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Enhancing Value-Based Healthcare with Reconstructability Analysis: Predicting Cost of Care in Total Hip Replacement

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Background

One way to improve predictions is through better modeling methods. (Other ways include better data or implementation.)

Current models are predominantly based on logistic regression (LR). This project applies *Reconstructability Analysis* (RA) to hip replacement surgery, considering whether RA can create useful models of outcomes.

Research Objective

Find **RA predictive models**

- Predict cost of care (DV) given a set of comorbidities and delivery system variables (IVs). Models look at the probability distribution of outcomes given a single IV or multiple IVs AND look at the probability of outcomes given complex interaction effects.

The Data

Data Set

- Hip data N = 3,205

Independent Variables (IVs)

- 231 patient risk factors (comorbidity IVs)
  - i.e diabetes, hypertension, age, etc.
- 8 additional delivery system IVs
  - i.e surgeon, location, case volume, etc.

Dependent Variable (DV):

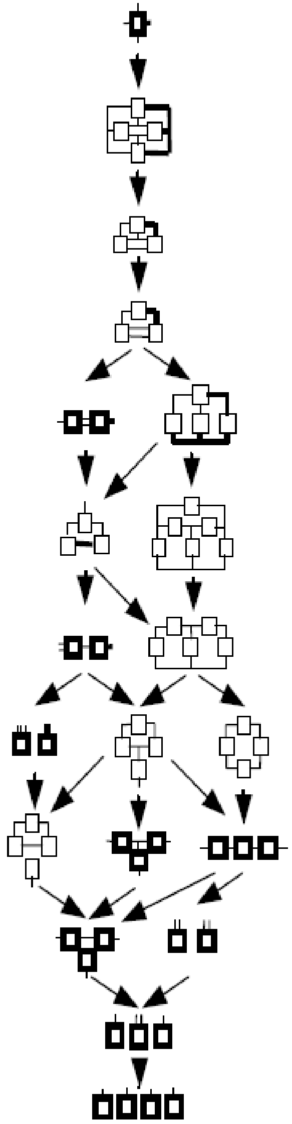
- Total Cost binned (**Tcb**)
  - Continuous variable, binned

Main Objective: RA Predictive Models

To construct a model, data is collected in order to capture information about a system. Yet the data is inherently complex.

A model is a reduction of the data to a simpler structure, which generalizes better to new data. However, oversimplifying results in loss of critical information. *This presents a tension inherent in the modeling process.*

In this project, modeling starts by assuming no predictive relations and then searches the space of possible models for incremental additions of predictive relations. This bottom-up approach allows one to construct a model whose complexity is statistically justified, but is still not overly complex.



RA - Search

RA Search – Single Predictors for **Tcb**

- Results show that knowing the *surgeon* (S) reduces the uncertainty in predicting **Total Cost Binned (Tcb)** by 24.2%. *Location* (L) is the next most individually predictive, with a %ΔH of 13.4, followed by *surgeon volume binned* (Svb) with %ΔH at 13.1.

MODEL	Δdf	ΔBIC	%ΔH	Variable description
COARSE, single predictors (top 10)				
S Tcb	84	1026.62	24.2	Surgeon
L Tcb	12	849.389	13.4	Location
Svb Tcb	4	893.509	13.1	Surgeon volume binned
Da Tcb	10	414.476	7.03	Day of admit
Ad Tcb	76	-333.31	3.98	Admit diagnosis
Fc Tcb	10	-7.3465	1.04	Financial class
Nrb Tcb	4	29.68	0.88	Number of risks binned
Rmo Tcb	2	19.2819	0.5	Morbid obesity (278.01)
Ageb Tcb	4	1.754	0.48	Age binned
Rrd Tcb	2	14.5431	0.44	Hypertensive renal disease (403.9)
MODEL	Δdf	ΔBIC	%ΔH	Variable description

RA Search – Loopless

- The best coarse (loopless) search allowing for multiple predictors but still one component is L Svb **Tcb**. Surgeon (S) is not in the best model selected by BIC, presumably because the complexity of the model (Δdf = 84) is not worth the information it adds. Apparently, surgeon volume (Svb) along with location (L) have enough information worth the complexity (Δdf = 40) with a %ΔH of 21.25.

MODEL	Δdf	ΔBIC	%ΔH	Variable description
COARSE, best model (loopless)				
ΔBIC				
L Svb Tcb	40	1173.50	21.25	Location, Surgeon volume binned
Inc.P & ΔAIC (same best model)				
S Tcb	84	1026.62	24.21	Surgeon

RA Search – Fine grained, with loops

- Allows for multiple components predicting the DV.
- Within each component, there may be interaction effects among the IVs in their prediction of the DV.
- This best fine-grained model by BIC, **L Tcb : Svb Tcb : Nrb Tcb**, has a slightly smaller %ΔH than the best coarse model L Svb Tcb of 21.25%, but the Δdf is exactly half with a Δdf of 20 rather than 40. This reduction in complexity more than compensates for the slightly smaller %ΔH.

MODEL	Δdf	ΔBIC	%ΔH	Variable description
FINE, best models (with loops)				
ΔBIC (best model)				
L Tcb : Svb Tcb : Nrb Tcb	20	1330.92	21.19	Location, Surgeon volume binned, Number of risks binned
Inc.P & ΔAIC (same best model)				
S Tcb : Nrb Tcb	88	1084.66	25.49	Surgeon, Number of risks binned

Expected Values – Total Cost

Total Cost binned (Tcb)

- The total cost per case is a continuous variable with values ranging from $11,147 - $71,264 per case, and an average of $18,593.
- These costs were binned to into 3 equal sample size bins to create the DV Total Cost (**Tcb**).

Hip, Total Cost Binned (Tcb)

Bin	Min Cost	Max Cost	Average Cost	Frequency
1	$11,147	$16,768	$15,244	1068
2	$16,772	$19,192	$17,997	1069
3	$19,195	$71,264	$22,534	1068

Expected Values – Total Cost

- Each of these bins has an average cost, and along with the product of the probabilities of each bin, an expected value is calculated and used in the interpretation of the results for the Total Cost DV.
- The model's conditional probability distribution includes the calculated probability of each of the model's IV states for the low-cost (bin 1), mid-cost (bin 2), and high cost (bin 3) bins. The product of the probabilities of each bin and each bin's average Total Cost was used to calculate an Expected Value (predicted Total Cost) for each IV state:

$$Expected\ Value = \frac{p(\mathrm{Tcb1}) \times Avg(\mathrm{Bin1}) + p(\mathrm{Tcb2}) \times Avg(\mathrm{Bin2}) + p(\mathrm{Tcb3}) \times Avg(\mathrm{Bin3})}{100}$$

RA - Fit

Predictive Models for Tcb

- Conditional probability distribution (partial), given the predicting IVs with Expected Values for model **L Tcb : Svb Tcb : Nrb Tcb**

	IVs			Data				Model						
					obs. p(DV|IV)			calc. q(DV|IV)						
#	L	Svb	Nrb	freq	Tcb=1	Tcb=2	Tcb=3	Tcb=1	Tcb=2	Tcb=3	Exp. Value	Ratio	rule	p(margin)
1	1	1	1	21	0.00	23.81	76.19	2.05	23.53	74.42	$21,317.04	1.15	3	0.00
2	1	2	1	81	2.47	25.93	71.61	1.94	26.00	72.06	$21,213.25	1.14	3	0.00
3	2	1	1	215	12.56	48.84	38.61	11.01	50.34	38.65	$19,447.72	1.05	2	0.00
4	2	1	2	214	4.21	44.39	51.40	7.51	45.10	47.39	$19,940.50	1.07	3	0.00
5	2	1	3	198	3.54	35.35	61.11	4.13	37.68	58.19	$20,523.33	1.10	3	0.00
6	2	2	1	172	9.30	59.88	30.81	10.05	53.77	36.18	$19,362.02	1.04	2	0.00
7	2	2	2	193	7.25	50.78	41.97	6.90	48.48	44.63	$19,832.19	1.07	2	0.00
8	2	2	3	168	7.14	37.50	55.36	3.83	40.87	55.31	$20,401.00	1.10	3	0.00
9	3	1	1	52	11.54	40.39	48.08	21.05	37.29	41.66	$19,307.42	1.04	3	0.17
10	3	1	2	77	12.99	31.17	55.84	14.52	33.81	51.67	$19,941.54	1.07	3	0.00
11	3	1	3	125	4.80	32.00	63.20	8.02	28.33	63.65	$20,664.32	1.11	3	0.00
12	3	2	1	36	8.33	30.56	61.11	19.60	40.63	39.77	$19,261.82	1.04	2	0.23
13	3	2	2	48	10.42	27.08	62.50	13.57	36.95	49.49	$19,868.89	1.07	3	0.01
14	3	2	3	51	7.84	29.41	62.75	7.53	31.15	61.32	$20,571.98	1.11	3	0.00
15	3	3	1	393	77.10	19.08	3.82	74.65	18.86	6.48	$16,235.60	0.87	1	0.00
16	3	3	2	396	68.94	23.23	7.83	67.20	22.31	10.49	$16,622.80	0.89	1	0.00

Predictive Models for Total Cost (Tcb)

Risk group IV states w/ ratio average and margin (All IVs)

- The best model (L Tcb : Svb Tcb : Nrb Tcb) identified several groups of patients whose particular combinations of IV states from the model would be expected to have higher total cost (Tcb).
- Considering all of these groups of patients together, 21.53% of the total patients were placed in the higher expected cost group, with an expected cost of $20,636.51, higher than the average of $18,591.45. For this same model, 28.30% of patients had a lower expected cost of $16,360.48.

Total Cost Binned (Tcb)				
Hip (All IVs)				
Model: L Tcb : Svb Tcb : Nrb Tcb	Freq	% of Cases	Ratio Average	Expected Value
Increased Expected Cost IV States	690	21.53%	1.11	$20,636.51
Decreased Expected Cost IV States	907	28.30%	0.88	$16,360.48
No difference (by significance or frequency)	1608	50.17%		
Total	3205			$18.591.45

Future Applications

- Enhancing value through better predictions is now an imperative for healthcare systems, across multiple clinical domains.

- As demonstrated in this project, Reconstructability Analysis is an approach that may strengthen or augment existing predictions and even perhaps replace existing methods.

- With risk and outcomes adequately predicted, areas for potential improvement become clearer, and focused changes can be made to drive improvements in patient care. Better predictions, such as those resulting from the Reconstructability Analysis methodology, can thus support improvement in value – better outcomes at a lower cost.

Thank you!

Reduction of Uncertainty (%ΔH) Explained

- Even small uncertainty reductions could be large in effect size
  - Like 1:1 → 2:1
- %ΔH is like %variance explained, but
  - Low %variance means effect size is ignorable
  - For %ΔH, even small numbers can have large effect sizes (because there is a log in expression for H).

Season is winter or summer and weather is rain or no rain. If you don't know what season it is, you face maximum uncertainty with a 1:1 chance of no-rain : rain.

However, if you know the season, uncertainty is reduced.

- If you know it is winter, then there is a 1:2 odds of no-rain : rain.
- If you know it is summer, then there is a 2:1 odds of no-rain : rain.

	rain	No-rain	
summer	1/6	2/6	1/2
winter	2/6	1/6	1/2
	1/2	1/2	

- Knowing the season changes the odds. This is a big effect size (but ΔH is only 8%).

Marginal Probability (Rain) (don’t know the season) 0.5

Summer

.33 (summer has lower risk of rain)

Winter

.67 (winter has a higher risk of rain

A **risk ratio** for <u>effect size</u>:

$$\frac{.33}{.5} \quad \text{or} \quad \frac{.67}{.5}$$

‘risk ratio’ = probability of an outcome (rain) for a particular IV state (summer or winter) divided by the marginal probability of the outcome (maximum uncertainty).