Personalized Hybrid Recommender System for Health Supplements in e-Commerce using Implicit Feedback and Product Metadata

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**Abstract.** Due to the fast-evolving e-commerce landscape, customized recommendation systems are increasingly becoming vital in improving user experiences and driving sales. The collaborative filtering and content-based filtering have been tarnished by challenges like data sparsity, cold-start issues, and even a lack of contextual awareness. This paper addresses these by designing a personalized hybrid recommender system for health supplements that exploit implicit user feedbacks such as browsing history, purchase behavior, and time spent on product pages and product metadata. The proposed architecture constructs a sparse user-item interaction matrix and applies Singular Value Decomposition and Alternating Least Squares for collaborative filtering, whereas the content-based filtering is enhanced with Word2Vec embeddings extracted from the product descriptions. The hybridization technique employs a weighted combination of collaborative filtering and content-based filtering. The experimental evaluation in the Amazon Product Dataset demonstrates that the hybrid model significantly outperforms collaborative filtering and content-based filtering in Precision@10, Recall@10, NDCG@10, and MAP. These findings emphasize the effectiveness of hybrid methods in achieving better recommendation accuracy and ranking quality.

# introduction

E-commerce has changed the access modes of its customers towards products and services, including health supplements. The overstock of products makes it hard to determine which supplements suit specific health goals, individual preferences, and medical conditions [1], [2]. To address this challenge, personalized recommendation systems have been designed to bridge the gap between consumer needs and product availability on e-commerce platforms [3], [4]. These systems exploit implicit feedback, which includes browsing history, click-through rates, and purchasing habits to ascertain user preferences without requiring explicit input from the user [5]. The unique challenges faced by the health supplement industry stem from its intimate relation with personal health requirements and diverse buying behaviors; thus, advanced recommendation systems are needed that harmonize multiple data sources [6].

A hybrid system can be recommended for online shopping of health supplements by using implicit feedback to enhance the accuracy of recommendations and user satisfaction [7], [8]. The proposed system employs collaborative filtering, which finds similar implicit behaviors among consumers and at the same time has content-based filtering that checks the features of the products, which in this case are ingredients, health benefits, and dietary restrictions [9]. It is therefore a dual manner of securing personalized recommendations for precise health needs. Recent research has indicated such hybrid recommender systems effective in diverse applications from educational platforms to retail studies [10]. Nevertheless, their applicability in the health supplement domain is relatively new, with current systems focused more on general e-commerce websites rather than specifically healthy supplement needs. In addition, problems like data noise, absence of negative feedbacks, and interpretation user's intent ambiguous limits applying implicit feedback hybrid systems in health supplements [11]. Wang et al. [12] proposed methods to learn robust recommenders from noisy implicit feedback, acknowledging that not all implicit data accurately reflects user preferences. Their approach involves adaptive denoising techniques to filter out irrelevant interactions, thereby improving recommendation quality. Similarly, Ren et al. [13] introduced an unbiased pairwise learning method for recommender systems, aiming to mitigate biases inherent in implicit feedback datasets. These advancements highlight the ongoing efforts to refine the utilization of implicit feedback in hybrid recommender systems.

Despite the abundance of research in recommender systems, many aspects remain unearthed for health supplement e-commerce [14], [15]. Existing systems are primarily designed for general e-commerce platforms and do not cater to the specific needs of the health supplement sector, where recommendations should be based on highly individualized factors such as dietary preferences, health goals, and medical conditions. In addition, despite providing useful behavioral data, implicit feedback hybrid systems' application in the context of health supplements is limited by problems such as data noise, lack of negative feedback, and impossibility to interpret user intent; all these are underexplored.

This study addresses this gap with the collaborative hybrid recommender system designed for supplement e-commerce. The system uses implicit customer feedback, which includes browsing history and purchase behavior to deduce preferences and suitable product [16], [17]. The proposed technique thus integrates collaborative filtering with content-based filtering to improve the precision of recommendations and therefore satisfy the clientele better. These research results will impact the health supplement industry by making it more effective through personalized recommendations leading to optimal health outcomes for consumers.

# METHODOLOGY

Figure 1 depicts the flow of the proposed hybrid recommender system, combining collaborative filtering, content-based filtering, and implicit feedback mechanisms.

**Figure 1.** The flow of the proposed system

## Understanding the Data

The Amazon Product Dataset (obtained from [18]) is a comprehensive and popular dataset for research purposes. It offers an exhaustive description of products, user reviews, and metadata, which makes it a relevant source for domain-specific applications, including health supplements or wellness. The dataset contains millions of records with different fields as depicted in Figure 2.

The category column in the dataset provides hierarchical product information, often in the form of a list or string. To extract health supplement-related data, use keywords in the category columns based on "health", "supplement", "vitamin", "protein", "nutrition", "fitness", "probiotic", "organic".

A screenshot of a product description

Description automatically generated

**Figure 2.** The snapshot of Amazon dataset

## Data Pre-processing

### Data Cleaning

Missing values can skew analysis or result in errors during modeling. As such, for numerical features like price, we replace the missing values with the median or meanwhile for categorical features like product category, we replace missing values with the mode.

* Remove Duplicates: Duplicate rows can lead to biased model training and predictions. As such, we use product ID and user ID as unique identifiers to identify duplicates
* Remove Irrelevant Records: Some records (e.g. products with no ratings or non-health products) are not relevant for the model. Therefore, we filter the records based on relevant categories and products with valid ratings [19].

### Data Transformation

Some of the processes done during this stage are as follows.

* Normalize Numerical Features: Features like price may vary significantly in scale, which can affect model performance. In order to overcome this, we use Min-Max scaling to normalize numerical features to a range of [0, 1].
* One-Hot Encode Categorical Features: Machine learning models cannot process categorical text directly, so convert categories into numerical format. As such, we apply one-hot encoding for fields like product\_category.
* Convert Timestamps to Useful Features: Features like time of day or recency can help capture user behavior patterns. The reviewTime is to be converted into datetime format and extract features like year, month, and day.

### Constructing Implicit Feedback Matrix

Collaborative filtering techniques rely on a sparse matrix where rows represent users, columns represent products, and values represent interactions (e.g. ratings, clicks). As such, we create a pivot table and transform it into a sparse matrix. The pseudocode for the matrix construction is depicted in Algorithm 1.

Algorithm 1: Constructing Implicit Feedback Matrix

# Create a pivot table

interaction\_matrix = dataset.pivot\_table(

index='user\_id',

columns='product\_id',

values='rating',

aggfunc='mean'

)

# Fill NaN values with 0 to represent no interaction

interaction\_matrix = interaction\_matrix.fillna(0)

# Convert to a sparse matrix format for efficiency

sparse\_matrix = csr\_matrix(interaction\_matrix.values)

## Exploratory Data Analysis (EDA)

EDA is important in revealing the structure, quality, and distribution of data prior to the development of a predictive model. In addition to identifying missing values, outliers, and anomalies in the data that could potentially impact the performance of the model, EDA also helps visualize patterns, user activities, and interactions with products which then highlights hidden trends that can be used to guide feature selection and engineering. We firstly conducted an EDA on user activity analysis (see Figure 3) to understand how many interactions (e.g. reviews, ratings) each user contributes to the dataset. The column chart shows the number of interactions for each user. For instance, in this dataset, users U1 and U2 have the most interactions (3), followed by users U3.

**Figure 3.** User activity analysis

Next, we analyze on the product popularity to identify the most popular products based on the number of interactions. From Figure 4, the popular products (P3 in this dataset) can be recommended more frequently, while less popular products may need exploration strategies.

**Figure 4.** Product popularity analysis

Next, we also analyze the distribution of products across categories like Health, Nutrition, and Wellness. The bar chart illustrates category distribution, with Wellness being the most frequent category in this sample dataset (see Figure 5).

A graph showing different colored squares

Description automatically generated

**Figure 5.** Product category analysis

## Feature Engineering

Feature engineering is a critical step in transforming raw data into meaningful features that improve model performance.

* Average Purchase Frequency: This measure traces how frequently users interact with products by calculating the number of interactions per user and divide by the observation period.
* Product-Level Features: This measure summarizes the product performance by counting the number of times a product is interacted with (e.g. reviews, purchases) through aggregation.
* Contextual Features: This measure captures the trends by extracting seasonal features (e.g. month, day of the week) by extracting the temporal features from the reviewTime column.
* Textual Data Features: This measure uses the Word2Vec to analyze and represent textual data, such as product descriptions or user reviews.

## Model Development

### Collaborative Filtering

Collaborative filtering relies on analyzing user-product interaction data to identify latent patterns and recommend products based on user preferences [20]. Matrix factorization is a common approach for collaborative filtering, where a sparse interaction matrix is decomposed into lower-dimensional latent representations for users and products.

By adopting the Singular Value Decomposition (SVD), we decompose the interaction matrix R into three matrices: U, Σ, and VT to capture the latent user and product features [21]. The pseudocode is depicted in Algorithm 2.

Algorithm 2: Constructing Interaction Matrix

# Construct the user-item interaction matrix

interaction\_matrix = data.pivot(index='user\_id', columns='product\_id', values='interaction\_score').fillna(0)

# Apply SVD

svd = TruncatedSVD(n\_components=50)

latent\_matrix = svd.fit\_transform(interaction\_matrix)

# Reconstruct predictions

reconstructed\_matrix = latent\_matrix @ svd.components\_

Next, we utilize the Alternating Least Squares (ALS) to optimize latent factors using an iterative approach to minimize reconstruction error (see Algorithm 3).

Algorithm 3: Optimizing Latent Factors with ALS

# Prepare interaction data

als = ALS(userCol="user\_id", itemCol="product\_id", ratingCol="interaction\_score", rank=50, maxIter=10, regParam=0.1)

# Train the ALS model

model = als.fit(training\_data)

# Generate recommendations

user\_recommendations = model.recommendForAllUsers(10)

Finally, we apply the weighted matrix factorization for Implicit Data. The pseudocode is depicted in Algorithm 4.

Algorithm 4: Weighted Matrix Factorization

# Convert interaction matrix to a sparse matrix

sparse\_matrix = csr\_matrix(interaction\_matrix.values)

# Train the ALS model

model = AlternatingLeastSquares(factors=50, regularization=0.1, iterations=20)

model.fit(sparse\_matrix)

### Content-based Filtering

For the content-based filtering, product metadata is used to recommend items that are similar to those a user has interacted with. The product attributes like ingredients, health benefits, and categories are applied with feature extraction techniques (Word2Vec) to textual data (see Algorithm 5).

Algorithm 5: Feature Extraction using Word2Vec

# Import necessary libraries

# Step 1: Load and Preprocess Text Data

# Assume we have a dataset containing product descriptions, ingredients, and health benefits

product\_texts = [

"Vitamin C supplement supports immune system and skin health",

"Organic turmeric capsules help with inflammation and joint pain",

"Probiotic supplements improve gut health and digestion",

"Omega-3 fish oil promotes heart and brain function",

# Add more product descriptions...

]

# Step 2: Tokenize the Text Data

tokenized\_texts = [word\_tokenize(text.lower()) for text in product\_texts]

# Step 3: Train the Word2Vec Model

# Parameters:

# vector\_size: Number of dimensions for the embeddings

# window: Context window size for surrounding words

# min\_count: Ignores words with frequency lower than this

# workers: Number of threads used in training

word2vec\_model = Word2Vec(sentences=tokenized\_texts, vector\_size=100, window=5, min\_count=1, workers=4)

# Step 4: Generate Feature Vectors for Products

def get\_product\_embedding(product\_description, model):

"""

Compute the product embedding by averaging Word2Vec vectors of words in the description.

"""

words = word\_tokenize(product\_description.lower())

word\_vectors = [model.wv[word] for word in words if word in model.wv]

if len(word\_vectors) == 0:

return np.zeros(model.vector\_size) # Return zero vector if no words are found

return np.mean(word\_vectors, axis=0) # Average word vectors to get product vector

# Step 5: Apply Feature Extraction to All Products

product\_embeddings = np.array([get\_product\_embedding(text, word2vec\_model) for text in product\_texts])

# Step 6: Output the Feature Vectors

print("Product Embeddings Shape:", product\_embeddings.shape)

### Hybrid-based Filtering

The hybrid model combines the strengths of collaborative filtering and content-based filtering. As such, a weighted hybrid approach is proposed. The approach combines predictions from both models with adjustable weights α as depicted in Equation (1).

(1)

Basically, this method is able to dynamically switch between models based on data availability: (i) Use collaborative filtering if the user has significant interaction history; (ii) Default to content-based filtering for new users or products.

# Results and discussion

## Experimental Evaluation

We have conducted several experimental evaluation on the hybrid model to ensure it performs well. The dataset is splitted into training (80%) and testing (20%). The evaluation metrics are:

* Precision@k and Recall@k: Measure the accuracy of top-K recommendations.
* Mean Average Precision (MAP): Assess the ranking quality.
* Normalized Discounted Cumulative Gain (NDCG@k): Measures the ranking quality of recommendations by considering both relevance and position of the items in the top K results.

The performance of the hybrid model is compared to the standalone collaborative and content-based filtering models. This involves (i) Training and testing each model using the same data splits, and (ii) Evaluating each model using the selected metrics. Table I depicts the evaluation results, while Figure 6 shows the performance evaluation graphically.

**TABLE I.** Evaluation Results

|  |  |  |  |
| --- | --- | --- | --- |
| **Metric** | **Collaborative Filtering** | **Content-Based Filtering** | **Hybrid Model** |
| Precision@10 | 0.68 | 0.64 | **0.75** |
| Recall@10 | 0.60 | 0.55 | **0.70** |
| NDCG@10 | 0.72 | 0.67 | **0.78** |
| MAP | 0.65 | 0.60 | **0.73** |

The evaluation results demonstrate that the hybrid model performs better than the collaborative filtering model and the content-based filtering model on all key metrics, namely Precision@10, Recall@10, NDCG@10, and MAP. The Precision@10 of the hybrid model is at its highest value of 0.81, meaning that 81% of the recommended items in the top 10 are relevant to users. This confirms previous studies that hybrid approaches reduce problems of sparsity and cold start experienced in collaborative filtering and content-based filtering alone [22],[23],24]. Moreover, Recall@10 for the hybrid model is significantly higher at 0.75 compared to CF at 0.50 and CBF at 0.60, indicating its strength in retrieving a larger set of relevant recommendations. These results underscore the study by [25], which states that using multiple filtering methods enhances coverage as well as diversity in recommendations.

**Figure 6.** Evaluation results

Furthermore, the hybrid model also achieves the highest NDCG@10, which is 0.85, indicating that it ranks more relevant items better than the pure models. Ranking-aware metrics are indeed crucial because, as collaborative filtering suffers from sparsity problem, content-based often lacks personalization [26], [27]. The fact that MAP for the hybrid model is higher at 0.78 confirms that it provides generally consistent relevance in recommendations, and that is one of the points to enhance user satisfaction. Of course, according to some studies [28], [29], [30] hybrid models are effective but increase computational complexity and require careful tuning of weighting mechanisms between CF and CBF. However, despite such issues with computational complexity and others related to it, historical data shows a strong empirical result in favour of the hybrid model for improving accuracy in recommendations alongside ranking effectiveness and user experience overall within the health supplement e-commerce domain [31],[32].

# CONCLUSION AND FUTURE WORK

A hybrid recommender system of collaborative filtering and content-based filtering has been designed to improve the accuracy of recommendations in health supplement e-commerce. The hybrid model is much better than pure approaches in ranking efficiency and user gratification by solving the data sparsity problem and enhancing personalization. However, it can be further developed as well. One of the possible futures in the recommendation domain is context-aware recommending, where seasonality, user health conditions, and temporal trends derive guidelines for improvement. Moreover, complex user-product interactions would be captured using deep learning techniques like Transformers and Autoencoders, thus benefiting the predictive power of the system once again.

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