Bayesian Decisions Using Regions of Practical Equivalence (ROPE) and Imprecise Loss Functions *

Patrick Schwaferts PATRICK.SCHWAFERTS@STAT.UNI-MUENCHEN.DE
Thomas Augustin THOMAS.AUGUSTIN@STAT.UNI-MUENCHEN.DE
Institut für Statistik, Ludwig-Maximilians Universität München (LMU), Munich, Germany

This poster depicts a contribution to decision rules for psychological research, which extends the work on regions of practical equivalence (ROPE) by Kruschke [e.g. 2] and considers an imprecisely specified loss function.

General Background Frequently, the practical purpose of an applied scientific investigation is to decide between two opposing actions, of which one is in accordance and the other in discordance with a parameter value of interest, called null value. In the face of the critique against specifying only the single null value within a hypothesis, especially in the context of significance tests in psychological research, Kruschke [e.g. 1, 2] argues to employ a region of practical equivalence (ROPE) around it and promotes the so called HDI+ROPE decision rule, which is currently gaining popularity: Therein, the Bayesian posterior highest density interval (HDI) is calculated and related to the ROPE. Depending on this relation, the null value is either accepted for practical purposes, rejected for practical purposes, or a decision is withheld.

The Optimal Decision In contrast to the HDI+ROPE decision rule, which is rather heuristic in nature, the optimal Bayesian decision depends on an appropriately specified loss function. Although it is typically inaccessible, it is to expect that at least some essential, potentially vague information about this loss function is available. In order to allow the inclusion of this partial information into the analysis, the applied researcher should be provided with an intuitive way to formalize it.

ROPE To do so, in a first step, the loss function might be simplified by considering the decision theoretic meaning of a ROPE: A region around the null value is specified, such that all parameter values within this region are in accordance with one action and all parameter values outside this region are in accordance with the other action. By further treating all parameter values within the region as practically equivalent to the null value, the loss function within this region is assumed to be constant. Similarly, also the parameter values outside this region might be treated as practically equivalent to each other, assuming a respective constant loss function. As this simplified loss function can be stated in regret form (in which a correct decision has zero loss), the applied researcher needs to specify only one single value with an intuitive meaning.

Imprecise Loss Still, an applied researcher might be unable to specify an exact value for this simplified loss function, as many different values might be in accordance with the available partial information about it. Therefore, in a second step, inspired by the framework of imprecise probabilities, this value might be specified imprecisely as an interval, representing a set of loss functions and allowing to capture the uncertainty within the available information. With this simplified imprecise loss function the optimal decision can be determined easily in the context of Bayesian decision theory. Furthermore, this framework is even able to indicate if information is lacking to unambiguously guide the decision.

Discussion This flexible modeling of Bayesian ROPE-based decisions uses the full Bayesian posterior distribution, the ROPE-limits, and information about loss-values to guide the decision. In contrast, the HDI+ROPE decision rule employs the less informative HDI instead of the full posterior information and only the ROPE-limits, but no information about respective loss-values. In that, it uses less of the available and essential information for guiding the decision than the flexible ROPE-based framework with imprecise loss.

References

[1] John K. Kruschke. *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. Academic Press, 2015.

[2] John K. Kruschke. Rejecting or accepting parameter values in Bayesian estimation. *Advances in Methods and Practices in Psychological Science*, 1(2):270–280, 2018.

* *Acknowledgments*: PS wants to thank the LMU Mentoring Program, which supports young researchers.