Social network code report

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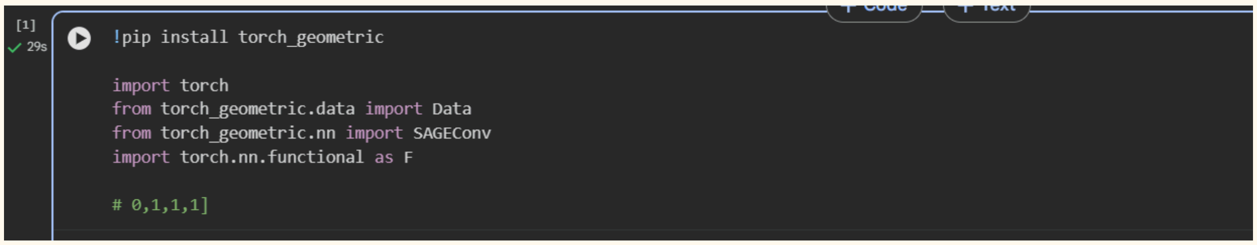
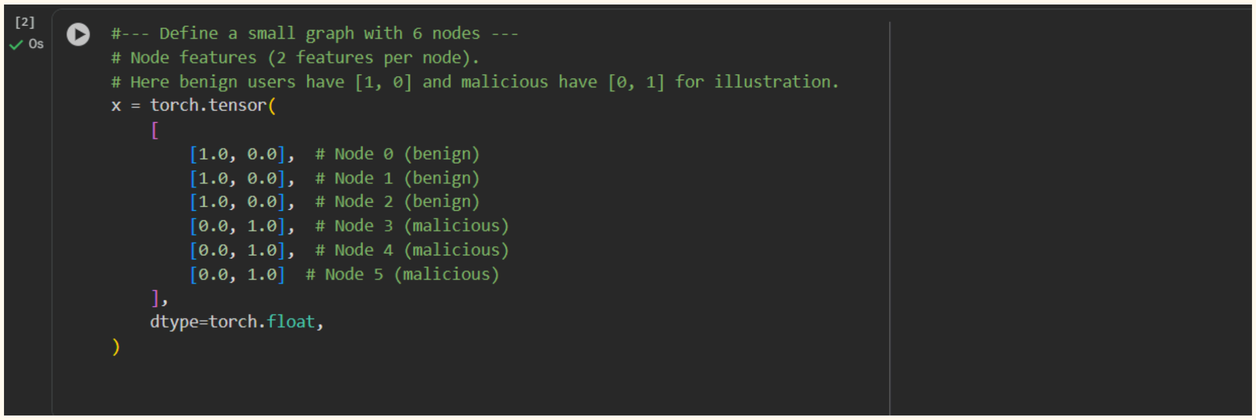


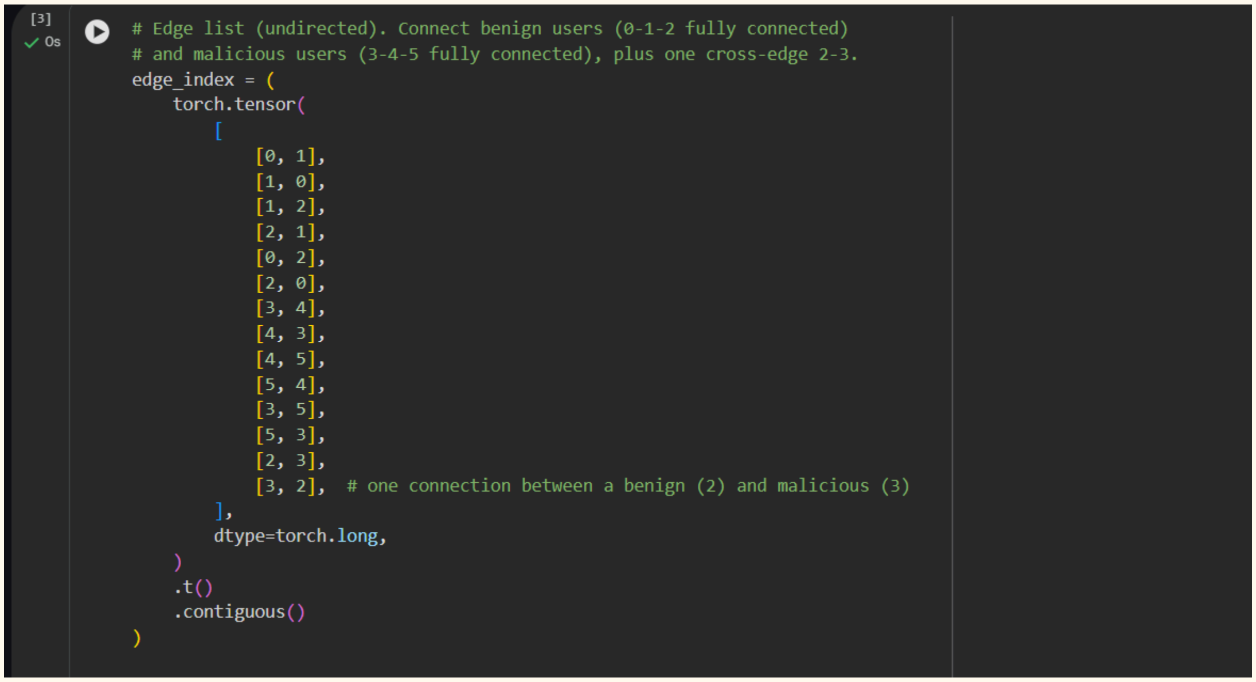
```
!pip install torch_geometric

import torch
from torch_geometric.data import Data
from torch_geometric.nn import SAGEConv
import torch.nn.functional as F

# 0,1,1,1]
```

This installs PyTorch Geometric and imports the tools needed to build models



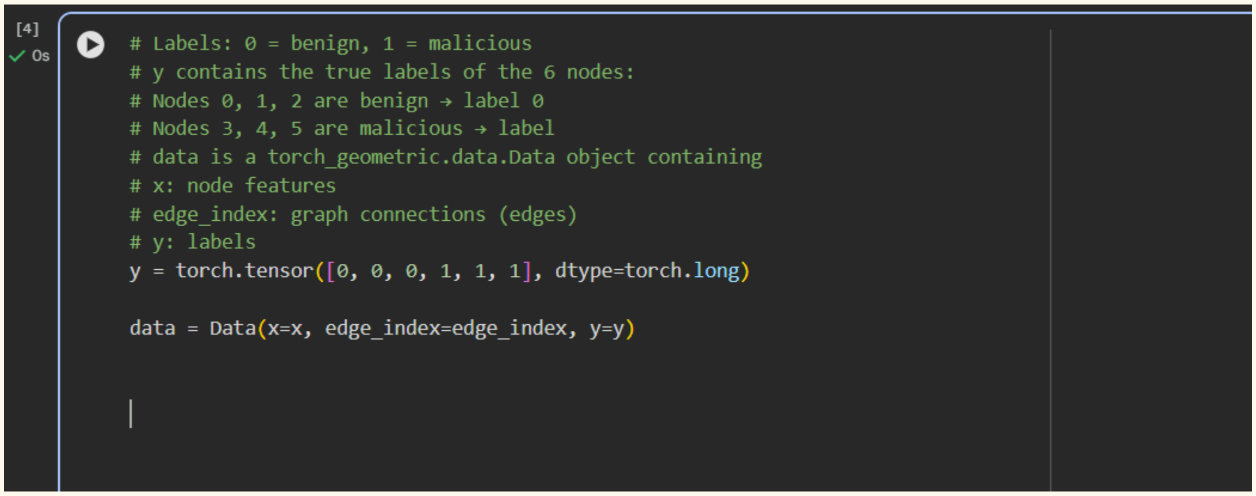
```
#--- Define a small graph with 6 nodes ---
# Node features (2 features per node).
# Here benign users have [1, 0] and malicious have [0, 1] for illustration.
x = torch.tensor(
    [
        [1.0, 0.0],  # Node 0 (benign)
        [1.0, 0.0],  # Node 1 (benign)
        [1.0, 0.0],  # Node 2 (benign)
        [0.0, 1.0],  # Node 3 (malicious)
        [0.0, 1.0],  # Node 4 (malicious)
        [0.0, 1.0]  # Node 5 (malicious)
    ],
    dtype=torch.float,
)
```

This creates a tensor of 6 nodes each with 2 features describing whether it’s benign [1,0] or malicious [0,1]

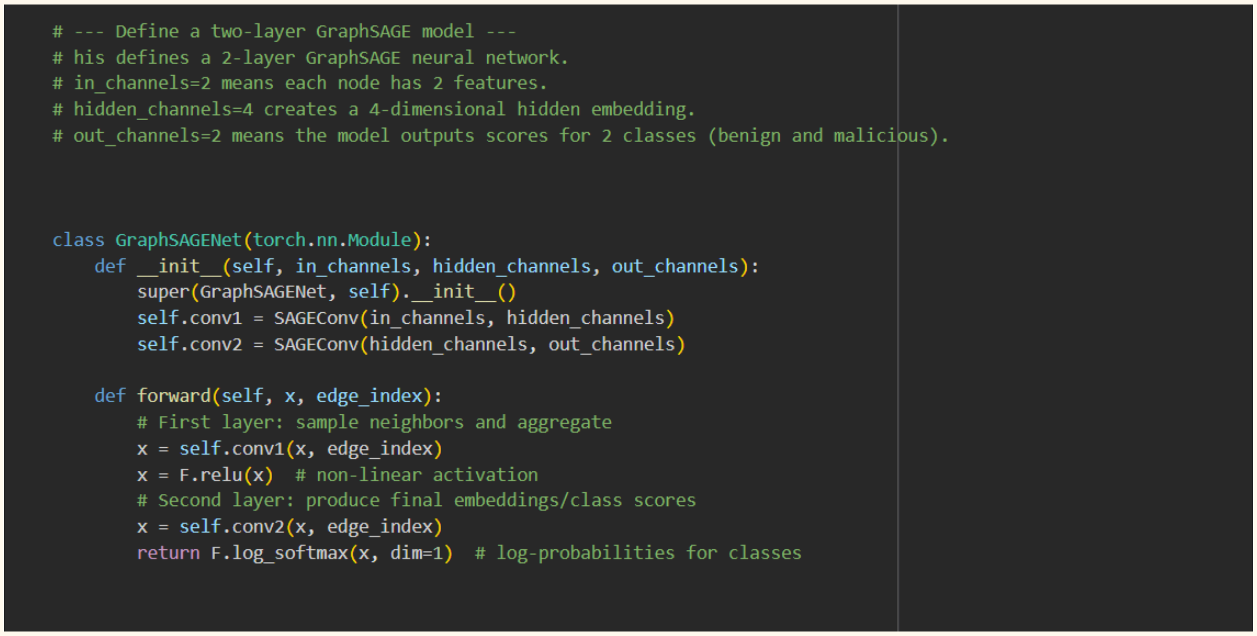


```
[3]
✓ 0s
# Edge list (undirected). Connect benign users (0-1-2 fully connected)
# and malicious users (3-4-5 fully connected), plus one cross-edge 2-3.
edge_index = (
    torch.tensor(
        [
            [0, 1],
            [1, 0],
            [1, 2],
            [2, 1],
            [0, 2],
            [2, 0],
            [3, 4],
            [4, 3],
            [4, 5],
            [5, 4],
            [3, 5],
            [5, 3],
            [2, 3],
            [3, 2],  # one connection between a benign (2) and malicious (3)
        ],
        dtype=torch.long,
    )
    .t()
    .contiguous()
)
```

This builds the graph's edges by listing which nodes are connected (benign fully connected, malicious fully connected, plus one cross-link)

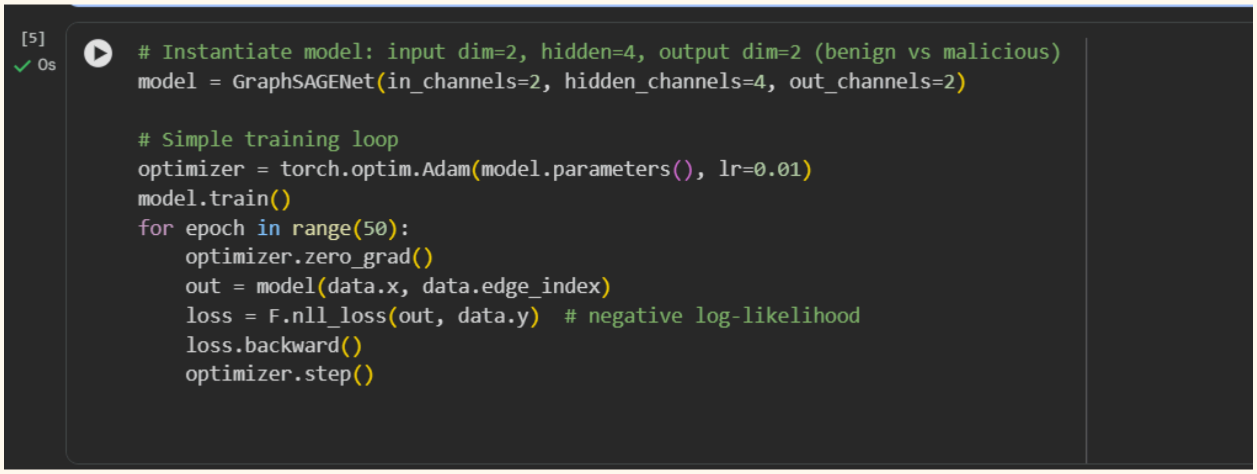


```
[4]
✓ 0s
# Labels: 0 = benign, 1 = malicious
# y contains the true labels of the 6 nodes:
# Nodes 0, 1, 2 are benign → label 0
# Nodes 3, 4, 5 are malicious → label
# data is a torch_geometric.data.Data object containing
# x: node features
# edge_index: graph connections (edges)
# y: labels
y = torch.tensor([0, 0, 0, 1, 1, 1], dtype=torch.long)

data = Data(x=x, edge_index=edge_index, y=y)
```



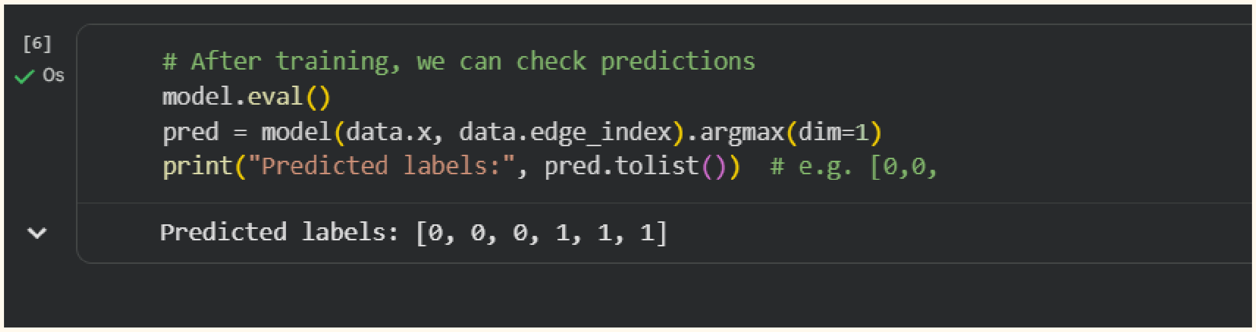
```
# --- Define a two-layer GraphSAGE model ---
# his defines a 2-layer GraphSAGE neural network.
# in_channels=2 means each node has 2 features.
# hidden_channels=4 creates a 4-dimensional hidden embedding.
# out_channels=2 means the model outputs scores for 2 classes (benign and malicious).



class GraphSAGENet(torch.nn.Module):
    def __init__(self, in_channels, hidden_channels, out_channels):
        super(GraphSAGENet, self).__init__()
        self.conv1 = SAGEConv(in_channels, hidden_channels)
        self.conv2 = SAGEConv(hidden_channels, out_channels)

    def forward(self, x, edge_index):
        # First layer: sample neighbors and aggregate
        x = self.conv1(x, edge_index)
        x = F.relu(x)  # non-linear activation
        # Second layer: produce final embeddings/class scores
        x = self.conv2(x, edge_index)
        return F.log_softmax(x, dim=1)  # log-probabilities for classes
```

This model takes each node then mixes its features with its neighbors and learns new representations then it outputs whether each node is benign or malicious



```
[5]
✓ 0s
# Instantiate model: input dim=2, hidden=4, output dim=2 (benign vs malicious)
model = GraphSAGENet(in_channels=2, hidden_channels=4, out_channels=2)

# Simple training loop
optimizer = torch.optim.Adam(model.parameters(), lr=0.01)
model.train()
for epoch in range(50):
    optimizer.zero_grad()
    out = model(data.x, data.edge_index)
    loss = F.nll_loss(out, data.y)  # negative log-likelihood
    loss.backward()
    optimizer.step()
```

This creates the model and trains it by repeatedly predicting node labels and adjusting weights to reduce the loss each loop updates the model so it gets better at classifying benign vs malicious nodes



```
[6]
0s
    # After training, we can check predictions
    model.eval()
    pred = model(data.x, data.edge_index).argmax(dim=1)
    print("Predicted labels:", pred.tolist())  # e.g. [0,0,

    Predicted labels: [0, 0, 0, 1, 1, 1]
```

Runs the trained model to predict each node's label then picks the class with the highest score

It prints the final predicted benign/malicious labels