Assignment

Amazon Apparel Recommendations

Overview of the data

In [1]:
```
#import all the necessary packages.

from PIL import Image
import requests
from io import BytesIO
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import warnings
from bs4 import BeautifulSoup
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import nltk
import math
import time
import re
import os
import seaborn as sns
from collections import Counter
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics import pairwise_distances
from matplotlib import gridspec
from scipy.sparse import hstack
import plotly
import plotly.figure_factory as ff
from plotly.graph_objs import Scatter, Layout
from PIL import Image
from IPython.display import display,  SVG, Math, YouTubeVideo

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

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

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

Terminology:

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

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

Of these 19 features, we will be using only 6 features in this workshop.

```
1. asin  ( Amazon standard identification nu
mber)
2. brand ( brand to which the product belongs
to )
3. color ( Color information of apparel, it c
an contain many colors as   a value ex: red a
nd black stripes )
4. product_type_name (type of the apperal, e
x: SHIRT/TSHIRT )
5. medium_image_url  ( url of the image )
6. title (title of the product.)
7. formatted_price (price of the product)
```

In [ ]:
```
data = data[['asin', 'brand', 'color', 'medium_image_url', 'pro
duct_type_name', 'title', 'formatted_price']]
```

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

Assignment

In [3]:
```
# load the original 16K dataset
data = pd.read_pickle('pickels/16k_apperal_data_preprocessed')
df_asins = list(data['asin'])
```

IDF_W2V title

In [4]:
```
# IDF_W2V of title
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

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

In [5]:
```
# vocab = stores all the words that are there in google w2v mod
el
# vocab = model.wv.vocab.keys() # if you are using Google word2
Vec

idf_title_vectorizer = CountVectorizer()
idf_title_features = idf_title_vectorizer.fit_transform(data['t
itle'])
```

```
vocab = model.keys()
# this function will add the vectors of each word and returns t
he 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[wo
rd] 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_vec
torizer.vocabulary_):
                featureVec = np.add(featureVec, idf_title_featu
res[doc_id, idf_title_vectorizer.vocabulary_[word]] * model[wor
d])
            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

# generating IDF W2v
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,'weigh
ted'))
    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)
```

Brand + Color feature + type feature

In [6]:
```
#Brand +Color feature
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_f
eatures)).tocsr()
```

Image Feature

In [7]:
```
# image feature
bottleneck_features_train = np.load('16k_data_cnn_features.npy'
)
asins = np.load('16k_data_cnn_feature_asins.npy')
asins = list(asins)
```

Modeling (Idf_w2v Title + Extra features + Image features)

In [8]:
```
# utility functions
def heat_map_w2v_brand(sentance1, sentance2, url, doc_id1, doc_
id2, model):

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

    # s1_s2_dist = np.array(#number of words in title1 * #numbe
r 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'].iloc[doc_id1],brands[doc_id1], col
ors[doc_id1], types[doc_id1]], # input apparel's features
                [data['asin'].iloc[doc_id2],brands[doc_id2], col
ors[doc_id2], types[doc_id2]]] # recommonded apparel's features

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

    # we create a table with the data_matrix
    table = ff.create_table(data_matrix, index=True, colorscale
=colorscale)
    # plot it with plotly
    plotly.offline.iplot(table, filename='simple_table')

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

    # in first 25*10 grids we plot heatmap
    ax1 = plt.subplot(gs[:, :-5])
    # ploting the heap map based on the pairwise distances
```

```
    ax1 = sns.heatmap(np.round(s1_s2_dist,6), annot=True)
    # set the x axis labels as recommended apparels title
    ax1.set_xticklabels(sentance2.split())
    # set the y axis labels as input apparels title
    ax1.set_yticklabels(sentance1.split())
    # set title as recommended apparels title
    ax1.set_title(sentance2)

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

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

    plt.show()


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

def get_word_vec(sentence, doc_id, m_name):

    vec = []
    for i in sentence.split():
        if i in vocab:
            if m_name == 'weighted' and i in  idf_title_vectori
zer.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 go
ogle word2vec corpus, we are just ignoring it
            vec.append(np.zeros(shape=(300,)))
    return  np.array(vec)


def get_distance(vec1, vec2):

    final_dist = []
    # for each vector in vec1 we caluclate the distance(euclide
an) to all vectors in vec2
    for i in vec1:
        dist = []
        for j in vec2:
            # np.linalg.norm(i-j) will result the euclidean dis
tance between vectors i, j
            dist.append(np.linalg.norm(i-j))
        final_dist.append(np.array(dist))
    return np.array(final_dist)
```

In [9]:

```
# re indexing of bottleneck_features_train
```

```
bottleneck_features_train_reindexing = np.zeros(bottleneck_feat
ures_train.shape)
for idx, i in enumerate(df_asins):
    bottleneck_features_train_reindexing[idx]=bottleneck_featur
es_train[asins.index(i)]

bottleneck_features_train_reindexing.shape
```

```
(16042, 25088)
```

In [18]:
```
def idf_w2vtitle__brand_color_type_image(doc_id, w1, w2, w3, nu
m_results):

    idf_w2v_dist  = pairwise_distances(w2v_title_weight , w2v_t
itle_weight[doc_id].reshape(1,-1) )
    ex_feat_dist = pairwise_distances( extra_features, extra_fe
atures[doc_id] )
    image_feature = pairwise_distances( bottleneck_features_tra
in_reindexing , bottleneck_features_train_reindexing[doc_id].re
shape(1,-1))

    pairwise_dist   = ((w1 * idf_w2v_dist) +  (w2 * ex_feat_dis
t) + (w3 * image_feature))/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])

    return (w1,w2,w3), pdists.sum()

#*************************************************************
************************************************************
******************

# choosing optimal weights of features on the basis of minimum
 eculidean distance
weight=[]
dist=[]
w1=[20,50,75,100,150,200]
w2=[20,50,75,100,150,200]
w3=[20,50,75,100,150,200]
for wi in w1:
    for wj in w2:
        for wk in w3:
            w,d=idf_w2vtitle__brand_color_type_image(12566, wi,
wj, wk, 15)
            weight.append(w)
            dist.append(d)
```

In [19]:
```
optimum_weights=weight[np.argmin(dist)]
print(f" optimum weight of titles: {optimum_weights[0]}\n optim
um weight of extra features: {optimum_weights[1]}\n optimum wei
ght of image_features: {optimum_weights[2]}")
```

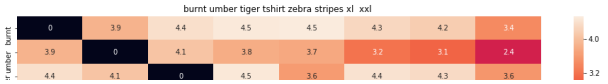
```
 optimum weight of titles: 200
```

```
optimum weight of extra features: 200
optimum weight of image_features: 20
```

In [20]:

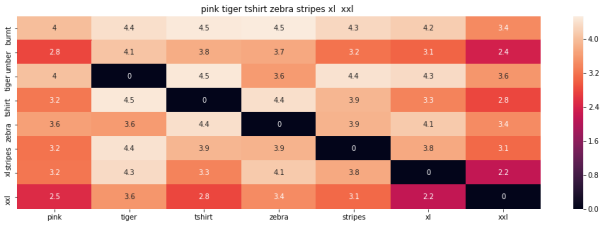
```
# Using optmum weights

def idf_w2vtitle__brand_color_type_image(doc_id, w1, w2, w3, nu
m_results):

    idf_w2v_dist  = pairwise_distances(w2v_title_weight , w2v_t
itle_weight[doc_id].reshape(1,-1) )
    ex_feat_dist = pairwise_distances( extra_features, extra_fe
atures[doc_id] )
    image_feature = pairwise_distances( bottleneck_features_tra
in_reindexing , bottleneck_features_train_reindexing[doc_id].re
shape(1,-1))

    pairwise_dist   = ((w1 * idf_w2v_dist) +  (w2 * ex_feat_dis
t) + (w3 * image_feature))/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(len(indices)):

        heat_map_w2v_brand(data['title'].iloc[indices[0]], data
['title'].iloc[indices[i]], data['medium_image_url'].iloc[indic
es[i]],
                                indices[0],indices[i],
                                'weighted')
        print('Product Title: ', data['title'].iloc[indices[i
]])
        print('Euclidean Distance from input feature:', pdists[
i])
        print('Amazon Url: www.amzon.com/dp/'+ data["asin"].ilo
c[indices[i]])

idf_w2vtitle__brand_color_type_image(12566,200,200, 20, 20)
```

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES



Product Title: burnt umber tiger tshirt zebra stripes x l xxl
Euclidean Distance from input feature: 0.000329028791402 86217
Amazon Url: www.amzon.com/dp/B00JXQB5FQ

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQA	Si-Row	Pink	TOYS_AND_GAMES



Product Title: pink tiger tshirt zebra stripes xl xxl
Euclidean Distance from input feature: 2.38496375600562
Amazon Url: www.amzon.com/dp/B00JXQASS6

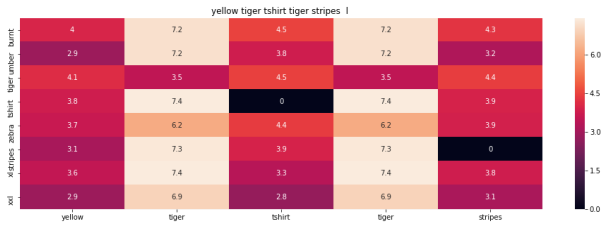
Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQC	Si-Row	Brown	TOYS_AND_GAMES

Product Title: brown white tiger tshirt tiger stripes xl xxl

Euclidean Distance from input feature: 2.7170361261967972

Amazon Url: www.amzon.com/dp/B00JXQCWTO

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQC	Si-Row	Yellow	TOYS_AND_GAMES

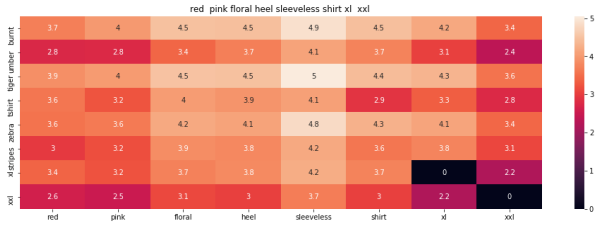


Product Title: yellow tiger tshirt tiger stripes l

Euclidean Distance from input feature: 3.5204009915330077

Amazon Url: www.amzon.com/dp/B00JXQCUIC

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JV63	Si-Row	Red	TOYS_AND_GAMES



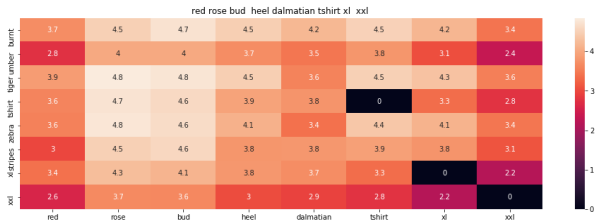
Product Title: red pink floral heel sleeveless shirt xl xxl

Euclidean Distance from input feature: 3.593773847313777

Amazon Url: www.amzon.com/dp/B00JV63QQE

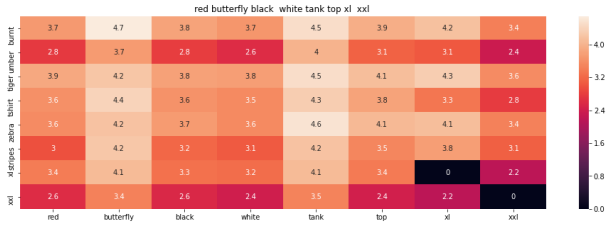
Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES

Asin	Brand	Color	Product type
B00JXQA	Si-Row	Red	TOYS_AND_GAMES



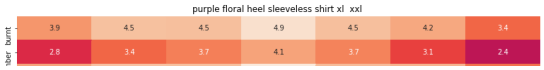
Product Title: red rose bud heel dalmatian tshirt xl xxl
Euclidean Distance from input feature: 3.652190490676975 5
Amazon Url: www.amzon.com/dp/B00JXQABB0

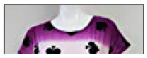
Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JV63	Si-Row	Red	TOYS_AND_GAMES



Product Title: red butterfly black white tank top xl xxl
Euclidean Distance from input feature: 3.669551155722313
Amazon Url: www.amzon.com/dp/B00JV63CW2

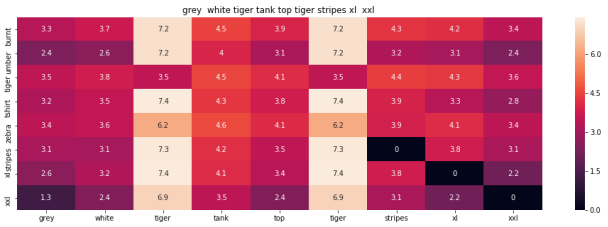
Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JV63	Si-Row	Purple	TOYS_AND_GAMES





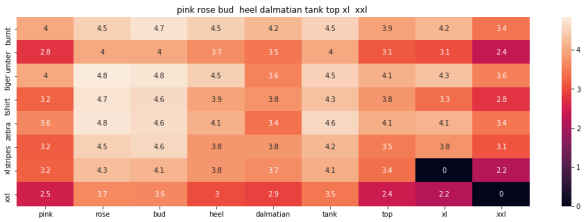
Product Title: purple floral heel sleeveless shirt xl xxl
Euclidean Distance from input feature: 3.6773345382278184
Amazon Url: www.amzon.com/dp/B00JV63VC8

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQA	Si-Row	Grey	TOYS_AND_GAMES



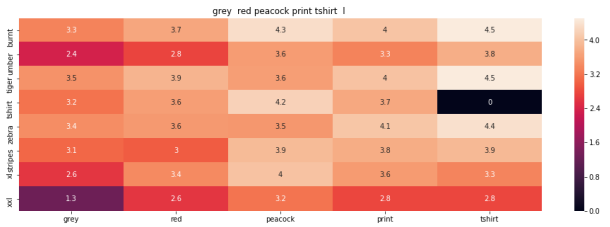
Product Title: grey white tiger tank top tiger stripes xl xxl
Euclidean Distance from input feature: 3.6983610019811475
Amazon Url: www.amzon.com/dp/B00JXQAFZ2

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQA	Si-Row	Pink	TOYS_AND_GAMES



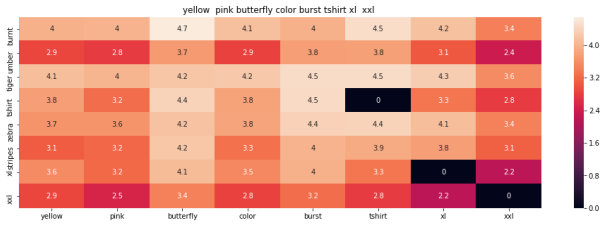
Product Title: pink rose bud heel dalmatian tank top xl xxl
Euclidean Distance from input feature: 3.70019749148232
Amazon Url: www.amzon.com/dp/B00JXQAX2C

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQC	Si-Row	Grey	TOYS_AND_GAMES



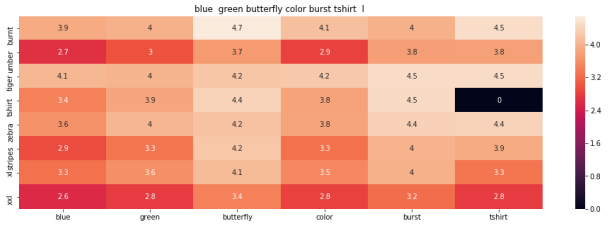
Product Title: grey red peacock print tshirt l
Euclidean Distance from input feature: 3.700996163262909
Amazon Url: www.amzon.com/dp/B00JXQCFRS

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQB	Si-Row	Yellow	TOYS_AND_GAMES



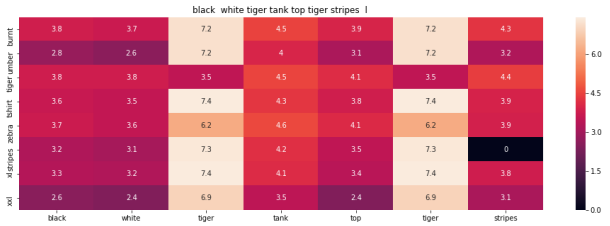
Product Title: yellow pink butterfly color burst tshirt xl xxl
Euclidean Distance from input feature: 3.749896719797049
Amazon Url: www.amzon.com/dp/B00JXQBBMI

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQC	Si-Row	Blue	TOYS_AND_GAMES



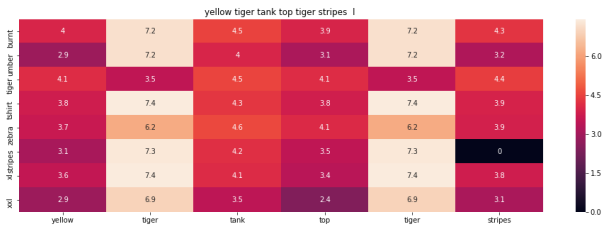
Product Title: blue green butterfly color burst tshirt l
Euclidean Distance from input feature: 3.798091798000961
Amazon Url: www.amzon.com/dp/B00JXQC0C8

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQA	Si-Row	White	TOYS_AND_GAMES



Product Title: black white tiger tank top tiger stripes l
Euclidean Distance from input feature: 3.8259186009190174
Amazon Url: www.amzon.com/dp/B00JXQAO94

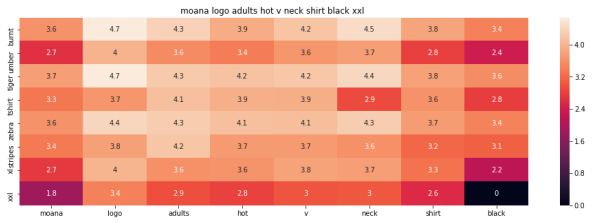
Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQA	Si-Row	Yellow	TOYS_AND_GAMES



Product Title: yellow tiger tank top tiger stripes l

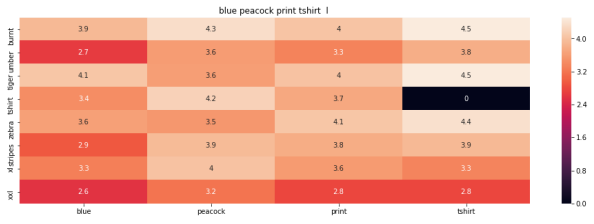
Euclidean Distance from input feature: 3.884656628487909
Amazon Url: www.amzon.com/dp/B00JXQAUWA

Asin	Brand	Color	Product type
B00JX	Si-Row	Brown	TOYS_AND_GAMES
B01LX	BOBOB	Black	BOOKS_1973_AND_LATER



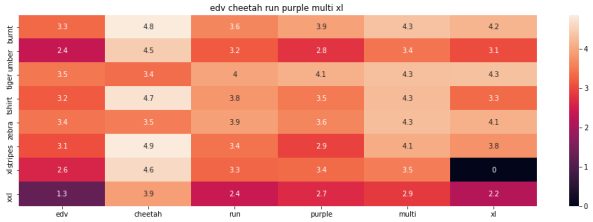
Product Title: moana logo adults hot v neck shirt black xxl
Euclidean Distance from input feature: 4.103921649817908
Amazon Url: www.amzon.com/dp/B01LX6H43D

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00JXQC	Si-Row	Blue	TOYS_AND_GAMES



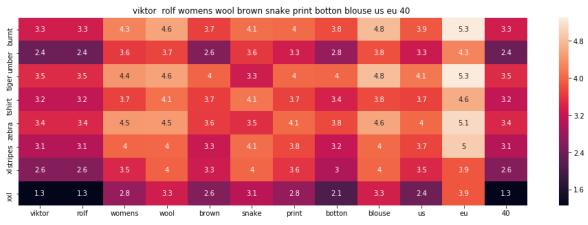
Product Title: blue peacock print tshirt l
Euclidean Distance from input feature: 4.121138356889411
Amazon Url: www.amzon.com/dp/B00JXQC8L6

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B01CUPY	Styleco	White	SHIRT



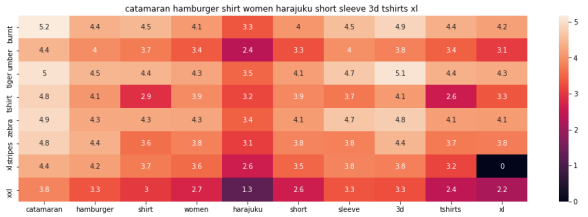
Product Title: edv cheetah run purple multi xl
Euclidean Distance from input feature: 4.132707641663055
Amazon Url: www.amzon.com/dp/B01CUPYBM0

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B00LEHN	Viktor-&-Rolf	Brown	BLAZER



Product Title: viktor rolf womens wool brown snake print botton blouse us eu 40
Euclidean Distance from input feature: 4.151090127658489
Amazon Url: www.amzon.com/dp/B00LEHNVZ4

Asin	Brand	Color	Product type
B00JXQB	Si-Row	Brown	TOYS_AND_GAMES
B01CR32	Catamaran	Brown	SHIRT



Product Title: catamaran hamburger shirt women harajuku short sleeve 3d tshirts xl

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Euclidean Distance from input feature: 4.15282457303717
Amazon Url: www.amzon.com/dp/B01CR325BE
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Conclusion

1. Combining Title features and extra features and image feature all together is definately giving better result.
2. Optimal weights I have got :

   optimum weight of titles: 200

   optimum weight of extra features: 200

   optimum weight of image_features: 20

In [ ]: