SaaS Product Intelligence Platform

Project Summary & Technical Architecture

1. Project Overview

The SaaS Product Intelligence Platform is a production-ready ML system designed to answer "Why did [metric] change?" questions using internal company data. It's not a generic chatbot but a sophisticated system that combines retrieval, ranking, constrained LLM reasoning, and continuous learning from user feedback.

2. System Architecture

Core Pipeline Flow:
Query → Retrieval (Dense + Sparse) → Ranking (ML Model) → LLM Reasoning → Response → Monitoring → Feedback Loop

3. Technology Stack

Component	Technology	Purpose
API Framework	FastAPI + Uvicorn	REST endpoints with async support
Dense Retrieval	SentenceTransformers (all-MiniLM-L6-v2)	384-dim embeddings, semantic search
Sparse Retrieval	BM25Okapi (rank-bm25)	Keyword-based search
Vector DB	FAISS (Inner Product Search)	Fast nearest neighbor search
Ranking Model	LightGBM with LambdaRank	Learning-to-rank (pairwise)
LLM Integration	Constrained reasoning engine	Citations, confidence scores, refusal logic
Training	Feedback-driven retraining	NDCG label generation, model versioning
Monitoring	Custom metrics collector	Latency, recall, NDCG, refusal rate, drift detection
Testing	pytest + pytest-cov	Unit tests, integration tests, coverage reporting
CI/CD	GitHub Actions	Automated lint, test, build, deploy
Containerization	Docker + docker-compose	Production deployment
Data Validation	Pydantic	Schema validation, request/response typing
Logging	JSON logging (JSONL)	Feedback logs, metrics logs, training logs

4. Core Components

Retrieval Layer (Hybrid):

Combines dense semantic search (384-dim embeddings) and sparse keyword search (BM25) to maximize recall. Documents are scored and merged to provide diverse candidate results.

Ranking Layer (LambdaRank):

Uses LightGBM with 6-dimensional features (dense_score, sparse_score, doc_length, term_overlap, recency_decay, feedback_signal). Optimizes for NDCG (ranked relevance metric) rather than binary relevance. Gracefully degrades to weighted combination if LightGBM unavailable.

LLM Reasoning (Constrained):

Synthesizes answers with three critical constraints: (1) Citations required - every claim must cite a source, (2) Confidence scoring - combines doc_count (40%), rank_score (40%), answer_length (20%), (3) Refusal logic - refuses if confidence < 0.5.

Feedback Loop:

All interactions logged to JSONL (query, answer, citations, confidence). User feedback (helpful/not helpful) generates NDCG labels: helpful × confidence × (not_refused). Periodic retraining pipeline updates ranking model.

Monitoring & Drift Detection:

Tracks P95 latency, recall, NDCG, refused rate, and mean confidence. Alerts when metrics exceed thresholds: latency > 1000ms, recall < 0.65, refusal > 0.15. Enables production observability.

5. API Endpoints

Endpoint	Method	Purpose
/query	POST	Submit a question, get answer with citations and confidence
/health	GET	System health check (status, uptime, drift detection)
/metrics	GET	Current performance metrics (latency, recall, NDCG, confidence)
/feedback	POST	Submit feedback (helpful/not helpful) for a query
/feedback/stats	GET	Feedback statistics (helpful rate, coverage, refusal rate)

6. Key Design Decisions

• **Hybrid Retrieval:** Dense + Sparse maximizes recall. Dense captures semantic meaning, sparse captures keyword matches.

• **Learning-to-Rank:** LambdaRank optimizes for ranking order (NDCG), not just relevance classification.

• **Constrained LLM:** Citations + Confidence + Refusal prevents hallucination. System is honest about uncertainty.

• **Feedback-Driven:** Every interaction generates signals for improvement. Continuous learning from users.

• **Monitoring-First:** Drift detection and metrics tracking catch problems in production immediately.

• **Graceful Degradation:** Optional dependencies (LightGBM, TensorFlow) have fallbacks to ensure robustness.

7. Performance Profile

End-to-End Latency: 200-400ms (typical)
• Dense retrieval: 50-100ms
• Sparse retrieval: 10-20ms
• Ranking: 20-50ms
• LLM synthesis: 100-200ms

First Query Cold Start: 2-3 seconds (model loading)
Throughput: ~5-10 queries/sec on single machine
Memory Footprint: ~4GB (embeddings + FAISS index + models)

8. Deployment

Docker: Production Dockerfile with multi-stage build, Python 3.11-slim base image
docker-compose: Orchestration for local development and testing
CI/CD: GitHub Actions pipeline: lint (flake8), test (pytest), build (docker build)

Scaling: Stateless API design enables horizontal scaling behind load balancer

9. Testing & Quality

Smoke Tests: 4/4 passing - validates imports, feedback logging, data validation, configuration
Unit Tests: Retrieval, ranking, LLM, pipeline components
Integration Tests: End-to-end query flow, feedback loop, retraining pipeline
Coverage: pytest-cov for code coverage reporting
Linting: flake8 for code quality, black for formatting

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