VIZEN ANALYTICS

Whitepaper: Improving Supply Chain Forecast Accuracy Utilizing AI-Enhanced Causal Data Modeling.

- **Introduction (including "Problem Statement")**

In today's global supply chain environment, complexity and disruption are making a significant impact on forecast accuracy results. For example, automotive industry companies have been especially hard hit. The Covid-19 pandemic, semiconductor shortage, and the war in Ukraine have introduced highly influential market factors previously unaccounted for in their business forecasts. These effects resulted in the destruction of just-in-time (JIT) planning processes. As a result, automotive suppliers and OEM's face material supply shortages, lead-time delays, cost overruns (expedite fees), lost sales and excessive holding costs. The overall cost of this problem is estimated to exceed $1 trillion annually across all industries. Traditional econometric forecasting, predictive machine learning (ML), and supply chain planning software are simply not robust enough to handle sophisticated market changes and new constraints that impact the accuracy and usability of supply chain forecasting.

- **Background (research-heavy)**

Why do standard statistical and ML forecasting methods fail in real-world scenarios? Standard methods rely on extracting a relationship between available data (features) and a target variable. These methods can describe the relationship in mathematical terms, but they usually fail to determine causality, i.e., answer the question: what is causing the problem? And yet, identifying the cause and the level of its effect is one of the most common goals of applied data science [2].

In general, causality is deduced from common sense logic. While this works well for simple problems, complex socio-economic systems are usually too sophisticated to be properly understood and analyzed according to simple logic. In fact, this often leads to poorly posed ML and forecasting problems that give mathematically correct results but in practice lead to disastrous business outcomes. For example, a predictive model for the supply chain may predict that an increase in demand will lead to an increase in production. Logically, this happens most of the time. However, a typical statistical or ML forecasting model will not be able to account for a variable, such as a new war or pandemic if this possibility is not specified in the model [1].

The difficulty of identifying causality is not new. The most common method for detecting causality in econometric data is Granger causality that applies a P-value Python formula that validates the statistical significance between two or more disparate time series data sources that they are correlating by chance. The lower the P-value below .05 the greater the probability that that there is a causal relationship [4]. By tracing the relationship between the variable in the current interval and the variable in the previous interval, Granger causality identifies the event that comes first and is therefore likely to be the cause. Another traditional way of detecting causality is AB testing, which is usually achieved through Randomized control trials [2]. Both Granger causality and AB tests depend on the problem formulation and cannot detect the cause if it is not encoded in the model variables.

With the advancement of ML, many companies are realizing that without proper identification of causal links, ML models do not perform as expected. To solve this problem, Judea Pearl, a researcher at UCLA, proposed a causal Bayesian network approach in ML [3]. The main idea is to decompose the data into a network where the nodes (features) are linked with weights assigned based on the conditional probability distribution [3]. This allows the causal structure of the data to be determined by combining artificial intelligence and human intelligence [1] - a task previously considered impossible without randomized controlled trials.

Causal-AI can be applied to improve the sustainable accuracy of forward supply chain forecasting. In this case, it's essential to discover and confirm the root causes and consequences present at different levels of the data that impact downstream results. This is accomplished via the use of a knowledge graph that maps the potential causal factors that are impacted by target variables as a combination of multiple contributing aspects [1]. In addition, the benefits of causal-AI include increases the robustness of training, reusability of model components, and better utilization of computational advanced statistical resources based on componentization of models, including the application of Granger P-value Python formulas to validate the probability that two or more data sources are causal in nature. [2].

- **Proposed solution.**

Vizen Analytics has developed a proprietary cloud-based causal AI solution. Our solution leverages the causal AI toolkit [5]: human intuition, causal links, transparency of causal modeling steps, variable confounding, counterfactuals, bias, and robust advanced statistical model componentization to validate the probability of causality between disparate data sources. Our solution's flexible interface allows analysts to combine their industry intelligence with powerful causal modeling and optimization. One example of an industrial application of our software is the supply chain modeling and optimization shown in Figure 1.

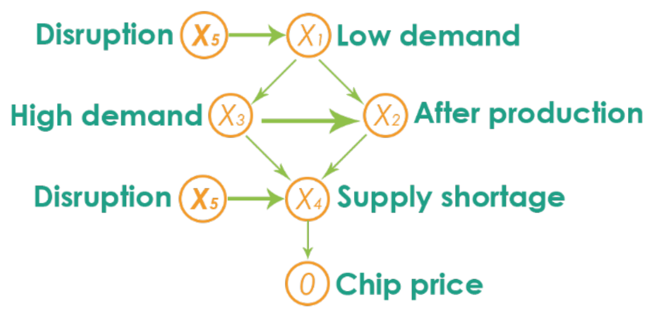

Figure 1. Causal network analysis of Microchip availability & price

The Covid-19 pandemic lowered demand for automotive suppliers and OEMs, reducing orders to microchip manufacturers (X1). Microchip manufacturers altered production in response to serve other industries (X2). As a result, when production returned to normal in the automotive industry (X3), it created a supply shortage (X4). Suppliers began to overpromise, miss delivery dates, and increase price for priority orders (O). In addition, the war in Ukraine created a second disruption impacting the availability of raw materials needed to make the microchips (X5). This simultaneously decreased availability and accelerated a price increase (O), directly affecting the automakers' bottom line. Figure 1 shows how Vizen's solution considers the experiential causal links (nodes and arrows) provided by our analysts and domain experts to create a causal network used in ML analysis to elucidate the contribution and interaction of all causal variables. The application of Figure 1. enables Vizen's software to accurately predict the supplier's lead-time delivery dates, the percentage that will be delivered in full, and the future bulk price of said microchips. This provides significant value to our clients by informing them of the best time to source and store the right quantity of raw materials at the best available price, while reducing on-hand materials and lowering excess inventory costs.

- **Conclusion.**

The core value of AI in business organizations such as automotive suppliers and OEMs lies in measuring the impacts of different causes to the bottom line. Vizen's supply chain optimization software solution combines historical forecasting, reinforcement learning and robust causal modeling for bottom-line improvements. Its robust measures of causal effects eliminate bias and use the improved insights to re-engineer the process for the best results. Ultimately, the application of Vizen's causal-AI software enables inventory optimization and cost savings.

- References or citations.

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