Comments on “Causal inference using invariant prediction: identification and confidence intervals” by Peters, Bühlmann and Meinshausen

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I consider that the genuine fundamental problem of causal inference is the need for (partially untestable) invariance assumptions to operationalize interventions, and I thank the authors for emphasizing the role of invariances in a stimulating paper. I would like to make some brief comments on how the ideas introduced here can also be helpful in the context of measurement problems.

Much of the contribution involves removing assumptions about the exact target of interventions. This is important: sometimes we may feel uncomfortable to speak of causal effects between some treatment X and outcome Y not because we cannot think of ways of intervening on X, but because we can think of *too many* ways of intervening. However, perhaps none may plausibly keep the relation between X and Y invariant. In this case, the methods in Peters et al. cannot be applied.

Many of these problems can be explained as a result of the difficulty of measuring X or Y. Invariance assumptions, fortunately, can be extended to accommodate measurement error. It can also clarify to some extent the nature of unobserved quantities. Consider the classical example of [2], of which a simplified version is shown in Figure 1. While it may be unrealistic to describe perfect interventions on gross national product that do not directly affect energy consumption, an alternative model postulates an abstract “industrialization level” index measured indirectly by these two variables. Assumptions of invariance under interventions F on this index could be tested by models that capture different regimes among latent variables but share the same measurement model. Identification of measurement models has been studied under the psychometrics [5], machine learning [4] and statistics literatures [3, 1] and these results can be used to build such a test of invariance.

Moreover, invariance under interventions provide further operational meaning to latent constructs: a quantity that acts as a mediator between an intervention and measurements, as well as other latent variables. Depending on which invariance assumptions are held as primitives (our “fundamental problem”), violations of measurement invariances may indicate lack of unidimensionality of the latent construct (a different take on the issue of “versions of a treatment” [6]), or further unmeasured confounding between measurements and latent variables. In either case, I predict that the valuable ideas introduced by Peters, Bühlmann and Meinshausen will also change the ways we build and interpret latent variable models in the future.

References

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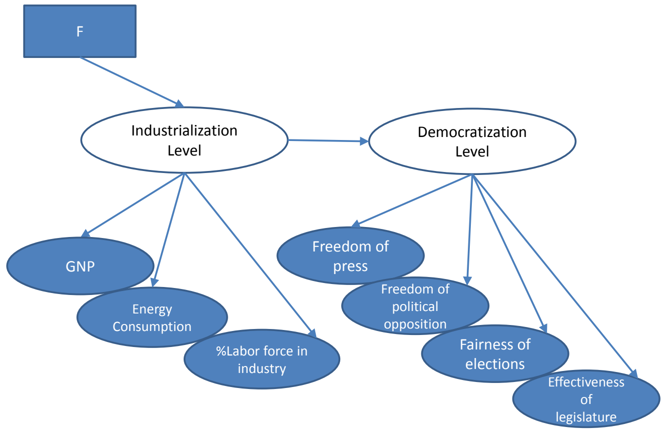

Figure 1: In the causal graph above, dark vertices represent observed vertices, with the square vertex indicating an intervention. Latent variables are represented as white vertices. This example is a simplification of the one described by [2].

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