Making AI Pervasive to Deliver Personalized Sales Assortment Recommendations
MAKING AI PERVERSIVE TO DELIVER PERSONALIZED SALES ASSORTMENT RECOMMENDATIONS

Small, independently owned “mom & pop” convenience stores are still the most prevalent format for consumer packaged goods (CPG) sales in South Asia. Hence, this segment is a critical distribution channel in the sales cycle. With shelf space at a premium it is essential to have the right product in the right store at the right time through effective placement and assortment. Consumers switching to a competing brand typically leads to not just a lost sale, but a steep erosion in customer lifetime value.

Therefore CPG companies rely on data-driven insights to ensure that every SKU in an assortment performs well. Providing their field sales agents and distributors with the right assortment recommendations can have additional positive sales impact. Responding to this business problem, Mindtree used artificial intelligence to help in assortment optimization and to equip the sales teams with a powerful tool.

The customer was a major global CPG producer with more than 1 million stores and 1,100 products across over 65 brands in more than 35 product categories. In this operating environment, ensuring optimal assortments in stores and providing correct recommendations is very challenging but is core to the CPG’s business. Each field sales agent in the region covers at least 30 stores and travels an average of 25
miles per day. Thus, the sales agent can spend only 5 to 7 minutes in each store. The time is used to nurture retailer relationships, discuss stock requirements and inspect merchandising displays and product placement orientation. There is an acute need to help agents optimize the time spent at each retailer. It is imperative to enable the field force with smart tools that can help selling by providing the ideal must-sell and cross-sell recommendations.

There were three key requirements for the solution. First, provide greater accuracy for ensuring better brand recall and market segmentation that could improve quality of recommendations. Second, ensure greater sales realization by providing accurate recommendations for higher sales revenue at the counter. Third, enable customizable solution to provide personalized recommendations that adjust for complexity related to geographies, stores and regions.

Mindtree designed a solution to provide targeted store-specific assortment recommendations that each sales agent could access on a mobile device, any day and time. The assortment plan provides the specific SKUs and quantities the agent should suggest. Recommendations are customized for each specific store and the time of year, thus cutting down the needed discussion time with the store owners on what to sell on a given day.

The recommendations are generated by a deep learning model and include customizations based on sales trends by region and specific neighborhood, specific store, time of year and other factors. The model was developed using a classification-based feedforward deep neural network. The self-learning model uses a variety of data sources that include store performance, store behavior and neighborhood behavior. Multiple neural networks are executed for various store segments using a cloud environment to condense 950 instance hours to 10 hours. The solution was built using technology components and libraries such as TensorFlow, the AWS cloud, Amazon EC2 Linux platform, Ubuntu and MySQL database technology.

The system is currently generating more than 2 million recommendations per quarter to ensure on-shelf availability and assortment growth at various store-segment levels. It has improved recommendation accuracy (measured by the sales revenue generated by the recommended assortment plans) using real-time market data with deep learning. The solution has delivered a twofold increase in incremental sales across this segment for its client, plus a 5 percent rise in achievement rates for target recommendations. Another sign of the project's success is that the rollout was accelerated, and six months after the launch the system was generating twice the initial number of recommendations.