

IEEE Transactions on Signal and Information Processing over Networks

Special Issue on Network Topology Inference

Making sense of large-scale datasets from a network-centric perspective will constitute a crucial step to obtain new insights in various areas in science and engineering. Machine learning (ML), in particular, can significantly benefit from graph-based representations, as they are instrumental to unveil inner data structures that can properly guide, for instance, unsupervised or semi-supervised learning algorithms. Similarly, the goal of graph signal processing (GSP) is to develop information processing algorithms that fruitfully leverage the data's relational structure. Most GSP efforts to date assume that the underlying network is known, and then analyze how the graph's algebraic and spectral characteristics impact the properties of the graph signals of interest. However, such an assumption is at times untenable in practice and a fundamental question is how to use information available from graph signals to learn the underlying network structure or a judicious network model. Inferring the underlying network structure is a key step for facilitating statistical learning, efficient signal representation, visualization, prediction, (nonlinear) dimensionality reduction, and (spectral) clustering.

This special issue aims at gathering the latest advances on network topology inference or graph learning methods. The goal is to selectively cover a diverse gamut of graph learning methods and application domains chosen on the basis of importance and relevance to signal processing (SP) expertise. It will also introduce readers to challenges and opportunities for SP and ML research in emerging topic areas at the crossroads of modeling, learning, and control of complex behavior arising with large-scale networked systems that evolve over time. Application-related submissions are especially welcome.

Topics relevant to the special issue include, but are not limited to:

- Graphical model selection with structural or physical network process constraints
- Learning graphs from the observation of smooth, stationary, or diffused signals
- Learning graph representations and embeddings
- Scalable, online, and decentralized algorithms for graph learning
- Probabilistic inference of network structure with uncertainties
- Theoretical studies of sample complexity, consistency, and robustness
- Tomographic network topology inference
- Learning directed graphs and causal inference
- Identifying the topology of dynamic networks and multi-layer graphs
- Graph learning for efficient signal representation and dimensionality reduction
- Neural networks for latent graph inference, network growth prediction, community detection
- Applications to geometric deep learning and natural language processing
- Applications to image and video processing, restoration, and compression
- Applications to infrastructure networks, the Internet, 5G, transportation, and energy grids
- Applications to neuroscience, systems biology, genomics, and bioinformatics
- Applications to social and information networks, the WWW, and financial data

Prospective authors should follow the instructions given on the IEEE TSIPN webpages and submit their manuscript through the web submission system at <https://mc.manuscriptcentral.com/tsipn-ieee>

Schedule:

Manuscript due:	July 1, 2019
First Review Completed:	September 1, 2019
Revised manuscript due:	October 1, 2019
Second Review Completed:	November 1, 2019
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