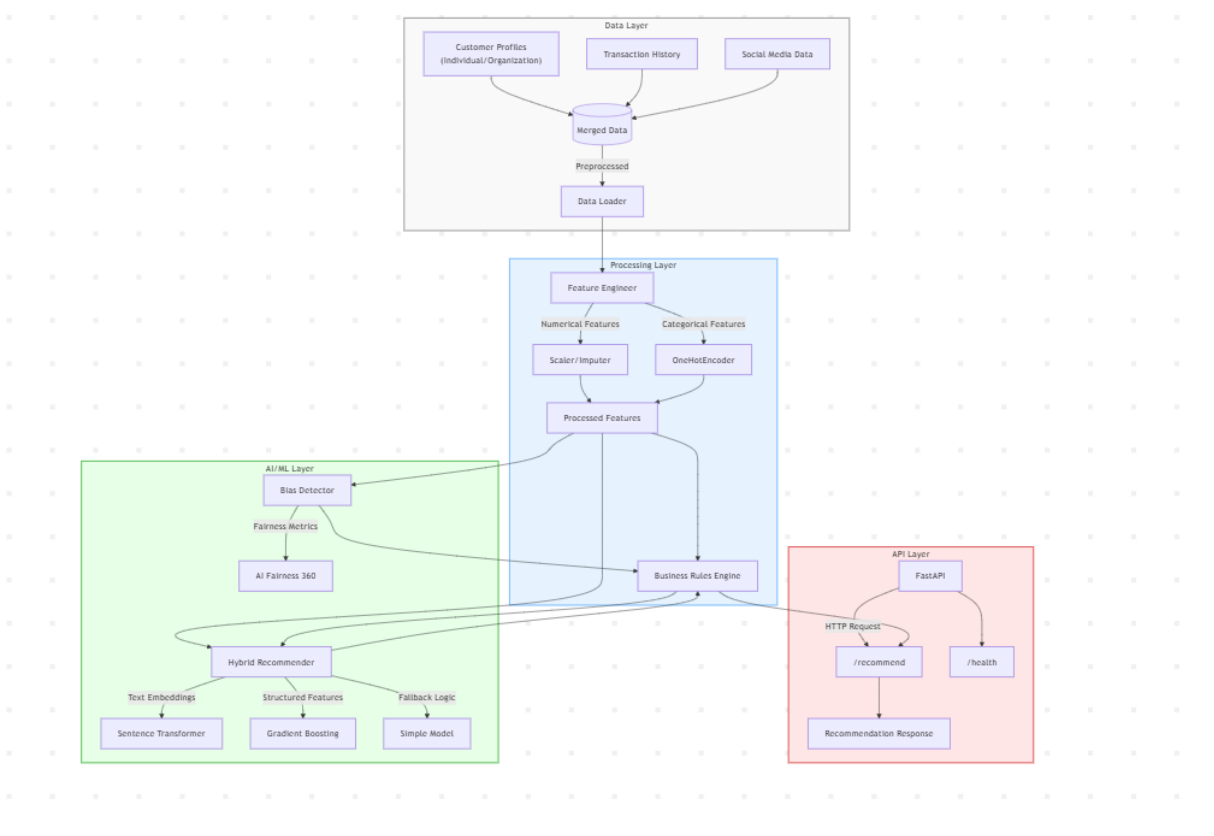# Financial Recommendation System Architecture
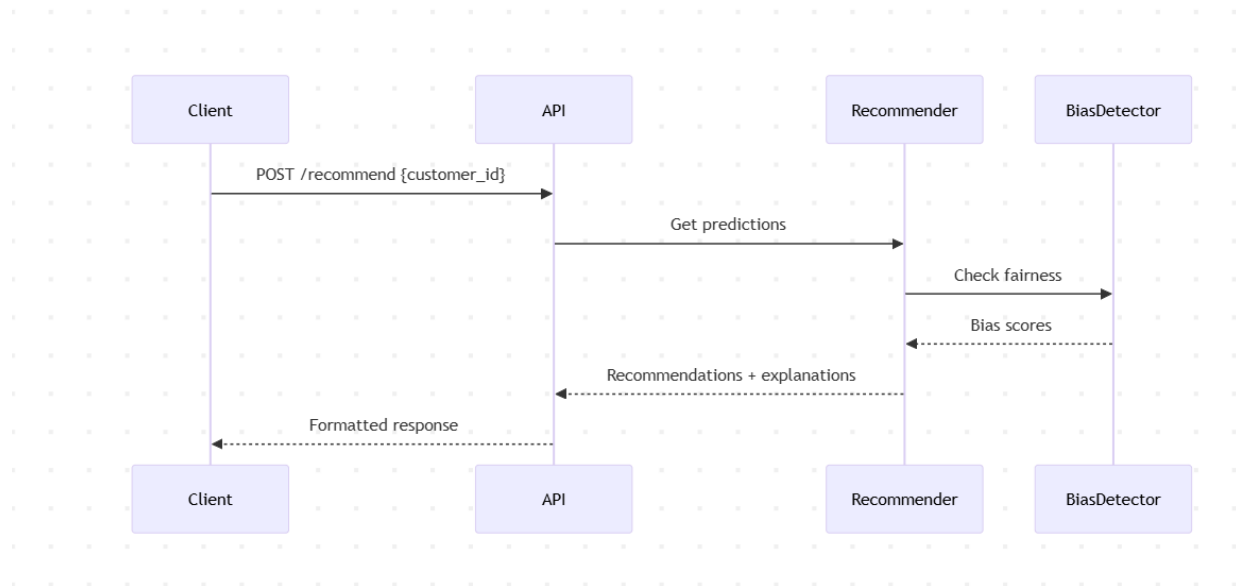
**Overview**

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`)**
    - Ingests multiple data sources (customer profiles, transactions, social media)
    - Performs comprehensive data cleaning and transformation
    - Handles missing values and type conversions
    - Merges datasets into a unified customer view
    - 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)
    - Creates consistent feature transformation for model training and inference
- **Business Rules Engine (`business_rules.py`)**
    - Applies domain-specific boosting rules
    - Adjusts recommendations based on customer attributes
    - Ensures business logic is incorporated into final recommendations

3. AI/ML Layer

- **Hybrid Recommender (`recommender.py`)**
    - Combines multiple ML techniques:

- Gradient Boosting for baseline predictions
- Sentence Transformers for text embeddings
- BERT for advanced text understanding
  - Includes sophisticated fallback mechanisms
  - Calculates financial risk profiles
  - 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)
  - Calculates disparate impact and statistical parity
  - Provides individual-level bias checks

4. API Layer (`app.py`)

- **FastAPI Application**
  - RESTful endpoints for recommendations
  - Health check and monitoring
  - 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, NumPy
- **Deployment**: 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.