

# iRF: extracting interactions from random forests

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DOI: [10.21105/joss.01077](https://doi.org/10.21105/joss.01077)

## Software

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Submitted: 04 October 2018

Published: 05 December 2018

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## Summary

Random forests (Breiman, 2001) are a popular class of supervised learning models that have demonstrated impressive empirical success across a wide variety of problems. The predictive accuracy of random forests stems from their ability to learn high-order, non-linear interactions in large datasets. Although approaches exist for evaluating the importance of individual features in a fitted random forest, identifying interactions that drive predictive accuracy remains a challenge. This challenge is in large part due to the enormous number of interactions that must be considered (i.e. there are  $O(p^s)$  possible interactions of size  $s$  among  $p$  features) and the instability of random forest decision paths.

The iterative Random Forest algorithm (iRF), and corresponding iRF R package, take a step towards addressing these issues with a computationally tractable approach to search for important interactions in a fitted random forest (Basu, Kumbier, Brown, & Yu, 2018, Kumbier, Basu, Brown, Celniker, & Yu (2018)). Our algorithm grows a series of feature weighted random forests (Amaratunga, Cabrera, & Lee, 2008) to perform soft regularization on the model based on predictive features. We then search for prevalent interactions in the fitted random forest using a generalization of random intersection trees (Shah & Meinshausen, 2014). Finally, we assess the stability of recovered interactions by repeating this search across random forests trained on bootstrap samples of the data. The iRF R package combines these steps into a single workflow. It is based on the source codes from the R packages `randomForest` (Liaw & Wiener, 2002) and `FSInteract` (Shah & Meinshausen, 2014). A detailed vignette is available [here](#).

## Acknowledgements

This research was supported in part by grants NHGRI U01HG007031, ARO W911NF1710005, ONR N00014-16-1-2664, DOE DE-AC02-05CH11231, NHGRI R00 HG006698, DOE (SBIR/STTR) Award DE-SC0017069, DOE DE-AC02-05CH11231, and NSF DMS-1613002. We thank the Center for Science of Information (CSoI), a US NSF Science and Technology Center, under grant agreement CCF-0939370. Research reported in this publication was supported by the National Library Of Medicine of the NIH under Award Number T32LM012417. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH. BY acknowledges support from the Miller Institute for her Miller Professorship in 2016-2017. SB acknowledges the support of UC Berkeley and LBNL, where he conducted most of his work on this paper as a postdoc. We thank P. Bickel and S. Shrotriya for helpful discussions and comments.

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