Discussion of Artificial Intelligence as Structural Estimation: Economic Interpretations of Deep Blue, Bonanza, and AlphaGo. by Mitsuru Igami

Whitney K. Newey
MIT

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SUMMARY

AI has achieved superhuman performance in

Chess: Deep Blue

Shogi: Bonanza

Go: AlphaGo

Each of these is a alternating play, two player, discrete choice game with binary outcome; Win or Lose.

The econometric methods each uses are:

Deep Blue: Move at each play chosen to maximize (grandmaster) calibrated value function; also select moves from opening or end game libraries.

Bonanza: Move chosen to maximize value function estimated via Rust (1987) nested fixed point algorithm.

AlphaGo: Deep neural net version of conditional choice probability approach of Hotz and Miller (1993). Estimates conditional choice probabilities by neural nets. Hotz, Miller, Sanders, Smith (1994) simulation estimator of value function from conditional choice probabilities.

COMMENTS

Machine learning methods good at prediction.

Not necessarily good for estimating objects of interest.

Seems remarkable how well methods have done has done in estimating decision rule in the 3 games.

More precisely, how well methods have done in estimating a decision rule that is superhuman.

Prediction versus estimation.

Good predictions are biased.

This can affect estimation; leads to bad confidence intervals.

Debias to correct.

Debiasing for estimating average treatment effect in Chernozhukov et al. (2014), Farrell (2015), Athey, Imbens, Wager (2017), Chernozhukov et al. (2018), Chernozhukov, Newey, Singh (2018):

Graphs: Distribution of plug-in estimator of regression coefficient of interest with many covariates is very biased but can debias.

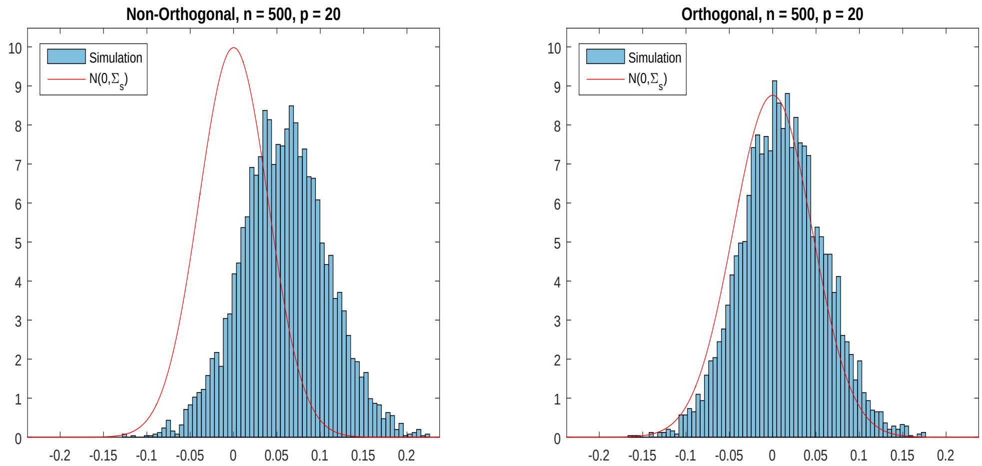

Figure 1. Left Panel: Behavior of a conventional (non-orthogonal) ML estimator, $\widehat{\theta}_0$, in the partially linear model in a simple simulation experiment where we learn g_0 using a random forest. The g_0 in this experiment is a very smooth function of a small number of variables, so the experiment is seemingly favorable to the use of random forests a priori. The histogram shows the simulated distribution of the centered estimator, $\widehat{\theta}_0 - \theta_0$. The estimator is badly biased, shifted much to the right relative to the true value θ_0. The distribution of the estimator (approximated by the blue histogram) is substantively different from a normal approximation (shown by the red curve) derived under the assumption that the bias is negligible. **Right Panel:** Behavior of the orthogonal, DML estimator, $\check{\theta}_0$, in the partially linear model in a simple experiment where we learn nuisance functions using random forests. Note that the simulated data are exactly the same as those underlying left panel. The simulated distribution of the centered estimator, $\check{\theta}_0 - \theta_0$, (given by the blue histogram) illustrates that the estimator is approximately unbiased, concentrates around θ_0, and is well-approximated by the normal approximation obtained in Section 3 (shown by the red curve).

Overcoming Regularization Biases using Orthogonalization. Now consider a second construction that employs an "orthogonalized" formulation obtained by directly partialling out the effect of X from D to obtain the orthogonalized regressor $V = D - m_0(X)$. Specifically, we obtain $\widehat{V} = D - \widehat{m}_0(X)$, where $\widehat{m}_0$ is an ML estimator of m_0 obtained using the auxiliary sample of observations. We are now solving an auxiliary prediction problem to estimate the conditional mean of D given X, so we are doing "double prediction" or "double machine learning".

After partialling the effect of X out from D and obtaining a preliminary estimate of g_0 from the auxiliary sample as before, we may formulate the following "debiased" machine learning estimator for θ_0 using the main sample of observations:[3]

$$\check{\theta}_0 = \Big(\frac{1}{n}\sum_{i\in I}\widehat{V}_i D_i\Big)^{-1}\frac{1}{n}\sum_{i\in I}\widehat{V}_i(Y_i - \widehat{g}_0(X_i)). \tag{1.5}$$

By approximately orthogonalizing D with respect to X and approximately removing the direct effect of confounding by subtracting an estimate of g_0, $\check{\theta}_0$ removes the effect of

[3]In Section 4, we also consider another debiased estimator, based on the partialling-out approach of Robinson (1988):

$$\check{\theta}_0 = \Big(\frac{1}{n}\sum_{i\in I}\widehat{V}_i\widehat{V}_i\Big)^{-1}\frac{1}{n}\sum_{i\in I}\widehat{V}_i(Y_i - \widehat{\ell}_0(X_i)), \quad \ell_0(X) = \mathrm{E}[Y|X].$$

DEBIASING

Straightforward, general, statistically good method for GMM estimation of "averages," like parameters of dynamic discrete choice.

Debiased moments

$$= \text{Identifying moments} + \text{Influence adjustment.}$$

Hasminskii and Ibragimov (1979), Bickel and Ritov (1988), Newey, Hsieh, Robins (1998, 2004), Robins et al. (2008), Chernozhukov et al. (2018).

Making progress towards automating this, Chernozhukov, Newey, Singh (2018).

Surprising that AlphaGo did so well without any explicit debiasing.

Perhaps some form debiasing implicit in the ways the decision rules are estimated.

Does happen in some other settings: Debiasing is built in when first step is obtained from maximizing the same objective function as object of interest, i.e. when first step consists of concentrating out (Newey, 1994).

"Under smoothing" (using richer specification than required for best prediction) can be used to debias. Perhaps that was implicit in method.

These interpretations are promising for structural estimation in other economic problems with high dimensional state spaces.

Most structural estimation deals with much smaller state spaces though the objective function and interactions among players more complicated.

Confirms potential for machine learning to improve decision making; also much revealed preference evidence on that.

Raises more speculative questions, like a structural methods "too good," not really modeling well the way people behave.

Paper's interpretation of success of the three games is excellent and raises interesting questions.