1172-62-353 **Elina Robeva*** (`erobeva@gmail.com`), 1984 Mathematics Road, 1984 Mathematics Road, Vancouver, BC V6T 1Z2, Canada. *Hidden Variables and Inference for Linear Non-Gaussian Causal Models.*

Identifying causal relationships between random variables from observational data is an important hard problem in many areas of data science. The presence of hidden variables, though quite realistic, pauses a variety of further problems. Linear structural equation models, which express each variable as a linear combination of all of its parent variables, have long been used for learning causal structure from observational data. Surprisingly, when the variables in a linear structural equation model are non-Gaussian the full causal structure can be learned without interventions, while in the Gaussian case one can only learn the underlying graph up to a Markov equivalence class. In this talk, we first discuss how one can use high-order cumulant information to learn the structure of a linear non-Gaussian structural equation model with hidden variables. While prior work posits that each hidden variable is the common cause of two observed variables, we allow each hidden variable to be the common cause of multiple observed variables. Next, we discuss hidden variable Gaussian causal models and the difficulties that arise with learning those. We show it is hard to describe the equivalence classes in this case, and we give a semi algebraic description of a large class of these models. (Received September 01, 2021)