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Commentary: Is machine learning needed to understand that heart failure is a risk in adult congenital cardiac surgery?

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Central Message:

It is no surprise that heart failure is a risk for morbidity and mortality after redo surgery for ACHD, and it’s not clear that machine learning is needed to demonstrate that.

Central Picture Legend:

Surely any good surgeon golfer thinks about gradient boosting to take their shots…. (image from Parr T, Howard J. Gradient boosting performs gradient descent. From https://explained.ai/gradient-boosting/descent)
Heart failure is a well-known risk factor for morbidity and mortality after cardiac surgery in adults with acquired heart disease and is itself associated with hospitalization rates and death in adults with congenital heart disease (ACHD). It is not surprising, therefore, that the current study in the Journal by Griffeth and co-workers finds that heart failure (ejection fraction) is a risk factor for a composite outcome of peri-operative morbidity and mortality after redo cardiac surgery in ACHD.\textsuperscript{1} The authors also found that unadjusted long-term survival was less in patients with heart failure (although the Cox regression results did not support this association). The implication is that we should attempt to intervene on repairable problems in ACHD prior to the onset of significant heart failure, especially when the intervention can either lessen the clinical degree of heart failure or, better yet, prevent or reverse some of the intrinsic myocardial pathophysiology underlying it. Precision timing of intervention is the challenge, however. This study did not attempt to solve that problem.

The authors make explicit note of using an “innovative machine learning model”. The technique, gradient boosting for regression, was actually formulated in the 1980’s and the explanatory Shapley statistics described 70 years ago.\textsuperscript{2,3} It is used extensively, though not so often in cardiac surgical research. As a simple example, the procedure begins with a “weak” model (such as a constant equal to the mean value of the observed outcomes), then calculates the residuals (difference between the predicted and actual values), constructs a somewhat better heuristic model of the residuals (often in the form of a “tree”), then adds some proportion (the “learning rate”) of that model to the original model. As a result, the updated model will have smaller residuals. One continues with these iterations until the mean square of the residuals is less than some threshold. Unlike conventional statistical models, the technique does not specify any \textit{a priori} functional form to the relationship. It can work with empty cells, outliers, and high
cardinality categorical values.\textsuperscript{4,5} The classic Shapley value is calculated as the average contribution of a covariate ("feature") value to the prediction in all models comprising all possible subsets ("coalitions") of the feature set. It tells one what the relative importance of each of the features is.\textsuperscript{6}

Those to whom this method is new should be careful in applying it casually. Multiple problems may arise from the selection of features, choice of the so-called "hyperparameters", and feature description (such as branching tree structure), especially when applied to small datasets.\textsuperscript{7,8} In the present paper, the authors performed both conventional regression and gradient boosting and compared results. The comparison was somewhat clouded by juggling covariates around the various constructed models but, in the end, the discriminatory powers of the two calculated models, as assessed by the C-statistic, were not significantly different. While the study may not have "sold" us on the use of this machine learning technique, it increased our awareness of its availability and its potentially huge advantages in analyzing large cohort populations with large numbers of features having complex interactions and whose models are anticipated to have complex functional forms.
References


