This project involves the development of a content-based recommendation engine that should take the name of a skincare product as input and return several similar products based on the product's ingredients.

```
import numpy as np
import pandas as pd
import re
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.decomposition import TruncatedSVD
from sklearn.manifold import TSNE

from bokeh.io import curdoc, push_notebook, output_notebook
from bokeh.layouts import column, layout
from bokeh.models import ColumnDataSource, Div, Select, Slider, TextInput, HoverTool
from bokeh.plotting import figure, show
from ipywidgets import interact, interactive, fixed, interact_manual
```

```
data=pd.read_csv("/content/skincare_products_clean.csv")
```

```
data.head()
```

	product_name	product_url	product_type	clean_ingreds	pri
0	The Ordinary Natural Moisturising Factors + HA...	https://www.lookfantastic.com/the-ordinary-nat...	Moisturiser	['capric triglyceride', 'cetyl alcohol', 'prop...	£5
1	CeraVe Facial Moisturising Lotion SPF 25	https://www.lookfantastic.com/cerave-facial-mo...	Moisturiser	['homosalate', 'glycerin', 'octocrylene'...	£13

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1138 entries, 0 to 1137
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   product_name   1138 non-null   object
 1   product_url    1138 non-null   object
 2   product_type   1138 non-null   object
 3   clean_ingreds  1138 non-null   object
 4   price          1138 non-null   object
dtypes: object(5)
memory usage: 44.6+ KB
```

Dataset has 1138 rows and 5 colums

We can see that there are no missing values

```
data.describe()
```

	product_name	product_url	product_type	clean_ingreds
count	1138	1138	1138	1138
unique	1138	1126	14	1071
top	The Ordinary Natural Moisturising	https://www.lookfantastic.com/lancome-advanced	Mask	['sodium chloride']

```
for i in range(len(data['clean_ingreds'])):
    data['clean_ingreds'].iloc[i] = str(data['clean_ingreds'].iloc[i]).replace('[', '').r
#performs a series of string replacement operations
```

```
all_ingreds = []

for i in data['clean_ingreds']:
    ingreds_list = i.split(', ')
    for j in ingreds_list:
        all_ingreds.append(j)
#splitting each element into individual ingredient strings based on commas (',').
#It then collects all these individual ingredient strings into a single list called all_i
```

```
all_ingreds = sorted(set(all_ingreds))  #Converts the list all_ingreds into a set to remo
all_ingreds[0:20]
```

```
['',
 '1,10-decanediol',
 '1,2-hexanediol',
 '1,2-hexanediol ',
 '1-methylhydantoin-2-imide',
 '10-hydroxydecanoic acid',
 '2,6-dimethyl-7-octen-2-ol',
 '2-bromo-2-nitropropane-1,3-diol',
 '2-oleamido-1',
 '3-o-ethyl ascorbic acid',
 '3-octadecanediol',
 '4-t-butylcyclohexanol',
 '7-dehydrocholesterol',
 'abies alba leaf oil',
 'abies balsamea extract',
 'abies sibirica oil',
 'acacia concinna fruit extract',
 'acacia decurrens wax',
 'acacia senegal gum',
 'acacia seyal gum extract']
```

```
all_ingreds.remove('')  #Removing Empty Strings
for i in range(len(all_ingreds)):   #Removing Trailing Spaces
    if all_ingreds[i][-1] == ' ':
        all_ingreds[i] = all_ingreds[i][0:-1]

all_ingreds = sorted(set(all_ingreds))  #Sorting and Removing Duplicates
all_ingreds[0:20]
```

```
['1,10-decanediol',
 '1,2-hexanediol',
 '1-methylhydantoin-2-imide',
 '10-hydroxydecanoic acid',
 '2,6-dimethyl-7-octen-2-ol',
 '2-bromo-2-nitropropane-1,3-diol',
 '2-oleamido-1',
 '3-o-ethyl ascorbic acid',
 '3-octadecanediol',
 '4-t-butylcyclohexanol',
 '7-dehydrocholesterol',
 'abies alba leaf oil',
 'abies balsamea extract',
 'abies sibirica oil',
 'acacia concinna fruit extract',
 'acacia decurrens wax',
 'acacia senegal gum',
 'acacia seyal gum extract',
 'acer saccharum extract',
 'acetate']
```

```
one_hot_list = [[0] * 0 for i in range(len(all_ingreds))]

for i in data['clean_ingreds']:   #Generating One-Hot Encoding
    k=0
    for j in all_ingreds:
        if j in i:
            one_hot_list[k].append(1)
        else:
            one_hot_list[k].append(0)
        k+=1

#If j is present in i, it appends 1 to the corresponding inner list in one_hot_list[k].
#If j is not present in i, it appends 0 to the corresponding inner list in one_hot_list[k
#Here, k is used to keep track of the index of the ingredient in all_ingreds.
ingred_matrix = pd.DataFrame(one_hot_list).transpose()
ingred_matrix.columns = [sorted(set(all_ingreds))]

ingred_matrix
```

	1,10-decanediol	1,2-hexanediol	1-methylhydantoin-2-imide	10-hydroxydecanoic acid	2,6-dimethyl-7-octen-2-ol	2-bromo-2 nitroprop 1,3-diol
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	
...	...	...	...	...	...	
1133	0	0	0	0	0	
1134	0	0	0	0	0	
1135	0	0	0	0	0	
1136	0	0	0	0	0	
1137	0	0	0	0	0	

1138 rows × 2405 columns

This matrix contains zeros and ones

In summary, this code snippet is generating a one-hot encoded matrix (ingred_matrix) to represent the presence or absence of each ingredient in each product based on their ingredient lists (clean_ingreds). The matrix is constructed using a list of lists (one_hot_list), where each inner list corresponds to an ingredient and stores binary values (0 or 1) indicating ingredient presence. The resulting DataFrame (ingred_matrix) is then transposed for a more conventional representation, with column names set to the sorted list of unique ingredients.

*Dimentionality Reduction *

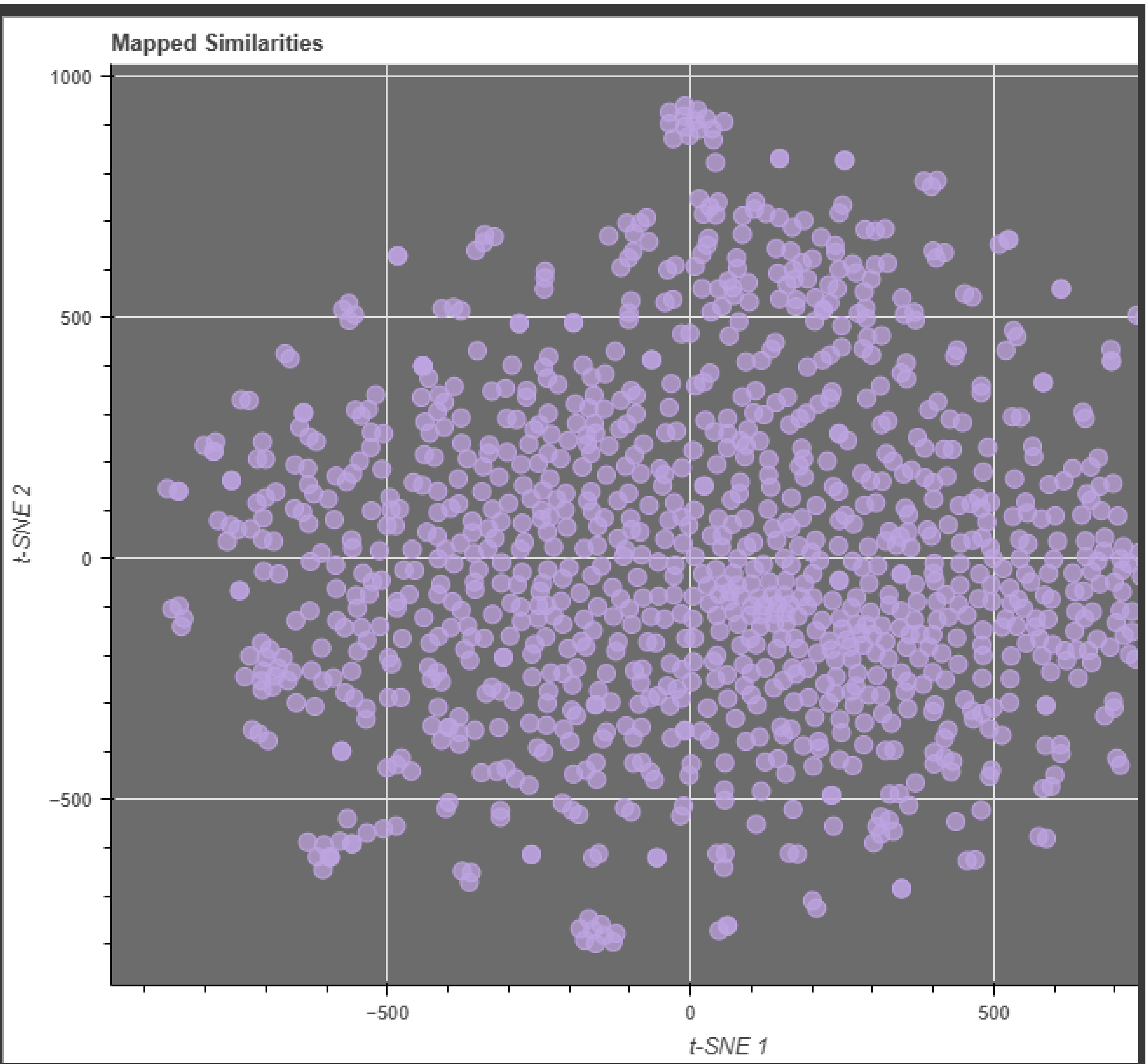
```
#We will use TruncatedSVD and TSNE to summarise the whole matrix in 2 values for each row
#These x and y values can be plotted to visualise the similarities between the products.
```

```
svd = TruncatedSVD(n_components=150, n_iter = 1000, random_state = 6) # firstly reduce fe
svd_features = svd.fit_transform(ingred_matrix)

tsne = TSNE(n_components = 2, n_iter = 1000000, random_state = 6) # reduce 150 features t
tsne_features = tsne.fit_transform(svd_features)

data['X'] = tsne_features[:, 0]
data['Y'] = tsne_features[:, 1]
```

->TruncatedSVD is a dimensionality reduction technique that uses singular value decomposition (SVD) to reduce the number of features (columns) in a matrix while preserving as much variance as possible. ->TSNE is another dimensionality reduction technique used for visualizing high-dimensional data in a lower-dimensional space, typically 2D or 3D.

```
unique_types = ['Moisturiser', 'Serum', 'Oil', 'Mist', 'Balm', 'Mask', 'Peel',
       'Eye Care', 'Cleanser', 'Toner', 'Exfoliator', 'Bath Salts',
       'Body Wash', 'Bath Oil']   #all the unique products

source = ColumnDataSource(data)
```

```
#creating bokeh plot
plot = figure(title = "Mapped Similarities", width = 800, height = 600)
plot.xaxis.axis_label = "t-SNE 1"
plot.yaxis.axis_label = 't-SNE 2'

plot.circle(x = 'X', y = 'Y', source = source, fill_alpha=0.7, size=10,
           color = '#c0a5e3', alpha = 1)

plot.background_fill_color = "#E9E9E9"
plot.background_fill_alpha = 0.3

hover = HoverTool(tooltips=[('Product', '@product_name'), ('Price', '@price')])
plot.add_tools(hover)

def type_updater(product_type = unique_types[0]):
    new_data = {'X' : data[data['product_type'] == product_type]['X'],
                'Y' : data[data['product_type'] == product_type]['Y'],
                'product_name' : data[data['product_type'] == product_type]['product_name
                'price' : data[data['product_type'] == product_type]['price']}
    source.data = new_data
    push_notebook()

output_notebook()
show(plot, notebook_handle = True)
interact(type_updater, product_type = unique_types)
```



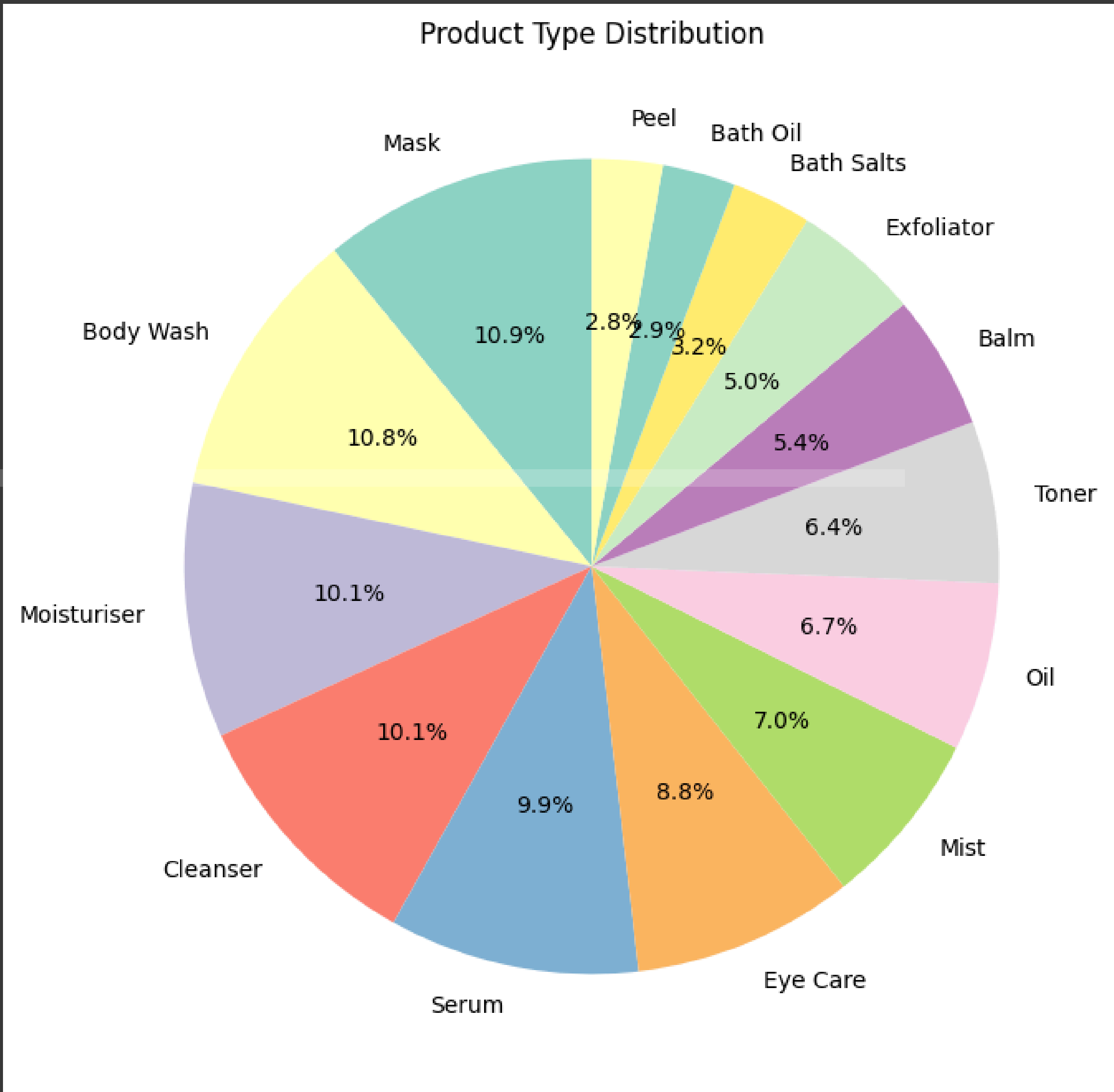
product_type Moisturiser

type_updater
def type_updater(product_type=unique_types[0])

<no docstring>

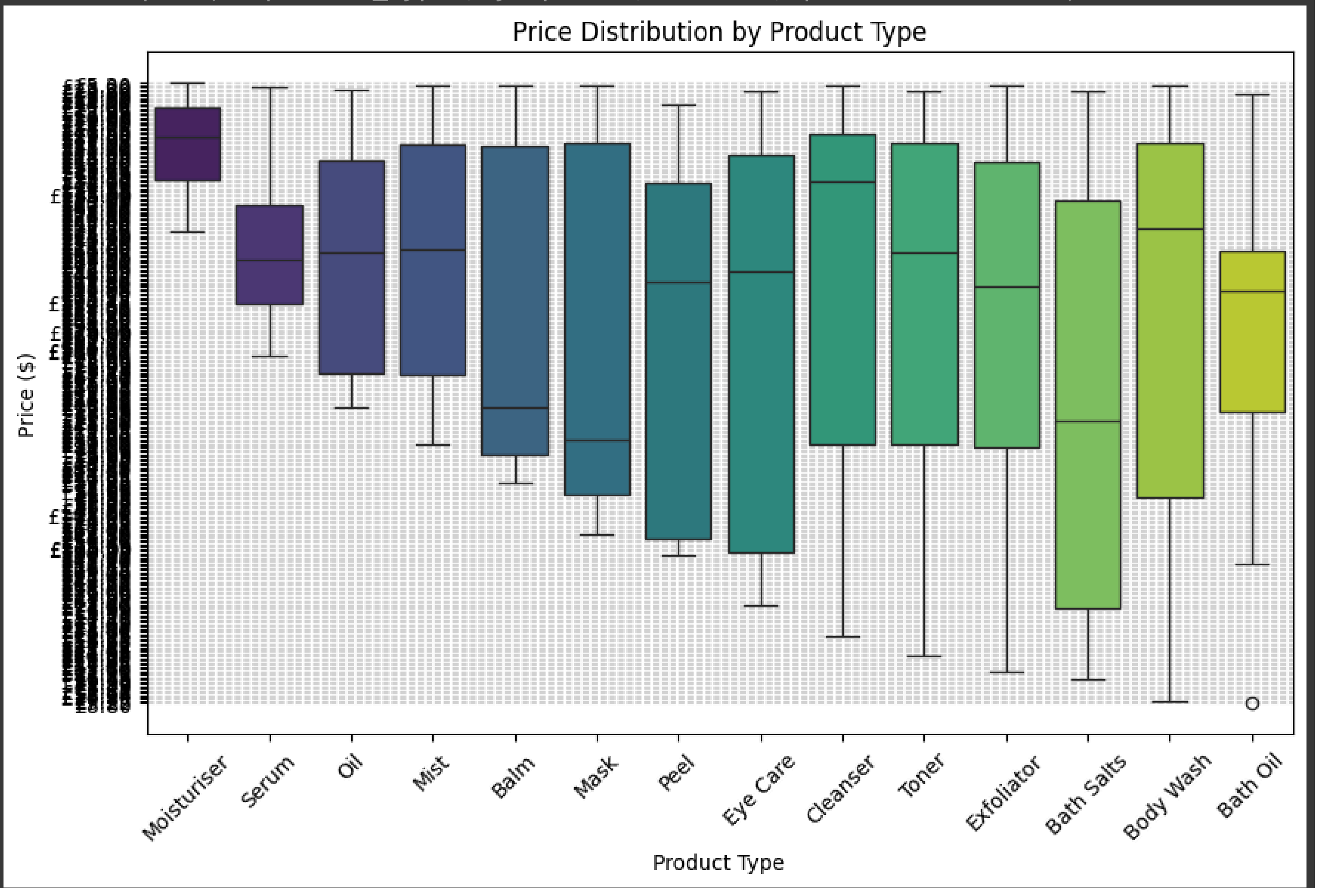
```
#product type distribution

data1 = {
    'product_name': data['product_name'].tolist(),
    'product_type': data['product_type'].tolist(),
    'price': data['price'].tolist()
}

df = pd.DataFrame(data1)

# Calculate product type counts
type_counts = df['product_type'].value_counts()

# Plotting a pie chart for product type distribution
plt.figure(figsize=(8, 8))
```

```
plt.pie(type_counts, labels=type_counts.index, autopct='%1.1f%%', startangle=90, colors=p
plt.title('Product Type Distribution')
plt.show()
```




```
# Plotting a box plot for price distribution by product type
plt.figure(figsize=(10, 6))
sns.boxplot(x='product_type', y='price', data=df, palette='viridis')
plt.title('Price Distribution by Product Type')
plt.xlabel('Product Type')
plt.ylabel('Price ($)')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.5)
plt.show()
```

```
<ipython-input-16-389655ca7759>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.

  sns.boxplot(x='product_type', y='price', data=df, palette='viridis')
```




```
brand_list = ["111skin", "a'kin", "acorelle", "adam revolution", "aesop", "ahava", "alchi
              "algenist", "alpha-h", "ambre solaire", "ameliorate", "american crew", "anth
              "apivita", "argentum", "ark skincare", "armani", "aromatherapy associates",
              "aurelia probiotic skincare", "aurelia skincare",
              "australian bodycare", "avant skincare", "aveda", "aveeno", "avene", "avène"
              "bakel", "balance me", "barber pro", "bareminerals", "barry m cosmetics",
              "baxter of california", "bbb london", "beautypro", "benefit", "benton", "bic
              "bioeffect", "bloom & blossom", "bloom and blossom", "bobbi brown", "bondi s
              "by terry", "carita", "caudalie", "cerave", "chantecaille", "clinique",
              "comfort zone", "connock london", "cosmetics 27", "cosrx", "cowshed", "cryst
              "cult51", "darphin", "dear, klairs", "decleor", "decléor", "dermalogica", "d
              "dr. brandt", "dr brandt", "dr. hauschka", "dr hauschka", "dr. jackson's", "
              "dr botanicals", "dr dennis", "dr. pawpaw", "ecooking", "egyptian magic",
              "eisenberg", "elemental herbology", "elemis", "elizabeth arden", "embryoliss
              "emma hardie", "erno laszlo", "espa", "estée lauder", "estee lauder", "eucer
              "eve lom", "eve rebirth", "fade out", "farmacy", "filorga", "first aid beaut
```

```
              "frank body", "freezeframe", "gallinée", "garnier", "gatineau", "glamglow",
              "green people", "hawkins and brimble", "holika holika", "house 99", "huxley"
              "ilapothecary", "ila-spa", "indeed labs", "inika", "instant effects", "insti
              "j.one", "jack black", "james read", "jason", "jo malone london", "juice bea
              "korres", "l:a bruket", "l'oréal men expert", "l'oreal men expert", "l'oréal
              "l'oréal paris", "lab series skincare for men",
              "lancaster", "lancer skincare", "lancôme", "lancome", "lanolips", "la roche-
              "liftlab", "little butterfly london", "lixirskin", "liz earle", "love boo",
              "löwengrip", "lowengrip", "lumene", "mac", "madara", "mádara", "magicstripes
              "mama mio", "mancave", "manuka doctor", "mauli", "mavala", "maybelline", "me
              "monu", "murad", "naobay", "nars", "natio", "natura bissé", "natura bisse",
              "neal's yard remedies", "neom", "neostrata", "neutrogena", "niod", "nip+fab"
              "oh k!", "omorovicza", "origins", "ortigia fico", "oskia", "ouai", "pai ", "
              "perricone md", "pestle & mortar", "pestle and mortar", "peter thomas roth",
              "philosophy", "pierre fabre", "pixi", "piz buin", "polaar", "prai", "project
              "radical skincare", "rapideye", "rapidlash", "real chemistry", "recipe for m
              "ren ", "renu", "revolution beauty", "revolution skincare", "rituals", "rmk"
              "sanctuary spa", "sanoflore", "sarah chapman", "sea magik", "sepai",
              "shaveworks", "shea moisture", "shiseido", "skin79", "skin authority", "skin
              "skinchemists", "skindoctors", "skin doctors", "skinny tan", "sol de janeirc
               "st. tropez", "starskin", "strivectin", "sukin",
              "svr", "swiss clinic", "talika", "tan-luxe", "tanorganic", "tanworx", "thalg
              "the hero project", "the inkey list", "the jojoba company", "the ordinary",
              "the organic pharmacy", "the ritual of namasté", "this works", "too faced",
              "ultrasun", "uppercut deluxe", "urban decay", "uriage", "verso", "vichy",
              "vida glow", "vita liberata", "wahl", "weleda", "westlab", "wilma schumann",
              "ysl", "zelens"]
brand_list = sorted(brand_list, key=len, reverse=True)
```

```
data['brand'] = data['product_name'].str.lower()

for k in range(len(data['brand'])):
    for j in brand_list:
        if j in data['brand'].iloc[k]:  # Use .iloc to access DataFrame element by index
            data.loc[k, 'brand'] = data['brand'].iloc[k].replace(data['brand'].iloc[k], j
data
```

	product_name	product_url	product_type	clean_ingred
0	The Ordinary Natural Moisturising Factors + HA...	https://www.lookfantastic.com/the-ordinary-nat...	Moisturiser	capric triglyceride cetyl alcoho propanedio.
1	CeraVe Facial Moisturising Lotion SPF 25 52ml	https://www.lookfantastic.com/cerave-facial-mo...	Moisturiser	homosalate glycerin octocrylene ethylhexyl,.
2	The Ordinary Hyaluronic Acid 2% + B5 Hydration...	https://www.lookfantastic.com/the-ordinary-hya...	Moisturiser	sodiur hyaluronate sodiur hyaluronate panthe.
3	AMELIORATE Transforming Body Lotion 200ml	https://www.lookfantastic.com/ameliorate-trans...	Moisturiser	ammonium lactate c12-15, glycerin prunus amy.
4	CeraVe Moisturising Cream 454g	https://www.lookfantastic.com/cerave-moisturis...	Moisturiser	glycerin, cetear alcohol, capri triglycerid.
...	...	...	...	.
1133	Elemis Life Elixirs Embrace Bath and Shower	https://www.lookfantastic.com/elemis-life-elix...	Bath Oil	prunus amygdalu dulcis, tipa-lauret sulfate,.

```
sorted(data.brand.unique())
```

```
 'Renu',
 'Revolution Skincare',
 'Rituals',
 'Rodial',
 'Salcura',
 'Sanctuary Spa',
 'Sarah Chapman',
 'Sea Magik',
 'Shea Moisture',
 'Shiseido',
 'Skin Doctors',
 'Skinceuticals',
 'Skinny Tan',
 'Sol De Janeiro',
 'Spa Magik Organiks',
 'Strivectin',
 'Sukin',
 'Svr',
 'Talika',
 'Tan-Luxe',
 'Tanorganic',
 'The Chemistry Brand',
 'The Inkey List',
 'The Ordinary',
 'The Ritual Of Namasté',
 'This Works',
 'Too Faced',
 'Trilogy',
 'Ultrasun',
 'Uriage',
 'Verso',
 'Vichy',
 'Weleda',
 'Westlab',
 'Yes To',
 'Zelens']
```

```
data['brand'] = data['brand'].replace(['Aurelia Probiotic Skincare'],'Aurelia Skincare')
data['brand'] = data['brand'].replace(['Avene'],'Avène')
data['brand'] = data['brand'].replace(['Bloom And Blossom'],'Bloom & Blossom')
data['brand'] = data['brand'].replace(['Dr Brandt'],'Dr. Brandt')
data['brand'] = data['brand'].replace(['Dr Hauschka'],'Dr. Hauschka')
data['brand'] = data['brand'].replace(["L'oreal Paris", 'L’oréal Paris'], "L'oréal Paris"
```

```
import ast

# Function to fix the format of ingredients
def fix_ingredients_format(ingredients_str):
    # Split the string and add quotes around each ingredient
    ingredients_list = [f"'{ing.strip()}'" for ing in ingredients_str.split(',')]
    # Join the list to form a valid Python list representation
    return f"[{', '.join(ingredients_list)}]"

# Apply the function to correct the 'clean_ingreds' column
data['clean_ingreds'] = data['clean_ingreds'].apply(fix_ingredients_format)

# Now, use ast.literal_eval to convert the strings to actual lists
```

```
data['clean_ingreds'] = data['clean_ingreds'].apply(ast.literal_eval)
```

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel

data['clean_ingreds_str'] = data['clean_ingreds'].apply(lambda x: ' '.join(x))

# Create TF-IDF vectorizer
tfidf_vectorizer = TfidfVectorizer()
tfidf_matrix = tfidf_vectorizer.fit_transform(data['clean_ingreds_str'])

# Extract features (X) and target (y)
X = tfidf_matrix
y = data['product_type']

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Train a Decision Tree Classifier
clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

```
# Predict product types
y_pred = clf.predict(X_test)

# Evaluate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy of Decision Tree Classifier:", accuracy)
```

```
Accuracy of Decision Tree Classifier: 0.43859649122807015
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Create Random Forest Classifier
rf_clf = RandomForestClassifier(random_state=42)

# Train the model
rf_clf.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
# Predict product types
y_pred_rf = rf_clf.predict(X_test)

# Evaluate accuracy
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print("Accuracy of Random Forest Classifier:", accuracy_rf)
```

```
Accuracy of Random Forest Classifier: 0.5570175438596491
```

```
from sklearn.svm import SVC

# Create SVM Classifier
svm_clf = SVC(kernel='linear', random_state=42)

# Train the model
svm_clf.fit(X_train, y_train)
```

```
SVC
SVC(kernel='linear', random_state=42)
```

```
# Predict product types
y_pred_svm = svm_clf.predict(X_test)

# Evaluate accuracy
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print("Accuracy of SVM Classifier:", accuracy_svm)
```

```
Accuracy of SVM Classifier: 0.5570175438596491
```

```
from sklearn.neighbors import KNeighborsClassifier

# Create KNN Classifier
knn_clf = KNeighborsClassifier(n_neighbors=5)

# Train the model
knn_clf.fit(X_train, y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier()
```

```
# Predict product types
y_pred_knn = knn_clf.predict(X_test)

# Evaluate accuracy
```

```
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print("Accuracy of KNN Classifier:", accuracy_knn)
```

```
Accuracy of KNN Classifier: 0.4298245614035088
```

```
from sklearn.neural_network import MLPClassifier

# Create MLP Classifier
mlp_clf = MLPClassifier(hidden_layer_sizes=(100,), max_iter=100, random_state=42)
# Train the model
mlp_clf.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptror
  warnings.warn(
```

```
▾ MLPClassifier
MLPClassifier(max_iter=100, random_state=42)
```

```
# Predict product types
y_pred_mlp = mlp_clf.predict(X_test)

# Evaluate accuracy
accuracy_mlp = accuracy_score(y_test, y_pred_mlp)
print("Accuracy of MLP Classifier:", accuracy_mlp)
```

```
Accuracy of MLP Classifier: 0.5570175438596491
```

```
from sklearn.ensemble import GradientBoostingClassifier

# Create Gradient Boosting Classifier
gbm_clf = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, random_state=42

# Train the model
gbm_clf.fit(X_train, y_train)
```

```
▾ GradientBoostingClassifier
GradientBoostingClassifier(random_state=42)
```

```
# Predict product types
y_pred_gbm = gbm_clf.predict(X_test)

# Evaluate accuracy
accuracy_gbm = accuracy_score(y_test, y_pred_gbm)
print("Accuracy of Gradient Boosting Classifier:", accuracy_gbm)
```

```
Accuracy of Gradient Boosting Classifier: 0.4956140350877193
```

```
from sklearn.naive_bayes import MultinomialNB

# Create Naive Bayes Classifier
nb_clf = MultinomialNB()

# Train the model
nb_clf.fit(X_train, y_train)
```

```
▾ MultinomialNB
MultinomialNB()
```

```
# Predict product types
y_pred_nb = nb_clf.predict(X_test)

# Evaluate accuracy
accuracy_nb = accuracy_score(y_test, y_pred_nb)
print("Accuracy of Naive Bayes Classifier:", accuracy_nb)
```

```
Accuracy of Naive Bayes Classifier: 0.3684210526315789
```

```
from sklearn.linear_model import LogisticRegression

# Create Logistic Regression Classifier
logreg_clf = LogisticRegression(max_iter=100, random_state=42)

# Train the model
logreg_clf.fit(X_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression(random_state=42)
```

```
# Predict product types
y_pred_logreg = logreg_clf.predict(X_test)

# Evaluate accuracy
accuracy_logreg = accuracy_score(y_test, y_pred_logreg)
print("Accuracy of Logistic Regression Classifier:", accuracy_logreg)
```

```
Accuracy of Logistic Regression Classifier: 0.5394736842105263
```

Creating the recommendation function

The function below recommends products by:

🔍 taking the name of a product as input

- only including products of the same type
- not recommending products of the same brand name
- calculating cosine similarities and returning top 5 similar products

```
def recommender(search):
    cs_list = []
    brands = []
    output = []
    binary_list = []
    idx = data[data['product_name'] == search].index.item()

    # Extract binary ingredient list for the searched product
    for i in ingred_matrix.iloc[idx][1:]:
        binary_list.append(i)

    # Reshape the binary ingredient list as a 1D array
    point1 = np.array(binary_list).reshape(1, -1)
    point1 = [val for sublist in point1 for val in sublist]

    # Get product type and brand of the searched product
    prod_type = data['product_type'][data['product_name'] == search].iat[0]
    brand_search = data['brand'][data['product_name'] == search].iat[0]

    # Filter data by product type
    data_by_type = data[data['product_type'] == prod_type]


    # Calculate cosine similarity with other products of the same type
    for j in range(data_by_type.index[0], data_by_type.index[0] + len(data_by_type)):
        binary_list2 = []
        for k in ingred_matrix.iloc[j][1:]:
            binary_list2.append(k)
        point2 = np.array(binary_list2).reshape(1, -1)
        point2 = [val for sublist in point2 for val in sublist]
        dot_product = np.dot(point1, point2)
        norm_1 = np.linalg.norm(point1)
        norm_2 = np.linalg.norm(point2)
        cos_sim = dot_product / (norm_1 * norm_2)
        cs_list.append(cos_sim)
    data_by_type = pd.DataFrame(data_by_type)
    data_by_type['cos_sim'] = cs_list
    data_by_type = data_by_type.sort_values('cos_sim', ascending=False)
    data_by_type = data_by_type[data_by_type.product_name != search]
    l = 0
    for m in range(len(data_by_type)):
        brand = data_by_type['brand'].iloc[l]
        if len(brands) == 0:
            if brand != brand_search:
                brands.append(brand)
                output.append(data_by_type.iloc[l])
        elif brands.count(brand) < 2:
            if brand != brand_search:
```

```
            brands.append(brand)
            output.append(data_by_type.iloc[l])
        l += 1

    return print('\033[1m', 'Recommending products similar to', search,':', '\033[0m'), p
```

This recommender function uses cosine similarity based on ingredient matrices (ingred_matrix) to recommend products similar to a searched product (search). It considers product type and brand to filter and recommend relevant products. The function prints the top 5 recommended products along with their cosine similarities based on ingredient similarity with the searched product.

```
recommender("Origins GinZing™ Energy-Boosting Tinted Moisturiser SPF40 50ml")
```

```
 Recommending products similar to Origins GinZing™ Energy-Boosting Tinted Moisturiser
                                          product_name   cos_sim
87  Clinique Moisture Surge SPF25 Sheertint Hydrat...  0.565322
44              Skin Doctors Sd White & Bright (50ml)  0.382546
54  Clinique Moisture Surge 72-Hour Auto-Replenish...  0.372046
34        Elemis Pro-Collagen Marine Cream SPF30 50ml  0.365339
42  Estée Lauder DayWear Multi-Protection Anti-Oxi...  0.362033
(None, None)
```

```
recommender('Avène Antirougeurs Jour Redness Relief Moisturizing Protecting Cream (40ml)'
```

```
 Recommending products similar to Avène Antirougeurs Jour Redness Relief Moisturizing
                                          product_name   cos_sim
40           La Roche-Posay Nutritic Intense Rich 50ml  0.408956
87   Clinique Moisture Surge SPF25 Sheertint Hydrat...  0.408248
12          First Aid Beauty Ultra Repair Cream (56.7g)  0.379663
15           First Aid Beauty Ultra Repair Cream (170g)  0.379663
100  Alpha-H Daily Essential Moisturiser Spf50+ (50ml)  0.369800
(None, None)
```

```
recommender('Bondi Sands Everyday Liquid Gold Gradual Tanning Oil 270ml')
```

```
 Recommending products similar to Bondi Sands Everyday Liquid Gold Gradual Tanning Oi
                                          product_name   cos_sim
238     Face by Skinny Tan Moisturising Oil Drops 30ml  0.442627
290        Erno Laszlo Detoxifying Cleansing Oil 195ml  0.400000
269                 The Chemistry Brand Glow Oil 100ml  0.353094
272  L'Oréal Paris Extraordinary Oil Sleeping Oil N...  0.345033
232      Clinique Take The Day Off Cleansing Oil 200ml  0.340168
(None, None)
```

```
recommender('Sukin Rose Hip Oil (25ml)')
```

```
 Recommending products similar to Sukin Rose Hip Oil (25ml) :
                                    product_name   cos_sim
257  Trilogy Certified Organic Rosehip Oil 45ml  1.000000
```

```
255   Trilogy Certified Organic Rosehip Oil 20ml  1.000000
231  Pai Skincare Rosehip BioRegenerate Oil 30ml  0.577350
292  Natio Ageless Rosehip Oil Cold Pressed 15ml  0.577350
259                      PIXI Rose Oil Blend 30ml  0.392232
(None, None)
```

```
recommender('La Roche-Posay Anthelios Anti-Shine Sun Protection Invisible SPF50+ Face Mis
```

```
Recommending products similar to La Roche-Posay Anthelios Anti-Shine Sun Protection
                                          product_name   cos_sim
306  Garnier Ambre Solaire Sensitive Hydrating Hypo...  0.901624
317  Garnier Ambre Solaire Sensitive Hypoallergenic...  0.714590
322  Lumene Nordic Hydra [Lähde] Arctic Spring Wate...  0.360119
315  Lumene Nordic Hydra Lähde Arctic Spring Water ...  0.341704
337  Revolution Skincare x Jake Jamie Tropical Quen...  0.328196
(None, None)
```

```
recommender('Clinique Even Better Clinical Radical Dark Spot Corrector + Interrupter 30ml
```

```
Recommending products similar to Clinique Even Better Clinical Radical Dark Spot Cor
                                          product_name   cos_sim
219  Darphin Dark Circle Relief and De-Puffing Eye ...  0.887904
180  Estée Lauder Idealist Pore Minimizing Skin Ref...  0.500390
223       Elizabeth Arden Prevage Advanced Daily Serum  0.453962
154  Estée Lauder Perfectionist Pro Multi-Defense A...  0.434549
177           Lancôme Génifique Double Drop Serum 20ml  0.393573
(None, None)
```

```
recommender("FOREO 'Serum Serum Serum' Micro-Capsule Youth Preserve")
```

```
Recommending products similar to FOREO 'Serum Serum Serum' Micro-Capsule Youth Prese
                                          product_name   cos_sim
200         Holika Holika 3 Seconds Starter (Collagen)  0.429935
160  Caudalie VineActiv Glow Activating Anti-Wrinkl...  0.423659
119  Estée Lauder Advanced Night Repair Synchronize...  0.403278
120  Estée Lauder Advanced Night Repair Synchronize...  0.403278
121  The Ordinary Hyaluronic Acid 2% + B5 Supersize...  0.374327
(None, None)
```

```
recommender('Garnier Organic Argan Mist 150ml')
```

```
Recommending products similar to Garnier Organic Argan Mist 150ml :
                                          product_name   cos_sim
378   The Ritual of Namasté Urban Hydrating Mist 100ml  0.526137
315  Lumene Nordic Hydra Lähde Arctic Spring Water ...  0.435011
322  Lumene Nordic Hydra [Lähde] Arctic Spring Wate...  0.429801
```