Final Report of Traineeship Program 2024

On

"Analysis of Chemical Components"

MEDTOUREASY

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ACKNOWLDEGMENT

The traineeship opportunity that I had with MedTourEasy was a great change for learning and understanding the intricacies of the subject of Data Visualizations in Data Analytics; and also, for personal as well as professional development. I am very obliged for having a chance to interact with so many professionals who guided me throughout the traineeship project and made it a great learning curve for me. Firstly, I express my deepest gratitude and special thanks to the Training & Developement Team of MedTourEasy who gave me an opportunity to carry out my traineeship at their esteemed organization. Also, I express my thanks to the team for making me understand the details of the Data Analytics profile and training me in the same so that I can carry out the project properly and with maximum client satisfaction and also for spearing his valuable time in spite of his busy schedule.

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ABSTRACT

This project aims to create a content-based recommendation system for cosmetic products based on their chemical components. The methodology involves collecting ingredient data for over 1,400 cosmetics, preprocessing this data to remove inconsistencies, and tokenizing ingredient lists into analyzable components. A document-term matrix is generated to analyze the relationships between ingredients, followed by dimensionality reduction using t-SNE to visualize ingredient similarities. Interactive dashboards were developed using Bokeh to provide users with an intuitive interface for exploring product compatibility, especially for sensitive skin types. The findings highlight the potential of data-driven approaches in simplifying cosmetic selection, offering users personalized recommendations based on chemical properties. This system not only addresses gaps in the cosmetic industry but also demonstrates the significance of combining machine learning and visualization techniques to enhance user experience. By processing ingredient lists and applying machine learning techniques such as t-SNE and Bokeh for visualization, the system enhances user experience by providing an intuitive and interactive platform. The visualization methods facilitate better understanding of ingredient similarities, aiding users in making informed decisions about product suitability for sensitive skin types. This approach not only simplifies the selection process but also highlights the practical implications of integrating advanced visualization tools in consumer-centric applications. The report details the methodology, implementation, and observations derived from the analysis.

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1. INTRODUCTION

1.1 About the Company

MedTourEasy, a global healthcare company, provides you the informational resources needed to evaluate your global options. MedTourEasy provides analytical solutions to our partner healthcare providers globally. The company behind this project specializes in leveraging data science to solve consumer-centric challenges. With a strong focus on applying machine learning and artificial intelligence, the company aims to provide innovative solutions that enhance user experiences and empower informed decision-making. By addressing gaps in various industries, including cosmetics, the company strives to create impactful tools that bridge the gap between complex data and user-friendly applications.

1.2 About the Project

Buying new cosmetic products is often challenging, especially for individuals with sensitive skin who are prone to adverse reactions. The difficulty lies in interpreting the ingredient lists on product labels, which often require a background in chemistry to understand. This project seeks to address this issue by developing a content-based recommendation system that predicts the suitability of cosmetic products based on their chemical components. By processing ingredient lists and applying machine learning techniques, the system aims to provide users with an interactive platform to explore ingredient similarities and make informed choices. The project emphasizes the use of advanced visualization tools to simplify complex data, ensuring accessibility for a diverse range of users.

1.3 Objectives and Deliverables

The primary objectives of the project are:

1. **Develop a Recommendation System**: Create a system that predicts cosmetic product suitability based on chemical components.
2. **Simplify Ingredient Analysis**: Provide an intuitive way to understand and compare ingredient lists.

3. **Enhance User Experience**: Utilize interactive visualizations to make data exploration engaging and accessible.
4. **Address Industry Gaps**: Offer a solution that empowers consumers with actionable insights.

Key deliverables include:

1. **Processed Dataset**: A cleaned and structured dataset of cosmetic ingredients.
2. **Interactive Dashboards**: Visualization tools developed using Bokeh to explore ingredient similarities and product compatibility.
3. **Documentation**: A comprehensive report detailing the methodology, implementation, and findings of the project.
4. **Future Recommendations**: Insights into potential enhancements and applications of the system.

2. METHODOLOGY

The methodology outlines the systematic approach adopted for the development and implementation of the project. It encompasses the flow of the project, the tools and platforms utilized, and the design processes that transformed raw data into actionable insights. Each step in the methodology was crucial in achieving the project objectives.

2.1 Flow of the Project

The project workflow was divided into distinct phases to ensure clarity and efficiency. These phases included:

1. **Requirement Gathering and Problem Statement Definition**: The initial phase involved understanding the scope of the project, identifying the target audience (users with sensitive skin), and defining the core problem of interpreting complex ingredient lists on cosmetic products.
2. **Data Collection**: Ingredient lists for 1,472 cosmetic products were collected from Kaggle. This data formed the foundation for analysis and visualization.
3. **Data Preprocessing**: The raw data was cleaned to remove inconsistencies, duplicates, and irrelevant entries. This step ensured that the data was reliable and ready for further processing.
4. **Tokenization and Document-Term Matrix (DTM) Creation**: The ingredient lists were tokenized into individual chemical components. A DTM was then initialized to represent the frequency of each ingredient across products.
5. **Dimensionality Reduction Using t-SNE**: To visualize ingredient similarities, t-SNE (t-Distributed Stochastic Neighbor Embedding) was applied. This machine learning technique reduced the high-dimensional DTM into a two-dimensional space.
6. **Visualization with Bokeh**: The reduced data was mapped using Bokeh, an interactive visualization library. Features like hover tools and dynamic mapping enhanced the user interface.
7. **Dashboard Development**: Dashboards were created to present the findings in an intuitive and interactive manner. Users could explore

ingredient similarities and identify products compatible with their skin type.

2.2 Use Case Diagram

The use case diagram illustrates the interactions between the user and the system. It highlights key functionalities.

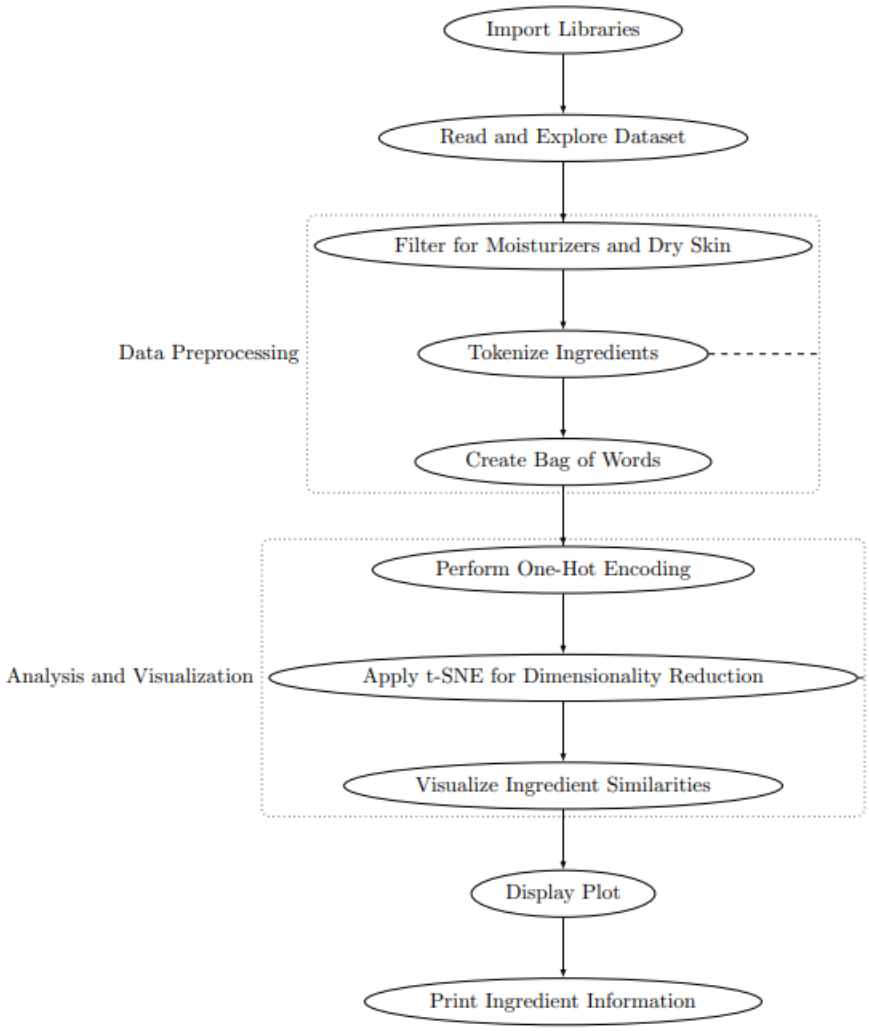


Figure 1: Use Case Diagram: Project Flow

This diagram was essential in understanding user requirements and ensuring the system's design aligned with those needs.

2.3 Language and Platform Used

The project leveraged several programming languages and platforms:

1. **Languages**:
    - **Python**: Used for data preprocessing, analysis, and visualization.
    - **SQL**: For designing and querying the database.
2. **Libraries and Tools**:
    - **Pandas and NumPy**: For data manipulation and analysis.
    - **scikit-learn**: For implementing t-SNE.
    - **Bokeh**: For interactive visualizations.
3. **Platforms**:
    - **Jupyter Notebook**: For coding and documenting the process.
    - **Kaggle Dataset**: The primary source of ingredient data.

This structured methodology ensured the project was executed efficiently, leading to insightful and actionable results.

3. IMPLEMENTATION

The implementation phase involved translating the planned methodology into a functional system. This section provides a detailed account of each step, from gathering requirements to developing interactive dashboards. The implementation was designed to address the challenges of interpreting chemical components in cosmetic products and delivering personalized recommendations to users.

3.1 Gathering Requirements and Defining Problem Statement

The first step was to identify the problem and establish the project's goals:

- **Problem Statement**: Users often struggle to interpret the chemical components listed on cosmetic products, especially those with sensitive skin. The goal was to create a system that simplifies this process by providing personalized recommendations based on ingredient analysis.
- **Requirements**:
    - A dataset containing cosmetic product information, including ingredient lists.
    - A system capable of processing and analyzing chemical components.
    - Interactive dashboards for user-friendly visualization.

3.2 Data Collection and Importing

- **Dataset**: A dataset of 1,472 cosmetic products was sourced from Kaggle. It included details such as product labels, ingredient lists, and skin compatibility features.
- **Tools**:
    - **Pandas** was used to load and manipulate the dataset.
    - Data was imported from a CSV file into a DataFrame for analysis.
- **Process**:
    - The dataset was inspected using methods like sample() to understand its structure.

- Counts of product types were calculated using value_counts() to determine the distribution of categories.

3.3 Designing Databases

A robust database structure was essential for managing the ingredient data efficiently:

- **Database Design**:
  - Tables were created to store product information, ingredient lists, and user preferences.
  - Relationships were defined to enable querying for ingredient similarities and product recommendations.
- **Tools**: SQL was used for database design and querying.

3.4 Data Cleaning

Data cleaning ensured the dataset was accurate and consistent:

- **Steps**:
  - Removed duplicate entries to avoid redundancy.
  - Standardized ingredient names to ensure uniformity.
  - Addressed missing values by imputing or removing incomplete records.
- **Outcome**: A clean and reliable dataset ready for further analysis.

3.5 Data Filtering

The dataset was filtered to focus on specific product categories and skin types:

- **Process**:
  - Products labeled as "Moisturizer" were extracted using filters on the Label column.
  - Further filtering was performed for products compatible with dry skin by checking the Dry column.
  - The filtered data was re-indexed for easier handling.

- **Result**: A subset of the dataset containing relevant products for users with dry skin.

3.6 Development of Dashboards

The final step was to develop interactive dashboards for users:

- **Tools**:
    - **t-SNE**: Reduced the high-dimensional ingredient data into two dimensions for visualization.
    - **Bokeh**: Used to create interactive maps of ingredient similarities.
- **Features**:
    - **Hover Tools**: Allowed users to view detailed information about ingredients and products by hovering over points on the map.
    - **Filters**: Enabled users to explore products by category, skin type, or ingredient.
- **Outcome**: Dashboards provided an intuitive interface for users to explore product recommendations and ingredient similarities.

4. CODE

Code:

```
# Import libraries
import pandas as pd
import numpy as np
from sklearn.manifold import TSNE

# Load the data
df = pd.read_csv('cosmetics.csv')

# Check the first five rows
display(df.sample(5))

# Inspect the types of products
print(df['Label'].value_counts())
# Filter for moisturizers
moisturizers = df[df['Label'] == 'Moisturizer']

# Filter for dry skin as well
moisturizers_dry = moisturizers[moisturizers['Dry'] == 1]

# Reset index
moisturizers_dry = moisturizers_dry.reset_index(drop=True)
# Display the first few rows of the moisturizers_dry DataFrame
```

```
print(moisturizers_dry.head())

# Initialize dictionary, list, and initial index

ingredient_idx = {}

corpus = []

idx = 0


# For loop for tokenization

for i in range(len(moisturizers_dry)):

    ingredients = moisturizers_dry['Ingredients'][i]

    ingredients_lower = ingredients.lower()  # Convert to lowercase

    tokens = ingredients_lower.split(', ')  # Split by comma and space

    corpus.append(tokens)  # Append tokens to corpus

    for ingredient in tokens:

        if ingredient not in ingredient_idx:

            ingredient_idx[ingredient] = idx  # Assign index to ingredient

            idx += 1  # Increment the index


# Check the result

print("The index for decyl oleate is", ingredient_idx['decyl oleate'])

print("The index for Water is", ingredient_idx['water'])

# Get the number of items (products) and the number of unique ingredients (tokens)

M = len(moisturizers_dry)  # Number of products in the 'moisturizers_dry' DataFrame
```

```
N = len(ingredient_idx)  # Number of unique ingredients in the 'ingredient_idx' dictionary


# Initialize a matrix of zeros with shape MxN
A = np.zeros((M, N))  # M rows (products) and N columns (ingredients)
def oh_encoder(tokens):
    # Initialize a zero vector of size N (number of unique ingredients)
    x = np.zeros(N)


    # Loop through each ingredient in the tokens list
    for ingredient in tokens:
        # Get the index for the ingredient from the ingredient_idx dictionary
        idx = ingredient_idx.get(ingredient, -1)  # Default to -1 if ingredient not found


        # If the ingredient is found in the dictionary, set the corresponding index to 1
        if idx != -1:
            x[idx] = 1


    return x
i = 0
for tokens in corpus:
    # Use the oh_encoder function to get the one-hot encoded vector for the tokens
```

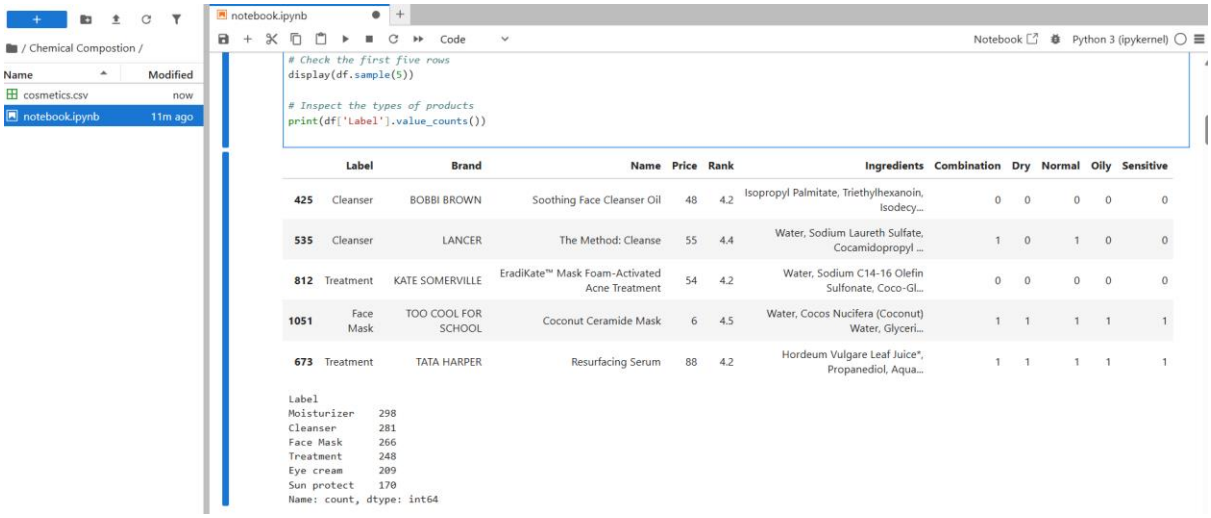
```
    one_hot_vector = oh_encoder(tokens)

    # Set the corresponding row in the matrix A to the one-hot vector
    A[i, :] = one_hot_vector

    # Increment the index for the next product
    i += 1
# Initialize t-SNE with specified parameters
model = TSNE(n_components=2, learning_rate=200, random_state=42)

# Apply t-SNE to the document-term matrix A
tsne_features = model.fit_transform(A)

# Create 'X' and 'Y' columns in the DataFrame to store the t-SNE results
moisturizers_dry['X'] = tsne_features[:, 0]
moisturizers_dry['Y'] = tsne_features[:, 1]
from bokeh.io import show, output_notebook
from bokeh.plotting import figure
from bokeh.models import ColumnDataSource, HoverTool

# Enable Bokeh output in the notebook
output_notebook()

# Create a ColumnDataSource from the DataFrame
```

```
source = ColumnDataSource(moisturizers_dry)

# Create a figure for the plot
plot = figure(x_axis_label='T-SNE 1',
              y_axis_label='T-SNE 2',
              width=500, height=400)

# Add a circle renderer for the scatter plot
plot.circle(x='X',
            y='Y',
            source=source,
            size=10,
            color='#FF7373',
            alpha=0.8)

# Show the plot
show(plot)
# Create a HoverTool object with the desired tooltips
hover = HoverTool(tooltips=[
    ('Item', '@Name'),        # Display the product name
    ('Brand', '@Brand'),      # Display the brand of the product
    ('Price', '$@Price'),     # Display the price of the product
    ('Rank', '@Rank')         # Display the rank of the product
])
```

```
# Add the hover tool to the plot
plot.add_tools(hover)


# Display the plot
show(plot)
# Print the ingredients of two similar cosmetics
cosmetic_1 = moisturizers_dry[moisturizers_dry['Name'] == "Color Control Cushion Compact Broad Spectrum SPF 50+"]
cosmetic_2 = moisturizers_dry[moisturizers_dry['Name'] == "BB Cushion Hydra Radiance SPF 50"]


# Display each item's data and ingredients
display(cosmetic_1)
print(cosmetic_1.Ingredients.values)
display(cosmetic_2)
print(cosmetic_2.Ingredients.values)
```

5. SAMPLE SCREENSHOTS AND OBSERVATIONS

5.1 Analysing Data



	Label	Brand	Name	Price	Rank	Ingredients	Combination	Dry	Normal	Oily	Sensitive
425	Cleanser	BOBBI BROWN	Soothing Face Cleanser Oil	48	4.2	Isopropyl Palmitate, Triethylhexanoin, Isodecy...	0	0	0	0	0
535	Cleanser	LANCER	The Method: Cleanse	55	4.4	Water, Sodium Laureth Sulfate, Cocamidopropyl ...	1	0	1	0	0
812	Treatment	KATE SOMERVILLE	EradiKate™ Mask Foam-Activated Acne Treatment	54	4.2	Water, Sodium C14-16 Olefin Sulfonate, Coco-Gl...	0	0	0	0	0
1051	Face Mask	TOO COOL FOR SCHOOL	Coconut Ceramide Mask	6	4.5	Water, Cocos Nucifera (Coconut) Water, Glyceri...	1	1	1	1	1
673	Treatment	TATA HARPER	Resurfacing Serum	88	4.2	Hordeum Vulgare Leaf Juice*, Propanediol, Aqua...	1	1	1	1	1

5.2 Ingredient Tokenization and Analysis

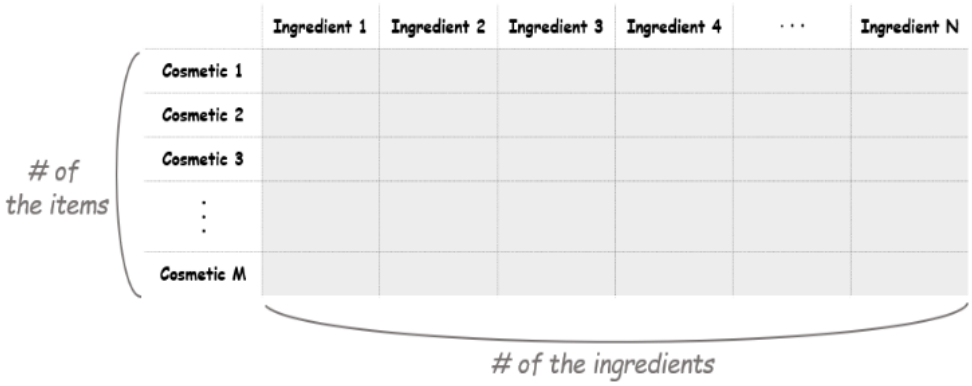
{ ***"ingredient"***: index value, ... }

[14]:
```
# Initialize dictionary, list, and initial index
ingredient_idx = {}
corpus = []
idx = 0

# For loop for tokenization
for i in range(len(moisturizers_dry)):
    ingredients = moisturizers_dry['Ingredients'][i]
    ingredients_lower = ingredients.lower()  # Convert to lowercase
    tokens = ingredients_lower.split(', ')  # Split by comma and space
    corpus.append(tokens)  # Append tokens to corpus
    for ingredient in tokens:
        if ingredient not in ingredient_idx:
            ingredient_idx[ingredient] = idx  # Assign index to ingredient
            idx += 1  # Increment the index

# Check the result
print("The index for decyl oleate is", ingredient_idx['decyl oleate'])
print("The index for Water is", ingredient_idx['water'])
```

```
The index for decyl oleate is 25
The index for Water is 23
```

The tokenized ingredients were derived from raw data

4.3 Document-Term Matrix (DTM)



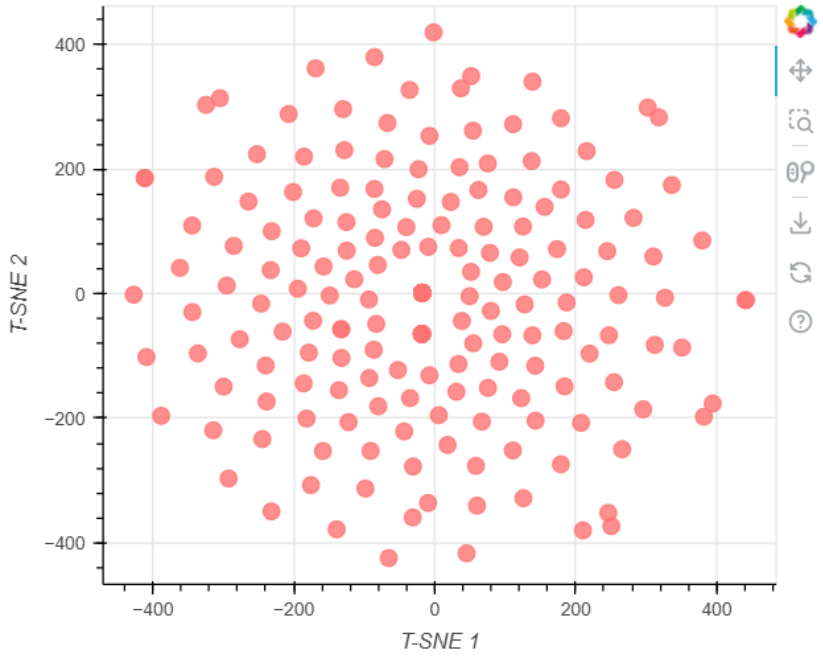
To create this m

The length of the matrix is the total number of cosmetic products in the data. The width of the matrix is the total r we'll fill it in the following tasks.

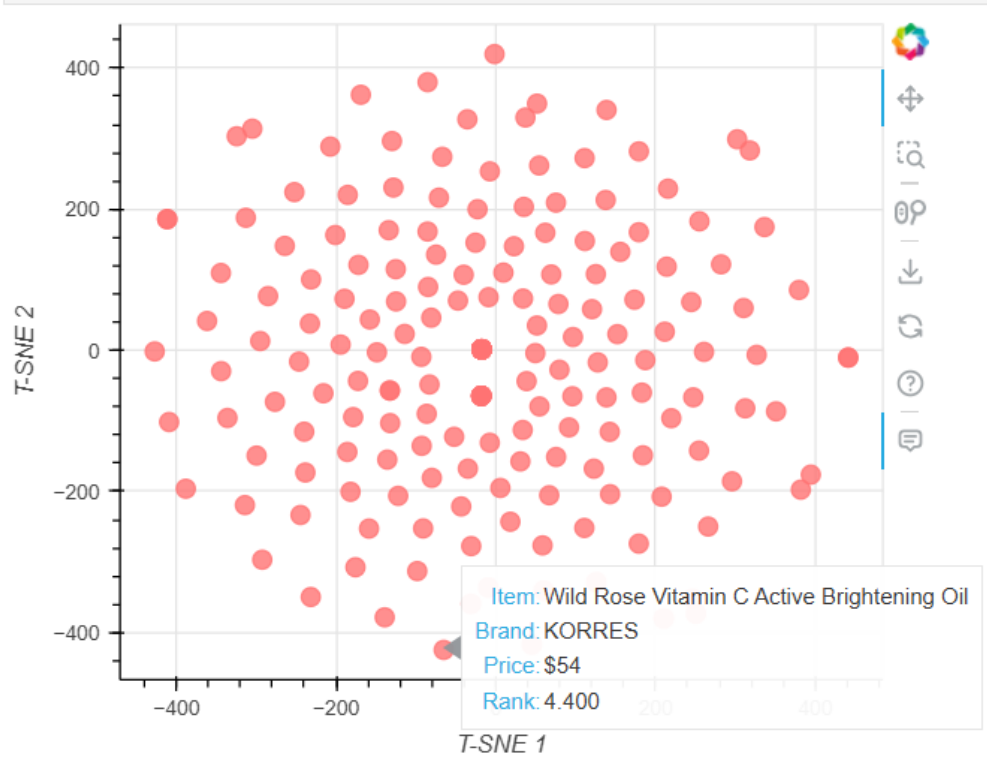
```
# Get the number of items (products) and the number of unique ingredients (tokens)
M = len(moisturizers_dry)  # Number of products in the 'moisturizers_dry' DataFrame
N = len(ingredient_idx)  # Number of unique ingredients in the 'ingredient_idx' dictionary

# Initialize a matrix of zeros with shape MxN
A = np.zeros((M, N))  # M rows (products) and N columns (ingredients)
```

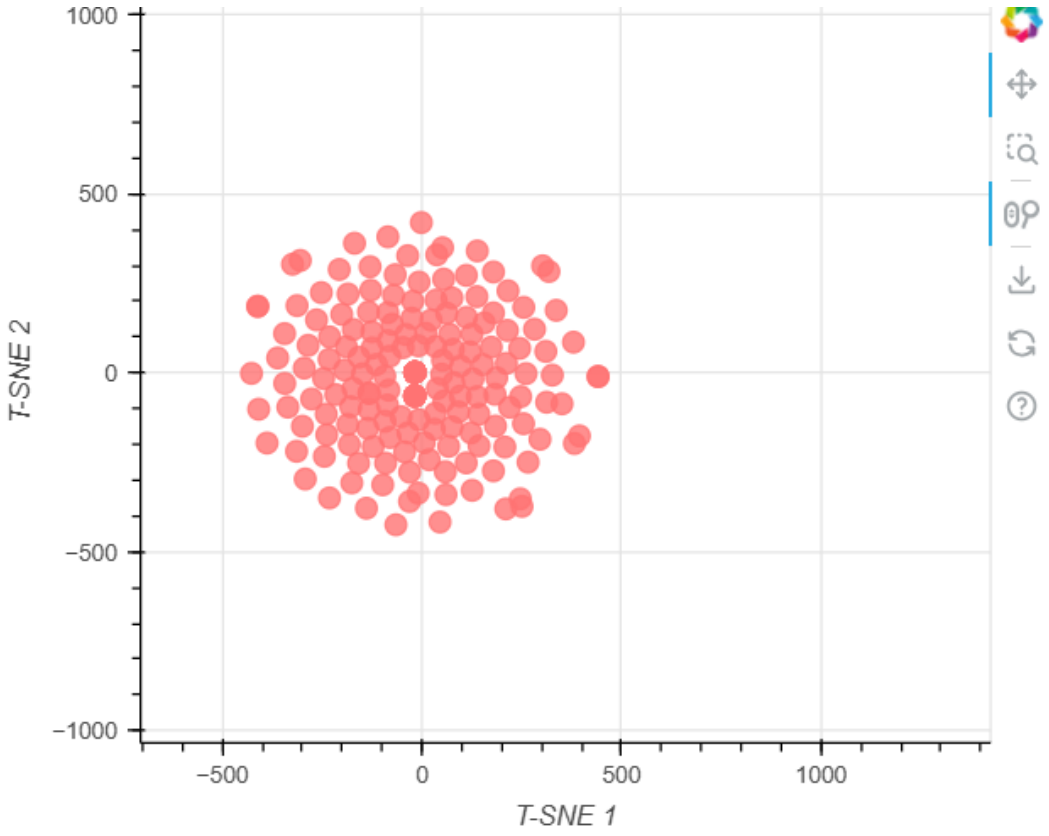
DTM, highlighting rows and columns representing products and ingredients.

5.4 t-SNE Visualization



5.5 Interactive Visualization





Bokeh-powered interactive visualization, with features like zoom, hover tool, and filtering options.

5.6 Comparison of Two Products

```
print(cosmetic_2.Ingredients.values)
```

	Label	Brand	Name	Price	Rank	Ingredients	Combination	Dry	Normal	Oily	Sensitive	X	Y
45	Moisturizer	AMOREPACIFIC	Color Control Cushion Compact Broad Spectrum S...	60	4.0	Phyllostachis Bambusoides Juice, Cyclopentasil...	1	1	1	1	1	-9.419198	-335.968231

```
['Phyllostachis Bambusoides Juice, Cyclopentasiloxane, Cyclohexasiloxane, Peg-10 Dimethicone, Phenyl Trimethicone, Butylene Glycol, Butylene Glycol Di
caprylate/Dicaprate, Alcohol, Arbutin, Lauryl Peg-9 Polydimethylsiloxyethyl Dimethicone, Acrylates/Ethylhexyl Acrylate/Dimethicone Methacrylate Copoly
mer, Polyhydroxystearic Acid, Sodium Chloride, Polymethyl Methacrylate, Aluminium Hydroxide, Stearic Acid, Disteardimonium Hectorite, Triethoxycapryly
lsilane, Ethylhexyl Palmitate, Lecithin, Isostearic Acid, Isopropyl Palmitate, Phenoxyethanol, Polyglyceryl-3 Polyricinoleate, Acrylates/Stearyl Acryl
ate/Dimethicone Methacrylate Copolymer, Dimethicone, Disodium Edta, Trimethylsiloxysilicate, Ethylhexyglycerin, Dimethicone/Vinyl Dimethicone Crosspol
ymer, Water, Silica, Camellia Japonica Seed Oil, Camillia Sinensis Leaf Extract, Caprylyl Glycol, 1,2-Hexanediol, Fragrance, Titanium Dioxide, Iron Ox
ides (Ci 77492, Ci 77491, Ci77499).']
```

	Label	Brand	Name	Price	Rank	Ingredients	Combination	Dry	Normal	Oily	Sensitive	X	Y
55	Moisturizer	LANEIGE	BB Cushion Hydra Radiance SPF 50	38	4.3	Water, Cyclopentasiloxane, Zinc Oxide (CI 7794...	1	1	1	1	1	-31.170496	-359.229309

```
['Water, Cyclopentasiloxane, Zinc Oxide (CI 77947), Ethylhexyl Methoxycinnamate, PEG-10 Dimethicone, Cyclohexasiloxane, Phenyl Trimethicone, Iron Oxid
es (CI 77492), Butylene Glycol Dicaprylate/Dicaprate, Niacinamide, Lauryl PEG-9 Polydimethylsiloxyethyl Dimethicone, Acrylates/Ethylhexyl Acrylate/Dim
ethicone Methacrylate Copolymer, Titanium Dioxide (CI 77891 , Iron Oxides (CI 77491), Butylene Glycol, Sodium Chloride, Iron Oxides (CI 77499), Alumin
um Hydroxide, HDI/Trimethylol Hexyllactone Crosspolymer, Stearic Acid, Methyl Methacrylate Crosspolymer, Triethoxycaprylylsilane, Phenoxyethanol, Frag
rance, Disteardimonium Hectorite, Caprylyl Glycol, Yeast Extract, Acrylates/Stearyl Acrylate/Dimethicone Methacrylate Copolymer, Dimethicone, Trimethy
lsiloxysilicate, Polysorbate 80, Disodium EDTA, Hydrogenated Lecithin, Dimethicone/Vinyl Dimethicone Crosspolymer, Mica (CI 77019), Silica, 1,2-Hexane
diol, Polypropylsilsesquioxane, Chenopodium Quinoa Seed Extract, Magnesium Sulfate, Calcium Chloride, Camellia Sinensis Leaf Extract, Manganese Sulfat
e, Zinc Sulfate, Ascorbyl Glucoside.']
```

[ ]:

5 CONCLUSION

This project aimed to develop a content-based recommendation system for cosmetic products by analyzing the chemical components listed in their ingredients. By focusing on a specific product category and skin type, this system aims to help users, especially those with sensitive skin, make more informed decisions when purchasing cosmetic products. The project successfully utilized various data science techniques to process and analyze a dataset containing 1472 cosmetics from Kaggle, which included tasks such as tokenizing ingredient lists, creating a document-term matrix (DTM), and reducing dimensionality using t-SNE.

The use of machine learning techniques like t-SNE for dimensionality reduction allowed for the visualization of ingredient similarity in an intuitive and interactive manner using Bokeh. By leveraging these methods, the project not only provided insights into the relationships between different ingredients but also helped visualize how similar products are to each other based on their chemical components. This enables users to identify products with ingredients that are more likely to be suitable for their skin type, especially those prone to skin troubles.

The project also demonstrated the power of data science in the beauty and cosmetics industry, showing how technical tools can be applied to solve real-world problems. By providing users with an effective way to navigate the complex ingredient lists of cosmetic products, this recommendation system has the potential to improve consumer experience, reduce skin-related issues, and promote healthier product choices.

In conclusion, the project achieved its goal of creating a functional recommendation system based on chemical components and provided a solid foundation for further improvements and enhancements in cosmetic product analysis. The integration of data science techniques into the beauty industry not only provides value to consumers but also opens up new possibilities for research and development in cosmetic formulations.

6 FUTURE SCOPE

While the current project successfully demonstrates the potential of content-based recommendation systems in the cosmetics industry, there are several avenues for future improvements and expansions. Some possible directions for future work include:

1. **Incorporating More Product Categories and Skin Types**: The current system focuses on moisturizers and dry skin. Expanding the dataset to include a wider range of product categories (e.g., sunscreens, serums, cleansers) and various skin types (e.g., oily, combination, sensitive) would provide a more comprehensive recommendation system. This would enable users with different skincare needs to benefit from the system.
2. **Advanced Machine Learning Techniques**: While t-SNE was used for dimensionality reduction, other advanced machine learning techniques, such as deep learning models (e.g., neural networks), could be explored to improve the accuracy of the recommendations. These models can potentially capture more complex relationships between ingredients and user preferences, leading to better recommendations.
3. **User Feedback and Personalization**: Incorporating user feedback into the system could enhance its effectiveness. By allowing users to rate products based on their experience, the system could learn from these ratings and offer more personalized recommendations over time. This would create a dynamic recommendation system that adapts to individual preferences.
4. **Ingredient Safety and Sensitivity Analysis**: In addition to ingredient similarity, the system could be enhanced to include a safety analysis based on common allergens or irritants for different skin types. This would be especially useful for individuals with sensitive skin or those prone to allergies, ensuring that the recommended products are not only similar but also safe to use.
5. **Integration with E-Commerce Platforms**: The recommendation system could be integrated with e-commerce platforms such as Kaggle, Amazon, or other online beauty retailers. This would allow users to receive real-time product recommendations based on their preferences and the chemical components of the products, making the system more practical and user-friendly.

6. **Real-Time Data Updates**: The system could be further developed to include real-time data updates, ensuring that users always have access to the most up-to-date product information. This could involve integrating APIs from cosmetic databases or e-commerce websites to automatically update the product catalog and ingredient lists.

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