DOM TEAM

DATASTORM 2025

Reconstructing Demand and Forecasting for Fresh Retail

A Data-driven Solution to the Demand Illusion

The Fresh Retail Dilema

The fresh food industry faces a high-stakes balancing act:

- Overstocking: Leads to spoilage, financial loss, and significant food waste.
- Understocking: Results in stockouts, lost sales, and reduced customer loyalty.

This is a fragile equilibrium between satisfying volatile demand and avoiding waste.

CORE PROBLEM

What it is

When a product stocks out, sales data records '0' or a capped amount.

The "Illusion”

Traditional models misinterpret these zeros as "no demand"

The Vicious Cycle

Stockout occurs
→ Model leanrs “low demand”
→ Retailer under-orders
→ Stockout happen sooner, reinforcing the false signal

Our Hypothesis

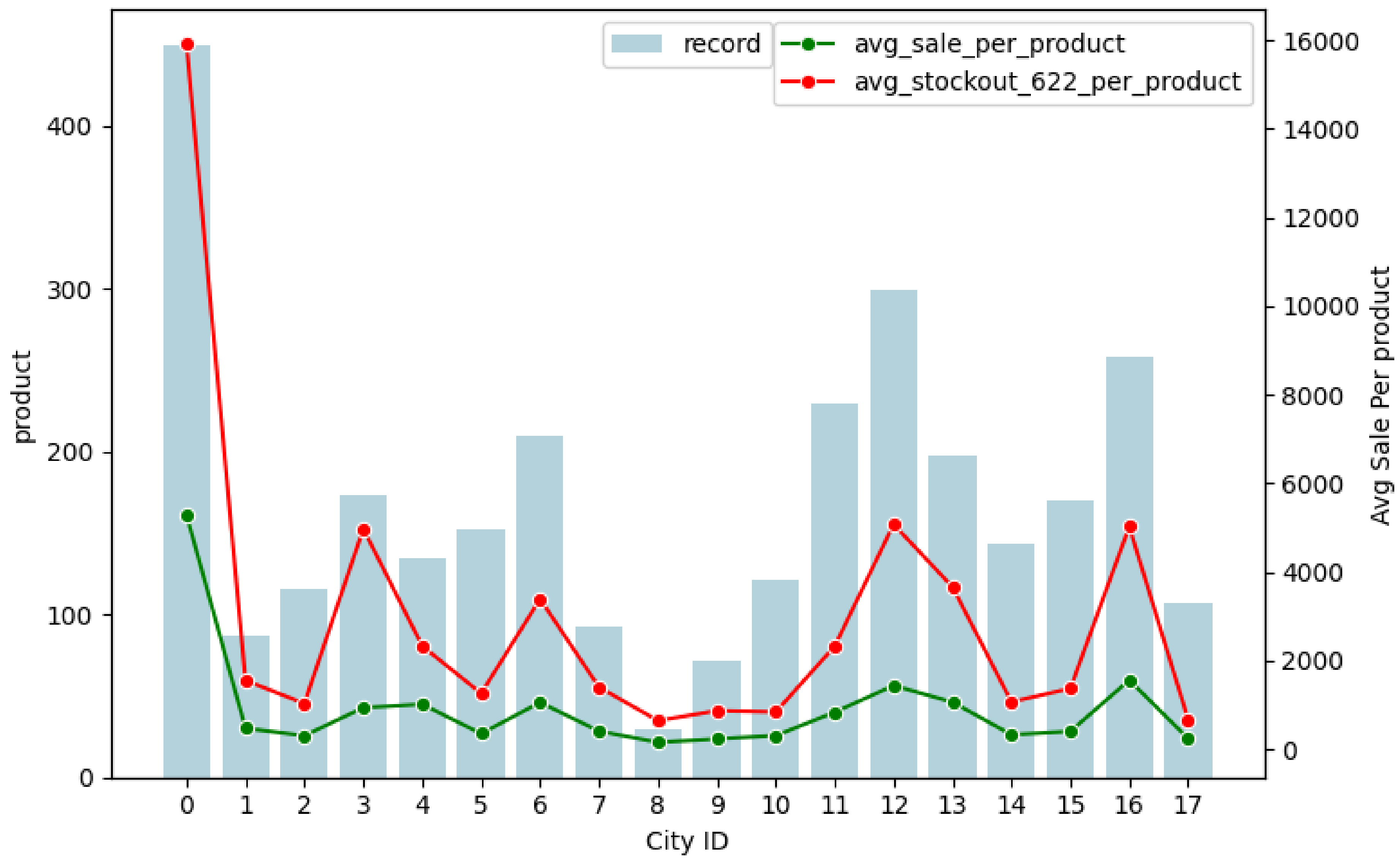
The Vicious Cycle is in the Data

- Dataset: FreshRetailNet-50K.
- Hypothesis: The "demand illusion" is not theoretical; it is an active, measurable flaw in this dataset.
- Our Goal: To find the statistical "signature" of demand censoring through Exploratory Data Analysis (EDA).

Proof of Concept (1/3)

Per-Product Analysis

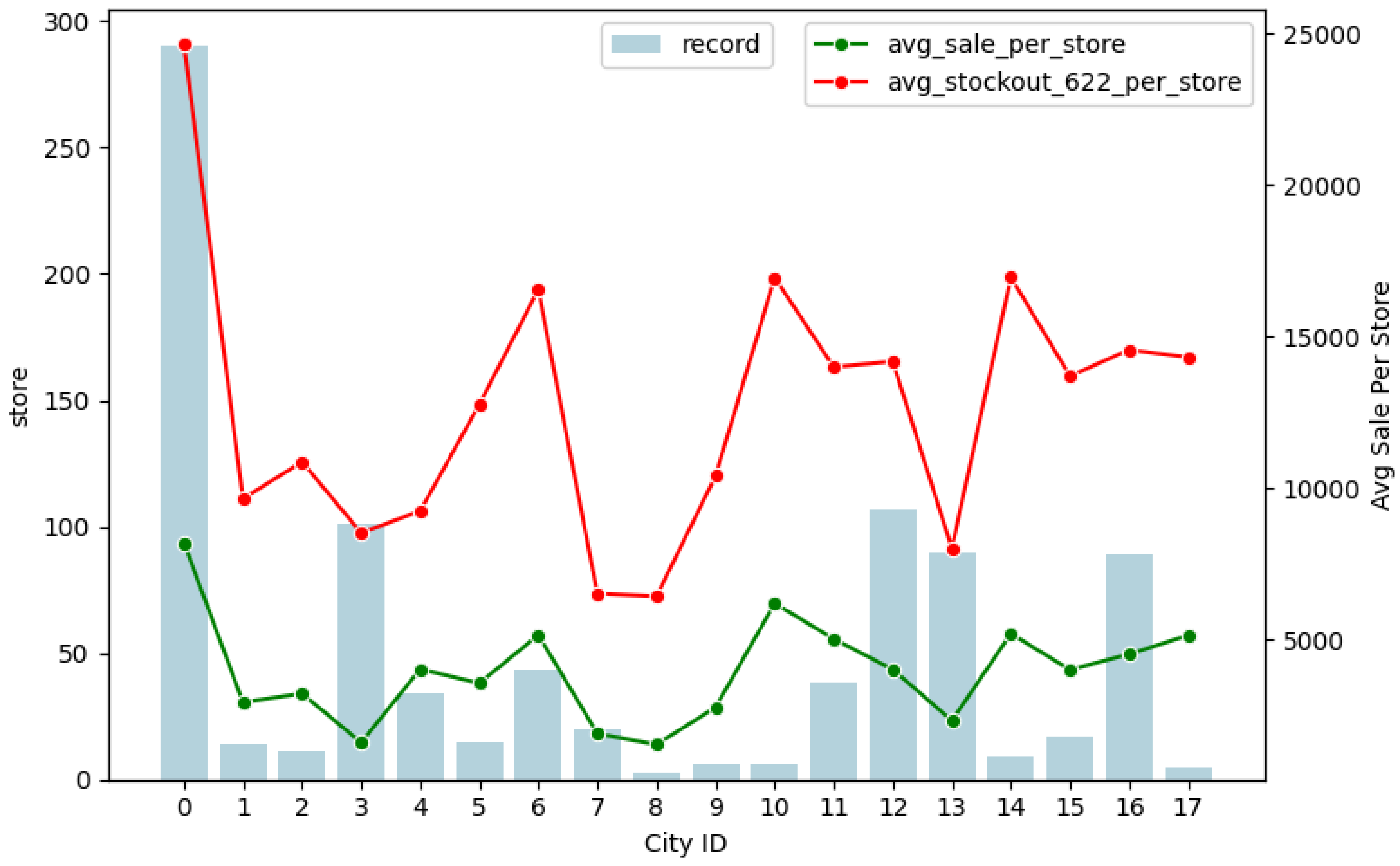
- High-performing products (e.g., City 0, 3, 12) see a corresponding spike in stockouts.
- This is the signature of demand censoring. Recorded sales (green line) are an understated representation of true demand.



Proof of Concept (2/3)

Per-Store Analysis

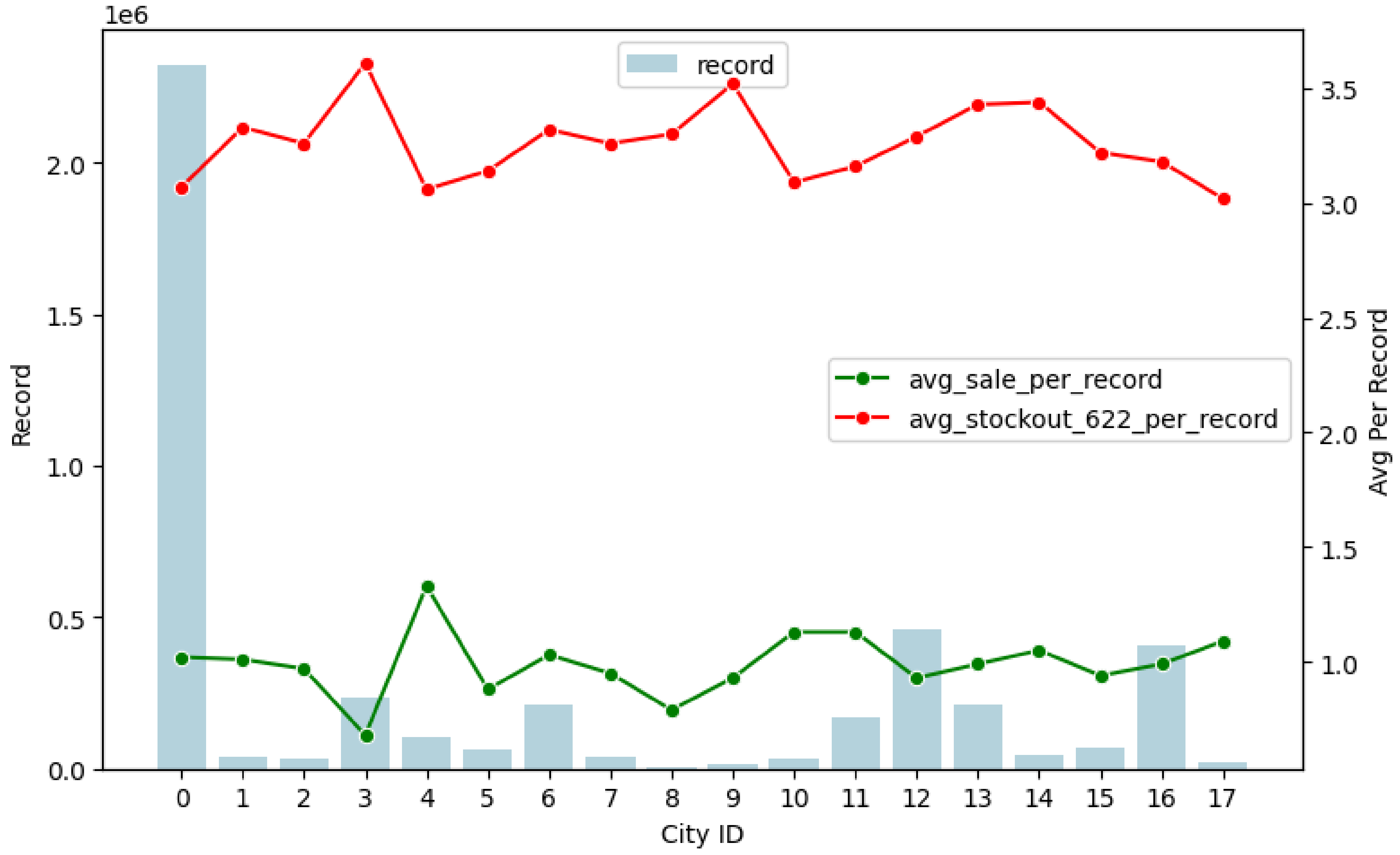
- High-Efficiency (e.g., City 3): High sales (green) with low stockouts (red). They manage inventory well.
- Low-Efficiency (e.g., City 10, 12): High sales but critically high stockout rates.



Proof of Concept (2/3)

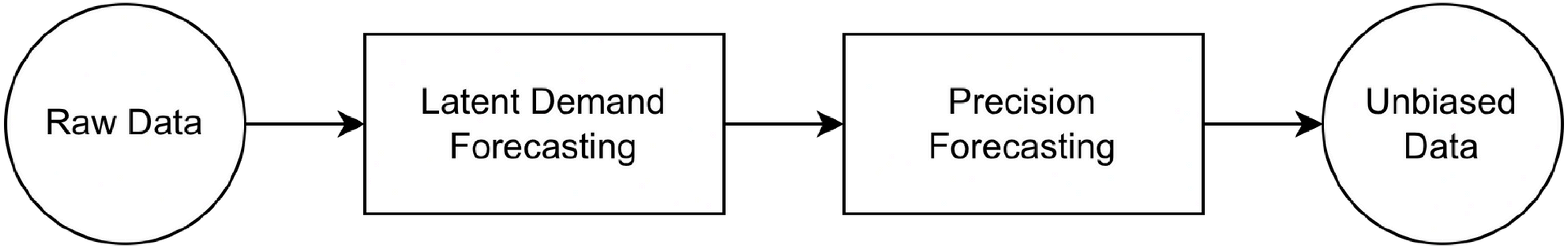
Per-Record Analysis

- The average stockout hours per record (red line) is consistently flat at ~3-3.5 hours for all cities
- Conclusion: It's an endemic flaw in the baseline inventory policy that artificially depresses sales data across the entire network



Our Vision

A Two-Stage Solution



Latent Demand Reconstruction

- Objective: To estimate the unobserved, "true" demand during stockout periods.
- Challenge: We must infer demand (D_t) when we only know that it was greater than or equal to the observed sales (S_t).
- Our Approach: A custom-designed neural network with a Hybrid Loss Function.
- For non-stockouts: Uses standard Mean Squared Error (MSE).
- For stockouts: Uses a "survival" loss, penalizing the model only if it predicts a demand lower than the observed sales.

Precision Forecasting

- Objective: To generate highly accurate, multi-horizon forecasts using the reconstructed demand data from Stage 1.
- Our Model: The Temporal Fusion Transformer (TFT).
- This state-of-the-art model was chosen for its unique advantages in solving this specific problem.

Why the Temporal Fusion Transformer (TFT)?

- Native Multi-Horizon Forecasting: Predicts the entire week at once, not just "one day at a time," which reduces error accumulation.
- Handles Heterogeneous Inputs: Seamlessly combines static data (store ID), known future data (promotions), and time-varying data (price, weather).
- Built-in Interpretability: It's not a "black box". It shows which past days and which features (e.g., "holiday," "promotion") were most important for its forecast

Measuring Success

Aligning Metrics with Value

- Primary Business Metric: WAPE (Weighted Absolute Percentage Error).
- Why? It avoids "division by zero" errors and, more importantly, weights errors by sales volume. A 10% error on a high-selling item is treated as more significant, aligning the model with financial impact.
- Primary Training Metric: RMSE + Quantile Loss.
- Why? This generates probabilistic forecasts (10th, 50th, 90th percentiles), giving managers a risk-adjusted range for ordering, not just a single number .

Strategic Impact

The Triple Bottom Line

- Profit (Economic): Maximizes revenue and optimizes inventory by eliminating forecasting bias.
- People (Social): Enhances customer satisfaction (fewer stockouts) and stabilizes workforce operations.
- Planet (Environmental): Directly reduces food waste by aligning orders with true demand.

Aligning with Global Goals

- By minimizing food waste through data-driven insights, our solution directly supports SDG 12: Responsible Consumption and Production.
- This moves beyond a simple technical exercise to create tangible environmental and social value.

Our Team

Role	Academic Focus	Core Skills
AI Architect	Computer Science (TDTU)	Deep Learning, Time-Series
ML Engineer	Software Engineering (VNU-HCM)	MLOps, Data Engineering, Backend/Frontend
Biz. Strategist	International Business (UEH)	Market Research, Business Case Dev.
Fin. Analyst	Auditing (UEH)	Financial Modeling, KPI Validation
Domain Expert	Logistics Technology (UEH)	Supply Chain, Inventory Management

Round 1 Project Roadmap (3 Weeks)

- Week 1 (26/10 - 2/11): Data Deep-Dive & PoC
- Week 2 (2/10 - 9/11): Solution Architecture
- Week 3 (9/11 - 16/11): Synthesis & Finalization

Risk Assessment & Mitigation

Risk	Description	Mitigation
R1 (Technical)	Stage 1 (Reconstruction) model is hard to train[68].	Develop simpler, robust statistical models (e.g., Tobit Regression) in parallel as a reliable fallback and benchmark[69].
R2 (Technical)	TFT model is computationally expensive and slow[70].	Conduct initial tuning on a smaller, representative data subset for rapid iteration. Optimize data pipelines for max GPU use[71].
R3 (Logistical)	Communication breakdown among multi-university team[72].	Implement formal project management from Day 1: daily stand-ups, centralized Trello board, and clearly defined roles[73].

Key Differentiators

- Novel Problem Formulation: We aren't just forecasting sales. We are solving for demand censoring—the hidden flaw behind most errors.
- Advanced Technical Approach: We apply a state-of-the-art model (TFT) to reconstructed demand data for unprecedented accuracy.
- Interdisciplinary Team: Our team combines technical (AI/SWE) with business (Finance/Logistics) expertise, ensuring the solution is not only accurate but commercially viable and operationally relevant.