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[1] Bernhard Schölkopf et al. "Toward Causal Representation Learning". In: *Proceedings of the IEEE* 109.5 (2021), pp. 612–634. DOI: 10.1109/JPROC.2021.3058954.

Paper overview: The paper helps us understand the relation between some of the open problems in machine learning and causal inference approach. The paper explained the contributions which causality can make toward the research of modern machine learning. Generation of high level causal variables from low level observational data is also mentioned. Some of the key research topics which lies at the intersection of this multidisciplinary research are also examined which summarises learning non-linear causal relations at scale, learning causal variables, understanding the biases of existing deep learning approaches, learning causally correct models of the world and the agent. The authors described different levels of modeling in physical systems, explaining independent causal mechanisms (ICM) principle as an important aspect in estimating the causal relations from data. Review of classical and modern reinterpretation approaches to estimate causal relations from descriptors are also provided. Discussion on models of reality which could be learned from causality data along with several machine learning problems from causality point of view is provided. While statistical models provide us a single probability distribution for a set of variables, causal models will provide a set of probability distribution for the same set of variables, one for each possible interventions. Medical research could benefit from causality as it will provide us with predictions from which we could infer on different possible results without the observational data.

Medical research applications: From the selected paper, I would like to focus on three aspects of causal learning which could contribute towards medical research. They are explained as follows:

- *Levels of causal modelling*: Researchers explained different levels of modelling a causal system and the importance of relations between the features while making a prediction with these systems. As statistical models will provide an output based on the data without providing insights on the relation between the features. This problem is solved by causal interpretation as the authors explained different methods on the levels of causal modelling. Specifically this could have significant medical applications, e.g. as a statistical model will infer that a particular feature will lead to a certain disease while causal model will explore the reason behind it, going a step higher on the level index.
- *Types of causal models and their inference*: The authors explained the different types of causal modelling and how these models differ from the traditional statistical models theoretically. The different methods are driven by independent and identically distributed (i.i.d.) data, Reichenbach principle, and structural causal models. Here I would like to focus on the structural causal models which could have decent medical applications when engaging with latent variables and confounders. Application of such models will provide us more insights into which variables are causally significant in reaching a certain medical decision which is less likely with statistical inference.
- *Learning causal variables*: Approaches related to the need of learning of causal variables are explained through three modern day machine learning problems. Specifically the authors mentioned learning disentangled representations, learning transferable mechanisms, and learning interventional world models and reasoning. Possible solutions to second problem could be through applying ICM. As the author explains our brain not needing any additional information to process same scene whether we see it in a sunny day or rainy day but the scene will differ to an intelligent system trained on sunny day data but untrained on rainy day data, during a rainy day. I could not find a medical application yet but this approach of modularity transfer learning using causal inference is interesting.