DATASTORM 2025

SALE DEMAND FORECASTING
FRESH RETAIL INDUSTRY

BY: DOM TEAM

HO CHI MINH CITY, 2025

CHAPTER 1. SUMMARY

1.1. The Challenge

The global fresh food retail industry – faces a major problem: fresh products spoil quickly. Excess inventory leads to waste; insufficient stock results in lost sales. Yet beyond this operational challenge lies a subtler issue known as demand illusion. When stockouts occur, sales data record zero, because there is nothing left to sell.

Traditional forecasting models misinterpret these zeros as an absence of demand, creating a self-reinforcing loop: stockouts lead to underestimation, underestimation leads to under-ordering, and under-ordering leads to more stockouts.

Statistically, this is a case of right-censoring – where observed data fail to reflect the true underlying distribution. As a result, standard forecasting models become unreliable in fast-moving, perishable categories. The outcome is not just inefficiency, but tangible losses in revenue, customer loyalty, and sustainability.

This proposal seeks to correct that by introducing a data-driven framework capable of reconstructing censored demand and delivering more accurate forecasts. Beyond economic performance, the solution aligns with SDG 12: responsible consumption and production, promoting smarter, less wasteful retail operations.

1.2. Our Vision

To break the underestimation cycle, this proposal introduces a two-stage framework designed to detect the "demand illusion" and forecast with high accuracy.

1.2.1. Latent Demand Reconstruction Stage

The first stage ingests raw sales data along with key stockout indicators. Rather than treating recorded sales as true demand, it employs advanced statistical and machine learning techniques to estimate the unobserved demand during periods of stock out. This process effectively de-corrupts historical data, creating an accurate representation of customer interest.

1.2.2. Precision Forecasting Stage

The second stage uses the reconstructed demand data to train a time-series forecasting model, the temporal fusion transformer (TFT). This model captures complex temporal patterns and leverages a wide array of contextual variables – such as promotions, day of the week, and price changes – to generate highly accurate, multi-horizon demand forecasts.

1.3. Our Team

- Computer science and software engineering, who will architect and implement AI models.
- International business and auditing, who will ensure market alignment and financial viability.
- Logistics technology, who will provide insights into supply chain dynamics and inventory management.

This combination of skills ensures a holistic approach, from model development to operational implementation, providing a robust foundation for delivering a comprehensive and impactful solution.

1.4. Strategic Impact

Building upon the identification of the demand illusion problem and the development of the proposed censorship-aware forecasting framework, this section highlights its broader strategic impact under the triple bottom line perspective – delivering value across profit, people, and planet dimensions.

The business implications of this framework are both profound and far-reaching. By providing retailers with a more accurate and unbiased understanding of true consumer demand, the solution unlocks significant operational and strategic value throughout the entire supply chain.

- **Economic:** maximizes revenue and optimizes inventory levels through bias-free forecasting.
- **Social:** enhances customer satisfaction and stabilizes workforce operations.
- **Environmental:** reduces food waste and supports sdg 12 through sustainable resource use.

By translating a technically advanced forecasting approach into tangible outcomes that generate economic gains, social benefits, and environmental value, the proposed model positions itself as a strategic enabler of sustainable competitive advantage in the global fresh food retail market.

1.5. Key Differentiators

- Novel problem formulation: tackles demand censoring – the hidden flaw behind most forecasting errors.
- Advanced technical approach: applies TFT to reconstructed demand data for unprecedented accuracy.

- Interdisciplinary team: ensures technical soundness, commercial viability, and real-world relevance.

Chapter 2. The Fresh Retail Forecasting Dilemma

2.1. The High-Stakes Environment Of Perishable Goods

Overstocking leads to spoilage, eroding margins and contributing to global food waste. According to pwc (2024), up to 40% of total food loss occurs during post-harvest and distribution stages, with a further 10–30% wasted at the consumer level. Retailers, at the end of this chain, face both financial and ethical pressure to minimize waste – now a defining component of corporate sustainability.

Conversely, understocking results in stockouts, lost sales, and reduced customer trust. A Deloitte (2023) report identifies spoilage (32%), storage limitations (24%), and pricing complexity (16%) as the top challenges in fresh food retailing. Together, these highlight the fragile equilibrium between satisfying volatile customer demand and avoiding overproduction.

Compounding this difficulty, demand for perishable goods fluctuates with seasonality, weather, promotions, and local consumption behavior. Traditional forecasting systems – originally designed for stable, non-perishable categories – perform poorly in such dynamic contexts. kpmg (2024) emphasizes that digital transformation and data-driven insights are essential to aligning supply with true demand, reducing waste, and improving transparency across supply chains.

In summary, forecasting in fresh retail must go beyond accuracy alone. Models must be flexible, context-aware, and capable of integrating real-time signals that capture the highly volatile nature of perishable goods.

2.2. The Vicious Cycle Of Demand Censoring

One of the most critical yet overlooked issues in fresh retail forecasting is the distortion of historical data due to stockouts – a statistical phenomenon known as right-censoring.

Consider a simple case: a grocery store stocks 20 units of fresh salmon on friday. by 3:00 pm, all are sold. The sales data records 20 units, yet the true demand could have been 25 or 30. The sales record is censored at the stockout point – it tells us demand was at least 20, but nothing more.

When a forecasting model learns from this truncated data, it systematically underestimates demand. The consequences form a destructive feedback loop:

1. A stockout occurs, and sales are capped by inventory.
2. The model interprets the capped sales as low demand.

3. The retailer orders less inventory next time.
4. The next stockout happens sooner, further reinforcing the false signal.

Over time, this loop creates a “demand illusion” – an entrenched bias where the model continuously under-forecasts, deepening both revenue loss and customer dissatisfaction.

2.3. Analyzing The Freshretailnet-50k Dataset

The competition's suggestion to use the freshretailnet-50k dataset is a clear signal that the judging panel is looking for solutions that address this deeper, more nuanced problem of demand censoring.

2.3.1. Exploratory Data Analysis (EDA)

A. Feature List

Feature	Data Type	Description
city_id	Int64	The Encoded City Id
store_id	Int64	The Encoded Store Id
management_group_id	Int64	The Encoded Management Group Id
first_category_id	Int64	The Encoded First Category Id
second_category_id	Int64	The Encoded Second Category Id
third_category_id	Int64	The Encoded Third Category Id
product_id	Int64	The Encoded Product Id
dt	Object	The Date
sale_amount	Float64	The Daily Sales Amount After Global Normalization
hours_sale	Object	The Hourly Sales Amount After Global Normalization
stock_hour6_22	Int32	The Number Of Out-Of-Stock House Between 6:00 To 22:00
hours_stock_status	Object	The Hourly Out-Of-Stock Status
discount	Float64	The Discount Rate (1.0: No Discount, 0.9: 10% Off)

holiday_flag	Int32	Holiday Indicator
activity_flag	Int32	Activity Indicator
precept	Float64	The Total Precipitation
avg_temperature	Float64	The Average Temperature
avg_humidity	Float64	The Average Humidity
avg_wind_level	Float64	The Average Wind Force

Table 2.3.1.1: Feature List

B. Missing Values And Unique Counts Report

Feature	**Unique Value**	**Description**
activity_flag	2	Binary Feature (Likely 0/1 → Indicates Whether There's A Promotion Or Not).
holiday_flag	2	Binary Feature (Holiday Vs Non-Holiday).
management_group_id	7	Small Number Of Management Groups.
stock_hour6_22_cnt	17	17 Unique Hourly Points From 6:00 Am To 22:00 Pm
city_id	18	18 Cities In The Dataset.
first_category_id	32	32 Main Product Categories.
second_category_id	84	84 Subcategories.
dt	90	90 Distinct Dates, From 28/03/2024 To 25/06/2024
third_category_id	233	Fine-Grained Product Group.
avg_wind_level	247	247 Float Weather Variable.
product_id	865	Each Product Has A Unique Id - Moderately Large But Still Manageable.
store_id	898	Nearly 900 Stores — Represents Store-Level Variation.
sale_amount	1363	Continuous Target Variable — Varies Widely

avg_temperature	1582	247 Float Temperature Variable
discount	2600	Continuous Or Ratio-Type Variable, Range From 0 To 1
avg_humidity	4817	4817 Float Humidity Variable
precpt	40117	Very High Number Of Unique Values - Continuous Precipitation Variable

Table 2.3.1.2: Feature List

C. A Proof of Concept for the "Demand Illusion"

While the feature lists provide a map of the data, a high-level aggregate analysis is required to validate our core hypothesis: that the "demand illusion" is not a theoretical problem but an active, measurable flaw within this dataset.

The following analysis, grouped by city, serves as the initial Proof of Concept (PoC). It confirms that stockouts are systemic, directly correlated with demand, and represent a significant operational failure.

1) Per-Product Analysis

- Finding: This chart reveals the most critical insight. There is a strong and consistent positive correlation between the average sales per product (green line) and the average stockout hours per product (red line).
- Analysis: In cities with high-performing products (e.g., City 0, 3, 12, 16), we see a corresponding spike in stockout hours. This is the statistical signature of demand censoring . The products that are most popular are precisely the ones that are most frequently unavailable.
- Conclusion: This chart proves that the recorded sale_amount is a censored, understated representation of true customer interest. The green line (recorded sales) is already high, but the red line (stockouts) proves that the true latent demand is significantly higher. This validates the absolute necessity of our Stage 1: Latent Demand Reconstruction model.

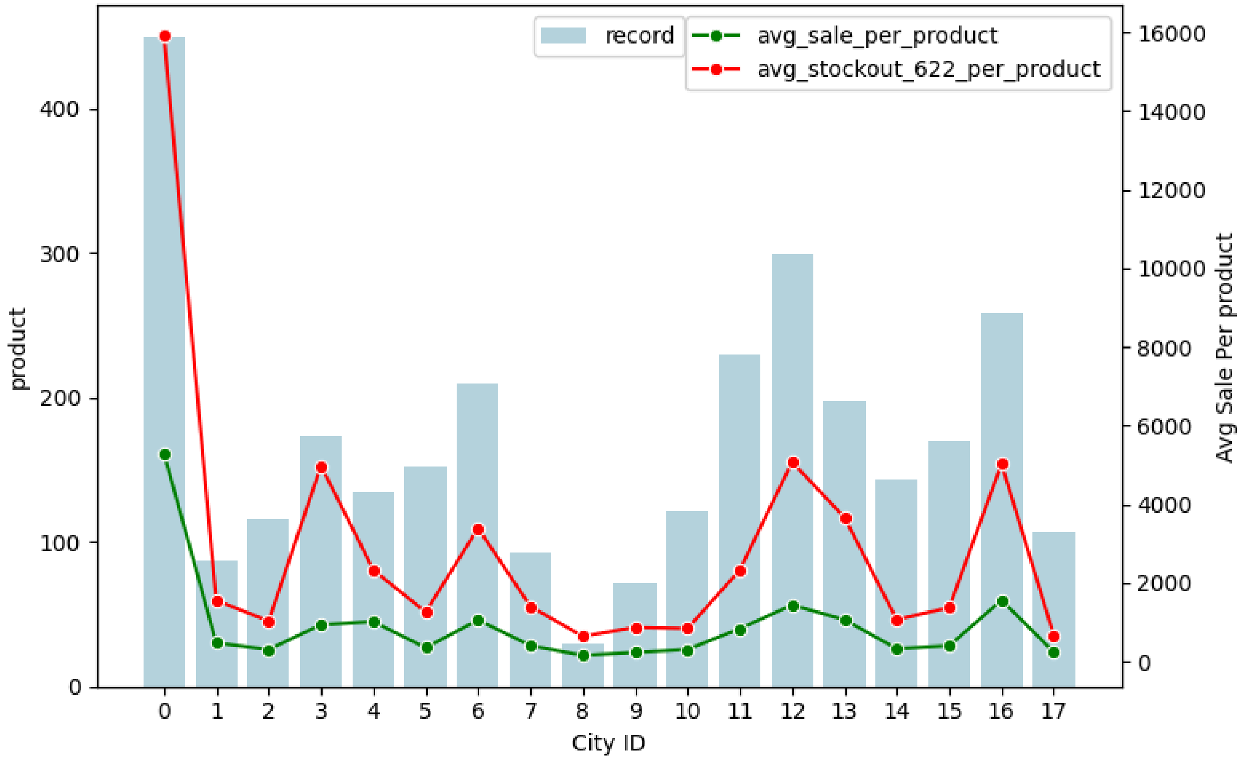

Figure 2.3.1.1: Average sale per product, Average stockout from 6 to 22 hour count per product and Number of Product each city.

2) Per-Store Analysis

- Finding: This chart highlights vast differences in operational efficiency across the network. Unlike the per-product view, the relationship here is not uniform.
- Analysis: We can identify two distinct operational archetypes:
- High-Efficiency (e.g., City 3): This city shows a high avg_sale_per_store (green line) but maintains a relatively low avg_stockout_622_per_store (red line). This represents effective inventory management.
- Low-Efficiency (e.g., City 6, 10, 12, 14): These cities also boast high average sales, but they suffer from critically high stockout rates.
- Conclusion: The problem is not simply "high demand." It is a logistics and planning failure. The fact that City 3 can succeed with low stockouts proves it is possible. This finding justifies our team's multidisciplinary approach, specifically integrating Logistics Technology expertise to solve a problem that is operational, not just statistical.

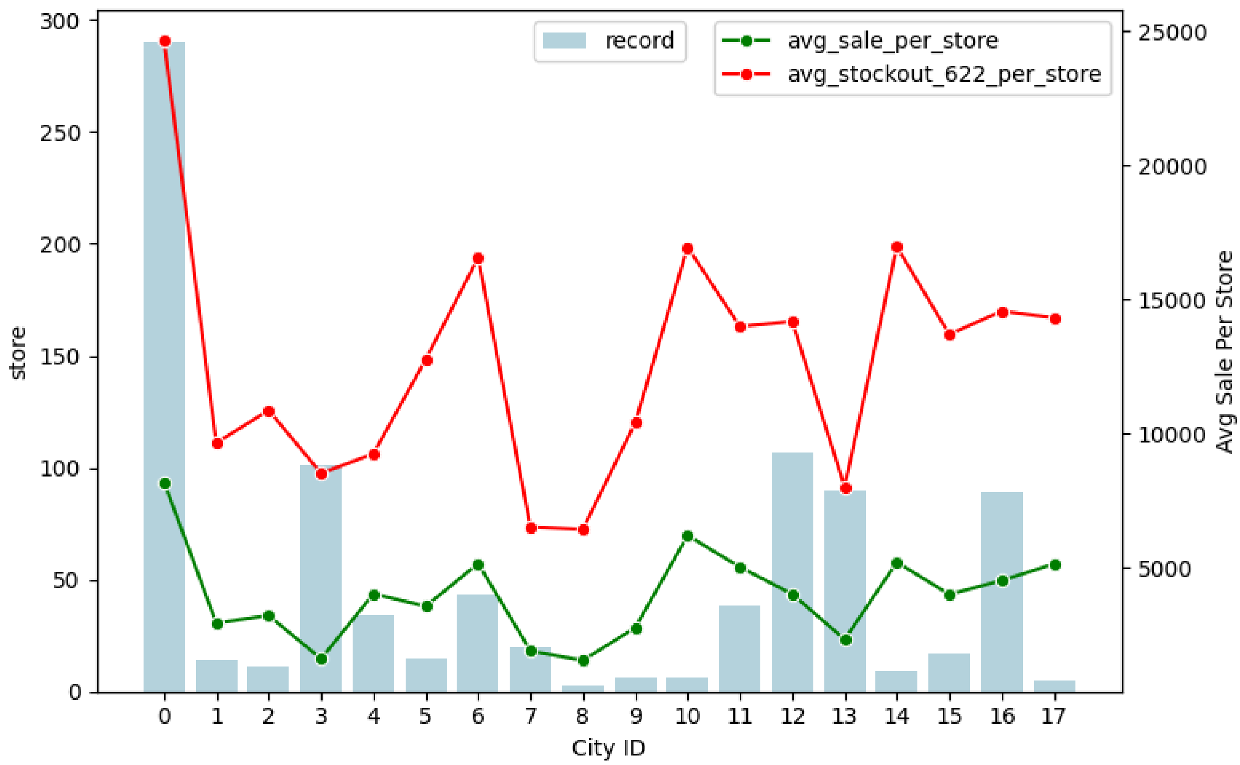

Figure 2.3.1.2: Average sale per store, Average stockout from 6 to 22 hour count per store and Number of Store each city.

3) Per-Record Analysis

- Finding: This chart reveals that the stockout problem is chronic and systemic. While the total number of records (blue bars) varies dramatically (City 0 is massive), the avg_stockout_622_per_record (red line) is consistently flat at approximately 3.0-3.5 hours for *all* cities.

- Analysis: This means that regardless of a city's size or traffic volume, any given (product, store, day) record carries an average ~3-hour stockout burden. The problem is not isolated to high-traffic areas; it is an endemic flaw in the baseline inventory policy.

- Conclusion: The stockout issue is a system-wide, chronic condition that artificially depresses sales data across the entire network.

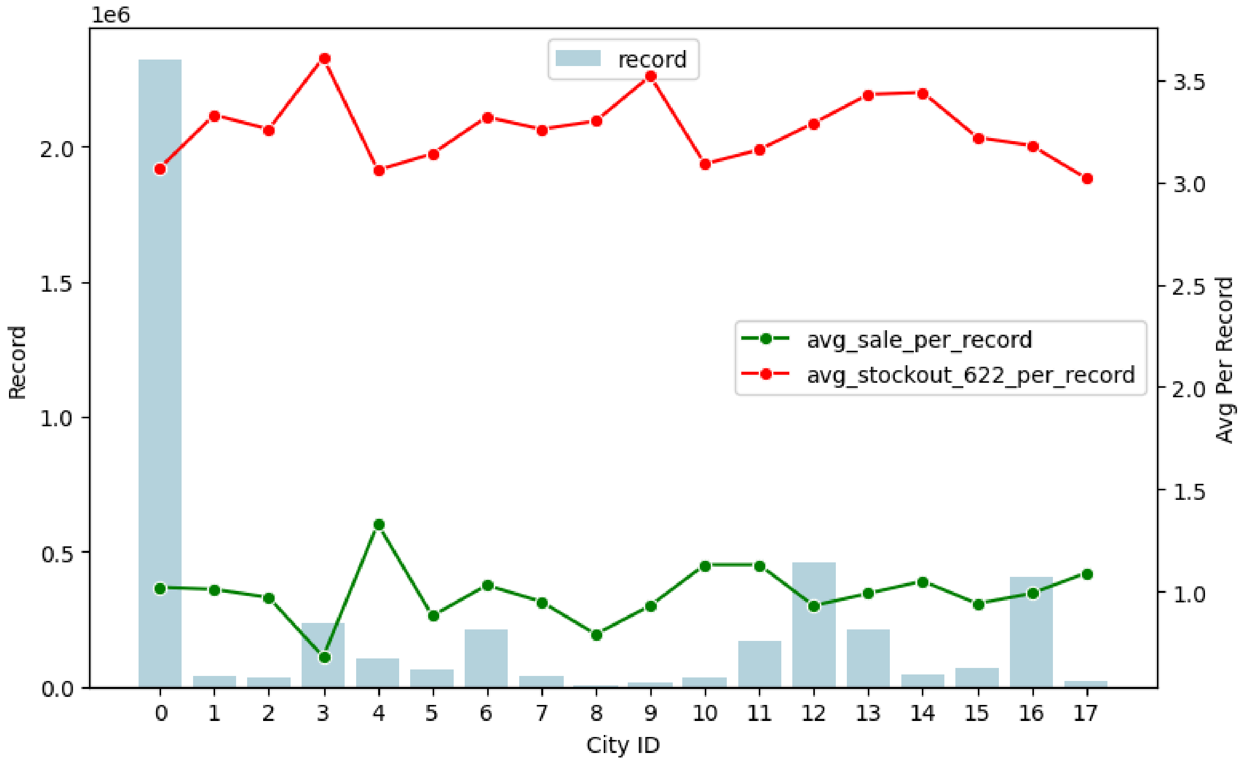

Figure 2.3.1.2: Average sale per record, Average stockout from 6 to 22 hour count per record and Number of record each city.

D. EDA Conclusion & Strategic Sampling Decision

This aggregate EDA has successfully validated our core premise. We have proven that the FreshRetailNet-50K dataset is deeply affected by demand censoring, which is (1) directly correlated with high demand, (2) exacerbated by operational inefficiency, and (3) systemic across all cities.

However, the dataset's immense size (4.5 million daily records, exploding to ~109 million hourly records) makes a full, deep-dive EDA computationally prohibitive for this stage.

Therefore, based on these findings, we will adopt a strategic sampling approach for our deeper hourly analysis. We will focus our efforts on two key cities that represent the most valuable case studies:

1. **City 0:** As the largest market by volume, it is the most critical component of the dataset and must be analyzed.
2. **City 10:** This city represents the "High-Potential, Low-Efficiency" archetype. It has high sales potential but suffers from one of the worst stockout rates. It is the perfect test case to demonstrate the maximum value of our censorship-aware solution.

By focusing on these two cities, we can perform a granular, hourly analysis to prove our solution's effectiveness in a way that is both representative and impactful.

CHAPTER 3. THE SOLUTION ARCHITECTURE

3.1. A Dual-Model Approach Overview

1. **Input:** reshretailnet-50k dataset, which includes time-series data (hourly_sales), binary indicators (hourly_stock_status), and various static and dynamic covariates (price, promotion status, product id, etc.).
2. **Stage 1 - latent demand reconstruction:** this stage processes the input data. For every timestep where the hourly_stock_status flag is false, the observed sales are assumed to be equal to the true demand. For every timestep where the flag is true, a specialized model estimates the unobserved latent demand. the output of this stage is a new, complete time-series dataset representing the reconstructed "true" demand history.
3. **Stage 2 - precision forecasting:** this stage takes the reconstructed demand data from stage 1 as its primary input. It trains a time-series model, The Temporal Fusion Transformer (TFT), on this clean data.
4. **Output:** the final output of the system is a set of unbiased demand forecasts, which can include both point estimates and probabilistic ranges (quantiles). These forecasts provide retailers with a clear and reliable prediction of future customer demand, free from the corrupting influence of past stockouts.

3.2. Latent Demand Reconstruction Stage

The objective of stage 1 is to infer the value of a variable (demand) that is only partially observed. This is a classic statistical problem that requires specialized modeling techniques.

3.2.1. Theoretical Foundation And Model Candidates

The core of this stage is to build a model that can predict demand following this equation:

$$S_t = min(D_t, I_t)$$

where, I is the available inventory, the demand is D and S is observed sales.

Then a stockout occurs, we only observe $T_t = I_t$, and we know that $D_t \geq S_t$. The goal is to estimate the most likely value of D_t given this information and other covariates. A spectrum of models will be explored to address this, ensuring methodological robustness.

- **Baseline heuristics:** as a starting point, simple and interpretable methods will be implemented. For instance, censored values could be replaced by the mean or median demand from similar, non-censored periods (e.g., the same hour on previous, non-stockout days). While naive, these baselines provide a crucial performance benchmark.

- **Statistical approach (censored regression):** a more principled approach involves using models designed for censored data. The tobit model is a classic example from econometrics. It assumes that there is an underlying latent variable (demand) which is normally distributed, but we only observe it if it is above a certain threshold (zero). This can be adapted to the stockout context, where the censoring point is the inventory level at the time of stockout.

- **Advanced deep learning approach:** the most powerful proposed method is a custom-designed neural network. This network would take as input the covariates (price, day of week, etc.) and the sales history leading up to the stockout. Its innovation lies in a specialized, hybrid loss function. For non-censored data points, the loss would be a standard mean squared error (mse):

  $$I_{uncensored} = (d_{predicted} - S_{actual})^2$$

  for censored data points, where we only know $d_{true} \geq s_{actual}$, the loss function would be based on principles from survival analysis, penalizing the model only if it predicts a demand lower than the observed sales:

  $$I_{censored} = max(0, S_{actual} - d_{predicted})$$

  The total loss would be a weighted sum of these two components, allowing the network to learn the underlying demand distribution even from incomplete information.

3.3. Precision Forecasting With Reconstructed Data Stage

Once a reliable, reconstructed demand history is created, the problem transforms into a more standard, albeit complex, time-series forecasting task. The choice of model for this stage is critical for achieving high accuracy and business utility.

3.3.1. Rationale For Temporal Fusion Transformer Selection

While traditional models like arima or simpler neural networks like LSTM have been used for forecasting, the Temporal Fusion Transformer (TFT) is selected for its state-of-the-art performance and unique architectural features that are perfectly suited to the fresh retail problem.

Native multi-horizon forecasting: unlike models that predict one step at a time and iterate, TFT is designed to generate predictions for multiple future timesteps simultaneously. This is highly efficient, as it mitigates the accumulation of errors inherent in iterative forecasting. This is crucial for weekly ordering cycles in retail.

- **Handling of heterogeneous inputs:** retail demand is driven by a mix of data types. tft's architecture is explicitly designed to handle this complexity. It can seamlessly incorporate static covariates (e.g., sku id, store location), known future inputs (e.g., a planned promotion next week), and other observed time-varying inputs (e.g., recent price changes, weather data).
- **Built-in interpretability:** this is a key differentiator. Many deep learning models are "black boxes," making it difficult for business users to trust their outputs. tft includes two forms of attention mechanisms. The first reveals which historical time steps were most influential for a given forecast. The second, a variable selection network, quantifies the importance of each input feature. This allows a planner to understand why the model is predicting a surge in demand (e.g., "due to the upcoming holiday and the ongoing promotion"), fostering trust and enabling more informed decision-making.

3.3.2. Architectural Deep Dive

The power of TFT stems from its sophisticated components. gating mechanisms, specifically gated residual networks (GRN), control the flow of information throughout the model, allowing it to skip over irrelevant parts of the architecture and adapt to different data patterns. Variable selection networks (VSN) act as a form of feature selection, pruning uninformative inputs before they are fed into the core of the model. The temporal processing is handled by a sequence-to-sequence layer with multi-head attention, similar to the original transformer, which allows the model to learn complex relationships across different time steps. This combination of specialized components makes tft exceptionally well-suited for capturing the intricate dynamics of retail demand.

3.4. Evaluation Protocol: Aligning Technical Rigor With Business Objectives

A successful forecasting system must be evaluated using metrics that reflect both its statistical accuracy and its real-world business value. Therefore, a dual-metric approach is proposed.

3.4.1. Primary Business Metric: Weighted Absolute Percentage Error

For evaluating the final forecasts from a business perspective, the weighted absolute percentage error (WAPE) will be the primary metric. it is calculated as:

$$wape = \frac{\sum_{t=1}^{n} \left| a_t - a_t \right|}{\sum_{t=1}^{n} \left| a_t \right|}$$

where a_t is the actual value and a_t is the forecast value. WAPE is superior to the more common mean absolute percentage error (MAPE) in a retail context for two key reasons. First, it avoids the "division by zero" error that occurs when actual sales are zero. Second, it weights errors by their sales volume, meaning that a 10% error on a high-selling item is treated as more significant than a 10% error on a low-selling item. This directly aligns the metric with financial impact, as errors on high-volume products are more costly.

3.4.2. primary training metric: root mean squared error

During model training and optimization, the root mean squared error (RMSE) will be used as a primary loss function. RMSE is sensitive to large errors, which is beneficial for penalizing significant forecast misses.

$$rmse = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (a_t - f_t)^2}$$

Furthermore, to provide richer information for inventory management, the model will also be trained using quantile loss. instead of producing a single point forecast, this allows the model to generate probabilistic forecasts–for example, predicting the 10th, 50th (median), and 90th percentiles of demand. This range is far more valuable to a supply chain manager than a single number. It allows them to make risk-adjusted decisions, for example, ordering up to the 90th percentile for a critical item to ensure a high service level, while ordering closer to the median for a less critical one.

CHAPTER 4. THE EXECUTION TEAM: CAPABILITIES AND SYNERGY

4.1. A Multidisciplinary Powerhouse For A Multifaceted Problem

solving the fresh retail forecasting problem is not solely a data science challenge; it is an integrated business, logistics, and technology challenge. A model, no matter how accurate, is useless if it is not grounded in commercial reality and operational feasibility. Recognizing this, the project team has been purpose-built to address every facet of this complex ecosystem. The team's composition brings together students from leading institutions - Tôn Đức Thắng University (TDTU), VNU - HCM University Of Science, and the University Of Economics Ho Chi Minh City (UEH) - creating a harmony synergy of technical prowess, business acumen, and domain-specific knowledge. This diversity is a strategic asset, ensuring that the proposed solution is not only technologically advanced but also relevant, viable, and impactful.

4.2. Core Competencies And Project Role Allocation

Each team member has been assigned a primary role that leverages their unique academic background and skills. This clear division of labor ensures comprehensive coverage of all project requirements, from initial data engineering to final business case presentation. The following capability matrix details this strategic allocation, explicitly linking each member's expertise to their project responsibilities and the competition's core judging criteria. This structure provides a clear and compelling demonstration of the team's readiness and capacity to execute this project successfully.

Ceam member	**Academic focus & university**	**Core skills & expertise**	**Primary project role**
Nguyễn Quang Huy	computer science (TDTU)	deep learning, time-series analysis, statistical modeling	responsible for the architecture, development, and training of the two-stage forecasting model.
Đặng Trường Nguyên	software engineering (VNU-HCM)	MLOPs, data engineering, frontend developer, backend developer.	responsible for building a robust and scalable data pipeline, implementing version control, and deploying a web application to visualize and present the ai model’s results.
Hoàng Nam Khánh	international business (UEH)	market research, competitive analysis, business case development, go-to-market strategy, presentation & communication	responsible for framing the business problem, quantifying the market opportunity and potential impact, and ensuring the solution aligns with real-world retail challenges.
Võ Đình Lộc	auditing (UEH)	financial modeling, kpi development, metric validation, risk assessment, quantitative analysis	responsible for co-designing the evaluation protocol, validating model performance against business-centric kpis, and assessing the financial viability of the solution.
Võ Quang	logistics technology	supply chain optimization, inventory management, warehouse operations, demand planning	responsible for ensuring the model's inputs and outputs are grounded in supply chain reality, providing

Dũng	(UEH)	principles	context on operational constraints, and translating forecasts into actionable inventory policies.

4.3. Collective Experience And Academic Foundations

Beyond their individual specializations, the team members possess a strong collective foundation in quantitative analysis, project management, and collaborative development. Prior academic projects in areas such as machine learning, market analysis, and operations management have equipped the team with the necessary hands-on experience to tackle a challenge of this scale. coursework in advanced algorithms, statistical inference, supply chain management, and financial modeling provides the theoretical underpinning for the proposed methodology. This blend of practical and theoretical knowledge ensures that the team can not only conceive of an innovative solution but also rigorously implement, test, and validate it according to the highest academic and professional standards. This history of relevant work and study serves as a further testament to the team's capability and commitment.

Chapter 5. Project Roadmap & Proof Of Concept

5.1. Qualifying Round 1: Concept Validation Phase

a. Week 1 (26/10 - 2/11): Data Deep-Dive & Problem Validation (PoC)

- Objective: To prove that the "demand illusion" is a real, severe, and systemic problem within the suggested dataset.
- Key Tasks:
  - Data Pipeline: Build the pre-processing script to handle the large-scale data (4.5M rows), specifically the parallelized explode process for hourly data (Lead: Đặng Trường Nguyên).
  - Aggregate PoC: Perform the high-level city-wide analysis (Per-Product, Per-Store, Per-Record) to validate the core hypothesis and identify key trends .
  - Strategic Sampling: Based on the aggregate PoC, make a data-driven decision to select City 0 (Largest Market) and City 10 (High-Potential, Low-Efficiency) for granular analysis .
  - Granular PoC: Analyze the sampled (City 0 & 10) hourly data to generate the core PoC charts:
    - "True Zero" vs. "Stockout Zero" Analysis.
    - The "U-Shape" Hourly Stockout Curve.

    - Impact of Promotions (activity_flag) on Stockout Rates.
- Deliverable: A complete set of PoC visualizations and analyses that serve as the foundation for Chapter 2.3 of this report.

b. Week 2 (2/10 - 9/11): Solution Architecture & Technical Design

- Objective: To design the 2-stage technical architecture that is directly justified by the evidence from Week 1.
- Key Tasks:
  - Stage 1 (Reconstruction) Research: Formally design the "Latent Demand Reconstruction" stage. Research and compare candidate models (e.g., Heuristics, Tobit Regression, Imputation models) and their trade-offs.
  - Stage 2 (Forecasting) Research: Research and select the primary forecasting model. Justify the selection of the Temporal Fusion Transformer (TFT) over alternatives (ARIMA, Prophet) based on its specific advantages for this problem (e.g., multi-horizon, interpretability) .
  - Evaluation Protocol Design: Define the business-centric and technical metrics for success (WAPE, RMSE, Quantile Loss). This will be led by our Auditing specialist to ensure alignment with financial impact.
- Deliverable: The complete architectural diagrams, model justifications, and evaluation protocols detailed in Chapter 3.

c. Week 3 (9/11- 16/11): Synthesis & Report Finalization

- Objective: To synthesize all findings into a comprehensive business case, technical proposal, and presentation, as required by Round 1.
- Key Tasks:
  - Business Case Writing: Draft the full report, focusing on the problem (Ch 1-2), team capabilities (Ch 4), and strategic impact (SDG 12) (Lead: Hoàng Nam Khánh, Võ Quang Dũng).
  - Technical Writing: Draft the technical architecture (Ch 3) and the full project plan, including risk assessment and tech stack (Ch 5) (Lead: Nguyễn Quang Huy, Đặng Trường Nguyên).
  - Presentation & Video: Create the summary slide deck and produce the 3-minute video presentation (Lead: Võ Đình Lộc, All Members).
  - Final Submission: Conduct a full team review and submit all deliverables by the October 26th deadline.

- Deliverable: The final Round 1 submission (Report, Slides, Video).

5.2. Technology Stack And Resource Plan

To ensure efficient and effective execution, the project will leverage a modern, open-source technology stack. This approach maximizes flexibility and allows the team to utilize powerful, industry-standard tools.

- AI:
    - programming language: python 3.9+
    - core libraries:
        - machine learning/deep learning: pytorch, pytorch forecasting (for tft), scikit-learn
        - data manipulation and analysis: pandas, numpy, scipy
        - baseline modeling: prophet, statsmodels
        - visualization: matplotlib, seaborn, plotly
- Website ui:
    - programming language: javascript
    - core libraries:
        - framework: nextjs, tailwindcss
        - support lib: just-validate (for frontend data's validation), shadcn ui (built-in ui components)
- Backend:
    - programming language: python 3.9+
    - core libraries:
        - framework: fastapi
        - authentication: jwt, bcrypt
        - support lib: pydantic (for backend data's validation)
- Cloud/compute resources: google colab pro
- Collaboration and version control:
    - code repository: git and github

- communication: a dedicated slack or discord channel will be used for daily communication and coordination.
- project management: a trello or asana board will be used to track tasks, deadlines, and progress against the project roadmap.

5.3. Risk Assessment And Proactive Mitigation Strategies

risk id	**risk description**	**likelihood**	**impact**	**mitigation strategy**
r1	**technical:** the advanced deep learning model for stage 1 (latent demand reconstruction) proves difficult to train or fails to produce a plausible demand reconstruction.	medium	high	a multi-tiered modeling approach will be used. simpler, more robust statistical models (e.g., tobit regression) will be developed in parallel. These will serve as a reliable fallback and a strong benchmark against which to evaluate the more complex model.
r2	**technical:** the temporal fusion transformer (tft) model is computationally expensive, leading to slow training and tuning cycles that jeopardize the project timeline.	medium	medium	initial hyperparameter tuning and feature engineering will be conducted on a smaller, representative subset of the data to allow for rapid iteration. the team will leverage transfer learning principles if pre-trained components are available and will optimize the data loading pipeline for maximum gpu utilization.
r3	**logistical:** inefficient division of labor or communication breakdowns among a multidisciplinary, multi-university team lead to project delays.	low	high	a formal project management structure will be implemented from day one. this includes daily 15-minute "stand-up" meetings to report progress and identify blockers, a centralized task board (trello), and clearly defined roles and responsibilities as outlined in chapter 4.

r4	**data:** the quality of the is_out_of_stock flag is inconsistent or noisy, making it an unreliable indicator for identifying censored data points.	low	high	The initial eda phase will include a specific sub-task to rigorously validate the stockout flag. This involves cross-referencing it with sales patterns (e.g., periods of sustained zero sales) to identify any anomalies. If noise is detected, data cleaning or rule-based adjustments will be applied.

Table 5.3.1: Risk management