



MLOps

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Data Science & Analytics Team

Team structure

Consists of Data Scientists who either specialise in Machine Learning or Analytics

Objective of the team

To build data science and analytics solutions for the businesses within the Digibank



Agenda

- ❖ MLOps Origins and Motivation
- ❖ MLOps vs. DevOps
- ❖ MLOps Lifecycle
- ❖ ML Tools Landscape
- ❖ Demo
- ❖ Q&A

State of AI in the enterprise



85%

Estimates of AI projects that will fail and deliver erroneous outcomes through 2022 (Gartner)

70%

Companies report minimal or no impact from AI

87%

Data science projects that never make it into production.

Origins and Motivation

Machine Learning: The High Interest Credit Card of Technical Debt

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young
SE4ML: Software Engineering for Machine Learning (NIPS 2014 Workshop)

The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction

Eric Breck, Shangqiang Cai, Eric Nielsen, Michael Salib, D. Sculley
Proceedings of IEEE Big Data (2017)

ARTICLE

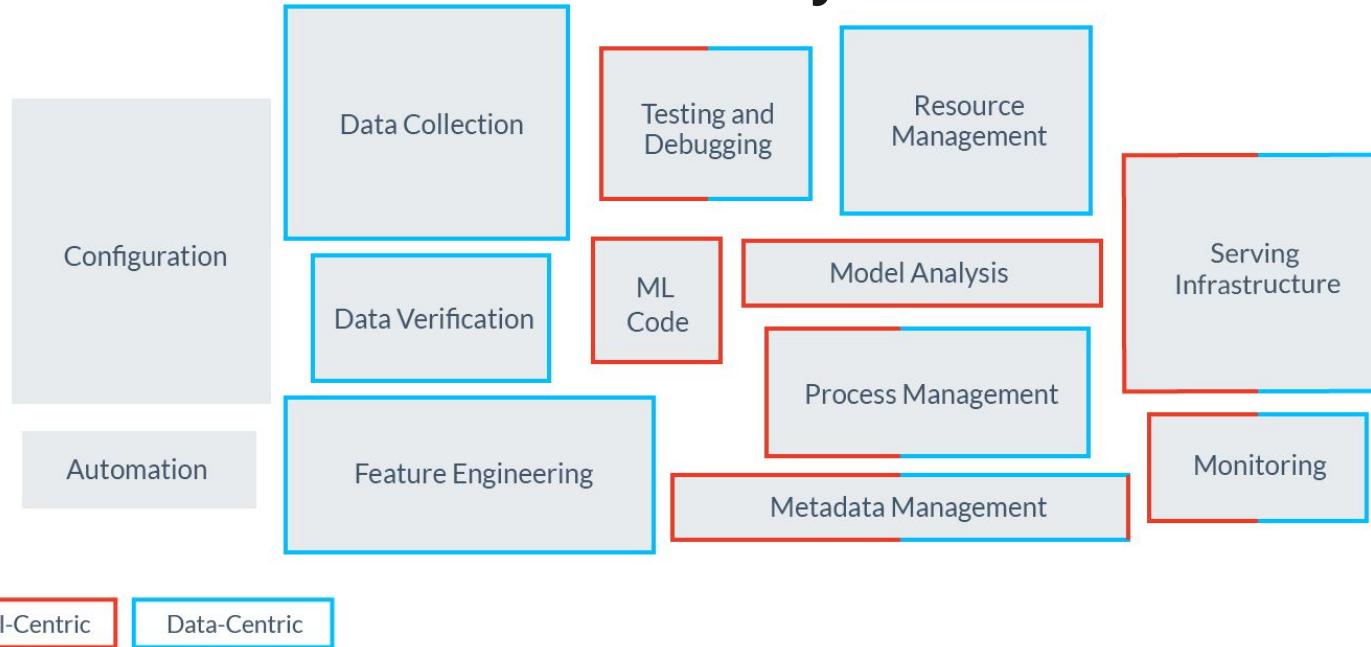
Hidden technical debt in Machine learning systems



Authors: D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-Francois Crespo, Dan Dennison [Authors Info & Affiliations](#)

NIPS'15: Proceedings of the 28th International Conference on Neural Information Processing Systems – Volume 2 • December 2015 • Pages 2503–2511

Hidden Technical Debt in ML Systems



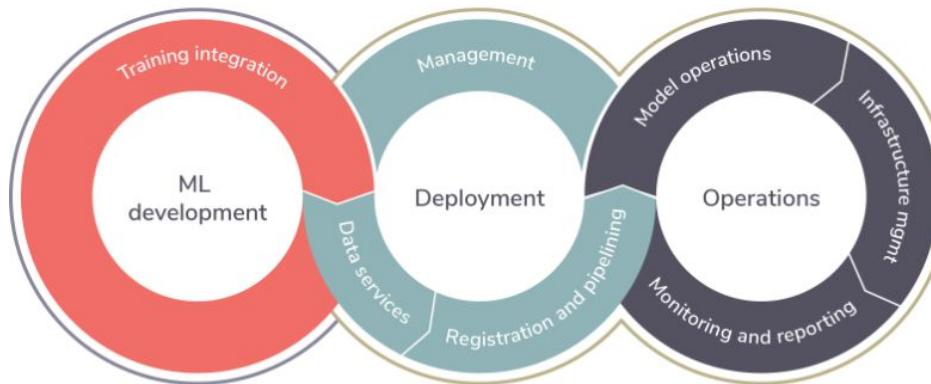


Hidden Technical Debt in ML Systems

- ML tech debt is worse than in software
- The nebulous nature of machine learning
- Data dependencies on top of regular software and operational dependencies
- Unfamiliar abstractions in ML systems
- Common anti-patterns (not-to-dos) in ML code
- Configuration debt
- The challenges of dealing with a constantly changing real world
- Meta-issues such as sanity checks, reproducibility, process management etc.

What is MLOps?

DevOps for Machine Learning



The term **Machine Learning Operations (MLOps)** is defined as "*the extension of the DevOps methodology to include Machine Learning and Data Science assets as first-class citizens within the DevOps ecology*" (by CD Foundation MLOps SIG)

Source: <https://ml-ops.org/>



What is MLOps?

Essentially, a collection of industry-accepted best practices to manage code, data, and models in your machine learning team. An MLOps system should help your team with *managing code, data and models, following ML best practices, and efficiently collaborating across teams*.

MLOps -

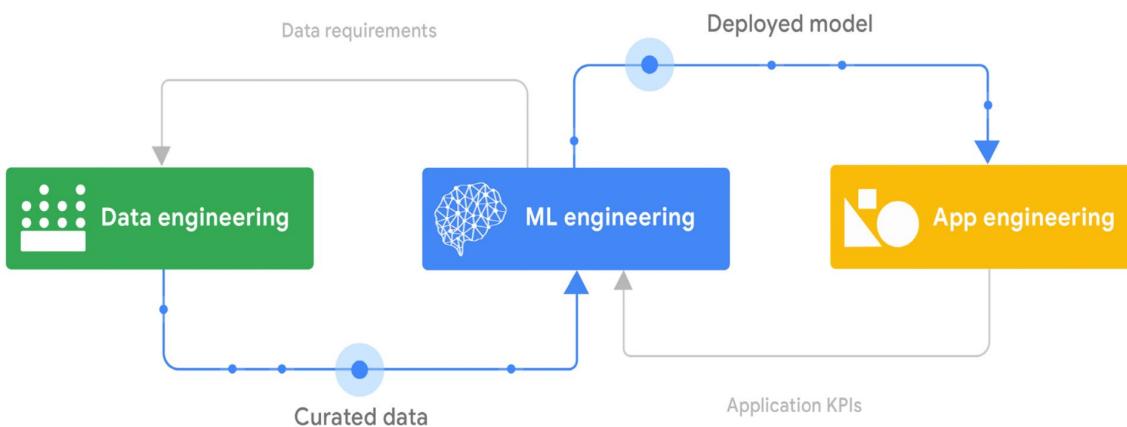
- Aims to unify the release cycle for machine learning and software application release.
- Enables automated testing of ML artifacts (e.g. data validation, ML model testing, and ML model integration testing)
- Enables the application of agile principles to ML projects.
- Enables supporting ML models and datasets to build these models as first-class citizens within CI/CD systems.
- Reduces technical debt across ML models.
- Is language-, framework-, platform-, and infrastructure-agnostic practice.

MLOps vs. DevOps

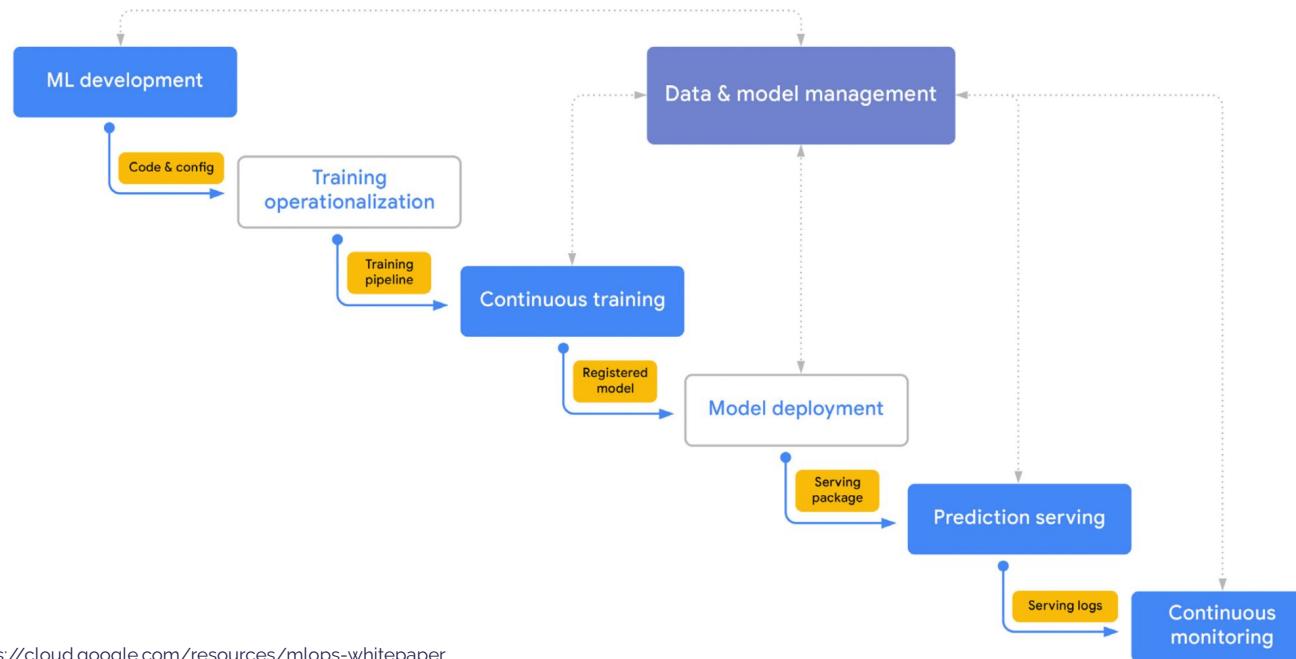
Item	DevOps	DevOps for ML
Code versioning	✓	✓
Compute environment	✓	✓
Continuous integration/delivery	✓	✓
Monitoring in production	✓	✓
Data provenance		✓
Datasets		✓
Models		✓
Hyperparameters		✓
Metrics		✓
Workflows		✓



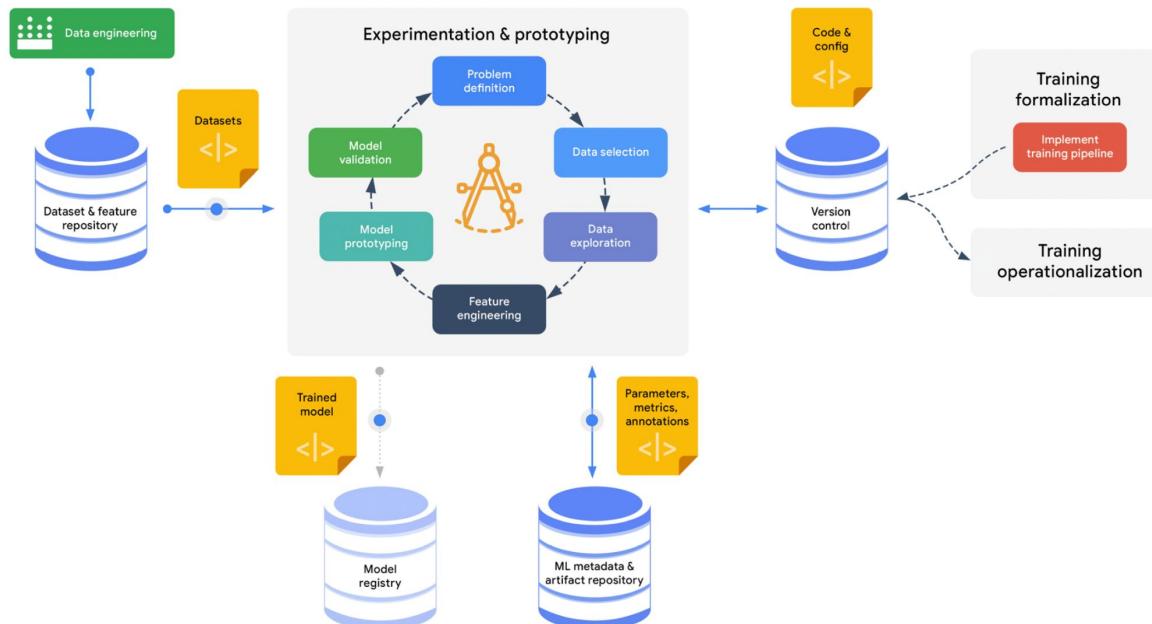
MLOps Lifecycle



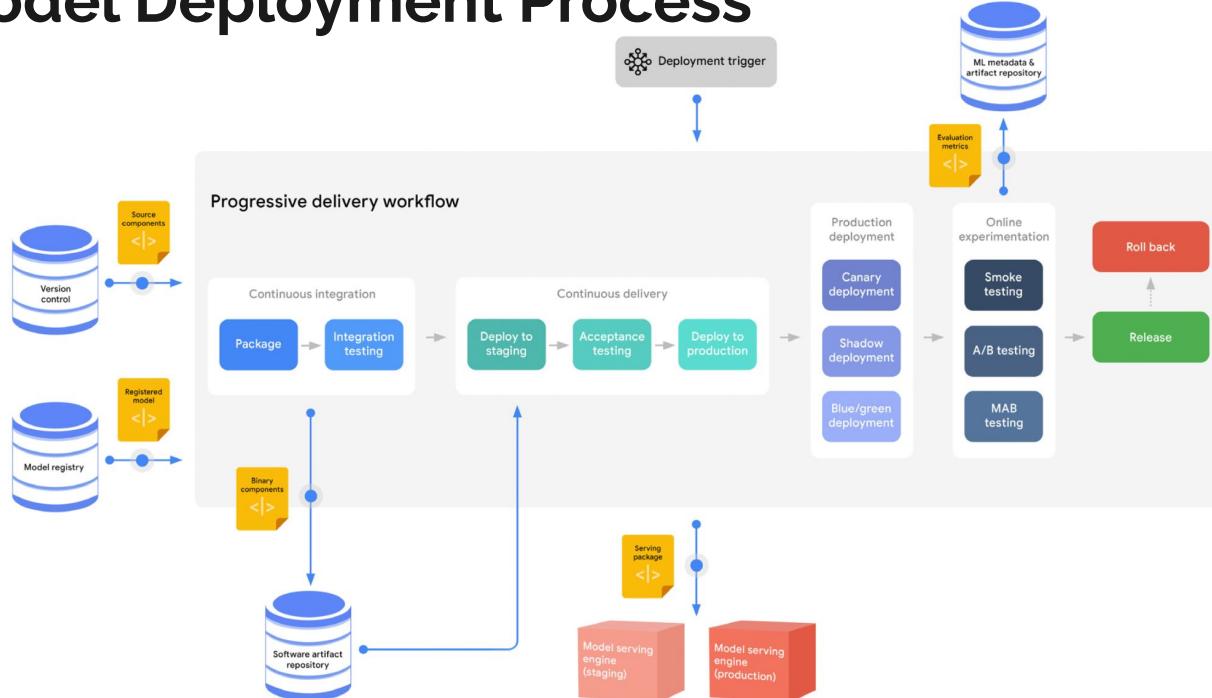
An end-to-end workflow



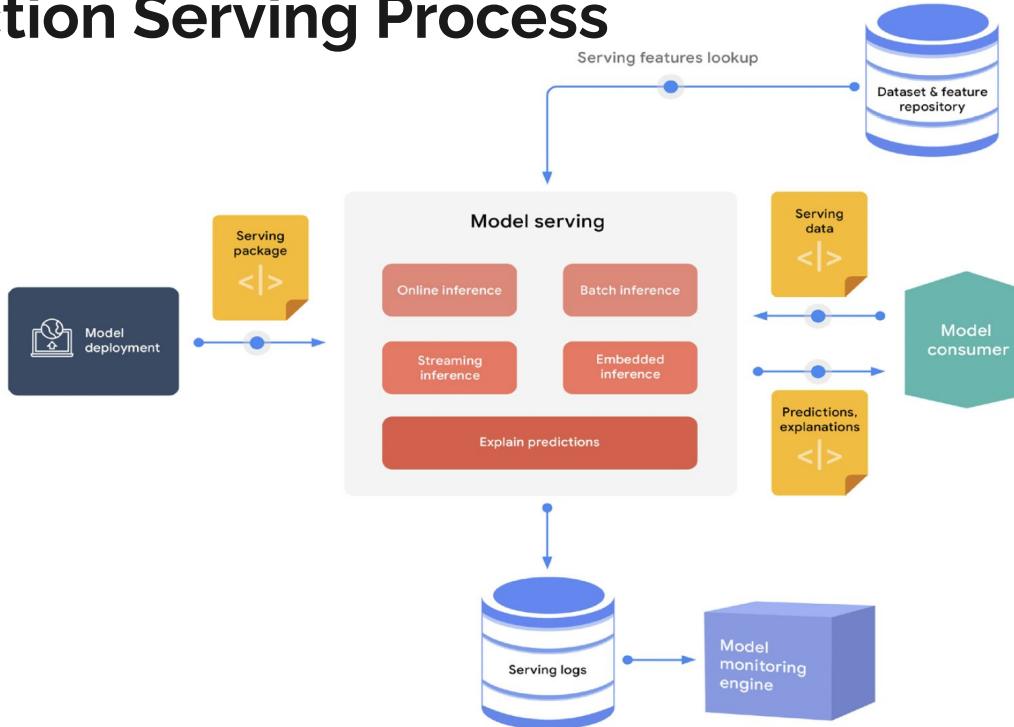
ML Development Process



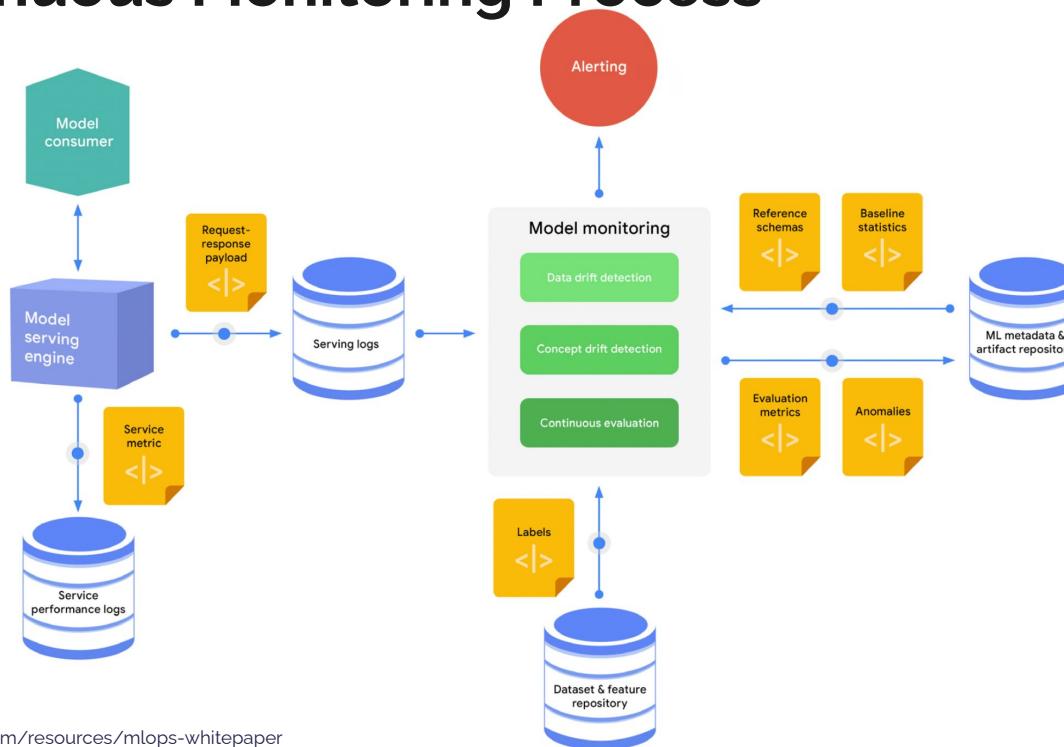
ML Model Deployment Process



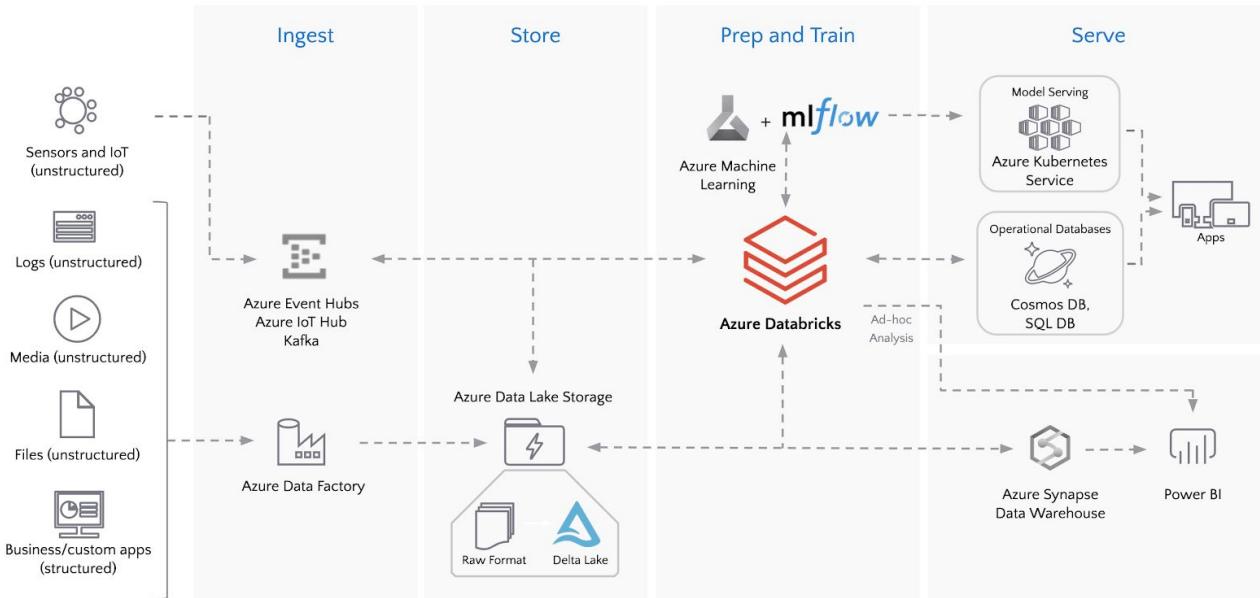
ML Prediction Serving Process



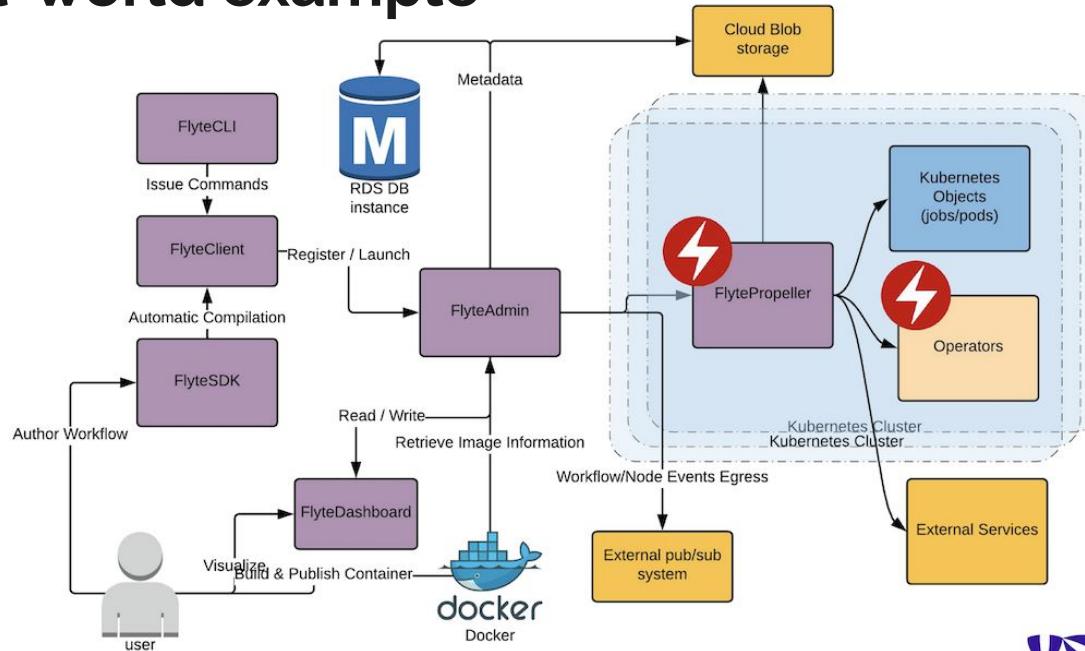
ML Continuous Monitoring Process



Azure architecture



Real-world example



Evolution of MLOps

Lack of tools and technologies to support ML in production (2015)



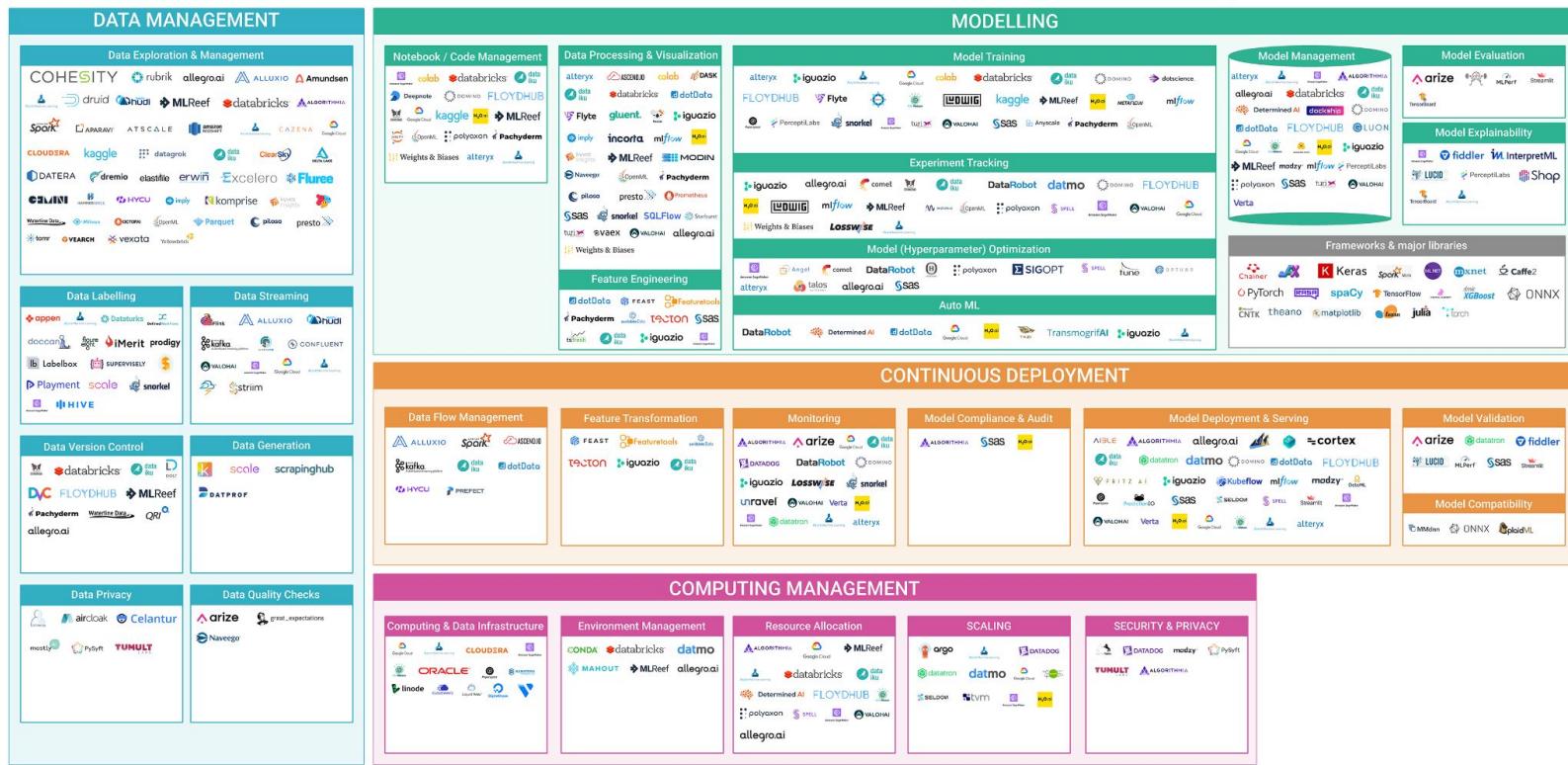
Tech giants, major cloud platforms and a gamut of startups promising a better way to productionize ML.

Too many options to choose from!

ML tools and platforms landscape

Machine Learning tools & platforms landscape - v.1.0 January 2021

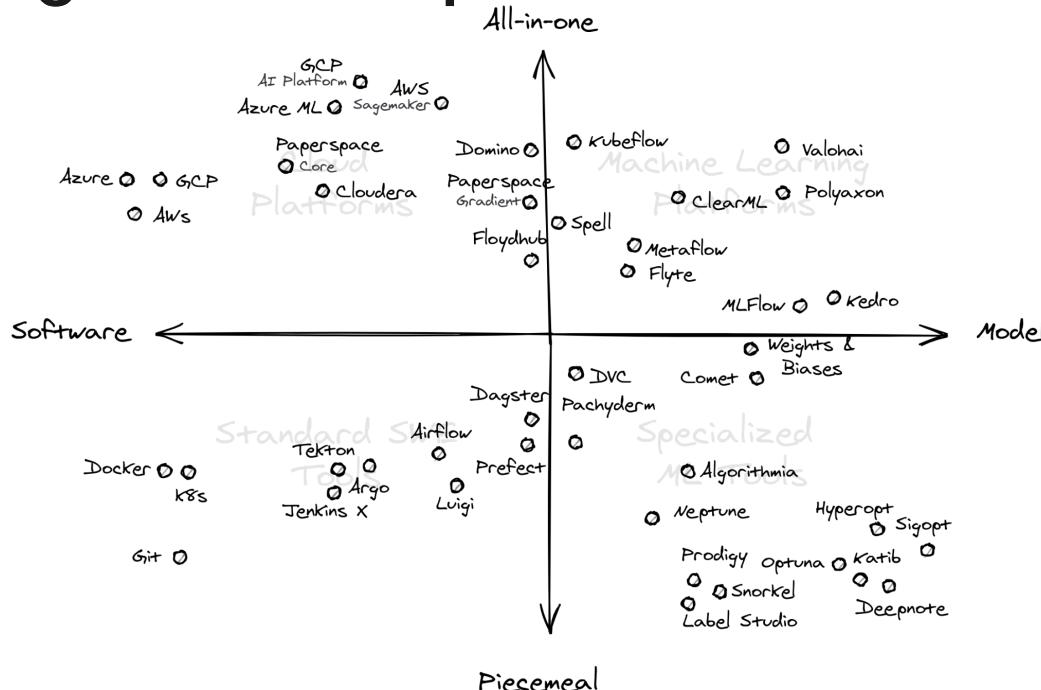
Presented by  **MLReef**



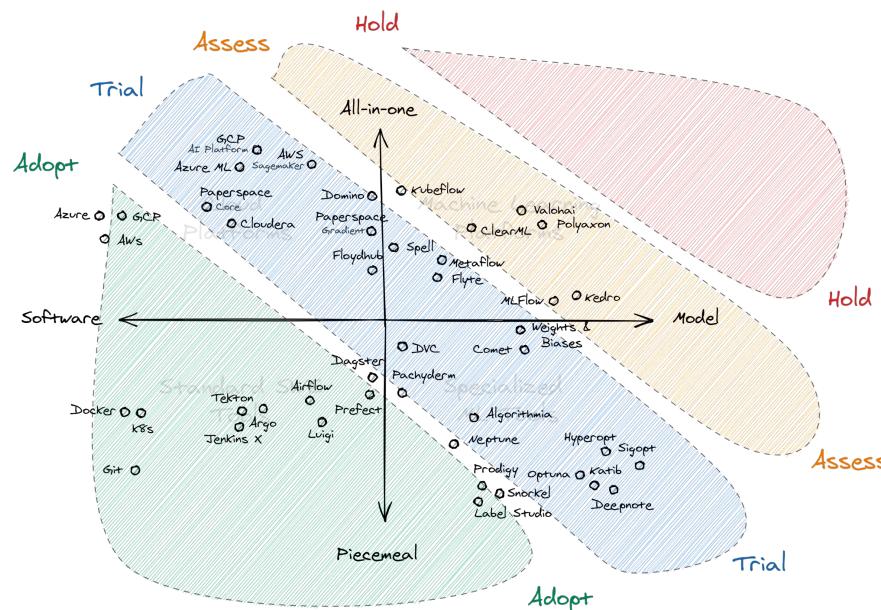
ML, AI and Data landscape



Navigating the landscape



Navigating the landscape



Source: <https://lvmiranda921.github.io/notebook/2021/05/30/navigating-the-mlops-landscape-part-3/>

Rings	Strategy	Example Actions
Adopt	Use this tech if you don't want to get left behind. No-brainer	Org-wide training, enforcement, adoption strategy
Trial	Pursue in a low-risk project or environment	Internal greenfield projects, small-scale work
Assess	Explore and understand how it will affect you and your team	Research projects, non client-facing work, dev spikes
Hold	Don't bother for now, they are too new to reasonably assess yet	Lunchtime brown-bags, attending conference sessions

To build or to buy?

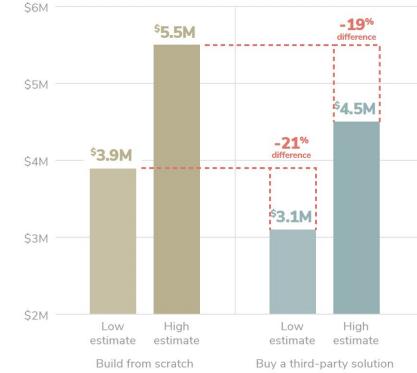
"Buy by default"

- Don't build if MLOps isn't the core business
- Build integrators and connectors between tools
- Buy specialized ML tools first

Reference frameworks for building MLOps pipelines

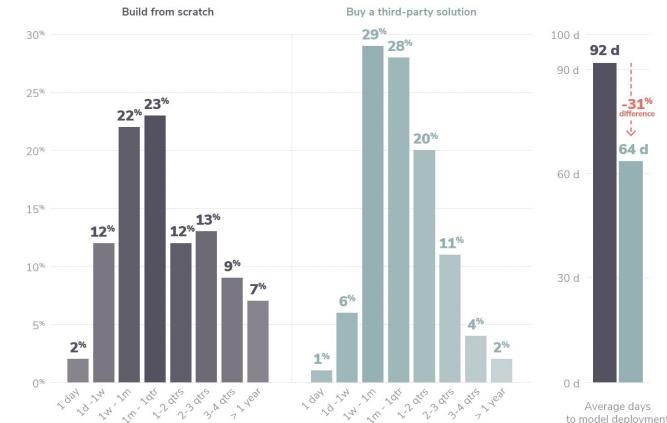
- ThoughtWorks Continuous delivery for ML (CD4ML)
- Google guidelines for ML Engineering, MLOps and Continuous Integration (CI)/Continuous delivery (CD) pipelines for ML

Buying a third-party solution costs 19-21% less than building your own



Respondents were asked to indicate their average annual infrastructure costs based on predefined ranges, such as "\$51-\$100K". The total average annual infrastructure cost was then estimated as a range. The low estimate is based on the lower bound for each predefined range (for example, \$51K for "\$51-\$100K"). The high estimate is based on the upper bound for each predefined range (for example, \$100K for "\$51-\$100K"). For the pre-defined range that represented the greatest cost ("more than \$10M"), the lower bound of the range was used for both the high and low estimate. The percent difference was calculated with the underlying data before rounding to the nearest percentage point.

The time required to deploy a model is 31% lower for organizations that buy a third-party solution





Broader considerations in production

- *ML system requirements* - system goals, user requirements, environment assumptions, quality beyond accuracy, measurement, risk analysis, planning for mistakes
- *Architecture & Design* - Modeling tradeoffs, deployment architecture, telemetry, monitoring, anticipating evolution, human-centric AI design
- *Quality assurance* - Model testing, data quality, infrastructure quality, debugging
- *Operations* - CI/CD, experimentation, versioning, configuration management
- *Teams and process* - DS and SWE workflows, team dependencies, collaboration, technical debt
- *Responsible AI/ML* - Explainability and interpretability, reproducibility, provenance, fairness, security and privacy, transparency and trust
- *Meta* - AI ethics, governance, regulation, compliance, organisational culture

Demo

Opportunities in SG

Grab hires interns & fresh graduates into different teams in Singapore



TERM TIME INTERNSHIPS

16-20 weeks commencing in Jan/Feb and Jul/ Aug

Application windows open in previous term



SUMMER INTERNSHIPS

12 weeks commencing in May

Application window open in Nov in prior year



GRADUATE PROGRAM

CFO Office Program - a 2 year rotation-based program in Finance commencing

in Jun each year. Application window opens in Sep of prior year



FRESH GRADUATE DIRECT HIRING

Direct hiring roles are posted on grab.careers



Intern Opportunities

Grab hires interns & fresh graduates into different teams in Singapore

TECHNOLOGY

- Data Analytics & Data Science
- Engineering
- Design
- Product Management

CORPORATE

- Grab Financial Group & Digibank
- Operations
- Merchants
- GrabAds

FUNCTIONS

- Business Development & Partnerships
- Grab Support
- Marketing
- Public Affairs
- ESG/ Social Impact
- Compliance
- Legal
- Finance
- People Operations
- Cyber Security



Application Process

How to get hired at Grab

01

APPLICATION

Submit your application via
grab.careers before the
deadline



02

ASSESSMENT

If shortlisted, you may have
be assigned a coding
assessment, a case study or
a take-home assignments
prior to interviews



03

INTERVIEWS

Interviewers will assess you
for cultural, job and team fit
(2-3 rounds)



04

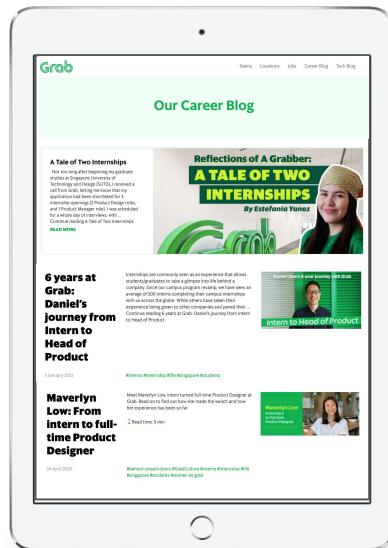
OFFER

Congratulations for making
it thus far. If you have been
selected, you will receive an
offer to join Grab.



Application Process

Read more at our Grab Careers page at <https://grab.careers/team-internships/?tm=Internships>



Summer 2022 Internship

We will be opening applications for Summer roles in 2 weeks, but please do scan the above QR code to be kept in the loop via email when we open applications

If you have any questions, please reach out to the Campus team at intern@grab.com

Internship opportunities with the team:

- 2 internships for Jan-Jun and July-Dec each year
- Scope:
 - Blue skies research
 - Software engineering
 - Dashboarding
- Example of internship posting:
<https://grab.careers/job-details/?id=786570a2663201b4ddf2d02c9d00cb1f>



Thank you