A Content-based Skincare Product Recommendation System

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***Abstract*—Consumer interest in cosmetics, and particularly skincare products, has surged globally in recent years. Traditional methods of selecting skincare products involve relying on best-sellers or in-store recommendations. However, these approaches are ineffective because they fail to account for individual variations in skin conditions and consumer compatibility. This research aims to design a skincare product recommendation system based on users' skin types and ingredient compositions of products. The proposed method employs content-based filtering to identify chemical components of products and find products with similar ingredient compositions. Unlike many existing systems that require users to input product names, the new system takes into account their desired beauty effects to accommodate those with limited skincare knowledge. The resulting system returns personalized recommendations across multiple product categories. It could contribute to improved compatibility between users and skincare products, enhanced user satisfaction and streamlined selection processes.**

***Index Terms*—content-based filtering, skincare recommender system, cosmetics**

I. Introduction

Hailed as the "fastest-growing category globally", skincare sales have overtaken makeup sales with increasing distance each year [1]. The number of global skincare consumers is estimated to grow from 2.4 billion in 2020 to 3.8 billion by 2024 [2]. The global skincare market is also expected to reach $207.22 billion by 2028, following a solid recovery after the COVID-19 pandemic. This growth is mainly due to the increased awareness of personal care across all age groups and genders [3], as well as demand for sustainable products and interest in anti-aging solutions.

The expansion of the skincare market has led to an increased need for advanced technology as more customers started visiting the cosmetics counter for product recommendations [4]. Nonetheless, existing technology for this purpose is often ineffective and time-consuming. The overwhelming quantity of accessible online information has also made it difficult for users to make informed choices [5]. While the abundance of online product information and reviews holds potential to be valuable, in the absence of effective solutions for leveraging this information it makes it difficult for users to discern information and select products to alleviate their specific concerns. As a result, there is a pressing need for personalized systems that can ease the access of online cosmetics data.

In an attempt to resolve the problem of information overload, researchers have proposed different recommender systems to facilitate decision making processes [6]. Among these systems, the two most commonly adopted methods are collaborative filtering and content-based filtering. More recently, a hybrid approach that combines the two techniques has been introduced to maximize the benefits of both methods while addressing their weaknesses. Nevertheless, it is still unclear which technique best measures the suitability of products for each customer. Many online cosmetics stores continue to recommend bestsellers to customers regardless of their skin conditions [7]. Although some brands have integrated quizzes or image scanners on their websites to provide personalized recommendations, these tools are constrained to the specific products offered by their brand. Consequently, there is a need for further investigation and improvement in the development of recommender systems for personal care that allows for broader application beyond brand-specific limitations.

This paper presents a content-based recommendation approach that assesses the similarity of ingredient composition among products. Instead of making recommendations within the same product category, this new system recommends products from multiple categories to enable more effective recommendations. Additionally, users have the option to provide minimal input to receive skincare product suggestions. We evaluate the system by calculating the percentage of recommended tags in the product ratings of users who have matching skin types.

II. Related Work

Existing recommendation methods can be largely classified into three main categories: collaborative filtering, content-based filtering, and a hybrid approach that combines elements from both techniques.

A. Collaborative Filtering

Collaborative filters take user-provided data such as clicks, likes and purchases to generate recommendations. Although they struggle with limited data (known as the *cold-start problem*), they perform well with sufficient behavioral data [8]. Collaborative filtering is based on the premise that finding

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similar users to help match customers with the right products. Matsunami et al. [9] and Okuda et al. [10] adopted a user similarity calculating method and analyzed reviews of cosmetic items. They used automatic scoring and k-means clustering to extract ratings and textual reviews containing individual preferences. Ye alleviated the data sparsity problem in traditional collaborative filtering methods by adopting an item-based approach [11]. Matsunami et al. and Okuda et al. relied on users' reviews for textual analysis without incorporating information about items. Recently, Qalbyassalam et al. introduced a deep learning-based skincare recommender system that leverages implicit product ratings acquired through sentiment analysis [12]. We propose to incorporate both the properties of items and user ratings. Although it does not filter products based on ratings, it employs them for evaluation.

B. Content-based Filtering

Content-based filtering is another commonly used recommendation method that considers item descriptions and user preferences [13]. However, it often suffers from an overspecialization problem, pursuing too narrow of a focus.

Putriany et al. adopted content-based filtering and designed their recommender system based on the items that were previously rated, liked, or chosen by a specific user [13]. They employed k-means clustering to categorize skincare products into five clusters based on users' skin types and preferences. An entity-relationship diagram was created along with a web-based system, which was then evaluated using purity (the extent to which clusters consist of a single class). The obtained purity score was 0.29, which is relatively low, as the score of 1 indicates 100% accuracy. Similarly, Patty et al. targeted user profiles but further enhanced the system by including additional factors such as cosmetic type, skin type, usage, price, description, and pictures [4]. This approach allows for personalization beyond users' shopping habits. They employed TF-IDF (Term Frequency-Inverse Document Frequency) and utilized both user profiles (skin type and price) and item profiles (cosmetic type and usage) to rank 40 selected products. The products were initially categorized into 17 groups based on the similarity between the cosmetic data and user input. To rank the items in descending order, cosine similarity was used, returning recommendations that aligned with their planning application. However, they did not provide any numerical measure for the accuracy of their method. Sato et al. modified content-based filtering by applying a statistical method to capture influence from other users [14]. The limitation of content-based filtering is that it only works for active users, and it can be difficult to provide accurate recommendations when available information is hard to categorize [13].

Recommending skincare products should be treated separately from recommending movies because of the complexity and sensitivity of individual skin conditions. Jeong tackled this problem by building a recommender system that focuses on the ingredients of cosmetics [15]. Honma et al. also took a similar approach and mapped users' skin types to the ingredients of cosmetics [16]. Their approach addresses the weakness of collaborative filtering, which performs worse as the number of ratings increases [13]. Jeong used Natural Language Processing (NLP) for ingredients to match products with different skin types [15]. She preprocessed 1472 products from Sephora[1] after scraping information about their brand, cost, rating, ingredients, and suitable skin types. She categorized skin types into five categories and product types into six, and assigned binary values to the ingredients in each product. The top five items were recommended based on calculated cosine similarities. Similar to this, Honma et al. used TF-IDF to recommend skin lotions containing ingredients with high beauty effects [16]. Their method considers 7 degrees of satisfaction, 15 types of effects (anti-aging, moisture, acne, etc.), reviews, and ingredients of skincare products. By the end of their study, the percentage of invalidated products for each recommended product group was less than 5%, indicating the reliability of their method. Since their method incorporates user ratings and desired beauty effects, it has the potential to enhance personalization of recommendations. Other studies have used deep learning methods [17] or image analysis [18] to make recommendations based on user profiles.

There is a consistent trend across different algorithms that prioritize user profiles over past purchase history. In order to address the overspecialization problem of content-based filtering, the newly proposed method closely follows Jeong's approach. It recommends items that are not limited to a single category, providing recommendations across all six categories to save users time. One drawback of Putriany et al. and Jeong's research is that their systems require users to select an initial product as an input. But this poses a challenge for users who struggle with the selection process.

In contrast, the proposed method offers an option for users to bypass the need for product input. Instead, it gathers other desired information from the user to provide recommendations that are not solely based on content. Another limitation of Jeong's research is the lack of validation measure for the system. To address this, the newly proposed method includes experiments to assess and ensure its reliability.

C. Hybrid Approach

Noticing the problems in the traditional methods, companies like Netflix and Google started adopting hybrid recommender systems using both collaborative and content-based filtering methods [19]. Experiments on the live traffic of the website done by Google suggest that the hybrid method improves the quality of recommendation [20]. With similar assumptions, some researchers have used hybrid filtering to maximize the benefits of both collaborative and content-based filtering.

Hansson proposed a hybrid recommender for online products using k-means++ [8]. Using the dataset from an online book retailer and fashion retailer, she obtained the values for precision and recall for each method tested on both datasets. She concluded that her algorithms do not have the same functionality across different datasets, and combinations of

[1] https://www.sephora.com

strong algorithms do not produce better results. James and Rajkumar also proposed a hybrid method and added the time sequence method for collaborative filtering [6]. Unlike Hansson's, their research is theory-based and was not tested on an actual dataset. They suggested three different directions for their algorithm: item similarity, bipartite projection, and spanning tree. Since the time sequence model learns the change in data over time, the authors concluded that it will generate higher accuracy by using static data.

Although a hybrid approach may have potential in the skincare domain, it requires a dataset that involves both the behavioral information of the user as well as the product information, which are scarce in skincare. Thus, our proposed method focuses only on content-based filtering.

III. Design and Implementation

We illustrate our proposed system in Fig. 1. The proposed system provides a choice between content-based filtering and non-content-based filtering (IF-IPF filtering), depending on whether the user provides an initial product input. This allows it to function well for users with both high (familiarity with and preferences among skincare products) and low existing skincare knowledge. We describe our process towards developing the system in the following subsections.

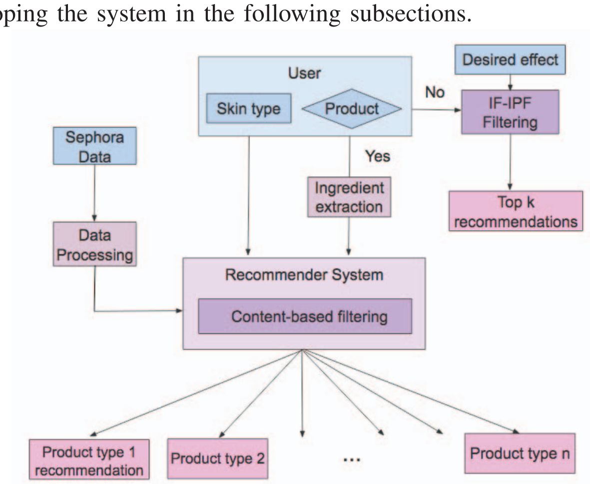

Fig. 1. Framework of the content-based recommender system

A. Task Formulation

1) Content-based Filtering: A user provides one of five skin types (combination, dry, normal, oily, and sensitive) and chooses a product from one of six categories (moisturizing cream, facial treatments, cleanser, face mask, eye treatment, and sun protection) defined by an existing dataset (additional details provided in §III-B). The selected skin type is directly mapped to the recommender system while ingredients are extracted from the product. The skin type and ingredients are then sent to the content-based recommender system, along with Sephora data that contain information about other products. Recommendations are generated across all six categories using this approach. By evaluating the similarity of ingredient composition within products, the system provides k recommendations for each of the n product types.

2) IF-IPF Filtering: When a user provides their skin type but not the product name, the system prompts them to select one desired beauty effect from anti-aging, moisturizing, oil control, acne treatment, redness control, and reduced pores. Subsequently, the system employs TF-IDF method to filter relevant products based on the selected beauty effect. Recommendations are then generated in a similar format to content-based filtering.

B. Data Collection

An existing dataset from Jeong's research was used in this project [15]. The data were scraped from Sephora, a popular store and website that offers a wide range of beauty and skincare products from various brands. Since the focus of this project was specifically on skincare products, six categories were selected for extraction: moisturizing cream, facial treatments, cleanser, facial mask, eye treatment, and sun protection. These categories represent the available skincare product categories on Sephora. Other categories such as hair or fragrance were not considered in this work. The dataset contains 1472 items with product information such as brand, name, price, rank, skin types, and chemical components. Additionally, star ratings for all 1472 items were collected from Sephora using Scrapestorm[2] along with the corresponding skin types of the reviewers. This dataset was specifically extracted to assess the effectiveness of the filtering method.

C. Ingredient Extraction

The ingredient extraction method closely follows Jeong's approach [15]. Initially, the collected data are filtered based on the user's skin type. When the user inputs a product name, the system extracts its ingredients and sends them to the recommender system along with the Sephora dataset. The list of all ingredients is obtained from the ingredients column of the dataset and then split into tokens. After checking for duplicates, each chemical element is assigned a unique index and stored in a dictionary.

The next step involves creating a document term matrix (DTM) that captures the relationship between the skincare products and their corresponding ingredients. An empty matrix is initialized, and all elements are filled with zeros. The number of rows in the matrix represents the total number of skincare products, while the number of columns represents the total number of ingredients. One-hot encoding is employed to populate the cosmetic-ingredient matrix with values of 1 (present) or 0 (not present) to indicate the presence of ingredients for each product. An example of such a matrix is depicted in Fig. 2.

	water	niacin	lanolin alcohol	Decyl oleate	serine	...	sh-polypeptide-1
Cosmetic 1	1	1	0	1	0	...	1

Fig. 2. Cosmetic-ingredient matrix [6]

[2]https://www.scrapestorm.com

D. Content-based Filtering

Once the ingredients are extracted and processed, they are fed into the recommender system along with the user's skin type. The recommender system utilizes content-based filtering, following Jeong's work [15]. In this method, cosine similarity is employed to measure the vector similarity of the ingredient composition between two products a and b, both with vector length l. It is applied to produce k recommendations for n product categories, effectively ranking cosmetics that exhibit similar properties to the original product.

The process described in §III-C is used to vectorize all cosmetic items. These vectors are then plugged into (1) to calculate the distances between different points (products).

$$\text{Cos}(a, b) = \frac{\vec{a} \cdot \vec{b}}{||\vec{a}||\ ||\vec{b}||} = \frac{\sum_1^l a_i b_i}{\sqrt{\sum_1^l a_i^2}\sqrt{\sum_1^l b_i^2}} \tag{1}$$

This results in a ranking of products from most to least similar to the target product. Since the dataset is labeled with different product types, the system uses this process to make recommendations across all available product categories.

E. IF-IPF Filtering

An advantage of our system over comparable alternatives is that if users have never used or liked any product from Sephora, they can still receive recommendations based on their skin type and desired beauty effect. The top ingredient that enhances specific beauty effects is determined by calculating product-specific TF-IDF values, referred to as ingredient frequency-inverse product frequency (IF-IPF). The IF-IPF values are computed using (2), (3), and (4) [16].

$$\text{IF}(i, X) = \sum_{p=1}^{m} \frac{n_p - \alpha_{p,i}}{n_p} \tag{2}$$

$$\text{IPF}(i) = \log \frac{N}{pf(i)} \tag{3}$$

$$\text{IF-IPF}(i, X) = \sum_{p=1}^{m} \frac{n_p - \alpha_{p,i}}{n_p} \times \log \frac{N}{pf(i)} \tag{4}$$

We define the variables used in these equations as follows:

- n_p: the number of unique ingredients included in product p in beauty effect group X
- m: the number of products in beauty effect group X
- $\alpha_{p,i}$: the rank of ingredient i listed in product p
- N: the number of products in the dataset
- $pf(i)$: the number of products including ingredient i

By leveraging these calculations, the system identifies ingredients that have the most influence on the desired beauty effect, enabling more targeted recommendations for users with limited prior product engagement. After identifying ingredients with the highest IF-IPF values, the system filters and sorts products that contain those ingredients. Finally, the system returns the top k recommendations from each product category, providing a diverse range of options for the user.

IV. Evaluation

A. Experimental Setup

To evaluate the performance of the content-based recommender system, user ratings filtered by the inputted skin type were extracted from Sephora. Some ratings had a tag labeled "recommends this product" while others did not. These labels serve as important indicators of user satisfaction with the product. The percentages for the number of reviews with recommended tags divided by the total number of reviews were then calculated to judge the effectiveness of the system. Specifically, for a given skincare category (c) $\times$ skin type (t), we computed the number of predicted recommendations with gold standard "recommends this product" reviews (rec_{ct}) divided by the the total number of reviews for those predicted recommendations (all_{ct}):

$$\text{Effectiveness}(c, t) = \frac{\text{rec}_{ct}}{\text{all}_{ct}} \tag{5}$$

We evaluated the system with two distinct sets of users to assess effectiveness for individuals with both high and low skincare product familiarity. For the group with high familiarity, we employed content-based filtering. For the group with low familiarity, we employed IF-IPF filtering. Sets and results are presented in the following subsection.

B. Results

1) Content-based Filtering: A group of five female students, each with a unique skin type, were asked to identify their skin type. To verify their skin type, they were asked to take an online quiz from Interact[3]. The students were then asked to provide a product they have used and liked from Sephora. The information was inputted into the content-based recommender system, resulting in the generation of five recommendations for each of the six product categories. Sample recommendations are shown in Fig. 3. The recommendations for each student were validated using the metric in (5). The

Moisturizer

	Name	dist
0	Future Solution LX Total Regenerating Cream	0.991317
1	Benefiance WrinkleResist24 Night Cream	0.991129
2	Vitamin C Glow Moisturizer	0.952674
3	Black Tea Firming Overnight Mask	0.873000
4	GenOptics Spot Essence Serum	0.861700

Fig. 3. Sample of content-based filtering result

aggregated effectiveness scores across all five students, for each skincare category $\times$ skin type, are shown in Table I. Results marked N/A could not be validated due to some products being discontinued, brands no longer selling them on Sephora, or the absence of reviews for certain skin types.

2) IF-IPF Filtering: Five male students with limited knowledge of skincare products were asked to provide their skin type and desired effect. They each had a unique skin type which was again verified using the online quiz. The students received recommendations based on their inputs. The evaluation of the outcomes is shown in Table II.

[3]https://www.tryinteract.com/quiz/what-skin-type-are-you

TABLE I
RECOMMENDER SYSTEM EFFECTIVENESS FOR STUDENTS WITH HIGH SKINCARE PRODUCT FAMILIARITY

	Normal	**Oily**	**Combination**	**Sensitive**	**Dry**
Moisturizer	86.96	85.71	54.12	85.71	93.81
Cleanser	77.14	52.94	82.21	50.00	73.20
Treatment	81.82	91.10	61.46	60.00	51.16
Face Mask	91.30	89.33	68.75	90.91	100.00
Eye Cream	75.53	76.19	N/A	94.44	70.49
Sun Protect	82.76	70.00	55.33	66.67	N/A
Average	82.59	77.55	64.37	74.62	77.73

TABLE II
RECOMMENDER SYSTEM EFFECTIVENESS FOR STUDENTS WITH LOW SKINCARE PRODUCT FAMILIARITY

	Normal	**Oily**	**Combination**	**Sensitive**	**Dry**
Moisturizer	72.00	80.47	80.62	76.00	76.38
Cleanser	85.11	85.65	85.98	N/A	50.00
Treatment	100.00	70.08	80.00	100.00	83.78
Face Mask	83.33	100.00	N/A	100.00	82.35
Eye Cream	81.25	93.13	70.31	92.86	76.81
Sun Protect	73.91	52.78	44.07	66.67	N/A
Average	82.60	80.35	72.19	87.10	73.87

C. Discussion

For students with normal skin, the CBF approach (used for students with high skincare product familiarity) achieved an average efficiency of 86.96% for all recommended product types, while the IF-IPF method (used for students with low skincare product familiarity) resulted in 82.60%. In the case of students with oily skin, the CBF approach yielded an average efficiency of 77.55%, while the IF-IPF method resulted in 80.35%. It is worth noting that outliers, such as 44.07% observed for the *Sun Protect* $\times$ *Combination* pairing, may have arisen due to the low cost-effectiveness of expensive skincare products. The remaining results are generally more consistent and reasonable, with percentages ranging from 70% to 100%. Furthermore, IF-IPF generally outperforms CBF in four out of five skin types, suggesting that a lack of prior product knowledge does not affect the quality of recommendations. However, the differences between the averaged results of CBF and IF-IPF are relatively small and both methods exhibit comparable efficiency. Thus, users can choose either method based on their specific needs and expect similar performance. It is important to consider that the number of reviews per product varied significantly, ranging from 20 to over 1000, possibly impacting the variability of the effectiveness scores.

V. CONCLUSION

In this study, content-based filtering and IF-IPF filtering methods were implemented to make personalized recommendations based on user profiles and needs. The evaluation of these methods revealed that IF-IPF performed slightly better on average than CBF. This finding highlights the robustness of IF-IPF and its ability to accurately provide recommendations tailored to different users. Since the results were derived from a small sample size, one could investigate more robust evaluation metrics to measure the efficiency. Another potential research direction could be developing a dataset that includes user profiles, product information, and user behavioral data to create a hybrid recommender system to generate more accurate and personalized recommendations.

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