MLOps and LLM Observability

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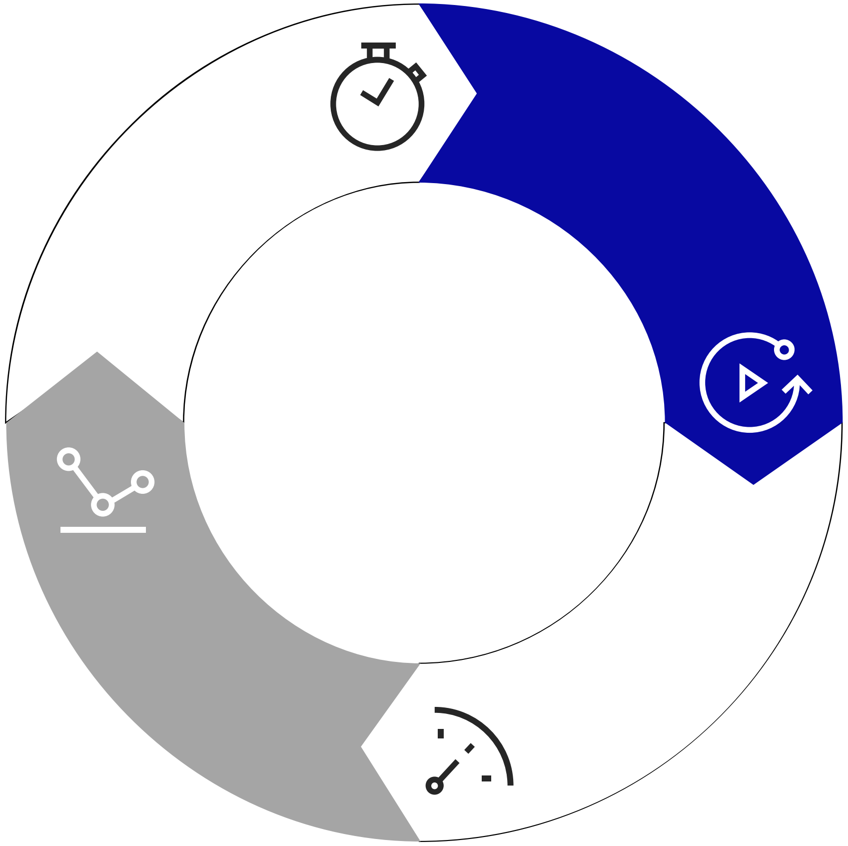
01

Overview

Topics



01 Evaluating model performance and metrics

02 Monitoring during training and inference

03 Model deployment basics with Flask/Streamlit

04 Hands-on lab: Deploy a simple model

02

Introduction to Model Validation Techniques

Introduction to Model Validation Techniques

What is model validation?

- Assessing how well your model generalizes to unseen data
- Prevents overfitting and underfitting

Common Techniques:

- **Hold-out validation:** Split data into train/test sets (e.g., 80/20)
- **K-fold cross-validation:** Rotate through K train/test splits for robust estimates
- **Stratified sampling:** Maintains class proportions in splits

Goal: Ensure your model performs well on real, unseen data.

03

Evaluating Model Performance and Metrics

Evaluating Model Performance and Metrics

Classification

(Metrics)

- **Accuracy:** Overall correctness of predictions
- **Precision/Recall/F1:** Quality and coverage of positive predictions
- **AUC-ROC:** Probability curve for distinguishing classes
- **Confusion Matrix:** Breakdown of true/false positives/negatives

Regression

(Metrics)

- R^2 Score: Proportion of variance explained by model
- MAE, RMSE: Average prediction errors

Best Practice

Always report multiple metrics and visualize them for every model.

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Interpreting Model Metrics

Why does metric choice matter?

> Different applications value metrics differently

Precision in fraud detection

Recall matters in health Diagnosis

How to flag issues?

High accuracy + low recall

Model misses many positives (false negatives)

High recall + low precision

Model creates many false alarms (false positives)

What’s a “good” score?

Depends on dataset, business context, and risk tolerance

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Monitoring Metrics During Training and Inference

Training Phase Monitoring

01

Loss curves

Watch for convergence or divergence

02

Accuracy over epochs

Detect over/underfitting

03

Early stopping

Halt training if validation loss increases

04

Time per epoch/batch

Performance monitoring

Inference (Production) Monitoring

Prediction latency

How fast are results returned?

Error rates and input distributions

Detecting data/model drift

Ongoing evaluation

Periodically validate with new data

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Introduction to Model Deployment

Goal

Make model available for real-world use

01

Why deploy?

Enable predictions via APIs or user-facing applications

Integrate into business processes

Deployment Methods

01

REST API (Flask/FastAPI)

02

Web app (Streamlit/Gradio)

03

Batch prediction

07

Deploying with Flask – RESTAPI Approach

Flask

01

Lightweight Python web framework

How it works

Model loaded as a Python object

Receives HTTP requests with input data

Returns predictions as JSON

Sample Flask API Structure

01

Example Code

```
@app.route('/predict', methods=['POST'])
def predict()features = request.json['features']
prediction = model.predict([features]).tolist()
return jsonify({'prediction': prediction})
```

02

Use Case

Easy integration with applications and microservices

08

Deploying with Streamlit – Interactive Web App

Deploying with Streamlit – Interactive Web App

01 Streamlit:

Tool for turning Python scripts into shareable web apps

02 Why Streamlit?

- Easily Display predictions, charts, explanations
- Instant web UIs with minimal code

Sample Streamlit UI

Example Code

```
import streamlit as st
input_val = st.number_input('Enter a value')
if st.button('Predict')pred = model.predict([[input_val]])
st.write(f"Prediction: {pred[0]}")
```

Use Case:

Demos, prototyping, data science reporting

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Comparing Deployment Patterns

Flask

01

	Flask	Streamlit
Type	REST API	Web App
Users	Developers, other systems	End-user,business stakeholders
Interactivity	API calls only	Full GUI, sliders, charts
Best for...	Production integration	Demos, rapid prototyping

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Lab Exercise – Deploy a Model

Objective

01

Make trained model accessible through Flask API and Streamlit app

Lab Steps

Prepare your trained model

Pickle/joblib save from Day 1 or Day 2

Flask Deployment

Write a /predict endpoint
Test with curl or Postman

Streamlit Deployment

Create input form for user features
Display prediction and basic metrics

Test & Validate

Try several prediction examples
Confirm outputs are correct and responsive

Thanks

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