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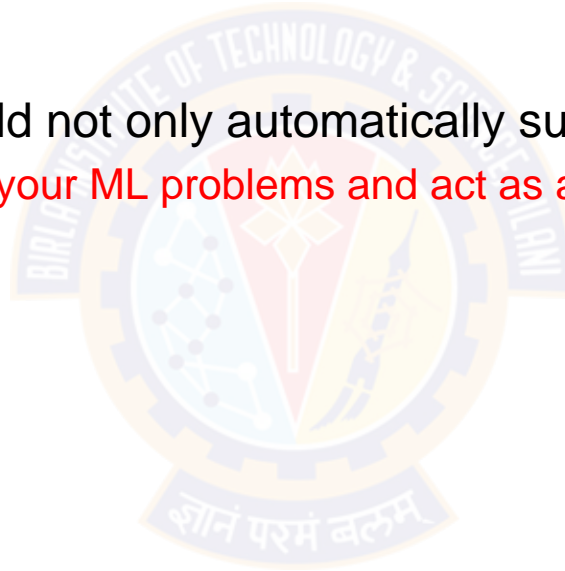
Machine Learning Observability

Pravin Y Pawar

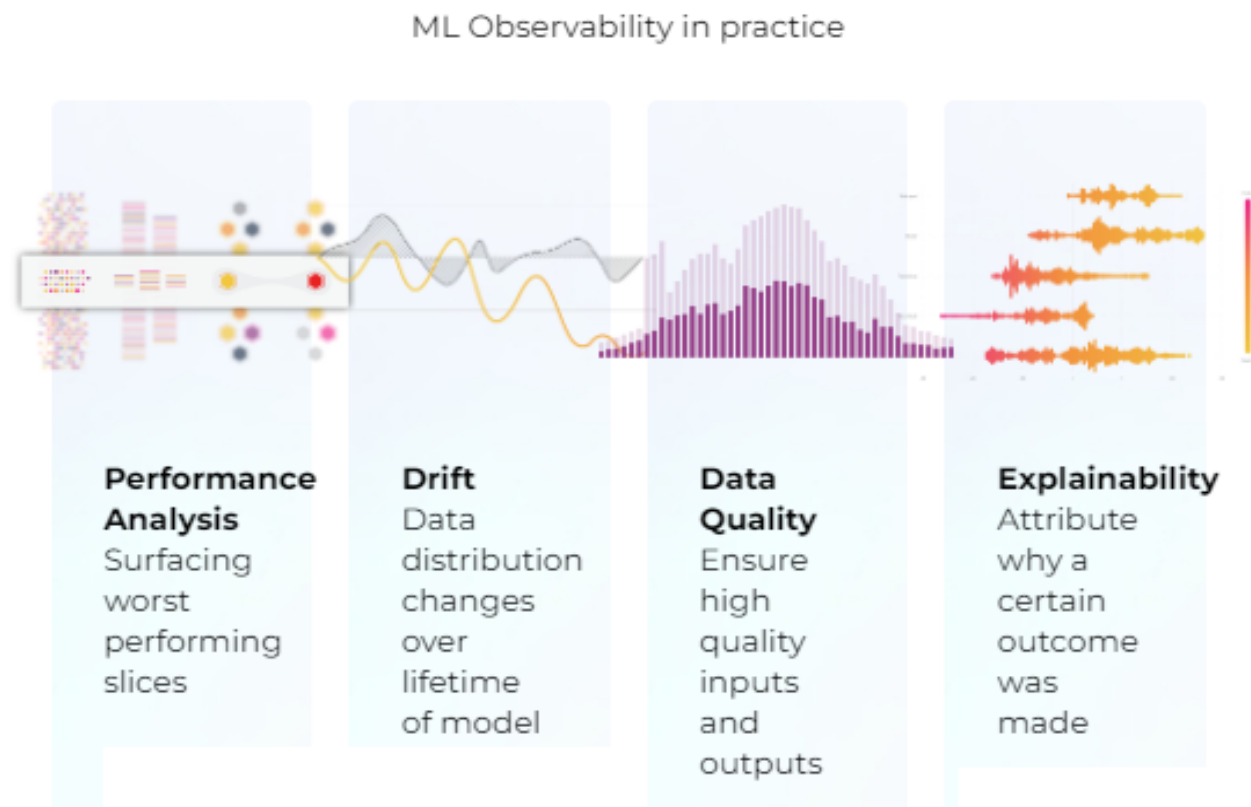
Adapted from [“Machine Learning Observability”](#)

What is ML Observability?

- ML Observability is a tool used to monitor, troubleshoot, and explain machine learning models
 - as they move from research to production environments
- An effective observability tool should not only automatically surface issues,
 - but drill down to the root cause of your ML problems and act as a guardrail for models in production

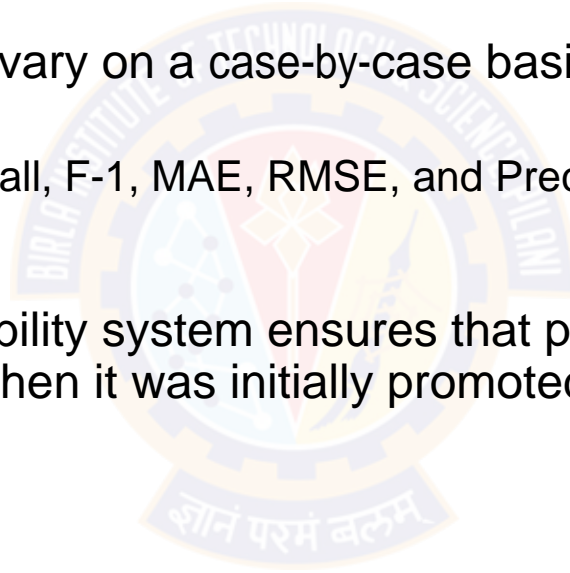


4 Pillars of ML Observability



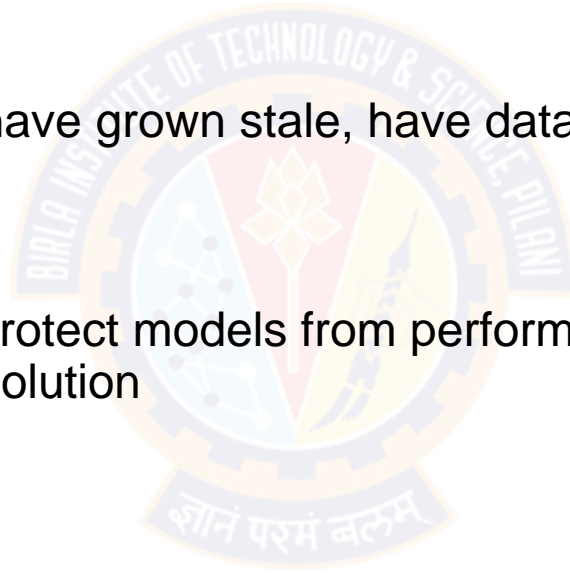
Performance Analysis

- ML observability enables fast actionable performance information on models deployed in production
- While performance analysis techniques vary on a case-by-case basis depending on model type and its use case in the real world,
 - common metrics include: Accuracy, Recall, F-1, MAE, RMSE, and Precision
- Performance analysis in an ML observability system ensures that performance has not degraded drastically from when it was trained or when it was initially promoted to production.



Drift

- ML observability encompasses drift to monitor for a change in distribution over time,
 - measured for model inputs, outputs, and actuals of a model
- Measure drift to identify if models have grown stale, have data quality issues, or if there are adversarial inputs in model
- Detecting drift in models will help protect models from performance degradation and allow to better understand how to begin resolution



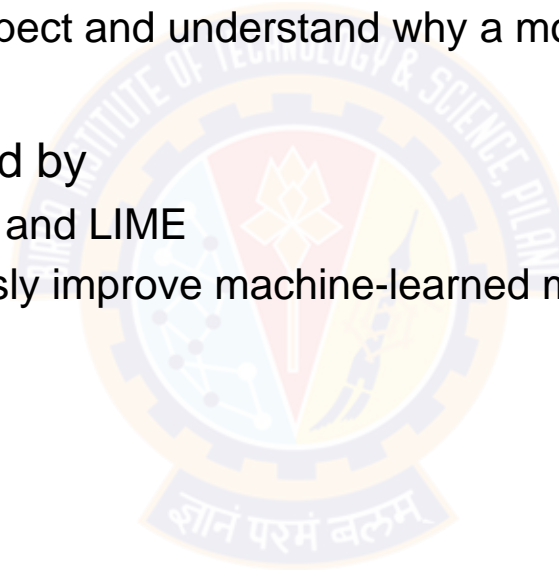
Data Quality

- Data quality checks in an ML observability system identify hard failures
 - within data pipelines between training and production
 - that can negatively impact a model's end performance
- Data quality includes
 - monitoring for cardinality shifts,
 - missing data,
 - data type mismatch,
 - out-of-range,
 - and more to better gauge model performance issues and ease RCA



Explainability

- Explainability in ML observability uncovers feature importance
 - across training, validation, and production environments
 - which provides the ability to introspect and understand why a model made a particular prediction
- Explainability is commonly achieved by
 - calculating metrics such as SHAP and LIME
 - to build confidence and continuously improve machine-learned models



ML observability in context

System/Infra Observability

- Infra/App timing as the base of monitoring
- App & system response time issues
- Tracing & troubleshooting response time



dynatrace

Data Observability

- Tables as the base of monitoring
- Monitoring data changes
- Schema monitoring




MONTE CARLO



Bigeye

ML Observability

- Models are the base of monitoring
- Distributions, vs baselines, model version, SHAP analysis and performance
- Deep model performance analysis vs data

 arize



Software/DevOps



Data Eng



ML Engineer & DS

[arize](https://arize.com)

How Can I Achieve ML Observability?

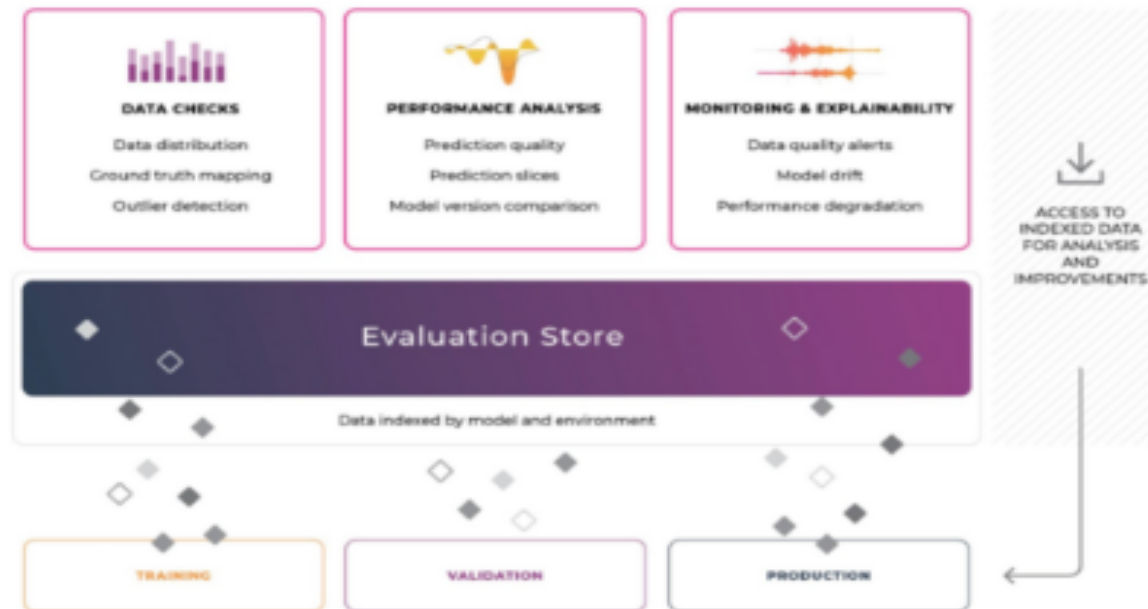
ML Observability with an Evaluation Store

Monitor drift, data quality issues, or anomalous performance degradations using baselines

Analyze performance metrics in aggregate (or slice) for any model, in any environment — production, validation, training

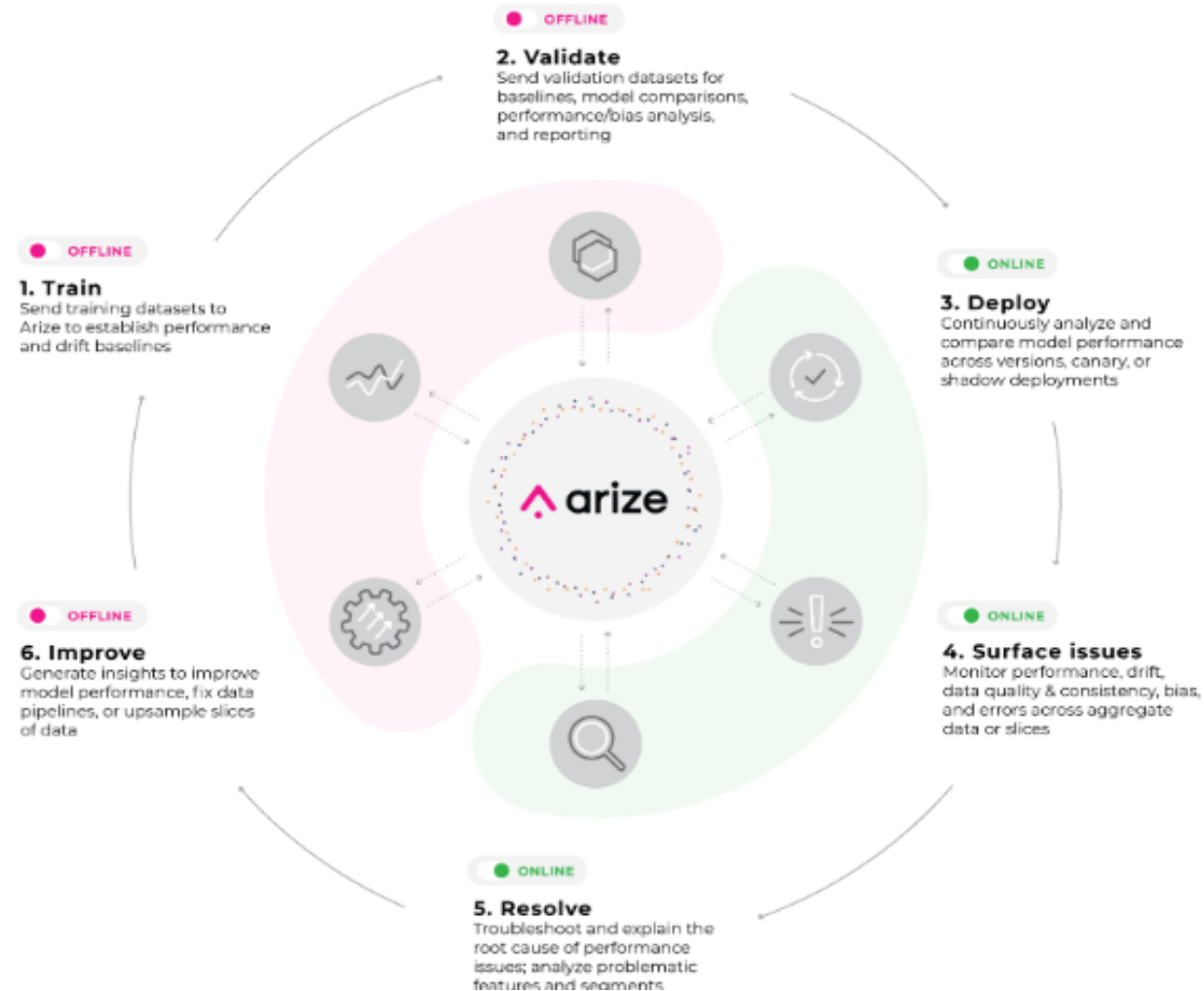
Root Cause Analysis to connect changes in performance to why they occurred

Enable feedback loop to **actively improve** model performance



ML Observability with Arize

- ML Observability is the practice of obtaining a deep understanding into model's data and performance across its lifecycle
 - Observability doesn't just stop at surfacing a red or green light,
 - but enables ML practitioners to root cause/explain why a model is behaving a certain way in order to improve it





Thank You!

In our next session: