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Social Network

```python
#--- 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,
)
```

We are creating a small graph with 6 Nodes (Users), and each Node has features that indicate whether it is normal or malicious.

We give the GCN data to input, from which it can distinguish between normal and malicious nodes, and learn patterns based on the connections between them.

```python
# Here benign users have [1, 0] and malicious have [0, 1] for illustration.

# 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()
)
```

The edge_index is where we define the connections between nodes in the graph.

It means who is connected to whom.

```python
# 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):
```


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```


```python
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
```

x → features

y → labels

SAGEConv 1 ,Takes the number of original features in_channels and outputs hidden representations

And Gathers information from neighbors (aggregate neighbors).

SAGEConv 2 , Takes the hidden presentation and calculates class scores .

```python
# 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()
```

Each Epoch model:

1. Takes the graph
2. Calculates predictions
3. Compares them to the labels
4. Calculates losses
5. Rewinds errors
6. Adjusts weights
7. Repeats the statement 50 times

Finally, the model learns to distinguish between normal and malicious nodes.

```python
# 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]
```

Testing