Amazon Apparel Recommendations

[4.2] Data and Code:

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

[4.3] Overview of the data

In [2]:

```
#import all the necessary packages.

import PIL.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")
```

In [3]:

```
# 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')
```

In [4]:

```
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
```

Terminology:

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

In [5]:

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

Out[5]:

```
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 an d 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)

In [6]:

```
data = data[['asin', 'brand', 'color', 'medium_image_url', 'product_type_name', 'title', 'formatted_price']]
```

In [7]:

```
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
```

Out[7]:

	asin	brand	color	medium_image_url	product_type_name	title	formatted_price
0	B016I2TS4W	FNC7C	None	https://images-na.ssl-images-amazon.com/images...	SHIRT	Minions Como Superheroes Ironman Long Sleeve R...	None
1	B01N49AI08	FIG Clothing	None	https://images-na.ssl-images-amazon.com/images...	SHIRT	FIG Clothing Womens Izo Tunic	None
2	B01JDPCOHO	FIG Clothing	None	https://images-na.ssl-images-amazon.com/images...	SHIRT	FIG Clothing Womens Won Top	None
3	B01N19U5H5	Focal18	None	https://images-na.ssl-images-amazon.com/images...	SHIRT	Focal18 Sailor Collar Bubble Sleeve Blouse Shi...	None
4	B004GSI2OS	FeatherLite	Onyx Black/ Stone	https://images-na.ssl-images-amazon.com/images...	SHIRT	Featherlite Ladies' Long Sleeve Stain Resistan...	$26.26

[5.1] Missing data for various features.

Basic stats for the feature: product_type_name

In [8]:

```
# 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
```

In [9]:

```
# 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']
```

In [10]:

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

Out[10]:

```
[('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

In [11]:

```
# 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
```

In [12]:

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

Out[12]:

```
[('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

In [13]:

```
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
```

In [14]:

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

Out[14]:

```
[(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

In [15]:

```

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
```

In [16]:

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

Out[16]:

```
[(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

In [17]:

```
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
```

In [18]:

```
data.to_pickle('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.

In [19]:

```
# 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
#print(data['formatted_price'].isnull())
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
```

In [20]:

```
# 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

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.

In [21]:

```
data.to_pickle('28k_apparel_data')
```

In [22]:

```
# 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')


'''
```

Out[22]:

```
"\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"
```

[5.2] Remove near duplicate items

[5.2.1] Understand about duplicates.

In [23]:

```
# read data from pickle file from previous stage
data = pd.read_pickle('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)

:B00AQ4GMCK	:B00AQ4GMTS
:B00AQ4GMLQ	:B00AQ4GN3I

These shirts exactly same except in color

:B00G278GZ6	:B00G278W6O
:B00G278Z2A	: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

In [24]:

```
# read data from pickle file from previous stage
data = pd.read_pickle('28k_apparel_data')
```

In [25]:

```
data.head()
```

Out[25]:

	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 Resistan...	$26.26
6	B012YX2ZPI	HX-Kingdom Fashion T-shirts	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	Women's Unique 100% Cotton T - Special Olympic...	$9.99
11	B001LOUGE4	Fitness Etc.	Black	https://images-na.ssl-images-amazon.com/images...	SHIRT	Ladies Cotton Tank 2x1 Ribbed Tank Top	$11.99
15	B003BSRPB0	FeatherLite	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	FeatherLite Ladies' Moisture Free Mesh Sport S...	$20.54
21	B014ICEDNA	FNC7C	Purple	https://images-na.ssl-images-amazon.com/images...	SHIRT	Supernatural Chibis Sam Dean And Castiel Short...	$7.50

In [26]:

```
# Remove All products with very few words in title
#print(data['title'].apply(lambda x: len(x.split())>4))

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
```

In [27]:

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

Out[27]:

	asin	brand	color	medium_image_url	product_type_name	title	formatted_price
61973	B06Y1KZ2WB	Éclair	Black/Pink	https://images-na.ssl-images-amazon.com/images...	SHIRT	Éclair Women's Printed Thin Strap Blouse Black...	$24.99
133820	B010RV33VE	xiaoming	Pink	https://images-na.ssl-images-amazon.com/images...	SHIRT	xiaoming Womens Sleeveless Loose Long T-shirts...	$18.19

	asin	brand	color	medium_image_url	product_type_name	xiaoming title	formatted_price
81461	B01DDSDLNS	xiaoming	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	Women's White Long Sleeve Single Brea...	$21.58
75995	B00X5LYO9Y	xiaoming	Red Anchors	https://images-na.ssl-images-amazon.com/images...	SHIRT	xiaoming Stripes Tank Patch/Bear Sleeve Anchor...	$15.91
151570	B00WPJG35K	xiaoming	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	xiaoming Sleeve Sheer Loose Tassel Kimono Woma...	$14.32

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

```
Titles 1:
16. woman's place is in the house and the senate shirts for Womens XXL White
17. woman's place is in the house and the senate shirts for Womens M Grey

Title 2:
25. tokidoki The Queen of Diamonds Women's Shirt X-Large
26. tokidoki The Queen of Diamonds Women's Shirt Small
27. tokidoki The Queen of Diamonds Women's Shirt Large

Title 3:
61. psychedelic colorful Howling Galaxy Wolf T-shirt/Colorful Rainbow Animal Print Head
Shirt for woman Neon Wolf t-shirt
62. psychedelic colorful Howling Galaxy Wolf T-shirt/Colorful Rainbow Animal Print Head
Shirt for woman Neon Wolf t-shirt
63. psychedelic colorful Howling Galaxy Wolf T-shirt/Colorful Rainbow Animal Print Head
Shirt for woman Neon Wolf t-shirt
64. psychedelic colorful Howling Galaxy Wolf T-shirt/Colorful Rainbow Animal Print Head
Shirt for woman Neon Wolf t-shirt
```

In [28]:

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

In [29]:

```
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', 'Diam
onds', '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 t
hose two apperals are different
        # if the number of words in which both strings differ are < 2 , we are considering it as t
hose 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]])

            # if the comaprision between is between num_data_points, num_data_points-1 strings and
they differ in more than 2 words we include both
            if j == num_data_points-1: stage1_dedupe_asins.append(data_sorted['asin'].loc[indices[j
]])

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

In [30]:

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

We removed the dupliactes which differ only at the end.

In [31]:

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

```
Number of data points :  17593
```

In [32]:

```
data.to_pickle('17k_apperal_data')
```

[5.2.3] Remove duplicates : Part 2

In the previous cell, we sorted whole data in alphabetical order of titles.Then, we removed titles which are adjacent and very similar title

But there are some products whose titles are not adjacent but very similar.

Examples:

Titles-1
86261. UltraClub Women's Classic Wrinkle-Free Long Sleeve Oxford Shirt, Pink, XX-Large
115042. UltraClub Ladies Classic Wrinkle-Free Long-Sleeve Oxford Light Blue XXL

```
TItles-2
75004.  EVALY Women's Cool University Of UTAH 3/4 Sleeve Raglan Tee
109225. EVALY Women's Unique University Of UTAH 3/4 Sleeve Raglan Tees
120832. EVALY Women's New University Of UTAH 3/4-Sleeve Raglan Tshirt
```

In [33]:

```
data = pd.read_pickle('17k_apperal_data')
```

In [34]:

```
# 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', 'Diam
onds', '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 t
hose two apperals are same, hence we are ignoring them
        if (length - count) < 3:
            indices.remove(j)
```

In [35]:

```
# 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)]
```

In [36]:

```
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:  16435
```

In [37]:

```
data.to_pickle('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.
```

6. Text pre-processing

In [38]:

```
data = pd.read_pickle('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()
```

In [39]:

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

In [40]:

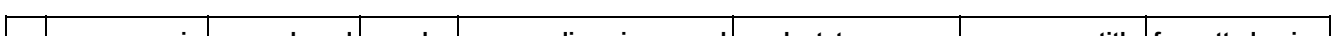
```
start_time = time.clock()
# we take each title and we text-preprocess it.
for index, row in data.iterrows():
    nlp_preprocessing(row['title'], index, 'title')
# we print the time it took to preprocess whole titles
print(time.clock() - start_time, "seconds")
```

```
36.65364800000043 seconds
```

In [41]:

```
data.head()
```

Out[41]:



	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 wor...	$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

In [42]:

```
data.to_pickle('16k_apperal_data_preprocessed')
```

Stemming

In [43]:

```
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
```

[8] Text based product similarity

In [44]:

```
data = pd.read_pickle('16k_apperal_data_preprocessed')
data.head()
```

Out[44]:

	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 wor...	$9.99
15	B003BSRPB0	FeatherLite	White	https://images-na.ssl-images-amazon.com/images...	SHIRT	featherlite ladies moisture free mesh sport sh...	$20.54

	asin	brand	color	medium_image_url	product_type_name	title	formatted_price
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

In [45]:

```
# 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 = PIL.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 w
rd 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)
```

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

In [46]:

```
from sklearn.feature_extraction.text import CountVectorizer
title_vectorizer = CountVectorizer()
title_features   = title_vectorizer.fit_transform(data['title'])
```

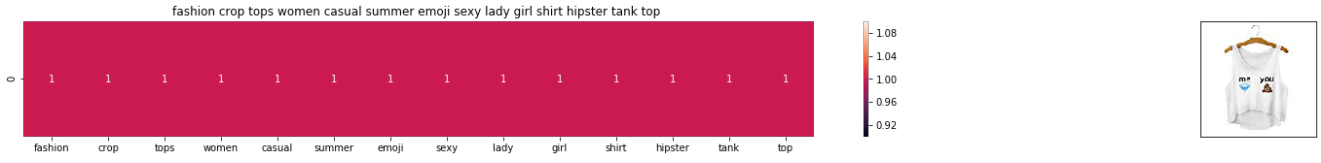
```
title_features.get_shape() # get number of rows and columns in feature matrix.
# title_features.shape = #data_points * #words_in_corpus
# CountVectorizer().fit_transform(corpus) returns
# the a sparase matrix of dimensions #data_points * #words_in_corpus

# What is a sparse vector?

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

Out[46]:

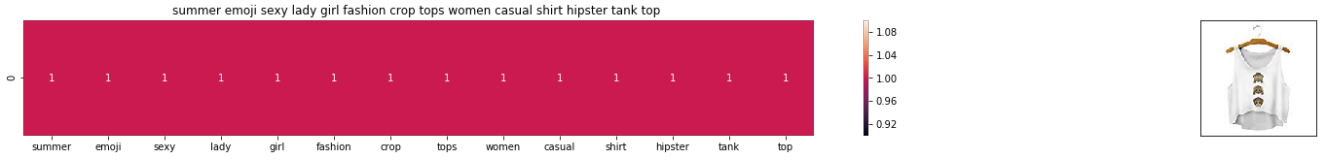
```
(16435, 12684)
```

In [47]:

```
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]], d
ata['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
```

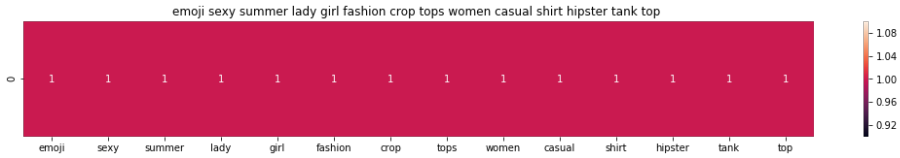



```
ASIN : B010V3B44G
Brand: Doxi Supermall
Title: fashion crop tops women casual summer emoji sexy lady girl shirt hipster tank top
Euclidean similarity with the query image : 0.0
============================================================
```

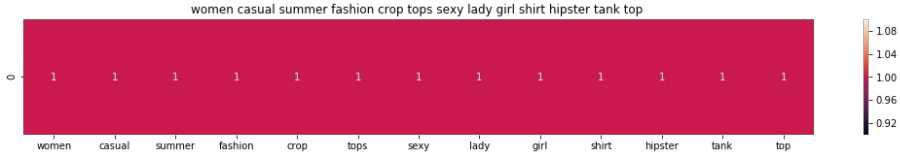



```
ASIN : B010V3BDII
Brand: Doxi Supermall
Title: summer emoji sexy lady girl fashion crop tops women casual shirt hipster tank top
```

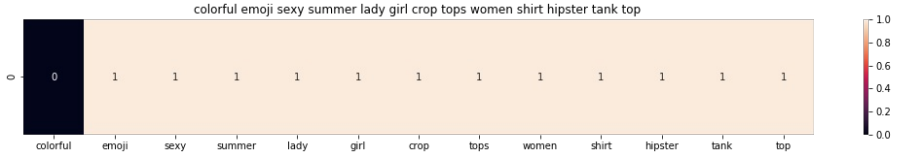
Euclidean similarity with the query image : 0.0
==



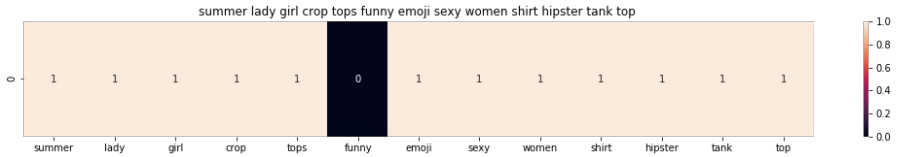
ASIN : B010V3BLWQ
Brand: Doxi Supermall
Title: emoji sexy summer lady girl fashion crop tops women casual shirt hipster tank top
Euclidean similarity with the query image : 0.0
==



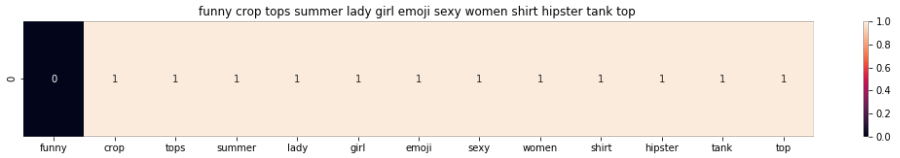
ASIN : B010V3AYSS
Brand: Doxi Supermall
Title: women casual summer fashion crop tops sexy lady girl shirt hipster tank top
Euclidean similarity with the query image : 1.0
==



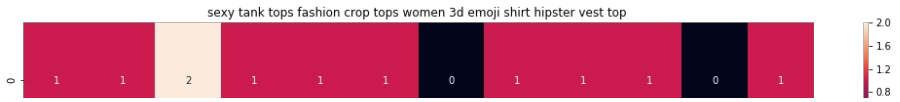
ASIN : B010V3BQZS
Brand: Doxi Supermall
Title: colorful emoji sexy summer lady girl crop tops women shirt hipster tank top
Euclidean similarity with the query image : 1.7320508075688772
==

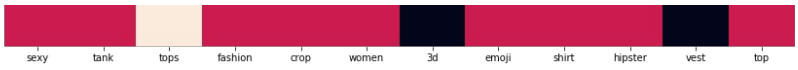


ASIN : B010V3BVMQ
Brand: Doxi Supermall
Title: summer lady girl crop tops funny emoji sexy women shirt hipster tank top
Euclidean similarity with the query image : 1.7320508075688772
==

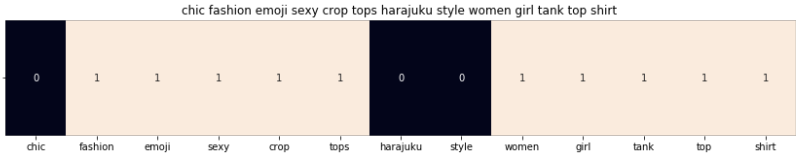


ASIN : B010V3C116
Brand: Doxi Supermall
Title: funny crop tops summer lady girl emoji sexy women shirt hipster tank top
Euclidean similarity with the query image : 1.7320508075688772
==

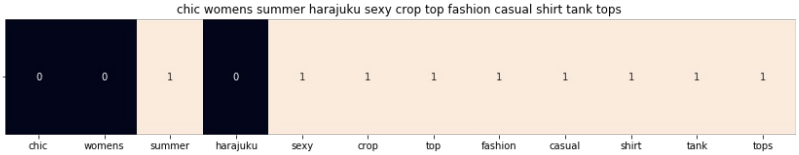




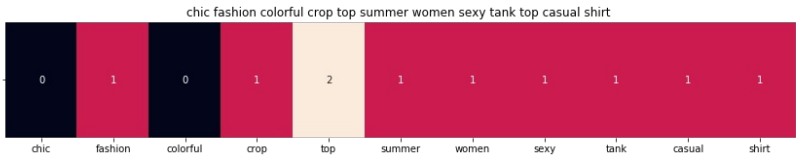
ASIN : B010V3DB9C
Brand: Doxi Supermall
Title: sexy tank tops fashion crop tops women 3d emoji shirt hipster vest top
Euclidean similarity with the query image : 2.6457513110645907
==========



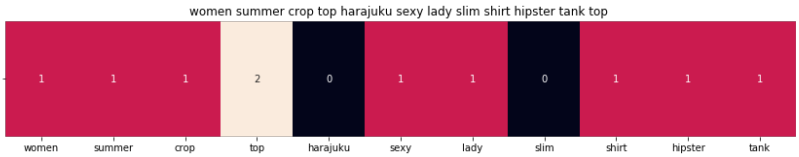
ASIN : B011RCJPR8
Brand: Chiclook Cool
Title: chic fashion emoji sexy crop tops harajuku style women girl tank top shirt
Euclidean similarity with the query image : 2.6457513110645907
==========



ASIN : B011RCJEMO
Brand: Chiclook Cool
Title: chic womens summer harajuku sexy crop top fashion casual shirt tank tops
Euclidean similarity with the query image : 2.8284271247461903
==========



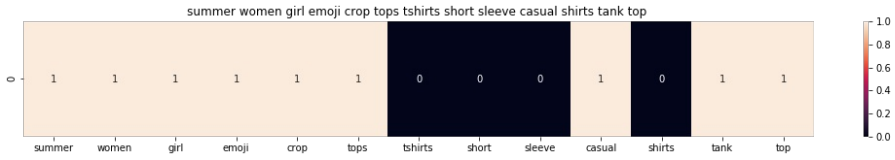
ASIN : B011RCJ6UE
Brand: Chiclook Cool
Title: chic fashion colorful crop top summer women sexy tank top casual shirt
Euclidean similarity with the query image : 2.8284271247461903
==========



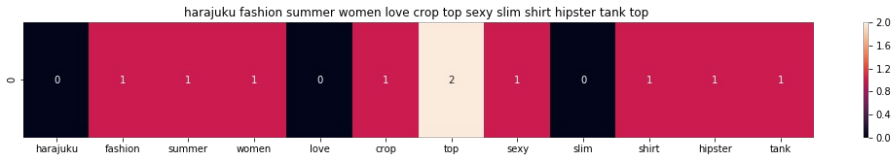
ASIN : B010V3EDEE
Brand: Doxi Supermall
Title: women summer crop top harajuku sexy lady slim shirt hipster tank top
Euclidean similarity with the query image : 2.8284271247461903
==========

ASIN : B0107UEPVM
Brand: Mang GO
Title: crop tops women fashion sexy character vest casual tshirt tank top

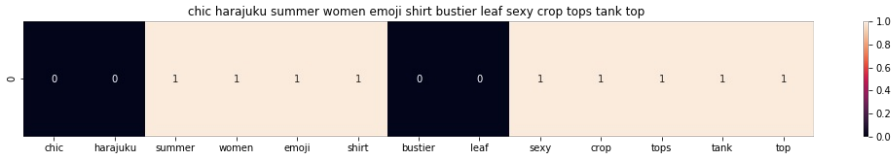
Euclidean similarity with the query image : 3.0
==========



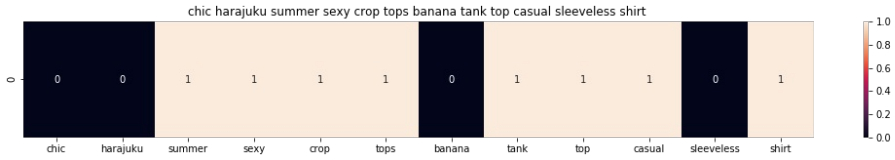
ASIN : B0124ECIU4
Brand: Doxi Supermall
Title: summer women girl emoji crop tops tshirts short sleeve casual shirts tank top
Euclidean similarity with the query image : 3.0
==========



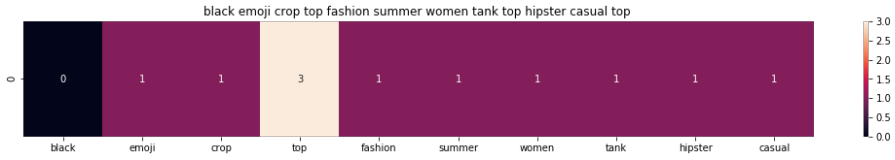
ASIN : B010V35OBU
Brand: Doxi Supermall
Title: harajuku fashion summer women love crop top sexy slim shirt hipster tank top
Euclidean similarity with the query image : 3.0
==========



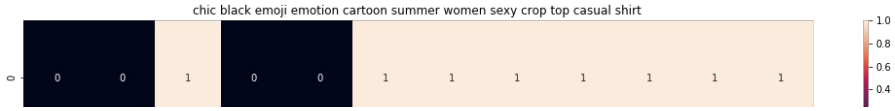
ASIN : B011UEXGH8
Brand: Chiclook Cool
Title: chic harajuku summer women emoji shirt bustier leaf sexy crop tops tank top
Euclidean similarity with the query image : 3.0
==========



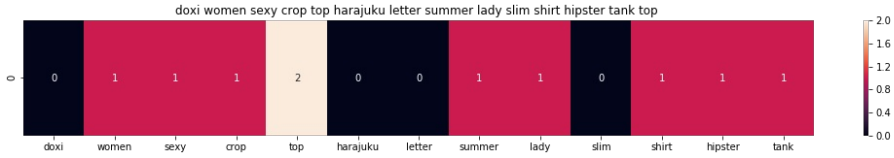
ASIN : B011RCIQBE
Brand: Chiclook Cool
Title: chic harajuku summer sexy crop tops banana tank top casual sleeveless shirt
Euclidean similarity with the query image : 3.1622776601683795
==========



ASIN : B0124E80M4
Brand: Doxi Supermall
Title: black emoji crop top fashion summer women tank top hipster casual top
Euclidean similarity with the query image : 3.1622776601683795
==========



ASIN : B011RCJ4M4
Brand: Chiclook Cool
Title: chic black emoji emotion cartoon summer women sexy crop top casual shirt
Euclidean similarity with the query image : 3.1622776601683795
==========



ASIN : B010V39146
Brand: Doxi Supermall
Title: doxi women sexy crop top harajuku letter summer lady slim shirt hipster tank top
Euclidean similarity with the query image : 3.1622776601683795
==========

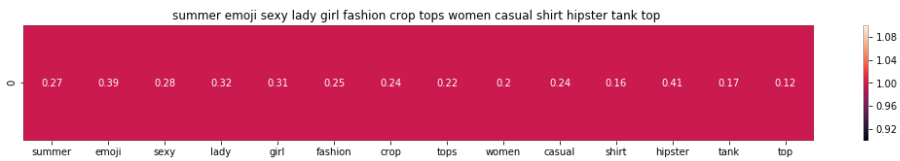
[8.5] TF-IDF based product similarity

In [48]:

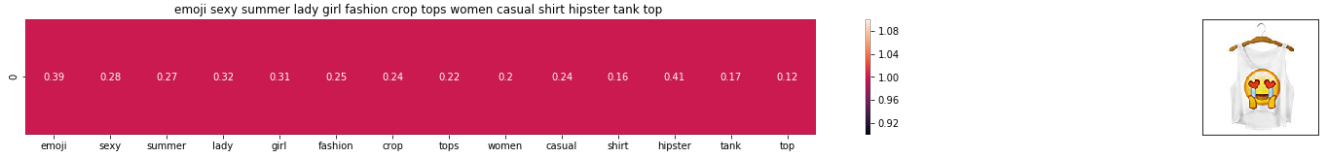
```
tfidf_title_vectorizer = TfidfVectorizer(min_df = 0)
tfidf_title_features = tfidf_title_vectorizer.fit_transform(data['title'])
# tfidf_title_features.shape = #data_points * #words_in_corpus
# CountVectorizer().fit_transform(courpus) returns the a sparase matrix of dimensions #data_points
* #words_in_corpus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

In [49]:

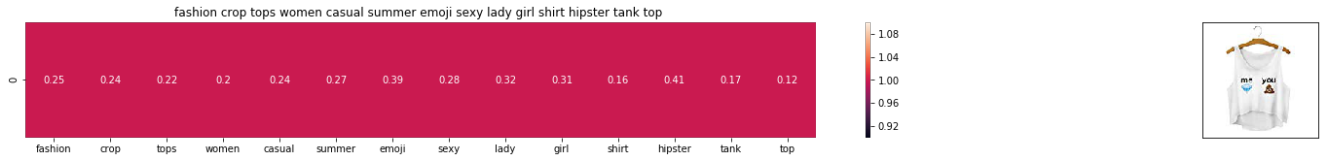
```
def tfidf_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # 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 repre
sents the intersection with inputs title
```



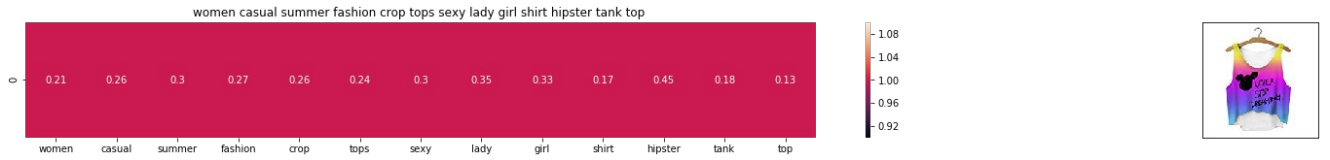
ASIN : B010V3BDII
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.0
==========



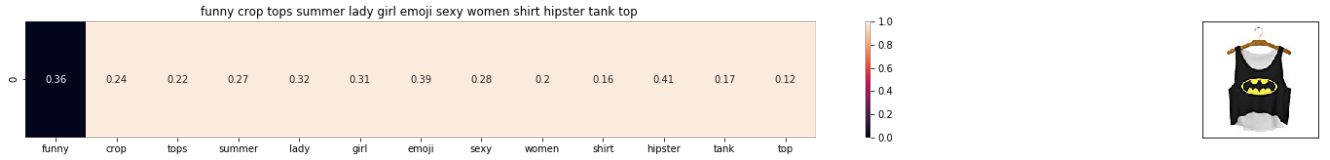
ASIN : B010V3BLWQ
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.0
==========



ASIN : B010V3B44G
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.0
==========

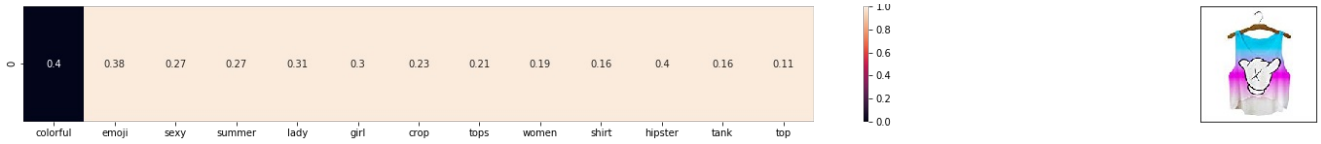


ASIN : B010V3AYSS
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.40138594750234946
==========

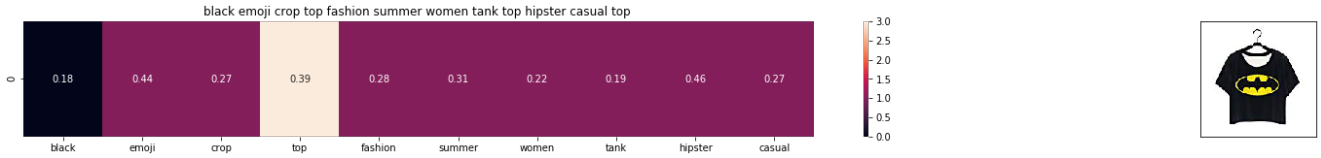


ASIN : B010V3C116
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.4954421553895553
==========

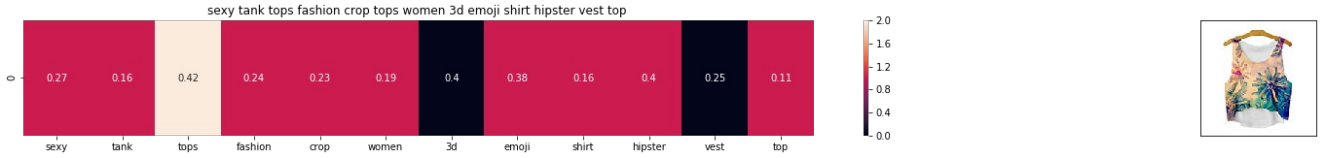
ASIN : B010V3BVMQ
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.4954421553895553
==========



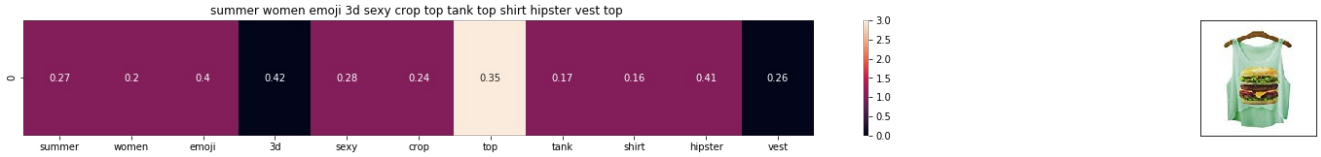
ASIN : B010V3BQZS
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.5241689140292635
==========



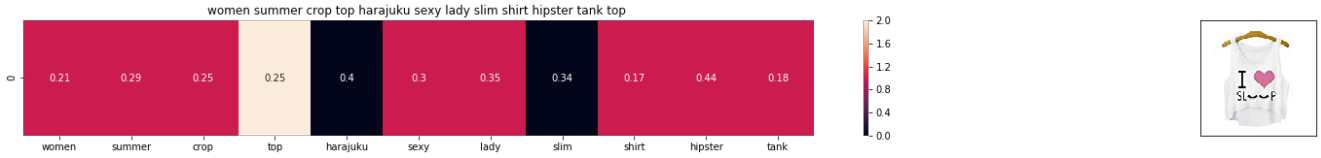
ASIN : B0124E80M4
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.6841581626642753
==========



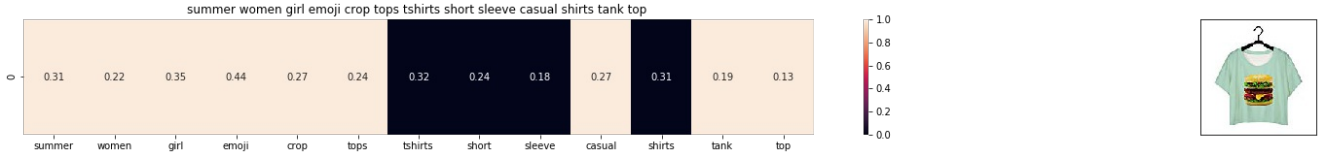
ASIN : B010V3DB9C
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.7731343455110793
==========



ASIN : B010V3E5EC
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.8128754313990525
==========

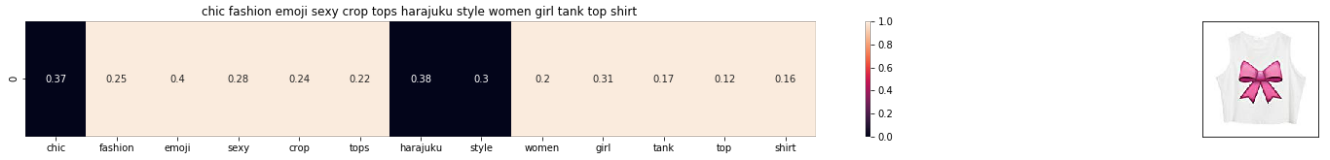


ASIN : B010V3EDEE
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.8437056912864757
==========

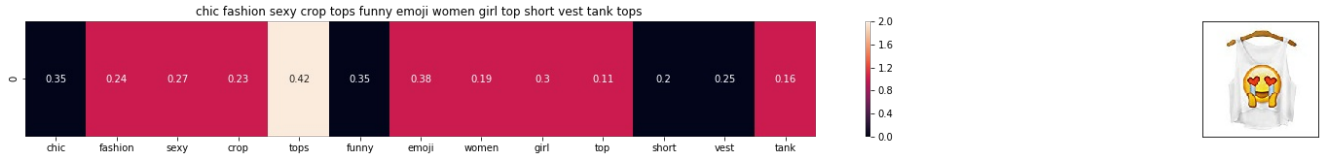


ASIN : B0124ECIU4

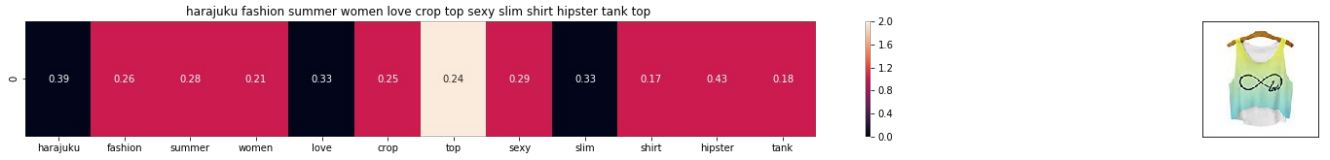
ASIN : B0124EC1O4
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.8553483954246196
==========



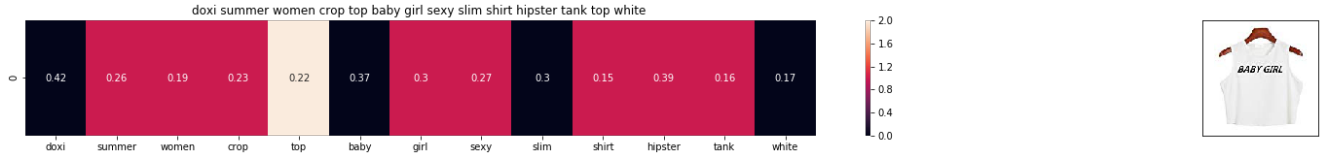
ASIN : B011RCJPR8
BRAND : Chiclook Cool
Eucliden distance from the given image : 0.8826321316686155
==========



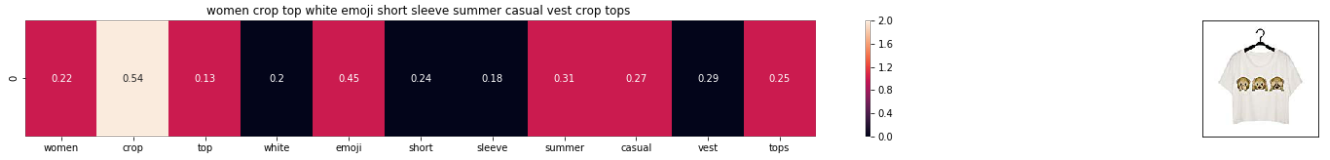
ASIN : B011RCJH58
BRAND : Chiclook Cool
Eucliden distance from the given image : 0.900401746801386
==========



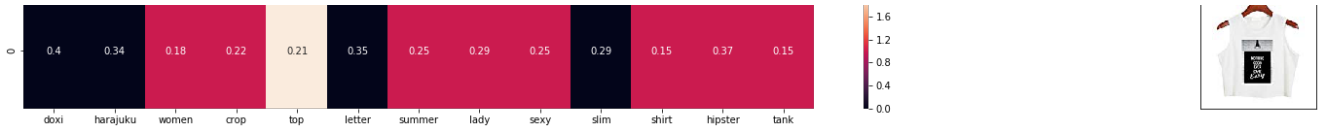
ASIN : B010V35OBU
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.9172816572673459
==========



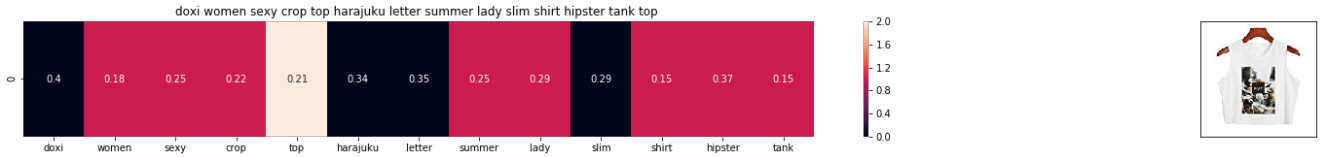
ASIN : B010V3A23U
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.9303848929561549
==========



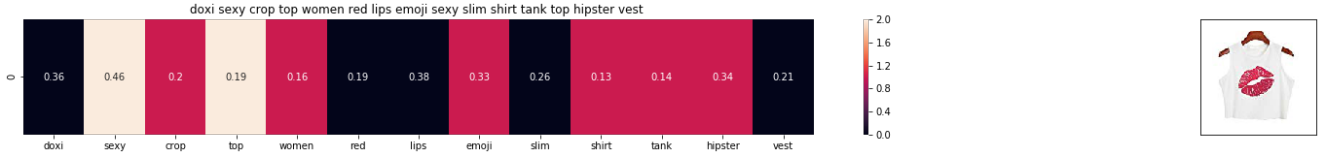
ASIN : B0124E7MHS
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.9334421080980748
==========



ASIN : B010V380LQ
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.9525344637195033
==========



ASIN : B010V39146
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.9525344637195033
==========



ASIN : B010TKXEHG
BRAND : Doxi Supermall
Eucliden distance from the given image : 0.9560708174154958
==========

[8.5] IDF based product similarity

In [50]:

```
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 d
oc
```

In [51]:

```
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)))
```

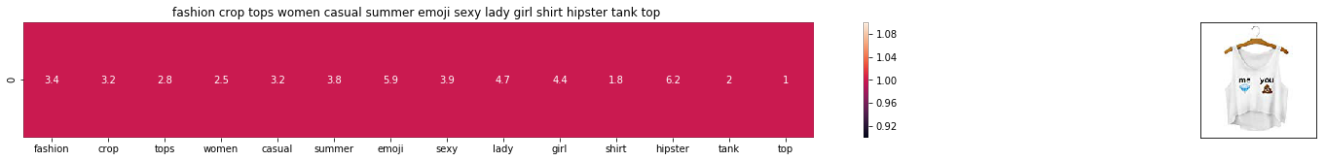
In [52]:

```
# 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 t
```

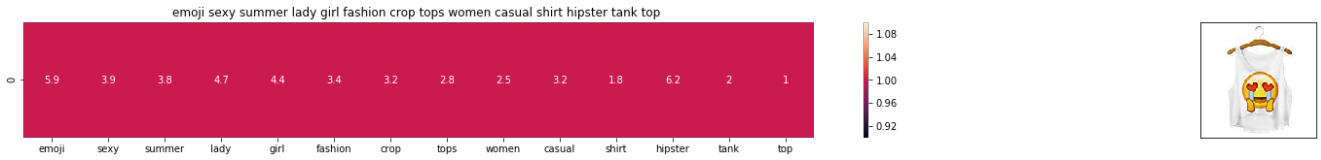
```
    # to calculate idf_title_features we need to replace the count values with the idf values of t
he word
    # idf_title_features[:, idf_title_vectorizer.vocabulary_[i]].nonzero()[0] will return all docu
ments in which the word i present
    for j in idf_title_features[:, idf_title_vectorizer.vocabulary_[i]].nonzero()[0]:

        # 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
```

In [53]:

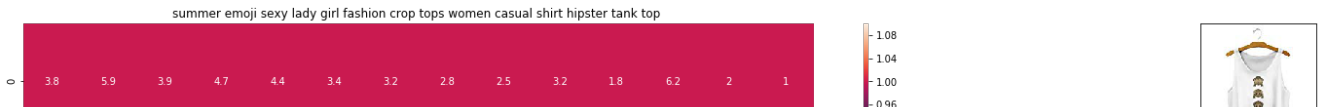
```
def idf_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # 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]], d
ata['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 represe
nts the intersection with inputs title
```



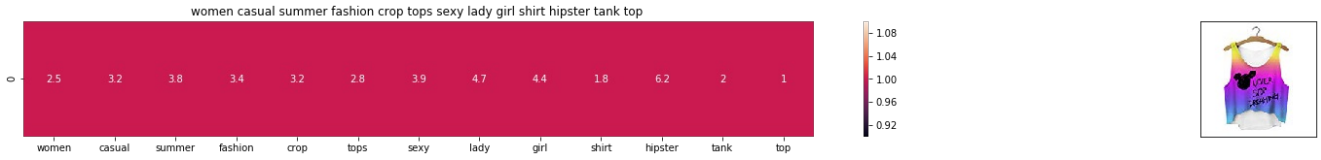

```
ASIN : B010V3B44G
Brand : Doxi Supermall
euclidean distance from the given image : 0.0
=============================================================================================================
======================
```



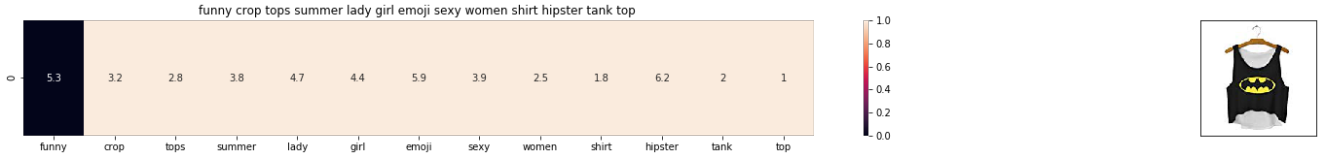

```
ASIN : B010V3BLWQ
Brand : Doxi Supermall
euclidean distance from the given image : 0.0
=============================================================================================================
======================
```



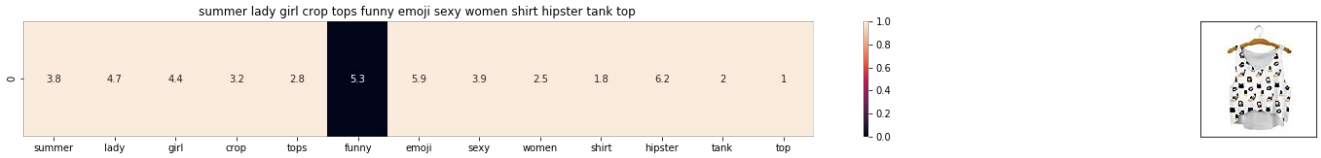
ASIN : B010V3BDII
Brand : Doxi Supermall
euclidean distance from the given image : 0.0
==========



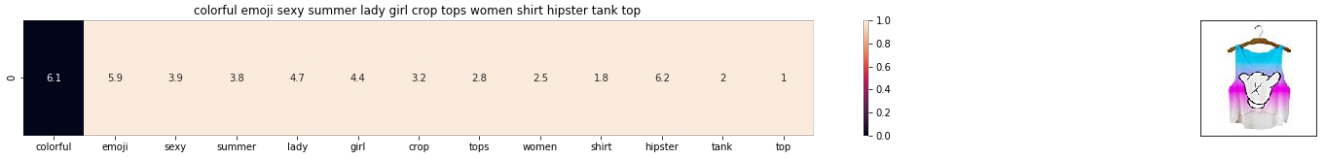
ASIN : B010V3AYSS
Brand : Doxi Supermall
euclidean distance from the given image : 5.922978852180059
==========



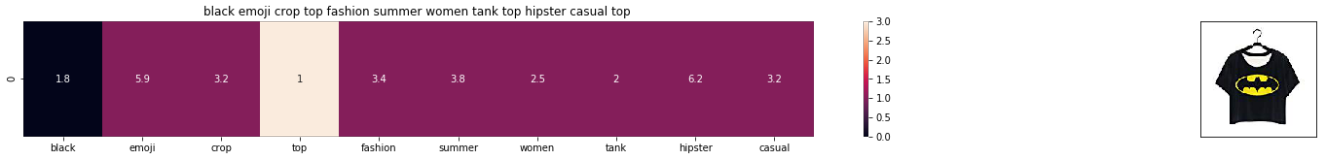
ASIN : B010V3C116
Brand : Doxi Supermall
euclidean distance from the given image : 7.037272185298332
==========



ASIN : B010V3BVMQ
Brand : Doxi Supermall
euclidean distance from the given image : 7.037272185298332
==========

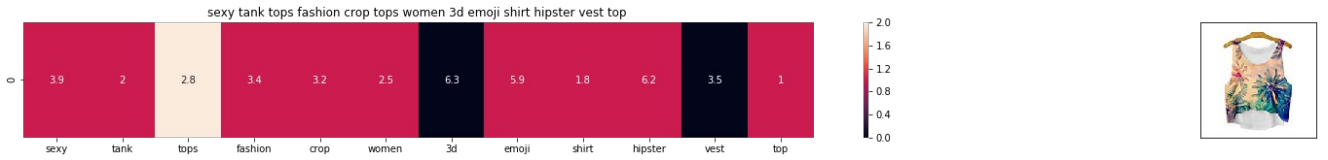


ASIN : B010V3BQZS
Brand : Doxi Supermall
euclidean distance from the given image : 7.667939547088641
==========

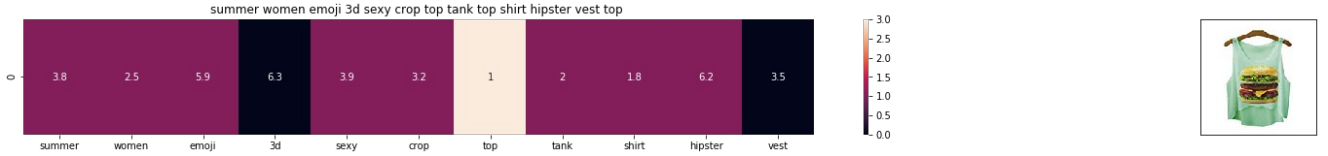


ASIN : B0124E80M4
Brand : Doxi Supermall
euclidean distance from the given image : 8.39863603811248
==========

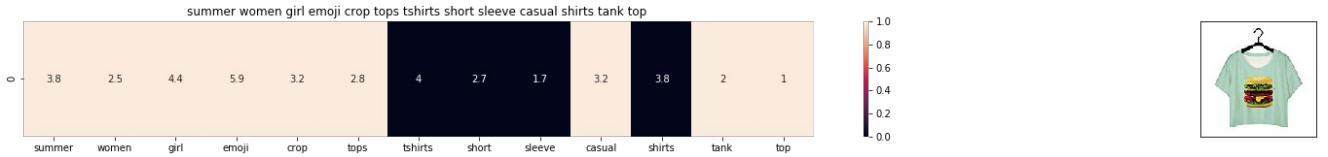
==========



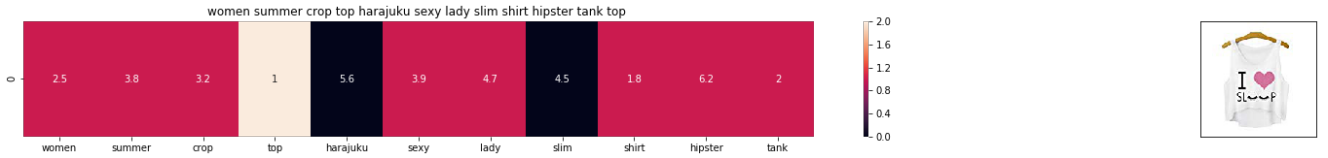
ASIN : B010V3DB9C
Brand : Doxi Supermall
euclidean distance from the given image : 10.835090137343855
==========
==========



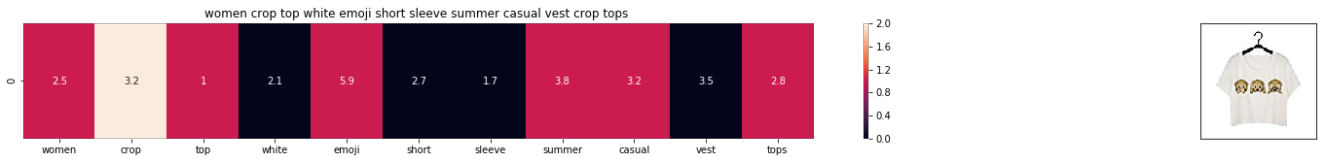
ASIN : B010V3E5EC
Brand : Doxi Supermall
euclidean distance from the given image : 11.060530175472811
==========
==========



ASIN : B0124ECIU4
Brand : Doxi Supermall
euclidean distance from the given image : 11.456017724459604
==========
==========

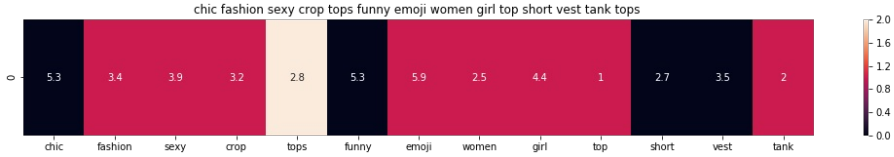


ASIN : B010V3EDEE
Brand : Doxi Supermall
euclidean distance from the given image : 11.635265990125815
==========
==========

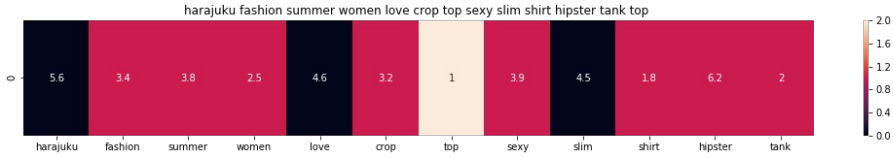


ASIN : B0124E7MHS
Brand : Doxi Supermall
euclidean distance from the given image : 11.844834283822053
==========
==========

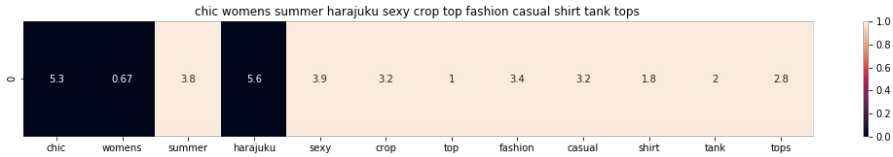
ASIN : B011RCJPR8
Brand : Chiclook Cool
euclidean distance from the given image : 12.760692810178545
==========



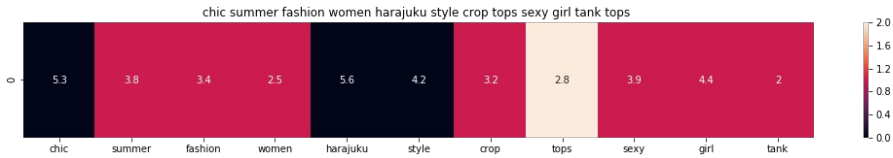
ASIN : B011RCJH58
Brand : Chiclook Cool
euclidean distance from the given image : 12.829128504563066
==========



ASIN : B010V35OBU
Brand : Doxi Supermall
euclidean distance from the given image : 12.92180694297083
==========



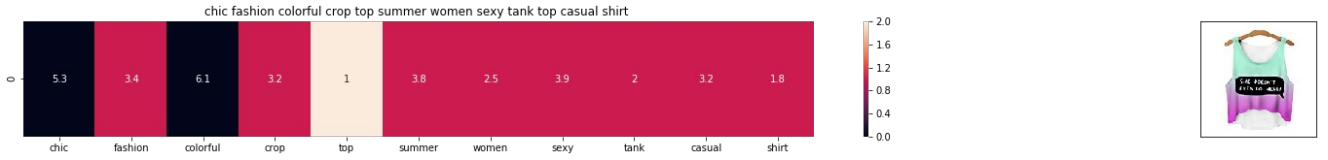
ASIN : B011RCJEMO
Brand : Chiclook Cool
euclidean distance from the given image : 13.474555736106787
==========



ASIN : B011OU51US
Brand : Chiclook Cool
euclidean distance from the given image : 13.713807644827545
==========

ASIN : B010V3A23U
Brand : Doxi Supermall
euclidean distance from the given image : 13.725325741546714
==========

```
======================
```




```
ASIN : B011RCJ6UE
Brand : Chiclook Cool
euclidean distance from the given image : 13.746787336587824
======================================================================================================
======================
```

[9] Text Semantics based product similarity

In [54]:

```
# 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)

'''
```

Out[54]:

```
'\n# Set values for various parameters\nnum_features = 300    # Word vector dimensionality
\nmin_word_count = 1    # Minimum word count                          \nnum_workers = 4       # Numbe
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'
```

In [55]:

```
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.dms', 'rb') as handle:
    model = pickle.load(handle)
```

In [56]:

```
# 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 lengt
h 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 lengt
h 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 appare
l
    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()
```

In [57]:

```
# 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.voc
abulary_[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
```

[9.2] Average Word2Vec product similarity.

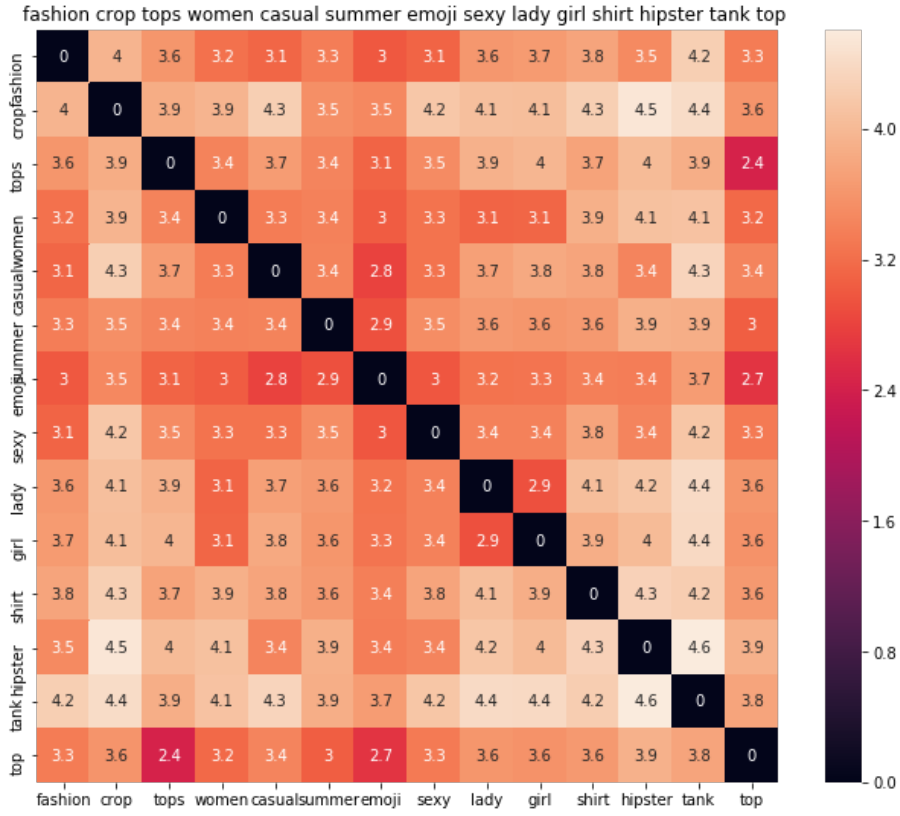
In [58]:

```
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)
```

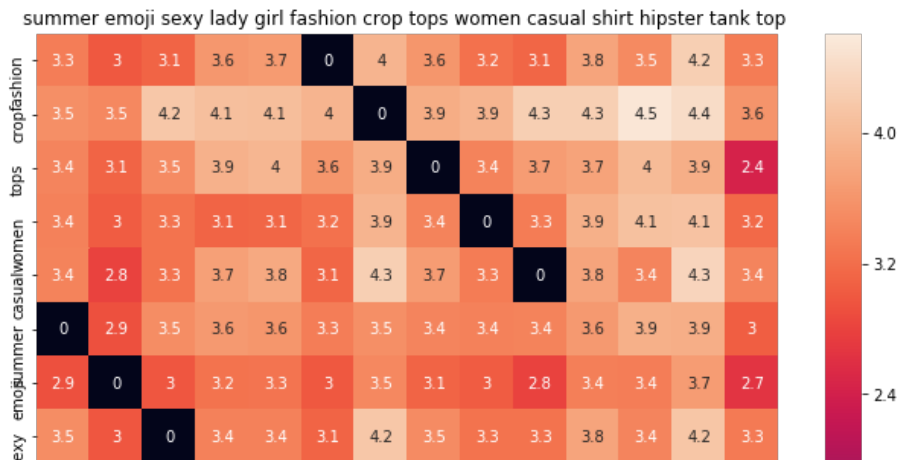
In [59]:

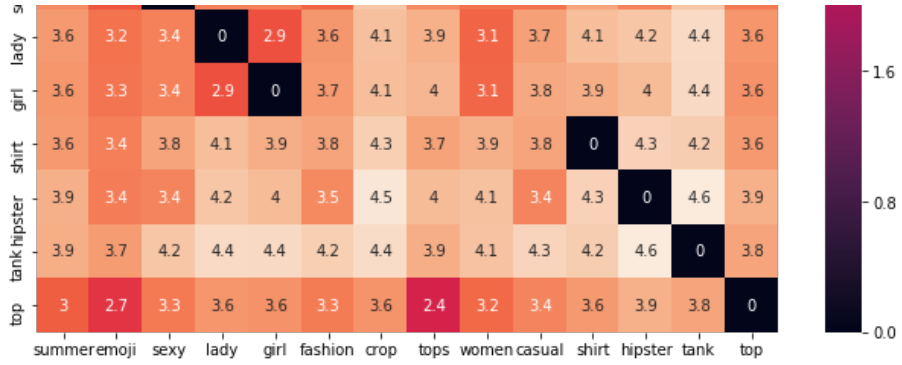
```
def avg_w2v_model(doc_id, num_results):
    # doc_id: apparel's id in given corpus

    # 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['mediu
m_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
```

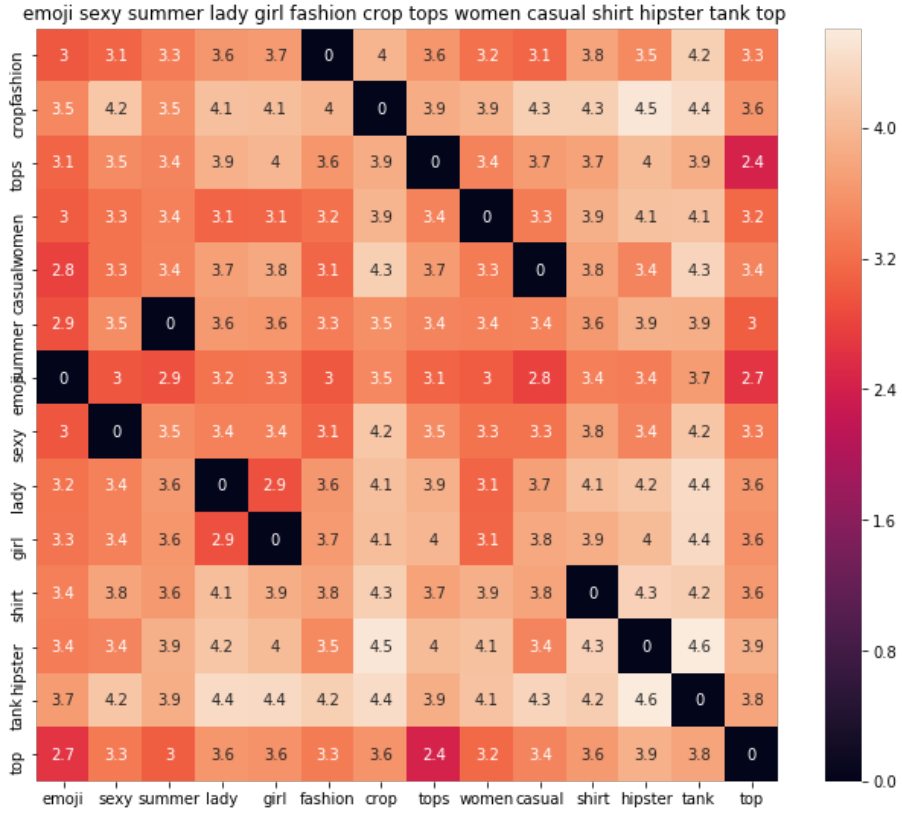



```
ASIN : B010V3B44G
BRAND : Doxi Supermall
euclidean distance from given input image : 3.6500243e-08
```

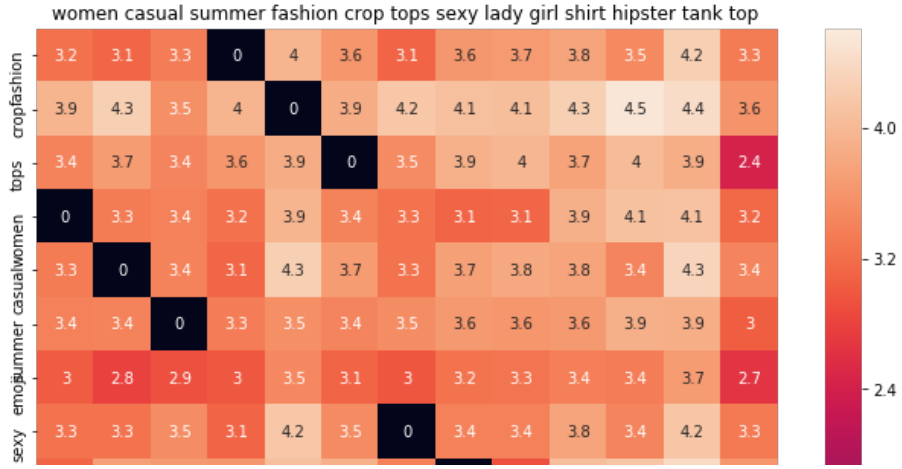


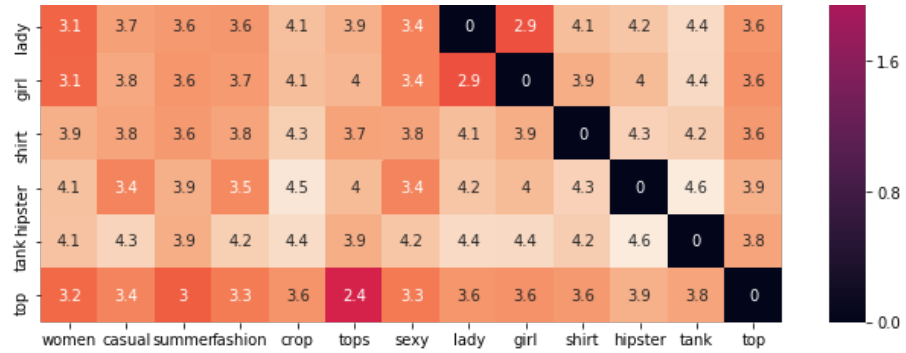


ASIN : B010V3BDII
BRAND : Doxi Supermall
euclidean distance from given input image : 3.6500243e-08
==========

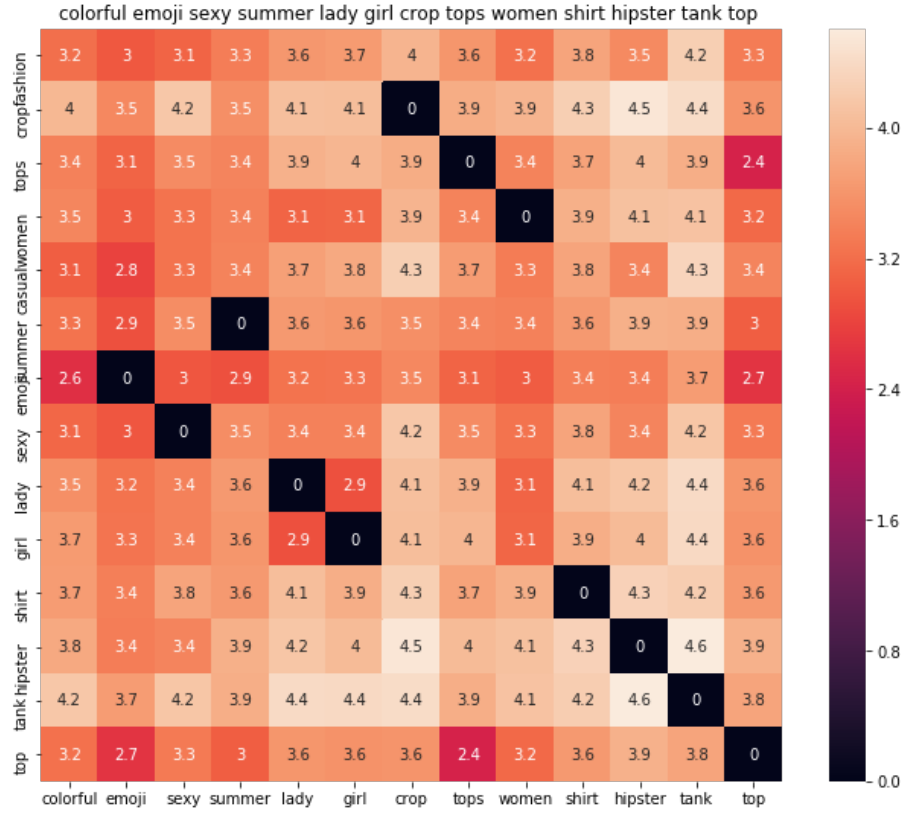


ASIN : B010V3BLWQ
BRAND : Doxi Supermall
euclidean distance from given input image : 3.6500243e-08
==========

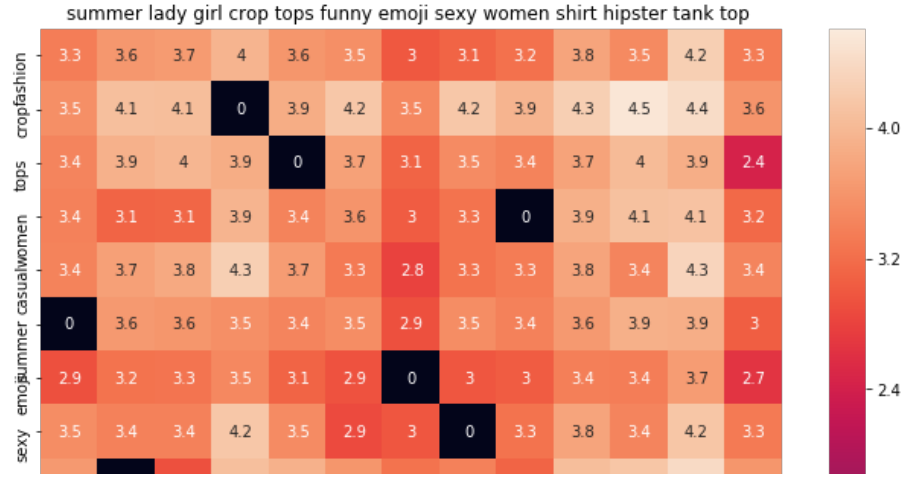


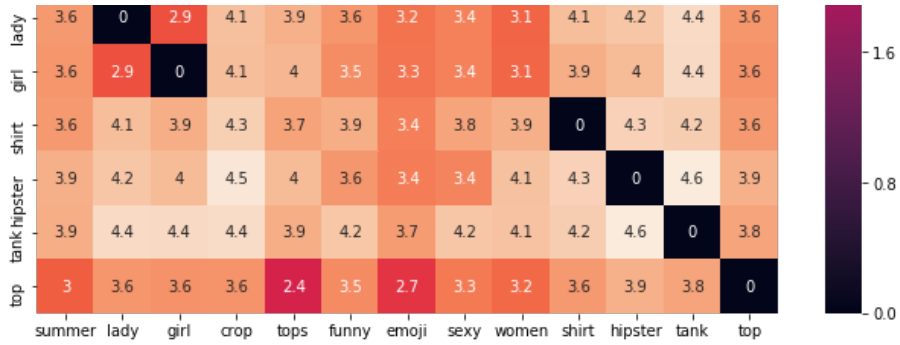


ASIN : B010V3AYSS
BRAND : Doxi Supermall
euclidean distance from given input image : 0.13368244
==========

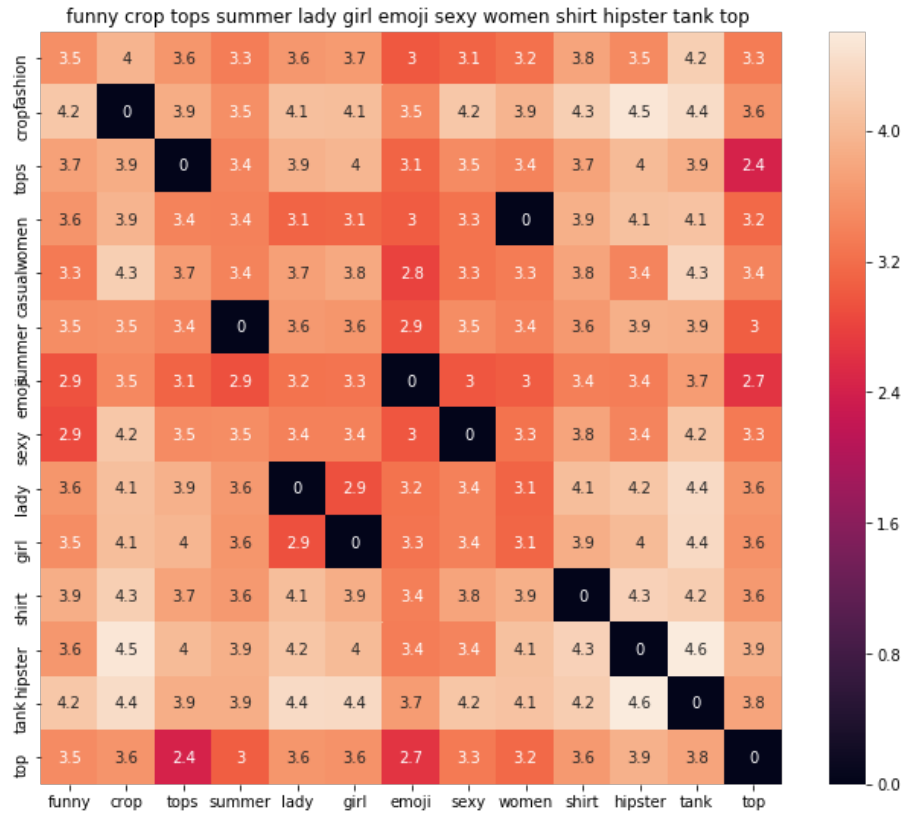


ASIN : B010V3BQZS
BRAND : Doxi Supermall
euclidean distance from given input image : 0.29837728
==========

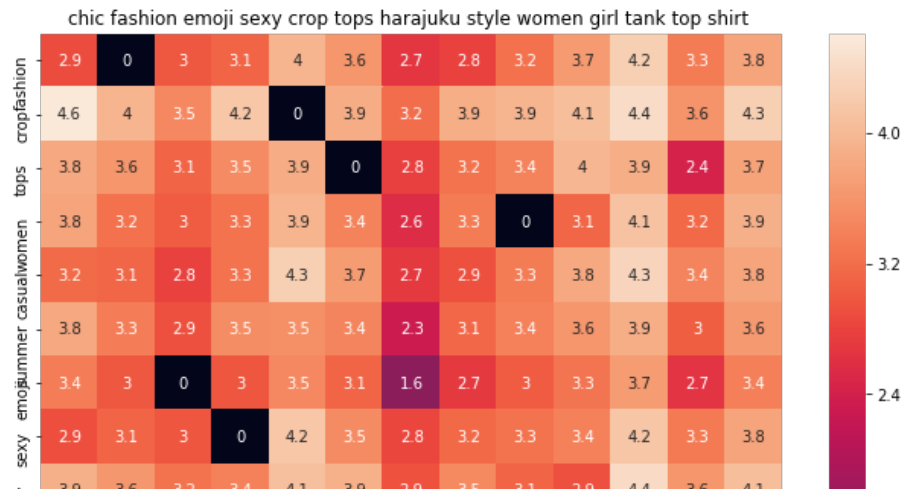


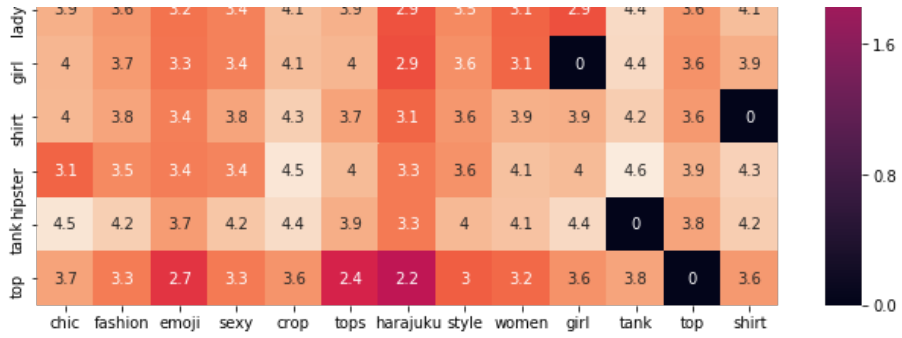


ASIN : B010V3BVMQ
BRAND : Doxi Supermall
euclidean distance from given input image : 0.3274634
==========

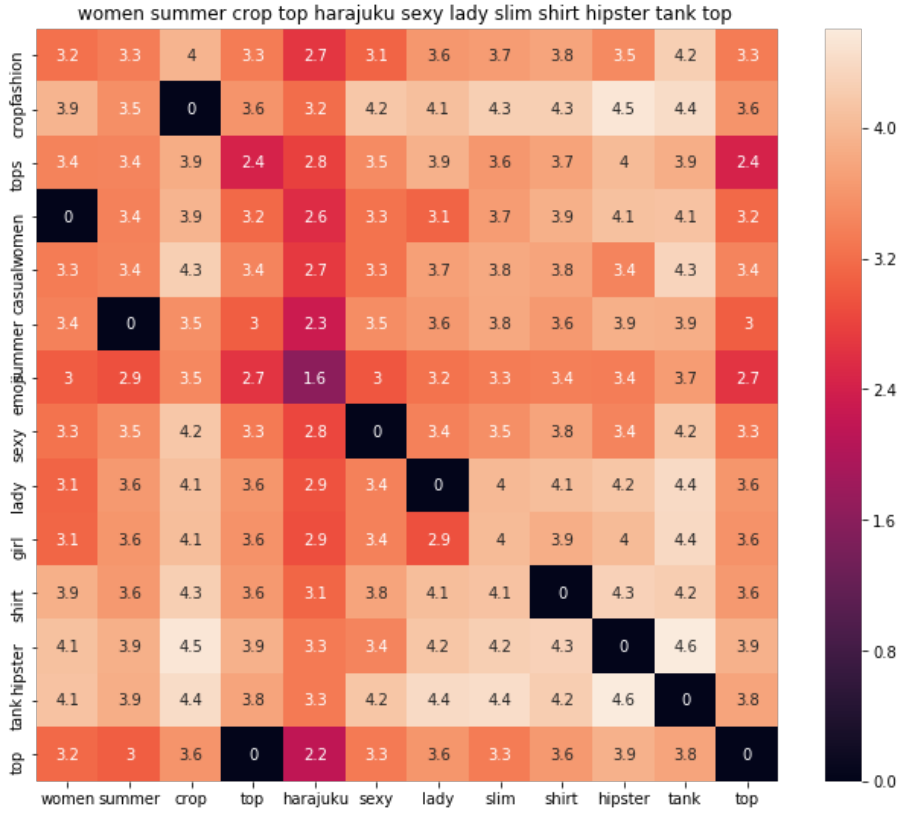


ASIN : B010V3C116
BRAND : Doxi Supermall
euclidean distance from given input image : 0.3274634
==========

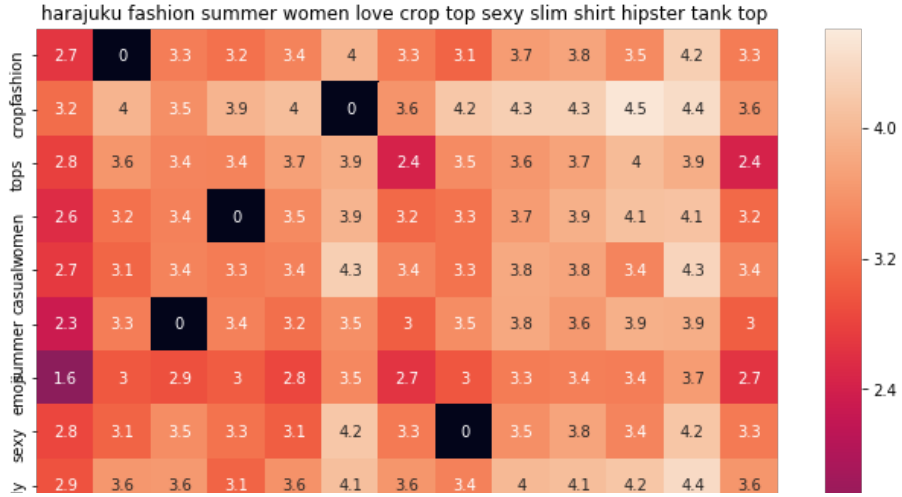


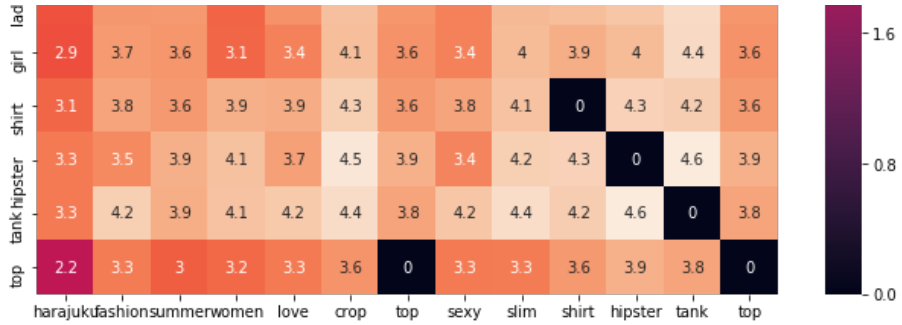


ASIN : B011RCJPR8
BRAND : Chiclook Cool
euclidean distance from given input image : 0.40975842
==========

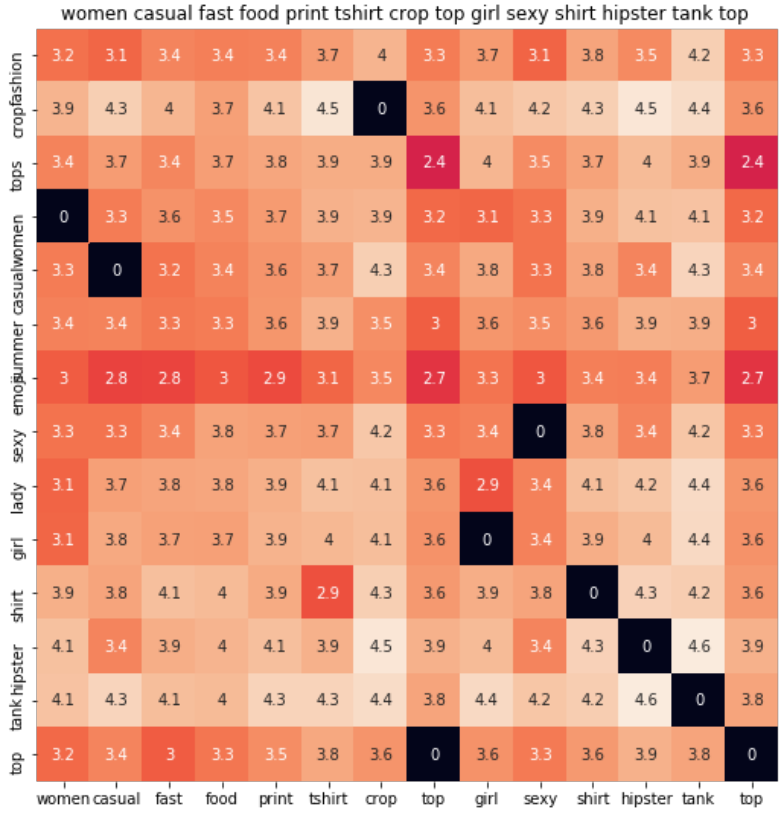


ASIN : B010V3EDEE
BRAND : Doxi Supermall
euclidean distance from given input image : 0.46806592
==========

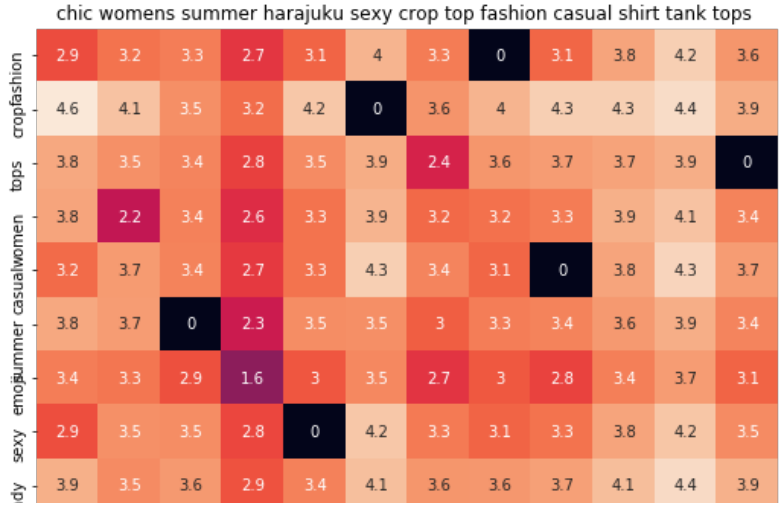


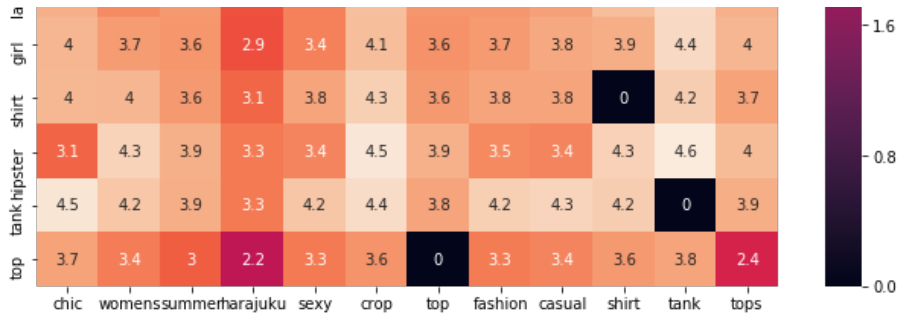


ASIN : B010V35OBU
BRAND : Doxi Supermall
euclidean distance from given input image : 0.4957314
==========

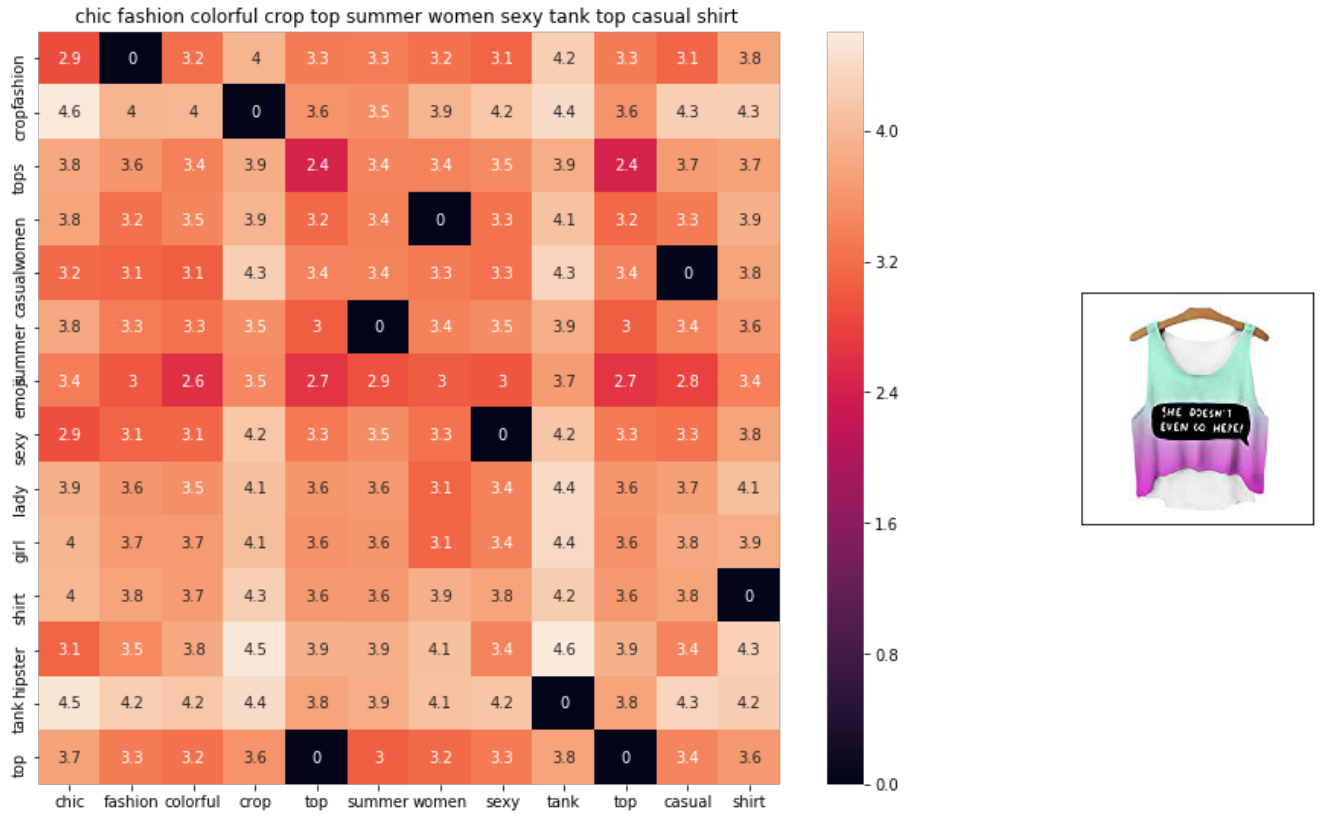


ASIN : B010V3AB5O
BRAND : Doxi Supermall
euclidean distance from given input image : 0.50107545
==========

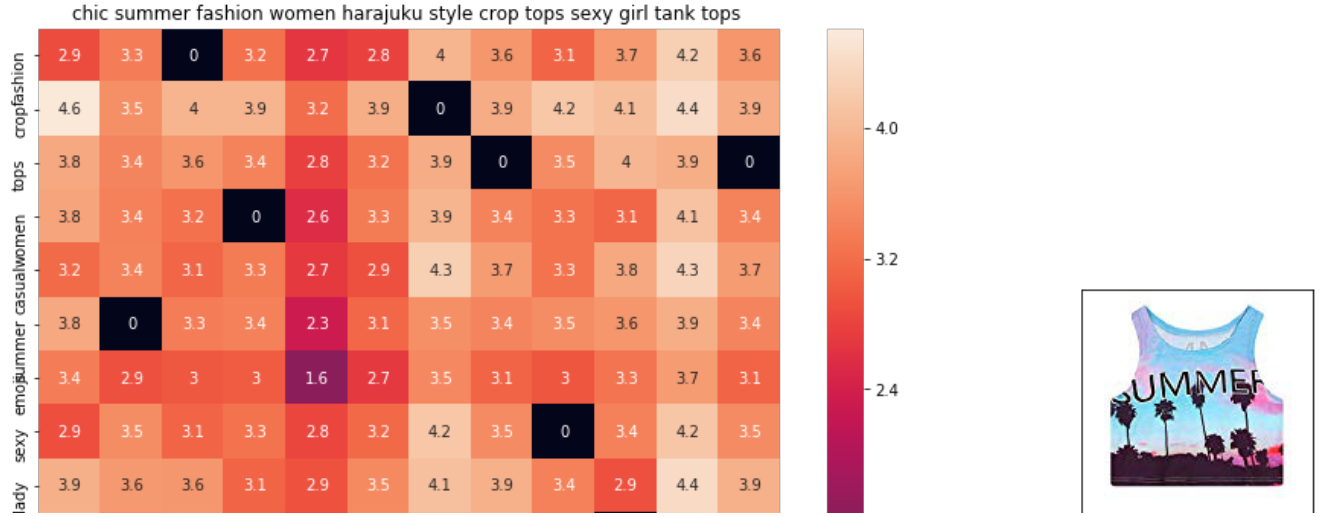


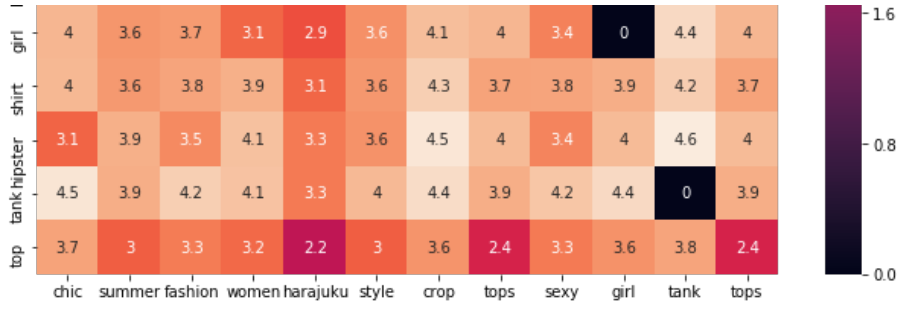


ASIN : B011RCJEMO
BRAND : Chiclook Cool
euclidean distance from given input image : 0.5027281
==========

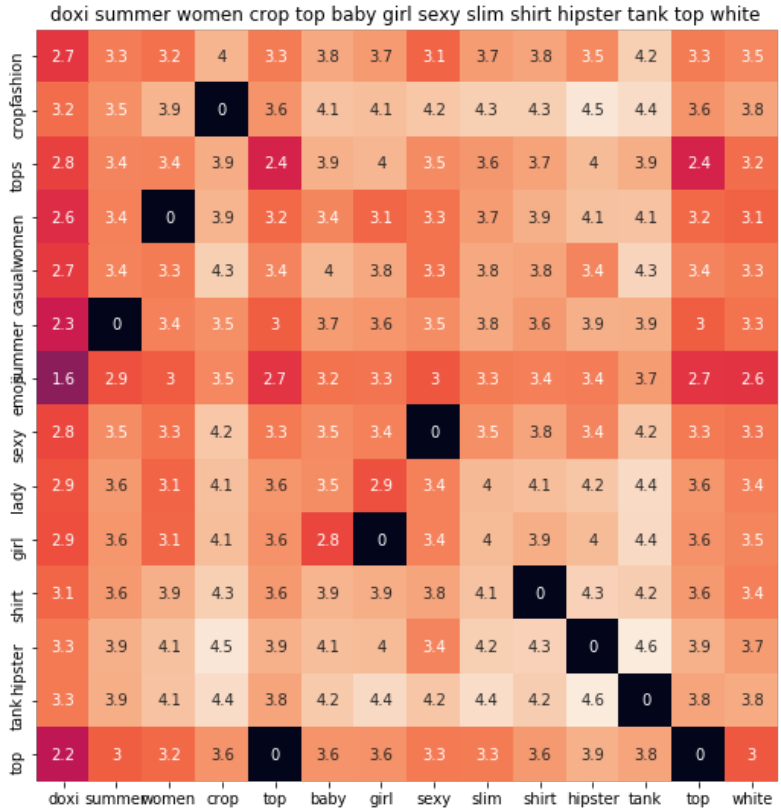


ASIN : B011RCJ6UE
BRAND : Chiclook Cool
euclidean distance from given input image : 0.5073639
==========

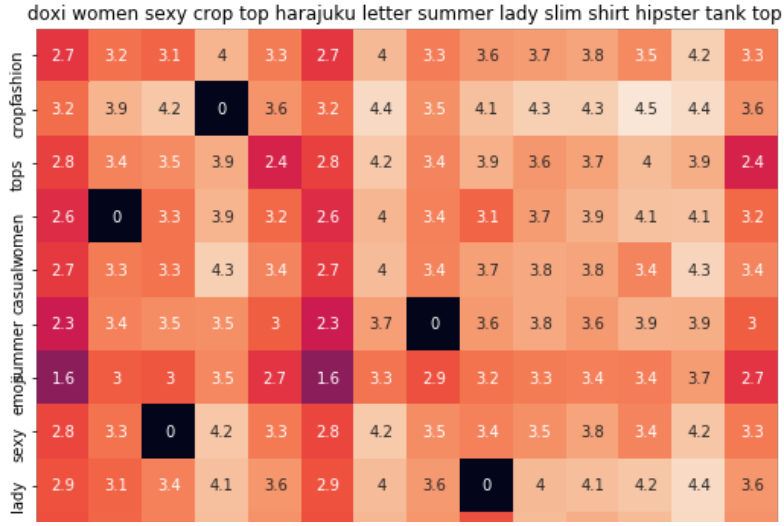


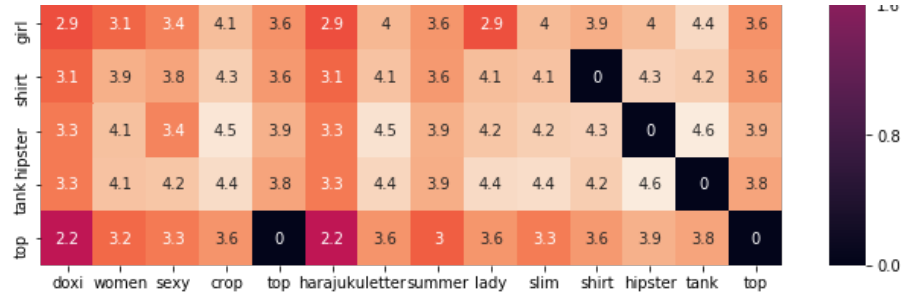


ASIN : B011OU51US
BRAND : Chiclook Cool
euclidean distance from given input image : 0.5160891
==========

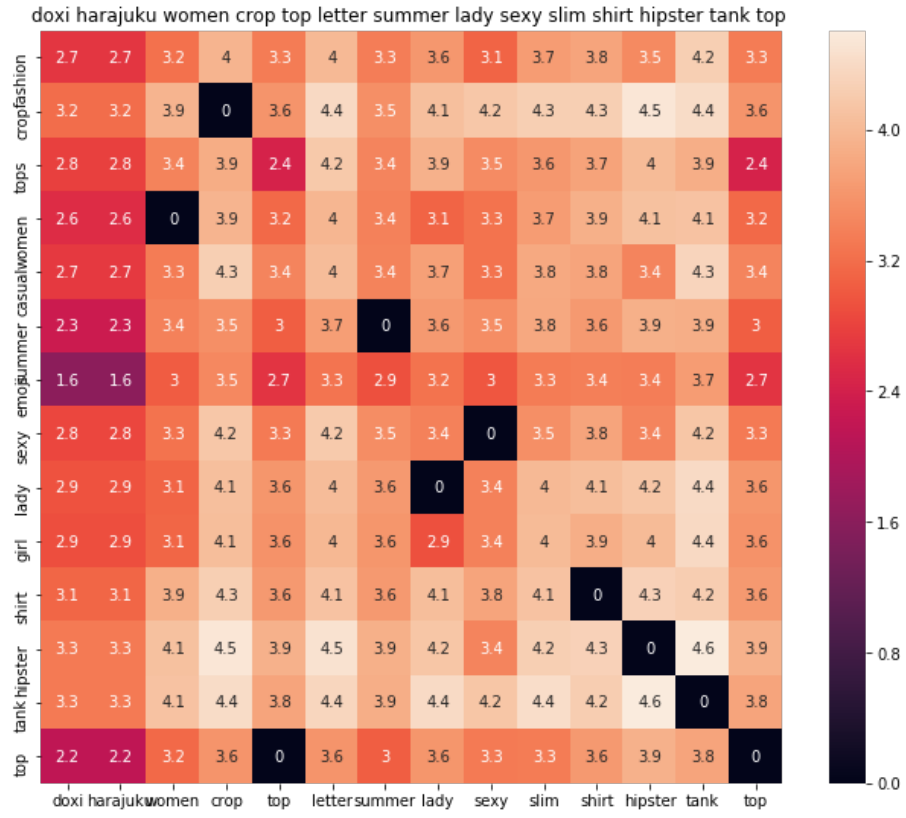


ASIN : B010V3A23U
BRAND : Doxi Supermall
euclidean distance from given input image : 0.5262789
==========

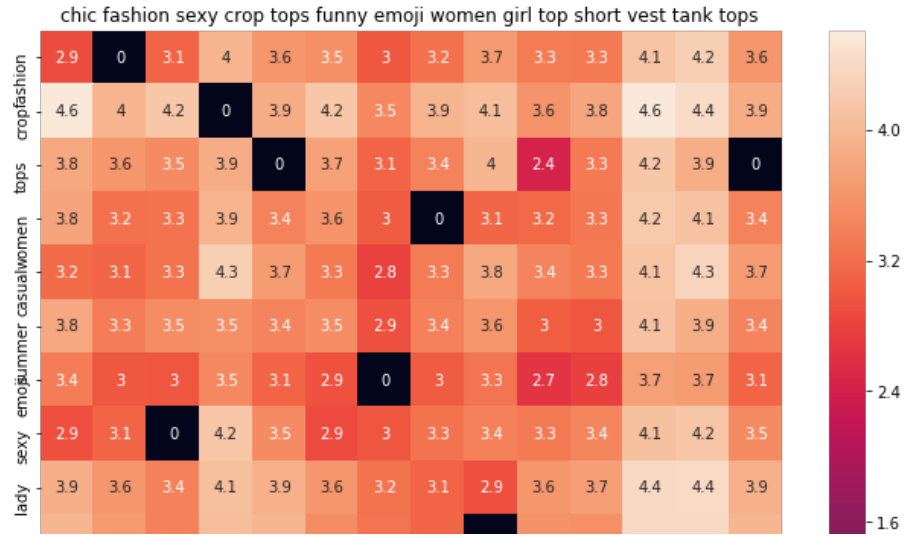


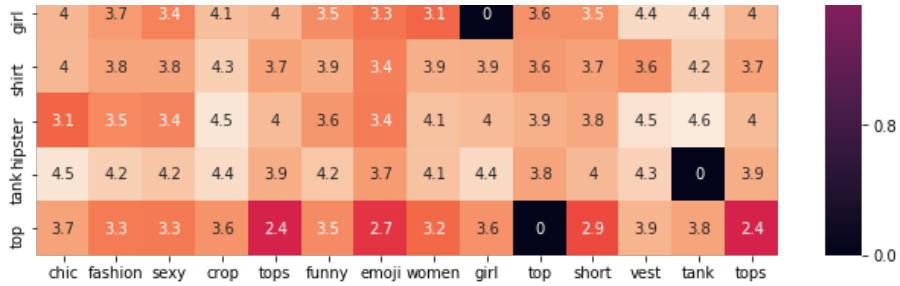


ASIN : B010V39146
BRAND : Doxi Supermall
euclidean distance from given input image : 0.5270717
==========

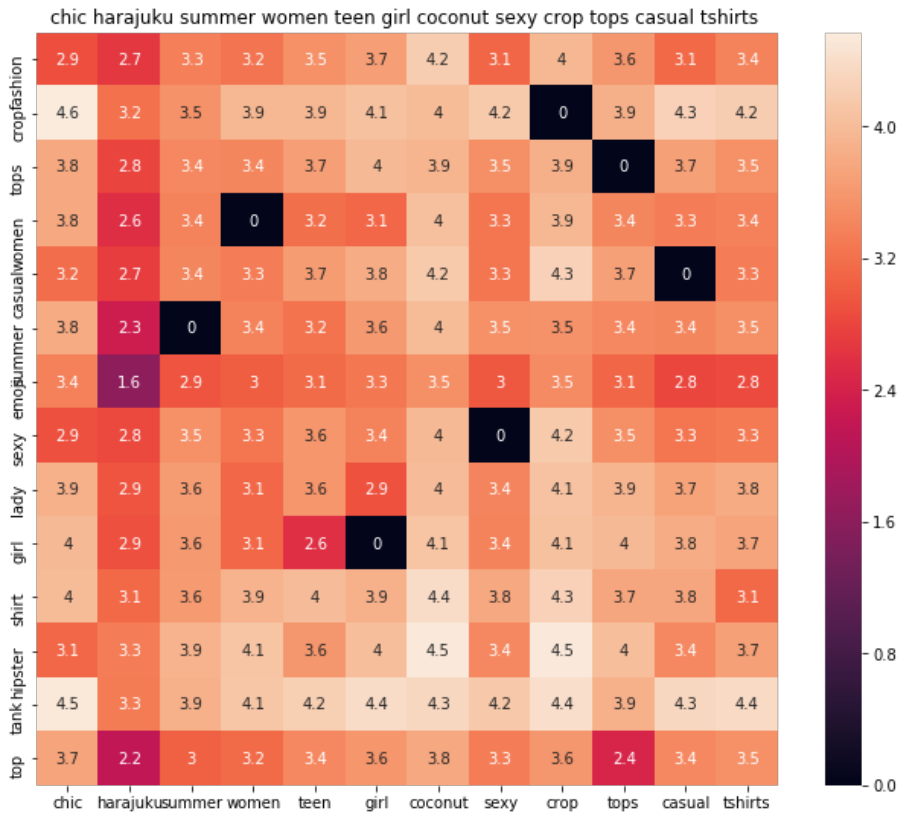


ASIN : B010V380LQ
BRAND : Doxi Supermall
euclidean distance from given input image : 0.5270717
==========

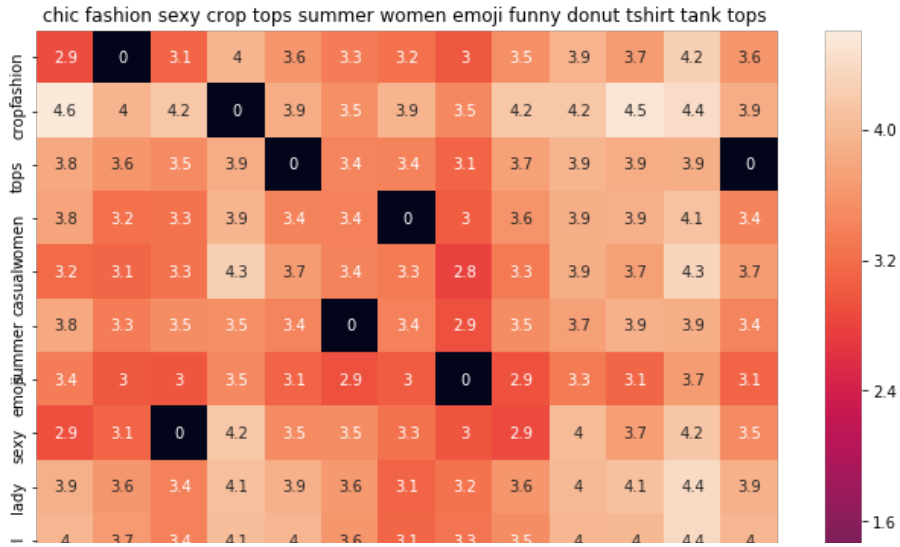


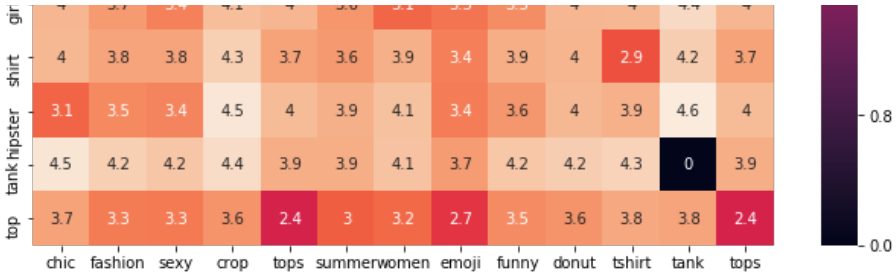


ASIN : B011RCJH58
BRAND : Chiclook Cool
euclidean distance from given input image : 0.52816993
==========



ASIN : B011OU4R08
BRAND : Chiclook Cool
euclidean distance from given input image : 0.5545634
==========






```
ASIN : B011UEUTQE
BRAND : Chiclook Cool
euclidean distance from given input image : 0.57349175
=============================================================================================================
======================
```

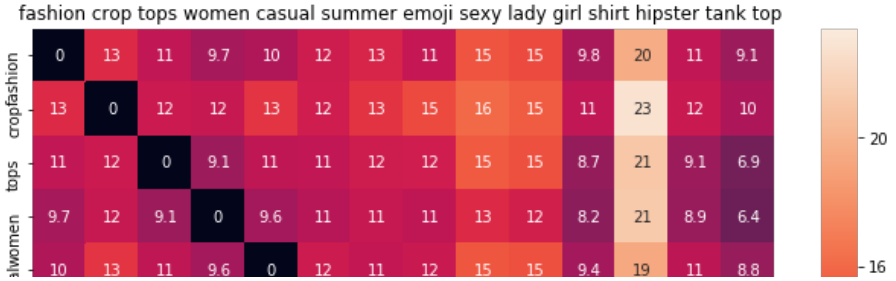
[9.4] IDF weighted Word2Vec for product similarity

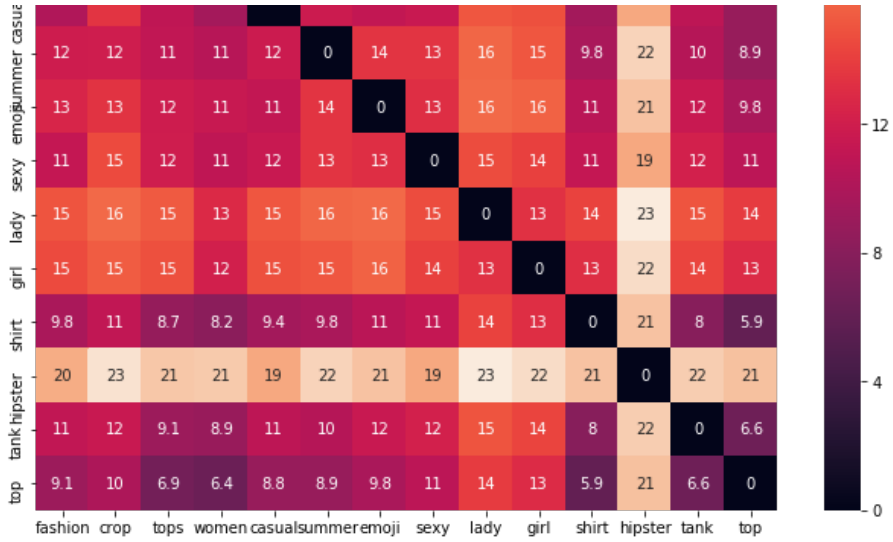
In [60]:

```
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)
```

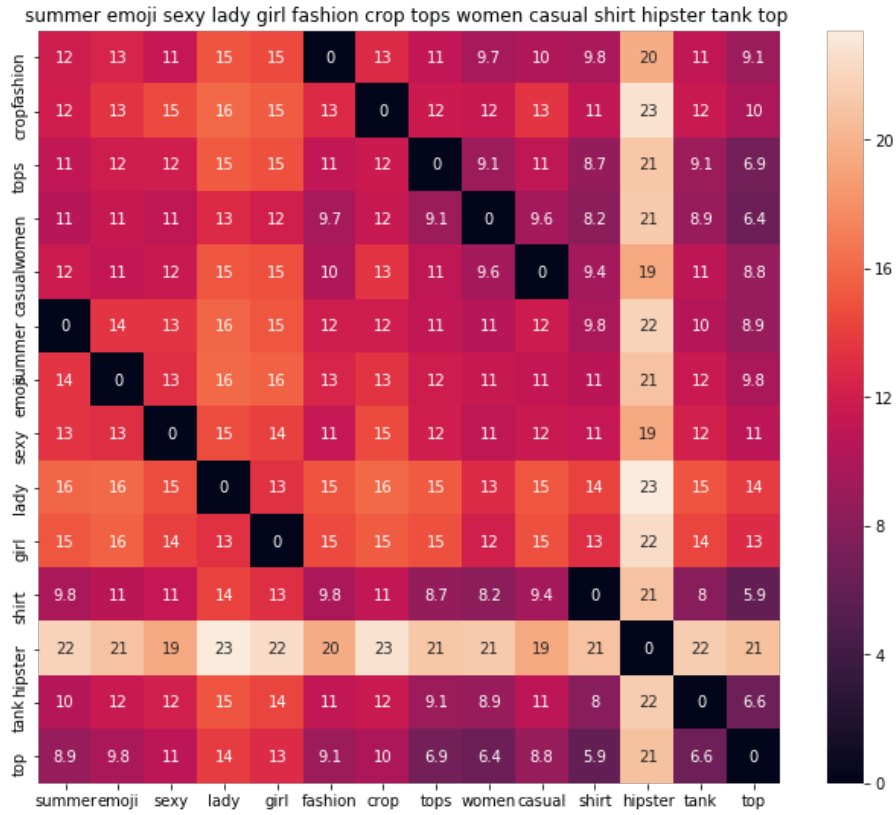
In [61]:

```
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['mediu
m_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
```

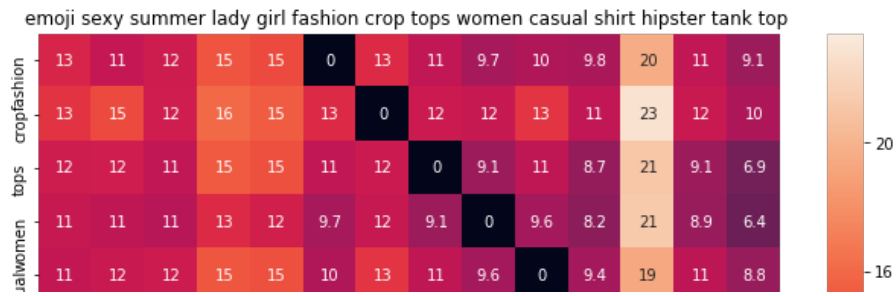


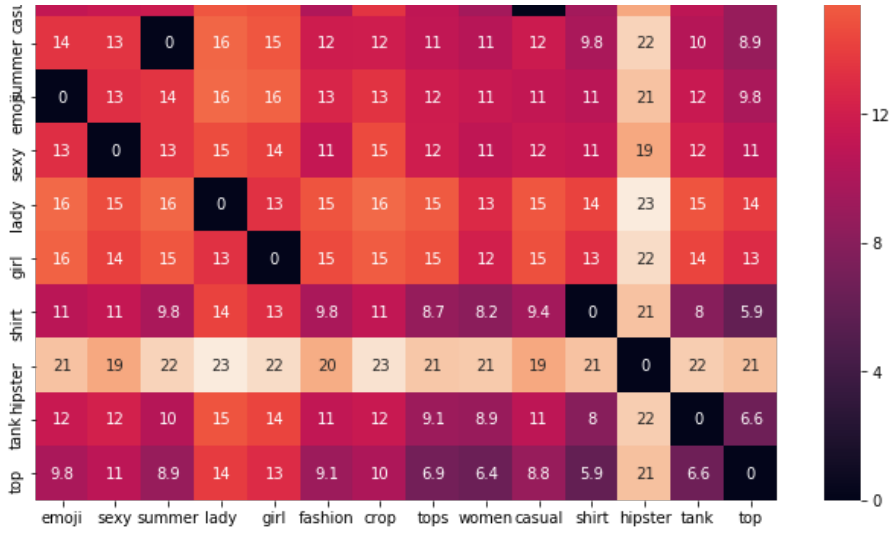


ASIN : B010V3B44G
Brand : Doxi Supermall
euclidean distance from input : 0.0
==========

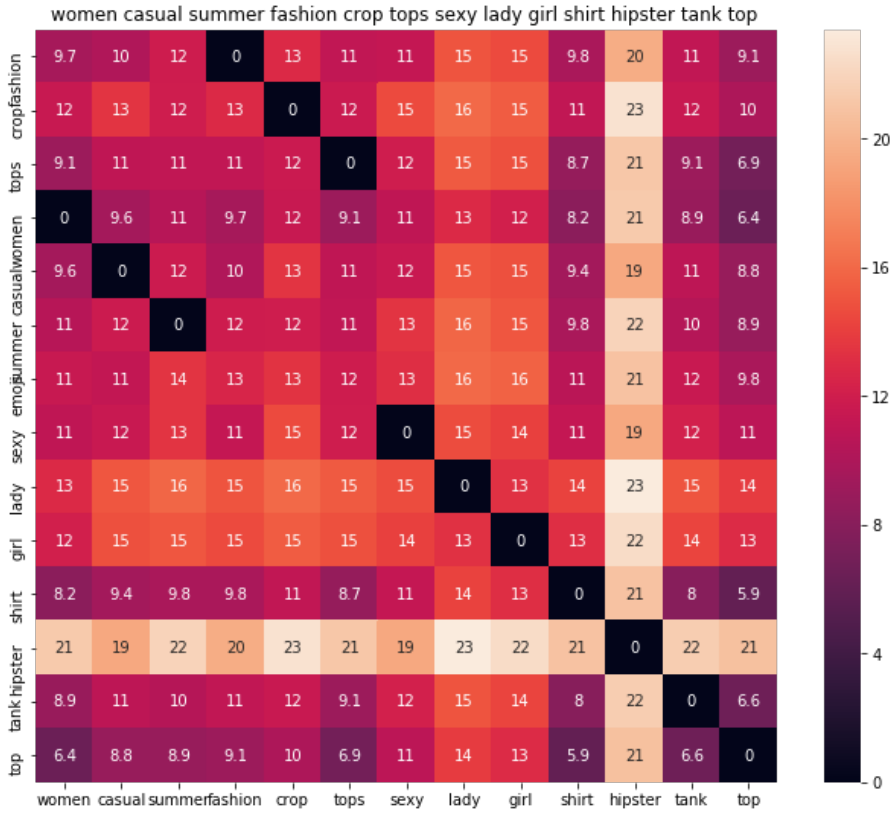


ASIN : B010V3BDII
Brand : Doxi Supermall
euclidean distance from input : 2.731428e-07
==========

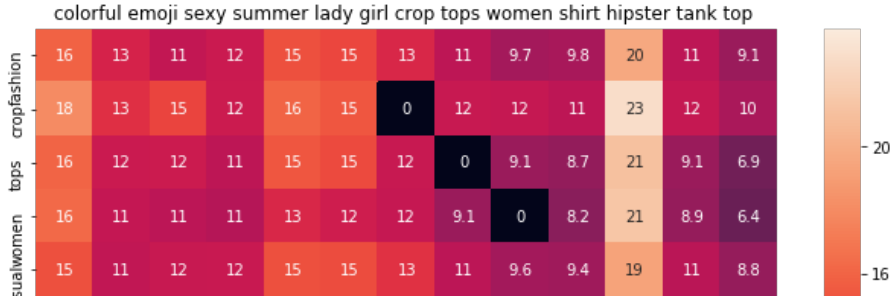


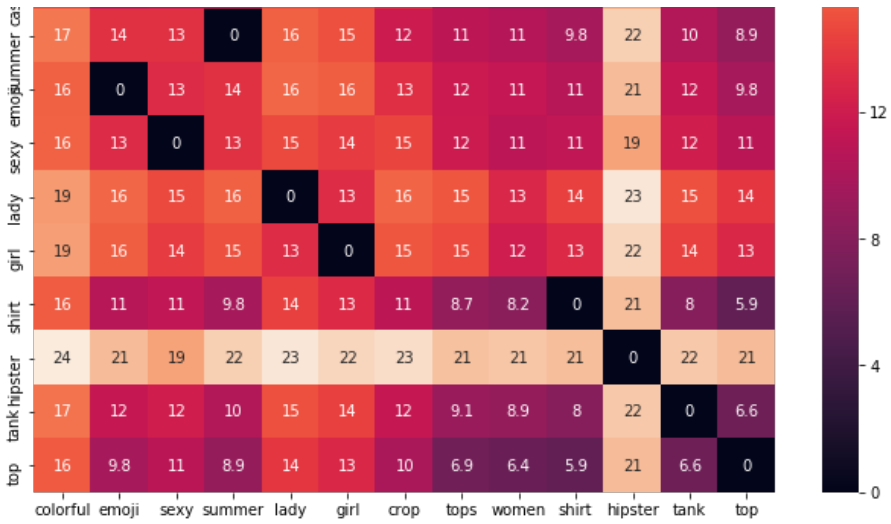


ASIN : B010V3BLWQ
Brand : Doxi Supermall
euclidean distance from input : 2.7957057e-07
==========

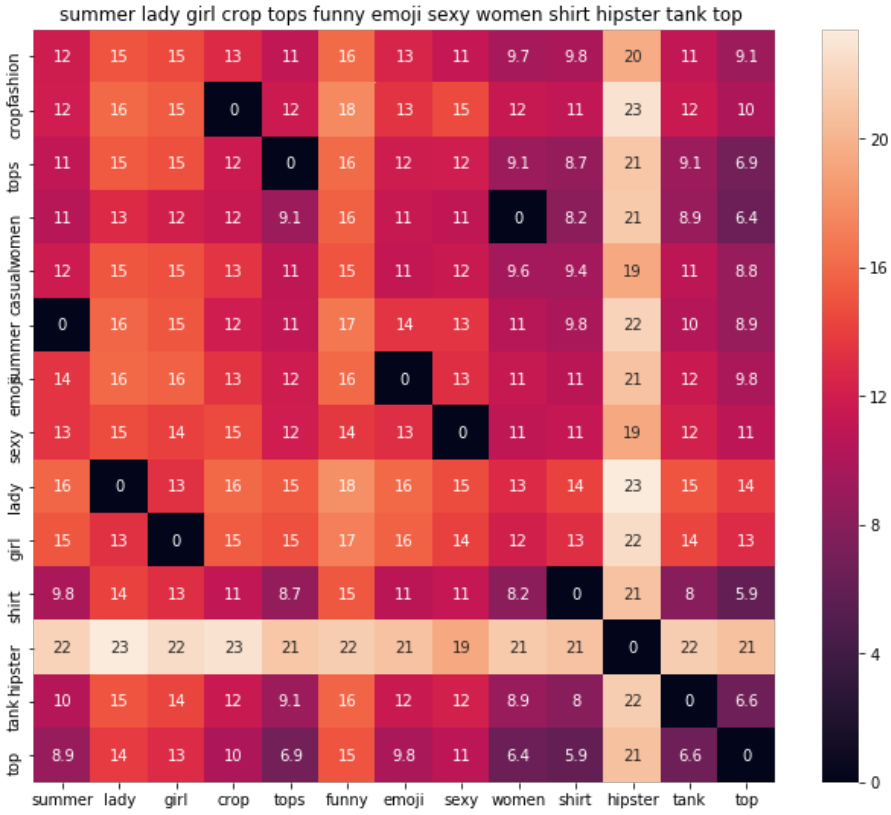


ASIN : B010V3AYSS
Brand : Doxi Supermall
euclidean distance from input : 0.6962319
==========

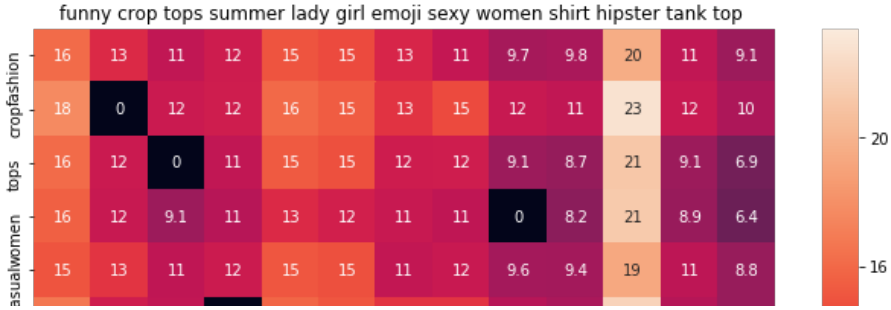


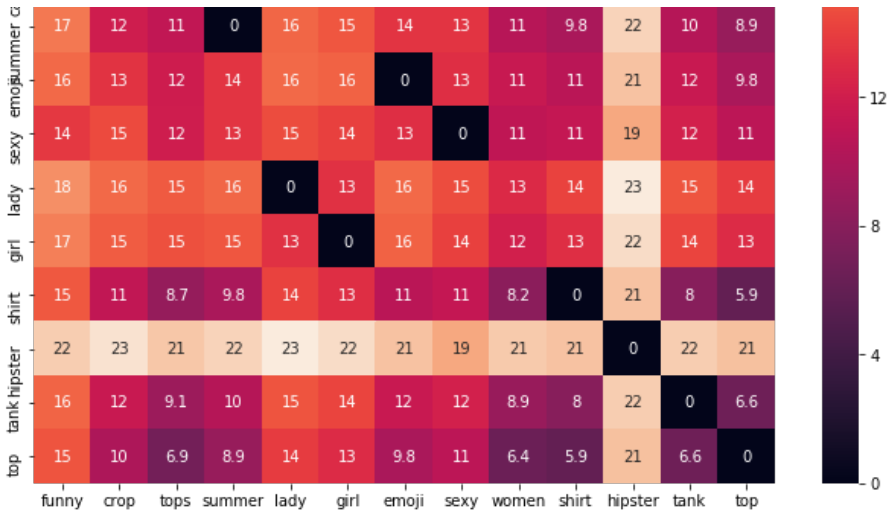


ASIN : B010V3BQZS
Brand : Doxi Supermall
euclidean distance from input : 1.2872719

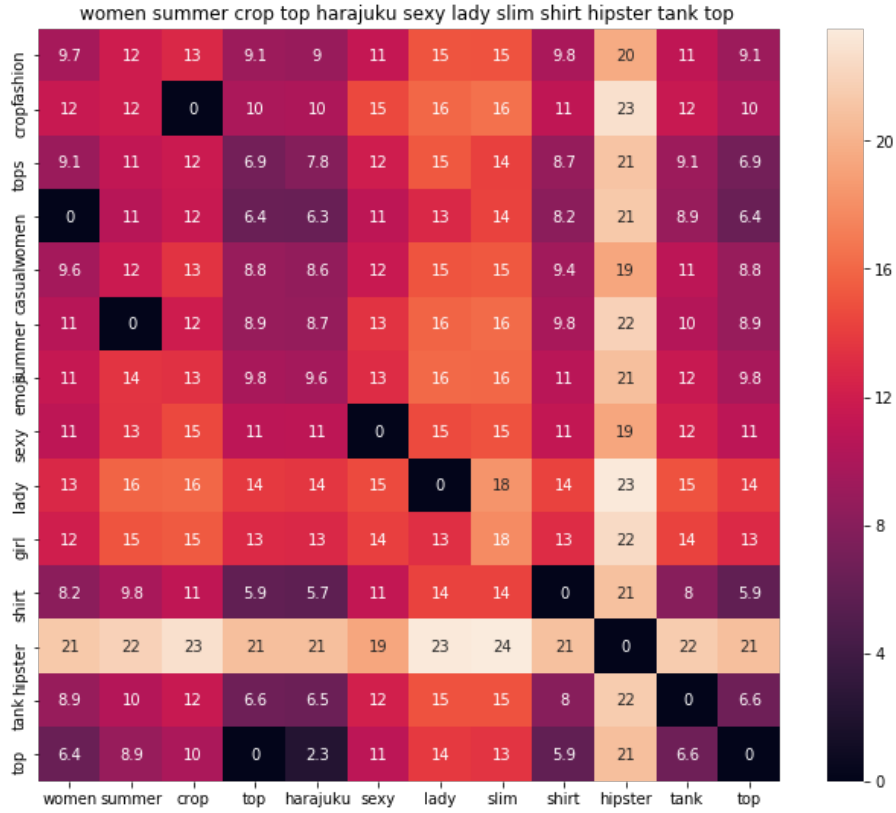


ASIN : B010V3BVMQ
Brand : Doxi Supermall
euclidean distance from input : 1.3530473

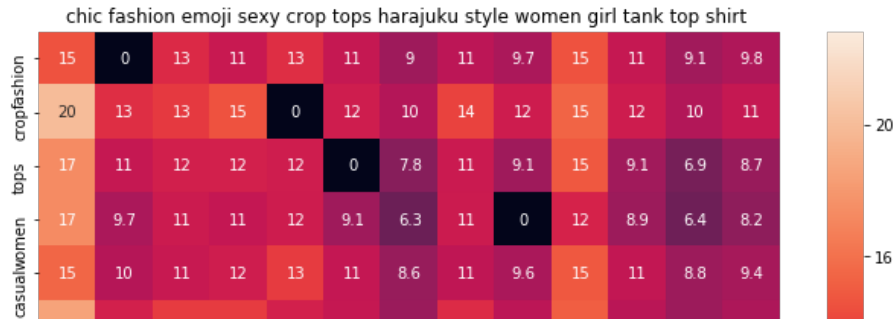


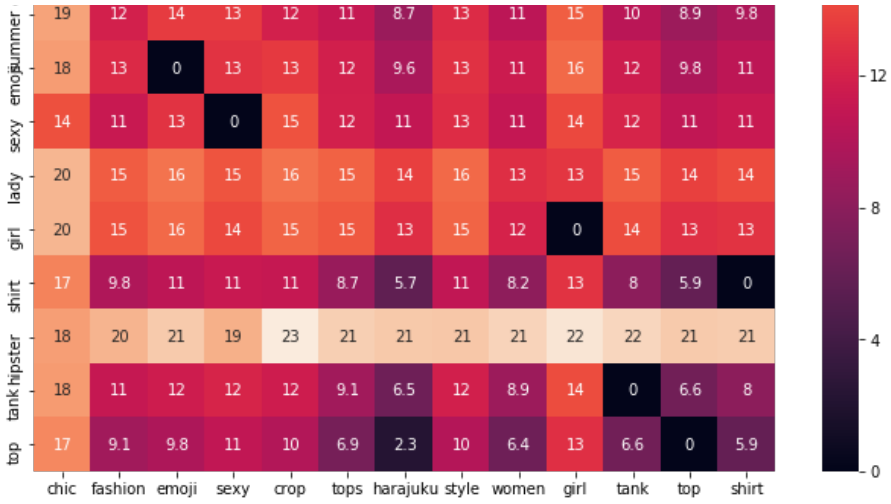


ASIN : B010V3C116
Brand : Doxi Supermall
euclidean distance from input : 1.3530474

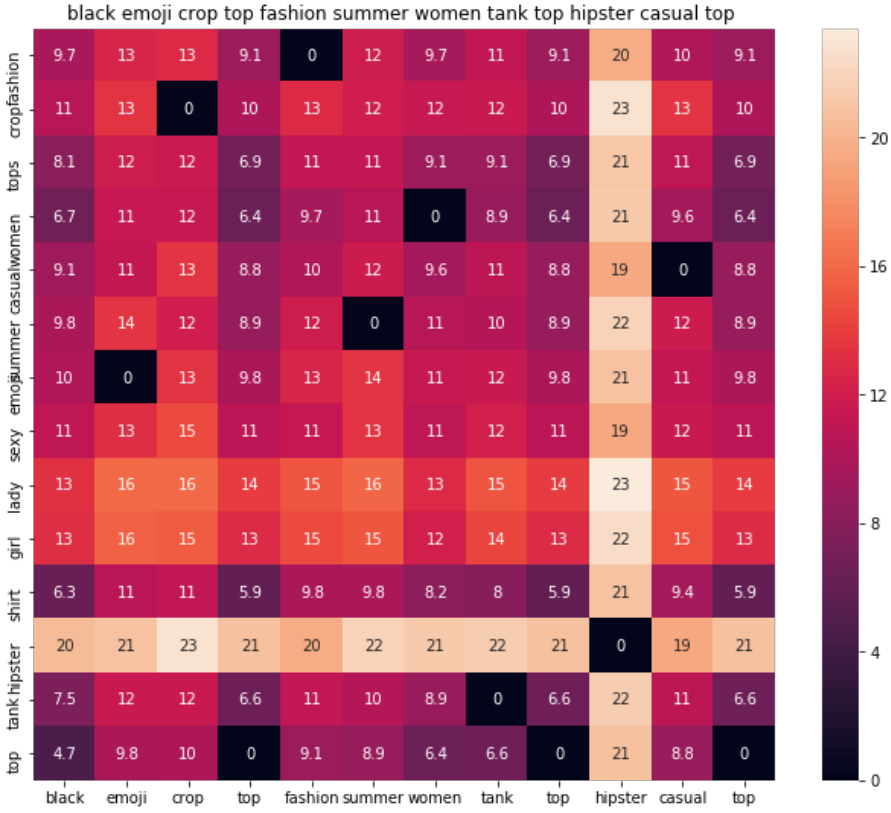


ASIN : B010V3EDEE
Brand : Doxi Supermall
euclidean distance from input : 1.7434151

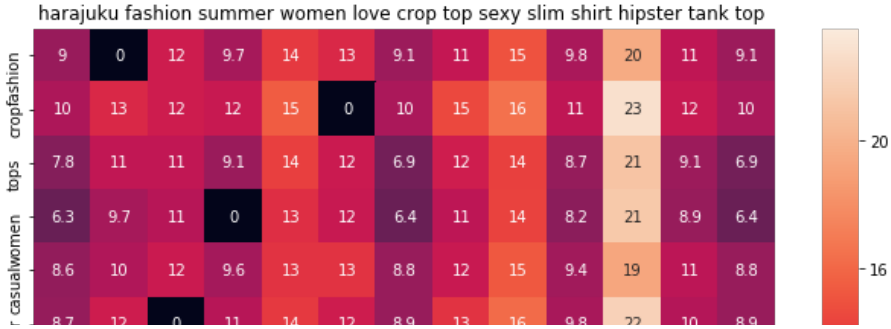


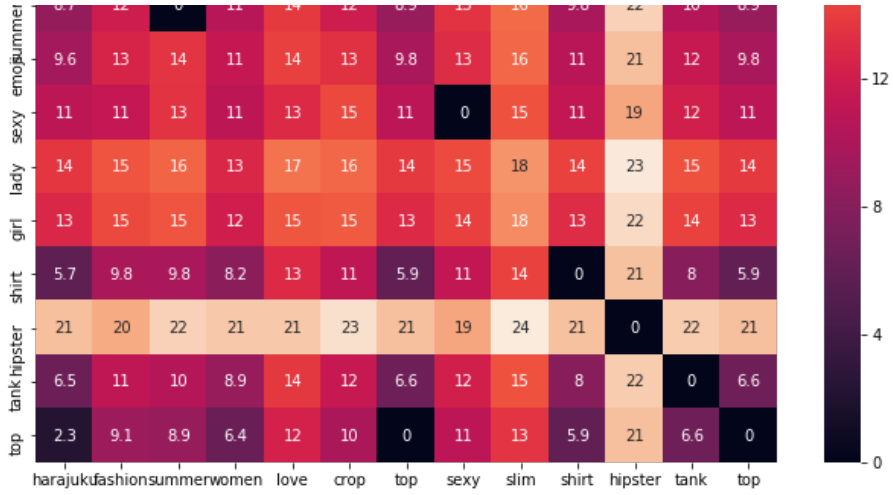


ASIN : B011RCJPR8
Brand : Chiclook Cool
euclidean distance from input : 1.934526

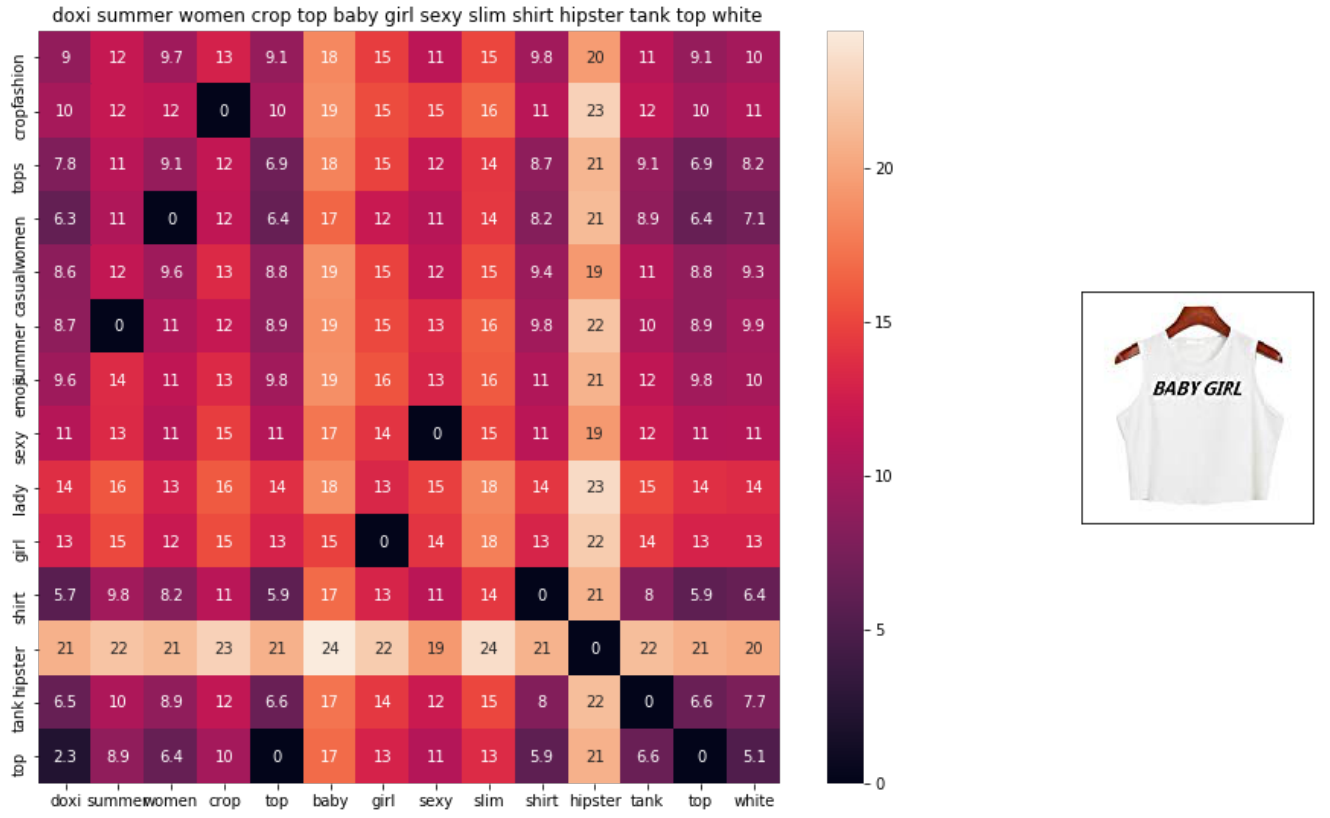


ASIN : B0124E80M4
Brand : Doxi Supermall
euclidean distance from input : 2.032144

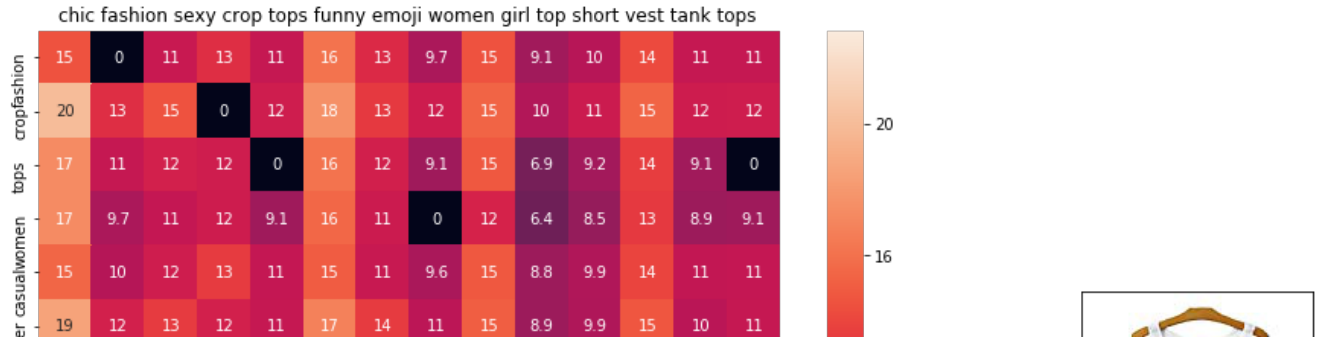


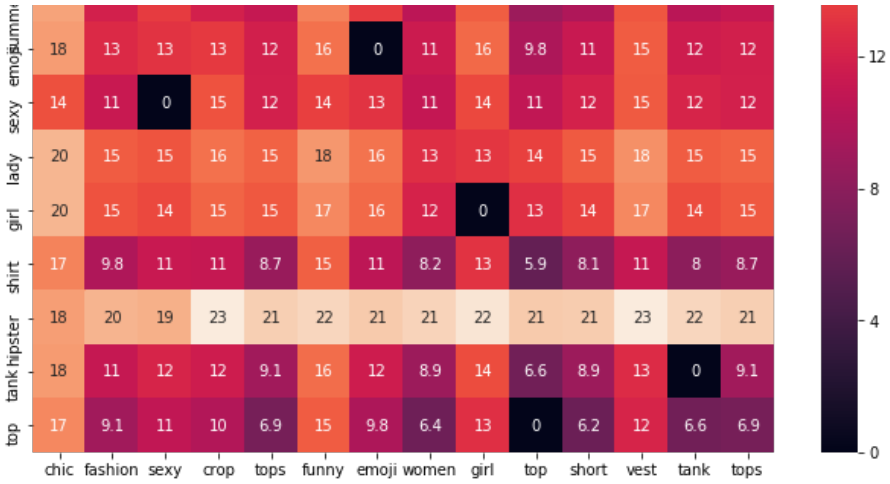


ASIN : B010V35OBU
Brand : Doxi Supermall
euclidean distance from input : 2.0631945

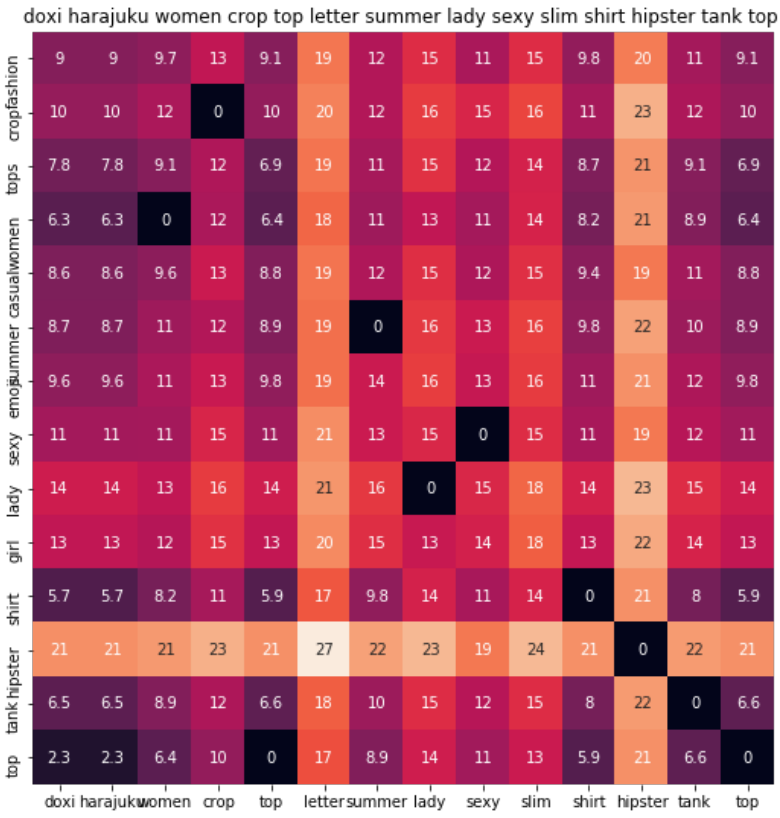


ASIN : B010V3A23U
Brand : Doxi Supermall
euclidean distance from input : 2.1243675

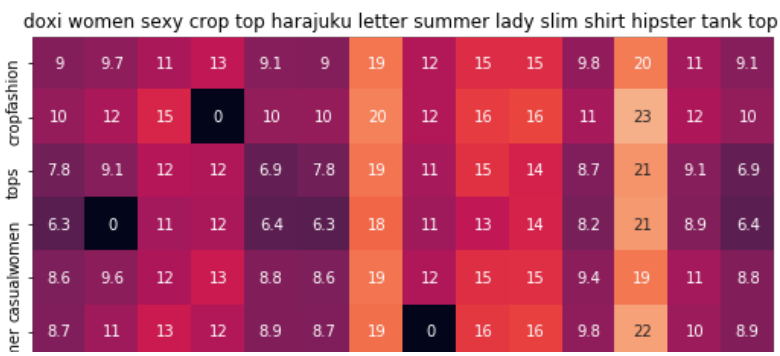


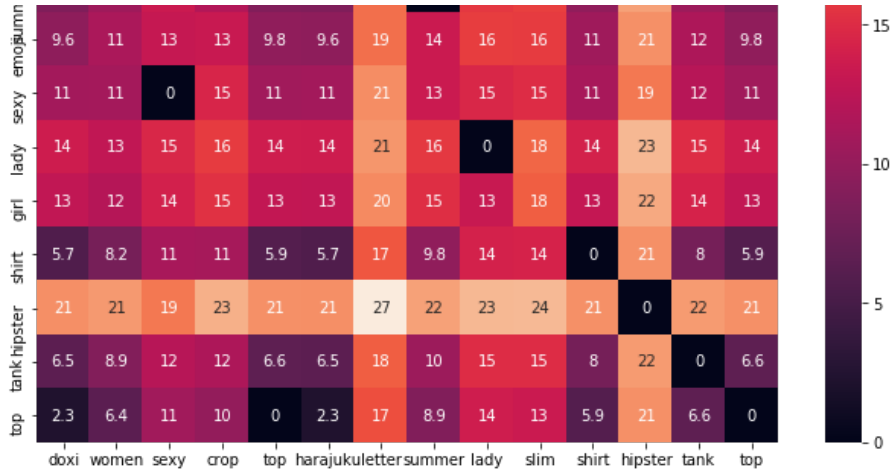


ASIN : B011RCJH58
Brand : Chiclook Cool
euclidean distance from input : 2.1507077
==========

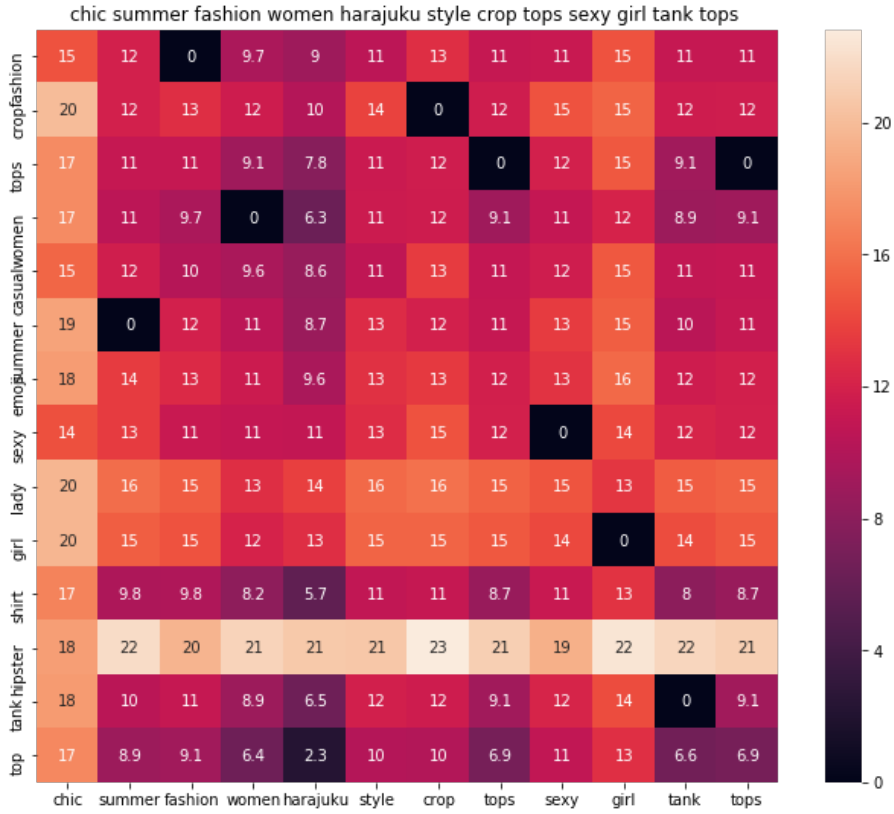


ASIN : B010V380LQ
Brand : Doxi Supermall
euclidean distance from input : 2.1674914
==========

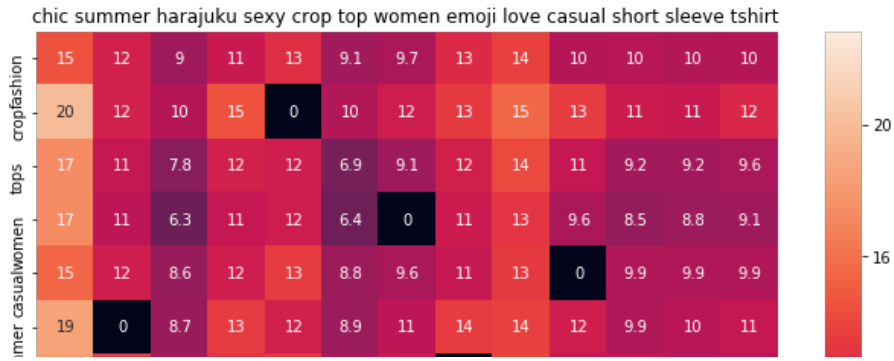


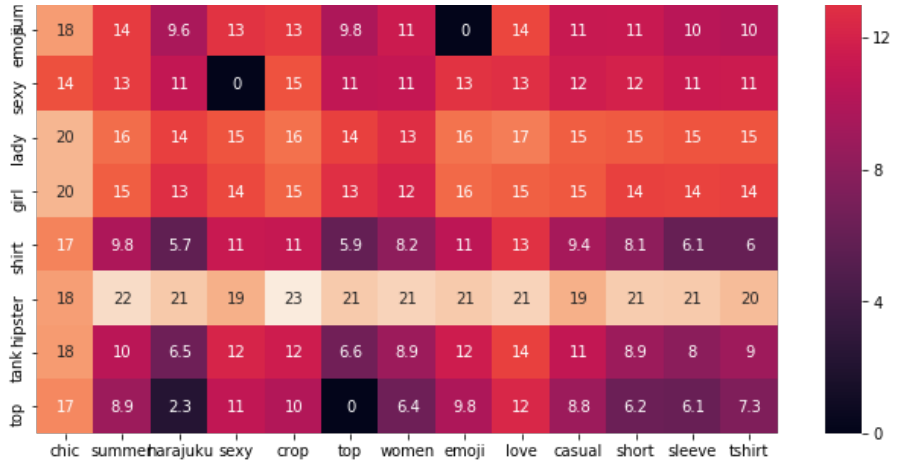


ASIN : B010V39146
Brand : Doxi Supermall
euclidean distance from input : 2.1674914
==========

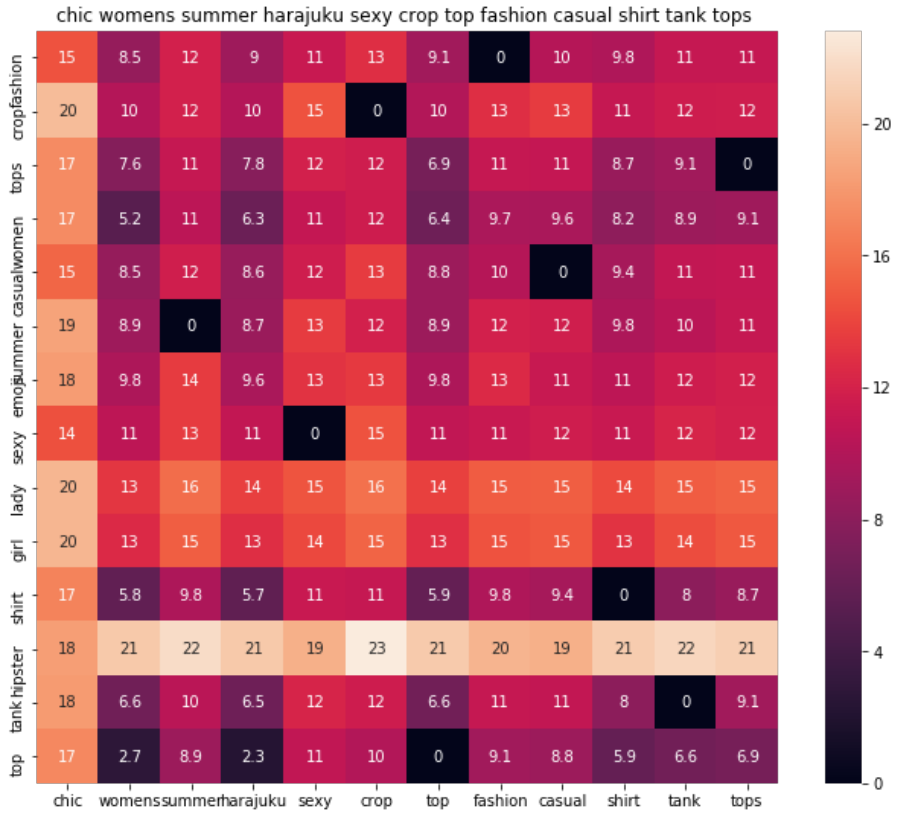


ASIN : B011OU51US
Brand : Chiclook Cool
euclidean distance from input : 2.2320173
==========

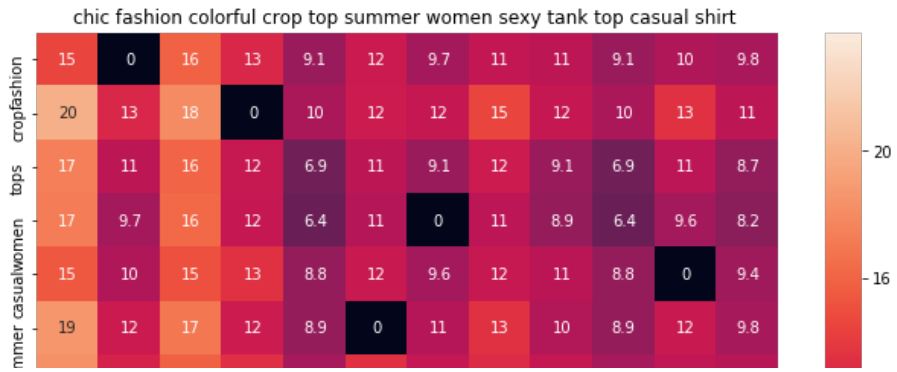


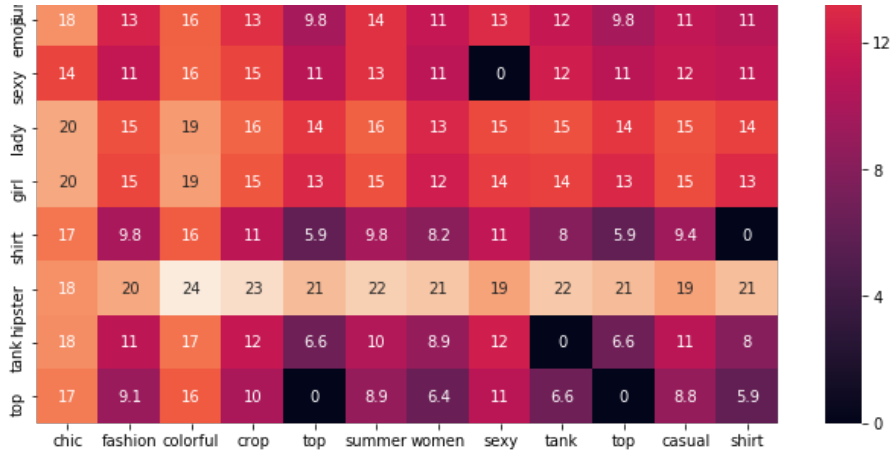


ASIN : B011UEVF4O
Brand : Chiclook Cool
euclidean distance from input : 2.3134534



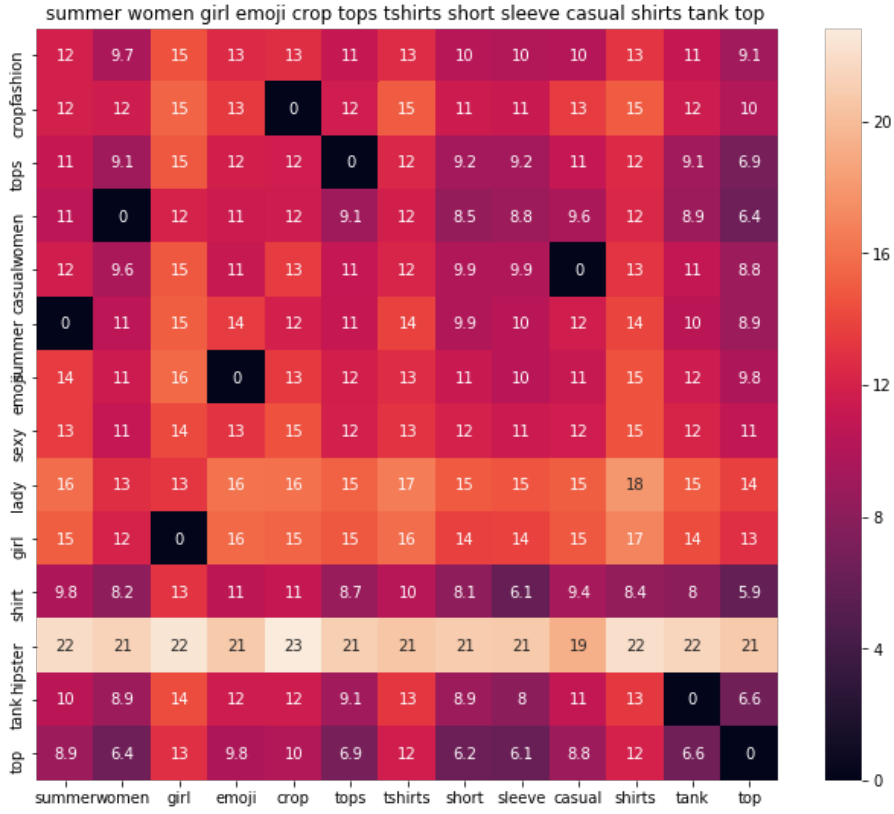
ASIN : B011RCJEMO
Brand : Chiclook Cool
euclidean distance from input : 2.3378792






```
ASIN : B011RCJ6UE
Brand : Chiclook Cool
euclidean distance from input : 2.5151837
```

```
==========================================================================================================
======================
```



```
ASIN : B0124ECIU4
Brand : Doxi Supermall
euclidean distance from input : 2.5520847
```

```
==========================================================================================================
======================
```

[9.6] Weighted similarity using brand and color.

In [62]:

```
# 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]
```

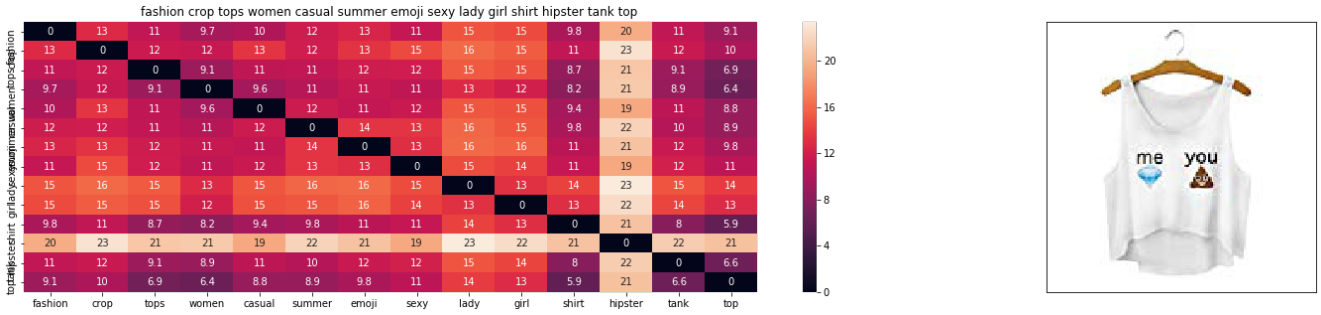
```
brand_vectorizer = CountVectorizer()
brand_features = brand_vectorizer.fit_transform(brands)

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()
```

In [63]:

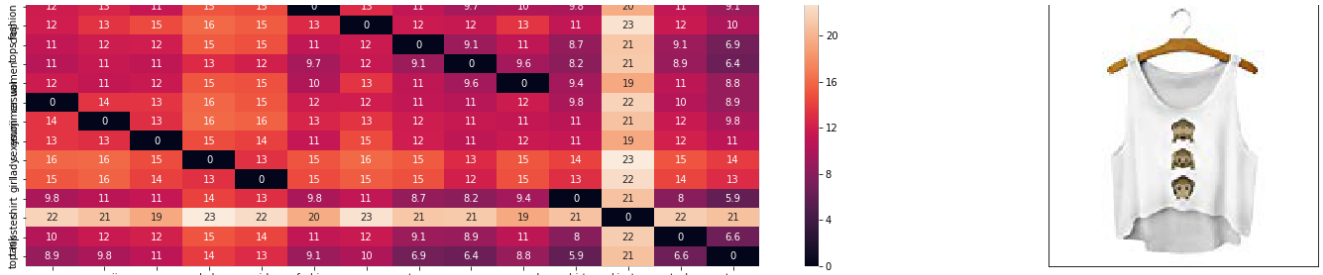
```
def heat_map_w2v_brand(sentance1, sentance2, url, doc_id1, doc_id2, df_id1, df_id2, model):

    # 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 lengt
h 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 lengt
h 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 cc
lumn

    # 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()
```

In [64]:

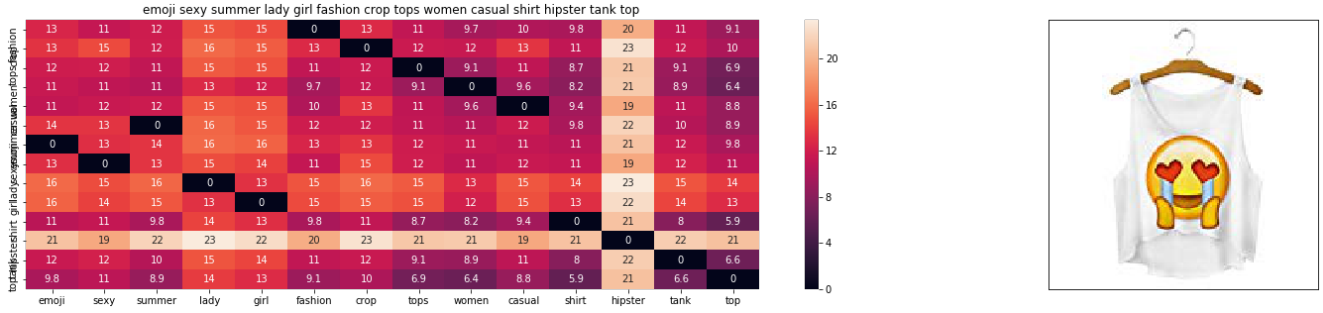
```
def idf_w2v_brand(doc_id, w1, w2, num_results):
    # doc_id: apparel's id in given corpus
    # w1: weight for  w2v features
    # w2: weight for brand and color features

    # 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], 'weigh
ted')
        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
```



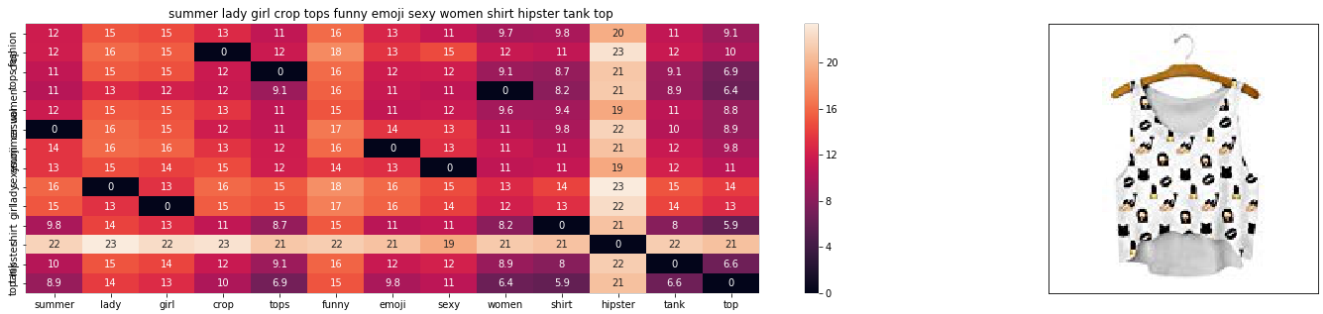
ASIN : B010V3B44G
Brand : Doxi Supermall
euclidean distance from input : 0.0
==========



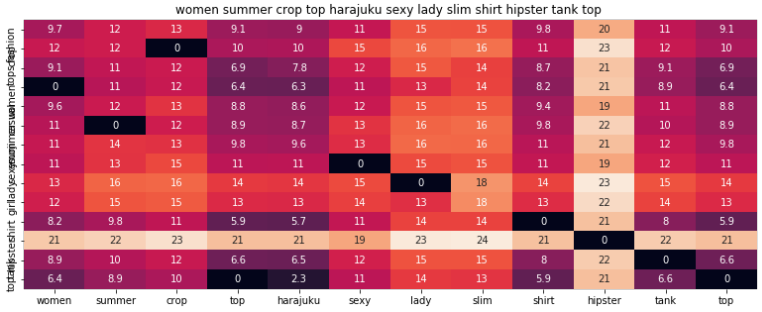
ASIN : B010V3BDII
Brand : Doxi Supermall
euclidean distance from input : 1.365714069834212e-07
==========



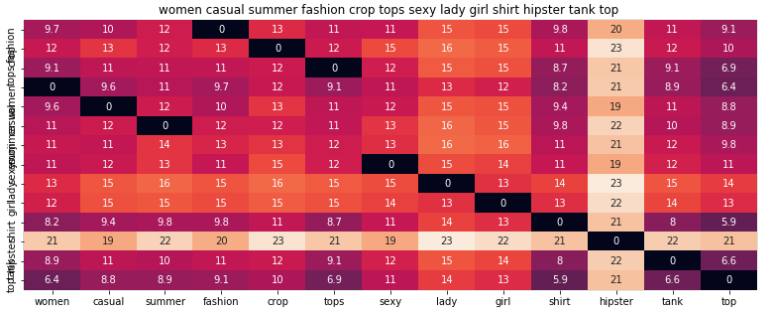
ASIN : B010V3BLWQ
Brand : Doxi Supermall
euclidean distance from input : 1.3978528841107617e-07
==========



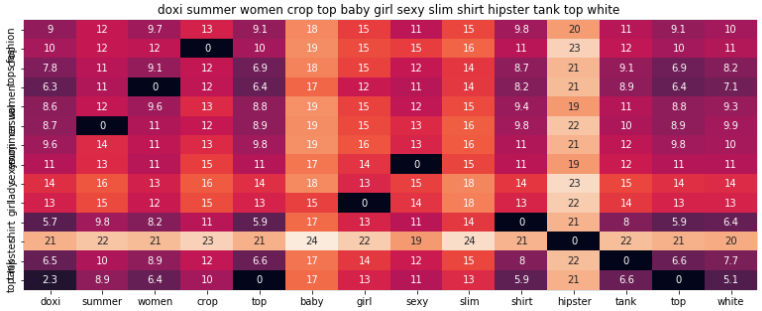
ASIN : B010V3BVMQ
Brand : Doxi Supermall
euclidean distance from input : 0.6765236377716064
==========



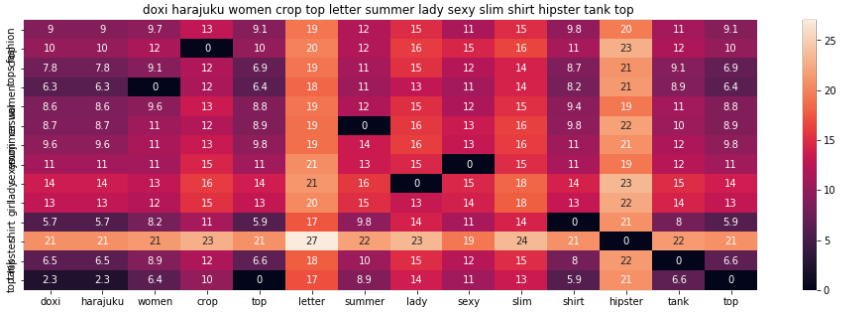
ASIN : B010V3EDEE
Brand : Doxi Supermall
euclidean distance from input : 0.871707534790039
==========



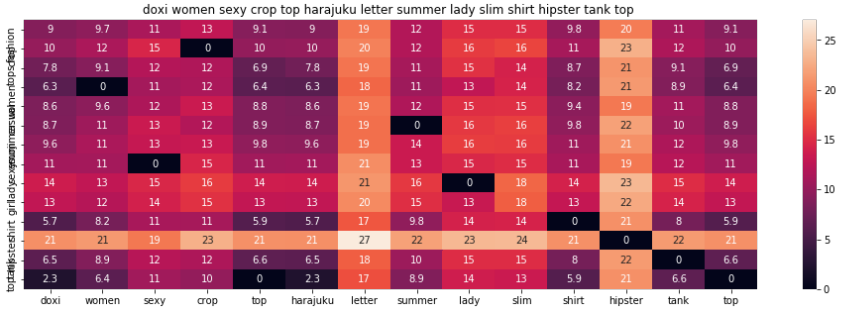
ASIN : B010V3AYSS
Brand : Doxi Supermall
euclidean distance from input : 1.0552227260489133
==========



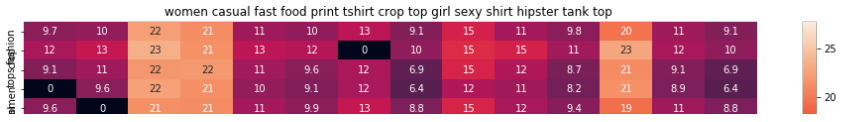
ASIN : B010V3A23U
Brand : Doxi Supermall
euclidean distance from input : 1.0621837615966796

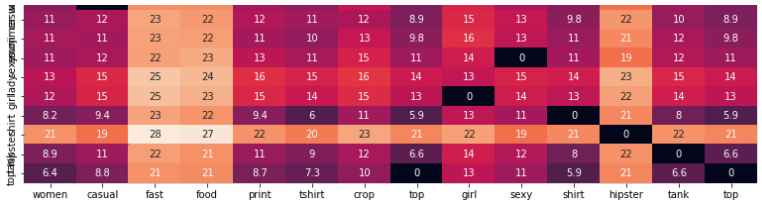


ASIN : B010V380LQ
Brand : Doxi Supermall
euclidean distance from input : 1.0837457656860352

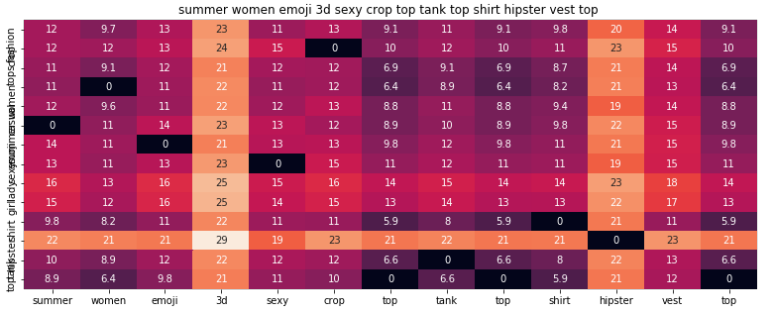


ASIN : B010V39146
Brand : Doxi Supermall
euclidean distance from input : 1.0837457656860352

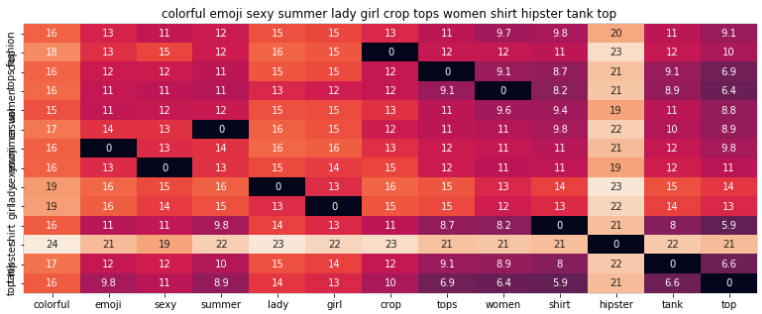




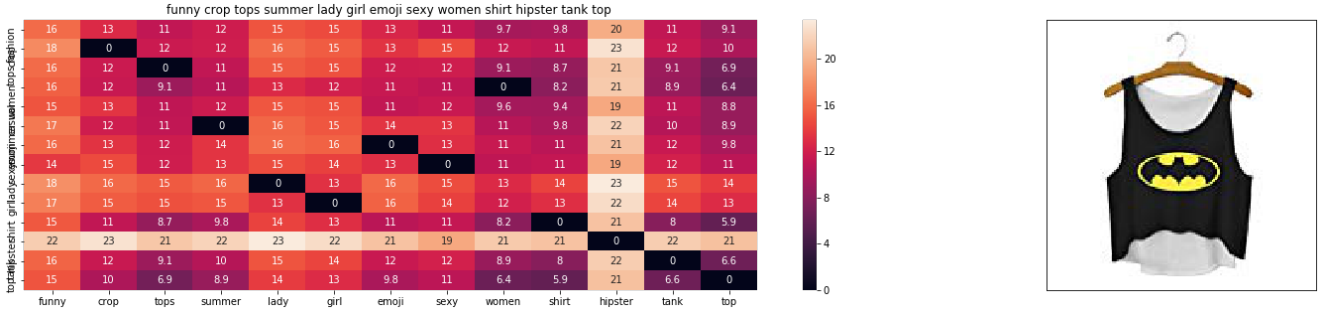
ASIN : B010V3AB5O
Brand : Doxi Supermall
euclidean distance from input : 1.3135894775390624
==========



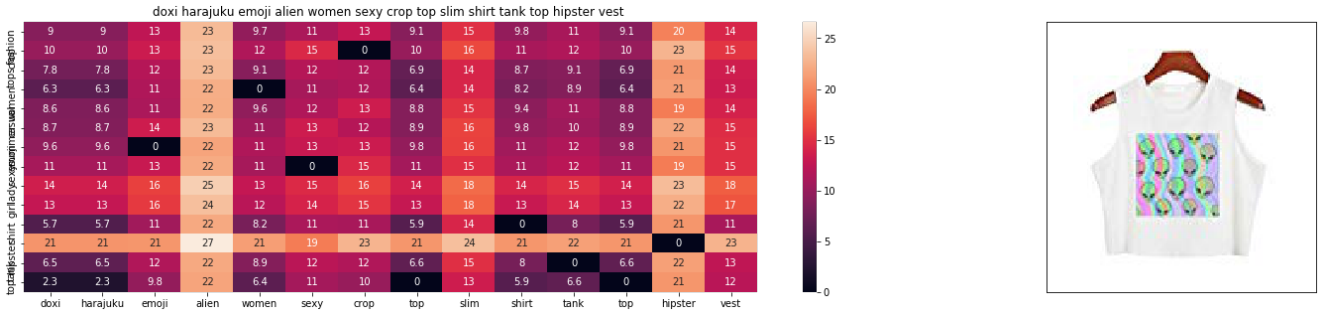
ASIN : B010V3E5EC
Brand : Doxi Supermall
euclidean distance from input : 1.3397350311279297
==========



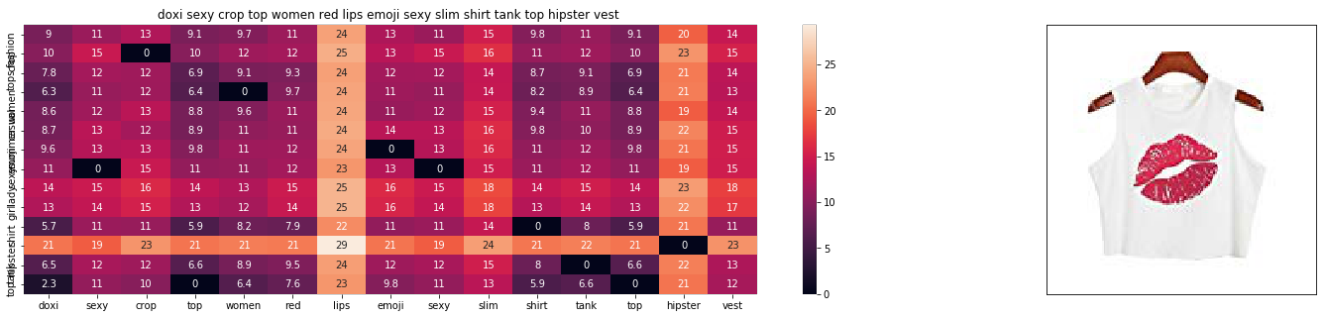
ASIN : B010V3BQZS
Brand : Doxi Supermall
euclidean distance from input : 1.3507427217383055
==========



ASIN : B010V3C116
Brand : Doxi Supermall
euclidean distance from input : 1.3836304666418697
==========
==========

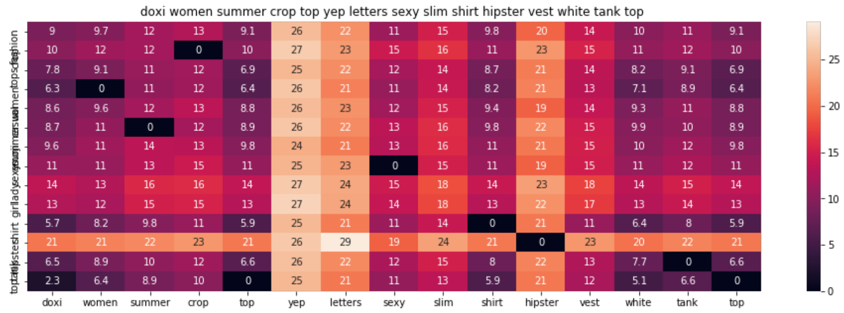


ASIN : B010TKXAI4
Brand : Doxi Supermall
euclidean distance from input : 1.387600803375244
==========
==========

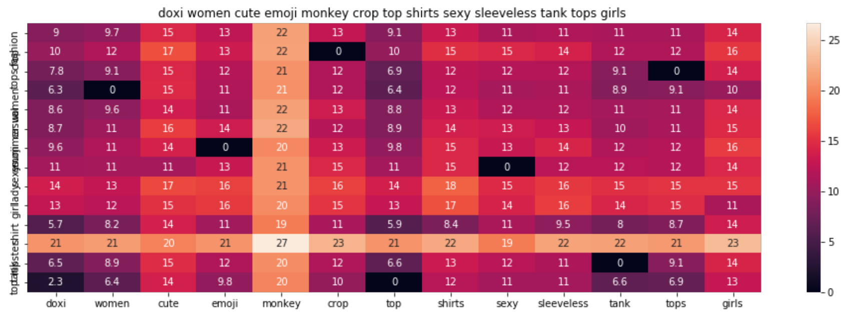


ASIN : B010TKXEHG
Brand : Doxi Supermall
euclidean distance from input : 1.4269560813903808

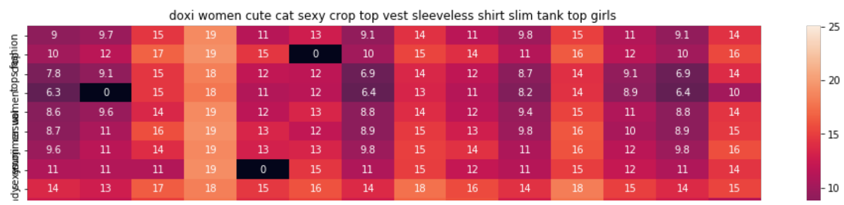
==

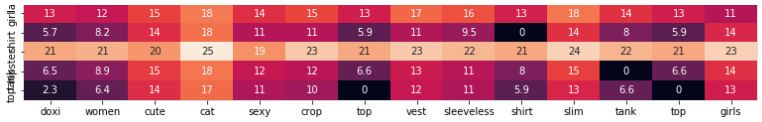


ASIN : B010V3487Q
Brand : Doxi Supermall
euclidean distance from input : 1.4681865692138671
==

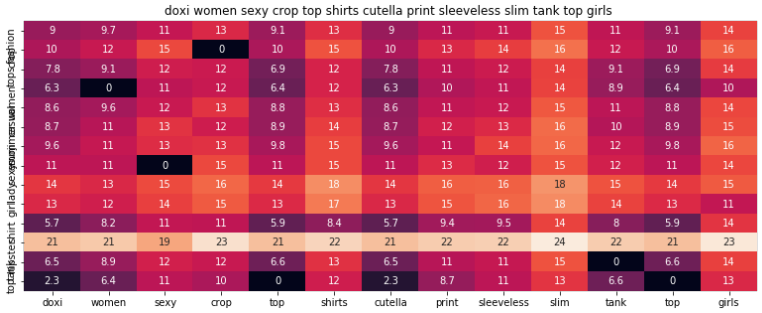


ASIN : B01LF90QTO
Brand : Doxi Supermall
euclidean distance from input : 1.4761534690856934
==

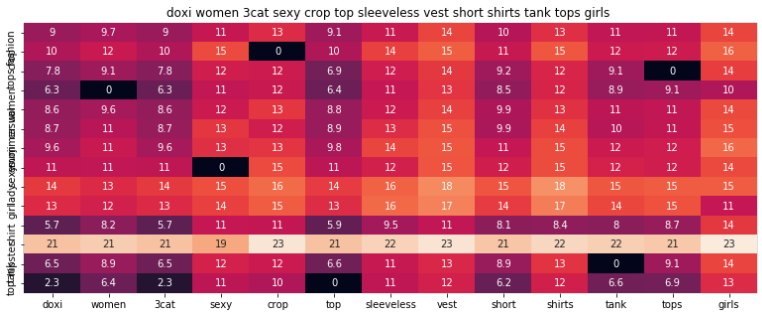




ASIN : B01LF90ROI
Brand : Doxi Supermall
euclidean distance from input : 1.482174777984619
==========
==========



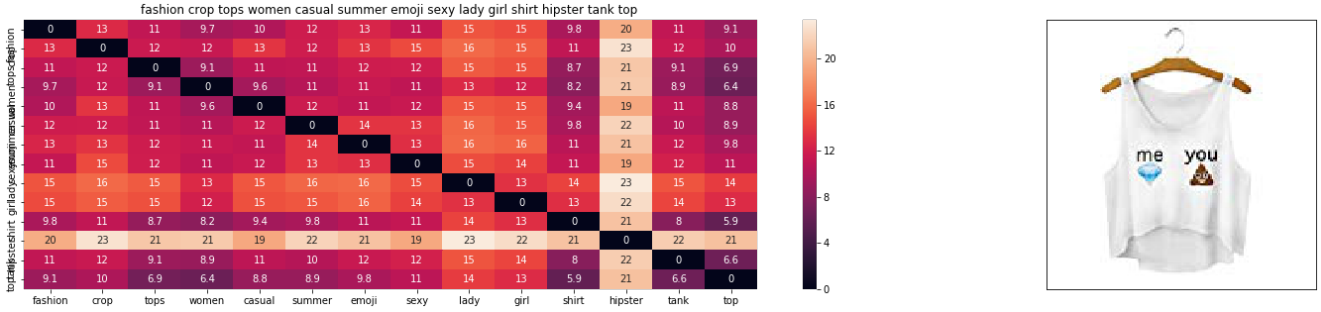
ASIN : B01LF90RKC
Brand : Doxi Supermall
euclidean distance from input : 1.5058938980102539
==========
==========



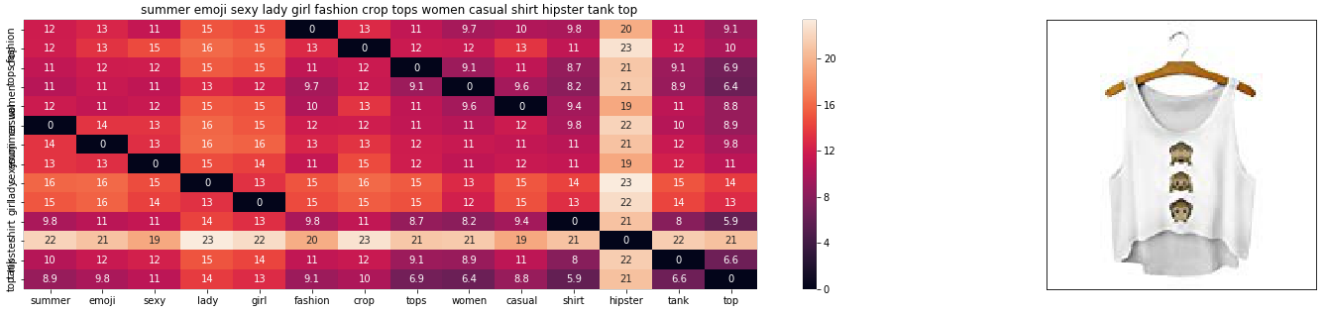
ASIN : B01LY4GQY0
Brand : Doxi Supermall
euclidean distance from input : 1.5098178863525390
==========
==========

In [65]:

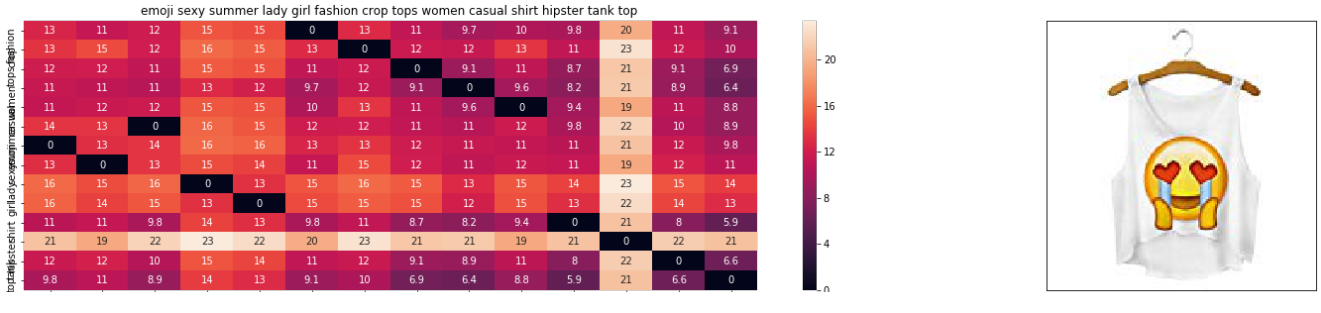
```
# brand and color weight =50
# title vector weight = 5

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



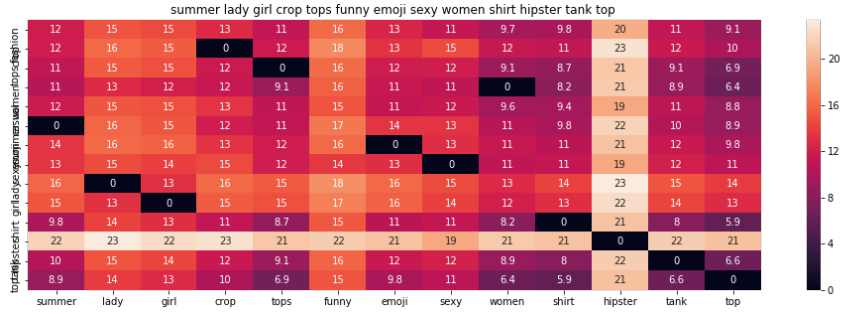
ASIN : B010V3B44G
Brand : Doxi Supermall
euclidean distance from input : 0.0
==========



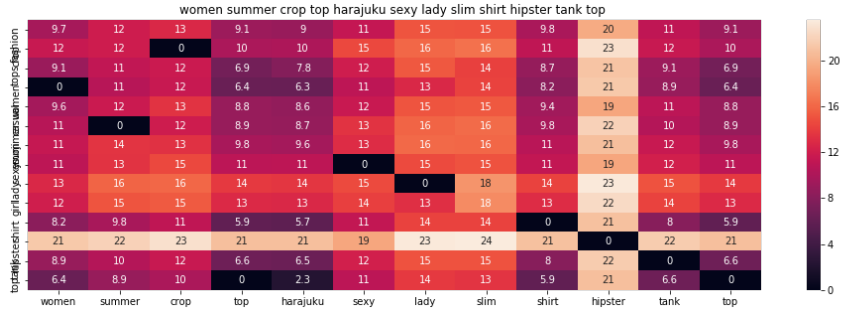
ASIN : B010V3BDII
Brand : Doxi Supermall
euclidean distance from input : 2.483116490607658e-08
==========



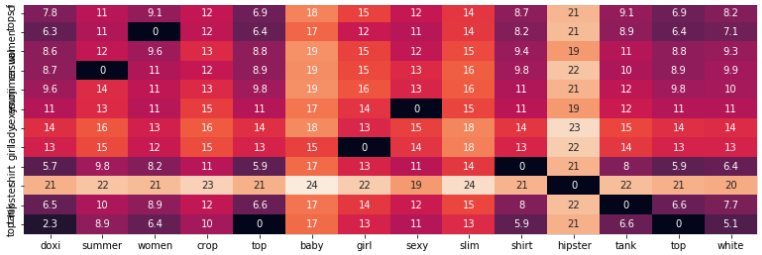
ASIN : B010V3BLWQ
Brand : Doxi Supermall
euclidean distance from input : 2.5415506983832033e-08
==========



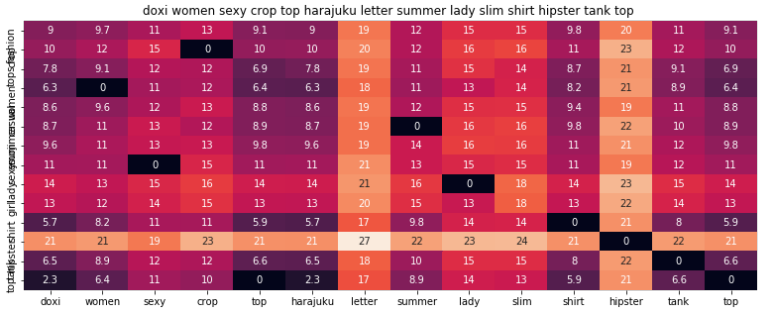
ASIN : B010V3BVMQ
Brand : Doxi Supermall
euclidean distance from input : 0.12300429777665571
==========



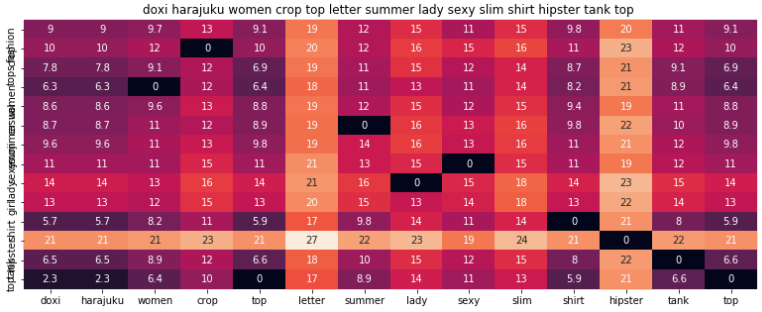
ASIN : B010V3EDEE
Brand : Doxi Supermall
euclidean distance from input : 0.15849227905273439
==========



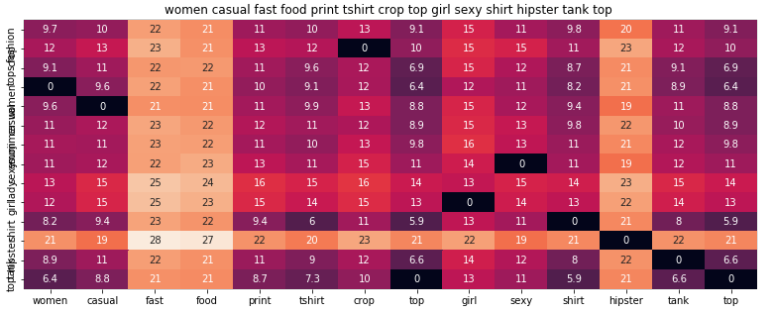
ASIN : B010V3A23U
Brand : Doxi Supermall
euclidean distance from input : 0.1931243202903054
==========
==========



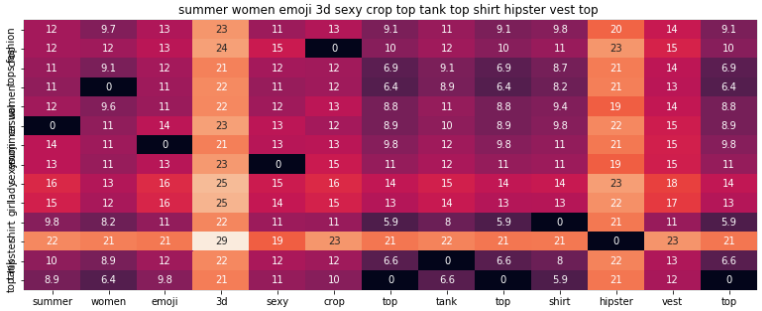
ASIN : B010V39146
Brand : Doxi Supermall
euclidean distance from input : 0.1970446846701882
==========
==========



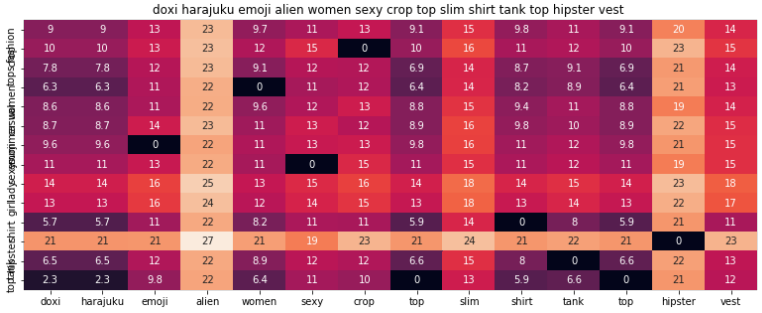
ASIN : B010V380LQ
Brand : Doxi Supermall
euclidean distance from input : 0.1970446846701882
==========
==========



ASIN : B010V3AB5O
Brand : Doxi Supermall
euclidean distance from input : 0.23883445046164772
==========

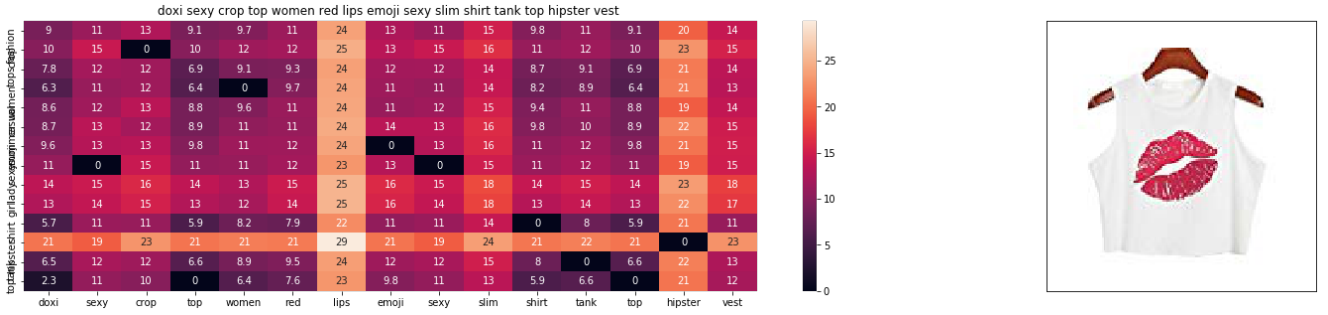


ASIN : B010V3E5EC
Brand : Doxi Supermall
euclidean distance from input : 0.2435881874778054
==========

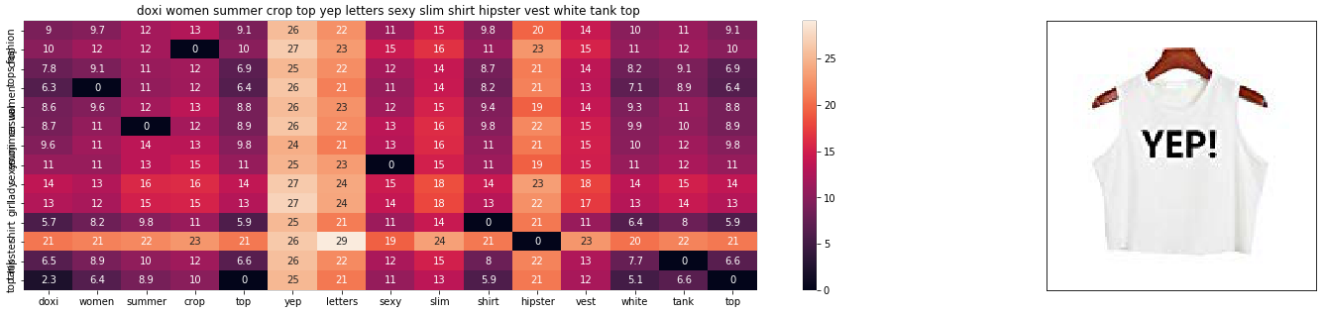


ASIN : B010TKXAI4

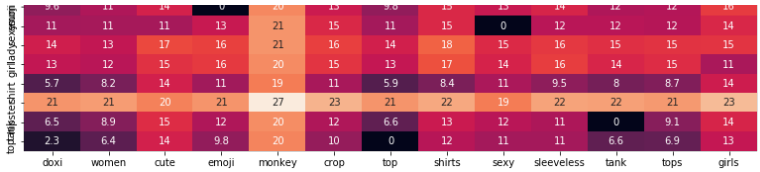
Brand : Doxi Supermall
euclidean distance from input : 0.2522910551591353
==========



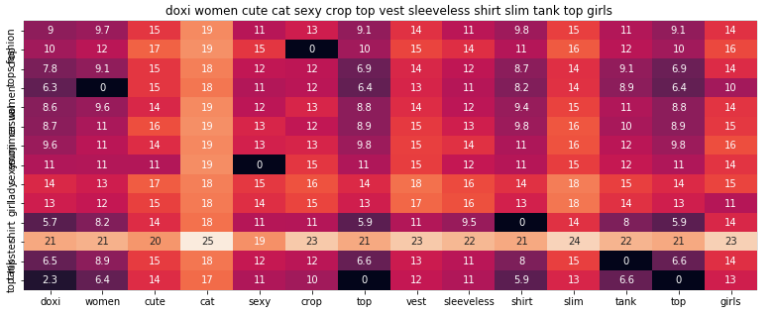
ASIN : B010TKXEHG
Brand : Doxi Supermall
euclidean distance from input : 0.2594465602527965
==========



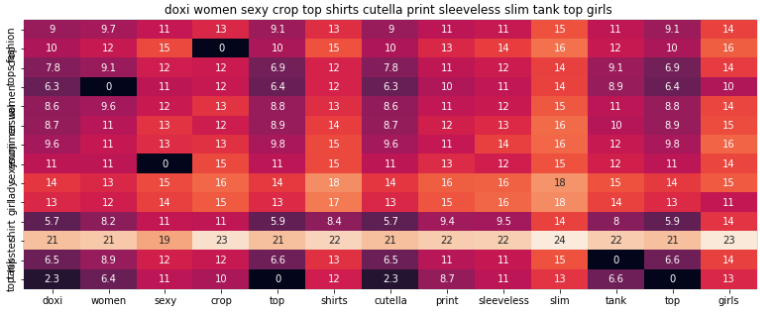
ASIN : B010V3487Q
Brand : Doxi Supermall
euclidean distance from input : 0.2669430125843395
==========



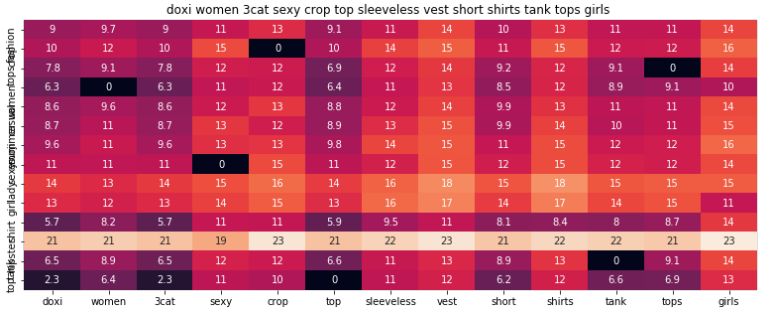
ASIN : B01LF90QTO
Brand : Doxi Supermall
euclidean distance from input : 0.2683915398337624
==========
==========



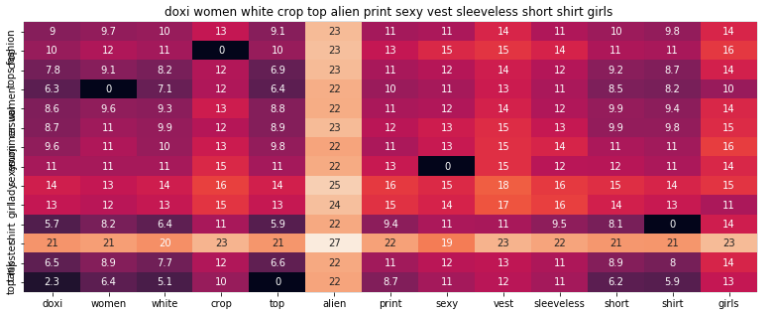
ASIN : B01LF90ROI
Brand : Doxi Supermall
euclidean distance from input : 0.26948632326993077
==========
==========



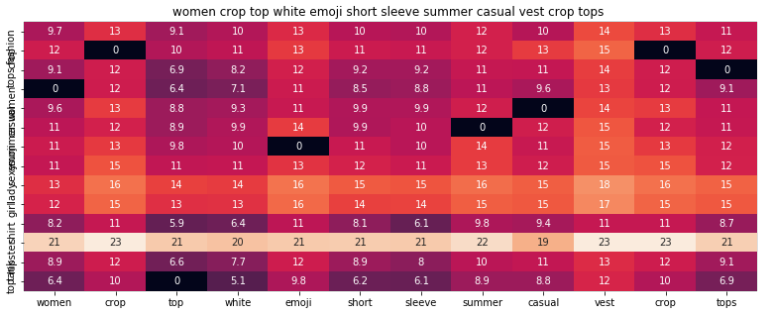
ASIN : B01LF90RKC
Brand : Doxi Supermall
euclidean distance from input : 0.2737988905473189
==========
==========



ASIN : B01LY4GQY0
Brand : Doxi Supermall
euclidean distance from input : 0.27451234297318894
==========

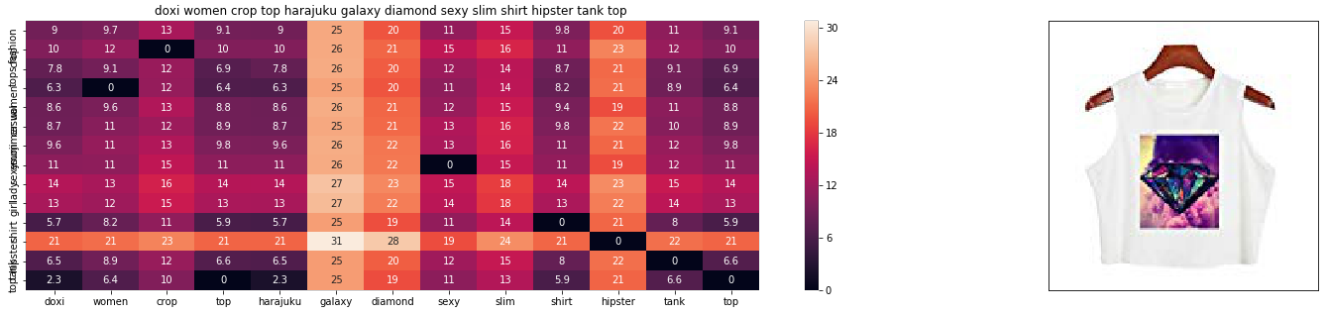


ASIN : B01LF90SCY
Brand : Doxi Supermall
euclidean distance from input : 0.28159143274480647
==========



ASIN : B0124E7MHS
Brand : Doxi Supermall
euclidean distance from input : 0.2871342398903587
==========

```
======================
```




```
ASIN : B010V39EUM
Brand : Doxi Supermall
euclidean distance from input : 0.30813397494229405
================================================================================================================
======================
```

[10.2] Keras and Tensorflow to extract features

In [80]:

```
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
```

```
Using TensorFlow backend.
```

In [ ]:

```
# https://gist.github.com/fchollet/f35fbc80e066a49d65f1688a7e99f069
# Code reference: https://blog.keras.io/building-powerful-image-classification-models-using-very-l
ittle-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()

'''
```

[10.3] Visual features based product similarity.

In [67]:

```
#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('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(12566, 20)
```

Product Title: fashion crop tops women casual summer emoji sexy lady girl shirt hipster tank top
Euclidean Distance from input image: 6.32596e-06
Amazon Url: www.amzon.com/dp/B010V3B44G

Product Title: chic women harajuku fashion funny emoji sexy crop tops sleeveless vest shirt
Euclidean Distance from input image: 18.585749
Amazon Url: www.amzon.com/dp/B011RCJNL6

Product Title: women quotes boys print white sleeveless crop top
Euclidean Distance from input image: 22.04546
Amazon Url: www.amzon.com/dp/B0748CKWF3

Product Title: women forever young print white sleeveless crop top
Euclidean Distance from input image: 22.321218
Amazon Url: www.amzon.com/dp/B0748CDWPH

Product Title: kingde self confident stretch vest tshirt suspendersbqn46
Euclidean Distance from input image: 22.724632
Amazon Url: www.amzon.com/dp/B015H2R3SC

Product Title: women three wise monkeys emoji print sleeveless crop top
Euclidean Distance from input image: 24.452633
Amazon Url: www.amzon.com/dp/B074VPC98H

Product Title: women infinity books print white sleeveless crop top
Euclidean Distance from input image: 25.067362
Amazon Url: www.amzon.com/dp/B074TYKHPL

Product Title: ladies crop top emoji women never grow shirt vest style tank tops
Euclidean Distance from input image: 26.787249
Amazon Url: www.amzon.com/dp/B013SPUM7O

Product Title: women fashion giant pink donut printed white sleeveless crop top
Euclidean Distance from input image: 28.364748
Amazon Url: www.amzon.com/dp/B017Q4BOCA

Product Title: women keep swimming print sleeveless crop top
Euclidean Distance from input image: 29.022312
Amazon Url: www.amzon.com/dp/B0749CCCY4

Product Title: women summer crop top harajuku sexy lady slim shirt hipster tank top
Euclidean Distance from input image: 29.029295
Amazon Url: www.amzon.com/dp/B010V3EDEE

Product Title: women fashion wanna hug printed white sleeveless crop top
Euclidean Distance from input image: 29.049513
Amazon Url: www.amzon.com/dp/B017R0CDOQ

Product Title: summer emoji sexy lady girl fashion crop tops women casual shirt hipster tank top
Euclidean Distance from input image: 29.482378
Amazon Url: www.amzon.com/dp/B010V3BDII

Product Title: women fashion love food printed white crop top
Euclidean Distance from input image: 29.615349
Amazon Url: www.amzon.com/dp/B017K0DQZ8

Product Title: kingde slim starbucks coffee small vest tshirt sling stretchbqn53
Euclidean Distance from input image: 29.690027
Amazon Url: www.amzon.com/dp/B015H2QWY8

Product Title: women fashion cute word printed name barbie sleeveless crop top
Euclidean Distance from input image: 29.862371
Amazon Url: www.amzon.com/dp/B01AK8SC10

Product Title: women fashion best friends printed best pattern one sleeveless crop top
Euclidean Distance from input image: 29.954865
Amazon Url: www.amzon.com/dp/B01GFJOGUE

Product Title: women yabish print white sleeveless crop top
Euclidean Distance from input image: 30.084488
Amazon Url: www.amzon.com/dp/B0748JNFL9

Product Title: women fashion cool quote printed sleeveless crop top
Euclidean Distance from input image: 30.100615
Amazon Url: www.amzon.com/dp/B018RVK1FM

Product Title: women pattern 8 cute baby alien print sleeveless crop top
Euclidean Distance from input image: 30.18043
Amazon Url: www.amzon.com/dp/B074BNJM8S

In [68]:

```
print(bottleneck_features_train.shape)
df=pd.DataFrame(bottleneck_features_train)
df1=pd.DataFrame({'asin':asins})
df.reset_index(drop=True, inplace=True)
df1.reset_index(drop=True, inplace=True)
#print(df1.head)
df2=pd.concat([df1,df],axis=1)
#print(df2.head())
final_df=pd.merge(df2, data, on='asin', how='inner')
print(final_df.shape)
df_new=final_df.iloc[:,1:25089]
print(df_new.shape)
print(df_new.head())
```

```
(16042, 25088)
(16035, 25095)
(16035, 25088)
      0      1      2      3         4      5      6      7      8      9      \
0  0.117596    0.0    0.0    0.0  0.144464    0.0    0.0    0.0    0.0    0.0
1  0.062407    0.0    0.0    0.0  0.000000    0.0    0.0    0.0    0.0    0.0
2  0.397362    0.0    0.0    0.0  0.244873    0.0    0.0    0.0    0.0    0.0
3  0.176354    0.0    0.0    0.0  0.080950    0.0    0.0    0.0    0.0    0.0
4  0.457714    0.0    0.0    0.0  0.426292    0.0    0.0    0.0    0.0    0.0

   ...     25078     25079     25080  25081  25082     25083  25084  25085  \
0  ...  1.889691  0.249676  0.465329    0.0    0.0  0.237450    0.0    0.0
1  ...  1.739319  0.125181  0.375731    0.0    0.0  0.432228    0.0    0.0
2  ...  1.785102  0.168693  0.193825    0.0    0.0  0.363563    0.0    0.0
3  ...  1.806306  0.312727  0.527630    0.0    0.0  0.462871    0.0    0.0
4  ...  1.690328  0.276663  0.342060    0.0    0.0  0.383315    0.0    0.0

      25086  25087
0  0.677545    0.0
1  0.659915    0.0
2  0.615460    0.0
3  0.538263    0.0
4  0.577400    0.0

[5 rows x 25088 columns]
```

In [74]:

```
final_df['brand'].fillna(value="Not given", inplace=True )

# replace spaces with hypen
brands = [x.replace(" ", "-") for x in final_df['brand'].values]
types = [x.replace(" ", "-") for x in final_df['product_type_name'].values]
colors = [x.replace(" ", "-") for x in final_df['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()
w2v_title_weight=w2v_title_weight[0:16035]
print(len(w2v_title_weight))
```

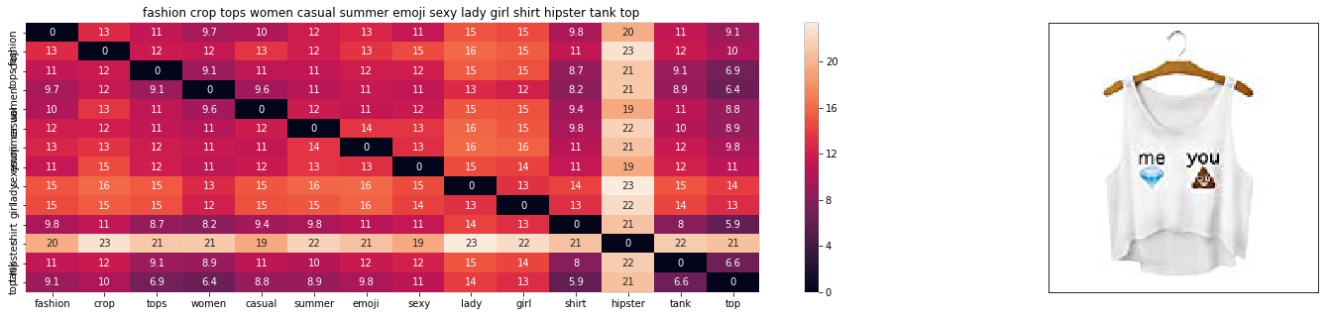
```
16035
```

In [77]:

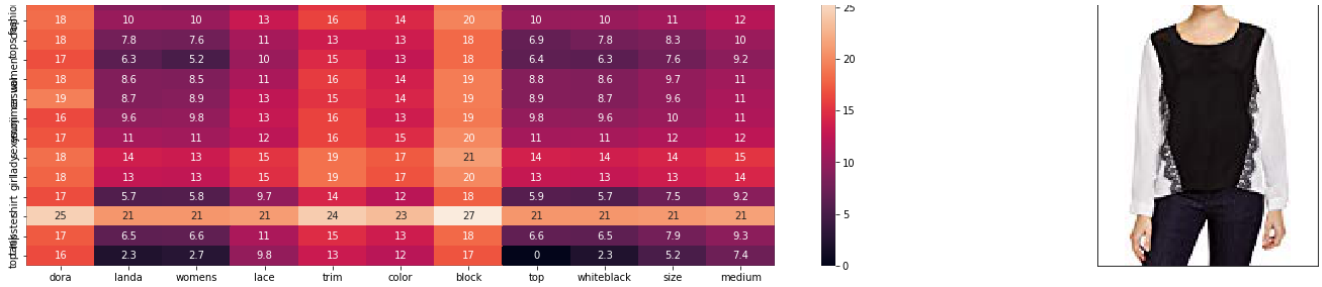
```
#df_new=df_new.as_matrix()
```

In [76]:

```
#With equal weights
def withimage(doc_id, w1, w2,w3, 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])
    image_feat_distance = pairwise_distances(df_new, df_new[doc_id].reshape(1,-1))
    doc_id = asins.index(df_asins[doc_id])
    #img_dist = pairwise_distances(df_new, df_new[doc_id].reshape(-1,1))
    pairwise_dist   = (w1 * idf_w2v_dist +  w2 * ex_feat_dist +w3*image_feat_distance)/float(w1 + w2+w3)

    # 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)

withimage(12566, 5, 5, 5,20)
```



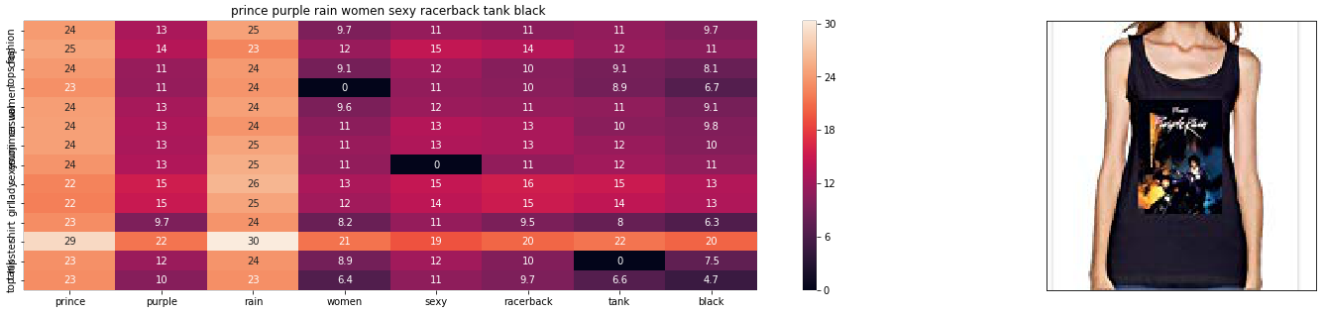

```
ASIN : B010V3B44G
Brand : Doxi Supermall
euclidean distance from input : 3.178914388020833e-07
=============================================================================================================
```



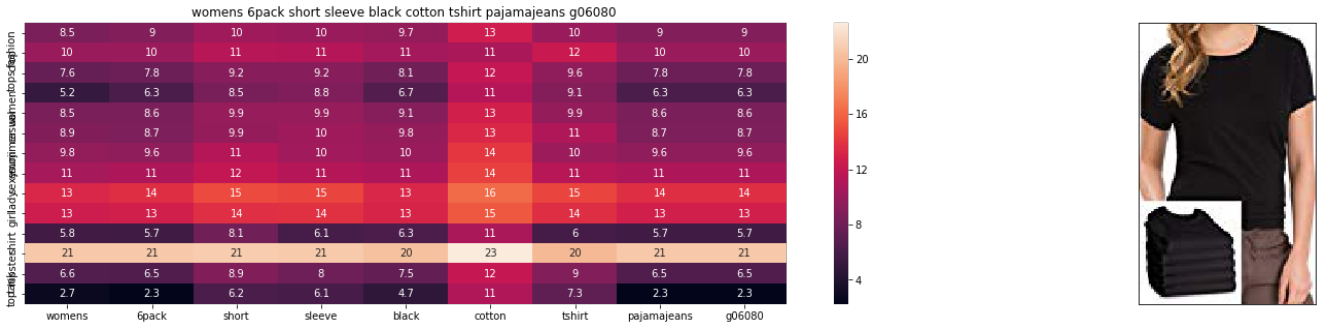
ASIN : B00KXDD0QK
Brand : Dora Landa
euclidean distance from input : 11.710339643986176
==========

ASIN : B00OUENQ1W
Brand : Huawen
euclidean distance from input : 11.828060150146484
==========

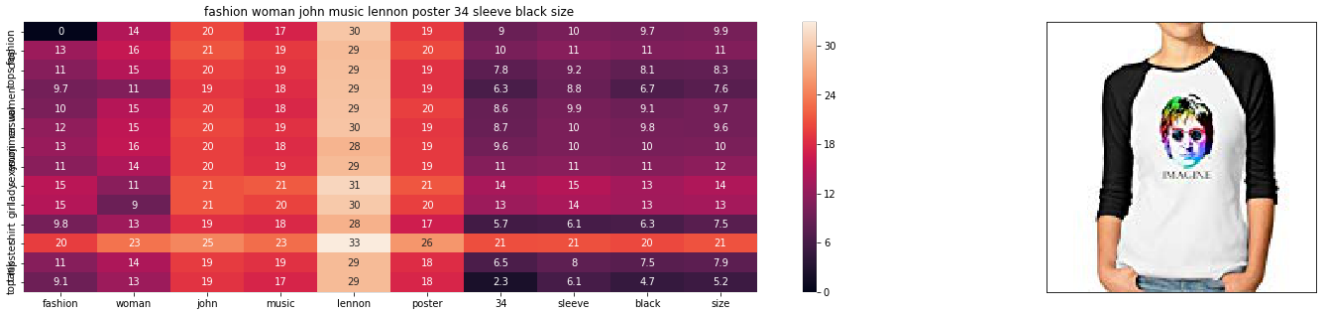
ASIN : B01B3Y99XA
Brand : Blansdi
euclidean distance from input : 11.939062413136439
==========



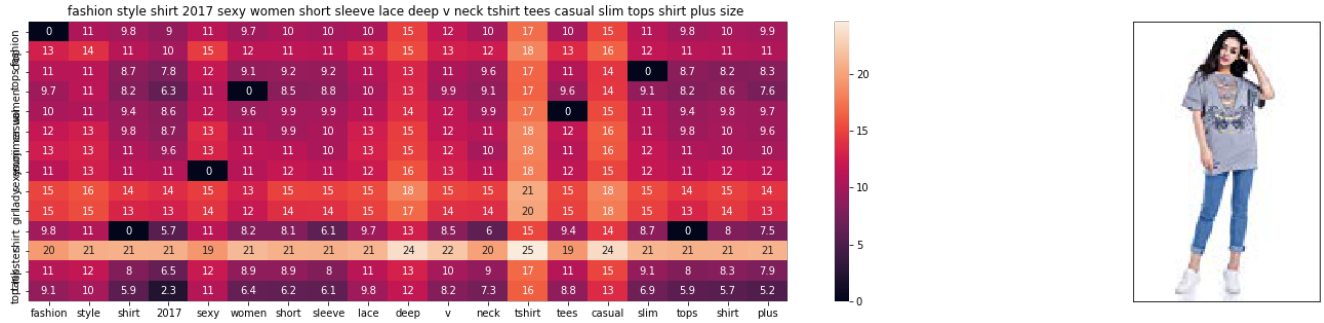
ASIN : B01EN8CCUK
Brand : Tanko
euclidean distance from input : 12.318347208261764
==========
==========



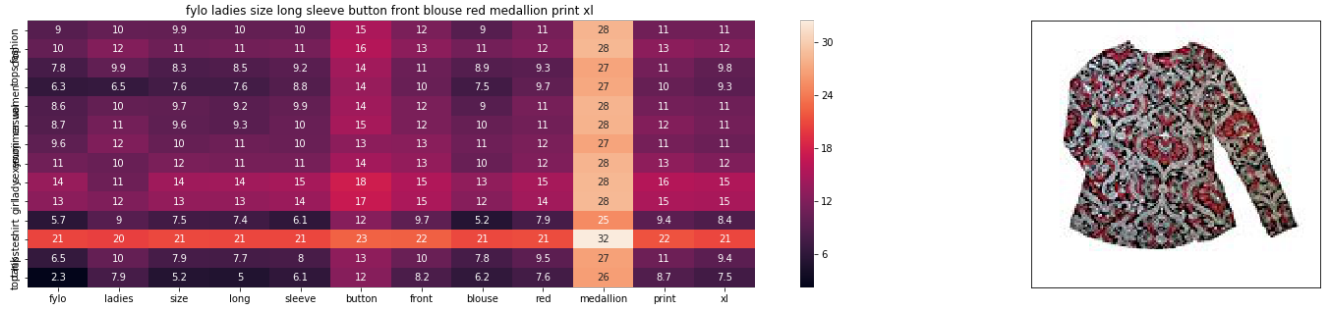
ASIN : B06XYQSPVL
Brand : Pajama Jeans
euclidean distance from input : 12.548929890553431
==========
==========



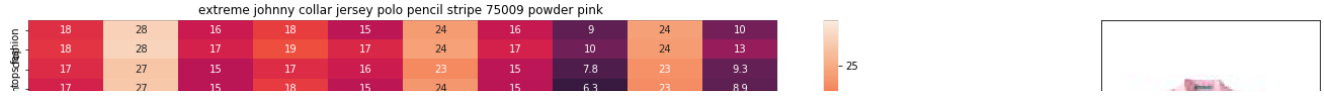
ASIN : B01FRPG7SG
Brand : LOVELIF Sleeve Raglan
euclidean distance from input : 12.59010585390642
==========
==========

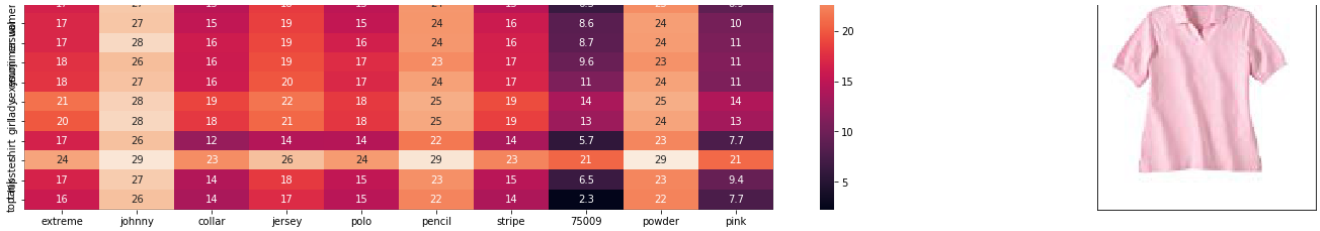


ASIN : B01MS2NG40
Brand : LHS Charmer
euclidean distance from input : 12.61359830110188
==========
==========

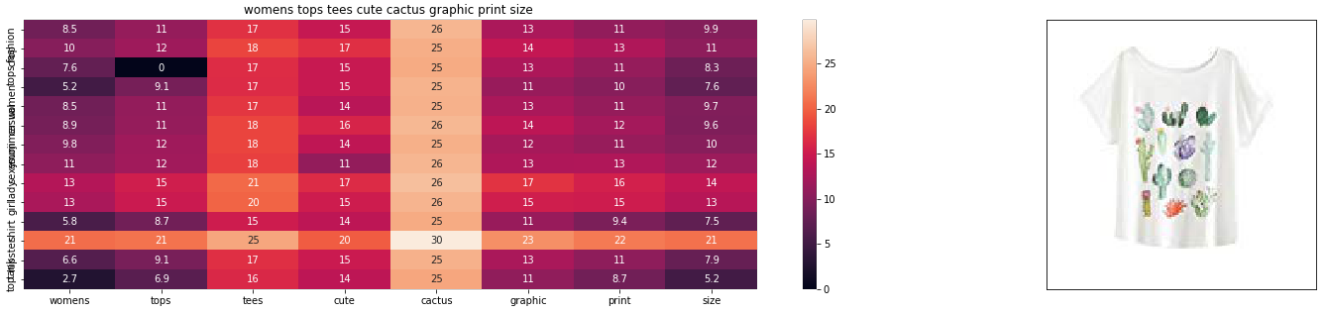


ASIN : B06Y2LZXN5
Brand : Fylo
euclidean distance from input : 12.728863784654878
==========
==========

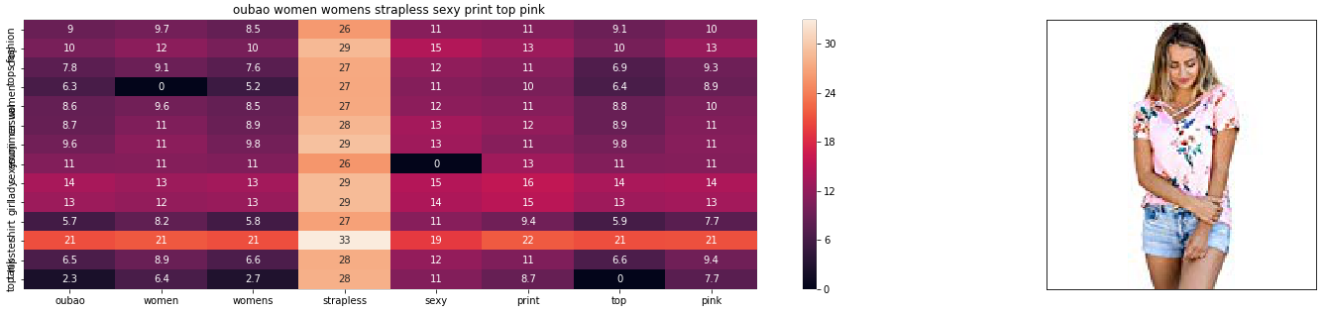




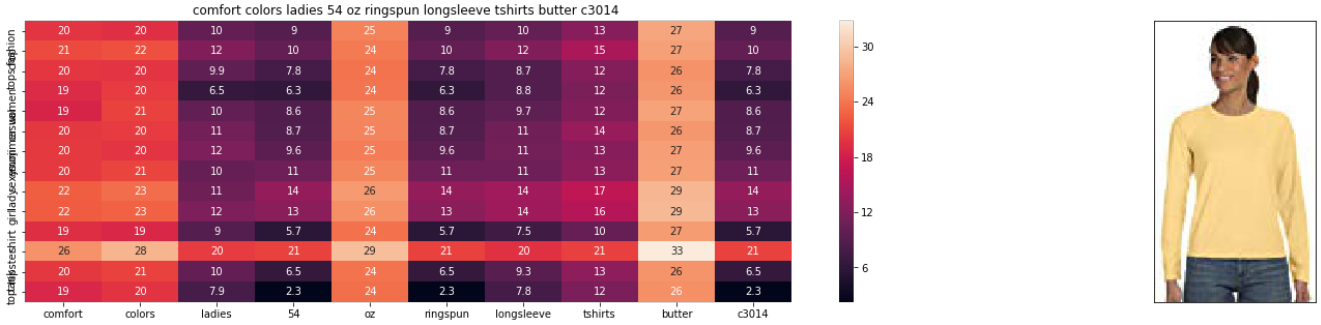
ASIN : B00ELCAEX6
Brand : Ash City
euclidean distance from input : 12.815218098958333
==========



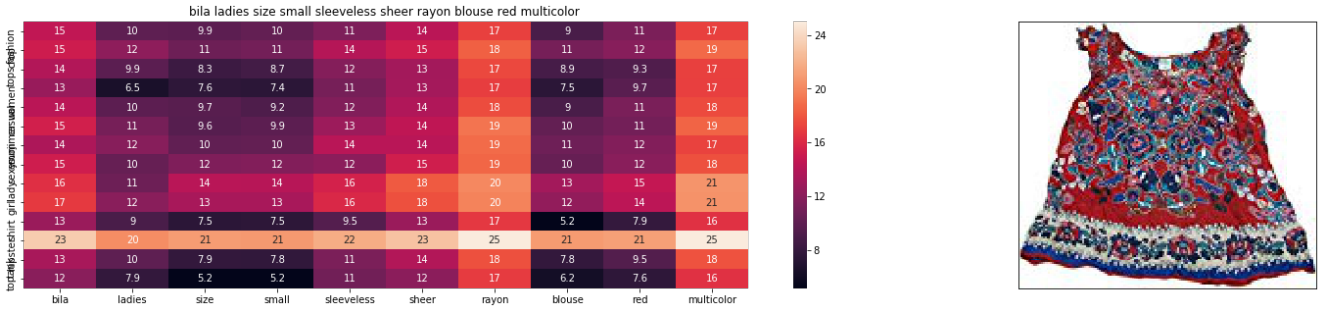
ASIN : B01M5H7LNO
Brand : namnoishop Crop Tops
euclidean distance from input : 12.974137537241257
==========



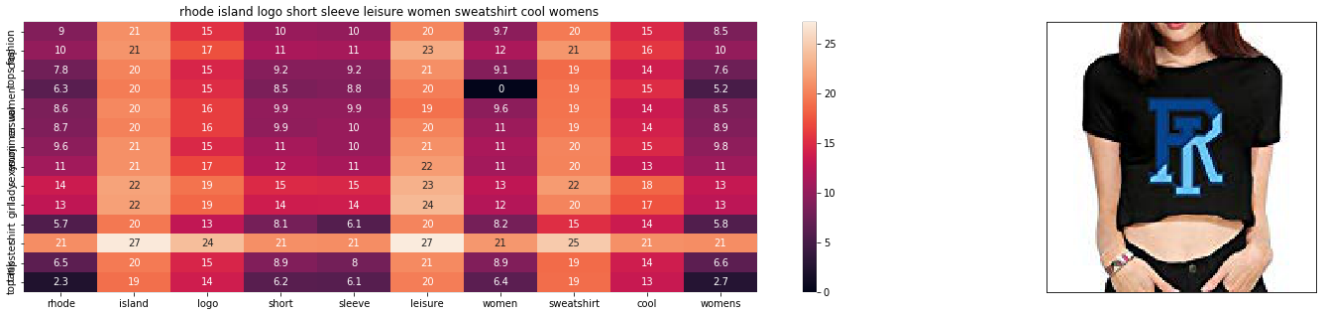
ASIN : B0725GD1BM
Brand : OUBAO
euclidean distance from input : 13.030591505854485
==========



ASIN : B00390D6FY
Brand : Comfort Colors
euclidean distance from input : 13.106572474026622
==========

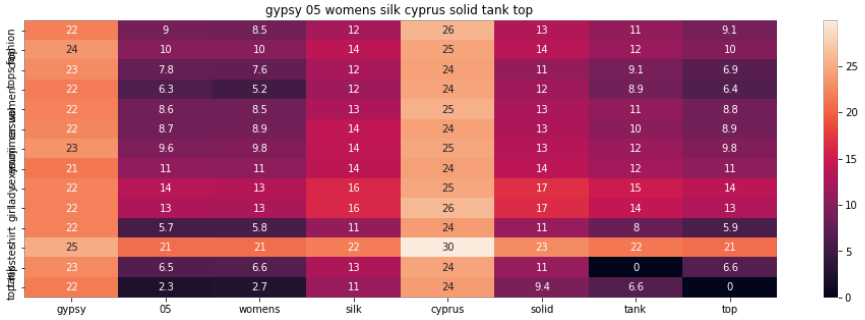


ASIN : B016VABRZY
Brand : Bila
euclidean distance from input : 13.118114378483245
==========

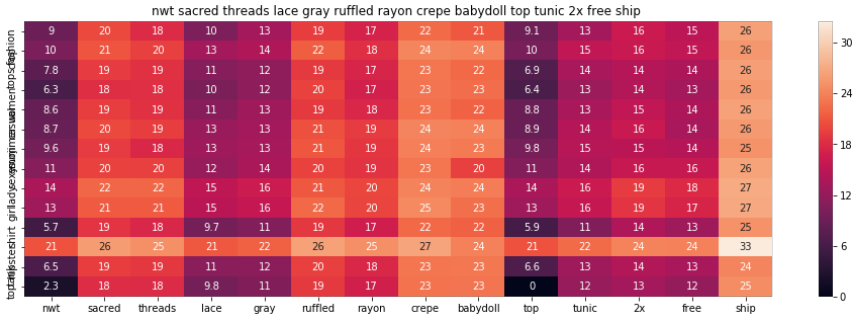


ASIN : B01FXI80LY

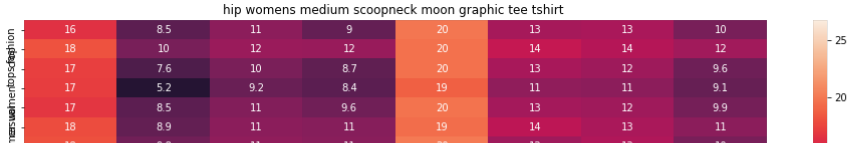
Brand : RUGUOKE11YI
euclidean distance from input : 13.251440053168874
==========

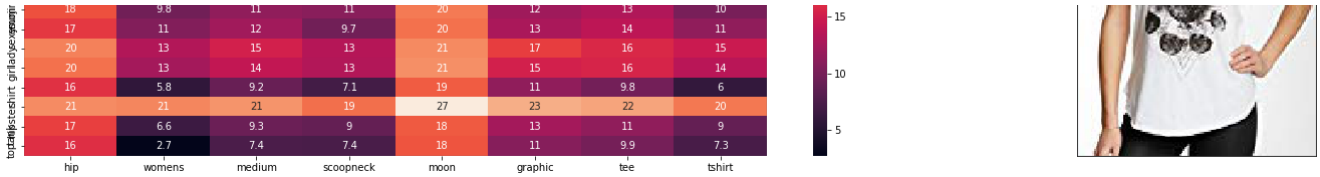


ASIN : B01MRGXOXH
Brand : Gypsy05
euclidean distance from input : 13.282687764350516
==========

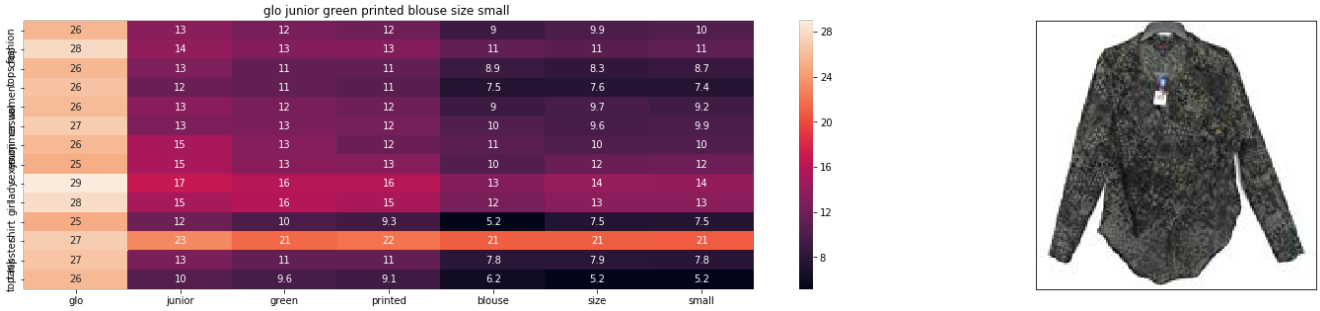


ASIN : B075753FDY
Brand : None
euclidean distance from input : 13.415929208287753
==========

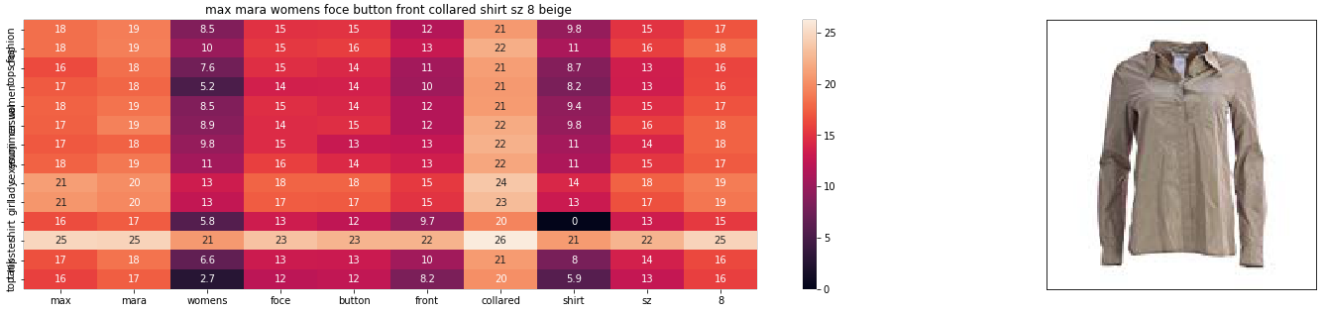




ASIN : B0758ZPKX5
Brand : Hip
euclidean distance from input : 13.605618962208704
==========
==========



ASIN : B071ZQX1JM
Brand : Glo
euclidean distance from input : 13.613105778876882
==========
==========

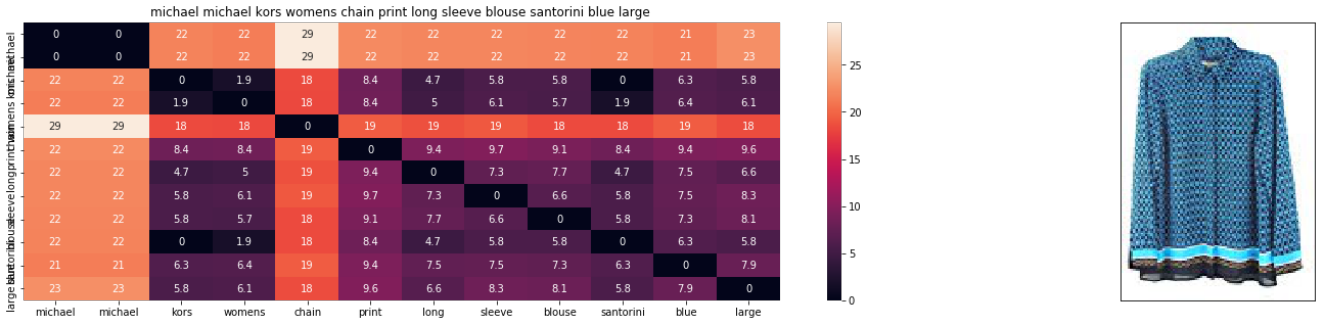


ASIN : B0749S36YR
Brand : MaxMara
euclidean distance from input : 13.614394378903027
==========
==========

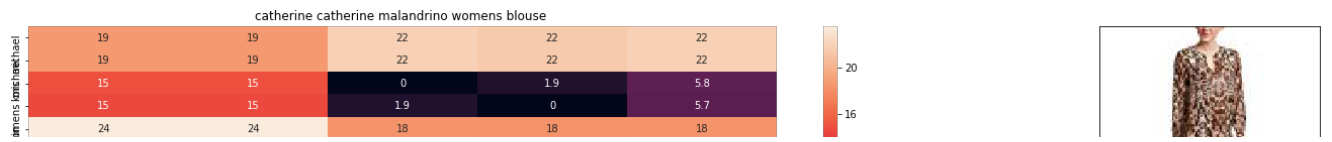
In [78]:

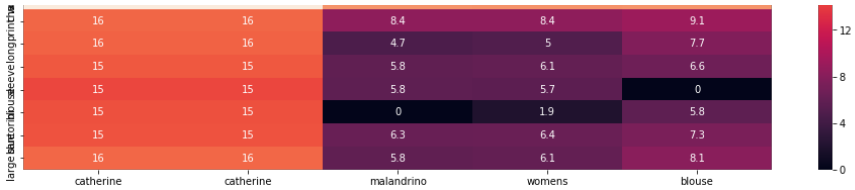
```
#With higher weights to the image features than the  others
def withimage(doc_id, w1, w2,w3, num_results):
    # doc_id: apparel's id in given corpus
```

```
    # 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])
    doc_id = asins.index(df_asins[doc_id])
    image_feat_distance = pairwise_distances(df_new, df_new[doc_id].reshape(1,-1))
    pairwise_dist   = (w1 * idf_w2v_dist +  w2 * ex_feat_dist+w3*image_feat_distance )/float(w1 + w
2+w3)

    # 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], 'weigh
ted')
        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)

withimage(12566, 5, 5,50, 20)
```

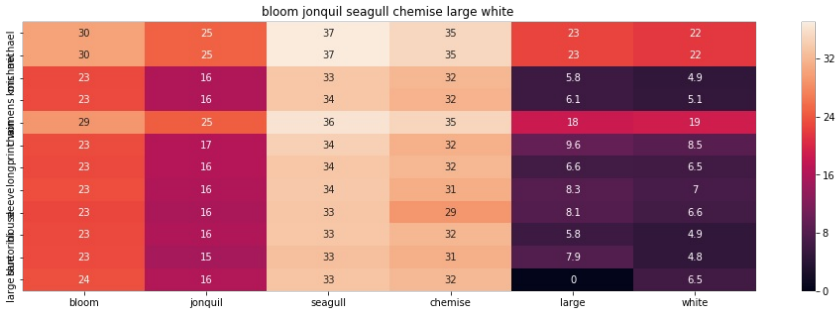


ASIN : B01FH19KVG
Brand : Michael Kors
euclidean distance from input : 0.6265154255266184

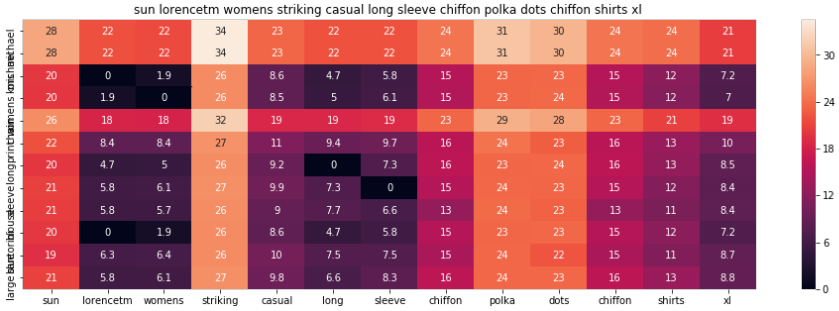




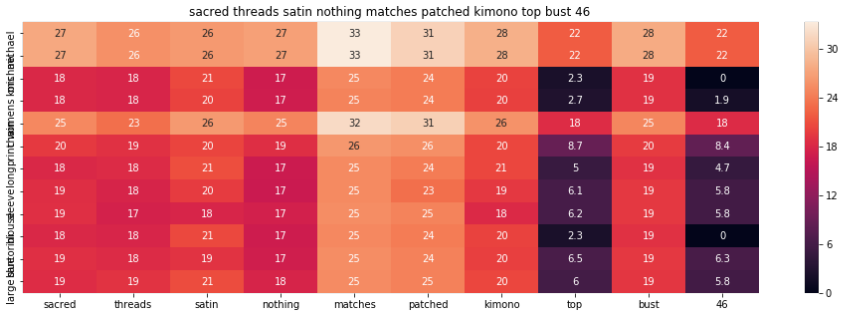
ASIN : B00FBBKYEK
Brand : CATHERINE CATHERINE MALANDRINO
euclidean distance from input : 22.23663978582683



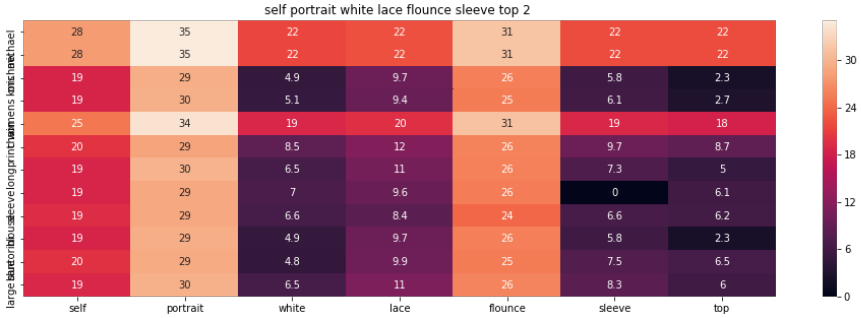
ASIN : B072F8W1ZS
Brand : In Bloom by Jonquil Seagull
euclidean distance from input : 26.39642182640462



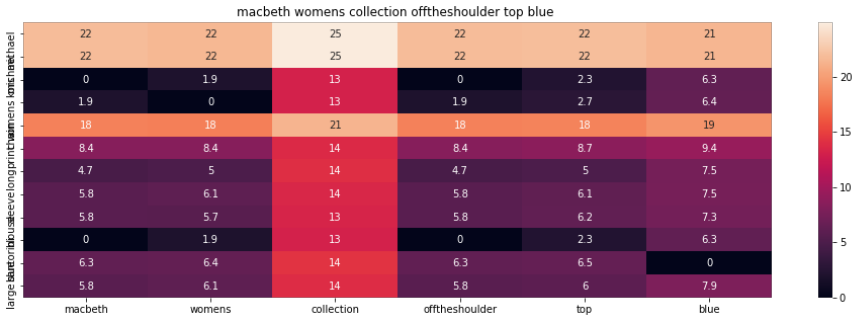
ASIN : B06XKFFWH2
Brand : Sun Lorence
euclidean distance from input : 26.997334639291594



ASIN : B06XYX5X1D
Brand : Sacred Threads
euclidean distance from input : 28.16143901797363
==========



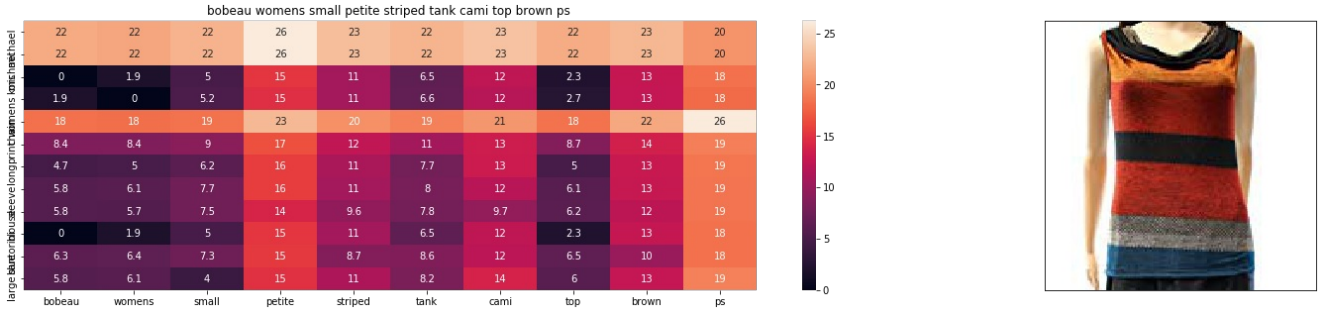
ASIN : B071174JP9
Brand : Self Portrait
euclidean distance from input : 28.469954598468828
==========



ASIN : B07112DDSM
Brand : Macbeth
euclidean distance from input : 28.761675018211275

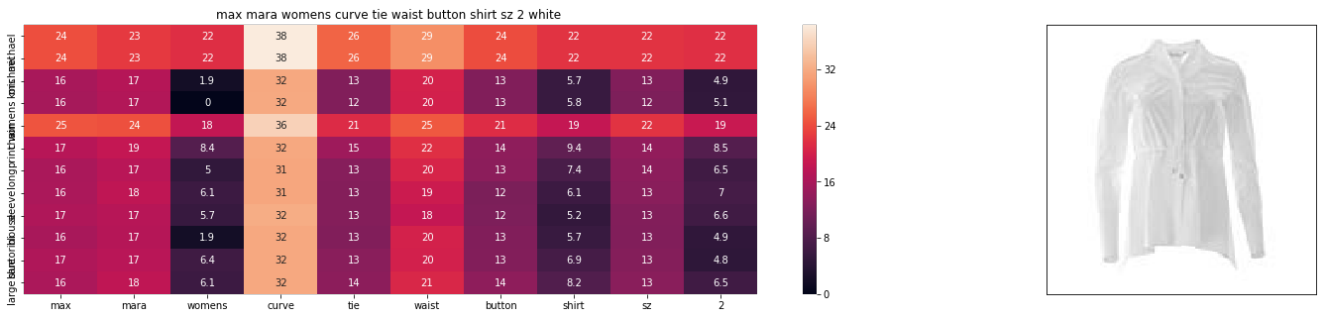
euclidean distance from input : 28.761675016211275

==========



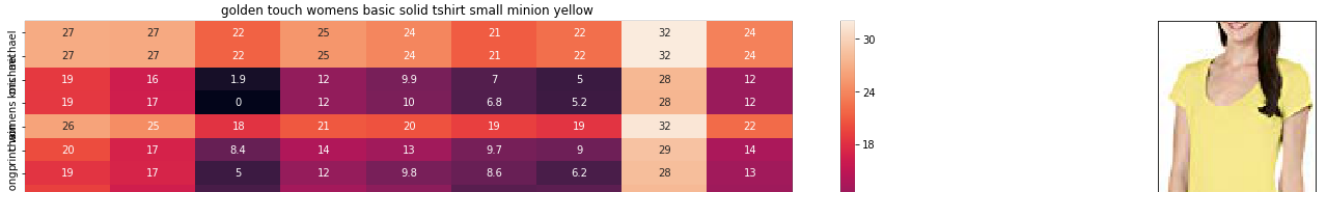
ASIN : B074P8YWV4
Brand : Bobeau
euclidean distance from input : 28.81174451164632

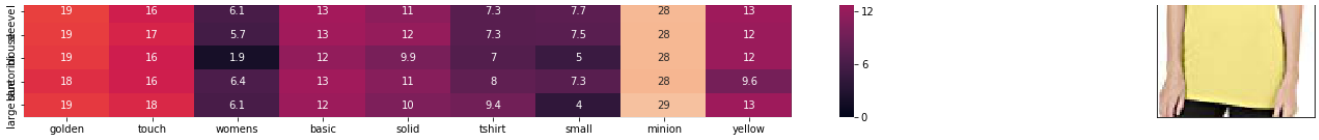
==========



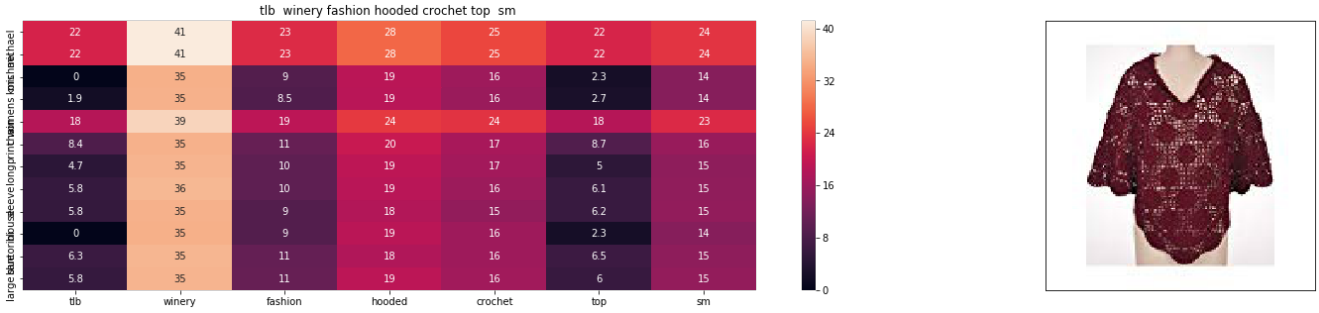
ASIN : B06WWJQ3P2
Brand : MaxMara
euclidean distance from input : 28.82067886988322

==========

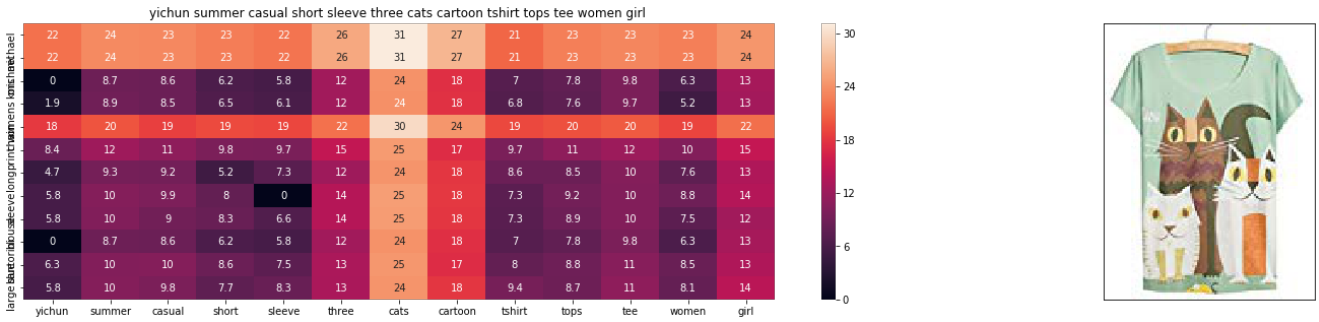




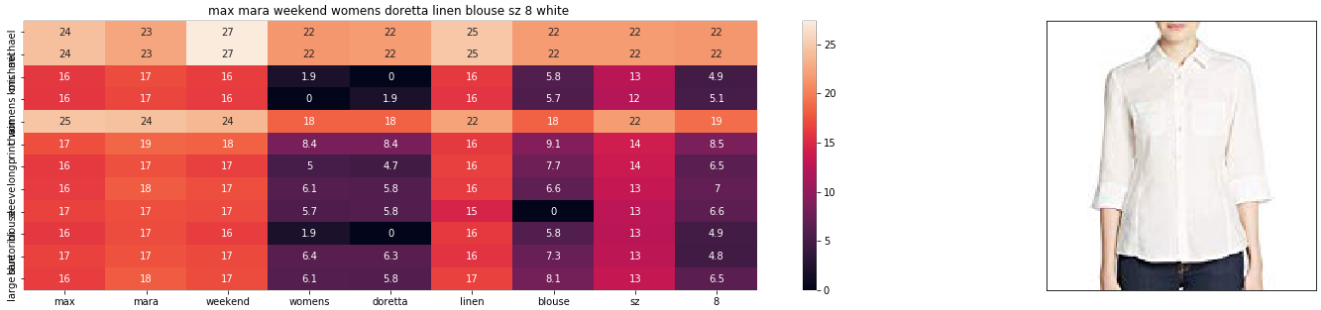
ASIN : B06XKSFJYN
Brand : Golden Touch
euclidean distance from input : 28.998895943683674
==========



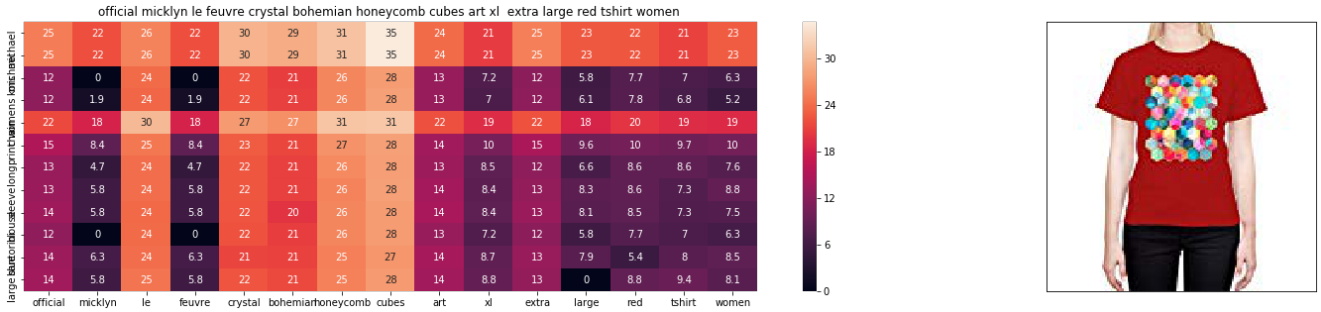
ASIN : B00NQV1YGO
Brand : TLB
euclidean distance from input : 29.094860915861815
==========



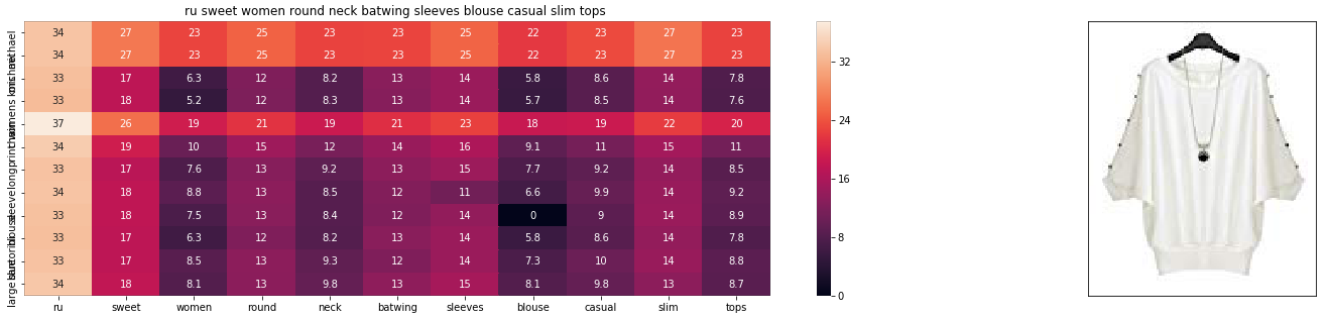
ASIN : B011VF95SK
Brand : YICHUN
euclidean distance from input : 29.221503206612955
==========



ASIN : B071NL8NML
Brand : MaxMara
euclidean distance from input : 29.613156839730628
==========

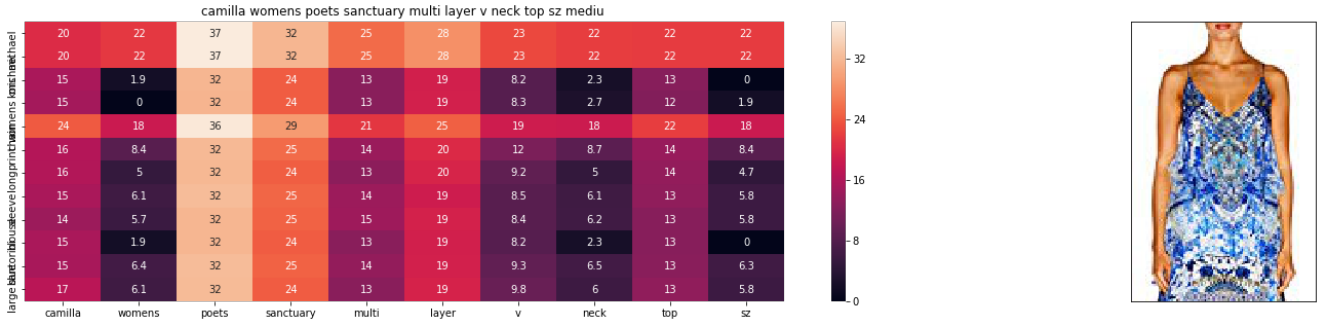


ASIN : B06XPGS6ZW
Brand : Head Case Designs
euclidean distance from input : 29.632492701272795
==========



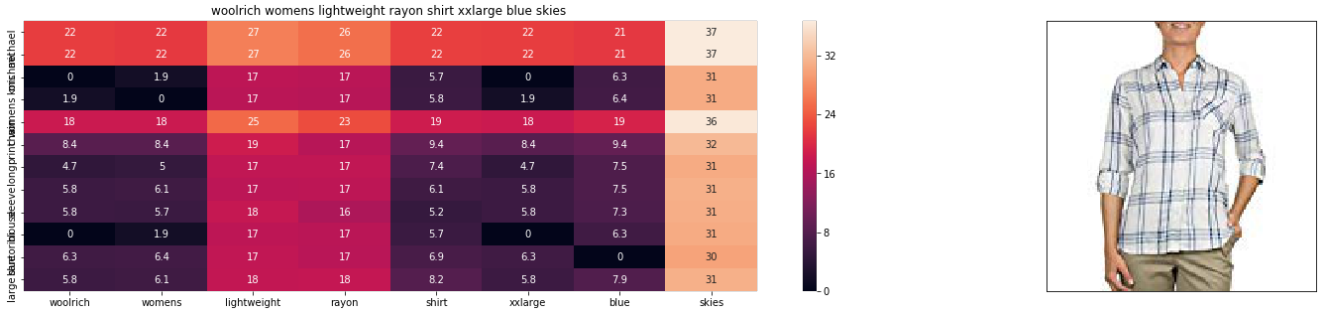
ASIN : B00X3LMJM0
Brand : Ru Sweet-Clothes
euclidean distance from input : 29.785912069922674
==========

_____



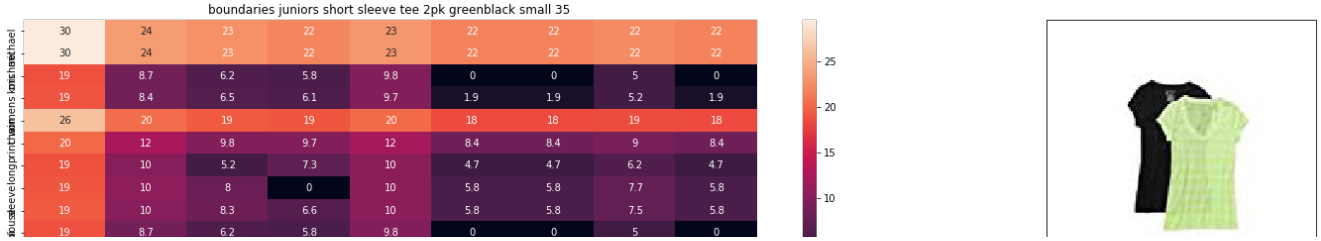
ASIN : B0753C23PV
Brand : Camilla
euclidean distance from input : 29.797502466561685

==========

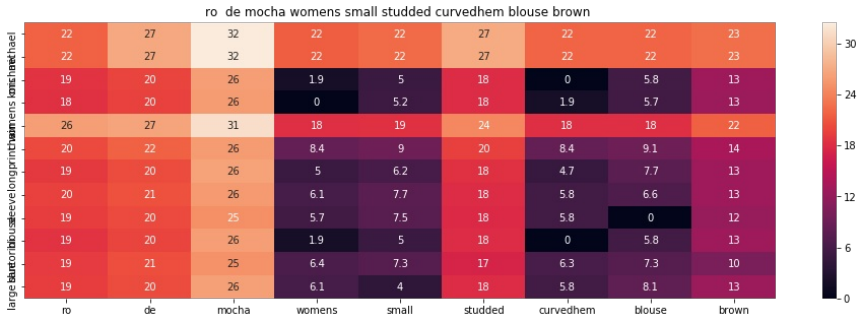


ASIN : B06XKR22JQ
Brand : W
euclidean distance from input : 30.290765772402356

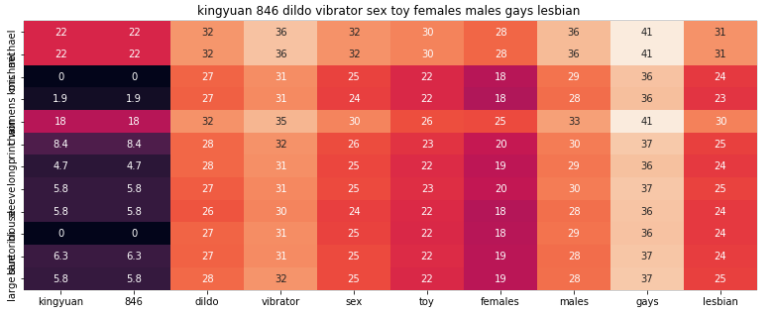
==========



ASIN : B06ZZLWV6V
Brand : No Boundaries
euclidean distance from input : 30.366182530445148
==========
==========



ASIN : B01M35MN7L
Brand : Rode
euclidean distance from input : 30.44303583516684
==========
==========

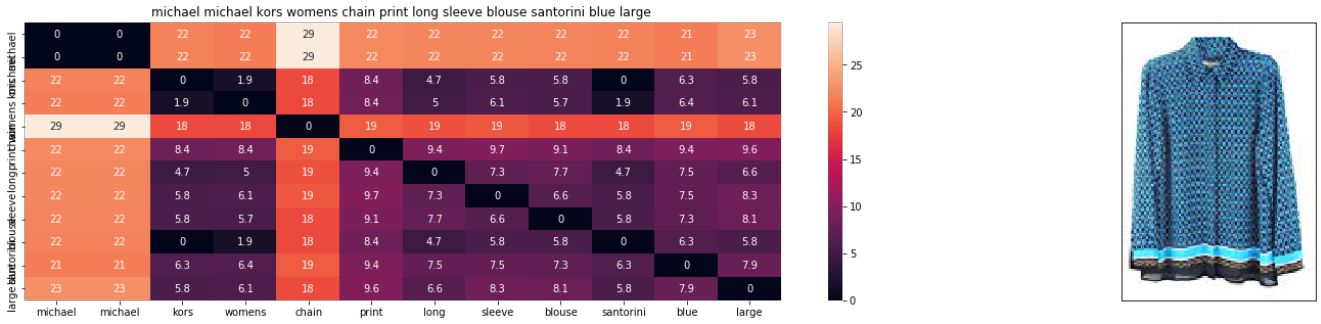


ASIN : B01LXAJZIG
Brand : KingYuan
euclidean distance from input : 30.556052653055023
==========
==========

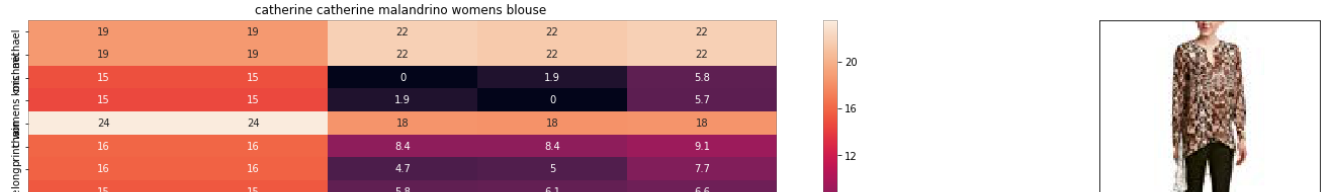
In [79]:

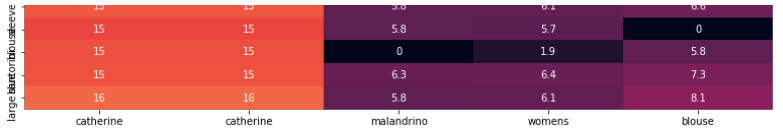
```
#With higher weights to the title than the  additional features
def withimage(doc_id, w1, w2,w3, num_results):
    # doc_id: apparel's id in given corpus
    # w1: weight for  w2v features
    # w2: weight for brand and color features

    # pairwise_dist will store the distance from given input apparel to all remaining apparels
```

```
    # 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])
    doc_id = asins.index(df_asins[doc_id])
    image_feat_distance = pairwise_distances(df_new, df_new[doc_id].reshape(1,-1))
    #img_dist = pairwise_distances(df_new, df_new[doc_id].reshape(-1,1))
    pairwise_dist   = (w1 * idf_w2v_dist +  w2 * ex_feat_dist+w3*image_feat_distance )/float(w1 + w
2+w3)

    # 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], 'weigh
ted')
        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)

withimage(12566, 50, 5,20, 20)
```

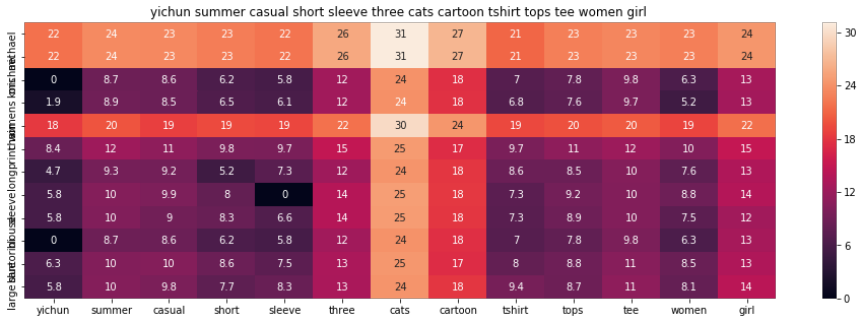



```
ASIN : B01FH19KVG
Brand : Michael Kors
euclidean distance from input : 3.5423940201018893
=============================================================================================================
======================
```

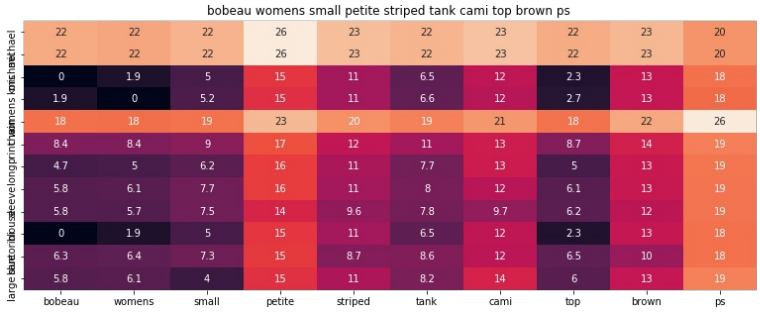




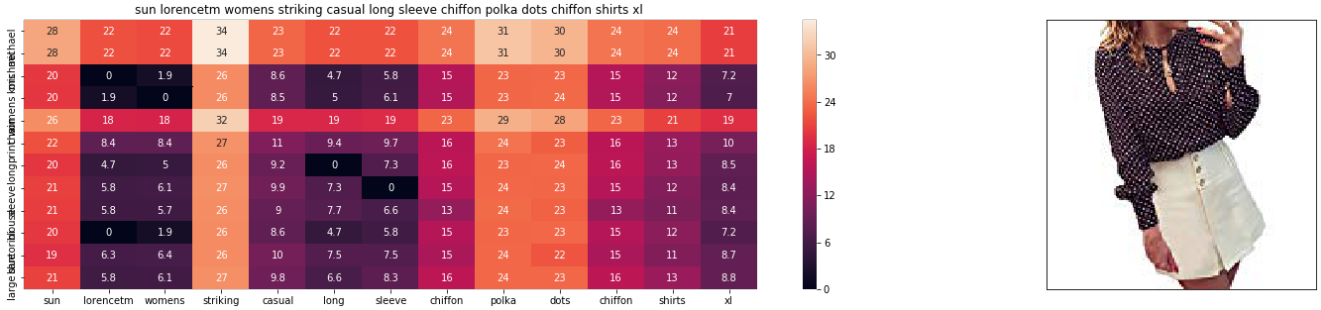
ASIN : B00FBBKYEK
Brand : CATHERINE CATHERINE MALANDRINO
euclidean distance from input : 11.228124796597662
==========



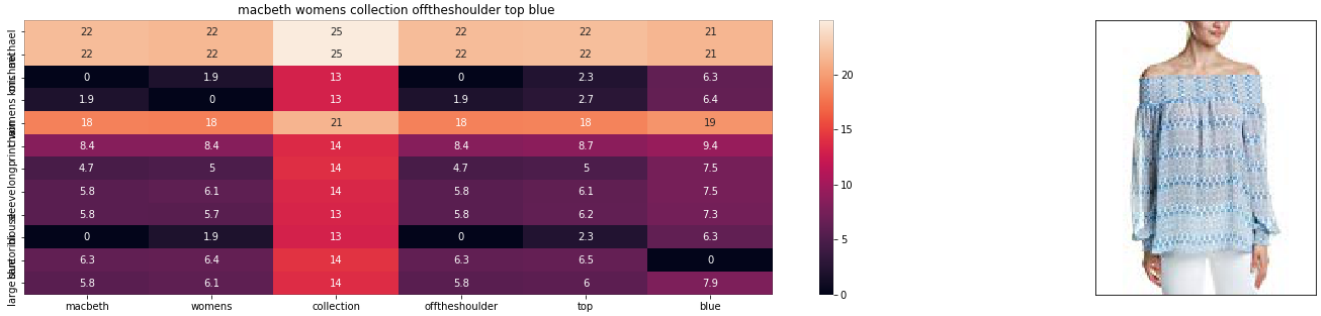
ASIN : B011VF95SK
Brand : YICHUN
euclidean distance from input : 11.707050943789712
==========



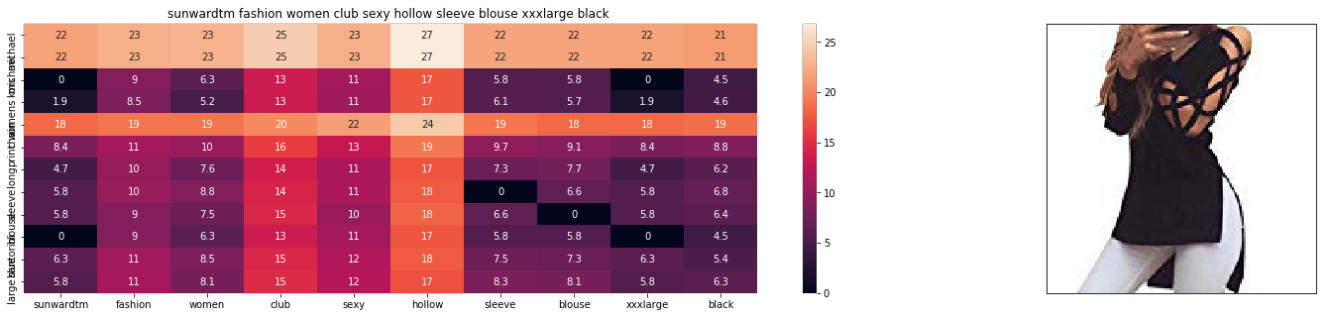
ASIN : B074P8YWV4
Brand : Bobeau
euclidean distance from input : 11.966309570091795
==========



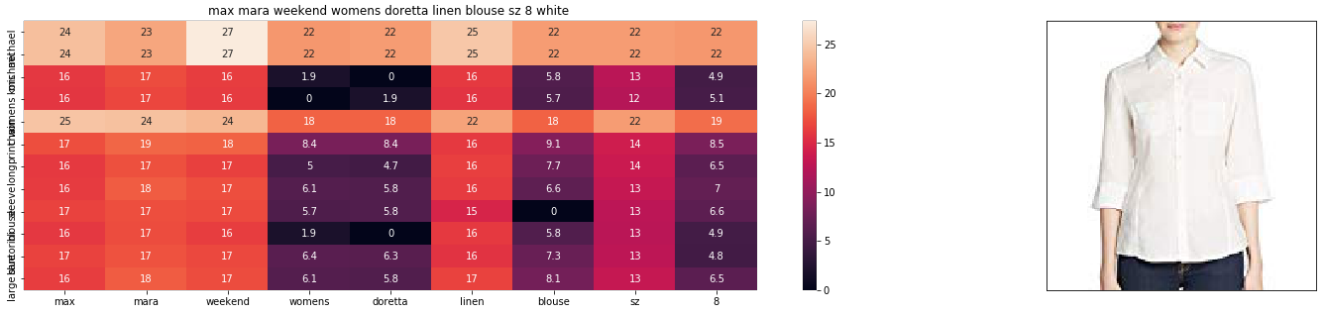
ASIN : B06XKFFWH2
Brand : Sun Lorence
euclidean distance from input : 12.006980590868496
==========



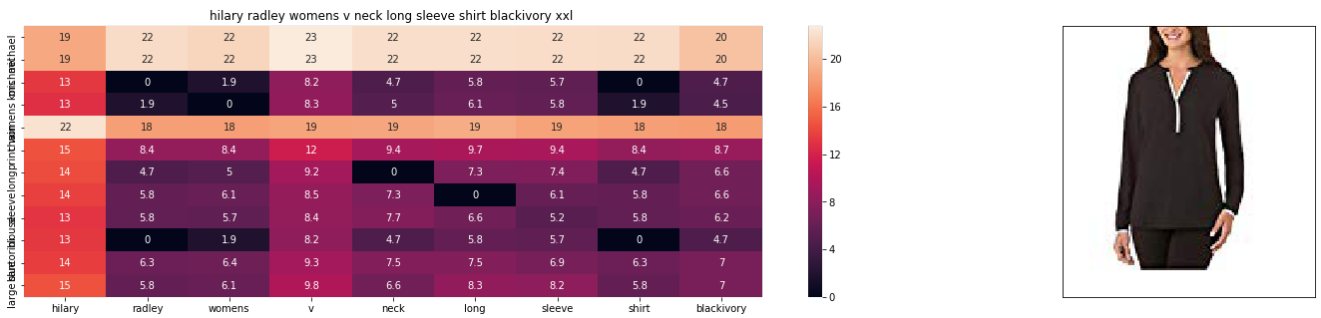
ASIN : B07112DDSM
Brand : Macbeth
euclidean distance from input : 12.0223557107767
==========



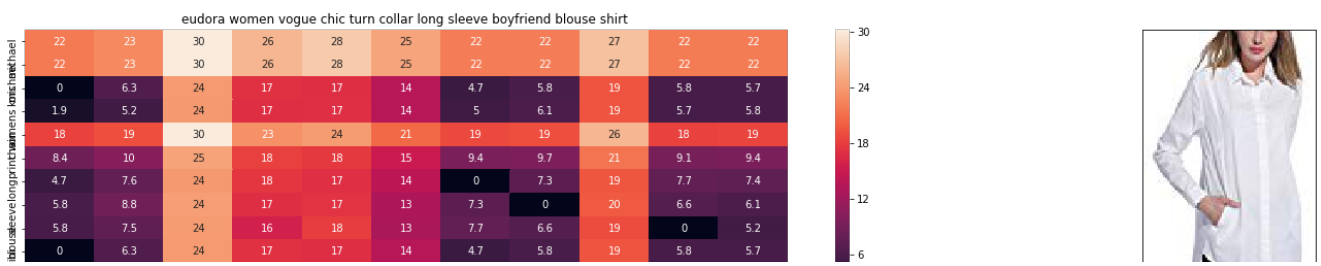
ASIN : B01LW8WHJ2
Brand : Sunward Clothing
euclidean distance from input : 12.314489135790371
==========



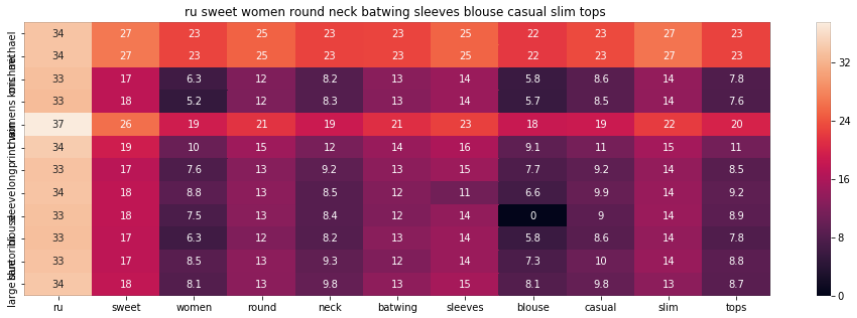
ASIN : B071NL8NML
Brand : MaxMara
euclidean distance from input : 12.451670084414712
==========



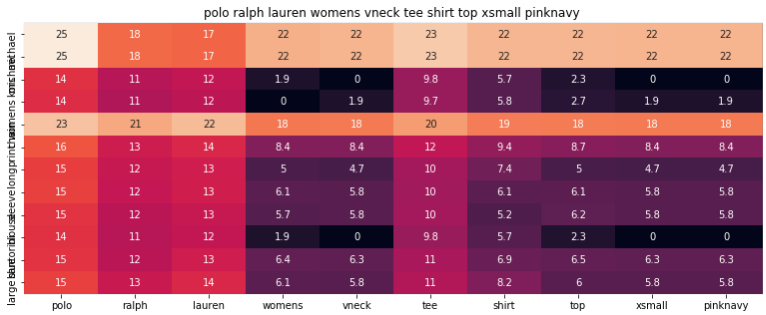
ASIN : B01MR25ZVJ
Brand : Hilary Radley
euclidean distance from input : 12.56742914934634
==========



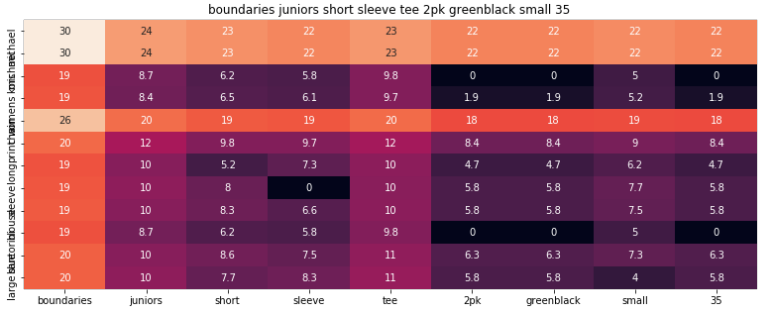
ASIN : B00X78CQ7W
Brand : EUDORA
euclidean distance from input : 12.651542154947917
==========



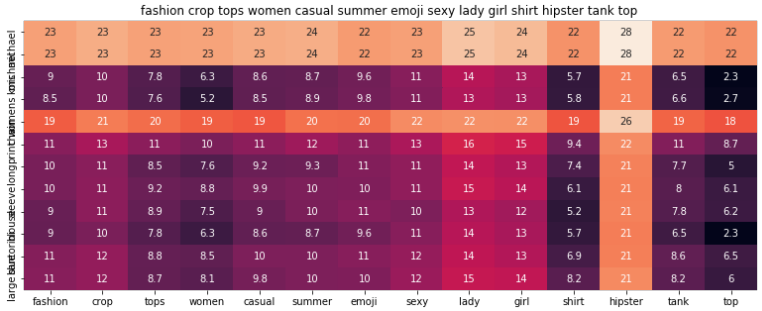
ASIN : B00X3LMJM0
Brand : Ru Sweet-Clothes
euclidean distance from input : 12.693749746677069
==========



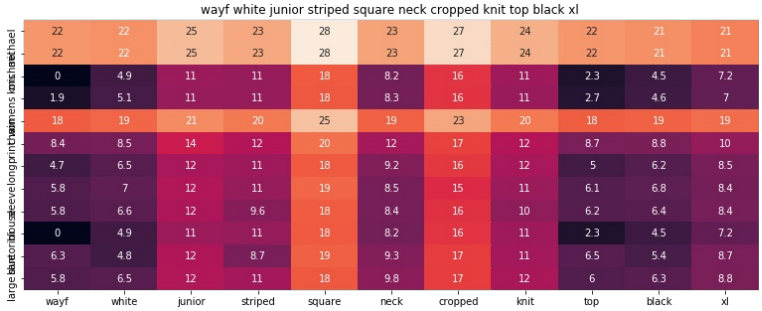
ASIN : B01ETUBK3W
Brand : RALPH LAUREN
euclidean distance from input : 12.74138362608138
==========



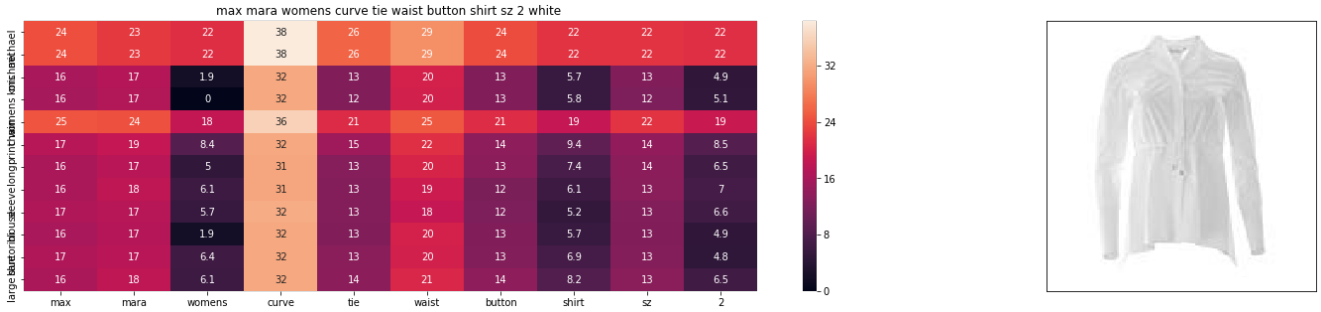
ASIN : B06ZZLWV6V
Brand : No Boundaries
euclidean distance from input : 12.748516397891274
==========



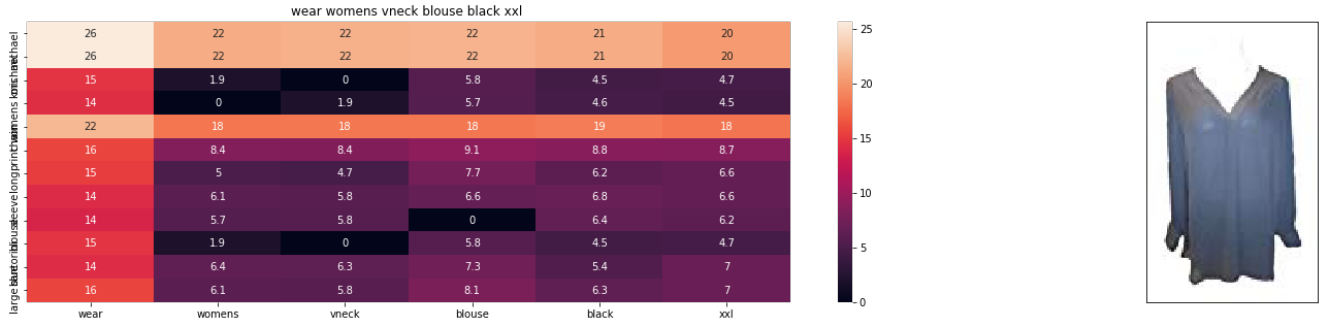
ASIN : B010V3B44G
Brand : Doxi Supermall
euclidean distance from input : 12.753396809895833
==========



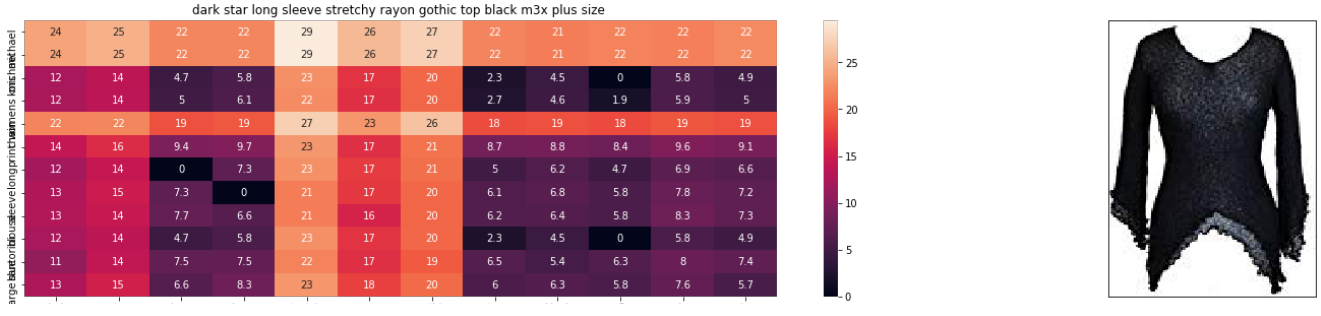
ASIN : B01HD7LXBM
Brand : WAYF
euclidean distance from input : 12.754872639973959
==========



ASIN : B06WWJQ3P2
Brand : MaxMara
euclidean distance from input : 12.806368408203125
==========

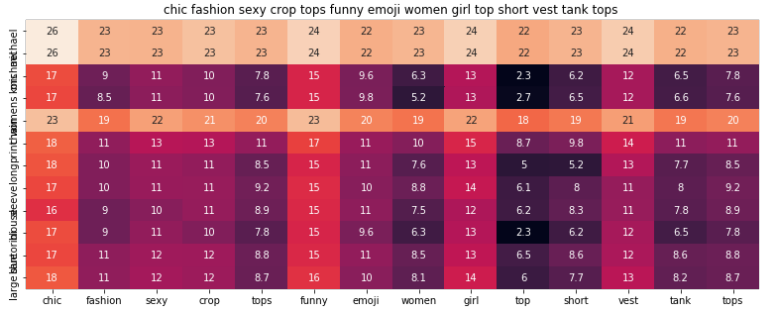


ASIN : B06Y6FH453
Brand : Who What Wear
euclidean distance from input : 12.81225524907162
==========

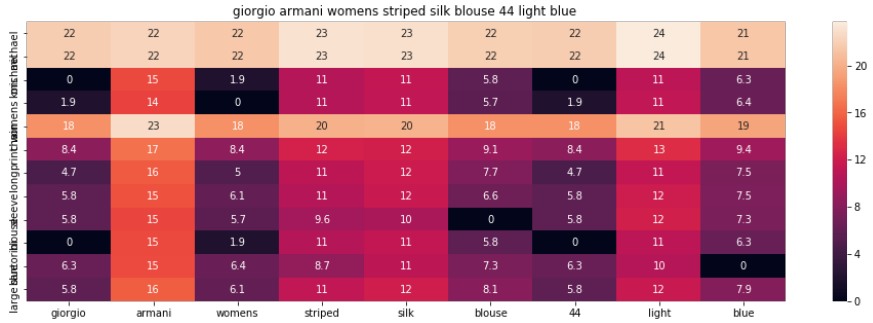


dark star long sleeve stretchy rayon gothic top black m3x plus size

ASIN : B01L4T8A0W
Brand : Darkstar
euclidean distance from input : 12.852653157331378
==========



ASIN : B011RCJH58
Brand : Chiclook Cool
euclidean distance from input : 12.864027863539048
==========



ASIN : B010RAVDJE
Brand : GIORGIO ARMANI
euclidean distance from input : 12.864993896532559
==========