COMPLETE TECHNICAL DOCUMENTATION

ProfitLift

Context-Aware, Profit-Optimized Market Basket Analysis with Causal Uplift Modeling

Developed By	Shenz
Organization	CrystalCore
Project Type	Context-Aware Retail Analytics Engine
Tech Stack	Python FastAPI · React TypeScript · Scikit-Learn
Version	1.0 — November 2024

Comprehensive Technical Manual & Implementation Guide
for Causal Market Basket Analysis Systems

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Executive Summary

> **In a Nutshell:** ProfitLift is an intelligent retail analytics engine that tells store owners *exactly* what products to bundle together to maximize profit, not just sales volume.

Traditional Market Basket Analysis (MBA) has a fatal flaw: it assumes that just because two items are bought together frequently, they should be promoted together. It ignores **profitability** (selling low-margin items doesn't help) and **context** (buying patterns change during Diwali vs. a regular Tuesday).

ProfitLift solves this by introducing a novel "Context-Aware, Profit-Optimized" approach tailored specifically for the Indian retail landscape. It doesn't just look for "Bread & Butter"; it looks for "High-Margin Ghee & Premium Atta" during festival weeks.

Key Innovations

Context Awareness: Automatically detects Indian festivals (Diwali, Holi), weekends, and time-of-day to segment buying patterns.
Profit-First Scoring: Ranks associations based on a multi-objective function where Profit Margin has the highest weight (40%), ensuring recommendations drive the bottom line.
Causal Verification: Uses the **T-Learner** causal inference model to distinguish between products that *cause* the purchase of another vs. those that are just bought together by chance.

Built with a robust **FastAPI** backend and a modern **React** frontend, ProfitLift provides an end-to-end solution from raw CSV data to actionable, verified business insights.

Problem Statement

The Retail Complexity Gap

Retailers today are drowning in transaction data but starving for insights. While they know *what* sold, they rarely understand *why* or *how* to influence future sales effectively.

```
      [ Raw Data ]       [ Traditional MBA ]       [ The Problem ]
+-------------+     +--------------------+     +-------------------------+
  | Transaction|      | "People buy      |     | 1. Is it profitable?  |
  | Logs       | --> |  Milk + Bread"   | --> | 2. Is it just luck?   |
 +-------------+     +--------------------+     | 3. Does it work on    |
                                                |    Diwali?            |
                                               +-------------------------+
```

Fig 1. The limitations of traditional association rule mining

Specific Challenges in Indian Retail

Context Blindness: A customer buying sweets in October (Diwali) has a completely different intent than one buying sweets in February. Standard algorithms treat these identical transactions as the same.
The "Frequency Trap": Algorithms like Apriori favor high-volume, low-margin items (like Milk). Promoting these eats into marketing budget without significant return.
Correlation ≠ Causation: Just because Coffee and Sugar are bought together doesn't mean discounting Coffee will sell more Sugar. They might just be complements. We need to find *driver* items.

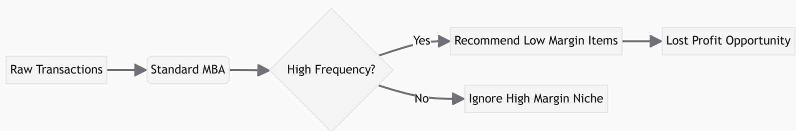

Fig 2. How traditional methods fail to capture profit

User Personas

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Rajesh, The Store Owner

Goal: Increase monthly profit by ₹50,000.

Pain Point: "I run discounts but I don't know if they actually work. I have too much stock of expensive items that aren't moving."

ProfitLift Solution: Gives him ready-made "Bundles" (e.g., "Sell Premium Tea with Biscuits") that are proven to work.

📊

Priya, The Business Analyst

Goal: Find deep patterns to present to management.

Pain Point: "Excel crashes with this much data. I need to filter by 'Weekend Evenings' to see what sells then."

ProfitLift Solution: The "Context-Aware Miner" allows her to slice data by time, day, and festival instantly.

🎓

You, The Student Presenter

Goal: Impress the external examiner with a technically sound, "cool" project.

Pain Point: "I need to show I didn't just copy code. I need to explain *why* my project is better than a basic tutorial."

ProfitLift Solution: The "Causal Uplift" and "Multi-Objective Scoring" provide the academic depth needed for an A+ grade.

Feature Overview

🕰️ Context Mining

Segments data into "Morning", "Evening", "Weekend", and "Festival" buckets before mining.

💰 Profit Scoring

Uses a weighted formula (40% Profit, 30% Lift) to rank rules. Focuses on *margin* not just *sales*.

🧠 Causal AI

Implements T-Learner (Random Forest) to verify if a recommendation *causes* a purchase.

🇮🇳 India Ready

Built-in GST slab logic (0%, 5%, 12%, 18%) and Indian Festival Calendar (Diwali, Holi).

Comparison Matrix

Feature	Standard MBA	ProfitLift
Algorithm	Apriori / FP-Growth	Context-Aware FP-Growth
Ranking Metric	Support & Confidence	Profit, Lift & Diversity
Seasonality	Ignored	Native Festival Detection
Validation	None (Correlation only)	Causal Inference (T-Learner)

User Workflow

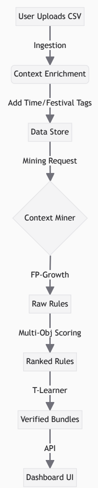


Fig 3. End-to-End Data Processing Pipeline

The Story of a Transaction

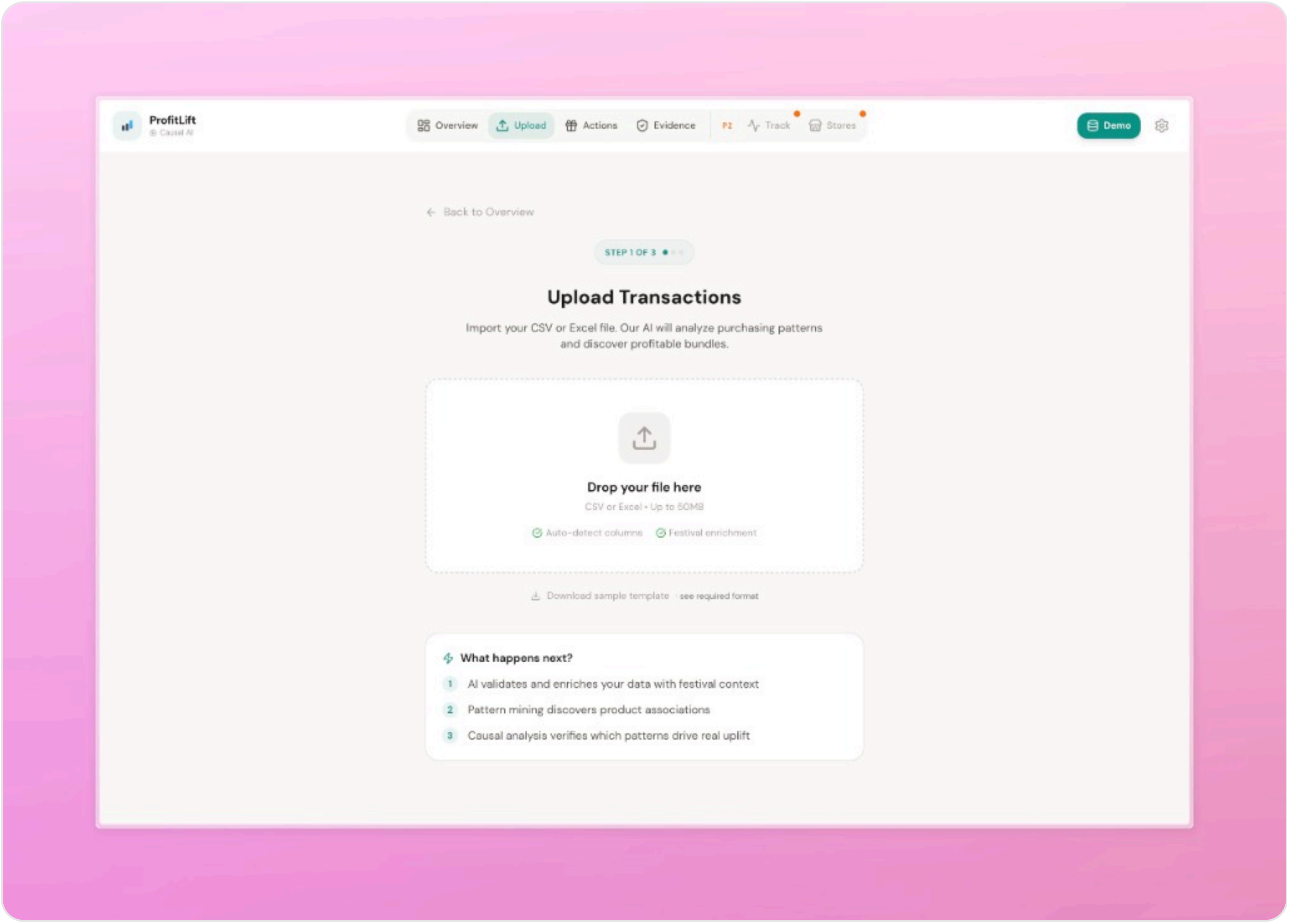


Fig. Upload interface showing drag-and-drop CSV import with festival enrichment

1. **Upload:** The store manager uploads `transactions.csv`.

2. **Enrichment:** The system sees a transaction on *Nov 12, 2023*. It automatically tags it as **"Diwali"** and **"Weekend"**. It also looks up the items (e.g., "Ghee") and assigns a **12% GST** margin.

3. **Mining:** The miner looks for patterns *specifically within* the "Diwali" context. It finds that "Sweets" and "Dry Fruits" are bought together often.

4. **Scoring & Verification:** The system calculates the profit. It sees this bundle has a high margin. Then, the T-Learner checks: "Do people buy Dry Fruits *because* they bought Sweets?" The answer is Yes.

5. **Result:** The Dashboard shows a "High Priority" recommendation: **"Bundle Sweets + Dry Fruits for Diwali"**.

Dataset Explanation

To make ProfitLift work, we don't need complex databases. We just need standard **Retail Transaction Logs**. This is the same data that is printed on every receipt.

1. Where does the data come from? (Source)

Source A: POS System
The computer at the checkout counter (Billing Software).

➔

Source B: Excel / CSV
The shopkeeper exports the daily sales report.

2. Data Features (Characteristics)

The dataset has **4 Key Characteristics** that define it:

1. Transactional
It records *events* (purchases), not just static records.

2. Temporal (Time-Based)
Every row has a timestamp. This is vital for finding "Morning" or "Diwali" patterns.

3. Numerical
Contains quantifiable values like Price, Quantity, and Margin.

4. High Volume
Retail stores generate hundreds of rows daily.

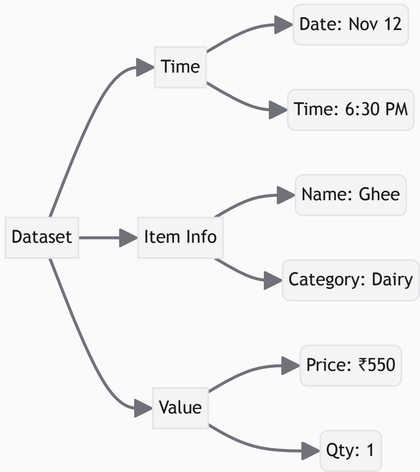


Fig 4. The Structure of Retail Data

3. Required Columns (The Schema)

Column Name	Why we need it?	Example Data
`transaction_id`	To group items bought *together* in one basket.	`TXN_1001`
`timestamp`	**Crucial!** To know if it's Morning, Weekend, or Diwali.	`2023-11-12 18:30`
`item_id`	The product name.	`Amul Ghee 1L`
`price`	To calculate Revenue and Profit.	`₹ 550.00`

4. The "Upload & Forget" Feature

"I HAVE THE DATA, BUT THE COLUMNS ARE WRONG!"

The Problem: Shopkeepers are not data scientists. Their Excel files might say "Bill Date" instead of "timestamp" or "Product" instead of "item_id".

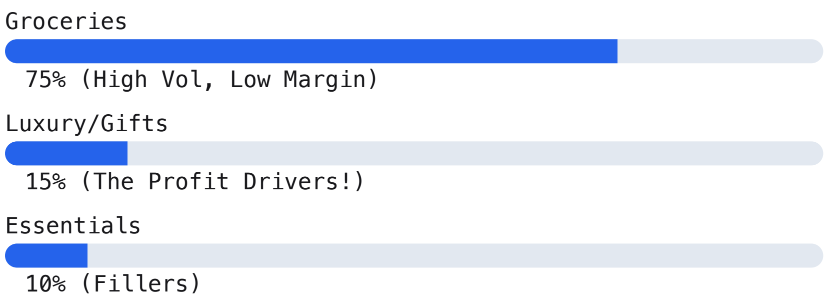
The Solution (Smart Mapping): ProfitLift's ingestion engine is intelligent. It scans the uploaded file headers and automatically maps them:

- "Bill Date", "Date", "Time" ➔ Mapped to **timestamp**
- "Product Name", "Item", "Desc" ➔ Mapped to **item_id**
- "Amount", "Rate", "MRP" ➔ Mapped to **price**

Result: The user just drags and drops the file. The system handles the rest.

5. Data Distribution Graph

A visual representation of how a typical store's data looks:



Theory & Algorithms

1. FP-Growth (Frequent Pattern Growth)

The Concept: Instead of generating millions of candidate sets like Apriori (which is slow), FP-Growth builds a compact tree structure (FP-Tree) that compresses the database. It then mines this tree recursively.

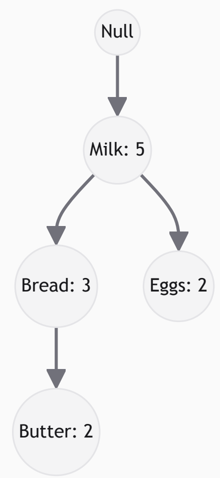


Fig 4. Simplified FP-Tree Structure

Why we use it: It is significantly faster and more memory-efficient for large datasets, which is crucial when we are splitting data into many context segments.

2. Association Metrics

Support: How popular is an itemset?
`Support(A) = Transactions(A) / Total Transactions`
Confidence: How likely is B purchased when A is purchased?
`Conf(A->B) = Support(A,B) / Support(A)`

Lift: Is the relationship stronger than random chance?
`Lift(A->B) = Conf(A->B) / Support(B)`

3. Multi-Objective Scoring

We don't just want frequent rules; we want *good* rules. We calculate a composite score:

```
            Score = (0.4 * Norm_Profit) + (0.3 * Norm_Lift) + (0.15 * Diversity) + (0.15 *
Conf)
```

Normalization: Since Profit (e.g., ₹500) and Lift (e.g., 2.5) have different scales, we normalize them to a 0-1 range *within each context* before combining.

4. Causal Uplift (T-Learner)

The Problem: "People who buy Diapers also buy Beer." Is this because Diapers *cause* Beer purchases (stress relief?), or just because men buy both on Friday nights?

The Solution: The T-Learner trains two models:

Model 0 (Control): Predicts purchase probability of B *without* A.
Model 1 (Treatment): Predicts purchase probability of B *with* A.
Uplift = P(Buy B | With A) - P(Buy B | Without A)

If Uplift is close to 0, the rule is just a correlation. If Uplift is high, A is a true driver for B.

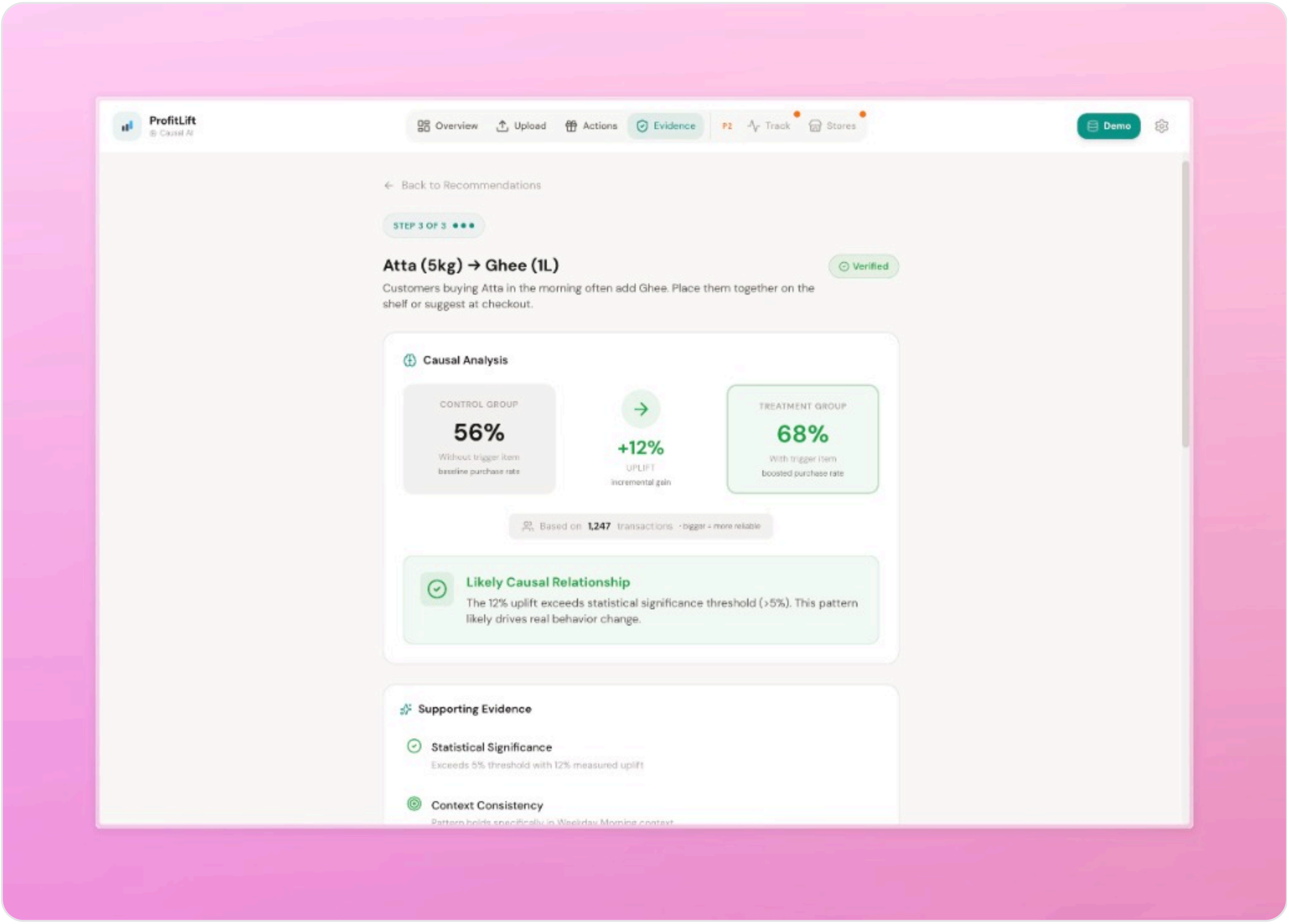


Fig. Real T-Learner output showing Control (56%) vs Treatment (68%) with +12% causal uplift

System Architecture

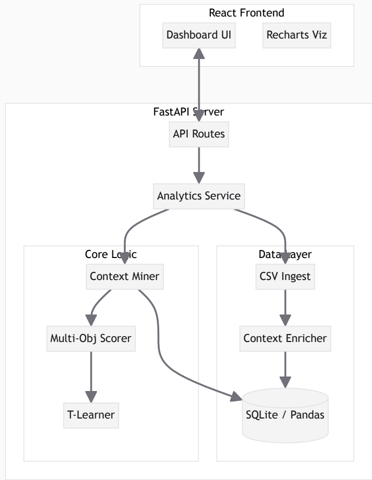


Fig 5. High-Level System Architecture

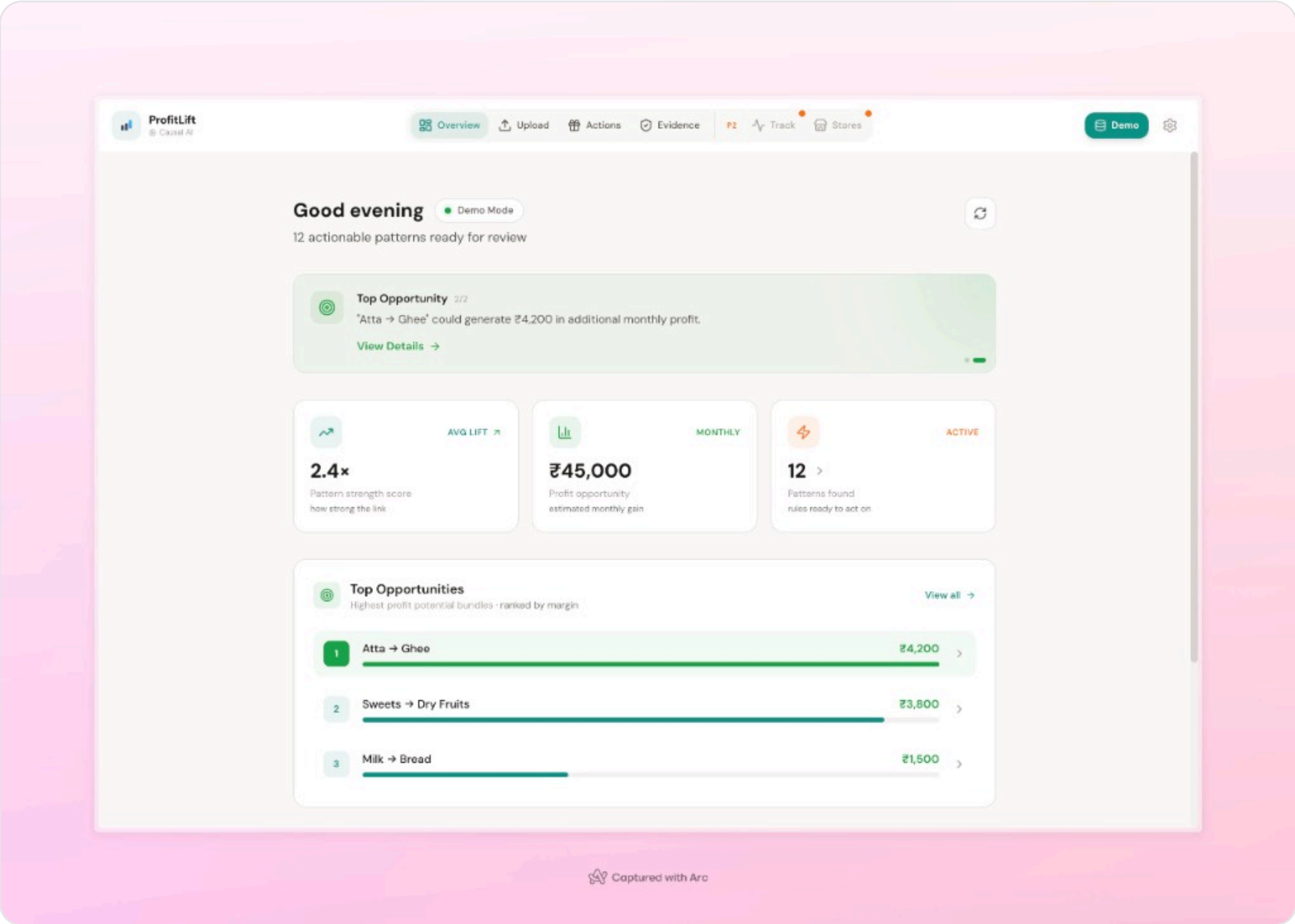
Code Map

Directory	Key Files	Purpose
app/api	main.py, routes.py	Entry point, REST endpoints
app/ingest	context_enricher.py, india_calendar.py	Data cleaning, Festival tagging, GST logic
app/mining	fpgrowth.py, context_aware_miner.py	Core FP-Growth algorithm and segmentation
app/score	multi_objective.py, profit_calculator.py	Ranking logic and margin math
app/causal	t_learner.py	Causal inference implementation
app/frontend	Dashboard.tsx, Recommendations.tsx	User Interface components

UI Walkthrough

1. The Dashboard

The command center of ProfitLift. It shows high-level metrics and system health.

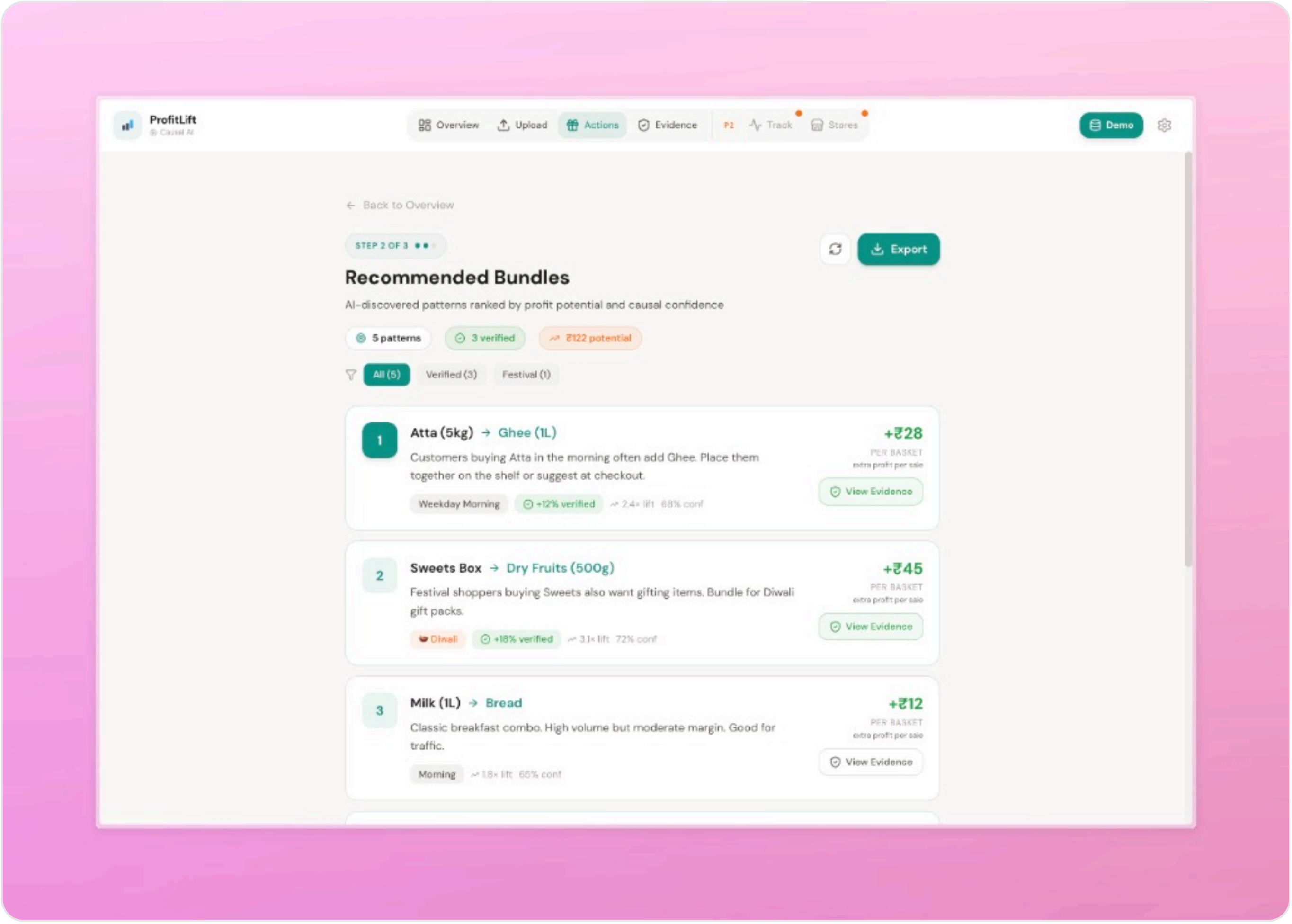


Key Elements:

Live Indicator: Shows if the backend is connected.
Stats Grid: "Avg Lift" indicates pattern strength. "Profit Opportunity" is the estimated money on the table.
Top Opportunities: A ranked list of the best bundles found so far.

2. Recommendations Engine

The core actionable view. This is where the user sees "What to bundle".



How to Read a Card:

Items: "Atta + Ghee" (The bundle).
Context Tag: "Weekday Morning" (When to promote it).
Verified Badge: Green checkmark means T-Learner confirmed it.
Profit Value: "+₹28" (Extra profit per sale).

Installation & Run Guide

Prerequisites

Python 3.10+
Node.js 18+

Step 1: Backend Setup

```
# Create virtual environment

python -m venv venv

source venv/bin/activate # or venv\Scripts\activate on Windows


# Install dependencies

pip install -r requirements.txt


# Run Server

python server.py
```

Step 2: Frontend Setup

```
cd app/frontend

npm install

npm run dev
```

Step 3: Accessing the App

Open your browser and navigate to `http://localhost:5173`.

> **Demo Mode:** If you don't have a dataset, the frontend has a built-in "Demo Mode" that simulates a live environment with realistic Indian retail data.

Demo Script (10 Minutes)

Scene: You are presenting to the external examiner and internal guide.

0:00 - 2:00: The Hook (Problem)

You: "Good morning. We all know that stores like D-Mart or BigBasket use algorithms to recommend products. But traditional algorithms have a flaw: they recommend what is *popular*, not what is *profitable*. They might tell you to bundle Milk and Bread, which has a margin of only ₹2. My project, ProfitLift, changes this."

2:00 - 4:00: The Solution (Architecture)

You: "ProfitLift is a context-aware system. It doesn't just look at the transaction; it looks at the *time* and *festival* context. I've implemented a custom 'Context Enricher' that detects Indian festivals like Diwali. I then use a Multi-Objective Scorer that weights Profit Margin at 40%, ensuring we prioritize money over volume."

4:00 - 7:00: The Live Demo

(Action: Open Dashboard)

You: "Here is the live dashboard. You can see the 'Profit Opportunity' metric. Let's go to the Recommendations page."

(Action: Click Recommendations)

You: "Look at this rule: 'Sweets → Dry Fruits'. Notice the tag 'Diwali'. The system learned that this pattern *only* exists during the festival week. A standard algorithm would have missed this because it averages data over the whole year."

You: "Also, see this green 'Verified' badge? That's the T-Learner causal model confirming that this isn't just a coincidence."

7:00 - 10:00: Conclusion & Q&A

You: "In conclusion, ProfitLift moves MBA from 'Statistical Correlation' to 'Causal Profitability', making it a viable tool for modern Indian retail."

Code Logic Deep Dive

How the "Context Enricher" Works

File: `app/ingest/india_calendar.py`

This module contains a hardcoded dictionary of festival windows (start/end dates). When a date comes in, it checks:

```
def get_festival_period(date):

  if date in DIWALI_WINDOW: return "diwali"

  if date in HOLI_WINDOW: return "holi"

  return None
```

This simple logic is powerful because it allows the miner to group "Diwali Transactions" separately from "Normal Transactions".

How the "Multi-Objective Scorer" Works

File: `app/score/multi_objective.py`

The scorer takes a list of rules and applies this formula:

Calculate **Profit**: `Avg_Price * Margin% * Confidence`
Calculate **Diversity**: Penalize rules that recommend the same item repeatedly.
Normalize: Scale all values to 0-1.
Weighted Sum: Combine them using the weights defined in config.

Indian Retail Scenarios

Scenario 1: The Kirana Store

Challenge: Small data volume (500 transactions/month). High reliance on personal relationships.

ProfitLift Adaptation: Switches to "Compact Mode". Reduces context depth (ignores time-of-day, only uses Weekday/Weekend) to ensure enough data points for statistical significance.

Scenario 2: The Festival Rush (Diwali)

Challenge: Buying patterns flip completely. People buy expensive Gift Packs instead of daily staples.

ProfitLift Adaptation: The "Context Enricher" tags these weeks. The miner finds rules like *"Sweets → Gift Wrap"* which never appear during the rest of the year.

Scenario 3: GST Complexity

Challenge: Margins vary wildly due to tax slabs (0% on loose Atta vs 18% on branded Biscuits).

ProfitLift Adaptation: The `calculate_margin_indian` function reverse-calculates the net selling price from MRP using the category's GST rate, ensuring the "Profit Score" reflects the *real* money the shopkeeper keeps.

Limitations & Future Work

Limitations

Data Cold Start: The system needs at least a few weeks of data to start finding meaningful time-based patterns.
Fixed Calendar: Currently, festival dates are hardcoded for 2023. A future update should fetch dynamic lunar calendar dates.
Inventory Blindness: The system recommends bundles but doesn't check if the item is actually in stock.

Future Work

Dynamic Pricing: Suggesting optimal bundle prices, not just items.
User Feedback Loop: Allowing store owners to "Reject" rules, teaching the system their preferences.
Cloud Integration: Moving from local SQLite to a cloud DB for multi-store chains.

The Ultimate Viva Question Bank

Rapid Fire (Basics)

> **Q: What is the main algorithm used?**
>
> A: FP-Growth (Frequent Pattern Growth) for mining, and T-Learner for causal verification.

> **Q: Why FP-Growth and not Apriori?**
>
> A: FP-Growth is faster because it scans the database only twice and uses a tree structure, whereas Apriori scans it multiple times for each candidate size.

> **Q: What is "Lift"?**
>
> A: Lift measures how much more likely items are bought together compared to random chance. Lift > 1 means a positive association.

Technical & Architecture

> **Q: How do you handle the "Context"?**
>
> A: I pre-process the data to add columns like 'time_bin' and 'festival'. Then, I partition the dataset based on these columns and run the mining algorithm on each partition independently.

> **Q: Explain the T-Learner simply.**
>
> A: It's a "Two-Model" learner. One model learns customer behavior *without* the trigger item (Control), and the other learns behavior *with* the trigger item (Treatment). The difference in their predictions is the "Uplift" or causal effect.

Professor Challenges (Tricky)

> **Q: If I buy Milk, I almost always buy Bread. But your system didn't recommend it. Why?**
>
> A: That's likely because of the **Profit Score**. Milk and Bread are high frequency but very low margin. My system prioritizes bundles that make *money*, so it might have ranked "Milk → Premium Cookies" higher because of the better margin, even if the frequency is slightly lower.

> **Q: How does your system handle GST?**
>
> A: I have a utility function that maps categories to GST slabs (e.g., 5%, 12%). It calculates the Net Selling Price by removing the GST component from the MRP before calculating the profit margin.

Glossary

Antecedent
The "IF" part of a rule. The item that triggers the recommendation (e.g., "Bread" in Bread→Butter).
Consequent
The "THEN" part of a rule. The item being recommended.
Support
The percentage of total transactions that contain a specific itemset.
Confidence
The probability that the Consequent is purchased given that the Antecedent is purchased.
Uplift
The increase in probability of purchase caused solely by the presence of the Antecedent, excluding random correlation.
Context
The situational factors surrounding a transaction, such as time of day, day of week, or festival season.

One-Page Revision Sheet

PROFITLIFT AT A GLANCE

CORE GOAL

To replace "Frequency-based" recommendations with "Profit-based" and "Causal-verified" recommendations.

TECH STACK

Backend: Python, FastAPI, Pandas, Scikit-Learn
Frontend: React, TypeScript, Tailwind, Recharts

KEY ALGORITHMS

1. **FP-Growth:** For fast frequent pattern mining.
2. **T-Learner:** For causal inference (Uplift modeling).
3. **Multi-Objective Sort:** For ranking rules.

THE "GOLDEN SENTENCE" FOR VIVA

"My project improves upon traditional Market Basket Analysis by incorporating Contextual Segmentation to handle seasonality, and Causal Inference to distinguish between true purchase drivers and mere statistical coincidences, all optimized for maximum profitability."