Title:	MLOPS
Course:	Data Mining
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Master:	Data Science and Business Analytics
Master:	Artificial Intelligence and Innovation
Master:	Finance and Financial Technologies
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What is MLOps?

- MLOps stands for Machine Learning Operations.
- It focuses on optimizing the end-to-end machine learning lifecycle.

Goals of MLOps

- Improve collaboration among teams
  - data scientists, developers, and operations
- Streamline and automate tasks in the ML workflow

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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.

The Role of Automation in MLOps

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

CI/CD Practices

Continuous Integration and Continuous Deployment

- Automates testing and deployment of models.
- Enables seamless integration of changes into production.

Real-time Monitoring and Logging

- Identifies issues and drift in data distributions.
- Monitors model performance in production environments.

Managing Model Versions - Model Registry

- Catalogs and manages different versions of trained models.
- Facilitates easy retrieval and deployment of specific model versions.

Infrastructure as Code (IaC) – Ensuring Consistency

- Defines infrastructure in code for reproducibility.
- Maintains consistency across different environments.

Security and Governance

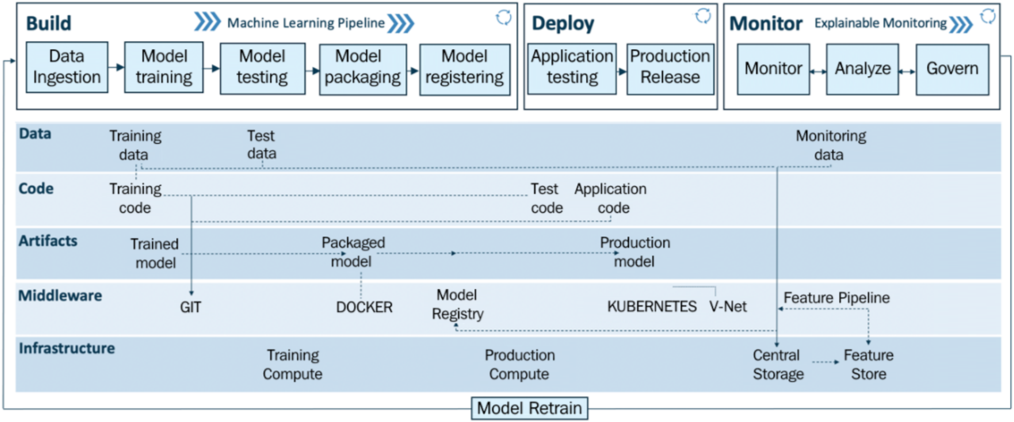
Protecting Data and Ensuring Compliance

- 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

A use case

- operationalize[1] 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).

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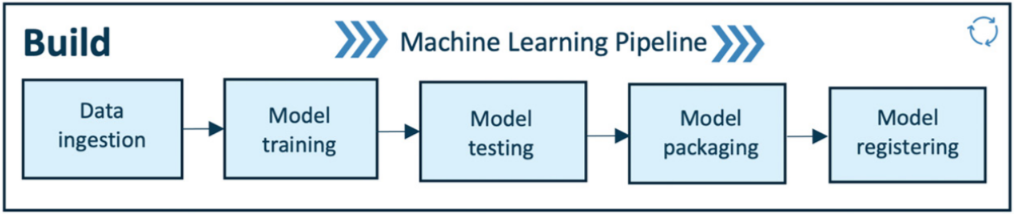
The MLOps pipeline

- operationalize[2] 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.

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 (CNN[3]) 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 ONNX [4] 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.

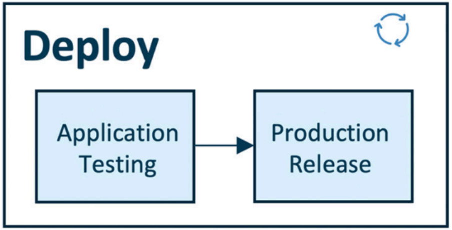
Model registering

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,
- Testaccuracy, 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.

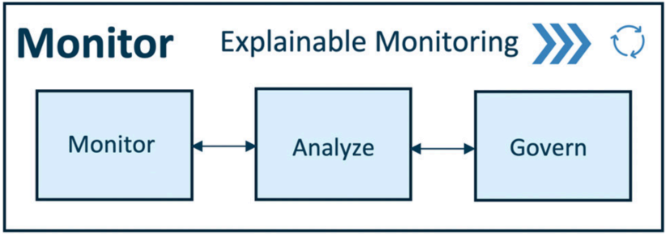
Deploy - Production release

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.

Monitoring

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



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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 wether 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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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 science and MLOps.
- Enables reproducibility and collaboration in a centralized environment.
- Supports version control, experiment tracking, and model deployment.
- Integrates with popular data science 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.
- **Lifecycle Stage**
  - CRISP-DM Encompasses the entire data mining or analytics project lifecycle.
  - MLOps Primarily focuses on the operational aspects of machine learning models.

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 science 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 science 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 science and machine learning lifecycle
- CRISP-DM guides the entire data science 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).
  Engineering MLOps : Rapidly Build, Test, and Manage Production-ready Machine Learning Life Cycles at Scale.
  Packt Publishers.