Course Description:
In the past decades, interesting advances were made in machine learning, computer science, statistics, and information theory for tackling long-standing causality problems, including how to discover causal knowledge from observational data, known as causal discovery, and how to infer the effect of interventions. A number of researchers have been recognized with the Turing Award (to Pearl in 2012) and the Nobel Prize (to Granger in 2003 and to Sims in 2011). Furthermore, it has recently been shown that the causal perspective may facilitate understanding and solving various machine learning (ML) / artificial intelligence (AI) problems such as transfer learning, semi-supervised learning, out-of-distribution prediction, disentanglement, and adversarial vulnerability. This course is accordingly concerned with understanding causality, learning causality from observational data, and using causality to tackle a large class of learning problems.

The course covers representations and usage of causal models, how causality is different from and connected to association, recent ML methods for causal discovery, and why and how the causal perspective helps in a class of learning tasks. We will try to answer the following questions. Why do we care about causality? How can we learning causality from observational data? What role does causality play in ML under data heterogeneity? Is causality an essential tool to achieve a higher-level AI? If it is, how? What can we benefit from a philosophical, causal view of "intelligence"? How can deep learning benefit from a causal view?

We will particularly focus on three key problems related to causality. The first is causal discovery. It is well known that "correlation does not imply causality," but we will make this statement more precise by asking what assumptions, what information in the data, and what procedures enable us to successfully recover causal information. Causal relations may happen between the underlying hidden variables, and what we measure may just be their reflections; so we will also see how to find hidden causal representations—the underlying hidden "causal" variables as well as their causal relations—by analyzing measured variables. Its implication in unsupervised deep learning will be discussed. The second is how to properly make use of causal information, for the purpose of identification of causal effects and counterfactual reasoning. The third is how to understand advanced ML or AI problems including reinforcement learning, transfer learning, domain generalization, and disentanglement from a causal perspective and how to advance methodological developments to deal with such problems.

Tentative Schedule:
Lecture 1:
Introduction: A big picture of causality and machine learning, and three dimensions of causal representation learning
Introduction to machine learning and artificial intelligence & how they relate to causality
Causality-related concepts, principles, and problems: definition of causality, motivation for causal analysis, directed acyclic graphs, interventions, structural equation models
Discussion: Why do we care about causality?
Research problems in causality: Causal discovery, causal representation learning, causality for machine learning, identification of causal effects, and counterfactual reasoning

Lecture 2:
Preliminaries: Probability theory and probabilistic graphical models, and causal models

Lecture 3 (Guest Lecturer: Dr. Peter Spirtes):
History of modern causality research

Lecture 4:
Identification of causal effects & counterfactual reasoning

Lecture 5:
Traditional constraint- or score-based causal discovery

Lecture 6 (Guest Lecturer: Dr. Peter Spirtes):
Dealing with latent confounders: FCI and representations of equivalence classes

Lecture 7:
Causal discovery with the linear, non-Gaussian, acyclic model (LiNGAM) and nonlinear models

Lecture 8:
Dealing with practical issues: nonlinear functional models, cycles, confounders, nonstionarity, missing data, and measurement error

Lecture 9:
Causal representation learning: Learning hidden variables and their causal relations from i.i.d. data, time series, and multiple-distribution data

Lecture 10:
A causal perspective of transfer learning, reinforcement learning, unsupervised deep learning, and algorithmic fairness