DSC 410/510
Multivariate Statistical Methods

Conjoint Analysis

1

What Is Conjoint Analysis?

- A technique for understanding how respondents develop preferences for products or services
- Also known as "trade-off analysis"
- Premise: consumers evaluate overall **utility** by combining values for each attribute of the product
  - Subjective preference judgment unique to each individual
  - Encompasses all product or service features
  - Products/services with higher utility are more preferred and have a better chance of choice

2

How Is Conjoint Analysis Done?

- Describe product/service in terms of its attributes/characteristics/features (**factors**)
- Select possible values for each factor (**levels**)
- Construct a set of products/services (**treatments** or **stimuli**) by combining levels of each factor
- Present stimuli to respondents who provide their overall evaluations
- Determine **preference structure** – influence of each factor and each level on respondent's utility judgment – individually and collectively

3

Hatco Example: Industrial Cleanser

- 3 factors: ingredients, form, brand
- 2 levels for each factor: phosphate-free/ phosphate-based, liquid/powder, Hatco/generic
- 2 x 2 x 2 = 8 stimuli, e.g. Hatco phosphate-free powder
- Hatco customers asked to:
  - either rank-order 8 stimuli
  - or rate each stimuli on a 1-10 preference scale

4

The Additive Model For Individuals

- Utility for any stimuli estimated from **part-worths**
- Utility for product with level i for factor 1, level j for factor 2, …, level n for factor N
  = part-worth for level i for factor 1
  + part-worth for level j for factor 2 + …
  + part-worth for level n for factor N
- For example, Hatco phosphate-free powder utility
  = part-worth of Hatco brand
  + part-worth of phosphate-free ingredients
  + part-worth of powder form

5

Empirical Example

- Two respondents ranked 8 stimuli:

Stimuli	Form	Ingredients	Brand	D1	D2	D3	Res 1	Res 2
S1	Liquid	Phosphate-free	Hatco	1	1	1	1	1
S2	Liquid	Phosphate-free	Generic	1	1	-1	2	2
S3	Liquid	Phosphate-based	Hatco	1	-1	1	5	3
S4	Liquid	Phosphate-based	Generic	1	-1	-1	6	4
S5	Powder	Phosphate-free	Hatco	-1	1	1	3	7
S6	Powder	Phosphate-free	Generic	-1	1	-1	4	5
S7	Powder	Phosphate-based	Hatco	-1	-1	1	7	8
S8	Powder	Phosphate-based	Generic	-1	-1	-1	8	6

6

Estimating Part-Worths

- Calculate average ranks of each level of each factor:

		Respondent 1			Respondent 2		
Factor	**Level**	**Ranks**	**Ave.**	**Part-Worth**	**Ranks**	**Ave.**	**Part-Worth**
Form	Liquid	1,2,5,6	3.5	1.0	1,2,3,4	2.50	2.00
	Powder	3,4,7,8	5.5	-1.0	5,6,7,8	6.50	-2.00
Ingredients	Phosphate-free	1,2,3,4	2.5	2.0	1,2,5,7	3.75	0.75
	Phosphate-based	5,6,7,8	6.5	-2.0	3,4,6,8	5.25	-0.75
Brand	Hatco	1,3,5,7	4.0	0.5	1,3,7,8	4.75	-0.25
	Generic	2,4,6,8	5.0	-0.5	2,4,5,6	4.25	0.25

- Part-Worths =

overall average rank (4.5) – average rank of level

7

Using Regression Instead

- We can obtain part-worths using regression
- Dependent variable = Rank
- Independent variables =
  - D1 = dummy variable for Form
  - D2 = dummy variable for Ingredients
  - D3 = dummy variable for Brand
- Dummy variables use effects-coding (see end of Chapter 2 and slide 28 from "Examining your data" class notes)
- See `hatco1res.xls` Excel Spreadsheet on web-site (under "data")

8

Conditional Relative Importance

- CRI, also known as "Factor Importance"
- Ignore over-complicated method in Table 7.3
- Calculate range of part-worths for each factor
- CRI for each factor is this range divided by the sum of the ranges across all factors
  - For example, respondent 1 ranges are 2 (form), 4 (ingredients) and 1 (brand), summing to 7
  - CRI values are therefore 2/7 = 28.6% (form), 4/7 = 57.1% (ingredients) and 1/7 = 14.3% (brand)

9

Predicting Rankings

- Sum the part-worths for each stimuli to find overall utilities
- Predict rankings based on these utilities
  - For example, respondent 1 utilities are 3.5, 2.5, –0.5, –1.5, 1.5, 0.5, –2.5, –3.5
  - Predicted rankings are therefore 1, 2, 5, 6, 3, 4, 7, 8 – perfect prediction!
- Excel spreadsheet also calculates the CRI's and predicted rankings
- Or use SAS software – see handout on website ("Empirical example from p394") and Excel spreadsheet (`hatco1raw.xls`)

10

Managerial Uses of Conjoint

- Discover object/concept with optimal qualities
- Establish relative contributions of each attribute and each level to utility
- Predict utilities for other stimuli not evaluated
- Identify segments of consumers who put differing importance on attributes
- Explore market potential for feature combinations currently unavailable

11

Unique Features of Conjoint

- Decompositional rather than compositional
- Separate models for predicting preference for *each* respondent (disaggregate)
- Individual results can be aggregated to calculate group utility also
- Handles nonlinear relationships as well as linear ones

12

Conjoint Decision Framework

1. Define objectives
2. Develop research design
3. Evaluate assumptions
4. Estimate model and assess fit
5. Interpret results
6. Validate results

13

Conjoint Decision Framework

1. **Define objectives**
2. Develop research design
3. Evaluate assumptions
4. Estimate model and assess fit
5. Interpret results
6. Validate results

14

Define Objectives

- Determine contributions of factors and their levels to consumer preference
  - e.g. how much does price contribute to willingness to buy, and which price is best?
- Find a valid model of consumer judgments
  - valid models enable prediction of preference for any combination of factors/levels
- What decision criteria do consumers use to make choices for this type of product/service?
  - turn these criteria into attributes that give value to the product/service

15

Choosing Factors and Levels

- Include all attributes that create or detract from overall utility of product/service
- Consider positive *and* negative levels for factors since:
  - focusing only on positive levels distorts respondents judgments
  - respondents can subconsciously employ omitted negative levels
- Only include *determinant* factors that differentiate between objects
  - e.g. car seat safety is important, but not determinant

16

Conjoint Decision Framework

1. Define objectives
2. **Develop research design**
3. Evaluate assumptions
4. Estimate model and assess fit
5. Interpret results
6. Validate results

17

Develop Research Design

- Select a conjoint method
  - traditional, adaptive or choice-based
- Define factors and levels
- Specify model
  - additive or interaction
  - linear, quadratic or separate part-worths
- Collect data
  - full-profile, pairwise, or trade-off comparison presentation
  - ranking or rating preferences
  - survey administration

18

Conjoint Methods

	Traditional	Adaptive	Choice-based
Max. # factors	9	30	6
Analysis level	Individual or Aggregate	Individual or Aggregate	Aggregate
Model form	Additive	Additive	Additive or Interaction

19

Factors and Levels

- Must be *communicable*, usually verbally (or use multimedia, virtual reality, or even actual products!)
- Must be *actionable*, i.e. distinct and implementable
- Can use preliminary study to determine important factors
- Increasing the number of factors/levels either requires larger number of stimuli or reduces reliability of results
- Min. # stimuli = total levels across factors – # factors + 1
- Beware *multicollinearity* (interattribute or environmental correlation among factors), e.g. HP and MPG for cars
  - create "superattributes", e.g. performance, or eliminate unbelievable stimuli, or constrain part-worth estimation to conform to a prespecified relationship

20

Factors and Levels (continued)

- Consider use of *price* as a factor carefully:
  - positively associated with many "quality" attributes
  - unrealistic high-quality low-price combinations
  - price can become down-weighted if there are many other "positive" features
  - price can interact with features such as brand
- Equalize number of levels across factors
- Increasing range of levels can reduce multicollinearity but also reduce believability
- Ensure levels are realistic and feasible

21

Model: Additive or Interaction

- Additive composition rule: add up part-worths for each factor/level combination to get overall utility
- Interaction effects: the whole is greater (or less) than the sum of its parts
  - particular factor/level combinations are especially liked or disliked
  - there is an interaction between factors A and B if rankings for levels of A vary with levels of B
  - identifying interaction can be difficult!

22

Example of Interaction

Stimuli	Form	Ingredients	Brand	Res 3
S1	Liquid	Phosphate-free	Hatco	1
S2	Liquid	Phosphate-based	Hatco	3
S3	Powder	Phosphate-free	Hatco	2
S4	Powder	Phosphate-based	Hatco	4
S5	Liquid	Phosphate-free	Generic	7
S6	Liquid	Phosphate-based	Generic	5
S7	Powder	Phosphate-free	Generic	8
S8	Powder	Phosphate-based	Generic	6

Respondent 3 prefers phosphate-free over phosphate-based for Hatco brand, but vice-versa for generic brand

23

Part-Worth Relationship

Most restrictive	⇦	⇨ Least restrictive
Most efficient estimation	⇦	⇨ Least efficient estimation
Linear	Quadratic or ideal point	Separate part-worths

- Can be specified separately for each factor
- Choice can be guided theoretically or empirically

24

Data Collection: Presentation Method

- Full-profile: [liquid / phosphate-free / Hatco] rate or rank each stimuli
- Pairwise: [liquid / phosphate-free] vs. [powder / phosphate-based]
- Trade-off:

	liquid	powder
Hatco	?	?
Generic	?	?

rank each combination

25

Data Collection: Creating Stimuli

- Full factorial uses all combinations (becomes unmanageable quickly)
- Fractional factorial allows estimation of all main effects with far fewer stimuli:
  - orthogonal, balanced designs are optimal, but …
  - can contain obvious or unbelievable stimuli, which …
  - can be deleted if resulting "near orthogonal" design is efficient and interattribute correlations are small (< .2)
- Bridging designs can be used with large number of factors
- Whatever the design, use no more than 20 or so stimuli

26

Creating Stimuli Using SAS

- The SAS "ADX" application can be used to generate experimental designs for conjoint analysis experiments
- Multiply the number of levels in each factor together to find the "full factorial" number of stimuli needed
  - If this is less than 20 then you can probably use the full factorial design, and there is no need to use SAS ADX
  - Otherwise, better to run a "fractional factorial" for which you'll need to use SAS ADX
- For an example, see Assignment 3 which is based on the "Jobs example from class" handout on the class website

27

Data Collection: Preference Measure

- Non-metric, i.e. rank-ordering (full-profile, pairwise, trade-off)
  - (+) easy for respondent
  - (–) can be difficult to administer
- Metric, i.e. Rating, e.g. 1-10 scale (full-profile, pairwise)
  - (+) easily analyzed and administered
  - (–) respondents can be less discriminating
- Personal interviews, mailed questionnaires, computer-based surveys, and telephone interviews can all work well

28

Conjoint Decision Framework

1. Define objectives
2. Develop research design
3. **Evaluate assumptions**
4. Estimate model and assess fit
5. Interpret results
6. Validate results

29

Evaluate Assumptions

- Few *statistical* assumptions
  - e.g. normality, homoscedasticity, independence checks not needed
- Strong *conceptual* assumptions
  - e.g. specify model form (additive vs. interaction) *before* data are collected

30

Conjoint Decision Framework

1. Define objectives
2. Develop research design
3. Evaluate assumptions
4. **Estimate model and assess fit**
5. Interpret results
6. Validate results

31

Estimate Model

- Rated preferences are analyzed using specialized software, e.g. SAS Proc Transreg, Conjoint Analyzer, or SPSS Conjoint Add-on or even regression with dummy variables (effects coding)
- Rank-ordered preferences:
  - can be analyzed using special procedures designed for ordinal data
  - or can be analyzed using procedures designed for metric data, e.g. regression (beware unequally spaced preferences however)
- Specify part-worth relationship (separate, quadratic, or linear) for each factor

32

Assess Fit

- Fit can be assessed at both individual and aggregate levels
- Compare actual and predicted ranks
- Compute “Multiple R”, i.e. correlation between responses and predictions (note: $R = \sqrt{(1/(1+df_2/df_1F))}$)
  - Pearson correlation for metric ratings
  - Spearman’s ρ (Pearson correlation for ranks) or Kendall’s τ (measure of concordant/discordant pairs) for rank-order preferences
  - If Multiple R value > 0.95, “additivity” assumption OK
- Use **validation** or **holdout** stimuli to avoid “over-fitting”
- For aggregate assessment, use holdout sample of respondents

33

Conjoint Decision Framework

1. Define objectives
2. Develop research design
3. Evaluate assumptions
4. Estimate model and assess fit
5. **Interpret results**
6. Validate results

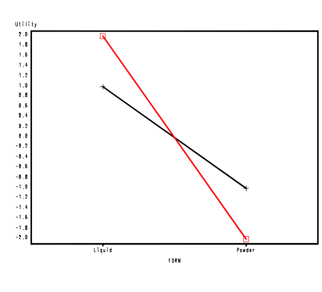
34

Interpret Results

- Interpretation possible at both individual and aggregate levels
- Consider part-worth estimates for each factor:
  - practical relevance
  - correspondence to theory
  - plot part-worths (y-axis) vs. levels (x-axis) to identify patterns: connect points with lines for each respondent or for aggregate results
  - if population exhibits homogeneous behavior, aggregate results can predict market share
- Consider conditional relative importance (CRI) of factors

35

Plot Results, e.g Form



36

Conjoint Decision Framework

1. Define objectives
2. Develop research design
3. Evaluate assumptions
4. Estimate model and assess fit
5. Interpret results
6. **Validate results**

37

Validate Results

- Internally
  - use a pre-test study to confirm which composition rule (additive or interaction) is appropriate
  - use holdout stimuli to assess predictive accuracy individually
  - use holdout sample of respondents to assess predictive accuracy collectively
- Externally
  - does the analysis predict *actual* choices?
  - how representative is the sample of a population?

38

Managerial Conjoint Applications

- Group respondents with similar part-worths or conditional relative importance values into **segments**
- Use a **choice simulator** to predict market share for a stimulus (real or hypothetical)
  - either assume respondents choose stimulus with highest predicted utility (**maximum utility** model)
  - or predict market share using a purchase probability measure (**Bradford-Terry-Luce** or **logit** models)
- Combine cost of each product with estimated market share and sales volume to predict **profitability**

39

Self-Explicated Conjoint

- Respondent directly rates desirability of each attribute level and relative attribute importance
  - (+) more manageable than traditional conjoint for 10+ attributes
  - (–) respondent accuracy often doubtful
  - (–) inter-attribute correlation more problematic than in traditional conjoint
  - (–) lack of realism since respondent does not perform a choice task

40

Adaptive (or Hybrid) Conjoint

- Self-explicated ratings used to create a manageable subset of stimuli, then traditional conjoint used with respondents rating different sets of stimuli
  - (+) more manageable than traditional conjoint for 10+ attributes
  - (+) predictive ability comparable to traditional
  - (–) requires specialized software, e.g. Sawtooth Software's Adaptive Conjoint Analysis (see `http://www.sawtoothsoftware.com`)

41

Choice-Based Conjoint

- Respondent chooses a full-profile stimulus from each of a number of **choice sets**
  - (+) better represents actual process of selecting a product from a set of competing ones
  - (+) a "no-choice" option can be incorporated
  - (–) cannot estimate a separate model for each respondent
  - (–) requires specialized software, e.g. Sawtooth Software's Choice-Based Conjoint

42

Choice-Based Conjoint (continued)

- Example: see cell-phone example in book, but note typo in Table 7.7: 6th row, 4th column (stimulus 6, factor TWC) should be 1 not 0
- Models constraint-based decision making well
- Often used in conjunction with other conjoint methods
- Allows closely comparable alternatives to be assessed
- Choice sets can be created to fit unique preferences
- Estimation technique based on *multinomial logit*
  - "independence of irrelevant alternatives" problem can be addressed with *random-coefficients models* or *hierarchical Bayes analysis*

43

Illustration of Conjoint Analysis

- See p 429-436 in the text-book
- See Excel spreadsheets on website:
  - **`hatco2raw.xls`** contains raw data which can be imported into SAS and analyzed using the Market Research application
  - **`hatco2res.xls`** contains results for 5 of the respondents

44