Tackling Fraudulent Financial Transactions

Objectives

Implement Machine Learning Pipeline Adaptive to Fast Evolving Fraudulent Behaviour

- 1. Real-time ingestion of high-volume financial data
- 2. Build & maintain robust data lakes
- 3. Automated model training & inference
- 4. Continuous monitoring of model performance

Primary Goal: Detect frauds while minimize false alarms

- F1-Score balances both objectives as our main success measure

Metrics

Key Trade-offs Monitored:

- Recall (fraud detection rate) ensure actual fraud not missed
- Precision (accuracy of alerts) keeps investigation workload manageable

Drift Detection:

- Alerts triggered once accuracy < 0.70
- Commercial team threshold is 0.60 this buffer provides lead time
 for model retraining

Data Schema

Transactions



- Core stream of transaction events
- 13M rows
- Base table

transactions_data.csv



Cards

- Card Metadata card type, credit limit, chip presence etc.
- 6.1K rows

cards_data.csv



User Profiles

- Demographics age, income, credit score, debt-related features
- 2K rows



users_data.csv Merchants

- Merchant Category merchant codes & descriptions
- 109 rows

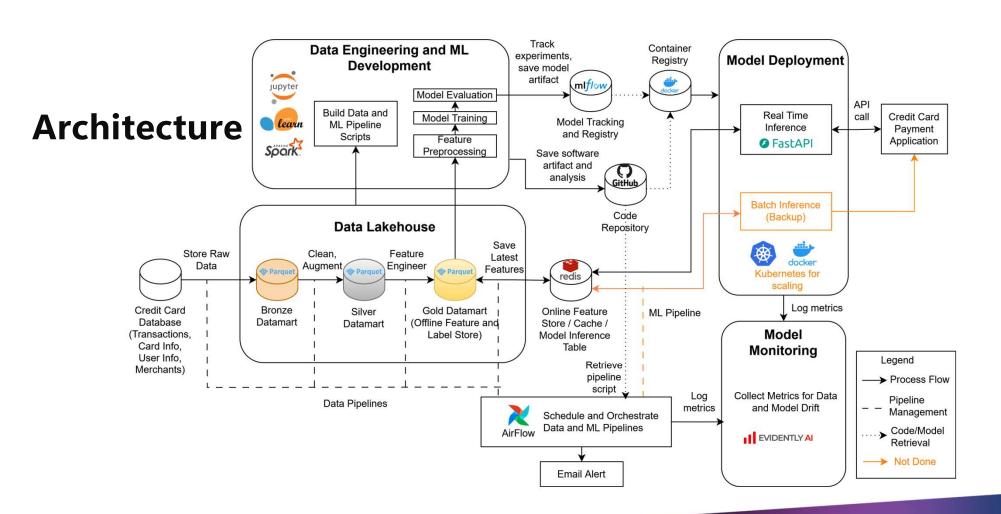
mcc_codes.json



Labels

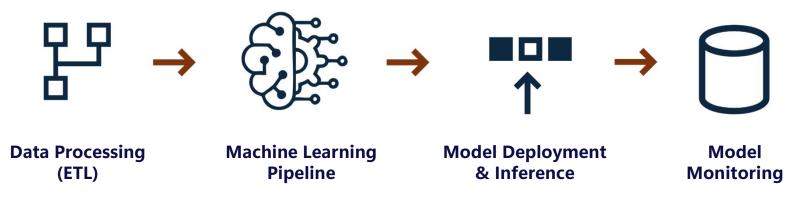
- Classification Target (fraud vs non-fraud)
- Highly imbalanced (0.15% fraud)

train_fraud_labels.json



Implementation Pipeline

- Orchestrated via Apache Airflow -



3 Core Design Principles

Modularity

Isolated containers for each stage

Scalability

Horizontal scaling via Docker & Airflow

Abstraction

Clear interfaces using FastAPI & Airflow

Medallion Architecture: From Raw to ML-Ready Data

BRONZE

Raw Ingestion

- Ingest source data (CSV/JSON)
- · No transformation or cleaning
- · Partition by snapshot date
- Save as Parquet to Bronze datamart

SILVER

Clean & Standardize

- Enforce schema & cast data types
- Trim, lowercase, remove symbols
- Handle nulls
- Save as Parquet to Silver datamart

GOLD

ML-Ready Enrichment & Feature Engineering

- Join: transactions + users + cards + MCC
- Compute feature store per snapshot date
- · Feature engineering
 - acct_opened_months
 - yrs_since_pin_changed
- Create label store
- · Save to Gold datamart

1. Model Selection & Assessment

Logistic Regression

- Simple and interpretable
- Efficient with engineered features
- Fastest inference

XGBoost

- Robust to class imbalance
- Sequential learning improves rare fraud detection
- Fastest inference

MLP (Neural Network)

- Capture complex, non-linear relationships
- Highest model capacity
- Higher risk of overfitting
- Slower inference

Decision Criteria: Real-time inference requirement

Model Development focused on Logistic Regression & XGBoost

2. Training Strategy

Preprocessing

Imputation, one-hot encoding, scaling

Data Split

80% training, 20% test, **7-day sequential OOT period.**

3. Optimization & Operations

Model Storage

Training parameters stored to **MLflow**

Handling Imbalance

SMOTE used to generate synthetic minority (fraud) samples

Hyperparameter Tuning

Used **Optuna** for efficient exploration, faster convergence, adaptively focuses on promising regions

Monitoring

Final training set persisted as reference for future monitoring

4. Model Validation - Data Split Strategy

- 12 months of training data to **learn long-term patterns**
- 3 OOT test periods to simulate real-world performance
- Forward-looking evaluation detects temporal drift & supports weekly monitoring



4. Model Validation – Model Comparison & Selection

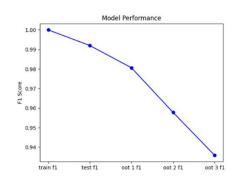
F1-Score: Primary Evaluation Metric

Chosen to balance fraud detection sensitivity (recall) and false alarm minimization (precision) under severe class imbalance.

(Optimizes both recall (catching frauds) and precision (avoiding false alarms), which is critical in fraud detection)

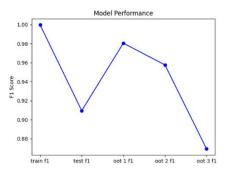
XGBoost

- F1-score gradually decays
- Smooth and stable degradation
- No overfitting, generalizes well
- Consistent under temporal shift



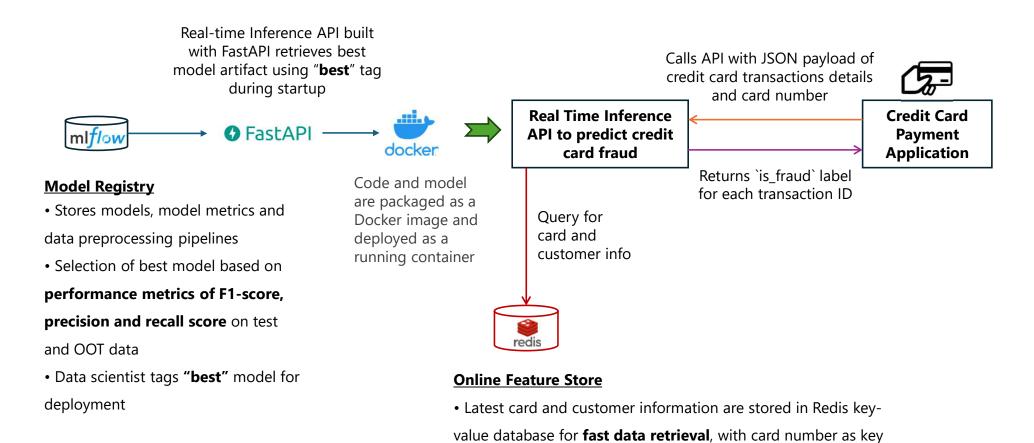
Logistic Regression

- F1-score shows high variance
- Indicates overfitting or model instability
- Not reliable for deployment



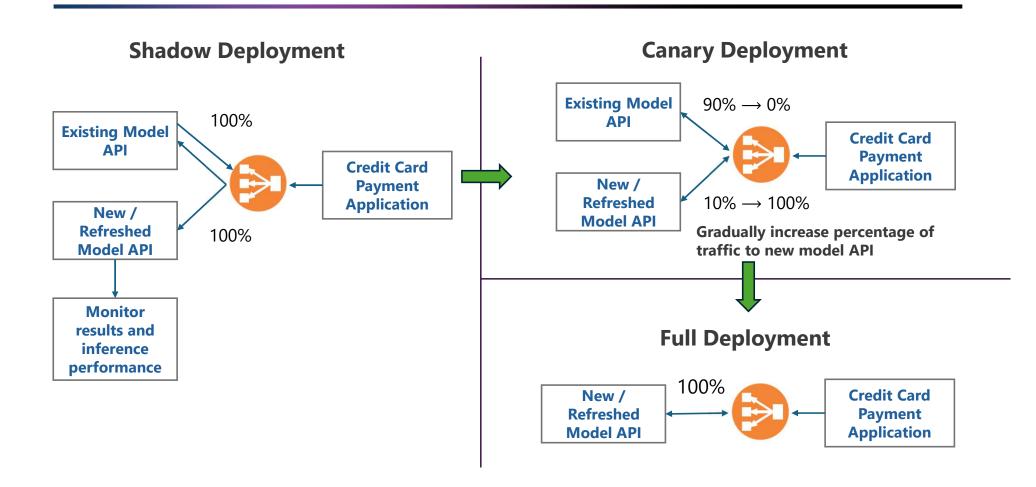
Selected

Model Inference



Stores model inference results

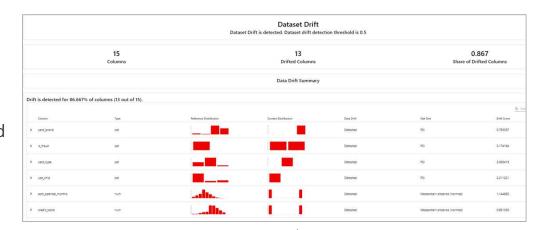
Model Deployment Strategy

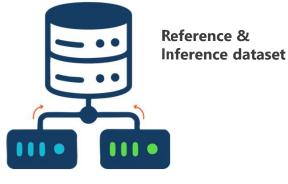


Model Monitoring

Detecting Data Drift Over Time

- Drift is calculated using EvidentlyAI and PSI
- Monitoring results are visualized in the dashboard



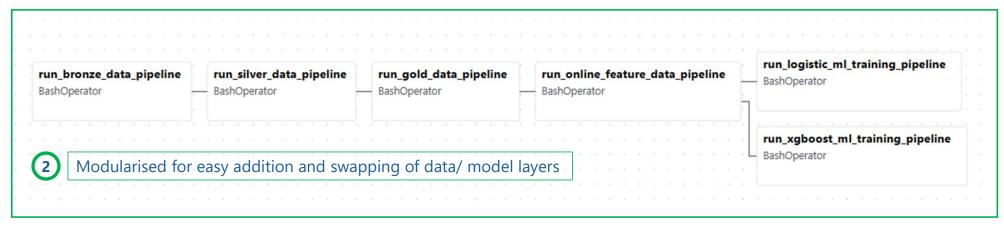


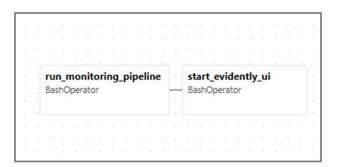
ML Pipeline Inference

Monitoring Pipeline

Airflow DAGs

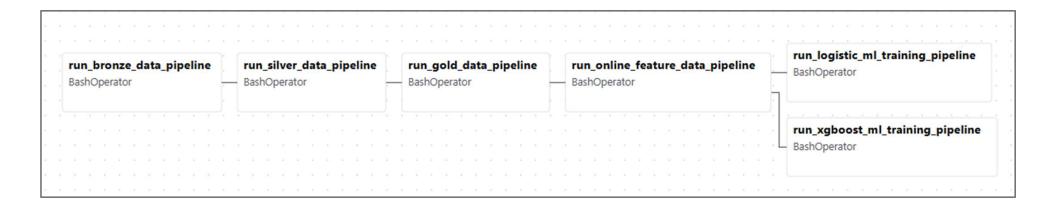






All DAGs are schedule ready with no backfill (clean start for each run)

Airflow DAGs





- Manual trigger once data and model training pipeline is finished
- Manual retrain for human-in-the-loop oversight
- 3 Data drift flagged when more than 50% of the columns show significant change

ETL & ML DAG

