Machine Learning Operations (MLOps)

Introduction to MLOps

Zeham Management Technologies BootCamp

by SDAIA

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الهيئة السعودية للبيانات والذكاء الاصطناعي
Saudi Data & AI Authority

Introduction to MLOps

Objectives

By the end of this module, trainees will have a comprehensive understanding of:

Master MLOps principles.

Distinguish between DevOps and MLOps Lifecyles.

Learn how to manage code changes.

Learn enhancing the ML pipeline and minimizing errors.

Explore different AutoML Examples.

Learn how to build and deploy ML models in production environments.

Agenda

Introduction to MLOps

MLOps Lifecycle

Setting Up Local Environment

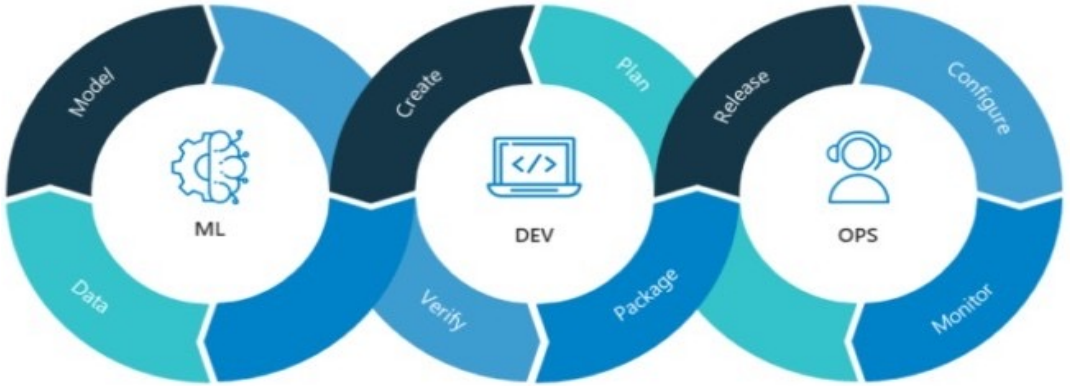
Version Control

Recent Trends in MLOps

References

What is MLOps ?

- Machine Learning Operations (MLOps) includes a series of steps to deploy an ML model into a production environment.
- It combines aspects of Machine Learning and DevOps
- Several steps must be completed before an ML model is ready for production.
- These steps ensure that your model can handle many users and work accurately.



Why do we need MLOps ?

- Creating an ML model that can predict based on the data you provide is simple. However, making a ML model that is reliable, fast, accurate, and can be used by many users is challenging.

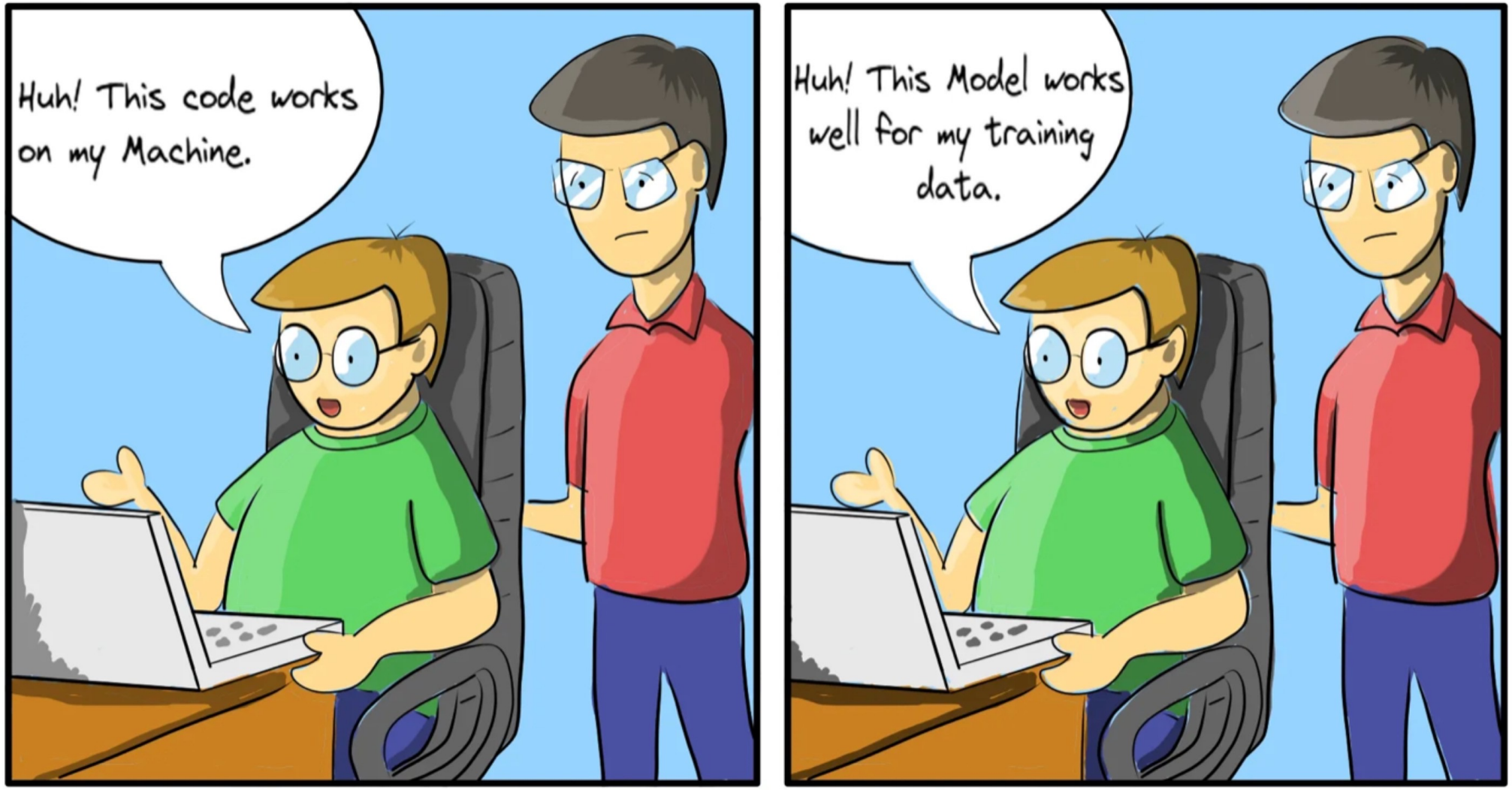
Importance of MLOps

- ML models depend on a large amount of data, which is hard for one person to manage.
- It is challenging to keep track of the parameters we adjust in ML models. Small changes can significantly impact the results.
- We need to monitor the features the model uses, as feature engineering is a separate task that greatly contributes to the model's accuracy.

Importance of MLOps

- Monitoring an ML model is different from monitoring a deployed software application or web app.
- Debugging an ML model is a highly complex skill.
- Models depend on real-world data for predictions, and as this data changes, the model must adapt. We need to monitor new data changes and ensure the model learns from them.

Importance of MLOps



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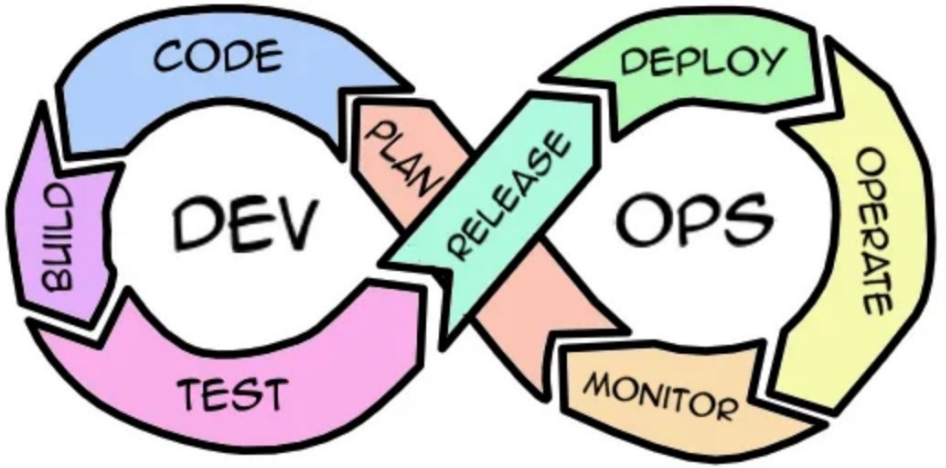
MLOps Lifecycle

DevOps life cycle

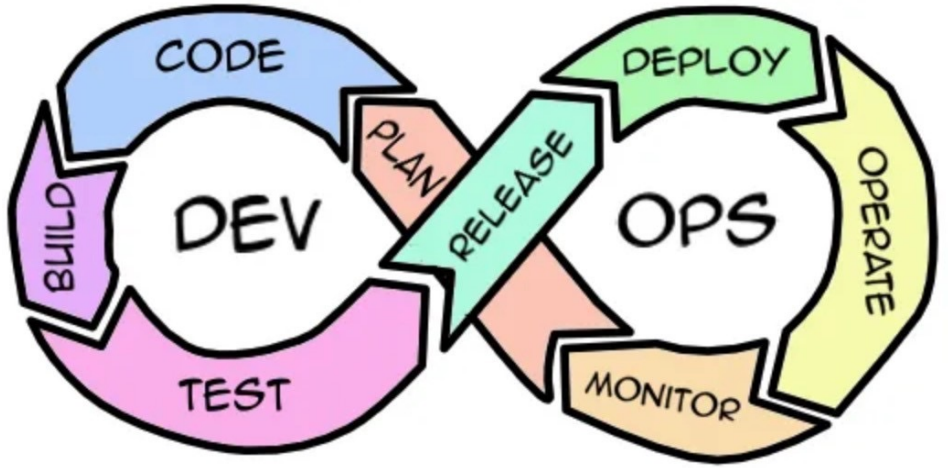
- You may be familiar with traditional DevOps, which involves building and deploying software applications. You might be curious about how MLOps differs from this process.



DevOps Cycle (Image by Author)

DevOps life cycle

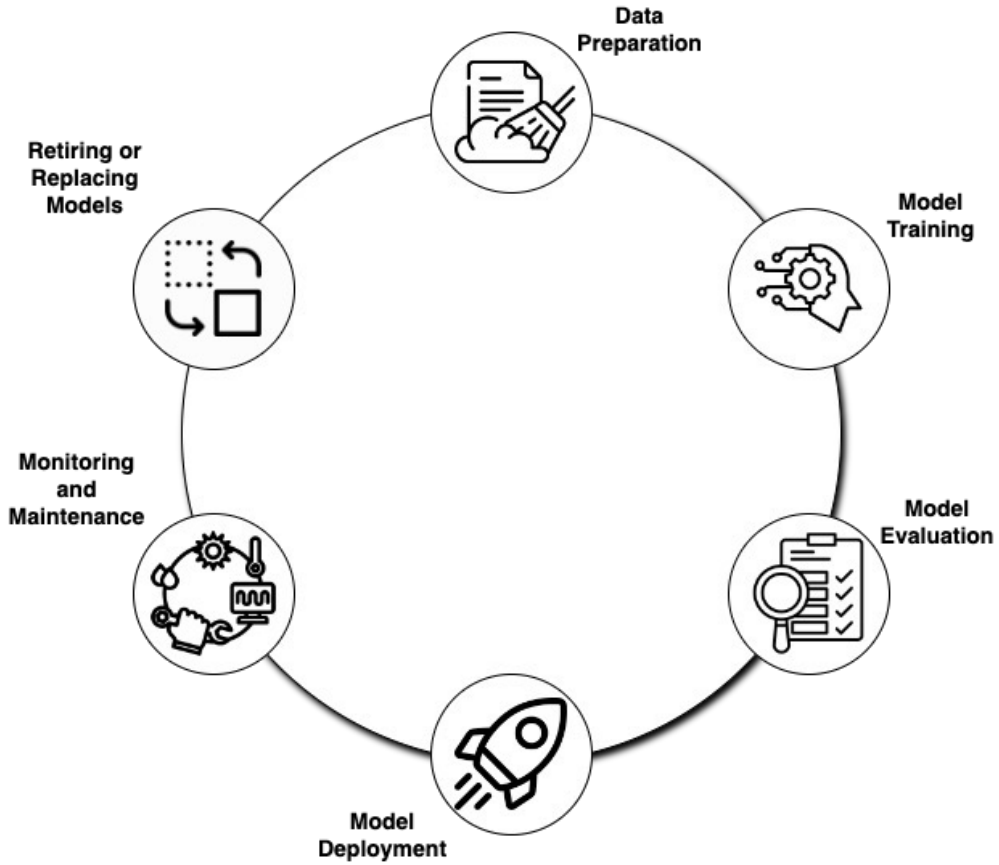
- DevOps stages focus on developing a software application. You start by planning the application's features, writing the code, building it, testing it, creating a release plan, and deploying it. You then monitor the infrastructure where the app is deployed. This cycle repeats until the application is fully developed.



DevOps Cycle (Image by Author)

MLOps Lifecycle (Data Preparation)

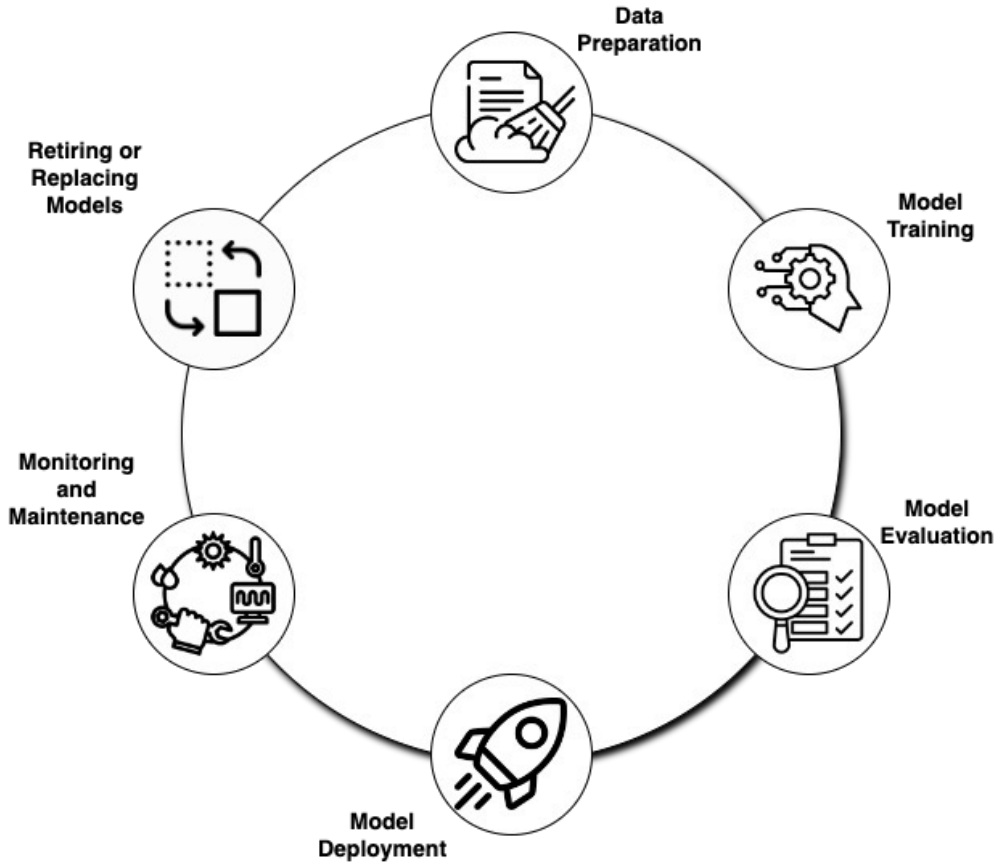
Data Preparation is the process of gathering, cleaning, and transforming raw data into a structured format suitable for machine learning.



MLOps Lifecycle (Data Preparation)

Steps:

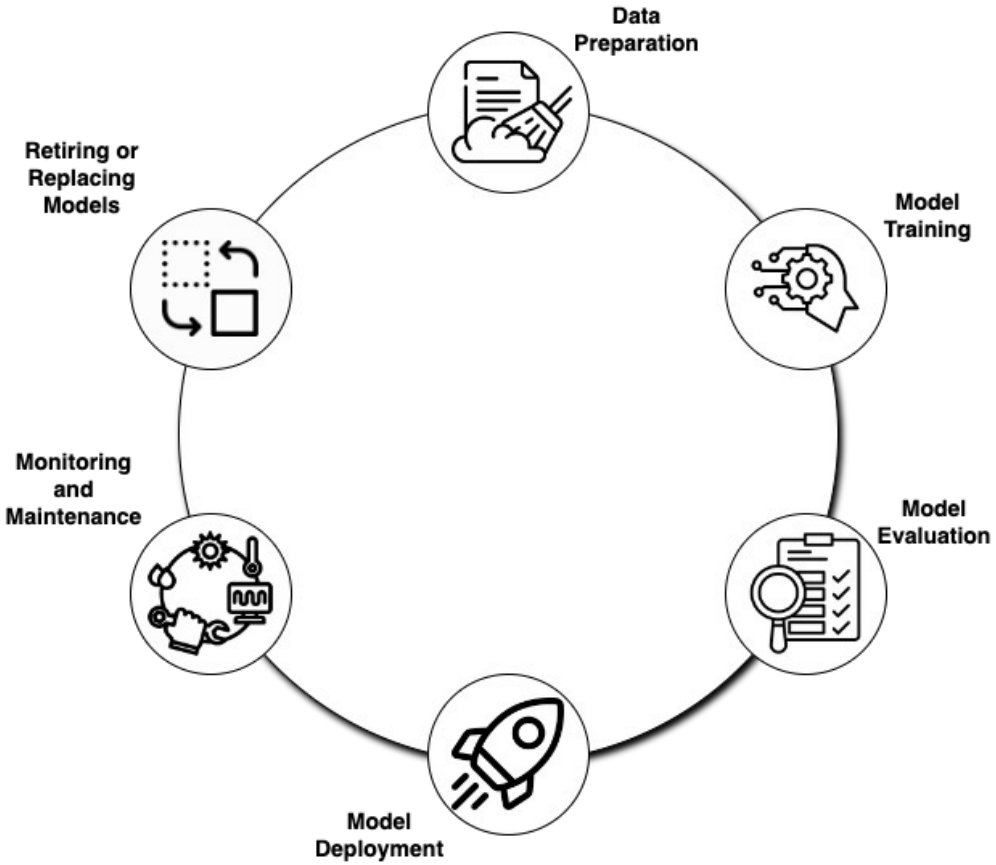
- **Data Collection:** Gather data from various sources like databases, APIs, sensors, etc.
- **Data Cleaning:** Remove or correct any errors, duplicates, or inconsistencies in the data.



MLOps Lifecycle (Data Preparation)

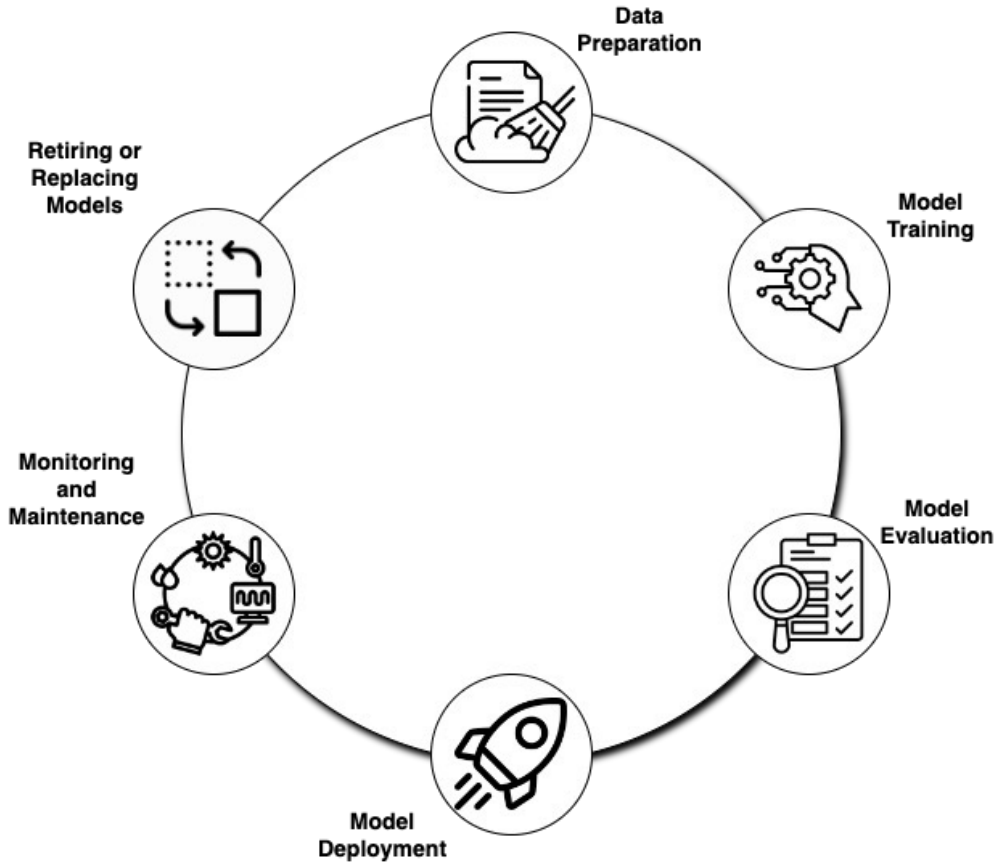
Steps:

- **Data Transformation:** Convert data into the required format, such as normalizing, encoding categorical variables, and scaling.
- **Data Splitting:** Divide the data into training, validation, and test sets.



MLOps Lifecycle (Model Training)

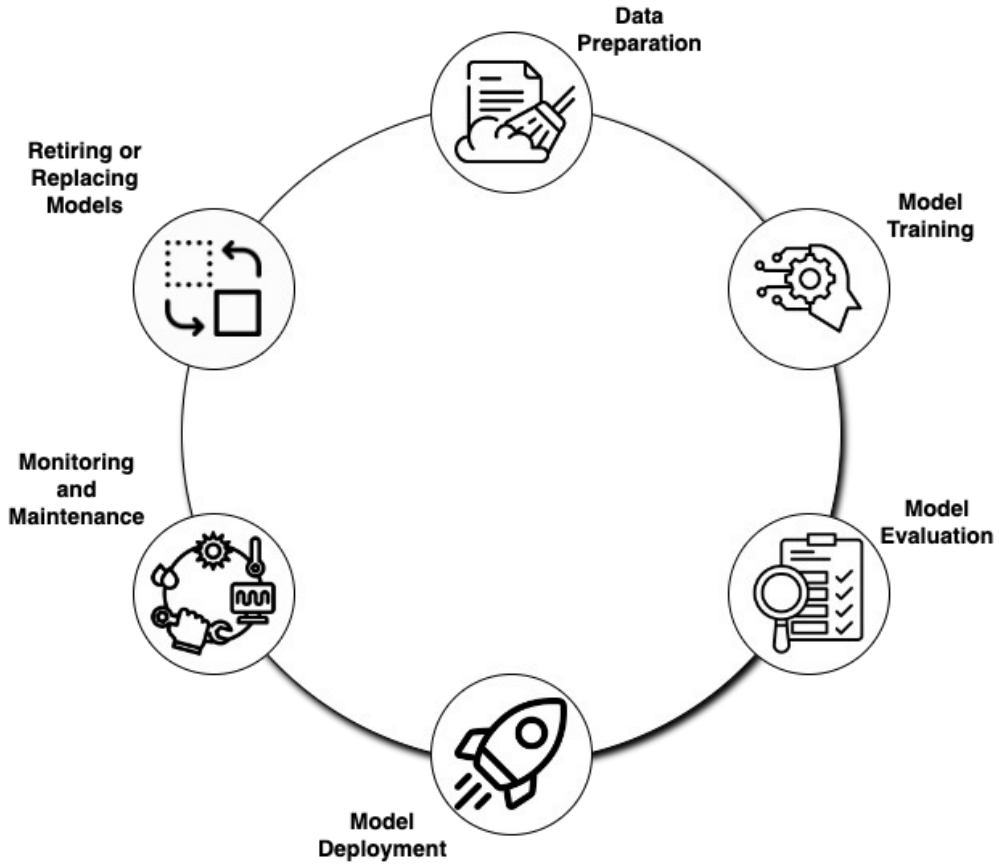
Model Training is the phase where data scientists and machine learning engineers design, build, and optimize machine learning models.



MLOps Lifecycle (Model Training)

Steps:

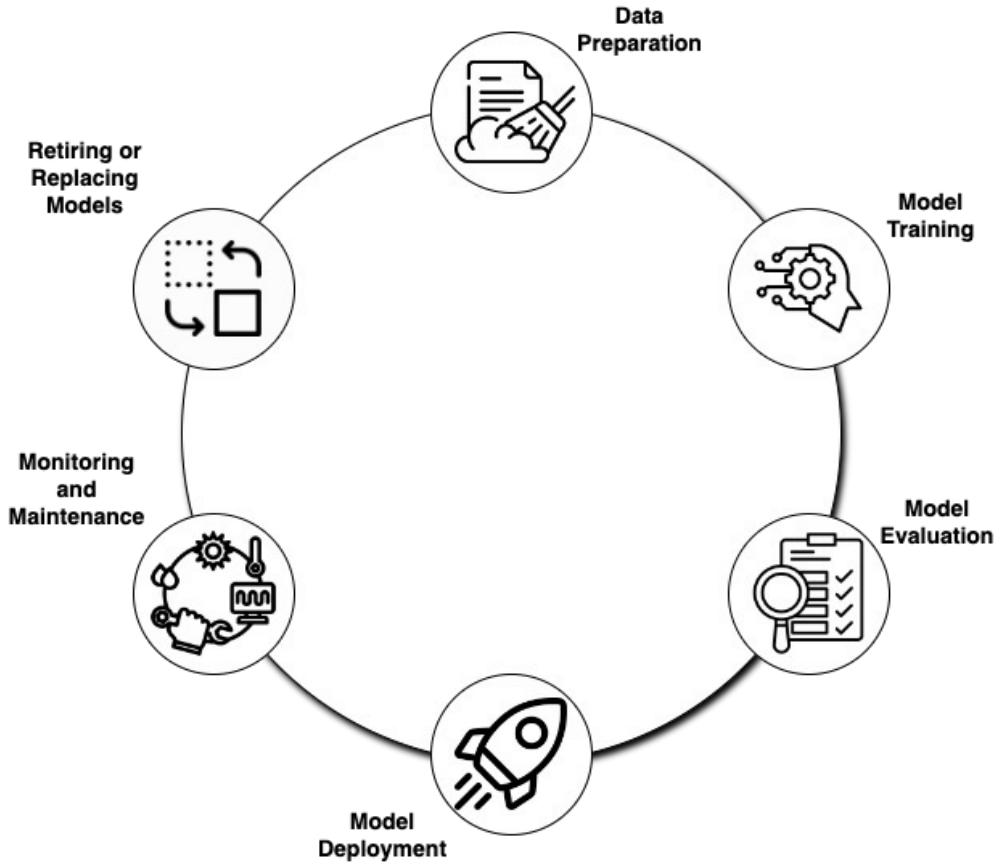
- **Algorithm Selection:** Choose the appropriate machine learning algorithm for the task.
- **Feature Engineering:** Create new features or select important features from the dataset to improve model performance.



MLOps Lifecycle (Model Training)

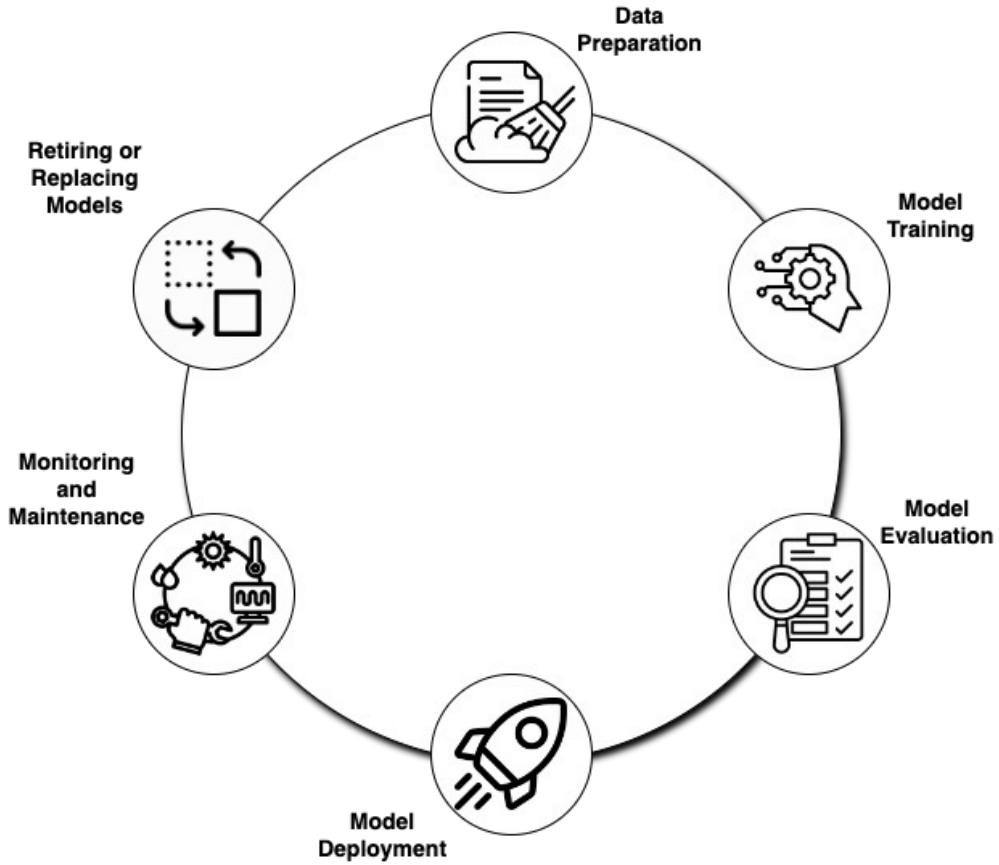
Steps:

- **Model Building:** Develop the first version of the model using selected algorithm and features.
- **Hyperparameter Tuning:** Adjust the hyperparameters to improve model performance.



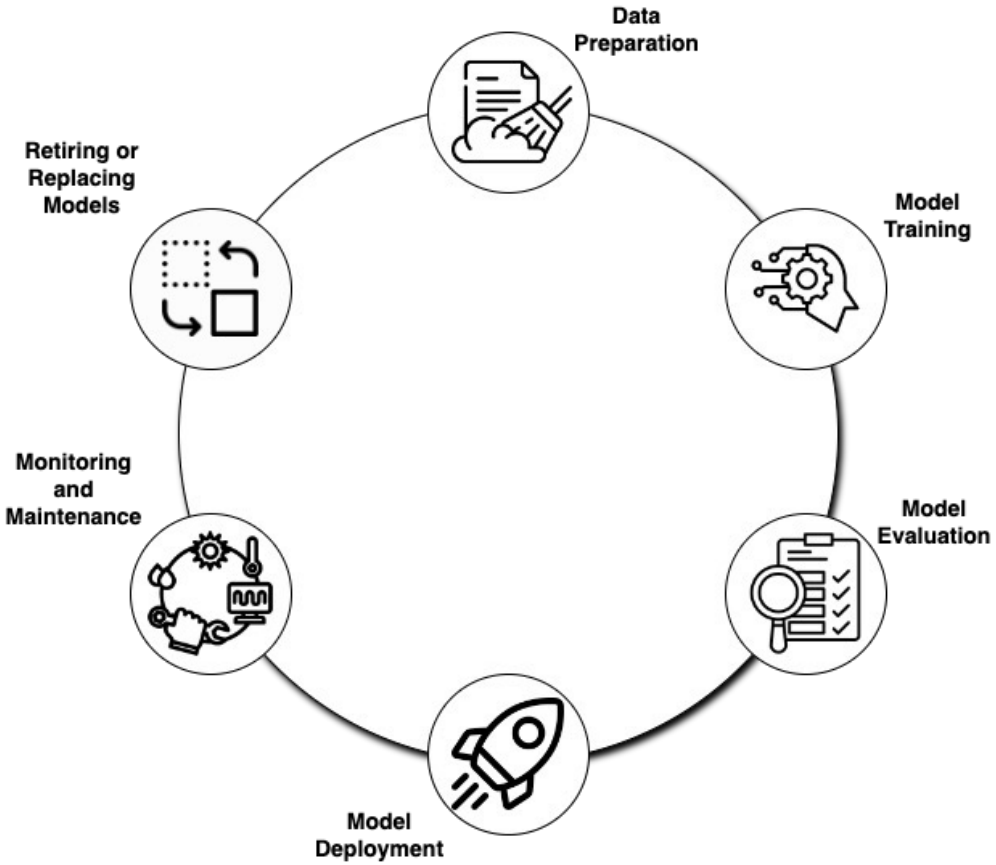
MLOps Lifecycle (Model Evaluation)

Model Evaluation step involves evaluation the model's performance using various metrics to ensure it meets the required standards before deployment.



MLOps Lifecycle (Model Evaluation)

Steps:
Validation Testing: Evaluate the model using the validation dataset to fine-tune it.
Performance Metrics: Calculate metrics such as accuracy, precision, recall, and F1-score.

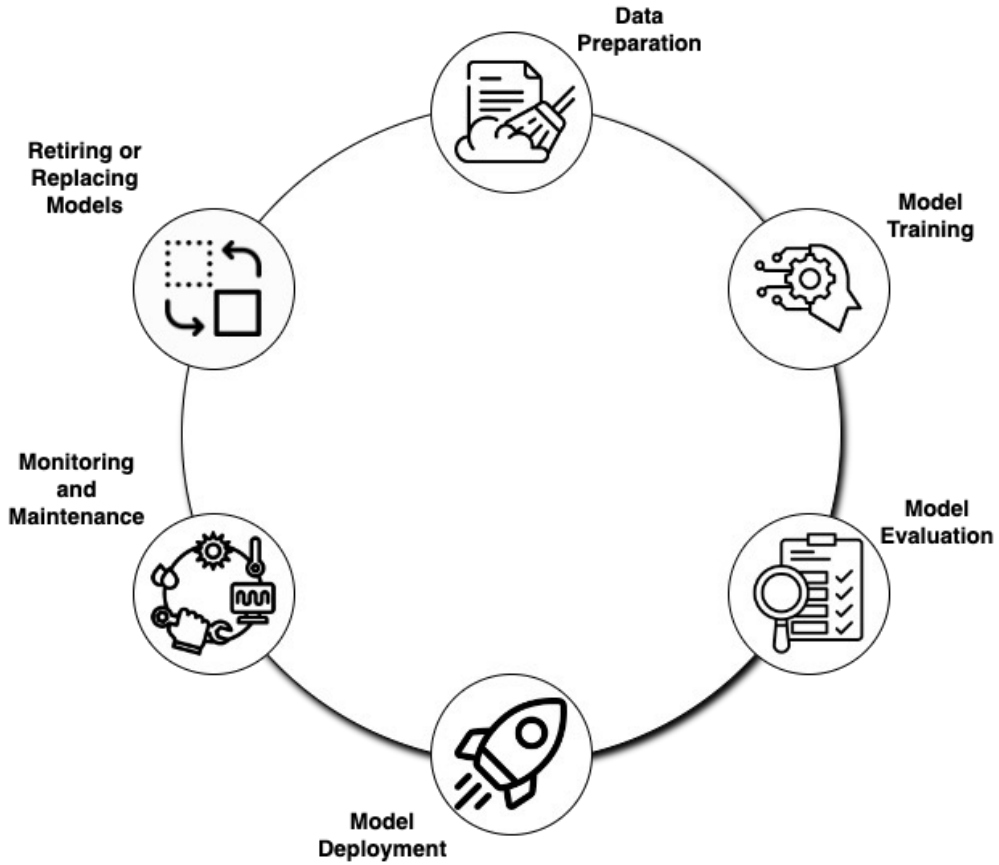


MLOps Lifecycle (Model Evaluation)

Steps:

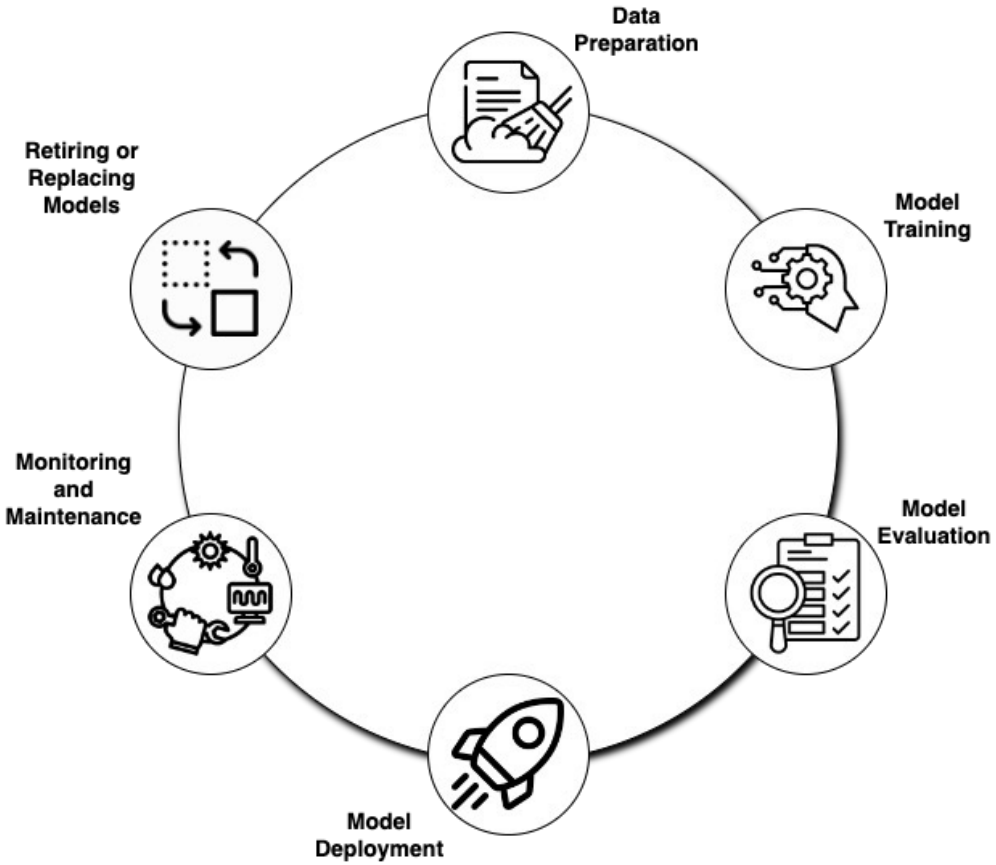
Cross-Validation: Perform cross-validation to ensure the model's robustness.

Bias and Fairness Testing: Check the model for biases and ensure fairness.



MLOps Lifecycle (Model Deployment)

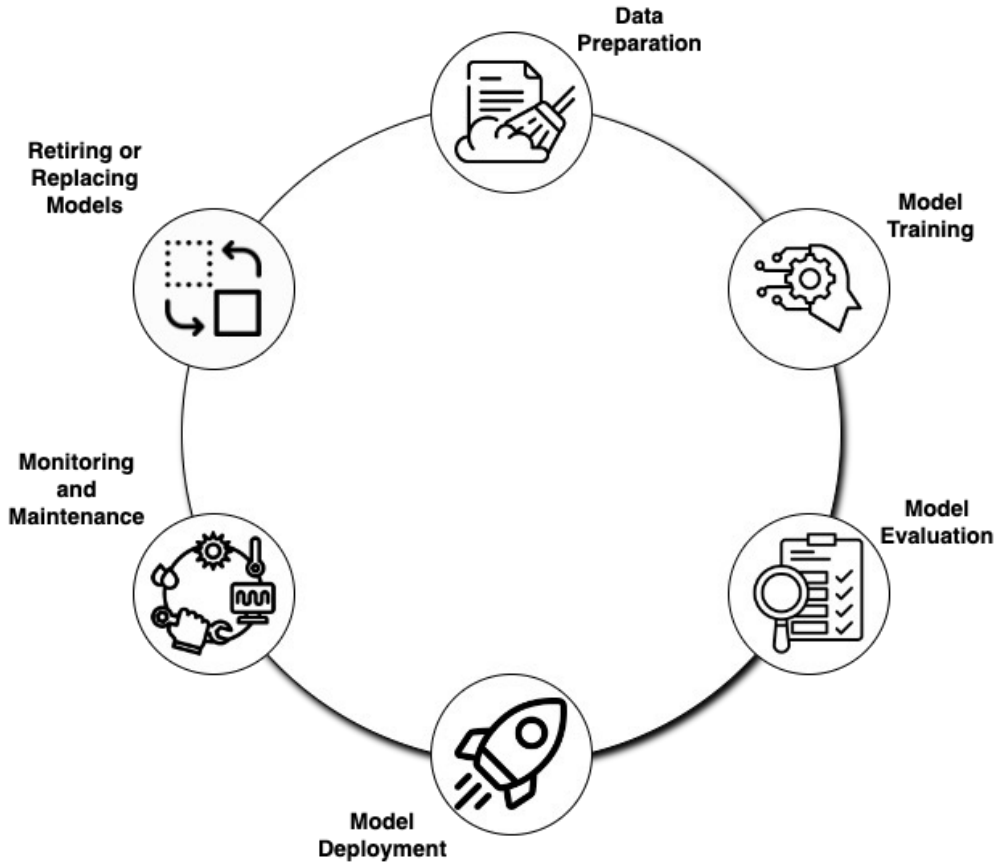
Model Deployment is deploying the validated model into a production environment where it can start making predictions on live data for example in Amazon's AWS, Google Cloud or even a private cloud.



MLOps Lifecycle (Model Deployment)

Steps:

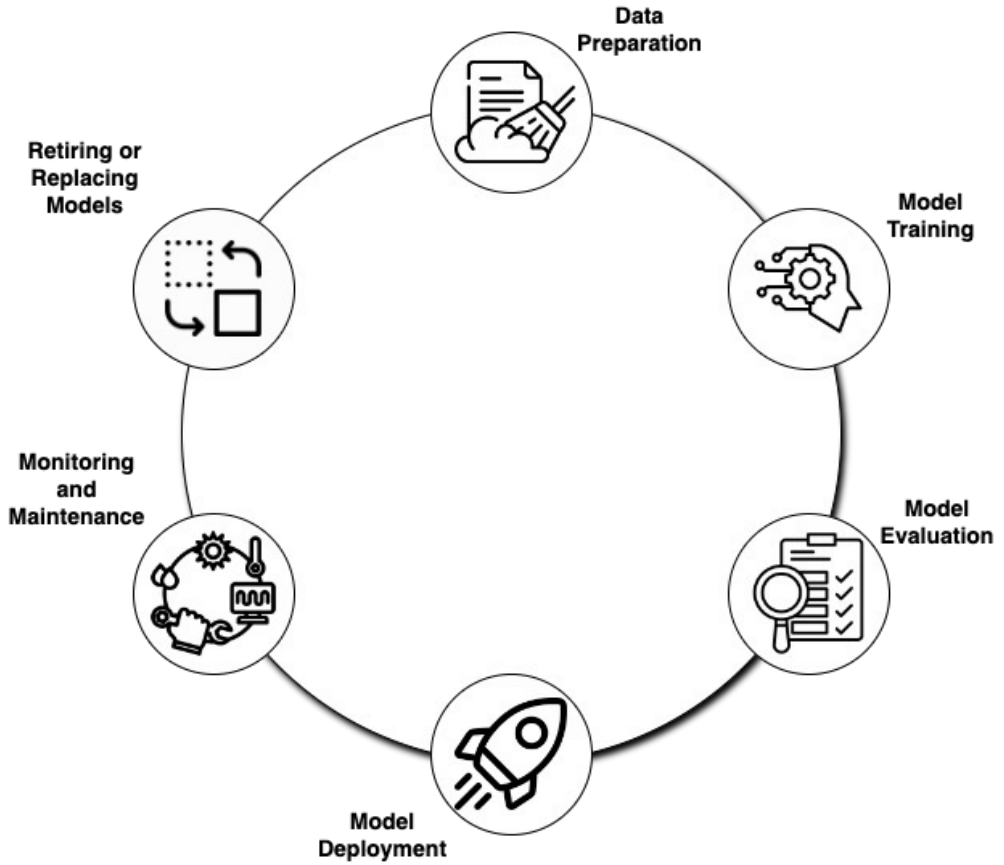
- **Infrastructure Setup:** Prepare the production environment and necessary infrastructure.
- **Model Integration:** Integrate the model with the existing systems and applications.



MLOps Lifecycle (Model Deployment)

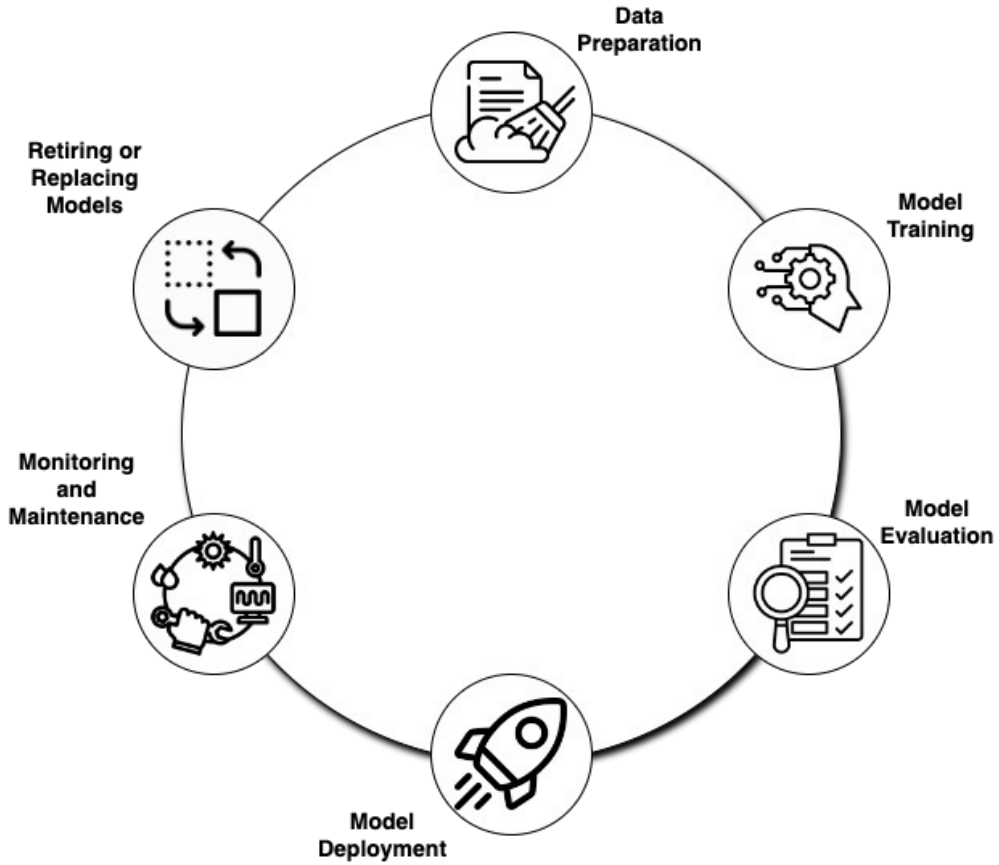
Steps:

- **Deployment Testing:** Conduct tests to ensure the model works correctly in the production environment.
- **Release:** Roll out the model for production use.



MLOps Lifecycle (Monitoring and Maintenance)

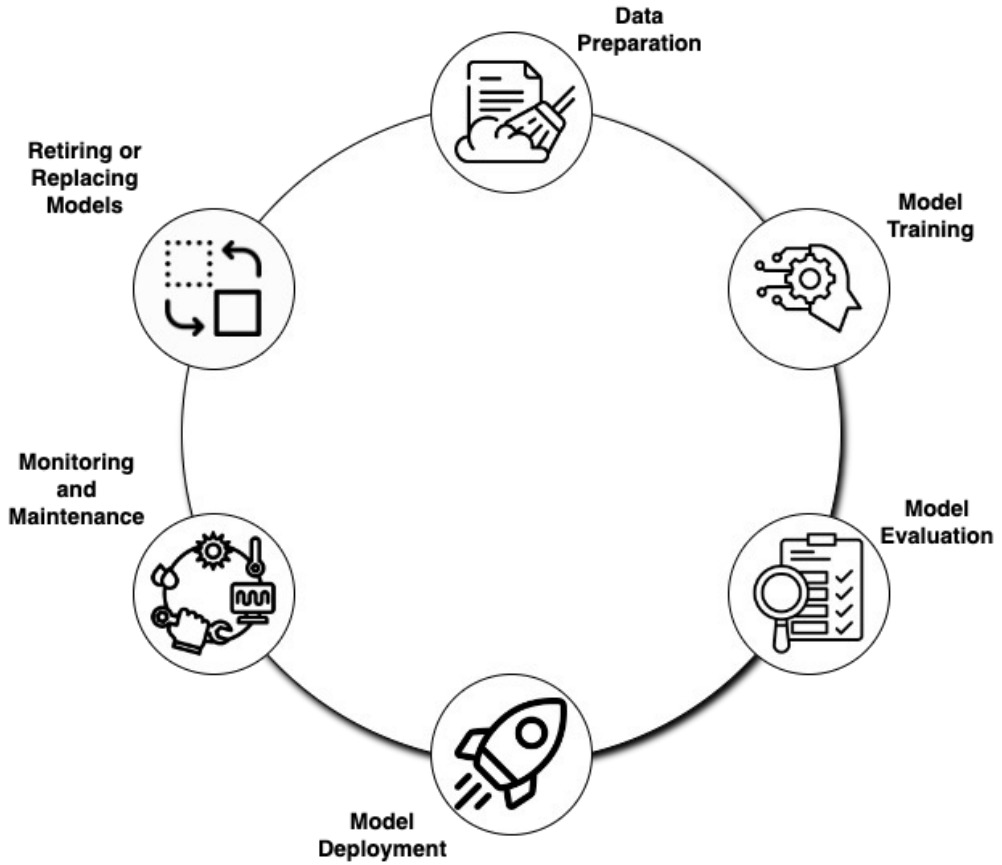
Monitoring and Maintenance is continuous monitoring the model's performance and maintaining it to ensure it continues to perform well over time.



MLOps Lifecycle (Monitoring and Maintenance)

Steps:

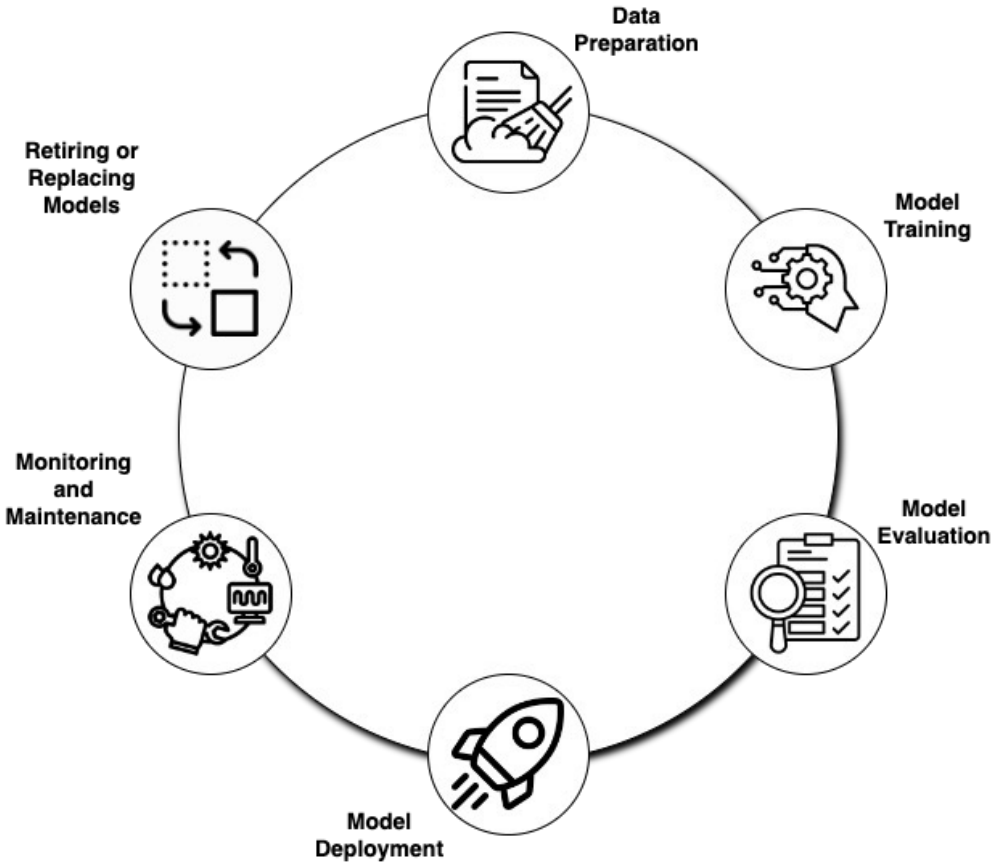
- **Performance Monitoring:** Track the model's performance on live data.
- **Error Analysis:** Identify and analyze errors to understand model weaknesses.



MLOps Lifecycle (Monitoring and Maintenance)

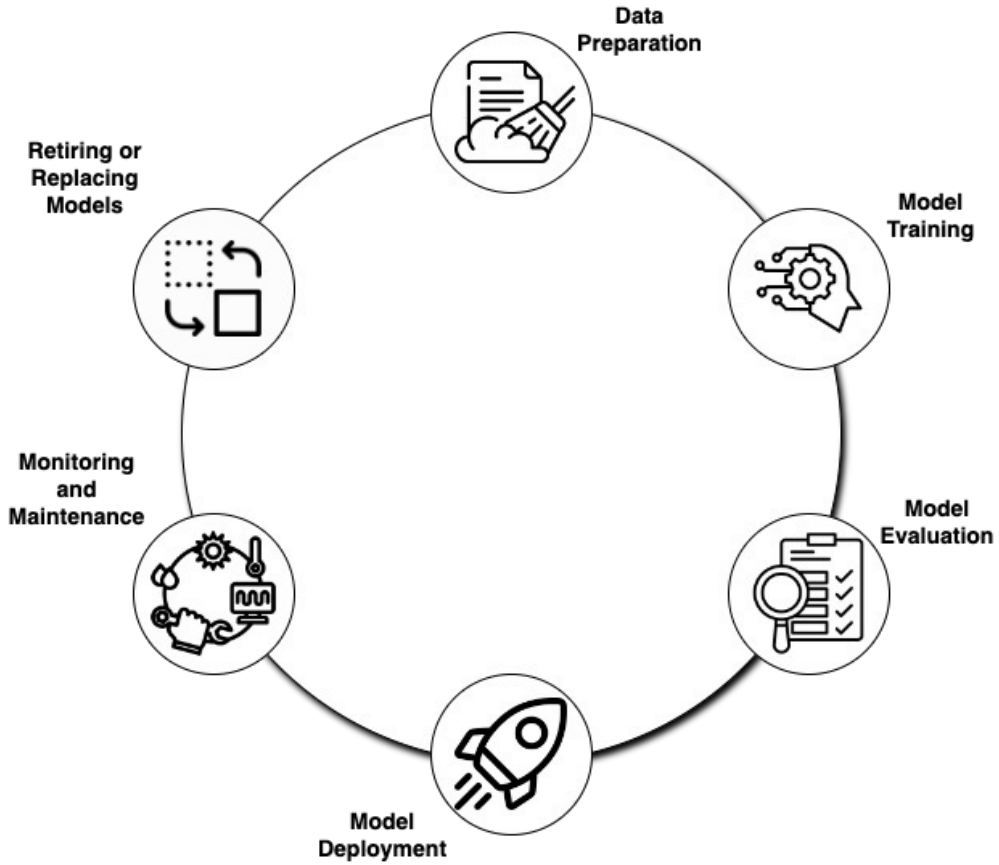
Steps:

- **Data Drift Detection:** Detect shifts in data distribution that could affect model performance.
- **Model Retraining:** Periodically retrain the model with new data to maintain accuracy.



MLOps Lifecycle (Retiring or Replacing Models)

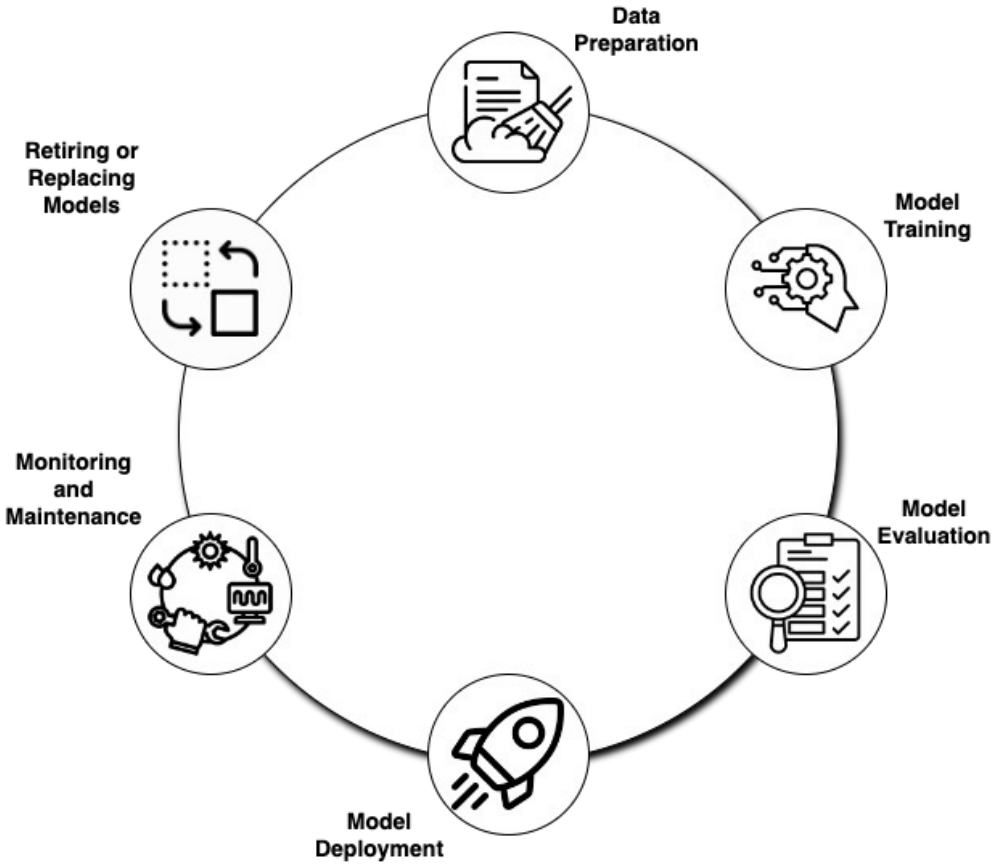
Retiring and Replacing is when a model no longer meets performance standards or becomes obsolete, it must be retired and replaced with a new or updated model.



MLOps Lifecycle (Retiring or Replacing Models)

Steps:

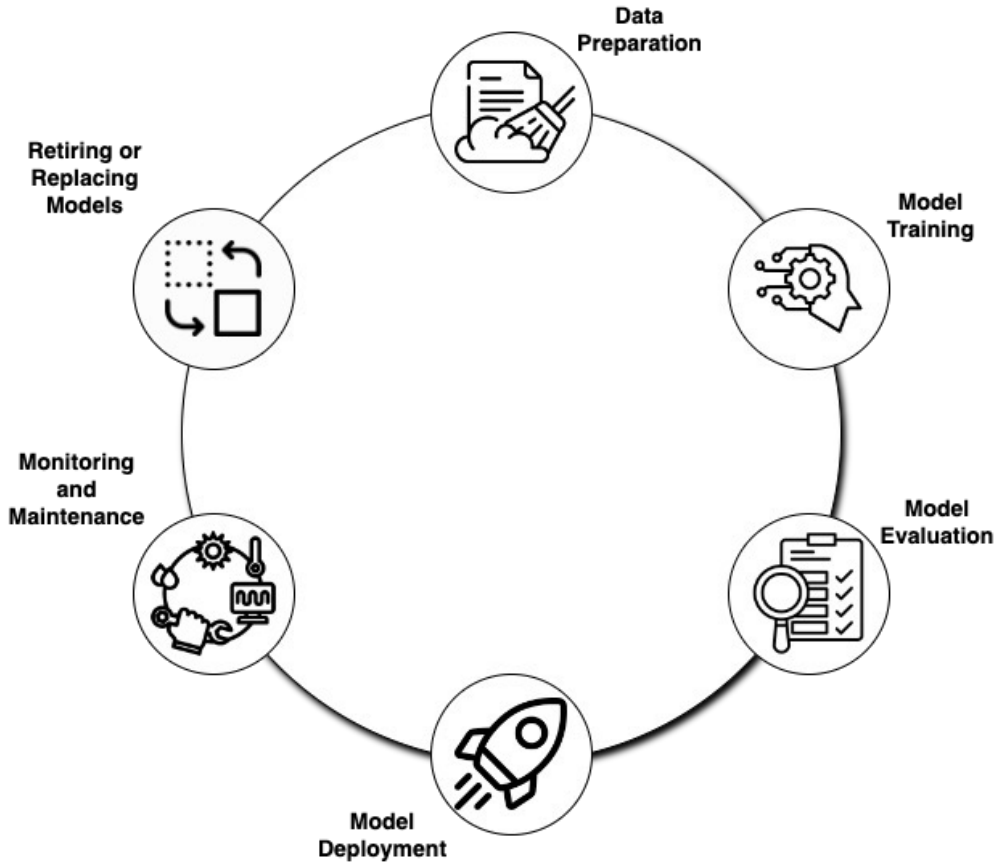
- **Performance Review:** Regularly review the model's performance and relevance.
- **Replacement Strategy:** Plan for replacing the outdated model with a new one.



MLOps Lifecycle (Retiring or Replacing Models)

Steps:

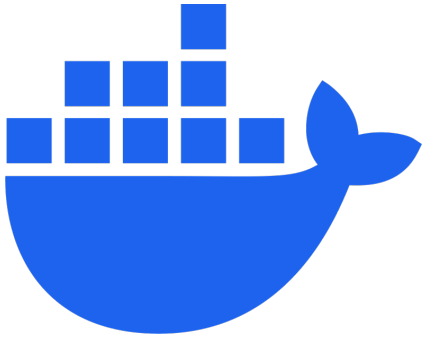
- **Model Decommissioning:** Safely retire the old model, ensuring a smooth transition.
- **New Model Deployment:** Deploy the updated model following the deployment steps.



Setting up local environment

Overview of Local Development Environment

A local development environment is a setup on your local device that allows you to develop, test, and debug machine learning models before deploying them to production.

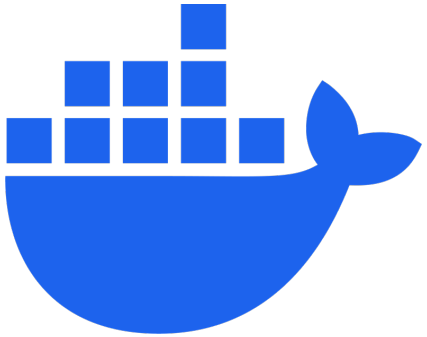


Overview of Local Development Environment

Programming Languages: Python is the most common choice for ML development.

- **IDE/Text Editor:** Popular options include VS Code, PyCharm, Jupyter Notebook.
- **Package Managers:** pip, conda for managing Python packages.



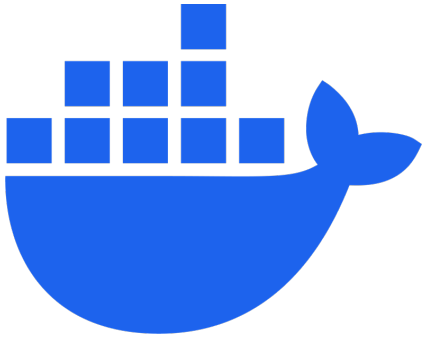


Overview of Local Development Environment

Programming Languages: Python is the most common choice for ML development.

- **Version Control:** Git for tracking changes and collaboration.
- **Containerization:** Docker for creating consistent environments.

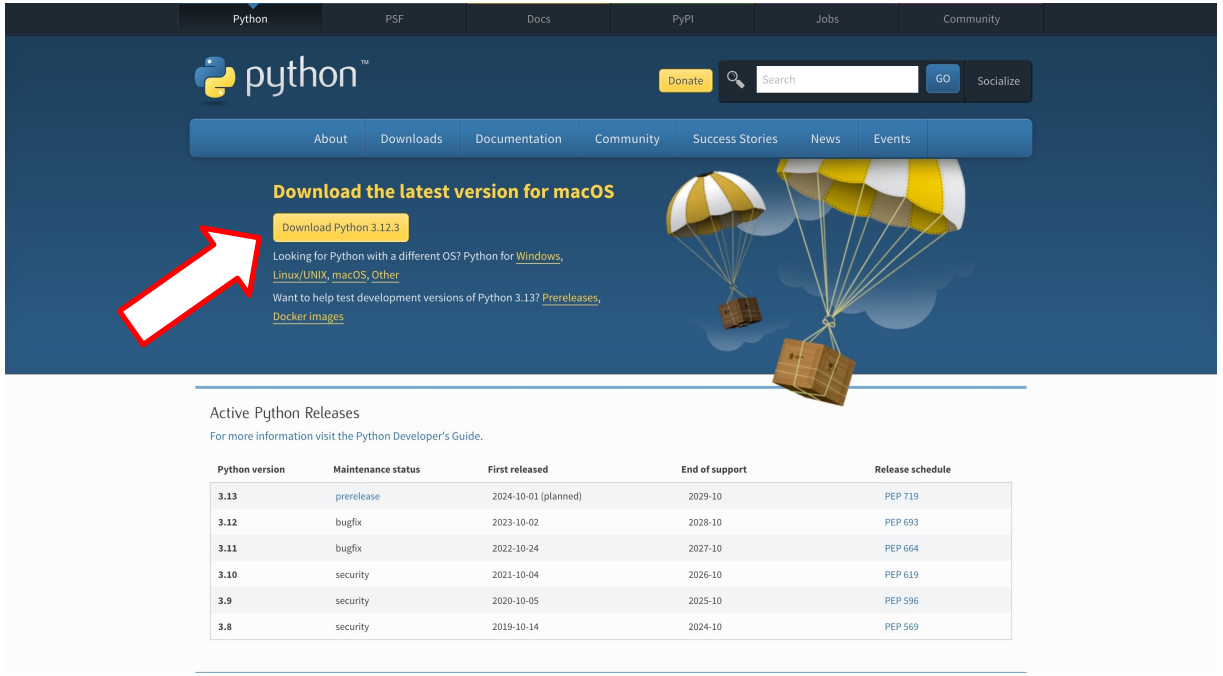




Installing Essential Tools (Python Installation)

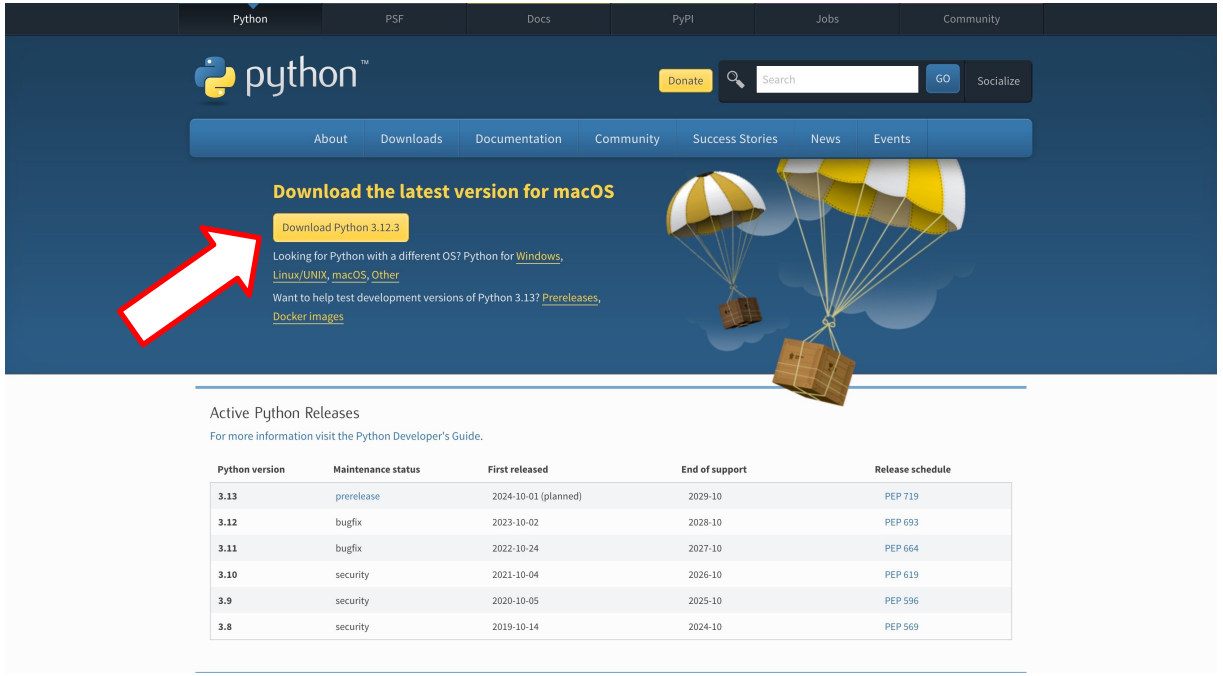
If you haven't ☺

To install the latest version of Python, visit the official website.



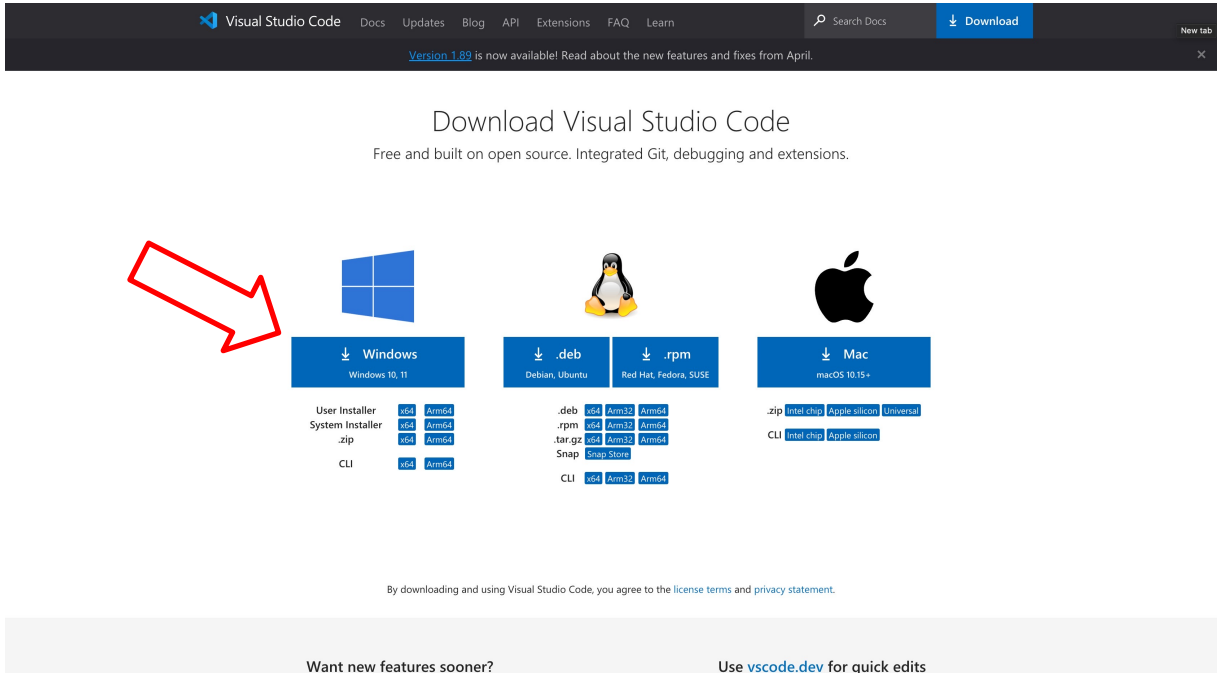
Installing Essential Tools (Package Managers)

pip comes with Python by default, so you don’t need to download it.



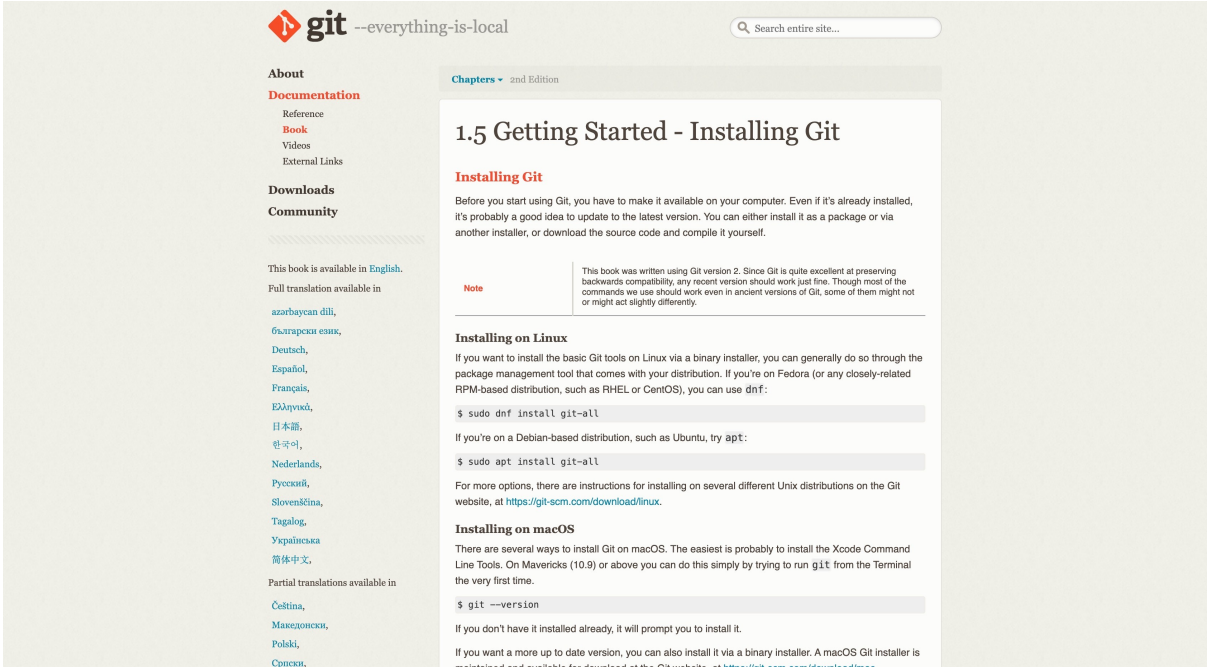
Installing Essential Tools (VS Cdoe)

To install VS Code, you will need to visit the official website and install the compatible version with your operating system.



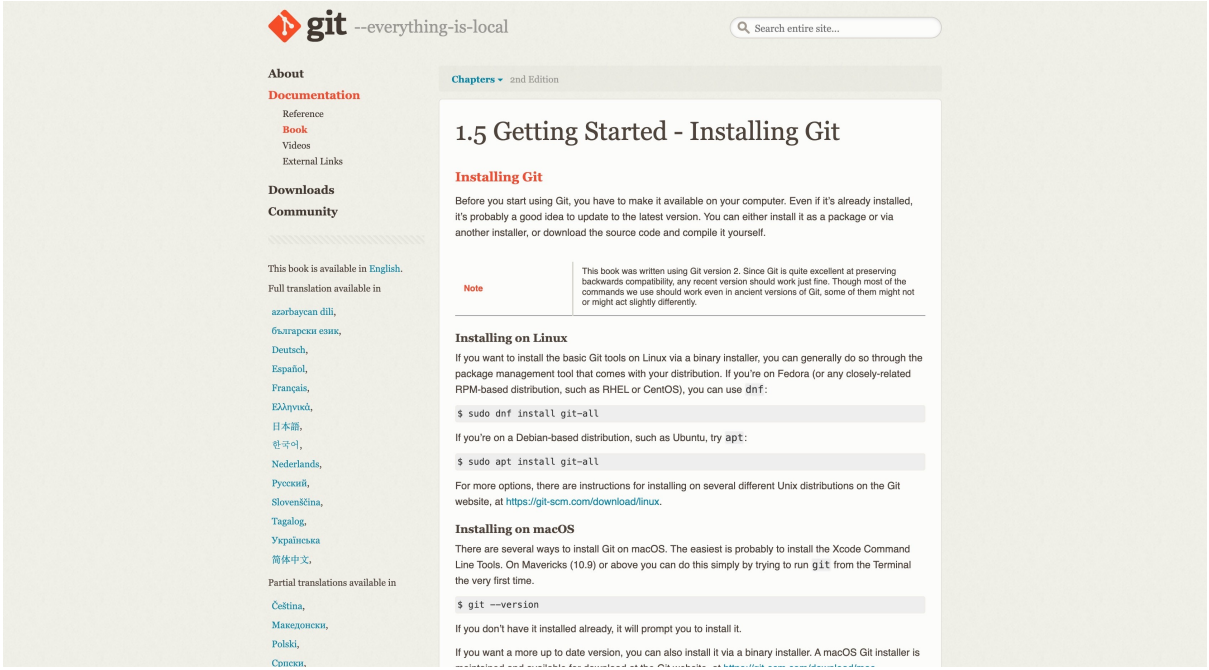
Setting Up Version Control (git - win)

To install git, you will need to visit the official website and install the compatible version with your operating system. For windows visit here.



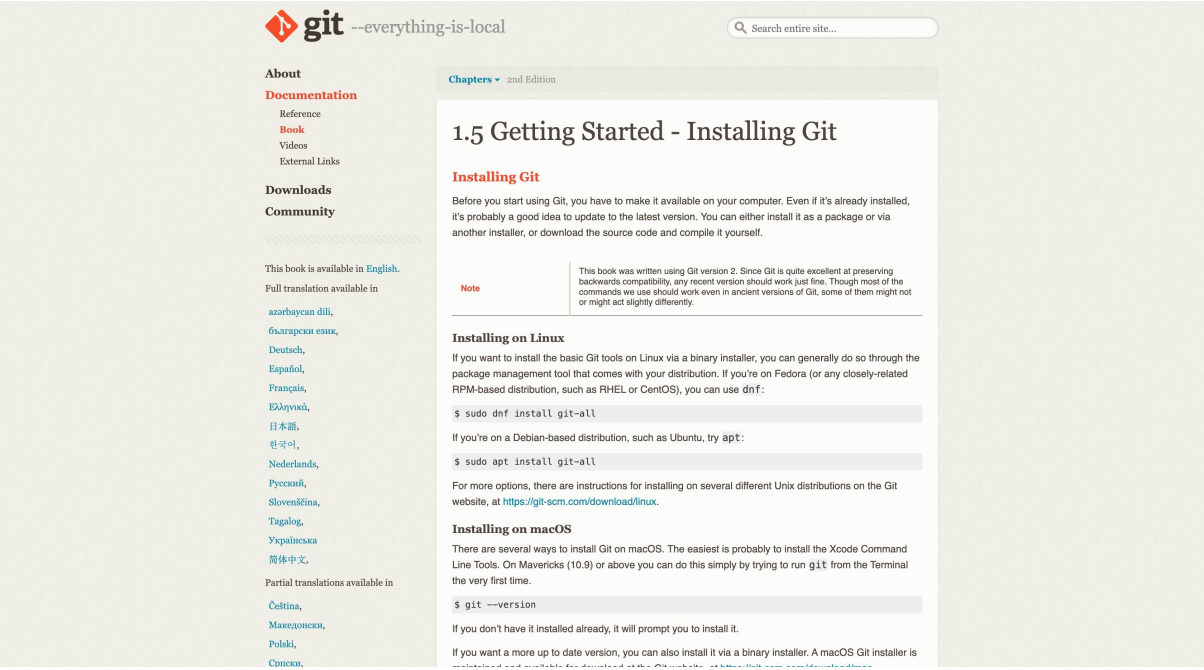
Setting Up Version Control (git - macOS)

To install git, you will need to visit the official website and install the compatible version with your operating system. For macOS use homebrew to install it via the command `brew install git`.



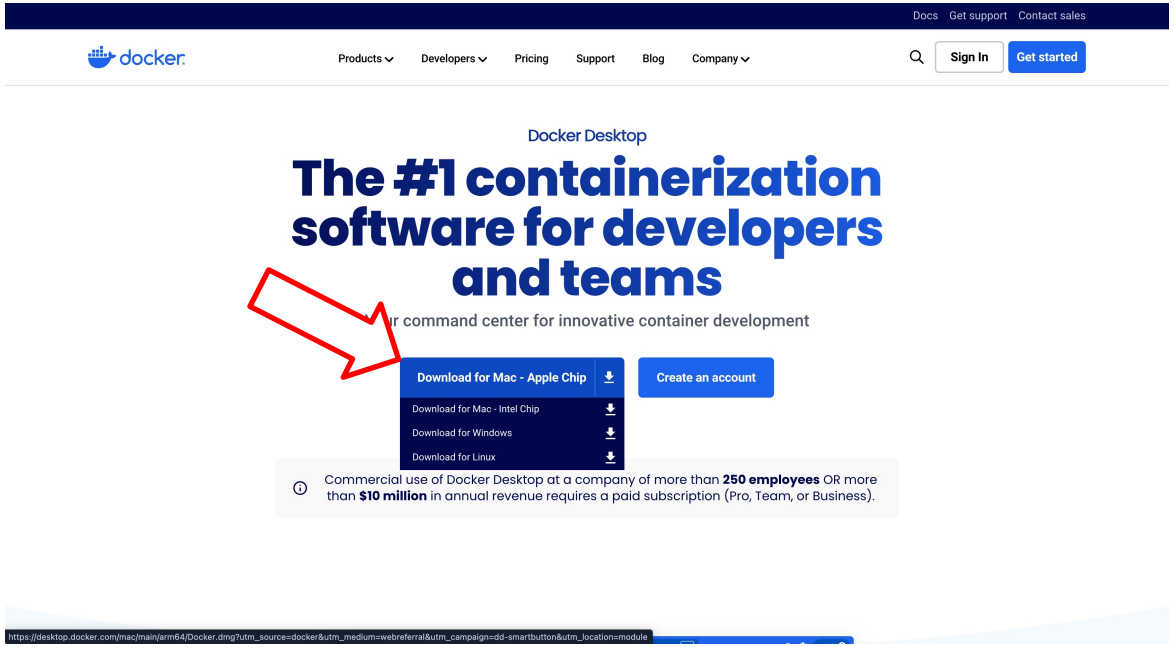
Setting Up Version Control (git - Linux)

To install git, you will need to visit the official website and install the compatible version with your operating system. For Linux install it via the command `apt-get install git`.



Containerization with Docker

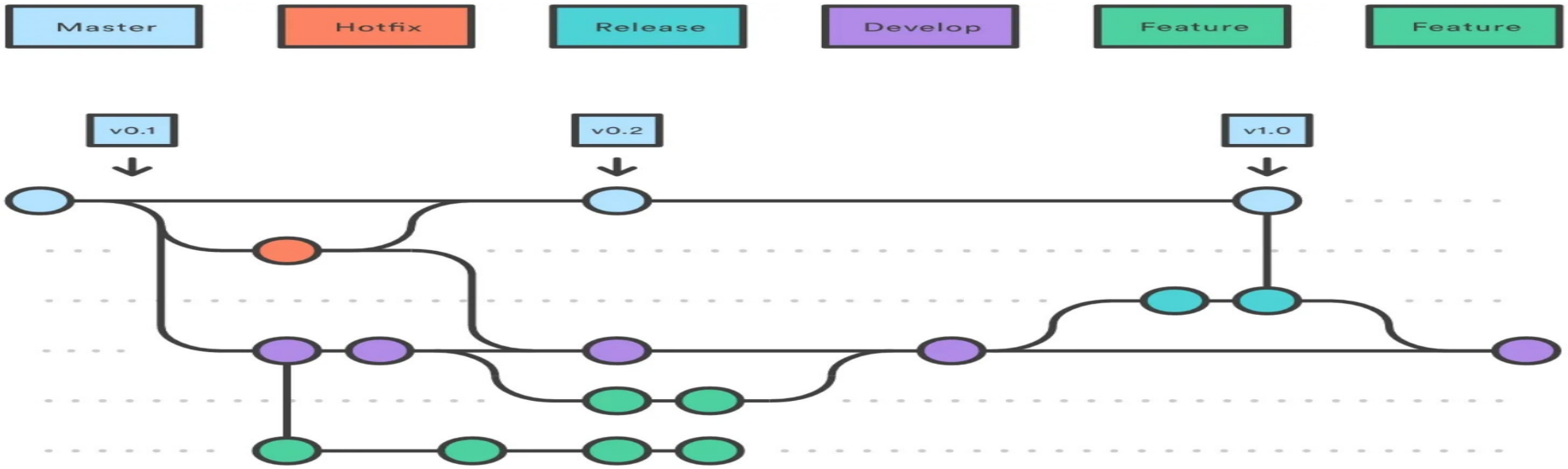
To install Docker, visit the official Docker website and follow installation instructions.



Version Control

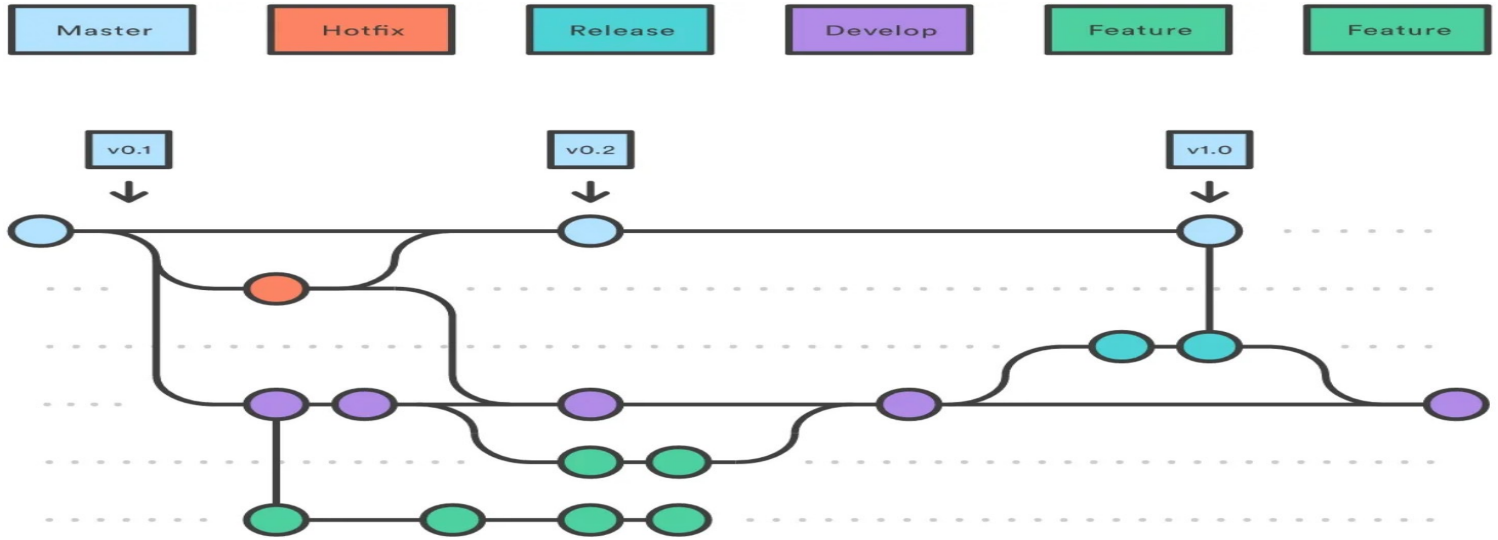
What is Version Control ?

- **Version control** is the process of managing changes to a set of files over time. It enables developers to track changes, collaborate with others, and revert to previous versions if needed. Version control systems (VCS) like Git and SVN are commonly used in software development to manage code changes. In ML projects, version control is also used to track changes to datasets, preprocessing scripts, training scripts, and model files.



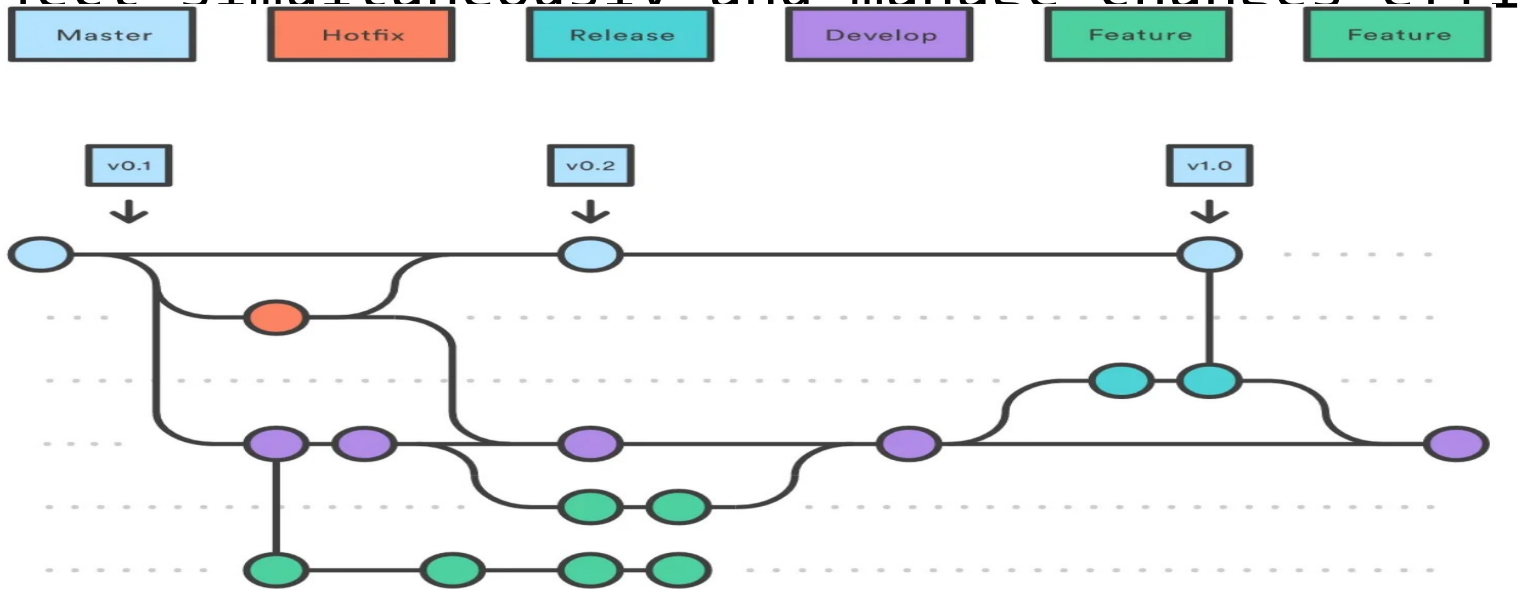
Why is Version Control important ?

- **Version control** is especially crucial in ML projects because of the large volumes of data and the iterative nature of model development. Without version control, it becomes difficult to track changes to datasets, preprocessing steps, and model architectures.
- **Version control** ensures reproducibility, which is essential for research and development.



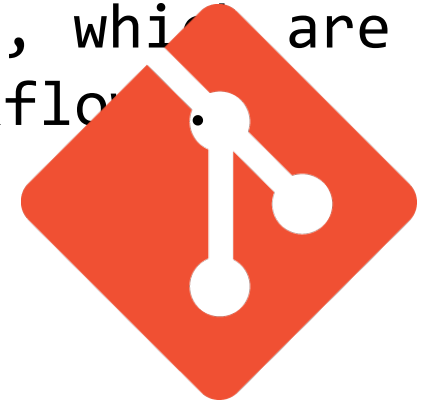
Why is Version Control important ?

- Reproducibility allows other researchers to validate results, compare methods, and build upon existing work.
- Additionally, version control facilitates collaboration by
  allowing multiple team members to work on the same project simultaneously and manage changes efficiently.



Choosing a Version control

- Several version control systems are available, including Git, SVN, and Mercurial.
- Git is by far the most popular and has become the standard
  for version controlling ML projects. As a distributed system, Git allows each user to have a complete copy of the repository, making collaboration and offline work easy.
- Git also offers powerful features like branching and merging, which are well-suited for managing complex ML workflows.



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Best practices for Version control

- Version control code using Git or a similar version control system.

- Version control data using a tool like DVC (see section 5 for more information on DVC).

- Track experiment results, such as performance metrics and visualizations, using a tool like MLflow or TensorBoard.

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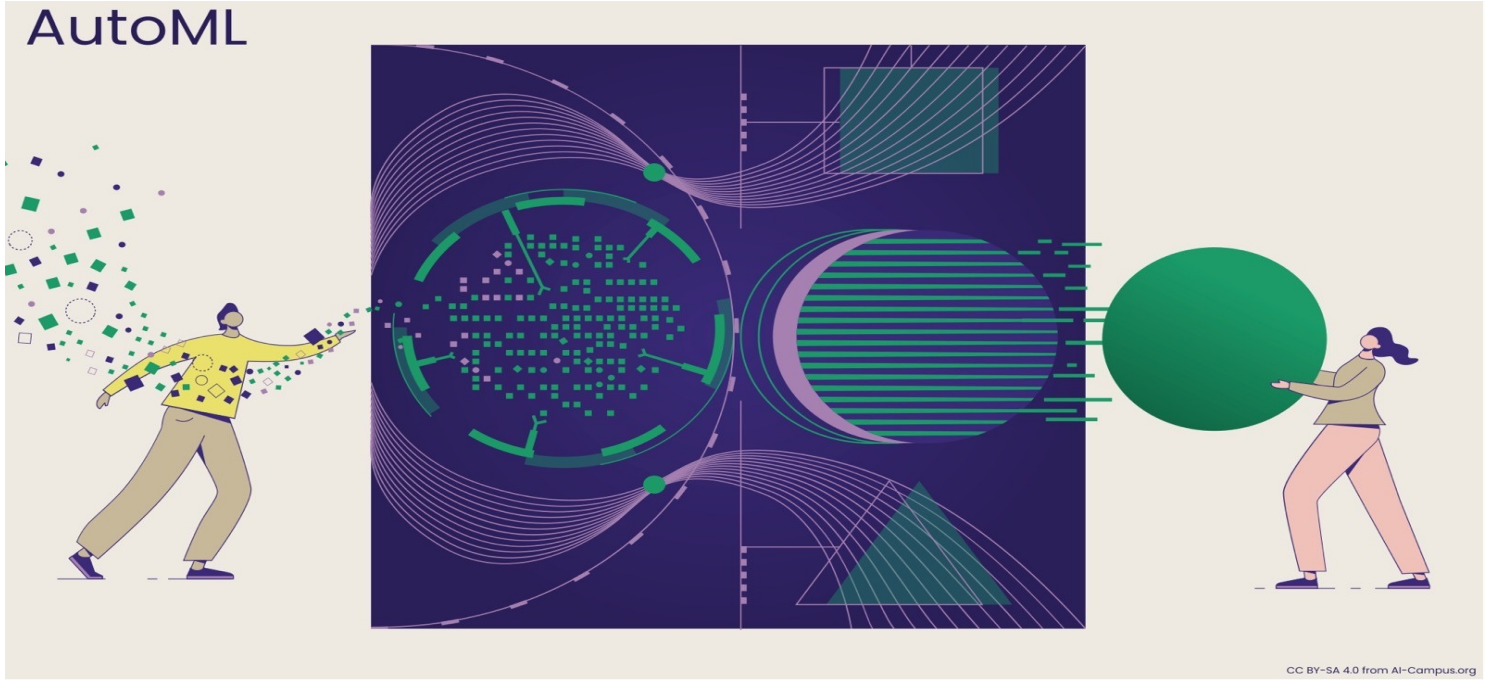
Recent Trends in MLOps

AutoML

•**AutoML** (Automated Machine Learning) streamlines the setup of Machine Learning (ML) models by enhancing the ML pipeline and minimizing errors. This makes the process quicker and more efficient.



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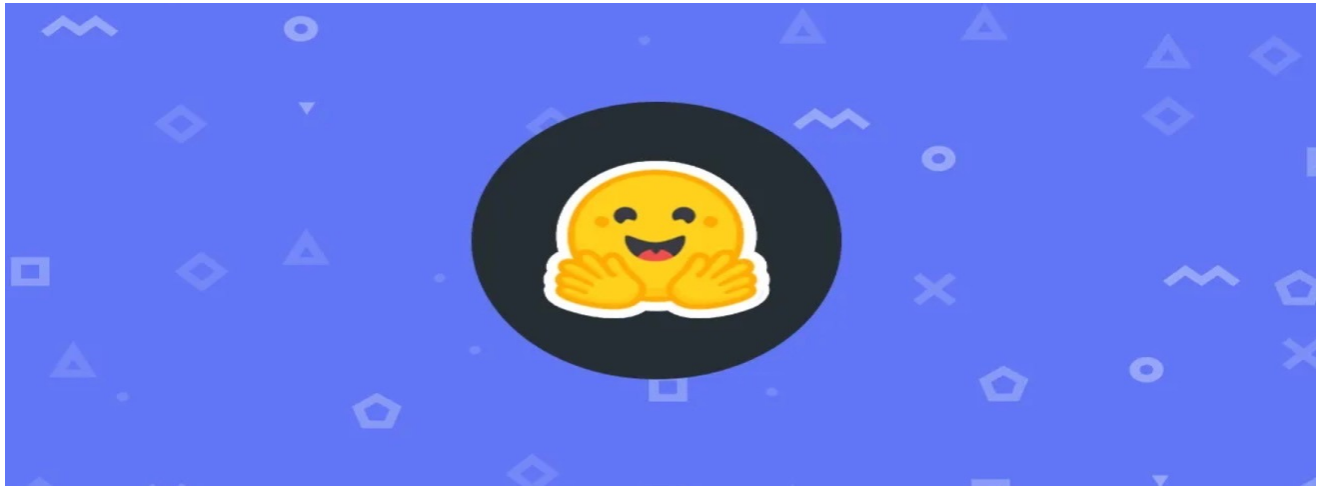
AutoML Example

- **Hugging face Auto NLP:**

Hugging Face AutoNLP is an AutoML tool specifically designed for natural language processing (NLP) tasks, automating the process of training and fine-tuning NLP models.



Source

AutoML Example

- **H2o.ai (H2O AutoML)**

H2O.ai offers a suite of AutoML tools, including H2O AutoML, which automates the machine learning model selection and hyperparameter optimization process.

Source

AutoML Example

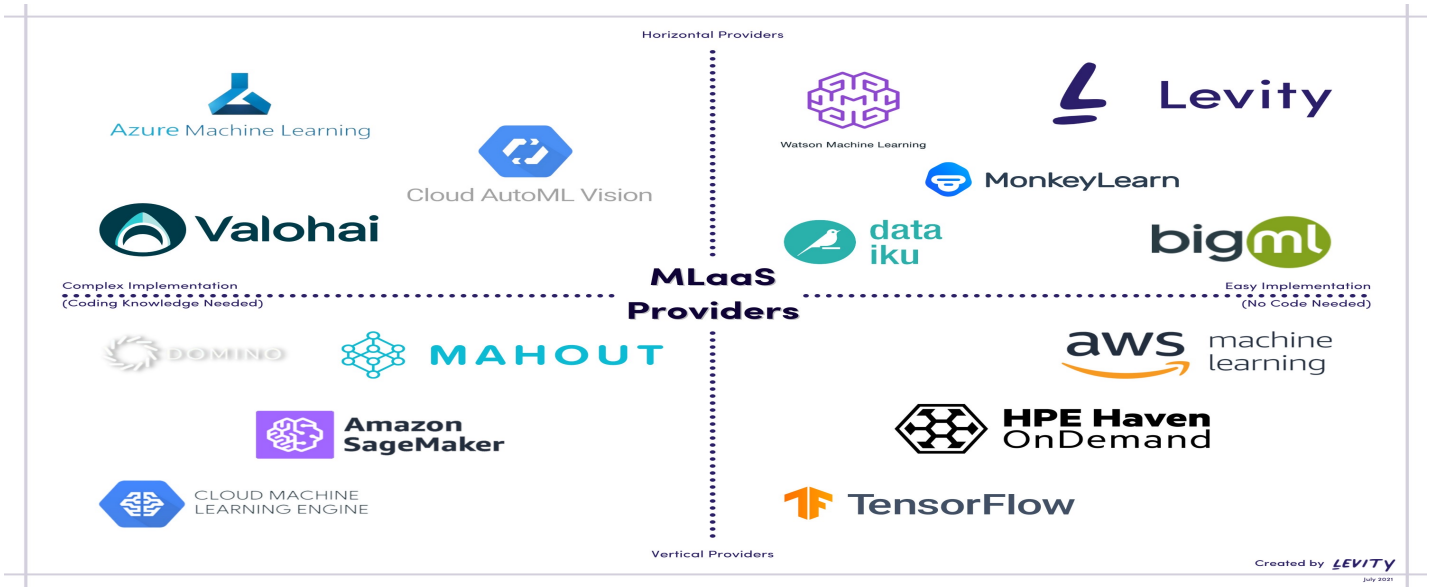
- **Google cloud AutoML**

Google Cloud AutoML provides a range of AutoML tools, such as AutoML Vision, AutoML Natural Language, and AutoML Tables, which automate the development of computer vision, NLP, and tabular data models.

Source

ML as a service

- **MLaaS** is the use of technology to automatically train, test, and deploy machine learning models for you, typically by leveraging an AI platform with offsite server farms (a “cloud”) to run them on behalf of the customer.



Source

MLaas Example

Amazon Machine Learning Services:

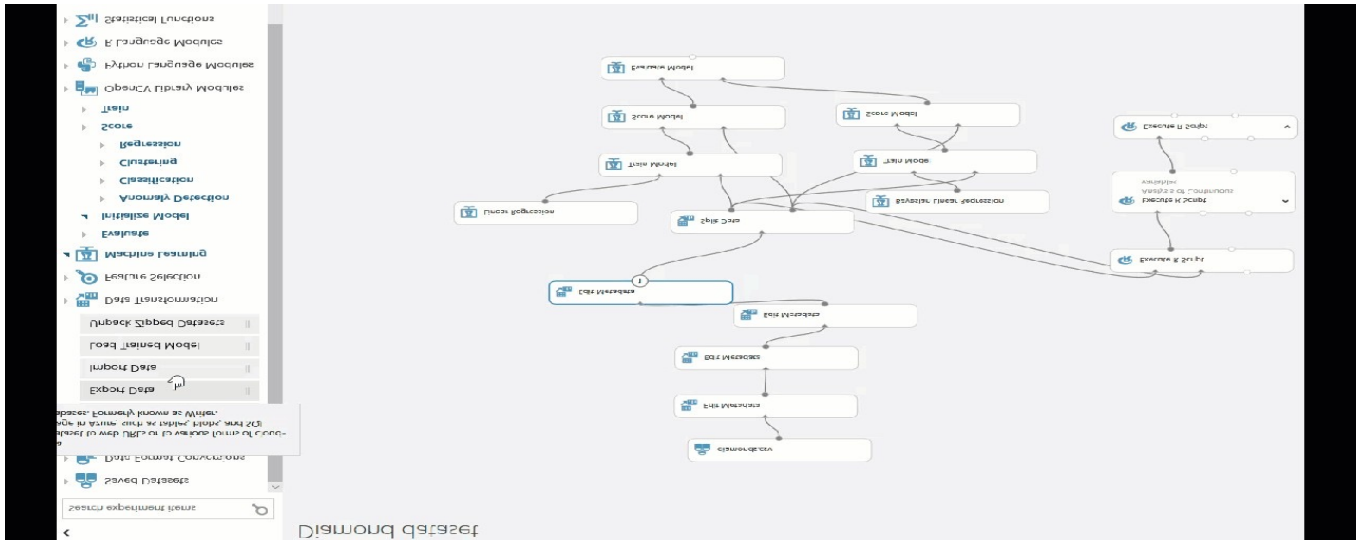
AWS Machine Learning Services let you create ML models without having to dabble with the algorithm. This makes it one of the most automated players in the MLaaS market and a service that's a good fit for deadline-centered businesses.

Source

MLaas Example

Microsoft Azure Machine Learning Studio:

A good selling point is ML Studio's variety of algorithms. It empowers users with over 100 methods that help with regression, classification, recommendation, Text Analysis, and anomaly detection.



Source

Future trends in MLOps

- **Explainable AI (XAI):**

Future MLOps workflows will likely integrate more tools and techniques for Explainable AI (XAI). These tools will help data scientists and stakeholders understand how ML models make decisions, thereby increasing transparency and trust in AI systems.

- **Model Governance and Compliance:**

As regulations around data privacy and model fairness continue to evolve, MLOps will increasingly emphasize model governance and compliance. Organizations will need to establish robust frameworks for tracking and auditing model behavior to ensure adherence to these regulations.

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