*A New Way to Estimate Interactions in Conjoint Analysis**

Chris Marketo
Alex Gofman
Howard Moskowitz

Moskowitz Jacobs Inc. USA

* Patent Pending

Sensometrics

July, 2004

Background

- Conjoint analysis is a well accepted approach to understanding the drivers of consumer needs
- Often these techniques provide main effects solutions and ignore interactions

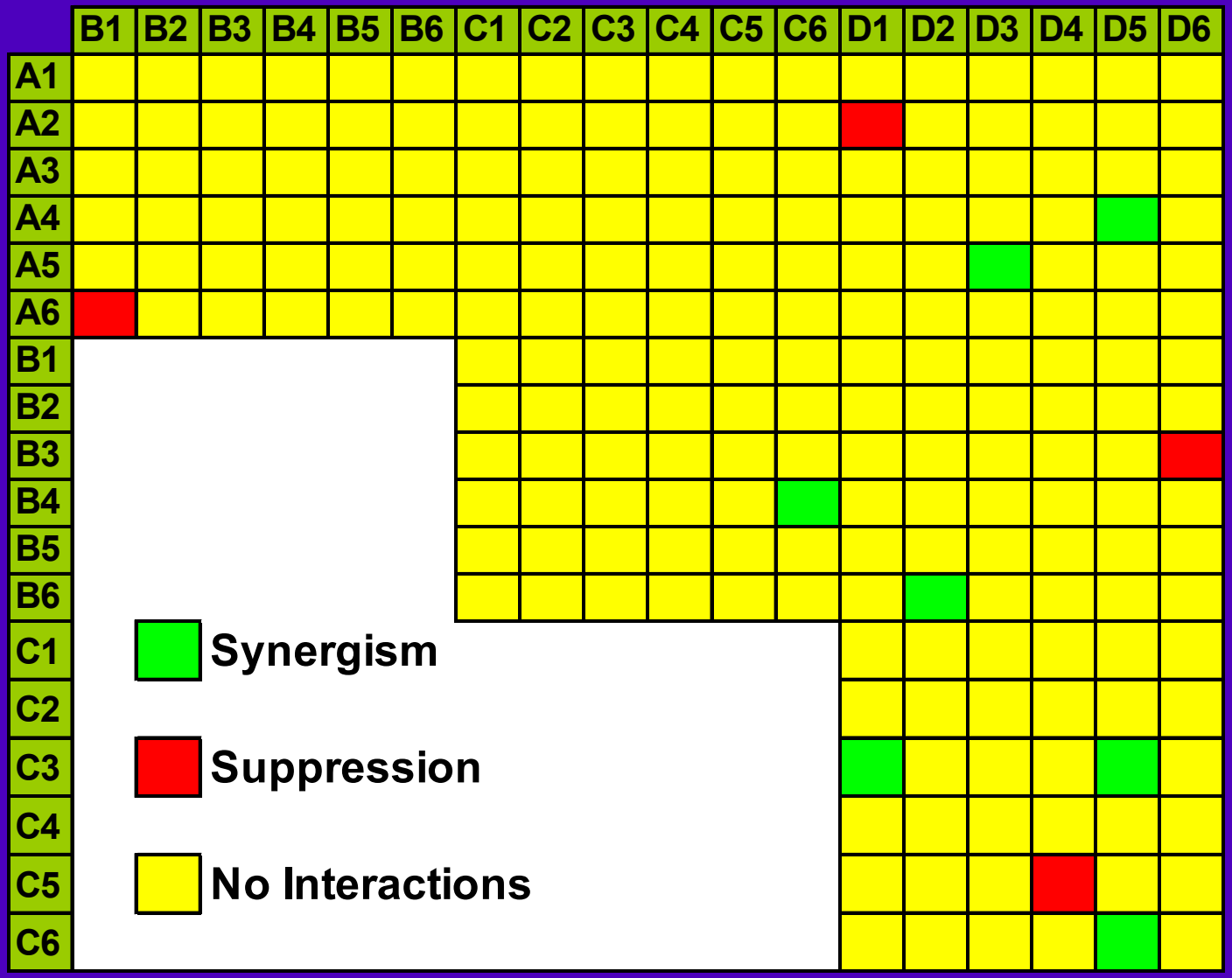
  One could understand interactions by first identifying relevant ones, and then building them in to the design

  - But .. What about the case where we don't know what is relevant, and we have a possible 100-200 interactions to sort through?

Classical challenge to interaction estimation

- Main effects estimation requires a number of concepts/ data points to be collected.
- Traditionally, estimating interactions requires additional concepts/ data points to be collected → additional time and cost
- Is there a way to gather the additional information for interactions within the main effects design? i.e. without the need to test and collect additional concepts/ data points

Here are the significant interactions..
How else could we ever discover them?



Let's turn the problem around 180°

- We know that we can't have a single respondent test all interactions
  - Just too many interactions

- But … let's use our main effects experimental design in a different way
  - Let each respondent be tested with a permutation of the basic design
  - The data still creates the correct design for individual level modeling
  - But … across all respondents … we have a chance to having all pairs of elements represented, allowing us to estimate the interactions

A 'revised' approach to estimating interactions within a main effects model

1. Select/ create a main effects experimental design
2. *Permute* this design to ensure that the integrity is maintain AND to allow the elements to be shuffled within each concept. Create 100+ permutations
3. Assign a respondent to one of the permutations of the basic design
4. Run the interview, allow the respondents to rate the concepts
5. Data is a large matrix of all combinations (embodying respondents, permutations)

An approach to estimating interactions within a main effects 'original design'

6. Create all possible interactions between pairs of elements from each category
   a. E.g., if there are 4 categories, then we have 4x3/2=6 pairs of categories
   b. And… if each category has 5 elements, then there are 25 pairs of elements, one from each category
7. Run stepwise regression… force linear terms and afterwards allow significant pair wise interactions to enter the model
8. Significant interactions add, above and beyond the linear terms

Illustrating the approach

Orange beverage example

4 categories or 4x3/2=6 interacting categories

6 elements per category, or 36 potential interactions per pair of categories

1. The sweetener concept design

- Product = orange drink
- 4 categories x 6 elements in each category
- The four categories, and a sample *element*
  - Type of product: Category A (A1-A6)
    - *An orange beverage that reminds you of Florida*
  - Sensory delivery: Category B (B1-B6)
    - *Icy cold, a full sensation*
  - Sweetener: Category C (C1-C6)
    - *Sucralose to give it a nice sweet taste*
  - Who the product is for: Category D (D1-D6)
    - *A great taste for your kids*

1. Main Effects Design dictates the set of combinations

Concept #	Concept Structure
1	A1 B5 D2
2	B1 D5
3	B6 C3 D6
4	A5 B1 C1 D1
5	A3 B3 D3
…	…
40	B3 C4

1. Allocate the elements

Brief Description

A1 Introducing a fabulous new orange beverage…

A2 A brand new orange beverage ….

A3 A new beverage that cools your mouth …

A4 An orange beverage that reminds you of Florida…..

A5 Introducing an outstanding new product - oranges!

A6 Ignite your senses with a burst of orange!

Sugar Description

C1 Sugar to give it a nice sweet taste

C2 Saccharin to give it a nice sweet taste

C3 Sucralose to give it a nice sweet taste

C4 Acesalfame K to give it a nice sweet taste

C5 Aspartame to give it a nice sweet taste

C6 High sweet corn syrup to give it a nice sweet taste

Sensory Appeal

B1 Drink it up - you'll love the taste!

B2 A cool sensation every time you sip…

B3 It warms your mouth - and your heart…

B4 It goes down smooth…….

B5 Icy cold - a full sensation!

B6 Brings you back to the islands…..

Target consumer

D1 Drink it for your self

D2 Buy it for your whole family

D3 A great taste for your kids

D4 Try it soon with your friends

D5 Try it soon with your husband or wife

D6 Great taste for the whole family

2. Permute the design

Description (A)	Design 1	Design 2	Design 3
Introducing a fabulous new beverage	A1	A4	A4
A brand new orange beverage	A2	A2	A3
A new orange beverage that cools your mouth	A3	A1	A2
An orange beverage that reminds you of Florida	A4	A3	A1
Sensory Appeal (B)			
Drink it up - you'll love the taste!	B1	B1	B4
A cool sensation every time you sip...	B2	B3	B3
It warms your mouth - and your heart...	B3	B4	B2
It goes down smooth.....	B4	B2	B1
Sweetener Description (C)			
Sugar to give it a nice sweet taste	C1	C1	C4
Saccharin to give it a nice sweet taste	C2	C2	C3
Sucralose to give it a nice sweet taste	C3	C4	C2
Acesalfame K to give it a nice sweet taste	C4	C3	C1

Concept #1 from design 1 & 2

Introducing a fabulous new beverage

Icy cold - a full sensation!

Buy it for your whole family

Concept #1, Consumer 1

An orange beverage that reminds you of Florida.....

Icy cold - a full sensation!

A great taste for your kids

Concept #1, Consumer 2

3. Assign a respondent to a permutation

- There is no worry at the individual respondent level because each design is isomorphic to every other design
- Each person's design allows estimation of a valid individual-level model
- An ancillary benefit .. No possibility that an unexpectedly strong or weak combination would bias the data …this is always a worry for situations where there is one set of combinations (e.g., 'cards')

4. Run the study

- Internet-based study
- Rapid, easy to set up
- Each respondent evaluates separate set of combinations of same elements
- Data returned in summarized form
- Raw data available in electronic form for subsequent analysis

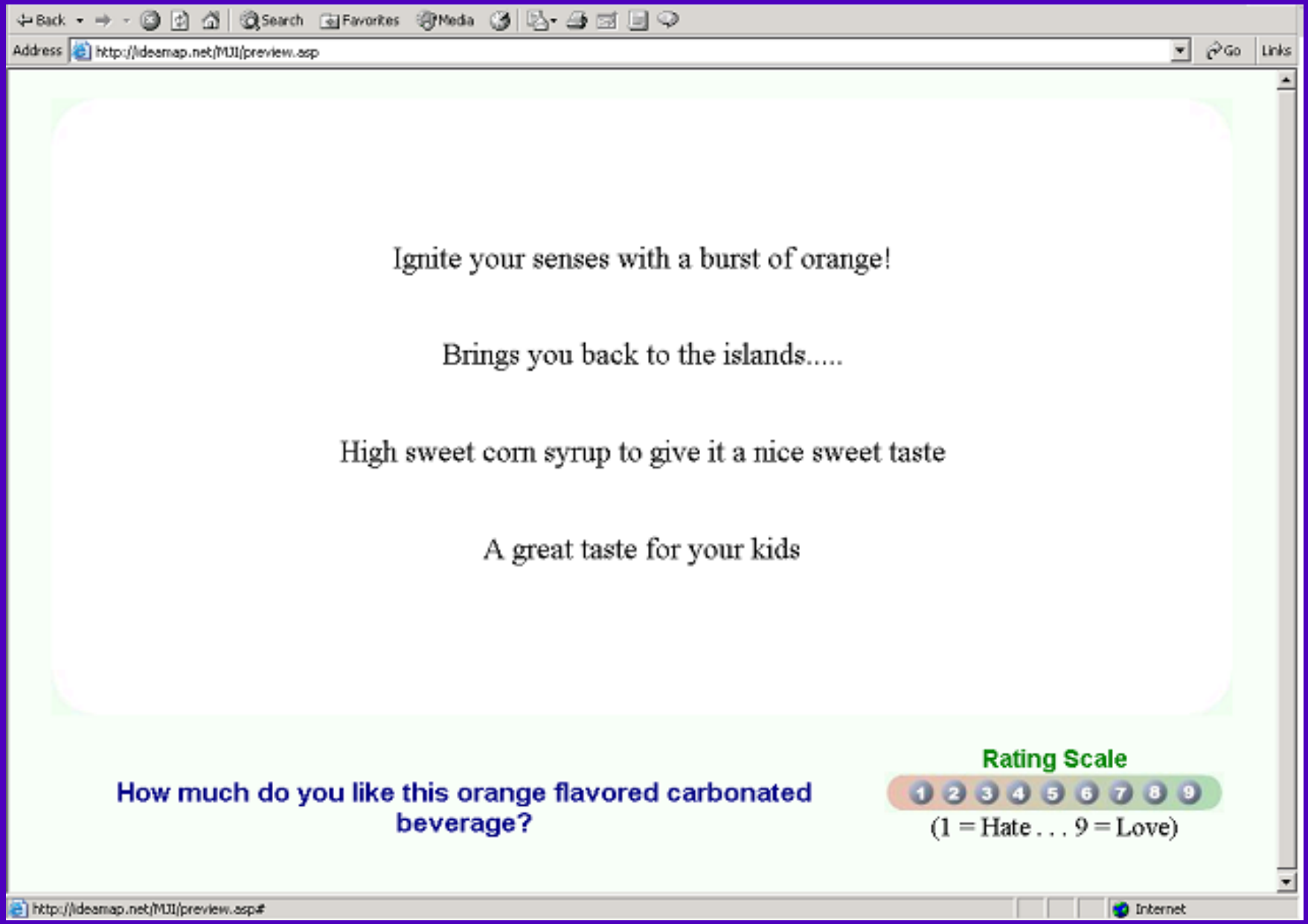
4. The interview

- Consumers see concepts and rate them on a scale…
  - How much do you like this orange flavored carbonated beverage?

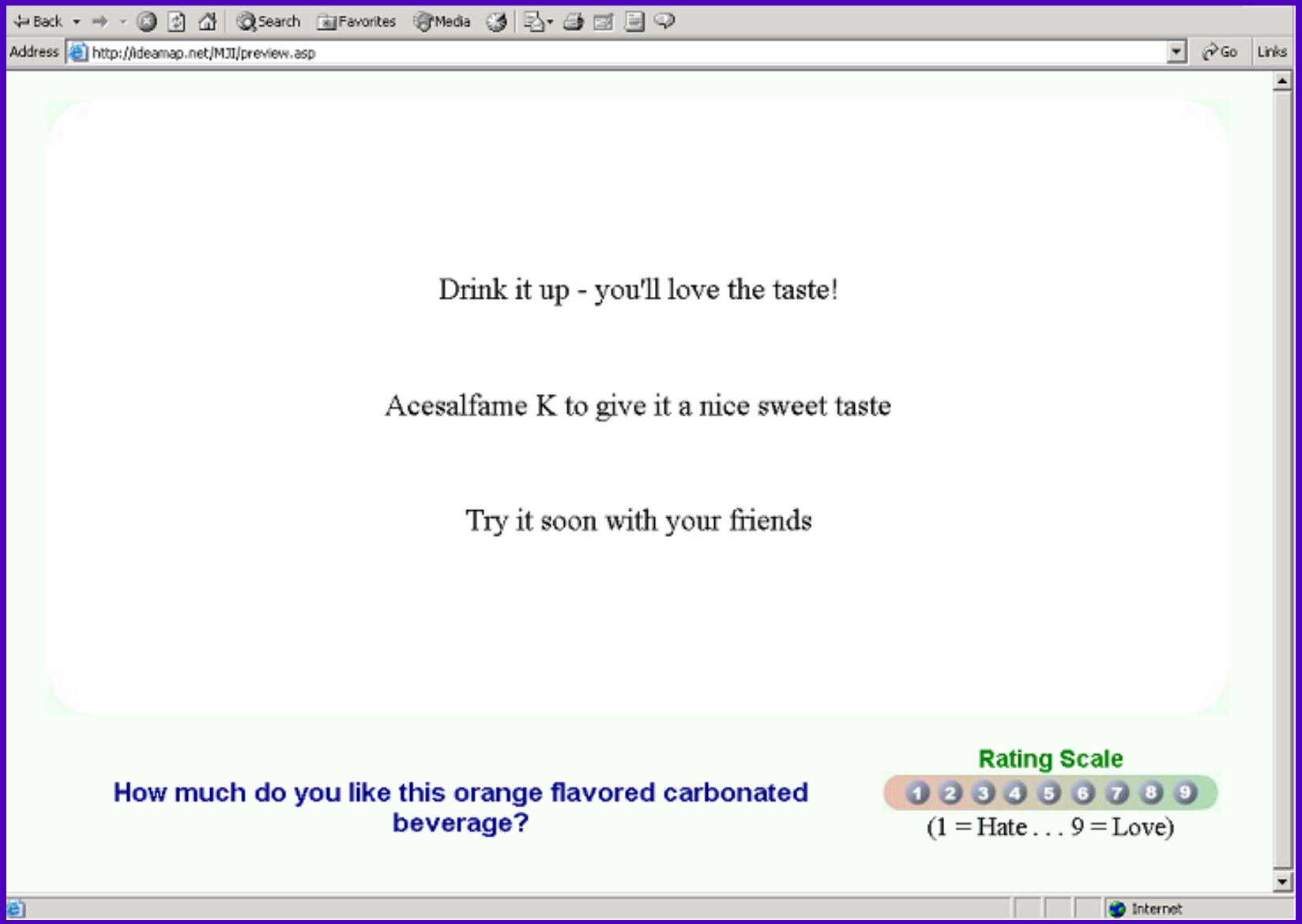
    (1=hate….9=love)
- Task is simple for the consumers; they do not know that there is a experimental design which is dynamically constructing the concepts

Orientation page setting up study

Concept with four elements



Concept with three elements



5. Transform Concepts into Binary Data

- Take each concept for each respondent.
- Create a column for each element
  - 4 categories x 6 elements = 24 columns
- If the element is present allocate a “1” if the element is absent allocate a “0” i.e. binary

Concept	UID	Concept	A1 ..	A3 ..	A5 ..	B1 ..	B3 ..	B5	B6	C1 ..	C3 ....
1	1	A1B5D2	1	0	0	0	0	1	0	0	0
2	1	B1D5	0	0	0	1	0	0	0	0	0
3	1	B6C3D6	0	0	0	0	0	0	1	0	1
4	1	A5B1C1D1	0	0	1	1	0	0	0	1	0
5	1	A3B3D3	0	1	0	0	1	0	0	0	0

Raw data is R rows x C Respondents

Concept	UID	Concept	Response
1	1	A1B5D2	7
2	1	B1D5	6
3	1	B6C3D6	6
4	1	A5B1C1D1	6
5	1	A3B3D3	1
40	1	B3C4	1
1	3	A4C4D4	6
2	3	A2B2C2D2	4
3	3	A1D3	7
4	3	A1B1C3D1	8
5	3	A6B5C5D5	2
40	3	A4B1C3	6
1	9	A6B3D3	4
2	9	A2B1C1	4
3	9	A3B6	4
4	9	A6B5C3	5
5	9	A3D5	3
40	9	A3B3C6	3

- Each respondent and concept is a row
- Raw data is in the form of 1's and 0's

6. Create all possible pair wise interactions between elements

- Create all pair wise interactions across categories by multiplying columns (e.g., in Excel)
  - Yes: A1*B1, A1*B2, A1*B3…. C6*D6
  - No: A1*A2, B3*B6 etc
- In the case of the orange beverage data, there are 216 pair wise combinations plus 24 main effect terms
- Model main effects and interactions
  - Response=constant+A1+A2…+D6+A1*B1+A1*B2+…+C6*D6

7. Run stepwise regression

- Run stepwise regression
- Follow this strategy
  - Force in linear terms
  - Afterwards allow significant pair-wise interactions to be included if they add appreciably more predictability
- Our permutation strategy ensures that there will be sufficient pairs of elements from different categories
  - And they will not be correlated with each other

Beverage … interaction model (1 of 2)

Step # 35 R = 0.610 R-Square = 0.372
Term entered: B6D2

In	Effect	Coefficient	Std Error	Std Coef	Tol.	df	F	'P'
1	Constant							
2	A1	0.070	0.169	0.010	0.70048	1	0.174	0.676
3	A2	0.325	0.174	0.047	0.65720	1	3.482	0.062
4	A3	0.064	0.172	0.009	0.67357	1	0.138	0.710
5	A4	0.284	0.177	0.041	0.63667	1	2.578	0.109
6	A5	0.134	0.175	0.019	0.64870	1	0.581	0.446
7	A6	0.430	0.173	0.063	0.66479	1	6.158	0.013
8	B1	0.326	0.172	0.047	0.67444	1	3.593	0.058
9	B2	0.333	0.169	0.048	0.69823	1	3.877	0.049
10	B3	-0.233	0.177	-0.034	0.63817	1	1.730	0.189
11	B4	-0.137	0.174	-0.020	0.65773	1	0.622	0.431
12	B5	0.389	0.168	0.057	0.70999	1	5.371	0.021
13	B6	0.062	0.176	0.009	0.64234	1	0.125	0.723
14	C1	-1.063	0.169	-0.155	0.69914	1	39.582	0.000
15	C2	-3.009	0.168	-0.438	0.70365	1	319.092	0.000
16	C3	0.005	0.181	0.001	0.60664	1	0.001	0.979
17	C4	-2.864	0.169	-0.417	0.69957	1	287.271	0.000
18	C5	-2.701	0.177	-0.393	0.63987	1	233.835	0.000

Non Drivers

Drivers

Beverage interaction (2 of 2)

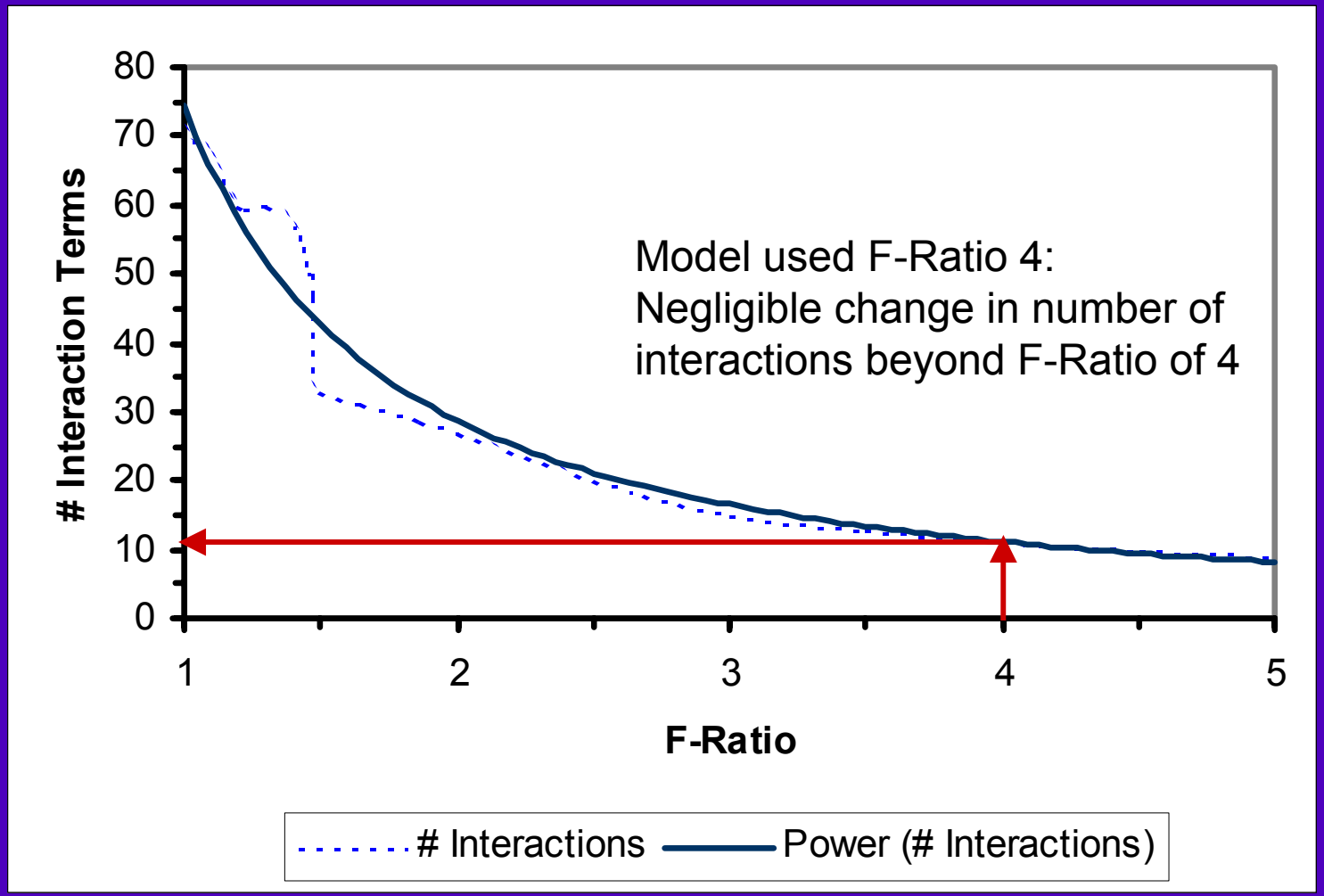
Linear terms forced in, strong interactions enter

Effect In		Coefficient	Std Error	Std Coef	Tol.	df	F	'P'
19	C6	-1.987	0.181	-0.289	0.60688	1	120.034	0.000
20	D1	0.060	0.180	0.009	0.61441	1	0.110	0.741
21	D2	-0.088	0.175	-0.013	0.64889	1	0.250	0.617
22	D3	0.255	0.175	0.037	0.65480	1	2.138	0.144
23	D4	0.147	0.175	0.021	0.65407	1	0.711	0.399
24	D5	-0.270	0.192	-0.039	0.54377	1	1.978	0.160
25	D6	0.147	0.177	0.021	0.63578	1	0.684	0.408
56	A2D1	-1.454	0.517	-0.063	0.83737	1	7.919	0.005
96	A4D5	0.952	0.437	0.051	0.76606	1	4.734	0.030
112	A5D3	1.152	0.506	0.052	0.82038	1	5.189	0.023
116	A6B1	-1.475	0.613	-0.052	0.88984	1	5.790	0.016
169	B3D6	-1.155	0.437	-0.062	0.76778	1	6.993	0.008
175	B4C6	1.251	0.491	0.058	0.82019	1	6.503	0.011
201	B6D2	0.946	0.452	0.049	0.78592	1	4.390	0.036
218	C3D1	1.268	0.505	0.057	0.82140	1	6.301	0.012
222	C3D5	1.333	0.521	0.058	0.82332	1	6.548	0.011
233	C5D4	-1.329	0.532	-0.056	0.84416	1	6.228	0.013
240	C6D5	1.130	0.494	0.052	0.81042	1	5.242	0.022

8. Some results

- The number of interaction terms decreases as we make the requirement to ‘enter’ more stringent
  - We used an F ratio of 4.0 to enter.
  - Like any other regression approach, the weaker the criteria to enter the equation, the more terms enter
- Interactions emerge and can be strong
  - They can be suppressive or additive
  - The magnitude has to be estimated empirically by adding the constant, and the utilities of the two terms (+ interactions)
  - We use the model for the rating scale to identify which pairs of elements interact, but can estimate effects on both rating and on ^% top 3 box

Impact of increasing the stringency (i.e. F-Ratio) on number of interactions allowed into the model



	Pure Linear Model 9-POINT RATING SCALE 2-element concept				Linear Model + Pairwise Interactions 9-POINT RATING SCALE 2-element concept					Difference In Sum of Utilities (Interaction Minus Linear)
	Constant	Utility 1st	Utility 2nd	Const + Two Utilities	Constant	Utility 1st	Utility 2nd	Utility of Pairwise Interact.	Const + Three Utilities	Diff
The statistically significant interaction leads to synergism (more than the sum you'd expect)										
A5D3	5.5	0.2	0.3	*6.0*	5.5	0.1	0.3	1.2	*7.1*	*1.1*
C3D1	5.5	0.3	0.0	*5.8*	5.5	0.0	0.1	1.3	*6.9*	*1.1*
B4C6	5.5	0.0	-1.7	*3.8*	5.5	-0.1	-2.0	1.3	*4.8*	*1.0*
B6D2	5.5	0.2	0.0	*5.7*	5.5	0.1	-0.1	0.9	*6.4*	*0.7*
C3D5	5.5	0.3	0.0	*5.8*	5.5	0.0	-0.3	1.3	*6.5*	*0.7*
A4D5	5.5	0.4	0.0	*5.9*	5.5	0.3	-0.3	1.0	*6.5*	*0.6*
C6D5	5.5	-1.7	0.0	*3.8*	5.5	-2.0	-0.3	1.1	*4.3*	*0.5*
The statistically significant interaction leads to suppression (less than the sum you'd expect)										
B3D6	5.5	-0.4	0.0	*5.1*	5.5	-0.2	0.1	-1.1	*4.3*	*-0.8*
C5D4	5.5	-2.9	0.0	*2.6*	5.5	-2.7	0.1	-1.3	*1.6*	*-1.0*
A2D1	5.5	0.2	0.0	*5.7*	5.5	0.3	0.1	-1.5	*4.4*	*-1.3*
A6B1	5.5	0.3	0.3	*6.1*	5.5	0.4	0.3	-1.5	*4.7*	*-1.4*

	Pure Linear Model % TOP 3 BOX				Linear Model + Pairwise Interactions % TOP 3 BOX					Difference In Sum of Utilities (Interaction Minus Linear)
	Constant	Utility 1st	Utility 2nd	Const + Two Utilities	Constant	Utility 1st	Utility 2nd	Utility of Pairwise Interact.	Const + Three Utilities	Diff
The statistically significant interaction leads to synergism (more than the sum you'd expect)										
A5D3	39	1	6	*46*	39	0	5	23	*67*	*21*
C3D1	39	1	0	*40*	39	-5	-1	28	*61*	*21*
B4C6	39	-2	-28	*9*	39	-5	-33	30	*31*	*22*
B6D2	39	2	4	*45*	39	1	2	11	*53*	*8*
C3D5	39	1	1	*41*	39	-5	-3	33	*64*	*23*
A4D5	39	4	1	*44*	39	3	-3	9	*48*	*4*
C6D5	39	-28	1	*12*	39	-33	-3	14	*17*	*5*
The statistically significant interaction leads to suppression (less than the sum you'd expect)										
B3D6	39	-7	0	*32*	39	-6	1	-7	*27*	*-5*
C5D4	39	-39	-2	*-2*	39	-38	-1	-3	*-3*	*-1*
A2D1	39	2	0	*41*	39	4	-1	-18	*24*	*-17*
A6B1	39	4	3	*46*	39	7	4	-31	*19*	*-27*

Here are some combinations that synergize versus combinations that suppress each other

- Synergy

  Introducing an outstanding new product – oranges!

  A great taste for your kids (A5D3)

  Sucralose to give it a nice sweet taste

  Drink it for yourself (C3D1)

- Suppression

  It warms your mouth - and your heart...

  Great taste for the whole family (B3D6)

  Aspartame to give it a nice sweet taste

  Try it soon with your friends (C5D4)

Summary of findings…

- Illustrated a method to use a main effects design with permutations to estimate interactions
- Need to maintain the integrity and independence of the main effects design in the permutation process
- Results indicated that
  - 5% of interactions were significant for the 4 x 6 orange beverage data
  - But .. How would we have found these otherwise?