demand_forecast

August 20, 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. Provide confidence levels and model limitations
5. Deliver actionable recommendations for business improvement

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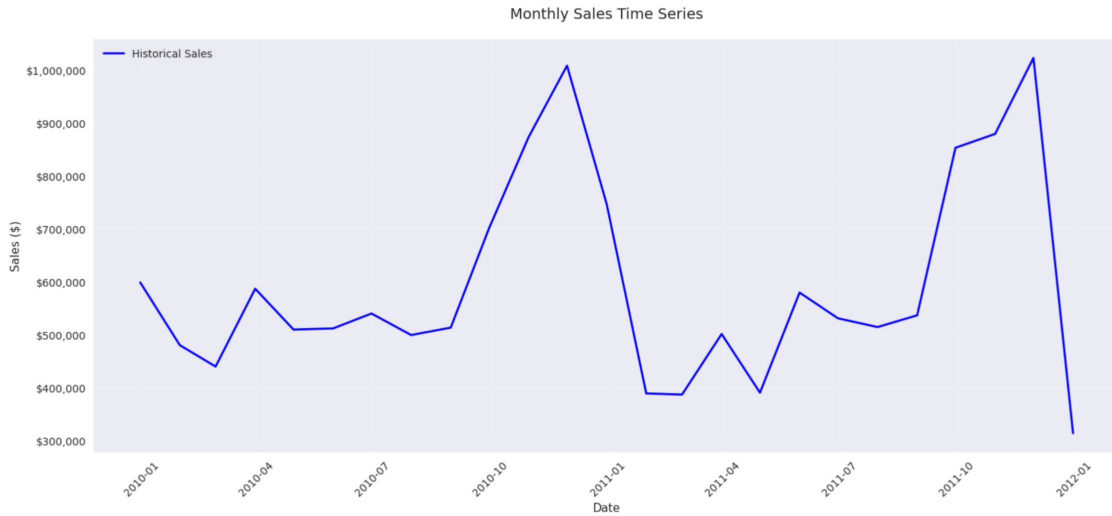
```
 All libraries imported successfully!
 Starting Retail Demand Forecasting Analysis…
============================================================

 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.

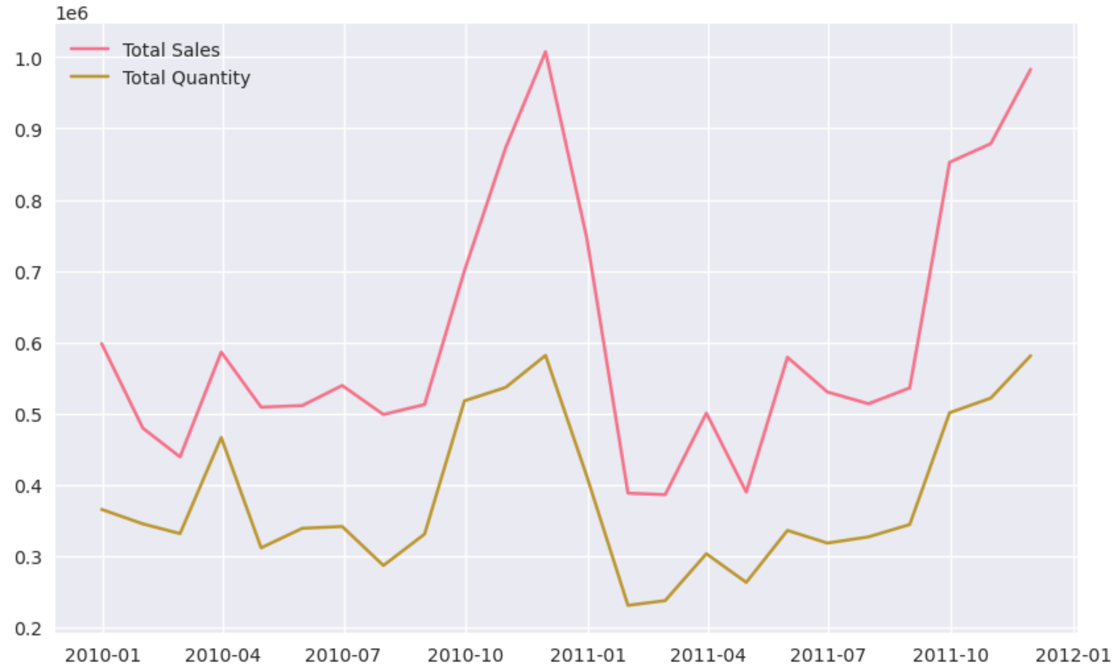
Lets start with standard time series model to see how it perform

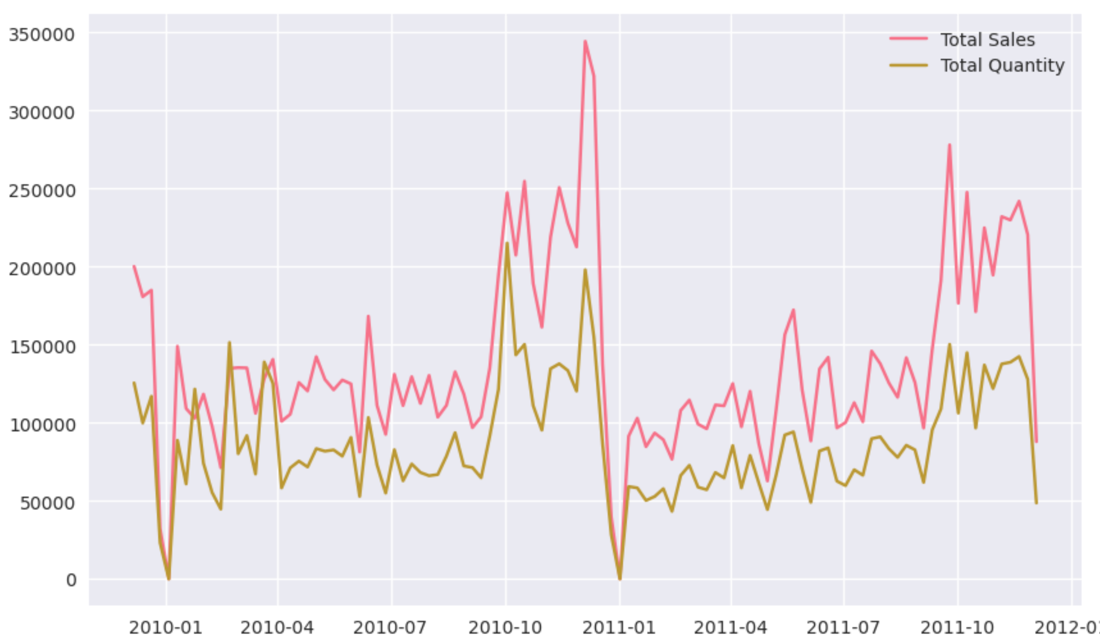
2 Data Preprocessing

```
 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: 9

============================================================
 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
```

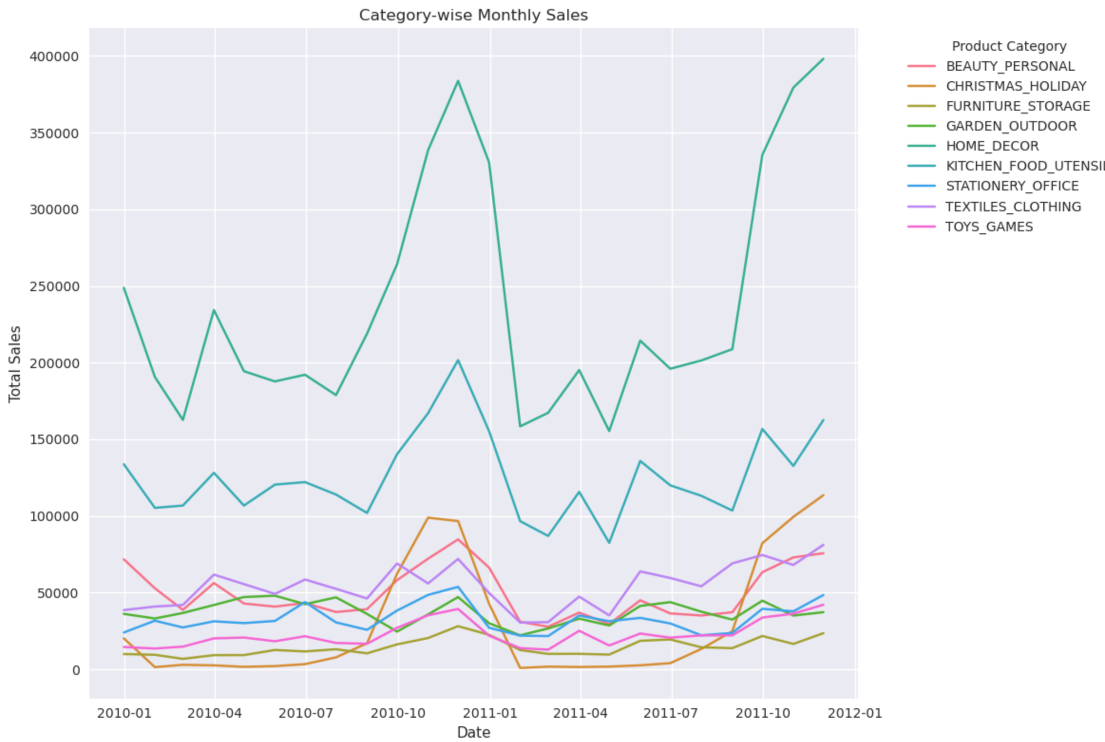
```
           order_date  unit_price  customer_id         country  total_amount  \
0 2009-12-01 07:45:00        6.95      13085.0  United Kingdom          83.4
1 2009-12-01 07:45:00        6.75      13085.0  United Kingdom          81.0
2 2009-12-01 07:45:00        6.75      13085.0  United Kingdom          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         HOME_DECOR

 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
```



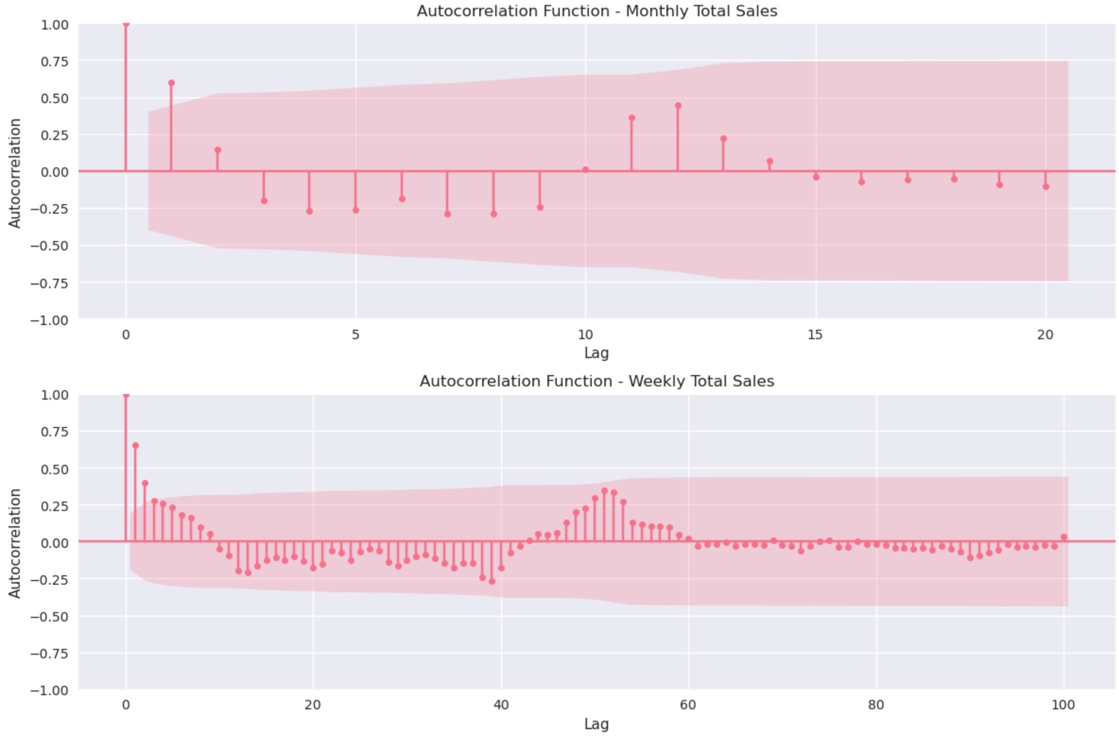


```
Creating category-wise time series…
  Monthly category data created: 216 records
  Weekly category data created: 927 records
```



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
```

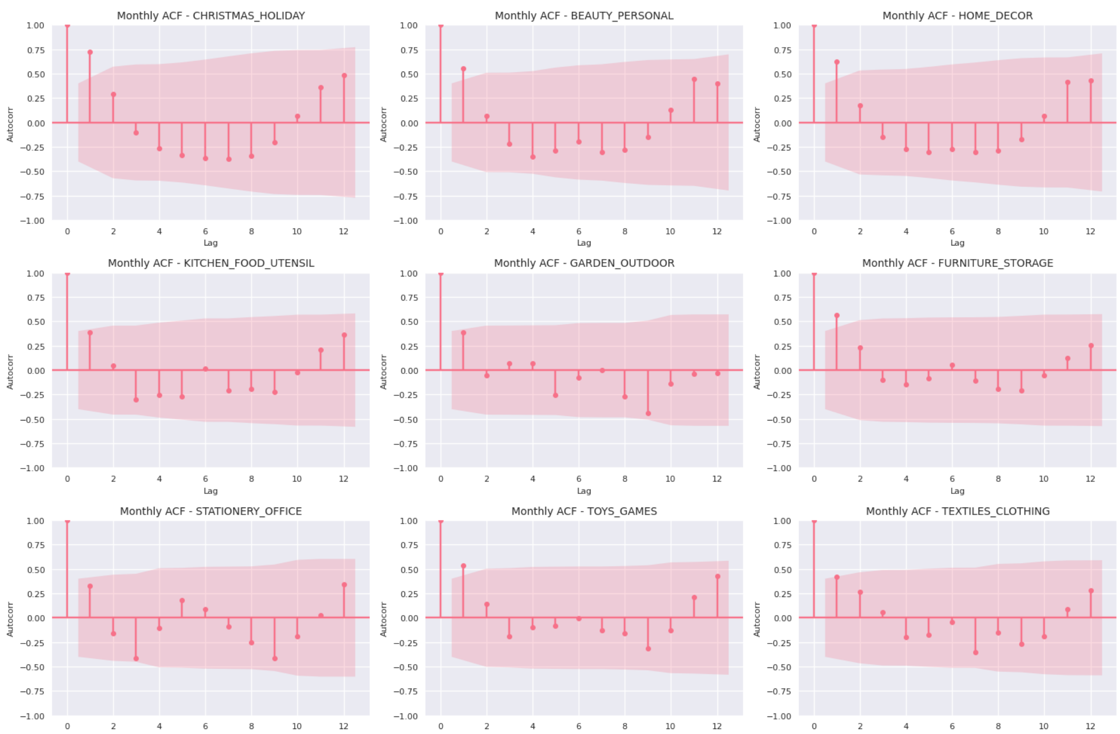
Here we can see from the autocorrelation analysis, that our data indeed have strong seasonality in 12 month cycle or yearly. The implication of this is that, looking at the cycle, we only have 2 cycle worth of data. This limited data can make it challenging to accurately capture and predict seasonal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

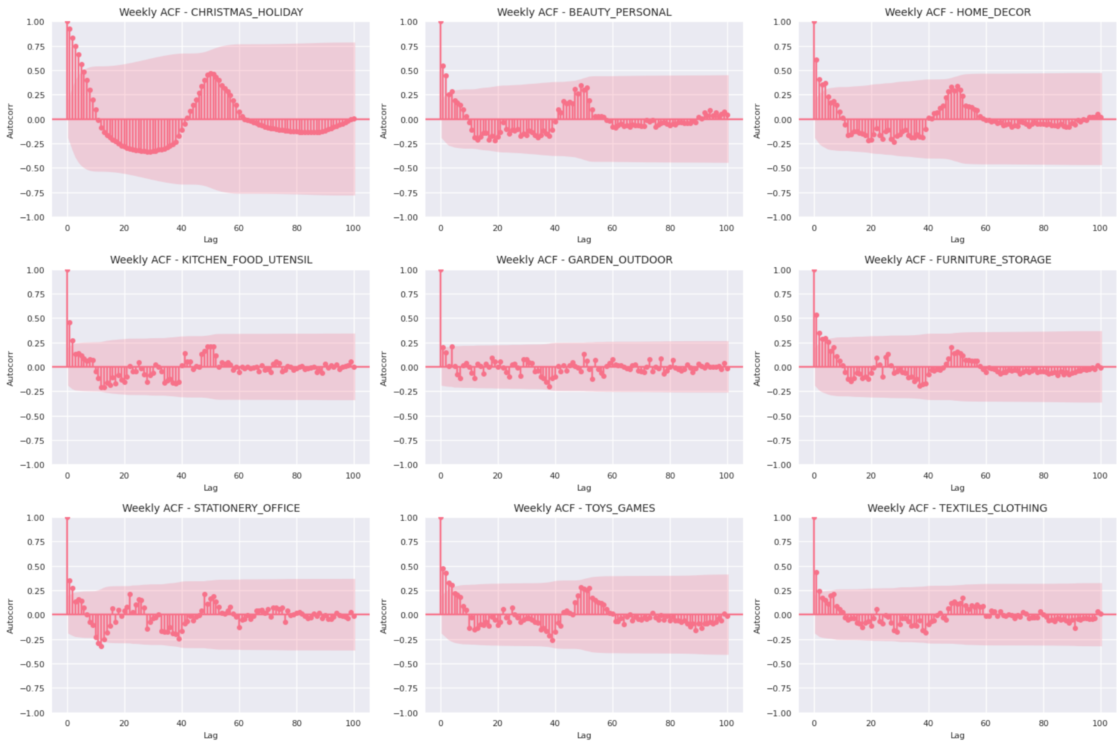
So we try to see if there is any seasonality in week scale and can get more cycle, but we see that the cycle is not as pronounced and still peaking at 1 year cycle, indicating that weekly patterns may be less significant or more variable.

```
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 9 product categories: ['CHRISTMAS_HOLIDAY', 'BEAUTY_PERSONAL',
'HOME_DECOR', 'KITCHEN_FOOD_UTENSIL', 'GARDEN_OUTDOOR', 'FURNITURE_STORAGE',
'STATIONERY_OFFICE', 'TOYS_GAMES', 'TEXTILES_CLOTHING']
```






```
Autocorrelation summary for monthly categorical sales:

CHRISTMAS_HOLIDAY (24 data points):
  Lag 0: 1.000
  Lag 1: 0.721
  Lag 2: 0.289
  Lag 3: -0.103
  Lag 4: -0.264
  Lag 5: -0.336
  Lag 6: -0.366

BEAUTY_PERSONAL (24 data points):
  Lag 0: 1.000
  Lag 1: 0.557
  Lag 2: 0.067
  Lag 3: -0.220
  Lag 4: -0.352
  Lag 5: -0.289
  Lag 6: -0.196

HOME_DECOR (24 data points):
  Lag 0: 1.000
  Lag 1: 0.622
```

```
  Lag 2: 0.174
  Lag 3: -0.146
  Lag 4: -0.274
  Lag 5: -0.302
  Lag 6: -0.271

KITCHEN_FOOD_UTENSIL (24 data points):
  Lag 0: 1.000
  Lag 1: 0.384
  Lag 2: 0.049
  Lag 3: -0.298
  Lag 4: -0.257
  Lag 5: -0.267
  Lag 6: 0.019

GARDEN_OUTDOOR (24 data points):
  Lag 0: 1.000
  Lag 1: 0.387
  Lag 2: -0.052
  Lag 3: 0.070
  Lag 4: 0.069
  Lag 5: -0.253
  Lag 6: -0.077

FURNITURE_STORAGE (24 data points):
  Lag 0: 1.000
  Lag 1: 0.565
  Lag 2: 0.235
  Lag 3: -0.097
  Lag 4: -0.145
  Lag 5: -0.089
  Lag 6: 0.055

STATIONERY_OFFICE (24 data points):
  Lag 0: 1.000
  Lag 1: 0.328
  Lag 2: -0.162
  Lag 3: -0.415
  Lag 4: -0.107
  Lag 5: 0.179
  Lag 6: 0.090

TOYS_GAMES (24 data points):
  Lag 0: 1.000
  Lag 1: 0.538
  Lag 2: 0.142
  Lag 3: -0.193
  Lag 4: -0.094
```

```
  Lag 5: -0.082
  Lag 6: -0.004

TEXTILES_CLOTHING (24 data points):
  Lag 0: 1.000
  Lag 1: 0.423
  Lag 2: 0.264
  Lag 3: 0.060
  Lag 4: -0.196
  Lag 5: -0.178
  Lag 6: -0.041
```

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

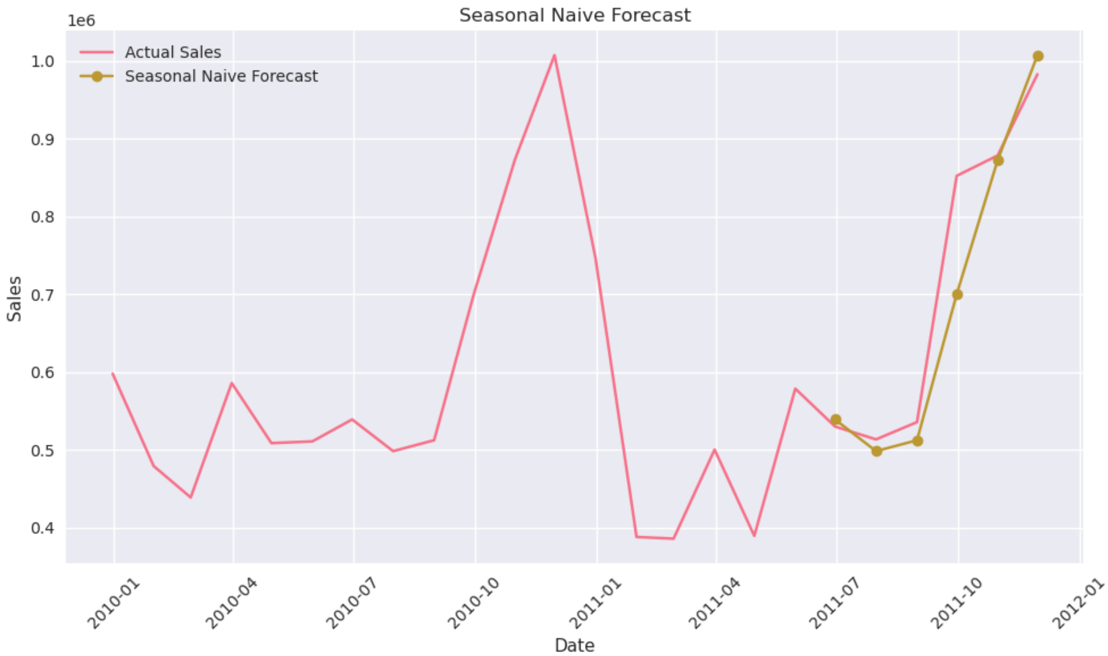
```
 Preparing data for forecasting models…
 Using clean dataset (December 2011 already removed)
 Data Split:
• Training period: 2009-12 to 2011-05 (18 months)
• Testing period: 2011-06 to 2011-11 (6 months)

 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%
============================================================
```

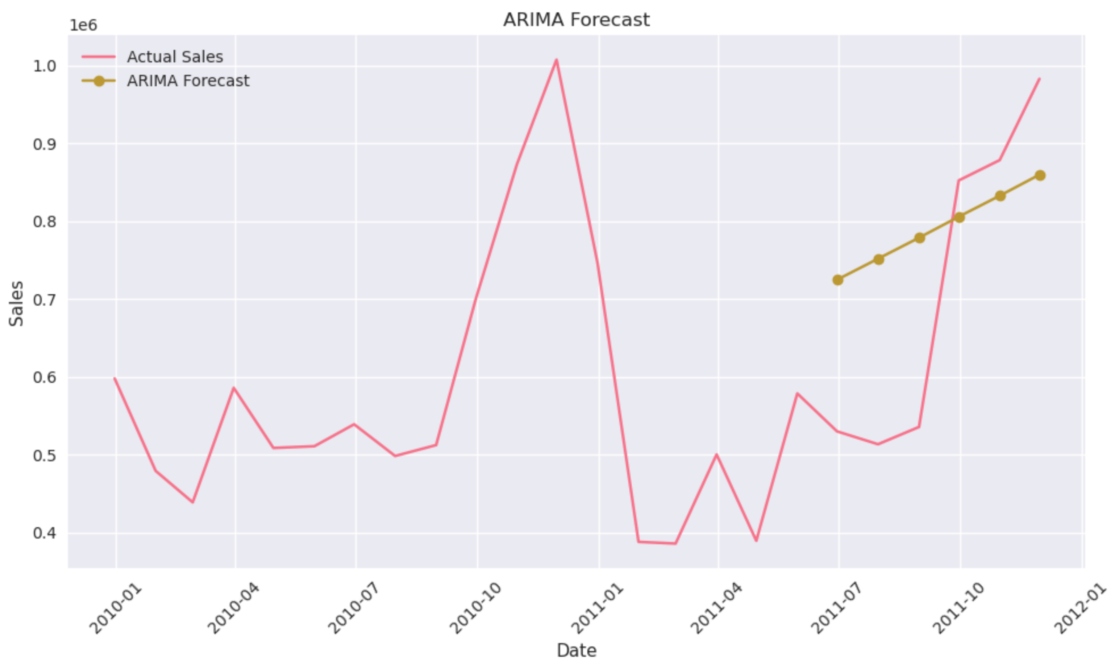


Here we can see from the backtest that the Seasonal Naive model performs strongly, achieving a low MAPE around 5% which a really good forecasting result. By simply repeating last year's pattern is already sufficient to capture the demand dynamics, since our sales are dominated by recurring yearly seasonality.

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%
============================================================
```

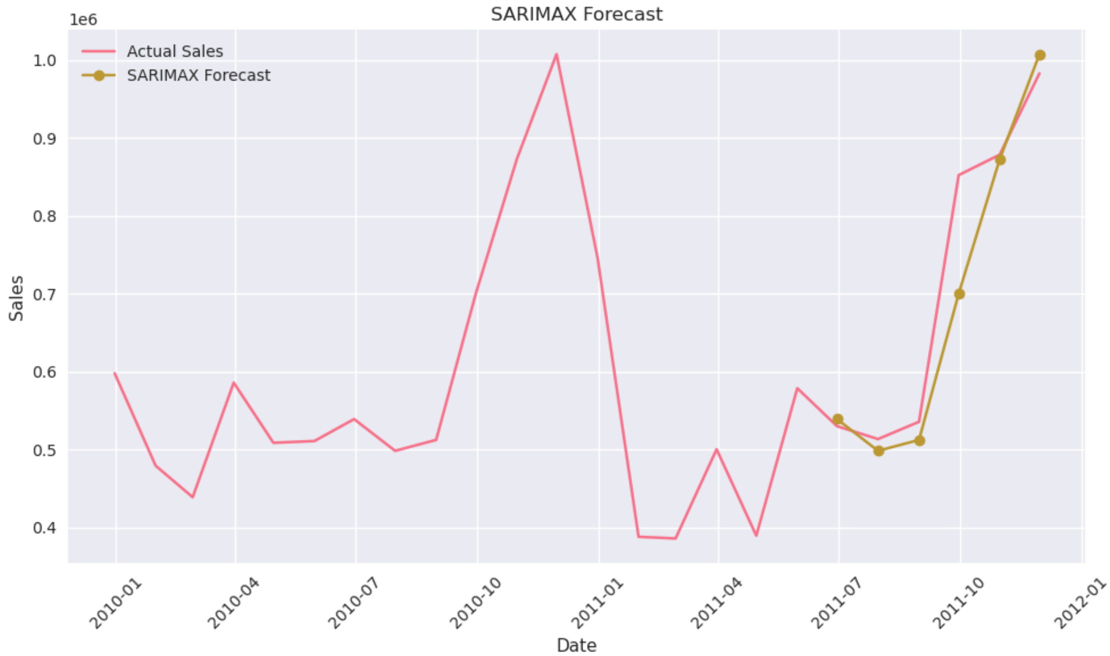


Here we can see from the ARIMA model results (0,2,2), it is not as strong as expected, with a MAPE of ~25%. The forecast line shows a smoother upward trend that fails to capture the clear December spike and seasonal dips observed in the actual data.

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.

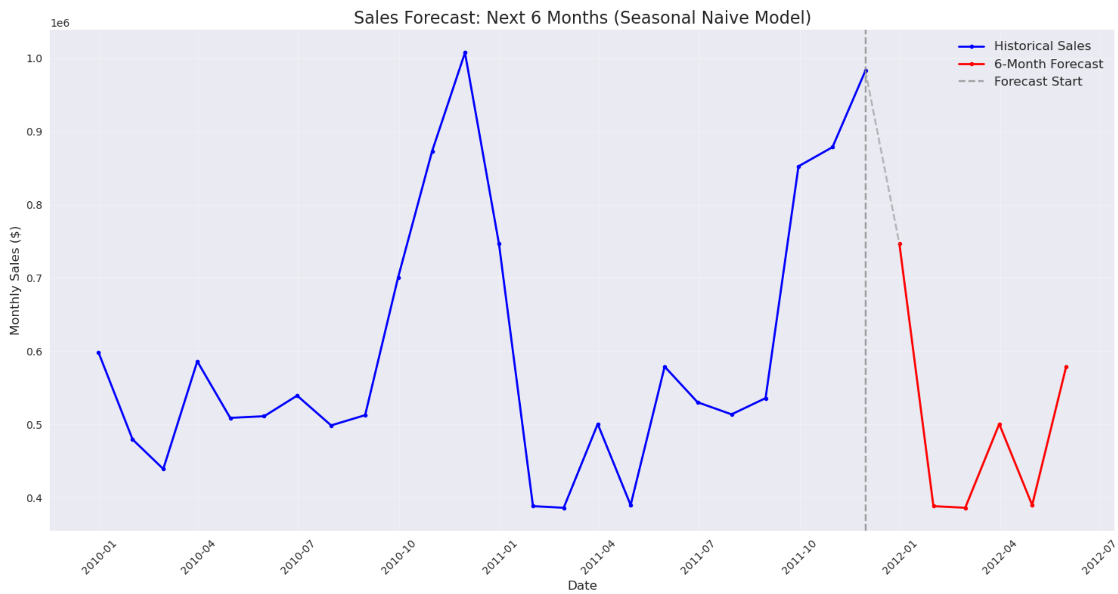
```
MODEL PERFORMANCE SUMMARY
--------------------------------------------------------------------------------


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
```

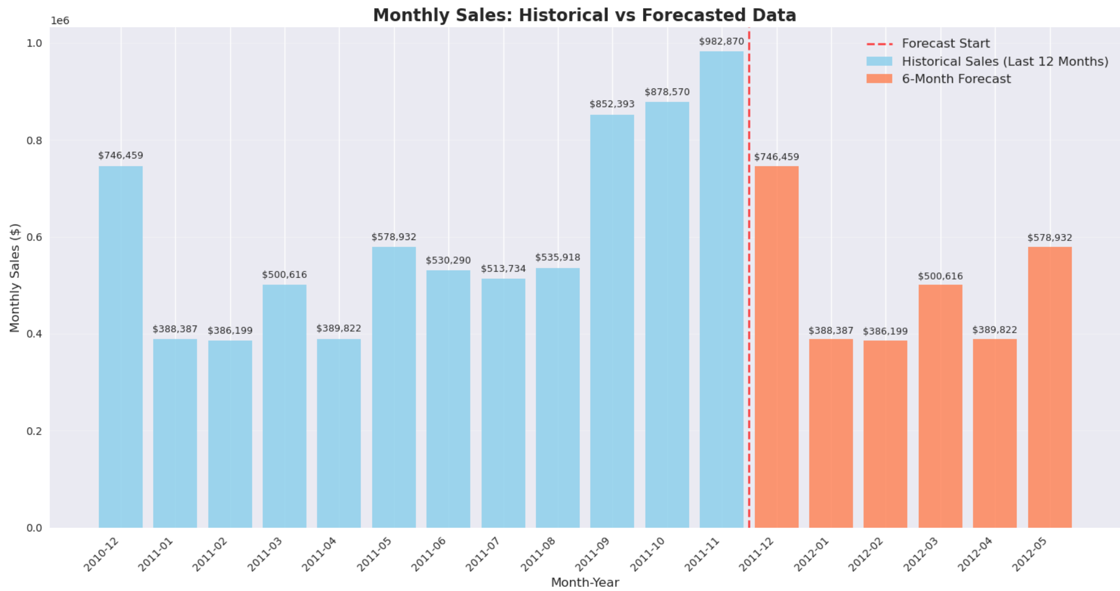
Here we can see from the performance summary that ARIMA(0,2,2) clearly underperforms, with a MAPE of ~25%, indicating it cannot capture the strong seasonal structure in the data. Both Seasonal Naïve and SARIMAX(2,0,1)(0,1,0,12) achieve a much lower MAPE of ~5%, with nearly identical MAE and RMSE.

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)

Inventory and merchandising vary by category (Christmas spikes vs core stability).

4.1 Prepare the categorical dataframe

```
Category Monthly Sales Data Shape: (24, 9)

Available Categories:
['BEAUTY_PERSONAL', 'CHRISTMAS_HOLIDAY', '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  FURNITURE_STORAGE  \
month_year
2009-12-01               71761.44           20258.20           10017.59
2010-01-01               52920.26            1475.87            9530.33
2010-02-01               38803.38            2993.03            6873.38
2010-03-01               56309.76            2648.19            9295.99
2010-04-01               42949.61            1665.67            9327.05

product_category  GARDEN_OUTDOOR  HOME_DECOR  KITCHEN_FOOD_UTENSIL  \
month_year
2009-12-01              36204.42   248822.76             133782.87
2010-01-01              33203.23   190725.73             105330.18
2010-02-01              36794.59   162667.08             106828.89
```

```
2010-03-01              41992.95   234315.55             128173.53
2010-04-01              47169.67   194428.25             106836.02

product_category  STATIONERY_OFFICE  TEXTILES_CLOTHING  TOYS_GAMES
month_year
2009-12-01                 24038.84           38654.20    14600.37
2010-01-01                 31767.38           40988.29    13594.32
2010-02-01                 27334.40           42013.59    14837.22
2010-03-01                 31357.20           61818.26    20223.26
2010-04-01                 30204.03           55608.35    20768.84
```

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 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 = 4358.28, RMSE = 5242.52
  ARIMA: MAE = 19078.90, RMSE = 20671.86
  SARIMA: MAE = 9074.28, RMSE = 10899.84
  → Best Model: Seasonal_Naive

CHRISTMAS_HOLIDAY:
```

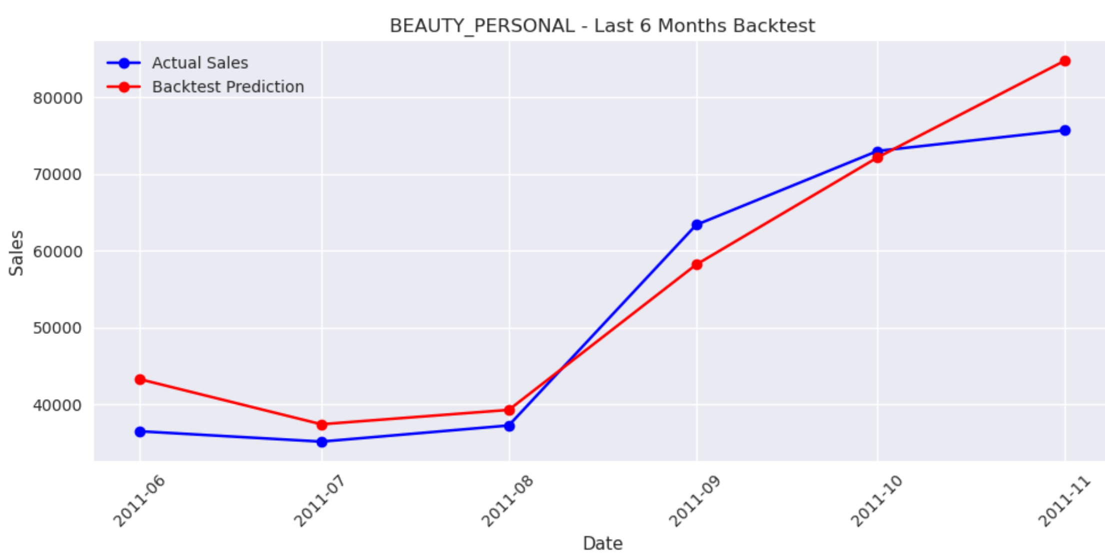
```
-----------------
  Seasonal_Naive: MAE = 8555.65, RMSE = 11366.45
  ARIMA: MAE = 53545.49, RMSE = 69020.92
  SARIMA: MAE = 9189.54, RMSE = 15478.41
  → Best Model: Seasonal_Naive

FURNITURE_STORAGE:
-----------------
  Seasonal_Naive: MAE = 4393.51, RMSE = 4829.16
  ARIMA: MAE = 3342.05, RMSE = 3661.43
  SARIMA: MAE = 8896.80, RMSE = 11086.32
  → Best Model: ARIMA

GARDEN_OUTDOOR:
--------------
  Seasonal_Naive: MAE = 7519.83, RMSE = 10057.29
  ARIMA: MAE = 4827.67, RMSE = 5290.83
  SARIMA: MAE = 5418.63, RMSE = 6760.25
  → Best Model: ARIMA

HOME_DECOR:
----------
  Seasonal_Naive: MAE = 27187.35, RMSE = 35569.19
  ARIMA: MAE = 84450.02, RMSE = 112682.84
  SARIMA: MAE = 45852.92, RMSE = 47563.70
  → Best Model: Seasonal_Naive

KITCHEN_FOOD_UTENSIL:
--------------------
  Seasonal_Naive: MAE = 15732.64, RMSE = 22306.22
  ARIMA: MAE = 20284.97, RMSE = 22256.43
  SARIMA: MAE = 36728.45, RMSE = 49948.05
  → Best Model: Seasonal_Naive

STATIONERY_OFFICE:
-----------------
  Seasonal_Naive: MAE = 6923.63, RMSE = 8301.68
  ARIMA: MAE = 8313.95, RMSE = 9258.51
  SARIMA: MAE = 6486.50, RMSE = 7418.53
  → Best Model: SARIMA

TEXTILES_CLOTHING:
-----------------
  Seasonal_Naive: MAE = 8716.69, RMSE = 11455.55
  ARIMA: MAE = 8584.82, RMSE = 9774.54
  SARIMA: MAE = 5982.74, RMSE = 8099.43
  → Best Model: SARIMA
```

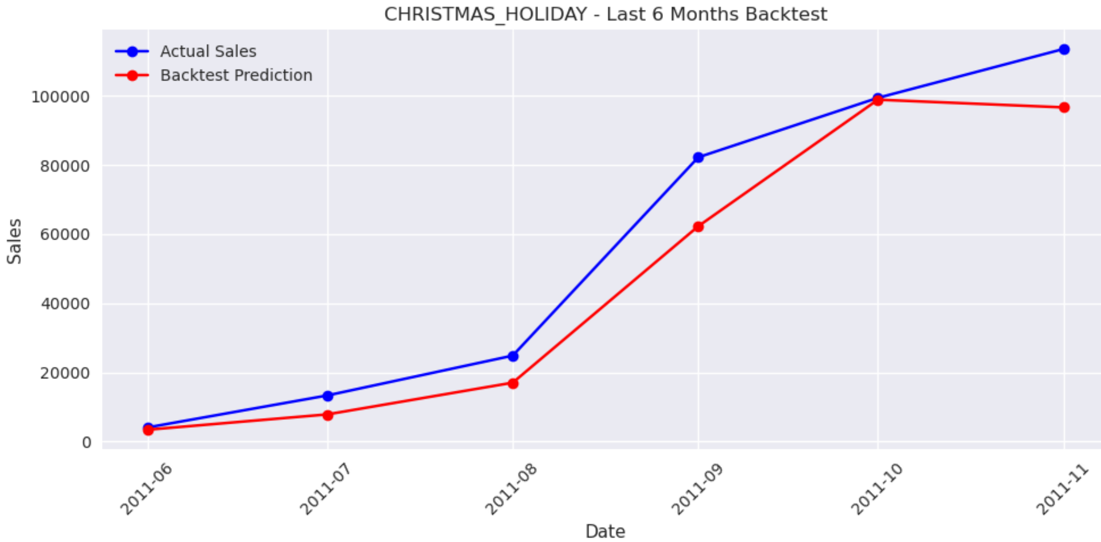
```
TOYS_GAMES:
----------
  Seasonal_Naive: MAE = 3644.07, RMSE = 4257.31
  ARIMA: MAE = 7876.60, RMSE = 10317.89
  SARIMA: MAE = 6306.59, RMSE = 8232.25
  → Best Model: Seasonal_Naive

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

               Category      Best_Model           MAE          RMSE
0        BEAUTY_PERSONAL  Seasonal_Naive   4358.280000   5242.517454
1      CHRISTMAS_HOLIDAY  Seasonal_Naive   8555.650000  11366.445325
2      FURNITURE_STORAGE           ARIMA   3342.046667   3661.430451
3         GARDEN_OUTDOOR           ARIMA   4827.675000   5290.834028
4             HOME_DECOR  Seasonal_Naive  27187.350000  35569.189466
5   KITCHEN_FOOD_UTENSIL  Seasonal_Naive  15732.635000  22306.222123
6      STATIONERY_OFFICE          SARIMA   6486.498139   7418.528749
7      TEXTILES_CLOTHING          SARIMA   5982.739082   8099.429870
8             TOYS_GAMES  Seasonal_Naive   3644.071667   4257.310219
```

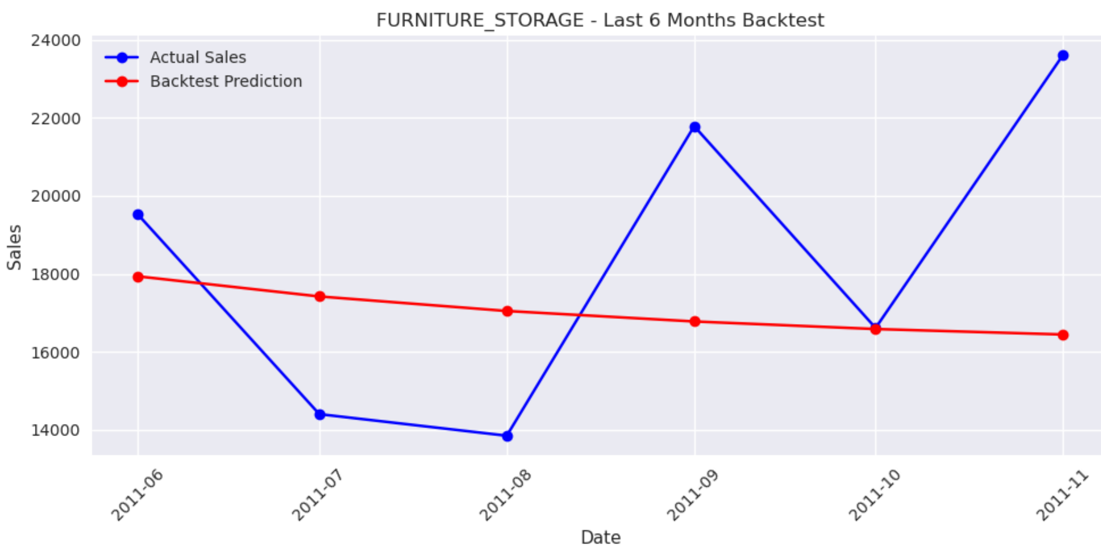
We already can see different kind of best model compared to using the total revenue. This showcase some category might have more stable seasonal patterns, allowing simpler models like Seasonal Naive to perform well. and some are more driven by momentum or other factors, making more complex models like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

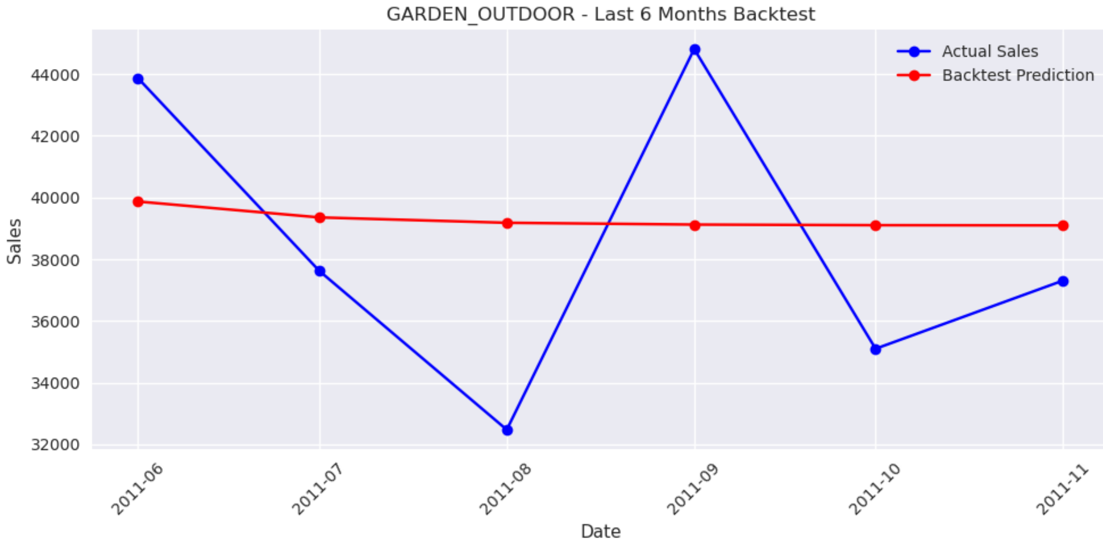
```
================================================================================
GENERATING CATEGORY-LEVEL FORECASTS
================================================================================

Generating forecast for BEAUTY_PERSONAL using Seasonal_Naive…

Generating forecast for CHRISTMAS_HOLIDAY using Seasonal_Naive…

Generating forecast for FURNITURE_STORAGE using ARIMA…

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 SARIMA…

Generating forecast for TEXTILES_CLOTHING using SARIMA…

Generating forecast for TOYS_GAMES using Seasonal_Naive…
```

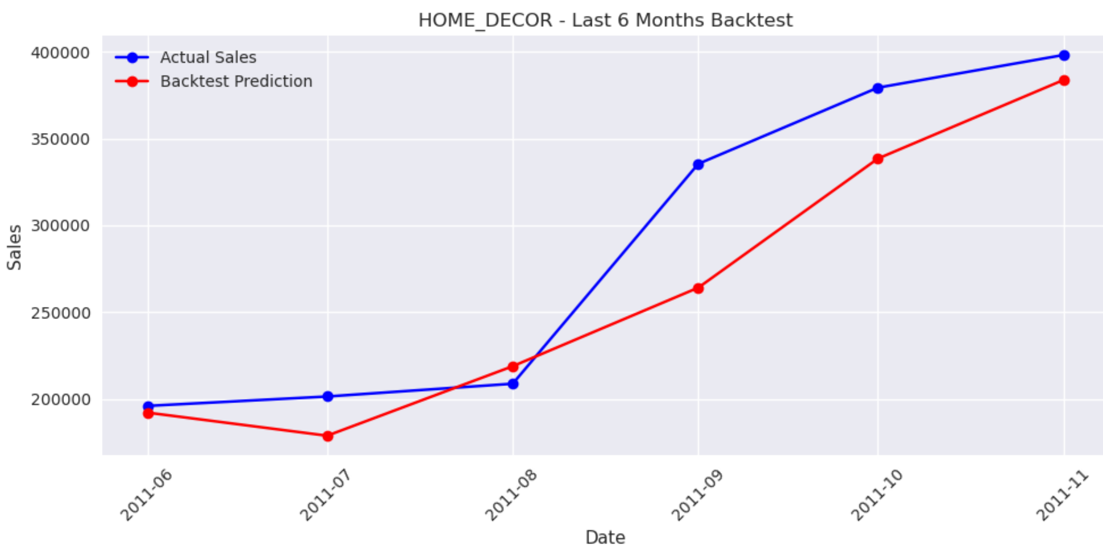
```
Forecast generation completed!

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

              Category          Model  Avg_Monthly_Forecast  \
0       BEAUTY_PERSONAL  Seasonal_Naive          39485.875000
1     CHRISTMAS_HOLIDAY  Seasonal_Naive           8584.026667
2     FURNITURE_STORAGE           ARIMA          20840.607063
3        GARDEN_OUTDOOR           ARIMA          37398.103908
4            HOME_DECOR  Seasonal_Naive         203550.908333
5   KITCHEN_FOOD_UTENSIL  Seasonal_Naive        112201.500000
6     STATIONERY_OFFICE          SARIMA          55593.197722
7     TEXTILES_CLOTHING          SARIMA          99509.019875
8            TOYS_GAMES  Seasonal_Naive          18807.631667

   Total_6Month_Forecast  Next_Month_Forecast
0           2.369152e+05         66356.730000
1           5.150416e+04         42752.850000
2           1.250436e+05         22155.427164
3           2.243886e+05         37375.148349
4           1.221305e+06        330526.200000
5           6.732090e+05        155294.250000
6           3.335592e+05         53133.415099
7           5.970541e+05         98289.893237
8           1.128458e+05         21935.000000
```

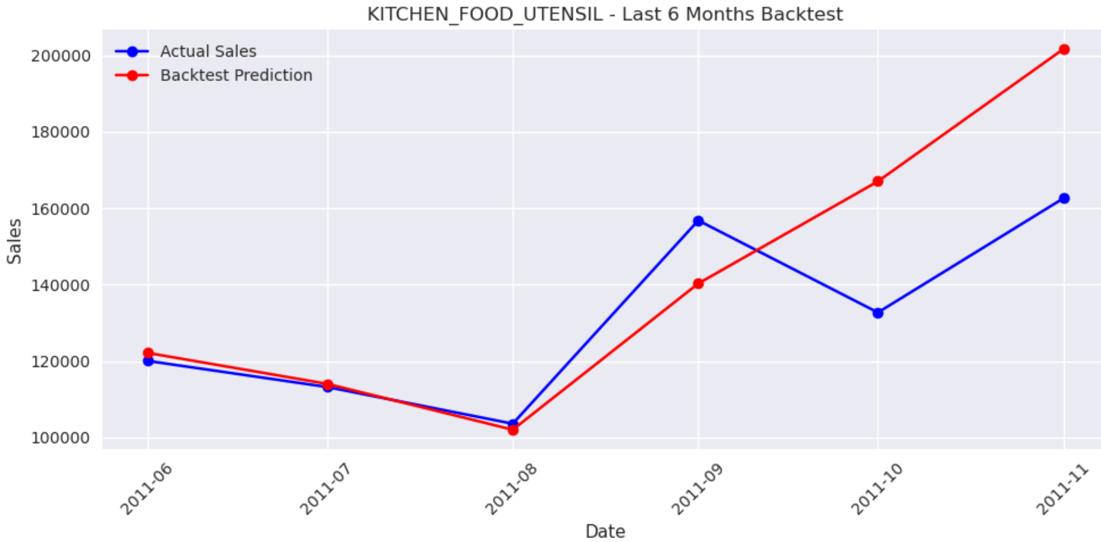


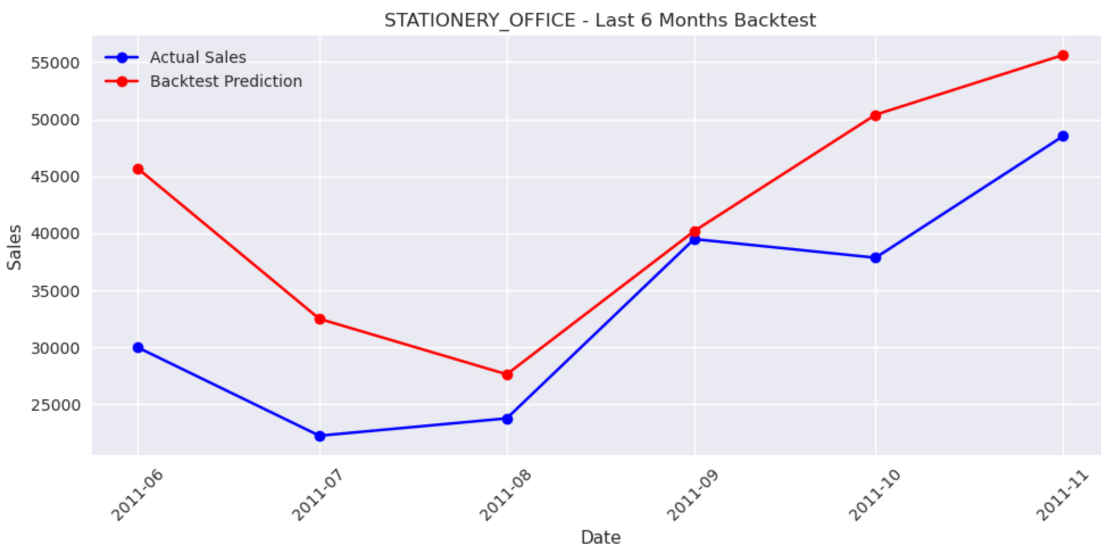

CHRISTMAS_HOLIDAY - Last 6 Months Backtest
Actual Sales
Backtest Prediction
Sales
0
20000
40000
60000
80000
100000
2011-06
2011-07
2011-08
2011-09
2011-10
2011-11
Date

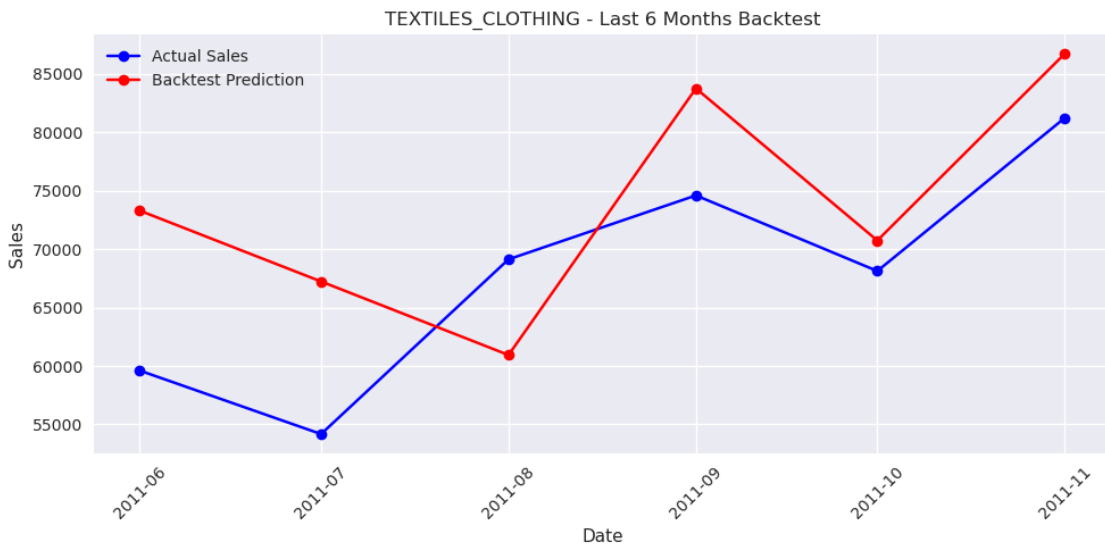

FURNITURE_STORAGE - Last 6 Months Backtest
Actual Sales
Backtest Prediction
Sales
14000
16000
18000
20000
22000
24000
2011-06
2011-07
2011-08
2011-09
2011-10
2011-11
Date

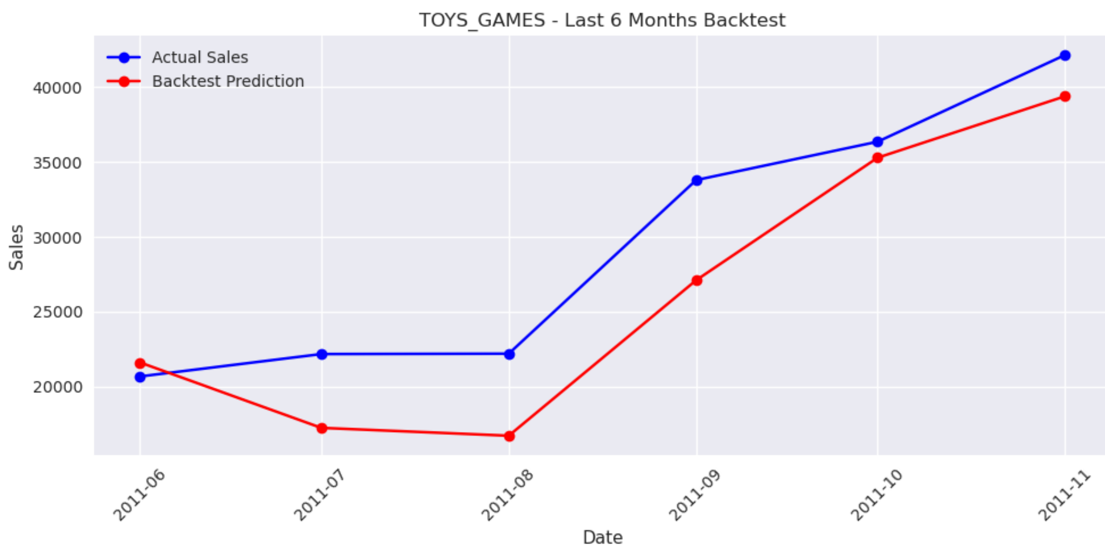

GARDEN_OUTDOOR - Last 6 Months Backtest
Actual Sales
Backtest Prediction
44000
42000
40000
38000
36000
34000
32000
Sales
2011-06
2011-07
2011-08
2011-09
2011-10
2011-11
Date


HOME_DECOR - Last 6 Months Backtest
Actual Sales
Backtest Prediction
400000
350000
300000
250000
200000
Sales
2011-06
2011-07
2011-08
2011-09
2011-10
2011-11
Date


KITCHEN_FOOD_UTENSIL - Last 6 Months Backtest
Actual Sales
Backtest Prediction
200000
180000
160000
140000
120000
100000
Sales
2011-06
2011-07
2011-08
2011-09
2011-10
2011-11
Date


STATIONERY_OFFICE - Last 6 Months Backtest
Actual Sales
Backtest Prediction
55000
50000
45000
40000
35000
30000
25000
Sales
2011-06
2011-07
2011-08
2011-09
2011-10
2011-11
Date



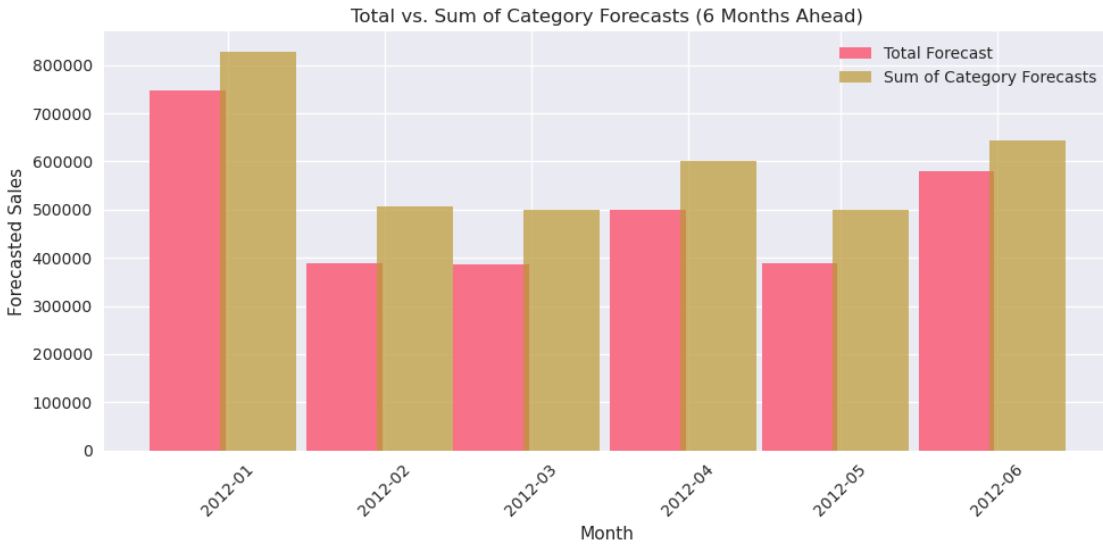


4.3 Reconciliation Check

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):
            Total_Forecast  Sum_Category_Forecast     Difference
date
2011-12-31       746458.82          827818.913849  -81360.093849
2012-01-31       388387.43          505941.688181 -117554.258181
```

2012-02-29	386198.68	498902.043749	-112703.363749
2012-03-31	500616.20	600851.855082	-100235.655082
2012-04-30	389822.19	499440.097275	-109617.907275
2012-05-31	578931.50	642870.623270	-63939.123270



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	21915	23903.65	23903.65	0.042538
1	BEAUTY_PERSONAL	22961	18789.20	42692.85	0.075975
2	BEAUTY_PERSONAL	84347	17033.24	59726.09	0.106287
3	BEAUTY_PERSONAL	84029E	15320.11	75046.20	0.133550
4	BEAUTY_PERSONAL	15056BL	12063.66	87109.86	0.155019
..	…	…	…	…	…
883	TOYS_GAMES	21918	2621.55	223254.41	0.766024
884	TOYS_GAMES	23390	2539.40	225793.81	0.774737
885	TOYS_GAMES	22175	2212.40	228006.21	0.782328
886	TOYS_GAMES	22380	1986.48	229992.69	0.789144
887	TOYS_GAMES	75049L	1931.15	231923.84	0.795770

```
[888 rows x 5 columns]
```

```
       product_category  top_sku_revenue_pct
0        BEAUTY_PERSONAL             0.799018
1      CHRISTMAS_HOLIDAY             0.796723
2      FURNITURE_STORAGE             0.797587
3         GARDEN_OUTDOOR             0.797316
4             HOME_DECOR             0.799639
5   KITCHEN_FOOD_UTENSIL             0.799520
6      STATIONERY_OFFICE             0.799704
7      TEXTILES_CLOTHING             0.796192
8             TOYS_GAMES             0.795770
```

```
product_category
BEAUTY_PERSONAL         124
CHRISTMAS_HOLIDAY        59
FURNITURE_STORAGE        23
GARDEN_OUTDOOR           57
HOME_DECOR              309
KITCHEN_FOOD_UTENSIL    166
STATIONERY_OFFICE        69
TEXTILES_CLOTHING        42
TOYS_GAMES               39
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          796
CHRISTMAS_HOLIDAY        224
FURNITURE_STORAGE         93
GARDEN_OUTDOOR           379
HOME_DECOR              1721
KITCHEN_FOOD_UTENSIL     813
STATIONERY_OFFICE        278
TEXTILES_CLOTHING        300
TOYS_GAMES               151
Name: product_id, dtype: int64
```

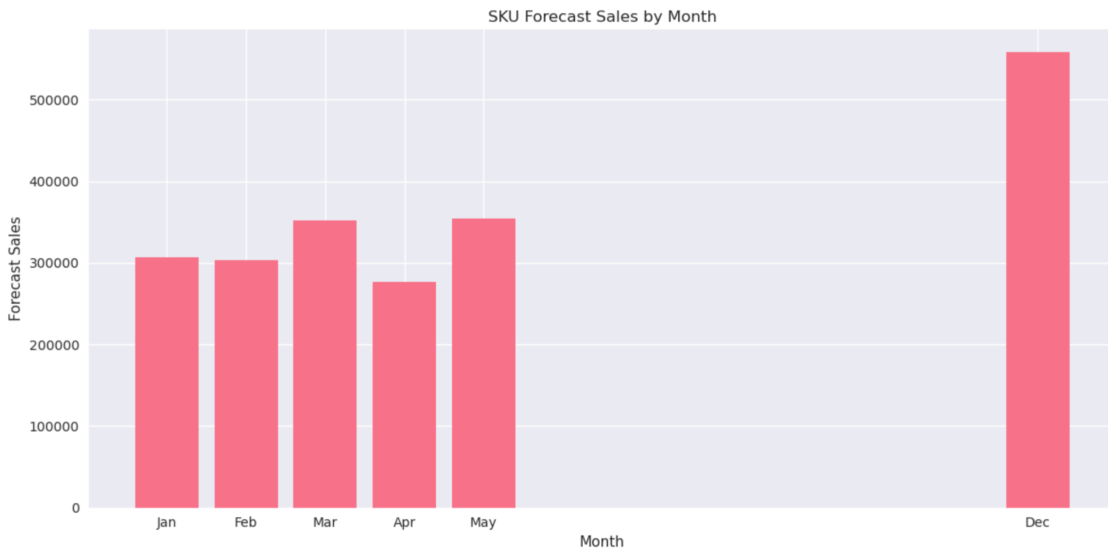
5.2 Forecast each SKU for the next 6 months

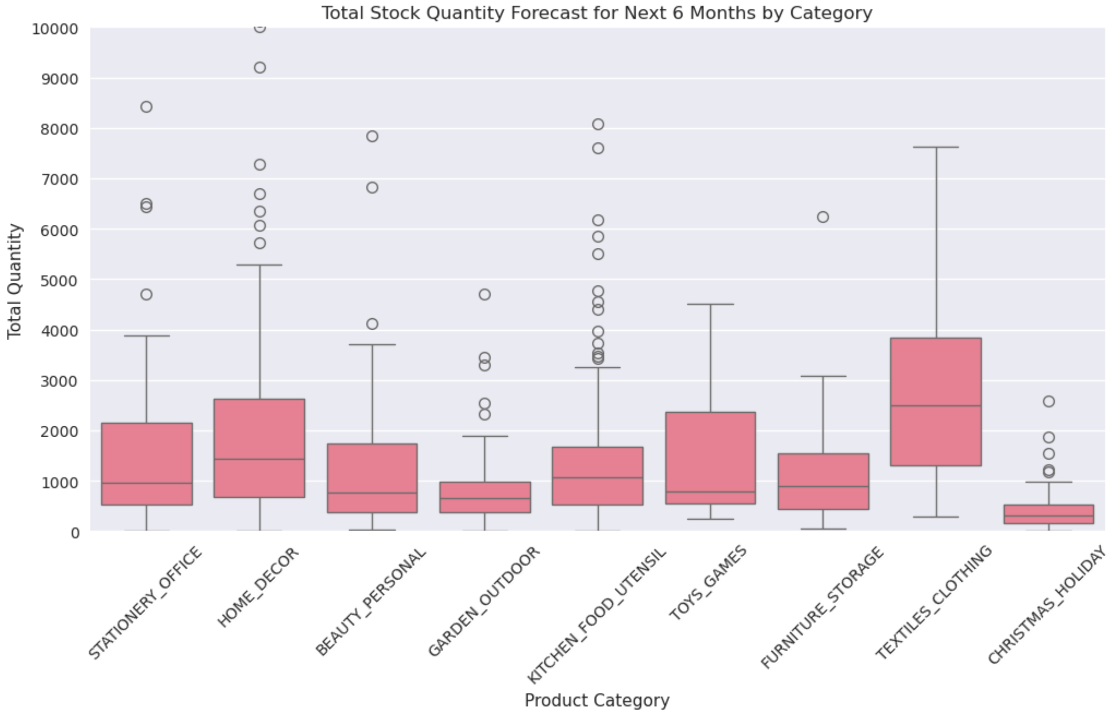
```
Forecasting each SKU for the next 6 months: 2011-12 to 2012-05
Could not forecast SKU 22795 in STATIONERY_OFFICE: too many indices for array:
array is 0-dimensional, but 1 were indexed
```

```
     product_id product_category forecast_month  forecast_sales
```

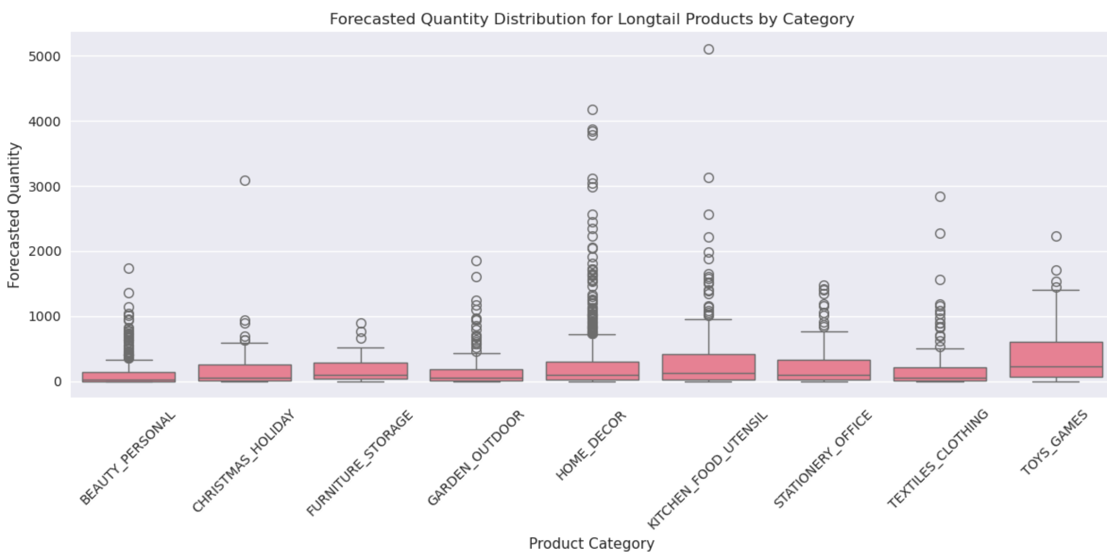
0	21915	BEAUTY_PERSONAL	2011-12-31	4361.16
1	21915	BEAUTY_PERSONAL	2012-01-31	679.40
2	21915	BEAUTY_PERSONAL	2012-02-29	783.95
3	21915	BEAUTY_PERSONAL	2012-03-31	1490.60
4	21915	BEAUTY_PERSONAL	2012-04-30	1403.12
…	…	…	…	…
3859	75049L	TOYS_GAMES	2012-01-31	33.75
3860	75049L	TOYS_GAMES	2012-02-29	38.75
3861	75049L	TOYS_GAMES	2012-03-31	106.60
3862	75049L	TOYS_GAMES	2012-04-30	195.70
3863	75049L	TOYS_GAMES	2012-05-31	563.35

[3864 rows x 4 columns]





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



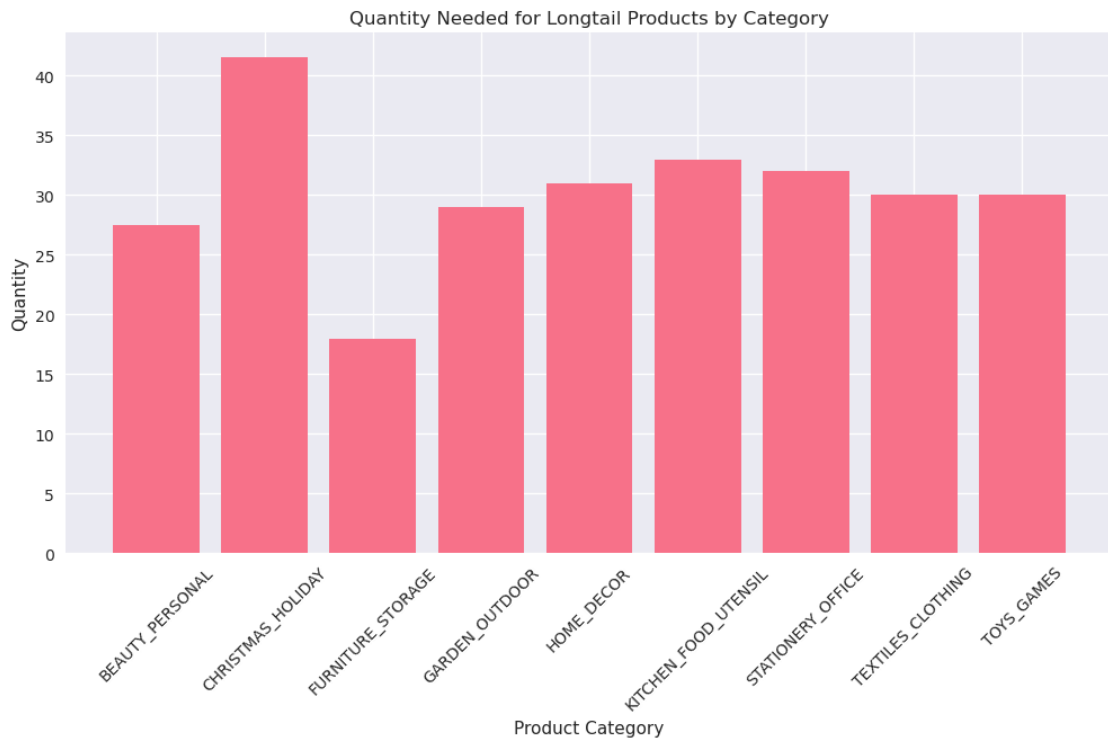

```
Median quantity of longtail products by category and month:

    product_category month_year  quantity
0    BEAUTY_PERSONAL    2009-12       3.0
```

```
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       4.0
..                …         …       …
211        TOYS_GAMES    2011-07       3.0
212        TOYS_GAMES    2011-08       6.0
213        TOYS_GAMES    2011-09       6.0
214        TOYS_GAMES    2011-10       4.0
215        TOYS_GAMES    2011-11       3.0

[216 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       3.0
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       4.0
..                …         …       …
211        TOYS_GAMES    2011-07       3.0
212        TOYS_GAMES    2011-08       6.0
213        TOYS_GAMES    2011-09       6.0
214        TOYS_GAMES    2011-10       4.0
215        TOYS_GAMES    2011-11       3.0

[216 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).

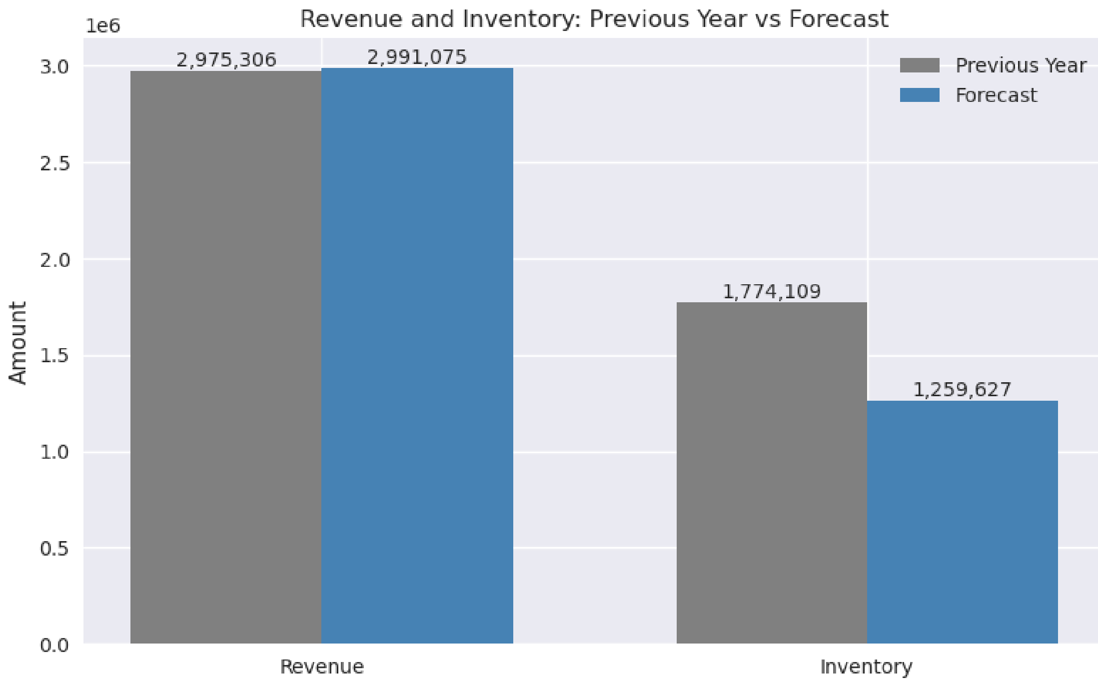
- **Revenue:**
  1. Calculate revenue from Pareto SKUs (each with its own forecasted quantity) and Longtail SKUs (each with the same average forecasted quantity).
  2. Compare to total revenue from the same period last year.
- **Inventory:**
  1. Calculate total forecasted quantity for Pareto and Longtail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

```
    product_id  product_category  total_quantity
0        10135  STATIONERY_OFFICE      754.993536
1        15036         HOME_DECOR    10239.626667
2       15044D  STATIONERY_OFFICE      543.947499
3      15056BL    BEAUTY_PERSONAL      783.764706
4       15056N     GARDEN_OUTDOOR     1574.760671
..         …                 …               …
639     85123A         HOME_DECOR    10009.966102
640     85132C         HOME_DECOR      378.051282
641      85150         HOME_DECOR     2094.952941
642      85152         HOME_DECOR     2754.542857
643     85184C         HOME_DECOR      701.474576

[629 rows x 3 columns]
```

```
Forecasted Revenue (Pareto): 2449544.0142629836
Forecasted Revenue (Longtail): 416562.21
Total Forecasted Revenue: 2866106.2242629835
Previous Year Revenue: 2975305.5499999993
Revenue Optimization (%): -3.670188621031404
Forecasted Inventory (Pareto): 1100496.876083287
Forecasted Inventory (Longtail): 122408.0
Total Forecasted Inventory: 1222904.876083287
Previous Year Inventory: 1774109
Inventory Optimization (%): -31.06934939830152
```

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): 2449544.0142629836
Forecasted Revenue (Longtail): 541530.8730000001
Total Forecasted Revenue: 2991074.8872629837
Previous Year Revenue: 2975305.5499999993
Revenue Optimization (%): 0.5300073218693243
Forecasted Inventory (Pareto): 1100496.876083287
Forecasted Inventory (Longtail): 159130.4
Total Forecasted Inventory: 1259627.2760832869
Previous Year Inventory: 1774109
Inventory Optimization (%): -28.999442757841436
```



We successfully maintain revenue while optimizing inventory levels!

7 Summary & Recommendations

7.1 Summary

7.1.1 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 Naïve 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 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: **holiday demand spikes, followed by a lull, and then stabilization.**

7.1.3 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 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.**
- **Why 1.3× median?**
  - 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 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.