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 notebook before attempting this assignment.

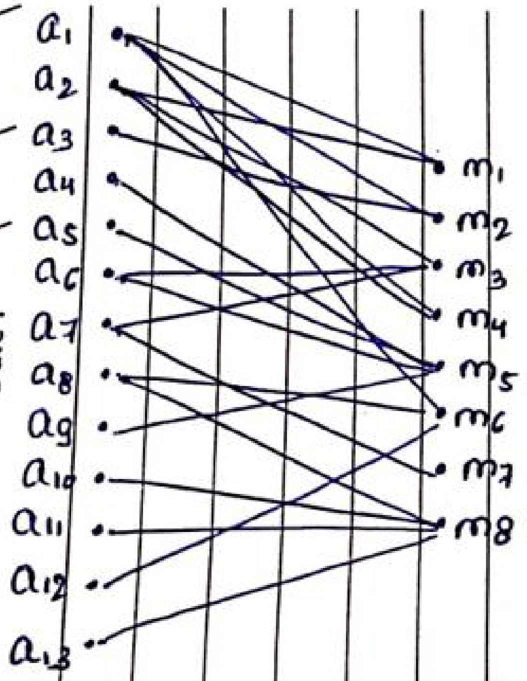
- Read graph from the given movie_actor_network.csv (note that the graph is bipartite graph.)
- Using stellergaph and gensim packages, get the dense representation(128dimensional vector) of every node in the graph. [Refer Clustering_Assignment_Reference.ipynb]
- Split the dense representation into actor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

Task 1 : Apply clustering algorithm to group similar actors

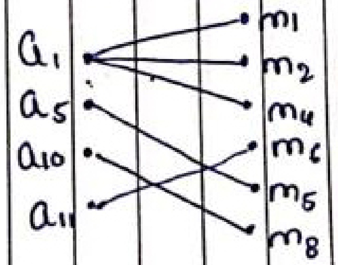
1. For this task consider only the actor nodes
2. Apply any clustering algorithm of your choice
   Refer : https://scikit-learn.org/stable/modules/clustering.html
3. Choose the number of clusters for which you have maximum score of $Cost1 * Cost2$
4. Cost1 = $\frac{1}{N} \sum_{\text{each cluster i}} \frac{\text{(number of nodes in the largest connected component in the graph with the actor nodes and its movie neighbours in cluster i)}}{\text{(total number of nodes in that cluster i)}}$
   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

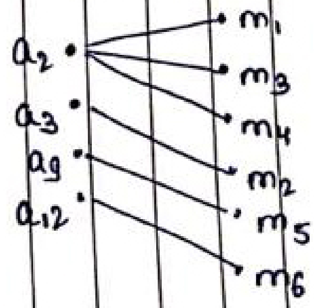
Date :



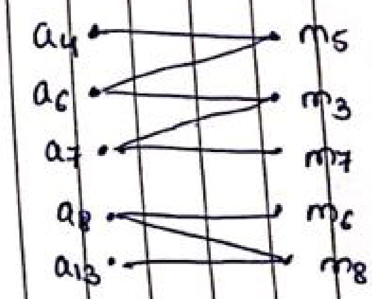
Cluster one ego graph



cluster two ego graph



cluster three ego graph



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

$= \frac{14}{30}$

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

$= \frac{18}{15}$

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
```

```
Requirement already satisfied: networkx==2.3 in /usr/local/lib/python3.7/dist-packages (2.3)
Requirement already satisfied: decorator>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from networkx==2.3) (4.4.
2)
```

In [2]:
```
!pip install stellargraph
```

```
Requirement already satisfied: stellargraph in /usr/local/lib/python3.7/dist-packages (1.2.1)
Requirement already satisfied: tensorflow>=2.1.0 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (2.5.
0)
Requirement already satisfied: numpy>=1.14 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (1.19.5)
Requirement already satisfied: matplotlib>=2.2 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (3.2.2)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (1.1.5)
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (1.4.1)
Requirement already satisfied: networkx>=2.2 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (2.3)
Requirement already satisfied: scikit-learn>=0.20 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (0.2
2.2.post1)
Requirement already satisfied: gensim>=3.4.0 in /usr/local/lib/python3.7/dist-packages (from stellargraph) (3.6.0)
Requirement already satisfied: typing-extensions~=3.7.4 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=
2.1.0->stellargraph) (3.7.4.3)
Requirement already satisfied: six~=1.15.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stellar
graph) (1.15.0)
Requirement already satisfied: gast==0.4.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stellar
graph) (0.4.0)
Requirement already satisfied: tensorboard~=2.5 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->st
ellargraph) (2.5.0)
Requirement already satisfied: protobuf>=3.9.2 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->ste
llargraph) (3.12.4)
Requirement already satisfied: google-pasta~=0.2 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->s
tellargraph) (0.2.0)
Requirement already satisfied: keras-preprocessing~=1.1.2 in /usr/local/lib/python3.7/dist-packages (from tensorflow>
=2.1.0->stellargraph) (1.1.2)
Requirement already satisfied: keras-nightly~=2.5.0.dev in /usr/local/lib/python3.7/dist-packages (from tensorflow>=
2.1.0->stellargraph) (2.5.0.dev2021032900)
Requirement already satisfied: absl-py~=0.10 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stell
argraph) (0.12.0)
Requirement already satisfied: flatbuffers~=1.12.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0-
>stellargraph) (1.12)
Requirement already satisfied: grpcio~=1.34.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stel
largraph) (1.34.1)
Requirement already satisfied: termcolor~=1.1.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->st
ellargraph) (1.1.0)
Requirement already satisfied: wheel~=0.35 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stellar
```

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graph) (0.36.2)
Requirement already satisfied: h5py~=3.1.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stellar
graph) (3.1.0)
Requirement already satisfied: opt-einsum~=3.3.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->s
tellargraph) (3.3.0)
Requirement already satisfied: tensorflow-estimator<2.6.0,>=2.5.0rc0 in /usr/local/lib/python3.7/dist-packages (from
tensorflow>=2.1.0->stellargraph) (2.5.0)
Requirement already satisfied: astunparse~=1.6.3 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->s
tellargraph) (1.6.3)
Requirement already satisfied: wrapt~=1.12.1 in /usr/local/lib/python3.7/dist-packages (from tensorflow>=2.1.0->stell
argraph) (1.12.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (fr
om matplotlib>=2.2->stellargraph) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.2->
stellargraph) (2.8.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.2->stellarg
raph) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib>=2.2->ste
llargraph) (1.3.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.24->stellargrap
h) (2018.9)
Requirement already satisfied: decorator>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from networkx>=2.2->stella
rgraph) (4.4.2)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.20->stell
argraph) (1.0.1)
Requirement already satisfied: smart-open>=1.2.1 in /usr/local/lib/python3.7/dist-packages (from gensim>=3.4.0->stell
argraph) (5.1.0)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in /usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (0.6.1)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/dist-packages (from tensorboard~=2.5->tens
orflow>=2.1.0->stellargraph) (3.3.4)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.7/dist-packages (from tensorboard~=2.5->
tensorflow>=2.1.0->stellargraph) (2.23.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/python3.7/dist-packages (from tensorbo
ard~=2.5->tensorflow>=2.1.0->stellargraph) (1.8.0)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.7/dist-packages (from tensorboard~=2.5->te
nsorflow>=2.1.0->stellargraph) (1.0.1)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.7/dist-packages (from tensorboard~=2.5->t
ensorflow>=2.1.0->stellargraph) (57.0.0)
Requirement already satisfied: google-auth<2,>=1.6.3 in /usr/local/lib/python3.7/dist-packages (from tensorboard~=2.5
->tensorflow>=2.1.0->stellargraph) (1.31.0)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/lib/python3.7/dist-packages (from tenso
rboard~=2.5->tensorflow>=2.1.0->stellargraph) (0.4.4)
Requirement already satisfied: cached-property; python_version < "3.8" in /usr/local/lib/python3.7/dist-packages (fro
m h5py~=3.1.0->tensorflow>=2.1.0->stellargraph) (1.5.2)
```

```
Requirement already satisfied: importlib-metadata; python_version < "3.8" in /usr/local/lib/python3.7/dist-packages
(from markdown>=2.6.8->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (4.5.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests<3,>=2.21.0
->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (2021.5.30)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests<3,>=2.21.0->tens
orboard~=2.5->tensorflow>=2.1.0->stellargraph) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests<3,>=2.21.0-
>tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages (fro
m requests<3,>=2.21.0->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (1.24.3)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from google-auth<2,>
=1.6.3->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (4.2.2)
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3.6" in /usr/local/lib/python3.7/dist-packages (from
google-auth<2,>=1.6.3->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (4.7.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.7/dist-packages (from google-auth<2,>=
1.6.3->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (0.2.8)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.7/dist-packages (from google-auth-o
authlib<0.5,>=0.4.1->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (1.3.0)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (from importlib-metadata; python_v
ersion < "3.8"->markdown>=2.6.8->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (3.4.1)
Requirement already satisfied: pyasn1>=0.1.3 in /usr/local/lib/python3.7/dist-packages (from rsa<5,>=3.1.4; python_ve
rsion >= "3.6"->google-auth<2,>=1.6.3->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (0.4.8)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/dist-packages (from requests-oauthlib>=0.
7.0->google-auth-oauthlib<0.5,>=0.4.1->tensorboard~=2.5->tensorflow>=2.1.0->stellargraph) (3.1.1)
```

In [3]:

```python
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 [4]:

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

In [5]:

```python
len(data)
```

Out[5]: 9650

In [6]:
```
data.values.tolist()[:5]
```

Out[6]: [['m1', 'a1'], ['m2', 'a1'], ['m2', 'a2'], ['m3', 'a1'], ['m3', 'a3']]

In [7]:
```
edges = [tuple(x) for x in data.values.tolist()]
```

In [8]:
```
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 [9]:
```
A = list(nx.connected_component_subgraphs(B))[0]
```

In [10]:
```
A
```

Out[10]: <networkx.classes.graph.Graph at 0x7f870de8f690>

In [11]:
```
list(nx.connected_component_subgraphs(B))[0]
```

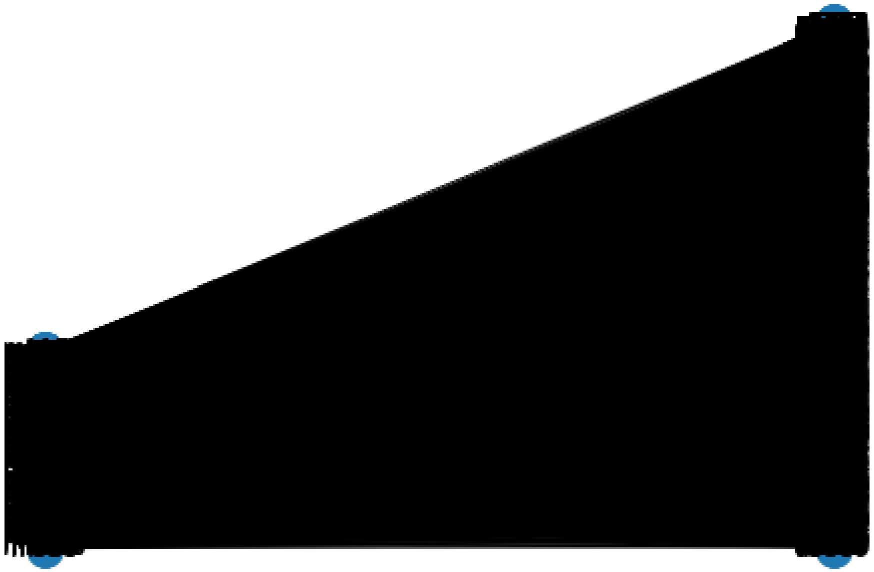
Out[11]: <networkx.classes.graph.Graph at 0x7f876120bd90>

In [12]:
```
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 [13]:
```
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 [14]:

```
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 [15]:

```
# Create the random walker
```

```python
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 [16]:

```python
from gensim.models import Word2Vec
model = Word2Vec(walks, size=128, window=5)
```

In [17]:

```python
model.wv.vectors.shape  # 128-dimensional vector for each node in the graph
```

Out[17]:

```
(4703, 128)
```

In [18]:

```python
# 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.node[node_id]['label'] for node_id in node_ids]
```

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

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

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

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

In [19]:
```
node_embeddings[:10]
```

Out[19]:
```
array([[-2.3096197 ,  1.4202939 , -1.3059871 , ..., -1.0428957 ,
         0.14832635, -1.0530851 ],
       [-1.4850763 ,  0.42532986, -0.7693434 , ..., -1.3436102 ,
         0.7418003 , -0.4161651 ],
       [ 1.2224945 ,  1.0988613 ,  0.25120473, ..., -0.86744505,
         1.6465839 ,  1.3121972 ],
       ...,
       [-1.6546379 ,  1.9013535 ,  3.0470285 , ...,  1.0641118 ,
         1.5468329 , -2.399592  ],
       [ 1.0469139 ,  2.4420593 , -0.6494191 , ...,  2.338668  ,
         3.3468666 ,  0.45089716],
       [-1.871989  ,  0.71408933, -1.227558  , ..., -0.2147621 ,
         0.5634736 , -0.02104896]], dtype=float32)
```

In [20]:
```
len(node_ids), len(node_targets), len(node_embeddings)
```

Out[20]:
```
(4703, 4703, 4703)
```

In [21]:
```
node_ids[5], node_targets[5], node_embeddings[5]
```

Out[21]:
```
('a970',
 'actor',
 array([-1.5725865 ,  0.03658107, -0.7970345 ,  0.08676033, -0.2815841 ,
         0.93020064, -1.4457265 ,  1.63103   ,  0.13858122, -1.6204854 ,
         0.6990445 ,  0.3968009 , -1.231417  , -0.04774383, -0.06956051,
        -0.31433883,  0.59390527, -0.06323108, -2.1532905 , -1.1720998 ,
        -2.2085907 , -0.6238491 , -0.22694066, -0.596925  ,  1.0623507 ,
         0.22474194, -0.88786477, -0.39263535,  1.6017164 ,  0.59724617,
        -2.0429506 , -2.6349778 ,  0.08489145, -0.7981158 ,  0.8312825 ,
         0.6984066 ,  0.3714528 , -0.12314478,  0.37042034,  1.1690298 ,
         0.6403906 , -1.7281272 ,  0.39399788, -0.30784136, -1.0098649 ,
        -0.8520263 ,  0.28040937, -0.5962035 ,  0.37742874,  0.9114598 ,
         0.6532941 ,  0.57217187,  0.06840012,  0.24353585,  0.06693898,
        -0.19059832,  1.4579582 , -1.4905374 , -2.1889665 ,  0.913337  ,
        -1.4801203 ,  0.19537248,  0.37669757, -0.28188047, -1.4401081 ,
        -1.1225641 ,  0.21901692, -1.0351126 ,  0.50192726,  0.7051145 ,
         1.0695002 , -0.06425002,  1.6822563 , -0.3363951 ,  1.1356838 ,
         1.3197243 ,  0.6243436 ,  1.0766546 , -0.13585512, -0.17172115,
```

```
       -0.4283355 ,  0.1639304 , -0.06435075, -0.13459885,  0.85694903,
       -0.55662847,  1.1788337 ,  0.59765893, -0.24420978,  0.92039126,
        0.20659657,  0.37565097,  0.75899065, -0.7487488 , -0.89834124,
       -0.32045126, -0.1834625 ,  1.6566807 , -0.37118155,  0.60583407,
        1.3744124 , -1.9367979 , -0.44460496, -0.04065654, -1.0072858 ,
       -1.3550351 ,  0.6868161 , -0.7289426 , -0.18156572,  0.46411    ,
        2.5107534 , -2.3239267 , -1.1450703 ,  1.2311404 , -0.5212157 ,
        1.4664905 , -1.3408208 ,  2.1058455 ,  1.4421028 ,  1.0025644 ,
        2.1260853 ,  0.72638464,  3.152586  ,  0.4416195 ,  2.0863397 ,
       -0.16179654,  1.0693449 , -1.5972528 ], dtype=float32))
```

In [22]:

```
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=[],[]

    # 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
    for i in range(len(node_ids)):
      if node_targets[i]=='actor':
        actor_nodes.append(node_ids[i])
        actor_embeddings.append(node_embeddings[i])

      if node_targets[i]=='movie':
        movie_nodes.append(node_ids[i])
        movie_embeddings.append(node_embeddings[i])

    return actor_nodes,movie_nodes,actor_embeddings,movie_embeddings
```

In [23]:

```
actor_nodes,movie_nodes,actor_embeddings,movie_embeddings=data_split(node_ids,node_targets,node_embeddings)
```

In [24]:

```
len(actor_nodes)
```

Out[24]:

```
3411
```

Grader function - 1

In [25]:

```
def grader_actors(data):
    assert(len(data)==3411)
    return True
grader_actors(actor_nodes)
```

Out[25]: True

Grader function - 2

In [26]:

```
def grader_movies(data):
    assert(len(data)==1292)
    return True
grader_movies(movie_nodes)
```

Out[26]: 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

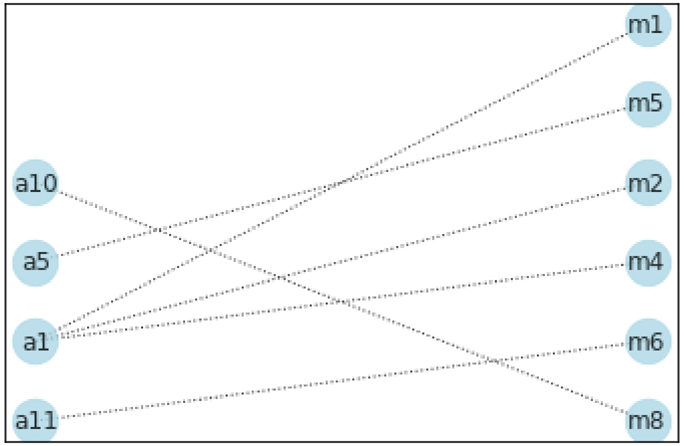
In [27]:

```
def cost1(graph,number_of_clusters):
    '''In this function, we will calculate cost1'''
    # cost1=0 # calculate cost1
    cost1=len(max(nx.connected_components(graph), key=len))/graph.number_of_nodes()
    cost1=cost1/number_of_clusters

    return cost1
```

In [28]:

```
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=5(
```



In [29]:

```
max(nx.connected_components(graded_graph), key=len)
```

Out[29]: {'a1', 'm1', 'm2', 'm4'}

In [30]:

```
len(max(nx.connected_components(graded_graph), key=len))
```

Out[30]: 4

Grader function - 3

In [31]:

```
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[31]: 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 [32]:
```
list(graded_graph.degree)
```

Out[32]:
```
[('a1', 3),
 ('a5', 1),
 ('a10', 1),
 ('a11', 1),
 ('m1', 1),
 ('m2', 1),
 ('m4', 1),
 ('m6', 1),
 ('m5', 1),
 ('m8', 1)]
```

In [33]:
```
def cost2(graph,number_of_clusters):
    '''In this function, we will calculate cost1'''
    # cost2=0 # calculate cost1
    lst = list(graph.degree)
    count = 0
    for i in range(len(lst)):
      if 'm' in lst[i][0]:
        count+=1
    degree = graph.number_of_edges()
    cost2 = degree/count
    cost2=cost2/number_of_clusters

    return cost2
```

Grader function - 4

In [34]:
```
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[34]: True

Grouping similar actors

In [35]:

```
clusters = [3, 5, 10, 30, 50, 100, 200, 500]
final_cost = []
for num_of_clusters in clusters:
  algo = KMeans(n_clusters=num_of_clusters)
  algo.fit(actor_embeddings)
  labels = algo.labels_
  centers = algo.cluster_centers_

  final_cost1 = 0
  final_cost2 = 0
  for i in centers:
    sim_point = model.similar_by_vector(i,topn=1,restrict_vocab=None) #source: Stackoverflow (Taking closer point to
    final_cost1 += cost1(nx.ego_graph(A,sim_point[0][0]),num_of_clusters)
    final_cost2 += cost2(nx.ego_graph(A,sim_point[0][0]),num_of_clusters)
  final_cost.append(final_cost1*final_cost2)
  print('cost for '+str(num_of_clusters)+' clusters is :'+str(final_cost1*final_cost2))
```

```
cost for 3 clusters is :1.0
cost for 5 clusters is :1.0
cost for 10 clusters is :1.7
cost for 30 clusters is :1.9000000000000004
cost for 50 clusters is :2.0000000000000013
cost for 100 clusters is :1.4100000000000017
cost for 200 clusters is :1.2149999999999998
cost for 500 clusters is :1.1280000000000014
```

In [36]:

```
print('Clusters that have max cost ', clusters[final_cost.index(max(final_cost))])
```

```
Clusters that have max cost  50
```

Displaying similar actor clusters

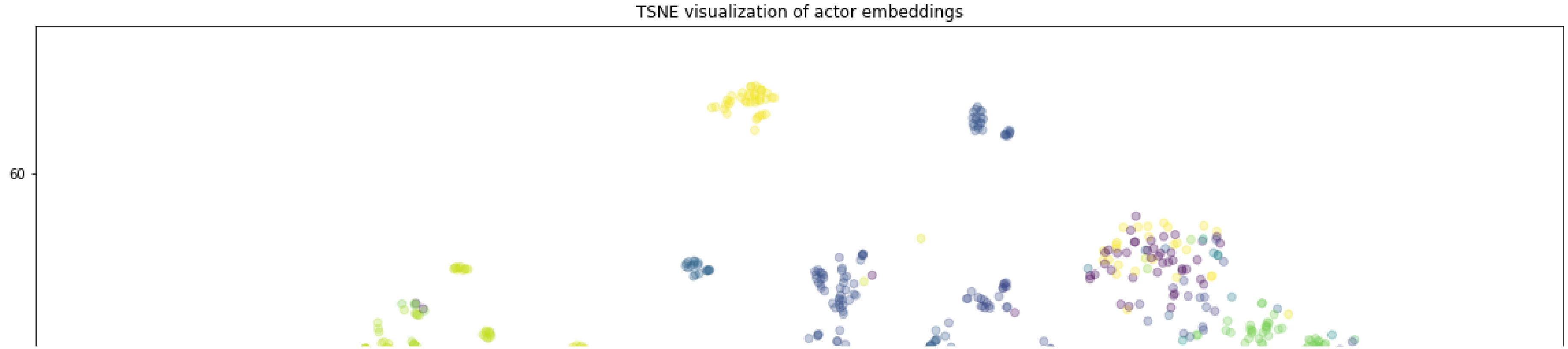
In [37]:

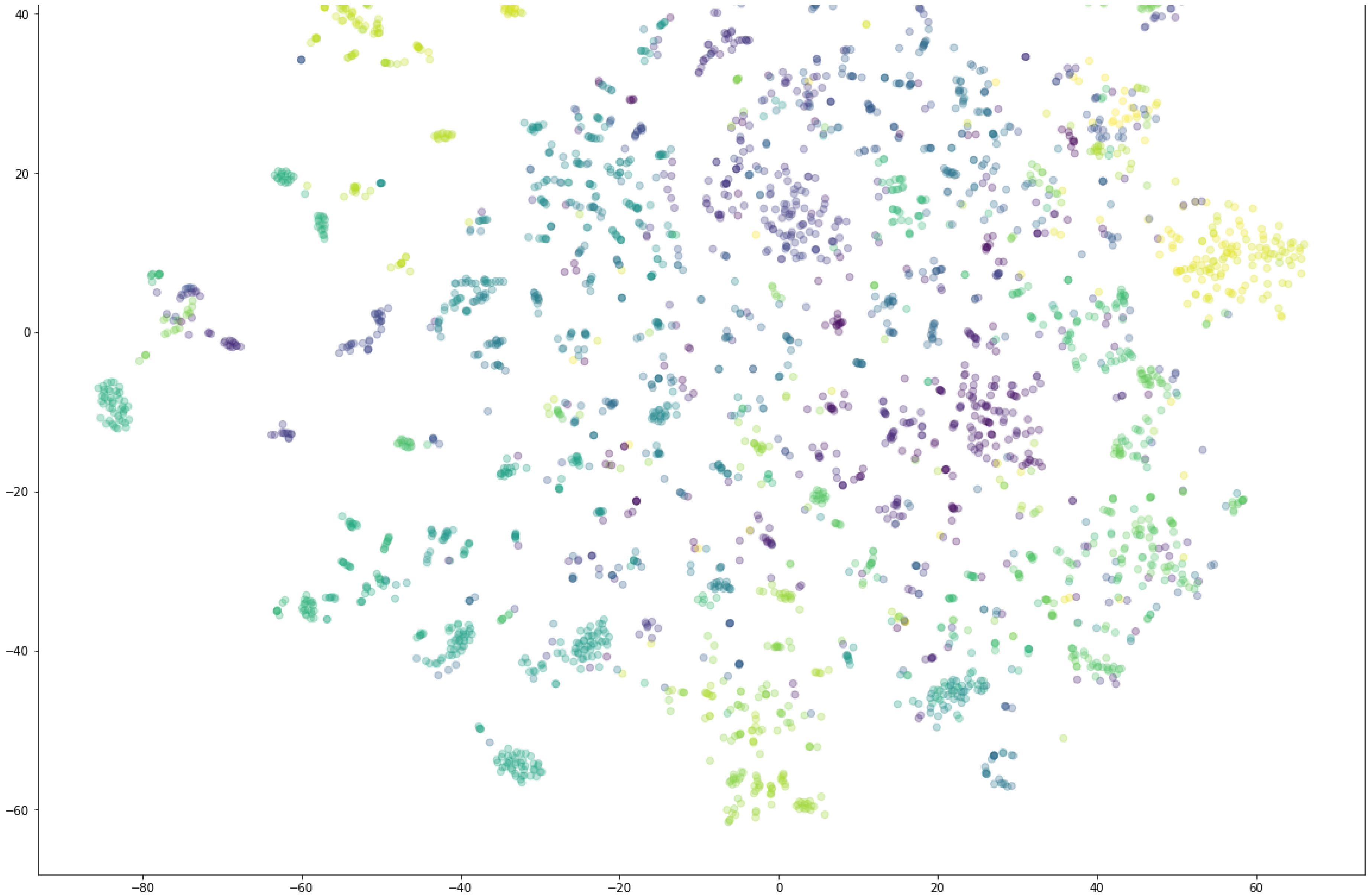
```
actor_nodes[5]
```

Out[37]: 'a970'

In [38]:

```
from sklearn.manifold import TSNE
transform = TSNE #PCA

trans = transform(n_components=2)
actor_tsne = trans.fit_transform(actor_embeddings)

import numpy as np
# draw the points

# for node in actor_nodes:


label_map = {l: i for i, l in enumerate(np.unique(actor_nodes))}
node_colours = [label_map[target] for target in actor_nodes]

plt.figure(figsize=(20,20))
plt.axes().set(aspect="equal")
plt.scatter(actor_tsne[:,0],
            actor_tsne[:,1],
            c=node_colours, alpha=0.3)
plt.title('{} visualization of actor embeddings'.format(transform.__name__))

plt.show()
```





Grouping similar movies

In [39]:
```
clusters = [3, 5, 10, 30, 50, 100, 200, 500]
```

```
final_cost = []
for num_of_clusters in clusters:
  algo = KMeans(n_clusters=num_of_clusters)
  algo.fit(movie_embeddings)
  labels = algo.labels_
  centers = algo.cluster_centers_

  final_cost1 = 0
  final_cost2 = 0
  for i in centers:
    sim_point = model.similar_by_vector(i,topn=1,restrict_vocab=None) #source: Stackoverflow (Taking closer point to
    final_cost1 += cost1(nx.ego_graph(A,sim_point[0][0]),num_of_clusters)
    final_cost2 += cost2(nx.ego_graph(A,sim_point[0][0]),num_of_clusters)
  final_cost.append(final_cost1*final_cost2)
  print('cost for '+str(num_of_clusters)+' clusters is :'+str(final_cost1*final_cost2))
```

```
cost for 3 clusters is :1.0
cost for 5 clusters is :2.0
cost for 10 clusters is :1.9000000000000001
cost for 30 clusters is :7.8
cost for 50 clusters is :10.499999999999998
cost for 100 clusters is :11.129999999999999
cost for 200 clusters is :11.30000000000001
cost for 500 clusters is :10.335999999999977
```

In [40]:

```
print('Clusters that have max cost :', clusters[final_cost.index(max(final_cost))])
```

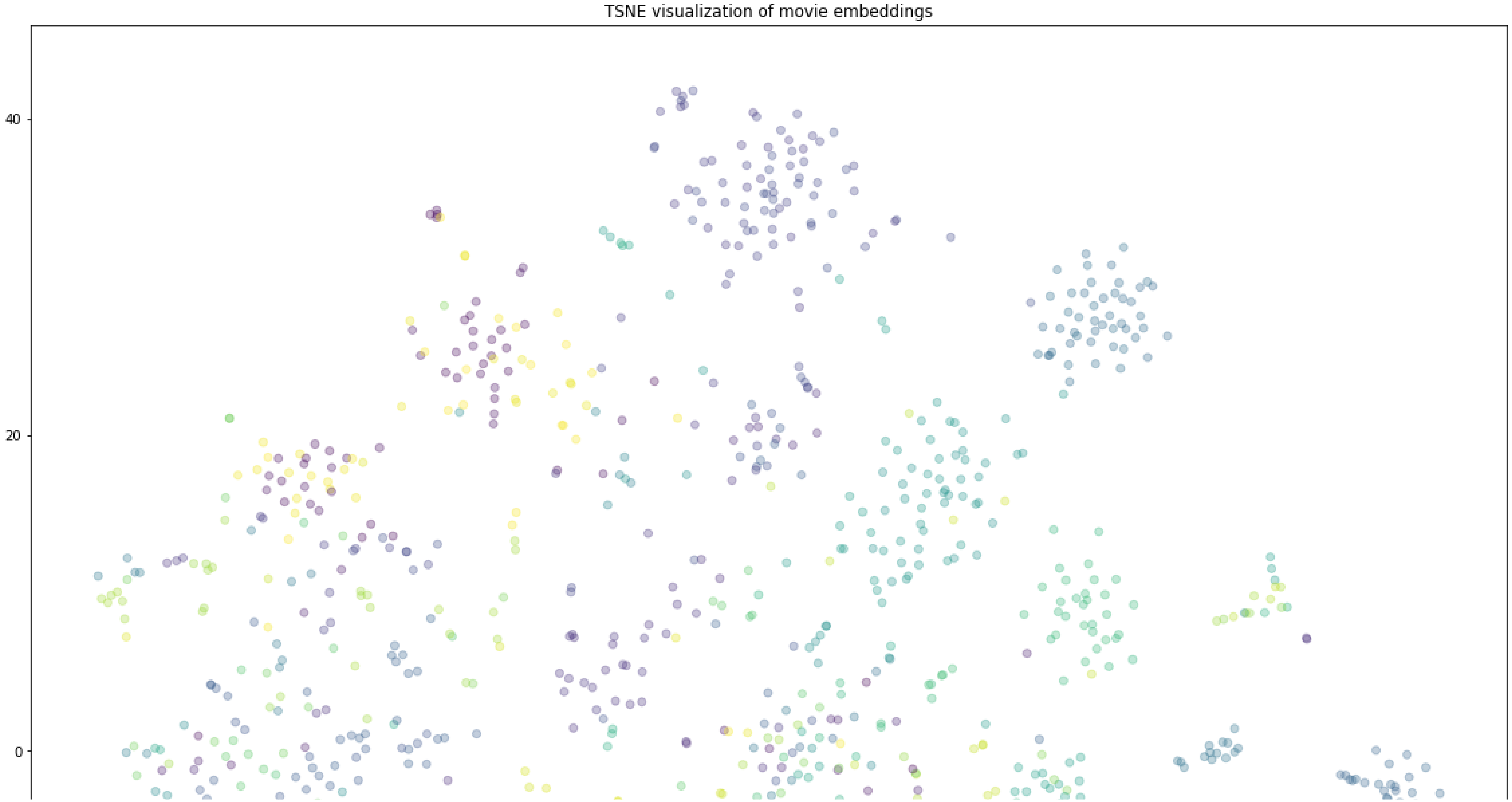
```
Clusters that have max cost : 200
```

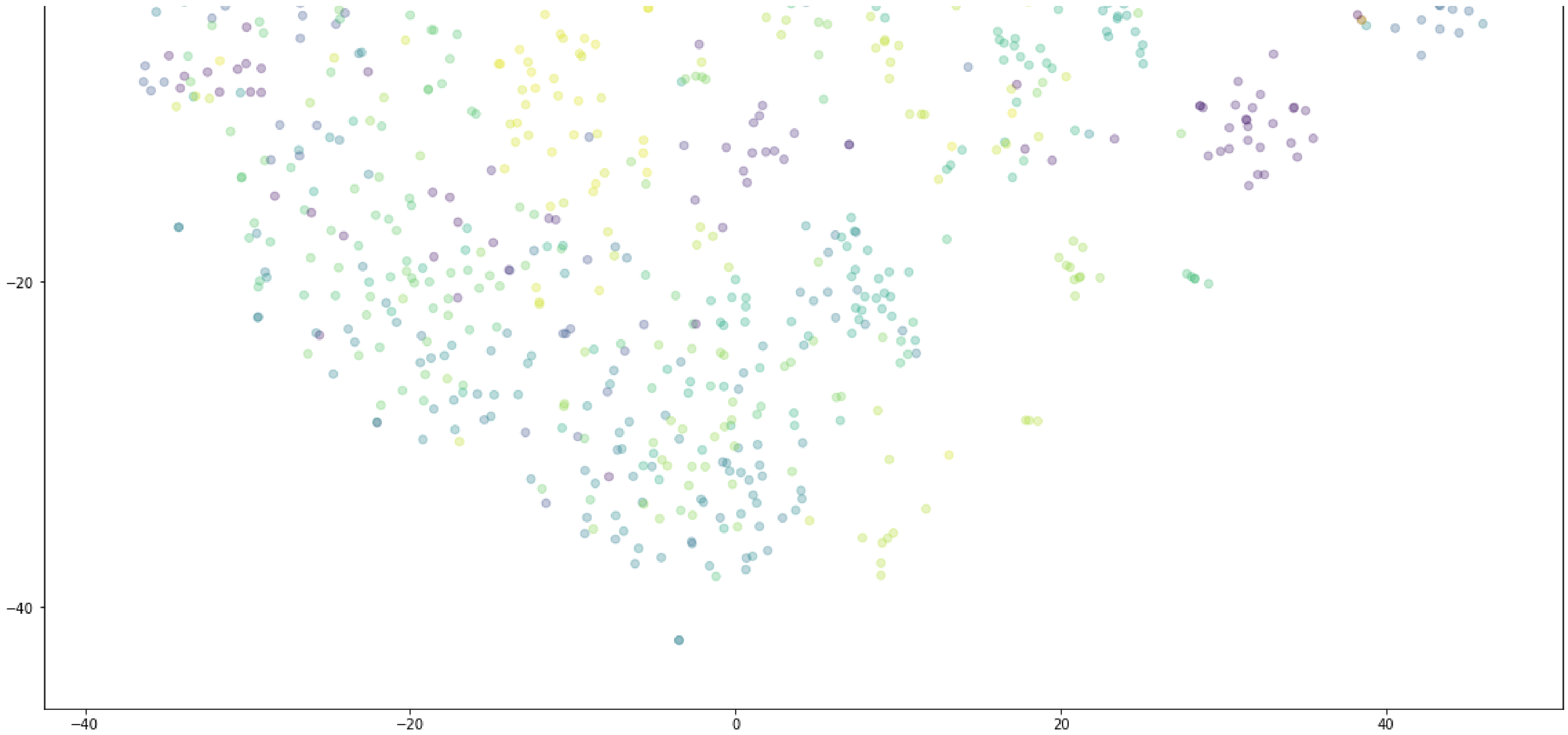
Displaying similar movie clusters

In [41]:

```
from sklearn.manifold import TSNE
transform = TSNE #PCA

trans = transform(n_components=2)
movie_tsne = trans.fit_transform(movie_embeddings)

import numpy as np
# draw the points
```

```
label_map = {l: i for i, l in enumerate(np.unique(movie_nodes))}
node_colours = [label_map[target] for target in movie_nodes]

plt.figure(figsize=(20,20))
plt.axes().set(aspect="equal")
plt.scatter(movie_tsne[:,0],
            movie_tsne[:,1],
            c=node_colours, alpha=0.3)
plt.title('{} visualization of movie embeddings'.format(transform.__name__))

plt.show()
```





In [41]: