Latent Variable Forests: Estimating Latent Variable Scores From Conditionally Causal Models

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We develop a latent variable forest (LV Forest) algorithm for the estimation of latent variable scores from conditionally causal models with one or more latent variables. LV Forest establishes conditional causality in confirmatory factor analysis (CFA) models with ordinal and/or numerical response variables. Furthermore, the algorithm estimates latent variable scores for the conditionally causal models. Through parametric model restrictions together with a non-parametric tree-based machine learning approach, LV Forest estimates latent variables scores that fulfill the main criteria for (conditional) construct validity (see APA, 2014).

SC Forest draws on the SEMTree approach (Arnold et al., 2021; Brandmaier et al., 2013) in order to grow trees that detect heterogeneity in model parameter estimates. In building a tree ensemble, LV Forest utilizes random split selection and bagging akin to the random forest algorithm by Breiman (2001) to increase tree diversity. For the estimation of parameters of conditionally causal models, we test for conditional stability of the latent variable's measurement paths using the generalized M-fluctuation test (Zeileis & Hornik, 2007). LV Forest eventually computes individual predictions of the latent variable scores for each iteration (i.e. each tree). Only those subgroups for which conditional causality in the models can be established are used for prediction. The individual predictions are then averaged across all trees.

In the context of latent state-trait modeling (Steyer et al., 2015), individual item difficulties may be estimated through item-eect variables (Classe & Steyer, 2022; Thielemann et al., 2017). However, item parameters of such longitudinal IRT models may still differ between subgroups in the population. Thus, the estimation of valid latent variable scores for latent trait models with latent item-effect variables could be improved through LV Forest.

We apply LV Forest to simulated data and show that for a latent state-trait model, parameter heterogeneity and subgroups with unconfounded measurement paths can be detected by the algorithm. Furthermore, prediction accuracy of the latent variable scores of the model is increased through LV Forest.

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