

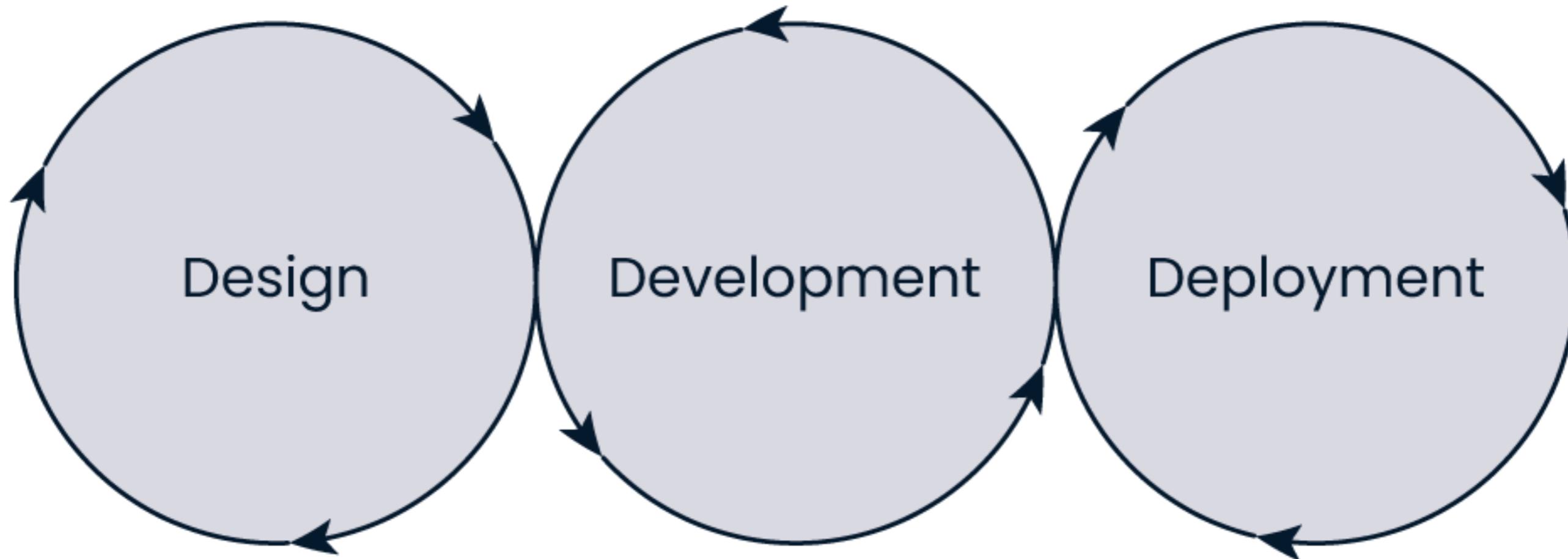
# Preparing model for deployment

MLOPS CONCEPTS



Folkert Stijnman  
ML Engineer

# Runtime environment

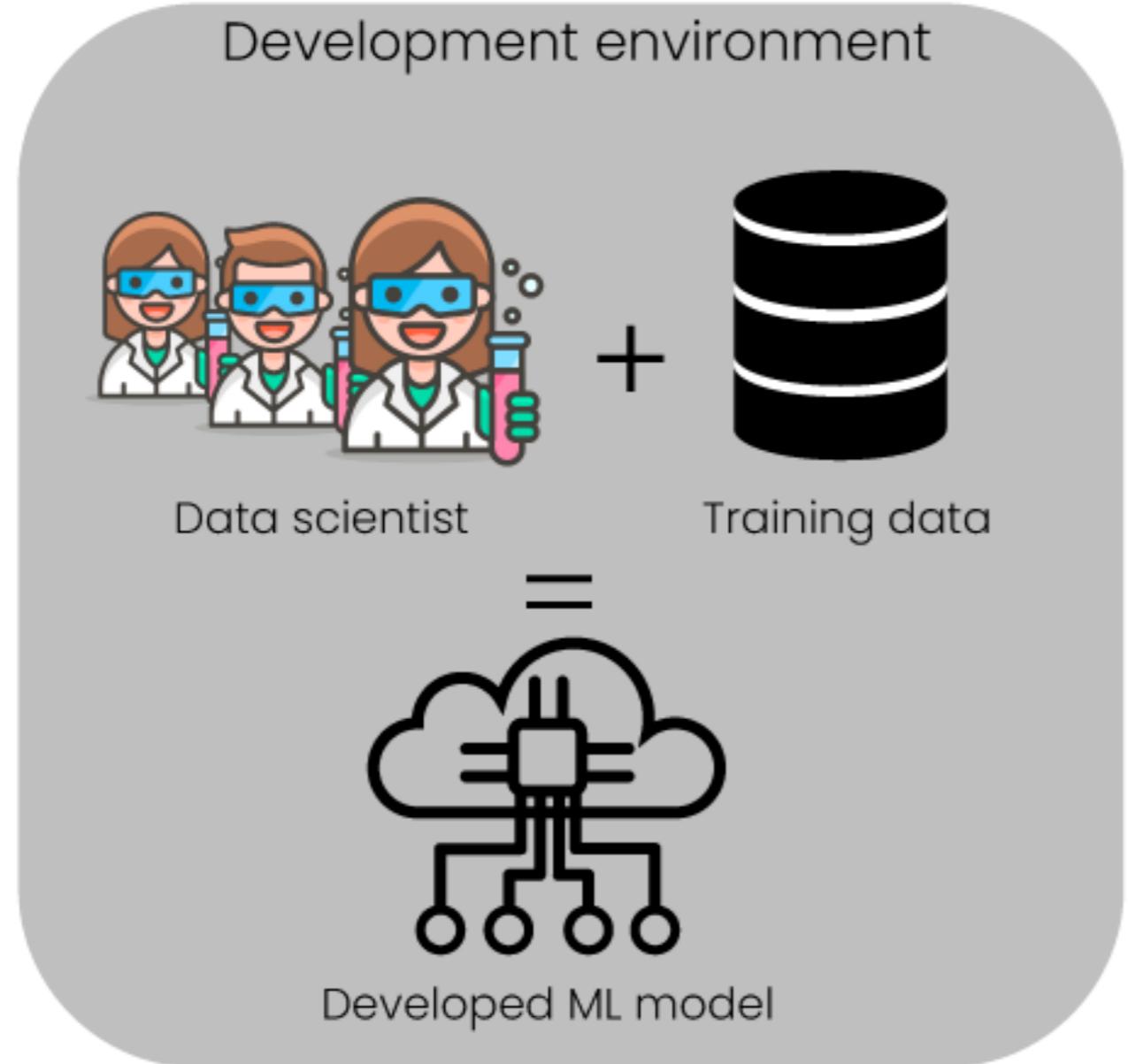


- Added value
- Business requirements
- Key metrics
- Data processing

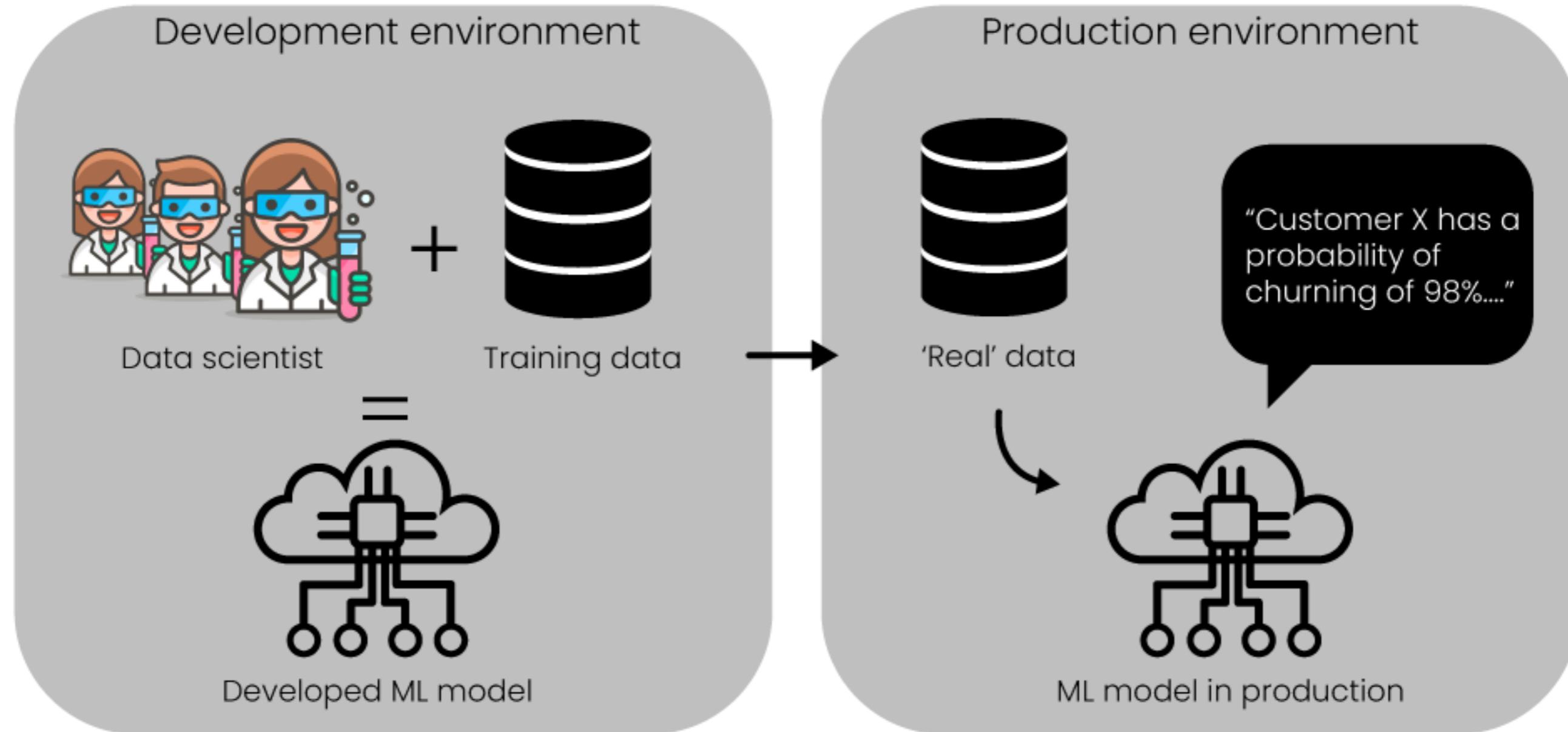
- Feature engineering
- Experiment tracking
- Model training & evaluation

- Runtime environments
- Microservices architecture
- CI/CD pipeline
- Monitoring & retraining

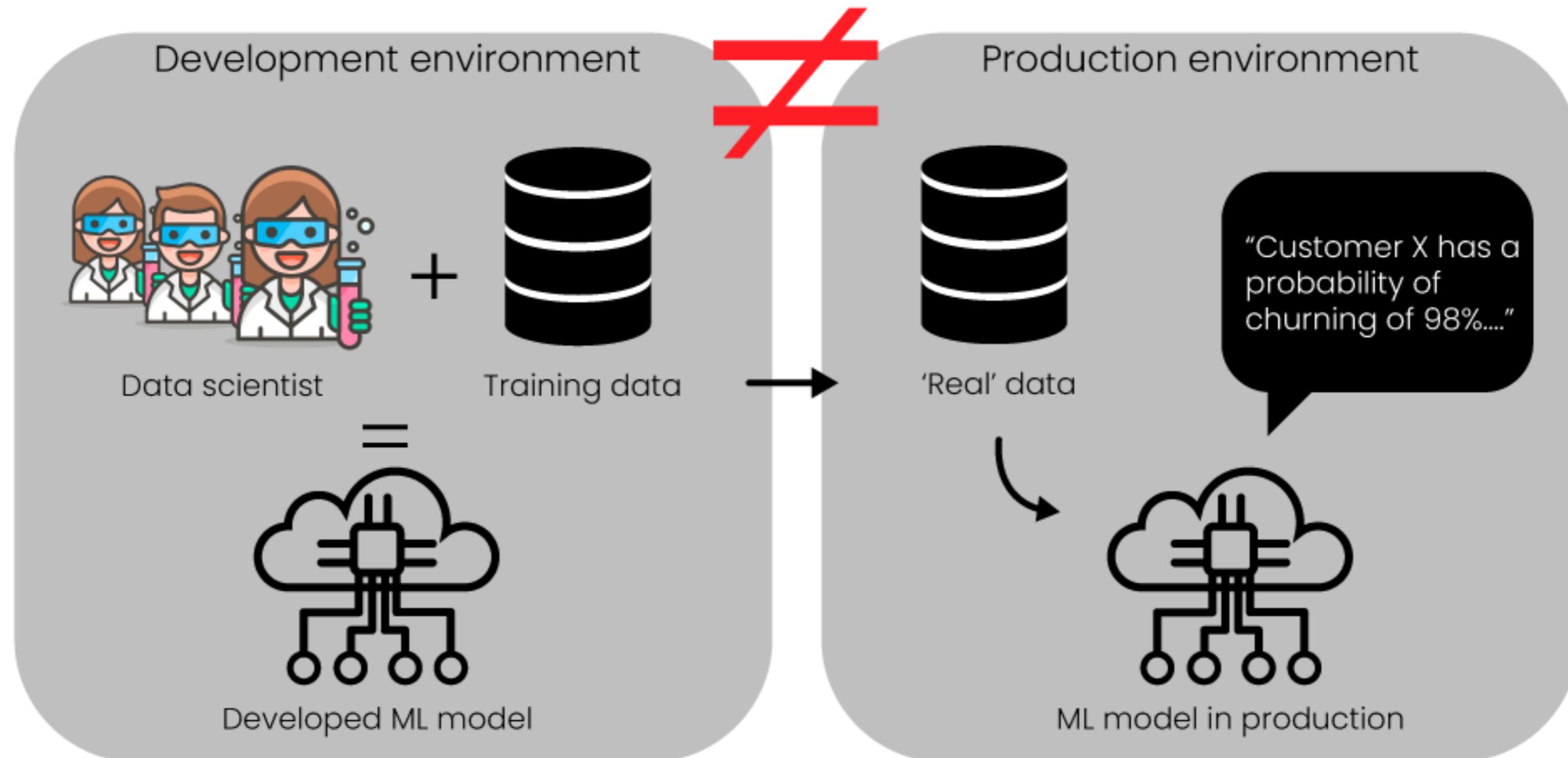
# Development to deployment



# Development to deployment



# Development to deployment



# Runtime environments



# Runtime environments

Development environment



Python 3.6



Pandas 1.24



Flask

Flask 2.1



Scikit learn 1.1.2

Production environment



Python 2.8



Pandas 0.24



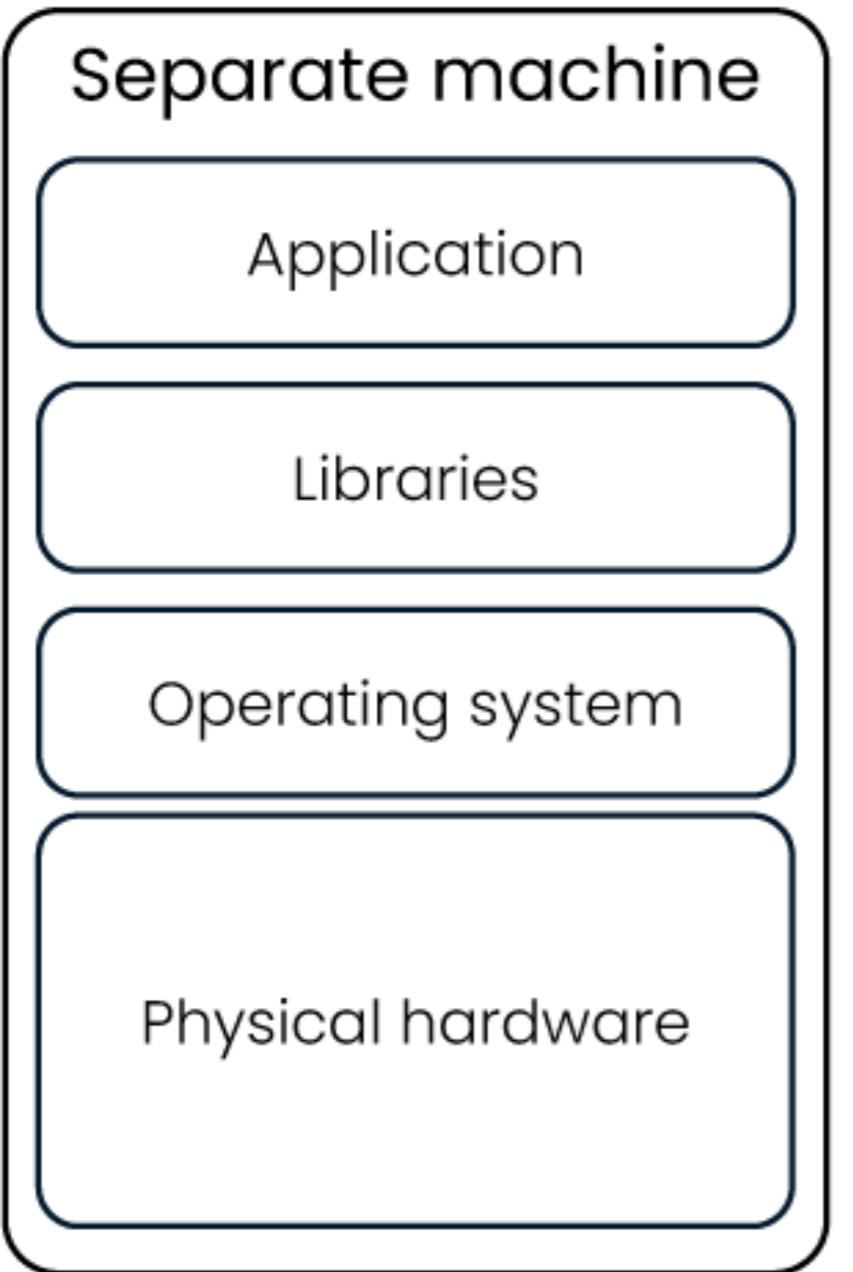
Flask

Flask 1.9

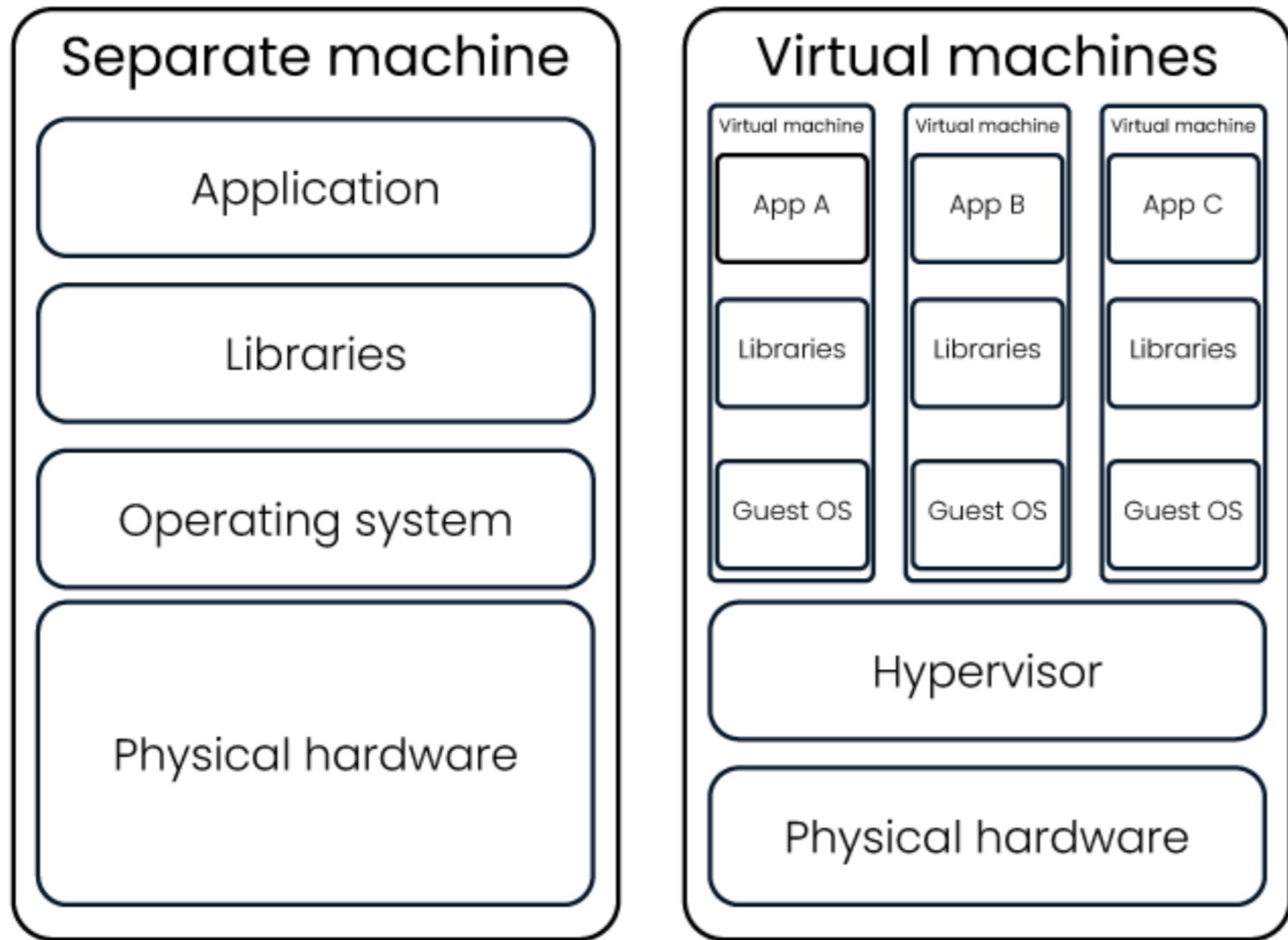


Scikit learn 0.21

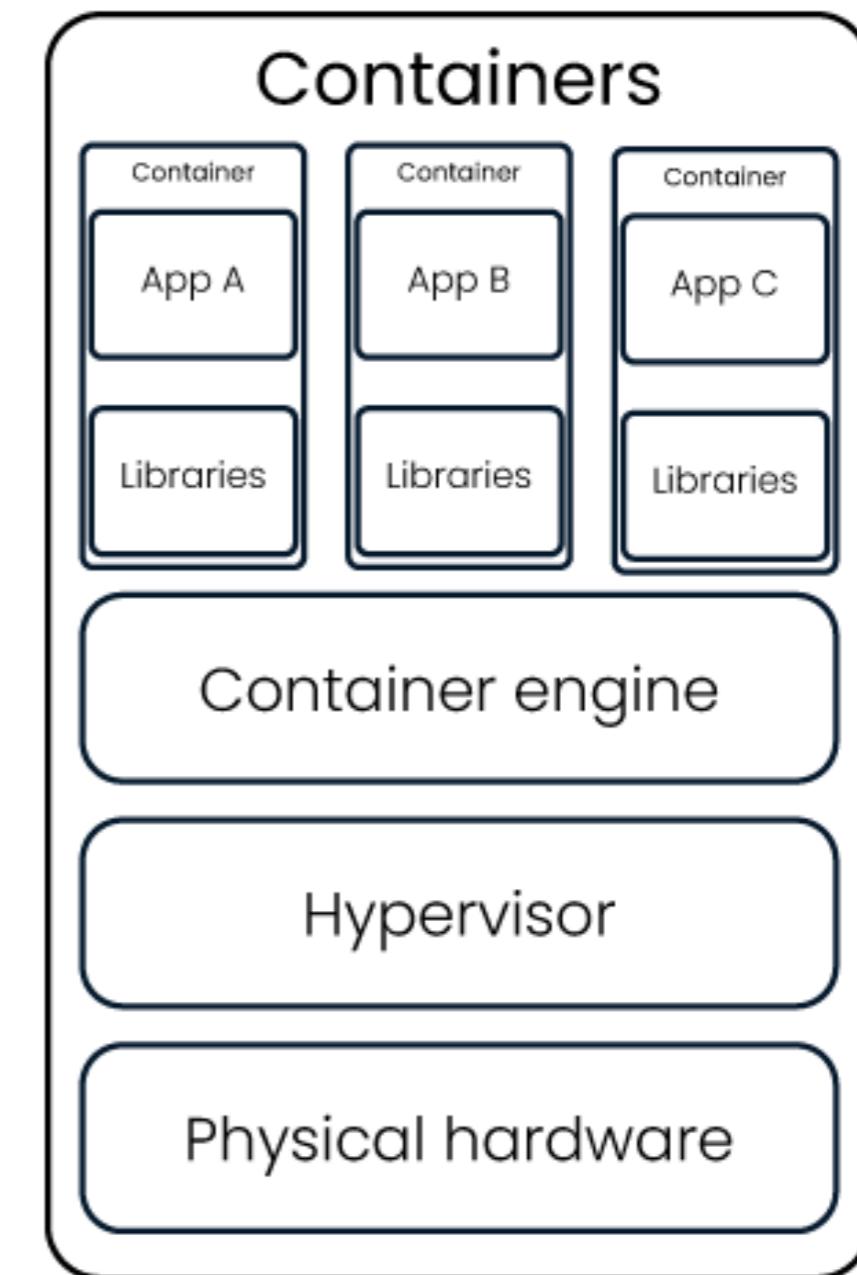
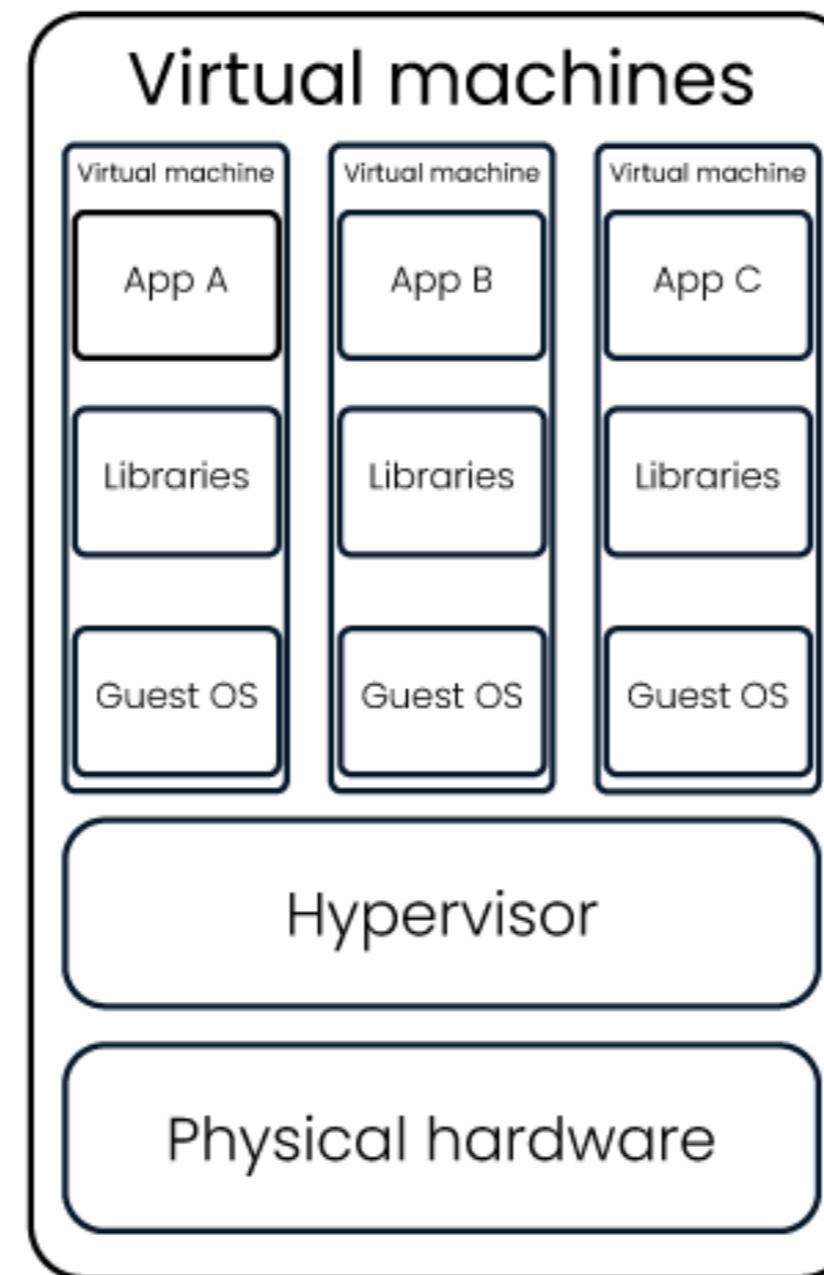
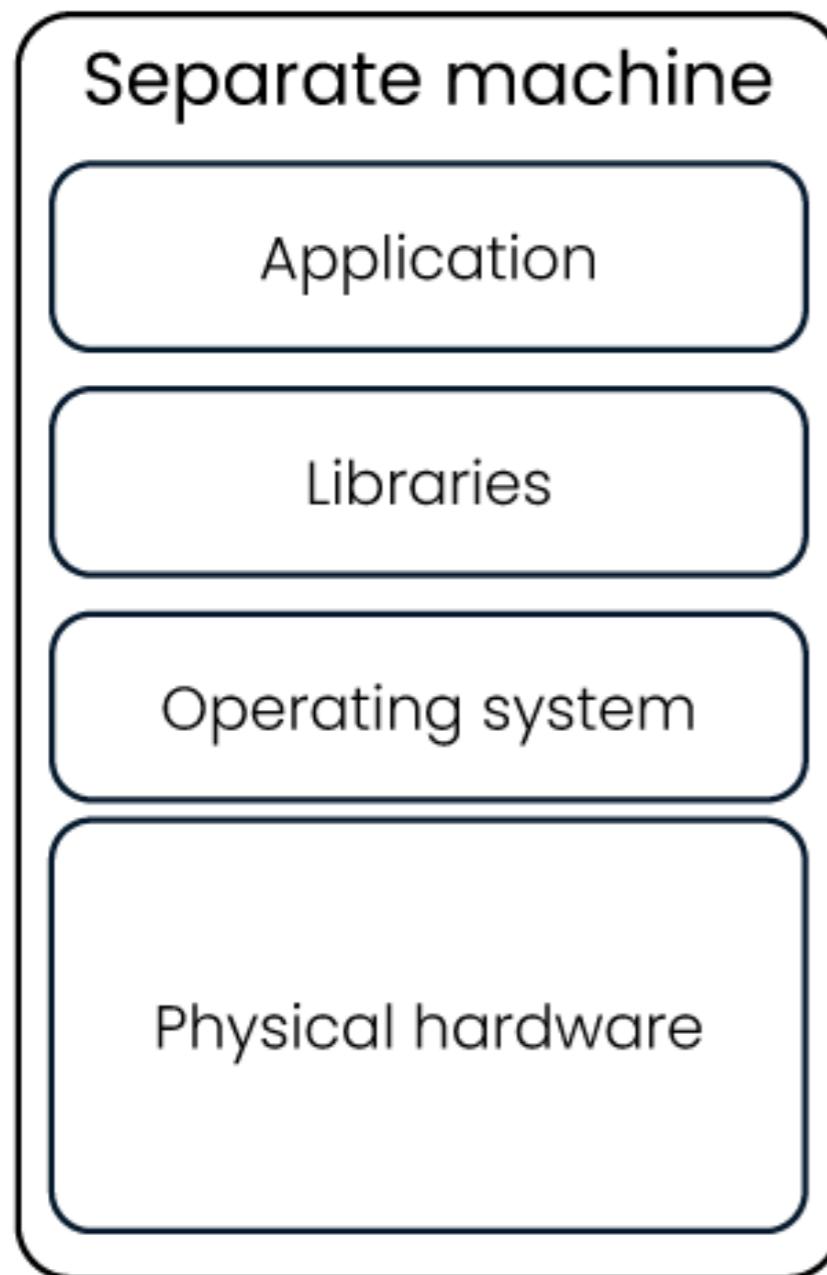
# Mitigate different environments



# Mitigate different environments



# Mitigate different environments



# Benefits containers

- Easier to maintain
- Portable
- Fast to start up



# Let's practice!

MLOPS CONCEPTS

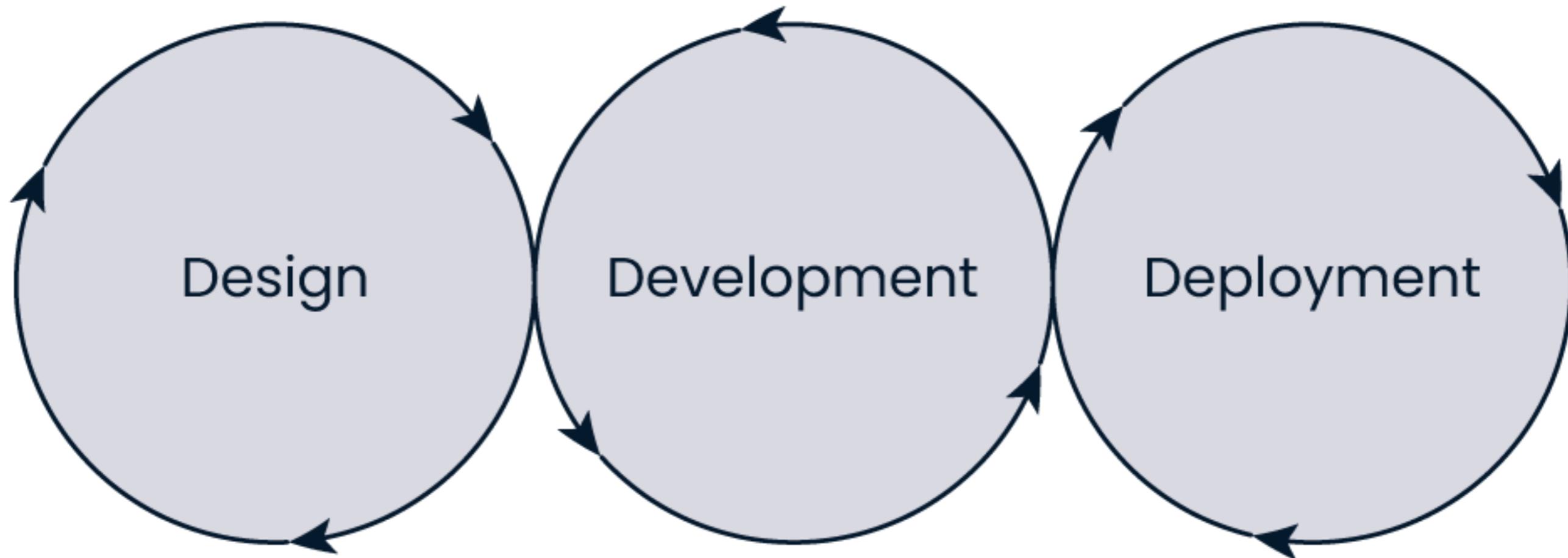
# Machine learning deployment architecture

MLOPS CONCEPTS



Folkert Stijnman  
ML Engineer

# Microservices architecture



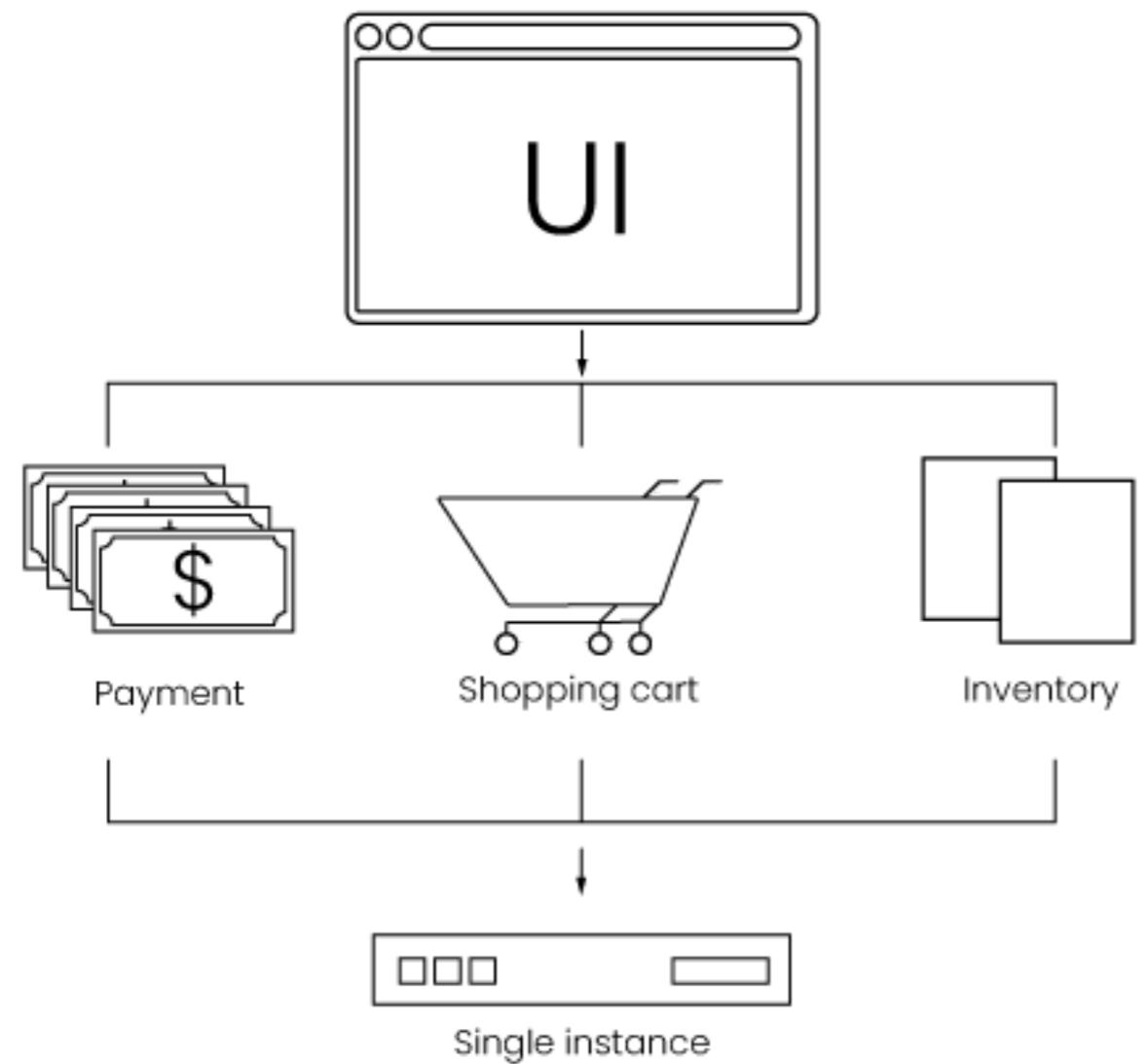
- Added value
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- Monitoring & retraining

# Monolith vs. microservice architecture

## Monolithic architecture

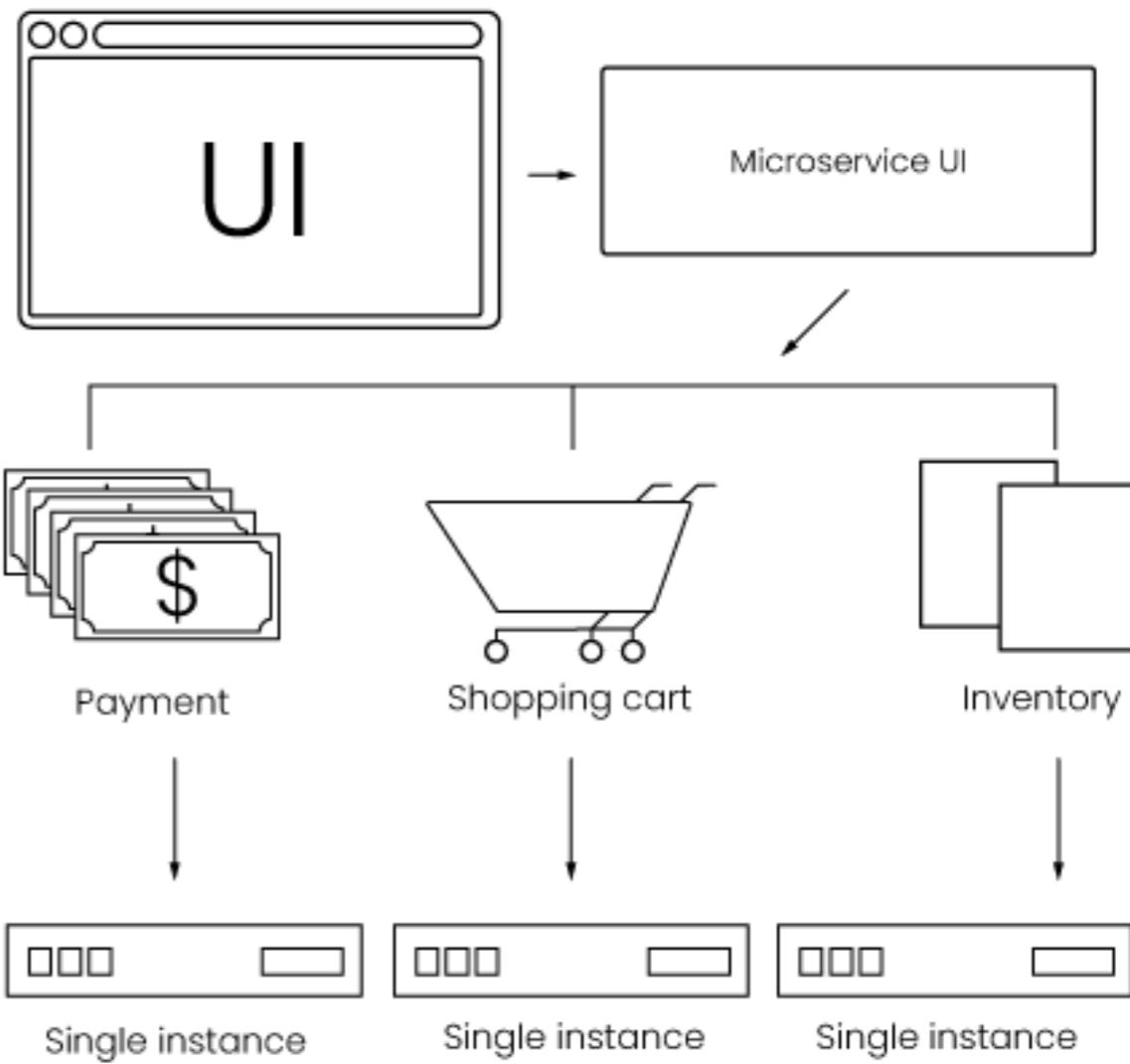


- One uniform application containing all services

# Monolith vs. microservice architecture

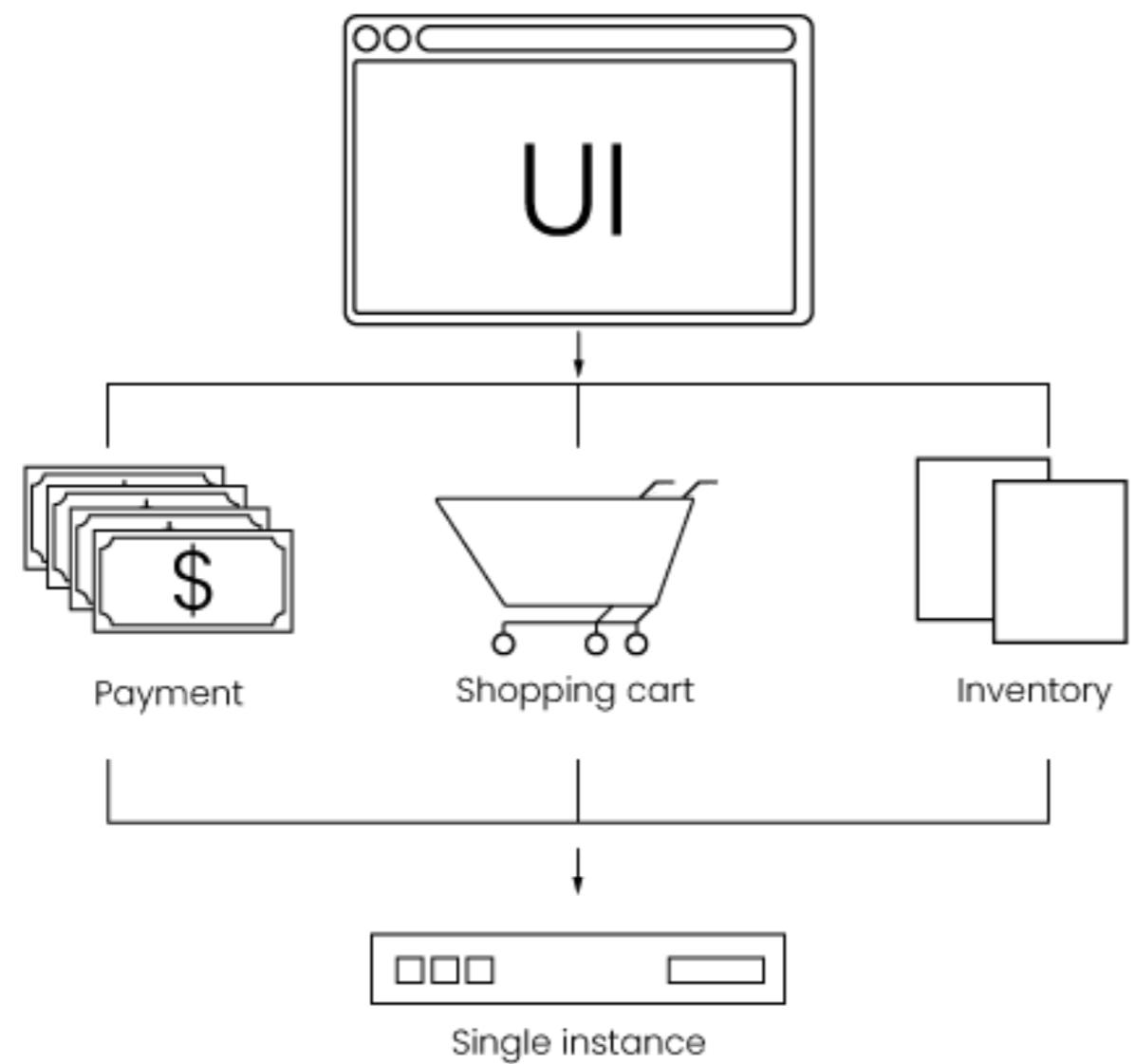
- Collection of smaller, independent services

Microservices architecture

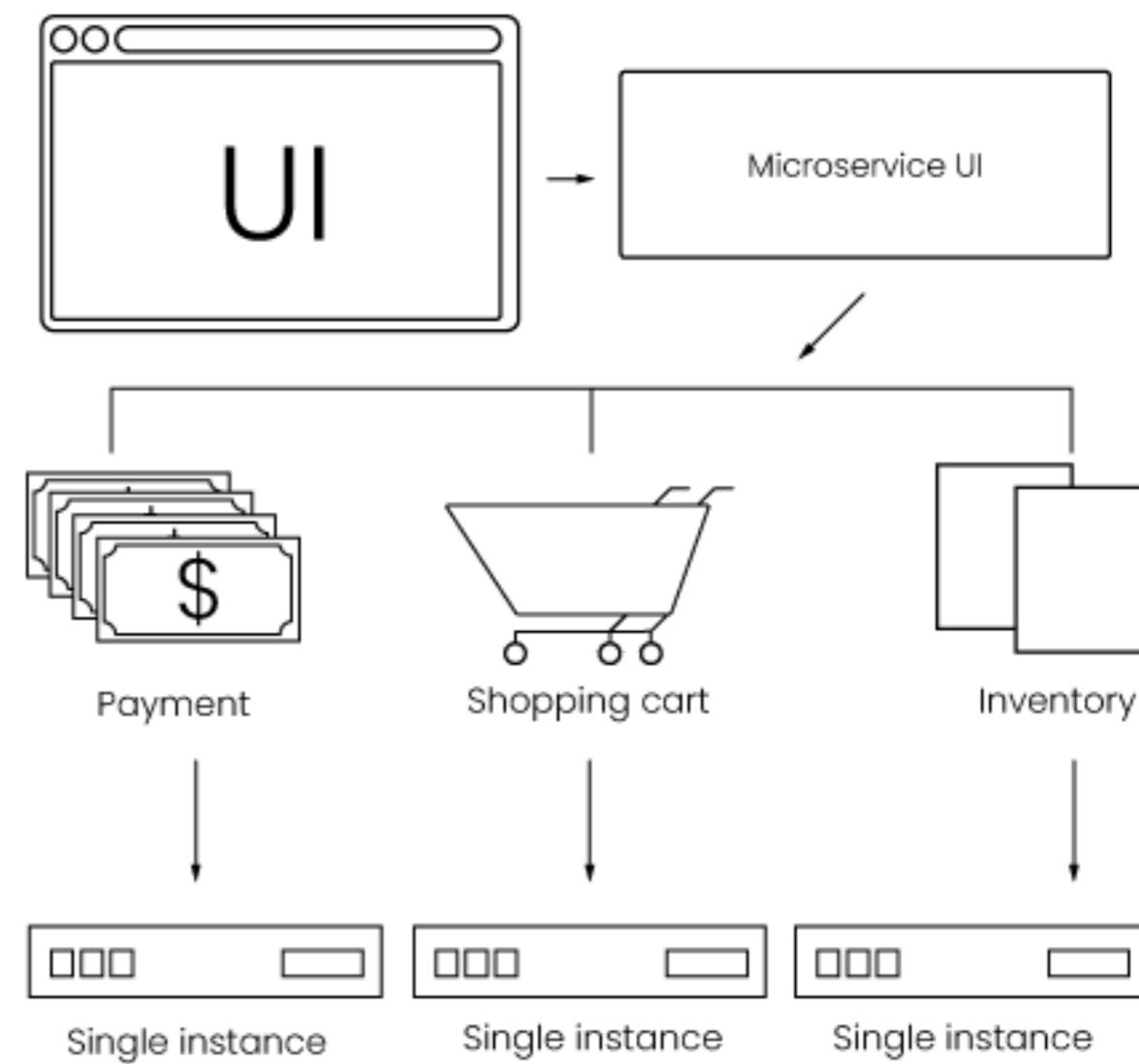


# Monolith vs. microservice architecture

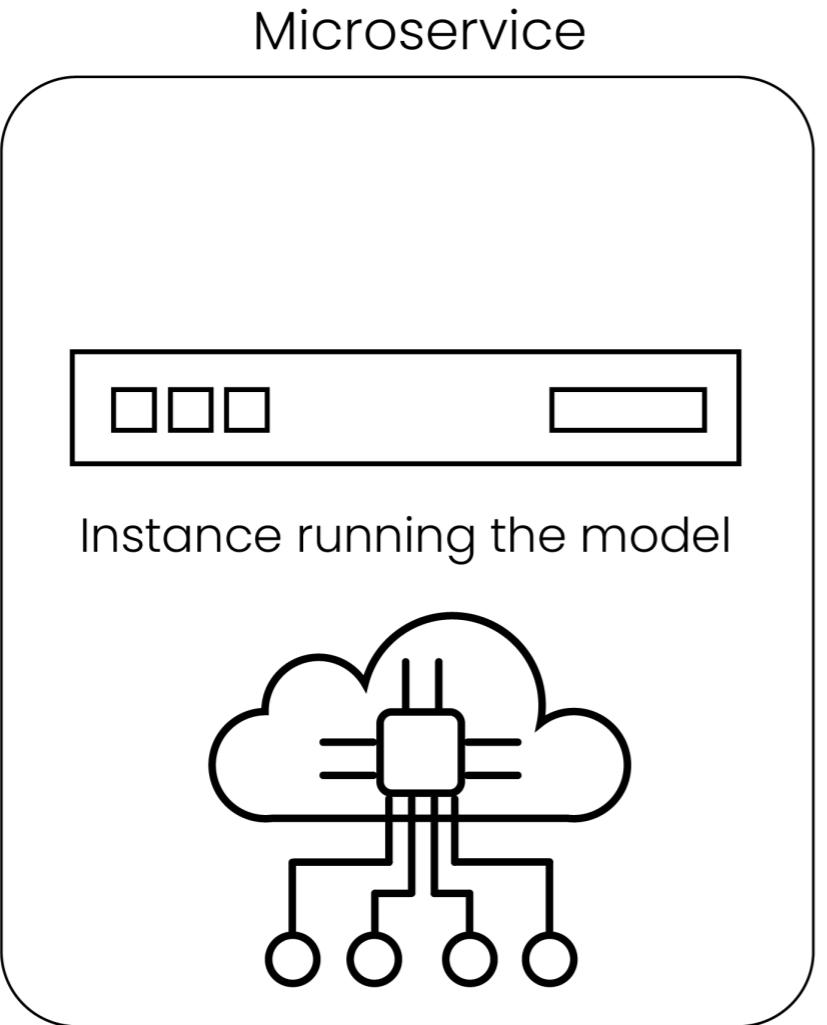
Monolithic architecture



Microservices architecture

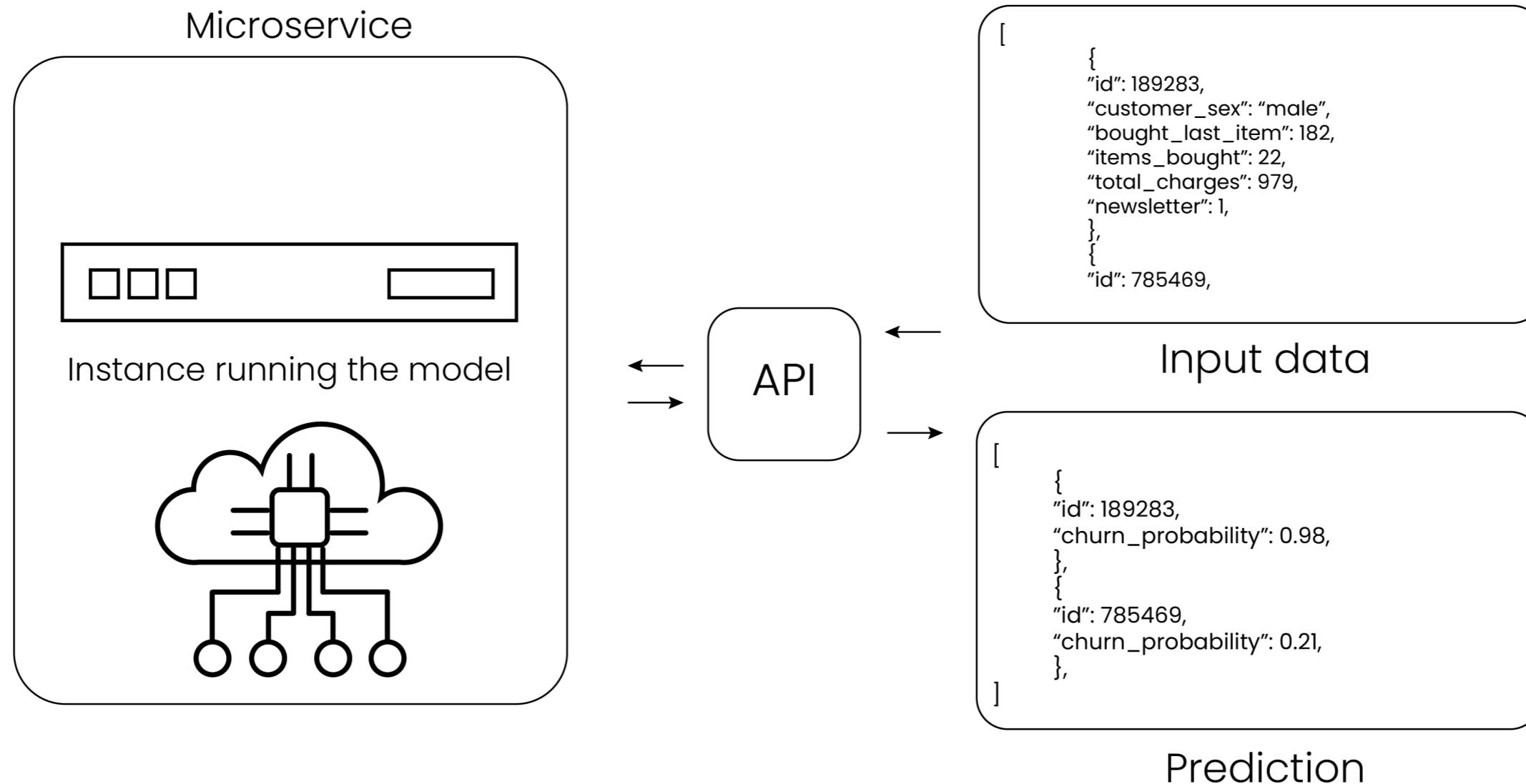


# Inferencing

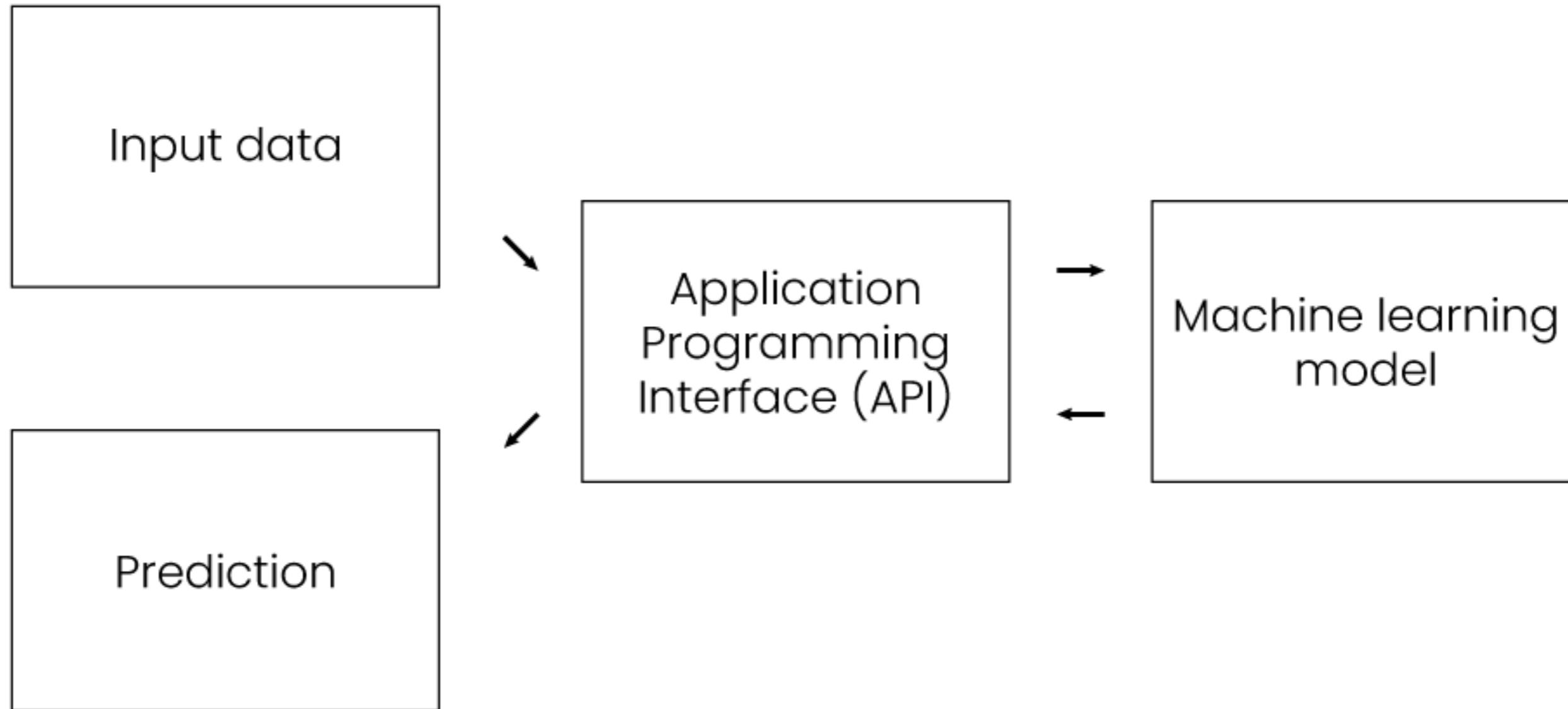


# Inferencing

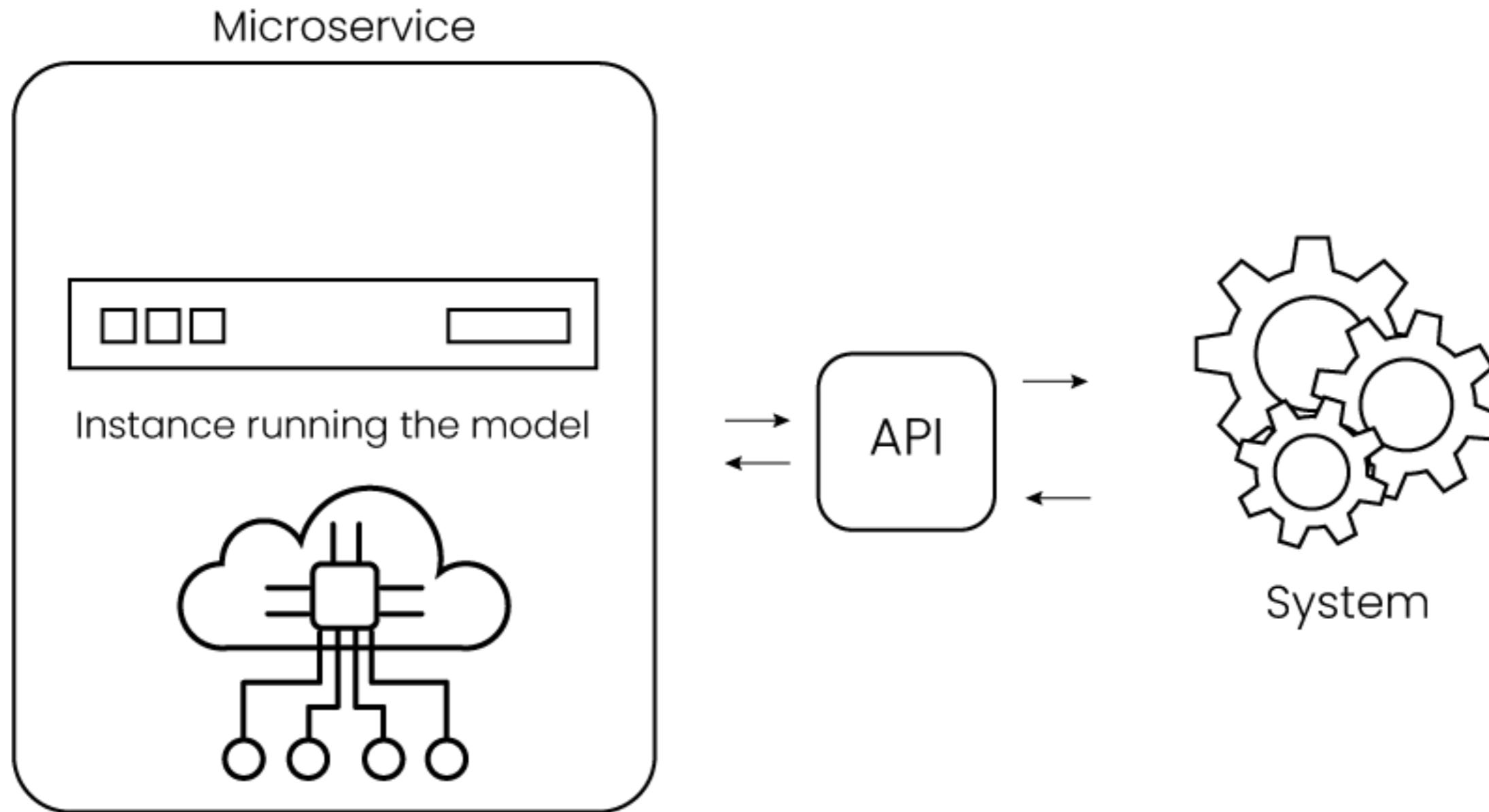
*Inferencing is the process in which we send new input to the machine learning model and receive output from the model.*



# Application Programming Interface (API)



# Integration



# Let's practice!

MLOPS CONCEPTS

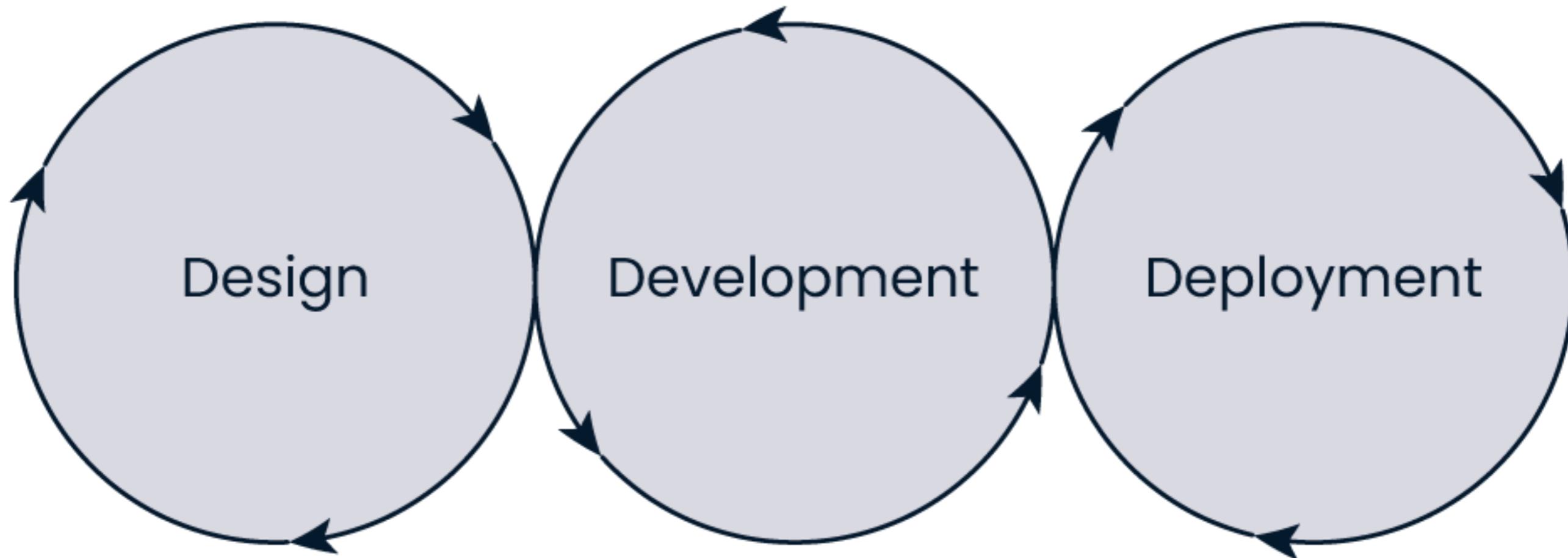
# CI/CD and deployment strategy

MLOPS CONCEPTS



Folkert Stijnman  
ML Engineer

# CI/CD pipeline

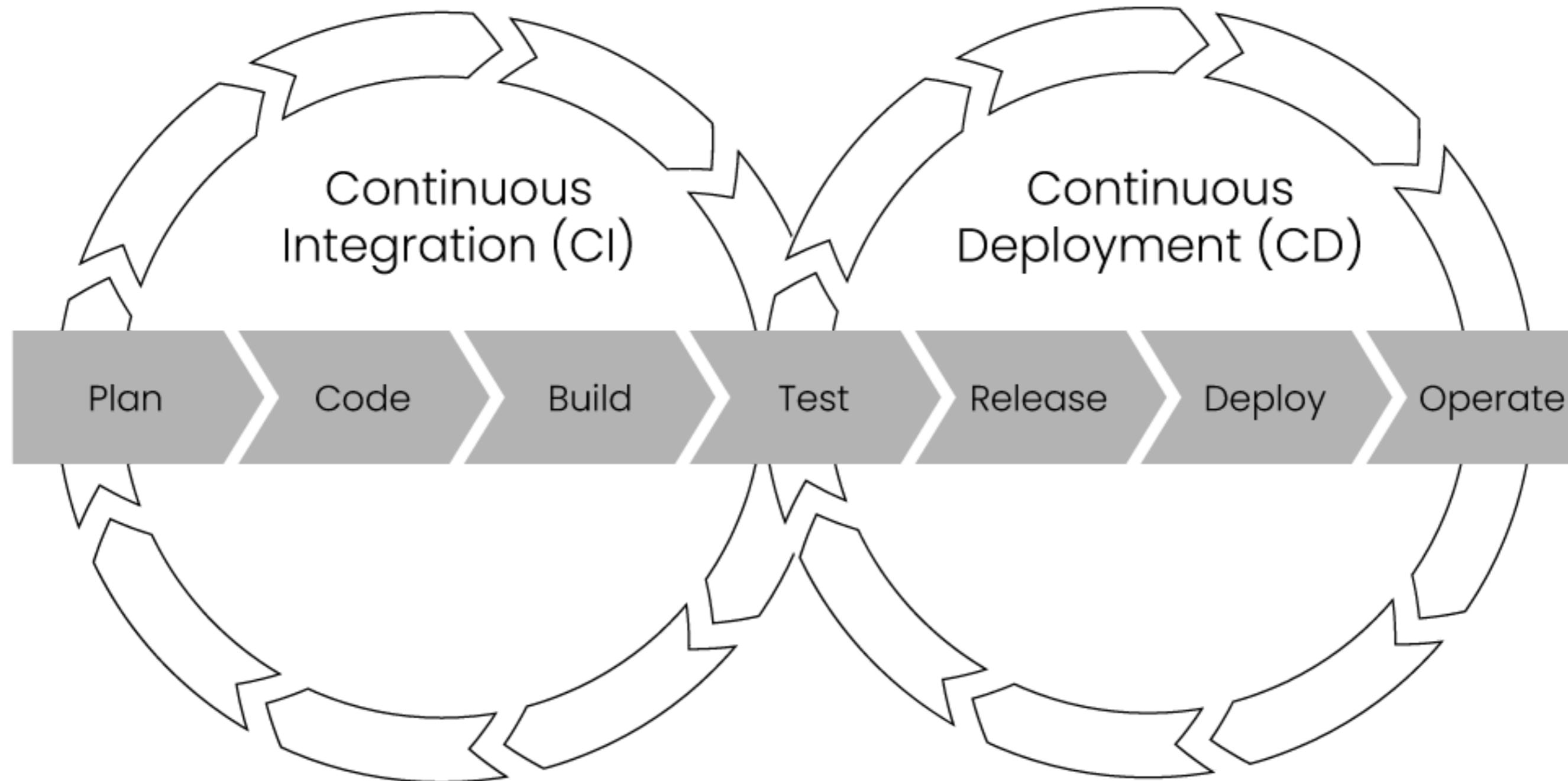


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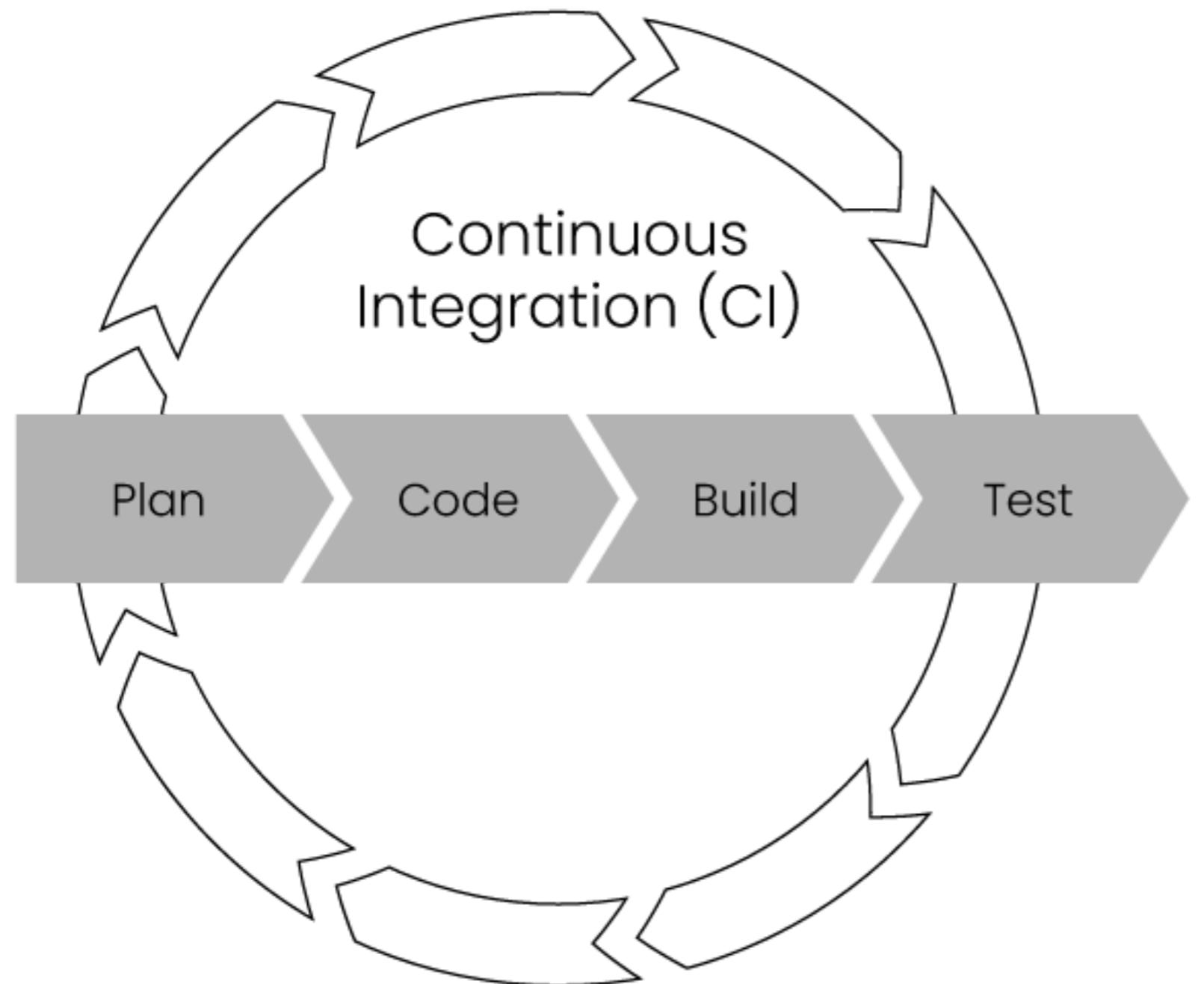
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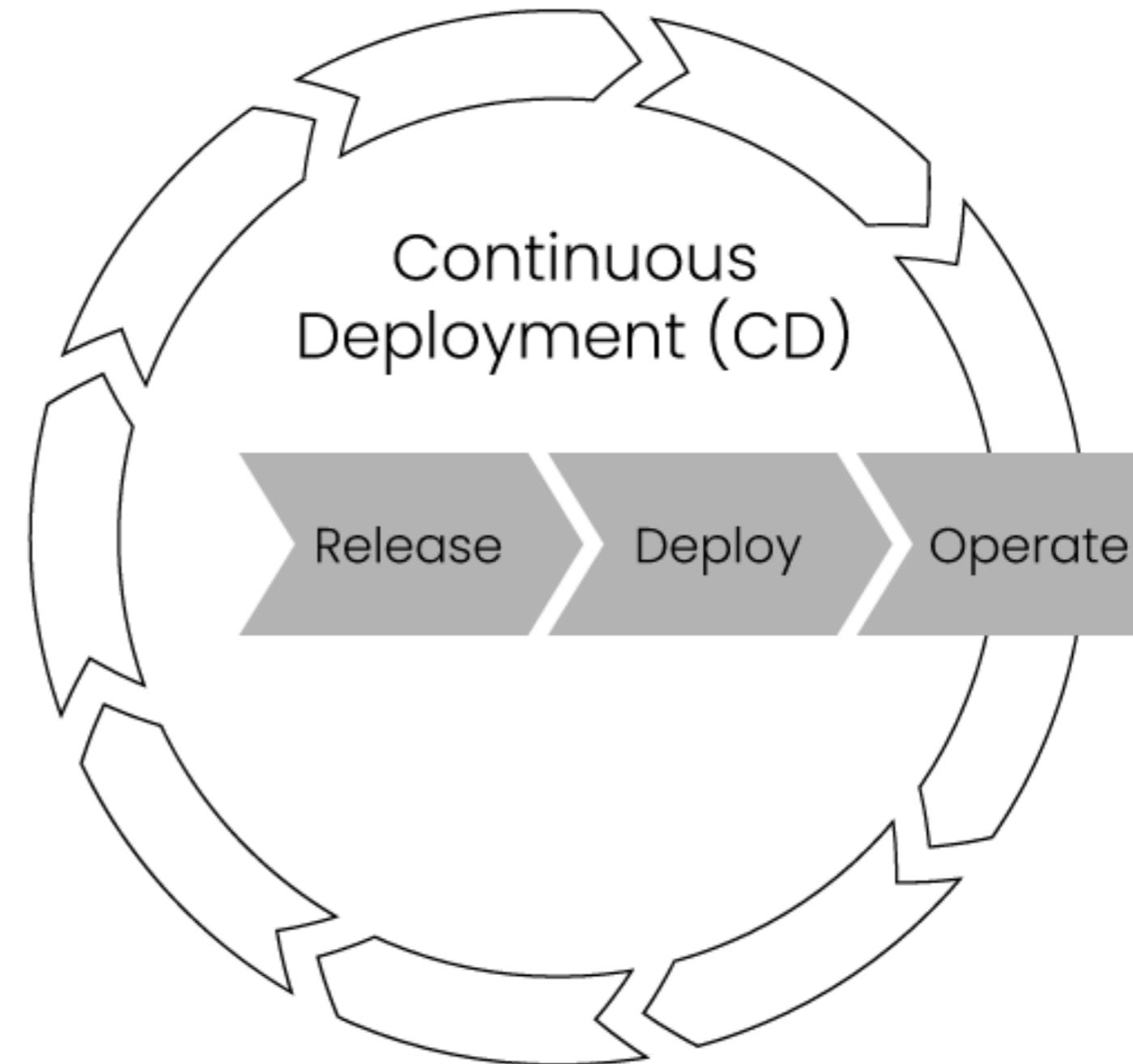
# CI/CD



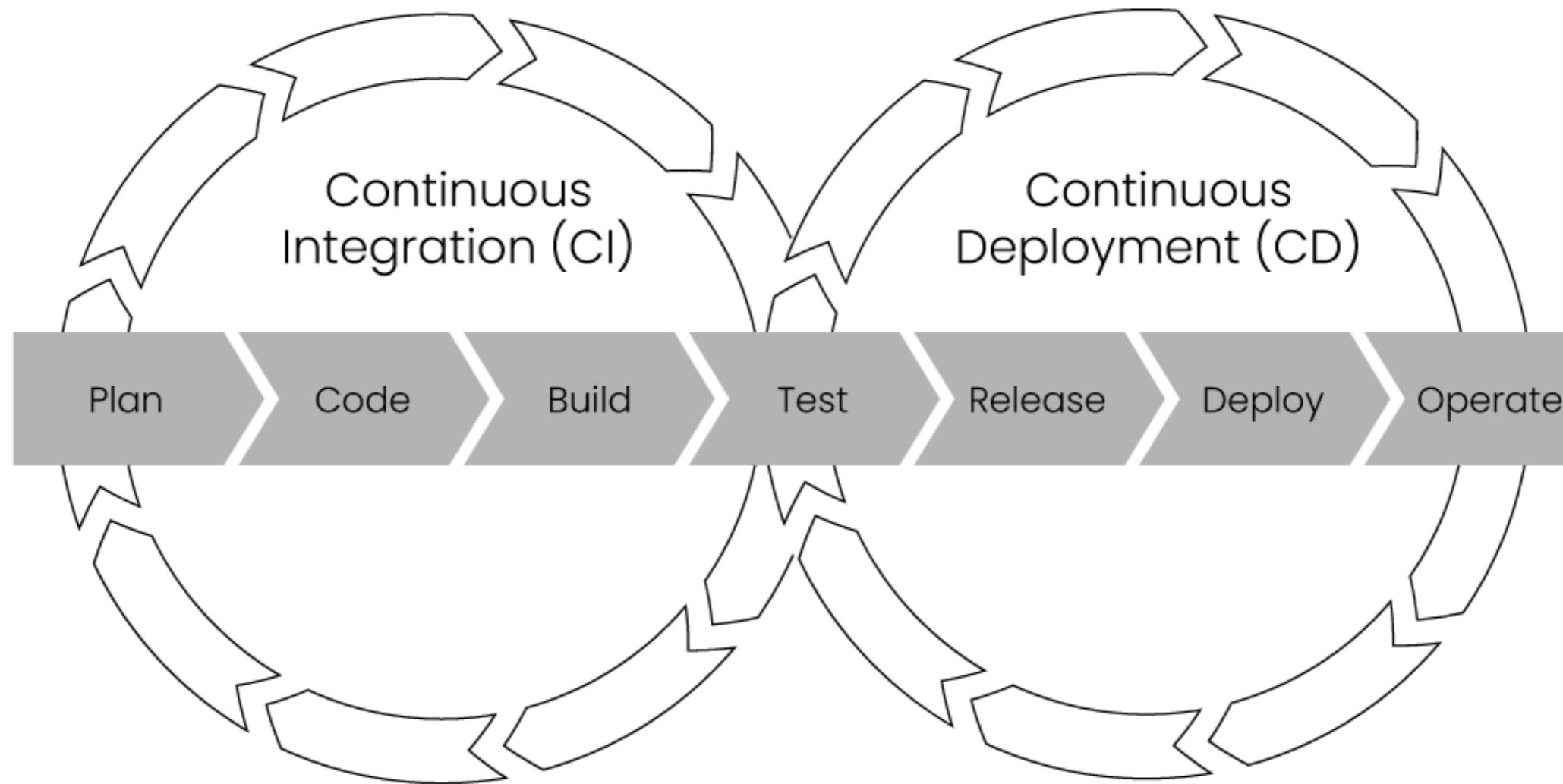
# Continuous Integration



# Continuous Deployment



# CI/CD pipeline

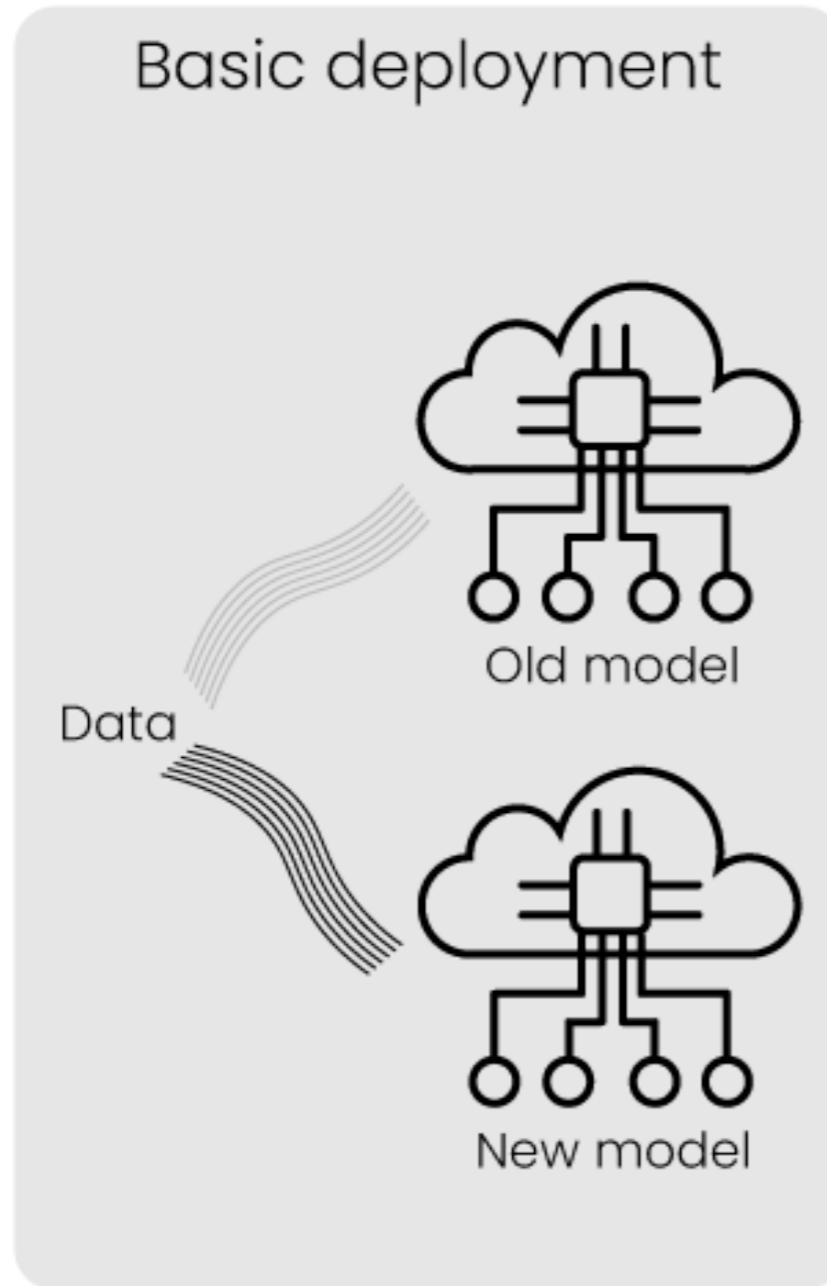


- Continuous integration: practices while code is being written
- Continuous deployment: practices after code is completed

# Deployment strategies

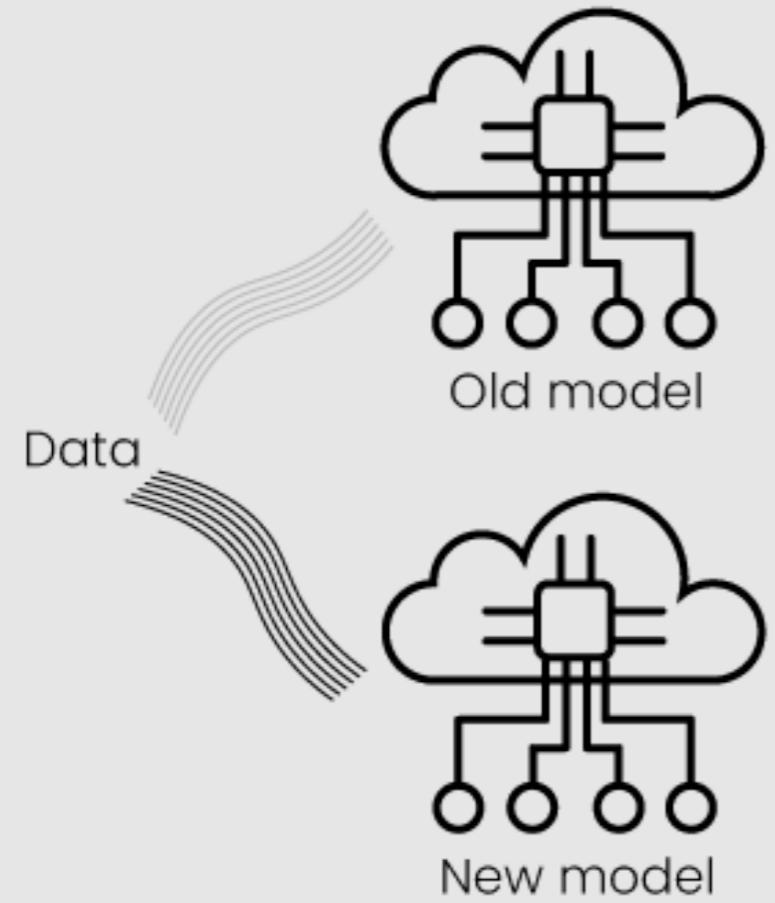
- Basic deployment
- Shadow deployment
- Canary deployment

# Deployment strategies

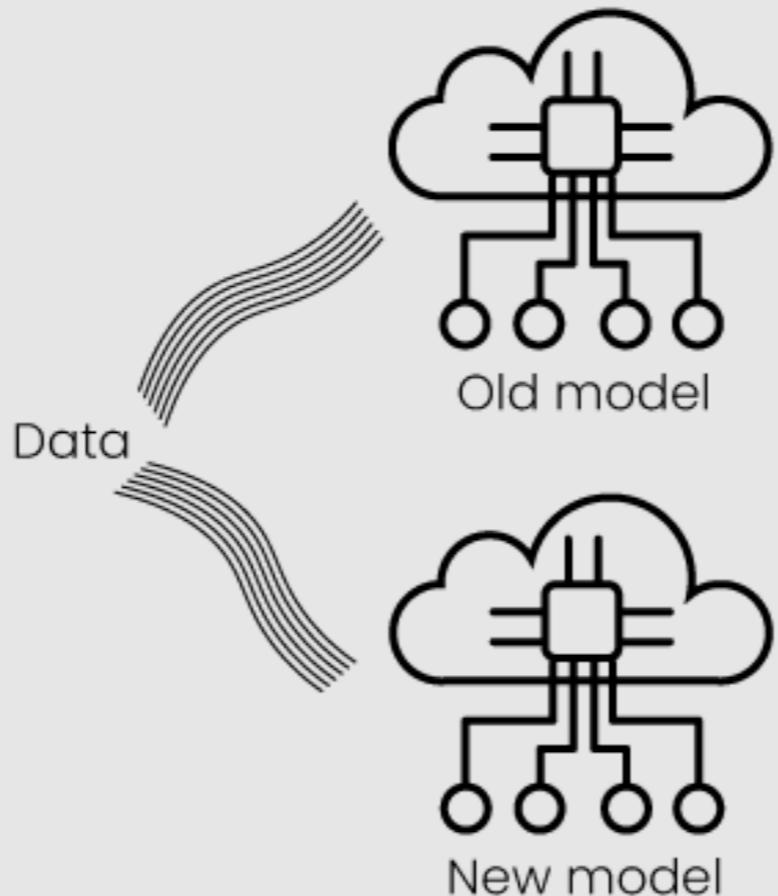


# Deployment strategies

Basic deployment

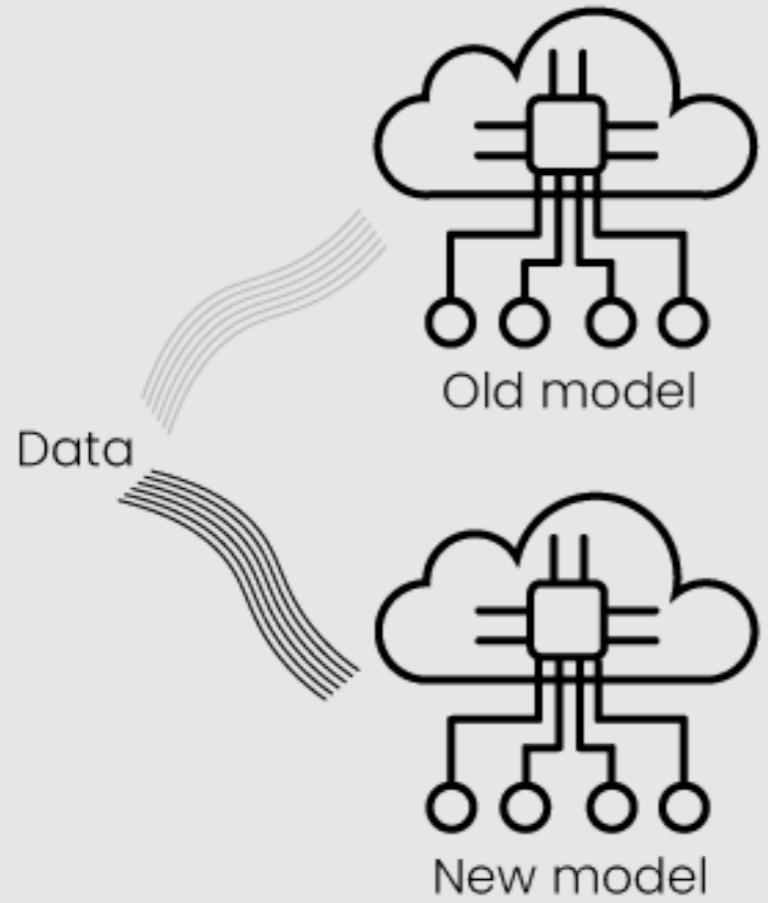


Shadow deployment

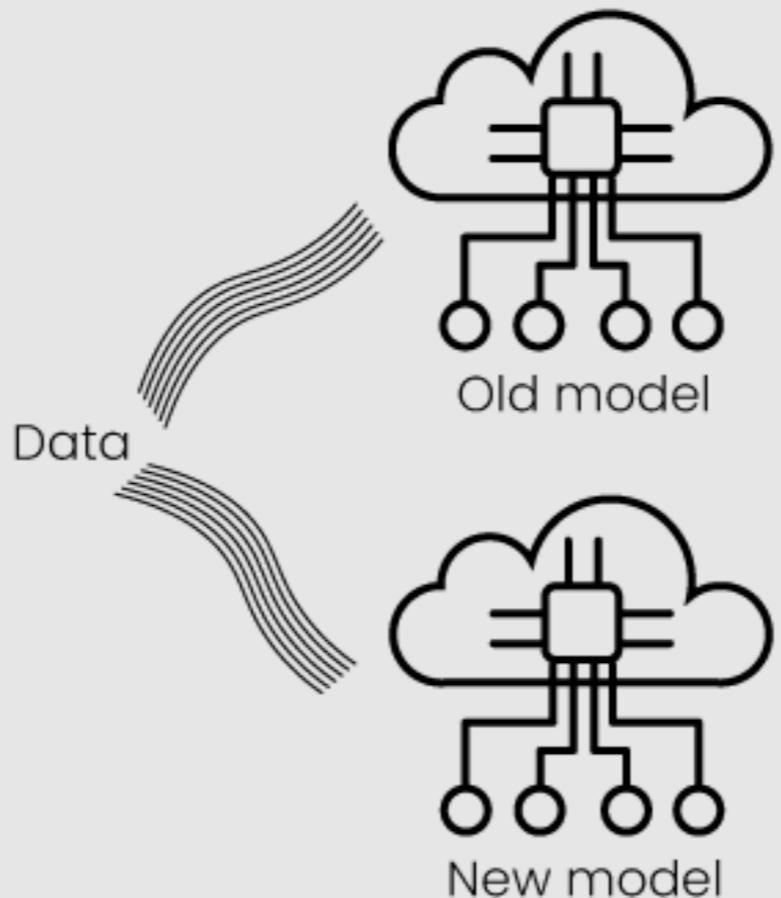


# Deployment strategies

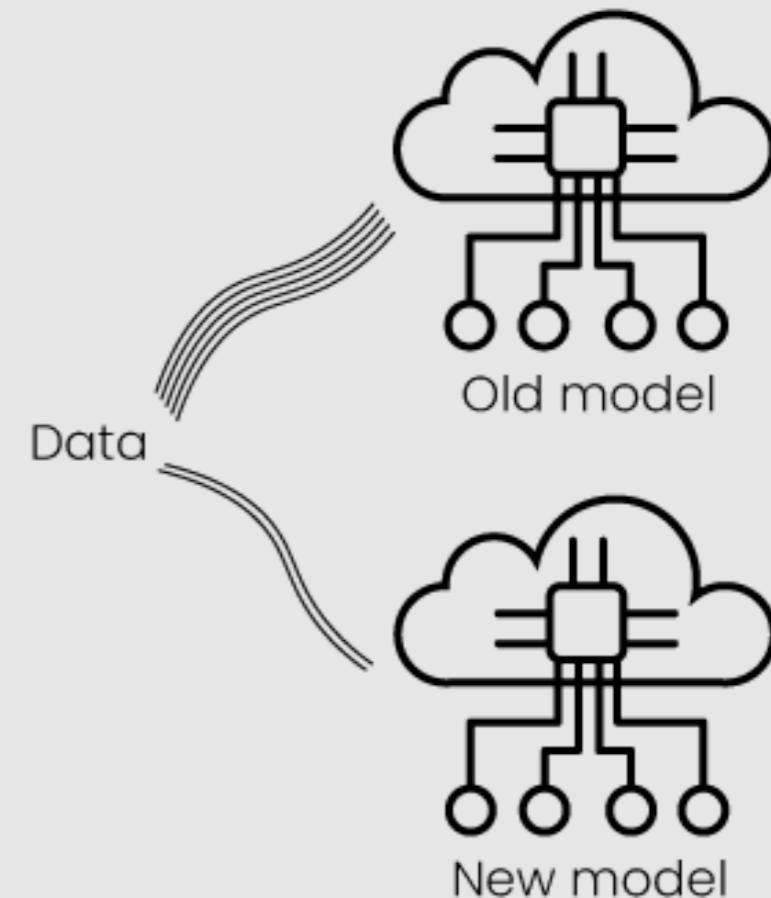
Basic deployment



Shadow deployment



Canary deployment



# Deployment strategies

Strategy	Pros	Cons
Basic deployment	Straightforward, easy to implement, low resources	High risk if the model does not work as expected.
Shadow deployment	Easy to implement, no risk if model does not work as expected	Double resources.
Canary deployment	Slightly harder to implement, medium amount of resources	Small risk if model does not work as expected.

# Let's practice!

MLOPS CONCEPTS

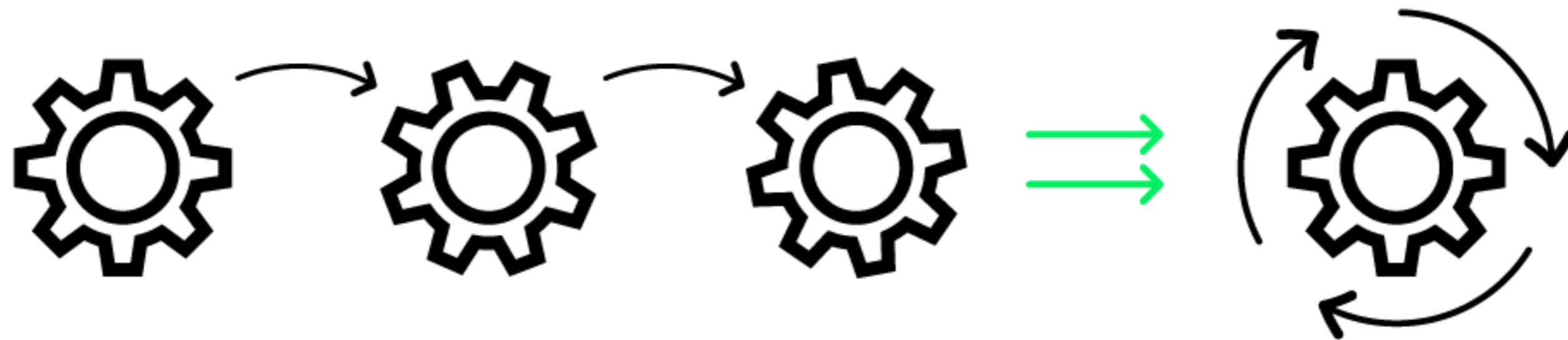
# Automation and scaling

MLOPS CONCEPTS

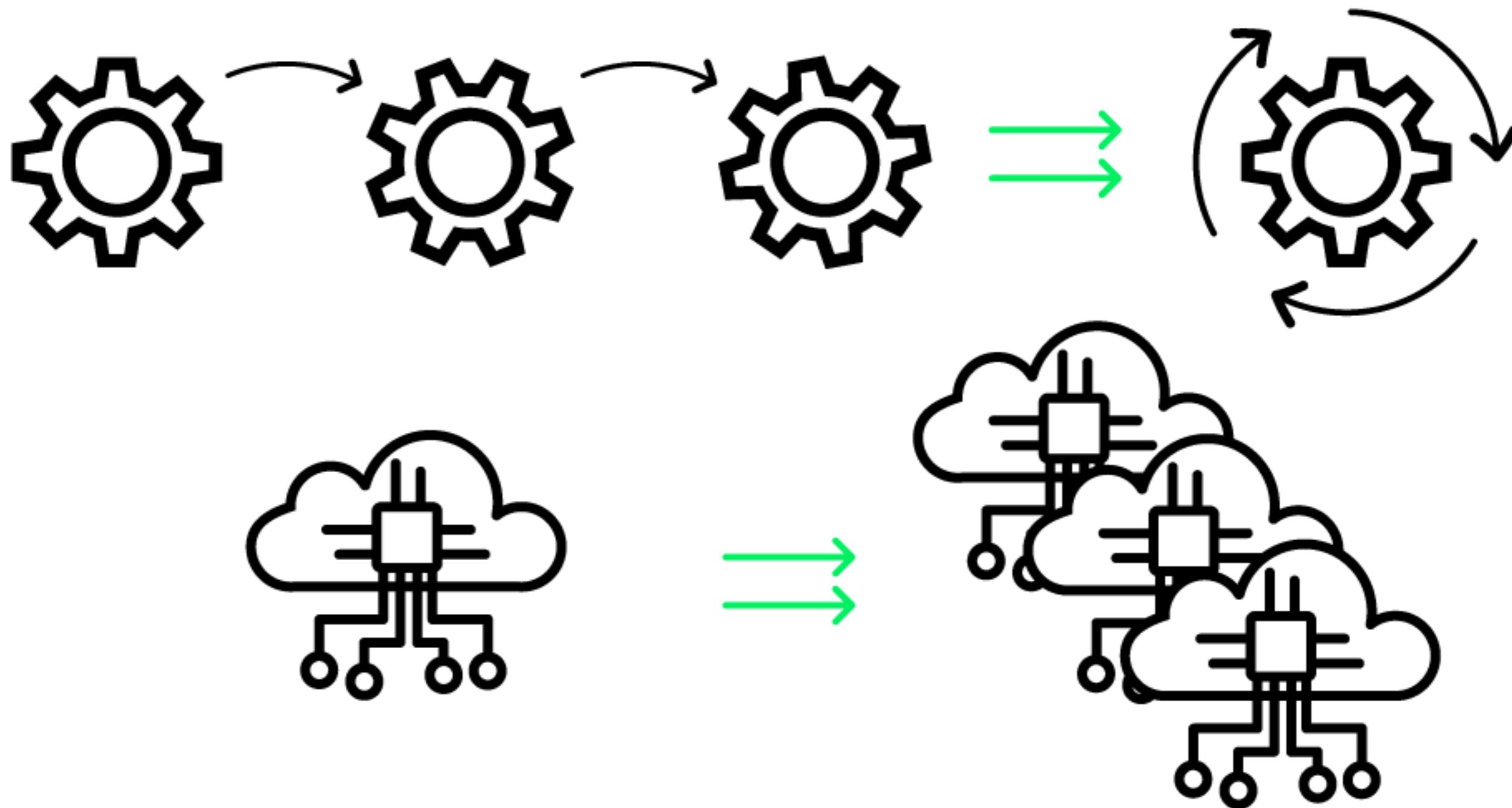


Folkert Stijnman  
ML Engineer

# Automation and scaling



# Automation and scaling



# Design phase

## Project requirements



## Project design

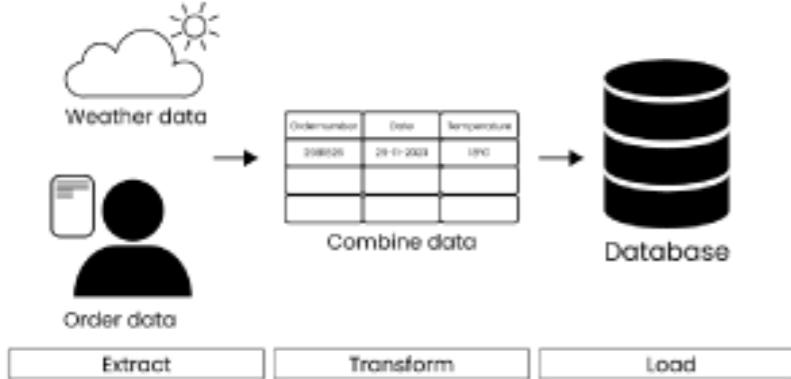
- Project design remains a manual process
- Use templates to automate and scale

# Design phase

## Project requirements



## ETL pipeline



## Data quality checks



## Project design

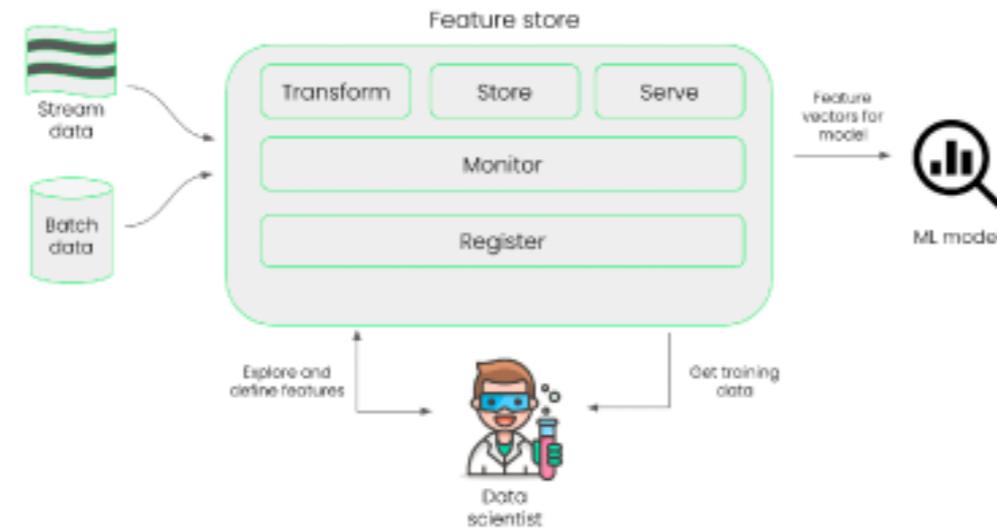
- Project design remains a manual process
- Use templates to automate and scale

## Data acquisition

- Can be automated
- Enables high data quality

# Development phase

## Feature store

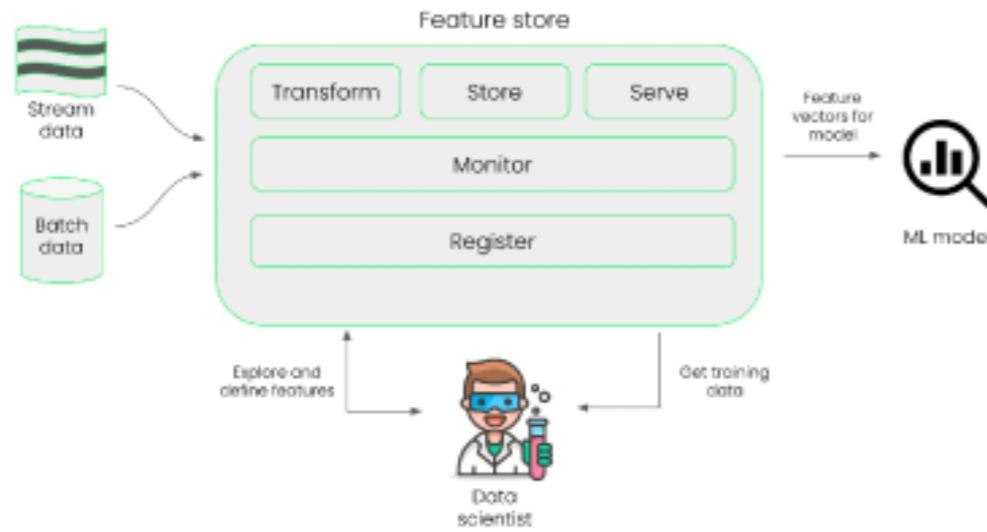


## Feature store

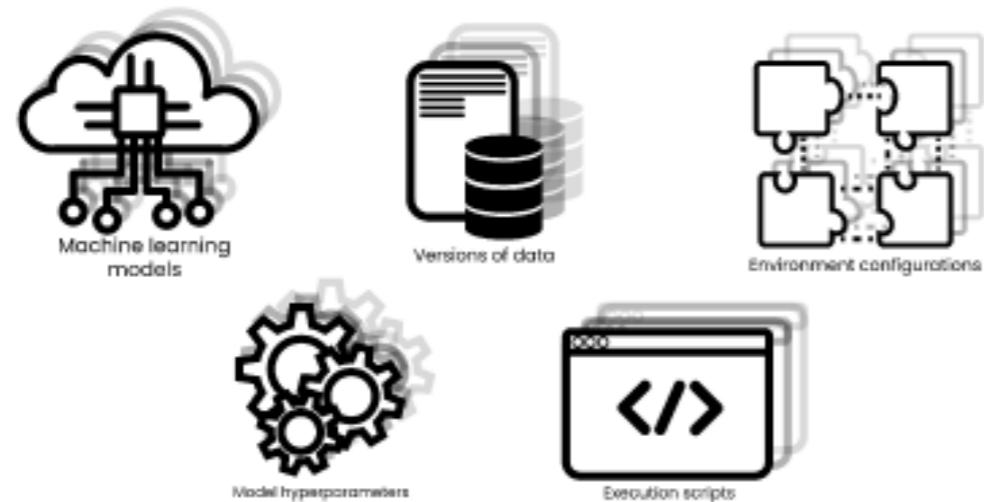
- Saves time building the same features
- Helps to scale

# Development phase

## Feature store



## Experiment tracking



## Feature store

- Saves time building the same features
- Helps to scale

## Experiment tracking

- Automates tracking
- Ensures reproducibility

# Deployment phase

## Containerization

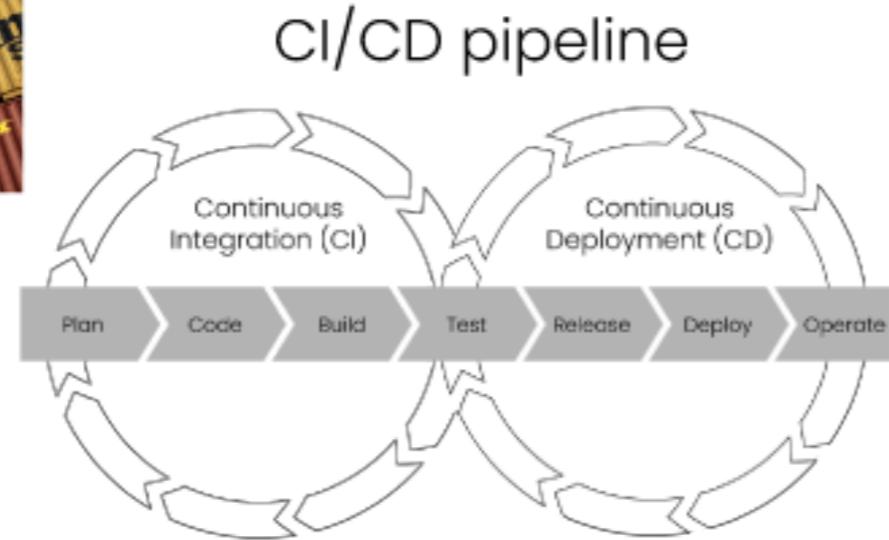


### Containerization

- Easy to start up copies of same application
- Improves scalability

# Deployment phase

Containerization



Containerization

- Easy to start up copies of same application
- Improves scalability

CI/CD pipeline

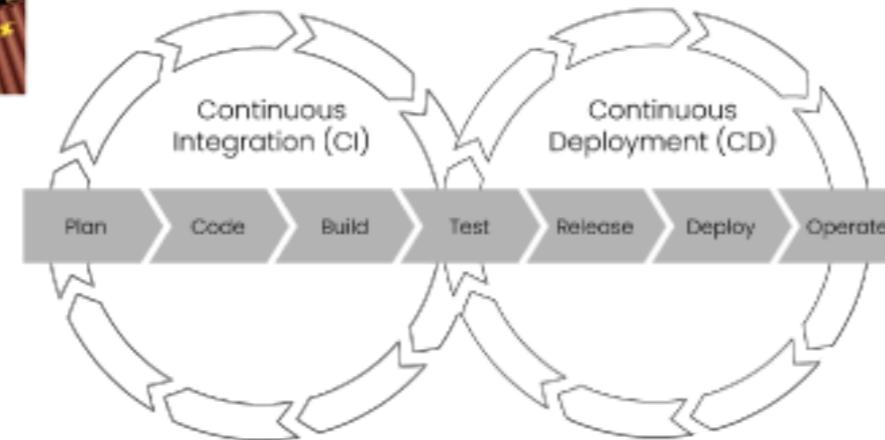
- Automates development and deployment
- Increases velocity of processes

# Deployment phase

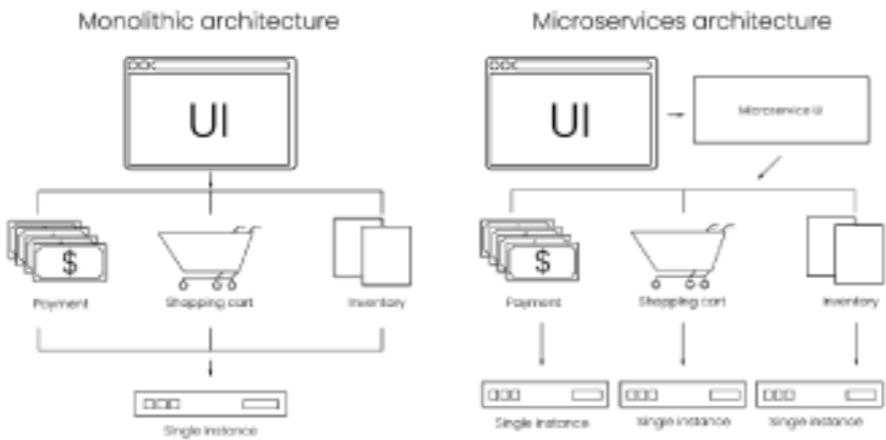
## Containerization



## CI/CD pipeline



## Microservice architecture



## Containerization

- Easy to start up copies of same application
- Improves scalability

## CI/CD pipeline

- Automates development and deployment
- Increases velocity of processes

## Microservices architecture

- Improves scalability
- Independent development and deployment

# Let's practice!

MLOPS CONCEPTS