A Missing Link in the ML Infrastructure Stack

Josh Tobin
Stealth Startup, UC Berkeley, Former OpenAI

Machine Learning is now a product engineering discipline

Mac … w a


Chip Huyen @chipro · Oct 12, 2020

Machine learning engineering is 10% machine learning and 90% engineering.

98 642 7.8K

Elon Musk

@elonmusk

Replying to @chipro

Yeah

8:09 PM · Oct 12, 2020 · Twitter for iPhone

104 Retweets 18 Quote Tweets 5.4K Likes

How did we get here?

ML analytics
2000s

ML hype
2010s

ML products
2020s?

- Simple models run offline on medium to large datasets to produce reports
- Value comes from incorporating model insights into decisions

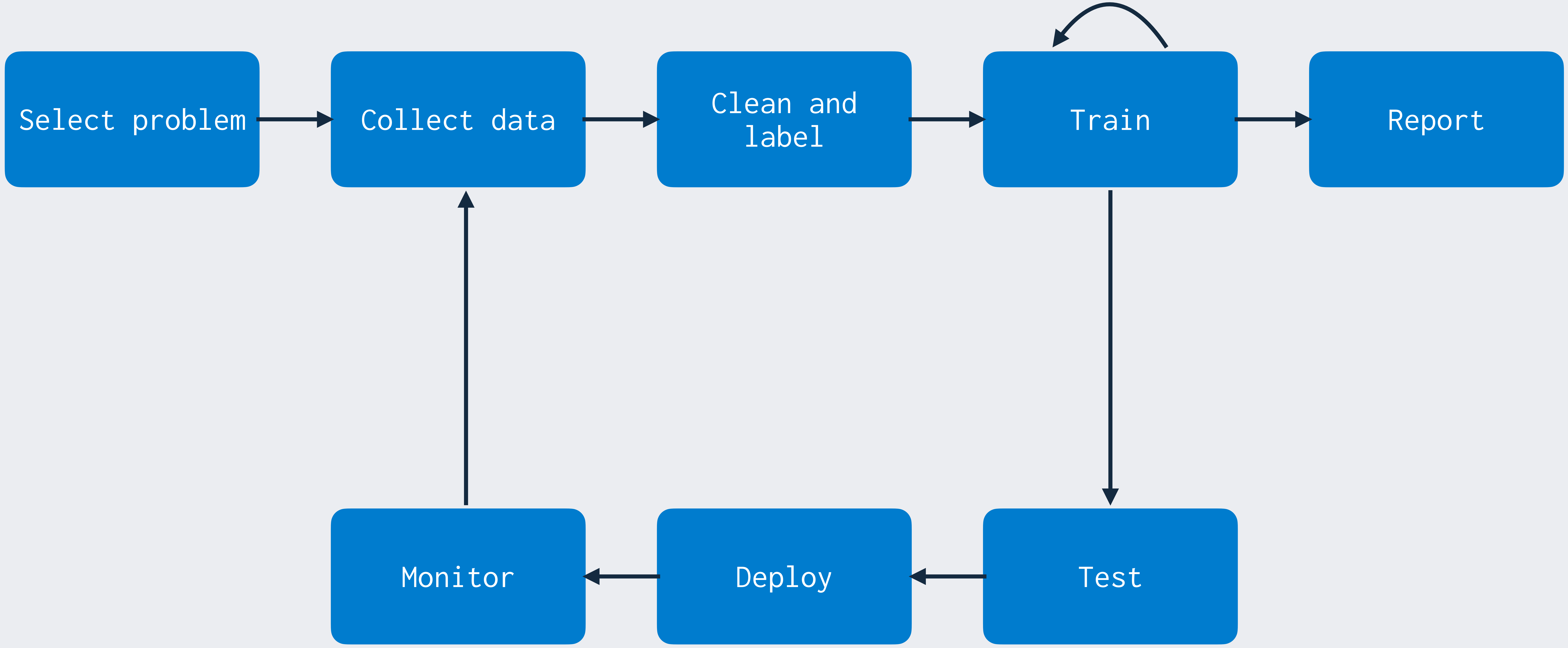
- Complicated models trained on massive datasets to produce papers
- Value comes from marketing potential of high-profile research output

- Reproducibility, scalability, and maintainability over complexity
- Value comes from models improving the business's products or services

ML products require a fundamentally new process

"Flat-earth" ML

ML products require a fundamentally new process



ML Product Engineering

ML teams that don't make the transition die

Uber sells ATG self-driving business to Aurora at $4 billion

By Krystal Hu, Tina Bellon, Jane Lanhee Lee

3 MIN READ

Montreal startup Element AI Inc. was running out of money and options when it inked a deal last month to sell itself for US$230-milion to Silicon Valley software company ServiceNow Inc., a confidential document obtained by the Globe and Mail reveals.

Of the 250 industrial firms Plutoshift surveyed,

- **over 72% found that they had taken far more time than anticipated** to implement the necessary data collection processes for applying machine learning.
- and perhaps as a result, **only 17% of those surveyed said they were actually at the full implementation stage of using A.I.,**
- while **about 70% said they were still studying what resources they'd need**, assessing possible business use cases, or conducting small pilot projects only.

TECH • OPENAI

Buzzy research lab OpenAI debuts first product as it tries to live up to the hype

BY JONATHAN VANIAN

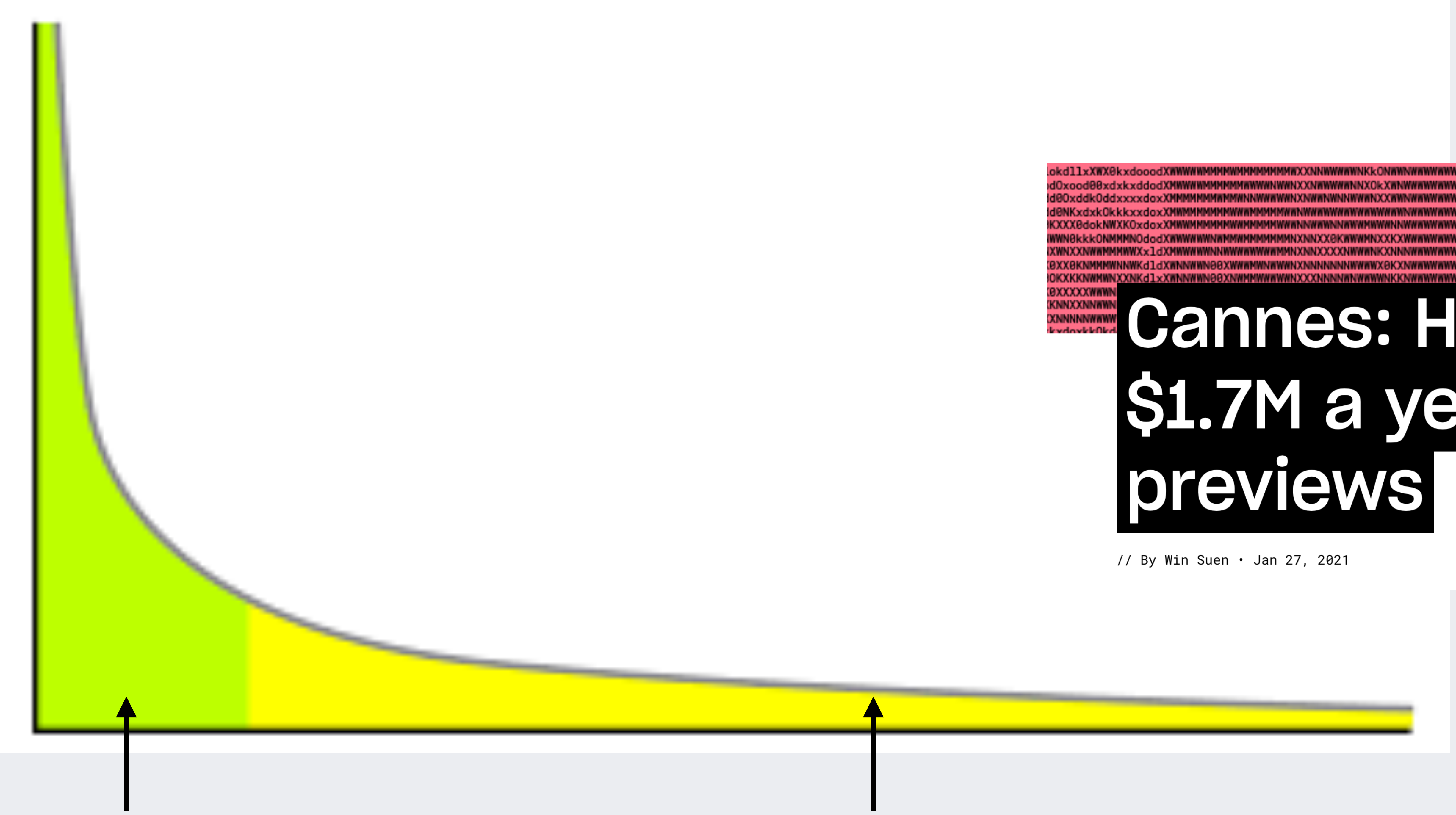
June 11, 2020 8:00 AM PDT

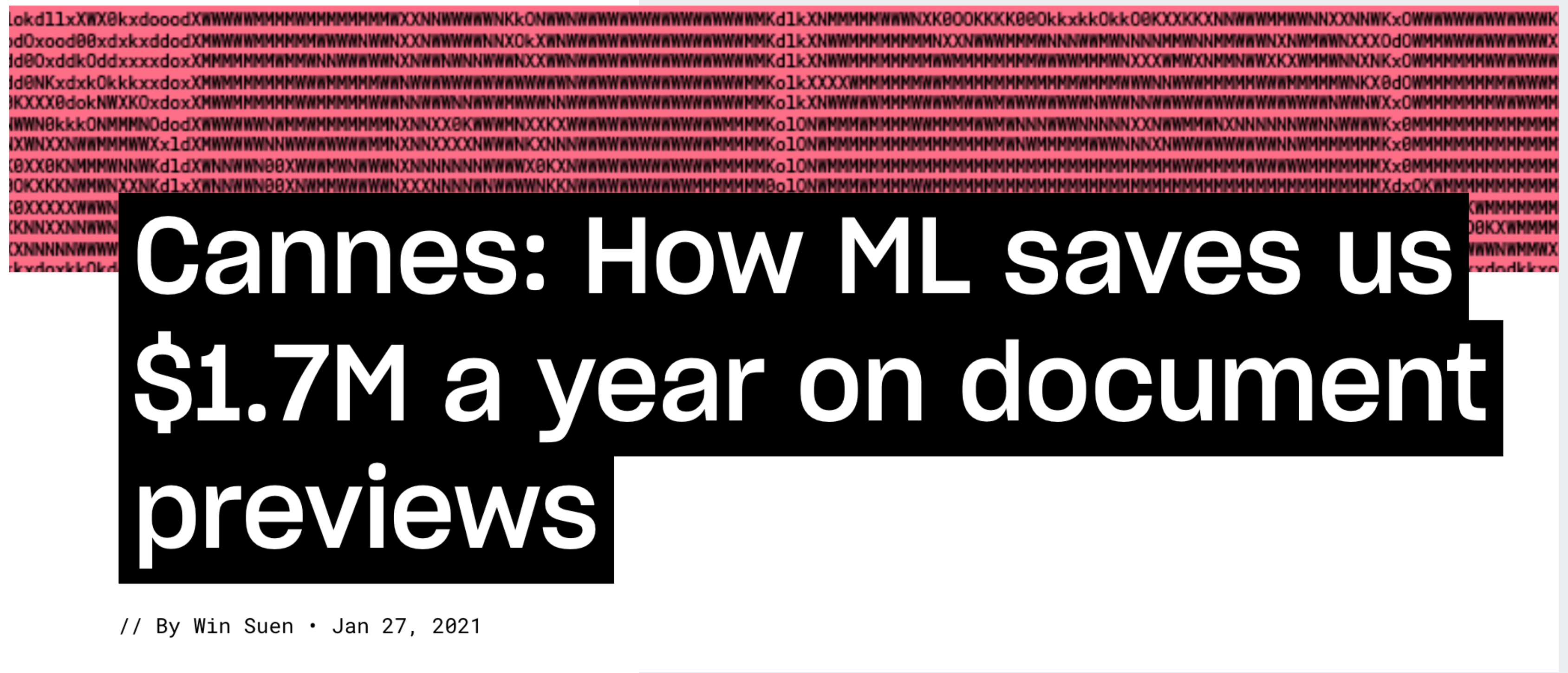
Worryingly, **almost 20% of companies cited "peer pressure" as the reason they had embarked on A.I. projects.**

What does it mean for you?

- Other disciplines will catch up to model training in prestige and pay
- The three Ps (papers, pie charts, PoCs) are no longer enough

Those that make the transition will create amazing things





- Autonomous Vehicles
- Real-time translation
- Drug discovery

- Marketing automation
- Personalization
- Document understanding
- Etc

Unlike flat-earth ML, ML products often:

- Run online and in real-time
- Deal with constantly evolving data distributions
- Handle messy, long-tail real world data
- Make predictions autonomously or semi-autonomously

This implies new ops & infra demands

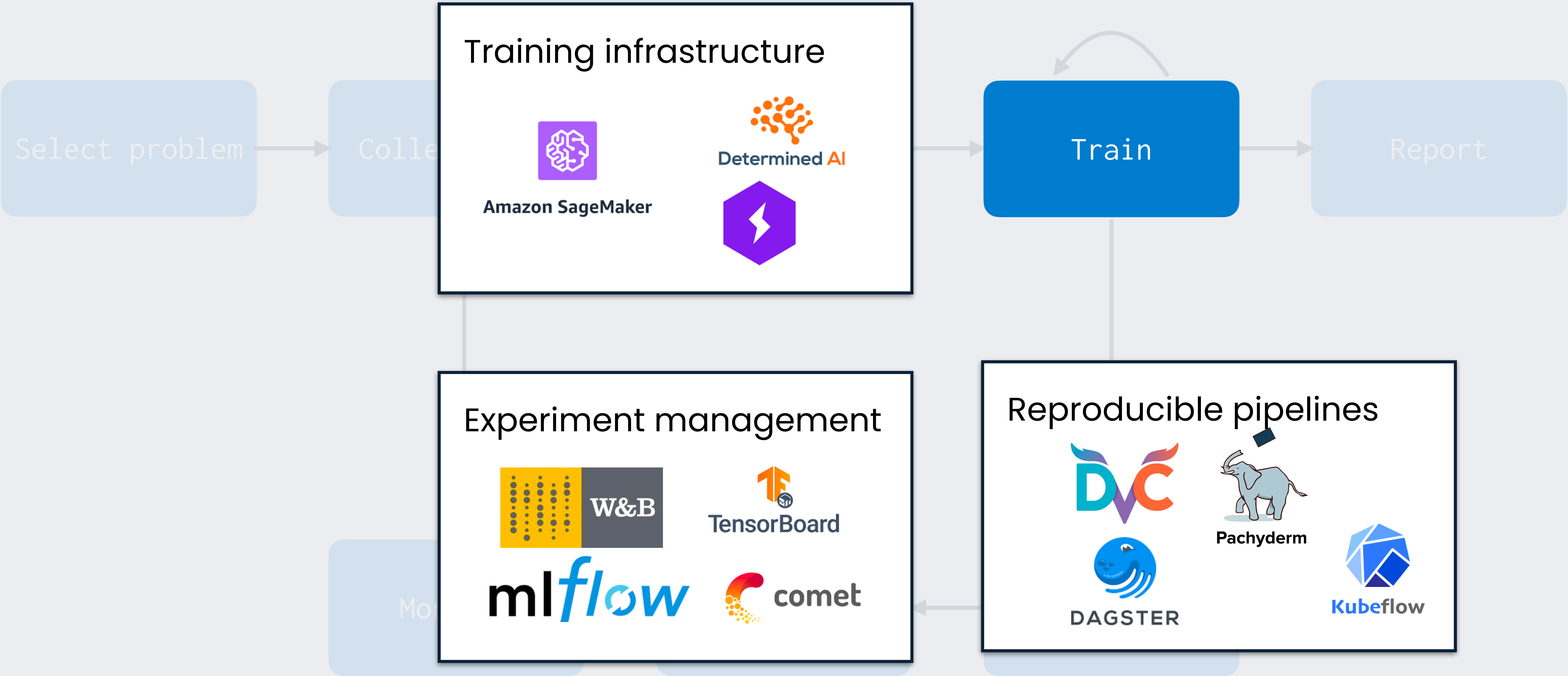
- Run online and in real-time
  Host and serve models with low latency

- Deal with constantly evolving data distributions
  Retrain models frequently, even continuously

- Handle messy, long-tail real world data
  Inspect your data scalable, manage slices and edge cases

- Make predictions autonomously or semi-autonomously
  Quickly catch and diagnose bugs and distribution changes

Is the infrastructure stack keeping up?



Is the infrastructure stack keeping up?

Select problem → Collect data → Clean and label → Train → Report

Test

Model perf exploration

W&B

Explainability tools

fiddler

Arthur

truera

CI/CD tools

GitHub Actions

circleci

Jenkins

What's still hard?

- Surfacing areas of poor performance
- Managing all your test cases

Is the infrastructure stack keeping up?

Select problem → Collect data → Train → Report

What's still hard?

- Experimentation (AB tests, shadow tests)
- Online / offline consistency

Feature stores

Amazon SageMaker Feature Store

Deploy

Model serving

Amazon SageMaker

Is the infrastructure stack keeping up?

Select problem

lean and label

Train

Report

What's still hard?
- Performance monitoring
- Drift is still a bit of an art

Data quality / drift

Deequ

TensorFlow Extended

great_expectations

Monitor

System monitoring

DATADOG

Amazon Cloudwatch

New Relic

st

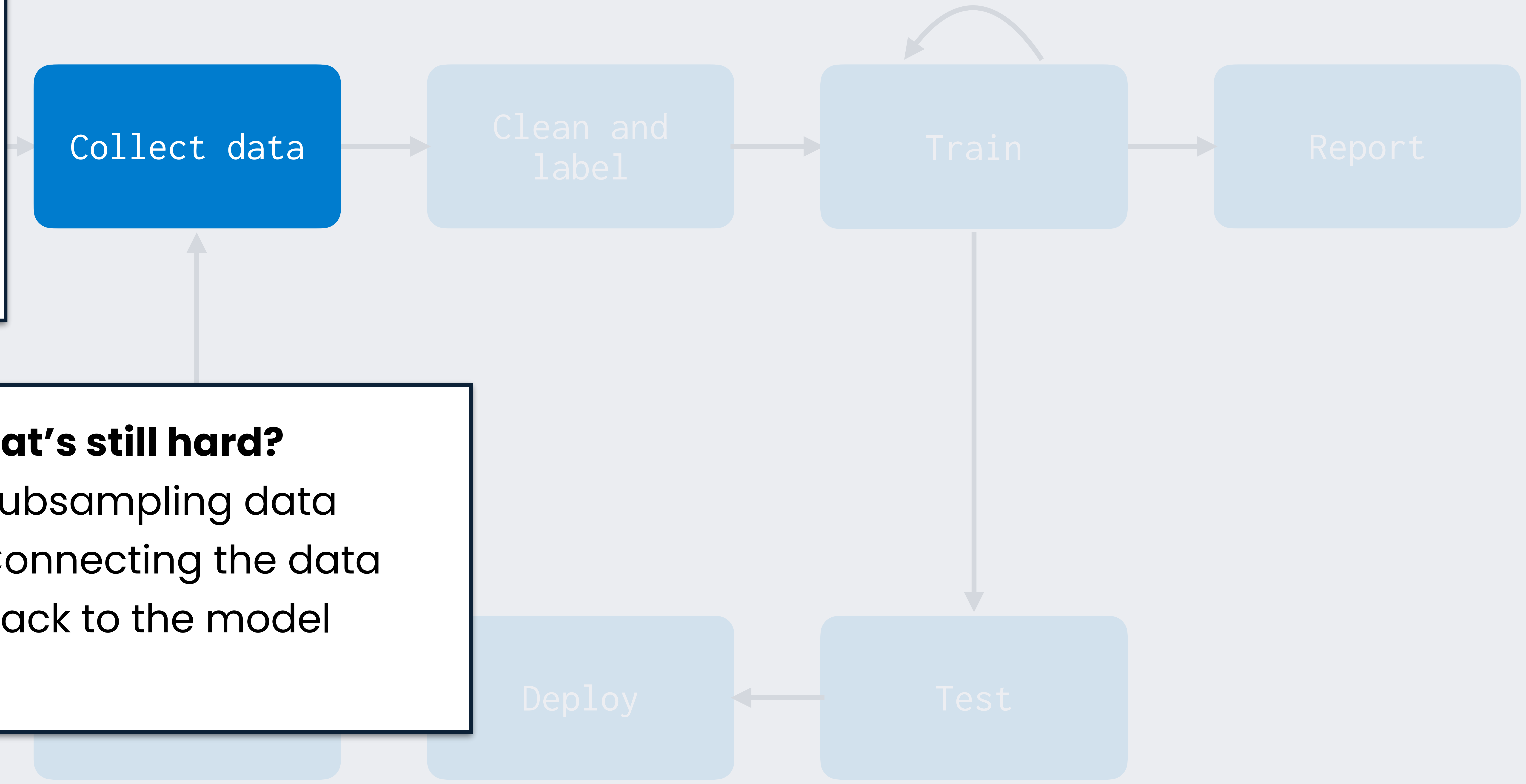
Is the infrastructure stack keeping up?

Data lakes, warehouses

DELTA LAKE

snowflake

Fivetran



What's still hard?

- Subsampling data
- Connecting the data back to the model

Is the infrastructure stack keeping up?

Select p

Labeling tools & services

scale
spaCy
figure eight
Labelbox

Clean and label

Active learning tools

scale Nucleus
Aquarium

port

What's still hard?

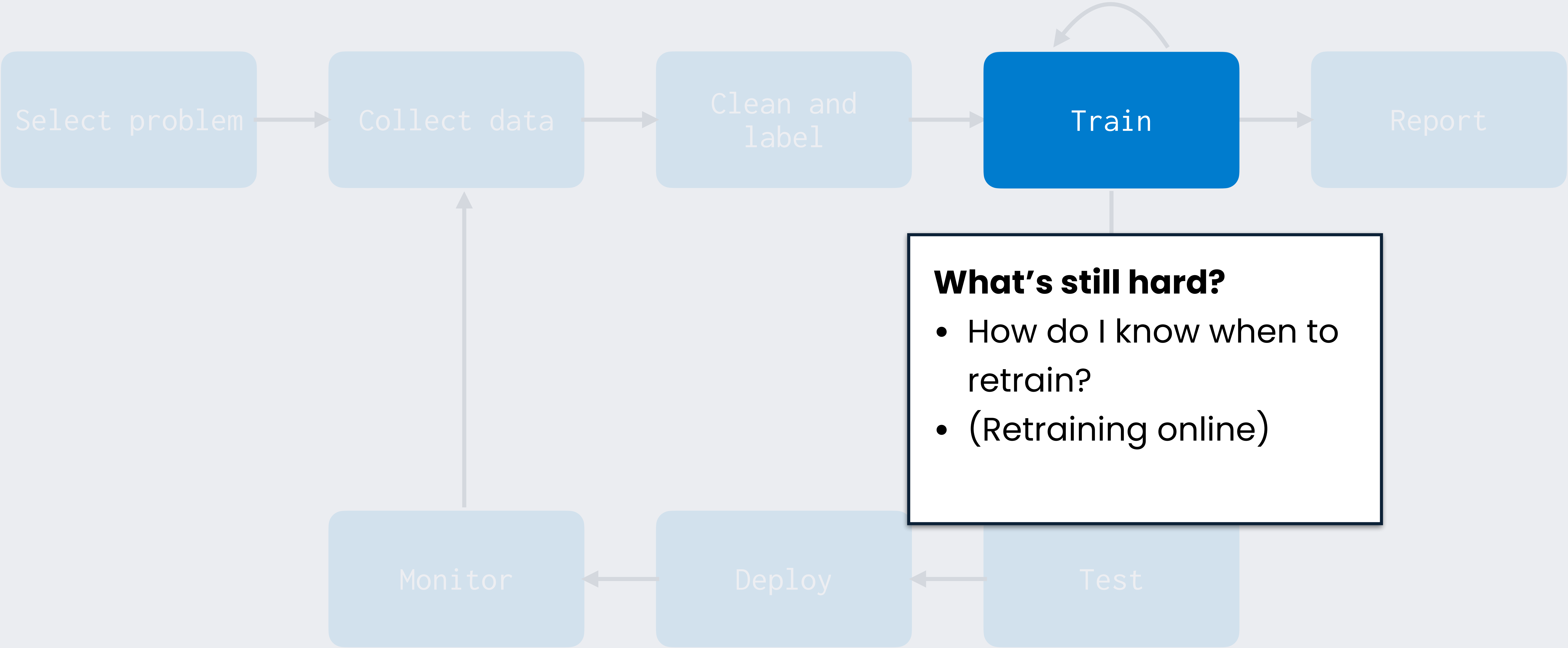
- What data should I label?
- What data should I train on?

Monitor

Deploy

Test

Is the infrastructure stack keeping up?



What's still hard?

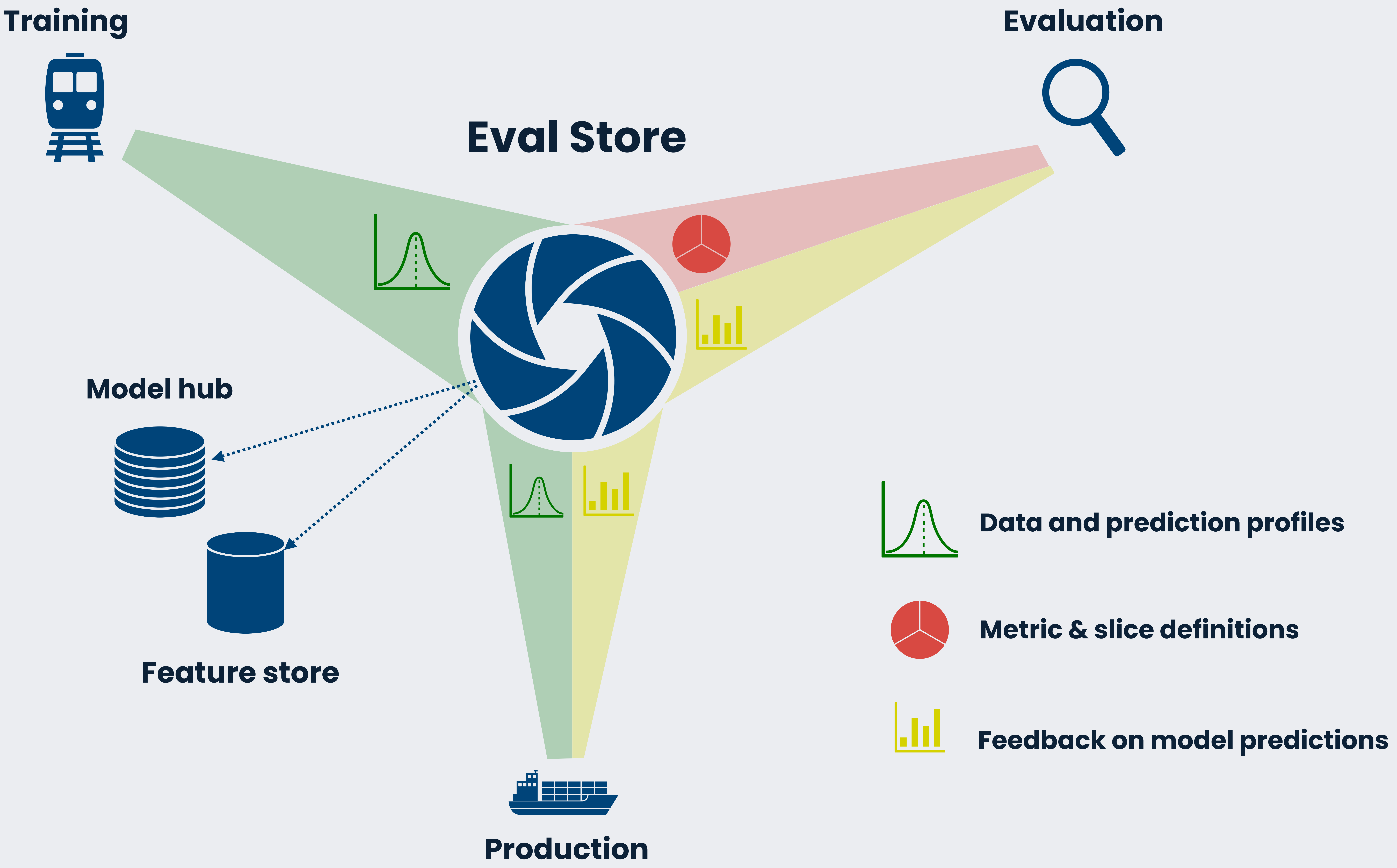
- How do I know when to retrain?
- (Retraining online)

Takeaways

- Many tools emerging to address the problems of ML product engineering
- Problems arise at the boundaries of the tools, especially anything that shepherds data through the process
- At all stages, granular understanding of model performance is lacking

The Evaluation Store

A central place to store and query **online and offline** *ground truth* and *approximate* **model quality metrics**


Training
Evaluation
Eval Store
Model hub
Feature store
Production
Data and prediction profiles
Metric & slice definitions
Feedback on model predictions

Querying the evaluation store

What form do queries take?

- Subset of models in the store
- Subset of metrics in the store
- Subset of slices in the store
- Specification of the window of data

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- Specification of the window of data

E.g.,

What is the importance-weighted average drift across all of my features in my production model in the last 60 minutes?

Monitoring

Querying the evaluation store

What form do queries take?

- Subset of models in the store
- Subset of metrics in the store
- Subset of slices in the store
- Specification of the window of data

E.g.,

How much worse is the my accuracy in the last 7 days than it was during training?

Monitoring

Querying the evaluation store

What form do queries take?

- Subset of models in the store
- Subset of metrics in the store
- Subset of slices in the store
- Specification of the window of data

E.g.,

How do all of the metrics compare for model A and model B across all slices in my main evaluation set?

Testing

Querying the evaluation store

What form do queries take?

- Subset of models in the store
- Subset of metrics in the store
- Subset of slices in the store
- Specification of the window of data

E.g.,

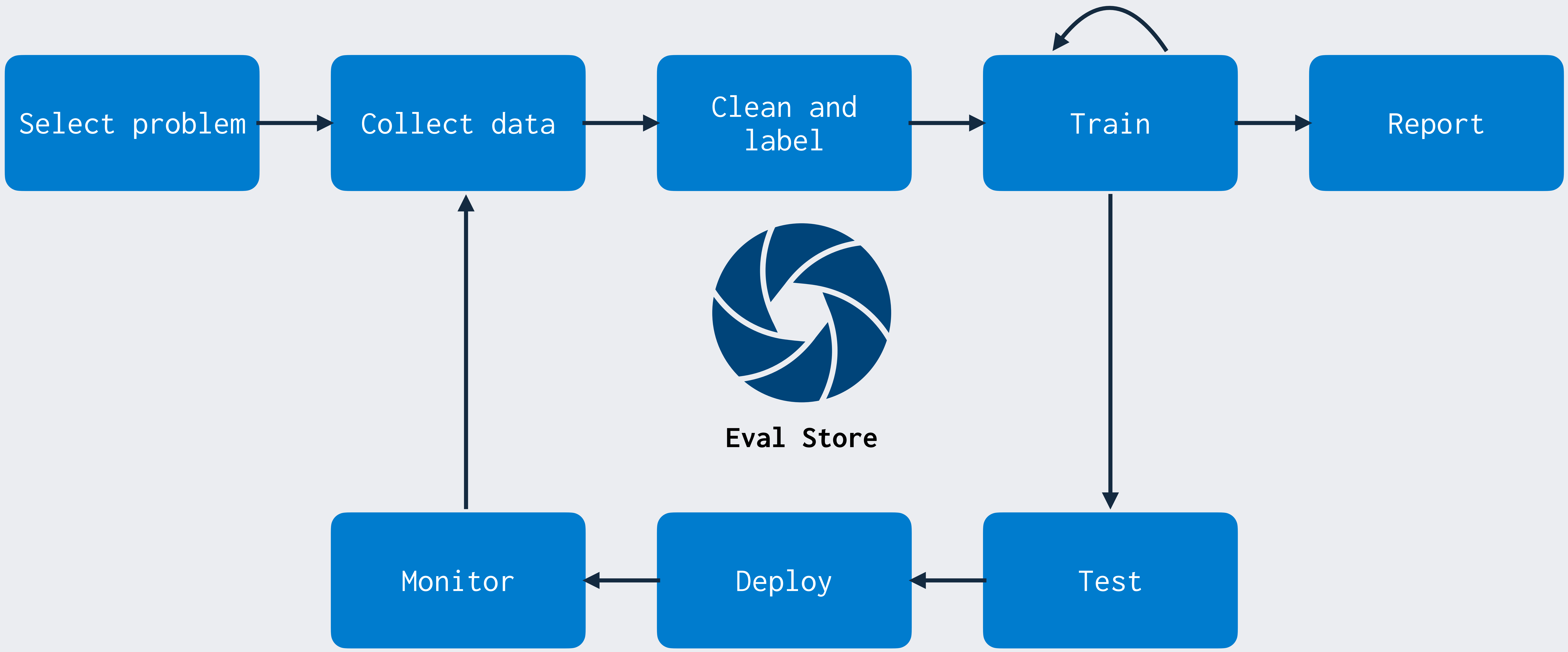
How do my business metrics compare for model A and model B in the last 60 minutes

AB testing

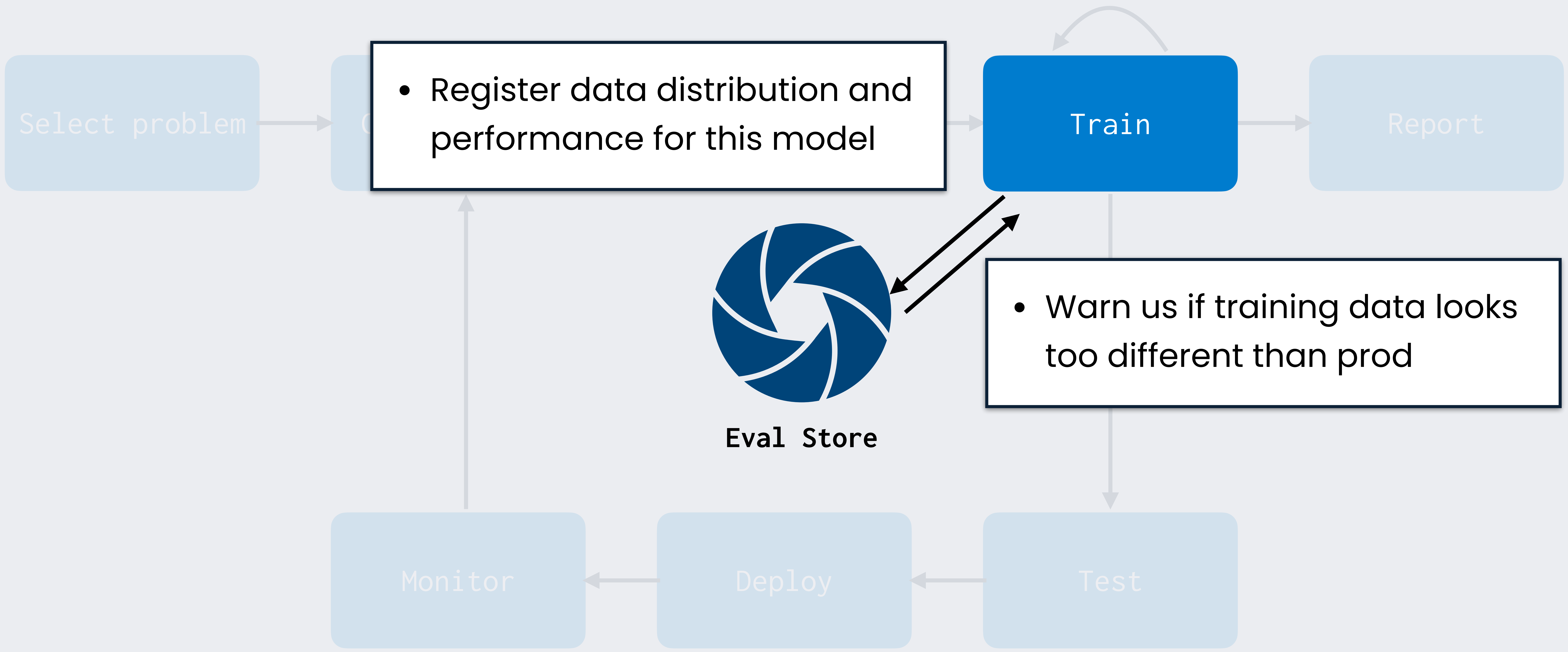
A digression: approximate performance metrics

- In a perfect world, we would know **right away** how well the model performs **on all data points seen in production**
- In the real world, labels are **unreliable, expensive, and delayed**
- Approximate performance metrics are ways to **guess** which data points may have poor performance
  - E.g., distribution distance between these data points and a reference distribution
  - E.g., outlier detection
  - E.g., weak supervision (a la Snorkel)
  - E.g., metrics about your users (like engagement)

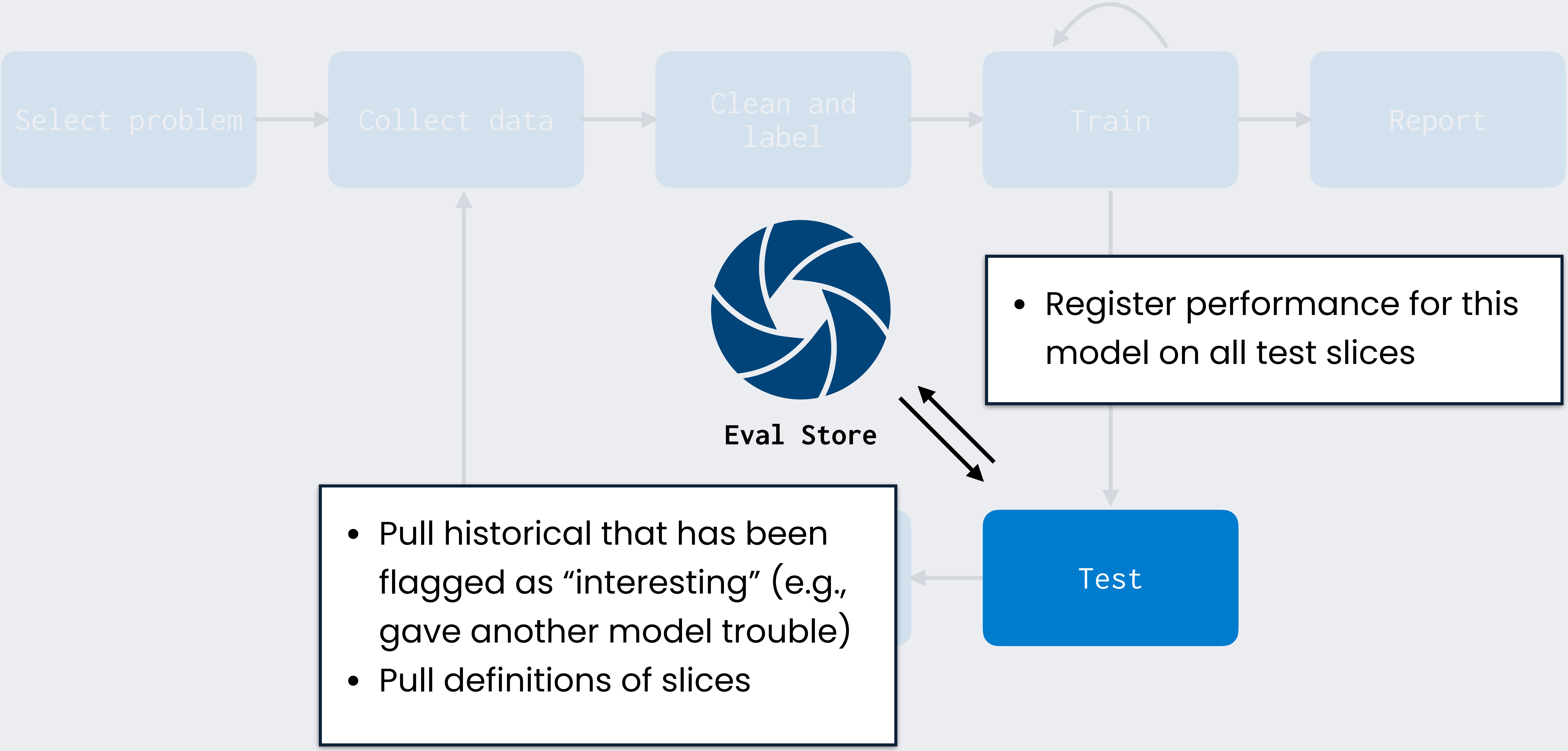
The Evaluation Store



The Evaluation Store



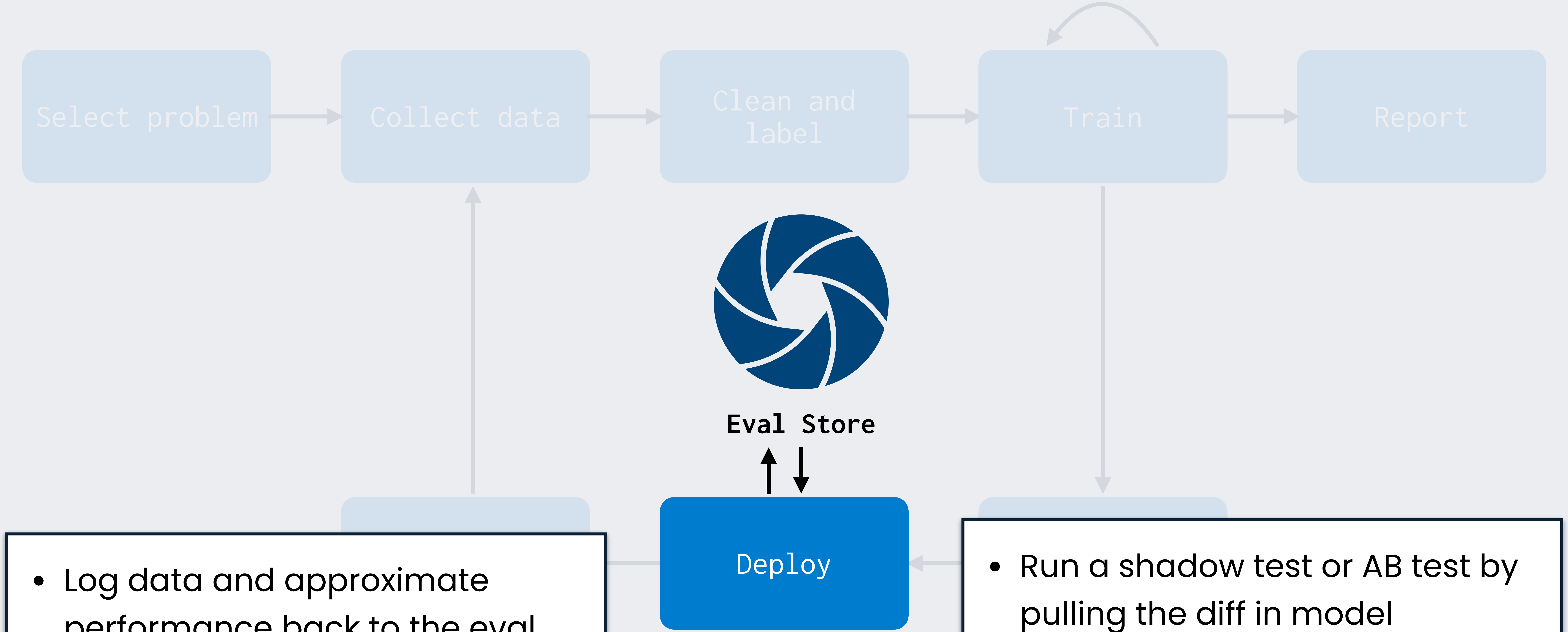
The Evaluation Store



- Register performance for this model on all test slices

- Pull historical that has been flagged as “interesting” (e.g., gave another model trouble)
- Pull definitions of slices

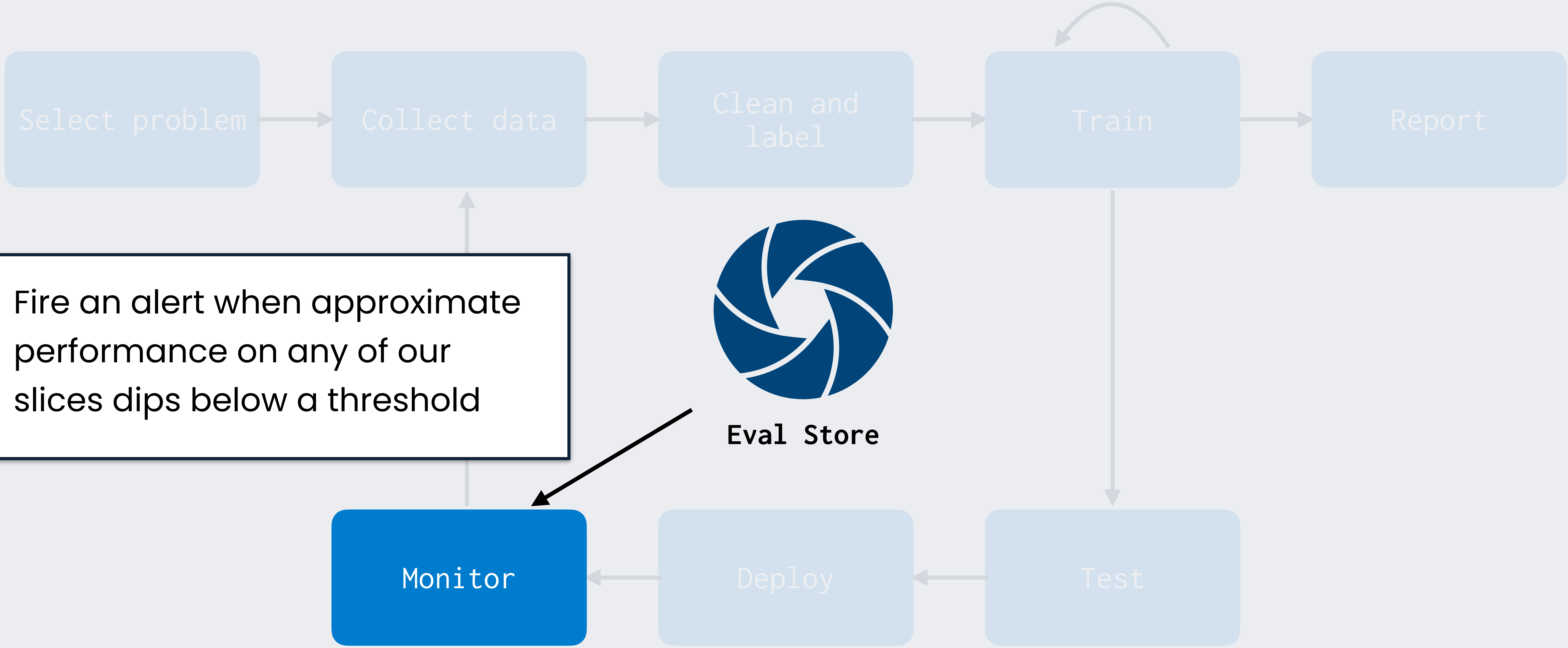
The Evaluation Store



- Log data and approximate performance back to the eval store

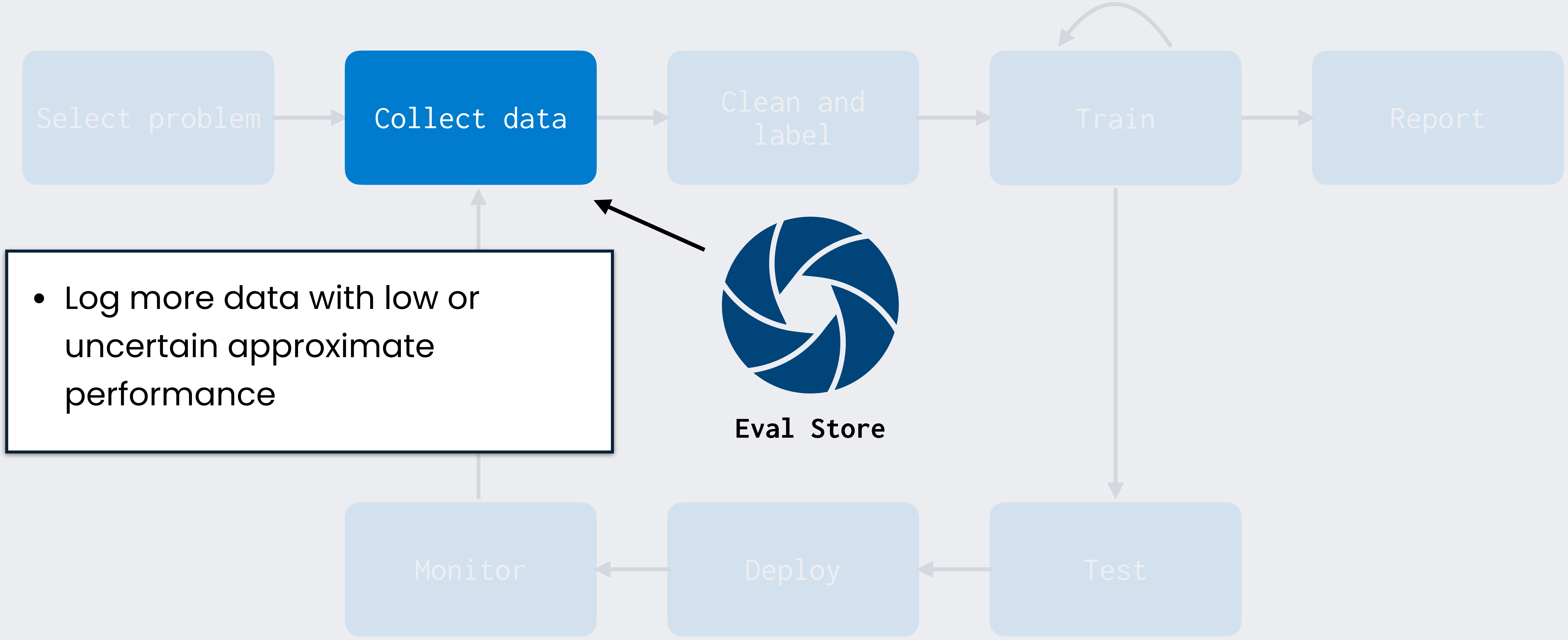
- Run a shadow test or AB test by pulling the diff in model performance between versions

The Evaluation Store



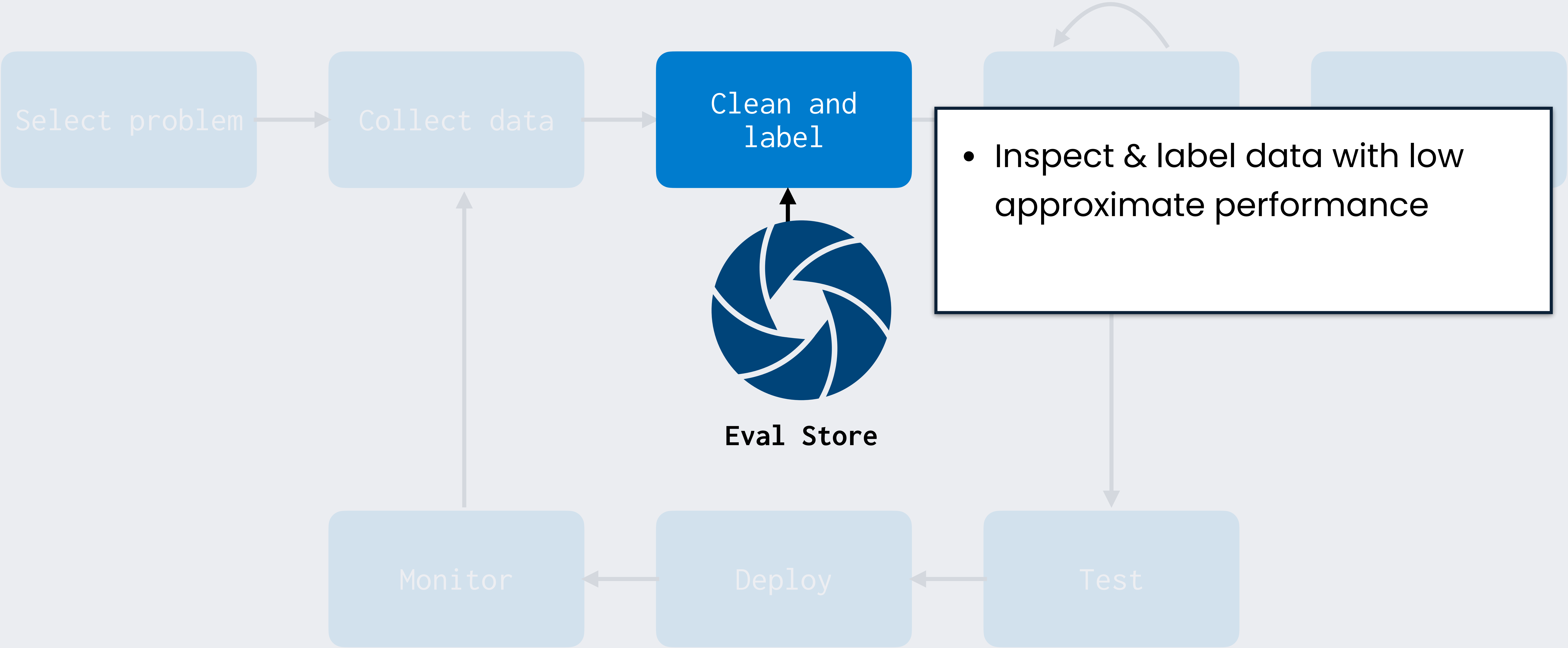
- Fire an alert when approximate performance on any of our slices dips below a threshold

The Evaluation Store



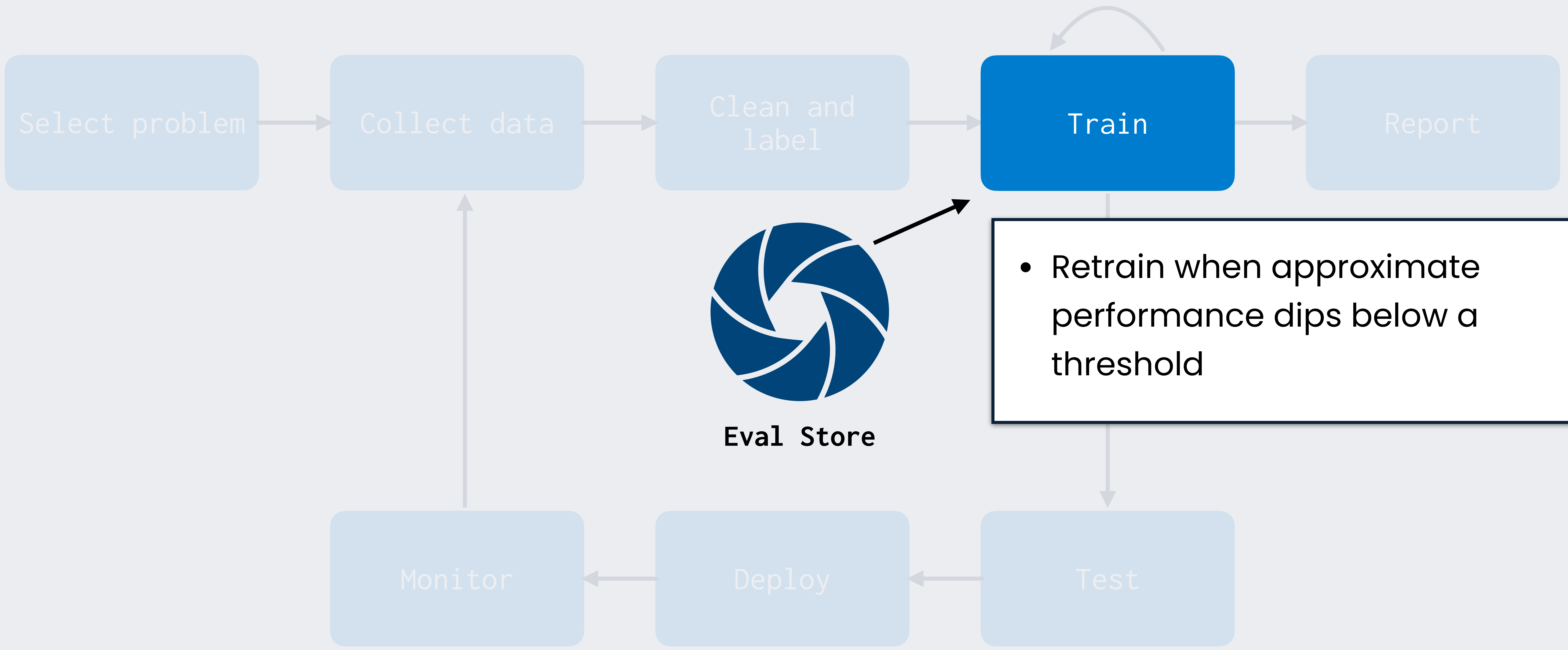
- Log more data with low or uncertain approximate performance

The Evaluation Store



- Inspect & label data with low approximate performance

The Evaluation Store



- Retrain when approximate performance dips below a threshold

What could an eval store help you with?

- **Reduce organization friction.** Get stakeholders (ML eng, ML research, PM, MLOps, etc) on the same page about metric and slice definitions
- **Deploy models more confidently.** Evaluate metrics and slices consistently in testing and prod. Make the metrics visible to stakeholders
- **Catch production bugs faster.** Catch degradations across any slice, and drill down to the data that caused the degradation
- **Reduce data-related costs.** Collect and label production data more intelligently
- **Make your model better.** Decide when to retrain. Pick the right data to retrain on.

Shouldn't the feature store do this?

- Feature store is **indexed by feature**, eval store is **indexed by model**
- A model taking a feature as input **doesn't mean** that it looks at the **entire distribution**
- A **"poor quality" feature** has **different effects** on **different models**
- **Not all data** will come through the feature store
- The two should talk to each other!

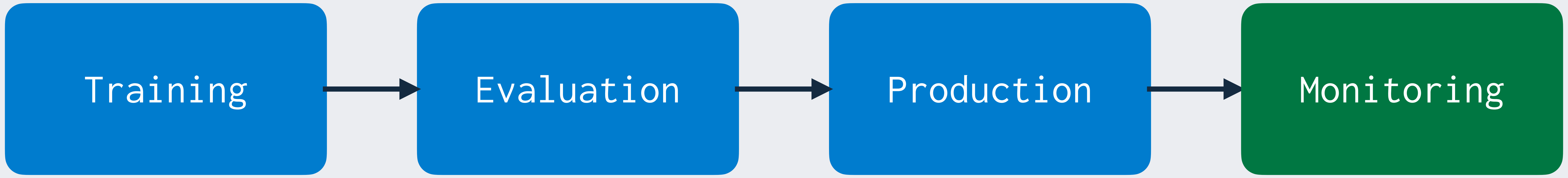
Wait, isn't this just ML monitoring?

- Yes
  - The hard part here is **approximating** how well your model **might be performing right now**
  - That's ML monitoring

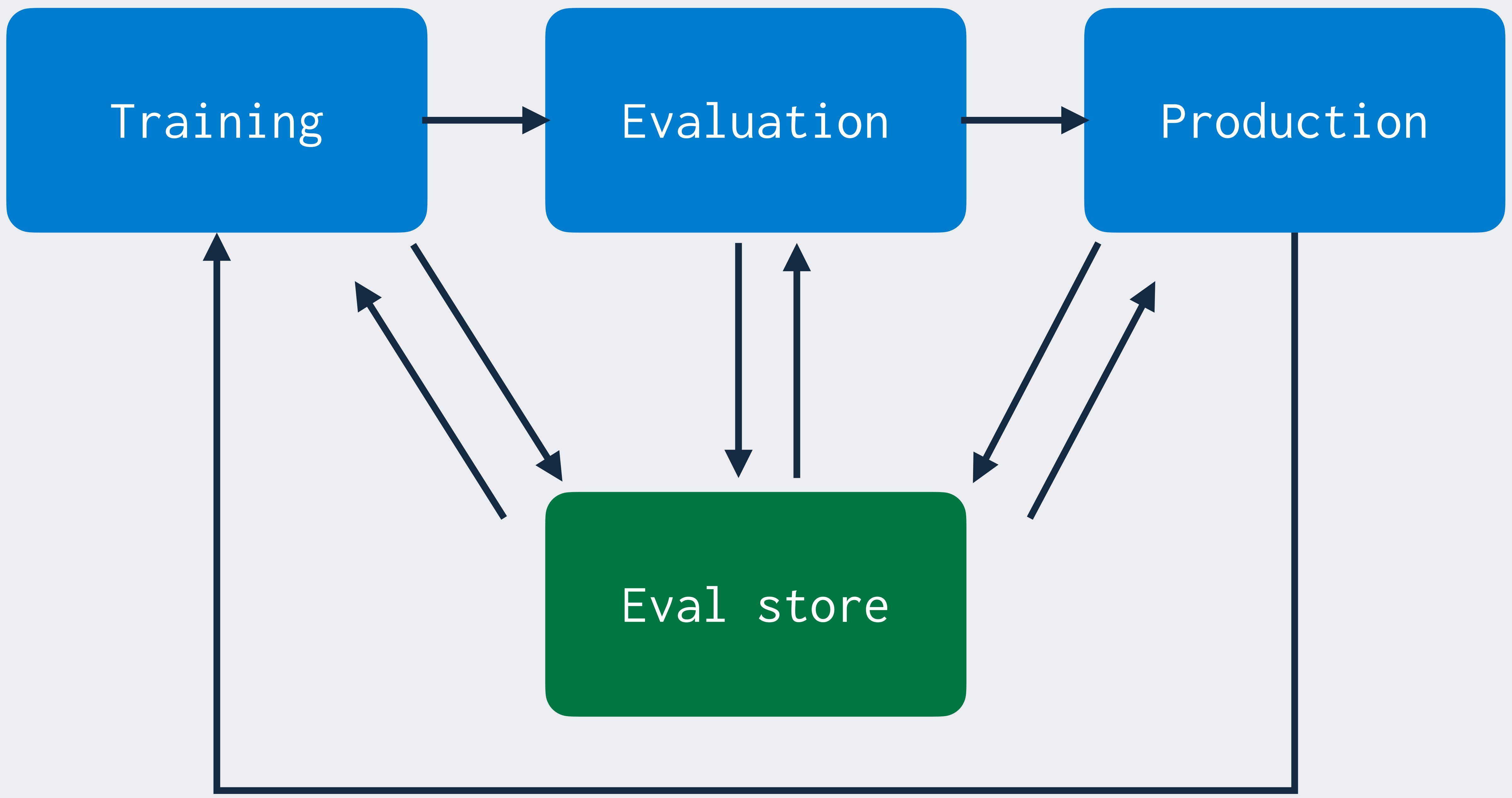
Wait, isn't this just ML monitoring?

- No
  - Eval store should provide a **consistent view** of **online and offline performance**
  - Eval store is **tightly integrated** into the entire MLOps stack
  - Eval store keeps track of **what data caused questions performance,** so it can be used for testing and retraining

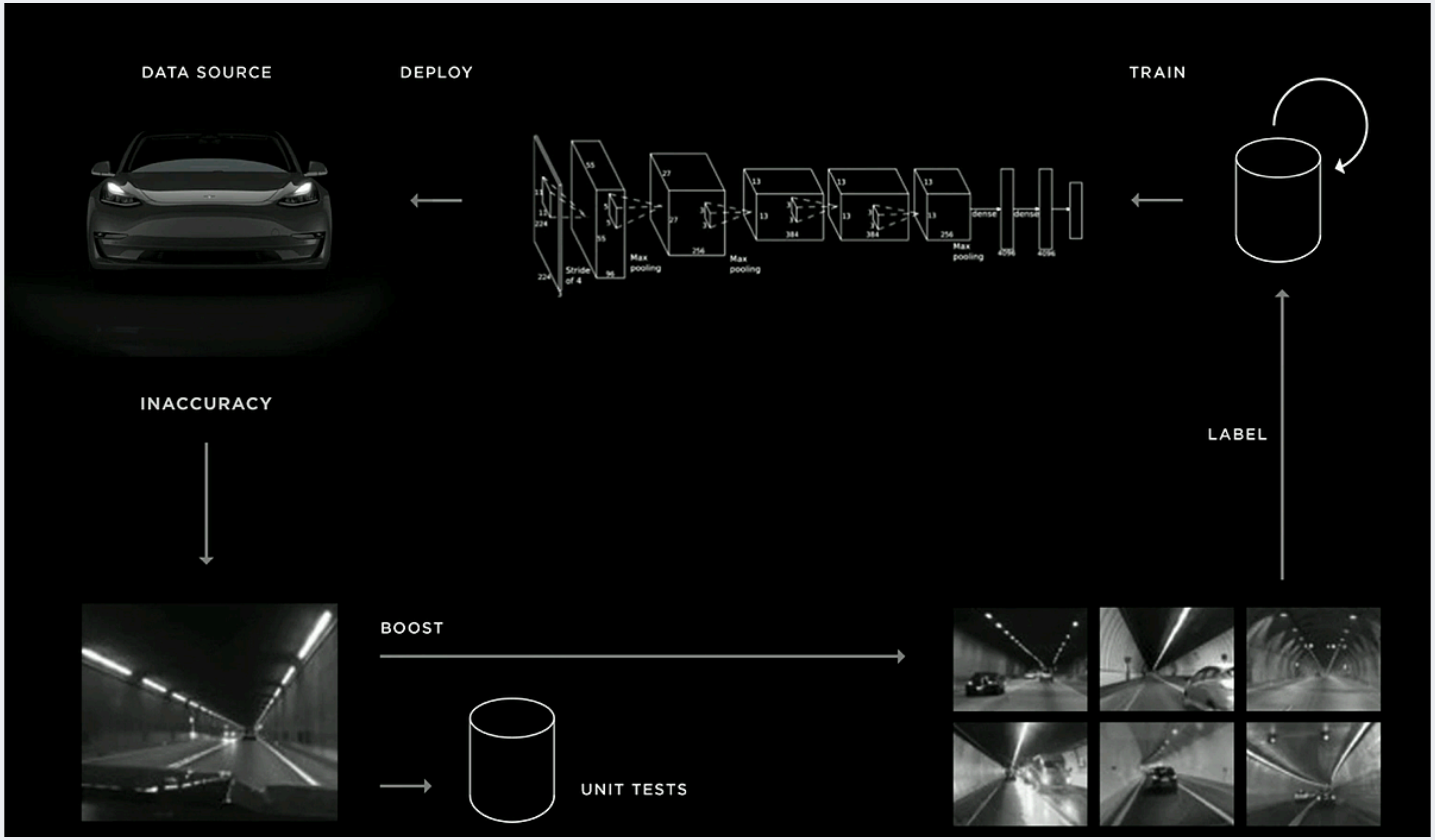
ML monitoring



Eval store

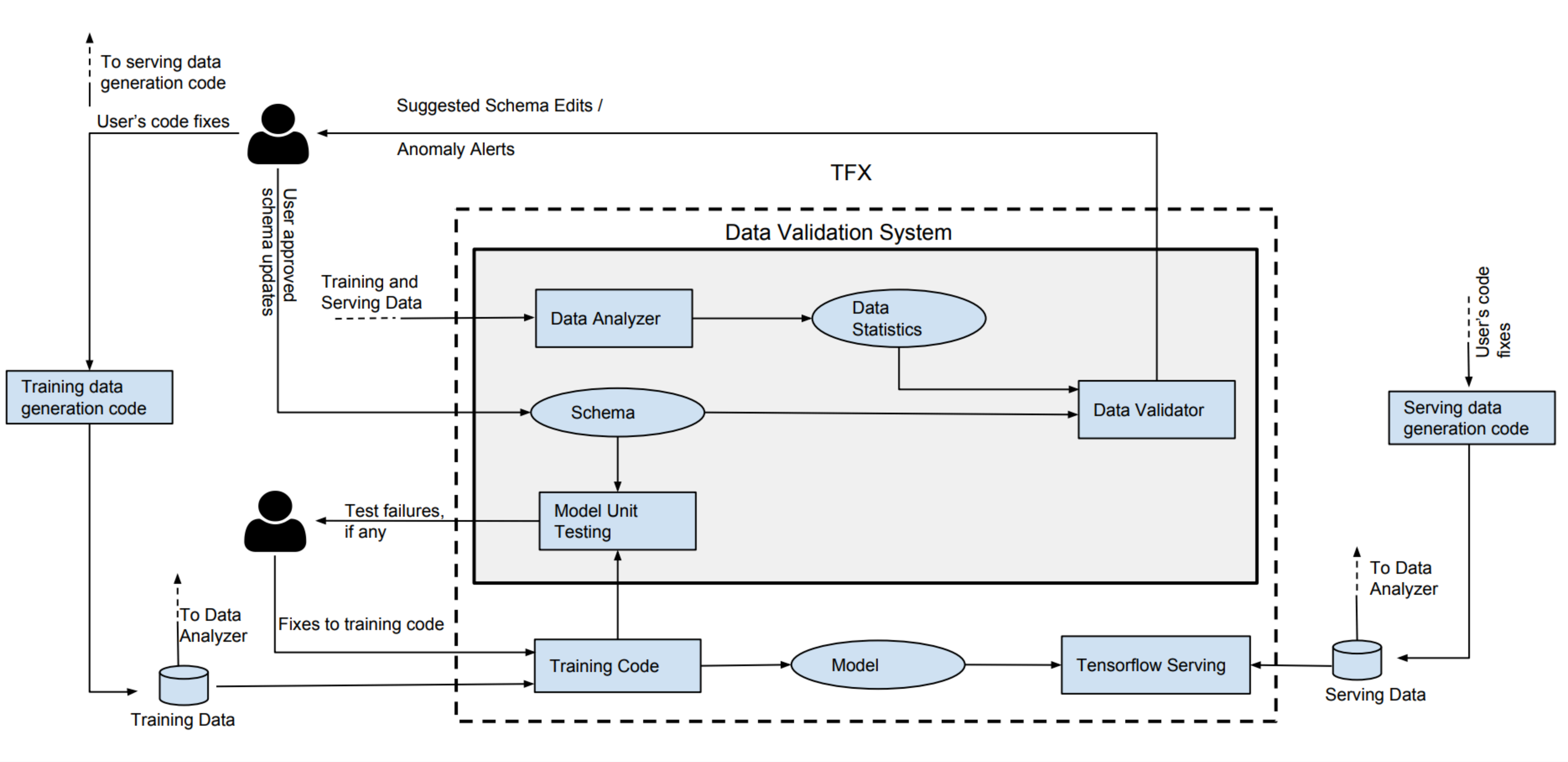


Case study 1: the Tesla data engine



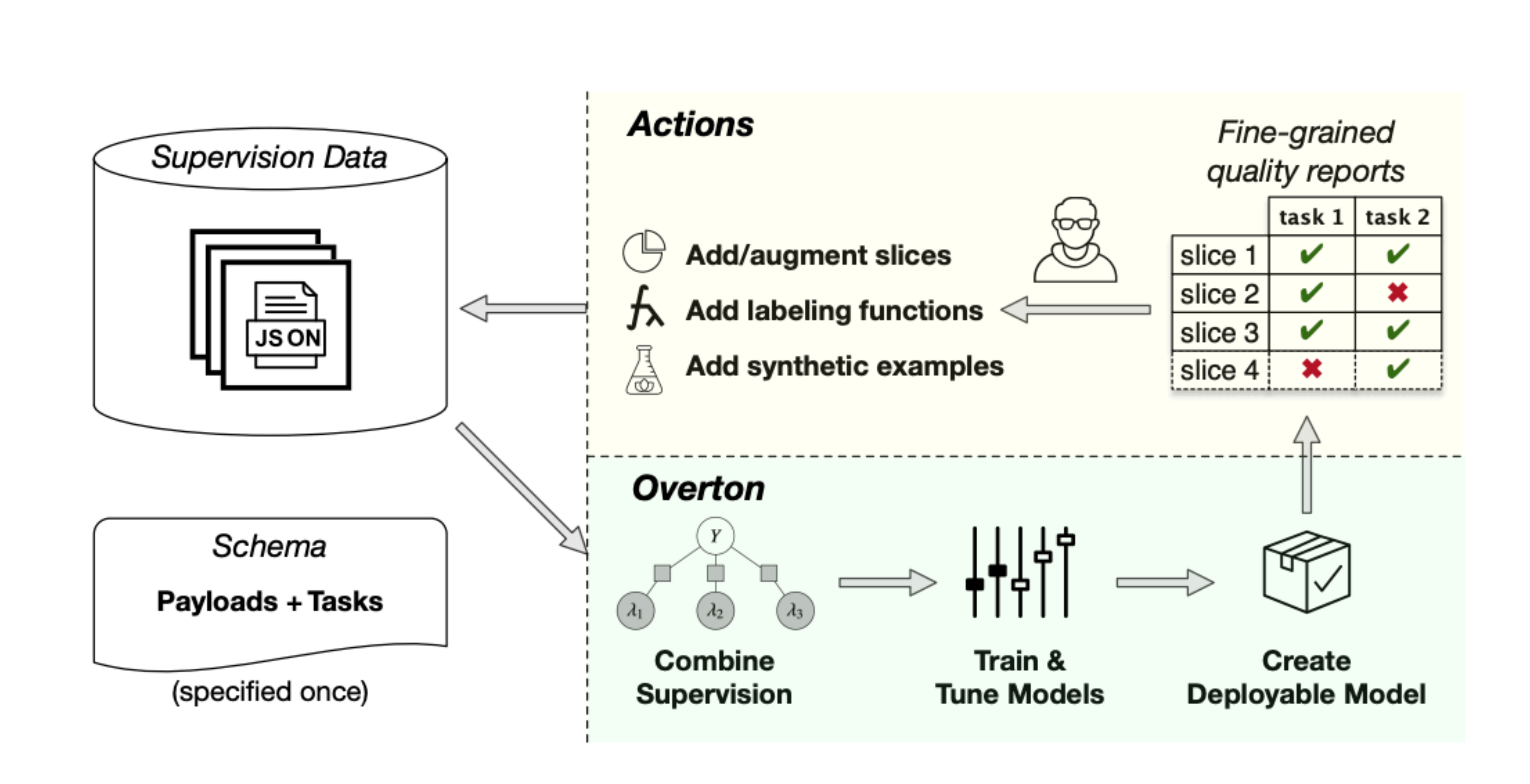
youtube.com/watch?t=7714&v=Ucp0TTmvqOE

Case study 2: TFX data validation



https://mlsys.org/Conferences/2019/doc/2019/167.pdf

Case study 3: Overton (Apple)



https://machinelearning.apple.com/research/overton

A Missing Link in the ML Infra Stack?

- To turn ML into a product engineering discipline, we need an infrastructure stack that helps create a data flywheel
- What's still missing?
  - Granular, online-offline understanding of model performance
  - Orchestrating data and models throughout the whole loop
- Maybe the Evaluation Store could help