

# Identifying Critical Nodes in Large Complex Systems Using Temporal Graph Convolutional Networks

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## Background/Problem

- Cyber-physical systems face many vulnerabilities and attack exposures due to high connectivity, heterogeneous networks, and reliance on shared resources.
- Given the scale of these interconnected systems and limited defense resources, it is challenging to determine which assets truly matter to prioritize defenses.
- Security teams rely on Common Vulnerability Scoring System (CVSS) scores to decide which vulnerabilities to address first.
- However, CVSS fails to incorporate contextual factors, such as how the devices are connected and which assets are critical.
- Without this context, CVSS can overlook vulnerabilities that pose disproportionate risks due to their position in the network.

## Our Approach

We develop a **Graph Convolutional Network GCN** that learns network topology and evolving behavior to rank nodes by criticality

### 1 Model the System as a Graph

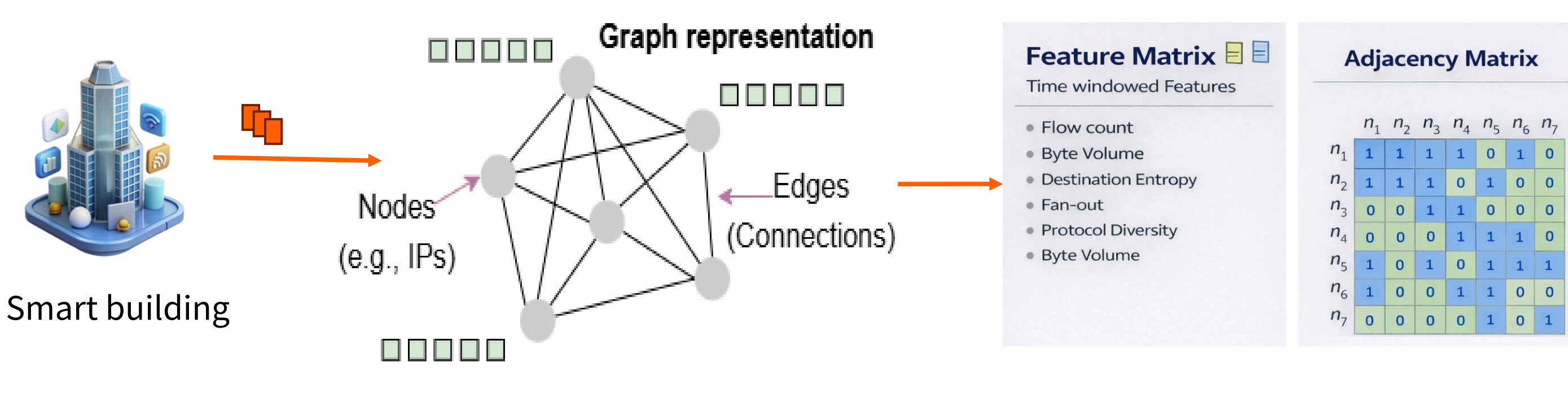
- Represent the cyber-physical system as  $G = (V, E)$
- Nodes:** assets (servers, PLCs, IoT, gateways)
- Edges:** communication relationships
- Captures topology and dependencies between assets

### 2 Extract Traffic & Temporal Features

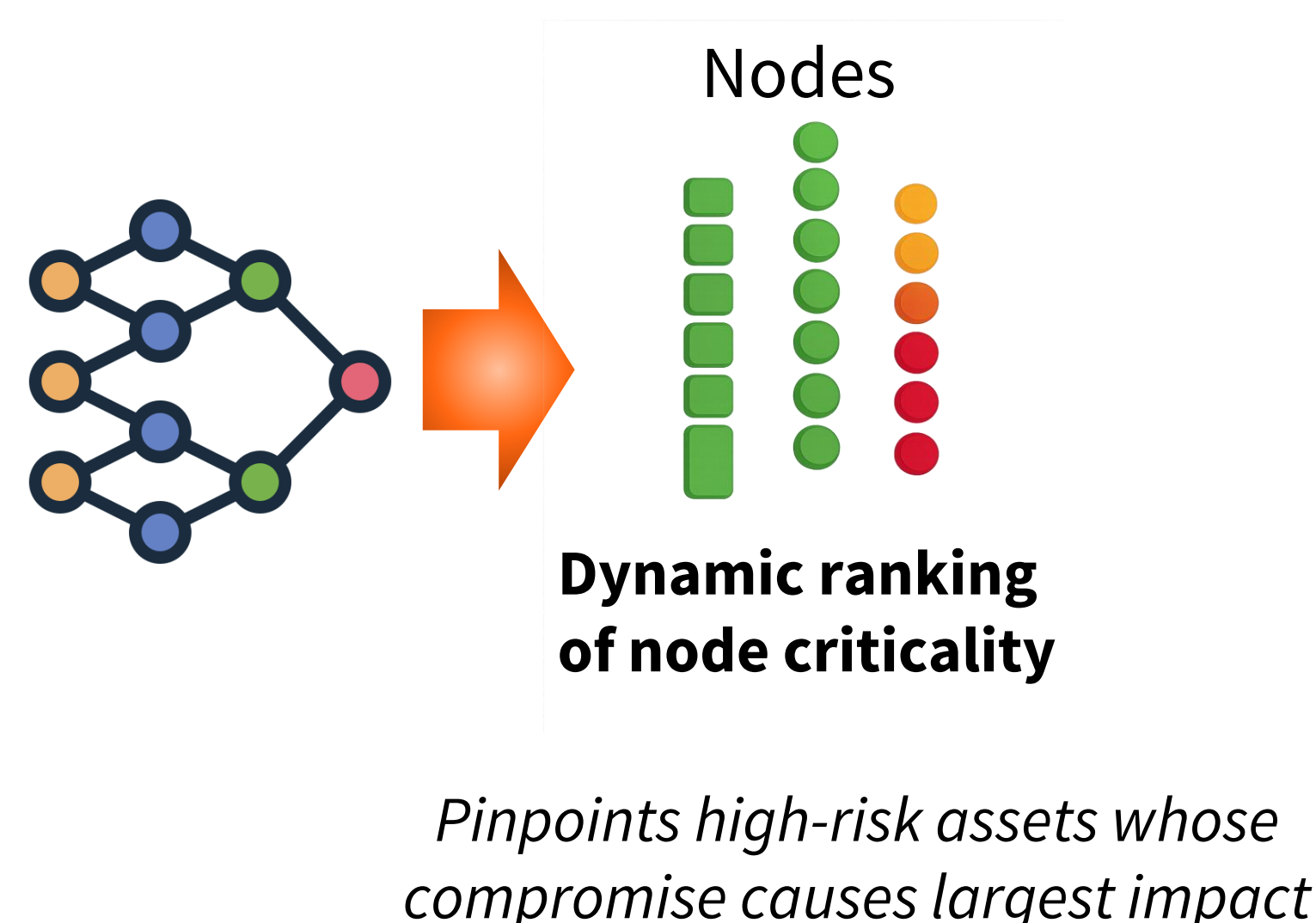
- Construct node feature matrix and adjacency matrix from normal traffic
- Features:** Flow count, byte volume, destination entropy, fan-out ratio, protocol diversity
- Use sliding windows to capture evolving behavior

### 3 Learn Spatio-Temporal Patterns with GCN

- GCN layers:** Learn structural importance from topology and node features
- Graph Attention Network (GAT) layers:** Assign different weights to neighbors during feature aggregation.
- Graph Recurrent Unit (GRU) layers:** Capture temporal evolution of node features and behavior.
- Train with hybrid ranking loss to preserve node ordering.



- GCN** → Learn network structure from traffic and topology
- Graph Attention Network (GAT)** → Assign different weights to neighbours
- Gated Recurrent Unit (GRU)** → Capture temporal patterns in traffic



## Evaluation

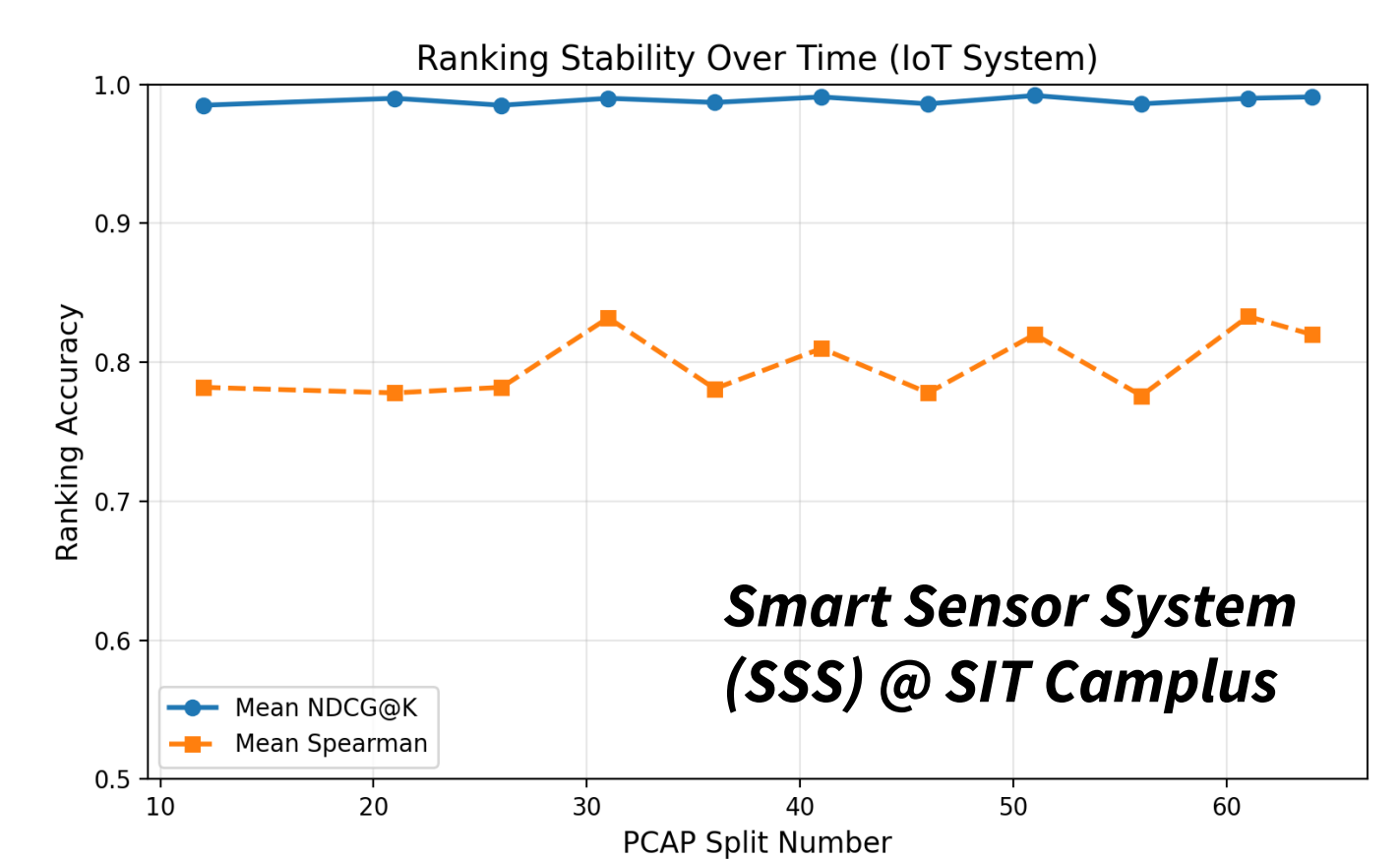
Validated using operational datasets from two real-world systems:

- SIT Campus @ Punggol Digital District**
  - Building Automation System (BAS)
  - Smart Sensor System (SSS)

Top 10 nodes (SSS) 6 Jun 2025, 12pm to 6:30pm

```

===== Train on capture-20250603.e2mcr1.pcap.split1
===== Test on capture-20250603.e2mcr1.pcap.split1
mean_spearman: 0.7837
mean_mae: 0.0630
mean_ndcg@k: 0.9873
Top 39 critical nodes:
1: 192.168.2.36      -> 0.989343
2: 192.168.0.23     -> 0.337363
3: 192.168.0.52     -> 0.179050
4: 192.168.0.220    -> 0.174647
5: 192.168.0.157    -> 0.174369
6: 192.168.0.253    -> 0.174215
7: 192.168.0.221    -> 0.174139
8: 192.168.0.243    -> 0.173376
9: 192.168.0.130    -> 0.172422
10: 192.168.0.45    -> 0.172223
    
```

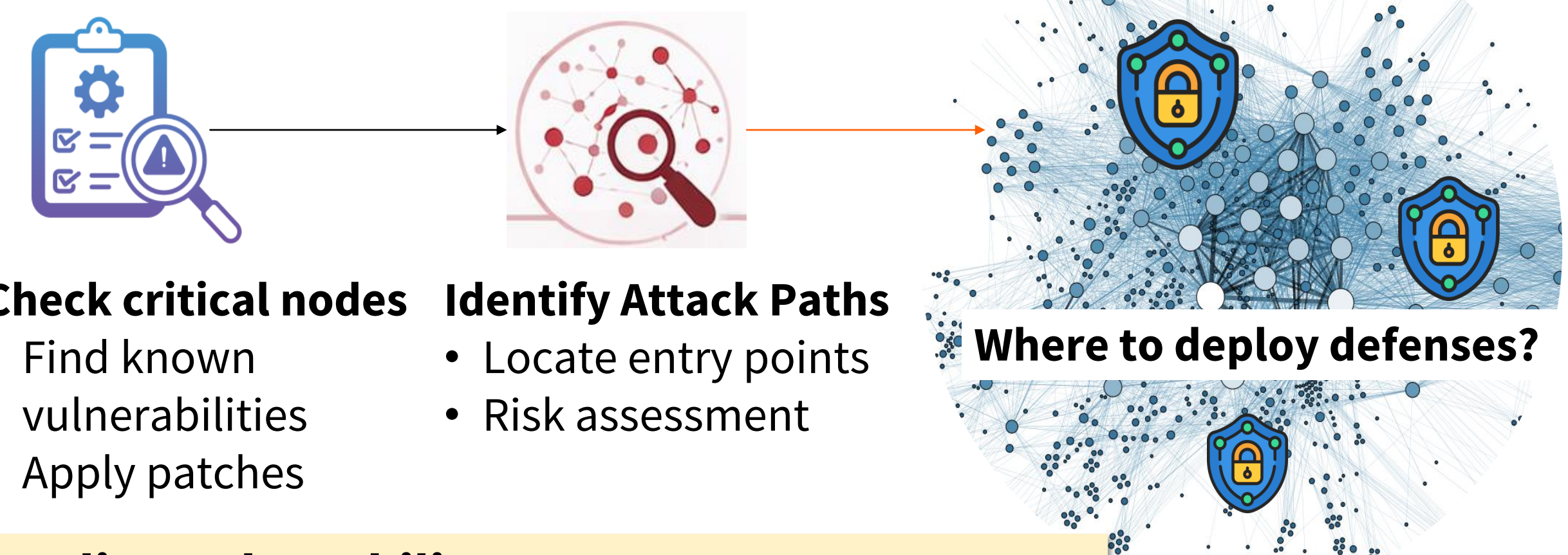


Rank nodes by criticality to prioritize defenses

**Stable rankings** → Normal operation

**Abrupt changes** → Topology / configuration updates

**Unexplained changes** → Possible attack (e.g., scanning, DoS)



**Streamline vulnerability assessment; Improve situational awareness & guide defense**

## Attack Detection with GCN

- Attacks induce **abnormal rank shifts** in influential nodes
- Targeted disruptions cause **instability in node importance**
- Deviations from baseline indicate **potential compromise**
- Criticality drift** = early indicator of cyber attack activity

