```python
import dgl
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
import tqdm
from dgl.data.knowledge_graph import FB15k237Dataset
from dgl.dataloading import GraphDataLoader
from dgl.nn.pytorch import RelGraphConv


# for building training/testing graphs
def get_subset_g(g, mask, num_rels, bidirected=False):
    src, dst = g.edges()
    sub_src = src[mask]
    sub_dst = dst[mask]
    sub_rel = g.edata["etype"][mask]

    if bidirected:
        sub_src, sub_dst = torch.cat([sub_src, sub_dst]), torch.cat(
            [sub_dst, sub_src]
        )
        sub_rel = torch.cat([sub_rel, sub_rel + num_rels])

    sub_g = dgl.graph((sub_src, sub_dst), num_nodes=g.num_nodes())
    sub_g.edata[dgl.ETYPE] = sub_rel
    return sub_g


class GlobalUniform:
    def __init__(self, g, sample_size):
        self.sample_size = sample_size
        self.eids = np.arange(g.num_edges())

    def sample(self):
        return torch.from_numpy(np.random.choice(self.eids, self.sample_size))


class NegativeSampler:
```

```
40          def __init__(self, k=10):  # negative sampling rate = 10
41              self.k = k
42
43          def sample(self, pos_samples, num_nodes):
44              batch_size = len(pos_samples)
45              neg_batch_size = batch_size * self.k
46              neg_samples = np.tile(pos_samples, (self.k, 1))
47
48              values = np.random.randint(num_nodes, size=neg_batch_size)
49              choices = np.random.uniform(size=neg_batch_size)
50              subj = choices > 0.5
51              obj = choices <= 0.5
52              neg_samples[subj, 0] = values[subj]
53              neg_samples[obj, 2] = values[obj]
54              samples = np.concatenate((pos_samples, neg_samples))
55
56              # binary labels indicating positive and negative samples
57              labels = np.zeros(batch_size * (self.k + 1), dtype=np.float32)
58              labels[:batch_size] = 1
59
60              return torch.from_numpy(samples), torch.from_numpy(labels)
61
62
63  class SubgraphIterator:
64      def __init__(self, g, num_rels, sample_size=30000, num_epochs=6000):
65          self.g = g
66          self.num_rels = num_rels
67          self.sample_size = sample_size
68          self.num_epochs = num_epochs
69          self.pos_sampler = GlobalUniform(g, sample_size)
70          self.neg_sampler = NegativeSampler()
71
72      def __len__(self):
73          return self.num_epochs
74
75      def __getitem__(self, i):
76          eids = self.pos_sampler.sample()
77          src, dst = self.g.find_edges(eids)
78          src, dst = src.numpy(), dst.numpy()
79          rel = self.g.edata[dgl.ETYPE][eids].numpy()
80
81          # relabel nodes to have consecutive node IDs
82          uniq_v, edges = np.unique((src, dst), return_inverse=True)
83          num_nodes = len(uniq_v)
84          # edges is the concatenation of src, dst with relabeled ID
85          src, dst = np.reshape(edges, (2, -1))
86          relabeled_data = np.stack((src, rel, dst)).transpose()
87
88          samples, labels = self.neg_sampler.sample(relabeled_data, num_nodes)
89
90          # use only half of the positive edges
91          chosen_ids = np.random.choice(
92              np.arange(self.sample_size),
93              size=int(self.sample_size / 2),
94              replace=False,
```

```
95              )
96              src = src[chosen_ids]
97              dst = dst[chosen_ids]
98              rel = rel[chosen_ids]
99              src, dst = np.concatenate((src, dst)), np.concatenate((dst, src))
100             rel = np.concatenate((rel, rel + self.num_rels))
101             sub_g = dgl.graph((src, dst), num_nodes=num_nodes)
102             sub_g.edata[dgl.ETYPE] = torch.from_numpy(rel)
103             sub_g.edata["norm"] = dgl.norm_by_dst(sub_g).unsqueeze(-1)
104             uniq_v = torch.from_numpy(uniq_v).view(-1).long()
105
106             return sub_g, uniq_v, samples, labels
107
108
109 class RGCN(nn.Module):
110     def __init__(self, num_nodes, h_dim, num_rels):
111         super().__init__()
112         # two-layer RGCN
113         self.emb = nn.Embedding(num_nodes, h_dim)
114         self.conv1 = RelGraphConv(
115             h_dim,
116             h_dim,
117             num_rels,
118             regularizer="bdd",
119             num_bases=100,
120             self_loop=True,
121         )
122         self.conv2 = RelGraphConv(
123             h_dim,
124             h_dim,
125             num_rels,
126             regularizer="bdd",
127             num_bases=100,
128             self_loop=True,
129         )
130         self.dropout = nn.Dropout(0.2)
131
132     def forward(self, g, nids):
133         x = self.emb(nids)
134         h = F.relu(self.conv1(g, x, g.edata[dgl.ETYPE], g.edata["norm"]))
135         h = self.dropout(h)
136         h = self.conv2(g, h, g.edata[dgl.ETYPE], g.edata["norm"])
137         return self.dropout(h)
138
139
140 class LinkPredict(nn.Module):
141     def __init__(self, num_nodes, num_rels, h_dim=500, reg_param=0.01):
142         super().__init__()
143         self.rgcn = RGCN(num_nodes, h_dim, num_rels * 2)
144         self.reg_param = reg_param
145         self.w_relation = nn.Parameter(torch.Tensor(num_rels, h_dim))
146         nn.init.xavier_uniform_(
147             self.w_relation, gain=nn.init.calculate_gain("relu")
148         )
149
150     def calc_score(self, embedding, triplets):
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```
151             s = embedding[triplets[:, 0]]
152             r = self.w_relation[triplets[:, 1]]
153             o = embedding[triplets[:, 2]]
154             score = torch.sum(s * r * o, dim=1)
155             return score
156
157         def forward(self, g, nids):
158             return self.rgcn(g, nids)
159
160         def regularization_loss(self, embedding):
161             return torch.mean(embedding.pow(2)) + torch.mean(self.w_relation.pow(2))
162
163         def get_loss(self, embed, triplets, labels):
164             # each row in the triplets is a 3-tuple of (source, relation, destination)
165             score = self.calc_score(embed, triplets)
166             predict_loss = F.binary_cross_entropy_with_logits(score, labels)
167             reg_loss = self.regularization_loss(embed)
168             return predict_loss + self.reg_param * reg_loss
169
170
171 def filter(
172     triplets_to_filter, target_s, target_r, target_o, num_nodes, filter_o=True
173 ):
174     """Get candidate heads or tails to score"""
175     target_s, target_r, target_o = int(target_s), int(target_r), int(target_o)
176     # Add the ground truth node first
177     if filter_o:
178         candidate_nodes = [target_o]
179     else:
180         candidate_nodes = [target_s]
181     for e in range(num_nodes):
182         triplet = (
183             (target_s, target_r, e) if filter_o else (e, target_r, target_o)
184         )
185         # Do not consider a node if it leads to a real triplet
186         if triplet not in triplets_to_filter:
187             candidate_nodes.append(e)
188     return torch.LongTensor(candidate_nodes)
189
190
191 def perturb_and_get_filtered_rank(
192     emb, w, s, r, o, test_size, triplets_to_filter, filter_o=True
193 ):
194     """Perturb subject or object in the triplets"""
195     num_nodes = emb.shape[0]
196     ranks = []
197     for idx in tqdm.tqdm(range(test_size), desc="Evaluate"):
198         target_s = s[idx]
199         target_r = r[idx]
200         target_o = o[idx]
201         candidate_nodes = filter(
202             triplets_to_filter,
203             target_s,
204             target_r,
205             target_o,
```

```
                num_nodes,
                filter_o=filter_o,
            )
            if filter_o:
                emb_s = emb[target_s]
                emb_o = emb[candidate_nodes]
            else:
                emb_s = emb[candidate_nodes]
                emb_o = emb[target_o]
            target_idx = 0
            emb_r = w[target_r]
            emb_triplet = emb_s * emb_r * emb_o
            scores = torch.sigmoid(torch.sum(emb_triplet, dim=1))

            _, indices = torch.sort(scores, descending=True)
            rank = int((indices == target_idx).nonzero())
            ranks.append(rank)
        return torch.LongTensor(ranks)


def calc_mrr(
    emb, w, test_mask, triplets_to_filter, batch_size=100, filter=True
):
    with torch.no_grad():
        test_triplets = triplets_to_filter[test_mask]
        s, r, o = test_triplets[:, 0], test_triplets[:, 1], test_triplets[:, 2]
        test_size = len(s)
        triplets_to_filter = {
            tuple(triplet) for triplet in triplets_to_filter.tolist()
        }
        ranks_s = perturb_and_get_filtered_rank(
            emb, w, s, r, o, test_size, triplets_to_filter, filter_o=False
        )
        ranks_o = perturb_and_get_filtered_rank(
            emb, w, s, r, o, test_size, triplets_to_filter
        )
        ranks = torch.cat([ranks_s, ranks_o])
        ranks += 1  # change to 1-indexed
        mrr = torch.mean(1.0 / ranks.float()).item()
    return mrr


def train(
    dataloader,
    test_g,
    test_nids,
    test_mask,
    triplets,
    device,
    model_state_file,
    model,
):
    optimizer = torch.optim.Adam(model.parameters(), lr=1e-2)
    best_mrr = 0
    for epoch, batch_data in enumerate(dataloader):  # single graph batch
```

```
            model.train()
            g, train_nids, edges, labels = batch_data
            g = g.to(device)
            train_nids = train_nids.to(device)
            edges = edges.to(device)
            labels = labels.to(device)

            embed = model(g, train_nids)
            loss = model.get_loss(embed, edges, labels)
            optimizer.zero_grad()
            loss.backward()
            nn.utils.clip_grad_norm_(
                model.parameters(), max_norm=1.0
            )  # clip gradients
            optimizer.step()
            print(
                "Epoch {:04d} | Loss {:.4f} | Best MRR {:.4f}".format(
                    epoch, loss.item(), best_mrr
                )
            )
            if (epoch + 1) % 500 == 0:
                # perform validation on CPU because full graph is too large
                model = model.cpu()
                model.eval()
                embed = model(test_g, test_nids)
                mrr = calc_mrr(
                    embed, model.w_relation, test_mask, triplets, batch_size=500
                )
                # save best model
                if best_mrr < mrr:
                    best_mrr = mrr
                    torch.save(
                        {"state_dict": model.state_dict(), "epoch": epoch},
                        model_state_file,
                    )
                model = model.to(device)


    if __name__ == "__main__":
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        print(f"Training with DGL built-in RGCN module")

        # load and preprocess dataset
        data = FB15k237Dataset(reverse=False)
        g = data[0]
        num_nodes = g.num_nodes()
        num_rels = data.num_rels
        train_g = get_subset_g(g, g.edata["train_mask"], num_rels)
        test_g = get_subset_g(g, g.edata["train_mask"], num_rels, bidirected=True)
        test_g.edata["norm"] = dgl.norm_by_dst(test_g).unsqueeze(-1)
        test_nids = torch.arange(0, num_nodes)
        test_mask = g.edata["test_mask"]
        subg_iter = SubgraphIterator(train_g, num_rels)  # uniform edge sampling
        dataloader = GraphDataLoader(
            subg_iter, batch_size=1, collate_fn=lambda x: x[0]
```

```
316         )
317
318         # Prepare data for metric computation
319         src, dst = g.edges()
320         triplets = torch.stack([src, g.edata["etype"], dst], dim=1)
321
322         # create RGCN model
323         model = LinkPredict(num_nodes, num_rels).to(device)
324
325         # train
326         model_state_file = "model_state.pth"
327         train(
328             dataloader,
329             test_g,
330             test_nids,
331             test_mask,
332             triplets,
333             device,
334             model_state_file,
335             model,
336         )
337
338         # testing
339         print("Testing...")
340         checkpoint = torch.load(model_state_file)
341         model = model.cpu()  # test on CPU
342         model.eval()
343         model.load_state_dict(checkpoint["state_dict"])
344         embed = model(test_g, test_nids)
345         best_mrr = calc_mrr(
346             embed, model.w_relation, test_mask, triplets, batch_size=500
347         )
348         print(
349             "Best MRR {:.4f} achieved using the epoch {:04d}".format(
350                 best_mrr, checkpoint["epoch"]
351             )
352         )
```