

Statistica Sinica Preprint No: SS-2019-0062

Title	Comment on 'Entropy Learning for Dynamic Treatment Regimes' by Binyan Jiang, Rui Song, et al.
Manuscript ID	SS-2019-0062
URL	http://www.stat.sinica.edu.tw/statistica/
DOI	10.5705/ss.202019.0062
Complete List of Authors	Hongxiang Qiu Alex Luedtke and Mark van der Laan
Corresponding Author	Hongxiang Qiu
E-mail	qihx@uw.edu
Notice: Accepted version subject to English editing.	

2.1 Dependence of the infinite-sample limit of the E-learning estimator on the treatment assignment probabilities

future stages $\pi(A_j, S_j)$, $t \leq j < T$. By this argument, one can show that, for all t , β_t^0 can depend on $\pi(A_j, S_j)$ for all $j = 1, \dots, T - 1$. Consequently, collecting two data sets in the same population, but with different treatment assignment probabilities, can lead to different infinite-sample limits for the E-learning estimators used in the two settings.

We illustrate the meaningful impact that this dependence on treatment assignment mechanism can have on the interpretation of study results through a simple two-stage example. We consider two different data generating mechanisms that are identical in all regards except for their treatment mechanisms. We denote the treatment mechanisms in the two settings by $\pi^{(1)}$ and $\pi^{(2)}$. We will show that the coefficients (referred to as “value” because it’s a special term) in (2.1) vary between the two scenarios. Specifically, we show that $\beta_1^0(\pi^{(1)}) \neq \beta_1^0(\pi^{(2)})$ and $\beta_2^0(\pi^{(1)}) \neq \beta_2^0(\pi^{(2)})$. In both examples, $S_1 = X_1$ is a standard normal $X_1 \sim \mathcal{N}(0, 1)$, $X_1 = x_1$ is a normal distribution with mean $a_1 x_1$ and variance σ^2 . We consider a setting where the investigator is trying to maximize the final reward, so that $R_1 = 0$ and $R = R_2$. The conditional regression is given by $\mathbb{E}[R|S_2 = s_2, A_2 = a_2] = \mathbb{1}\{a_2 = 1\} [2x_1^2 \mathbb{1}\{a_1 = 1\} + \mathbb{1}\{a_1 = -1\} + 2x_2^2] + \mathbb{1}\{a_2 = -1\}$. We let $\pi_t^{(k)}$ denote $P(A_t = 1|S_t)$ in each scenario k . In the first scenario, we let $\pi_1^{(1)} = \pi_2^{(1)} = 0.5$. In the second scenario, we let $\pi_1^{(2)} = 0.9$ when $X_1 < 0.5$

