

# Restricted vs. Unrestricted Optimal Analysis: Smoking Behavior of College Undergraduates

Paul R. Yarnold, Ph.D.  
 Optimal Data Analysis, LLC

Maximum-accuracy statistical methods involving (un)restricted class variables are used to identify underlying relationships among year in school and cigarette smoking habit for a sample of 3,809 Anglo-American, male and female college undergraduates.

This report compares use of a restricted<sup>1</sup> (ODA) vs. unrestricted<sup>2</sup> (novometry) class variable to evaluate exploratory hypotheses in a commonly-utilized design. Perhaps an interested researcher will compare the use of legacy methods to evaluate the hypotheses examined herein. The data investigated presently are given in Table 1.

Table 1: Study Data<sup>3</sup>

<i>Smoking</i>	<i>College Undergraduate Year</i>				<i>Gender</i>
	<i>Fresh</i>	<i>Soph</i>	<i>Junior</i>	<i>Senior</i>	
Never	121	125	92	77	Male
	249	197	179	162	Female
Experimental	196	218	187	155	Male
	201	174	195	146	Female
Ex-Occasional	66	58	54	53	Male
	34	21	34	36	Female
Ex-Regular	17	21	22	28	Male
	7	9	15	9	Female
Current Occasional	33	40	32	25	Male
	22	21	31	33	Female
Current Regular	29	68	97	116	Male
	8	21	29	46	Female

Because the theoretical and mechanical differences between novometric vs. alternative methods are discussed in detail elsewhere<sup>2</sup> the present exposition focuses (to the extent that is possible) on empirical results.

Consideration of the response options for the smoking behavior item suggest an underlying *categorical ordinal* measurement scale.<sup>1,2</sup> Moving from response option 1 (never smoked) to 6 (current regular smoker) the options reflect increasing cigarette consumption, with prior consumption assigned a lower weight (2, 3, 4) than current consumption (5, 6). Analysis was conducted to investigate the veracity of this conceptualization of the smoking behavior measurement scale.

## Smoking and Year in College

Separately for males and females, two analysis sets (ODA, novometry) examined the relationship between college year (treated as the class variable) and the smoking score—first treated as an ordered attribute, then as a multi-categorical attribute. In every analysis results

are presented for training (total sample) and jackknife analysis.<sup>1,2</sup>

In ODA the class variable is *restricted* in the sense that in the omnibus test the algorithm classifies observations into all class categories if possible, or into as many class categories as is possible otherwise (a degenerate model fails to predict membership into at least one class category).<sup>1,2</sup> Table 2 summarizes the performance of ODA models predicting year in school, treating smoking as an ordered or as a multicategorical attribute, separately for males and females.

Table 2: ODA Omnibus Models

**Males**

*Ordered Attribute*

ODA Model	Model Sensitivity		
	Year	Training	Jackknife
Score $\leq$ 3 → FRE	FRE	82.9	82.9
Score=4 → JUN	SOP	7.6	7.6
Score=5 → SOP	JUN	4.6	4.6
Score=6 → SEN	SEN	25.6	25.6

*Multicategorical Attribute*

ODA Model	Model Sensitivity		
	Year	Training	Jackknife
Score $\leq$ 3 → FRE	FRE	82.9	82.9
Score=5 → SOP	SOP	7.6	7.6
Score=4,6 → SEN	JUN	0	0
	SEN	31.7	31.7

**Females**

*Ordered Attribute*

ODA Model	Model Sensitivity		
	Year	Training	Jackknife
Score=1 → FRE	FRE	47.8	47.8
Score=2,3 → JUN	SOP	2.0	0
Score=4 → SOP	JUN	47.4	7.0
Score=5,6 → SEN	SEN	18.3	18.3

*Multicategorical Attribute*

ODA Model	Model Sensitivity		
	Year	Training	Jackknife
Score=1 → FRE	FRE	47.8	47.8
Score=2,4 → JUN	SOP	0	0
Score=3,5,6 → SEN	JUN	43.5	43.5
	SEN	26.6	26.6

Red coloring in the Table highlights non-linearity in the predicted class ordering, or in the model threshold ordering considered in relation to the predicted class ordering. All four of the ODA models were statistically reliable and returned a relatively weak effect. Predictive accuracy was identical in training and jackknife analyses for combinations of: males and ordered attribute (ESS=6.8,  $p<0.0001$ ); males and multicategorical attribute (ESS=7.4,  $p<0.0001$ ); and females and multicategorical attribute (ESS=6.0,  $p<0.0002$ ). However, predictive accuracy obtained in training (total sample) analysis (ESS=5.2,  $p<0.0011$ ) for the combination of females and ordered attribute declined to a level worse than expected by chance in jackknife analysis (ESS= -9.0, *ns*). Models using the ordered attribute accurately classified Freshmen (20% accuracy is expected by chance for each year<sup>1,2</sup>), and models using the categorical attribute accurately classified Freshmen and Seniors. Both multicategorical models were degenerate: the male model made no classifications into the Junior category, and the female model made no classifications into the Sophomore category.

As in legacy methods used with ordered (one-way ANOVA) or multicategorical (one-way chi-square) attributes, finding a statistically significant omnibus effect is not the end of the analysis (unless ESS equals or approaches 100), but rather it is the beginning.<sup>1,2,4,5</sup> If the omnibus effect is *not* statistically reliable then it is concluded that the groups cannot be discriminated. However, if the omnibus effect *is* statistically reliable then it is concluded that at least two groups can be discriminated from each other, and all-possible pairwise comparisons or a more efficient (optimal) range test are conducted to exactly specify the *pattern* of the underlying effect.<sup>1,2,6-9</sup> For example, for males, using the ordered attribute, conducting all possible pairwise comparisons revealed that the pattern of the training effect was: smoking behavior score of Freshman < Sophomore < Junior = Senior. In jackknife analysis the effect was: smoking score

of Freshman < Sophomore = Junior = Senior, and score of Sophomore < Senior.

While this procedure disentangles the omnibus effect, it fails to identify the model that explicitly maximizes ESS obtained predicting year as a function of smoking behavior score: this is accomplished via novometric analysis.<sup>2</sup> In novometric statistical analysis the class variable is *unrestricted* in the sense that the algorithm identifies the specific threshold value (for ordered class variables) or class category membership subset (for multicategorical class variables) that explicitly yields maximum ESS for models of any level of complexity (operationalized as the number of model endpoints).<sup>2</sup>

For the combination of male, ordered attribute the novometric model was: if year= Freshman, predict smoking score $\leq 3$ , otherwise predict score $>3$ . Male Freshmen thus consumed less tobacco (82.9% had smoking score $\leq 3$ ) than higher-classmen (69.4% had smoking score $\leq 3$ ), who could not be discriminated from each other on the basis of their smoking behavior scores. This model was statistically reliable ( $p < 0.0001$ ) but relatively weak (ESS= 13.5), and stable in jackknife analysis. The ESS returned by the 2-strata novometric model was 98.5% greater vs. the 2-strata ODA model.

For the combination of male, multicategorical attribute the novometric model was: if year=Senior, then predict smoking score=4 or 6; otherwise predict score=1, 2, 3, or 5. Thus, male Seniors were more likely to be ex- or current regular users (31.7% had a smoking score of 4 or 6) than lower-classmen (17.2% had a smoking score of 4 or 6), who could not be discriminated from each other on the basis of their smoking behavior scores. This model was statistically reliable ( $p < 0.0001$ ), relatively weak (ESS=14.5), and stable in jackknife analysis. ESS for the 2-strata novometric model was 95.9% greater vs. the 2-strata ODA model.

For males both unrestricted novometric models returned twice the normed accuracy (and nevertheless were relatively weak<sup>1,2</sup>) of the cor-

responding ODA models. Conceptualizing the smoking behavior measurement scale as being ordered (weighting past behavior less than current behavior), the Freshmen had lower tobacco consumption (never any regular use, no current use) compared to older classmen. Conceptualizing the smoking behavior measurement scale as being categorical, Seniors had greater “habitual” tobacco consumption (Ex-regular use, current regular use) than younger classmen.

For the combination of female, ordered attribute the novometric model was: if year= Senior, then predict smoking score $\geq 3$ , otherwise predict score $<3$ . Thus, proportionally more female Seniors (28.7%) at some time (now or in the past) consumed tobacco occasionally or more often compared to younger-classmen (17.4%), who could not be discriminated from each other on the basis of their smoking behavior scores. This model was statistically reliable ( $p < 0.0001$ ) but relatively weak (ESS= 11.3), and stable in jackknife analysis. The ESS returned by the 2-strata novometric model was 117.3% greater vs. the 2-strata ODA model *training* accuracy (recall that jackknife accuracy was worse than chance for the latter model).

Finally, for the combination of female, multicategorical attribute the novometric model was: if year=Freshman, predict smoking score= 1, 2, or 4; otherwise predict score=3, 5, or 6. Thus, female Freshman were more likely to be ex-smokers and never regular users (26.6%) than upper-classmen (15.3%), who could not be discriminated from each other on the basis of their smoking behavior scores. This model was statistically reliable ( $p < 0.0001$ ), relatively weak (ESS=11.5), and stable in jackknife analysis. ESS for the 2-strata novometric model was 90.0% greater vs. the 2-strata ODA model.

For females both unrestricted novometric models returned twice the (relatively weak) normed accuracy of the corresponding ODA models. Conceptualizing the smoking behavior measurement scale as ordered, Seniors had greater tobacco consumption (occasionally

or more often) vs. younger classmen. Conceptualizing the smoking behavior measurement scale as being categorical, Freshman were more likely to be ex-smokers and never regular users vs. the older classmen.

### Gender and Smoking

Table 3 summarizes the performance of ODA models predicting gender, treating smoking as an ordered or a multicategorical attribute, separately by year in school. All ODA models were statistically reliable and returned a relatively weak effect. Predictive accuracy was identical in training and jackknife analyses for Freshmen (ESS=21.6,  $p < 0.0001$ ), Sophomores (ESS=20.9,  $p < 0.0001$ ), and Juniors (ESS= 19.8,  $p < 0.0001$ ), regardless of whether the attribute was treated as being ordered or multicategorical. However, for Seniors assessed on an ordered attribute the predictive accuracy (ESS=20.5,  $p < 0.0001$ ) was marginally lower than a model using a multicategorical attribute (ESS=22.7,  $p < 0.0001$ ) Novometric models were identical to corresponding ODA models.

### Gender and Year in College

The ODA and novometric models were identical: if year=1 then predict gender=female; otherwise predict gender=male. This model had identical performance in training and jackknife analysis, yielding sensitivity=27.7% for females and 76.1% for males: ESS=3.8,  $p < 0.030$ .

### Comments

In the present example the advantage of modeling using an unrestricted class variable is clearly demonstrated in the analysis involving an ordered class variable and a complex attribute that may be conceptualized as being ordered or multicategorical: the corresponding optimal models were comparably (in)accurate, and had different theoretical substantive implications for smoking research.

Table 3: ODA Omnibus Models

#### Freshman

##### Ordered and Multicategorical Attribute

Model Sensitivity			
<u>ODA Model</u>	<u>Gender</u>	<u>Training</u>	<u>Jackknife</u>
Score $\leq$ 1 → Female	Female	47.8	47.8
Score $\geq$ 2 → Male	Male	73.8	73.8

#### Sophomore

##### Ordered and Multicategorical Attribute

Model Sensitivity			
<u>ODA Model</u>	<u>Gender</u>	<u>Training</u>	<u>Jackknife</u>
Score $\leq$ 1 → Female	Female	44.5	44.5
Score $\geq$ 2 → Male	Male	76.4	76.4

#### Junior

##### Ordered and Multicategorical Attribute

Model Sensitivity			
<u>ODA Model</u>	<u>Gender</u>	<u>Training</u>	<u>Jackknife</u>
Score $\leq$ 2 → Female	Female	77.4	77.4
Score $\geq$ 3 → Male	Male	42.4	42.4

#### Senior

##### Ordered Attribute

Model Sensitivity			
<u>ODA Model</u>	<u>Gender</u>	<u>Training</u>	<u>Jackknife</u>
Score $\leq$ 1 → Female	Female	37.5	37.5
Score $\geq$ 2 → Male	Male	83.0	83.0

##### Multicategorical Attribute

Model Sensitivity			
<u>ODA Model</u>	<u>Gender</u>	<u>Training</u>	<u>Jackknife</u>
Score=1, 5 → Female	Female	45.1	45.1
Score=2-4, 6 → Male	Male	77.5	77.5

Effects identified herein were relatively to extremely weak, which may explain why the original report presented exclusively qualitative discussion regarding these data.

### References

<sup>1</sup>Yarnold PR, Soltysik RC (2005). *Optimal data analysis: A guidebook with software for Windows*. Washington, DC, APA Books.

<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>Zagona SV (1967). Psycho-social correlates of smoking behavior and attitudes for a sample of Anglo-American, Mexican-American, and Indian-American high school students. In: Zagona SV (Ed.), *Studies and issues in smoking behavior*. Tucson, AZ: University of Arizona Press (pp. 157-180).

<sup>4</sup>Grimm LG, Yarnold PR (1995). *Reading and Understanding Multivariate Statistics*. Washington, DC: APA Books.

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<sup>8</sup>Yarnold PR (2013). Univariate and multivariate analysis of categorical attributes with many response categories. *Optimal Data Analysis*, 2, 177-190.

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### Author Notes

The study analyzed de-individuated data and was exempt from Institutional Review Board review. No conflict of interest was reported.

Mail: Optimal Data Analysis, LLC  
6348 N. Milwaukee Ave., #163  
Chicago, IL 60646