Improving the Causal treatment effect estimation with propensity scores by the Bootstrap

Maeregu W. Arisido, Fulvia Mecatti and Paola Rebora

Supplementary Appendix

The results in Table 1 below include additional simulation results from the stabilized IPSW (SIPSW). Technically, SIPSW is a normalized version of the unstabilized IPSW. That means, after estimating IPSW as described in section 3.3 of the paper, SIPSW is computed by multiplying IPSW by the marginal probability of assigning the given treatment (see Hernán and Robins 2020, for further detail and implementation).

Table 1: Simulation results of average treatment effect as estimated by the Naïve method, Stabilized IPSW (SIPSW), unstabilized IPSW (IPSW), BC-IPSW and BC-SIPSW. The data was generated under the overlap misspecification by setting the true treatment effect $\beta \in (-0.3, 0.4)$ and $n = 290$. Bias, absolute percentage bias (%Bias), mean squared error (MSE) and 95% coverage probabilities (CP) are reported.

		large overlap				partial overlap			
β	Method	Bias	%Bias	MSE	CP	Bias	%Bias	MSE	CP
	Naïve	-0.015	5.000	0.037	93	-0.015	5.000	0.043	93
-0.3	IPSW	-0.028	9.333	0.034	89	0.048	16.000	0.042	75
	BC-IPSW	0.005	1.667	0.031	95	0.037	12.000	0.042	93
	SIPSW	-0.022	7.333	0.033	90	0.046	15.333	0.039	76
	BC-SIPSW	0.006	2.000	0.033	94	0.038	12.666	0.043	91
	Naïve	0.013	3.250	0.046	94	0.013	3.250	0.044	94
0.4	IPSW	0.031	7.750	0.057	92	0.037	9.250	0.056	80
	BC-IPSW	0.019	4.750	0.055	94	0.028	7.000	0.055	93
	SIPSW	0.030	7.500	0.049	92	0.035	8.750	0.055	82
	BC-SIPSW	0.018	4.500	0.098	93	0.030	7.500	0.053	94

Table 2 below compares simulation results based on with and without administrative censoring of the survival endpoint. The administrative censoring time was generated from a random uniform distribution with the end date administratively known in advance, year 4, as in the case of ERSD data. For the non-administrative censoring, subjects complete the course of the follow-up randomly with no pre-specified end date. This censoring was generated from the uniform distribution with a specified censoring rate and number of samples (see Mazucheli et al. 2016; Worms and Worms 2018, for further detail and implementation).

Table 2: Simulation results of average treatment effect as estimated by the Naïve method, IPSW adjusted and BC-IPSW. The censoring of the survival endpoint was generated based on two censoring mechanisms: Administrative censoring with the end of the follow-up pre-specified and Non-administrative censoring with no pre-specified end point to stop the follow-up. Both censorings were generated with 20% and 40% censoring rates. The true treatment effect was set $\beta = -0.3$ and $n = 290$. Bias, absolute percentage bias (%Bias), mean squared error (MSE) and 95% coverage probabilities (CP) are reported.

		Administrative censoring				Non-administrative censoring			
Censoring rate	Method	Bias	%Bias	MSE	CP	Bias	%Bias	MSE	CP
	Naïve	-0.015	5.000	0.041	95	-0.017	5.600	0.042	93
20%	IPSW	0.010	3.333	0.039	95	0.012	4.000	0.036	93
	BC-IPSW	0.002	0.667	0.041	95	0.003	1.000	0.041	94
	Naïve	-0.028	9.33	0.058	93	-0.035	11.666	0.064	91
40%	IPSW	0.018	6.000	0.040	93	0.025	8.333	0.060	91
	BC-IPSW	0.011	3.667	0.038	94	0.015	5.000	0.048	92

References

Hernán, M.A., Robins, J.M.: Causal Inference: What If. Chapman and Hall/CRC, Boca Raton (2020)

Mazucheli, J., Fernandes, L.B., de Oliveira, R. P.: LindleyR: the Lindley distribution and its modifications. R package. version 1 (2016)

Worms, J. and Worms, R.: Extreme value statistics for censored data with heavy tails under competing risks. Metrika, 81, 849-889 (2018)