How Machine Learning can Revolutionize Inventory Optimization

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Abstract

A key concern for manufacturers today is to maintain optimum inventory levels to drive business growth with better prediction of future sales. With rapid advancements in analytics and machine learning (ML), companies can now proactively examine master and transactional data in near real-time and use the insights derived to plug the gaps and revenue losses. ML algorithms and the models they are based on, excel at finding anomalies, patterns, and predictive insights in large data sets. Predictive analytics can anticipate any spikes or dips in demand and suggest which items should be replenished when along with quantity and location/store. This paper highlights some of the key challenges in inventory management and recommends a data-intensive, ML-based methodology to address two major problems – inventory planning by sales forecasting and high volume of return orders.

1 Introduction

Enterprises require a technology vision for the future that is continuously learning and evolving – this means that an enterprise that can make decisions intuitively. If we look at any enterprise today, there are many decisions, which can potentially be automated, with minimal human involvement. These enterprises can think ahead of what the customer or business needs, can predict, forecast, and help with insights to assist with timely decision making at the right time. They can change as per the changing business needs and customer demands and can quickly respond to market dynamics.

Such a technology vision could bring in a revolution in inventory management. With globalization, the supply chain has become more complex, and enterprises, especially manufacturers and retailers, are facing challenges in managing inventory effectively. Traditional inventory management techniques are not adequate to assist manufacturers with inventory optimization in today's global supply chain ecosystem. Even advanced inventory management packages and tools are found lacking in delivering significant outcomes and benefits on reduced inventory costs.

A new paradigm has emerged in the last few years. The manufacturer's operations teams and planning teams are applying the latest techniques and technologies to improve inventory visibility, control, and management across the supply network. This is called 'Inventory Optimization', and it helps manufacturers to control their inventory driven costs and address today's demand volatility and supply chain complexity. Inventory optimization can enable smarter product launches, lower direct material cost of goods, and faster manufacturing, distribution, and sales execution.

In the retail industry, inventory demand planning and sales forecasting is the key to being competitive and having happy customers without excess spending on inventory. Inventory demand forecasting determines sufficient just-in-time replenishment, timely buying decisions, effective supply chain decisions, and inventory spend optimization. Overprediction or underprediction of demand also costs in terms of out-of-stock percentages, inventory aging, and logistics costs.

2 The Need for Change

There are several reasons why manufacturers are increasing focus on applying the latest tools and technologies to optimize inventory. A key driver lies in the recognition that traditional techniques are failing to reign in inventories in the wake of increased supply chain complexity. Demand is more volatile and thus, less predictable. Three strategies have traditionally addressed the uncertainty caused by this complexity:

- Increase inventory levels to hedge against uncertainty
- Develop supply chain flexibility to be more responsive to uncertainty
- Improve forecast accuracy so that less uncertainty propagates to the manufacturing floor

Inventory optimization techniques and technologies map to the flexibility and accuracy strategies.

The non-predictive inventory planning, which is the spreadsheet-based manual forecasting or tool/package based approach is not suitable for staying ahead of the competition and improving the bottom line. Manual adjustments of forecasts in the traditional methods leave all inventory spend decisions to human judgment, which pushes towards generalized decisions rather than going with product, vendor, and market-specific indicators. Issues arise when decisions are mostly based on historical sales numbers without considering dynamically evolving business factors.

Supply chain risks can be circumvented if demand and opportunities based planning are plugged in the inventory management techniques. Inefficiencies in the demand-driven supply chain ecosystem can often lead to potential revenue losses, increasing costs, and poor customer service, thus ultimately diminishing profits. Uncertainties trigger a series of business and operational issues. Inventory planning sees many uncertainties, the root causes of which differ on a day-to-day basis and are difficult to forecast using pre-defined rules. For instance, customer demand fulfillment takes more than 25 days instead of the scheduled 15 days in a dairy equipment delivery. Typically, the delays are triggered due to the unavailability of a finished product in a particular store. In contrast, certain other low demand items are lying in the store for more than three months, thereby locking the value.

ML allows real-time analytics and action points, which can play an important role in understanding the challenges related to inventory planning and predicting them well in advance based on the sales forecast. ML uses algorithm models that can process large volumes of data very quickly, something that is not possible through manual methods. This approach can drive efficient order execution, reduce revenue losses from delayed and return orders, and improve overall customer satisfaction.

According to Gartner, in 2020, 95% of Supply Chain Planning vendors are relying on supervised and unsupervised machine learning in their solutions. Gartner has also predicted that by 2023, intelligent algorithms and AI techniques will be an embedded or augmented component across 25% of all supply chain technology solutions.

3 Machine Learning Models for Inventory Optimization

Critical parameters required for inventory optimization include demand, sales, and return orders. Building machine learning models for:

- Predicting sales (demands) for a particular month, season, geography, customer, or item
- Predicting the probability of return orders to help take preventive measures

This requires sale-specific information such as item details, transaction date, shipment information, acceptance/rejection details, customer profile, and location. These models then make use of vast historical data to equip machine learning algorithms to visualize, draw insights, and predict future needs.

Insights that are derived using ML models help in identifying parameters that are critical to plug the gaps and remove inefficiencies in sales driven inventory management. The algorithms can be customized based on business-specific challenges and constraints. This can include:

- Collecting and combining data from all relevant sources and sifting out the relevant information. The data variables can be categorized as mandatory and optional.
- Cleaning of irrelevant and error-prone data by filling-out/removing missing values, deleting duplicate data, removing columns with low variance, and handling outliers having a z-score greater than 3 or 4.
- Performing feature engineering by improving the existing features and brainstorming/creating new features if needed.
- Selecting dependent and independent variables based on the problem statement.

Robust ML algorithms like linear regression, random forest, support vector machine, and gradient boosting can then be applied to train the transactional dataset and help in forecasting. The sequence is shown in Figure 1.

4 Navigate the Next with Machine Learning: A Use Case

There are myriad use cases to demonstrate the impact ML approaches bring in inventory optimization for manufacturers. The application of ML algorithms has been able to predict better and faster, thereby improving supply chain effectiveness. One such example is of a

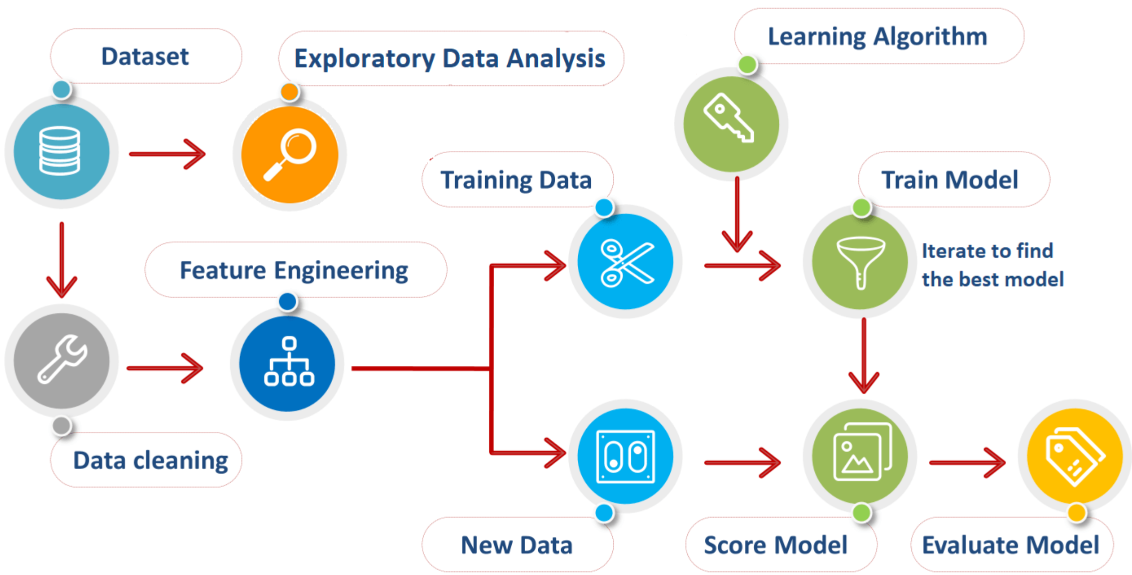

Figure 1: *ML systems learn, and then infer results, from data*

Item No	Transaction Date	Transaction Type	Store Code	Quantity	Customer Code	Country Code	Area Code	Unit of Measure Code	Item Category Code
3R03420	19-11-19 00:00	Sale	F06	1	0018291	USA	GA	EA	DAIRY
3R03435	19-11-19 00:00	Sale	A02	1	0018292	USA	MI	EA	DAIRY
3R05014	19-11-19 00:00	Sale	G07	15	0018293	CANADA	RP	EA	DAIRY
3R05025	19-11-19 00:00	Sale	F06	1	0018294	USA	VT	EA	DAIRY
3R05045	19-11-19 00:00	Sale	B01	20	0018295	USA	WA	EA	DAIRY
3R06120	20-11-19 00:00	Sale	A18	2	0018296	USA	SF	EA	DAIRY
3R01400	20-11-19 00:00	Sale	C11	1	0018297	USA	RP	EA	DAIRY
3R03030	20-11-19 00:00	Sale	C11	1	0018298	USA	MI	EA	DAIRY
3R03115	20-11-19 00:00	Return	F02	1	0018299	USA	GA	EA	DAIRY
3R03215	20-11-19 00:00	Sale	D15	1	0018300	USA	VT	EA	DAIRY
3R03265	20-11-19 00:00	Sale	A05	1	0018301	USA	WA	EA	DAIRY
1H00251	20-11-19 00:00	Sale	C09	60	0018302	USA	MI	EA	HARDWARE
1H00254	21-11-19 00:00	Sale	A18	60	0018303	USA	GA	EA	HARDWARE
1H07005	21-11-19 00:00	Sale	D12	15	0018304	USA	SF	EA	HARDWARE
1R00762	21-11-19 00:00	Sale	G07	360	0018305	CANADA	MI	LNFT	STEEL
1R01240	21-11-19 00:00	Sale	C02	122	0018306	USA	SF	EA	DAIRY
1R01260	22-11-19 00:00	Sale	C02	122	0018307	USA	VT	EA	DAIRY
1R01340	22-11-19 00:00	Sale	A02	200	0018308	USA	GA	EA	HARDWARE
3R03395	22-11-19 00:00	Sale	A18	120	0018309	USA	WA	FT	DAIRY
3K00143	22-11-19 00:00	Return	E13	23	0018310	USA	SF	EA	DAIRY
3F01625	22-11-19 00:00	Sale	B02	10	0018311	USA	WA	EA	DAIRY
1S30250	22-11-19 00:00	Sale	D07	200	0018312	USA	RP	LNFT	STEEL
3F00522	23-11-19 00:00	Sale	F16	18	0018313	USA	VT	EA	DAIRY
3F01181	23-11-19 00:00	Return	C11	48	0018314	USA	RP	EA	HARDWARE
3K00530	23-11-19 00:00	Return	A03	48	0018315	USA	RP	EA	HARDWARE

Figure 2: *Part of the data set (data changed due to confidentiality) to give a gist of the data requirements to build the model*

leading American full-service dairy solutions provider. They provide barn design and consultation, and manufacturing and installation of the equipment put in it. Here are the key properties of the company:

- Total number of stores: 100+
- Total number of items: 9000+
- Planning cycle: monthly
- Average sales transactions: ~2500 per month
- Average return transactions: ~150 per month
- Average inter-store transfers: ~1000 per month

An ML approach was piloted to forecast demand for the items and also predict the likelihood of return orders. After collecting four years' data on goods orders, the data was analyzed. Figure 2 shows the data set that was studied for this use case. It was discovered that forecast information was diffused across multiple stores and regions, which added to data complexity. While some novel sales trends happened at one store, other kinds of spikes occurred at another store. Those novelties arise for various reasons and ask for modeling all the stores into a single model to capture the overall dynamics of the business.

All items were divided into different groups based on their total and monthly balance of share of the sales vector. These were also reviewed for the number of returns. Figures 3-6 show some examples of the results of the data analysis.

After performing an extensive exploratory data analysis, a statistical time-series method called ARIMA was used for forecasting. This model is straightforward to implement and works well for demand planning in most cases. The acronym ARIMA stands for Auto-Regressive Integrated Moving Average. ARIMA models are generally denoted as ARIMA(p,d,q) models, where parameters p, d, and q are non-negative integers:

- p is the number of autoregressive terms
- d is the number of nonseasonal differences needed for stationarity
- q is the number of lagged forecast errors in the prediction equation

The method of differencing was applied to the time-series data to make it stationary. The sales of items sold by the manufacturer were forecasted for the coming months, and the R^2 score was calculated. R^2 was chosen as it gives scale-free results, which is advantageous in cases where items have varied sales trends. R^2 ranges from $-\infty$ to 1, and its ideal value is 1. The closer the value of R^2 to 1, the better is the model fitted. The ARIMA model worked quite well with an average R^2 score between 0.7 and 0.8, and some items scoring as high as 0.9. Figures 7-9 show the forecasting predictions for the three most popular items.

Such inventory and demand forecasting is a challenge because the sales and demand curves are highly unpredictable with unexpected spikes and other artifacts. The ARIMA model used is a very basic time-series method, yet we get a good average score for most items. To improve the accuracy of forecasts, more advanced and holistic ML-driven models, such as deep learning models which are based on deep neural nets, can be used. These models learn deep patterns

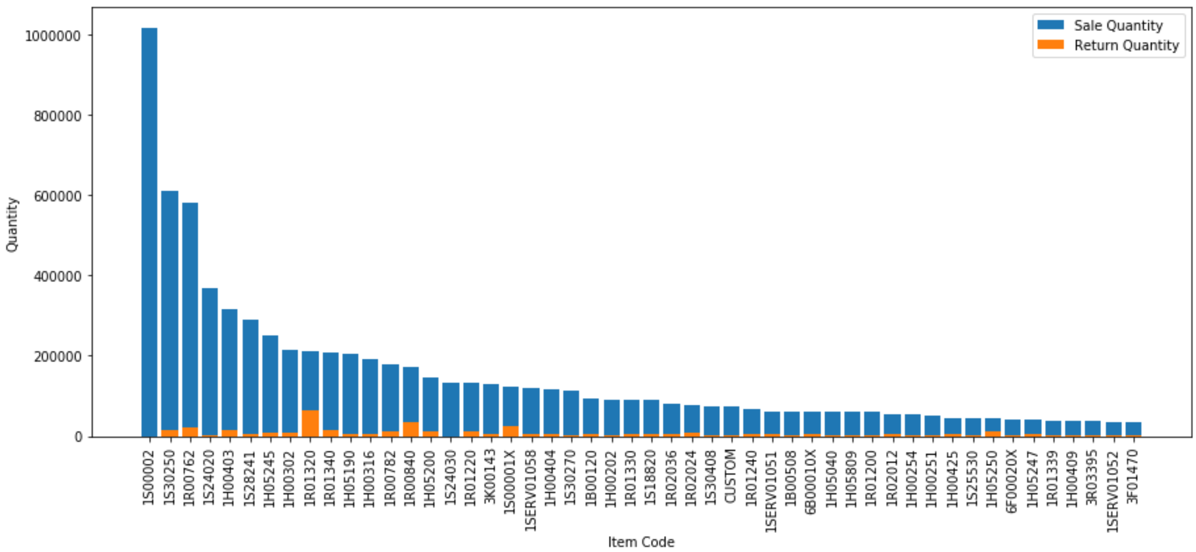

***Figure 3:** Top 50 selling items (in descending order), with return quantity for each item – to get a glimpse of the fast-moving items*

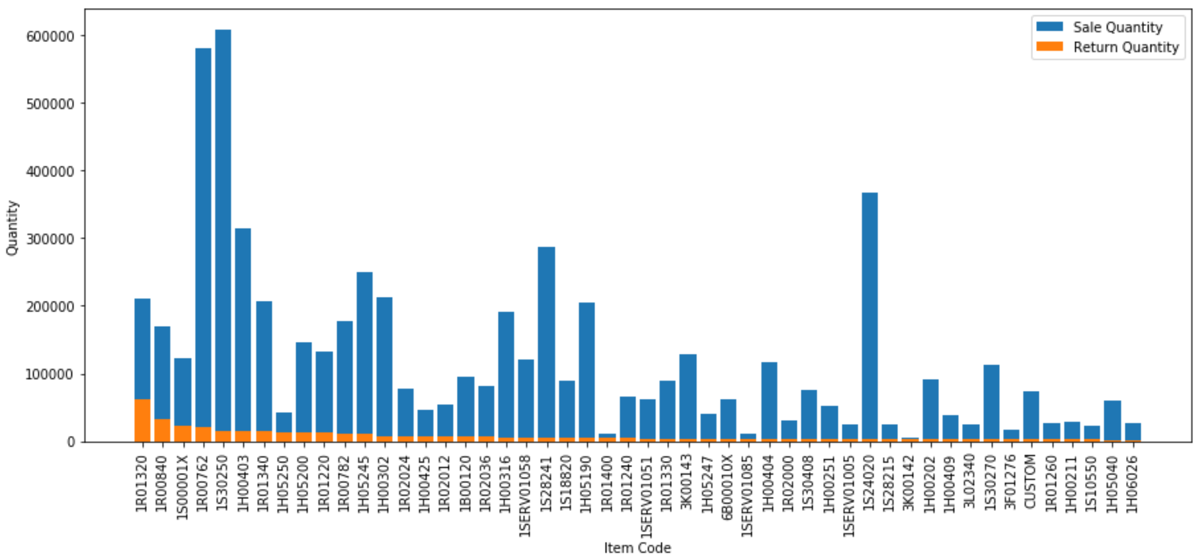

***Figure 4:** Top 50 returned items (in descending order), along with sales – to formulate strategies to minimize returns thereby saving costs*

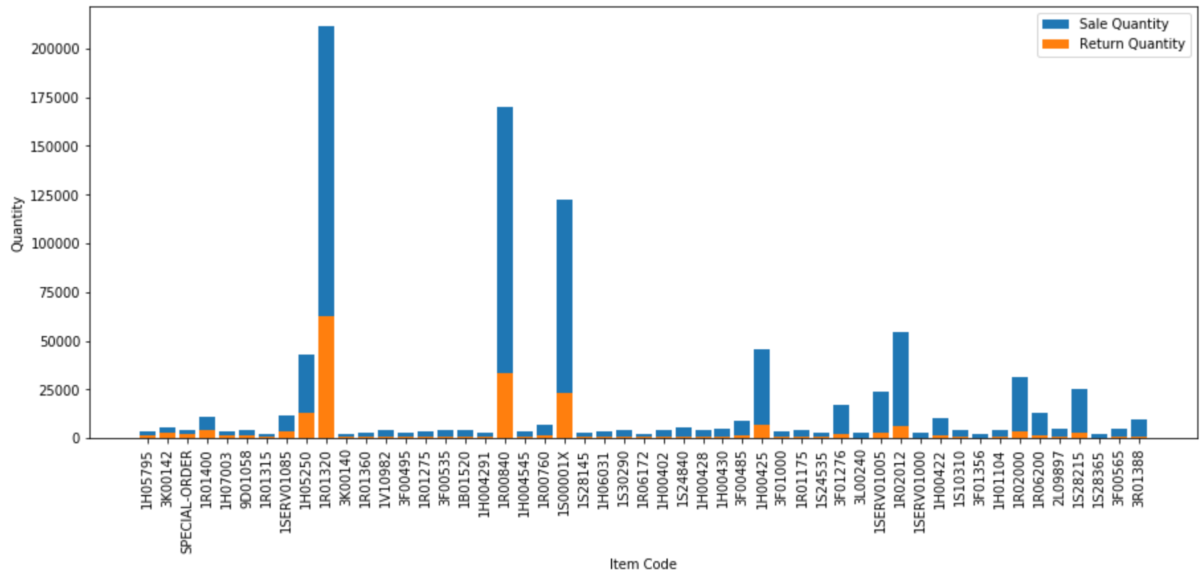

Figure 5: *Items with a high return percentage (>10% of sale) – to look for reasons to circumvent in future, thereby increasing customer satisfaction*

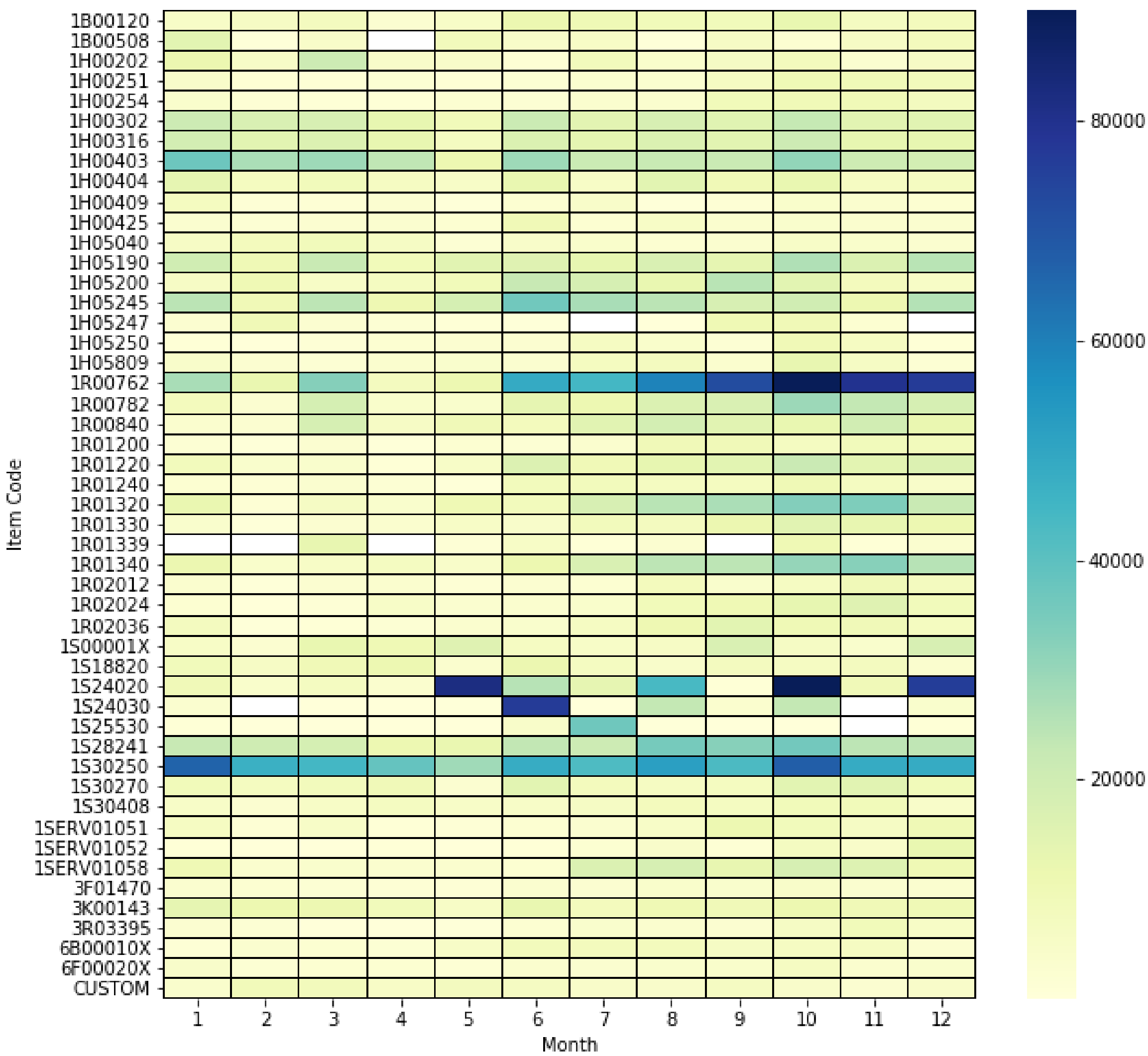

Figure 6: *Monthly trend of top-selling items – to predict monthly sales thereby planning optimum inventory to execute orders efficiently*

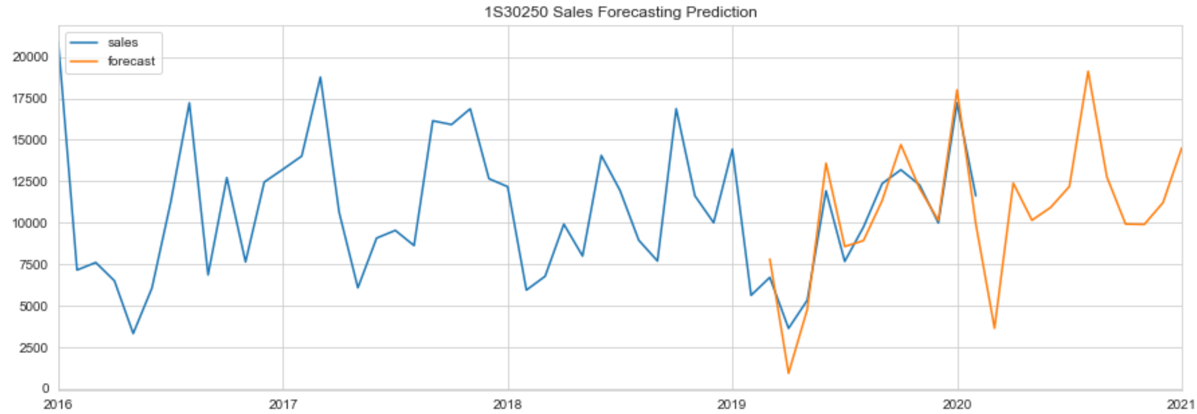

Figure 7: *Sales forecasting prediction for item – 1*

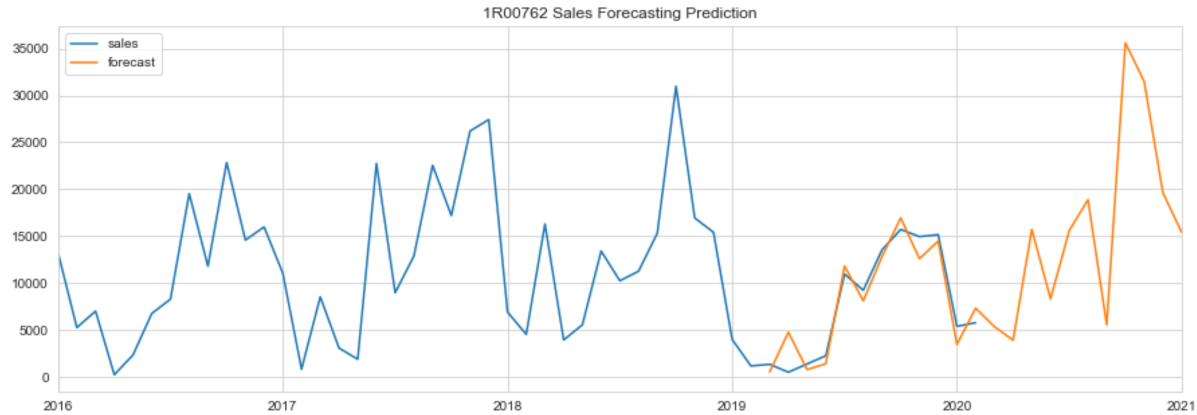

Figure 8: *Sales forecasting prediction for item – 2*

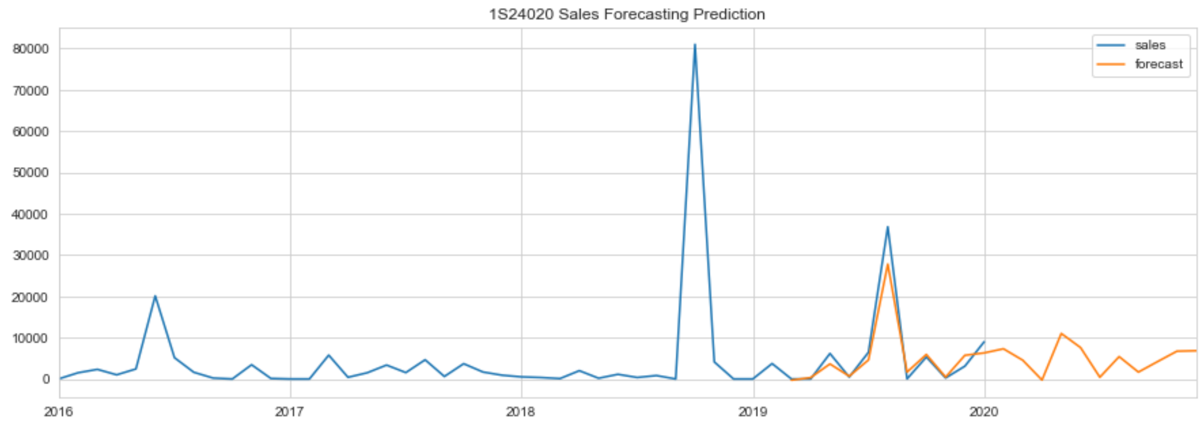

Figure 9: *Sales forecasting prediction for item – 3*

and fluctuations caused by demand perturbations of complementary data signals and related item sales, and are very effective in tackling the nonlinearity present in the sales signals. Moreover, they demonstrate ever-evolving learning and adaptation. They learn from human intervention, anomalous business decline events, and other nuances in trends over the lifetime of the system.

5 Conclusion

There is a strong need to roll out novel approaches to manage inventory costs across the supply chain due to increased complexities and uncertainties involved in manufacturing, distribution, and demands. Businesses can rely on innovative next-generation technologies such as ML and deep learning to draw valuable insights from the past data and devise intelligent and predictive solutions to address these challenges. These solutions can help optimize inventory, serve customer demands on time, and derive desired business outcomes. Businesses can gain with reduced inventory and operational costs while providing better customer experience in this digital age of ever-changing customer needs.

6 References

- Anonymous, 5 Steps to an AI Proof of Concept.
- Greg Scheuffele and Anupam Kulshreshtha, Inventory Optimization: A Necessity Turning to Urgency.
- Louis Columbus, How To Improve Supply Chains With Machine Learning: 10 Proven Ways.
- Muhammad Tariq, Demand Forecasting: How to Slash Inventory Using Signal Processing & Machine Learning.
- Rahul Agrawal and Avneet Saxena, Using Machine Learning to Transform Supply Chain Management.