AI/Machine Learning for the Supply Chain—
How Do We Use It?
Practical and Visionary Use Cases

ChainLink Research
November 2020

Table of Contents

This paper is part of a series on AI/Machine Learning for the Supply Chain.
We recommend that readers acquaint themselves with AI and Machine Learning with:
AI/Machine Learning—Debunking the Myths

AI in the Supply Chain—Definitions

Introduction

New innovations in supply chain technology are bringing opportunities for needed change in how we serve our customers and design, manage, and measure our supply chains. It may be that some of our guiding principles and approaches are, well, kind of obsolete. Past methods used to be the only practical way to measure and process data. Today, they appear simplistic and, possibly, dated.

Stability was the name of the game in process, products, and data, controlled by policies enacted across trading networks and industries. And there is no getting around that it has helped make supply chains more reliable. Yet, when we look at the last twenty years or so, rather than seeing a stable environment, we see constant change. And in the last decade, dramatically. So, why are some of us clinging to the stability game?

Maybe, then, it is not so bold as to say obsolete because as planners, we *know* we have been working with inexactitude for a really long time. Outside the door, there are major forces at work: global warming, sustainable supply chains,[1] culture wars (based on demographics and gender, for example). Then there are various crises such as political and international divisions and trade wars, volatile economics, and the latest, the pandemic. Depending on our industry, these forces have made us confront our values and our management norms. When we talk to many executives, they admit this is the new normal and we won't be going back. In our 24/7 global marketplace, we have needed to rethink some of our values.

Technology has not taken a back seat in dealing with these issues, providing solutions to enable more visibility, sustainability, compliance, fair trade, and responsiveness to change. Right now, AI and machine learning developers are taking a leadership role in helping supply chain deal with all the uncertainty.

AI/machine learning, big data, IoT, clouds, last mile, and end-to-end visibility are all part of the technology mix. But we are only recently *really* learning and grappling with these technologies and capabilities. AI/ML queries are topping the list of what users want to hear about. They are learning that AI and machine learning are not some esoteric algorithmic black box applied to far-out demand problems, but are used to address day-to-day tasks.

Things have changed dramatically in our technology. And accompanying this is the dramatic change in our perspective about our world and our supply chains. Things are happening so fast and unpredictably that we do need methods to help us keep up and, yes, survive and thrive in such a dynamic world.

Given all that, how are AI and machine learning helping? What are some of the applications and use cases that real users are doing today?

[1] Greener products, fair trade

Practical and Visionary Use Cases

In spite of the great strides we made in mathematical systems over the decades, we still have many challenges with accurately planning, pricing, and achieving profitability. AI/ML algorithms and the big data they leverage can open the door to new possibilities.

AI/ML, though, is most often applied to fix a lot of pesky, pernicious issues in planners' day-to-day work, allowing them to shift from manually fixing bad data to *automatically* cleansing data and constantly scanning the data for important issues that might impact plans.

Let's look at a few of the new possibilities and the day-to-day use cases and see how AI/ML is helping upgrade our processes and tasks.[2]

Pricing

Pricing is one of the diciest areas of supply chain. Though often considered the domain of marketing and product planning, pricing has a huge impact on how supply chains are funded—determining budgets for production and logistics, and inventory investments. Supply chain, as well, is responsible for analyzing and implementing price changes from product launch through EOL. Price has its own lifecycle which is impacted cross-functionally, with different stakeholders having a greater say as the product's life goes on. The issue is how can we manage this in an auditable way?[3]

Part of the problem is that data and methods reside all over the place, within our channels as well as within functional groups—product marketing, sales, supply chain, and finance. These groups often use different data sources, systems, formats, and metrics. Data may be locked up in spreadsheets or as web data, e.g., capturing dynamic pricing from various websites, and customer sentiment from social systems. That does not lead to the ability to create holistic, auditable plans.

How AI/Machine Learning Helps:

AI/machine learning can translate much of these sources and formats (structured and unstructured data) into a coherent format. Importantly, it can validate the quality and accuracy of these the data and determine which are valid inputs to be included in future planning and execution tasks.

Pricing can become a lot more scientific and granular by assessing prices by many channels, customer demographics, product attributes, and so on, as well as demand over the life of the product. This accuracy can lead to greater sales and profit, and, we often hear, much better communication between the people involved in this work!

---

[2] Also read *AI For Supply Chain—Debunking the Myths,* where we talk about "intractable supply chain challenges."
[3] Note: We will use the term "auditable" within this paper to mean consistent, compliant, repeatable, verifiable, and able to be used by multiple systems.

On the web, with dynamic pricing, AI-based content search can help find and identify competitor pricing, and machine learning can find useful patterns in the data to help inform when these price dynamics could impact our pricing.

Promotions

Promotions are not just about pricing. The goal should also be to attract new customers, beat the competition and, of course, move product. However, the lofty goals often get lost in the challenges of execution and in some hard facts about promotions—sometimes they just don't work. That is, they impact pre-and post-sales, often reducing sales in their run-up and post-promotional periods,[4] which reduces the value of the promotion. In creating promotions, companies consider a host of ideas such as price, product bundling, special promotional packaging and sizing, special ordering or fulfillment terms, channel-specific deals (trade promotions), and so on.

In addition, promotions cost money to execute, from building additional inventory to support the promotion, to channel coordination, advertising, special logistics, packaging and display costs, and so on. When you consider these factors, you quickly realize that the typical approach to measuring promotions may be limited. And we do know that promotions, though they may temporarily draw customers, tend to fail at any broader goal.[5]

How AI/Machine Learning Helps:

AI/ML analyzes past promotional performance across *all the variable factors* and then helps to develop insights to improve the current planned promotion. Promotions, even in the same product category, are not the same. Other factors such as the product attributes, packing in a specific channel, target customer (and their lifestyle, demographic, and geography) and so on[6] can now be included and compared to previous promotions. Or, as is often the case in new AI/machine learning implementations, determining which variables are important for your products or the markets you service and then setting up a data store to make these evaluations in the future.[7]

AI/machine learning can set parameters within the planning engine to find and include other data or ranges of the data, such as promotions of the past and any associated factors. For example: the weather the week the promotion ran, competitive move or countermove, or late execution. From there machine learning may select or modulate the algorithms that might be used for a specific promotion or product.

---

[4] When many users first systematically implement pricing and promotion systems that have all the relevant costs, they are shocked to find out they are consistently losing. Some organizations know this, but need to conform to their channels' requirements. In both cases, learning to actually manage promotions to your benefit is the key.

[5] such as acquiring new customers who *stay*

[6] AI/machine learning could also include and rationalize cross-functional data such as logistics that support or impact promotion (extra warehouse or transport costs that dampen margin).

[7] Given the ability to capture the raw data and past plans, data scientists can sort through the history and apply learning exercises to see what methods and algorithms might have fit to achieve a different (better) result. Read: *It's All About The Data*.

From these exercises, machine learning can evaluate the best planning algorithm at that point to fine tune this specific promotion, drawing parallels and contradictions between this plan and what happened in similar circumstances in the past.

Demand Planning and Forecasting

The closer we can get to the mind of the customer, the better our demand planning will get. Unfortunately, *the mind* is not an entity that fits neatly into digital data buckets with fixed field lengths. Demand signals coming from our customers adhere to the customer's prerogatives and we need to translate and ensure the data quality. In addition, there are so many streams of data that all have nuggets to inform our forecasting, such as SNEW (Social, News, Events, Weather) data and other environmental impacts (such as pandemics). Again, we are confronted with the same challenge—how to organize data so we can process it.

Other *elements of critical importance are the forecast methods/algorithms we use against the data*.
As conditions change, they necessitate changing the algorithm. The algorithms deployed need to reflect the reality of that product for that channel/customer. Today, most companies are ill equipped to do this sticking with the same formula for years.

The Data in Context
AI/machine learning can be applied to specific products and their attributes and the way in which product demand behaves under different phases of the lifecycle and conditions. This requires a richer data model than is conceived in ERP systems.

Products have rich relationships with many processes, stakeholders, and trading partners, all of whom apply product data in a different context. For continuity and real learning, we need a data model with associated databases—warehouses, stores, and lakes that are consistent, auditable, shareable, and informative.

One timely example is that products that had a steady state—a replenishment-type product—may now have lumpy demand or worse. Due to weather or other crises, they may have huge spikes in demand. Or one channel comes to a screeching halt and demand shifts dramatically to other channels, requiring vastly different packaging and logistics. As a result, the forecast method used last week may not fit the need today. Not only do we need the ability to change to different algorithms to forecast, *we need to sense quickly, or predictively, that those changes are needed **before** the crisis hits*.

How AI/Machine Learning Helps:[8]

Many companies have done various scenario plans of sorts—changes in supply, weather, and so on, events that had occurred in the past. To identify various models from external sources to gain some accuracy about the impact of a crisis by geography, for example, companies need to gather these data sources and swiftly apply them within a forecasting model. AI/machine learning is being applied fairly well in these areas.

---

[8] Here, we want to avoid being too technical so that managers can read and lead without getting bogged down in the nitty-gritty math. These techniques should be provided by an AI/ML-rich supply-chain solution provider. For some excellent detail on specific algorithmic approaches, read *2020 Plan Tip: Eight Methods to Improve Forecast Accuracy*.

This leads us to the actual forecasting. AI can evaluate various [parameters] for their inclusion in the forecast process, and machine learning can be used to select the best algorithm to fit the conditions of each product.

New Product Introduction continues to be an issue that plagues even the smartest companies. Often, we are not clear on what drove demand for our products, especially those with a rich variety of features/attributes. Discerning that is part of the learning process. Thus, we need to begin to create a data model and demand profiles so we can track sales at that next level of detail. Rather than looking at the product family, we can examine how products sell by these relevant *attributes.*

Attribute-based models can actually be leveraged for many demand challenges. For new product introduction, it is key for product designers to see what actually is creating interest with the customer, unencumbered by mark downs and so on. Initially, the profile for a launch inventory and distribution plan is created by leveraging history. Once the product is launched, these profiles can be changed based on early data coming in from the market. This allows, if needed, lots of changes in the configuration, production cycle, and procurement, which can increase sales and reduce excess inventory. It then informs the next product development cycle early on (which is probably already in process). This fine tuning of product demand in the *current* sales cycle can also allow marketing and sales to adjust promotional plans.

Applying these methods historical context now becomes more information rich. This gets really interesting when mapped against other demand elements such as seasonality, specific holidays (back-to-school, Halloween, Chanukah and Christmas, for example), geography, customer groupings, or other demand characteristics.

Demand sensing methods are designed to detect changes in the day-to-day, week-to-week replenishment models. Many suppliers apply, not only the weekly forecast, but POS and customer warehouse receipts to modulate their build/ship plans. With AI/ML, demand sensing can take a broader and more microscopic look at those weekly *sensings*. For example, the week launches with plans in place, and then, icy conditions on the major highways obstruct and delay shipments. AI/ML-based demand sensing can spot these and other short-term events to replan allocations, fulfillment, or just provide assurance that there is still time in the schedule to recover and get back to normal. No action—or additional expense—required.

In *volatile demand scenarios*, *there may not initially be a discernable pattern to apply*. A few companies told us that in the early stages of the pandemic, they were just putting thumbs in dikes without a clear view into how demand was shaping up. AI/ML will keep evaluating, seeking a usable pattern to help identify appropriate parameter changes to enable a forecast. As data comes in, the system will keep learning to adjust and build more accuracy into the process.

In *building a consensus*, machine learning can also evaluate/validate the accuracy of various forecast scenarios, forecasters (sales, marketing, supply chain) as well as the types of data and their sources.

Engaging the voice of the customer. In a world where consumers are constantly voicing their opinions, we need a way to include this in our plans. Natural language processing helps interpret unstructured data—social, text, voice, graphical data—and help derive insights.[9] Over time, some of these sources can actually inform forecasts, as well as be used in product lifecycle plans.

Inventory Management

Inventory management suffers from similar issues as the above-mentioned tasks, as there is product across the chain in various stages of production—components or ingredients, finished goods, packaged or staged, with the inventory requirement at that stage often governed by different systems with different rules. As well, there is inventory data from various sources—suppliers in transit with carriers, 3rd party warehouse, in the channel, as well as in use at a customer site. It seems the data issues persist!

Within the organization, there are also stakeholders who have various opinions about what constitutes the "right level" of inventory, from financial and the lean-practitioner minimalist to jittery sales teams who want to make sure there is always more than enough stock. This leads to debates about the right rules and planning methods, as justifications for carrying cost expense are debated.

Also, inventory planning needs to change at each stage of the product lifecycle. For example, at new product launch we have no history of how the product will be accepted and at what pace. In this instance in the past, we adopted historical patterns of product sales and closely monitored how things were unfolding. Hopefully, we would have set things in place so we could up or downshift, given actual results. This is true for end-of-life or special promotions. In the recent past, we did have the ability to receive more timely data from the market to respond more quickly. But again, we were basically using the same math. And this is probably more than most companies are actually practicing.

One positive outcome of the 2020 pandemic is the building of greater cross-functional linkages within the enterprise.
For example:

- Demand planners are working with logistics to modulate the pace of inbound inventory flows to the warehouse based on shutdown and/or social distancing norms, yet support actual demand and avoid cash being tied up in stockpiles.
- Product planning is working with supply chain and the supplier to recalibrate changing customer product choices due to lifestyle constraints.
- Supply chain and channel sales work together to deal with the dramatic shift in customers' channel preferences.

For user examples, read *A Crisis Is a Terrible thing to Waste.*

How AI/Machine Learning Can Help:

Learning what impacted demand over time and how well inventory met those requirements is foundational to better inventory optimization. Most multi-echelon inventory optimization

[9] There is a lot of work involved in leveraging social data within the process of categories, and validating the data. But the rewards are there for the diligent. Over time, this data can be validated against sales, for example, and then be further refined.

(MEIO) systems use efficiency frontier concepts[10] to decide on a good inventory number per echelon (location). More modern MEIO, driven by machine learning, *differentiates each node's requirements*,[11] seeing the interrelationship between the nodes. Then, it chooses the right math to plan inventory for that location (not based just on past data) to look at near-term demand and supply, statistically evaluating the subtlety in consumption curves—steepness, speed, and so on, as well as the external factors that might influence demand and fulfillment lead times to that node.

Then, we need to build a consensus on the right level of safety stock. As mentioned above, creating a consensus is vital to a healthy learning organization. *Who gets to make the call on the build or buy plan is critically important.* With machine learning, we can look at historical trends and validate a source over time to see how closely it matched outcomes.[12] In addition, companies can use external, curated data services and feeds (POS; weather forecasting; logistics performance data such as rail, air, and shipping schedules and delays) and the millions of unstructured sources. The sheer volume and potential complexity of this data makes it nigh impossible for people to visualize and understand all this without some help.[13]

Use Cases Abound in AI/Machine Learning

The above are just a few instances of supply-chain use cases and how AI/machine learning can help and is being deployed to address them. These are offered as examples to illustrate the ongoing issues of process, systems, and data obstacles that have persisted in spite of great system developments in the past.[14] There are solutions to problems and also queries that have no past traditions beyond the flat file, fixed B2B data we have been processing for decades. In particular, a more systemic engagement with consumers is a new world and we are just beginning to enter into this realm.

There is a lot more to consider such as how users actually access solutions and what might be the differences—and there are—in implementing a machine learning/AI system.

---

[10] such as service level vs. inventory investment

[11] Modern inventory planning systems are augmented with very specific weather and social patterns, and other real-time events to anticipate requirements. This approach, when added to a solid inventory optimizing foundation will note, for instance, more shoppers going online; or that since there is no snow in Colorado, more vacationers will flock to warmer climates for vacation; or that other factors will increase traffic to any one specific location.

[12] for example, source data from other functional groups such as marketing

[13] One analysis was done for a consumer product which appeared to have a seasonal demand curve, but never turned out right—the company experienced large out-of-stock variability over the season. This was easily solved once various web-calendar sources were included which revealed that key events such as local sporting events or large gatherings (conventions, local events/celebrations) were occurring around many of these out-of-stocks. Since each year these event schedules varied future forecasting plans included these major events, and out-of-stocks significantly dropped.

[14] For more examples, read AI/Myths section on intractable supply chain challenges

Rethinking the Process of Getting Results from Systems

AI/machine learning is a rapidly evolving area within the supply chain planning world. Major solution providers are working to blend the new algorithms or are modifying tried and true methods of the past to fit new data opportunities with broader visibility and types of data, data rationalization, and curated data, and making the data accurate and relevant to their customers' situations.[15] They provide a flexible, highly dynamic platform environment where users have a range of options—from very hands-on to semi-autonomous.

This is unlike traditional systems implementations where we identified a needed capability such as a seasonal forecast, and selected some programs from a stock list of algorithms to run our forecast and inventory plan. Then we sought out and cleansed data sources, often manually. After some machinations in an implementation, we turned it on. Post implementation, our "questioning/learning" technology was based on perpetually writing new reports.

Machine learning and artificial intelligence stake out a different position—creating a different process—a process of evolution in learning and self-automating as *we and the system get smarter.*

The key to modern supply chain management systems implementation is to look at the data first, see the patterns that emerge, and then pick the right method and algorithms. Often, algorithms are used in combinations to coax out the nuances in the data and create the right forecast. Through machine learning, the cycle of continuous learning, we can see buying patterns, supplier sources, production conditions, channels, and delivery methods change over time and we adjust methods as circumstances change.[16]

With added extendable computer power, we can apply that automated learning to every single product and understand what the individual disruptions, changes, and causals are at every single supply point and at every selling/consumption point.[17] That change method is a *best fit* approach: what fits the data—now.

From a systems implementation point of view, that means establishing a hierarchy of data stores—data lakes, databases, data warehouses—and, as we mentioned earlier, a richer data resource management tool set appropriate for an AI/ML empowered supply chain[18].

To be clear:
in an AI/machine learning environment we lead with the data and let the system tell us the best fit, verses deciding the method upfront and then sourcing the data. In addition, we don't have just a single application-centric database. We need data lakes to store source and raw data with a variety of structured and unstructured formats, the application database, as well as data warehouses for scenario modeling and reporting.

[15] Read *It's All About the Data.*

[16] Relying on what we learned many years ago as "the" forecast method may not fit now. And what we choose today may not fit next year.

[17] This data can be stored in data lakes and used as a reference point when evaluating the history of forecast; and actuals, which would be the forecasting system's database.

[18] The changes to the development/implementation systems process will be discussed further in the next paper in this series, *AI-Machine Learning – Into the Future*

Best Fit

Best fit is a dynamic capability which is applied at initial systems implementation and then becomes part of the overall operational capability within the planning system.

Best fit should be a standard that organizations rely on in their planning system, since there is a tremendous amount of variability in plans as products move along the lifecycle from design and evolving features/attributes, to sourcing, manufacturing (and ingredient or components), logistics, sales, customer use/valuation, realization, and maintenance, through end-of-life. Additionally, there are the associated costs, discounts, promotions and pricing, as well as the varying objectives of planning (revenue or supply chain operating). That is a mouthful, for sure. And users know it is really complex if you start to dive into how even one data element's value can be influenced and can change over time.

At each stage, and under various conditions, demand or supply characteristics change. That is just too much for a human to handle if there are a lot of products and activities on one's plate. However, this is where machine intelligence and learning really shine!

Best Fit Has Lots of *Intelligence*

We hear a lot about best fit. But did you ever think about what's involved?

Here are just a few things that a best fit capability would do in a planning system:

- Evaluate history to see if there are leverageable data and models—times, series, seasonal, linear relationships and so on. Sometimes history can be an anomaly and is not relevant to the current cycle.
- Based on new data, machine learning identifies patterns and creates a model that fits the circumstance.
- Utilize various smoothing methods to create a forecast/trend line with ranges, etc.
- Monitor incoming data to detect changes in actual conditions compared to the plan in use
- If the current data no longer fit, identify and test different algorithmic choices and recommend changes

Conclusion: We Have to Face Change

Seeking stability was the name of the game in supply chain for a long time. We used to say, "I don't want too much *nervousness in my supply chain*." This was knowing full well that change could happen at any time. At some level we were blissfully unaware, since we simply did not have as much information thrust upon us. Now that we do, we are forced to deal with the reality brought by all that visibility and detail, as well as with all the forces we discussed earlier.

With this knowledge, we need to modify our approach to supply chain management. Change won't happen by piling on more people, and, anyway, it's difficult to find and hire the required analytical types.[19] In manufacturing, the high-labor models of the past are gone. The obvious conclusion is there will be more automation based on data science.

The path forward will require our full attention. It will require commitment to allow people to learn and grow. It will require investment. And with all this, there still will be some unseen twists and turns on the way. But, if change is a constant, why be a victim of it? Why not make it a positive change, taking us on the road to supply chain transformation, smarter solutions, and a better future?

[19] Read *The Emergence of the Supply Chain Scientist* and *The Data Scientists, Software Engineers and Data Managers.*

What's next? What will that future be? We already have some hints. So, in our next installment, we will discuss the path forward, *Into the Future with AI/Machine Learning for Supply Chain*.[20]

Further Reading

In-depth on AI/ML techniques in forecasting:
2020 Plan Tip: Eight Methods to Improve Forecast Accuracy

For some excellent research on consumer choice patterns:
https://www.sciencedirect.com/science/article/pii/S0167811618300259

AI in Supply Chain—Some Definitions

AI for Supply Chain—Debunking the Myths

For some excellent blog posts:
https://www.logility.com/blog/artificial-intelligence-ai-machine-learning-ml-in-supply-chain-planning

[20] Planned publication date January 2021

About ChainLink Research

ChainLink is a recognized leader in custom research and advisory services, with a focus on supply chain, Internet of Things, and blockchain. Founded in 2002, our emphasis from the start has been on inter-enterprise interactions and architectures ('the links in the chain'). We have conducted over 75 primary research projects, interviewing and surveying over 10,000 executives and professionals. Much of our research focuses on industry-specific use cases, business cases and ROI, and drivers/inhibitors of technology adoption, and business change. As a result, we have developed a deep, multi-industry practice, founded on real-world, validated, supply chain-wide, end-to-end perspectives that have helped our clients understand, plan, and succeed as they move into the future.

For more information, contact ChainLink Research at:

321 Walnut Street, Suite 442, Newton, MA 02460-1927

Tel: (617) 762-4040. Email: info@clresearch.com Website: www.clresearch.com