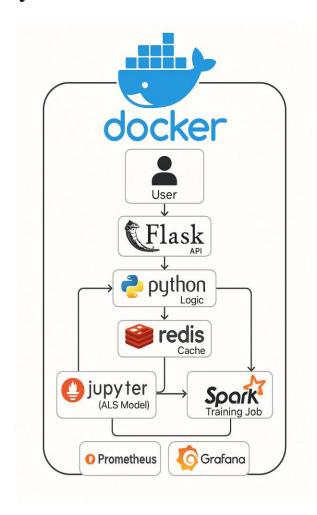
Netflix- Redis-Cache-Recommendation Engine

A full-stack, end-to-end ML pipeline simulating a real-world recommendation system for a streaming service. This project includes data ingestion, model training with Spark, REST API serving via Flask, Redis caching, Prometheus + Grafana monitoring, and containerized orchestration using Docker Compose.

☐ Technologies Used

- Docker + Docker Compose
- Apache Spark (PySpark)
- Redis
- Flask
- Prometheus & Grafana
- Jupiter Notebook (for exploration)

☐ System Architecture



☐ Project Structure

```
docker-compose.yml
prometheus.yml
flask-api/
app.py
Dockerfile
requirements.txt
jupyter/
train_model.py
data/
synthetic_streaming_data.csv
grafana/ (provisioning dashboards)
```

☐ Docker Compose Setup

docker-compose up --build

Access:

- Flask API: http://localhost:5000
- Prometheus: http://localhost:9090
- Grafana: http://localhost:3000
- Jupyter Notebook: http://localhost:8888

☐ Prometheus Configuration

```
global:
 scrape interval: 15s
 evaluation interval: 15s
 scrape timeout: 10s
scrape configs:
 - job name: 'prometheus'
    static configs:
      - targets: ['prometheus:9090']
  - job name: 'node-exporter'
    static configs:
      - targets: ['metrics-server:9100']
  - job name: 'flask-api'
    static_configs:
      - targets: ['flask-api:5000']
  - job name: 'jupyter-notebook'
    static configs:
      - targets: ['host.docker.internal:8001']
```

☐ Flask API Endpoints

- GET /health Health check
- POST /watched Simulates a user watching a film

```
{
   "user_id": "U1001",
   "content_id": "C1010"
}
```

- GET /recommend/<user id> Returns recommendation
- GET /metrics Prometheus metrics

■ Monitoring

- Prometheus scrapes metrics from Flask and Jupyter
- Grafana dashboards show:
 - Cache hits & misses
 - Fallback usage
 - o Model training runtime

☐ ML Training Pipeline

Location: train model.py

- Loads streaming data
- Encodes user id and content id
- Trains ALS (collaborative filtering) model
- Caches top recommendation for each user into Redis

Sample Output:

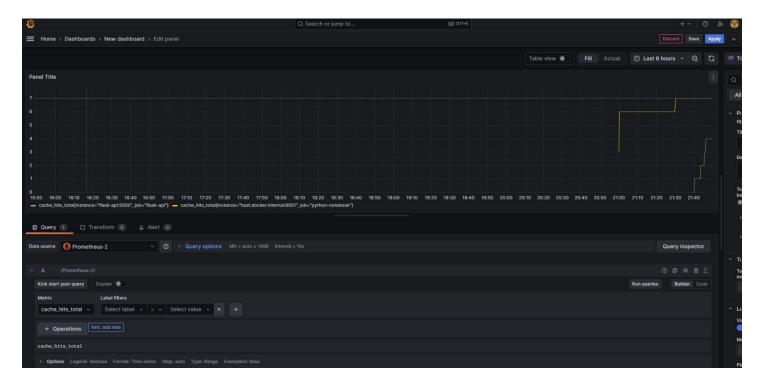
☐ Screenshots

\square Recommendation Output:

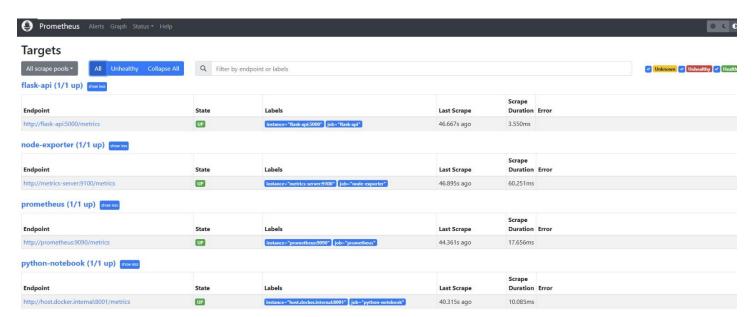
\$ curl http://localhost:5000/recommend/U1001

{ "cache_hit":true, "recommendation": "C1045", "user_id": "U1001"}

☐ Grafana Dashboard:



☐ API with Prometheus Metrics:



♥TODO Next Add Kafka ingestion Replace fallback logic with real-time inference Federated learning for edge recommendations **Maintainer** Built by Rahul Raj - striving for ML-powered personalized streaming. ☐ License MIT License **Netflix-Style Recommendation System Demo Overview** This project showcases a real-time, containerized recommendation pipeline using Docker Compose. It integrates services like Spark, Flask API, Redis, Prometheus, and Grafana to simulate a Netflix-style recommendation system. **∜Step 1: Show the System is Running** ☐ Narration: "I've containerized and automated the entire Netflix-style recommendation pipeline using Docker Compose.

bash CopyEdit docker ps

☐ Command:

Everything you see here is real-time and monitored."

□ Expected Output:

bash CopyEdit				
CONTAINER ID	IMAGE	COMMAND	STATUS	PORTS
abc123	spark	"/bin/bash"	Up 5 minutes	
def456	jupyter	"start-notebook.sh"	Up 5 minutes	
ghi789	flask-api	"python app.py"	Up 5 minutes	5000/tcp
jk1012	redis	"docker-entrypoint.sh"	Up 5 minutes	6379/tcp
mno345	prometheus	"/bin/prometheus"	Up 5 minutes	9090/tcp
pqr678	grafana	"/run.sh"	Up 5 minutes	3000/tcp

☐ Screenshot Placeholder:

Insert a screenshot of the terminal displaying the docker ps output.

∜Step 2: Simulate a User Watching a Movie

☐ Narration:

"Let's say user U999 watches C1010, which is, say, Stranger Things. The system automatically predicts and caches the next likely show."

☐ Command:

```
bash
CopyEdit
curl -X POST http://localhost:5000/watched \
  -H "Content-Type: application/json" \
  -d '{"user_id": "U999", "content_id": "C1010"}'
```

☐ Expected Response:

```
json
CopyEdit
{
    "user_id": "U999",
    "watched": "C1010",
    "predicted_next": "C1045"
}
```

☐ Screenshot Placeholder:

Insert a screenshot of the terminal displaying the curl response.

∜Step 3: Retrieve Cached Recommendation

☐ Narration:

"Now, the user comes back to the app and asks: what should I watch next? We instantly return the prediction from Redis."

☐ Command:

```
bash
CopyEdit
curl http://localhost:5000/recommend/U999
```

☐ Expected Response:

```
json
CopyEdit
{
   "user_id": "U999",
   "recommendation": "C1045",
   "cache_hit": true
}
```

☐ Screenshot Placeholder:

Insert a screenshot of the terminal displaying the curl response.

∜Step 4: Handle New User Scenario

☐ Narration:

"If the user is new and we don't have predictions yet, the system handles it gracefully with a fallback."

☐ Command:

```
bash
CopyEdit
curl http://localhost:5000/recommend/U1234
```

☐ Expected Response:

```
json
CopyEdit
{
    "user_id": "U1234",
    "recommendation": "C000",
    "cache_hit": false,
    "fallback_used": true
}
```

☐ Screenshot Placeholder:

Insert a screenshot of the terminal displaying the curl response.

♥Step 5: Monitor System Metrics with Prometheus ☐ Narration: "We also expose Prometheus metrics for system health and activity." ☐ Access: Navigate to http://localhost:9090 in your browser. ☐ Metrics to Observe: cache hits cache misses fallbacks used ☐ Screenshot Placeholder: Insert a screenshot of the Prometheus dashboard displaying the relevant metrics. **∜Step 6: Visualize Data with Grafana** ☐ Narration: "Here's the Grafana dashboard tracking live recommendations, cache efficiency, fallback trends, and more." ☐ Access: Navigate to http://localhost:3000 in your browser. ☐ Login Credentials: Username: admin Password: adminReddit+2Netflix TechBlog+2Medium+2Medium+12doc.ic.ac.uk+12Learn R, Python & Data Science Online+12 ☐ Screenshot Placeholder: Insert a screenshot of the Grafana dashboard displaying the relevant panels. **□** Bonus Features Develop a simple HTML/JS frontend or CLI to simulate the watch and recommend flow.

Highlight the pipeline's extensibility for federated learning, edge caching, or A/B testing. AWS in Plain

Display Spark job logs within JupyterLab or via Docker logs.

English