

Introduction to fully automated MLOps

FULLY AUTOMATED MLOPS



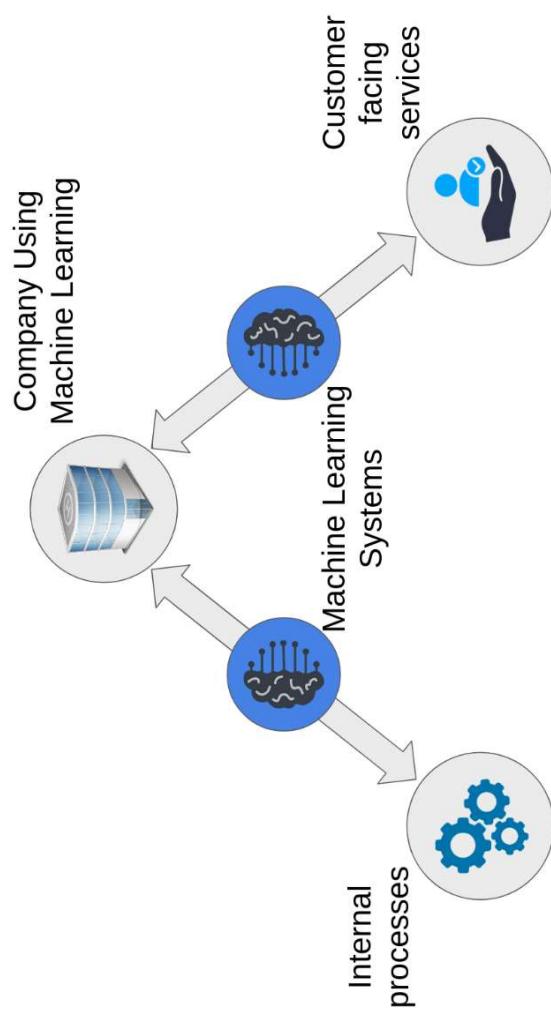
Arturo Opsetmoen Amador
Senior Consultant - Machine Learning



MLOps in an industrial setting

What are common goals companies have when using machine learning?

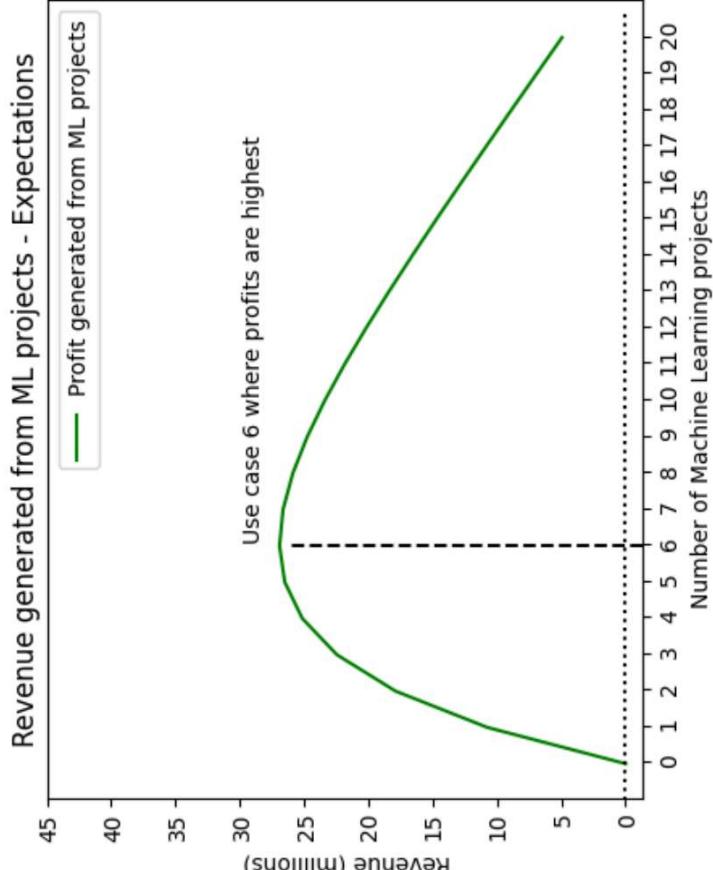
- Develop ML tools and products that use data to
 - Better serve customers
 - Optimize processes



Optimizing for value generation

Companies aim to maximize profits

- Machine learning can be used to increase profitability
- By analyzing costs and revenues, a company can estimate potential profits
- Deploying the right number of ML use-cases can result in profits



Costs in software development

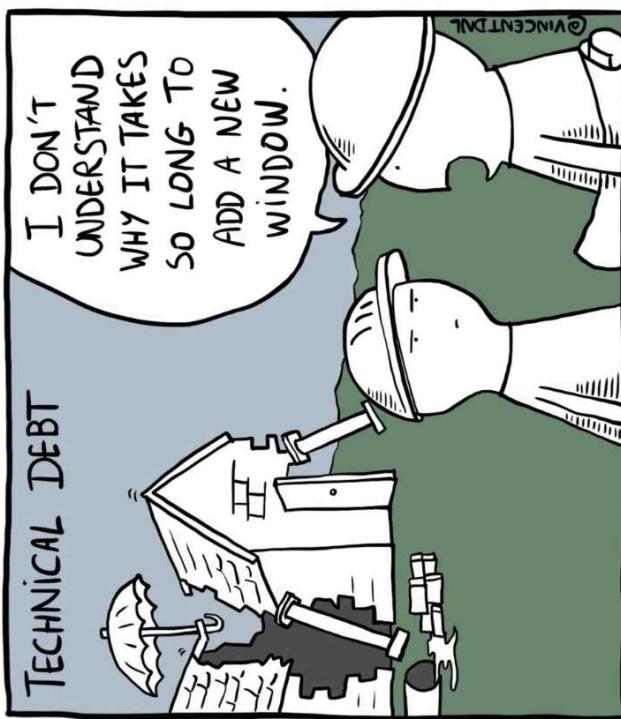
Expected costs in a traditional software development project:

- Development costs
- Project management
- UI/UX design
- Quality assurance

Technical debt in software development

Technical debt or design debt:

- Cost of rework caused by poor design



¹ <https://vincentdnl.com/drawings/>

Hidden technical debt in ML systems

Machine Learning: "The high-interest credit card of technical debt"^[1].

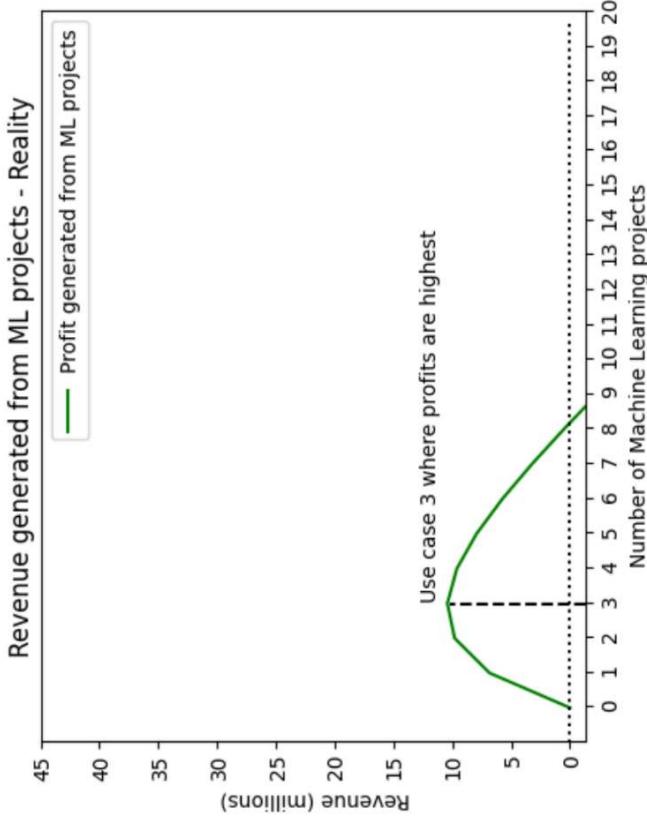
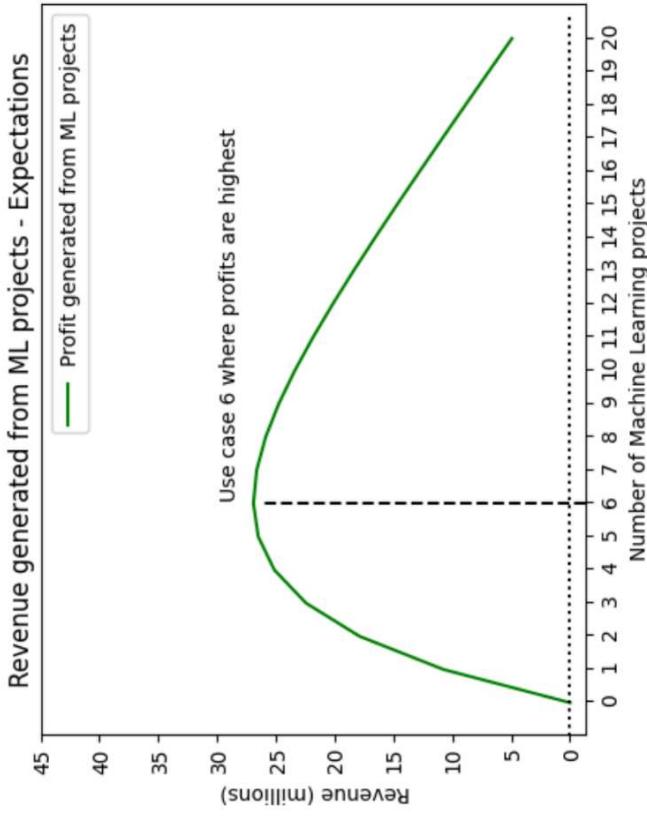
Hidden technical debt can be related to:

1. The data used to train the ML models
2. The models powering the ML system
3. The infrastructure used by the ML system
4. The monitoring of the ML system

¹ <https://research.google/pubs/pub43146/>

Costs of machine learning projects

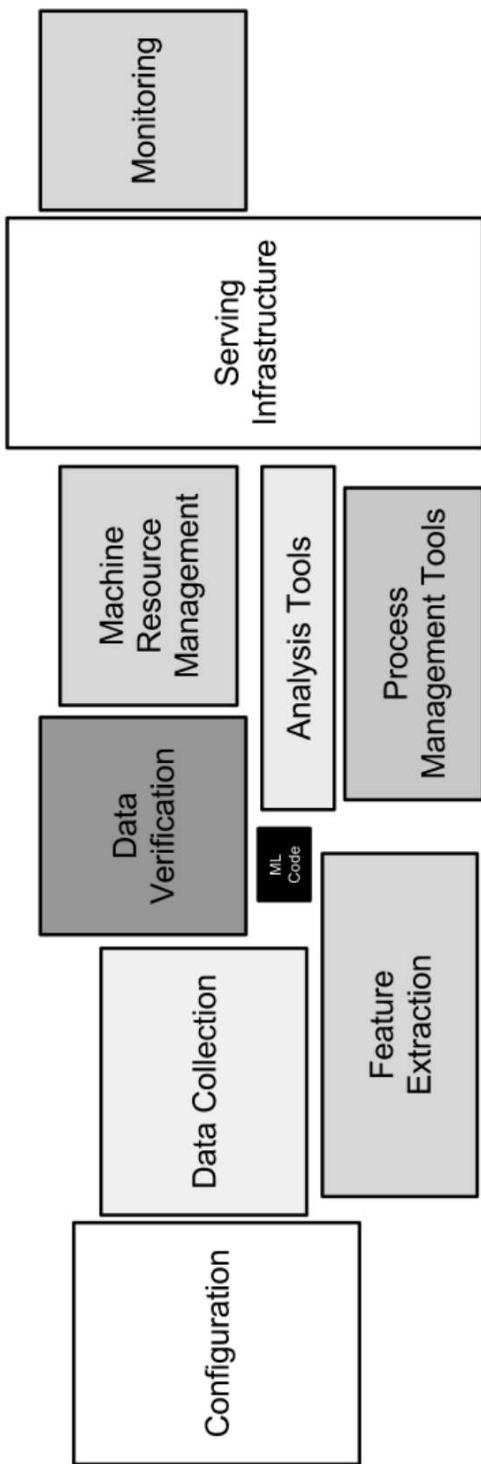
Reduced profit due to technical debt in ML systems:



Technical debt

The high-interest credit card of technical debt

ML systems can be complex and become unruly.



MLOps: The best-known way to pay

If ML is the high-interest credit card of technical debt, MLOps is the best way to pay for it.

MLOps can include:

- Automated testing
- Automated experiment tracking
- Automated monitoring

To keep the technical debt to a minimum

Let's practice!

FULLY AUTOMATED MLOPS

MLOps lifecycle stages

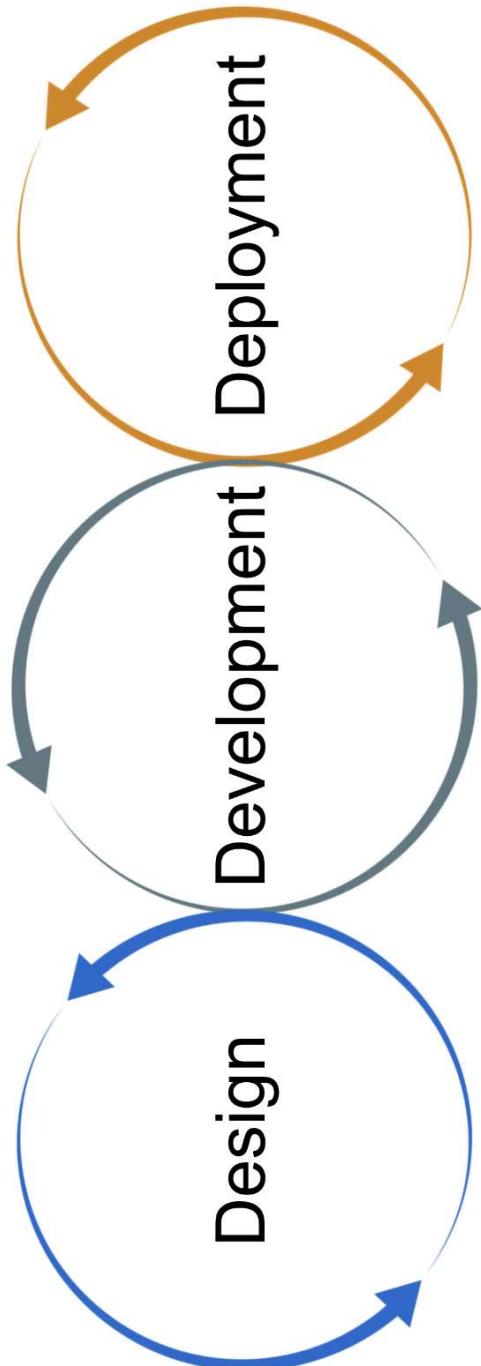
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The MLOps lifecycle

The MLOps lifecycle includes three core stages:

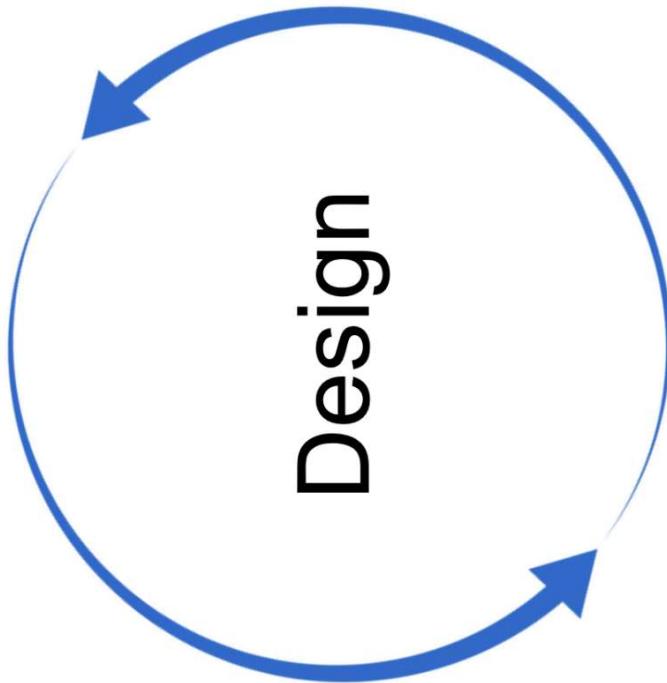


- The three stages are iterative
- The three stages are interconnected and rely on each other
- It is normal to go back and forth between stages

MLOps in the ML lifecycle - Design

The Design stage includes:

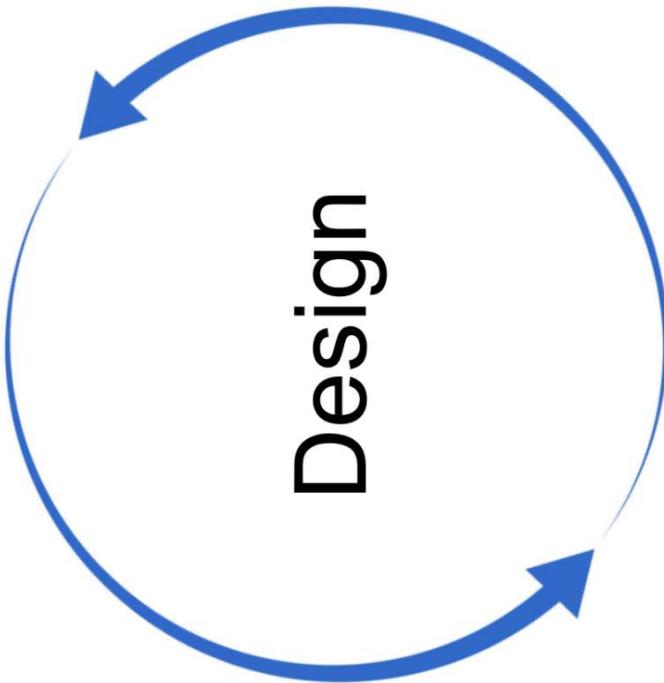
- BUSINESS UNDERSTANDING
- DATA UNDERSTANDING
- DESIGNING THE ML SOLUTION



MLOps in the ML lifecycle - Design

The Design stage includes:

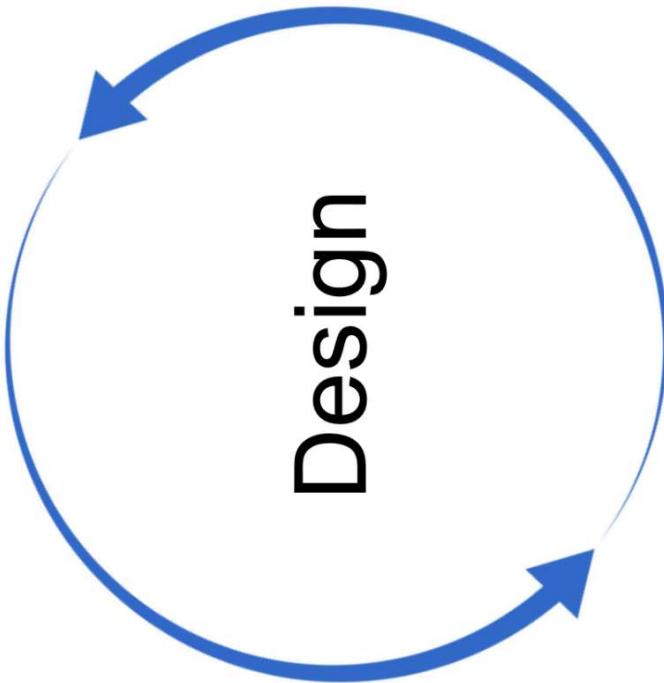
- **BUSINESS UNDERSTANDING**
 - Understanding the business context
 - Establishing the business goals



MLOps in the ML lifecycle - Design

The Design stage includes:

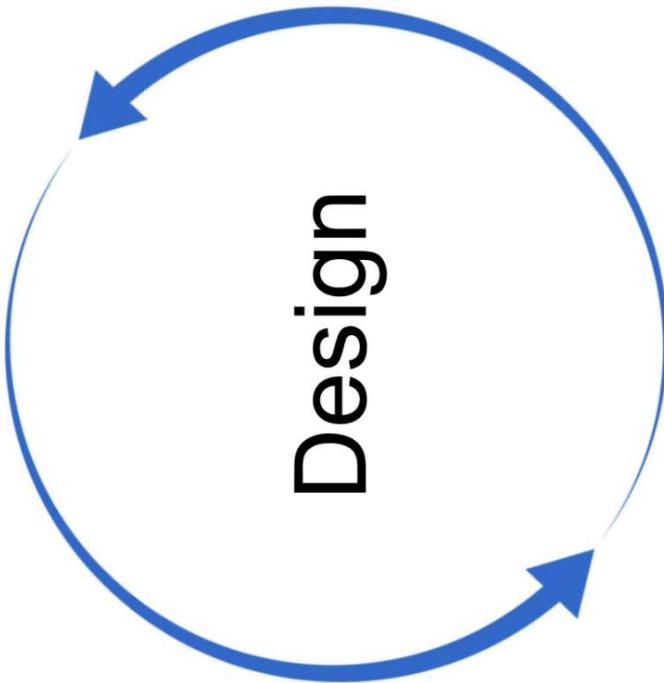
- DATA UNDERSTANDING
 - Data exploration
 - Data visualization



MLOps in the ML lifecycle - Design

The Design stage includes:

- SYSTEM DESIGN
 - System architecture design
 - Data security
 - Data privacy

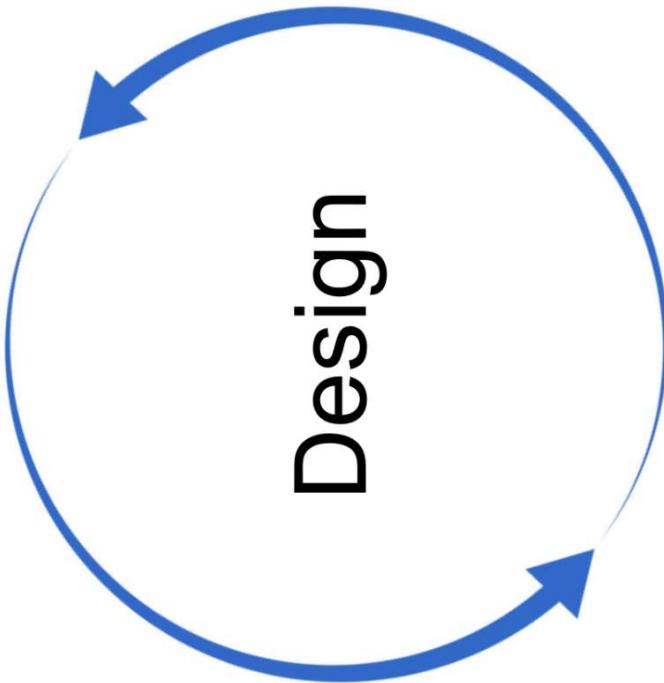


MLOps in the ML lifecycle - Design

The Design stage includes:

- BUSINESS UNDERSTANDING
- DATA UNDERSTANDING
- DESIGNING THE ML SOLUTION

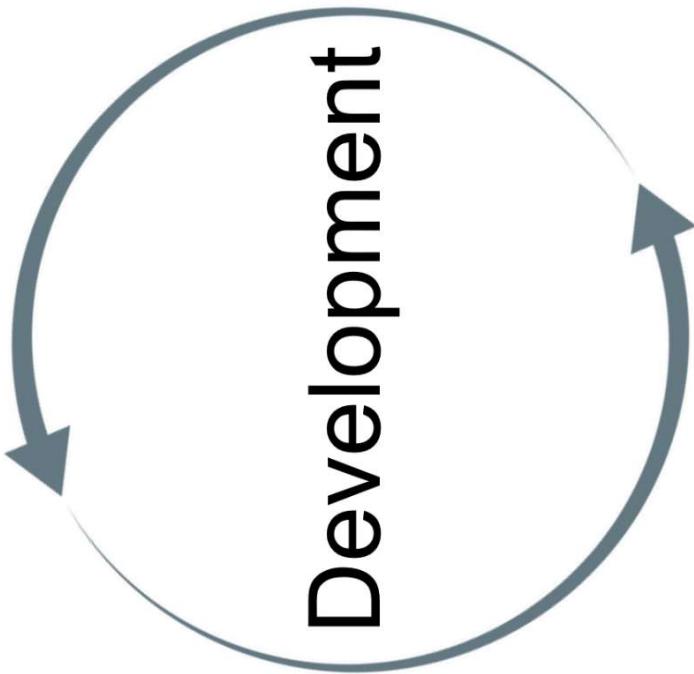
Much of the design phase can't be automated



MLOps in the ML lifecycle - Development

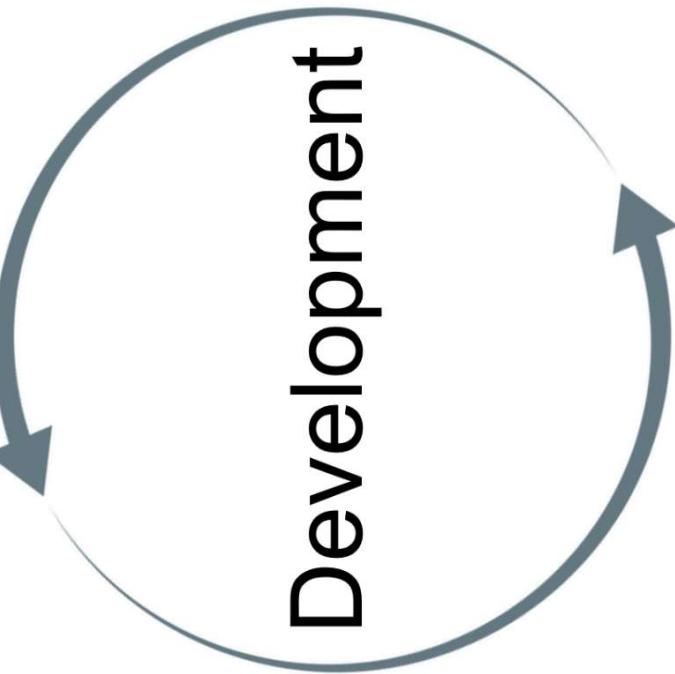
The ML experimentation and development stage includes:

- DEVELOPING PROOF-OF-CONCEPTS (POCs)
- DATA ENGINEERING
- MODEL DEVELOPMENT



MLOps in the ML lifecycle - Development

The ML experimentation and development stage includes:



- **DEVELOPING PROOF-OF-CONCEPTS (POCs)**

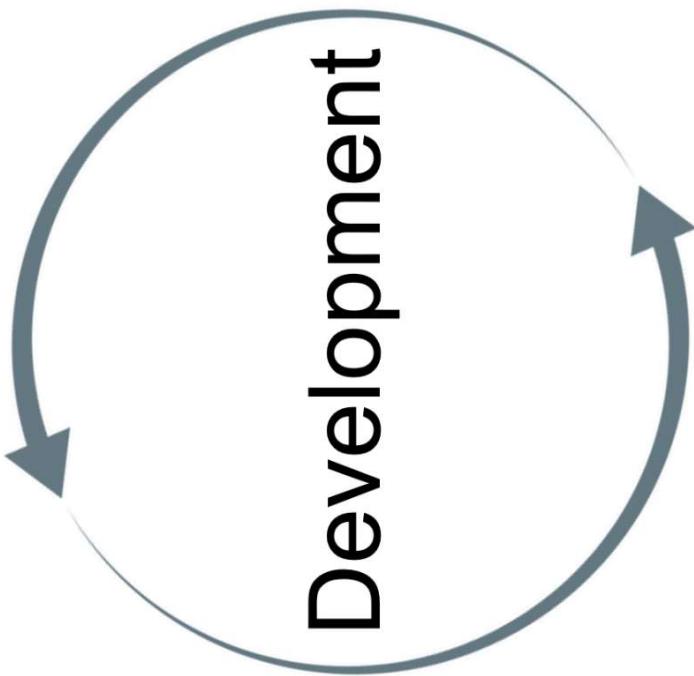
- Combination of process & automation
- Use of frameworks

MLOps in the ML lifecycle - Development

The ML experimentation and development stage includes:

- DATA ENGINEERING (POCs)

- Use of automation --> Quality assurance

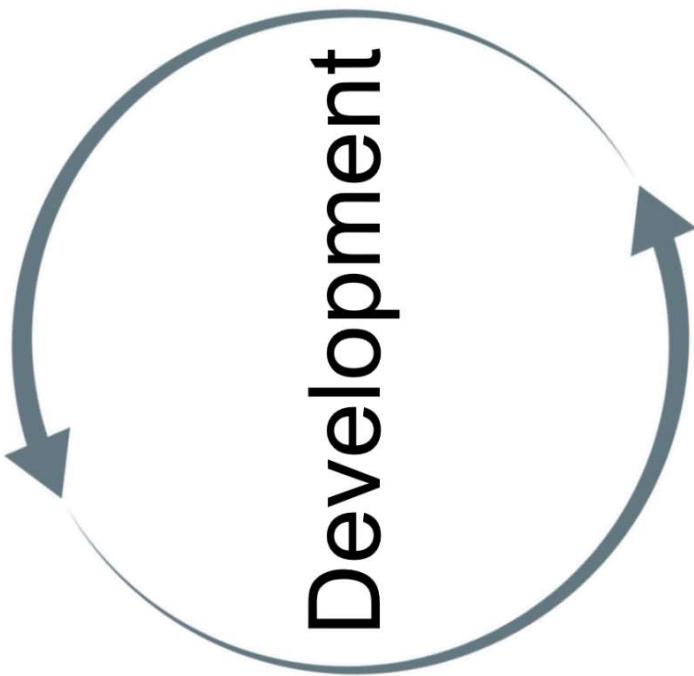


MLOps in the ML lifecycle - Development

The ML experimentation and development stage includes:

- MODEL DEVELOPMENT (POCs)

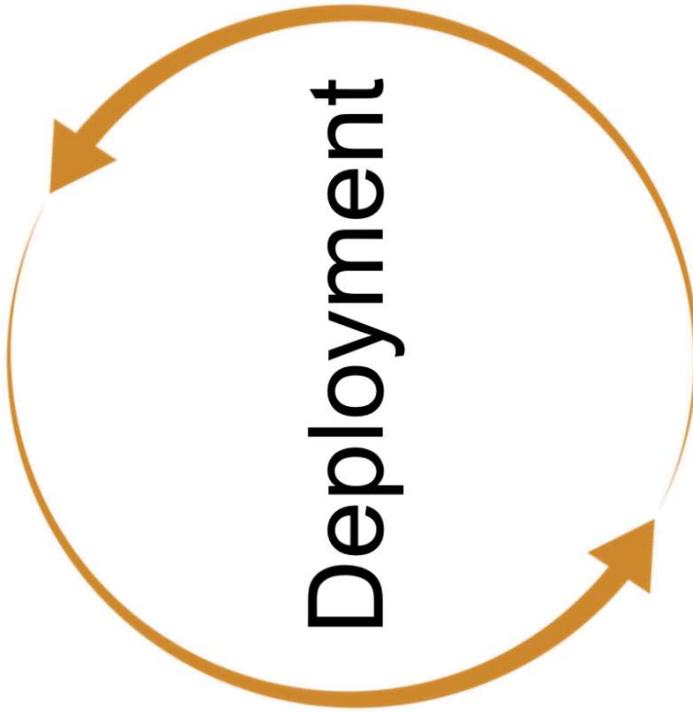
- Experiment tracking
- Automated training
- Automated hyperparameter tuning



MLOps in the ML lifecycle - Deployment

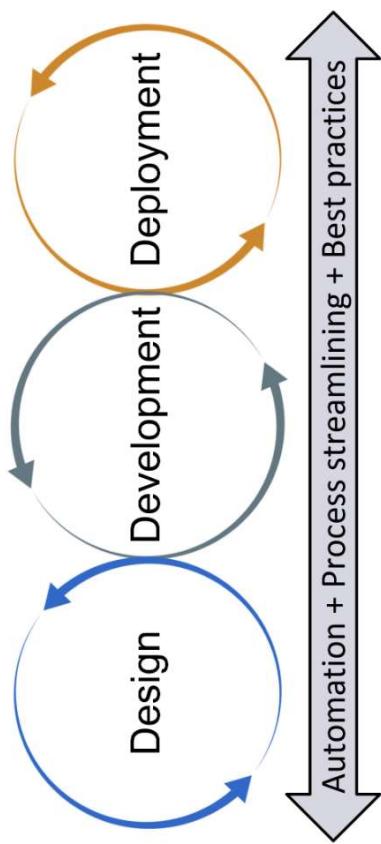
The ML deployment and operations phase include:

- Productionization
 - Testing
 - Versioning
 - Continuous delivery
 - Monitoring



Building for scale: Automation first

We use process streamlining, best practices, and automation



When no automation, process streamlining:

- CRISP-DM
- TDSP [1]

¹ <https://www.ibm.com/docs/en/spss-modeler/saas?topic=dm-crisp-help-overview>

Process streamlining and best practices

DESIGN PHASE

DEVELOPMENT PHASE

- Best practices
 - Include domain expertise
 - Involve business stakeholders
 - Get feedback from end-users
- Best practices
 - Write clean code
 - Document our work

Let's practice!

FULLY AUTOMATED MLOPS

Reference architecture: Fully automated MLOps

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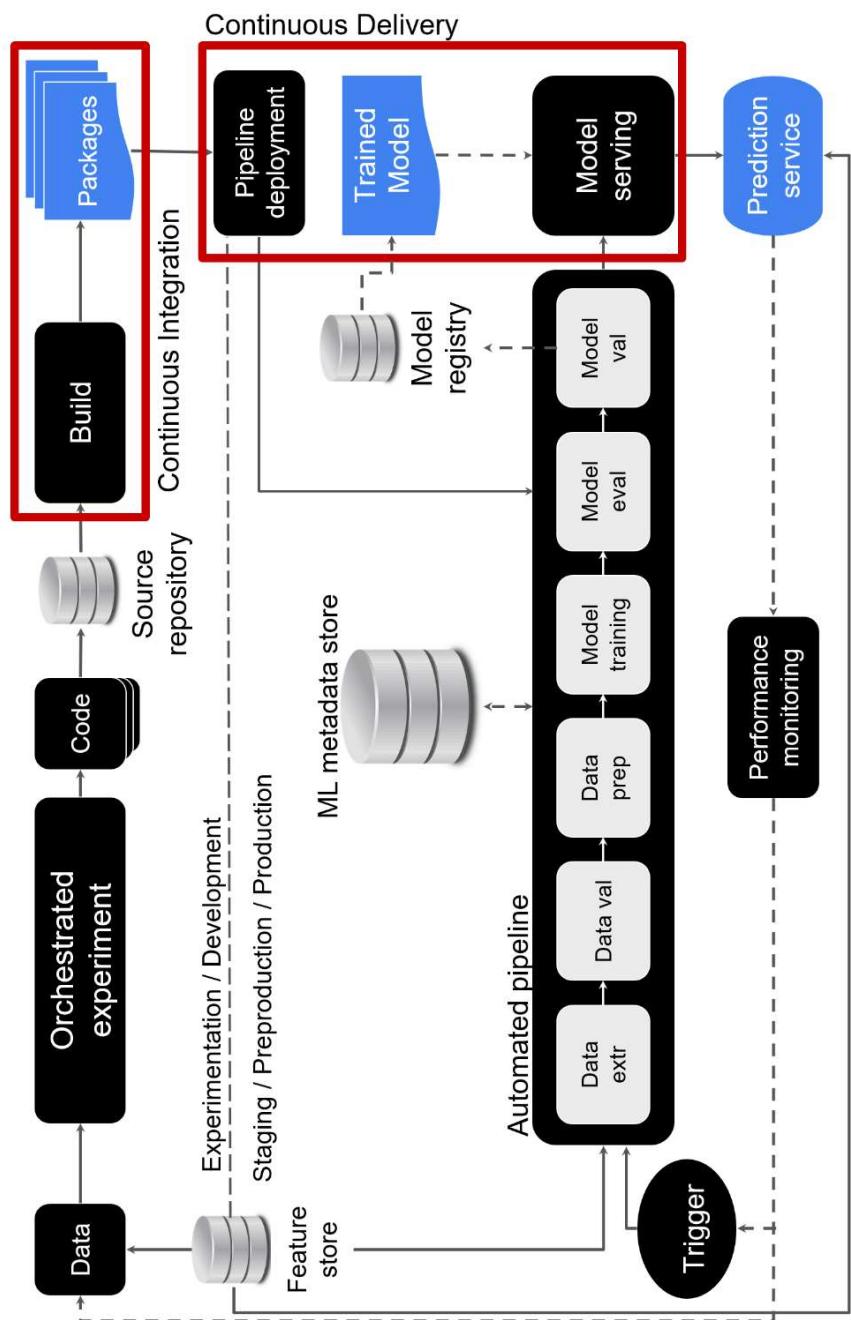
What is a reference architecture?

A reference architecture is a template we can use to design solutions in different IT domains.

A set of documents with:

- Structures and integrations of IT elements
- Patterns commonly present in IT systems, including ML systems
- Leverage experience and best practice from industry players

Fully automated MLOps architecture

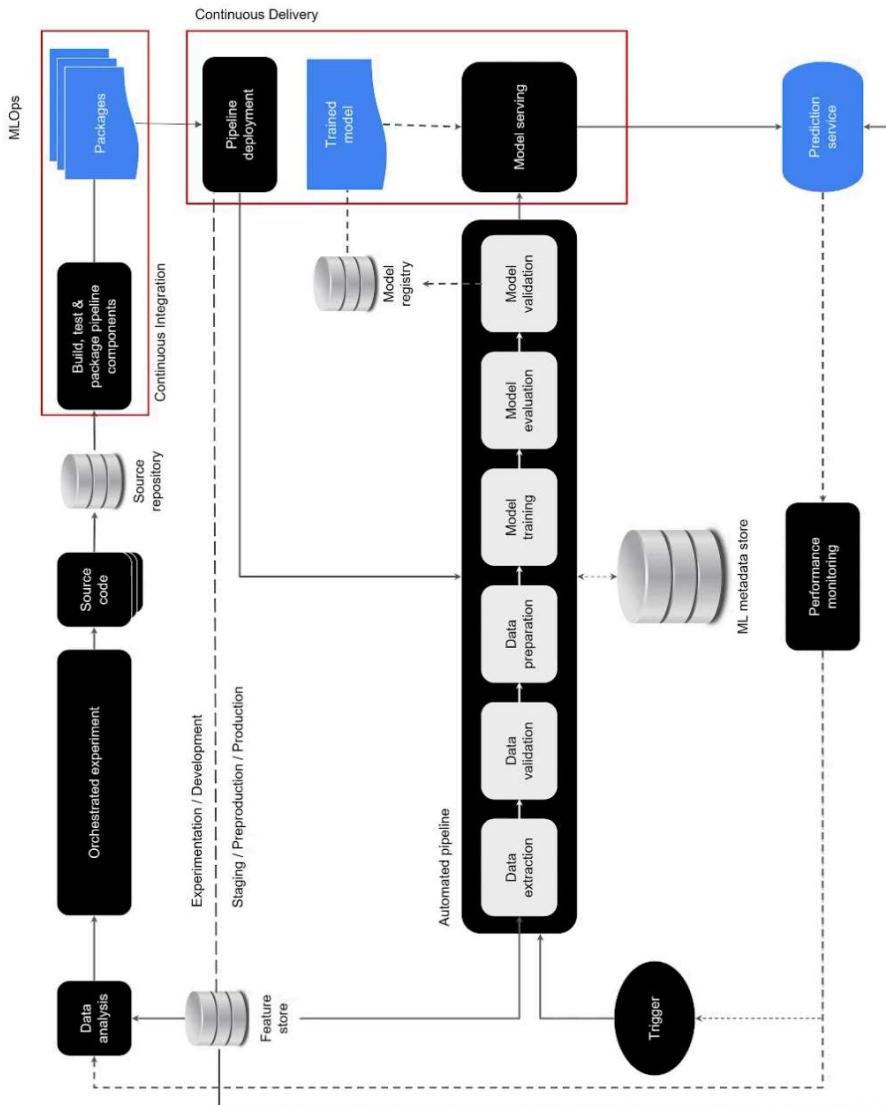


¹ <https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning>

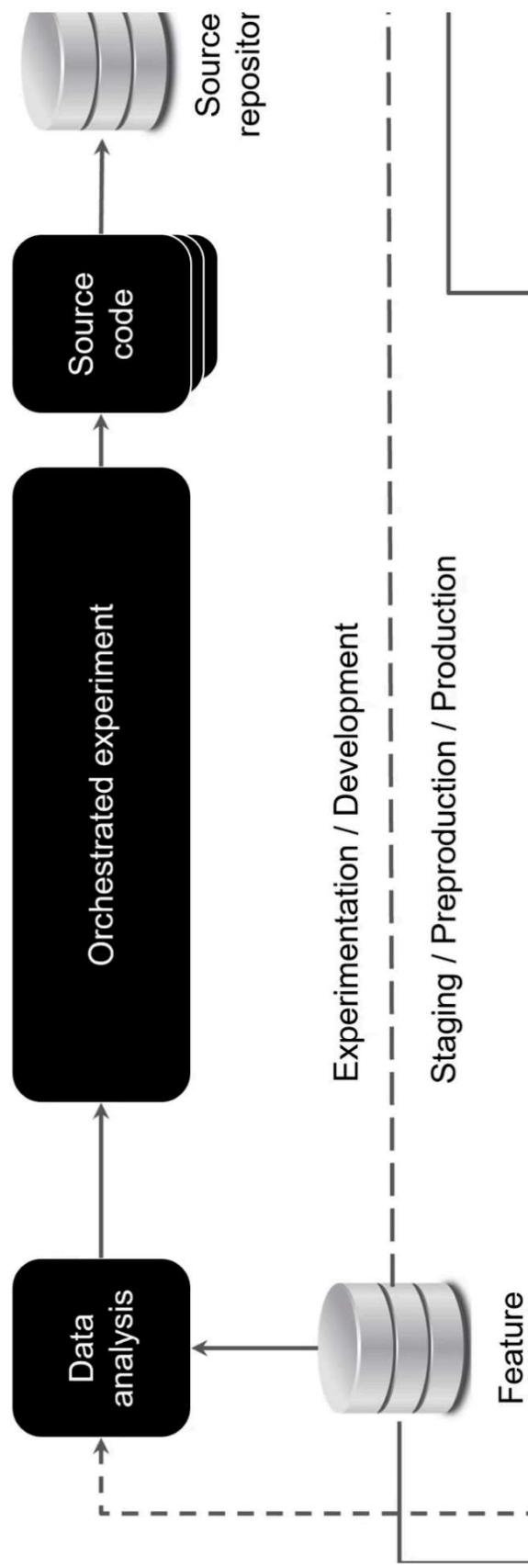


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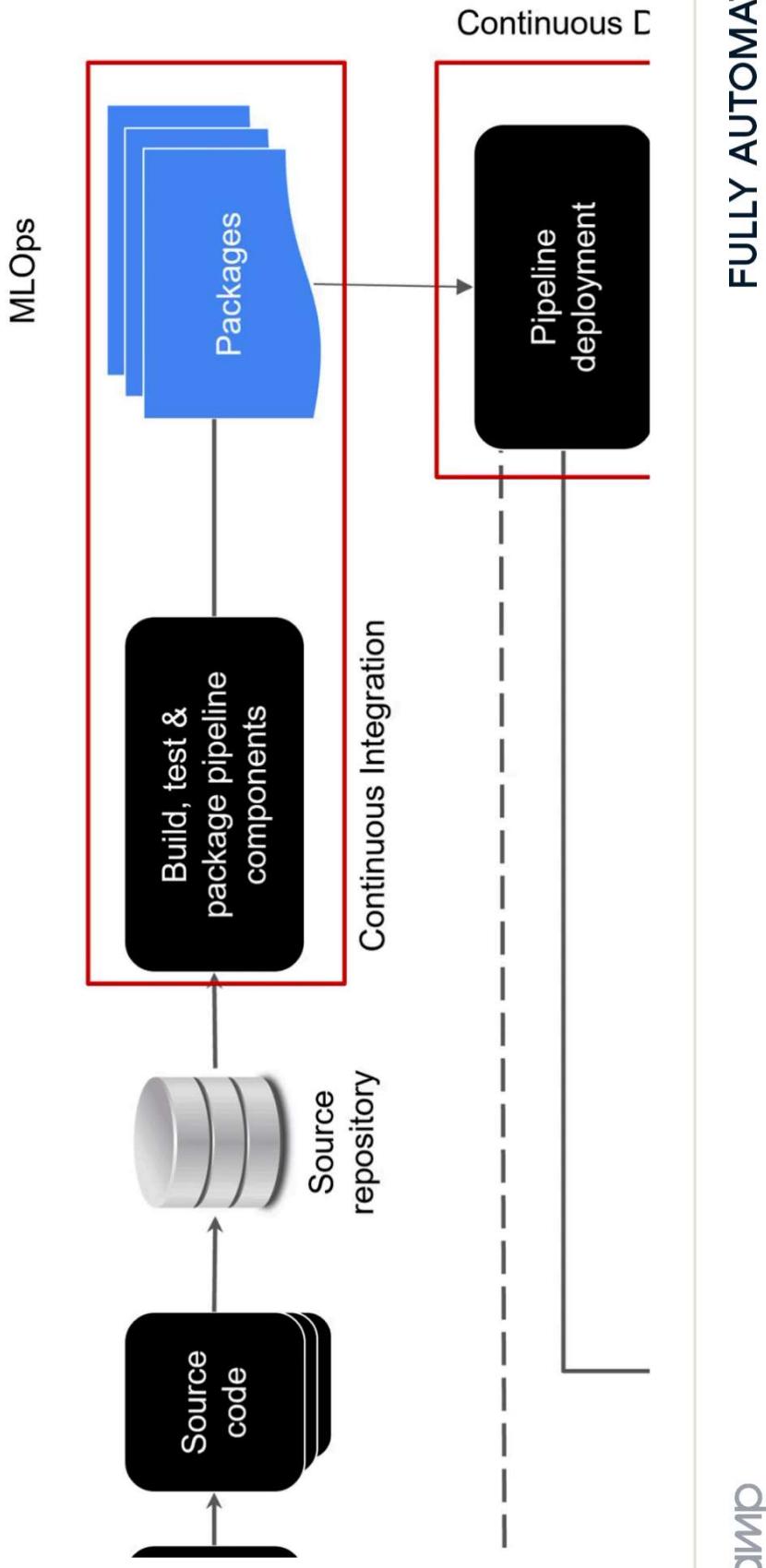
Reference architecture - Orchestrated experiments



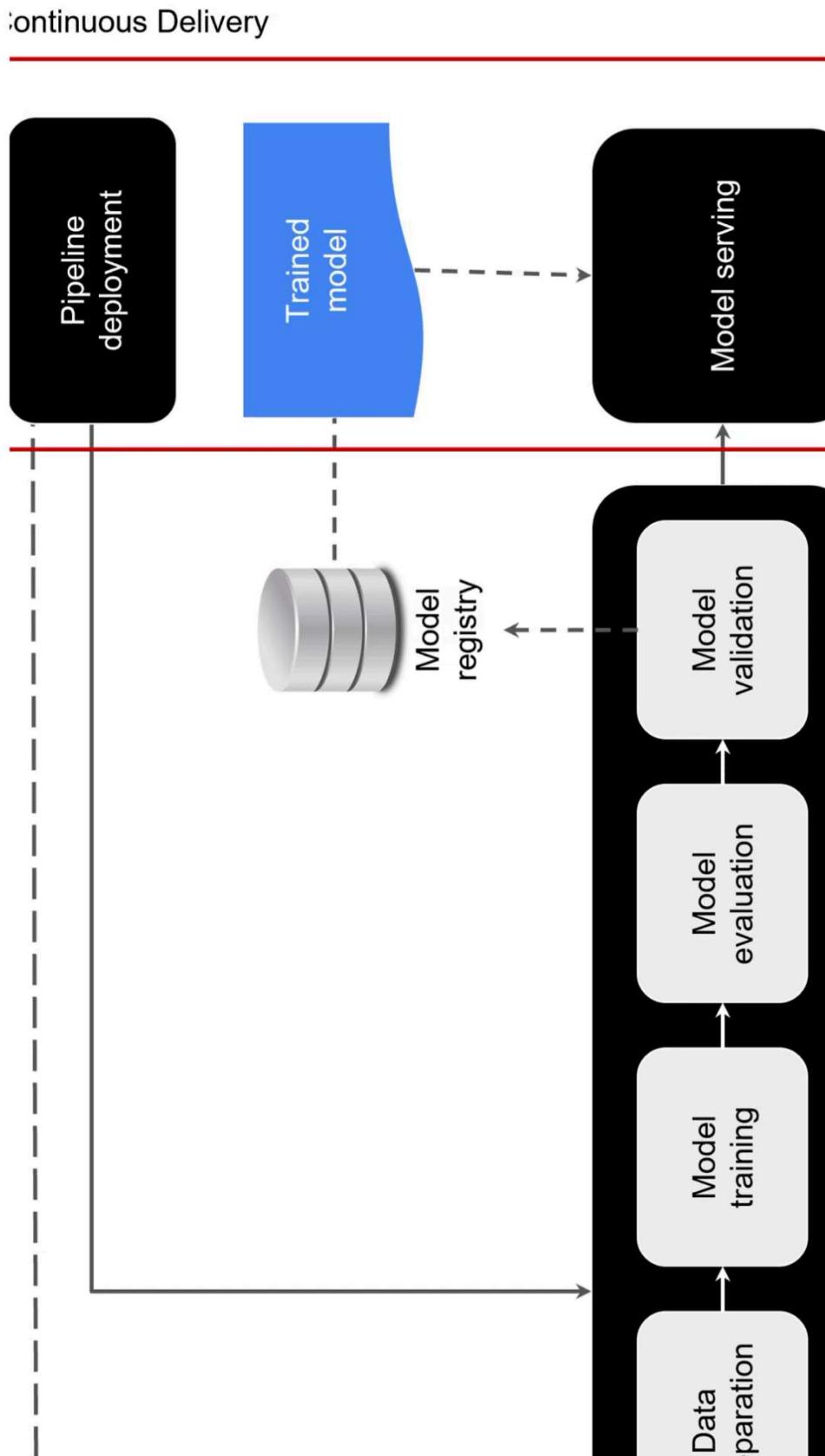
Reference architecture - Source code & CI



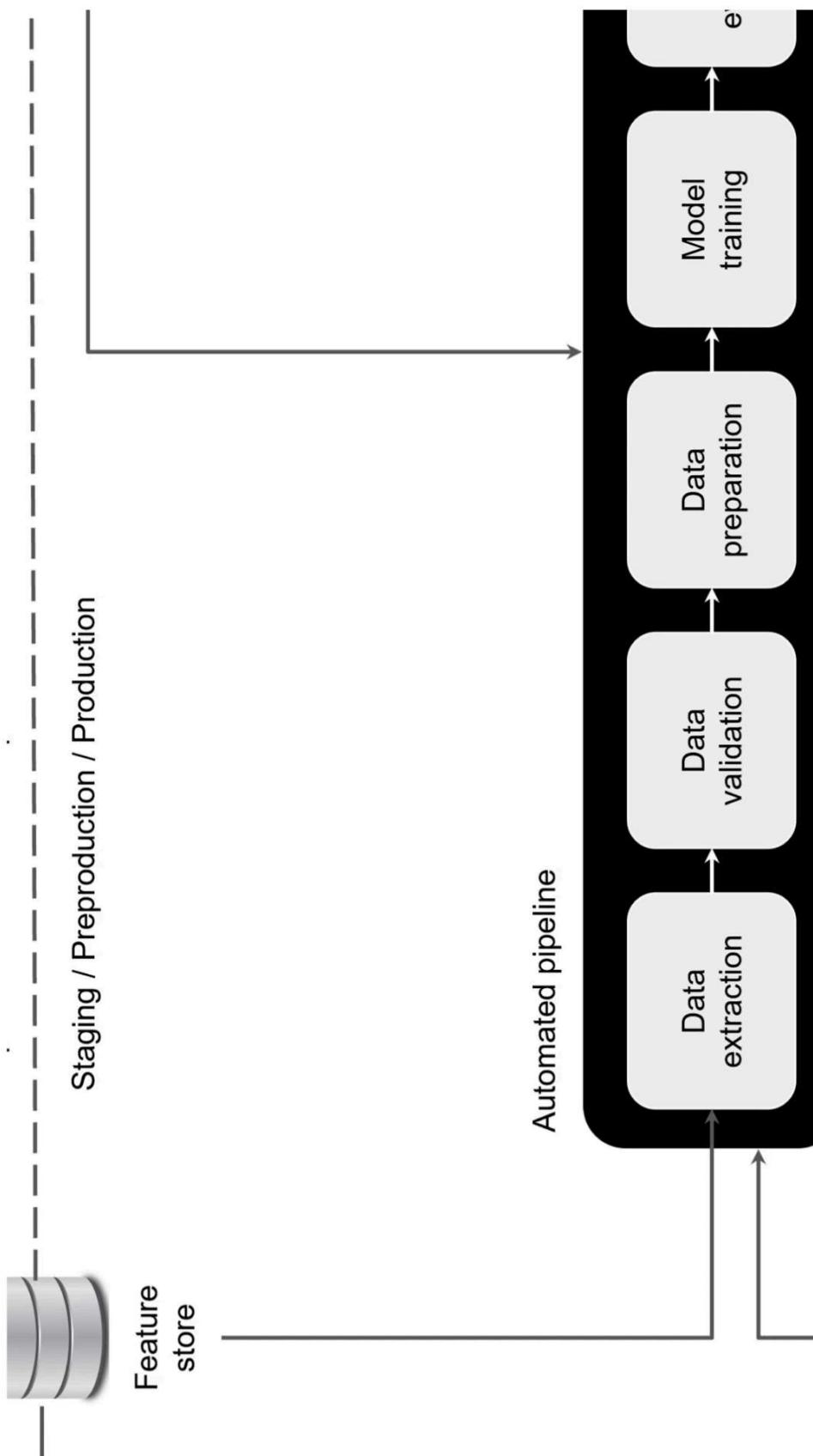
Reference architecture - Artifacts & CD



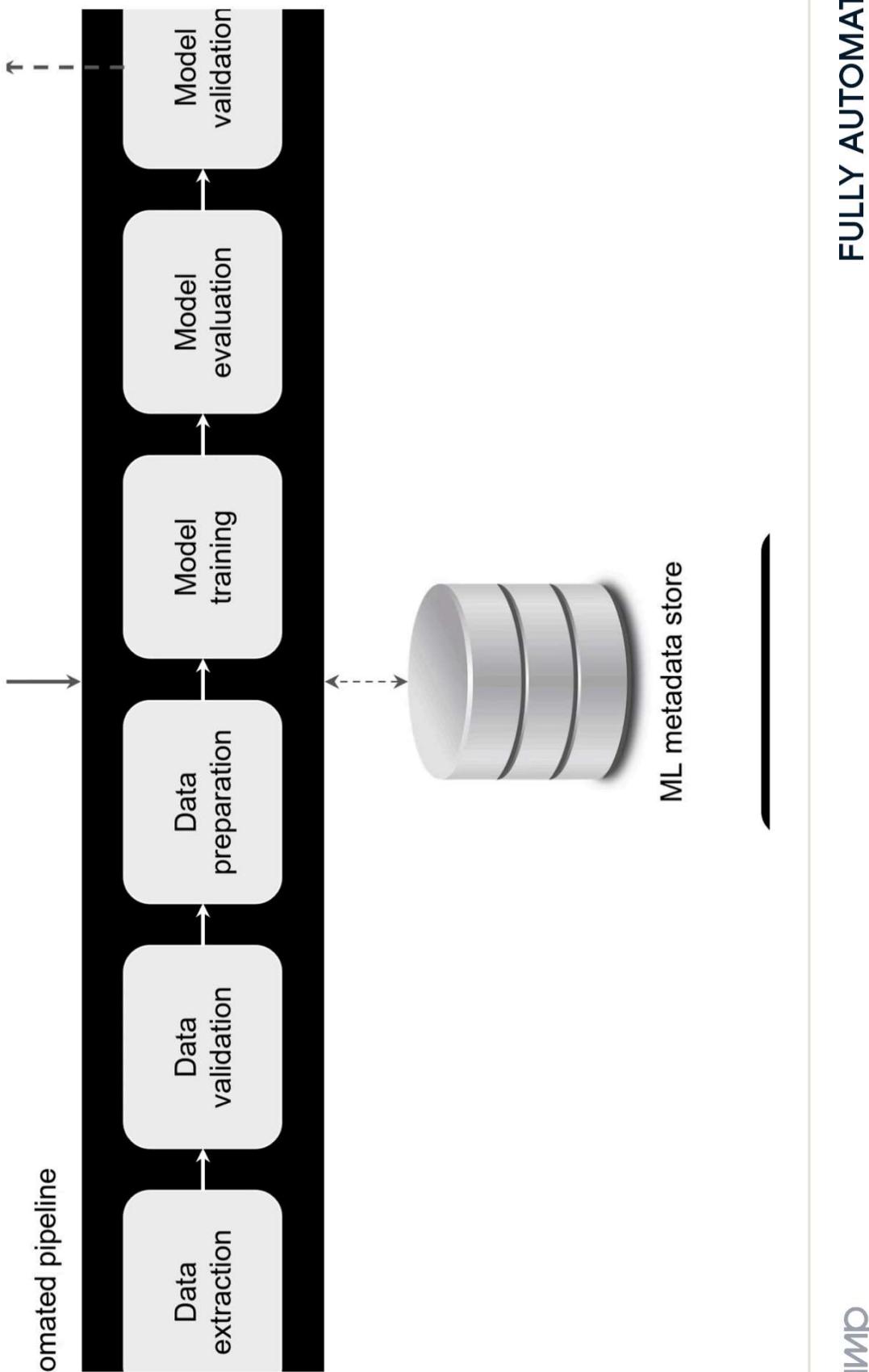
Reference architecture - ML pipeline deployment



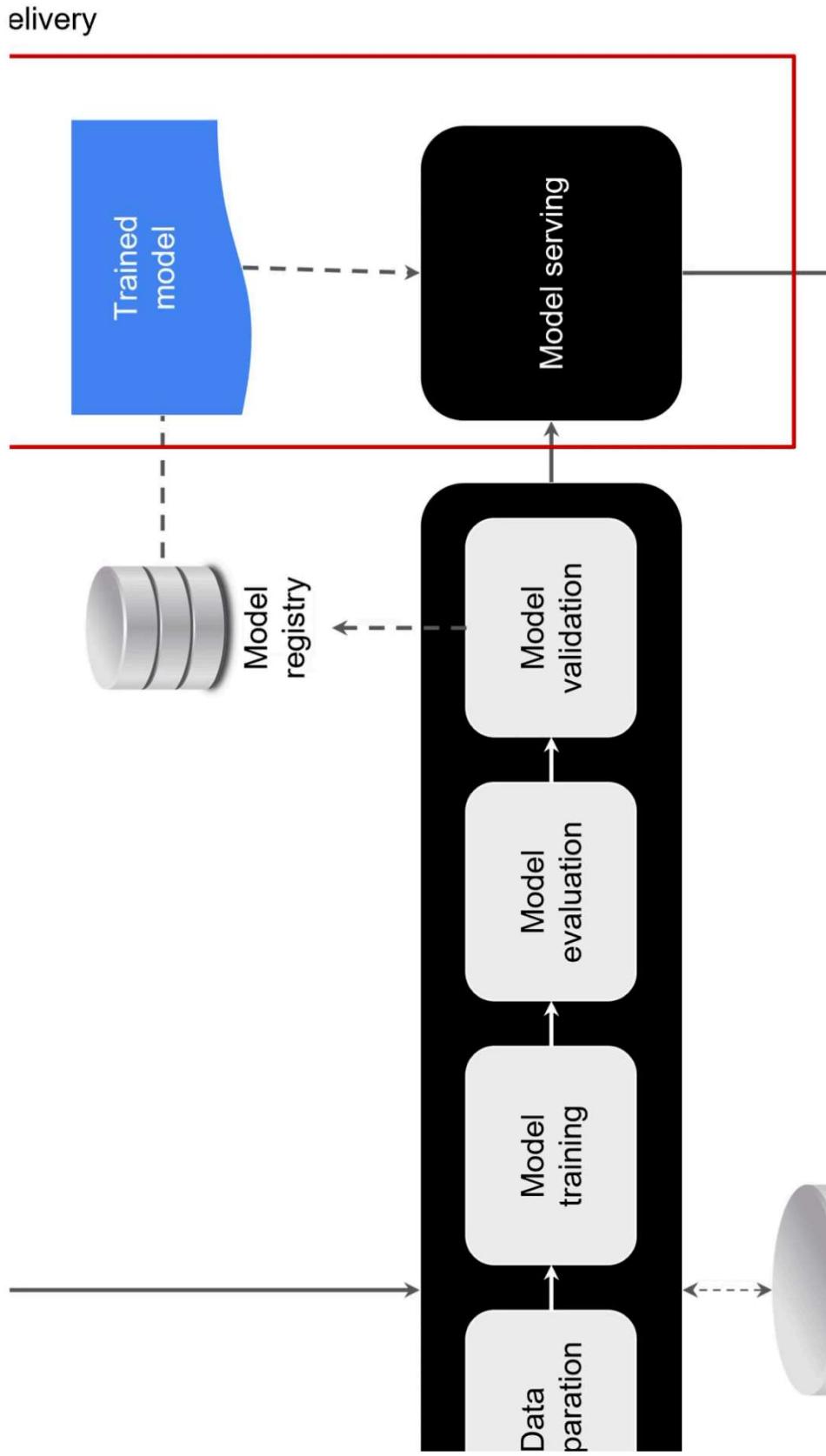
Reference architecture - The metadata store



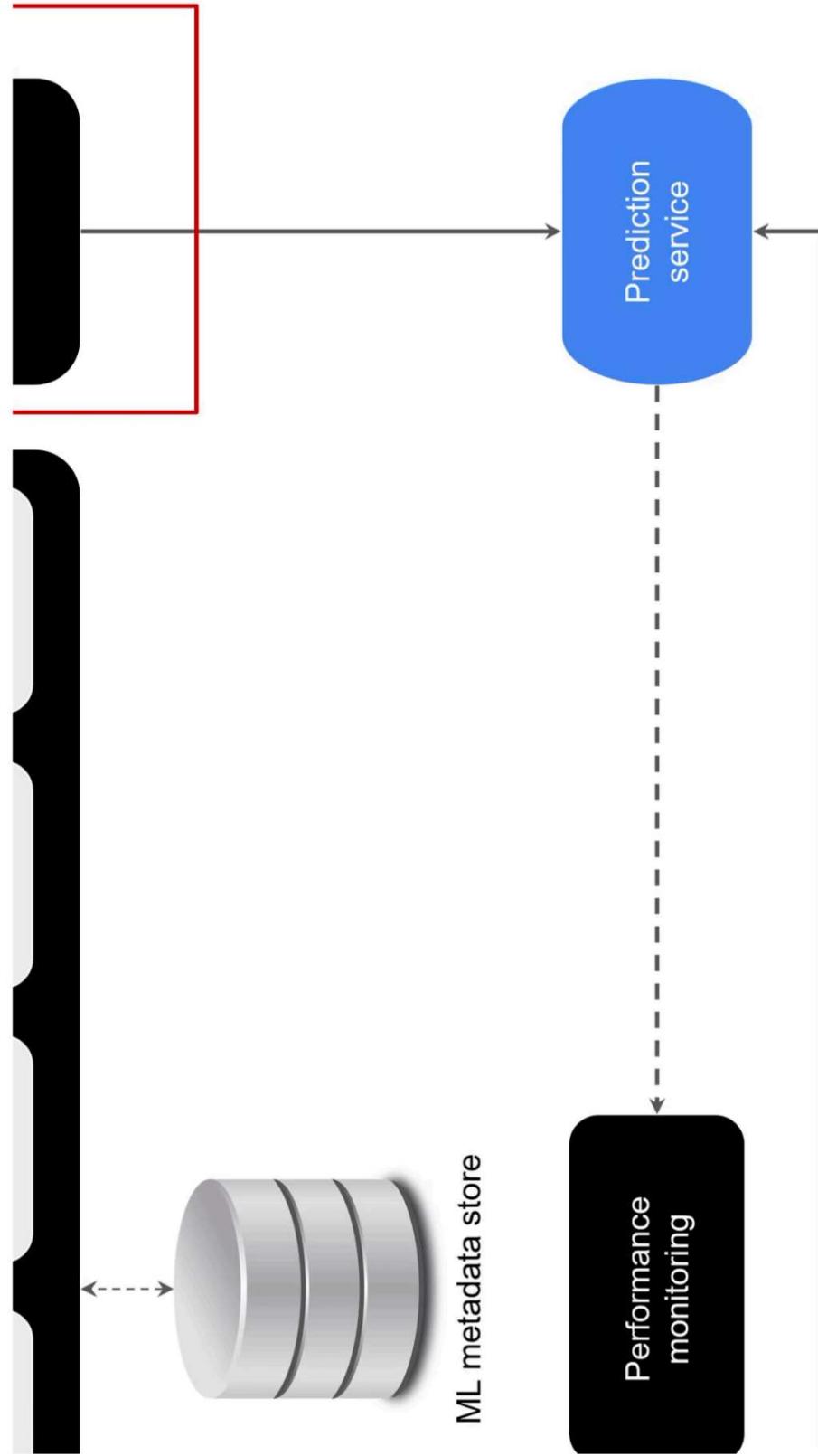
Reference architecture - The model registry



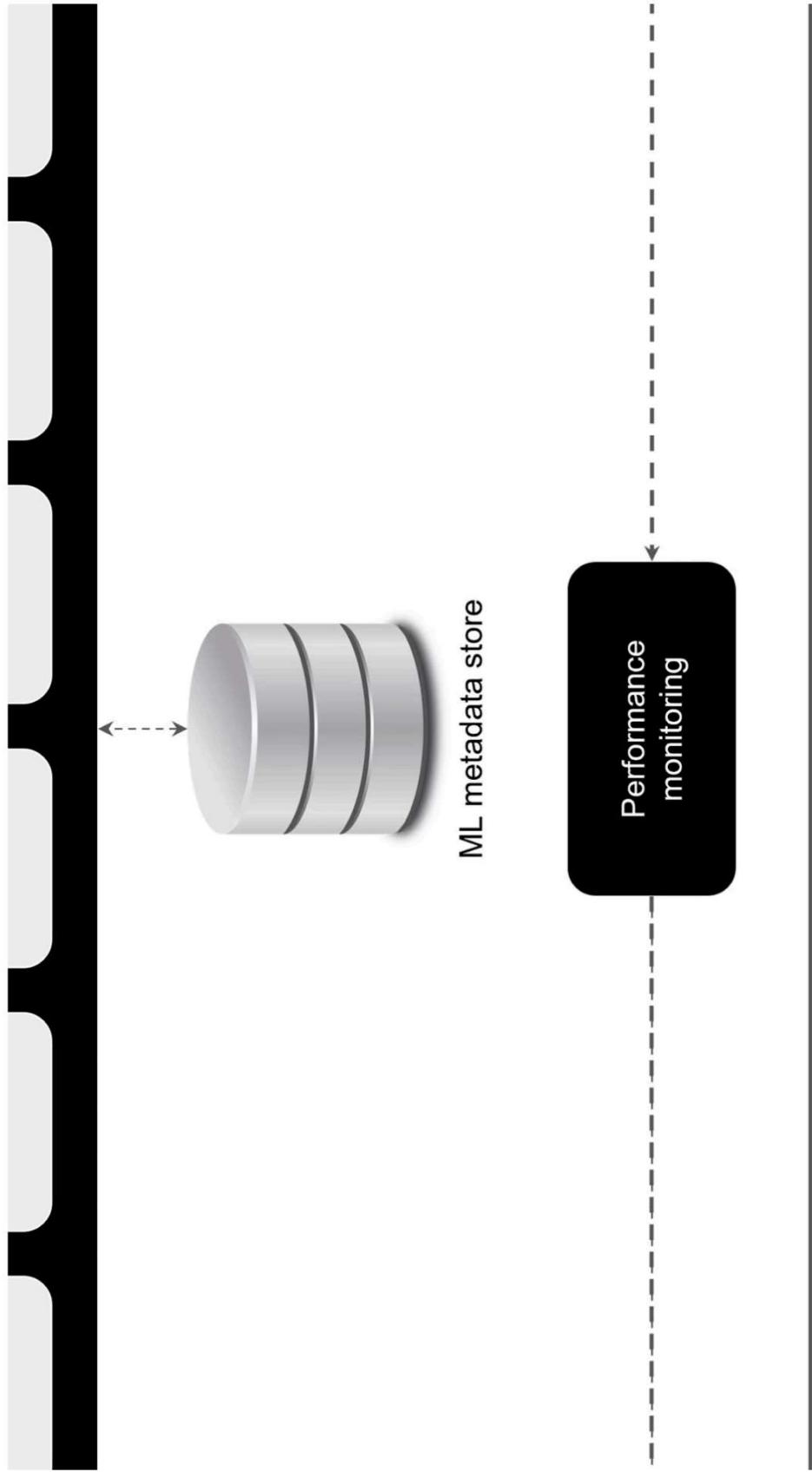
Reference architecture - Prediction services



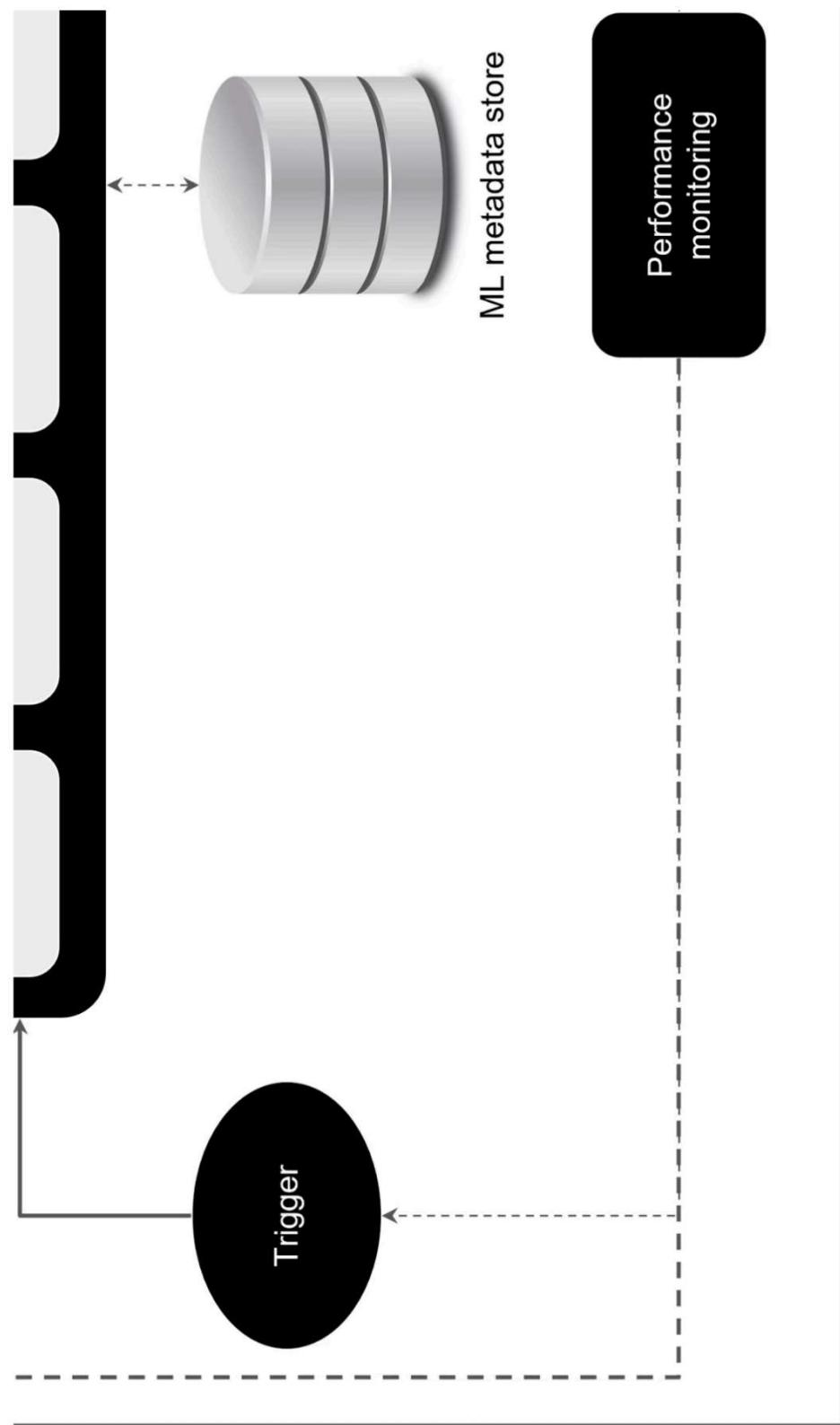
Reference architecture - Continuous monitoring



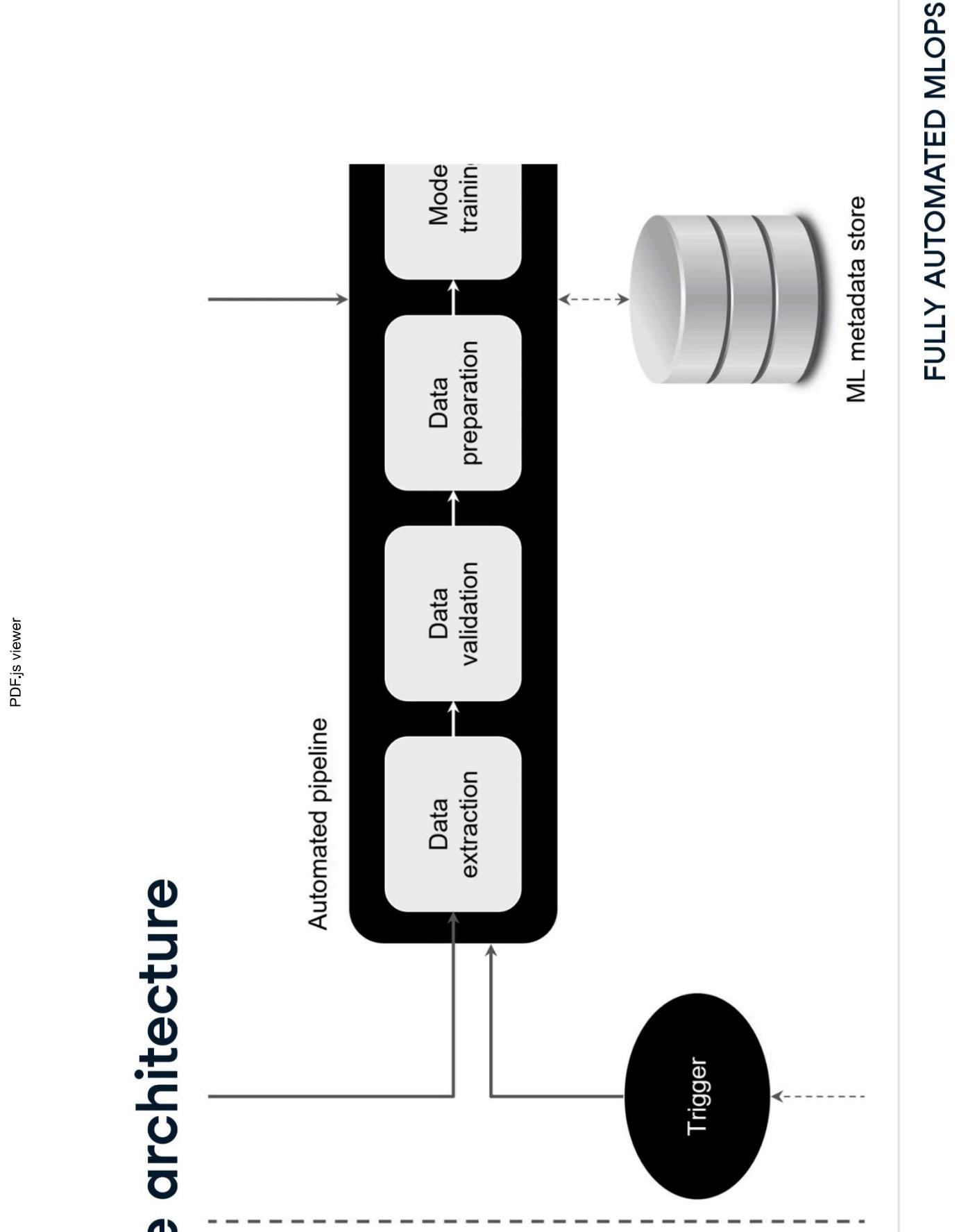
Reference architecture - Automated trigger



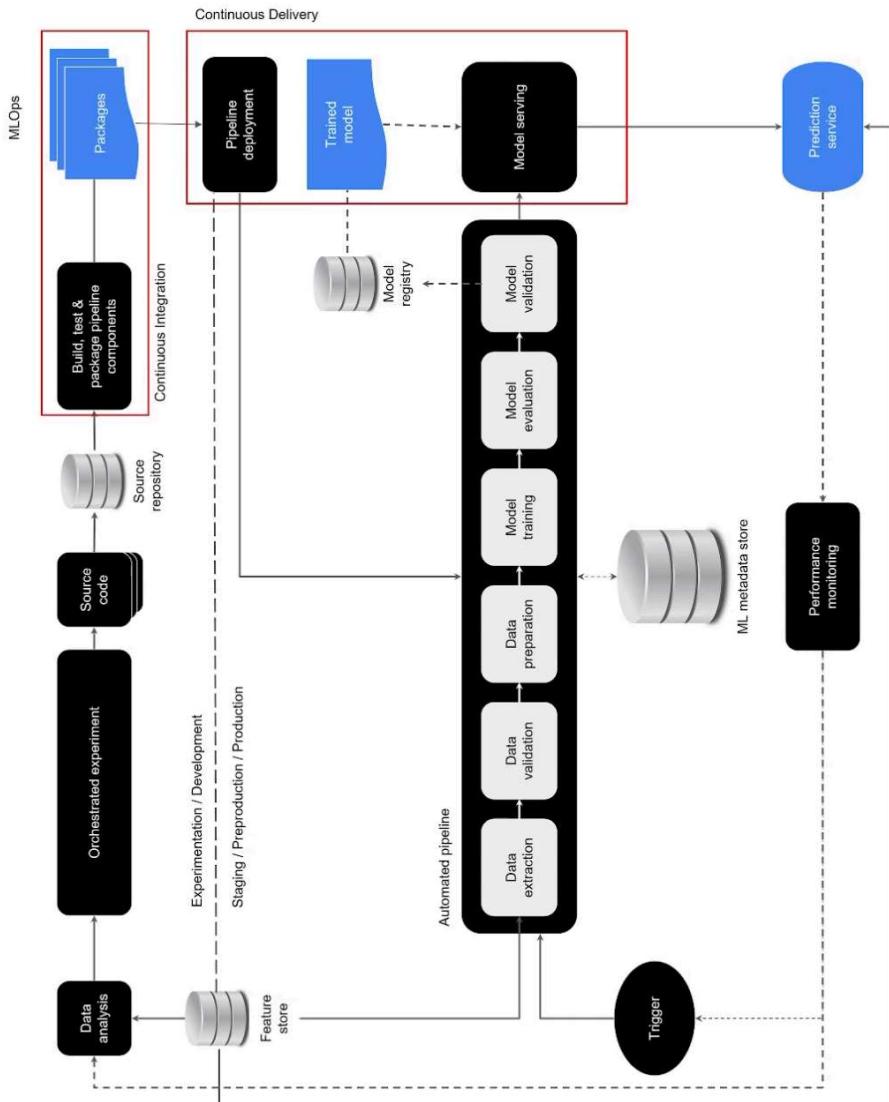
Reference architecture - Automated retraining



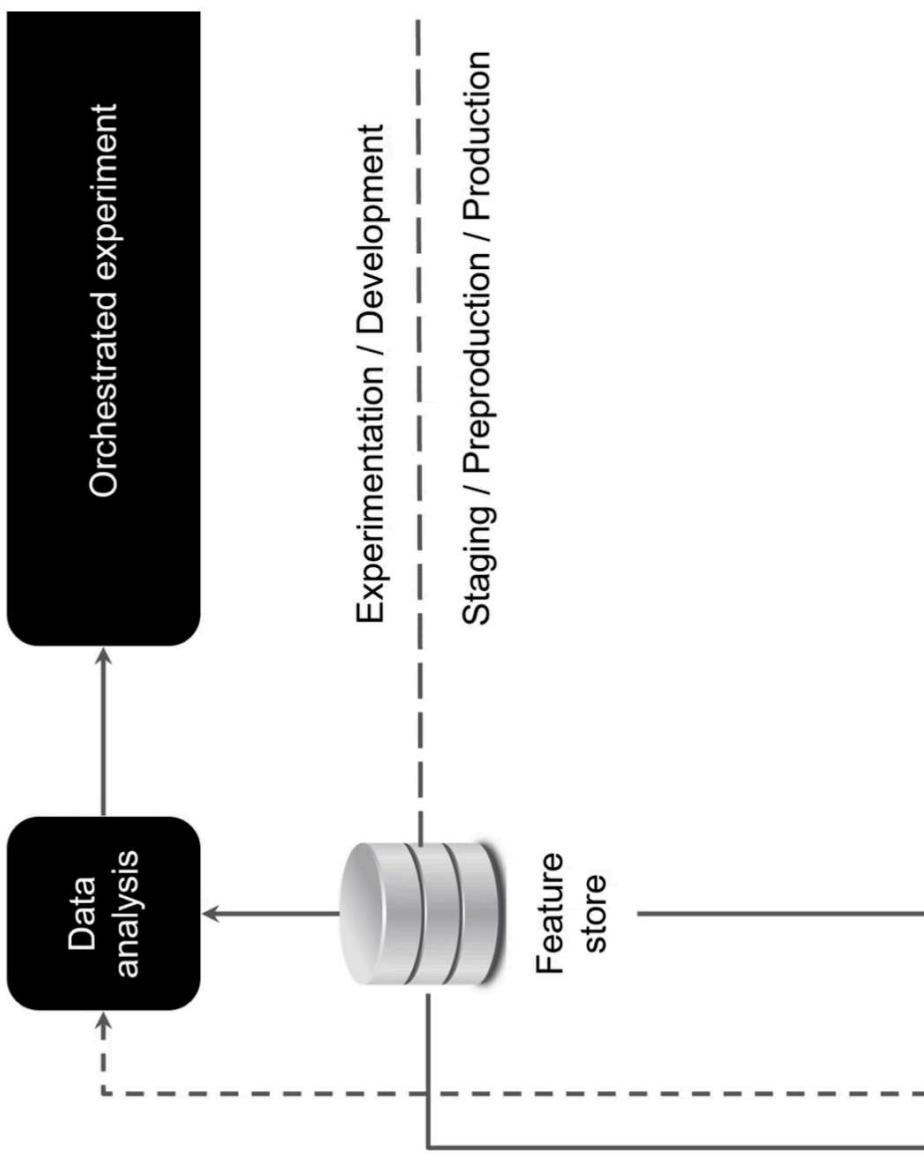
Reference architecture



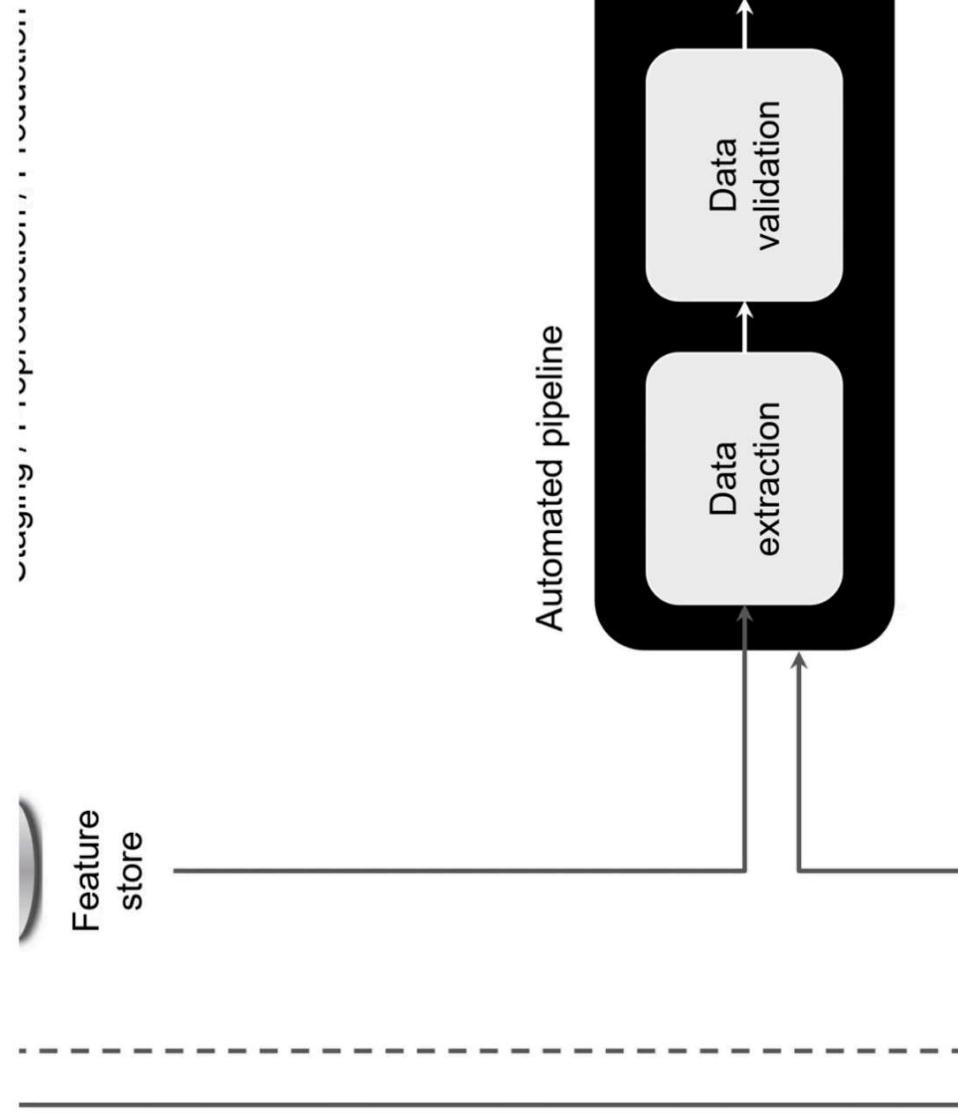
Reference architecture - The feature store



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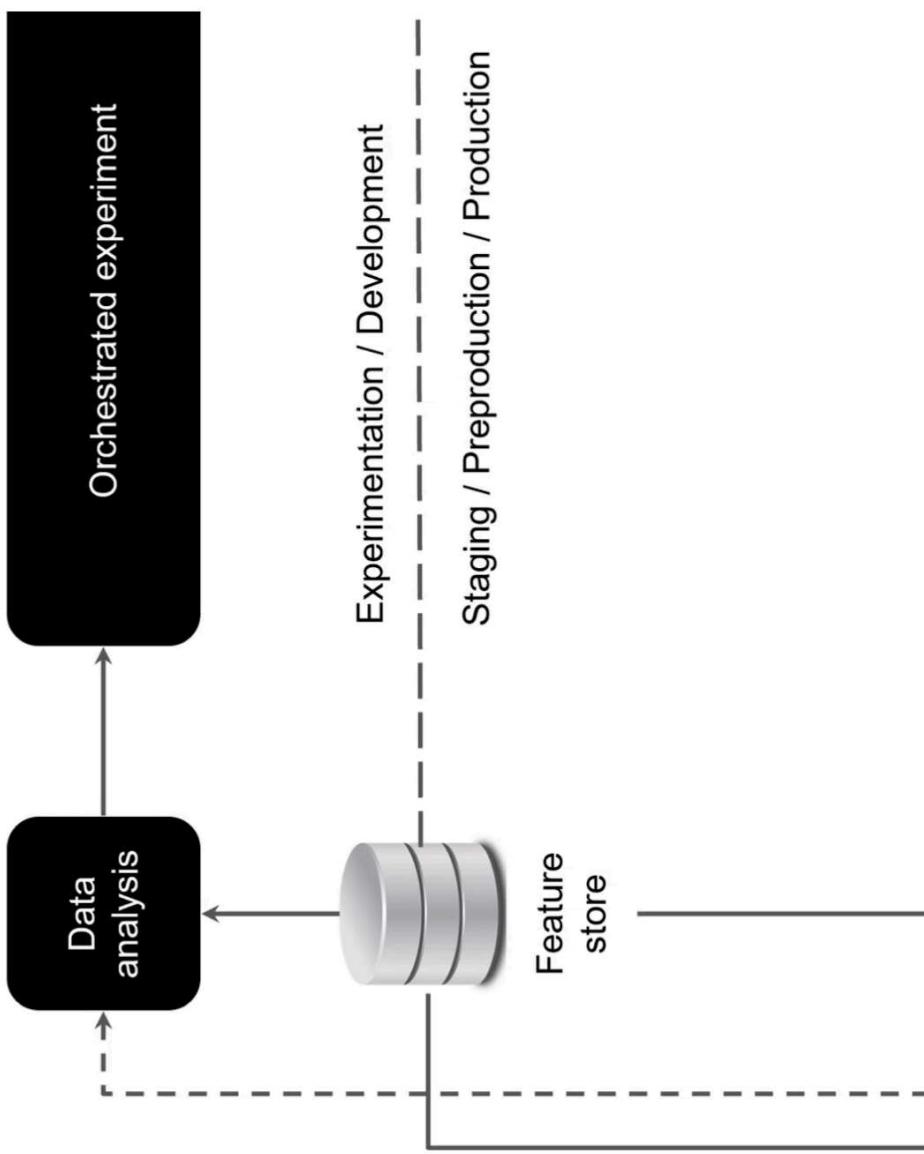


Reference architecture - The feature store

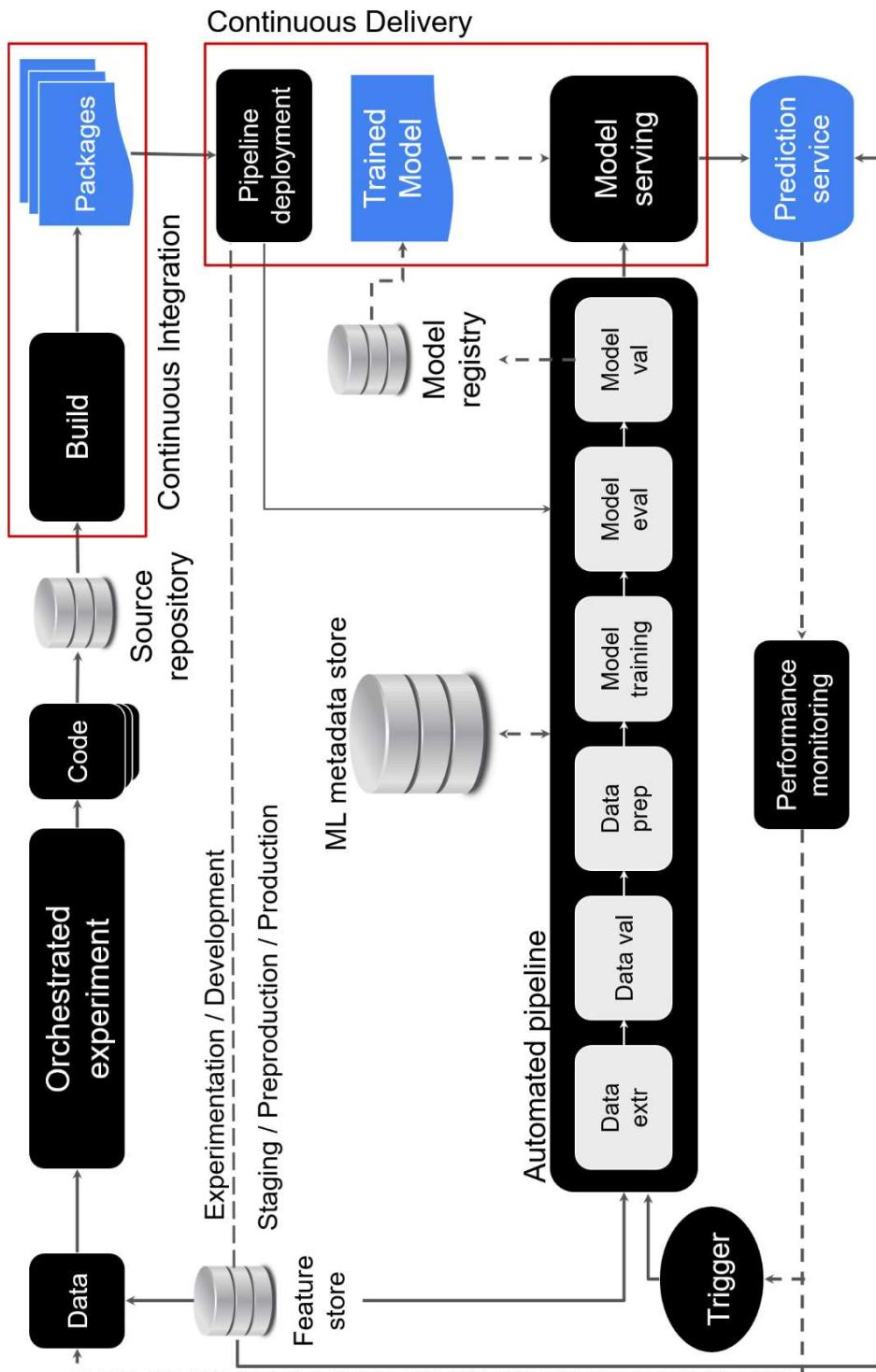


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Reference architecture - The feature store



Fully automated MLOps architecture



Let's practice!

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