

Choosing the right MLOps Platform: Key Capabilities & Model Monitoring Insights



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MLOps definition and components

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MLOps platforms/tools

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Model Performance Monitoring

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Key takeaways



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Model Performance Monitoring

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Key takeaways



| MLOps definition and components |



DevOps

set of **practices and tools**
to streamline the **software**
development lifecycle

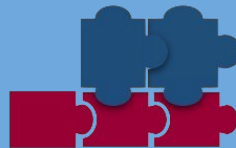


code | infra | env

MLOps

set of **practices and tools** to
streamline the **machine learning**
model lifecycle

data | model



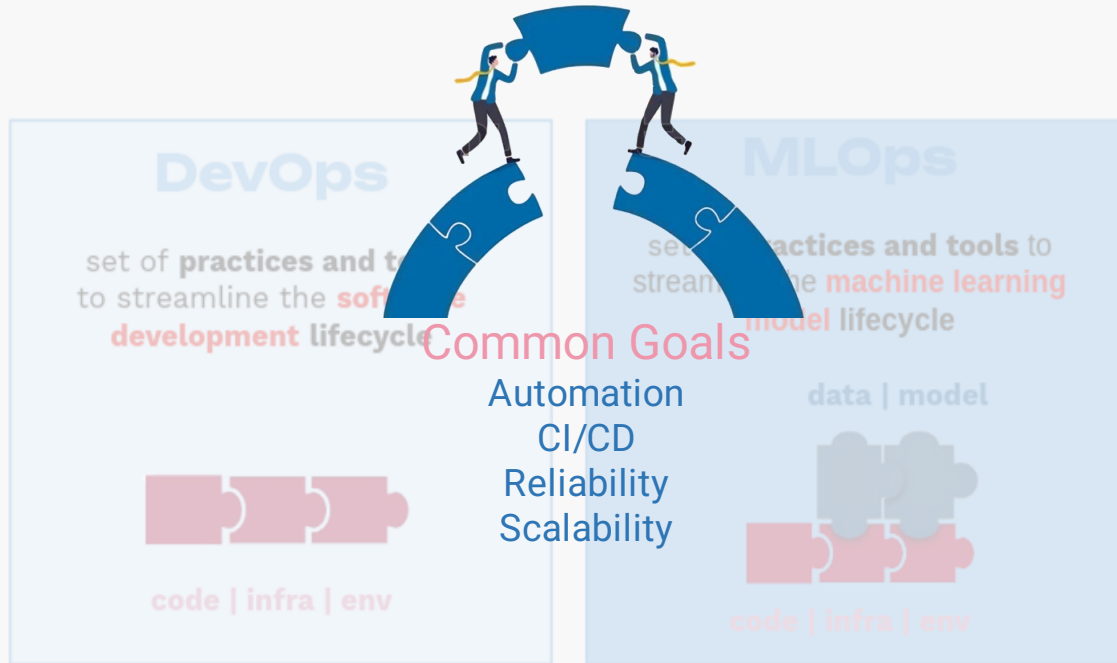
code | infra | env

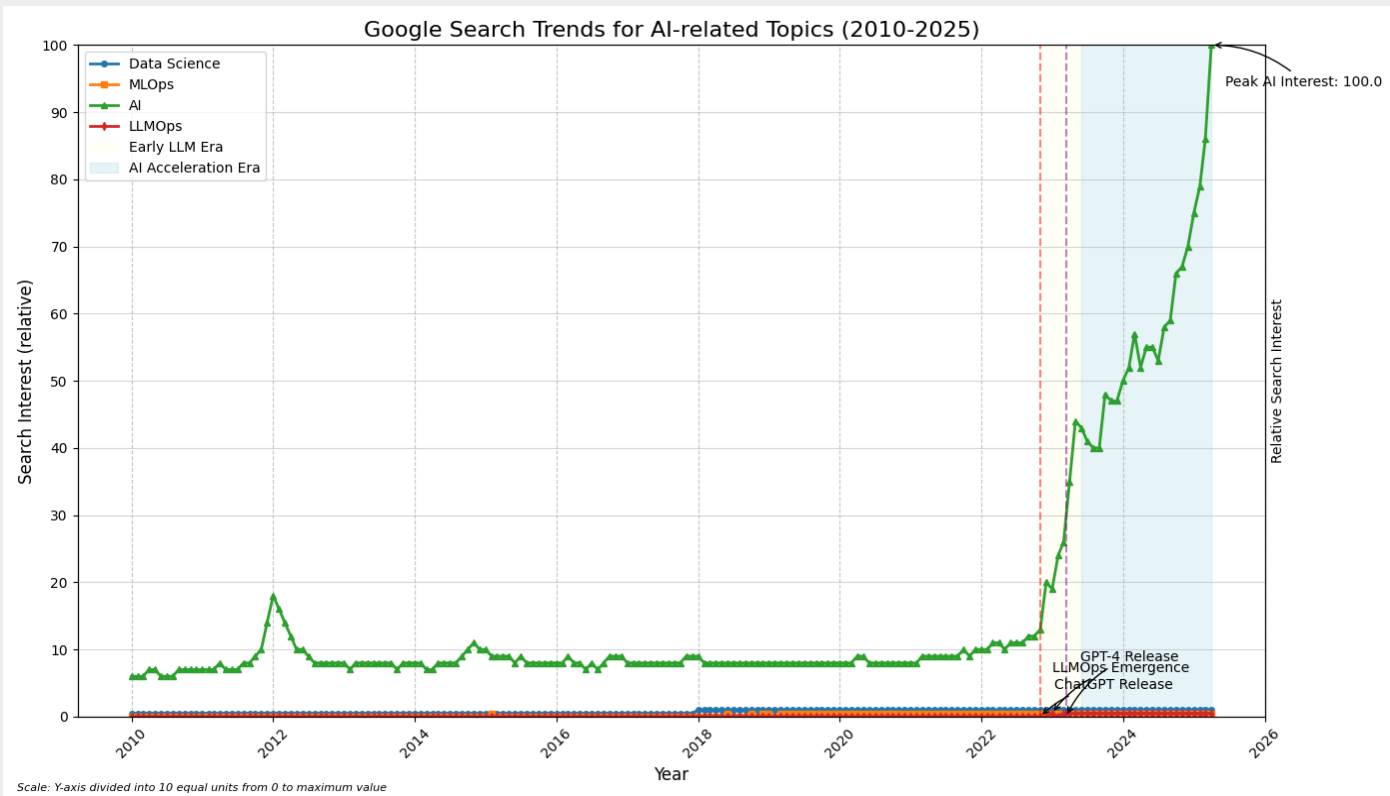


AI4



DevOps vs MLOps

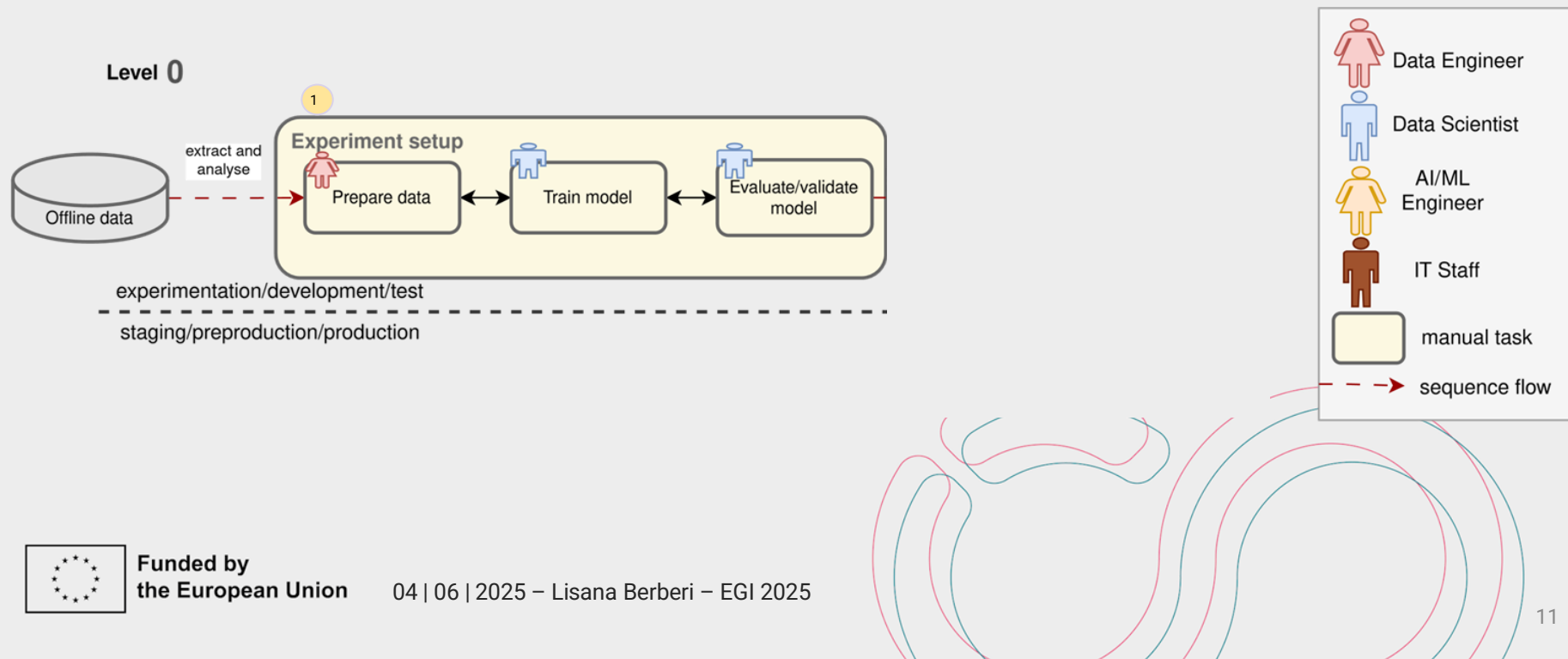




AI4 | eosC MLOps components

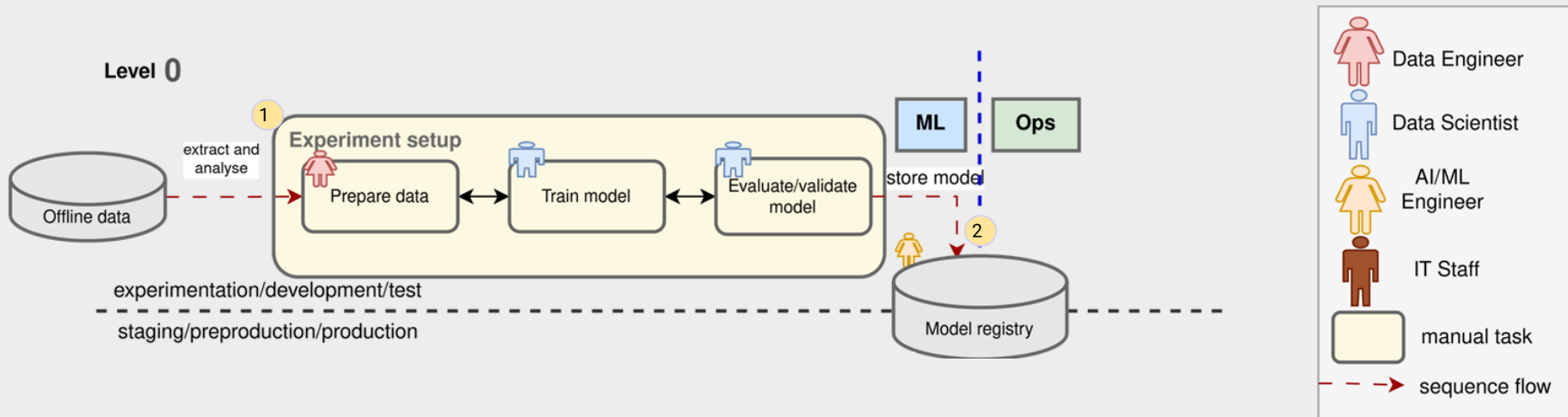
Adapted from Google

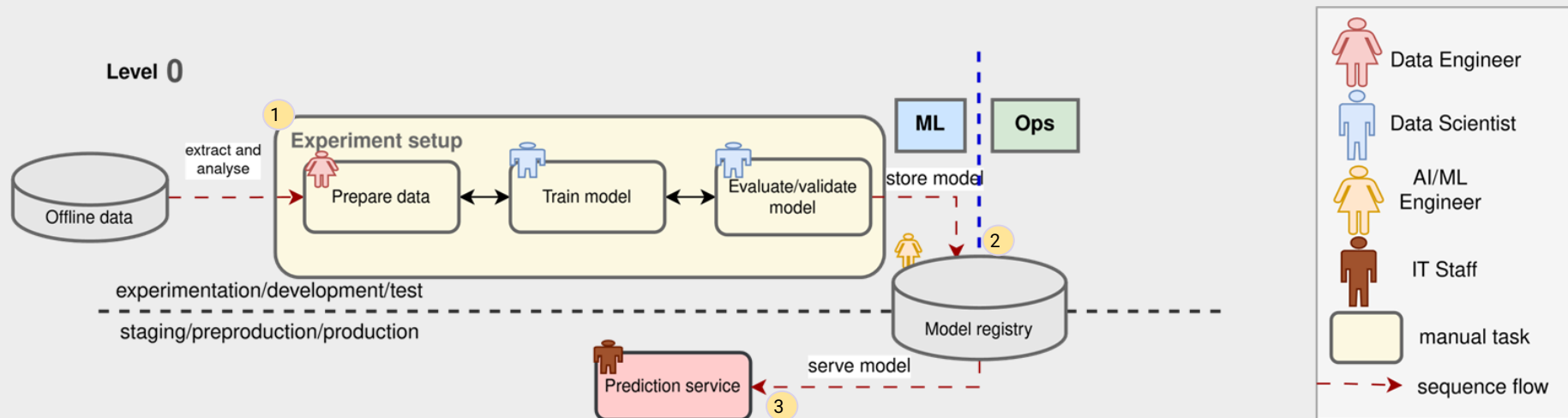
([MLOps: Continuous delivery and automation pipelines in machine learning](#))

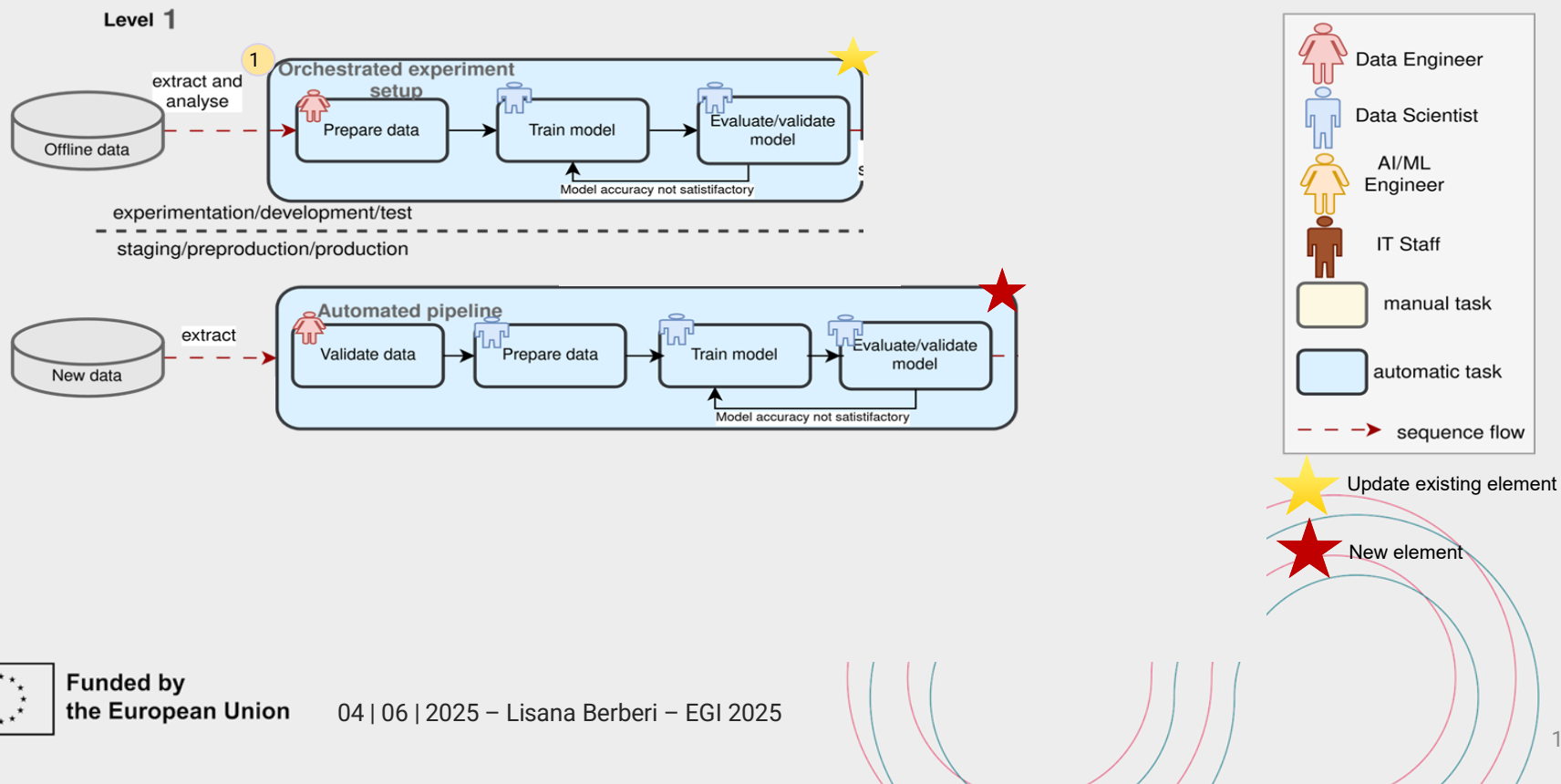


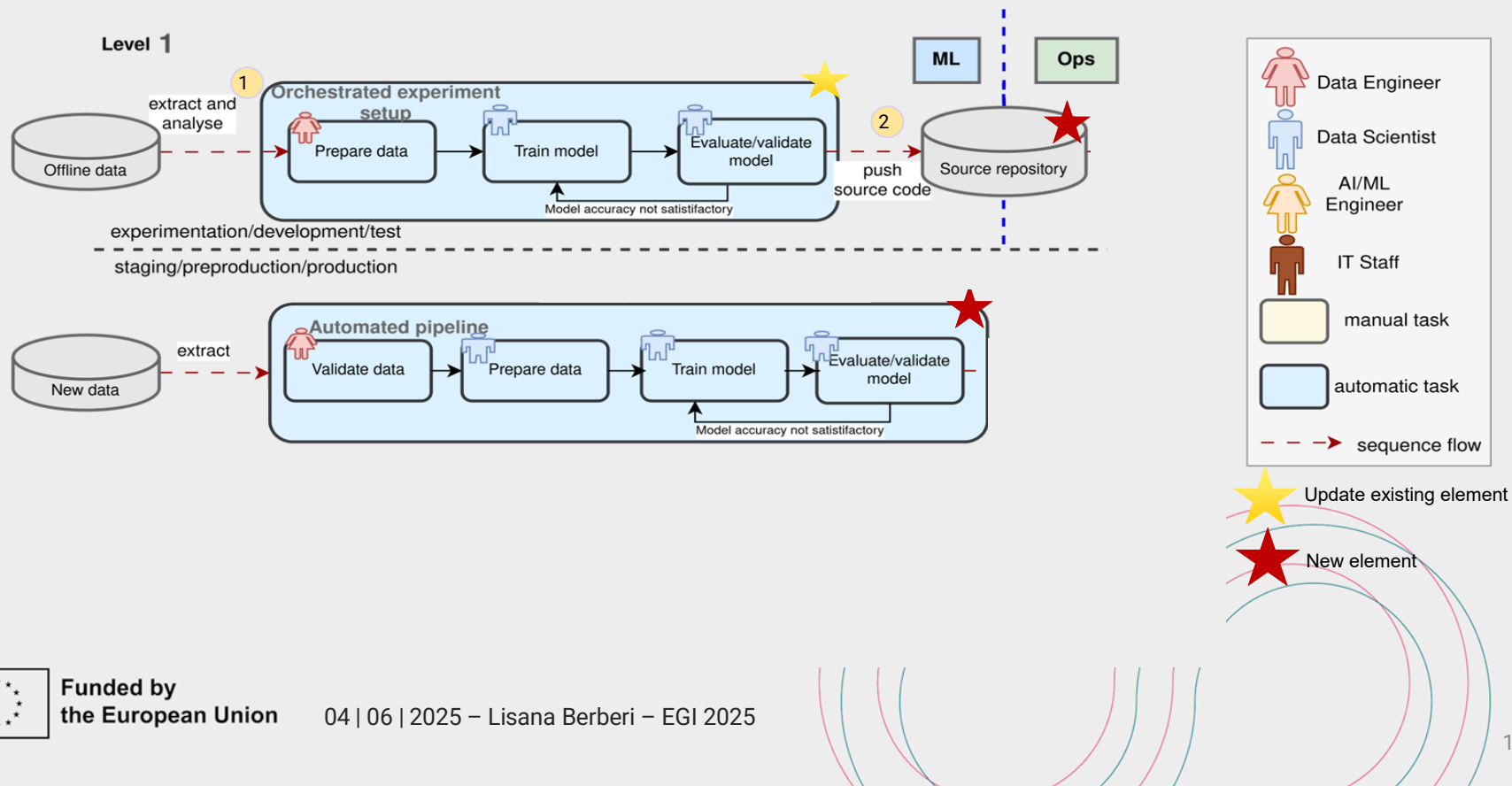
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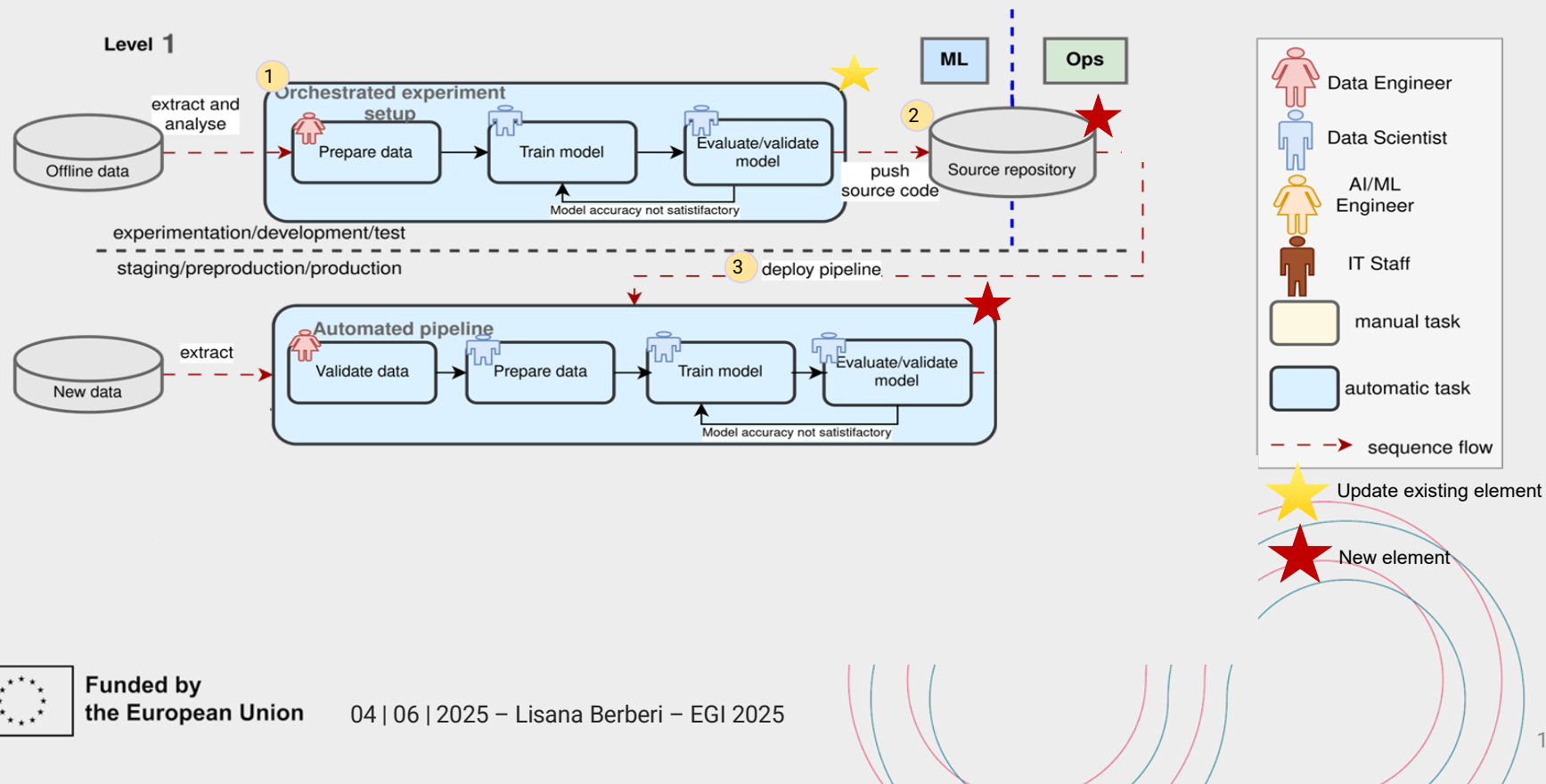
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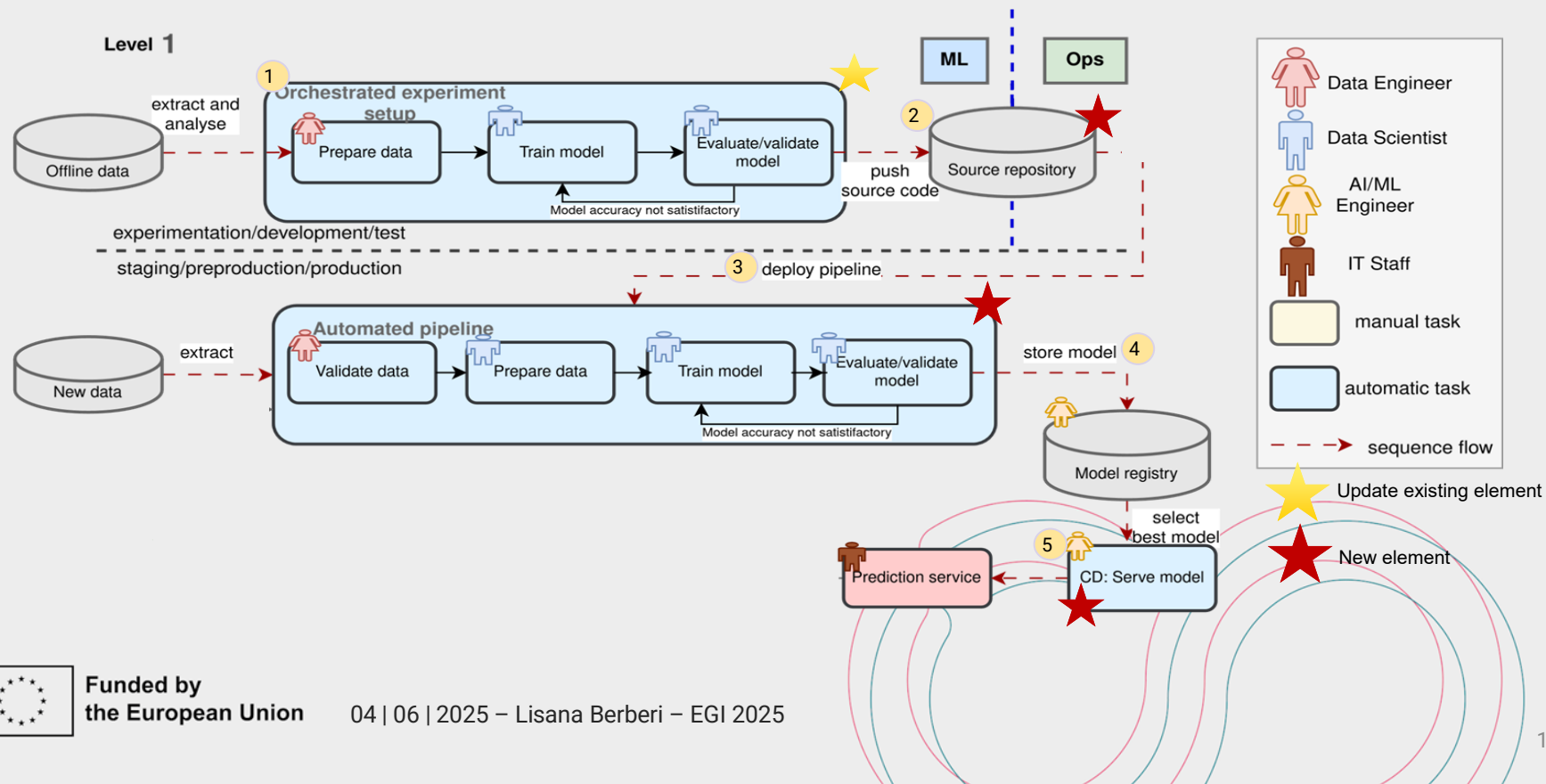


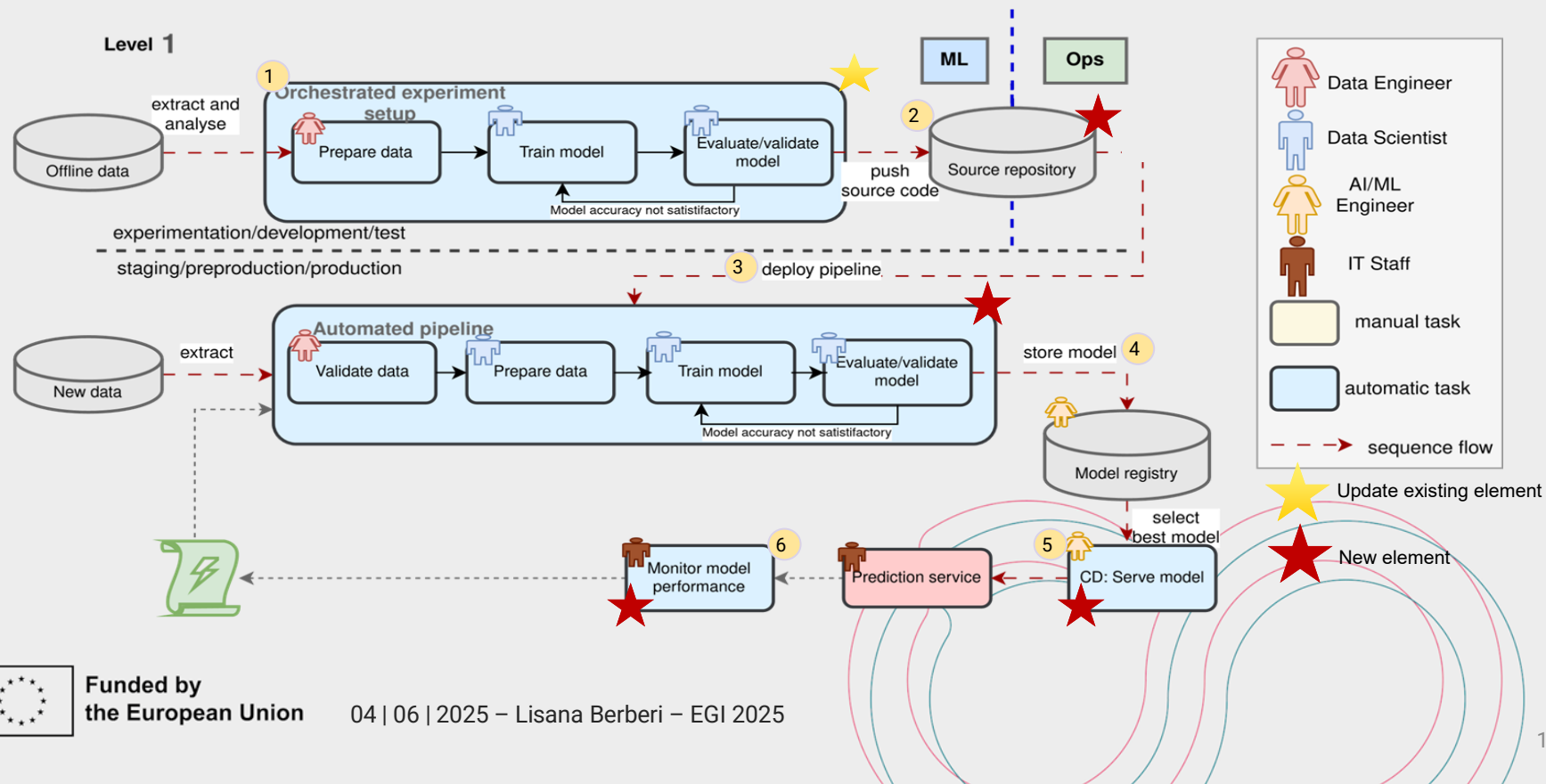




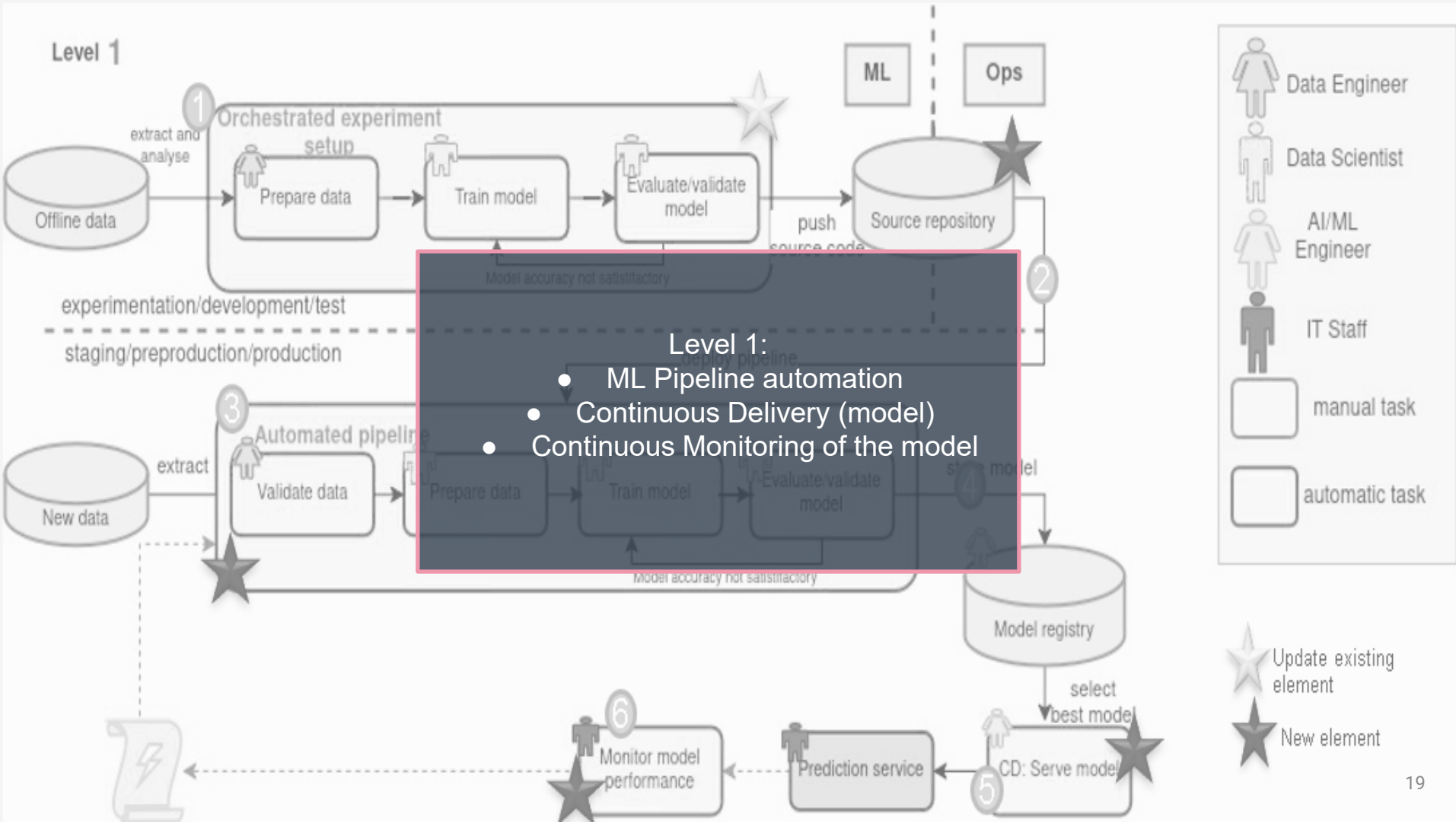




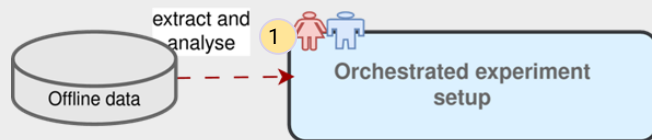




Level 1

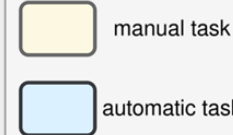
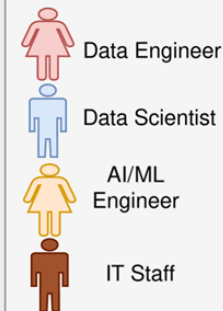
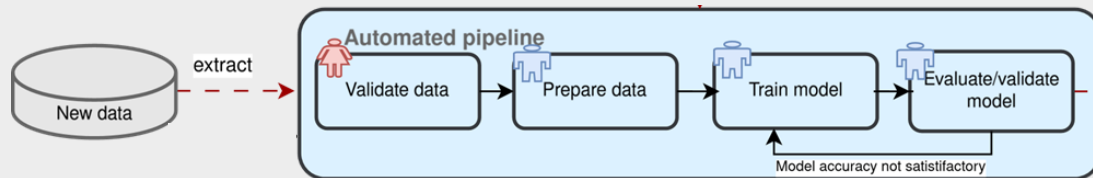


Level 2

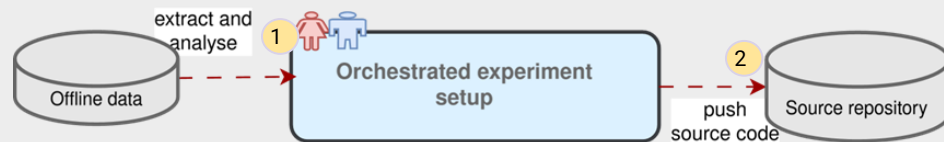


experimentation/development/test

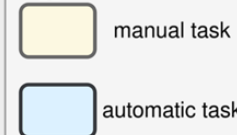
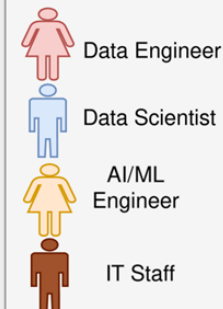
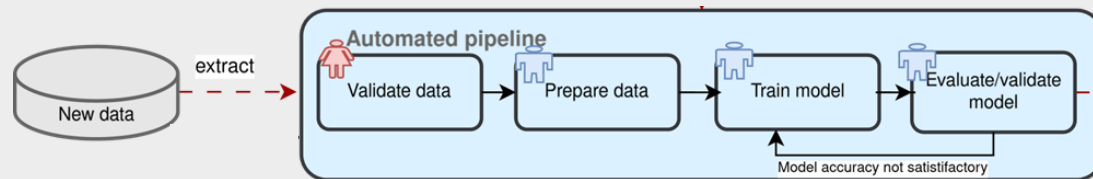
staging/preproduction/production



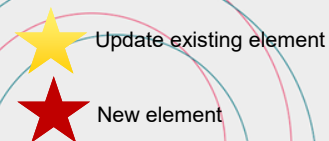
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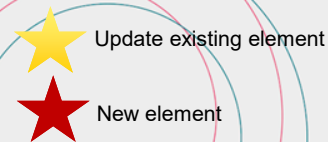
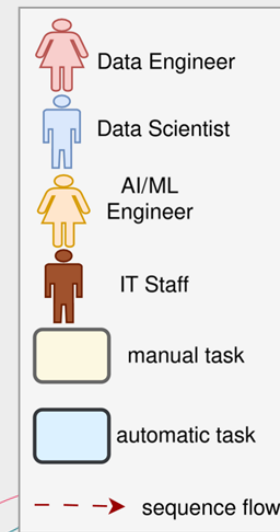
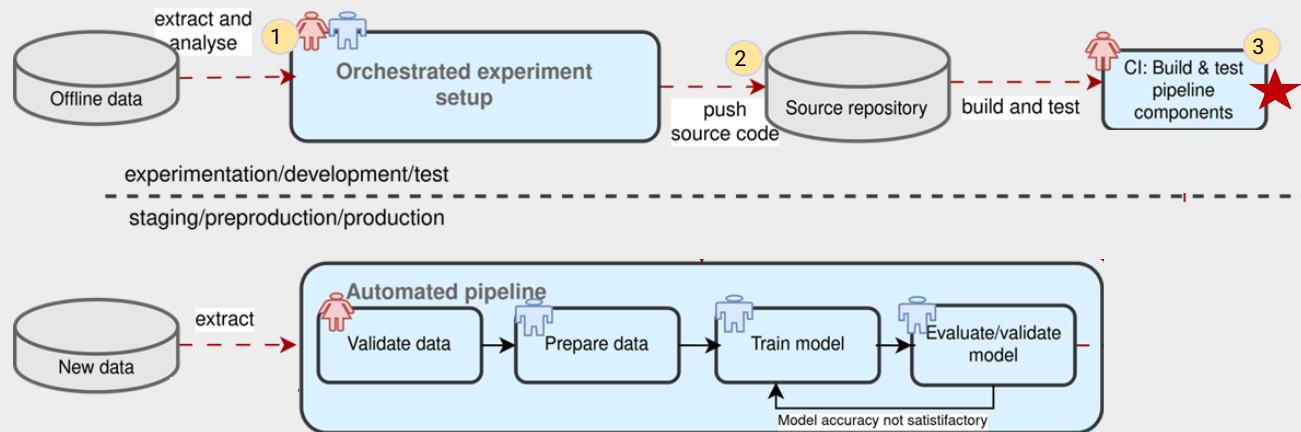
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staging/preproduction/production



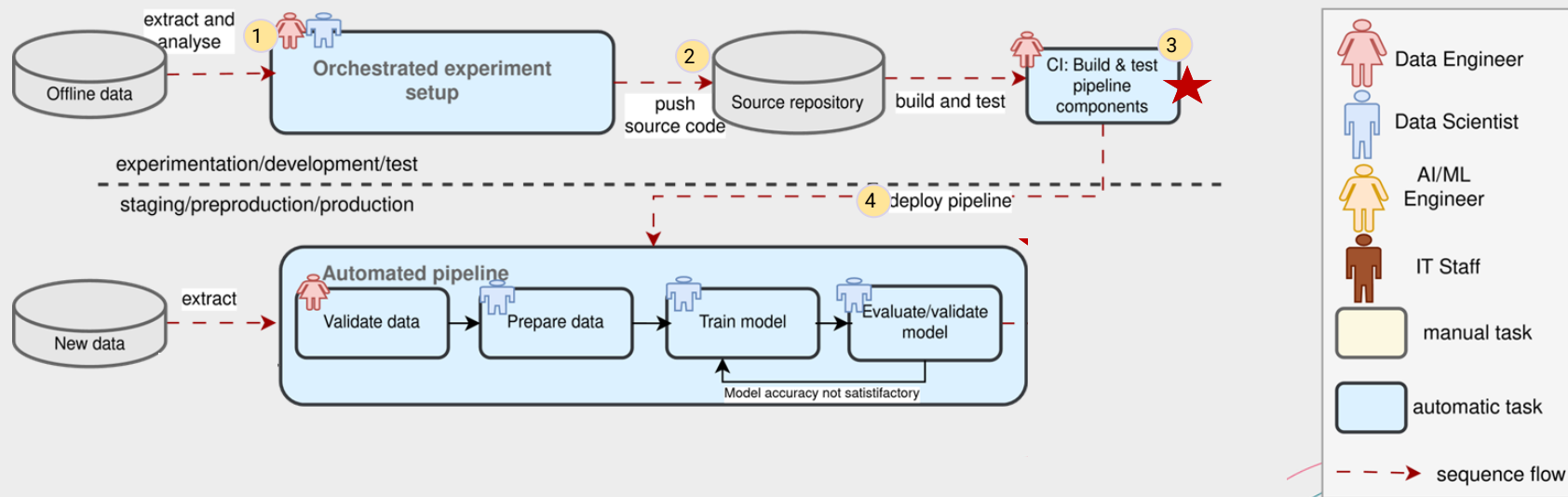
sequence flow (red dashed arrow)



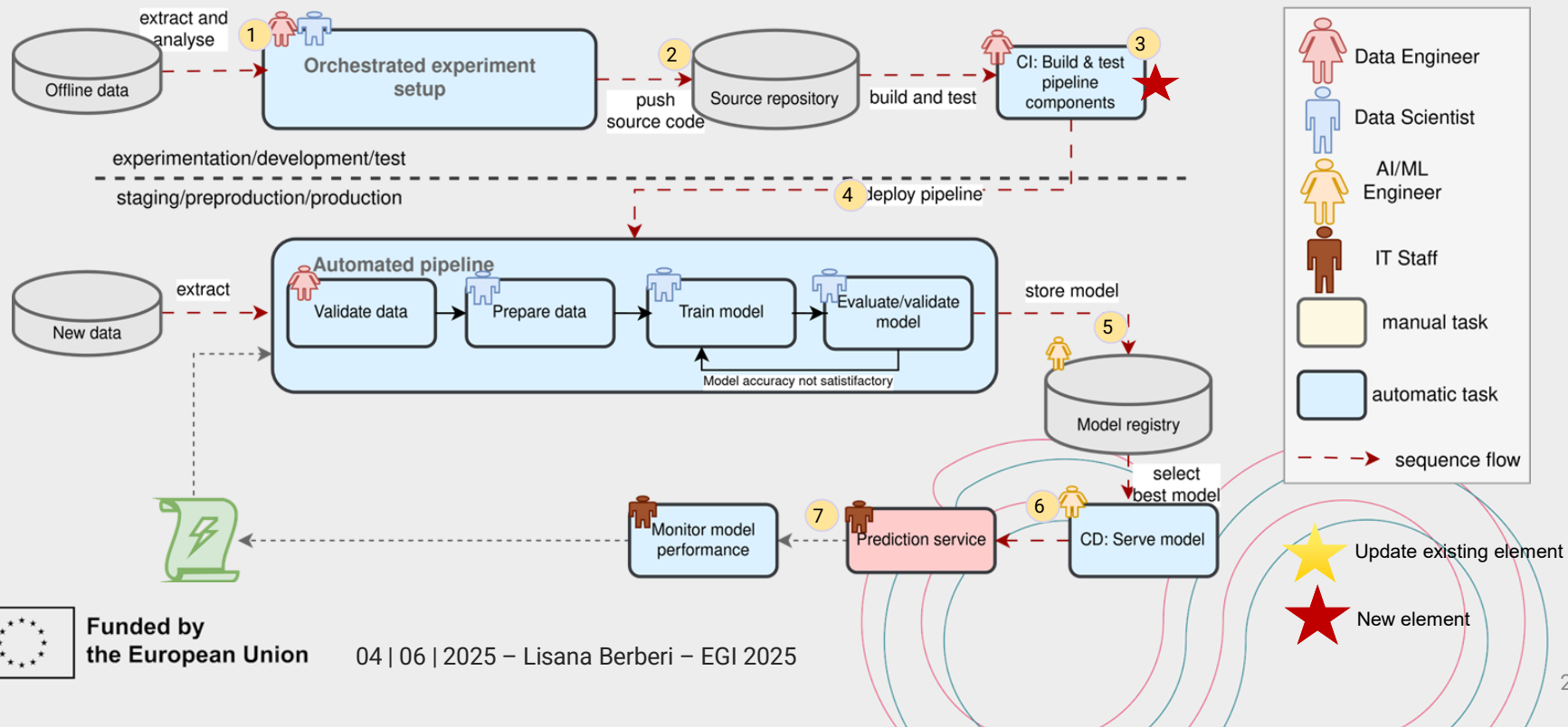
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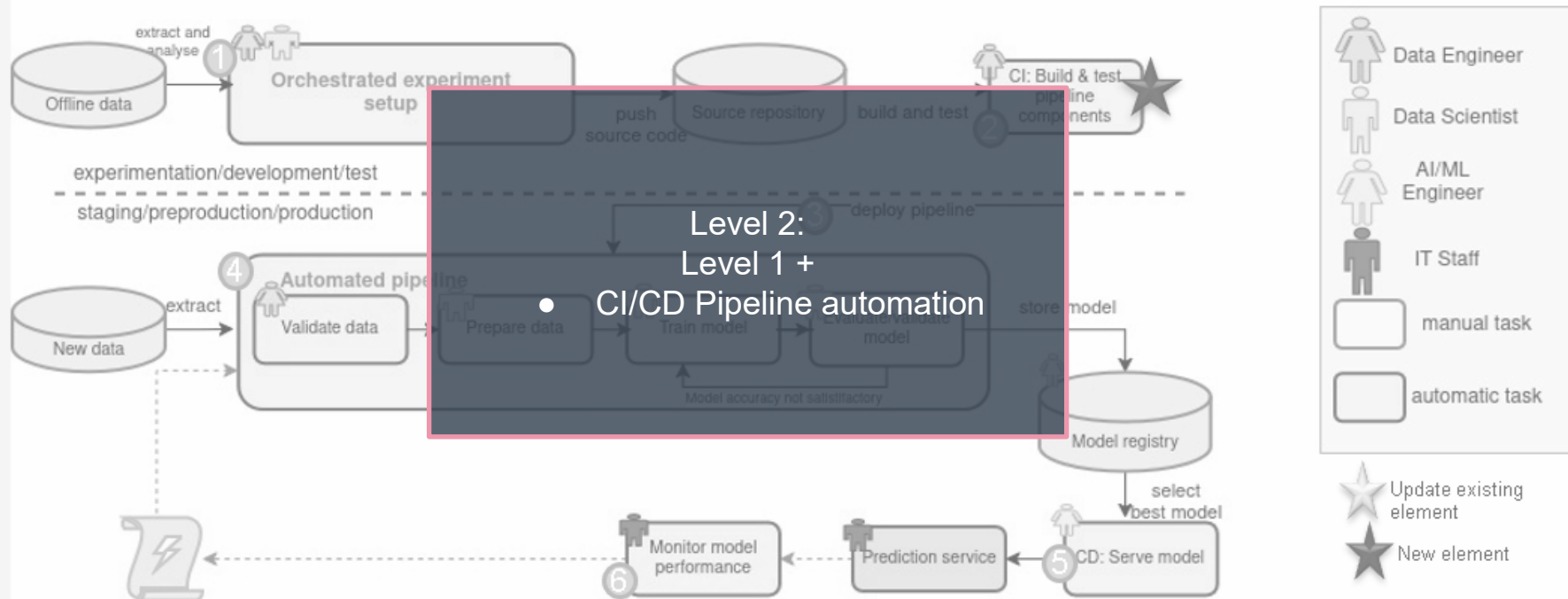
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Level 2



Level 2



| MLOps Platform/Tools |

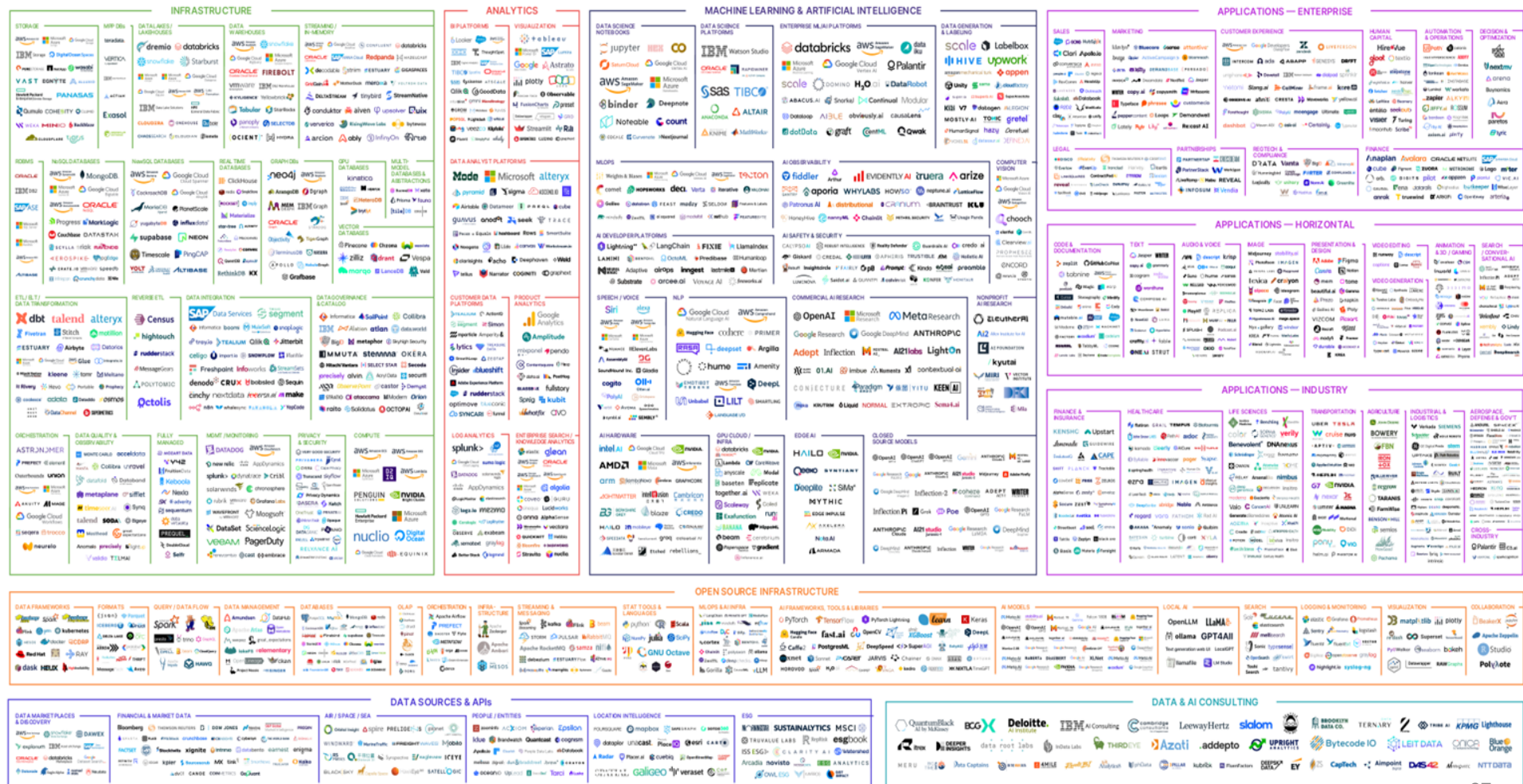


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THE 2024 MAD (MACHINE LEARNING, ARTIFICIAL INTELLIGENCE & DATA) LANDSCAPE



- Three-step evaluation framework [[L. Berberi et al. \(2025\)](#)]



Step 1



Feature/ Capability Analysis

- Evaluated 16 MLOps open source platforms across core capabilities.
- 10 capabilities drawn from the AI-Infrastructure Report (2023) and academic literature.
- Focus: Experiment tracking, model development, orchestration etc.



- Three-step evaluation framework [L. Berberi et al. (2025)]

Step 1



Feature/ Capability Analysis

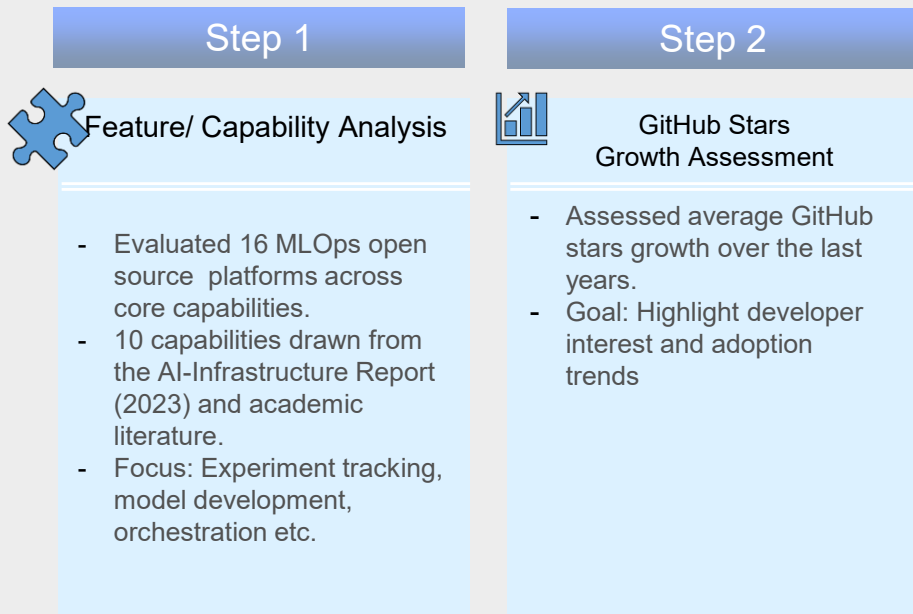
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Table 3 Notable open-source MLOps platforms

Product	GitHub Stars	O Orchestration	DT Distributed Training	CM Code Management	MDV Model Development	MTV Model Testing/-Validation	MI Model Inference	MDP Model Deployment	ETMS Experiment Tracking and Meta-data Store	DVM Data Versioning and Management	MPM Model Performance Monitoring	Full Score	Partial Score
MLflow	19 K			✓			✓✓	✓✓	✓✓			30%	10%
Prefect	17.7 K	✓✓		✓						✓✓		20%	10%
Kubeflow	14.5 K	✓✓	✓✓	✓	✓✓	✓	✓✓	✓✓	✓✓			60%	20%
Dagster	12 K	✓✓					✓	✓✓		✓✓		30%	10%
W&B (WB)	9.2 K	✓	✓✓	✓✓	✓✓	✓✓		✓	✓✓	✓✓	✓✓	70%	10%
MetaFlow	8.3 K	✓✓	✓✓	✓					✓✓	✓	✓	20%	30%
Mage	8 K	✓✓					✓✓	✓	✓	✓✓	✓	30%	30%
Pachyderm	6.2 K	✓✓	✓	✓✓	✓✓	✓✓	✓✓	✓	✓	✓✓		60%	30%
Flyte	5.8 K	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓		90%	0%
ClearML	5.7 K	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	100%	0%
Seldon core	4.4 K	✓✓				✓✓	✓✓	✓✓	✓		✓✓	50%	10%
ZenML	4.2 K	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	100%	0%
Polyaxon	3.6 K	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓	✓	✓✓	90%	10%
TFX	2.1 K	✓✓	✓✓	✓✓	✓✓	✓	✓✓	✓✓	✓	✓✓		70%	20%
MLLeap	1.5 K	✓✓					✓✓	✓✓			✓	30%	10%
MLRun	1.5 K	✓✓	✓✓	✓	✓✓	✓	✓✓	✓✓	✓✓	✓✓	✓✓	80%	20%



- Three-step evaluation framework [[L. Berberi et al. \(2025\)](#)]



- Three-step evaluation framework [L. Berberi et al. (2025)]

Step 1



Feature/ Capability Analysis

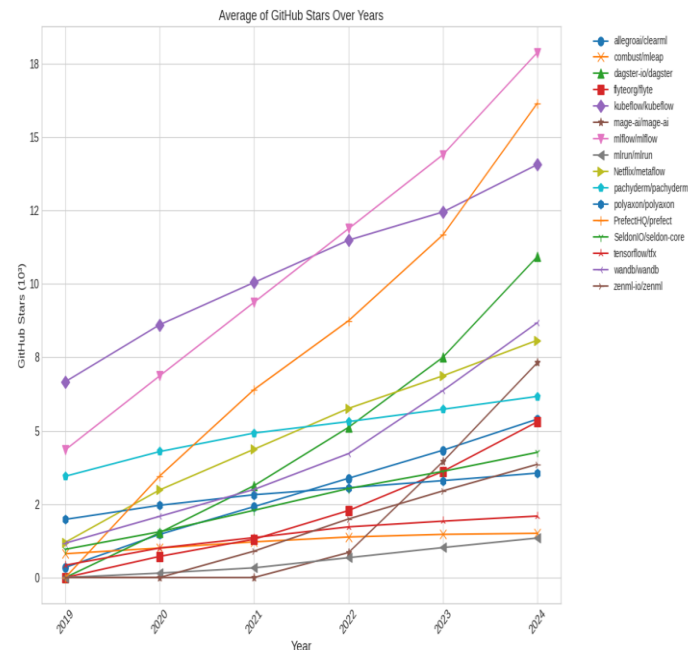
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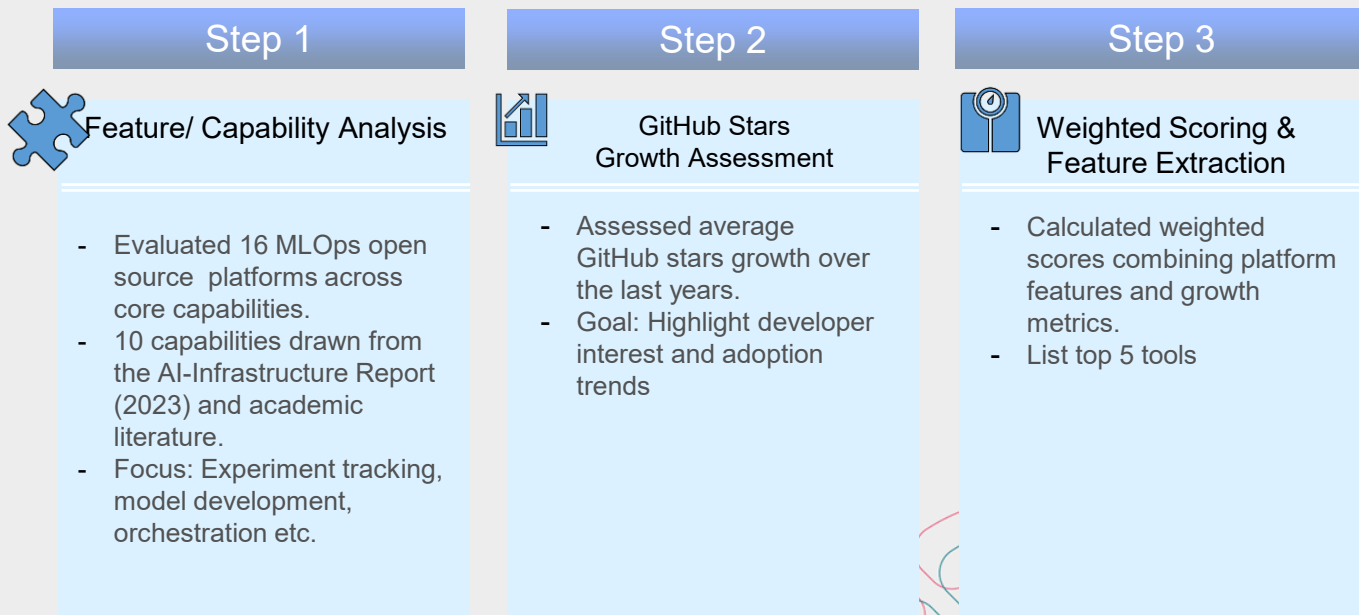


GitHub Stars Growth Assessment

- Assessed average GitHub stars growth over the last years.
- Goal: Highlight developer interest and adoption trends



- Three-step evaluation framework [[L. Berberi et al. \(2025\)](#)]



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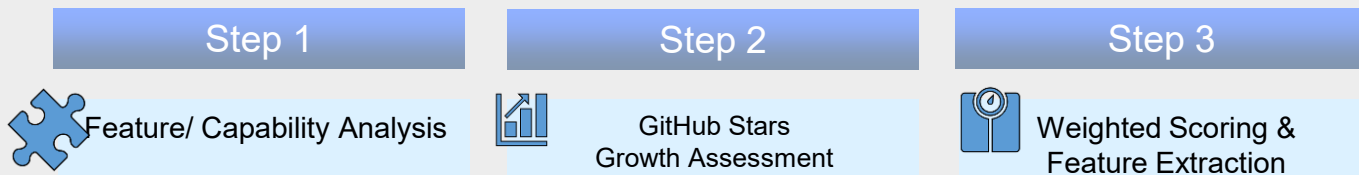


Table 4 The weighted score for each product

Product	Weight (w_i)	Feature-Score	Weighted-Score
Kubeflow	8.89	7	62.21
WandB (W&B)	4.79	8	38.30
MLflow	10.00	3.5	35.00
Pachyderm	4.34	7.5	32.55
ClearML	2.94	10	29.38
Flyte	2.98	9	26.82
Polyaxon	2.65	9.5	25.22
ZenML	2.20	10	22.01
Dagster	6.13	3.5	21.44
Prefect	8.35	2.5	20.87
Mage	3.98	4.5	17.90
Metaflow	4.11	3.5	14.40
Seldon core	2.59	5.5	14.23
TFX	1.30	8	10.40
MLRun	1.00	9	9.00
MLEap	1.32	3.5	4.61

- Three-step evaluation framework [L. Berberi et al. (2025)]



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Product	Weight (w_i)	Feature-Score	Weighted-Score
Kubeflow	8.89	7 <small>Kubernetes bound</small>	62.21
WandB (W&B)	4.79	8 <small>limited features in the free version</small>	38.30
MLflow	10.00	3.5	35.00
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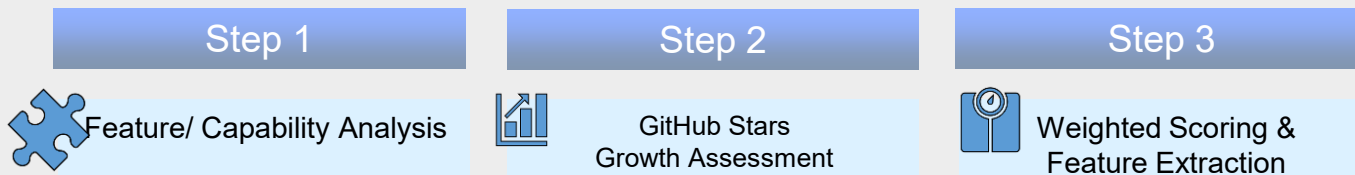


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| Model Performance Monitoring |



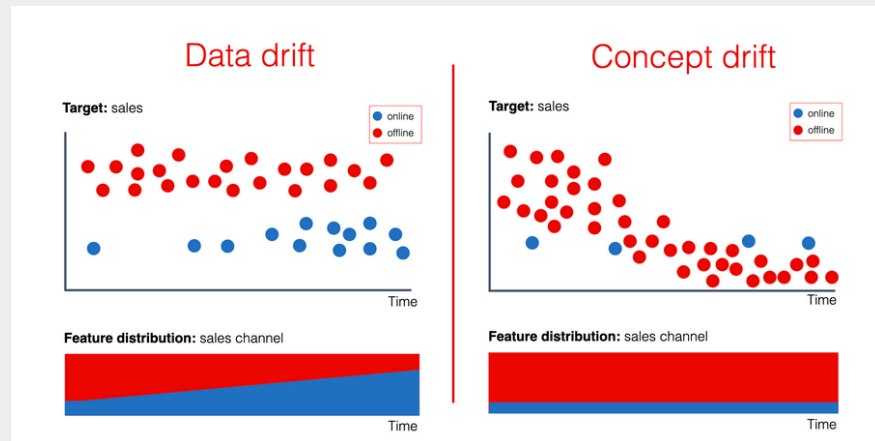
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Drift frameworks comparison

- Data drift is a shift in the distributions of the ML model input features.
- Concept drift is a change in input-output relationships.
- **Different modes of execution:**
 - streaming: data arrives sequentially, e.g. online monitoring
 - batch: full dataset available at time of test, e.g. offline model evaluation
- Frameworks:
 - [Frouros](#)
 - [River](#)
 - [Evidently](#)
 - [NannyML](#)
 - [Alibi-Detect](#)
- Dataset:
 - Energy Data
 - Heating energy consumption data from educational buildings (schools/universities)



Data drift vs concept drift (source EvidentlyAI)



Drift frameworks comparison

- original repo D3bench: <https://github.com/mohamedyd/D3Bench>

- Publication:



Scan me!

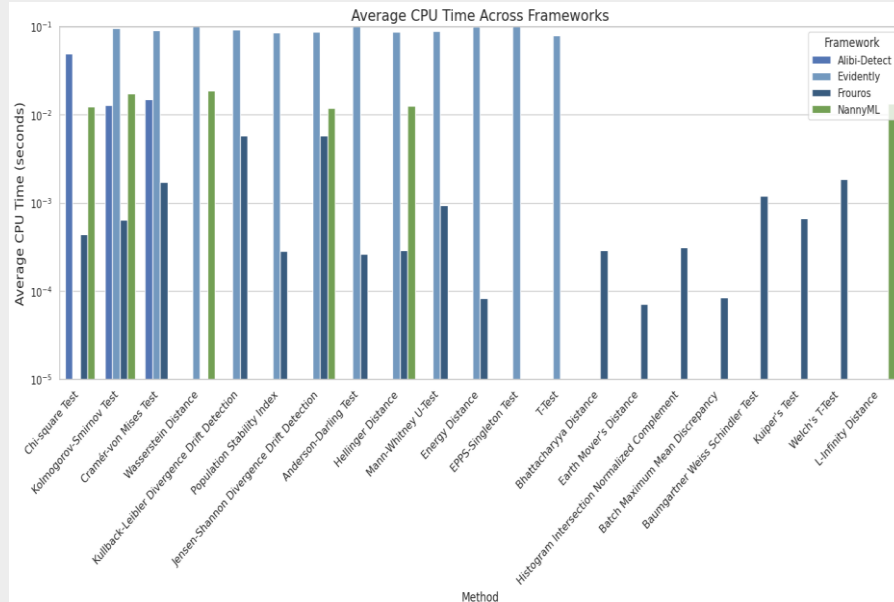
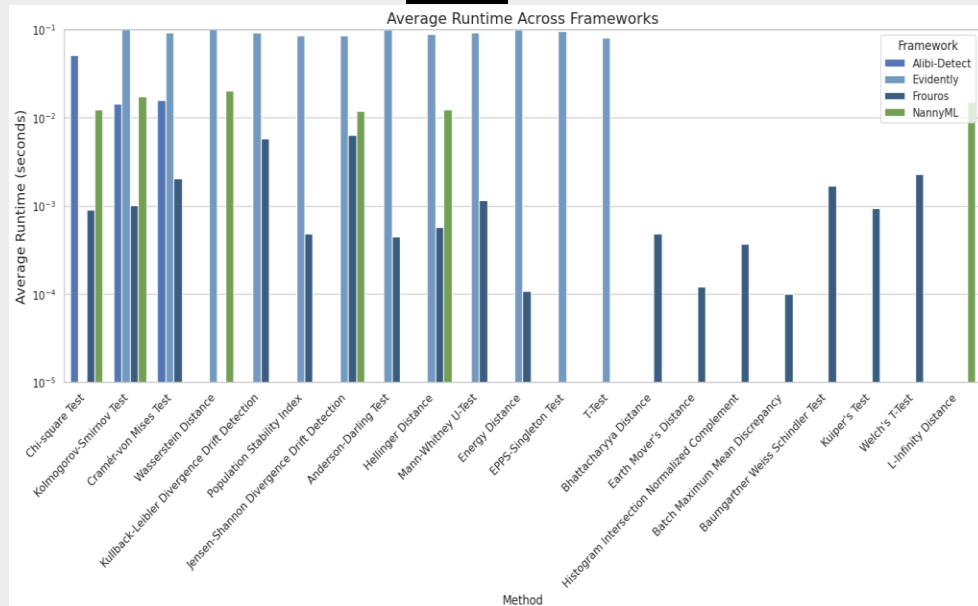
- Extended repo:

<https://github.com/BorjaEst/D3Bench/tree/dev/results>

- Poster:

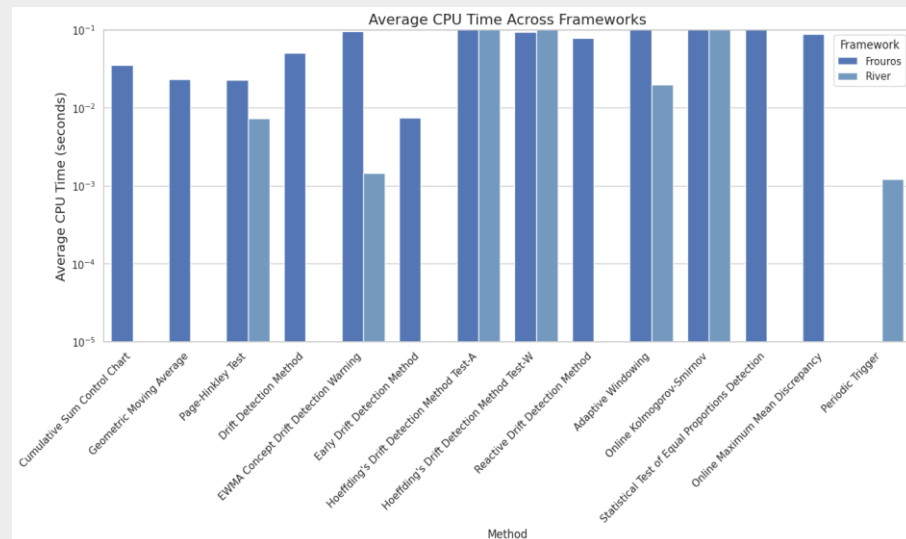
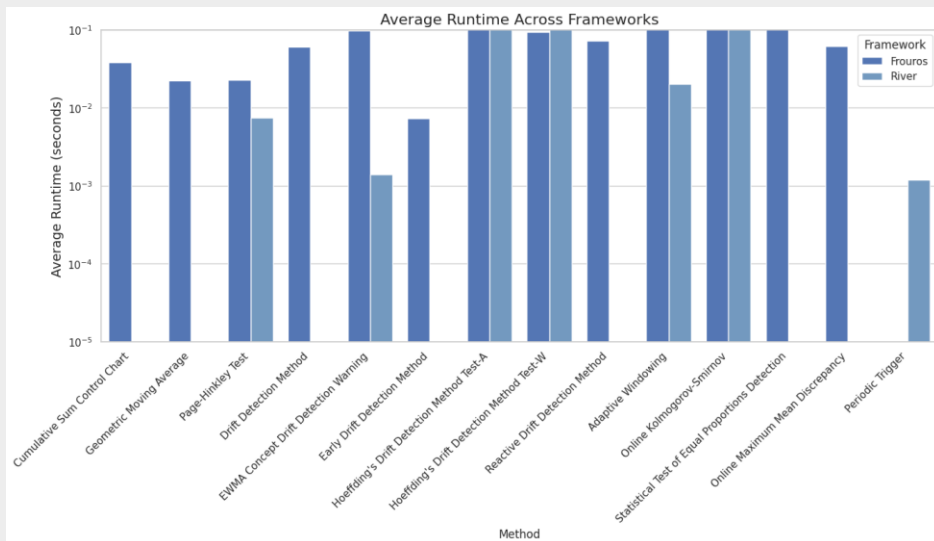


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Drift frameworks comparison

- Tool evaluation results:



Online Concept Drift Detection methods



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| Key takeaways |



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AI4 | eosc Key takeaways

- MLOps is critical for scaling machine learning beyond experimentation into production.
- MLOps maturity levels help assess and plan ML lifecycle automation.
- Evaluate state-of-the-art drift frameworks using the Extended D3Bench tool



MLflow cloud



MLflow video-1



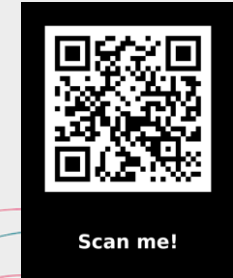
MLflow video-2



AI4EOSC
Dashboard



AI4EOSC MLflow
Docs



D3bench extension



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Reach us!

Thank you for your attention

The AI4EOSC consortium

