Progess of the Project

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2023/10/27

Outline

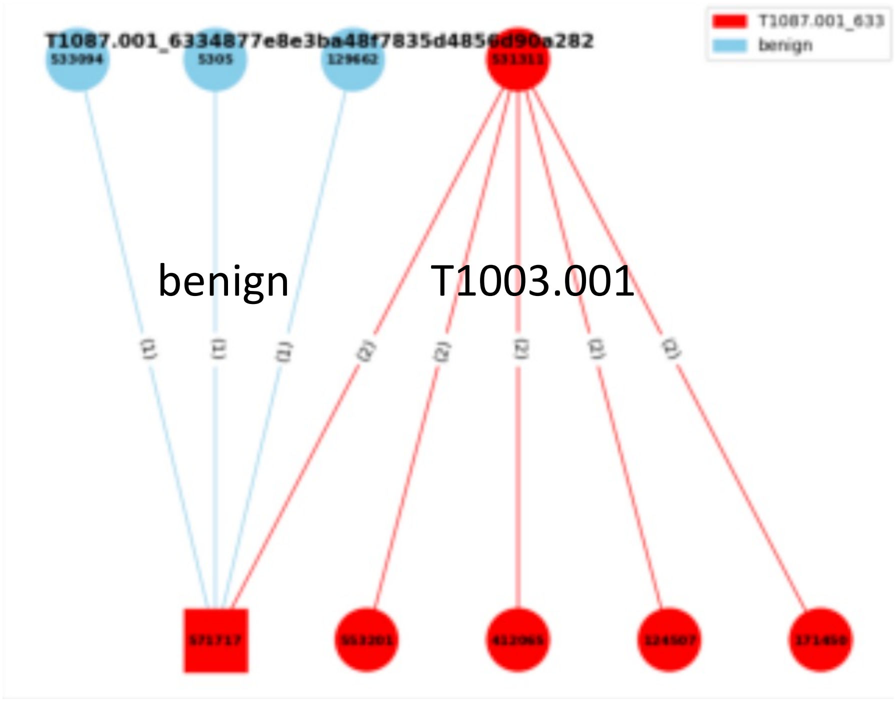
- **GNN**
  - **How to solve the data imbalance problem**
    - **Over-Sampling**
    - **With K-Fold Cross Validation**
    - **GCN model**
- **Future Work**

GNN

Experiment 3

- **Experiment 3:**
  - Consider the **neighbor** benign nodes
  - Edge classification

  - Given a graph → label the triplets with the benign or the specific AP



Experiment 3 - Oversampling

- Current Problem:
  - Can’t predict the edge in the small graphs consist of single triplet

	precision	recall	f1-score	support
T1003.003_9f73269695e54311dd61dc68940fb3e1	0.0	0.0	0.0	100.0
T1003.003_f049b89533298c2d6cd37a940248b219	0.0	0.0	0.0	100.0
T1007_c6607391-d02c-44b5-9b13-d3492ca58599	0.0	0.0	0.0	100.0
T1016_14a21534-350f-4d83-9dd7-3c56b93a0c17	0.0	0.0	0.0	100.0
T1016_71b3d2945679566b9d94d8cb11df4b70	0.0	0.0	0.0	100.0
T1016_921055f4-5970-4707-909e-62f594234d91	0.0	0.0	0.0	100.0
T1016_a0676fe1-cd52-482e-8dde-349b73f9aa69	0.0	0.0	0.0	100.0

```
Number of support=100: 54
Number of support=100 and f1-score<=0.2: 53
Number of support=100 and f1-score=0: 48
Number of support=200 and f1-score=0: 6
Number of support>200 and f1-score=0: 0
```

Experiment 3 - Oversampling

- Current Trial: hope to see the result on **training** dataset
  - At least let the model **overfit** first(remember the data with single triplet)
  - Use data with **320** times single triplet → # of training data = 13657600
  - Larger hidden **dimension** → more neurons to remember the data

- Hidden_dim = 256

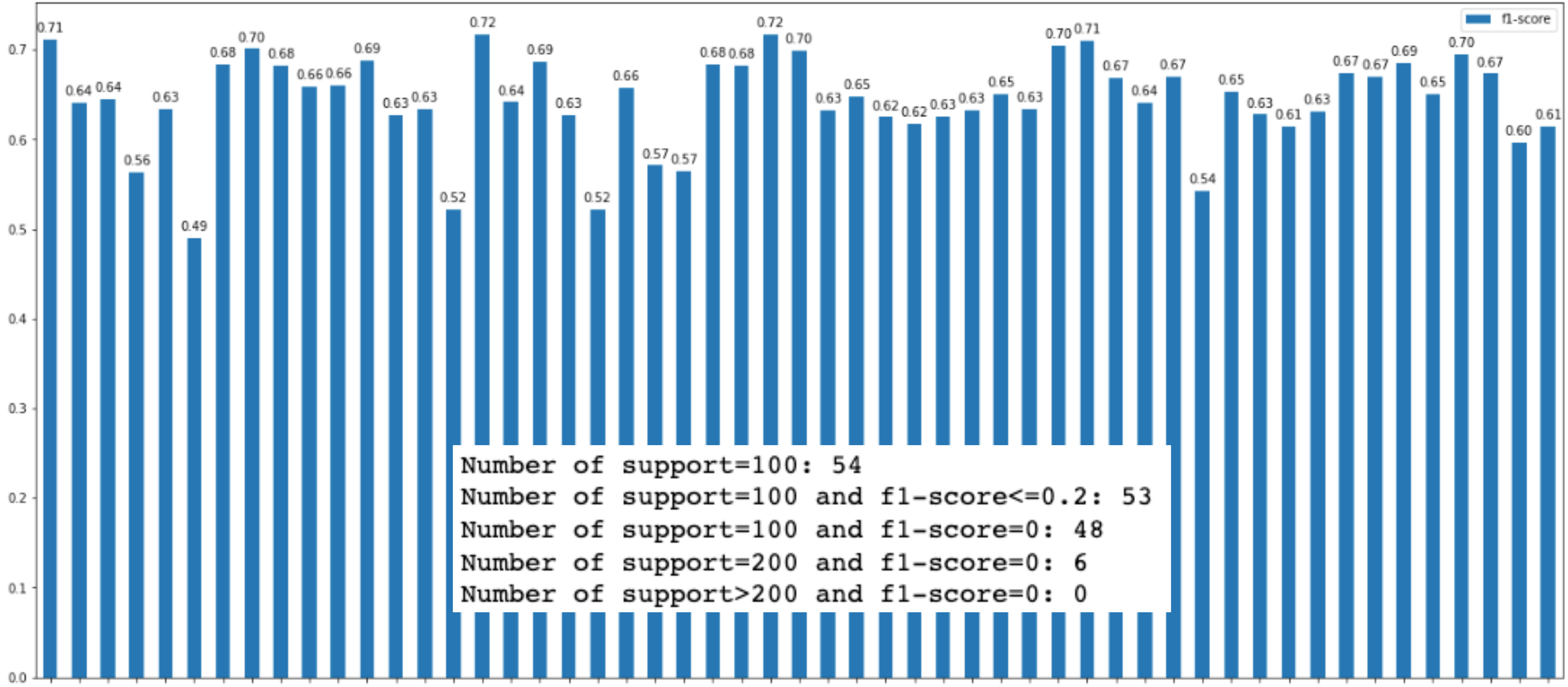
```
Number of single triplet: 53
Number of single triplet and f1-score<=0.2: 0
Number of single triplet and f1-score<=0.5: 1
Number of single triplet and f1-score>0.5: 52

    accuracy                           0.70  16008233
   macro avg       0.80      0.79      0.79  16008233
weighted avg       0.71      0.70      0.70  16008233
```

- Hidden_dim = 512

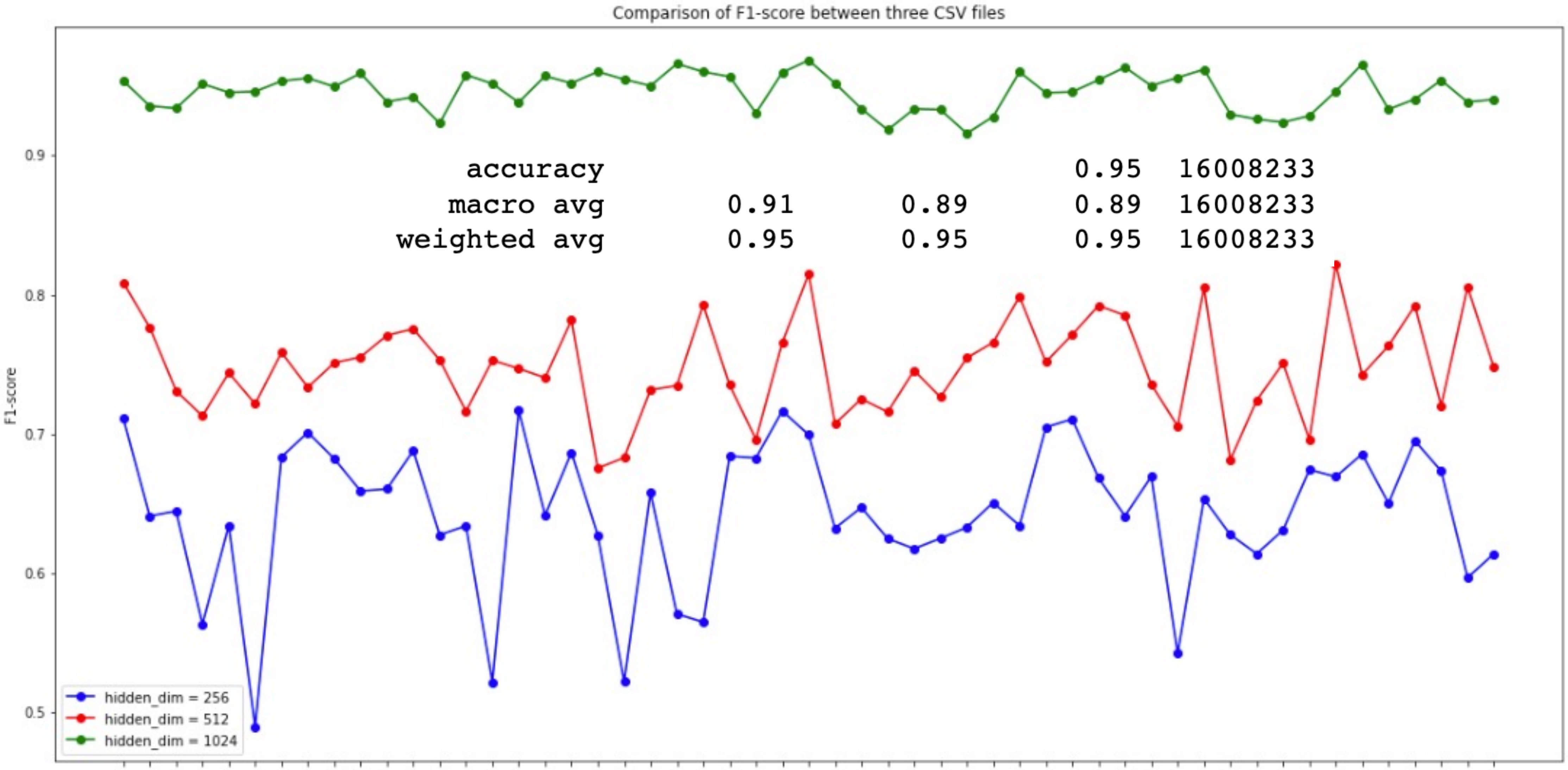
```
Number of single triplet: 53
Number of single triplet and f1-score<=0.2: 0
Number of single triplet and f1-score<=0.5: 0
Number of single triplet and f1-score>0.5: 53

    accuracy                           0.79  16008233
   macro avg       0.84      0.82      0.82  16008233
weighted avg       0.80      0.79      0.79  16008233
```

Experiment 3 - Oversampling

Bar Chart of hidden dimension = 256:

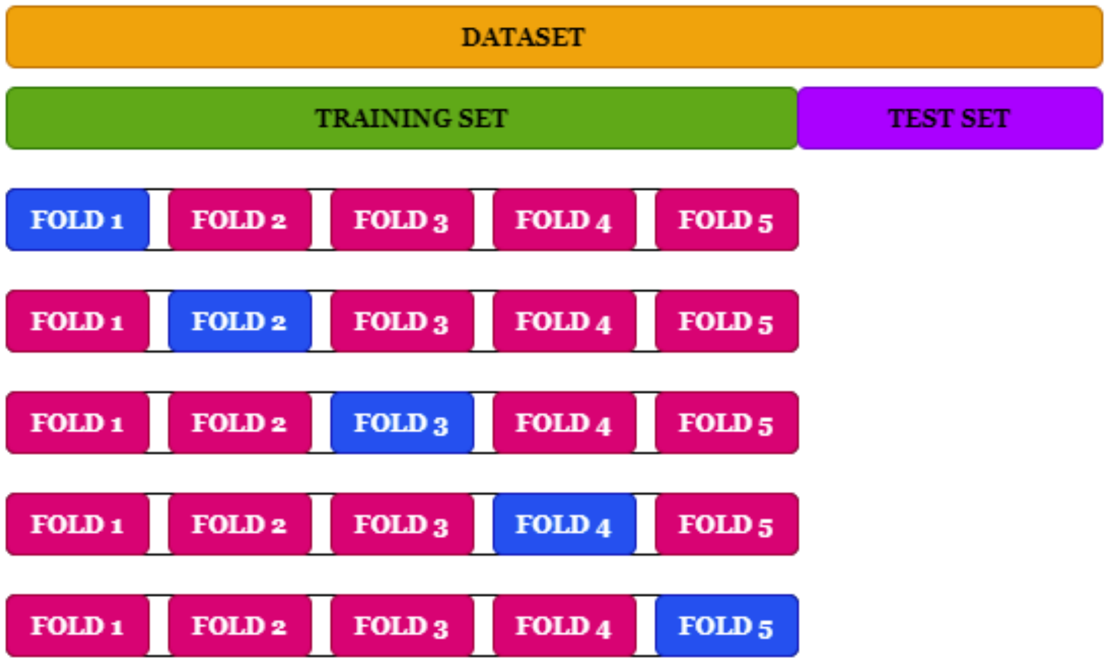


Experiment 3 - Oversampling



accuracy			0.95	16008233
macro avg	0.91	0.89	0.89	16008233
weighted avg	0.95	0.95	0.95	16008233

Experiment 3 – K-Fold Cross Validation



- Cross-validation should always be done **before** over-sampling the data, just as how feature selection should be implemented.
- Only by **resampling** the data repeatedly, **randomness** can be introduced into the dataset to make sure that there won't be an **overfitting** problem.
- Training is not finished yet

https://www.kdnuggets.com/2017/06/7-techniques-handle-imbalanced-data.html

Experiment 3 – GCN model

```
class GCN(nn.Module):
    def __init__(self, in_dim, hidden_dim, out_dim):
        super(GCN, self).__init__()
        self.layer1 = dglnn.GraphConv(in_dim, hidden_dim, allow_zero_in_degree=True)
        self.layer2 = dglnn.GraphConv(hidden_dim, out_dim, allow_zero_in_degree=True)
#         self.dropout = nn.Dropout(0.25)

    def forward(self, g, inputs):
        h = self.layer1(g, inputs)
        h = F.relu(h)
#         h = self.dropout(h)
        h = self.layer2(g, h)
        return h
```

- Maybe a easier model could remember the easier data? (single triplet graph in our case)

```
    accuracy                           0.80   2482633
   macro avg       0.36      0.27      0.30   2482633
weighted avg       0.80      0.80      0.78   2482633
```

Future Work

Future Work

- **GNN**
  - Try some other methods to improve the performance of single triplet issue
    - Maybe try some other embeddings?
    - Maybe try some other models?
    - Maybe try some data augmentation methods?
    - …
  - Could I train a specific model for small graph and then
    - Decide which model to be used based on the data
    - Ensemble
    - …

Thanks!!

Appendix

Experiment 3 - Oversampling

- Current Trial: Duplicate the data with single triplets → 20, 40, 80, 320 times

20 times

```
Number of support=100: 54
Number of support=100 and f1-score<=0.2: 53
Number of support=100 and f1-score=0: 21
Number of support=200 and f1-score=0: 10
Number of support>200 and f1-score=0: 1
```

accuracy	0.971560	0.971560	0.971560	0.97156
macro avg	0.597445	0.600577	0.594684	310263.00000
weighted avg	0.970613	0.971560	0.970482	310263.00000

40 times

```
Number of support=100: 54
Number of support=100 and f1-score<=0.2: 53
Number of support=100 and f1-score=0: 14
Number of support=200 and f1-score=0: 10
Number of support>200 and f1-score=0: 2
```

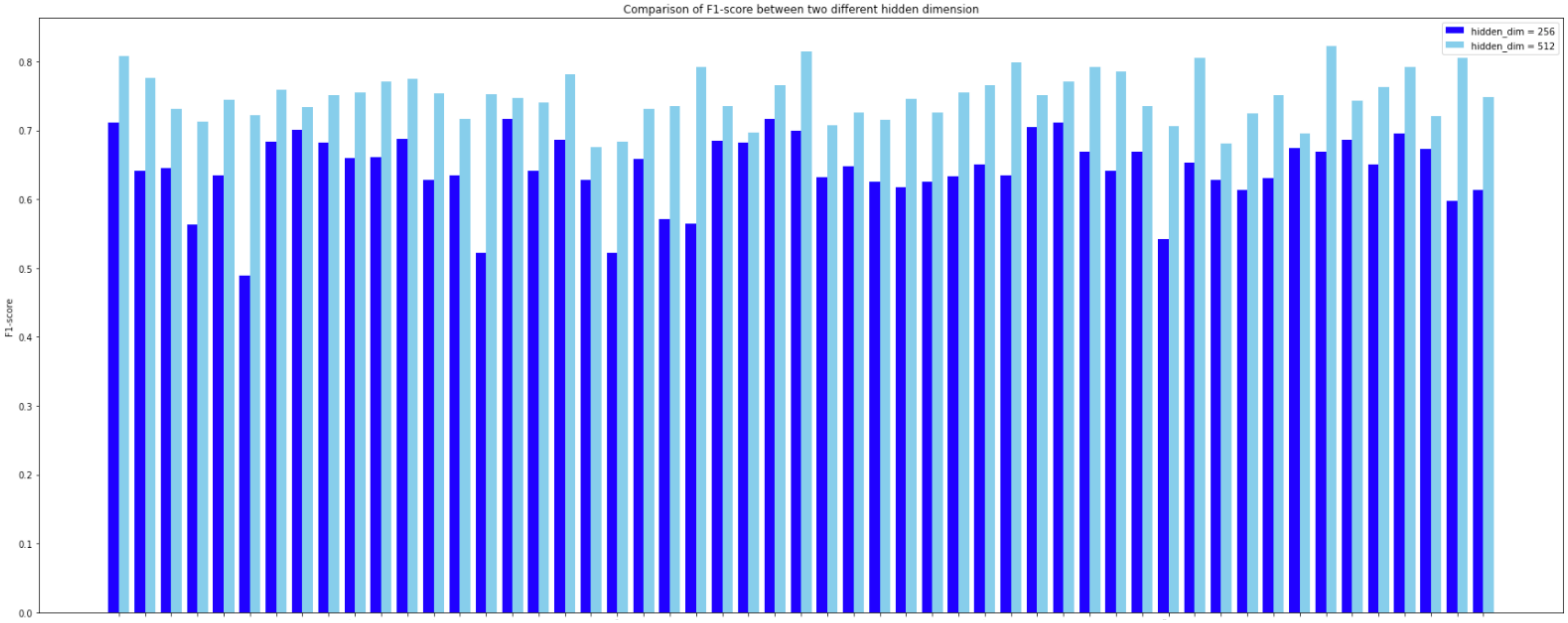
accuracy	0.971318	0.971318	0.971318	0.971318
macro avg	0.602542	0.597866	0.594387	310263.000000
weighted avg	0.971349	0.971318	0.970477	310263.000000

80 times

```
Number of support=100: 54
Number of support=100 and f1-score<=0.2: 53
Number of support=100 and f1-score=0: 18
Number of support=200 and f1-score=0: 10
Number of support>200 and f1-score=0: 3
```

accuracy	0.971463	0.971463	0.971463	0.971463
macro avg	0.596490	0.598077	0.594237	310263.000000
weighted avg	0.970626	0.971463	0.970567	310263.000000

Experiment 3 - Oversampling



Experiment 3 - Model

- Concept from the DGL official website:
  1. Let the dgl graph's edge data have the attribute: **edata["label"]**
  2. Use **GraphSAGE** model to get the new **node embedding**
  3. Use **MLP** model to get the **score** of the edge
  4. Concatenate these two models
  5. Train the final model

```
g.ndata['feat'] = th.tensor(data["node_feat"])
g.edata['feat'] = th.tensor(data["edge_attr"])
g.edata['label'] = th.tensor(data["labels"])
```

```
def model_fn(batched_g, model, criterion, device, count=1, which_type='train'):
    """Forward a batch through the model."""
    batched_g = batched_g.to(device)
    labels = batched_g.edata['label'].to(device)

    logits = model(batched_g, batched_g.ndata['feat'].float())
    loss = criterion(logits, labels)

    output = torch.softmax(logits, dim=1)
    preds = output.argmax(1)

    accuracy = torch.mean((preds == labels).float())
```

Experiment 3 - Model

```
class GraphSAGE(nn.Module):
    def __init__(self, in_dim, hidden_dim, out_dim):
        super(GraphSAGE, self).__init__()
        self.layer1 = dglnn.SAGEConv(in_dim, hidden_dim, 'pool')
        self.layer2 = dglnn.SAGEConv(hidden_dim, out_dim, 'pool')

    def forward(self, g, inputs):
        h = self.layer1(g, inputs)
        h = torch.relu(h)
        h = self.layer2(g, h)
        return h
```

```
class MLPPredictor(nn.Module):
    def __init__(self, out_feats, out_classes):
        super().__init__()
        self.W = nn.Linear(out_feats*2, out_classes)

    def apply_edges(self, edges):
        h_u = edges.src['h']
        h_v = edges.dst['h']
        score = self.W(torch.cat([h_u, h_v], 1))
        return {'score': score}

    def forward(self, graph, h):
        with graph.local_scope():
            graph.ndata['h'] = h
            graph.apply_edges(self.apply_edges)
            return graph.edata['score']
```

```
class Model(nn.Module):
    def __init__(self, in_features, hidden_features, out_features, num_classes):
        super().__init__()
        self.sage = GraphSAGE(in_features, hidden_features, out_features)
        self.pred = MLPPredictor(out_features, num_classes)

    def forward(self, g, node_feat, return_logits=False):
        h = self.sage(g, node_feat)
        logits = self.pred(g, h)

        return logits
```

Experiment 3 - Result

- **Format of the edge labels:**
  - Label 65 is benign

```
labels of Test: tensor([155,  65, 155, 155, 155], device='cuda:0') torch.Size([5])
predicted of Test: tensor([155,  65, 155, 155, 155], device='cuda:0') torch.Size([5])
labels of Test: tensor([61, 61, 61], device='cuda:0') torch.Size([3])
predicted of Test: tensor([61, 61, 61], device='cuda:0') torch.Size([3])
```

- **Classification report**:
  - transR_50:

4a0dc2e1f5d1a	0.00	0.00	0.00	100
167175e8a019a	1.00	1.00	1.00	800
c3579e9e3737b	1.00	1.00	1.00	6200
43d838e0791ca	1.00	1.00	1.00	600
benign	1.00	1.00	1.00	134563
accuracy			0.97	310263
macro avg	0.60	0.61	0.60	310263
weighted avg	0.97	0.97	0.97	310263

  - secureBERT_50:

714a0dc2e1f5d1a	0.00	0.00	0.00	100
fb167175e8a019a	0.98	1.00	0.99	800
2ac3579e9e3737b	0.97	0.98	0.98	6200
0243d838e0791ca	0.91	0.83	0.87	600
benign	0.99	1.00	0.99	134563
accuracy			0.92	310263
macro avg	0.52	0.48	0.49	310263
weighted avg	0.90	0.92	0.91	310263

- **Macro average** is similar to previous experiments → won't be affected by benign
- **Weighted average** is very high since the # of the benign is high(unbalanced) and predictable
- TransX family performs better than secureBERT

Experiment 3 – Noise

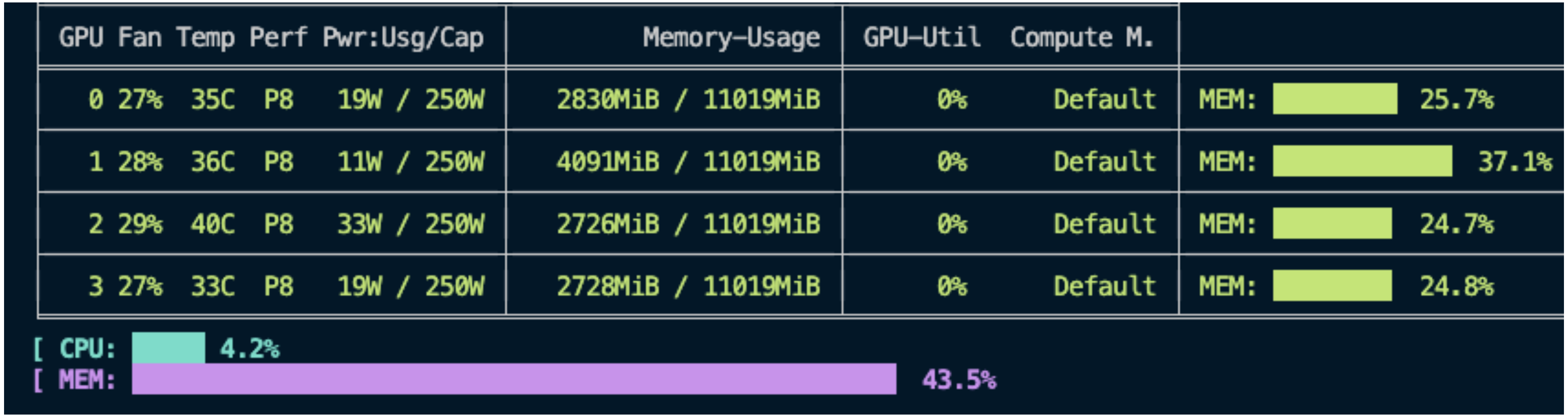
- Current Trial 1:
  - Add the **noise** to the node feature

```
def collate(samples):
    data_list = samples
    batched_graphs = []
    for data in data_list:
        g = dgl.graph((th.tensor(data["edge_index"][0]), th.tensor(data["edge_index"][1])), num_nodes=data["num_nodes"]

        node_feat = th.tensor(data["node_feat"])

        noise = th.normal(mean=0, std=0.01, size=node_feat.shape, device=node_feat.device)
        node_feat += noise

        g.ndata['feat'] = node_feat
        g.edata['feat'] = th.tensor(data["edge_attr"])
        g.edata['label'] = th.tensor(data["labels"])  # Add edge labels to graph

        batched_graphs.append(g)

    return dgl.batch(batched_graphs)
```

```
Number of support=100: 54
Number of support=100 and f1-score<=0.2: 53
Number of support=100 and f1-score=0: 46
Number of support=200 and f1-score=0: 4
Number of support>200 and f1-score=0: 0
```

Experiment 3 – Probable Issue

- Probable Issue:
  - While trying repeat 320 times:



→ seems like the computation resource might be a probelm