Part 2: Graph Convolutional Networks (GCN)

Assignment 2

Name: Saikat Moi

Roll Number: 20CS10050

In [ ]:
```
# import important libbraries

import os
import math
import numpy as np
import time

#for plotting

import matplotlib.pyplot as plt
import seaborn as sns

import tqdm

# pytorch

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.utils.data as data
import torch.optim as optim

# torchvision
import torchvision
from torchvision.datasets import CIFAR10
from torchvision import transforms


import pytorch_lightning as pl
from pytorch_lightning.callbacks import LearningRateMonitor, ModelCheckpoint

device = torch.device("cuda:0") if torch.cuda.is_available() else torch.device("
print(device)
```

```
cpu
```

In [ ]:
```
import torch_geometric
import torch_geometric.nn as g_nn
import torch_geometric.data as g_data
import networkx as nx
```

In [ ]:
```
import numpy as np
import networkx as nx
import torch
```

```
import torch.nn as nn
import torch.optim as optim
from torch.nn.functional import relu, dropout
from sklearn.model_selection import train_test_split
import torch.nn.functional as F
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

def load_data():
    # Read .content file to get node features and labels
    with open("../../dataset/cora.content", "r") as content_file:
        content_lines = content_file.readlines()

    # Read .cites files to build the citation graph
    train_cites = np.loadtxt("../../dataset/cora_train.cites", dtype=int)
    test_cites = np.loadtxt("../../dataset/cora_test.cites", dtype=int)

    # Create a directed graph
    citation_graph = nx.DiGraph()
    train_graph = nx.DiGraph()
    test_graph = nx.DiGraph()

    # Add edges to the graph
    for paper1, paper2 in train_cites:
        citation_graph.add_edge(paper2, paper1)  # Adding the edge with correct
        train_graph.add_edge(paper2, paper1)



    for paper1, paper2 in test_cites:
        citation_graph.add_edge(paper2, paper1)  # Adding the edge with correct
        test_graph.add_edge(paper2, paper1)


    # Extract node features and labels
    node_features = {}
    node_labels = {}
    labels = []
    for line in content_lines:
        data = line.strip().split()
        paper_id = int(data[0])
        class_label = data[-1]
        node_features[paper_id] =([int(x) for x in data[1:-1]])
        global features_dimension
        features_dimension=len(node_features[paper_id])
        node_labels[paper_id] = class_label
        labels.append(class_label)


    #print(labels)
    my_set = set(labels)
    print(my_set)
    labels=list(my_set)


    # Map paper IDs to one-hot encoded labels
    for line in content_lines:
        data = line.strip().split()
        paper_id = int(data[0])
        class_label = data[-1]
        node_labels[paper_id] = labels.index(class_label)
```

```python
    return node_features, node_labels, citation_graph,train_graph,test_graph


node_features, node_labels, citation_graph,train_graph,test_graph= load_data()

features_train = []
labels_train=[]
for node_id in train_graph.nodes():
    features_train.append(node_features[node_id])
    labels_train.append(node_labels[node_id])

features_test = []
labels_test=[]

for node_id in test_graph.nodes():

    features_test.append(node_features[node_id])
    labels_test.append(node_labels[node_id])


features_all = []
labels_all=[]
for node_id in citation_graph.nodes():
    features_all.append(node_features[node_id])
    labels_all.append(node_labels[node_id])


adj_train= nx.adjacency_matrix(train_graph).todense()
adj_test=nx.adjacency_matrix(test_graph).todense()
adj_all=nx.adjacency_matrix(citation_graph).todense()


# Convert adjacency matrix and feature matrix to PyTorch tensors
adj_train = torch.FloatTensor(adj_train)
adj_test = torch.FloatTensor(adj_test)
features_train = torch.FloatTensor(features_train)
features_test = torch.FloatTensor(features_test)
labels_train = torch.LongTensor(labels_train)
labels_test = torch.LongTensor(labels_test)
adj_all = torch.FloatTensor(adj_all)
labels_all = torch.LongTensor(labels_all)
features_all = torch.FloatTensor(features_all)
```

```
{'Theory', 'Reinforcement_Learning', 'Probabilistic_Methods', 'Case_Based', 'Gene
tic_Algorithms', 'Rule_Learning', 'Neural_Networks'}
```

In [ ]:

```python
class GraphConvolutionLayer(nn.Module):
    def __init__(self, input_dim, output_dim):
        super(GraphConvolutionLayer, self).__init__()
        self.linear = nn.Linear(input_dim, output_dim)

    def forward(self, adjacency_matrix, input_features):
        output = torch.mm(adjacency_matrix, input_features)
        output = self.linear(output)
        return output
```

```python
class GCN(nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout_rate):
        super(GCN, self).__init__()
        self.gc1 = GraphConvolutionLayer(input_dim, hidden_dim)
        self.gc2 = GraphConvolutionLayer(hidden_dim, output_dim)
        self.dropout = nn.Dropout(dropout_rate)

    def forward(self, adjacency_matrix, input_features):
        h = self.gc1(adjacency_matrix, input_features)
        h = F.relu(h)
        h = self.dropout(h)
        h = self.gc2(adjacency_matrix, h)
        return h
```

In [ ]:

```python
# Initialize model
input_dim = features_dimension
hidden_dim = 16
output_dim = 7
dropout_rate = 0.5
model = GCN(input_dim, hidden_dim, output_dim, dropout_rate)

# Define loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)

# Training loop
epochs = 500
for epoch in range(epochs):
    model.train()
    optimizer.zero_grad()
    output = model(adj_train, features_train)
    loss = criterion(output, labels_train)
    loss.backward()
    optimizer.step()
    print(f'Epoch [{epoch + 1}/{epochs}], Loss: {loss.item()}')
```

```
Epoch [1/500], Loss: 1.9907572269439697
Epoch [2/500], Loss: 1.8694099187850952
Epoch [3/500], Loss: 1.724833607673645
Epoch [4/500], Loss: 1.6306660175323486
Epoch [5/500], Loss: 1.5436969995498657
Epoch [6/500], Loss: 1.4944558143615723
Epoch [7/500], Loss: 1.4548755884170532
Epoch [8/500], Loss: 1.4074416160583496
Epoch [9/500], Loss: 1.3831820487976074
Epoch [10/500], Loss: 1.3370227813720703
Epoch [11/500], Loss: 1.279876947402954
Epoch [12/500], Loss: 1.2909314632415771
Epoch [13/500], Loss: 1.2848511934280396
Epoch [14/500], Loss: 1.2377833127975464
Epoch [15/500], Loss: 1.2289363145828247
Epoch [16/500], Loss: 1.2160353660583496
Epoch [17/500], Loss: 1.2297110557556152
Epoch [18/500], Loss: 1.18934166431427
Epoch [19/500], Loss: 1.197855830192566
Epoch [20/500], Loss: 1.1703835725784302
Epoch [21/500], Loss: 1.1651896238327026
Epoch [22/500], Loss: 1.1777784824371338
Epoch [23/500], Loss: 1.1843152046203613
Epoch [24/500], Loss: 1.163120985031128
Epoch [25/500], Loss: 1.1713186502456665
Epoch [26/500], Loss: 1.100006103515625
Epoch [27/500], Loss: 1.1339242458343506
Epoch [28/500], Loss: 1.1218980550765991
Epoch [29/500], Loss: 1.0960325002670288
Epoch [30/500], Loss: 1.1087911128997803
Epoch [31/500], Loss: 1.1045496463775635
Epoch [32/500], Loss: 1.1002633571624756
Epoch [33/500], Loss: 1.093818187713623
Epoch [34/500], Loss: 1.0655086040496826
Epoch [35/500], Loss: 1.0944523811340332
Epoch [36/500], Loss: 1.0716192722320557
Epoch [37/500], Loss: 1.0821068286895752
Epoch [38/500], Loss: 1.0528711080551147
Epoch [39/500], Loss: 1.0410399436950684
Epoch [40/500], Loss: 1.0594406127929688
Epoch [41/500], Loss: 1.0232419967651367
Epoch [42/500], Loss: 1.071642518043518
Epoch [43/500], Loss: 1.0434397459030151
Epoch [44/500], Loss: 1.0145444869995117
Epoch [45/500], Loss: 1.0321778059005737
Epoch [46/500], Loss: 1.03225576877594
Epoch [47/500], Loss: 1.0231047868728638
Epoch [48/500], Loss: 1.0442315340042114
Epoch [49/500], Loss: 1.0165643692016602
Epoch [50/500], Loss: 1.0125741958618164
Epoch [51/500], Loss: 1.0592106580734253
Epoch [52/500], Loss: 1.00715970993042
Epoch [53/500], Loss: 1.0264480113983154
Epoch [54/500], Loss: 1.0281530618667603
Epoch [55/500], Loss: 1.0119985342025757
Epoch [56/500], Loss: 1.015369176864624
Epoch [57/500], Loss: 1.0303844213485718
Epoch [58/500], Loss: 1.0078376531600952
Epoch [59/500], Loss: 1.0028682947158813
Epoch [60/500], Loss: 0.9992695450782776
```

```
Epoch [61/500], Loss: 1.0004359483718872
Epoch [62/500], Loss: 1.0358837842941284
Epoch [63/500], Loss: 1.021578073501587
Epoch [64/500], Loss: 0.9934242963790894
Epoch [65/500], Loss: 0.9974661469459534
Epoch [66/500], Loss: 1.0046353340148926
Epoch [67/500], Loss: 0.9930729269981384
Epoch [68/500], Loss: 0.9790947437286377
Epoch [69/500], Loss: 0.9917680621147156
Epoch [70/500], Loss: 0.9829255938529968
Epoch [71/500], Loss: 0.9693365693092346
Epoch [72/500], Loss: 0.9881731271743774
Epoch [73/500], Loss: 0.99625164270401
Epoch [74/500], Loss: 0.9996519684791565
Epoch [75/500], Loss: 0.9770867824554443
Epoch [76/500], Loss: 0.9935956597328186
Epoch [77/500], Loss: 1.0019992589950562
Epoch [78/500], Loss: 0.9740859866142273
Epoch [79/500], Loss: 0.9816660284996033
Epoch [80/500], Loss: 1.0159611701965332
Epoch [81/500], Loss: 0.9650564789772034
Epoch [82/500], Loss: 0.9766110181808472
Epoch [83/500], Loss: 0.9817866086959839
Epoch [84/500], Loss: 1.0028403997421265
Epoch [85/500], Loss: 0.9914678931236267
Epoch [86/500], Loss: 0.9567320942878723
Epoch [87/500], Loss: 0.9965534210205078
Epoch [88/500], Loss: 0.9652073979377747
Epoch [89/500], Loss: 0.9703359007835388
Epoch [90/500], Loss: 0.9664762616157532
Epoch [91/500], Loss: 0.9674874544143677
Epoch [92/500], Loss: 0.9999275803565979
Epoch [93/500], Loss: 0.9831199645996094
Epoch [94/500], Loss: 0.9831196069717407
Epoch [95/500], Loss: 0.963995635509491
Epoch [96/500], Loss: 0.992749810218811
Epoch [97/500], Loss: 0.956269383430481
Epoch [98/500], Loss: 0.982742190361023
Epoch [99/500], Loss: 0.9793300628662109
Epoch [100/500], Loss: 0.9637381434440613
Epoch [101/500], Loss: 0.9593134522438049
Epoch [102/500], Loss: 0.9568652510643005
Epoch [103/500], Loss: 0.9544134140014648
Epoch [104/500], Loss: 0.9548237323760986
Epoch [105/500], Loss: 0.9458826184272766
Epoch [106/500], Loss: 0.9511628746986389
Epoch [107/500], Loss: 0.951880693435669
Epoch [108/500], Loss: 0.9524262547492981
Epoch [109/500], Loss: 0.9932789206504822
Epoch [110/500], Loss: 0.9570776224136353
Epoch [111/500], Loss: 0.9739176034927368
Epoch [112/500], Loss: 0.9622536301612854
Epoch [113/500], Loss: 0.9827479124069214
Epoch [114/500], Loss: 0.9510622024536133
Epoch [115/500], Loss: 0.9528394937515259
Epoch [116/500], Loss: 0.944375932216644З
Epoch [117/500], Loss: 0.9403854012489319
Epoch [118/500], Loss: 0.9446915984153748
Epoch [119/500], Loss: 0.9432061910629272
Epoch [120/500], Loss: 0.9461051225662231
```

```
Epoch [121/500], Loss: 0.9519770741462708
Epoch [122/500], Loss: 0.9350654482841492
Epoch [123/500], Loss: 0.9864267110824585
Epoch [124/500], Loss: 0.9402122497558594
Epoch [125/500], Loss: 0.965722382068634
Epoch [126/500], Loss: 0.9504103660583496
Epoch [127/500], Loss: 0.9422392845153809
Epoch [128/500], Loss: 0.947454571723938
Epoch [129/500], Loss: 0.9331234097480774
Epoch [130/500], Loss: 0.9597346782684326
Epoch [131/500], Loss: 0.9568707346916199
Epoch [132/500], Loss: 0.9702214002609253
Epoch [133/500], Loss: 0.9435354471206665
Epoch [134/500], Loss: 0.9248656034469604
Epoch [135/500], Loss: 0.9429652094841003
Epoch [136/500], Loss: 0.9612581133842468
Epoch [137/500], Loss: 0.9769671559333801
Epoch [138/500], Loss: 0.9389456510543823
Epoch [139/500], Loss: 0.9415068030357361
Epoch [140/500], Loss: 0.934863269329071
Epoch [141/500], Loss: 0.9316192865371704
Epoch [142/500], Loss: 0.9544432163238525
Epoch [143/500], Loss: 0.9561641812324524
Epoch [144/500], Loss: 0.9417693614959717
Epoch [145/500], Loss: 0.9080535173416138
Epoch [146/500], Loss: 0.9402350187301636
Epoch [147/500], Loss: 0.9364340901374817
Epoch [148/500], Loss: 0.947908878326416
Epoch [149/500], Loss: 0.9374920725822449
Epoch [150/500], Loss: 0.9434450268745422
Epoch [151/500], Loss: 0.9346715211868286
Epoch [152/500], Loss: 0.9422457814216614
Epoch [153/500], Loss: 0.9302016496658325
Epoch [154/500], Loss: 0.9476856589317322
Epoch [155/500], Loss: 0.9624768495559692
Epoch [156/500], Loss: 0.9483362436294556
Epoch [157/500], Loss: 0.9294965863227844
Epoch [158/500], Loss: 0.949915885925293
Epoch [159/500], Loss: 0.9155649542808533
Epoch [160/500], Loss: 0.931063175201416
Epoch [161/500], Loss: 0.9399330615997314
Epoch [162/500], Loss: 0.9446491003036499
Epoch [163/500], Loss: 0.9591941237449646
Epoch [164/500], Loss: 0.950667142868042
Epoch [165/500], Loss: 0.9174148440361023
Epoch [166/500], Loss: 0.9314610958099365
Epoch [167/500], Loss: 0.9677612781524658
Epoch [168/500], Loss: 0.9441847205162048
Epoch [169/500], Loss: 0.9312463998794556
Epoch [170/500], Loss: 0.947960615158081
Epoch [171/500], Loss: 0.931433379650116
Epoch [172/500], Loss: 0.9391054511070251
Epoch [173/500], Loss: 0.9483273029327393
Epoch [174/500], Loss: 0.9397791028022766
Epoch [175/500], Loss: 0.9468643069267273
Epoch [176/500], Loss: 0.9274630546569824
Epoch [177/500], Loss: 0.9385272264480591
Epoch [178/500], Loss: 0.9215957522392273
Epoch [179/500], Loss: 0.9269213676452637
Epoch [180/500], Loss: 0.9696810245513916
```

```
Epoch [181/500], Loss: 0.926384449005127
Epoch [182/500], Loss: 0.9158620238304138
Epoch [183/500], Loss: 0.9183326363563538
Epoch [184/500], Loss: 0.9214701652526855
Epoch [185/500], Loss: 0.9464172720909119
Epoch [186/500], Loss: 0.9832576513290405
Epoch [187/500], Loss: 0.9384325742721558
Epoch [188/500], Loss: 0.9322514533996582
Epoch [189/500], Loss: 0.950735867023468
Epoch [190/500], Loss: 0.9102767109870911
Epoch [191/500], Loss: 0.922783374786377
Epoch [192/500], Loss: 0.9106476306915283
Epoch [193/500], Loss: 0.9248608350753784
Epoch [194/500], Loss: 0.9381411075592041
Epoch [195/500], Loss: 0.9881974458694458
Epoch [196/500], Loss: 0.9382089376449585
Epoch [197/500], Loss: 0.9139071106910706
Epoch [198/500], Loss: 0.9433798789978027
Epoch [199/500], Loss: 0.9194853901863098
Epoch [200/500], Loss: 0.918971061706543
Epoch [201/500], Loss: 0.9233530163764954
Epoch [202/500], Loss: 0.9275185465812683
Epoch [203/500], Loss: 0.943453311920166
Epoch [204/500], Loss: 0.9343857169151306
Epoch [205/500], Loss: 0.9134299755096436
Epoch [206/500], Loss: 0.9247334003448486
Epoch [207/500], Loss: 0.9196376800537109
Epoch [208/500], Loss: 0.9155341982841492
Epoch [209/500], Loss: 0.9352285265922546
Epoch [210/500], Loss: 0.9303115010261536
Epoch [211/500], Loss: 0.948742151260376
Epoch [212/500], Loss: 0.9212631583213806
Epoch [213/500], Loss: 0.9321876764297485
Epoch [214/500], Loss: 0.9136770963668823
Epoch [215/500], Loss: 0.946442186832428
Epoch [216/500], Loss: 0.952808141708374
Epoch [217/500], Loss: 0.9276226758956909
Epoch [218/500], Loss: 0.9257791042327881
Epoch [219/500], Loss: 0.9321933388710022
Epoch [220/500], Loss: 0.9171388149261475
Epoch [221/500], Loss: 0.933039665222168
Epoch [222/500], Loss: 0.9303864240646362
Epoch [223/500], Loss: 0.9419950842857361
Epoch [224/500], Loss: 0.9134314656257629
Epoch [225/500], Loss: 0.9275945425033569
Epoch [226/500], Loss: 0.9388922452926636
Epoch [227/500], Loss: 0.9161747694015503
Epoch [228/500], Loss: 0.9109079241752625
Epoch [229/500], Loss: 0.9209831953048706
Epoch [230/500], Loss: 0.929007351398468
Epoch [231/500], Loss: 0.9186239838600159
Epoch [232/500], Loss: 0.9260671734809875
Epoch [233/500], Loss: 0.9225654602050781
Epoch [234/500], Loss: 0.9377326965332031
Epoch [235/500], Loss: 0.9289158582687378
Epoch [236/500], Loss: 0.9171422123908997
Epoch [237/500], Loss: 0.9197167754173279
Epoch [238/500], Loss: 0.9141910672187805
Epoch [239/500], Loss: 0.9268507957458496
Epoch [240/500], Loss: 0.9114560484886169
```

```
Epoch [241/500], Loss: 0.9556702971458435
Epoch [242/500], Loss: 0.9267643690109253
Epoch [243/500], Loss: 0.9409753084182739
Epoch [244/500], Loss: 0.9048813581466675
Epoch [245/500], Loss: 0.9424949884414673
Epoch [246/500], Loss: 0.9221315383911133
Epoch [247/500], Loss: 0.9314953088760376
Epoch [248/500], Loss: 0.8991910815238953
Epoch [249/500], Loss: 0.9207116365432739
Epoch [250/500], Loss: 0.9167050719261169
Epoch [251/500], Loss: 0.9380404949188232
Epoch [252/500], Loss: 0.9504674673080444
Epoch [253/500], Loss: 0.9183362126350403
Epoch [254/500], Loss: 0.9275029301643372
Epoch [255/500], Loss: 0.9227020144462585
Epoch [256/500], Loss: 0.9320732355117798
Epoch [257/500], Loss: 0.96501624584198
Epoch [258/500], Loss: 0.9235602617263794
Epoch [259/500], Loss: 0.9241986870765686
Epoch [260/500], Loss: 0.9144902229309082
Epoch [261/500], Loss: 0.929702639579773
Epoch [262/500], Loss: 0.9243789315223694
Epoch [263/500], Loss: 0.9381933212280273
Epoch [264/500], Loss: 0.9229588508605957
Epoch [265/500], Loss: 0.9623239040374756
Epoch [266/500], Loss: 0.9188292622566223
Epoch [267/500], Loss: 0.9361987113952637
Epoch [268/500], Loss: 0.9041332602500916
Epoch [269/500], Loss: 0.9345743656158447
Epoch [270/500], Loss: 0.9229862093925476
Epoch [271/500], Loss: 0.9094985127449036
Epoch [272/500], Loss: 0.9187889099121094
Epoch [273/500], Loss: 0.9330623149871826
Epoch [274/500], Loss: 0.9204555749893188
Epoch [275/500], Loss: 0.9387593269348145
Epoch [276/500], Loss: 0.9462670683860779
Epoch [277/500], Loss: 0.9321793913841248
Epoch [278/500], Loss: 0.9062191247940063
Epoch [279/500], Loss: 0.9564568996429443
Epoch [280/500], Loss: 0.9416362047195435
Epoch [281/500], Loss: 0.9364190697669983
Epoch [282/500], Loss: 0.9624088406562805
Epoch [283/500], Loss: 0.9207748770713806
Epoch [284/500], Loss: 0.9163626432418823
Epoch [285/500], Loss: 0.9426984190940857
Epoch [286/500], Loss: 0.9190382361412048
Epoch [287/500], Loss: 0.9274793267250061
Epoch [288/500], Loss: 0.9371085166931152
Epoch [289/500], Loss: 0.9038017392158508
Epoch [290/500], Loss: 0.9201565384864807
Epoch [291/500], Loss: 0.9290509819984436
Epoch [292/500], Loss: 0.9304041266441345
Epoch [293/500], Loss: 0.9421055912971497
Epoch [294/500], Loss: 0.9347652792930603
Epoch [295/500], Loss: 0.9217808842658997
Epoch [296/500], Loss: 0.9124235510826111
Epoch [297/500], Loss: 0.8951705694198608
Epoch [298/500], Loss: 0.9276357293128967
Epoch [299/500], Loss: 0.9428894519805908
Epoch [300/500], Loss: 0.9421648979187012
```

```
Epoch [301/500], Loss: 0.9063853025436401
Epoch [302/500], Loss: 0.9317530989646912
Epoch [303/500], Loss: 0.9221009016036987
Epoch [304/500], Loss: 0.9162665605545044
Epoch [305/500], Loss: 0.9238988757133484
Epoch [306/500], Loss: 0.9064803123474121
Epoch [307/500], Loss: 0.9468411207199097
Epoch [308/500], Loss: 0.9345094561576843
Epoch [309/500], Loss: 0.9334520101547241
Epoch [310/500], Loss: 0.9491555690765381
Epoch [311/500], Loss: 0.9112547636032104
Epoch [312/500], Loss: 0.9169077277183533
Epoch [313/500], Loss: 0.8977096676826477
Epoch [314/500], Loss: 0.9379801750183105
Epoch [315/500], Loss: 0.9104684591293335
Epoch [316/500], Loss: 0.9362452626228333
Epoch [317/500], Loss: 0.8963572978973389
Epoch [318/500], Loss: 0.9262198805809021
Epoch [319/500], Loss: 0.9095538258552551
Epoch [320/500], Loss: 0.9581807851791382
Epoch [321/500], Loss: 0.9222671389579773
Epoch [322/500], Loss: 0.9222143888473511
Epoch [323/500], Loss: 0.9028392434120178
Epoch [324/500], Loss: 0.9241093397140503
Epoch [325/500], Loss: 0.9390047192573547
Epoch [326/500], Loss: 0.9238476753234863
Epoch [327/500], Loss: 0.9171134829521179
Epoch [328/500], Loss: 0.9266464710235596
Epoch [329/500], Loss: 0.9265332221984863
Epoch [330/500], Loss: 0.9250684976577759
Epoch [331/500], Loss: 0.9074585437774658
Epoch [332/500], Loss: 0.9114964604377747
Epoch [333/500], Loss: 0.9075149297714233
Epoch [334/500], Loss: 0.9211422204971313
Epoch [335/500], Loss: 0.9067593216896057
Epoch [336/500], Loss: 0.9059107899665833
Epoch [337/500], Loss: 0.9203882217407227
Epoch [338/500], Loss: 0.9284389615058899
Epoch [339/500], Loss: 0.9281641840934753
Epoch [340/500], Loss: 0.9212895631790161
Epoch [341/500], Loss: 0.902187168598175
Epoch [342/500], Loss: 0.9098930358886719
Epoch [343/500], Loss: 0.9183240532875061
Epoch [344/500], Loss: 0.9193541407585144
Epoch [345/500], Loss: 0.9246594905853271
Epoch [346/500], Loss: 0.9320050477981567
Epoch [347/500], Loss: 0.902243971824646
Epoch [348/500], Loss: 0.9076677560806274
Epoch [349/500], Loss: 0.9209301471710205
Epoch [350/500], Loss: 0.93646240234375
Epoch [351/500], Loss: 0.9210680723190308
Epoch [352/500], Loss: 0.9237872958183289
Epoch [353/500], Loss: 0.9153597354888916
Epoch [354/500], Loss: 0.9230595827102661
Epoch [355/500], Loss: 0.9097591042518616
Epoch [356/500], Loss: 0.9189672470092773
Epoch [357/500], Loss: 0.9346181750297546
Epoch [358/500], Loss: 0.9116185307502747
Epoch [359/500], Loss: 0.9182547330856323
Epoch [360/500], Loss: 0.9173974990844727
```

```
Epoch [361/500], Loss: 0.9123983979225159
Epoch [362/500], Loss: 0.9092115759849548
Epoch [363/500], Loss: 0.901499330997467
Epoch [364/500], Loss: 0.9125919938087463
Epoch [365/500], Loss: 0.9073087573051453
Epoch [366/500], Loss: 0.9071293473243713
Epoch [367/500], Loss: 0.9508063197135925
Epoch [368/500], Loss: 0.9107100963592529
Epoch [369/500], Loss: 0.9083660244941711
Epoch [370/500], Loss: 0.9105296730995178
Epoch [371/500], Loss: 0.9087877869606018
Epoch [372/500], Loss: 0.9125149250030518
Epoch [373/500], Loss: 0.9238805174827576
Epoch [374/500], Loss: 0.8996308445930481
Epoch [375/500], Loss: 0.931239128112793
Epoch [376/500], Loss: 0.9151391983032227
Epoch [377/500], Loss: 0.913375198841095
Epoch [378/500], Loss: 0.9281057715415955
Epoch [379/500], Loss: 0.9226700663566589
Epoch [380/500], Loss: 0.9333652257919312
Epoch [381/500], Loss: 0.9002450704574585
Epoch [382/500], Loss: 0.917557954788208
Epoch [383/500], Loss: 0.9093394875526428
Epoch [384/500], Loss: 0.9197918772697449
Epoch [385/500], Loss: 0.9435898065567017
Epoch [386/500], Loss: 0.9153598546981812
Epoch [387/500], Loss: 0.9226590394973755
Epoch [388/500], Loss: 0.9163167476654053
Epoch [389/500], Loss: 0.9538434743881226
Epoch [390/500], Loss: 0.9166688323020935
Epoch [391/500], Loss: 0.9206324815750122
Epoch [392/500], Loss: 0.9096022248268127
Epoch [393/500], Loss: 0.9111061692237854
Epoch [394/500], Loss: 0.912706732749939
Epoch [395/500], Loss: 0.9238115549087524
Epoch [396/500], Loss: 0.911986768245697
Epoch [397/500], Loss: 0.9411163330078125
Epoch [398/500], Loss: 0.925309419631958
Epoch [399/500], Loss: 0.909292459487915
Epoch [400/500], Loss: 0.9193797707557678
Epoch [401/500], Loss: 0.909937858581543
Epoch [402/500], Loss: 0.9173546433448792
Epoch [403/500], Loss: 0.9072943925857544
Epoch [404/500], Loss: 0.9356609582901001
Epoch [405/500], Loss: 0.9202641248703003
Epoch [406/500], Loss: 0.923132598400116
Epoch [407/500], Loss: 0.9228233695030212
Epoch [408/500], Loss: 0.9060561656951904
Epoch [409/500], Loss: 0.9249104857444763
Epoch [410/500], Loss: 0.9328151345252991
Epoch [411/500], Loss: 0.9152110815048218
Epoch [412/500], Loss: 0.9249963760375977
Epoch [413/500], Loss: 0.9104793071746826
Epoch [414/500], Loss: 0.9189267158508301
Epoch [415/500], Loss: 0.9035393595695496
Epoch [416/500], Loss: 0.8968620300292969
Epoch [417/500], Loss: 0.898086428642273
Epoch [418/500], Loss: 0.9382323026657104
Epoch [419/500], Loss: 0.9222335815429688
Epoch [420/500], Loss: 0.8982816934585571
```

```
Epoch [421/500], Loss: 0.9278834462165833
Epoch [422/500], Loss: 0.9157591462135315
Epoch [423/500], Loss: 0.9018852710723877
Epoch [424/500], Loss: 0.9278015494346619
Epoch [425/500], Loss: 0.934533417224884
Epoch [426/500], Loss: 0.9270431399345398
Epoch [427/500], Loss: 0.9307982921600342
Epoch [428/500], Loss: 0.925994336605072
Epoch [429/500], Loss: 0.9298396706581116
Epoch [430/500], Loss: 0.916325032711029
Epoch [431/500], Loss: 0.9174274206161499
Epoch [432/500], Loss: 0.8997889161109924
Epoch [433/500], Loss: 0.9083521962165833
Epoch [434/500], Loss: 0.9052244424819946
Epoch [435/500], Loss: 0.9357300996780396
Epoch [436/500], Loss: 0.9180675745010376
Epoch [437/500], Loss: 0.9204069375991821
Epoch [438/500], Loss: 0.9368655681610107
Epoch [439/500], Loss: 0.9030745625495911
Epoch [440/500], Loss: 0.9051777124404907
Epoch [441/500], Loss: 0.8873710632324219
Epoch [442/500], Loss: 0.9185841679573059
Epoch [443/500], Loss: 0.9210028052330017
Epoch [444/500], Loss: 0.896934449672699
Epoch [445/500], Loss: 0.9215736985206604
Epoch [446/500], Loss: 0.9205340147018433
Epoch [447/500], Loss: 0.9111537933349609
Epoch [448/500], Loss: 0.9118665456771851
Epoch [449/500], Loss: 0.9251173138618469
Epoch [450/500], Loss: 0.9126029014587402
Epoch [451/500], Loss: 0.9163674712181091
Epoch [452/500], Loss: 0.9072287082672119
Epoch [453/500], Loss: 0.9215280413627625
Epoch [454/500], Loss: 0.8992323875427246
Epoch [455/500], Loss: 0.8982726335525513
Epoch [456/500], Loss: 0.8982397317886353
Epoch [457/500], Loss: 0.9050416350364685
Epoch [458/500], Loss: 0.9388568997383118
Epoch [459/500], Loss: 0.9262137413024902
Epoch [460/500], Loss: 0.907198429107666
Epoch [461/500], Loss: 0.8988863825798035
Epoch [462/500], Loss: 0.9463318586349487
Epoch [463/500], Loss: 0.9113886952400208
Epoch [464/500], Loss: 0.9223356246948242
Epoch [465/500], Loss: 0.9034886360168457
Epoch [466/500], Loss: 0.8993865847587585
Epoch [467/500], Loss: 0.9043990969657898
Epoch [468/500], Loss: 0.9093490839004517
Epoch [469/500], Loss: 0.9138242602348328
Epoch [470/500], Loss: 0.9280813336372375
Epoch [471/500], Loss: 0.9245758652687073
Epoch [472/500], Loss: 0.9336972236633301
Epoch [473/500], Loss: 0.9284990429878235
Epoch [474/500], Loss: 0.9411030411720276
Epoch [475/500], Loss: 0.9163273572921753
Epoch [476/500], Loss: 0.904469907283783
Epoch [477/500], Loss: 0.9045798778533936
Epoch [478/500], Loss: 0.9130051732063293
Epoch [479/500], Loss: 0.9090794324874878
Epoch [480/500], Loss: 0.924267590045929
```

```
Epoch [481/500], Loss: 0.925037145614624
Epoch [482/500], Loss: 0.8994665145874023
Epoch [483/500], Loss: 0.9268143177032471
Epoch [484/500], Loss: 0.9334433078765869
Epoch [485/500], Loss: 0.9108511209487915
Epoch [486/500], Loss: 0.9350407123565674
Epoch [487/500], Loss: 0.9013826251029968
Epoch [488/500], Loss: 0.9006767272949219
Epoch [489/500], Loss: 0.899770975112915
Epoch [490/500], Loss: 0.9104081988334656
Epoch [491/500], Loss: 0.9053065180778503
Epoch [492/500], Loss: 0.9158172607421875
Epoch [493/500], Loss: 0.9266479015350342
Epoch [494/500], Loss: 0.8996240496635437
Epoch [495/500], Loss: 0.9263523817062378
Epoch [496/500], Loss: 0.9141717553138733
Epoch [497/500], Loss: 0.9444454908370972
Epoch [498/500], Loss: 0.913339376449585
Epoch [499/500], Loss: 0.9404551982879639
Epoch [500/500], Loss: 0.9052669405937195
```

In [ ]:

```python
from sklearn.metrics import classification_report

# Define the class labels
class_labels = ['Theory', 'Reinforcement_Learning', 'Probabilistic_Methods',
                'Case_Based', 'Genetic_Algorithms', 'Rule_Learning', 'Neural_Net


model.eval()
with torch.no_grad():
    output = model(adj_test, features_test)
    predicted_labels = torch.argmax(output, dim=1)

# Convert predicted labels and ground truth labels to numpy arrays
predicted_labels_np = predicted_labels.numpy()
labels_test_np = labels_test.numpy()
```

In [ ]:

```python
report = classification_report(labels_test_np, predicted_labels_np, target_names

# Print the classification report
print(report)

# Write the classification report to a file
with open("gcn_metrics.txt", "w") as file:
    file.write(report)
```

	precision	recall	f1-score	support
Theory	0.40	0.10	0.16	174
Reinforcement_Learning	0.56	0.04	0.07	128
Probabilistic_Methods	0.72	0.10	0.18	207
Case_Based	0.72	0.16	0.26	166
Genetic_Algorithms	0.82	0.18	0.29	210
Rule_Learning	0.37	0.07	0.12	98
Neural_Networks	0.30	0.95	0.45	366
accuracy			0.34	1349
macro avg	0.56	0.23	0.22	1349
weighted avg	0.54	0.34	0.26	1349