Why and When to Employ MLOps
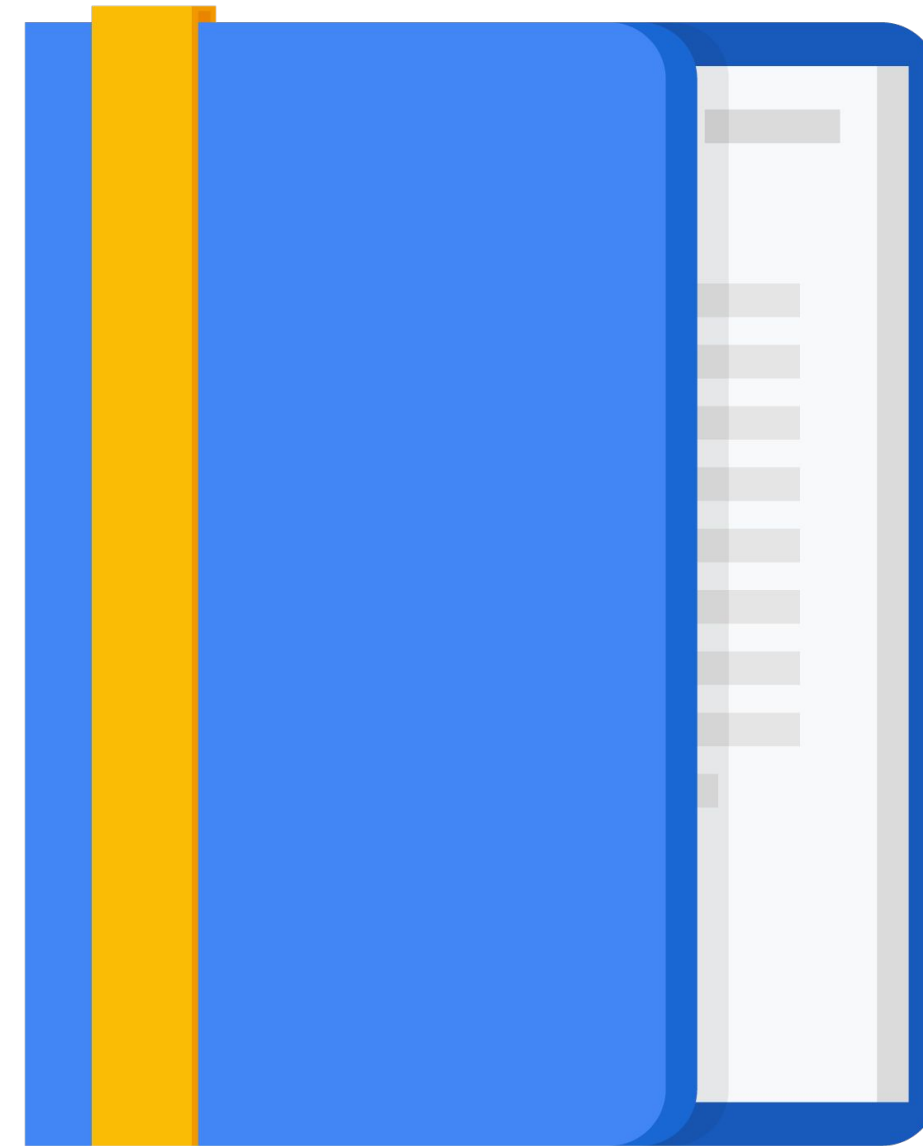
Agenda

Data Scientists' Pain Points

The concept of DevOps in ML

Machine Learning Lifecycle
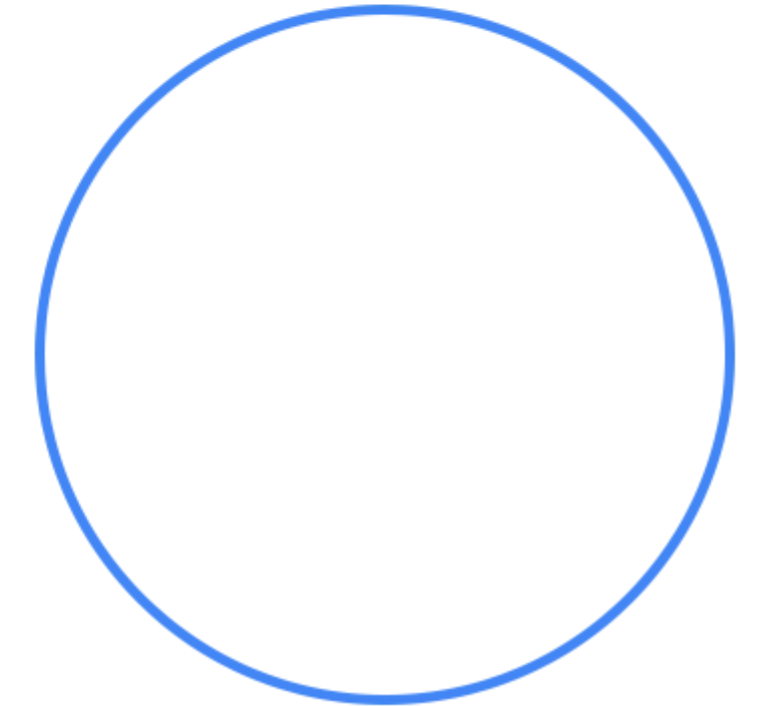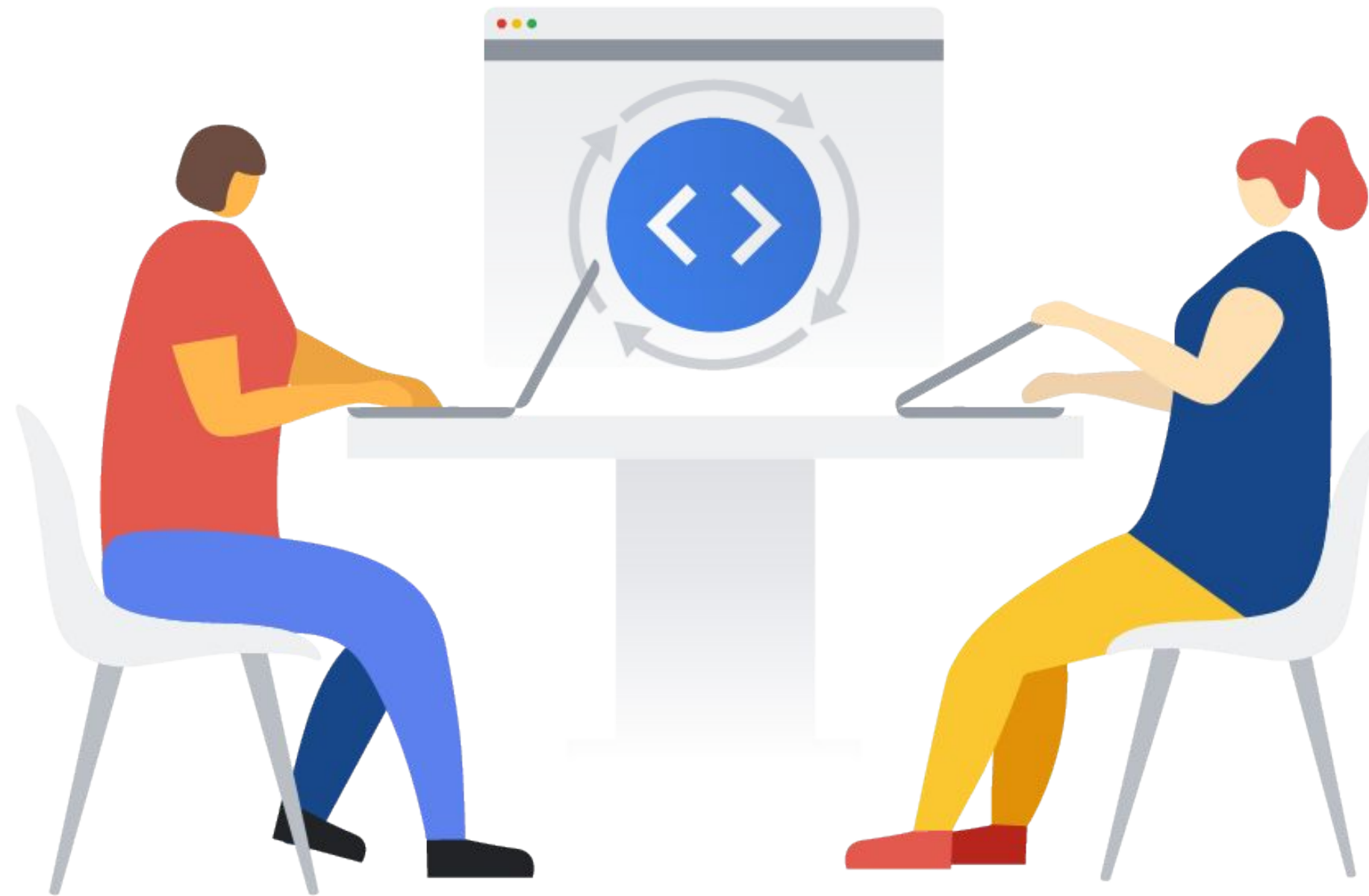
What we hear from most data scientists

What we hear from most data scientists

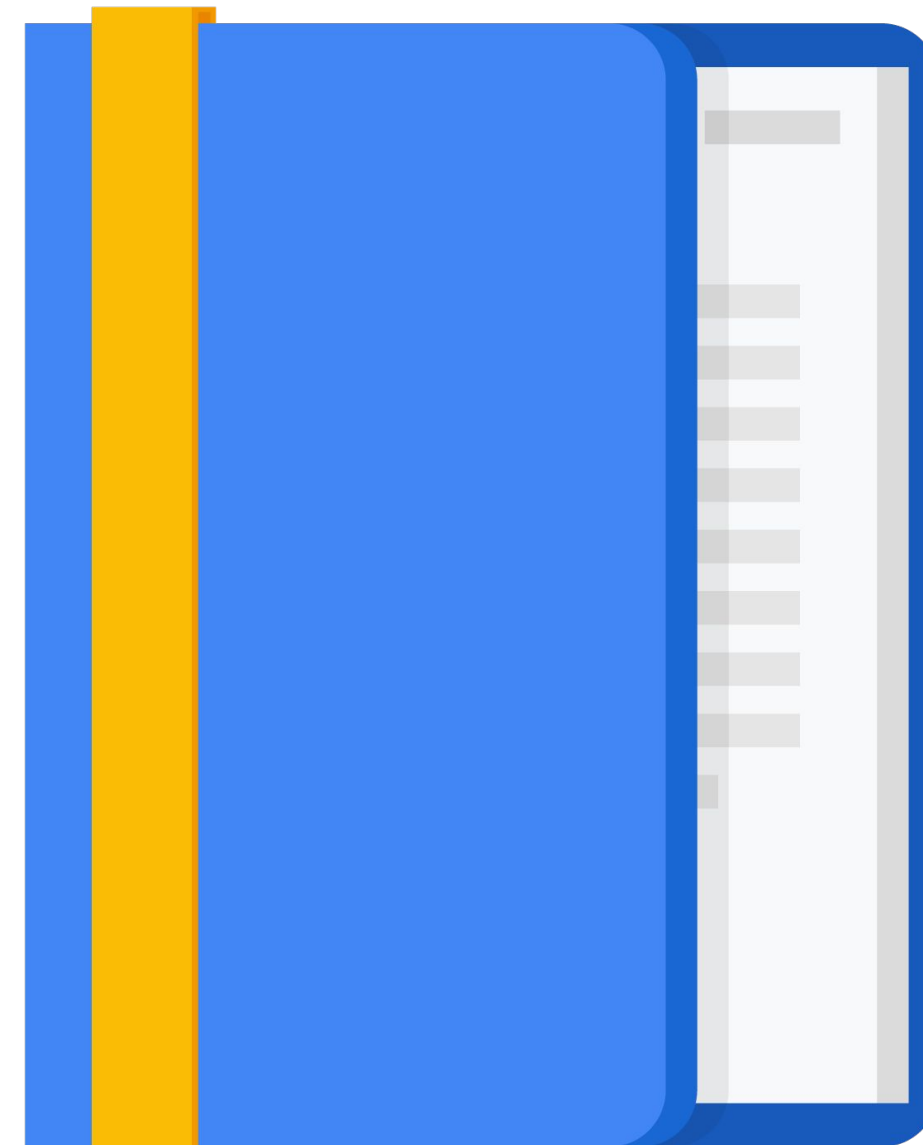Operationalizing a model means balancing time, resources, and quality throughout the whole system

Agenda
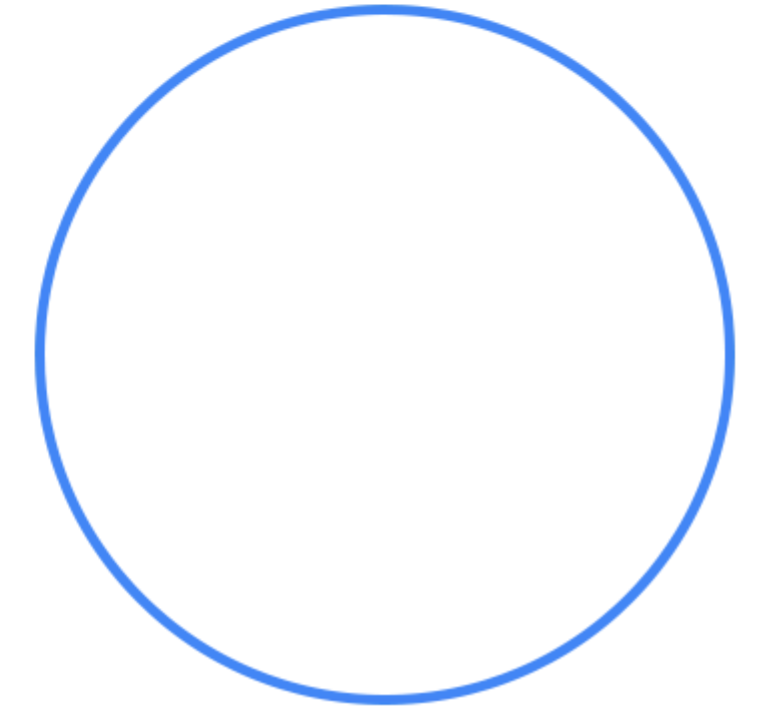
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Machine Learning Lifecycle

MLOps is a lifecycle management discipline for machine learning

Some DevOps concepts translate directly to MLOps

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But MLOps differs from DevOps in important ways

	DevOps	MLOps
1	Test and validate code and components	Also test and validate data, data schemas, and models

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But MLOps differs from DevOps in important ways

DevOps	MLOps
1 Test and validate code and components	Also test and validate data, data schemas, and models
2 Focus on a single software package or service	Also consider the whole system: the ML training pipeline
3 Deploy code and move to the next task	Constantly monitor, retrain, and serve the model

Machine learning is the high-interest credit card of technical debt

Credit Card Bill

This is a bill you have to pay. If you do not pay within one month, a 30-day surcharge is assessed.

Name: A. Developer
Address: 29 Dev Team Street
Bill received: 20/07/2020

Your Transactions

Item	Price
Not enough time on data selection	30 days
Insufficient Feature Engineering	45 days
Batch processing of live data	30 days
Different data in live model	90 days
Sub-total	195 days
Penalties and interest	60 days
Total to Pay	255 days

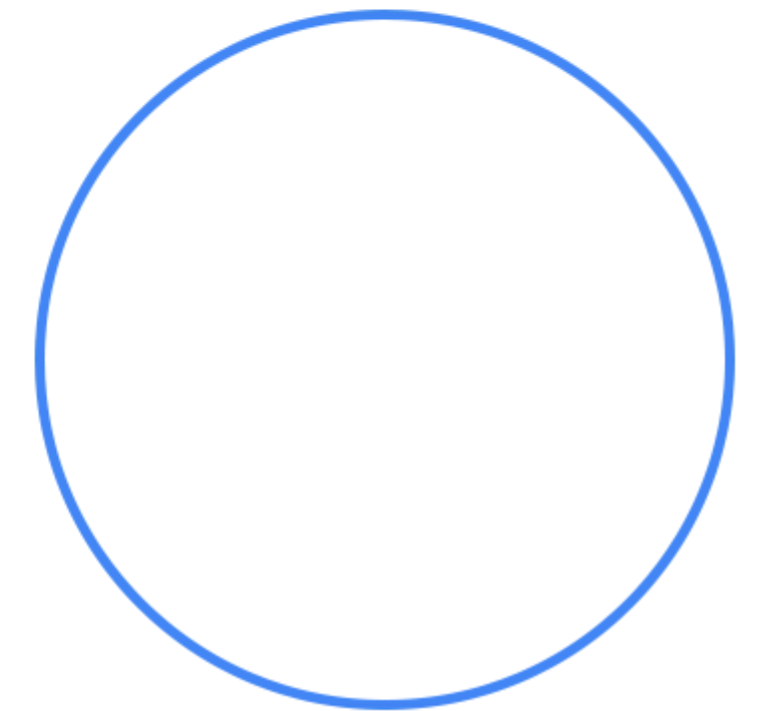# ML systems can easily build up technical debt

Multi-functional teams

ML systems can easily build up technical debt

Multi-functional teams

Experimental nature
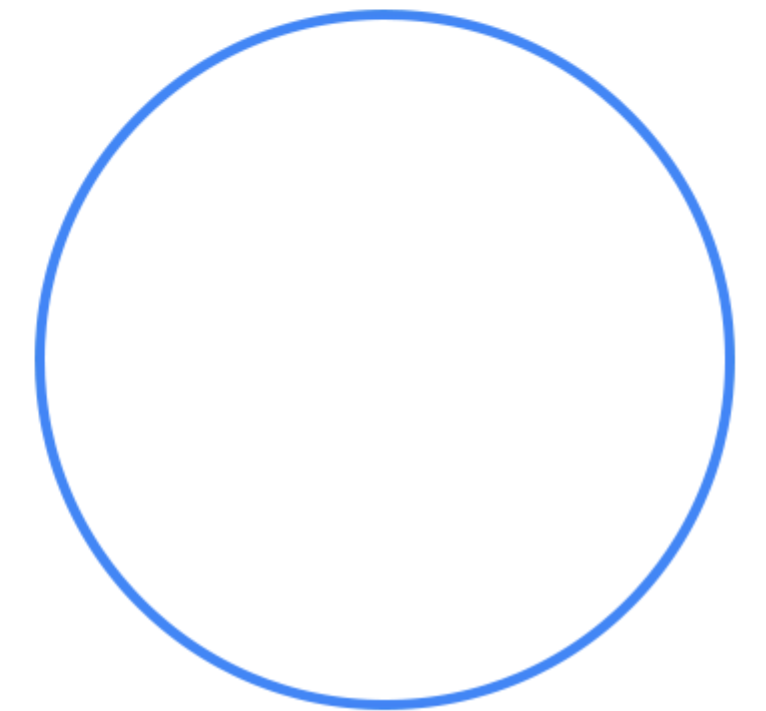
ML systems can easily build up technical debt

Multi-functional teams

Experimental nature

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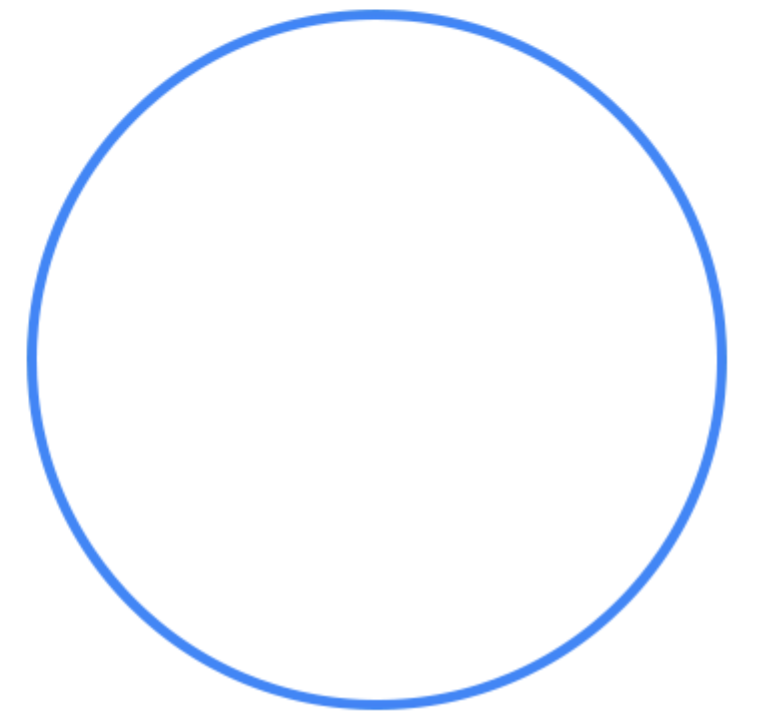# ML systems can easily build up technical debt

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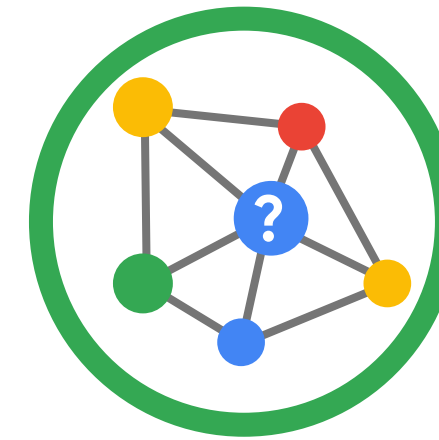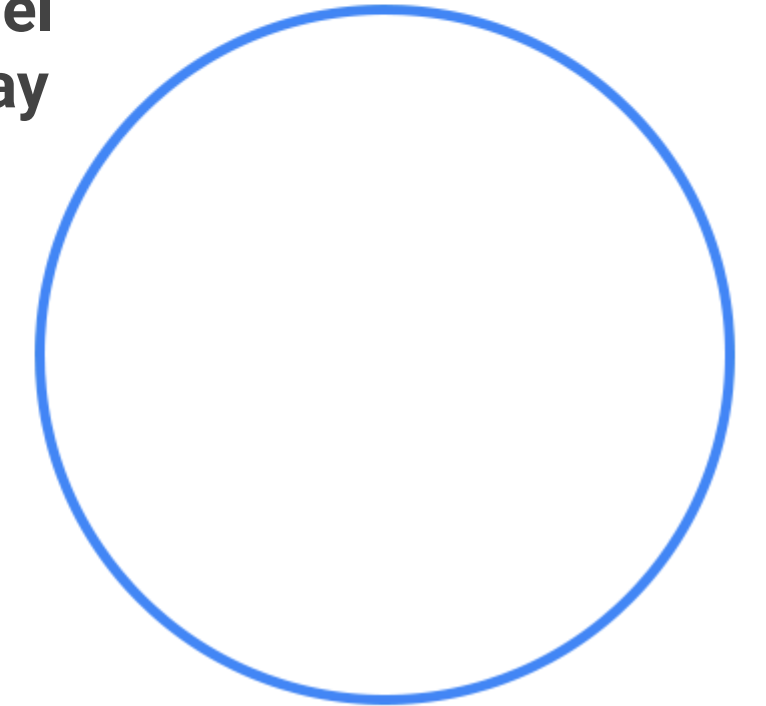**Experimental nature**

Testing complexity

Deployment complexity

Model decay

Agenda
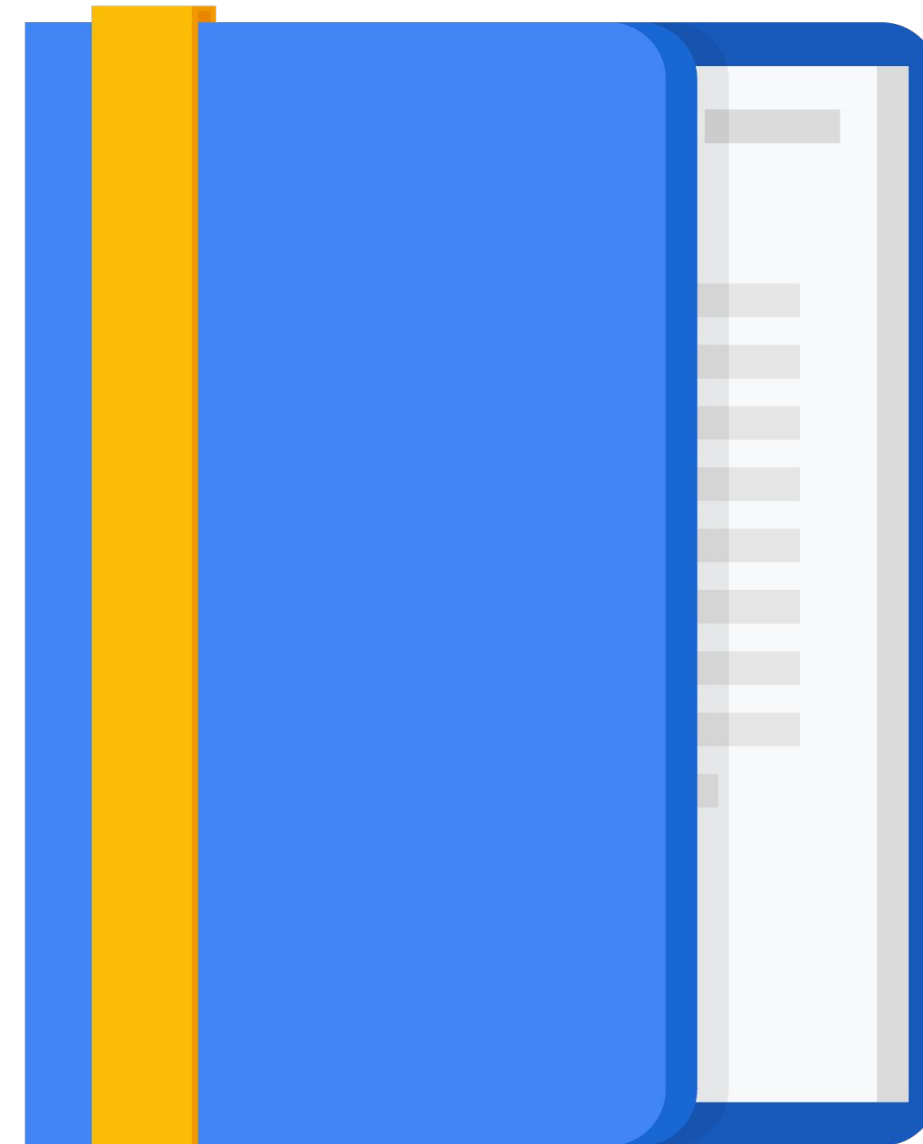
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Phases of a machine learning project

1 **Define business use cases**

Discovery Phase

2 **Data exploration**

Phases of a machine learning project

1. Define business use cases

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Is developing a model for this use case feasible?

3. Select algorithm

Phases of a machine learning project

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6 Evaluate

7 Present results

Development Phase

Phases of a machine learning project

1 Define business use cases

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Is developing a model for this use case feasible?

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Iterate on approach

Present results 7

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Development Phase

Phases of a machine learning project

Monitor model 10 — 1 Define business use cases

Operationalize model 9

Deployment Phase

Plan for deployment 8

Present results 7

Evaluate 6 — 5 Build ML model

Iterate on approach

2 Data exploration

Discovery Phase

Is developing a model for this use case feasible?

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Development Phase
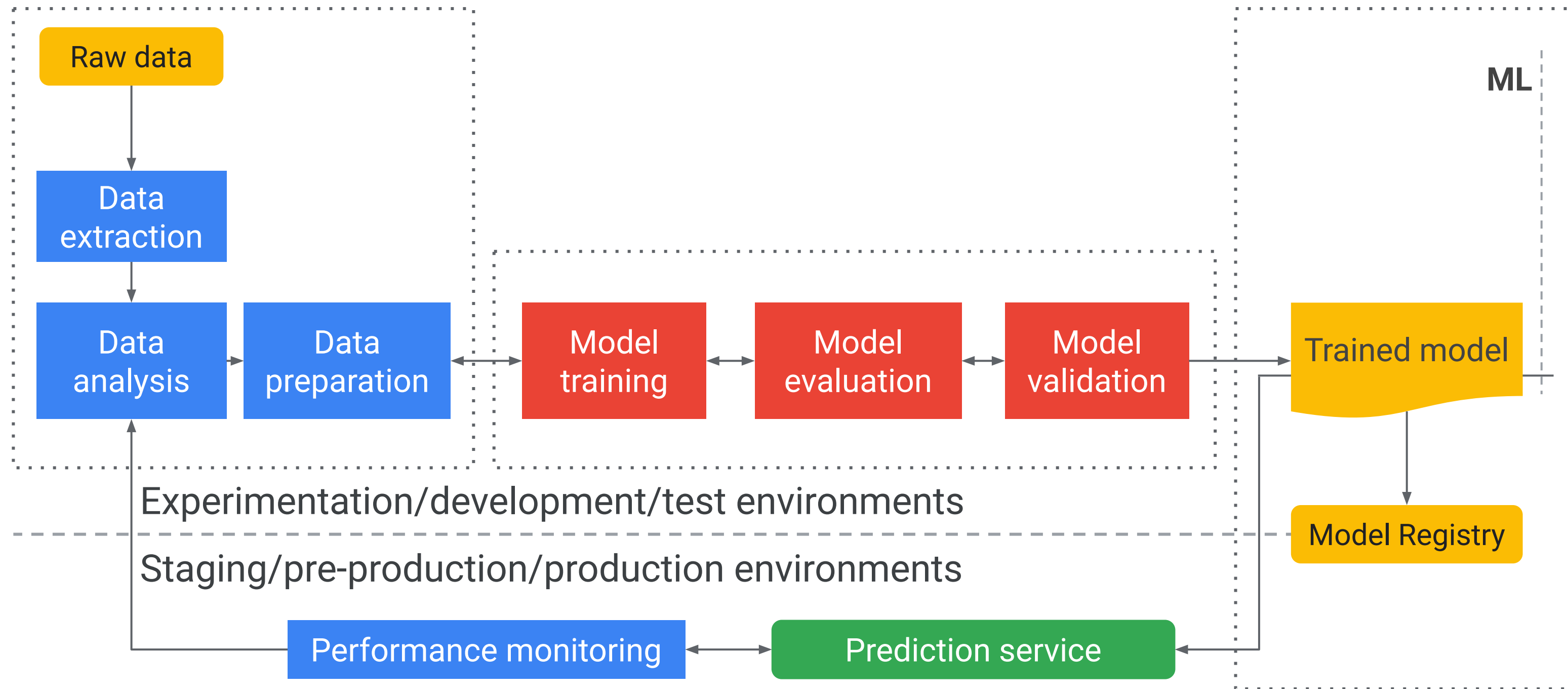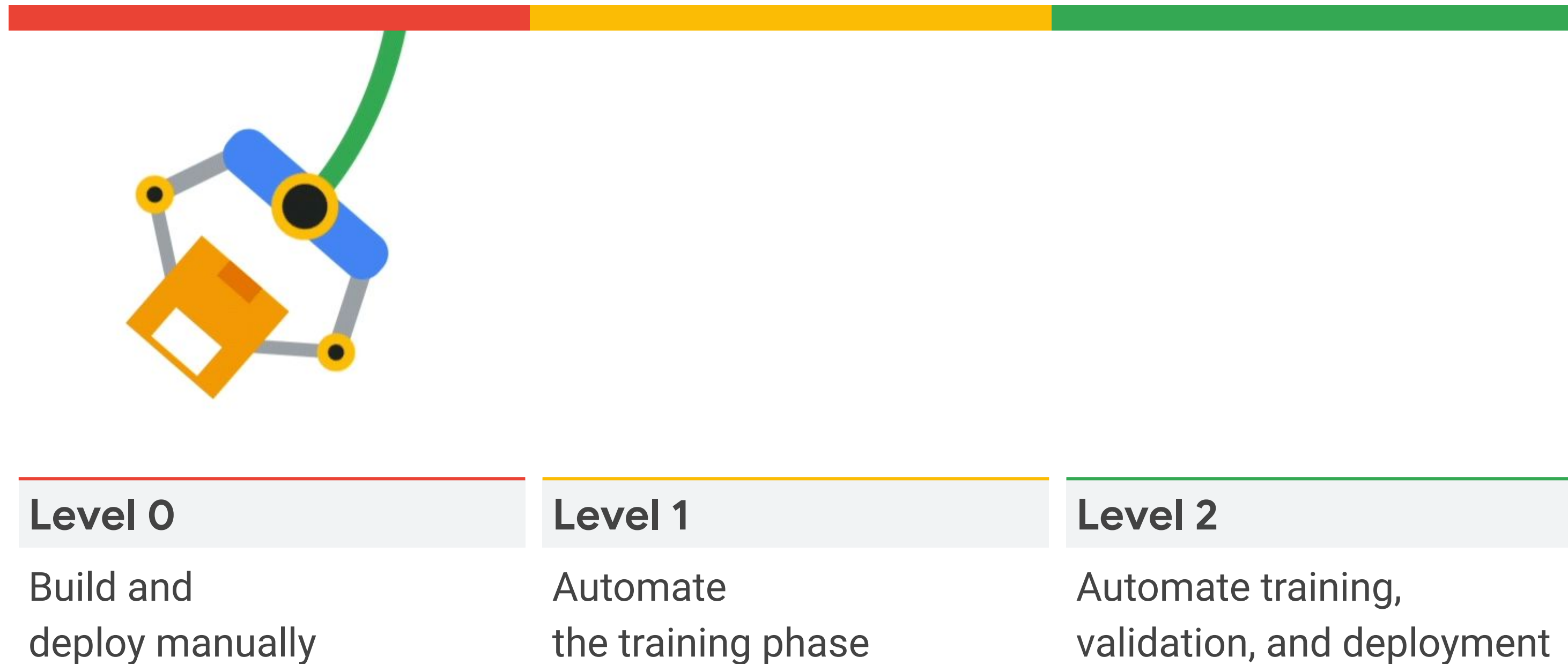
An ML pipeline contains well-defined processes

The level of automation defines the maturity of the ML process

Level 0	Level 1	Level 2
Build and deploy manually	Automate the training phase	Automate training, validation, and deployment

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