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Towards Turning MLOps into a Continuous Learning Process



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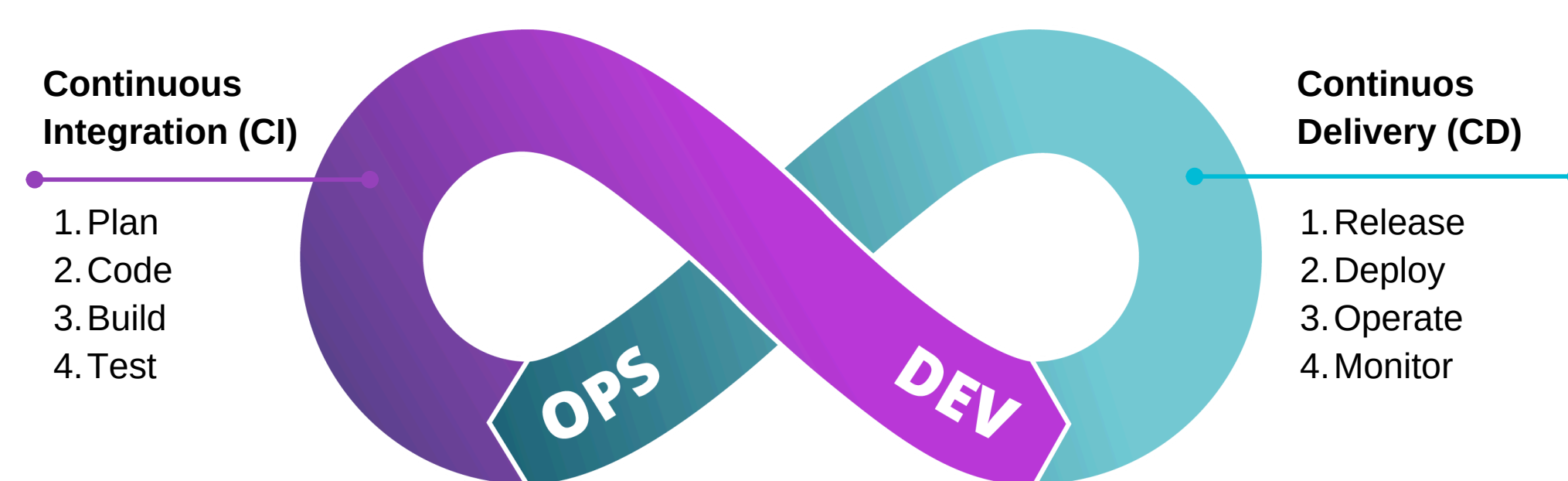
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1- PRELIMINARY KNOWLEDGE

DevOps stands for "Development Operations" and is commonly used in software engineering. The main objective of DevOps is to remove the obstacles that have traditionally divided developers and operational teams. The ultimate goal of DevOps is to provide a set of best practices for the more reliable and swift delivery of software.



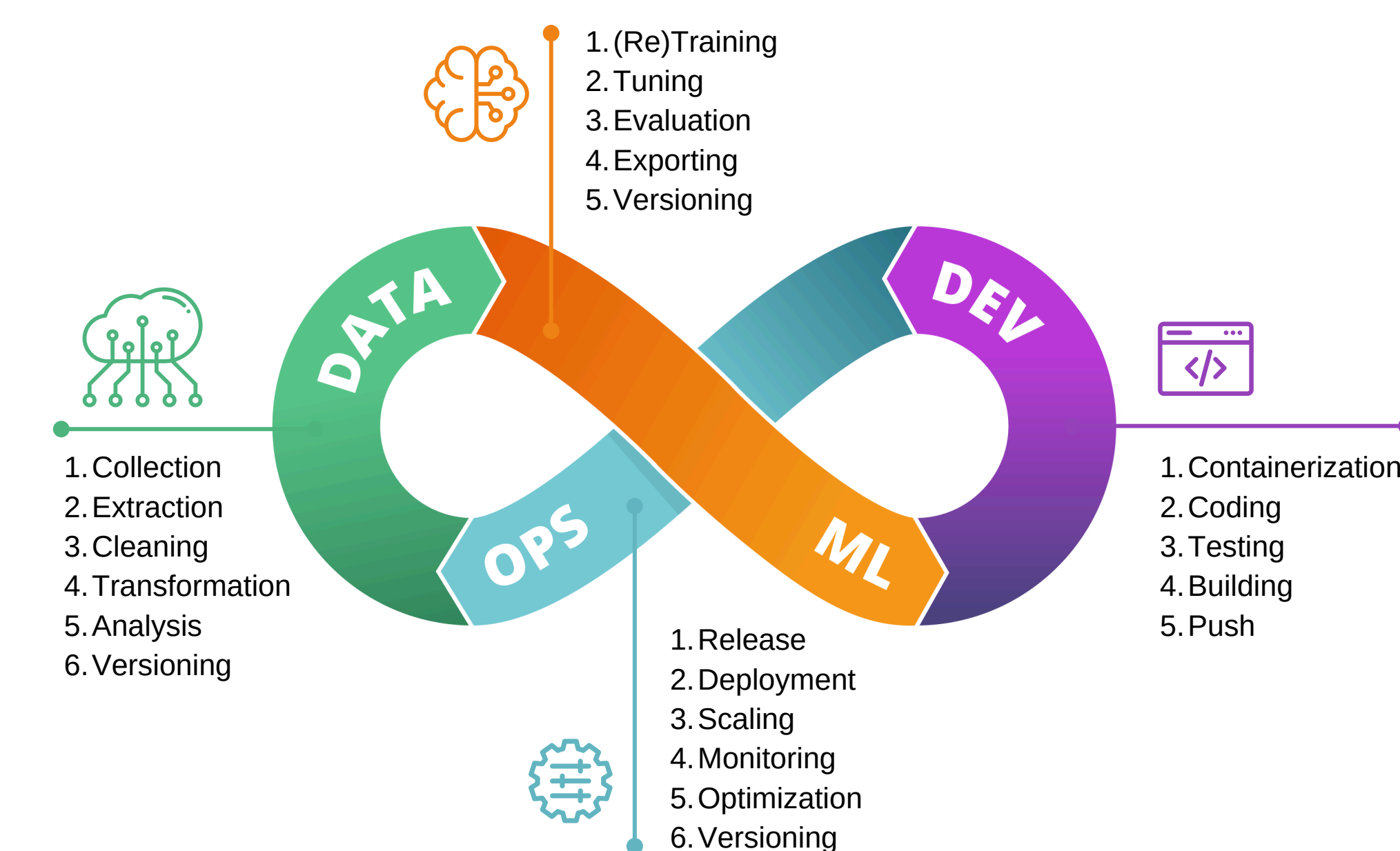
The main pillars of DevOps are: CI and CD.

- **Continuous Integration (CI):** Code updates are regularly merged into a shared repository. Automated testing ensures that code changes adhere to quality requirements before deploying.
- **Continuous Delivery (CD)** builds upon CI by automating the deployment process, enabling teams to consistently and swiftly deliver software upgrades.

2- THE MLOPS RECIPE

MLOps emerged after a 2015 publication by Scully et al [1] about Technical Debt in ML Systems. In a nutshell, MLOps is DevOps applied to Machine Learning models. We adopt the following recipe for the MLOps process [2]:

MLOps = Data + ML + Dev + Ops.



In addition to CI/CD principles of DevOps, MLOps promotes:

- **Continuous Training (CT):** MLOps involves the regular retraining of Machine Learning models to ensure they stay accurate and updated when new data is received.
- **Continuous Monitoring:** Through feedback loops, ML models are monitored in production. Alerts are sent to engineers when drift occurs to refine the code.
- **Model & Data Versioning:** With MLOps, both ML models and data are versioned, ensuring reproducibility.

3- INSIGHTS FROM THE LITERATURE

A - MLOps Challenges

Based on our review, we observe some challenges in the current MLOps literature:

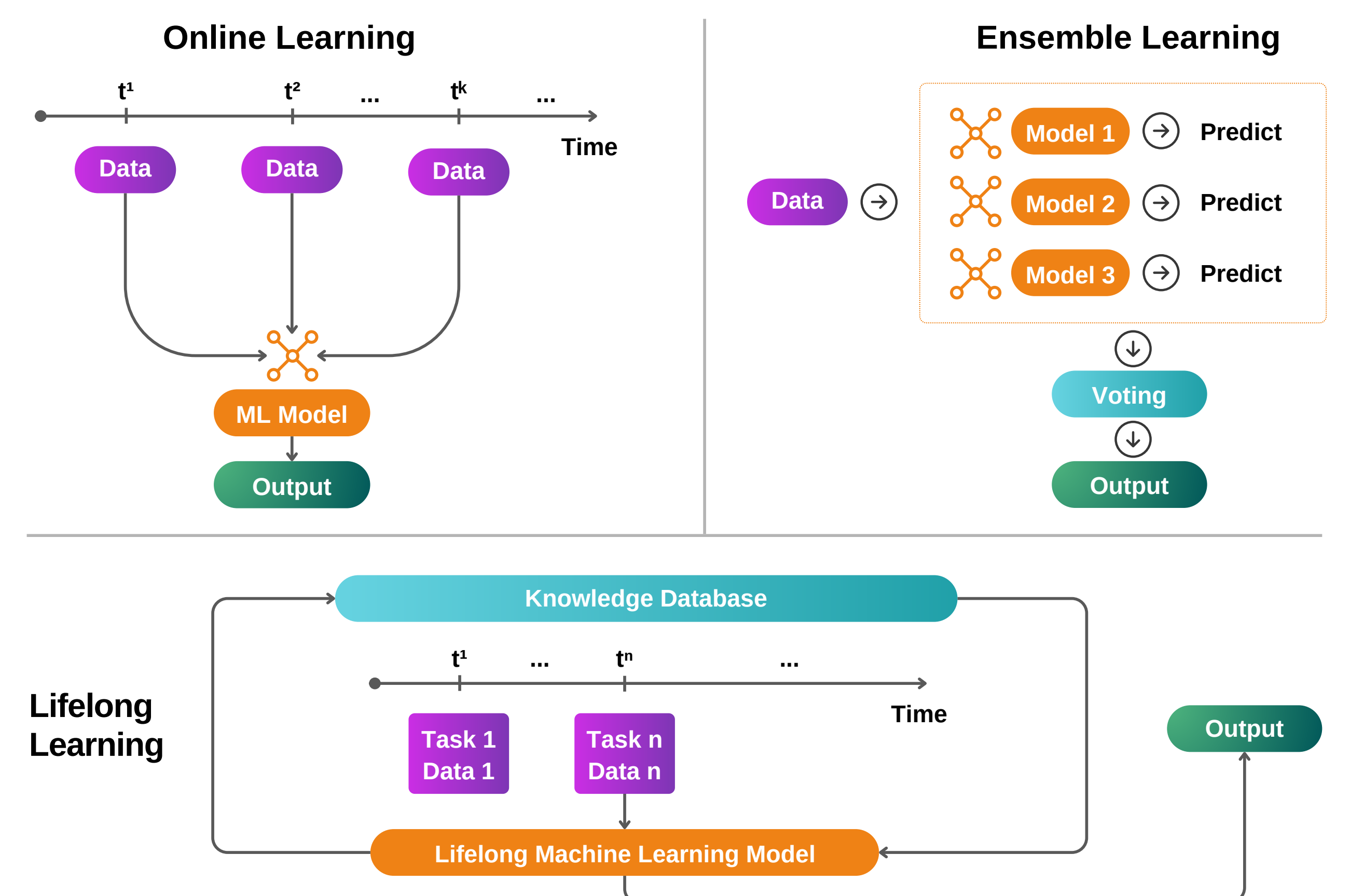
- **Data Versioning:** Although several studies emphasize the Data Versioning [3-6] component within MLOps processes, there are still some studies [7-10] that fail to mention Data Versioning in their methodologies.
- **Data Drift Handling:** Data drift is addressed in only a limited number of studies [3,6]. When it is managed, the process is typically automated.
- **Concept Drift Handling:** Researchers recognize the challenges posed by Concept Drift in MLOps. Several studies have focused on addressing this issue through human intervention [3-5]. However, there is a growing interest [7-9] in minimizing human involvement.

Most literature studies indicate that most MLOps components are well implemented. However, the components mentioned above face significant challenges that affect their effective integration in MLOps and the automation of its processes.

B - Machine Learning Paradigms

Alongside the advancement of MLOps, various ML paradigms emerge that can effectively address the numerous challenges encountered in Machine Learning [11]. Based on our review, the most relevant ones are described below.

- **Online Learning:** The "learn-as-you-go" allows models to learn incrementally, processing one instance at a time and updating their parameters promptly.
- **Ensemble Learning:** The overall prediction is determined by a voting process among the weighted outcomes of several independent individual models.
- **Lifelong Learning:** It mimics human learning and retains knowledge. The learning outcomes from the training process are collected and integrated.



Paradigm vs ML Challenges Summary Table

| | Optimized Performance | Concept Drift Handling | Continuous Data Flow | Noisy Data |
|-------------------|-----------------------|------------------------|----------------------|------------|
| Lifelong Learning | ● | ● | ● | ● |
| Online Learning | ● | ● | ● | ● |
| Ensemble Learning | ● | ● | ○ | ○ |

● Yes: the paradigm effectively handles the challenge in question. ○ No: the paradigm does not handle the challenge in question.

Research on these ML paradigms can advance MLOps since they address some ML challenges related to deploying and managing ML models in production.

4- OPEN QUESTIONS

We introduce a new pillar in our work: Continuous Learning (CL). CL represents an iterative process where ML models **gather knowledge from their evolving environment to support new dimensions for model adaptation** (model type, training strategy, learning paradigms, etc.) [12]. Unlike CT, CL is not focused on re-training the model on new data. Instead, CL emphasizes the integration of ML paradigms into the MLOps process to enable models to adapt dynamically.

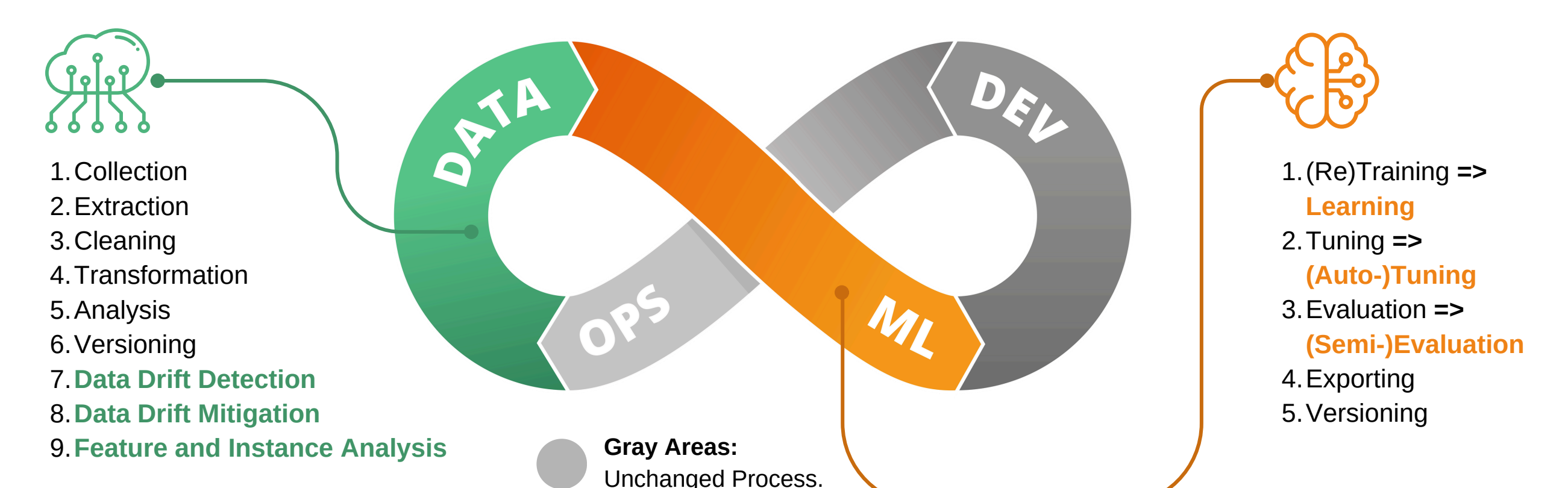
- **Main Question:** With a continuous flow of production data, how Continuous Learning, in an MLOps architecture, will reduce data and concept drifts as well as human intervention while respecting the best practices for developing and deploying Machine Learning models?

From the question above, two sub-questions can be inferred:

- **Sub-Question 1:** Is it always possible to design an automated MLOps process that utilizes the Continuous Learning Paradigms?
- **Sub-Question 2:** Can this same MLOps process, with the Continuous Learning pillar, mitigate the effect of data and concept drift through prevention and control techniques?

5- TOWARDS IMPROVED MLOPS

Incorporating ML paradigms into existing MLOps could establish a **Continuous Learning Process** and mitigate the challenges observed in MLOps literature.



Perspectives:

- Create a data ingestion pipeline.
- Detect data drift using statistical methods and other approaches.
- Mitigate the effects of data drift and concept drift by employing CL paradigms.
- Analyze data attributes and instances to assess their impact on the model in production.
- Save previous decisions and results for future reference.