Task 3: Fraud detection in a government agency (spotlight: MLOps)

Course: DLBDSMTP01 – Project: From Model to Production
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Code: https://github.com/shevchukum/fraud/

Presentation outline

1. Introduction
2. Conceptual architecture
3. Data collection
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5. FastAPI
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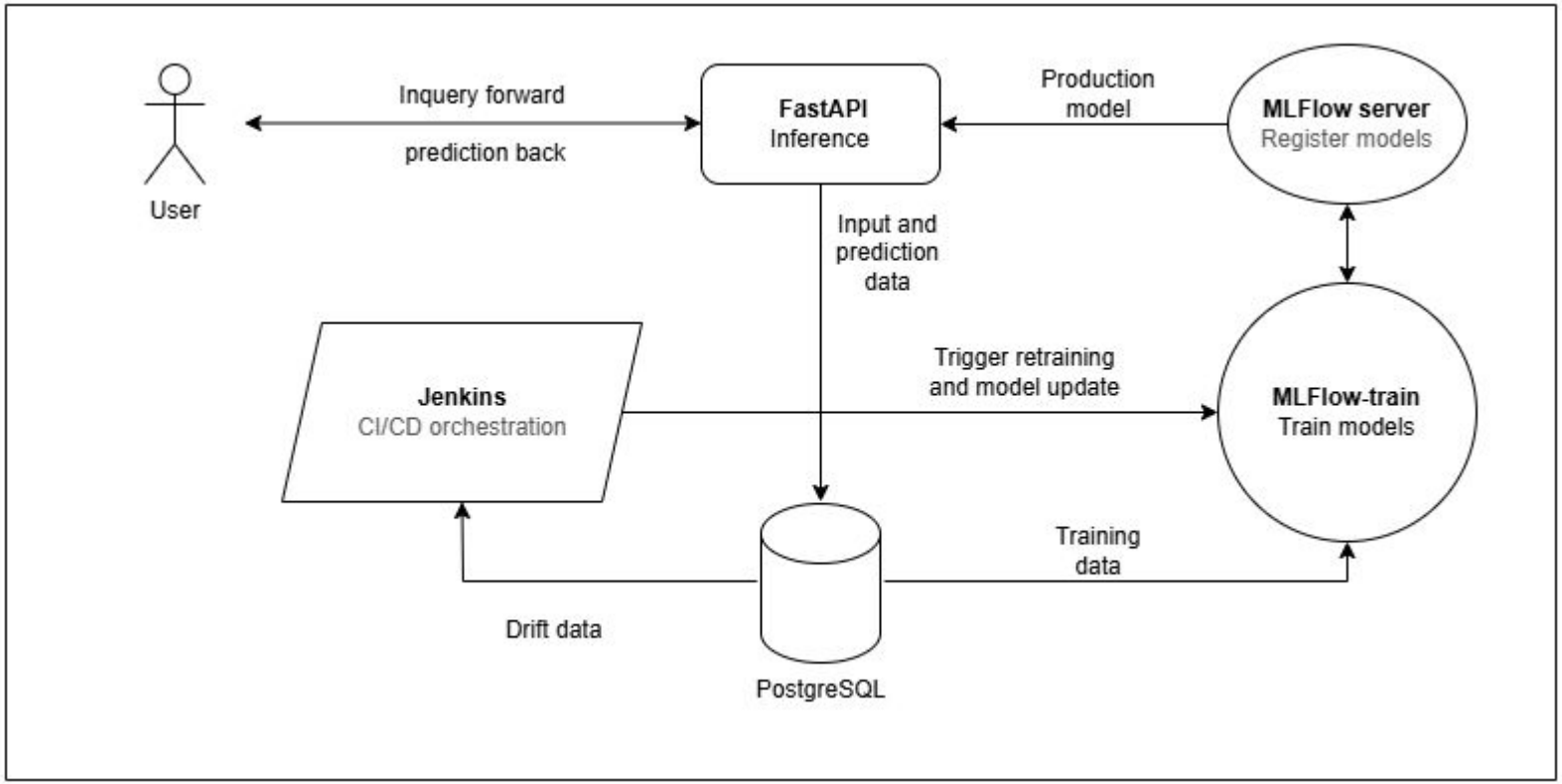
Introduction

1. **Background:** Our agency is focused on improving fertility rates. Research shows that married couples tend to have 50% more children than cohabiting ones. We designed a program offering low % loan up to 25K EUR for the first time marrying couples to start-up their families.
2. **Problem:** increasing number of fraud applications when people divorce shortly after receiving the loan making it harder for real couples to get support due to limited amount of loans available each year.
3. **Solution:** we need to develop a fraud marriage scoring system, make it available through RESTful API and implement MLOps practices.

Conceptual architecture



Conceptual architecture

Service	Purpose	Exposed Ports
`postgres`	PostgreSQL database for logs and training data	*Internal only*
`mlflow-server`	MLflow Tracking Server for experiments and artifacts	*Internal only*
`mlflow-train`	Image that performs training and logs models to MLflow	No ports exposed
`fastapi`	Prediction API and pretected access to MLflow UI	`8000:8000`
`jenkins`	CI/CD server for automated retraining and monitoring	`8080:8080`

Data collection

Data: Auto Loan Default Prediction
https://www.kaggle.com/code/saurabhbagchi/auto-loan-default-prediction-wip/data

1. ‘Default’ -> ‘Divorce’, Filter ‘Credit_Amount’ < 25000, 'Client_Education' -> 'Education_Days', Scale down ‘Age_Days’: make people over 30 younger on 10 years
2. 10 features, ‘Divorce’, ‘Date’ -> 107K samples 2023-2024
3. Another 87K random samples + 20K new wave: age < 27y and 50% divorce rate in 2025-2026.
4. Dump to ‘Divorce_database_20250513.sql’ -> ‘initdb’ folder

Simple fraud detection model

1. XGBClassifier
2. Minimal grid_search
3. Target metric: Area Under the Precision-Recall Curve (AUC PR) - good for fraud detection (rare positive class)
4. Test: 10% of the most recent data, validation is 10% of the data right before test dataset.
5. Integrated to mlflow-train service

FastAPI

1. FastAPI is faster than Flask and uses Pydantic for input validation
2. Endpoints

localhost:8000/predict	Returns prediction on a single input
localhost:8000/batch_predict	Returns predictions on the input batch
localhost:8000/mlflow	Checks password and redirects to MLFlow server
localhost:8000/update-model	Updates the model from MLFlow server
localhost:8000/model-info	Returns info on the current model

MLFlow server and train

1. MLFlow server registers models and logs artifacts in /mlflow/mlruns.
2. Accessible through localhost:8000/mlflow with password.
3. MLFlow-train - separate container:
   - downloads training data from postgres
   - trains the model
   - compares the metric to the current production model
   - promotes it to production if the metric is better
   - logs artifacts to MLFlow server

Jenkins

1. Accessible at localhost:8080 with password.
2. 3 pipelines:
   - Check the drift every 24 hours
   - Update the model every month
   - Run update 12 months ahead (test)
3. drift_checker.py -> custom_jenkins container

Tests

1. Single request is checked by

```
curl -X POST \
    http://localhost:8000/predict \
   -H "Content-Type: application/json" \
   -d "$(cat request_1.json)"
```

```
probability
-----------
0.39910775423049927
```

Tests

2. Drift check

```
curl -X POST \
     http://localhost:8000/batch_predict \
    -H "Content-Type: application/json" \
    -d "$(cat request_drift.json)"
```

And run drift-monitor-pipeline in Jenkins. It will find the drift in Age_Days, retrains the model and promotes it to production. Check localhost:8000/mlflow and localhost:8000/model-info to see that model is updated.

Tests

3. Start test-retraining pipeline in Jenkins -> 12 consecutive model training and update processes. Check localhost:8000/mlflow and localhost:8000/model-info to see that model is updated.

Conclusion

1. Integrate a predictive model into a service: fraud marriage scoring system.
2. Challenges:
   - Model version control
   - Dependency management
   - Input validation and preprocessing
   - Performance and latency (memory/CPU/GPU)
   - Error handling and logging
   - Security and access control
   - Data drift
   - Data privacy and compliance (encryption, anonymization, and auditability)