International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Mastering Demand Forecasting with Gradient Boosting and Random Forest

Hiranmayee Panda

B. Tech Student, Department of IT, GMR Institute of Technology, Rajam-532127, Andhra Pradesh, India
Email: 21341A12A2@gmrit.edu.in

ABSTRACT

Demand forecasting involves predicting the future demand for a product. With increasing competition among retailers, companies are increasingly turning to predictive analytics techniques to lower costs and boost productivity and profit. Overstock and stock shortages pose significant challenges for companies, leading them to address these issues through demand forecasting. By utilizing historical data, demand forecasting estimates sales increases and decreases for specific products, aiding in demand planning and reducing confusion around production quantities. Exploring various types of demand forecasting, understanding factors influencing it, and overcoming challenges associated with forecasting are essential. To predict product demand accurately, a machine learning model is constructed using methods like random forest and gradient boosting. Training this model with previous year data enables businesses to optimize stocks, cut costs, increase product sales, boost profits, and gauge customer loyalty. The benefits of demand forecasting extend beyond manufacturers to retail shop owners and customers, making it applicable to any product manufacturing business aiming for substantial profits.

Keywords: Machine Learning, historical data, demand forecasting, demand planning, machine learning model, random forest, gradient boosting, optimize stocks.

INTRODUCTION

In the world of supply chains, knowing what customers will want in the future is like having a crystal ball for success. Demand forecasting helps us in pursuing it. Demand forecasting is a systematic process of estimating the future demand for a product or service.

Here we'll break down the basics of demand forecasting and show how it can help companies keep just the right amount of products on hand, make customers happy, and stay competitive in the market. Accurate demand predictions also assist in efficient resource use, risk management, and smart decision-making across different business areas.

This paper explores the integration of two robust ensemble learning techniques Gradient Boosting and Random Forest revealing their crucial role in navigating the intricacies of consumer behaviour, global markets, and economic fluctuations.

Accurately predicting product demand yields significant benefits, enabling businesses to optimize inventory, enhance production efficiency, and streamline supply chain operations. This precision minimizes the risks of overstocking or stockouts, resulting in cost savings and improved customer satisfaction. Overall, accurate demand forecasting empowers businesses to make informed decisions, reduce operational inefficiencies, and navigate market dynamics with greater adaptability.

RESEARCH APPROACH

Accurate sales forecasting for new products holds great significance for fashion retailers as it enhances overall management efficiency and customer satisfaction. In this study, the paper introduces a two-layer (TLs) model designed to forecast the total sales of new products. The initial layer involves estimating demand through linear regression (LR). In the second layer of the model, sales are not only influenced by demand but also by inventory levels. To address this two-layered (TLs) model, feature selection is tackled using a gradient-boosting decision tree method (GBDT). Considering product heterogeneity, a mixed k-means algorithm is employed for product clustering, and a genetic algorithm is utilized for parameter estimation within each cluster. The model is validated using real-world data from a Singaporean company. Experimental results demonstrate the superiority of our model over LR, GBDT, support vector regression (SVR), and artificial neural network (ANN) in most instances. Additionally, two key indicators—the average conversion rate and the marginal conversion rate—are introduced to assess product competitiveness and determine the optimal inventory level. These indicators offer valuable insights for decision-making among fashion industry managers.

METHODOLOGY:

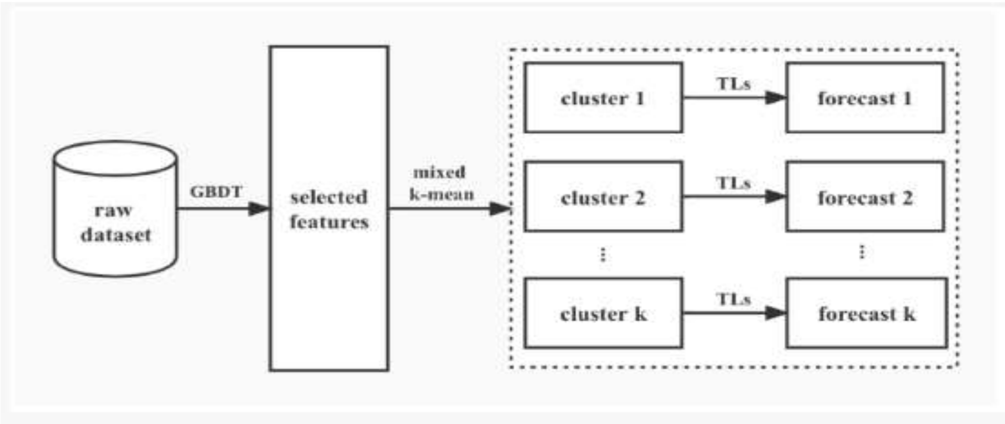

Fig-1: The schematic workflow proposed methodology.

It is suggested to use the two-layer (TLs) model to forecast the overall sales of new fashion items. To determine the products' demand, linear regression (LR) is employed in the first layer. Sales are modelled in the second layer as a function of inventory level and demand. The gradient-boosting decision tree method (GBDT) is used for feature selection in order to solve the TLs model. To take into account the variability in products, a mixed k-mean technique is used for product clustering.

A genetic method is used in each cluster for parameter estimation. In most cases, the model outperforms LR, GBDT, support vector regression (SVR), and artificial neural networks (ANNs) when tested on real-world data from a Singaporean corporation.

Two indicators, the average conversion rate and the marginal conversion rate, are developed to measure product competitiveness and explore the optimal inventory level, respectively. The methodology involves using a two-layer model with LR and GBDT for demand estimation and feature selection, respectively. It also includes product clustering, parameter estimation, and the development of indicators for decision-making in the fashion industry.

RESULTS

Category	Method	Cluster 1		Cluster 2		Cluster 3		Total	
		MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE
Shoes	TLs	**0.1531**	**6.3392**	**0.1359**	**6.9151**	**0.1481**	**4.5365**	**0.1482**	**5.6539**
	LR	0.2610	10.2327	0.2861	9.4790	0.2012	5.6482	0.2392	8.1336
	GBDT	0.1648	8.2280	0.1381	7.7411	0.1656	5.3156	0.1609	6.8932
	SVR	0.1631	9.2175	0.1482	10.0306	0.1530	5.8745	0.1564	7.9057
	ANN	0.2134	9.2214	0.2491	10.5849	0.1787	5.6153	0.2042	7.8846
Belts	TLs	0.1468	8.1172	**0.1488**	**6.3018**	**0.1365**	**3.8445**	**0.1466**	5.9736
	LR	0.1110	4.8785	0.1559	6.4324	0.1537	4.2487	0.1530	5.9648
	GBDT	0.1763	8.6786	0.1606	8.0955	0.1526	4.6342	0.1602	7.5236
	SVR	0.2134	9.6330	0.1934	11.8215	0.1457	4.8524	0.1862	10.4831
	ANN	**0.1087**	**4.1958**	0.1557	6.4796	0.1476	4.0534	0.1516	**5.9291**

Table-1: Forecasting performance of the five forecasters and one benchmark over two categories in the test data

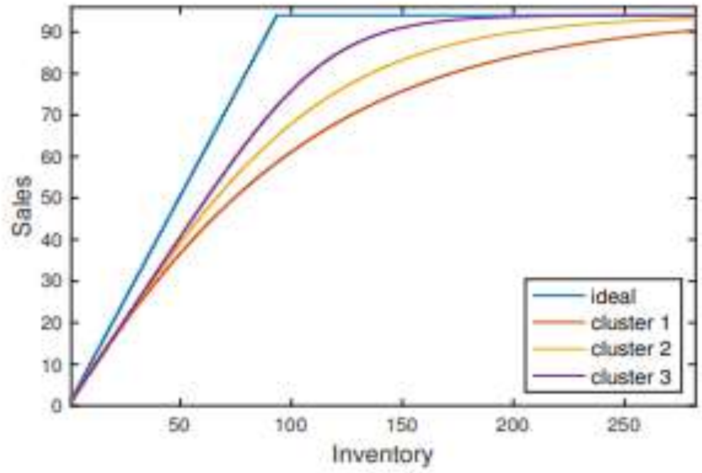

Fig-2: Sales forecast related to inventory of the dataset on shoes and compared with the ideal conversion rate of sales.

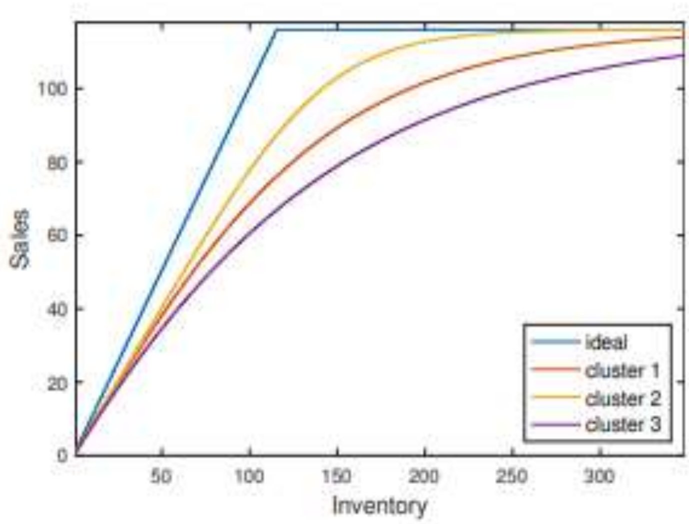

Fig-3: Sales forecast related to inventory of the dataset on belts and compared with the ideal conversion rate of sales

CONCLUSION

In conclusion, demand forecasting plays a pivotal role in modern business strategies, providing organizations with valuable insights into future market trends and customer preferences. By leveraging advanced analytical tools, historical data, and market intelligence, businesses can make informed decisions regarding production, inventory management, and resource allocation. Accurate demand forecasting not only enhances operational efficiency but also contributes to customer satisfaction by ensuring products are readily available when needed. As industries continue to evolve and become increasingly dynamic, the ability to anticipate and adapt to changing demand patterns becomes a competitive advantage. Therefore, investing in robust demand forecasting systems and methodologies is essential for businesses seeking to thrive in the ever-changing landscape of global markets.

References

1. Ensafi, Y., Amin, S. H., Zhang, G., & Shah, B. (2022). Time-series forecasting of seasonal items sales using machine learning–A comparative analysis. International Journal of Information Management Data Insights, 2(1), 100058

2. Zeynep Hilal Kilimci, A. Okay Akyuz, Mitat Uysal, Selim Akyokus, M. Ozan Uysal, Berna Atak Bulbul, Mehmet Ali Ekmis, "An Improved Demand Forecasting Model Using Deep Learning Approach and Proposed Decision Integration Strategy for Supply Chain", Complexity, vol. 2019, Article ID 9067367, 15 pages, 2019.

3. Priyadarshi, R., Panigrahi, A., Routroy, S., & Garg, G. K. (2019). Demand forecasting at retail stage for selected vegetables: a performance analysis. Journal of Modelling in Management, 14(4), 1042-1063.

4. Hexu Wang, Fei Xie, Qun Duan, Jing Li, "Federated Learning for Supply Chain Demand Forecasting", Mathematical Problems in Engineering, vol. 2022, Article ID 4109070, 8 pages, 2022.
5. Ye, Chen, D., Liang, W., Zhou, K., & Liu, F. (2022). Sales Forecasting for Fashion Products Considering Lost Sales. Applied Sciences, 12(14), 7081
6. Abolghasemi, M., Beh, E., Tarr, G., & Gerlach, R. (2020). Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion. Computers & Industrial Engineering, 142, 106380..
7. Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data, 7(1), 1-22..
8. Kochak, A., & Sharma, S. (2015). Demand forecasting using neural network for supply chain management. International journal of mechanical engineering and robotics research, 4(1), 96-104.
9. Carbonneau, R., Vahidov, R., & Laframboise, K. (2007). Machine learning-based demand forecasting in supply chains. International journal of intelligent information technologies (IJIIT), 3(4), 40-57.
10. Babai, M. Z., Boylan, J. E., & Rostami-Tabar, B. (2022). Demand forecasting in supply chains: a review of aggregation and hierarchical approaches. International Journal of Production Research, 60(1), 324-348.
11. Hofmann, E., & Rutschmann, E. (2018). Big data analytics and demand forecasting in supply chains: a conceptual analysis. The international journal of logistics management, 29(2), 739-766.
12. Feizabadi, J. (2022). Machine learning demand forecasting and supply chain performance. International Journal of Logistics Research and Applications, 25(2), 119-142.
13. Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. European journal of operational research, 184(3), 1140-1154.
14. Husna, A., Amin, S. H., & Shah, B. (2021). Demand forecasting in supply chain management using different deep learning methods. In Demand forecasting and order planning in supply chains and humanitarian logistics (pp. 140-170). IGI Global.
15. Zhu, X., Ninh, A., Zhao, H., & Liu, Z. (2021). Demand forecasting with supply‐chain information and machine learning: Evidence in the pharmaceutical industry. Production and Operations Management, 30(9), 3231-3252.
16. Aburto, L., & Weber, R. (2007). Improved supply chain management based on hybrid demand forecasts. Applied Soft Computing, 7(1), 136-144.
17. Kilimci, Z. H., Akyuz, A. O., Uysal, M., Akyokus, S., Uysal, M. O., Atak Bulbul, B., & Ekmis, M. A. (2019). An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. Complexity, 2019.
18. Nia, A. R., Awasthi, A., & Bhuiyan, N. (2021). Industry 4.0 and demand forecasting of the energy supply chain: A literature review. Computers & Industrial Engineering, 154, 107128.
19. Ferbar, L., Čreslovnik, D., Mojškerc, B., & Rajgelj, M. (2009). Demand forecasting methods in a supply chain: Smoothing and denoising. International Journal of Production Economics, 118(1), 49-54.
20. Aamer, A., Eka Yani, L., & Alan Priyatna, I. (2020). Data analytics in the supply chain management: Review of machine learning applications in demand forecasting. Operations and Supply Chain Management: An International Journal, 14(1), 1-13