Planting Decision Trees: Human-Friendly Interpretation of Monte Carlo Simulations, Multiverse Analyses and Multivariate Posterior Distributions

Michael S. Truong, Gabriel Crone, Udi Alter and Ji Yeh Choi

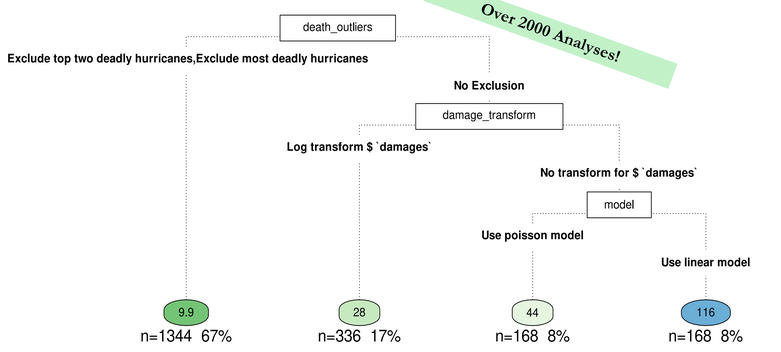
Quantitative Methods
Dept. of Psychology - York University

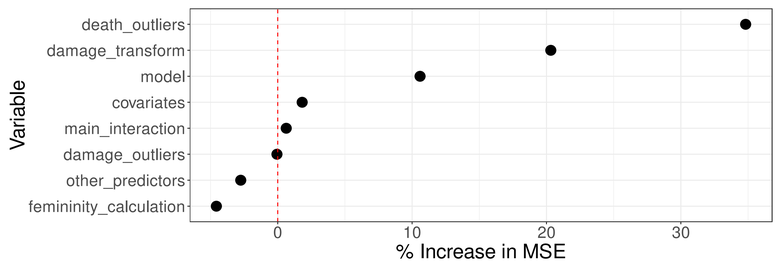
York University
Université York

Abstract: Monte Carlo simulations, multiverse analyses and multivariate prior distributions are all core elements of modern data science. However, interpreting each of these elements is frequently a cumbersome ordeal that leaves much to be desired. Monte Carlo simulations are frequently presented as a large multi-way table that can be both intimidating and difficult to extract key findings from. Similarly, multiverse analyses may have so many branching decisions that it becomes difficult to parse which decision may have been most critical to the final results. Multivariate posterior distributions are featured heavily in Bayesian data analysis, but selecting the dimensions to visualize the largest changes in probability is challenging due to their high-dimensional nature. In response to these challenges, we investigate and illustrate the use of the classic machine learning technique of decision trees to extract the key aspects of each of these elements. In a typical machine learning context, decision trees are a powerful way of discovering the largest main effects and higher-order interactions in an interpretable fashion. The adoption of effective applications of decision trees to each of these elements offers a human-friendly interpretation of Monte Carlo simulations, multiverse analyses, and multivariate prior distributions.

Decision Tree Multiverse Analysis: Which analytical decisions were most dramatic?

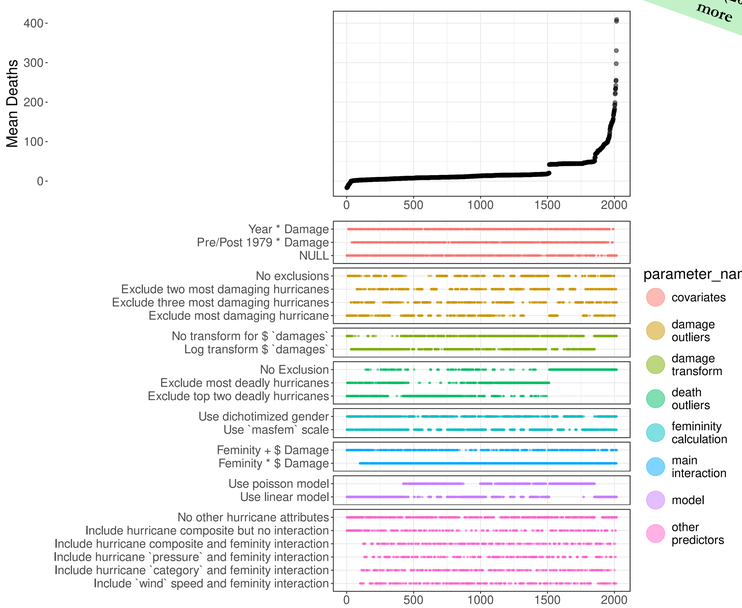
Over 2000 Analyses!





Competitor:

Data and Code Associated with Sarma et al. (2022) based on Jung et al. (2014) and more

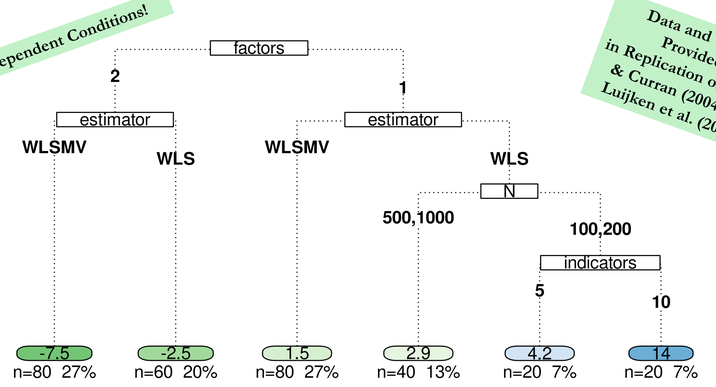


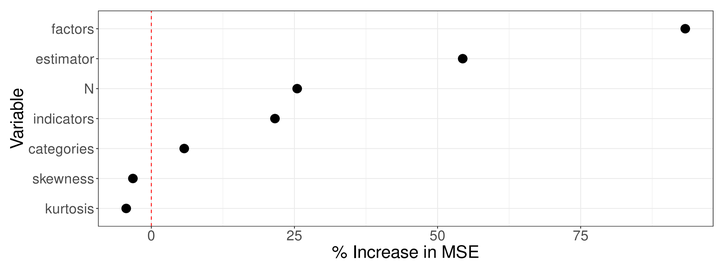
Decision Tree Monte Carlo Simulation: Which conditions had the most bias?

First proposed by Gonzalez et al. (2018)

300 Independent Conditions!

Data and Code Provided in Replication of Flora & Curran (2004) by Luijken et al. (2024)





Competitor:

1F, 5X

Table 8			WLS			WLSMV		
N	s	k	M_lambda	SD_lambda	RB_lambda	M_lambda	SD_lambda	RB_lambda
100	0.00	0.00	0.71	0.08	1.88	0.70	0.08	0.60
100	0.75	1.75	0.72	0.08	3.32	0.71	0.08	1.18
100	0.75	3.75	0.73	0.08	4.12	0.72	0.08	2.44
100	1.25	1.75	0.72	0.08	3.56	0.71	0.08	1.12
100	1.25	3.75	0.73	0.08	4.09	0.72	0.08	2.92
200	0.00	0.00	0.71	0.05	1.57	0.70	0.05	0.13
200	0.75	1.75	0.72	0.06	2.45	0.71	0.06	0.95
200	0.75	3.75	0.72	0.06	3.30	0.71	0.05	1.78
200	1.25	1.75	0.72	0.05	2.29	0.70	0.05	0.62
200	1.25	3.75	0.73	0.05	3.64	0.72	0.05	2.35
500	0.00	0.00	0.70	0.03	0.67	0.70	0.03	0.07
500	0.75	1.75	0.71	0.03	1.37	0.71	0.03	1.04
500	0.75	3.75	0.71	0.04	2.06	0.71	0.03	1.50
500	1.25	1.75	0.71	0.03	1.08	0.70	0.03	0.65
500	1.25	3.75	0.72	0.03	2.65	0.71	0.03	1.81
1,000	0.00	0.00	0.70	0.02	0.41	0.70	0.02	0.15
1,000	0.75	1.75	0.71	0.02	1.07	0.71	0.02	0.88
1,000	0.75	3.75	0.71	0.02	1.63	0.71	0.02	1.46
1,000	1.25	1.75	0.71	0.02	0.75	0.70	0.02	0.59
1,000	1.25	3.75	0.72	0.02	2.22	0.71	0.02	1.99

1F, 10X

Table 9			WLS			WLSMV		
N	s	k	M_lambda	SD_lambda	RB_lambda	M_lambda	SD_lambda	RB_lambda
100	0.00	0.00	0.78	0.08	11.22	0.70	0.07	0.49
100	0.75	1.75	0.78	0.08	11.43	0.71	0.07	1.86
100	0.75	3.75	0.78	0.08	11.83	0.72	0.07	2.37
100	1.25	1.75	0.78	0.08	10.79	0.71	0.07	1.39
100	1.25	3.75	0.79	0.08	12.99	0.72	0.07	2.93
200	0.00	0.00	0.75	0.05	6.68	0.70	0.05	0.37
200	0.75	1.75	0.75	0.05	7.39	0.71	0.05	0.87
200	0.75	3.75	0.76	0.05	8.46	0.71	0.05	1.77
200	1.25	1.75	0.74	0.05	6.36	0.71	0.05	1.09
200	1.25	3.75	0.76	0.05	8.65	0.71	0.05	2.13
500	0.00	0.00	0.72	0.03	2.89	0.70	0.03	0.23
500	0.75	1.75	0.73	0.03	3.68	0.71	0.03	0.99
500	0.75	3.75	0.73	0.03	4.34	0.71	0.03	1.56
500	1.25	1.75	0.72	0.03	3.10	0.70	0.03	0.54
500	1.25	3.75	0.73	0.03	4.84	0.71	0.03	2.10
1,000	0.00	0.00	0.71	0.02	1.43	0.70	0.02	-0.01
1,000	0.75	1.75	0.72	0.02	2.26	0.71	0.02	0.81
1,000	0.75	3.75	0.72	0.02	2.99	0.71	0.02	1.56
1,000	1.25	1.75	0.71	0.02	1.91	0.70	0.02	0.52
1,000	1.25	3.75	0.72	0.02	3.33	0.71	0.02	2.02

2F, 5X

Table 10			WLS			WLSMV		
N	s	k	M_lambda	SD_lambda	RB_lambda	M_lambda	SD_lambda	RB_lambda
100	0.00	0.00	0.68	0.12	-2.24	0.64	0.09	-8.65
100	0.75	1.75	0.69	0.12	-1.90	0.65	0.09	-7.42
100	0.75	3.75	0.69	0.12	-1.41	0.65	0.09	-7.33
100	1.25	1.75	0.70	0.12	-0.65	0.65	0.09	-7.31
100	1.25	3.75	0.70	0.12	-0.61	0.65	0.09	-6.51
200	0.00	0.00	0.66	0.07	-5.04	0.64	0.07	-8.78
200	0.75	1.75	0.67	0.07	-4.43	0.64	0.07	-7.86
200	0.75	3.75	0.67	0.07	-3.58	0.65	0.07	-7.25
200	1.25	1.75	0.67	0.07	-3.74	0.65	0.06	-7.60
200	1.25	3.75	0.68	0.07	-3.00	0.65	0.07	-6.78
500	0.00	0.00	0.65	0.04	-7.40	0.64	0.04	-8.98
500	0.75	1.75	0.65	0.04	-6.56	0.64	0.04	-8.20
500	0.75	3.75	0.66	0.04	-5.87	0.65	0.04	-7.46
500	1.25	1.75	0.66	0.04	-6.08	0.65	0.04	-7.46
500	1.25	3.75	0.66	0.04	-5.49	0.65	0.04	-7.10
1,000	0.00	0.00	0.64	0.03	-8.16	0.64	0.03	-8.95
1,000	0.75	1.75	0.65	0.03	-7.32	0.64	0.03	-8.12
1,000	0.75	3.75	0.65	0.03	-6.69	0.65	0.03	-7.46
1,000	1.25	1.75	0.65	0.03	-6.97	0.65	0.03	-7.63
1,000	1.25	3.75	0.66	0.03	-6.21	0.65	0.03	-6.92

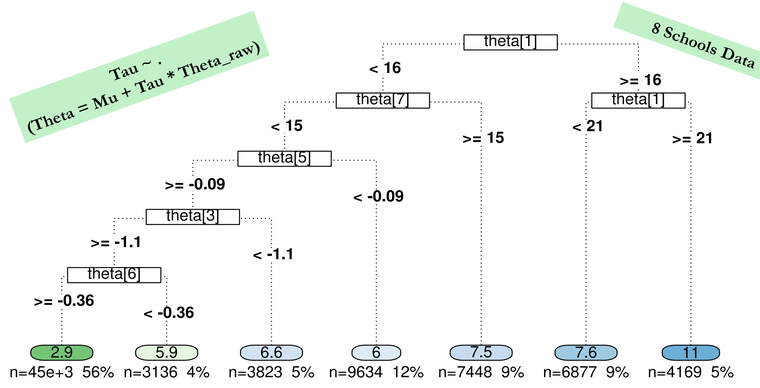
2F, 10X

Table 11			WLS			WLSMV		
N	s	k	M_lambda	SD_lambda	RB_lambda	M_lambda	SD_lambda	RB_lambda
100	0.00	0.00				0.64	0.08	-8.41
100	0.75	1.75				0.65	0.08	-7.65
100	0.75	3.75				0.65	0.08	-7.04
100	1.25	1.75				0.65	0.08	-7.19
100	1.25	3.75				0.65	0.08	-6.45
200	0.00	0.00				0.64	0.06	-8.72
200	0.75	1.75				0.64	0.06	-8.06
200	0.75	3.75				0.65	0.06	-7.34
200	1.25	1.75				0.65	0.05	-7.36
200	1.25	3.75				0.65	0.06	-6.85
500	0.00	0.00	0.68	0.04	-3.08	0.64	0.04	-8.90
500	0.75	1.75	0.69	0.04	-2.13	0.64	0.03	-8.07
500	0.75	3.75	0.69	0.04	-1.69	0.65	0.04	-7.46
500	1.25	1.75	0.69	0.04	-1.67	0.65	0.03	-7.52
500	1.25	3.75	0.69	0.04	-1.00	0.65	0.03	-6.97
1,000	0.00	0.00	0.66	0.03	-5.99	0.64	0.03	-8.94
1,000	0.75	1.75	0.66	0.03	-5.08	0.64	0.02	-8.17
1,000	0.75	3.75	0.67	0.03	-4.50	0.65	0.03	-7.56
1,000	1.25	1.75	0.67	0.03	-4.62	0.65	0.02	-7.15
1,000	1.25	3.75	0.67	0.03	-4.02	0.65	0.02	-6.99

Decision Tree Multivariate Posterior Distribution: Which variables best predict Tau?

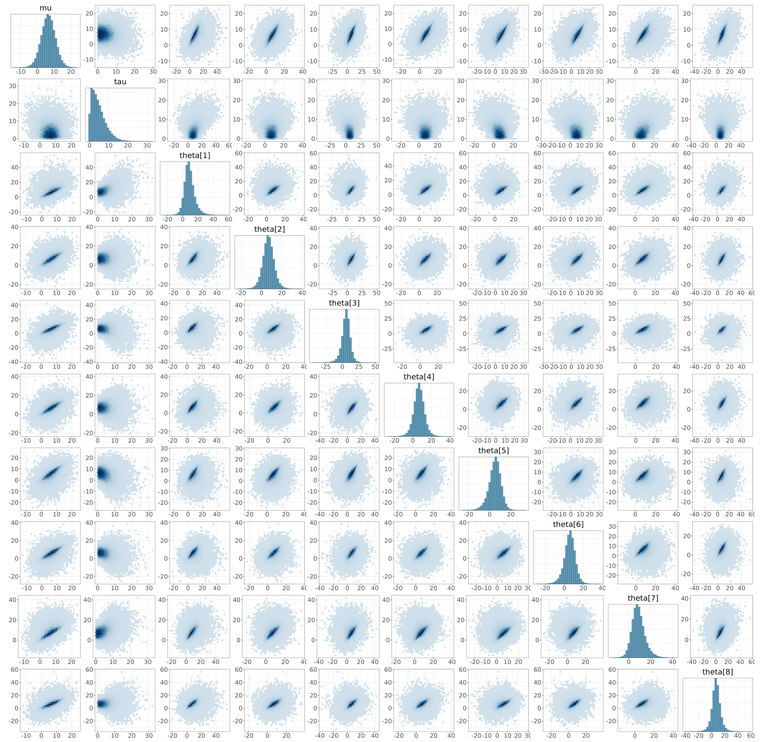
Tau ~ . (Theta = Mu + Tau * Theta_raw)

8 Schools Data



- Examples of Multi-Modal Posterior Distribution?
- Conditional Distribution?
- What Might be a Good Future Avenue?

Competitor:



Jung, K., Shavitt, S., Viswanathan, M., & Hilbe, J. M. (2014). Female hurricanes are deadlier than male hurricanes. Proceedings of the National Academy of Sciences, 111(24), 8782–8787. https://doi.org/10.1073/pnas.1402786111

Sarma, A., Kale, A., Moon, M., Taback, N., Chevalier, F., Hullman, J., & Kay, M. (2021). multiverse: Multiplexing alternative data analyses in R notebooks (version 0.6.1). OSF Preprints. https://github.com/MUCollective/multiverse

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve: Descriptive and inferential statistics on all reasonable specifications. *Nature Human Behaviour*, *4*, 1208–1214. https://doi.org/10.1038/s41562-020-0912-z

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing transparency through a multiverse analysis. *Perspectives on Psychological Science*, *11*(5), 702–712. https://doi.org/10.1177/1745691616658637

Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*, *14*(4), 323–348. https://doi.org/10.1037/a0016973

Flora, D. B., & Curran, P. J. (2004). An Empirical Evaluation of Alternative Methods of Estimation for Confirmatory Factor Analysis With Ordinal Data. Psychological Methods, 9, 466–491. https://doi.org/10.1037/1082-989X.9.4.466

Gonzalez, O., O'Rourke, H. P., Wurpts, I. C., & Grimm, K. J. (2018). Analyzing Monte Carlo Simulation Studies With Classification and Regression Trees. Structural Equation Modeling: A Multidisciplinary Journal, 25(3), 403–413. https://doi.org/10.1080/10705511.2017.1369353

Luijken, K., Lohmann, A., Alter, U., Claramunt Gonzalez, J., Clouth, F. J., Fossum, J. J. L., Hesen, L., Huizing, A. H. J., Ketelaar, J., Montoya, A. K., Nab, L., Nijman, R. C. C., Penning de Vries, B. B. L., Tibbe, T. D., Wang, Y. A., & Groenwold, R. H. H. (2024). Replicability of simulation studies for the investigation of statistical methods: The RepliSims project. Royal Society Open Science, 11(1), 231003. https://doi.org/10.1098/rsos.231003

Gabry, J., Češnovar, R., & Johnson, A. (2023). cmdstanr: R Interface to "CmdStan" [Manual].
Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). Bayesian data analysis (Third edition). CRC Press.
Stan Development Team. (2024). RStan: The R interface to Stan. https://mc-stan.org/