Inventory Optimisation

Detailed Analysis on
Inventory Optimsation
and Demand Forecasting

Introduction

This presentation includes enhancing inventory management by leveraging data analytics and forecasting techniques to optimise stock levels, reduce carrying costs and improve demand planning. Using ARIMA models, ABC analysis, Economic Order Quantity (EOQ), and Reorder Point Analysis (ROP), we identified inefficiencies in inventory flow and developed data-driven solutions to enhance operational efficiency.

Initial Assessment

Sales Performance Metrics

This analysis offers a comprehensive evaluation of our retailer's sales performance across various product lines, providing a foundation for advanced analytics and strategic insights.

	Brand	SalesQuantity	SalesDollars	avg_price	avg_price_bought	avg_markup	avg_profit_per_product	total_profit
0	58	288	3741.12	12.990000	9.28	0.399784	3.710000	1068.48
1	60	124	1358.76	10.957742	7.40	0.480776	3.557742	441.16
2	61	24	335.76	13.990000	10.60	0.319811	3.390000	81.36
3	62	162	6552.38	40.446790	28.67	0.410770	11.776790	1907.84
4	63	131	5552.69	42.386947	30.46	0.391561	11.926947	1562.43
...	...	...	...	...	...	...	...	...
7653	90084	2	63.98	31.990000	NaN	NaN	NaN	NaN
7654	90085	2	73.98	36.990000	23.86	0.550293	13.130000	26.26
7655	90086	1	51.99	51.990000	34.20	0.520175	17.790000	17.79
7656	90087	1	469.99	469.990000	NaN	NaN	NaN	NaN
7657	90089	27	3239.73	119.990000	NaN	NaN	NaN	NaN

7658 rows × 8 columns

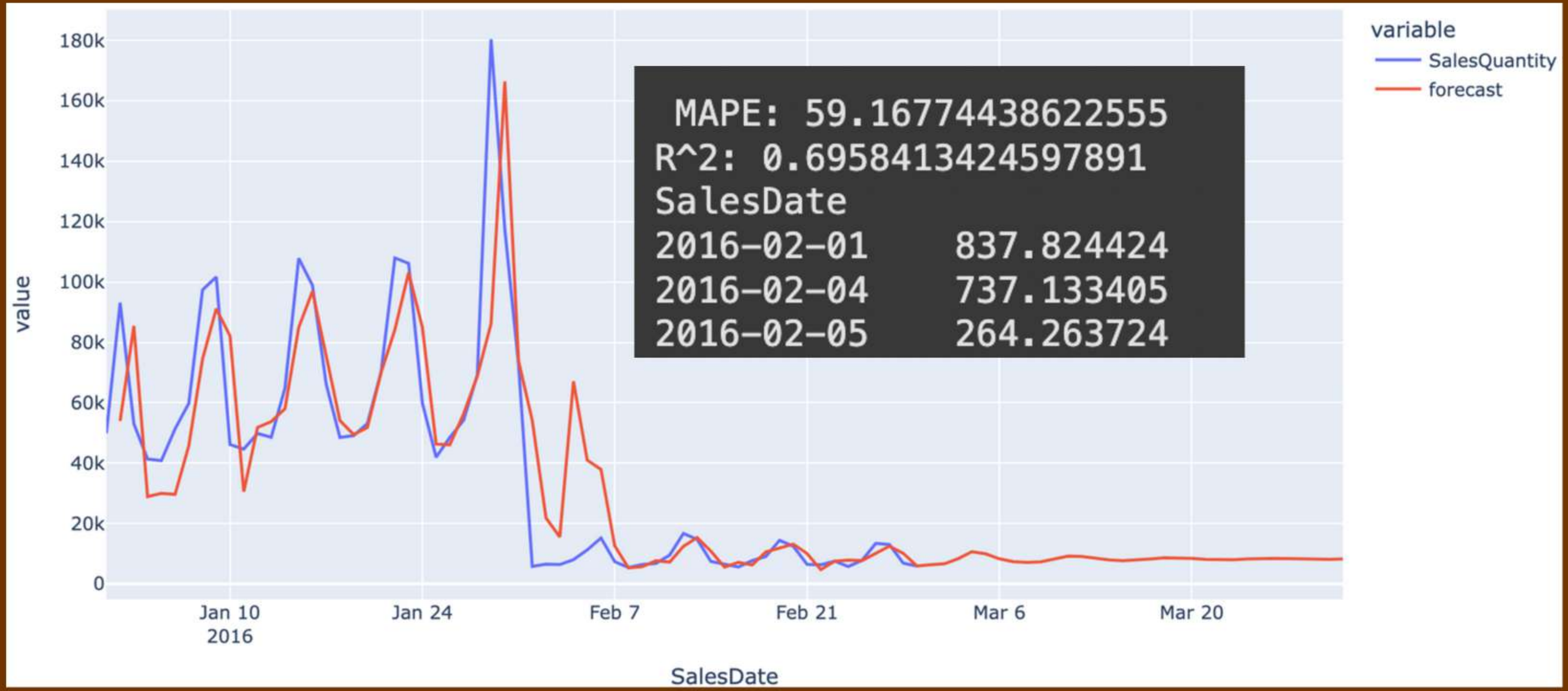
Key Business Metrics

```
Total SKUs: 11,485
Total Current Stock: 4,885,776
Total Items Sold (Two Months): 2,451,169
Total Revenue: $33,139,375.29
Total Profit: $10,721,400.90
Items Sold for Prices Between $0.49 and $4,999
```

This Data suggests a high volume business with a wide range of products, given the number of SKU's and the broad price range.The business appears to be quite profitable, the current stock level is about twice the number of items sold in the past two months which could indicate a well stocked inventory or potentially overstocking issue

Demand Forecasting With Time Series Analysis

Defining sales quantity as demand, the graph reveals pronounced weekly and monthly seasonality. Peaks occur consistently on Thursdays and Fridays, likely due to vendor restocking, and significantly decline on Sundays, a company holiday. A notable monthly peak at January 29th (Thursday/Friday) with 180k sales sharply drops to 16.7k in early February, a 91% reduction, confirming strong monthly seasonality.



Model Selection – ARIMA(5,1,1)

1. Why ARIMA?

- It's a widely used time-series forecasting model that captures trends and patterns in data
- The (p, d, q) parameters define the autoregression, differencing, and moving average components.
- Why (5,1,1)?
  - Chosen iteratively to minimise error (trial & error).
  - The model was tested with different values, and (5,1,1) gave the best initial performance.

2. Model Performance Metrics

- MAPE (Mean Absolute Percentage Error) – 59.17%
  - Represents the average forecasting error as a percentage of actual values.
  - A higher MAPE means the model struggles to predict accurately.
- R^2 (Coefficient of Determination) – 0.696
  - Indicates how well the model explains the variability in sales data.
  - Closer to 1 is better, but 0.696 shows moderate accuracy.

3. Observed Forecasting Errors

- The model missed an important pattern – a monthly sales drop in February.
- Key errors:
  - Feb 1 (MAPE ~800%) The model couldn't predict the sudden drop.
  - Feb 4-5 (Thursday-Friday peaks) High sales on these days, which the model did not capture well.
- Main issue: The model does not yet account for seasonality (weekly/monthly patterns).

4. Key Takeaways

- The model identifies some trends but struggles with seasonal changes.
- High forecasting errors occur due to monthly sales fluctuations.
- Next steps: Need to include seasonality factors (weekly/monthly patterns) in the model

Incorporating Seasonality

1. Why Seasonality Matters?

- The initial ARIMA(5,1,1) model struggled to predict demand accurately.
- Large errors were observed in February due to a strong monthly sales drop.
- The model failed to capture weekly peaks (Thursdays/Fridays) and monthly patterns.
- To improve accuracy, we need to explicitly account for seasonality in our forecasting model.

```python
fourierM = CalendarFourier(freq="ME", order=6)
dp = DeterministicProcess(
    index=sales_quantity_price.index,
    constant=True,
    order=4,
    seasonal=True,
    additional_terms=[fourierM],
)
X = dp.in_sample()
model = LinearRegression().fit(X, sales_quantity_price['SalesQuantity'])
y_pred = pd.Series(
  model.predict(X),
  index = X.index,
  name="fitted"
)
y_pred = pd.Series(
  model.predict(X),
  index = X.index,
  name="fitted"
)
sales_quantity_price["forecast"] = y_pred
```

2. How Do We Incorporate Seasonality?

- We introduce CalendarFourier and DeterministicProcess, which are statistical tools to model seasonal effects.
- These methods help generate features that represent periodic fluctuations in sales.
- Instead of relying purely on historical sales trends, we use mathematical functions (Fourier series) to identify recurring patterns.

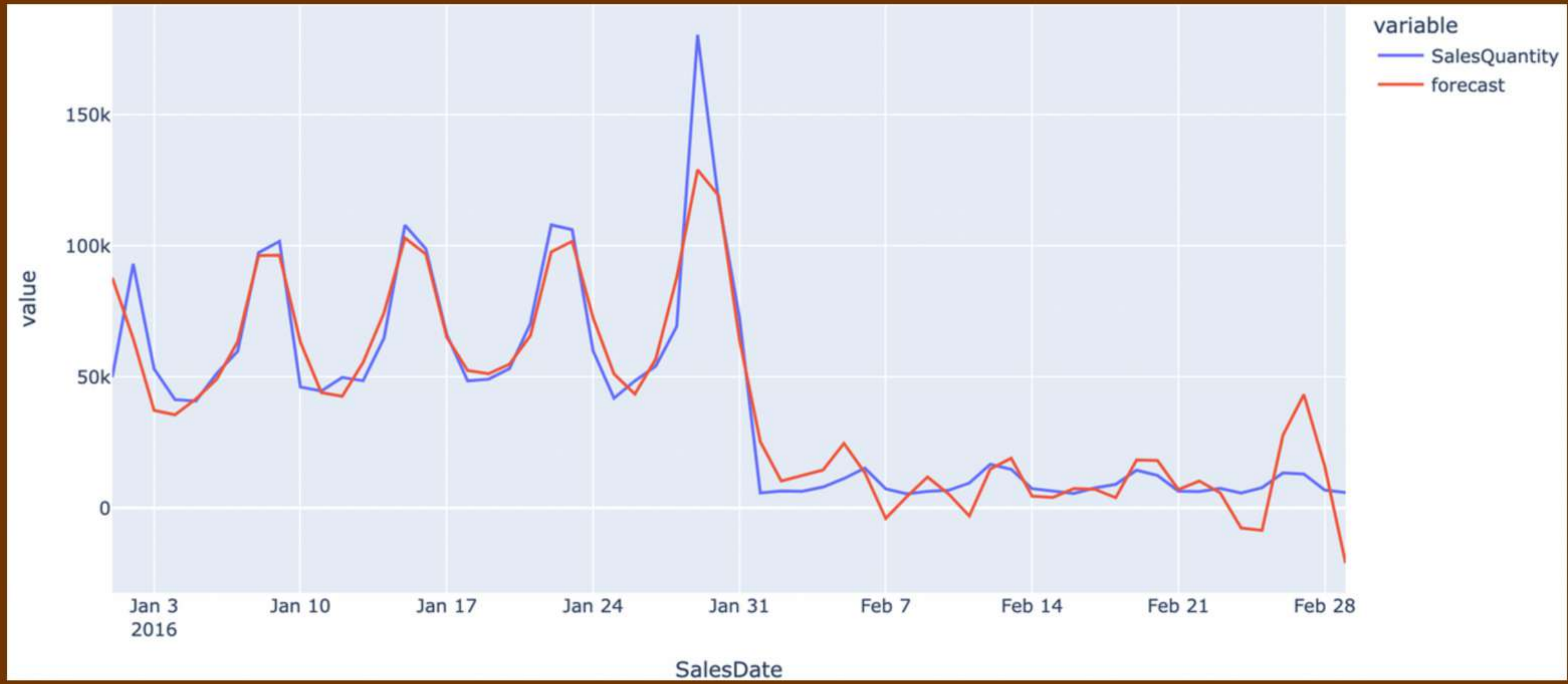
3. Using Fourier Terms & Deterministic Process

- CalendarFourier (Monthly Effect - ME, Order 6)
  -> This breaks down recurring monthly variations into components that the model can understand.
  -> Order 6 means the model considers multiple frequency terms to represent the monthly seasonality pattern.
- DeterministicProcess
  -> Helps structure the data in a way that allows the regression model to incorporate seasonal trends efficiently.
  -> It provides the regression model with seasonal indicators (like monthly cycle effects).
- Linear Regression Model
  -> Once we create seasonal features, we fit a Linear Regression model.
  -> The goal is to adjust for seasonal fluctuations while keeping the model simple and interpretable.

Model Evaluation And Results

1. Evaluating Model Accuracy

- MAPE (Mean Absolute Percentage Error): 54.73%
- R^2 (Goodness of Fit): 0.884
- Performance Comparison:
  -> Initial ARIMA(5,1,1): MAPE = 59.17%, R^2 = 0.696
  -> Updated Model (with Seasonality): MAPE = 54.73%, R^2 = 0.884
  -> Improvement in accuracy after incorporating seasonality, but significant errors remain.



2. Measuring Prediction Errors

- Top 3 Errors Observed:
  -> Feb 29: 456.13% error Possible data anomaly or seasonality misalignment.
  -> Feb 1: 338.89% error Sharp monthly drop in demand not well captured.
  -> Feb 27: 232.72% error Weekly seasonality misalignment.
- Analysis of Errors:
- The model struggles to adapt to sudden sales fluctuations.
- Large errors indicate a need for more refined seasonal adjustments.
- Additional historical data could improve trend recognition and reduce anomalies.

Key Takeaway

- Demand forecasting is an iterative process requiring continuous refinement.
- The updated model improves accuracy but still struggles with key date anomalies.
- Further enhancements are necessary, including data expansion, model tuning, and external factor inclusion.

3. Potential Improvements

- More Data: Essential for capturing long-term trends and seasonality patterns.
- Hyperparameter Tuning: Further refinement of model parameters for better accuracy.
- External Factors: Incorporate external influences like promotions, holidays, and market shifts.
- Model Comparison: Test alternative forecasting models to evaluate performance gains.

```
 MAPE: 54.73053211676396
R^2: 0.8844938809617982
SalesDate
2016-02-29    456.128454
2016-02-01    338.889938
2016-02-27    232.721077
```

Inventory Analysis Techniques

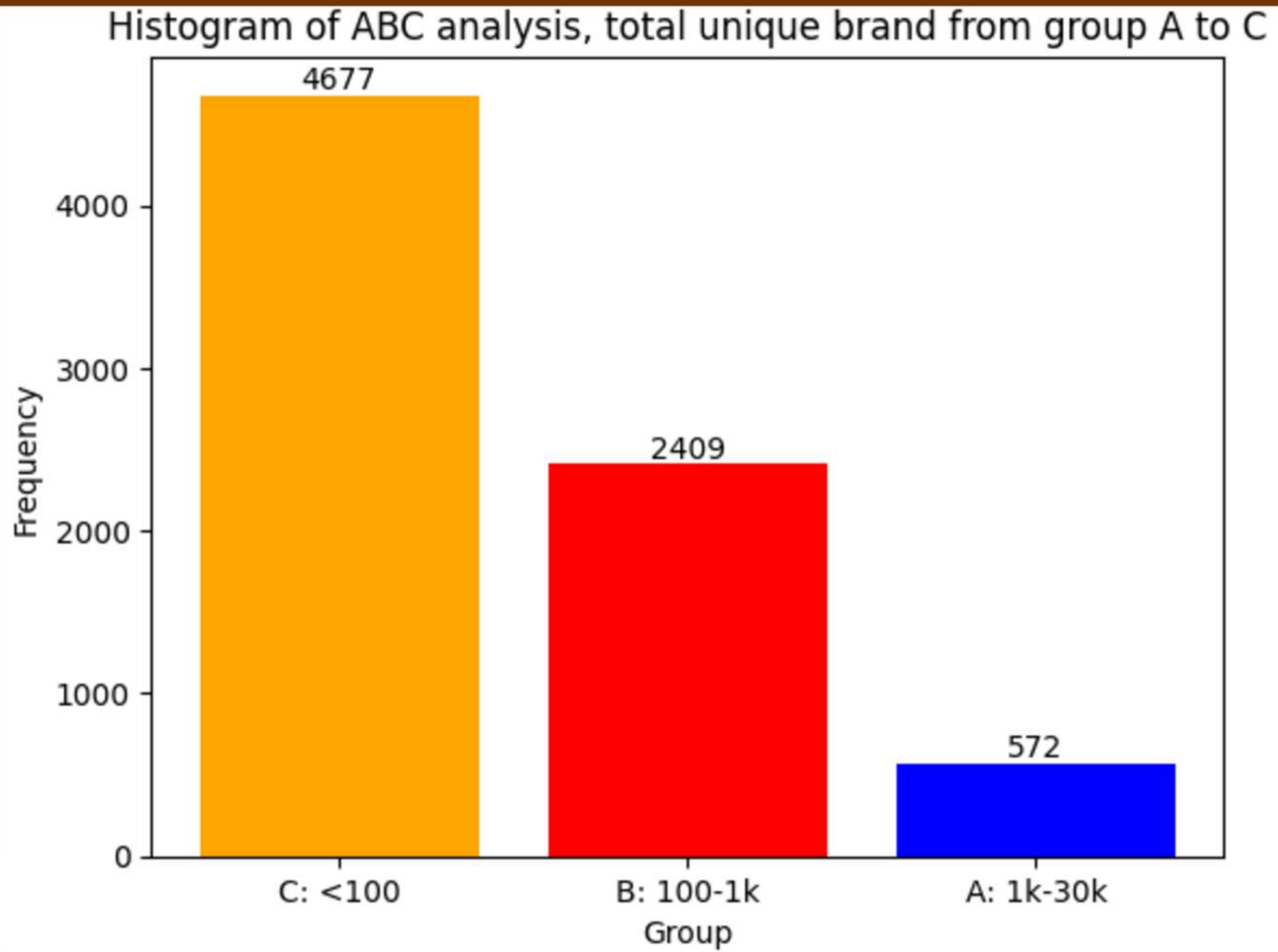
ABC Analysis

A
- Expensive Inventory
- Accurate Control Required

B
- Moderate Value Inventory
- Moderate Control Required

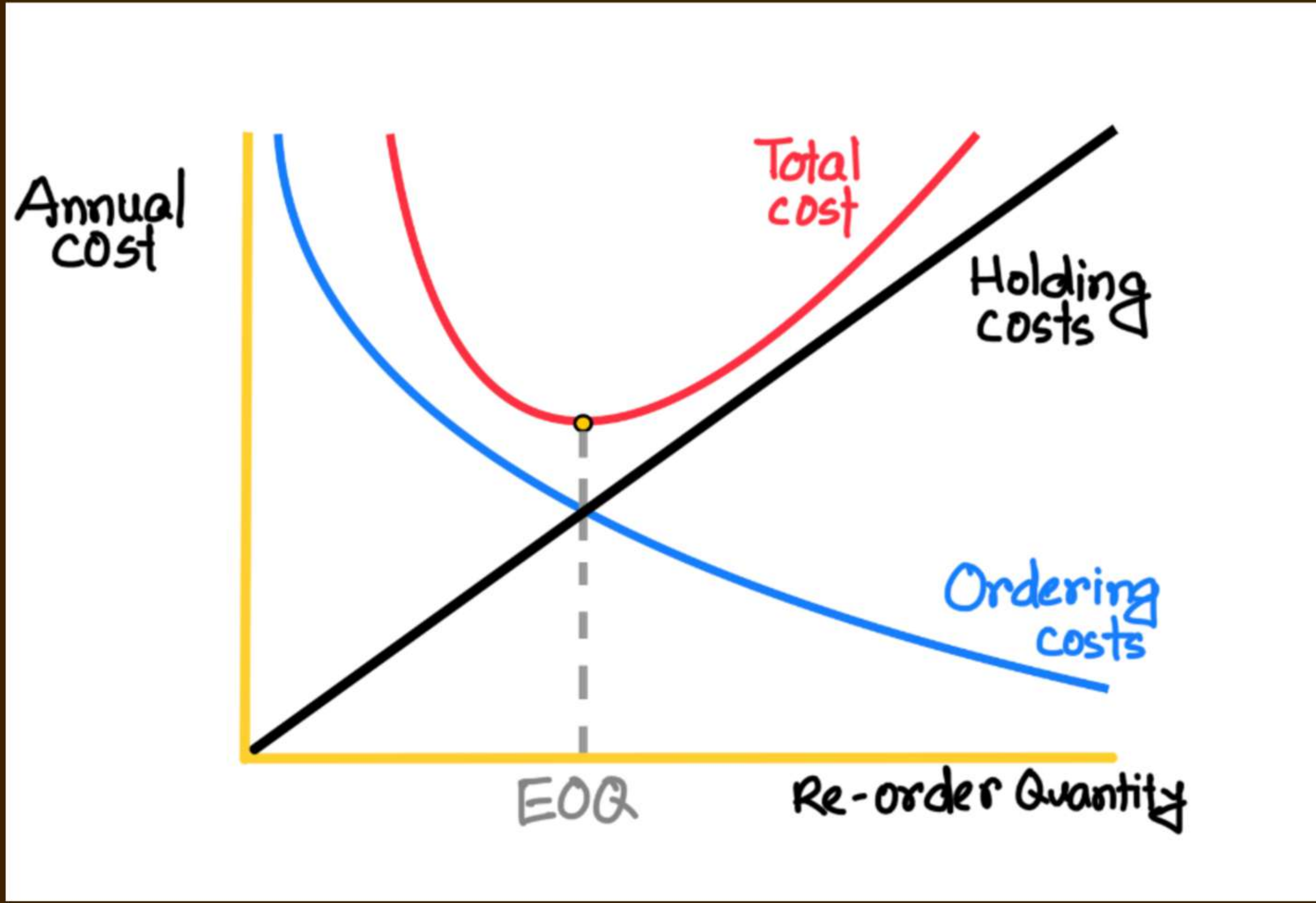
C
- Low Cost Inventory
- Minimum Control Required

An ABC analysis was performed to categorize brands based on their sales volume. Brands with sales exceeding 1,000 units were classified as Category A, those with sales between 100 and 1,000 units as Category B, and those with less than 100 units as Category C. While Category C comprises the majority of brands (4677), its total sales volume (114k) is significantly lower than Category A (1.5 million), which represents only 12% of the total brands. This analysis underscores the importance of focusing on Category A brands in inventory management and exploring strategies to improve the performance of brands in Categories B and C, such as research and development, enhanced marketing, and optimized supply chains.



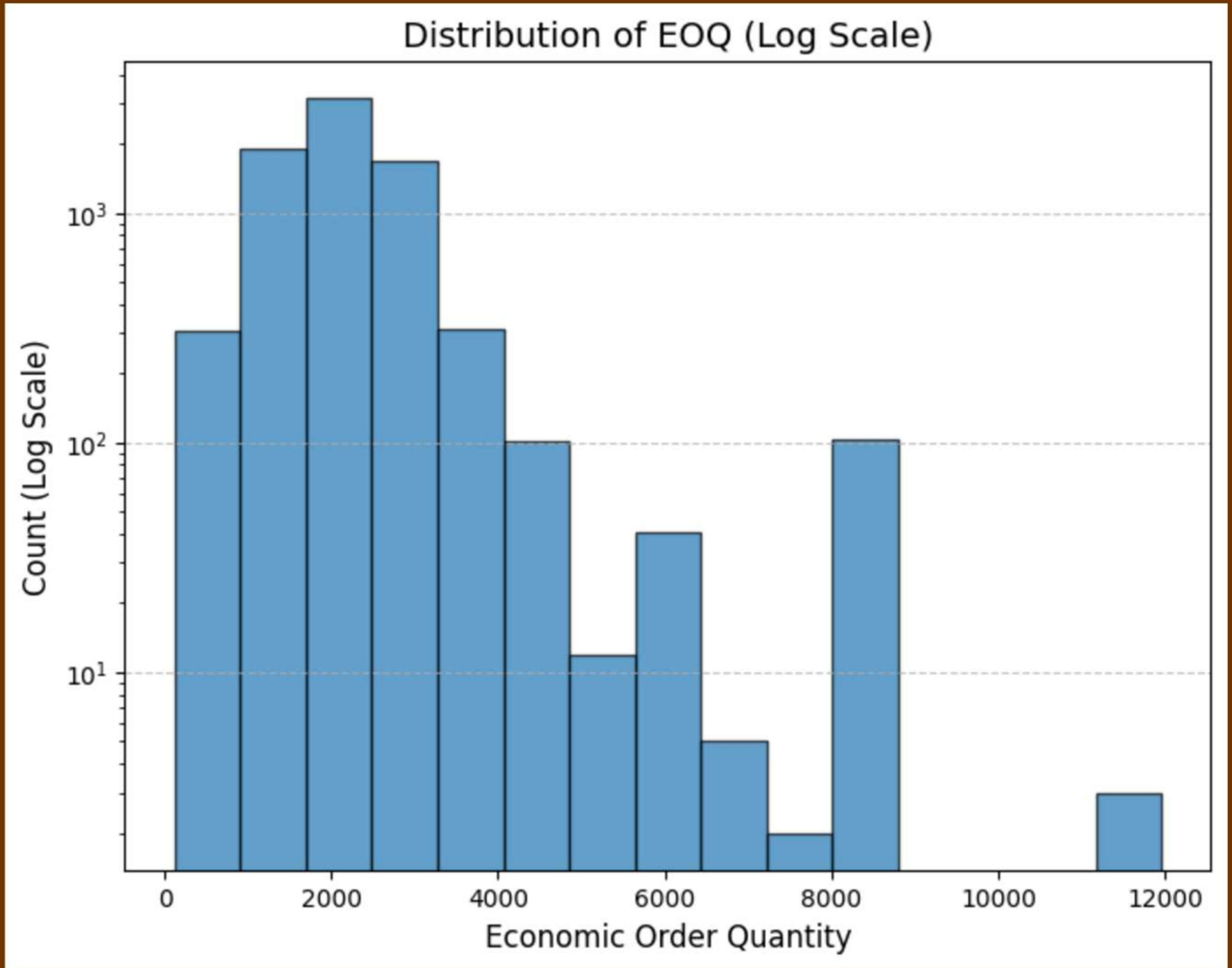
EOQ Calculations

Economic Order Quantity (EOQ) represents the optimal order size that minimizes the combined costs of ordering and holding inventory. Calculating EOQ requires understanding the Order Placement Cost (OPC) and the Stock Ownership Cost (SOC). OPC quantifies the expense of placing an order, while SOC represents the cost of holding inventory. These costs vary significantly across contexts and require specific data not available in this dataset. Therefore, I'm using estimated values: $30 for OPC and 10% of an item's value for annual SOC.

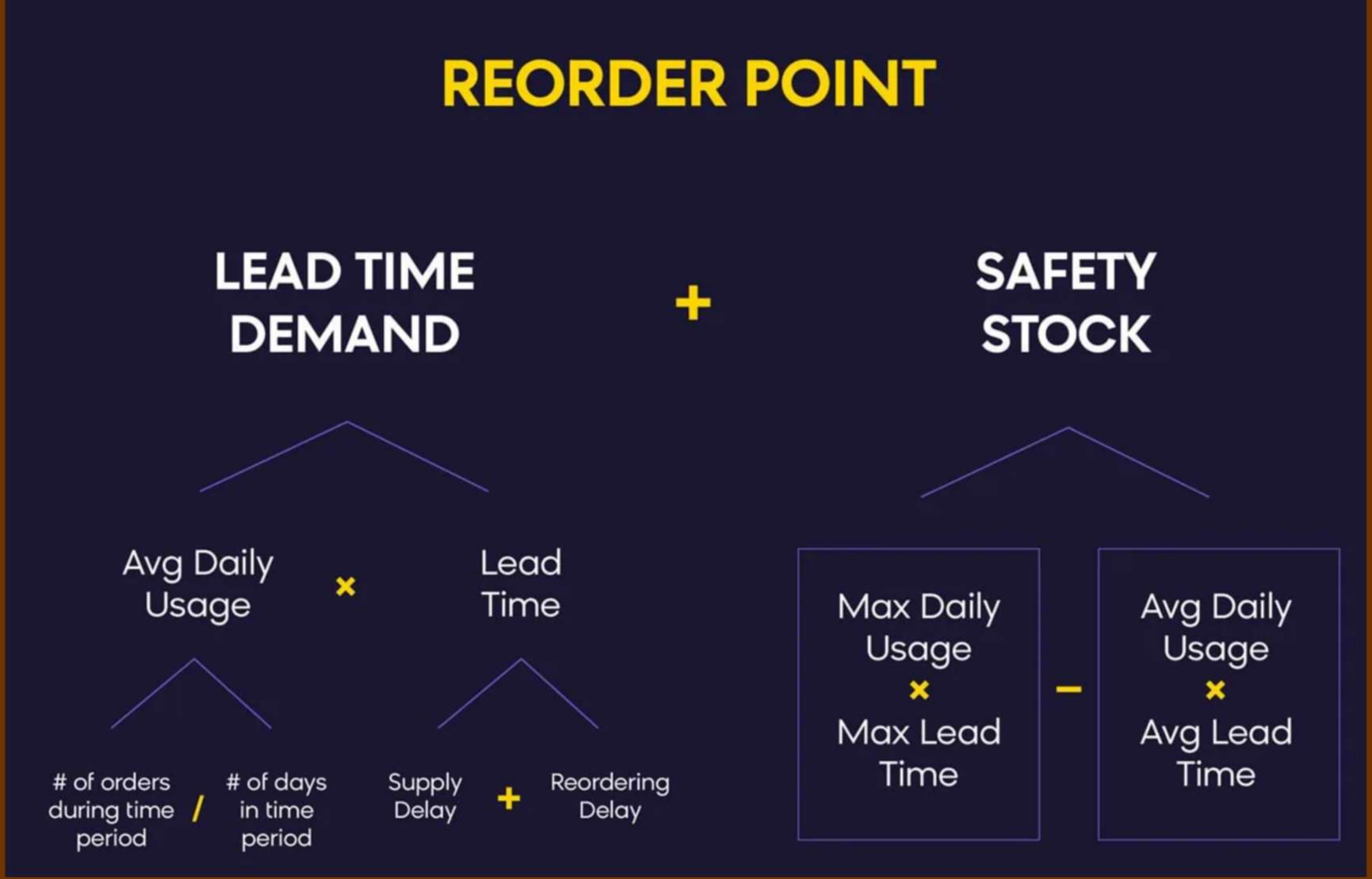


Observations

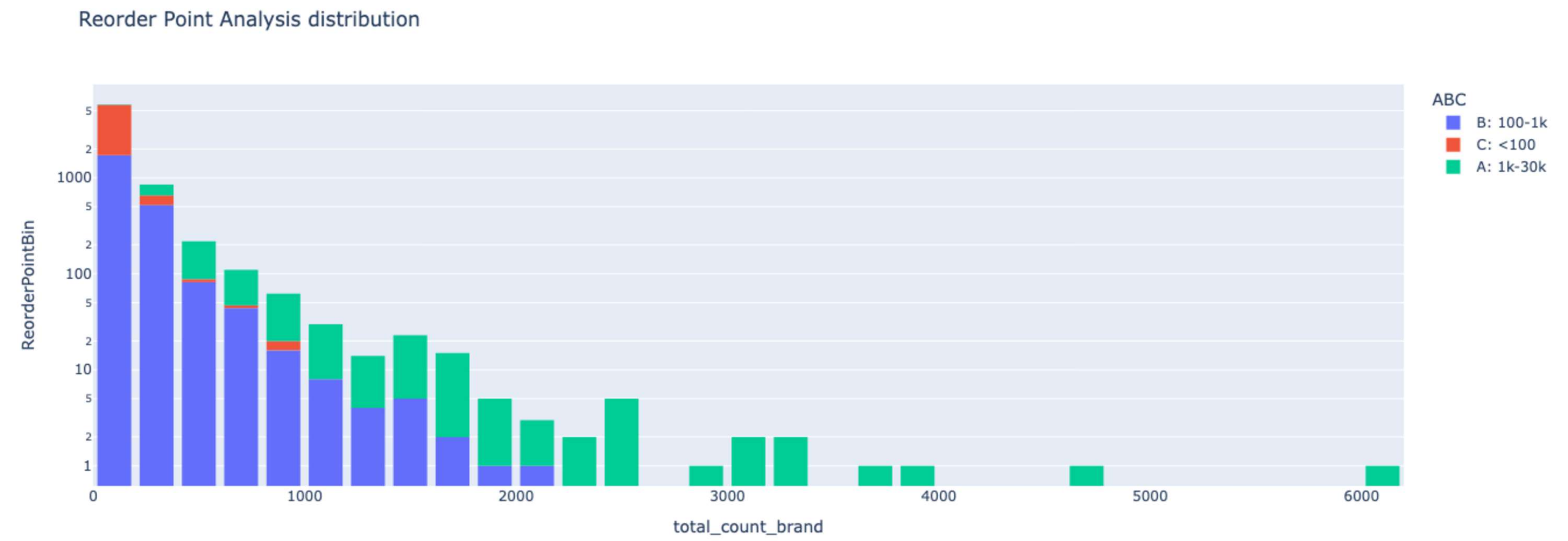
- Most EOQ values are concentrated between 0 and 4000, suggesting that a majority of items have a relatively small optimal order quantity.
- There are fewer occurrences of very high EOQ values (above 6000), indicating that only a few products require large order quantities.
- The log scale on the y-axis suggests a left skewed distribution, where small EOQ values dominate, but a few large EOQs still exist.
- There may be outliers around 8000 and 12000, representing items that require significantly larger order quantities.



This EOQ distribution graph highlights the variability in optimal order quantities across products. The clustering around specific ranges reveals demand patterns, while outliers indicate high-demand or high-cost items. The log scale emphasizes small-frequency differences, aiding identification of optimization opportunities. Insights can guide cost reduction, inventory balancing, and improved supply chain efficiency.



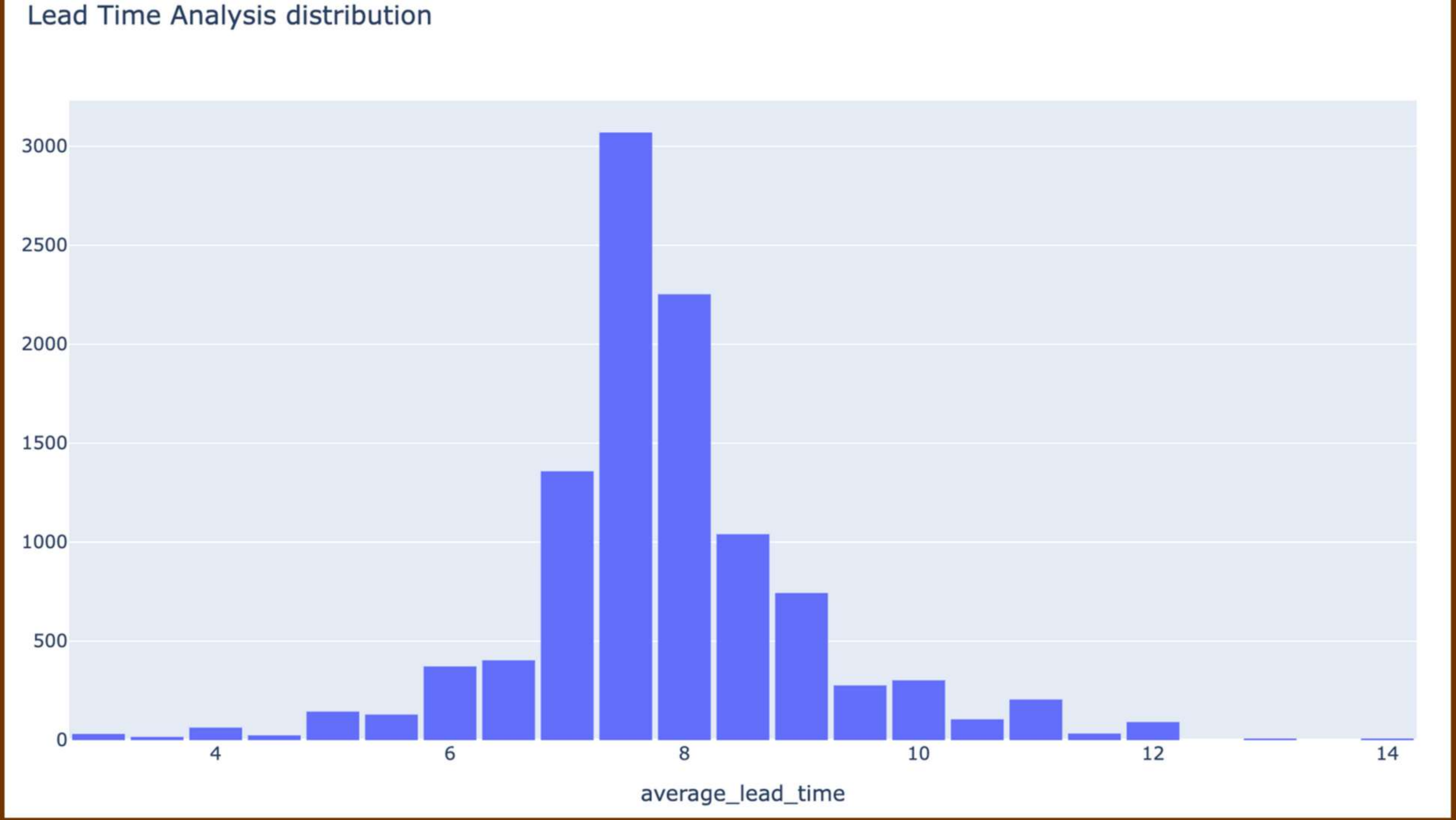
The reorder point signifies the minimum stock level triggering a replenishment order. Reorder Point is dynamic, influenced by purchase and sales cycles, and unique to each product. Its primary purpose is to prevent stockouts while mitigating overstocking, thereby optimizing shipping costs and enhancing forecasting accuracy.



In this analysis, safety stock is defined as the difference between maximum daily sales multiplyed by the max lead time and average daily sales multiplyed by the average lead time for a brand. The Reorder Point Analysis Distribution reveals that a majority of brands (5799 out of 7146), primarily from the C category, have Reorder Point values between 0 and 199 units. Conversely, a few outliers, predominantly from the high-demand, high-priority A category, exhibit significantly higher ROP values reaching thousands of units. This aligns with expectations, as the rapid sales velocity of A-level brands necessitates larger reorder Points to prevent stockouts. Furthermore, the consistent demand for A-level products, unlike the infrequent orders for C-level products, ensures a smoother product flow and minimizes inventory holding costs.

Lead Time Analysis

Lead time analysis involves examining the time taken from placing an order to receiving it. Shorter lead times can help reduce safety stock requirements and improve responsiveness to customer demand, directly impacting inventory levels.



Discussion:

- **The distribution of average lead times follows a normal pattern, with most brands having a mean lead time of 7.25 to 8.25 days.**
- **The shortest average lead time falls within the 2.75 to 3.25-day range.**
- **Since the majority of brands have a lead time exceeding a week, inventory management strategies must be adjusted accordingly. To prevent stock levels from reaching the safety stock threshold or causing stockouts, new orders should be placed at least 1 to 2 weeks in advance.**

Carrying Cost Analysis

	Price	Description	total_value	onHand	RPA	carrying_cost	carrying_cost_if_RPA	carrying_cost_saved
Brand								
1233	34.99	Jack Daniels No 7 Black	526494.53	15047	1208.0	131623.6325	10566.9800	121056.6525
3545	29.99	Ketel One Vodka	502932.30	16770	1483.0	125733.0750	11118.7925	114614.2825
2753	59.99	Johnnie Walker Black Label	470861.51	7849	1612.0	117715.3775	24175.9700	93539.4075
8068	23.49	Absolut 80 Proof	366631.92	15608	2828.0	91657.9800	16607.4300	75050.5500
3405	28.99	Tito's Handmade Vodka	355649.32	12268	1498.0	88912.3300	10856.7550	78055.5750
...	...	...	...	...	...	...	...	...
25201	18.99	Ch Croix de Jaugue St Emilio	0.00	0	132.0	0.0000	626.6700	-626.6700
45993	10.99	Casa Liliana Good Merlot	0.00	0	18.0	0.0000	49.4550	-49.4550
2943	119.99	The Macallan 18 Yr Old	0.00	0	11.0	0.0000	329.9725	-329.9725
24975	17.99	Tenshen White	0.00	0	182.0	0.0000	818.5450	-818.5450
19754	10.99	BV Coastal Estate Moscato	0.00	0	4.0	0.0000	10.9900	-10.9900

6460 rows × 8 columns

Carrying Cost Analysis measures the total expense of holding inventory over a specific period, which can be significant for businesses with large stock volumes. Our analysis revealed a total carrying cost of approximately $17.6 million. However, if RPA guidelines had been strictly followed, this cost would have been $4.2 million, indicating a potential loss of $13.3 million due to inefficiencies. (Assuming a carrying cost of 25% of the total product cost.)

carrying_cost	carrying_cost_if_RPA	carrying_cost_saved
$17,598,942	$4,285,973	$13,312,969

Inventory Turnover Analysis

Inventory turnover analysis measures how many times inventory is sold or used over a specific period.

An inventory turnover ratio of 4.2 indicates that a company sells and replenishes its inventory approximately four times per year or every 86 days. This moderate turnover rate generally indicates efficient inventory management, leading to several benefits:

- Reduced carrying costs: Lower inventory holding periods translate to lower storage, insurance, and opportunity costs.
- Improved cash flow: Faster inventory movement accelerates cash recovery from sales. Reduced risk of obsolescence: Minimises the risk of products becoming outdated or unsaleable.

However, potential concerns include:

- Risk of Stockout : If turnover is too high, it may increase the risk of stockout due to insufficient safety stock.
- Competitive pressures: Higher turnover rates among competitors could provide them with a competitive edge.

```
COGS = beg_inv_total+purchase_total-end_inv_total
COGS
```

```
310249512.65000004
```

```
avg_inv = beg_inv_total+end_inv_total
avg_inv = avg_inv/2
avg_inv
```

```
73879315.65
```

```
Ita = COGS/avg_inv
Ita
```

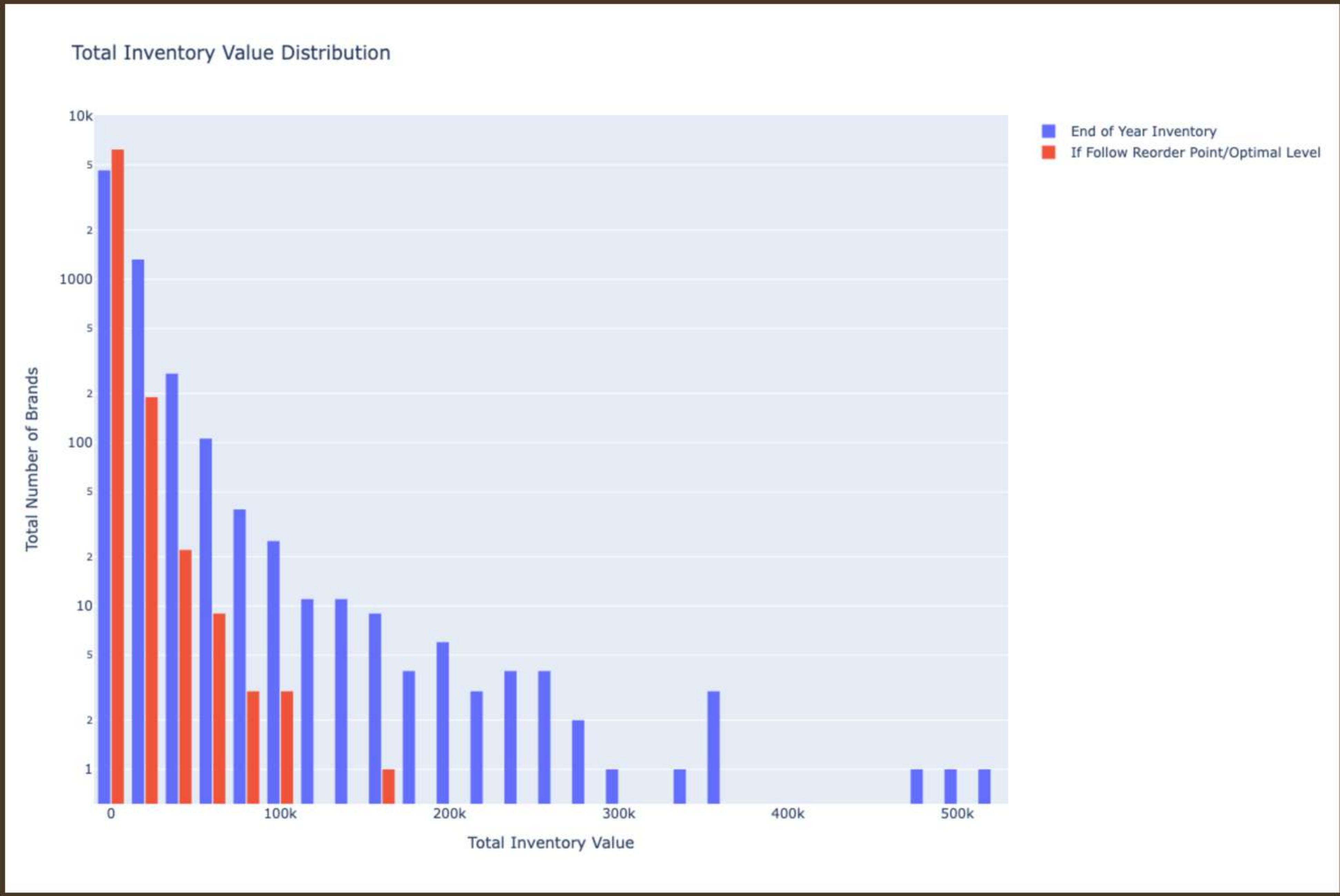
```
4.1994096713049345
```

Recommendations

The company's year-end inventory value totaled $70 million. Analysis of the top 10 products by inventory value revealed significant discrepancies between actual inventory levels and those suggested by the reorder point model, which was based on only two months of sales data. This limited data scope introduces uncertainty, as actual sales patterns may have deviated from the initial two-month trend.

The reorder point model, if strictly adhered to, would have resulted in a total inventory value of approximately 70 million dollars, representing a potential savings of around $53.2 million compared to the actual inventory value. For the top 10 inventory value brands, this translates to potential savings of 250k to 500k. Considering a carrying cost of 20-25%, this could translate to annual savings of 50k to 100k dollars.

The analysis also highlighted instances where brands were out of stock at year-end, despite the reorder point suggesting sufficient inventory levels. This emphasizes the need for ongoing monitoring and adjustments to the reorder point model to account for evolving sales patterns and prevent stockout. By optimising inventory levels, the company can minimise carrying costs, reduce the risk of dead stock, and ensure product availability to meet customer demand.



total_value	total_value_if_RPA	total_value_saved_if_RPA
$70,395,768	$17,141,031	$53,254,737

Improvement Strategies

- Regularly review lead times and, if possible, work with vendors to reduce them, especially for products with longer lead times.
- Maintain an adequate safety stock based on sales volumes and lead times to prevent stock shortages.
- Reduce excess inventory for products that are not selling as expected to decrease inventory-holding costs.
- Rebalance inventory for products with high sales but low stock.
- Prioritize maintaining safety stock for category A items as they yield high sales.
- Place immediate reorder requests for high-value products that require larger reorder amounts.
- Regularly review the ABC categorization and adjust the inventory accordingly. Specifically, consider removing category C items that have very low selling prices or do not sell at all and replace them with products that might generate better revenue.
- Consider removing slow-selling items from the next year's list and replace them with high-demand products.
- Evaluate store performances and consider closing or improving the worst-performing stores.
- Be mindful of the product sizes that sell the most and prioritize ordering these sizes.
- Monitor sales trends and adjust inventory levels accordingly to meet demand, especially during peak sales periods.

Thank you!

Do you have any questions?