

From Code to Cloud

Generative AI Bootcamp – Week 1, Day 5, Session 1

November 21, 2025

Learning Objectives

- Understand the end-to-end journey: **code** → **container** → **cloud**
- Review the **MLOps workflow** and how it supports generative AI applications
- Explore practical deployment paths using **Docker**, **Cloud Run**, and **Vertex AI**



From Local Code to Deployed AI Service

1. **Develop locally:** write, test, and refactor Python code
2. **Package:** environment consistency and code reusability
3. **Containerize:** build and run anywhere
4. **Deploy and monitor:** scale using cloud infrastructure

MLOps Lifecycle Overview

1. **Development**
2. **Packaging** → consistency and reusability
3. **Containerization** → platform abstraction and scalability
4. **Deployment**
5. **Monitoring & Maintenance**

Each phase introduces automation and reliability to AI delivery.

Development Phase

- Version control with **Git & GitHub**
- Code testing using **PyTest**
- Continuous Integration (CI) for automatic validation
- Style & quality checks with **ruff / flake8, black, mypy**

Packaging & Containerization

- Package code into Python distributions (`pyproject.toml`)
- Use **Docker** to containerize environments
- Build container environment using `requirements.txt`

Docker Essentials Recap

- **Image** = blueprint of environment
- **Container** = running instance
- **Dockerfile** defines build steps
- **Registry** stores and shares images (e.g., Docker Hub, Artifact Registry)



Deployment Targets

Cloud Platform	Deployment Option	Description
Vertex AI	Cloud Run / Model Garden	Serverless deployment for AI microservices
AWS	ECS / Lambda	Container orchestration / serverless runtime
Watson X	AI Workbench	Deployment and monitoring for foundation models

Continuous Deployment (CD)

- CI pipeline triggers build & test
- Docker image pushed to registry
- CD step deploys new version automatically
- Use GitHub Actions or Cloud Build for automation

Monitoring & Logging

- Log structured data using `logging` and `rich`
- Track latency, errors, and uptime
- Use Cloud Monitoring / CloudWatch, or Prometheus + Grafana for metrics visualization
- Integrate alerts for model drift or service failure

MLOps in Generative AI Context

- Each component (LLM, vector DB, API) becomes a microservice
- CI/CD ensures coordinated updates
- Containers ensure consistent environments across the stack

Example: Deploying a FastAPI AI Service

1. Build Docker image: `docker build -t ai-service .`
2. Test locally: `docker run -p 8000:8000 ai-service`
3. Push to registry: `docker push gcr.io/.../ai-service`
4. Deploy to Cloud Run: `gcloud run deploy ai-service --image ...`

Integration with Vertex AI & Watson X

- Use APIs to connect to model endpoints
- Deploy services as managed containers
- Combine with **BigQuery** or **FAISS** for RAG-based architectures



Trade-offs & Design Decisions

Approach	Pros	Cons
Docker + Cloud Run	Fast, scalable, serverless	Cold starts
Vertex AI Pipelines	Integrated AI ecosystem	Higher setup complexity
On-prem (Docker Compose)	Control, cost-effective	Maintenance burden

Best Practices for Cloud-ready AI Apps

- Externalize configs (`.env` , secrets)
- Write stateless microservices
- Log everything in structured JSON
- Version data and models explicitly

Key Takeaways

- MLOps bridges development and deployment
- Containers = reproducibility and scalability
- CI/CD automates quality and rollout
- Cloud platforms abstract infrastructure for speed and reliability