MLOps: The Production Pipelines of Machine Learning Models

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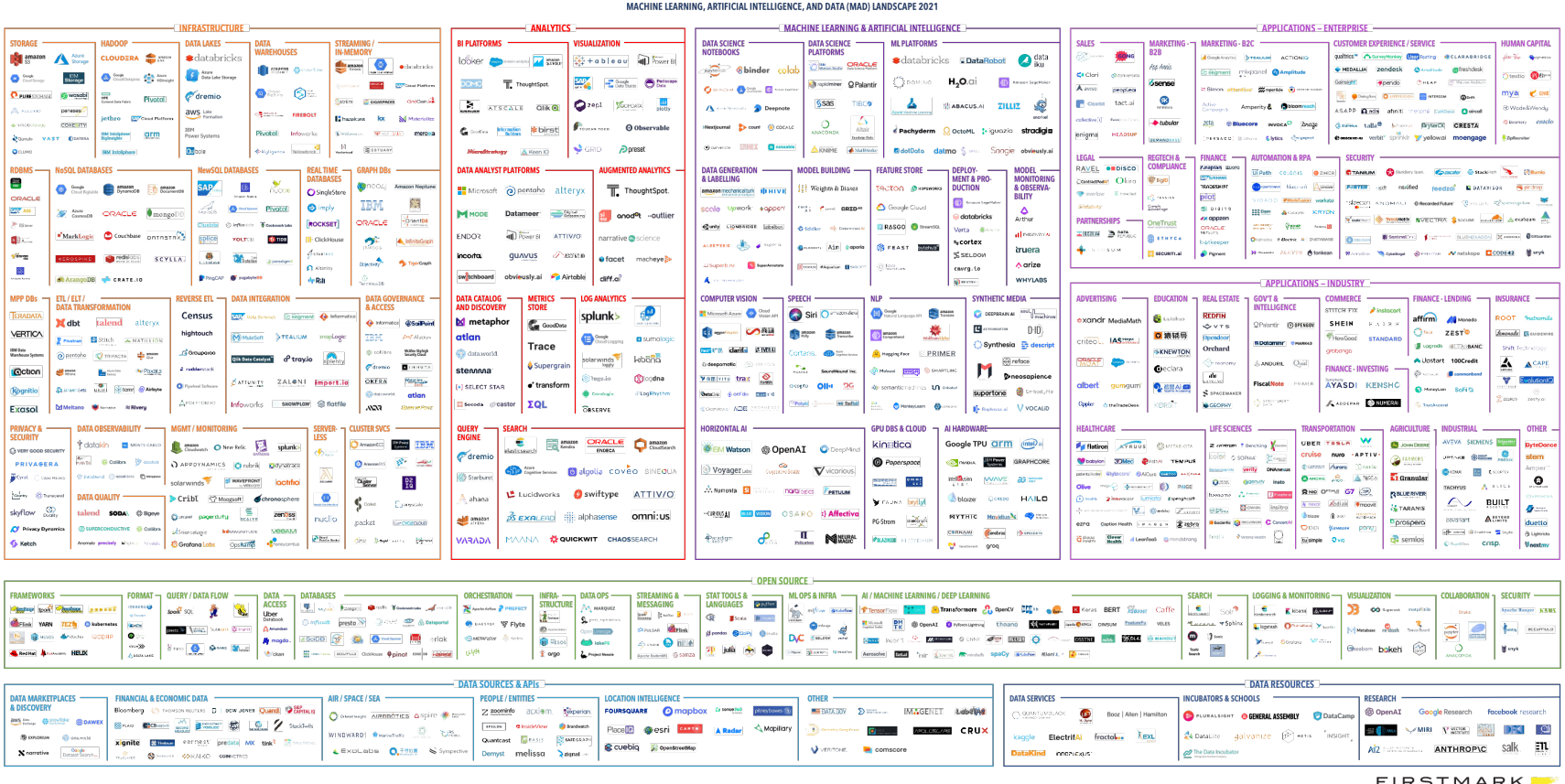
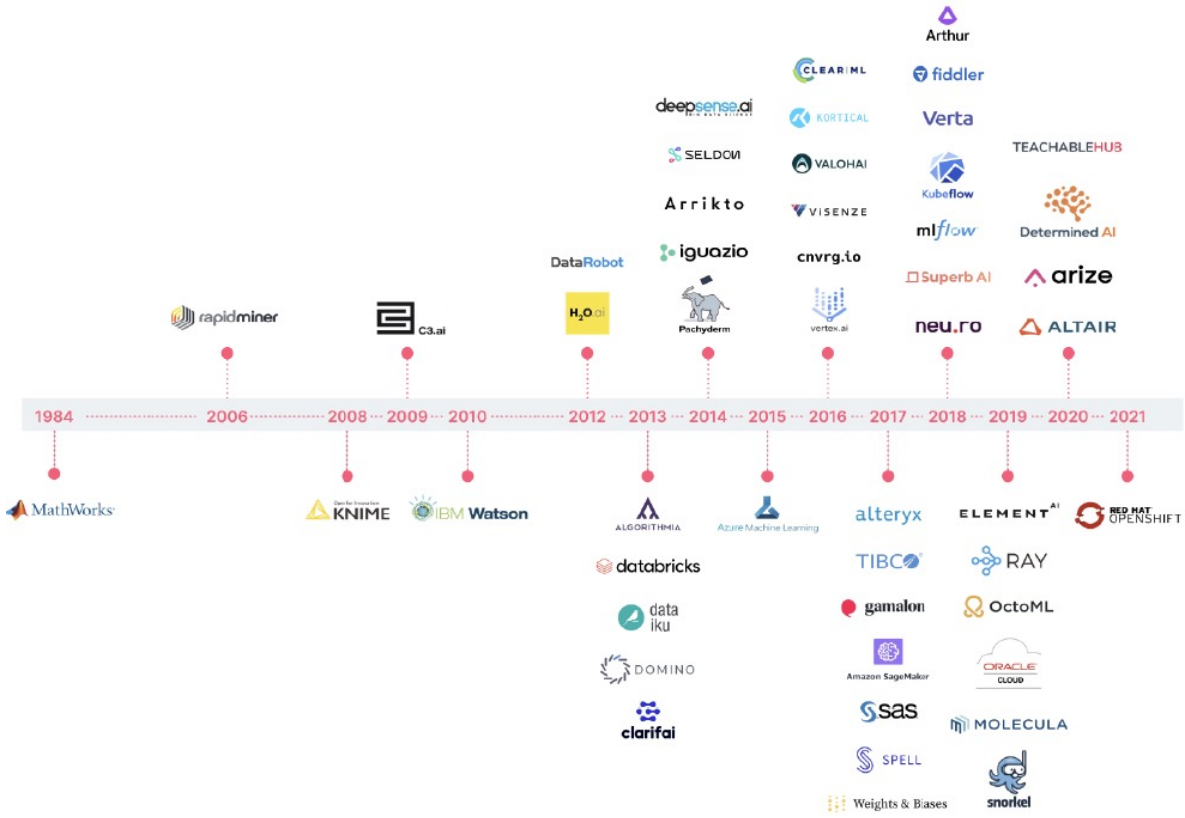
Machine Learning Artificial Intelligence, and Data (MAD) landscape 2021



The "Glut of Innovation"[1]

The explosion of MLOps tools is one part of the overall MAD landscape

- Why do we need MLOps tools?
- How to decide the best one for your team?



[1] Surge in Innovation in Data Science and ML Platforms, Says Gartner, April 2021
https://www.cdotrends.com/story/15491/surge-innovation-data-science-and-ml-platforms-says-gartner

[2] Guite to Evaluating MLOps Platforms, ThoughtWorks whitepaper, November 2021
https://www.thoughtworks.com/what-we-do/data-and-ai/cd4ml/guide-to-evaluating-mlops-platforms

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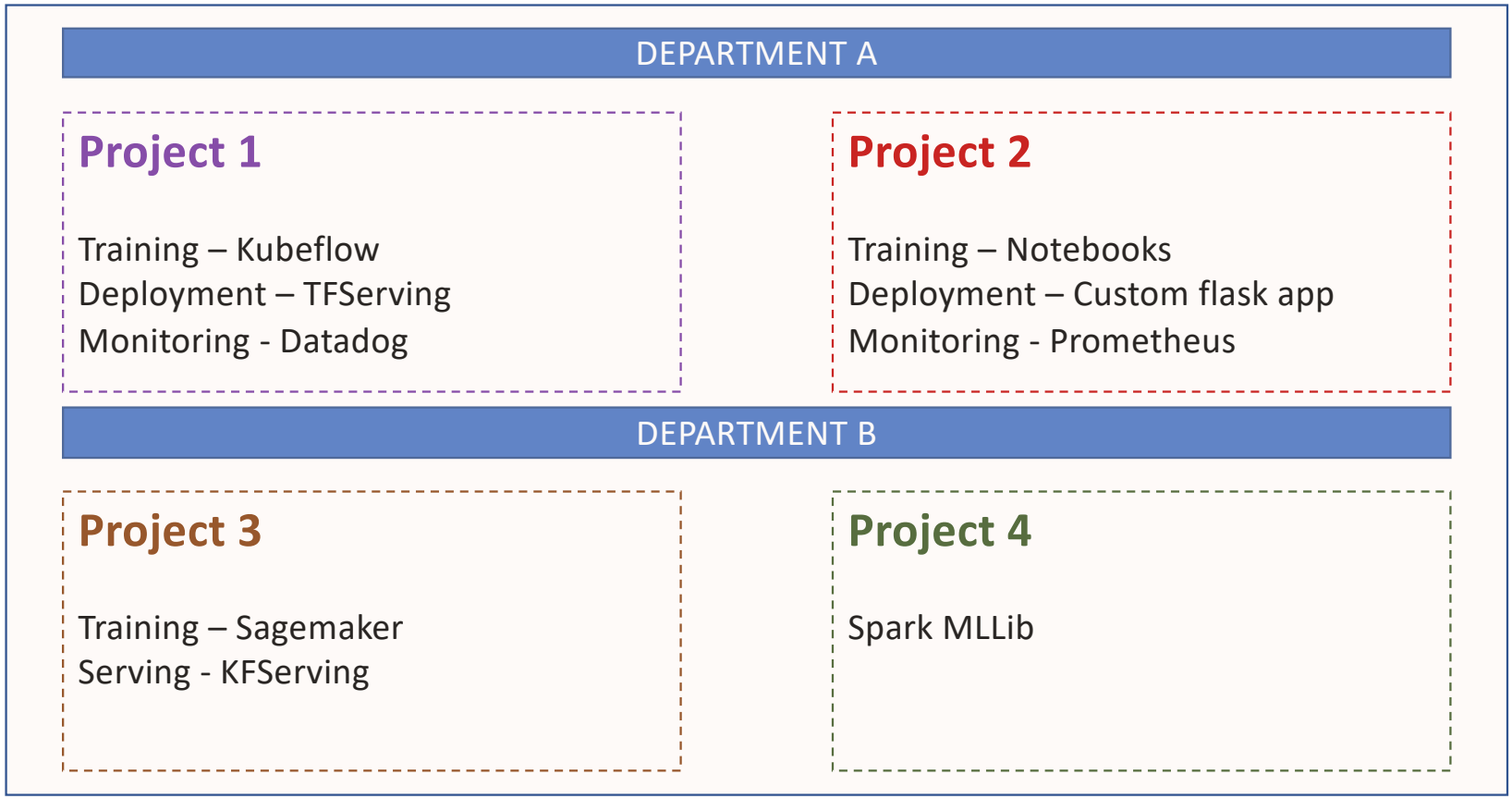
Avoid the MLOps tools "zoo" in your organization



[1] Guite to Evaluating MLOps Platforms, ThoughtWorks whitepaper, November 2021
https://www.thoughtworks.com/what-we-do/data-and-ai/cd4ml/guide-to-evaluating-mlops-platforms

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Machine Learning is not just code, it's code plus data

ML Ops is a set of practices that combines Machine Learning, DevOps and Data Engineering, which aims to deploy and maintain ML systems in production reliably and efficiently

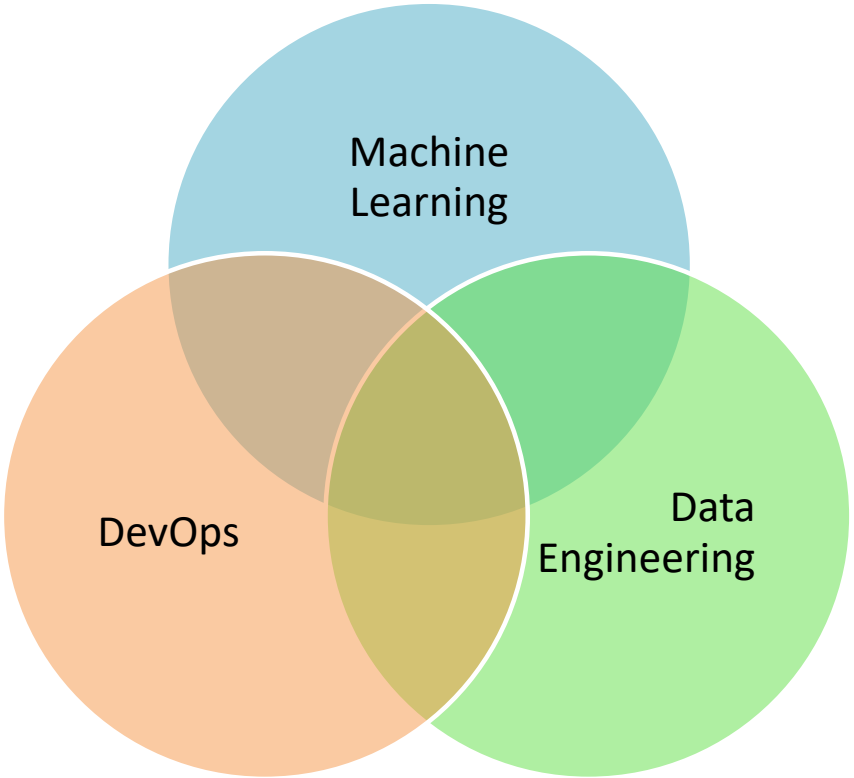
Cristiano Breuel, Machine Learning Engineer

Machine Learning Models in Production

Risks

- Slow, brittle and inconsistent deployment
- Lack of reproducibility
- Performance reduction (training-serving skew)

To avoid such risks we need to combine practices from DevOps, Data Engineering and Machine learning know-how



Purpose of MLOps Platforms

Collection of tools that aims to bring value from Machine Learning (ML) systems

- Automate tasks involved in building ML-enabled systems
- Make it easier to bring value from ML

Good solution is not only about choosing the "best" tools![1]

- The tools should git together as a shared solution that provides consistency in end-to-end ML-enabled system
- Consistency across the organization as a single platform for different projects and departments

[1] Guite to Evaluating MLOps Platforms, ThoughtWorks whitepaper, November 2021
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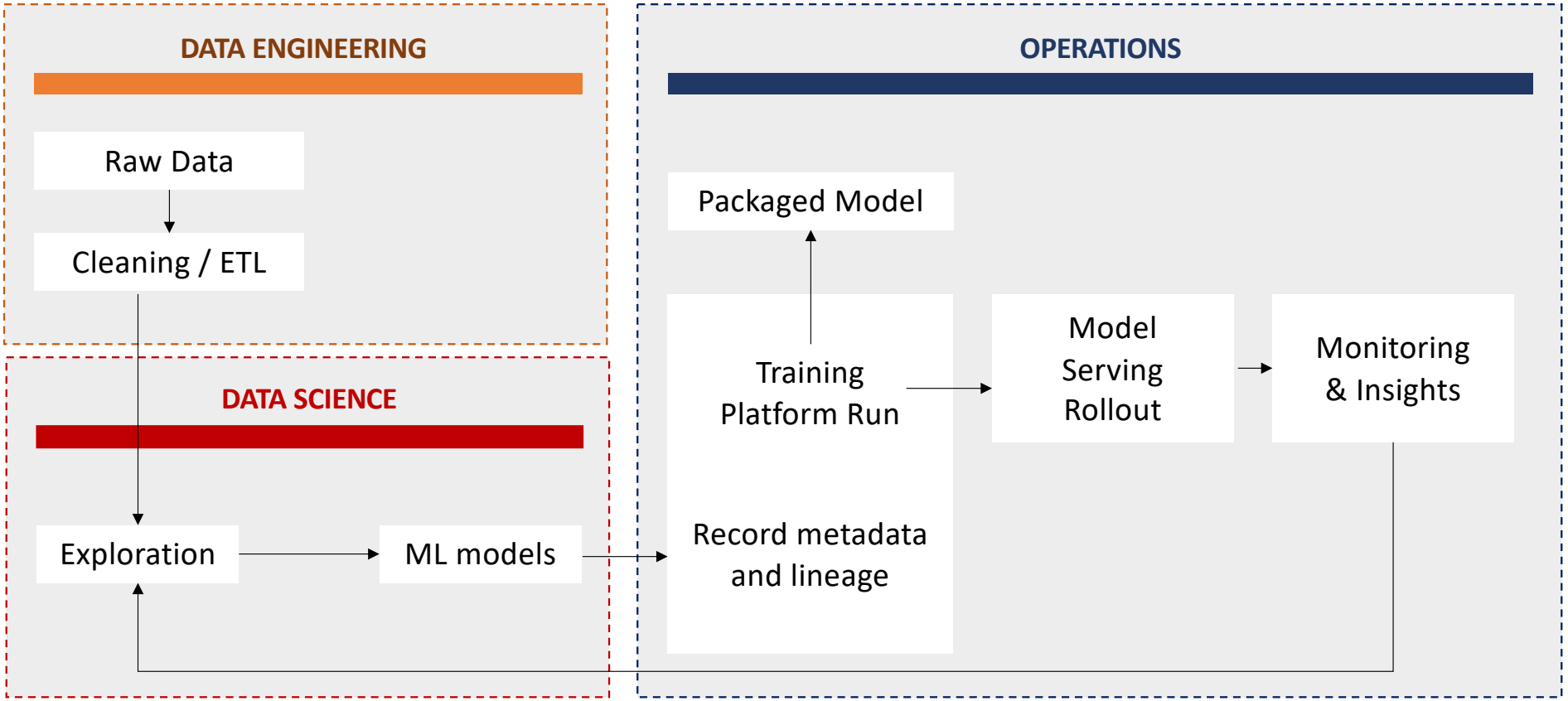
Who performs which MLOps tasks?



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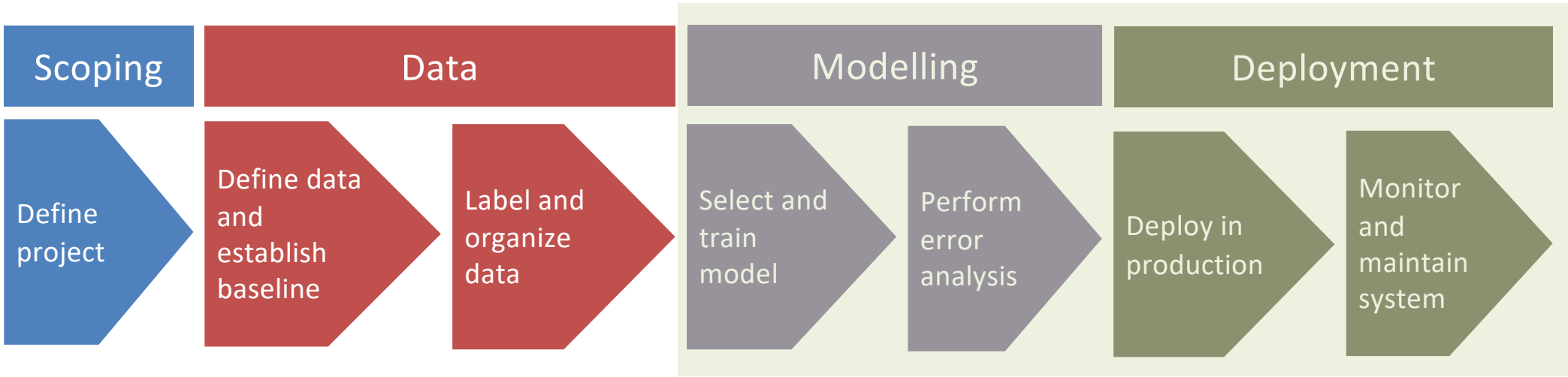
Machine Learning (ML) Lifecycle



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Modelling
Model Performance

Deploy a model that performs good on average

but presents <u>poor results on relevant tests</u> is not acceptable

Evaluate the model separately to guarantee

- Overall quality
- Is fully aligned with key tests aligned with stakeholders
- Avoid discriminatory behavior

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Modelling Deployment

Deployment should not be framed as binary outcome but instead as a **spectrum of varying degrees of automation**

Degrees of automation varies on use case and business alignment

Not always there is a full automation

e.g., partial-automation with a human in the loop might be an AI-based solution for medical diagnostics

[1] https://www.data4v.com/machine-learning-deployment-strategies/

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Modelling
Deployment Scenarios

Shadow

How: ML model runs in parallel together with human workflow
Rational: Validate model performance together with humans to ensure the outcome is aligned

Canary

How: Deploy model on a smaller fraction of the target output e.g., 5% email targeting or traffic
Rational: Evaluate the model without exposing it to all targets

Blue-Green

How: replace partially or completely an existing model (blue) with a new model version (green) whereas Blue- and Green- model have nearly identical production environments
Rational: Ensure the downtime to users is minimum and, in case of a problem, roll-back with this deployment strategy

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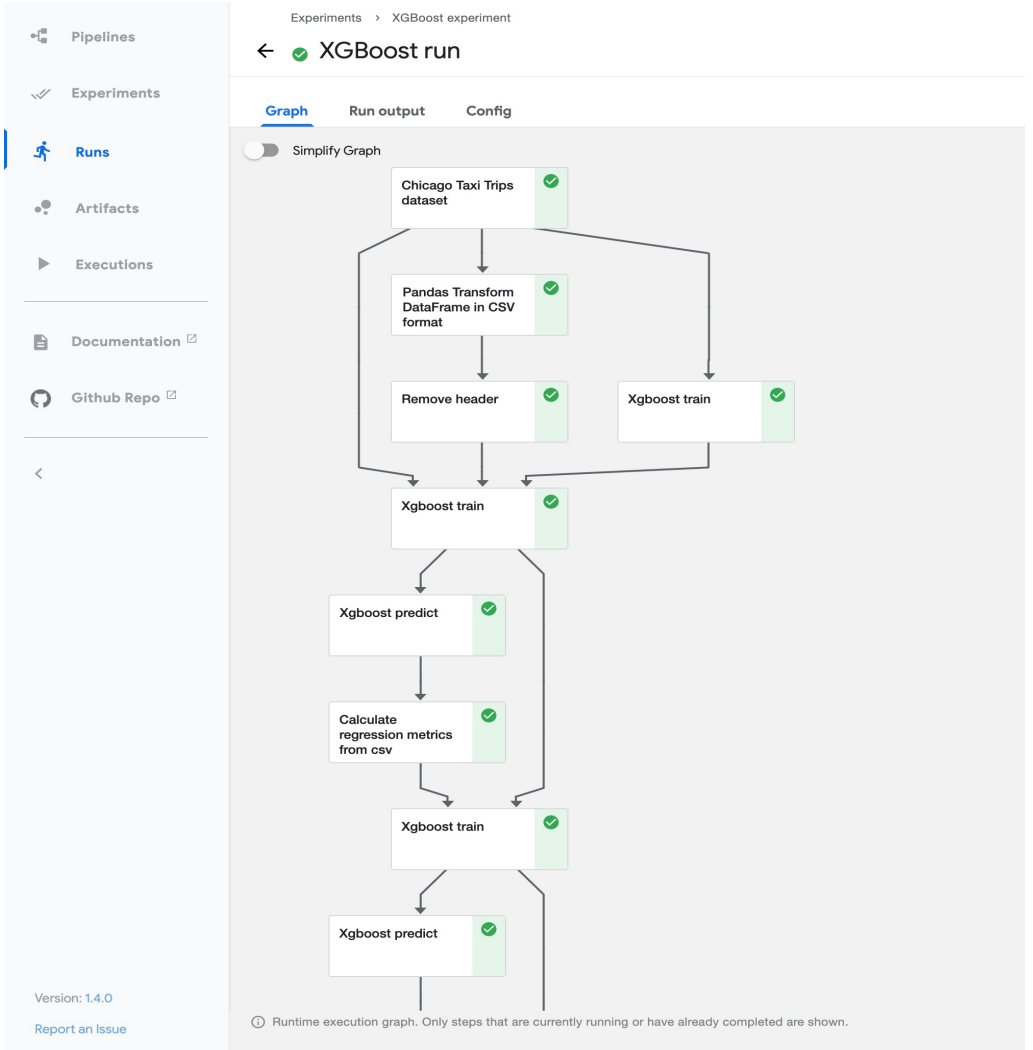
ML Deployment

Visual representation of ML pipeline

Kubeflow Pipelines

- ML training can have many components
- Data pipeline, training, prediction, deploy..
- In general, needs 2 versions of the pipeline
  - 1 for training and 1 for serving



https://www.kubeflow.org/docs/images/pipelines-xgboost-graph.png

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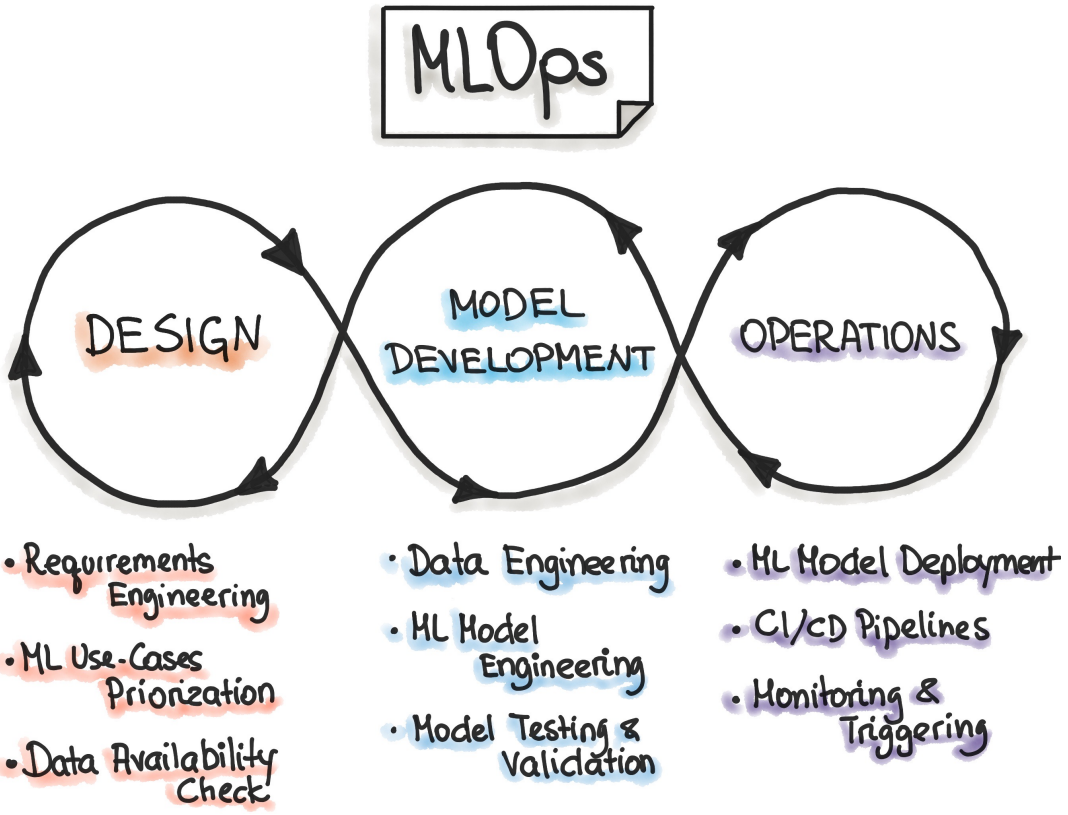
ML Pipeline is pure code artifact which means that is possible to track its versions in source control and automate its deployment using CI/CD[1] pipelines



https://ml-ops.org/content/mlops-principles

[1] Continuous Integration & Continuous Development

Modelling
System Monitoring

Define metrics to monitor

- Input metrics e.g., data drift, missing values
- Output metrics e.g., model drift, volume target predictions
- Software metrics e.g., server load, latency

Build a dashboard and/or produce automatic alarmistic systems

Modelling
System Monitoring

Define metrics to monitor

- Input metrics e.g., data drift, missing values
- Output metrics e.g., model drift, volume target predictions
- Software metrics e.g., server load, latency

But.. which metrics to track?

Build a dashboard and/or produce automatic alarmistic systems

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Model and Data Monitoring

Models and metadata can be tracked using versioning tools (e.g., Git) **but in general data is too large and dynamic/mutable for that to be a realistic option**

ML should be continuous

Decompose each part of ML pipeline into small, manageable components to be tested and developed separately e.g., processing data and training the model

If the metrics are chosen based on the component purpose the monitoring implementation will become a lot easier

Model Monitoring

In general, ML models do not provide 100% correct results

Model validation should be of statistical nature instead of traditional software development binary pass/fail test

How we decide if the model is good enough for deployment?

- Based on the model nature

  e.g., ensemble models track adjustments to parameters and/or hyperparameters

- Decide on thresholds for acceptable values

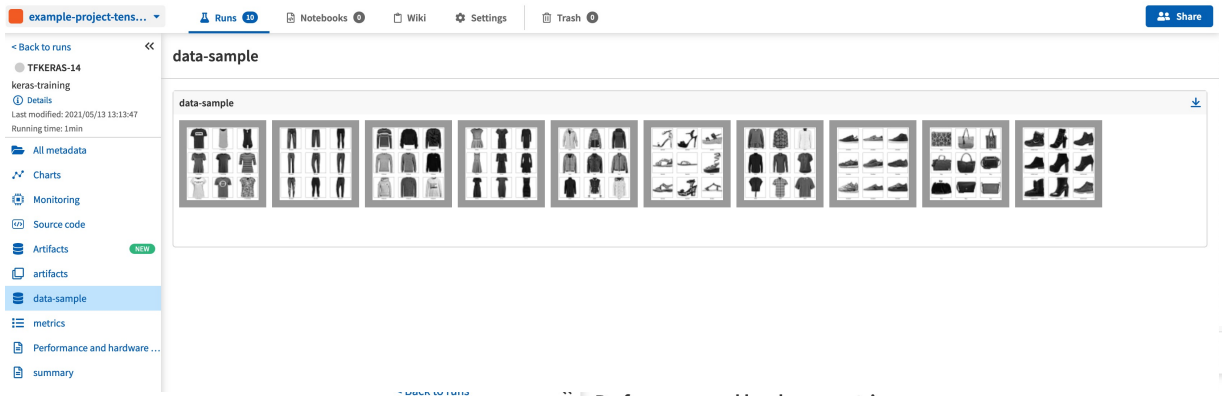
  e.g., compare with performance from previous model runs

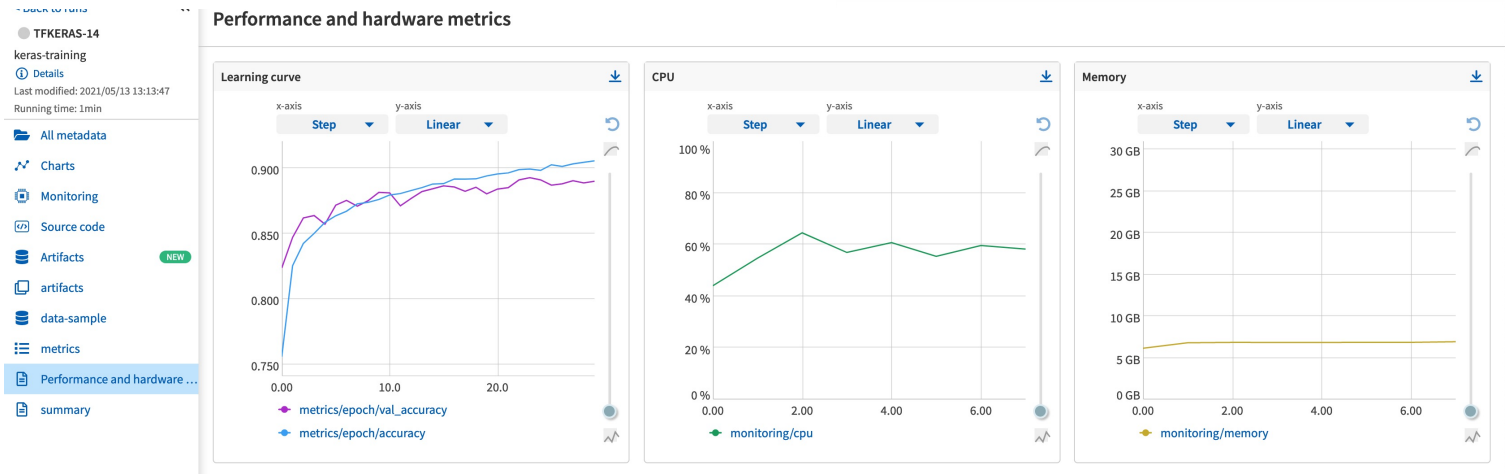
- Sometimes performance cannot be seen as a ”whole” therefore slices of test data are taken to validate model performance for specific relevant features

  e.g., gender and/or country

Let’s have a look at some tools

neptune.ai





https://ui.neptune.ai/
Example from app.neptune.ai

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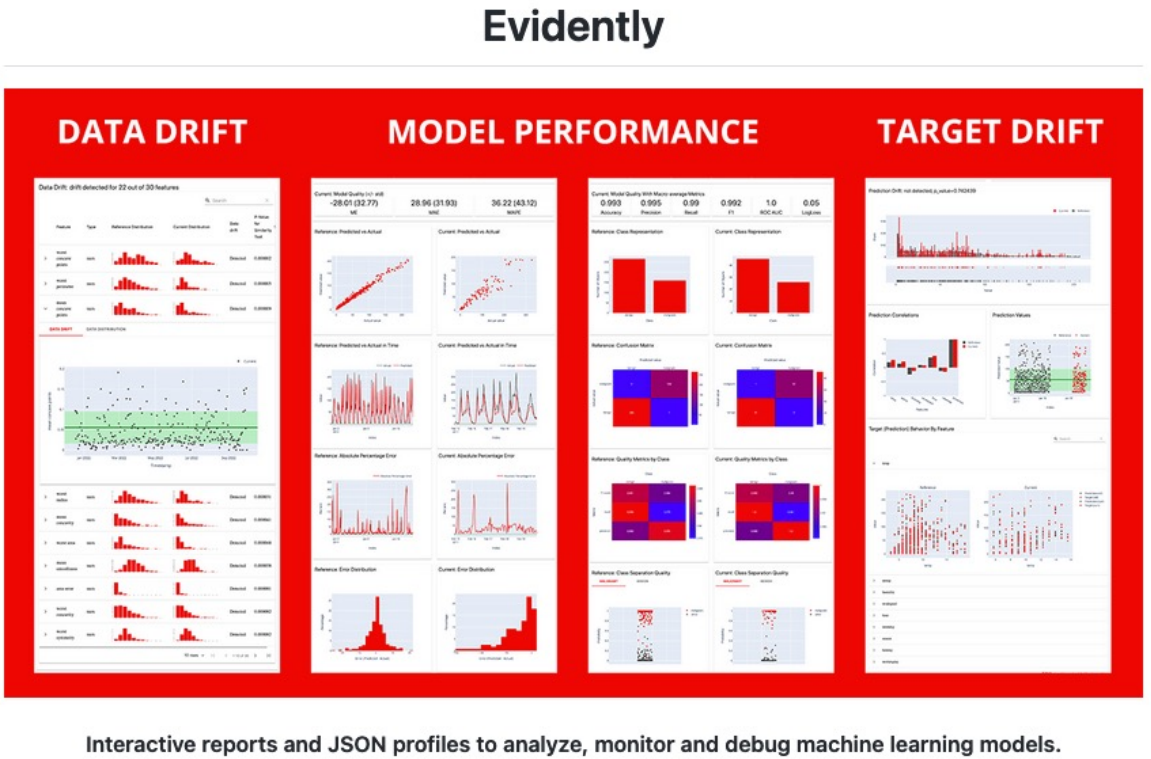
Evidently

Evidently[1] helps evaluate machine learning models during validation and monitor them in production. The tool generates interactive visual reports and JSON profiles from pandas DataFrame or csv files.



Interactive reports and JSON profiles to analyze, monitor and debug machine learning models.

[1] https://github.com/evidentlyai/evidently

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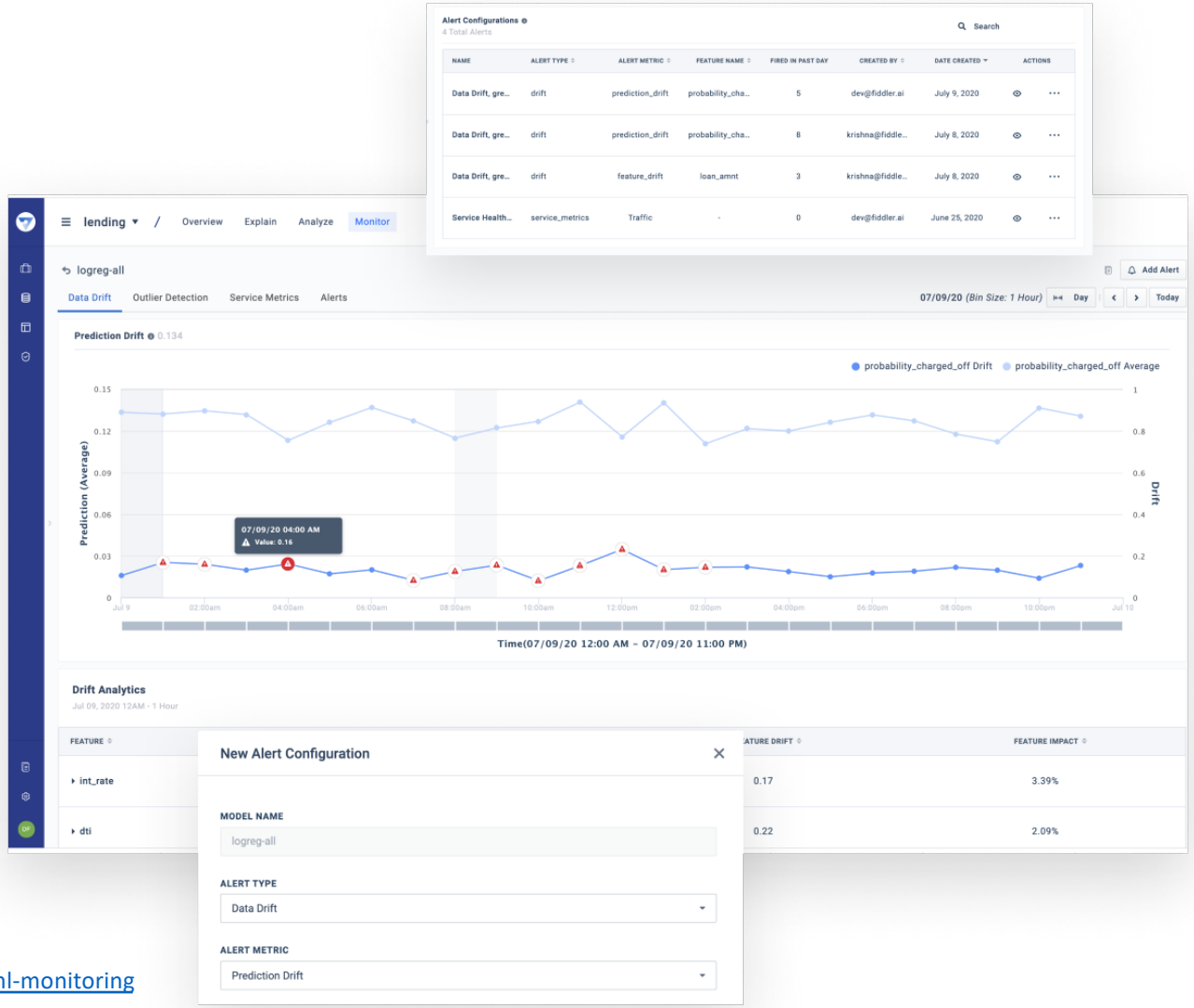
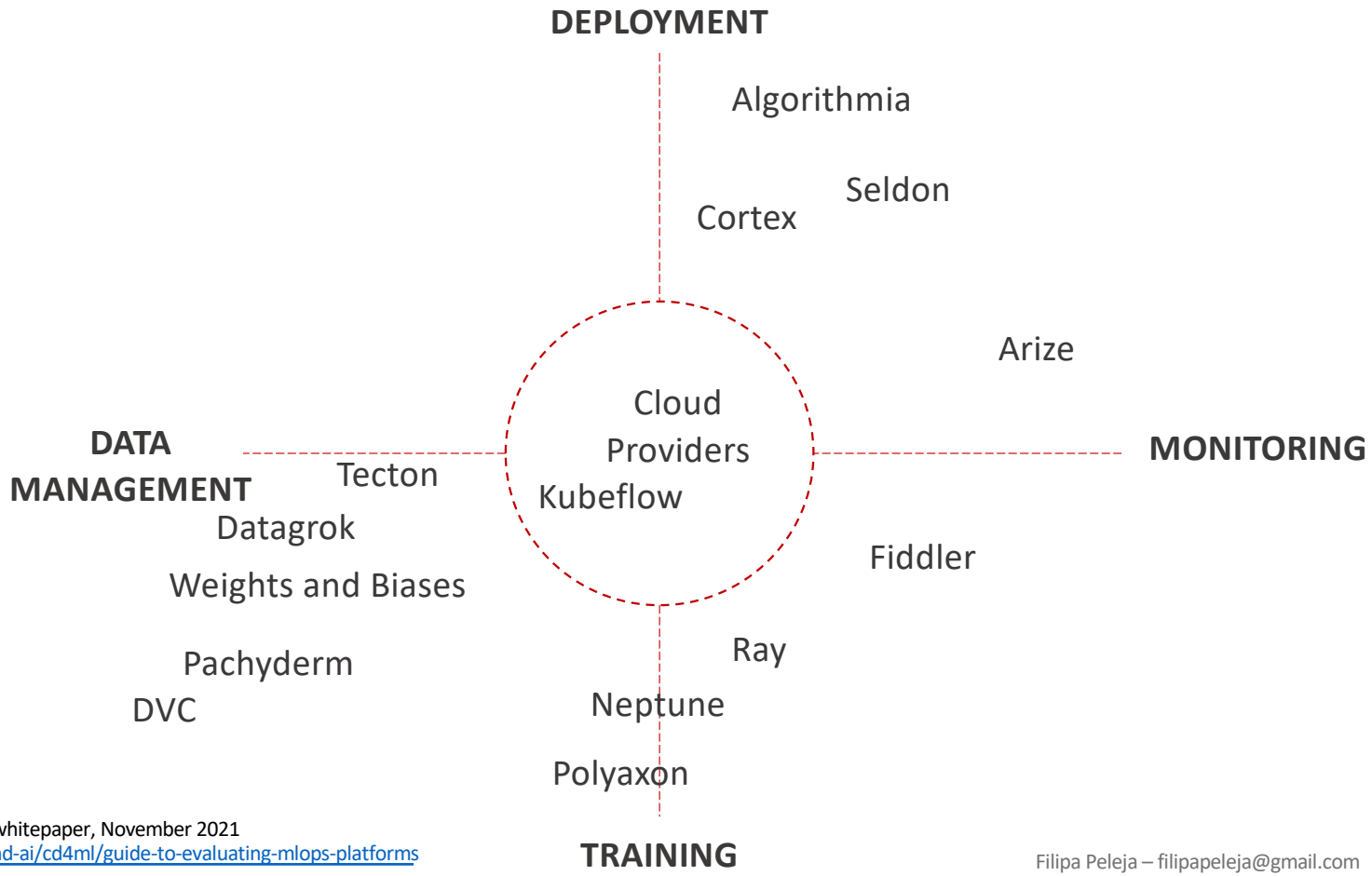
Fiddler



[1] https://www.fiddler.ai/ml-monitoring

Visualise the tools in terms of specialization

- Based on your requirements you main lean to different tools
- If the objective is to have a most balanced all-in-one then the ones in the middle cover different aspects more equally



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Recap

Practice	DevOps	Data Engineering	ML Ops
Version control	Code version control	Code version control Data lineage	**Code version control + Data versioning + Model versioning (linked for reproducibility)**
Pipeline	n/a	Data pipeline/ETL	**Training ML Pipeline, Serving ML Pipeline**
Behavior validation	Unit tests	Unit tests	**Model validation**
CI/CD	Deploys code to production	Deploys code to data pipeline	**Deploys code to production + training ML pipeline**
Data validation	n/a	Format and business validation	**Statistical validation**
Monitoring	SLO-based	SLO-based	**SLO + differential monitoring, statistical sliced monitoring**

https://geniusee.com/single-blog/mlops-practices-and-its-benefits

Presentation available at
https://github.com/Peleja/DSPA_17122021

Image from "but Asking Can Hurt," She Writes - Ask Questions

Thank you!

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