PURDUE UNIVERSITY | Elmore Family School of Electrical and Computer Engineering

ECE/CS Seminar

Associate Professor Bryon Aragam

Booth School of Business, University of Chicago

Thursday, October 16, 2025
Presentation: 10:30 – 11:45 A.M.
DSAI 1069

Bridging Causality and Deep Learning with Causal Generative Models

Abstract Generative models for vision and language have shown remarkable capacities to emulate creative processes but still lack fundamental skills that have long been recognized as essential for genuinely autonomous intelligence. Difficulties with causal reasoning and concept abstraction highlight critical gaps in current models, despite their nascent capacities for reasoning and planning. Bridging this gap requires a synthesis of deep learning's expressiveness with the powerful framework of statistical causality.

We will discuss our recent efforts towards building generative models that extract causal knowledge from data while retaining the flexibility and expressivity of deep learning. Unlike traditional causal methods that rely on predefined causal structures, we tackle the more complex problem of learning causal structure directly from data—even when the causal variables themselves are not explicitly observed. This introduces significant challenges, including (non)identifiability, nonconvexity, and the exponential complexity of combinatorial search. We will present progress towards resolving these challenges with differentiable approaches to causal discovery and representation learning.

Note: Bryon will be giving another talk in the stats department on Friday, Oct 17 from 10:30-11:30 A.M. in WALC 1132 that continues this theme:
In the second talk, we will discuss our ongoing work towards understanding causal discovery and model selection in nonparametric models. State of the art machine learning algorithms implicitly extract useful models from raw, unstructured data, but how this is possible is somewhat mysterious. To explore this, we will present recent results on structure learning in nonparametric graphical models. Surprisingly, it turns out that even basic subroutines are not fully understood, and we show how we can improve over classical "optimal" algorithms from the literature. At the same time, fundamental computational lower bounds and the curse of dimensionality present challenges. As a special case, our results provide a complete resolution to the problem of nonparametric estimation in high-dimensional graphical models.

Biography Bryon Aragam is an Associate Professor and Topel Faculty Scholar in the Booth School of Business at the University of Chicago. He studies causality, statistical machine learning, and probabilistic modeling. His current interests involve causal machine learning, deep generative models, latent variable models, and statistical learning theory. In particular, this work focuses on applications of artificial intelligence, including tools such as ChatGPT and DALL-E. He is also involved with developing open-source software and solving problems in interpretability, ethics, and fairness in artificial intelligence. His work is supported by the NSF and the NIH. Prior to joining the University of Chicago, he was a project scientist and postdoctoral researcher in the Machine Learning Department at Carnegie Mellon University. He completed his PhD in Statistics and a Masters in Applied Mathematics at UCLA, where he was an NSF graduate research fellow. Bryon has also served as a data science consultant for technology and marketing firms, where he has worked on problems in survey design and methodology, ranking, customer retention, and logistics.

Hosts: David Inouye (ECE) and Bruno Ribeiro (CS)