Node Classification using Graph Convolutional Networks

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This node classification task uses CORA dataset from https://lings.soe.ucsc.edu/data

The dataset consists of 2708 nodes which correspond to scientific publications.

The nodes are classified into **7** categories indicating the topics of each document.

The edges indicate whether a document is cited by the other or vice versa.

Each node has 1433 features which is described by a 0/1-valued vector, indicating the bag-of-words from the dictionary.

This is an undirected graph problem

```
In [ ]: #importing dependencies
        import numpy as np
        import os
        import networkx as nx
        from keras.utils import to_categorical
        from sklearn.preprocessing import LabelEncoder
        from sklearn.utils import shuffle
        from sklearn.metrics import classification_report
        from spektral.layers import GraphConv
        from tensorflow.keras.models import Model
        from tensorflow.keras.layers import Input, Dropout, Dense
        from tensorflow.keras import Sequential
        from tensorflow.keras.optimizers import Adam
        from tensorflow.keras.callbacks import TensorBoard, EarlyStopping
        import tensorflow as tf
        from tensorflow.keras.regularizers import 12
        from collections import Counter
        from sklearn.manifold import TSNE
        import matplotlib.pyplot as plt
```

Data Loading and Preprocessing

We are going to use the edges connecting the (from file cora.cites).

The nodes are loaded from file **cora.content**.

In cora.content file:

The **first** element indicates the **node name**

The **second** until the last second elements indicate the **node features**

The last element indicates the label of that particular node

In cora.cites file:

Each line indicates the tuple of connected nodes

Parsing the data

```
In [ ]: #parse the data
        labels = []
        nodes = []
        X = []
        for i,data in enumerate(all_data):
            elements = data.split('\t')
            labels.append(elements[-1])
            X.append(elements[1:-1])
            nodes.append(elements[0])
        X = np.array(X,dtype=int)
        N = X.shape[0] #the number of nodes
        F = X.shape[1] #the size of node features
        print('X shape: ', X.shape)
        #parse the edge
        edge_list=[]
        for edge in all_edges:
            e = edge.split('\t')
            edge_list.append((e[0],e[1]))
        print('\nNumber of nodes (N): ', N)
        print('\nNumber of features (F) of each node: ', F)
        print('\nCategories: ', set(labels))
        num_classes = len(set(labels))
        print('\nNumber of classes: ', num_classes)
        X shape: (2708, 1433)
        Number of nodes (N): 2708
        Number of features (F) of each node: 1433
        Categories: {'Neural_Networks', 'Reinforcement_Learning', 'Probabilistic_Methods', 'Genetic_Algorithms', 'Ru
        le_Learning', 'Theory', 'Case_Based'}
        Number of classes: 7
```

Select examples for training, validation, and test then set the mask

```
#get the indices that do not go to traning data
    rest_idx = [x for x in range(len(labels)) if x not in train_idx]
#get the first val_num
    val_idx = rest_idx[:val_num]
    test_idx = rest_idx[val_num:(val_num+test_num)]
    return train_idx, val_idx,test_idx

train_idx,val_idx,test_idx = limit_data(labels)

In []: #set the mask
    train_mask = np.zeros((N,),dtype=bool)
    train_mask[train_idx] = True

    val_mask = np.zeros((N,),dtype=bool)
    val_mask[val_idx] = True

test_mask = np.zeros((N,),dtype=bool)
    test_mask[test_idx] = True
```

Show Data Distribution

```
In []: print("All Data Distribution: \n{}".format(Counter(labels)))

All Data Distribution:
    Counter({'Neural_Networks': 818, 'Probabilistic_Methods': 426, 'Genetic_Algorithms': 418, 'Theory': 351, 'Case_Based': 298, 'Reinforcement_Learning': 217, 'Rule_Learning': 180})

In []: print("Training Data Distribution: \n{}".format(Counter([labels[i] for i in train_idx])))

    Training Data Distribution:
    Counter({'Reinforcement_Learning': 20, 'Probabilistic_Methods': 20, 'Neural_Networks': 20, 'Case_Based': 20, 'Theory': 20, 'Genetic_Algorithms': 20, 'Rule_Learning': 20})

In []: print("Validation Data Distribution: \n{}".format(Counter([labels[i] for i in val_idx])))

    Validation Data Distribution:
    Counter({'Neural_Networks': 172, 'Genetic_Algorithms': 78, 'Probabilistic_Methods': 72, 'Theory': 63, 'Case_B ased': 58, 'Reinforcement_Learning': 35, 'Rule_Learning': 22})
```

Convert the labels to one hot encoding

```
In [ ]: def encode_label(labels):
    label_encoder = LabelEncoder()
    labels = label_encoder.fit_transform(labels)
    labels = to_categorical(labels)
    return labels, label_encoder.classes_
labels_encoded, classes = encode_label(labels)
```

Build a graph on NetworkX using the obtained nodes and edges list

```
In []: #build the graph
    G = nx.Graph()
    G.add_nodes_from(nodes)
    G.add_edges_from(edge_list)

#bbtain the adjacency matrix (A)
    A = nx.adjacency_matrix(G)
    print('Graph info: ', nx.info(G))

Graph info: Name:
    Type: Graph
    Number of nodes: 2708
    Number of edges: 5278
    Average degree: 3.8981
```

Building and Training Graph Convolutional Networks

```
In [ ]: # Parameters
        channels = 16
                                # Number of channels in the first layer
        dropout = 0.5  # Dropout rate for the features
12_reg = 5e-4  # L2 regularization rate
        learning_rate = 1e-2  # Learning rate
        epochs = 100 # Number of training epochs
es_patience = 50 # Patience for early stopping
        # Preprocessing operations
        A = GraphConv.preprocess(A).astype('f4')
        # Model definition
        X_in = Input(shape=(F, ))
        fltr_in = Input((N, ), sparse=True)
        dropout 1 = Dropout(dropout)(X in)
        graph_conv_1 = GraphConv(channels,
                                 activation='relu',
                                 kernel_regularizer=12(12_reg),
                                 use_bias=False)([dropout_1, fltr_in])
        dropout 2 = Dropout(dropout)(graph conv 1)
        graph_conv_2 = GraphConv(num_classes,
                                 activation='softmax',
                                 use_bias=False)([dropout_2, fltr_in])
        # Build model
        model = Model(inputs=[X_in, fltr_in], outputs=graph_conv_2)
        optimizer = Adam(lr=learning_rate)
        model.compile(optimizer=optimizer,
                      loss='categorical_crossentropy',
                      weighted metrics=['acc'])
        model.summary()
        tbCallBack_GCN = tf.keras.callbacks.TensorBoard(
            log_dir='./Tensorboard_GCN_cora',
        callback_GCN = [tbCallBack_GCN]
        Model: "model"
        Layer (type)
                                        Output Shape
                                                             Param #
        input_1 (InputLayer)
                                        [(None, 1433)]
        dropout (Dropout)
                                        (None, 1433)
                                                             0
                                                                         input_1[0][0]
                                        [(None, 2708)]
        input_2 (InputLayer)
                                                             0
                                                             22928
        graph_conv (GraphConv)
                                        (None, 16)
                                                                         dropout[0][0]
                                                                         input_2[0][0]
        dropout_1 (Dropout)
                                        (None, 16)
                                                                         graph_conv[0][0]
        graph_conv_1 (GraphConv)
                                        (None, 7)
                                                                         dropout_1[0][0]
                                                             112
                                                                         input_2[0][0]
        ______
        Total params: 23,040
        Trainable params: 23,040
        Non-trainable params: 0
In [ ]: # Train model
        validation_data = ([X, A], labels_encoded, val_mask)
        model.fit([X, A],
                  labels_encoded,
                  sample_weight=train_mask,
                  epochs=epochs,
```

```
batch_size=N,
validation_data=validation_data,
shuffle=False,
callbacks=[
    EarlyStopping(patience=es_patience, restore_best_weights=True),
    tbCallBack_GCN
])
```

```
Epoch 1/100
1/1 [============] - 0s 434ms/step - loss: 0.1162 - acc: 0.1429 - val_loss: 0.3662 - val_ac
c: 0.2420
Epoch 2/100
n_batch_end) is slow compared to the batch update (0.195233). Check your callbacks.
c: 0.3440
Epoch 3/100
c: 0.3960
Epoch 4/100
1/1 [============= ] - 0s 300ms/step - loss: 0.0976 - acc: 0.5571 - val_loss: 0.3371 - val_ac
c: 0.4100
Epoch 5/100
1/1 [============ ] - 0s 290ms/step - loss: 0.0918 - acc: 0.5357 - val_loss: 0.3280 - val_ac
c: 0.4220
Epoch 6/100
1/1 [=========== ] - 0s 266ms/step - loss: 0.0872 - acc: 0.5929 - val loss: 0.3197 - val ac
c: 0.4280
Epoch 7/100
1/1 [==============] - 0s 249ms/step - loss: 0.0831 - acc: 0.5714 - val_loss: 0.3115 - val_ac
c: 0.4420
Fnoch 8/100
c: 0.4760
Epoch 9/100
c: 0.5280
Epoch 10/100
c: 0.5740
Epoch 11/100
c: 0.5980
Epoch 12/100
1/1 [============= ] - 0s 263ms/step - loss: 0.0732 - acc: 0.7429 - val_loss: 0.2731 - val_ac
c: 0.6360
Epoch 13/100
c: 0.6600
Epoch 14/100
1/1 [============= ] - 0s 240ms/step - loss: 0.0694 - acc: 0.8143 - val_loss: 0.2597 - val_ac
c: 0.6900
Epoch 15/100
1/1 [============= ] - 0s 242ms/step - loss: 0.0648 - acc: 0.8571 - val_loss: 0.2531 - val_ac
c: 0.7140
Epoch 16/100
c: 0.7340
Epoch 17/100
1/1 [=========== ] - 0s 247ms/step - loss: 0.0636 - acc: 0.8857 - val loss: 0.2404 - val ac
c: 0.7540
Epoch 18/100
c: 0.7640
Epoch 19/100
1/1 [=========== ] - 0s 257ms/step - loss: 0.0618 - acc: 0.9143 - val loss: 0.2288 - val ac
c: 0.7760
Epoch 20/100
c: 0.7820
Epoch 21/100
1/1 [============= ] - 0s 236ms/step - loss: 0.0588 - acc: 0.9143 - val_loss: 0.2191 - val_ac
c: 0.7820
Epoch 22/100
1/1 [===========] - 0s 206ms/step - loss: 0.0571 - acc: 0.9000 - val_loss: 0.2149 - val_ac
c: 0.7860
Epoch 23/100
1/1 [===========] - 0s 243ms/step - loss: 0.0564 - acc: 0.9000 - val_loss: 0.2111 - val_ac
c: 0.7820
```

```
Epoch 24/100
1/1 [============= ] - 0s 237ms/step - loss: 0.0565 - acc: 0.8929 - val_loss: 0.2076 - val_ac
c: 0.7880
Epoch 25/100
c: 0.7840
Epoch 26/100
1/1 [============ ] - 0s 244ms/step - loss: 0.0543 - acc: 0.9214 - val_loss: 0.2023 - val_ac
c: 0.7880
Epoch 27/100
c: 0.7900
Epoch 28/100
1/1 [=========== ] - 0s 247ms/step - loss: 0.0530 - acc: 0.9357 - val loss: 0.1978 - val ac
c: 0.7940
Epoch 29/100
c: 0.7920
Epoch 30/100
1/1 [============= ] - 0s 200ms/step - loss: 0.0511 - acc: 0.9214 - val_loss: 0.1941 - val_ac
c: 0.7880
Epoch 31/100
c: 0.7960
Epoch 32/100
c: 0.7960
Epoch 33/100
c: 0.7940
Epoch 34/100
1/1 [============= ] - 0s 183ms/step - loss: 0.0466 - acc: 0.9643 - val_loss: 0.1859 - val_ac
c: 0.7960
Epoch 35/100
c: 0.7960
Epoch 36/100
c: 0.7940
Epoch 37/100
c: 0.7940
Epoch 38/100
c: 0.7940
Epoch 39/100
1/1 [============ ] - 0s 163ms/step - loss: 0.0447 - acc: 0.9143 - val loss: 0.1802 - val ac
c: 0.7980
Epoch 40/100
c: 0.7960
Epoch 41/100
1/1 [============ ] - 0s 170ms/step - loss: 0.0442 - acc: 0.9286 - val_loss: 0.1778 - val_ac
c: 0.7940
Epoch 42/100
1/1 [============== ] - 0s 190ms/step - loss: 0.0436 - acc: 0.9500 - val_loss: 0.1768 - val_ac
c: 0.7960
Epoch 43/100
c: 0.7960
Epoch 44/100
c: 0.7900
Epoch 45/100
c: 0.7900
Epoch 46/100
c: 0.7840
Epoch 47/100
1/1 [=====================] - 0s 169ms/step - loss: 0.0406 - acc: 0.9786 - val_loss: 0.1712 - val_ac
```

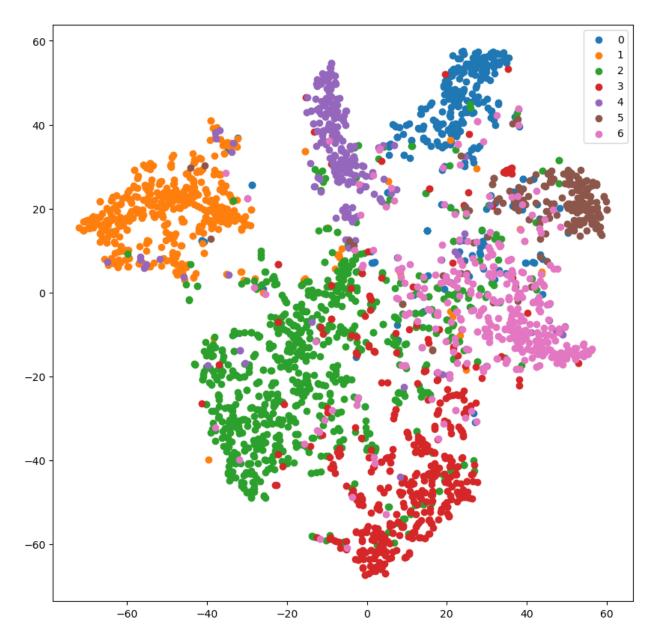
```
c: 0.7860
Epoch 48/100
c: 0.7900
Epoch 49/100
1/1 [============= ] - 0s 166ms/step - loss: 0.0418 - acc: 0.9429 - val_loss: 0.1692 - val_ac
c: 0.7840
Epoch 50/100
1/1 [===========] - 0s 170ms/step - loss: 0.0403 - acc: 0.9500 - val_loss: 0.1679 - val_ac
c: 0.7800
Epoch 51/100
c: 0.7800
Epoch 52/100
1/1 [============= ] - 0s 174ms/step - loss: 0.0393 - acc: 0.9500 - val_loss: 0.1663 - val_ac
c: 0.7820
Epoch 53/100
1/1 [===========] - 0s 169ms/step - loss: 0.0396 - acc: 0.9500 - val_loss: 0.1657 - val_ac
c: 0.7860
Epoch 54/100
c: 0.7820
Epoch 55/100
c: 0.7820
Epoch 56/100
c: 0.7820
Epoch 57/100
1/1 [============= ] - 0s 188ms/step - loss: 0.0373 - acc: 0.9571 - val_loss: 0.1646 - val_ac
c: 0.7840
Epoch 58/100
c: 0.7780
Epoch 59/100
c: 0.7780
Epoch 60/100
c: 0.7800
Epoch 61/100
c: 0.7880
Epoch 62/100
c: 0.7860
Epoch 63/100
1/1 [============= ] - 0s 184ms/step - loss: 0.0363 - acc: 0.9500 - val_loss: 0.1611 - val_ac
c: 0.7840
Epoch 64/100
c: 0.7860
Epoch 65/100
1/1 [============== ] - 0s 270ms/step - loss: 0.0354 - acc: 0.9357 - val_loss: 0.1605 - val_ac
c: 0.7920
Epoch 66/100
1/1 [============= ] - 0s 200ms/step - loss: 0.0350 - acc: 0.9500 - val_loss: 0.1594 - val_ac
c: 0.8020
Epoch 67/100
c: 0.7960
Epoch 68/100
1/1 [============ ] - 0s 188ms/step - loss: 0.0353 - acc: 0.9429 - val loss: 0.1592 - val ac
c: 0.7960
Epoch 69/100
c: 0.7920
Epoch 70/100
1/1 [============= ] - 0s 180ms/step - loss: 0.0346 - acc: 0.9857 - val_loss: 0.1597 - val_ac
c: 0.7800
Epoch 71/100
```

```
c: 0.7700
Epoch 72/100
1/1 [============= ] - 0s 195ms/step - loss: 0.0334 - acc: 0.9714 - val_loss: 0.1599 - val_ac
c: 0.7700
Epoch 73/100
c: 0.7720
Epoch 74/100
c: 0.7760
Epoch 75/100
1/1 [============= ] - 0s 183ms/step - loss: 0.0342 - acc: 0.9429 - val_loss: 0.1555 - val_ac
c: 0.7820
Epoch 76/100
1/1 [============= ] - 0s 183ms/step - loss: 0.0337 - acc: 0.9500 - val_loss: 0.1541 - val_ac
c: 0.7880
Epoch 77/100
1/1 [=========== ] - 0s 190ms/step - loss: 0.0353 - acc: 0.9714 - val loss: 0.1531 - val ac
c: 0.7940
Epoch 78/100
c: 0.8040
Fnoch 79/100
c: 0.8040
Epoch 80/100
c: 0.7960
Epoch 81/100
c: 0.7840
Epoch 82/100
c: 0.7840
Epoch 83/100
1/1 [============= ] - 0s 189ms/step - loss: 0.0316 - acc: 0.9714 - val_loss: 0.1551 - val_ac
c: 0.7820
Epoch 84/100
c: 0.7880
Epoch 85/100
1/1 [============= ] - 0s 185ms/step - loss: 0.0323 - acc: 0.9500 - val_loss: 0.1537 - val_ac
c: 0.7820
Epoch 86/100
c: 0.7860
Epoch 87/100
c: 0.7740
Epoch 88/100
1/1 [=========== ] - 0s 182ms/step - loss: 0.0335 - acc: 0.9357 - val loss: 0.1546 - val ac
c: 0.7660
Epoch 89/100
c: 0.7700
Epoch 90/100
1/1 [=========== ] - 0s 180ms/step - loss: 0.0310 - acc: 0.9714 - val loss: 0.1569 - val ac
c: 0.7660
Epoch 91/100
c: 0.7740
Epoch 92/100
1/1 [============= ] - 0s 187ms/step - loss: 0.0290 - acc: 0.9571 - val_loss: 0.1554 - val_ac
c: 0.7820
Epoch 93/100
1/1 [============= ] - 0s 187ms/step - loss: 0.0330 - acc: 0.9500 - val_loss: 0.1542 - val_ac
c: 0.7940
Epoch 94/100
c: 0.8000
```

```
Epoch 95/100
      c: 0.7980
     Epoch 96/100
     c: 0.7920
     Epoch 97/100
     1/1 [============= ] - 0s 185ms/step - loss: 0.0280 - acc: 0.9857 - val_loss: 0.1499 - val_ac
      c: 0.7800
      Epoch 98/100
     c: 0.7800
     Epoch 99/100
     1/1 [=========== ] - 0s 187ms/step - loss: 0.0296 - acc: 0.9786 - val loss: 0.1482 - val ac
      c: 0.7780
      Epoch 100/100
      c: 0.7780
Out[]: <tensorflow.python.keras.callbacks.History at 0x1309f37b648>
In [ ]: # Evaluate model
     X_{te} = X[test_mask]
     A_te = A[test_mask,:][:,test_mask]
     y_te = labels_encoded[test_mask]
     y_pred = model.predict([X_te, A_te], batch_size=N)
     report = classification_report(np.argmax(y_te,axis=1), np.argmax(y_pred,axis=1), target_names=classes)
     print('GCN Classification Report: \n {}'.format(report))
     GCN Classification Report:
                                recall f1-score
                       precision
                                            support
              Case_Based
                         0.68
                                0.72
                                       0.70
                                               114
        Genetic_Algorithms
                         0.86
                                0.87
                                       0.87
                                               156
                         0.80
                                0.68
                                       0.74
                                               290
          Neural_Networks
      Probabilistic_Methods
                         0.78
                                0.74
                                       0.76
                                               172
                                0.79
      Reinforcement_Learning
                         0.70
                                       0.74
                                               85
                         0.56
                                0.73
                                       0.64
                                               60
            Rule_Learning
                Theory
                         0.61
                                0.68
                                       0.64
                                               123
                                       0.74
                                              1000
               accuracy
                          0.71
                                0.74
                                       0.73
                                              1000
               macro avg
            weighted avg
                          0.75
                                0.74
                                       0.74
                                              1000
```

Get hidden layer representation for GCN

```
In [ ]: layer_outputs = [layer.output for layer in model.layers]
        activation model = Model(inputs=model.input, outputs=layer_outputs)
        activations = activation model.predict([X,A],batch size=N)
        #Get t-SNE Representation
        #get the hidden layer representation after the first GCN layer
        x_tsne = TSNE(n_components=2).fit_transform(activations[3])
In [ ]: def plot_tSNE(labels_encoded,x_tsne):
            color_map = np.argmax(labels_encoded, axis=1)
            plt.figure(figsize=(10,10))
            for cl in range(num_classes):
                indices = np.where(color_map==cl)
                indices = indices[0]
                plt.scatter(x_tsne[indices,0], x_tsne[indices, 1], label=cl)
            plt.legend()
            plt.show()
        plot_tSNE(labels_encoded,x_tsne)
```



Comparison to Fully-Connected Neural Networks

Building and Training FNN

```
model_fnn.compile(optimizer=optimizer,
              loss='categorical_crossentropy',
              weighted_metrics=['acc'])
#define TensorBoard
tbCallBack_FNN = TensorBoard(
    log_dir='./Tensorboard_FNN_cora',
#Train model
validation_data_fnn = (X, labels_encoded, val_mask)
model_fnn.fit(
                X,labels_encoded,
                sample_weight=train_mask,
                epochs=epochs,
                batch_size=N,
                validation_data=validation_data_fnn,
                shuffle=False,
                callbacks=[
                  EarlyStopping(patience=es_patience, restore_best_weights=True),
                 tbCallBack_FNN
          ])
```

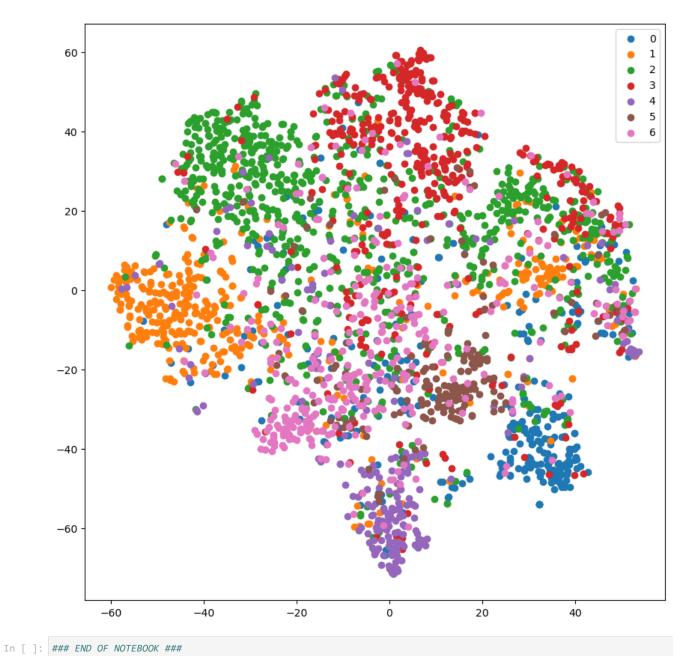
```
Epoch 1/100
1/1 [============] - 0s 302ms/step - loss: 0.2181 - acc: 0.1786 - val_loss: 0.4333 - val_ac
c: 0.3040
Epoch 2/100
n_batch_end) is slow compared to the batch update (0.168763). Check your callbacks.
c: 0.4340
Epoch 3/100
c: 0.5120
Epoch 4/100
1/1 [============= ] - 0s 185ms/step - loss: 0.1091 - acc: 0.7714 - val_loss: 0.3299 - val_ac
c: 0.5480
Epoch 5/100
1/1 [============ ] - 0s 184ms/step - loss: 0.0850 - acc: 0.8286 - val_loss: 0.2965 - val_ac
c: 0.5880
Epoch 6/100
1/1 [=========== ] - 0s 190ms/step - loss: 0.0630 - acc: 0.8857 - val loss: 0.2728 - val ac
c: 0.5760
Epoch 7/100
1/1 [==============] - 0s 187ms/step - loss: 0.0523 - acc: 0.9143 - val_loss: 0.2673 - val_ac
c: 0.5560
Fnoch 8/100
c: 0.5640
Epoch 9/100
c: 0.5600
Epoch 10/100
c: 0.5760
Epoch 11/100
c: 0.5460
Epoch 12/100
c: 0.5300
Epoch 13/100
c: 0.5100
Epoch 14/100
1/1 [============= ] - 0s 284ms/step - loss: 0.0378 - acc: 0.9929 - val_loss: 0.3877 - val_ac
c: 0.5200
Epoch 15/100
1/1 [============= ] - 0s 261ms/step - loss: 0.0364 - acc: 0.9929 - val_loss: 0.4196 - val_ac
c: 0.4940
Epoch 16/100
c: 0.4960
Epoch 17/100
1/1 [=========== ] - 0s 250ms/step - loss: 0.0300 - acc: 1.0000 - val loss: 0.4248 - val ac
c: 0.5000
Epoch 18/100
c: 0.5120
Epoch 19/100
1/1 [=========== ] - 0s 273ms/step - loss: 0.0263 - acc: 0.9786 - val loss: 0.4404 - val ac
c: 0.5240
Epoch 20/100
1/1 [============== ] - 0s 298ms/step - loss: 0.0228 - acc: 1.0000 - val_loss: 0.4463 - val_ac
c: 0.5380
Epoch 21/100
1/1 [============= ] - 0s 272ms/step - loss: 0.0252 - acc: 0.9786 - val_loss: 0.4559 - val_ac
c: 0.5160
Epoch 22/100
c: 0.4940
Epoch 23/100
c: 0.4980
```

```
Epoch 24/100
1/1 [============= ] - 0s 297ms/step - loss: 0.0195 - acc: 0.9929 - val_loss: 0.3978 - val_ac
c: 0.5220
Epoch 25/100
1/1 [============] - 0s 278ms/step - loss: 0.0247 - acc: 0.9571 - val_loss: 0.3813 - val_ac
c: 0.5020
Epoch 26/100
1/1 [============= ] - 0s 254ms/step - loss: 0.0214 - acc: 0.9857 - val_loss: 0.3844 - val_ac
c: 0.4860
Epoch 27/100
c: 0.4980
Epoch 28/100
1/1 [=========== ] - 0s 306ms/step - loss: 0.0279 - acc: 0.9500 - val loss: 0.3631 - val ac
c: 0.4920
Epoch 29/100
c: 0.4660
Epoch 30/100
1/1 [============= ] - 0s 270ms/step - loss: 0.0210 - acc: 0.9929 - val_loss: 0.3902 - val_ac
c: 0.4660
Epoch 31/100
c: 0.4780
Epoch 32/100
c: 0.4960
Epoch 33/100
c: 0.5040
Epoch 34/100
1/1 [============= ] - 0s 248ms/step - loss: 0.0246 - acc: 0.9786 - val_loss: 0.3403 - val_ac
c: 0.5260
Epoch 35/100
1/1 [============ ] - 0s 345ms/step - loss: 0.0255 - acc: 0.9857 - val loss: 0.3351 - val ac
c: 0.5160
Epoch 36/100
c: 0.5040
Epoch 37/100
c: 0.4960
Epoch 38/100
c: 0.5000
Epoch 39/100
1/1 [============ ] - 0s 238ms/step - loss: 0.0248 - acc: 1.0000 - val loss: 0.3361 - val ac
c: 0.5040
Epoch 40/100
c: 0.5240
Epoch 41/100
1/1 [============= ] - 0s 236ms/step - loss: 0.0241 - acc: 1.0000 - val_loss: 0.3213 - val_ac
c: 0.5380
Epoch 42/100
c: 0.5500
Epoch 43/100
c: 0.5540
Epoch 44/100
c: 0.5680
Epoch 45/100
c: 0.5820
Epoch 46/100
c: 0.5800
Epoch 47/100
1/1 [================] - 0s 194ms/step - loss: 0.0209 - acc: 0.9929 - val_loss: 0.3061 - val_ac
```

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```
c: 0.5740
     Epoch 48/100
     c: 0.5680
     1/1 [============= ] - 0s 188ms/step - loss: 0.0201 - acc: 0.9929 - val_loss: 0.3084 - val_ac
     c: 0.5460
     Epoch 50/100
     c: 0.5300
     Epoch 51/100
     c: 0.5200
     Epoch 52/100
     c: 0.5080
     Epoch 53/100
     c: 0.5200
     Epoch 54/100
     c: 0.5320
     Epoch 55/100
     1/1 [=========== ] - 0s 184ms/step - loss: 0.0162 - acc: 0.9929 - val loss: 0.3083 - val ac
     c: 0.5320
     1/1 [==============] - 0s 173ms/step - loss: 0.0156 - acc: 0.9929 - val_loss: 0.3087 - val_ac
     c: 0.5340
     Epoch 57/100
     1/1 [============ ] - 0s 188ms/step - loss: 0.0150 - acc: 0.9929 - val_loss: 0.3097 - val_ac
Out[]: <tensorflow.python.keras.callbacks.History at 0x130ad831f48>
In [ ]: # Evaluate model
     y_pred = model_fnn.predict(X_te)
     report = classification_report(np.argmax(y_te,axis=1), np.argmax(y_pred,axis=1), target_names=classes)
     print('FCNN Classification Report: \n {}'.format(report))
     FCNN Classification Report:
                             recall f1-score support
                     precision
            Case Based
                       0.53
                             0.48
                                    0.50
                                           114
                             0.83
        Genetic_Algorithms
                       0.59
                                    0.69
                                           156
         Neural_Networks
                       0.72
                             0.47
                                    0.57
                                           290
     Probabilistic_Methods
                       0.76
                             0.47
                                   0.58
                                           172
     Reinforcement_Learning
                       0.43
                             0.59
                                   0.50
                                           85
                       0.38
                             0.72
                                    0.49
           Rule_Learning
                                           60
               Theory
                       0.41
                             0.50
                                    0.45
                                           123
              accuracy
                                    0.56
                                          1000
                       0.54
                             0.58
             macro avg
                                    0.54
                                          1000
           weighted avg
                       0.60
                             0.56
                                    0.56
                                          1000
```

Get hidden layer representation for FNN



file:///C:/Users/USER PC/Documents/HCMUT/221/Mathematical/Graph_Convolutional_Networks_Node_Classification/output/100.html