Machine Learning Based Prediction of In-Hospital Mortality with Acute Myocardial Infarction

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Methods

Objectives

To determine if the application of machine learning techniques can improve prediction of in-hospital mortality in patients with AMI compared with previous models

To compare the performance of different machine learning approaches

Data

Patient data is taken from ACTION-GWTG registry, a national quality improvement registry for AMI collected from 655 participating hospitals over 10 years, and encompassing over 1 million patients

Models are built on 96 patient variables available at time of presentation including history, risk factors, demographics, and initial laboratory values (except where otherwise noted for LR model)

Meta-classifier Approach (Meta): uses an XGBoost model to combine the output of four models including Logistic Regression with Lasso, XGBoost, a Neural Network, and K-Nearest Neighbors.

Four modeling approaches are considered here:

1. Logistic Regression (LR): fits a conventional logistic regression model using the same 9 parsimonious variables as included in the McNamara et al. study

2. Logistic Regression with Lasso (Lasso): couples a conventional logistic regression approach with a cost function (Lasso), which results in a parsimonious set of variables that maximizes predictive capabilities

3. Gradient Descent Boosting (XGBoost): leverages the creation of many weak decision trees to produce a final, accurate prediction via weighted majority vote (“boosting”); unlike logistic regression, XGBoost is able to account for non-linear, higher-order interactions among variables


Results

Four independent models each trained on the same initial 40% training sample

Level 1 classifiers consist of four models such as XGBoost and the meta-classifier

Level 2 classifiers

Logistic Regression with Lasso

XGBoost

Neural Net

K-Nearest Neighbors

Figure 1: Computational approach. Level 1 classifiers consist of four independent models each trained on the same initial 40% training sample (A). The next 40% training sample (B) is then input into the Level 1 classifiers, resulting in one risk estimate from each Level 1 model. These four risk estimates are then used to train the Level 2 XGBoost classifier (C). A final sample (D) is used to test the performance of the Level 1 and Level 2 classifiers.

Table 1: Summary of model performance for LR, Lasso, XGBoost, and Meta models

<table>
<thead>
<tr>
<th>Model</th>
<th>ROC AUC (C-statistic)</th>
<th>PR AUC</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>PPV</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>0.872</td>
<td>0.900</td>
<td>0.929</td>
<td>0.930</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lasso</td>
<td>0.36</td>
<td>0.42</td>
<td>0.55</td>
<td>0.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>XGBoost</td>
<td>0.41</td>
<td>0.45</td>
<td>0.53</td>
<td>0.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Meta</td>
<td>0.97</td>
<td>0.57</td>
<td>0.98</td>
<td>0.98</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 2: Receiver-Operator Characteristic Curves

Table 2: Shift table comparison of individual risk estimates from Lasso and XGBoost/Meta models

<table>
<thead>
<tr>
<th>Meta risk</th>
<th>Low (&lt; 1%)</th>
<th>Moderate (1-5%)</th>
<th>High (&gt; 5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>0.2% (88,777)</td>
<td>0.5% (43,080)</td>
<td>0.4% (677)</td>
</tr>
<tr>
<td>Lasso</td>
<td>1.8% (1,233)</td>
<td>4.1% (21,409)</td>
<td>3.8% (13,301)</td>
</tr>
<tr>
<td>XGBoost</td>
<td>9.5% (258)</td>
<td>11.6% (6,473)</td>
<td>26.1% (30,630)</td>
</tr>
<tr>
<td>Meta</td>
<td>0.2% (89,567)</td>
<td>0.5% (47,061)</td>
<td>0.4% (565)</td>
</tr>
</tbody>
</table>

Conclusions

Machine learning based approaches outperform conventional logistic regression in predicting in-hospital mortality with AMI, and therefore have the potential to both enhance hospital-specific risk adjustment for retrospective profiling, and improve risk-stratification of AMI patients

Amongst the machine learning methods, non-linear models such as XGBoost and the meta-classifier outperform the linear Lasso model in predicting in-hospital mortality with AMI

References


