Effective Observability for MLOps Pipelines at Scale

Presenting Today:

Rishit Dagli

CIVO

University of Toronto

Special Thanks to:

Shivay Lamba

WasmEdgeRuntime

Ambassador

monitoring

- SLOs
- System Failures
- …

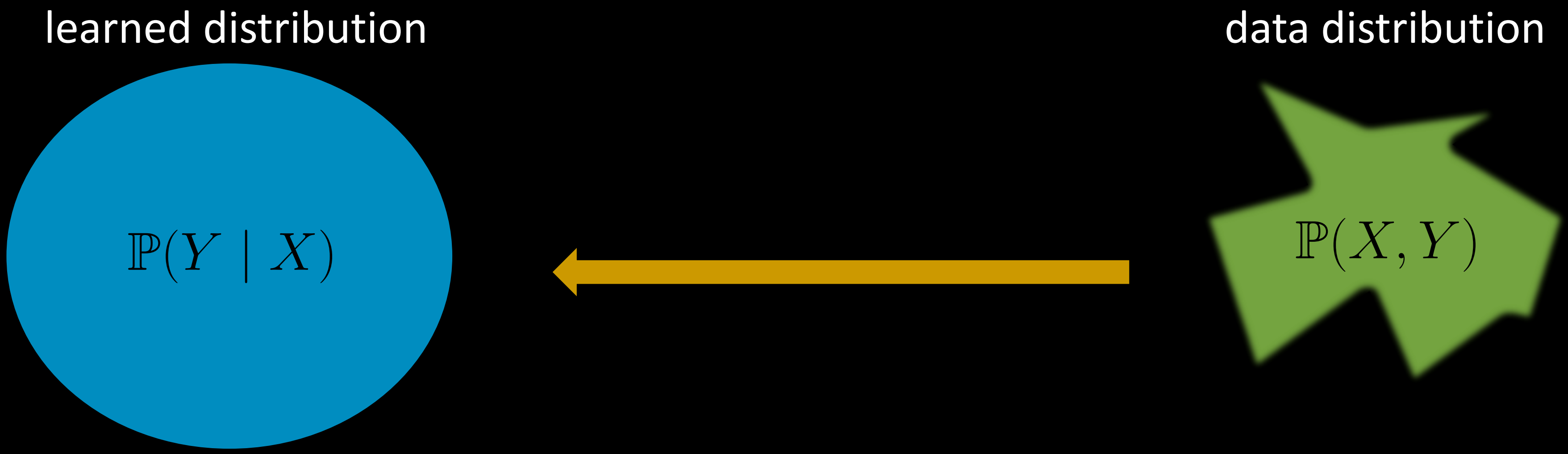
why Observability?

- standard for all software
- ensure software is reliable and available
- measure performance characteristics
- enables quick reactions to system failures

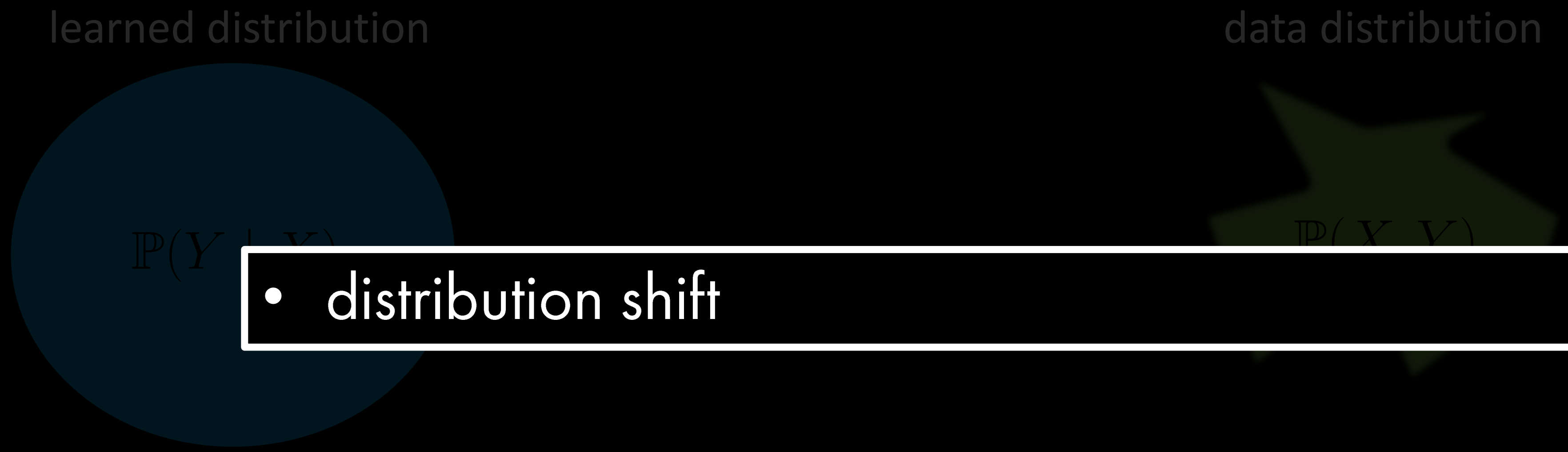
Why ML Observability

- different challenges
  - model edge cases
  - data distribution has shifted
  - misconfigured models
- model still makes a prediction, but predictions are not useful

how can this happen?

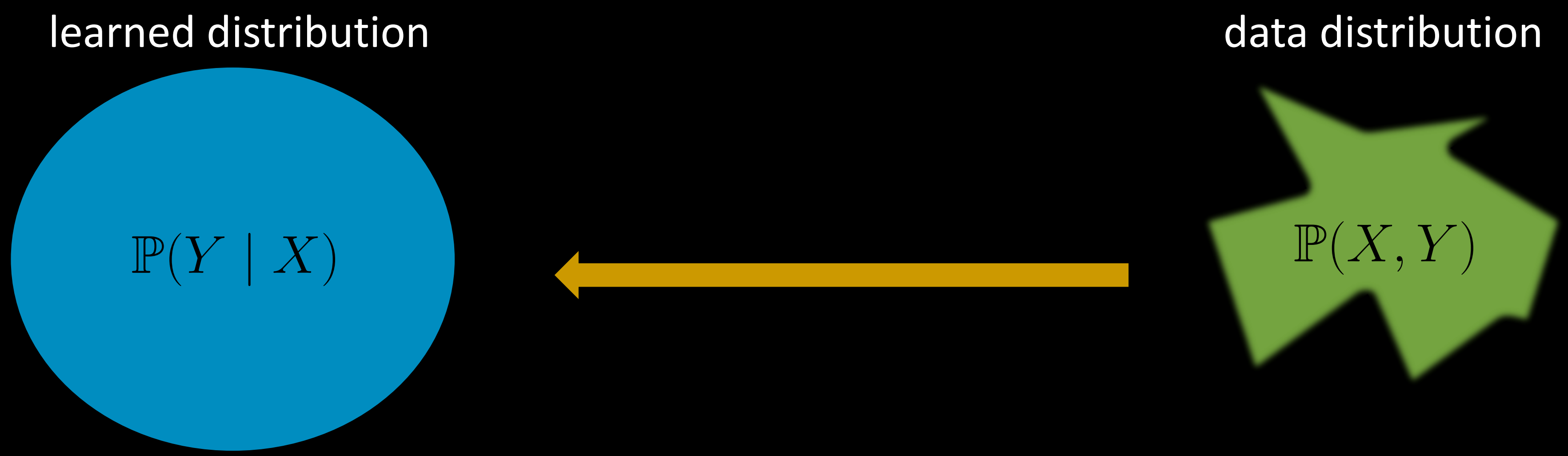


how can this happen?



- distribution shift

how can this happen?



$\mathbb{P}(X)$ gets changed but not $\mathbb{P}(Y \mid X)$

$\mathbb{P}(Y)$ gets changed but not $\mathbb{P}(X \mid Y)$

$\mathbb{P}(Y \mid X)$ gets changed but not $\mathbb{P}(X)$

how can this happen?

learned distribution

data distribution

- feature change
- (label priors) schema change

$\mathbb{P}(X)$ gets changed but not $\mathbb{P}(Y \mid X)$

$\mathbb{P}(Y)$ gets changed but not $\mathbb{P}(X \mid Y)$

$\mathbb{P}(Y \mid X)$ gets changed but not $\mathbb{P}(X)$

how can this happen?

learned distribution

data distribution

- outliers
- edge cases

$\mathbb{P}(X)$ gets changed but not $\mathbb{P}(Y \mid X)$

$\mathbb{P}(Y)$ gets changed but not $\mathbb{P}(X \mid Y)$

$\mathbb{P}(Y \mid X)$ gets changed but not $\mathbb{P}(X)$

how can this happen?

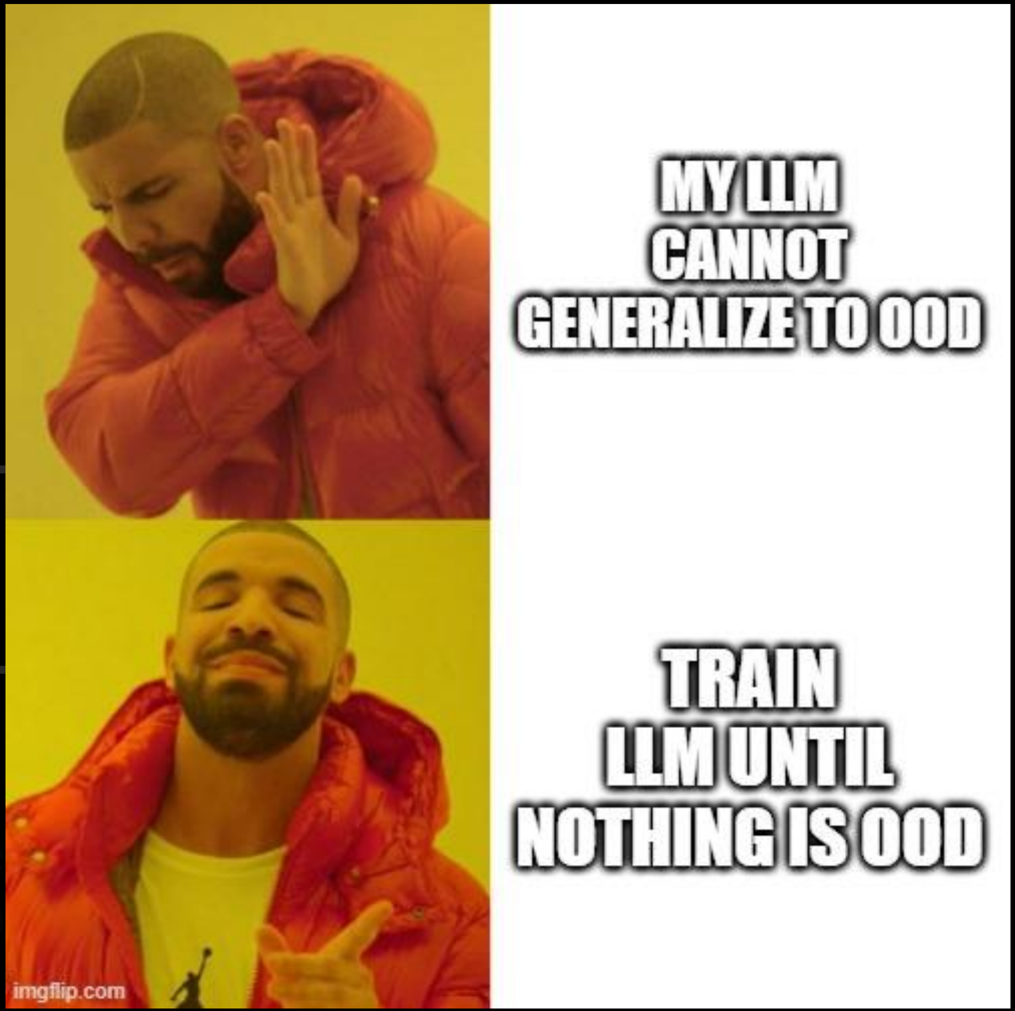
learned distribution

$\mathbb{P}(Y \mid X)$

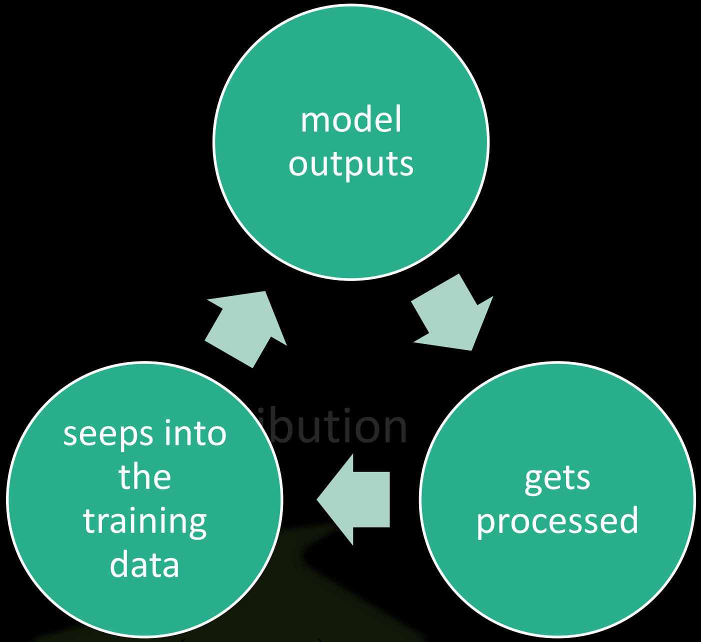
- outliers
- edge cases

$\mathbb{P}(X)$ gets changed but not $\mathbb{P}(Y \mid X)$

$\mathbb{P}(Y)$ gets change but not $\mathbb{P}(X \mid Y$



how can this happen?



learned distribution

- outliers
- edge cases
- messed up feedback loops

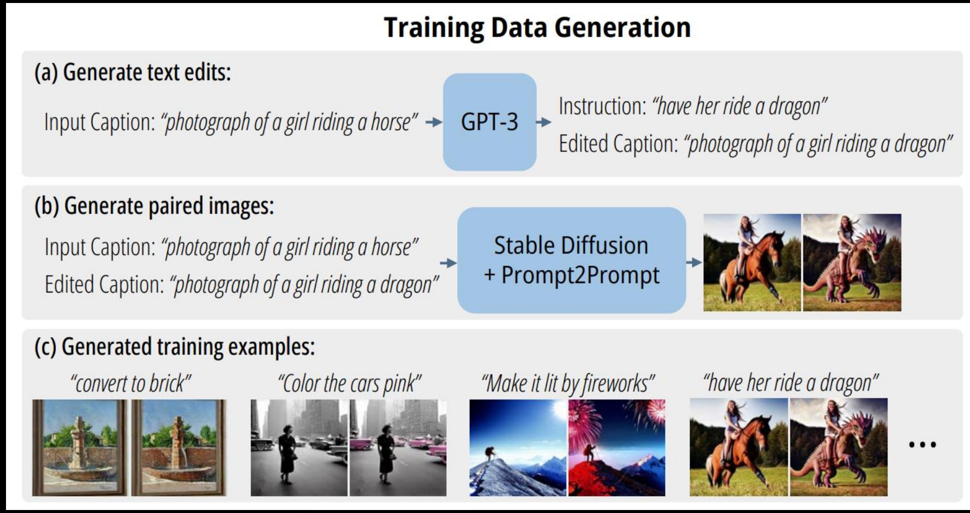
$\mathbb{P}(X)$ gets changed but not $\mathbb{P}(Y \mid X)$

$\mathbb{P}(Y)$ gets changed but not $\mathbb{P}(X \mid Y)$

$\mathbb{P}(Y \mid X)$ gets changed but not $\mathbb{P}(X)$

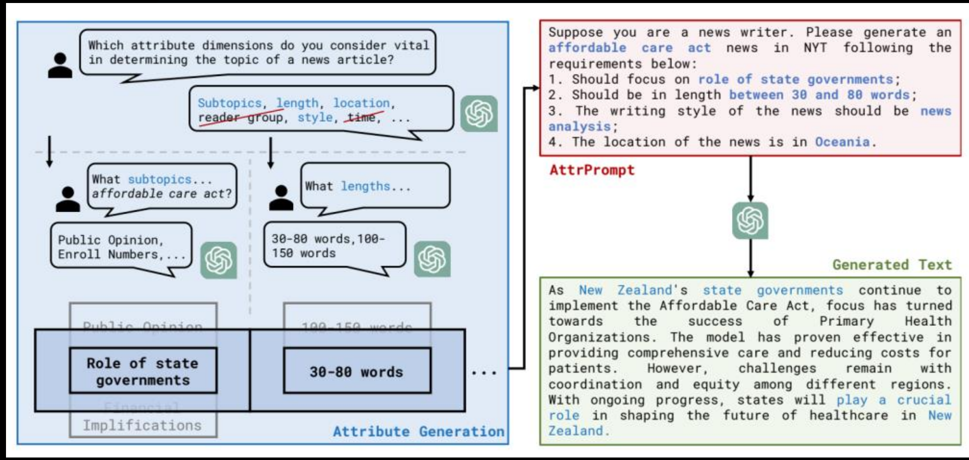
how can this happen?

[3]



learned distribution

[4]



ack loops

$\mathbb{P}(X)$ gets changed but not $\mathbb{P}(Y \mid X)$

$\mathbb{P}(Y)$ gets changed but not $\mathbb{P}(X \mid Y)$

$\mathbb{P}(Y \mid X)$ gets changed but not $\mathbb{P}(X)$

monitoring machine learning models

- Different challenges
  - Model edge cases
  - Data distribution has shifted
  - Misconfigured models
- Model still makes a prediction but predictions are not useful

monitoring machine learning models

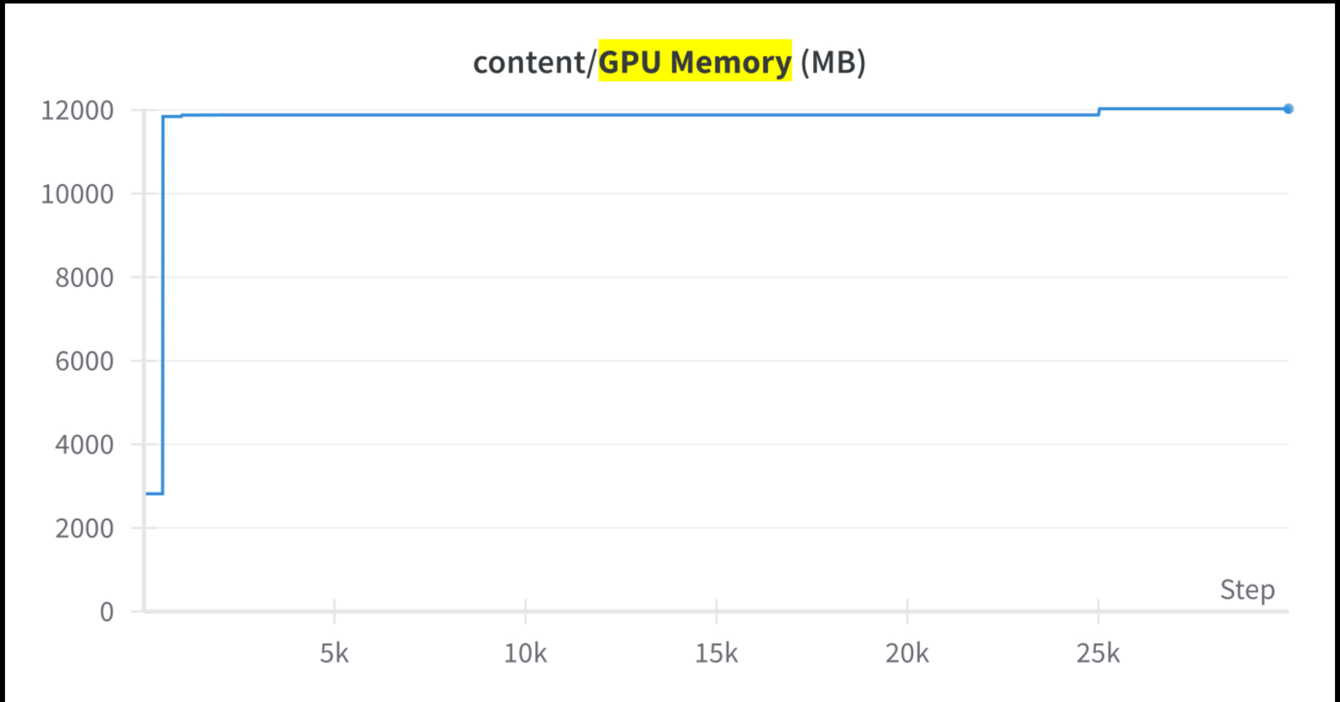
- we need to monitor all these
  - often not straightforward
  - monitoring systems is simply checking for 404, OOM, seg fault, ...
- can we use training metrics?

what do I log then?

- system metrics
  - interpreting these would be a bit different

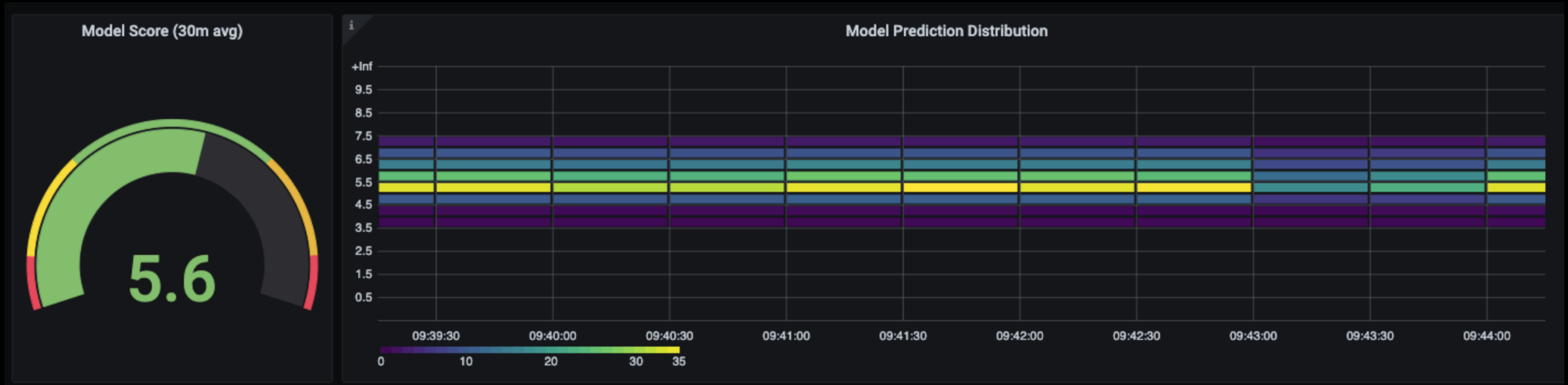
what do I log then?

- system metrics
  - interpreting these would be a bit different



what do I log then?

- system metrics
  - interpreting these would be a bit different
- model-related metrics
  - eval metrics
  - prediction distribution



what do I log then?

- system metrics
  - interpreting these would be a bit different
- model-related metrics
  - eval metrics
  - prediction distribution
  - feature distributions and inputs

are these observability metrics or just monitoring?

- yes, partly
- can make decisions on when to retrain and so on

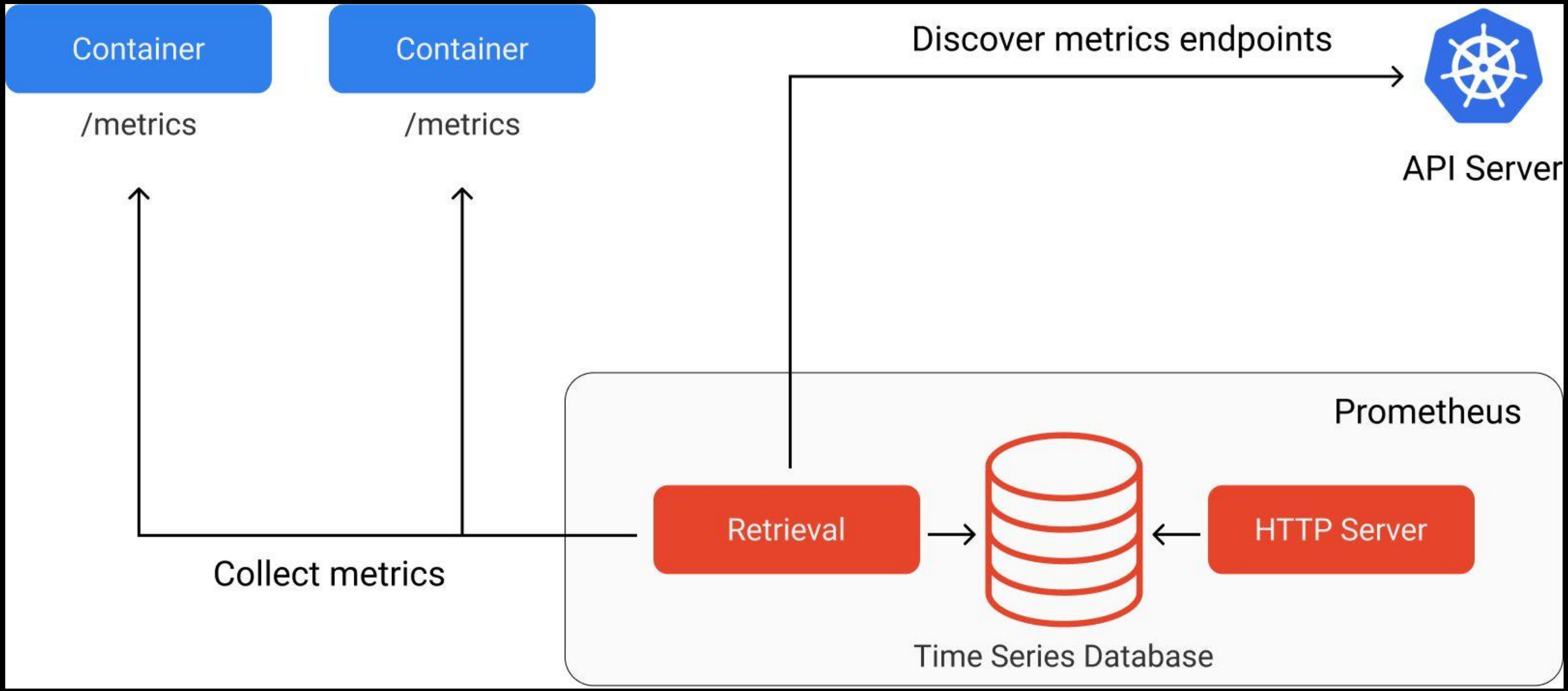
let’s see it in action

- create a REST service to expose the model
- instrument the server to collect metrics which are exposed via a separate metrics endpoint
- use prometheus-fastapi-instrumentator
- deploy Prometheus to collect and store metrics
- deploy Grafana to visualize the collected metrics
- locus to Simulate

let’s see it in action

- create a REST service to expose the model
- instrument the server to collect metrics which are exposed via a separate metrics endpoint
- use prom
- deploy Prometheus to collect and store metrics
- deploy Grafana to visualize the collected metrics
- locus to Simulate

- + what we said we want to do


Container
/metrics
Container
/metrics
Discover metrics endpoints
API Server
Prometheus
Retrieval
HTTP Server
Time Series Database
Collect metrics

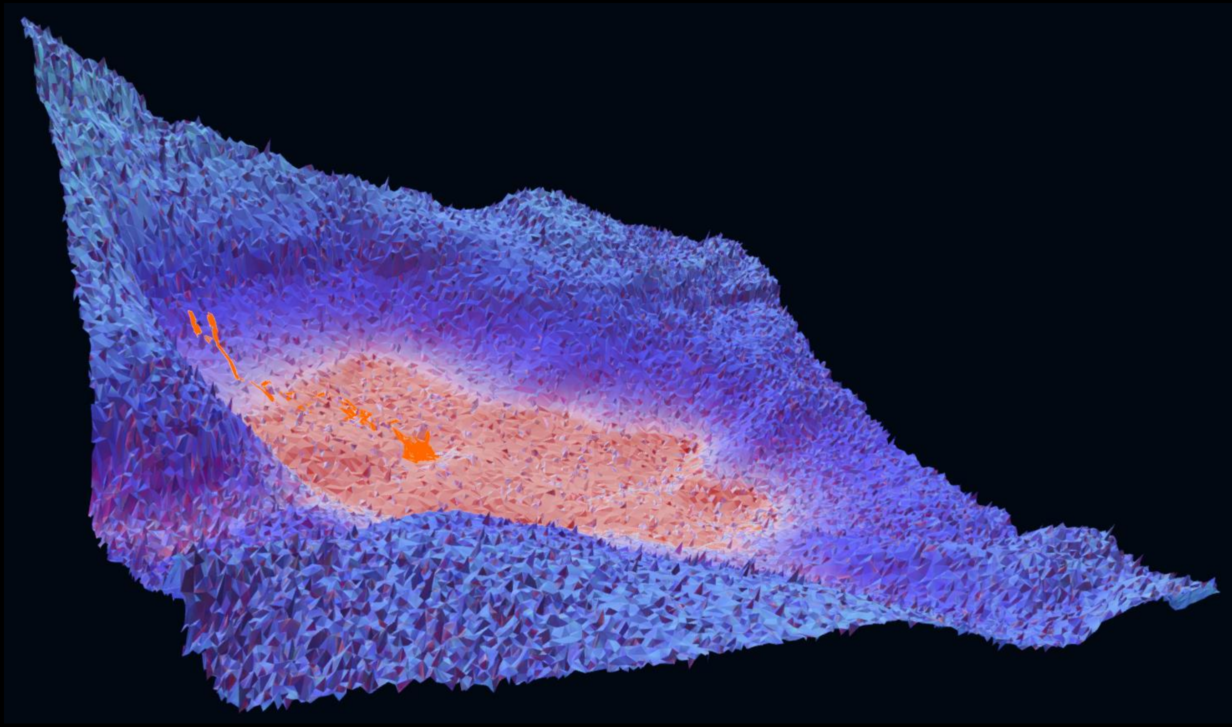
[7]

[1] The Manim Community Developers. Manim – Mathematical Animation Framework. v0.17.3, 2023, https://www.manim.community/.
[2] Helbling, Alec, et al. 'ManimML: Communicating Machine Learning Architectures with Animation'. arXiv [Cs.LG]
[3] Brooks, Tim, Aleksander Holynski, and Alexei A. Efros. "Instructpix2pix: Learning to follow image editing instructions." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.
[4] Yu, Y., Zhuang, Y., Zhang, J., Meng, Y., Ratner, A. J., Krishna, R., ... & Zhang, C. (2024). Large language model as attributed training data generator: A tale of diversity and bias. Advances in Neural Information Processing Systems, 36.

additional readings building for the motivated listener:

[5] Huyen, Chip (2022). Data Distribution Shifts and Monitoring. https://huyenchip.com/2022/02/07/data-distribution-shifts-and-monitoring.html
[6] Huang, Y., Zhang, H., Wen, Y., Sun, P., & Ta, N. B. D. (2021). Modelci-e: Enabling continual learning in deep learning serving systems. arXiv preprint arXiv:2106.03122.
[7] Jordan, Jeremy (2021). A simple solution for monitoring ML systems. https://www.jeremyjordan.me/ml-monitoring/
[8] Rabanser, S., Günnemann, S., & Lipton, Z. (2019). Failing loudly: An empirical study of methods for detecting dataset shift. Advances in Neural Information Processing Systems, 32.
[9] Lipton, Z., Wang, Y. X., & Smola, A. (2018, July). Detecting and correcting for label shift with black box predictors. In International conference on machine learning (pp. 3122-3130). PMLR.
[10] Karumuri, S., Solleza, F., Zdonik, S., & Tatbul, N. (2021). Towards observability data management at scale. ACM SIGMOD Record, 49(4), 18-23.

all visualizations by the author were created using [1, 2].



- losslandscape by Javier Ideami

Shivay Lamba
shivaylamba@gmail.com
WasmEdgeRuntime
Ambassador

Rishit Dagli
rishit.dagli@civo.com
CIVO
and University of Toronto