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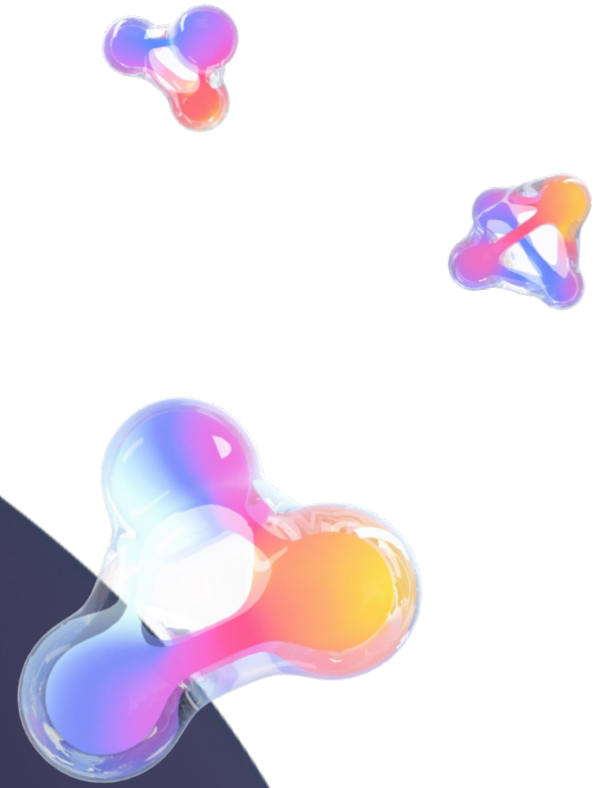
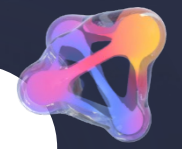


Iguazio and MLOps

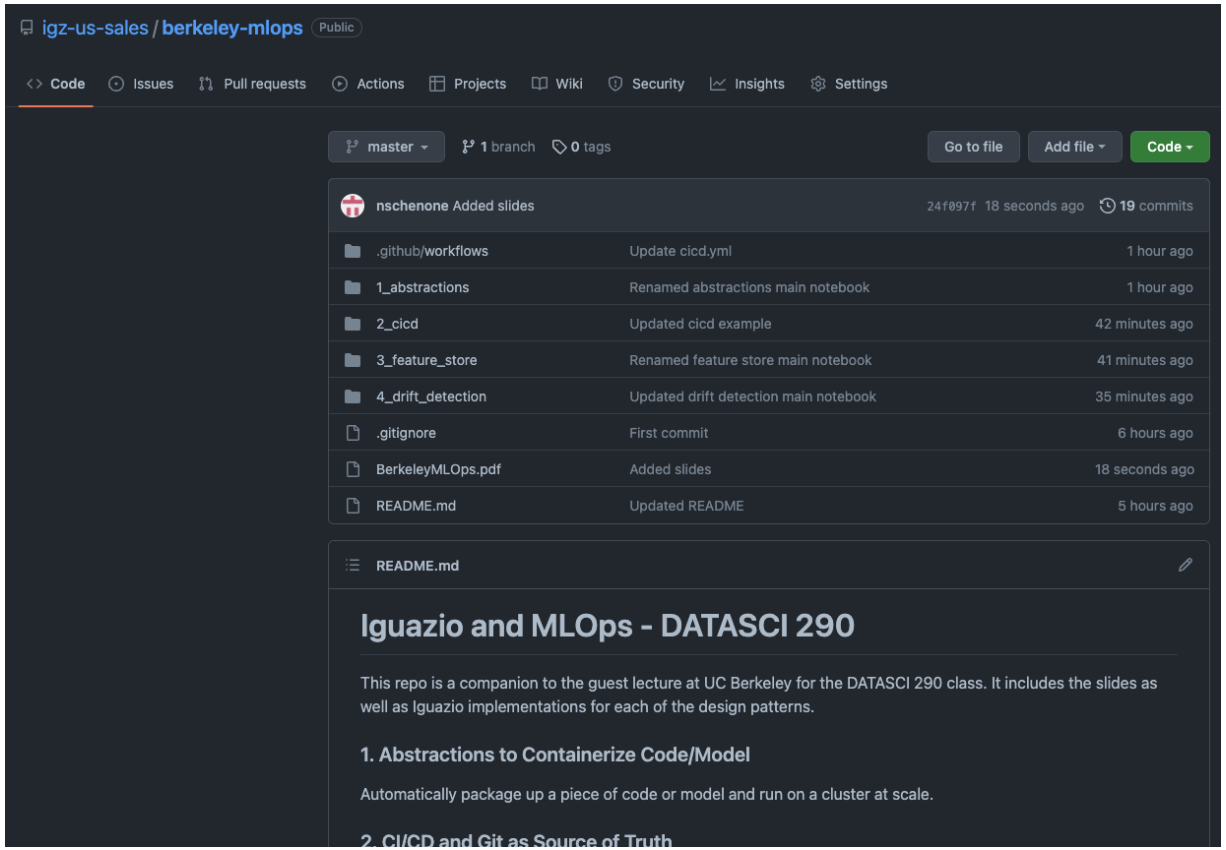
Nick Schenone – DATASCI 290

Agenda



- What is MLOps?
- Challenges in an ML System
- Requirements for an ML System
- Design Patterns + Iguazio Implementation

GitHub Companion Repo



Link

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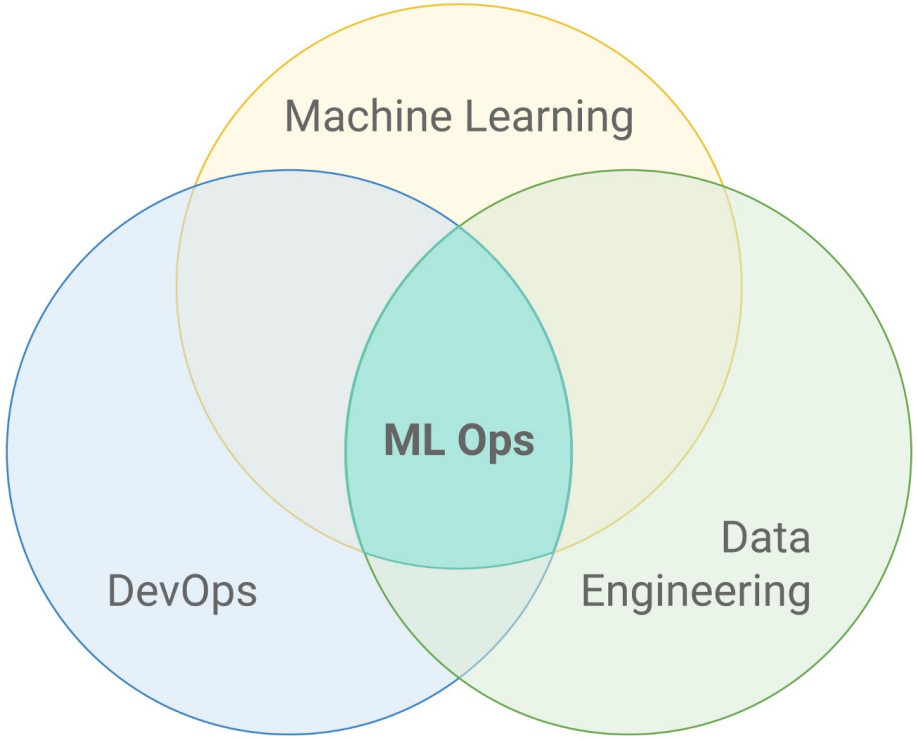
What is MLOps?

Machine Learning Operations



"ML Ops: Machine Learning as an Engineering Discipline".

Set of practices that aims to deploy and maintain machine learning models in production reliably and efficiently

"ML Ops: Machine Learning as an Engineering Discipline".

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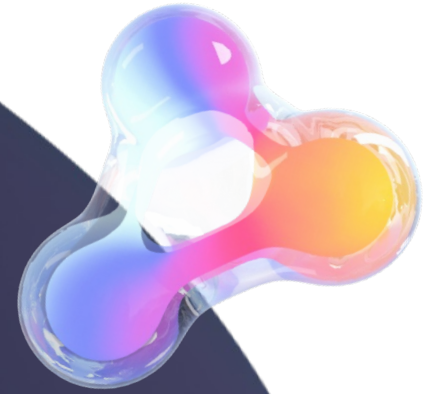
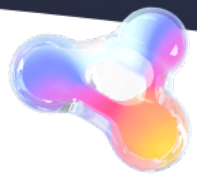


Challenges in an ML System

Technical Challenges

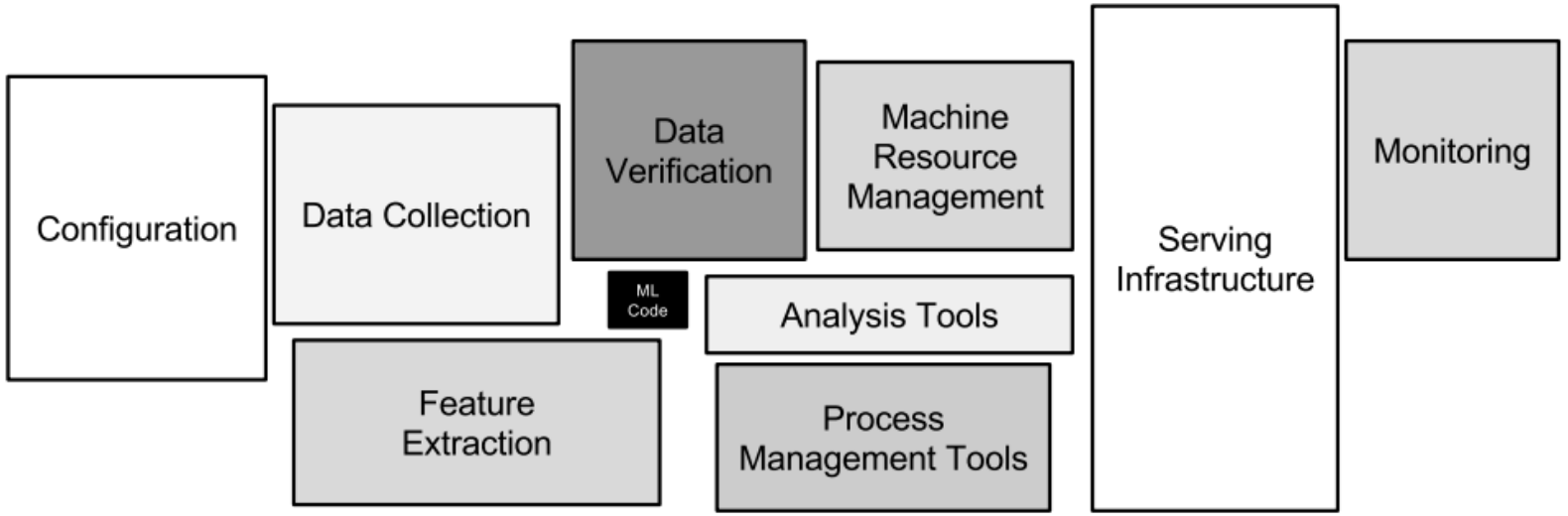
ML Systems are More than Code



- Data
- Feature Engineering
- Training/Serving Code
- Models

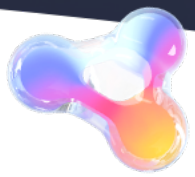
- Metrics/Hyperparamters
- Pipelines
- Docker Images
- Logs

ML at Scale is Hard



Hidden Technical Debt in Machine Learning Systems (2015)

Research ≠ Production



	Research	Production
Model Architecture	Cutting edge	Tried and true
Main Concern	Performance (accuracy, f1, etc.)	Latency, performance, bias, explainability, etc.
Data	Benchmark or Synthesized	Real data (requires cleaning)
Changes in Data	Static	Constantly evolving
Prediction Type	Batch	Real-Time + Batch

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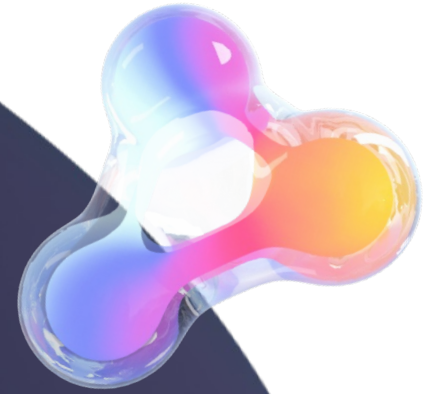


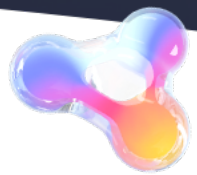
Challenges in an ML System

Business Challenges

1. *Your ML System exists to drive business value*

2. *ML and MLOps is an investment*

Productionizing an ML Model Takes a Lot of Time and Effort



DevOps

1. Write code + local testing
2. Build code and Docker image
3. CI/CD Pipeline
4. Add logging and monitoring
5. Harden security
6. Provision servers + OS
7. Handle data/event feed
8. Handle failures/auto-scaling
9. Handle rolling upgrades
10. Configuration management

Weeks **Months**

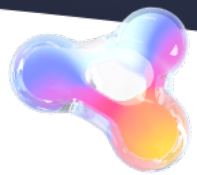
Siloed Work is Not Efficient

Data Engineer

Data Scientist

MLOps Engineer

Auditing and Compliance



Reproducibility

Explainability

Bias

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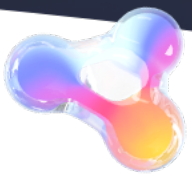
Requirements for an ML System

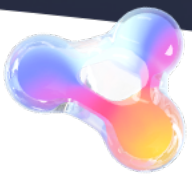
Addressing Technical and Business Challenges

ML System Should Be



- **Faster, easier to use, more reliable and more efficient than doing things by hand**
- Able to keep track of all the pieces (data, code, etc.)
- Able to run at scale
- Able to facilitate research and production needs
- Reproducible, explainable, and (relatively) bias-free

ML System Should Be



- Automated end to end – I should be able to train and serve a model with a push of a button

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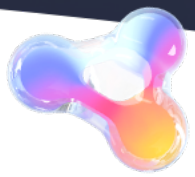
Design Patterns

+ Iguazio Implementations

- Abstractions to Containerize Code/Model
- CI/CD and Git as Source of Truth
- Feature Store as a Hub for ML*
- Monitoring Drift + Automated Re-Training*

Abstractions to Containerize Code/Model



- Spend more time writing code than worrying about infrastructure
- Abstract underlying implementation from the interface
- Allows DS to easily containerize pipeline steps and deployments with high level syntax – WITHOUT in-depth Docker/K8s knowledge
- Kick off jobs/pipelines/deployments from Jupyter notebook or laptop

Turn Code to Serverless Functions

MLRun Function

Name + Tag: “my_function:latest”

Code:

Runtime:

Image: “mlrun/mlrun”

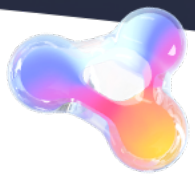
Resources: MEM, CPU, GPU

Turn Code to Serverless Functions

MLRun Function

```
fn = code_to_function(
  name="test",
  project="my_project",
  filename="test.py", # .py or .ipynb
  kind="job",
  image="mlrun/mlrun",
  handler="my_func"
)
fn.run()
```

Advanced Configuration



Assign Resources

```
fn.with_requests(mem="1G", cpu=1)
fn.with_limits(mem="2G", cpu=2, gpus=1)
```

Specify Scaling Behavior

```
fn.spec.replicas = 2
```

```
fn.spec.min_replicas = 1
fn.spec.min_replicas = 4
```

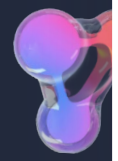
Mount Persistent Storage

```
fn.apply(
    mlrun.platforms.mount_pvc(
        pvc_name="data-claim",
        volume_name="data",
        volume_mount_path="/data"
    )
)
```

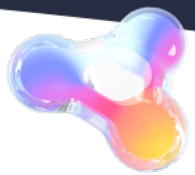
Pod Priority and Node Selection

```
fn.with_priority_class(name="igz-workload-medium")
fn.with_node_selection(
    node_selector={
        "app.iguazio.com/lifecycle": "non-preemptible"
    }
)
```

Demo



CI/CD and Git as Source of Truth



- Keep all code and pipelines in one place
- Pairs well with Infrastructure as Code (IaC)
- Restrict who is deploying to dev, staging, prod environments
- Keep a human in the loop to approve model (re)deployments

MLRun Project - IaC

project.yaml /User

```yaml
kind: project
metadata:
  name: heart-disease-classifier
  created: '2022-07-05T16:12:14.068000+00:00'
spec:
  functions:
  - url: components/get_data.py
    name: get-data
    kind: job
    image: mlrun/mlrun
  - url: components/train.py
    name: train
    kind: job
    image: mlrun/mlrun
  - url: hub://v2_model_server
    name: serving
  - url: components/simulate_traffic.py
    name: simulate-traffic
    kind: nuclio
    image: mlrun/mlrun
  workflows:
  - name: main
    path: pipelines/training_pipeline.py
    engine: null
  artifacts: []
  source: ''
  desired_state: online
  owner: nick
status:
  state: online

```

Run with Python

```python
run_id = project.run(
    name="main",
    arguments={
        "source_url" : "store://feature-vectors/heart-disease-classifier/heart-disease-vec:latest",
        "label_column" : "target"
    }
)
```

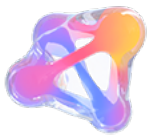
Run with CLI

```
mlrun project --run main \
    --arguments source_url=store://feature-vectors/heart-disease-classifier/heart-disease-vec:latest \
    --arguments label_column=target
```

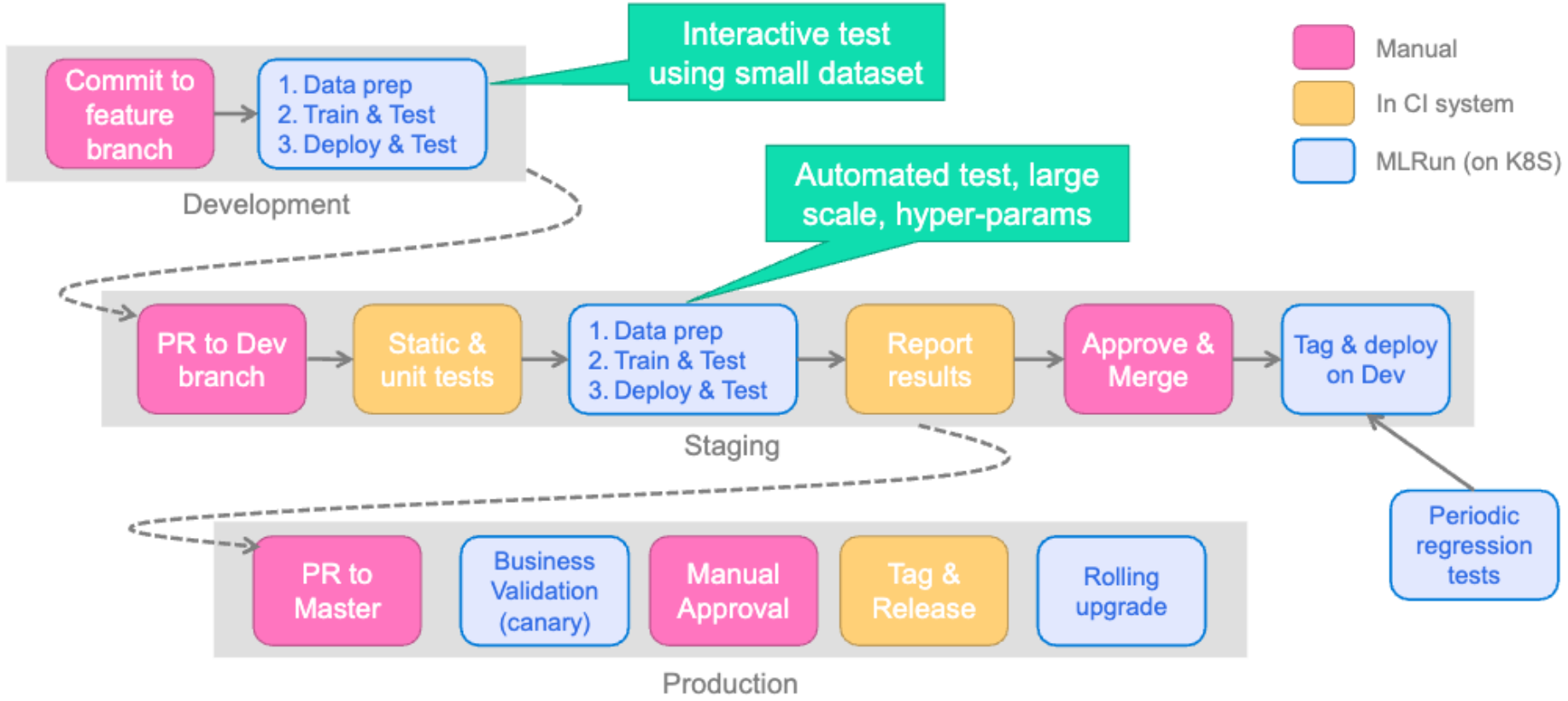
CI/CD Example – GitHub Actions

project.yaml | workflow.yml | /User | Untitled.ipynb

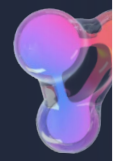
```yaml
name: mlrun-project-workflow
on: [issue_comment]

jobs:
  submit-project:
    if: github.event.issue.pull_request != null && startsWith(github.event.comment.body, '/run')
    runs-on: ubuntu-latest

    steps:
    - uses: actions/checkout@v2
    - name: Set up Python 3.7
      uses: actions/setup-python@v1
      with:
        python-version: '3.7'
        architecture: 'x64'

    - name: Install mlrun
      run: python -m pip install pip install mlrun

    - name: Submit pipeline
      run: python -m mlrun project --r main ${CMD:5}
      env:
        CMD: ${{ github.event.comment.body}}
        V3IO_USERNAME: ${{ secrets.V3IO_USERNAME }}
        V3IO_API: ${{ secrets.V3IO_API }}
        V3IO_ACCESS_KEY: ${{ secrets.V3IO_ACCESS_KEY }}
        MLRUN_DBPATH: ${{ secrets.MLRUN_DBPATH }}
        GITHUB_TOKEN: ${{ secrets.GITHUB_TOKEN }}
        SLACK_WEBHOOK: ${{ secrets.SLACK_WEBHOOK }}

```



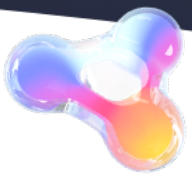
Dev -> Staging -> Prod



Demo

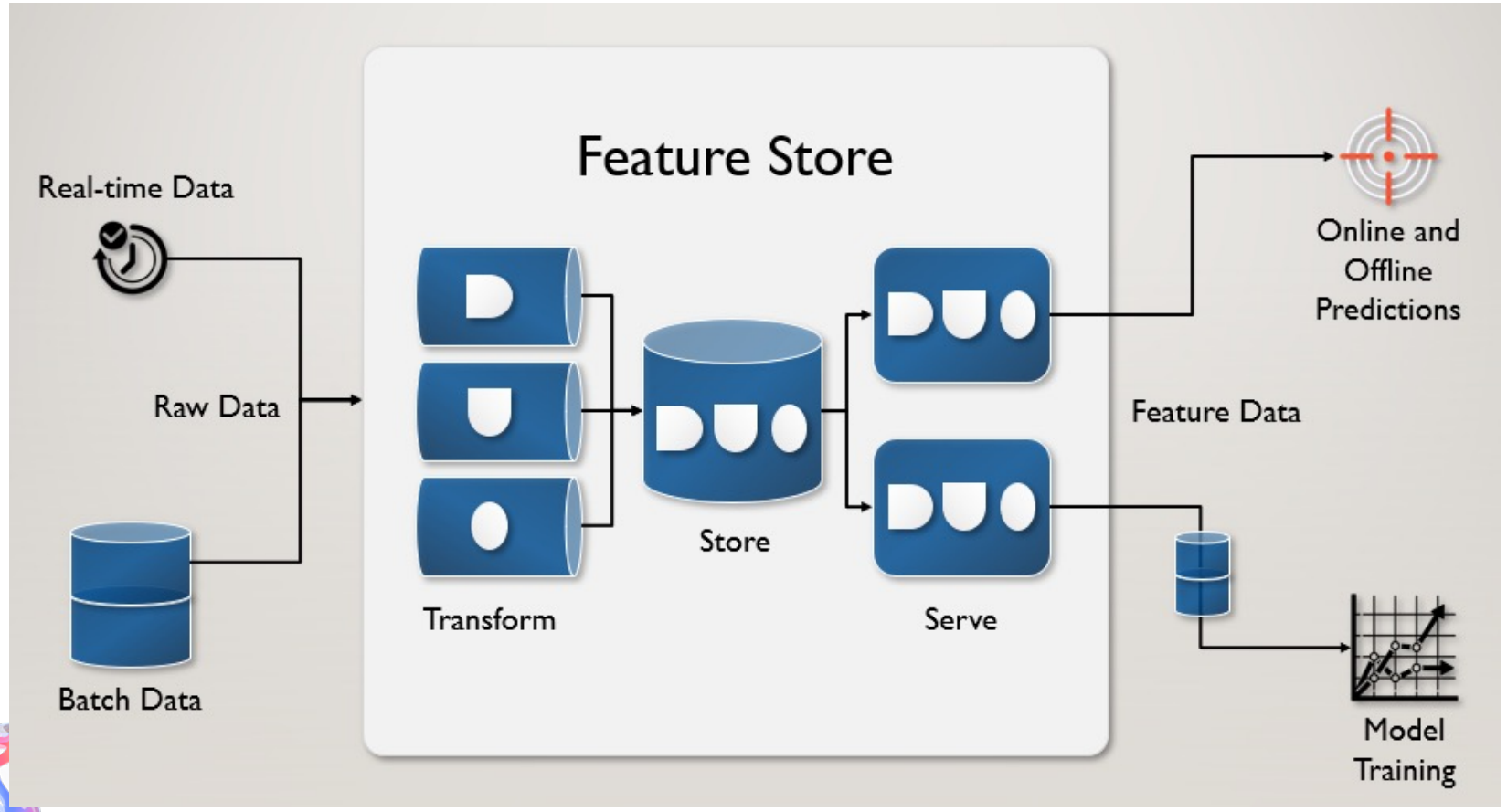


Feature Store as a Hub for ML



- Feature store is a gift from one developer to another
- Allows users to re-use existing features from a central location for use in other models/projects/pipelines/teams
- Ingest, transform, join multiple data sources in batch and real-time
- Re-use transformations to mitigate train/serve skew
- Excellent for larger organizations with many models, may not be necessary for others

Feature Store Architecture

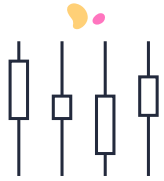


- Experiment Tracking
- Model Serving
- Model Monitoring

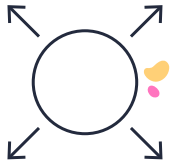
MLOps: Building a Feature Store? Here are the top things to keep in mind

Feature Store in Overall ML Workflow

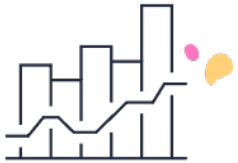
Data Ingestion & Prep



Model Training & Evaluation



Model Deployment



Model Monitoring

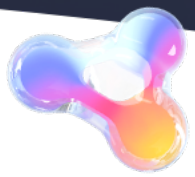
- Ingest Batch + Real-Time
- Feature Engineering

- Use Batch Features
- Experiment Tracking

- Feature Engineering
- Lookups + Imputation

- Monitor Data Drift
- Automate Re-Training

Feature Store Ingestion



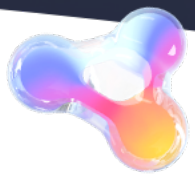
```python
import mlrun.feature_store as fstore

heart_disease_target_set = fstore.FeatureSet(
    name="heart_target",
    entities=[fstore.Entity("PATIENT_ID")],
    description="Heart disease targets via parquet"
)
```

```python
resp = fstore.ingest(
    featureset=heart_disease_target_set,
    source=ParquetSource(
        path=f"{data_path}/heart_disease_target_sf.parquet"
    )
)
```

```python
resp = fstore.ingest(
    featureset=heart_disease_categorical,
    source=CSVSource(
        path="s3://igz-us-sales/heart/heart_disease_categorical_sf.csv"
    )
)
```

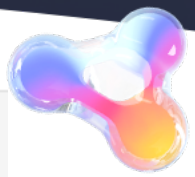
```python
fstore.ingest(
    featureset=heart_disease_continuous_set,
    run_config=spark_config,
    source=SnowflakeSource(
        name="snowflake_heart_disease",
        url = os.getenv("SF_URL"),
        user = os.getenv("SF_USER"),
        password = os.getenv("SF_PASSWORD"),
        database = os.getenv("SF_DATABASE"),
        schema = os.getenv("SF_SCHEMA"),
        warehouse = os.getenv("SF_WAREHOUSE"),
        query = "SELECT * FROM MLRUN_DEMO.HEART_DISEASE.CONTINUOUS"
    )
)
```

Feature Store Retrieval



```
vector = fstore.FeatureVector(
    name="heart-disease-vec",
    features=[
        "heart_categorical.AGE_mapped_toddler",
        "heart_categorical.AGE_mapped_child",
        "heart_categorical.AGE_mapped_adult",
        "heart_categorical.AGE_mapped_elder",
        "heart_continuous.*"
    ],
    label_feature="heart_target.TARGET",
)
```

Feature Store Retrieval (Training)

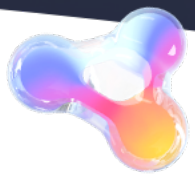


```
df = fstore.get_offline_features("heart-disease-vec").to_dataframe()
df
```

	AGE_mapped_toddler	AGE_mapped_child	AGE_mapped_adult	AGE_mapped_elder	TRESTBPS	CHOL	RESTECG	THALACH	OLDPEAK	CA	TARGET
0	0	0	1	0	125	212	1	168	1.0	2.0	0
1	0	0	1	0	140	203	0	155	3.1	0.0	0
2	0	0	0	1	145	174	1	125	2.6	0.0	0
3	0	0	1	0	148	203	1	161	0.0	1.0	0
4	0	0	1	0	138	294	1	106	1.9	3.0	0
...	...	...	...	...	...	...	...	...	...	...	...
963	0	0	1	0	140	221	1	164	0.0	0.0	1
964	0	0	1	0	125	258	0	141	2.8	1.0	0
965	0	0	1	0	110	275	0	118	1.0	1.0	0
966	0	0	1	0	110	254	0	159	0.0	0.0	1
967	0	0	1	0	120	188	1	113	1.4	1.0	0

968 rows × 11 columns

Feature Store Retrieval (Serving)



```
feature_service = fstore.get_online_feature_service("heart-disease-vec")
feature_service.get(
    [
        {"PATIENT_ID" : "e443544b-8d9e-4f6c-9623-e24b6139aae0"},
        {"PATIENT_ID" : "8227d3df-16ab-4452-8ea5-99472362d982"}
    ]
)
```

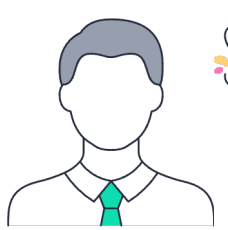
```
[{'AGE_mapped_toddler': 0,
  'AGE_mapped_child': 0,
  'AGE_mapped_adult': 1,
  'AGE_mapped_elder': 0,
  'TRESTBPS': 125.0,
  'CHOL': 212.0,
  'RESTECG': 1.0,
  'THALACH': 168.0,
  'OLDPEAK': 1.0,
  'CA': 2.0},
 {'AGE_mapped_toddler': 0,
  'AGE_mapped_child': 0,
  'AGE_mapped_adult': 1,
  'AGE_mapped_elder': 0,
  'TRESTBPS': 140.0,
  'CHOL': 203.0,
  'RESTECG': 0.0,
  'THALACH': 155.0,
  'OLDPEAK': 3.1,
  'CA': 0.0}]
```

Feature Store in Team Workflows

Data Engineer

Unified Interface for Data Ingestion (Batch + RT)

Don’t Need to Provide Features



Data Scientist

Retrieve Features from Snowflake with Python

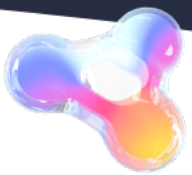
Re-Use Features Across Models/Projects/Teams

MLOps Engineer

Don’t Need to Build Online Feature Infra

Drift-Detection + Re-Training

Monitoring Drift + Automated Re-Training



- Models are not forever – it will decay over time
- Various types of drift, but the result is usually reduced model performance
- Automated re-training will keep your model up-to-date using fresh data and mitigate the performance decay over time

Types of Drift (non-exhaustive)

Covariate Shift / Data Drift / Virtual Drift

When the data underlying the model changed, but the model's performance did not

P(X) changes but P(Y|X) remains the same

Label Shift / Prior Drift

When the model's output or label distribution shifts

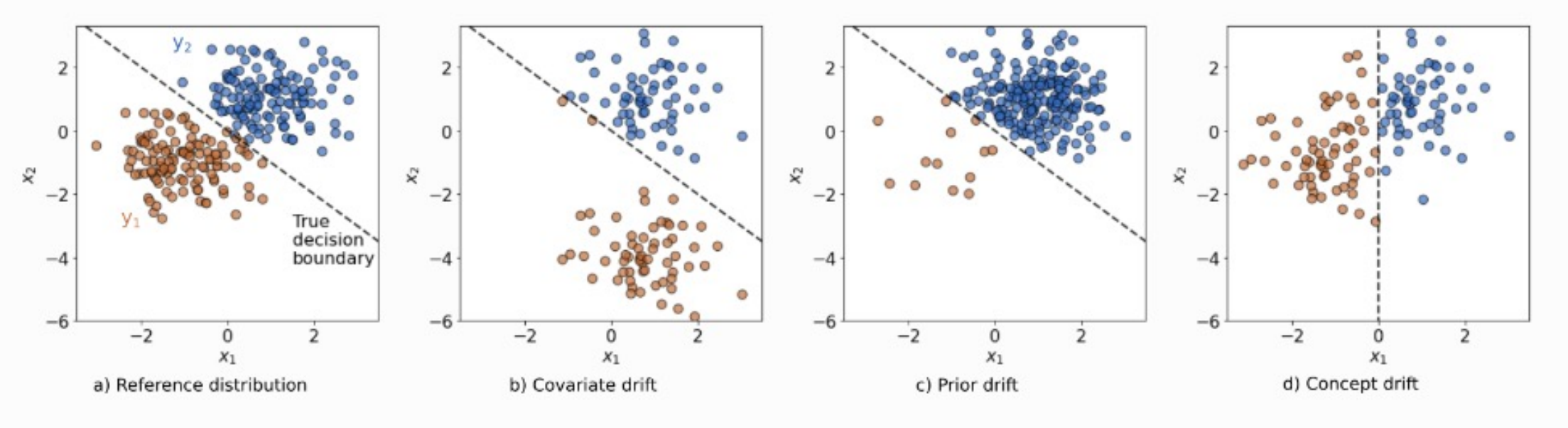
P(Y) changes but P(X|Y) remains the same

Concept Drift

When the meaning (statistical properties) of the input data has changed

P(Y|X) changes but P(X) remains the same

Types of Drift (non-exhaustive)



Seldon Alibi – What is Drift?

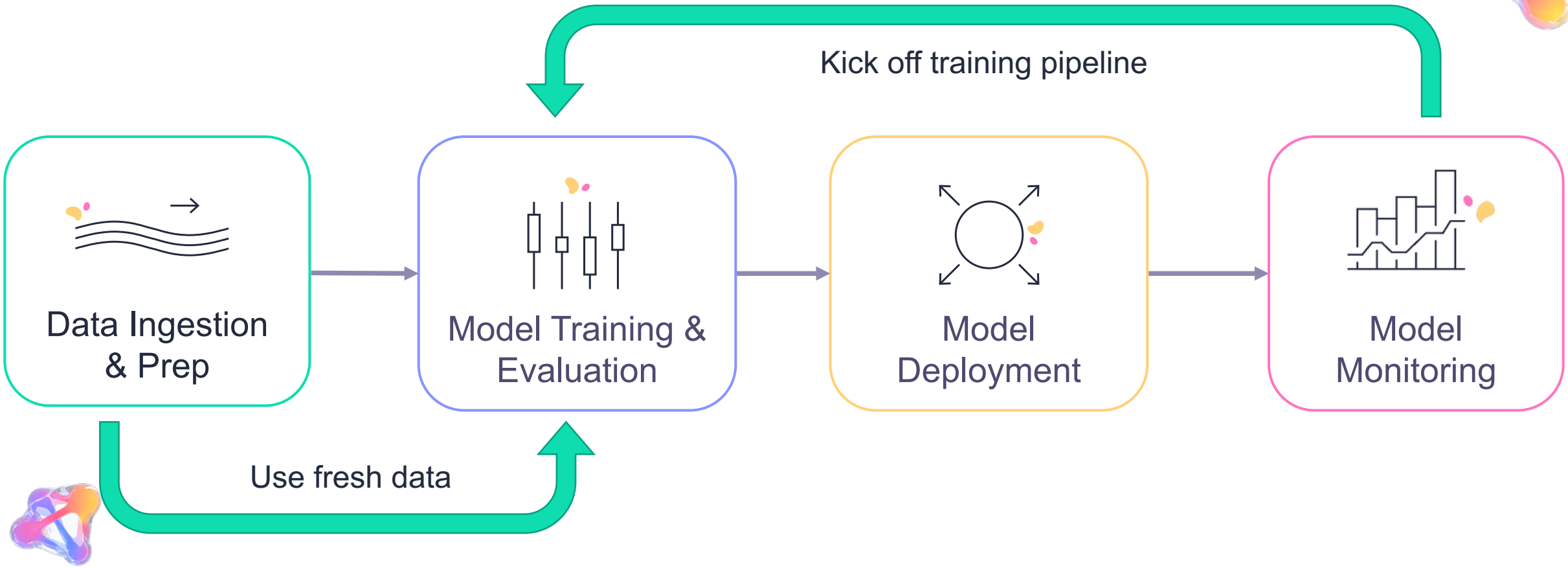
Types of Drift Detection Algorithms

Detector	Tabular	Image	Time Series	Text	Categorical Features	Online	Feature Level
Kolmogorov-Smirnov	✔	✔		✔	✔		✔
Cramér-von Mises	✔	✔				✔	✔
Fisher's Exact Test	✔				✔	✔	✔
Least-Squares Density Difference	✔	✔		✔	✔	✔	
Maximum Mean Discrepancy (MMD)	✔	✔		✔	✔	✔	
Learned Kernel MMD	✔	✔	✔	✔	✔		
Context-aware MMD	✔	✔	✔	✔	✔		
Chi-Squared	✔				✔		✔
Mixed-type tabular	✔				✔		✔
Classifier	✔	✔	✔	✔	✔		
Spot-the-diff	✔	✔	✔	✔	✔		✔
Classifier Uncertainty	✔	✔	✔	✔	✔		
Regressor Uncertainty	✔	✔	✔	✔	✔		

Most drift detection algorithms are for tabular data, however some apply to unstructured data too

Seldon Alibi – Algorithm Overview

Drift Detected Should Start Re-Training



Stateful Training vs Stateless Re-Training

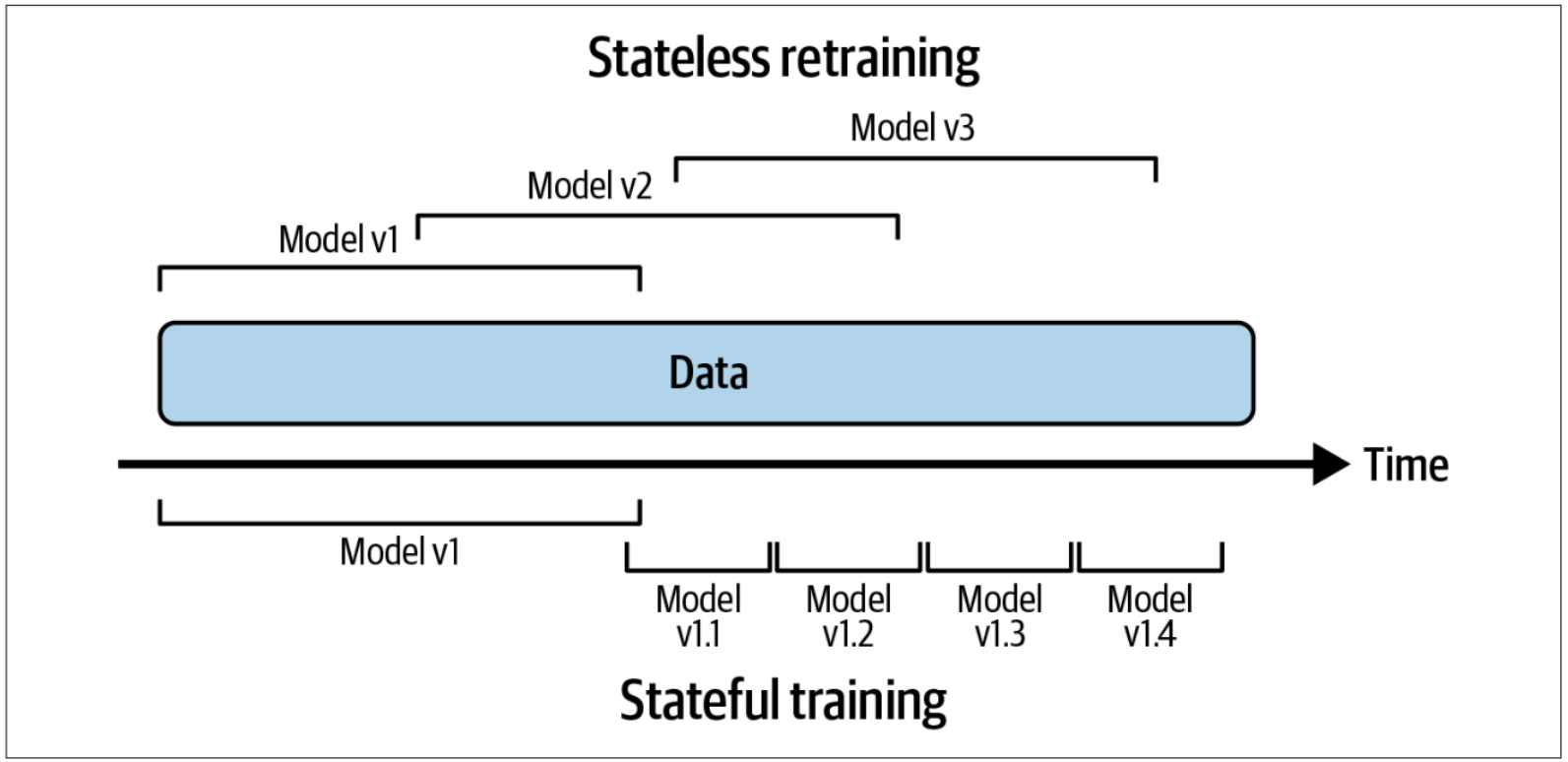


Figure 9-2. Stateless retraining versus stateful training

Stateful training allows you to update your model with less data

If you fine-tune your model from yesterday's checkpoint, you only need to use data from the last day

Designing Machine Learning Systems (Huyen)

Model Evaluation/Deployment Strategy

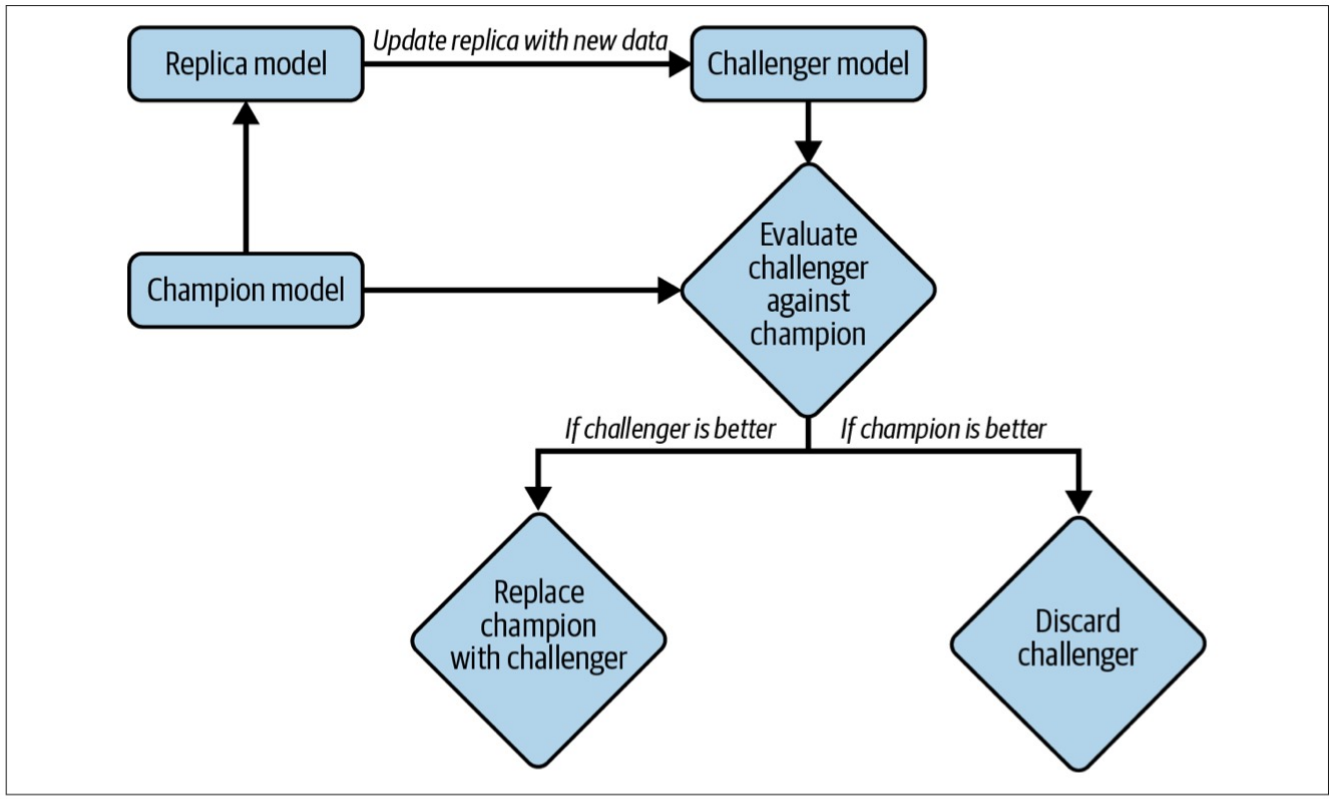


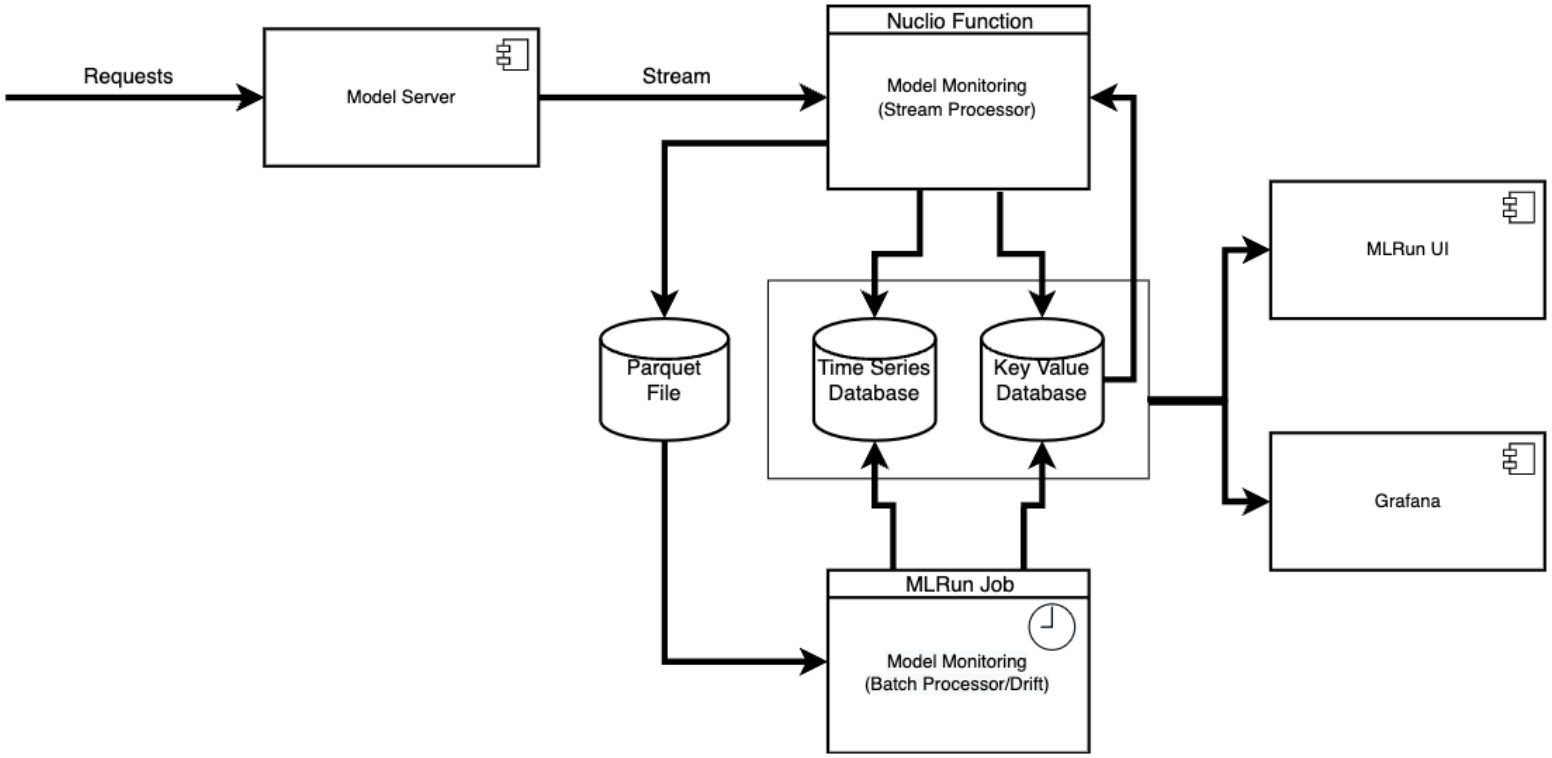
Figure 9-1. A simplification of how continual learning might work in production. In reality, the process of handling the failed challenger is a lot more sophisticated than simply discarding it.

Once you have a new model, compare to the existing one to decide whether to deploy

Can also do more advanced strategies like shadow or canary deployment

Designing Machine Learning Systems (Huyen)

Drift Detection in Iguazio - Architecture



Backend architecture automatically deployed with model serving service

MLRun - Model monitoring overview

Drift Detection in Iguazio – Statistical Tests

Total Variation Distance (TVD) — The statistical difference between the actual predictions and the model's trained predictions.

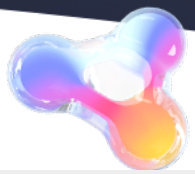
Hellinger Distance — A type of f-divergence that quantifies the similarity between the actual predictions, and the model's trained predictions.

Kullback–Leibler Divergence (KLD) — The measure of how the probability distribution of actual predictions is different from the second model's trained reference probability distribution.

Drift calculated on hourly basis using these tests

MLRun - Model monitoring overview

Drift Detection in Iguazio - Dashboards



Models | Model Endpoints (Beta)

Labels:key1,key2=value,...

Name

sklearn_ensemble_Ran...

sklearn_ensemble_Ada...

sklearn_linear_model_L...

sklearn_ensemble_RandomForestClassifier

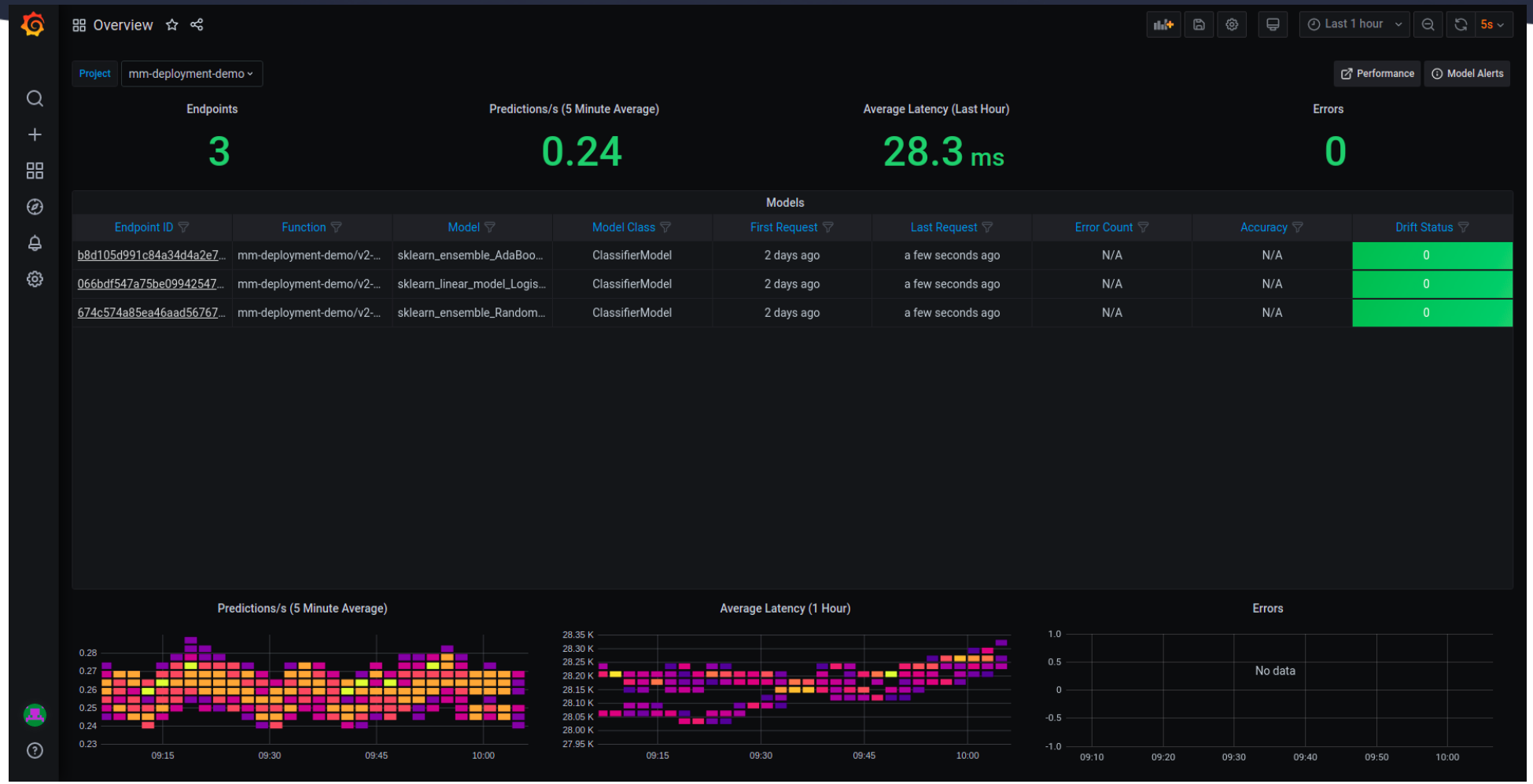
fbd36f09b988eff41ea8bc52422edd2ffe0fce77

Overview | Drift Analysis | Features Analysis

Feature	Mean		Std		Min		Max		TVD	Hellinger	KLD	Histogram	
	Expected	Actual	Expected	Actual	Expected	Actual	Expected	Actual				Expected	Actual
sepal_length_cm	5.84	5.82	0.83	0.78	4.30	4.30	7.90	7.60	0.41	0.43	2.00		
sepal_width_cm	3.06	3.05	0.44	0.47	2	2.40	4.40	4.40	0.37	0.43	2.09		
petal_length_cm	3.76	3.59	1.77	1.67	1	1.10	6.90	6.60	0.25	0.31	1.06		
petal_width_cm	1.20	1.07	0.76	0.66	0.10	0.10	2.50	2.10	0.57	0.53	2.91		

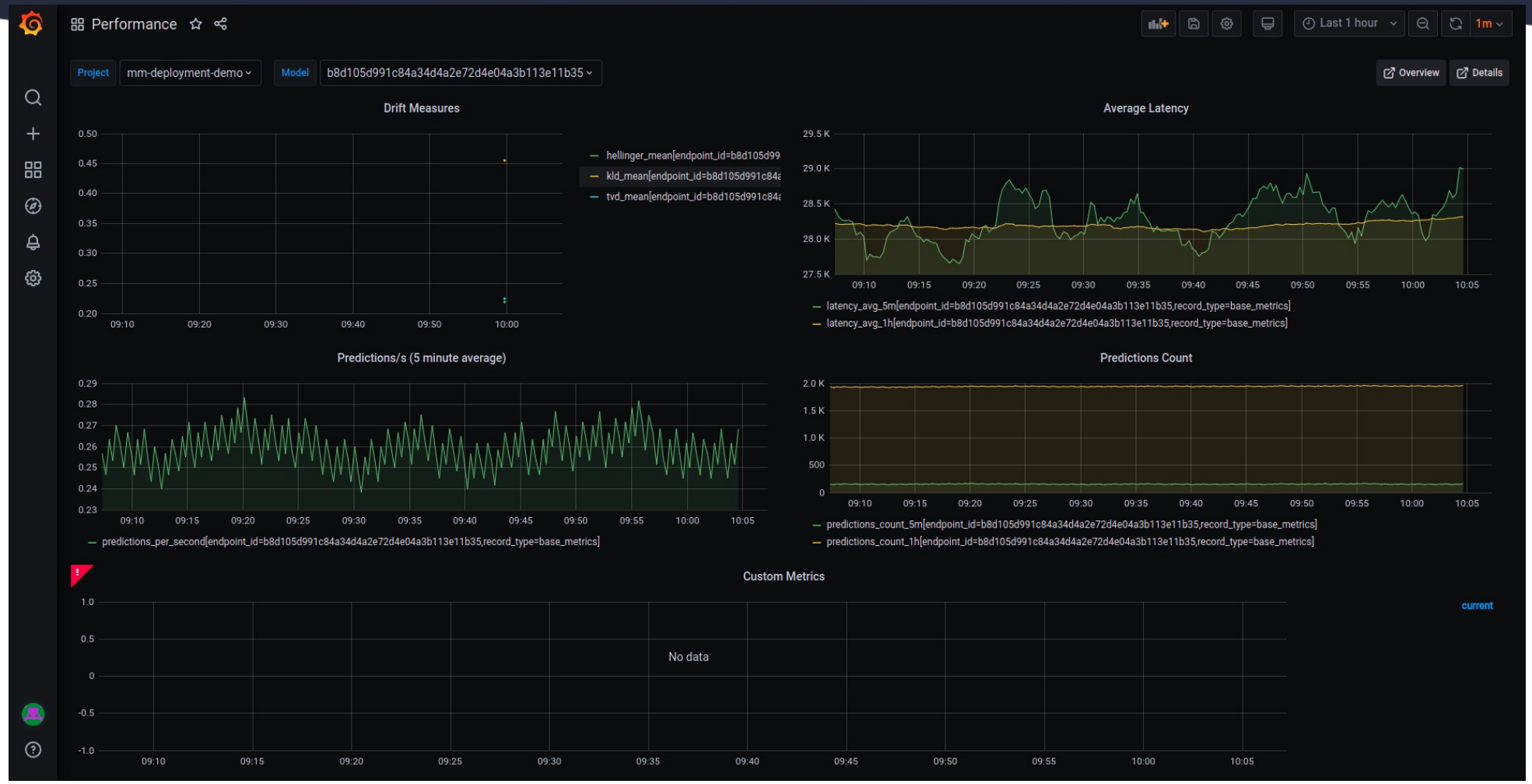
MLRun - Model monitoring overview

Drift Detection in Iguazio - Dashboards



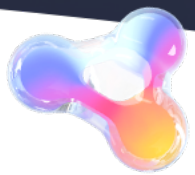
[MLRun - Model monitoring overview]

Drift Detection in Iguazio - Dashboards



[MLRun - Model monitoring overview]

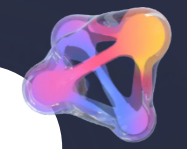
Drift Detection in Iguazio – Re-Training Trigger



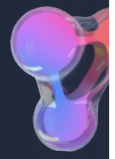
- Every drift calculation is posted in a stream
- Process will watch drift stream for events denoting possible or probable drift -> kick off CI/CD pipeline

```
> 2022-09-01 20:00:07,860 [info] Drift status: {'endpoint_id': 'd2891403ac07d5c6cdc672130a061eac29a6adef', 'drift_status': 'NO_DRIFT', 'drift_measure': 0.05010798456956764}
> 2022-09-01 20:00:08,098 [info] Done updating drift measures v3io:///projects/heart-disease-classifier/model-
endpoints/parquet/key=d2891403ac07d5c6cdc672130a061eac29a6adef/year=2022/month=09/day=01/hour=19
```

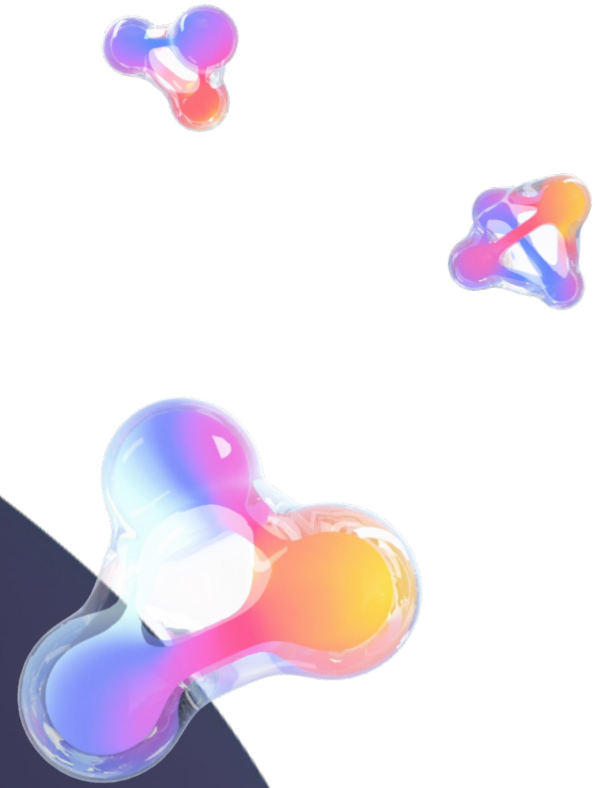
Check out MLRun for Open Source MLOps



- MLRun Website
- MLRun GitHub
- MLRun Docs
- MLRun Function Marketplace
- MLOps Live Slack Community



iguazio



Iguazio and MLOps

Nick Schenone – DATASCI 290