Phantom Inventory Detection & Prediction: A New Light On Out-Of-Stocks

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Introduction

Phantom inventory, also known as ghost inventory, refers to discrepancies where inventory exists in records but not in reality. This issue may arise from theft, misplacement, and data entry inaccuracies, leading to sale loss, customer dissatisfaction, and operational inefficiencies.

Retailers worldwide lose over $1.8 trillion annually due to inventory distortion, like phantom inventory, as well as inefficient supply chain. Inaccurate stock records frustrate customers, reduce loyalty, and force employees to spend time searching for nonexistent products. Addressing phantom inventory is crucial for improving business efficiency, customer experience, and profitability.

Business Problem

Due to phantom inventory—where the system indicates stock availability while the actual inventory is depleted—data accuracy is compromised. This discrepancy affects restocking decisions.

Constraints

The brand has multiple product lines and sales channels, with inventory data from different systems, causing integration challenges.

Stakeholders

- Inventory management team
- Supply chain department
- Sales department
- Senior management
- Store Operations Team

Why Important

Incorrect restocking decisions lead to:

- Sales loss
- Decreased customer experience impacts brand reputation.
- Overstocking leads to increased costs.

Analytics problem

Problem Framing

Using historical sales and inventory data, the model identifies potential phantom inventory and predicts future stockouts.

Assumptions

- Historical data reveals future trends.
- External factors have a minimal impact on model.

Success Metrics

- Precision: Correct phantom inventory alerts.
- Recall: Actual phantom inventory detected.
- RMSE: Measures the error in demand values.

Result

Who Benefit

01 **Retail Executives**
- Data-Driven Decision Support
- Improved Inventory Accuracy
- Lower Inventory Costs

02 **Store Associates**
- Less Time Search for Items
- Reduce Conflicts with Customers

03 **Suppliers**
- More Accurate Restocking Needs

04 **Shoppers**
- Fewer Stockouts
- More Reliable Availability
- Enhanced Shopping Experience

Data Overview

The dataset is provided by a major U.S. grocer and comprises 14,385 unique products across four diverse categories and includes three data tables with key features, as outlined below:

Product Feature	Shelf Availability	Sales Transactions
Product Name **Product SKU** Location Historic Sales Balance on Hand Count (BOH)	**Product SKU** Out-of-Shelf (OOS) Timestamps	**Product SKU** Transaction Timestamps Transaction Quantity

Methodology

Data → Exploratory Data Analysis

Data Preprocess
- Dataset Cleaning
- Dataset Merging
- Standardizing Column Names
- Imputing Missing Values

Feature Engineering
- Feature Creation
- K-Means Clustering as a Feature
- Feature Selection
- Feature Transformation (Log, Scaling)

Data Splitting (80 | 20)

Phase 1: Detection for 'Phantom Inventory'

Model Selection
- Random Forest
- CatBoost
- XGBoost
- LightGBM

Model Building
- Hyperparameter Tuning with Cross-Validation
- Classification with Threshold Optimization
- Evaluation Metrics: Precision and Recall.

Phase 2: Prediction for 'Product Stockout Day'

Model Selection
- LSTM
- ARIMA/SARIMA
- Naive Forecast

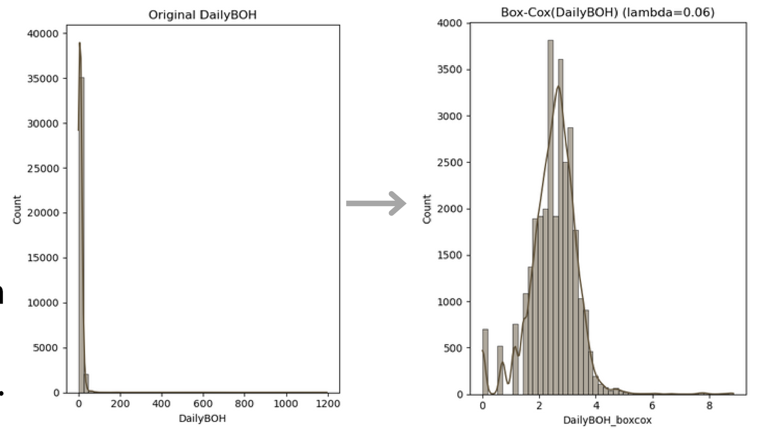
Model Building
- Detect Time Patterns with Sliding Window
- Use Single-layer LSTM
- Evaluation Metric: RMSE

Model Result

Feature Engineering

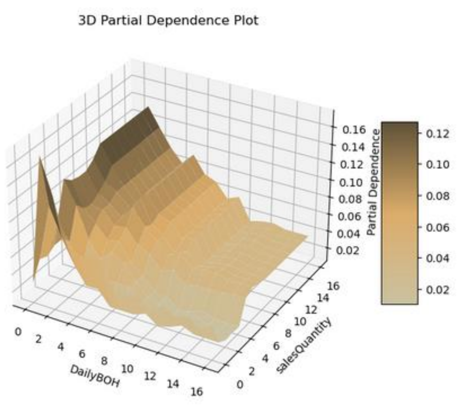
Feature Transformation

The original data is skewed, so a log transformation to smooth the distribution and enhance model performance is applied.



Partial Dependence Plot

The Random Forest model captures the nonlinear relationship between inventory and sales. It detects high inventory with low sales as a potential sign of phantom inventory.



Model Building

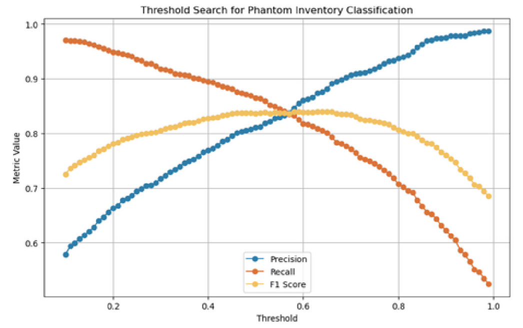
Phase 1: Detection for 'Phantom Inventory'

WHY

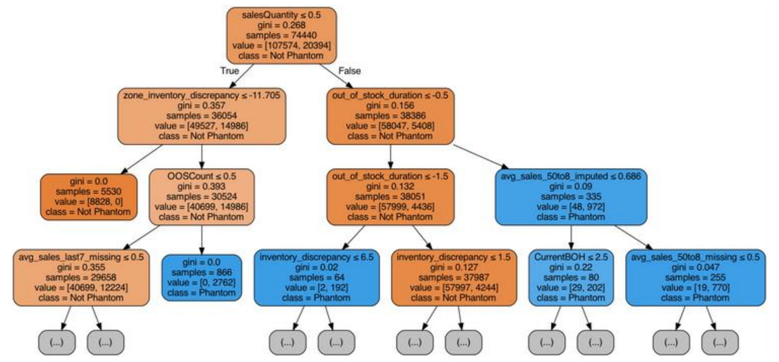
Detecting phantom inventory—where the balance on hand (BOH) indicates availability but the camera system labels an empty shelf—is crucial for addressing stock records inaccuracies and hence allowing timely restocking. K-means clustering groups products with similar stock patterns, while Random Forest detects and classifies phantom inventory.

HOW

The Precision, Recall, and F1 Score vary depending on the threshold. Therefore, we are searching for the best threshold, which is 0.57, for classification.



We demo Tree 85, the most influential tree, with a correlation of 0.9619. A Random Forest model was used to detect phantom inventory by combining predictions from multiple decision trees. This approach improves accuracy and identifies key factors driving inventory discrepancies.



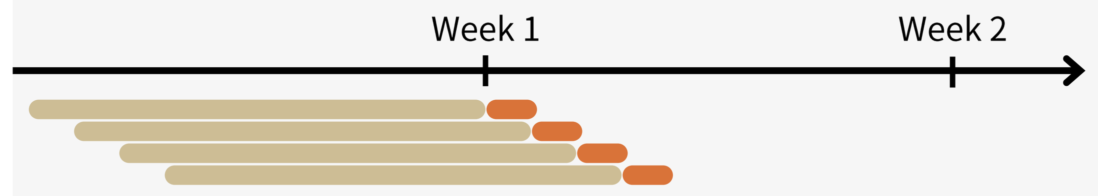
Phase 2: Prediction for 'Product Stockout Day'

WHY

Predicting product stockout events with accuracy to the day can effectively reduce possibility of future phantom inventory occurrence, and can ultimately optimize the replenishment and supply chain management.

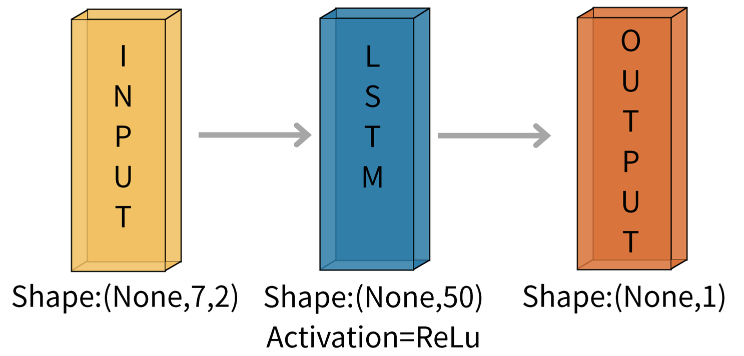
LSTM Time Series Model captures the sequential patterns hidden in the November' s daily BOH data and enables the prediction of future BOH trend on daily basis. This model facilitates the prediction of product stockout days that may occur in the future. Due to the timeframe of the dataset, we choose to use the past week data to predict the next day, as shown on the right.

HOW



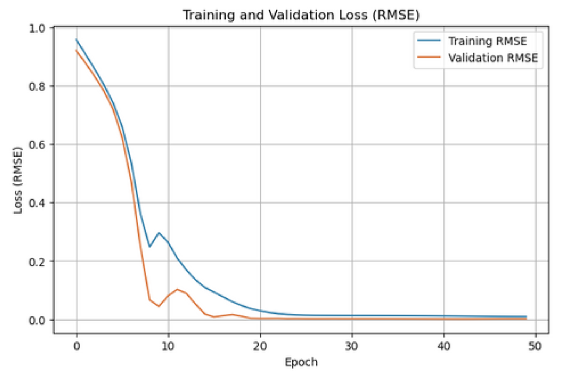
The sliding window is set to 7, meaning it use the past 7 days of data to create a forecast for the target value for the next day.

MODEL STRUCTURE



A single-layer LSTM trained on 7-day rolling sequences of BOH data effectively captured inventory trends while maintaining model simplicity. The architecture incorporates **TimeGAN**-based data augmentation to enhance sequence diversity and model robustness. Extensive experimentation with BiLSTM, BiGRU, and stacked LSTM showed the single-layer model to be the most efficient and reliable for this application.

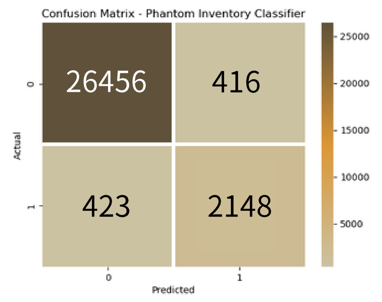
TRAIN/VAL LOSS



Both training and validation loss consistently decrease, indicating effective learning. The small gap between the two curves suggests strong generalization, with minimal overfitting during training.

Model Results

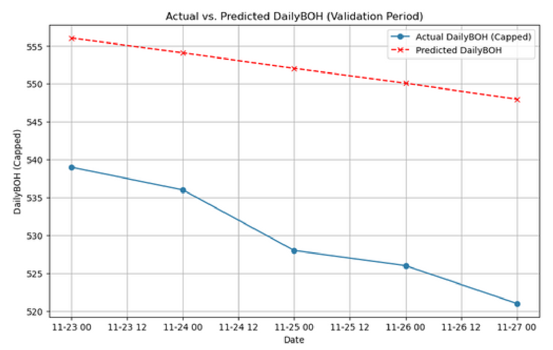
Phase 1: Detection for 'Phantom Inventory'



- Precision for phantom inventory: 0.8377
- Recall for phantom inventory: 0.8355

Due to the inherent trade-off relationship between Precision and Recall for phantom items detection, we select the best result for both metrics in a balanced way.

Phase 2: Prediction for 'Product stockout day'



- LSTM Training Loss (RMSE) for this SKU: 0.0084
- Forecasted run-out day for this SKU: None

The LSTM model captures the overall downward trend in DailyBOH, with a high Pearson correlation, indicating strong alignment with actual inventory patterns. While the RMSE is slightly higher than the baseline, the model generalizes well and shows no signs of overfitting. No stockout was predicted for this SKU within the forecast window, indicating relatively stable inventory levels.

Deployment & Life Cycle Management

WHO	HOW	ESTIMATED IMPACT
Retail Executives	Real-time Dashboard Updates	Better Inventory Visibility
Store Operations	Predict Phantom Inventory Early	Fewer Stockouts
Store Associates	Flagged SKUs in Dashboard	Less Manual Stock Checking
Suppliers	Smarter Signals to Suppliers	Accurate Restocking

1 **Prototype Model Development**
- Model trained on historical sales + inventory data
- Output: Stockout prediction per SKU per day

2 **Pilot Testing**
- Model integrated into the store dataset
- Store operation teams report stockouts to validate model accuracy

3 **Business Feedback & Validation**
- Gather stakeholder feedback
- Monitor stockout reduction and faster replenishment

4 **Future Scope**
- Deploy to more stores
- System flags phantom inventory SKUs without manual checks

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