Temple University

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Department of Computer and Information Sciences

Higher-order Representation Learning on Graphs

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Abstract: Geometric Deep Learning (GDL) is an emerging direction aiming to advance deep learning methodology to non-Euclidean objects such as graphs and manifolds. Most recently, GDL models such as Graph Neural Networks (GNNs) have also proven to be a new powerful alternative for spatio-temporal forecasting. However, despite their success, GNNs tend to be limited in their ability to simultaneously infer latent temporal relations and encode higher-order interactions among entities. My research tackles these limitations across a spectrum of higher-order network learning, from topological data analysis to simplicial complexes on graphs. In particular, in my most recent papers, (i) I have developed a novel time-conditioned topological representation, and made the first step on a path of bridging the two emerging directions, namely, time-aware GDL with time-conditioned topological representations of complex dynamic networks, and (ii) I have bridged the recently emerging concepts of convolutional architectures on simplicial complexes with topological signal processing on graphs, with applications ranging from link prediction to strategies on the epidemic intervention in social networks.

This talk will highlight two of my most recent projects that epitomize these methodologies. First, I will present our topology-based spatio-temporal GDL model TAMP-S2GCNets --- the first effort to bridge topology-based GDL model with time-aware multiparameter persistent homology representations of the data in learning complex multivariate spatio-temporal processes (ICLR'22 Spotlight). I will illustrate our approach in application to traffic flow forecasting, Ethereum blockchain price prediction, and COVID-19 hospitalizations forecasting, and will also discuss computational gains and utility of the proposed time-conditioned topological descriptors for encoding the time-conditioned knowledge. Second, I will present a novel block simplicial complex neural networks model (BScNets) for link prediction tasks (AAAI'22). The proposed block Hodge-style representation module in BScNets allows us to capture latent geometric, topological, and combinatorial characteristics which are largely inaccessible with the prevailing approaches. I will discuss how simplicial convolution and BScNets, in particular, can enhance link prediction tasks in a broad range of applications, from social network analysis to bioinformatics to COVID-19 biosurveillance. Finally, I will conclude with a number of emerging applications and future research directions.

Bio: Yuzhou Chen is a Postdoctoral scholar in Department of Electrical and Computer Engineering at Princeton University. He is also currently an NSF Research Fellow at Lawrence Berkeley National Laboratory. He received his Ph.D. in Statistics at Southern Methodist University in 2021. Before that, he was a research fellow at the National Renewable Energy Laboratory and INRIA, respectively. He received his M.S. degree from University of Texas at Dallas and B.S. degree from Zhejiang Gongshang University. His main research interests are in geometric deep learning, topological data analysis, knowledge discovery in graphs and spatio-temporal data, with applications to power systems, biosurveillance and blockchain data analytics. His research has appeared in the top machine learning and data mining top conferences, including ICML, ICLR, NeurIPS, KDD, AAAI, ICDM, etc. He was the recipient of 2022 and 2021 Best Paper Award of the Section for Statistics in Defense and National Security (SDNS) of the American Statistical Association (ASA) and 2021 Chateaubriand Fellowship from the Embassy of France in the United States.