

# Novometric vs. Logit Analysis: Abortion Attitude by Religion and Time

Paul R. Yarnold, Ph.D.

Optimal Data Analysis, LLC

Prior research<sup>1</sup> using logit analysis to model abortion attitude (oppose=0; favor=2) as a function of religion (Protestant=1; Catholic=2; Jewish=3; Other=4) and time (1972=72; 1978=78) found: “The best fitting model...has separate effects for being Catholic or non-Catholic and for being Protestant or non-Protestant. The categories of Jewish and Other have no separate effects and are implicitly grouped or collapsed together. The result is a religious trichotomy. ...The odds on a favorable response are identical in both years: .89 for Protestants, .64 for Catholics, and 3.44 for Jews and Others” (pp. 70-72). For these data exploratory novometric analysis<sup>2-28</sup> predicting abortion attitude (class variable) as a function of religion (multicategorical attribute) and time (ordered attribute) identified a parsimonious, relatively weak model with stable classification training and LOO performance.

SAS<sup>TM</sup> code used to construct the data analyzed herein<sup>1</sup> is given in the Appendix. Novometric analysis identified a single two-strata model that had stable classification performance in LOO analysis: if religion=Protestant or Catholic predict attitude=oppose; otherwise predict attitude=favor. Table 1 is the confusion matrix for this model: relatively weak ESS=11.39, D=15.56,  $p<0.001$ ).

As seen, the model accurately classified 19 in 20 people who oppose abortion, but only 1 in 7 people who favor abortion (50% sensitivity is expected by chance for each class category in two-category designs that do not use analytic weights<sup>2,30-35</sup>). The deficient performance of the model for predicting favorable ratings is likely attributable to the category “other”, notorious for riddling the literature with paradoxically-confounded results.<sup>2,36-38</sup>

Table 1: Optimal Model Confusion Matrix

		Predicted Attitude		
		Oppose	Favor	
Actual Attitude	Oppose	1464	63	95.9%
	Favor	1182	217	15.1%

## References

- <sup>1</sup>Knoke D, Burke PJ (1980). *Log-linear models*. Beverly Hills, CA: Sage (pp. 47-48).
- <sup>2</sup>Yarnold PR, Soltysik RC (2016). *Maximizing predictive accuracy*. Chicago, IL: ODA Books. DOI: 10.13140/RG.2.1.1368.3286

<sup>3</sup>Yarnold PR, Linden A (2016). Novometric analysis with ordered class variables: The optimal alternative to linear regression analysis, *Optimal Data Analysis*, 5, 65-73.

<sup>4</sup>Yarnold PR, Bennett CL (2016). Novometrics vs. correlation: Age and clinical measures of PCP survivors, *Optimal Data Analysis*, 5, 74-78.

<sup>5</sup>Yarnold PR, Bennett CL (2016). Novometrics vs. multiple regression analysis: Age and clinical measures of PCP survivors, *Optimal Data Analysis*, 5, 79-82.

<sup>6</sup>Yarnold PR (2016). Novometrics vs. regression analysis: Literacy, and age and income, of ambulatory geriatric patients. *Optimal Data Analysis*, 5, 83-85.

<sup>7</sup>Yarnold PR (2016). Novometrics vs. regression analysis: Modeling patient satisfaction in the Emergency Room. *Optimal Data Analysis*, 5, 86-93.

<sup>8</sup>Yarnold PR (2016). Matrix display of pairwise novometric associations for ordered variables. *Optimal Data Analysis*, 5, 94-101.

<sup>9</sup>Yarnold PR, Batra M (2016). Matrix display of pairwise novometric associations for mixed-metric variables. *Optimal Data Analysis*, 5, 104-107.

<sup>10</sup>Yarnold PR (2016). Novometrics vs. ODA vs. One-Way ANOVA: Evaluating comparative effectiveness of sales training programs, and the importance of conducting LOO with small samples. *Optimal Data Analysis*, 5, 131-132.

<sup>11</sup>Yarnold PR (2016). Parental smoking behavior, ethnicity, gender, and the cigarette smoking behavior of high school students. *Optimal Data Analysis*, 5, 136-140.

<sup>12</sup>Yarnold PR (2016). Using gender of an imaginary rated smoker, and subject's gender, ethnic-

ity, and smoking behavior to identify perceived differences in peer-group smoking standards of American high school students. *Optimal Data Analysis*, 5, 141-143.

<sup>13</sup>Yarnold PR (2016). Novometric models of smoking habits of male and female friends of American college undergraduates: Gender, smoking, and ethnicity. *Optimal Data Analysis*, 5, 146-150.

<sup>14</sup>Yarnold PR (2016). Predicting daily television viewing of senior citizens using education, age and marital status. *Optimal Data Analysis*, 5, 151-152.

<sup>15</sup>Yarnold PR (2016). Novometric statistical analysis and the Pearson-Yule debate. *Optimal Data Analysis*, 5, 162-165.

<sup>16</sup>Yarnold PR (2016). Comparing WAIS-R qualitative information for people 75 years and older, with vs. without brain damage. *Optimal Data Analysis*, 5, 166-170.

<sup>17</sup>Yarnold PR (2016). Using novometrics to disentangle complete sets of sign-test-based multiple-comparison findings. *Optimal Data Analysis*, 5, 175-176.

<sup>18</sup>Yarnold PR (2016). Novometric analysis vs. MANOVA: MMPI codetype, gender, setting, and the MacAndrew Alcoholism scale. *Optimal Data Analysis*, 5, 177-178.

<sup>19</sup>Yarnold PR (2016). Novometric vs. ODA reliability analysis vs. polychoric correlation with relaxed distributional assumptions: Inter-rater reliability of independent ratings of plant health. *Optimal Data Analysis*, 5, 179-183.

<sup>20</sup>Yarnold PR (2016). Novometrics vs. polychoric correlation: Number of lambs born over two years. *Optimal Data Analysis*, 5, 184-185.

<sup>21</sup>Yarnold PR (2016). Comparing MMPI-2 *F-K* Index normative data among male and female

psychiatric and head-injured patients, individuals seeking disability benefits, police and priest job applicants, and substance abusers. *Optimal Data Analysis*, 5, 186-193.

<sup>22</sup>Yarnold PR, Linden A (2016). Theoretical aspects of the D statistic. *Optimal Data Analysis*, 5, 171-174.

<sup>23</sup>Yarnold PR (2016). Novometric analysis predicting voter turnout: Race, education, and organizational membership status. *Optimal Data Analysis*, 5, 194-197.

<sup>24</sup>Yarnold PR (2016). Novometrics vs. Yule's Q: Voter turnout and organizational membership. *Optimal Data Analysis*, 5, 198-199.

<sup>25</sup>Yarnold PR (2016). Novometric vs. recursive causal analysis: The effect of age, education, and region on support of civil liberties. *Optimal Data Analysis*, 5, 200-203.

<sup>26</sup>Yarnold PR (2016). Novometric analysis vs. GenODA vs. log-linear model: Temporal stability of the association of presidential vote choice and party identification. *Optimal Data Analysis*, 5, 204-207.

<sup>27</sup>Yarnold PR (2016). Novometric analysis vs. ODA vs. log-linear model in analysis of a two-wave panel design: Assessing temporal stability of Catholic party identification in the 1956-1960 SRC panels. *Optimal Data Analysis*, 5, 208-212.

<sup>28</sup>Yarnold PR (2016). Novometric vs. logit vs. probit analysis: Using gender and race to predict if adolescents ever had sexual intercourse. *Optimal Data Analysis*, 5, 218-222.

<sup>29</sup>Bryant FB, Harrison PR (2013). How to create an ASCII input data file for UniODA and CTA software. *Optimal Data Analysis*, 2, 2-6.

<sup>30</sup>Yarnold PR, Soltysik RC (2005). *Optimal data analysis: A guidebook with software for Windows*. Washington, DC, APA Books.

<sup>31</sup>Linden A, Yarnold PR (In Press). Combining machine learning and propensity score weighting to estimate causal effects in multi-valued treatments. *Journal of Evaluation in Clinical Practice*.

<sup>32</sup>Linden A, Yarnold PR (In Press). Combining machine learning and matching techniques to improve causal inference in program evaluation. *Journal of Evaluation in Clinical Practice*.

<sup>33</sup>Linden A, Yarnold PR (In Press). Using machine learning to assess covariate balance in matching studies. *Journal of Evaluation in Clinical Practice*. DOI: 10.1111/jep.12538

<sup>34</sup>Linden A, Yarnold PR (In Press). Using data mining techniques to characterize participation in observational studies. *Journal of Evaluation in Clinical Practice*.

<sup>35</sup>Yarnold PR, Soltysik RC (1991). Theoretical distributions of optima for univariate discrimination of random data. *Decision Sciences*, 22, 739-752.

<sup>36</sup>Yarnold PR (1996). Characterizing and circumventing Simpson's paradox for ordered bivariate data. *Educational and Psychological Measurement*, 56, 430-442.

<sup>37</sup>Soltysik RC, Yarnold PR (2010). The use of unconfounded climatic data improves atmospheric prediction. *Optimal Data Analysis*, 1, 67-100.

<sup>38</sup>Yarnold PR (2015). Estimating inter-rater reliability using pooled data induces paradoxical confounding: An example involving Emergency Severity Index triage ratings. *Optimal Data Analysis*, 4, 21-23.

### Author Notes

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

## Appendix

SAS™ Code used to Construct (Reproduce<sup>1</sup>) the Data File for Analysis by ODA Software<sup>2,29</sup>

```
data real;                                Do n=1 to 147;                            end;
infile datalines;                        put '2 72 1';                            Do n=1 to 6;
input group row                          end;                                       put '3 78 0';
column;                                   Do n=1 to 240;                            end;
cards;                                    put '2 72 0';                            Do n=1 to 65;
1 1 1                                     end;                                       put '4 72 1';
;                                          Do n=1 to 151;                            end;
Data example;                             put '2 78 1';                            Do n=1 to 17;
Do n=1 to 460;                            end;                                       put '4 72 0';
put '1 72 1';                             Do n=1 to 225;                            end;
end;                                       put '2 78 0';                            Do n=1 to 88;
Do n=1 to 498;                            end;                                       put '4 78 1';
put '1 72 0';                             Do n=1 to 41;                            end;
end;                                       put '3 72 1';                            Do n=1 to 30;
Do n=1 to 424;                            end;                                       put '4 78 0';
put '1 78 1';                             Do n=1 to 10;                            end;
end;                                       put '3 72 0';                            Output;
Do n=1 to 501;                            end;                                       Run;
put '1 78 0';                             Do n=1 to 23;                            put '3 78 1';
end;                                       put '3 78 1';
```