Sales Prediction and Inventory Management System

Analysis Report

Approach Overview:

The sales prediction and inventory management system developed in this project represents a sophisticated approach to tackling the complex challenge of SKU-level forecasting. By leveraging machine learning techniques, specifically neural networks, the system aims to provide accurate sales predictions while simultaneously offering practical inventory management solutions. This dual focus on prediction and actionable insights sets the foundation for a robust, data-driven inventory management tool.

Data Preparation and Feature Engineering:

One of the critical decisions in developing this system was the choice of time granularity for sales prediction. As evidenced by the table below, when the system considers daily, weekly, and monthly aggregations of sales data, we can clearly see that all of the granularities have the same level of correlation.

Period	Mean	Median	std	Abs Mean	Sig_Lags_Frac
Daily	0.21	0.17	0.18	0.22	0.91
Weekly	0.20	0.17	0.23	0.23	0.92
Monthly	0.04	0	0.25	0.19	0.92

Tab: General Lag Correlation for all SKUs sales (check notebook)

The decision to primarily use a weekly step size for predictions and inventory management recommendations is particularly noteworthy. This choice strikes a balance between the granularity of daily data and the stability of monthly aggregations. Weekly data provides several advantages in this context:

1. Reduced noise: Daily sales data can be highly volatile, influenced by factors such as specific weekdays or short-term fluctuations that may not be indicative of broader trends.

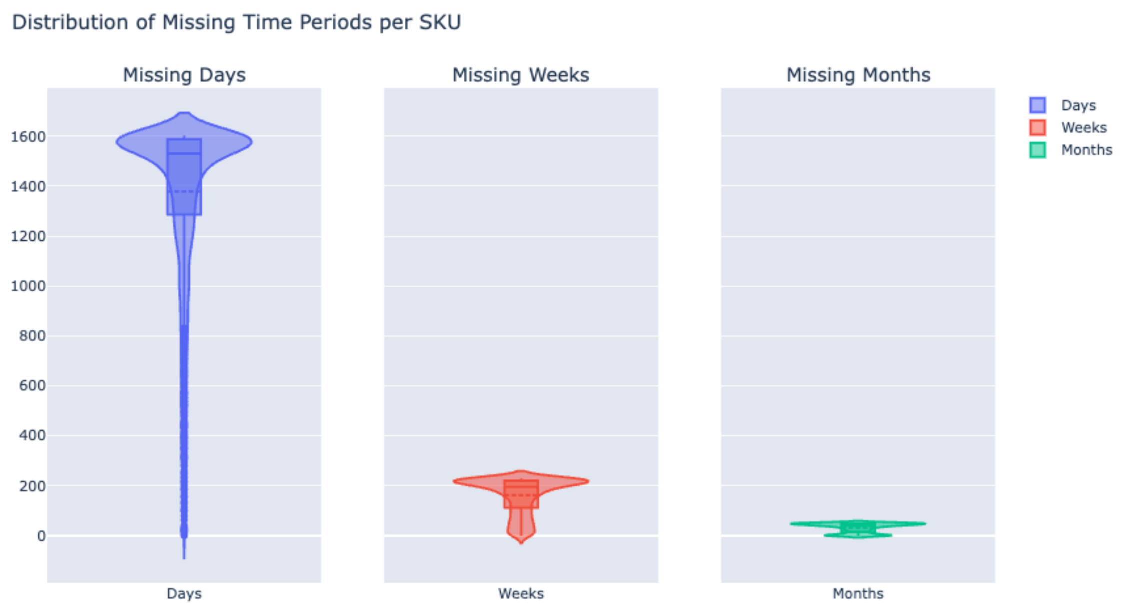
Weekly aggregation helps smooth out this day-to-day noise while still capturing important short-term patterns.

2. Alignment with business practices: Many businesses operate on weekly cycles for inventory management and replenishment. Using a weekly step size aligns the system's recommendations with these common operational practices, making it easier for inventory managers to implement the suggested actions.

3. Optimal correlation balance: As shown in the table above, weekly lag correlations (Mean: 0.204995, Median: 0.171094) are stronger than monthly correlations (Mean: 0.047928, Median: -0.015083) while being more stable than daily correlations (Mean: 0.217431, Median: 0.176710). This suggests that weekly data provides a good balance between predictive power and stability.

4. Computational efficiency: Compared to daily data, weekly aggregation reduces the volume of data that needs to be processed, leading to more efficient model training and prediction generation without significant loss of information.

The importance of this weekly focus is further reinforced by the "Distribution of Missing Time Periods per SKU" visualisation in the figure below. This figure clearly shows that while there are missing periods across all time granularities, the distribution of missing weeks is more compact and centred compared to missing days or months. This pattern suggests that weekly data provides a more consistent and complete picture of sales history for most SKUs, which is crucial for reliable forecasting.



Feature Engineering and Model Architecture:

The system's feature engineering process is comprehensive, incorporating lag features that capture historical sales patterns. The high Sig_Lags_Frac values for daily (0.919427) and weekly (0.925706) periods, as shown in table above, indicate that these lagged features are highly significant predictors of future sales. This observation justifies the inclusion of multiple lag features in the model, allowing it to capture both recent trends and longer-term seasonality. We also computed many date related features and rolling averages as shown in the data preparation notebook.

The neural network architecture employed in this system is carefully designed to balance complexity and generalizability. By using an embedding layer for SKUs, the model can capture unique characteristics of each product that may not be explicitly represented in the numerical features. This is particularly valuable in a retail context where factors like brand reputation, product lifecycle, or market positioning can significantly influence sales patterns.

The multiple fully connected layers with ReLU activation functions allow the model to learn complex, non-linear relationships in the data. This flexibility is crucial when dealing with the diverse range of SKUs typically found in a retail environment, each potentially following distinct sales patterns.

Neural Network Performance Analysis:

The section above is mainly based on this notebook.

The performance of the neural network model is a critical aspect of the sales prediction and inventory management system. By examining the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE), we can gain valuable insights into the model's predictive accuracy and reliability.

As reported in the evaluation metrics after removing outliers:

- MAE: Mean 19.68, Median 11.13
- RMSE: Mean 26.17, Median 13.89
- MAPE: Mean 81.42%, Median 51.52%

These figures reveal several important aspects of the model's performance:

1. Central Tendency: The median MAE of 11.13 suggests that, for half of the predictions, the model's estimates are off by about 11 units or less. This indicates reasonably good performance for many SKUs, especially considering the potential variability in retail sales data.
2. Outlier Impact: The substantial difference between mean and median values, particularly for MAPE (mean 81.42% vs median 51.52%), suggests that the model's performance is skewed by some SKUs with very high error rates. These could be products with highly volatile or unpredictable sales patterns.

3. Percentage Error: The median MAPE of 51.52% indicates that for half of the predictions, the model's estimates deviate from actual values by about 51.52% or less. While this might seem high, it's important to consider the context of retail sales, where demand can be inherently variable and influenced by many external factors.
4. Error Distribution: The RMSE being higher than MAE (median 13.89 vs 11.13) suggests that the model occasionally makes larger errors, as RMSE gives more weight to larger errors compared to MAE.

Interpreting these metrics in the context of inventory management:

- For many SKUs, especially those represented by the median performance, the model provides a solid basis for inventory decisions. An MAE of 11.13 units could be quite acceptable for products with moderate to high sales volumes.
- The higher mean values indicate that some SKUs are significantly more challenging to predict. These might require additional attention or alternative forecasting methods.
- The wide range of MAPE values suggests that the model's reliability varies across different types of products. It performs very well for some (minimum MAPE of 18.70%) but struggles with others (maximum MAPE of 555.32%).

It's crucial to note that these metrics alone don't tell the full story. In an inventory management context, the cost of errors can be asymmetric – understocking might lead to lost sales, while overstocking ties up capital and storage space. Therefore, the system's overall effectiveness should also be judged by its impact on real-world inventory outcomes, such as the reported 94.75% reduction in potential stockouts.

The performance metrics suggest that while the neural network model provides valuable predictions for many SKUs, there's room for improvement, particularly in handling SKUs with more erratic sales patterns. Potential strategies for enhancement could include:

1. SKU segmentation and specialised models for different product categories.
2. Incorporation of additional features or external data sources to capture more sales-influencing factors.

Inventory Management and Reordering:

A key strength of this system is its integration of predictive analytics with practical inventory management principles. The reordering algorithm, which demonstrates a high stockout prevention rate of 94.75% (you can check this notebook for more details), translates the model's predictions into actionable inventory decisions. This significant reduction in potential stockouts (from 2325 to 122) showcases the system's effectiveness in balancing inventory levels against the risk of stockouts.

The system's use of dynamic safety stock calculations, based on prediction error and lead time, represents a more sophisticated approach compared to traditional static safety stock methods. This adaptive strategy allows for more precise inventory control, potentially leading to reduced holding costs without compromising product availability.

Recommender Application:

The recommenderApp.py file represents the culmination of the analytical work, providing a user-friendly interface for inventory managers to interact with the system's predictions and recommendations. The Streamlit-based application offers features such as SKU selection, time navigation, and interactive plots that make it easy to analyse and make decisions for specific products.

The application's ability to display sales predictions, actual sales, inventory levels, and reorder points in a single, comprehensive plot is particularly valuable. This visual representation, combined with clear, actionable recommendations for reordering, bridges the gap between complex predictive analytics and day-to-day operational decisions.

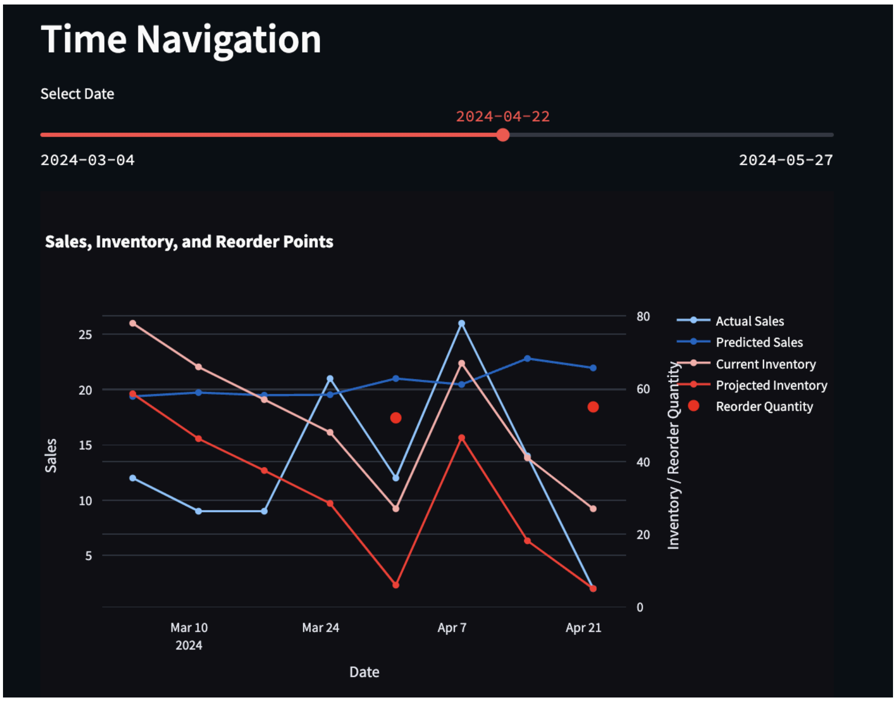


Fig: Reordering plan for a given SKU over time

Conclusion:

In conclusion, this sales prediction and inventory management system represents a solution to the challenges of SKU-level forecasting and inventory optimization. The choice of weekly time steps, the comprehensive feature engineering process, and the integration of machine learning predictions with practical inventory management principles create a powerful tool for data-driven decision-making in retail operations.

While there is always room for further refinement, particularly in areas such as handling SKUs with limited historical data or incorporating external factors into predictions, the current system provides a foundation for improving inventory turnover, reducing stockouts, and enhancing overall operational efficiency in a retail environment.