We build a ML pipeline after we deploy

by Alyona Galyeva
for EuroPython 2021

Agenda

1. Introduction

2. The awesome solution:
   - ML pipeline out of the box in 1 line of code
   - add ML pipeline anytime even in prod env

Agenda

1. Introduction

2. ML Pipeline:
   - why and when
   - building blocks
   - engineering
   - debugging and monitoring
   - open-source Python libraries to save your time

Introduction


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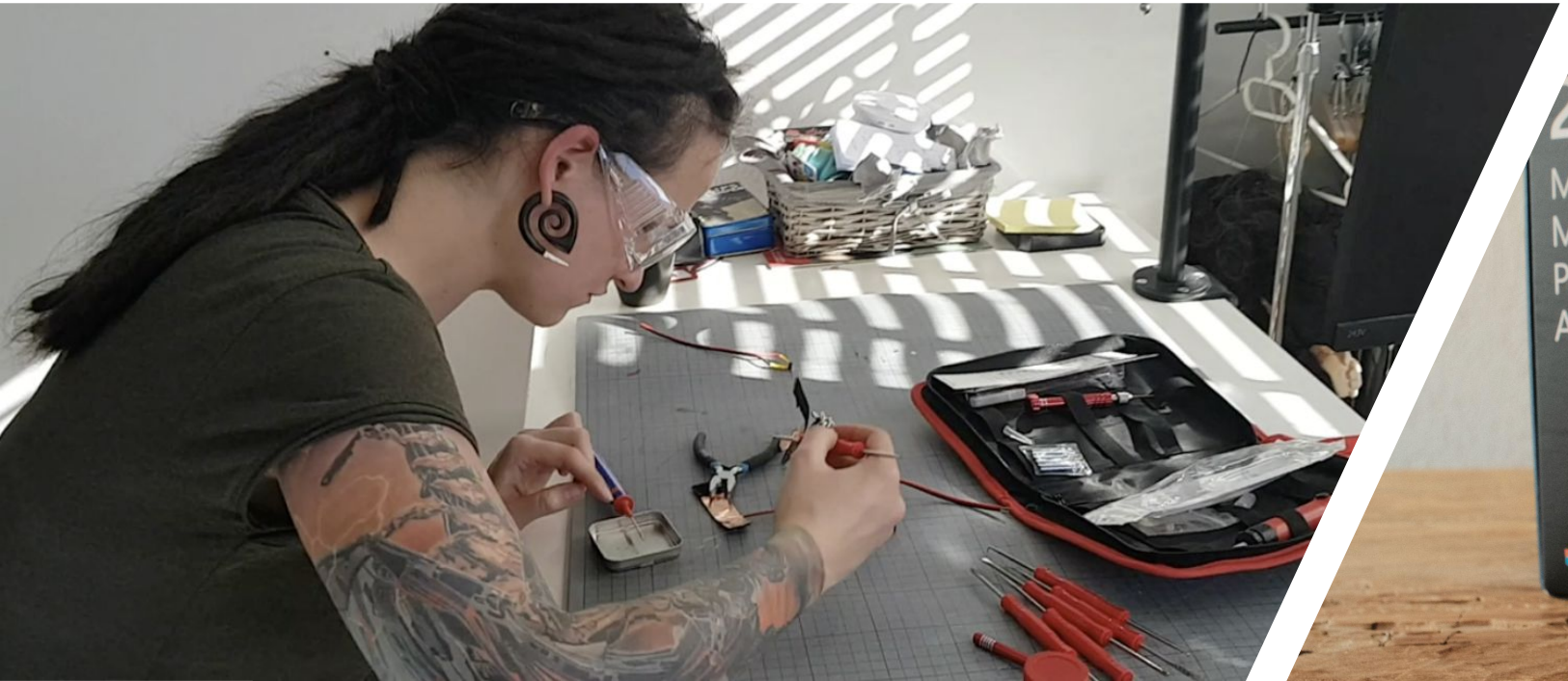


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ML Pipeline: why and when

Why?

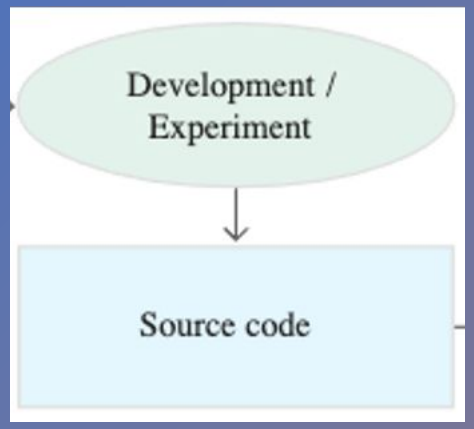
reduce the cost of data science projects:

- focus on new cases/models
- prevent bugs
- audit

When?

- go from PoC to MVP
- time to scale

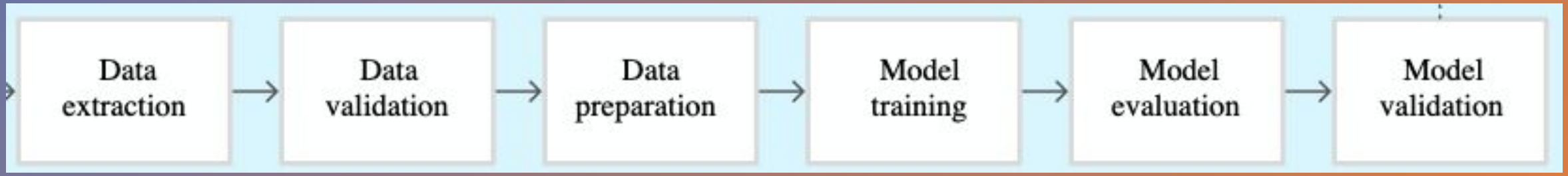
ML Pipeline: building blocks



Development and experimentation

Try new ML algorithms with orchestrated experiment steps

Output: ML pipeline steps source code



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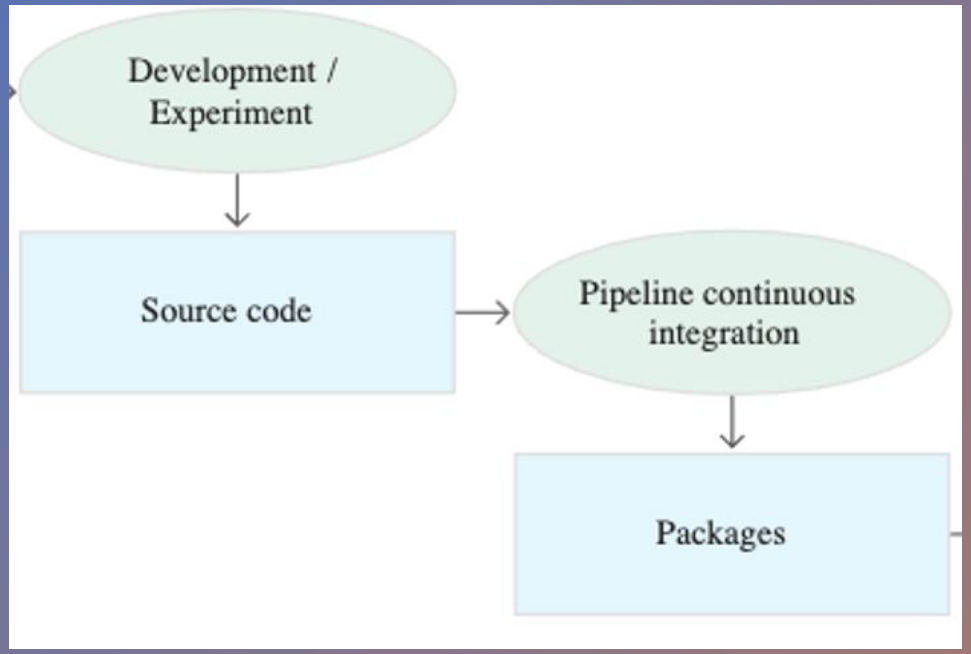

ML pipeline continuous integration

Build source code, run tests

Output: ML pipeline components to deploy

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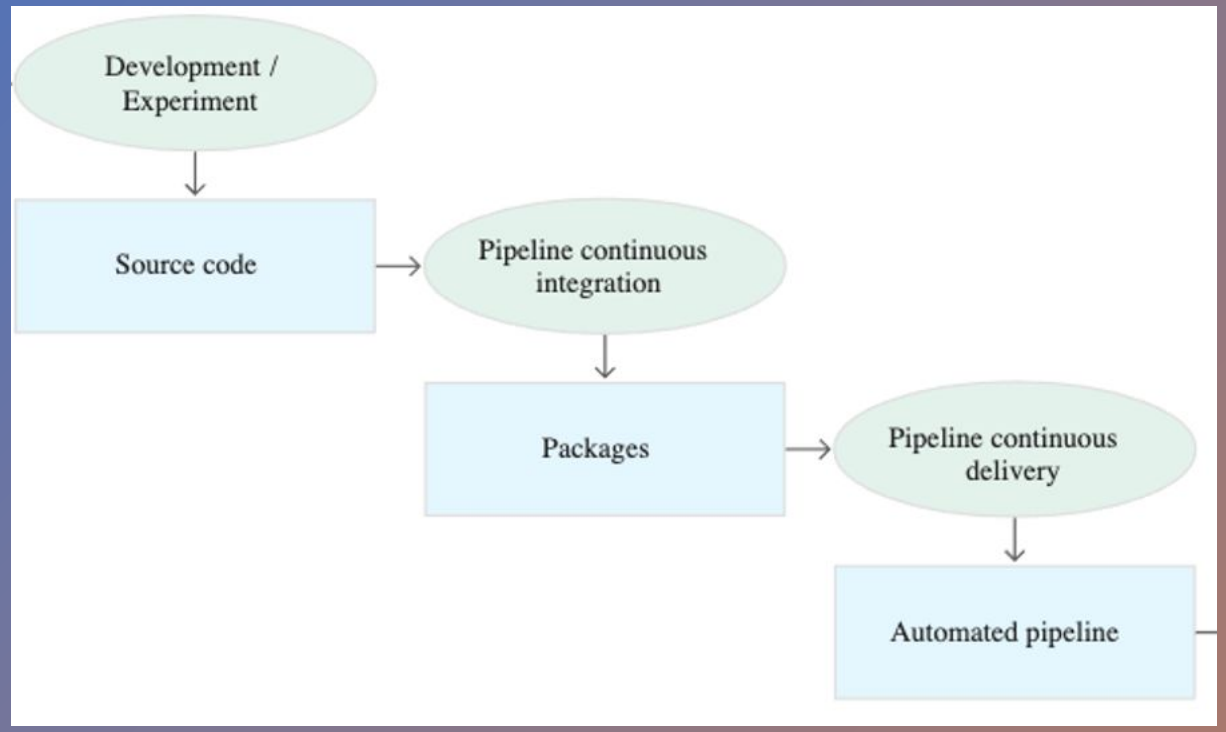

ML pipeline continuous delivery

Deploy artifacts to the target env

Output: deployed ML pipeline

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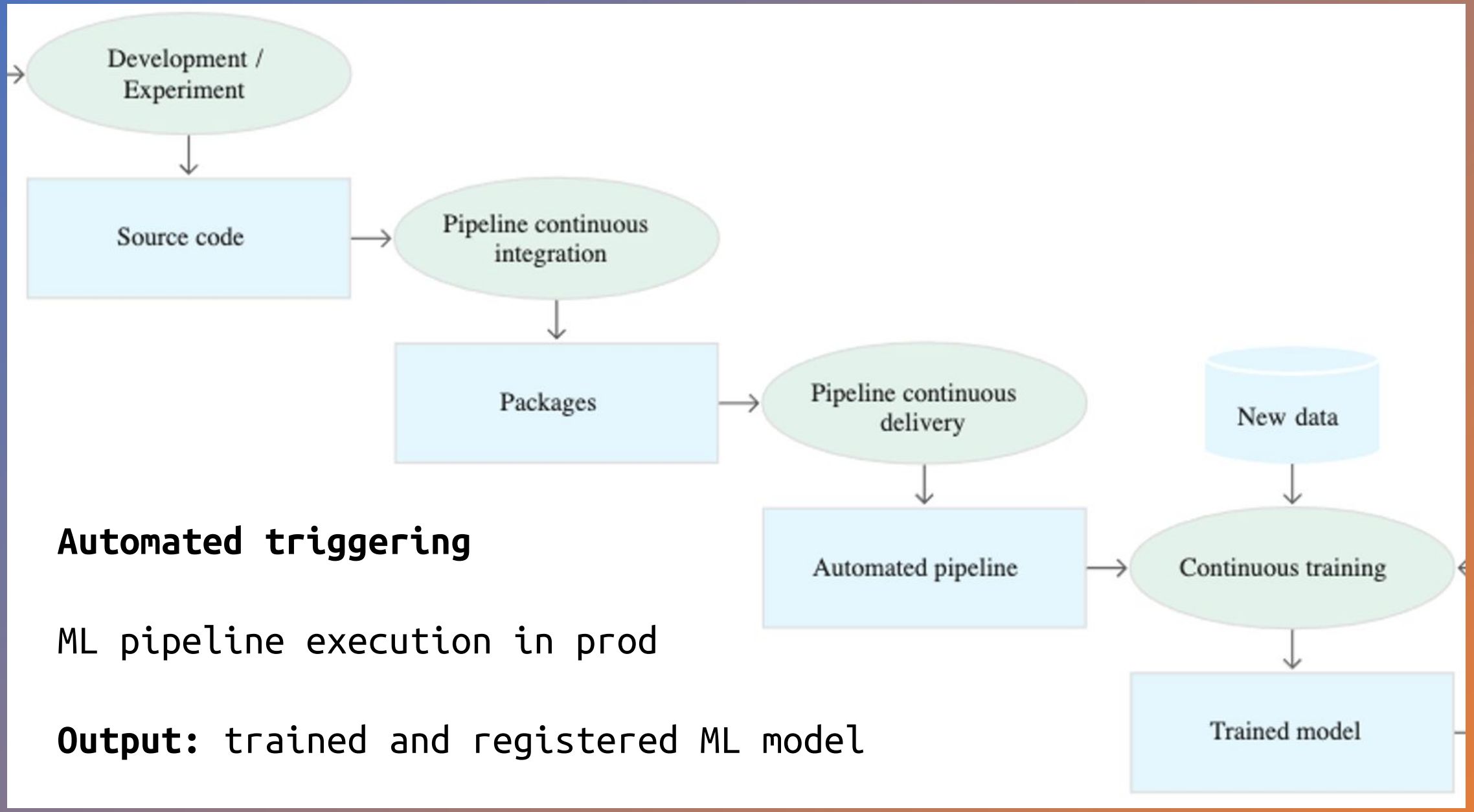

Automated triggering

ML pipeline execution in prod

Output: trained and registered ML model

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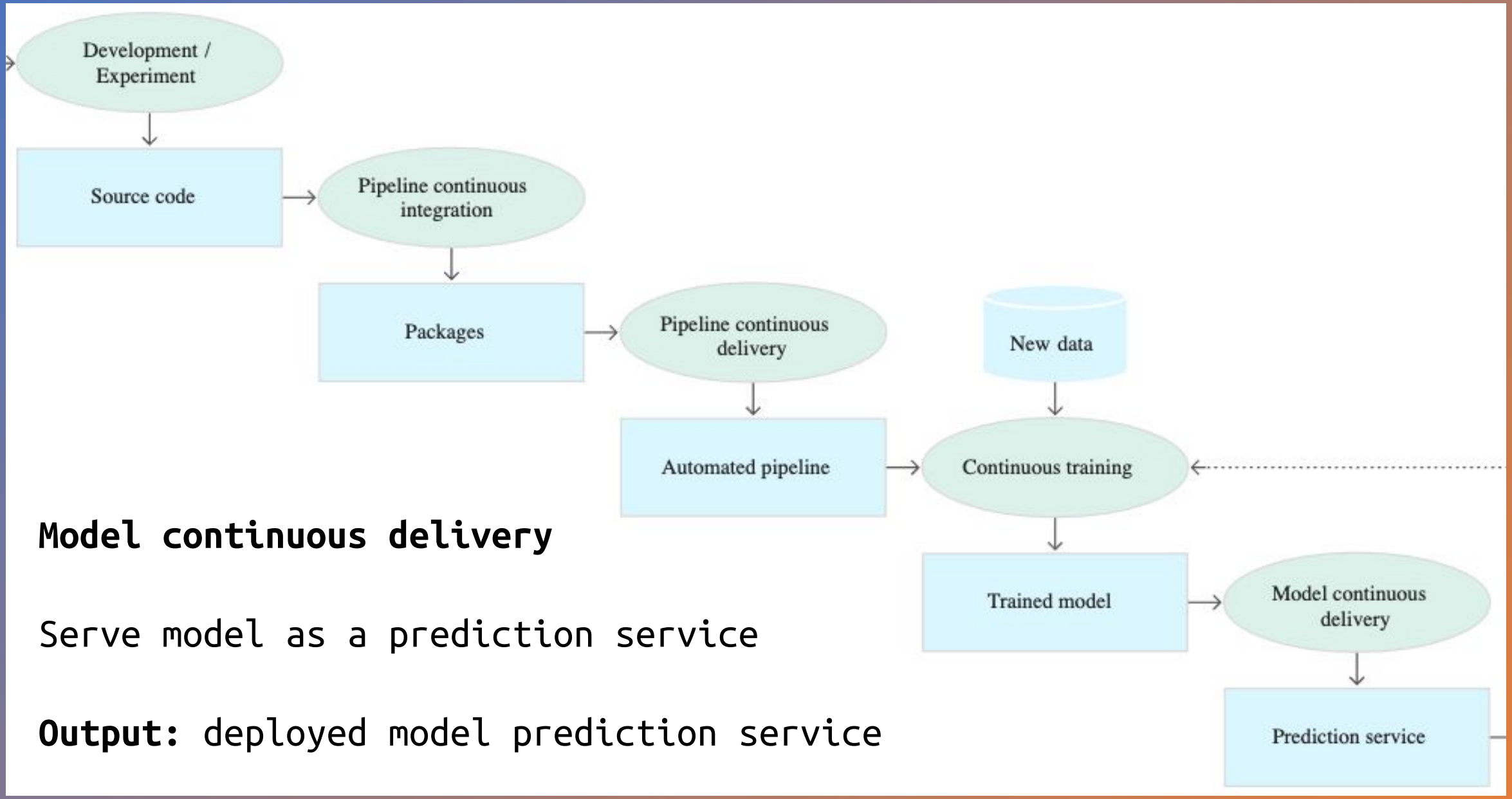

Model continuous delivery

Serve model as a prediction service

Output: deployed model prediction service

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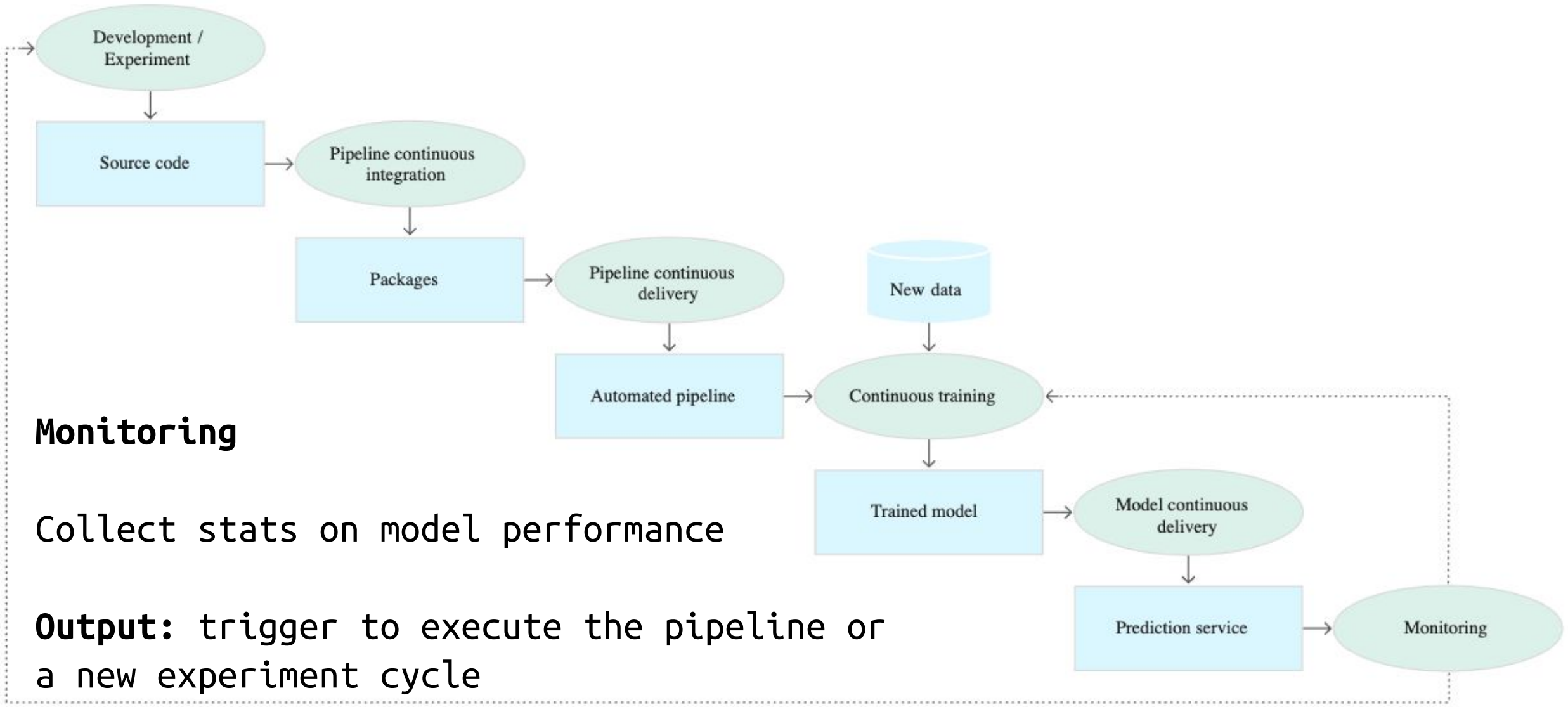

Monitoring

Collect stats on model performance

Output: trigger to execute the pipeline or a new experiment cycle

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ML Pipeline: engineering

Engineer around failures

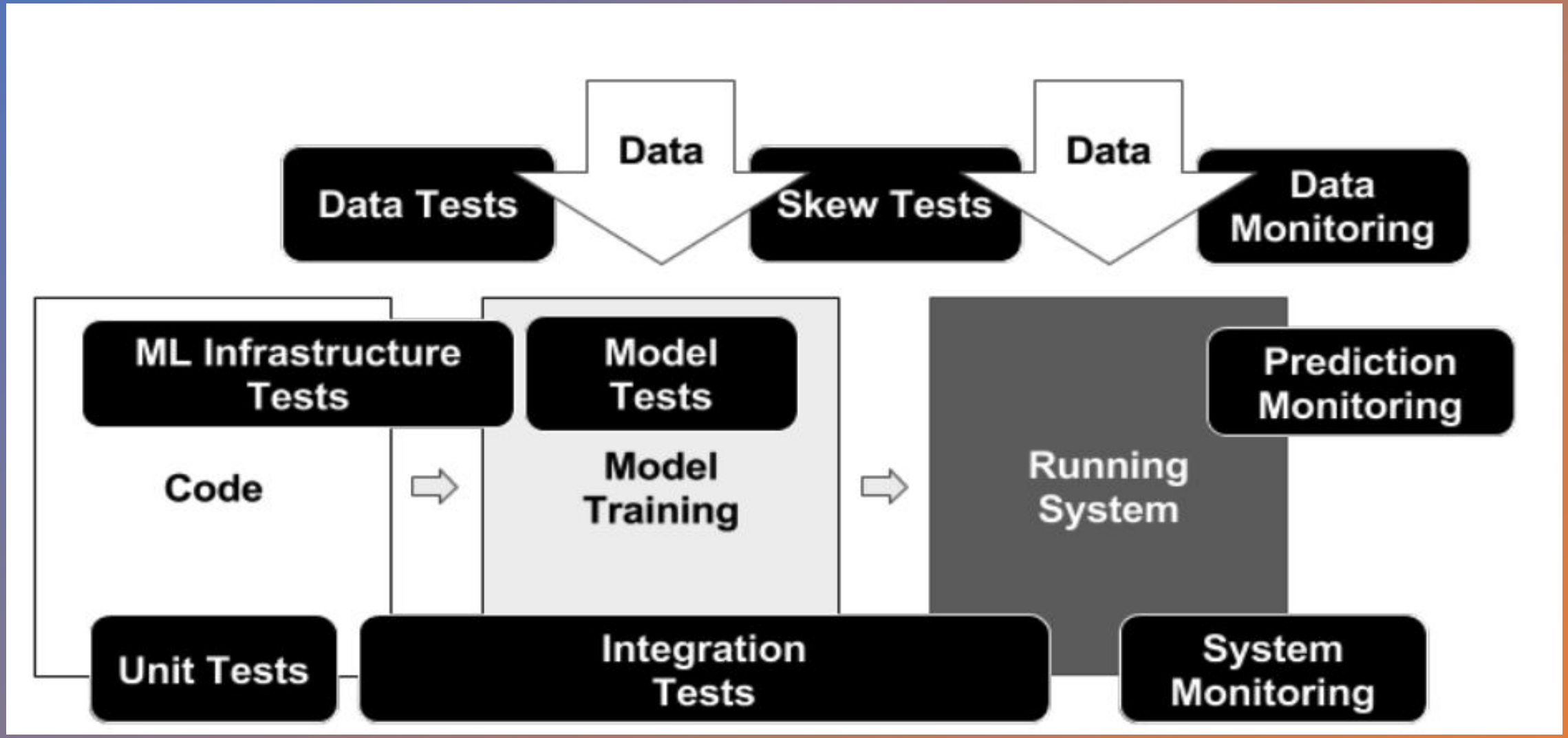
- input checks
- output checks
- model fallback

Engineer for performance

- scale
- caching
- feedback collection

ML Pipeline: debugging and monitoring

ML debugging and monitoring



Source: https://research.google/pubs/pub46555/

Top 3 debugging issues

- unpinned libraries
- data pre-processing
- scattered config for diff envs

Monitoring

- system monitoring
- data monitoring
- model monitoring

ML Pipeline:
Python libraries

Delta lake, DVC - data versioning
Airflow - data processing
Great Expectations - data validation
Feast - feature store
Hyperopt, Katib - tuning
Kubeflow, Pachyderm, TensorFlow Extended- platform
LIME, SHAP, Alibi Explain- model interpretability
Mlflow - lifecycle management
Seldon Core - model serving
FastAPI - restful APIs
Pytest, locust - testing
Evidently, Alibi Detect - debugging and monitoring

Questions?