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Graph Neural Networks for temporal graphs: State of the art, open challenges, and opportunities

Keywords: Temporal Networks, Graph Neural Networks, Temporal Neural Network, Geometric Deep Learning, Dynamic Pattern

Extended Abstract

The ability to process temporal graphs is becoming increasingly important in a variety of fields such as social network analysis [4], recommendation systems [16], face-to-face interactions [9], epidemic modeling [3], and many others. Traditional graph-based models are not well suited for analyzing temporal graphs as they assume a fixed structure and are unable to capture its temporal evolution. Therefore, in the last few years, several models able to directly encode temporal graphs have been developed, such as random walk-based methods [15], temporal motif-based methods [8] and matrix factorization-based approaches [1].

In the realm of static graph processing, Graph Neural Networks (GNNs) [13] have progressively emerged as the leading paradigm, thanks to their ability to efficiently propagate information along the graph and learn rich node and graph representations. Overall, the success of GNNs highlights the importance of developing deep learning techniques to handle non-Euclidean data, and in particular the potential of these architectures to revolutionize the way we analyze and understand complex graph-structured systems.

Recently, GNNs have been successfully applied also to temporal graphs, achieving state-of-the-art results on temporal link prediction [12] and node classification [11] with approaches ranging from attention-based methods [18] to Variational Graph-Autoencoder (VGAE) [6]. However, despite the potential of GNN-based models for temporal graph processing and the variety of different approaches that emerged, a systematization of the literature is still missing. Existing surveys either discuss general techniques for learning over temporal graphs, only briefly mentioning temporal extensions of GNNs [7, 2, 17], or focus on specific topics, like temporal link prediction [10, 14] or temporal graph generation [5]. This work aims to fill this gap by providing a systematization of existing GNN-based methods for temporal graphs, or Temporal GNNs (TGNNs), and a formalization of the tasks being addressed. Our main contributions are the following: (i) we propose a coherent formalization of the different learning settings and of the tasks that can be performed on temporal graphs, unifying existing formalism and informal definitions that are scattered in the literature, and highlighting substantial gaps in what is currently being tackled; (ii) we organize existing TGNN works into a comprehensive taxonomy that groups methods according to the way in which time is represented and the mechanism with which it is taken into account; (iii) we highlight the limitations of current TGNN methods, discuss open challenges that deserve further investigation and present critical real-world applications where TGNNs could provide substantial gains.

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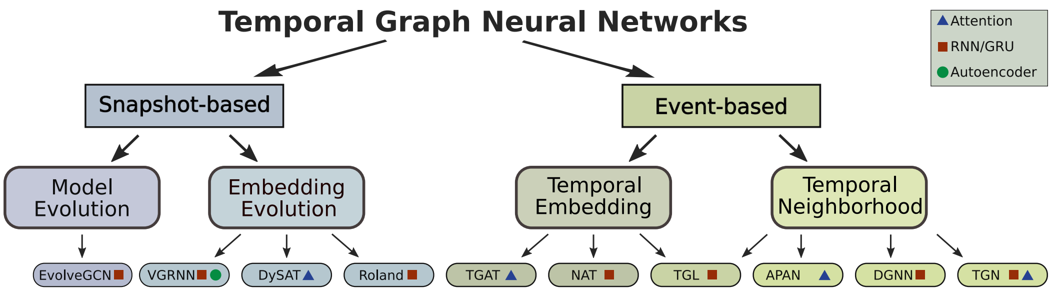

Figure 1: Proposed Taxonomy