

Glow AI Skin recommendation system

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Abstract

This project focuses on creating a system that recommends skincare products. It uses content-based techniques to make these recommendations. We got our information from 1mg. com, a famous online pharmacy and healthcare website, by using a method called web scraping with Selenium. The process of collecting data had two main steps: getting links and getting information about the products. We faced some difficulties with the website design changes, but we managed to gather a large amount of data for analysis.

After preparing our text data, we created recommendation models using cosine similarity and Euclidean distance metrics. When we compared them, we found that the cosine similarity metric gave better results. To make our system work better, we added more information to our dataset from the EU ingredients dataset. This helped us have more details about the products and give better recommendations.

Using the improved dataset helped improve the model. Afterwards, we built a backend using Flask and used MongoDB as our NoSQL database to effectively handle data. The front part of the website was created using React, a flexible tool in JavaScript, to give users a smooth and interactive experience. To make it better for users, we added features to let them log in and log out using Firebase.

In summary, our skin care recommendation system provides a complete solution for giving personalized suggestions about skincare products. We combine smart advice systems with an easy-to-use interface to help users choose the right skincare routine. Our future plans include adding pictures to suggest products that users might like, improving our recommendation system to make sure it works well.

Introduction

In today's fast-moving world of skincare, where there are so many options for products, it can feel overwhelming to find the right skincare routine that fits your needs and preferences. The many options and changing trends in skincare can make people feel confused and unsure about where to begin. Recommendation systems are helpful tools that give users recommendations based on what they like and need. They make things easier for users by suggesting things that they might like.

In this project, our main goal was to make a smart recommendation system just for skincare. Our system is different because it considers every user's specific preferences, concerns, and desired results, instead of assuming one solution fits everyone. Our system carefully looks at the ingredients in skincare products to give you helpful suggestions. This makes it easier for you to choose the right products.

Imagine a world where you don't have to read lots of confusing labels and words to choose products. Instead, you have a helpful digital assistant with you. This assistant knows what you want for your skin and helps you find the right skincare products. Our recommendation system



carefully examines what users like and compares it with the qualities of skincare products. By combining feedback from users and information about products, our system becomes a trustworthy guide, offering choices that align with each person's likes and dislikes.

In simple terms, our project is not just about technology; it's about helping people feel more confident when choosing skincare products. We want to change how people find skincare products by using recommendation systems. Our system helps people find the best skincare products by collecting data, using smart technology, and providing an easy-to-use interface. This makes it easier and more enjoyable to achieve healthy and glowing skin.

Methodology:

Scrapping Details:

My skin care proposal framework depends on web scratching procedures utilizing the Selenium system. The method includes two primary steps: collecting joins to different skin care items and extricating nitty gritty depictions from those joins. Selenium permits computerized browsing, which was utilized to explore through diverse online stores, accumulate item URLs, and compile a comprehensive list of items for examination.

Once the item joins were assembled, the following stage included jumping more profound into each product's webpage. Selenium was utilized to visit these pages and extricate key data such as fixings, benefits, utilization informational, and client reviews. This step pointed to make enlightening and point by point product descriptions, which are basic for the suggestion calculation to form educated recommendations.

The summit of these endeavors could be a personalized skin care suggestion framework. By utilizing the scratched item portrayals and client audits, the framework utilizes suggestion calculations to coordinate clients with items that suit their specific skin concerns and inclinations. The integration of web scratching guarantees the framework remains up-to-date with the most recent items, permitting clients to create more educated choices around their skin care schedules.

Dataset Details:

We gathered information from the 1mg website using a tool called Selenium that helps extract data from websites. The dataset has information about each skincare product.

ID: A special code given to each product to tell them apart.

Category: Category refers to the specific group or type that a skincare product belongs to.

The webpage link that takes you to the page about the product.

Image URL: Image URL is the website link that takes you to the picture of the product.

Title: The name or label given to a product.



number ratings: This is the total number of ratings and reviews that the product has received.

rating element: The overall score that people give to the product on average.

description: A short summary of the product's features.

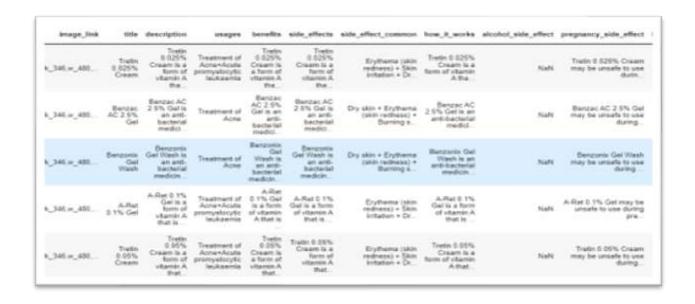
Price: How much the product costs.

Quantity: The number or overall size of the product.

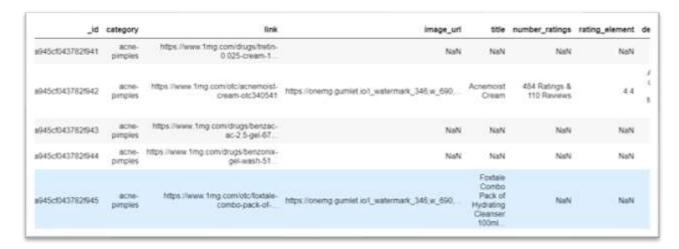
Highlights: Important parts or possible uses shown for the product.

We have another set of data scrapped from 1 mg website:

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	255 non-null	int64
1	image_link	255 non-null	object
0 1 2 3 4 5 6 7 8	title	255 non-null	object
3	description	255 non-null	object
4	usages	255 non-null	object
5	benefits	255 non-null	object
6	side_effects	255 non-null	object
7	side_effect_common	255 non-null	object
8	how_it_works	255 non-null	object
9	alcohol_side_effect		
10	pregnancy side effect	255 non-null	object
11	breastfeeding_side_effect	255 non-null	object
12	driving_side_effect	8 non-null	object
13	kidney_side_effect	8 non-null	object
14	liver_side_effect	8 non-null	object
15	price	120 non-null	object
16	qty	255 non-null	object
17	category	255 non-null	object
18	link	255 non-null	object
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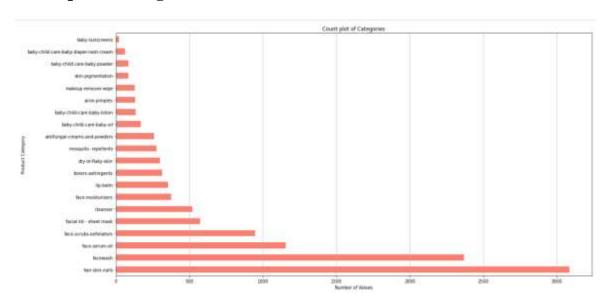






EDA and Visualization

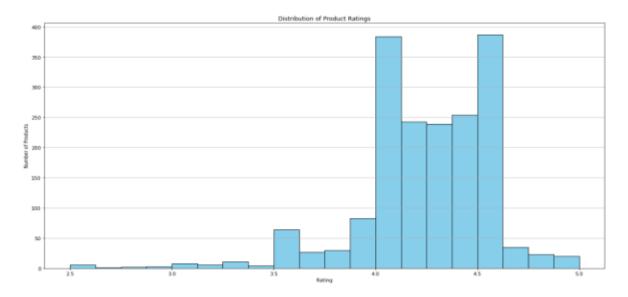
Count plot of categories:



The product offers cover a wide range of categories, catering to a variety of beauty and skincare requirements. The hair-skin-nails category offers a diverse range of 3,085 goods that address a wide range of issues. variations abound in the field of facial care, with 2,370 variations in facewash alone, allowing a personalised approach to cleansing procedures. For more specialised treatment, there are 1,157 different face serums and oils to choose from, and 948 different face scrubs and exfoliators to revitalise skincare regimes. A chosen selection of 574 face kits and sheet masks adds to the delight of all-inclusive pampering sessions. This collection represents a commitment to meeting a wide range of beauty preferences, with a large selection ready to cater to specific regimens and preferences.

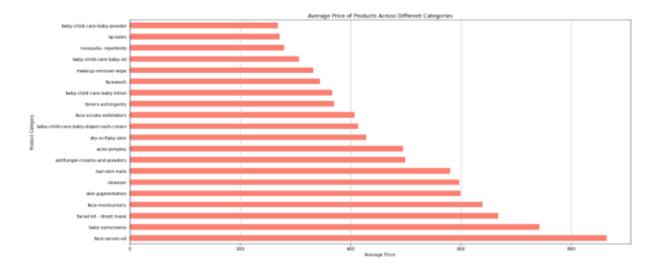


Distribution plot of Product Rating:



A considerable fraction of the products receive extremely high evaluations, frequently nearing the maximum value of 5. This attests to the outstanding quality and efficacy of these offerings, which are well received by the consumer base. The majority of goods receive ratings ranging from 4 to 5, indicating a general sense of contentment among purchasers. This mid-to-high range denotes a constant degree of product performance that corresponds to client expectations and aspirations. In contrast, a smaller percentage of products receive ratings below 4, indicating that occurrences of lesser satisfaction are uncommon. This distribution emphasises the brand's commitment to offering items that mostly meet and even exceed consumer satisfaction, with only a small number falling of these high standards.

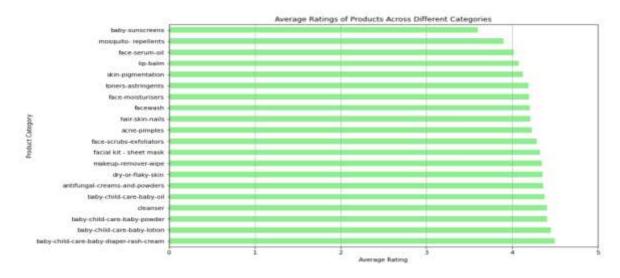
Average Price of Products Across Different Categories:





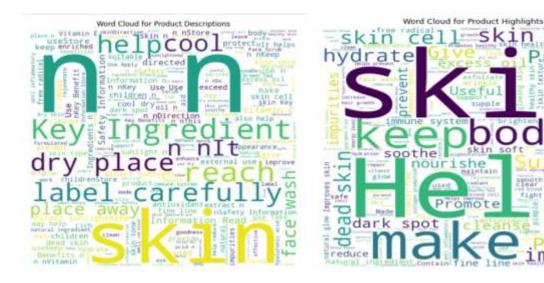
With higher averages, the face-serum-oil category emerges as the most expensive, while baby sunscreens and skin pigmentation products also fetch high prices. Lip balm, makeup remover wipes, and toners-astringents, on the other hand, are more affordable. These pricing trends show a smart mix of quality offers and inexpensive necessities, effectively responding to a diverse spectrum of consumer tastes.

Average Ratings of product Across Different categories:



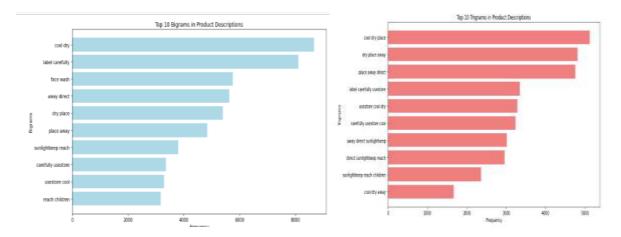
- Several product categories, such as baby sunscreens and skin pigmentation, have average ratings near 5 stars.
- Toners-astringents, facewash, and face scrubs-exfoliators have slightly lower average ratings than others, but they are still rather high (above 4).

Word Cloud for Product Descriptions and product Highlights:



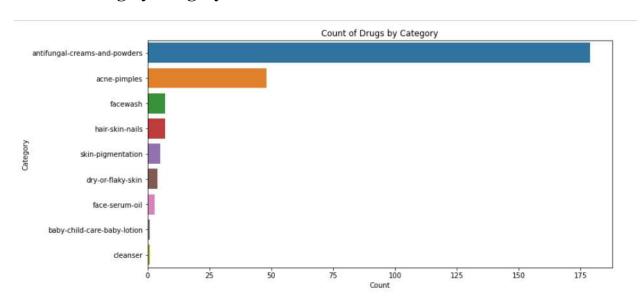


Bigram and Trigram for product description:



The examination of commonly occurring bigrams and trigrams in product descriptions yields useful insights into common themes. Specifically, terms such as 'cold, dry' and 'label, properly' appear frequently, emphasising storage directions and careful reading. Trigrams like 'cool, dry, place' (5,121 occurrences) emphasise the significance of good storage conditions. Similarly, the phrase 'dry, place, away' (4,813 times) supports this idea, whereas 'place, away, direct' (4,761 times) warns against sun exposure. These findings shed light on repeating trends, notably in storage instructions, and provide succinct yet significant information about common messaging methods in these product descriptions.

Count of drug by category:



- The category "acne-pimples" has the most entries, showing that there are several acne and pimples.
- This is followed by categories such as "acidity", "allergy", "abdominal pain" and so on.



Word cloud for drug related data:



Description: The phrases "skin", "gel", "cream", "used", and "treatment" stand out significantly, indicating that many of the medications in this dataset are topicals for skin treatment.

Usages: The words "acne", "pimples", "skin", and "infections" predominate, indicating an emphasis on skin-related disorders.

Benefits: The words "skin", "acne", "bacteria", and "infections" are highlighted.

Adverse Reactions: Words such as "skin", "dry", "burning", "irritation", and "peeling" are evident, signifying frequent medication adverse effects.

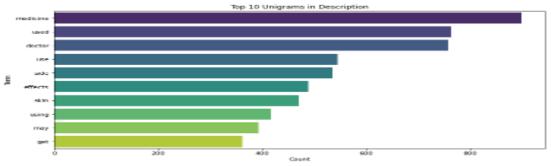
Unigram, bigram, Trigram:

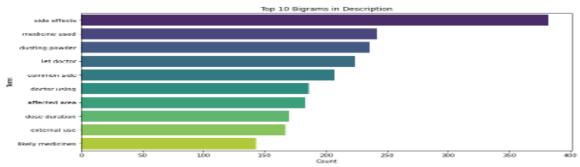
Unigrams: Words like "skin", "used", "gel", "cream", and "acne" are frequently used in drug descriptions.

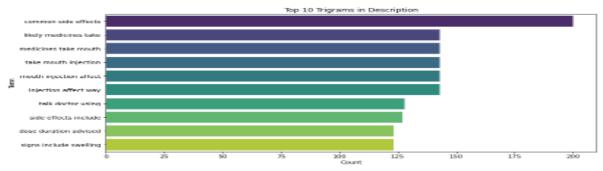
Bigrams: Drug descriptions frequently include phrases like "used to treat", "skin infections", and "form vitamin".

Trigrams: Some of the typical trigrams are "form vitamin used", "gel form vitamin", and "treat skin infections".

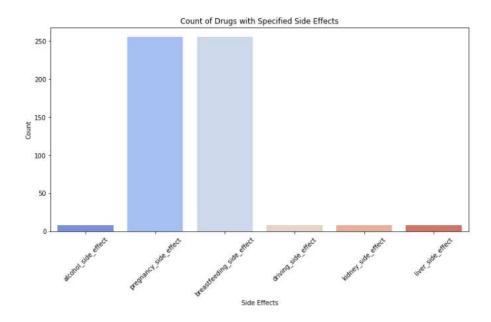








Count of drug with special side effect:





Pregnancy and Breastfeeding adverse Effects: Almost every medicine in the dataset has linked pregnancy and breastfeeding adverse effects or precautions.

Alcohol, Driving, Kidney, and Liver Side Effects: These side effects are less common throughout the dataset, with only a few medicines explicitly mentioning them.

Data cleaning and preprocessing:

Missing Values:

The dataset contains a number of columns with missing values:

image_url: Around 292 listings are missing the URL to the product pictures.

title: Similarly, 292 items lack product titles or names.

number_ratings: A large number of 9,523 entries do not provide a tally of the number of ratings and reviews received by the relevant products.

rating_element: In addition to the aforementioned, 9,523 entries are missing the average rating score awarded to the products.

Approximately 525 items lack brief descriptions summarising the important features of the products.

pricing: The price information for the products is missing in 311 entries.

qty: Similarly, 292 entries do not give product quantity or size information.

highlights: For about 1,548 entries, the highlighted features are missing.

_id	0	
category	0	
link	0	
image_url	292	
title	292	
number_ratings	9523	
rating_element	9523	
description	525	
price	311	
qty	292	
highlights	1548	
dtype: int64		

But we haven't taken these missing values into consideration as we mostly needed the text data.

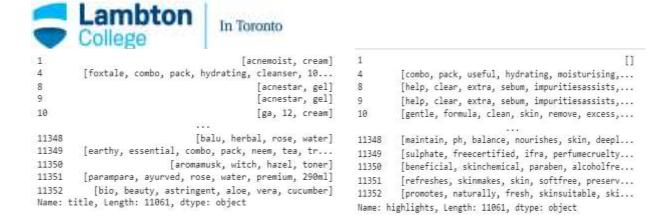


Text Preprocessing:

In arrange to get ready the content information for investigation, a comprehensive preprocessing pipeline was executed. The taking after steps were performed to guarantee that the content was clean, standardized, and prepared for assist preparing:

- 1. Lowercasing: All content was changed over to lowercase to guarantee consistency and to treat words with distinctive capitalizations as the same. This disposes of the plausibility of copy representations of words based on capitalization.
- 2. Dealing with Extraordinary Characters: Extraordinary characters such as URLs and hashtags were supplanted with placeholders. URLs were supplanted with 'URL', and hashtags were supplanted with 'HASHTAG'. This step guarantees that these components are treated as unmistakable substances and don't meddled with ensuing investigation.
- 3. Expelling Accentuation: Accentuation marks were evacuated from the content. Usually done to streamline the content and avoid accentuation from being treated as partitioned tokens amid tokenization.
- 4. Tokenization: The content was tokenized into person words. Tokenization breaks down the content into its constituent words, making it less demanding to analyze and handle.
- 5. Removing Stopwords: Stopwords, which are commonly utilized words that ordinarily don't carry critical meaning (e.g., "and", "the", "is"), were evacuated from the content. This step decreases the dimensionality of the information and centers the examination on important substance words.
- 6. Lemmatization: The words were lemmatized, which includes lessening words to their base or root frame. This makes a difference in solidifying diverse shapes of the same word (e.g., "running" and "ran" both ended up "run"), supporting in more precise investigation.

By utilizing this preprocessing pipeline, the content information was changed into a organized and cleaned arrange appropriate for different sorts of examination, such as assumption investigation, point modeling, and more. This pipeline viably upgrades the quality of the information whereas holding its basic meaning, clearing the way for more exact and shrewder comes about.



highlight	qty	price	description	rating_element	number_ratings	title	image_url	tink
	60 gm Cream	t 319	(acnemoist, cream, specially, formulated, oil,	4.4	484 Ratings & 110 Reviews	(acnemoist cream)	https://oneng.gumlet.iol_watermark_346.w_690	com/otc/acnemost- cream-otc340541
(combo, pack useful, hydrating moisturising,	bottles	1 994	[floxdaile, combo, plack, hydrating, cleanser, 10	Nan	NaN	[foxtale, combo, pack, hydrating, cleanser, 10	https://onemg.gumlet.io/1_watermark_346.ar_690	Img.com/oto/foxhare- combo-pack-of-
(help, clear, extra sebun impuritiesassists,	22 gm Sei	₹90	Jacnestar gel, useful, various, reason, serum.	43	270 Ratings & 25 Revens	[acnestar gel]	https://onemg.gumlet.io/_watermark_346.w_660,	ng com/otc/acnestar- gel-otc356988
(help, clear, extra sebun imputtiesassists,	22 gm Gel	₹96	[acnestar gel, useful, various, reason, serum.	43	270 Ratings & 25 Reviews	(acnestar get)	https://oneng.gumlet.iol_watermark_346.w_690,	ng com/ofc/acnestar- gel-ofc356988
(gentie, formula clean, skir remove, excess,	30 gm Cream	₹164	[ga. 12, cream, specialized, oil, free, formul	4.3	141 Ratings & 19 Reviews	iga, 12 creami	https://onemg.gumlet.io/t_watermark_346.w_690	ting.com/otc/ga-12- cream-otc/15193

Feature Engineering

TF-IDF Vectorization:

TF-IDF Vectorization is a method used to convert text into numerical vectors that can be understood by machine learning models. It is commonly used in natural language processing tasks. On the other hand, User Input Representation refers to how user inputs or queries are transformed into a format that can be processed by a system.

The most important part of our recommendation system is based on the idea of TF-IDF vectorization. Term Frequency-Inverse Document Frequency (TF-IDF) is a way to measure how important words are in a document compared to all the documents combined. This process turns text data into numbers so that it can be easily studied and analyzed.

Before analyzing the data, the TF-IDF vectorizer was used on the dataset's collection of text. Each item was now shown as a direction in a space with many dimensions. Each dimension matches a different word and its importance in that item.



Modelling:

To create personalized recommendations, the user's input descriptions were processed in a similar way. The descriptions were converted into TF-IDF vectors using the same tool. These user vectors, which are in the same space as the product vectors, were helpful for comparing and measuring similarity.

Finding Similarity and Making Suggestions:

Cosine similarity became the preferred way to measure how similar user vectors and product vectors are to each other. This calculation measures how closely two vectors line up with each other in a high-dimensional space. The similarity scores show how similar the user's input is to each product.

The process of recommending products involves arranging them in a list based on how similar they are, with the most similar products appearing at the top of the list. Higher scores mean that the text is more closely related to what the user asked for. The products that are most similar are chosen as recommendations.

The content-based suggestion system is really good at giving personalized suggestions for products by looking at the words in the content. This system helps users find things they like by using technology that understands and learns from human language and choices.

Front and backend:

The skincare product recommender system is a cool computer program that suggests skincare products based on your needs and preferences. The system is made with a strong structure that combines different technologies. Firebase is used to verify users, Flask processes information in the background, and MongoDB stores data. The main aim is to make the user's experience better by suggesting skincare products that match their questions and needs.

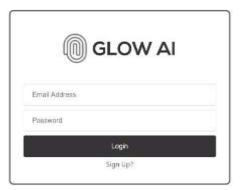
User interaction refers to the way users engage system or software. Authentication is the process of verifying the identity of a user.







GLOW AI



The process starts with either signing up or logging in. To keep things safe and make sure the information is correct, the system uses Firebase to confirm who the user is. After the user's information is checked and confirmed, they are smoothly sent to the search page. This security process not only protects user information but also gives users a personalized experience. It makes sure users get recommendations and see previous questions that are related to their profile.

Three User engagement on the search page means how users interact and participate with the search page.

The search page is like the main place where users can do things. Users can see the questions they have asked before. These questions are taken from MongoDB through the Flask backend. This tool helps users keep track of their skin issues and questions as time goes on. Also, the

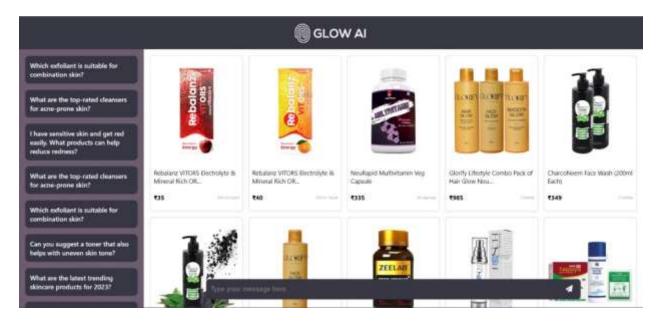


search page allows users to create new product recommendations by asking questions or stating their skincare needs.



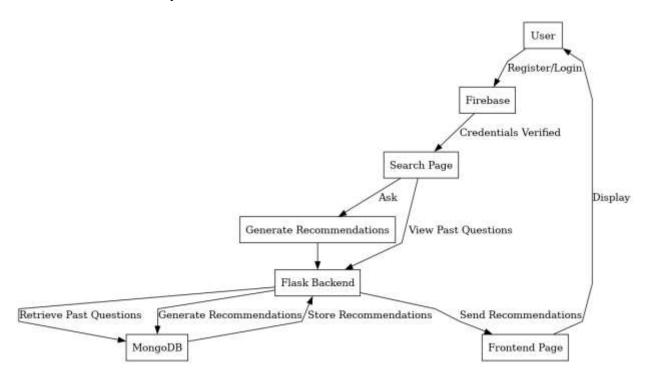
Backend processing refers to the handling and organizing of data in a computer system. This includes activities like sorting, filtering, and storing information. Data storage is the process of keeping data in a secure and accessible location for future use.

When a user asks for product suggestions, the system starts the Flask backend. The backend does all the work to fulfill the user's request and comes up with a list of ten good skincare products. After the suggestions are given, they are saved in MongoDB to keep a record of all recommendations. MongoDB is very important because it does two things. It saves suggestions and keeps old questions, so it is easy to find the information we need.





After the Flask backend finishes processing the suggestions and saves them in MongoDB, the information is sent to the frontend webpage. The website's main page, created to be easy to use, shows the user a carefully selected list of skincare products. This efficient process makes sure users get the right product suggestions at the right time, which improves their overall experience with the recommender system.



Evaluation Metrics:

Precision at K is an important measure that tells us how good the recommendations are in a system that suggests things to us. This measurement evaluates how many of the top 'K' recommended items are actually useful for the user. In this system, when K is set to 5, the precision_at_k function figures out how many of the top 5 recommended products are really relevant to what the user asked for. A high Precision at 5 score means that most of the top 5 recommended products are useful, which shows that the system is giving good quality suggestions to users.

Recall measures how many recommendations are included, complementing the Precision metric. While Precision at K assesses the accuracy of the top 'K' recommendations, Recall at K determines the proportion of all relevant items included in those top 'K' suggestions. For this system, when using the recall_at_k function with K set to 5, the metric calculates how many of the relevant products are included in the top 5 recommended products. A high Recall at 5 value means that the system is good at suggesting important products to the user, ensuring a complete recommendation list. User satisfaction and feedback are about how happy users are with a product or service, and what they think about it.



Understanding how satisfied users are is very important for the success of any recommendation system, not merely relying on numerical measures. Adding a feedback option lets users rate how useful each suggested product is. This gives helpful feedback on how well the system is working. By letting users' rate or comment on the suggested products, the system can collect direct feedback on how accurate and relevant the suggestions are. This feedback loop helps to improve the recommendation algorithm and make sure the system changes according to the users' preferences and needs. Over time, studying this feedback can help make customized and user-focused product recommendations, making users more satisfied overall.

Our system suggests things that are both correct and thorough. This can be seen with the measurements of Precision and Recall at K. It wants to make sure users are happy and keep making things better based on what they say.

Results:

The project's goal was to create a skincare product recommendation system through the use of content-based approaches and web scraping. Data was gathered from the 1mg.com website using Selenium-based web scraping, which included two major steps: gathering product links and extracting detailed product information. Despite the difficulties provided by modifications in website design, a significant dataset was acquired. For product-user matching, the recommendation system used TF-IDF vectorization and cosine similarity. To improve recommendations, additional data from the EU ingredients collection was added.

The system's backend was developed with Flask, and the frontend was constructed with React to provide an interactive user experience. Firebase was used to provide user authentication. The precision at K and recall at K measures were used to assess the system's correctness and relevance, while user satisfaction was acquired through direct feedback. The dataset's detailed analysis yielded insights on product categories, ratings, and pricing trends. The system gave personalised skincare recommendations after carefully evaluating user preferences, easing the process of picking relevant goods. The system aimed to increase its accuracy and respond to individual skincare needs through user feedback and continual improvement.

Conclusion:

Finally, our project has successfully created a powerful skincare recommendation system using Selenium and web scraping techniques. We handled the obstacles given by dynamic website designs and gathered a sizable dataset for analysis through a thorough data collection process from 1mg.com. We created a system that provides customers accurate and personalized skincare product suggestions by leveraging the power of recommendation models based on cosine similarity and combining extra information.



Looking ahead, our initiative has laid the groundwork for future improvements and developments in skincare suggestions. We intend to expand our system's capabilities by incorporating product photos, allowing users to make more visually informed judgments. Furthermore, refining and optimizing our recommendation systems remains a top priority to enhance the precision and relevancy of the recommendations presented constantly. Through these iterative efforts, we want to solidify our system's status as a trustworthy and invaluable tool in assisting consumers in curating successful and personalized skincare routines.

Future Work:

In the future, we plan to keep making our skin care recommendation system better and bigger. We want to add a feature that suggests skincare products based on pictures. This feature would use the appearance of the skincare items to make recommendations. In addition, our goal is to improve and strengthen our recommendation system by trying out more advanced methods and algorithms. We want our system to be a very helpful tool for people who want the best skincare options.

References

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Title: Bi, Tri, and N-grams with Python

URL: https://levelup.gitconnected.com/bi-tri-and-n-grams-with-python-a9717264e6f2

Github Repo Link: https://github.com/JashVaghasiya/GlowAI