Statistical Methods for Predicting Adverse Outcomes after Percutaneous Coronary Intervention

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Introduction

Goal: To evaluate statistical methods for predicting adverse outcomes among patients undergoing percutaneous coronary interventions

Background :

Percutaneous Coronary Intervention (PCI):

- known as angioplasty with stent
- non-surgical procedure that uses a catheter to place a stent to open up blood vessels in the heart that have been narrowed by atherosclerosis

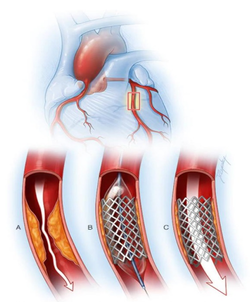


Fig A: Coronary angiography and stents

Risk stratification and prediction models

- important for optimizing care of patients undergoing PCI
- help healthcare providers, patients, and their families better comprehend attendant procedural risks and provide and objective basis for decision making

Reference: https://www.mayoclinic.org/tests-procedures/coronary-angioplasty/about/pac-20384761

Methods

Data: 15167 patients who underwent PCI at Mayo Clinic between January, 2000 and 2016. For patients with multiple PCIs within this period, only the first is used.

Exclusion criteria:

- Patients with primary outcome missing
- Patients with recorded age smaller than 18
- Patients without research authorization

Primary outcomes:

- Major bleed: bleeding complications within 72 hours
- Acute kidney injury: increased in serum creatinine of more than 0.25mg/dL from baseline

Statistical Methods:

1. **LASSO**: shrinkage and selection method for (logistic) regression where some estimates are set to zero
   - Pros: performs variable selection; model is easy to interpret
   - Cons: with correlated features, only one is selected
2. **Elastic net**: regularized regression method where some estimates are set to zero
   - Pros: performs variable selection; easy to interpret
   - Cons: more computationally intensive compared to LASSO
3. **Classification tree:** tree-based method stratifying predictor space into a number of simple regions for class outcomes
   - Pros: Easy to interpret and to explain
   - Cons: non-robust and potentially overfitting
4. **Gradient boosting machine (GBM):** creates a large number of weak trees, that when combined produce powerful predictions
   - Pros: generally high predictive accuracy, incorporates interactions
   - Cons: computationally intensive; 'black box'

Data Description

Characteristics	N=15167
Age*	68 (59, 77)
Sex: male	10604 (69.9%)
BMI*	29.3 (25.9, 33.3)
Diabetes	4507 (29.7%)
Peripheral arterial disease	2001 (13.2%)
Chronic lung disease	1903 (12.5%)
Prior PCI	3941 (26%)
CHF status	Current: 2549 (16.8%) No: 11932 (78.7%) Previous: 686 (4.5%)
Cardiogenic shock	546 (36%)
Cardiac arrest within 24hrs	161 (1.1%)
Unstable angina	8492 (56%)
Hemoglobin*	14 (12.3, 14.5)
Creatinine*	1.1 (0.9, 1.3)
Pre-PCI Ventricular support	127 (0.8%)
Predominate symptom: Asymptomatic	52 (0.3%)
Femoral access	12627 (83.3%)
IABP	301 (2.0%)
Contrast volume*	177.9 (150.0, 204.2)
Outcome	
Bleed	650 (4.3%)
AKI	1184 (7.8%)
Death	247 (1.6%)

**numerical variables with median, 1st quantile, and 3rd quantile reported*

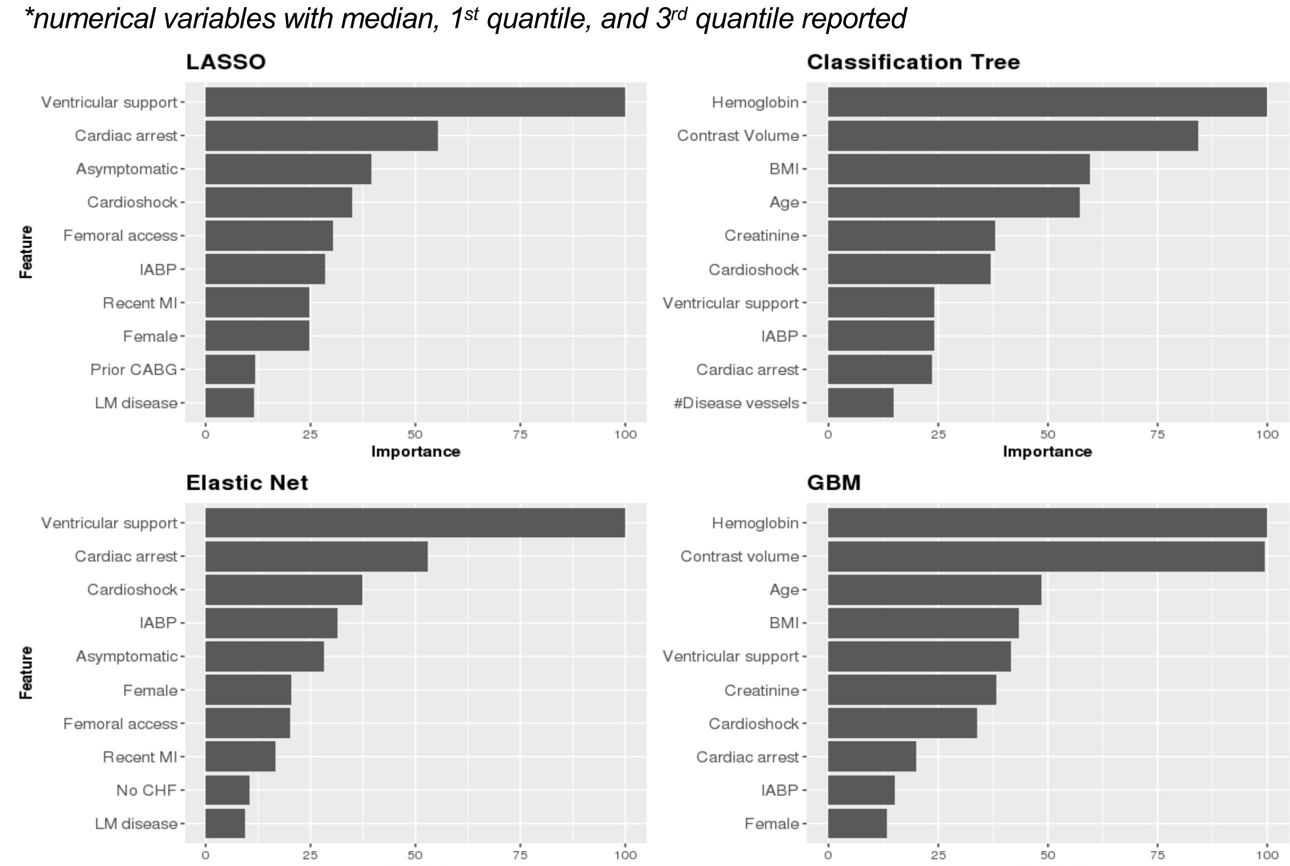


Fig.B: Variable importance plot for outcome bleed

Calibration

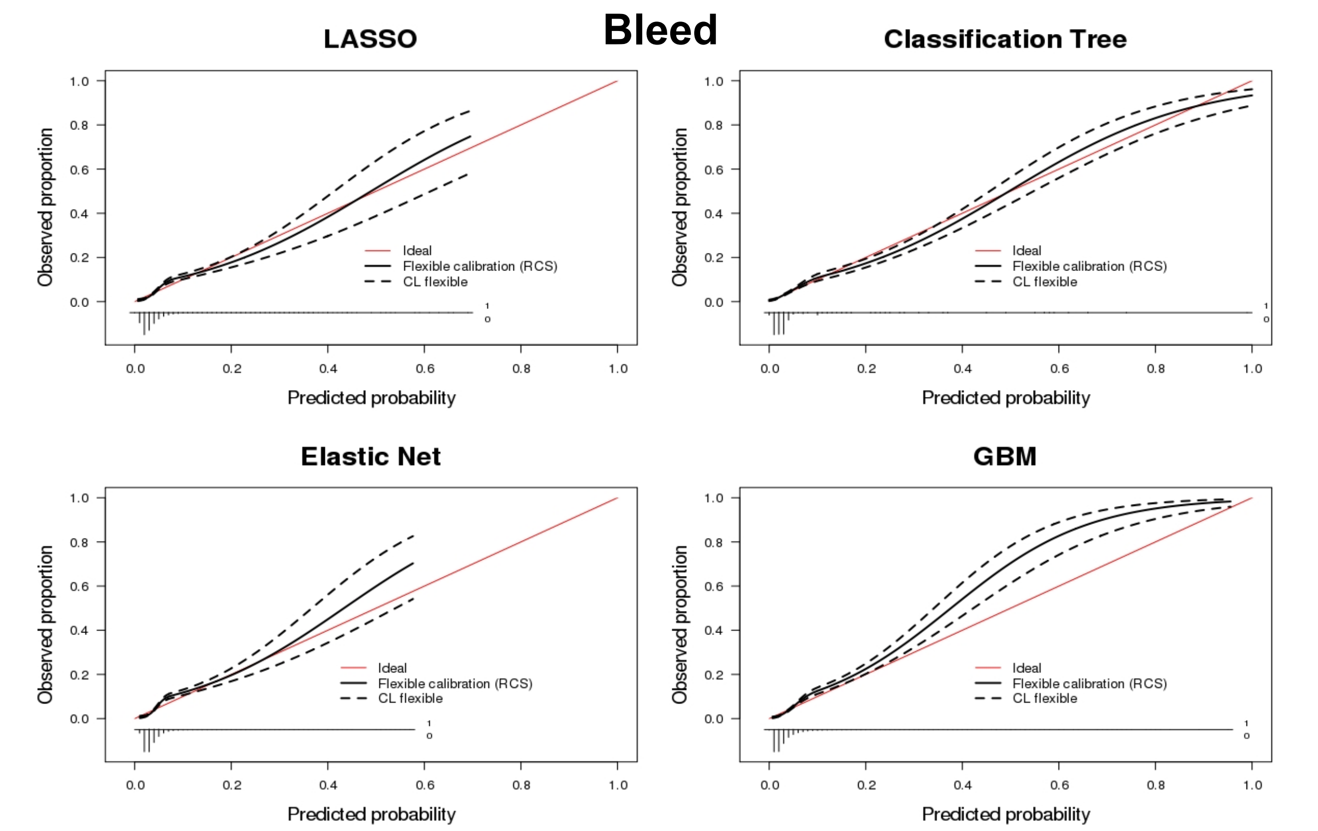


Figure C: Calibration plots for outcome bleed

Model	Calibration slope	Brier score	P-value (Hoesmer-Lemeshow)
LASSO	1.15 (1.05, 1.26)	0.039	0.79
Elastic net	1.29 (1.17, 1.40)	0.039	0.42
Classification tree	1.00 (0.93, 1.07)	0.036	1
GBM	1.30 (1.21, 1.39)	0.036	0.70

Table 1: Calibration results for outcome bleed. A 95% CI for calibration slope is also reported

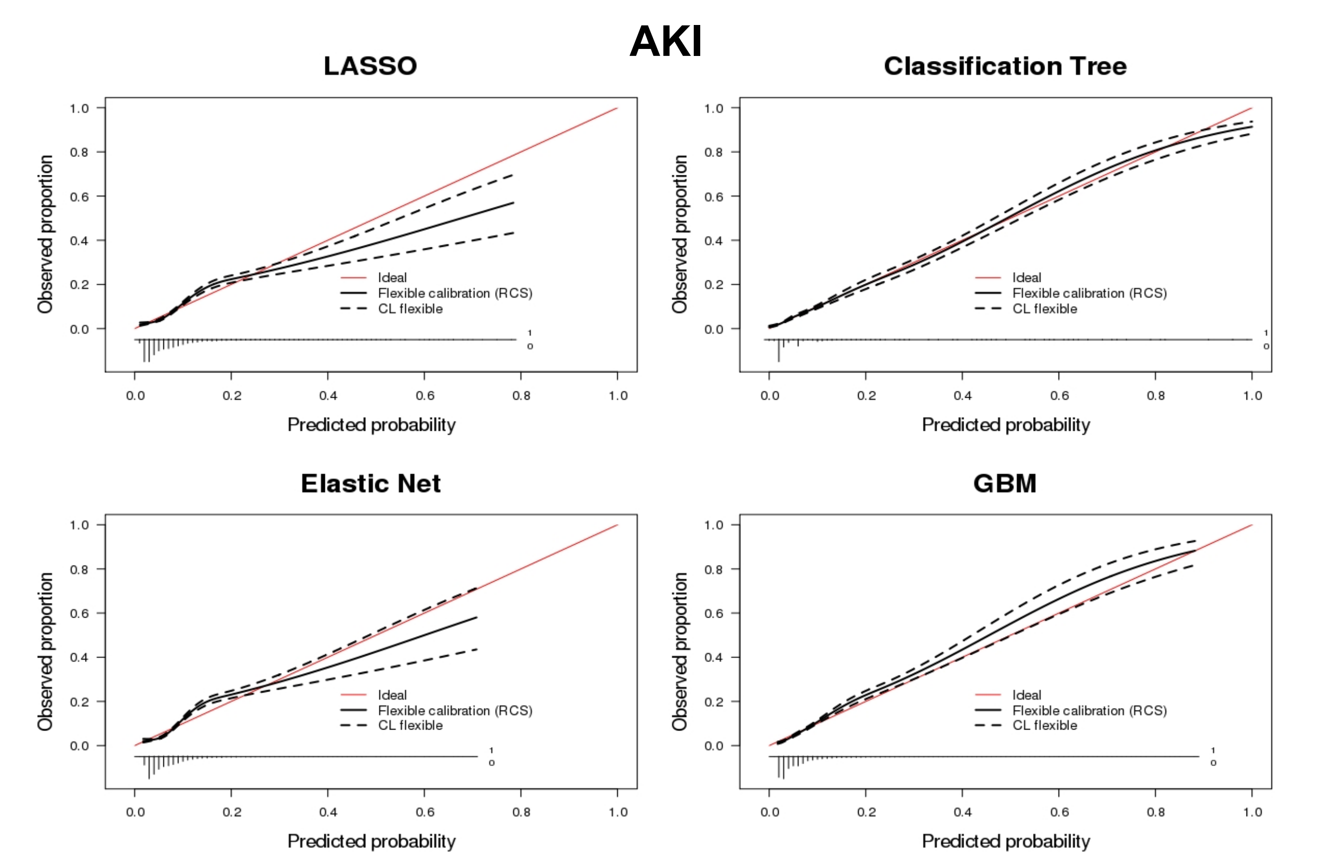
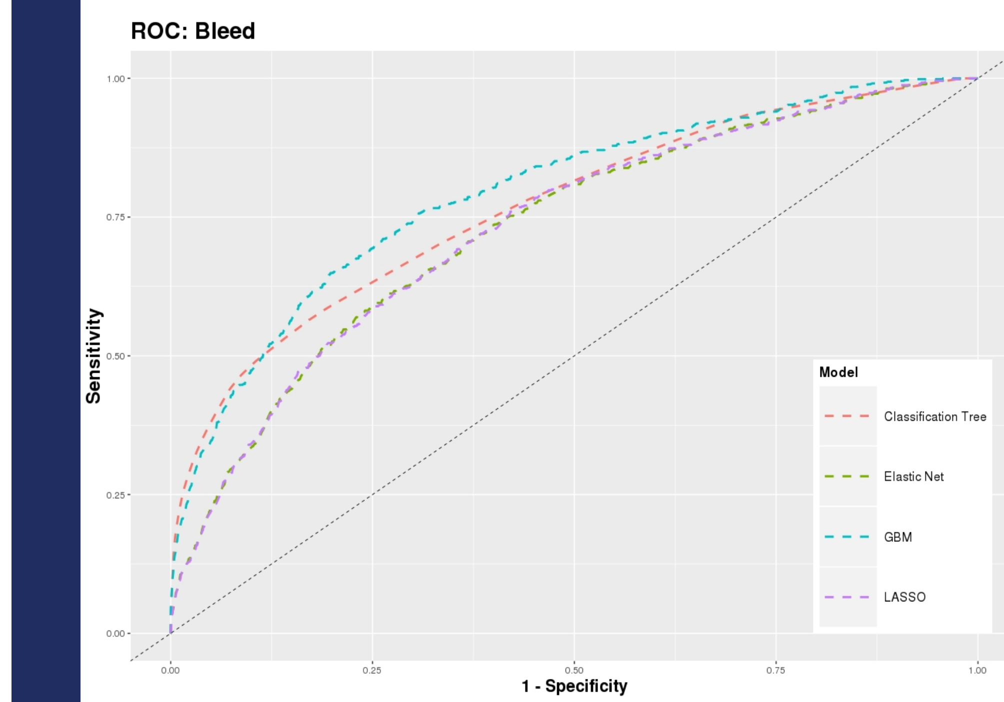


Figure D: Calibration plots for outcome AKI

Model	Calibration slope	Brier score	P-value (Hoesmer-Lemeshow)
LASSO	1.05 (0.98, 1.13)	0.067	0.14
Elastic net	1.21 (1.13, 1.29)	0.067	0.34
Classification tree	1.00 (0.95, 1.05)	0.056	1
GBM	1.16 (1.10, 1.22)	0.063	0.52

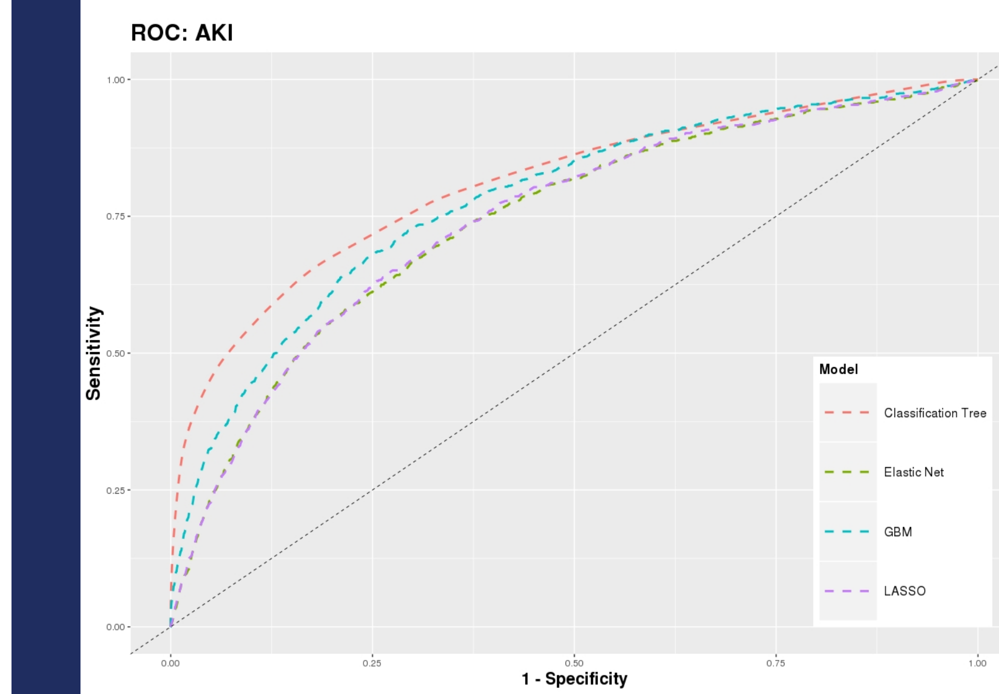
Table 2: Calibration results for outcome AKI. A 95% CI for calibration slope is also reported

Discrimination



Model	C-index
LASSO	0.73 (0.71, 0.75)
Elastic net	0.73 (0.71, 0.75)
Classification tree	0.76 (0.74, 0.78)
GBM	0.77 (0.75, 0.79)

Figure E: ROC curves for different models with outcome bleed. The c-index is included in the table for each model. A 95% CI with 2000 bootstrap replicates is also included for each model.



Model	C-index
LASSO	0.74 (0.73, 0.76)
Elastic net	0.74 (0.73, 0.76)
Classification tree	0.81 (0.79, 0.82)
GBM	0.78 (0.77, 0.80)

Figure F: ROC curves for different models with outcome AKI. The c-index is included in the table for each model. A 95% CI for c-index with 2000 bootstrap replicates is also included for each model.

Discussion

- We also tried other methods such as Random Forest, C5.0, and Adaboost, but performance was poor
- Death was also analyzed as an outcome; models performed similarly
- Based on the variable importance for both bleed and AKI, some of the important variables are: age, BMI, cardio shock, cardiac arrest, sex, IABP, unstable angina, creatinine, hemoglobin, femoral access, and contrast volume
- For calibration, classification tree has the lowest Brier score as well as a calibration slope closest to 1 for both adverse outcomes
- For Hosmer-Lemeshow for goodness of fit, all models suggested reasonable model calibration
- For both bleed and AKI outcomes, classification tree and GBM generally have a higher c-index compare to LASSO and Elastic net. For outcome bleed, the c-index for classification tree and GBM are almost identical, but for outcome AKI, classification tree performs noticeably better
- Overall, classification trees performed well, suggesting good model discrimination (c-index) and calibration (calibration slope, Brier score)
- Validation in an external sample would be a useful next step to confirm these model results