Brochure

The Power of Smart Data Farming

Understanding and applying supply chain data signs

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Introduction

The digitalization of the supply chain has connected organizations and created a wealth of new data. But, for most companies, this has brought both opportunities and risks. What data is important? What is trivial? And how exactly should data be applied?

While artificial intelligence (AI) and machine learning (ML) can help by detecting patterns and applying sophisticated algorithms, data farming is still a complex problem that most companies struggle with. Since data is the foundation for fact-based decision making and real-time responsiveness, it is critical that organizations install the capability to identify and apply the wealth of "supply chain data signs" that are readily available, but may be hidden deep in the end-to-end network.

Gathering and leveraging these rich data insights can help companies manage challenges such as increasing demand uncertainty, channel complexity and growing customer expectations. More than ever, data farming is a core competency that separates the leaders from the followers.

The evolution of planning processes

As supply chains become more horizontally and vertically integrated, traditional response-planning solutions are transforming to support "predict and pivot" planning processes that enable greater speed and agility when potential disruptions are sensed. This is a natural step in the evolution of planning systems, and it will naturally create needed synergies between the old generation of batch planning systems and Blue Yonder's new generation of cognitive Luminate Planning systems.

Just as the analytical left side, and the intuitive right side, of human brains are complementary to each other, batch planning and cognitive planning systems complement each other as well. The co-existence of these systems within a single organization can lead to the creation of a truly autonomous and self-learning supply chain ecosystem, where each system can thrive on the other's outputs (see Figure 1).

How exactly does this planning evolution relate to data? In a traditional batch planning system, the data is refreshed for every cycle. This means that, with every new cycle, precious data is lost for good. Also lost is the opportunity to track this data over time and learn from it.

Yet this data is crucial to the effectiveness of cognitive planning systems that use AI and ML. By leveraging these advanced technologies, along with associated cognitive planning capabilities, organizations can use this previously discarded data to improve forecast accuracy, generate recommendations, enable automated resolution, perform cognitive segmentation, make stock-out predictions, generate exception clustering and manage other essential tasks. The use of AI and ML in planning is gaining a lot of traction recently, as systems capable of holding and processing large volumes of data become accessible to every business.

If we let go of the past, we will never learn from mistakes. **—Sarah Van WaterSchoot**

Supply chain data signs

Unlike traditional planning processes, cognitive planning is predicated on identifying and applying the hidden signs of supply chain data. For this to happen effectively, the data needs to be harvested in a way that is best suited for strategic analysis. This process is referred to as **smart data farming (SDF)** in this document. **Smart data farming can be defined as a process that manages supply chain data so that every critical event and entity is tagged, recorded and analyzed to reveal useful insights.**

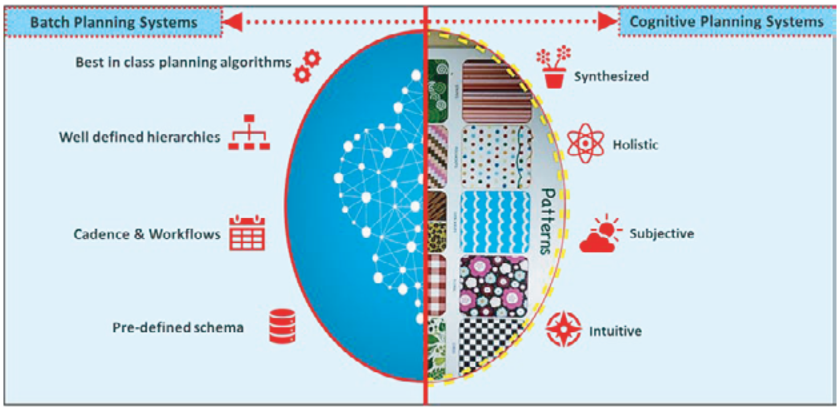

Figure 1: Left and Right Brains of Supply Chain Planning

Just as every key invention in the world is inspired by nature, the thought process that underlies smart data farming attempts to draw inspiration in a similar fashion from the natural patterns of dynamic supply chain operation.

The six-fold symmetry of a snowflake, the fractal pattern of flowers, the meander pattern of rivers, the wave pattern of sand dunes, crack formation in inelastic mud or the logarithmic growth pattern of Nautilus shells are all a result of forces of nature acting over a given time period (see Figure 2). Many noted philosophers and scientists have tried to identify mathematical rules underlying these patterns.

Similarly, over a given time period, supply chain entities are also subjected to “push and pull” forces in conjunction with the demand-and-supply balance, and as other forces emanate from inside or outside an organization. This results in the formation of definite patterns in data, which can be analyzed for subsequent course correction. These patterns represent the supply chain data signs that can have a significant impact on strategic and financial results if they are identified and acted upon via SDF.

Figure 2: Patterns in Nature

Quantifying the impact of supply chain entities and events

The key entities of any supply chain are material, capacity, demand and time. These form the most fundamental molecular structure of the supply chain (see Figure 3). In turn, many such interconnected combinations of these molecular structures form the complex supply chain network of an organization.

Every supply chain is connected to every other supply chain, either directly or indirectly. What is perceived as an end customer for a given supply chain may not truly be the end node in the context of an extended supply chain. Given these interconnections, an event occurring in any part of the world can create disruptive ripple effects across many other supply chains. A key objective of supply chain management is bringing the supply chain system back to its steady state, helping it recover from current disruptions and guard against any future disruptions. Obviously, accurately managing the entities of material, capacity, demand and time plays a huge role in achieving this steady state.

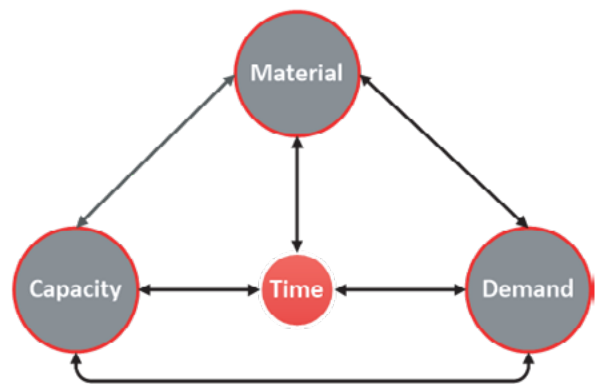

Figure 3: The Supply Chain Molecule

In addition to managing entities, managing events across the supply chain, or extended network, also contributes significantly to achieving a steady state. An event can be defined as any occurrence in time that results in a change of state for an entity such as material, capacity or a demand. Examples of events include any supply, consumption or shipping action (see Figure 4). An event, or state change, could result in modified inventory levels, order status, allocations or capacities. When observed carefully, these occurrences exhibit definite patterns over a period of time. It is these patterns that define the very fundamental and unique DNA of a supply chain.

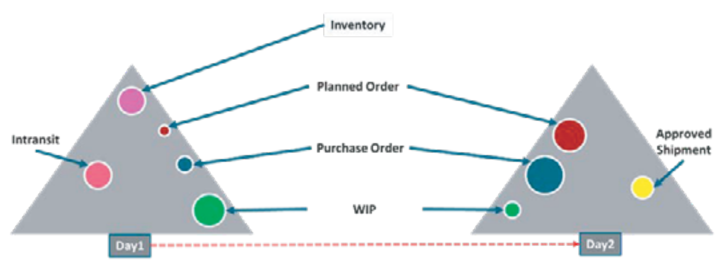

Figure 4: Occurrence of Events

The state change of a planning entity can be related to a given planning instance or occur across multiple planning instances. Planning instances can be defined as any batch processing system output that addresses a specific planning need, such as a weekly MRP run, a daily DRP run or a monthly S&OP run.

It is important to remember that every batch planning instance has an intended purpose. Based on that purpose, the planning system generates future supply chain recommendations based on actuals, projections and assumptions. But only the actuals are real. Given that disruption is inevitable, projections and assumptions can always go wrong.

Today's plans are expected to be realized as actuals at some point in the future, but there will always be deviations that result from many factors. Some of these factors could be random, and some could be systematic. A data-based analysis of these deviations could reveal many insights into the underlying root causes, enabling an organization to take necessary remedial actions and re-plan proactively to improve performance each week (see Figure 5).

Being able to tag every event occurring on every critical entity of the supply chain helps organizations to better understand the underlying patterns. **Tagging makes the events occurring across multiple planning instances, affecting the same entity, mathematically relative to each other.** This is required to analyze the deviations. The tag should be unique for each planning cycle.

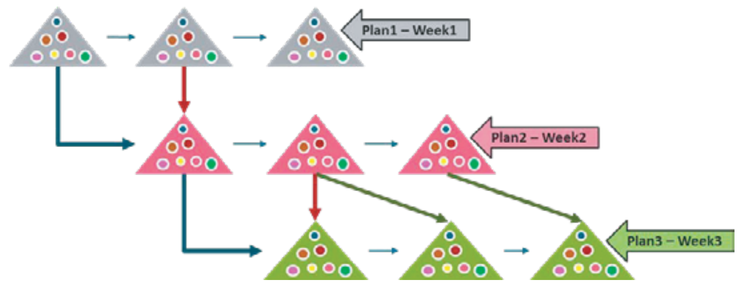

Figure 5: Plan Versus Actuals Across Multiple Cycles

An effective and simple approach to determine a tag could be through use of a **PlanID, which is a combination of planning instance and plan date.** This means that all the events and entities of a planning run will be tagged with the corresponding PlanID to make each one unique. **More complex correlations between multiple events, entities and planning instances can also be established through smart data farming.**

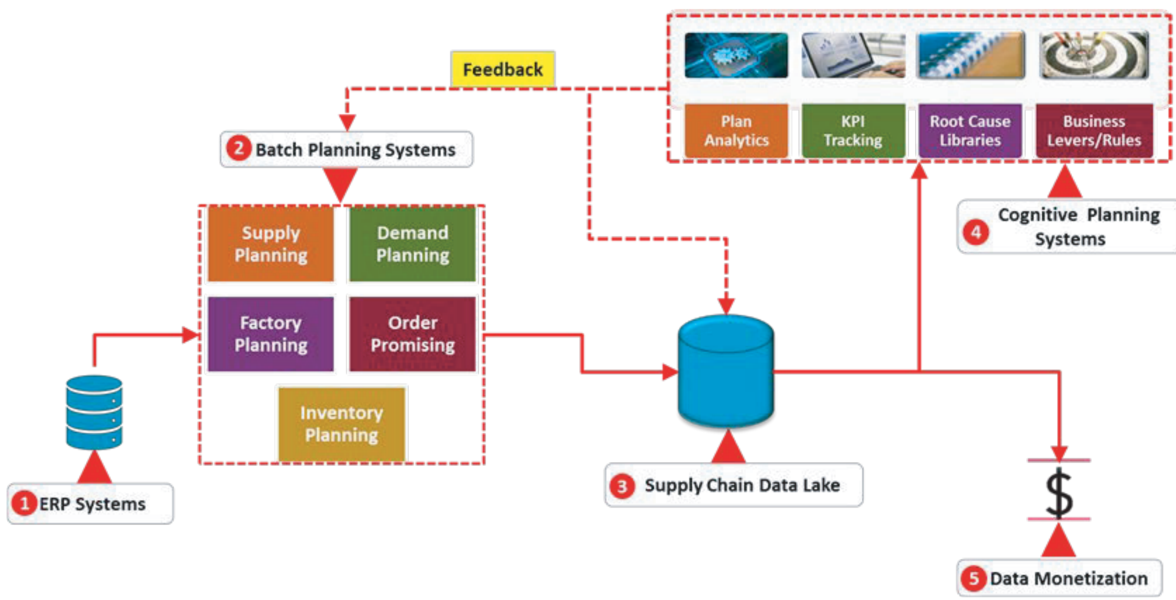

Figure 6: Convergence of Batch Planning and Cognitive Planning Systems

The detailed data flow between batch and cognitive planning systems is shown in Figure 6.

As shown in this figure, the data from multiple batch planning systems such as master planning, factory planning and demand planning is harvested and fed to a repository called a supply chain data lake (SCDL). The data in the SCDL can be processed further to perform plan analytics, to track KPIs over an extended period of time, to establish root-cause libraries and to fine-tune business rules. The feedback from these processes is iteratively fed back into the batch planning systems, resulting in a truly autonomous, self-correcting planning system.

Smart data farming at work

So how can smart data farming be applied to real-world supply chain situations? Following is one example.

Figure 7 shows a simple supply chain where a raw material (RAW) is procured from external suppliers and is used to manufacture a finished good (FG). FG is further shipped to a distribution center (DC) from which customers are served.

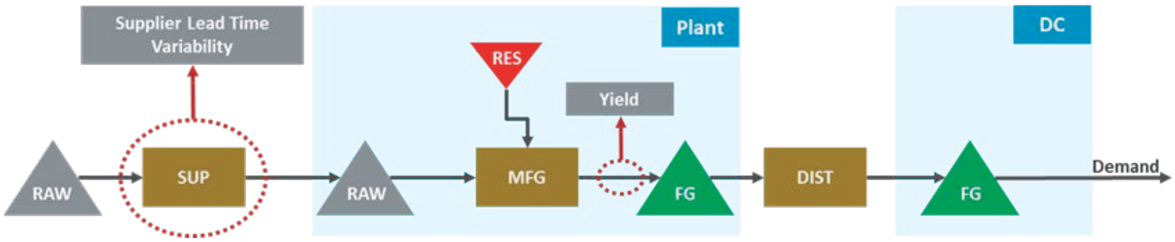

Figure 7: Paper Model of Sample Supply Chain

Computation of lead-time variability via SDF

In a typical planning workflow, supplier lead time is assumed to be constant, based on the transportation time and the time required to have the product ready to be shipped. When a manufacturer places a purchase requisition, the supplier, in turn, commits to a delivery date based on availability. This committed quantity, which is also referred to as a purchase order, flows back into the planning system as a “frozen supply.” As the supply chain moves forward in time, this frozen supply subsequently gets converted to in-transit and inventories at the plant.

As Figure 8 demonstrates, the planned quantity is a purchase requisition (PR) placed on the supplier. Actuals are those supplies that are finally accounted for as inventories in the system. But there will always be deviations in what is planned to be available and what is actually available, resulting in a time lag in he expected events. These deviations need to be analyzed and accounted for in the future planning cycles in order to be able to bridge the gap between plan versus actuals. The data to perform this analysis is generally readily available in the planning systems, but it must be harnessed appropriately.

In this example, for a planned event occurring on WX, the receipts are expected at the beginning of the week. But the actuals are only realized in parts on Day2, Day5 and Day7. The same is the case with week WY.

Assuming that lead time is the time it takes for a material to transit from source to destination, organizations need to be able to group the actuals against the plan, compute weighted lead times of the actuals, and average lead times to finally get to lead time variability.

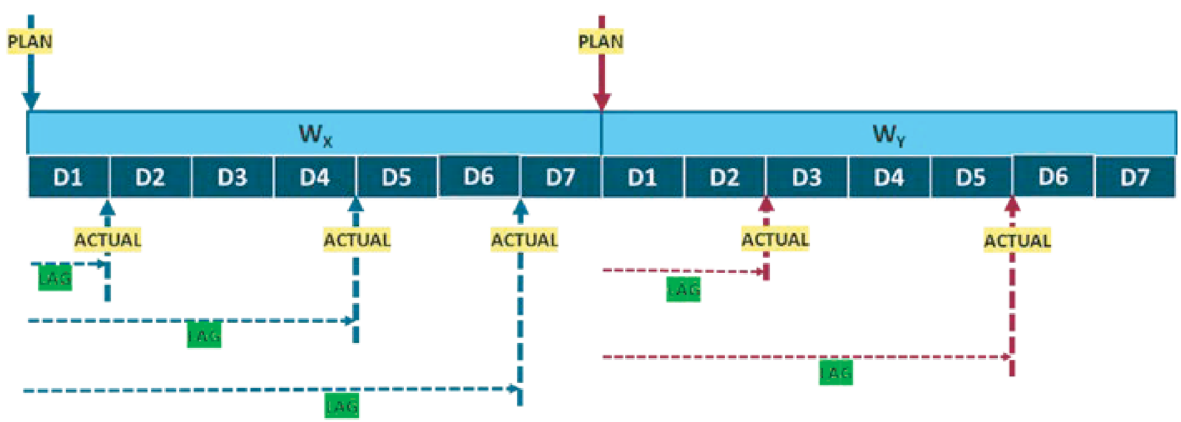

Figure 8: Time Lag of Events

This is formulated as √(∑(wi*(ILTD)^2) where:

- wi = Weight of the actuals based on the ratios of quantities delivered versus planned
- WLT = weighted lead time, a product of weight(wi), with actuals lead time measured against each receipt
- ILTD = individual lead time difference, the lead time difference of the actuals against the average lead time (ALT)
- ALT = computed by taking the average of all WLT

Once computed using this formula, lead-time variability can further be used as an input to the computation of safety stocks at the given node of the supply chain.

This is just one example of the kind of analysis that Luminate Planning, a cognitive solution from Blue Yonder, performs via an automated, invisible process. This solution saves manual labor and analysis, instead delivering the end insights planners need to take a corrective action such as parameter tuning. Smart data farming is most effective if it is driven by the speed, power and automation of artificial intelligence instead of relying on human analysts and manual processes.

Production yield tuning via SDF

Like lead times, production yields are influenced by many factors. These include changeover losses, line breakdowns, material and capacity constraints, quality of the product and weather conditions. Yield is an important input to the planning process. An inaccurate yield factor could result in not being able to produce as planned.

Organizations can again use the plan versus actual deviations to determine the correction factor. For a given bucket, planned quantities can be higher or lower, depending on the prevailing conditions on the shop floor. Weighted cumulative bias can be an option to determine the correction factor for manufacturing yields.

FG-at-Plant	Scheduled	Produced	Scrap	True Sellable Quantity	True Delta	Weightage
Week1	x1	y1	s1	y1-s1	x1-(y1-s1)	w1
Week2	x2	y2	s2	y2-s2	x2-(y2-s2)	w2
Week3	x3	y3	s3	y3-s3	x3-(y3-s3)	w3
Week4	x4	y4	s4	y4-s4	x4-(y4-s4)	w4
Week5	x5	y5	s5	y5-s5	x5-(y5-s5)	w5
Week6	x6	y6	s6	y6-s6	x6-(y6-s6)	w6
Week7	x7	y7	s7	y7-s7	x7-(y7-s7)	w7
Week8	x8	y8	s8	y8-s8	x8-(y8-s8)	w8
Week9	x9	y9	s9	y9-s9	x9-(y9-s9)	w9
Week10	x10	y10	s10	y10-s10	x10-(y10-s10)	w10
Week11	x11	y11	s11	y11-s11	x11-(y11-s11)	w11
Week12	x12	y12	s12	y12-s12	x12-(y12-s12)	w12
Week13	x13	y13	s13	y13-s13	x13-(y13-s13)	w13
Week14	x14	y14	s14	y14-s14	x14-(y14-s14)	w14
Week15	x15	y15	s15	y15-s15	x15-(y15-s15)	w15

Figure 9: Production Actuals

Figure 9 shows a sample case where:

x1, x2, x3...x15 are the scheduled production quantities by week.

y1, y2, y3 .... y15 are the actual production quantities by week.

s1, s2, s3 .... S15 are the scrap quantities by week.

The true sellable quantities are y1-s1, y2-s2, y3-s3, etc.

The true difference between scheduled versus actual is x1-(y1-s1), x2-(y2-s2), x3-(y3-s3), etc.

The correction factor to be applied can be formulated as wb = $(1/(\sum_{i=1}^{n} wi)) \times \sum_{i=1}^{n} wi(x\,i - yi + si)$

where:

wi = weightage for a bucket

xi = quantity scheduled to be produced in a bucket

yi = quantity produced in a bucket

si = quantity scrapped

wb = the correction factor that needs to be applied in the subsequent planning cycles

More recent time buckets can be given a higher weight than older ones. The above computation assumes a static yield, and it can also be extended to fine-tune time-varying yields where yields exhibit seasonal patterns. Again, Luminate Planning solutions from Blue Yonder can automate this type of analysis behind the scenes, allowing planners to focus on the higher-level, more strategic issues that result from the analysis.

Capture the opportunity

Today's supply chains are facing a new era of uncertainty. Global disruption, channel complexity, demand volatility, trade concerns and supply chain skill shortages are givens, and time is the new currency.

To support success in this environment, today's planning solutions must be more intelligent, more intuitive, more predictive and more capable of delivering to customers when, how and where they want. Through new cognitive planning processes, organizations will be empowered with a machinelearning powered planning solution which has the built-in visibility, intelligence, context and collaboration tools to enable fast and effective action.

Smart data farming opens a whole new world of opportunities in the field of supply chain planning and optimization. Data is the fundamental pre-requisite for any analysis. Having a structured and extensible framework of data farming helps propel Blue Yonder's next-generation Luminate planning solutions. By levering Luminate, most of the back-end analysis and tuning can be delegated to machine learning algorithms, paving the way for performance improvement and market leadership.

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