In [1]:

```
#Basic Libraries
import numpy as np
import pandas as pd

#Visualization Libraries
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

#Text Handling Libraries
import re
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
```

In [2]:

```
df = pd.read_csv('../input/bigbasket-entire-product-list-28k-datapoints/BigBasket Products.csv',index_col='index')
```

In [3]:

```
df.head()
```

Out[3]:

	product	category	sub_category	brand	sale_price	market_price
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220.0
2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162.0

In [4]:

```
df.shape
```

Out[4]:

```
(27555, 9)
```

In [5]:

```
df.isnull().sum()
```

Out[5]:

```
product            1
category           0
sub_category       0
brand              1
sale_price         0
market_price       0
type               0
rating          8626
description      115
dtype: int64
```

In [6]:

```
print('Total Null Data')
null_count = df.isnull().sum().sum()
total_count = np.product(df.shape)
print("{:.2f}".format(null_count/total_count * 100))
```

```
Total Null Data
3.53
```

So overall 3% data is missing but 31% of ratings are missing. Since we are going to create a recommender system, let's drop the null values as their will still be over 69% data for recommendation purposes which is enough for us.

In [7]:

```
df = df.dropna()
```

In [8]:

```
df.isnull().sum()
```

Out[8]:

```
product         0
category        0
sub_category    0
brand           0
sale_price      0
market_price    0
type            0
rating          0
description     0
dtype: int64
```

In [9]:

```
df.shape
```

Out[9]:

```
(18840, 9)
```

In [10]:

```
# df.to_csv('data_cleaned.csv')
```

So even after dropping null data, 18000+ products are available for recommendation. Let's recommend now!!

Exploratory Data Analysis!!

In [11]:

```
df.head()
```

Out[11]:

	product	category	sub_category	brand	sale_price	market_price
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220.0
2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162.0

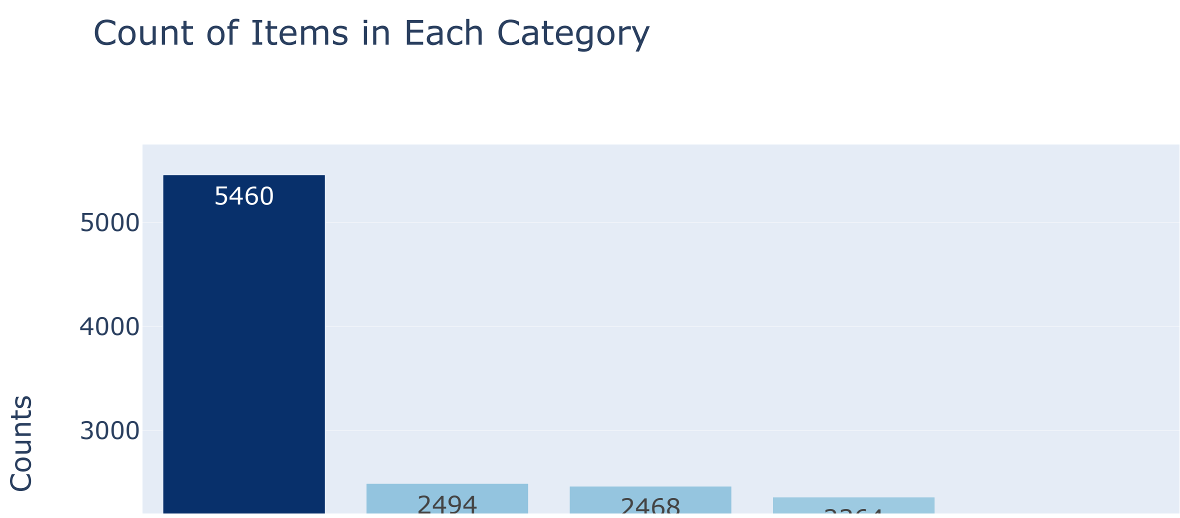
In [12]:

```
counts = df['category'].value_counts()

counts_df = pd.DataFrame({'Category':counts.index,'Counts':counts.values})
```

In [13]:

```
px.bar(data_frame=counts_df,
 x='Category',
 y='Counts',
 color='Counts',
 color_continuous_scale='blues',
 text_auto=True,
 title=f'Count of Items in Each Category')
```



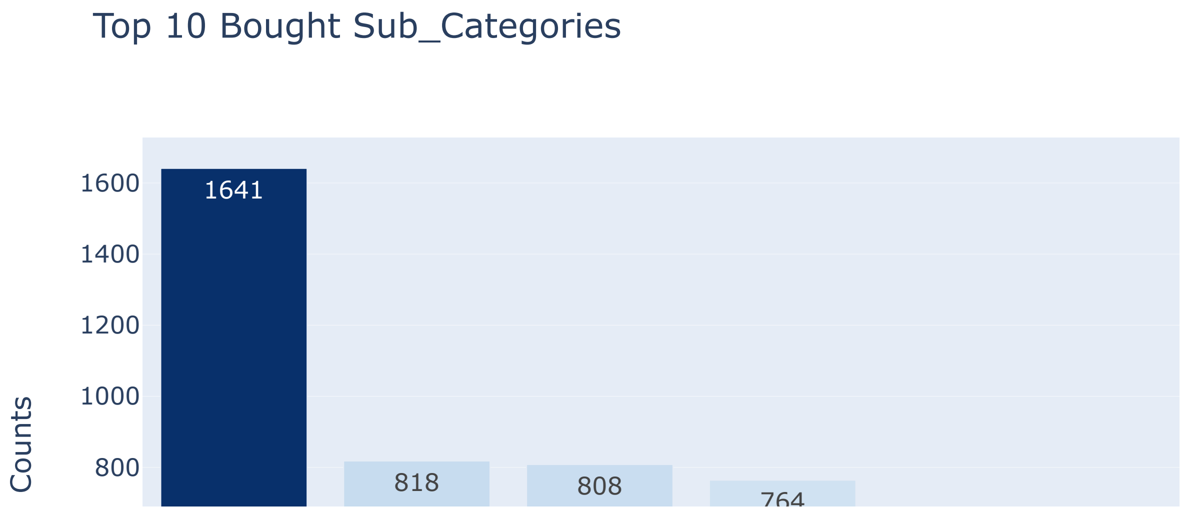
In [14]:

```
counts = df['sub_category'].value_counts()

counts_df_1 = pd.DataFrame({'Category':counts.index,'Counts':counts.values})[:1
0]
```

In [15]:

```
px.bar(data_frame=counts_df_1,
 x='Category',
 y='Counts',
 color='Counts',
 color_continuous_scale='blues',
 text_auto=True,
 title=f'Top 10 Bought Sub_Categories')
```



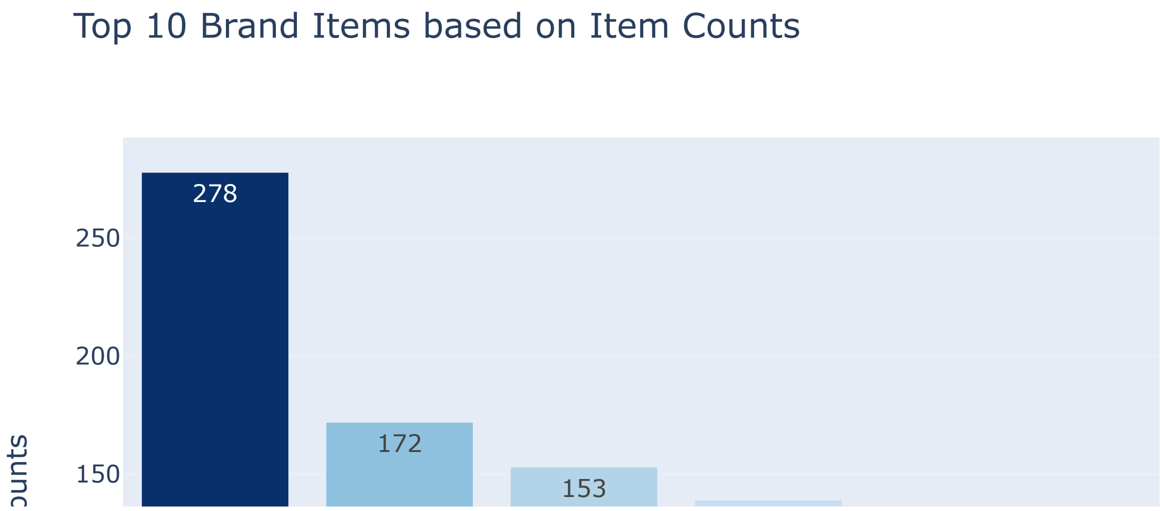
In [16]:

```
counts = df['brand'].value_counts()

counts_df_brand = pd.DataFrame({'Brand Name':counts.index,'Counts':counts.value
s})[:10]
```

In [17]:

```
px.bar(data_frame=counts_df_brand,
 x='Brand Name',
 y='Counts',
 color='Counts',
 color_continuous_scale='blues',
 text_auto=True,
 title=f'Top 10 Brand Items based on Item Counts')
```



In [18]:

```
counts = df['type'].value_counts()

counts_df_type = pd.DataFrame({'Type':counts.index,'Counts':counts.values})[:10]
```

In [19]:

```
px.bar(data_frame=counts_df_type,
 x='Type',
 y='Counts',
 color='Counts',
 color_continuous_scale='blues',
 text_auto=True,
 title=f'Top 10 Types of Products based on Item Counts')
```

DEMOGRAPHIC FILTERING!!

Demographic Filtering is like recommeding items based on a feature. Like the top 10 rated items or the top 10 items in a particular category.

In [20]:

```
def sort_recommendor(col='rating',sort_type = False):
    """
    A recommendor based on sorting products on the column passed.
    Arguments to be passed:

    col: The Feature to be used for recommendation.
    sort_type: True for Ascending Order
    """
    rated_recommend = df.copy()
    if rated_recommend[col].dtype == 'O':
        col='rating'
    rated_recommend = rated_recommend.sort_values(by=col,ascending = sort_type)
    return rated_recommend[['product','brand','sale_price','rating']].head(10)
```

In [21]:

```
help(sort_recommendor)
```

```
Help on function sort_recommendor in module __main__:

sort_recommendor(col='rating', sort_type=False)
    A recommendor based on sorting products on the column passed.
    Arguments to be passed:

    col: The Feature to be used for recommendation.
    sort_type: True for Ascending Order
```

In [22]:

```
sort_recommendor(col='sale_price',sort_type=True)
```

Out[22]:

	product	brand	sale_price	rating
index				
21313	Serum	Livon	3.0	2.5
18291	Sugar Coated Chocolate	Cadbury Gems	5.0	4.2
21229	Dish Shine Bar	Exo	5.0	4.2
14539	Cadbury Perk - Chocolate Bar	Cadbury	5.0	4.2
19539	Layer Cake - Chocolate	Winkies	5.0	4.2
2979	Sugar Free Chewing Gum - Mixed Fruit	Orbit	5.0	4.2
15927	Dreams Cup Cake - Choco	Elite	5.0	3.9
6015	Good Day Butter Cookies	Britannia	5.0	4.1
27414	Layer Cake - Orange	Winkies	5.0	4.1
11307	Happy Happy Choco-Chip Cookies	Parle	5.0	4.2

Notice that our top product has rating of 2.5 which is quite bad so let's filter down by setting a threshold rating.

In [23]:

```
C= df['rating'].mean()
C
```

Out[23]:

```
3.9430626326963902
```

So the average rating of products is 3.94 Let's use 3.5 as the threshold.

In [24]:

```
def sort_recommendor(col='rating',sort_type = False):
    """
    A recommendor based on sorting products on the column passed.
    Arguments to be passed:

    col: The Feature to be used for recommendation.
    sort_type: True for Ascending Order
    """
    rated_recommend = df.copy().loc[df['rating'] >= 3.5]
    if rated_recommend[col].dtype == 'O':
        col='rating'
    rated_recommend = rated_recommend.sort_values(by=col,ascending = sort_type)
    return rated_recommend[['product','brand','sale_price','rating']].head(10)
```

In [25]:

```
sort_recommendor(col='sale_price',sort_type=True)
```

Out[25]:

	product	brand	sale_price	rating
index				
2762	Orbit Sugar-Free Chewing Gum - Lemon & Lime	Wrigleys	5.0	4.2
3446	Marie Light Biscuits - Active	Sunfeast	5.0	4.5
14604	50-50 Timepass Biscuits	Britannia	5.0	3.9
17641	Hand Wash - Moisture Shield	Savlon	5.0	4.4
27491	50-50 Timepass Salted Biscuits	Britannia	5.0	4.2
26585	Polo - The Mint With The Hole	Nestle	5.0	4.4
2979	Sugar Free Chewing Gum - Mixed Fruit	Orbit	5.0	4.2
19539	Layer Cake - Chocolate	Winkies	5.0	4.2
19203	Bounce Biscuits - Choco Creme	Sunfeast	5.0	4.2
14539	Cadbury Perk - Chocolate Bar	Cadbury	5.0	4.2

Notice that the 2.5 rated product is not recommended now!! This was our first recommendor. Quite easy yet effective and used a lot !!

CONTENT BASED RECOMMMENDOR!!

In [26]:

```
df.head()
```

Out[26]:

	product	category	sub_category	brand	sale_price	market_price
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220.0
2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162.0

We will be using NLP here to extract useful info from the features especially Description so let's understand TF-IDF before using it.

TF-IDF stands for term frequency-inverse document frequency.

What is TF(Term Frequency):

Term frequency works by looking at the frequency of a particular term you are concerned with relative to the document. There are multiple measures, or ways, of defining frequency: Number of times the word appears in a document (raw count).

Term frequency adjusted for the length of the document (raw count of occurences divided by number of words in the document). Logarithmically scaled frequency (e.g. log(1 + raw count)). Boolean frequency (e.g. 1 if the term occurs, or 0 if the term does not occur, in the document).

What is IDF (inverse document frequency)?

Inverse document frequency looks at how common (or uncommon) a word is amongst the corpus. IDF is calculated as follows where t is the term (word) we are looking to measure the commonness of and N is the number of documents (d) in the corpus (D).. The denominator is simply the number of documents in which the term, t, appears in.

Word	TF		IDF	TF*IDF	
	A	B		A	B
The	1/7	1/7	log(2/2) = 0	0	0
Car	1/7	0	log(2/1) = 0.3	0.043	0
Truck	0	1/7	log(2/1) = 0.3	0	0.043
Is	1/7	1/7	log(2/2) = 0	0	0
Driven	1/7	1/7	log(2/2) = 0	0	0
On	1/7	1/7	log(2/2) = 0	0	0
The	1/7	1/7	log(2/2) = 0	0	0
Road	1/7	0	log(2/1) = 0.3	0.043	0
Highway	0	1/7	log(2/1) = 0.3	0	0.043

In [27]:

```
tfidf = TfidfVectorizer(stop_words='english')
tfidf_matrix = tfidf.fit_transform(df['description'])
tfidf_matrix.shape
```

Out[27]:

```
(18840, 23342)
```

Now to compute the similarity score, let's use Linear_Kernel. Linear Kernel which Calculates the Dot Product of the tfidf_matrix and returns an aggreate value depicting the Similarity score.

In [28]:

```
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
cosine_sim
```

Out[28]:

```
array([[1.        , 0.01632718, 0.00999603, ..., 0.01056047, 0.0113
3156,
        0.        ],
       [0.01632718, 1.        , 0.00719713, ..., 0.        , 0.
,
        0.        ],
       [0.00999603, 0.00719713, 1.        , ..., 0.00635776, 0.
,
        0.        ],
       ...,
       [0.01056047, 0.        , 0.00635776, ..., 1.        , 0.
,
        0.        ],
       [0.01133156, 0.        , 0.        , ..., 0.        , 1.
,
        0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.
,
        1.        ]])
```

So we will be recommending items based on similarity score. But our problem is that we will be getting back the similarity scores so we will be sorting the scores. Now we need a reverse-map to get the title and that is what indices is for.

In [29]:

```
indices = pd.Series(df.index, index=df['product']).drop_duplicates()

def get_recommendations_1(title, cosine_sim=cosine_sim):

    idx = indices[title]
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:11]
    movie_indices = [i[0] for i in sim_scores]
    return df['product'].iloc[movie_indices]
```

In [30]:

```
get_recommendations_1('Water Bottle - Orange')
```

Out[30]:

```
index
1677          Brass Nanda Stand Goblets - No.1
2162          Brass Kachua Stand Deepam - No.1
2756      Brass Angle Deep Stand - Plain, No.2
5400        Brass Lakshmi Deepam - Plain, No.2
6520                  Brass Kuber Deepam - No.1
10504                 Brass Kuber Deepam - No.2
11226     Brass Angle Deep Stand - Plain, No.3
11504     Brass Angle Deep Stand - Plain, No.1
12699         Brass Kachua Stand Deepam - No.2
18572                 Brass Kuber Deepam - No.3
Name: product, dtype: object
```

In [31]:

```
get_recommendations_1('Cadbury Perk - Chocolate Bar')
```

Out[31]:

```
index
27049                            Pickle - Mixed
6601                      Pickle - Kaduku Mango
17934                    Pickle - Mix Vegetable
27105                            Pickle - Prawn
3962                      Pickle - Tender Mango
16875                  Olive Oil - Carrot Pickle
3444                         Pickle - Cut Mango
17237        Andhra Special Red Chilli Pickle
27234      Pickle - Lime (South Indian Style)
4955                        Pickle - Gooseberry
Name: product, dtype: object
```

Our search was chocolate yet we got Cashews and Nuts recommended. We need to optimize this based on category, sub_category and brand.

In [32]:

```
df2 = df.copy()
```

In [33]:

```
df2.head()
```

Out[33]:

	product	category	sub_category	brand	sale_price	market_price
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	Beauty & Hygiene	Hair Care	Sri Sri Ayurveda	220.0	220.0
2	Water Bottle - Orange	Kitchen, Garden & Pets	Storage & Accessories	Mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	Cleaning & Household	Pooja Needs	Trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	Cleaning & Household	Bins & Bathroom Ware	Nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	Beauty & Hygiene	Bath & Hand Wash	Nivea	162.0	162.0

In [34]:

```
df2.shape
```

Out[34]:

```
(18840, 9)
```

In [35]:

```
rmv_spc = lambda a:a.strip()
get_list = lambda a:list(map(rmv_spc,re.split('& |, |\*|\n', a)))
```

In [36]:

```
get_list('A & B, C')
```

Out[36]:

```
['A', 'B', 'C']
```

In [37]:

```
for col in ['category', 'sub_category', 'type']:
    df2[col] = df2[col].apply(get_list)
```

In [38]:

```
df2.head()
```

Out[38]:

	product	category	sub_category	brand	sale_price	market_price
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	[Beauty, Hygiene]	[Hair Care]	Sri Sri Ayurveda	220.0	220.0
2	Water Bottle - Orange	[Kitchen, Garden, Pets]	[Storage, Accessories]	Mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	[Cleaning, Household]	[Pooja Needs]	Trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	[Cleaning, Household]	[Bins, Bathroom Ware]	Nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	[Beauty, Hygiene]	[Bath, Hand Wash]	Nivea	162.0	162.0

To avoid duplicacy, we will be converting everything to lowercase and also removing spaces between words. This will ensure that our recommendor doesn't consider Chocolate of Cholocate IceCream and Chocolate Bar as the same.

In [39]:

```
def cleaner(x):
    if isinstance(x, list):
        return [str.lower(i.replace(" ", "")) for i in x]
    else:
        if isinstance(x, str):
            return str.lower(x.replace(" ", ""))
        else:
            return ''
```

In [40]:

```
for col in ['category', 'sub_category', 'type','brand']:
    df2[col] = df2[col].apply(cleaner)
```

In [41]:

```
df2.head()
```

Out[41]:

	product	category	sub_category	brand	sale_price	market_pric
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	[beauty, hygiene]	[haircare]	srisriayurveda	220.0	220.0
2	Water Bottle - Orange	[kitchen, garden, pets]	[storage, accessories]	mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	[cleaning, household]	[poojaneeds]	trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	[cleaning, household]	[bins, bathroomware]	nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	[beauty, hygiene]	[bath, handwash]	nivea	162.0	162.0

In [42]:

```
def couple(x):
    return ' '.join(x['category']) + ' ' + ' '.join(x['sub_category']) + ' '+x
['brand']+' ' +' '.join( x['type'])
df2['soup'] = df2.apply(couple, axis=1)
```

In [43]:

```
df2['soup'].head()
```

Out[43]:

```
index
1    beauty hygiene haircare srisriayurveda hairoil...
2    kitchen garden pets storage accessories master...
3       cleaning household poojaneeds trm lamp lampoil
4    cleaning household bins bathroomware nakoda la...
5    beauty hygiene bath handwash nivea bathingbars...
Name: soup, dtype: object
```

We need to Count the String Vectors and then compute the Cosine Similarity Score.

In [44]:

```
df2.head()
```

Out[44]:

	product	category	sub_category	brand	sale_price	market_pric
index						
1	Garlic Oil - Vegetarian Capsule 500 mg	[beauty, hygiene]	[haircare]	srisriayurveda	220.0	220.0
2	Water Bottle - Orange	[kitchen, garden, pets]	[storage, accessories]	mastercook	180.0	180.0
3	Brass Angle Deep - Plain, No.2	[cleaning, household]	[poojaneeds]	trm	119.0	250.0
4	Cereal Flip Lid Container/Storage Jar - Assort...	[cleaning, household]	[bins, bathroomware]	nakoda	149.0	176.0
5	Creme Soft Soap - For Hands & Body	[beauty, hygiene]	[bath, handwash]	nivea	162.0	162.0

In [45]:

```
df2.to_csv('data_cleaned_1.csv')
```

In [46]:

```
count = CountVectorizer(stop_words='english')
count_matrix = count.fit_transform(df2['soup'])
```

We need to Count the String Vectors and then compute the Cosine Similarity Score.

In [47]:

```
cosine_sim2 = cosine_similarity(count_matrix, count_matrix)
cosine_sim2
```

Out[47]:

```
array([[1.        , 0.        , 0.        , ..., 0.        , 0.        
,
         0.27216553],
       [0.        , 1.        , 0.        , ..., 0.        , 0.        
,
         0.        ],
       [0.        , 0.        , 1.        , ..., 0.        , 0.        
,
         0.        ],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 0.        
,
         0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 1.        
,
         0.        ],
       [0.27216553, 0.        , 0.        , ..., 0.        , 0.        
,
         1.        ]])
```

In [48]:

```
df2 = df2.reset_index()
indices = pd.Series(df2.index, index=df2['product'])
```

In [49]:

```
def get_recommendations_2(title, cosine_sim=cosine_sim):
    idx = indices[title]

    sim_scores = list(enumerate(cosine_sim[idx]))

    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

    sim_scores = sim_scores[1:11]

    movie_indices = [i[0] for i in sim_scores]

    return df2['product'].iloc[movie_indices]
```

Comparing Old and New Recommedations

In [50]:

```
old_rec = get_recommendations_1('Water Bottle - Orange').values
new_rec = get_recommendations_2('Water Bottle - Orange', cosine_sim2).values

pd.DataFrame({'Old Recommendor': old_rec,'New Recommendor':new_rec})
```

Out[50]:

	Old Recommendor	New Recommendor
0	Rectangular Plastic Container - With Lid, Mult...	Glass Water Bottle - Aquaria Organic Purple
1	Jar - With Lid, Yellow	Glass Water Bottle With Round Base - Transpare...
2	Round & Flat Storage Container - With lid, Green	H2O Unbreakable Water Bottle - Pink
3	Premium Rectangular Plastic Container With Lid...	Water Bottle H2O Purple
4	Premium Round Plastic Container With Lid - Yellow	H2O Unbreakable Water Bottle - Green
5	Premium Rectangular Plastic Container With Lid...	Regel Tritan Plastic Sports Water Bottle - Black
6	Premium Round & Flat Storage Container With Li...	Apsara 1 Water Bottle - Assorted Colour
7	Premium Round Plastic Container With Lid - Blue	Glass Water Bottle With Round Base - Yellow, B...
8	Premium Round Plastic Container With Lid - Mul...	Trendy Stainless Steel Bottle With Steel Cap -...
9	Premium Round Plastic Container With Lid - Pink	Penta Plastic Pet Water Bottle - Violet, Wide ...

In [51]:

```
old_rec = get_recommendations_1('Cadbury Perk - Chocolate Bar').values
new_rec = get_recommendations_2('Cadbury Perk - Chocolate Bar', cosine_sim2).val
ues

pd.DataFrame({'Old Recommendor': old_rec,'New Recommendor':new_rec})
```

Out[51]:

	Old Recommendor	New Recommendor
0	Cadbury Perk - Chocolate Bar	Nutties Chocolate Pack
1	Choco Stick - Hexagon Pack	5 Star Chocolate Bar
2	Luvit Chocwich White Home Delights 187 g	Dairy Milk Silk - Hazelnut Chocolate Bar
3	Luvit Chocwich Home Delights 187 g	Perk - Chocolate, Home Treats, 175.5 g, 27 Units
4	Wafer Biscuits - Chocolate Flavor	Dark Milk Chocolate Bar
5	Drinking Chocolate - Original	Dairy Milk Silk Mousse - Chocolate Bar
6	Drinking Chocolate - Original	Dark Milk Chocolate Bar
7	Biscuit - Bourbon Creams	Chocolate Bar - Fuse
8	Wafers With Hazelnut Cream	Choclairs Gold Coffee
9	Choco Stick - Chocolate	5 Star Chocolate Home Pack, 200 g, 20 units

Our new recommendation are much better compared to the old ones.