

# 1차 실험 결과

```
# IGTN-MovieLen
Testing EPOCH[91/100] loss 0.1682 0.1654 0.0028 - |Sample:0.33| | Results Top-k (pre, recall, ndcg): 0.36277, 0.24925, 0.44152

EPOCH[91/100] loss 0.1682 0.1654 0.0028 - |Sample:0.33| | 00:01mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[92/100] loss 0.1717 0.1689 0.0028 - |Sample:0.42| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[93/100] loss 0.1699 0.1671 0.0028 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[94/100] loss 0.1719 0.1691 0.0029 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[95/100] loss 0.1710 0.1681 0.0029 - |Sample:0.41| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[96/100] loss 0.1712 0.1684 0.0029 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[97/100] loss 0.1695 0.1666 0.0029 - |Sample:0.36| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[98/100] loss 0.1648 0.1618 0.0029 - |Sample:0.41| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[99/100] loss 0.1694 0.1664 0.0030 - |Sample:0.32| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152
EPOCH[100/100] loss 0.1660 0.1630 0.0030 - |Sample:0.32| | 00:00mins | Results val Top-k (recall, ndcg): 0.24925, 0.44152

# loss: 16.6% (+0.02%)
# precision: 36.277% (+0.065%)
# recall: 24.925% (+0.211%)
# ndcg: 44.152% (-0.042%)
```

```
# GTN-MovieLen
Testing EPOCH[91/100] loss 0.1691 0.1663 0.0028 - |Sample:0.33| | Results Top-k (pre, recall, ndcg): 0.36212, 0.24714, 0.44194

EPOCH[91/100] loss 0.1691 0.1663 0.0028 - |Sample:0.33| | 00:01mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[92/100] loss 0.1718 0.1690 0.0028 - |Sample:0.42| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[93/100] loss 0.1687 0.1659 0.0028 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[94/100] loss 0.1724 0.1696 0.0028 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[95/100] loss 0.1710 0.1682 0.0029 - |Sample:0.41| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[96/100] loss 0.1723 0.1694 0.0029 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[97/100] loss 0.1706 0.1677 0.0029 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[98/100] loss 0.1644 0.1615 0.0029 - |Sample:0.42| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[99/100] loss 0.1678 0.1649 0.0029 - |Sample:0.33| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194
EPOCH[100/100] loss 0.1658 0.1628 0.0030 - |Sample:0.34| | 00:00mins | Results val Top-k (recall, ndcg): 0.24714, 0.44194

# loss: 16.58%
# precision: 36.212%
# recall: 24.714%
# ndcg: 44.194%
```

# IGCN(1)

```
1 def inductive_rep_layer(self, feat_mat):
2     padding_tensor = torch.empty([max(self.feat_mat.shape) - self.feat_mat.shape[1], self.embedding_size],
3                                   dtype=torch.float32,
4                                   device=self.device)
5     padding_features = torch.cat([self.embedding.weight, padding_tensor], dim=0)
6
7     # print(padding_tensor.shape)
8     # print(padding_features.shape)
9
10    row, column = feat_mat.indices()
11    g = dgl.graph((column, row), num_nodes=max(self.feat_mat.shape), device=self.device)
12    x = dgl.ops.gspmm(g, 'mul', 'sum', lhs_data=padding_features, rhs_data=feat_mat.values())
13    x = x[:self.feat_mat.shape[0], :]    #[ : 2063, : ]
14    return x
15
16 def get_rep(self):
17     feat_mat = NGCF.dropout_sp_mat(self, self.feat_mat)
18     representations = self.inductive_rep_layer(feat_mat)    # ! 이거를 잘라가면 됨
19
20     # ! =====
21     # LightGCN으로 학습되기 전에 반환
22     return representations
23     # ! =====
```

# IGCN(2)



```
1 all_layer_rep = [representations]
2 row, column = self.norm_adj.indices()
3 g = dgl.graph((column, row), num_nodes=self.norm_adj.shape[0], device=self.device)
4
5 # 밑에는 LightGCN 로직
6 for _ in range(self.n_layers):
7     representations = dgl.ops.gspmm(g, 'mul', 'sum', lhs_data=representations, rhs_data=self.norm_adj.values())
8     all_layer_rep.append(representations)
9 all_layer_rep = torch.stack(all_layer_rep, dim=0)
10 final_rep = all_layer_rep.mean(dim=0)
11
12 # print('\n#####INMO EMBEDDING#####\n')
13 # # print(type(final_rep)) # <class 'torch.Tensor'>
14 # # print(final_rep.shape) # torch.Size([2063, 64])
15 # # print(final_rep.tolist())
16 # print('\n#####\n')
17 # exit()
18
19 return final_rep
```

# GTN(1)

```
1 def computer(self, corrupted_graph=None):
2     """
3     propagate methods for lightGCN
4     """
5
6     # print('\n#####\n')
7     # # # print(type(self.embedding_user))    # <class 'torch.nn.modules.sparse.Embedding'>
8     # # # # print(self.embedding_user.shape)
9     # # # print('\n\n\n')
10    # # # print(type(self.embedding_user.weight))    # <class 'torch.nn.parameter.Parameter'>
11    # # print(self.embedding_user.weight.shape)    # torch.Size([458, 64])
12    # # print(self.embedding_item.weight.shape)    # torch.Size([1605, 64])    # 총합 2063
13    # print('\n#####\n')
14    # exit()
15
16
17    users_emb = self.embedding_user.weight
18    items_emb = self.embedding_item.weight
19    all_emb = torch.cat([users_emb, items_emb])    # ! 여기에 붙이면 됨 → 아님
20    # <class 'torch.Tensor'>
21    # torch.Size([2063, 64])
```

## GTN(2)



```
1  # our GCNs
2  x = all_emb
3  rc = g_dropped.indices()
4  r = rc[0]
5  c = rc[1]
6  num_nodes = g_dropped.shape[0]
7  edge_index = SparseTensor(row=r,
8                             col=c,
9                             value=g_dropped.values(),
10                             sparse_sizes=(num_nodes, num_nodes))
11  emb, embs = self.gp.forward(x, edge_index, mode=self.args.gcn_model)
12  light_out = emb
13
14  # 합친 뒤 학습시키고 분리하는 것 같음
15  users, items = torch.split(light_out, [self.num_users, self.num_items])
16  return users, items
```

# GTN(3)

```
1 # ? ===== 연결 =====
2 import igcn_copy
3
4 final_rep=igcn_copy.main()
5
6 all_emb=torch.split(final_rep, [self.num_users, self.num_items])
7 e_user, e_item=all_emb[0], all_emb[1]
8
9 emb_user=nn.Embedding.from_pretrained(e_user, freeze=False)
10 emb_item=nn.Embedding.from_pretrained(e_item, freeze=False)
11
12 '''
13 <class 'torch.nn.modules.sparse.Embedding'>
14 <class 'torch.nn.parameter.Parameter'>
15 torch.Size([458, 64])
16
17 <class 'torch.nn.modules.sparse.Embedding'>
18 <class 'torch.nn.parameter.Parameter'>
19 torch.Size([1605, 64])
20 '''
21 # print(type(emb_user))
22 # print(type(emb_user.weight))
23 # print(emb_user.weight.shape)
24 # print()
25 # print(type(emb_item))
26 # print(type(emb_item.weight))
27 # print(emb_item.weight.shape)
28
29 self.embedding_user = emb_user
30 self.embedding_item = emb_item
```

# 문제점

- ▶ **IGCN은 BPR loss + self-enhanced loss를 사용함**

- ▶ IGTN은 GTN 코드를 이용해서 구현됐기 때문에 BPR loss로만 학습됨

- ▶ IGTN이 self-enhanced loss 역시 고려했을 때 성능이 유의미하게 향상될 경우

- ▶ Inductive 시나리오에서 테스트 해보아야 함

- ▶ MovieLens(작은 데이터셋)를 Inductive 시나리오에 맞게 가공해야 함