Colab1

September 22, 2021

1 CS224W - Colab 1

In this Colab, we will write a full pipeline for **learning node embeddings**. We will go through the following 3 steps.

To start, we will load a classic graph in network science, the Karate Club Network. We will explore multiple graph statistics for that graph.

We will then work together to transform the graph structure into a PyTorch tensor, so that we can perform machine learning over the graph.

Finally, we will finish the first learning algorithm on graphs: a node embedding model. For simplicity, our model here is simpler than DeepWalk / node2vec algorithms taught in the lecture. But it's still rewarding and challenging, as we will write it from scratch via PyTorch.

Now let's get started!

Note: Make sure to **sequentially run all the cells**, so that the intermediate variables / packages will carry over to the next cell

2 1 Graph Basics

To start, we will load a classic graph in network science, the Karate Club Network. We will explore multiple graph statistics for that graph.

2.1 Setup

We will heavily use NetworkX in this Colab.

[1]:
```
import networkx as nx
```

2.2 Zachary's karate club network

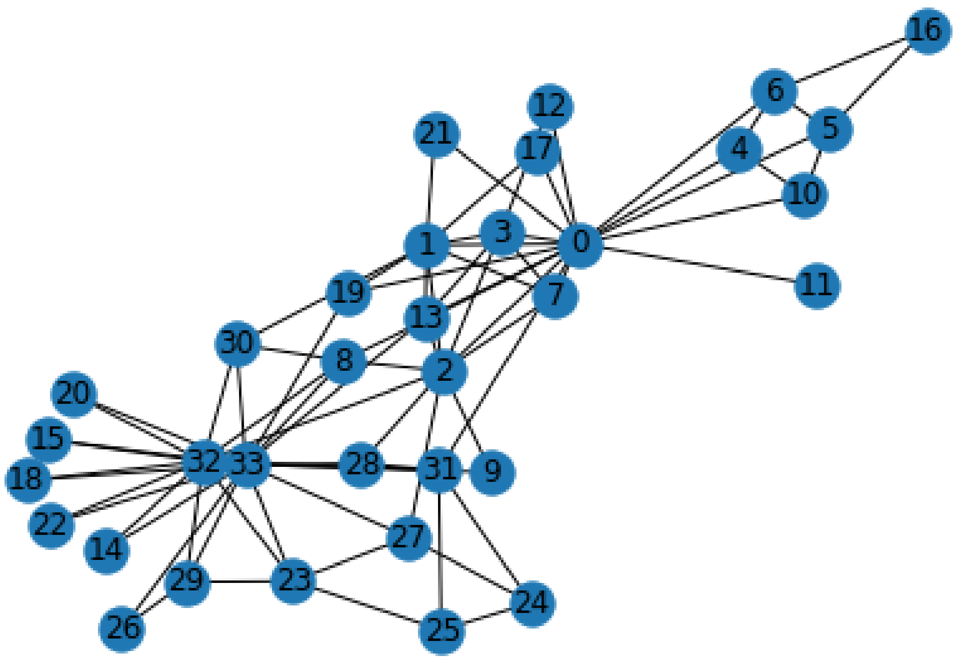
The Karate Club Network is a graph describes a social network of 34 members of a karate club and documents links between members who interacted outside the club.

[2]:
```
G = nx.karate_club_graph()

# G is an undirected graph
type(G)
```

[2]: networkx.classes.graph.Graph

[3]:
```
# Visualize the graph
nx.draw(G, with_labels = True)
```



2.3 Question 1: What is the average degree of the karate club network? (5 Points)

[4]:
```
def average_degree(num_edges, num_nodes):
  # TODO: Implement this function that takes number of edges
  # and number of nodes, and returns the average node degree of
  # the graph. Round the result to nearest integer (for example
  # 3.3 will be rounded to 3 and 3.7 will be rounded to 4)

  avg_degree = 0

  ############# Your code here ############

  avg_degree = round(num_edges/num_nodes)

  #########################################

  return avg_degree
```

```python
num_edges = G.number_of_edges()
num_nodes = G.number_of_nodes()
avg_degree = average_degree(num_edges, num_nodes)
print("Average degree of karate club network is {}".format(avg_degree))
```

```
Average degree of karate club network is 2
```

2.4 Question 2: What is the average clustering coefficient of the karate club network? (5 Points)

[5]:
```python
def average_clustering_coefficient(G):
  # TODO: Implement this function that takes a nx.Graph
  # and returns the average clustering coefficient. Round
  # the result to 2 decimal places (for example 3.333 will
  # be rounded to 3.33 and 3.7571 will be rounded to 3.76)

  avg_cluster_coef = 0

  ############# Your code here ############
  ## Note:
  ## 1: Please use the appropriate NetworkX clustering function

  avg_cluster_coef = round(nx.average_clustering(G),2)

  #########################################

  return avg_cluster_coef

avg_cluster_coef = average_clustering_coefficient(G)
print("Average clustering coefficient of karate club network is {}".
 ↪format(avg_cluster_coef))
```

```
Average clustering coefficient of karate club network is 0.57
```

2.5 Question 3: What is the PageRank value for node 0 (node with id 0) after one PageRank iteration? (5 Points)

Please complete the code block by implementing the PageRank equation: $r_j = \sum_{i \to j} \beta \frac{r_i}{d_i} + (1-\beta)\frac{1}{N}$

[6]:
```python
def one_iter_pagerank(G, beta, r0, node_id):
  # TODO: Implement this function that takes a nx.Graph, beta, r0 and node id.
  # The return value r1 is one interation PageRank value for the input node.
  # Please round r1 to 2 decimal places.

  r1 = 0
```

```
  ############# Your code here ############
  ## Note:
  ## 1: You should not use nx.pagerank

  for neighbor in G.neighbors(node_id):
    r1 += beta*r0/G.degree[neighbor]
  r1 += (1-beta)/G.number_of_nodes()
  r1 = round(r1,2)

  #########################################

  return r1

beta = 0.8
r0 = 1 / G.number_of_nodes()
node = 0
r1 = one_iter_pagerank(G, beta, r0, node)
print("The PageRank value for node 0 after one iteration is {}".format(r1))
```

```
The PageRank value for node 0 after one iteration is 0.13
```

2.6 Question 4: What is the (raw) closeness centrality for the karate club network node 5? (5 Points)

The equation for closeness centrality is $c(v) = \frac{1}{\sum_{u \neq v} \text{shortest path length between } u \text{ and } v}$

[7]:
```
def closeness_centrality(G, node=5):
  # TODO: Implement the function that calculates closeness centrality
  # for a node in karate club network. G is the input karate club
  # network and node is the node id in the graph. Please round the
  # closeness centrality result to 2 decimal places.

  closeness = 0

  ## Note:
  ## 1: You can use networkx closeness centrality function.
  ## 2: Notice that networkx closeness centrality returns the normalized
  ## closeness directly, which is different from the raw (unnormalized)
  ## one that we learned in the lecture.

  closeness = round(nx.closeness_centrality(G,node), 2)

  #########################################

  return closeness

node = 5
```

```
closeness = closeness_centrality(G, node=node)
print("The karate club network has closeness centrality {}".format(closeness))
```

```
The karate club network has closeness centrality 0.38
```

3 2 Graph to Tensor

We will then work together to transform the graph G into a PyTorch tensor, so that we can perform machine learning over the graph.

3.1 Setup

Check if PyTorch is properly installed

[8]:
```
import torch
print(torch.__version__)
```

```
1.9.0+cu102
```

3.2 PyTorch tensor basics

We can generate PyTorch tensor with all zeros, ones or random values.

[9]:
```
# Generate 3 x 4 tensor with all ones
ones = torch.ones(3, 4)
print(ones)

# Generate 3 x 4 tensor with all zeros
zeros = torch.zeros(3, 4)
print(zeros)

# Generate 3 x 4 tensor with random values on the interval [0, 1)
random_tensor = torch.rand(3, 4)
print(random_tensor)

# Get the shape of the tensor
print(ones.shape)
```

```
tensor([[1., 1., 1., 1.],
        [1., 1., 1., 1.],
        [1., 1., 1., 1.]])
tensor([[0., 0., 0., 0.],
        [0., 0., 0., 0.],
        [0., 0., 0., 0.]])
tensor([[0.5903, 0.1552, 0.1427, 0.5153],
        [0.7826, 0.3062, 0.0978, 0.4393],
        [0.1320, 0.6661, 0.8469, 0.6831]])
torch.Size([3, 4])
```

PyTorch tensor contains elements for a single data type, the `dtype`.

[10]:
```
# Create a 3 x 4 tensor with all 32-bit floating point zeros
zeros = torch.zeros(3, 4, dtype=torch.float32)
print(zeros.dtype)

# Change the tensor dtype to 64-bit integer
zeros = zeros.type(torch.long)
print(zeros.dtype)
```

```
torch.float32
torch.int64
```

3.3 Question 5: Getting the edge list of the karate club network and transform it into `torch.LongTensor`. What is the `torch.sum` value of `pos_edge_index` tensor? (10 Points)

[11]:
```
def graph_to_edge_list(G):
  # TODO: Implement the function that returns the edge list of
  # an nx.Graph. The returned edge_list should be a list of tuples
  # where each tuple is a tuple representing an edge connected
  # by two nodes.

  edge_list = []

  ############# Your code here ############

  edge_list = list(G.edges())

  #########################################

  return edge_list

def edge_list_to_tensor(edge_list):
  # TODO: Implement the function that transforms the edge_list to
  # tensor. The input edge_list is a list of tuples and the resulting
  # tensor should have the shape [2 x len(edge_list)].

  edge_index = torch.LongTensor([])

  ############# Your code here ############

  edge_index = torch.LongTensor(edge_list).T

  #########################################

  return edge_index
```

```
pos_edge_list = graph_to_edge_list(G)
pos_edge_index = edge_list_to_tensor(pos_edge_list)
print("The pos_edge_index tensor has shape {}".format(pos_edge_index.shape))
print("The pos_edge_index tensor has sum value {}".format(torch.
 ↪sum(pos_edge_index)))
```

```
The pos_edge_index tensor has shape torch.Size([2, 78])
The pos_edge_index tensor has sum value 2535
```

3.4 Question 6: Please implement following function that samples negative edges. Then you will answer which edges (edge_1 to edge_5) can be negative ones in the karate club network? (10 Points)

[12]:
```
import random

def sample_negative_edges(G, num_neg_samples):
  # TODO: Implement the function that returns a list of negative edges.
  # The number of sampled negative edges is num_neg_samples. You do not
  # need to consider the corner case when the number of possible negative edges
  # is less than num_neg_samples. It should be ok as long as your␣
 ↪implementation
  # works on the karate club network. In this implementation, self loop should
  # not be considered as either a positive or negative edge. Also, notice that
  # the karate club network is an undirected graph, if (0, 1) is a positive
  # edge, do you think (1, 0) can be a negative one?

  neg_edge_list = []

  ############# Your code here ############

  pos_edge_list = graph_to_edge_list(G)
  for i in G.nodes():
    for j in G.nodes():
      if i >= j or (i,j) in pos_edge_list:
        continue
      neg_edge_list.append((i,j))
  neg_edge_list = random.sample(neg_edge_list,num_neg_samples)

  #########################################

  return neg_edge_list

# Sample 78 negative edges
neg_edge_list = sample_negative_edges(G, len(pos_edge_list))

# Transform the negative edge list to tensor
```

```
neg_edge_index = edge_list_to_tensor(neg_edge_list)
print("The neg_edge_index tensor has shape {}".format(neg_edge_index.shape))

# Which of following edges can be negative ones?
edge_1 = (7, 1)
edge_2 = (1, 33)
edge_3 = (33, 22)
edge_4 = (0, 4)
edge_5 = (4, 2)

############# Your code here ############
## Note:
## 1: For each of the 5 edges, print whether it can be negative edge

def neg_edge(edge):
  if edge in pos_edge_list or (edge[1],edge[0]) in pos_edge_list:
    print("no")
  else:
    print("yes")
neg_edge(edge_1)
neg_edge(edge_2)
neg_edge(edge_3)
neg_edge(edge_4)
neg_edge(edge_5)

#########################################
```

```
The neg_edge_index tensor has shape torch.Size([2, 78])
no
yes
no
no
yes
```

4 3 Node Emebedding Learning

Finally, we will finish the first learning algorithm on graphs: a node embedding model.

4.1 Setup

[13]:
```
import torch
import torch.nn as nn
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

print(torch.__version__)
```

1.9.0+cu102

To write our own node embedding learning methods, we'll heavily use the `nn.Embedding` module in PyTorch. Let's see how to use `nn.Embedding`:

[14]:
```
# Initialize an embedding layer
# Suppose we want to have embedding for 4 items (e.g., nodes)
# Each item is represented with 8 dimensional vector

emb_sample = nn.Embedding(num_embeddings=4, embedding_dim=8)
print('Sample embedding layer: {}'.format(emb_sample))
```

```
Sample embedding layer: Embedding(4, 8)
```

We can select items from the embedding matrix, by using Tensor indices

[15]:
```
# Select an embedding in emb_sample
id = torch.LongTensor([1])
print(emb_sample(id))

# Select multiple embeddings
ids = torch.LongTensor([1, 3])
print(emb_sample(ids))

# Get the shape of the embedding weight matrix
shape = emb_sample.weight.data.shape
print(shape)

# Overwrite the weight to tensor with all ones
emb_sample.weight.data = torch.ones(shape)

# Let's check if the emb is indeed initilized
ids = torch.LongTensor([0, 3])
print(emb_sample(ids))
```

```
tensor([[-0.4852,  0.0553, -0.7192, -0.5815, -0.1160, -0.7977,  1.0060,
1.1413]],
       grad_fn=<EmbeddingBackward>)
tensor([[-0.4852,  0.0553, -0.7192, -0.5815, -0.1160, -0.7977,  1.0060,
1.1413],
        [-1.1993,  0.4037, -0.0466,  1.6998, -0.6454,  0.1823,  0.1226,
-0.1198]],
       grad_fn=<EmbeddingBackward>)
torch.Size([4, 8])
tensor([[1., 1., 1., 1., 1., 1., 1., 1.],
        [1., 1., 1., 1., 1., 1., 1., 1.]], grad_fn=<EmbeddingBackward>)
```

Now, it's your time to create node embedding matrix for the graph we have! - We want to have **16 dimensional** vector for each node in the karate club network. - We want to initalize the matrix under **uniform distribution**, in the range of $[0, 1)$. We suggest you using `torch.rand`.

[16]:
```
# Please do not change / reset the random seed
torch.manual_seed(1)

def create_node_emb(num_node=34, embedding_dim=16):
  # TODO: Implement this function that will create the node embedding matrix.
  # A torch.nn.Embedding layer will be returned. You do not need to change
  # the values of num_node and embedding_dim. The weight matrix of returned
  # layer should be initialized under uniform distribution.

  emb = None

  ############# Your code here ############

  emb = nn.Embedding(num_embeddings=num_nodes, embedding_dim=embedding_dim)
  emb.weight.data = torch.rand(num_nodes,embedding_dim)

  #########################################

  return emb

emb = create_node_emb()
ids = torch.LongTensor([0, 3])

# Print the embedding layer
print("Embedding: {}".format(emb))

# An example that gets the embeddings for node 0 and 3
print(emb(ids))
```

```
Embedding: Embedding(34, 16)
tensor([[0.2114, 0.7335, 0.1433, 0.9647, 0.2933, 0.7951, 0.5170, 0.2801, 0.8339,
         0.1185, 0.2355, 0.5599, 0.8966, 0.2858, 0.1955, 0.1808],
        [0.7486, 0.6546, 0.3843, 0.9820, 0.6012, 0.3710, 0.4929, 0.9915, 0.8358,
         0.4629, 0.9902, 0.7196, 0.2338, 0.0450, 0.7906, 0.9689]],
       grad_fn=<EmbeddingBackward>)
```

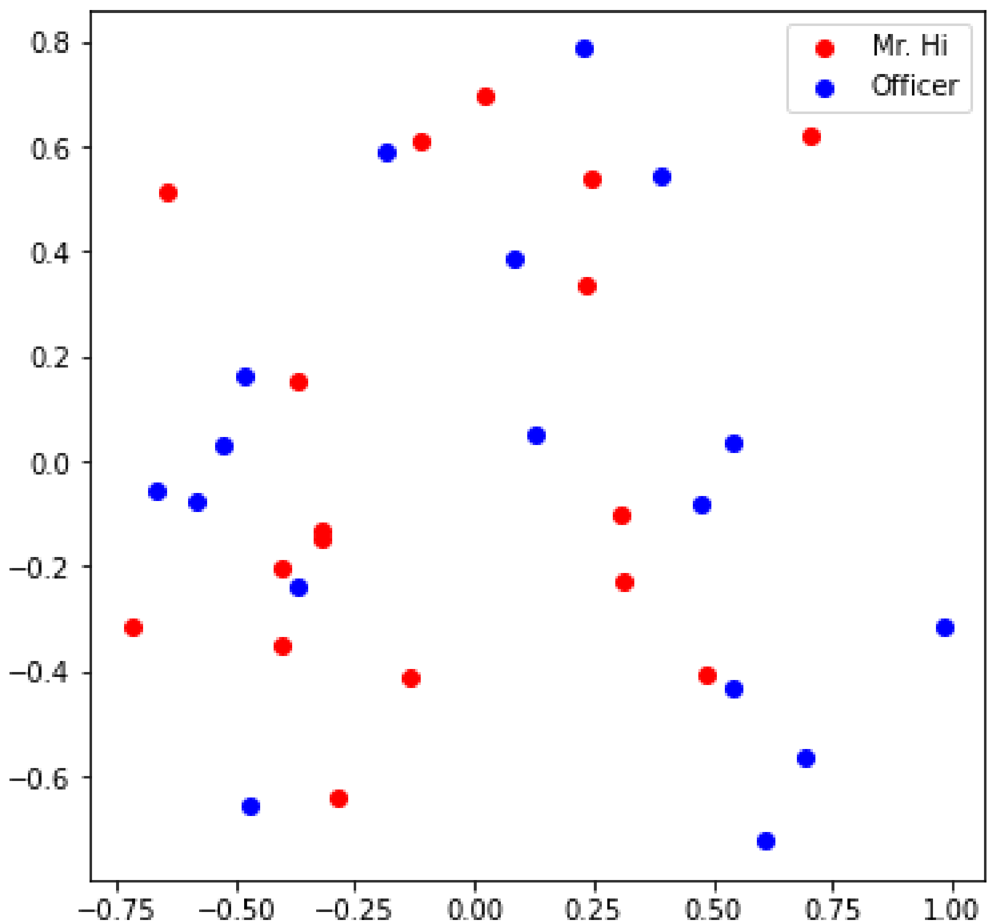
4.2 Visualize the initial node embeddings

One good way to understand an embedding matrix, is to visualize it in a 2D space. Here, we have implemented an embedding visualization function for you. We first do PCA to reduce the dimensionality of embeddings to a 2D space. Then visualize each point, colored by the community it belongs to.

[17]:
```
def visualize_emb(emb):
  X = emb.weight.data.numpy()
  pca = PCA(n_components=2)
  components = pca.fit_transform(X)
  plt.figure(figsize=(6, 6))
```

```
  club1_x = []
  club1_y = []
  club2_x = []
  club2_y = []
  for node in G.nodes(data=True):
    if node[1]['club'] == 'Mr. Hi':
      club1_x.append(components[node[0]][0])
      club1_y.append(components[node[0]][1])
    else:
      club2_x.append(components[node[0]][0])
      club2_y.append(components[node[0]][1])
  plt.scatter(club1_x, club1_y, color="red", label="Mr. Hi")
  plt.scatter(club2_x, club2_y, color="blue", label="Officer")
  plt.legend()
  plt.show()

# Visualize the initial random embeddding
visualize_emb(emb)
```



4.3 Question 7: Training the embedding! What is the best performance you can get? Please report both the best loss and accuracy on Gradescope. (20 Points)

[18]:
```
from torch.optim import SGD


def accuracy(pred, label):
  # TODO: Implement the accuracy function. This function takes the
  # pred tensor (the resulting tensor after sigmoid) and the label
  # tensor (torch.LongTensor). Predicted value greater than 0.5 will
  # be classified as label 1. Else it will be classified as label 0.
  # The returned accuracy should be rounded to 4 decimal places.
  # For example, accuracy 0.82956 will be rounded to 0.8296.

  accu = 0.0

  ############# Your code here ############
  pred = pred.ge(0.5)
  accu = torch.sum(pred==label)/pred.shape[0]
  accu = accu.item()

  #########################################

  return round(accu,4)

def train(emb, loss_fn, sigmoid, train_label, train_edge):
  # TODO: Train the embedding layer here. You can also change epochs and
  # learning rate. In general, you need to implement:
  # (1) Get the embeddings of the nodes in train_edge
  # (2) Dot product the embeddings between each node pair
  # (3) Feed the dot product result into sigmoid
  # (4) Feed the sigmoid output into the loss_fn
  # (5) Print both loss and accuracy of each epoch
  # (as a sanity check, the loss should decrease during training)

  epochs = 500
  learning_rate = 0.1

  optimizer = SGD(emb.parameters(), lr=learning_rate, momentum=0.9)

  for i in range(epochs):

    ############# Your code here ############
    optimizer.zero_grad()
```

```python
    # Get the embedings of the nodes in train_edge
    node_emb0 = emb(train_edge[0])
    node_emb1 = emb(train_edge[1])

    # Dot product the embeddings of the nodes in train_edge
    dotp = torch.sum(node_emb0*node_emb1,1)

    # Feed dot product into sigmoid
    sig = sigmoid(dotp)

    # Feed sig into lossfn
    loss = loss_fn(sig,train_label)

    loss.backward()
    optimizer.step()

    # Print results
    print("Epoch ",i,"Loss ",loss.item(),"Accu ", accuracy(sig,train_label))


    #########################################

loss_fn = nn.BCELoss()
sigmoid = nn.Sigmoid()

# Generate the positive and negative labels
pos_label = torch.ones(pos_edge_index.shape[1], )
neg_label = torch.zeros(neg_edge_index.shape[1], )

# Concat positive and negative labels into one tensor
train_label = torch.cat([pos_label, neg_label], dim=0)

# Concat positive and negative edges into one tensor
# Since the network is very small, we do not split the edges into val/test sets
train_edge = torch.cat([pos_edge_index, neg_edge_index], dim=1)

train(emb, loss_fn, sigmoid, train_label, train_edge)
```

```
Epoch  0 Loss  2.0520997047424316 Accu  0.5
Epoch  1 Loss  2.0382442474365234 Accu  0.5
Epoch  2 Loss  2.0121307373046875 Accu  0.5
Epoch  3 Loss  1.9753713607788086 Accu  0.5
Epoch  4 Loss  1.9295581579208374 Accu  0.5
Epoch  5 Loss  1.8762335777282715 Accu  0.5
Epoch  6 Loss  1.8168731927871704 Accu  0.5
Epoch  7 Loss  1.7528722286224365 Accu  0.5
```

```
Epoch  8 Loss  1.6855337619781494 Accu  0.5
Epoch  9 Loss  1.6160619258880615 Accu  0.5
Epoch  10 Loss  1.5455574989318848 Accu  0.5
Epoch  11 Loss  1.4750118255615234 Accu  0.5
Epoch  12 Loss  1.4053034782409668 Accu  0.5
Epoch  13 Loss  1.3371955156326294 Accu  0.5
Epoch  14 Loss  1.271332025527954 Accu  0.5
Epoch  15 Loss  1.2082380056381226 Accu  0.5
Epoch  16 Loss  1.1483200788497925 Accu  0.5
Epoch  17 Loss  1.0918701887130737 Accu  0.5
Epoch  18 Loss  1.0390719175338745 Accu  0.5
Epoch  19 Loss  0.990010678768158 Accu  0.5
Epoch  20 Loss  0.9446856379508972 Accu  0.5
Epoch  21 Loss  0.9030229449272156 Accu  0.5064
Epoch  22 Loss  0.8648912310600281 Accu  0.5064
Epoch  23 Loss  0.8301149010658264 Accu  0.5064
Epoch  24 Loss  0.798488199710846 Accu  0.5192
Epoch  25 Loss  0.7697864174842834 Accu  0.5449
Epoch  26 Loss  0.7437759041786194 Accu  0.5577
Epoch  27 Loss  0.7202226519584656 Accu  0.5641
Epoch  28 Loss  0.6988973617553711 Accu  0.5705
Epoch  29 Loss  0.679580807685852 Accu  0.5833
Epoch  30 Loss  0.6620659828186035 Accu  0.5897
Epoch  31 Loss  0.6461609601974487 Accu  0.5962
Epoch  32 Loss  0.6316890120506287 Accu  0.609
Epoch  33 Loss  0.6184890270233154 Accu  0.6218
Epoch  34 Loss  0.6064154505729675 Accu  0.641
Epoch  35 Loss  0.5953372120857239 Accu  0.6603
Epoch  36 Loss  0.5851373076438904 Accu  0.6667
Epoch  37 Loss  0.5757114887237549 Accu  0.6667
Epoch  38 Loss  0.566967248916626 Accu  0.6667
Epoch  39 Loss  0.5588229298591614 Accu  0.6603
Epoch  40 Loss  0.5512060523033142 Accu  0.6731
Epoch  41 Loss  0.5440533757209778 Accu  0.6795
Epoch  42 Loss  0.5373089909553528 Accu  0.6859
Epoch  43 Loss  0.5309237837791443 Accu  0.7051
Epoch  44 Loss  0.5248546600341797 Accu  0.7179
Epoch  45 Loss  0.5190641283988953 Accu  0.7179
Epoch  46 Loss  0.5135190486907959 Accu  0.75
Epoch  47 Loss  0.5081906914710999 Accu  0.7564
Epoch  48 Loss  0.503053605556488 Accu  0.7628
Epoch  49 Loss  0.49808579683303833 Accu  0.7949
Epoch  50 Loss  0.4932679831981659 Accu  0.8141
Epoch  51 Loss  0.4885829985141754 Accu  0.8269
Epoch  52 Loss  0.48401620984077454 Accu  0.8333
Epoch  53 Loss  0.479554682970047 Accu  0.8333
Epoch  54 Loss  0.4751869738101959 Accu  0.8397
Epoch  55 Loss  0.4709031581878662 Accu  0.8462
```

```
Epoch  56 Loss  0.4666946232318878 Accu  0.8462
Epoch  57 Loss  0.46255356073379517 Accu  0.8526
Epoch  58 Loss  0.45847341418266296 Accu  0.8526
Epoch  59 Loss  0.45444825291633606 Accu  0.8654
Epoch  60 Loss  0.45047301054000854 Accu  0.8782
Epoch  61 Loss  0.44654303789138794 Accu  0.8782
Epoch  62 Loss  0.44265449047088623 Accu  0.8782
Epoch  63 Loss  0.4388037919998169 Accu  0.8782
Epoch  64 Loss  0.4349880814552307 Accu  0.8846
Epoch  65 Loss  0.4312044382095337 Accu  0.8846
Epoch  66 Loss  0.427450567483902 Accu  0.8846
Epoch  67 Loss  0.42372459173202515 Accu  0.8974
Epoch  68 Loss  0.42002448439598083 Accu  0.8974
Epoch  69 Loss  0.41634881496429443 Accu  0.9038
Epoch  70 Loss  0.4126962125301361 Accu  0.9038
Epoch  71 Loss  0.4090653955936432 Accu  0.9103
Epoch  72 Loss  0.4054553806781769 Accu  0.9103
Epoch  73 Loss  0.40186530351638794 Accu  0.9103
Epoch  74 Loss  0.3982943892478943 Accu  0.9231
Epoch  75 Loss  0.3947419226169586 Accu  0.9231
Epoch  76 Loss  0.3912074863910675 Accu  0.9231
Epoch  77 Loss  0.38769054412841797 Accu  0.9231
Epoch  78 Loss  0.38419073820114136 Accu  0.9295
Epoch  79 Loss  0.3807078003883362 Accu  0.9359
Epoch  80 Loss  0.37724146246910095 Accu  0.9359
Epoch  81 Loss  0.37379157543182373 Accu  0.9359
Epoch  82 Loss  0.37035802006721497 Accu  0.9359
Epoch  83 Loss  0.36694082617759705 Accu  0.9359
Epoch  84 Loss  0.3635398745536804 Accu  0.9359
Epoch  85 Loss  0.36015522480010986 Accu  0.9359
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Epoch  100 Loss  0.3114454448223114 Accu  0.9679
Epoch  101 Loss  0.30834606289863586 Accu  0.9679
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Epoch  428 Loss  0.02616489864885807 Accu  1.0
Epoch  429 Loss  0.026054630056023598 Accu  1.0
Epoch  430 Loss  0.025945130735635757 Accu  1.0
Epoch  431 Loss  0.02583642490208149 Accu  1.0
Epoch  432 Loss  0.025728488340973854 Accu  1.0
Epoch  433 Loss  0.025621306151151657 Accu  1.0
Epoch  434 Loss  0.025514887645840645 Accu  1.0
Epoch  435 Loss  0.025409216061234474 Accu  1.0
Epoch  436 Loss  0.025304287672042847 Accu  1.0
Epoch  437 Loss  0.025200089439749718 Accu  1.0
Epoch  438 Loss  0.025096625089645386 Accu  1.0
Epoch  439 Loss  0.024993881583213806 Accu  1.0
```

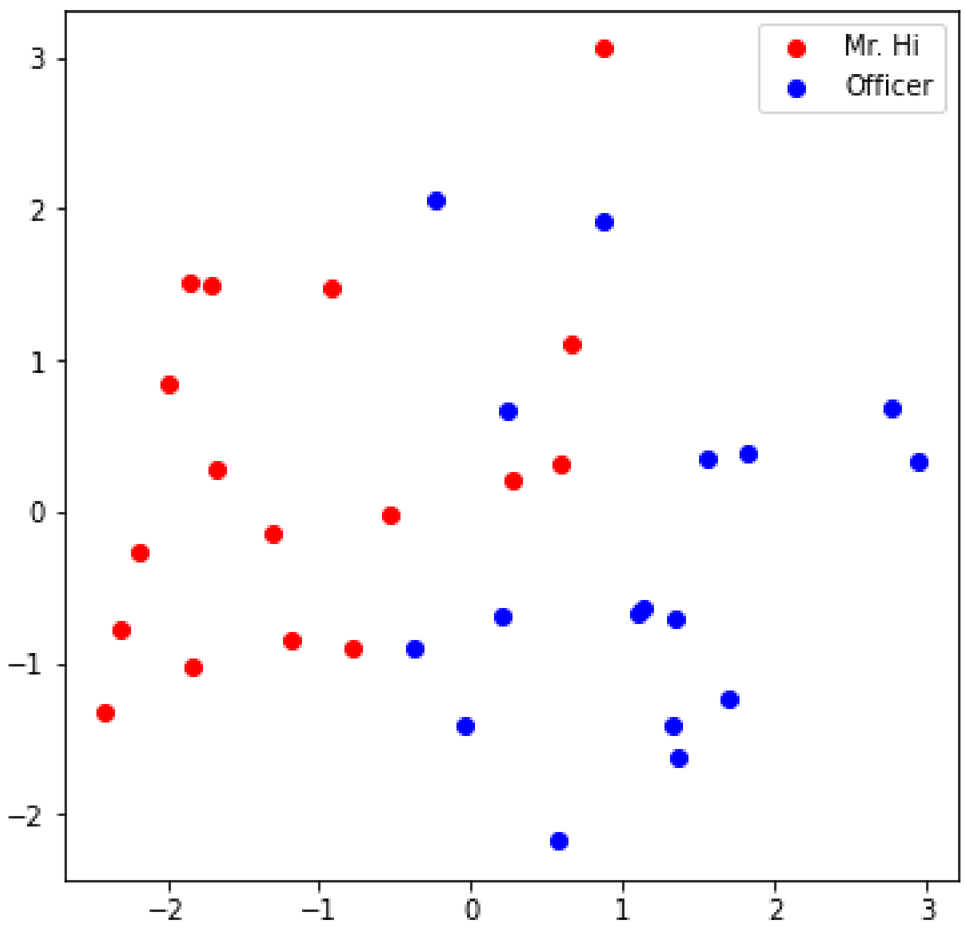
```
Epoch  440 Loss  0.024891844019293785 Accu  1.0
Epoch  441 Loss  0.02479051798582077 Accu  1.0
Epoch  442 Loss  0.024689890444278717 Accu  1.0
Epoch  443 Loss  0.024589957669377327 Accu  1.0
Epoch  444 Loss  0.024490708485245705 Accu  1.0
Epoch  445 Loss  0.024392144754529 Accu  1.0
Epoch  446 Loss  0.024294253438711166 Accu  1.0
Epoch  447 Loss  0.024197028949856758 Accu  1.0
Epoch  448 Loss  0.024100469425320625 Accu  1.0
Epoch  449 Loss  0.024004559963941574 Accu  1.0
Epoch  450 Loss  0.023909302428364754 Accu  1.0
Epoch  451 Loss  0.023814698681235313 Accu  1.0
Epoch  452 Loss  0.023720718920230865 Accu  1.0
Epoch  453 Loss  0.023627372458577156 Accu  1.0
Epoch  454 Loss  0.023534651845693588 Accu  1.0
Epoch  455 Loss  0.023442555218935013 Accu  1.0
Epoch  456 Loss  0.023351071402430534 Accu  1.0
Epoch  457 Loss  0.023260196670889854 Accu  1.0
Epoch  458 Loss  0.023169921711087227 Accu  1.0
Epoch  459 Loss  0.02308024652302265 Accu  1.0
Epoch  460 Loss  0.02299116551876068 Accu  1.0
Epoch  461 Loss  0.02290266565978527 Accu  1.0
Epoch  462 Loss  0.02281475067138672 Accu  1.0
Epoch  463 Loss  0.02272740937769413 Accu  1.0
Epoch  464 Loss  0.022640638053417206 Accu  1.0
Epoch  465 Loss  0.022554442286491394 Accu  1.0
Epoch  466 Loss  0.022468801587820053 Accu  1.0
Epoch  467 Loss  0.022383710369467735 Accu  1.0
Epoch  468 Loss  0.022299179807305336 Accu  1.0
Epoch  469 Loss  0.022215191274881363 Accu  1.0
Epoch  470 Loss  0.02213173918426037 Accu  1.0
Epoch  471 Loss  0.0220488291233778 Accu  1.0
Epoch  472 Loss  0.02196645550429821 Accu  1.0
Epoch  473 Loss  0.021884603425860405 Accu  1.0
Epoch  474 Loss  0.021803269162774086 Accu  1.0
Epoch  475 Loss  0.021722448989748955 Accu  1.0
Epoch  476 Loss  0.021642155945301056 Accu  1.0
Epoch  477 Loss  0.021562358364462852 Accu  1.0
Epoch  478 Loss  0.021483076736330986 Accu  1.0
Epoch  479 Loss  0.021404286846518517 Accu  1.0
Epoch  480 Loss  0.021325992420315742 Accu  1.0
Epoch  481 Loss  0.021248191595077515 Accu  1.0
Epoch  482 Loss  0.021170878782868385 Accu  1.0
Epoch  483 Loss  0.021094050258398056 Accu  1.0
Epoch  484 Loss  0.021017689257860184 Accu  1.0
Epoch  485 Loss  0.020941810682415962 Accu  1.0
Epoch  486 Loss  0.020866407081484795 Accu  1.0
Epoch  487 Loss  0.020791465416550636 Accu  1.0
```

```
Epoch  488 Loss  0.020716974511742592 Accu  1.0
Epoch  489 Loss  0.020642954856157303 Accu  1.0
Epoch  490 Loss  0.020569385960698128 Accu  1.0
Epoch  491 Loss  0.020496264100074768 Accu  1.0
Epoch  492 Loss  0.02042359486222267 Accu  1.0
Epoch  493 Loss  0.02035137265920639 Accu  1.0
Epoch  494 Loss  0.02027958072721958 Accu  1.0
Epoch  495 Loss  0.020208220928907394 Accu  1.0
Epoch  496 Loss  0.020137306302785873 Accu  1.0
Epoch  497 Loss  0.02006680890917778 Accu  1.0
Epoch  498 Loss  0.01999674178659916 Accu  1.0
Epoch  499 Loss  0.019927095621824265 Accu  1.0
```

4.4 Visualize the final node embeddings

Visualize your final embedding here! You can visually compare the figure with the previous embedding figure. After training, you should oberserve that the two classes are more evidently separated. This is a great sanitity check for your implementation as well.

[19]:
```
# Visualize the final learned embedding
visualize_emb(emb)
```



5 Submission

In order to get credit, you must go submit your answers on Gradescope.