Demand forecasting

Specialized co-manufacturer of beauty and personal care products

Streamlined the demand forecasting process by leveraging advanced forecasting algorithms and developed a unique method to handle situations of intermittent demand

Specialized co-manufacturer of beauty and personal care products needs demand forecasting

Picture this…

You're looking to develop an automated, data-driven intermittent demand forecasting model for their top-10 customers (85% Sales share) to optimize Material Resource Planning and ensure efficient order fulfillment. Growing rapidly in recent months, but their forecasting method was inadequate. They relied on customer-level conversations to predict future demand, which only gave them a short-term outlook of two to three months.

You turn to Accordion.

We partner with your team to streamline the demand forecasting process by leveraging advanced forecasting algorithms and developed a unique method to handle situations of intermittent demand , including:

1) Leveraging pattern recognition to identify and aggregate similar SKUs with limited historical data, resulting in a reliable and robust forecast
2) Leveraging a novel algorithm to address the challenge of highly irregular & intermittent demand data for SKUs to forecast 'zero-demand' months
3) Leveraging advanced forecasting models such as FbProphet, ARIMA, SARIMA, Holt's etc. to forecast customer-SKU and customer-product type monthly demand forecasts for the next 12 months
4) Developing an Excel-based dashboard for visualizing and analyzing forecasted demand at the SKU, product category, and customer level
5) Improving order fulfillment planning by providing monthly forecasts, ensuring timely availability of raw materials and resources at a granular level

Your value is enhanced.

- You have reduced manhours required for baseline forecast generation from 2 weeks to 1 day facilitating swift decision-making
- You have achieved high accuracies of ~90% in forecasting the demand's monetary value compared to the actual demand over a 12-month period
- The data-driven monthly demand forecast of next 12 months for the top-10 customers aided in yearly budget planning and strategic targeting

DEMAND FORECASTING

KEY RESULT

- Reduced manhours forecast generation from 2 weeks to 1 day
- Achieved high accuracies of ~90% in forecasting
- Monthly demand forecast of next 12 months for the top-10 customers aided

VALUE LEVERS PULLED

- Demand forecasting
- 12 months planning dashboard

Demand forecasting for beauty and personal care products co-manufacturer

Situation

- The client had been growing rapidly in recent months, but their forecasting method was inadequate. They relied on customer-level conversations to predict future demand, which only gave them a short-term outlook of two to three months
- Partnered with the client to develop an automated, data-driven intermittent demand forecasting model for their top-10 customers (85% Sales share) to optimize Material Resource Planning and ensure efficient order fulfillment

Accordion Value Add

- Leveraged pattern recognition to identify and aggregate similar SKUs with limited historical data, resulting in a reliable and robust forecast
- Leveraged a novel algorithm to address the challenge of highly irregular & intermittent demand data for SKUs to forecast 'zero-demand' months
- Leveraged advanced forecasting models such as FbProphet, ARIMA, SARIMA, Holt's etc. to forecast customer-SKU and customer-product type monthly demand forecasts for the next 12 months
- Developed an Excel-based dashboard for visualizing and analyzing forecasted demand at the SKU, product category, and customer level
- Improved order fulfillment planning by providing monthly forecasts, ensuring timely availability of raw materials and resources at a granular level

Impact

- Reduced manhours required for baseline forecast generation from 2 weeks to 1 day facilitating swift decision-making
- Achieved high accuracies of ~90% in forecasting the demand's monetary value compared to the actual demand over a 12-month period
- The data-driven monthly demand forecast of next 12 months for the top-10 customers aided in yearly budget planning and strategic targeting

Methodology: RSD - data availability matrix

Customers	Data Availability Bucket # of SKU [0-5] months	[6-11] months	[12-23] months	>=24 months	Total # of SKU
Customer 1	5				5
Customer 2	113	12	4	3	132
Customer 3	24	21	3		48
Customer 4	26	10	13		49
Customer 5	2	1	1		4
Customer 6	61	30	5		96
Customer 7	3	4	3	4	14
Customer 8			3		3
Customer 9	23	5	11		39
Customer 10	38	2			40
Grand Total	**295**	**85**	**43**	**7**	**430**

RSD[1]-Data availability matrix

RSD vs Data Availability	>100% RSD	60-100% RSD	<60% RSD
> 24 Months			
12-24 Months			
<12 Months			

Increasing confidence in forecasting

Highly intermittent demand, necessitates prioritizing SKUs based on Revenue contribution and RSD-Data availability Matrix, while remaining SKUs are aggregated to Product type and forecasted at that level

1. RSD – Relative Standard Deviation

Models leveraged

Time series forecasting models leveraged

- ARIMAX
- SARIMAX
- Weighted Average
- Holt's
- Holt Winter's
- FbProphet

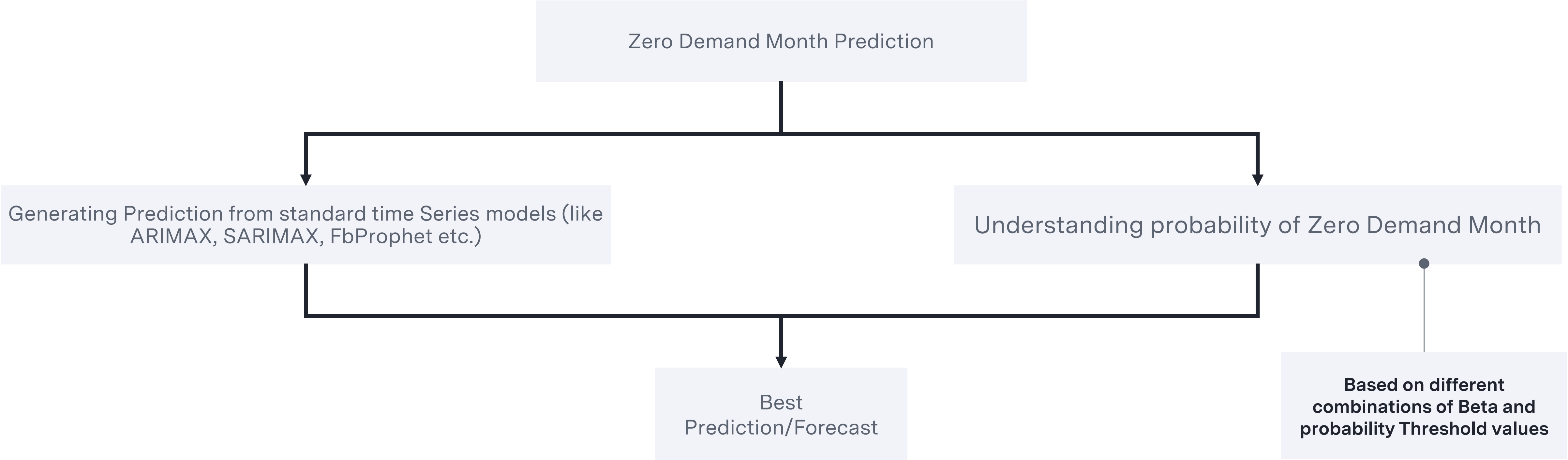
Specialized time series models for intermittent demand forecasting

- CROSTON
- CROSTON TSB
- ADIDA
- IMAPA

While normal time series forecasting algorithms do well for consistent data, they tend to miss out on month of zero demand hence we need a specialized time series algorithms

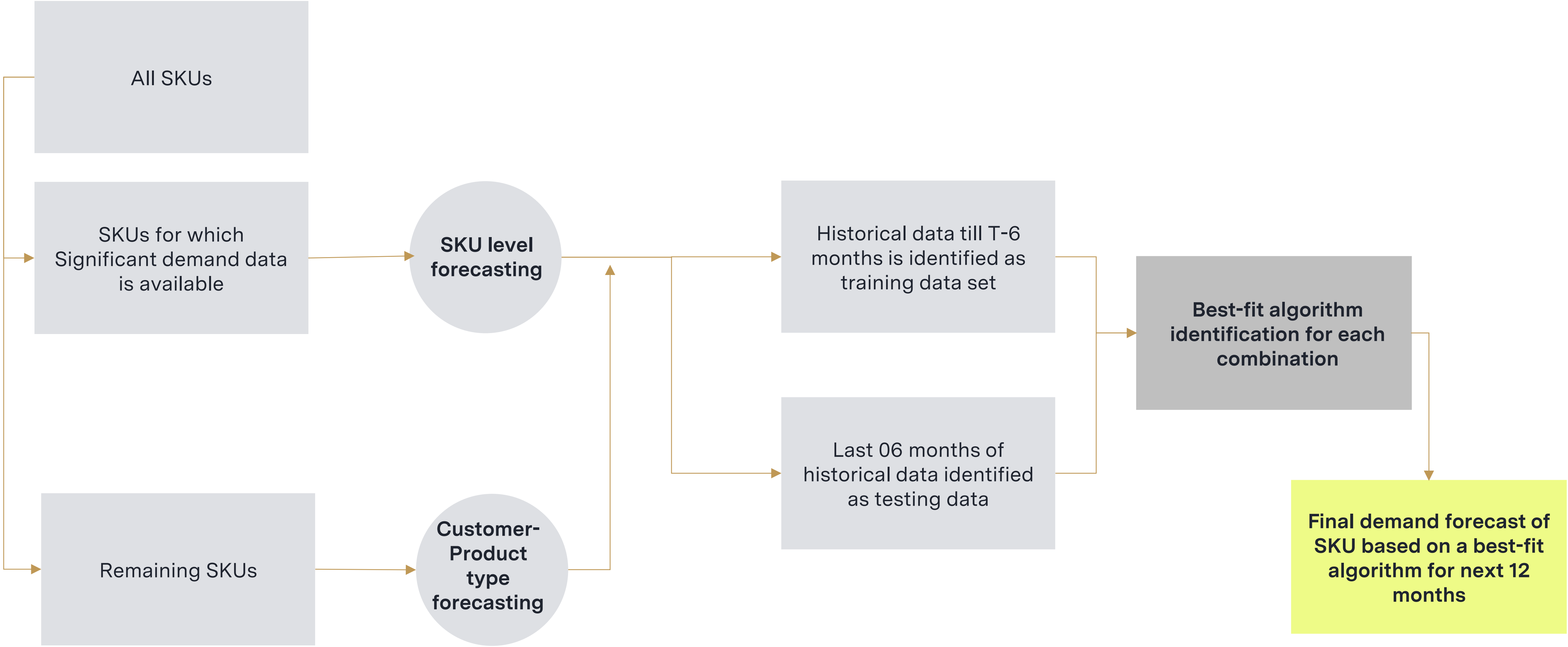
Unique proposition for intermittent demand

- Considering the intermittent data availability across SKUs and product types, we included an additional simple exponential time series model to detect the probability of having a zero-demand month.
- Based on different hyperparameter values (Beta) and threshold values for the calculation of the probabilities, we combined the results (test set predictions and future forecasts) of our traditional time series models along with this probability function to arrive at the best prediction/forecast values.



As the predicted values of specialized models were not ideal, we are taking prediction values from standard time series models, and we are adding a layer from Croston TSB model to predict the probability of demand of a month being zero.

Overall framework & methodology



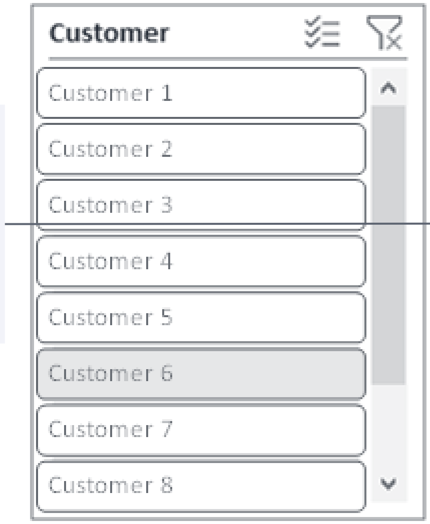
1. Algorithm considered include ARIMA, Holt-Winters –Seasonal, Holt-Winters – Non-seasonal, Simple Exponential Smoothening and FB Prophet, Neural Prophet Best-fit algorithm is identified based on the MAPE of each algorithm

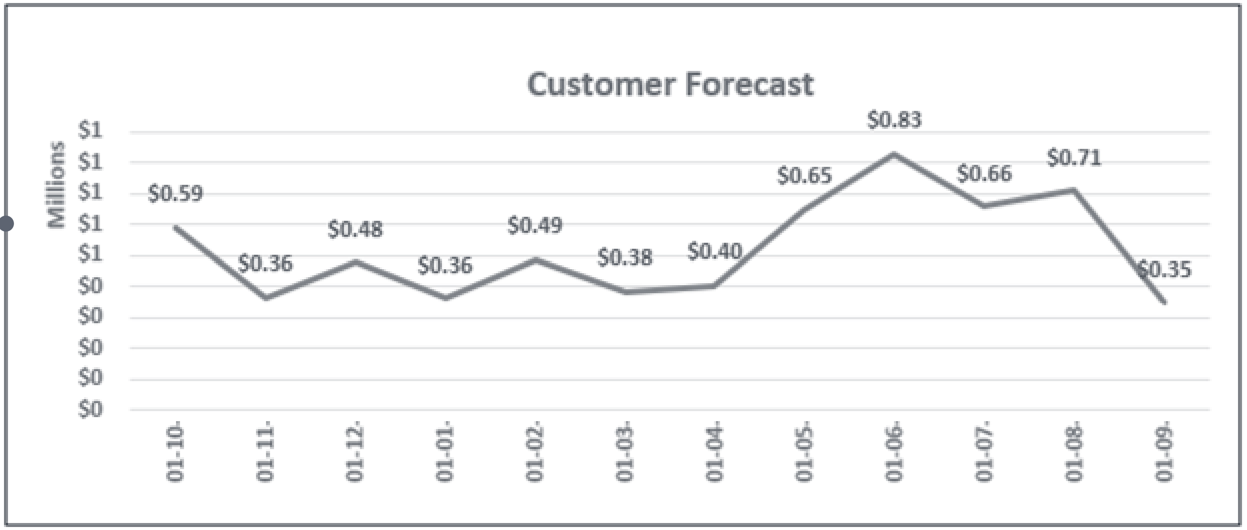
ILLUSTRATIVE

Customer level monthly demand forecast

Customer	10/1	11/1	12/1	1/1	2/1	3/1	4/1	5/1	6/1	7/1	8/1	9/1	Grand Total
Customer 1	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
Customer 2	$1.46	$0.75	$0.74	$1.67	$0.96	$0.97	$0.97	$0.92	$1.24	$1.62	$1.86	$1.56	$14.71
Customer 3	$2.62	$2.82	$2.97	$2.98	$3.67	$3.11	$3.44	$3.55	$3.73	$3.67	$4.42	$3.91	$40.89
Customer 4	$3.25	$3.66	$3.79	$3.86	$4.12	$4.12	$4.26	$4.54	$4.70	$4.83	$4.92	$5.11	$51.16
Customer 5	$0.48	$0.46	$0.47	$0.47	$0.61	$0.55	$0.66	$0.62	$0.62	$0.61	$0.63	$0.68	$6.84
Customer 6	$0.59	$0.36	$0.48	$0.36	$0.49	$0.38	$0.40	$0.65	$0.83	$0.66	$0.71	$0.35	$6.25
Customer 7	$0.77	$0.48	$0.93	$0.71	$0.78	$0.57	$0.76	$0.65	$1.25	$0.65	$0.73	$0.36	$8.62
Customer 8	$0.08	$0.08	$0.06	$0.06	$0.08	$0.12	$0.03	$0.07	$0.06	$0.03	$0.06	$0.04	$0.77
Customer 9	$0.58	$0.59	$0.60	$0.61	$0.62	$0.63	$0.64	$0.65	$0.66	$0.67	$0.68	$0.69	$7.63
Customer 10	$0.06	$0.14	$1.16	$0.97	$0.23	$0.05	$0.23	$0.61	$1.50	$1.19	$0.28	$0.05	$6.46
Grand Total	**$9.87**	**$9.34**	**$11.20**	**$11.68**	**$11.56**	**$10.50**	**$11.39**	**$12.26**	**$14.59**	**$13.93**	**$14.28**	**$12.75**	**$143.34**

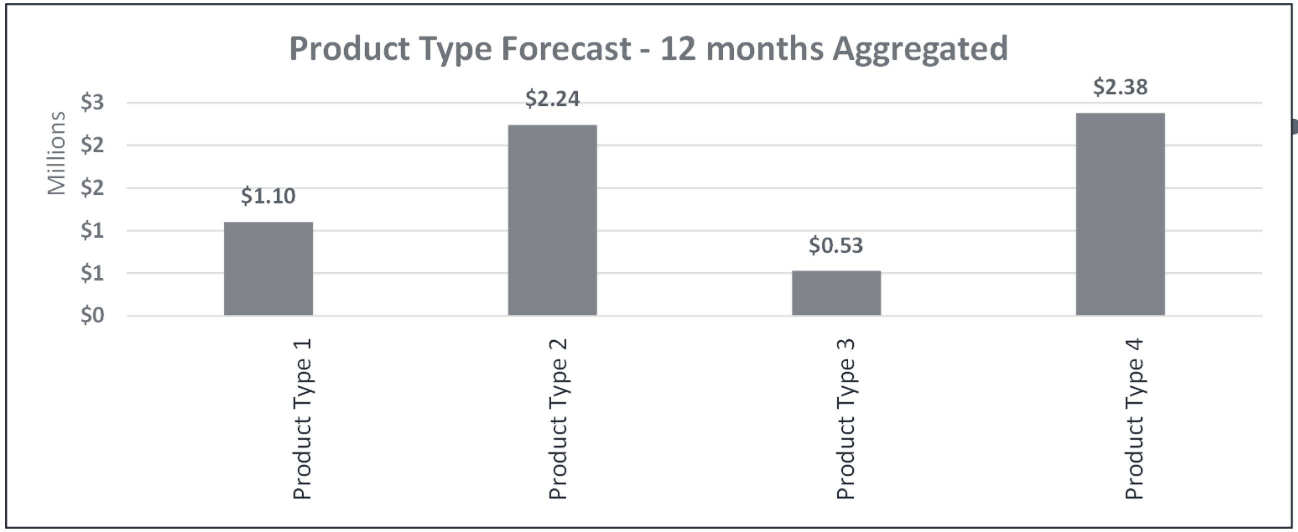
Customer level overall monthly projections for top-10 customers to maximize profitability and customer satisfaction.





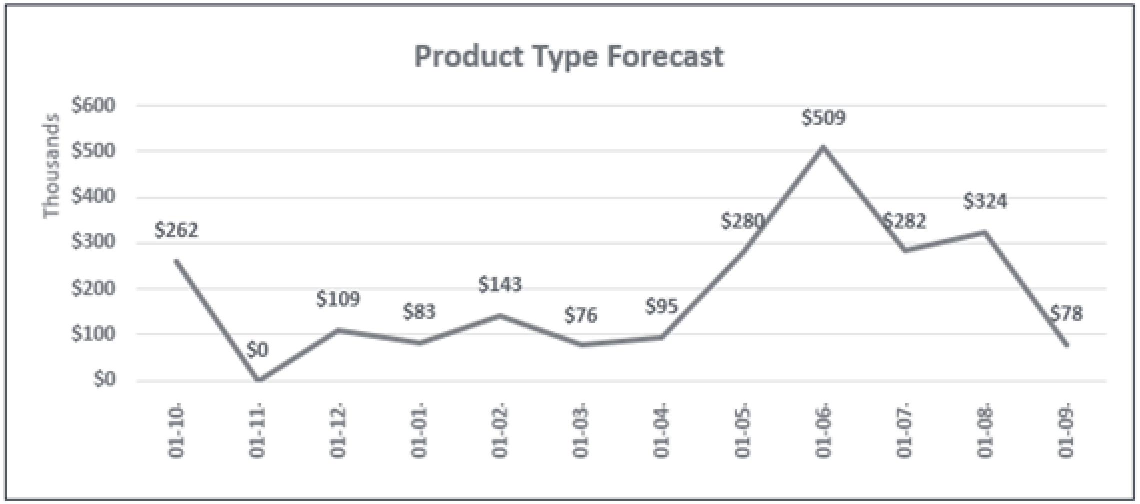
Overall monthly demand forecasts for top-10 customers to provide broader level view

Monthly product type level demand forecast



Aggregated Product type Level forecast to maximize profitability and efficiently plan strategy for MRP.

Overall **monthly demand forecasts** for all the product categories of the customer to provide granular level view



Learnings

Minimal Business involvement

- Automated aggregation of SKU based on versions
- Automated classification of forecasting approach i.e., individual SKU vs Product Type level data
- Requirement of minimal business inputs

By leveraging automation for multiple phases, very low run time and faster output refresh process was achieved

Novel Methodology for intermittent demand

- Considering limited forecasting ability for classical models for intermittent SKUs and product categories, we created another model to estimate probability of being a zero-demand month.
- A simple exponential time series model was leveraged to estimate the probability.
- Unique probability threshold for each SKU and product category was determined to factor in their individual characteristics.

Leveraging this approach led us to a better visibility into demand patterns for SKUs

Accuracy of the model greatly depends on the data availability so over the time accuracy will improve, while various business inputs will help in improving the accuracy for new SKUs.