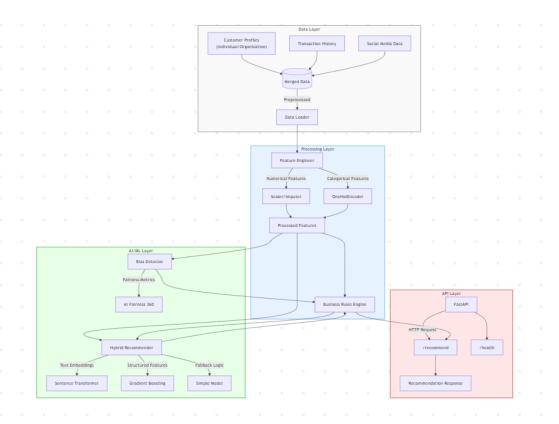


Al-Driven Hyper Personalization & Recommendations Architecture

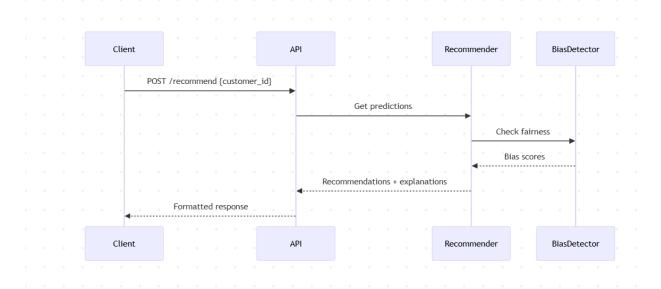
Overview

This solution provides a hyper-personalized, bias-aware recommendation system for financial products, combining transactional data, customer profiles, and social media signals to deliver tailored financial product suggestions.

Architecture:



Sequential Diagram:



Architectural Components

1. Data Layer

Data Loader (data_loader.py)

- o Ingests multiple data sources (customer profiles, transactions, social media)
- o Performs comprehensive data cleaning and transformation
- Handles missing values and type conversions
- Merges datasets into a unified customer view
- o Includes sentiment analysis on social media content

2. Processing Layer

• Feature Engineering (feature_engineer.py)

- Defines categorical and numerical feature pipelines
- Implements standard preprocessing (imputation, scaling, encoding)
- o Creates consistent feature transformation for model training and inference

Business Rules Engine (business_rules.py)

- Applies domain-specific boosting rules
- o Adjusts recommendations based on customer attributes
- o Ensures business logic is incorporated into final recommendations

3. AI/ML Layer

• Hybrid Recommender (recommender.py)

o Combines multiple ML techniques:

- Gradient Boosting for baseline predictions
- Sentence Transformers for text embeddings
- BERT for advanced text understanding
- o Includes sophisticated fallback mechanisms
- Calculates financial risk profiles
- o Handles class imbalance with SMOTE and balanced classifiers

Bias Detection (bias detector.py)

- Uses AIF360 toolkit for fairness metrics
- Monitors protected attributes (gender, age, location)
- o Calculates disparate impact and statistical parity
- Provides individual-level bias checks

4. API Layer (app.py)

• FastAPI Application

- o RESTful endpoints for recommendations
- Health check and monitoring
- o Request/response validation with Pydantic
- Comprehensive logging

Key Design Patterns

1. Modular Pipeline Architecture

- a. Clear separation between data loading, feature engineering, and modeling
- b. Each component can be developed and tested independently

2. Hybrid Recommendation Approach

- a. Combines traditional ML with transformer-based embeddings
- b. Business rules provide final adjustment layer

3. Progressive Enhancement

- a. Sophisticated models when data is sufficient
- b. Graceful degradation to simpler models when needed
- c. Intelligent fallback recommendations

4. Bias-Aware Design

- a. Built-in fairness monitoring at both dataset and individual levels
- b. Protected attribute tracking throughout pipeline

5. Explainability

- a. Explanations generated for recommendations
- b. Transparent risk scoring

Data Flow

1. Initialization

- a. Load and merge all data sources
- b. Train recommendation models
- c. Set up bias detection baselines

2. Recommendation Process

```
Customer Request → Feature Transformation →
Model Prediction → Business Rules Adjustment →
Bias Check → Explanation Generation →
Final Recommendation
```

3. Monitoring

- a. Continuous bias auditing
- b. Model performance tracking
- c. Data quality checks

Technical Stack

- **Core Framework**: FastAPI (Python)
- ML Frameworks: Scikit-learn, PyTorch, Transformers
- NLP: Sentence Transformers, NLTK
- Bias Detection: AIF360
- Data Processing: Pandas, NumPyDeployment: Uvicorn ASGI server

Quality Attributes

- 1. **Fairness**: Built-in bias detection at multiple levels
- 2. **Resilience**: Multiple fallback mechanisms
- 3. **Explainability**: Clear explanations for recommendations
- 4. **Performance**: Efficient feature engineering and model serving
- 5. **Maintainability**: Modular design with clear interfaces

This architecture provides a robust foundation for delivering personalized financial recommendations while maintaining ethical AI practices and business alignment.