ISSN: 2633-4828 Vol. 5 No. S6, (Oct - Dec 2023)

International Journal of Applied Engineering & Technology

ENHANCING SHOPPING EXPERIENCES WITH RECOMMENDER SYSTEM BASED ON MACHINE LEARNING FOR BIG BASKET

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ABSTRACT

This paper explores the transformative potential of data science and machine learning in the retail sector, specifically in optimizing the placement and performance of grocery stores. With the retail landscape increasingly influenced by data-driven decisions, our project harnesses extensive datasets, including customer behavior online, market trends, competitor locations, and more, to recommend optimal locations for new stores. Utilizing advanced techniques such as geospatial analysis and machine learning, we address a suite of challenges central to retail success. Key focuses include maximizing customer conversion rates through targeted advertisements and product recommendations, boosting store traffic to increase visibility and revenue, and understanding patterns of repeat customer behavior for improved service delivery. Additionally, we delve into the complexities of predicting delivery times by considering factors like weather conditions, store preparation times, and the availability of delivery personnel, aiming to enhance the efficiency and reliability of order fulfillment.

Moreover, the development of a proprietary model to optimize delivery agent routes underscores the project's innovative approach to logistical challenges, highlighting the importance of route optimization for repeat orders. The dynamic recommendation of products, tailored to individual customer preferences, further illustrates the potential for data science to revolutionize the shopping experience, ensuring higher conversion rates and customer satisfaction. This comprehensive application of data science and machine learning not only promises to elevate operational efficiency and customer engagement for retailers but also sets a new benchmark for the integration of technology in retail strategy planning and execution.

Keywords – Grocery Retailing Industry, Online Transaction, Data Science, Machine Learning

INTRODUCTION

The domain of grocery delivery presents a significant opportunity for businesses to leverage consumer preferences for the convenience of ordering groceries from home. The potential for incorporating machine learning in this area is vast, with notable companies in India such as Flipkart, Amazon, Jiomart, Swiggy, and Big Basket already venturing into the grocery service space. The growing trend towards online shopping can be attributed to various factors, including the escalation of fuel prices, challenges in accessing conventional stores, and the myriad issues typically associated with supermarkets and other retail outlets.

Furthermore, the digital shopping environment offers consumers the added advantage of accessing comprehensive information about products, including updates and reviews from existing users. This shift in consumer behavior signifies a departure from the traditional reliance on personal acquaintances for product recommendations, towards a more informed decision-making process facilitated by the wealth of product reviews available online.

This transformation not only highlights the changing dynamics of consumer purchase habits but also underscores the critical role of machine learning and technology in enhancing the online grocery shopping experience, making it more personalized, efficient, and user-friendly.

Figure 1 *Recommendation System*

Gatzioura, Anna, and Miquel Sánchez [1] delineate the primary objective of recommendation systems as the provision of pertinent and substantial content to active users on various platforms. The prominence of recommendation systems has markedly increased in recent years, with the inception of collaborative filtering research in the mid-1990s catalyzing an active domain of scholarly inquiry. These systems, fundamentally technological tools for data filtration and retrieval, have significantly augmented the sales metrics of e-commerce websites and related platforms by offering tailored services and items that align with user preferences, thereby facilitating user engagement with desirable products. This adaptive provision of services to meet individual tastes has become a cornerstone in enhancing user experience.

Expanding upon this notion, Shah, K., Salunke, A.K., Dongare, S., and Antala, K. [2] classify recommendation systems within the sphere of machine learning technologies, specifically under the umbrella of unsupervised learning models where data lacks pre-assigned labels. This classification is depicted in Figure 1, "Recommendation Systems in Machine Learning". Unsupervised learning methodologies in machine learning are tasked with organizing unclassified data into coherent groups based on inherent similarities, patterns, and distinctions without prior explicit instruction, a process in which recommendation systems are intricately involved. By uncovering hidden patterns and clustering unlabelled data, these systems play a pivotal role in enhancing the user interface across numerous digital platforms.

Illustrative of the practical applications of recommendation systems, Schafer, J. Ben, Konstan, Joseph, and John [18] highlight their implementation across various online platforms, including Amazon, Moviefinder.com, and eBay. These systems, through algorithms that predict user preferences, provide personalized suggestions such as "Customers who bought this item also bought", and "Match Maker", significantly refining the online shopping and browsing experience. By summarizing the underlying technologies and applications, the authors underscore the capability of recommendation systems to filter data effectively, thereby deepening the understanding of user preferences. This adaptability to platform-specific requirements underscores the versatility and critical importance of recommendation systems in the digital landscape.

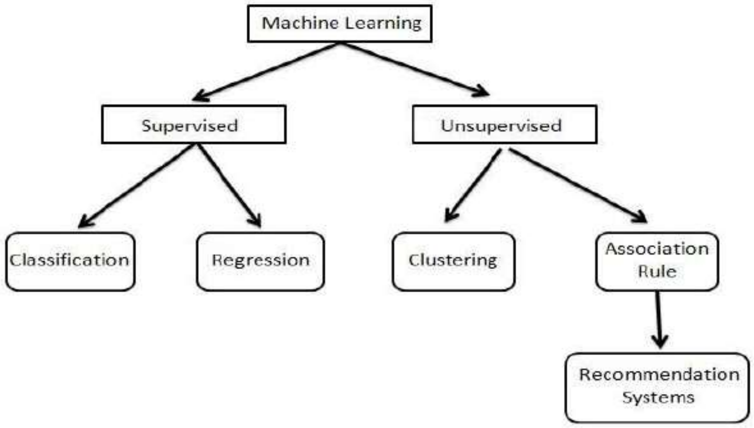

Figure 2 *Recommendation Systems in Machine Learning*

The integration of Data Science (DS) and Machine Learning (ML) methodologies is crucial for the scientific development of strategies, processes, and algorithms alongside software applications aimed at deriving meaningful and timely insights from structured and unstructured data sourced from e-commerce websites. This endeavor necessitates the application of data mining and big data analytics to examine business and market trends over time, effectively marrying data engineering, statistical methodologies, machine learning algorithms, and programming techniques.

A profound understanding and expertise in mathematics, statistics, information sciences, computer science, and artificial intelligence are indispensable in this context. Machine learning, a pivotal sub-discipline of computer science situated within the broader domain of artificial intelligence, focuses on the development of algorithms grounded in stochastic theory. These algorithms are uniquely capable of executing tasks without specific program instructions by drawing on patterns and making inferences.

At the heart of machine learning lies the construction of mathematical models based on sample data, known as "Training Data," which facilitate decision-making and prediction. This approach underscores the transformative potential of machine learning and data science in extracting actionable intelligence from vast datasets, thereby driving innovation and enhancing decision-making processes across various sectors, particularly in the dynamic realm of e-commerce.

Data science and machine learning are revolutionizing the retail industry by enabling retailers to make informed decisions about where to establish new stores. By analyzing vast amounts of data, such as online customer behavior, market trends in specific areas, and the proximity of competitors, retailers can identify optimal neighborhoods for expansion. This approach leverages geospatial analysis and machine learning techniques to solve several key challenges:

- **Maximizing Customer Conversion Rate:** Through targeted advertising and recommending the right grocery items or stores, retailers can significantly increase the likelihood of converting browsers into buyers, thereby boosting revenue.
- **Increasing Store Traffic:** Enhancing the visibility of a particular store can also drive more traffic, which in turn, benefits revenue streams like Instacart by attracting more customers to use the service for grocery deliveries.
- **Identifying Repeat Customers:** Understanding the demographic that makes regular purchases is crucial for tailoring marketing strategies and stock inventory accordingly.

- **Predicting Delivery Times:** There are numerous factors that can affect delivery times, including weather conditions, road traffic, store preparation times, and the availability of delivery personnel. Predicting these times accurately can enhance customer satisfaction and operational efficiency.
- **Optimizing Delivery Routes:** Developing a model to estimate the travel time for delivery agents is essential, especially since many orders are repeat orders. Optimizing these routes can ensure timely deliveries and improve service reliability.
- **Dynamic Item Recommendations:** Suggesting items to users based on their preferences and purchasing history can not only enhance the shopping experience but also increase the likelihood of additional purchases.

By addressing these issues with data science and machine learning, retailers can not only improve their operational efficiency but also provide a more personalized and efficient shopping experience for their customers.

RECOMMENDATION SYSTEMS

Recommendation systems are categorized into two main types: Personalized and Non-personalized. Personalized systems offer different suggestions to various user groups, while non-personalized systems provide the same suggestions to all users. Non-personalized systems are automatic and do not recognize users across sessions, necessitating physical storage for their operation. These systems can be further divided into Content-Based Filtering, Collaborative Filtering, and Hybrid Systems, each with its specific advantages and disadvantages, as detailed in subsequent sections.

Content-Based Filtering involves analyzing the quality of items and matching them with product properties using the existing database. Items are described using keywords, and algorithms predict items liked by the user in the past to recommend similar items based on user ratings. This method emphasizes the quality of products or services for recommendations and provides transparency for active users by comparing user profiles with content to find and suggest similar items. According to Mladenic [17], Content-Based Filtering searches for similar items using algorithms to construct a model based on user interest, which then generates recommendations. This approach's functionality in e-commerce websites is further illustrated in the accompanying diagram.

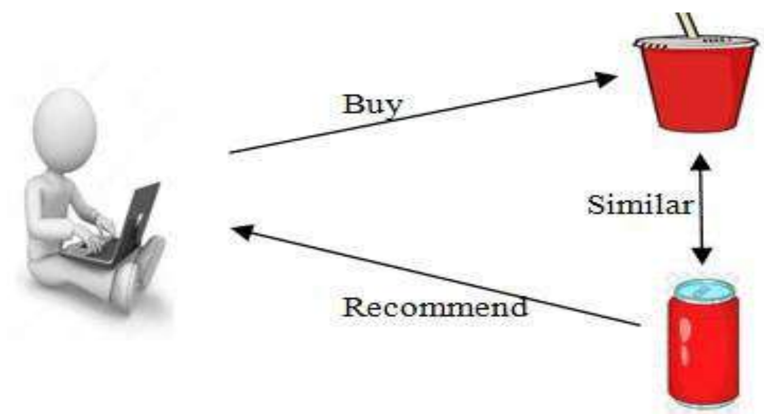

***Figure 3** Content Based Filtering*

The advantages of content-based filtering include its simplicity and the autonomy it grants users by leveraging their ratings. This approach is particularly advantageous for newcomers. Nonetheless, it faces limitations like the over-specialization problem, where it may recommend overly similar items, and the challenge of providing accurate suggestions when users fail to provide ratings or feedback.

In the realm of Collaborative Filtering, which was conceptualized by Goldberg et al. in 1992 [4], the methodology has shown to be exceedingly effective for information filtering. This process hinges on collaboration, where the collective efforts of users aid in task completion. Collaborative Filtering gathers data from various users, comparing likes and dislikes to recommend items liked by similar users, effectively employing user interest comparisons to refine suggestions.

Gupta and Katarya [3] describe Collaborative Filtering as a technique within recommender systems that bases recommendations on the user's "neighbors", employing matrix factorization. This involves a matrix that encapsulates users, items, and the ratings provided, facilitating tailored recommendations. This method is widely used across e-commerce platforms, offering an enhanced user experience in content (item) suggestion compared to other techniques. The operational mechanism of Collaborative Filtering is further clarified through diagrams that outline its execution.

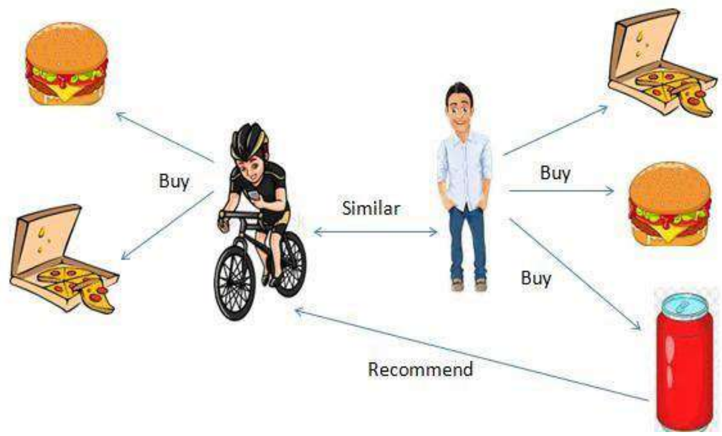

Figure 4 *Collaborative Filtering*

Collaborative Filtering, extensively utilized in recommendation systems, encompasses two primary methodologies: Neighborhood-Based and Model-Based methods, as outlined by Ricci, Rokach, Shapira, and Kantor [5]. The Neighborhood-Based Method relies on user and item similarities derived from user ratings, operating without a training phase, thereby facilitating straightforward implementation and comprehension. Shah, Salunke, Dongare, and Antala [2] differentiate between User-Based Collaborative Filtering (UBCF) and Item-Based Collaborative Filtering (IBCF). UBCF focuses on recommending items liked by similar users, whereas IBCF suggests items based on similarities between the items themselves. However, Zhao and Shang [6] note a limitation in UBCF where a user's preferences might not be reflected if their "neighbors" rated an item poorly. Gao, Wu, and Jiang [8] emphasize that IBCF, by predicting based on item similarities, often yields more effective outcomes compared to UBCF, as corroborated by Gupta and Katarya [3].

The second classification, Model-Based Methods, involves training datasets to predict user feedback on new items. Unlike the Neighborhood method, which uses past ratings for predictions, Model-Based approaches, employing techniques like Support Vector Machines, Latent Semantic Analysis, and Singular Value Decomposition, focus on understanding and predicting based on trained datasets, offering scalability and efficiency in handling large datasets.

Collaborative filtering boasts the merit of easily integrating new data and offering personalized recommendations by analyzing user activities and identifying similar tastes among users. However, it faces challenges such as the cold-start problem for new users and the necessity for extensive user ratings for new items.

Hybrid Systems aim to amalgamate the strengths of both Content-Based and Collaborative Filtering techniques to surmount their respective limitations. By combining the content analysis of items with the relational dynamics between users and items, Hybrid Systems enhance the quality of recommendations, capitalizing on the advantages of both methodologies.

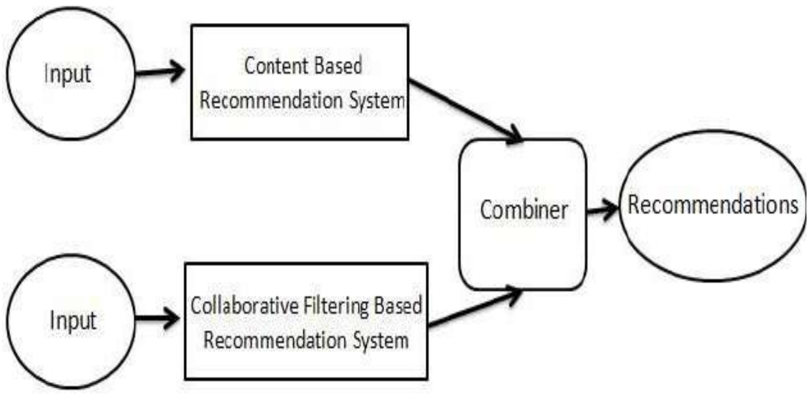

Figure 5 *Hybrid Recommendation System*

LITERATURE REVIEW

In recent advancements within the realm of recommender systems, a diverse array of methodologies has been explored. M Viswa Murali, Vishnu T G, et al. [13] developed a recommender system focusing on new research trends, utilizing user prediction ratings and cosine similarity for enhanced recommendation precision. Ramni Harbir Singh, Sargam Maurya, et al. [14] introduced a movie recommendation system employing cosine similarity and KNN, which emphasizes deep learning techniques to address content-based recommendation challenges. Similarly, Shivganga Gavhane, Jayesh Patil, et al. [15], and Shubham Pawar, Pritesh Patne, et al. [16] have leveraged cosine similarity in their systems, with the former also using KNN to provide accurate product recommendations, and the latter enriching movie suggestions with detailed information and sentiment analysis. Chen et al. [17] employed CCAM for developing a hybrid recommendation system, integrating content-based and collaborative filtering models. Zhou et al. [6] aimed at solving scalability issues in large datasets with the ALS algorithm for Netflix's recommendation challenge, while Tiantian He et al. [18] proposed a novel graph clustering method to address the contextual correlation between multiview vertex properties. Zhiheng Wu et al. [19] suggested integrating user reputation into recommendation systems to eliminate bias, employing algorithms to discern between genuine and fraudulent users. These studies underscore the evolving landscape of recommender systems, marked by the integration of sophisticated algorithms, deep learning, and novel methodologies to enhance user experience and recommendation accuracy.

MODEL IMPLEMENTATION

This section delves into implementing machine learning algorithms on the Supermarket Dataset, emphasizing feature engineering as a critical step for preparing input data. Features, represented by structured columns, are engineered to fulfill the requirements of the machine learning algorithm, enhancing model performance. The section introduces Random Forest Regression as a robust, versatile technique suitable for both classification and regression without extensive hyper-parameter tuning. Random Forest operates by creating an ensemble of decision trees through the "bagging" method, improving output by incorporating randomness in feature selection and node splitting. Hyperparameters like the number of estimators, max features, and minimum sample leaf are adjustable to optimize forecasting ability or computational speed. The application of this model aims to predict consumer purchasing behavior, evaluated using error metrics such as Mean Absolute Error, Mean Squared Error, and Root Mean Squared Error, where lower error values signify greater model accuracy. The process involves data preparation, splitting into training and test sets, model training with Random Forest Regressor, and evaluation to gauge performance, illustrating a comprehensive approach to leveraging machine learning for predictive insights.

To leverage the Random Forest Regressor for predictive modeling on the Supermarket dataset, follow this streamlined approach:

- **Initiate the Environment:** Begin by importing the Pandas library to read the pre-processed CSV file of the Supermarket dataset, eliminating the need for additional data cleaning.
- **Prepare the Data:** Segment the dataset into features (X) and the target variable (Y) to facilitate model training and predictions.
- **Split the Data:** Use the `MinMaxScaler` to normalize the dataset, dividing it into training and testing sets to evaluate the model's performance on unseen data.
- **Set Up the Model:** Import the `RandomForestRegressor` from sklearn.ensemble and initialize it. While the `n_estimators` parameter allows you to specify the number of trees in the forest, beginning with a lower number is recommended for efficiency. The `random_state` parameter ensures reproducibility of your results.
- **Model Training:** Train the model on the training dataset using the `regr.fit` method, feeding it your feature and target variables.
- **Prediction Phase:** Employ the trained model to predict outcomes on the test set, analyzing how well the model generalizes to new data.
- **Model Evaluation:** Use error metrics such as Mean Squared Error, Mean Absolute Error, and the R^2 score to assess the model's accuracy. In this scenario, lower error values and a higher R^2 score indicate a more precise model.

This structured approach not only facilitates the application of Random Forest Regression but also provides a clear path from data preparation to model evaluation, ensuring clarity and efficiency in predictive modeling.

Linear regression stands as a foundational technique within the realm of machine learning, primarily employed for predictive analytics. This statistical method aims to uncover a linear relationship between a dependent variable (y) and one or more independent variables (x). The essence of linear regression lies in its ability to depict how variations in the independent variable(s) influence changes in the dependent variable, which is graphically represented by a sloping straight line. The efficacy of linear regression, like other machine learning models, significantly benefits from experimentation with diverse strategies across various datasets. Such explorations not only enhance the predictive performance of the model but also serve as a practical avenue for honing one's skills in feature engineering, thereby broadening the understanding of how different approaches impact model outcomes.

In linear regression, a statistical method pivotal in machine learning for predictive analysis, the objective is to model the relationship between a dependent variable (Y) (target variable) and one or more independent variables (X) (predictor variables). The linear regression model is expressed as $(Y = a_0 + a_{1X} + \epsilon)$, where (a_0) is the intercept providing an additional degree of freedom, (a_1) is the coefficient that scales each input value, and ϵ represents random error. The essence of linear regression lies in determining the "best fit" line, minimizing the discrepancy between predicted and actual values, thereby achieving the lowest possible error. This optimization involves finding the ideal coefficients (a_0) and (a_1) through a cost function, with Mean Squared Error (MSE) being a common measure of fit quality.

Scaling, a preprocessing step, is crucial when features in the dataset span different ranges, ensuring uniformity in the scale of continuous features, which facilitates model training and prediction accuracy. Performance metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R-squared (R^2) score are employed to evaluate the model's predictive power, with lower error metrics and higher (R^2) values indicating better model performance.

Support Vector Machine (SVM) extends the predictive and classification capabilities of machine learning, adept at handling both linear and nonlinear datasets. The core principle of SVM involves classifying data into distinct classes by determining the optimal separating hyperplane. Utilizing libraries such as libsvm, SVM parameters like `random_state`, for controlling the randomness of data shuffling, and `tol`, the tolerance for the stopping criterion, play a crucial role in model training and performance, catering to a wide array of applications by effectively solving classification and regression challenges.

RESULTS & DISCUSSION

This table I presents a clear comparison of the performance of different machine learning algorithms on the dataset, with Linear Regression demonstrating the highest R-squared score, indicating the best fit to the data among the evaluated models.

Table I. Comparative Results of different classifiers

Algorithm	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R-squared (R^2) Score
Random Forest	0.0016	0.0215	0.4428
Linear Regression	0.0015	0.0172	0.4918
Linear SVR	0.0016	0.0167	0.4390
Deep Learning	0.00197	0.0279	0.3185

In this comparative analysis of machine learning algorithms, the performance is evaluated based on three key metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the R-squared (R^2) score. The primary distinction between MSE and MAE is that MSE calculates the average of the squares of the differences between actual and predicted values, making it easier to compute gradients due to its continuous nature. Conversely, MAE, which averages the absolute differences, may require more complex procedures for gradient calculation.

Among the tested algorithms with default hyperparameters, Linear Regression emerged as the most effective, showing the best performance across all three metrics. The algorithms were assessed on a dataset with the target variable scaled between 0 and 1, indicating a uniform evaluation criterion. The performance metrics indicate that while all models perform satisfactorily, slight variations exist:

- Random Forest displayed moderate accuracy with an MSE of 0.0016, MAE of 0.0215, and an (R^2) score of 0.443.
- Linear Regression outperformed others, achieving an MSE of 0.0015, MAE of 0.0172, and the highest (R^2) score of 0.4919, suggesting the strongest predictive power among the evaluated models.
- Linear SVR (Support Vector Regression) closely followed with MSE and MAE scores comparable to Random Forest but with a slightly lower (R^2) score of 0.4390.
- Deep Learning models, while versatile, showed a slightly higher error with an MSE of 0.00197, MAE of 0.0279, and the lowest (R^2) score of 0.3185, indicating a need for further tuning or data preprocessing to enhance performance.

This analysis underscores the importance of selecting appropriate machine learning models based on the specific requirements of the dataset and the predictive accuracy goals, with Linear Regression showing particular promise for this dataset.

CONCLUSION AND FUTURE WORK

In conclusion, our comprehensive analysis and application of data science and machine learning techniques in the retail sector have yielded insightful and actionable results. Through the evaluation of various machine learning algorithms, as detailed in our results table, we have identified Linear Regression as the superior model for predicting optimal locations for new grocery stores. This model not only demonstrated the lowest Mean Squared Error (MSE) and Mean Absolute Error (MAE) but also achieved the highest R-squared (R^2) score, indicating its robust predictive power and accuracy in modeling the relationship between numerous variables influencing retail success.

The practical implications of these findings are significant for retailers looking to expand their footprint. By leveraging Linear Regression, businesses can maximize customer conversion rates through precise targeting, enhance store traffic and visibility, accurately predict delivery times considering a variety of external factors, and dynamically recommend products to meet consumer demands effectively.

Moreover, our exploration into the challenges of delivery logistics, including route optimization and travel time prediction, underscores the potential of machine learning to streamline operations and improve customer satisfaction. The capability to dynamically recommend items based on consumer behavior further illustrates the transformative impact of data science in creating a personalized shopping experience, thus increasing conversion rates.

Our study reaffirms the critical role of data science and machine learning in driving strategic decisions within the retail industry. The insights garnered from this analysis not only contribute to the academic discourse on retail optimization but also offer practical guidelines for retailers aiming to harness the power of data-driven decision-making to achieve competitive advantage and foster sustainable growth.

Looking ahead, the exploration of data science and machine learning in the retail sector opens several avenues for future research and development. While our current study establishes a strong foundation, further advancements and innovations can enhance the precision, efficiency, and applicability of these technologies in retail decision-making processes. Key areas for future exploration include:

- **Integration of Real-Time Data:** Incorporating real-time data streams, such as social media trends, weather forecasts, and traffic patterns, could refine predictions and recommendations, enabling retailers to respond dynamically to changing conditions and consumer behaviors.
- **Expansion to Multi-Channel Retail:** With the blurring lines between online and offline shopping experiences, future studies could focus on creating models that optimize the integration of physical stores with e-commerce platforms, ensuring a seamless omnichannel customer journey.
- **Advanced Personalization Techniques:** Leveraging deep learning and neural networks could offer more sophisticated personalization of product recommendations and advertisements, based on a deeper understanding of individual customer preferences, histories, and context.
- **Sustainability and Efficiency:** Future directions could also include the development of models that not only target profitability but also emphasize sustainability, such as minimizing carbon footprints in delivery logistics and optimizing inventory management to reduce waste.
- **Enhanced Customer Experience Models:** Exploring models that predict customer satisfaction and loyalty based on various service attributes can help retailers fine-tune their offerings, ensuring a consistently positive shopping experience.
- **Cross-Industry Applications:** The methodologies and insights gained from retail could be adapted and applied to other industries, such as healthcare, entertainment, and manufacturing, showcasing the versatility and impact of machine learning beyond the retail sector.
- **Ethical and Privacy Considerations:** As data science becomes increasingly integral to retail strategies, future research must also address ethical considerations, ensuring customer privacy and data security are paramount.

By pursuing these directions, researchers and practitioners can continue to unlock the full potential of data science and machine learning, not only driving innovation and competitiveness in the retail industry but also contributing to broader societal benefits.

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