

Distinguishing Death from Disenrollment: Applying a Predictive Algorithm to Reduce Bias in Estimating the Risk of Rehospitalization

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BACKGROUND

- The inability to identify death dates in several insurance claims data sources results in biased estimates when death is a competing event.
- Deaths result in disenrollment from health plans. When dates of death are not available, death is typically treated as non-informative censoring.
- ORACL (Observational Research Algorithm for Claims) was built using machine learning methods to predict when plan disenrollment is due to death.
- ORACL was developed and validated using MarketScan insurance claims data

OBJECTIVES

We illustrate how ORACL can be used to identify deaths in insurance claims data, and how treating predicted deaths as competing risks can reduce bias in study estimates.

METHODS

Data Source:

- 20% sample of Medicare claims, 2007-2017

Study Population:

- 66+ years of age with an inpatient admission for AMI
- At least 1 year of prior continuous enrollment with an employer-sponsored supplemental insurance plan

Outcome: Rehospitalization within 90-days of discharge from hospitalization for AMI

We Compare Three Methods of Estimating the Risk of 90-day Readmission

1.
Using true death data, account for death as a competing risk.
Cumulative Incidence Functions

2.
Mimicking scenarios where death data are unavailable, treat death as non-informative censoring at the time of disenrollment

3.
Use ORACL to predict when disenrollment is death, and treat predicted deaths (predicted probability >0.99) as a competing risk

The ORACL model can predict death in insurance claims, enabling competing risk analyses to reduce bias

RESULTS

Table 1. Risk of 90-day rehospitalization using 3 different methods of accounting for death.

Analysis Version	Death Data	Death treated as...	Risk (95% Confidence Interval)
Benchmark	Validated CMS Death Data	A competing risk	21.6% (20.8%, 22.3%)
Obscured Death	Obscured Death	Non-informative censoring (equivalent to disenrollment)	24.8% (23.9%, 25.6%)
ORACL	ORACL Predicted Death	ORACL predicted death treated as a competing risk	21.7% (21.0%, 22.5%)

Table 2. ORACL performance in the Medicare hospitalized AMI population.

Predicted Probability Threshold	% of disenrollments above the threshold	Sensitivity	Specificity	ROC
0.10	100.0%	1.000	0.000	0.94
0.20	99.9%	1.000	0.002	
0.30	99.6%	1.000	0.012	
0.40	98.8%	1.000	0.033	
0.50	97.9%	1.000	0.063	
0.60	96.4%	1.000	0.105	
0.70	94.5%	0.999	0.162	
0.80	91.4%	0.998	0.248	
0.90	86.8%	0.996	0.380	
0.950	82.1%	0.992	0.502	
0.975	77.1%	0.983	0.623	
0.990	71.0%	0.967	0.754	
0.995	65.9%	0.937	0.837	
0.999	53.8%	0.811	0.948	

CONCLUSIONS

- Failure to account for death as a competing risk results in an estimate that is biased upwards.
- Using ORACL to predict death produced estimates of risk that closely mirrored estimates using validated death data
- In situations where death data are unavailable, ORACL can help alleviate biases related to competing risks
- In this example, when using ORACL, we were able to eliminate a 15% overestimation

DISCLOSURES

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