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Optimal Statistical Analysis Involving Multiple Confounding Variables

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This paper demonstrates a maximum-accuracy statistical approach that assesses the effect of two or more confounding variables on the estimated association of a class variable and attribute(s). An example involves modeling patient self-ratings of the likelihood that they will recommend an Emergency Department to others (class variable), based on five patient-rated dimensions of physician care behavior (attributes), and patient satisfaction ratings for amount of time waiting to see the physician, and for amount of time waiting in the registration room before going to the treatment area (confounders).

The use of optimal[1] (maximum-accuracy) *c*lassification *t*ree *a*nalysis[2-15] (CTA) to create statistical models for predicting observations' class category status—in applications involving one or more attributes and a single confounding variable—has recently been discussed.[16] CTA is an algorithm that chains successive *uni*variate *o*ptimal *d*ata (*d*iscriminant) *a*nalysis (UniODA) models[17-26] to create a (non)linear multivariable system that explicitly maximizes accuracy—normed versus chance—for the specific sample, data geometry, and hypothesis under investigation.[27-31] Three forms of CTA have been developed: hierarchically-optimal (HO-CTA) enters the attribute yielding greatest normed accuracy in each step of the analysis; enumerated-optimal (EO-CTA) enumerates the first three nodes of the CTA model in order to obtain the model yielding maximum normed accuracy; and globally-optimal (GO-CTA) identifies the CTA model manifesting the best combination of accuracy and parsimony.[16,31]

Study Context

The study setting was an 800-bed urban university-based level 1 Trauma center with an annual census of 48,000 patients.[32] One week following their discharge patients were mailed a survey assessing their satisfaction with the care they received in the Emergency Department (ED). There was a 17% survey return rate.

Ratings were obtained of the likelihood that the patient will recommend the ED to others, and of patient satisfaction with administrative, nurse, physician, laboratory, and family/friend aspects of care. Ratings were made using a five-point Likert-type scale with 1=*very poor*, 2=*poor*, 3=*fair*, 4=*good*, and 5=*very good*.

The binary *class variable* being modeled is whether a patient is *ambivalent* (rating=3, N=239) or *likely* (rating=4, N=584) to recommend the ED to others (total N=823 patients).

Satisfaction ratings of aspects of care received from physicians—courtesy, took the

Optimal Data Analysis
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2155-0182/10/$3.00

patient's problem seriously, concern for patient comfort, and explanation of test/treatment and of illness/injury—are treated as the *attributes* (possible predictors).

One Confounder

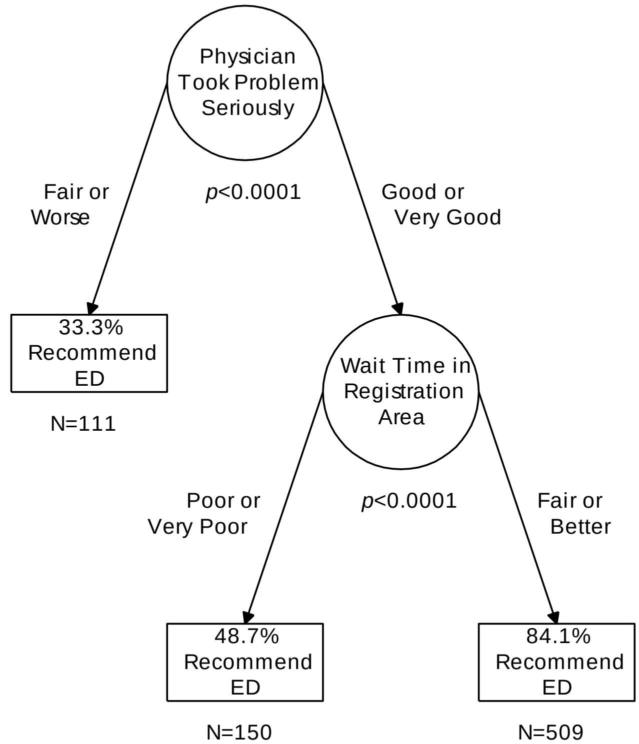
Time spent in the treatment area waiting to be seen by the physician—to some extent a function of case mix—is known to predict patient self-ratings of satisfaction with received care, as well as likelihood of recommending the ED to others.[32-39] Because waiting time isn't directly or reliably subject to physician control, recent research sought to identify factors that are subject to physician control and also capable of influencing patient recommendation ratings beyond the effect of waiting time—which here is conceptualized as a *confounding* variable.[16]

By definition, analysis showed that for all five dimensions of rated physician behavior, the GO-CTA solution minimized the distance (*D*)—defined as the number of additional equivalent effects needed to achieve the theoretically ideal model that maximizes both accuracy and parsimony for the application.[27,31] The GO-CTA model for every rated physician behavior had the identical two-attribute structure—including discriminant thresholds. In every analysis the actionable physician behavior was the model root attribute: waiting time in the treatment area was statistically salient for physician ratings of "good" or "very good".[16] Overall the best GO-CTA model (*D*=3.8) involved ratings of the degree to which the physician "took the patient's problem seriously".

Multiple Confounders

In addition to patient ratings of their satisfaction with waiting time in the *treatment area*, patient ratings were also available for their satisfaction with waiting time in the *registration area*, before going to wait in the treatment area. Figure 1 shows the GO-CTA model obtained by including the second confounder in the analysis.

Figure 1: GO-CTA Model Predicting Self-Rated Likelihood of Recommending the ED to Others



Overall classification performance of this GO-CTA model is summarized in Table 2.

Table 2: Confusion Table for GO-CTA Model Predicting Patient's Self-Rated Likelihood of Recommending the ED to Others

		Predicted Ambivalent (3) or Likely to Recommend (4)	
		3	4
Actual Patient	3	151	81
Self-Rating	4	110	428

For this model *D* = 3.72, marginally superior to the identical model (including discriminant thresholds) developed earlier[16] using waiting time in the treatment area in the bottom node (*D* = 3.8). When a GO-CTA model was

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attempted using only the two confounding waiting times as potential attributes, no multi-attribute model was identified. The best model was a UniODA involving a single threshold on waiting time in the treatment area (*D* = 4.50).

In the model in Figure 1 the root node involves ratings of some of the last (most recent) interactions of the patient and "the ED": considered in this context the patient-doctor interaction is reminiscent of a recency effect. And, in the model in Figure 1 the bottom node involves ratings of some of the first (earliest) interactions of the patient and "the ED": considered in this context waiting time in the registration area is reminiscent of a primacy effect.

For the left-most endpoint, 2 in 3 patients are ambivalent about recommending the ED, and for the right-most endpoint, 7 in 8 patients are likely to recommend the ED to others. Neither of these strata is perfectly homogeneous: by definition, perfect predictive accuracy requires perfect homogeneity within all sample strata identified by the model.[27] The middle endpoint is most heterogeneous, with 1 in 2 patients ambivalent about recommending the ED to others. This middle strata represents 150 / 770 or 19.5% of the overall sample. The greatest opportunity for meaningful increase in model accuracy (i.e., biggest decrease in *D*) lies in improving homogeneity in the middle strata.

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Author Notes

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