2024

Production ML System Design

From System Design to Deployment

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OUTLINE

1. System Architecture
2. Deployment and Serving
3. Data Engineering
4. Model Development
5. Testing, Monitoring, and Scalability
6. Infrastructure

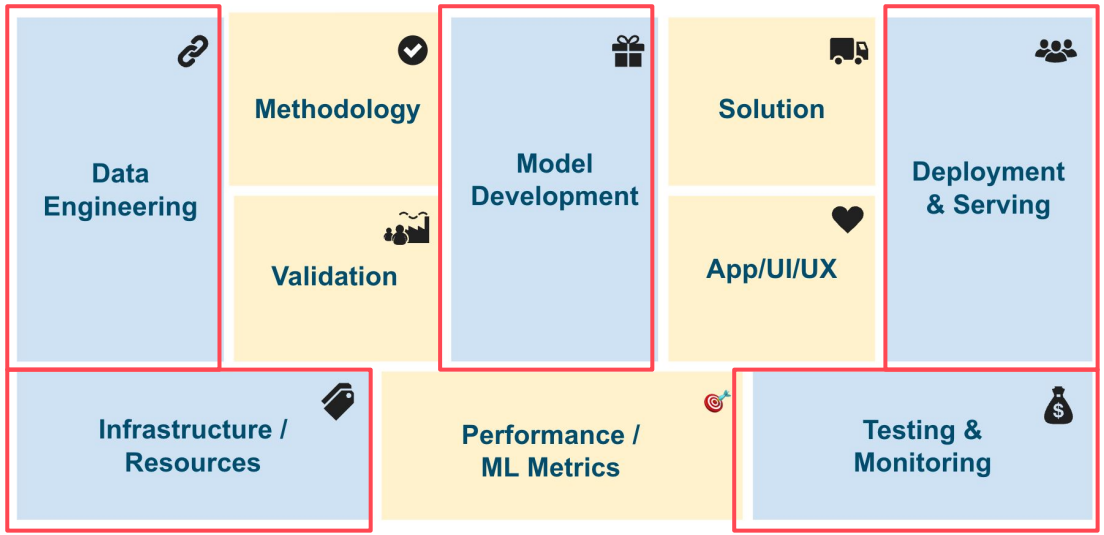
5.x - Production ML System Design

Purpose

- Frame the ML solution

Guiding questions:

- How does the ML could help?



MODULE DETAILS

Goals

- Learn to design scalable and maintainable ML systems
- Understand the challenges of deploying ML models in production
- Develop skills to monitor and maintain ML systems over time

Learning Outcomes

- Design production-ready ML architectures
- Develop deployment and serving strategies
- Implement effective data engineering pipelines
- Create comprehensive testing and monitoring plans

System Architecture

Production ML System Design

> Guide: 5.1 - High-level design

5.1 - High-level design

What are the key components of the ML System?

Purpose

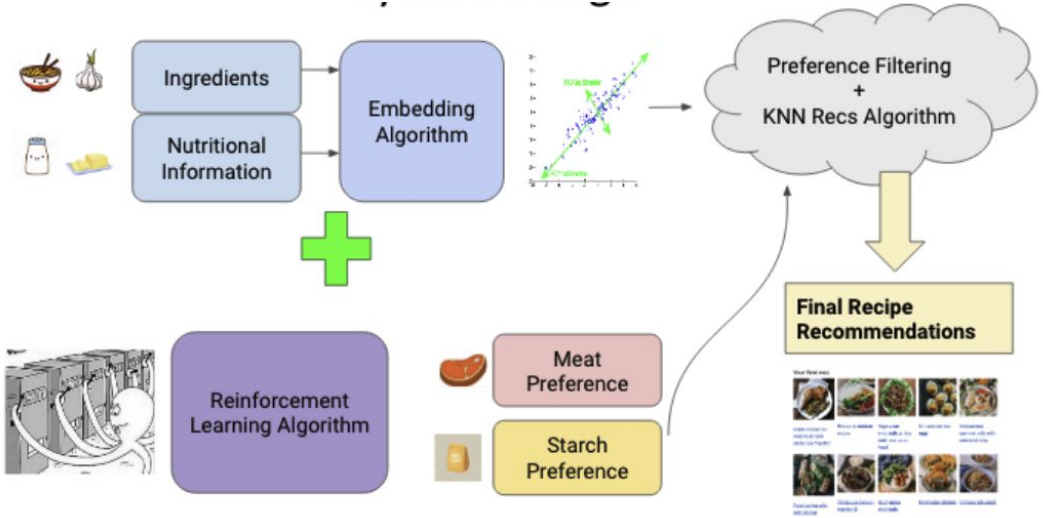
- To ensure all technical stakeholders understand how the system will be built and how data will flow through it

Guiding questions:

- How will the ML system integrate with our current infrastructure?
- What are the key components of our data processing pipeline?
- How will we ensure efficient data flow through the system?

Case: recipes recommendation

[screenshot of our evaluation page]

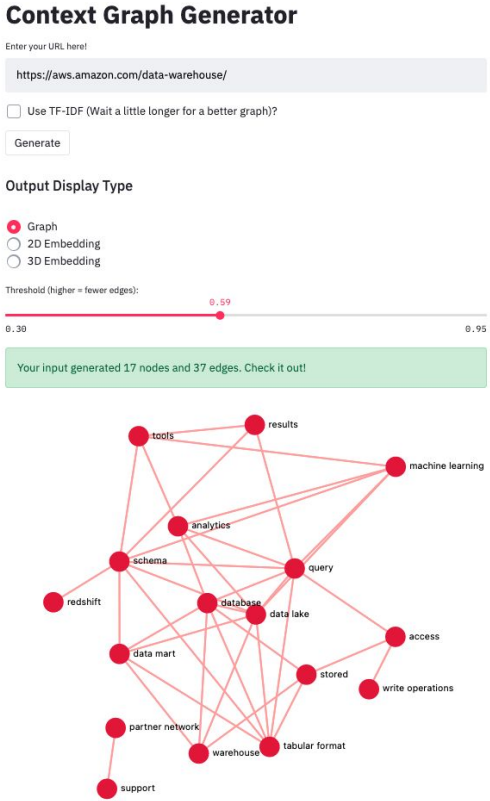


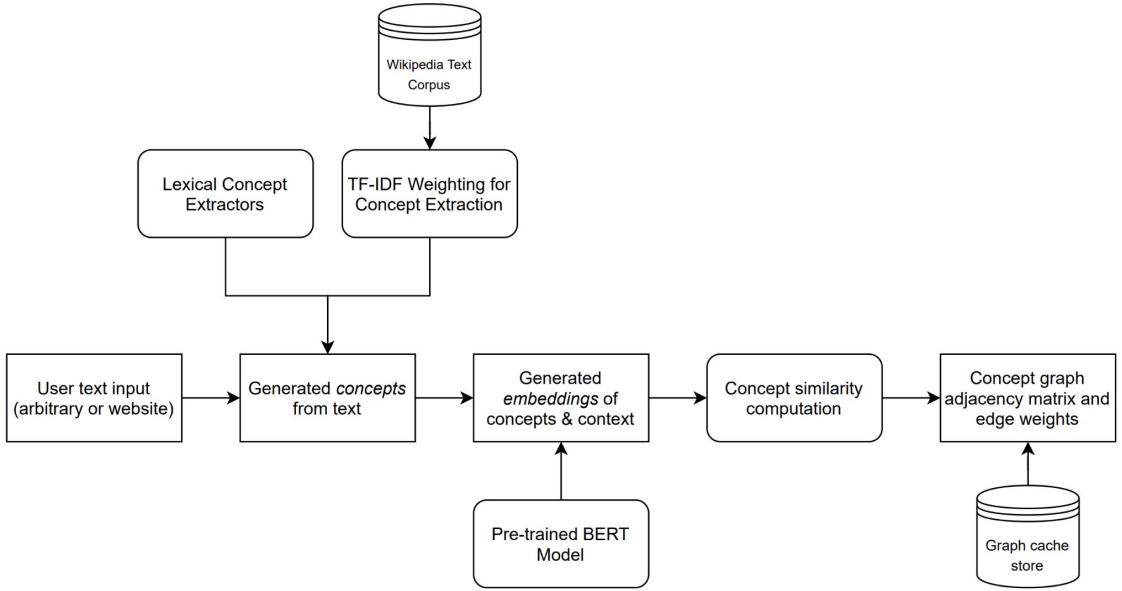
[System diagram to show the moving components of our application]

Project: Tender Matching People to Recipes

Sourel: https://stanford-cs329s.github.io/reports/tender-recipe-recommendations/

Case: article graph summarization





Project: Building a Context Graph Generator

Sourel: https://stanford-cs329s.github.io/reports/context-graph-generator/

Exercise: High-level design

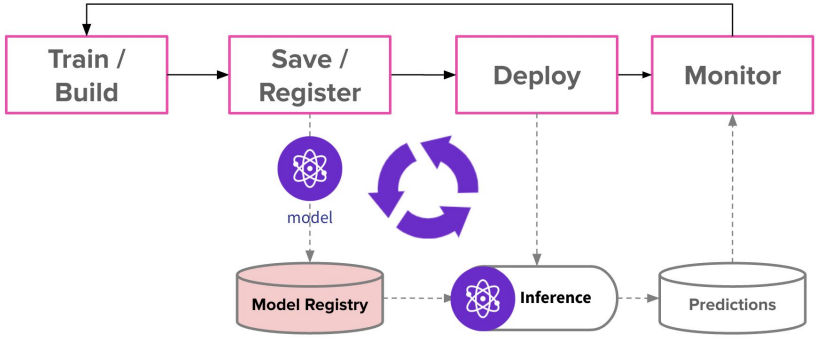
How to ensure generalization and robustness?

Group task:

- Create a draft of the ML System Architecture. Complete the Production ML System Design section:
  - 5.1 - High-level design
- 5 min

Key points:

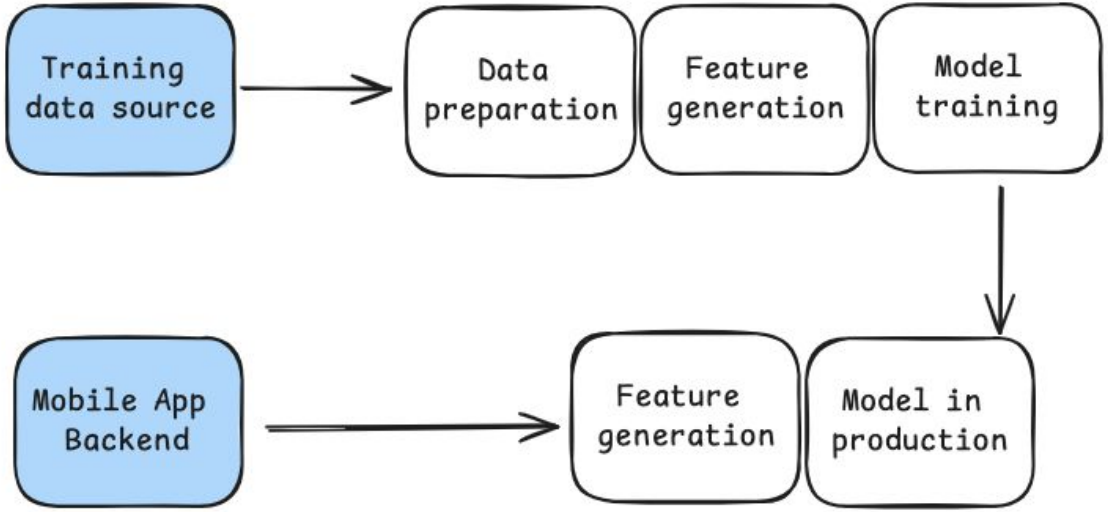
- System architecture diagram regardless of tools/services you use
- Data flow and processing pipeline
- Integration with existing infrastructure



Practice

5.1 - High-level design

What are the key components of the ML System?

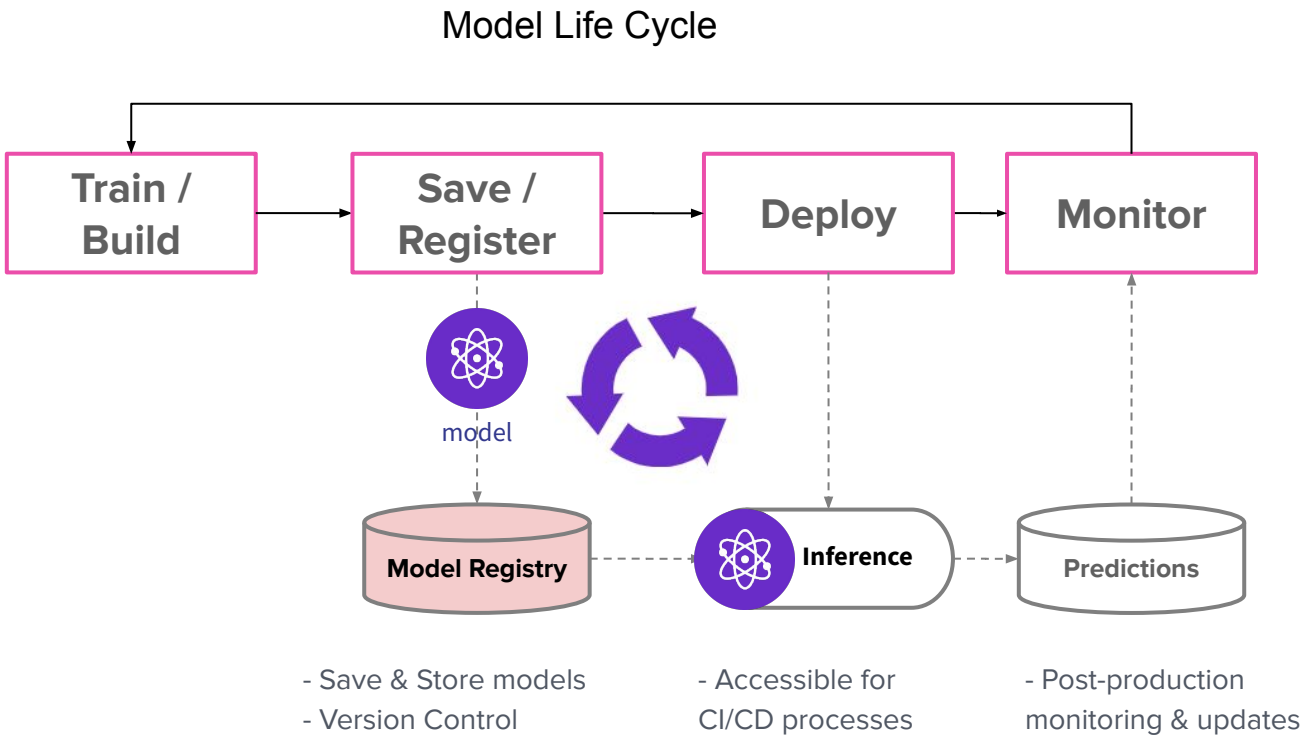


Example

Deployment and Serving

Production ML System Design
> Guide: 5.2 - Deployment and Serving

Deployment defines details of your system

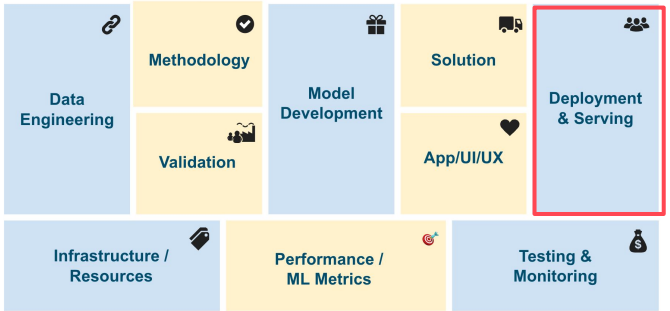


5.2 – Deployment and Serving

How do we deploy and serve the model?

Purpose

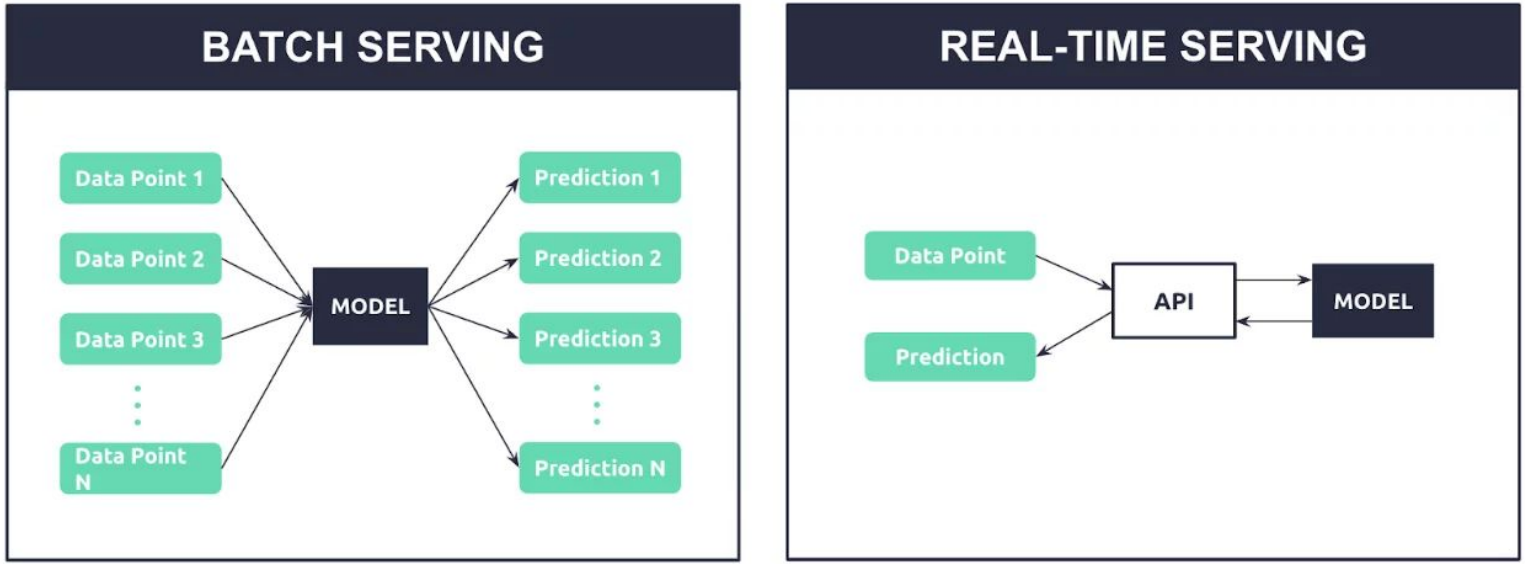
- To ensure smooth deployment and reliable serving of model predictions.



Guiding questions:

- Do we want to perform batch (offline) or real-time (online) inference? What tools should we use?
- What infrastructure is needed to serve the ML service?
- How will we deploy the model with minimal disruption? Do we need human checks? How do we test the models before deployment to be sure they doesn't break prod?
- Do we need to support online A/B testing, canary deployment, etc?

ML inference: batch vs. online



Source: https://www.iguazio.com/glossary/model-serving-pipeline/

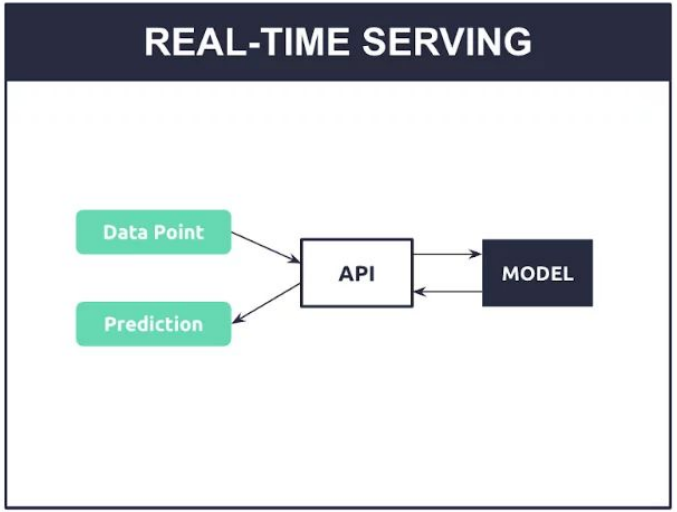
Online Serving

Typical requirements:

- Get predictions on demand
- Latency < 1 sec
- REST API

Applications:

- Chat bot Assistants
- eCommerce Recommendation System



FastAPI Flask mlflow

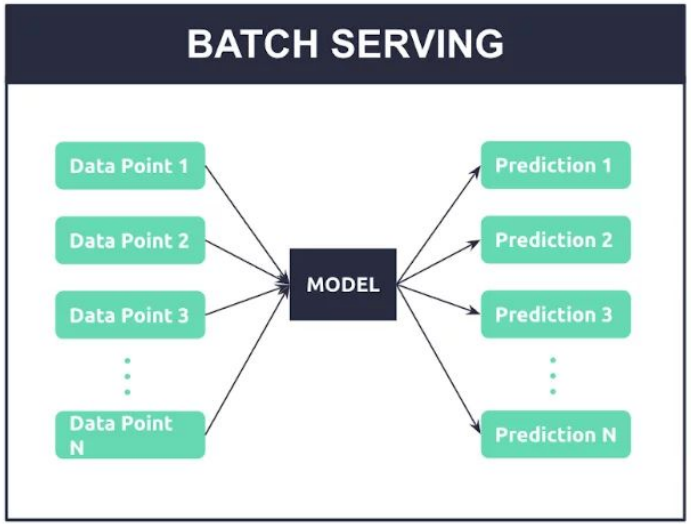
Batch Serving

Typical requirements:

- Get predictions for a large dataset at once
- Latency mins-hours
- Scheduled
- HDFS, S3, Hive, files

Applications:

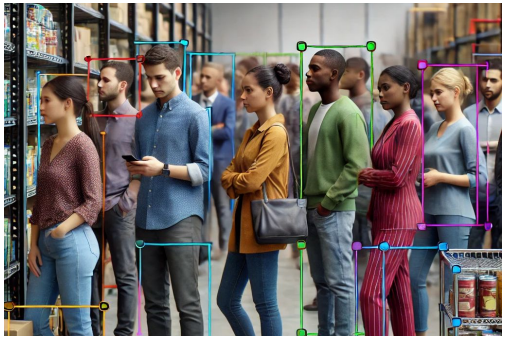
- Sales forecast
- Churn prediction



Apache Airflow PREFECT DVC

Exercise: Select correct deployment method?

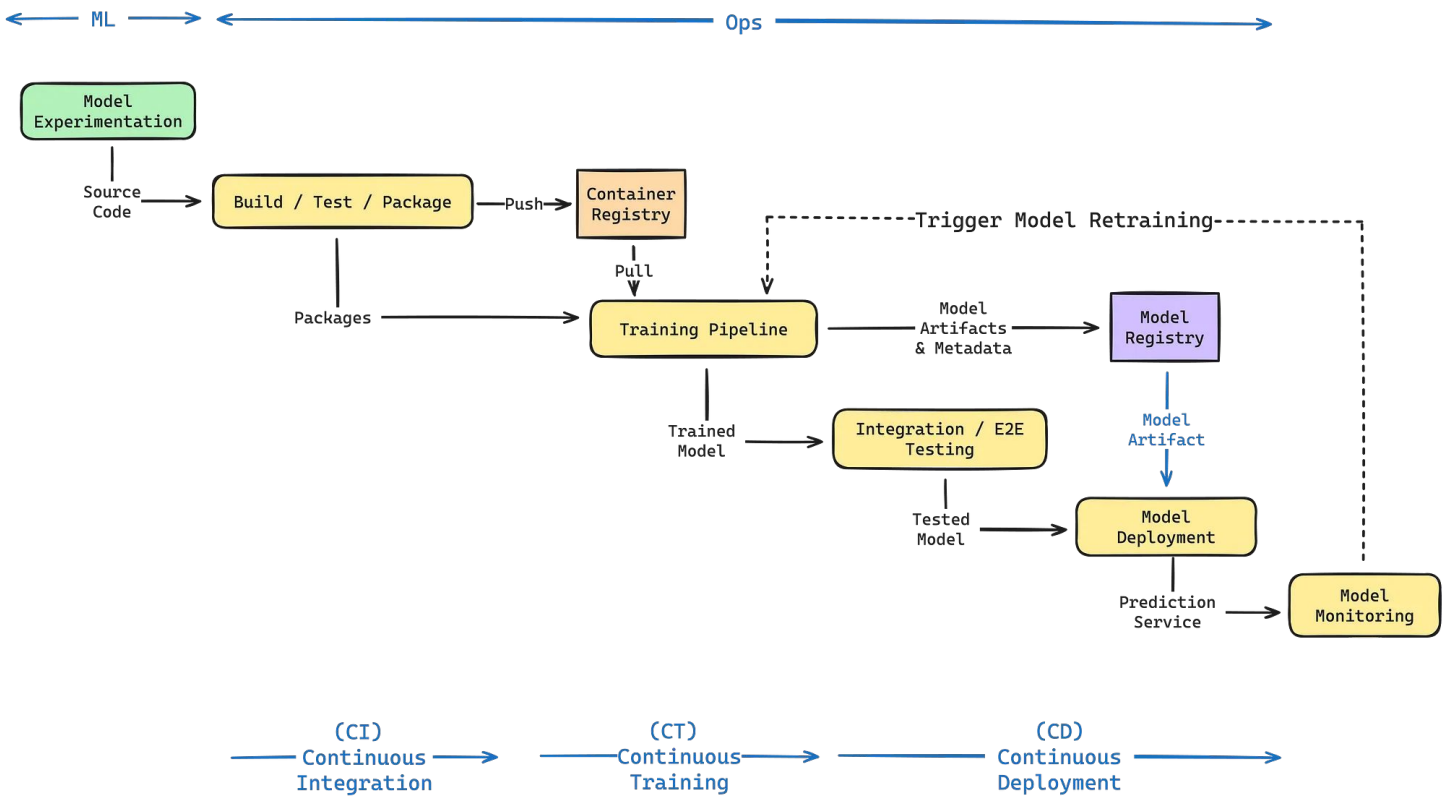
New pizza waiting time prediction



Shop queue detection [CV]

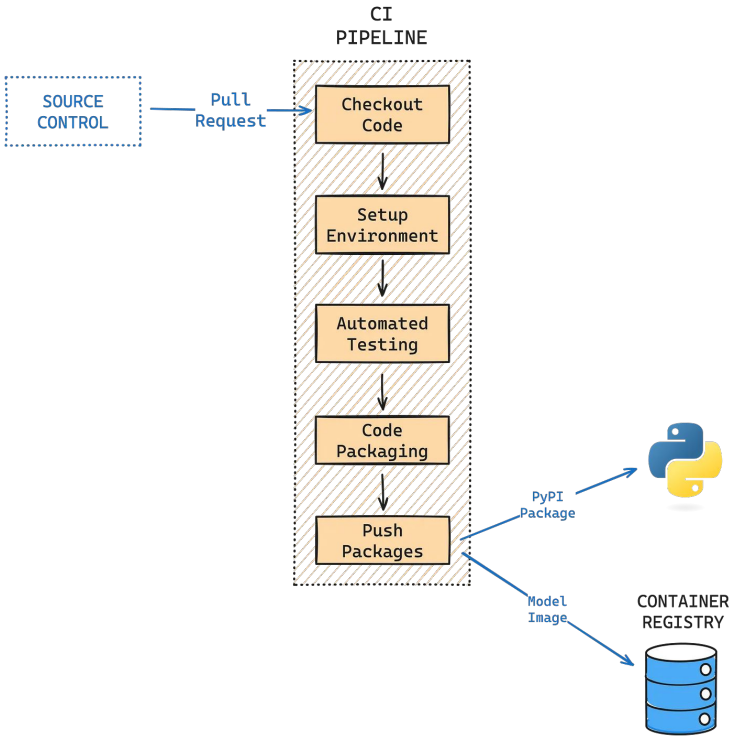
NY Taxi trip duration prediction

CI/CD automates process of Model Deployment



Source: [CI/CD for Machine Learning in 2024: Best Practices to Build, Train, and Deploy]

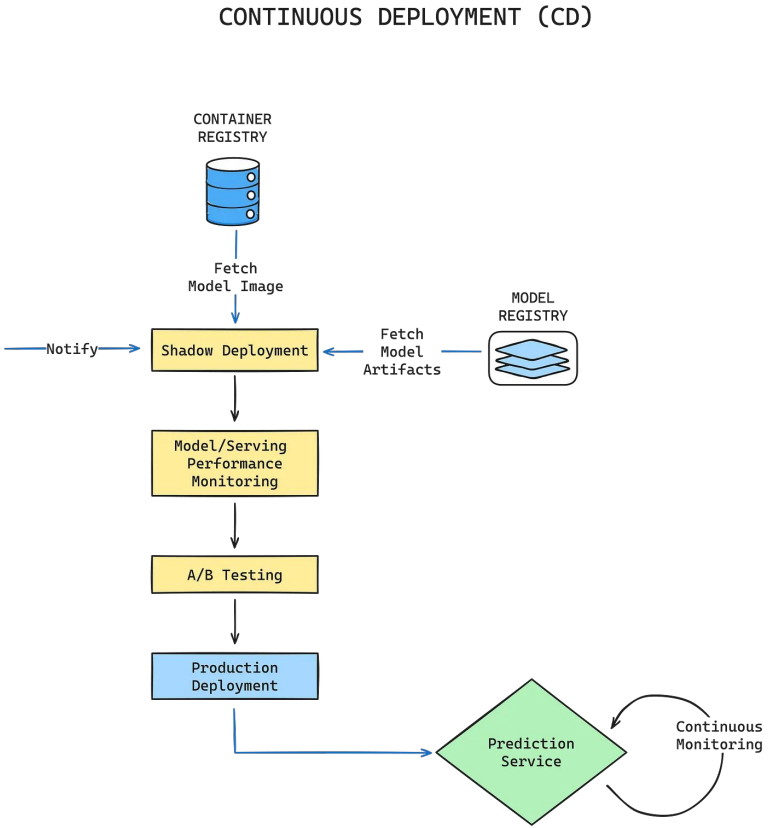
Continuous Integration (CI)



- "Integrates" a new code into the existing code base
- Ensures the code quality and functionality, preparing the codebase for subsequent phases of the ML lifecycle

Source: CI/CD for Machine Learning in 2024: Best Practices to Build, Train, and Deploy

Continuous Deployment (CD)



- the systematic and automated retraining of ML modelsc

Source: CI/CD for Machine Learning in 2024: Best Practices to Build, Train, and Deploy

Exercise: Deployment and Serving

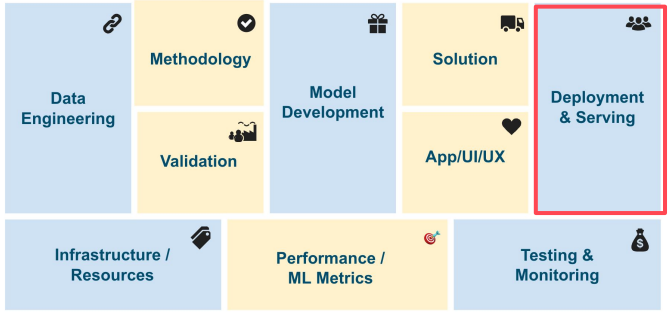
How do we deploy and serve the model?

Group task:

- Complete the Production ML System Design section:
  - 5.2 - Deployment and Serving
- 5 min

Key points:

- Inference Type
- CI/CD approach
- Serving Infrastructure: tools your are going to use for deployment and serving
- Deployment Methodology: important things to consider about deploy



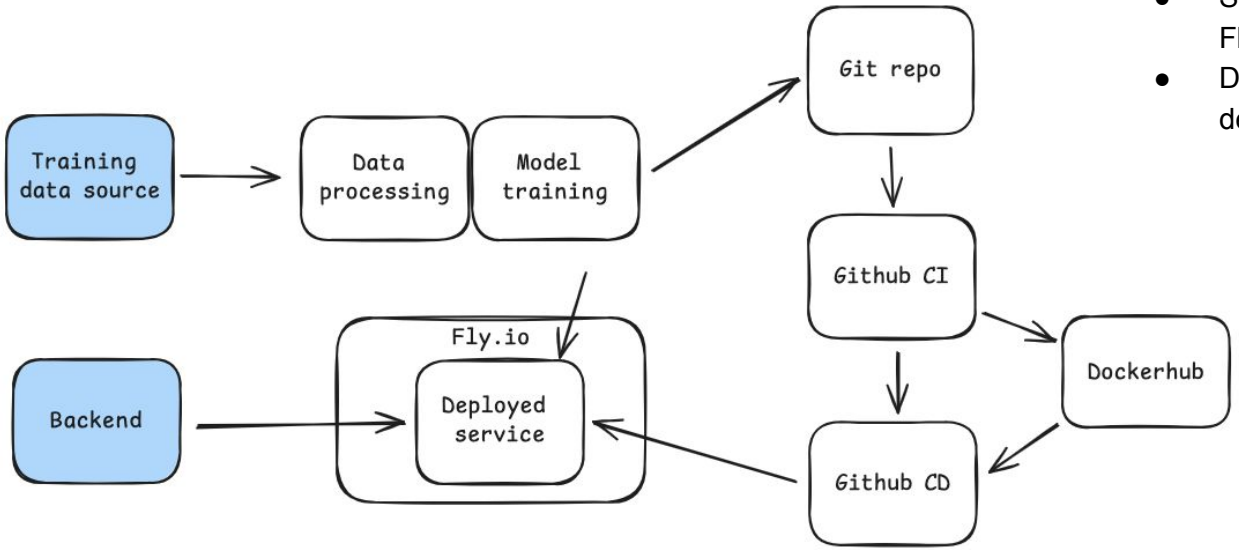
Practice

5.2 – Deployment and Serving

How do we deploy and serve the model?

Overview:

- The deployment involves a CI/CD pipeline, Docker Compose for containerization, and a shadow deployment mode for testing.



Key points:

- Inference Type: Real-time.
- CI/CD: Automated deployment pipeline in GitHub Actions (GHA)
- Serving Infrastructure: FastAPI, Docker, Fly.io
- Deployment Methodology: Shadow deployment.

Example

ML System Design - Production: EasyRide Taxi

Data Engineering

-
-

Methodology

- Problem Type: Regression.
- Approach: Supervised learning.
- Metric: MAPE.
- Baseline: Current predictions.

Validation

- Validation Methodology: Shadow deployment, A/B testing.
- Pilot Scope: 1 week
- Success Criteria: Lower MAPE, higher booking rates.

Model Development

-
-

Solution

- Target: trip duration
- Format: Duration in minutes
- Components: Taxi App, Data Ingestion, ML Solution, Backend

App/UI/UX

- UI: ETA, trip duration and cost/earnings.
- UX: Requesting a ride, viewing the predicted cost, booking the ride.

Deployment & Serving

Inference Type: Real-time.

CI/CD: Automated deployment pipeline in GitHub CI

Serving Infrastructure: FastAPI, Docker, Fly.io, PosgreSQL

Deployment Methodology: Shadow deployment, canary releases.

Infrastructure / Resources

-
-

Performance / ML Metrics

- Prediction accuracy (MAPE) <= 15%
- Prediction latency < 500ms
- Business Metrics: Booking rate, Revenue Increase
- Timeline: Daily metric evaluation.

Testing & Monitoring

-
-

Data Engineering

Production ML System Design
> Guide: 5.3 - Data Engineering

5.3 - Data Engineering

How do we ingest and store data?

Purpose

- To ensure reliable, efficient data processing and feature engineering in production.

Guiding questions:

- How will we handle data ingestion and storage?
- What ETL processes are needed to prepare data for the model?
- How will we track data versions and lineage?

Exercise: Data Engineering

How do we ingest and store data?

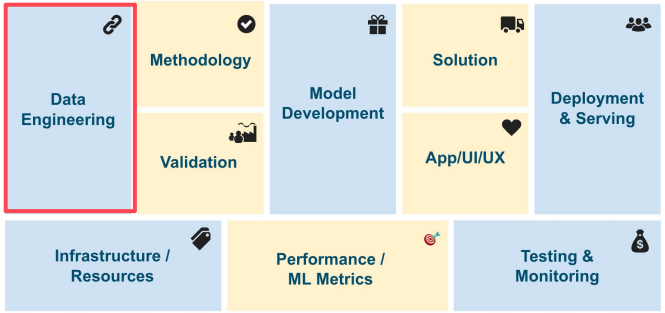
Group task:

- Complete the Production ML System Design section:
  - 5.3 - Data Engineering
- 5 min

Key points:

- Data ingestion and storage solutions
- ETL processes (data pipelines)
- Data versioning and lineage tracking
- Feature Stores (Data Marts)

Practice



5.3 - Data Engineering

How do we ingest and store data?

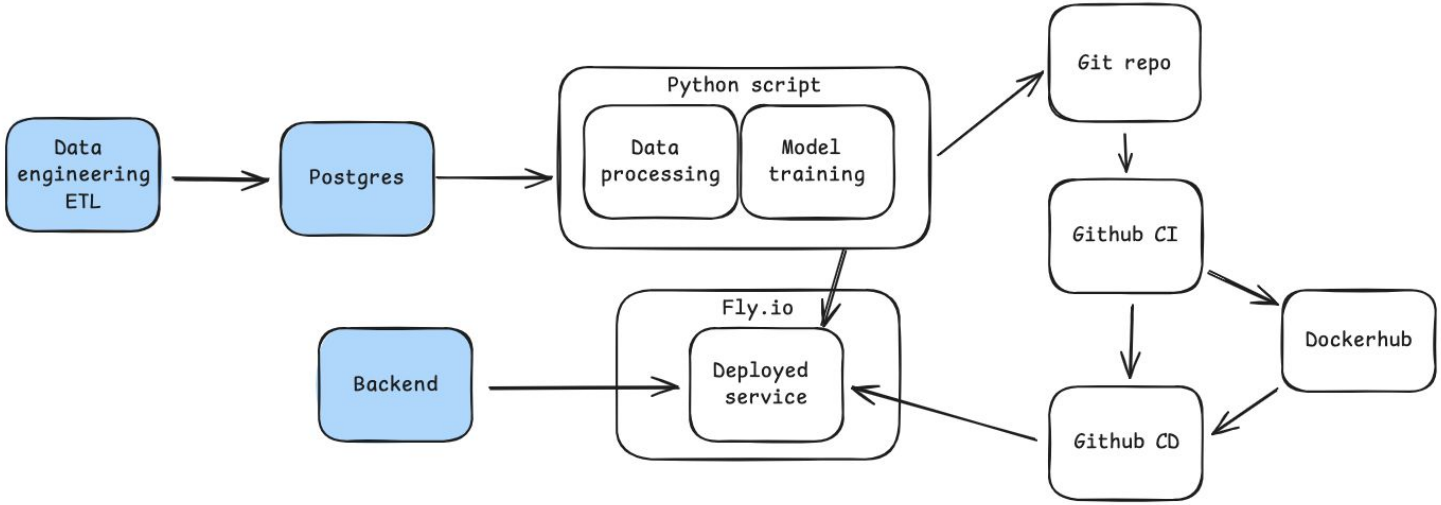
Overview:

- Data is ingested from Postgres, processed via ETL pipelines, and features are stored in a feature store. Data lineage and versioning are tracked.

Key points:

- Data Ingestion: From Postgres every 30 minutes.
- Data Versioning: Ensuring reproducibility.

Example



ML System Design - Production: EasyRide Taxi

Data Engineering

Data Ingestion: From Postgres every 30 minutes.

ETL Processes: Data cleaning, feature engineering.

Data Versioning: Ensuring reproducibility.

Methodology

Problem Type: Regression.

Approach: Supervised learning.

Metric: MAPE.

Baseline: Current predictions.

Validation

Validation Methodology: Shadow deployment, A/B testing.

Pilot Scope: 1 week

Success Criteria: Lower MAPE, higher booking rates.

Model Development

Solution

Target: trip duration

Format: Duration in minutes

Components: Taxi App, Data Ingestion, ML Solution, Backend

App/UI/UX

UI: ETA, trip duration and cost/earnings.

UX: Requesting a ride, viewing the predicted cost, booking the ride.

Deployment & Serving

Inference Type: Real-time.

CI/CD: Automated deployment pipeline in GitHub CI

Serving Infrastructure: FastAPI, Docker, Fly.io, PosgreSQL

Deployment Methodology: Shadow deployment, canary releases.

Infrastructure / Resources

Performance / ML Metrics

Prediction accuracy (MAPE) <= 15%

Prediction latency < 500ms

Business Metrics: Booking rate, Revenue Increase

Timeline: Daily metric evaluation.

Testing & Monitoring

Model Development

Production ML System Design
> Guide: 5.4 - Model Development Lifecycle

5.4 – Model Development Lifecycle

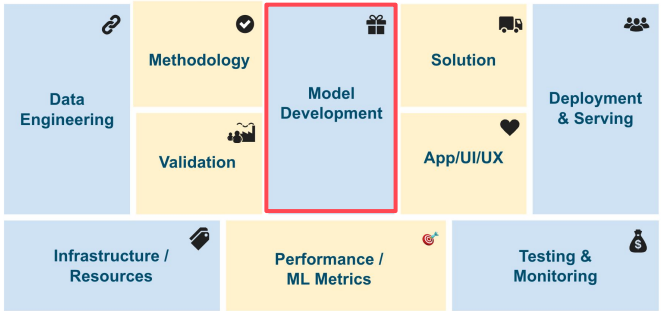
How to ensure reproducibility and reliability?

Purpose

- To ensure continuous improvement and reliable updates to the ML system..

Guiding questions:

- How to organize training in a pipeline?
- How often to re-train? When to do that?
- How will we manage model versions? Where we store them? How do we start a deployment process?



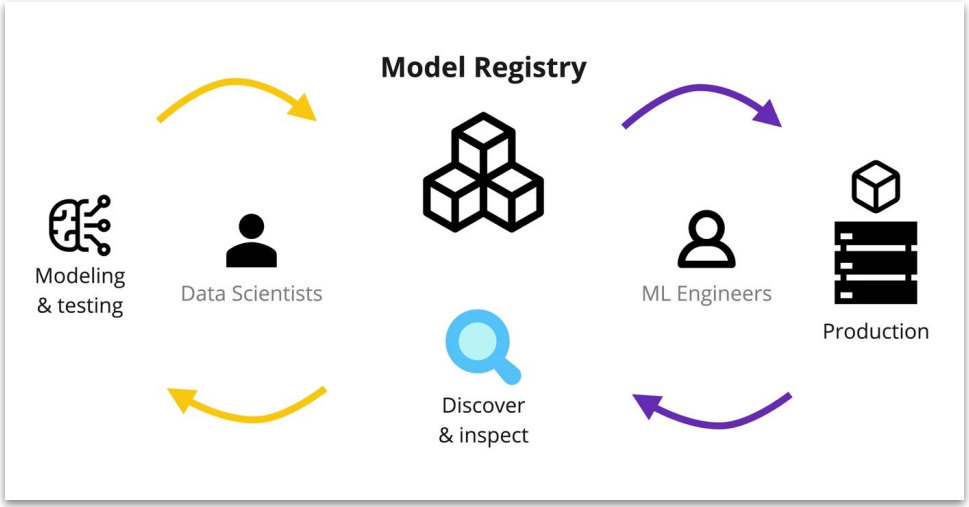
Requirements for efficient Model Development

- Model versioning & registering
- Pipelines Automation
- Reproducibility
- Metrics Tracking
- Continuous Training (CT)

What is a Model Registry?

Model Registry is a centralized repository that manages and stores machine learning models:

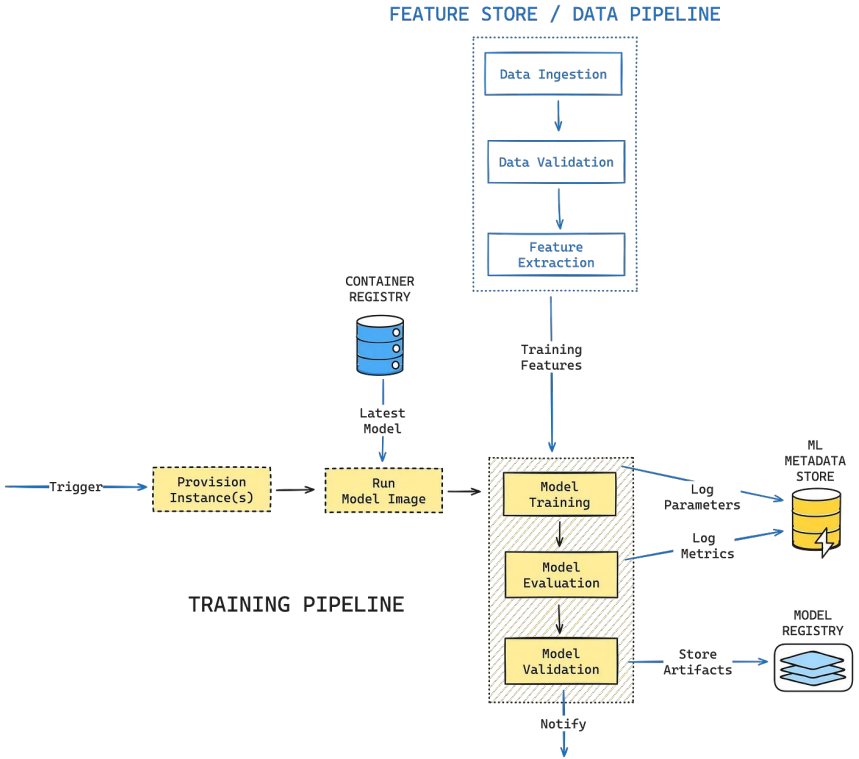
- to discover
- to track changes to models
- to version
- to deploy
- to share & collaborate



MLOps from modeling to production
Source: https://dvc.org/doc/use-cases/model-registry

mlflow Model Registry DVC

Continuous Training (CT)

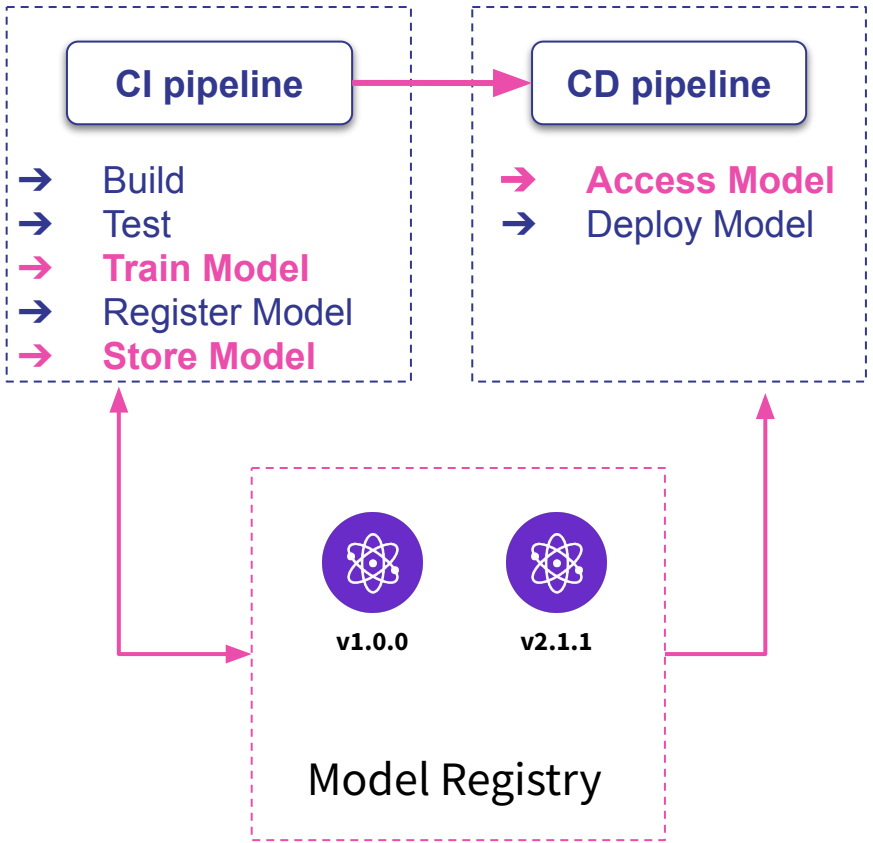


- the systematic and automated retraining of ML modelsc

Source: [CI/CD for Machine Learning in 2024: Best Practices to Build, Train, and Deploy]

Automated CI/CD pipelines: train & register

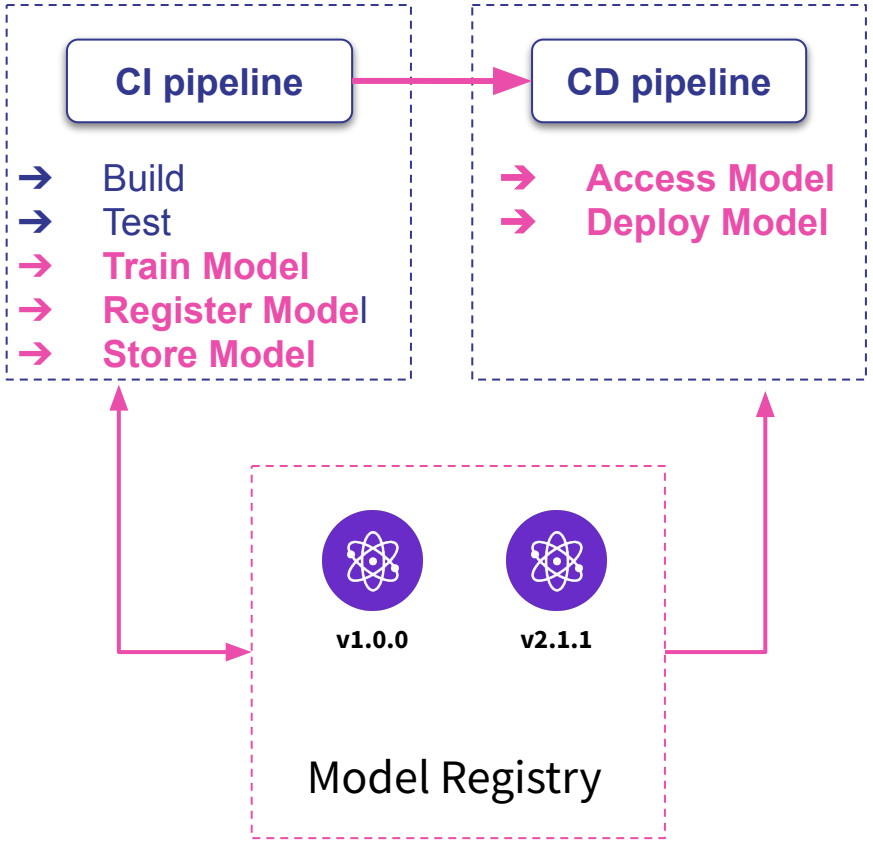
```yaml
name: Train
...
jobs:
  deploy-runner:
    runs-on: ubuntu-latest
    steps:
        ...
        run: |
          cml runner \
              --cloud-spot \
              --cloud=aws \
              --cloud-region=us-east-1 \
              --cloud-type=g4dn.xlarge \
              --labels=cml-runner
  train-model:
    needs: deploy-runner
    runs-on: [self-hosted, cml-runner]
    container:
      image: iterativeai/cml:0-dvc2-base1
      options: --gpus all
    environment: cloud
    steps:
      - name: dvc-repro-cml
        run: |
          dvc pull
          dvc exp run
          dvc push
          ...
          # Create CML report
          echo "## Metrics" >> report.md
          dvc metrics show --md >> report.md
          cml send-comment --pr --update report.md
```



Automated CI/CD pipelines: deploy

```yaml
name: Act on artifact registrations and promotions
on:
  push:
    tags:
      - "*"

jobs:
  act:
    name: Figure out what was registered/promoted and act on it
    runs-on: ubuntu-latest
    steps:
    - uses: actions/checkout@v3
    - name: "Model Registry scenarios"
      id: gto
      uses: iterative/gto-action@v1
    # ...

    - name: "Publish: on registering a new version"
      if: steps.gto.outputs.event == 'registration'
      run: |
        echo "Version '${{ steps.gto.outputs.version }}' "
        echo "Model '${{ steps.gto.outputs.name }}' "
        echo "Run command to publish it!"

    - name: "Deploy: on assigning a new stage)"
      if: steps.gto.outputs.event == 'assignment'
      run: |
        echo "Model '${{ steps.gto.outputs.name }}' of version '${{
        steps.gto.outputs.version }}' promoted to stage '${{ steps.
        gto.outputs.stage }}'"

        echo "Run command to deploy it!"
```

Example: https://github.com/iterative/example-gto/tree/main



Exercise: Model Development

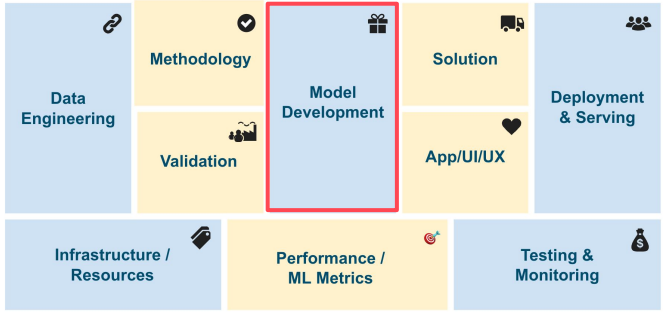
How do we ingest and store data?

Group task:

- Complete the Production ML System Design section:
  - 5.4 - Model Development Lifecycle
- 5 min

Key points:

- Requirements for automation, reproducibility, reliability
- Model versioning
- Model updating and retraining process
- Model Registry



Practice

5.4 – Model Development Lifecycle

How do we ingest and store data?

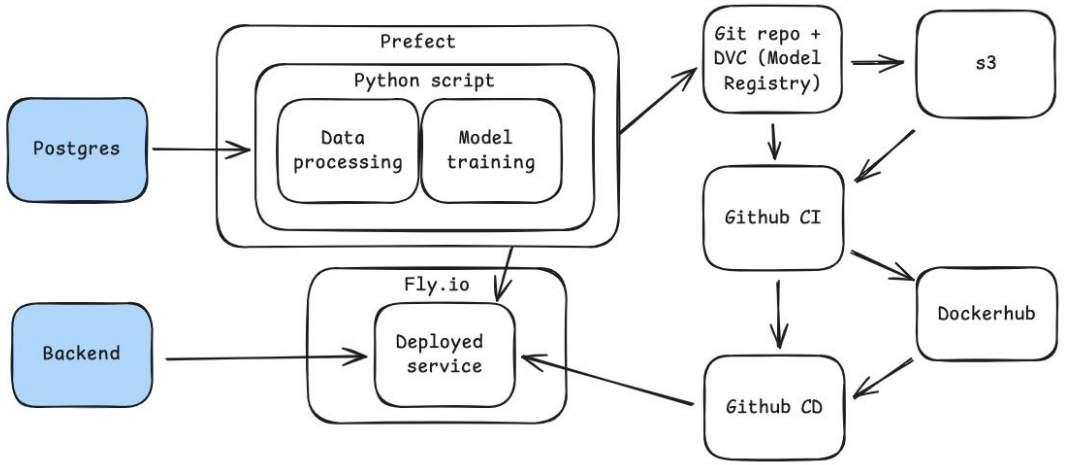
Overview:

- The model development follows a CI/CD pipeline with automated training, versioning using DVC, and deployment via Docker.

Key points:

- Automation: Training, deployment automation.
- Versioning: Model Registry with DVC.
- CI/CD: Continuous integration and deployment pipeline.

Example



ML System Design - Production: EasyRide Taxi

Data Engineering

Data Ingestion: From Postgres every 30 minutes.

ETL Processes: Data cleaning, feature engineering.

Data Versioning: Ensuring reproducibility.

Methodology

Problem Type: Regression.

Approach: Supervised learning.

Metric: MAPE.

Baseline: Current predictions.

Validation

Validation Methodology: Shadow deployment, A/B testing.

Pilot Scope: 1 week

Success Criteria: Lower MAPE, higher booking rates.

Model Development

Automation: Training, deployment automation.

Versioning: Model Registry with DVC.

CI/CD: Continuous integration and deployment pipeline.

Solution

Target: trip duration

Format: Duration in minutes

Components: Taxi App, Data Ingestion, ML Solution, Backend

App/UI/UX

UI: ETA, trip duration and cost/earnings.

UX: Requesting a ride, viewing the predicted cost, booking the ride.

Deployment & Serving

Inference Type: Real-time.

CI/CD: Automated deployment pipeline in GitHub CI

Serving Infrastructure: FastAPI, Docker, Fly.io, PosgreSQL

Deployment Methodology: Shadow deployment, canary releases.

Infrastructure / Resources

Performance / ML Metrics

Prediction accuracy (MAPE) <= 15%

Prediction latency < 500ms

Business Metrics: Booking rate, Revenue Increase

Timeline: Daily metric evaluation.

Testing & Monitoring

Testing and Monitoring

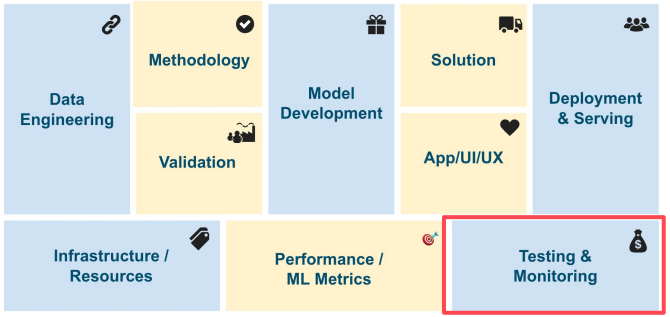
Production ML System Design
> Guide: 5.5 - Testing and Monitoring

5.5 - Testing and Monitoring

What is the post-training quality assurance processes?

Purpose

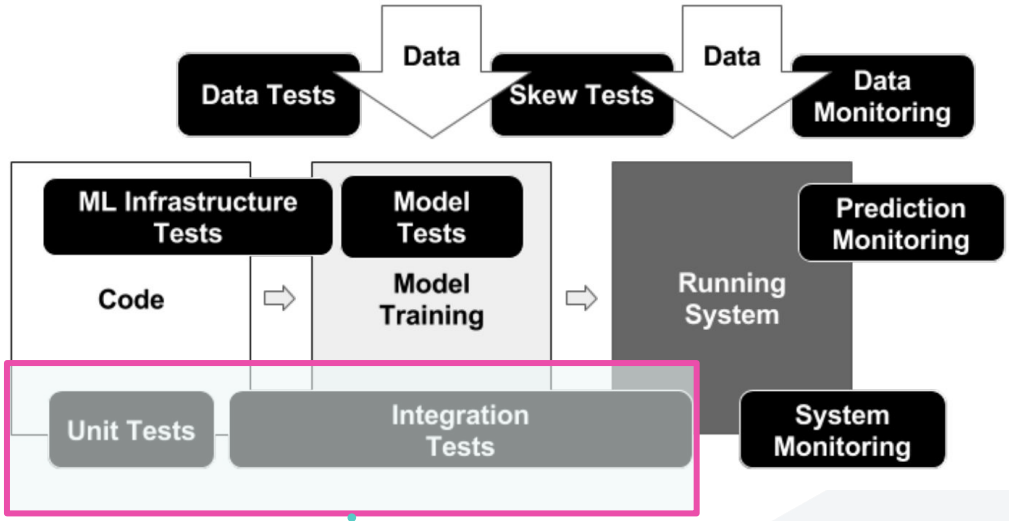
- To maintain system reliability and catch issues before they impact business operations.



Guiding questions:

- How will we monitor the system's performance in production?
- What testing procedures will ensure system reliability?
- How will we maintain quality as the system evolves?
- How we understand the model performs well?
- How will you log events in your system? What metrics will you monitor and how? Will you have alarms if a metric breaches a threshold or something else goes wrong?
- What are model and data metrics to track?

ML testing VS. traditional software testing



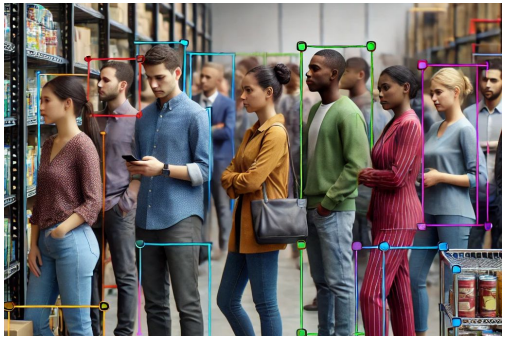
Traditional tests

Image source: The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction" Breck et al. (2017)
https://research.google/pubs/pub46555/

Exercise: What should we car about?

Brainstorming on testing and monitoring needs

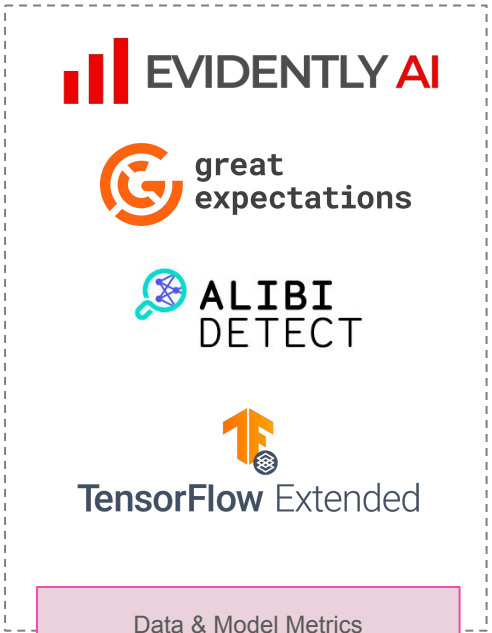
New pizza waiting time prediction

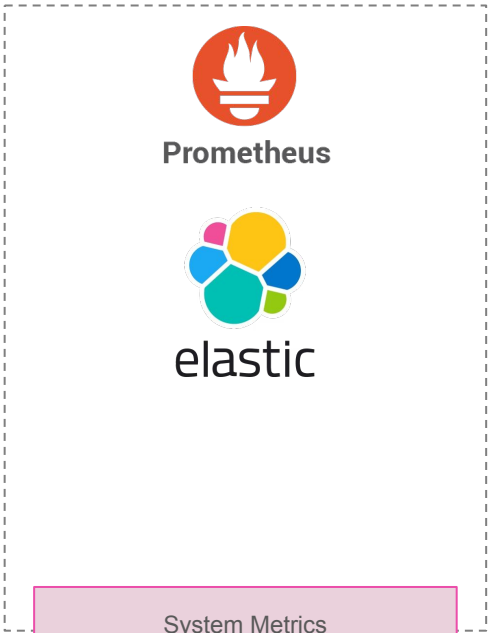


Shop queue detection [CV]

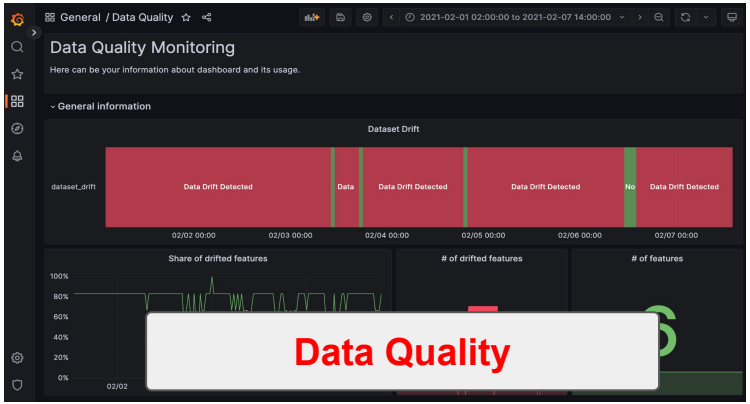
NY Taxi trip duration prediction

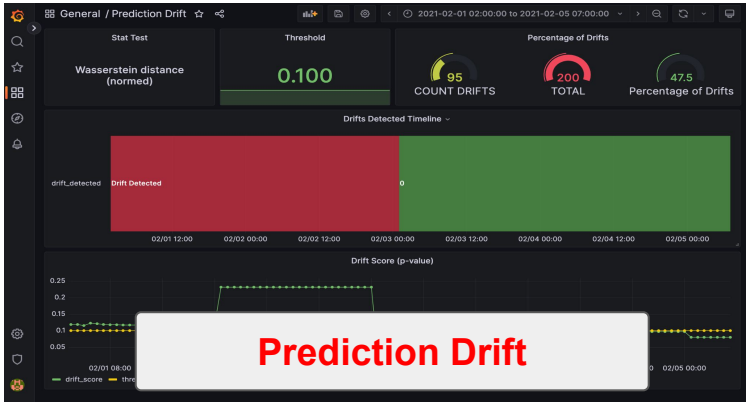
Monitoring tools

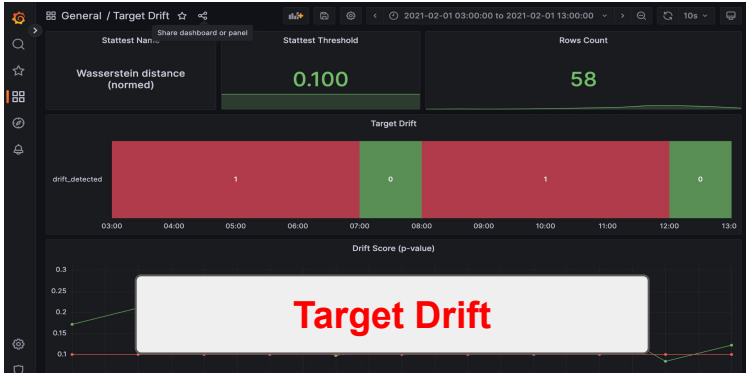




Model Monitoring: Evidently + Grafana







Exercise: Testing and Monitoring

How do we ingest and store data?

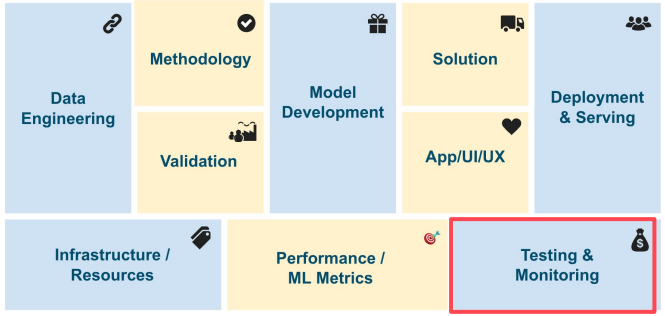
Group task:

- Complete the Production ML System Design section:
  - 5.5 - Testing and Monitoring
- 5 min

Key points:

- Testing strategy (unit, integration, system tests) and important tests
- Monitoring system design
- Monitoring metrics
- Biases and misuses of your model (if applicable)

Practice



5.5 – Testing and Monitoring

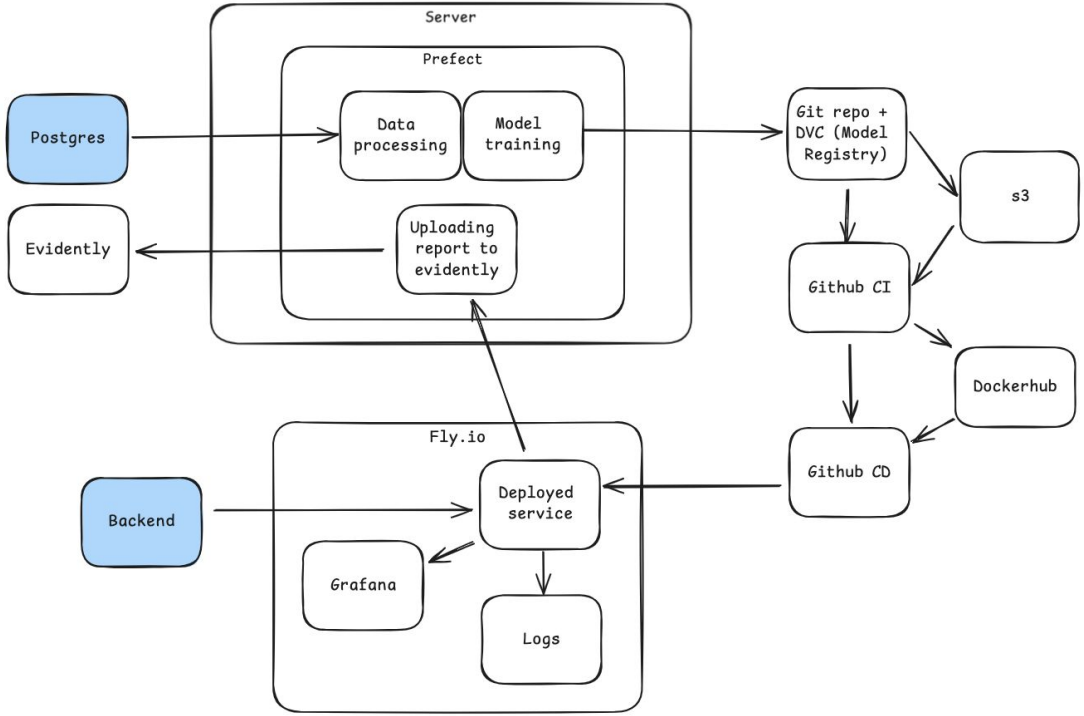
How do we ingest and store data?

Overview:

- System quality is maintained through rigorous testing and monitoring, including unit tests, integration tests, and performance monitoring using Evidently.

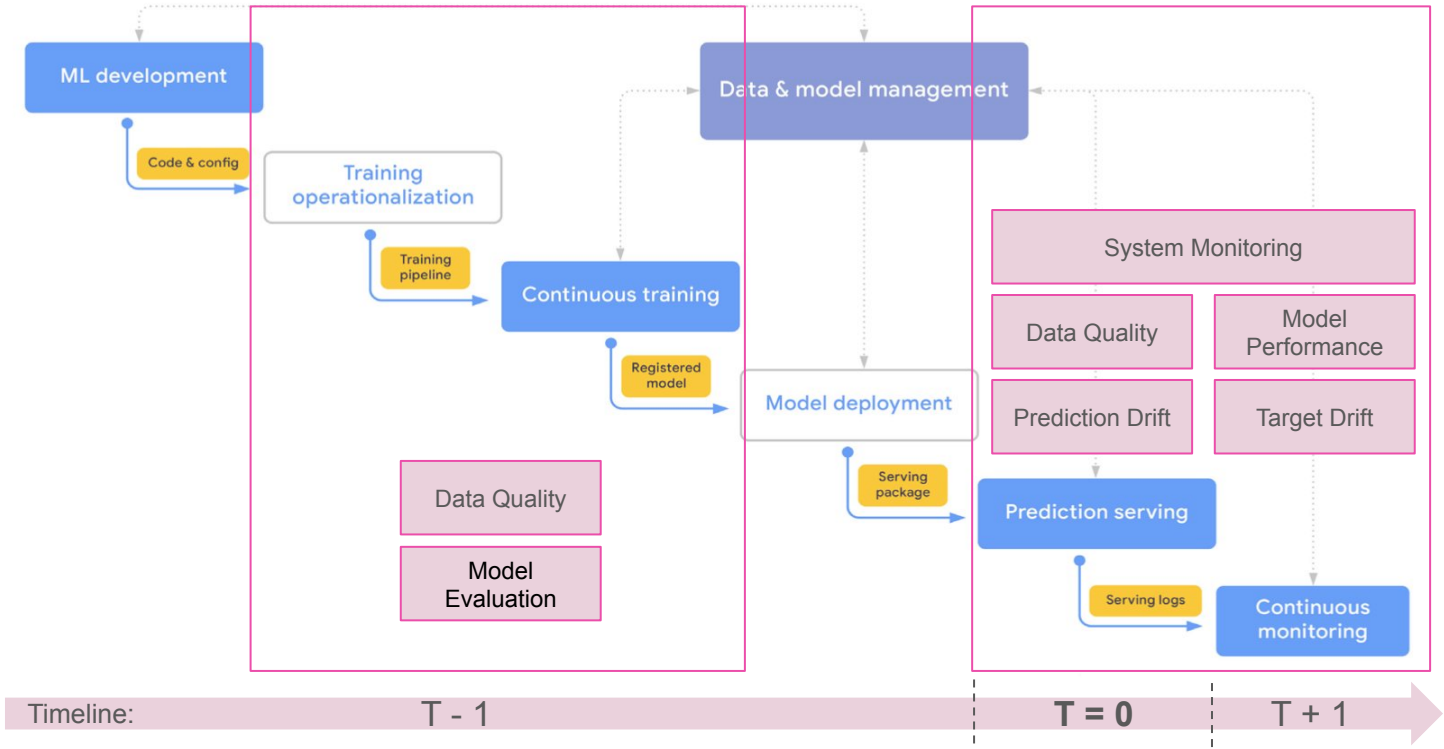
Key points:

- Monitoring: Performance metrics, alerts.
- Testing Strategy: Unit, integration, system tests.
- Quality Assurance: Regular testing/monitoring.



Example

Data monfrom a prototype to monitoring



Source: https://services.google.com/fh/files/misc/practitioners_guide_to_mlops_whitepaper.pdf

ML System Design - Production: EasyRide Taxi

Data Engineering

Data Ingestion: From Postgres every 30 minutes.

ETL Processes: Data cleaning, feature engineering.

Data Versioning: Ensuring reproducibility.

Methodology

Problem Type: Regression.

Approach: Supervised learning.

Metric: MAPE.

Baseline: Current predictions.

Validation

Validation Methodology: Shadow deployment, A/B testing.

Pilot Scope: 1 week

Success Criteria: Lower MAPE, higher booking rates.

Model Development

Automation: Training, deployment automation.

Versioning: Model Registry with DVC.

CI/CD: Continuous integration and deployment pipeline.

Solution

Target: trip duration

Format: Duration in minutes

Components: Taxi App, Data Ingestion, ML Solution, Backend

App/UI/UX

UI: ETA, trip duration and cost/earnings.

UX: Requesting a ride, viewing the predicted cost, booking the ride.

Deployment & Serving

Inference Type: Real-time.

CI/CD: Automated deployment pipeline in GitHub CI

Serving Infrastructure: FastAPI, Docker, Fly.io, PosgreSQL

Deployment Methodology: Shadow deployment, canary releases.

Infrastructure / Resources

-
-

Performance / ML Metrics

Prediction accuracy (MAPE) <= 15%

Prediction latency < 500ms

Business Metrics: Booking rate, Revenue Increase

Timeline: Daily metric evaluation.

Testing & Monitoring

Monitoring: Performance metrics, alerts.

Testing Strategy: Unit, integration, system tests.

Quality Assurance: Regular testing and monitoring.

Scalability and Infrastructure

Production ML System Design

> Guide: 5.6 - Scalability and Infrastructure Planning

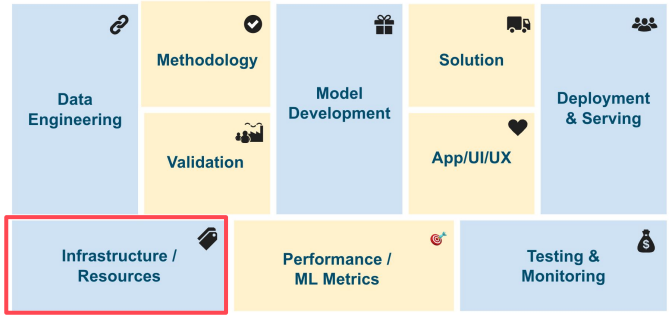
> Guide: 5.7 - Requirements & Constraints

5.6 – Scalability and Infrastructure

What infrastructure do we need?

Purpose

- To ensure the system can grow with the business and handle increased load.

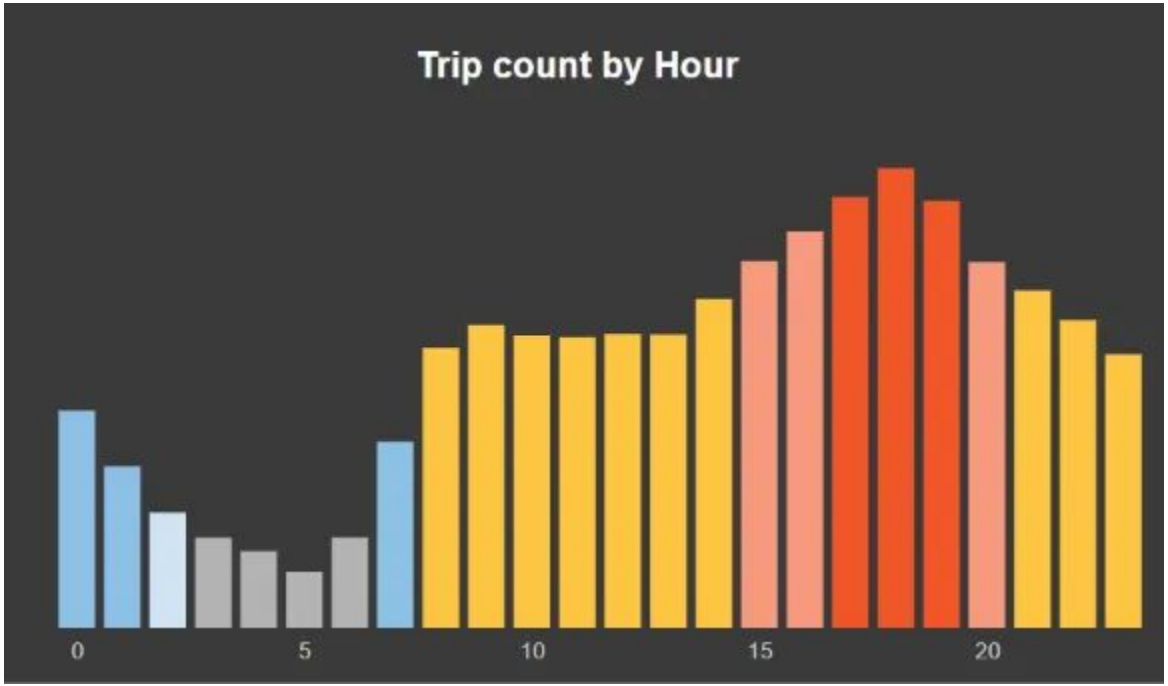


Guiding questions:

- What infrastructure do you need to train and serve the model (CPU, GPU…)?
- How will you host your system? On-premise, cloud, or hybrid?
- How will your system meet the performance (throughput and latency) requirements? Will it scale vertically or horizontally?
- How much will it cost to build and operate your system? Share estimated monthly costs (e.g., EC2 instances, Lambda, etc.)

Exercise: NY Taxi trip counts by hour

Calculate costs for a static and flexible serving infrastructure



Source: https://medium.com/@dustinhsu0605/nyc-taxi-trips-challenge-646a89a05bfd

Exercise: Scalability and Infrastructure

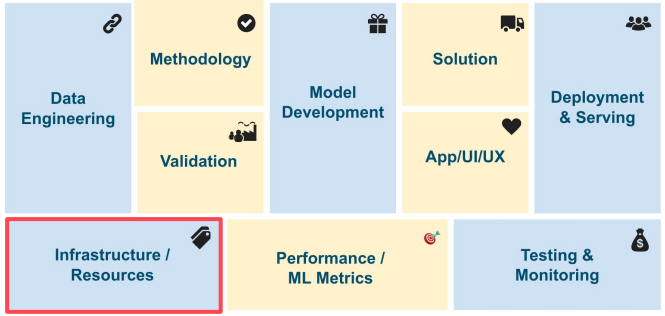
How do we ingest and store data?

Group task:

- Complete the Production ML System Design section:
  - 5.6 - Scalability and Infrastructure
- 5 min

Key points:

- Infrastructure requirements (CPU, GPU…)
- Scalability requirements and approach
- Infrastructure costs



Practice

5.6 – Scalability and Infrastructure

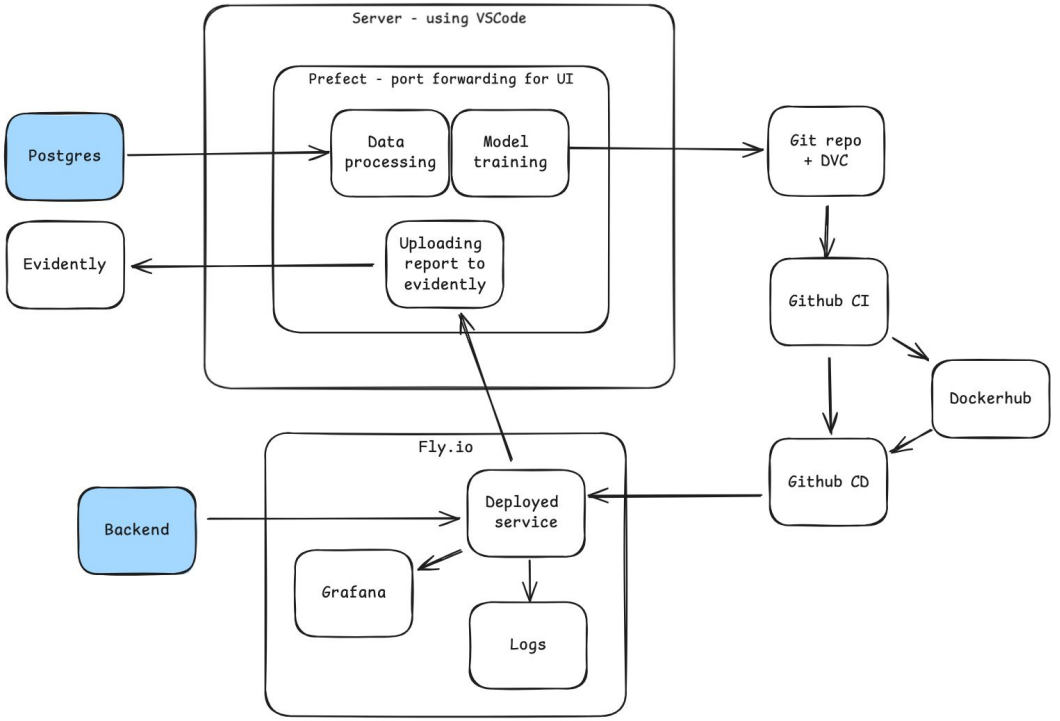
How do we ingest and store data?

Overview:

- The system is designed for scalability, with plans for future infrastructure growth and performance optimization strategies.

Key points:

- Cloud: Fly.io
- Resources:
  - ETL & Train: 16GB RAM, 4vcpu
  - Inference: 1GB RAM, 1vcpu
- Scalability: Not required at this step



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Business Metrics: Booking rate, Revenue Increase

Timeline: Daily metric evaluation.

Testing & Monitoring

Monitoring: Performance metrics, alerts.

Testing Strategy: Unit, integration, system tests.

Quality Assurance: Regular testing and monitoring.

Assignment

Start with Production ML System Design!

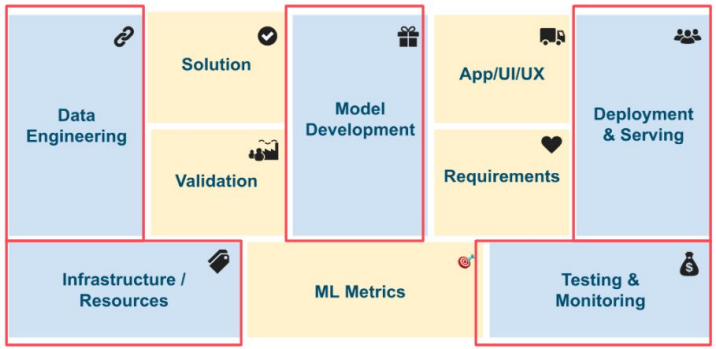
Prerequisites

- Complete ML Product Design: Business Understanding
- Complete ML Product Design: Solution
- Complete ML Product Design: Methodology

Practice: Production ML System

Automate and scale!

- Brainstorm a Production ML System design for for your project
- Follow the guide to describe each section in **Production ML System**
- Summarise **Production ML System** on the canvas
- Update “ML Solution” blocks if needed
- Update the “Cost Structure” if needed



Materials & Links

- Course Materials: Google Drive
- Practice - EasyRide Taxi - PUBLIC
- Guide - ML System Design - Canvas