Using Design of Experiments to Determine Consumer Preference with Applications to Health Science

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Two-level Block Fractional Factorial Designs (BFFDs)

- A FFD with k two-level attributes: 2^{k-p}
  - Treatment defining contrast subgroup: p defining words and their products
  - Resolution: length of the shortest word in the treatment defining contrast subgroup
  - Let $A_{i,0}$ be the number of words of length i ($i = 1, \ldots, k$) in the treatment defining contrast subgroup
  - Consider designs with resolution III or higher: $A_{1,0} = A_{2,0} = 0$
  - Treatment wordlength pattern: $W_t = (A_{3,0}, \ldots, A_{k,0})$
- Two-level BFFD: 2^{k-p} FFD in 2^q blocks with blocks of size 2^{k-p-q}
  - Two defining contrast subgroups: the treatment defining contrast subgroup and the block defining contrast subgroup
  - Let $A_{i,1}$ be the number of treatment words of length i that are confounded with a block effect ($A_{1,1} = 0$)
  - Block wordlength pattern: $W_b = (A_{2,1}, \ldots, A_{k,1})$
- A main effect or a two-factor interaction is *clear* in a BFFD if it is not aliased with any other main effects or two-factor interactions, or confounded with any block effects

Examples

Example 1: 2^{5-1} FFD

- Treatment defining contrast subgroup $I = ABCDE$
- Treatment wordlength pattern: $W_t = (A_{3,0}, A_{4,0}, A_{5,0}) = (0, 0, 1)$

Example 2: 2^{5-1} FFD in into $2^q = 2^2$ blocks, each of size $2^{k-p-q} = 2^{5-1-2}$

- Treatment defining contrast subgroup: $I = ABCDE$
- Block defining contrast subgroup: $b_1 = AB, b_2 = AC$, and $b_3 = b_1 b_2 = BC$
- All five main effects are clear plus seven two-factor interactions
- Block wordlength pattern: $W_b = (A_{2,1}, A_{3,1}, A_{4,1}, A_{5,1}) = (3, 3, 0, 0)$, i.e., three two-factor interactions (AB, AC, BC) and three three-factor interactions (CDE, BDE, ADE) are confounded with block effects.

Minimum Aberration Criteria

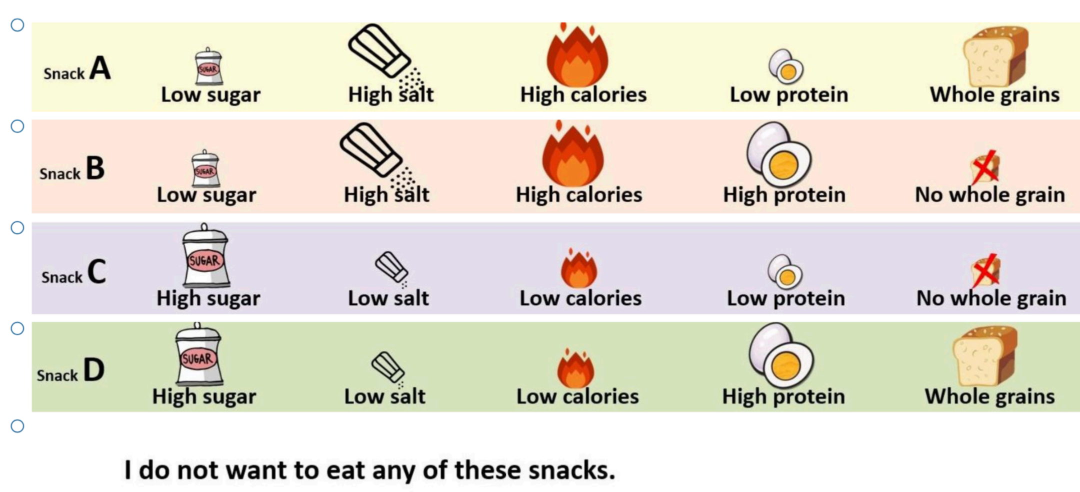
- Propose the MA criteria for selecting BFFDs to construct DCEs
- For any two 2^{k-p} designs d_1 and d_2, let r be the smallest integer such that $A_r(d_1) \neq A_r(d_2)$. Then d_1 is said to have less aberration than d_2 if $A_r(d_1) < A_r(d_2)$. If there is no design with less aberration than d_1, then d_1 has minimum aberration (Wu and Hamada, 2009)

Discrete Choice Experiments (DCEs)

- Method for understanding subjects preferences and their decision-making process
  - Present subjects with various choice sets of two or more options
  - Options consist of several attributes at one or more levels
  - Subjects are shown each choice set in turn and asked which option they prefer
  - The option chosen in each choice set is the most beneficial (utility)

Evidence from a Discrete Choice Experiment

- Goal: Determine which snack factors affect school-aged children snack preferences and to quantify their relative importance using Discrete Choice Experiments



Simulation

- Multinomial logit (MNL) model: common model for modeling responses and analyzing data from a DCE
- Assume true model: 5 main effects plus 3 two-factor interactions

$$\mu = 0.5x_A - 0.5x_B + 0.5x_C - 0.5x_D + 0.5x_E + 0.25x_Ax_C - 0.25x_Ax_D + 0.25x_Bx_E$$

- Consider three 2^{5-1} FFDs in 2^2 blocks and for each design we fit two models:
  1. Main effects only
  2. All main effects and all clear two-factor interactions plus one two-factor interaction from each aliased set not confounded with block

Design	Treatment defining words	Block defining words	W_t	W_b
Design 1	$I = ABCDE$	$b_1 = AB, b_2 = AC, b_3 = BC$	$(0, 0, 1)$	(3,3,0,0)
Design 2	$I = ABCE$	$b_1 = ACD, b_2 = BCD, b_3 = AB$	$(0, 1, 0)$	(2,4,0,0)
Design 3	$I = ABE$	$b_1 = AC, b_2 = ABCD, b_3 = BD$	$(1, 0, 0)$	(2,3,1,0)

Main Effects Only Models

Effect	Design 1	Design 2	Design 3
A	0.604 (0.032)	0.772 (0.033)	0.889 (0.041)
B	-0.455 (0.032)	-0.391 (0.033)	-0.567 (0.040)
C	0.509 (0.032)	0.609 (0.029)	0.471 (0.032)
D	-0.557 (0.027)	-0.502 (0.026)	-0.606 (0.028)
E	0.387 (0.026)	0.341 (0.029)	0.512 (0.037)

Main Effects Plus Two-Factor Interactions

Effect	Design 1	Design 2	Design 3
A	0.506 (0.048)	0.555 (0.044)	0.792 (0.051)
B	-0.524 (0.048)	-0.503 (0.045)	-0.533 (0.051)
C	0.549 (0.048)	0.464 (0.044)	0.497 (0.051)
D	-0.484 (0.048)	-0.435 (0.046)	-0.456 (0.041)
E	0.454 (0.048)	0.482 (0.045)	0.502 (0.051)
AB	–	–	–
AC	–	0.467 (0.045)	–
AD	-0.246 (0.048)	-0.28 (0.038)	-0.262 (0.039)
AE	0.028 (0.048)	-0.025 (0.041)	–
BC	–	–	0.029 (0.050)
BD	0.038 (0.048)	0.039 (0.045)	–
BE	0.239 (0.048)	–	–
CD	-0.005 (0.048)	-0.015 (0.038)	0.011 (0.029)
CE	0.012 (0.048)	–	-0.053 (0.051)
DE	-0.017 (0.048)	-0.041 (0.045)	-0.057 (0.041)

Simulation Results

1. Effects confounded with block effects are not estimable, but do not bias estimate of other effects
2. Aliasing causes bias, but aliased effects are estimable if all aliases are negligible
3. Aliasing or missing a significant two-factor interaction can bias estimation of main effects even if all main effects and two-factor interactions are clear

Hence, it is essential at the design stage to know the aliasing and confounding structure of the design.

Discussion

- Understanding school-aged adolescents' snack preferences could help tailor nutrition education programs at school to educate students to make better snack choices outside school

Snack Factors	Log-likelihood	Relative Effect	Relative Importance
Whole Grain	-915.750	0.253	1
Salt	-914.227	0.243	2
Protein	-908.196	0.204	3
Calories	-900.004	0.150	4
Sugar	-899.939	0.150	4
Full Model	-877.259		

- Our designs are optimal for estimating parameters in the MNL model under the assumption that all options are equally attractive (Bush, 2014)
  - Locally optimal (or D-optimal) designs
  - A potential problem with this approach is that if the nominal values are misspecified, the locally optimal design may be potentially inefficient
  - Alternative design approaches: Bayesian approach, maximin approach, or sequential approach