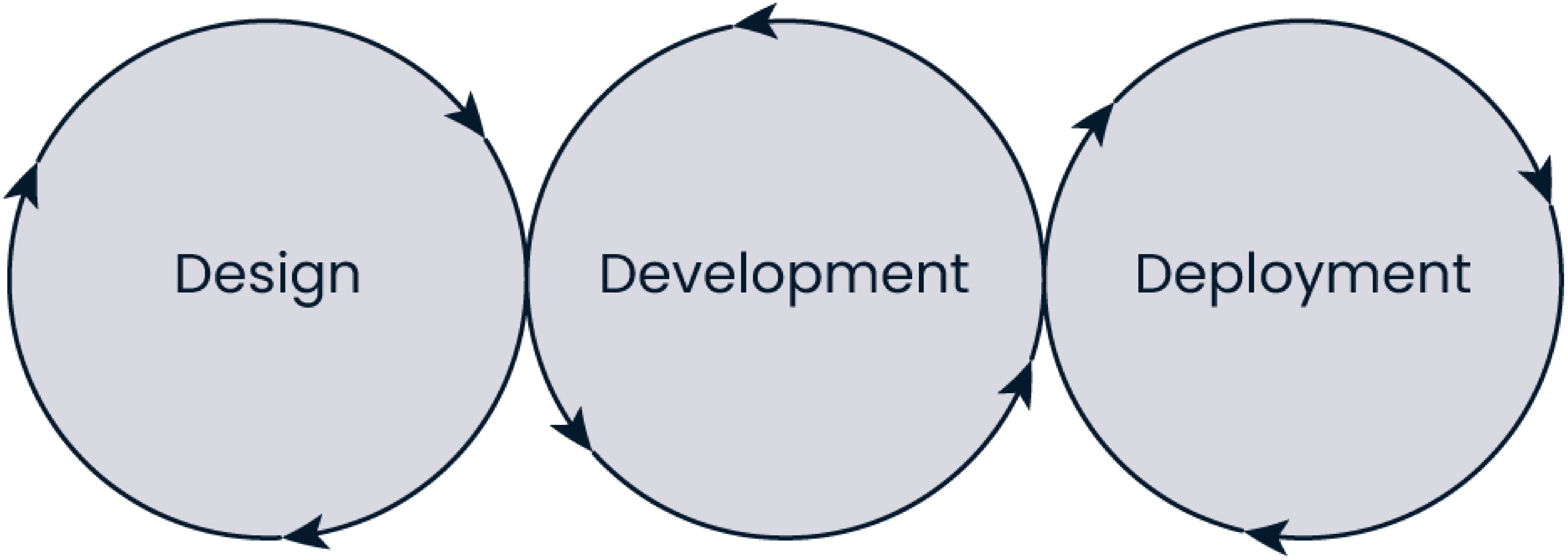
Monitoring machine learning models

MLOPS CONCEPTS

Folkert Stijnman
ML Engineer

Monitoring & retraining

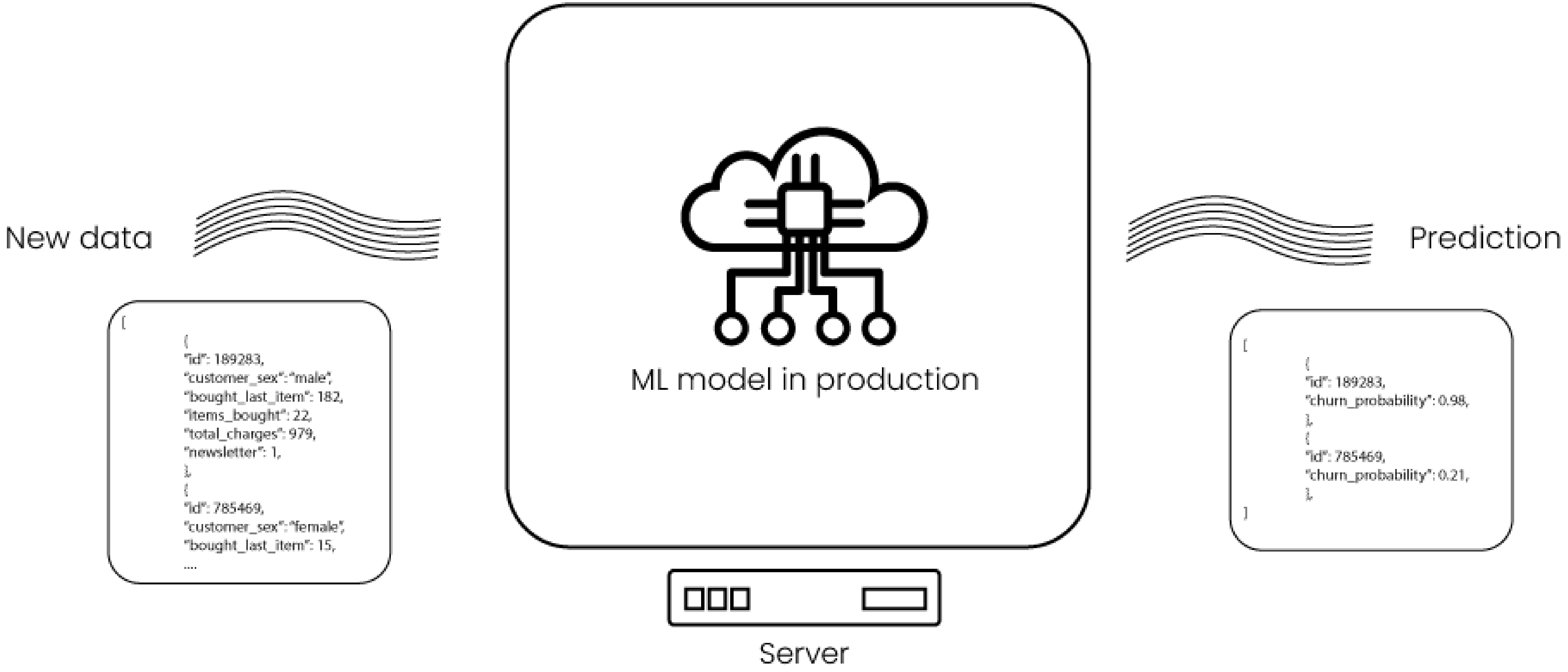


- Added value
- Business requirements
- Key metrics
- Data processing

- Feature engineering
- Experiment tracking
- Model training & evaluation

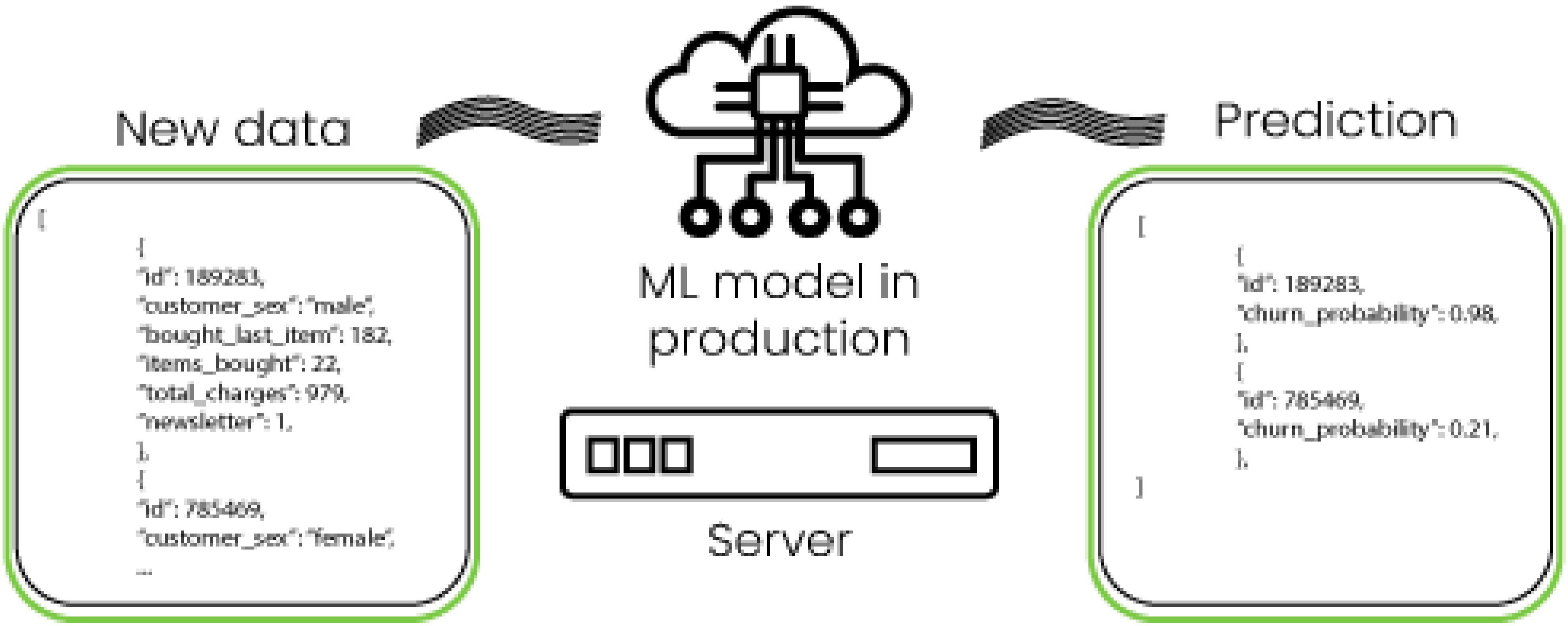
- Runtime environments
- Microservices architecture
- CI/CD pipeline
- Monitoring & retraining

Monitoring



New data
[
{
"id": 189283,
"customer_sex":"male",
"bought_last_item": 182,
"items_bought": 22,
"total_charges": 979,
"newsletter": 1,
},
{
"id": 785469,
"customer_sex":"female",
"bought_last_item": 15,
....
ML model in production
Server
Prediction
[
{
"id": 189283,
"churn_probability": 0.98,
},
{
"id": 785469,
"churn_probability": 0.21,
},
]

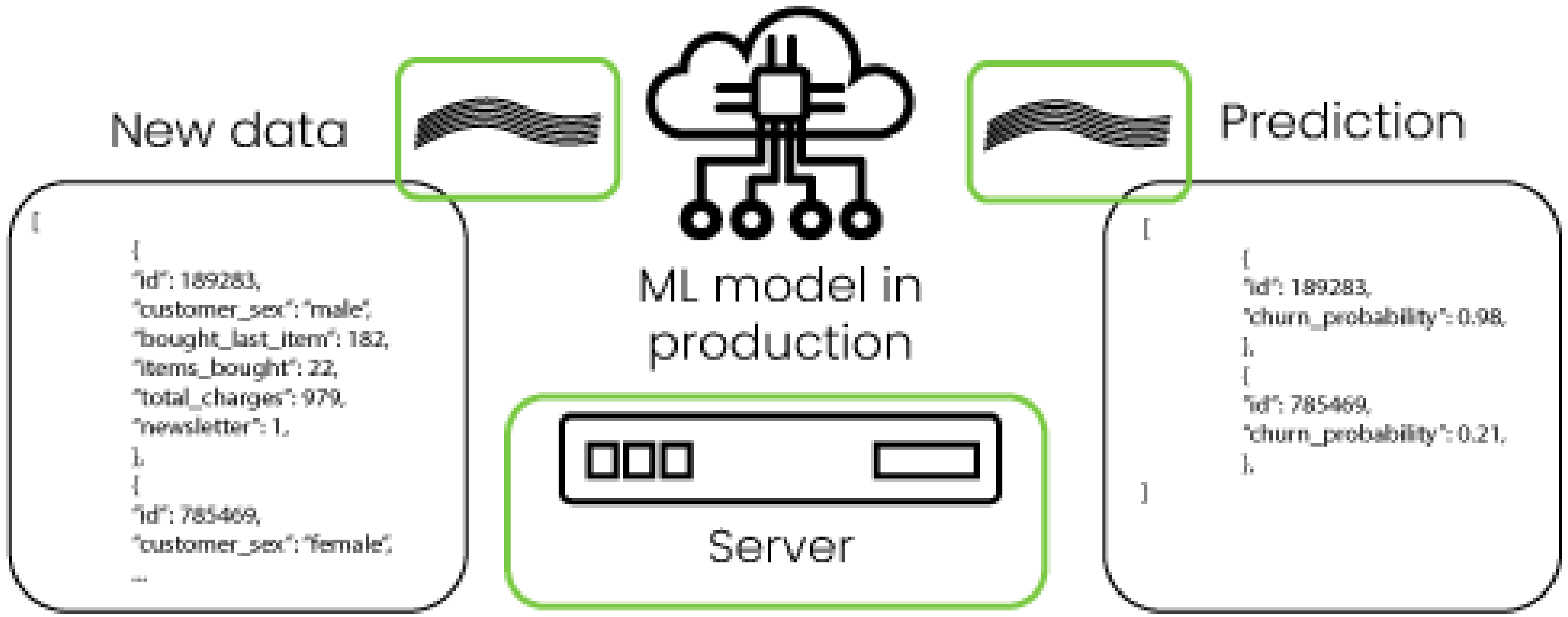
Types of monitoring



Statistical monitoring: focuses on the input and output data, including predictions

Examples: customer X has a 72% probability of churning, customer Y has a 31% probability of not churning

Types of monitoring

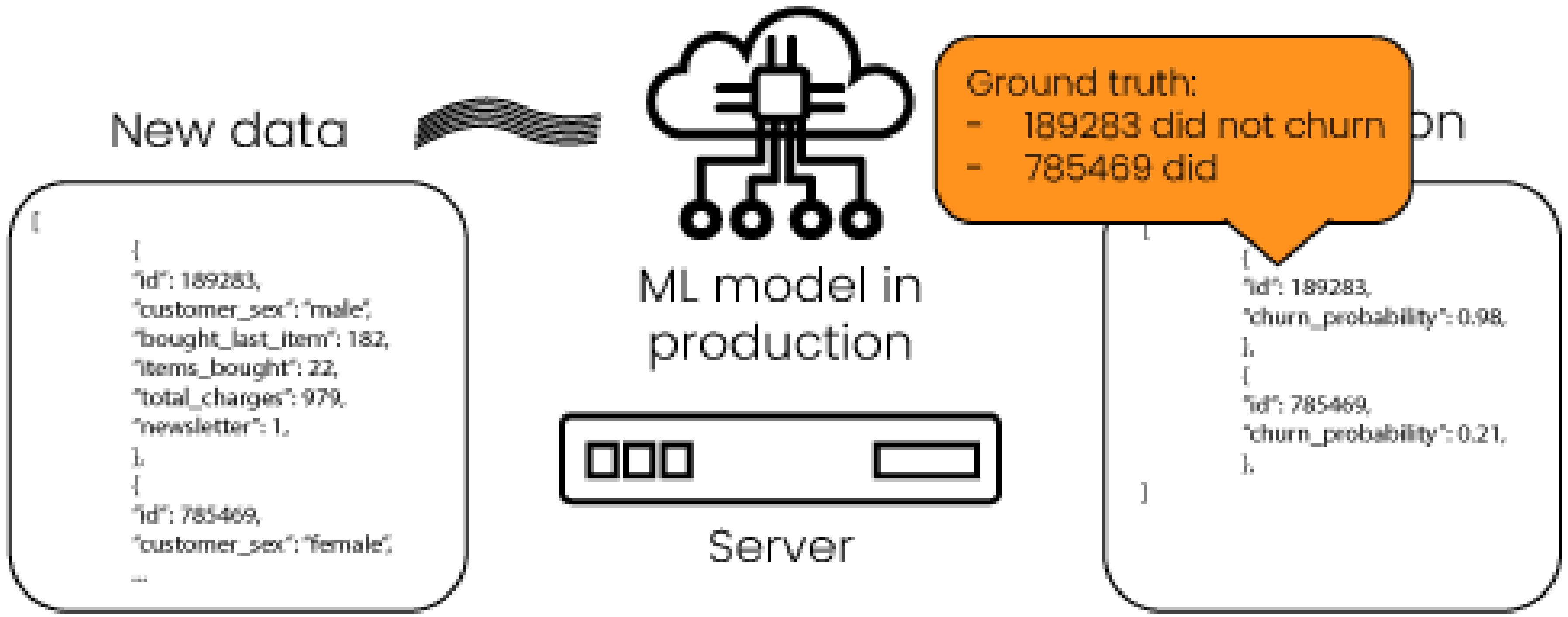


Computational monitoring: focuses on technical metrics

Examples: server CPU usage, number of incoming requests, number of predictions, downtime of server

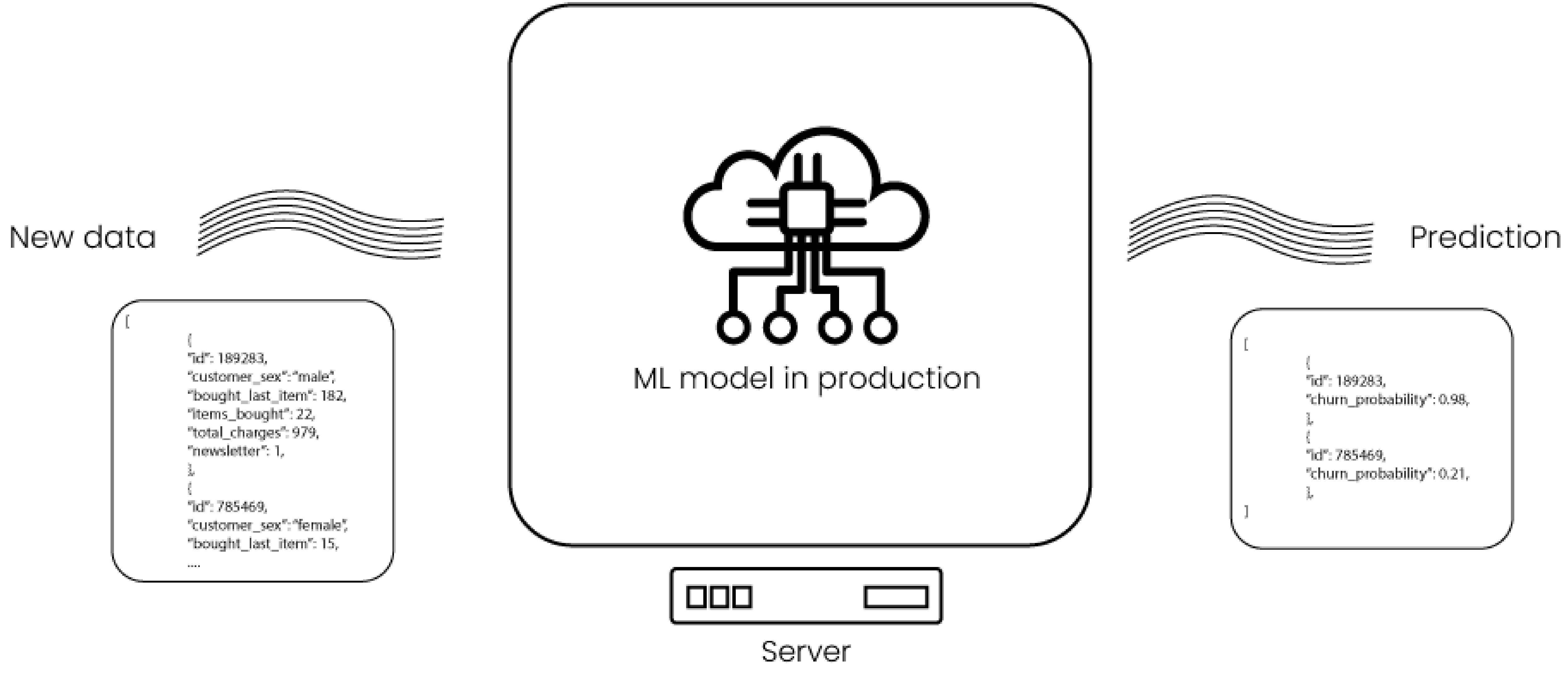
Statistical and computational monitoring

Feedback loop



Feedback loop: the process through which the ground truth is used to improve the machine learning model

Monitoring in production



Let's practice!

MLOPS CONCEPTS

Retraining a machine learning model

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ML Engineer

Retraining after changes

Retraining: use new data to develop a fresh version of the machine learning model

Drift in data

Input data			Target
Customer	Last order	Items bought	Churn
2981826	29-11-2023	17	0
2091826	10-02-2022	4	1
...	...	...	...

Data drift

Input data

Customer	Last order	Items bought
2981826	29-11-2023	17
2091826	10-02-2022	4
...	...	...

Target

Churn
0
1
...

Data drift: changes in the input data

Concept drift

Input data			Target
Customer	Last order	Items bought	Churn
2981826	29-11-2023	17	0
2091826	10-02-2022	4	1
...	...	...	...

Concept drift: changes in the relationship between input and output data

How often to retrain?

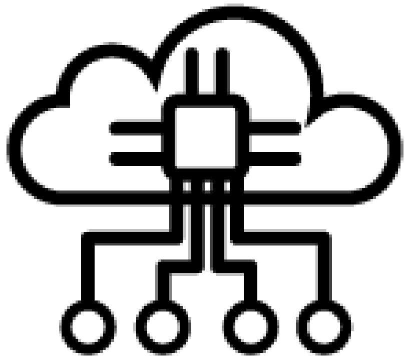
- **Business environment:** how volatile is the data?
- **Cost:** how much does it cost to retrain?
- **Business requirements:** what is the required model performance?

Retraining methods

Old data

Customer	Last order	Items bought
2981826	29-11-2023	17
2091826	10-02-2022	4
...	...	...

Churn
0
1
...

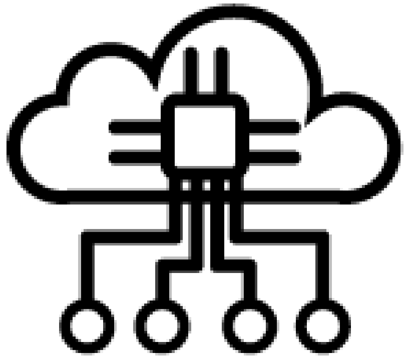


Original model

New data

Customer	Last order	Items bought
3029712	12-01-2024	17
4900298	18-04-2024	81
...	...	...

Churn
1
0
...



New model

Retraining methods

Old data

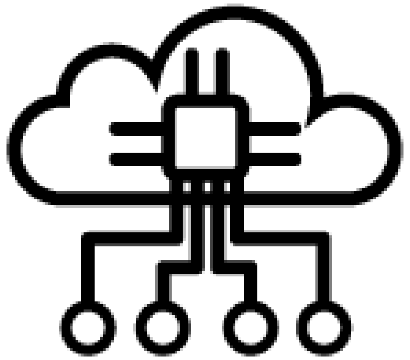
Customer	Last order	Items bought
2981826	29-11-2023	17
2091826	10-02-2022	4
...	...	...

Churn
0
1
...

New data

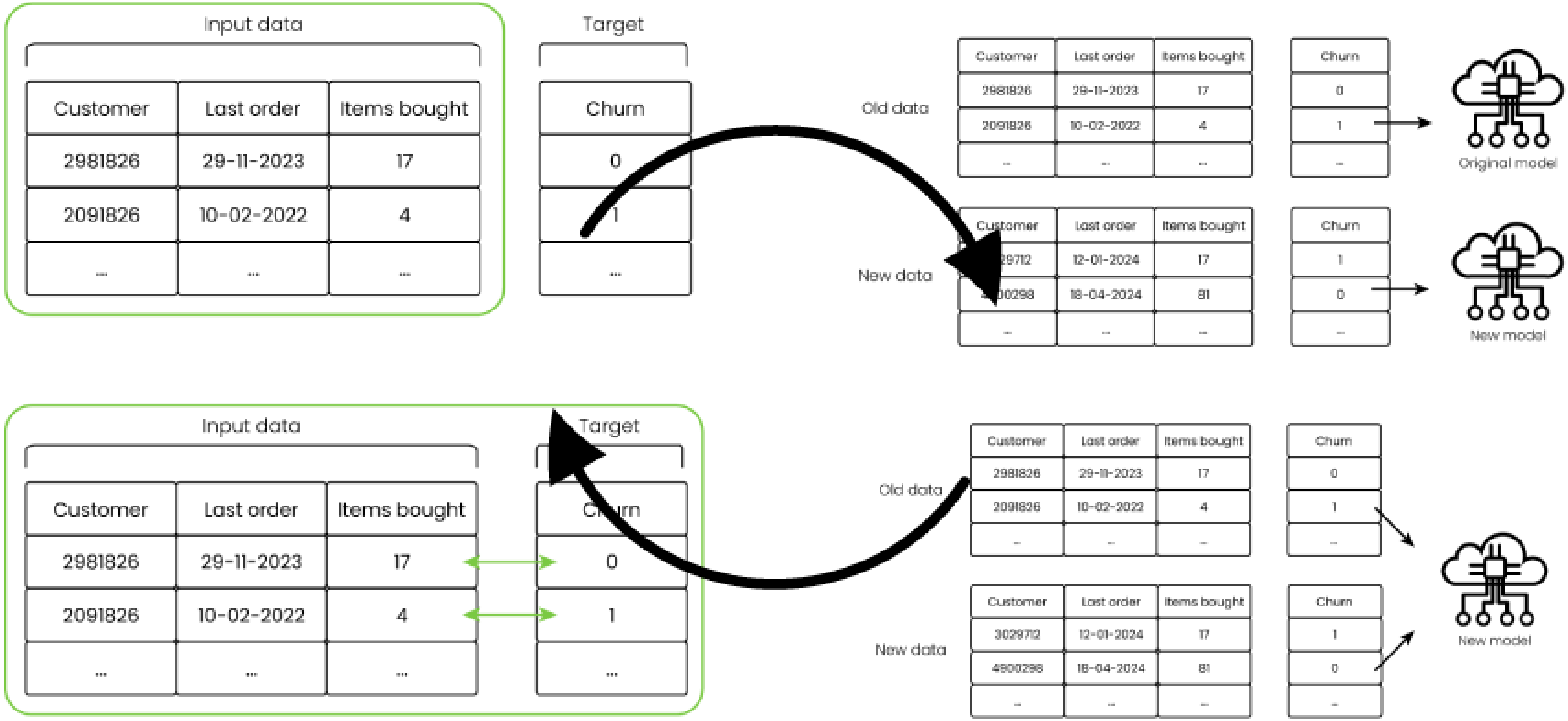
Customer	Last order	Items bought
3029712	12-01-2024	17
4900298	18-04-2024	81
...	...	...

Churn
1
0
...



New model

Automatic retraining



Let's practice!

MLOPS CONCEPTS

Levels of MLOps maturity

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ML Engineer

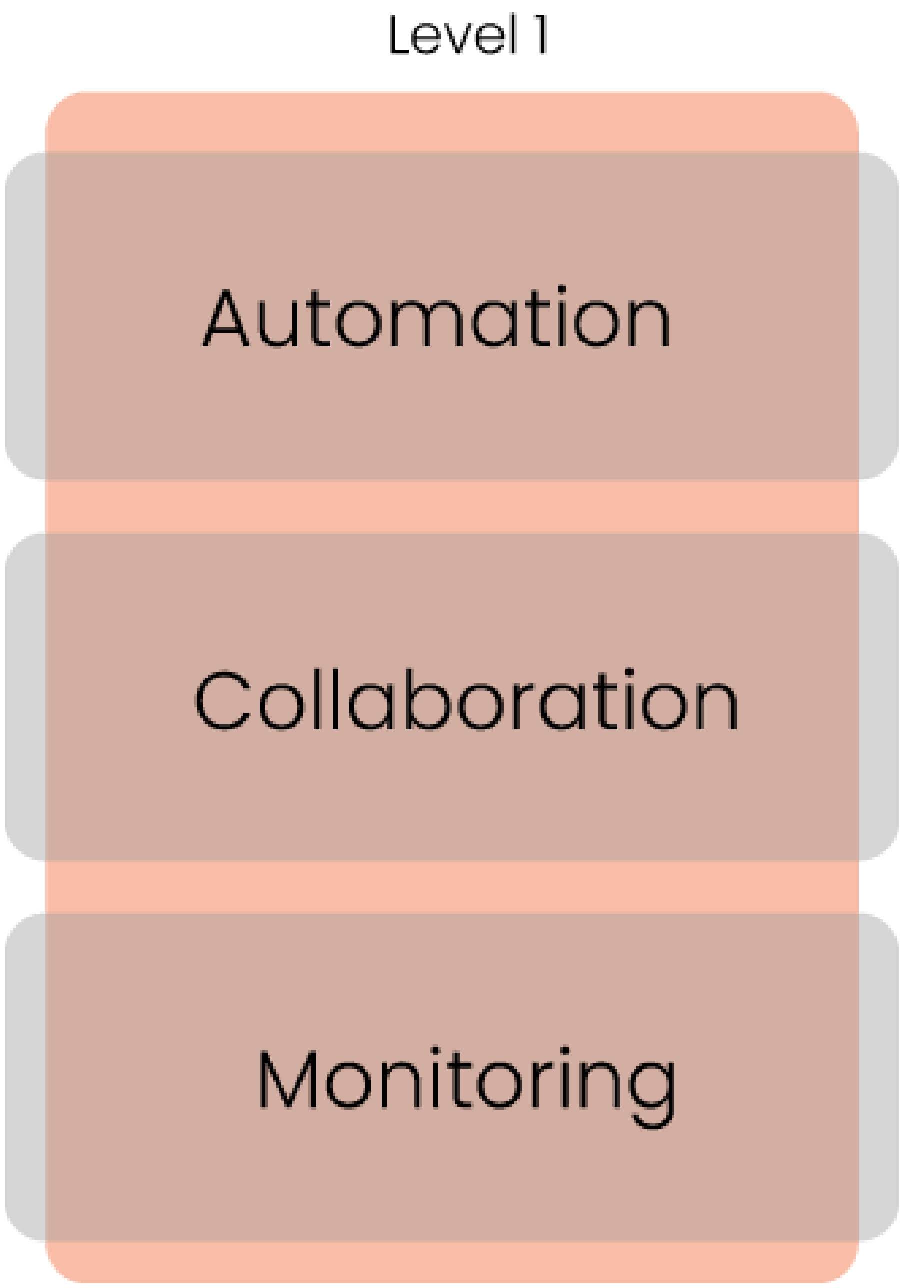
MLOps maturity

- Level of **automation**, **collaboration**, and **monitoring** within MLOps processes
- Higher level is not necessarily better
- Focus on development and deployment phase

Levels of MLOps maturity

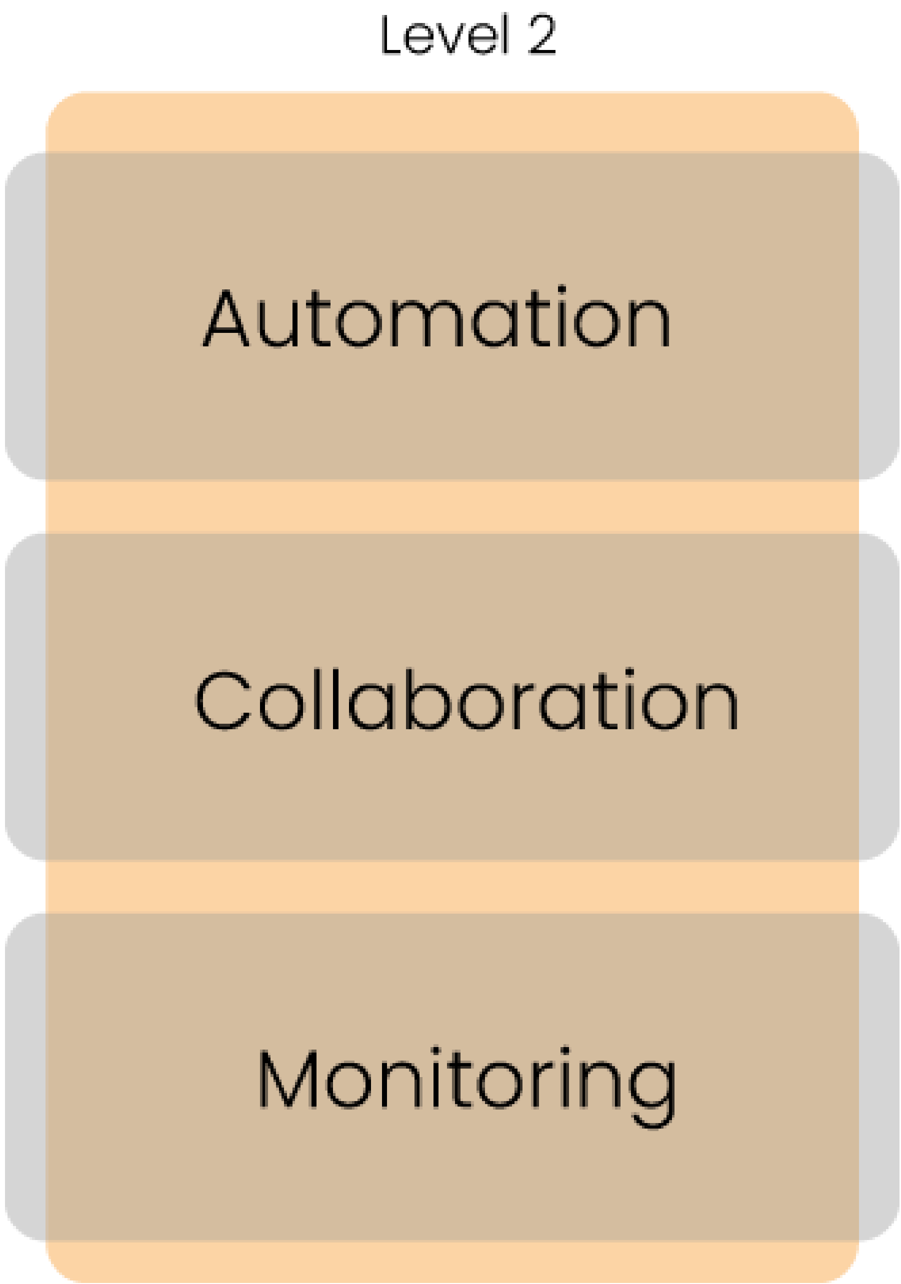
	Level 1	Level 2	Level 3
Automation	Manual processes	Automated development (CI)	Full automation
Collaboration	Distinction machine learning and operations	Collaboration during handover from development	Close collaboration
Monitoring	No monitoring	Development tracking (experiments, feature store)	Full monitoring

Level 1: Manual processes



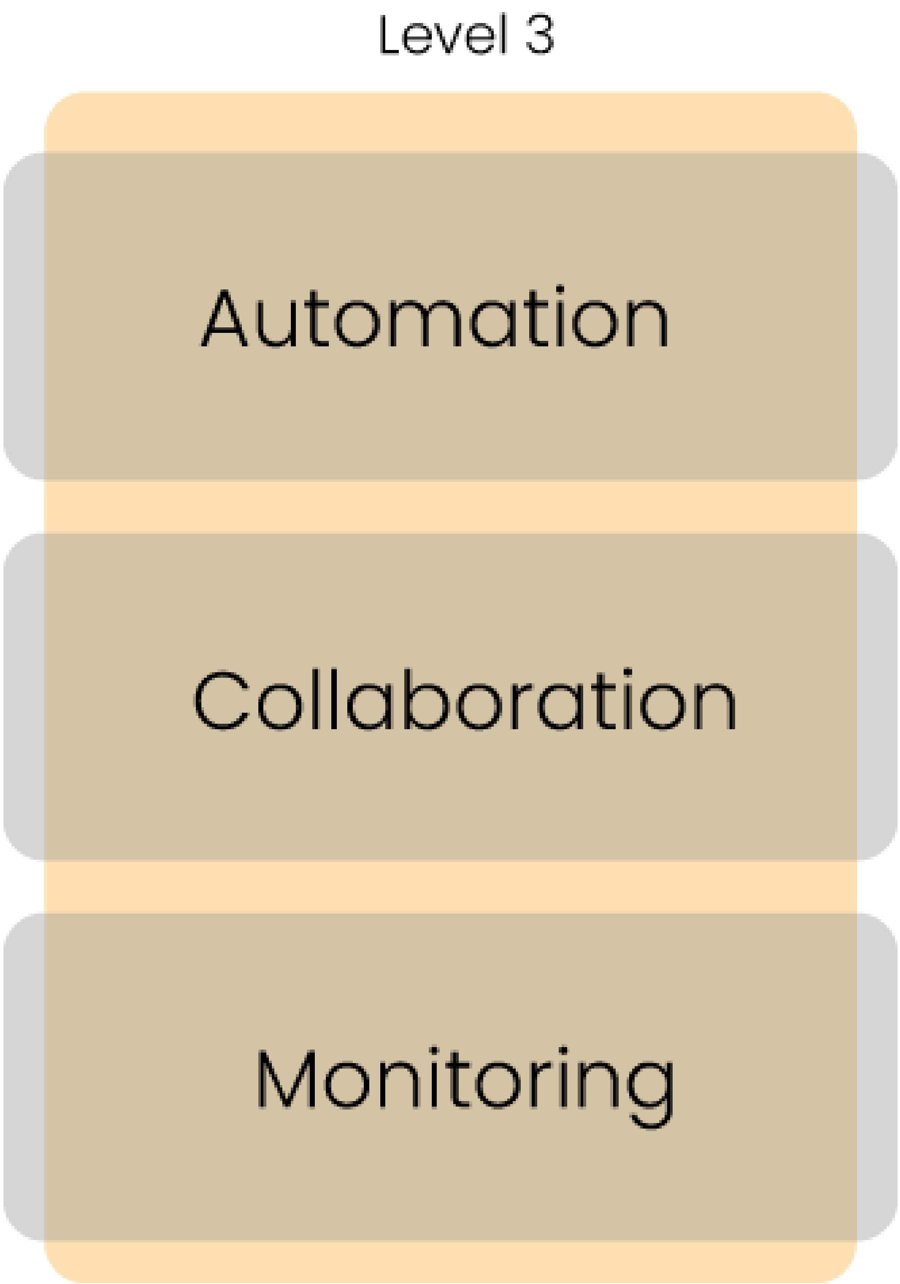
- Manual process for development
- Manual process for deployment
- No collaboration between ML and operations
- Teams work in isolation
- No tracking of development
- No monitoring after deployment

Level 2: Automated development



- Automated development pipeline (Continuous integration)
- Manual process for deployment
- After development teams will collaborate to deploy model
- Tracking of ML experiments and features
- Little monitoring after deployment

Level 3: Automated development and deployment



- Automated development pipeline (CI)
- Automated deployment pipeline (CD)
- Close collaboration between teams
- Monitoring of development and deployment
- Potentially automatically triggering retraining

Let's practice!

MLOPS CONCEPTS

MLOps tools

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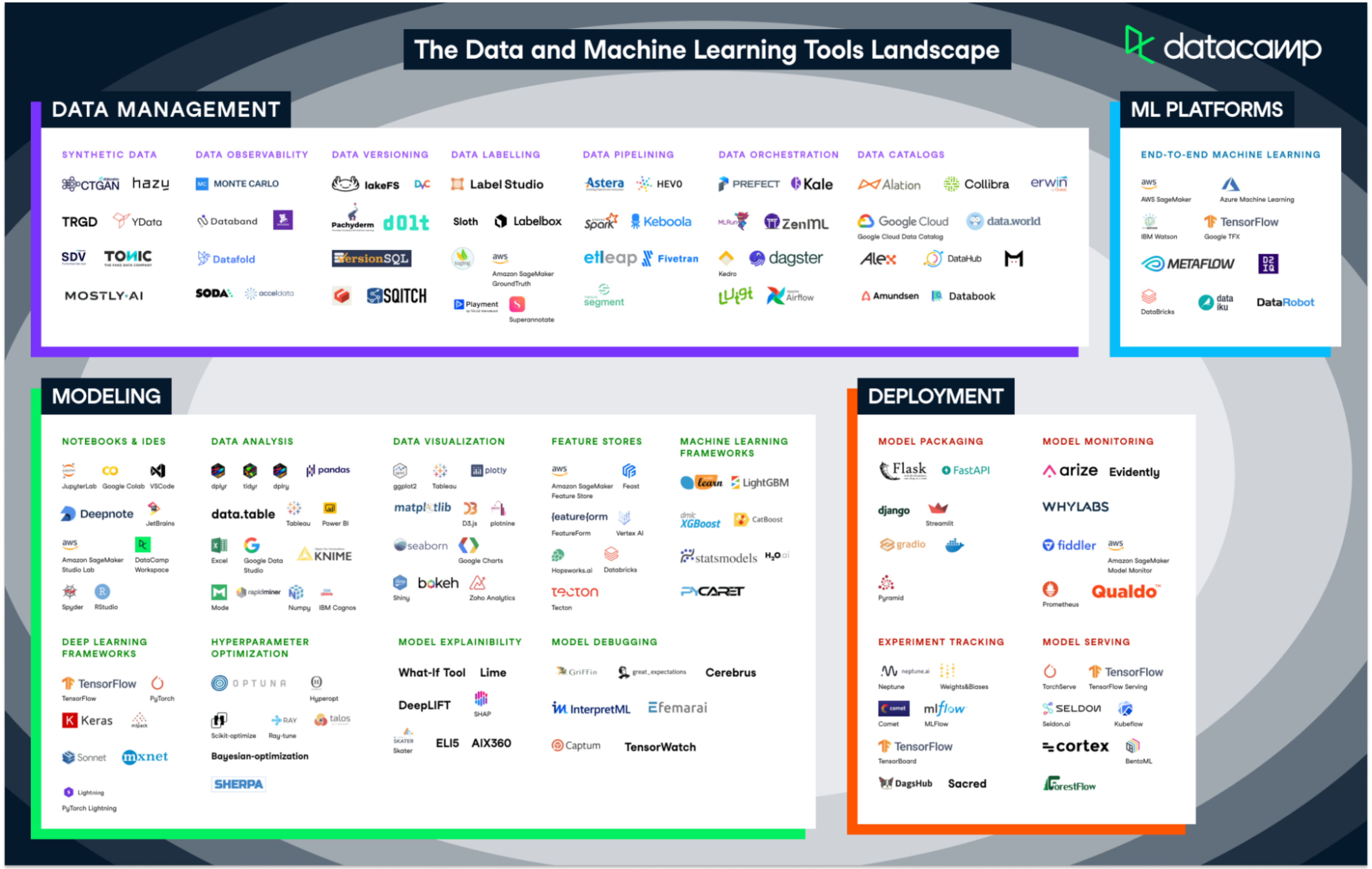
MLOps tools



[1] https://www.datacamp.com/blog/infographic-data-and-machine-learning-tools-landscape

Feature store

- Both open-source
- **Feast:** self-managed
- **Hopsworks:** part of larger platform

Experiment tracking

- **MLFlow and ClearML:** full machine learning lifecycle tools
- **Weights and Biases:** tracking and visualizing experiments

Containerization

- **Docker:** containerizing applications
- **Kubernetes:** running containerized applications
- **Cloud providers:** provides Kubernetes-like services

docker

kubernetes

Amazon EKS

Azure Kubernetes Service (AKS)

Google Kubernetes Engine

CI/CD pipeline

- **Jenkins:** open-source continuous integration tool
- **GitLab:** code sharing and version control through repositories

Monitoring

- **Fiddler:** machine learning model monitoring
- **Great expectations:** data monitoring

MLOps platforms

Tools for full machine learning lifecycle

- **AWS Sagemaker**
- **Azure Machine Learning**
- **Google Cloud AI platform**

Let's practice!

MLOPS CONCEPTS

Recap: MLOps concepts

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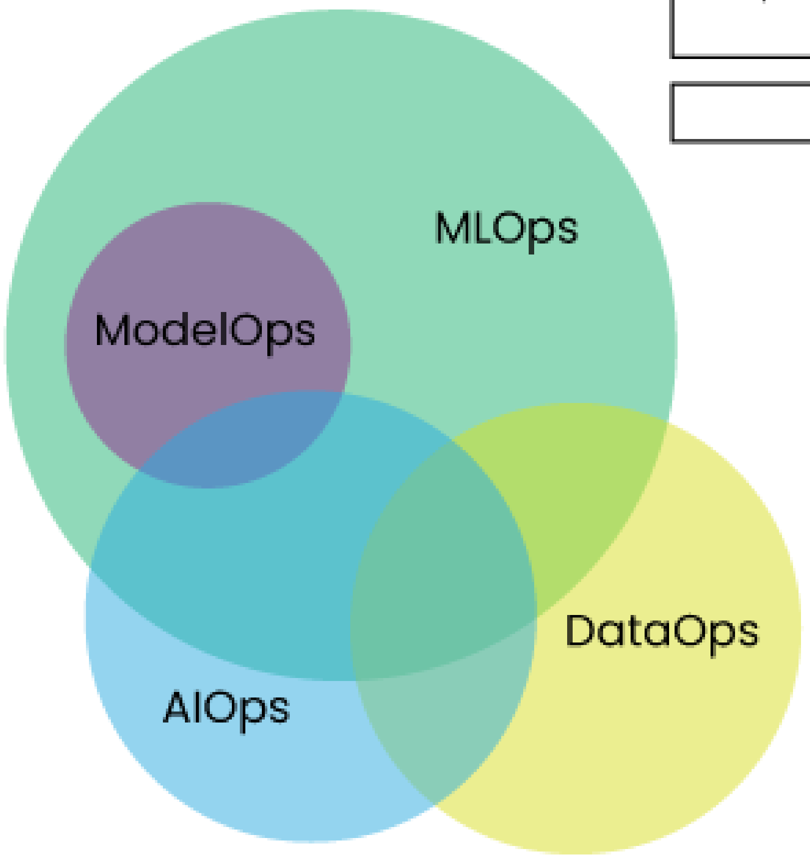
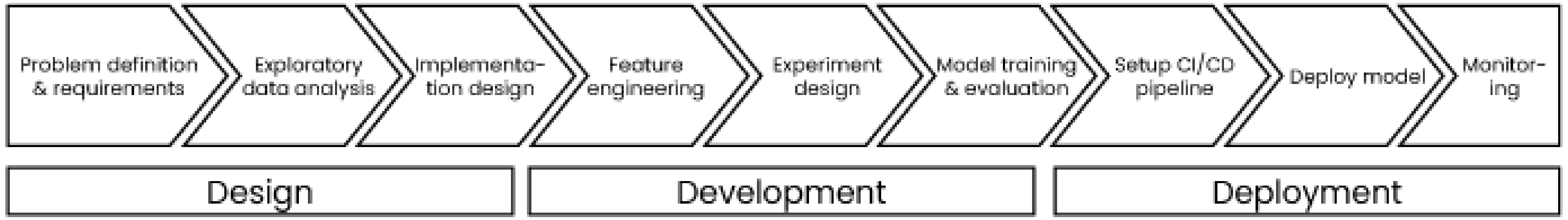
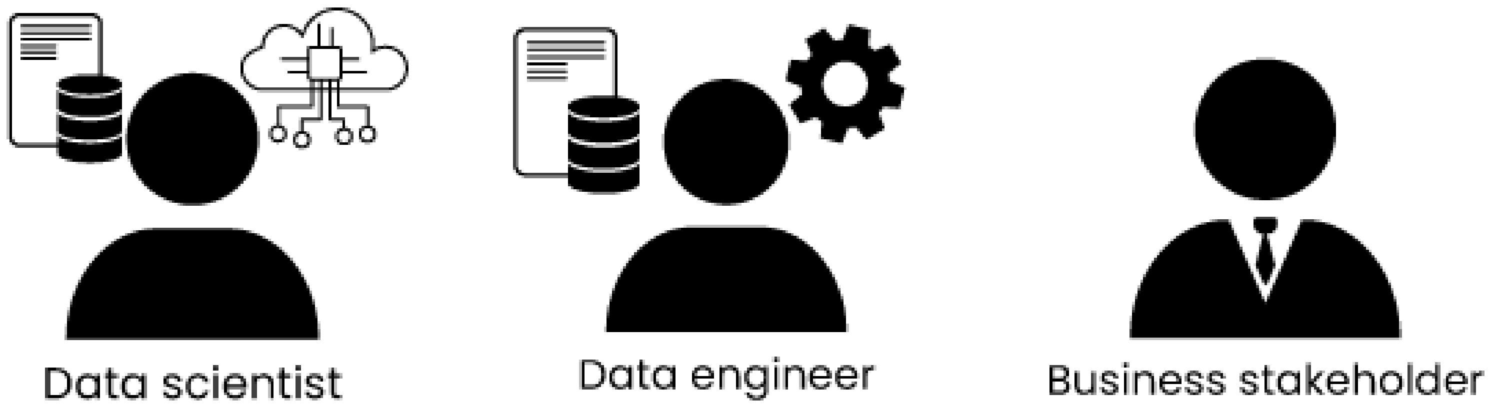
ML Engineer

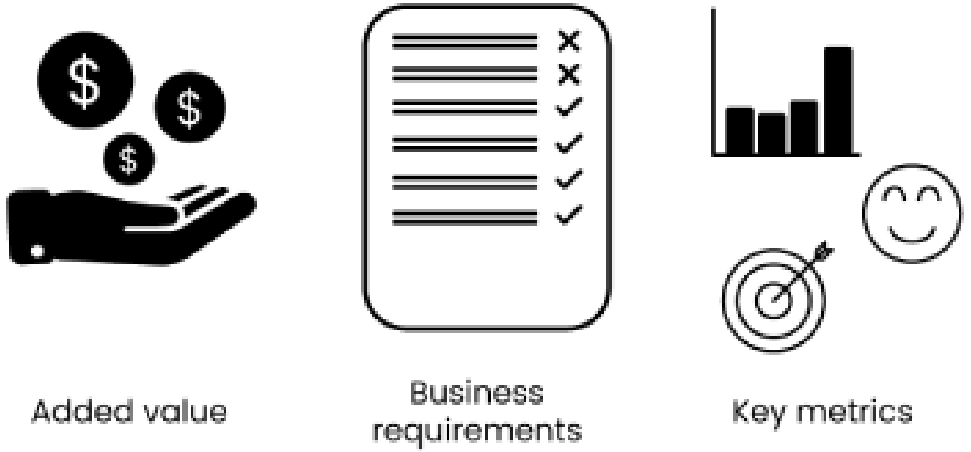
What is MLOps?

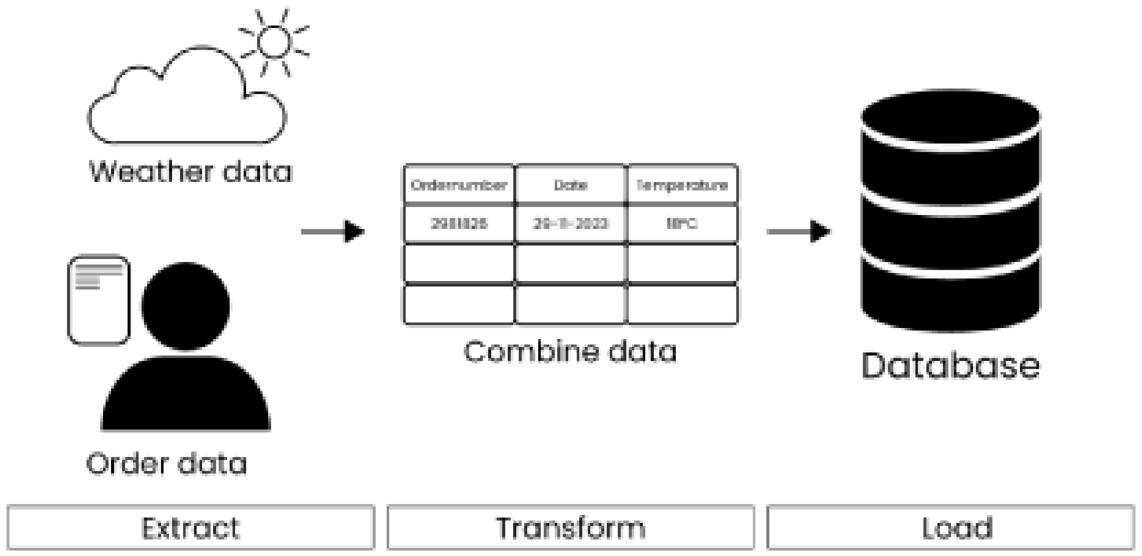


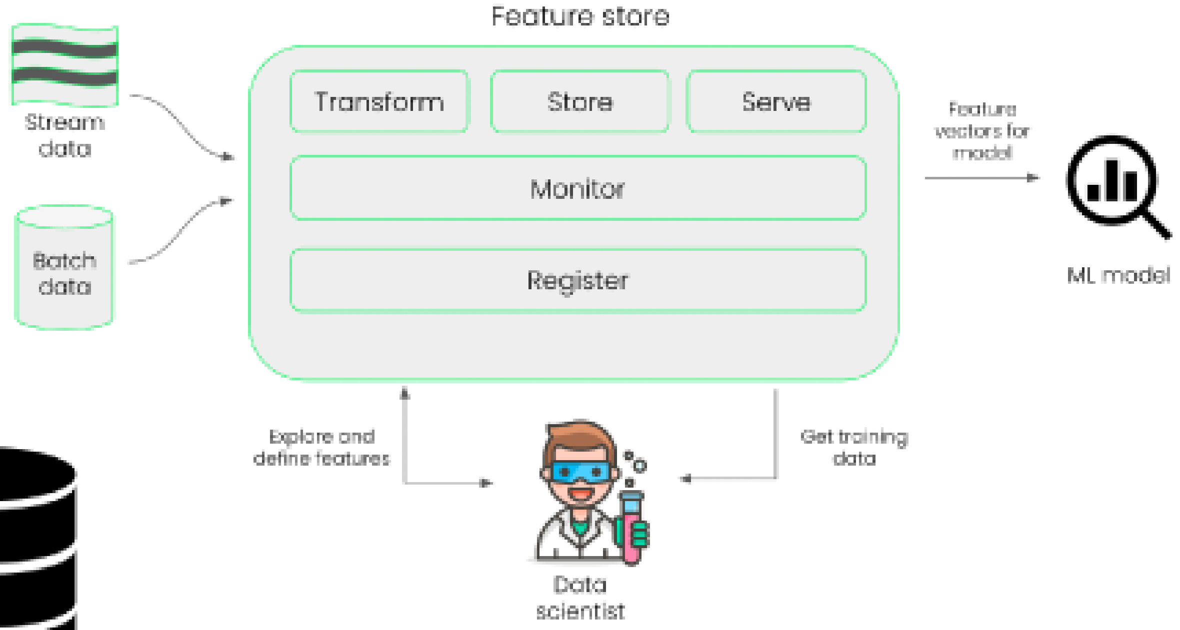




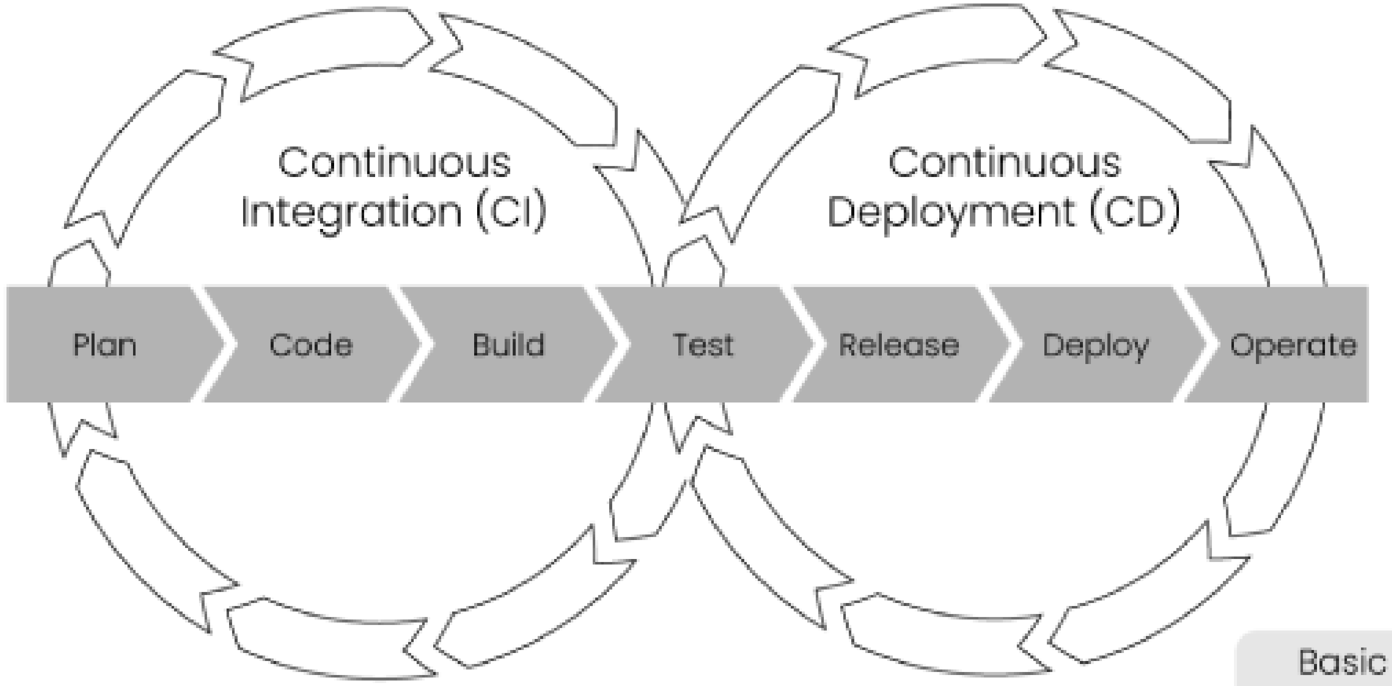
Design and development

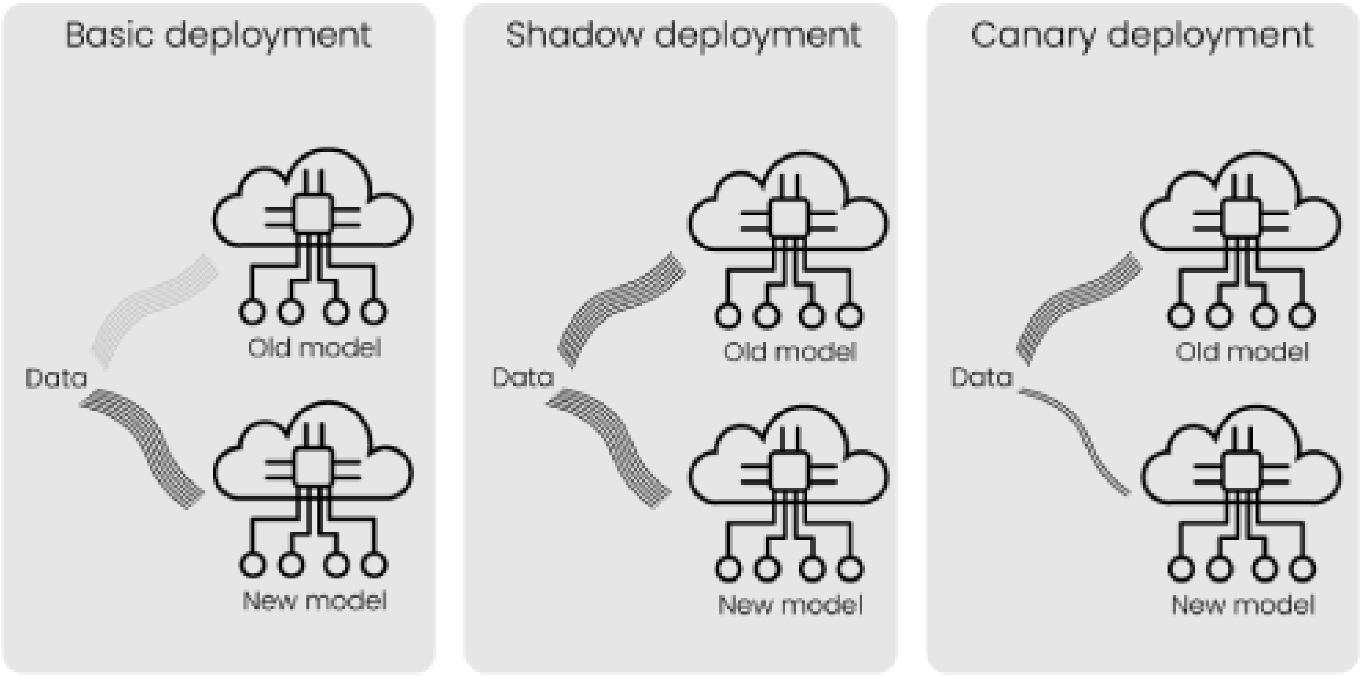






Deployment


Continuous
Integration (CI)
Continuous
Deployment (CD)
Plan
Code
Build
Test
Release
Deploy
Operate


Basic deployment
Old model
Data
New model
Shadow deployment
Old model
Data
New model
Canary deployment
Old model
Data
New model

Maintaining machine learning

	Level 1	Level 2	Level 3
Automation	Manual processes	Automated development (CI)	Full automation
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Congratulations!

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