
Machine learning proving worth in readmission risk prediction



Healthcare is seeing increased use of machine learning tools, which allows medical professionals to do their jobs more efficiently. A prime example is how machine learning has helped improve accuracy of a health system's readmission risk prediction model, resulting in a significant reduction in case managers' work hours.

Bon Secours Charity Hospital's EHR system was using a risk scoring algorithm that was not very accurate, such that some high-risk patients were missed and other patients "wrongly" classified as high-risk. In addition, the automated daily report sent to case managers included only patients who had primary care doctors. Moreover, the case managers wasted a lot of effort reviewing charts to determine which patients to prioritise and which interventions to select. That reduced the amount of time they had to spend with patients.

Enter Health Catalyst, a vendor whose data operating system includes an open source machine learning package that can be used to predict readmission risk with a high degree of accuracy. To create the predictive model, Simer Sodhi and Lauren Torres of Bon Secours worked with Health Catalyst using the records of 54,000 patients who had been discharged from hospitals under the Westchester Center Health Network, or WMCHHealth. (Bon Secours, a three-hospital health system, is part of WMCHHealth.) Bon Secours's collaboration with Health Catalyst resulted in 24 risk factors that would be applied to the data in WMCHHealth's enterprise data warehouse.

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The next step would be validating the risk model's predictions against particular patient cohorts. The objective was to "determine whether the algorithm would improve its accuracy as it learned from working with our data," said Deborah Viola, vice president of data management and analytics at WMCHHealth. Validation of the risk model showed a 17 percent increase in the number of discharges correctly classified as high- and low-risk. This was driven by an 8 percent increase in true positives (actual readmissions correctly classified as high-risk) and a 30 percent decrease in false positives (actual non-readmissions incorrectly classified as high-risk).

As Sodhi noted, machine learning tools should be applied to the data on a health system's patient population to increase the accuracy of readmission risk scores.

After the validation phase, "we added the risk scores to discharge lists on a new readmission risk platform that we integrated with our population health management registry software," Viola explained. The risk scores were paired with EHR data and the information was displayed on a dashboard that guided the case managers in identifying care opportunities and choosing interventions.

"The case managers used the discharge lists and risk scores to organise their work and prioritise the patients who needed to be engaged," Viola pointed out. "Having more accurate, more accessible data enabled them to follow up with at-risk patients faster. They also used this information in conversations with primary care doctors and specialists."

As a result, the case managers were able to obtain follow-up appointments faster – usually within seven days – and to connect patients with the services they needed to prevent emergency department visits and hospital readmissions.

Since the new discharge platform was implemented, it has cut the amount of time that the case managers need to prepare for their daily work from an average of 35 minutes to eight minutes. As a result, the case managers are saving a total of 1,327 hours per year. More importantly, the case managers have had more time to spend with patients and have been able to take on more patients who need their assistance.

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