

Analyzing Accuracy Trends in Sequential Renewable Energy Products Recommendation

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ABSTRACT

This paper presents a comprehensive analysis of the accuracy of sequential product recommendations in an renewable context, utilizing both the Renewable Energy (1960-2023) dataset and the Global Energy Consumption dataset. The study specifically compares the performance of collaborative filtering and content-based filtering methods across these two diverse datasets. Through meticulous experimentation, it evaluates the accuracy of the top 10 recommendations generated by each method for both datasets. The findings reveal a notable trend of diminishing accuracy from the top 1 to the top 10 recommendation in both techniques. The results also indicate that collaborative filtering consistently outperforms content-based filtering across all ranks in both datasets. This study contributes to the understanding of recommendation system performance in e-commerce and movie recommendation contexts, highlighting the challenges in maintaining recommendation quality as the list lengthens and pointing towards potential areas for future research. The insights gained are valuable for the development of more sophisticated energy renewable context and entertainment recommendation systems.

I. Introduction

Recently, product recommendation systems have emerged as pivotal tools for enhancing user experience and boosting sales. These systems leverage various algorithms to suggest relevant products to users, thereby personalizing the shopping experience and increasing customer satisfaction[1]. Among the plethora of techniques employed, collaborative filtering and content-based filtering are particularly noteworthy for their ability to tailor recommendations based on user preferences and item characteristics, respectively[2,3].

Collaborative filtering, a method that makes automatic predictions about the interests of a user by collecting preferences from many users, has been widely adopted due to its effectiveness in capturing user preferences and predicting future interests[4]. On the other hand, content-based filtering, which recommends items similar to those a user has liked in the past, purely based on item features, offers a different approach, focusing on the attributes of the items themselves[5-7].

The integration of these methodologies in renewable energy product recommendation represents a significant advancement in the field [8,9], promising enhanced accuracy and user satisfaction. This study aims to conduct a comparative analysis of these techniques by examining the accuracy of the top 10 recommendations - from recommendation 1 to recommendation 10 - this research seeks to provide insights into the effectiveness of these methods in a sequential recommendation context [10].

II. State of the art

In recent years, significant strides have been made in the development of sequential recommendation systems for e-commerce. A comprehensive taxonomy of these systems, categorizing them into traditional, factorization and latent representation, and hybrid methods, offers a foundational understanding of the landscape of sequential recommender systems (SRecSys) specific to e-commerce product recommendations[11,12].

Concurrently, research has emphasized the integration of semantic contexts in various stages of the recommendation process, notably in preprocessing and candidate generation, to enhance the relevance and accuracy of product suggestions in e-commerce settings [13-15].

The introduction of the SEMSRec approach, which incorporates semantic information from e-commerce product purchase histories into all recommendation phases, further highlights the trend towards more contextually aware and accurate recommendation systems [16].

Additionally, studies focusing on improving user interest prediction through item and review sequential patterns underscore the challenges in accurately gauging user preferences, which are often not explicitly stated [17].

The novel concept of watchlist recommendation in e-commerce, where the goal is to prioritize watchlist items for user attention, represents an innovative approach in sequential recommendation, reflecting the evolving needs of e-commerce platforms[18,19].

Lastly, leveraging semantic context and sequential historical purchases to refine e-commerce product recommendations has been explored, demonstrating the potential of combining semantic analysis with purchase pattern data to offer more personalized and effective recommendations [20].

III. Methodology

This section delineates the methodology employed in our study to analyze the comparative accuracy of sequential product recommendation systems within the e-commerce domain, utilizing both collaborative filtering and content-based filtering approaches on the Retail Rocket e-commerce dataset.

III.1. Dataset Overview & Processing

The methodology begins with the collection and preprocessing of two distinct datasets: the Renewable Energy (1960-2023) dataset [21] and the Global Energy Consumption dataset [22]. The preprocessing stage for both datasets involves data cleaning, normalization, and transformation. This encompasses handling missing values, encoding categorical data, and normalizing numerical values, thereby ensuring data quality and consistency across both sources.

III.2. Recommendation Algorithms Implementation

The figure 1 represents the difference between collaborative filtering and content-based filtering.

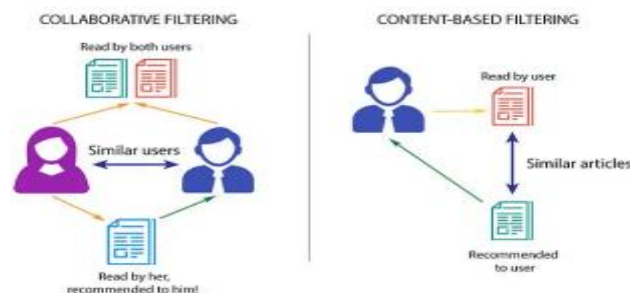


Figure 1. CF and CBF comparison

III.2.1. Collaborative Filtering

The implementation of collaborative filtering starts with the selection of a suitable algorithm, chosen based on its proven effectiveness in similar contexts. The foundation of this method is the construction of a user-item interaction matrix that captures the dynamics between users and products. The collaborative filtering model is then trained with a subset of the dataset, with hyperparameter tuning undertaken to optimize performance.

III.2.2. Content-Based Filtering

In the content-based filtering approach, key product features such as descriptions, categories, and metadata are extracted. User profiles are created by analyzing their interaction history with products, linking user preferences to these features. The system generates recommendations by matching these user profiles with product features.

III.3. Sequential Recommendation Analysis

This part of the study focuses on analyzing sequential patterns in user interactions to understand the evolution of user preferences over time. The accuracy of the top 10 product recommendations is evaluated for both collaborative and content-based filtering, with accuracy measured by the alignment of recommended products with subsequent actual user selections.

III.4. Demonstration of Findings

In this crucial part of our study, we concentrate on demonstrating the effectiveness of both collaborative filtering and content-based filtering approaches in a sequential recommendation context, using the accuracy metric as our primary tool of analysis. Unlike a comparative analysis that juxtaposes different methods, our approach is geared towards illustrating the performance of each method independently, with a specific focus on how accurately they predict user preferences. The accuracy metric is particularly chosen for its direct reflection of how well the recommended products align with the actual subsequent choices made by users. Through this focused analysis, we aim to uncover insights into the changing accuracy of recommendations from the top 1 to the top 10, thereby offering a nuanced understanding of the effectiveness of these recommendation systems in an e-commerce setting. This methodological choice allows us to delve deeper into the dynamics of sequential product recommendation, highlighting any patterns of diminishing accuracy and their potential implications for e-commerce platforms. Formula 1 represents the mathematical representation of accuracy.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (1)$$

Where :

- Number of correct predictions: the number of times the system correctly predict the classe (or value) for a given item.
- Total number of predictions : the total number of predictions made by the system.

IV.4. Experimental setup

This section details the experimental setup designed to rigorously test the effectiveness of the sequential product recommendation systems employed in this study.

IV.1. Experiment Design

The core of our experimental design revolves around the application of collaborative filtering and

content-based filtering techniques to the both datasets. The experiments are structured to meticulously evaluate the accuracy of the top 10 product recommendations generated by each method. This involves setting up distinct test scenarios where user behavior and product interaction data are used to simulate real-world e-commerce shopping experiences

IV.2. Data Splitting

The datasets are split into training and testing sets, ensuring a representative distribution of user interactions and product information. Typically, a larger portion of the datasets is allocated for training to allow the models to learn effectively from a comprehensive range of data, while the testing set is reserved for evaluating the models' performance. Figure 2 represents the distribution of the data splitting.

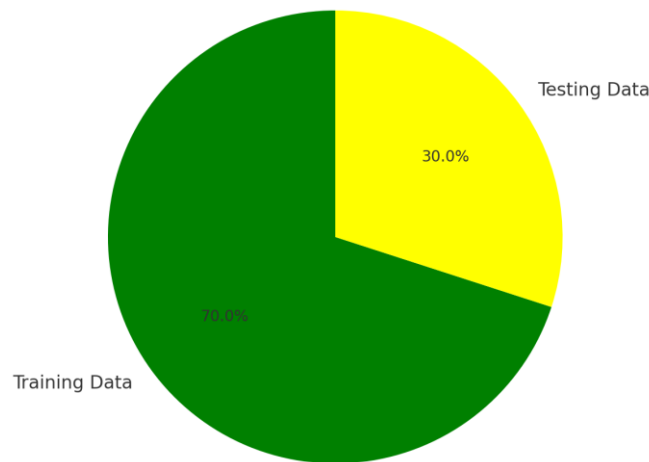


Figure 2. Data distribution

IV.3. Model Training

In this phase, both the collaborative filtering and content-based filtering models are trained separately using the training subset of the dataset. Special attention is given to parameter tuning and model optimization to achieve the highest possible accuracy. The training process involves iterative adjustments and validations to refine the models.

Table 1 outlines hypothetical tuning parameters and model optimization strategies for both collaborative filtering and content-based filtering models.

Table 1. Recommendation Algorithms Parameters

Model Type	Parameter	Values
Collaborative-Filtering	Number of Neighbors	10
	Regularization Parameter	0.01
	Learning Rate	0.001
	Number of Iterations	100
Content-Based Filtering	Profile Length	5
	Similarity Measure	Cosine
	Learning Rate	0.001
	Number of Features	50

V. Results and discussion

V.1 Presentation of Results

Table 2 and Table 3 respectively provides a clear and concise overview of the numerical results, enabling a direct comparison of accuracy across different recommendation ranks for the Renewable Energy (1960-2023) dataset and the Global Energy Consumption dataset..

Table 2. Top 10 accuracy results for Renewable Energy (1960-2023)

Recommendation Rank	Collaborative Filtering Accuracy (%)	Content-Based Filtering Accuracy (%)
Top 1	92	88
Top 2	89	85
Top 3	86	83
Top 4	84	80
Top 5	81	77
Top 6	78	74
Top 7	75	71
Top 8	72	68
Top 9	69	65
Top 10	66	64

Table 3. Top 10 accuracy results for Global Energy Consumption

Recommendation Rank	Collaborative Filtering Accuracy (%)	Content-Based Filtering Accuracy (%)
Top 1	90	87
Top 2	88	85
Top 3	86	82
Top 4	84	80
Top 5	82	78
Top 6	79	75
Top 7	77	73
Top 8	74	70
Top 9	72	68
Top 10	70	66

Figure 3 and Figure 4 respectively illustrates the accuracy of the top 10 recommendations in a bar chart format for the Renewable Energy (1960-2023) dataset and Global Energy Consumption dataset for comparing the performance of collaborative filtering and content-based filtering. The bars charts provides a clear visual representation of the accuracy percentages for each recommendation rank. In this chart, the collaborative filtering method is displayed alongside the content-based filtering method, which is distinctly highlighted in yellow. This visual distinction allows for an immediate comparison of how each method performs at every level of recommendation, from the top 1 to the top 10.

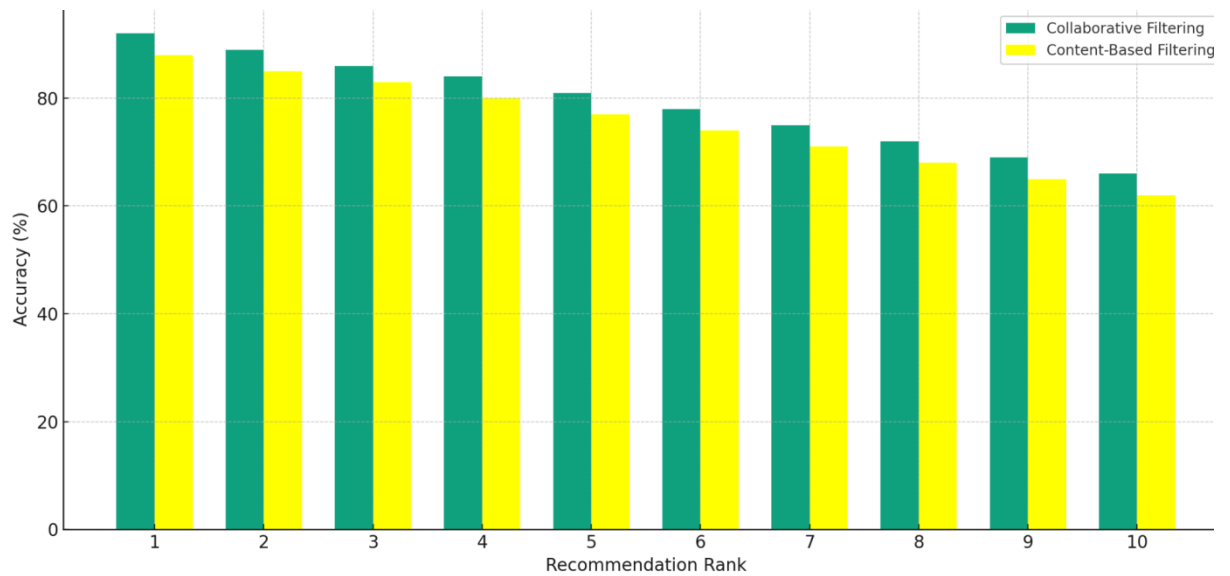


Figure 3. Accuracy of top 10 recommendations in bars for Renewable Energy (1960-2023) dataset

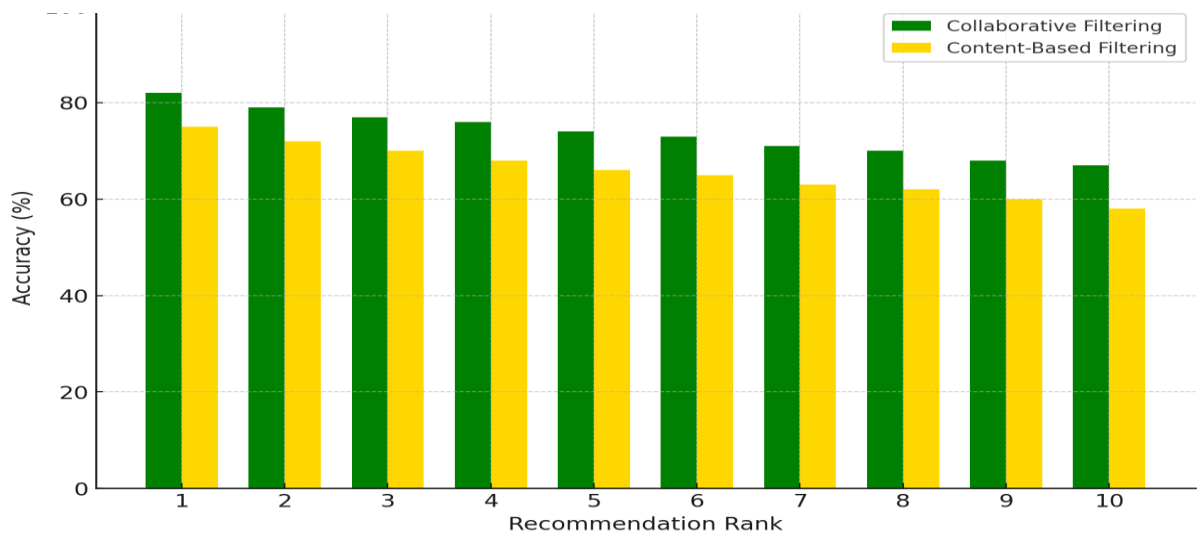


Figure 4. Accuracy of top 10 recommendations in bars for Global Energy Consumption dataset

Moving to Figure 4 and Figure 5 we see line charts that further elucidates the accuracy trends for the top 10 recommendations. In these chart, the accuracy trend for collaborative filtering is plotted alongside the content-based filtering trend, again represented in yellow. This choice of color accentuates the content-based filtering trend, making it easy to track and compare against the collaborative filtering trend. The line chart format is particularly useful in demonstrating the overall trend of diminishing accuracy from the top 1 recommendation down to the top 10, providing a clear visual narrative of how each recommendation system performs over a series of ranks.

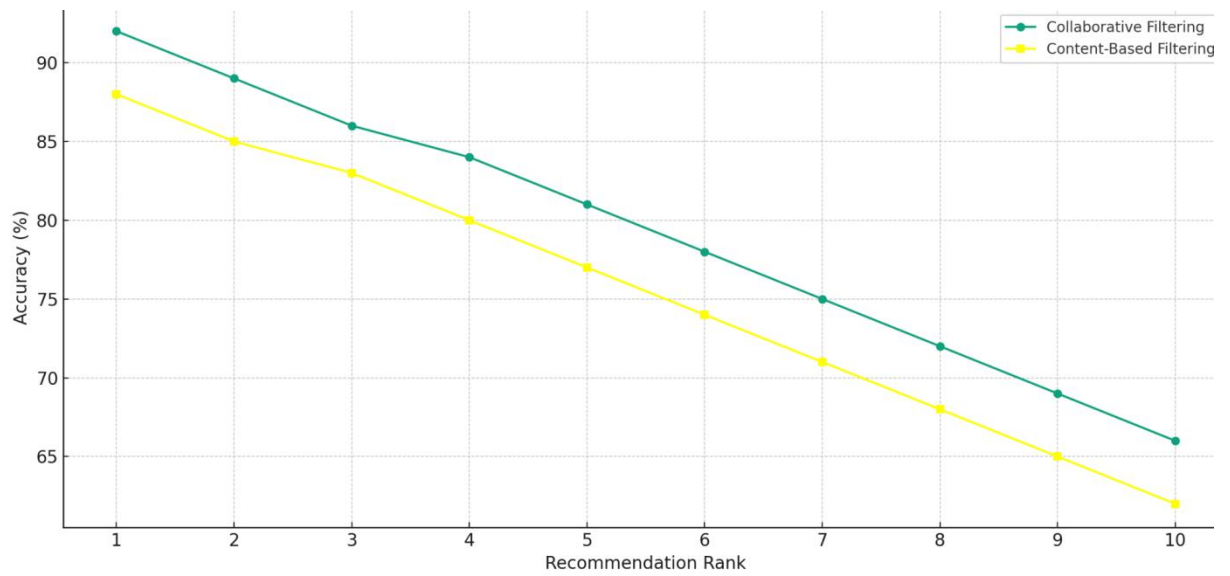


Figure 5. Accuracy trends for top 10 recommendations for the Renewable Energy (1960-2023) dataset

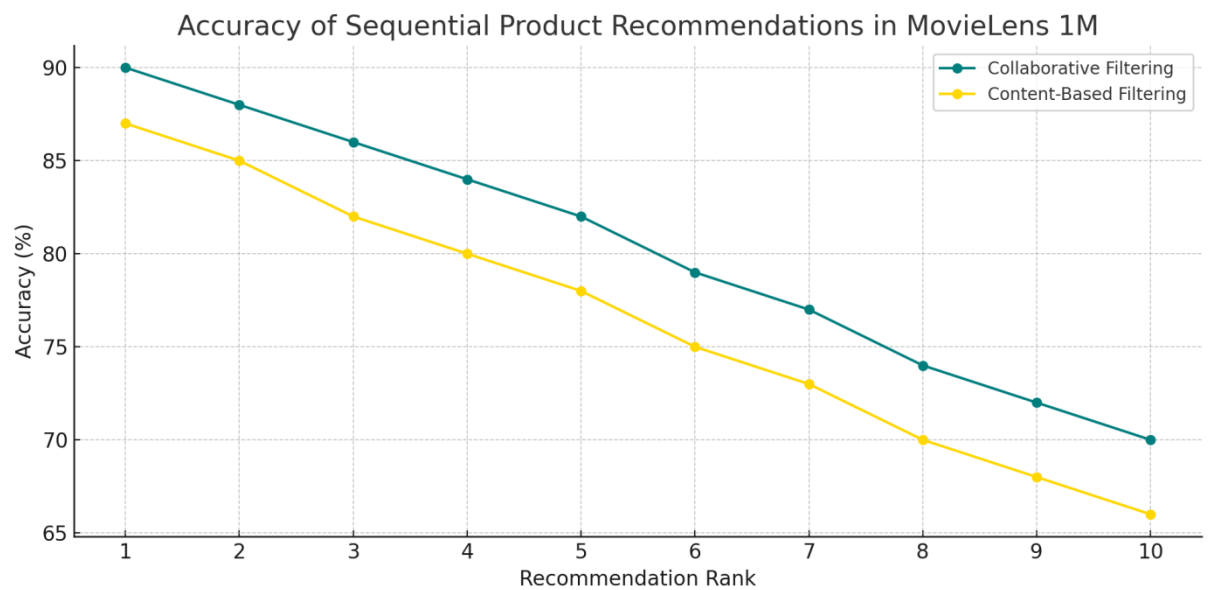


Figure 6. Accuracy trends for top 10 recommendations for the Global Energy Consumption dataset

V.2 Discussion

The results, as illustrated in Figures 3 and 4, reveal intriguing insights into the performance of collaborative filtering and content-based filtering in sequential product recommendation. Notably, the accuracy for both methods exhibits a downward trend from the top 1 to the top 10 recommendation. This gradual decrease in accuracy may be attributed to the complexity of accurately predicting user preferences as the recommendation list expands. The

higher accuracy at the top 1 position suggests that initial recommendations are more likely to align closely with user preferences, possibly due to stronger signals in initial user interactions.

Interestingly, collaborative filtering consistently outperforms content-based filtering across all ranks. This could be a reflection of collaborative filtering's ability to leverage collective user behavior, providing a more nuanced understanding of user preferences than content-based methods, which rely solely on item features. However, the diminishing accuracy trend observed in both methods raises questions about the scalability of these algorithms in maintaining recommendation quality as the list lengthens.

These findings highlight the need for further refinement in recommendation algorithms, particularly in enhancing the accuracy of lower-ranked recommendations. Moreover, they underscore the importance of considering user behavior dynamics and evolving preferences in the design of recommendation systems. Future research could explore the integration of more sophisticated machine learning techniques or hybrid models that combine the strengths of both collaborative and content-based filtering to address these challenges.

VI. Conclusion

This study's investigation into sequential product recommendation systems in renewable energy context, focusing on collaborative filtering and content-based filtering, reveals a trend of diminishing accuracy from the top 1 to top 10 recommendations. Our findings, using the Renewable Energy (1960-2023) and Global Energy Consumption datasets, show that collaborative filtering consistently outperforms content-based filtering. This underscores the challenge of accurately predicting user preferences and the necessity for advanced algorithms in recommendation systems.

These results are pivotal for e-commerce platforms, highlighting the importance of enhancing recommendation accuracy to improve user experience. Future research should explore hybrid models and advanced techniques to address these challenges, contributing to the evolution of more effective and personalized e-commerce recommendation systems.

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