



A Knowledge Representation and Information Fusion Framework for Decision Making in Complex Cyber-Physical Systems

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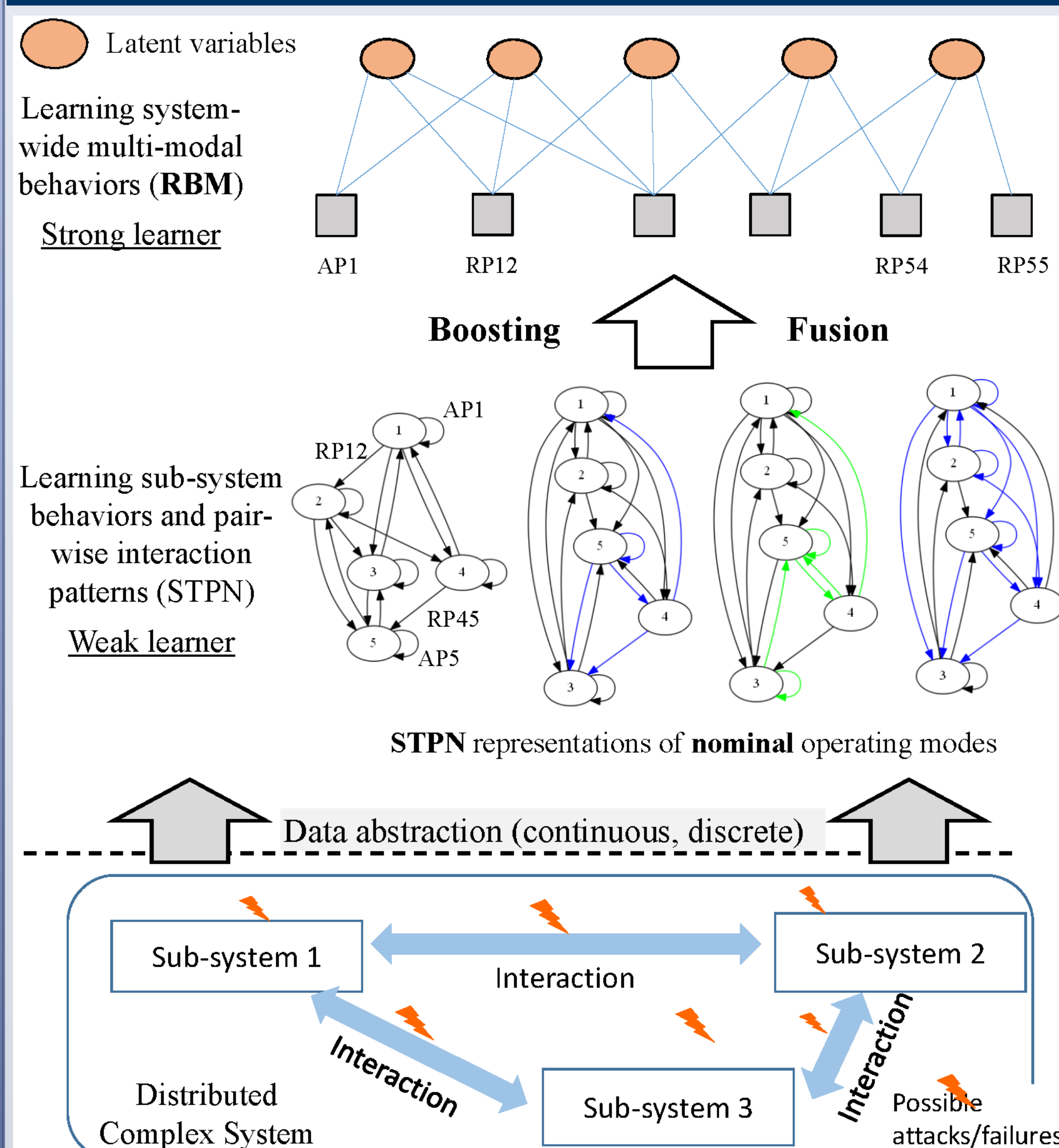
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Project Objectives

- Develop a **data-driven modeling framework** for CPSs that reliably captures cyber and physical sub-system behaviors as well as their interaction characteristics.
- To address the need of **performance monitoring and fault detection & diagnostics (FDD)** in distributed CPSs (e.g., integrated building), with **cyber attacks and physical anomalies**.
- Challenge: **Inference and root cause analysis** in complex CPSs with **multiple (possibly unforeseen) anomalies** at the same time, **system wide impact estimation** in a large interconnected system.

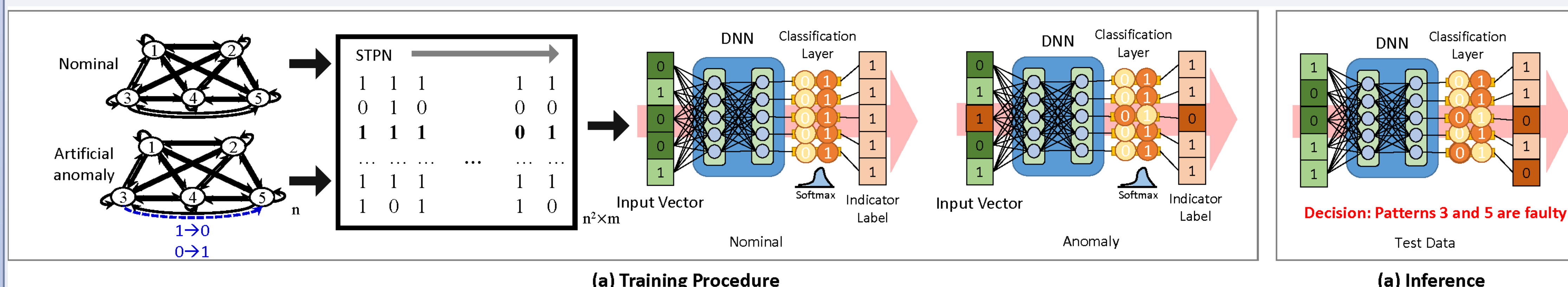
Previous work: Anomaly detection



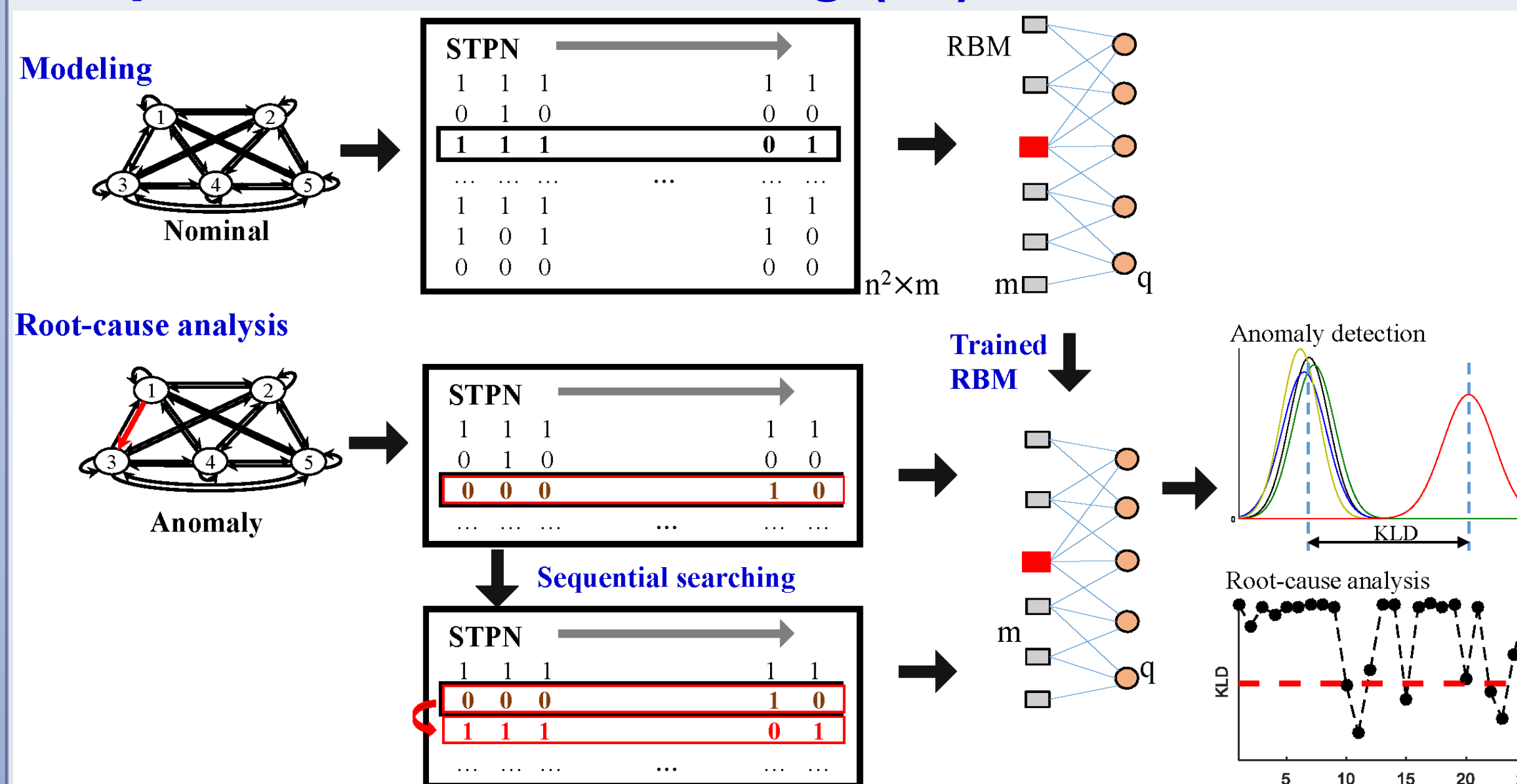
- A data-driven framework for **system-wide anomaly detection** was proposed, noted as the **STPN+RBM** model, to implement **unsupervised anomaly detection** with **spatiotemporal causal graphical modeling**.
- Validation on synthetic data and real system shows the proposed framework can handle **mixed data types, local and global anomalies**, and capture **multiple nominal modes**.

Root-cause analysis of complex CPSs via spatiotemporal causal graphical modeling

Artificial anomaly association (A^3)



Sequential state switching (S^3)



Accuracy metrics

$$\alpha_1 = \frac{\sum_{j=1}^{n^2} \sum_{i=1}^m \chi_1(T_{ij} = P_{ij})}{mn^2}$$

where T_{ij} denotes the ground truth state (nominal/anomalous) of the j th pattern of the i th test sample. P_{ij} is the corresponding predicted state.

$$Recall = \frac{TP}{TP + FN} \quad Precision = \frac{TP}{TP + FP}$$

$$F - measure = \frac{2}{1/precision + 1/recall}$$

where TP is true positive rate, FN is false negative rate, and FP is false positive rate

Case study with synthetic data

Learning of multiple nominal modes and root-cause analysis of failed patterns

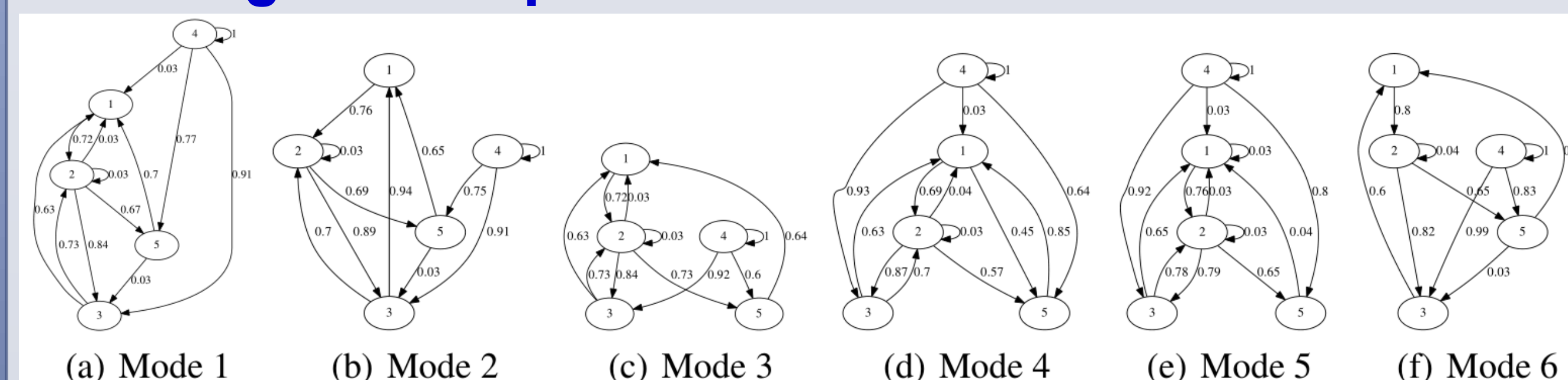


Table 1: Root-cause analysis results in S^3 method and A^3 method with synthetic data.

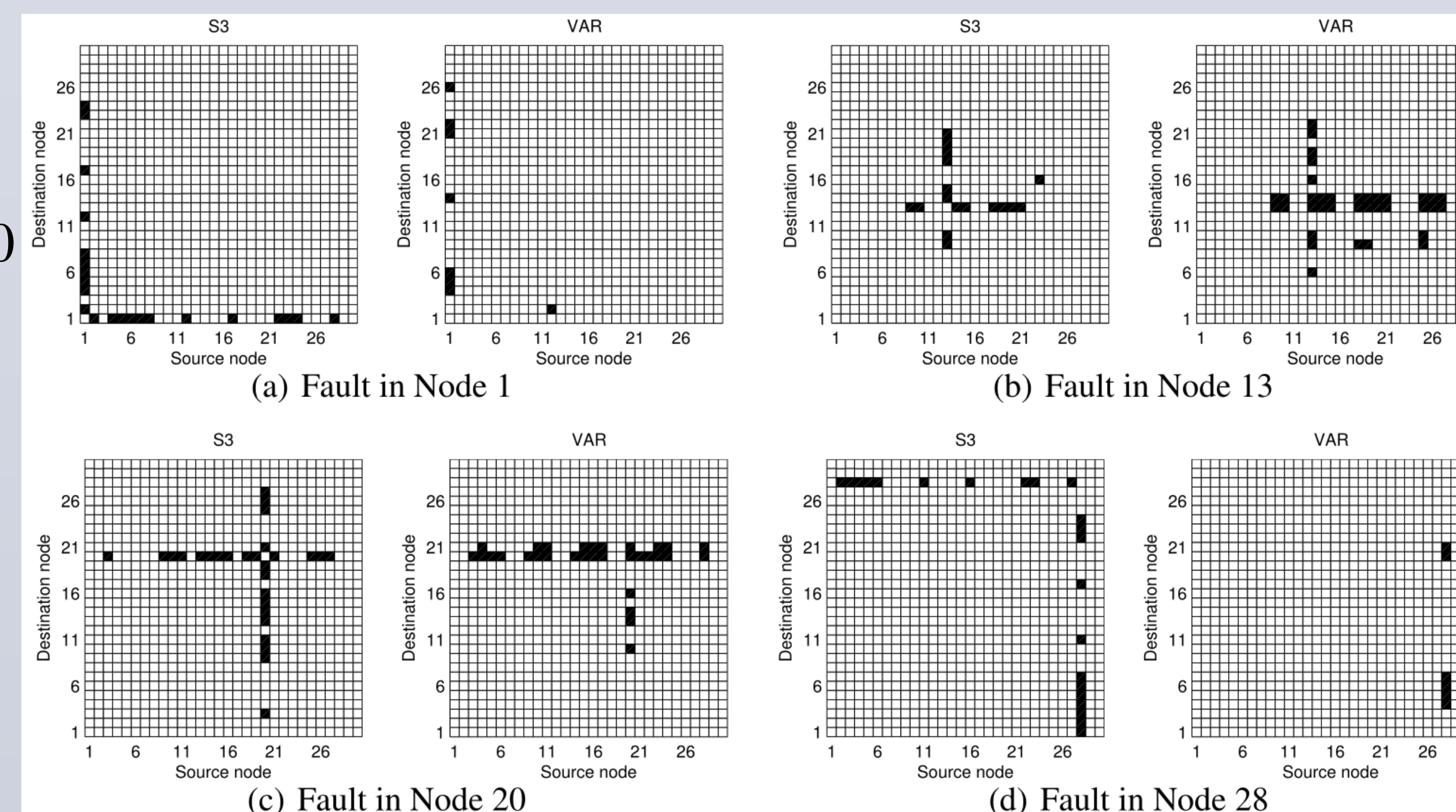
Approach	Training samples	Testing samples	Accuracy α_1 (%)	Recall (%)	Precision (%)	F-measure (%)
S^3	11,400	57,000	97.04	99.40	97.10	98.24
A^3	296,400	57,000	98.66	90.46	95.95	93.12

Root-cause analysis of failed node Scalability analysis

- Dataset: 5-node and 30-node systems, 5 and 30 anomalies via simulating every node failure respectively.
- Methods: Sequential state switching (S^3) and Vector autoregressive (VAR) model.

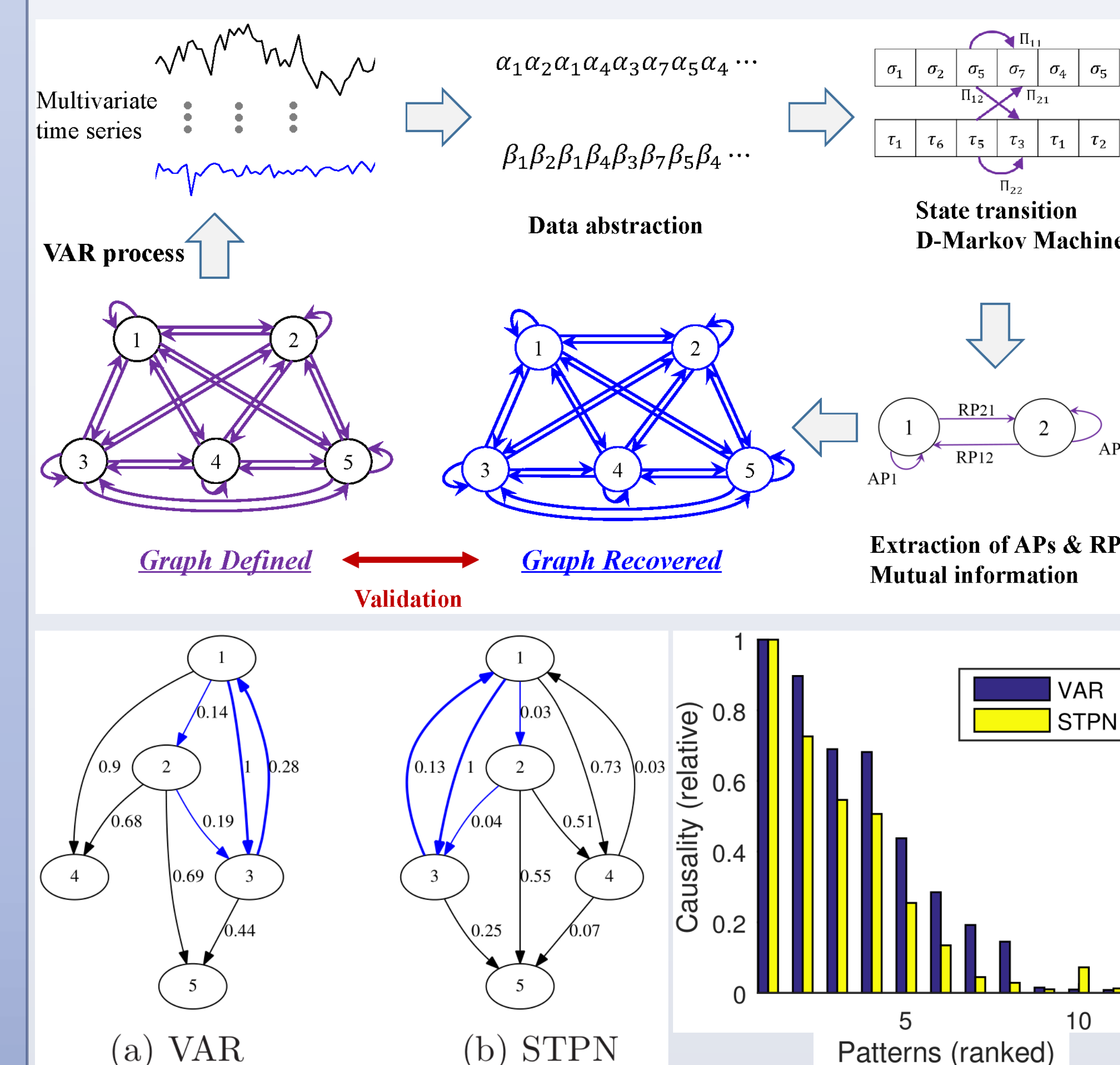
Table 2: Comparison of root-cause analysis results with S^3 and VAR.

Approach	Dataset 2 (5 nodes)			Dataset 3 (30 nodes)		
	$ \{\Lambda^{ano}\} $	$ \{\Lambda^c\} $	ϵ (%)	$ \{\Lambda^{ano}\} $	$ \{\Lambda^c\} $	ϵ (%)
S^3	13	2	15.38	653	18	2.76
VAR	20	4	20.00	521	113	21.69



STPN for recovering graphical models

- To validate the efficacy of STPN in interpreting causality in graphical models, case studies are carried out and compared with VAR model.



Conclusions & Future Work

- Sequential state switching (S^3) and artificial anomaly association (A^3)—are proposed for root-cause analysis in complex cyber-physical systems.
- With synthetic data, proposed approaches are validated and showed high accuracy in finding failed patterns and diagnose for anomalous node.

Further works will pursue the following:

- Inference** approach in node failure including **single node and multiple nodes**
- Detection and root-cause analysis of **simultaneous multiple faults** in distributed complex systems.

Team & Acknowledgments

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Undergraduate Students: Minghao Wang (Fall REU)

PostDoc Fellow: Chao Liu, PhD

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