Project

MLOps experimental

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Intro

Project

The project is a practical implementation of **MLOps practices.**

For all life cycle of ML are create two project that represent the phases: develop and production.

Develop phase

- Data Ingestion
- Data Preparation
- Model Building & Training
- Experimentation
- Model Deploy
- Model Serving

Production phase

- Prediction Service
- Monitoring
- Alerting
- Application & Trigger

Tools & libraries

Develop phase

Workflow orchestration

Kedro

Data analysis and manipulation

pandas

Model training

scikit learn

Experimentation management

mlflow

Model packaging and serving

BENTOML

Data versioning

DVC

Code versioning

GitHub

Deploying pipeline kedro

kedro-docker

Tools & libraries

Production phase

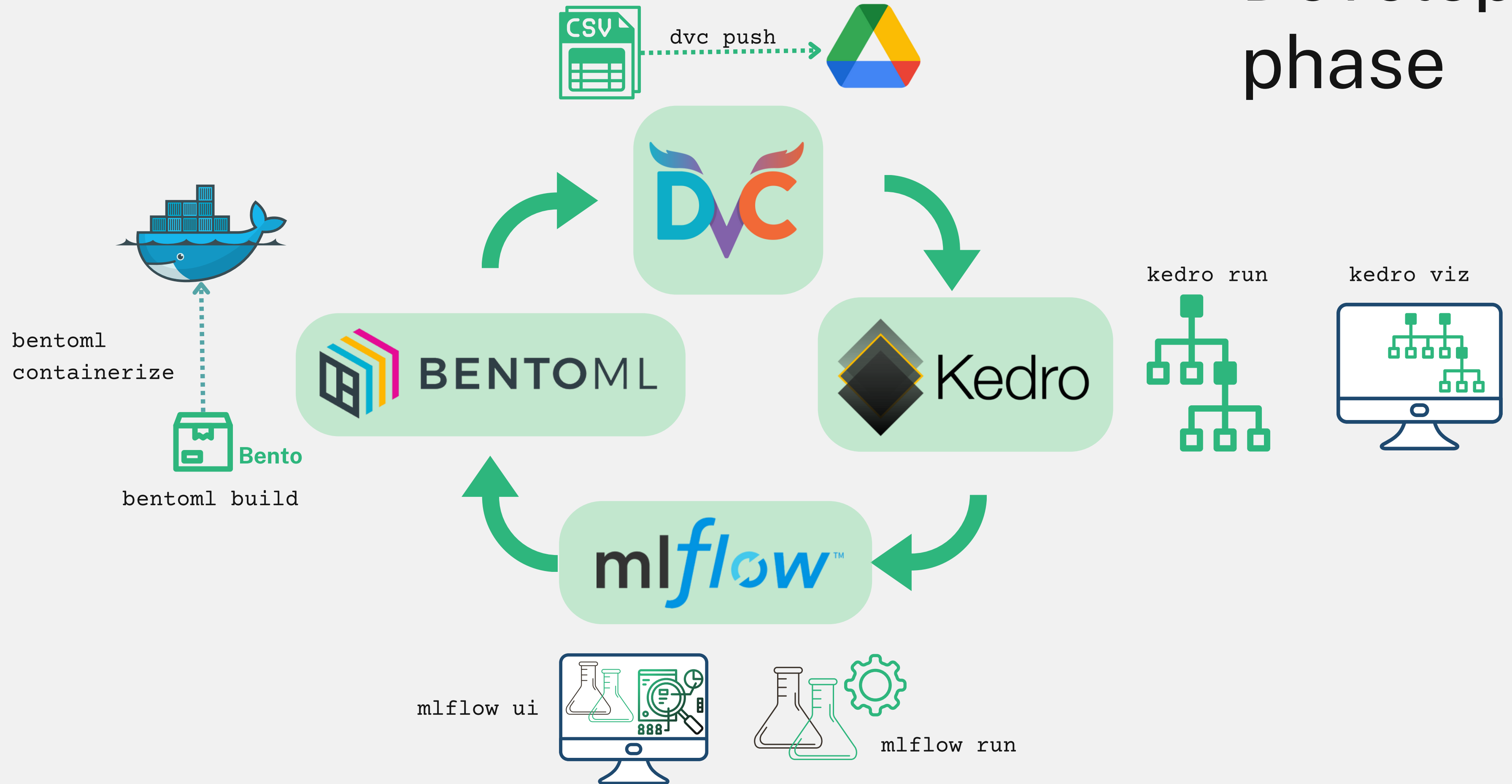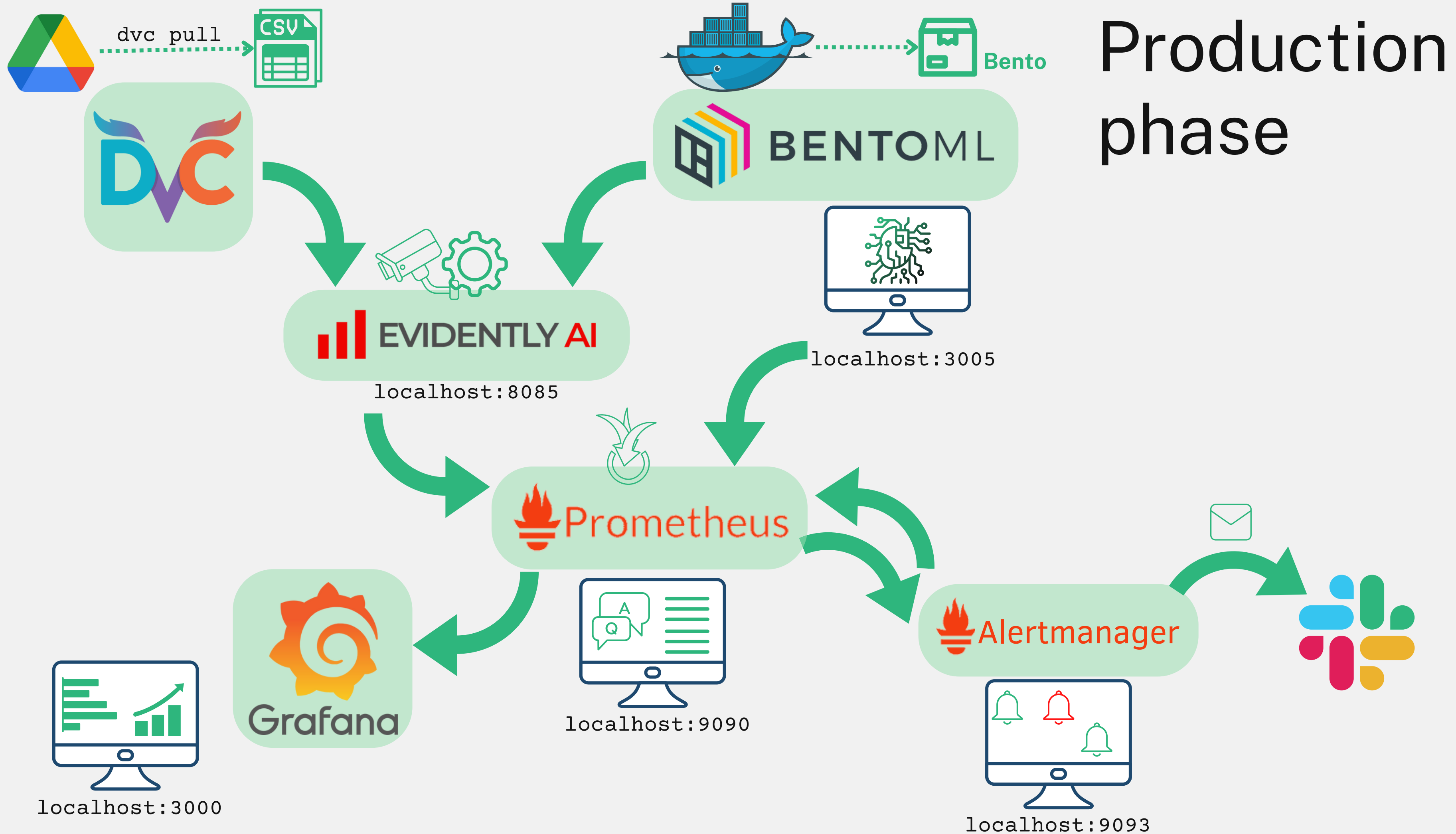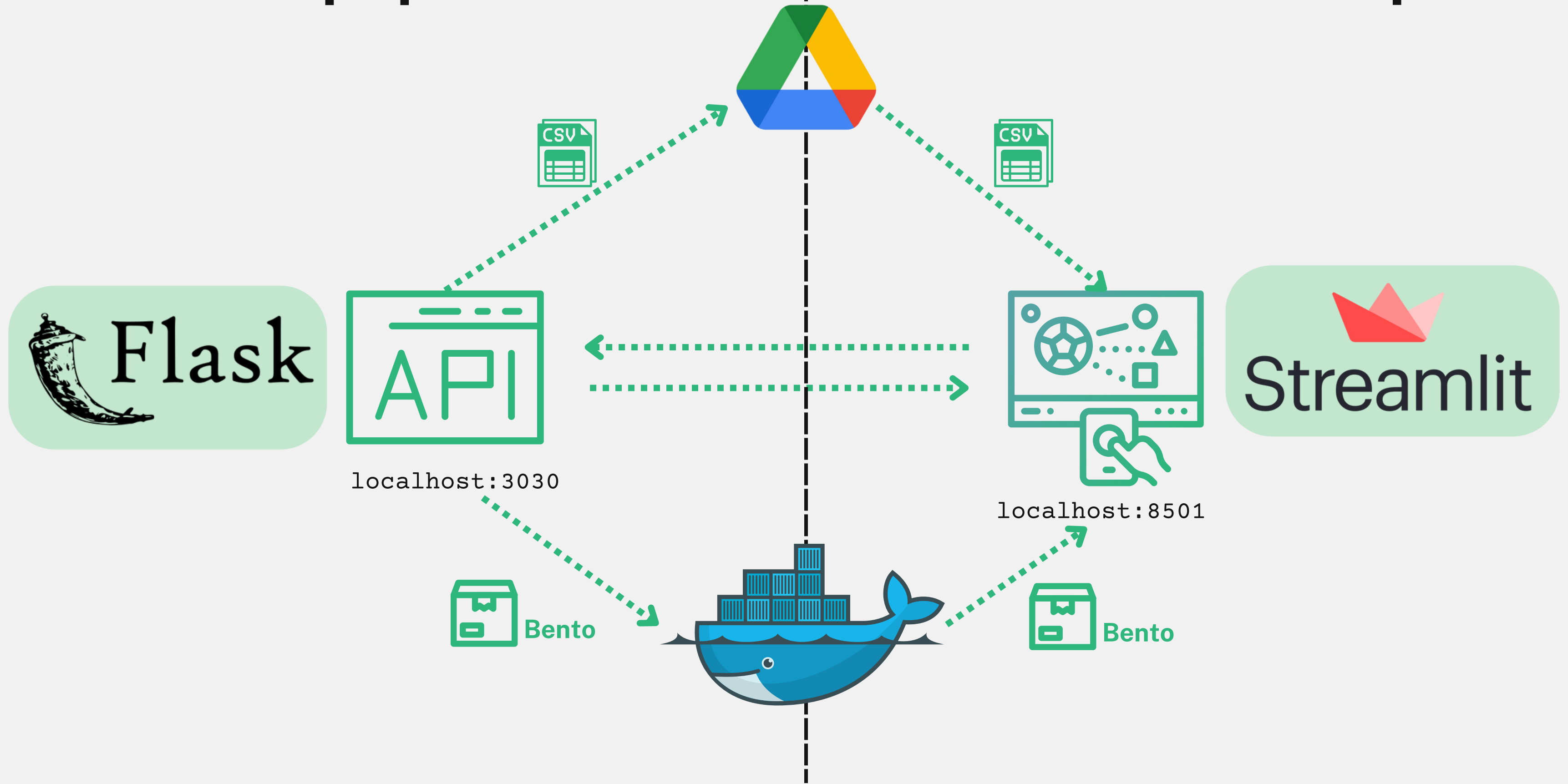| Drift and model monitoring	Systems monitoring and alerting	Alert management	Managed observability platform	Building application
EVIDENTLY AI	Prometheus	Alertmanager	Grafana	Streamlit

Develop phase

CSV — dvc push →

DVC

bentoml containerize

Bento

bentoml build

BENTOML

Kedro

kedro run   kedro viz

mlflow

mlflow ui   mlflow run

dvc pull

Bento

Production phase

localhost:8085

localhost:3005

Prometheus

Grafana

Alertmanager

localhost:3000

localhost:9090

localhost:9093

Commands line	Develop phase file: run.py
`python run.py pipeline`	open kedro ui to localhost:4141
`python run.py exp`	open mlflow ui to localhost:5000
`python run.py pipeline-docker`	create docker image about pipeline to create ml model
`python run.py run`	run training model and building bento service
`python run.py new-dataset <global_url>`	upload dataset from file csv with <global_url>
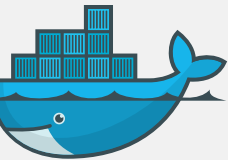
Flask app

Develop phase file: app.py

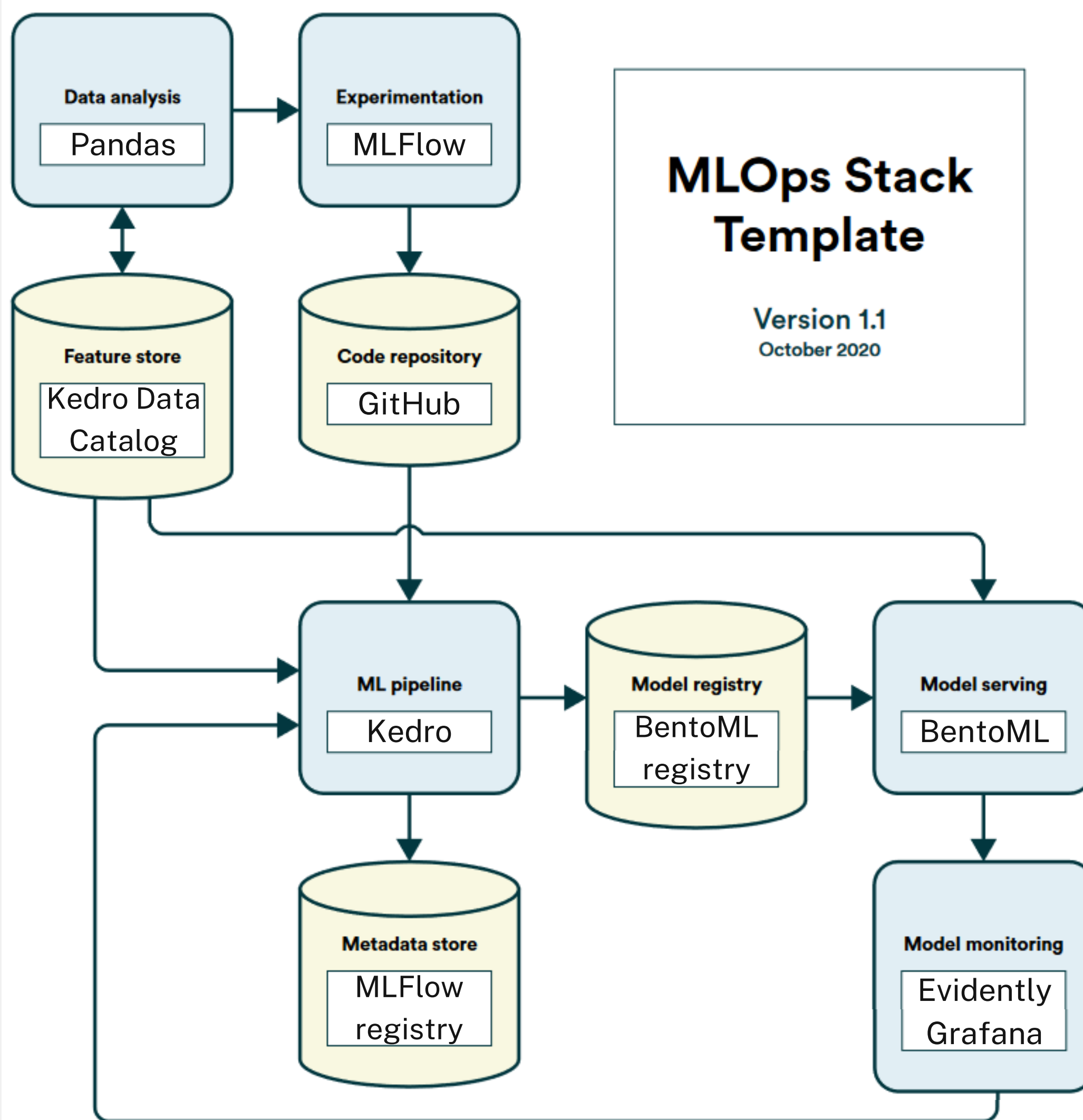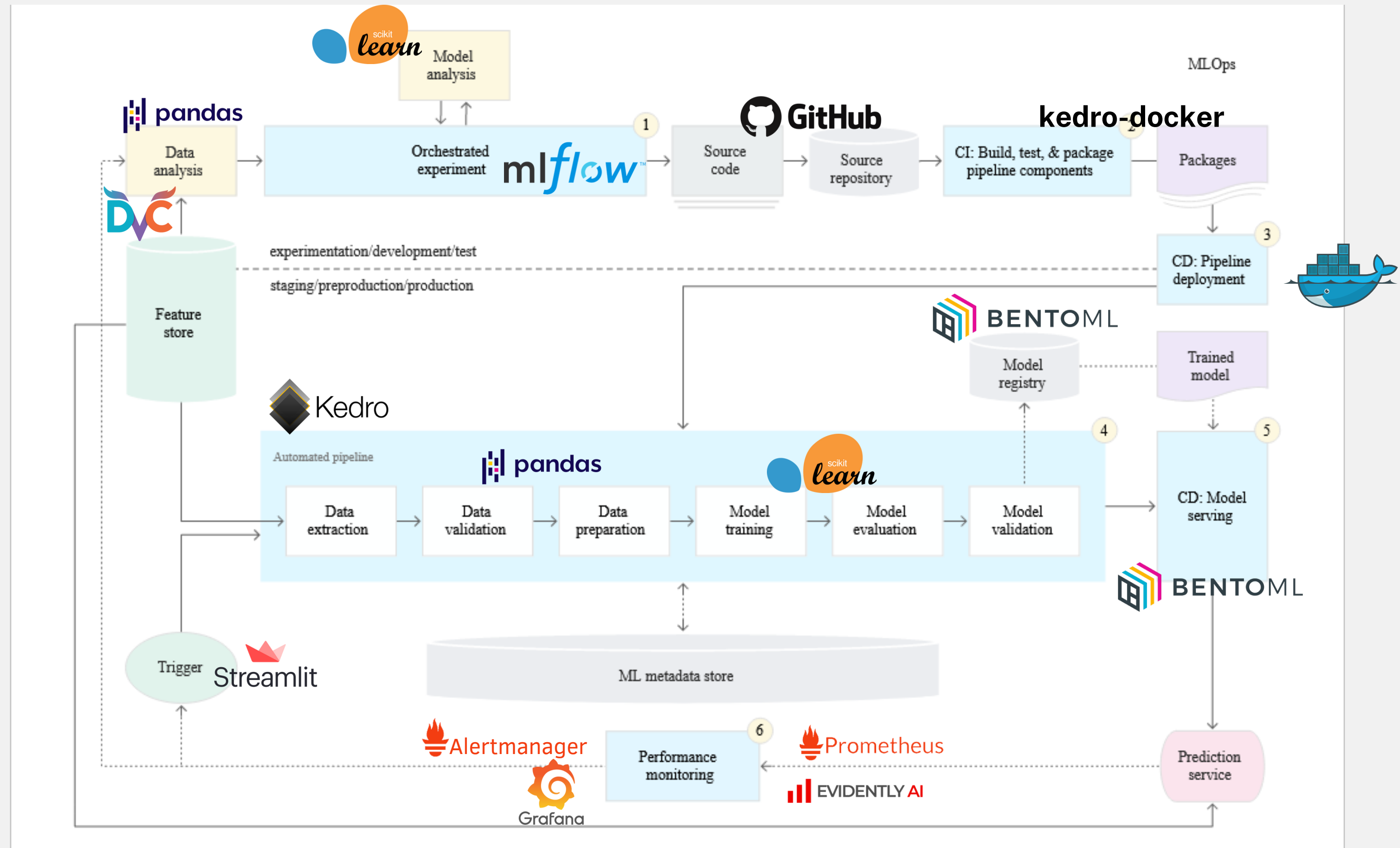|	
`@app.get("/dvc_file")`	return the code for take reference dataset from Google Drive.
`@app.route("/load_new_data", methods=["POST"])`	receive a dataframe to load as new reference dataset.
`@app.get("/retrain")`	load in Google drive new dataset, run mlflow to training model, build and dockerize bento.
`@app.get("/bento")`	build and dockerize bento.
`@app.get("/header")`	return name columns of dataset header.

MLOps Stack Canvas

Project name: MLOps tirocinio	**Team members:** Giorgia Bertacchini

Data analysis & experiment management

For data analysis uses Pandas, a Python library. For experiment management uses MLFlow, an open source platform.

Feature store & workflows

Feature are manipulate by Pandas, to work with Dataframe, and are collect by Kedro versioning they.

Data Sources & Data Versioning

Data sources are static file in table format, as csv. Use specialized data versioning systems as DVC to save in a Google Drive folder the raw dataset. Another system use is Kedro that save each versions of intermediate and output data and of ml model.

Value Proposition

This project would predict the quality of each case receive from csv file.

MLOps Dilemmas

Tooling: are all open-source.
Platforms: using a hybrid solution, with more platforms.

Foundations

For source version control system uses GitHub.

ML pipeline orchestration

The DAG (directed acyclic graph) is create by Kedro tool, an open-source Python framework.

Model & Data & Application Monitoring

To observing the model there are Evidently and Prometheus tools, which can alerts user and Grafana provide a dashboard for users.

Model registry & Model versioning

All model are collect in MLFlow ui and in BentoML platform.

Model deployment

Ml model and its environment are deployment through BentoML, that create deployable artifacts (Bentos).

Prediction serving

BentoML provide a service, to require predictions to ml model in Bentos.

MLOps Stack Template

Version 1.1
October 2020

Data analysis
Pandas

Experimentation
MLFlow

Feature store
Kedro Data Catalog

Code repository
GitHub

ML pipeline
Kedro

Model registry
BentoML registry

Model serving
BentoML

Metadata store
MLFlow registry

Model monitoring
Evidently Grafana

MLOps stack - Level 2

MLOps stack - Level 2: Specifications

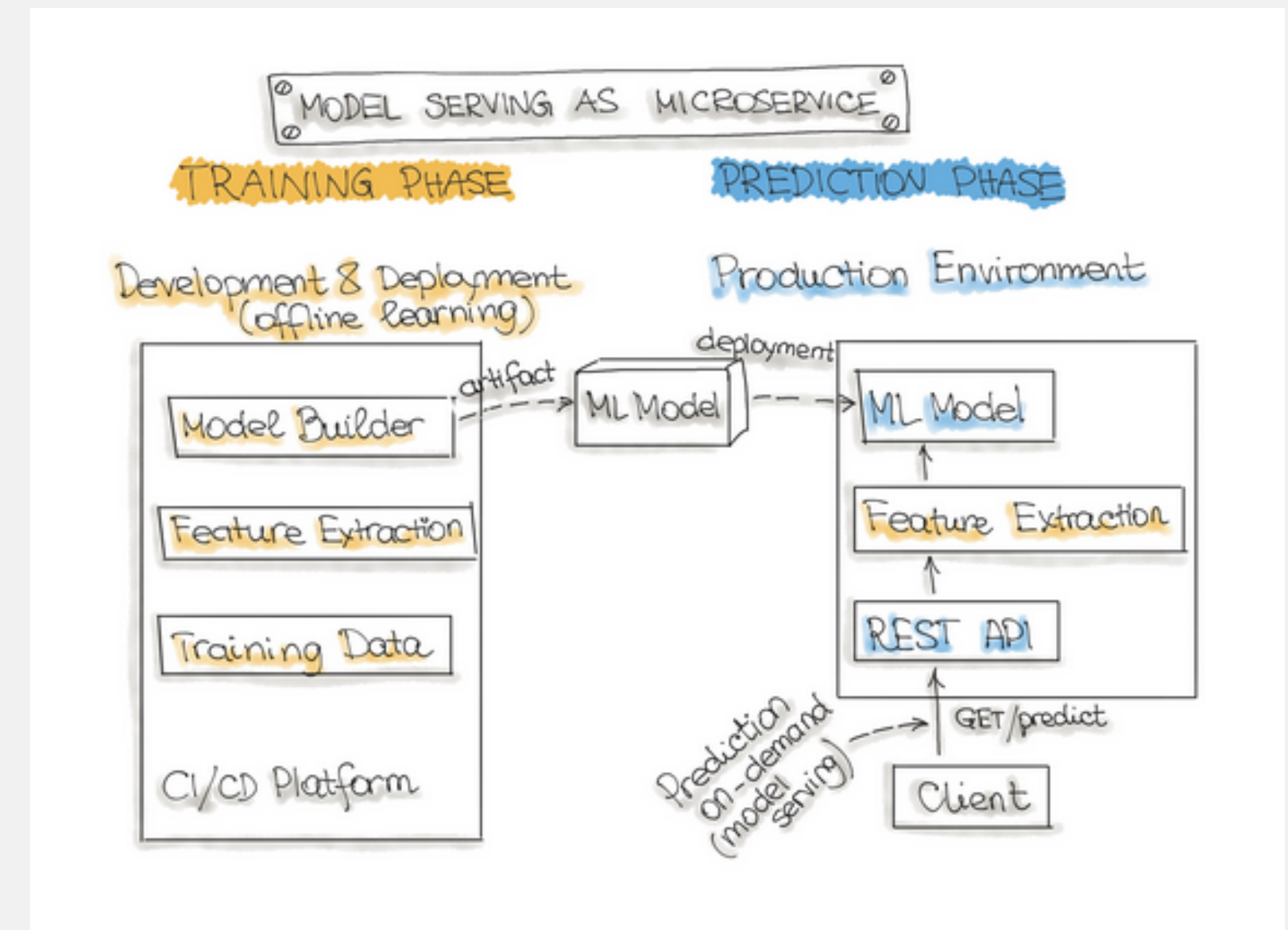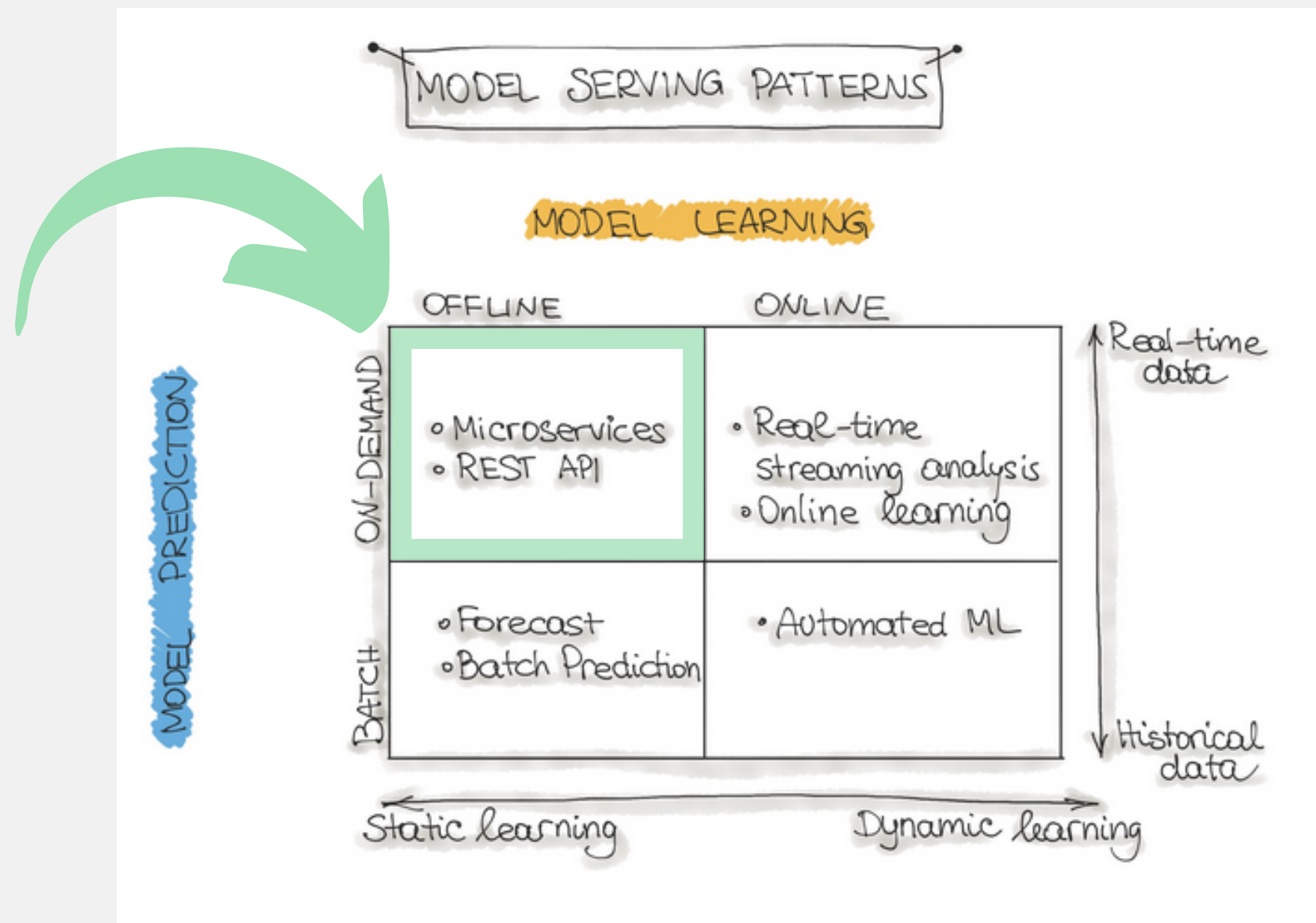|	
mlflow GitHub	**Development and experimentation**: you iteratively try out new ML algorithms and new modeling where the experiment steps are orchestrated. The output of this stage is the source code of the ML pipeline steps, which are then pushed to a source repository.
scikit learn Kedro	**Pipeline continuous integration**: The outputs of this stage are pipeline components (packages, executables, and artifacts) to be deployed in a later stage. Model validation via cross-validation for choose hyperparameters.
kedro-docker	**Pipeline continuous delivery**: you deploy the artifacts produced by the CI stage to the target environment. The output of this stage is a deployed pipeline with the new implementation of the model.
Streamlit	**Automated triggering**: the pipeline is automatically executed in production based on a schedule or in response to a trigger. The output of this stage is a newly trained model that is pushed to the model registry.
BENTOML	**Model continuous delivery**: you serve the trained model as a prediction service for the predictions. The output of this stage is a deployed model prediction service.
Prometheus Grafana	**Monitoring**: you collect statistics on model performance based on live data. The output of this stage is a trigger to execute the pipeline or to execute a new experiment cycle.

MLOps stack - Level 2
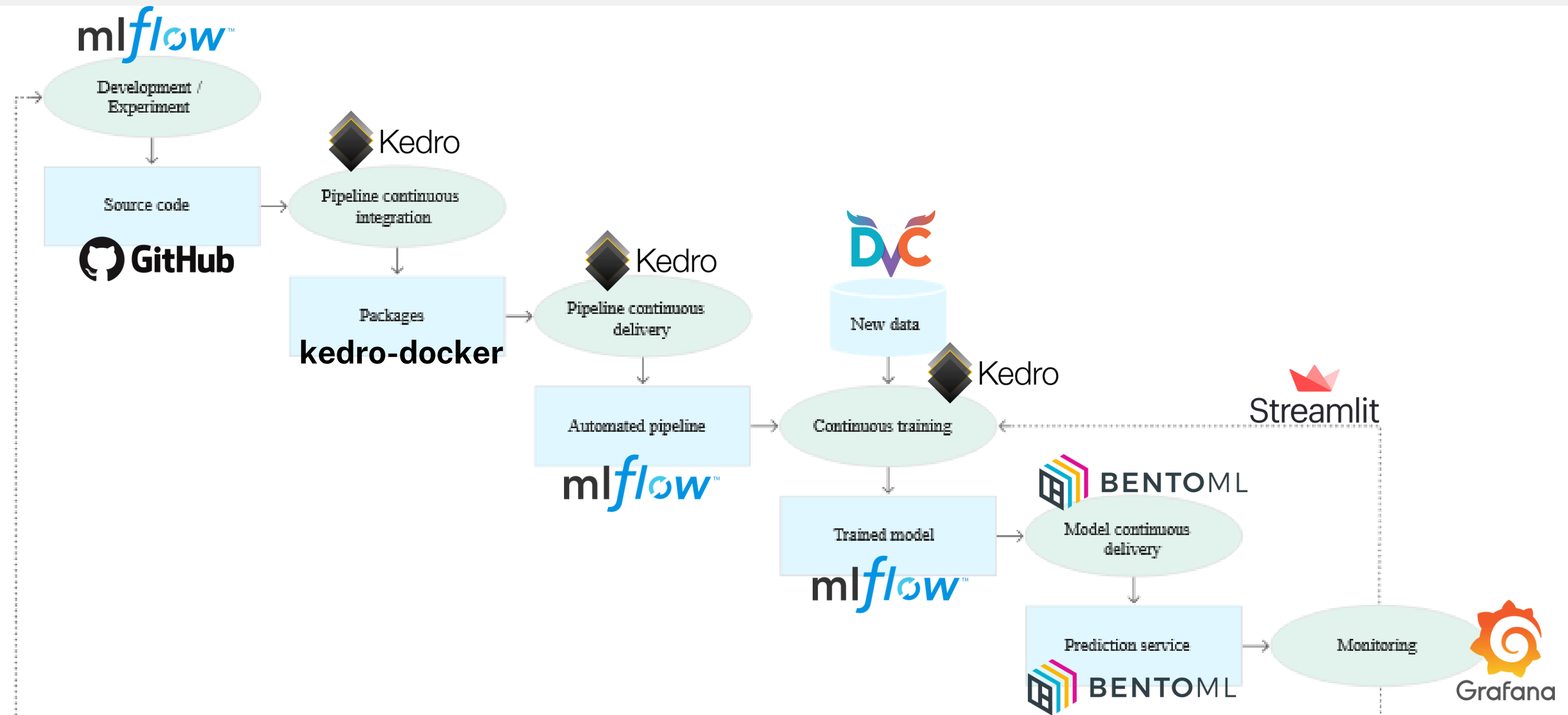
To classified the project

This project have:
- Model learning Offline
- Model predictions On-Demand

So use Microservices and Rest API application.

As we can see the next schema is very similar to previous schema, where the two phase are separate but connected.

GitHub url

Develop phase:
https://github.com/giorgiaBertacchini/MLOps-kedro-auto/tree/experiment-finally

Production phase:
https://github.com/giorgiaBertacchini/MLOps/tree/main/MLOps%20-observability