Hao Chen

School of Mathmatical Sciences, Shanghai Jiao Tong University

Personal Information

Email: chen_hao1@sjtu.edu.cn
Tel: 13476745629
GitHub Page: https://github.com/utulie

Education

Shanghai Jiao Tong University major: Statistics 2022.9 - 2027.7 in China

- Doctoral Student Academic Scholarship in 2022-2024

Wuhan University major: Statistics 2018.9 - 2022.6 in China

- KPMG Scholarship in 2021

Research

Causal Structure learning 2023-2024

Score-matching-based Structure Learning for Temporal Data on Networks

Causal discovery is pivotal for establishing causal relationships from empirical data, and a variety of algorithms are currently available for this purpose. However, existing algorithms are primarily designed for independent and identically distributed (i.i.d.) data and encounter significant computational complexity during the pruning phase when dealing with dense Directed Acyclic Graphs (DAGs). We have developed a rapid causal discovery algorithm that is applicable to a wide range of complex datasets.

Contribution

- The proposed algorithm achieves a time complexity reduction by an order of magnitude compared to the baseline approach, while maintaining comparable accuracy in causal structure prediction.
- In addition to independent and identically distributed datasets, our algorithm is capable of processing time-series datasets with sample correlations while maintaining high accuracy in practical applications.

Graph Neural Networks 2022-2023

Lower and upper bounds for numbers of linear regions of graph convolutional networks

A common measure of expressive power is the number of linear regions in neural networks equipped with piecewise linear activation functions. In this study, we present estimates for the number of linear regions of classical Graph Convolutional Networks (GCNs) with the ReLU activation function for both single-layer and multi-layer scenarios.

Contribution

- Based on the results for the number of linear regions, our work theoretically establishes upper and lower bound formulas for the expressive power of multi-layer Graph Convolutional Networks (GCNs), with comprehensive numerical experiments designed to validate the theoretical bounds.
- The theoretical analysis establishes that deep Graph Convolutional Networks (GCNs) demonstrate superior expressive power compared to their shallow counterparts.

Skills

Technical Communication Skills

professional English Proficiency (IELTS 7.5) with demonstrated experience in technical documentation writing, and cross-team collaboration

Skilled in Frontier Technologies of Causal Science

- proficient in theoretical frameworks including Structural Causal Models (SCM) and Potential Outcomes Framework, along with their fundamental algorithms
- experience with causal discovery algorithms (PC/FCI/LiNGAM) and developing a causal structure learning system for high dimensional data

Capability in Machine Learning Algorithm Development

- proficient in Python, including scientific computing tools like NumPy and Pandas
- expertise in mathematical foundations and optimization strategies of classical machine learning algorithms (Random Forest, XGBoost, etc.)
- familiar with modern neural network architectures such as GNN, Diffusion Models, and VAE