Demand Forecasting in Supply Chain

Topic	Forecast Demand vs. Firm Demand
Team	Team 008
Team Members	Maria Sequeira, Yuchin Chen, Balbir Singh, Rasika Teli, Harsh Kevadiya
Client information	Company Name: Avnet, Inc. Sponsoring Organization Name: Avnet Velocity Sponsoring Organization Address: 2211 S 47 th St Phoenix, AZ 85034

1. Executive Summary

This project aimed to improve Avnet's weekly shipment forecasting (Jan–May 2025) by comparing a model developed by ASU with customer-submitted forecasts. After data preparation and exploratory analysis, models including SARIMAX, Prophet, Random Forest, and XGBoost were tested, with XGBoost selected for its superior accuracy. Applied at the customer level, it enabled a direct comparison against actual shipments. The study also reviewed NASDAQ trends, which showed limited short-term influence but offered context for future planning.

2. Background

Avnet distributes electronic components and relies on demand forecasts to manage supply chain planning. However, customer-provided forecasts often diverge from actual demand due to varied ordering behaviors. This project evaluates whether a machine learning model can more accurately predict shipment demand and explores whether short-term market trends like the NASDAQ index contribute to forecast accuracy, with the aim of strengthening Avnet's planning process.

3. Problem Statement

Avnet's shipment planning depends on customer forecasts, but these often don't match actual demand. This project evaluates whether ASU's forecasting model offers more accurate weekly demand estimates for January to May 2025. It also explores if short-term NASDAQ trends influence shipment patterns, with the goal of improving Avnet's data-driven planning.

4. Data Preparation

To prepare the dataset for model training, we selected historical shipment records from the years 2023 to 2024, while excluding data from 2022, 2026, and 2027 to ensure consistency and focus on the most relevant period. The dataset contained no missing values, and duplicate entries were retained. This preparation process resulted in a total of 20,587 rows.

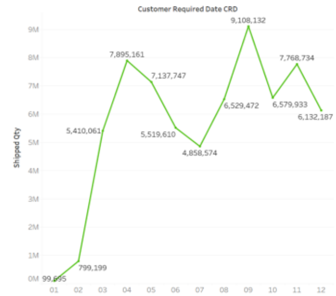
5. Exploratory Data Analysis

5.1 Historical Insight

The analysis was based on shipment data from 2023 to 2024, covering **920 unique material IDs.** A total of approximately **67.84 million units were shipped** during this period.

5.1.1 Monthly Shipped Quantity Trend

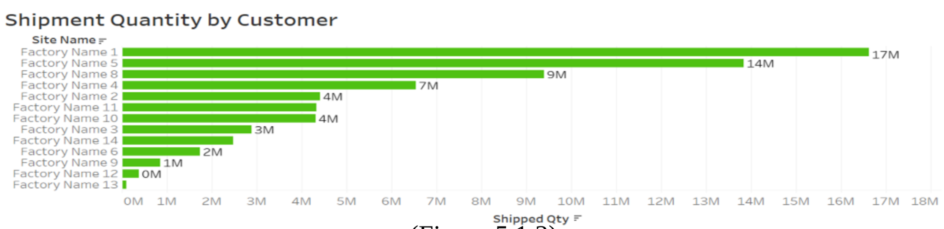
Shipment volume increased sharply from March and remained high, though with notable fluctuations. After October, the overall quantity declined slightly, but irregular patterns in demand persisted.



(Figure 5.1.1)

5.1.2 Shipment Quantity by Customer

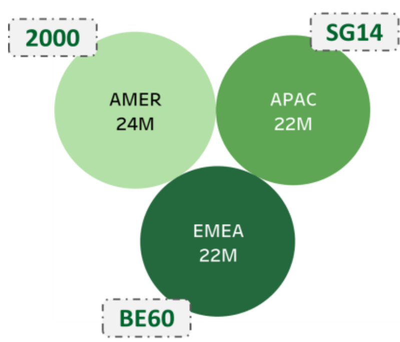
Based on the graph below the top three customers with the highest expected shipment volumes are Customer 1, Customer 5, and Customer 8.



(Figure 5.1.2)

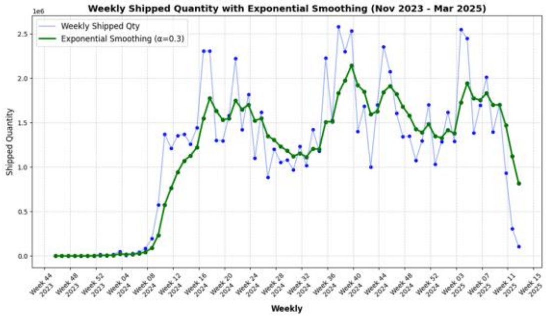
5.1.3 Shipment Quantity by Region

The chart illustrates shipment quantities across different regions. The AMER region recorded the highest volume at 24 million units, while both APAC and EMEA followed closely, each with approximately 22 million units.

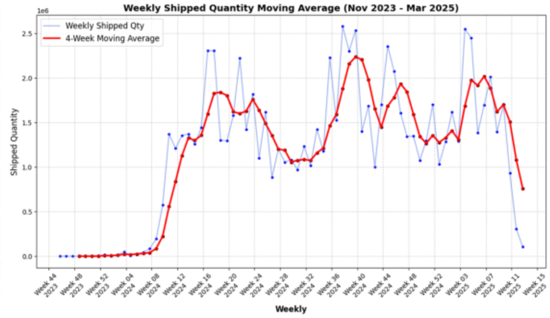


(Figure 5.1.3)

6. Trend Analysis



(Figure 6.1)



(Figure 6.2)

We applied two statistical methods, Exponential Smoothing (Figure 6.1) and Moving Average (Figure 6.2), to better understand the shipment trend. Both methods reveal that the trend is non-linear and exhibits significant fluctuations. This suggests that **a more flexible, non-linear model would be more appropriate for accurate forecasting.**

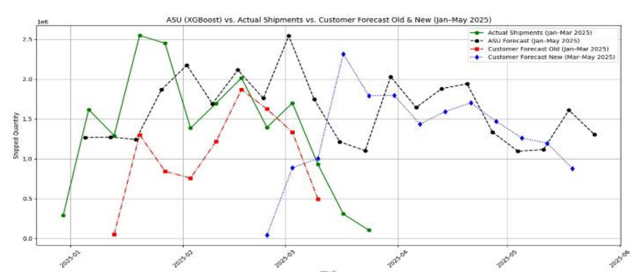
7. Model Evaluation

We tested a few different models to forecast Avnet's weekly demand from January to May 2025. **SARIMAX** helped identify general trends and seasonality **but didn't adapt well beyond the training period, leading to less reliable results after March** (MAPE: 0.5786%, **RMSE: 803,865**).

Prophet allowed for trend changes and holidays; however, due to limited historical data, **it tended to overextend past trends and failed to capture week-to-week fluctuations in demand** (**MAPE: 209.98%, RMSE: 1,069,484**).

Random Forest captured non-linear patterns in the data but missed some of the seasonal and cyclical behavior. **However, it failed to extend the learned trend and predicted near-zero values after March**, due to conservative averaging and a lack of temporal awareness (**MAPE: 298.96%, RMSE: 5,932**).

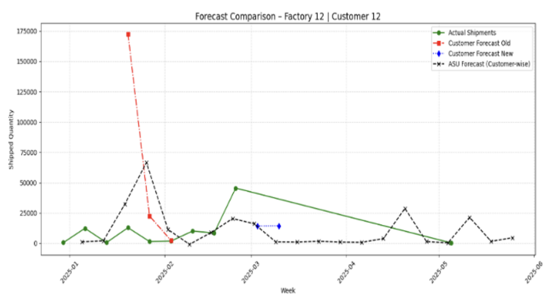
XGBoost was chosen as the final model. Its MAPE was at 2.05%, and it handled changing demand patterns and customer differences more effectively, making it a better fit for the type of variation we observed in Avnet's shipments.
(**MAPE :2.05%, RMSE: 768,209**)



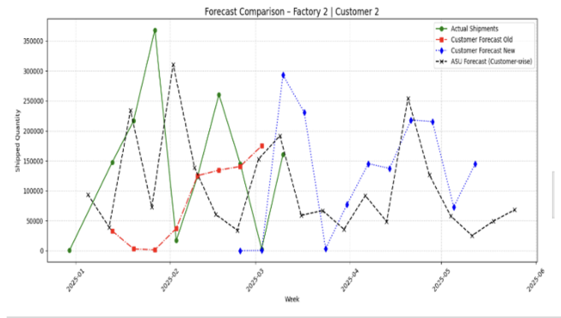
(Figure 7.1)

8. Customer-Wise Forecast Behavior in Avnet's Planning

To better understand forecast challenges, we analyzed customers with distinct behaviors. Instead of focusing only on accuracy, this analysis reveals how customer inputs vary and how our ASU model responds more consistently.



(Figure 8.1)



(Figure 8.2)

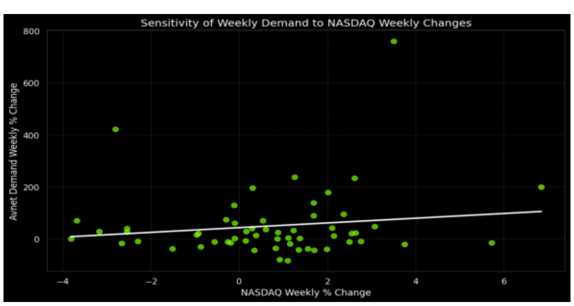
Customer 12 (Figure 8.1) significantly over forecasted demand early in the year, with a sharp spike that never materialized. Even the updated forecast failed to align with actual shipments, while the ASU model tracked the true demand more realistically and avoided unnecessary overproduction.

Customer 2 (Figure 8.2) under forecasted early demand, missing a clear spike. Although later updates improved slightly, they still lagged. In contrast, the ASU model responded earlier and supported better preparedness.

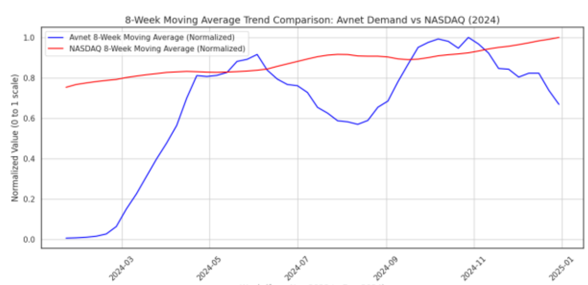
These patterns show that forecast behavior varies widely by customer. Relying only on their inputs can introduce risk. The ASU model adds consistency enabling smarter decisions and proactive planning across the supply chain.

9. NASDAQ Analysis in Avnet's Forecasting

To explore external factors that might influence Avnet's demand, we looked at the NASDAQ index as a potential indicator. Since many of Avnet's customers are in the tech sector, changes in NASDAQ could reflect shifts in business confidence.



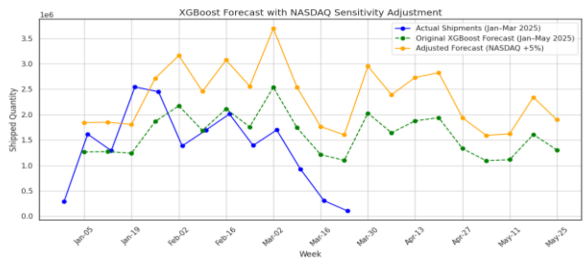
(Figure 9.1)



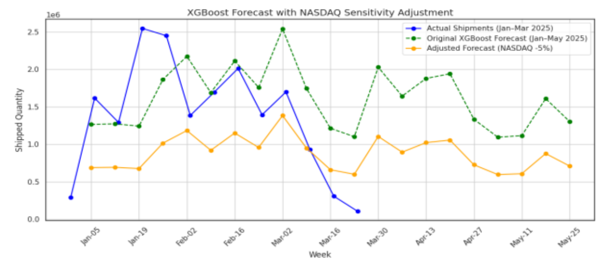
(Figure 9.2)

The scatter plot (Figure 9.1) shows a weak positive relationship between weekly NASDAQ and Avnet demand changes, suggesting that while there's some connection, it's not strong enough to explain demand on its own.

Using an 8-week moving average (Figure 9.2), we compared broader trends. We observed that Avnet demand sometimes moved in line with NASDAQ shifts, especially during mid-2024, hinting at some influence during certain periods.



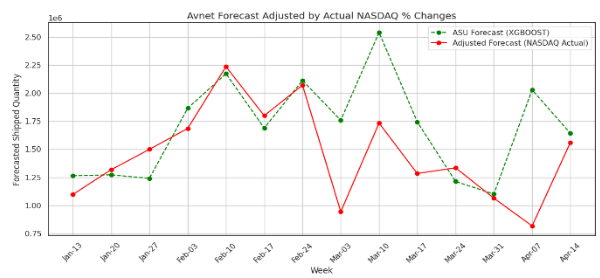
(Figure 9.3)



(Figure 9.4)

To test this further, we adjusted our XGBoost forecast based on hypothetical ±5% NASDAQ movements (Figures 9.3 & 9.4). This helped us see how economic optimism or caution could impact shipment expectations.

Finally, we applied actual NASDAQ data to our forecast (Figure 9.5). While the adjustment aligned better with the actual model in some weeks, it had limited impact in others. This suggests NASDAQ data may be useful as a secondary input—helpful for planning, but not a standalone predictor.



(Figure 9.5)

10. Conclusion

This project explored advanced forecasting methods to enhance Avnet's weekly demand predictions. Among the models evaluated, XGBoost demonstrated superior performance in capturing demand variability compared to SARIMAX, Prophet, and Random Forest. The ASU-developed model consistently outperformed customer forecasts, underscoring the value of machine learning in improving forecast accuracy and reducing planning risk. Although the NASDAQ index showed only a weak correlation with demand, it may still serve as a supplementary indicator. Overall, the integration of data-driven models and customer-level analysis offers a more robust foundation for Avnet's demand planning efforts.

Reference

Avnet. (n.d.). *Avnet Americas*. Retrieved from https://www.avnet.com/americas/