Data Platform Architectures & Machine Learning Operations (MLOps)

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Data platform architectures & MLOps

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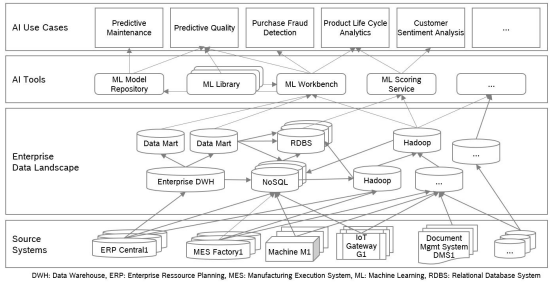
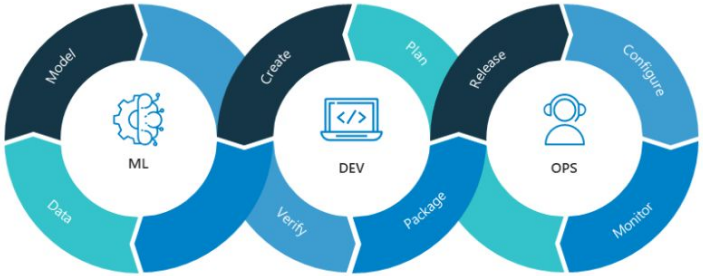
Themenschwerpunkte
- Datenplattform-architektur
- Open Source Technologien (bspw. Delta Lake, Kubeflow, TFX)
- Machine Learning Operations
- Entwicklung in Python





Im Rahmen des Projekts soll mit Hilfe von Open-Source-Software eine prototypische state-of-the-art **Data Lake bzw. Datenplattformarchitektur** (bspw. Lakehouse) für die Realisierung unterschiedlicher Machine Learning Anwendungsfälle konzipiert und implementiert werden.

In der Architektur sollen für eine möglichst umfassende Automatisierung des **Machine Learning Lifecycles** Komponenten der Disziplin **Machine Learning Operations (MLOps)** berücksichtigt werden (bspw. feature store, model registry, data pipelines).

“… [we need to] help companies progress on their AI journey, from one-off AI experimentation to gaining a robust organization-wide capability that acts as a source of competitive agility and growth.”

Accenture (2019)

The Proof of Concept Factory

Most companies...

- … conduct AI experiments and pilots but achieve a low scaling success rate
- … have significant AI under investments, yielding low returns

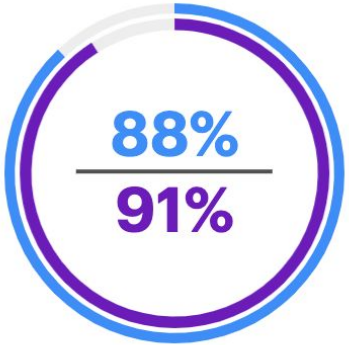
accenture

80-85% PoC Factory

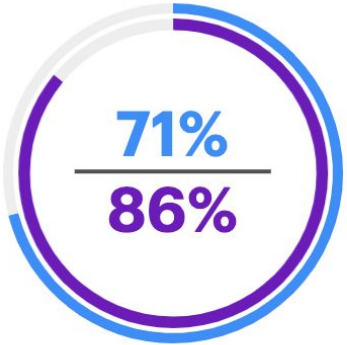
Source: Accenture (2019) https://www.accenture.com/us-en/insights/artificial-intelligence/ai-investments

How crucial is scaling AI to your business?

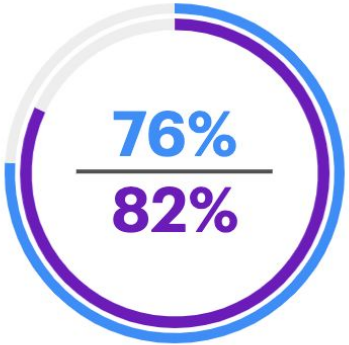
UNITED STATES vs. GERMANY



of executives say they won't achieve their growth objectives without scaling AI.



of executives believe they risk going out of business in 5 years if they don't scale AI.



of executives acknowledge they know how to pilot, but struggle to scale AI across the business.

Source: Accenture (2019); n = 1,500 C-suite executives from organizations across 16 industries https://www.accenture.com/us-en/insights/artificial-intelligence/ai-investments

“[…] AI is currently done in an insular fashion leading to a polyglot and heterogeneous enterprise data landscape. This makes systematic **data management**, comprehensive **data democratization** and an overall **data governance** considerably challenging and prevents the wide-spread use of AI in industrial enterprises.”

Gröger (2021)

Data platform architectures

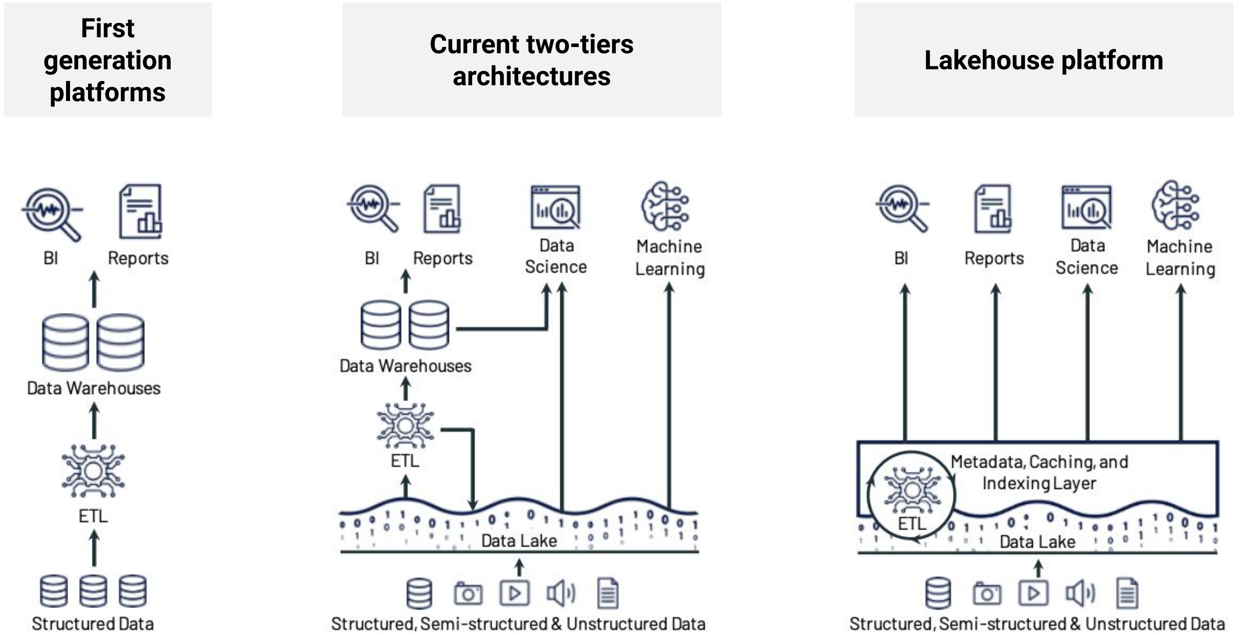
Evolution

Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics

Michael Armbrust[1], Ali Ghodsi[1,2], Reynold Xin[1], Matei Zaharia[1,3]

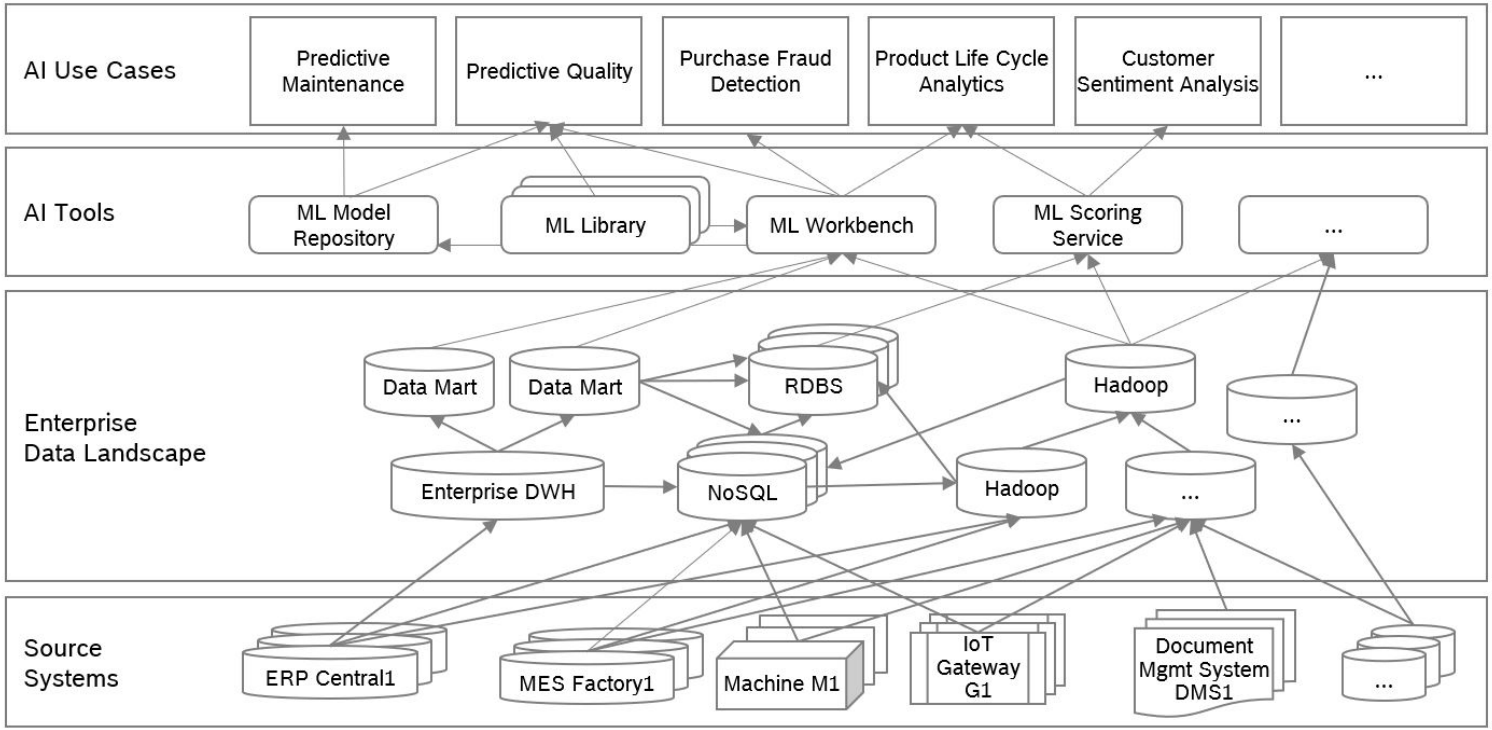
[1]Databricks, [2]UC Berkeley, [3]Stanford University

https://databricks.com/de/wp-content/uploads/2020/12/cidr_lakehouse.pdf



Source: Armbrust et al (2021)

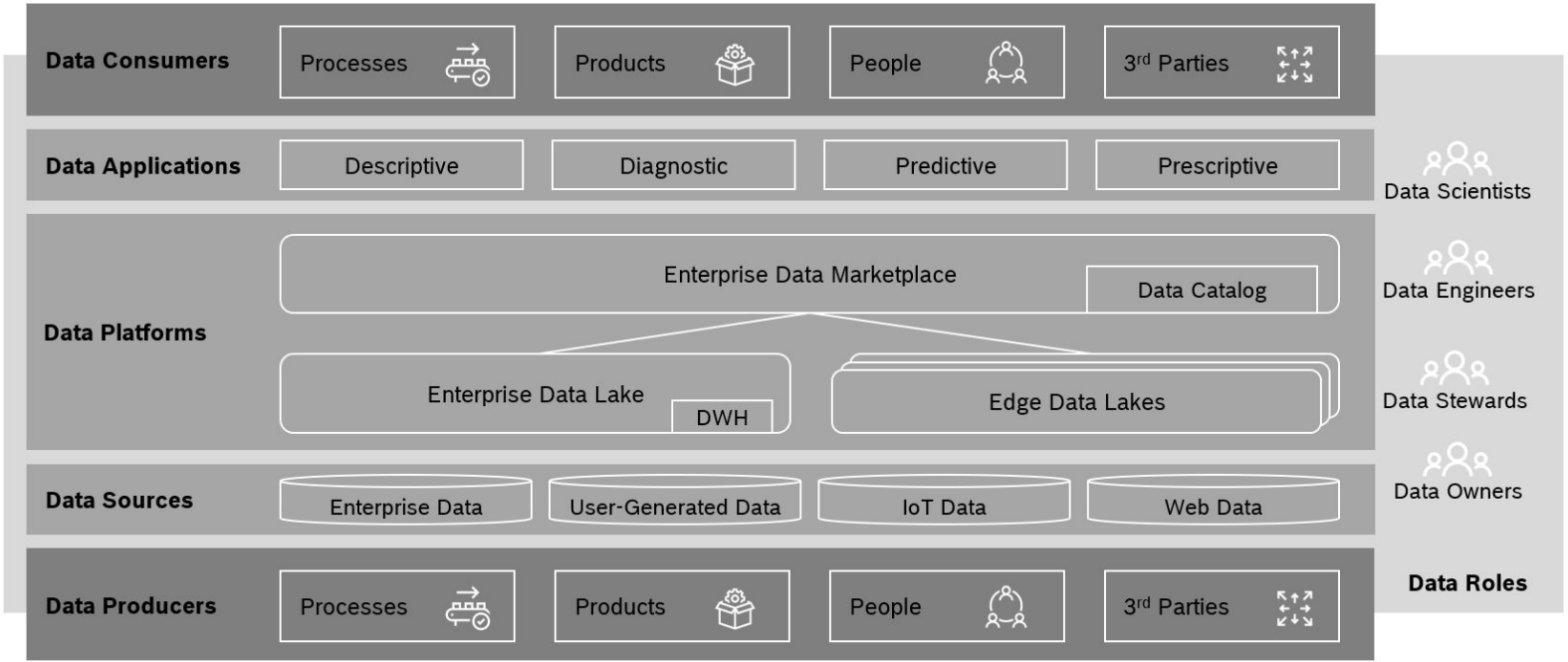
Insular AI and Enterprise Data Landscape



DWH: Data Warehouse, ERP: Enterprise Ressource Planning, MES: Manufacturing Execution System, ML: Machine Learning, RDBS: Relational Database System

Source: Gröger (2021) http://christophgroeger.de/download/Groeger_There_Is_No_AI_Without_Data.pdf

Data platforms
for industrial enterprises



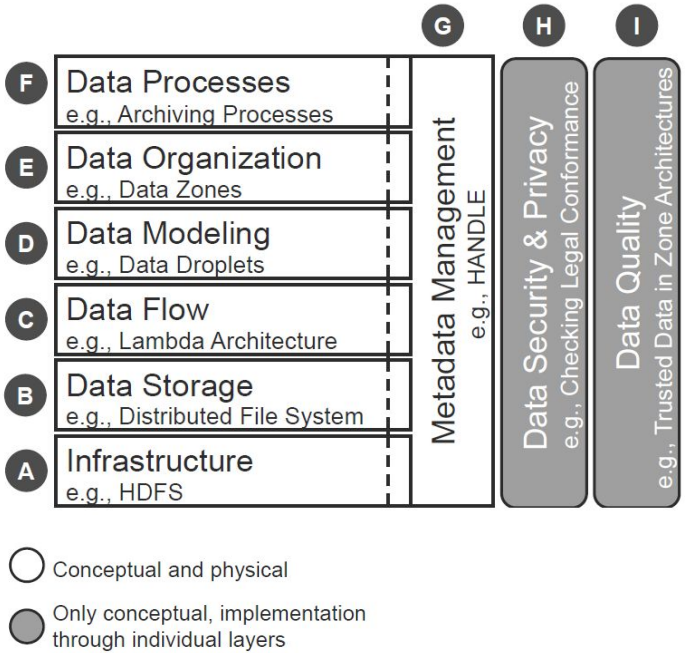
Core elements of a data ecosystem for industrial enterprises

Source: Gröger (2021)

Data platform architectures

Architecture aspects

Aspects



Example

DLAF Layer	AIRPORTS DL [Ma17a]
A. Infrastructure	Hadoop (HDFS, MapReduce), Apache Flume, Apache Spark, Apache Oozie, Apache Pig, Apache Atlas, R Studio, Shiny, Apache Sqoop
B. Data Storage	Single File System
C. Data Flow	Data are ingested as streams, but processed as batches
D. Data Modeling	Raw Messages, AIRPORTS Data Model
E. Data Organization	Four Zone Architecture
F. Data Processes	Processing Pipeline for Messages (ETL Processes), Processes for Ingestion and Use
G. Metadata Management	Managed by Apache Atlas
H. Data Security & Privacy	Tracking manipulation of data
I. Data Quality	Tracking manipulation of data, Quality through Zones

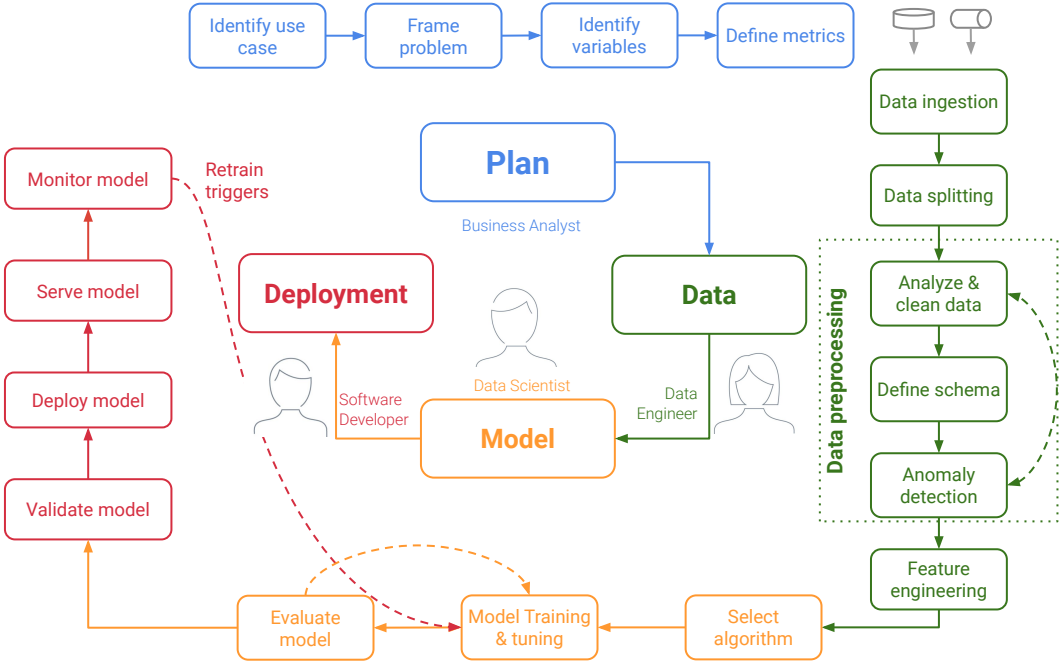
Source: Giebler et al. (2021) https://dx.doi.org/10.18420/btw2021-19

Machine Learning Lifecycle, Data Platform Architectures & Machine Learning Operations (MLOps)

Prof. Dr. Jan Kirenz

Lifecycle
of an ML System

Plan | Data | Model | Deployment



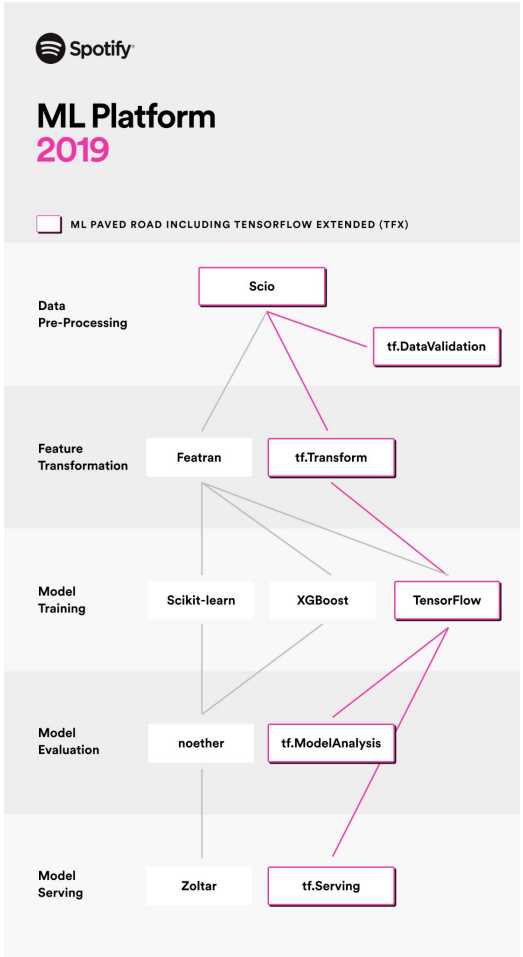
Source: Kirenz (2021)

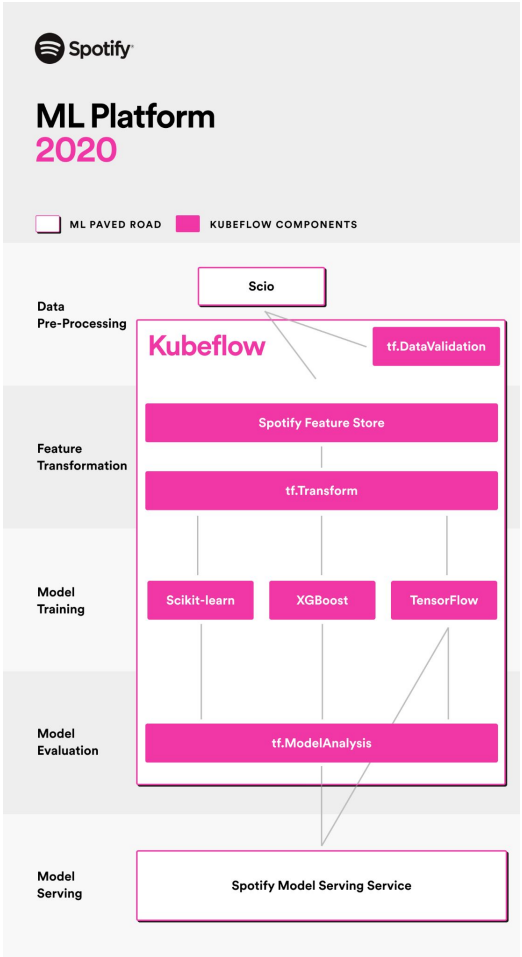
ML platform @ Spotify
Reference architecture

The Winding Road to Better Machine Learning Infrastructure Through Tensorflow Extended and Kubeflow

December 13, 2019
Published by Josh Baer, Samuel Ngahane

https://engineering.atspotify.com/2019/12/13/the-winding-road-to-better-machine-learning-infrastructure-through-tensorflow-extended-and-kubeflow/

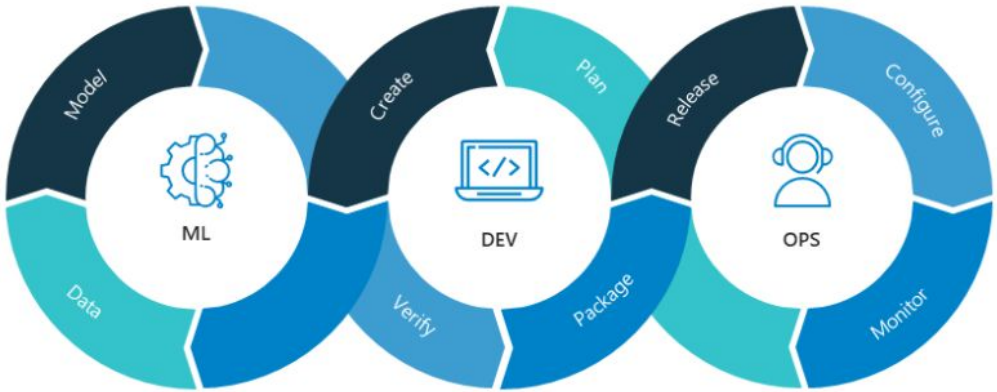




Source: Baer & Ngahane (2019)

Machine learning operations (MLOps)

- ML Engineering culture and practice that aims at **unifying** ML System **development** (Dev) and ML system **operations** (Ops)
- Tools and principles to support workflow **standardization** and **automation** through the ML system lifecycle**.**

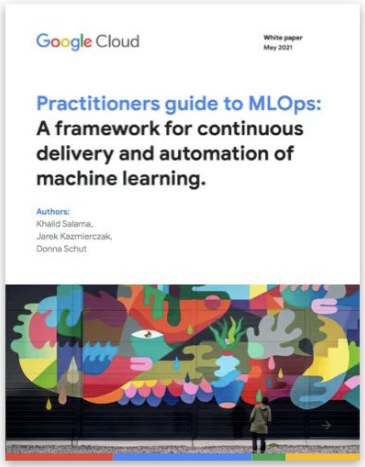


Source: Nvidia (2021) https://blogs.nvidia.com/blog/2020/09/03/what-is-mlops/

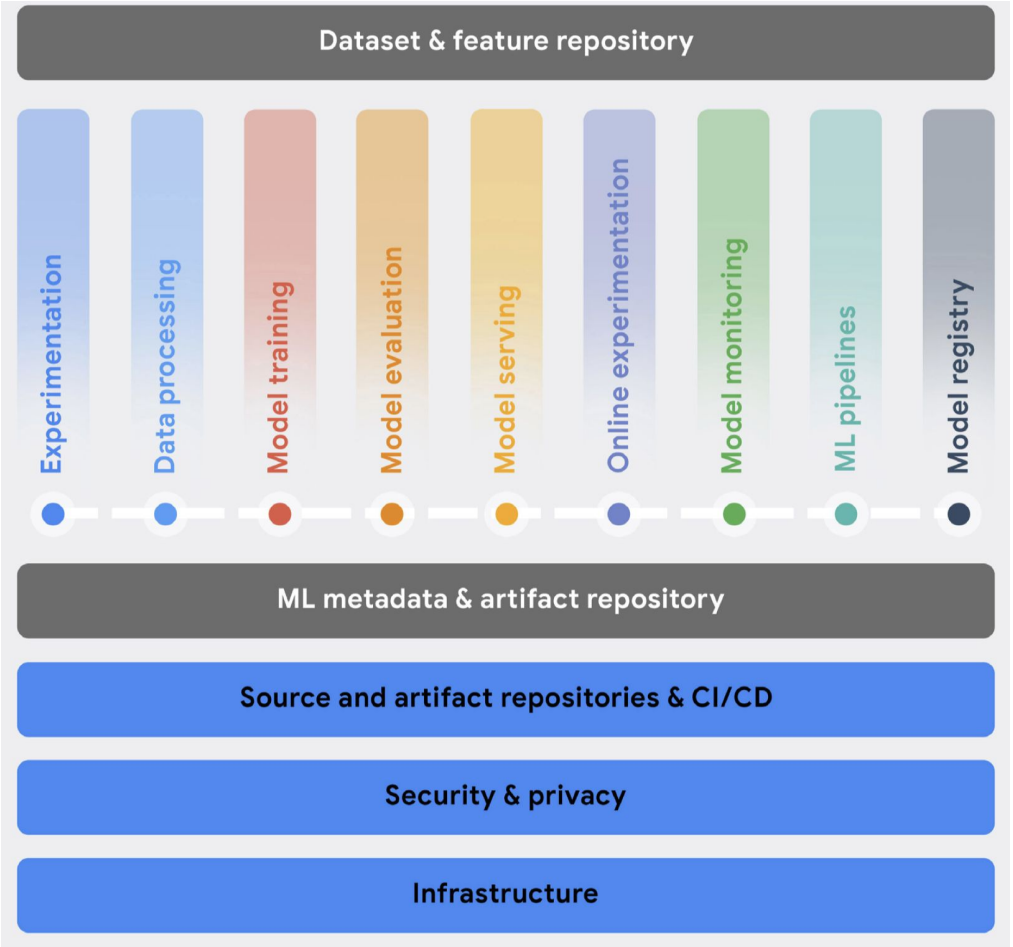
Source: Salama, Kazmierczak & Schut (2021)

MLOps
Introduction

Learn the basics of MLOps



https://cloud.google.com/resources/mlops-whitepaper



MLOps Core technical capabilities

Source: Salama, Kazmierczak & Schut (2021)

Introduction to Machine Learning Operations

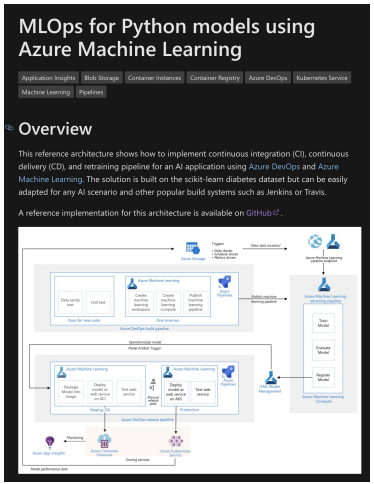
Source: Keating (2020)

MLOps demo (including Kubeflow)

MLOps in Azure

Reference architectures

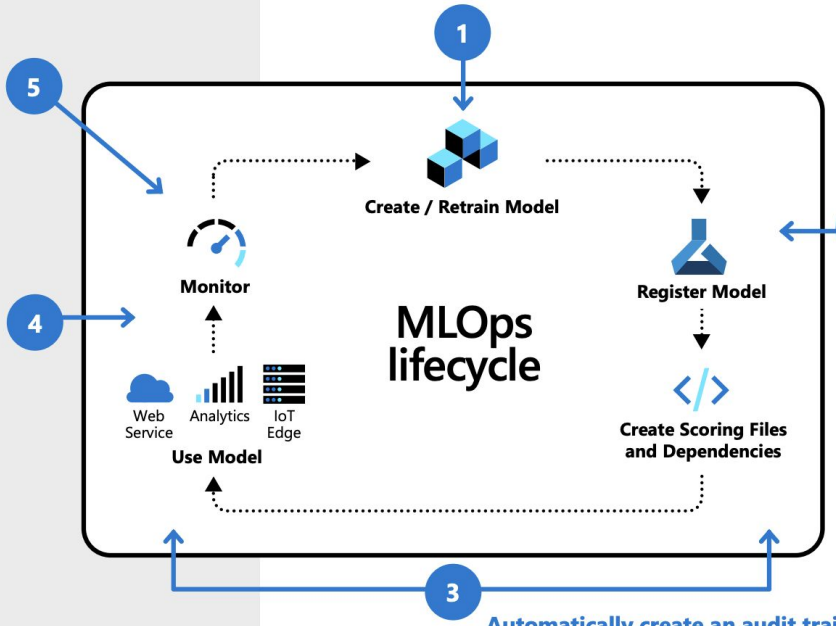
https://azure.microsoft.com/de-de/services/machine-learning/mlops/



https://docs.microsoft.com/en-us/azure/architecture/reference-architectures/ai/mlops-python

5 Best Practices to optimize your MLOps lifecycle on Azure:

Create models with reusable ML pipelines using the Azure Machine Learning extension for Azure DevOps. Store your code in GitHub so it automatically integrates into your MLOps pipeline.



Observe data drift and feed back model information to improve future training.

Deploy and monitor performance so you can release models with confidence and know when to retrain.

Automate your MLOps rollout using Azure DevOps + Azure Machine Learning for version models with rich metadata and event management.

Automatically create an audit trail for all artifacts in your MLOPs pipeline ensure asset integrity and meet regulatory requirements.

Source: Microsoft (2021)

Resources

Armbrust, M., Ghodsi, A., Xin, R. & Zaharia, M. (2021). Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics. 11th Annual Conference on Innovative Data Systems Research (CIDR '21), January 11–15, 2021, Online https://databricks.com/de/wp-content/uploads/2020/12/cidr_lakehouse.pdf

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