Title Slide

- Title: Comprehensive Overview of MLflow
- Subtitle: Tracking, Serving, Prompting, and Deployment

Slide 1: MLflow Tracking Server Options

- Default:
- Command: mlflow ui
- Access: http://localhost:5000
- Ideal for quick local testing and development
- Stores runs in local file store (mlruns/ directory)
- · Custom Ports:
- Command: mlflow ui --port 1234
- Access: http://localhost:1234
- Useful to avoid port conflicts or run multiple servers
- Ensure to use a browser-safe port (avoid 6000, 6666, etc.)
- Remote Hosting for Teams:
- Dagshub: Free for small teams, easy integration, GitHub-like interface
- · AWS:
 - Store artifacts in S3
 - Host server using EC2
 - Track metadata in RDS (PostgreSQL/MySQL)
- Azure: Blob storage for model data, Azure ML for workflow automation
- GCP: Use GCS for artifacts, BigQuery for tracking, and GKE for scalable deployments

Slide 2: MLflow Tracking Features

- · Model Tracking:
- Automatically or manually track models (via mlflow.log_model())
- Track model versions, source, and associated metrics
- · Code Tracking:
- Log Git commit hash or manually add as tags
- Ensures reproducibility and version control

· Data Tracking:

- Manually log dataset versions/paths
- Integrate with tools like DVC for better tracking

Artifact Tracking:

- Log model files, plots, images, and artifacts
- Supports metadata: run_id , experiment_id , owners , tags , requirements.txt

Metrics:

- Log scalar metrics like accuracy, loss, F1, etc.
- Visualize them over time across different runs

Model Comparisons:

- UI-based comparison of metrics across runs
- Filter and sort experiments using tags/parameters

• Parent-Child Run Hierarchy:

• Create sub-runs to track nested steps (e.g., CV folds)

· Hyperparameter Tuning:

- Log each trial using GridSearchCV/RandomizedSearchCV
- Auto-log best parameters and scores

Slide 3: Model Lifecycle and Serving

· Lifecycle Stages:

- None : Default unassigned state
- Staging: Models ready for further evaluation
- Production : Deployed and stable version
- Archived : No longer in use

Promotion/Demotion:

• Use mlflow.transition_model_version_stage() or UI

- · Keep history of promotions
- · Model Serving:
- Serve via REST API: mlflow models serve -m <model_uri>
- Integrate with Flask, FastAPI to add UI or auth layers

Slide 4: Prompt Tracking in MLflow

- Track Prompts via UI or Code:
- | mlflow.genai.register_prompt() | to log prompt templates
- Track prompt name, template, version, and usage
- Versioning & Aliases:
- Use aliases like production, staging, beta for better control
- Roll back to older prompt versions if needed
- Audit Prompt Evolution:
- Track who committed what version, with commit messages
- Compare how different versions affect performance

Slide 5: Hugging Face Model Integration

- Integration with Transformers Library:
- · Log pre-trained or fine-tuned models
- Track tokenizer config and model weights
- Storage & Versioning:
- Store HF models in MLflow Registry
- Use metadata to track versions, dataset, performance
- API Serving:
- Serve using mlflow models serve with HF wrappers
- Wrap in FastAPI for custom inference routes

Slide 6: Gunicorn and Docker Deployment

- Gunicorn (Linux Only):
- Run Flask/FastAPI with multiple workers for production
- Command: gunicorn -w 4 -b 0.0.0:8000 app:app
- · Docker for Windows:
- Use Docker to containerize app + Gunicorn
- Enables Linux-style deployments on any OS
- Production Readiness:
- Add NGINX as reverse proxy, SSL termination, load balancing
- Set environment variables and secrets via Docker/ENV

Slide 7: Legacy Model Logging and Serving

- Re-logging Old Models:
- Wrap pre-MLflow models using mlflow.pyfunc.log_model()
- Add conda/requirements to serve properly
- Add Signatures:
- Define input/output schema manually for API exposure
- Improves model validation and compatibility
- Serve with MLflow CLI:
- mlflow models serve -m <model_uri>
- Enables quick local API deployment for legacy models