Smarter Decisions in Non-Online Retail Environments: An Adaptive Hybrid Approach

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***Abstract*—Enhancing the customer experience and optimizing inventory management are crucial goals for non-online retail stores, yet achieving them remains a complex task in the absence of detailed interaction data and automated decision-support tools. Traditional recommendation systems, designed for digital platforms, rely heavily on explicit user feedback and online behavioral data, which are often scarce or unavailable in offline retail settings. Similarly, existing forecasting models struggle to adapt to the complexity and contextual variability of in-store environments, where purchasing behavior is influenced by factors such as product placement, promotions, and customer flow. To address these challenges, this work proposes an adaptive hybrid system that integrates multiple recommendation paradigms, namely content-based, collaborative filtering, and popularity-based approaches, with predictive modeling techniques including Recurrent Neural Networks and data-driven statistical models. The system is designed to infer user preferences from implicit signals such as purchase patterns and contextual data collected via in-store IoT devices, enabling it to deliver personalized recommendations even in the absence of explicit feedback. At the same time, it provides managers with accurate demand forecasts to inform inventory planning and operational strategies. Preliminary evaluations conducted on publicly available datasets, adapted to emulate offline retail scenarios, demonstrate the system's ability to balance personalization, accuracy, and robustness. Results based on metrics such as Precision@K, NDCG@K, and Hit Rate@K highlight the advantages of the proposed approach in supporting intelligent decision-making in non-online retail environments.**

***Index Terms*—Recommender Systems, Sales Forecasting, Offline Retail**

I. Long Abstract

The non-online retail sector represents a critical domain where technological advancements have the potential to significantly improve both customer satisfaction and operational efficiency. Physical stores, such as supermarkets, department stores, and specialized shops, operate in complex environments where decision-making processes are often based on human intuition, static rules, or manual analyses. Unlike their online counterparts, in-person retailers lack access to extensive digital interaction data, such as browsing histories, clickstreams, and real-time feedback [1]. This absence of rich digital signals severely limits the applicability of traditional recommendation and forecasting techniques, which have been extensively developed and optimized for e-commerce platforms. Furthermore, in-store purchasing behaviors are influenced by numerous contextual factors, such as store layout, product placement, in-the-moment promotions, and customer flow, adding layers of complexity that are rarely accounted for in standard algorithms [2].

The so-called *cold-start* problem makes this challenge particularly difficult [3]. A cold start occurs when the system must provide relevant recommendations to new users or for newly introduced items despite the absence of an interaction history. Addressing these challenges requires the development of intelligent systems capable of operating effectively within the unique constraints of non-online retail environments.

This work introduces an adaptive hybrid system designed to enhance decision-making processes in such contexts. The system is built around two main objectives: providing customers with personalized product recommendations and assisting store managers with accurate sales forecasting to optimize inventory management, reduce waste, and improve profitability. By bridging the gap between customer engagement and operational planning, the system aims to create a cohesive data-driven framework for physical retail environments.

At the heart of the system is a hybrid recommendation engine that combines multiple paradigms to overcome the data sparsity inherent in offline settings. Content-based filtering utilizes item metadata [4], such as product descriptions, categories, and brand information, to identify similarities and suggest alternatives. These features are represented using vectorization techniques such as TF-IDF, which capture term importance across the product catalog and enable item-to-item similarity calculations [5].

Collaborative filtering exploits patterns of co-purchase behavior, inferring user preferences based on the habits of similar customers, while popularity-based models ensure robust performance even in the absence of personalized data by leveraging aggregate sales trends. The combination of these methods allows the system to mitigate the cold-start issue by ensuring that meaningful recommendations can still be generated for users or products with limited historical data. These methods are integrated through a dynamic weighting strategy that adapts the influence of each module based on contextual factors such as data availability, item novelty, and user interaction history. For instance, the system can emphasize popularity-based recommendations for new users with no prior interactions while relying more on collaborative and content-based approaches as user profiles evolve over time.

Complementing the recommendation module is a forecasting component that addresses the challenges of predicting product demand in dynamic, non-online environments. The forecasting system employs a hybrid modeling approach that integrates sequential models, specifically Long Short-Term Memory (LSTM) networks [6], a variant of Recurrent Neural Networks (RNNs) designed to mitigate the vanishing gradient problem, with statistical learning techniques like gradient boosting. RNNs are particularly effective at capturing temporal dependencies in sales data, identifying trends, seasonality, and recurring patterns [7], while gradient boosting models provide interpretable insights by capturing structured relationships among features such as day of the week, holidays, and promotional periods [8]. This combination allows the system to generate forecasts that are both accurate and actionable, supporting inventory optimization, pricing strategies, and promotion planning. A distinctive feature of the proposed system is its ability to operate with limited explicit feedback. In non-online retail settings, customer preferences are often inferred through indirect signals, such as purchase history, basket composition, or time spent in specific store areas, rather than explicit ratings or reviews. The system is designed to integrate these implicit signals, augmented by contextual information gathered through in-store IoT devices [9].

Technologies such as RFID tags, Bluetooth beacons, motion sensors, and cameras provide real-time data on customer movements, product interactions, and environmental conditions [10], enabling the system to contextualize recommendations and forecasts dynamically. For example, the system can adjust recommendations based on product availability, prioritize items in promotional campaigns, or highlight time-sensitive offers such as discounts on perishable goods.

The architecture is modular and scalable, facilitating integration with existing store infrastructure, including point-of-sale systems, inventory databases, and mobile applications. The system's components communicate through well-defined interfaces, ensuring flexibility and adaptability across different retail formats and store sizes. This design also allows for the incorporation of additional data sources, such as loyalty programs, customer demographics, and external factors like weather forecasts or local events, further enriching the system's decision-making capabilities.

Preliminary evaluations leveraged publicly available datasets such as the UCSD Amazon dataset from the University of California San Diego [11], adapted to emulate offline retail scenarios. While acknowledging the limitations of these datasets, initial experiments highlight the system's ability to deliver personalized recommendations that outperform traditional single-paradigm models in terms of Precision@K, NDCG@K, and Hit Rate@K. The system also demonstrates resilience to cold-start scenarios, maintaining recommendation quality for both new users and items lacking prior interactions. These results highlight the system's ability to balance personalization and robustness in complex retail environments.

This research contributes to the growing field of intelligent retail systems by presenting an integrated approach that aligns customer-facing personalization with backend operational support. By bridging the gap between recommendation and forecasting capabilities, the system offers a comprehensive solution for non-online retail contexts, where data scarcity and contextual variability pose significant challenges. The proposed system demonstrates how hybrid architectures can enhance decision-making processes by leveraging the strengths of different modeling paradigms while compensating for their individual limitations.

Future work will focus on real-world deployments in physical stores to validate the system's performance under operational constraints, including variability in data quality, latency in data transmission, and user adoption challenges. Additional research directions include refining the hybrid weighting mechanisms through adaptive learning techniques, and developing methods for explaining system recommendations and predictions to end-users and store managers.

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