AppliedAIWorkshop

November 8, 2019

Amazon Apparel Recommendations

0.0.1 [4.2] Data and Code:

https://drive.google.com/open?id=0BwNkduBnePt2VWhCYXhMV3p4dTg

0.0.2 [4.3] Overview of the data

[159]:
```
#import all the necessary packages.

from PIL import Image
import requests
from io import BytesIO
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import warnings
from bs4 import BeautifulSoup
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import nltk
import math
import time
import re
import os
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 matplotlib import gridspec
from scipy.sparse import hstack
import plotly
import plotly.figure_factory as ff
from plotly.graph_objs import Scatter, Layout
```

```
plotly.offline.init_notebook_mode(connected=True)
warnings.filterwarnings("ignore")
```

[6]:
```
# we have give a json file which consists of all information about
# the products
# loading the data using pandas' read_json file.
data = pd.read_json('tops_fashion.json')
```

[7]:
```
print ('Number of data points : ', data.shape[0], \
       'Number of features/variables:', data.shape[1])
```

```
Number of data points :  183138 Number of features/variables: 19
```

0.0.3 Terminology:

What is a dataset? Rows and columns Data-point Feature/variable

[8]:
```
# each product/item has 19 features in the raw dataset.
data.columns # prints column-names or feature-names.
```

[8]:
```
Index(['asin', 'author', 'availability', 'availability_type', 'brand', 'color',
       'editorial_reivew', 'editorial_review', 'formatted_price',
       'large_image_url', 'manufacturer', 'medium_image_url', 'model',
       'product_type_name', 'publisher', 'reviews', 'sku', 'small_image_url',
       'title'],
      dtype='object')
```

Of these 19 features, we will be using only 6 features in this workshop. 1. asin (Amazon standard identification number) 2. brand (brand to which the product belongs to) 3. color (Color information of apparel, it can contain many colors as a value ex: red and black stripes) 4. product_type_name (type of the apperal, ex: SHIRT/TSHIRT) 5. medium_image_url (url of the image) 6. title (title of the product.) 7. formatted_price (price of the product)

[9]:
```
data = data[['asin', 'brand', 'color', 'medium_image_url', 'product_type_name',␣
 ↪'title', 'formatted_price']]
```

[10]:
```
print ('Number of data points : ', data.shape[0], \
       'Number of features:', data.shape[1])
data.head() # prints the top rows in the table.
```

```
Number of data points :  183138 Number of features: 7
```

[10]:

	asin	brand	color	medium_image_url	product_type_name
0	B016I2TS4W	FNC7C	None	https://images-na.ssl-images-amazon.com/images...	SHIRT
1	B01N49AI08	FIG Clothing	None		
2	B01JDPCOHO	FIG Clothing	None		
3	B01N19U5H5	Focal18	None		
4	B004GSI2OS	FeatherLite	Onyx Black/ Stone		

```
1  https://images-na.ssl-images-amazon.com/images...              SHIRT
2  https://images-na.ssl-images-amazon.com/images...              SHIRT
3  https://images-na.ssl-images-amazon.com/images...              SHIRT
4  https://images-na.ssl-images-amazon.com/images...              SHIRT

                                                 title formatted_price
0  Minions Como Superheroes Ironman Long Sleeve R...              None
1                      FIG Clothing Womens Izo Tunic              None
2                        FIG Clothing Womens Won Top              None
3  Focal18 Sailor Collar Bubble Sleeve Blouse Shi...              None
4  Featherlite Ladies' Long Sleeve Stain Resistan...           $26.26
```

0.0.4 [5.1] Missing data for various features.

Basic stats for the feature: product_type_name

[11]:
```
# We have total 72 unique type of product_type_names
print(data['product_type_name'].describe())

# 91.62% (167794/183138) of the products are shirts,
```

```
count     183138
unique        72
top        SHIRT
freq      167794
Name: product_type_name, dtype: object
```

[12]:
```
# names of different product types
print(data['product_type_name'].unique())
```

```
['SHIRT' 'SWEATER' 'APPAREL' 'OUTDOOR_RECREATION_PRODUCT'
 'BOOKS_1973_AND_LATER' 'PANTS' 'HAT' 'SPORTING_GOODS' 'DRESS' 'UNDERWEAR'
 'SKIRT' 'OUTERWEAR' 'BRA' 'ACCESSORY' 'ART_SUPPLIES' 'SLEEPWEAR'
 'ORCA_SHIRT' 'HANDBAG' 'PET_SUPPLIES' 'SHOES' 'KITCHEN' 'ADULT_COSTUME'
 'HOME_BED_AND_BATH' 'MISC_OTHER' 'BLAZER' 'HEALTH_PERSONAL_CARE'
 'TOYS_AND_GAMES' 'SWIMWEAR' 'CONSUMER_ELECTRONICS' 'SHORTS' 'HOME'
 'AUTO_PART' 'OFFICE_PRODUCTS' 'ETHNIC_WEAR' 'BEAUTY'
 'INSTRUMENT_PARTS_AND_ACCESSORIES' 'POWERSPORTS_PROTECTIVE_GEAR' 'SHIRTS'
 'ABIS_APPAREL' 'AUTO_ACCESSORY' 'NONAPPARELMISC' 'TOOLS' 'BABY_PRODUCT'
 'SOCKSHOSIERY' 'POWERSPORTS_RIDING_SHIRT' 'EYEWEAR' 'SUIT'
 'OUTDOOR_LIVING' 'POWERSPORTS_RIDING_JACKET' 'HARDWARE' 'SAFETY_SUPPLY'
 'ABIS_DVD' 'VIDEO_DVD' 'GOLF_CLUB' 'MUSIC_POPULAR_VINYL'
 'HOME_FURNITURE_AND_DECOR' 'TABLET_COMPUTER' 'GUILD_ACCESSORIES'
 'ABIS_SPORTS' 'ART_AND_CRAFT_SUPPLY' 'BAG' 'MECHANICAL_COMPONENTS'
 'SOUND_AND_RECORDING_EQUIPMENT' 'COMPUTER_COMPONENT' 'JEWELRY'
 'BUILDING_MATERIAL' 'LUGGAGE' 'BABY_COSTUME' 'POWERSPORTS_VEHICLE_PART'
 'PROFESSIONAL_HEALTHCARE' 'SEEDS_AND_PLANTS' 'WIRELESS_ACCESSORY']
```

[13]:
```
# find the 10 most frequent product_type_names.
product_type_count = Counter(list(data['product_type_name']))
product_type_count.most_common(10)
```

[13]:
```
[('SHIRT', 167794),
 ('APPAREL', 3549),
 ('BOOKS_1973_AND_LATER', 3336),
 ('DRESS', 1584),
 ('SPORTING_GOODS', 1281),
 ('SWEATER', 837),
 ('OUTERWEAR', 796),
 ('OUTDOOR_RECREATION_PRODUCT', 729),
 ('ACCESSORY', 636),
 ('UNDERWEAR', 425)]
```

Basic stats for the feature: brand

[14]:
```
# there are 10577 unique brands
print(data['brand'].describe())

# 183138 - 182987 = 151 missing values.
```

```
count     182987
unique     10577
top         Zago
freq          223
Name: brand, dtype: object
```

[15]:
```
brand_count = Counter(list(data['brand']))
brand_count.most_common(10)
```

[15]:
```
[('Zago', 223),
 ('XQS', 222),
 ('Yayun', 215),
 ('YUNY', 198),
 ('XiaoTianXin-women clothes', 193),
 ('Generic', 192),
 ('Boohoo', 190),
 ('Alion', 188),
 ('Abetteric', 187),
 ('TheMogan', 187)]
```

Basic stats for the feature: color

[16]:
```
print(data['color'].describe())


# we have 7380 unique colors
# 7.2% of products are black in color
```

```
# 64956 of 183138 products have brand information. That's approx 35.4%.
```

```
count     64956
unique     7380
top       Black
freq      13207
Name: color, dtype: object
```

[17]:
```
color_count = Counter(list(data['color']))
color_count.most_common(10)
```

[17]:
```
[(None, 118182),
 ('Black', 13207),
 ('White', 8616),
 ('Blue', 3570),
 ('Red', 2289),
 ('Pink', 1842),
 ('Grey', 1499),
 ('*', 1388),
 ('Green', 1258),
 ('Multi', 1203)]
```

Basic stats for the feature: formatted_price

[18]:
```
print(data['formatted_price'].describe())

# Only 28,395 (15.5% of whole data) products with price information
```

```
count      28395
unique      3135
top       $19.99
freq          945
Name: formatted_price, dtype: object
```

[19]:
```
price_count = Counter(list(data['formatted_price']))
price_count.most_common(10)
```

[19]:
```
[(None, 154743),
 ('$19.99', 945),
 ('$9.99', 749),
 ('$9.50', 601),
 ('$14.99', 472),
 ('$7.50', 463),
 ('$24.99', 414),
 ('$29.99', 370),
 ('$8.99', 343),
 ('$9.01', 336)]
```

Basic stats for the feature: title

[20]:
```
print(data['title'].describe())

# All of the products have a title.
# Titles are fairly descriptive of what the product is.
# We use titles extensively in this workshop
# as they are short and informative.
```

```
count                                                183138
unique                                               175985
top       Nakoda Cotton Self Print Straight Kurti For Women
freq                                                     77
Name: title, dtype: object
```

[21]:
```
data.to_pickle('pickels/180k_apparel_data')
```

We save data files at every major step in our processing in "pickle" files. If you are stuck anywhere (or) if some code takes too long to run on your laptop, you may use the pickle files we give you to speed things up.

[22]:
```
# consider products which have price information
# data['formatted_price'].isnull() => gives the information
#about the dataframe row's which have null values price == None/Null
data = data.loc[~data['formatted_price'].isnull()]
print('Number of data points After eliminating price=NULL :', data.shape[0])
```

```
Number of data points After eliminating price=NULL : 28395
```

[23]:
```
# consider products which have color information
# data['color'].isnull() => gives the information about the dataframe row's␣
 ↪which have null values price == None/Null
data =data.loc[~data['color'].isnull()]
print('Number of data points After eliminating color=NULL :', data.shape[0])
```

```
Number of data points After eliminating color=NULL : 28385
```

We brought down the number of data points from 183K to 28K. We are processing only 28K points so that most of the workshop participants can run this code on thier laptops in a reasonable amount of time.

For those of you who have powerful computers and some time to spare, you are recommended to use all of the 183K images.

[24]:
```
data.to_pickle('pickels/28k_apparel_data')
```

[25]:
```
# You can download all these 28k images using this code below.
# You do NOT need to run this code and hence it is commented.


'''
```

```
from PIL import Image
import requests
from io import BytesIO

for index, row in images.iterrows():
        url = row['large_image_url']
        response = requests.get(url)
        img = Image.open(BytesIO(response.content))
        img.save('images/28k_images/'+row['asin']+'.jpeg')


'''
```

[25]:
```
"\nfrom PIL import Image\nimport requests\nfrom io import BytesIO\n\nfor index,
row in images.iterrows():\n        url = row['large_image_url']\n
response = requests.get(url)\n        img =
Image.open(BytesIO(response.content))\n
img.save('images/28k_images/'+row['asin']+'.jpeg')\n\n\n"
```

0.0.5 [5.2] Remove near duplicate items

[5.2.1] Understand about duplicates.

[26]:
```
# read data from pickle file from previous stage
data = pd.read_pickle('pickels/28k_apparel_data')

# find number of products that have duplicate titles.
print(sum(data.duplicated('title')))
# we have 2325 products which have same title but different color
```

```
2325
```

These shirts are exactly same except in size (S, M,L,XL) <img src="dedupe/B00AQ4GMCK.jpeg",width=100,height=100> :B00AQ4GMCK
<img src="dedupe/B00AQ4GMTS.jpeg",width=100,height=100> :B00AQ4GMTS
<img src="dedupe/B00AQ4GMLQ.jpeg",width=100,height=100> :B00AQ4GMLQ
<img src="dedupe/B00AQ4GN3I.jpeg",width=100,height=100> :B00AQ4GN3I

These shirts exactly same except in color <img src="dedupe/B00G278GZ6.jpeg",width=100,height=100> :B00G278GZ6
<img src="dedupe/B00G278W6O.jpeg",width=100,height=100> :B00G278W6O
<img src="dedupe/B00G278Z2A.jpeg",width=100,height=100> :B00G278Z2A
<img src="dedupe/B00G2786X8.jpeg",width=100,height=100> :B00G2786X8

In our data there are many duplicate products like the above examples, we need to de-dupe them for better results.

[5.2.2] Remove duplicates : Part 1

[27]:
```
# read data from pickle file from previous stage
data = pd.read_pickle('pickels/28k_apparel_data')
```

[28]:
```
data.head()
```

[28]:
```
          asin                        brand              color  \
4   B004GSI2OS                   FeatherLite  Onyx Black/ Stone
6   B012YX2ZPI  HX-Kingdom Fashion T-shirts              White
11  B001LOUGE4                 Fitness Etc.              Black
15  B003BSRPB0                   FeatherLite              White
21  B014ICEDNA                         FNC7C             Purple

                                    medium_image_url product_type_name  \
4   https://images-na.ssl-images-amazon.com/images...              SHIRT
6   https://images-na.ssl-images-amazon.com/images...              SHIRT
11  https://images-na.ssl-images-amazon.com/images...              SHIRT
15  https://images-na.ssl-images-amazon.com/images...              SHIRT
21  https://images-na.ssl-images-amazon.com/images...              SHIRT

                                               title formatted_price
4   Featherlite Ladies' Long Sleeve Stain Resistan...          $26.26
6   Women's Unique 100% Cotton T - Special Olympic...           $9.99
11            Ladies Cotton Tank 2x1 Ribbed Tank Top          $11.99
15  FeatherLite Ladies' Moisture Free Mesh Sport S...          $20.54
21  Supernatural Chibis Sam Dean And Castiel Short...           $7.50
```

[29]:
```
# Remove All products with very few words in title
data_sorted = data[data['title'].apply(lambda x: len(x.split())>4)]
print("After removal of products with short description:", data_sorted.shape[0])
```

```
After removal of products with short description: 27949
```

[30]:
```
# Sort the whole data based on title (alphabetical order of title)
data_sorted.sort_values('title',inplace=True, ascending=False)
data_sorted.head()
```

[30]:
```
              asin     brand        color  \
61973   B06Y1KZ2WB    Éclair   Black/Pink
133820  B010RV33VE  xiaoming         Pink
81461   B01DDSDLNS  xiaoming        White
75995   B00X5LYO9Y  xiaoming  Red Anchors
151570  B00WPJG35K  xiaoming        White

                                     medium_image_url product_type_name  \
61973   https://images-na.ssl-images-amazon.com/images...              SHIRT
133820  https://images-na.ssl-images-amazon.com/images...              SHIRT
81461   https://images-na.ssl-images-amazon.com/images...              SHIRT
75995   https://images-na.ssl-images-amazon.com/images...              SHIRT
151570  https://images-na.ssl-images-amazon.com/images...              SHIRT
```

```
                                                    title formatted_price
61973   Éclair Women's Printed Thin Strap Blouse Black...          $24.99
133820  xiaoming Womens Sleeveless Loose Long T-shirts...          $18.19
81461   xiaoming Women's White Long Sleeve Single Brea...          $21.58
75995   xiaoming Stripes Tank Patch/Bear Sleeve Anchor...          $15.91
151570  xiaoming Sleeve Sheer Loose Tassel Kimono Woma...          $14.32
```

Some examples of dupliacte titles that differ only in the last few words.

[31]:
```
indices = []
for i,row in data_sorted.iterrows():
    indices.append(i)
```

[32]:
```
import itertools
stage1_dedupe_asins = []
i = 0
j = 0
num_data_points = data_sorted.shape[0]
while i < num_data_points and j < num_data_points:

    previous_i = i

    # store the list of words of ith string in a, ex: a = ['tokidoki', 'The',␣
↪'Queen', 'of', 'Diamonds', 'Women's', 'Shirt', 'X-Large']
    a = data['title'].loc[indices[i]].split()

    # search for the similar products sequentially
    j = i+1
    while j < num_data_points:

        # store the list of words of jth string in b, ex: b = ['tokidoki',␣
↪'The', 'Queen', 'of', 'Diamonds', 'Women's', 'Shirt', 'Small']
        b = data['title'].loc[indices[j]].split()

        # store the maximum length of two strings
        length = max(len(a), len(b))

        # count is used to store the number of words that are matched in both␣
↪strings
        count  = 0

        # itertools.zip_longest(a,b): will map the corresponding words in both␣
↪strings, it will appened None in case of unequal strings
        # example: a =['a', 'b', 'c', 'd']
        # b = ['a', 'b', 'd']
```

```
        # itertools.zip_longest(a,b): will give [('a','a'), ('b','b'),␣
↪('c','d'), ('d', None)]
        for k in itertools.zip_longest(a,b):
            if (k[0] == k[1]):
                count += 1

        # if the number of words in which both strings differ are > 2 , we are␣
↪considering it as those two apperals are different
        # if the number of words in which both strings differ are < 2 , we are␣
↪considering it as those two apperals are same, hence we are ignoring them
        if (length - count) > 2: # number of words in which both sensences␣
↪differ
            # if both strings are differ by more than 2 words we include the␣
↪1st string index
            stage1_dedupe_asins.append(data_sorted['asin'].loc[indices[i]])


            # start searching for similar apperals corresponds 2nd string
            i = j
            break
        else:
            j += 1
    if previous_i == i:
        break
```

[33]:
```
data = data.loc[data['asin'].isin(stage1_dedupe_asins)]
```

We removed the dupliactes which differ only at the end.

[34]:
```
print('Number of data points : ', data.shape[0])
```

```
Number of data points :  17592
```

[35]:
```
data.to_pickle('pickels/17k_apperal_data')
```

[5.2.3] Remove duplicates : Part 2

[36]:
```
data = pd.read_pickle('pickels/17k_apperal_data')
```

[37]:
```
# This code snippet takes significant amount of time.
# O(n^2) time.
# Takes about an hour to run on a decent computer.

indices = []
for i,row in data.iterrows():
    indices.append(i)

stage2_dedupe_asins = []
```

```
while len(indices)!=0:
    i = indices.pop()
    stage2_dedupe_asins.append(data['asin'].loc[i])
    # consider the first apperal's title
    a = data['title'].loc[i].split()
    # store the list of words of ith string in a, ex: a = ['tokidoki', 'The',␣
 ↪'Queen', 'of', 'Diamonds', 'Women's', 'Shirt', 'X-Large']
    for j in indices:

        b = data['title'].loc[j].split()
        # store the list of words of jth string in b, ex: b = ['tokidoki',␣
 ↪'The', 'Queen', 'of', 'Diamonds', 'Women's', 'Shirt', 'X-Large']

        length = max(len(a),len(b))

        # count is used to store the number of words that are matched in both␣
 ↪strings
        count  = 0

        # itertools.zip_longest(a,b): will map the corresponding words in both␣
 ↪strings, it will appened None in case of unequal strings
        # example: a =['a', 'b', 'c', 'd']
        # b = ['a', 'b', 'd']
        # itertools.zip_longest(a,b): will give [('a','a'), ('b','b'),␣
 ↪('c','d'), ('d', None)]
        for k in itertools.zip_longest(a,b):
            if (k[0]==k[1]):
                count += 1

        # if the number of words in which both strings differ are < 3 , we are␣
 ↪considering it as those two apperals are same, hence we are ignoring them
        if (length - count) < 3:
            indices.remove(j)
```

[77]:
```
# from whole previous products we will consider only
# the products that are found in previous cell
data = data.loc[data['asin'].isin(stage2_dedupe_asins)]
```

[78]:
```
print('Number of data points after stage two of dedupe: ',data.shape[0])
# from 17k apperals we reduced to 16k apperals
```

```
Number of data points after stage two of dedupe:  16434
```

[79]:
```
data.to_pickle('pickels/16k_apperal_data')
# Storing these products in a pickle file
# candidates who wants to download these files instead
# of 180K they can download and use them from the Google Drive folder.
```

1 6. Text pre-processing

[80]:
```
data = pd.read_pickle('pickels/16k_apperal_data')

# NLTK download stop words. [RUN ONLY ONCE]
# goto Terminal (Linux/Mac) or Command-Prompt (Window)
# In the temrinal, type these commands
# $python3
# $import nltk
# $nltk.download()
```

[81]:
```
# we use the list of stop words that are downloaded from nltk lib.
stop_words = set(stopwords.words('english'))
print ('list of stop words:', stop_words)

def nlp_preprocessing(total_text, index, column):
    if type(total_text) is not int:
        string = ""
        for words in total_text.split():
            # remove the special chars in review like '"#$@!%^&*()_+-~?>< etc.
            word = ("".join(e for e in words if e.isalnum()))
            # Conver all letters to lower-case
            word = word.lower()
            # stop-word removal
            if not word in stop_words:
                string += word + " "
        data[column][index] = string
```

```
list of stop words: {'after', "it's", 'hers', 'if', 'is', 'doing', 'all', 've',
'are', 'than', 'they', 'were', "aren't", 'him', 'the', "mightn't", 'some',
'did', 'herself', 'this', 'myself', "couldn't", 'a', 'weren', "isn't", 'theirs',
'for', 'my', 'his', 'no', 'wasn', 'whom', 'when', 'by', 'nor', 'their', 'here',
'couldn', 'shan', 'doesn', 'me', 'once', "you've", "shouldn't", 'isn',
'through', 'now', 'while', 'should', 'about', "needn't", 'on', "hasn't",
'where', "wasn't", 'such', 'below', 'which', 're', 'hadn', 'mightn', 'mustn',
's', 'those', 'she', 'yourself', 'am', 'will', 'off', 'was', "you're", 'from',
'in', 'i', "wouldn't", 'it', "weren't", 'don', "shan't", 'our', 'has', 'more',
'before', 'being', 'do', 'then', "won't", 'needn', 'didn', "mustn't", 'can',
'shouldn', 'had', 'he', 'have', 'of', 'same', 'just', "didn't", 'and',
'because', 'into', 'other', 'there', 'hasn', 'above', "should've", 'under',
'won', 'over', 'yours', 'own', "you'll", 'itself', 'so', 'its', 'what', "don't",
'not', 'haven', 'having', 'between', 'ain', 'o', 'both', 'again', 'yourselves',
'd', 'y', 'how', 'them', 'wouldn', 'against', "hadn't", 'but', 'only', 'until',
'we', 'to', 'down', 'very', 'most', 'themselves', 'why', 'out', "that'll",
'does', 'or', "you'd", "doesn't", 'as', 'been', 'any', "haven't", 'each',
'aren', "she's", 'who', 'that', 'few', 'your', 't', 'up', 'with', 'these',
'you', 'ourselves', 'ours', 'too', 'himself', 'her', 'ma', 'm', 'further', 'll',
'at', 'an', 'during', 'be'}
```

[82]:
```
start_time = time.clock()
# we take each title and we text-preprocess it.
for index, row in data.iterrows():
    nlp_preprocessing(row['title'], index, 'title')
# we print the time it took to preprocess whole titles
print(time.clock() - start_time, "seconds")
```

```
3.7841757999995025 seconds
```

[83]:
```
data.head()
```

[83]:

	asin	brand	color	\
4	B004GSI2OS	FeatherLite	Onyx Black/ Stone	
6	B012YX2ZPI	HX-Kingdom Fashion T-shirts	White	
15	B003BSRPB0	FeatherLite	White	
27	B014ICEJ1Q	FNC7C	Purple	
46	B01NACPBG2	Fifth Degree	Black	

	medium_image_url	product_type_name	\
4	https://images-na.ssl-images-amazon.com/images...	SHIRT	
6	https://images-na.ssl-images-amazon.com/images...	SHIRT	
15	https://images-na.ssl-images-amazon.com/images...	SHIRT	
27	https://images-na.ssl-images-amazon.com/images...	SHIRT	
46	https://images-na.ssl-images-amazon.com/images...	SHIRT	

	title	formatted_price
4	featherlite ladies long sleeve stain resistant...	$26.26
6	womens unique 100 cotton special olympics worl...	$9.99
15	featherlite ladies moisture free mesh sport sh...	$20.54
27	supernatural chibis sam dean castiel neck tshi...	$7.39
46	fifth degree womens gold foil graphic tees jun...	$6.95

[84]:
```
data.to_pickle('pickels/16k_apperal_data_preprocessed')
```

1.1 Stemming

[85]:
```
from nltk.stem.porter import *
stemmer = PorterStemmer()
print(stemmer.stem('arguing'))
print(stemmer.stem('fishing'))


# We tried using stemming on our titles and it didnot work very well.
```

```
argu
fish
```

2 [8] Text based product similarity

[86]:
```
data = pd.read_pickle('pickels/16k_apperal_data_preprocessed')
data.head()
```

[86]:

	asin	brand	color	medium_image_url	product_type_name	title	formatted_price
4	B004GSI2OS	FeatherLite	Onyx Black/ Stone	https://images-na.ssl-images-amazon.com/images...	SHIRT	featherlite ladies long sleeve stain resistant...	$26.26
6	B012YX2ZPI	HX-Kingdom Fashion T-shirts	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	womens unique 100 cotton special olympics worl...	$9.99
15	B003BSRPB0	FeatherLite	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	featherlite ladies moisture free mesh sport sh...	$20.54
27	B014ICEJ1Q	FNC7C	Purple	https://images-na.ssl-images-amazon.com/images...	SHIRT	supernatural chibis sam dean castiel neck tshi...	$7.39
46	B01NACPBG2	Fifth Degree	Black	https://images-na.ssl-images-amazon.com/images...	SHIRT	fifth degree womens gold foil graphic tees jun...	$6.95

[87]:
```
# Utility Functions which we will use through the rest of the workshop.


#Display an image
def display_img(url,ax,fig):
    # we get the url of the apparel and download it
    response = requests.get(url)
    img = Image.open(BytesIO(response.content))
    # we will display it in notebook
    plt.imshow(img)

#plotting code to understand the algorithm's decision.
def plot_heatmap(keys, values, labels, url, text):
        # keys: list of words of recommended title
        # values: len(values) ==  len(keys), values(i) represents the occurence␣
 ↪of the word keys(i)
        # labels: len(labels) == len(keys), the values of labels depends on the␣
 ↪model we are using
                # if model == 'bag of words': labels(i) = values(i)
                # if model == 'tfidf weighted bag of words':labels(i) =␣
 ↪tfidf(keys(i))
```

```
                # if model == 'idf weighted bag of words':labels(i) =␣
↪idf(keys(i))
        # url : apparel's url

        # we will devide the whole figure into two parts
        gs = gridspec.GridSpec(2, 2, width_ratios=[4,1], height_ratios=[4,1])
        fig = plt.figure(figsize=(25,3))

        # 1st, ploting heat map that represents the count of commonly ocurred␣
↪words in title2
        ax = plt.subplot(gs[0])
        # it displays a cell in white color if the word is intersection(lis of␣
↪words of title1 and list of words of title2), in black if not
        ax = sns.heatmap(np.array([values]), annot=np.array([labels]))
        ax.set_xticklabels(keys) # set that axis labels as the words of title
        ax.set_title(text) # apparel title

        # 2nd, plotting image of the the apparel
        ax = plt.subplot(gs[1])
        # we don't want any grid lines for image and no labels on x-axis and␣
↪y-axis
        ax.grid(False)
        ax.set_xticks([])
        ax.set_yticks([])

        # we call dispaly_img based with paramete url
        display_img(url, ax, fig)

        # displays combine figure ( heat map and image together)
        plt.show()

def plot_heatmap_image(doc_id, vec1, vec2, url, text, model):

    # doc_id : index of the title1
    # vec1 : input apparels's vector, it is of a dict type {word:count}
    # vec2 : recommended apparels's vector, it is of a dict type {word:count}
    # url : apparels image url
    # text: title of recomonded apparel (used to keep title of image)
    # model, it can be any of the models,
        # 1. bag_of_words
        # 2. tfidf
        # 3. idf

    # we find the common words in both titles, because these only words␣
↪contribute to the distance between two title vec's
    intersection = set(vec1.keys()) & set(vec2.keys())
```

```
    # we set the values of non intersecting words to zero, this is just to show␣
↪the difference in heatmap
    for i in vec2:
        if i not in intersection:
            vec2[i]=0

    # for labeling heatmap, keys contains list of all words in title2
    keys = list(vec2.keys())
    #  if ith word in intersection(lis of words of title1 and list of words of␣
↪title2): values(i)=count of that word in title2 else values(i)=0
    values = [vec2[x] for x in vec2.keys()]

    # labels: len(labels) == len(keys), the values of labels depends on the␣
↪model we are using
        # if model == 'bag of words': labels(i) = values(i)
        # if model == 'tfidf weighted bag of words':labels(i) = tfidf(keys(i))
        # if model == 'idf weighted bag of words':labels(i) = idf(keys(i))

    if model == 'bag_of_words':
        labels = values
    elif model == 'tfidf':
        labels = []
        for x in vec2.keys():
            # tfidf_title_vectorizer.vocabulary_ it contains all the words in␣
↪the corpus
            # tfidf_title_features[doc_id, index_of_word_in_corpus] will give␣
↪the tfidf value of word in given document (doc_id)
            if x in  tfidf_title_vectorizer.vocabulary_:
                labels.append(tfidf_title_features[doc_id,␣
↪tfidf_title_vectorizer.vocabulary_[x]])
            else:
                labels.append(0)
    elif model == 'idf':
        labels = []
        for x in vec2.keys():
            # idf_title_vectorizer.vocabulary_ it contains all the words in the␣
↪corpus
            # idf_title_features[doc_id, index_of_word_in_corpus] will give the␣
↪idf value of word in given document (doc_id)
            if x in  idf_title_vectorizer.vocabulary_:
                labels.append(idf_title_features[doc_id, idf_title_vectorizer.
↪vocabulary_[x]])
            else:
                labels.append(0)

    plot_heatmap(keys, values, labels, url, text)
```

```
# this function gets a list of wrods along with the frequency of each
# word given "text"
def text_to_vector(text):
    word = re.compile(r'\w+')
    words = word.findall(text)
    # words stores list of all words in given string, you can try 'words = text.
 ↪split()' this will also gives same result
    return Counter(words) # Counter counts the occurence of each word in list,␣
 ↪it returns dict type object {word1:count}



def get_result(doc_id, content_a, content_b, url, model):
    text1 = content_a
    text2 = content_b

    # vector1 = dict{word11:#count, word12:#count, etc.}
    vector1 = text_to_vector(text1)

    # vector1 = dict{word21:#count, word22:#count, etc.}
    vector2 = text_to_vector(text2)

    plot_heatmap_image(doc_id, vector1, vector2, url, text2, model)
```

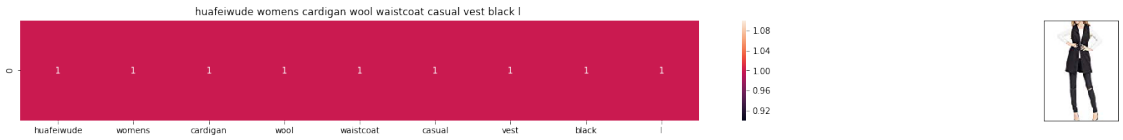
2.1 [8.2] Bag of Words (BoW) on product titles.

[88]:
```
from sklearn.feature_extraction.text import CountVectorizer
title_vectorizer = CountVectorizer()
title_features   = title_vectorizer.fit_transform(data['title'])
title_features.get_shape() # get number of rows and columns in feature matrix.
# title_features.shape = #data_points * #words_in_corpus
# CountVectorizer().fit_transform(corpus) returns
# the a sparase matrix of dimensions #data_points * #words_in_corpus

# What is a sparse vector?

# title_features[doc_id, index_of_word_in_corpus] = number of times the word␣
 ↪occured in that doc
```

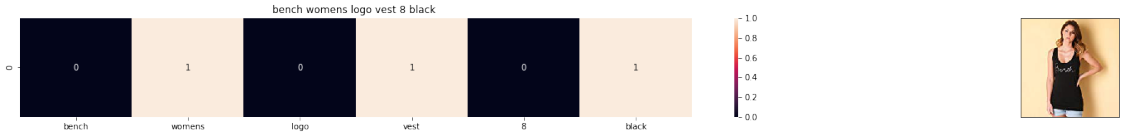
[88]:
```
(16434, 12684)
```

[91]:
```
def bag_of_words_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus
```

```
    # pairwise_dist will store the distance from given input apparel to all␣
 ↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
 ↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    pairwise_dist = pairwise_distances(title_features,title_features[doc_id])

    # np.argsort will return indices of the smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])

    for i in range(0,len(indices)):
        # we will pass 1. doc_id, 2. title1, 3. title2, url, model
        get_result(indices[i],data['title'].loc[df_indices[0]], data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]],␣
 ↪'bag_of_words')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print ('Brand:', data['brand'].loc[df_indices[i]])
        print ('Title:', data['title'].loc[df_indices[i]])
        print ('Euclidean similarity with the query image :', pdists[i])
        print('='*60)

#call the bag-of-words model for a product to get similar products.
bag_of_words_model(12566, 20) # change the index if you want to.
# In the output heat map each value represents the count value
# of the label word, the color represents the intersection
# with inputs title.

#try 12566
#try 931
```



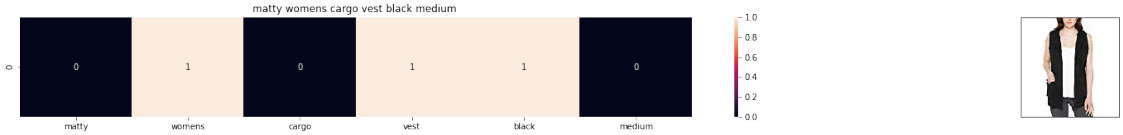

```
ASIN : B01MT96PXZ
Brand: Huafeiwude
Title: huafeiwude womens cardigan wool waistcoat casual vest black l
Euclidean similarity with the query image : 0.0
============================================================
```



ASIN : B01MXMPTAD
Brand: Bench
Title: bench womens logo vest 8 black
Euclidean similarity with the query image : 2.6457513110645907
==========

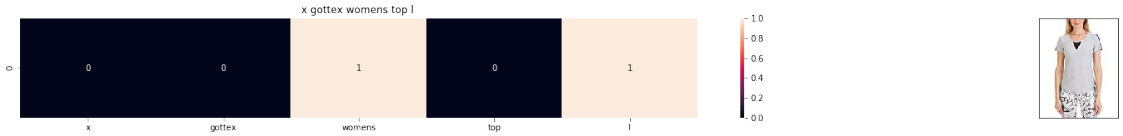
ASIN : B074KN55WS
Brand: J. McLaughlin
Title: jmclaughlin womens blouse black
Euclidean similarity with the query image : 2.8284271247461903
==========

ASIN : B074TSFJHM
Brand: M Missoni
Title: missoni womens top black
Euclidean similarity with the query image : 2.8284271247461903
==========

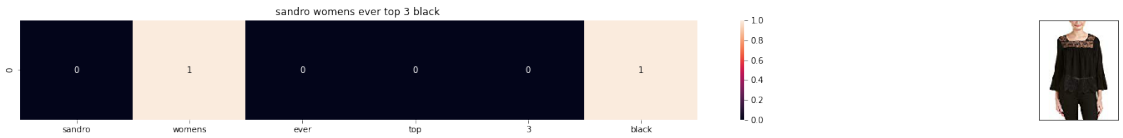


ASIN : B01LXQ055O
Brand: Matty M
Title: matty womens cargo vest black medium
Euclidean similarity with the query image : 2.8284271247461903
==

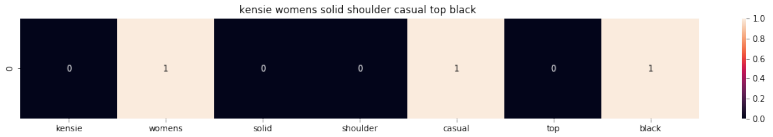
ASIN : B01EF0WPFI
Brand: ONEPICE
Title: onepice womens tegan sara waistcoat black
Euclidean similarity with the query image : 2.8284271247461903
==



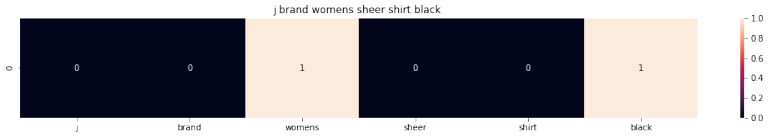
ASIN : B073M78XLP
Brand: X by Gottex
Title: x gottex womens top l
Euclidean similarity with the query image : 3.0
==



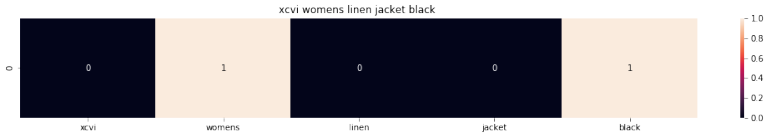
ASIN : B06XKX3BZL
Brand: Sandro
Title: sandro womens ever top 3 black
Euclidean similarity with the query image : 3.0
==



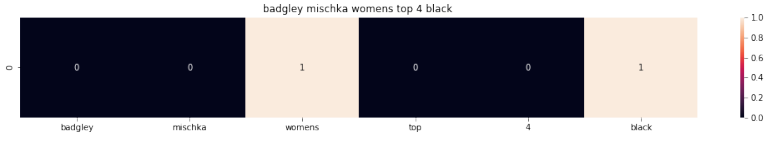
ASIN : B072HLFGT5
Brand: kensie
Title: kensie womens solid shoulder casual top black
Euclidean similarity with the query image : 3.0
==========



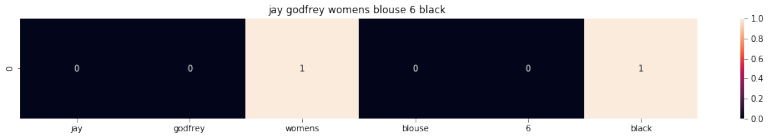
ASIN : B013L1V8PK
Brand: J Brand Jeans
Title: j brand womens sheer shirt black
Euclidean similarity with the query image : 3.0
==========



ASIN : B01M31Q4ZO
Brand: XCVI
Title: xcvi womens linen jacket black
Euclidean similarity with the query image : 3.0
==========

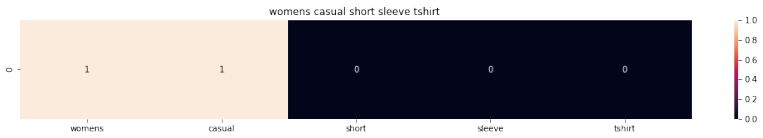


ASIN : B074TWLMJ8
Brand: Badgley Mischka
Title: badgley mischka womens top 4 black
Euclidean similarity with the query image : 3.0
==

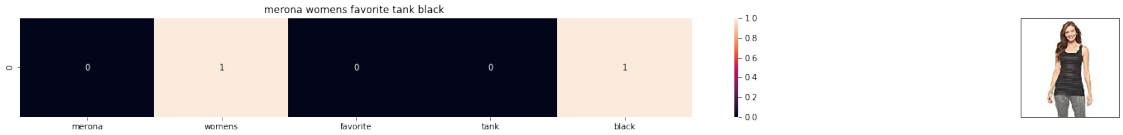


ASIN : B075B1NXKV
Brand: Jay Godfrey
Title: jay godfrey womens blouse 6 black
Euclidean similarity with the query image : 3.0
==

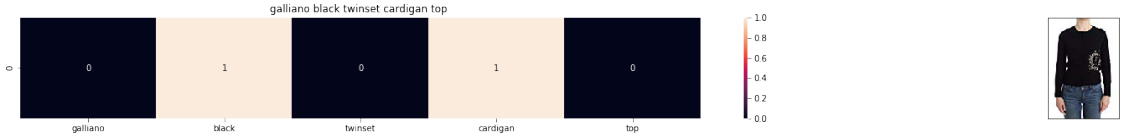
ASIN : B01IXZLJIA
Brand: Moonflow
Title: kongos lunatic womens tshirt black
Euclidean similarity with the query image : 3.0
==



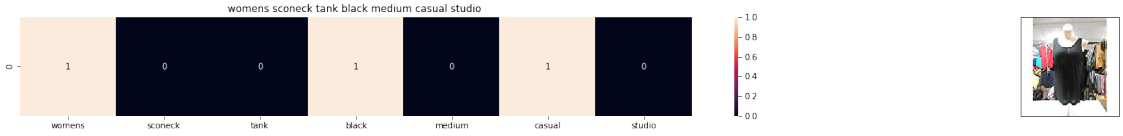
ASIN : B074T9KG9Q
Brand: Rain
Title: womens casual short sleeve tshirt
Euclidean similarity with the query image : 3.0
==



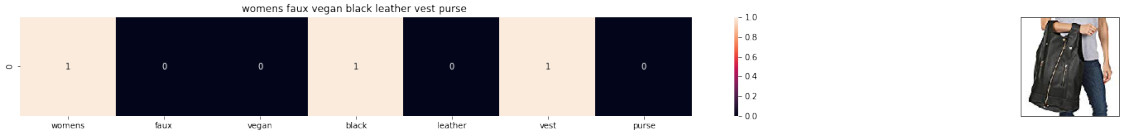
ASIN : B01KBGZE4Y
Brand: Merona
Title: merona womens favorite tank black
Euclidean similarity with the query image : 3.0
==========



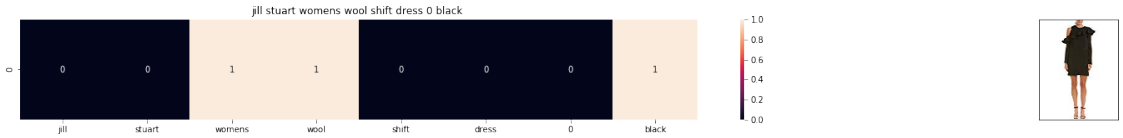
ASIN : B074G57HQJ
Brand: Galliano
Title: galliano black twinset cardigan top
Euclidean similarity with the query image : 3.0
==========



ASIN : B06ZZCKDQW
Brand: Casual Studio
Title: womens sconeck tank black medium casual studio
Euclidean similarity with the query image : 3.0
==========



```
ASIN : B01M34NPAM
Brand: WHAT ON EARTH
Title: womens faux vegan black leather vest purse
Euclidean similarity with the query image : 3.0
============================================================
```



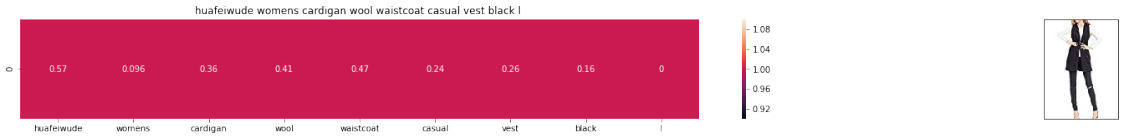

```
ASIN : B07591PX36
Brand: Jill Stuart
Title: jill stuart womens wool shift dress 0 black
Euclidean similarity with the query image : 3.0
============================================================
```

2.2 [8.5] TF-IDF based product similarity

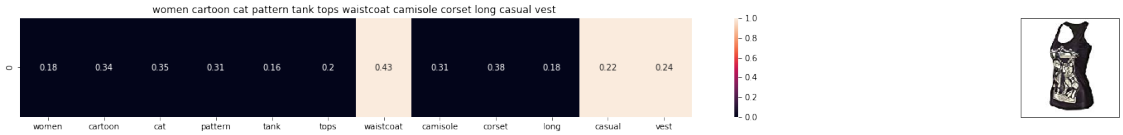
[92]:
```
tfidf_title_vectorizer = TfidfVectorizer(min_df = 0)
tfidf_title_features = tfidf_title_vectorizer.fit_transform(data['title'])
# tfidf_title_features.shape = #data_points * #words_in_corpus
# CountVectorizer().fit_transform(courpus) returns the a sparase matrix of␣
 ↪dimensions #data_points * #words_in_corpus
# tfidf_title_features[doc_id, index_of_word_in_corpus] = tfidf values of the␣
 ↪word in given doc
```

[93]:
```
def tfidf_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # pairwise_dist will store the distance from given input apparel to all␣
 ↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
 ↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    pairwise_dist =␣
 ↪pairwise_distances(tfidf_title_features,tfidf_title_features[doc_id])

    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])
```

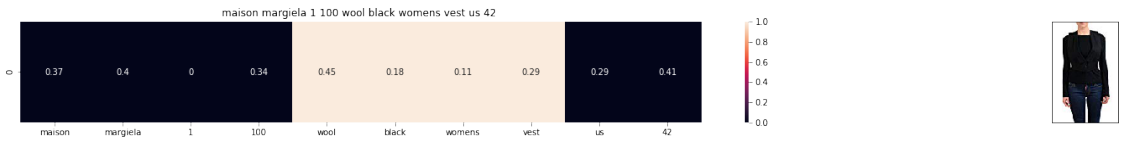
```
    for i in range(0,len(indices)):
        # we will pass 1. doc_id, 2. title1, 3. title2, url, model
        get_result(indices[i], data['title'].loc[df_indices[0]], data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], 'tfidf')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('BRAND :',data['brand'].loc[df_indices[i]])
        print ('Eucliden distance from the given image :', pdists[i])
        print('='*125)
tfidf_model(12566, 20)
# in the output heat map each value represents the tfidf values of the label␣
 ↪word, the color represents the intersection with inputs title
```



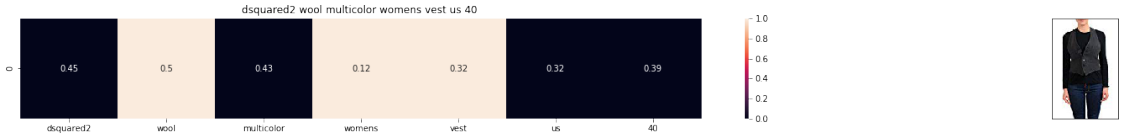

```
ASIN : B01MT96PXZ
BRAND : Huafeiwude
Eucliden distance from the given image : 0.0
=============================================================================
============================================
```




```
ASIN : B011R13YBM
BRAND : Huayang
Eucliden distance from the given image : 1.1722779213868204
=============================================================================
============================================
```



ASIN : B01N58BIEH
BRAND : Maison Margiela
Eucliden distance from the given image : 1.1859602292161415
==========
==========



ASIN : B01N2MU4DR
BRAND : DSQUARED2
Eucliden distance from the given image : 1.188600377321188
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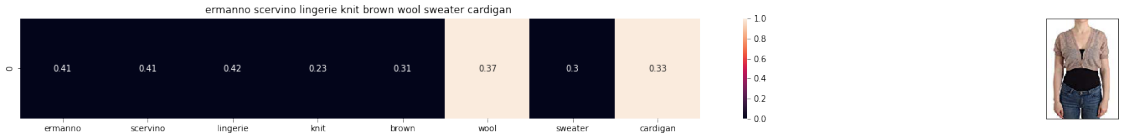

ASIN : B074G59T11
BRAND : ERMANNO SCERVINO
Eucliden distance from the given image : 1.2063594858450013
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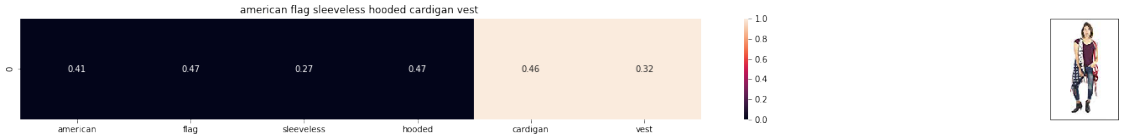

ASIN : B01MF523XO
BRAND : A&O International
Eucliden distance from the given image : 1.225015799943407
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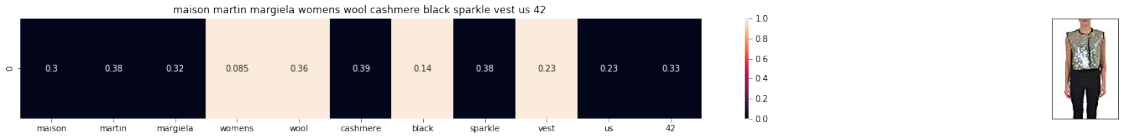

ASIN : B0175G7C20
BRAND : Maison Martin Margiela
Eucliden distance from the given image : 1.235195856747571
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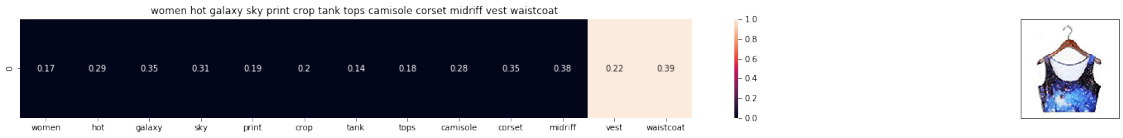

ASIN : B011R13I5Y
BRAND : Huayang
Eucliden distance from the given image : 1.2360155382228821
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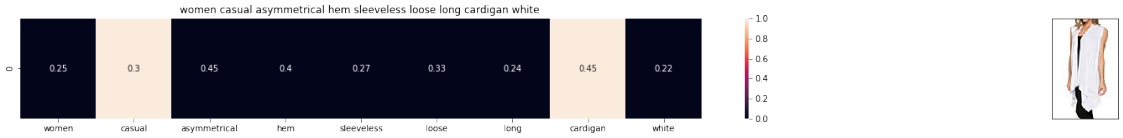

ASIN : B019V3MIP6
BRAND : KingField
Eucliden distance from the given image : 1.2364678792669093
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ASIN : B011R13T2Q
BRAND : Huayang
Eucliden distance from the given image : 1.2395445383327488
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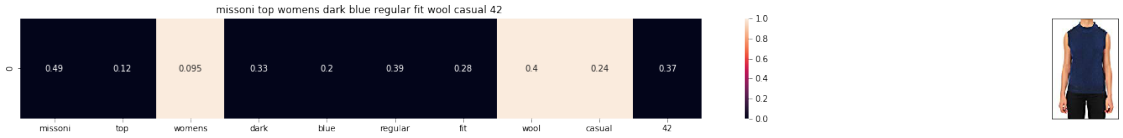

ASIN : B06XY144C5
BRAND : Missoni
Eucliden distance from the given image : 1.2415915469686625
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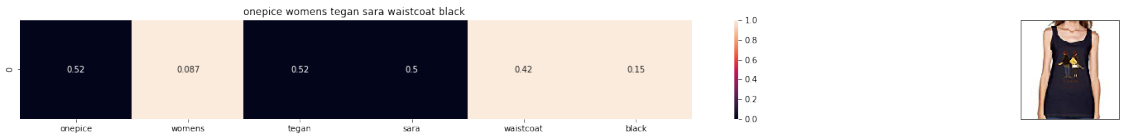

ASIN : B01EF0WPFI
BRAND : ONEPICE
Eucliden distance from the given image : 1.2416544379264938
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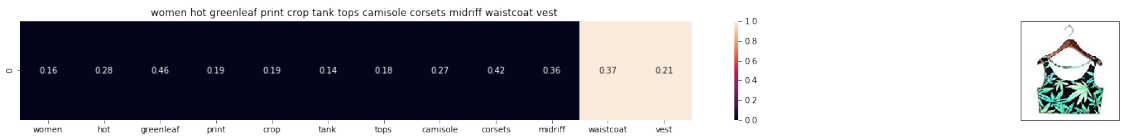

ASIN : B011R13OVW
BRAND : Huayang
Eucliden distance from the given image : 1.2428237398407327
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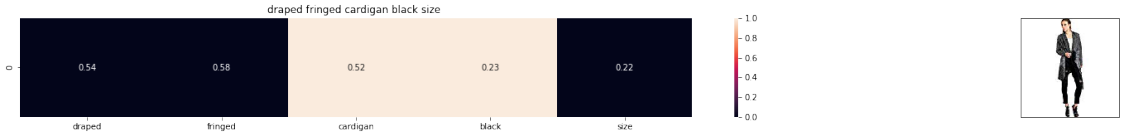

ASIN : B01CB33866
BRAND : Flying Tomato
Eucliden distance from the given image : 1.2439474778333675
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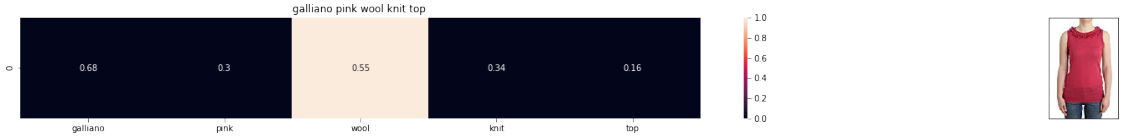

ASIN : B074G4V6NJ
BRAND : Galliano
Eucliden distance from the given image : 1.2460746241142522
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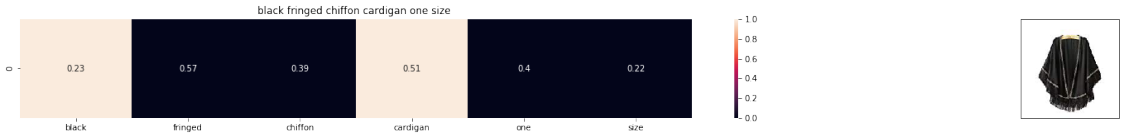

ASIN : B010AMAMLY
BRAND : HP-LEISURE
Eucliden distance from the given image : 1.2463648318197245
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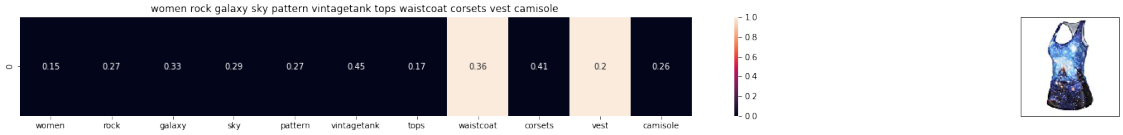

ASIN : B011R13M1O
BRAND : Huayang
Eucliden distance from the given image : 1.2479129830677687
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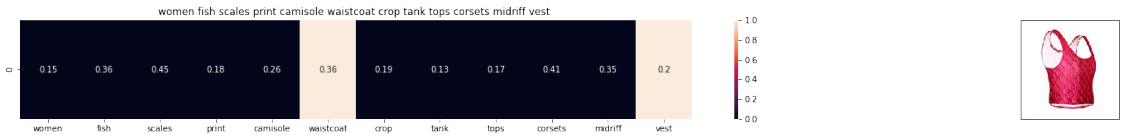

ASIN : B011R13BDS
BRAND : Huayang
Eucliden distance from the given image : 1.2479613023819631
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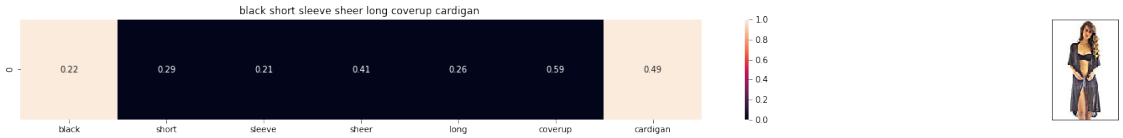

ASIN : B01GIP26MA
BRAND : Luxury Divas
Eucliden distance from the given image : 1.2521865818430968
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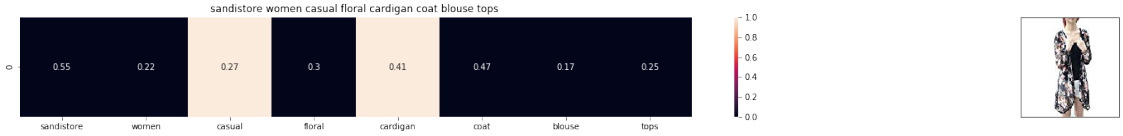


ASIN : B01AVX8IOU
BRAND : Sandistore
Eucliden distance from the given image : 1.252743839034683
==
==

2.3 [8.5] IDF based product similarity

[94]:
```
idf_title_vectorizer = CountVectorizer()
idf_title_features = idf_title_vectorizer.fit_transform(data['title'])

# idf_title_features.shape = #data_points * #words_in_corpus
# CountVectorizer().fit_transform(courpus) returns the a sparase matrix of␣
 ↪dimensions #data_points * #words_in_corpus
# idf_title_features[doc_id, index_of_word_in_corpus] = number of times the␣
 ↪word occured in that doc
```

[95]:
```
def n_containing(word):
    # return the number of documents which had the given word
    return sum(1 for blob in data['title'] if word in blob.split())

def idf(word):
    # idf = log(#number of docs / #number of docs which had the given word)
    return math.log(data.shape[0] / (n_containing(word)))
```

[96]:
```
# we need to convert the values into float
idf_title_features  = idf_title_features.astype(np.float)

for i in idf_title_vectorizer.vocabulary_.keys():
    # for every word in whole corpus we will find its idf value
    idf_val = idf(i)

    # to calculate idf_title_features we need to replace the count values with␣
 ↪the idf values of the word
    # idf_title_features[:, idf_title_vectorizer.vocabulary_[i]].nonzero()[0]␣
 ↪will return all documents in which the word i present
    for j in idf_title_features[:, idf_title_vectorizer.vocabulary_[i]].
 ↪nonzero()[0]:

        # we replace the count values of word i in document j with  idf_value␣
 ↪of word i
        # idf_title_features[doc_id, index_of_word_in_courpus] = idf value of␣
 ↪word
        idf_title_features[j,idf_title_vectorizer.vocabulary_[i]] = idf_val
```

[97]:
```
def idf_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # pairwise_dist will store the distance from given input apparel to all␣
 ↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
 ↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    pairwise_dist =␣
 ↪pairwise_distances(idf_title_features,idf_title_features[doc_id])
```

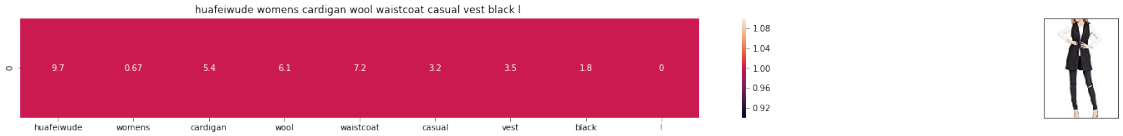
```
    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])

    for i in range(0,len(indices)):
        get_result(indices[i],data['title'].loc[df_indices[0]], data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], 'idf')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('Brand :',data['brand'].loc[df_indices[i]])
        print ('euclidean distance from the given image :', pdists[i])
        print('='*125)



idf_model(12566,20)
# in the output heat map each value represents the idf values of the label␣
 ↪word, the color represents the intersection with inputs title
```




```
ASIN : B01MT96PXZ
Brand : Huafeiwude
euclidean distance from the given image : 0.0
=============================================================================
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```


```
ASIN : B074T9KG9Q
Brand : Rain
euclidean distance from the given image : 15.615323652053057
=============================================================================
============================================
```

ASIN : B00JPOZ9GM
Brand : Sofra
euclidean distance from the given image : 15.744264266781588
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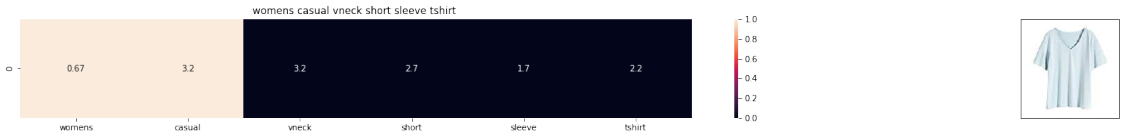

ASIN : B074V45DCX
Brand : Rain
euclidean distance from the given image : 15.945600577587768
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ASIN : B00KF2N5PU
Brand : Vietsbay
euclidean distance from the given image : 16.01194197210101
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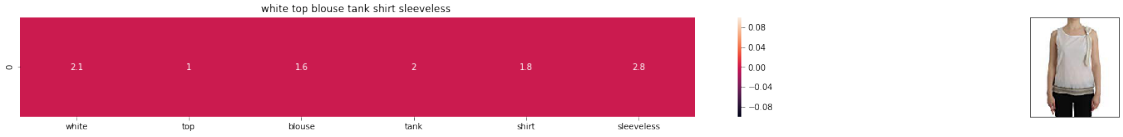

ASIN : B074G5G5RK
Brand : ERMANNO SCERVINO
euclidean distance from the given image : 16.193269507398313
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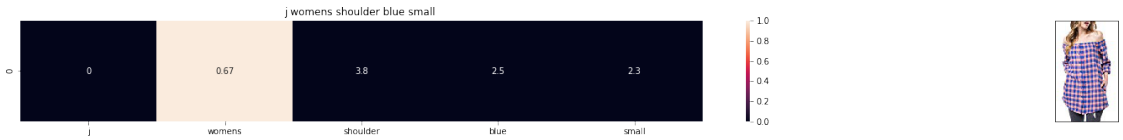

ASIN : B07583CQFT
Brand : Very J
euclidean distance from the given image : 16.2686385443419
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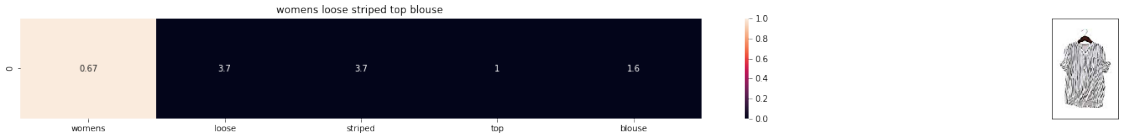

ASIN : B00ZZMYBRG
Brand : HP-LEISURE
euclidean distance from the given image : 16.426585216722245
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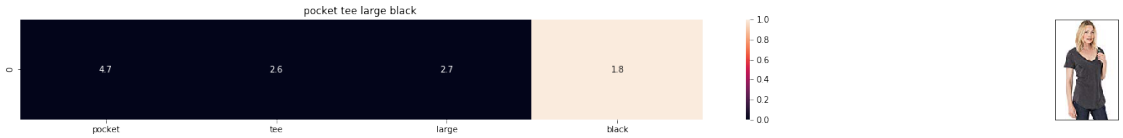

ASIN : B017I2YWUQ
Brand : Z SUPPLY
euclidean distance from the given image : 16.486585572396056
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ASIN : B073JWSM1V
Brand : Fuming
euclidean distance from the given image : 16.5367556138437
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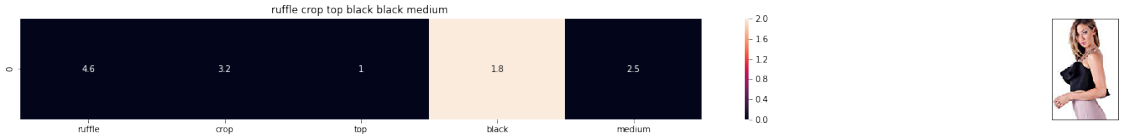

ASIN : B01HTOOL3K
Brand : Lushfox
euclidean distance from the given image : 16.564678175488137
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ASIN : B073GJGVBN
Brand : Ivan Levi
euclidean distance from the given image : 16.6575495972295
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ASIN : B00ZZPR4Y0
Brand : HP-LEISURE
euclidean distance from the given image : 16.65800447522085
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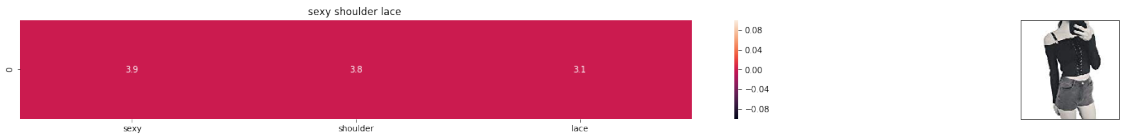

ASIN : B01JVWUB3S
Brand : bylexie
euclidean distance from the given image : 16.67188980155837
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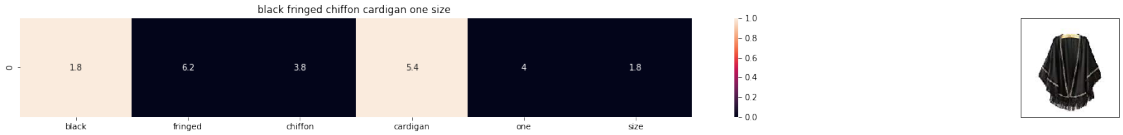

ASIN : B010AMAMLY
Brand : HP-LEISURE
euclidean distance from the given image : 16.68256175427422
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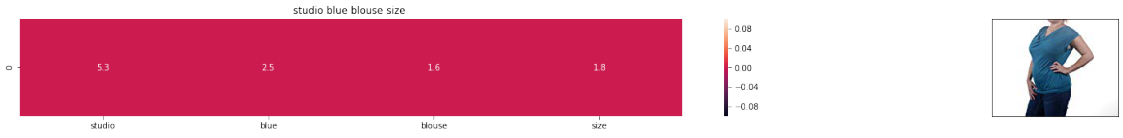

ASIN : B016P80OKQ
Brand : Studio M
euclidean distance from the given image : 16.692865428465016
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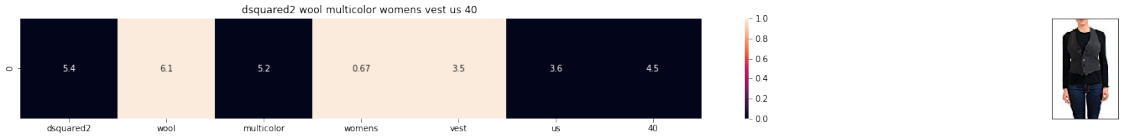

ASIN : B01N2MU4DR
Brand : DSQUARED2
euclidean distance from the given image : 16.69820390236253
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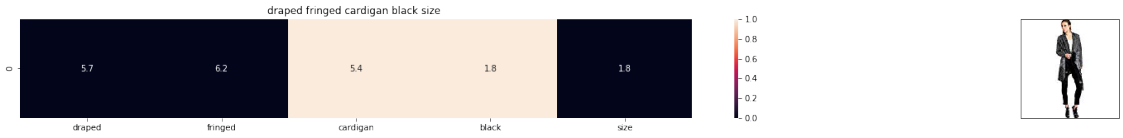

ASIN : B01CB33866
Brand : Flying Tomato
euclidean distance from the given image : 16.724506545515847
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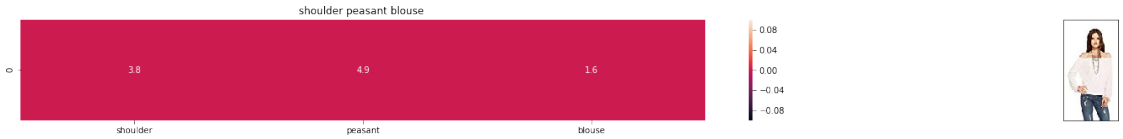

ASIN : B01E1QD5PK
Brand : CHASER
euclidean distance from the given image : 16.727657052754815
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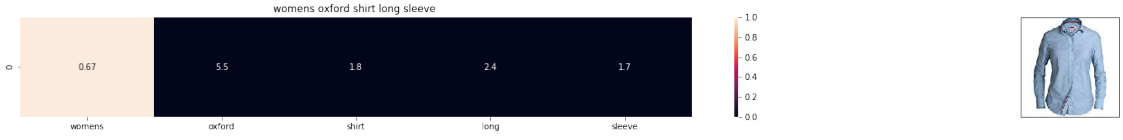

```
ASIN : B01577JZOC
Brand : Boast
euclidean distance from the given image : 16.75030833776132
================================================================================
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```

3 [9] Text Semantics based product similarity

[98]:
```
# credits: https://www.kaggle.com/c/word2vec-nlp-tutorial#part-2-word-vectors
# Custom Word2Vec using your own text data.
# Do NOT RUN this code.
# It is meant as a reference to build your own Word2Vec when you have
# lots of data.

'''
# Set values for various parameters
num_features = 300    # Word vector dimensionality
min_word_count = 1    # Minimum word count
num_workers = 4       # Number of threads to run in parallel
context = 10          # Context window size
downsampling = 1e-3   # Downsample setting for frequent words

# Initialize and train the model (this will take some time)
from gensim.models import word2vec
print ("Training model...")
model = word2vec.Word2Vec(sen_corpus, workers=num_workers, \
            size=num_features, min_count = min_word_count, \
            window = context)

'''
```

[98]:
```
'\n# Set values for various parameters\nnum_features = 300    # Word vector
dimensionality                      \nmin_word_count = 1    # Minimum word count
\nnum_workers = 4       # Number of threads to run in parallel\ncontext = 10
# Context window size
\ndownsampling = 1e-3   # Downsample setting for frequent words\n\n# Initialize
and train the model (this will take some time)\nfrom gensim.models import
word2vec\nprint ("Training model...")\nmodel = word2vec.Word2Vec(sen_corpus,
workers=num_workers,            size=num_features, min_count = min_word_count,
window = context)\n    \n'
```

[99]:
```
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

# in this project we are using a pretrained model by google
```

```
# its 3.3G file, once you load this into your memory
# it occupies ~9Gb, so please do this step only if you have >12G of ram
# we will provide a pickle file wich contains a dict ,
# and it contains all our courpus words as keys and  model[word] as values
# To use this code-snippet, download "GoogleNews-vectors-negative300.bin"
# from https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM/edit
# it's 1.9GB in size.

'''
model = KeyedVectors.load_word2vec_format('GoogleNews-vectors-negative300.bin',␣
 ↪binary=True)
'''

#if you do NOT have RAM >= 12GB, use the code below.
with open('word2vec_model', 'rb') as handle:
    model = pickle.load(handle)
```

[100]:
```
# Utility functions

def get_word_vec(sentence, doc_id, m_name):
    # sentence : title of the apparel
    # doc_id: document id in our corpus
    # m_name: model information it will take two values
        # if  m_name == 'avg', we will append the model[i], w2v representation␣
 ↪of word i
        # if m_name == 'weighted', we will multiply each w2v[word] with the␣
 ↪idf(word)
    vec = []
    for i in sentence.split():
        if i in vocab:
            if m_name == 'weighted' and i in  idf_title_vectorizer.vocabulary_:
                vec.append(idf_title_features[doc_id, idf_title_vectorizer.
 ↪vocabulary_[i]] * model[i])
            elif m_name == 'avg':
                vec.append(model[i])
        else:
            # if the word in our courpus is not there in the google word2vec␣
 ↪corpus, we are just ignoring it
            vec.append(np.zeros(shape=(300,)))
    # we will return a numpy array of shape (#number of words in title * 300 )␣
 ↪300 = len(w2v_model[word])
    # each row represents the word2vec representation of each word (weighted/
 ↪avg) in given sentance
    return  np.array(vec)

def get_distance(vec1, vec2):
```

```
    # vec1 = np.array(#number_of_words_title1 * 300), each row is a vector of␣
↪length 300 corresponds to each word in give title
    # vec2 = np.array(#number_of_words_title2 * 300), each row is a vector of␣
↪length 300 corresponds to each word in give title

    final_dist = []
    # for each vector in vec1 we caluclate the distance(euclidean) to all␣
↪vectors in vec2
    for i in vec1:
        dist = []
        for j in vec2:
            # np.linalg.norm(i-j) will result the euclidean distance between␣
↪vectors i, j
            dist.append(np.linalg.norm(i-j))
        final_dist.append(np.array(dist))
    # final_dist = np.array(#number of words in title1 * #number of words in␣
↪title2)
    # final_dist[i,j] = euclidean distance between vectors i, j
    return np.array(final_dist)


def heat_map_w2v(sentence1, sentence2, url, doc_id1, doc_id2, model):
    # sentance1 : title1, input apparel
    # sentance2 : title2, recommended apparel
    # url: apparel image url
    # doc_id1: document id of input apparel
    # doc_id2: document id of recommended apparel
    # model: it can have two values, 1. avg 2. weighted

    #s1_vec = np.array(#number_of_words_title1 * 300), each row is a␣
↪vector(weighted/avg) of length 300 corresponds to each word in give title
    s1_vec = get_word_vec(sentence1, doc_id1, model)
    #s2_vec = np.array(#number_of_words_title1 * 300), each row is a␣
↪vector(weighted/avg) of length 300 corresponds to each word in give title
    s2_vec = get_word_vec(sentence2, doc_id2, model)

    # s1_s2_dist = np.array(#number of words in title1 * #number of words in␣
↪title2)
    # s1_s2_dist[i,j] = euclidean distance between words i, j
    s1_s2_dist = get_distance(s1_vec, s2_vec)



    # devide whole figure into 2 parts 1st part displays heatmap 2nd part␣
↪displays image of apparel
    gs = gridspec.GridSpec(2, 2, width_ratios=[4,1],height_ratios=[2,1])
```

```
    fig = plt.figure(figsize=(15,15))

    ax = plt.subplot(gs[0])
    # ploting the heap map based on the pairwise distances
    ax = sns.heatmap(np.round(s1_s2_dist,4), annot=True)
    # set the x axis labels as recommended apparels title
    ax.set_xticklabels(sentence2.split())
    # set the y axis labels as input apparels title
    ax.set_yticklabels(sentence1.split())
    # set title as recommended apparels title
    ax.set_title(sentence2)

    ax = plt.subplot(gs[1])
    # we remove all grids and axis labels for image
    ax.grid(False)
    ax.set_xticks([])
    ax.set_yticks([])
    display_img(url, ax, fig)

    plt.show()
```

[101]:
```
# vocab = stores all the words that are there in google w2v model
# vocab = model.wv.vocab.keys() # if you are using Google word2Vec

vocab = model.keys()
# this function will add the vectors of each word and returns the avg vector of␣
 ↪given sentance
def build_avg_vec(sentence, num_features, doc_id, m_name):
    # sentace: its title of the apparel
    # num_features: the lenght of word2vec vector, its values = 300
    # m_name: model information it will take two values
        # if  m_name == 'avg', we will append the model[i], w2v representation␣
 ↪of word i
        # if m_name == 'weighted', we will multiply each w2v[word] with the␣
 ↪idf(word)

    featureVec = np.zeros((num_features,), dtype="float32")
    # we will intialize a vector of size 300 with all zeros
    # we add each word2vec(wordi) to this fetureVec
    nwords = 0

    for word in sentence.split():
        nwords += 1
        if word in vocab:
            if m_name == 'weighted' and word in  idf_title_vectorizer.
 ↪vocabulary_:
```

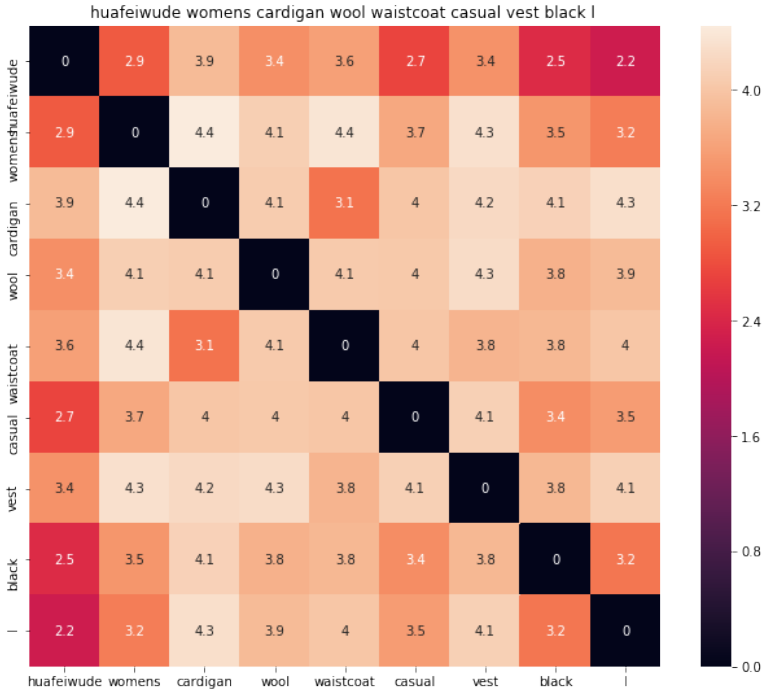
```
                featureVec = np.add(featureVec, idf_title_features[doc_id,␣
↪idf_title_vectorizer.vocabulary_[word]] * model[word])
            elif m_name == 'avg':
                featureVec = np.add(featureVec, model[word])
    if(nwords>0):
        featureVec = np.divide(featureVec, nwords)
    # returns the avg vector of given sentance, its of shape (1, 300)
    return featureVec
```

3.0.1 [9.2] Average Word2Vec product similarity.

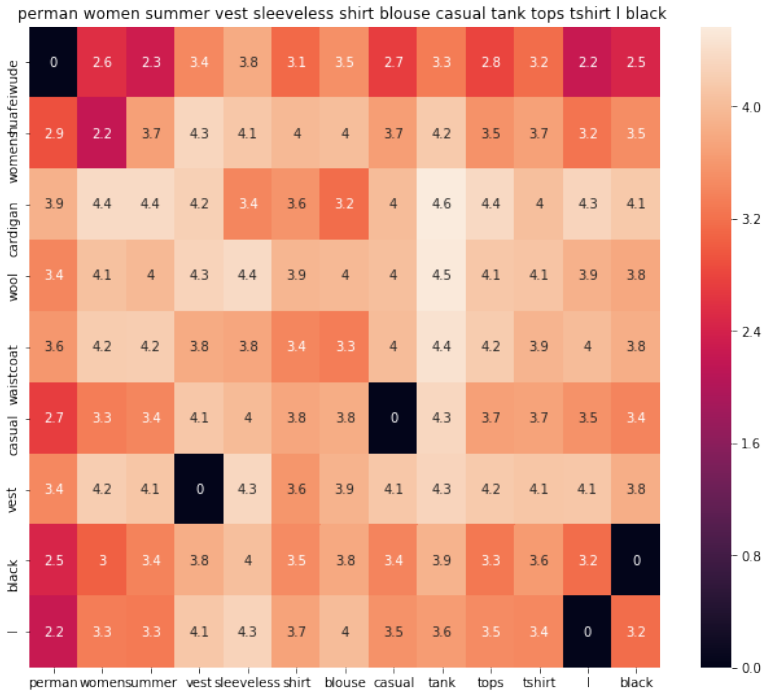
[102]:
```
doc_id = 0
w2v_title = []
# for every title we build a avg vector representation
for i in data['title']:
    w2v_title.append(build_avg_vec(i, 300, doc_id,'avg'))
    doc_id += 1

# w2v_title = np.array(# number of doc in courpus * 300), each row corresponds␣
↪to a doc
w2v_title = np.array(w2v_title)
```

[104]:
```
def avg_w2v_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # dist(x, y) = sqrt(dot(x, x) - 2 * dot(x, y) + dot(y, y))
    pairwise_dist = pairwise_distances(w2v_title, w2v_title[doc_id].
↪reshape(1,-1))

    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])

    for i in range(0, len(indices)):
        heat_map_w2v(data['title'].loc[df_indices[0]],data['title'].
↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], indices[0],␣
↪indices[i], 'avg')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('BRAND :',data['brand'].loc[df_indices[i]])
        print ('euclidean distance from given input image :', pdists[i])
        print('='*125)
```

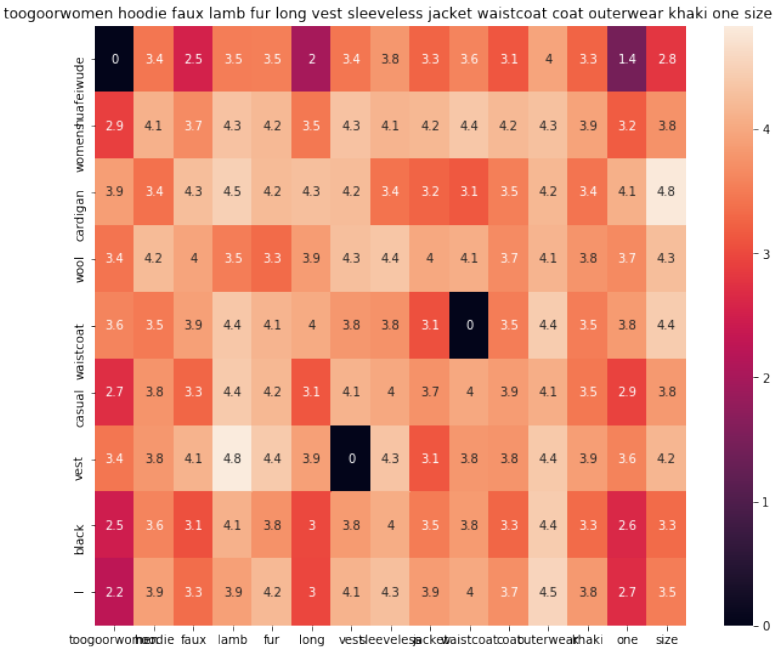
```
avg_w2v_model(12566, 20)
# in the give heat map, each cell contains the euclidean distance between words␣
 ↪i, j
```



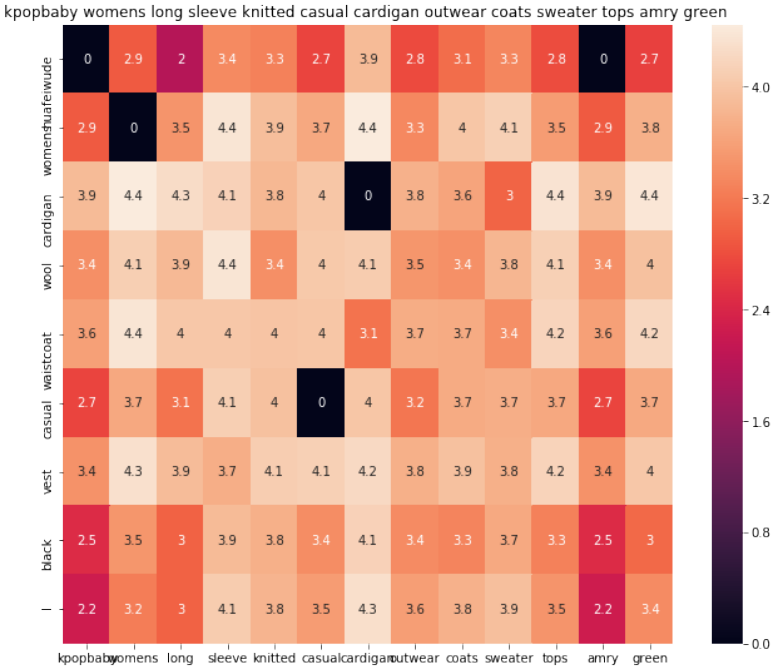
```
ASIN : B01MT96PXZ
BRAND : Huafeiwude
euclidean distance from given input image : 0.0
============================================================================
============================================
```



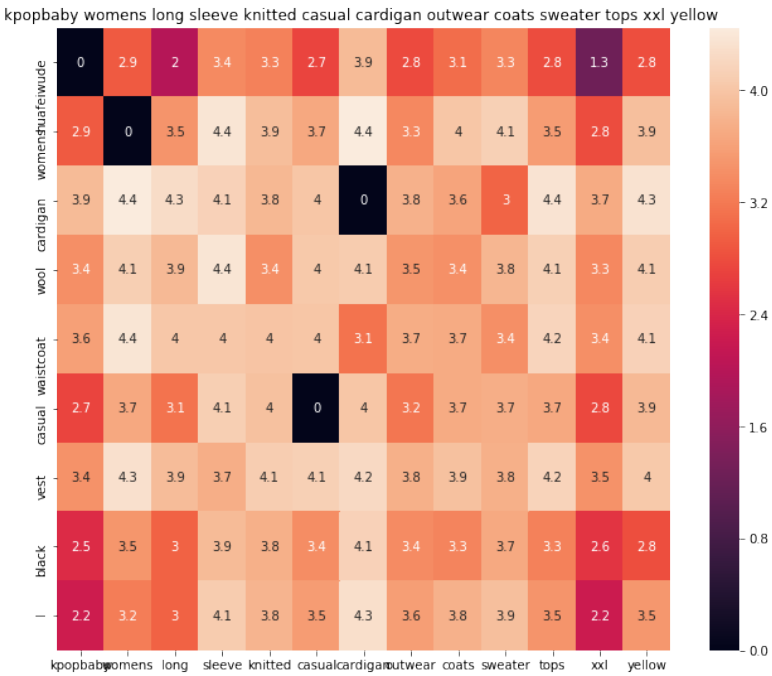
ASIN : B01F852VDK
BRAND : Perman
euclidean distance from given input image : 0.8539957
==========
==========



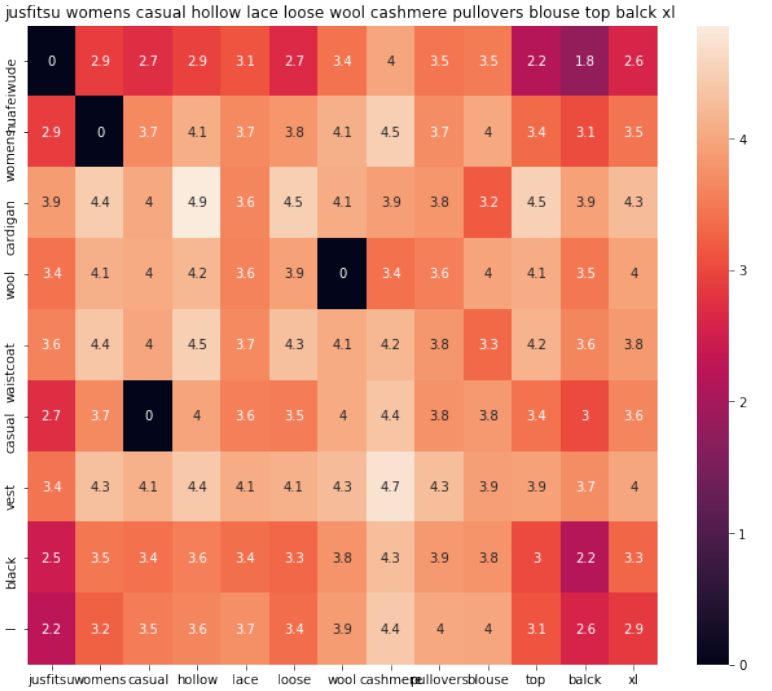
ASIN : B00R10GCHC
BRAND : TOOGOO(R)
euclidean distance from given input image : 0.8619427
==========
==========



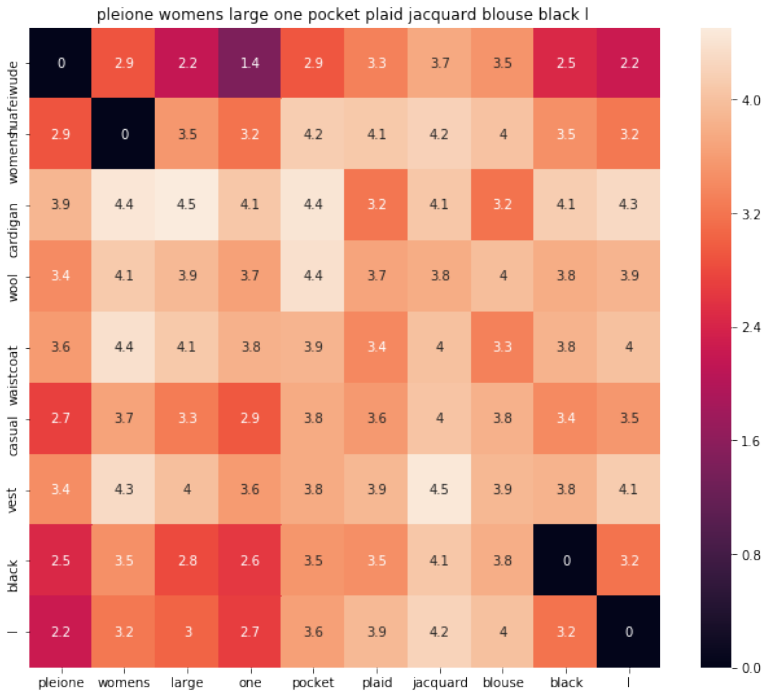
ASIN : B074LD7G7K
BRAND : KpopBaby
euclidean distance from given input image : 0.87473196
==========
==========



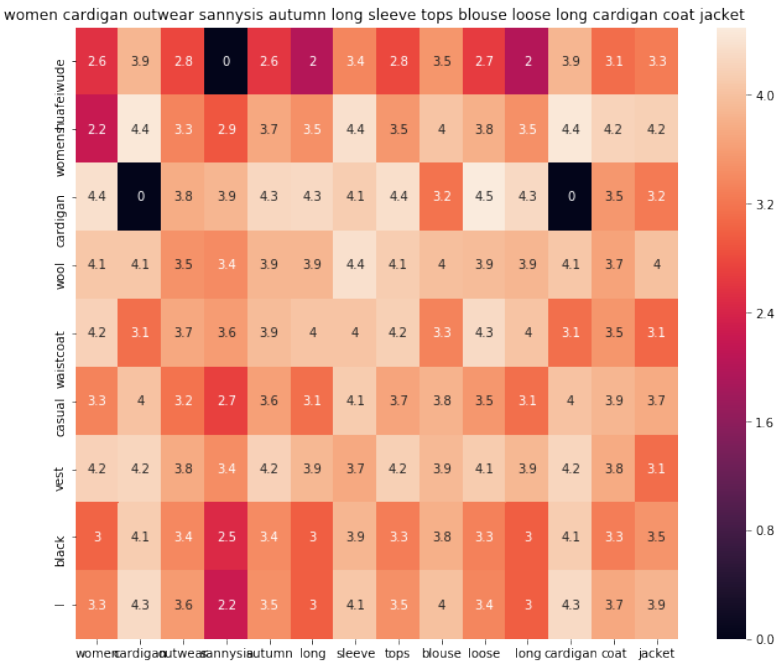
ASIN : B074LCPJJZ
BRAND : KpopBaby
euclidean distance from given input image : 0.88326466
==========
==========



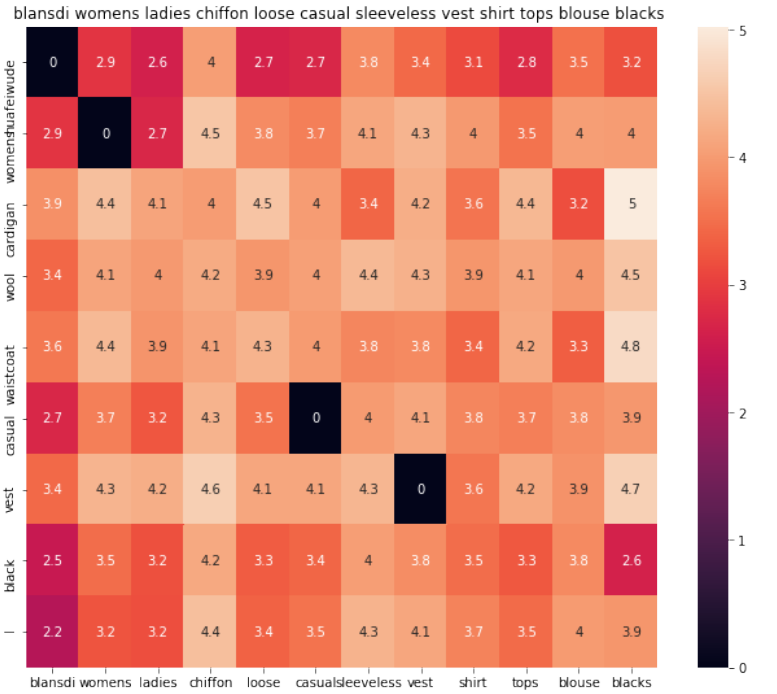
ASIN : B01N96GX38
BRAND : Jusfitsu
euclidean distance from given input image : 0.8868851
==========
==========



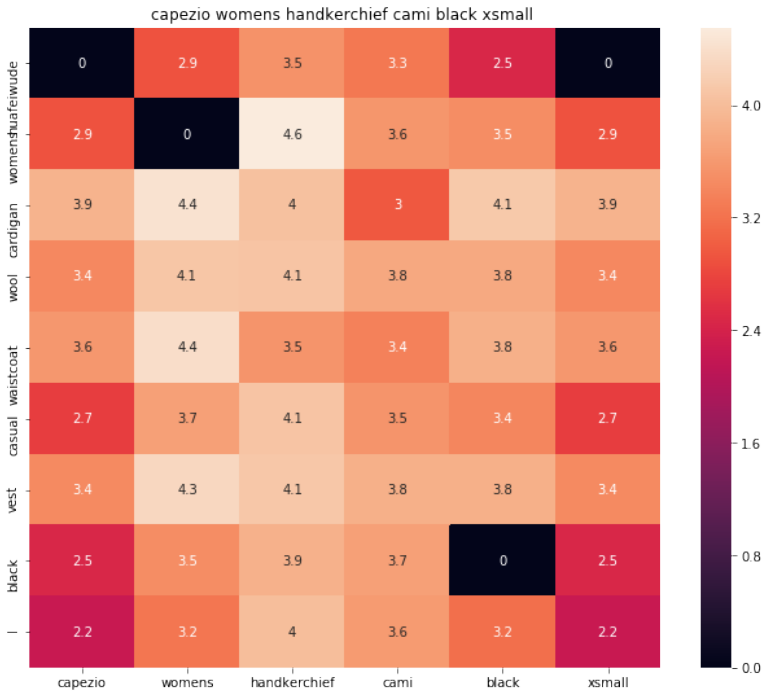
ASIN : B06XGQ9CSM
BRAND : Pleione
euclidean distance from given input image : 0.8881678
==========
==========



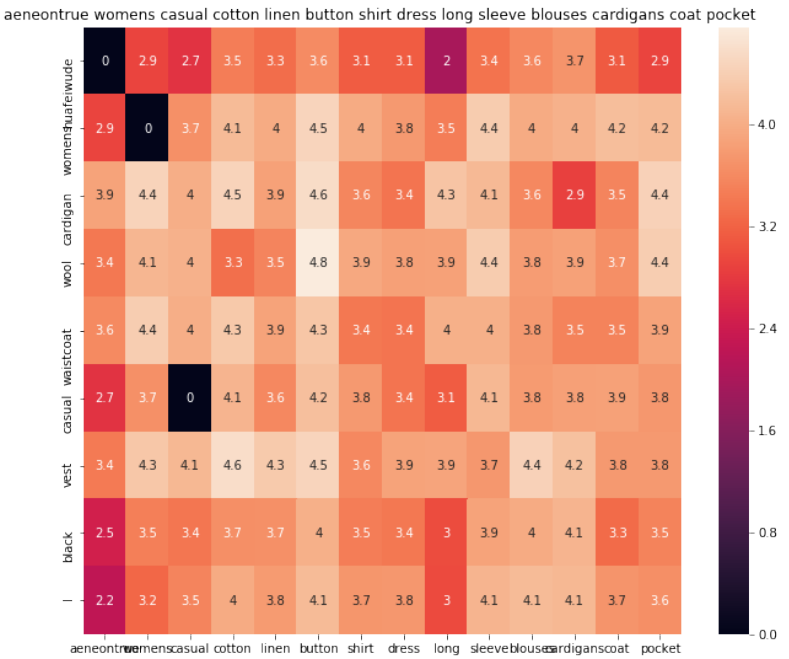
ASIN : B07473KFK1
BRAND : Sannysis
euclidean distance from given input image : 0.89271647
==========
==========



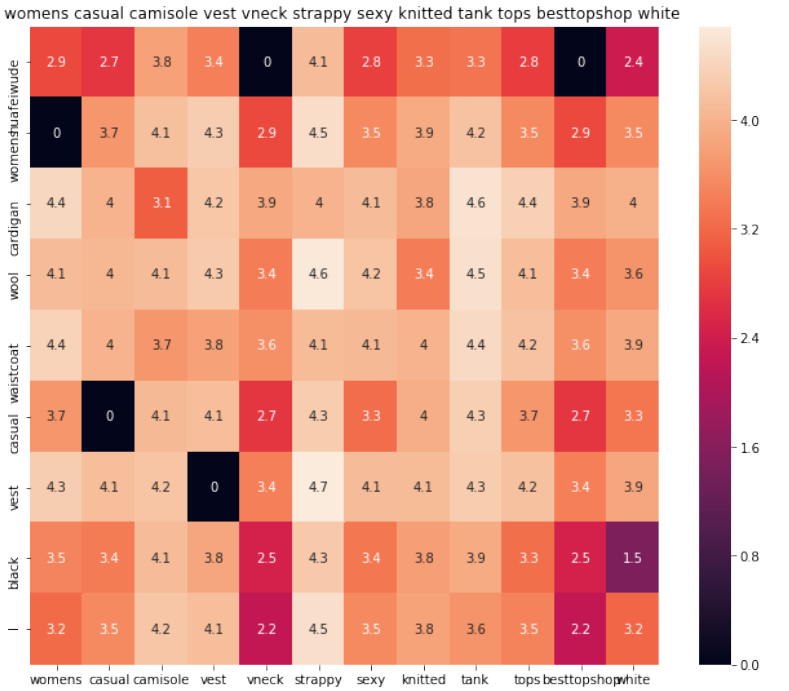
ASIN : B01B3Y99XA
BRAND : Blansdi
euclidean distance from given input image : 0.8936688
==========
==========



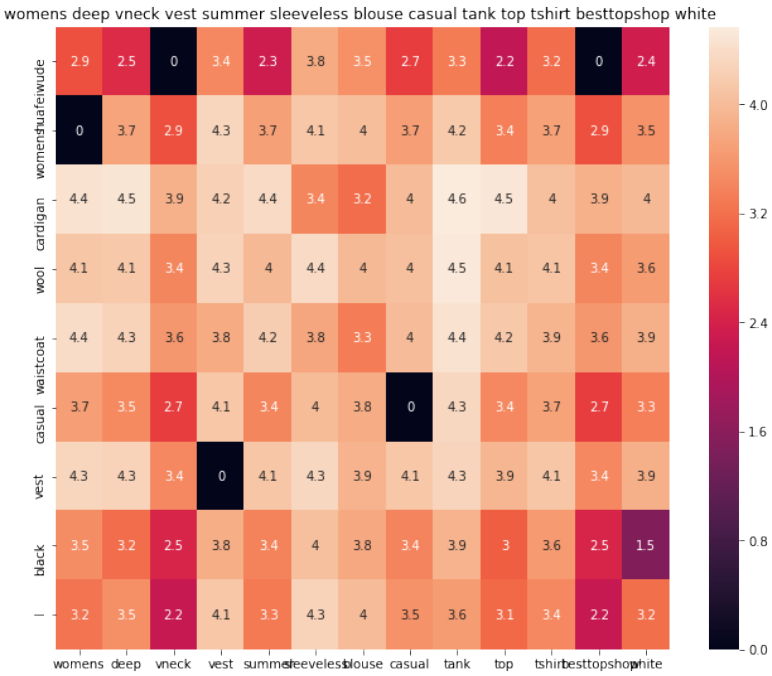
ASIN : B00ZIY47WA
BRAND : Capezio
euclidean distance from given input image : 0.89525115
==========
==========



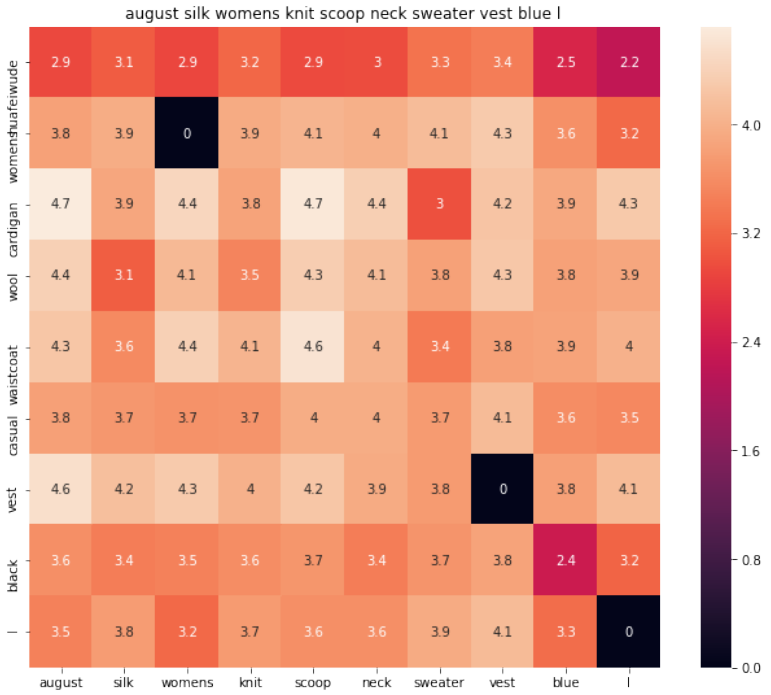
ASIN : B074V1K5QJ
BRAND : Aeneontrue
euclidean distance from given input image : 0.9028107
==========
==========



ASIN : B071XV9DKH
BRAND : Best Music Posters
euclidean distance from given input image : 0.9065367
==========
==========

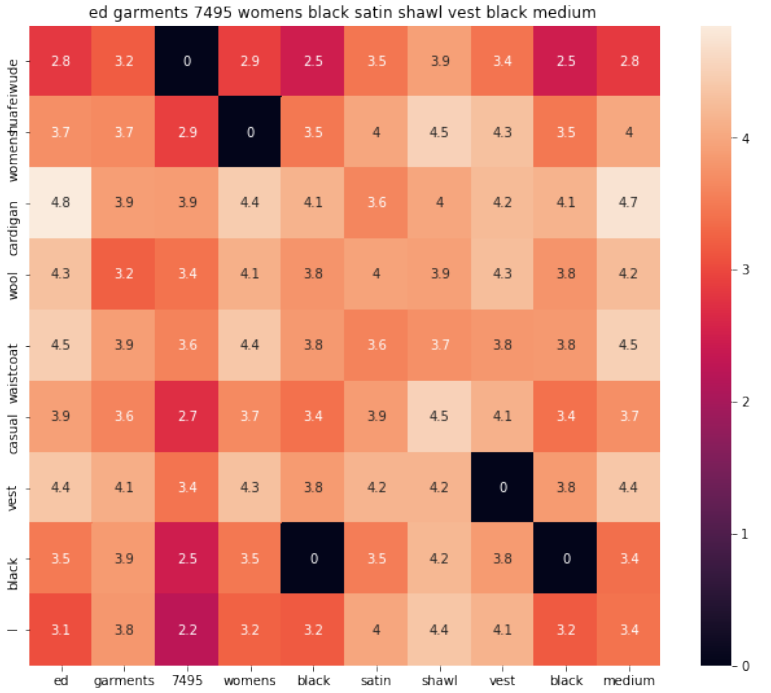


ASIN : B071Y6W6D8
BRAND : Best Music Posters
euclidean distance from given input image : 0.9093141
==========
==========

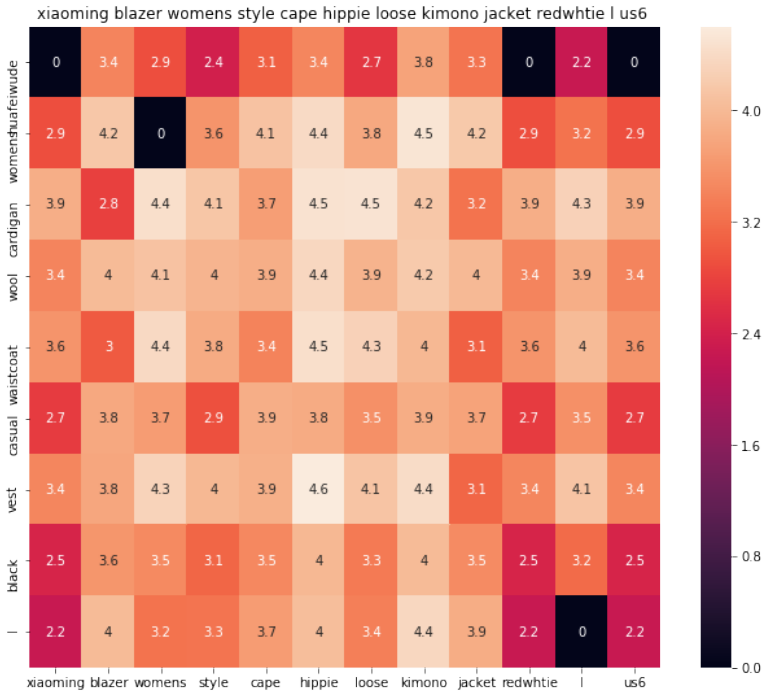


ASIN : B06X6N47HY
BRAND : August Silk
euclidean distance from given input image : 0.9097892
==========
==========

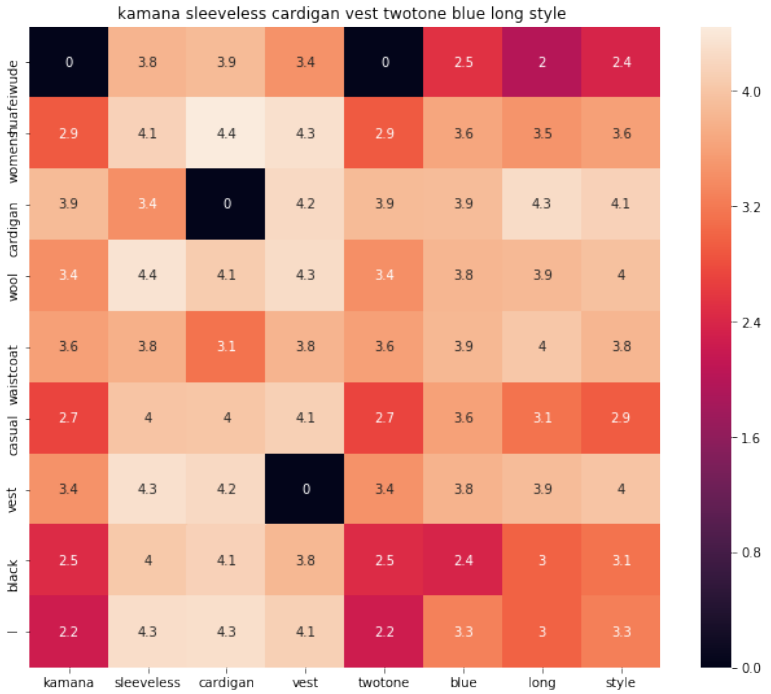
ASIN : B0175AT71K
BRAND : Just Cavalli
euclidean distance from given input image : 0.9117741
==========
==========



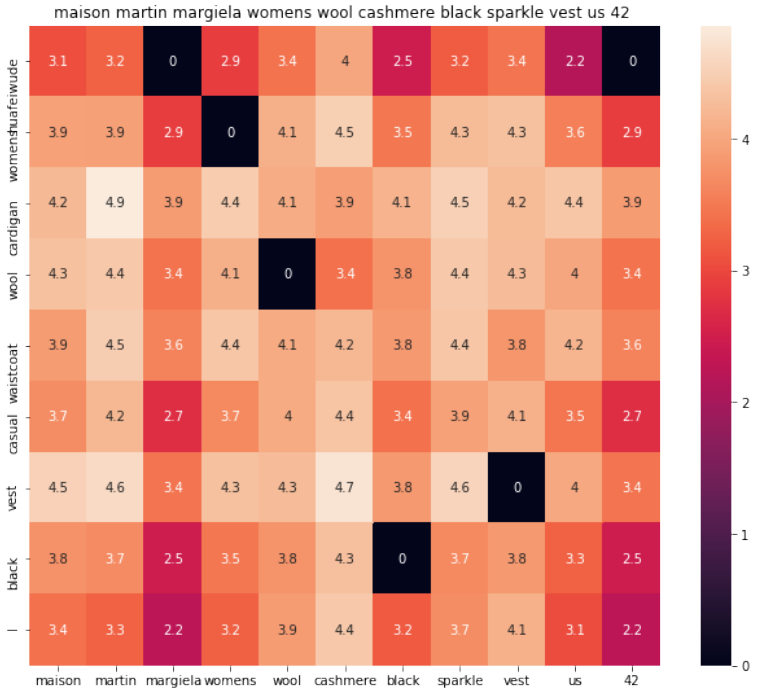
ASIN : B007X49OCG
BRAND : Edwards Garment
euclidean distance from given input image : 0.91356814
==========
==========



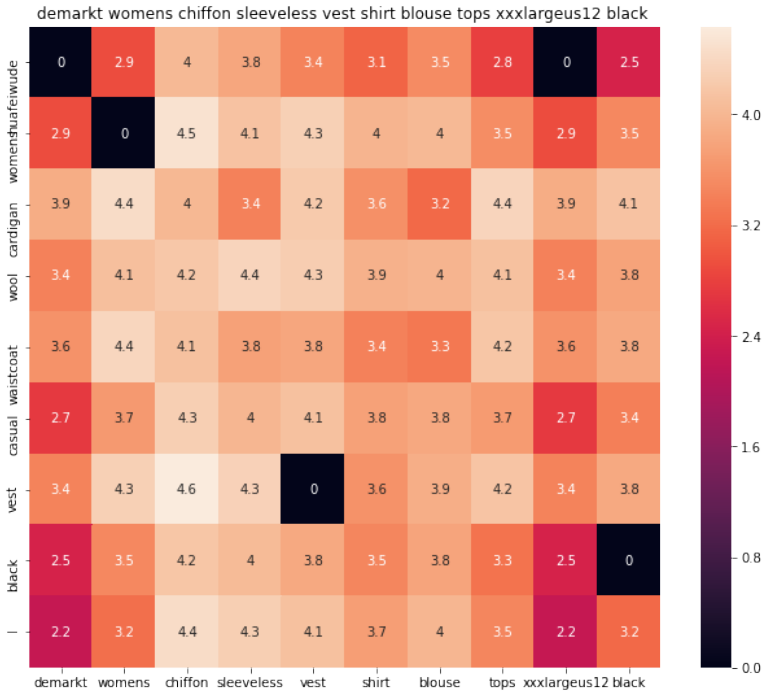
ASIN : B00WPK4T4G
BRAND : xiaoming
euclidean distance from given input image : 0.9149437
==========
==========



ASIN : B0751686K7
BRAND : Kamana
euclidean distance from given input image : 0.917094
==========
==========



ASIN : B0175G7C20
BRAND : Maison Martin Margiela
euclidean distance from given input image : 0.9177549
==========
==========



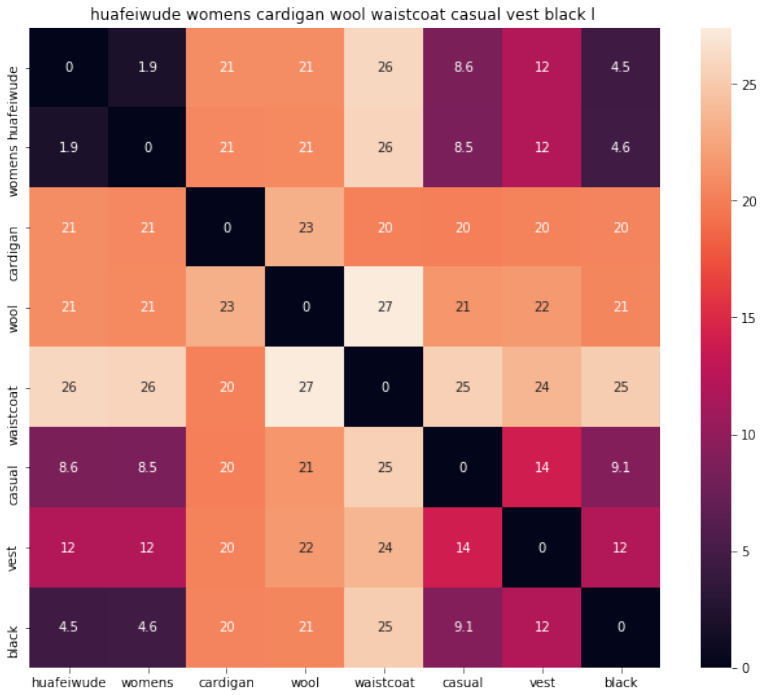
```
ASIN : B00JKCQZJE
BRAND : Demarkt
euclidean distance from given input image : 0.917883
================================================================================
============================================
```

3.0.2 [9.4] IDF weighted Word2Vec for product similarity

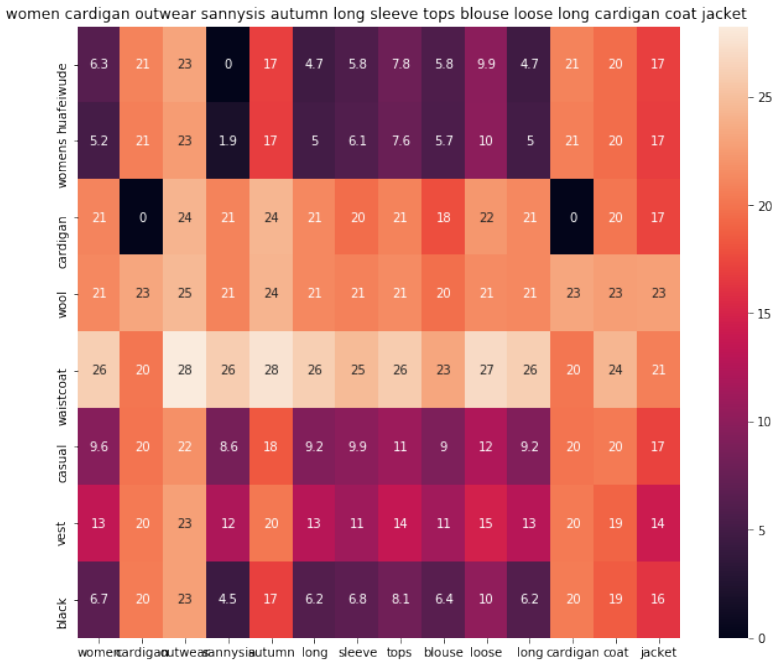
[105]:
```
doc_id = 0
w2v_title_weight = []
# for every title we build a weighted vector representation
for i in data['title']:
    w2v_title_weight.append(build_avg_vec(i, 300, doc_id,'weighted'))
    doc_id += 1
# w2v_title = np.array(# number of doc in courpus * 300), each row corresponds␣
 ↪to a doc
w2v_title_weight = np.array(w2v_title_weight)
```

[106]:
```
def weighted_w2v_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # pairwise_dist will store the distance from given input apparel to all␣
 ↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
 ↪Y) = <X, Y> / (||X||*||Y||)
```

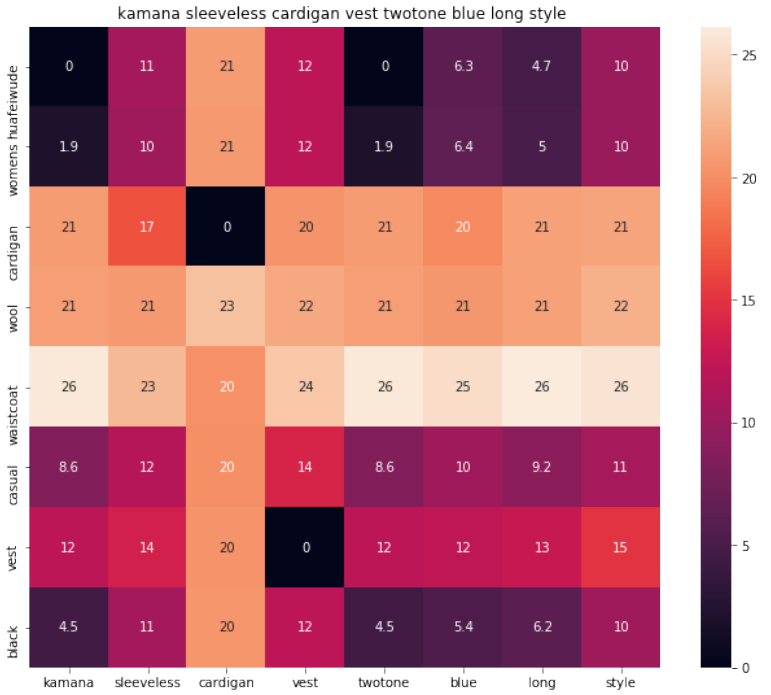
```
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    pairwise_dist = pairwise_distances(w2v_title_weight,␣
 ↪w2v_title_weight[doc_id].reshape(1,-1))

    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])

    for i in range(0, len(indices)):
        heat_map_w2v(data['title'].loc[df_indices[0]],data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], indices[0],␣
 ↪indices[i], 'weighted')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('Brand :',data['brand'].loc[df_indices[i]])
        print('euclidean distance from input :', pdists[i])
        print('='*125)

weighted_w2v_model(12566, 20)
#931
#12566
# in the give heat map, each cell contains the euclidean distance between words␣
 ↪i, j
```



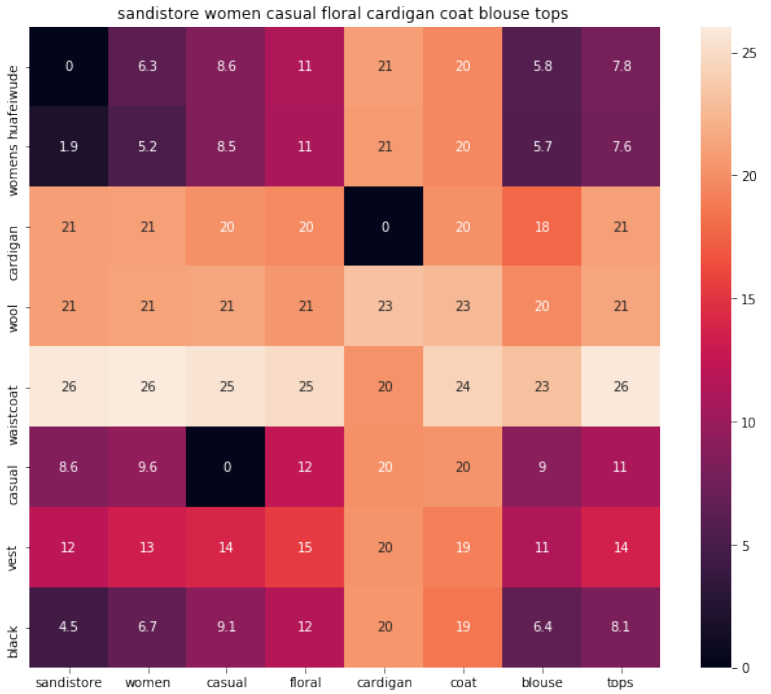
ASIN : B01MT96PXZ
Brand : Huafeiwude
euclidean distance from input : 0.0
==========
==========



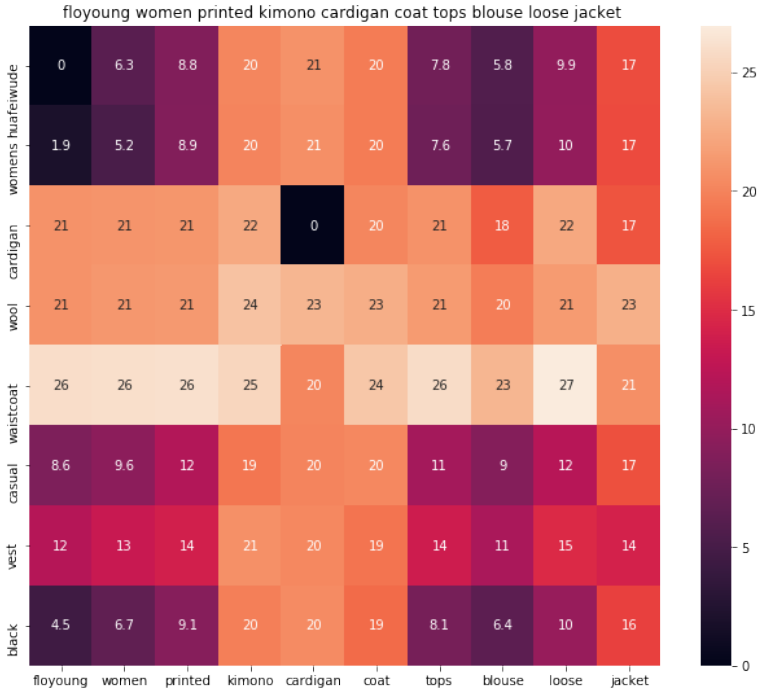
ASIN : B07473KFK1
Brand : Sannysis
euclidean distance from input : 3.7969613
==========
==========



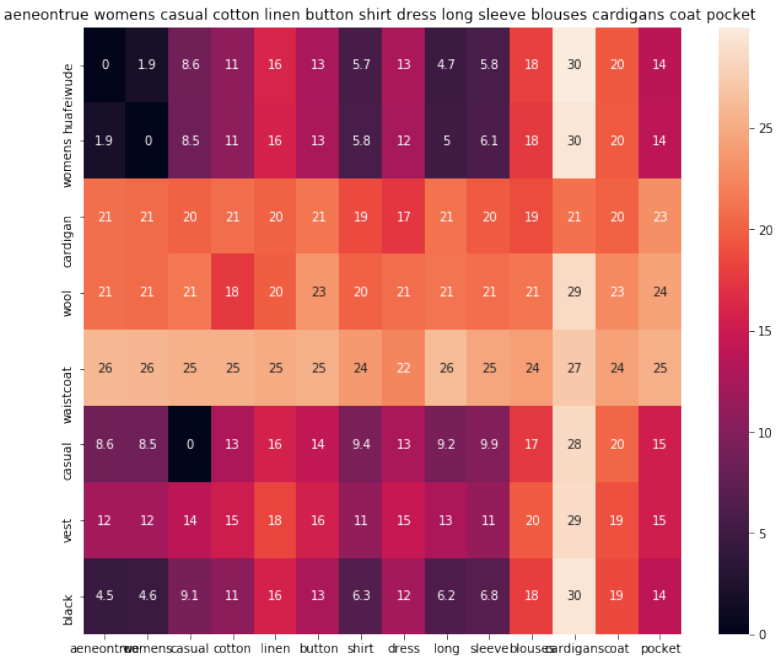
ASIN : B0751686K7
Brand : Kamana
euclidean distance from input : 3.9051597
==========
==========



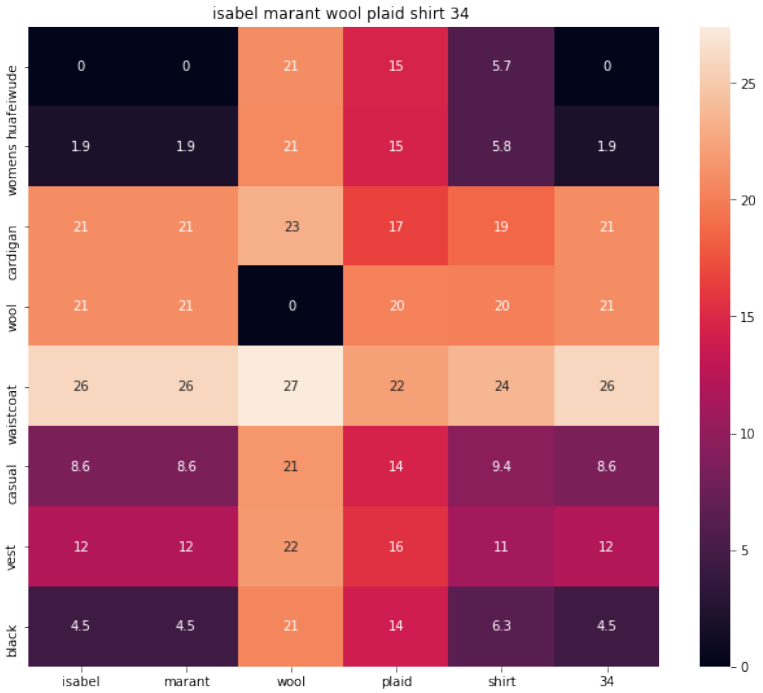
ASIN : B01AVX8IOU
Brand : Sandistore
euclidean distance from input : 3.9728305
==
==



ASIN : B01D6EUG3W
Brand : FloYoung
euclidean distance from input : 3.9933598
==
==



ASIN : B074V1K5QJ
Brand : Aeneontrue
euclidean distance from input : 4.0558114
==========
==========



ASIN : B074NBDL2W
Brand : Isabel Marant
euclidean distance from input : 4.211965
==========
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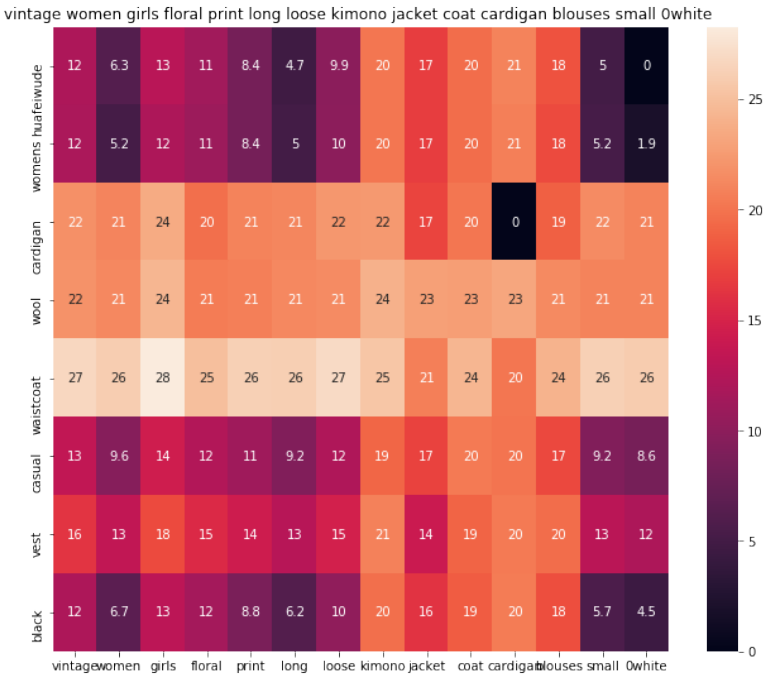

ASIN : B07375JCKD
Brand : ACEFAST INC
euclidean distance from input : 4.2146835
==========
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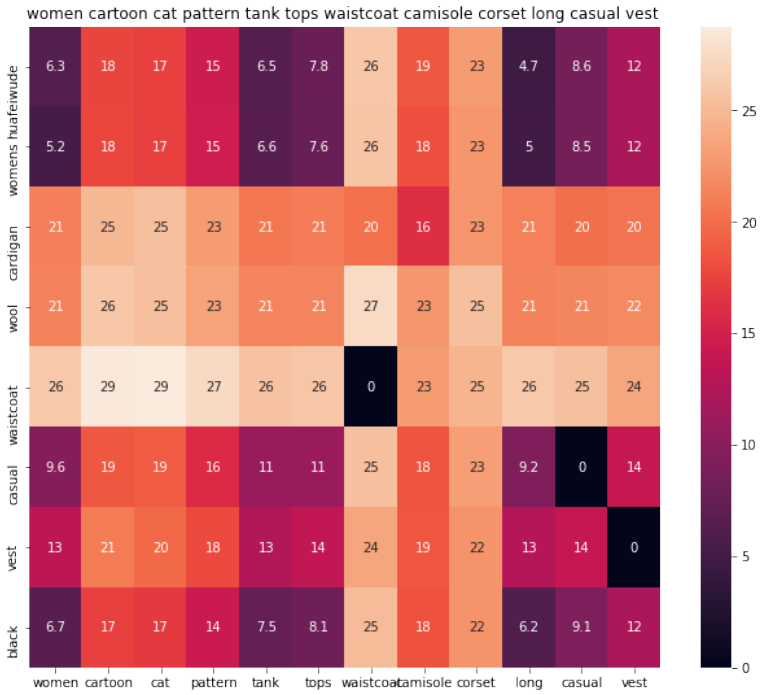

ASIN : B011R13YBM
Brand : Huayang
euclidean distance from input : 4.2270885
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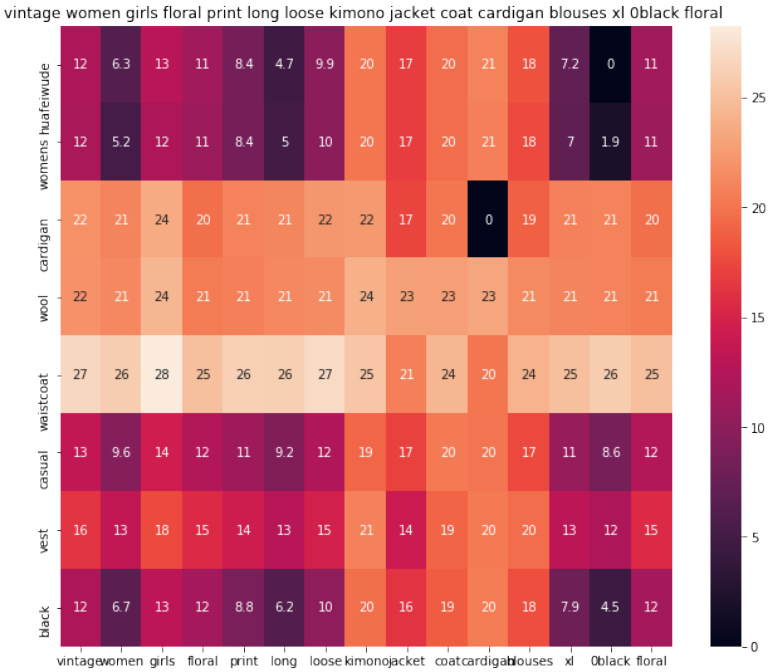

ASIN : B073PNYB2S
Brand : ACEFAST INC
euclidean distance from input : 4.2848
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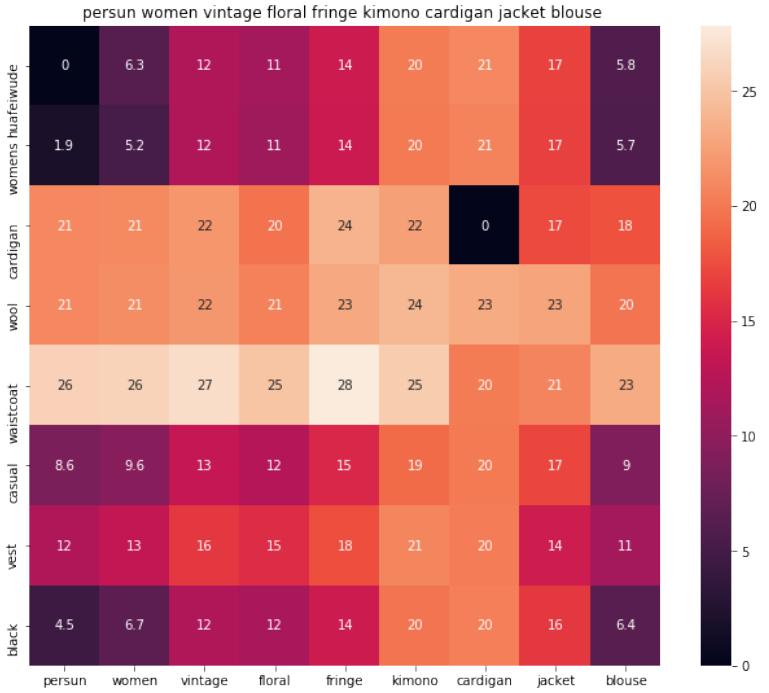

ASIN : B00Y26RSRQ
Brand : Persun
euclidean distance from input : 4.2976522
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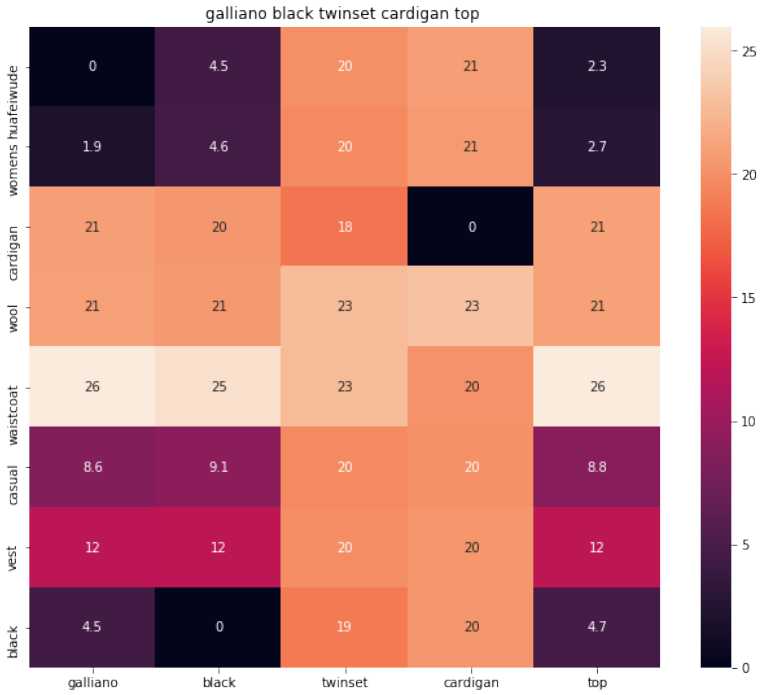

ASIN : B074G57HQJ
Brand : Galliano
euclidean distance from input : 4.3163776
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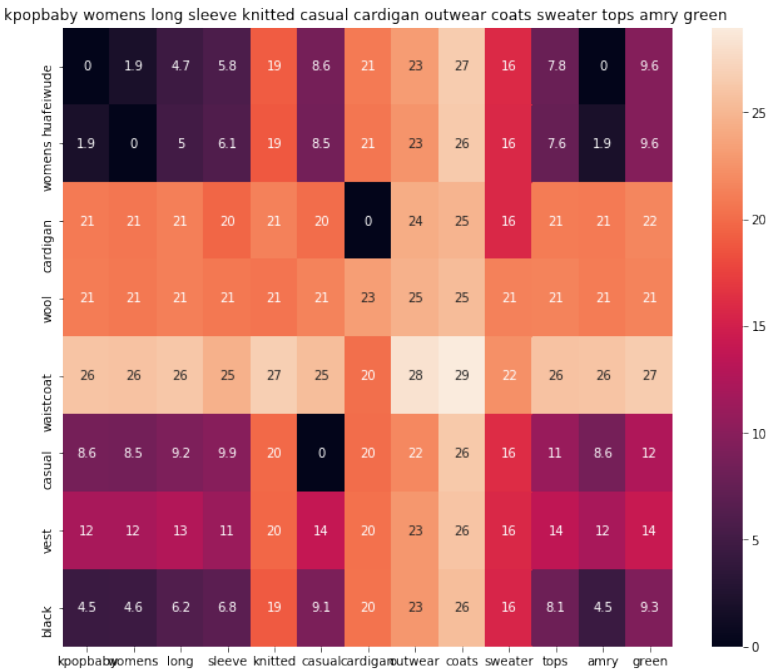

ASIN : B074LD7G7K
Brand : KpopBaby
euclidean distance from input : 4.35567
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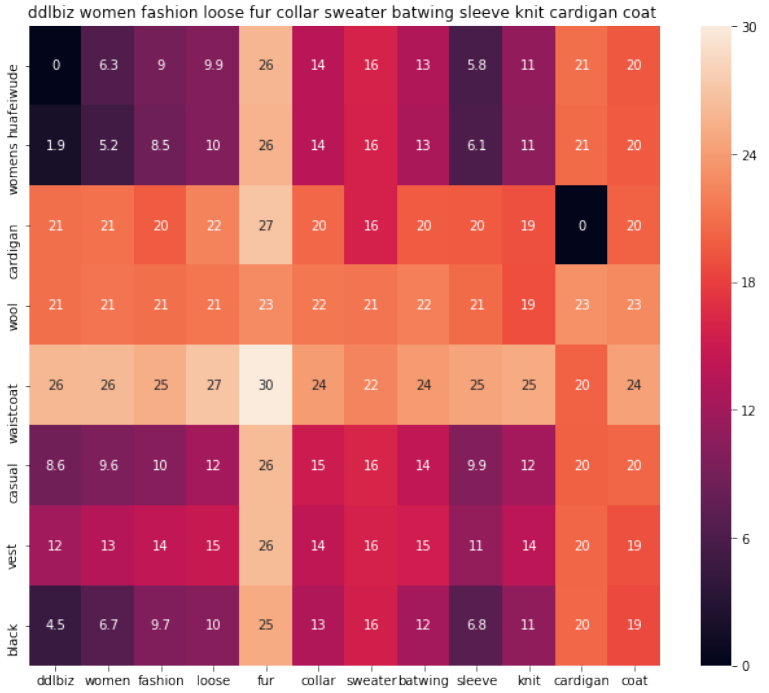

ASIN : B01MY76AQJ
Brand : DDLBiz
euclidean distance from input : 4.408304
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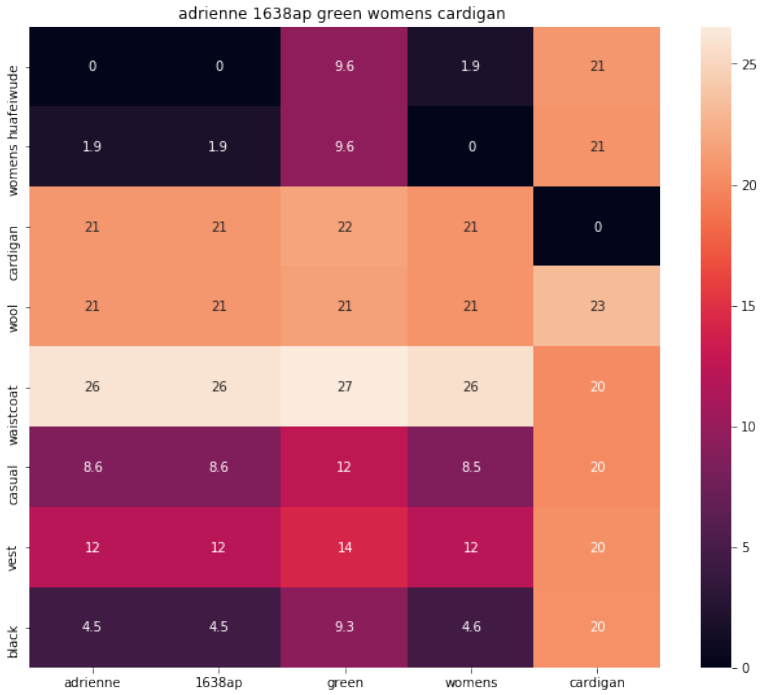

ASIN : B00O1HWO5W
Brand : Liuqiuhu
euclidean distance from input : 4.422664
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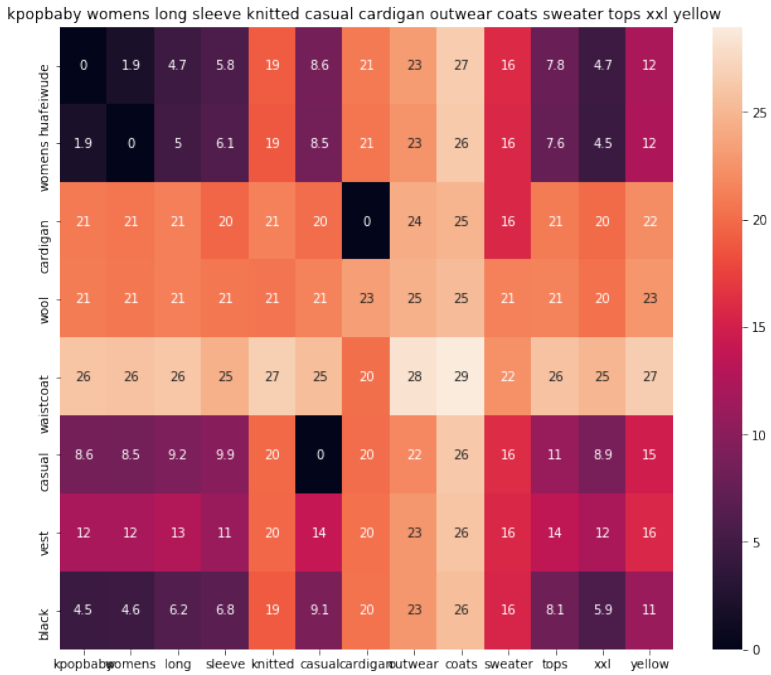

ASIN : B074LCPJJZ
Brand : KpopBaby
euclidean distance from input : 4.499772
==
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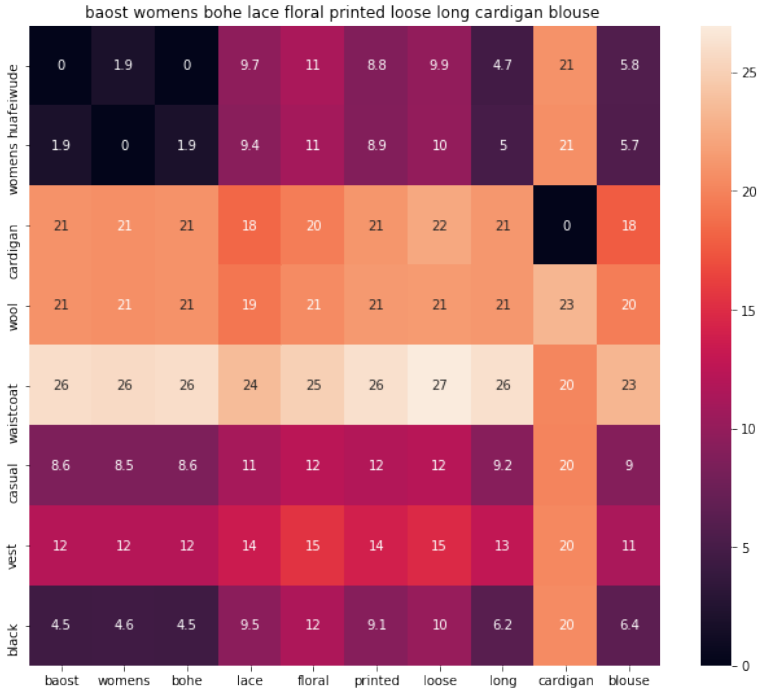

ASIN : B01GTA9352
Brand : Baost
euclidean distance from input : 4.5200267
==
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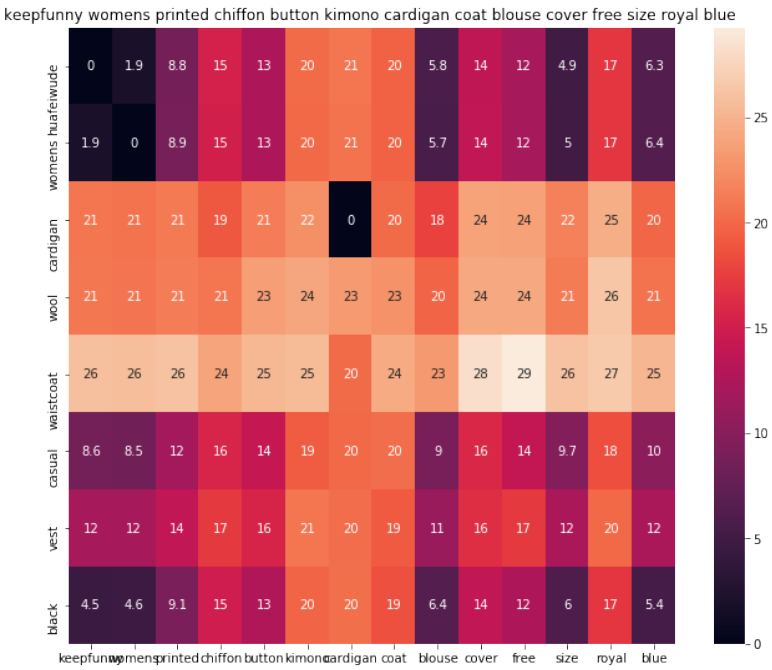

ASIN : B01IV2EEAK
Brand : KEEPFUNNY
euclidean distance from input : 4.5225873
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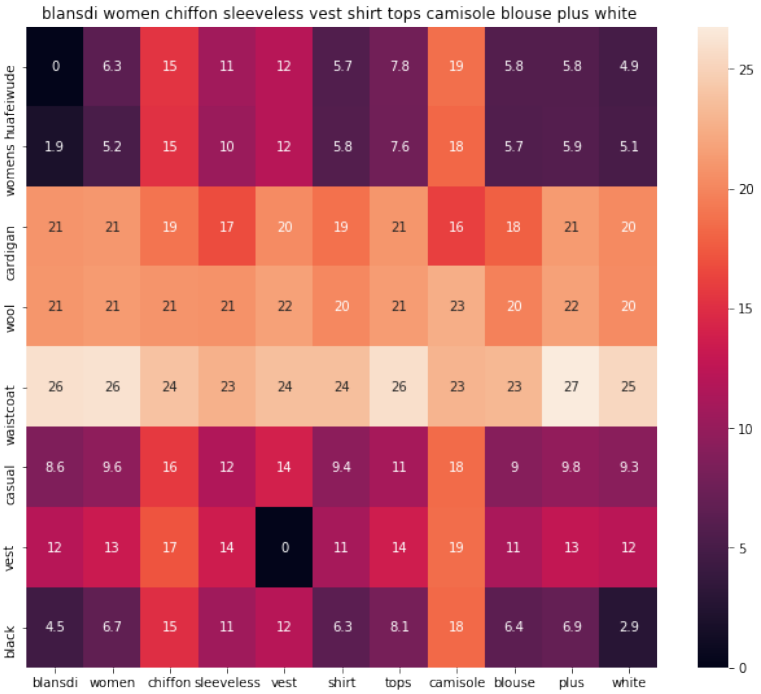

```
ASIN : B01AYVHQE2
Brand : Blansdi
euclidean distance from input : 4.534905
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```

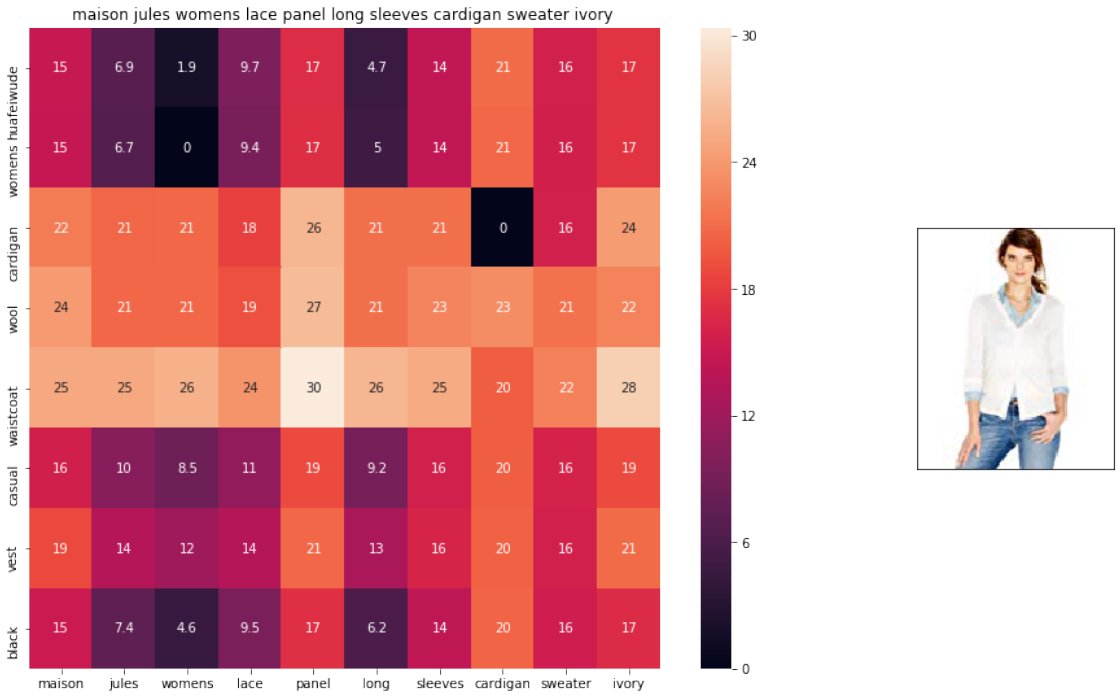


```
ASIN : B01DOKN4WS
Brand : Maison Jules
euclidean distance from input : 4.535721
================================================================================
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```

3.0.3 [9.6] Weighted similarity using brand and color.

[107]:
```
# some of the brand values are empty.
# Need to replace Null with string "NULL"
data['brand'].fillna(value="Not given", inplace=True )

# replace spaces with hypen
brands = [x.replace(" ", "-") for x in data['brand'].values]
types = [x.replace(" ", "-") for x in data['product_type_name'].values]
colors = [x.replace(" ", "-") for x in data['color'].values]
```

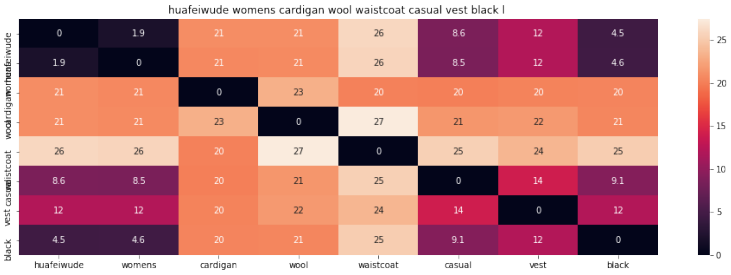
```
brand_vectorizer = CountVectorizer()
brand_features = brand_vectorizer.fit_transform(brands)

type_vectorizer = CountVectorizer()
type_features = type_vectorizer.fit_transform(types)

color_vectorizer = CountVectorizer()
color_features = color_vectorizer.fit_transform(colors)

extra_features = hstack((brand_features, type_features, color_features)).tocsr()
```

[108]:
```
def heat_map_w2v_brand(sentance1, sentance2, url, doc_id1, doc_id2, df_id1,␣
↪df_id2, model):

    # sentance1 : title1, input apparel
    # sentance2 : title2, recommended apparel
    # url: apparel image url
    # doc_id1: document id of input apparel
    # doc_id2: document id of recommended apparel
    # df_id1: index of document1 in the data frame
    # df_id2: index of document2 in the data frame
    # model: it can have two values, 1. avg 2. weighted

    #s1_vec = np.array(#number_of_words_title1 * 300), each row is a␣
↪vector(weighted/avg) of length 300 corresponds to each word in give title
    s1_vec = get_word_vec(sentance1, doc_id1, model)
    #s2_vec = np.array(#number_of_words_title2 * 300), each row is a␣
↪vector(weighted/avg) of length 300 corresponds to each word in give title
    s2_vec = get_word_vec(sentance2, doc_id2, model)

    # s1_s2_dist = np.array(#number of words in title1 * #number of words in␣
↪title2)
    # s1_s2_dist[i,j] = euclidean distance between words i, j
    s1_s2_dist = get_distance(s1_vec, s2_vec)

    data_matrix = [['Asin','Brand', 'Color', 'Product type'],
                [data['asin'].loc[df_id1],brands[doc_id1], colors[doc_id1],␣
↪types[doc_id1]], # input apparel's features
                [data['asin'].loc[df_id2],brands[doc_id2], colors[doc_id2],␣
↪types[doc_id2]]] # recommonded apparel's features

    colorscale = [[0, '#1d004d'],[.5, '#f2e5ff'],[1, '#f2e5d1']] # to color the␣
↪headings of each column

    # we create a table with the data_matrix
    table = ff.create_table(data_matrix, index=True, colorscale=colorscale)
```

```
    # plot it with plotly
    plotly.offline.iplot(table, filename='simple_table')

    # devide whole figure space into 25 * 1:10 grids
    gs = gridspec.GridSpec(25, 15)
    fig = plt.figure(figsize=(25,5))

    # in first 25*10 grids we plot heatmap
    ax1 = plt.subplot(gs[:, :-5])
    # ploting the heap map based on the pairwise distances
    ax1 = sns.heatmap(np.round(s1_s2_dist,6), annot=True)
    # set the x axis labels as recommended apparels title
    ax1.set_xticklabels(sentance2.split())
    # set the y axis labels as input apparels title
    ax1.set_yticklabels(sentance1.split())
    # set title as recommended apparels title
    ax1.set_title(sentance2)

    # in last 25 * 10:15 grids we display image
    ax2 = plt.subplot(gs[:, 10:16])
    # we dont display grid lins and axis labels to images
    ax2.grid(False)
    ax2.set_xticks([])
    ax2.set_yticks([])

    # pass the url it display it
    display_img(url, ax2, fig)

    plt.show()
```

[109]:
```
def idf_w2v_brand(doc_id, w1, w2, num_results):
    # doc_id: apparel's id in given corpus
    # w1: weight for  w2v features
    # w2: weight for brand and color features

    # pairwise_dist will store the distance from given input apparel to all␣
↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    idf_w2v_dist  = pairwise_distances(w2v_title_weight,␣
↪w2v_title_weight[doc_id].reshape(1,-1))
    ex_feat_dist = pairwise_distances(extra_features, extra_features[doc_id])
    pairwise_dist   = (w1 * idf_w2v_dist +  w2 * ex_feat_dist)/float(w1 + w2)

    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
```

```
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])


    for i in range(0, len(indices)):
        heat_map_w2v_brand(data['title'].loc[df_indices[0]],data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], indices[0],␣
 ↪indices[i],df_indices[0], df_indices[i], 'weighted')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('Brand :',data['brand'].loc[df_indices[i]])
        print('euclidean distance from input :', pdists[i])
        print('='*125)

idf_w2v_brand(12566, 5, 5, 20)
# in the give heat map, each cell contains the euclidean distance between words␣
 ↪i, j
```



```
ASIN : B01MT96PXZ
Brand : Huafeiwude
euclidean distance from input : 0.0
=============================================================================================
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```

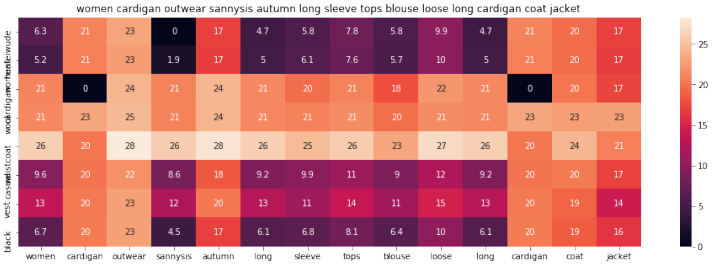

ASIN : B07473KFK1
Brand : Sannysis
euclidean distance from input : 2.8984806060791017
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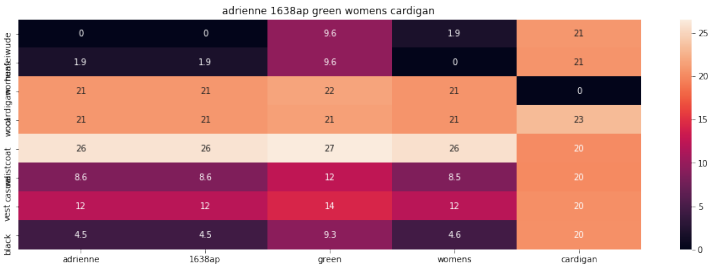

ASIN : B00O1HWO5W
Brand : Liuqiuhu
euclidean distance from input : 2.9184389116186766
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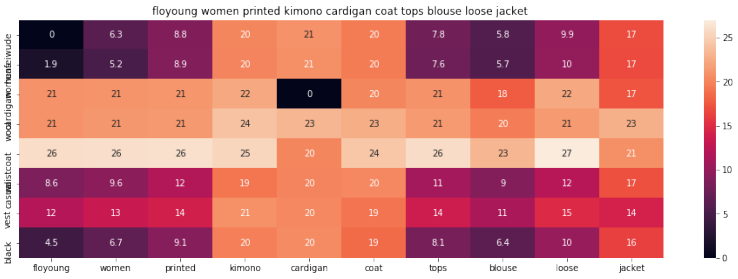

ASIN : B01D6EUG3W
Brand : FloYoung
euclidean distance from input : 2.9966798782348634
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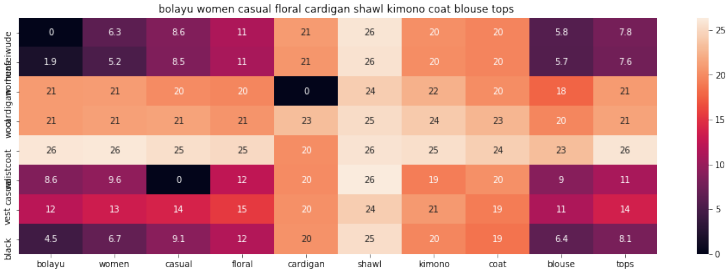

ASIN : B01F6UHWEU
Brand : Bolayu
euclidean distance from input : 3.0006389619726805
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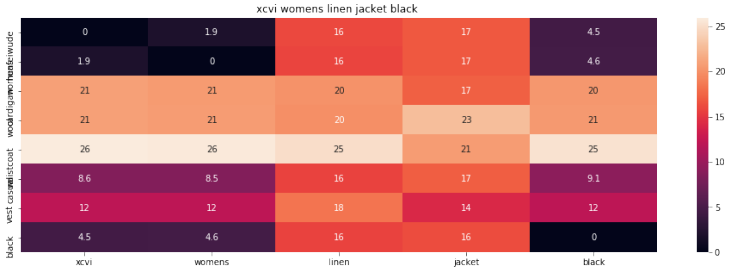

ASIN : B01M31Q4ZO
Brand : XCVI
euclidean distance from input : 3.0484086992163326
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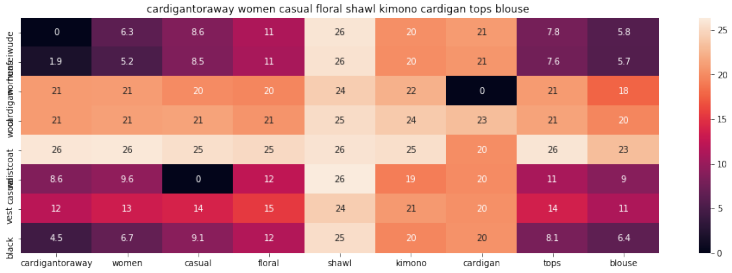

ASIN : B01CZMPCY4
Brand : Toraway
euclidean distance from input : 3.050865936459985
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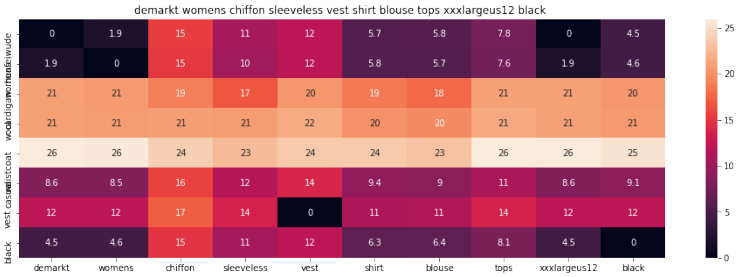

ASIN : B00JKCQZJE
Brand : Demarkt
euclidean distance from input : 3.081585693540063
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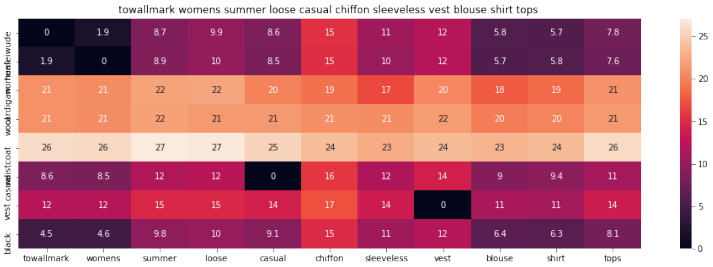

ASIN : B00QGEJ3MA
Brand : Towallmark
euclidean distance from input : 3.0982917787451414
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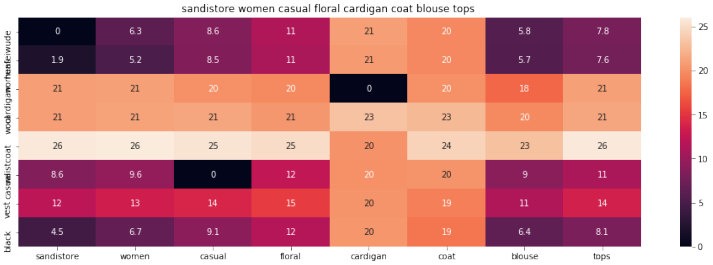

ASIN : B01AVX8IOU
Brand : Sandistore

euclidean distance from input : 3.1044492795824143

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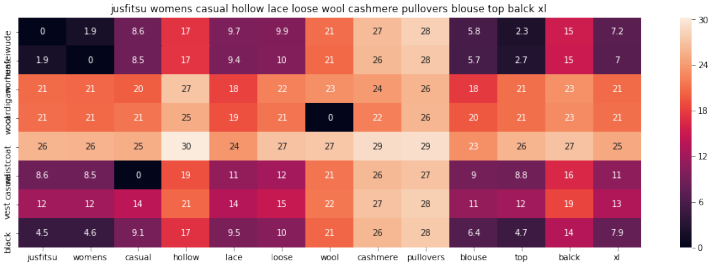

ASIN : B01N96GX38

Brand : Jusfitsu

euclidean distance from input : 3.1124135972876217

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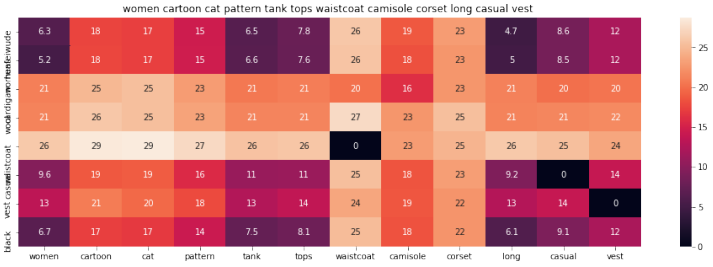

ASIN : B011R13YBM

Brand : Huayang

euclidean distance from input : 3.1135442733764647

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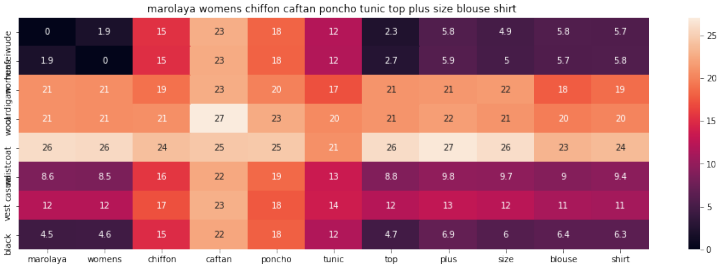

ASIN : B01CE40UW2
Brand : Marolaya
euclidean distance from input : 3.126744651975122
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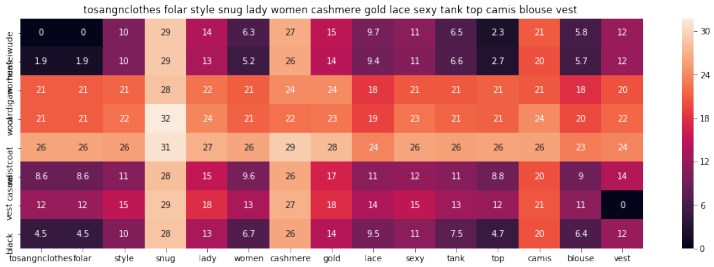

ASIN : B06XFRDH4J
Brand : Tosangn_Clothes
euclidean distance from input : 3.1292724611181884
==========
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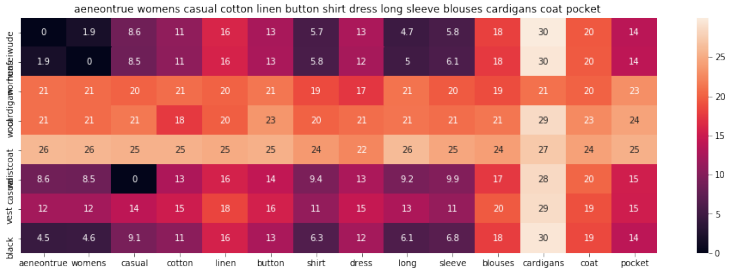

ASIN : B074V1K5QJ
Brand : Aeneontrue
euclidean distance from input : 3.1459396436571216
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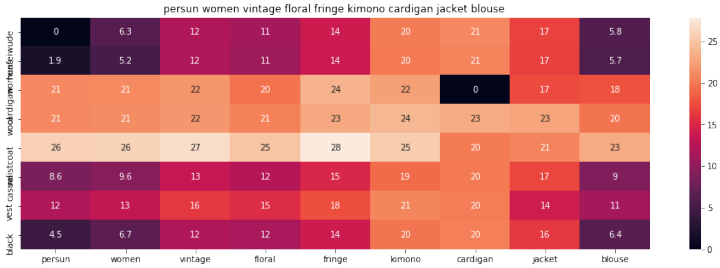

ASIN : B00Y26RSRQ
Brand : Persun
euclidean distance from input : 3.1488262176513673
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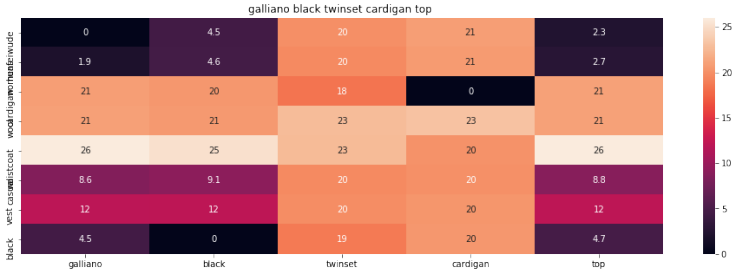

ASIN : B074G57HQJ
Brand : Galliano
euclidean distance from input : 3.158188819885254
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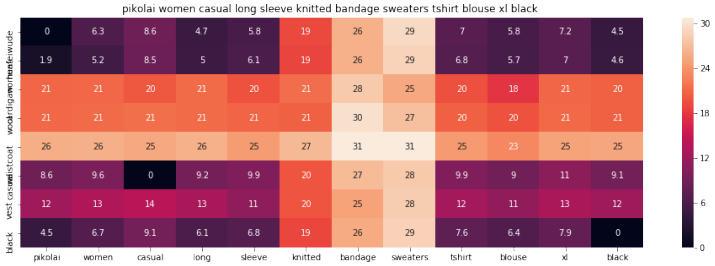

ASIN : B01LZ2B1HT
Brand : Pikolai
euclidean distance from input : 3.159334373654809
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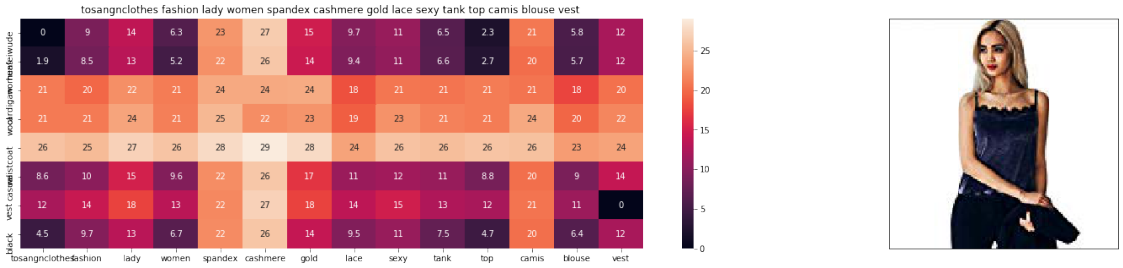


```
ASIN : B06XFFQLPL
Brand : Tosangn_Clothes
euclidean distance from input : 3.1688568117041256
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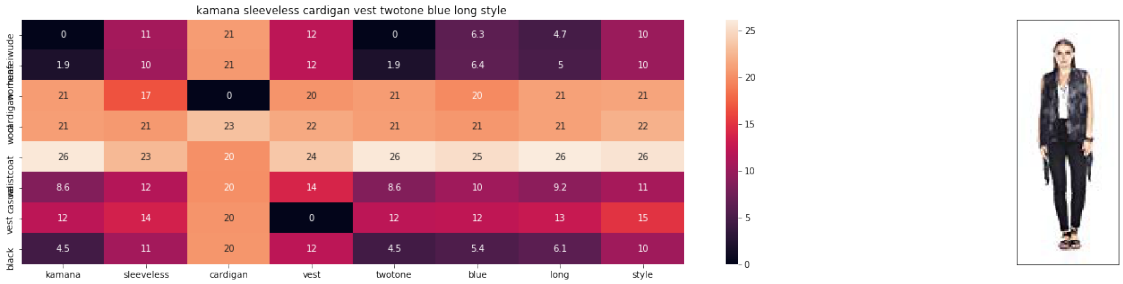



```
ASIN : B0751686K7
Brand : Kamana
euclidean distance from input : 3.177324751152331
================================================================================
==========================================
```

[110]:
```
# brand and color weight =50
# title vector weight = 5

#idf_w2v_brand(12566, 5, 50, 20)
```

4 [10.2] Keras and Tensorflow to extract features

[111]:
```
# import numpy as np
# from keras.preprocessing.image import ImageDataGenerator
# from keras.models import Sequential
# from keras.layers import Dropout, Flatten, Dense
```

```
# from keras import applications
# from sklearn.metrics import pairwise_distances
# import matplotlib.pyplot as plt
# import requests
# from PIL import Image
# import pandas as pd
# import pickle
```

[130]:
```
# https://gist.github.com/fchollet/f35fbc80e066a49d65f1688a7e99f069
# Code reference: https://blog.keras.io/
 ↪building-powerful-image-classification-models-using-very-little-data.html



# This code takes 40 minutes to run on a modern GPU (graphics card)
# like Nvidia  1050.
# GPU (NVidia 1050): 0.175 seconds per image

# This codse takes 160 minutes to run on a high end i7 CPU
# CPU (i7): 0.615 seconds per image.

#Do NOT run this code unless you want to wait a few hours for it to generate␣
 ↪output

# each image is converted into 25088 length dense-vector


'''
# dimensions of our images.
img_width, img_height = 224, 224

top_model_weights_path = 'bottleneck_fc_model.h5'
train_data_dir = 'images2/'
nb_train_samples = 16042
epochs = 50
batch_size = 1


def save_bottlebeck_features():

    #Function to compute VGG-16 CNN for image feature extraction.

    asins = []
    datagen = ImageDataGenerator(rescale=1. / 255)

    # build the VGG16 network
    model = applications.VGG16(include_top=False, weights='imagenet')
```

```
    generator = datagen.flow_from_directory(
        train_data_dir,
        target_size=(img_width, img_height),
        batch_size=batch_size,
        class_mode=None,
        shuffle=False)

    for i in generator.filenames:
        asins.append(i[2:-5])

    bottleneck_features_train = model.predict_generator(generator,␣
↪nb_train_samples // batch_size)
    bottleneck_features_train = bottleneck_features_train.
↪reshape((16042,25088))

    np.save(open('16k_data_cnn_features.npy', 'wb'), bottleneck_features_train)
    np.save(open('16k_data_cnn_feature_asins.npy', 'wb'), np.array(asins))


save_bottlebeck_features()

'''
print("Cell commented as we are loading cnn features from csv")
```

```
Cell commented as we are loading cnn features from csv
```

5 [10.3] Visual features based product similarity.

[156]:
```
bottleneck_features_train.shape
```

[156]:
```
(16434, 25088)
```

[157]:
```
#load the features and corresponding ASINS info.
bottleneck_features_train = np.load('16k_data_cnn_features.npy')
asins = np.load('16k_data_cnn_feature_asins.npy')
asins = list(asins)

# load the original 16K dataset
data = pd.read_pickle('pickels/16k_apperal_data_preprocessed')
df_asins = list(data['asin'])


from IPython.display import display, Image, SVG, Math, YouTubeVideo


#get similar products using CNN features (VGG-16)
def get_similar_products_cnn(doc_id, num_results):
```

```
    doc_id = asins.index(df_asins[doc_id])
    pairwise_dist = pairwise_distances(bottleneck_features_train,␣
 ↪bottleneck_features_train[doc_id].reshape(1,-1))

    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    for i in range(len(indices)):
        rows = data[['medium_image_url','title']].
 ↪loc[data['asin']==asins[indices[i]]]
        for indx, row in rows.iterrows():
            display(Image(url=row['medium_image_url'], embed=True))
            print('Product Title: ', row['title'])
            print('Euclidean Distance from input image:', pdists[i])
            print('Amazon Url: www.amzon.com/dp/'+ asins[indices[i]])

get_similar_products_cnn(12, 20)
```

```
Product Title:  fifteentwenty womens shirred hem ruffle blouse eggshell medium
Euclidean Distance from input image: 4.2649613e-06
Amazon Url: www.amzon.com/dp/B01I5GRO18
```

Product Title: h bordeaux womens plus dolman sleeve ribbed knit top black 1x
Euclidean Distance from input image: 40.83886
Amazon Url: www.amzon.com/dp/B01M9AD4HJ

Product Title: inc international concepts ribbed halter top size
Euclidean Distance from input image: 41.42038
Amazon Url: www.amzon.com/dp/B06WP2LRXR

Product Title: planet gold juniors blue bliss top size l
Euclidean Distance from input image: 42.52908
Amazon Url: www.amzon.com/dp/B01N5GBW58

Product Title: aqua womens navy black lace shell us medium
Euclidean Distance from input image: 42.926544
Amazon Url: www.amzon.com/dp/B0734CMCTX

Product Title: tahari asl womens plus vneck chain blouse white 2x
Euclidean Distance from input image: 43.125458
Amazon Url: www.amzon.com/dp/B01M5FU3MC

Product Title: ella moss womens faux wrap sheer contrast silk blouse red xs
Euclidean Distance from input image: 43.41721
Amazon Url: www.amzon.com/dp/B074TVM7LX

Product Title: eyeshadow crochet back racerback tank cami junior knit top black xl
Euclidean Distance from input image: 43.491356
Amazon Url: www.amzon.com/dp/B074P97729

Product Title: aqua ruched racerback raw edge trim tank top extra small jade green
Euclidean Distance from input image: 43.504623
Amazon Url: www.amzon.com/dp/B00X1FZVAK

Product Title: dressori womens silk trapeze textured hi lo top plus sz 2x black 270078e
Euclidean Distance from input image: 43.583805
Amazon Url: www.amzon.com/dp/B0757WQSSP

Product Title: socialite womens fringeneckline keyhole blouse blue xl
Euclidean Distance from input image: 43.768414
Amazon Url: www.amzon.com/dp/B073FKCJ8S

Product Title: bcx juniors sleeveless orange top size xxs
Euclidean Distance from input image: 43.999203
Amazon Url: www.amzon.com/dp/B01M9I6PTX

Product Title: rag bonejean camden striped tank bright white size
Euclidean Distance from input image: 44.11474
Amazon Url: www.amzon.com/dp/B074NBXX3J

Product Title: galliano pink wool knit top
Euclidean Distance from input image: 44.252876
Amazon Url: www.amzon.com/dp/B074G4V6NJ

Product Title: august silk creme brulee sleeveless top size
Euclidean Distance from input image: 44.318443
Amazon Url: www.amzon.com/dp/B01NCU68G2

Product Title: pleione blush womens medium high low tank blouse pink
Euclidean Distance from input image: 44.45496
Amazon Url: www.amzon.com/dp/B074V9KXYT

Product Title: splendid soft womens small ribbedknit marl tank top white
Euclidean Distance from input image: 44.465874
Amazon Url: www.amzon.com/dp/B06XCRNFXM

Product Title: collective concepts womens small sheer vneck blouse green
Euclidean Distance from input image: 44.4843
Amazon Url: www.amzon.com/dp/B071HT6B8H

Product Title: alex evenings womens large sequin knit tank blouse purple l
Euclidean Distance from input image: 44.53023
Amazon Url: www.amzon.com/dp/B072MM59TT

```
Product Title:  dsquared2 womens 100 silk offwhite see blouse top us 40
Euclidean Distance from input image: 44.651653
Amazon Url: www.amzon.com/dp/B01N46WQPQ
```

[160]:
```
def idf_w2v_brand(doc_id, wt, wb, wc, wi, num_results):
    # doc_id: apparel's id in given corpus
    # w1: weight for  w2v features
    # w2: weight for brand and color features

    # pairwise_dist will store the distance from given input apparel to all␣
↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    #extra_features = hstack((brand_features, type_features, color_features)).
↪tocsr()

    brand = pairwise_distances(brand_features, brand_features[doc_id])
    color = pairwise_distances(color_features, color_features[doc_id])
    idf_w2v_dist  = pairwise_distances(w2v_title_weight,␣
↪w2v_title_weight[doc_id].reshape(1,-1))
    cnn_feature = pairwise_distances(bottleneck_features_train,␣
↪bottleneck_features_train[doc_id].reshape(1,-1))
    print(brand.shape)
    print(color.shape)
    print(idf_w2v_dist.shape)
    print(cnn_feature.shape)
    pairwise_dist   = (wt * idf_w2v_dist +  wi * cnn_feature +  wb * brand + ␣
↪wc * color)/float(wt + wi + wb + wc)

    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
```

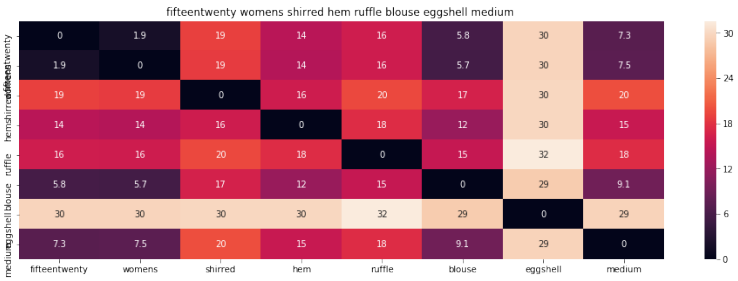
```
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])

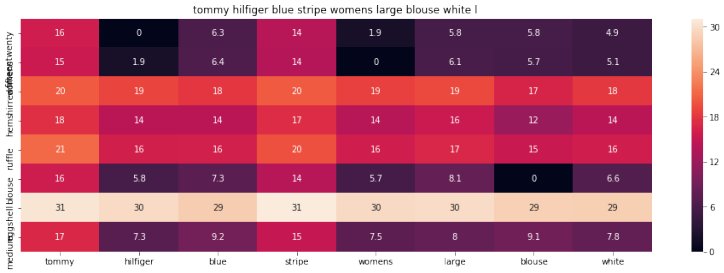

    for i in range(0, len(indices)):
        heat_map_w2v_brand(data['title'].loc[df_indices[0]],data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], indices[0],␣
 ↪indices[i],df_indices[0], df_indices[i], 'weighted')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('Brand :',data['brand'].loc[df_indices[i]])
        print('euclidean distance from input :', pdists[i])
        print('='*125)

idf_w2v_brand(12, 5, 5, 5, 5, 20)
# in the give heat map, each cell contains the euclidean distance between words␣
 ↪i, j
```

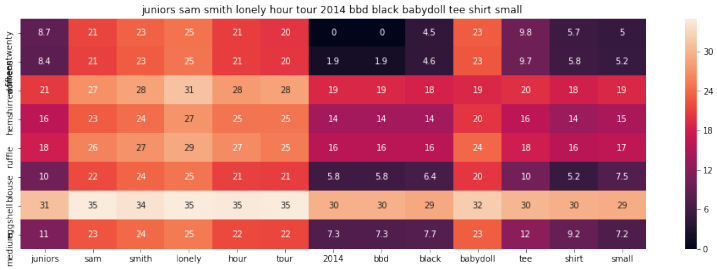
```
(16434, 1)
(16434, 1)
(16434, 1)
(16434, 1)
```



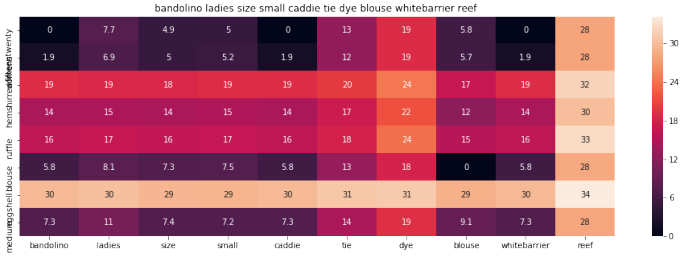
```
ASIN : B01I5GRO18
Brand : FIFTEEN TWENTY
euclidean distance from input : 1.5634152077836915e-06
=============================================================================
=============================================
```



ASIN : B0716WTNQ3
Brand : Tommy Hilfiger
euclidean distance from input : 2.427044010252698
==========
==========



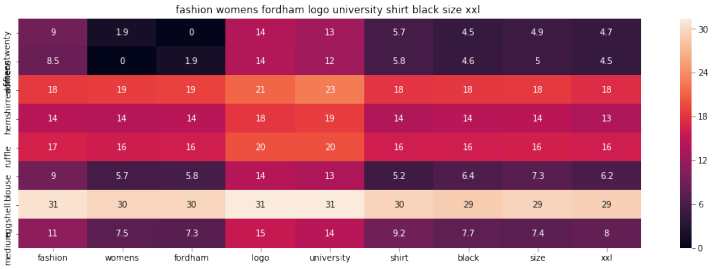
ASIN : B00Y125DYQ
Brand : Bay Island Sportswear
euclidean distance from input : 11.335025218952596
==========
==========



ASIN : B06XNZLTWC
Brand : Bandolino

euclidean distance from input : 11.763416602038705

==========

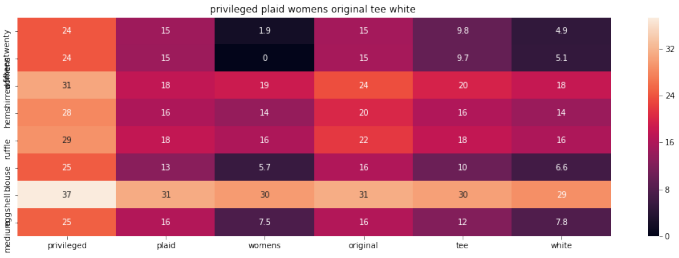


ASIN : B01IY8TYAQ

Brand : Aip Yep Novelty Fashion

euclidean distance from input : 11.7951326744336

==========

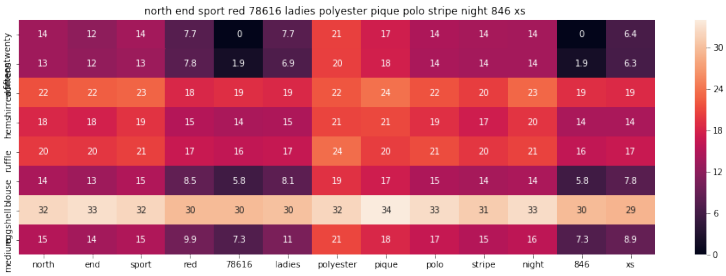


ASIN : B01LZO08UI

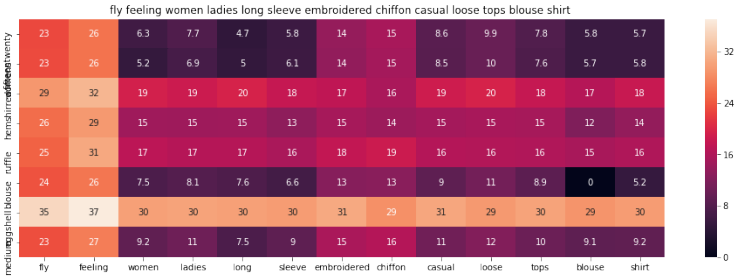
Brand : Privileged and Plaid

euclidean distance from input : 11.856599620808066

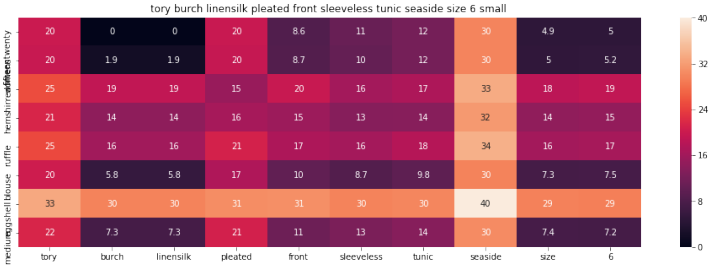
==========



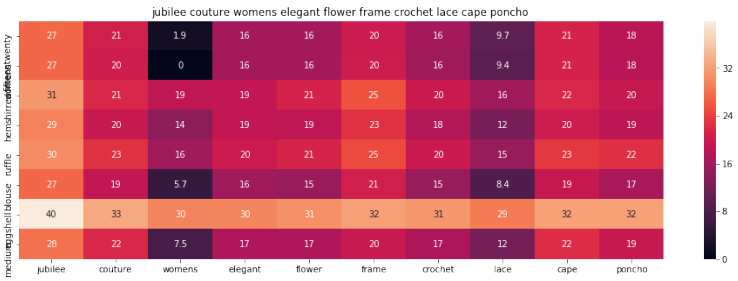
ASIN : B00R9D6V2M
Brand : Ash City - North End Sport Red
euclidean distance from input : 11.916846778000643
==========
==========



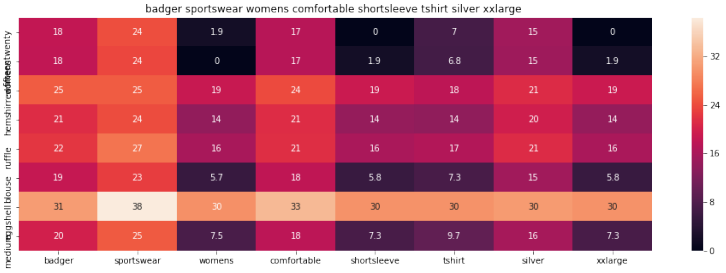
ASIN : B01MQISHRW
Brand : ACEFAST INC
euclidean distance from input : 11.998045730681165
==========
==========



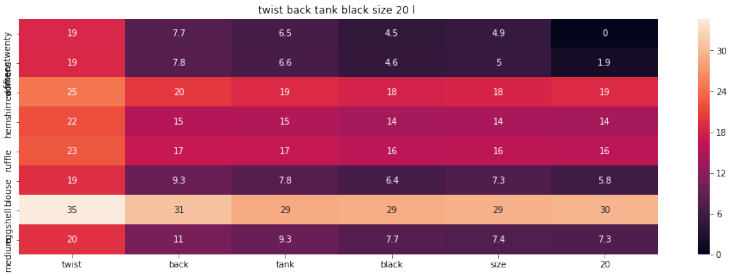
ASIN : B06ZY9L8QH
Brand : Tory Burch
euclidean distance from input : 12.040629959196789
==========
==========



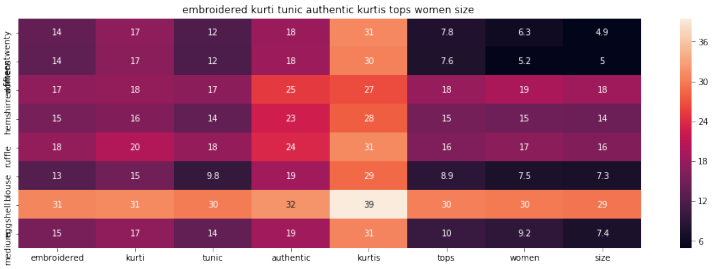
ASIN : B01BLXH6O2
Brand : Jubilee Couture
euclidean distance from input : 12.102769019030891
==========
==========



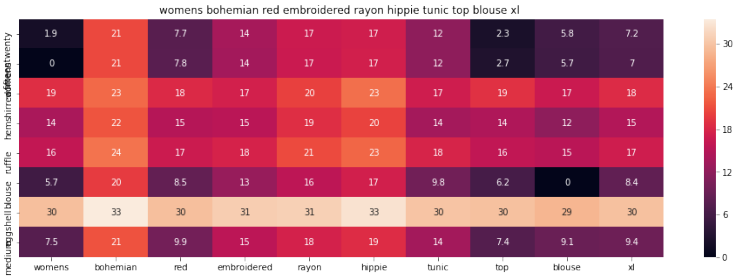
ASIN : B002H1F4WY
Brand : BADGER
euclidean distance from input : 12.11514427852065
==========
==========



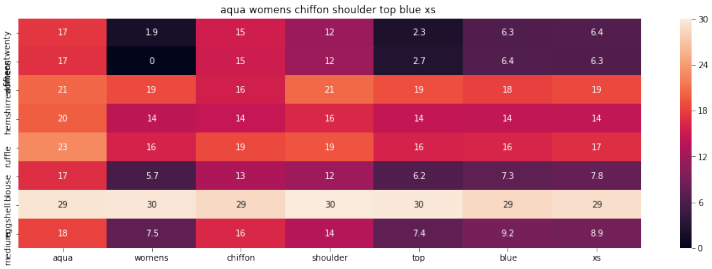
ASIN : B0721QWTJL
Brand : City Chic
euclidean distance from input : 12.122605514616712
==========
==========



ASIN : B00L235IU6
Brand : ShalinIndia
euclidean distance from input : 12.130438162797994
==========
==========

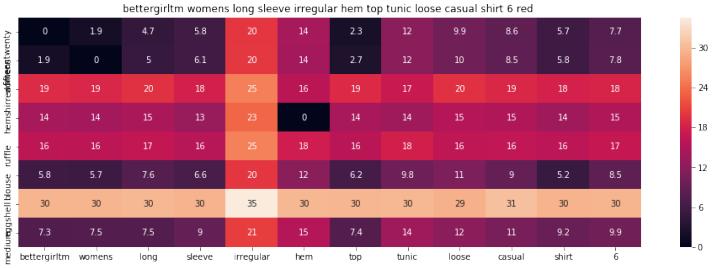


ASIN : B01LYZGLYJ
Brand : Mogul Interior
euclidean distance from input : 12.13425560006593
==========
==========

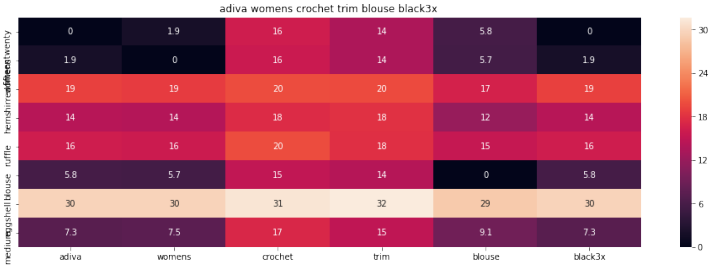


ASIN : B01LZRLKT4
Brand : Aqua

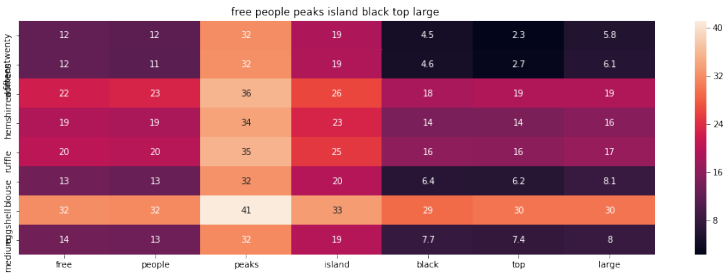
euclidean distance from input : 12.136582877153462



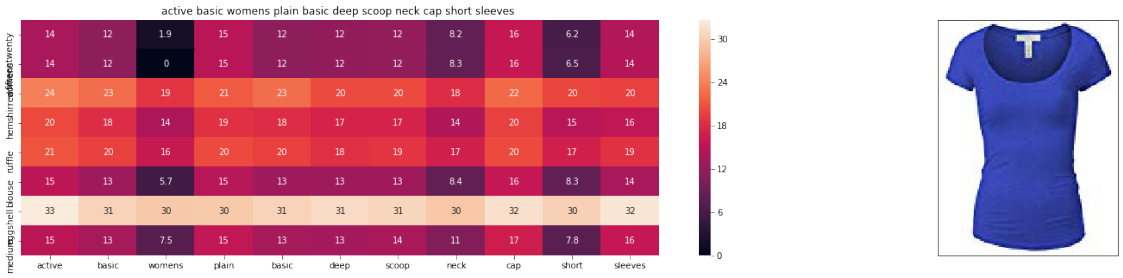
ASIN : B01NBHHQDI
Brand : BetterGirl
euclidean distance from input : 12.15269310664565



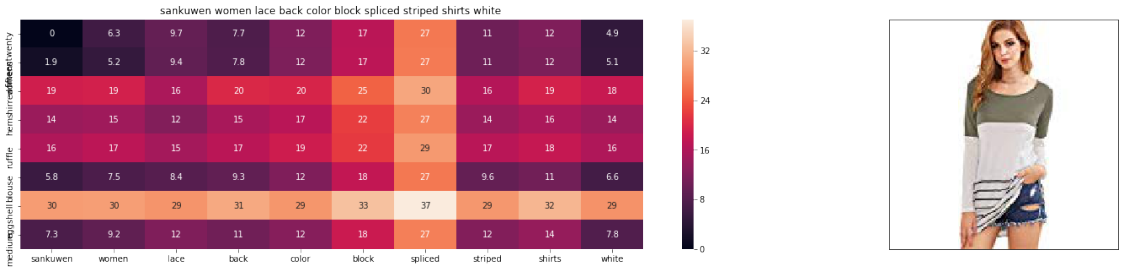
ASIN : B01KE0XZPW
Brand : ADIVA
euclidean distance from input : 12.18221199702651



```
ASIN : B01M1OC0NX
Brand : Free People
euclidean distance from input : 12.209418869108898
================================================================================
================================================
```




```
ASIN : B01A9L040A
Brand : Active Products
euclidean distance from input : 12.228110815905891
================================================================================
================================================
```




```
ASIN : B06WW3LPR5
Brand : Sankuwen
euclidean distance from input : 12.261517264360494
================================================================================
================================================
```

[161]:
```
def idf_w2v_brand(doc_id, wt, wb, wc, wi, num_results):
    # doc_id: apparel's id in given corpus
    # w1: weight for  w2v features
    # w2: weight for brand and color features
```

```
    # pairwise_dist will store the distance from given input apparel to all␣
↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    #extra_features = hstack((brand_features, type_features, color_features)).
↪tocsr()

    brand = pairwise_distances(brand_features, brand_features[doc_id])
    color = pairwise_distances(color_features, color_features[doc_id])
    idf_w2v_dist  = pairwise_distances(w2v_title_weight,␣
↪w2v_title_weight[doc_id].reshape(1,-1))
    cnn_feature = pairwise_distances(bottleneck_features_train,␣
↪bottleneck_features_train[doc_id].reshape(1,-1))
    print(brand.shape)
    print(color.shape)
    print(idf_w2v_dist.shape)
    print(cnn_feature.shape)
    pairwise_dist   = (wt * idf_w2v_dist +  wi * cnn_feature +  wb * brand + ␣
↪wc * color)/float(wt + wi + wb + wc)

    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

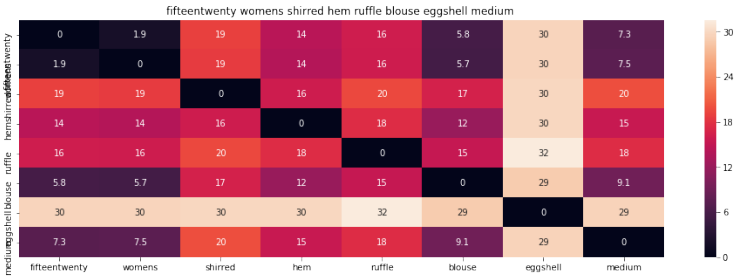
    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])


    for i in range(0, len(indices)):
        heat_map_w2v_brand(data['title'].loc[df_indices[0]],data['title'].
↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], indices[0],␣
↪indices[i],df_indices[0], df_indices[i], 'weighted')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('Brand :',data['brand'].loc[df_indices[i]])
        print('euclidean distance from input :', pdists[i])
        print('='*125)

idf_w2v_brand(12, 5, 10, 7, 10, 20)
# in the give heat map, each cell contains the euclidean distance between words␣
↪i, j
```

```
(16434, 1)
(16434, 1)
(16434, 1)
```

(16434, 1)



ASIN : B01I5GRO18
Brand : FIFTEEN TWENTY
euclidean distance from input : 1.9542690097296145e-06
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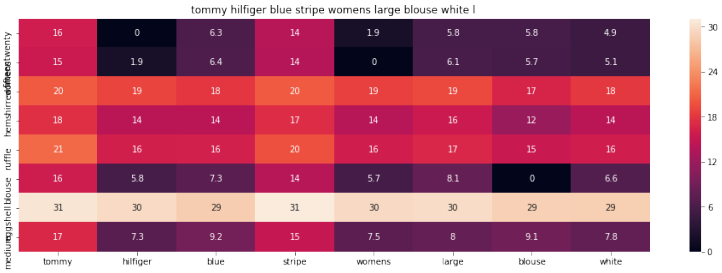

ASIN : B0716WTNQ3
Brand : Tommy Hilfiger
euclidean distance from input : 1.9177918673352157
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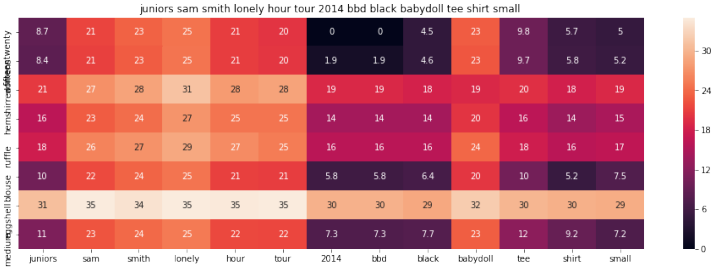

ASIN : B00Y125DYQ
Brand : Bay Island Sportswear
euclidean distance from input : 12.910208134603522
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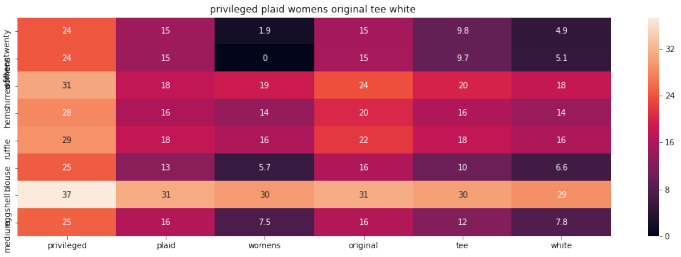

ASIN : B01LZO08UI
Brand : Privileged and Plaid
euclidean distance from input : 13.439730076742194
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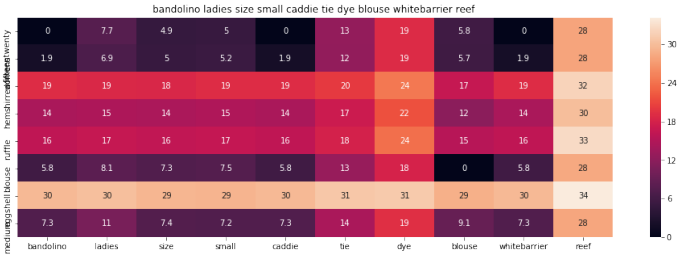

ASIN : B06XNZLTWC
Brand : Bandolino
euclidean distance from input : 13.497250946640177
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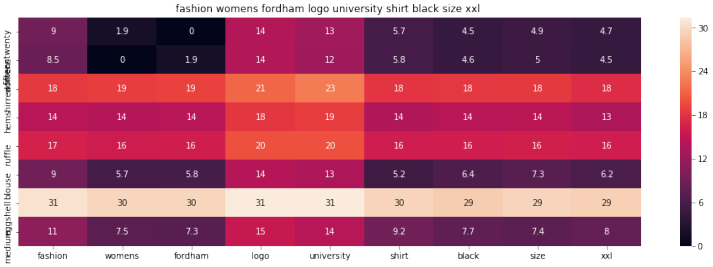

ASIN : B01IY8TYAQ
Brand : Aip Yep Novelty Fashion
euclidean distance from input : 13.545347641943058
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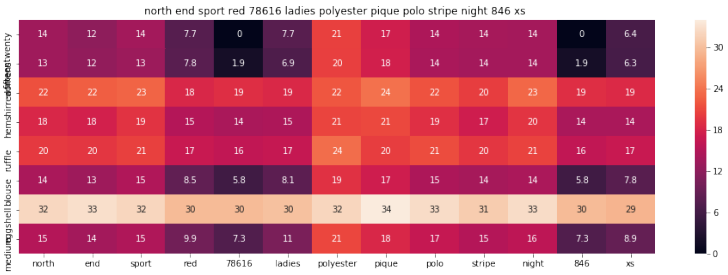

ASIN : B00R9D6V2M
Brand : Ash City - North End Sport Red
euclidean distance from input : 13.6644171583879
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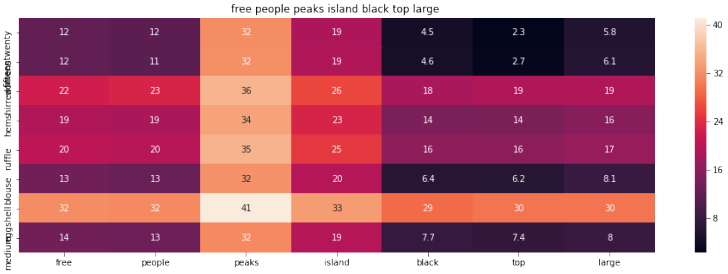

ASIN : B01M1OC0NX
Brand : Free People
euclidean distance from input : 13.697968149264232
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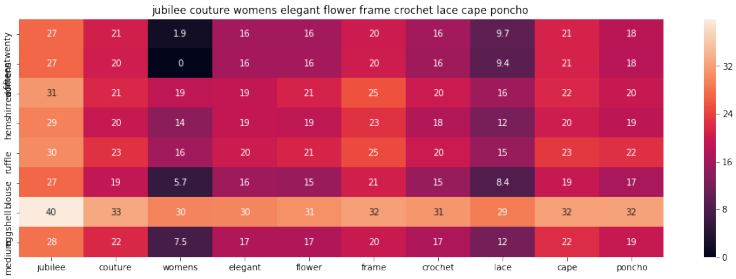

ASIN : B01BLXH6O2
Brand : Jubilee Couture
euclidean distance from input : 13.841207395588798
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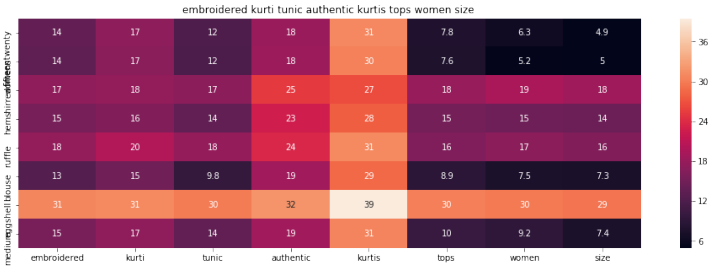

ASIN : B00L235IU6
Brand : ShalinIndia
euclidean distance from input : 13.856432017046988
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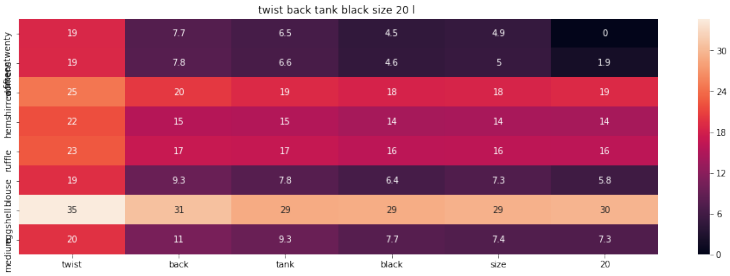

ASIN : B0721QWTJL
Brand : City Chic
euclidean distance from input : 13.884284639437572
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ASIN : B002H1F4WY
Brand : BADGER
euclidean distance from input : 13.912078913409292
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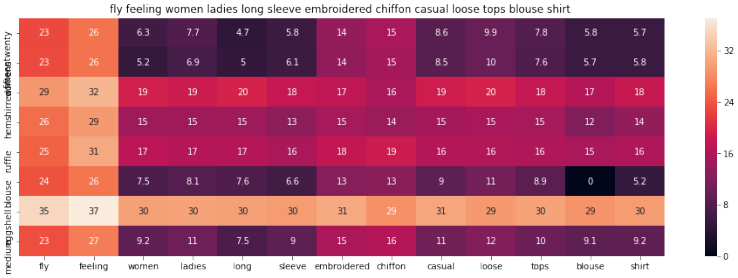

ASIN : B01MQISHRW
Brand : ACEFAST INC
euclidean distance from input : 13.916268968661205
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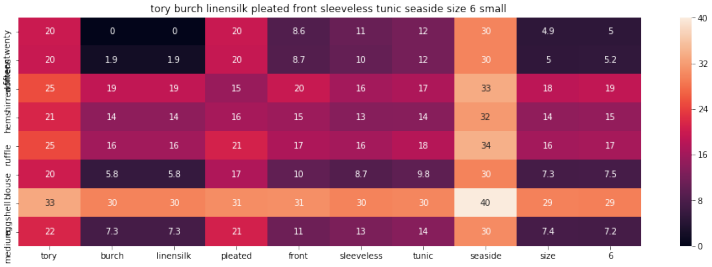

ASIN : B06ZY9L8QH
Brand : Tory Burch
euclidean distance from input : 13.96704640396394
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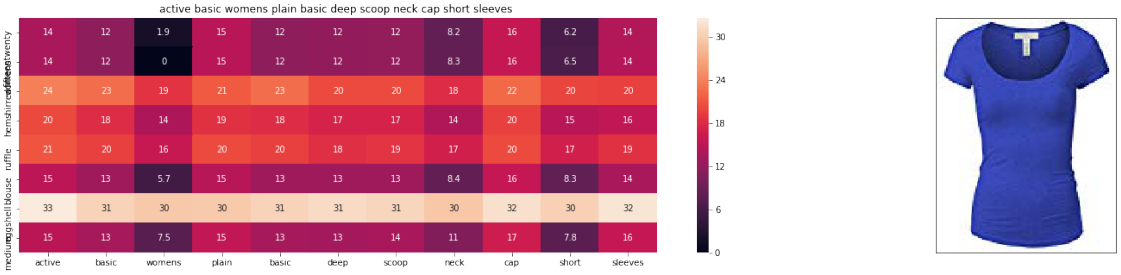

ASIN : B01A9L040A
Brand : Active Products
euclidean distance from input : 14.018928419148368
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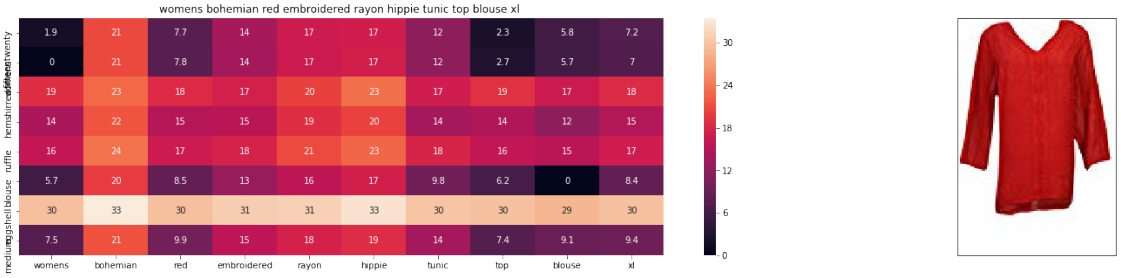

ASIN : B01LYZGLYJ
Brand : Mogul Interior
euclidean distance from input : 14.058140420992748
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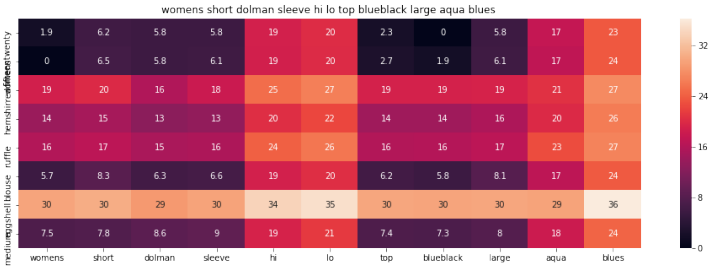

ASIN : B06XTPZGHP
Brand : Aqua Blues
euclidean distance from input : 14.088808904683036
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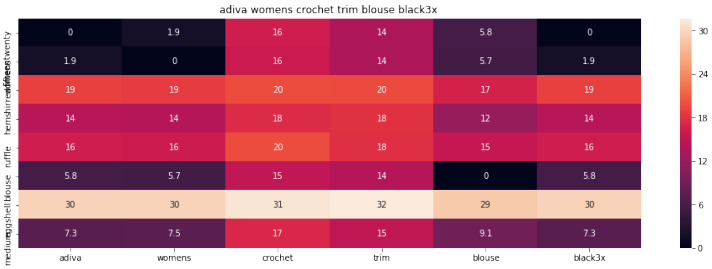

ASIN : B01KE0XZPW
Brand : ADIVA
euclidean distance from input : 14.10830503340441
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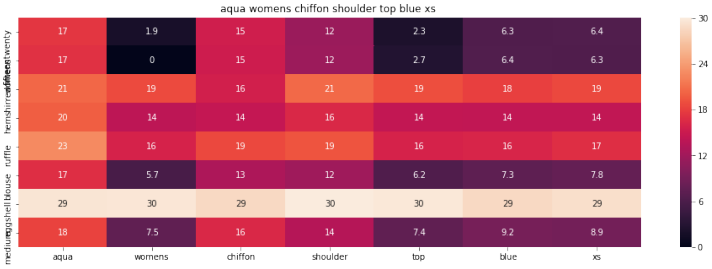

ASIN : B01LZRLKT4
Brand : Aqua

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euclidean distance from input : 14.120062884051382
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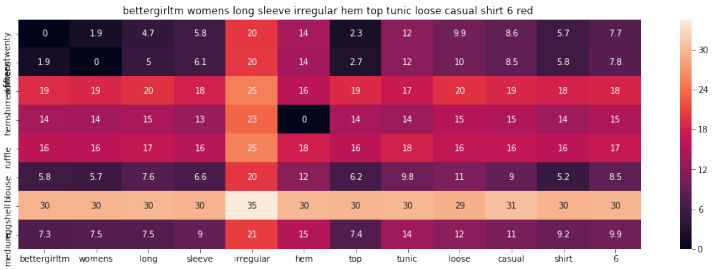


```
ASIN : B01NBHHQDI
Brand : BetterGirl
euclidean distance from input : 14.123115595538199
================================================================================
================================================
```

[162]:
```
def idf_w2v_brand(doc_id, wt, wb, wc, wi, num_results):
    # doc_id: apparel's id in given corpus
    # w1: weight for  w2v features
    # w2: weight for brand and color features

    # pairwise_dist will store the distance from given input apparel to all␣
↪remaining apparels
    # the metric we used here is cosine, the coside distance is mesured as K(X,␣
↪Y) = <X, Y> / (||X||*||Y||)
    # http://scikit-learn.org/stable/modules/metrics.html#cosine-similarity
    #extra_features = hstack((brand_features, type_features, color_features)).
↪tocsr()

    brand = pairwise_distances(brand_features, brand_features[doc_id])
    color = pairwise_distances(color_features, color_features[doc_id])
    idf_w2v_dist  = pairwise_distances(w2v_title_weight,␣
↪w2v_title_weight[doc_id].reshape(1,-1))
    cnn_feature = pairwise_distances(bottleneck_features_train,␣
↪bottleneck_features_train[doc_id].reshape(1,-1))
    print(brand.shape)
    print(color.shape)
    print(idf_w2v_dist.shape)
    print(cnn_feature.shape)
    pairwise_dist   = (wt * idf_w2v_dist +  wi * cnn_feature +  wb * brand + ␣
↪wc * color)/float(wt + wi + wb + wc)
```

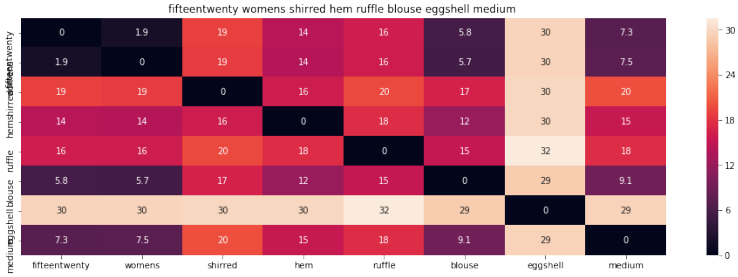
```
    # np.argsort will return indices of 9 smallest distances
    indices = np.argsort(pairwise_dist.flatten())[0:num_results]
    #pdists will store the 9 smallest distances
    pdists  = np.sort(pairwise_dist.flatten())[0:num_results]

    #data frame indices of the 9 smallest distace's
    df_indices = list(data.index[indices])


    for i in range(0, len(indices)):
        heat_map_w2v_brand(data['title'].loc[df_indices[0]],data['title'].
 ↪loc[df_indices[i]], data['medium_image_url'].loc[df_indices[i]], indices[0],␣
 ↪indices[i],df_indices[0], df_indices[i], 'weighted')
        print('ASIN :',data['asin'].loc[df_indices[i]])
        print('Brand :',data['brand'].loc[df_indices[i]])
        print('euclidean distance from input :', pdists[i])
        print('='*125)

idf_w2v_brand(12, 1, 2, 3, 5, 20)
# in the give heat map, each cell contains the euclidean distance between words␣
 ↪i, j
```

```
(16434, 1)
(16434, 1)
(16434, 1)
(16434, 1)
```



```
ASIN : B01I5GRO18
Brand : FIFTEEN TWENTY
euclidean distance from input : 2.8425731050612573e-06
================================================================================
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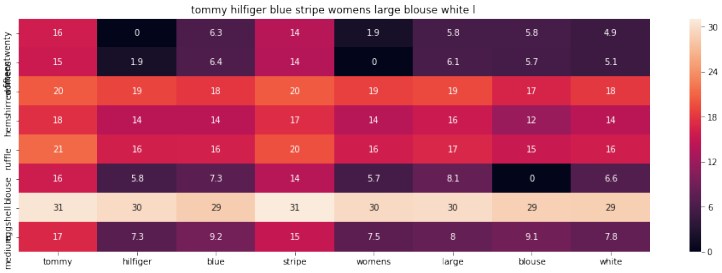
```



ASIN : B0716WTNQ3
Brand : Tommy Hilfiger
euclidean distance from input : 1.321511676193306
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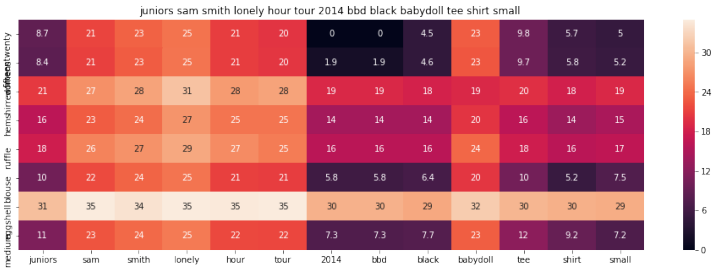

ASIN : B00Y125DYQ
Brand : Bay Island Sportswear
euclidean distance from input : 17.121682742056972
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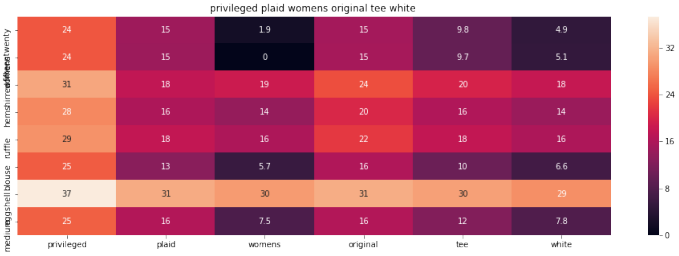
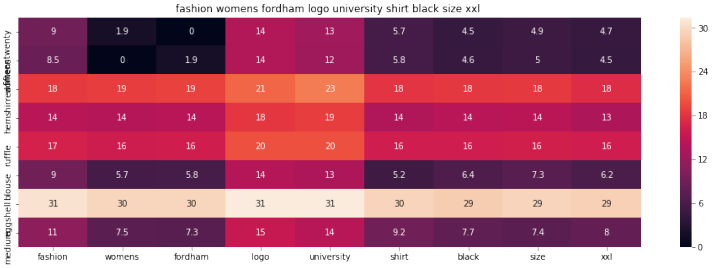


ASIN : B01LZO08UI
Brand : Privileged and Plaid

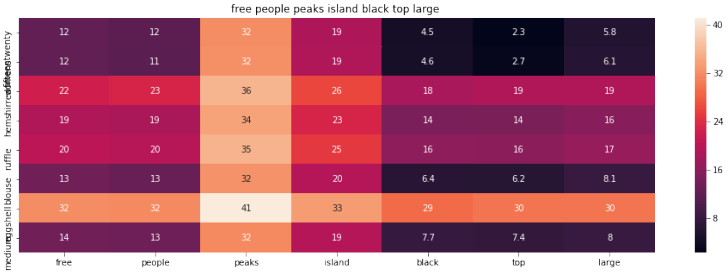
euclidean distance from input : 17.7850336276216



ASIN : B01IY8TYAQ

Brand : Aip Yep Novelty Fashion

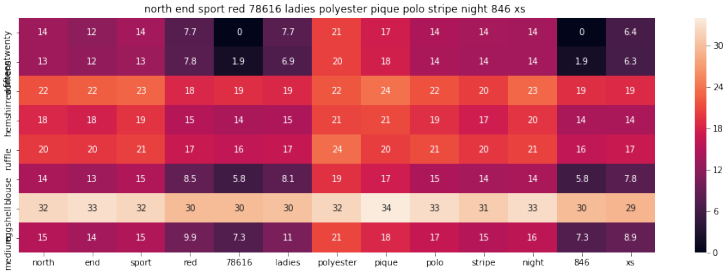
euclidean distance from input : 18.039684253536052



ASIN : B01M1OC0NX

Brand : Free People

euclidean distance from input : 18.06551388837093



ASIN : B00R9D6V2M
Brand : Ash City - North End Sport Red
euclidean distance from input : 18.092225016187125
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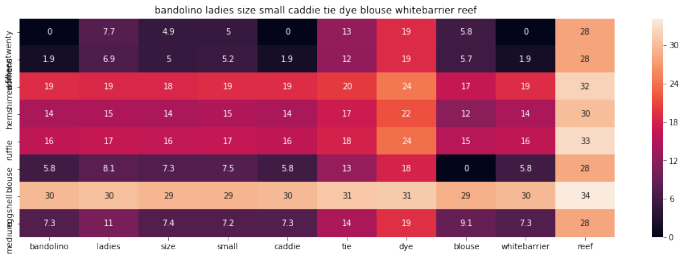

ASIN : B06XNZLTWC
Brand : Bandolino
euclidean distance from input : 18.179316244575734
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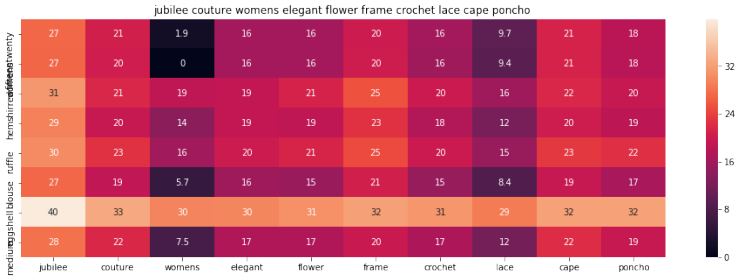

ASIN : B01BLXH6O2
Brand : Jubilee Couture
euclidean distance from input : 18.526772301655857
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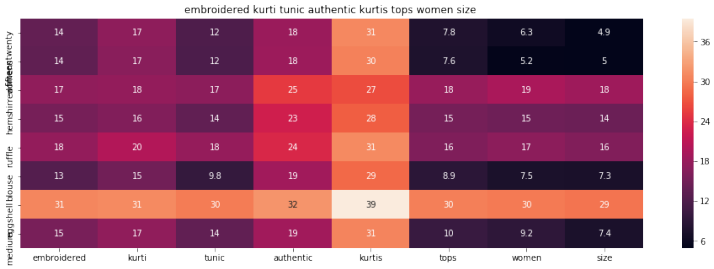

ASIN : B00L235IU6
Brand : ShalinIndia
euclidean distance from input : 18.593539239391976
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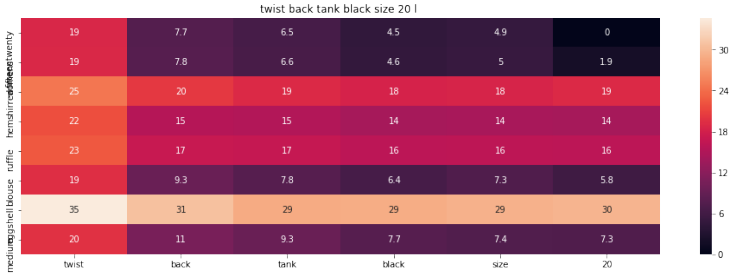

ASIN : B0721QWTJL
Brand : City Chic
euclidean distance from input : 18.593828652220363
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ASIN : B002H1F4WY
Brand : BADGER

euclidean distance from input : 18.739729535911863

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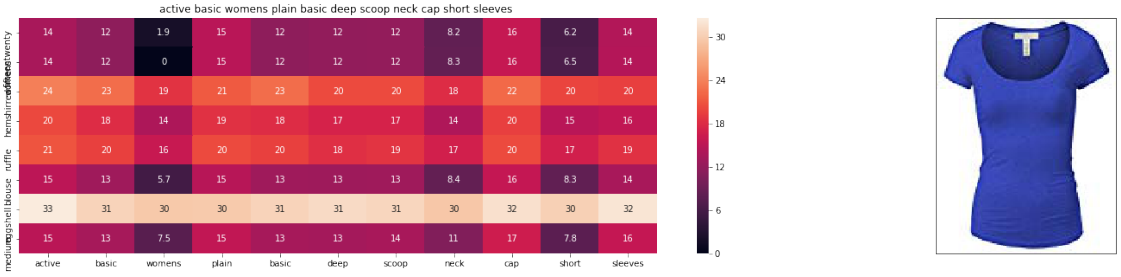

ASIN : B01A9L040A

Brand : Active Products

euclidean distance from input : 18.80364164203228

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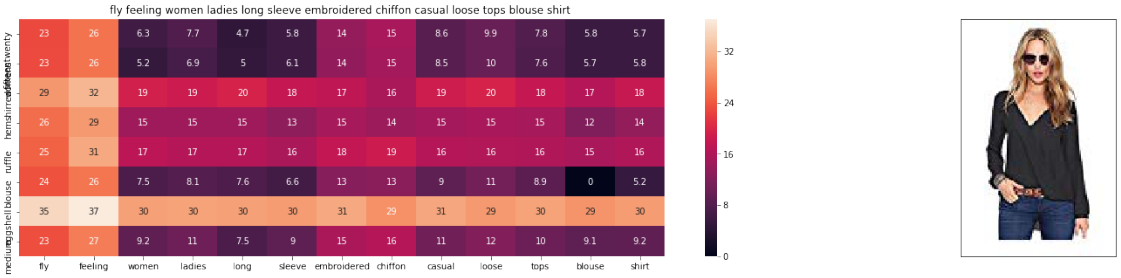

ASIN : B01MQISHRW

Brand : ACEFAST INC

euclidean distance from input : 18.804147477682008

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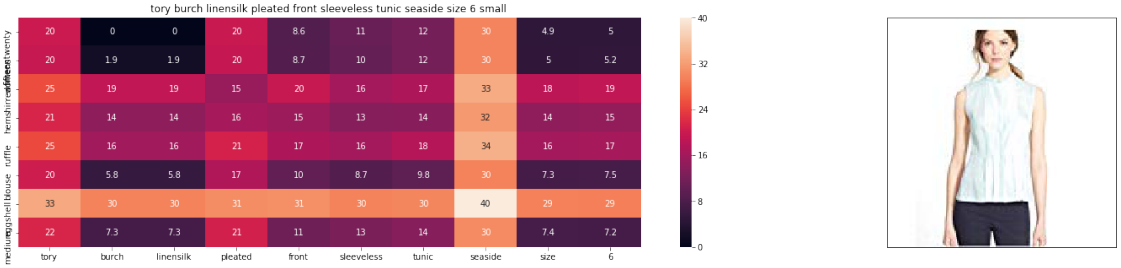

ASIN : B06ZY9L8QH
Brand : Tory Burch
euclidean distance from input : 18.875863786275758
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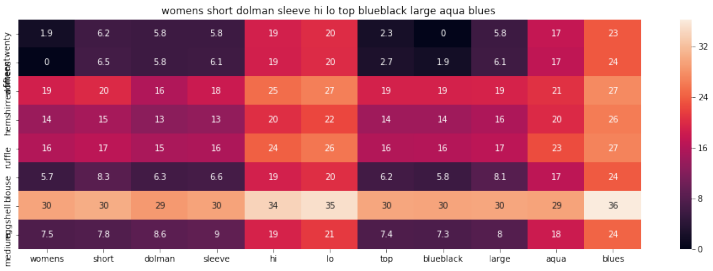

ASIN : B06XTPZGHP
Brand : Aqua Blues
euclidean distance from input : 18.909871944322763
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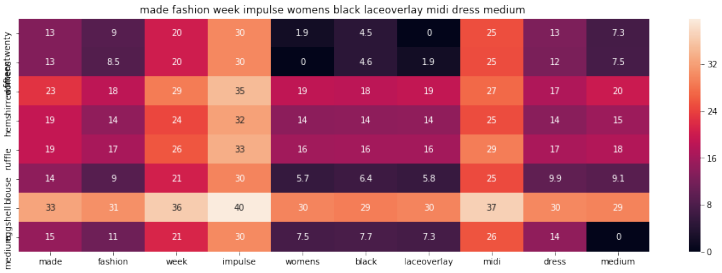

ASIN : B00YQEUED4
Brand : Made Fashion Week for Impulse
euclidean distance from input : 18.965878040542474
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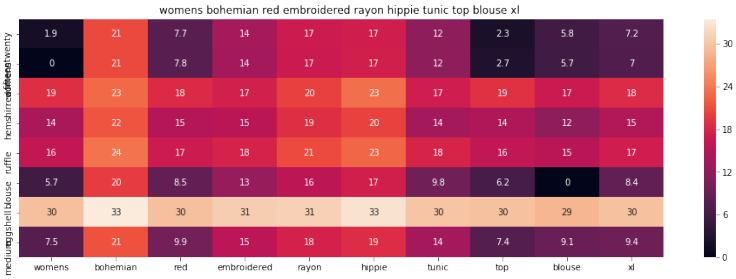

ASIN : B01LYZGLYJ
Brand : Mogul Interior
euclidean distance from input : 18.985728454688402
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ASIN : B01N8Z2K60
Brand : James Perse
euclidean distance from input : 19.08706623434039
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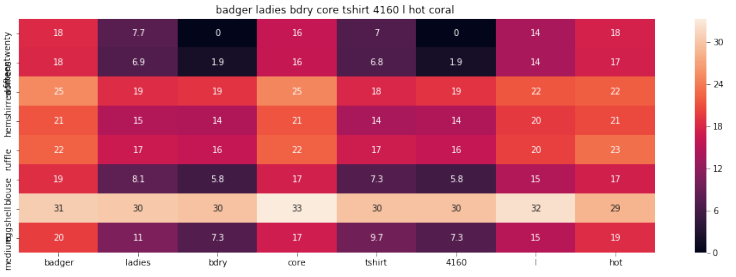

```
ASIN : B00DNMUL88
Brand : BADGER
euclidean distance from input : 19.103134722101622
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Actaul weights can be set by business rules

[ ]: