Can the 'additive tree' model expand machine learning in medicine?

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A representation of how often the Additive Tree outperformed CART and gradient boosting (GBS) within the study. Credit: Perelman School of Medicine at the University of Pennsylvania

When health care providers order a test or prescribe a medicine, they want to be 100 percent confident in their decision. That means being able to explain their decision and study it over depending upon how a patient responds. As artificial intelligence's footprint increases in medicine, that ability to check work and follow the path of a decision can become a bit muddied. That's why the discovery of a once-hidden through-line between two popular predictive models used in artificial intelligence opens the door much wider to confidently spread machine learning further throughout health care. The discovery of the linking algorithm and the subsequent creation of the "additive tree" is now detailed in the *Proceedings of the National Academy of Sciences* (*PNAS*).

"In medicine, the cost of a wrong decision can be very high," said one of the study's authors, Lyle Ungar, PhD, a professor of Computer and Information Science at Penn. "In other industries, for example, if a company is deciding which advertisement to show its consumers, they likely don't need to double-check why the computer selected a given ad. But in health care, since it's possible to harm someone with a wrong decision, it's best to know exactly how and why a decision was made."

The team led by Jose Marcio Luna, PhD, a research associate in Radiation Oncology and member of the Computational Biomarker Imaging Group (CBIG) at Penn Medicine, and Gilmer Valdes, PhD, an assistant professor of Radiation Oncology at the University of California, San Francisco, uncovered an algorithm that runs from zero to one on a scale. When a predictive model is set to zero on the algorithm's scale, its predictions are most accurate but also most difficult to decipher, similar to "gradient boosting" models. When a model is set to one, it is easier to interpret, though the predictions are less accurate, like "classification and regression trees" (CARTs). Luna and his co-authors subsequently developed their decision tree somewhere in the middle of the algorithm's scale.

"Previously, people used CART and gradient boosting separately, as two different tools in the toolbox," Luna said. "But the algorithm we developed shows that they both exist at the extreme ends of a spectrum. The additive tree uses that spectrum so that we get the best of both worlds: high accuracy and graphical interpretability."

In the study, the researchers found that the additive tree displayed superior predictive performance to CART in 55 of 83 different tasks. On the other end, gradient boosting performed better in prediction in 46 of 83 scenarios. While this was not significantly better, it does show that the additive tree was competitive while still being more interpretable.

Moving forward, the additive tree provides an attractive option for health care systems, especially for diagnostics and the generation of prognoses in an era when there is more demand for precision medicine. Furthermore, the additive tree has the potential to assist in making informed decisions in other high-stakes domains such as criminal justice and finance, where interpreting the models could help overcoming possible serious risks.

More information: José Marcio Luna et al. Building more accurate decision trees with the additive tree, *Proceedings of the National Academy of Sciences* (2019). DOI: 10.1073/pnas.1816748116

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