Predictive Modeling of Emergency Hospital Transport in Older Adults

Comparison of Machine Learning Algorithms in R

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Rapid growth in Emergency Department visits

Society is ageing: 15% of the US population is 65 years or older.
Most older persons have multiple chronic health conditions.

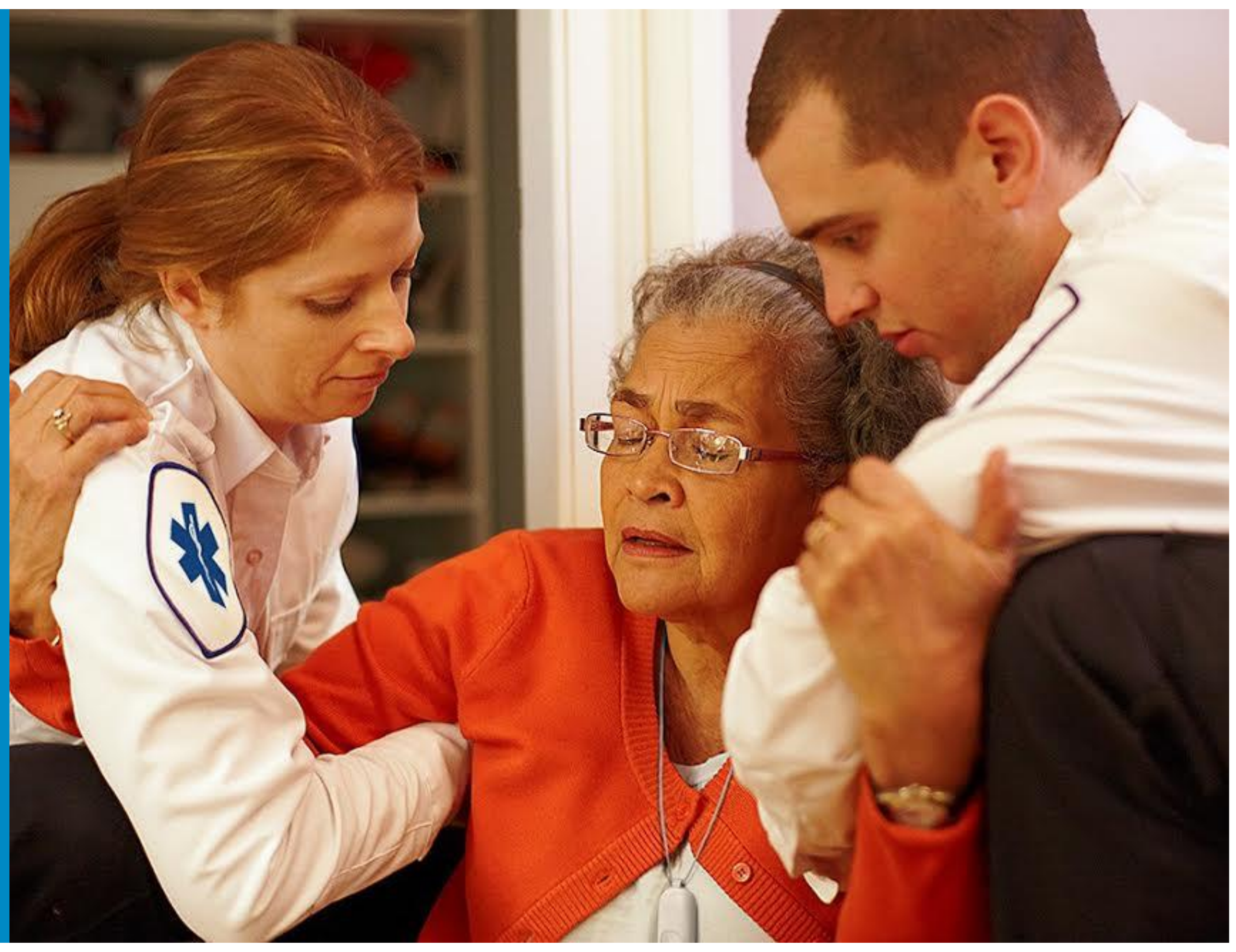
- Arthritis, cancer, heart conditions, diabetes, hypertension…

Acute emergency situations result from worsening of chronic conditions.

- Falls, respiratory problems, chest pain, …
- 20 million ED visits each year by 65+ persons
- Distressing for patients & extremely costly for society

Philips Lifeline medical alert service gets people help fast in an emergency.

Can emergency hospital transport be predicted using medical alert service data?



1. User summons help

2. Contact with response agent

3. Help is sent to user

Predictive modeling of 30-day emergency hospital transport in R

- Medical alert service data of 581,675 individuals
  - Falls and other incidents
  - Social & check-in calls
  - Self-reported medical conditions
- Independent model development and validation cohorts
- Comparison with clinical outcomes in a subpopulation of Lifeline users with linked electronic health record (EHR) data
- Comparison of gradient tree boosting to logistic regression models

581,675 Lifeline users →
- Model development: 290,434 Lifeline users, January 1, 2014
- Validation: 289,426 Lifeline users, February 1, 2014
- Comparison with clinical outcomes: 1,815 Lifeline users, February 1, 2014

Figure 1. Cohorts used for model development, model validation and comparison with clinical outcomes

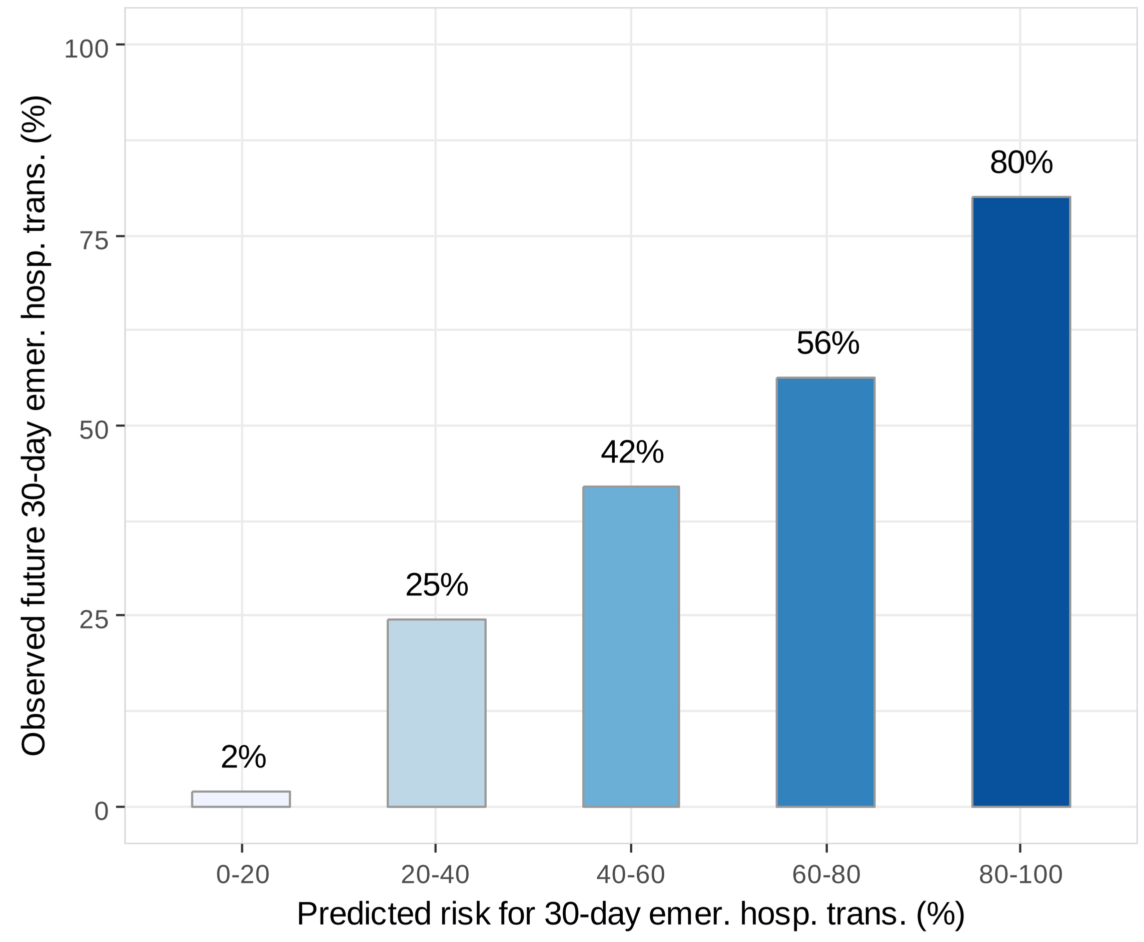


Figure 2. Observed 30-day emergency transport vs. predicted risk

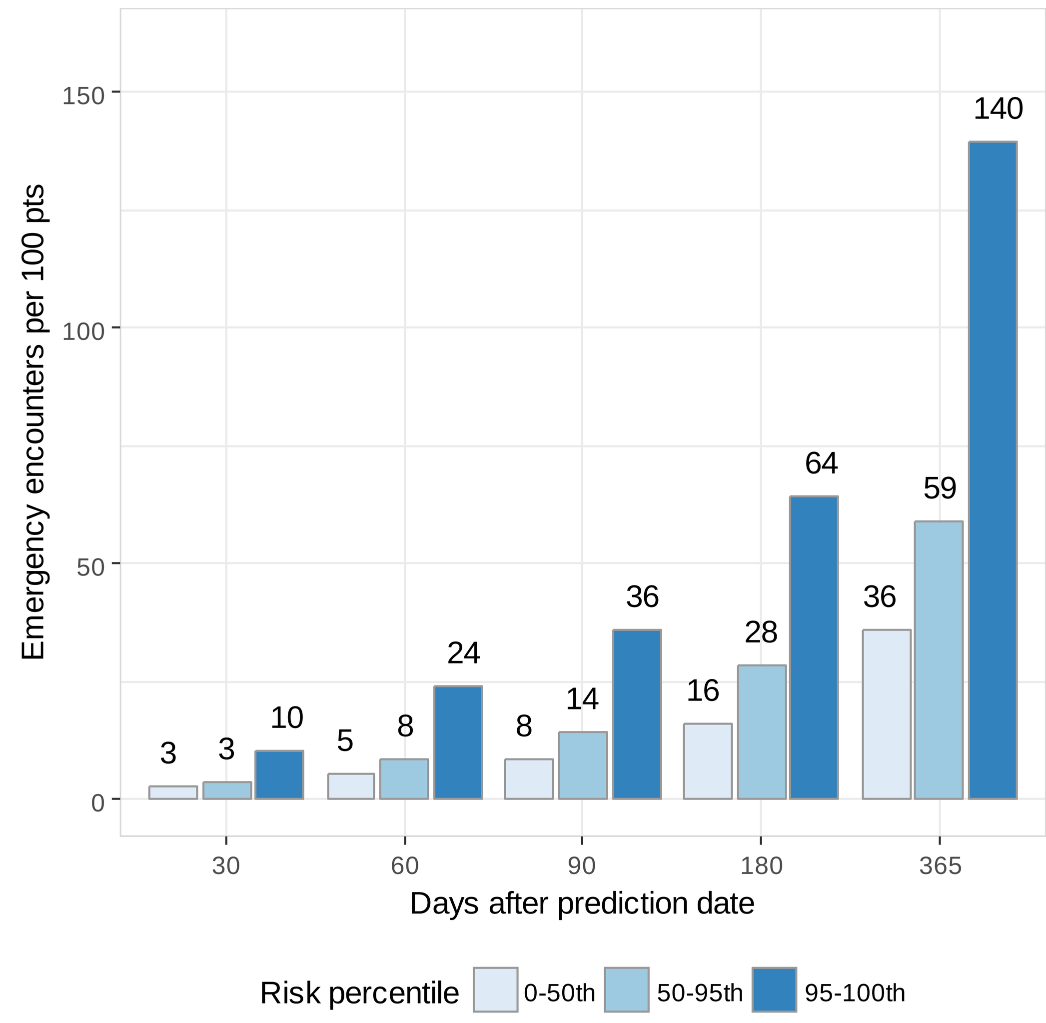


Figure 3. Comparison of predicted risk with emergency hospital encounters in the year following prediction, derived from the EHR

Table 1. Comparison of performance metrics of predictive models evaluated at threshold corresponding to 99th percentile. 95% CI from bootstrapping (n = 1,000)

	AUC	Sensitivity	PPV	Accuracy
Gradient boosting (xgboost)	0.779* [0.774-0.785]	11.5% [10.7-12.3]	25.5% [24.1-27.2]	97.3% [97.3-97.3]
Logistic regression (glm)	0.767 [0.761-0.773]	10.9% [10.1-11.7]	24.2% [22.7-25.6]	97.3% [97.2-97.3]

Key Takeaways

Medical alert service data enables prediction of emergency hospital transport.

- Predictive model built on large data set from over 580,000 Lifeline subscribers
- Observed outcomes increased with increasing predicted risk for 30-day emergency transport
- Good discriminatory accuracy, AUC = 0.78

Risk scores for emergency hospital transport correlate with clinical outcomes.

- Four times higher rate of emergency hospital encounters in high risk patients

State-of-the-art machine learning algorithms in R yield high predictive performance.

- Extreme gradient boosting outperformed logistic regression
- Significantly increased AUC
- Higher sensitivity and positive predictive value

Predictive model of emergency hospital transport incorporated in the Philips CareSage Predictive Analytics Engine

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