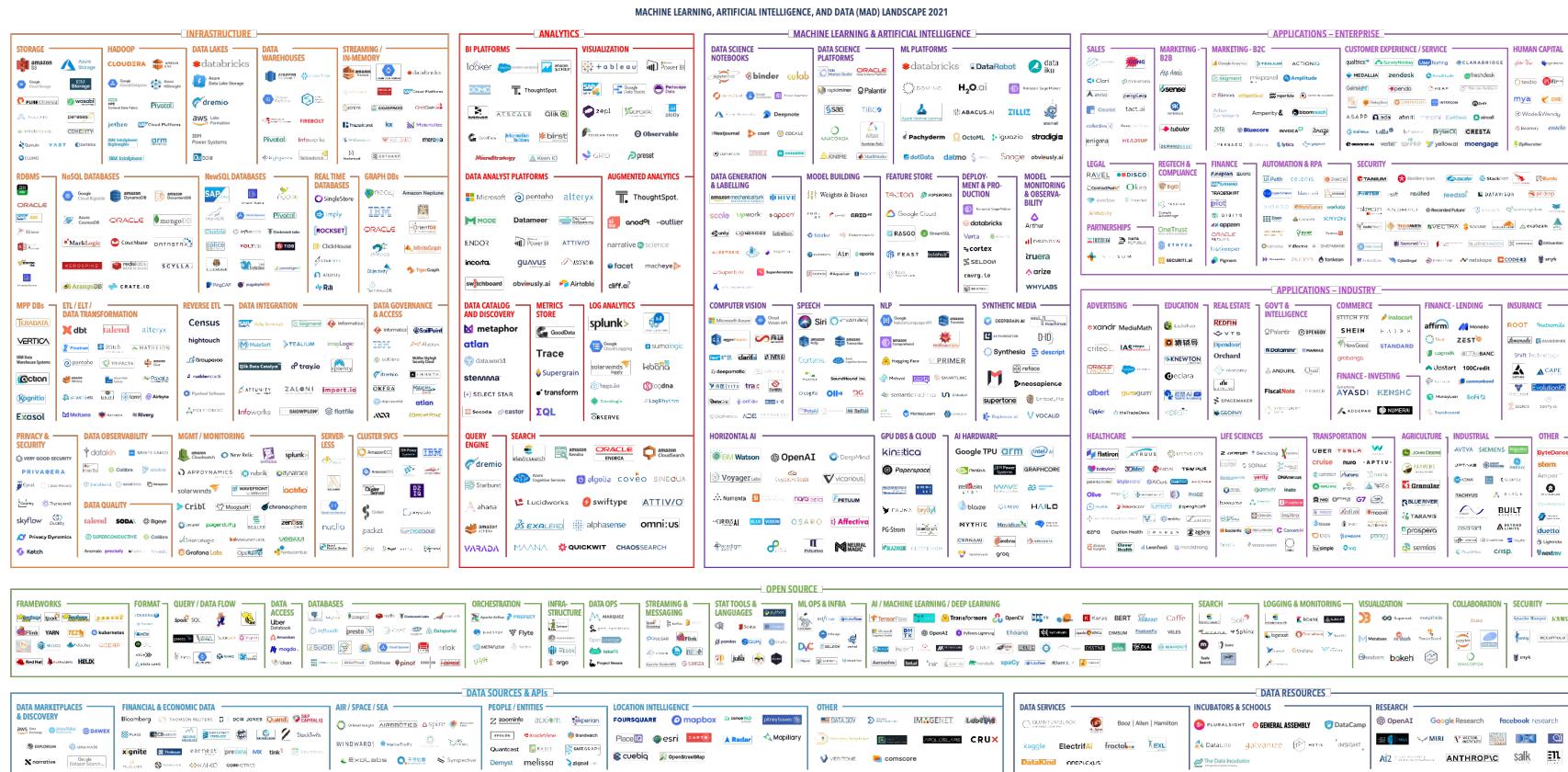


MLOps: The Production Pipelines of Machine Learning Models

Filipa Peleja
Lead Data Scientist at Levi Strauss & Co Europe
17 December 2021

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



Version 3.0 November 2021

© Matt Turck (@mattturck), John Wu (@john_d_wu) & FirstMark (@firstmarkcap)

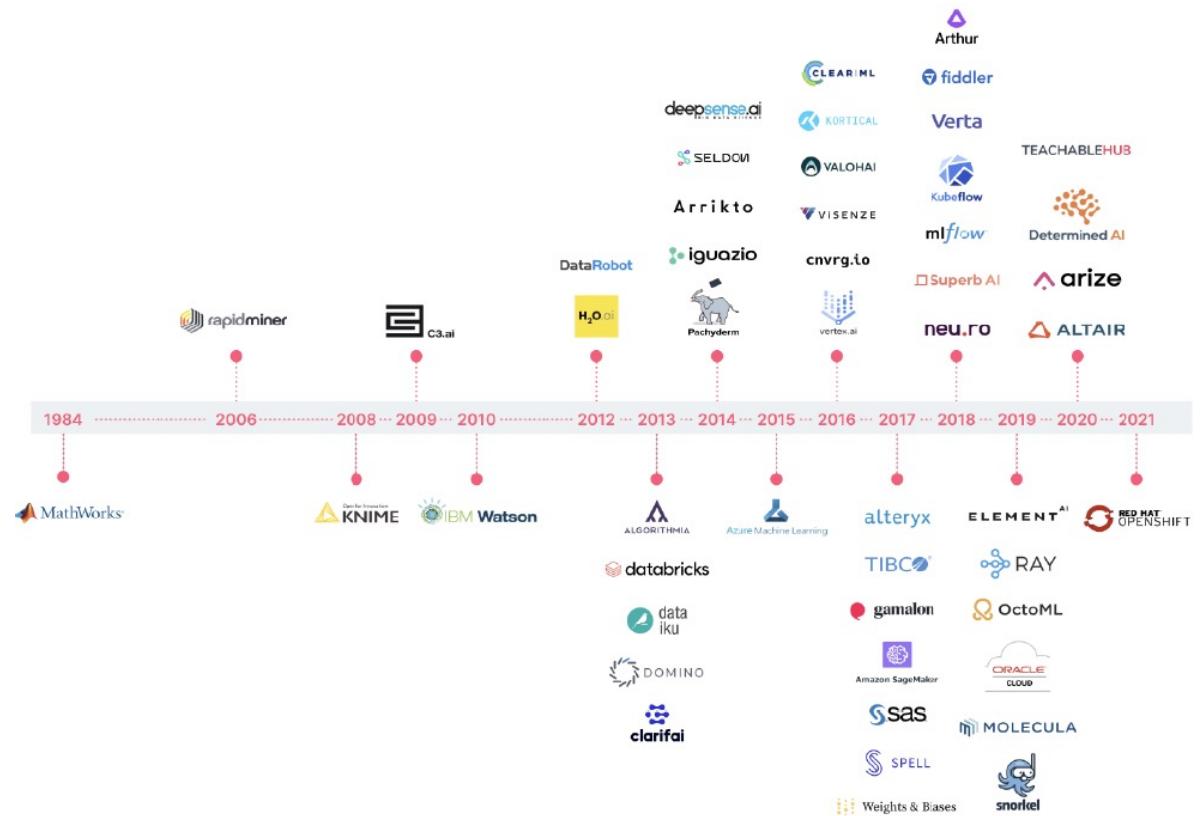
mattturck.com/data203

FIRSTMARK
EARLY STAGE VENTURE CAPITAL

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?



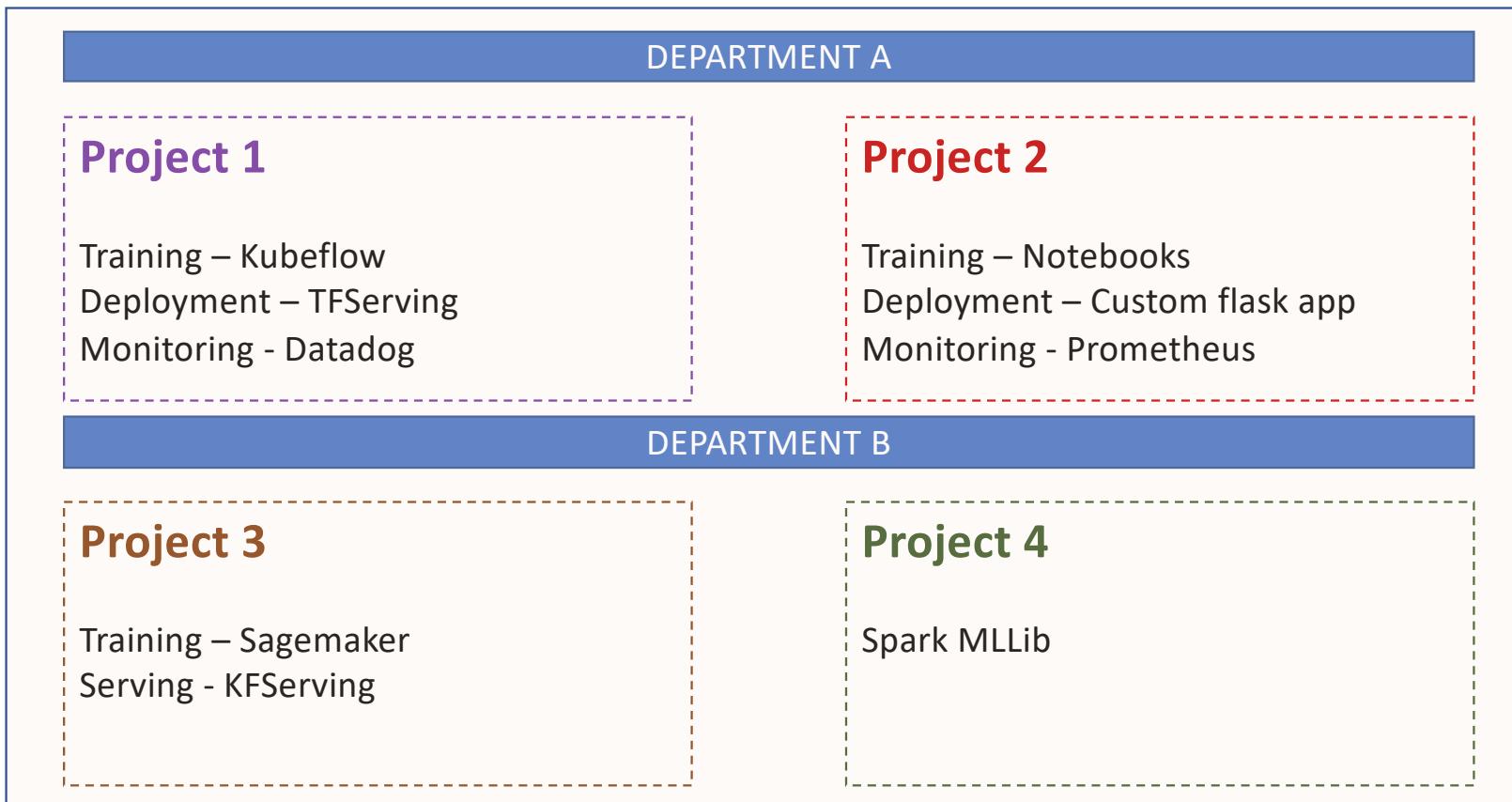
¹ Surge in Innovation in Data Science and ML Platforms, Says Gartner, April 2021

<https://www.cdotrends.com/story/15491/surge-innovation-data-science-and-ml-platforms-says-gartner>

² Guide to Evaluating MLOps Platforms, ThoughtWorks whitepaper, November 2021

<https://www.thoughtworks.com/what-we-do/data-and-ai/cd4ml/guide-to-evaluating-mlops-platforms>

Avoid the MLOps tools "zoo" in your organization



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

*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

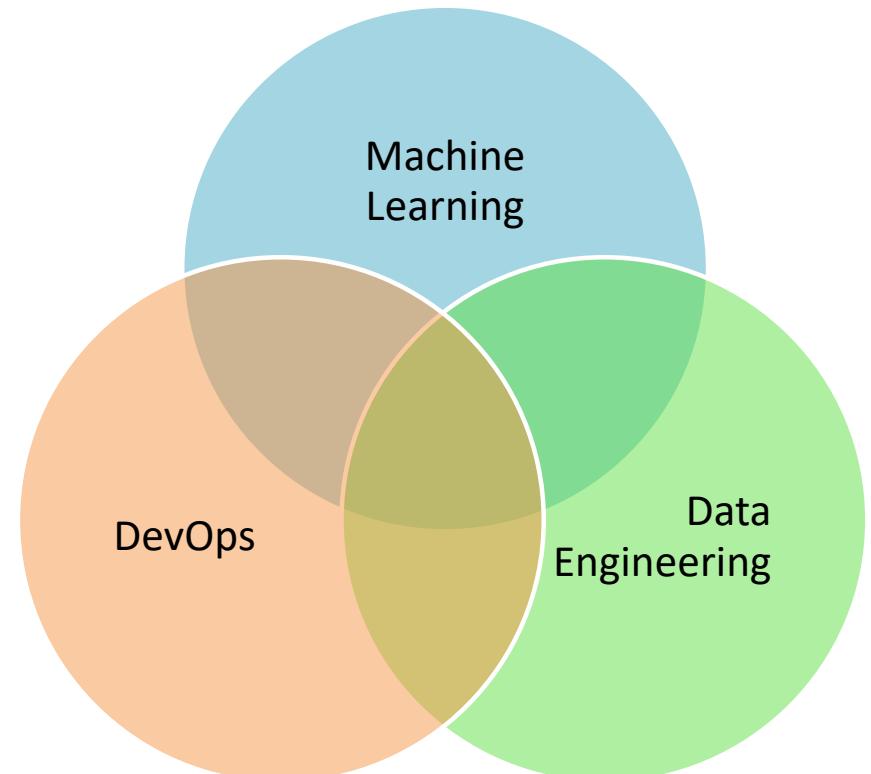
Cristiano Breuel, Machine Learning Engineer

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

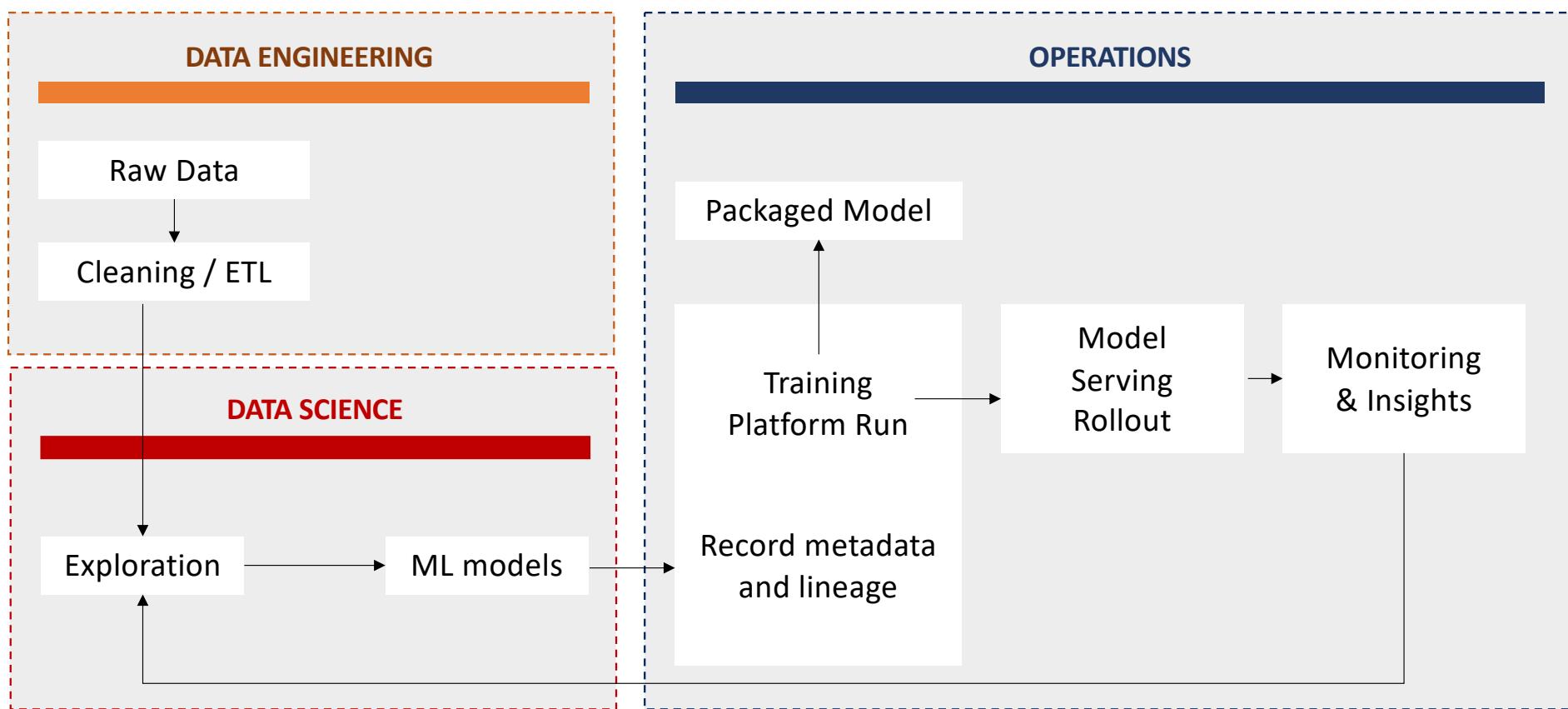
Good solution is not only about choosing the "best" tools!¹

- The tools should work 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 Guide to Evaluating MLOps Platforms, ThoughtWorks whitepaper, November 2021
<https://www.thoughtworks.com/what-we-do/data-and-ai/cd4ml/guide-to-evaluating-mlops-platforms>

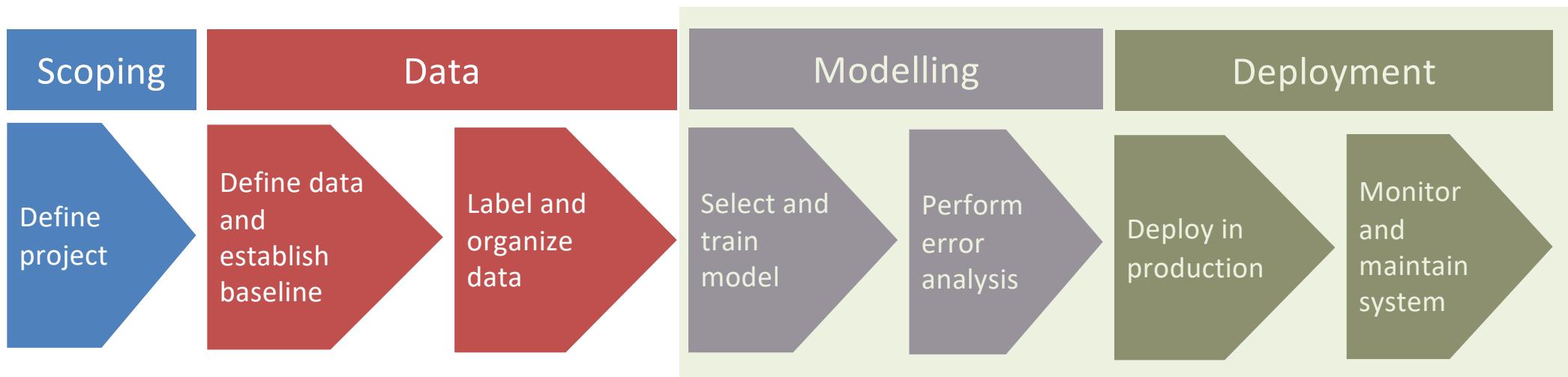
Filipa Peleja – filipapeleja@gmail.com

Who performs which MLOps tasks?



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

Machine Learning (ML) Lifecycle



Modelling: Model Performance

**Deploy a model that performs good on average
but presents poor results on relevant tests is not acceptable**

Evaluate the model separately to guarantee

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

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/>

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

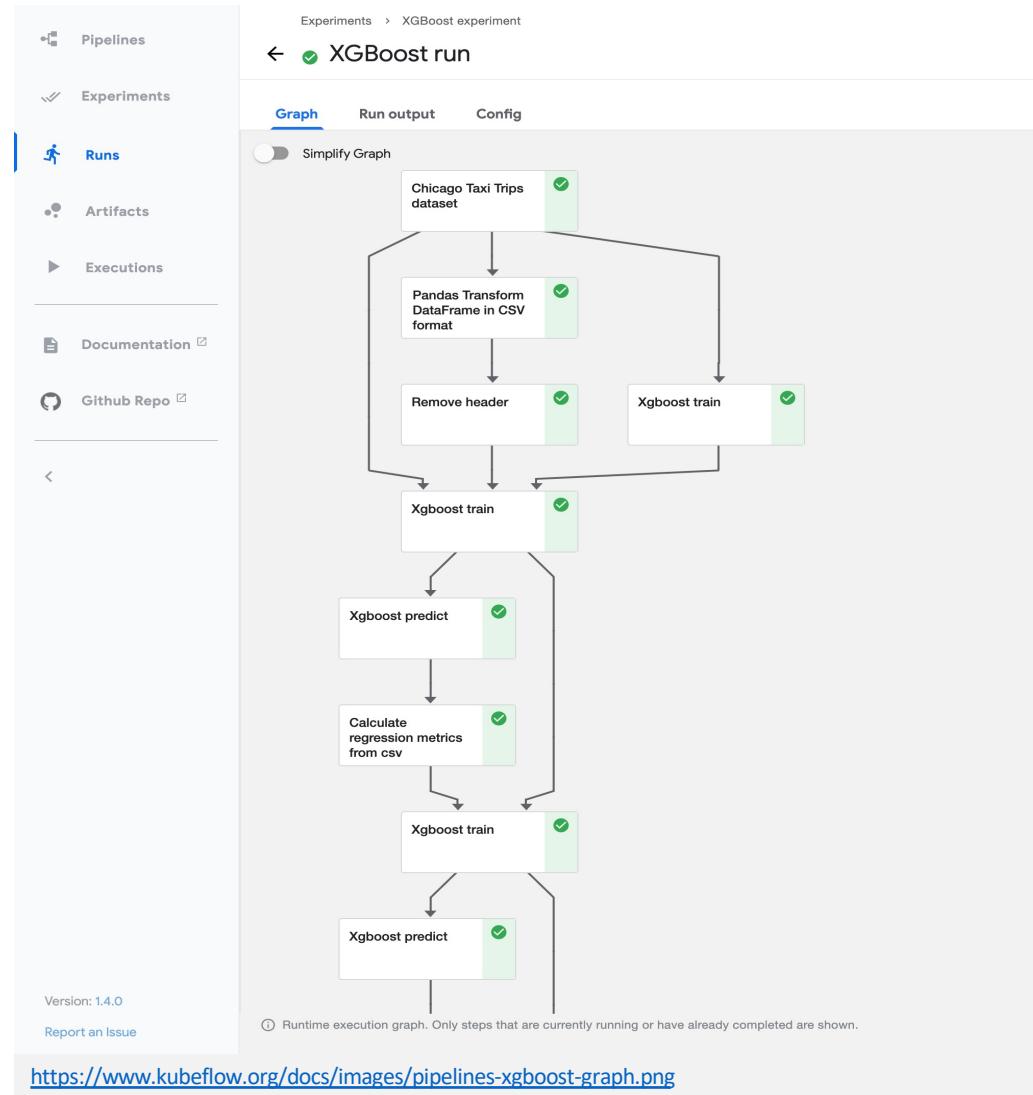
Rational: Ensure the downtime to users is minimum and, in case of a problem, roll-back with this deployment strategy

ML Deployment

Visual representation of
ML pipeline

Kubeflow Pipelines

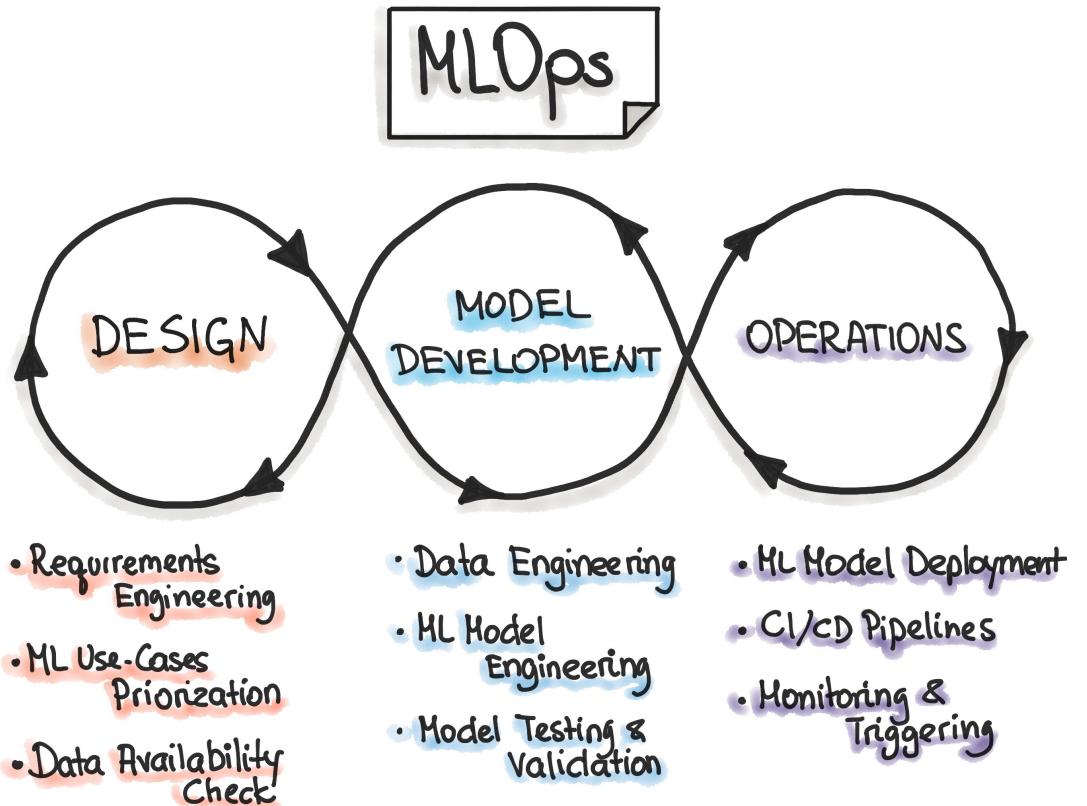
- ML training can have many components
- Data pipeline, training, prediction, deploy..
- In general, needs 2 versions of the pipeline
 - 1 for training and 1 for serving



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

Filipa Peleja – filipapeleja@gmail.com

ML Pipeline is pure code artifact which means that is possible to track its versions in source control and automate its deployment using CI/CD¹ 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

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

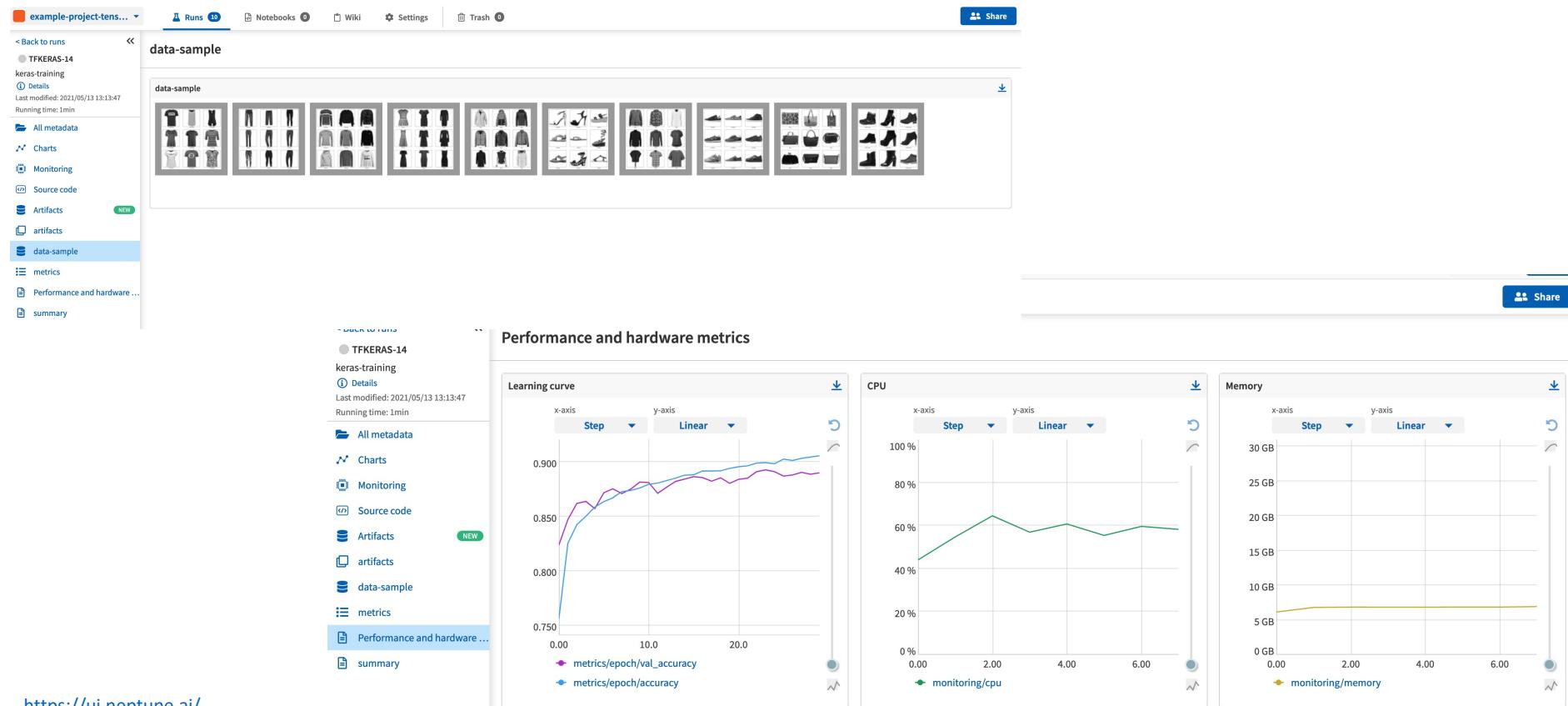
Model validation should
be of statistical nature
instead of traditional
software development
binary pass/fail test

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

Filipa Peleja – filipapeleja@gmail.com

Evidently

Evidently¹ 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.

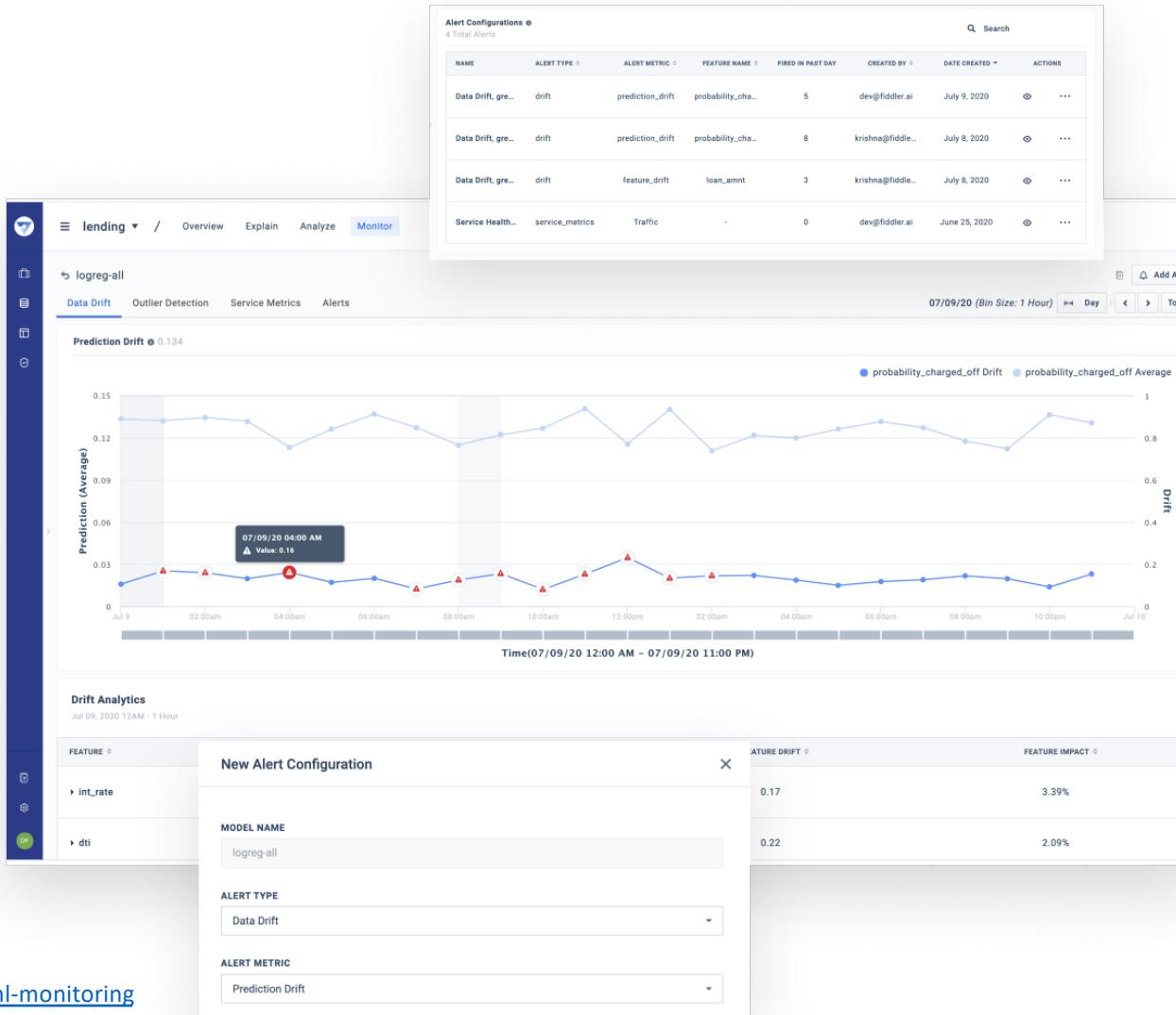
Licensed under the Apache License, Version 2.0 (the "License")



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

¹ <https://github.com/evidentlyai/evidently>

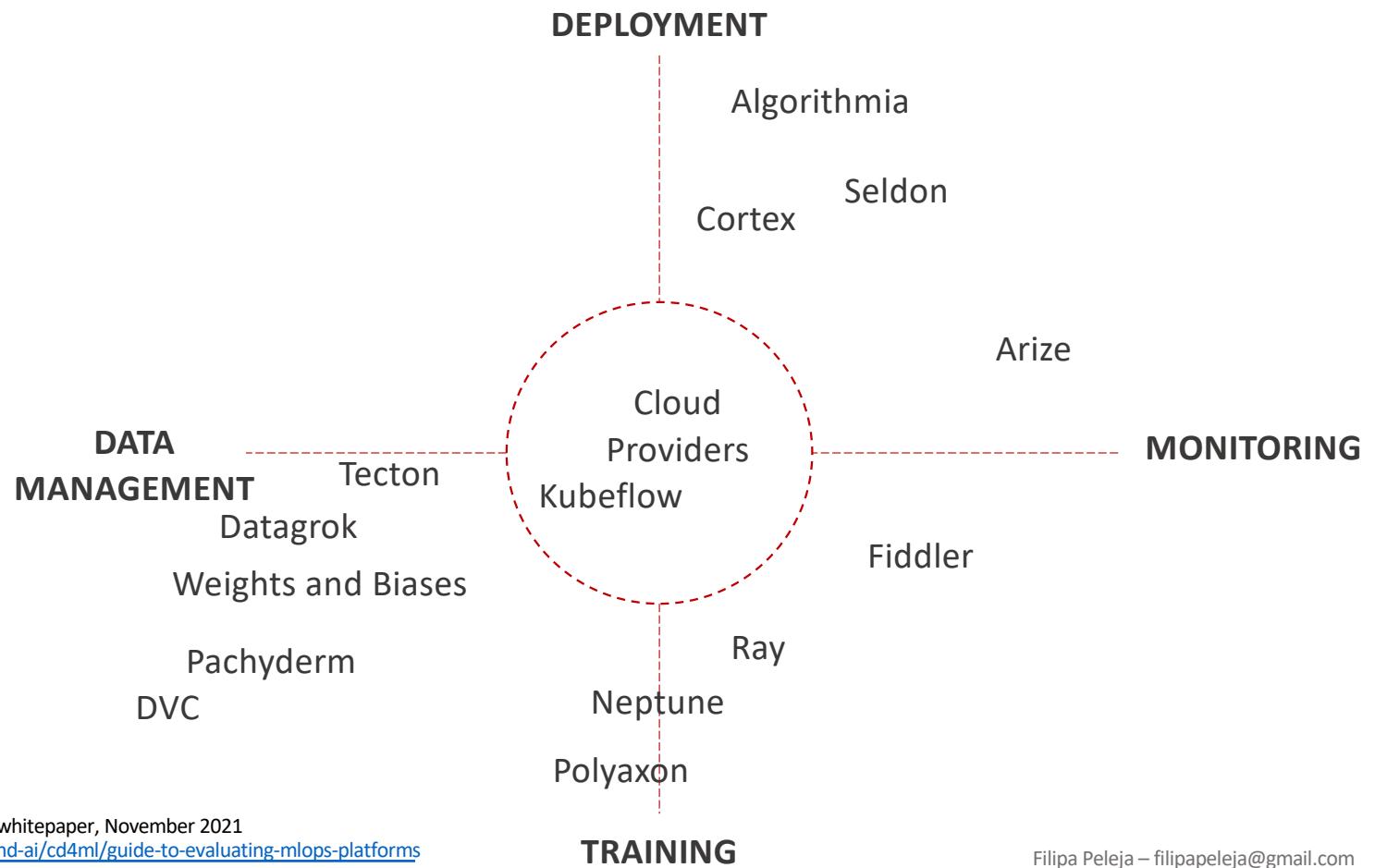
Fiddler



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



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

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>

Filipa Peleja – filipapeleja@gmail.com

Presentation available at

https://github.com/Peleja/DSPA_17122021



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

Filipa Peleja

<https://www.linkedin.com/in/peleja/>

Filipa Peleja – filipapeleja@gmail.com