

# PRODUCT RECOMMENDATION SYSTEM AND ECOMMERCE

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# OBJECTIVE

- TO RECOMMEND TOP 10 BEAUTY PRODUCTS ON AMAZON APP BASED ON CUSTOMER REVIEWS

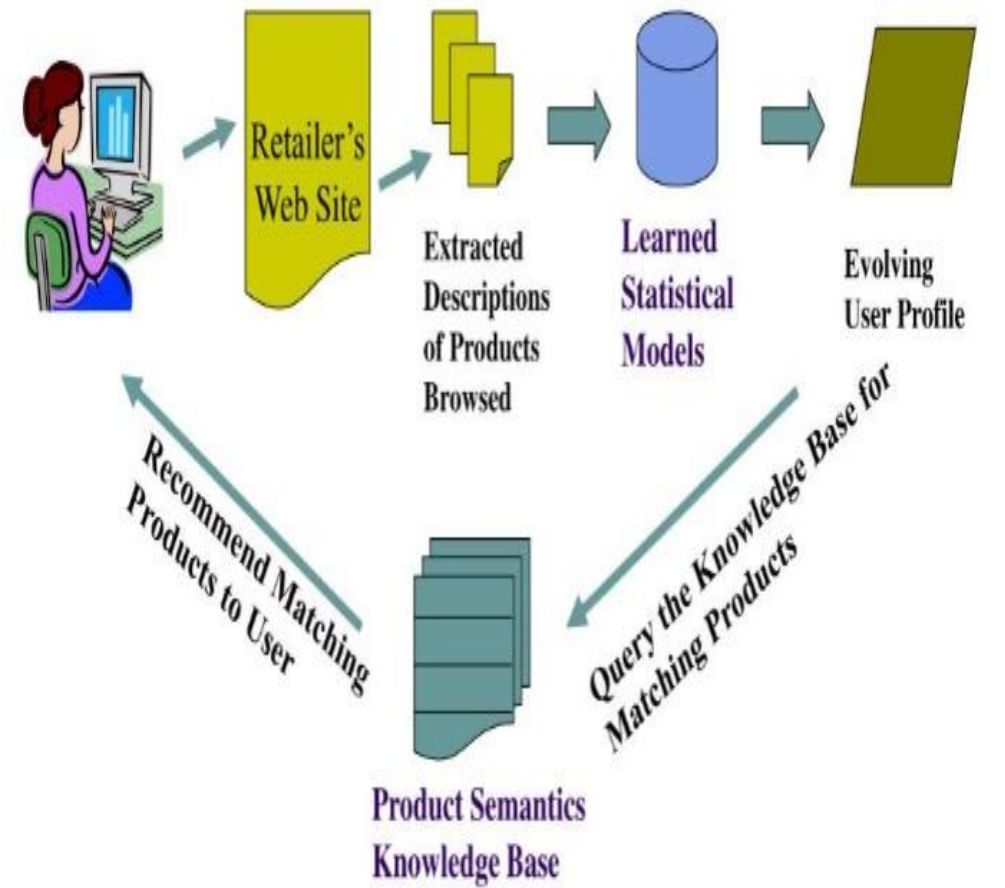


amazon  
BEST  
products


# Abstract

This technical report examines the literature and explains the Recommender System ideas. A recommendation engine is a system that filters information to bring movies , music, books etc to the user. A set of tools to a user , this data has been vetted to ensure that it is likely to pique the user's interest .

## Recommender System



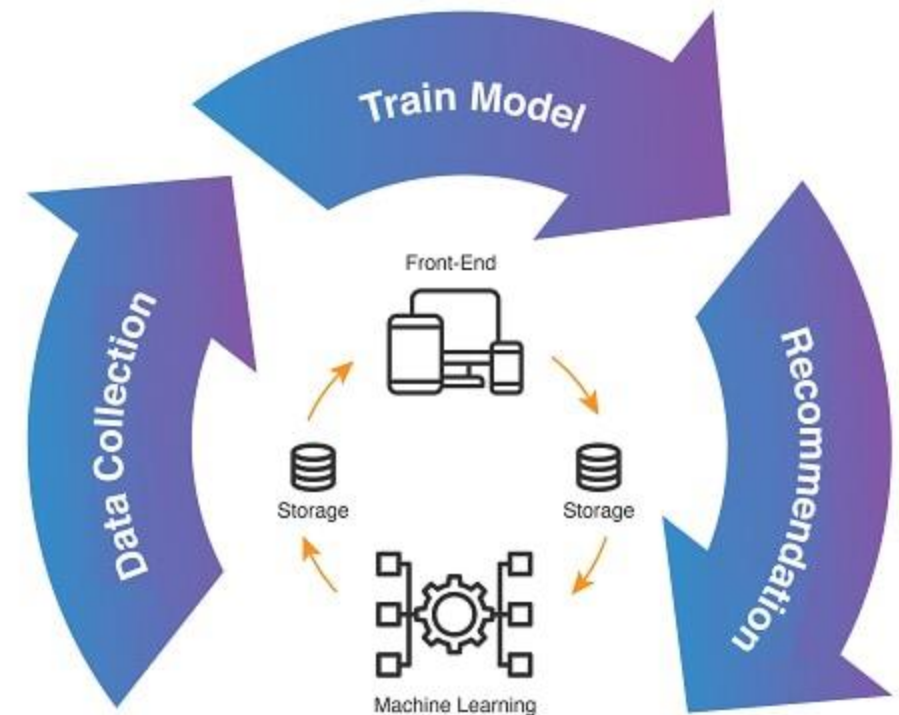


The background features a dark blue-to-purple gradient. A horizontal band of solid black color runs across the middle. Overlaid on this are several concentric circles and arcs in white and light blue. Some arcs are complete, while others are partial, creating a sense of motion or a stylized globe. Small white dots are scattered throughout the design.

# Introduction to Recommender Systems and E-Commerce

# R E C O M M E N D E R S Y S T E M S

- ❑ Recommendation system is a technology which is used for filter and retrieval the data .
  - ❑ In the methods of unsupervised machine learning ,the task of machine or model is to group the uncategorized data , according to similarities, patterns and differences without given any kind of training to the machine
- ❑ These can be based on various criteria ,including past purchases ,search history, demographic information , and other factors





# E-COMMERCE

- “E-commerce” or “electronic commerce” is the trading of goods and services on the internet. It is your bustling city center or brick-and-mortar shop translated into zeroes and ones on the internet superhighway.

pepperfry®

JABONG.COM

ebay

mynta.com

flipkart.com

amazon

ShopClues.com

snapdeal.com

HOME SHOP 18

yebhi.com

## LARGEST ECOMMERCE SITES

- ❑ Ecommerce works by connecting buyers and sellers using various electronic channels.

For example, you need a channel, such as a website or social media, so customers can find products and services to purchase. Then a payment processor enables the exchange of the goods or services. Once the transaction succeeds, the customer receives a confirmation email or SMS, and a printable receipt.

# Literature Review

SIVAPALAN

- The significant challenges of collaborative filtering -- sparsity  
-- scalability
- Collaborative filtering measures -- cosine metric  
-- jaccard coefficient  
-- personalized data
- Due to data sparsity, sales volumes on large e-commerce are decreasing.
- Suggested that the **developers of RSs** should stop using **the nearest neighbouring**

**G . GUPTA & R . KATARYA**

➤ In UBCF techniques ,the recommendations are generated acc to the like or dislike of the neighbours node

➤ In IBCF technique, the similarity between the items are calculated

**ZHAO , ZHI-DAN  
&  
MING**

The drawback of UBCF ---- if user U like an item I but his/her neighbours not gave good ratings good ratings to that item I will not be recommended

IBCF calculates similarity between two items



## ○ Source of the data

Collected the data of amazon beauty products from Kaggle website

<https://www.kaggle.com/skillsmugger/amazon-ratings>

## SAMPLE DATA

This is the sample data of size 20

UserId	ProductId	Rating	Timestamp
A39HTATAQ9V7YF	205616461	5	1369699200
A3JM6GV9MNOF9X	558925278	3	1355443200
A1Z513UWSAAO0F	558925278	5	1404691200
A1WMRR494NWEWV	733001998	4	1382572800
A3IAAVS479H7M7	737104473	1	1274227200
AKJHHD5VEH7VG	762451459	5	1404518400
A1BG8QW55XHN6U	1304139212	5	1371945600
A22VW0P4VZHDE3	1304139220	5	1373068800
A3V3RE4132GKRO	130414089X	5	1401840000
A327B0I7CYTEJC	130414643X	4	1389052800
A1BG8QW55XHN6U	130414643X	5	1372032000
AIFAAVTUYHEHB	130414643X	4	1378252800
AVOGV98AYOFG2	1304146537	5	1372118400
A22VW0P4VZHDE3	130414674X	5	1371686400
AVOGV98AYOFG2	1304168522	5	1372118400
A6R426V4J7AOM	1304168522	5	1373414400
A22VW0P4VZHDE3	1304174778	5	1372896000
AKGB62WGF35J8	1304174778	5	1372896000
A22VW0P4VZHDE3	1304174867	5	1373068800

# Data Description

This dataset contains product reviews and metadata from Amazon, including 142.8 million reviews spanning May 1996 - July 2014.

❖ It contains

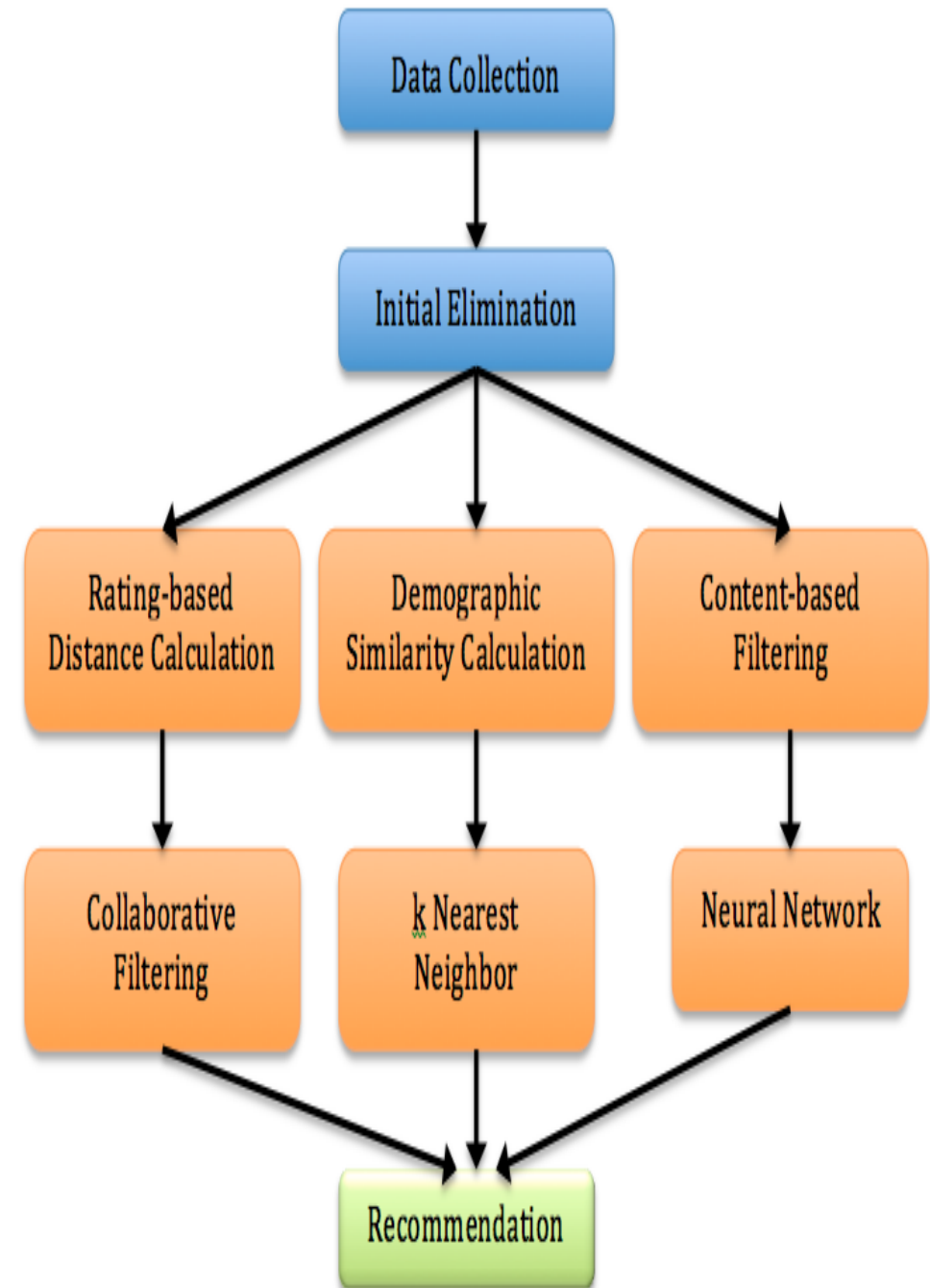
- the unique **UserId** (Customer Identification),
- the product **ASIN** (Amazon's unique product identification code for each product),
- **Ratings** (ranging from 1-5 based on customer satisfaction) and
- of the rating (in UNIX time) the **Timestamp**

# Methodology

Model based collaborative system

## POPULARITY BASED RECOMMENDATION SYSTEM

- Popularity based are a great strategy to target the new customers with the most popular products sold on a business's website and is very useful to cold start a recommendation engine.





# STATISTICAL TECHNIQUES

## CONTENT BASED RECOMMENDATION SYSTEM

Comparing user interests to product features . The products that have the most overlapping features with user interests are what's recommended

## Collaborative Filtering

Measures or techniques used are -

- neighbour(cosine, correlation)
- clustering
- Graph theory

Commonly used techniques -

- Bayesian approach
- clustering
- Artificial neural networks
- Linear regression
- Probabilistic models

## HYBRID RECOMMENDATION SYSTEM

Uses both collaborative data and content based . Simultaneously which helps to suggest a similar or close item to the users

- ❖ Methods we used are **content based & collaborative filtering** and techniques we used is **correlation matrix based on data**

The background is a dark blue to purple gradient. It features several concentric circles and arcs. A prominent white arc is on the right side, and another is on the left. A horizontal band of dark blue/black is across the middle. The text 'DATA VISUALIZATION' is centered in this band.

# DATA VISUALIZATION

# Popularity based Recommendation System

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

plt.style.use("ggplot")

import sklearn
from sklearn.decomposition import TruncatedSVD
```

```
In [3]: amazon_ratings = pd.read_csv('C:\\Users\\KISHORE\\Desktop\\kkkkk\\ratings_Beauty.csv')
amazon_ratings = amazon_ratings.dropna()
amazon_ratings.head()
```

Out[3]:

	UserId	ProductId	Rating	Timestamp
0	A39HTATAQ9V7YF	205616461	5	1369699200
1	A3JM6GV9MNOF9X	558925278	3	1355443200
2	A1Z513UWSAAO0F	558925278	5	1404691200
3	A1WMRR494NWEWV	733001998	4	1382572800
4	A3IAAVS479H7M7	737104473	1	1274227200



```
In [4]: amazon_ratings.shape
```

```
Out[4]: (1048575, 4)
```

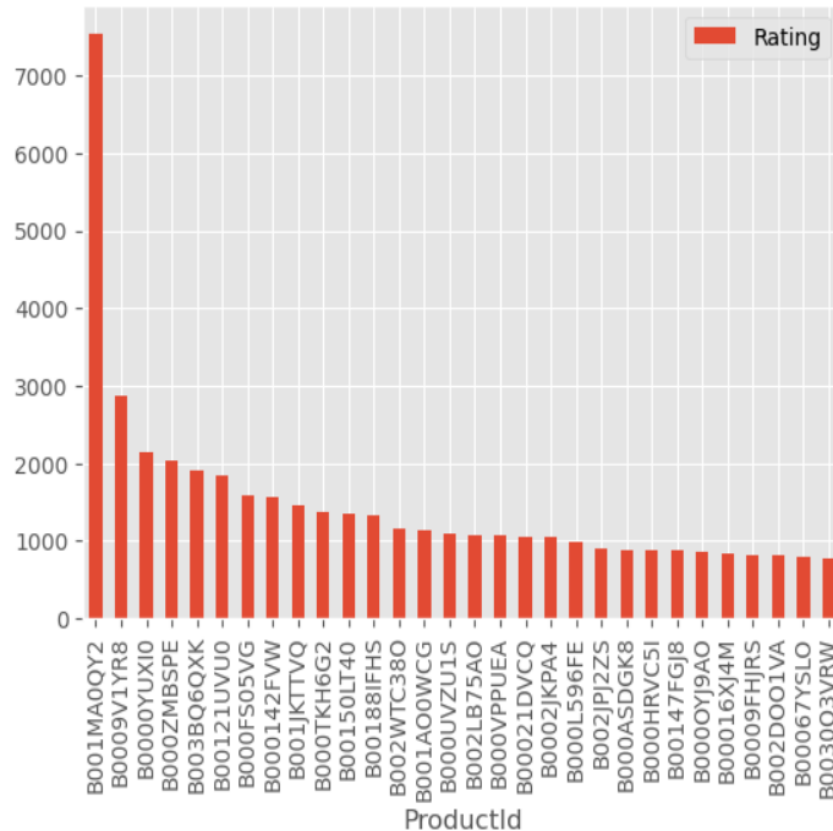
```
In [5]: popular_products = pd.DataFrame(amazon_ratings.groupby('ProductId')['Rating'].count())  
most_popular = popular_products.sort_values('Rating', ascending=False)  
most_popular.head(10)
```

```
Out[5]:
```

	Rating
ProductId	
B001MA0QY2	7533
B0009V1YR8	2869
B0000YUXI0	2143
B000ZMBSPE	2041
B003BQ6QXK	1918
B00121UVU0	1838
B000FS05VG	1589
B000142FVW	1558
B001JKTTVQ	1468
B000TKH6G2	1379

```
In [6]: most_popular.head(30).plot(kind = "bar")
```

```
Out[6]: <Axes: xlabel='ProductId'>
```



### Analysis:

- The above graph gives us the most popular products (arranged in descending order) sold by the business.
- For example, product, ID # B001MA0QY2 ( Maybelline New York Sky High washable Masacara ) has sales of over 7000, the next most popular product, ID # B0009V1YR8 ( PanOxyl Acne Foaming Wash ) has sales of 3000, etc.

# Item based collaborative using correlation matrix

```
In [7]: amazon_ratings1 = amazon_ratings.head(10000)
```

```
In [8]: ratings_utility_matrix = amazon_ratings1.pivot_table(values='Rating', index='UserId', columns='ProductId', fill_value=0)
ratings_utility_matrix.head()
```

Out[8]:

	ProductId	1304139212	1304139220	130414089X	130414643X	1304146537	130414674X	1304168522	1304174778	1304174867	1304174905	...	E
	UserId												
A00205921JHJK5X9LNP42		0	0	0	0	0	0	0	0	0	0	0	...
A024581134CV80ZBLIZTZ		0	0	0	0	0	0	0	0	0	0	0	...
A03056581JJIOL5FSKJY7		0	0	0	0	0	0	0	0	0	0	0	...
A03099101ZRK4K607JVHH		0	0	0	0	0	0	0	0	0	0	0	...
A0505229A7NSH3FRXRR4		0	0	0	0	0	0	0	0	0	0	0	...

5 rows × 886 columns



```
In [9]: ratings_utility_matrix.shape
```

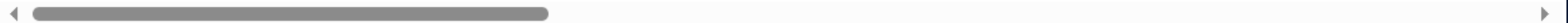
```
Out[9]: (9697, 886)
```

```
In [10]: X = ratings_utility_matrix.T  
X.head()
```

```
Out[10]:
```

	UserId A00205921JHJK5X9LNP42	A024581134CV80ZBLIZTZ	A03056581JJJOL5FSKJY7	A03099101ZRK4K607JVHH	A0505229A7NSH3FRXRR4	A05492663T95K1
ProductId						
1304139212	0	0	0	0	0	0
1304139220	0	0	0	0	0	0
130414089X	0	0	0	0	0	0
130414643X	0	0	0	0	0	0
1304146537	0	0	0	0	0	0

5 rows × 9697 columns



```
In [11]: X.shape
```

```
Out[11]: (886, 9697)
```

```
In [12]: X1 = X
```

```
In [14]: SVD = TruncatedSVD(n_components=10)
decomposed_matrix = SVD.fit_transform(X)
decomposed_matrix.shape
```

```
Out[14]: (886, 10)
```

```
In [15]: correlation_matrix = np.corrcoef(decomposed_matrix)
correlation_matrix.shape
```

```
Out[15]: (886, 886)
```

```
In [16]: X.index[99]
```

```
Out[16]: '6162071103'
```

```
In [17]: i = "6117036094"

product_names = list(X.index)
product_ID = product_names.index(i)
product_ID
```

```
Out[17]: 96
```

```
In [18]: correlation_product_ID = correlation_matrix[product_ID]
correlation_product_ID.shape
```

```
Out[18]: (886,)
```

```
In [24]: Recommend = list(X.index[correlation_product_ID > 0.90])
Recommend.remove(i)

Recommend[0:9]
```

### Conclusion:

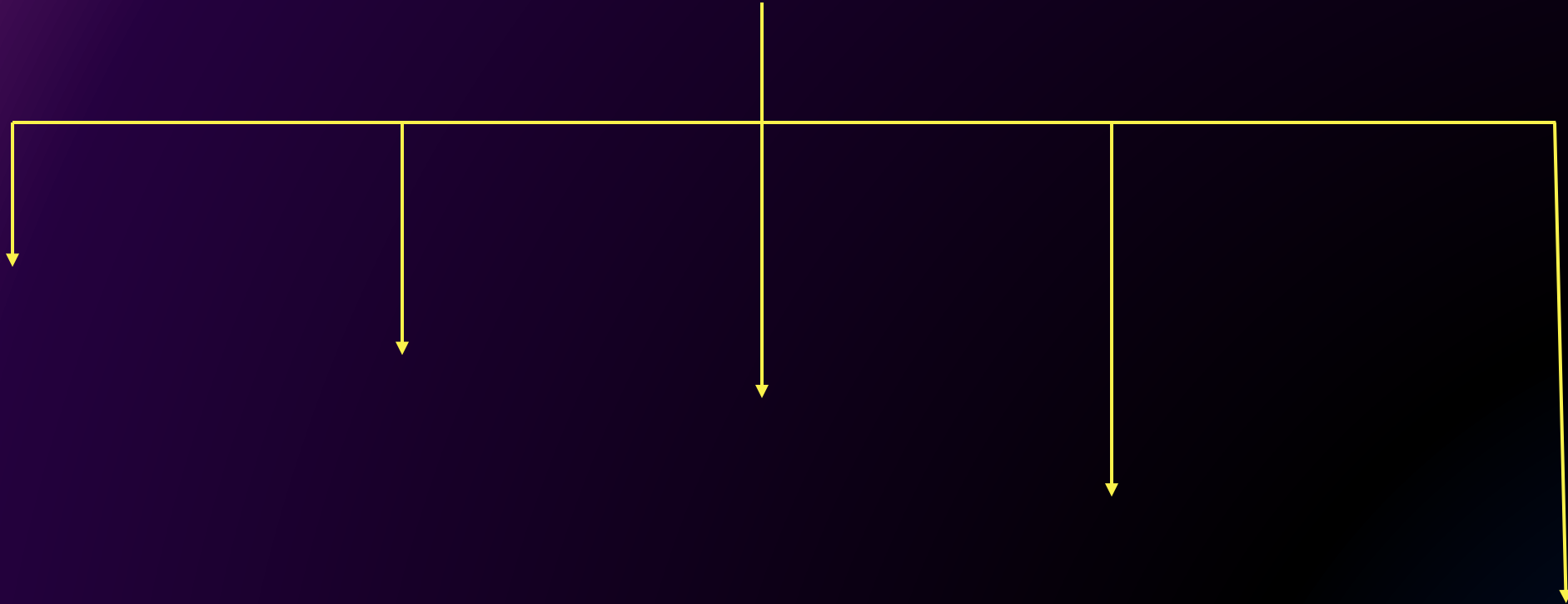
Here are the top 10 products to be displayed by the recommendation system to the above customer based on the purchase history of other customers in the

- website. Products named
  - L'Oreal Paris Voluminous Lash Paradise
  - Maybelline Instant Age Rewind
  - Differin GEL
  - Olaplex No.5 conditioner
  - Sol De Janeiro body fragrance
  - Laneige Lip Sleeping Mask
  - Revlon One-step Volumiser
  - Maybelline New York Matte ink liquid lipstick
  - Truskin Naturals vitamin C serum
  - Heeta scalp MAssager

```
[ '0733001998',
  '1304139212',
  '1304139220',
  '130414089X',
  '130414643X',
  '130414674X',
  '1304174778',
  '1304174867',
  '1304174905' ]
```



# Work Distribution



# REFERENCE

- <https://www.kaggle.com/code/shawamar/product-recommendation-system-for-e-commerce>
- <https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.investopedia.com/terms/e/ecommerce.asp&ved=2ahUKEwif1enlyfeCAxXW1jgGHbmWDr4QFnoECEUQAQ&usg=AOvVaw3RYZWh2DHXhEBdLbNOdBIS>
- <https://www.nvidia.com/en-us/glossary/recommendation-system/>
- <https://www.techtarget.com/searchcio/definition/e-commerce>
- <https://www.turing.com/kb/collaborative-filtering-in-recommender-system>
- <https://www.miquido.com/blog/perks-of-recommendation-systems-in-business/>



THANK YOU