Machine Learning Operations

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Introduction

> *Imagine you have a magic cookbook that can teach you how to make the best cookies ever. But it's not just any cookbook, it's a special one that learns and gets better every time you make cookies.*
>
> *Now, making cookies is a bit like solving a puzzle. You need the right ingredients (like flour, sugar, and chocolate chips) and you need to mix them together in just the right way. Sometimes, you might make a mistake and your cookies don't turn out quite right.*
>
> *That's where MLOps comes in! MLOps is like having a team of helpful fairies who watch over you while you're baking. They make sure you're using the right ingredients, they help you mix everything together perfectly, and they even give you tips on how to make your cookies even better next time.*
>
> *So, with MLOps, you can keep making cookies and your magic cookbook will keep learning from each batch. And before you know it, you'll be making the most delicious cookies anyone has ever tasted!*
>
> — Chuks Okoli

Hello there, and welcome to Machine Learning Operations. This work is a culmination of hours of effort to create my reference for machine learning operations. All of the explanations are in my own words but majority of the content are based on Alexey Grigorev's DataTalksClub MLOps Zoomcamp course.

1.1 What is MLOps?

> *MLOps, also known as DevOps for machine learning, is an umbrella term that encompasses philosophies, practices, and technologies that are related to implementing machine learning lifecycles in a production environment.*
>
> — Microsoft Blog

Machine Learning Operations (MLOps) is a set of best practices for putting machine learning models into production. The process for a machine learning project involves:

- Design - define if machine learning is the right tool for solving the problem
- Train - train the model to find the best possible model
- Operate - deploy the model, and monitor degradation or quality of the model

MLOps is a set of practices for automating everything and working together as a team on a machine learning project.

Fun Fact: MLOps Principles

As machine learning and AI become more common in software, it's important to create guidelines and tools for testing, deploying, managing, and monitoring ML models in real-world use. This is where MLOps comes in. It helps prevent "technical debt" in machine learning projects by ensuring smooth operation and maintenance of models throughout their lifecycle.

MLOps helps to manage and orchestrate the end-to-end machine learning lifecycle by ensuring models are consistently accessible, reproducible, and scalable. It focuses on automating deployment and monitoring of ML pipelines while optimizing the model development process.

The three-phase approach to implementing machine learning (ML) solutions are:

- **Business Understanding and Design**: This phase involves identifying user needs, designing ML solutions to address them, and assessing project development. Prioritizing ML use cases and defining data requirements are key steps. The architecture of the ML application, serving strategy, and testing suite are designed based on functional and non-functional requirements.
- **ML Experimentation and Development**: This phase focuses on verifying

the applicability of ML by implementing Proof-of-Concept models. It involves iteratively refining ML algorithms, data engineering, and model engineering to deliver a stable, high-quality ML model for production.

- **ML Operations**: Here, the emphasis is on deploying the developed ML model into production using established DevOps practices. Testing, versioning, continuous delivery, and monitoring are essential aspects of this phase.

These phases are interconnected, with design decisions influencing experimentation and deployment options.

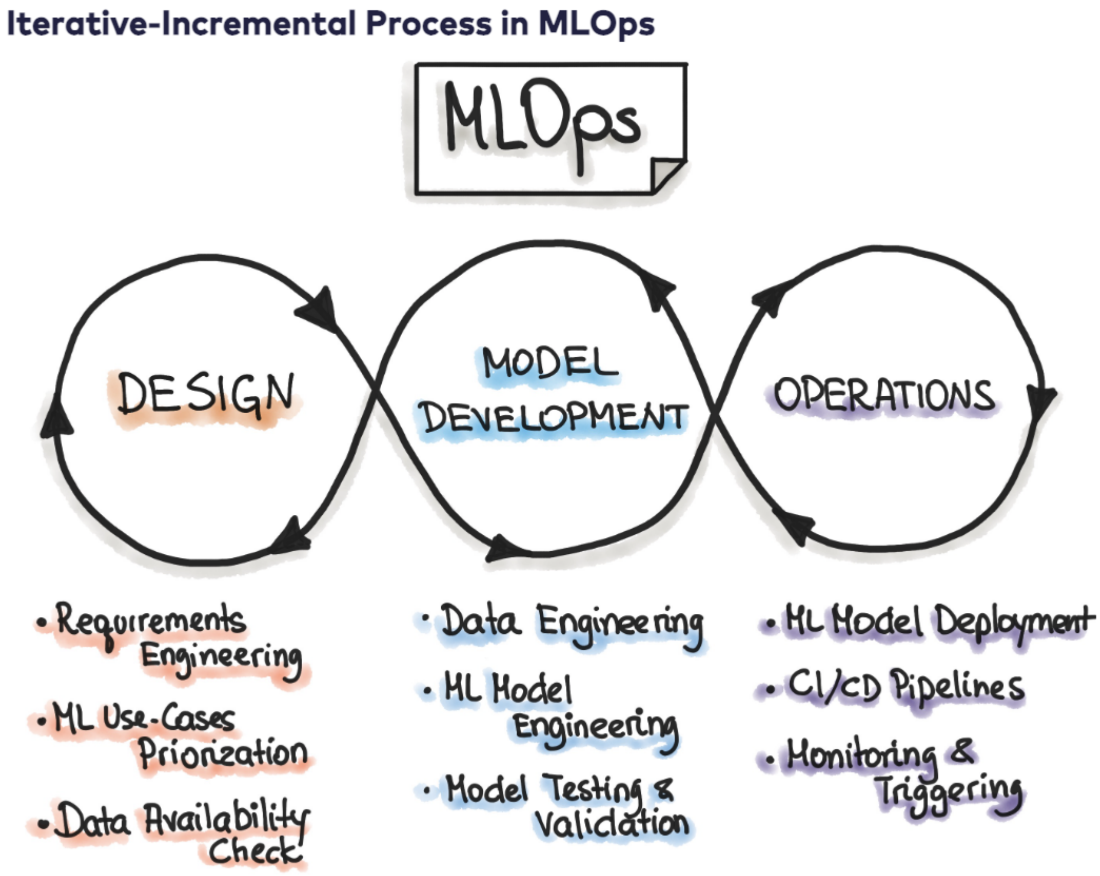

Iterative-Incremental Process in MLOps
MLOps
DESIGN
MODEL DEVELOPMENT
OPERATIONS
• Requirements Engineering
• ML Use-Cases Priorization
• Data Availability Check
• Data Engineering
• ML Model Engineering
• Model Testing & Validation
• ML Model Deployment
• CI/CD Pipelines
• Monitoring & Triggering

Figure 1.1: The complete MLOps process includes three broad phases of "Designing the ML-powered application", "ML Experimentation and Development", and "ML Operations".

MLOps leverages various tools to simplify the machine learning lifecycle.

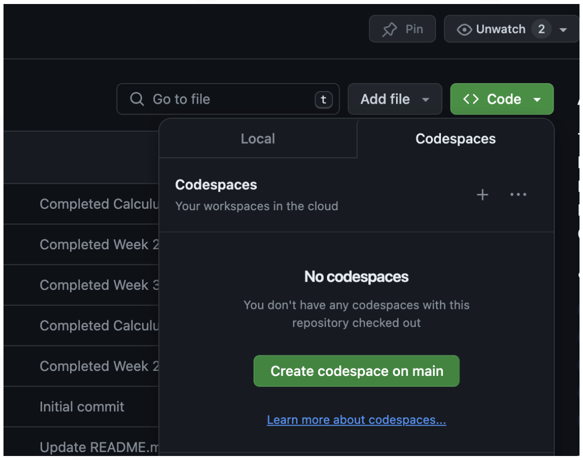
- **Machine learning frameworks** like Kubernetes, TensorFlow and PyTorch for model development and training.
- **Version control systems** like Git for code and model version tracking.

- **CI/CD tools** such as Jenkins or GitLab CI/CD for automating model building, testing and deployment.
- **MLOps platforms** like Kubeflow and MLflow manages model lifecycles, deployment and monitoring.
- **Cloud computing platforms** like AWS, Azure and IBM Cloud provide scalable infrastructure for running and managing ML workloads.

1.2 Environment Preparation

1.2.1 Configuring Environment with GitHub Codespaces

To configure the environment using GitHub codespaces, first create a repository on GitHub, give the repository a name, add a "README" file and a `.gitignore` template, choose a license and create the repo. In the repo main page, click on `Create codespace on main` as shown in **Fig. 1.2**.



Codespaces

Your workspaces in the cloud

No codespaces

You don't have any codespaces with this repository checked out

Figure 1.2: GitHub Codespaces setup

A connection to Visual Studio Code can be made through Codespaces. Start a new terminal, change directory to the workspaces and download and install Anaconda distribution of python in it using the step below.

- **Step 1**: Download and install the Anaconda distribution of Python

```
wget https://repo.anaconda.com/archive/Anaconda3-2022.05-Linux-
    x86_64.sh
```

- **Step 2**: Run this command:

```
bash Anaconda3-2022.05-Linux-x86_64.sh
```

After installing Anaconda, initialize it. In a new terminal, confirm that Anaconda is running in the workspaces

```
(base) @your_username -> /workspaces/mlops-zoomcamp-2024 (main) $
   which python
/home/codespace/anaconda3/bin/python
```

- **Step 3**: Make sure to install `pyarrow` in order to download parquet file

```
!pip install pyarrow
```

- **Step 4**: Run jupyter notebook

```
jupyter notebook
```

1.2.2 Configuring Environment with Amazon Web Service (AWS)

To install using AWS, create an account in AWS, go to EC2 and create an instance. Select the OS to use e.g. Ubuntu with 64-bit(x86) architecture. Select the instance type that will be sufficient for your project. Configure the cloud resources and launch. Recommended development environment: Linux

- **Step 1**: Download and install the Anaconda distribution of Python

```
wget https://repo.anaconda.com/archive/Anaconda3-2022.05-Linux-
   x86_64.sh
bash Anaconda3-2022.05-Linux-x86_64.sh
```

- **Step 2**: Update existing packages

```
sudo apt update
```

- **Step 3**: Install Docker

```
sudo apt install docker.io
```

To run docker without sudo:

```
sudo groupadd docker
sudo usermod -aG docker \$USER
```

- **Step 4**: Install Docker Compose Install docker-compose in a separate directory

```
mkdir soft
cd soft
```

To get the latest release of Docker Compose, go to https://github.com/docker/compose and download the release for your OS.

```
wget https://github.com/docker/compose/releases/download/v2.5.0/
   docker-compose-linux-x86_64 -O docker-compose
```

Make it executable

```
chmod +x docker-compose
```

Add the soft directory to PATH. Open the .bashrc file with nano:

```
nano ~/.bashrc
```

In .bashrc, add the following line:

```
export PATH="${HOME}/soft:${PATH}"
```

Save it and run the following to make sure the changes are applied:

```
source ~/.bashrc
```

- **Step 5**: Run Docker

```
docker run hello-world
```

1.3 Model Development

1.3.1 Taxi trip prediction with machine learning

Example 1.1: **TLC Trip Prediction**

In this section, we use machine learning to predict the trip duration for trips in New York. The data used were collected from the NYC Taxi and Limousine Commission (TLC). This dataset contains yellow and green taxi trip records include fields capturing pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances, itemized fares, rate types, payment types, and driver-reported passenger counts. The data is stored in the PARQUET format. We built a simple linear regression model and save the model as a pickle file for subsequent use later one. See the duration prediction notebook.

We can download parquet file using:

```
# download parquet data
!wget https://d37ci6vzurychx.cloudfront.net/trip-data/
   green_tripdata_2021-01.parquet
```

1.4 MLOps Maturity Model

The MLOps maturity model helps clarify the Development Operations (DevOps) principles and practices necessary to run a successful MLOps environment. The maturity is the extent to which MLOps is implemented in a team. The MLOps maturity model encompasses five levels of technical capability.

Level	Description	Highlights	Technology
0	No MLOps	• Hard to manage lifecycle • Disparate teams • Systems as "black boxes"	• Manual builds/deployments • Manual testing • No centralized tracking
1	DevOps but no MLOps	• Less painful releases • Limited feedback • Hard to reproduce results	• Automated builds • Automated tests for application code
2	Automated Training	• Managed, traceable training • Easy to reproduce model • Low friction releases	• Automated model training • Centralized tracking of model training performance • Model management
3	Automated Deployment	• Releases are low friction and automatic • Full traceability from deployment back to original data • Entire environment managed: train > test > production	• Integrated A/B testing • Automated tests for all code • Centralized tracking
4	Full MLOps Automated Operations	• Fully automated, monitored • Systems provide improvement information • Zero-downtime	• Automated training/testing • Centralized metrics

Table 1.1: Machine Learning operations maturity model (culled from Microsoft Blog

Experiment Tracking and Model Management

2.1 Introduction to Experiment Tracking

Fun Fact: MLflow

MLflow is an open-source platform that helps manage the end-to-end machine learning lifecycle. It provides a set of tools to streamline and automate various stages of the machine learning process, from experimentation to deployment.

Machine Learning experiment is the process of building an ML model. Experiment run represents each trial in an ML experiment. A run artifact is any file associated with an ML run. The experiment metadata is all the information related to the experiment. *Experiment tracking* is the process of keeping track of all the **relevant information** from an **ML experiment**, which includes:

- Source code
- Environment
- Data
- Models
- Hyperparameters
- Metrics

Why is Experiment Tracking so important

Experiment tracking is important because of **Reproducibility**, **Organization**, and **Optimization**

Experiment tracking is done using MLflow. MLflow is "an open source platform for the machine learning lifecycle". In practice, it's just a Python package that can be installed with pip, and it contains four main modules:

- Tracking
- Models
- Model Registry
- Projects

The MLflow Tracking module allows you to organize your experiments into runs, and to keep track of:

- Parameters
- Metrics
- Metadata
- Artifacts
- Models

Along with this information, MLflow automatically logs extra information about the run:

- Source code i.e., the name of the file that was used to run the experiment
- Version of the code (git commit)
- Start and end time
- Author

2.1.1 How MLflow Helps Manage Machine Learning Experiments

Here are some key ways in which MLflow can help with machine learning experiments:

Experiment Tracking

MLflow Tracking allows you to log and query experiments using APIs or a web-based interface. Key features include:

- **Log Parameters and Metrics:** Easily log hyperparameters, metrics, and artifacts (such as model files) for each run.
- **Organize and Compare Runs:** Organize runs by experiments and compare results visually.
- **Search and Query:** Search and filter experiments using a web UI or API, allowing you to quickly find runs with specific attributes.

Reproducibility

MLflow promotes reproducibility of experiments by providing:

- **Code Versioning:** Integrates with version control systems (like Git) to log the version of the code that produced a particular run.

- **Environment Management:** Capture and reproduce the software environment using Conda environments or Docker images.
- **Artifacts:** Store and retrieve artifacts such as datasets, models, and images, ensuring all elements of an experiment are preserved.

Model Management

MLflow Models facilitate model packaging, sharing, and deployment:

- **Standardized Format:** Save models in a standardized format that includes the model itself along with its dependencies and environment.
- **Multi-Platform Support:** Export models to various formats (e.g., TensorFlow, PyTorch, scikit-learn) and deploy them to different environments (e.g., cloud services, Docker).
- **Model Registry:** Register and version models, track model lineage, and transition models through stages (e.g., “staging”, “production”).

Deployment

MLflow provides tools for deploying models to various platforms:

- **Built-in Deployment Options:** Deploy models to cloud platforms like AWS SageMaker, Azure ML, and Google Cloud ML Engine.
- **Custom Deployments:** Create custom deployment logic using the MLflow REST API or the command-line interface (CLI).
- **Batch and Real-Time Serving:** Support for both batch and real-time serving of models, enabling various deployment scenarios.

Collaboration

MLflow facilitates collaboration among team members by providing:

- **Centralized Tracking Server:** A centralized tracking server where team members can log and view experiment runs.
- **Sharing and Collaboration:** Share results, models, and insights easily within the team, fostering better collaboration and knowledge sharing.
- **Integration with CI/CD:** Integrate MLflow with continuous integration and continuous deployment (CI/CD) pipelines for automated testing and deployment of models.

Scalability

MLflow is designed to scale with your needs:

- **Distributed Tracking:** Support for tracking experiments across distributed environments, making it suitable for large-scale machine learning projects.
- **Flexible Storage Options:** Use various backend storage systems for logging data, including file systems, databases, and cloud storage.

By integrating MLflow into your machine learning workflow, you can enhance the management, reproducibility, and deployment of your experiments. It provides a comprehensive set of tools that streamline the entire lifecycle of machine learning models, making it easier to track, reproduce, and deploy models at scale.

2.2 Experiment tracking with MLflow

To start experiment tracking, we need to create a conda environment for tracking experiment and activate it.

```
conda create -n exp-tracking-env python=3.9
conda activate exp-tracking-env
```

Once the environment is activated, install the "requirements.txt" file using:

```
pip install -r requirements.txt
```

Check the installed packages using:

```
pip list
```

To launch mlflow, and store all the artifacts in an sqlite database, we run:

```
mlflow ui --backend-store-uri sqlite:///mlflow.db --port 5001
```

The updated notebook with experiment tracking using MLflow and logged predictions in MLflow UI is shown here.

2.3 On Colorful Boxes

There are lots of different boxes you can make:

- Like this one,

  > which is wrapped in gray. I use it for notes. . .

- Or this one,

> which is wrapped in red. I use it for fun facts or other asides…

- Or this one,

> which is wrapped in blue and used for mathy stuff.

- Or this last one,

> which is wrapped in green. With a title, it's used for enumerated examples (see `\extitle` and `\excounter`). Observe:

Example 2.1: Test

This is an example. What's the answer to $2 + 2$?

Answer: Obviously 4, lol.

Example 2.2: Test Again

This one will increment the counter automatically, resetting for each chapter.

- For red and blue boxes, there are custom commands for titles, too:

One Title

Like this

Two Titles: A Subtitle

Or this

These styles also automatically apply to theorems and claims.

Theorem 2.1 (Pythagorean Theorem)**.** *For any right triangle with legs a, b and hypotenuse c:*

$$a^2 + b^2 = c^2 \tag{2.1}$$

Proof. This is left as an exercise to the reader. ■

Claim 2.1. *This is the greatest note template in the world.*

There are different ways to quote things, too, depending on how you want to emphasize:

> *This is a simple, indented quote with small letters and italics usually suitable for in-text quotations when you just want a block.*

Alternatively, you can use the `\inspiration` command from the chapter heading, which leverages the `thickleftborder` frame internally, but adds a little more padding and styling (there's also just `leftborder` for a thinner variant):

> Hello there!

2.4 On Cross-Referencing

This is the standard way to include margin notes. There are also commands to link to source papers directly (see `\lesson`).

You can reference most things—see Theorem 2.1 or (2.1) or the Introduction chapter—directly and easily as long as you give them labels. These are "built-ins." However, you can also create a **custom term** that will be included in the index, then include references to it that link back to the original definition. Try clicking: custom term. Building the index is on you, though. You can also reference by using a different term for the text: like this. Sometimes it doesn't fit the **grammatical structure** of the sentence so you can define the term one way and visualize it another way (this creates a **grammar** entry in the index). There's also **math terms** and a way to reference them: math terms (clickable), but they do **not** show up in the index.

2.5 On Math

Most of the math stuff is just macros for specific things like the convolution operator, $\circledast$, probabilities, $\Pr[A \mid B = C]$, or big-O notation, $\mathcal{O}(n^2 \log n)$ but there's also a convenient way to include explanations on the side of an equation:

$$\begin{aligned} 1+1 &\overset{?}{=} 2 && \text{first we do this}\\ 2 &\overset{?}{=} 2 && \text{then we do this}\\ 2 &= 2 \quad \blacksquare \end{aligned}$$

These are all in the `CustomCommands.sty` file.