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Obtaining a Hierarchically Optimal CTA Model via UniODA Software

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The use of UniODA software to obtain a hierarchically optimal (maximum-accuracy) classification tree analysis (HO-CTA) model is demonstrated.

The initial paper discussing the development of hierarchically optimal classification tree analysis (HO-CTA) models created using UniODA statistical software[1] was presented for an application involving discriminating geriatric versus non-geriatric ambulatory patients via responses on a functional status survey.[2] HO-CTA models have been published in numerous medical disciplines and topics[3] including behavioral[4,5], gastrointestinal[6], internal[7], neurological[8-10], nutritional[11], oncological[12], outcomes[13], pediatric[14], pulmonary[15-18], psychiatric[19-22], and rehabilitation[23] fields of medicine, for example. HO-CTA models have also been published in numerous psychological disciplines[24] including child/clinical[25-32], cognitive[33,34], criminal and forensic[35-39], educational[40], medical[41,42], military[43,44], outcomes[45], positive[46], satisfaction[47], services[48-50], and substance abuse[51] fields, for example. These HO-CTA models were more accurate than linear models based on legacy general linear model and maximum-likelihood paradigms: that is, HO-CTA models correctly classified more observations above and beyond what was possible by chance alone. HO-CTA models were also more parsimonious, involving a smaller subset of predictor ("independent") variables included in the classification model.

Fourteen years after the development of HO-CTA, a second-generation method known as enumerated optimal classification tree analysis[52] (EO-CTA) was developed, that yields substantially more accurate and parsimonious models than are obtained by HO-CTA.[25,53,54] Finally, in 2014 the discovery of the third generation of maximum-accuracy classification tree modeling methodology—known as globally-optimal classification tree models (GO-CTA)—was motivated by the development of novometric theory, conceptually parallel to quantum mechanics for classical (versus atomic) data.[55-62]

Despite the development of more accurate and parsimonious EO and GO models, techniques used to identify HO-CTA models remain useful for two reasons. First, learning to mechanically obtain an HO-CTA model improves understanding of the internal operations of all three CTA methods, thereby enhancing skills in experimental design and hypothesis development, measurement practices, and interpretative skills. Second, UniODA software allows systematic manipulation of CTA models and precise exploration of the effect of substituting variables within the models. The mechanical steps required to obtain an HO-CTA model are now illustrated.

Context of the Exposition

The data for this example come from a study investigating factors that increase the likelihood of an ambivalent Emergency Department (ED) patient recommending the ED to others. The study was set in an urban 800 bed university-based level 1 Trauma center with annual census of 48,000 patients.[58] One week post discharge, patients were mailed a survey assessing their satisfaction with the care they received in the ED. The survey elicited ratings of the likelihood of recommending the ED to others, and satisfaction with aspects of administration, nurse, physician, laboratory, and care of family/friends. A total of 2,109 surveys with completed recommendation ratings were returned over a six-month period (17% return rate). Likelihood to recommend ("recom" in the UniODA code) was rated using a five-point Likert-type scale: scores of 3 (fair, N=239) indicate *ambivalence*; and scores of 4 (good, N=584) reflect *likely to recommend*.[63] Analysis included a total of 823 patients responding with recommendation ratings of 3 or 4.

For this exposition, only the satisfaction ratings of aspects of care received from nurses were used as potential attributes: n1=courtesy; n2=took problem seriously; n3=attention; n4= informed patient about treatment; n5=concern for privacy; and n6=technical skill. Satisfaction items were completed using five-point Likert-type scales: scores of 1=very poor satisfaction, 2=poor, 3=fair, 4=good and 5=very good satisfaction. Data file requirements for UniODA software are discussed elsewhere.[63]

Determining the Minimum *N* for HO-CTA Model Endpoints

The first step in developing any CTA model is to determine *a priori* the minimum appropriate sample size for any (every) endpoint in the model. Two issues that require consideration in this context include statistical power and cross-generalizability.[1] To estimate statistical power, in the absence of strong supporting information regarding the anticipated effect strengths (ESS values) to be expected, an excellent heuristic is to assume an ESS value of 37.5, which lies in the middle of the range used to define a moderate effect (25-50).[1] Examination of Table 3 (p. 29) in Soltysik & Yarnold[64] reveals that a minimum endpoint sample size of N=40 for a Cohen's d value of between 0.7 and 0.8 corresponds to an ESS value of 37.5 (ESS values in the Table are divided by 100 to convert them to a percentage). Referring to Table 2 (p. 28) in Soltysik & Yarnold reveals that statistical power for this sample size (p<0.05) lies near 90%, the standard for statistical power in funded research. To estimate cross-sample generalizability of the model, particularly in application to smaller overall samples, the heuristic used in our laboratory is to constrain the minimum endpoint sample size to be between 5% and 10% of the total sample. Assuming proportional sample reduction as the depth of the CTA model increases, a total sample size of 1,000 observations is reduced to an endpoint value of 500 for a one-node, two-endpoint model; 250 for a three-node, four-endpoint model; 125 for a seven-node, eight-endpoint model; and so forth. For a replication sample half the size of the training sample, these endpoint values would be reduced to 250, 125, and 62, respectively. Thus the reduced model would have sufficient statistical power to support an attempted replication for a half-sample seven-node model. In the present application, the total sample is N=823 observations, and 5% of this value is 41.25 observations. Thus, upon consideration of both statistical power and cross-generalizable considerations, the minimum endpoint value in this application is rounded-up to a value of 42 observations. To enter the HO-CTA model, the attribute with the highest ESS value must meet the criterion for experimentwise significance, and also have an endpoint consisting of 42 or more observations.

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Growing the HO-CTA Model

To identify the initial (root) node[2] of the HO-CTA model, UniODA[1] is conducted for every attribute used to discriminate the class variable—rating of likelihood to recommend the ED to others (3 or 4)—for the entire sample. The attribute yielding the highest value for the effect strength for sensitivity (ESS) statistic is selected as the root node of the HO-CTA model so long the attribute has associated $p<0.05$. ESS is the critical criterion by which the HO-CTA model is grown, and which HO-CTA model maximizes. ESS is a normed measure of accuracy that may be used to directly contrast different maximum-accuracy models, regardless of *structural* (number of class categories, attribute metrics, hypothesis) and/or *configural* (total *N*, base rate of class categories) differences. ESS is based on the mean sensitivity (i.e., proportion of observations in a given class category that are correctly classified) of the model across all class categories.[1] An errorless model achieves a mean sensitivity of 1, and in a two-category problem, if the two class categories cannot be discriminated, then a chance model achieves a mean sensitivity of 0.5. For a two-category problem, ESS is computed as: ESS = [(mean sensitivity – 0.5) / 0.5] x 100%. If the model correctly classifies all observations then ESS = [(1 - 0.5) / 0.5] x 100% = 100. If the model correctly classifies half of the observations of each class category then ESS = [(0.5 – 0.5) / 0.5] x 100% = 0. Thus, ESS=0 is the level of classification accuracy that is expected by chance alone, and ESS=100 is perfect, errorless classification.[1]

UniODA analysis conducted to identify the root node was accomplished using the following UniODA[1] (and MegaODA[65-67]) code:

```
OPEN recom.dat;
OUTPUT recom.out;
VARS recom n1 to n6;
CLASS recom;
ATTR n1 to n6;
MISSING all (-9);
MC ITER 10000;
GO;
```

The rating of attention paid to the patient by the nurse (n3) yielded greatest ESS=35.1, $p<0.0001$. In an effort to prevent over-fitting, all CTA models only include attributes for which Type I error satisfies the experimentwise criterion for statistical significance.[1,2] In ODA software this is accomplished by using a sequentially-rejective Sidak Bonferroni-type multiple comparisons procedure, in concert with *a priori* alpha splitting if appropriate for the investigation.[1] Here the UniODA model was: if $n3 \leq 3$ then predict recom=3; and if n3>3 then predict recom=4. Table 1 presents the confusion table for this model applied to the data (note that the sample is reduced to N=766 due to missing data for n3).

Table 1: Confusion Table for
First UniODA Analysis

		Predicted Recommendation 3	Predicted Recommendation 4
Actual Recommendation	3	126	97
	4	116	427

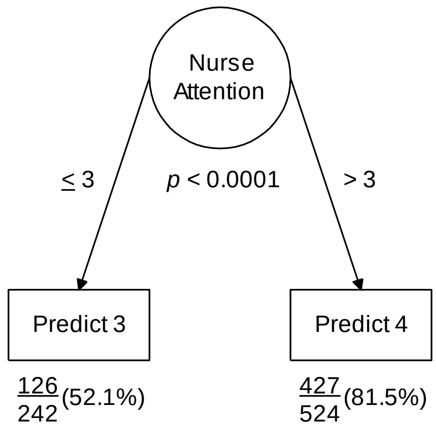
As seen, when the model predicted a recommended likelihood score of 3, a total of 116 observations were misclassified; and when the model predicted a recommended likelihood score of 4, a total of 97 observations were misclassified. The sensitivity of this model for class category 3 is 126 / (126 + 97) = 0.565, and the sensitivity of this model for class category 4 is 427 / (427 + 116) = 0.786. The mean sensitivity is thus 0.676, and ESS = [(0.676 – 0.5) / 0.5] x 100% = 35.1.

Figure 1 illustrates the HO-CTA model as it exists at this point in the analysis.

Optimal Data Analysis
Vol. 4 (May 11, 2015), 36-53

2155-0182/10/$3.00

Figure 1: HO-CTA Model
After First Step of Analysis



In the second step of the analysis, an attribute that can improve classification accuracy for the left-hand endpoint is sought. This second analysis was accomplished by including one additional UniODA (MegaODA) command before the GO command:

INCLUDE n3<4;

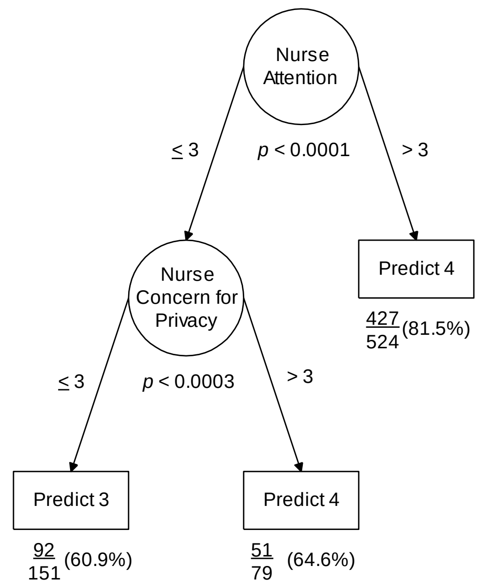
The rating of nurse concern for privacy (n5) yielded greatest ESS=23.0, p<0.0003. The UniODA model was: if n5≤3 then predict that recom=3; and if n5>3 then predict recom=4. Table 2 presents the confusion table for this model applied to the data.

Table 2: Confusion Table for Second UniODA Analysis

		Predicted Recommendation	
		3	4
Actual	3	92	28
Recommendation	4	59	51

As seen, when the model predicted a recommended likelihood score of 3, a total of 59 observations were misclassified; and when the model predicted a recommended likelihood score of 4, a total of 28 observations were misclassified. Figure 2 illustrates the HO-CTA model as it exists at this point in the analysis.

Figure 2: HO-CTA Model
After Second Step of Analysis



To ascertain the accuracy of the model at this point in its development, an integrated confusion table is created.[2] In Figure 2, the left-most endpoint correctly predicts that 92 of 151 (60.9%) observations were from class 3. The middle endpoint correctly predicts that 51 of 79 (64.6%) observations were from class 4. And, the right-most endpoint correctly predicts that 427 of 524 (81.5%) observations were from class 4. The integrated confusion table, for which ESS=31.4, is shown in Table 3 (computation of ESS is discussed elsewhere[1]). Note that the sample was reduced to N=754 (versus N= 823 with complete recommendation ratings) because of missing data for the two attributes.

Table 3: Integrated Confusion Table After Second UniODA Analysis

		Predicted Recommendation	
		3	4
Actual	3	92	125
Recommendation	4	59	478

In the third step of the analysis, an attribute that can improve classification accuracy for the left-most endpoint of the HO-CTA model is sought. This analysis was accomplished using the following modified UniODA (MegaODA) command:

INCLUDE n3<4 n5<4;

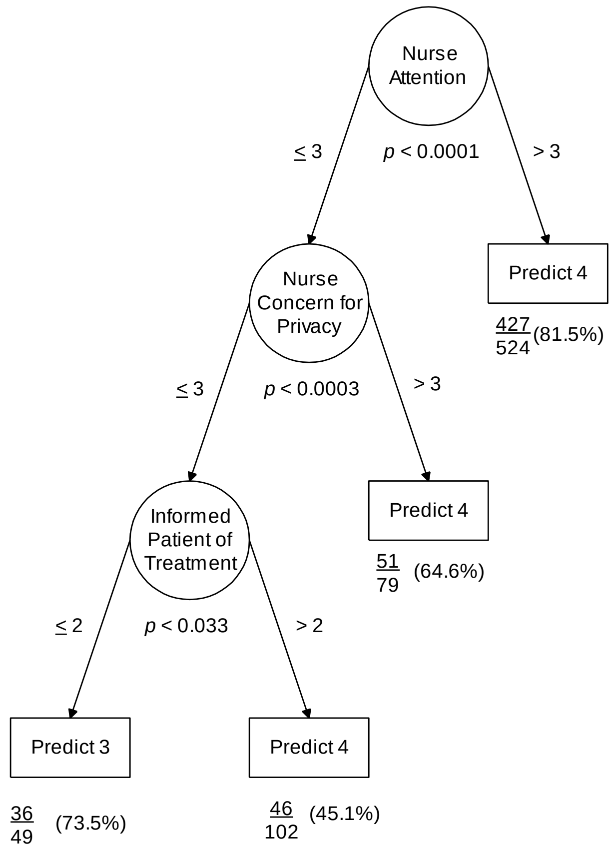
The rating of information regarding treatment (n4) yielded greatest ESS=17.1, $p<0.033$. The UniODA model was: if n4≤2 then predict that recom=3; and if n4>2 then predict recom=4. Table 4 presents the confusion table for this model applied to the data.

Table 4: Confusion Table for Third UniODA Analysis

		Predicted Recommendation	
		3	4
Actual	3	36	56
Recommendation	4	13	46

As seen in Table 4, when the model predicted a recommended likelihood score of 3 a total of 13 observations were misclassified, and when the model predicted a recommended likelihood score of 4 a total of 56 observations were misclassified. Figure 3 illustrates the HO-CTA model as it exists at this point in the analysis.

Figure 3: HO-CTA Model After Third Step of Analysis



To ascertain the accuracy of the model at this point in its development, an integrated confusion table is created. In Figure 3, the left-most endpoint correctly predicts that 36 of 49 (73.5%) observations were from class 3; the second-from-the-left endpoint correctly predicts that 42 of 102 (45.1%) observations were from class 4; the third-from-the-left endpoint correctly predicts that 51 of 79 (64.6%) observations were from class 4; and the right-most endpoint correctly predicts that 427 of 524 (81.5%) observations were from class 4. The integrated confusion table, for which ESS=13.8, is shown in Table 5. Note that the sample was reduced to N=750 because of missing data for the included attributes.

2155-0182/10/$3.00

Table 5: Integrated Confusion Table After Third UniODA Analysis

		Predicted Recommendation	
		3	4
Actual	3	36	185
Recommendation	4	13	516

Note that because the left-most endpoint has only 49 observations and the third-from-the left endpoint has only 79 observations, no additional endpoints may be added at either branch since there are too few observations remaining to satisfy the minimum requirement of 42 observations per endpoint.

In the fourth step of the analysis, an attribute that can improve classification accuracy for the second-from-the-left endpoint of the HO-CTA model is sought. This fourth analysis was accomplished using the following modified UniODA (MegaODA) code:

```
INCLUDE n3<4 n5<4 n4>2;
```

Because none of the attributes achieved a Type I error rate that was statistically significant at the experimentwise criterion, this branch of the HO-CTA model cannot be expanded.

In the fifth step of the analysis, an attribute that can improve classification accuracy for the right-most endpoint of the HO-CTA model is sought. This fifth analysis was accomplished using the following modified UniODA (MegaODA) code:

```
INCLUDE n3>3;
```

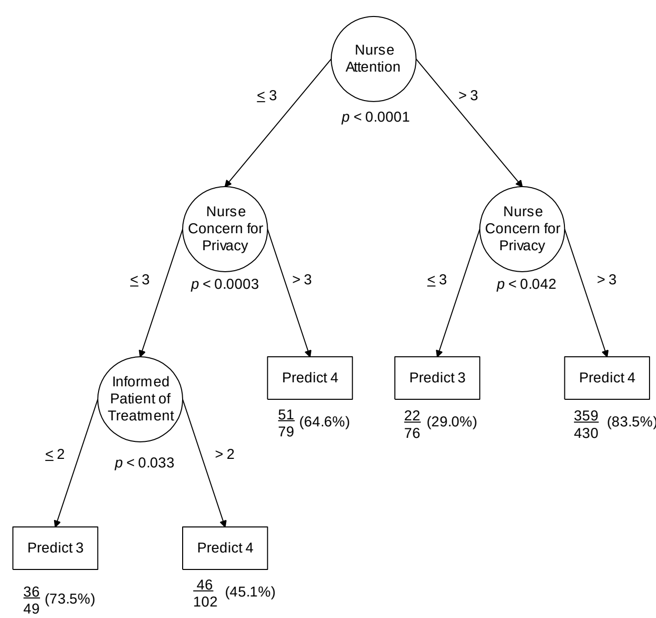
The rating of nurse concern for privacy (n5) yielded greatest ESS=10.6, p<0.042. The UniODA model was: if n5≤3 then predict that recom=3; if n5>3 then predict recom=4. Table 6 presents the confusion table for this model applied to the data.

Table 6: Confusion Table for Fifth UniODA Analysis

		Predicted Recommendation	
		3	4
Actual	3	22	71
Recommendation	4	54	359

As seen in Table 6, when the model predicted a recommended likelihood score of 3 a total of 54 observations were misclassified, and when the model predicted a recommended likelihood score of 4 a total of 71 observations were misclassified. Figure 4 illustrates the HO-CTA model as it exists at this point in the analysis.

Figure 4: HO-CTA Model After Fifth Step of Analysis



Controlling Experimentwise Type I Error

Because of the requirement that all Type I error estimates in the model are statistically significant at the experimentwise criterion, the model depicted in Figure 4 is untenable. That is,

2155-0182/10/$3.00

in the sequentially-rejective Sidak Bonferroni-type multiple comparisons procedure that is used to control alpha inflation in the ODA paradigm, the *p*-values associated with each node in the HO-CTA model are arranged in order of decreasing magnitude: the largest (least statistically significant) *p*-value is at the top of the ordered list, and the smallest (most statistically significant) *p*-value is at the bottom of the ordered list.[1] Table 6 illustrates this ordering for the model depicted in Figure 4.

Table 7: Actual *p*-Values and Corresponding Sidak Critical *p*-Values

Actual *p*-value	Sidak Critical *p*-Value
0.042	0.05000
0.033	0.02533
0.0003	0.01696
0.0001	0.01275

Each actual *p*-value is compared with the corresponding Sidak critical *p*-value starting at the bottom of the ordered list. At each step of the procedure the actual and critical p-value is compared. If the actual p-value is less than or equal to the critical p-value, then the actual p-value is statistically significant at the experimentwise criterion of $p<0.05$. However, if the actual *p*-value is greater than the critical *p*-value, then the actual *p*-value is not statistically significant at the experimentwise criterion of $p<0.05$.

In the first step of the evaluation of the statistical significance of the actual *p*-values, because the most statistically significant actual *p*-value ($p<0.0001$) is smaller than the corresponding critical *p*-value ($p<0.01275$), this actual *p*-value is statistically significant with experimentwise $p<0.05$.

In the second step of the evaluation of the statistical significance of the actual *p*-values, because the second-most statistically significant actual *p*-value ($p<0.0003$) is smaller than the corresponding critical p-value ($p<0.01696$), this actual *p*-value is also statistically significant with experimentwise $p<0.05$.

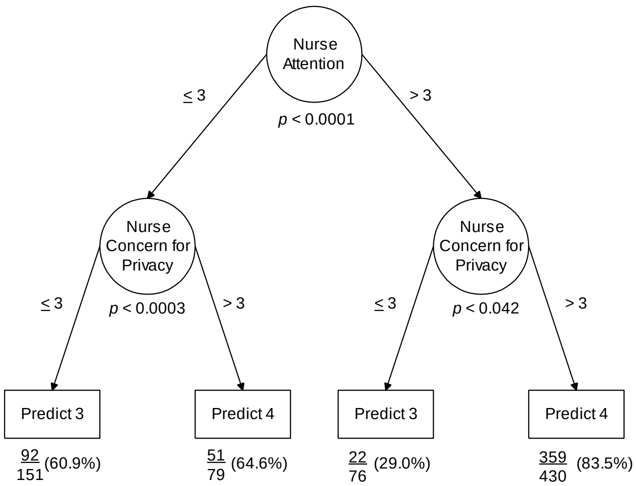
In the third step of the evaluation of the statistical significance of the actual *p*-values, because the third-most statistically significant actual *p*-value ($p<0.033$) is *larger* than the corresponding critical p-value ($p<0.02533$), this actual *p*-value is *not* statistically significant with experimentwise $p<0.05$. Thus, the HO-CTA node with this actual *p*-value is not statistically reliable.

In this methodology, once a statistically unreliable *p*-value is identified, then the actual *p*-value that failed to fall at or beneath the Sidak critical *p*-value, and all of the less-statistically significant actual *p*-values higher in the ordered list, are considered statistically unreliable at the experimentwise criterion. Note that had the third *p*-value instead been lower than the Sidak criterion ($p<0.02533$), then in the fourth and final step of the evaluation of the statistical significance of the actual *p*-values, because the least statistically significant actual *p*-value ($p<0.042$) is less than the corresponding critical p-value ($p<0.05$), this actual *p*-value would have been statistically significant with experimentwise $p<0.05$.

In the construction of HO-CTA models the standard is to eliminate the non-statistically-significant comparison that corresponds to the *deepest node* in the tree model. Presently this means that the node indicating that the nurse kept the patient aware of treatment progress is dropped from the model.

Figure 5 presents the final fully-grown HO-CTA model that meets the *a priori* criterion that all actual *p*-values are statistically significant with experimentwise $p<0.05$ (in Table 7 the second actual *p*-value from the top of the list is dropped, and only the three remaining actual *p*-values are evaluated).

Figure 5: Corrected HO-CTA Model After Fifth Step of Analysis



To ascertain the accuracy of the model at this point in the development, an integrated confusion table is created, shown in Table 8 (ESS= 31.9). Note that the sample was reduced to N= 736 due to missing data on included attributes.

Table 8: Integrated Confusion Table After Corrected Fifth UniODA Analysis

		Predicted Recommendation	
		3	4
Actual	3	114	99
Recommendation	4	113	410

In the sixth step of the analysis, an attribute that can improve classification accuracy for the right-most endpoint of the HO-CTA model is sought. This sixth analysis was conducted by the following modified UniODA (MegaODA) command:

```
INCLUDE n3>3 n5 >3;
```

Because none of the attributes achieved a Type I error rate that was statistically significant at the experimentwise criterion, this branch of the HO-CTA model cannot be expanded.

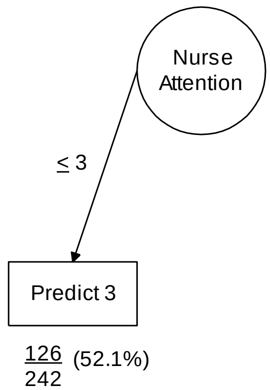
A table of critical Sidak values for up to 200 comparisons is provided as Appendix A in Yarnold and Soltysik[1], and Chapter 4 of this text covers *a priori* alpha splitting, a procedure used to partition the experimentwise Type I error rate between various analyses presented within a single project (manuscript) and prevent overly conservative criteria for statistical reliability.

Pruning the Fully-Grown HO-CTA Model to Ensure Maximum-Accuracy

At this point the first phase of the analysis—growth of the HO-CTA model—has been completed. However, subsequent to the initial development of this methodology, it was discovered that full-grown HO-CTA models must be *pruned* in order to explicitly maximize ESS and identify the final, maximum-accuracy HO-CTA model.[68] Pruning involves deconstructing the initial HO-CTA model (Figure 5) into all possible nested sub-branches, and then selecting the combination of sub-branches that explicitly maximizes ESS. Sub-branches are constructed separately for the branches emanating from the left-hand side of the root (top) node of the model, and for branches emanating from the right-hand side of the root node. Sub-branches are indicated using a letter (L for left-hand side, R for right-hand side) and a number (the number of nodes in the sub-branch). Figures 6A-6D show the two left-hand sub-branches, and the two right-hand sub-branches, for the HO-CTA model in Figure 5.

For the final step of the maximum accuracy pruning procedure, Table 9 presents integrated confusion tables for all four possible combinations of left (L1, L2) and right (R1, R2) sub-branches, and their associated ESS. As seen in Table 8, the combination L1-R2 has the greatest ESS=35.1, and thus is selected as the maximum-accuracy HO-CTA model (Figure 7).

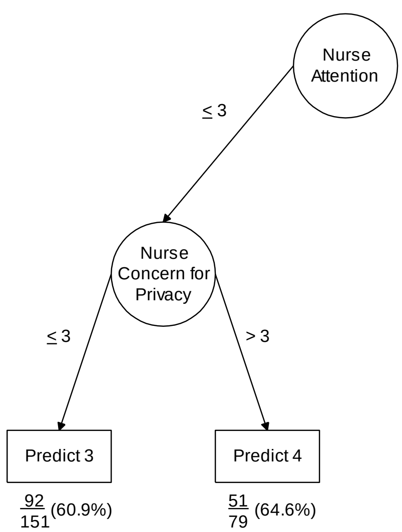
Figure 6A:
L1 Sub-Branch and Confusion Table



L1 Predicted

		3	4
Actual	3	126	0
	4	116	0

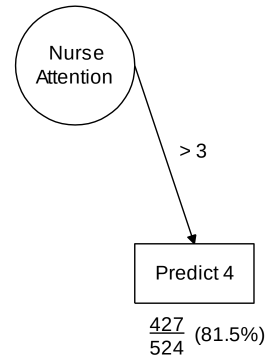
Figure 6B:
L2 Sub-Branch and Confusion Table



L2 Predicted

		3	4
Actual	3	92	28
	4	59	51

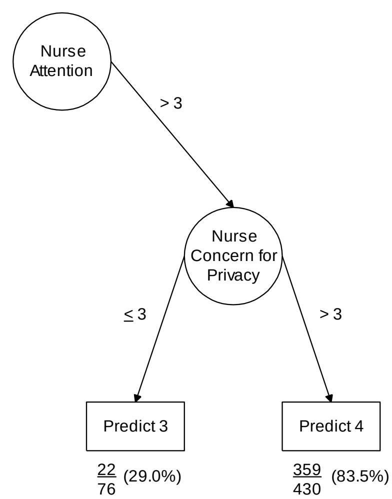
Figure 6C:
R1 Sub-Branch and Confusion Table



R1 Predicted

		3	4
Actual	3	0	97
	4	0	427

Figure 6D:
R2 Sub-Branch and Confusion Table



R1 Predicted

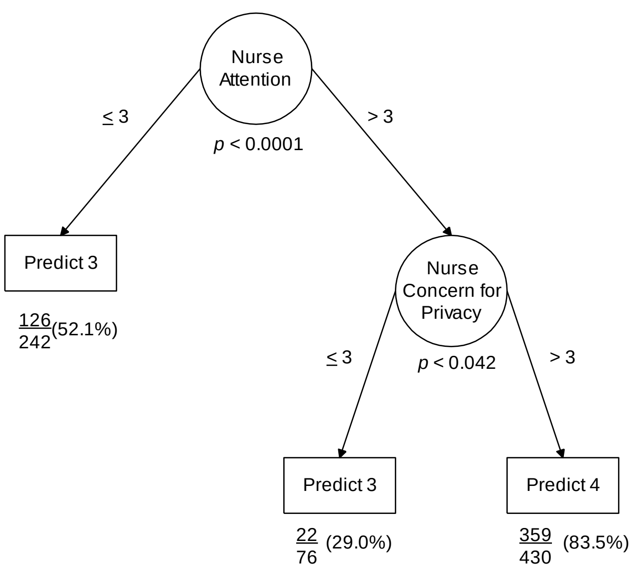
		3	4
Actual	3	22	71
	4	54	359

2155-0182/10/$3.00

Table 9: Classification Results for Every Combination of Left (L1-L2) and Right (R1-R2) Sub-Branch

Model	Confusion Table			Model	Confusion Table		
L1-R1		Predicted		*L1-R2*		Predicted	
		3	4			3	4
Actual	3	126	97	Actual	3	148	71
	4	116	427		4	170	359
		ESS=35.1				ESS=35.4	
L2-R1		Predicted		*L2-R2*		Predicted	
		3	4			3	4
Actual	3	92	125	Actual	3	114	99
	4	59	478		4	113	410
		ESS=31.4				ESS=31.9	

Figure 7: Final Pruned Maximum-Accuracy HO-CTA Model



Discussion

As seen, construction of a maximum-accuracy HO-CTA model is a complex and an analysis-intensive enterprise. HO-CTA models reward analytic rigor with accurate, parsimonious models that are impossible to obtain using legacy linear-based statistical methods. An additional advantage is that unlike legacy methods, in the ODA paradigm all analyses are based on algorithms, and exclude problems otherwise associated with guess-work, eyeball analysis, unwarranted assumptions, and paradoxical confounding—all of which are prevalent in the use of legacy statistical methods.[69]

Additional considerations that are imperative in UniODA and CTA modeling, that are not illustrated herein, include the treatment of categorical variables, correct transformation of serial data, assessing cross-generalizability of HO-CTA models, and the use of weights. With respect to treatment of categorical variables, unlike the general linear model or maximum-likelihood paradigms, in the ODA paradigm multicategorical variables with more than two response categories are *not* transformed into a series of binary (“dummy”) variables; instead the multicategorical attribute is treated as a single categorical attribute having different categorical options.[70-73] With respect to serial measurements, an ipsative standardization is essential in order to prevent anomalous measurement artifacts including paradoxical confounding.[74-77] The potential cross-generalizability of maximum-accuracy models is easily estimated using "leave-one-out" jackknife analysis, and assessed using hold-out validity samples, via commands offered in UniODA and MegaODA software.[78] If individual observations are assigned weights, the HO-CTA model will maximize weighted classification accuracy.[1,79,80]

The methodology discussed within this article focuses on identification of the HO-CTA model that achieves maximum accuracy normed against chance—that is, the greatest possible integrated ESS. However, it is important to note that sub-branches of exploratory and of sub-optimal (less than maximum ESS) HO-CTA models sometimes identify non-linear models (sub-branches) that perform exceptionally well in describing (ESS) or in predicting (effect strength for predictive value or ESP[1,81]) important class categories.[37] Such sub-branches are often identified in the process of obtaining the maximum-accuracy HO-CTA model, and may be valuable to researchers interested in specific multivariable interactions that have strong sensitivity and/or predictive value.

It is important to note that while this article discusses *how to obtain* a HO-CTA model, it does not consider *how to report* the findings of a HO-CTA model. A host of relatively well-known reporting statistics, such as confusion tables, and summary indices including sensitivities, predictive values, and overall classification accuracy, are discussed in this article and in numerous articles cited herein. The ODA book also covers these topics in addition to model diagrams, and normed accuracy (ESS and ESP) scores.[1,81] The article that introduces automated EO-CTA models additionally discusses the construction of staging tables (instrumental in creating easy-to-use scoring templates, and in computing odds, odds ratios, and propensity scores), the use of pie charts to visually represent identified strata, and the attribute importance in discrimination (AID) statistic—the optimal analogue to R^2 in linear modeling.[52] And, a suite of recent articles discusses fundamentally important concepts, such as the definition of an ideal statistical model, assessing the quality of an empirical model in light of the theoretical ideal, and computation of exact discrete confidence intervals for parameters of exact models and chance.[55-62]

Finally, numerous researchers in many laboratories have undertaken the analysis-intensive and complex task of *manually constructing* HO-CTA models using UniODA, the only software that can accomplish this feat. Time and effort invested by these researchers was greatly compensated by their rewards: in disciplines such as medicine[3], psychology[24], neurology, education, criminal science, engineering, and pharmacology, in every instance the HO-CTA model obtained was more accurate, parsimonious, and theoretically apropos than was any other non-HO-CTA analysis published in the applications of inquiry. However, the inherent complexity of manual construction served as the motivation for development of software that automated the algorithms involved in growing and pruning optimal classification trees, and the automation of maximum-accuracy trees resulted in evolution of this methodology in the form of enumerated EO-CTA models.[52] The automated CTA program thus enables one to grow and prune the tree model automatically while employing a user-specified minimum *N* for model endpoints as well as a Sidak alpha-correction procedure, thereby saving hours of labor and avoiding the possibility of manual computation errors. Suffice it to whet the reader's intellectual appetite that a forthcoming sequel[82] to the present article discusses application of automated CTA software to the data in this study: the HO-CTA model identified presently and a more accurate EO-CTA model were obtained in a total of 4 CPU seconds using a PC.

References

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Author Notes

This study involved secondary data analysis of published de-identified data and was exempt from Institutional Review Board review.

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