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COLLABORATIVE FILTERING APPROACH: SKINCARE PRODUCT RECOMMENDATION USING SINGULAR VALUE DECOMPOSITION (SVD)

Farhatun Nissa[1], Arum Handini Primandari[1], Achmad Kurniansyah Thalib[2]
[1] Statistics Study Program, Universitas Islam Indonesia, Indonesia
[2] Purwadika Digital Technology School, Indonesia

e-mail: primandari.arum@uii.ac.id

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Abstract: The recommendation system provides recommendations for something, be it goods, songs, or movies. The term system is not limited to a service system but concerns a model that can provide recommendations. With recent technological advances, many companies provide various skincare products because current generations are increasingly aware of self-care. With various choices, someone may experience confusion in determining the product they want to buy. Therefore, we need a system that can provide product recommendations run on any platform we use. The most common method for recommendation systems often comes with Collaborating Filtering (CF) where it relies on the past user and item dataset. The singular value decomposition (SVD) method uses a matrix factorization technique that predict the user's rating based on historical ratings. The measurement of the model's accuracy is the RMSE average of 1.01276, indicating that this value results from the best parameters. The results focus on showing skincare product recommendations to users sorted based on rating predictions.

1. INTRODUCTION

Skin is one of assets possessed by human to cover their bodies. Almost every one of all ages takes a good care of their skin, specifically their facial skin, so that it gets healthier, brighter, and is protected from premature skin aging. Applying skincare is one of the efforts to take care of the skin using certain products in order to maintain its good condition and health, especially on facial skin. Skincare products are most effective when applied following the correct order. Choosing what skincare products are best for users does not solely based on friends' or families' recommendation. More importantly, users do not randomly pick skincare products as wrong skincare products may harm their facial skin's health. They usually will look for skincare product information through internet prior to the skincare usage. Femaledaily is one of the platforms that ease users to search for product usage references since it accommodates various product reviews, mainly skincare products, from users. In addition, it also provides reviews for other products such as body care, hair treatment, and makeup products. Review giving usually goes together with rating giving using a particular scale; the higher the rating, the better the benefits of the products.

Product reviews are reviews from various sources like books, news, and other sources so that the advantages, disadvantages, and quality of the products are known. The aim of reviews includes helping and making it clear for the users to understand what they need on certain topics. The recommender system is a system or algorithm used to recommend something, for instance, products, movies, or others. Collaborative Filtering (CF) is the most commonly used approach in the recommender system, which utilizes user habits based on others' opinion, for the same users and similar product can be liked by other users as their choice recommendation. Users' preferences are observed as ratings for something in collaborative filtering recommender systems, and each extra rating adds to the system's knowledge and influences how accurately it makes recommendations. The effectiveness of the recommendations tends to increase with the number of ratings that the users provide (Elahi et al., 2016; Isinkaye et al., 2015). The problem rises with the popularity of internet use; the more user, the more extensive the size of the sparse matrix.

In order to solve issues with sparsity rating matrix, we usually employed Matrix Factorization (MF) such as SVD, PCA (Principal Component Analysis), also PMF (Probability Matrix Factorization). SVD is one of the techniques in the model-based CF method which can calculate the similarity of items interacting with the users and other items based on rating. This technique is then used to reduce dimensionality and improve performance (Bokde et al., 2015; Zhang et al., 2005).

This research is conducted with the aim of giving a recommendation for the users to find skincare products on Femaledaily based on the products' rating so that they can get product recommendation which has been given an estimated rating specifically for them. The recommender system is addressed to minimize searching for products that are going to be used and ignore other factors such as skin type. Data was collected by scrapping the Femaledaily.com website.

2. LITERATURE REVIEW

The research about Collaborative Filtering (CF) applied in phone accessories recommendation examines a store selling smartphone cases to provide recommendations for users to ease them when choosing products to buy (Prasetyo et al., 2019). Applying equation calculation, namely the weighted average of deviation, to calculate each product's prediction values, the average MAE value of this research was 0.572039. Even though the execution process took 6.4 seconds, the results were pretty accurate.

Another research, on improving CF algorithm, observed four algorithms comparison to determine which algorithm yielded better accuracy (Vegeborn & Rahmani, 2017). The examined algorithms included K-Nearest Neighbour (KNN), Slope One, Singular Value Decomposition (SVD), and Average Least Square (ALS) used in the CF method (Wang et al., 2019). The data used was a collection of movie rating data on Movielens with several different data sizes. The results showed that the SVD algorithm had the best accuracy with an RMSE of 0.8190 in the data size of 1M and an increase of 0.09936%, from 100 thousand data to 1M. In addition, a non-matrix factorization algorithm, namely Slope One and KNN, had adequately good performances compared with ALS. Basically, the KNN algorithm works the same as the KNN which is used to classify based on the similarity of a data with other data. The similarity measurement most commonly used is the Euclidean distance. The issue regarding KNN is the selection of the optimal number of neighbors (Widiharih & Mukid, 2018).

The use SVD algorithm on e-commerce's product recommendation (Akter et al., 2017) generate two predictive matrices according to its initial values. A product catalog is a core element of all e-commerce products from which the users can find that element in two ways. First, they can input product keywords into the system to find what they need. Second, assumed they do not precisely know the item, the e-commerce system will recommend them multiple similar products. In this case, the approach could be carried out on well-known data mining techniques, namely the recommender system. The historical data of the recommender system is the product rating score given by users, then predict unknown ratings to be recommended to specific users. The recommender system can be built from the matrix; the Singular Value Decomposition (SVD) method is one of the robust algorithms for predicting unknown ratings by reducing insignificant features. The initial values for predictive matrices were zero and the others were replacing the unknown value of the average item rating and then subtracted the corresponding average user rating from that value. The estimated level of rating accuracy has been justified over the sample data set.

For data with a high rate of change, such as streaming for music, video, movies, and so all, SVD still performs well in making recommendations. When the data is abundant, SVD can overcome the sparsity matrix (Mohamed et al., 2020; Przystupa et al., 2021; Barathy & Citra, 2020).

Based on this research, this study uses a similar method, SVD, to predict product user ratings. The case study is data about skincare products that are popular among women (based on history on famous websites). Historical ratings came from factual users collected to provide recommendations to other users.

2.1. Singular Value Decomposition (SVD)

SVD is a classic method of linear algebra based on the matrix factorization technique. The matrix factorization technique uses a matric structure, namely rows as users and columns as items. This technique factorizes $m \times n$ of A matrix into three matrices; the form of singular value decomposition is shown below (Akter et al., 2017; Sahoo et al., 2019).

$$\boldsymbol{A} = \boldsymbol{U} \times \boldsymbol{S} \times \boldsymbol{V^T} \quad (1)$$

U, **V** are $m \times r$ and $r \times n$ sized orthogonal matrices, respectively, where r is the dimension of matrix **A**. The **S** is an $r \times r$ sized diagonal matrix, possessing all singular values of matrix **A**'s main diagonal. Stages in conducting SVD calculation are defined below (Akter et al., 2017; Bokde et al., 2015; Guan et al., 2016; Vozalis & Margaritis, 2007).

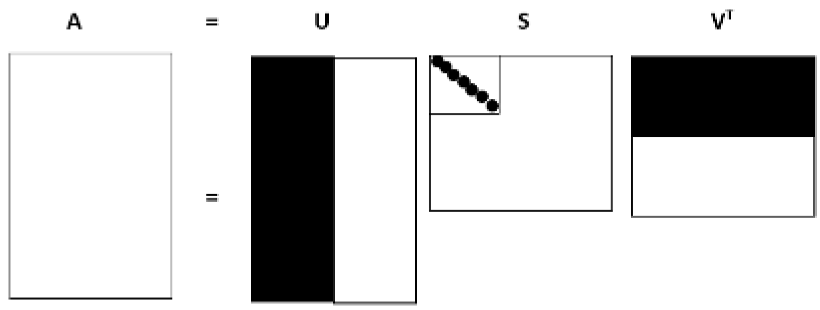

Figure 1. Illustration of SVD Matrices

1. Creating matrix **A** from ratings where user (m) = rows, item (n) = column.
2. Filling empty values on the rating data (the empty values are products that are not rated by users) by substituting average values of corresponding items. Calculating the average row values, then subtracting them from the corresponding elements.

3. By calculating r rank from matrix **A**, the dimensions of the column space used can be calculated.
4. Calculating $\boldsymbol{M} = \boldsymbol{A}^T\boldsymbol{A}$ matrix of size $n \times n$.
5. Calculating the eigenvalues and eigenvectors by det($\lambda\boldsymbol{I} - \boldsymbol{A}$) = 0, where $\lambda = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$ is the set of eigenvalues in descending order and I is the identity matrix of size $n \times n$.
6. Forming a V matrix of $r \times n$ size where r is the rank and n is the number of collected items from the vector of $\boldsymbol{M} = \boldsymbol{A}^T\boldsymbol{A}$ matrix.
7. Forming a U matrix of size $m \times r$ from the eigenvector matrix $\boldsymbol{M} = \boldsymbol{A}\boldsymbol{A}^T$ with size $n \times n$.
8. Calculating the **S** values by rooting the eigenvalues of the V matrix, then transform it into the main diagonal matrix.
9. Forming $\boldsymbol{A}_n = \boldsymbol{U} \times \boldsymbol{S} \times \boldsymbol{V}^T$ matrix and adding the subtracted values (average of users/rows).

2.2. Alternating Least Square (ALS)

Alternating Least Square (ALS) is a prominent method for improving regression models like Matrix Factorization (MF) and graph regularization. It works by optimizing one parameter at a time while leaving the others unchanged. The optimization sub-problem must be analytically solved in order for ALS to work (He et al., 2016).

Using Alternating Least Squares can repair either the unknown u_i or the unknown v_j. When one is determined, the least-squares problem can be used to determine the other. This method is advantageous since it converts a non-convex issue into a quadratic that can be solved optimally. The following is a general description of the ALS algorithm for collaborative filtering (Vozalis & Margaritis, 2007):

1. Create matrix **V** by filling in the first row with the average rating and the following entries with small random integers.
2. By minimizing the RMSE function, fix **V** and solve **U.**
3. After you've fixed **U**, solve **V** by minimizing the RMSE function in the same way.
4. Repeat Steps 2 and 3 until converge.

3. MATERIAL AND METHOD

3.1. Data

This research used rating data from reviews of each skincare product's users (facial wash, toner, sleeping mask, serum essence, and sunscreen) on the Femaledaily website from November 12, 2020, until January 12, 2021. The data was obtained by scrapping. The samples used in this research were the five categories of skincare routine order, including facial wash, toner, sleeping mask, serum essence, and sunscreen, in which each was scraped based on the five most popular products on the Femaledaily website.

3.2. Research Method

The method used in this research was a recommender system method using collaborative filtering with a singular value decomposition (SVD) model. The recommender system is a system or algorithm used for giving recommendations of one item. One method of recommender system is collaborative filtering. It utilizes an item transaction based on user behavior and is used to recommend an item, making it easier for the users to choose. The recommendation quality of this method is highly dependent on other users' reviews. Meanwhile, the singular value decomposition is a model-based technique using previous rating values to learn the model used. Figure 2 is this research's flowchart.

The followings are steps in the research process:

1. Deciding the topic that will be raised as the research material. Afterwards, conducting literature study to obtain in-depth understanding of the method used.
2. Formulating problem identifications and research purposes.
3. Collecting data on the Femaledaily website by scraping utilizing the data miner application to gain datasets.
4. Conducting data cleaning by selecting which variables used for the research, namely user_id, item_id, item, and rating. Subsequently, inputting clean data into python.
5. Conducting pre-processing: encoding data which is converting data on rating variables from integers to ordinal-scale categorical data and splitting data for training and testing data distribution.
6. Fitting the model with the singular value decomposition (SVD) method. Then determine the cross validation by using the average RMSE (Root Mean Squared Error) value. In addition, calculating Alternating Least Square (ALS) as a comparison method
7. Conducting hyperparameter tuning to SVD to find out the optimum parameter to build the model.
8. Creating the recommender system model using item-based singular value decomposition to yield skincare product recommendations for users based on ratings.

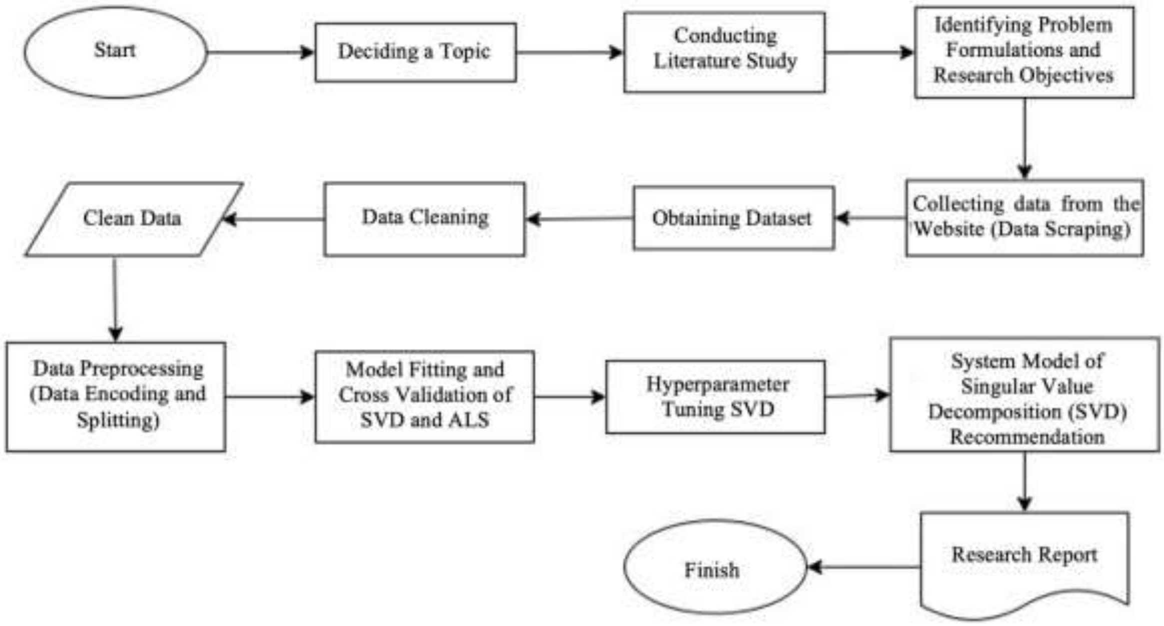

Figure 2. Research Flowchart

The programming utilized to help the calculation was python with surprise package and other supported packages such as numpy, pandas, etc (Harris et al., 2020; Hug, 2020; McKinney & Others, 2010).

4. RESULTS AND DISCUSSION

The data used in this research was rating data from skincare product reviews on Femaledaily from November 12, 2020, until January 12, 2021. Based on the descriptive analysis of the number of users giving ratings to overall skincare products. The X-axis (horizontal) is the rating scale using an interval of 1 to 5 for users' satisfaction toward skincare products. Meanwhile, Y-axis (vertical) is the number of users giving ratings for products. The data consisted of 10584 ratings from 6662 users giving reviews for 25 skincare products. The higher number indicates the better the review of the products. Of the 6662 users, 2609 users left bad ratings on the products they used, as seen in Figure 3.

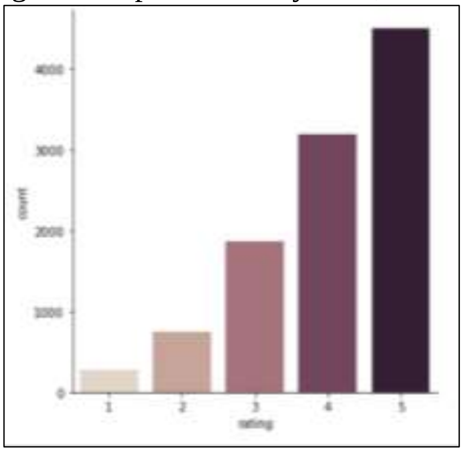

Figure 3. Descriptive Analysis

Singular Value Decomposition (SVD)

Table 1 presents Femaledaily data ratings collected from multiple samples. Among the ratings, there are some unknown ratings. Hence, step-by-step procedures will be explained to predict unknown ratings.

Table 1. Femaledaily Data Rating

User	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	4	2	-	4	1
User 2	5	-	-	5	5
User 3	5	-	-	-	3
User 4	-	5	1	-	3
User 5	-	-	4	-	4
User 6	4	-	5	-	-

Data in Table 1 would be stored in matrix **A**; the user is the row and the item is the matrix column. Some ratings that the users did not rate would be substituted by calculating the average value of the corresponding columns and rows.

$$\boldsymbol{A} = \begin{bmatrix} 4 & 2 & - & 4 & 1 \\ 5 & - & - & 5 & 5 \\ 5 & - & - & - & 3 \\ - & 5 & 1 & - & 3 \\ - & - & 4 & - & 4 \\ 4 & - & 5 & - & - \end{bmatrix} \tag{2}$$

The M matrix was formed after substituting the average values of corresponding columns and rows. The rank for the matrix is 5, which is easy to see from the dimension of column spaces or the number of items used.

$$\boldsymbol{M} = \begin{bmatrix} 1.25 & -0.75 & -0.58 & 1.25 & -1.75 \\ 0 & -1.5 & -1.67 & 0 & 0 \\ 1 & -0.5 & -0.67 & 0.5 & -1 \\ 1.5 & 2 & -2 & 1.5 & 0 \\ 0.5 & -0.5 & 0 & 0.5 & 0 \\ -0.5 & -1 & 0.5 & 0 & -1.3 \end{bmatrix} \tag{3}$$

The eigen value matrix **M** (equation 3) can be calculated using det($\lambda \boldsymbol{I} - \boldsymbol{A}$) = 0. Since the **M** matrix was a 5×5 matrix, the eigenvalue obtained was 5. The set of eigenvalues is $\lambda = \{16.7635367,\ 10.4160466,\ 3.9272430,\ 0.6655358,\ 0.1687292\}$. Afterward, the $r \times n$ -sized **V** matrix formed from the eigenvector corresponding with the eigenvalue can be seen in Equation 4.

$$\boldsymbol{V} = \begin{bmatrix} -0.546120 & -0.0261443 & -0.177075 & 0.629510 & 0.522906 \\ -0.212139 & 0.8116059 & -0.401086 & -0.352082 & 0.107059 \\ 0.593434 & -0.0231053 & -0.708488 & 0.374382 & -0.072002 \\ -0.491341 & -0.0521519 & -0.227992 & 0.186848 & -0.817907 \\ 0.251336 & 0.5808259 & 0.503824 & 0.551980 & -0.202363 \end{bmatrix} \qquad (3)$$

Subsequently, the U matrix was formed by calculating the second M matrix in $m \times m$.

$$\boldsymbol{M} = \begin{bmatrix} 7.0864 & 2.0936 & 4.3886 & 3.41 & 1.625 & -0.165 \\ 2.0936 & 5.0389 & 1.8689 & 0.34 & 0.75 & 0.665 \\ 4.3886 & 1.8689 & 2.9489 & 2.59 & 1 & 0.965 \\ 3.41 & 0.34 & 2.59 & 12.5 & 0.5 & -3.75 \\ 1.625 & 0.75 & 1 & 0.5 & 0.75 & 0.25 \\ 2.11 & 0.665 & 0.9650 & -3.75 & 0.25 & 3.19 \end{bmatrix} \qquad (5)$$

Calculating the eigenvalue as the previous step, the set of eigenvalues gained was $\lambda = 16.76354,\ 14.1605,\ 3.927243,\ 0.665358,\ 0.1687292, -9.583041 \times 10^{-16}\}$.
Therefore, the U matrix formed from the eigenvector of $m \times r$ size is shown in Equation 6.

$$\boldsymbol{U} = \begin{bmatrix} -0.475462 & -0.529722 & -0.34126190 & -0.124296 & 0.1293885 \\ -0.166464 & -0.365256 & 0.90063061 & 0.119018 & 0.0982196 \\ -0.330209 & -0.317089 & -0.06038408 & -0.117870 & -0.7571886 \\ -0.783633 & 0.480877 & 0.00363568 & 0.279958 & 0.2054177 \\ -0.102097 & -0.137867 & -0.00100456 & -0.716128 & 0.4894021 \\ 0.112616 & -0.484962 & -0.26219146 & 0.604381 & 0.3443343 \end{bmatrix} \qquad (6)$$

Following the creation of **U**, **V**, and **S** matrices is the calculation below.

$$\begin{bmatrix} -0.475462 & -0.529722 & -0.34126190 & -0.124296 & 0.1293885 \\ -0.166464 & -0.365256 & 0.90063061 & 0.119018 & 0.0982196 \\ -0.330209 & -0.317089 & -0.06038408 & -0.117870 & -0.7571886 \\ -0.783633 & 0.480877 & 0.00363568 & 0.279958 & 0.2054177 \\ -0.102097 & -0.137867 & -0.00100456 & -0.716128 & 0.4894021 \\ 0.112616 & -0.484962 & -0.26219146 & 0.604381 & 0.3443343 \end{bmatrix}$$
$$\times \begin{bmatrix} 4.041862 & 0 & 0 & 0 & 0 \\ 0 & 3.22739 & 0 & 0 & 0 \\ 0 & 0 & 1.981727 & 0 & 0 \\ 0 & 0 & 0 & 0.8158037 & 0 \\ 0 & 0 & 0 & 0 & 0.4107666 \end{bmatrix} \qquad (7)$$
$$\times \begin{bmatrix} -0.546120 & -0.0261443 & -0.177075 & 0.629510 & 0.522906 \\ -0.212139 & 0.8116059 & -0.401086 & -0.352082 & 0.107059 \\ 0.593434 & -0.0231053 & -0.708488 & 0.374382 & -0.072002 \\ -0.491341 & -0.0521519 & -0.227992 & 0.186848 & -0.817907 \\ 0.251336 & 0.5808259 & 0.503824 & 0.551980 & -0.202363 \end{bmatrix}$$

The final prediction of $\boldsymbol{A}_n$ matrix was gained by adding subtracted the average value of the rows. Hence, the prediction results of the 5×6 $\boldsymbol{A}_n$ matrix were 5 items and 6 users, as seen in Equation 8.

$$A_n = \begin{bmatrix} 3.9 & 2.1 & 2.1 & 3.9 & 0.9 \\ 5 & 3.4 & 3.4 & 5 & 5 \\ 4.6 & 3.5 & 3.3 & 5 & 3 \\ 4.9 & 4.9 & 1.2 & 4.4 & 3.2 \\ 4 & 4 & 3.5 & 4 & 3.3 \\ 4.8 & 3.2 & 5 & 4.5 & 3.7 \end{bmatrix} \quad (8)$$

The result of $\boldsymbol{A_n}$ matrix showed that each cell was an item recommendation based on ratings for each user. The first column indicates that item1 is more recommended for the user2, given that the rating prediction is 5. At the same time, the second column shows that item2 is more recommended for the user4 since the rating prediction is 4.9. The fifth column suggests that item5 is not recommended for user1 as the prediction rating is 0.9, but it is recommended for the user2 because the rating prediction is 5. This recommender system will recommend items in an orderly manner for users following the rating prediction.

Table 2. Rating Prediction Data of Femaledaily

User	Item 1	Item 2	Item 3	Item 4	Item 5
User 1	3.9	2.1	2.1	3.9	0.9
User 2	5.0	3.4	3.4	5.0	5.0
User 3	4.6	3.5	3.3	5.0	3.0
User 4	4.9	4.9	1.2	4.4	3.2
User 5	4.0	4.0	3.5	4.0	3.3
User 6	4.8	3.2	5.0	4.5	3.7

In case of netflix prizwa, they use a factorization model mapping users and items into the latent factor space of the dimensions so that ratings are modeled as products in that space. The optimization method employed was the stochastic gradient descent (SGD) method used to optimize the equation $\min_{q*,p*} \sum_{(u,i,t)\epsilon K} (r_{ui} - q_i^T p_u)^2 + \lambda(||q_i||^2 + ||p_u||^2)$ where the algorithm repeats all ratings in the training data. For each given training set, the system predicts $\hat{r}_{ui}$.

The ALS method is used as a comparative method to SVD. RMSE results with a 10-fold CV from the ALS method are 1.00949. Its value is greater than those from the SVD method that is 1.00915.The hyperparameter tuning was carried out to obtain optimum parameters including epoch values, learning rates, and regularization. In this research, the optimum parameter for number epochs, learning rate, and regularization are 10, 0.02, and 0.4, respectively. By using the parameters, we obtained the RMSE of 1.01276.

Recommendation Model

The recommendation model is the final results of the skincare product recommendation for Femaledaily users recommended according to ratings. These results can help users find suitable skincare products. The recommender system is built following a based model on collaborative filtering using the SVD method. There were 25 products used by 10584 account users of Femaledaily. T presents product recommendation results based on ratings for each user.

Table 3. Hyperparameter Tuning with GridSearchCV Method

Parameter Training	Best Parameter
n_epochs: [5, 10, 15 ,20]	n_epochs: [5]
lr_all: [0.002, 0.005, 0.05, 0.1]	lr_all: [0.05]
reg_all: [0.4, 0.6, 0.8]	reg_all: [0.4]

The skincare product recommendation by product reatings can be seen in Table 4.

Table 4. Recommendation Results by Products

Item_id	Product Name	Category	User_id	Rating
7	Hadalabo: gokyujung ultimate moisturizing	Toner	5376	4.462966
7	Hadalabo: gokyujung ultimate moisturizing	Toner	10446	4.461178
7	Hadalabo: gokyujung ultimate moisturizing	Toner	9463	4.457152
7	Hadalabo: gokyujung ultimate moisturizing	Toner	4102	4.454428
7	Hadalabo: gokyujung ultimate moisturizing	Toner	2144	4.54187

Table 4 shows that the 7th item_id under the product name "Hadalabo: Gokujyun ultimate moisturizing lotion" is the toner category most recommended for user_id 5376 with the rating prediction of 4.42966; from user_id 10446 to user_id 6475, this recommendation order is sorted by the highest rating for each user.

Table 5. Recommendation Results by User

Item_id	Product Name	Category	User_id	Rating
1	Cetpahil: gentle skin cleanser	Facial wash	10	4.175572
7	Hadalabo: gokyujung ultimate moisturizing	Toner	10	4.362329
14	Lacoco: watermelon glow mask	Sleeping Mask	10	4.379424
19	Skin1004: Madagascar centella Asiatic ampoule	Serum & Essence	10	4.278820
23	Skinaqua: uv moisture milk	Sun Protection	10	4.188628

Of five categories, five products are recommended for one user, supposing that Table 5 is sorted based on rating. The recommended product for the facial wash category is Cetaphil: Gentle Skin Cleanser, the face mask category is Lacoco: Watermelon Glow Mask, serum and essence category is Skin1004: Madagascar Centella Asiatic Ampoule, and for sun protection category is Skinaqua: UV Moisture Milk. Since this research focuses on recommended items for users based on ratings, table 4 presents the products that are recommended to user.

5. CONCLUSION

Recommending a skincare product to the user on the Femaledaily account based on a rating can utilize the singular value decomposition (SVD) method with matrix factorization in the recommendation system process. This process built a matrix which was then divided into three matrices to obtain a recommendation; each was obtained from different size eigenvalues and eigenvectors by predicting all unknown rating values. Afterward, the stochastic gradient descent was applied to minimize the regularized squared error. The collected recommendation results gave product recommendations to users according to the given ratings, as in Hadalabo: Gokujyun Ultimate Moisturizing Lotion served as the most recommended toner for user_id 5376 as the rating prediction was 4.462966, it was then was recommended for user_id 10446 to the last user_id in accordance with the rating prediction.

Conducting this research is vital for developing the model/system. It adds to discovering that a simple method such as SVD can become very handy in giving a prognosis.

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