



Title: MLOPS

Course: Data Mining

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What is MLOps?

- Machine Learning Operations
- Focuses on optimizing the end-to-end machine learning lifecycle
- Goals
 - Improve collaboration among teams
 - data scientists, developers, and operations
 - Streamline and automate tasks in the ML workflow

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OPTIONAL

Components of MLOps I

- Collaboration and Communication
 - Facilitate effective communication between teams
- Version Control
 - Track changes in code, data, and models for reproducibility
- Automation
 - Automate tasks like model training, testing, and deployment
- CI/CD Practices
 - Implement Continuous Integration and Continuous Deployment for seamless workflows
- Monitoring and Logging
 - Use monitoring tools to track real-time model performance

Components of MLOps II

- Model Registry
 - Catalog and manage different **versions** of trained models
- Infrastructure as Code (IaC)
 - Define **model deployment** infrastructure in code for consistency
- Security and Governance
 - Ensure security and compliance with **regulations**

Definition: Infrastructure as Code (IaC)

Managing and provisioning infrastructure through machine-readable configuration files instead of manual processes

Key Characteristics:

- Infrastructure setup is automated, repeatable, and version-controlled
- Enables rapid deployment and scaling across environments (e.g., dev, test, prod)
- Reduces configuration drift and human error

Popular Tools: Terraform, Ansible, AWS CloudFormation, Pulumi, Chef

Example Use Case: Provisioning a virtual network and VM instances in a cloud provider using a declarative configuration file

Infrastructure as Code: Pros and Cons

Advantages:

- **Automation:** Enables rapid, repeatable deployments
- **Consistency:** Reduces configuration drift across environments
- **Version Control:** Infrastructure changes are tracked and auditable
- **Scalability:** Easily replicate infrastructure at scale
- **Disaster Recovery:** Fast restoration using predefined configurations

Disadvantages:

- **Learning Curve:** Requires knowledge of tools and syntax
- **Complexity:** Large-scale IaC can become difficult to manage
- **Tooling Limitations:** Not all resources or platforms may be fully supported
- **Potential for Misconfiguration:** Errors in code can scale quickly

The Role of Automation in MLOps

- Reduces manual errors
- Increases efficiency
- Ensures consistency in deployment processes

Security and Governance

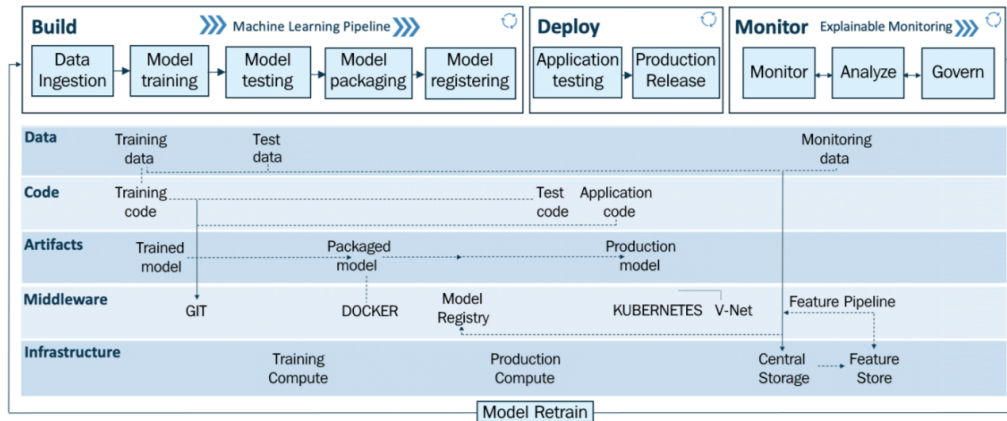
Protecting Data and Ensuring Compliance

- Considers security measures for sensitive data
- Ensures compliance with regulations

Benefits of MLOps

- Reliable and scalable deployment of machine learning models
- Consistent and reproducible workflows
- Enhanced collaboration and communication among teams

MLOps Workflow - I



MLOps Workflow - II

- MLOps pipeline (build, deploy, and monitor)
 - the upper layer
- Drivers: Data, code, artifacts, middleware, and infrastructure
 - mid and lower layers

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A use case

- operationalize¹ an image classification service to classify cats and dogs in a pet park in Barcelona, Spain.
- The service will identify cats and dogs in real time from the inference data coming from a CCTV camera installed in the pet park
- The pet park provides you access to the data and infrastructure needed to operationalize the service

¹ prototyping and deploying for production

Data and Infrastructure

- Data
 - The pet park has given you access to their data lake containing 100,000 labeled images of cats and dogs, which we will be used for training the model
- Infrastructure
 - Public cloud (IaaS)

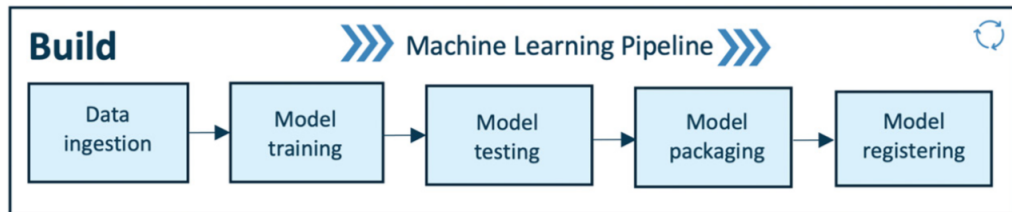
The MLOps pipeline

- operationalize² an image classification service to classify cats and dogs in a pet park in Barcelona, Spain.
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² prototyping and deploying for production

Build

- core ML pipeline
 - training, packaging, and versioning the ML models
- includes computation facilities
 - for example, the CPU or GPU on the cloud or distributed computing



BUILD – Model training

- Modular scripts or code perform all the traditional steps in ML, before training or retraining any model
 - data preprocessing, feature engineering, and feature scaling
- The ML model is trained while performing hyperparameter tuning to fit the model to the dataset (training set).
 - efficient and automatic solutions such as Grid Search or Random Search exist

Model training

Use case implementation

- We implement all the important steps to train the image classification model.
- For this case, we train a convolutional neural network (CNN³) for the image classification service.
- The following steps are implemented: data preprocessing, feature engineering, and feature scaling before training, followed by training the model with hyperparameter tuning.
- As a result, we have a CNN model to classify cats and dogs with 97% accuracy

3 <https://towardsdatascience.com/wtf-is-image-classification-8e78a8235acb>

BUILD – Model testing

- evaluate the trained model performance on a separated set of data points named test data
 - which was split and versioned in the data ingestion step.
- The inference of the trained model is evaluated according to selected metrics as per the use case.
- The output of this step is a report on the trained model's performance

Model testing

Use case implementation

- In this case, we look for precision and the recall score
 - to validate the model's performance in classifying cats and dogs
 - to assess false positives and true positives to get a realistic understanding of the model's performance.
- If and when we are satisfied with the results, we can *proceed to the next step*
- or else *reiterate the previous steps* to get a decent performing model for the pet park image classification service

BUILD – Model packaging

- the model can be **serialized** into a file
- or **containerized** (using Docker) to be exported to the production environment

Model packaging

Use case implementation

- The model we trained and tested in the previous steps is serialized to an ONNX⁴ file
- It is ready to be deployed in the production environment

⁴ <https://onnx.ai>

BUILD – Model registering

- The model that was serialized or containerized in the previous step is **registered and stored** in the **model registry**.
- A registered model is a logical collection or package of one or more files that assemble, represent, and execute your ML model.
- e.g. a classification model can be comprised of a **vectorizer**, **model weights**, and **serialized model files**.
- All these files can be registered as one single model.
- After registering, the model (all files or a single file) can be downloaded and deployed as needed

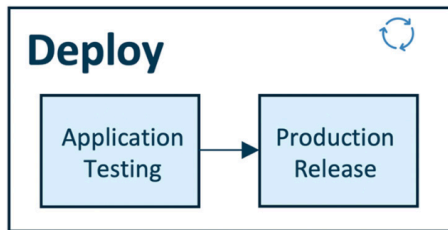
Model registering

Use case implementation

- The serialized model in the previous step is registered on the model registry and is available for quick deployment into the pet park production environment
- By implementing the preceding steps, we successfully execute the ML pipeline designed for our use case.
- As a result, we have trained models on the model registry ready to be deployed in the production setup.
- Next, we will look into the workings of the deployment pipeline

Deploy

- Make the ML models **operational**
- Test model performance and behavior in a production or production-like (test) environment to ensure the robustness and scalability of the ML model for production use
- Streamlined CI/CD pipelines connecting the development to production environments



Deploy - Application testing

- Rigorously test all the trained models for **robustness** and **performance** in a **production-like** environment called a test environment
- Deploy the models in the test environment
- Perform predictions using **test data**
 - not used for training the model; test data is sample data from a production environment
- Performance results are automatically or manually reviewed by a quality assurance expert

Deploy - Application testing

Use case implementation

- We deploy the model as an API service on an on-premises computer in the pet park, which is set up for testing purposes.
- This computer is connected to a CCTV camera in the park to fetch real-time inference data to predict cats or dogs in the video frames.
- The model deployment is enabled by the CI/CD pipeline.
- Test the robustness of the model in a production-like environment, that is, whether the model is performing inference consistently,
- Test accuracy, fairness, and error analysis.
- At the end of this step, a quality assurance expert certifies the model if it meets the standards

Deploy - Production release

- Previously tested and approved models are deployed in the production environment for model inference to generate business or operational value.
- This production release is deployed to the production environment enabled by CI/CD pipelines

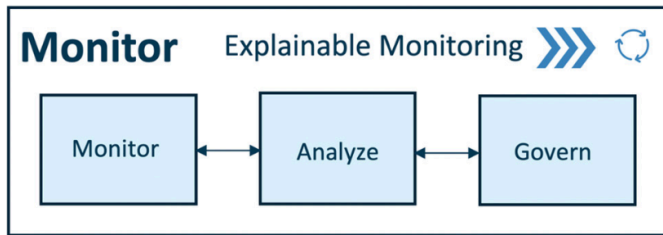
Deploy - Production release

Use case implementation

- We deploy a previously tested and approved model (by a quality assurance expert) as an API service on a computer connected to CCTV in the pet park (production setup).
- This deployed model performs ML inference on the incoming video data from the CCTV camera in the pet park to classify cats or dogs in real time

Monitor

- Works in sync with the deploy module
- Pre-defined metrics
- Telemetry data
- Explainability methods



Monitor

- Capture critical information to monitor data integrity, model drift, and application performance

Analyze I

- Statistical properties of the target variable
- Explainability techniques
- Over time, the statistical properties of the target variable can change in unforeseen ways.
- This change is called **model drift**
 - For example, in a case where we have deployed a recommender system model to suggest suitable items for users, user behavior may change due to unforeseeable trends that could not be observed in historical data that was used for training the model.

Analyze II

- It is essential to consider unforeseen factors to ensure deployed models provide the best and most relevant business value
- In case of model drift
 - alert the stakeholders or the quality assurance officer
 - switch or update the models
 - re-train the pipeline

Govern

- Generate alerts to trigger govern actions
- Compliance with the laws
 - explainability
 - transparency
 - end-to-end traceability

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OPTIONAL

What is good data for ML?

- Good ML models are a result of training on good-quality data.
- A pre-requisite is to have good-quality data.
- We need to process the data to increase its quality.
- Determining the quality of data is essential.
- Five characteristics

Five characteristics of good data for ML I

- Accuracy

- Inaccurate data lead to poor ML models
- Confirm whether the data represent adequately the real world

- Completeness

- Check the comprehensiveness of the data
- e.g. consider the coverage of time and space dimensions, population, product families ...

Five characteristics of good data for ML II

- Reliability
 - Contradictions and duplications
 - Bias and distributions
- Relevance
 - with respect to the ML task at hand
- Timeliness

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OPTIONAL

TensorFlow Extended (TFX)

- Developed by Google for TensorFlow users
- End-to-end platform for deploying production-ready machine learning models
- Supports component-based architecture for flexibility
- Integrates with Apache Airflow for orchestration

MLflow

- Open-source platform developed by Databricks
- Designed for managing the end-to-end machine learning lifecycle
- Components include Tracking, Projects, Models, and Registry
- Language-agnostic and supports multiple ML libraries

Kubeflow

- Kubernetes-native platform for deploying and managing ML models
- Supports end-to-end orchestration, from data preprocessing to model deployment
- Integrates various tools like TensorFlow, PyTorch, and Jupyter notebooks
- Extensible and customizable for different workflows

Apache Airflow

- Open-source platform for orchestrating complex workflows
- Widely used in MLOps for scheduling and monitoring data workflows
- DAG (Directed Acyclic Graph) structure for defining workflows
- Integrates with various databases, storage systems, and ML platforms

DataRobot

- Automated machine learning platform
- Provides end-to-end automation from data preparation to model deployment
- Focus on democratizing machine learning for users with varying skill levels
- Supports collaboration and model explainability

Domino Data Lab

- Collaboration platform for data mining and MLOps
- Enables reproducibility and collaboration in a centralized environment
- Supports version control, experiment tracking, and model deployment
- Integrates with popular data mining tools

Azure Machine Learning

- Microsoft's cloud-based MLOps platform
- Integrates with popular Azure services for data storage, compute, and deployment
- Provides tools for model training, deployment, and monitoring
- Supports a wide range of frameworks and languages

DVC (Data Version Control)

- Open-source version control system for machine learning projects
- Focuses on managing datasets and models in a reproducible way
- Works well with existing version control systems like Git
- Supports experimentation tracking and collaboration

Seldon Core

- Open-source platform for deploying, scaling, and managing machine learning models on Kubernetes
- Supports a wide range of ML frameworks
- Provides features for A/B testing, canary deployments, and scaling
- Enables production-ready model serving

Algorithmia

- MLOps platform for deploying, managing, and scaling machine learning models
- Supports model deployment via REST APIs
- Provides model versioning, monitoring, and collaboration features
- Focuses on making models available as microservices

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Differences between CRISP-DM and MLOps I

- Purpose and Focus
 - **CRISP-DM** Structured methodology for data mining projects, covering the entire project lifecycle
 - **MLOps** Focuses on the operationalization and management of machine learning models in production

Differences between CRISP-DM and MLOps II

- Activities
 - **CRISP-DM** Involves business understanding, data preparation, modeling, evaluation, and deployment
 - **MLOps** Involves model deployment, continuous integration, continuous delivery, monitoring, and managing the machine learning model lifecycle
- Methodological vs. Operational
 - **CRISP-DM** Methodological framework for structuring the data mining process
 - **MLOps** Operational practices and tools for managing machine learning models in production

Differences between CRISP-DM and MLOps III

- Timing
 - **CRISP-DM** Applied throughout the entire data mining project
 - **MLOps** Becomes prominent once the machine learning model is ready for deployment and continues throughout its operational lifecycle
- Collaboration
 - **CRISP-DM** Emphasizes collaboration between business stakeholders, data scientists, and domain experts
 - **MLOps** Encourages collaboration between data scientists, developers, and operations teams for deployment and maintenance

CRISP-DM and MLOps – Summary

- Distinct concepts addressing different aspects of the data mining and machine learning lifecycle
- CRISP-DM guides the entire data mining project
- MLOps specifically addresses the operational aspects of managing machine learning models in production
- They are complementary in an end-to-end workflow

Bibliography

- Raj, E. (2021).
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