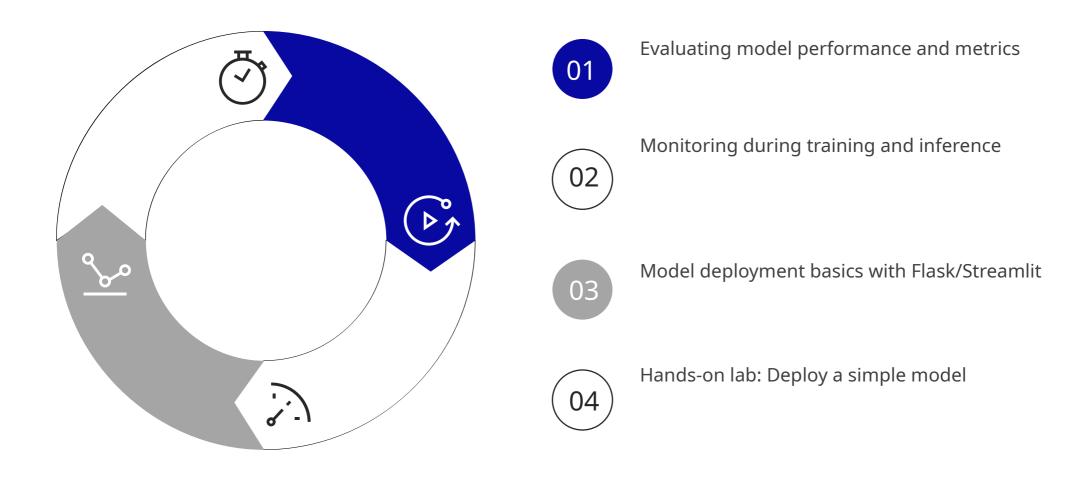
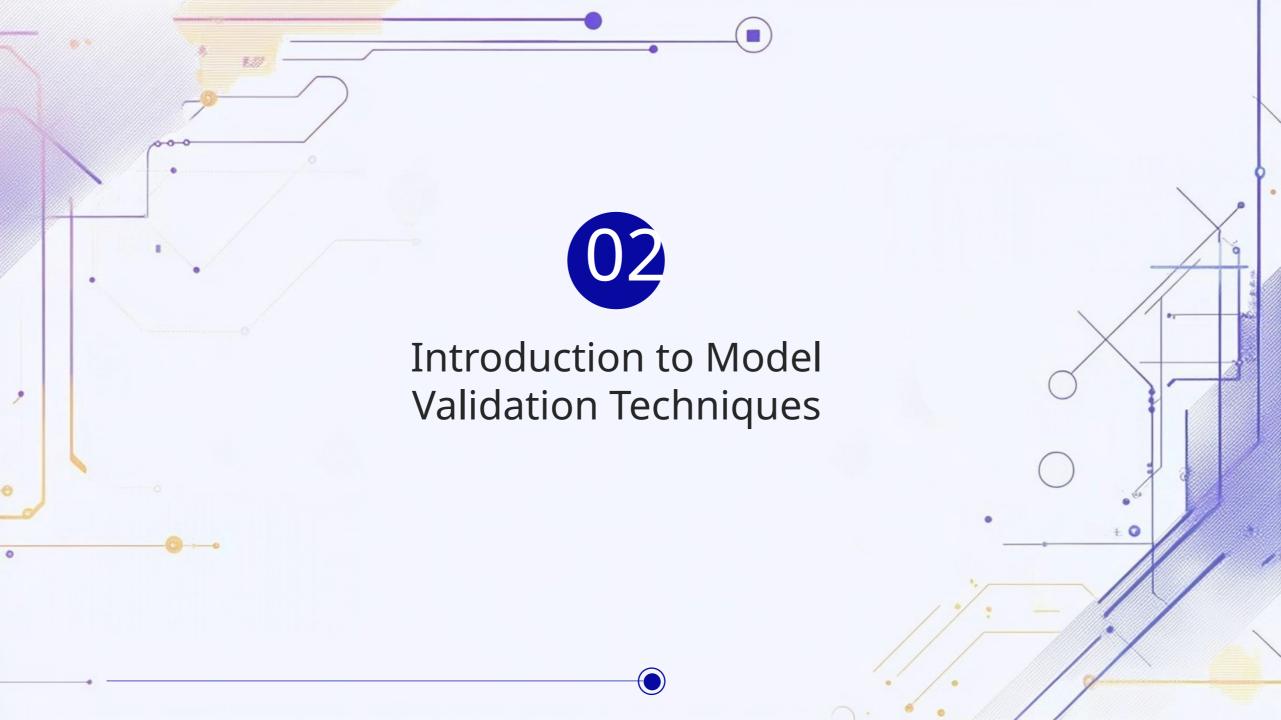




## Topics





#### Introduction to Model Validation Techniques



#### What is model validation?

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

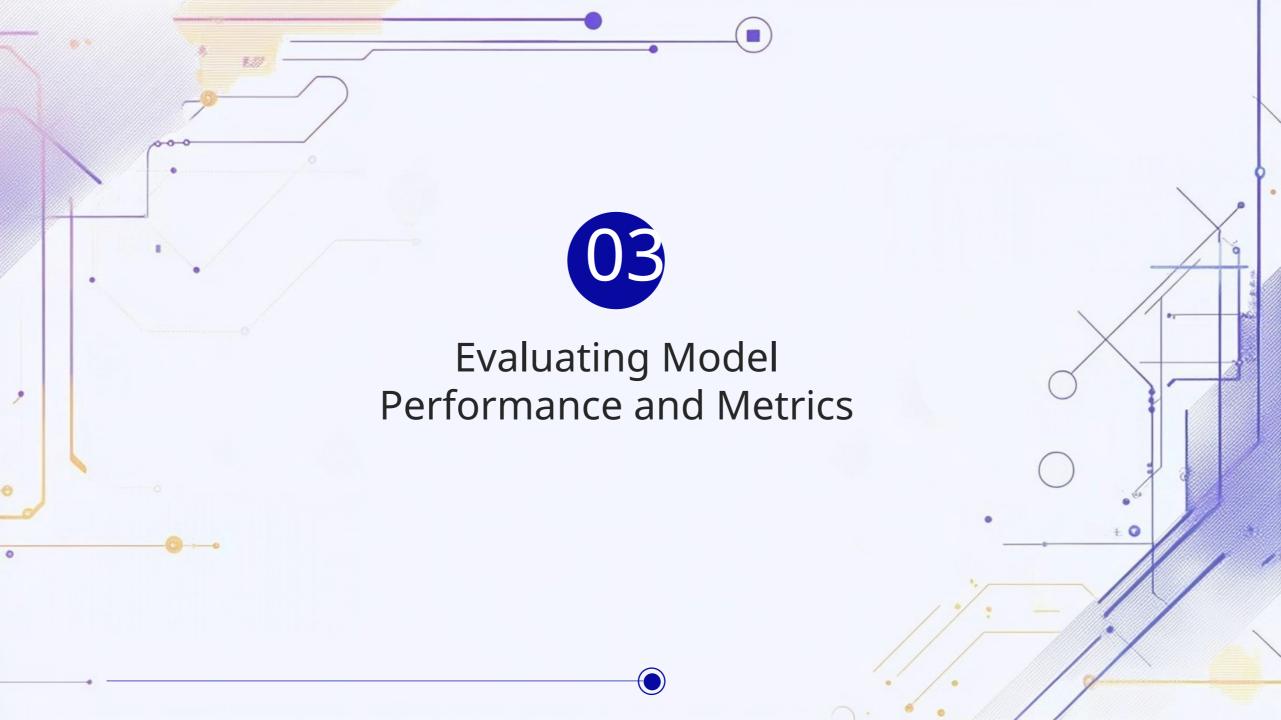


#### Common Techniques:

- **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.



### 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

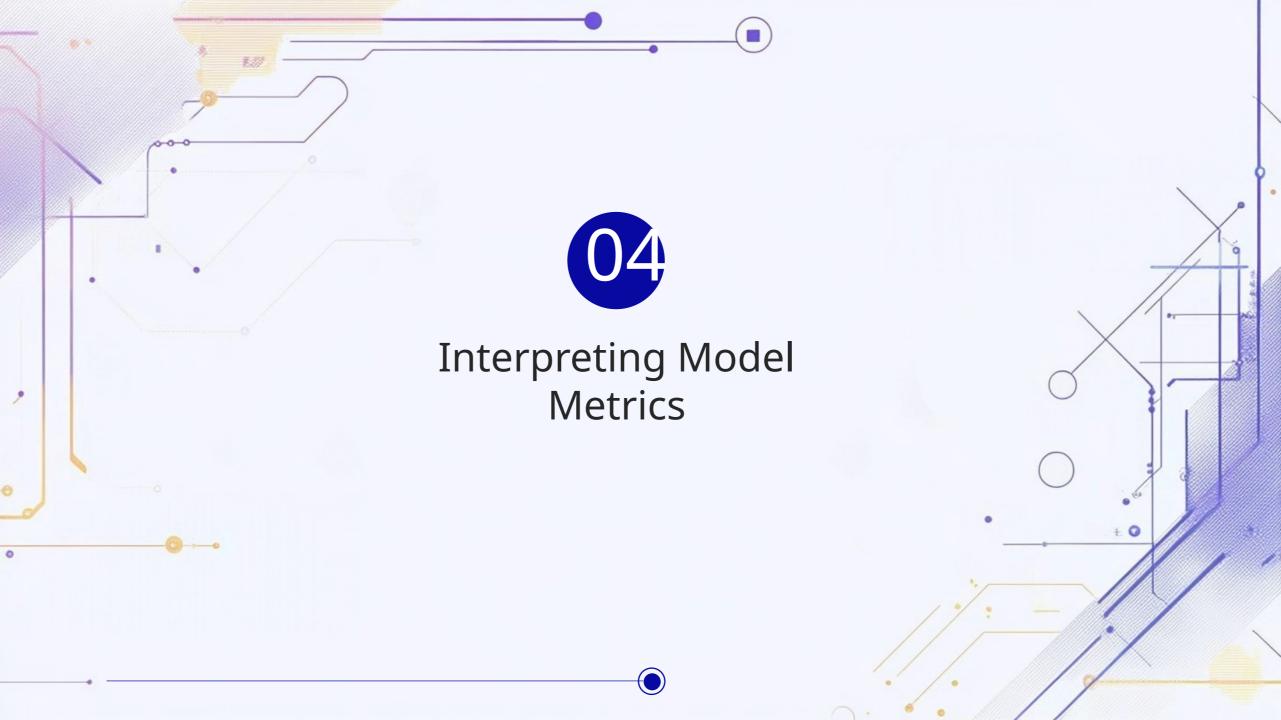
#### Regression

(Metrics)

- R<sup>2</sup> Score: Proportion of variance explained by model
- MAE, RMSE: Average prediction errors

#### **Best Practice**

Always report multiple metrics and visualize them for every model.



## 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)



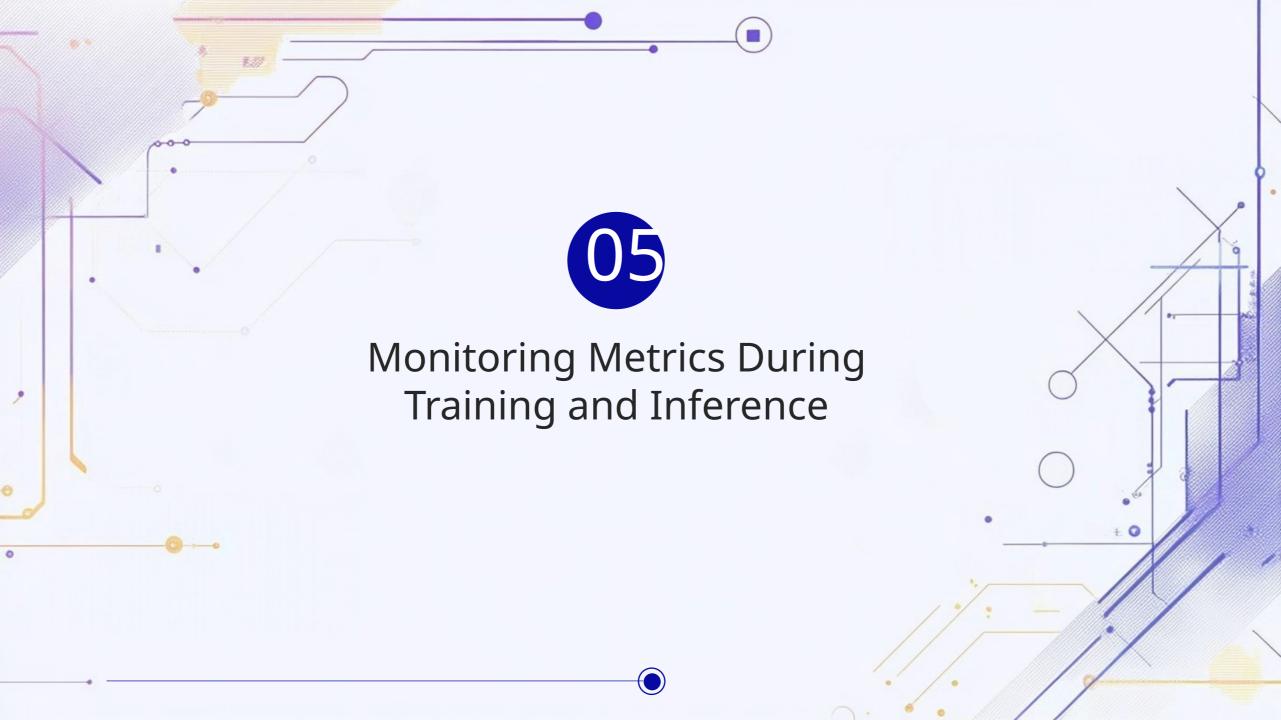
#### High recall + low precision

Model creates many false alarms (false positives)

# What's a "good" score?



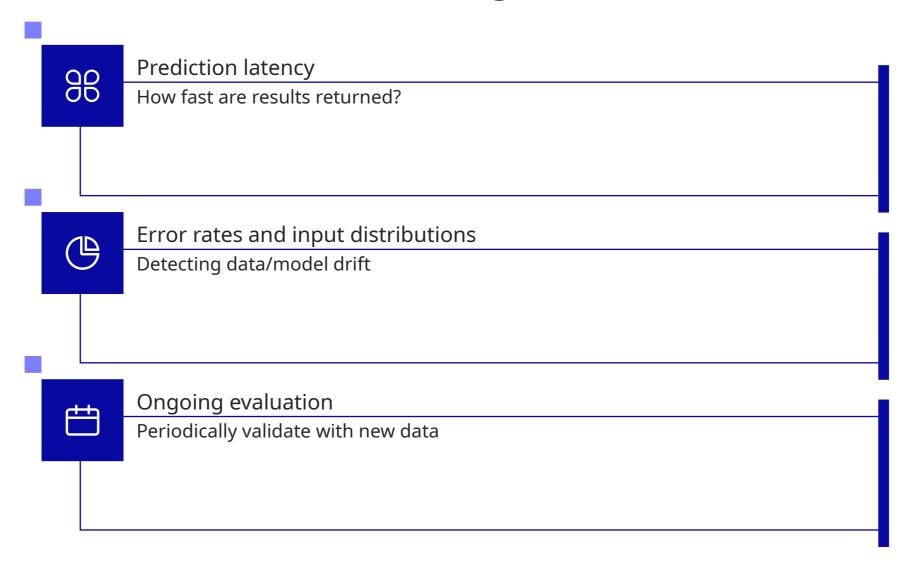
Depends on dataset, business context, and risk tolerance



### Training Phase Monitoring

Accuracy over Time per Early stopping Loss curves epochs epoch/batch Watch for convergence Halt training if Detect Performance validation loss or divergence over/underfitting monitoring increases

#### Inference (Production) Monitoring







Make model available for real-world use

## Why deploy?



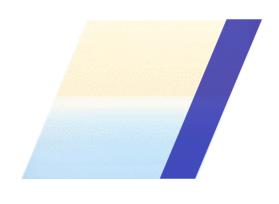
Enable predictions via APIs or user-facing applications Integrate into business processes

# Deployment Methods









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





#### 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

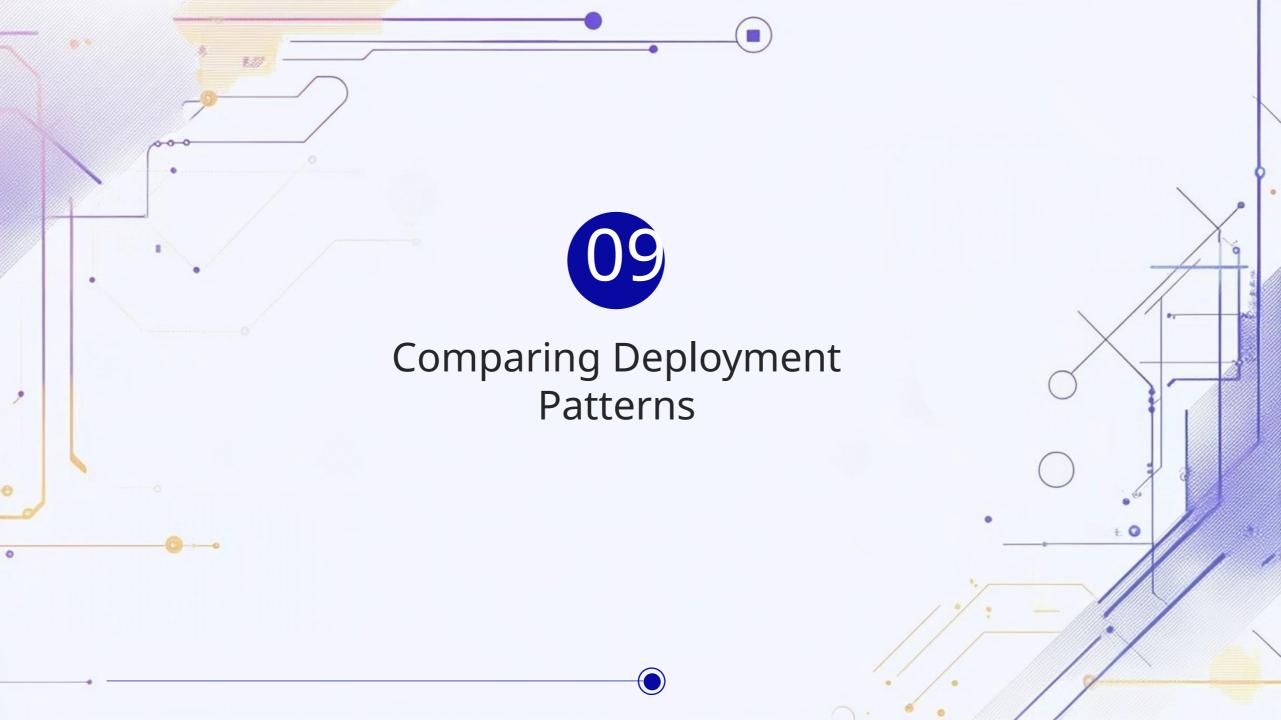


#### Example Code

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:

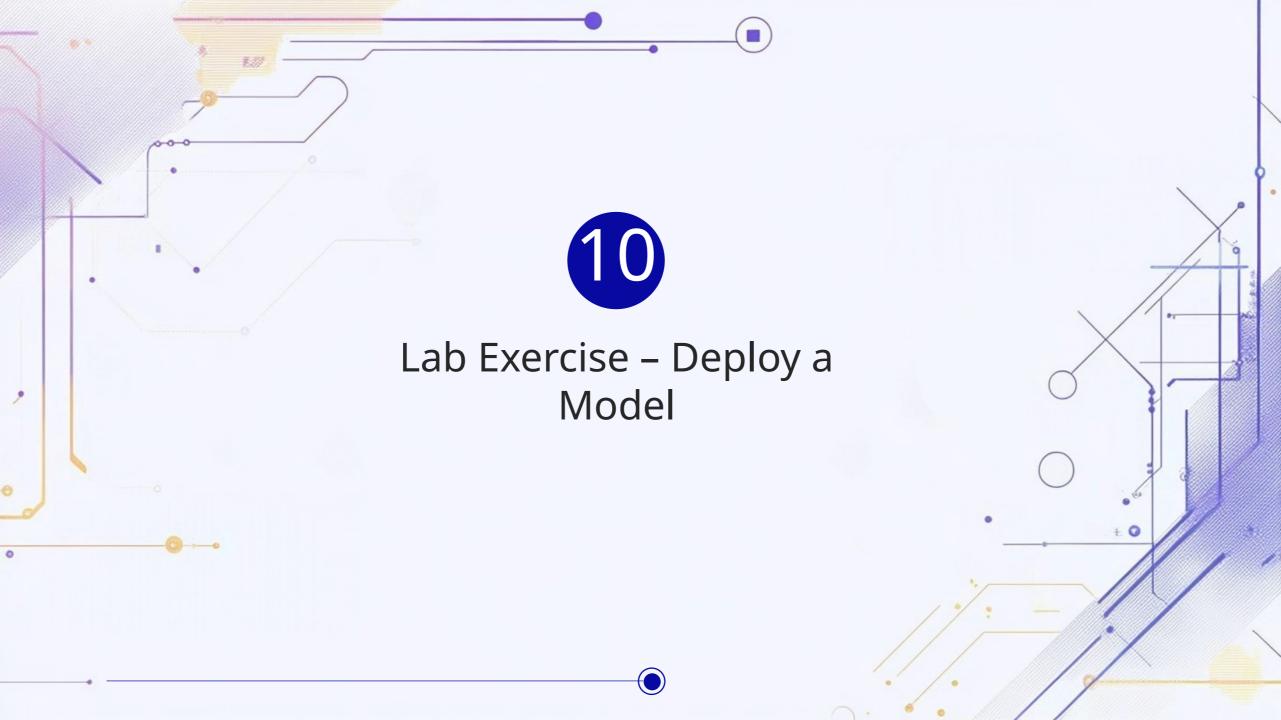
Demos, prototyping, data science reporting





Type: REST API Users: Developers, other systems Interactivity: API calls only

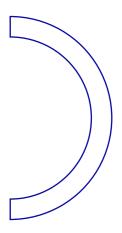
Best for: Production integration



# Objective



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

