Why Learned Behavior Models Trump Supply Chain Visibility on the Value Scale

Supply chain professionals readily recognize the value of real-time visibility, but most do not understand the implications—or value—of behavior models. Pings from IoT devices such as sensors, satellites, radar, smartphones, meters, control devices, etc., provide organizations with a near real-time picture of conveyances in motion, WIP in manufacturing, inventory in warehouses and finished goods heading to customers, but those pings are still just snapshots in time.

While it's helpful to know exactly where on the Pacific Ocean inbound parts are from Asia, it's far more valuable to know when they will arrive at the port of destination, or better yet, when the container will be offloaded from the vessel, clear customs and be available for pick up. Armed with that knowledge, days in advance, a supply chain professional can schedule a dray carrier to pick up the container right on time, rather than having it sit at the port for days, racking up demurrage charges, unaware that it has arrived.

Even more valuable is the ability to accurately predict when those same parts will arrive at the manufacturing facility, and not just the parts on a single container, but all the inbound parts from around the world, tightly orchestrated to arrive at the same time to support a manufacturing plan. This level of predictability, weeks in advance (while the parts are still in the middle of the Pacific Ocean), helps to eliminate manufacturing disruptions, reduces the need to carry excess buffer stock and cuts down on expedited freight.

[Figure 1: Understanding the impact of independent variables (weather, traffic, port congestion) on a dependent variable (wait time)]

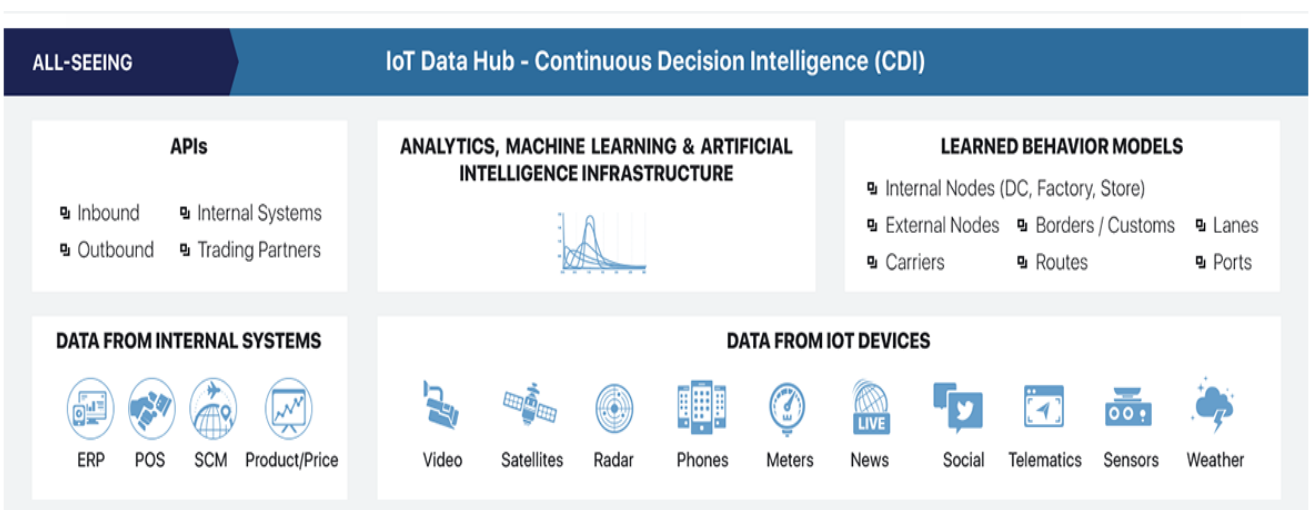
Similarly, having real-time visibility of finished goods on trucks rolling away from a manufacturing facility is nice, but it’s far more valuable to accurately predict when those trucks will arrive at the DCs. Armed with accurate predicted times of arrival, warehouse managers can effectively coordinate dock and labor schedules, eliminating back-ups and reducing overtime.

Again, while nice to provide customers with real-time visibility of their orders en route, it's far more valuable to provide them with accurate predicted times of arrival. Doing so boosts net promoter score (NPS) and reduces charges associated with early or late arrivals.

In each of the scenarios described above, real-time visibility is a means to an end. The ultimate goal is to understand and fulfill dynamic demand with dynamic supply, and to do so while minimizing inventory levels and reducing supply chain costs.

Meeting that goal requires something far more valuable than just real-time visibility; it calls for predictability. How can a solution accurately predict the throughput from a foreign supplier or one's own manufacturing facility, or the turnaround time at a DC? How can a solution accurately predict the performance of carriers on different lanes and dynamically calculate accurate times of arrival? How can a solution accurately predict customer and consumer demand?

Making these kinds of predictions requires an understanding of behavior. Seeing that an ocean vessel has just pulled away from the port of Shanghai, in real-time, is a good start, but to predict when it will arrive, a solution must have a real-time and predicted understanding of the circumstances surrounding that shipment and learned behavior models for how the vessel will behave when it encounters those circumstances.



[Figure 2: Digital Supply Chain Platforms require big data streams, advanced analytics engines, and learned behavior models.]

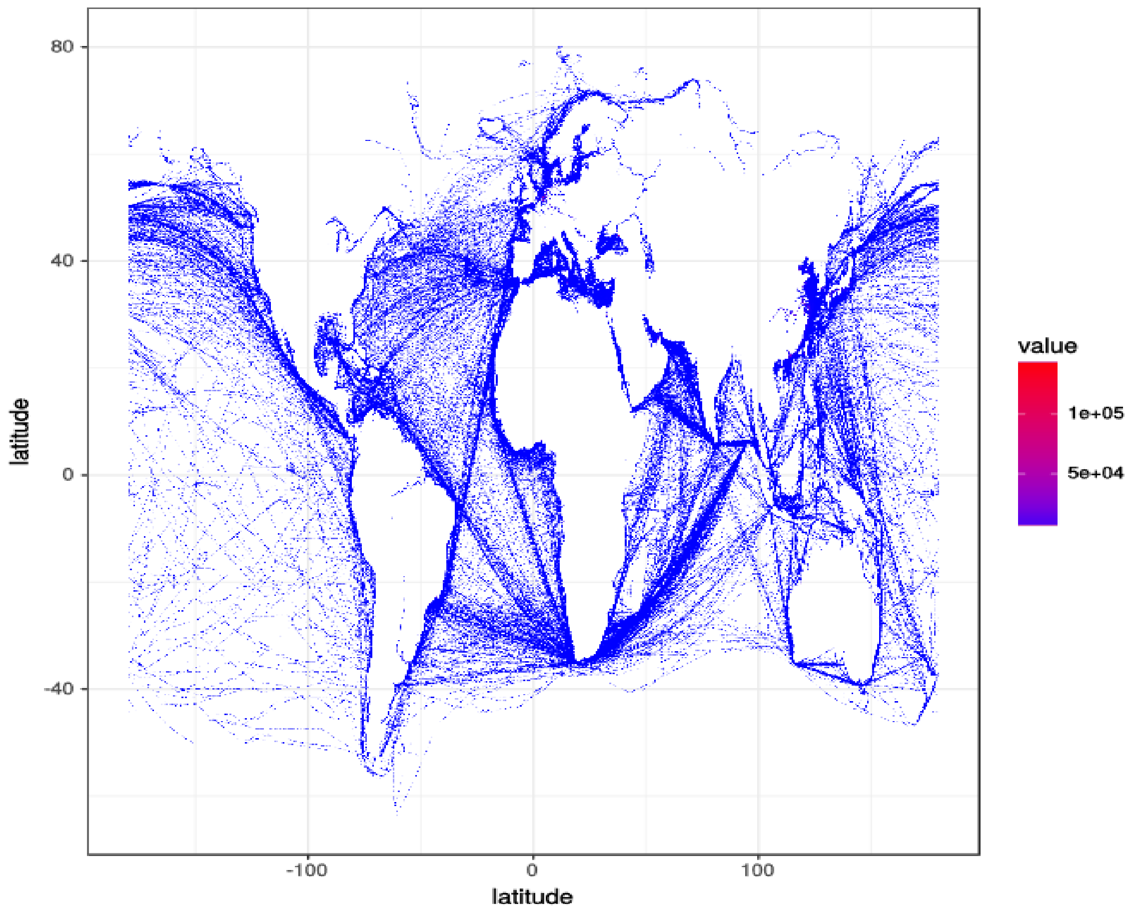
What percentage of the time does an ocean carrier make unscheduled port stops on the lane in question? Are those unscheduled port stops more frequent during different months of the year, or do they correspond to fluctuations in spot rates? By how much do 18-foot swells on the ocean typically delay a shipment, and what if those weather conditions are predicted to be present during a four-day stretch of the voyage? How long does it take for a vessel to berth, unload and for goods to clear customs at the port of Long Beach, for example, when 10 vessels arrive at the same time vs. 20 vessels vs. 40 vessels?

What are typical truck transit times along specific routes during a range of weather conditions, at different times of the day, when there is road construction or a professional sporting event nearby? How long does it take to receive and unload a truck at a DC when there are ten dock hands working vs. seven? What does that turnaround time look like when eight trucks arrive within a 30-minute window vs. 20 trucks?

What do temperature fluctuations, competitor pricing, a nearby concert or road race, do to consumer demand? How about the tone and volume of chatter on social media?

To answer these questions, a solution must continuously learn and understand behavior. It must watch events unfold time and time again, tracking the performance of a dependent variable (e.g., ocean carrier), factoring the impact of a range of independent variables (i.e., month of year, spot rates, weather, port congestion, etc.). By watching and analyzing the performance of a dependent variable dozens, or hundreds, of times, a solution can establish learned behavior models.

Learned behavior models are far more sophisticated than simply averaging transit times across all carriers on a specific lane over time, for example. They require massive amounts of real-time big data and advanced analytics to correlate events, implement continuous machine learning and to extrapolate outcomes.



[Figure 3: Time series plotting of cargo ships and tankers.]

What is the value of this level of sophistication? Predictive analytics fueled by learned behavior models are delivering predicted times of arrival that are 50-80% more accurate than carrier provided ETAs. On an ocean journey, that's 3-5 days of cycle time improvement, while on air or truck, that's 4 hours to 1.5 days, per leg. Including more accurate throughput and variability predictions for nodes (e.g., ports, warehouses, manufacturing facilities), end-to-end cycle time improvements from foreign supplier to customer door range from 7-10 days. And that's only factoring tighter coordination of inventory hand-offs between trading partners and supply chain nodes (e.g., coordinating the JIT arrival of a dray carrier to pick up a container instead of the container sitting in the yard for days).

More cycle time improvements, cost reductions and revenue opportunities can be realized from initiating prescriptive recommendations (i.e., dynamically adjust inventory models or book an alternate carrier that is more likely to arrive on time than the preferred carrier), but we will discuss the mechanics behind and benefits from prescriptive recommendations in another edition.

Digital supply chains are evolving rapidly, and it is important for supply chain executives and practitioners to understand their underpinnings and value proposition. The key takeaway here is to understand the difference between real-time visibility and predictive insights powered by learned behavior models. Learned behavior models, coupled with real-time visibility, trump standalone supply chain visibility every time.

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