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Optimal Analyses for Cohort Tables

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Cross-classification tables may be created for one or more "cohorts"—groups of observations defined by a common event such as the year of one's birth, graduation, employment, marriage, disease diagnosis or incarceration—and assessed at two or more points in time on one or more variables reflecting the substantive focus of the study. This article demonstrates exploratory maximum-accuracy evaluation of cohort, aging, and time effects for a standard cohort table.

Adapted from Glenn (p. 47) and derived from American Gallup Surveys, data are the number of observations who approved (class=1) *vs*. disapproved (class=0) of China's admission to the United Nations (UN), assessed in six cohorts obtained between 1954 and 1969 (Table 1).[1]

Table 1: Number of Gallup Survey Respondents Approving *vs*. Disapproving China's Admission to the UN

Age	Opinion	1954	1957	1958	1964	1965	1969
20-29	Approve	24	44	100	337	338	122
	Disapprove	308	212	322	778	807	136
30-39	Approve	34	69	147	245	353	104
	Disapprove	369	305	523	911	965	182
40-49	Approve	21	41	125	246	268	119
	Disapprove	338	274	460	1062	1145	210
50-59	Approve	13	25	90	167	213	79
	Disapprove	207	211	583	960	968	178
60-69	Approve	8	14	51	84	188	54
	Disapprove	155	172	341	806	945	152
70-79	Approve	6	4	25	48	74	29
	Disapprove	115	66	186	482	414	88

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First, the *cohort effect* was statistically assessed via MegaODA software.[2-8] The ODA model was: if Year≤1964 then predict class=0 (disapprove); otherwise predict the observation approved (class=0) of admission of China to the UN. The effect was relatively weak (ESS= 11.8, $p<0.0001$), and stable in leave-one-out (LOO) generalizability analysis ($p<0.0001$). The model correctly classified 49.7% (1,941/3,909) of the observations who approved the admission of China to the UN (50% correct classification is expected by chance[2,6,7]), and 62.1% (10,146/ 16,336) of the observations who disapproved.

ODA was also used to assess the cohort effect separately by age[9] (Table 2): all effects were relatively weak and stable in LOO analysis, and all had $p<0.0001$.

Table 2: Cohort Effects Separately Within Age

Age	Predict Approve if Year ≥	Model Sensitivity Approve	Disapprove	ESS
20-29	1964	82.6%	32.8%	15.44
30-39	1965	48.8%	64.8%	12.77
40-49	1958	92.4%	17.5%	9.98
50-59	1965	49.7%	63.1%	12.86
60-69	1965	60.6%	57.3%	17.98
70-70	1965	55.4%	62.8%	18.22

The *age effect* was assessed next.[10] The ODA model was: if Age≤39 then predict class= approve (class=1); otherwise predict the observation disapproved (class=0) of admission of China to the UN. The relatively weak (ESS= 13.4, $p<0.0001$) effect was stable in LOO analysis ($p<0.0001$). The model correctly classified 49.0% (1,917/3,909) of observations approving of the admission of China to the UN, and 64.4% (10,518/16,336) of those who disapproved.

ODA was also used to assess age effects separately by cohort[11] (Table 3): all effects were relatively weak, stable in LOO analysis, and had $p<0.0001$ (except the 1954 cohort, $p<0.13$).

Table 3: Age Effects Separately Within Cohort

Cohort	Predict Approve if Age ≤	Model Sensitivity Approve	Disapprove	ESS
1954	39	54.7%	54.6%	9.34
1957	39	57.4%	58.3%	15.67
1958	49	69.1%	46.0%	15.11
1964	49	73.5%	45.0%	18.44
1965	39	48.2%	66.2%	14.40
1969	49	68.1%	44.2%	12.23

Cohorts may also be followed over time, as observations age. Cohort progression across time is visualized by moving from *left*-to-*right* down a diagonal in the cohort table. The cohort with longest follow-up time appears in the top left-hand corner cell of Table 1: this cohort aged 20-29 years was initially surveyed in 1954, and was resampled for the sixth time in 1969.

For example, conducting non-directional (exploratory) ODA[2,6,7] analysis, the binary class variable being discriminated (predicted) is the "approve" *vs*. "disapprove" response (coded as 1 *vs*. 0, respectively), and the six (re)tests of the initial 20-29 year-old cohort (which are coded as 1954, 1957, 1958, 1964, 1965, and 1969) constitute a 6-level attribute.

If year is treated as an *ordered* attribute then the ODA model is: if Year=1954 predict disapprove; otherwise predict approve. This model correctly classified 578/602 (96.0%) of the observations who approved, and 308/3,066 (10.1%) of the observations who disapproved, yielding a relatively weak ESS=6.06 ($p<0.0091$) which was stable in LOO analysis.

And, if year is treated as a *categorical* attribute[1] then the ODA model is: if Year=1954 or 1964 predict disapprove; otherwise predict approve. This model correctly classified 411/

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602 (68.3%) of the approving observations, and 1,268/3,066 (41.4%) of the observations who disapproved, yielding a relatively weak ESS= 9.63 (p<0.0001) stable in LOO analysis.

Finally, novometric analysis[6,7,12-27] was used to model (dis)approval as a function of age and cohort. The descendant family consisted of six CTA models and two ODA models, however the *age effect* identified earlier for the total sample (if age≤39 then predict approve) emerged as the globally optimal solution presently.

The simple example presented here was selected to maximize expositional clarity. Such design simplicity limits exposition of extraordinary capabilities of novometric methods used in applications involving numerous covariates and weighting by time and propensity scores.[12,18-26] Novometric analysis[6,7] equips researchers to evaluate *precisely* specific *confirmatory* hypotheses. Optimal use of novometry requires research authentically capable of constructing (hopefully successful) *a priori* hypotheses, samples affording adequate statistical power, and empirical measures which are psychometrically capable of measuring experimental phenomena with sufficient precision so as to be theoretically capable of identifying the hypothesized effects.

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8. MegaODA syntax used in this analysis was:
    VARS age year response;
    CLASS response;
    ATTRIBUTE year;
    LOO;
    MCARLO ITER 25,000;
    GO;

9. Earlier MegaODA syntax[8] was modified:
    IN age=29;GO;
    IN age=39;GO;
    IN age=49;GO;
    IN age=59;GO;
    IN age=69;GO;
    IN age=79;GO;

10. Earlier MegaODA syntax[8] was modified:
    ATTRIBUTE age;

11. Earlier MegaODA syntax[8] was modified:
    IN year=1954;GO;
    IN year=1957;GO;
    IN year=1958;GO;
    IN year=1964;GO;
    IN year=1965;GO;
    IN year=1969;GO;

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Author Notes

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