Inventory Management: A More Robust Forecast

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Introduction

Retail stores often seek to improve inventory management methods to overcome supply shortages on certain product lines and categories. This report aims to predict consumer demand for specific inventory, separated by product line, based on historical sales data of a chain superstore. The objective is to apply predictive analytics methods and forecasting tools to determine if a store can improve the reliability of its inventory demand estimates, minimizing error and deviance. With the results of this report, retail stores can ideally assess and modify their existing supply strategy of certain product lines, apply better inventory management methods and evaluate the impact of real-life supply shocks against a predicted outcome within the same timeframe.

This report was built upon the post-pandemic need for improved supply chain management globally. Many companies leveraged "lean manufacturing" processes that relied on highly specialized and accurate demand forecasts to eliminate waste and improve production efficiencies. However, the COVID-19 pandemic instituted a massive supply shock that affected almost all industries, with many failing to account for unexpected shifts in their demand forecasting.[1] The unprecedented scale of the pandemic, combined with rapidly changing governmental regulations, meant that businesses lacked the foresight to assess future inventory levels. This resulted in a global undersupply of product lines, affecting consumer behaviour and price inflation in the process. In fact, the consumer price index approached record-high levels in April 2022 at 8.3%, while inflation-adjusted earnings continued to decline for workers, falling 2.6% over the past year.[2]

[1] https://prospect.org/economy/how-we-broke-the-supply-chain-intro/
[2] https://www.cnbc.com/2022/05/11/cpi-april-2022.html

Accordingly, this report leveraged a superstore dataset containing sales data from 2015 to 2018, broken down by month and subsequently by product line. Categories include office supplies, furniture, and technology, amongst others.[3]

Methodology

The report begins analysis of the superstore dataset by conducting some preparation, including converting the data into a time series within R, as well as decomposing and smoothing the data. The report then applies a variety of forecasting methods, including mean, naive, seasonal naive, and random walk forecasts. More advanced forecasting methods such as linear regression, seasonal autoregressive integrated moving average (SARIMA) and recursive neural networks (RNN) were also leveraged. Each forecasting method is then compared and ranked based on the error metrics of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Moreover, qualitative analysis of each forecasting method is done to assess how it handles outliers such as supply shocks, aligns with historical knowledge, and adds value to the business case. Finally, a conclusion can be drawn as to which forecasting model would be ideal in assessing future demand for retail locations based on accuracy.

Preliminary Analysis

Before analyzing Superstore sales fluctuations, data preparation involved three steps, to ensure ability to see year-to-year trends, as well as seasonal fluctuations during the year.

[3] https://www.kaggle.com/datasets/ibrahimelsayed182/superstore

1. Converting the data to a time series: this ensures we can see how sales behave over time
2. Decomposing the data: seeing what fluctuations are attributed to a specific trend and seasonality as opposed to what is random
3. Smoothing the data: enables us to better see trend and smooth out irregular data points

After conducting this data preparation, the data presents clarity on trends and seasonality (Figure 1). Year-to-year, there is an upwards trend, meaning that the average sales per year is increasing, implying annual increases in consumer demand. Additionally, despite the Superstore sample not containing "traditionally seasonal" products (such as Christmas trees, etc.), there is clear seasonality within the dataset, with two peaks at the end of the year. These likely correspond with consumer holidays Black Friday and Boxing Day. Additionally, this seasonality is multiplicative, meaning that the magnitude of seasonality changes over time.

However, the "random" portion of the data decomposition identifies that there is quite a bit of residual with the data. This indicates that trend and seasonality alone are insufficient to accurately predict future sales and therefore demand. Therefore, there are likely some external factors that the model itself cannot account for, such as geopolitical events, economic conditions, and other news that may impact demand or supply of products. Nevertheless, a forecasting model encompassing the trend and seasonality alone can produce a baseline estimation for inventory levels. These forecasts may need to be adjusted by Superstore management after they qualitatively analyze the impact of worldwide events.

To further understand whether the yearly trend was evenly distributed across all months, two-year growth was calculated for each month (Figure 1). The spring months (April-June) seem to have the highest growth from 2016-2018, slowing significantly in the summer months (July-August). Therefore, when forecasting, it is important to consider that the trend is projected on all the months differently.

Forecasting Methods

To ensure highest accuracy of sales forecasts, it is imperative to test the various forecasting methods on a training set and compare the estimated results with what actually happened. Data from January 2015 until December 2017 was leveraged as the training set in all the below forecasting methods, with the prediction output being compared to 2018 sales as a test set.

Simple Forecasting Methods

Firstly, data for 2018 was forecasted using the mean, naive, seasonal naive, and radom walk forecasting methods (Figure 2). Based on the preliminary analysis conducted above, it is crucial that the forecasting method captures both the trend and seasonality of the data. However, the mean and naive methods apply a constant value as the prediction for the following period and therefore do not account for trend or seasonality. Consequently, neither of these methods are satisfactory in predicting future sales. The random walk method captures the trend, but fails to account for the seasonality throughout the year, and therefore also cannot be used for forecasts. The seasonal naive method does capture the trend and seasonality of the data, however, the gap between the forecasted data and the actual data seems to be increasing as time passes. This inaccuracy is evident by the seasonal naive forecast's RMSE of 18932.10 (Figure 4).

Linear Regression Forecasting

Another method of forecasting future sales to account for both trend and seasonality is to use linear regression (Figure 3). Predicting the 2018 sales using the linear regression model produces forecasts that follow the trend and seasonality of the actual sales. Although the forecast correctly predicts where the data will spike and dip, the magnitude of the seasonal fluctuations seems to be exaggerated slightly, with the dips going much lower than the seasonal naive forecast and the actual data. Additionally, similar to the seasonal naive method, the forecasts seem to be underestimating the sales amounts, especially towards the end of 2018. It is expected that this gap would continue to increase as time progresses, resulting in further inaccuracies.

Seasonal Autoregressive Integrated Moving Average (SARIMA)

Since the inventory data is seasonal, it was imperative to apply the Seasonal ARIMA method, rather than the traditional ARIMA methods, to capture trends and seasonality at the same time (Figure 3). To obtain the optimal model parameters, the auto.arima() function was used. The function returned (0,1,1) for trend, (0,1,0) for seasonality, and 12 for the length of a season. As seen in Figure 3, although the 2018 sales prediction using the SARIMA model captures the trend and seasonality of actual data, it exaggerates both spikes and dips. Although SARIMA leaves out time to manually do trials and errors, there is still need to be mindful of its predictive instability: the scope of prediction deviations from true values varies from time to time. For instance, at the start of 2018, the prediction perfectly matched the true value. However, a significant deviation occurred in the following months. Several management issues, such as inventory backlog or undersupply, could happen when SARIMA fails to predict a particular month's inventory levels accurately.

Neural Networks Forecasting (RNN)

The biggest advantage of using Recursive Neural Network is that, unlike previous models, it makes no assumptions about the linearity of the trend (Figure 3). This is crucial for improving the accuracy of inventory predictions. Applying RNN and comparing it with previous forecasting methods allows unpredictable factors to be taken into consideration, especially when the trend follows an exponential pattern. An applicable use case of this includes when demand shocks occur. On the other hand, RNN's implementation details are inaccessible, which restricts further tuning of the parameters in efforts of improving the model's accuracy. Additionally, RNN is the most time-consuming to train among all the forecasting models. As Figure 3 shows, the forecast for 2018 seems overly exaggerated at first but gradually fitted with real data at the end of the prediction period.

Error Metrics

Aside from visual observations and qualitative analysis of each forecasting method, error metrics were calculated to determine which method produced the most accurate results. In specific, the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were calculated for each method and then ranked (Figure 4).

- Linear regression has the lowest RMSE, followed closely by SARIMA. This indicates that these two forecasting methods, on aggregate, have the lowest magnitude differences between actual and predicted sales.
- Linear regression also has the lowest MAPE, followed by SNaive. This means that on average, they have the lowest percentage difference between the actual and predicted sales.

Unsurprisingly, the forecasting methods that account for both trend and seasonality tend to have lower error metrics. Overall, linear regression has the lowest error (using both RMSE and MAPE) and therefore is the most accurate method tested. As such, linear regression will be the technique used to predict the 2019 sales for each individual product line in the dataset.

Results

Based on the chosen method of analysis, linear regression, sales figures were successfully forecasted for the year of 2019 (Figures 5 & 6). Results were calculated using the linear regression forecasting method for each individual product line; these point forecasts were then compiled into a table that includes the overall totals for each corresponding product category. These results can be followed as a guideline for inventory management, as they outline the monthly sales values for each product line, throughout 2019. The predictions seemed consistent with the upwards trend of previous years, with overall technology, furniture, and office supply sales increasing from 2018 levels by 8.9%, 9.2%, and 6.8%, respectively.

Seasonality was apparent in the results, with November and December marking peak months for all product categories—likely due to an increase in demand from the holiday shopping period. Overall seasonalities were consistent with the dataset as well: the beginning of the projected year sees a trough in demand, followed by a moderate spike mid-year, with a large spike into the end of the year. Furthermore, seasonality appears to be high, with peak months representing far greater sales magnitudes than trough months. For example, furniture sales in February 2019 are projected to be $8,096, compared to a projected $34,516 in December. This shows a clear need to appropriately manage inventory levels to optimize cost-savings, further cementing the use case described in this report's initial motivation.

March represented an unexpected peak for the technology category, with sales of $31,588 (the next highest being December, with sales of $32,210). For the other product categories, March represents a much smaller spike, even when considering the data from previous years. This denotes the possibility of different seasonal peaks for individual categories, and future analyses can attempt to pinpoint this effect to better optimize inventory levels.

Recommendation

Based on the results, it is recommended to use the sales figures outlined by the algorithm's predictions as a guideline, while considering other qualitative factors in the business. The model accounts for both trend and seasonality, which are both necessary for predicting the sales levels of a growing supermarket (in a likely growing economy), and the RMSE and MAPE of the linear regression model both indicate a high accuracy. The model, however, is slightly conservative with estimates, and appears to exaggerate dips in demand. Furthermore, no model can predict externalities and global events that affect the demand of a supermarket (e.g. natural disasters). Therefore, these results should only be used as a supplement to business decisions and as a contrast for further analysis between actual and predicted data points. For example, the projected spike in March for technology sales can be used to introduce a March discount on technology items, capitalizing on previously overlooked seasonality. With this data, business decisions involving inventory will have quantitative support, allowing the company a strong numerical foothold to decide order quantities. Moreover, using this data as a guideline should allow the business to actively monitor its accuracy, improving upon it overtime and allowing for further optimization in inventory management.

Limitations of our model

Firstly, a trade-off was made when selecting the dataset. Although the current dataset contains metrics of high granularity (for each product line, it is broken down into several more detailed sub-products), the total data points we use for training and testing the forecasting models are limited. Although the error metrics indicate a slight deviation of the testing set from the actual value, we might run into overfitting. For our models to generalize unseen data (which involves more fluctuations that current models have not captured), we need to collect more data points, incorporate them into the current dataset, and optimize our models.

Secondly, there exist inherent flaws which we cannot simply avoid by tunning the models' parameters. As previously mentioned, no model can take into account unexpected events (outliers that severely deviate from the general trend). Therefore, managers should be mindful of those quantitative metrics' imperfections when using those predicting tools and avoid overly depending on them. In fact, a highly applicable use case of this report's analysis would be to contrast the actual sales data affected by supply shocks with the predicted estimate done by the report. A reasonable proportion of both numbers and qualitative factors (e.g. different stores' geographical differences and recent industry trends) should be considered when making business decisions.

Thirdly, although RNN was initially expected to produce the highest accuracy, as it assumes no linearity of trends, the result illustrated it lacked accuracy relative to the linear regression forecasting method. This is due to RNN sufferig from vanishing gradients, which arises when large error gradients accumulate and ultimately producing very large updates to the neural network model during the training process. Longer training time and inaccuracy due to vanishing gradients has resulted in poor forecasting, as shown in our case, and thus was not applied in the final result.

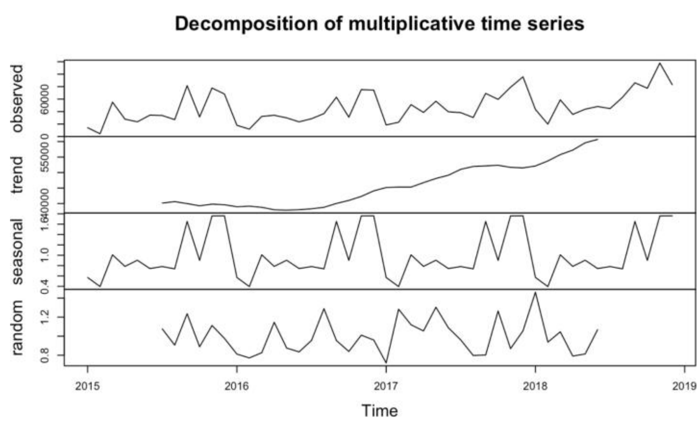
Conclusion

The results of this data can be used to address problems outlined prior. Firstly, with an understanding of expected inventory levels, the models can be used to address supply shortages as companies can adjust purchasing levels as necessary. Additionally, having an understanding of the seasonality of the supply will increase customer satisfaction as supply will be better suited for busy holiday periods. Finally, these factors will help tackle inflation, as supply and demand will be better met.

While these models are useful for forecasting the future based on the path, the qualitative human element is equally as important. For example, these models would not have predicted the 2020 supply issues as a result of COVID, or would not adjust if Superstore underwent a scandal and customers began boycotting. Any quantitative model only goes so far, and should be used to supplement business decisions, not make them.

Appendix

Figure 1: Decomposed Data with Two-Year Monthly Growth Rates.



Month	Two.Year.Sales.Percentage.Increase
1	0.3379031
2	0.3727505
3	0.4386291
4	0.5066867
5	0.5742581
6	0.5965151
7	0.2716403
8	0.2793499
9	0.3047683
10	0.3326044
11	0.2983665
12	0.2997955

Figure 2: 2018 Sales Forecasts from Simple Forecasting Methods (Mean, Naive, SNaive, Random Walk).

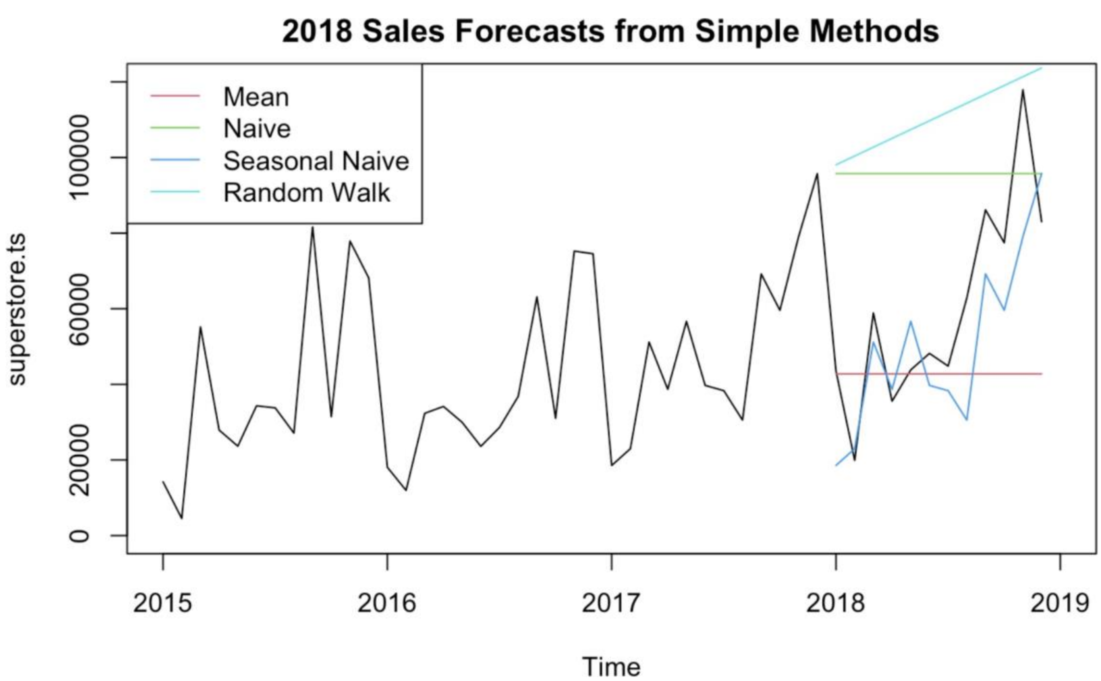


Figure 3: 2018 Sales Forecasts from Advanced Forecasting Methods (Linear Regression, SARIMA, RNN).

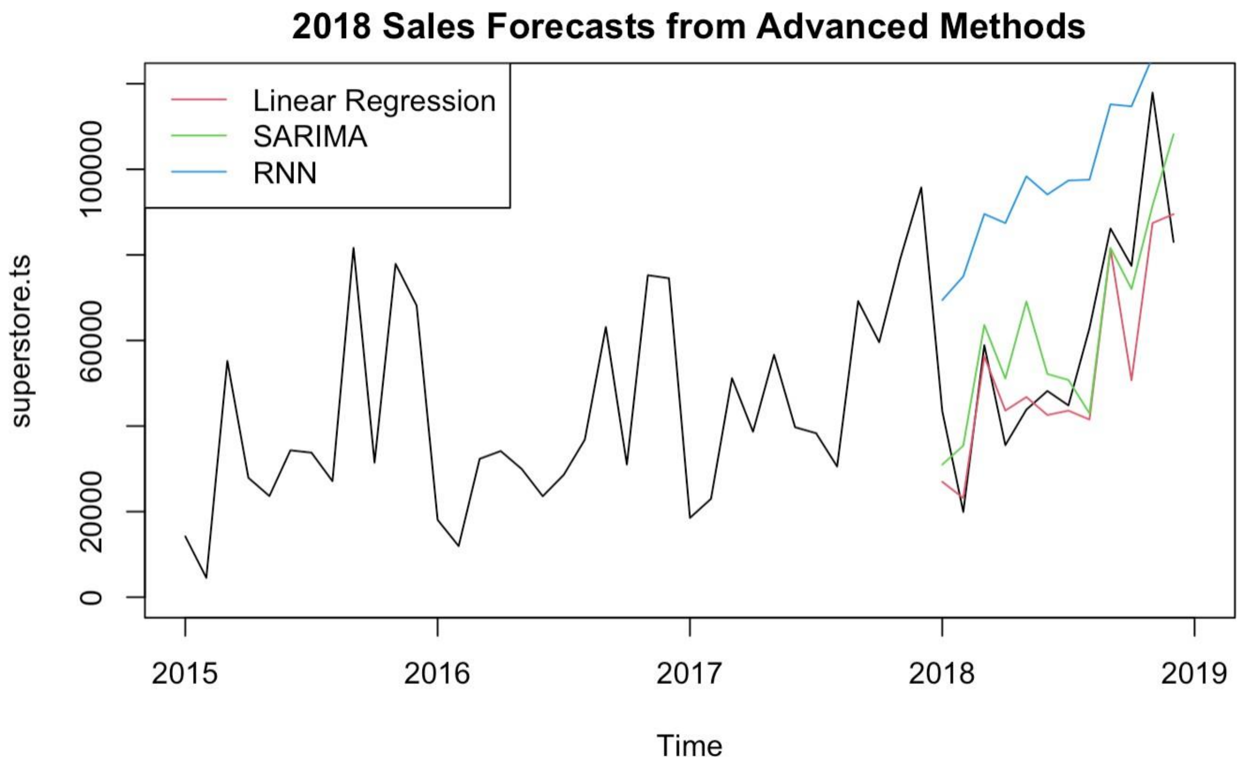


Figure 4: Error Metrics for each Forecasting Method, ranked quantitatively.

	Forecasting.Method <chr>	Root.Mean.Square.Error <dbl>	Mean.Absolute.Percentage.Error <dbl>
5	Regression	14610.45	1.752178e-01
6	SARIMA	16141.02	1.614102e+04
3	SNaive	18932.10	2.486467e-01
1	Mean	31131.16	3.513268e-01
7	NN	42401.14	4.240114e+04
2	Naive	43945.62	9.872954e-01
4	Random Walk	54422.34	1.204475e+00

Figure 5: Chart Forecasts for Specific Product Lines (Office Supplies, Furniture, Technology).

	Appliances	Art	Binders	Envelopes	Fasteners	Labels	Paper	Storage	Supplies	TOTAL
Jan 2019	2417.907	407.4105	5101.857	158.52396	40.63558	113.4470	1477.315	3780.713	1459.1968	14957.01
Feb 2019	2857.093	458.1965	3107.552	138.19146	60.66358	136.7510	1636.961	3032.338	430.6918	11858.44
Mar 2019	3303.976	502.0765	5230.448	379.18196	58.24458	296.8075	2495.328	4907.029	3017.5403	20190.63
Apr 2019	3125.911	770.6880	5358.505	204.58046	85.43658	169.2885	1932.233	5221.081	1912.3402	18780.06
May 2019	3444.544	736.5255	4315.548	245.06496	48.16108	269.6850	2468.969	5168.666	632.8633	17330.03
Jun 2019	2892.411	696.9425	5302.572	99.48946	49.71158	357.2990	2546.169	5957.849	675.0012	18577.45
Jul 2019	2579.660	695.3030	4186.284	271.06996	66.21258	484.7845	1978.500	4623.871	2562.3333	17448.02
Aug 2019	4851.034	601.3515	7136.226	146.31996	81.64808	276.7685	2547.085	5877.604	574.7462	22092.78
Sep 2019	4161.328	1092.4705	11340.946	464.30846	122.25908	427.2095	3549.546	8873.039	1943.0733	31974.18
Oct 2019	3911.746	652.4580	6556.178	321.83896	102.27608	366.1375	2187.928	5738.556	567.8772	20405.00
Nov 2019	6366.329	1128.4720	7232.439	697.83196	158.33758	524.3310	3935.502	10756.959	694.0688	31494.27
Dec 2019	5728.818	1080.2740	9718.324	558.20946	126.93058	405.7885	3745.902	8912.209	1435.5958	31712.05

	Bookcases	Chairs	Furniture	Tables	TOTAL
Jan 2019	1728.9542	4065.254	2022.272	4212.444	12028.924
Feb 2019	803.2704	3139.697	1598.075	2528.842	8069.884
Mar 2019	2132.9771	6447.936	2331.908	4771.601	15684.422
Apr 2019	1570.9847	5875.608	2926.737	3952.710	14326.039
May 2019	1963.2600	7717.419	2708.688	3796.494	16185.861
Jun 2019	2677.7719	6143.334	2314.507	5557.897	16693.509
Jul 2019	2538.1103	6787.860	2918.764	4015.078	16259.812
Aug 2019	1796.2508	5636.835	2044.857	5696.697	15174.639
Sep 2019	6233.9972	13838.052	3763.456	6359.409	30194.915
Oct 2019	2452.6003	7196.040	2389.051	6530.155	18567.846
Nov 2019	6110.2867	13183.965	5214.323	9770.040	34278.615
Dec 2019	3135.2107	15601.224	4576.122	11204.344	34516.900

	Accessories	Copiers	Machines	Phones	TOTAL
Jan 2019	3508.061	4662.664	1235.0556	5250.862	14656.64
Feb 2019	3523.884	3672.684	1678.8813	4108.673	12984.12
Mar 2019	4335.424	10070.118	8194.3738	8988.093	31588.01
Apr 2019	4113.919	4642.657	3978.8386	6298.897	19034.31
May 2019	4536.848	8272.632	2248.3286	8017.650	23075.46
Jun 2019	4377.696	3897.677	2477.0291	8505.691	19258.09
Jul 2019	6432.107	6117.632	447.5898	7748.429	20745.76
Aug 2019	5187.451	5105.159	996.7753	8841.840	20131.23
Sep 2019	8130.651	5432.636	6027.8121	11335.325	30926.42
Oct 2019	5413.350	12927.623	2084.6711	8545.253	28970.90
Nov 2019	8562.859	7460.155	7883.2226	15930.971	39837.21
Dec 2019	9103.202	8372.597	3233.8538	11501.104	32210.76

Figure 6: Graph Forecasts for Specific Product Lines (Office Supplies, Furniture, Technology).