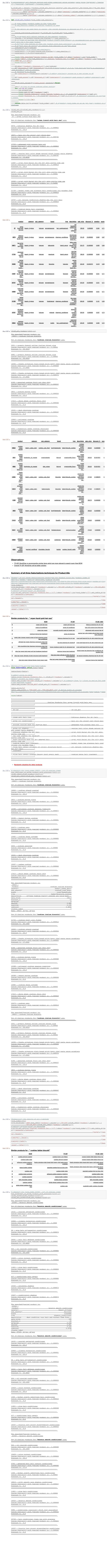
**Model and Feature Engineering** <u>In [1]:</u> #import all the necessary packages. import matplotlib.pyplot as plt import numpy as np import pandas as pd import warnings warnings.filterwarnings("ignore") from nltk.corpus import stopwords from nltk.tokenize import word tokenize import nltk import seaborn as sns from collections import Counter from sklearn.feature\_extraction.text import CountVectorizer from sklearn.feature extraction.text import TfidfVectorizer from sklearn.metrics.pairwise import cosine similarity from sklearn.metrics import pairwise distances from scipy.sparse import hstack <u>In [2]:</u> # loading preprocessed data data=pd.read csv(r'preprocessed with clusterlabel.csv',index col=0) #index col=0 to get rid of unnamed column data.head(2) Out [2]: product category sub category <u>brand</u> type description sale price discount % negative neut this product garlic oil <u>contains</u> haircare srisriayurveda garlic oil <u>vegetarian</u> beauty hygiene hairoil serum <u>220.0</u> 0.0 0.046 0.6 that known <u>capsule</u> <u>each</u> product <u>water</u> <u>microwave</u> mastercook water fridgebottles 180.0 0.0 0.000 1 <u>bottle</u> kitchen garden pets storage accessories 0.6 <u>safe</u> <u>orange</u> <u>refrigerator</u> <u>safe ...</u> data.shape <u>In [3]:</u> Out[3]: (27164, 13) data.columns <u>In [4]:</u> Out[4]: Index(['product', 'category', 'sub\_category', 'brand', 'type', 'description', <u>'sale\_price', 'discount %', 'negative', 'neutral', 'positive',</u> <u>'compound', 'cluster label'],</u> <u>dtype='object')</u> Model-1 Bag of words for Preprocessed Product, One Hot encoding for categorical <u>features(category,sub\_category,brand,type)</u> # Bag of words for product feature <u>In [5]:</u> vectorizer=CountVectorizer() product bow=vectorizer.fit transform(data['product'].values) print("After vectorization") print ('The shape of product feature vector', product bow.shape) After vectorization The shape of product feature vector (27164, 8687) In [6]: # one hot encoding for category feature ohe=CountVectorizer() category ohe=ohe.fit transform(data['category'].values) print("After vectorization") print('The shape of category ohe vector', category ohe.shape) After vectorization The shape of category ohe vector (27164, 11) In [7]: # one hot encoding for sub category feature ohe=CountVectorizer() sub\_category\_ohe=ohe.fit\_transform(data['sub\_category'].values) print("After vectorization") print('The shape of sub category ohe vector', sub category ohe.shape) After vectorization The shape of sub\_category ohe vector (27164, 90) In [8]: # one hot encoding for sub category feature brandohe=CountVectorizer() brand ohe=brandohe.fit transform(data['brand'].values) print("After vectorization") print('The shape of brand ohe vector', brand ohe.shape) After vectorization The shape of brand ohe vector (27164, 2294) In [9]: # one hot encoding for sub category feature ohe=CountVectorizer() type\_ohe=ohe.fit\_transform(data['type'].values) print("After vectorization") print('The shape of type ohe vector', type ohe.shape) <u>After vectorization</u> The shape of type ohe vector (27164, 433) In [10]: # concatenating all feature vectors and other numerical value columns(,sale price, 'negative', 'neutra 1', 'positive','compound', 'cluster\_label') from scipy.sparse import hstack X bow = hstack ((product bow, category ohe, sub category ohe, brand ohe, type ohe, data['sale price'].values  $\underline{\text{reshape}(-1,1)}$ , <u>data['negative'].values.reshape(-1,1),data['neutral'].values.reshape(-1,1),data['positive'</u> ].values.reshape(-1,1), \ data['compound'].values.reshape(-1,1),data['cluster\_label'].values.reshape(-1,1)).tocsr() In [11]: print('Shape of BOW feature vector:', X bow.shape) Shape of BOW feature vector: (27164, 11521) In [12]: # Model on bag of words for product feature def bag of words product(prod index, num results): # prod index: product index in the given data # num results: number of similar products to show # the metric we used here is cosine, the coside distance is mesured as  $K(X, Y) = \langle X, Y \rangle / (||X||^*||$ <u>Y||)</u> cosine sim=cosine similarity(X bow, X bow[prod index]) # np.argsort will return indices of the nearest products indices = np.argsort(cosine sim.flatten())[-num results:-1] # -1 given to exclude the searched product itself from showing in recommendations as cosinine simil <u>arity will be 1 for same product</u> # flipping the indices so that the product with more similarity is shown first # argsort will do sorting of indices from smallest to largest value indices=np.flip(indices) # to get sorting in descending order #psimilarity will store the similarity psimilarity = np.sort(cosine sim.flatten())[-num results:-1] psimilarity = np.flip(psimilarity) print('The searched product is:\n',prod index,":",data['product'].loc[prod index]) ##https://appdividend.com/2022/07/27/how-to-print-bold-python-text/ print('\nTop '+str(num\_results-1)+' Similar products for "'+'\033[1m'+data['product'].loc[prod\_inde  $x] + ' \ 033 [0m' + '' are:')$ print("="\*70,'\n') for i in range (0,len(indices)): print(indices[i],":",data['product'].loc[indices[i]]) print('Cosine similarity:',np.round(psimilarity[i],6)) print("-"\*50,'\n') return data.loc[np.append([prod\_index],[indices])] # appending prod\_index so as we get query produc t in dataframe #https://numpy.org/doc/stable/reference/generated/numpy.append.html In [13]: bag of words product(57,11) # without adding discount % # rankimg of similar recommendations is based on cosine similarity only The searched product is: <u>57 : argan liquid gold hair spa</u> Top 10 Similar products for "argan liquid gold hair spa" are: \_\_\_\_\_\_ 15854 : cream anti hair loss Cosine similarity: 0.999901 \_\_\_\_\_ 18644 : premium henna hair treatment Cosine similarity: 0.999897 \_\_\_\_\_ 3738 : apple cider vinegar organic argan oil hair shampoo argan hair conditioner Cosine similarity: 0.999896 \_\_\_\_\_ 10754 : argan hair cream Cosine similarity: 0.999896 17996 : ultimate hair repair shampoo moroccan argan hair conditioner Cosine similarity: 0.999894 \_\_\_\_\_ 20841 : ultra nourishing hair shampoo moroccan argan hair conditioner Cosine similarity: 0.999894 \_\_\_\_\_ 23782 : gliss hair repair total repair anti hair breakage treatment Cosine similarity: 0.999892 21884 : gliss hair repair ultimate oil elixir structure build treatment Cosine similarity: 0.99989 \_\_\_\_\_ 12150 : argan oil conditioner Cosine similarity: 0.99989 \_\_\_\_\_\_ 21762 : gliss hair repair intense therapy bond repair mask Cosine similarity: 0.999889 Out [13]: description sale price discount % negative neu product <u>category</u> <u>sub category</u> brand <u>our</u> <u>beautifully</u> <u>argan</u> crafted hair 0.054 <u>liquid gold</u> beauty\_hygiene hair scalptreatment 199.50 5.0 0. 57 haircare aromatreasures <u>spa</u> hair spa <u>collection</u> <u>pr...</u> <u>himalaya</u> anti hair <u>cream anti</u> <u>15854</u> 25.0 0.068 <u>haircare</u> <u>himalayawellness</u> 243.75 0. beauty\_hygiene hair\_scalptreatment loss cream hair loss promotes <u>hair gr...</u> used treat <u>premium</u> <u>hair fall hair</u> beauty\_hygiene <u> 18644</u> henna hair madilu hair\_scalptreatment 225.00 0.0 0.000 0. haircare growth early treatment greying... apple cider apple cider <u>vinegar</u> <u>vinegar</u> <u>argan</u> **3738** beauty\_hygiene <u>haircare</u> <u>stbotanica</u> shampoo\_conditioner <u>898.00</u> 0.0 0.004 0. <u>organic</u> <u>shampoo</u> <u>argan oil</u> gentle and hair sha... <u>n...</u> <u>inatur</u> moroccan argan hair <u>10754</u> 440.00 20.0 0.000 0. beauty\_hygiene <u>haircare</u> <u>inatur</u> hair\_scalptreatment <u>argan oil</u> <u>cream</u> hair cream contains ... <u>ultimate</u> <u>stbotanica</u> hair repair moroccan <u>17996</u> stbotanica shampoo\_conditioner 898.00 0.0 0.065 0. beauty\_hygiene <u>shampoo</u> <u>haircare</u> <u>argan oil</u> moroccan conditioner argan ha... affo... <u>ultra</u> nourishing nourishing <u>hair</u> <u>20841</u> beauty\_hygiene <u>haircare</u> <u>stbotanica</u> shampoo\_conditioner <u>shampoo</u> <u>898.00</u> 0.0 0.034 0. <u>shampoo</u> proven lock moroccan moisture ... <u>argan h...</u> gliss hair <u>liquid</u> <u>repair total</u> <u>keratin</u> **23782** <u>775.00</u> 0.0 0.102 <u>repair anti</u> beauty\_hygiene <u>haircare</u> schwarzkopf hair\_scalptreatment reconstructs 0. <u>hair</u> the hair and break... renew... gliss hair schwarzkopf <u>repair</u> gliss hair **21884** ultimate oil 775.00 0.0 0.039 0. beauty\_hygiene schwarzkopf hair\_scalptreatment <u>haircare</u> repair with <u>elixir</u> liquid kera... structur.. <u>biotique</u> <u>argan oil</u> <u>argan oil</u> <u>12150</u> 247.50 <u>25.0</u> 0.039 0. beauty hygiene <u>haircare</u> biotique shampoo conditioner conditioner conditioner made from botan... gliss hair gliss hair <u>repair</u> <u>repair</u> <u>intense</u> <u>intense</u> beauty hygiene 0.038 21762 schwarzkopf hair scalptreatment 775.00 0.0 0. haircare therapy therapy bond repair bond <u>repair ...</u> Taking discount % for ranking the similar items along with similarity <u>In [14]:</u> # taking discount % for ranking the similar items #https://www.geeksforgeeks.org/sort-rows-or-columns-in-pandas-dataframe-based-on-values/ def bag of words product with discount(prod index,num results): # prod index: product index in the given data # num results: number of similar products to show # the metric we used here is cosine, the coside distance is mesured as  $K(X, Y) = \langle X, Y \rangle / (||X||^*||$ <u>Y| | )</u> cosine sim=cosine similarity(X bow, X bow[prod index]) # np.argsort will return indices of the nearest products indices = np.argsort(cosine\_sim.flatten())[-num\_results:-1] -1 given to exclude the searched product itself from showing in recommendations as cosinine simil arity will be 1 for same product # flipping the indices so that the product with more similarity is shown first # argsort will do sorting of indices from smallest to largest value <u>indices=np.flip(indices)</u> #psimilarity will store the similarity psimilarity = np.sort(cosine sim.flatten())[-num results:-1] psimilarity = np.flip(psimilarity) print('The searched\Queried product is:\n',prod\_index,":",data['product'].loc[prod\_index]) print('\nTop '+str(num results-1)+' Similar products for "'+'\033[1m'+data['product'].loc[prod inde <u>x]+'\033[0m' +'" are:')</u> print("="\*70,'\n') df=data[['product','discount %']].loc[indices] df['discount %']=df['discount %']\*0.5/100 # multiplied by 0.5 to give half weightage to discount % and divided by 100 to convert # percentage to decimal <u>df['similarity']=psimilarity.tolist() # adding similarity scores as s new column to df</u> <u>df['rank score'] = df['discount %'] + df['similarity'] # creating rank score by adding similarity and</u> discount df=df.sort values(by='rank score',ascending=False) <u>lst=[] # list to store indices after sorting</u> for ind in df.index: <u>lst.append(ind)</u> print(ind,":",df['product'][ind]) print('Cosine Similarity with queried product is :',np.round(df['similarity'][ind],6)) print('Discount %: ',np.round(df['discount %'][ind]/0.5\*100,4)) # restoring discount to origina print('-'\*50,'\n') return data.loc[np.append([prod\_index],lst)] # appending prod\_index so as we get query product in d In [15]: bow 57=bag of words product with discount(57,11) The searched\Queried product is: 57 : argan liquid gold hair spa Top 10 Similar products for "argan liquid gold hair spa" are: 15854 : cream anti hair loss Cosine Similarity with queried product is: 0.999901 Discount %: 25.0 -----12150 : argan oil conditioner Cosine Similarity with queried product is: 0.99989 Discount %: 25.0 \_\_\_\_\_ 10754 : argan hair cream Cosine Similarity with queried product is: 0.999896 Discount %: 20.0 \_\_\_\_\_ 10611 Cosine Similarity with queried product is: 0.999897 Discount %: 0.0 3738 : apple cider vinegar organic argan oil hair shampoo argan hair conditioner <u>Similarity with queried product is</u> Discount %: 17996 : ultimate hair repair shampoo moroccan argan hair conditioner Cosine Similarity with queried product is: 0.999894 Discount %: <u>ultra nourishing hair shampoo moroccan argan hair conditioner</u> Cosine Similarity with queried product Discount %: 0.0 23782 : gliss hair repair total repair anti hair breakage treatment <u>Cosine Similarity with queried product is: 0.999892</u> 21884 : gliss hair repair ultimate oil elixir structure build treatment Cosine Similarity with queried product is: 0.99989 Discount %: intense <u>therapy bond repair mask</u> <u>repair</u> Discount %: 0.0 Out[15]: type description sale\_price discount\_% negative neu <u>product</u> <u>category</u> <u>sub\_category</u> <u>brand</u> <u>our</u> <u>beautifully</u> crafted hair beauty hygiene <u>liquid gold</u> 0.054 57 haircare aromatreasures hair scalptreatment <u>199.50</u> <u>5.0</u> 0. <u>spa</u> <u>hair spa</u> <u>collection</u> <u>pr...</u> <u>himalaya</u> <u>anti hair</u> <u>cream anti</u> <u>15854</u> beauty\_hygiene <u>25.0</u> 0.068 <u>haircare</u> <u>himalayawellness</u> hair\_scalptreatment loss cream <u>243.75</u> 0. hair loss promotes <u>hair gr...</u> <u>biotique</u> <u>argan oil</u> <u>argan oil</u> 247.50 <u>25.0</u> 0.039 0. <u>12150</u> beauty\_hygiene <u>haircare</u> biotique shampoo\_conditioner conditioner conditioner made from botan... <u>inatur</u> moroccan <u>argan hair</u> 0.000 <u>10754</u> <u>440.00</u> 20.0 beauty\_hygiene 0. <u>haircare</u> <u>inatur</u> hair\_scalptreatment <u>argan oil</u> cream hair cream contains ... used treat <u>premium</u> <u>hair fall hair</u> <u>18644</u> <u>henna hair</u> <u>madilu</u> hair\_scalptreatment 225.00 0.0 0.000 0. <u>beauty\_hygiene</u> haircare growth early treatment greying... apple cider apple cider vinegar <u>vinegar</u> <u>argan</u> <u>3738</u> <u>beauty\_hygiene</u> <u>haircare</u> stbotanica shampoo\_conditioner <u>898.00</u> 0.0 0.004 0. <u>organic</u> <u>shampoo</u> <u>argan oil</u> gentle and <u>hair sha...</u> <u>ultimate</u> stbotanica <u>hair repair</u> moroccan <u>17996</u> stbotanica shampoo conditioner 898.00 0.0 0.065 shampoo beauty\_hygiene <u>haircare</u> <u>argan oil</u> <u>moroccan</u> conditioner argan ha... <u>affo...</u> ultra <u>ultra</u> <u>nourishing</u> nourishing hair beauty hygiene 0.034 <u>20841</u> <u>haircare</u> <u>898.00</u> 0.0 0. stbotanica shampoo\_conditioner <u>shampoo</u> <u>shampoo</u> proven lock <u>moroccan</u> moisture ... <u>argan h...</u> g<u>liss hair</u> <u>liquid</u> repair total <u>keratin</u> 23782 repair anti beauty\_hygiene 0.102 <u>775.00</u> 0.0 0. <u>haircare</u> <u>schwarzkopf</u> hair\_scalptreatment <u>reconstructs</u> the hair and <u>hair</u> break... renew... gliss hair <u>schwarzkopf</u> <u>repair</u> gliss hair 21884 ultimate oil beauty\_hygiene <u>schwarzkopf</u> <u>775.00</u> 0.0 0.039 <u>haircare</u> hair\_scalptreatment <u>repair with</u> <u>elixir</u> liquid kera... structur... gliss hair g<u>liss hair</u> <u>repair</u> <u>repair</u> <u>intense</u> <u>intense</u> beauty hygiene 0.038 21762 <u>haircare</u> <u>schwarzkopf</u> hair scalptreatment 775.00 0.0 0. therapy. therapy <u>bond</u> bond repair repair ... In [16]: bag of words product with discount (18623,11) The searched\Queried product is: <u> 18623 : cookies italian biscotti</u> Top 10 Similar products for "cookies italian biscotti" are: 16664 : cookies almond roasted Cosine Similarity with queried product is: 0.999902 Discount %: 20.0 3853 : cookies butter pista <u>Cosine Similarity with queried product is: 0.999924</u> Discount %: 10.0 <u>15398</u>: artisanal cookies seasons greetings Cosine Similarity with queried product is: 0.999877 Discount %: 10.0 26398 : peanut butter cookies Cosine Similarity with queried product is: 0.999891 Discount %: 0.0 22473 : cookies oats <u>Cosine Similarity with queried product is: 0.999889</u> Discount %: 0.0 10<u>682 : cookies kesar supreme</u> Cosine Similarity with queried product is: 0.999885 Discount %: \_\_\_\_\_ 4404 : cookies assorted Cosine Similarity with queried product is: 0.99986 Discount %: 0.0 15231 : dark chocolate cookies Cosine Similarity with queried product is: 0.999854 Discount %: 0.0 15267 : cashew cookies Cosine Similarity with queried product is: 0.999846 Discount %: 0.0 17415 : whole wheat cookies choco chip Cosine Similarity with queried product 0.999845 Discount %: 0.0 Out[16]: product category sub category <u>brand</u> type description sale price discount % negative <u>eggless</u> <u>premium</u> cookies <u>quality</u> <u>18623</u> <u>166.5</u> 10.0 0.0 <u>bakery\_cakes\_dairy\_cookies\_rusk\_khari\_lovelybakestudio\_bakerybiscuits\_cookies\_</u> italian almonds <u>biscotti</u> are twice bake... <u>eggless</u> <u>premium</u> cookies <u>almonds</u> <u>16664</u> <u>148.0</u> 20.0 0.0 <u>bakery\_cakes\_dairy\_cookies\_rusk\_khari\_lovelybakestudio\_bakerybiscuits\_cookies\_</u> almond and roasted <u>goodness</u> butter co... <u>eggless</u> <u>crunchy</u> cookies <u>buttery</u> 0.1 <u>166.5</u> 10.0 <u>3853</u> <u>bakery\_cakes\_dairy\_cookies\_rusk\_khari\_lovelybakestudio\_bakerybiscuits\_cookies\_</u> butter tasteful <u>pista</u> baked perfect... cookie man <u>artisanal</u> presents cookies bakery cakes dairy cookies rusk khari cookieman bakerybiscuits cookies <u>15398</u> <u>175.5</u> 10.0 0.0 <u>delightful</u> seasons pack greetings artisanal ... enjoy the <u>baker</u> <u>peanut</u> dozen 0.0 **26398** <u>butter</u> bakery cakes dairy cookies rusk khari thebakersdozen bakerybiscuits cookies <u>170.0</u> 0.0 <u>healthy</u> <u>cookies</u> peanut butter co... power the with <u>wholesome</u> <u>cookies</u> <u>159.0</u> 0.0 22473 bakery cakes dairy cookies rusk khari <u>bhealthy</u> <u>bakerybiscuits cookies</u> 0.0 <u>whole</u> wheat oat cooke... momkhatai <u>kesar</u> <u>cookies</u> <u>supreme</u> 0.0 <u>10682</u> kesar bakery cakes dairy cookies rusk khari momkhatai bakerybiscuits cookies <u>160.0</u> 0.0 are supreme handmade cookies w... momkhatai <u>assorted</u> <u>cookies</u> 4<u>404</u> 140.0 0.0 0.0 <u>bakery cakes dairy</u> <u>cookies rusk khari</u> momkhatai bakerybiscuits cookies cookies assorted contain four delici... <u>crunchy</u> butter <u>dark</u> <u>cookies</u> 15231 chocolate <u>bakery cakes dairy</u> <u>cookies rusk khari</u> <u>170.0</u> 0.0 0.0 <u>thebakersdozen</u> <u>premiumcookies</u> with loads cookies dark chocola... <u>crunchy</u> butter <u>cookies</u> <u>cashew</u> 15267 bakery cakes dairy cookies rusk khari thebakersdozen <u>150.0</u> 0.0 0.0 premiumcookies <u>with</u> cookies <u>cashews</u> chunks the... whole whole <u>wheat</u> wheat wheat <u>17415</u> cookies bakery cakes dairy cookies rusk khari <u>bhealthy</u> <u>bakerybiscuits\_cookies</u> <u>cookie filled</u> <u>159.0</u> 0.0 0.0 with choco <u>choco</u> <u>chip</u> chips and... **Observatios:**  Even though we searched for cookies its showing similar items milkshake mix will see with other featurization techniques Model-2 **Tf-ldf for Product title** In [17]: tfidf vectorizer = TfidfVectorizer() tfidf product = tfidf vectorizer.fit transform(data['product']) print('shape of product title after TF-IDF featurisation:',tfidf\_product.shape) shape of product title after TF-IDF featurisation: (27164, 8687) # concatenating all feature vectors and other numerical value columns (, sale price, 'negative', 'neutra <u>In [18]:</u> <u>l', 'positive','compound', 'cluster label')</u> X tfidf = hstack ((tfidf product, category ohe, sub category ohe, brand ohe, type ohe, data['sale price'].va <u>data['negative'].values.reshape(-1,1),data['neutral'].values.reshape(-1,1),data['positive'</u> ].values.reshape(-1,1), \ <u>data['compound'].values.reshape(-1,1),data['cluster label'].values.reshape(-1,1))).tocsr()</u> In [19]: print ('Shape of TF-IDF feature vector:', X tfidf.shape) Shape of TF-IDF feature vector: (27164, 11521) In [20]: def tfidf product(prod index, num results): # prod\_index: product index in the given data # num results: number of similar products to show # the metric we used here is cosine, the coside distance is mesured as  $K(X, Y) = \langle X, Y \rangle / (||X||^*||$ <u>Y||)</u> cosine sim=cosine similarity(X tfidf,X tfidf[prod index]) # np.argsort will return indices of the nearest products indices = np.argsort(cosine sim.flatten())[-num results:-1] # -1 given to exclude the searched product itself from showing in recommendations as cosinine simil <u>arity will be 1 for same product</u> # flipping the indices so that the product with more similarity is shown first # argsort will do sorting of indices from smallest to largest value indices=np.flip(indices) #psimilarity will store the similarity psimilarity = np.sort(cosine\_sim.flatten())[-num\_results:-1] <u> psimilarity = np.flip(psimilarity)</u> print('The searched\Queried product is:\n',prod index,":\n",data.loc[prod index]) print('\nTop '+str(num results-1)+' Similar products for "'+'\033[1m'+data['product'].loc[prod inde <u>x]+'\033[0m' +'" are:')</u> print("="\*70,'\n') df=data[['product','discount\_%']].loc[indices] df['discount %']=df['discount %']\*0.5/100 # multiplied by 0.5 to give half weightage to discount % and divided by 100 to convert # percentage to decimal df['similarity']=psimilarity.tolist() # adding similarity scores as s new column to df <u>df['rank\_score'] = df['discount\_%'] + df['similarity'] # creating rank score by adding similarity and </u> <u>df=df.sort\_values(by='rank\_score',ascending=False)</u> lst=[] # list to store indices after sorting for ind in df.index: <u>lst.append(ind)</u> print(ind,":",df['product'][ind]) print('Cosine Similarity with queried product is :',np.round(df['similarity'][ind],6)) print('Discount %: ',np.round(df['discount\_%'][ind]/0.5\*100,4)) # restoring discount to origina <u> print('-'\*50,'\n')</u> return data.loc[np.append([prod index],lst)] # appending prod index so as we get query product in d <u>In [21]: tfidf 57=tfidf product(57,11)</u> tfidf 57 The searched\Queried product is: 5<u>7 :</u> <u>argan liquid gold hair spa</u> <u>product</u> <u>category</u> <u> beauty\_hygiene</u> <u>sub category</u> <u>aromatreasures</u> brand <u>hair\_scalptreatment</u> <u>type</u> description our beautifully crafted hair spa collection pr... <u>sale price</u> discount % <u>negative</u> neutral 0.233 <u>positive</u> compound cluster label Name: 57, dtype: object Top 10 Similar products for "argan liquid gold hair spa" are: \_\_\_\_\_\_ 15854 : cream anti hair loss Cosine Similarity with queried product is: 0.999959 Discount %: 25.0 <u>\_\_\_\_\_</u>\_\_\_ 12150 : argan oil conditioner Cosine Similarity with queried product is: 0.999943 Discount %: 25.0 26263 : avocado nourish mask for fragile hair Cosine Similarity with queried product is: 0.999952 \_\_\_\_\_\_ <u>21421 : argan oil shampoo</u> Cosine Similarity with queried product is: 0.999942 Discount %: 20.0 \_\_\_\_\_ 5979 : hibiscus shampoo for dry hair Cosine Similarity with queried product is: 0.999951 Discount %: 15.0 \_\_\_\_\_ 12993 : tea tree shampoo for dandruff <u>Cosine Similarity with queried product is: 0.99995</u> Discount %: 10.0 8976 : honey moisture mask for dry damaged hair Cosine Similarity with queried product is: 0.999958 18644 : premium henna hair treatment Cosine Similarity with Discount %: 21884 : gliss hair repair ultimate oil elixir structure build treatment Cosine Similarity with queried product is: 0.999941 21762 : gliss hair repair intense therapy bond repair mask Cosine Similarity with queried product Discount %: 0.0 Out [21]: product category sub category **brand** description sale price discount % negative neu type <u>our</u> <u>beautifully</u> <u>argan</u> crafted hair <u>liquid gold</u> <u>beauty\_hygiene</u> <u>5.0</u> 0.054 0 <u>haircare</u> <u>aromatreasures</u> hair\_scalptreatment <u>199.50</u> <u>spa</u> hair spa collection <u>pr...</u> <u>himalaya</u> anti hair cream anti <u>15854</u> beauty hygiene <u>himalayawellness</u> hair scalptreatment 243.75 <u>25.0</u> 0.068 0 haircare loss cream <u>hair loss</u> promotes <u>hair gr...</u> b<u>iotique</u> <u>argan oil</u> <u>argan oil</u> <u>12150</u> beauty hygiene biotique shampoo conditioner 247.50 <u>25.0</u> 0.039 0 <u>haircare</u> conditioner conditioner made from botan. with <u>avocado</u> <u>frequent</u> <u>nourish</u> exposure <u> 26263</u> beauty\_hygiene <u>haircare</u> <u>godrejprofessional</u> hair\_scalptreatment 200.00 <u>20.0</u> 0.028 0 <u>mask for</u> <u>pollution</u> fragile hair sun and <u>styli...</u> <u>argan oil</u> <u>nutri hydrant</u> <u>argan oil</u> <u>21421</u> 240.00 20.0 0.023 0 beauty\_hygiene <u>haircare</u> inatur shampoo\_conditioner <u>shampoo</u> <u>shampoo</u> <u>enriched</u> <u>with ...</u> rich formula <u>hibiscus</u> with natural 0.000 <u>5979</u> <u>shampoo</u> <u>beauty\_hygiene</u> <u>haircare</u> <u>aromatreasures</u> <u>shampoo\_conditioner</u> <u>191.25</u> <u> 15.0</u> 0 <u>ingredients</u> for dry hair which pe... thanks its tea tree <u>balanced</u> <u>shampoo</u> <u>formula</u> 12993 202.50 <u>10.0</u> 0.000 0 beauty hygiene <u>aromatreasures</u> <u>shampoo\_conditioner</u> <u>haircare</u> <u>for</u> <u>which</u> <u>dandruff</u> <u>purifies</u> <u>the...</u> <u>honey</u> <u>godrej</u> <u>moisture</u> professional mask for <u>honey</u> beauty\_hygiene <u>8976</u> 250.00 0.0 0.042 0 <u>haircare</u> <u>godrejprofessional</u> hair\_scalptreatment <u>dry</u> moisture <u>damaged</u> <u>mask</u> <u>hair</u> infuse... used treat premium hair fall hair 0.000 <u> 18644</u> <u>henna hair</u> beauty\_hygiene <u>haircare</u> <u>madilu</u> hair\_scalptreatment <u>225.00</u> 0.0 0 growth early <u>treatment</u> greying... gliss hair schwarzkopf <u>repair</u> gliss hair 21884 ultimate oil beauty\_hygiene 775.00 0.039 0 <u>haircare</u> <u>schwarzkopf</u> hair\_scalptreatment 0.0 repair with <u>elixir</u> <u>liquid kera...</u> structur... gliss hair gliss hair <u>repair</u> <u>repair</u> <u>intense</u> <u>intense</u> **21762** <u>775.00</u> 0.038 beauty\_hygiene <u>haircare</u> <u>schwarzkopf</u> hair\_scalptreatment 0.0 <u>therapy</u> therapy <u>bond</u> bond repair <u>repair</u>. **Observations:**  We can see that for product index:57 the top 10 similar products using TF-IDF product featurization are different and much better than those of Bag of Words Only 3 products are common in both approches Model-3 TF-IDF weighted Word2Vec for Product title feature # using pre trained word2vec from glove vectors <u>In [22]:</u> #https://nlp.stanford.edu/projects/glove/ import pickle with open('glove vectors', 'rb') as f: model = pickle.load(f) glove words = set(model.keys()) # we are converting a dictionary with word as a key, and the idf as a value <u>In [23]:</u> dictionary = dict(zip(tfidf\_vectorizer.get\_feature\_names(), list(tfidf\_vectorizer.idf\_))) <u>tfidf words = set(tfidf vectorizer.get feature names())</u> tfidf\_W2V vectorization of product feature <u>In [24]:</u> #vectorizing train data using tfidf-W2v # average Word2Vec # compute tfidf word2vec for each product. from tqdm import tqdm product tfidf w2v vectors = []; # the avg-w2v for each product is stored in this list for product in tqdm(data['product']): # for each product title vector = np.zeros(300) # as word vectors are of zero length tf\_idf\_weight =0; # num of words with a valid vector in the product for word in product.split(): # for each word in product title if (word in glove words) and (word in tfidf words): vec = model[word] # getting the vector for each word # here we are multiplying idf value(dictionary[word]) and the tf value((product.count(wor d) /len (product.split()))) <u>tf\_idf = dictionary[word] \* (product.count(word) / len(product.split())) # getting the tfidf va</u> lue for each word vector += (vec \* tf idf) # calculating tfidf weighted w2v tf idf weight += tf\_idf if tf idf weight != 0: vector /= tf idf weight product tfidf w2v vectors.append(vector) <u>| 27164/27164 [00:01<00:</u>00, 15309.58it/s] 100% | In [25]: print(len(product tfidf w2v vectors)) print(len(product tfidf w2v vectors[0])) 27164 300



In [40]: #Summarizing the results of all 3 methods prod index=22349 d=pd.DataFrame({'BOW':bow 22349['product'].values[1:],'TF-IDF':tfidf 22349['product'].values[1:], \ 'TF-IDF W2V':tfidf w2v 22349['product'].values[1:]}) # setting caption(title) to dataframe d.style.set\_caption('Similar products for : '+'" '+data['product'].loc[prod index]+'"').set table style s([{'selector':'caption', 'props':[('col or', 'black'), ('fon t-weight', 'bold'), t-align', 'left'), ('font <u>-size', '16px')]}])</u> Out[40]: <u>Similar products for : " keratin smooth conditioner"</u> TF-IDF **BOW** TF-IDF W2V oil nourish conditioner 0 nourish replenish conditioner nourish replenish conditioner <u>1</u> climate protection conditioner climate protection conditioner color protect conditioner advanced hair fall control conditioner 2 aqua halo rejuvenating conditioner aqua halo rejuvenating conditioner <u>3</u> hair fall defense conditioner hair fall defense conditioner herbal orange lemongrass hair conditioner 4 oil nourish conditioner oil nourish conditioner silky smooth care shampoo conditioner <u>5</u> color protect conditioner color protect conditioner aloe hair conditioner <u>6</u> aloe hair conditioner herbal orange lemongrass hair conditioner keratin smooth conditioner <u>7</u> conditioner hair repair <u>aloe hair conditioner</u> <u>conditioner lusciously thick long nourishing</u> satreetha shampoo 8 conditioner hair repair hair conditioner green tea with aloevera 9 conditioning shampoo fructis long strong strengthening conditioner fructis long strong strengthening conditioner # checking for prod index 789 , top 10 similar items <u>In [41]:</u> bow\_789=bag\_of\_words\_product\_with\_discount(789,11) tfidf\_789=tfidf\_product(789,11) tfidf w2v 789=tfidf w2v product (789,11) The searched\Queried product is: 789 : tomato salsa dip enjoy with nacho chips Top 10 Similar products for "tomato salsa dip enjoy with nacho chips" are: \_\_\_\_\_\_ 11994 : yummy dip out Cosine Similarity with queried product is: 0.999797 Discount %: 20.0 22526 : pizza foundue dip cheese Cosine Similarity with queried product is: 0.999779 Discount %: 20.0 5431 : yogurt dip cilantro jalapeno Cosine Similarity with queried product is: 0.999778 Discount %: 20.0 4439 : dip hot cheese <u>Cosine Similarity with queried product is: 0.999764</u> Discount %: 20.0 3005 : very creamy salsa spicy chipotle Cosine Similarity with queried product is: 0.999761 Discount %: 5516 : ranch mint herb Cosine Similarity with queried product is: 0.999758 Discount %: 20.0 347 : chunky salsa mild Cosine Similarity with queried product is: 0.999765 <u>Discount %: 15.0</u> 19954 : chunky salsa hot Cosine Similarity with queried product is: 0.999765 Discount %: 15.0 \_\_\_\_\_\_ 22781 : soy with chilli Cosine Similarity with queried product is: 0.999763 Discount %: 0.0 7745 : sriracha dip sauce <u>Cosine Similarity with queried product is: 0.999761</u> Discount %: 0.0 The searched\Queried product is: <u> 789 :</u> tomato salsa dip enjoy with nacho chips <u>product</u> <u>category</u> <u>gourmet\_worldfood</u> <u>sub\_category</u> <u>sauces\_spreads\_dips</u> <u>brand</u> <u>habanero</u> <u>type</u> <u>hummus cheese salsadip</u> description traditional mexican style family gathering hav... <u>sale\_price</u> discount\_% negative <u>neutral</u> <u>positive</u> 0.143 <u>compound</u> 0.7184 cluster\_label\_\_\_\_ Name: 789, dtype: object Top 10 Similar products for "tomato salsa dip enjoy with nacho chips" are: <u>15737 : all natural salsa peri peri salsa</u> Cosine Similarity with queried product is: 0.999932 Discount %: 20.0 12246 : very cheesy salsa salsa con queso <u>Cosine Similarity with queried product is: 0.999929</u> Discount %: 20.0 \_\_\_\_\_\_ 3005 : very creamy salsa spicy chipotle Cosine Similarity with queried product is: 0.999928 Discount %: 20.0 -----22526 : pizza foundue dip cheese Cosine Similarity with queried product is: 0.999925 Discount %: 20.0 -----11994 : yummy dip out Cosine Similarity with queried product is: 0.999925 Discount %: 20.0 5431 : yogurt dip cilantro jalapeno Cosine Similarity with queried product is : 0.999925 Discount %: 20.0 \_\_\_\_\_\_ 8799 : all natural hummus spicy sriracha <u>Cosine Similarity with queried product is: 0.99992</u> Discount %: 20.0 \_\_\_\_\_\_ 16573 : all natural hummus fresh hummus Cosine Similarity with queried product is: 0.999919 Discount %: 20.0 \_\_\_\_\_\_ 5516 : ranch mint herb Cosine Similarity with queried product is: 0.999918 Discount %: 20.0 \_\_\_\_\_ 3854 : all natural hummus roasted garlic Cosine Similarity with queried product is: 0.999917 Discount %: 20.0 \_\_\_\_\_ The searched/Queried product is: 789 : tomato salsa dip enjoy with nacho chips Top 10 Similar products for "tomato salsa dip enjoy with nacho chips" are: \_\_\_\_\_\_ 26463 : very cheesy dip pepper jack Cosine Similarity with queried product is : 0.999784 Discount %: 20.0 3005 : very creamy salsa spicy chipotle Cosine Similarity with queried product is: 0.999781 Discount %: 20.0 \_\_\_\_\_\_ 12246 : very cheesy salsa salsa con queso Cosine Similarity with queried product is : 0.999761 Discount %: 20.0 \_\_\_\_\_ 8799 : all natural hummus spicy sriracha <u>Cosine Similarity with queried product is: 0.999754</u> Discount %: 20.0 <u> 22526 : pizza foundue dip cheese</u> <u>Cosine Similarity with queried product is: 0.999751</u> Discount %: 20.0 \_\_\_\_\_ 11994 : yummy dip out <u>Cosine Similarity with queried product is: 0.99975</u> Discount %: 20.0 \_\_\_\_\_ <u>3854 : all natural hummus roasted garlic</u> Cosine Similarity with queried product is : 0.999726 Discount %: 20.0 <u>15737 : all natural salsa peri peri salsa</u> Cosine Similarity with queried product is: 0.999701 4439 : dip hot cheese Cosine Similarity with queried product is: 0.999694 Discount %: 20.0 4848 : potato crisp chips hot spicy Cosine Similarity with queried product is: 0.999692 Discount %: 0.0 <u>In [42]:</u> #Summarizing the results of all 3 methods prod index=789 d=pd.DataFrame({'BOW':bow\_789['product'].values[1:], 'TF-IDF':tfidf\_789['product'].values[1:], \ 'TF-IDF\_W2V':tfidf\_w2v\_789['product'].values[1:]}) # setting caption(title) to dataframe d.style.set\_caption('Similar products for : '+'" '+data['product'].loc[prod\_index]+'"').set table style s([{'selector':'caption', <u>'props':[('col</u> or', 'black'), <u>('fon</u> t-weight', 'bold'), t-align','left'), ('font -size', '16px')]}]) Out [42]: Similar products for : " tomato salsa dip enjoy with nacho chips" **BOW** TF-IDF TF-IDF\_W2V very cheesy dip pepper jack 0 yummy dip out all natural salsa peri peri salsa <u>1</u> <u>pizza foundue dip cheese</u> <u>very cheesy salsa salsa con queso</u> very creamy salsa spicy chipotle <u>2</u> yogurt dip cilantro jalapeno very creamy salsa spicy chipotle very cheesy salsa salsa con queso dip hot cheese all natural hummus spicy sriracha <u>3</u> pizza foundue dip cheese 4 very creamy salsa spicy chipotle pizza foundue dip cheese yummy dip out <u>5</u> ranch mint herb yogurt dip cilantro jalapeno <u>yummy dip out</u> all natural hummus spicy sriracha <u>6</u> chunky salsa mild all natural hummus roasted garlic <u>7</u> chunky salsa hot all natural hummus fresh hummus all natural salsa peri peri salsa 8 ranch mint herb dip hot cheese soy with chilli all natural hummus roasted garlic 9 sriracha dip sauce potato crisp chips hot spicy # checking for prod index 6786 , top 10 similar items <u>In [43]:</u> bow\_6786=bag\_of\_words\_product\_with\_discount(6786,11) tfidf 6786=tfidf product(6786,11) tfidf w2v 6786=tfidf w2v product(6786,11) The searched\Queried product is: 6786 : dressing thousand island Top 10 Similar products for "dressing thousand island" are: 14832 : thousand island dressing lite Cosine Similarity with queried product is: 0.999992 Discount %: 0.0 8328 : french dressing Cosine Similarity with queried product is: 0.999977 Discount %: 0.0 488 : dressing creamy caesar Cosine Similarity with queried product is: 0.999972 Discount %: 0.0 4733 : italian dressing less fat <u>Cosine Similarity with queried product is: 0.999965</u> 3757 : mayonnaise Cosine Similarity with queried product is: 0.999955 Discount %: 0.0 9203 : tulsi honey Cosine Similarity with queried product is: 0.999954 Discount %: 0.0 1427 : nutella ready <u>Cosine Similarity with queried product is: 0.999953</u> Discount %: 0.0 22517 : red pepper sauce Cosine Similarity with queried product is: 0.999953 Discount %: 0.0 -----18661 : syrup pancake Cosine Similarity with queried product is: 0.999952 Discount %: 0.0 <u>16290 : mayonnaise mayolite</u> <u>Cosine Similarity with queried product is: 0.99995</u> Discount %: 0.0 -----The searched\Queried product is: 67<u>86 :</u> \_product dressing thousand island \_\_\_\_\_\_gourmet\_worldfood category <u>sub category</u> <u>sauces spreads dips</u> americangarden <u>brand</u> saladdressings description american garden thousand island takes you cook... <u>sale price</u> discount % <u>negative</u> neutral 0.107 <u>positive</u> compound 0.34 cluster\_label Name: 6786, dtype: object Top 10 Similar products for "dressing thousand island" are: \_\_\_\_\_ 6304 : original recipe italian herb mayo <u>Cosine Similarity with queried product is: 0.999971</u> Discount %: 30.0 14832 : thousand island dressing lite Cosine Similarity with queried product is: 0.999997 Discount %: 0.0 -----488 : dressing creamy caesar Cosine Similarity with queried product is: 0.99999 Discount %: 0.0 \_\_\_\_\_ 4733 : italian dressing less fat Cosine Similarity with queried product is: 0.999989 Discount %: 0.0 -----8328 : french dressing Cosine Similarity with queried product is: 0.999989 Discount %: 0.0 772 : peanut butter chunky <u>Cosine Similarity with queried product is: 0.999972</u> Discount %: 0.0 -----20889 : barbeque sauce original Cosine Similarity with queried product is: 0.999971 Discount %: 0.0 \_\_\_\_\_ 18661 : syrup pancake <u>Cosine Similarity with queried product is: 0.999971</u> Discount %: 0.0 22517 : red pepper sauce Cosine Similarity with queried product is : 0.999969 Discount %: 0.0 \_\_\_\_\_ 9203 : tulsi honey Cosine Similarity with queried product is: 0.999969 -----The searched/Queried product is: 6786 : dressing thousand island Top 10 Similar products for "dressing thousand island" are: 7531 : olive oil extra virgin <u>Cosine Similarity with queried product is: 0.99986</u> <u>Discount %: 58.6429</u> <u>25645 : san remo pasta disano olive oil american garden pasta sauce</u> <u>Cosine Similarity with queried product is: 0.999861</u> <u>Discount %: 32.3486</u> 3957 : spanish extra virgin olive oil Cosine Similarity with queried product is: 0.999863 Discount %: 30.0 11204 : cashew nuts whole natural premium king size <u>Cosine Similarity with queried product is: 0.999861</u> <u>Discount %: 24.726</u> 10647 : chinese five spice powder shaker Cosine Similarity with queried product is: 0.999863 Discount %: 10.0 14832 : thousand island dressing lite Cosine Similarity with queried product is: 0.999979 Discount %: 0.0 4733 : italian dressing less fat Cosine Similarity with queried product is: 0.999888 Discount %: 0.0 22173 : phantom hot tomato ketchup sauce made with world hottest ghost pepper Cosine Similarity with queried product is: 0.999865 Discount %: 0.0 7620 : olive oil tomato and porcini mushroom pasta sauce with extra virgin Cosine Similarity with queried product is: 0.999862 Discount %: 0.0 <u>27007</u>: american garden peanut butter chunky jar Cosine Similarity with queried product is: 0.999861 Discount %: 0.0 In [44]: #Summarizing the results of all 3 methods prod\_index=6786 d=pd.DataFrame({'BOW':bow\_6786['product'].values[1:], 'TF-IDF':tfidf\_6786['product'].values[1:], \ 'TF-IDF W2V':tfidf w2v\_6786['product'].values[1:]}) # setting caption(title) to dataframe d.style.set\_caption('Similar products for : '+'" '+data['product'].loc[prod\_index]+'"').set table style s([{'selector':'caption', <u>'props':[('col</u> or','black'), ('fon t-weight', 'bold'), <u>('tex</u> t-align','left'), ('font <u>-size', '16px')]}])</u> Out [44]: <u>Similar products for : " dressing thousand island"</u> **BOW** TF-IDF TF-IDF\_W2V **0** thousand island dressing lite original recipe italian herb mayo olive oil extra virgin <u>1</u> san remo pasta disano olive oil american garden pasta sauce french dressing thousand island dressing lite <u>2</u> spanish extra virgin olive oil dressing creamy caesar dressing creamy caesar cashew nuts whole natural premium king size <u>3</u> italian dressing less fat italian dressing less fat chinese five spice powder shaker mayonnaise french dressing <u>5</u> tulsi honey peanut butter chunky thousand island dressing lite italian dressing less fat 6 nutella ready barbeque sauce original <u>7</u> syrup pancake phantom hot tomato ketchup sauce made with world hottest ghost pepper red pepper sauce 8 syrup pancake red pepper sauce olive oil tomato and porcini mushroom pasta sauce with extra virgin american garden peanut butter chunky jar 9 mayonnaise mayolite <u>tulsi honey</u> In [47]: # checking for prod index 2607 , top 10 similar items bow\_2607=bag\_of\_words\_product\_with\_discount(2607,11) tfidf 2607=tfidf product (2607,11) tfidf w2v 2607=tfidf w2v product(2607,11) The searched\Queried product is: <u> 2607 : organic rava idli mix</u> Top 10 Similar products for "organic rava idli mix" are: \_\_\_\_\_\_ <u>11541 : instant mix rava idli</u> <u>Cosine Similarity with queried product is: 0.999615</u> 3597 : organic masala rava idli ready mix <u>Cosine Similarity with queried product is: 0.999746</u> Discount %: 0.0 9853 : organic rice idli ready <u>Cosine Similarity with queried product is: 0.999591</u> Discount %: 0.0 <u>23692 : ragi dosa mix</u> <u>Cosine Similarity with queried product is: 0.999561</u> \_\_\_\_\_ <u> 24212 : breakfast mix upma</u> <u>Cosine Similarity with queried product is: 0.999561</u> Discount %: 0.0 20410 : mix millet pongal Cosine Similarity with queried product is : 0.999556 Discount %: 0.0 17737 : multigrain thalipeeth mix <u>Cosine Similarity with queried product is: 0.999531</u> \_\_\_\_\_\_ 12169 : organic ragi dosa ready mix <u>Cosine Similarity with queried product is: 0.999526</u> Discount %: 0.0 7218 : organic rice dosa ready mix <u>Cosine Similarity with queried product is: 0.999525</u> Discount %: 0.0 <u> 16997 : ready mix sambar</u> Cosine Similarity with queried product is : 0.999525 \_\_\_\_\_ The searched\Queried product is: <u>2607</u>: <u>organic rava idli mix</u> snacks brandedfoods <u>sub\_category</u> <u>readytocook\_eat</u> phaladapure\_sure breakfast\_snackmixes <u>type</u> rava idli variation the popular south indian b... description <u>sale\_price</u> discount\_% <u>negative</u> 0.9744 <u>cluster\_label</u> Name: 2607, dtype: object Top 10 Similar products for "organic rava idli mix" are: \_\_\_\_\_\_ 7582 : breakfast mix oats pongal <u>Cosine Similarity with queried product is: 0.999768</u> Discount %: 28.8 <u>26671</u>: breakfast mix little millet upma Cosine Similarity with queried product is: 0.999763 Discount %: 28.8 2994 : breakfast mix little millet pongal Cosine Similarity with queried product is: 0.999762 Discount %: 28.8 8288 : specialty idli dosa batter <u>Cosine Similarity with queried product is: 0.999765</u> <u>Discount %: 18.0952</u> 3597 : organic masala rava idli ready mix Cosine Similarity with queried product is: 0.999847 Discount %: 0.0 9853 : organic rice idli ready Cosine Similarity with queried product is: 0.999784 Discount %: 0.0 23692 : ragi dosa mix <u>Cosine Similarity with queried product is: 0.99977</u> Discount %: 0.0 24212 : breakfast mix upma Cosine Similarity with queried product is: 0.999768 Discount %: 0.0 20410 : mix millet pongal Cosine Similarity with queried product is: 0.999764 Discount %: 0.0 7218 : organic rice dosa ready mix Cosine Similarity with queried product is: 0.999759 Discount %: 0.0 The searched/Queried product is: 2607 : organic rava idli mix Top 10 Similar products for "organic rava idli mix" are: 168 : organic dosa mix jowar Cosine Similarity with queried product is: 0.999716 Discount %: 0.0 3597 : organic masala rava idli ready mix Cosine Similarity with queried product is: 0.999403 Discount %: 0.0 12169 : organic ragi dosa ready mix <u>Cosine Similarity with queried product is: 0.999401</u> Discount %: 0.0 10347 : organic mix dal Cosine Similarity with queried product is: 0.999389 16854 : organic rice mix flaxseed <u>Cosine Similarity with queried product is: 0.999361</u> Discount %: 0.0 20190 : organic dosa mix mixed millet Cosine Similarity with queried product is: 0.999343 Discount %: 0.0 7218 : organic rice dosa ready mix <u>Cosine Similarity with queried product is: 0.99928</u> Discount %: 0.0 467 : organic rasam ready mix long pepper Cosine Similarity with queried product is: 0.999071 Discount %: 0.0 4598 : organic dosa mix little millet Cosine Similarity with queried product is: 0.999024 Discount %: 0.0 20562 : organic pongal mix foxtail millet Cosine Similarity with queried product is: 0.999016 Discount %: 0.0 In [48]: #Summarizing the results of all 3 methods prod index=2607 d=pd.DataFrame({ 'BOW':bow 2607['product'].values[1:], 'TF-IDF':tfidf 2607['product'].values[1:], \ <u>'TF-IDF\_W2V':tfidf\_w2v\_2607['product'].values[1:]})</u> # setting caption(title) to dataframe d.style.set\_caption('Similar products for : '+'" '+data['product'].loc[prod index]+'"').set table style s([{'selector':'caption', 'props':[('col or', 'black'), t-weight', 'bold'), ('tex t-align','left'), ('font <u>-size', '16px')]}])</u> Out[48]: Similar products for : " organic rava idli mix" **BOW** TF-IDF TF-IDF W2V breakfast mix oats pongal 0 instant mix rava idli organic dosa mix jowar 1 organic masala rava idli ready mix breakfast mix little millet upma organic masala rava idli ready mix 2 organic rice idli ready breakfast mix little millet pongal organic ragi dosa ready mix <u>3</u> specialty idli dosa batter organic mix dal <u>ragi dosa mix</u> <u>4</u> <u>breakfast mix upma</u> <u>organic masala rava idli ready mix</u> organic rice mix flaxseed organic dosa mix mixed millet <u>5</u> mix millet pongal organic rice idli ready <u>6</u> multigrain thalipeeth mix <u>ragi dosa mix</u> organic rice dosa ready mix <u>7</u> <u>breakfast mix upma</u> organic ragi dosa ready mix organic rasam ready mix long pepper <u>8</u> organic rice dosa ready mix mix millet pongal organic dosa mix little millet 9 ready mix sambar organic rice dosa ready mix organic pongal mix foxtail millet

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