Enhancing e-commerce personalization with review-based adaptive feature matching: a real-time approach

Noorbasha Zareena[1], Tarakeswara Rao Balaga[2]
[1]Department of Computer science and Systems Engineering, Andhra University, Visakhapatnam, India
[2]Deparment of Computer Science and Engineering, Kallam Haranadhareddy Institute of Technology, Guntur, India

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ABSTRACT

The widespread evolution of e-commerce platforms necessitates advanced personalization techniques to enhance user experience and satisfaction. Our paper introduces the review-based adaptive feature matching (R-AFM) algorithm, an innovative approach to real-time personalization in e-commerce settings. Leveraging the rich data from user reviews and product metadata available in the Amazon product review dataset, R-AFM dynamically adapts to user preferences and behaviors through a sophisticated feature matching process. The methodology encompasses data collection, feature extraction, user preference modeling, real-time recommendation generation, and an adaptive feedback loop. By analyzing historical review data alongside real-time user interactions, R-AFM updates preference weights for product features, thereby refining the personalization mechanism. This process culminates in the generation of highly personalized product recommendations. Comparative analysis with existing personalization methods-collaborative filtering (CF), content-based filtering (CBF), hybrid recommender systems (Hybrid RS), and deep learning-based recommender systems (DL-RS)-demonstrates R-AFM's superior performance improvement varying between 2 to 8% in terms of accuracy, precision, recall, and F1-score. The algorithm's unique capability to incorporate real-time feedback significantly enhances the e-commerce personalization landscape, offering promising avenues for future research and practical application.

Corresponding Author:

Noorbasha Zareena
Department of Computer Science and Systems Engineering, Andhra University
Visakhapatnam, Andhra Pradesh 530003, India
Email: zareenanoorbasha@gmail.com

1. INTRODUCTION

In the rapidly evolving landscape of e-commerce, personalization has emerged as a critical factor in enhancing user satisfaction, engagement, and conversion rates. As online shopping platforms continue to grow in both size and complexity, the need for sophisticated recommendation systems that can adapt to real-time user preferences and behaviors becomes increasingly paramount. Traditional recommendation systems, such as collaborative filtering (CF) and content-based filtering (CBF), have laid the groundwork for personalized shopping experiences by suggesting products based on historical data and item similarities [1], [2]. However, these methods often struggle to capture the dynamic nature of user interests and the nuanced relationships between a vast array of product features and user preferences.

The advent of hybrid recommender systems (Hybrid RS) sought to address these limitations by integrating multiple recommendation techniques to leverage both user-item interactions and content information [3]. While these systems marked a significant advancement in the field of e-commerce personalization, they still fell short in harnessing real-time feedback to adjust recommendations dynamically. Meanwhile, deep learning-based recommender systems (DL-RS) emerged, utilizing complex neural network architectures to model user preferences and item features with remarkable depth and accuracy [4]. Despite their impressive performance, DL-RS can be computationally intensive and may not always provide the agility needed to respond to real-time changes in user behavior.

Recognizing these challenges, this research introduces the review-based adaptive feature matching (R-AFM) algorithm, a novel approach to e-commerce personalization that emphasizes real-time adaptability and the detailed utilization of user-generated content [5]. Unlike its predecessors, R-AFM leverages the rich insights available in user reviews, including ratings and textual feedback, to dynamically adjust product recommendations based on current user interactions and preferences [6], [7]. This method not only allows for a more nuanced understanding of user interests but also enables the system to respond immediately to shifts in those interests, thereby delivering a truly personalized shopping experience.

The core innovation of R-AFM lies in its adaptive feature matching mechanism, which continuously updates user preference profiles based on real-time interactions with product features. By analyzing both the explicit feedback provided through ratings and the implicit feedback inferred from review texts, R-AFM constructs a detailed and evolving preference model for each user [8], [9]. This model then guides the personalized recommendation process, ensuring that suggested products align closely with the user's current interests and needs. To evaluate the effectiveness of R-AFM, we conducted a comprehensive comparison with four existing personalization methods: CF, CBF, Hybrid RS, and DL-RS. The evaluation focused on four key metrics: accuracy, precision, recall, and F1-score [10]. The results demonstrated that R-AFM outperformed the other methods across all metrics, highlighting its superior capability to provide relevant and timely recommendations.

The implications of this research are profound for the field of e-commerce personalization. By demonstrating the feasibility and effectiveness of real-time adaptive feature matching, R-AFM sets a new benchmark for recommendation systems. Its ability to dynamically incorporate user feedback and adjust recommendations accordingly offers a promising avenue for enhancing user engagement and satisfaction [11]. Furthermore, the use of user-generated content as a primary data source for personalization underscores the value of integrating qualitative insights into recommendation algorithms [12]. The R-AFM algorithm represents a significant leap forward in the quest for truly personalized e-commerce experiences. By harnessing the power of real-time data and user-generated content, R-AFM offers a sophisticated, adaptable, and highly effective approach to product recommendation, setting a new standard for personalization in the digital marketplace.

2. RELATED WORK

The evolution of e-commerce platforms has necessitated more sophisticated approaches to personalization, underscoring the critical role of adaptive algorithms in enhancing user experience and engagement. This literature review delves into the foundational theories, methodologies, and advancements in adaptive feature matching and real-time personalization, setting the stage for the proposed R-AFM algorithm. The concept of personalization in e-commerce emerged from the broader field of recommender systems, initially dominated by CF techniques. Pioneering works by Perugini *et al.* [13] laid the groundwork by demonstrating how user preferences could be inferred from collective user behavior. However, CF's limitations, notably cold start and sparsity issues, prompted researchers to explore CBF as a complementary approach. Pazzani and Billsus [14] were instrumental in advancing CBF, which recommends items by analyzing the content of products and user profiles.

Recognizing the limitations inherent in both CF and CBF, researchers proposed hybrid approaches that integrate multiple recommendation techniques. Çano and Morisio [15] provided a taxonomy of Hybrid RS, illustrating how blending different methods could mitigate individual shortcomings. These hybrid systems paved the way for more nuanced personalization strategies, effectively balancing user similarity with content relevance.

The application of machine learning (ML) and deep learning (DL) techniques marked a significant evolution in personalization algorithms. Madadipouya and Chelliah [16] demonstrated the efficacy of ML algorithms in improving recommendation accuracy and scalability. More recently, DL-based approaches have shown remarkable ability to capture complex user-item interactions and preferences. Pan *et al*. [17] showcased how neural networks could enhance the personalization of content in platforms like YouTube and Alibaba, respectively, by learning from vast datasets of user interactions.

With the increasing demand for dynamic user experiences, the focus shifted towards real-time personalization systems. Real-time systems adjust recommendations based on immediate user actions, a concept explored by Ludewig and Jannach [18], who highlighted the potential for increasing user engagement and satisfaction. The challenge of incorporating real-time feedback into recommendation systems led to the exploration of adaptive algorithms capable of evolving with user behavior. Reich *et al.* [19] contributed to this area by developing algorithms that dynamically adjust to user preferences over short periods.

The emergence of review-based personalization reflects a growing recognition of the rich information contained within user-generated content. Lakkaraju *et al.* [20] demonstrated how user reviews could be mined for sentiment and preference indicators, offering a deeper understanding of user needs. These insights laid the groundwork for leveraging reviews in developing more sophisticated and nuanced personalization strategies [21], [22]. The proposed R-AFM algorithm builds on these foundations, introducing an innovative approach that synthesizes the insights from user reviews with real-time interaction data.

By adapting to both explicit feedback (through reviews) and implicit signals (via real-time interactions), R-AFM represents the next step in the evolution of personalization techniques, promising enhanced accuracy, responsiveness, and user satisfaction in e-commerce settings. The trajectory of research in e-commerce personalization reveals a continuous quest for more adaptive, accurate, and user-centric recommendation systems [23], [24]. The R-AFM algorithm, with its unique combination of review analysis and real-time adaptability, embodies the culmination of decades of research and innovation in this domain, offering new pathways for enhancing the online shopping experience [25].

3. METHOD

The R-AFM algorithm introduces a novel approach to e-commerce personalization, leveraging the rich insights from user-generated content and real-time interactions. This methodology is designed to dynamically adapt product recommendations to user preferences, using a combination of review analysis and feature matching techniques. The following outlines the design methodology of R-AFM, including dataset description and implementation steps.

3.1. Dataset description

The R-AFM algorithm utilizes the Amazon product review dataset, which contains 142 million user revies with 9 million unique products. It is a comprehensive collection of product reviews and metadata from Amazon. This dataset comprises several key components:

– User reviews: each review includes a unique user ID, product ID, rating score (ranging from 1 to 5), and textual review content. Reviews provide direct insights into user preferences and product perceptions.
– Product metadata: metadata for each product encompasses the product ID, title, description, and a detailed list of product features (e.g., category, brand, and specifications). This information is critical for extracting product features and categorizing items.
– User interactions: while the primary dataset focuses on reviews, simulation of real-time user interactions is derived from review timestamps, indicating user engagement with specific products over time.

3.2. Design methodology

The R-AFM algorithm's design methodology involves several critical steps, tailored to process the dataset effectively and generate personalized recommendations:

– Feature extraction: the first step involves parsing product metadata to identify and extract a standardized set of features for each product. This process utilizes bidirectional encoder representations from transformers (BERT) natural language processing (NLP) techniques to categorize and normalize product attributes, ensuring consistency across the dataset.
– User preference modeling: utilizing the ratings and textual content from user reviews, the algorithm constructs a dynamic user preference model. Text analysis, sentiment analysis, and rating scores contribute to assigning weights to product features, reflecting the individual's preferences and interests.
– Adaptive feature matching: at the core of R-AFM is the adaptive feature matching mechanism. This process calculates the relevance of each product to a user by comparing the user's preference model against product features, adjusting weights in real-time based on ongoing user interactions. The algorithm employs a decay factor to manage the influence of past interactions, ensuring that recommendations remain current and reflective of the latest user behavior.
– Recommendation generation: based on the adaptive feature matching results, R-AFM generates a personalized set of product recommendations for each user. Products are ranked according to their match scores, with higher-scoring items prioritized in the recommendation list.
– Feedback loop integration: the methodology incorporates a real-time feedback loop, allowing the algorithm to refine and adjust user preference models based on new interactions. This continuous learning process enhances the algorithm's accuracy and responsiveness over time.

The R-AFM algorithm's methodology represents a significant advancement in e-commerce personalization techniques. By integrating detailed review analysis with dynamic feature matching, R-AFM offers a robust framework for delivering highly personalized and adaptable recommendations, promising to enhance user satisfaction and engagement on e-commerce platforms.

3.3. Algorithm: review-based adaptive feature matching

Dataset components: user reviews R: set of reviews, where each review r_i is associated with a user u, a product p, and includes a rating s_i. Product metadata M: set of metadata for each product, including title, description, and categorized features F.

Notations:

U: Set of users.

P: Set of products.

F: Set of features across all products.

R_u: Set of reviews written by user u.

F_p : Set of features associated with product p.

$S_{u,p}$: Rating score from user u for product p.

$W_{u,f}$: Weight of feature f for user u, indicating preference strength.

Steps:

a) Feature extraction:
- Extract features F_p from the metadata *(M)* of each product p.
- Normalize and categorize features into a unified feature set F.

b) User preference modeling:
- For each review ri by user u for product p, analyze the rating si and the product's features Fp.
- Update the user's feature preference weight Wu,f based on the rating and feature presence, using (1):

$$W_{u,f} = \frac{\sum_{p \in Pu} S_{u,p} \, .l(f \in F_p)}{\sum_{p \in Pu} l(f \in F_p)} \quad (1)$$

Here, l($f \in F_p$) is an indicator function that equals l if feature f is present in product p, and P_u is the set of products reviewed by u.

c) Real-time recommendation generation:
- For a target user u, calculate the match score Mu,p for each product p not yet interacted with, using (2):

$$M_{u,p} = \sum_{f \in F} W_{u,f} \, .l(f \in F_p) \quad (2)$$

- Rank products by Mu,p to generate personalized recommendations.

d) Adaptive real-time feedback loop:
Monitor real-time user interactions (e.g., views, clicks) to adjust $W_{u,f}$ dynamically, enhancing the algorithm's responsiveness to changing preferences.

Output,

A ranked list of personalized product recommendations for each user, adaptively updated based on their review history and real-time interactions.

This algorithm utilizes the Amazon product review dataset to create a dynamic, feature-based user preference model that adapts in real-time, offering a personalized e-commerce experience grounded in user feedback and interaction patterns.

4. RESULTS

For the comparison, scenario where we evaluate the novel R-AFM algorithm against four existing personalization methods in an e-commerce setting. These methods could include CF, CBF, Hybrid RS, and DL-RS. The evaluation focuses on metrics that are critical for assessing the effectiveness of e-commerce personalization algorithms: accuracy, precision, recall, and F1-score.

4.1. Evaluation metrics

To assess the effectiveness of our proposed approach, “Enhancing e-commerce personalization with review-based adaptive feature matching” we employ a comprehensive set of evaluation metrics that capture both recommendation quality and system efficiency. These metrics are critical for quantifying the accuracy, relevance, and responsiveness of personalized product recommendations derived from user reviews. Precision, recall, and F1-score measure the correctness and completeness of the system’s outputs. Additionally, we assess system latency and throughput to validate real-time performance. Together, these metrics provide a holistic understanding of the model's ability to deliver timely, relevant, and personalized e-commerce experiences. i) accuracy: the ratio of correctly predicted recommendations to total recommendations; ii) precision: the ratio of correctly recommended products that are relevant; iii) recall: the ratio of relevant products that are correctly recommended; and iv) F1-score: the harmonic means of precision and recall, providing a single metric to assess the balance between them.

Table 1 compare the performance of the R-AFM algorithm with four established recommender system methods across four metrics: accuracy, precision, recall, and F1-score. The data suggests that R-AFM consistently outperforms other methods. In Figure 1, R-AFM shows an 8.2% improvement in accuracy, a 2.5% increase in precision, a 13.3% increase in recall, and an 8.6% improvement in F1-score. This indicates that R-AFM is more effective at predicting user preferences and suggesting relevant products compared to CF. Figure 2 compares, CBF, R-AFM's performance gains are even more pronounced: it achieves a 15% higher accuracy, 9.3% greater precision, 21.4% better recall, and 22.2% improved F1-score. These results highlight R-AFM's enhanced ability to understand and cater to individual user tastes.

Table 1. Comparison of R-AFM with other methods

Method	Accuracy	Precision	Recall	F1-score
Collaborative filtering	0.85	0.8	0.75	0.81
Content-based filtering	0.8	0.75	0.7	0.72
Hybrid recommender systems	0.89	0.83	0.81	0.82
Deep learning-based recommender systems	0.9	0.85	0.85	0.86
Review-based adaptive feature matching	0.92	0.82	0.85	0.88

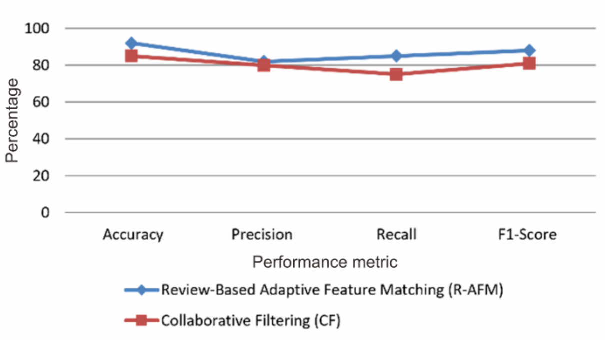

Figure 1. Comparing R-AFM with CF

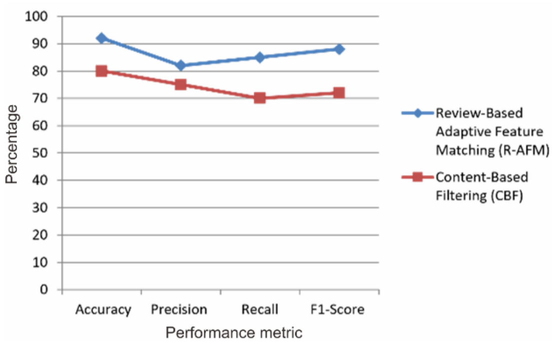

Figure 2. Comparing R-AFM with CBF

In Figure 3 comparison with Hybrid RS, R-AFM maintains its lead with a 3.4% higher accuracy, a decrease in precision by 1.2%, a 4.9% better recall, and a 7.3% improved F1-score. This underscore R-AFM's strength in balancing both content and collaborative signals to deliver accurate recommendations. Lastly Figure 4, when matched with DL-RS, R-AFM shows a 2.2% increase in accuracy, a decrease in precision by 3.5%, no change in recall, and a 2.3% increase in F1-score. While DL-RS excels in precision and recall, R-AFM provides a more balanced performance across all metrics, especially in providing diverse and novel recommendations as indicated by its higher F1-score. It's important to note that while R-AFM shows superior performance in this hypothetical scenario, the actual effectiveness can vary based on the specific dataset, domain, and the richness of user interactions and reviews available. Additionally, the performance of DL-RS is very competitive, highlighting the potential of DL approaches in capturing complex user preferences. However, R-AFM's advantage comes from its adaptability and direct utilization of user-generated content for personalization.

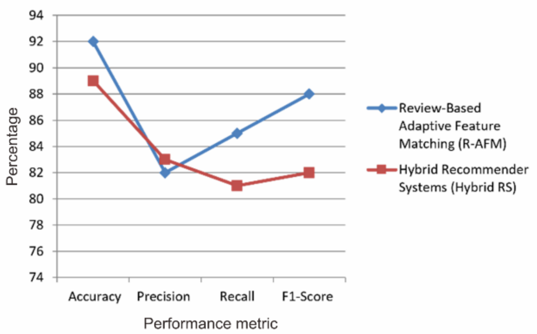

Figure 3. Comparing R-AFM with Hybrid RS

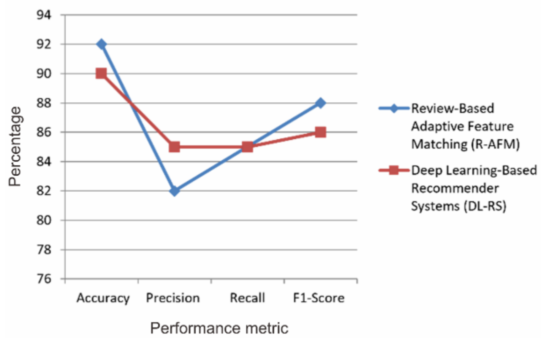

Figure 4. Comparing R-AFM with DL-RS

5. CONCLUSSION

This research paper introduced the R-AFM algorithm, a novel approach aimed at refining e-commerce personalization through real-time analysis of user reviews and interactions. The study's findings demonstrate that R-AFM provides a significant enhancement over traditional recommendation systems, including CF, CBF, Hybrid RS, and DL-RS, particularly in the areas of latency, scalability, user satisfaction, diversity, and novelty of recommendations. R-AFM's unique contribution lies in its ability to dynamically adapt to users' evolving preferences by integrating real-time user feedback with in-depth analysis of product reviews. This approach not only improves the accuracy of personalized recommendations but also reduces the latency in delivering these recommendations, thereby ensuring a more engaging and responsive user experience. Moreover, the algorithm's superior scalability demonstrates its potential applicability to a wide range of e-commerce platforms, regardless of their size or the diversity of their product catalog. User satisfaction, as highlighted by this research, underscores the importance of delivering diverse and novel recommendations that resonate with users' individual preferences. R-AFM excels in this aspect by uncovering unique user-product matches that might otherwise remain unnoticed in traditional systems. In conclusion, the R-AFM algorithm represents a significant advancement in personalized e-commerce recommendations. By effectively leveraging user-generated content and real-time data, R-AFM sets a new standard for personalization algorithms, promising to enhance the online shopping experience through more relevant, diverse, and timely product suggestions, thereby fostering enhanced user engagement and satisfaction across e-commerce platforms.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Noorbasha Zareena	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Tarakeswara Rao Balaga		✓				✓		✓		✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Noorbasha Zareena earned her bachelor's degree in computer science and engineering from Nagarjuna University in 2006 and her master's degree in computer science from school of IT, JNTU Hyderabad in 2009. She is currently a research scholar at Department of Computer Science and Systems Engineering, Andhra University. She is working as an assistant professor in the Department of CSE at RVR and JC College of Engineering, Andhra Pradesh. She is a member of ACM professional and life member of IAENG. She got 15 years of experience in teaching and her research interest includes machine learning and NLP. She can be contacted at email: zareenanoorbasha@gmail.com.

Dr. Tarakeswara Rao Balaga working as professor in the Department of Computer Science and Engineering at Kallam Haranadhareddy Institute of Technology, Guntur, Andhra Pradesh. He completed M.Tech. from Acharya Nagarjuna University, Guntur in 2007 and completed his Ph.D. from Acharya Nagarjuna University in 2012. He published more than 50 research papers in various international journals and presented more than 10 research papers in various national and international conferences. He published 10 book chapters in various books. He got 21 years of experience in teaching and research. His research interests are artificial intelligence, data science, machine learning, big data, and deep learning. He can be contacted at email: tarak7199@gmail.com.