TRANSFORMING INVENTORY OPTIMIZATION WITH EXPLAINABLE NETWORK BASED MACHINE LEARNING

The key competitive advantage businesses want from next generation solutions involve building the right inventory level to precisely match the demand variance in coming months, thereby avoiding locking up capital in excess inventory while always meeting on time delivery. By applying Innovative Machine Learning Albeado has developed to uncover causation from interconnected data and events, businesses can arm their supply chain inventory planners with the ability to accurately predict the demand dips and spikes deep into the future.

ALBEADO

EXECUTIVE SUMMARY

For most manufacturing companies and their enterprise customers, a major portion of their capital and expenses are typically directed at building and maintaining the inventory of products they sell. Creating a goldilocks supply chain, where customers can always be guaranteed on-time delivery (OTD) without locking up huge amount of cash to build excess inventory is a strong competitive advantage for such businesses.

We believe innovative machine learning (ML) solution can play a critical role today to automate the process of identifying hidden drivers for fluctuating demand deep into the future and predict precise build plan and dynamic inventory level to assist the planner improve customer satisfaction and reduce inventory cost. While such solutions can create a prediction system that continuously evolves, based on historical demand and current economic indicators and market factors, serious challenge for existing machine learning include

- Supply chain data is notorious for being limited and sparse. For a product which has a year worth of historical data, in reality there are only 52 weekly build and pull data – an impossibly limiting number of rows and columns to create a training set for supervised ML.
- Inventory time series data specifically, is intermittent and extremely volatile, making it difficult to predict the future demand spikes and dips only with statistical correlation-based ML tools.
- Demand planning for enterprises has become significantly more complicated as the number of influencing factors increase. As a result, to the supply chain planners, customer pull data fluctuates in a seemingly unpredictable way.

This white paper reveals how Albeado's Explainable Network based Machine Learning (XNML) technology is helping supply chain planners today to resolve many of the challenges that roil the industry like dealing with seemingly sudden sharp variances in demand (or how they bunch up back to back) without adding unnecessary inventory - thereby reducing inventory cost while maintaining OTD (On-time Delivery) requirements.

PRISM® IOP Overview

Demand forecasting systems used by planners today produces significant gap with actual customer pull because they fall short in identifying and reasoning about fluctuations and trends in the demand data. As a result, they provide limited understanding of the underlying causes of demand variability for their products. In a typical supply chain planning flow, inventory optimization depends on precisely balancing the demand of a product ('pulls') weeks or months in the future to allow the manufacturer to produce enough finished goods ('pushes') to avoid time lags in production considered unacceptable by the customer, while preventing the expensive accumulation of its inventory in the warehouse.

Although it seems like a straight-forward time series prediction in theory, **Figure 1** below show how long stretches of zero-demand weeks and extreme surges of demand following low demand weeks skew the distribution of the pull values to be predicted towards zero which violates assumptions held by prediction models and traditional evaluation metrics.

This creates problems for traditional machine learning pipelines because they work under the assumption that data is ***independent and identically distributed*** **(IID)**. Figure 1B (right) clearly shows that pulls data belong to more than one population, which violates the IID assumption that all data belongs to the same distribution and makes results unreliable without appropriate adjustments. Further, the assumption that the samples are independent fails to consider the relationships *between* pull events, thus neglecting potentially useful information that could improve a model's predictive power.

Also, without proper understanding of the drivers for the changing market patterns and economic fluctuations, the planner's ability to avoid the forecasting errors is limited, often resulting in expensive inventory build-up or stock outs. Albeado's PRISM Inventory Optimization Product (IOP) not only improves prediction accuracy but explains the rationale of the demand forecast of a product ('pulls'). This allows the planner to produce enough finished goods to avoid time lags in procurement and production, while preventing the expensive build-up of its inventory in the warehouse.

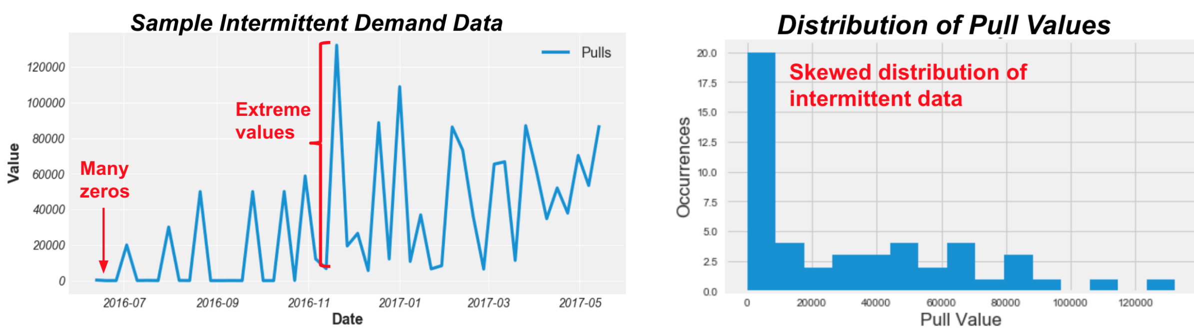


Figure 1A & 1B *- Intermittent Data – 1A (Left) shows an example trace of weekly demand data for one of Customer-X's products.*

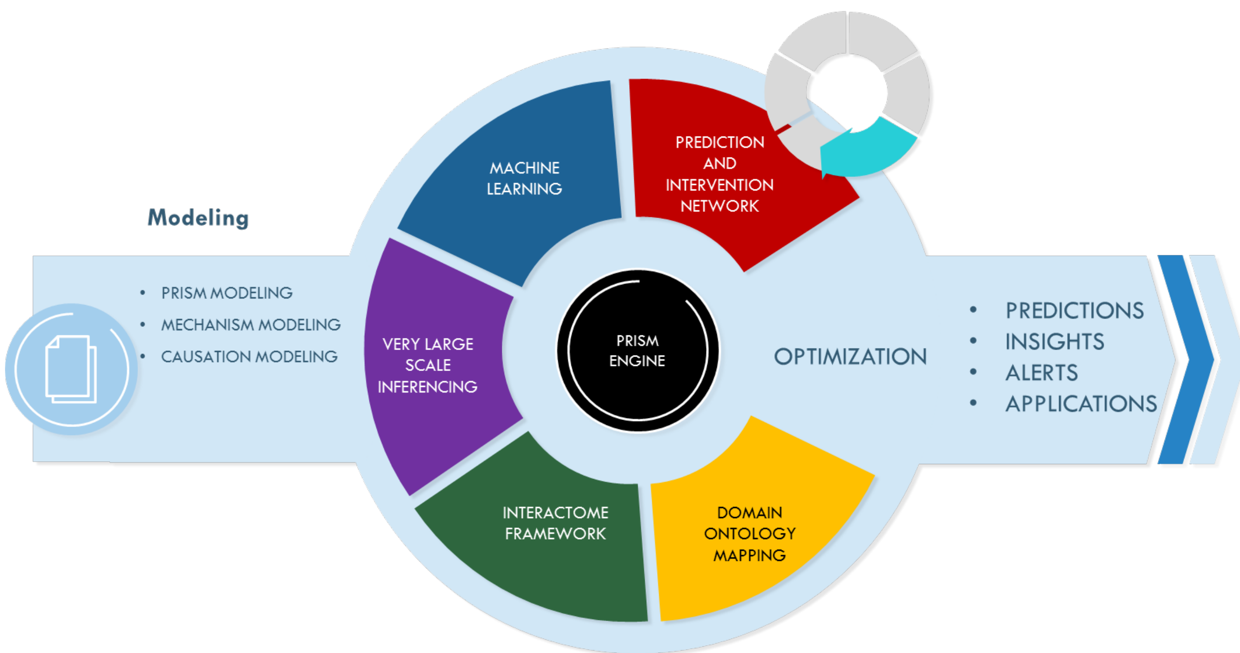
TECHNOLOGY OVERVIEW

Recognizing that most business events and social phenomena driving customer demand are influenced by and interacting with other pieces of a complex interconnection of events and actions, PRISM's solution philosophy begins with the understanding that enterprise data emanates from interactions between events and actions within and without the enterprise. Network data is generated from interactions and activities in multiple interconnected domains within the enterprise like accounts receivable, supplier payment, production schedule etc. as well as market factors and economic indices like forex data which influences the global supply chain or sectoral indices like semiconductor or biotech.

By augmenting available data sets with parameters of the multi-partite computational multi graph (called *Interactome*) built iteratively, PRISM® combines network and vector features and includes elements of standard vector space at the vertices of the graph which are interconnected via a complex setting of graph structures and topological properties. Non-obvious predictors from an interactome are calculated from multimodal feature analysis using an ensemble of analytical, modeling and reasoning techniques.

This novel machine learning framework for analyzing the interrelatedness and the structure of the complex network data driving business and social interactions also addresses the *Sparse* and *Limited data* challenge that characterizes the supply chain inventory optimization like problems. PRISM generates predictive features in multiple stages using proprietary XNML based on front-ended unsupervised machine learning and reasoning techniques.

The following diagram (Fig. 2) gives an overview of the core functional modules making up PRISM.



HOW WE GENERATE PREDICTIONS WITH SPARSE and LIMITED DATA

To address the Sparse and Limited data challenge, PRISM generates predictive features in multiple stages using proprietary XNML based unsupervised machine learning and reasoning techniques. By augmenting available data sets with multi-partite computational multi graph, PRISM® combines network and vector features and includes elements of standard vector space at the vertices of the graph which are interconnected via a complex setting of graph structures and topological properties.

The following diagram shows the typical inventory data set PRISM starts with, which consists of N-weeks of historical build and pull data. PRISM generates the XNML enhanced training set using unsupervised learning over relational network and vector features.

Historical weekly demand (push and pull) – limited and sparse training data

WEEKLY DEMAND DATA			
Dataset	**Date**	**Pulls**	**Pushes**
Training	1	Data	Data
Training	2	Data	Data
Training	3	Data	Data
Training	4	Data	Data
Training	5	Data	Data
Training	6	Data	Data
Training	7	Data	Data
Training	8	Data	Data
Training	9	Data	Data
Training	10	Data	Data
Training	11	Data	Data
Training	12	Data	Data
Training	13	Data	Data
Training	14	Data	Data

Transformed to smart, enriched training data with unsupervised XNML learning

XNML Enriched Dataset

WEEKLY DEMAND, INTERNAL & EXTERNAL DATA						Time Series Features			XNML Features			
Dataset	Date	Pulls	Pushes	DATA	DATA	Feature 1	Feature2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7
Training	1	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	2	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	3	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	4	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	5	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	6	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	7	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	8	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	9	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	10	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	11	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	12	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	13	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data
Training	14	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data	Data

KEY INNOVATIONS IN XNML LEARNING

- Patented XNML techniques find relationships between entities based on shared interactions, structural or vector attributes and grouping.

- Proprietary techniques to combine entity attributes and features of entities with *relationship*s between them and incorporating group properties and anomalies as predictive features in a combined model.
- Innovative network and graph theoretic modeling of structure and influence of relationships among entities enhance the data set with key predictors identified by iterative testing against business KPIs rather than just theoretical KPIs. Innovative graph projection techniques leverage hidden relationships without the exponential explosion as the models scale up.
- Unsupervised learning reveals anomalous relations of entities and calculates their impact to uncertainties and fluctuations. Combining entity attributes with strengths and influences of relationships between them as training data for machine learning to turbo charge predictive accuracy.
- All temporal and cross-sectional data attributes and network features are then integrated with the rest of the features for each entity so that we get the best ensemble pull forecast.

SHORT (MONTHLY) AND LONG (12-16 WEEKS) HORIZON PREDICTIONS

We produce both short-term (one month) and long-term (e.g., three additional months) predictions. The short-term predictions (aka horizons) are made with single-day time resolution (one day buckets), while the long-term forecasts are made with single-week time resolution (one-week buckets). Thus, at any given date, PRISM provides roughly 46 forecasts for every finished good in our finished goods list (~30 forecasts for every day in the next month, 16 forecasts for the 16 weeks in the next three months).

In summary, using proprietary unsupervised learning and reasoning techniques comprising XNML, Albeado's PRISM smartly enriches limited and sparse supply chain data with network-derived structural features which unlock hidden relations and influences of supply chain entities and generate strong demand predictors.

EXPLAINABILITY

Although understanding the reasoning behind predictions is quite fundamental if one plans to take action based on a prediction, ML models of today mostly appear to be a black-box to their users. Explanations of causal factors leading to such understanding also provides insights into the model, which can transform an untrustworthy model or prediction into a trustworthy one for the users. Albeado's PRISM IOP solution, as shown in the example below, helped uncover that forex volatility was a key influencer driving prediction accuracy, which remain untapped in most calculations of inventory.

HIGH ACCURACY AND EXPLAINABIILTY – BENDING THE CURVE WITH XNML

Improving explainability while maintaining a high level of learning performance for a range of machine learning techniques is challenging because of the inherent tension between machine learning performance (predictive accuracy) and explainability. The highest performing methods (e.g., deep learning) often are the least explainable, and the most explainable (e.g., decision trees) delivers poor accuracy.

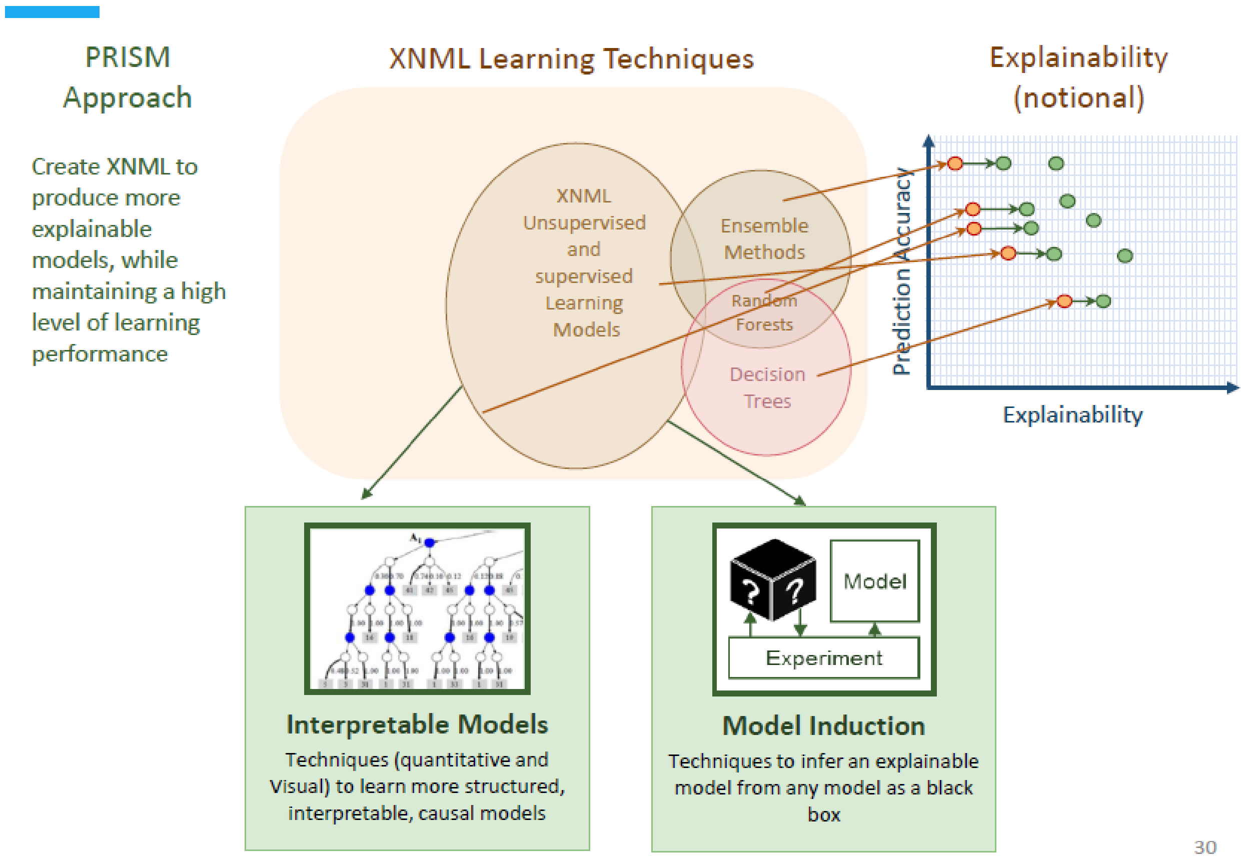


Fig. 4: Improving the Accuracy-Explainability performance curve (Adapted from DARPA Distribution under Statement "A") with Albeado PRISM XNML combining interpretable models and model induction.

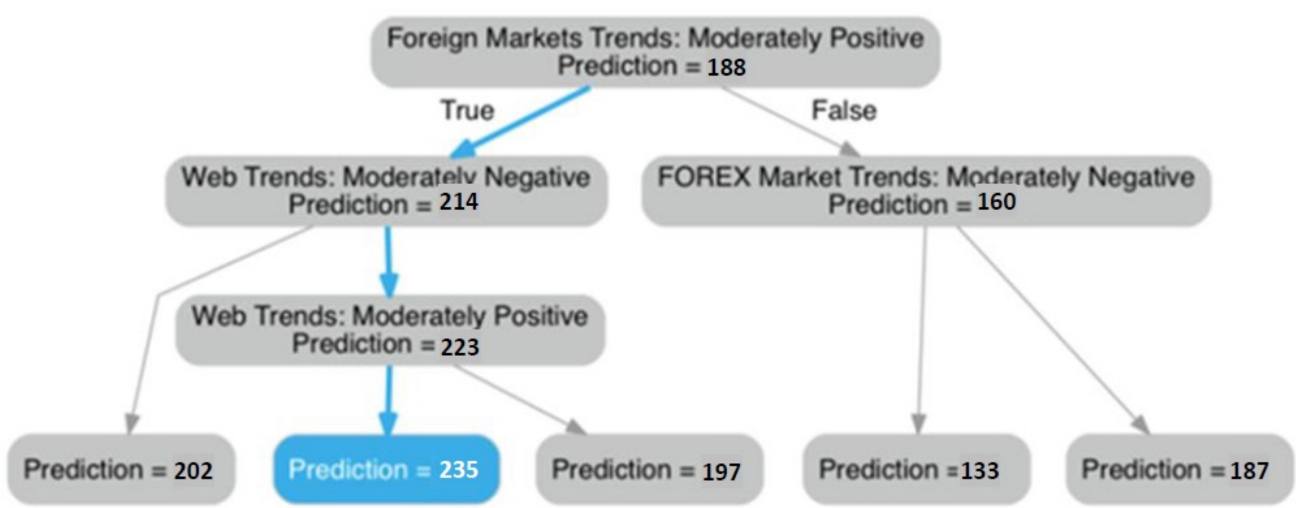
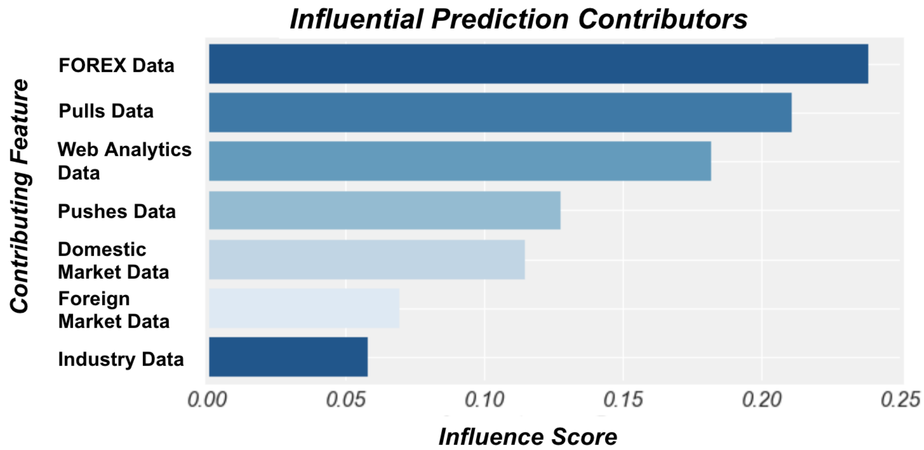


Fig. 5: Model Induction improving Explainability: Equivalent Decision Tree created through Learning from Perturbation of XNML Ensemble models



CONCLUSION

Demand prediction in the context of supply-chain is notoriously unpredictable as the inventory time series data is sparse, intermittent, extremely volatile, often lacking any clear trend or seasonality and is sensitive to the length and depth of the supply chain[1]. It is extremely hard to create reliable demand forecast 3-4 months in advance which is vital to address procurement and production lead time risk. Even advanced forecasting methods like ARIMA, STL etc. used by MRP systems therefore produce suboptimal results, especially with demand spikes which can fluctuate up to 25 times of baseline demand week over week. This results in either excess inventory locking up cash or failure to deliver on time because of inventory stock outs

Inability of existing forecasting systems to leverage sparse data (i.e., insufficient for training machine learning algorithms) make the planners' job of precisely matching future demand extremely difficult and results in sub-optimal inventory cash management and suboptimal customer experience. Supply chain planners will have to find predictors in internal and external data influencing demand fluctuations, connecting such data to calculate their hidden relationships and obtain a network view of cause and effect which are complex and increasingly non-intuitive.

Using proprietary unsupervised learning and reasoning techniques to produce super engineered XNML features, PRISM delivers accuracy boost in predicting the demand variance, the *bete noire* of all the supply chain planners and buyers. Further, using explainable ML algorithms, it provides transparency to causative rationale of the predictions without sacrificing predictive accuracy.

The commercial benefits of PRISM XNML AI and ML system however is not limited to generating accurate demand or inventory forecast to make the procurement and production planning job accurate and easier. The near real-time visibility and the new-found predictability with accuracy and explainability of the supply chain PRISM delivers is a crucial competitive advantage for organizations allowing them to react before others.

References and Related work

1. Supply Chain Forecasting: Theory, practice, their gap and the future. *European Journal of Operational Research.* 252 (2016) 1–26.
2. Another Look at Forecast-Accuracy Metrics for Intermittent Demand. *FORESIGHT.* 4 (2016) 43-46.
3. Ribeiro, M. et al. *Why Should I Trust You? Explaining the Predictions of Any Classifier.* (2016). arXiv:1602.04938
4. Lundberg, S. et al. *Consistent Individualized Feature Attribution for Tree Ensembles.* (2018). arXiv:1802.03888v1
5. Scott M. Lundberg, Su-In Lee. 'An unexpected unity among methods for interpreting model predictions.' In: arXiv preprint arXiv: 1611.07478v3 (2016).

To learn more about PRISM IOP please contact us at info@albeado.com