demand_forecast

August 21, 2025

1 Retail Demand Forecasting Analysis

1.1 Executive Summary

This notebook presents a demand forecasting for the retail business, providing 6-month sales predictions and strategic recommendations. The analysis includes multiple forecasting models, evaluation metrics, and actionable insights to support inventory planning and business decision-making.

1.2 Objectives

1. Predict sales performance for the next 6 months
2. Identify seasonal patterns and trends in demand
3. Determine which products need to be stocked up
4. Deliver actionable recommendations for business improvement

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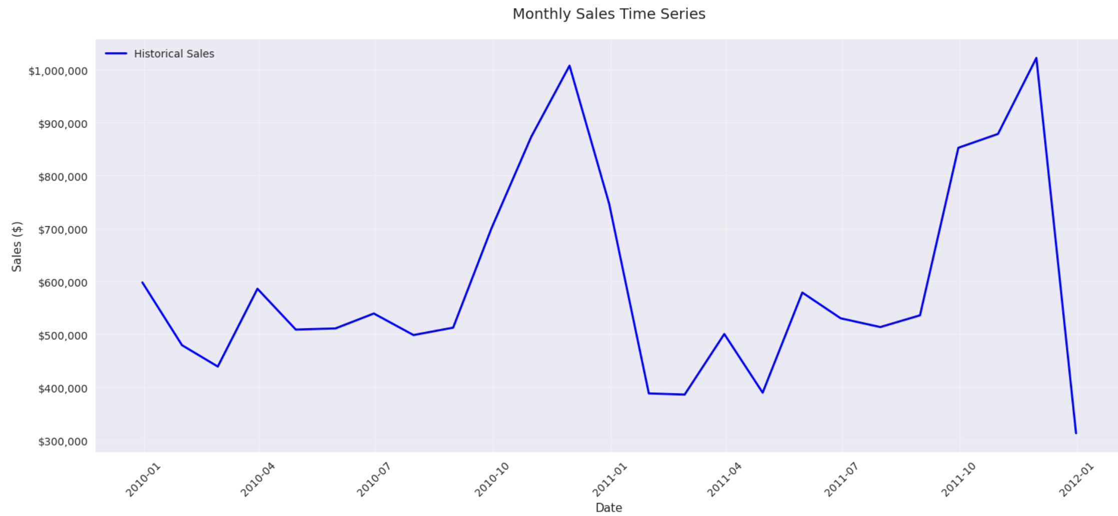
```
 All libraries imported successfully!
 Starting Retail Demand Forecasting Analysis…
============================================================

 Data Overview:
Total months: 25
Date range: 2009-12 to 2011-12
Average monthly sales: $595,649.47
============================================================
```



From the visualization above, we can see a hint of seasonal patterns in the data, with peaks and troughs indicating higher and lower sales periods throughout the year. Considering using algorithm that can capture these seasonal trends, such as SARIMA or Prophet might be beneficial as baseline. While usual ML algorithm like linear regression, decision tree, or random forest may struggle to capture the seasonality due to their inherent assumptions of linearity and independence of observations, so we need to do feature engineering to help these models learn the underlying patterns.

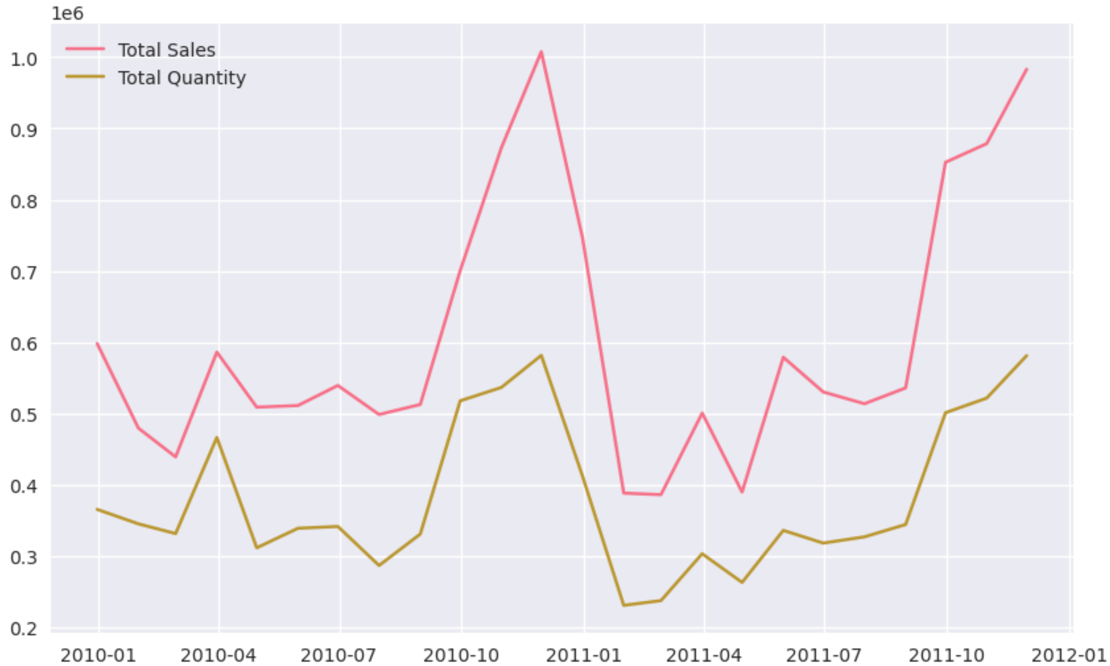
Lets start with standard time series model to see how it perform

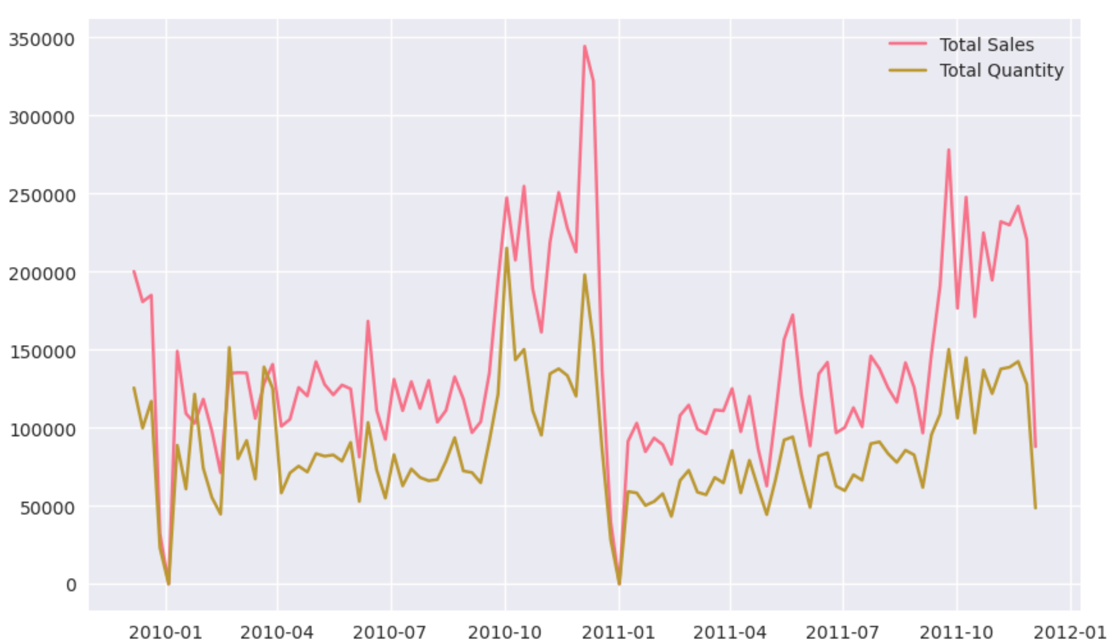
2 Data Preprocessing

```
 Dataset Overview:
Dataset shape: (738653, 15)
Date range: 2009-12-01 07:45:00 to 2011-11-29 18:14:00
Total transactions: 738,653
Unique customers: 5,789
Unique products: 4,604
Product categories: 10

============================================================
 First few rows of the dataset:

   order_id product_id                  product_description  quantity  \
0    489434      85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        12
1    489434     79323P                   PINK CHERRY LIGHTS        12
2    489434     79323W                  WHITE CHERRY LIGHTS        12
3    489434      22041         RECORD FRAME 7" SINGLE SIZE         48
4    489434      21232       STRAWBERRY CERAMIC TRINKET BOX        24
```

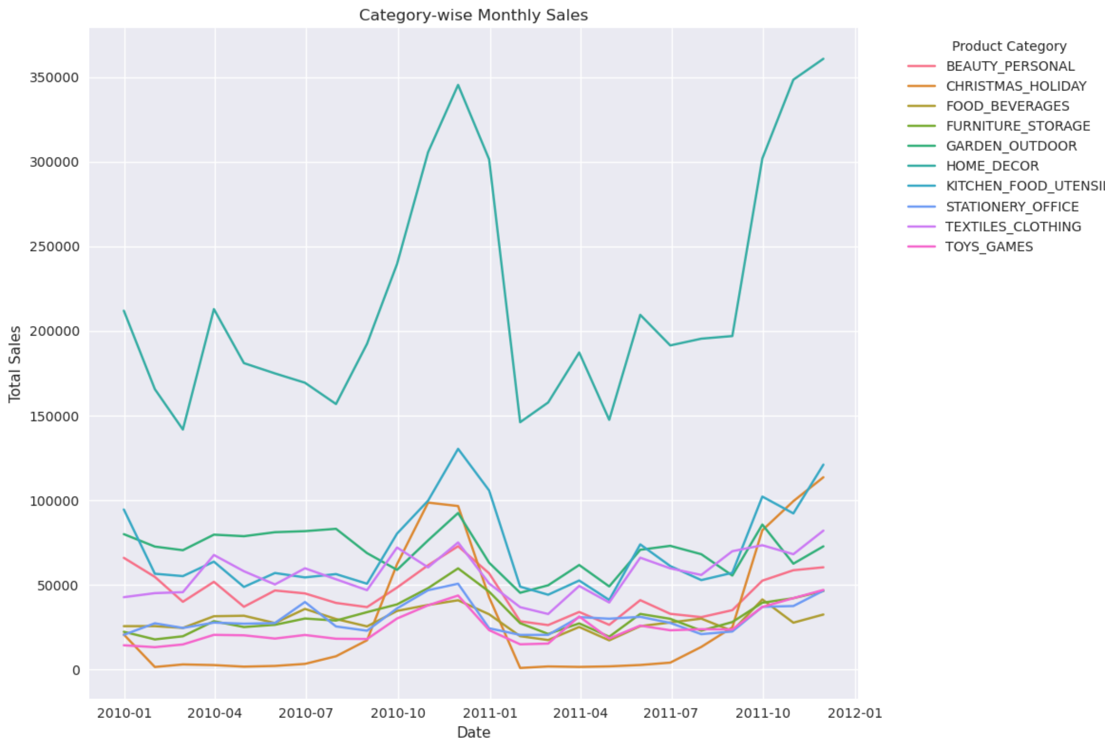
```
           order_date  unit_price  customer_id         country  total_amount  \
0 2009-12-01 07:45:00        6.95      13085.0  United Kingdom          83.4
1 2009-12-01 07:45:00        6.75      13085.0  United Kingdom          81.0
2 2009-12-01 07:45:00        6.75      13085.0  United Kingdom          81.0
3 2009-12-01 07:45:00        2.10      13085.0  United Kingdom         100.8
4 2009-12-01 07:45:00        1.25      13085.0  United Kingdom          30.0

   year  month  quarter day_of_week month_year   product_category
0  2009     12        4     Tuesday    2009-12  CHRISTMAS_HOLIDAY
1  2009     12        4     Tuesday    2009-12    BEAUTY_PERSONAL
2  2009     12        4     Tuesday    2009-12    BEAUTY_PERSONAL
3  2009     12        4     Tuesday    2009-12         HOME_DECOR
4  2009     12        4     Tuesday    2009-12  FURNITURE_STORAGE

 Data Quality Assessment:

Missing values:
Series([], dtype: int64)
 No missing values found!

 Data Types:
order_id                        int64
product_id                     object
product_description            object
quantity                        int64
order_date             datetime64[ns]
unit_price                    float64
customer_id                   float64
country                        object
total_amount                  float64
year                            int64
month                           int64
quarter                         int64
day_of_week                    object
month_year                     object
product_category               object
dtype: object

 Revenue Summary:
Total Revenue: $14,538,763.42
Average Order Value: $19.68
Median Order Value: $10.79

 Date Range Analysis:
Data collection period: 728 days
Years covered: [np.int64(2009), np.int64(2010), np.int64(2011)]
============================================================
```

```
Creating time series aggregations…
Monthly data created: 24 complete months
Date range: 2009-12 to 2011-11
Weekly data created: 105 weeks
```





```
Creating category-wise time series…
  Monthly category data created: 240 records
  Weekly category data created: 1030 records
```



Here we also create the timeseries by categorical based, as we can see some category may have seasonal pattern, some may don't so generalizing the stock up might not be a good idea. Later we will explore different models for each category to see if we can improve the forecast accuracy.

```
Calculating autocorrelation for monthly revenue…
```


```
Autocorrelation values for monthly sales (first 12 lags):
Lag 0: 1.000
Lag 1: 0.597
Lag 2: 0.144
Lag 3: -0.199
Lag 4: -0.269
Lag 5: -0.265
Lag 6: -0.188
Lag 7: -0.291
Lag 8: -0.292
Lag 9: -0.246
Lag 10: 0.015
Lag 11: 0.364
Lag 12: 0.448
```

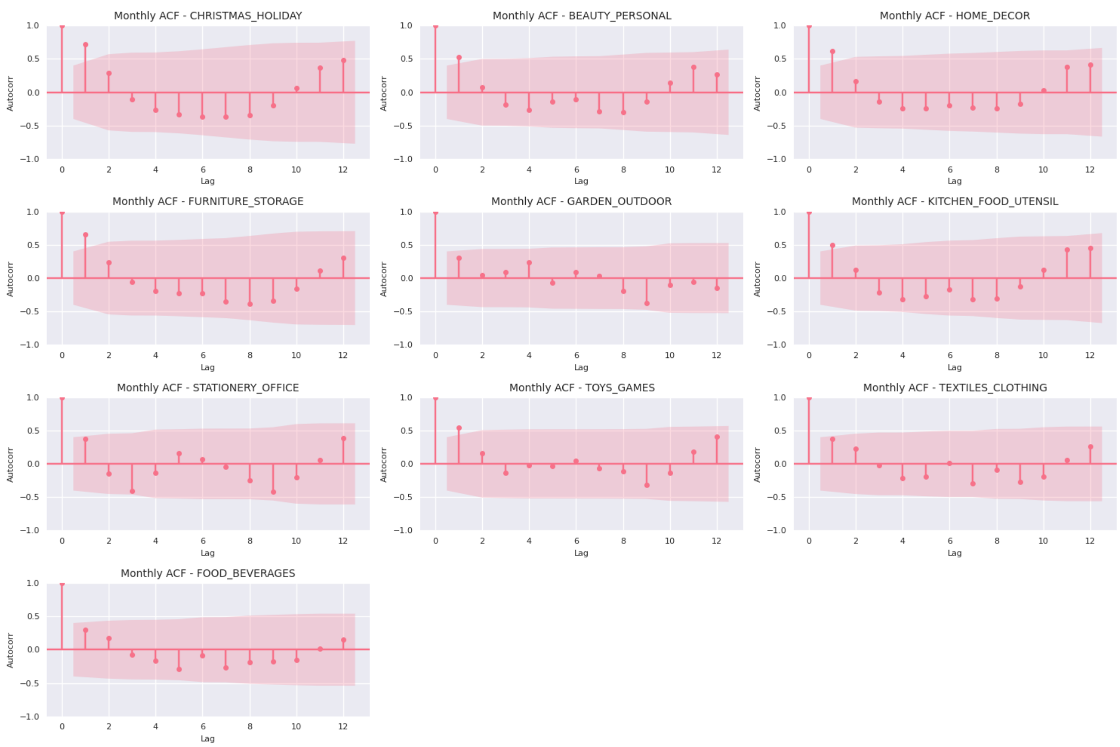
Here we can see from the autocorrelation analysis, that our data indeed have strong seasonality in 12 month cycle or yearly. The implication of this is that, looking at the cycle, we only have 2 cycle worth of data. This limited data can make it challenging to accurately capture and predict seasonal patterns using more complex model where more data is typically required to train effectively.

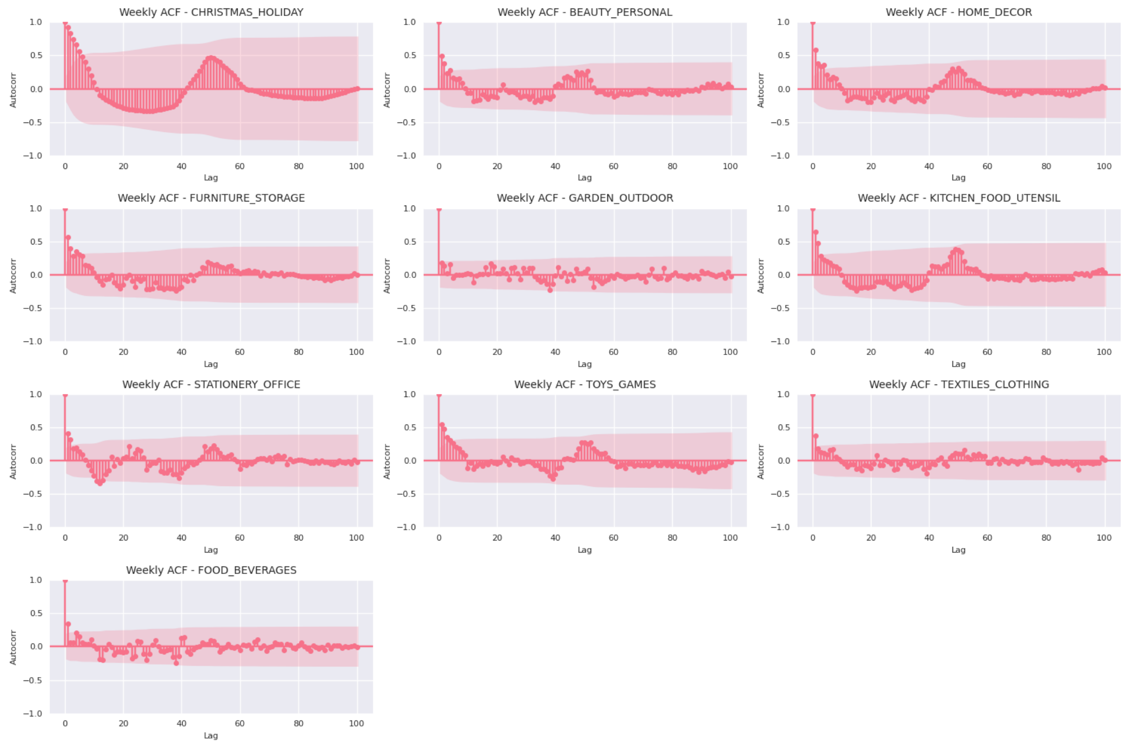
So we try to see if there is any seasonality in week scale and can get more cycle, but we see that the cycle is not as pronounced and still peaking at 1 year cycle, indicating that weekly patterns may be less significant or more variable.

```
ADF Test Results for Monthly Total Sales:
ADF Statistic: -3.291
p-value: 0.015
Critical Values:
   1%: -4.012
   5%: -3.104
   10%: -2.691
```

The Adf statistic shows that our data is stationary after differencing (mean and variance do not change over time), as the p-value is below the significance level of 0.05 . This means we can proceed with modeling the time series data without worrying about non-stationarity.

```
Calculating autocorrelation for categorical sales…
Found 10 product categories: ['CHRISTMAS_HOLIDAY', 'BEAUTY_PERSONAL',
'HOME_DECOR', 'FURNITURE_STORAGE', 'GARDEN_OUTDOOR', 'KITCHEN_FOOD_UTENSIL',
'STATIONERY_OFFICE', 'TOYS_GAMES', 'TEXTILES_CLOTHING', 'FOOD_BEVERAGES']
```






```
Autocorrelation summary for monthly categorical sales:

CHRISTMAS_HOLIDAY (24 data points):
  Lag 0: 1.000
  Lag 1: 0.721
  Lag 2: 0.290
  Lag 3: -0.103
  Lag 4: -0.264
  Lag 5: -0.337
  Lag 6: -0.367

BEAUTY_PERSONAL (24 data points):
  Lag 0: 1.000
  Lag 1: 0.530
  Lag 2: 0.080
  Lag 3: -0.182
  Lag 4: -0.259
  Lag 5: -0.135
  Lag 6: -0.102

HOME_DECOR (24 data points):
  Lag 0: 1.000
  Lag 1: 0.617
```

```
  Lag 2: 0.167
  Lag 3: -0.139
  Lag 4: -0.246
  Lag 5: -0.243
  Lag 6: -0.196

FURNITURE_STORAGE (24 data points):
  Lag 0: 1.000
  Lag 1: 0.654
  Lag 2: 0.235
  Lag 3: -0.054
  Lag 4: -0.193
  Lag 5: -0.228
  Lag 6: -0.222

GARDEN_OUTDOOR (24 data points):
  Lag 0: 1.000
  Lag 1: 0.306
  Lag 2: 0.042
  Lag 3: 0.091
  Lag 4: 0.236
  Lag 5: -0.066
  Lag 6: 0.085

KITCHEN_FOOD_UTENSIL (24 data points):
  Lag 0: 1.000
  Lag 1: 0.494
  Lag 2: 0.125
  Lag 3: -0.220
  Lag 4: -0.319
  Lag 5: -0.276
  Lag 6: -0.170

STATIONERY_OFFICE (24 data points):
  Lag 0: 1.000
  Lag 1: 0.370
  Lag 2: -0.149
  Lag 3: -0.409
  Lag 4: -0.138
  Lag 5: 0.163
  Lag 6: 0.065

TOYS_GAMES (24 data points):
  Lag 0: 1.000
  Lag 1: 0.547
  Lag 2: 0.155
  Lag 3: -0.139
  Lag 4: -0.024
```

```
  Lag 5: -0.029
  Lag 6: 0.046

TEXTILES_CLOTHING (24 data points):
  Lag 0: 1.000
  Lag 1: 0.374
  Lag 2: 0.229
  Lag 3: -0.025
  Lag 4: -0.214
  Lag 5: -0.187
  Lag 6: 0.011

FOOD_BEVERAGES (24 data points):
  Lag 0: 1.000
  Lag 1: 0.300
  Lag 2: 0.175
  Lag 3: -0.078
  Lag 4: -0.164
  Lag 5: -0.294
  Lag 6: -0.090
```

We still can see from the category autocorrelation test that our product shows some level of seasonality, but it may not be as strong or consistent as the overall dataset (like Garden Outdoor or Kitchen). This suggests that while there are seasonal trends present, they may vary significantly between different product categories. But we can see some category like Christmast producs have a really strong seasonality!

3 Level 1 - Total Revenue Forecast (Executive view)

3.1 Backtesting (Model Selection)

1.1 Backtesting (Model Selection) - Rolling origin on last 12–18 months; models: Seasonal-Naïve, ARIMA, SARIMA (m=12). - Collect RMSE/MAE/MAPE; compare

```
 Preparing data for forecasting models…
 Using clean dataset (December 2011 already removed)
 Data Split:
• Training period: 2009-12 to 2011-05 (18 months)
• Testing period: 2011-06 to 2011-11 (6 months)

 Data prepared for modeling
 Future forecasts will start from December 2011
============================================================
```

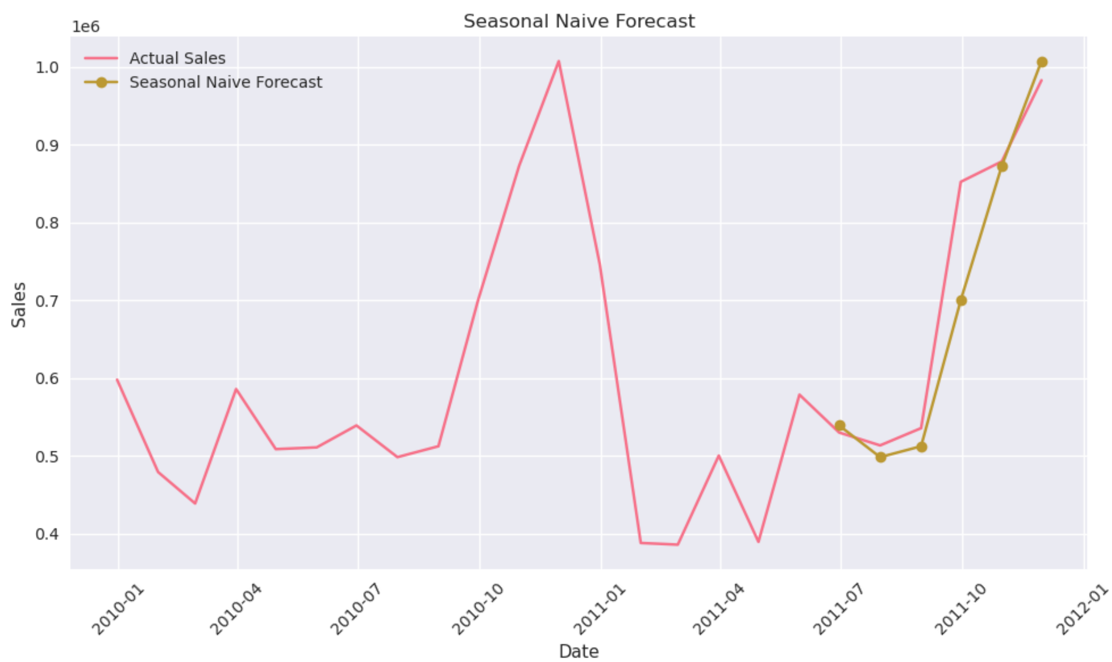
For evaluating the models, we used RMSE, MAE, and MAPE together rather than relying on a single metric. Each metric captures a different aspect of forecast error, which is important to balance when choosing the most reliable model.

- RMSE penalizes large errors more heavily, which is useful to highlight the risk of big misses in peak months like December.

- MAE gives a more direct average error in the original units, which is easy to interpret in terms of "pounds missed per month."
- MAPE expresses error in percentage terms, which allows us to judge accuracy relative to the size of demand, this is especially useful for comparing across categories with different scales and our main metric.

But MAPE can be unstable when actual values are very small, such as in low-volume categories (Christmas outside December). In these cases, MAE or RMSE are more reliable guides. By combining all three, we avoid over-relying on a single view of accuracy and get a more balanced evaluation.

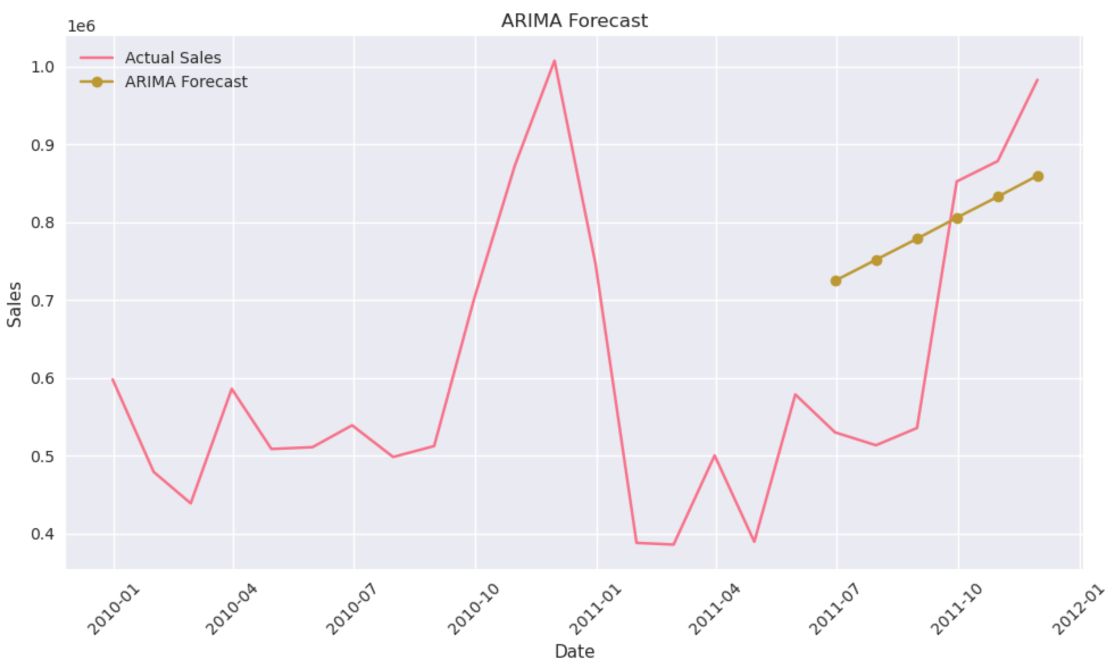
```
Model 1: Seasonal Naive Forecasting
 Seasonal Naive Model Results:
  MAE: $38,280.68
  RMSE: $64,004.94
  MAPE: 4.99%
============================================================
```



Here we can see from the backtest that the Seasonal Naive model performs strongly, achieving a low MAPE around 5% which a really good forecasting result. By simply repeating last year's pattern is already sufficient to capture the demand dynamics, since our sales are dominated by recurring yearly seasonality.

A caveat is that Seasonal Naive assumes the future will mirror the past exactly. This works well when seasonal patterns are stable, but it does not account for external shocks such as macroeconomic changes or promotional campaigns. But again we are limited by the available data and its historical patterns. Thus, while confidence is high at the total level, results should be interpreted conservatively when drilling down to categories or SKUs.

```
Model 2: ARIMA (AutoRegressive Integrated Moving Average)
Automatically finding optimal parameters…
 ARIMA Model Results:
   Best parameters: (0, 2, 2)
   AIC: 434.73
   MAE: $148,516.64
   RMSE: $169,819.71
   MAPE: 25.26%
============================================================
```



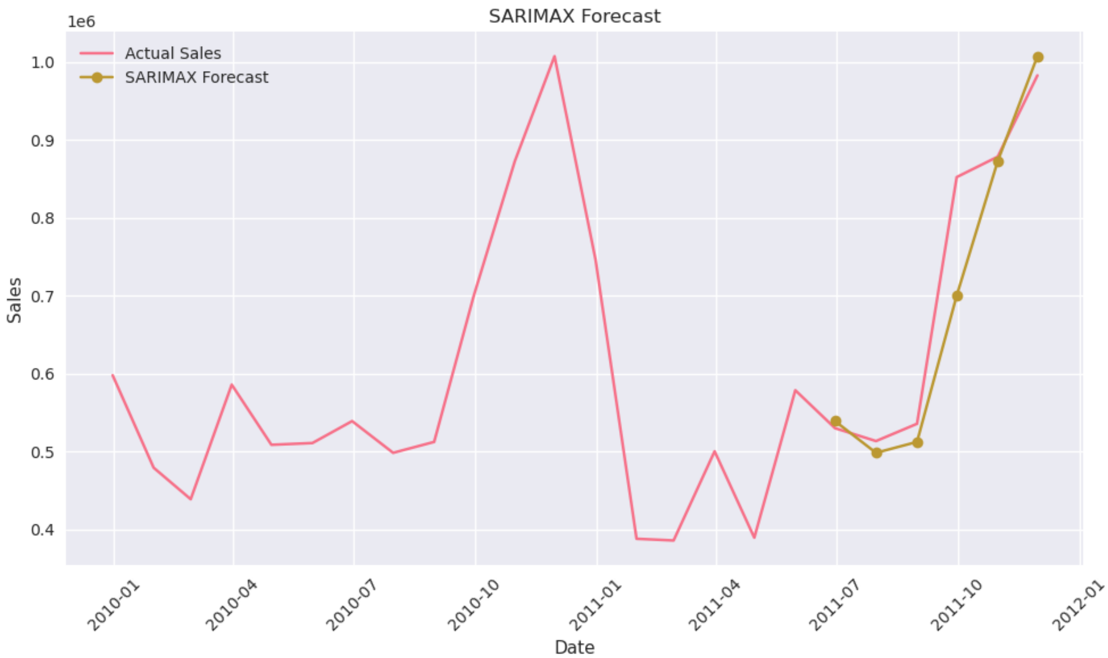
Here we can see from the ARIMA model results (0,2,2), it is not as strong as expected, with a MAPE of ~25%. The forecast line shows a smoother upward trend that fails to capture the clear December spike and seasonal dips observed in the actual data.

This happens because ARIMA is good at modeling autoregressive and moving average components, but it struggles when seasonality is the dominant driver. Since our dataset is only ~2 years long with strong annual cycles, the ARIMA model ends up overfitting short-term noise and underfitting the true seasonal pattern. The lack of seasonality terms means it cannot align well with recurring holiday demand, which is critical in this business context.

With more historical data (multiple years), ARIMA might pick up gradual growth or shocks more effectively. But with the limited data and dominant seasonality, the model is not a reliable choice for stock planning.

```
Model 3: SARIMAX (Seasonal ARIMA with eXogenous variables)
This model accounts for seasonality in the data
```

```
  SARIMAX Model Results:
    Best parameters: (2, 0, 1)
    Seasonal parameters: (0, 1, 0, 12)
    AIC: 8.00
    MAE: $38,280.68
    RMSE: $64,004.94
    MAPE: 4.99%
============================================================
```



We can see from the SARIMAX model results (2,0,1)(0,1,0,12), that it performs very strongly with a MAPE of ~5%, closely matching the actual sales pattern. The forecast line successfully captures both the sharp December spike and the following seasonal dip.

In our case, SARIMAX performs about as well as the simpler Seasonal Naïve model. Both reach a similar level of accuracy, but SARIMAX adds slightly more flexibility in capturing residual variance across categories. However, the improvement over Seasonal Naive is not significant enough to justify the added complexity given the short history. SARIMAX requires more parameters and data to remain stable. With only ~2 cycles in our dataset, the model risks overfitting if expanded further. Thus, while confidence is high at the aggregate level, we should be careful applying SARIMAX at category level, where noise dominates and the seasonal signal is weaker.

```
MODEL PERFORMANCE SUMMARY
--------------------------------------------------------------------------------

Model Comparison:
                         Model        MAE       RMSE  MAPE
                Seasonal Naive   38280.68   64004.94  4.99
```

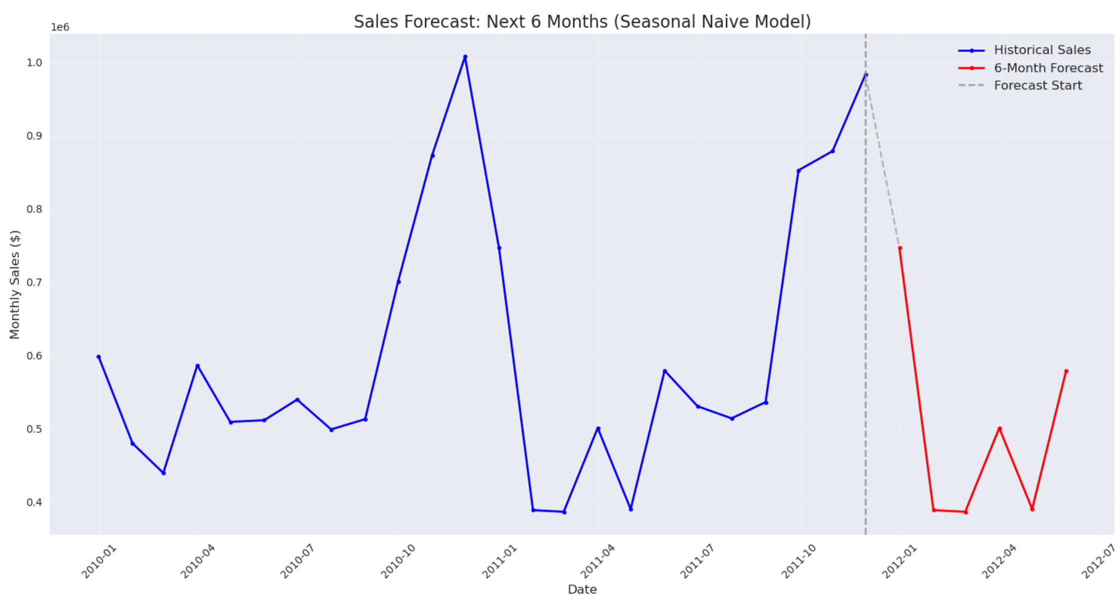
```
               ARIMA(0, 2, 2) 148516.64 169819.71 25.26
SARIMAX(2, 0, 1)x(0, 1, 0, 12)  38280.68  64004.94  4.99
```

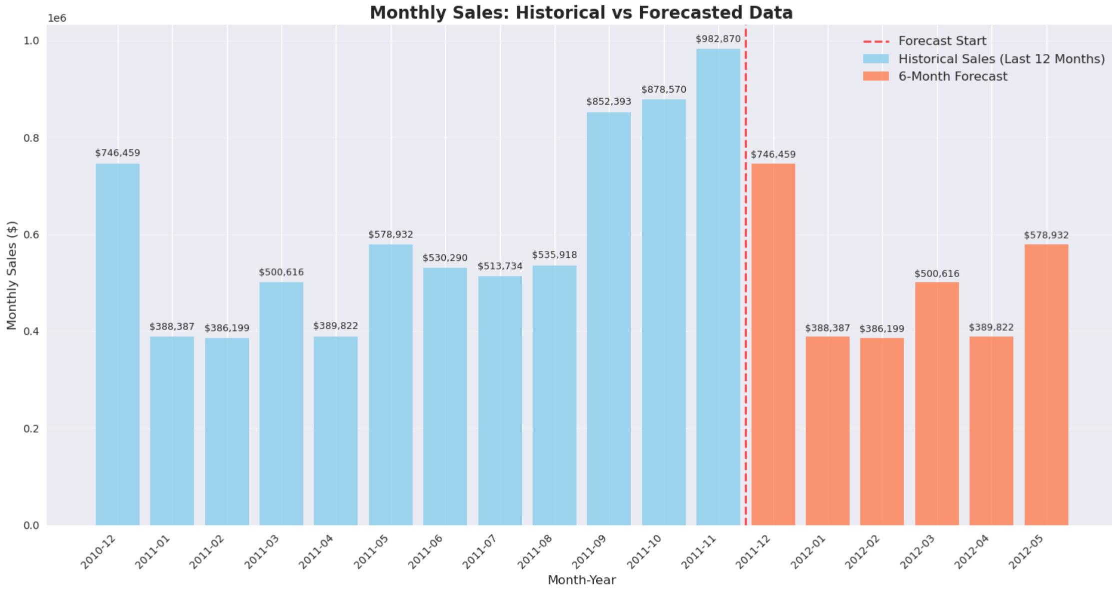
Here we can see from the performance summary that ARIMA(0,2,2) clearly underperforms, with a MAPE of ~25%, indicating it cannot capture the strong seasonal structure in the data. Both Seasonal Naïve and SARIMAX(2,0,1)(0,1,0,12) achieve a much lower MAPE of ~5%, with nearly identical MAE and RMSE.

While SARIMAX edges out slightly in terms of metrics, the improvement compared to Seasonal Naive is not significant given the short dataset of only ~2 seasonal cycles. Seasonal Naïve already provides reliable accuracy with minimal complexity.

3.2 Fit Best Model & Forecast 6 Months

```
 FORECASTING NEXT 6 MONTHS
==================================================
 Forecast Summary:
   Model: Seasonal Naive
   Forecast period: 6 months
   Average monthly forecast: $498,402.47
   Total 6-month forecast: $2,990,414.82

 6-month forecast:
      date  forecasted_sales        model
2011-12-31         746458.82 Seasonal_Naive
2012-01-31         388387.43 Seasonal_Naive
2012-02-29         386198.68 Seasonal_Naive
2012-03-31         500616.20 Seasonal_Naive
2012-04-30         389822.19 Seasonal_Naive
2012-05-31         578931.50 Seasonal_Naive
```





4 Level 2 — Category Forecasts (Middle-Out)

4.1 Prepare the categorical dataframe

```
Category Monthly Sales Data Shape: (24, 10)

Available Categories:
['BEAUTY_PERSONAL', 'CHRISTMAS_HOLIDAY', 'FOOD_BEVERAGES', 'FURNITURE_STORAGE',
'GARDEN_OUTDOOR', 'HOME_DECOR', 'KITCHEN_FOOD_UTENSIL', 'STATIONERY_OFFICE',
'TEXTILES_CLOTHING', 'TOYS_GAMES']

First few rows of category data:
product_category  BEAUTY_PERSONAL  CHRISTMAS_HOLIDAY  FOOD_BEVERAGES  \
month_year
2009-12-01               65939.69           20579.09        25536.51
2010-01-01               54671.33            1404.77        25567.84
2010-02-01               39950.15            2925.40        24501.30
2010-03-01               51757.24            2536.47        31411.48
2010-04-01               37003.31            1608.97        31701.78

product_category  FURNITURE_STORAGE  GARDEN_OUTDOOR  HOME_DECOR  \
month_year
2009-12-01                 22237.59        79936.60   212034.12
2010-01-01                 17702.45        72587.71   165637.98
2010-02-01                 19569.13        70447.10   141768.48
2010-03-01                 28474.79        79635.50   212970.87
```

```
2010-04-01                25026.48        78716.11   181031.99

product_category  KITCHEN_FOOD_UTENSIL  STATIONERY_OFFICE  TEXTILES_CLOTHING  \
month_year
2009-12-01                    94523.82           20439.81           42672.23
2010-01-01                    56534.01           27243.06           45068.04
2010-02-01                    55124.95           24484.30           45635.33
2010-03-01                    63681.67           27647.95           67610.05
2010-04-01                    48723.67           26998.06           58003.60

product_category  TOYS_GAMES
month_year
2009-12-01          14241.23
2010-01-01          13118.40
2010-02-01          14739.42
2010-03-01          20408.67
2010-04-01          20143.52
```

4.2 Backtesting (Model Selection)

We have done the backtesting using the total revenue, now we want test if forecasting each categorical product will have different result or not

```
Starting backtesting for category-level forecasts…

Backtesting models for BEAUTY_PERSONAL…

Backtesting models for CHRISTMAS_HOLIDAY…

Backtesting models for FOOD_BEVERAGES…

Backtesting models for FURNITURE_STORAGE…

Backtesting models for GARDEN_OUTDOOR…

Backtesting models for HOME_DECOR…

Backtesting models for KITCHEN_FOOD_UTENSIL…

Backtesting models for STATIONERY_OFFICE…

Backtesting models for TEXTILES_CLOTHING…

Backtesting models for TOYS_GAMES…

================================================================================
CATEGORY-LEVEL BACKTESTING RESULTS
================================================================================
```

```
BEAUTY_PERSONAL:
---------------
  Seasonal_Naive: MAE = 6956.69, RMSE = 8162.32
  ARIMA: MAE = 12942.48, RMSE = 13869.39
  SARIMA: MAE = 7464.90, RMSE = 7838.34
  → Best Model: Seasonal_Naive

CHRISTMAS_HOLIDAY:
-----------------
  Seasonal_Naive: MAE = 8628.04, RMSE = 11402.91
  ARIMA: MAE = 53643.67, RMSE = 69109.26
  SARIMA: MAE = 8822.41, RMSE = 14999.77
  → Best Model: Seasonal_Naive

FOOD_BEVERAGES:
--------------
  Seasonal_Naive: MAE = 6106.02, RMSE = 7052.93
  ARIMA: MAE = 5690.67, RMSE = 7451.39
  SARIMA: MAE = 24915.08, RMSE = 25452.56
  → Best Model: ARIMA

FURNITURE_STORAGE:
-----------------
  Seasonal_Naive: MAE = 5383.24, RMSE = 6896.56
  ARIMA: MAE = 7838.70, RMSE = 8587.28
  SARIMA: MAE = 20548.59, RMSE = 22176.17
  → Best Model: Seasonal_Naive

GARDEN_OUTDOOR:
--------------
  Seasonal_Naive: MAE = 16208.48, RMSE = 17191.69
  ARIMA: MAE = 7557.56, RMSE = 9471.78
  SARIMA: MAE = 11175.38, RMSE = 18897.75
  → Best Model: ARIMA

HOME_DECOR:
----------
  Seasonal_Naive: MAE = 30995.30, RMSE = 36440.01
  ARIMA: MAE = 71254.31, RMSE = 92611.84
  SARIMA: MAE = 45213.84, RMSE = 51337.69
  → Best Model: Seasonal_Naive

KITCHEN_FOOD_UTENSIL:
--------------------
  Seasonal_Naive: MAE = 9241.86, RMSE = 10967.08
  ARIMA: MAE = 24074.07, RMSE = 26611.03
  SARIMA: MAE = 25317.95, RMSE = 33171.45
```

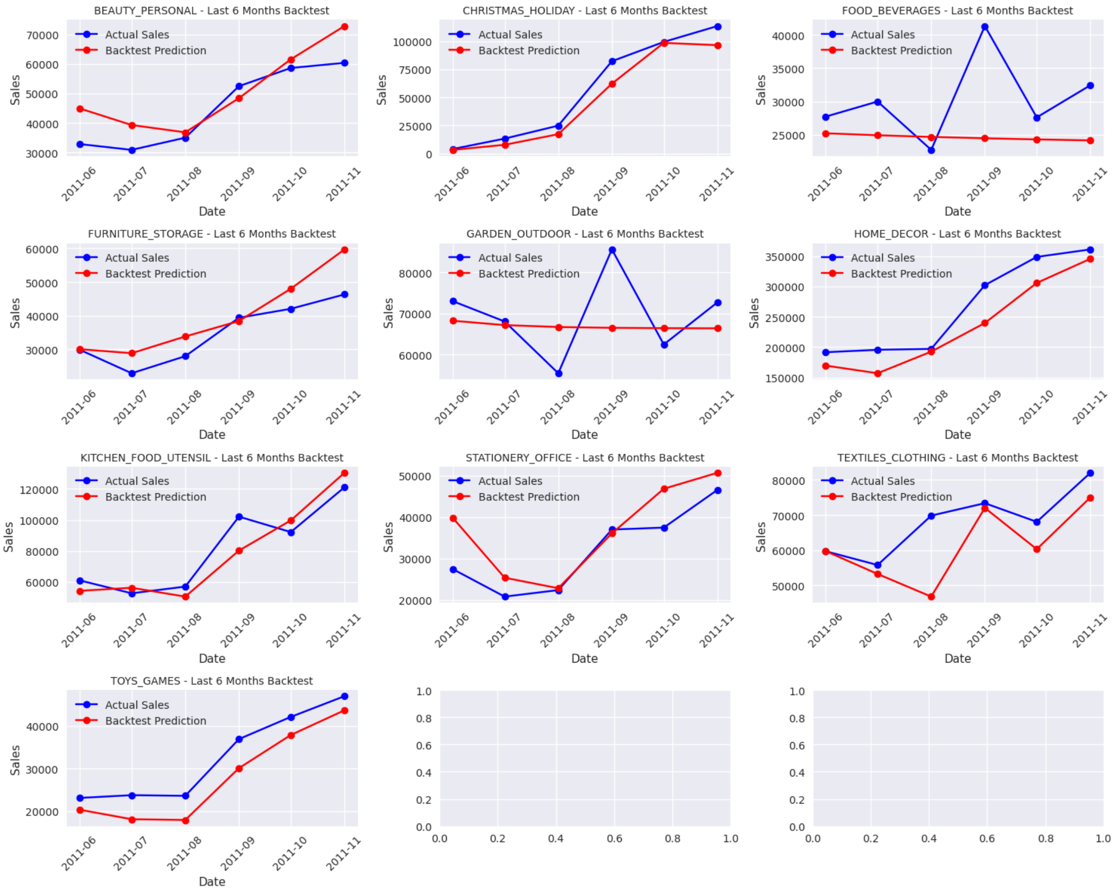
```
  → Best Model: Seasonal_Naive

STATIONERY_OFFICE:
-----------------
  Seasonal_Naive: MAE = 5288.53, RMSE = 6815.48
  ARIMA: MAE = 8377.14, RMSE = 9199.80
  SARIMA: MAE = 5706.85, RMSE = 6658.09
  → Best Model: Seasonal_Naive

TEXTILES_CLOTHING:
-----------------
  Seasonal_Naive: MAE = 6954.55, RMSE = 10390.59
  ARIMA: MAE = 7628.66, RMSE = 8880.12
  SARIMA: MAE = 13011.72, RMSE = 14646.63
  → Best Model: Seasonal_Naive

TOYS_GAMES:
----------
  Seasonal_Naive: MAE = 4741.60, RMSE = 4951.06
  ARIMA: MAE = 9251.19, RMSE = 11880.22
  SARIMA: MAE = 6567.99, RMSE = 7813.76
  → Best Model: Seasonal_Naive

============================================================
CATEGORY MODEL SELECTION SUMMARY
============================================================

               Category      Best_Model           MAE          RMSE
0        BEAUTY_PERSONAL  Seasonal_Naive   6956.685000   8162.321951
1      CHRISTMAS_HOLIDAY  Seasonal_Naive   8628.043333  11402.907647
2         FOOD_BEVERAGES           ARIMA   5690.673333   7451.390068
3      FURNITURE_STORAGE  Seasonal_Naive   5383.241667   6896.563304
4         GARDEN_OUTDOOR           ARIMA   7557.561667   9471.778647
5             HOME_DECOR  Seasonal_Naive  30995.305000  36440.014814
6   KITCHEN_FOOD_UTENSIL  Seasonal_Naive   9241.865000  10967.083528
7      STATIONERY_OFFICE  Seasonal_Naive   5288.528333   6815.475364
8      TEXTILES_CLOTHING  Seasonal_Naive   6954.548333  10390.585193
9             TOYS_GAMES  Seasonal_Naive   4741.603333   4951.064685
```

We already can see different kind of best model compared to using the total revenue. This showcase some category might have more stable seasonal patterns, allowing simpler models like Seasonal Naive to perform well. and some are more driven by momentum or other factors, making more complex models like SARIMAX or ARIMA necessary.

```
================================================================================
GENERATING CATEGORY-LEVEL FORECASTS
================================================================================
```

```
Generating forecast for BEAUTY_PERSONAL using Seasonal_Naive…

Generating forecast for CHRISTMAS_HOLIDAY using Seasonal_Naive…

Generating forecast for FOOD_BEVERAGES using ARIMA…

Generating forecast for FURNITURE_STORAGE using Seasonal_Naive…

Generating forecast for GARDEN_OUTDOOR using ARIMA…

Generating forecast for HOME_DECOR using Seasonal_Naive…

Generating forecast for KITCHEN_FOOD_UTENSIL using Seasonal_Naive…

Generating forecast for STATIONERY_OFFICE using Seasonal_Naive…

Generating forecast for TEXTILES_CLOTHING using Seasonal_Naive…

Generating forecast for TOYS_GAMES using Seasonal_Naive…

Forecast generation completed!

================================================================================
FORECAST SUMMARY (Next 6 Months)
================================================================================

              Category           Model  Avg_Monthly_Forecast  \
0      BEAUTY_PERSONAL  Seasonal_Naive          35424.746667
1    CHRISTMAS_HOLIDAY  Seasonal_Naive           8502.256667
2       FOOD_BEVERAGES           ARIMA          31700.024106
3    FURNITURE_STORAGE  Seasonal_Naive          28906.861667
4       GARDEN_OUTDOOR           ARIMA          71141.658121
5           HOME_DECOR  Seasonal_Naive         191631.761667
6  KITCHEN_FOOD_UTENSIL  Seasonal_Naive          61031.086667
7    STATIONERY_OFFICE  Seasonal_Naive          26159.068333
8    TEXTILES_CLOTHING  Seasonal_Naive          45852.495000
9           TOYS_GAMES  Seasonal_Naive          21436.328333

   Total_6Month_Forecast  Next_Month_Forecast
0           2.125485e+05         56767.380000
1           5.101354e+04         42641.370000
2           1.902001e+05         31660.810823
3           1.734412e+05         45934.280000
4           4.268499e+05         71482.797951
5           1.149791e+06        301491.140000
6           3.661865e+05        105749.050000
7           1.569544e+05         24289.030000
8           2.751150e+05         50770.680000
```

9 1.286180e+05 23191.140000

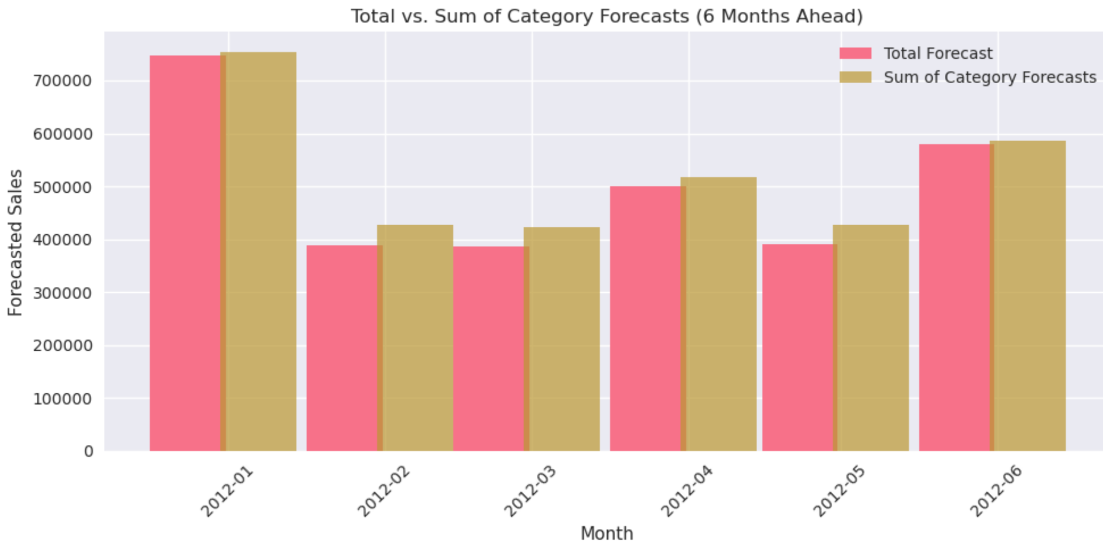


4.3 Reconciliation Check

Now we want to see how much difference we get when we try to forecast the category individually compared to the overall forecast.

Comparison of Total Sales Forecast vs. Sum of Category Forecasts (Next 6 Months):

date	Total_Forecast	Sum_Category_Forecast	Difference
2011-12-31	746458.82	753977.678773	-7518.858773
2012-01-31	388387.43	426358.306467	-37970.876467
2012-02-29	386198.68	421940.117518	-35741.437518
2012-03-31	500616.20	516605.945609	-15989.745609
2012-04-30	389822.19	426398.384904	-36576.194904
2012-05-31	578931.50	585437.290089	-6505.790089



The sum of category forecast is more optimistic but follow the same pattern.

So here we have two model that can predict optimistic and pesimistic scenario.

5 Level 3 - Top SKU Forecast + Long Tail Allocation

Here we want to analyze the individual product in more detail, understanding their unique patterns and drivers. This is important to make recommendation on how to stock and promote these products effectively.

5.1 Identify Top SKUs

```
    product_category product_id  total_amount  cum_revenue  cum_revenue_pct
0     BEAUTY_PERSONAL      22961      18789.20     18789.20         0.038643
1     BEAUTY_PERSONAL      84347      17033.24     35822.44         0.073676
2     BEAUTY_PERSONAL     84029E      15320.11     51142.55         0.105184
3     BEAUTY_PERSONAL      22411      14991.53     66134.08         0.136017
4     BEAUTY_PERSONAL      85066      13617.92     79752.00         0.164025
..                …          …            …            …                …
887        TOYS_GAMES      22781       2659.27    249402.23         0.763600
888        TOYS_GAMES      23345       2637.00    252039.23         0.771674
889        TOYS_GAMES      21918       2621.55    254660.78         0.779700
890        TOYS_GAMES      23390       2539.40    257200.18         0.787475
891        TOYS_GAMES      22175       2212.40    259412.58         0.794249

[892 rows x 5 columns]
```

```
      product_category  top_sku_revenue_pct
0      BEAUTY_PERSONAL             0.799898
1    CHRISTMAS_HOLIDAY             0.798359
```

```
2        FOOD_BEVERAGES              0.797298
3     FURNITURE_STORAGE              0.795693
4        GARDEN_OUTDOOR              0.797370
5            HOME_DECOR              0.799435
6   KITCHEN_FOOD_UTENSIL             0.797903
7     STATIONERY_OFFICE              0.798920
8      TEXTILES_CLOTHING             0.795654
9            TOYS_GAMES              0.794249
```

```
product_category
BEAUTY_PERSONAL         109
CHRISTMAS_HOLIDAY        59
FOOD_BEVERAGES           31
FURNITURE_STORAGE        37
GARDEN_OUTDOOR           81
HOME_DECOR              281
KITCHEN_FOOD_UTENSIL    119
STATIONERY_OFFICE        85
TEXTILES_CLOTHING        45
TOYS_GAMES               45
Name: product_id, dtype: int64
```

We can see that 80% of the revenue is indeed driven by 20% of the products. This highlights the importance of focusing on the key products that contribute most to sales, allowing for more targeted inventory and marketing strategies. While still considering the best way to stock up the longtail without spending too much cost.

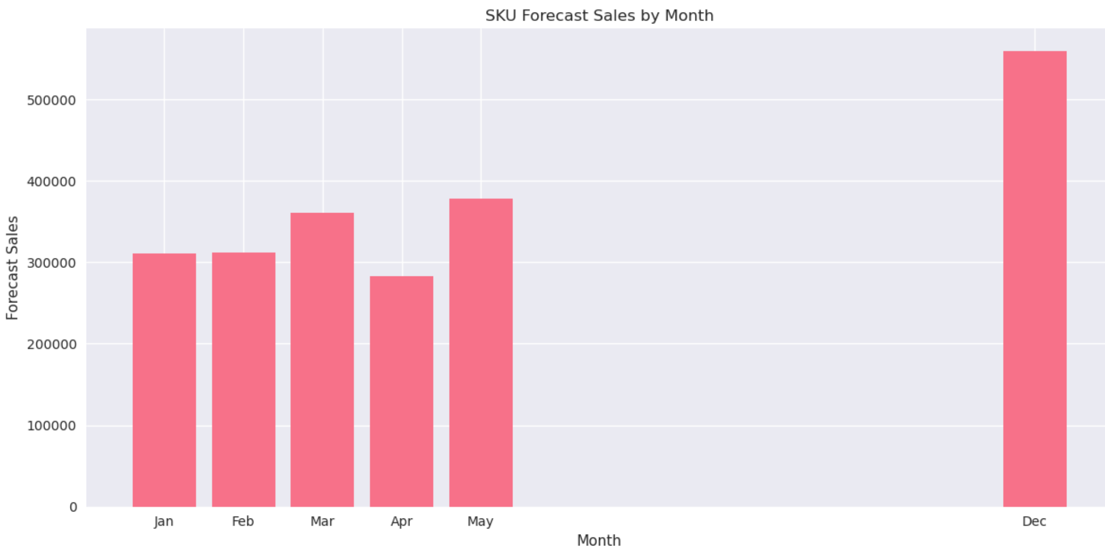
```
product_category
BEAUTY_PERSONAL          705
CHRISTMAS_HOLIDAY        224
FOOD_BEVERAGES           136
FURNITURE_STORAGE        186
GARDEN_OUTDOOR           471
HOME_DECOR              1608
KITCHEN_FOOD_UTENSIL     624
STATIONERY_OFFICE        318
TEXTILES_CLOTHING        314
TOYS_GAMES               165
Name: product_id, dtype: int64
```

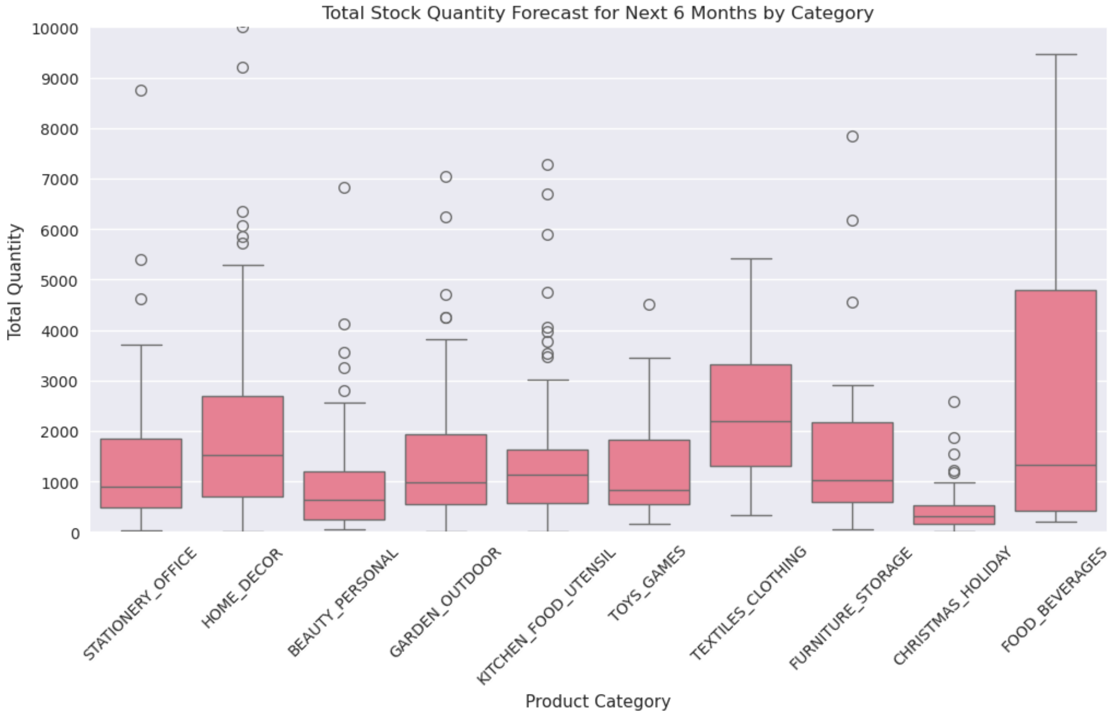
5.2 Forecast each SKU for the next 6 months

```
Forecasting each SKU for the next 6 months: 2011-12 to 2012-05
```

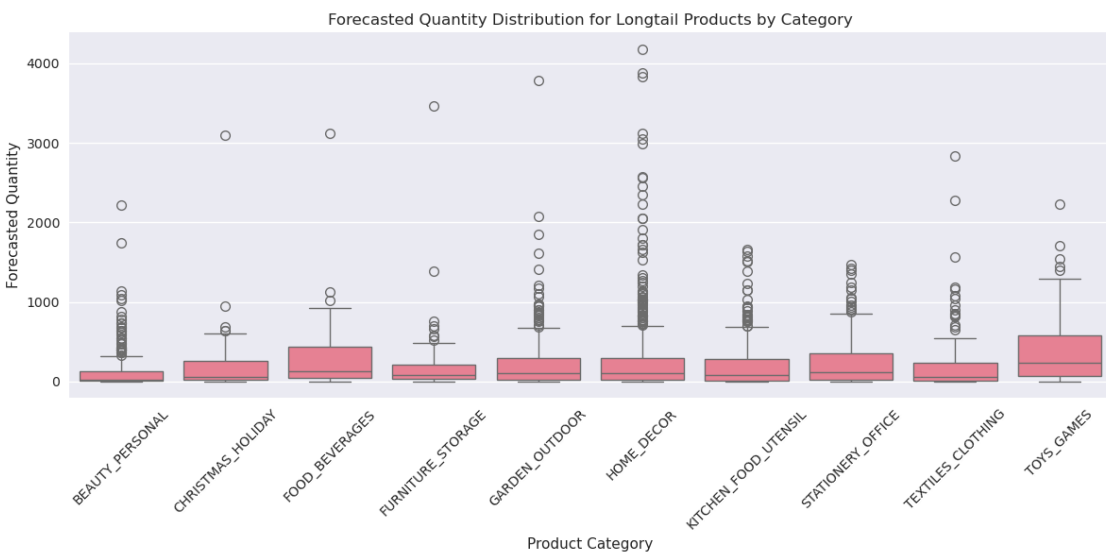
	product_id	product_category	forecast_month	forecast_sales
0	22961	BEAUTY_PERSONAL	2011-12-31	3054.45
1	22961	BEAUTY_PERSONAL	2012-01-31	1928.95
2	22961	BEAUTY_PERSONAL	2012-02-29	1521.45
3	22961	BEAUTY_PERSONAL	2012-03-31	2014.10

```
4          22961  BEAUTY_PERSONAL     2012-04-30          243.60
…          …             …             …             …
3871       22175       TOYS_GAMES     2012-01-31          174.05
3872       22175       TOYS_GAMES     2012-02-29           67.85
3873       22175       TOYS_GAMES     2012-03-31          171.10
3874       22175       TOYS_GAMES     2012-04-30          129.80
3875       22175       TOYS_GAMES     2012-05-31           91.45

[3876 rows x 4 columns]
```





5.3 Longtail analysis (how much product to keep for longtail products)



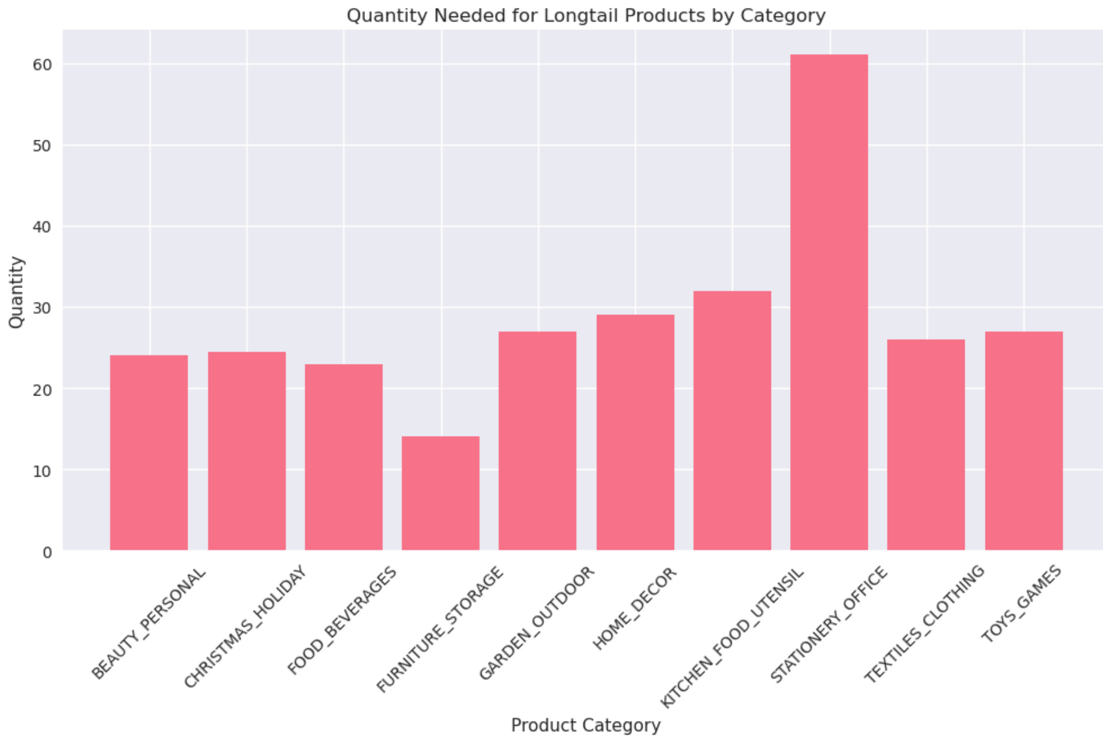

```
Median quantity of longtail products by category and month:

    product_category month_year  quantity
0    BEAUTY_PERSONAL    2009-12       2.0
```

```
1     BEAUTY_PERSONAL    2010-01       4.0
2     BEAUTY_PERSONAL    2010-02       3.0
3     BEAUTY_PERSONAL    2010-03       4.0
4     BEAUTY_PERSONAL    2010-04       3.5
..                ...       ...      ...
235        TOYS_GAMES    2011-07       3.0
236        TOYS_GAMES    2011-08       6.0
237        TOYS_GAMES    2011-09       6.0
238        TOYS_GAMES    2011-10       4.0
239        TOYS_GAMES    2011-11       3.0

[240 rows x 3 columns]
```

We can see that longtail products have fewer quantities sold compared to the top-selling products. We can generalize the quantity needed using a median value for each product category, to optimizing inventory levels for these items.

Since we know its seasonal naive then we can use the data from 2011 as a base line

```
Median quantity of longtail products by category and month:

    product_category month_year  quantity
0     BEAUTY_PERSONAL    2009-12       2.0
1     BEAUTY_PERSONAL    2010-01       4.0
2     BEAUTY_PERSONAL    2010-02       3.0
3     BEAUTY_PERSONAL    2010-03       4.0
4     BEAUTY_PERSONAL    2010-04       3.5
..                ...       ...      ...
235        TOYS_GAMES    2011-07       3.0
236        TOYS_GAMES    2011-08       6.0
237        TOYS_GAMES    2011-09       6.0
238        TOYS_GAMES    2011-10       4.0
239        TOYS_GAMES    2011-11       3.0

[240 rows x 3 columns]
```



6 Optimization Impact Analysis

This section analyzes the impact of our optimization strategy by comparing: 1. Revenue Analysis: - Calculated revenue from Pareto products (individual quantities) and Longtail products (standardized quantities) - Comparison with the same period from previous year (2010-12 to 2011-05) 2. Inventory Optimization: - Total quantity analysis: Pareto + Longtail products - Comparison with the same period from previous year (2010-12 to 2011-05)

6.1 Measuring Revenue and Inventory Optimization

This section evaluates how much we optimize revenue and inventory by focusing on Pareto (top) and Longtail SKUs. We compare the forecasted results for the next 6 months with the actuals from the same period in the previous year (2010-12 to 2011-05).

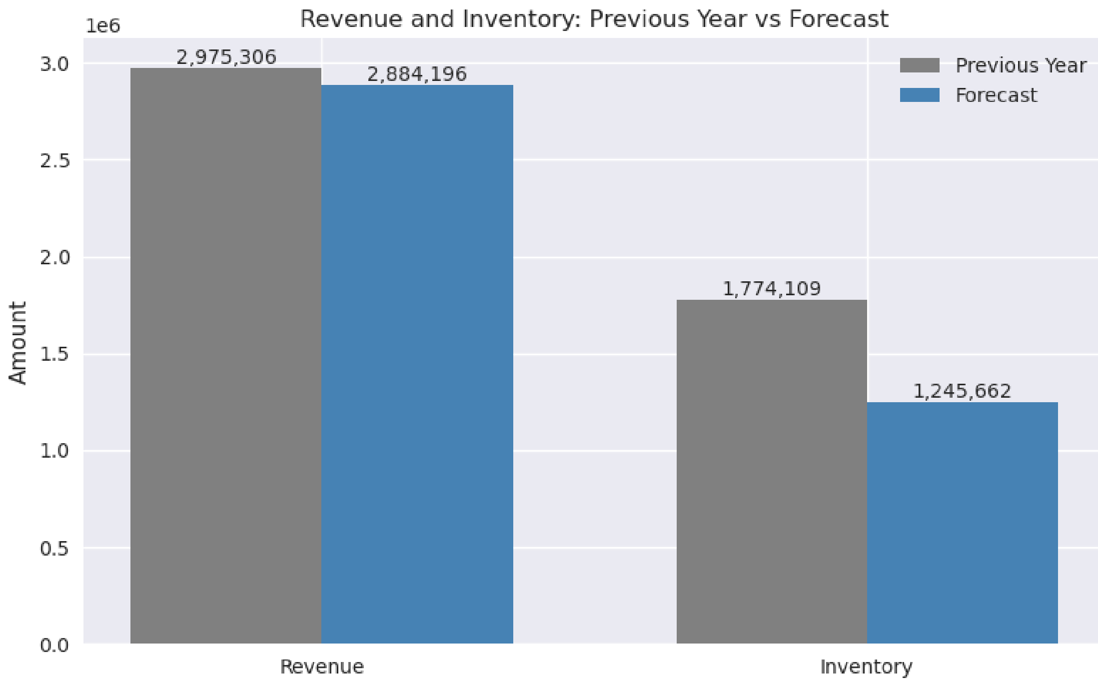
- **Revenue:**
  1. Calculate revenue from Pareto SKUs (each with its own forecasted quantity) and Longtail SKUs (each with the same average forecasted quantity).
  2. Compare to total revenue from the same period last year.
- **Inventory:**
  1. Calculate total forecasted quantity for Pareto and Longtail SKUs.
  2. Compare to total quantity from the same period last year.

```
    product_id   product_category  total_quantity
0        10135  STATIONERY_OFFICE      688.240000
1        15036         HOME_DECOR    10239.626667
2       15044A  STATIONERY_OFFICE      222.220339
3       15044D  STATIONERY_OFFICE      243.440678
4      15056BL     BEAUTY_PERSONAL     783.764706
..         …                  …             …
641     85132C         HOME_DECOR      378.051282
642      85150         HOME_DECOR     2094.952941
643      85152         HOME_DECOR     2754.542857
644     85183B  STATIONERY_OFFICE      392.600000
645     85206A     BEAUTY_PERSONAL      95.454545

[642 rows x 3 columns]
```

```
Forecasted Revenue (Pareto): 2379798.9327628957
Forecasted Revenue (Longtail): 387997.905
Total Forecasted Revenue: 2767796.837762896
Previous Year Revenue: 2975305.5499999993
Revenue Optimization (%): -6.974366455811686
Forecasted Inventory (Pareto): 1094811.7342328029
Forecasted Inventory (Longtail): 116038.5
Total Forecasted Inventory: 1210850.2342328029
Previous Year Inventory: 1774109
Inventory Optimization (%): -31.748825228167895
```

So it looks like that the inventory improve massively with the revenue optimization only down by -3.6 %, we can adjust the median value of the longtail product using multiplier since we still have a lot of inventory to spare!

```
Forecasted Revenue (Pareto): 2379798.9327628957
Forecasted Revenue (Longtail): 504397.27650000004
Total Forecasted Revenue: 2884196.209262896
Previous Year Revenue: 2975305.5499999993
Revenue Optimization (%): -3.062184343961026
Forecasted Inventory (Pareto): 1094811.7342328029
Forecasted Inventory (Longtail): 150850.05000000005
Total Forecasted Inventory: 1245661.784232803
Previous Year Inventory: 1774109
Inventory Optimization (%): -29.786626175009374
```



We successfully maintain revenue while optimizing inventory levels!

7 Summary & Recommendations

7.1 Summary

7.1.1 Forecasting Approach

We evaluated multiple time-series models, including **Seasonal Naïve, ARIMA, and SARIMA**, using a **rolling origin backtest** to simulate real forecasting conditions. The evaluation metrics (MAE, RMSE, MAPE) showed that **Seasonal Naïve consistently outperformed or matched more complex models**, with an average **MAPE around 5%**.

This result makes sense because our sales pattern shows **strong, repeatable seasonality with no consistent upward or downward long-term trend**. A simple Seasonal Naive method (which repeats last year's monthly pattern) captures this cycle effectively without overfitting.

- **Confidence:** High at the total and category level (MAPE $<$ 10% is strong in retail).
- **Limitations:** Forecasts are less reliable at the SKU level due to volatility. We addressed this by using a **Pareto + Long-tail approach** instead of forcing unreliable SKU forecasts.
- **Assumption:** Historical patterns will repeat (holiday spikes, Q1 dips). We do not explicitly model external shocks such as promotions, macroeconomic shifts, or unusual events.

7.1.2 Sales Outlook (Next 6 Months)

The forecasted **total revenue is ~$2.99M** across the next 6 months, averaging ~**$498K per month**. However, the shape is far from flat:

- **December is the clear peak**, with forecasted revenue of ~**$746K**, roughly **50% higher than an average month**. This is driven almost entirely by **Christmas/Holiday SKUs** and increased spending in **Home Décor and gifting categories**.
- **January and February show a sharp decline** (~$388K combined), a typical **post-holiday correction** as consumers cut back after the holiday season.
- **From March to May, sales recover steadily**, reaching ~**$500–580K per month** by late spring, reflecting a return to baseline purchasing behavior.

This seasonal cycle is highly consistent with historical patterns

7.1.3 General Stock-Up Strategy (Principles)

From this analysis, several strategic stocking principles emerge:

1. **Prioritize Top SKUs (Pareto Principle):** Roughly **20% of SKUs generate ~80% of sales**. These SKUs are the company's revenue engine. They must be forecasted individually and stocked according to their specific demand patterns. If any of these SKUs go out of stock, the revenue impact is immediate and significant.

2. **Over-Stock Seasonal Categories:** Categories like **Christmas/Holiday and certain Home Décor items** drive massive but short-lived spikes in demand. Understocking here means lost opportunity in the highest-revenue period of the year, which cannot be recovered later. It is better to overstock moderately and carry a small surplus than to miss the December window.

3. **Maintain Steady Baseline Categories: Kitchen/Food and Beauty/Personal** products show stable, predictable demand throughout the year. They don't exhibit big spikes, but they are critical for customer loyalty and repeat purchases. Running out here risks disappointing repeat buyers, which hurts retention.

4. **Constrain Long-Tail Exposure:** The majority of SKUs contribute very little individually to revenue but provide **assortment and stickiness**. Customers expect variety, even if they rarely buy from these SKUs. The right strategy is to stock them evenly at a modest level, ensuring availability without tying up capital.

5. **Buffer Uncertain Categories:** Highly seasonal or volatile categories (e.g., Toys & Games) should carry a **small safety stock buffer (~10%)** above forecasted demand to protect against forecast error.

7.1.4 Next 6-Month Stock-Up Recommendation (Quantity-Based Strategy)

1. **Pareto Products (~20% of SKUs, ~80% of Revenue)**

   - For these high-impact SKUs, we assign **individual forecasted quantities** directly from the model output. This ensures that each revenue-driving SKU is stocked exactly in line with its expected demand.
   - **Why this matters:** These products are responsible for the majority of sales. If even a few are understocked, the revenue loss would be far greater than any savings in inventory. Conversely, stocking them properly guarantees that the company captures its projected ~$3M sales.
   - **Example categories:** Best-selling Home Décor lines, core Kitchen/Food items, and a select set of Beauty products.

2. **Long-Tail Products (~80% of SKUs, ~20% of Revenue)**

   - For these SKUs, instead of forecasting individually (which is unreliable due to noise), we apply a **uniform stocking rule: 1.3× their historical median monthly quantity.**
   - Using the median avoids overstocking based on a few historical spikes.
   - Multiplying by 1.3 provides a small uplift, ensuring we don't run short, while still keeping inventory lean.
   - **Why this matters:** These SKUs are not primary revenue drivers, but they are important for **basket size, customer stickiness, and perception of variety**. The uniform stocking ensures customers always see them available, but we avoid wasting capital on slow movers.

3. **Combined Impact of Pareto + Long-Tail**

   - By combining **forecast-based quantities for Pareto SKUs** and **uniform median-based stocking for long-tail**, we achieve:
   - **Revenue preserved:** The company can still deliver its ~$3M forecasted sales.
   - **Inventory reduced:** Overall inventory levels are ~30% lower than pre-optimization, meaning less capital tied up and fewer risks of unsold stock.
   - **Why this matters:** This approach balances the **need for revenue protection (Pareto SKUs)** with the **need for efficiency (long-tail SKUs)**. It delivers a leaner, smarter inventory strategy.

7.1.5 Calls-to-Action

1. **Procurement:**

   - Immediately secure full 6-month coverage using the **Pareto + 1.3× median strategy**.
   - Allocate the bulk of budget to Pareto SKUs, but ensure long-tail is modestly stocked to maintain assortment.

2. **Merchandising/CRM:**

   - Feature Pareto SKUs prominently in promotions and holiday campaigns, as they are the forecasted revenue drivers.
   - Use the December peak to **cross-sell Kitchen/Beauty** items, helping absorb steady-stock categories during the Q1 slowdown.

3. **Finance & Logistics:**

   - Plan for **30% lower inventory levels** while sustaining ~$3M in sales — this frees up working capital for marketing and customer retention initiatives.
   - Expect **seasonal peaks and troughs** in revenue; align staffing and cash flow accordingly.