PÔSTER - RESUMO - SENSORES E BIOSSENSORES

FROM SENSORS TO GRAPHS: A COMPARATIVE STUDY OF GNNS AND NETWORK AUTOMATA FOR PATTERN RECOGNITION

Elioenai Markson Ferreira Diniz (elioenaidiniz@gmail.com_old)

Victor Richard Cardoso (v.richard@usp.br)

Odemir Bruno (bruno@ifsc.usp.br)

Sensors and biosensors increasingly produce heterogeneous, high-dimensional data streams that range from structured multivariate measurements (vectors and matrices) to semi-structured or unstructured outputs (events, sequences, irregular sampling, and multimodal signals). A key challenge is to represent these diverse observations in a unified way that preserves relational structure across sensing channels, time, and operating conditions, enabling robust pattern recognition for tasks such as classification, detection, and condition monitoring. Graphs provide a natural and flexible representation for this purpose: virtually any data modality can be modeled as a network by encoding samples, sensor channels, temporal segments, or extracted components as nodes, and defining edges through physical connectivity, functional similarity, temporal coupling, or learned relationships. This makes graph-based modeling particularly suitable for multi-sensor and biosensor scenarios where interactions and dependencies carry essential information.

In this work, we investigate and compare two complementary families of machine learning approaches for pattern recognition on data modeled as graphs. First, we evaluate modern graph neural network (GNN) architectures—

including graph convolutional networks and related message-passing variants—designed to learn task-oriented node, edge, or whole-graph embeddings directly from topology and attributes. Second, we consider complex-network-inspired methods that characterize graphs through interpretable structural measurements, as well as network automata models, with emphasis on the Life-Like Network Automata (LLNA) framework, which embeds cellular automaton dynamics on a network topology and converts the resulting spatio-temporal patterns into discriminative feature vectors (Miranda et al., Scientific Reports, 2016).

We present a concise comparative study across multiple graph datasets that reflect different regimes commonly found in sensing and biosensing applications, such as sparse versus dense connectivity, varying levels of attribute informativeness, and differences in graph size and heterogeneity. Our analysis highlights practical trade-offs between approaches: GNNs tend to excel when sufficient labeled data and informative attributes are available, leveraging end-to-end representation learning; in contrast, complex-network descriptors and LLNA-based features can offer competitive performance and improved interpretability in settings with limited labels, weak attributes, or where topology-driven dynamics capture class-specific signatures. These findings provide guidance for selecting graph-based learning strategies tailored to the characteristics of sensor- and biosensor-derived graphs, supporting more reliable and explainable decision-making in real-world deployments.

Palavras-chave: graph neural network; network automata; complex network.