



Google Cloud
Tech-talk with ML professionals



Design Thinking of MLOps

The Strategic Approach to MLOps

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SENIOR AWS AI ML SOLUTION ARCHITECT AT 



Google Cloud
Gandhinagar



About Me

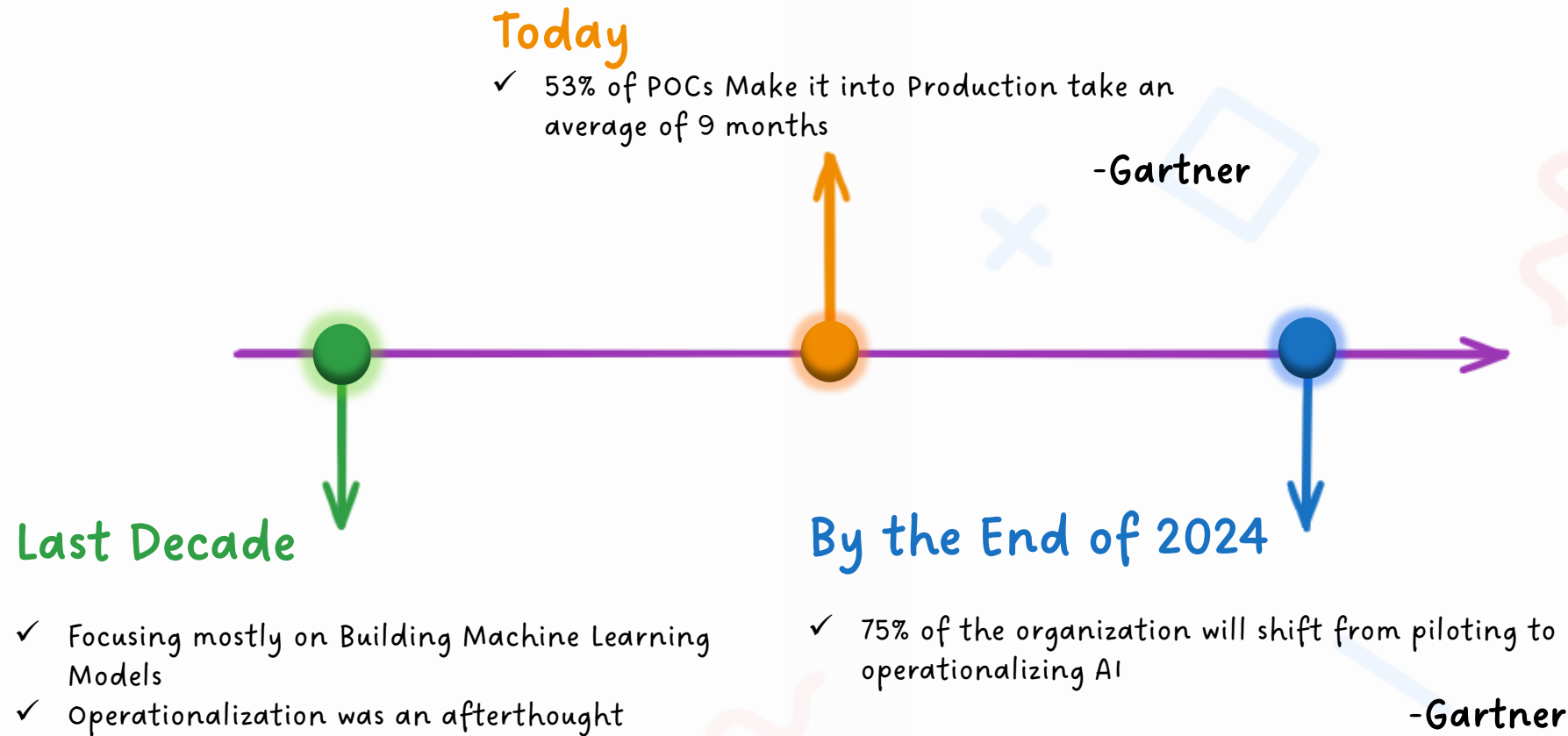
- I am a Sr. AWS AI ML Solution Architect and AI researcher at IBM with this Generative AI Expert, Quantum Machine Learning Practitioner and technical book reviewer(Packt Publication, Manning, Apress).
- I am the author of the Book: **Hands-on Time Series Analytics with Python**, published by Apress Springer Publication
- with over 11+ years of experience in the field of AI, I have a keen interest and ambition to conduct research in the following domains: machine learning Operations, machine learning, deep learning, time series analysis, natural language processing, reinforcement learning, audio analytics, signal processing, sensor technology, the Internet of things, computer vision, spatial-temporal data, satellite time series, quantum computing, etc.
- I published more than 15+ research papers in the field of data science with reputed publications such as IEEE, Taylor, Francis, Springer, etc.
- I holed Rank 3 as a kernel master in Kaggle.
- I am a LinkedIn influencer with more than 85k+ followers.
- I hold a GitHub repository containing more than 25k+ stars and 6k+ followers with a Specialists profile. I am technical book reviewer with review more than 63+ Books in AI technology.
- I am certified with IBM Advanced Badge, more than 15+Quantum Computing Practitioners Challenges, and Quantum Machine Learning Certified from Coding Schools (MIT, University of Oxford Venture, and IBM)



Outline

- Why MLOps?
- Introduction to MLOps
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- MLOps Key Principle and Best Practises
- MLOps at Your Organization
- Hidden Technical debt in ML System
- MLOps Maturity Models
- Books and Research Paper

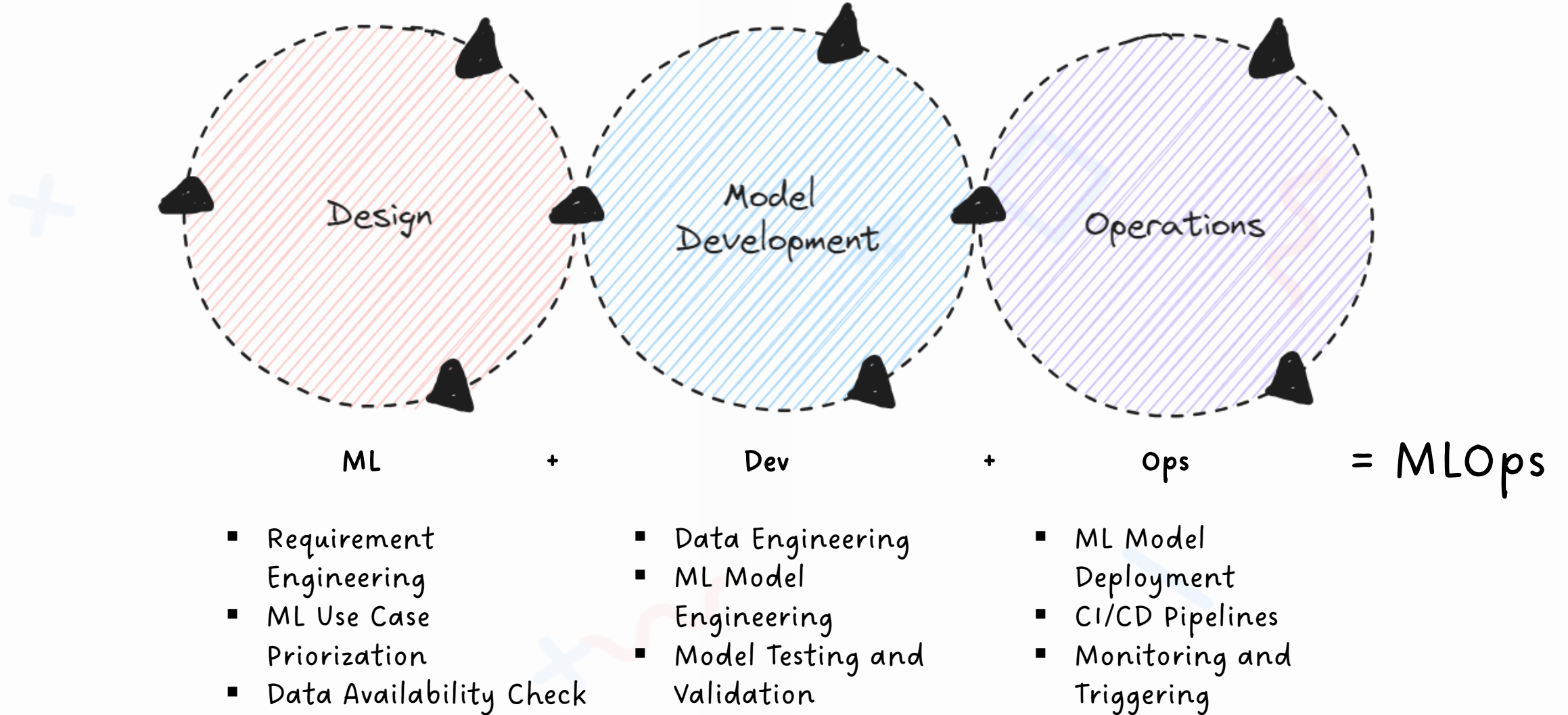
Why MLOps?

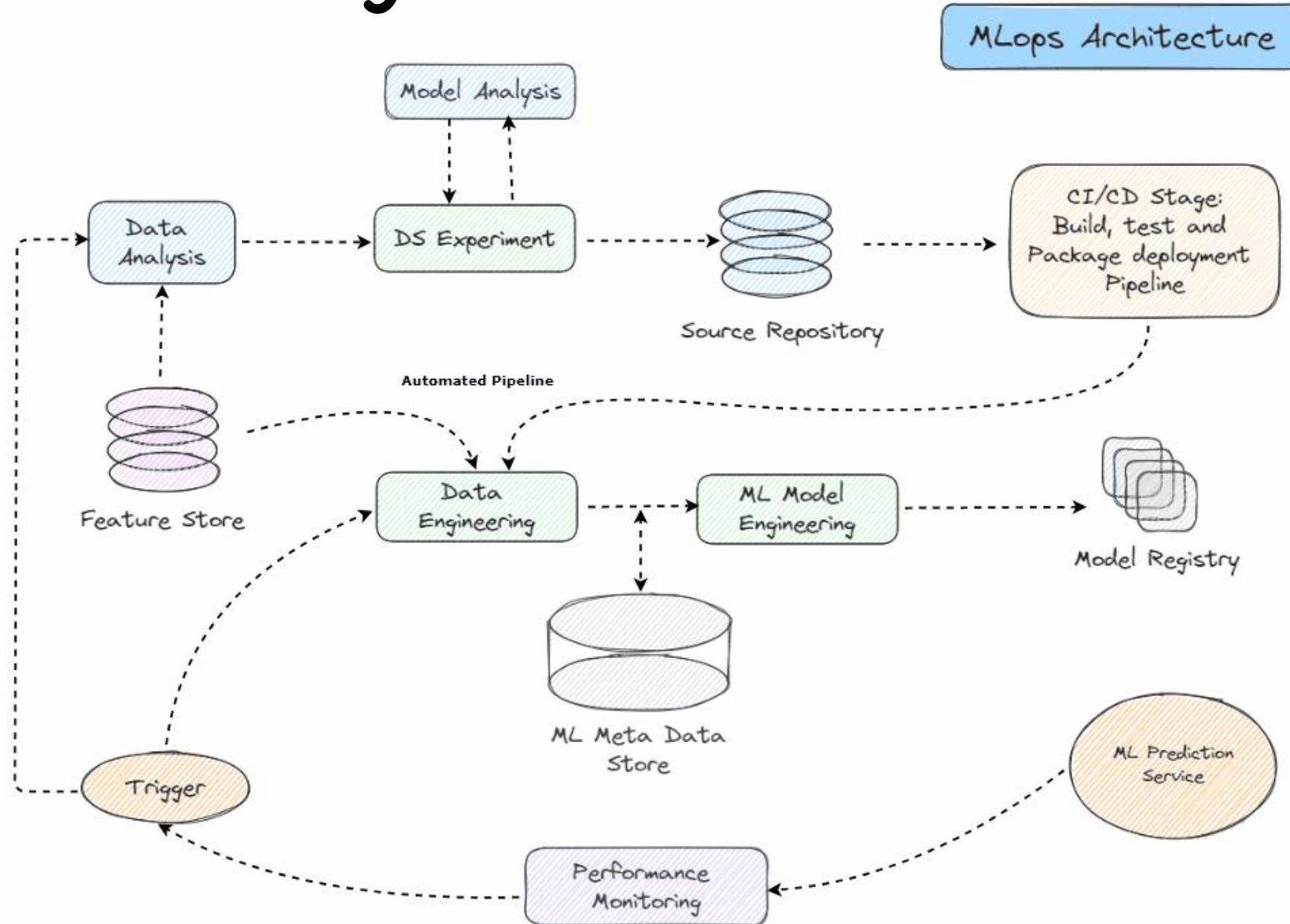


Introduction to MLOps



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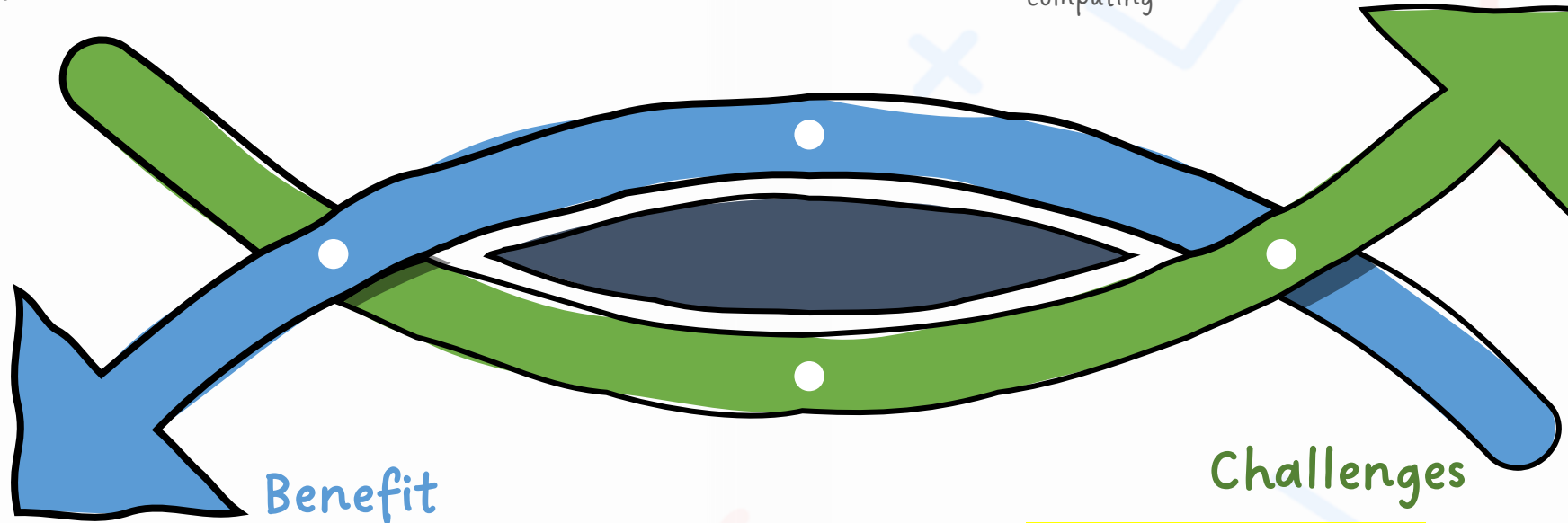
MLOps Benefit and Challenges

Benefit

- **Faster time to market:** MLOps can help to get ML models to production faster, allowing businesses to reap the benefits of their investments in ML sooner.
- **Better governance:** MLOps can help to ensure that ML models are compliant with regulations and ethical guidelines.

Challenges

- **Cultural shift:** Implementing MLOps requires a cultural shift within organizations, as it requires a more collaborative and DevOps-oriented approach to ML development.
- **Technical complexity:** MLOps can be technically complex to implement, as it requires expertise in a variety of areas, such as DevOps, ML, and cloud computing

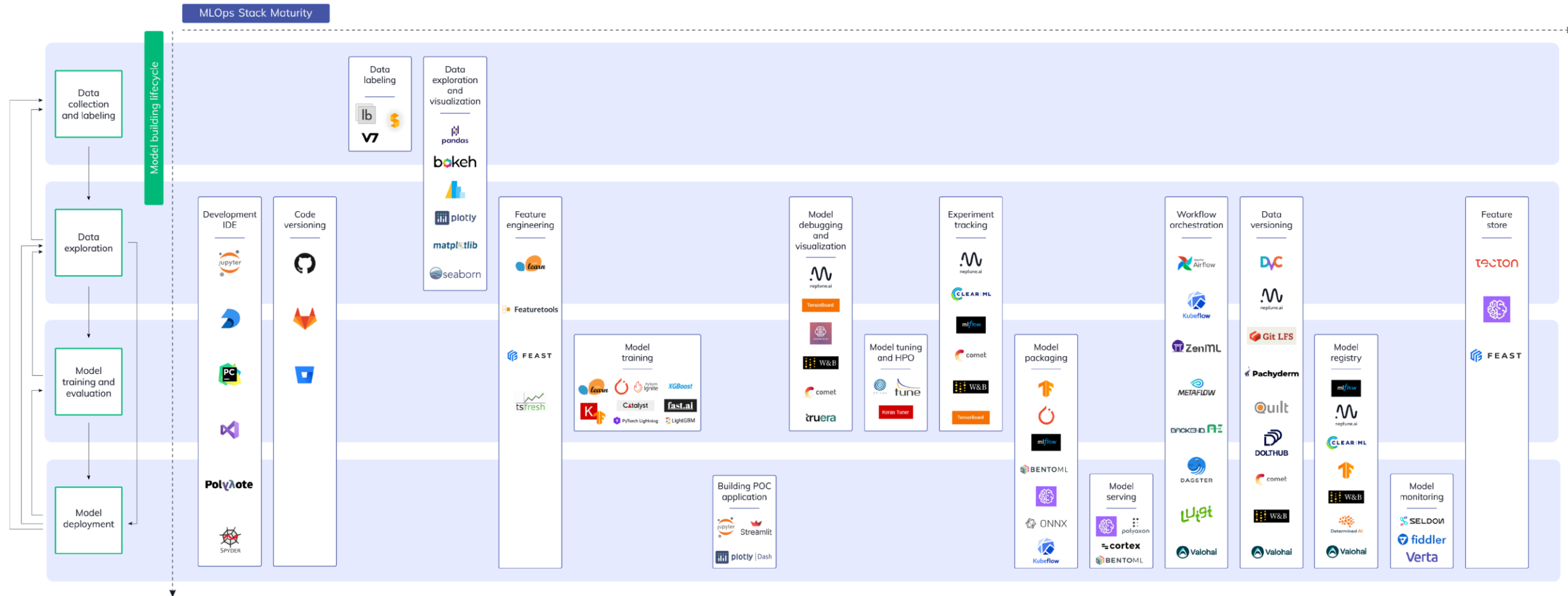


- **Improved efficiency:** MLOps can automate and standardize the ML lifecycle, making it more efficient and less prone to human error.
- **Improved quality:** MLOps can help to ensure that ML models are developed, trained, and deployed in a controlled and consistent manner, leading to higher quality models.

Challenges

- **Lack of tools and standards:** There is a lack of mature and standardized tools and platforms for MLOps, which can make it difficult to get started.
- **Cost:** Implementing MLOps can be expensive, as it requires investment in tools, infrastructure, and training.

MLOps Technology Landscape



DevOps vs MLOps

	DevOps	MLOps
Code versioning	✓	✓
Compute environment	✓	✓
Continuous Integration/ Delivery(CI/CD)	✓	✓
Monitoring in Production	✓	✓
Data Provenance		✓
Datasets		✓
Models		✓
Hyperparameters		✓
Metrics		✓
Workflows		✓

MLOps - End to End ML Life Cycle Management

[MLOps: The Epoch of Productionizing ML Models](#) | by Aditya Soni | Analytics Vidhya | Medium

CI/CD for MLOps

Phase 1: Research / Experiment(CI)

Question: " Can ML be used to address this issue? "

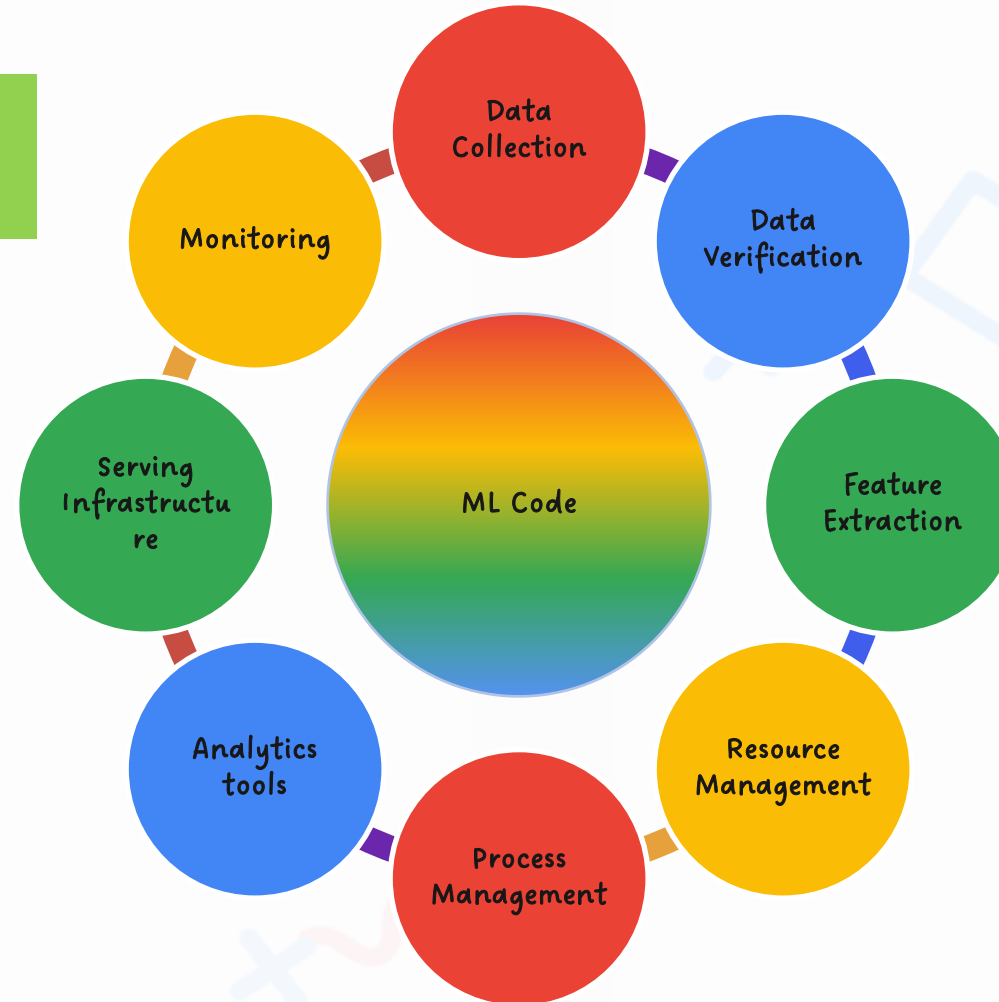
- ✓ "Is it possible to..."
- ✓ "Can we use this data to solve the following problem?"
- ✓ "Surely, we must be able to..."

Typical Scenarios

- ✓ Scientific Projects
- ✓ Proofs-of-concept (PoCs)

Continuous integration (CI):

Automates the testing and building of models, ensuring quality and consistency.



Phase 2: Operational(CD)

Question: " How do we implement this method at scale? "

- ✓ "How do we pipe the data into the model promptly?"
- ✓ "How do we collect, store and transform data so models can be retrained consistently?"
- ✓ "How do we build an A/B testing environment to test future model iterations?"

Typical Scenarios

- ✓ After PoC, bringing your ML models to production
- ✓ Migration of existing models into ML Platform

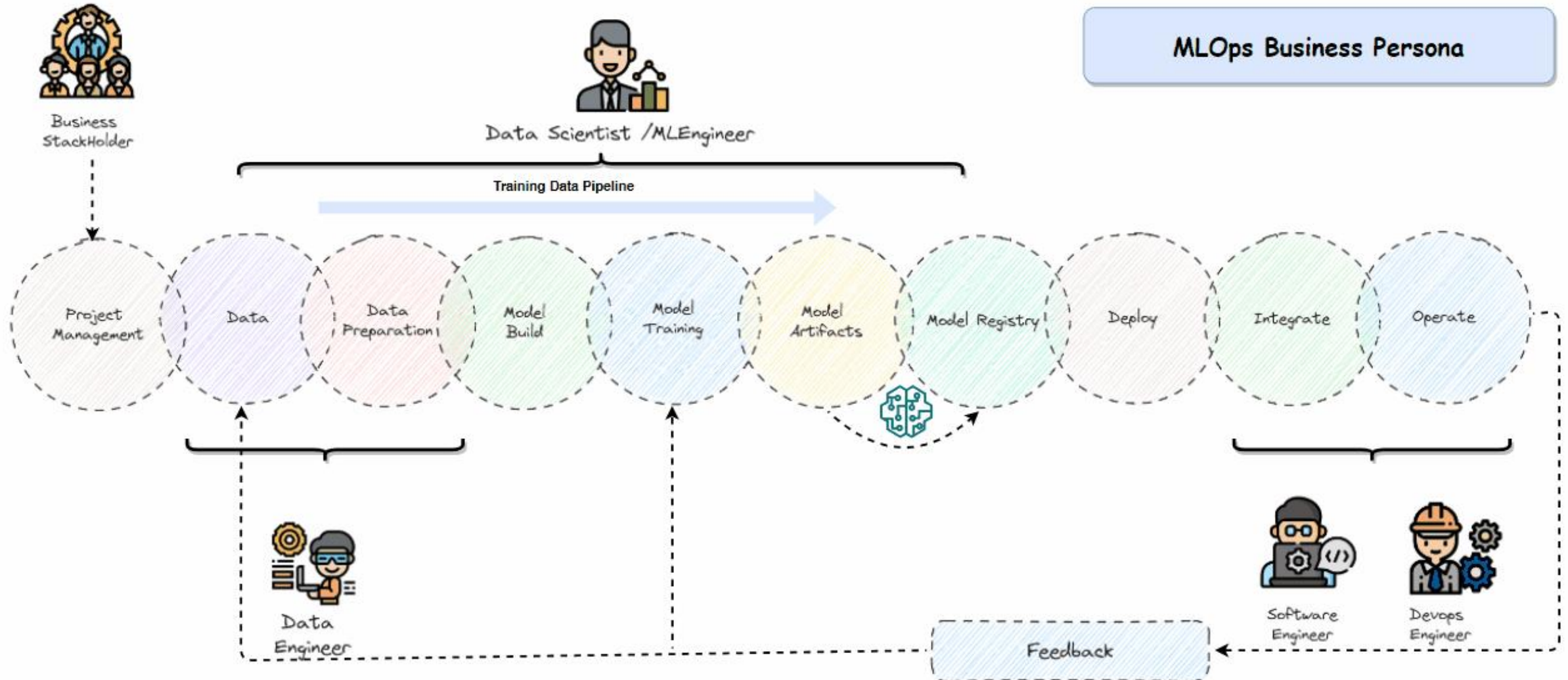
Continuous delivery (CD):

Automates the deployment of models to production, enabling rapid releases and updates

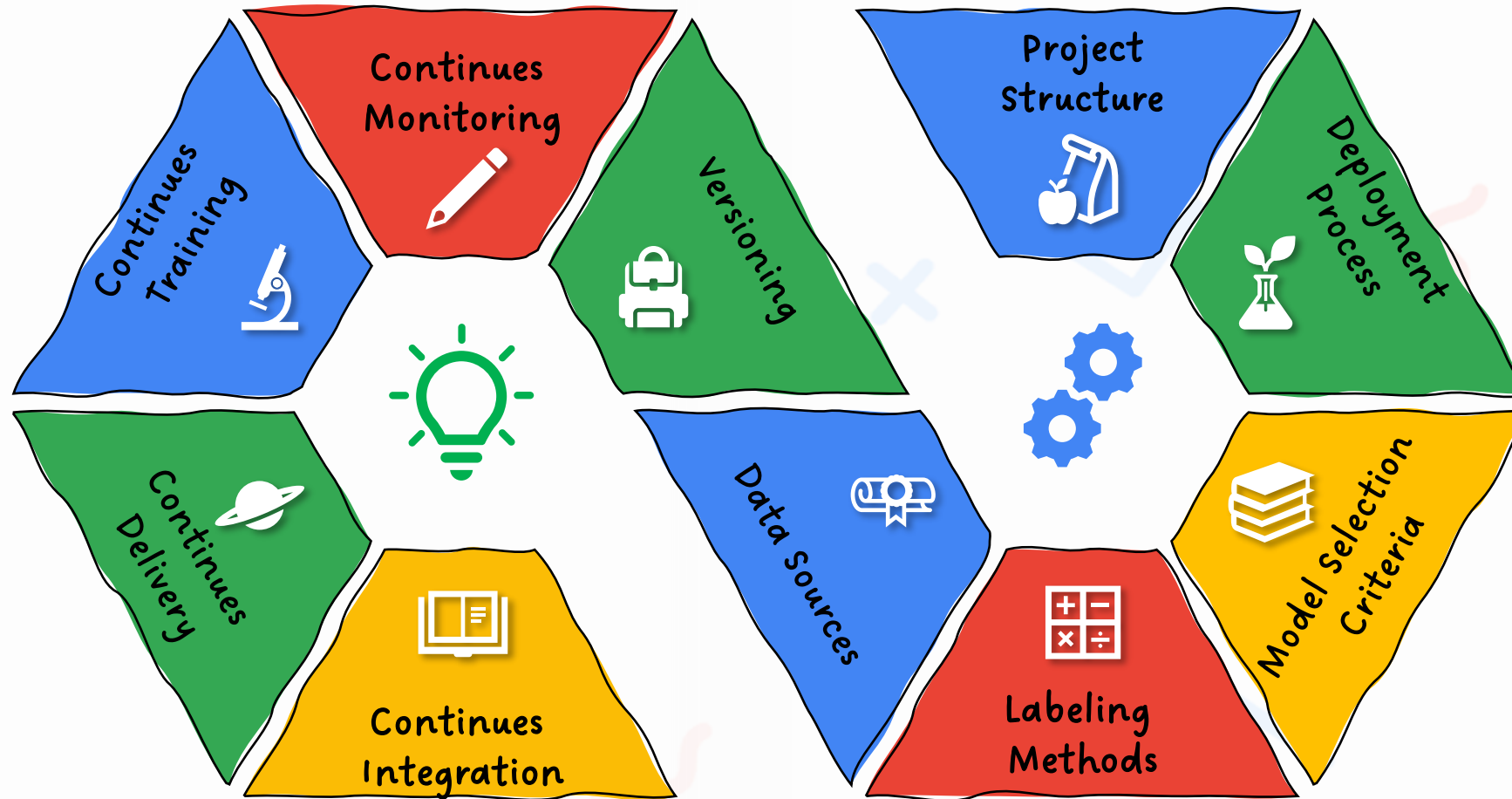
Persona of MLOps



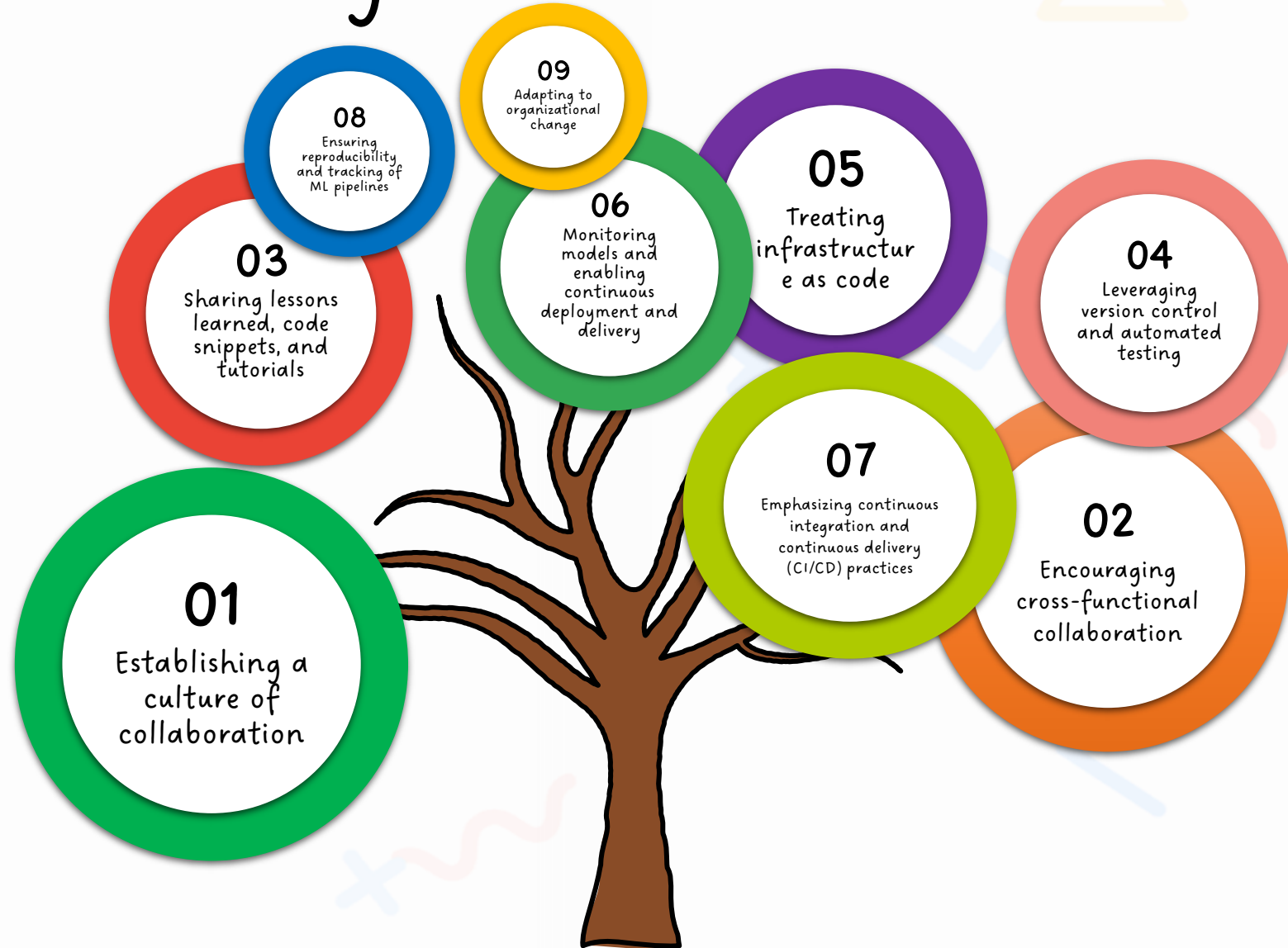
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MLOps Key Principle and Best Practises

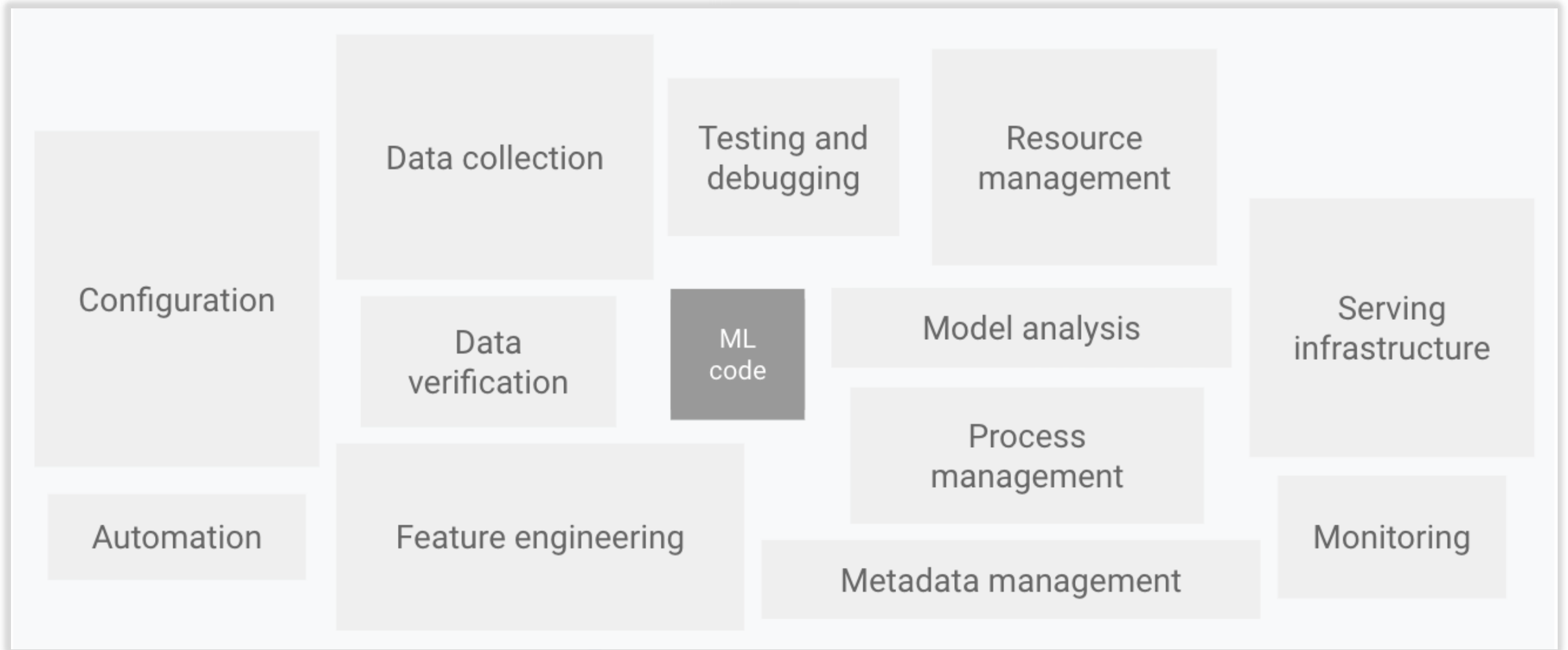


MLOps at Your Organization



MLOps in an organization

Hidden Technical debt in ML System



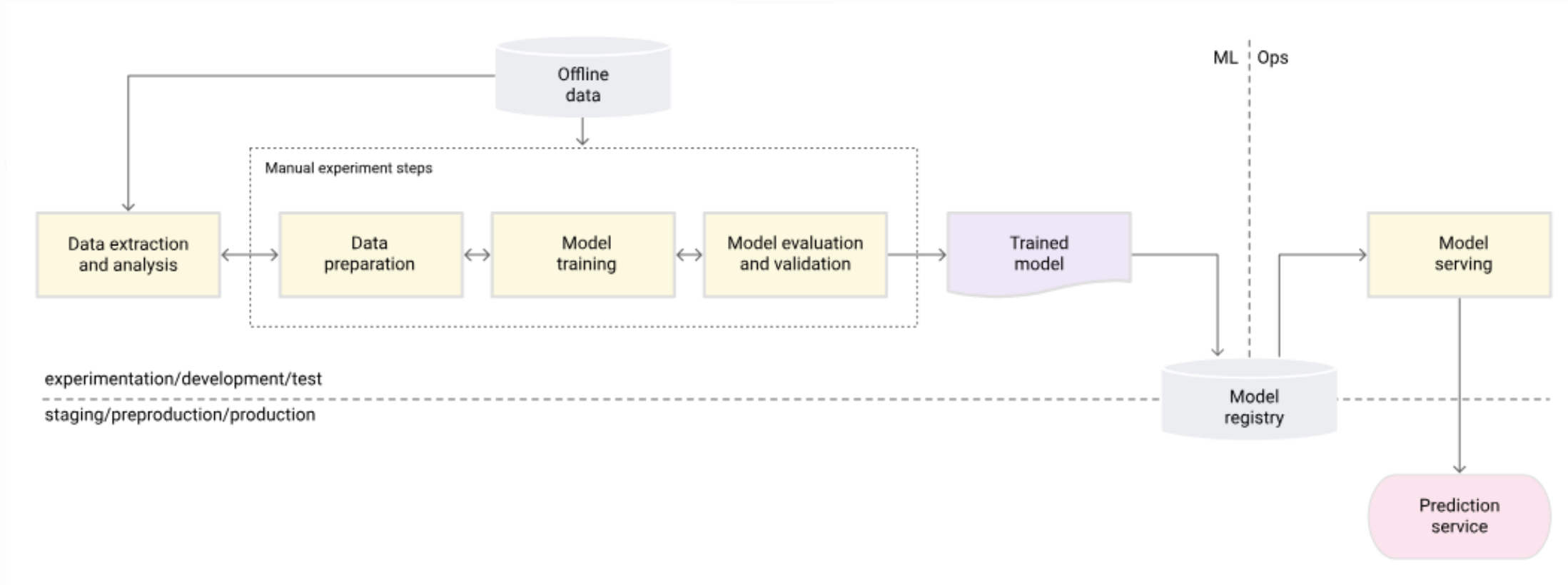
[Hidden Technical Debt in Machine Learning Systems.](#)

ML Maturity Models

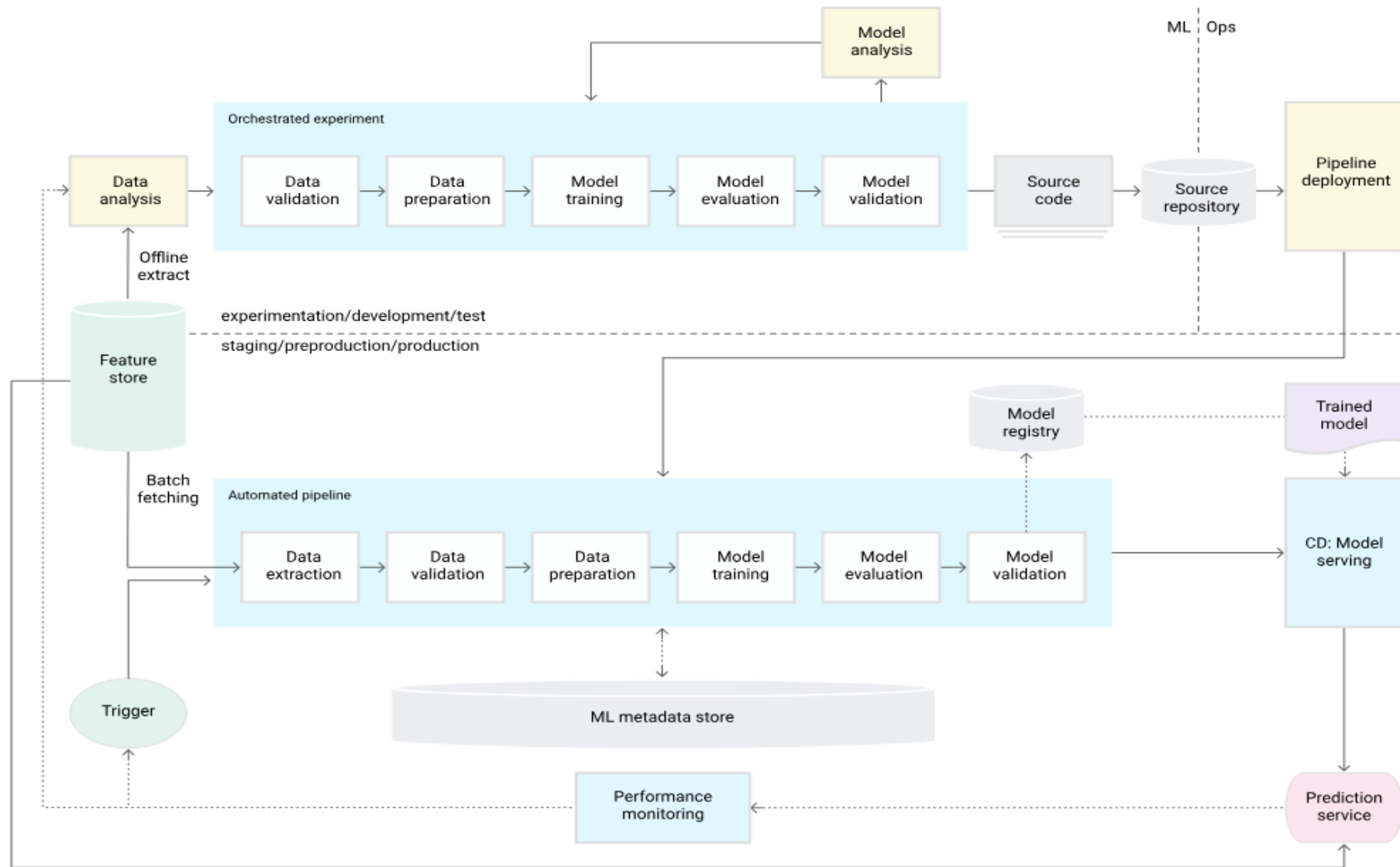
MLOps Level0: Manual Process



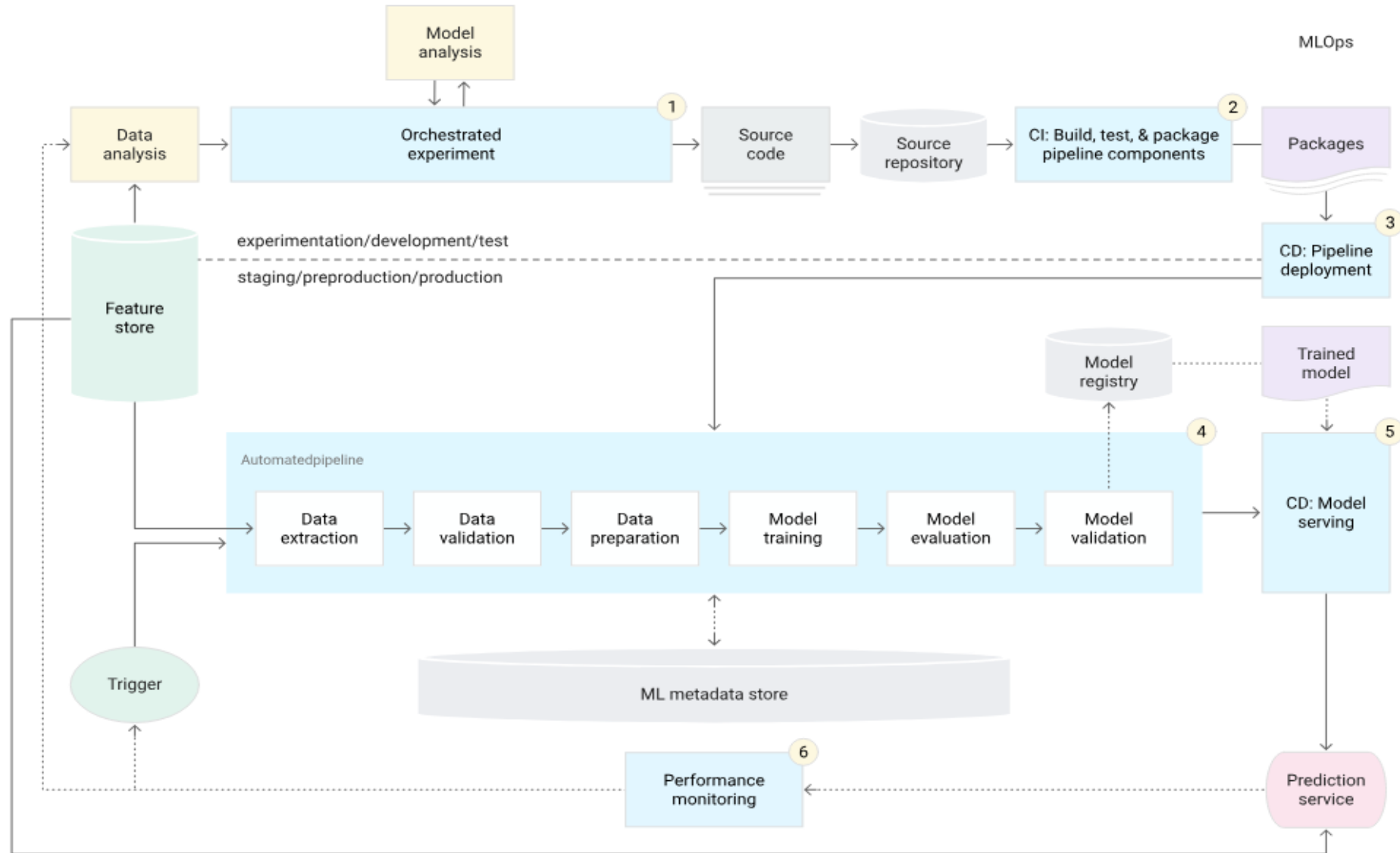
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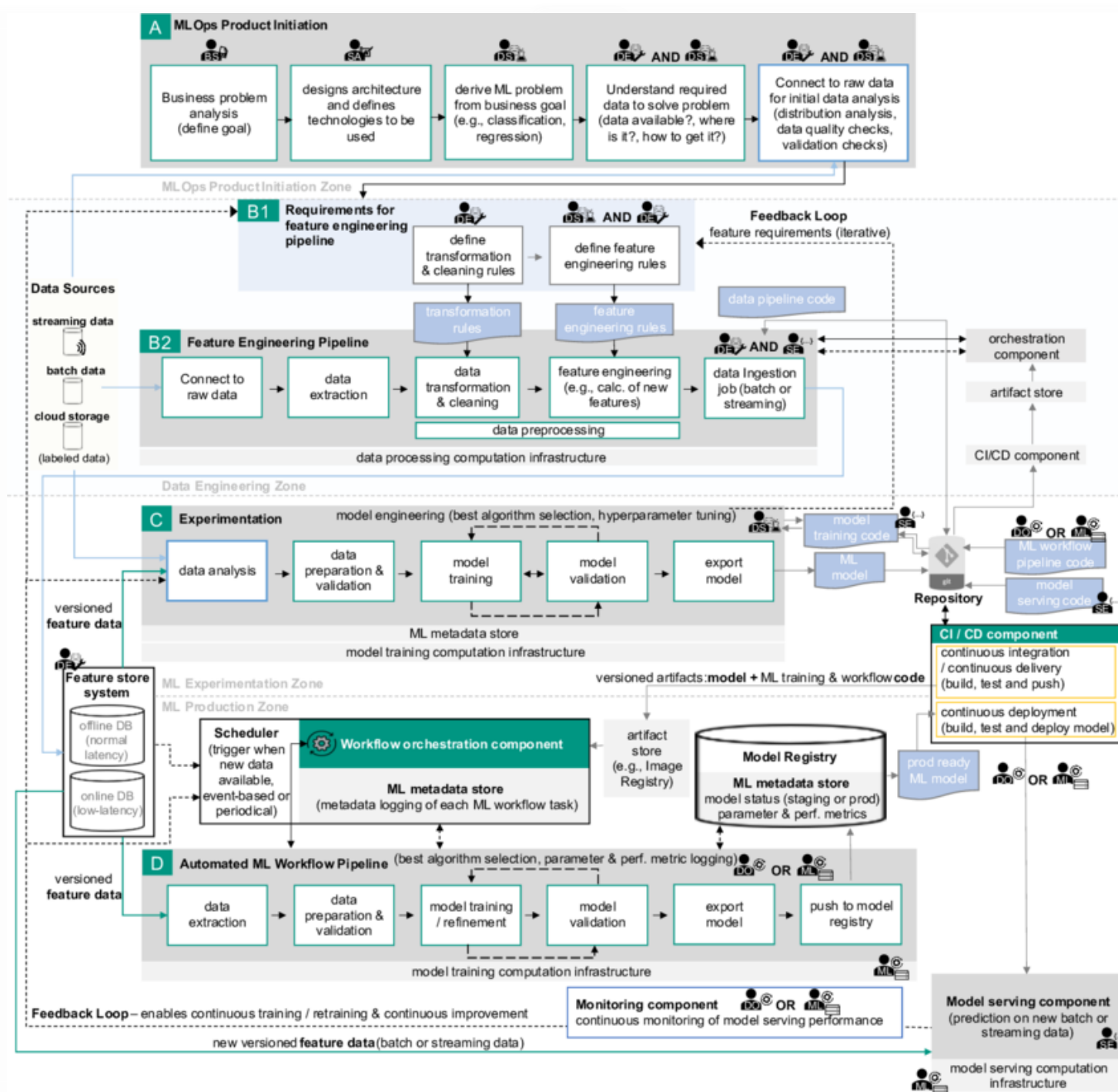
MLOps Level1: ML pipeline automation



MLOps Level2: ML pipeline automation



MLOps Architecture and Workflow



References:

- Machine Learning Operations (MLOps): Overview, Definition, and Architecture (<https://arxiv.org/abs/2205.02302>)
- MLOps - Definitions, Tools and Challenges (<https://arxiv.org/pdf/2201.00162.pdf>)
- MLOps: A Review(<https://arxiv.org/pdf/2308.10908.pdf>)
- MLOps: A Step Forward to Enterprise Machine Learning(<https://arxiv.org/pdf/2305.19298.pdf>)