Progess of the Project

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Outline

- GAT
 - Dataset
 - Experiment
- TRAM
- Future Work

Graph Attention Network - GAT

Graph Attention Network - GAT

Model:

```
class GAT(nn.Module):
    def init (self, in dim, hidden dim, out dim, num heads, dropout prob=0.2):
        super(GAT, self). init ()
        # do not check the zero in degree since we have all the complete graph
        self.layer1 = GATConv(in dim, hidden dim, num heads=num heads, activation=F.relu, allow zero in degree=True)
        self.layer2 = GATConv(hidden dim * num heads, out dim, num heads=num heads, allow zero in degree=True)
        # Adding Dropout for regularization
        self.dropout = nn.Dropout(dropout prob)
    def forward(self, g, h):
        # Apply GAT layers
        h = self.layerl(q, h)
        h = h.view(h.shape[0], -1)
       h = F.relu(h)
        h = self.dropout(h)
        h = self.layer2(g, h).squeeze(1)
        # Store the output as a new node feature
        g.ndata['h out'] = h
        # Use mean pooling to aggregate this new node feature
        h agg = dgl.mean nodes(g, feat='h out')
        return h agg
```

Use the **new** verison of the dataset

Dataset

Format:

```
{"label": 10, "num_nodes": 3, "node_feat": [205565, 733769, 250773], "edge_attr": [23, 23], "edge_index": [[0, 0], [1, 2]]}
{"label": 11, "num_nodes": 3, "node_feat": [470650, 663446, 627322], "edge_attr": [23, 23], "edge_index": [[0, 0], [1, 2]]}
{"label": 15, "num_nodes": 2, "node_feat": [9863, 103498], "edge_attr": [23], "edge_index": [[0], [1]]}
{"label": 16, "num_nodes": 2, "node_feat": [157277, 753159], "edge_attr": [23], "edge_index": [[0], [1]]}
{"label": 22, "num_nodes": 36, "node_feat": [83068, 614681, 444724, 266227, 121794, 623948, 116790, 769462, 255741, 169794,
```

- Have 165 APs, each AP has 1000 variation → nodes are different but relations are same
- 0~99 test, 100~199 validation, 200~999 train → 1:1:8
- Use transR_50, transE_50, transH_50, secureBERT... as embedding → 8 versions
- Benign → benign.txt

Experiment

Experiment 1:

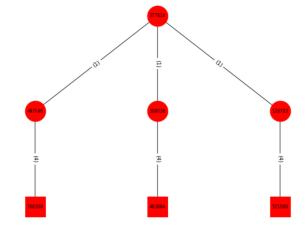
- Dataset is 165 APs with 8 versions of embedding
- Graph classification

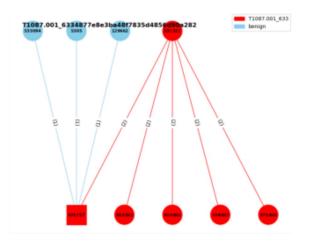
Experiment 2:

- Experiment 1 + **benign** data
- Benign made from benign.txt → 1000 graphs
- Graph classification

Experiment 3:

- Consider the neighbor benign nodes
- Edge classification





Experiment 1

- Total: 100 epochs
- About 30 epochs, they seem to be have the similar performance
- Except secureBERT, all about 40% test accuracy
- secureBERT early stopped at epoch 50 with 10% test accuracy
 - Since the dimension of the embedding is way more larger ?!
 - Dimension of SeureBERT's node embedding is from 768 → 250

- Record the training in a log file
- Also record the classification report supported by sklearn

Experiment 1

• Log file:

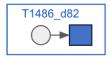
• Classification report:

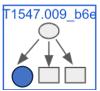
		precision	recall	f1-score	support
	Γ1003.001_0ef4cc7b-611c-4237-b20b-db36b6906554	1.00	1.00	1.00	100
	T1003.001_35d92515122effdd73801c6ac3021da7	1.00	1.00	1.00	100
	T1003.002_5a484b65c247675e3b7ada4ba648d376	0.00	0.00	0.00	100
	T1003.002_7fa4ea18694f2552547b65e23952cabb	1.00	1.00	1.00	100
	T1003.003_9f73269695e54311dd61dc68940fb3e1	0.00	0.00	0.00	100
	T1003.003_f049b89533298c2d6cd37a940248b219	0.00	0.00	0.00	100

Similar with the MLP, RNN: More triplets, more accurate

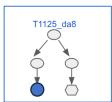
Experiment 2 & 3

- Experiment 2:
 - Haven't made the dataset of benign yet
 - Dataset would be
 - 400: Leaf nodes + their source nodes





- 300: Leaf nodes + their source nodes with source nodes' neighbor nodes
- 200: Leaf nodes + their 2 layer source nodes
- 100: Leaf nodes + their 2 layer source nodes with source nodes' neighbor nodes



- Experiment 3:
 - After finishing the experiment 2, discuss with Euni

TRAM

Format

On TRAM:

- 1 [2] Enterprise T1219 Remote Access Software RTM has used a modified version of TeamViewer and Remote Utilities for remote access.
 - [2] Enterprise T1204 .002 User Execution: Malicious File RTM has attempted to lure victims into opening e-mail attachments to execute malicious code.
- [2] Enterprise T1102 .001 Web Service: Dead Drop Resolver RTM has used an RSS feed on Livejournal to update a list of encrypted C2 server names.



Technique Add	Confidence
T1102 - Web Service	63.7%

Exported json file:

Json file includes: Text, attack id, confidence

Should be processed based on the confidence

Result

json files \rightarrow csv files:

The post also directed users as to how they could avail of th	T1543
There has been no subsequent activity from corinda	T1068
Do not be shy' These posts were recovered the	T1070.004
A 'Regular' campaign will necessitate a decryption key for e	T1573



All csv files \rightarrow xlsx file:

file_name	T1218	T1021.002	T1562.003
Report for Cyberattack-on-Ukrainian-state-authorities-using-the-Cobalthtml	0	0	0
Report for Group-description-Cleaver.html	0	0	0
Report for Analysis-Report-FiveHands-Ransomware.html	0	0	0

- with all files and TTPs
- Record the # of the labels detected in the specific file
- 141 unique TTPs
- pdf: 109/751, html: 378/3937

Future Work

Future Work

• GNN

- Do the experiment 2 and 3
- Improve the performance of the model (if available)

TRAM

- Figure out the reason of low efficiency
- Processed the data based on the confidence

Thanks!!

Appendix

Graph Convolutional Network - GCN

Graph Convolutional Network - GCN

Model:

```
class GCN(nn.Module):
    def __init__(self, in_feats, hidden_size, num_classes):
        super(GCN, self).__init__()
        self.conv1 = GraphConv(in_feats, hidden_size)
        self.conv2 = GraphConv(hidden_size, num_classes)

def forward(self, g, inputs):
    h = self.conv1(g, inputs):
    h = torch.relu(h)
    h = self.conv2(g, h)

    g.ndata['h'] = h
    hg = dgl.mean_nodes(g, 'h')
    return hg
```

- Use the **old** verison of the dataset
- Use **DGL** to be our library
- DGL data format:

Result:

• GAT applied on the old data has the similar result

Appendix

