distribution, changes in user behavior, or external events.
When data drift occurs, the data that the model encounters in production may differ significantly from the data it was trained on.

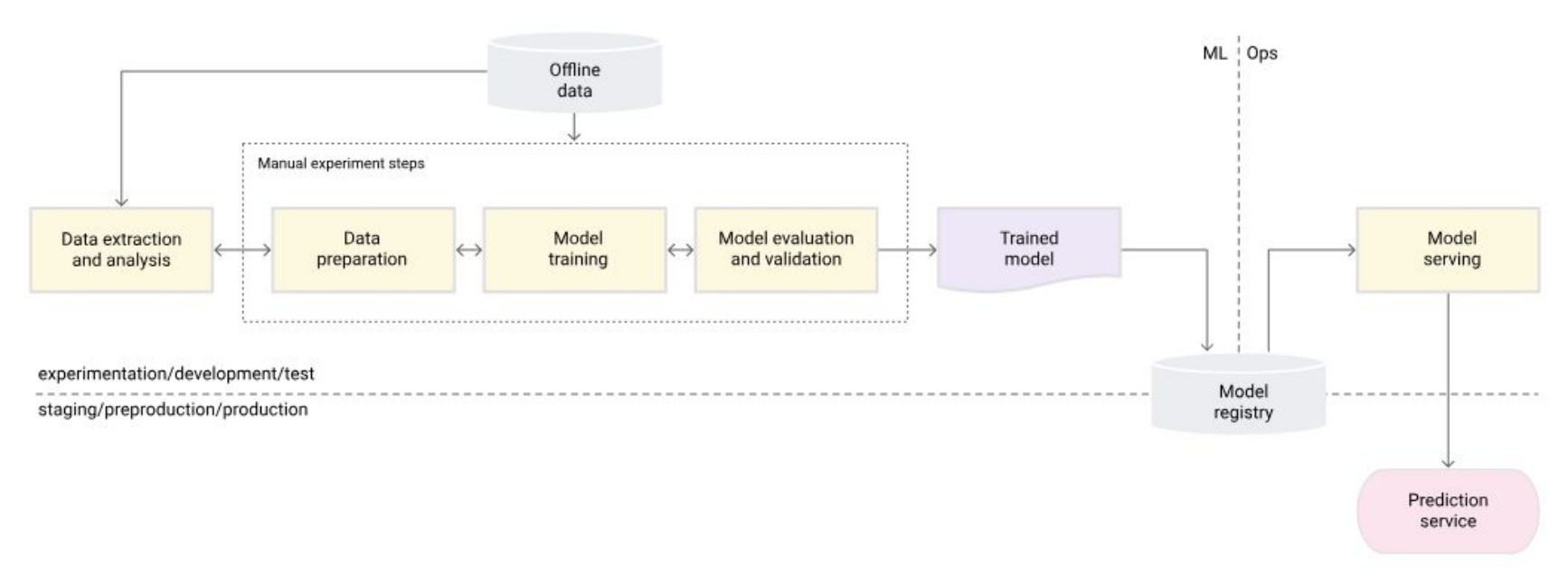
# Concept Drift



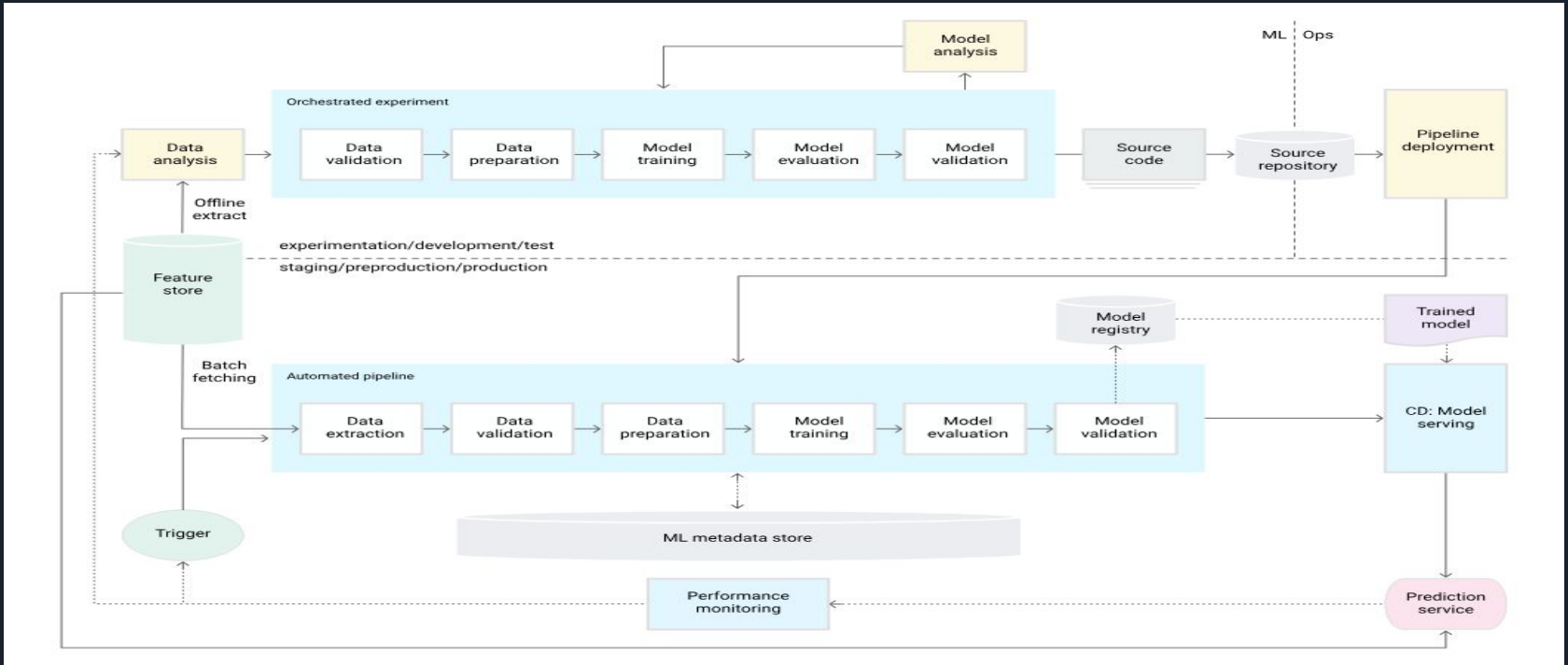

**Concept drift** is closely related to data drift but focuses on the underlying relationships between features and labels rather than just statistical properties. It occurs when the relationships between input features and the target variable change over time.
This means that the assumptions the model was built upon are no longer valid. Concept drift can be more subtle and challenging to detect than data drift. Continuous monitoring is necessary to identify concept drift and to retrain or update the model as needed to maintain its

# MLOPS PIPELINE

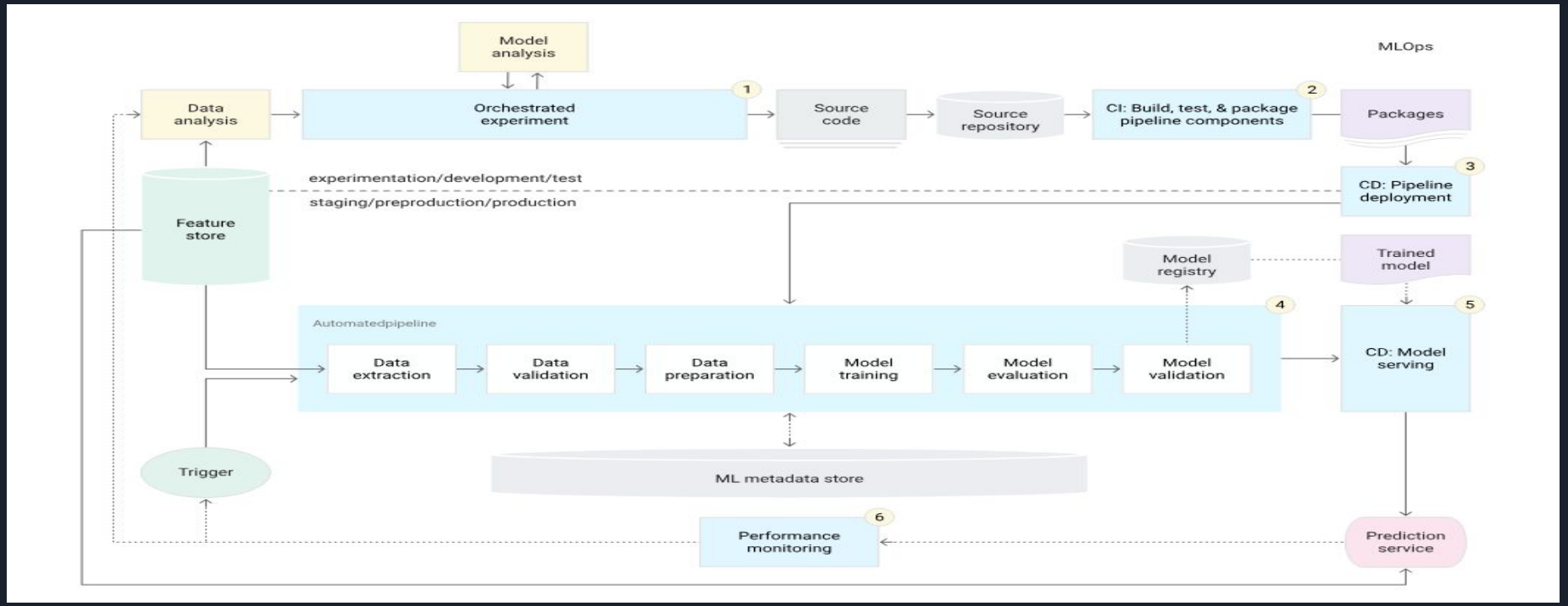
# MLOps level 0: Manual process



# MLOps level 1: ML pipeline automation



# MLOps level 2: CI/CD pipeline automation



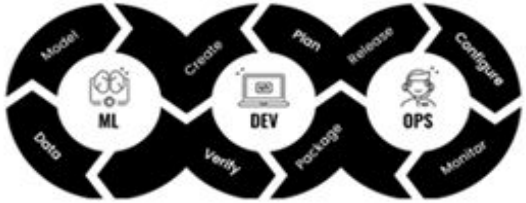
# Google Cloud MLops

https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

Designed by author Shanthababu

# Machine Learning Operations (MLOps)

## MLOps = ML + Dev + Ops




Line of Business

Business requirement

**Machine Learning Lifecycle**

### Data Collection
- Collecting data from various data sources

SMEs
Data Scientists

### Data Pipeline
- Data Pipeline Prep
- Data Clean up
- Data Transformation
- Data management Data drift monitoring
- Data support automation scripts/Tools

Data Engineer

### Model Building
- Model selection
- Model training
- Evaluation of Scoring
- Experimentation on accuracy
- Model validation

ML Engineer

### Model Deployment
- Scaling deployment model
- Model monitoring
- Model drift monitoring
- Model validation
- Assess the streaming and batch process

ML Engineer

### DevOps
- CI/CD pipeline
- Testing model
- Monitoring
  - Logging
  - Notification
  - Scaling deployment model
- Versioning
  - Model
  - Code
  - Data
- Model drift monitoring

MLOps Engineers

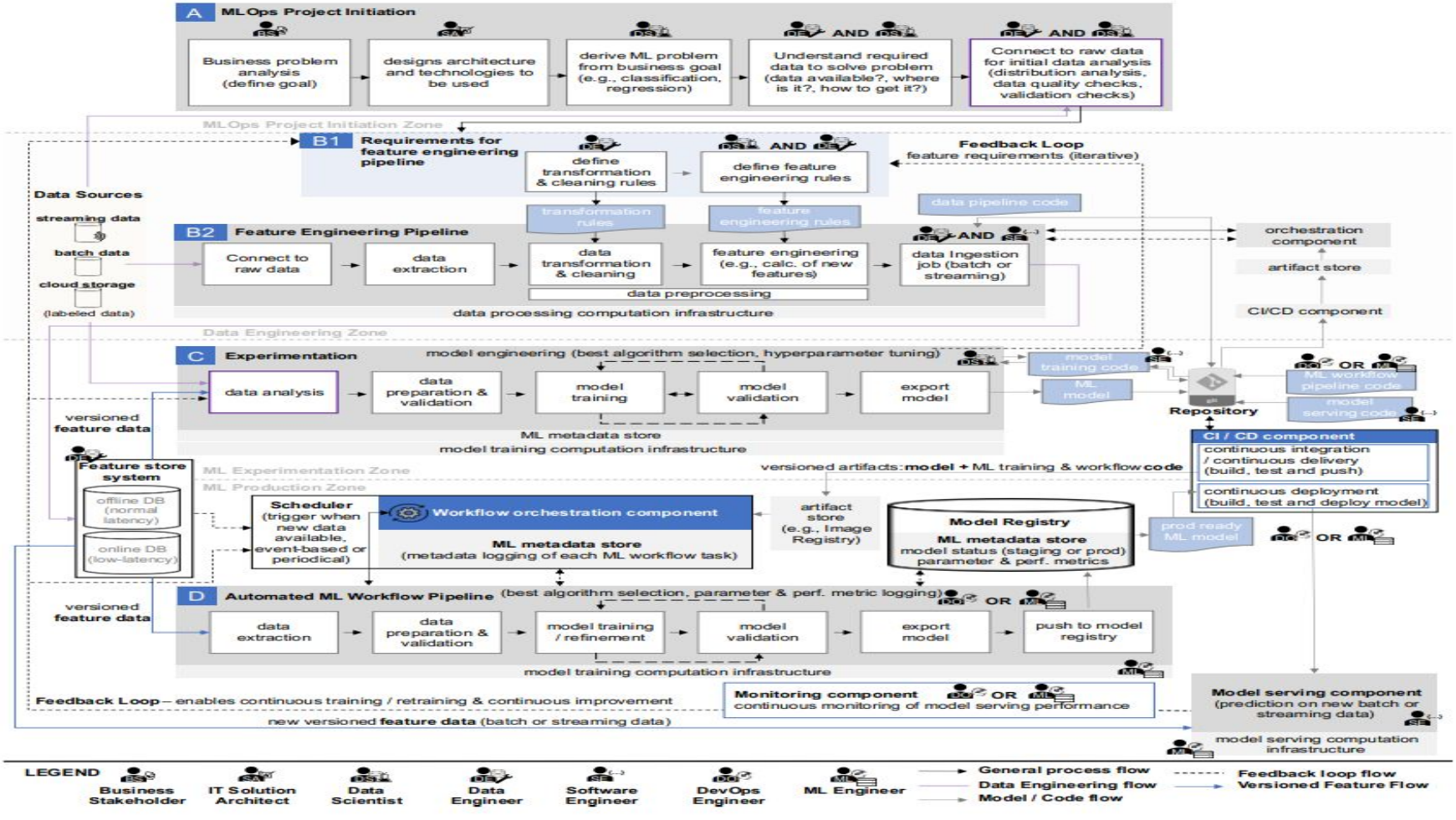
### Catalogs
- Dataset
- Feature
- Model

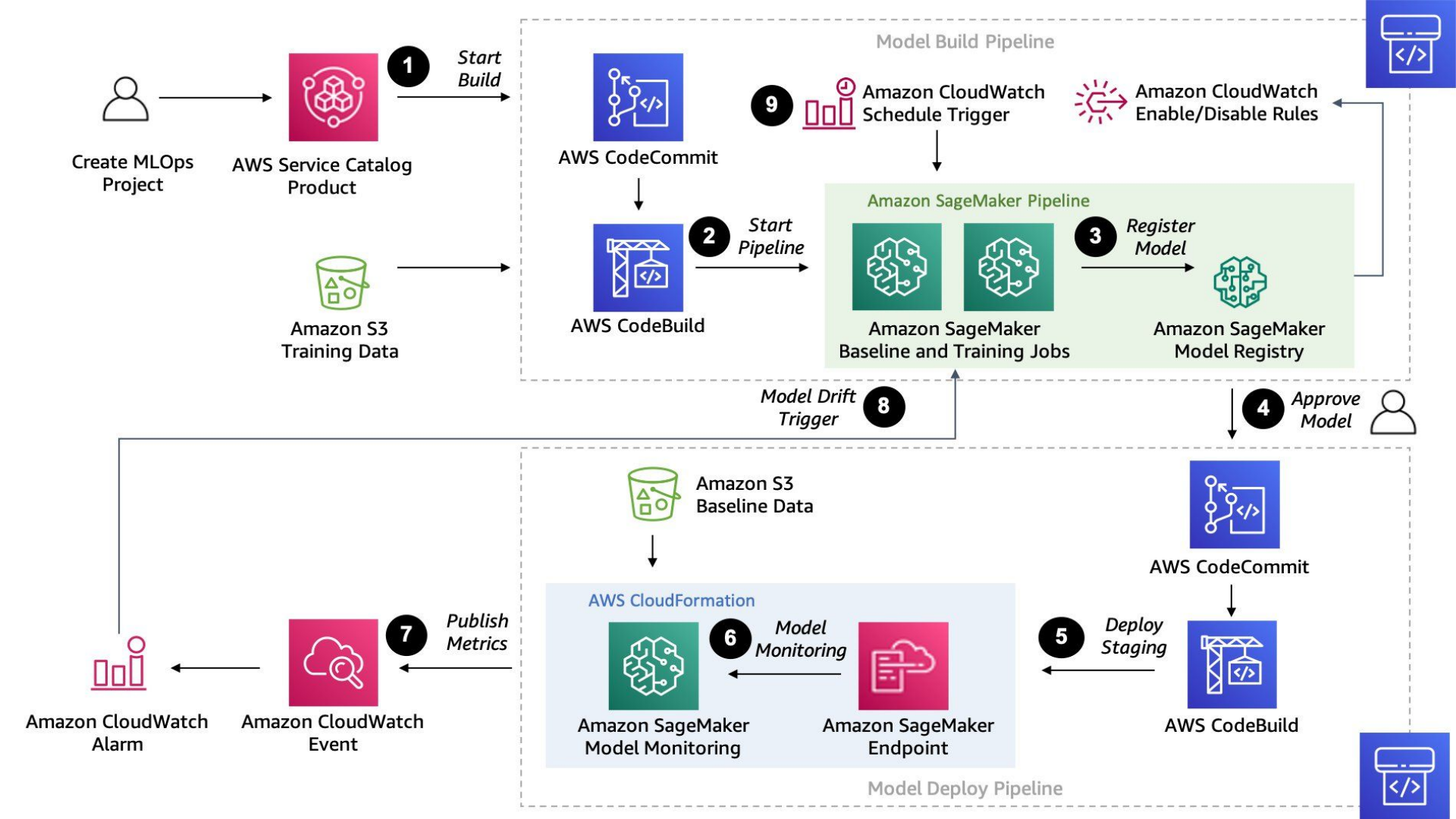
ML Archives

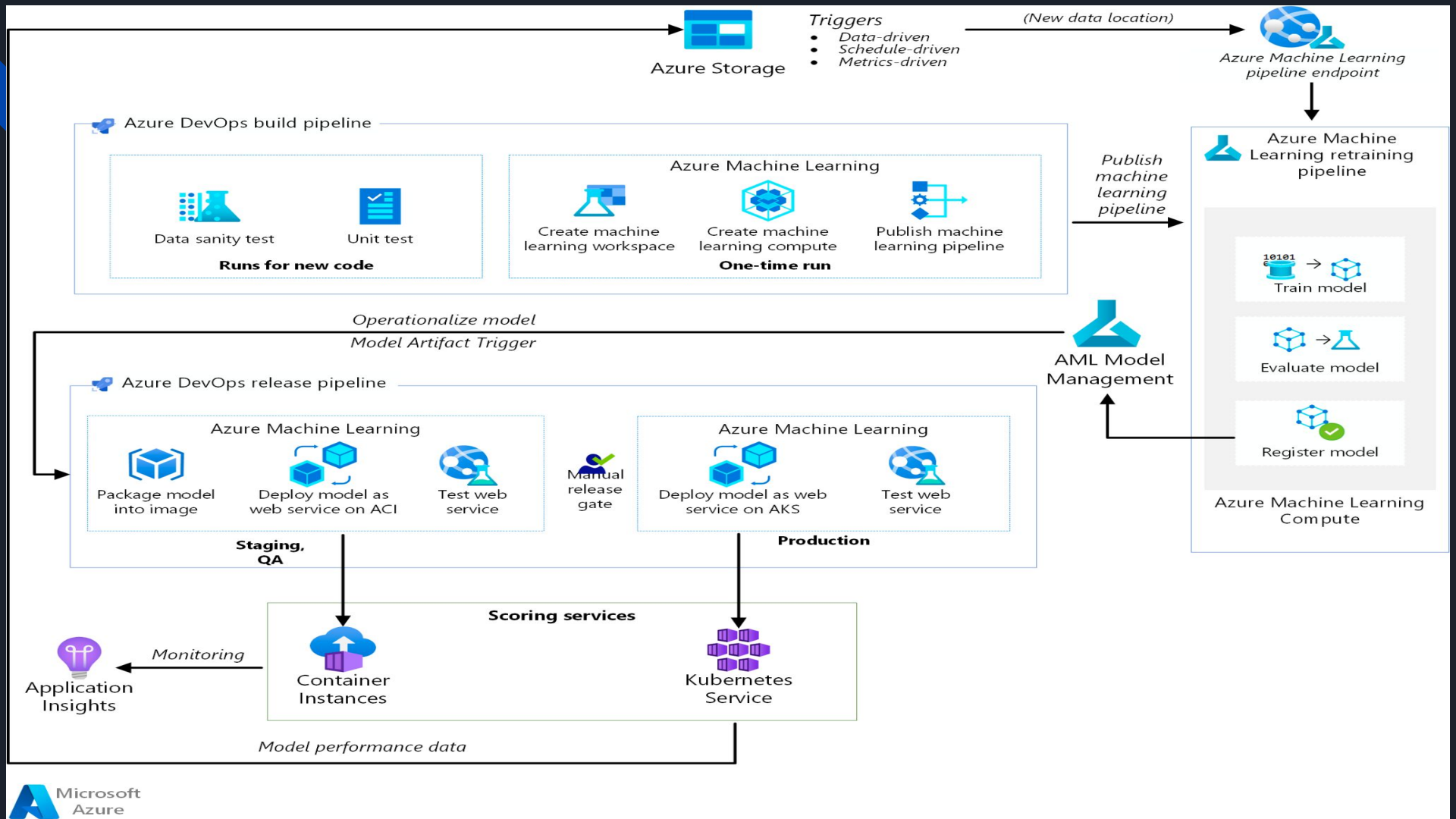
### Governance
- Access control
- Security
- GDPR/CCPA

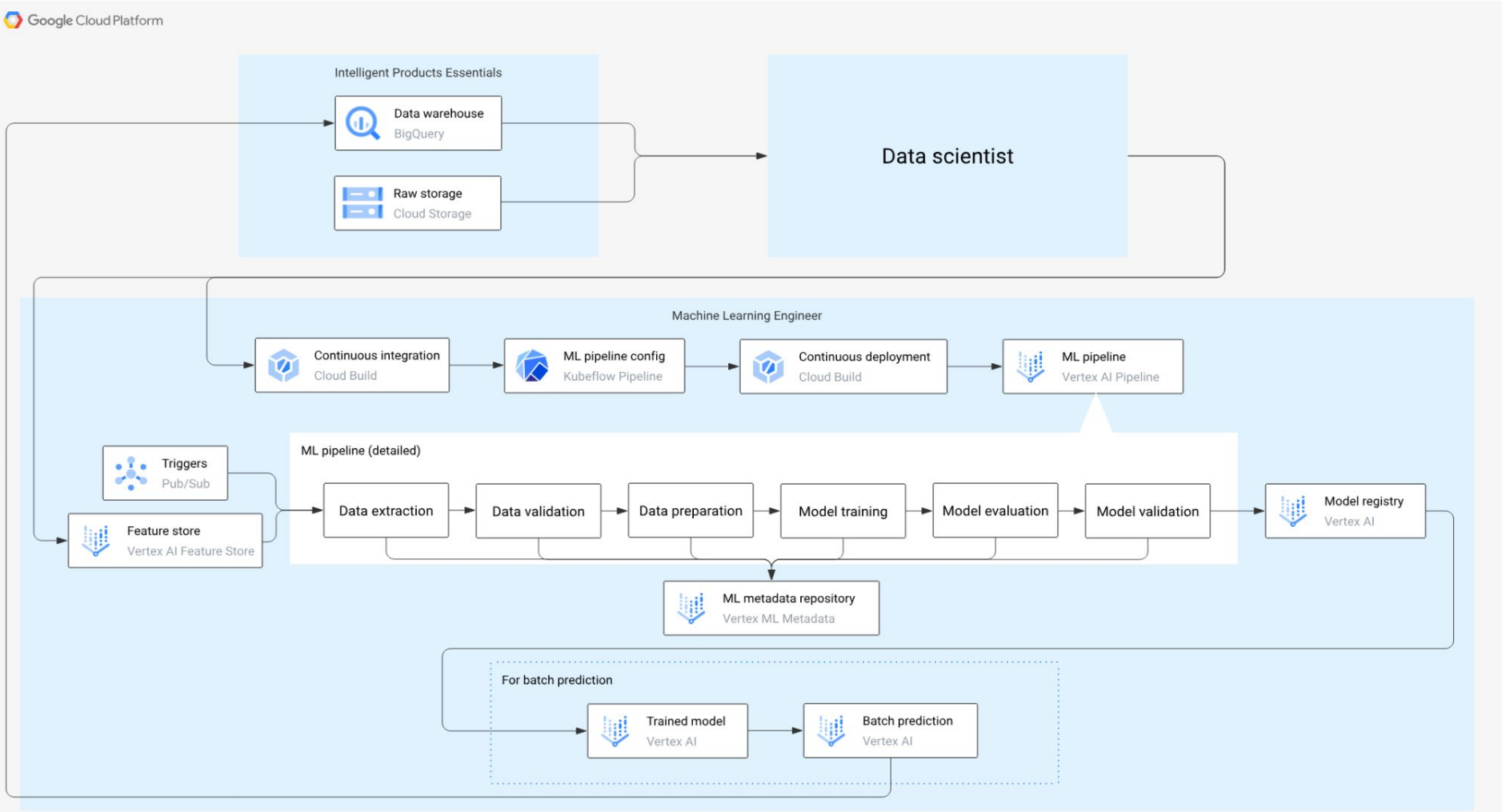
ML Governance

ML Architect


A MLOps Project Initiation
Business problem analysis (define goal)
designs architecture and technologies to be used
derive ML problem from business goal (e.g., classification, regression)
Understand required data to solve problem (data available?, where is it?, how to get it?)
Connect to raw data for initial data analysis (distribution analysis, data quality checks, validation checks)
AND
MLOps Project Initiation Zone
B1 Requirements for feature engineering pipeline
define transformation & cleaning rules
define feature engineering rules
transformation rules
feature engineering rules
Feedback Loop
feature requirements (iterative)
data pipeline code
Data Sources
streaming data
batch data
cloud storage
(labeled data)
B2 Feature Engineering Pipeline
Connect to raw data
data extraction
data transformation & cleaning
feature engineering (e.g., calc. of new features)
data Ingestion job (batch or streaming)
data preprocessing
data processing computation infrastructure
orchestration component
artifact store
CI/CD component
Data Engineering Zone
C Experimentation
model engineering (best algorithm selection, hyperparameter tuning)
data analysis
data preparation & validation
model training
model validation
export model
model training code
ML model
OR
ML workflow pipeline code
model serving code
Repository
versioned feature data
ML metadata store
model training computation infrastructure
CI / CD component
continuous integration / continuous delivery (build, test and push)
continuous deployment (build, test and deploy model)
Feature store system
offline DB (normal latency)
online DB (low-latency)
ML Experimentation Zone
ML Production Zone
versioned artifacts: model + ML training & workflow code
Scheduler (trigger when new data available, event-based or periodical)
Workflow orchestration component
ML metadata store (metadata logging of each ML workflow task)
artifact store (e.g., Image Registry)
Model Registry
ML metadata store
model status (staging or prod)
parameter & perf. metrics
prod ready ML model
D Automated ML Workflow Pipeline
(best algorithm selection, parameter & perf. metric logging)
data extraction
data preparation & validation
model training / refinement
model validation
export model
push to model registry
model training computation infrastructure
Feedback Loop – enables continuous training / retraining & continuous improvement
Monitoring component
continuous monitoring of model serving performance
new versioned feature data (batch or streaming data)
Model serving component
(prediction on new batch or streaming data)
model serving computation infrastructure
LEGEND
Business Stakeholder
IT Solution Architect
Data Scientist
Data Engineer
Software Engineer
DevOps Engineer
ML Engineer
General process flow
Data Engineering flow
Model / Code flow
Feedback loop flow
Versioned Feature Flow


Model Build Pipeline
Create MLOps Project
AWS Service Catalog Product
1
Start Build
AWS CodeCommit
9
Amazon CloudWatch Schedule Trigger
Amazon CloudWatch Enable/Disable Rules
Amazon S3 Training Data
AWS CodeBuild
2
Start Pipeline
Amazon SageMaker Pipeline
3
Register Model
Amazon SageMaker Baseline and Training Jobs
Amazon SageMaker Model Registry
Model Drift Trigger
8
4
Approve Model
Amazon S3 Baseline Data
AWS CodeCommit
AWS CloudFormation
7
Publish Metrics
6
Model Monitoring
5
Deploy Staging
Amazon CloudWatch Alarm
Amazon CloudWatch Event
Amazon SageMaker Model Monitoring
Amazon SageMaker Endpoint
AWS CodeBuild
Model Deploy Pipeline

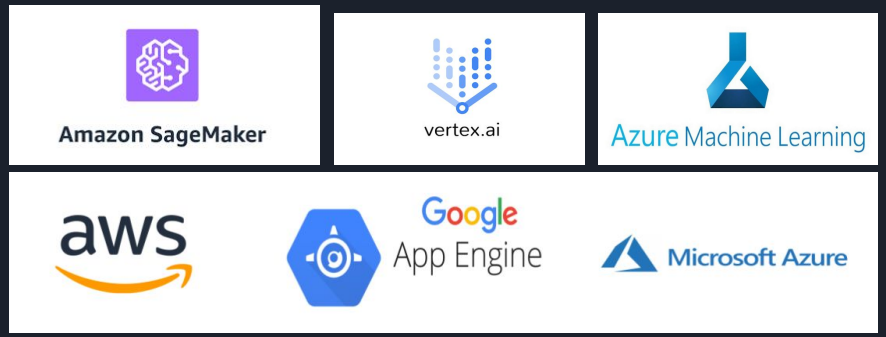

Azure Storage
Triggers
Data-driven
Schedule-driven
Metrics-driven
(New data location)
Azure Machine Learning pipeline endpoint
Azure DevOps build pipeline
Data sanity test
Unit test
Runs for new code
Azure Machine Learning
Create machine learning workspace
Create machine learning compute
Publish machine learning pipeline
One-time run
Publish machine learning pipeline
Azure Machine Learning retraining pipeline
Train model
Evaluate model
Register model
Azure Machine Learning Compute
Operationalize model
Model Artifact Trigger
AML Model Management
Azure DevOps release pipeline
Azure Machine Learning
Package model into image
Deploy model as web service on ACI
Test web service
Staging, QA
Manual release gate
Azure Machine Learning
Deploy model as web service on AKS
Test web service
Production
Scoring services
Container Instances
Kubernetes Service
Monitoring
Application Insights
Model performance data
Microsoft Azure


Google Cloud Platform
Intelligent Products Essentials
Data warehouse
BigQuery
Raw storage
Cloud Storage
Data scientist
Machine Learning Engineer
Continuous integration
Cloud Build
ML pipeline config
Kubeflow Pipeline
Continuous deployment
Cloud Build
ML pipeline
Vertex AI Pipeline
Triggers
Pub/Sub
Feature store
Vertex AI Feature Store
ML pipeline (detailed)
Data extraction
Data validation
Data preparation
Model training
Model evaluation
Model validation
Model registry
Vertex AI
ML metadata repository
Vertex ML Metadata
For batch prediction
Trained model
Vertex AI
Batch prediction
Vertex AI

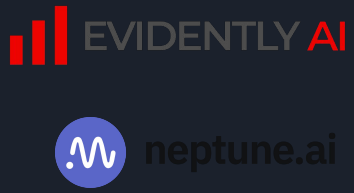

Version Control


CI/CD


Containerization and Orchestration




Model Deployment





Monitoring and Observability

# END