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Novometric *vs*. Log-Linear Analysis: Church Attendance, Age and Religion

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Prior research[1] using log-linear analysis to model church attendance (1=low; 2=medium; 3=high) as a function of age (young=0; old=1) and religion (non-Catholic=0; Catholic=1) found that the best fitting model {AR}{AC}{RC} had L^2=7.25, df=2, indicating insufficient badness-of-fit (pp. 67-69). For these data exploratory novometric analysis[2-28] predicting church attendance (ordered class variable) using religion (categorical attribute) and age (ordered attribute) identified a parsimonious, relatively weak model with stable classification training and LOO performance.

SAS™ code used to construct the data analyzed herein[1] is given in the Appendix. Novometric analysis identified a single two-strata model with stable classification performance in LOO analysis: if religion=non-Catholic then predict attendance=low or medium; otherwise predict attendance=high. Table 1 presents the confusion matrix for this model: relatively weak ESS= 22.27, D=6.98, p<0.001).

Table 1: Optimal Model Confusion Matrix

		Predicted Attendance		
		Low/Med	High	
Actual	Low/Med	848	185	82.1%
Attendance	High	335	225	40.2%

The model accurately classified 7 in 8 people with low or medium church attendance, and 2 in 5 people with high attendance (50% sensitivity is expected by chance for each class in two-category designs that do not use analytic weights[2,30-35]). The relatively weak performance of the model is attributable to the use of arbitrary parses to define attendance and age, and to the use of the non-specific categories "Catholic" and "non-Catholic"—in both of which observations are heterogeneous on more attributes than they are homogeneous.[2,36-38]

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Author Notes

This study analyzed publically available data. No conflict of interest was reported.

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Appendix

SAS™ Code used to Construct (Reproduce[1]) the Data File for Analysis by ODA Software[2,29]

```
data real;
infile datalines;
input religion age
attend;
cards;
1 1 1
;
Data example;
Do n=1 to 322;
put '0 0 1';
end;
Do n=1 to 124;
put '0 0 2';
end;
Do n=1 to 141;
put '0 0 3';
end;
Do n=1 to 250;
put '0 1 1';
end;
Do n=1 to 152;
put '0 1 2';
end;
Do n=1 to 194;
put '0 1 3';
end;
Do n=1 to 88;
put '1 0 1';
end;
Do n=1 to 45;
put '1 0 2';
end;
Do n=1 to 106;
put '1 0 3';
end;
Do n=1 to 28;
put '1 1 1';
end;
Do n=1 to 24;
put '1 1 2';
end;
Do n=1 to 119;
put '1 1 3';
end;
Output;
Run;
```