UC San Diego

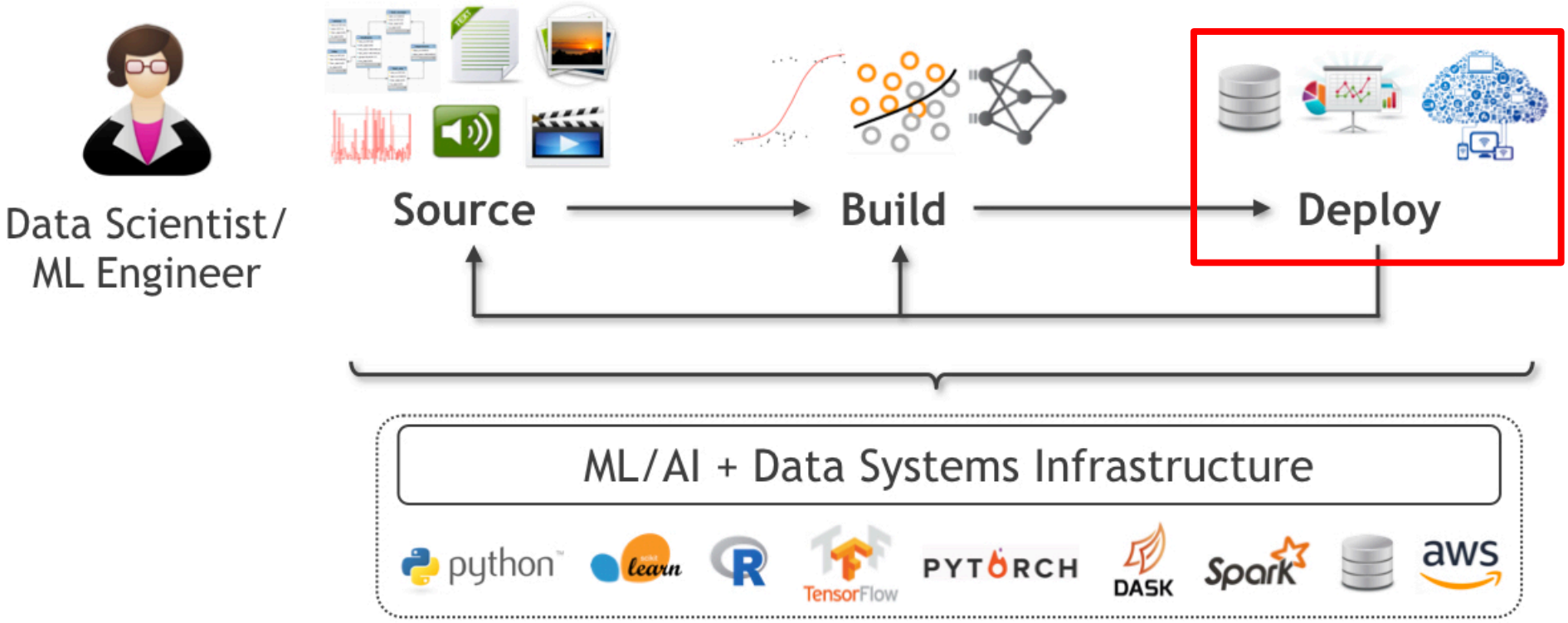
CSE 234
Data Systems for Machine Learning

Arun Kumar

Topic 6: ML Deployment and MLOps

Chapter 8.5 of MLSys book

ML Deployment in the Lifecycle



Data acquisition
Data preparation

Feature Engineering
Training & Inference
Model Selection

Serving
Monitoring

ML Deployment in the Lifecycle

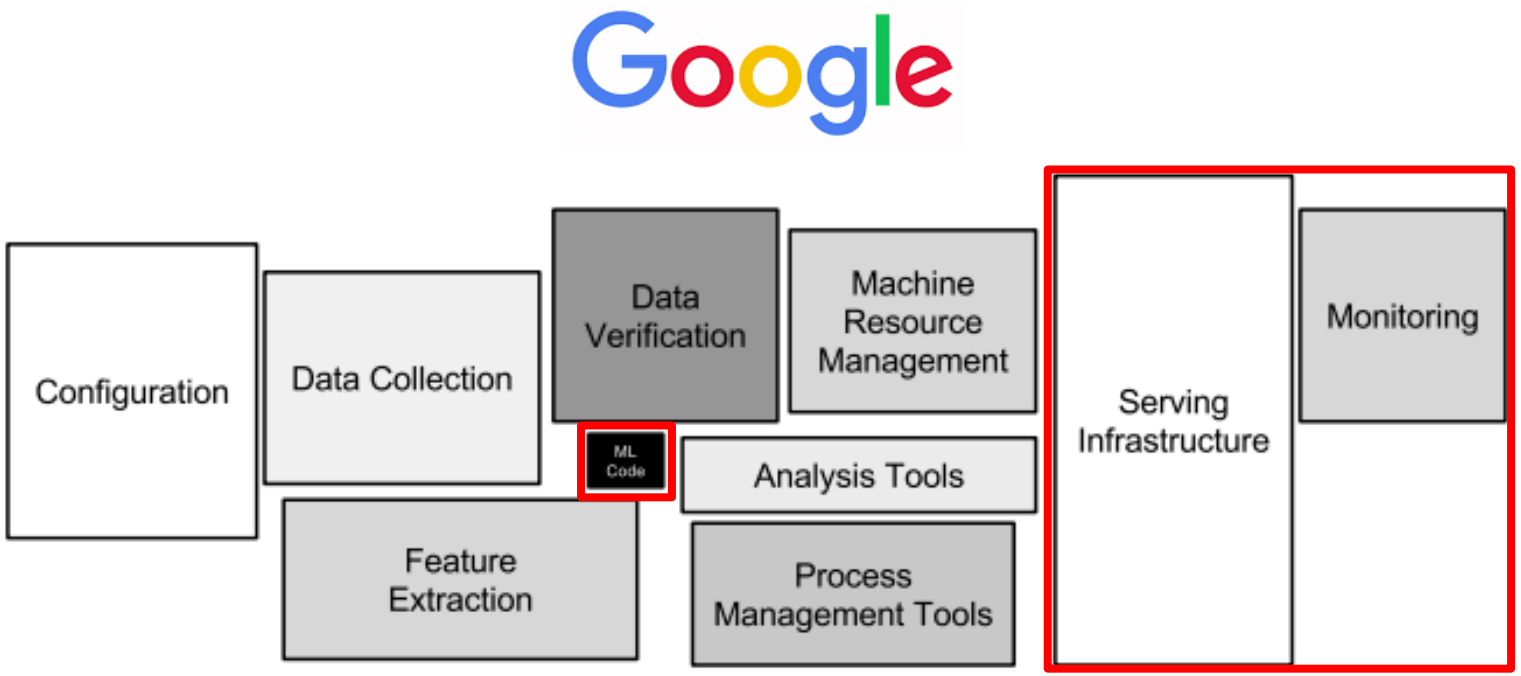


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Outline

- Offline ML Deployment
- MLOps:
  - Online Prediction Serving
  - The “3 Vs” of MLOps
  - Monitoring and Versioning
- Federated ML

Offline ML Deployment

- **Given:** A trained prediction function f(); a *set* of (unlabeled) data examples
- **Goal:** Apply inference with f() to all examples *efficiently*
  - Key metrics: *Throughput*, cost, latency
- Historically, offline was the most common scenario
  - Still is among most enterprises, sciences, healthcare
  - Typically once a quarter / month / week / day
  - Aka model *scoring* in some settings

Offline ML Deployment: Systems

- Not particularly challenging in most applications
- All ML systems support inference by default

In-memory:

Disk-based files:

Layered on RDBMS/Spark:

Cloud-native:


Azure Machine Learning

Amazon SageMaker

"AutoML" platforms:

DataRobot

Decision tree-oriented:

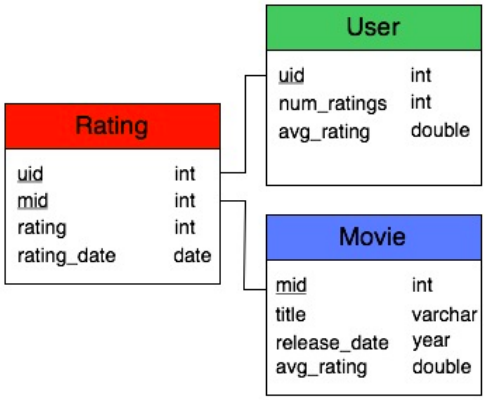
Microsoft LightGBM

Deep learning-oriented:

Offline ML Deployment: Optimizations

Q: What systems-level optimizations are possible here?

- **Parallelism:**
  - Inference is *embarrassingly parallel* across examples
- **Factorized ML (e.g., in Morpheus):**
  - Push ML computations down through joins
  - Pre-computes some FLOPS and reuses across examples



$$x_i = [x_{i,R}; x_{i,U}; x_{i,M}]$$

Example: GLM inference:

$$w^T x_i = w_R^T x_{i,R} + \boxed{w_U^T x_{i,U}} + \boxed{w_M^T x_{i,M}}$$

Offline ML Deployment: Optimizations

***Q:** What systems-level optimizations are possible here?*

- **More general pre-computation / caching / batching:**
  - Factorized ML is a specific form of sharing/caching
  - Other forms of "multi-query optimization" possible

Example: Batched inference for separate GLMs:

$$X_{n\times d}(w_1)_{d\times 1} \quad Xw_2 \quad Xw_3 \longrightarrow X[w_1; w_2; w_3]_{d\times 3}$$

Reduces memory stalls for X; raises hardware efficiency

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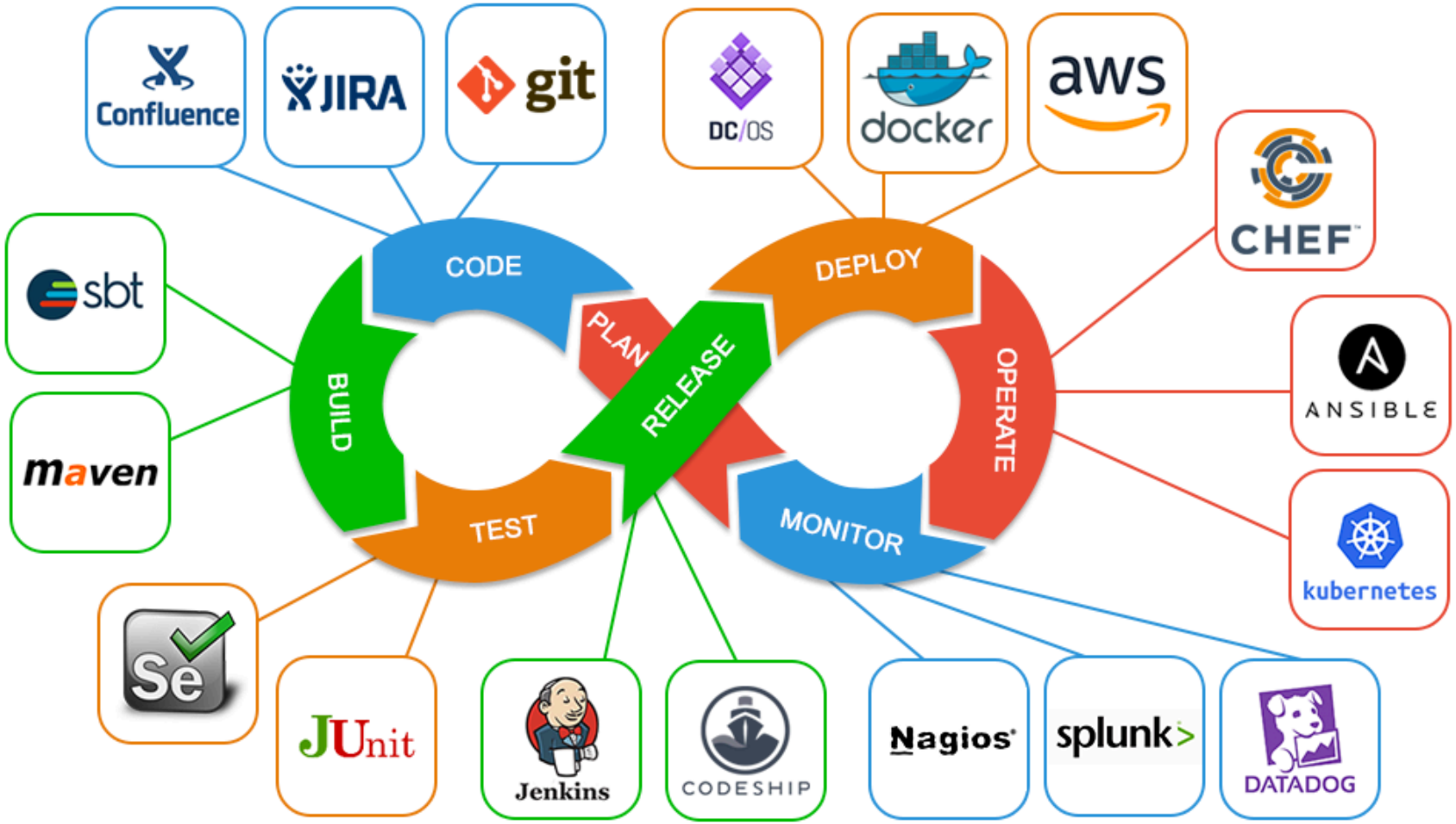
Background: DevOps

- Software Development + IT Operations (DevOps) is a long standing subarea of *software engineering*
- No uniform definition but loosely, the science+eng. of administering software in “production”
  - Fuses many historically separate job roles
- Cloud and “Agile” s/w eng. have revolutionized DevOps

Background: DevOps



https://medium.com/swlh/how-to-become-an-devops-engineer-in-2020-80b8740d5a52

Key Parts of DevOps Stack/Practice

Logging & Monitoring

Building & Testing

Continuous Integration (CI) & Continuous Delivery (CD)

Version Control

Infrastructure-as-Code (IaC), including Config. & Policy

Microservices / Containerization & Orchestration

Content Credit: Manasi Vartak, Verta.AI
https://aws.amazon.com/devops/what-is-devops/

The Rise of MLOps

- MLOps = DevOps for ML-infused software
  - Much harder than for deterministic software!
- Things that matter beyond just ML model codes:
  - Training and validation datasets
  - Data cleaning/prep/featurization codes/scripts
  - Hyperparameters, other training configs
  - Post-inference rules/configs/ensembling
  - Software versions/configs?
  - Training hardware/configs?

Content Credit: Manasi Vartak, Verta.AI

The Rise of MLOps

- Need to change DevOps for ML program semantics
- **Online Prediction Serving**
- **Logging & Monitoring:**
  - Prediction failures; concept drift; feature inflow changes
- **Version Control:**
  - Anything can change: ML code, data, configs, etc.
- **Build & Test; CI & CD:**
  - Rigorous train-val-test splits; beware insidious overfitting
- New space with a lot of R&D; no consensus on standards

Content Credit: Manasi Vartak, Verta.AI

The “3 Vs of MLOps”

Operationalizing Machine Learning: An Interview Study

Shreya Shankar*, Rolando Garcia*, Joseph M. Hellerstein, Aditya G. Parameswaran
University of California, Berkeley

- **Velocity:**
  - Need for rapid experimentation, prototyping, and deployment with minimal friction
- **Validation:**
  - Need for checks on quality and integrity of data, features, models, predictions
- **Versioning:**
  - Need to keep track of deployed models and features to ensure provenance and fallback options

https://arxiv.org/pdf/2209.09125.pdf

The “3 Vs of MLOps”

Operationalizing Machine Learning: An Interview Study

Shreya Shankar*, Rolando Garcia*, Joseph M. Hellerstein, Aditya G. Parameswaran
University of California, Berkeley

- Interplay/tussles between the 3 Vs shapes decisions on tools, processes, and people management in MLOps
- **Examples:**
  - Should Jupyter notebooks be deployed to production? Velocity vs. Validation
  - Are feature stores needed? Velocity vs. Versioning
  - Relabel/augment val. data? Validation vs. Versioning

https://arxiv.org/pdf/2209.09125.pdf

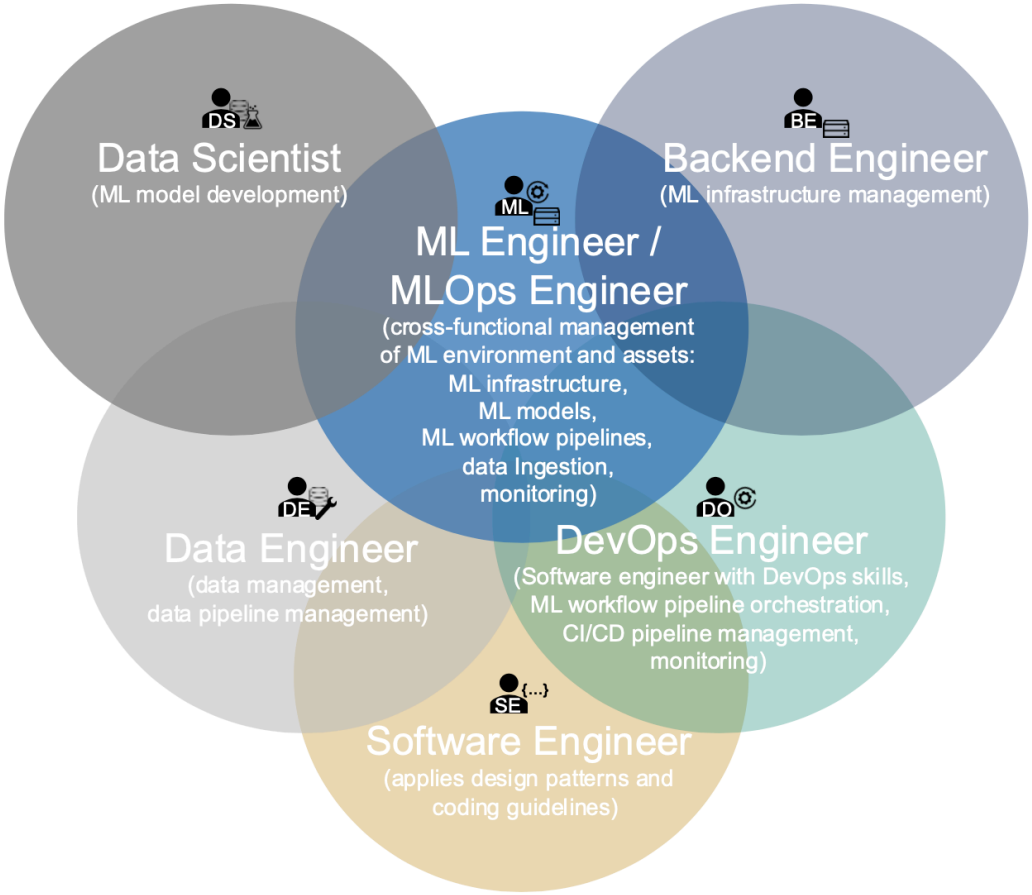
Birds-eye View of MLOps

Machine Learning Operations (MLOps):
Overview, Definition, and Architecture

Dominik Kreuzberger
KIT
Germany

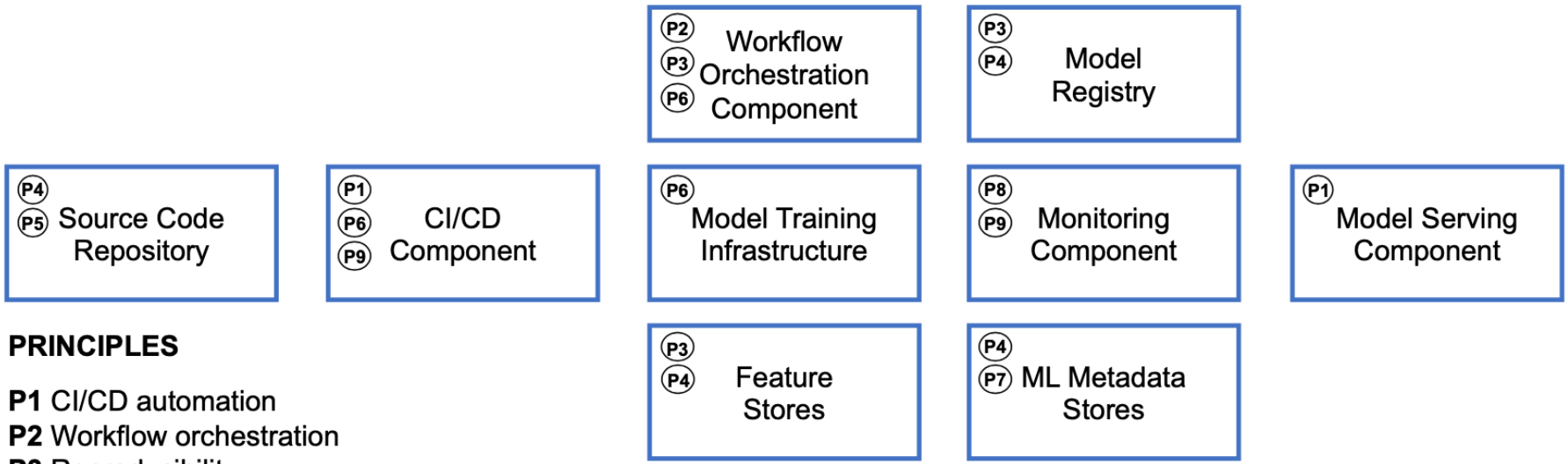
Niklas Kühl
KIT
Germany

Sebastian Hirschl
IBM†
Germany



https://arxiv.org/pdf/2205.02302.pdf

Birds-eye View of MLOps



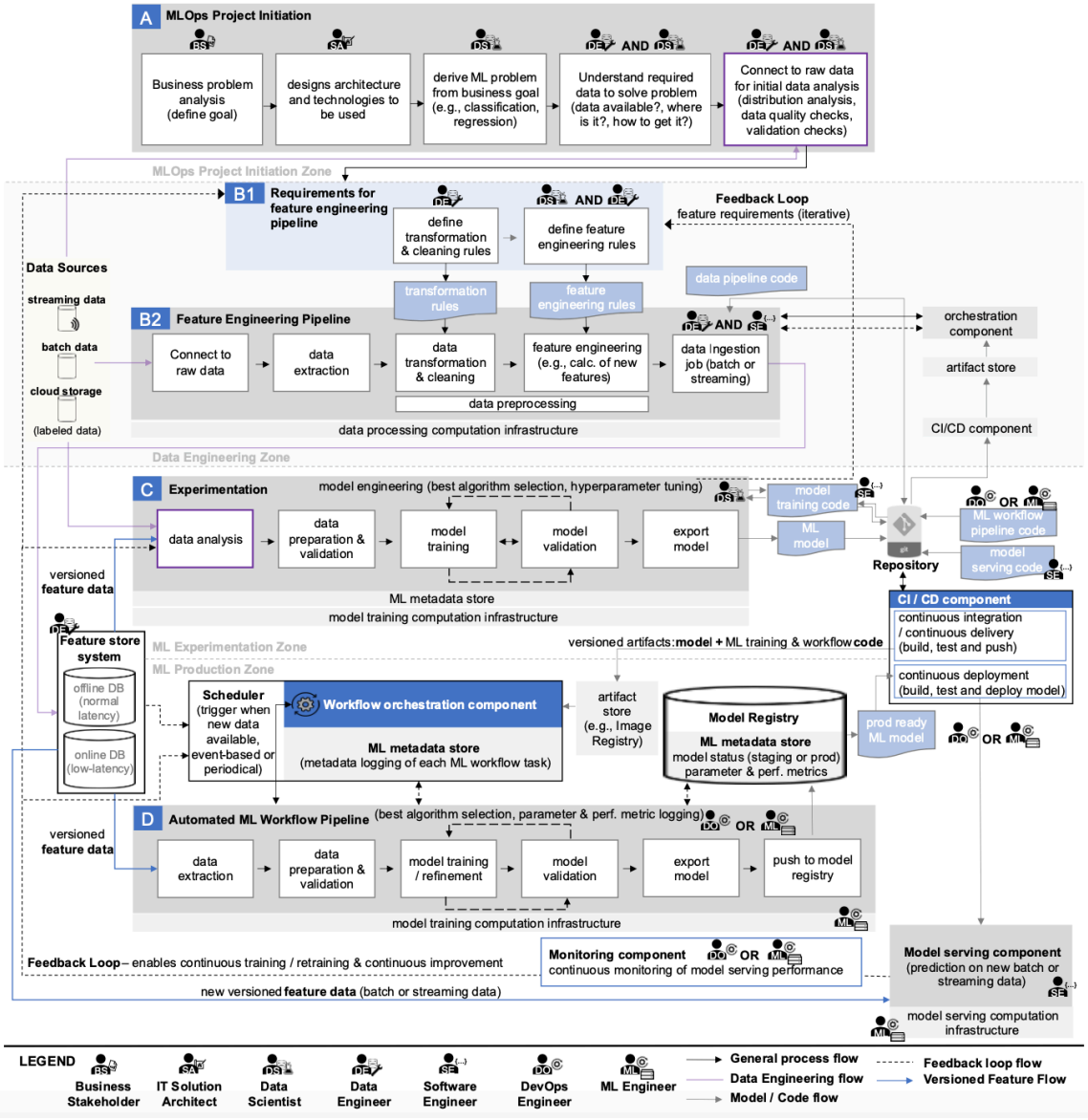
PRINCIPLES

P1 CI/CD automation
P2 Workflow orchestration
P3 Reproducibility
P4 Versioning of data, code, model
P5 Collaboration
P6 Continuous ML training & evaluation
P7 ML metadata tracking
P8 Continuous monitoring
P9 Feedback loops

COMPONENT

https://arxiv.org/pdf/2205.02302.pdf

Birds-eye View of MLOps



(See the paper PDF for full res)

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- Offline ML Deployment
- MLOps:
  - Online Prediction Serving
    - Monitoring and Versioning
- Federated ML

Online Prediction Serving

- Standard setting for Web and IoT deployments of ML
  - Usually need to be *realtime*; < 100s of milliseconds!
  - Aka *model serving*
- **Given:** A trained prediction function f(); a *stream* of unlabeled data example(s)
- **Goal:** Apply f() to all/each example *efficiently*
  - Key metrics: *Latency*, *memory footprint*, cost, throughput

Online Prediction Serving

- Surprisingly challenging to do well in ML systems practice!
  - Still an immature area; lot of R&D; many startups
- **Key Challenges:**
  - **Heterogeneity** of environments: webpages, cloud-based apps, mobile apps, vehicles, IoT, etc.
  - **Unpredictability** of load: need to elastically upscale or downscale resources
  - **Function's complexity**: model, featurization and data prep code, output thresholds, etc.
    - May straddle libraries, dependencies, even PLs!
    - Hard to optimize end to end in general

The Rise of Serverless Infra.

- Prediction serving is now a “killer app” for Function-as-a-Service (FaaS), AKA serverless cloud infra.
  - Extreme pay-as-you-go; can rent at millisecond level!

- Still, many open efficiency issues for ML deployment:
  - Memory footprints, input access restrictions, logging / output persistence restrictions, latency

Online Prediction Serving: Systems

- A variety of ML serving systems have sprung up recently

General-purpose (supports multiple ML tools):

Amazon SageMaker

Azure Machine Learning

ML system-specific:

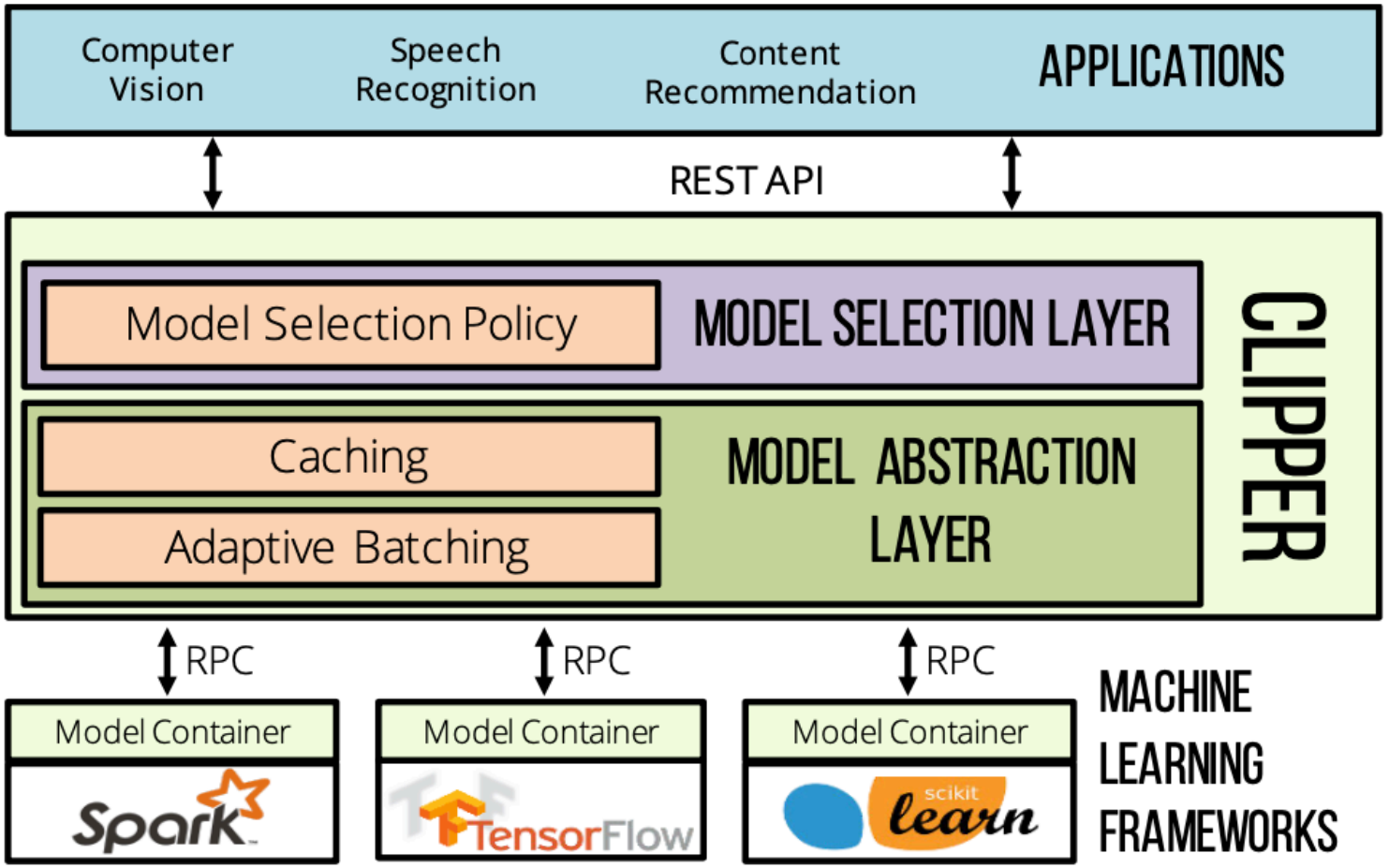
TensorFlow Extended

TF Serving

TorchServe

Clipper

- A pioneering general-purpose ML serving system



Clipper: Principles and Techniques

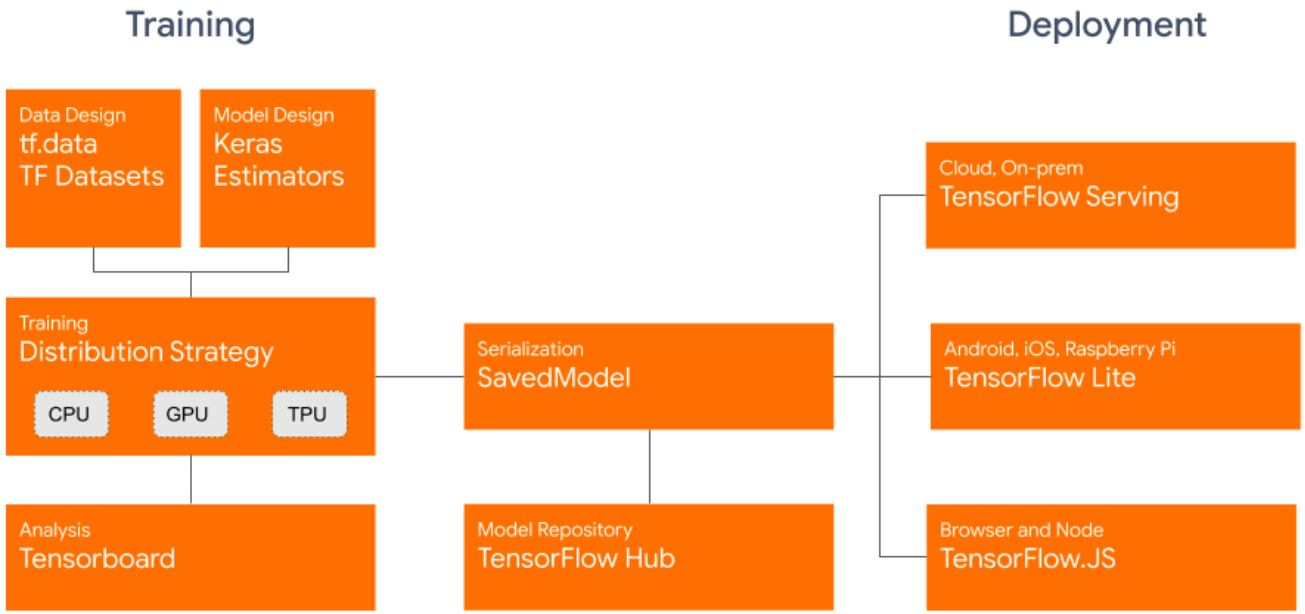
- **Generality and modularity:**
  - One of the first to use *containers* for ML serving
  - Supports multiple ML tools in unified layered API
- **Efficiency:**
  - Some basic optimizations: *batching* to raise throughput; *caching* of frequently access models/vectors
- **Multi-model deployment and flexibility:**
  - A heuristic “model selection” layer to dynamically pick among multiple deployed models; ensembling

Your Reviews on Clipper Paper

- (Walked through in class)

TensorFlow Serving

- TF Serving is a mature ML serving system, also pioneering
  - Optimized for TF model formats; also supports batching
  - Dynamic reloading of weights; multiple data sources



- TF Lite and TF.JS optimized for more niche backends/ runtime environments

Comparing ML Serving Systems

- Advantages of **general-purpose** vs. system-specific:
  - Tool heterogeneity is a reality for many orgs
  - More nimble to customize accuracy post-deployment with different kinds of models/tools
  - Flexibility to swap ML tools; no “lock-in”
- Advantages of **ML system-specific** vs general-purpose:
  - Generality may not be needed (e.g., Google); lower complexity of MLOps
  - Likely more amenable to code/pipeline optimizations
  - Likely better hardware utilization, lower cloud costs

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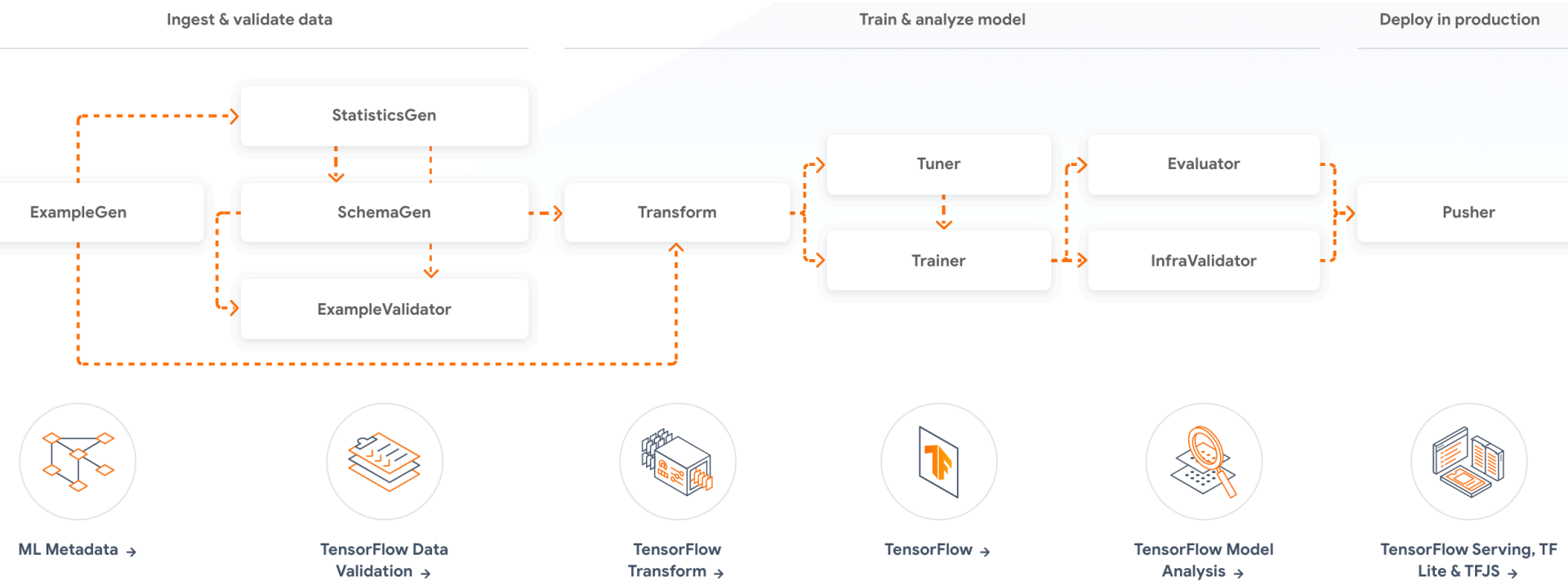
Example for ML Monitoring: TFX

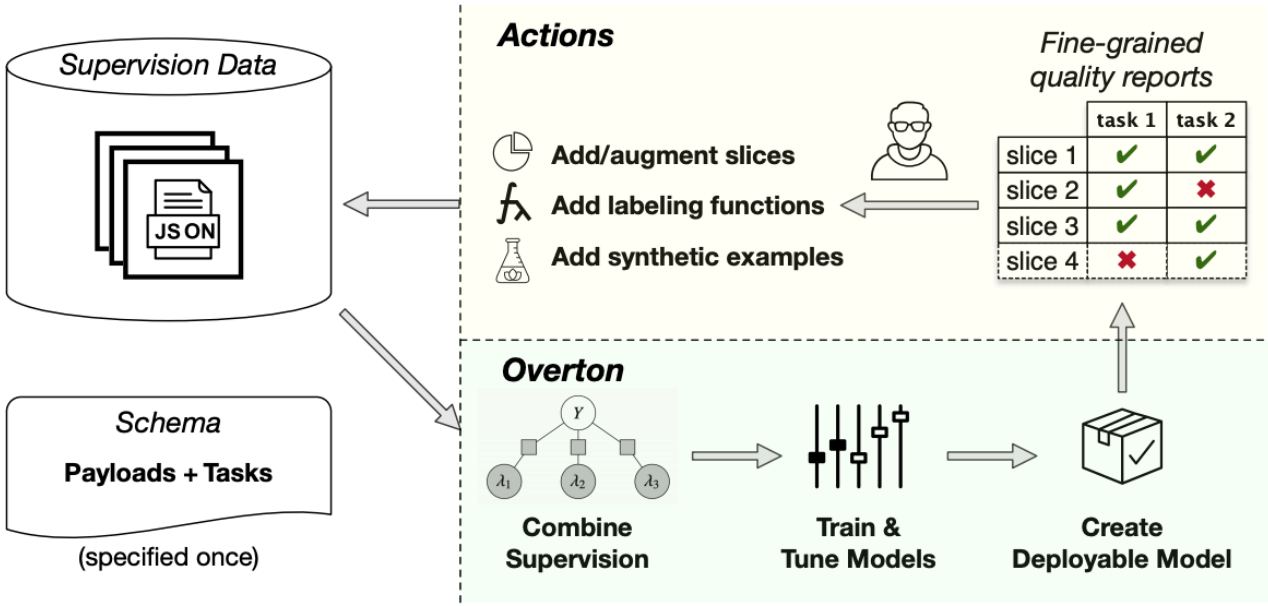
- TFX's "Model Analysis" lets user specify metrics, track over time automatically, alert on-call
- Can specify metrics for feature-based data "slices" too



https://www.tensorflow.org/tfx/guide/tfma

Example for ML Monitoring: Overton

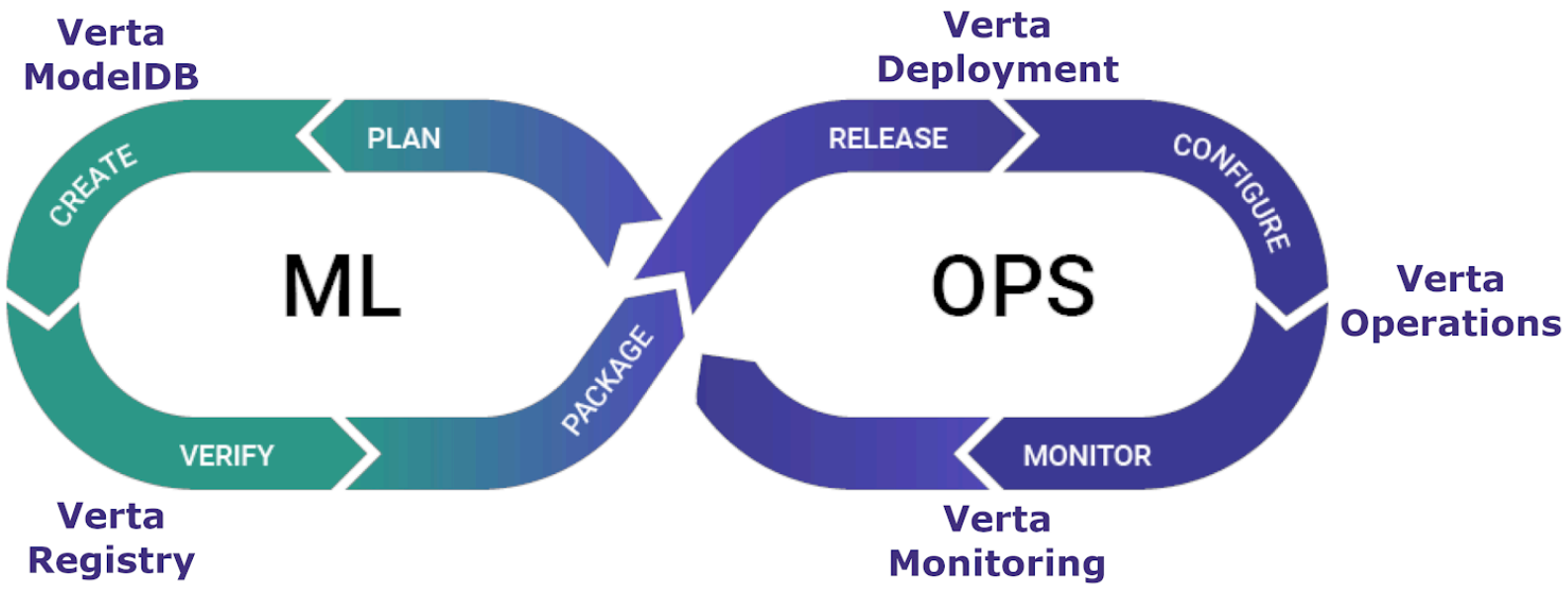
- Envisions “code-free” ML monitoring for appl. engineers
  - Decouples prediction appl. “task schema” and data
- Emphasizes monitoring of critical training subsets, specifiable using “tags” and “slices”



https://arxiv.org/pdf/1909.05372.pdf

Example for ML Versioning: Verta

- Started with ModelDB for storing and tracking ML artifacts
  - ML code; data; configuration; environment
- APIs as hooks into ML dev code; SDK and web app./GUI
- Registry for versions and workflows



https://blog.verta.ai/blog/the-third-wave-of-operationalization-is-here-mlops

Open Research Questions in MLOps

- Efficient and consistent version control for ML datasets and featurization codes
- Automate ML prediction failure detection and recovery
- Detect concept drift in an actionable manner; prescribe fixes
- Velocity and complexity of streaming ML applications
- Seamless CI & CD for mass-produced models without insidious overfitting
- Automated end-to-end optimizations spanning feature stores and model serving infrastructure
- …

Example: MLOps Insights from TFX Traces

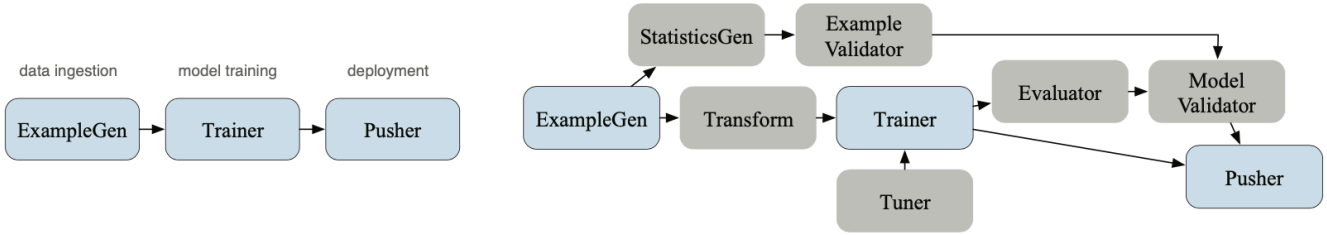
Production Machine Learning Pipelines:
Empirical Analysis and Optimization Opportunities

Doris Xin*
University of California, Berkeley

Hui Miao
Google
huimiao@google.com

Aditya Parameswaran
University of California, Berkeley

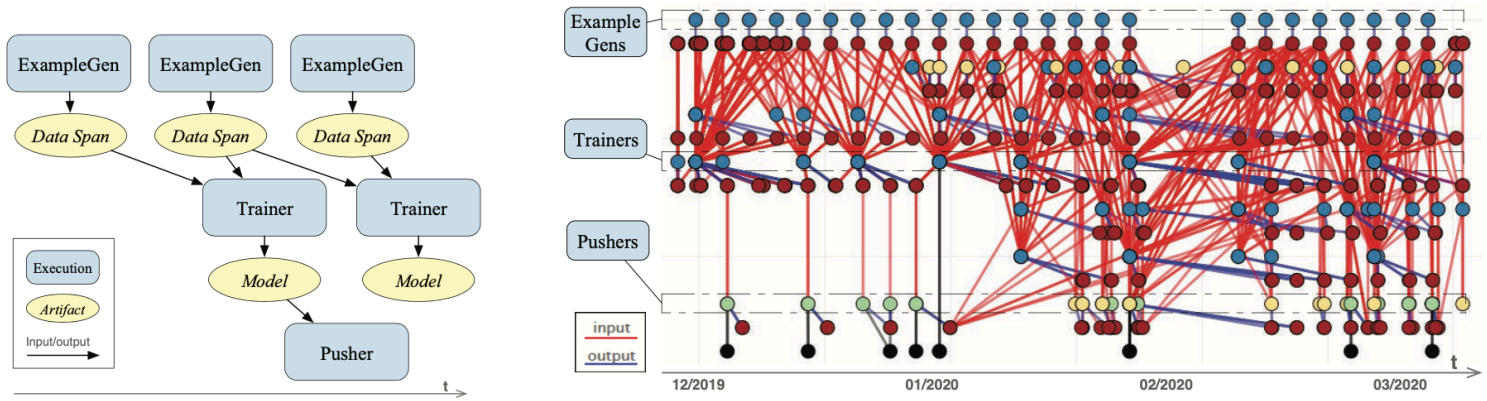
Neoklis Polyzotis
Google
npolyzotis@google.com



(a) A simple TFX pipeline comprising three operators: *ExampleGen*, *Trainer*, and *Pusher*. Edges denote the input/output dependencies.

(b) A more typical TFX pipeline that comprises additional operators for data preprocessing, data and model validation, and tuning. Shaded operators correspond to the additional functionality compared to (a).

Figure 1: Examples of TFX pipelines



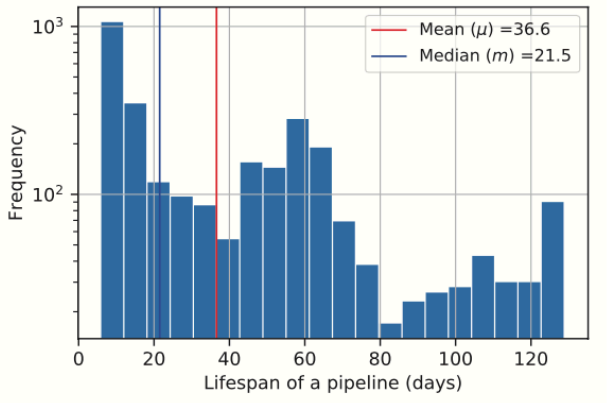
(a) A simple trace for the pipeline in Fig. 1(a).

(b) A real-world trace from our corpus, using operators shown in Fig. 1(b).

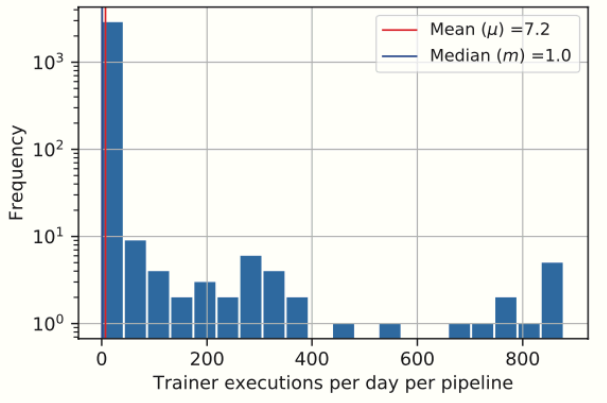
Figure 2: Examples of pipeline traces. The left-to-right order preserves the time of artifact generation.

https://arxiv.org/pdf/2103.16007.pdf

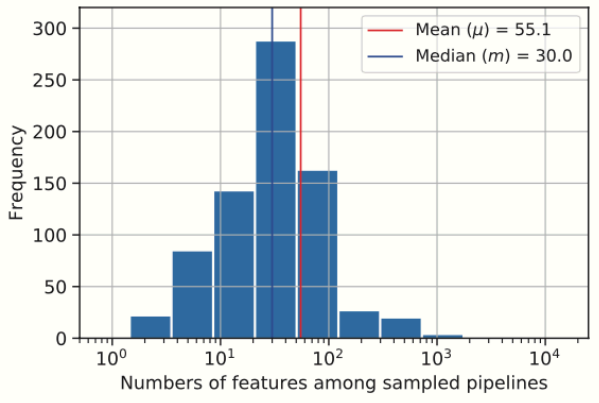
Example: MLOps Insights from TFX Traces



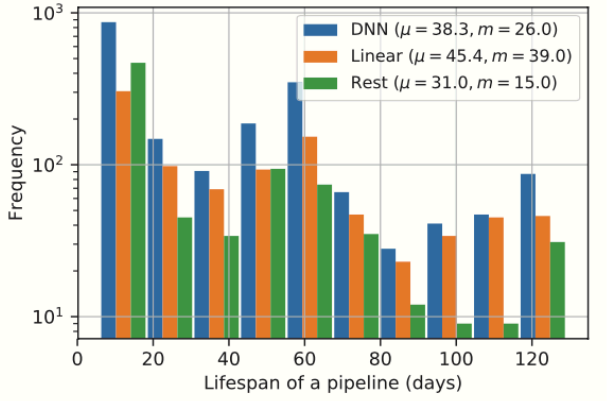
(a) Distribution of pipeline span.



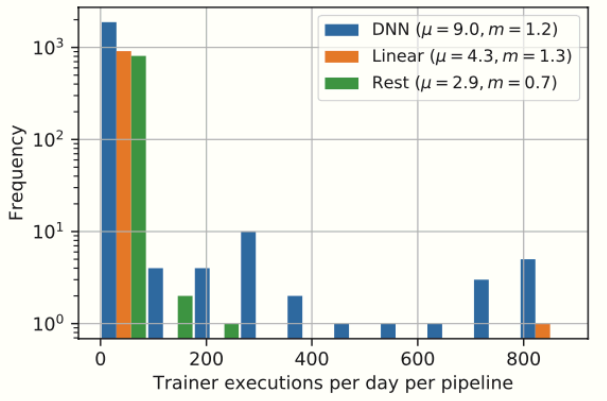
(b) Distribution of trained models per day.



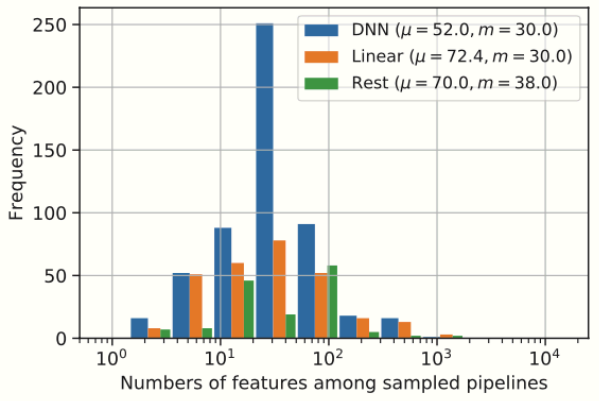
(c) Distribution of the number of features.



(d) Distribution of pipeline span.



(e) Distribution of trained models per day.



(f) Distribution of the number of features.

Figure 3: Pipeline Activity and Data Complexity Analysis Results.

https://arxiv.org/pdf/2103.16007.pdf

Example: MLOps Insights from TFX Traces

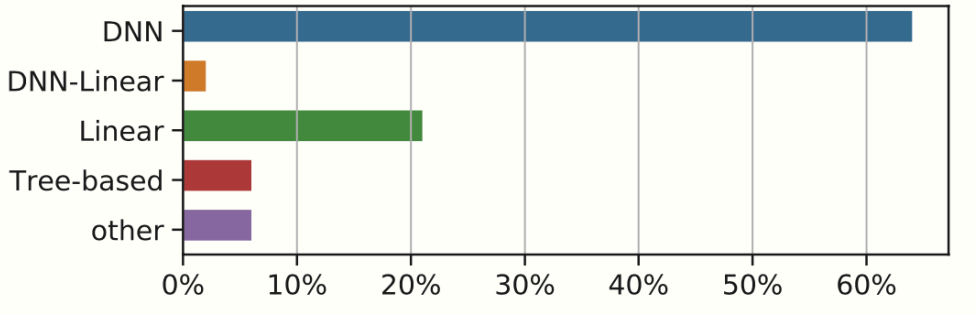


Figure 5: Percentage of Trainer runs with each model type

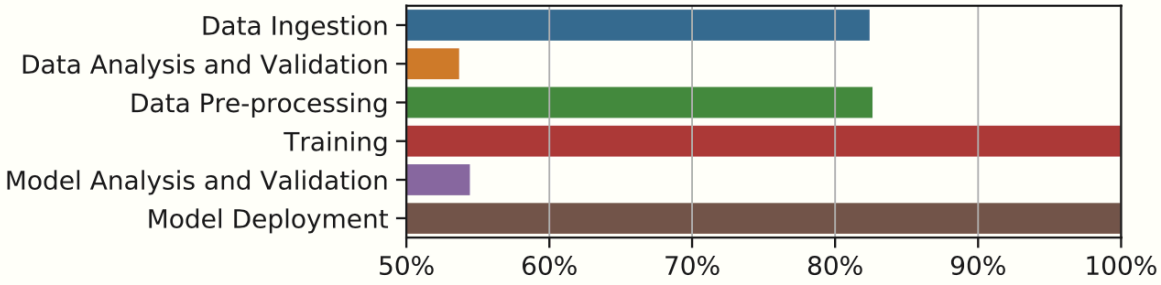


Figure 6: Percentage of pipelines with different operators.

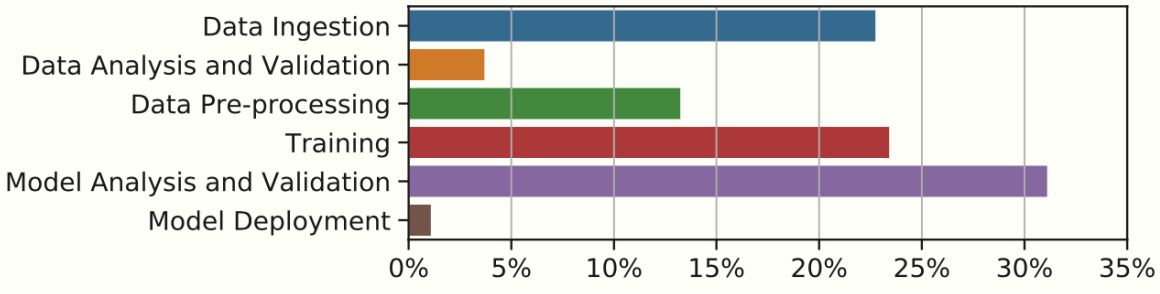


Figure 7: Compute cost of different operators.

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- Offline ML Deployment
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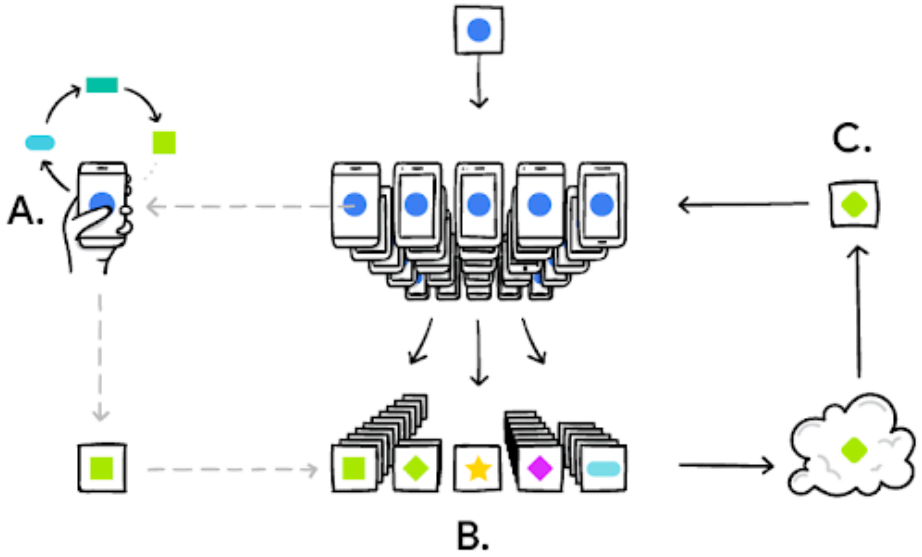
- ML Monitoring and Versioning
- Federated ML

Federated ML

- Pioneered by Google for ML/AI applications on smartphones
- Key benefit is more **user privacy**:
  - User's (labeled) data does not leave their device
  - Decentralizes ML model training/finetuning to user data



https://ai.googleblog.com/2017/04/federated-learning-collaborative.html
https://mlsys.org/Conferences/2019/doc/2019/193.pdf

Federated ML

- **Key challenge:** Decentralize SGD to intermittent updates
- They proposed a simple “federated averaging” algorithm

$$\min_{w \in \mathbb{R}^d} f(w) \qquad \text{where} \qquad f(w) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^{n} f_i(w).$$

$$f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \quad \text{where} \quad F_k(w) = \frac{1}{n_k} \sum_{i \in \mathcal{P}_k} f_i(w).$$

- User-partitioned updates breaks IID assumption; skews arise
- Turns out SGD is still pretty robust (recall async. PS); open theoretical questions still being studied

https://arxiv.org/abs/1602.05629

Federated ML

- **Privacy/security-focused improvements:**
  - New SGD variants; integration with differential privacy
  - Cryptography to anonymize update aggregations
- Apart from *strong user privacy*, *communication and energy efficiency* also major concerns on battery-powered devices
- **Systems+ML heuristic optimizations:**
  - Compression and quantization to save upload bandwidth
  - Communicate only “high quality” model updates
  - Novel federation-aware ML algorithmics

https://arxiv.org/abs/1602.05629
https://arxiv.org/pdf/1610.02527.pdf
https://eprint.iacr.org/2017/281.pdf

Federated ML

- Federated ML protocol has become quite sophisticated to ensure better stability/reliability, accuracy, and manageability

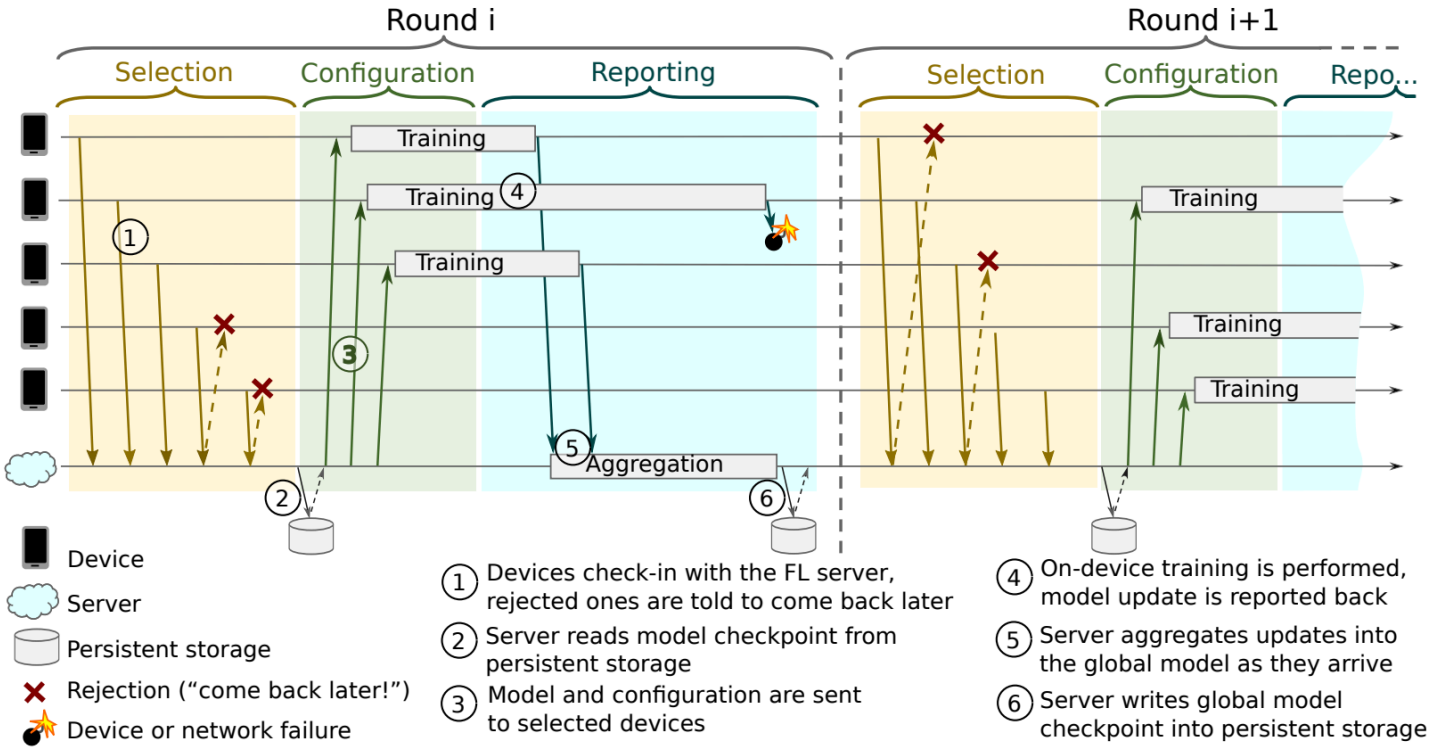
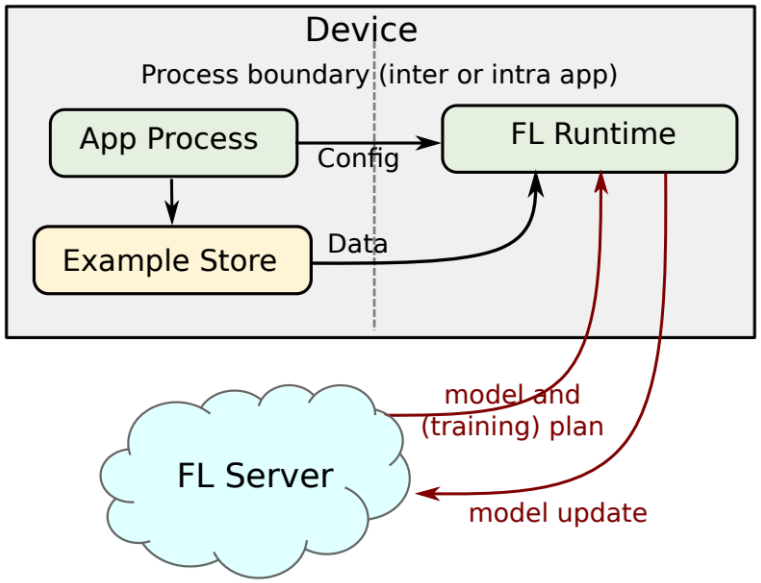


Figure 1: Federated Learning Protocol

https://mlsys.org/Conferences/2019/doc/2019/193.pdf

Federated ML

- Google has neatly abstracted the client-side (embedded in mobile app.) and server-side functionality with actor design



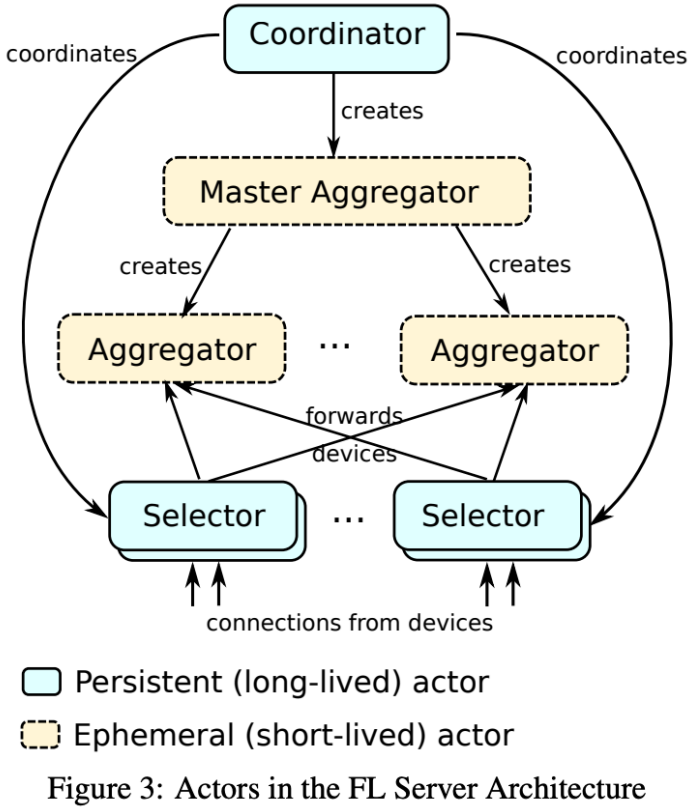
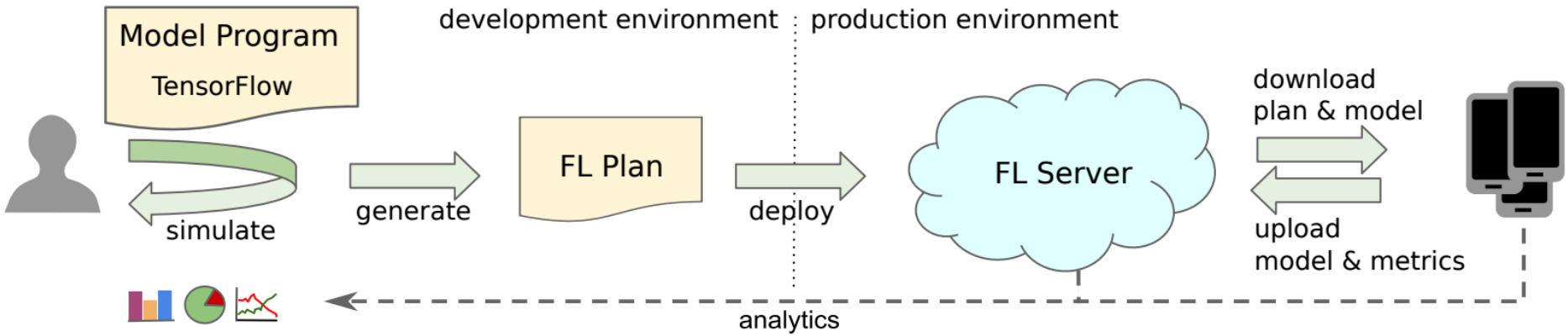


Figure 3: Actors in the FL Server Architecture

https://mlsys.org/Conferences/2019/doc/2019/193.pdf

Federated ML

- Notion of “FL Plan” and simulation-based tooling for data scientists to tailor ML for this deployment regime
  - (Users’) Training data is out of reach!
  - Model is updated asynchronously automatically
  - Debugging and versioning became even more difficult



https://mlsys.org/Conferences/2019/doc/2019/193.pdf

Review Questions

1. Briefly explain 2 reasons why online prediction serving is typically more challenging in practice than offline deployment.
2. Briefly describe 2 systems optimizations performed by Clipper for prediction serving.
3. Briefly discuss 1 systems-level optimization amenable to both offline ML deployment and online prediction serving.
4. Name 3 things that must be versioned for rigorous version control in MLOps.
5. Briefly explain 2 reasons why ML monitoring is needed.
6. Briefly explain 2 reasons why federated ML is more challenging for data scientists to reason about.

Peer Instruction Activity

(Switch slides)

Thank you for taking CSE 234!

Please do submit your course evals before 5pm PT Sunday.

Additional Content
(Optional; not included for Final)

Additional Readings/Resources

https://arxiv.org/abs/2108.07258

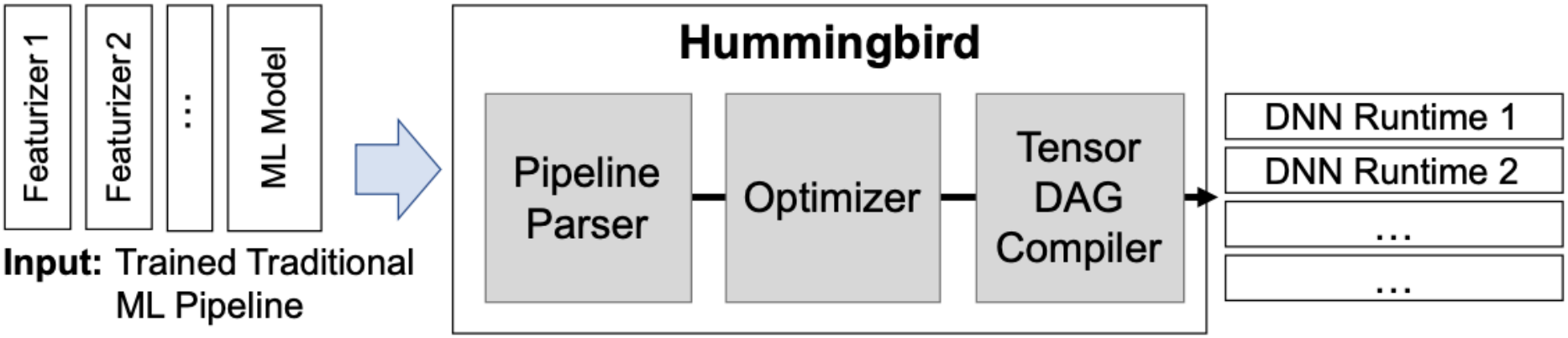
On the Opportunities and Risks of Foundation Models

https://www.stateof.ai/

State of AI Report 2022

Hummingbird: Classical ML on DL Tools

- An optimizing compiler to convert classical ML inference computations, especially *tree-based methods*, to tensor ops to exploit DL runtimes, GPU/TPU, etc.
- Branch-heavy instructions -> dense tensor arithmetic



Hummingbird: Classical ML on DL Tools

- Interestingly, it pays off to embed “useless” calculations in tensor (beyond what is exactly needed for tree) due to massive parallelism of tensor backends!

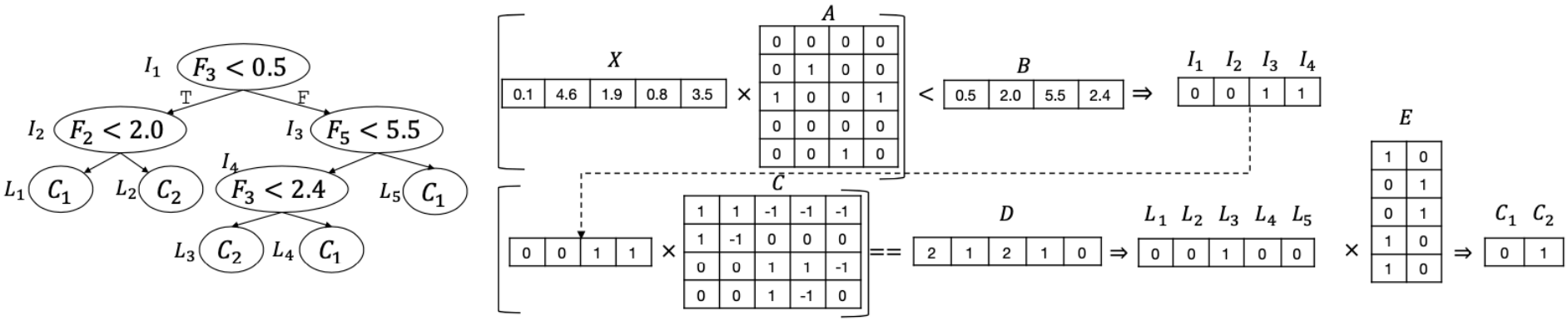
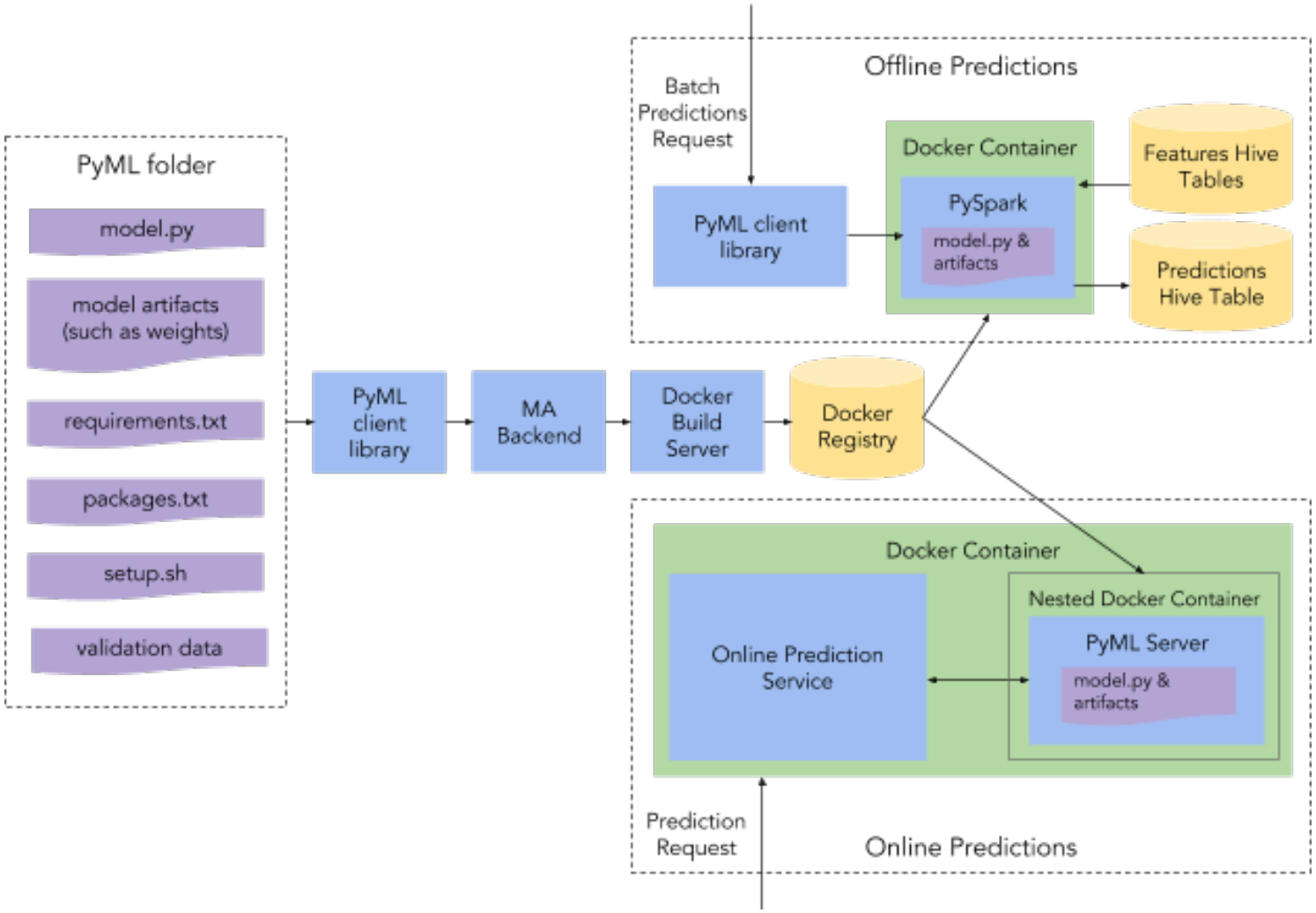


Figure 3: Compiling an example decision tree using the GEMM strategy (algorithm 1).

- Slower on 1 or few examples; faster on larger batches
- 2x-3x faster than SKLearn/ONNX on CPU; 10x on GPU

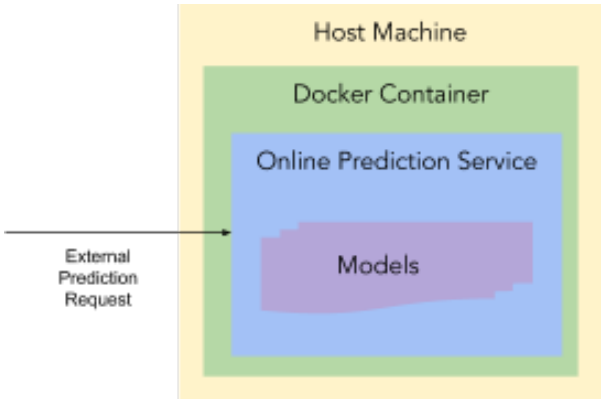
Uber's PyML

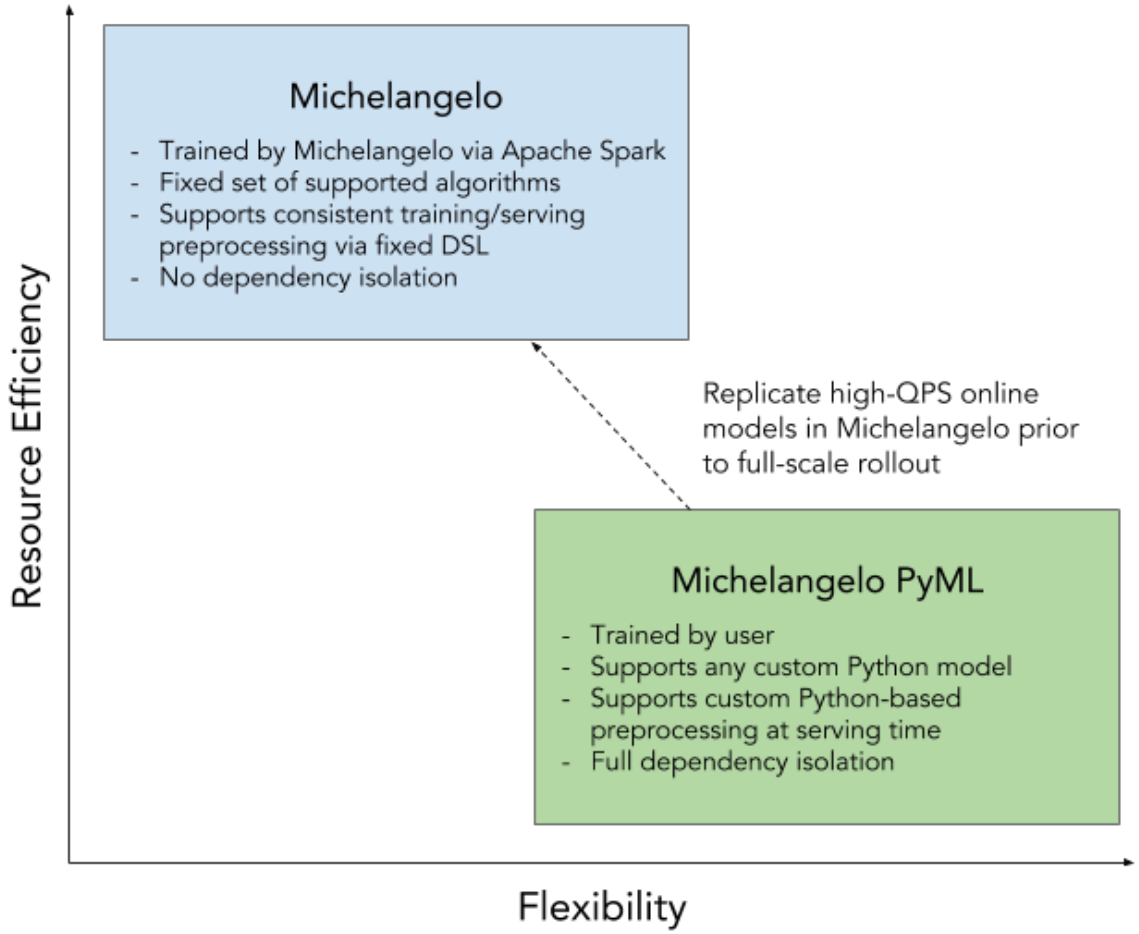


https://eng.uber.com/michelangelo-pyml/

Uber's PyML

- Older approach had coupled models with Java-based online prediction service, reducing flexibility





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