torch

February 10, 2022

1 Links

https://chrsmrrs.github.io/datasets/docs/datasets/

[34]:
```
## Standard libraries
import os
import json
import math
import numpy as np
import time
import pandas as pd
import sklearn
from sklearn.linear_model import LogisticRegression

## Imports for plotting
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('svg', 'pdf') # For export
from matplotlib.colors import to_rgb
from mpl_toolkits.mplot3d import Axes3D
matplotlib.rcParams['lines.linewidth'] = 2.0
import seaborn as sns
sns.reset_orig()
sns.set()

# Plotly
import plotly.graph_objects as go

# NetworkX
import networkx as nx

# Gensim
import gensim
import gensim.downloader as api
from gensim.models.word2vec import Word2Vec
```

```python
## PyTorch
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.nn import Linear
import torch.utils.data as data
import torch.optim as optim

# Geometric
import torch_geometric
import torch_geometric.nn as geom_nn
from torch_geometric.nn import GCNConv, GraphConv, global_mean_pool
import torch_geometric.data as geom_data
from torch_geometric.datasets import TUDataset
from torch_geometric.loader import DataLoader,ClusterData, ClusterLoader
from torch_geometric.utils import to_networkx

# PyTorch Lightning
import pytorch_lightning as pl
```

[245]:

```python
def visualize_graph(ax, G, color=None, labels=False, title=None, layout=lambda␣
↪G : nx.spring_layout(G, seed=42)):
    ax.set_xticks([])
    ax.set_yticks([])
    node_color = 'white'
    if color is not None: node_color = color
    nx.draw_networkx(G, pos=layout(G), with_labels=labels,
                     node_color=node_color, cmap="Set2", node_size=100, ax=ax)
    if title: ax.set_title(title)

def visualize_embedding(ax, h, color, epoch=None, loss=None, title=None):
    ax.set_xticks([])
    ax.set_yticks([])
    h = h.detach().cpu().numpy()
    ax.scatter(h[:, 0], h[:, 1], s=140, c=color, cmap="Set2")
    if epoch is not None and loss is not None:
        ax.set_xlabel(f'Epoch: {epoch}, Loss: {loss.item():.4f}', fontsize=10)
    if title: ax.set_title(title)

def visualize_model_embedding_spaces(models, modelnames):
    fig, ax = plt.subplots(1, len(models), figsize=(len(models)*4,4))
    x_min, x_max = -1, 1
    y_min, y_max = -1, 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02), np.arange(y_min, y_max,␣
↪0.02))
    for i, model in enumerate(models):
        assert model.classifier.in_features == 2
```

```
        name = modelnames[i]
        pred = model.classifier(torch.from_numpy(np.c_[xx.ravel(), yy.ravel()]).
 ↪float()).detach().numpy()
        zz = np.argmax(pred, axis=1).reshape(xx.shape)
        ax[i].pcolormesh(xx, yy, zz)
        ax[i].set_title(name)
    plt.tight_layout()

def plot_results(losses, acc, modelnames):
    assert list(losses.keys()) == modelnames and list(acc.keys()) == modelnames
    n_models = len(modelnames)
    fig, ax = plt.subplots(2, n_models, figsize=(3*n_models,6))
    for i in range(n_models):
        model_acc = acc[modelnames[i]]
        ax[0,i].set_title(f'{modelnames[i]}: accuracy')
        ax[0,i].plot(np.arange(len(model_acc)), [x[0] for x in model_acc],␣
 ↪label='train acc')
        ax[0,i].plot(np.arange(len(model_acc)), [x[1] for x in model_acc],␣
 ↪label='test acc')
        ax[0,i].set_xlabel('# epochs')
        ax[0,i].legend(loc='lower right')
        ax[0,i].set_ylim(([0,1]))

        model_losses = losses[modelnames[i]]
        ax[1,i].set_title(f'{modelnames[i]}: loss')
        ax[1,i].plot(np.arange(len(model_losses)), model_losses)
        ax[1,i].set_xlabel('# epochs')
        ax[1,i].set_ylim(([0,1]))
    plt.tight_layout()

def plot_subgraph_3d(graph, data, N=100):

    subgraph_idx = np.random.choice(np.arange(len(graph.nodes)), N,␣
 ↪replace=False)
    subgraph_labels = data.y[subgraph_idx]
    subgraph = graph.subgraph(subgraph_idx)

    spring_3D = nx.spring_layout(subgraph, dim = 3, k = 0.7) # k regulates the␣
 ↪distance between nodes
    nodes3d = [[spring_3D[key][i] for key in spring_3D.keys()] for i in␣
 ↪range(3)]
    edges3d = [[], [], []]
    for edge in subgraph.edges():
        for i in range(3):
            edges3d[i] += [spring_3D[edge[0]][i],spring_3D[edge[1]][i],None]
```

```
    trace_edges = go.Scatter3d(x=edges3d[0], y=edges3d[1], z=edges3d[2],
        mode='lines',
        line=dict(
            color='black',
            width=.1),
        hoverinfo='none')

    trace_nodes = go.Scatter3d(x=nodes3d[0], y=nodes3d[1], z=nodes3d[2],
        mode='markers',
        marker=dict(
            symbol='circle',
            size=6,
            color=subgraph_labels),
        hovertemplate=[f'<b>{l}</b><extra></extra>' for l in subgraph_labels])

    fig = go.Figure(data=[trace_edges, trace_nodes])
    fig.show()
```

2 Twitter

2.0.1 Each graph in this dataset represents a tweet, and each node in a graph is represented by a 1323-dimensional vector, corresponding to one of 1323 different words listed in the `readme.txt` file.

2.0.2 Each graph is labeled with 0 or 1, corresponding to sentiment. The source doesn't indicate what the sentiment is. So far, no clear sentiment seems apparent from observation.

[9]:
```
twitter = torch_geometric.datasets.TUDataset(root='data/',␣
 ↪name='TWITTER-Real-Graph-Partial')
```

[11]:
```
print(f'Dataset: {twitter}:')
print('======================')
print(f'Number of graphs: {len(twitter)}')
print(f'Number of features: {twitter.num_features}')
print(f'Number of classes: {twitter.num_classes}')
```

```
Dataset: TWITTER-Real-Graph-Partial(144033):
======================
Number of graphs: 144033
Number of features: 1323
Number of classes: 2
```

2.0.3 Because nodes correspond to words, we will consider using word embeddings as feature representations of the nodes in a tweet.

2.0.4 If tweets include words not in the embedding corpus, we embed the word as a zero vector

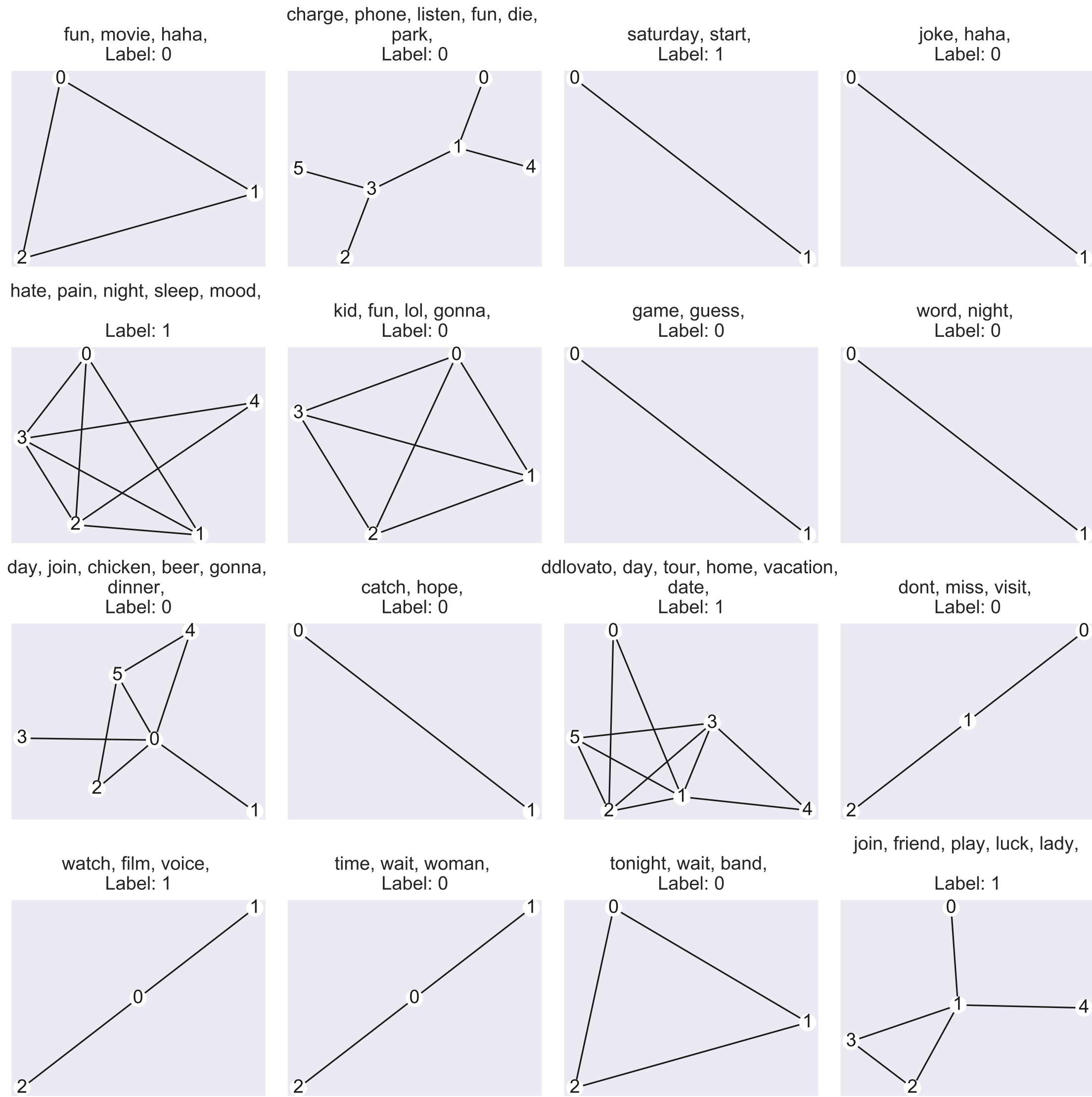
[127]:
```python
# convert integers to their corresponding words
id2word = {}
word2id = {}
with open('data/TWITTER-Real-Graph-Partial/raw/readme.txt') as f:
    lines = f.readlines()
    for n in range(51, 51+1323):
        l = lines[n].split()
        id2word[int(l[0])] = l[1]
        word2id[l[1]] = int(l[0])

# get word embeddings from GenSim word2vec.
word2vec_model = Word2Vec.load("word2vec.model")

# get word embeddings from Gensim glove-twitter-25
glove_vectors = api.load('glove-twitter-25')

embeddings = {
    'word2vec' : {'size' : 100, 'model' : word2vec_model.wv},
    'glove' : {'size' : 25, 'model' : glove_vectors}
}

# add unused words as a zero embedding
for w in word2id.keys():
    for emb in embeddings:
        if w not in embeddings[emb]['model'].index_to_key:
            embeddings[emb][w] = np.zeros(embeddings[emb]['size'])

keywords = ['nervous', 'palms']
for emb in embeddings:
    print(f'{emb} similar to {keywords}: ', [x[0] for x in␣
 ↪embeddings[emb]['model'].most_similar(positive=keywords, topn=3)])
```

```
word2vec similar to ['nervous', 'palms']:  ['digestive', 'vascular',
'endocrine']
glove similar to ['nervous', 'palms']:  ['rough', 'resting', 'dragging']
```

```
/Users/maxcembalest/opt/anaconda3/lib/python3.8/site-
packages/gensim/models/keyedvectors.py:772: RuntimeWarning:

invalid value encountered in true_divide
```

2.1 According to the dataset source on github, words are connected if they "co-occur". What does that mean in a tweet?

[44]:
```
def format_ax_title(tweets, words):
    title = ''
    for i in range(len(words)):
        title += words[i] + ', '
        if i%4==0 and i > 0:
            title += '\n'
    title += '\n' + 'Label: ' + str(tweets.y[0].numpy())
    return title

fig, ax = plt.subplots(4, 4, figsize=(10,10))
sample_idx = np.random.choice(np.arange(len(twitter)), 16, replace=False)
feature_vector_to_word = lambda v : id2word[np.where(v)[0][0]]
for i, idx in enumerate(sample_idx):
    tweets = twitter[idx]
    words = [feature_vector_to_word(tweets.x[j]) for j in range(tweets.x.
 ↪shape[0])]
    tweetG = to_networkx(tweets, to_undirected=True)
    title = format_ax_title(tweets, words)
    visualize_graph(ax[i//4,i%4], tweetG, labels=True, title=title)
plt.tight_layout()
```



2.2 Load data

[184]:
```
N_train = 50000
N_test = 1000
batch_size_train=128
batch_size_test=32

twitter_train_idx = np.random.choice(np.arange(len(twitter)), N_train,␣
↪replace=False)
twitter_test_idx = np.random.choice(np.arange(len(twitter)), N_test,␣
↪replace=False)
```

```
twitter_train_dataset = twitter[twitter_train_idx]
twitter_test_dataset = twitter[twitter_test_idx]

twitter_train_loader = DataLoader(twitter_train_dataset,␣
↪batch_size=batch_size_train, shuffle=True)
twitter_test_loader = DataLoader(twitter_test_dataset,␣
↪batch_size=batch_size_test, shuffle=False)
```

2.3 Build models

[185]:
```
class TwitterGNN(torch.nn.Module):
    def __init__(self, hidden_channels, embedding=None):
        super(TwitterGNN, self).__init__()
        if embedding:
            in_D = embeddings[embedding]['size']
            self.embedding_map = lambda x : torch.
↪tensor(embeddings[embedding]['model'][torch.where(x)[1].numpy()])
        else:
            in_D = twitter.num_features
            self.embedding_map = None
        self.conv1 = GraphConv(in_D, hidden_channels)
        self.conv2 = GraphConv(hidden_channels, hidden_channels//2)
        self.lin = Linear(hidden_channels//2, twitter.num_classes)

    def forward(self, x, edge_index, batch):
        # 0. apply optional word embeddings
        if self.embedding_map:
            x = self.embedding_map(x)

        # 1. GCN embeddings
        x = self.conv1(x, edge_index)
        x = x.relu()
        x = self.conv2(x, edge_index)

        # 2. Readout layer, to obtain a graph-level representation
        x = global_mean_pool(x, batch)

        # 3. Apply a final classifier
        x = F.dropout(x, p=0.5, training=self.training)
        x = self.lin(x)

        return x

# todo: compare these models against nlp-only baselines to see the impact of␣
↪the GCN
twitter_gnn_model = TwitterGNN(64)
twitter_gnnword2vec_model = TwitterGNN(64, embedding='word2vec')
```

```
twitter_gnnglove_model = TwitterGNN(64, embedding='glove')
twitter_models = [twitter_gnn_model, twitter_gnnword2vec_model,␣
↪twitter_gnnglove_model]
twitter_modelnames = ['GNN', 'Word2Vec GNN', 'Glove GNN']
for i in range(len(twitter_models)):
    print(twitter_modelnames[i], ':', twitter_models[i])
```

```
GNN : TwitterGNN(
  (conv1): GraphConv(1323, 64)
  (conv2): GraphConv(64, 32)
  (lin): Linear(in_features=32, out_features=2, bias=True)
)
Word2Vec GNN : TwitterGNN(
  (conv1): GraphConv(100, 64)
  (conv2): GraphConv(64, 32)
  (lin): Linear(in_features=32, out_features=2, bias=True)
)
Glove GNN : TwitterGNN(
  (conv1): GraphConv(25, 64)
  (conv2): GraphConv(64, 32)
  (lin): Linear(in_features=32, out_features=2, bias=True)
)
```

2.4 Train models

[186]:
```
learning_rate = .001
optimizers = [torch.optim.Adam(m.parameters(), lr=learning_rate) for m in␣
↪twitter_models]
criterion = torch.nn.CrossEntropyLoss()
assert len(twitter_models) == len(twitter_modelnames) == len(optimizers)

def train_step(model, loader, optimizer):
    model.train()
    losses = 0
    for data in loader:  # Iterate in batches over the training dataset.
        out = model(data.x, data.edge_index, data.batch)  # Perform a single␣
↪forward pass.
        loss = criterion(out, data.y)  # Compute the loss.
        losses += loss
        loss.backward()  # Derive gradients.
        optimizer.step()  # Update parameters based on gradients.
        optimizer.zero_grad()  # Clear gradients.
    return losses.detach().numpy()/len(loader) # average batch loss

def test(model, loader):
    model.eval()
    correct = 0
```

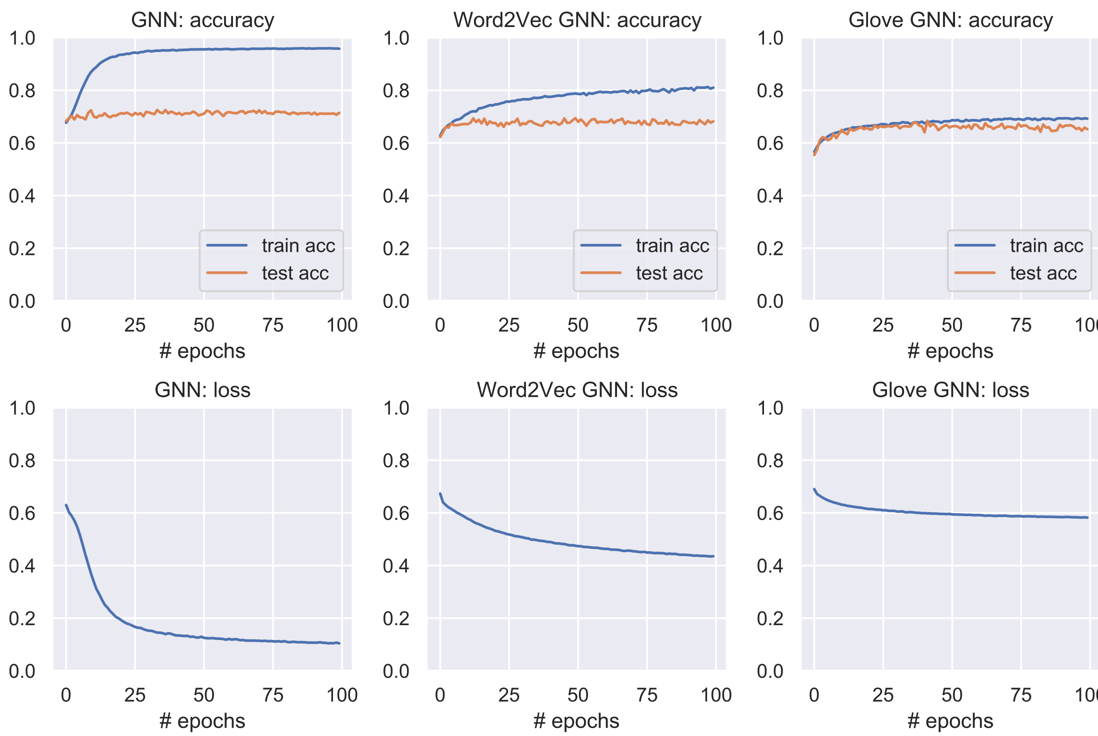
```
    for data in loader:  # Iterate in batches over the training/test dataset.
        out = model(data.x, data.edge_index, data.batch)
        pred = out.argmax(dim=1)  # Use the class with highest probability.
        correct += int((pred == data.y).sum())  # Check against ground-truth␣
↪labels.
    return correct / len(loader.dataset)  # percent correct label

evaluate = lambda model : (test(model, twitter_train_loader), test(model,␣
↪twitter_test_loader))

twitterlosses = {m : [] for m in twitter_modelnames}
twitteracc = {m : [] for m in twitter_modelnames}
for i, model in enumerate(twitter_models):
    print(twitter_modelnames[i])
    for epoch in range(100):
        loss = train_step(model, twitter_train_loader, optimizers[i])
        train_acc, test_acc = evaluate(model)
        twitterlosses[twitter_modelnames[i]].append(loss)
        twitteracc[twitter_modelnames[i]].append((train_acc, test_acc))
        if epoch%10==9: print(f'Epoch: {epoch}, loss: {np.around(loss, 2)}, acc:
↪ {np.around(test_acc, 2)}')
```

```
GNN
Epoch: 0, loss: 0.63, acc: 0.68
Epoch: 9, loss: 0.37, acc: 0.72
Epoch: 18, loss: 0.21, acc: 0.7
Epoch: 27, loss: 0.16, acc: 0.71
Epoch: 36, loss: 0.14, acc: 0.72
Epoch: 45, loss: 0.13, acc: 0.71
Epoch: 54, loss: 0.12, acc: 0.72
Epoch: 63, loss: 0.12, acc: 0.72
Epoch: 72, loss: 0.11, acc: 0.72
Epoch: 81, loss: 0.11, acc: 0.71
Epoch: 90, loss: 0.11, acc: 0.72
Epoch: 99, loss: 0.1, acc: 0.71
Word2Vec GNN
Epoch: 0, loss: 0.67, acc: 0.62
Epoch: 9, loss: 0.58, acc: 0.67
Epoch: 18, loss: 0.54, acc: 0.68
Epoch: 27, loss: 0.51, acc: 0.68
Epoch: 36, loss: 0.49, acc: 0.67
Epoch: 45, loss: 0.48, acc: 0.69
Epoch: 54, loss: 0.47, acc: 0.68
Epoch: 63, loss: 0.46, acc: 0.68
Epoch: 72, loss: 0.45, acc: 0.68
Epoch: 81, loss: 0.45, acc: 0.67
Epoch: 90, loss: 0.44, acc: 0.68
```

```
Epoch: 99, loss: 0.44, acc: 0.68
Glove GNN
Epoch: 0, loss: 0.69, acc: 0.55
Epoch: 9, loss: 0.63, acc: 0.64
Epoch: 18, loss: 0.62, acc: 0.65
Epoch: 27, loss: 0.61, acc: 0.66
Epoch: 36, loss: 0.6, acc: 0.68
Epoch: 45, loss: 0.6, acc: 0.65
Epoch: 54, loss: 0.59, acc: 0.66
Epoch: 63, loss: 0.59, acc: 0.66
Epoch: 72, loss: 0.59, acc: 0.66
Epoch: 81, loss: 0.59, acc: 0.66
Epoch: 90, loss: 0.58, acc: 0.66
Epoch: 99, loss: 0.58, acc: 0.65
```

2.5 Plot evaluation

[243]:
```
plot_results(twitterlosses, twitteracc, twitter_modelnames)
```



3 Airports

[17]:
```
airports = torch_geometric.datasets.Airports(root='data/', name='USA')
```

[236]:
```
print(f'Dataset: {airports}:')
print('======================')
print(f'Number of graphs: {len(airports)}')
print(f'Number of features: {airports.num_features}')
print(f'Number of classes: {airports.num_classes}')
airport_data = airports[0]
airport_graph = to_networkx(airport_data)
airport_df = pd.DataFrame(airport_data.y, columns=['label'])

airport_df['num_neighbors'] = [len(list(airport_graph.neighbors(i))) for i in␣
↪range(airport_data.num_features)]

print(airport_data)
```

```
Dataset: UsaAirports():
======================
Number of graphs: 1
Number of features: 1190
Number of classes: 4
Data(x=[1190, 1190], edge_index=[2, 13599], y=[1190])
```

3.1 Withouth knowing which airport is which, we will plot them as points in 3d, and draw lines between nodes if their airports are connected in the UsaAirports dataset

3.2 Without knowing what the labels mean, it seems the labels have something to do with the connectedness of the nodes. The labels are equally balanced (1190=297+297+297+299)

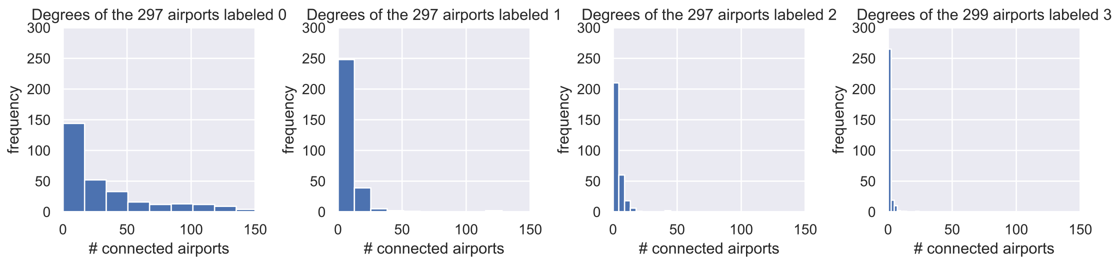
3.3 Here we are viewing approximately 40% of the nodes of the graph, since it is too dense to view the whole thing

[246]:
```
plot_subgraph_3d(airport_graph, airport_data, N=500)
```

3.3.1 A correlation between node degree (# of neighbors) and the label

[35]:
```
fig, ax = plt.subplots(1, 4, figsize=(12,3))

for i in range(4):
    subdf= airports_df[airports_df['label']==i]
    ax[i].hist(subdf.num_neighbors)
    ax[i].set_xlabel('# connected airports')
    ax[i].set_ylabel('frequency')
    ax[i].set_xlim((0,150))
```

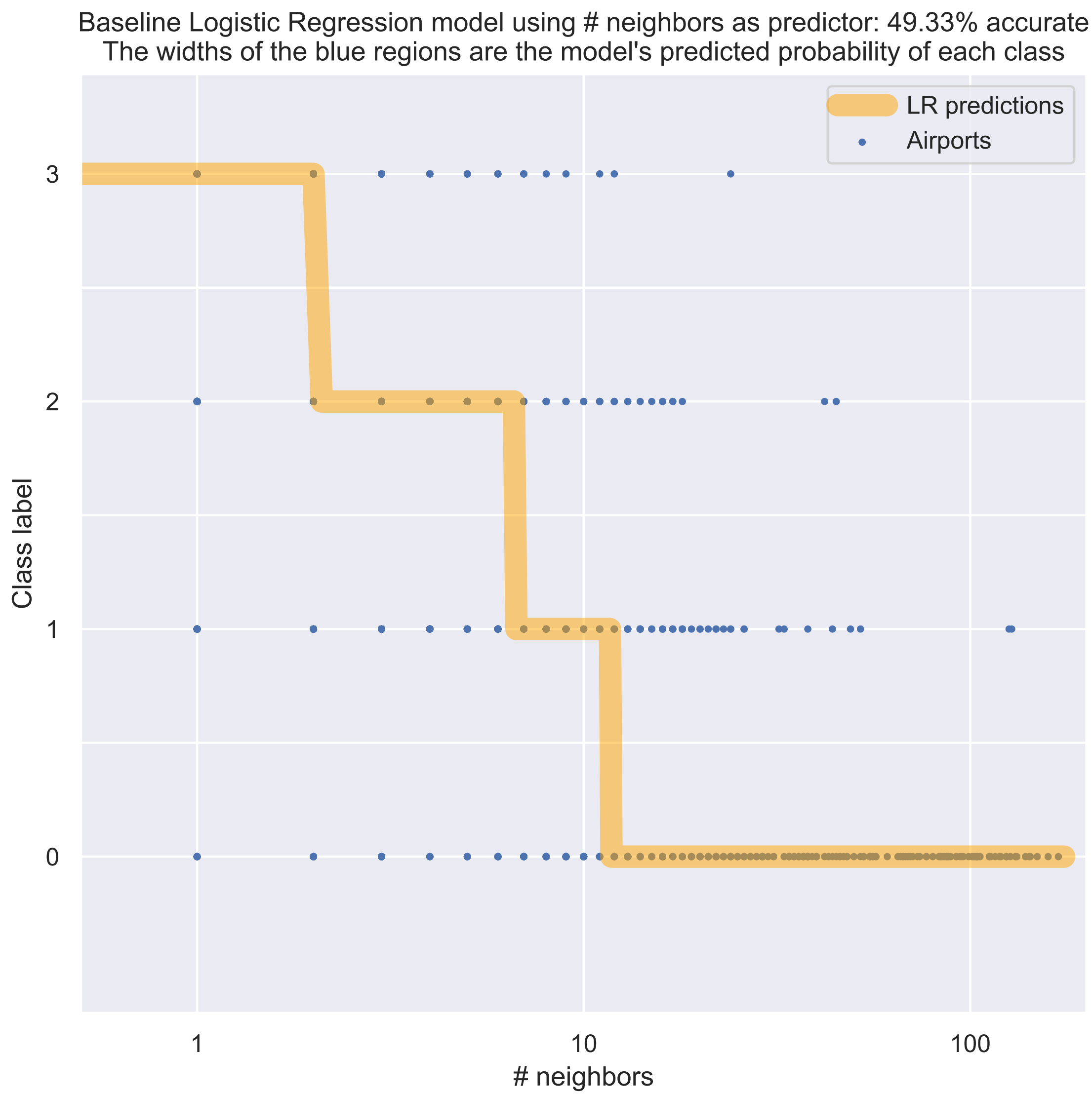
```
    ax[i].set_ylim((0,300))
    ax[i].set_title(f'Degrees of the {len(subdf)} airports labeled {i}')
plt.tight_layout()
```



3.4 As a baseline against a GNN, here is a logistic regression model using the # of neighbors as its only feature

[194]:
```
fig, ax = plt.subplots(figsize=(7,7))

# plot airports by their # of neighbors and class label
ax.scatter(airports_df.num_neighbors, airports_df.label, sizes=5*np.
 ↪ones(len(airports_df)), label='Airports')

# fit logistic regression model just using the # neighbors to predict the label
train_idx = np.random.choice(np.arange(len(airports_df)), 700, replace=False)
test_idx = np.random.choice(np.arange(len(airports_df)), 300, replace=False)
dftrain, dftest = airports_df.loc[train_idx], airports_df.loc[test_idx]
xtrain, ytrain, xtest, ytest = dftrain.num_neighbors.values, dftrain.label.
 ↪values, dftest.num_neighbors.values, dftest.label.values
lr = LogisticRegression()
lr.fit(xtrain.reshape(-1,1), ytrain)
ypred = lr.predict(xtest.reshape(-1,1))
probs = lr.predict_proba(xplot.reshape(-1,1))
accuracy = sklearn.metrics.accuracy_score(ytest, ypred)

# plot logistic regression model predictions
xplot = np.arange(0,175,.1)
plotpreds = lr.predict(xplot.reshape(-1,1))
ax.plot(xplot, plotpreds, linewidth=10, color='orange', alpha=0.5, label = 'LR␣
 ↪predictions')

# fill a region of space whose width changes proportional to the predicted␣
 ↪probabiltiy of the LR model for each class
for i in range(4):
    ax.fill_between(xplot, i - 0.5*probs[:,i], i + 0.5*probs[:,i], linewidth=5,␣
 ↪color='blue', alpha=0.3)
```

```python
# format
title = f'Baseline Logistic Regression model using # neighbors as predictor:␣
↪{round(accuracy*100,2)}% accurate'
title += '\nThe widths of the blue regions are the model\'s predicted␣
↪probability of each class'
ax.set_title(title)
ax.set_xscale('log')
ax.set_xlim([.5,200])
ax.set_xticks([1, 10, 100])
ax.set_xticklabels(['1', '10', '100'])
ax.set_yticks(np.arange(0,3.5,0.5))
ax.set_yticklabels(['0','','1','','2','','3'])
ax.set_xlabel('# neighbors')
ax.set_ylabel('Class label')
ax.legend(loc='best')

plt.tight_layout()
```



3.5 Load data

[216]:
```
N_train = 70
N_test = 30

airport_train_idx = np.random.choice(np.arange(airports.num_features), N_train,␣
↪replace=False)
airport_test_idx = np.random.choice(np.arange(airports.num_features), N_test,␣
↪replace=False)

airport_train_mask = np.array([idx in airport_train_idx for idx in␣
↪range(airports.num_features)])
```

```
airport_test_mask = np.array([idx in airport_test_idx for idx in range(airports.
↪num_features)])
```

3.6 Build models

[225]:
```
class AirportGNN(torch.nn.Module):
    def __init__(self, layer):
        super().__init__()
        self.conv1 = layer(airports.num_features, 100)
        self.conv2 = layer(100, 10)
        self.conv3 = layer(10, 2)
        self.classifier = Linear(2, airports.num_classes)

    def forward(self, x, edge_index):
        h = self.conv1(x, edge_index)
        h = h.tanh()
        h = self.conv2(h, edge_index)
        h = h.tanh()
        h = self.conv3(h, edge_index)
        h = h.tanh()  # Final GNN embedding space.

        # Apply a final (linear) classifier.
        out = self.classifier(h)

        return out, h

airport_gcnconv_model = AirportGNN(GCNConv)
airport_graphconv_model = AirportGNN(GraphConv)
airport_models = [airport_gcnconv_model, airport_graphconv_model]
airport_modelnames = ['GCNConv', 'GraphConv']
for i in range(len(airport_models)):
    print(airport_modelnames[i], ':', airport_models[i])
```

```
GCNConv : AirportGNN(
  (conv1): GCNConv(1190, 100)
  (conv2): GCNConv(100, 10)
  (conv3): GCNConv(10, 2)
  (classifier): Linear(in_features=2, out_features=4, bias=True)
)
GraphConv : AirportGNN(
  (conv1): GraphConv(1190, 100)
  (conv2): GraphConv(100, 10)
  (conv3): GraphConv(10, 2)
  (classifier): Linear(in_features=2, out_features=4, bias=True)
)
```

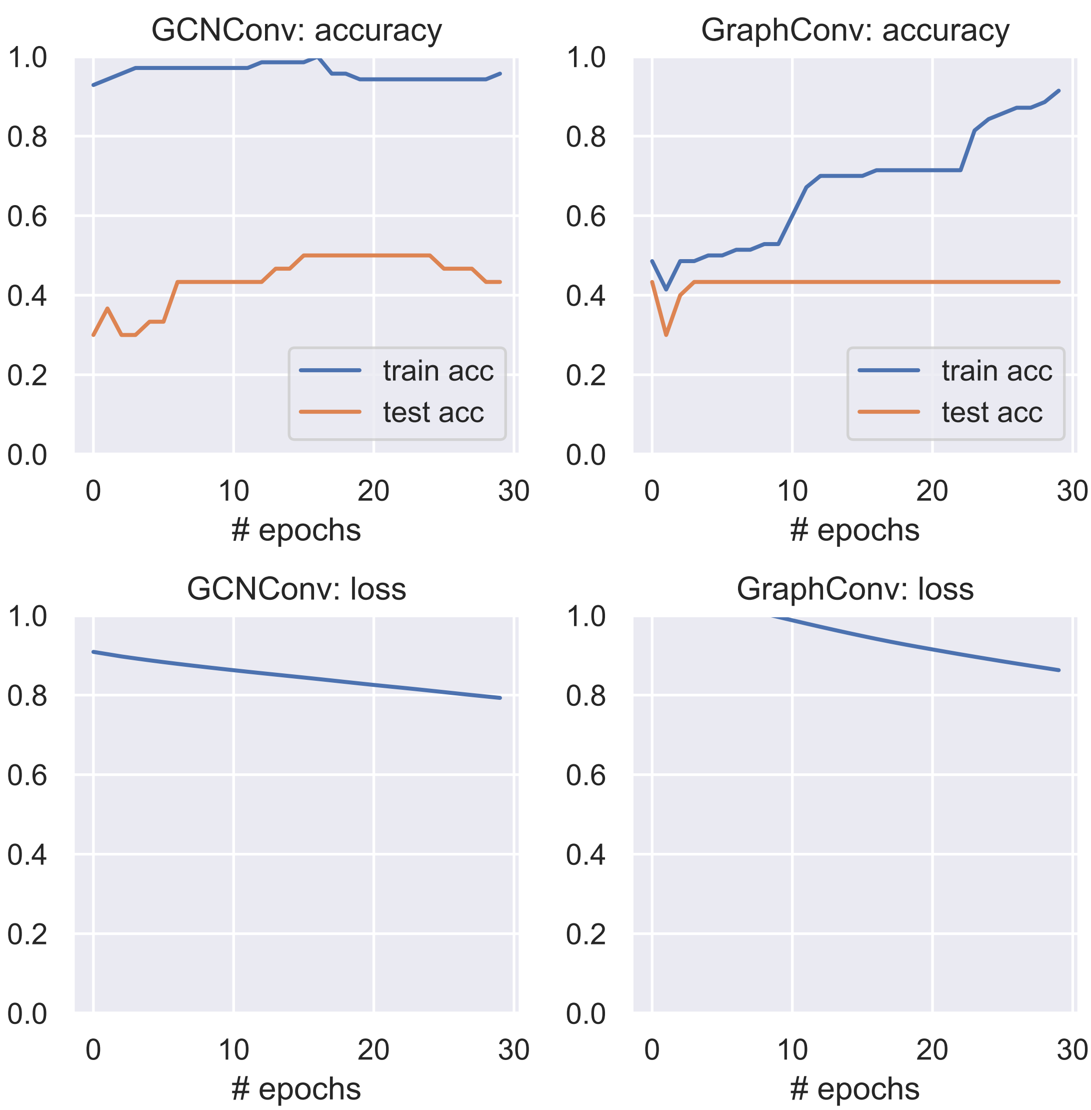
3.7 Train models

[231]:
```
learning_rate = .003
optimizers = [torch.optim.Adam(m.parameters(), lr=learning_rate) for m in␣
↪airport_models]
criterion = torch.nn.CrossEntropyLoss()
assert len(airport_models) == len(airport_modelnames) == len(optimizers)

def train_step(model, optimizer):
    model.train()
    optimizer.zero_grad()  # Clear gradients
    out, h = model(airports_data.x, airports_data.edge_index)  # Forward pass␣
↪on whole graph
    loss = criterion(out[airport_train_mask], airports_data.
↪y[airport_train_mask])  # Loss on training nodes
    loss.backward()  # Calculate gradients
    optimizer.step()  # Update parameters based on gradients
    return loss.detach().numpy(), out, h

def test(out, mask):
    pred = out[mask].argmax(dim=1)  # Use the class with highest probability
    acc = int((pred == airports_data.y[mask]).sum()) / mask.sum() # Percent␣
↪correct
    return acc

evaluate = lambda out : (test(out, airport_train_mask), test(out,␣
↪airport_test_mask))

airportlosses = {m : [] for m in airport_modelnames}
airportacc = {m : [] for m in airport_modelnames}
airportemb = {m : [] for m in airport_modelnames}

# sample_idx = np.random.choice(np.arange(airports.num_features), 100)
n_epochs=30

for i, model in enumerate(airport_models):
    name = airport_modelnames[i]
    print(name)
    for epoch in range(n_epochs):
        loss, out, h = train_step(model, optimizers[i])
        train_acc, test_acc = evaluate(out)
        airportlosses[name].append(loss)
        airportacc[name].append((train_acc, test_acc))
        airportemb[name].append(h)
        if epoch%10==9:
            print(f'Epoch: {epoch}, loss: {np.around(loss, 2)}, acc: {np.
↪around(test_acc, 2)}')
```

```
GCNConv
Epoch: 9, loss: 0.8700000047683716, acc: 0.43
Epoch: 19, loss: 0.8299999833106995, acc: 0.5
Epoch: 29, loss: 0.7900000214576721, acc: 0.43
GraphConv
Epoch: 9, loss: 1.0, acc: 0.43
Epoch: 19, loss: 0.9200000166893005, acc: 0.43
Epoch: 29, loss: 0.8600000143051147, acc: 0.43
```

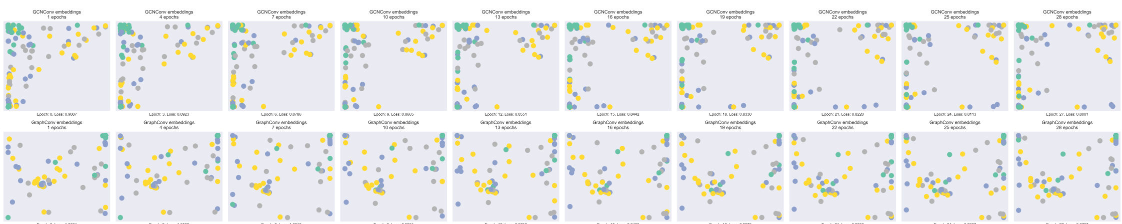
3.8 Plot evaluation

[248]:
```
plot_results(airportlosses, airportacc, airport_modelnames)
```



3.9 Visualize the change in the last layer embeddings during training

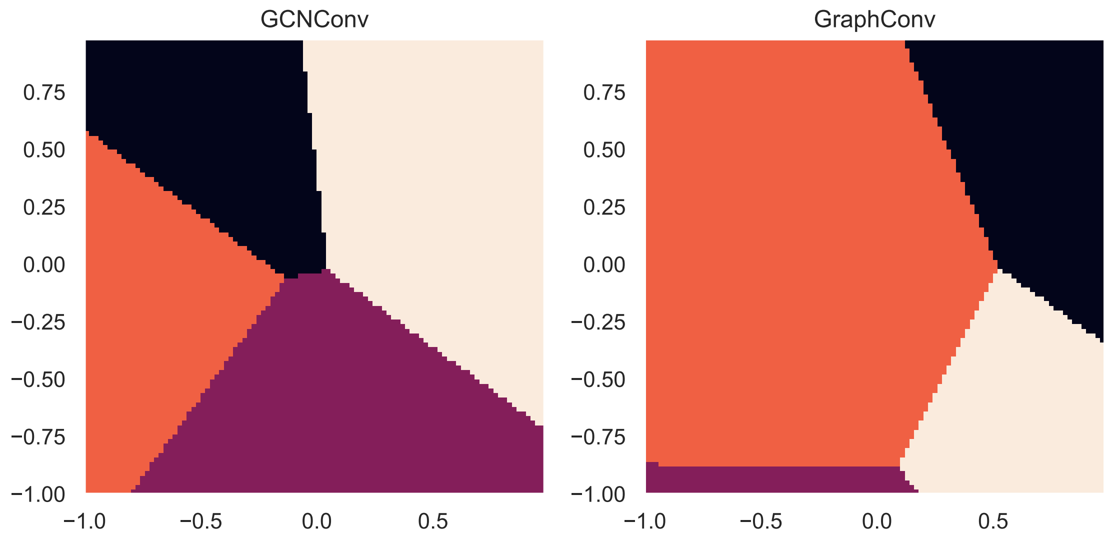
[249]:
```
sample_idx = np.random.choice(np.arange(airports.num_features), 100)
n_plots=10
n_models = 2
fig, ax = plt.subplots(n_models, n_plots, figsize=(4*n_plots,4*n_models))

for i, model in enumerate(airport_models):
    name = airport_modelnames[i]
    for n in range(n_plots):
        epoch = n*n_epochs//n_plots
        h = airportemb[name][epoch]
        loss = airportlosses[name][epoch]
        visualize_embedding(ax[i,n], h[sample_idx], color=airports_data.y[sample_idx], epoch=epoch, loss=loss, title=f'{name} embeddings\n{epoch+1} epochs')
plt.tight_layout()
```



3.10 Visualize the the last layer embedding space after training

[316]:
```
visualize_model_embedding_spaces(airport_models, airport_modelnames)
```

```
<ipython-input-297-e4104e03d506>:13: MatplotlibDeprecationWarning:

shading='flat' when X and Y have the same dimensions as C is deprecated since
3.3.  Either specify the corners of the quadrilaterals with X and Y, or pass
shading='auto', 'nearest' or 'gouraud', or set rcParams['pcolor.shading'].  This
will become an error two minor releases later.
```


GCNConv
GraphConv
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.0
−0.5
0.0
0.5

[ ]: