Clustering Assignment

There will be some functions that start with the word "grader" ex: grader_actors(), grader_movies(), grader_cost1() etc, you should not change those function definition.

Every Grader function has to return True.

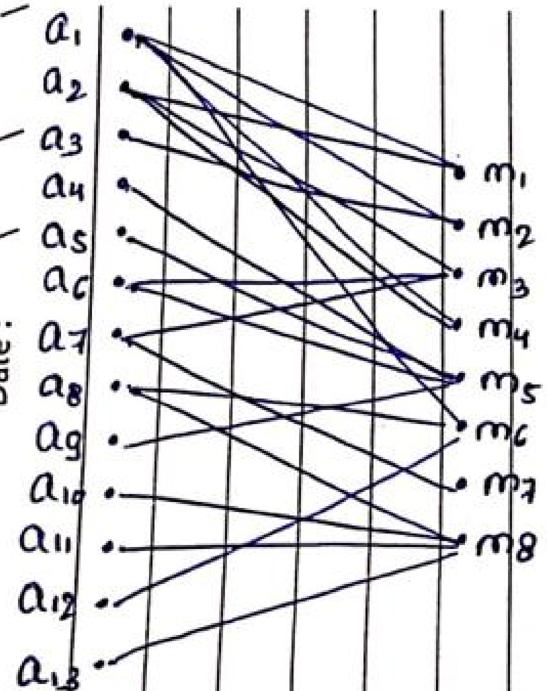
Please check [clustering assignment helper functions (https://drive.google.com/file/d/1V29KhKo3YnckMX32treEgdtH5r90DIjU/view?usp=sharing)](https://drive.google.com/file/d/1V29KhKo3YnckMX32treEgdtH5r90DIjU/view?usp=sharing) notebook before attempting this assignment.

- Read graph from the given movie_actor_network.csv (note that the graph is bipartite graph.)
- Using stellergaph and gensim packages, get the dense representation(128dimensional vector) of every node in the graph. [Refer Clustering_Assignment_Reference.ipynb]
- Split the dense representation into actor nodes, movies nodes.(Write you code in def data_split())

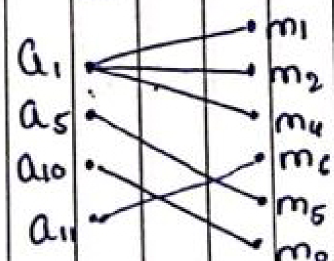
Task 1 : Apply clustering algorithm to group similar actors

1. For this task consider only the actor nodes
2. Apply any clustering algorithm of your choice
   Refer : [https://scikit-learn.org/stable/modules/clustering.html (https://scikit-learn.org/stable/modules/clustering.html)](https://scikit-learn.org/stable/modules/clustering.html)
3. Choose the number of clusters for which you have maximum score of $Cost1 * Cost2$
4. Cost1 = $\frac{1}{N}\sum_{\text{each cluster i}} \frac{\text{(number of nodes in the largest connected component in the graph with the actor nodes and its movie neighbours in cluster i)}}{\text{(total number of nodes in that cluster i)}}$ where N= number of clusters
   (Write your code in def cost1())
5. Cost2 = $\frac{1}{N}\sum_{\text{each cluster i}} \frac{\text{(sum of degress of actor nodes in the graph with the actor nodes and its movie neighbours in cluster i)}}{\text{(number of unique movie nodes in the graph with the actor nodes and its movie neighbours in cluster i)}}$ where N= number of clusters
   (Write your code in def cost2())
6. Fit the clustering algorithm with the opimal number_of_clusters and get the cluster number for each node
7. Convert the d-dimensional dense vectors of nodes into 2-dimensional using dimensionality reduction techniques (preferably TSNE)
8. Plot the 2d scatter plot, with the node vectors after step e and give colors to nodes such that same cluster nodes will have same color

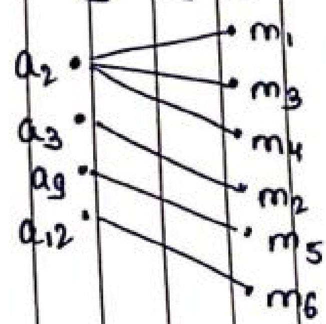
Date :



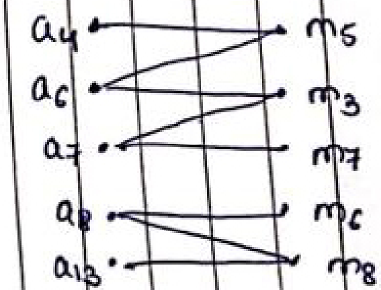
Cluster one ego graph



cluster two ego graph



cluster three ego graph



Cost 1: $\frac{1}{3}\left(\frac{4}{10} + \frac{4}{10} + \frac{6}{10}\right)$

$= \frac{14}{30}$

number of movies = 8

number of actors = 13

Edges = [(a_1,m_1) (a_1,m_2) (a_1,m_4) (a_1,m_6)
(a_2,m_1) (a_2,m_3) (a_2,m_4) (a_3,m_2)
(a_4,m_5) (a_5,m_5) (a_6,m_3) (a_6,m_5)
(a_7,m_3) (a_7,m_7) (a_8,m_6) (a_8,m_8)
(a_9,m_5) (a_{10},m_8) (a_{11},m_8) (a_{12},m_6)
(a_{13},m_8)]

Cost 2: $\frac{1}{3}\left(\frac{6}{6} + \frac{6}{6} + \frac{8}{5}\right)$

$= \frac{18}{15}$

Total Cost : $\frac{14}{30} \times \frac{18}{15} = \frac{252}{450}$

$= 0.56$

Task 2 : Apply clustering algorithm to group similar movies

1. For this task consider only the movie nodes
2. Apply any clustering algorithm of your choice 3.Choose the number of clusters for which you have maximum score of $Cost1 * Cost2$

   Cost1 = $\frac{1}{N} \sum_{\text{each cluster i}} \frac{\text{(number of nodes in the largest connected component in the graph with the movie nodes and its actor neighbours in cluster i)}}{\text{(total number of nodes in that cluster i)}}$ where N= number of clusters
   (Write your code in def cost1())
3. Cost2 = $\frac{1}{N} \sum_{\text{each cluster i}} \frac{\text{(sum of degress of movie nodes in the graph with the movie nodes and its actor neighbours in cluster i)}}{\text{(number of unique actor nodes in the graph with the movie nodes and its actor neighbours in cluster i)}}$ where N= number of clusters
   (Write your code in def cost2())

Algorithm for actor nodes

```
for number_of_clusters in [3, 5, 10, 30, 50, 100, 200, 500]:
    algo = clustering_algorith(clusters=number_of_clusters)
    # you will be passing a matrix of size N*d where N number of actor nodes and d is dimension from gensim
    algo.fit(the dense vectors of actor nodes)
    You can get the labels for corresponding actor nodes (algo.labels_)
    Create a graph for every cluster(ie., if n_clusters=3, create 3 graphs)
    (You can use ego_graph to create subgraph from the actual graph)
    compute cost1,cost2
       (if n_cluster=3, cost1=cost1(graph1)+cost1(graph2)+cost1(graph3) # here we are doing summation
        cost2=cost2(graph1)+cost2(graph2)+cost2(graph3)
    computer the metric Cost = Cost1*Cost2
return number_of_clusters which have maximum Cost
```

In [1]:
```
# !pip install networkx==2.3 #uncomment to install networkx
```

In [2]:
```
import networkx as nx
from networkx.algorithms import bipartite
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import numpy as np
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
# you need to have tensorflow
from stellargraph.data import UniformRandomMetaPathWalk
from stellargraph import StellarGraph
```

In [3]:
```
data=pd.read_csv('movie_actor_network.csv', index_col=False, names=['movie','actor'])
```

In [4]:
```
data.head()
```

Out[4]:

	movie	actor
0	m1	a1
1	m2	a1
2	m2	a2
3	m3	a1
4	m3	a3

In [5]:
```
edges = [tuple(x) for x in data.values.tolist()]
```

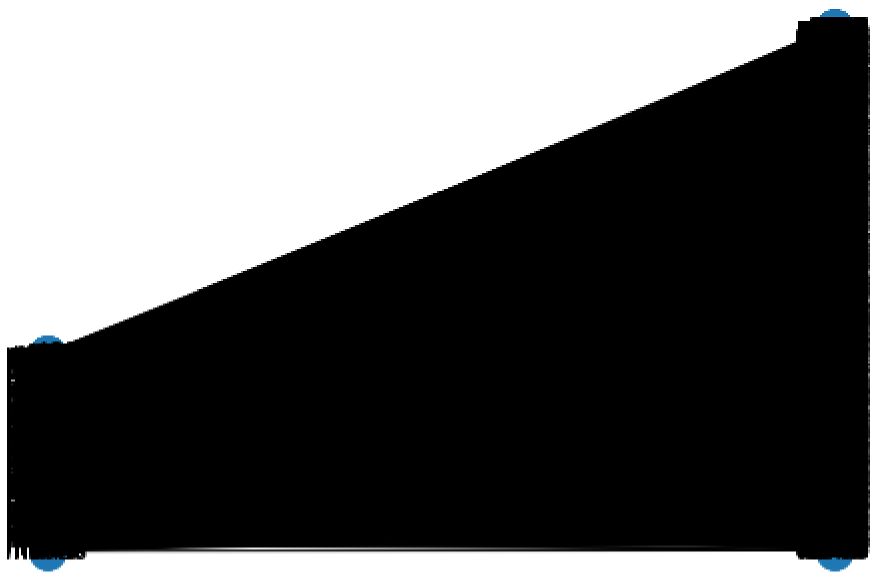
In [6]:
```
B = nx.Graph()
B.add_nodes_from(data['movie'].unique(), bipartite=0, label='movie')
B.add_nodes_from(data['actor'].unique(), bipartite=1, label='actor')
B.add_edges_from(edges, label='acted')
```

In [7]:
```
# A = list(nx.connected_component_subgraphs(B))[0]

# connected_component_subgraphs is deprecated in latest version of networkx
# https://networkx.org/documentation/networkx-2.1/reference/algorithms/generated/networkx.algorithms.componen
ts.connected_component_subgraphs.html

A = (B.subgraph(c) for c in nx.connected_components(B))
A = list(A)[0]
```

In [8]:
```
print("number of nodes", A.number_of_nodes())
print("number of edges", A.number_of_edges())
```

```
number of nodes 4703
number of edges 9650
```

In [9]:
```
l, r = nx.bipartite.sets(A)
pos = {}

pos.update((node, (1, index)) for index, node in enumerate(l))
pos.update((node, (2, index)) for index, node in enumerate(r))

nx.draw(A, pos=pos, with_labels=True)
plt.show()
```



In [10]:
```
movies = []
actors = []
for i in A.nodes():
    if 'm' in i:
        movies.append(i)
    if 'a' in i:
        actors.append(i)
print('number of movies ', len(movies))
print('number of actors ', len(actors))
```

```
number of movies  1292
number of actors  3411
```

In [11]:
```
# Create the random walker
rw = UniformRandomMetaPathWalk(StellarGraph(A))

# specify the metapath schemas as a list of lists of node types.
metapaths = [
    ["movie", "actor", "movie"],
    ["actor", "movie", "actor"]
]

walks = rw.run(nodes=list(A.nodes()), # root nodes
               length=100,  # maximum length of a random walk
               n=1,        # number of random walks per root node
               metapaths=metapaths
              )

print("Number of random walks: {}".format(len(walks)))
```

```
Number of random walks: 4703
```

In [ ]:

In [ ]:

In [12]:
```
from gensim.models import Word2Vec
model = Word2Vec(walks, size=128, window=5)
```

In [13]:
```
model.wv.vectors.shape  # 128-dimensional vector for each node in the graph
```

Out[13]:
```
(4703, 128)
```

In [ ]:

In [14]:
```
# Retrieve node embeddings and corresponding subjects
node_ids = model.wv.index2word  # list of node IDs
node_embeddings = model.wv.vectors  # numpy.ndarray of size number of nodes times embeddings dimensionality
node_targets = [ A.nodes[node_id]['label'] for node_id in node_ids]
```

In [15]:
```
node_ids[0], node_targets[0], node_embeddings[0]
```

Out[15]:
```
('a973',
 'actor',
 array([ 2.2968585 , -0.481915  , -0.43713924,  1.2701852 , -0.8966316 ,
         1.4080553 , -1.619453  ,  1.1629772 ,  0.994609  , -0.5850619 ,
        -1.2671071 ,  0.23165676,  1.429213  , -2.8537445 ,  0.14174591,
         0.2834468 , -1.2952908 ,  2.482297  , -1.9159162 ,  1.9180504 ,
         0.21335179,  0.5009746 ,  0.07260773, -0.379147  , -0.77380496,
        -0.84458405, -0.9913918 , -0.44498122,  0.67585707,  0.06902331,
         0.31722096,  1.5159738 ,  0.15437867,  0.4415659 , -0.39734492,
        -1.2906413 ,  1.487657  , -0.54228234, -0.14592542, -0.28020644,
         2.5177538 ,  0.11102276, -0.85957307, -0.44956657,  0.38228267,
         0.04148212, -0.24888979, -0.64588577, -1.848014  , -0.28318986,
         0.5169563 ,  0.03273879, -2.0253596 , -0.44164178,  0.03246303,
         2.229213  ,  0.32977495, -1.0699527 ,  0.30627018, -0.99502593,
        -1.8092214 , -1.303003  ,  0.4241739 ,  0.7529667 ,  1.2752202 ,
         0.00554102, -0.5980257 , -0.74489146, -0.9693183 , -0.01203422,
        -0.39773276,  0.17494904,  0.02703475, -1.8156651 , -1.1123124 ,
        -0.8603358 ,  1.1241848 , -1.7352138 ,  0.7512506 , -0.31279984,
        -0.04327781,  0.39271602,  1.5754392 , -0.4598708 ,  1.6300242 ,
        -1.2455506 , -1.1276588 ,  0.6748437 , -0.7362103 ,  0.60345197,
         2.4748397 ,  1.2732104 , -1.3796223 , -0.28726923,  0.75743157,
        -0.22351755, -0.67965466, -1.5441713 ,  0.7493191 , -1.6967695 ,
         2.4657078 ,  0.4606642 ,  0.2395187 ,  0.5226207 , -1.3260115 ,
         0.8837158 ,  0.03520358, -0.00665034, -0.9289621 ,  0.30980533,
        -2.0069249 , -0.38652894, -1.3866936 , -0.4214411 , -0.8607843 ,
         0.41078565, -0.9233692 , -0.4657977 ,  0.17229994, -1.014574  ,
         1.4161849 , -0.17088512,  0.57251257, -1.154305  ,  0.45072812,
        -1.8683103 ,  0.17081064,  0.14868128], dtype=float32))
```

```
print(node_ids[:15], end='')
```

```
['a973', 'a967', 'a964', 'a1731', 'a969', 'a970', 'a1028', 'a1057', 'a965', 'a1003', 'm1094', 'a966', 'm67', 'a988', 'm1111']
```

```
print(node_targets[:15],end='')
```

```
['actor', 'actor', 'actor', 'actor', 'actor', 'actor', 'actor', 'actor', 'actor', 'actor', 'movie', 'actor', 'movie', 'actor', 'movie']
```

In [201]:
```
def data_split(node_ids,node_targets,node_embeddings):
    '''In this function, we will split the node embeddings into actor_embeddings , movie_embeddings '''
    actor_nodes,movie_nodes=[],[]
    actor_embeddings,movie_embeddings=[],[]

    for i in range(len(node_ids)):
        if node_targets[i] == 'actor':
            actor_nodes.append(node_ids[i])
            actor_embeddings.append(node_embeddings[i])
        elif node_targets[i] == 'movie':
            movie_nodes.append(node_ids[i])
            movie_embeddings.append(node_embeddings[i])
    # split the node_embeddings into actor_embeddings,movie_embeddings based on node_ids
    # By using node_embedding and node_targets, we can extract actor_embedding and movie embedding
    # By using node_ids and node_targets, we can extract actor_nodes and movie nodes

    return actor_nodes,movie_nodes,actor_embeddings,movie_embeddings
```

Grader function - 1

In [202]:
```
actor_nodes,movie_nodes,actor_embeddings,movie_embeddings = data_split(node_ids, node_targets, node_embedding
s)
```

In [ ]:
```

```

In [18]:
```
def grader_actors(data):
    assert(len(data)==3411)
    return True
grader_actors(actor_nodes)
```

Out[18]: True

Grader function - 2

In [19]:
```
def grader_movies(data):
    assert(len(data)==1292)
    return True
grader_movies(movie_nodes)
```

Out[19]: True

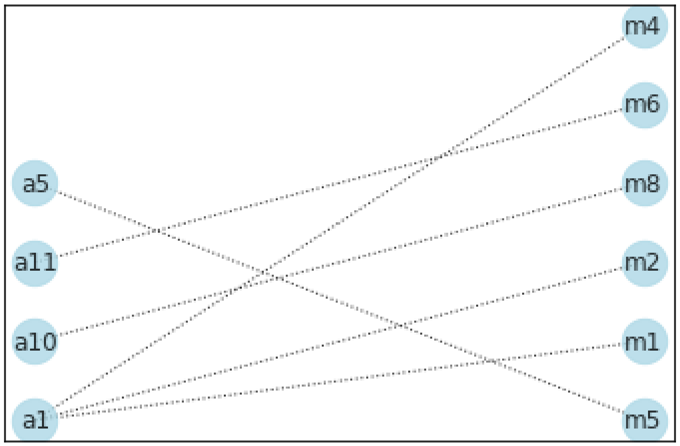
Calculating cost1

Cost1 = $\frac{1}{N} \sum_{\text{each cluster i}} \frac{\text{(number of nodes in the largest connected component in the graph with the actor nodes and its movie neighbours in cluster i)}}{\text{(total number of nodes in that cluster i)}}$ where N= number of clusters

1. total no.of nodes in the cluster i
2. largest connected component in the graph with the actor nodes and its movie neighbors in cluster i a. find graph with actor nodes

In [20]:
```
def cost1(graph,number_of_clusters):
    '''In this function, we will calculate cost1'''
    cost1 = 0# calculate cost1

    # largest connected component **** calculating Numerator
    largest_cc = max(nx.connected_components(graph), key=len)

    # total no.of nodes **** calculating denominator
    total_n_nodes = graph.number_of_nodes()

    # cost1
    cost1 = (1/number_of_clusters)*(len(largest_cc)/total_n_nodes)

    return cost1
```

In [21]:
```
import networkx as nx
from networkx.algorithms import bipartite
graded_graph= nx.Graph()
graded_graph.add_nodes_from(['a1','a5','a10','a11'], bipartite=0) # Add the node attribute "bipartite"
graded_graph.add_nodes_from(['m1','m2','m4','m6','m5','m8'], bipartite=1)
graded_graph.add_edges_from([('a1','m1'),('a1','m2'),('a1','m4'),('a11','m6'),('a5','m5'),('a10','m8')])
l={'a1','a5','a10','a11'};r={'m1','m2','m4','m6','m5','m8'}
pos = {}
pos.update((node, (1, index)) for index, node in enumerate(l))
pos.update((node, (2, index)) for index, node in enumerate(r))
nx.draw_networkx(graded_graph, pos=pos, with_labels=True,node_color='lightblue',alpha=0.8,style='dotted',node
_size=500)
```



In [ ]:

Grader function - 3

In [22]:
```
graded_cost1=cost1(graded_graph,3)
def grader_cost1(data):
    assert(data==((1/3)*(4/10))) # 1/3 is number of clusters
    return True
grader_cost1(graded_cost1)
```

Out[22]: True

Calculating cost2

Cost2 = $\frac{1}{N} \sum_{\text{each cluster i}} \frac{\text{(sum of degress of actor nodes in the graph with the actor nodes and its movie neighbours in cluster i)}}{\text{(number of unique movie nodes in the graph with the actor nodes and its movie neighbours in cluster i)}}$ where N= number of clusters

In [ ]:

In [43]:
```
def cost2(graph,number_of_clusters):
    '''In this function, we will calculate cost2'''
    cost2= 0 # calculate cost1

    # sum of degree of graph is nothing but no.of edges in the graph.
    numerator_of_cost2 = len(graph.edges())

    # calculating denominator for actor nodes
    # no.of unique movie nodes in the graph.
    m_nodes = []

    for i in graph.nodes():
        if 'm' in i:
            m_nodes.append(i)
    denominator_of_cost2 = len(m_nodes)

    cost2 = (1/number_of_clusters) * (numerator_of_cost2/denominator_of_cost2)
    return cost2
```

Grader function - 4

In [44]:
```
graded_cost2=cost2(graded_graph,3)
def grader_cost2(data):
    assert(data==((1/3)*(6/6))) # 1/3 is number of clusters
    return True
grader_cost2(graded_cost2)
```

Out[44]: True

Grouping similar actors

In [ ]:

```

```

In [149]:
```
no_of_clusters = [3, 5, 10, 30, 50, 100, 200, 500]
labels = [] # it stores the labels for each hyper-parameter k
costs = []
for k in tqdm(no_of_clusters):
    # initializing clustering algrithm with no.of clusters k
    algo = KMeans(n_clusters=k)

    # fitting the clustering algorithm
    algo.fit(np.array(actor_embeddings))

    # getting labels of the cluster
    label=algo.labels_
    labels.append(algo.labels_)


    ####################################################################################
    # creating graph for every cluster(i.e. if n_clusters=3, create 3 graphs)
    # using ego_graph to create subgraph from the actual graph

    clusters = [] # to store k no.of clusters
    subgraphs = [] # store subgraphs for each clusters


    dictionary_of_actor_nodes = dict(zip(actor_nodes, label))
    # https://www.geeksforgeeks.org/python-grouping-dictionary-keys-by-value/#:~:text=Method%20%3A%20Using%20sorted()%20%2B%20items()%20%2B%20defaultdict()&text=The%20defaultdict()%20is%20used,is%20helped%20by%20sorted().
    res = {} # all node in the forms of cluster stored in the res
    for i, v in dictionary_of_actor_nodes.items():
        res[v] = [i] if v not in res.keys() else res[v]+[i]

    for i in range(k): # for k no.of clusters
        cluster=res[i]

        # append the value of cluster
        clusters.append(cluster)

        ################################################################
        # creating subgraph using ego_graph
        # subgraph = nx.generators.ego_graph(B, cluster)

        # create empty subgraph object
```

```
        subgraph=nx.Graph()
        for c in cluster: # for each node(actor) in the cluster

            # using ego_graph() function we will create subgraph for node c
            cluster_graph = nx.ego_graph(B, c, radius=3)

            # considering neighbors nodes by using nodes() function
            subgraph.add_nodes_from(cluster_graph.nodes())
            # considering edges related to c and neighbor nodes by using edges() function
            subgraph.add_edges_from(cluster_graph.edges())


        # append the subgraph to list subgraphs
        subgraphs.append(subgraph)
    ####################################################################################

    ####################################################################################
    # finding cost

    cost = 0
    cost_1 = 0
    cost_2 = 0

    for i in range(k):
        cost_1 += cost1(subgraphs[i],k)
        cost_2 += cost2(subgraphs[i],k)

    cost = cost_1*cost_2

    costs.append(cost)
```

```
100%|██████████████████████████████████████████| 8/8 [04:27<00:00,
33.42s/it]
```

In [161]:
```
losses = dict(zip(no_of_clusters, costs)) # radius is 3 in subgraph
losses
```

Out[161]:
```
{3: 7.348771042519499,
 5: 7.073581659496938,
 10: 6.311903767847192,
 30: 4.9867566716467975,
 50: 4.247489923611839,
 100: 3.347193333596669,
 200: 2.6472657644254403,
 500: 2.047604271928263}
```

In [179]:
```
max_cost = max(losses.values())
best_k = [key for key in losses if losses[key]==max_cost][0]
best_k
```

Out[179]:
```
3
```

In [ ]:
```
```

Displaying similar actor clusters

In [180]:
```
from sklearn.cluster import KMeans
from tqdm import tqdm
```

In [181]:
```
%%time
algo = KMeans(n_clusters=best_k)
algo.fit(actor_embeddings)
label = algo.labels_
```

```
Wall time: 379 ms
```

In [182]:
```
# algo.get_params()
```

In [183]:
```
len(actor_embeddings) == len(algo.labels_)
```

Out[183]:
```
True
```

In [184]:
```
from sklearn.manifold import TSNE
```

In [185]:
```
tsne = TSNE() # initializing TSNE
```

In [186]:
```
%%time
actor_embeddings_2d = tsne.fit_transform(actor_embeddings)
```

```
Wall time: 44.6 s
```

In [187]:
```
np.array(actor_embeddings).shape, algo.labels_.shape
```

Out[187]:
```
((4703, 128), (4703,))
```

In [188]:
```
actor_embeddings = np.array(actor_embeddings)
actor_cluster_labels = np.array(algo.labels_).reshape(-1,1)
```

In [189]:
```
actor_embeddings_2d.shape
```

Out[189]:
```
(4703, 2)
```

In [190]:
```
tsne_data = np.hstack((actor_embeddings_2d, actor_cluster_labels))
tsne_data.shape
```

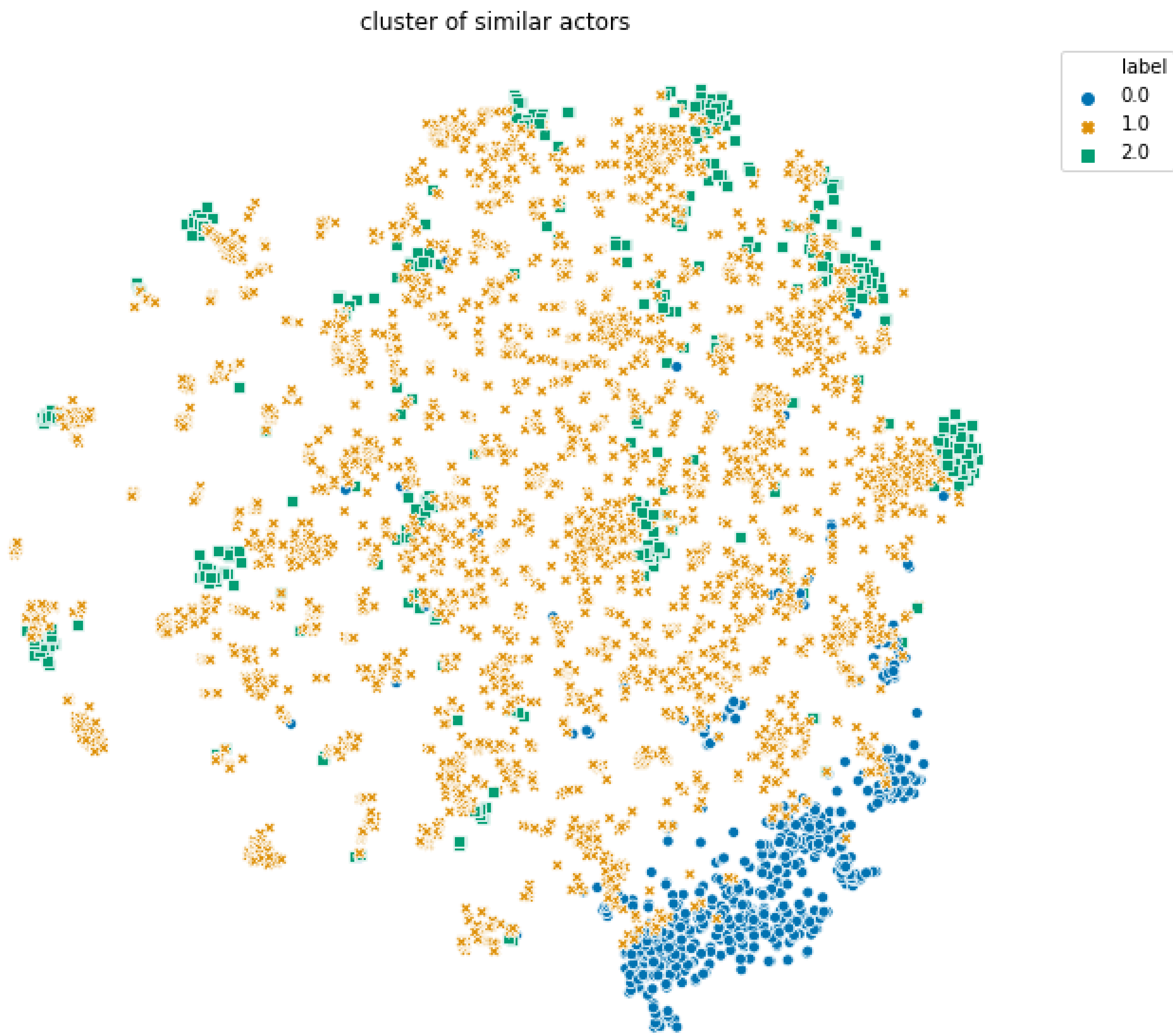
Out[190]:
```
(4703, 3)
```

In [191]:
```
tsne_df = pd.DataFrame(data=tsne_data, columns=["dim_1", "dim_2", "label"])
```

In [226]:
```
#plotting the result of TSNE
# import seaborn as sns
# sns.FacetGrid(tsne_df, hue="label", size=7).map(plt.scatter, 'dim_1', 'dim_2')
# plt.legend()
```

In [253]:
```
plt.figure(figsize=(10,10))
sns.scatterplot(data=tsne_df, x='dim_1', y='dim_2', hue='label',palette='colorblind', style='label')
plt.title('cluster of similar actors')
plt.legend(bbox_to_anchor=(1.15,1))
plt.axis(False)
```

Out[253]: (-99.99903945922851, 76.74806289672851, -80.71826934814453, 72.78759002685547)



In [ ]:

Grouping similar movies

```
we will have to redefine cost2 for task2
```

In [194]:
```
def cost2_task2(graph,number_of_clusters):
    '''In this function, we will calculate cost2'''
    cost2= 0 # calculate cost1

    # sum of degree of graph is nothing but no.of edges in the graph.
    numerator_of_cost2 = len(graph.edges())

    # calculating denominator for actor nodes
    # no.of unique movie nodes in the graph.
    m_nodes = []

    for i in graph.nodes():
        if 'm' in i:
            m_nodes.append(i)
    denominator_of_cost2 = len(m_nodes)

    cost2 = (1/number_of_clusters) * (numerator_of_cost2/denominator_of_cost2)
    return cost2
```

In [204]:
```
np.array(movie_embeddings).shape
```

Out[204]:
```
(1292, 128)
```

In [205]:
```
no_of_clusters = [3, 5, 10, 30, 50, 100, 200, 500]
movie_labels = [] # it stores the labels for each hyper-parameter k
movie_costs = []
for k in tqdm(no_of_clusters):
    # initializing clustering algrithm with no.of clusters k
    algo = KMeans(n_clusters=k)

    # fitting the clustering algorithm
    algo.fit(np.array(movie_embeddings))

    # getting labels of the cluster
    movie_label=algo.labels_
    movie_labels.append(algo.labels_)


    ##################################################################################
    # creating graph for every cluster(i.e. if n_clusters=3, create 3 graphs)
    # using ego_graph to create subgraph from the actual graph

    clusters = [] # to store k no.of clusters
    subgraphs = [] # store subgraphs for each clusters


    dictionary_of_movie_nodes = dict(zip(movie_nodes, movie_label))
    # https://www.geeksforgeeks.org/python-grouping-dictionary-keys-by-value/#:~:text=Method%20%3A%20Using%20
sorted()%20%2B%20items()%20%2B%20defaultdict()&text=The%20defaultdict()%20is%20used,is%20helped%20by%20sorted
().
    res = {} # all node in the forms of cluster stored in the res
    for i, v in dictionary_of_movie_nodes.items():
        res[v] = [i] if v not in res.keys() else res[v]+[i]

    for i in range(k): # for k no.of clusters
        cluster=res[i]

        # append the value of cluster
        clusters.append(cluster)

        ##############################################################
        # creating subgraph using ego_graph
        # subgraph = nx.generators.ego_graph(B, cluster)

        # create empty subgraph object
```

```
        subgraph=nx.Graph()
        for c in cluster: # for each node(actor) in the cluster

            # using ego_graph() function we will create subgraph for node c
            cluster_graph = nx.ego_graph(B, c, radius=3)

            # considering neighbors nodes by using nodes() function
            subgraph.add_nodes_from(cluster_graph.nodes())
            # considering edges related to c and neighbor nodes by using edges() function
            subgraph.add_edges_from(cluster_graph.edges())


        # append the subgraph to list subgraphs
        subgraphs.append(subgraph)
    ###################################################################################

    ###################################################################################
    # finding cost

    cost = 0
    cost_1 = 0
    cost_2 = 0

    for i in range(k):
        cost_1 += cost1(subgraphs[i],k)  # cost1 is same for both tasks
        cost_2 += cost2_task2(subgraphs[i],k) # cost2_task2 is for task2

    cost = cost_1*cost_2

    movie_costs.append(cost)
```

```
100%|██████████████████████████████████████████████████| 8/8 [04:05<00:00,
30.65s/it]
```

In [207]:
```
movie_losses = dict(zip(no_of_clusters, movie_costs))
movie_losses
```

Out[207]:
```
{3: 7.8094703366210485,
 5: 8.096429972663195,
 10: 8.792184226293946,
 30: 9.38208562079421,
 50: 9.858718825969907,
 100: 9.767095498512367,
 200: 9.729484165561164,
 500: 9.056170747277505}
```

In [208]:
```
max_cost = max(movie_losses.values())
best_k2 = [key for key in movie_losses if movie_losses[key]==max_cost][0]
best_k2
```

Out[208]:
```
50
```

In [ ]:

Displaying similar movie clusters

In [206]:
```
from sklearn.cluster import KMeans
```

In [209]:
```
%%time
movie_algo = KMeans(n_clusters=best_k2)
movie_algo.fit(np.array(movie_embeddings))
label2 = movie_algo.labels_
```

```
Wall time: 1.38 s
```

In [ ]:

In [210]:
```
from sklearn.manifold import TSNE
tsne = TSNE()
movie_embeddings_2d = tsne.fit_transform(np.array(movie_embeddings))
```

In [211]:
```
movie_embeddings_2d.shape
```
Out[211]:
```
(1292, 2)
```

In [212]:
```
movie_embeddings = np.array(movie_embeddings)
movie_embeddings.shape
```
Out[212]:
```
(1292, 128)
```

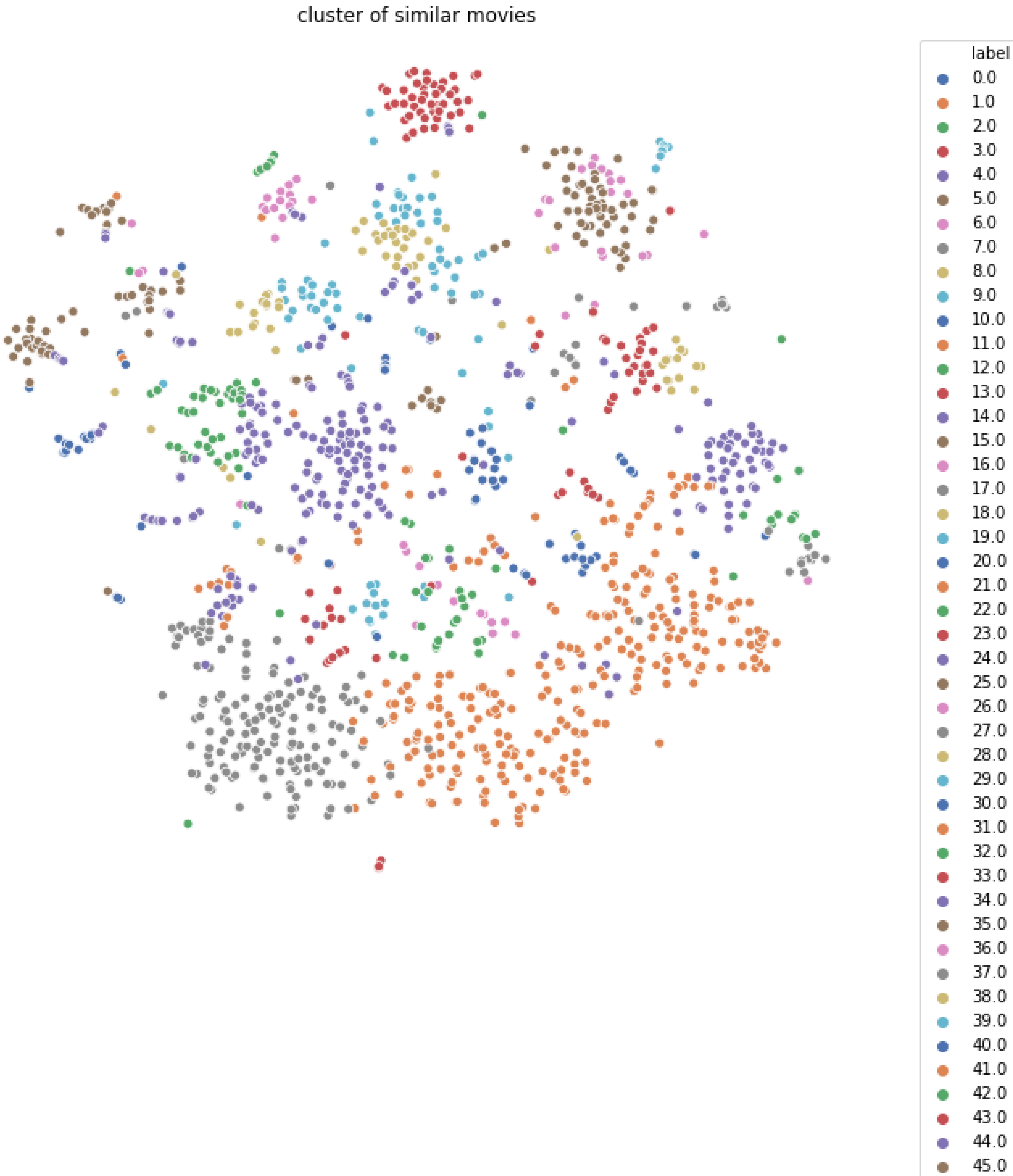
In [213]:
```
movie_cluster_labels = np.array(movie_algo.labels_).reshape(-1,1)
```

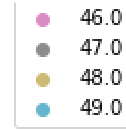
In [214]:
```
tsne_data2 = np.hstack((movie_embeddings_2d, movie_cluster_labels))
tsne_df2 = pd.DataFrame(data=tsne_data2, columns=["dim_1","dim_2","label"])
```

In [228]:
```
# import seaborn as sns
# sns.FacetGrid(tsne_df2, hue='label', size=7).map(plt.scatter, 'dim_1', 'dim_2')
# plt.legend()
```

In [254]:
```
plt.figure(figsize=(10,10))
sns.scatterplot(data=tsne_df2, x='dim_1', y='dim_2', hue='label', palette='deep')
# https://www.delftstack.com/howto/matplotlib/how-to-place-legend-outside-of-the-plot-in-matplotlib/
plt.legend(bbox_to_anchor=(1.05, 1))
plt.title('cluster of similar movies')
plt.axis('off')
```

```
Out[254]: (-43.47442779541016, 42.865518188476564, -47.57805061340332, 50.2537784576416)
```


cluster of similar movies
label
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0
11.0
12.0
13.0
14.0
15.0
16.0
17.0
18.0
19.0
20.0
21.0
22.0
23.0
24.0
25.0
26.0
27.0
28.0
29.0
30.0
31.0
32.0
33.0
34.0
35.0
36.0
37.0
38.0
39.0
40.0
41.0
42.0
43.0
44.0
45.0




```
In [ ]:
```