P5706

Finding predictors and causes of cardiac surgery ICU readmission using machine learning and causal inference

J. Lee[1], N. Ahmidi[2], R. Srinivasan[1], D. Alejo[3], J. Dinatale[3], S. Schena[3], G. Whitman[3], M. Sussman[3], I. Shpitser[1]

[1]Johns Hopkins University, Department of Computer Science, Baltimore, United States of America; [2]Helmholtz Center Munich - German Research Center for Environment and Health, Institute of Computational Biology, Munich, Germany; [3]Johns Hopkins Medicine, Division of Cardiac Surgery, Baltimore, United States of America

Funding Acknowledgement: National Institutes of Health, Office of Naval Research, Defense Advanced Research Projects Agency

Background: “Bounce-back” to the intensive care unit (ICU) occurs when patients return to the ICU for critical changes in clinical status within the same hospital admission. Bounce-backs post-cardiac surgery increase resource utilisation, total cost of care, are associated with higher mortality and morbidity. However, prediction of bounce-back has proved to be challenging. Previous work addressed the feasibility of predicting bounce-back, but these models required significant physician input to design and calibrate the predictive variables.

Purpose: We aimed to develop an automated machine learning model that would identify patients at risk of bounce-back by selecting the most relevant variables from those available before onset of bounce-back. Additionally, we highlight the differences between predictive and causal inference, to demonstrate that purely associative methods of prediction can mislead clinical decision-making.

Methods: Clinical records of adult cardiac surgery patients between 2011 to 2016 were collected from our institutional Society for Thoracic Surgeons (STS) database and our institutional electronic health record (EHR) system. For bounce-back prediction, an L1 regularised logistic regression model was applied, which also automatically determined important variables with highest prediction effect from the initial 151 variables. For causal inference, the g-computation algorithm was used to compare the differences between causal and predictive regression effects. We quantified the performance of our system on clinically relevant metrics such as specificity, sensitivity, and area under the ROC curve (AUC).

Results: Of the 6189 patients, 357 (5.7%) bounced back to the ICU. The prediction model achieved an AUC score of 0.75 (0.03) and 22% specificity at 95% sensitivity, Further analysis showed 79% of the false positive patients had faced other severe postoperative complications but none of the false negative patients had downstream complications. Subsequent causal analysis revealed that the actual causal effects of treatments differed from the predictive model estimates, e.g. administration of intraoperative tranexamic acid increased the probability of bounce-back by 13% but its causal effect on bounce-back after removing confounders was negligible (an increase of only 0.5%).

Conclusions: Our predictive machine-learning model can successfully predict patients at risk of ICU bounce-backs, using linked STS registry data with the comprehensive electronic health record. The prediction model automatically detects important subset of variables. In addition, we note that causal and predictive model estimates of the same parameters differed, indicating that reliance on predictive models for interventional clinical decision-making may not be appropriate.