

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 Glader 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 stellargraph 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 your code in `def data_split()`)

Task 1 : Apply clustering algorithm to group similar actors

- For this task consider only the actor nodes
- Apply any clustering algorithm of your choice
Refer : <https://scikit-learn.org/stable/modules/clustering.html>
Cost1 = $\frac{1}{N} \sum_{i=1}^N \sum_{j \in \text{each cluster } i} (\text{number of degree of actor nodes in the graph with the actor nodes and its actor neighbours in cluster } i) - \frac{(\text{total number of nodes in that cluster})^2}{N}$ where N= number of clusters
(Write your code in `def cost1()`)
- Choose the number of clusters for which you have maximum score of `Cost1 + Cost2`
Cost2 = $\frac{1}{N} \sum_{i=1}^N \sum_{j \in \text{each cluster } i} (\text{sum of degree of actor nodes in the graph with the actor nodes and its movie neighbours in cluster } i) - \frac{(\text{total number of nodes in that cluster})^2}{N}$ where N= number of clusters
(Write your code in `def cost2()`)
- Fit the clustering algorithm with the optimal number of clusters and get the cluster number for each node
- Convert the d-dimensional dense vectors of nodes into 2-dimensional using dimensionality reduction techniques (preferably TSNE)
- 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



Task 2 : Apply clustering algorithm to group similar movies

- For this task consider only the movie nodes
- Apply any clustering algorithm of your choice 3.Choose the number of clusters for which you have maximum score of `Cost1 + Cost2`
Cost1 = $\frac{1}{N} \sum_{i=1}^N \sum_{j \in \text{each cluster } i} (\text{number of nodes in the largest connected component in the graph with the movie nodes and its actor neighbours in cluster } i) - \frac{(\text{total number of nodes in that cluster})^2}{N}$ where N= number of clusters
(Write your code in `def cost1()`)
- Cost2 = $\frac{1}{N} \sum_{i=1}^N \sum_{j \in \text{each cluster } i} (\text{sum of degree of movie nodes in the graph with the movie nodes and its actor neighbours in cluster } i) - \frac{(\text{total number of nodes in that cluster})^2}{N}$ 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_algorithm(cluster_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_clusters=3, cost1=cost1(graph1)+cost1(graph2)+cost1(graph3) # here we are doing summation
    cost2=cost2(graph1)+cost2(graph2)+cost2(graph3)
    compute the metric Cost = Cost1*Cost2
    return number_of_clusters which have maximum Cost
```

```
In [1]: #!pip install networkx==3
In [2]: #!pip install stellargraph
In [99]: %matplotlib inline
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 [100]: data=pd.read_csv('movie_actor_network.csv', index_col=False, names=['movie', 'actor'])

In [101]: For Google Colab

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

In [102]: data=pd.read_csv('/content/drive/MyDrive/14 Clustering on Graph Dataset/movie_actor_network.csv', index_col=False, names=['movie', 'actor'])

In [103]: edges = [tuple(x) for x in data.values.tolist()]

In [104]: 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 [105]: A = list(nx.connected_component_subgraphs(B))[0]

In [106]: #A = B.subgraph(c) for c in nx.connected_components(B)
#A = list(A)[0]

In [107]: 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 [108]: 1, r = nx.bipartite.sets(A)
pos = {}

pos.update((node, (1, index)) for index, node in enumerate(1))
pos.update((node, (2, index)) for index, node in enumerate(r))
nx.draw(A, pos=pos, with_labels=True)
plt.show()

In [109]: movies = []
actors = []
for i in A.nodes():
    if 'a' in i:
        movies.append(i)
    if 'm' 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 [110]: # 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
               nst, # number of random walks per root node
               metapaths=metapaths
            )

print("Number of random walks: {}".format(len(walks)))
Number of random walks: 4703

In [111]: from gensim.models import Word2Vec
model = Word2Vec(walks, size=128, window=5)

In [112]: model.wv.vectors.shape # 128-dimensional vector for each node in the graph
Out[112]: (4703, 128)

In [113]: # Retrieve node embeddings and corresponding subjects
node_ids = model.wv.indexword # list of node IDs
node_embeddings = model.wv.vectors # numpy ndarray of size N*d where N nodes times embeddings dimensionality
node_targets = [A.nodes[node_id]['label'] for node_id in node_ids]

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 [114]: 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
# using node_embeddings and node_targets, we can extract actor_embeddings and movie_embeddings
# by using node_ids and node_targets, we can extract actor_nodes and movie_nodes
actor_nodes, movie_nodes=[], []
actor_embeddings, movie_embeddings=[], []
actor_target, movie_target = [], []

for i in range(len(node_targets)):
    if node_targets[i] == 'actor':
        actor_nodes.append(node_ids[i])
        actor_embeddings.append(node_embeddings[i])
        actor_target.append(node_targets[i])
    else:
        movie_nodes.append(node_ids[i])
        movie_embeddings.append(node_embeddings[i])
        movie_target.append(node_targets[i])
return actor_nodes, movie_nodes, actor_embeddings, movie_embeddings

In [115]: actor_nodes, movie_nodes, actor_embeddings, movie_embeddings = data_split(node_ids, node_targets, node_embeddings)

Grader function - 1

In [116]: def grader_actors(data):
assert(len(data)==3411)
return True
grader_actors(actor_nodes)

Out[116]: True

Grader function - 2

In [117]: def grader_movies(data):
assert(len(data)==1292)
return True
grader_movies(movie_nodes)

Out[117]: True

Calculating cost1

Cost1 = 1/N * sum_{i=1}^N sum_{j in each cluster i} (number of nodes in the largest connected component in the graph with the actor nodes and its movie neighbours in cluster i) - (total number of nodes in that cluster)^2 / N where N= number of clusters

In [118]: import operator as op
def cost1(graded_graph, k):
    actor_node_list = []
    for i in graded_graph.nodes if 'a' in i:
        total_nodes_in_cluster = len(set(list(graded_graph.nodes(i))))
        nodewise_connected_ele = []
        for i in actor_node_list:
            connected_nodes = nx.ego_graph(graded_graph, i)
            print('selected_node_graph_nodes()')
            nodewise_connected_ele.append(len(selected_node_graph_nodes(i)))
            nodewise_connected_ele.append(len(selected_node_graph_nodes(i)))

        #Now select node with max connected components
        #print(cost1(actor_node_list, nodewise_connected_ele))
        cluster_cost1 = op.truediv(max(nodewise_connected_ele), (total_nodes_in_cluster))
        cluster_cost1 = op.truediv(cluster_cost1, k)

    return cluster_cost1

In [119]: import networkx as nx
from networkx.algorithms import bipartite
graded_graph = nx.Graph()
graded_graph.add_nodes_from(['a1', 'a5', 'a10', 'a11', 'a12', 'a13', 'a14', 'a15', 'a16', 'a17', 'a18', 'a19', 'a20', 'a21', 'a22', 'a23', 'a24', 'a25', 'a26', 'a27', 'a28', 'a29', 'a30', 'a31', 'a32', 'a33', 'a34', 'a35', 'a36', 'a37', 'a38', 'a39', 'a40', 'a41', 'a42', 'a43', 'a44', 'a45', 'a46', 'a47', 'a48', 'a49', 'a50', 'a51', 'a52', 'a53', 'a54', 'a55', 'a56', 'a57', 'a58', 'a59', 'a60', 'a61', 'a62', 'a63', 'a64', 'a65', 'a66', 'a67', 'a68', 'a69', 'a70', 'a71', 'a72', 'a73', 'a74', 'a75', 'a76', 'a77', 'a78', 'a79', 'a80', 'a81', 'a82', 'a83', 'a84', 'a85', 'a86', 'a87', 'a88', 'a89', 'a90', 'a91', 'a92', 'a93', 'a94', 'a95', 'a96', 'a97', 'a98', 'a99', 'a100', 'a101', 'a102', 'a103', 'a104', 'a105', 'a106', 'a107', 'a108', 'a109', 'a110', 'a111', 'a112', 'a113', 'a114', 'a115', 'a116', 'a117', 'a118', 'a119', 'a120', 'a121', 'a122', 'a123', 'a124', 'a125', 'a126', 'a127', 'a128', 'a129', 'a130', 'a131', 'a132', 'a133', 'a134', 'a135', 'a136', 'a137', 'a138', 'a139', 'a140', 'a141', 'a142', 'a143', 'a144', 'a145', 'a146', 'a147', 'a148', 'a149', 'a150', 'a151', 'a152', 'a153', 'a154', 'a155', 'a156', 'a157', 'a158', 'a159', 'a160', 'a161', 'a162', 'a163', 'a164', 'a165', 'a166', 'a167', 'a168', 'a169', 'a170', 'a171', 'a172', 'a173', 'a174', 'a175', 'a176', 'a177', 'a178', 'a179', 'a180', 'a181', 'a182', 'a183', 'a184', 'a185', 'a186', 'a187', 'a188', 'a189', 'a190', 'a191', 'a192', 'a193', 'a194', 'a195', 'a196', 'a197', 'a198', 'a199', 'a200', 'a201', 'a202', 'a203', 'a204', 'a205', 'a206', 'a207', 'a208', 'a209', 'a210', 'a211', 'a212', 'a213', 'a214', 'a215', 'a216', 'a217', 'a218', 'a219', 'a220', 'a221', 'a222', 'a223', 'a224', 'a225', 'a226', 'a227', 'a228', 'a229', 'a230', 'a231', 'a232', 'a233', 'a234', 'a235', 'a236', 'a237', 'a238', 'a239', 'a240', 'a241', 'a242', 'a243', 'a244', 'a245', 'a246', 'a247', 'a248', 'a249', 'a250', 'a251', 'a252', 'a253', 'a254', 'a255', 'a256', 'a257', 'a258', 'a259', 'a260', 'a261', 'a262', 'a263', 'a264', 'a265', 'a266', 'a267', 'a268', 'a269', 'a270', 'a271', 'a272', 'a273', 'a274', 'a275', 'a276', 'a277', 'a278', 'a279', 'a280', 'a281', 'a282', 'a283', 'a284', 'a285', 'a286', 'a287', 'a288', 'a289', 'a290', 'a291', 'a292', 'a293', 'a294', 'a295', 'a296', 'a297', 'a298', 'a299', 'a300', 'a301', 'a302', 'a303', 'a304', 'a305', 'a306', 'a307', 'a308', 'a309', 'a310', 'a311', 'a312', 'a313', 'a314', 'a315', 'a316', 'a317', 'a318', 'a319', 'a320', 'a321', 'a322', 'a323', 'a324', 'a325', 'a326', 'a327', 'a328', 'a329', 'a330', 'a331', 'a332', 'a333', 'a334', 'a335', 'a336', 'a337', 'a338', 'a339', 'a340', 'a341', 'a342', 'a343', 'a344', 'a345', 'a346', 'a347', 'a348', 'a349', 'a350', 'a351', 'a352', 'a353', 'a354', 'a355', 'a356', 'a357', 'a358', 'a359', 'a360', 'a361', 'a362', 'a363', 'a364', 'a365', 'a366', 'a367', 'a368', 'a369', 'a370', 'a371', 'a372', 'a373', 'a374', 'a375', 'a376', 'a377', 'a378', 'a379', 'a380', 'a381', 'a382', 'a383', 'a384', 'a385', 'a386', 'a387', 'a388', 'a389', 'a390', 'a391', 'a392', 'a393', 'a394', 'a395', 'a396', 'a397', 'a398', 'a399', 'a400', 'a401', 'a402', 'a403', 'a404', 'a405', 'a406', 'a407', 'a408', 'a409', 'a410', 'a411', 'a412', 'a413', 'a414', 'a415', 'a416', 'a417', 'a418', 'a419', 'a420', 'a421', 'a422', 'a423', 'a424', 'a425', 'a426', 'a427', 'a428', 'a429', 'a430', 'a431', 'a432', 'a433', 'a434', 'a435', 'a436', 'a437', 'a438', 'a439', 'a440', 'a441', 'a442', 'a443', 'a444', 'a445', 'a446', 'a447', 'a448', 'a449', 'a450', 'a451', 'a452', 'a453', 'a454', 'a455', 'a456', 'a457', 'a458', 'a459', 'a460', 'a461', 'a462', 'a463', 'a464', 'a465', 'a466', 'a467', 'a468', 'a469', 'a470', 'a471', 'a472', 'a473', 'a474', 'a475', 'a476', 'a477', 'a478', 'a479', 'a480', 'a481', 'a482', 'a483', 'a484', 'a485', 'a486', 'a487', 'a488', 'a489', 'a490', 'a491', 'a492', 'a493', 'a494', 'a495', 'a496', 'a497', 'a498', 'a499', 'a500', 'a501', 'a502', 'a503', 'a504', 'a505', 'a506', 'a507', 'a508', 'a509', 'a510', 'a511', 'a512', 'a513', 'a514', 'a515', 'a516', 'a517', 'a518', 'a519', 'a520', 'a521', 'a522', 'a523', 'a524', 'a525', 'a526', 'a527', 'a528', 'a529', 'a530', 'a531', 'a532', 'a533', 'a534', 'a535', 'a536', 'a537', 'a538', 'a539', 'a540', 'a541', 'a542', 'a543', 'a544', 'a545', 'a546', 'a547', 'a548', 'a549', 'a550', 'a551', 'a552', 'a553', 'a554', 'a555', 'a556', 'a557', 'a558', 'a559', 'a560', 'a561', 'a562', 'a563', 'a564', 'a565', 'a566', 'a567', 'a568', 'a569', 'a570', 'a571', 'a572', 'a573', 'a574', 'a575', 'a576', 'a577', 'a578', 'a579', 'a580', 'a581', 'a582', 'a583', 'a584', 'a585', 'a586', 'a587', 'a588', 'a589', 'a590', 'a591', 'a592', 'a593', 'a594', 'a595', 'a596', 'a597', 'a598', 'a599', 'a600', 'a601', 'a602', 'a603', 'a604', 'a605', 'a606', 'a607', 'a608', 'a609', 'a610', 'a611', 'a612', 'a613', 'a614', 'a615', 'a616', 'a617', 'a618', 'a619', 'a620', 'a621', 'a622', 'a623', 'a624', 'a625', 'a626', 'a627', 'a628', 'a629', 'a630', 'a631', 'a632', 'a633', 'a634', 'a635', 'a636', 'a637', 'a638', 'a639', 'a640', 'a641', 'a642', 'a643', 'a644', 'a645', 'a646', 'a647', 'a648', 'a649', 'a650', 'a651', 'a652', 'a653', 'a654', 'a655', 'a656', 'a657', 'a658', 'a659', 'a660', 'a661', 'a662', 'a663', 'a664', 'a665', 'a666', 'a667', 'a668', 'a669', 'a670', 'a671', 'a672', 'a673', 'a674', 'a675', 'a676', 'a677', 'a678', 'a679', 'a680', 'a681', 'a682', 'a683', 'a684', 'a685', 'a686', 'a687', 'a688', 'a689', 'a690', 'a691', 'a692', 'a693', 'a694', 'a695', 'a696', 'a697', 'a698', 'a699', 'a700', 'a701', 'a702', 'a703', 'a704', 'a705', 'a706', 'a707', 'a708', 'a709', 'a710', 'a711', 'a712', 'a713', 'a714', 'a715', 'a716', 'a717', 'a718', 'a719', 'a720', 'a721', 'a722', 'a723', 'a724', 'a725', 'a726', 'a727', 'a728', 'a729', 'a730', 'a731', 'a732', 'a733', 'a734', 'a735', 'a736', 'a737', 'a738', 'a739', 'a740', 'a741', 'a742', 'a743', 'a744', 'a745', 'a746', 'a747', 'a748', 'a749', 'a750', 'a751', 'a752', 'a753', 'a754', 'a755', 'a756', 'a757', 'a758', 'a759', 'a760', 'a761', 'a762', 'a763', 'a764', 'a765', 'a766', 'a767', 'a768', 'a769', 'a770', 'a771', 'a772', 'a773', 'a774', 'a775', 'a776', 'a777', 'a778', 'a779', 'a780', 'a781', 'a782', 'a783', 'a784', 'a785', 'a786', 'a787', 'a788', 'a789', 'a790', 'a791', 'a792', 'a793', 'a794', 'a795', 'a796', 'a797', 'a798', 'a799', 'a800', 'a801', 'a802', 'a803', 'a804', 'a805', 'a806', 'a807', 'a808', 'a809', 'a810', 'a811', 'a812', 'a813', 'a814', 'a815', 'a816', 'a817', 'a818', 'a819', 'a820', 'a821', 'a822', 'a823', 'a824', 'a825', 'a826', 'a827', 'a828', 'a829', 'a830', 'a831', 'a832', 'a833', 'a834', 'a835', 'a836', 'a837', 'a838', 'a839', 'a840', 'a841', 'a842', 'a843', 'a844', 'a845', 'a846', 'a847', 'a848', 'a849', 'a850', 'a851', 'a852', 'a853', 'a854', 'a855', 'a856', 'a857', 'a858', 'a859', 'a860', 'a861', 'a862', 'a863', 'a864', 'a865', 'a866', 'a867', 'a868', 'a869', 'a870', 'a871', 'a872', 'a873', 'a874', 'a875', 'a876', 'a877', 'a878', 'a879', 'a880', 'a881', 'a882', 'a883', 'a884', 'a885', 'a886', 'a887', 'a888', 'a889', 'a890', 'a891', 'a892', 'a893', 'a894', 'a895', 'a896', 'a897', 'a898', 'a899', 'a900', 'a901', 'a902', 'a903', 'a904', 'a905', 'a906', 'a907', 'a908', 'a909', 'a910', 'a911', 'a912', 'a913', 'a914', 'a915', 'a916', 'a917', 'a918', 'a919', 'a920', 'a921', 'a922', 'a923', 'a924', 'a925', 'a926', 'a927', 'a928', 'a929', 'a930', 'a931', 'a932', 'a933', 'a934', 'a935', 'a936', 'a937', 'a938', 'a939', 'a940', 'a941', 'a942', 'a943', 'a944', 'a945', 'a946', 'a947', 'a948', 'a949', 'a950', 'a951', 'a952', 'a953', 'a954', 'a955', 'a956', 'a957', 'a958', 'a959', 'a960', 'a961', 'a962', 'a963', 'a964', 'a965', 'a966', 'a967', 'a968', 'a969', 'a970', 'a971', 'a972', 'a973', 'a974', 'a975', 'a976', 'a977', 'a978', 'a979', 'a980', 'a981', 'a982', 'a983', 'a984', 'a985', 'a986', 'a987', 'a988', 'a989', 'a990', 'a991', 'a992', 'a993', 'a994', 'a995', 'a996', 'a997', 'a998', 'a999', 'a1000', 'a1001', 'a1002', 'a1003', 'a1004', 'a1005', 'a1006', 'a1007', 'a1008', 'a1009', 'a1010', 'a1011', 'a1012', 'a1013', 'a1014', 'a1015', 'a1016', 'a1017', 'a1018', 'a1019', 'a1020', 'a1021', 'a1022', 'a1023', 'a1024', 'a1025', 'a1026', 'a1027', 'a1028', 'a1029', 'a1030', 'a1031', 'a1032', 'a1033', 'a1034', 'a1035', 'a1036', 'a1037', 'a1038', 'a1039', 'a1040', 'a1041', 'a1042', 'a1043', 'a1044', 'a1045', 'a1046', 'a1047', 'a1048', 'a1049', 'a1050', 'a1051', 'a1052', 'a1053', 'a1054', 'a1055', 'a1056', 'a1057', 'a1058', 'a1059', 'a1060', 'a1061', 'a1062', 'a1063', 'a1064', 'a1065', 'a1066', 'a1067', 'a1068', 'a1069', 'a1070', 'a1071', 'a1072', 'a1073', 'a1074', 'a1075', 'a1076', 'a1077', 'a1078', 'a1079', 'a1080', 'a1081', 'a1082', 'a1083', 'a1084', 'a1085', 'a1086', 'a1087', 'a1088', 'a1089', 'a1090', 'a1091', 'a1092', 'a1093', 'a1094', 'a1095', 'a1096', 'a1097', 'a1098', 'a1099', 'a1100', 'a1101', 'a1102', 'a1103', 'a1104', 'a1105', 'a1106', 'a1107', 'a1108', 'a1109', 'a1110', 'a1111', 'a1112', 'a1113', 'a1114', 'a1115', 'a1116', 'a1117', 'a1118', 'a1119', 'a1120', 'a1121', 'a1122', 'a1123', 'a1124', 'a1125', 'a1126', 'a1127', 'a1128', 'a1129', 'a1130', 'a1131', 'a1132', 'a1133', 'a1134', 'a1135', 'a1136', 'a1137', 'a1138', 'a1139', 'a1140', 'a1141', 'a1142', 'a1143', 'a1144', 'a1145', 'a1146', 'a1147', 'a1148', 'a1149', 'a1150', 'a1151', 'a1152', 'a1153', 'a1154', 'a1155', 'a1156', 'a1157', 'a1158', 'a1159', 'a1160', 'a1161', 'a1162', 'a1163', 'a1164', 'a1165', 'a1166', 'a1167', 'a1168', 'a1169', 'a1170', 'a1171', 'a1172', 'a1173', 'a1174', 'a1175', 'a1176', 'a1177', 'a1178', 'a1179', 'a1180', 'a1181', 'a1182', 'a1183', 'a1184', 'a1185', 'a1186', 'a1187', 'a1188', 'a1189', 'a1190', 'a1191', 'a1192', 'a1193', 'a1194', 'a1195', 'a1196', 'a1197', 'a1198', 'a1199', 'a1200', 'a1201', 'a1202', 'a1203', 'a1204', 'a1205', 'a1206', 'a1207', 'a1208', 'a1209', 'a1210', 'a1211', 'a1212', 'a1213', 'a1214', 'a1215', 'a1216', 'a1217', 'a1218', 'a1219', 'a1220', 'a1221', 'a1222', 'a1223', 'a1224', 'a1225', 'a1226', 'a1227', 'a1228', 'a1229', 'a1230', 'a1231', 'a1232', 'a1233', 'a1234', 'a1235', 'a1236', 'a1237', 'a1238', 'a1239', 'a1240', 'a1241', 'a1242', 'a1243', 'a1244', 'a1245', 'a1246', 'a1247', 'a1248', 'a1249', 'a1250', 'a1251', 'a1252', 'a1253', 'a1254', 'a1255', 'a1256', 'a1257', 'a1258', 'a1259', 'a1260', 'a1261', 'a1262', 'a1263', 'a1264', 'a1265', 'a1266', 'a1267', 'a1268', 'a1269', 'a1270', 'a1271', 'a1272', 'a1273', 'a1274', 'a1275', 'a1276', 'a1277', 'a1278', 'a1279', 'a1280', 'a1281', 'a1282', 'a1283', 'a1284', 'a1285', 'a1286', 'a1287', 'a1288', 'a1289', 'a1290', 'a1291', 'a1292', 'a1293', 'a1294', 'a1295', 'a1296', 'a1297', 'a1298', 'a1299', 'a1300', 'a1301', 'a1302', 'a1303', 'a1304', 'a1305', 'a1306', 'a1307', 'a1308', 'a1309', 'a1310', 'a1311', 'a1312', 'a1313', 'a1314', 'a1315', 'a1316', 'a1317', 'a1318', 'a1319', 'a1320', 'a1321', 'a1322', 'a1323', 'a1324', 'a1325', 'a1326', 'a1327', 'a1328', 'a1329', 'a1330', 'a1331', 'a1332', 'a1333', 'a1334', 'a1335', 'a1336', 'a1337', 'a1338', 'a1339', 'a1340', 'a1341', 'a1342', 'a1343', 'a1344', 'a1345', 'a1346', 'a1347', 'a1348', 'a1349', 'a1350', 'a1351', 'a1352', 'a1353', 'a1354', 'a1355', 'a1356', 'a1357', 'a1358', 'a1359', 'a1360', 'a1361', 'a1362', 'a1363', 'a1364', 'a1365', 'a1366', 'a1367', 'a1368', 'a1369', 'a1370', 'a1371', 'a1372', 'a1373', 'a1374', 'a1375', 'a1376', 'a1377', 'a1378', 'a1379', 'a1380', 'a1381', 'a1382', 'a1383', 'a1384', 'a1385', 'a1386', 'a1387', 'a1388', 'a1389', 'a1390', 'a1391', 'a1392', 'a1393', 'a1394', 'a1395', 'a1396', 'a1397', 'a1398', 'a1399', 'a1400', 'a1401', 'a1402', 'a1403', 'a1404', 'a1405', 'a1406', 'a1407', 'a1408', 'a1409', 'a1410', 'a1411', 'a1412', 'a1413', 'a1414', 'a1415', 'a1416', 'a1417', 'a1418', 'a1419', 'a1420', 'a1421', 'a1422', 'a1423', 'a1424', 'a1425', 'a1426', 'a1427', 'a1428', 'a1429', 'a1430', 'a1431', 'a1432', 'a1433', 'a1434', 'a1435', 'a1436', 'a1437', 'a1438', 'a1439', 'a1440', 'a1441', 'a1442', 'a1443', 'a1444', 'a1445', 'a1446', 'a1447', 'a1448', 'a1449', 'a1450', 'a1451', 'a1452', 'a1453', 'a1454', 'a1455', 'a1456', 'a1457', 'a1458', 'a1459', 'a1460', 'a1461', 'a1462', 'a1463', 'a1464', 'a1465', 'a1466', 'a1467', 'a1468', 'a1469', 'a1470', 'a1471', 'a1472', 'a1473', 'a1474
```