# IEEE Transactions on Neural Networks and Learning Systems (IEEE TNNLS)
# Special Issue on
# *Causal Discovery and Causality-Inspired Machine Learning*

Causality is a fundamental notion in science and engineering. It has attracted much interest across research communities in statistics, Machine Learning (ML), healthcare, and Artificial Intelligence (AI), and is becoming increasingly recognized as a vital research area. One of the fundamental problems in causality is how to find the causal structure or the underlying causal model. Accordingly, one focus of this special issue is on *causal discovery*, i.e., how can we discover causal structure from observational data with automated procedures? Besides learning causality, another focus is on using causality to help understand and advance ML, that is, *causality-inspired ML.*

There has been impressive progress in theoretical and algorithmic developments on causal discovery from various types of data (e.g., i.i.d. data with or without latent confounding, selection bias, or missing data, and non-i.i.d. data in non-stationary settings). Moreover, recent years have also witnessed its practical applications in several scientific fields including neuroscience, climate, biology, and epidemiology. However, a number of practical issues, including confounding, large scale of the data, the presence of measurement error, and complex causal mechanisms, are still to be properly addressed, in order to achieve reliable causal discovery in real-world scenarios. On the other hand, causality-inspired ML (in the context of transfer learning, reinforcement learning, deep learning, etc.) leverages ideas from causality to improve generalization, adaptivity, robustness, interpretability, or sample efficiency, and is attracting more and more interest in ML and AI. Despite the benefit of the causal view in transfer learning and reinforcement learning, several tasks in ML, such as dealing with adversarial attacks and learning disentangled representations, are closely related to the causal view and worth careful investigation, and cross-disciplinary efforts may facilitate the anticipated progress.

Inspired by such achievements and challenges, this special issue aims at reporting progress in fundamental principles, practical methodologies, efficient implementations, and applications of causal discovery methods. The special issue also welcomes contributions in causality-inspired machine learning, in particular in relation to transfer learning and reinforcement learning.

**Scope of the Special Issue**

We invite submissions on all topics of causal discovery and causality-inspired ML, including but not limited to:

- Causal discovery in complex environments
- Efficient causal discovery in large-scale datasets
- Causal effect identification
- Real-world applications of causal discovery
- Assessment of causal discovery methods and benchmark datasets
- Causal perspectives on problems of generalizability, transportability, transfer learning, and life-long learning
- Causally-enriched reinforcement learning and active learning
- Representation learning and development of safe AI from a causal perspective

**Timeline**

- Submission deadline: **October 22, 2021**
- Notification of first review: December 10, 2021
- Submission of revised manuscript: January 21, 2022
- Notification of final decision: **February 18, 2022**

**Guest Editors**

- Kun Zhang (Carnegie Mellon University)
- Ilya Shpitser (Johns Hopkins University)
- Sara Magliacane (University of Amsterdam)
- Davide Bacciu (University of Pisa)
- Fei Wu (Zhejiang University)
- Changshui Zhang (Tsinghua University)
- Peter Spirtes (Carnegie Mellon University)

**Submission Instructions**

- Read the Information for Authors at http://cis.ieee.org/tnnls, and submit your manuscript at the TNNLS webpage (http://mc.manuscriptcentral.com/tnnls), following the submission procedure. Please indicate both on the first page of the manuscript and in the cover letter that it is submitted to this special issue.
- Early submissions are welcome; we will start the review process as soon as we receive your contributions.