Orthogonal Causal Calibration (Extended Abstract)

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Estimates of heterogeneous treatment effects such as conditional average treatment effects (CATEs) and conditional quantile treatment effects (CQTEs) play an important role in real-world decision making. Given this importance, one should ensure these estimates are calibrated. While there is a rich literature on calibrating estimators of non-causal parameters, very few methods have been derived for calibrating estimators predicting heterogeneous causal effects (van der Laan et al., 2023). In this work, we develop general algorithms for reducing the task of causal calibration to that of calibrating a standard (non-causal) predictive model.

We assume the learner is interested in calibrating some model $\theta : \mathcal{X} \to \mathbb{R}$ predicting a heterogeneous causal effect θ_0. We assume θ_0 is specified as a conditional minimizer of a loss, i.e. $\theta_0(x) \in \arg\min_{\nu \in \mathbb{R}} \mathbb{E}[\ell(\nu, g_0; Z) \mid X = x]$. Here, $\ell : \mathbb{R} \times \mathcal{G} \times \mathcal{Z} \to \mathbb{R}$ is some generic loss function involving nuisance $g \in \mathcal{G}$ and g_0 denotes the true, unknown nuisance component (e.g. a regression function or propensity score). We define the L^2 calibration error as $\mathrm{Cal}(\theta, g) := \left(\int_{\mathcal{X}} \mathbb{E}[\partial\ell(\theta, g; Z) \mid \theta(X) = \theta(x)]^2 P_X(dx)\right)^{1/2}$, and say θ is perfectly calibrated if $\mathrm{Cal}(\theta, g_0) = 0$. Under this definition, an estimate $\theta(X)$ of the CATE $\theta_{\mathrm{CATE}}(X) := \mathbb{E}[Y(1) - Y(0) \mid X]$ is perfectly calibrated if $\mathbb{E}[Y(1) - Y(0) \mid \theta(X)] = \theta(X)$ almost surely. Likewise, an estimate $\theta(X)$ of the conditional quantile under treatment $\theta_{\mathrm{QUT}}(X) := F^{-1}_{Y(1)}(Q \mid X)$ is calibrated if $\mathbb{P}(Y(1) \le \theta(X) \mid \theta(X)) = Q$.

We study the calibration of θ under the assumption that ℓ satisfies robustness properties similar to Neyman orthogonality (Chernozhukov et al., 2018). In particular, we either assume ℓ satisfies *universal orthogonality*, a robustness condition due to Foster and Syrgkanis (2023), or *conditional orthogonality*, a novel, more general robustness property described in our main paper. Under these assumptions, we show an L^2 calibration error bound of

$$\underbrace{\mathrm{Cal}(\theta, g_0)}_{L^2 \text{ calibration error under } \ell(\theta(x), g_0; w)} \lesssim \underbrace{\mathrm{err}(g, g_0)}_{\text{nuisance estimation error}} + \underbrace{\mathrm{Cal}(\theta, g)}_{L^2 \text{ calibration error under } \ell(\theta(x), g; w)},$$

where generally $\mathrm{err}(g, g_0) = O(\|g - g_0\|^2_{L^2})$. In short, once the learner pays a small, upfront price for nuisance estimation error, they can pretend they are operating in a world where the learned nuisances reflect reality. From this decomposition, we derive generic sample splitting and cross-fitting algorithms that allow the learner to plug-in arbitrary algorithms for nuisance estimation and calibration (e.g. the learner could estimate nuisances using gradient boosted trees and perform calibration using histogram binning).[1]

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1. Extended Abstract. Full version available at https://arxiv.org/abs/2406.01933v2.

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