

Improved Demand Forecasting Accuracy with Advanced AI & ML Models

Fortune 100 Global Sportswear Brand



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AI-Powered Demand Forecasting: Unlocking Millions

For large manufacturers and retailers, accurate demand forecasting has been a long-standing requirement for success. Category and inventory managers need unbiased, data-driven insights in order to avoid losses from stockouts, unsold inventory and markdowns to maximise revenues.

However, to effectively achieve this, a holistic, multi-level solution that takes into account various internal streams of data along with external factors both micro and macro, is imperative. With Affine's 360 degree approach, powerful AI and ML solutions allow for accurate demand forecasting, unlocking millions in revenue.

The Problem

A Fortune 100 global sportswear brand wanted to develop a demand forecasting engine at two product hierarchy levels, customer-category and style level, to help in inventory allocation planning using accurate product demand estimations.

The client's existing systems offered only a 60-65% forecasting accuracy, which was sub-optimal.



The Solutions:

In order to build an effective demand forecasting engine, forecasting would need to happen at two levels:

1. Customer-Category Level (High Level) - to forecast overall demand in the market for individual categories using Deep Learning models.

2. Style Level (Granular Level) - to forecast demand for each individual SKU to be manufactured using Machine Learning models.





		LSTM FEATURE CREATION	MODEL DEVELOPMENT
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Analytical Framework: Category Level Forecasting

As described in the above analytical framework for category-level forecasting, the analytical dataset consisted of sales data rolled up at the account level, as well as derived variables from internal and external data that took into account macro-factors affecting overall sales at the category level. External factors like GDP, CPI, PPP, location-specific demographic make-up, income, etc. were fed into the deep learning model.

The model was built by training on 70% of the available dataset and predictions were tested against 30%. Among the various deep learning models tested such as ARIMA/ARIMAX and LSTM, the latter emerged as the champion model with the best results.



LSTM Architecture



Forecast Trend Dashboard



600 models were built and Grid Search was used to optimize and automate the models.

Analytical Framework: Style Level Forecasting





Demand forecasting at the style level was split into two types:

- 1. Forecasting for existing styles
- 2. Forecasting for new styles

For existing styles, the factors that were taken into account were the product attributes, historical sales performance, macroeconomic data, trends and seasonality of styles and supply chain.

As can be seen in the graph above, these styles were further classified into 4 types depending on how long each style has been in the market and its sales volume.

Various ML regression and time series models like Linear Regression (LR), Random Forest (RF), Generalized Additive Mode (GAM), etc. were tested and the champion model for each type was selected.

For new styles, historical sales performance being unavailable, launch data (if any) was used instead. Additionally, the cannibalization effect of each style was accounted for in the model. This would enable a smarter demand forecast and allow an optimal launch date to be arrived at for each new style.

RF and XGBoost based ML models were tested and the champion model arrived as the suitable model.

Testimonial

"Affine is our preferred partner in Analytics. We owe it to them for our success, we now have reduced stockouts with better inventory management, thanks to their Demand Forecasting Engine and accuracy in Predictive Analytics.

We were able to understand the different dynamics driving the market demand with the help of Affine's Deep Learning Models, allowing us to proactively respond to changing market scenarios."

Analytics Head, USA Global leader in the Sportswear Industry



Outcome

A launch tool was developed to help in achieving pertinent supply planning with fewer manual interventions for better inventory decisions.



Analytical Framework: Style Level Forecasting

Analytical Framework: Style Level Forecasting



The above is a screenshot of an example of one such simulation, specifically for new launches of collectible and limited-edition shoes. The simulation also allowed for variations in the launch plans of different styles.





About Affine

Affine is a Data Sciences & AI services provider, offering capabilities across the analytical value chain from data engineering to analytical modelling and business intelligence to solve strategic & day to day business challenges of organizations world-wide.

Affine is a strategic analytics partner to medium and large-sized organizations (majorly Fortune 500 & Global 1000) around the globe that creates cutting-edge creative solutions for their business challenges.

Affine develop solutions for multiple verticals such as Oil & Gas, Manufacturing, High-Technology, BFSI, Media & other verticals and is respected as one of the Marquee names in the "Consultancies for Transformation" space.

Talk to Our Supply Chain Experts

Discover how Affine can support your business transformation journey.



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