Business Analytics Using Forecasting - January 2024

Team No. 1

Optimized Inventory Management in Retail: A Comparative Analysis of Direct vs. Channel-Specific Sales Volume Forecasting for Perishable Goods to Enhance ROI

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Executive Summary

Business Challenge

Retail suppliers struggle to balance inventory levels for perishable goods, needing precise sales forecasts to avoid overstocking or stock-outs.

Data Analysis Approach

- **Data Source:** 714-day sales data from major retail stores, provided by Nuqleous.
- **Forecasting Methods:**
  - Direct Forecasting of total weekly sales.
  - Channel-Specific Aggregation across different sales channels.

Key Forecasting Models

Employed models like Naive, Seasonal Naive, ETS, TSLM, and ARIMA, tailored to specific data segments.

Core Findings

- **Cost Efficiency:** Channel-specific aggregation methods generally proved more cost-effective than direct forecasting.
- **Performance Note:** Similar results for both methods when using regression, Naive, or Seasonal Naive models.
- **Exception Case:** SKU 1538336 showcased better performance in the General Level during validation.

SKU	Period	General Level General		Purchase Level Linear	
		.model	Cost	.model	Cost
1272962	Training	arima	$ 645.05	arima	$ 633.97
1326507	Training	reg	$ 445.24	reg	$ 445.24
1394919	Training	reg	$ 472.99	reg	$ 472.99
1538298	Training	reg	$ 232.55	reg	$ 232.55
1538336	Training	reg	$ 136.06	reg	$ 136.06
1602373	Training	reg	$ 240.70	reg	$ 240.70
1765845	Training	ets	$ 348.90	ets	$ 348.70
1823273	Training	reg	$ 108.32	reg	$ 108.32
1931136	Training	reg	$ 298.85	reg	$ 298.85
1984241	Training	reg	$ 724.95	reg	$ 724.95
1272962	Validation	snaive	$ 216.79	snaive	$ 216.79
1326507	Validation	arima	$ 395.05	arima	$ 379.64
1394919	Validation	naive	$ 278.83	arima	$ 253.23
1538298	Validation	reg	$ 415.06	reg	$ 415.06
1538336	Validation	arima	$ 193.44	snaive	$ 244.54
1602373	Validation	reg	$ 149.11	reg	$ 149.11
1765845	Validation	snaive	$ 223.98	snaive	$ 223.98
1823273	Validation	ets	$ 317.23	ets	$ 299.99
1931136	Validation	ets	$ 306.69	arima	$ 297.98
1984241	Validation	naive	$ 1,069.98	naive	$ 1,069.98

Comparative Analysis: Cost Results of Best-Performing Forecasting Models in Purchase Channel Level vs. Benchmark General Level

Recommendations

- **Data Duration:** Minimum two-year data span for robust forecasting.
- **Benchmarking:** Essential to compare new methods against existing standards.

Conclusion

Channel-specific forecasting tends to yield better cost outcomes, except when certain models like regression or Naive are used, underscoring its importance in effective inventory management and ROI enhancement.

Detailed report

Problem Description:

Business Problem

In the ecosystem of the retail industry, suppliers manage the inventory of perishable goods. The main task of a supplier to a major retailer is to maintain optimum stock levels in order to avoid overstocking and stock-outs.

To achieve this, suppliers mandate data analysis companies such as Nuqleous to use various forecasting techniques to predict sales volumes. Forecasting in inventory management relies on a variety of methods and models, each influenced by diverse factors such as market dynamics, consumer preferences, and external variables, making it a multifaceted and adaptive process.

Our mission is to assess if the combination of individual channel-specific sales forecasts results in a more precise prediction of total weekly sales volume, in comparison to directly forecasting the overall sales volume. This provides suppliers, the stakeholder of our project, with greater accuracy in the forecasts they use, enabling them to improve their return on investment.

Goal

The ultimate aim of our analysis is to minimize the overestimation or underestimation of projections in order to improve suppliers' return on investment (ROI).

Success metrics

Two different success metrics has been used to assess the forecasts:

1. **Cost Savings**: The cost savings from reduced overstocking and avoiding stock outs.
2. **ROI improvement**: The return on investment that we can measure by comparing financial performances before and after the implementation of our solution.

Forecasting Goal

Our objective is then to compare two different forecasting approaches to determine the most accurate method for weekly sales quantity.

- **Method 1**: Directly forecast the total weekly sales volume.
- **Method 2**: Forecasted the weekly sales volume across various purchasing methods (Store Pickup, Store Delivery, In-Store, Online) and aggregate them into total weekly sales volume.

Data description:

Our dataset is provided by Nuqleous, a company based in the US that helps suppliers with their data analysis and automation. It contains daily data of perishable food items of large retail stores, covering a period of nearly two years (May 2021 to Mid April 2023). The dataset includes attributes such as SKU Numbers, Building Number, Purchase Channel, Sales quantities, and Sales. There are a total of ten unique items in SKU Number. *Refer to the appendix A7 for the 10 row samples for each item.*

Data Preparation:

- **Missing Values: Weeks '202213' and '202214'**
  These missing weeks were calculated based on the average sales from two weeks prior and two weeks after the missing date.
- **Outliers: Weeks '202210' and '202310'**
  These values were replaced with the average sales of the prior week and the week after, ensuring a more consistent and realistic trend in the data.

Newly created datasets for this report

Refer to the appendix A9 and A10 for the 10 row sample of the new datasets.

1. **General_Level:** shows the aggregated sales quantity for each week from all purchase channels.
2. **Purchase_Channel_Level:** shows the sales quantity for each purchase channel.

Forecasting Solution:

Methods

Refer to Appendix A3 ~ A6 for the exact parameters in each model

- **NAIVE:** Assumes sales will be the same as the last observed period.
- **SNAIVE:** Projects sales based on the same period last year, using 52-week seasonality.
- **ETS:** Adjusts for trends and seasonality, with parameters chosen automatically to fit historical sales volume.
- **TSLM:** Linear model with a yearly trend and seasonal components based on 52-week cycles. Equation: Sales.Qty ~ trend() + season(52).
- **ARIMA:** Fits a model to the sales data, optimizing its parameters without preset values.

Why we did not use neural networks:

It took around 25 minutes to run the models, which made neural networks less suitable for practical business use compared to simpler forecasting methods.

Utilization of the data:

We utilized a roll-forward method for predicting sales volume, focusing on a 3-week forecast horizon. Our approach involved:

- **Training Period:** Data up to 2023 (87 weeks) was used for training, enabling our models to learn from a comprehensive historical dataset.
- **Validation Period:** Data from 2023 onwards (15 weeks) was used for validation to assess the models' ability to predict recent trends.

For each 3-week cycle, we updated the models with the latest data. This continuous refinement helped translate sales volume forecasts into financial outcomes by evaluating the associated costs, thereby providing a practical measure of performance.

Cost Function:
It is used to measure the financial implications of forecasting accuracy from a supplier's perspective. This function is integral in translating forecasting errors into concrete financial terms, specifically addressing under and over forecasting scenarios.

- **Cost Function Formula:**
  $Cost = I(1) \times (Profit\ per\ Item \times Error) + (1 - I(1)) \times (Price\ Supplier \times |Error|)$
- **Under Forecasting:** When actual sales exceed forecasted sales, we incur lost margins. This scenario is represented by an indicator function I(1), which equals 1 in cases of under forecasting. The cost here is calculated as the product of profit per item and the magnitude of the forecasting error.
- **Over Forecasting:** In instances where forecasted sales are higher than actual sales, there's a cost linked to managing or replacing excess stock. This occurs when 1 - I(1) equals 1. The associated cost is the product of the price paid by the supplier and the absolute value of the error.

This Cost Function provides a tangible measure of the financial outcomes of forecasting errors, taking into account both the lost sales and excess stock costs. It offers a more practical perspective compared to abstract metrics like MAPE or RMSE, making it highly relevant for financial and procurement decisions in inventory management. The results are visualized through box plots and bar charts for clarity and compared against aggregated general sales volumes, a standard industry benchmark, ensuring that the model evaluations are both practical and applicable.

Evaluation

The comparison in Table 1 assesses the cheapest costs across SKU/Period combinations for each dataset—General Level and Purchase Level. The data reveals that in 95% of the cases, the Purchase Level presented the lowest cost. It's crucial to note that in 13 of these comparisons, the lowest cost was identical to that of the General Level as shown in Figure 1. Divergence in performance was observed only six times, wherein the Purchase Level exhibited superior cost efficiency, owing to the employment of models that were distinct from those at the General Level. An exceptional case was observed with SKU 1538336 during the validation period, where the General Level demonstrated a better cost outcome than the Purchase Level. The Regression Model dominated the training period selections (80%), while the ARIMA Model was the top choice in the validation period (40%).

For a detailed comparison of all forecasting model results and cost analysis per item, please see the box-plot in Appendix A11.

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Table 1 - Comparative Analysis: Cost Results of Best-Performing Forecasting Models in Purchase Channel Level vs. Benchmark General Level

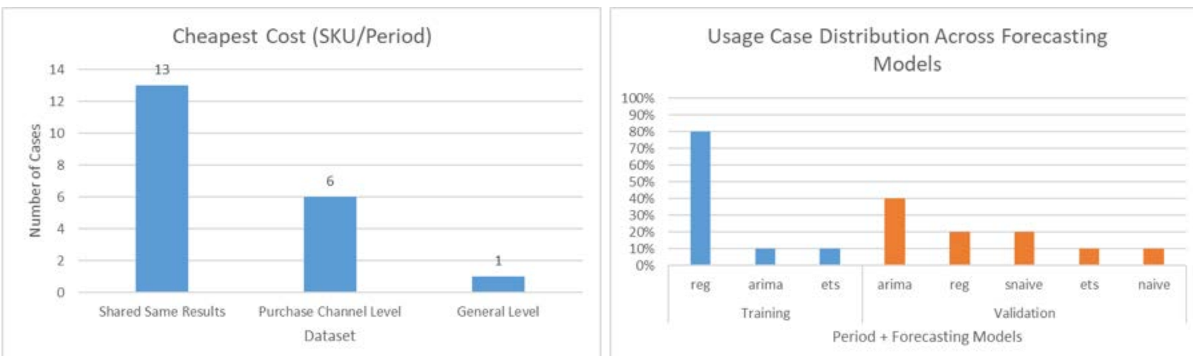

Figure 1 - Usage Case Distribution Across Datasets and Models.

Conclusions

Concluding, the analysis suggests that the Purchase Level tends to be more cost-effective only when the models used are not regression, Naive, or Seasonal naive. When these models are in use, the performance in terms of cost between the General Level and Purchase Level is equivalent.

Two main recommendations stand out. Firstly, a dataset of at least two years is preferable for robust modeling in the training period; our training period doesn't cover the ideal two years of data, meaning we miss completing two full 52-week seasonal cycles. As a result, most models haven't captured all seasonal trends effectively. Secondly, it is essential to benchmark our forecast results against the existing forecasting standards of suppliers. This comparison is key to evaluating whether our new methods provide not just comparable, but substantially better outcomes.