

Hierarchical Bayesian Methods in Psychology of Consumer Behavior

(Quantitative Studies in Consumer Behavior)

MEETING TIME

We will be meeting once a week to discuss ongoing research and relevant papers:

Monday 2.00-3.30pm CH212

TENTATIVE LIST

Week 1 (Sept 27)

Shiling Ruan, (Statistics) "Experiences and unsolved market research problems encountered this summer at Merkle" (information about her summer internship)

Week 2 (Oct 4)

Qing Liu (Statistics). "Experimental design for conjoint studies" (a survey of papers)

week 3 (Oct 11)

a). Greg Allenby (Marketing) and Steve MacEachern (Statistics).  
A competition in modeling!

b) Cheryl LeSaint (Statistics)

'Fitting Response Time Models  
by Adaptive Importance Sampling''.

week 4 (Oct 18)

Sandeep Rao and Greg Allenby (Marketing)

week 5 (Oct 25)

Longjuan Liang and Michael Browne (Psychology)

" An alternative formulation of Q-factor analysis with potential applications in consumer base segmentation."

week 6 (Nov 1)

Ed Merkle (Psychology). 'Modeling confidence with the Poisson race model''.

week 7 (Nov 8)  
Thomas Otter, Greg Allenby (Marketing) and Trish Van Zandt  
(Psychology).  
‘‘Response time in conjoint analysis’’.  
\*\*\* Abstract below\*\*\*

week 8 (Nov 15)  
Shiling Ruan (Statistics)  
\*\*\* Abstract below\*\*\*

week 9 (Nov 22)  
Qingzhao Yu (Statistics)  
\*\*\* Abstract below\*\*\*

week 10 (Nov 29) (AD absent)  
Discussion of results of the competition.  
Plans for next term

\*\*\*\*\*ABSTRACTS \*\*\*\*\*8

week 7 (Nov 8)

An Integrated Model of Choice and Response Time  
with Applications to Conjoint Analysis

Thomas Otter, Greg Allenby, Trish van Zandt

With the proliferation of computer and web-based interviewing tools, process data such as response time arises as a natural by-product of many conjoint applications. Despite the immediate availability of this data, surprisingly few attempts to integrate response time into choice models have been made. Available models that take response time into account treat the observed response times as another explanatory variable and conduct conditional inference on the probability of choice,  $\pi(y | X, t, \theta)$  (see Haijjer, Kamakura, Wedel 2000), where  $y$  indicate the choice,  $t$  represents time,  $X$  is a set of exogenous covariates, and  $\theta$  is a parameter vector. Moreover, existing approaches that rely on linear models cannot easily use response times to improve inference about important attribute-levels. Intuitively, one would expect that quick response

times correspond to easy choices where one of the choice alternatives is clearly superior, and longer response times to be present when the alternatives are less attractive to the respondent. Our model integrates choice data, which indicates a relative ranking of the choice alternatives, with response times that point to the magnitude that the best alternative is preferred.

We investigate use of a model that treats choice and time as dependent variables of an underlying psychological process,  $\pi(y, t | X, \theta)$ . Product profiles in a choice set induce a signal generating process in the respondent's mind, where more attractive profiles are assumed to generate signals at a faster rate. The profile that first generates a cumulative number of signals equal to a consumer-specific threshold is chosen. Thus the underlying psychological process links the conditional choice probability  $\pi(y | X, t, \theta)$  to the marginal density of response time  $\pi(t | \theta)$  via some parameter vector  $\theta$  that needs to be estimated. In the most basic form of the model,  $\theta$  is comprised of the individual part-worths and the individual thresholds. Moreover, we show how to obtain the marginal choice probabilities  $\pi(y | X, \theta) = \int_{\mathbb{R}^+} \pi(y, t | X, \theta) dt$  which can be used in choice simulators to explore the effects of changes in product formulation.

Extensions that take into account learning effects, no-choice options, and the effect of utility balance will be discussed. Estimation is carried out fully Bayesian using MCMC methods. The MATLAB code is available from the authors.

## References

- Haaïjer, Rinus, Wagner Kamakura, and Michel Wedel (2000), Response Latencies in the Analysis of Conjoint Experiments, *Journal of Marketing Research*, 37 (August), 376-382
- Smith, Philip L. and Trisha van Zandt (2000), Time-dependent Poisson counter models of response latency in simple judgment, *British Journal of Mathematical and Statistical Psychology*, 53, 293-315

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Week 8

Shiling Ruan (Statistics)

Today I am going to give an informal discussion of literature review on the partial profile conjoint experiment, including brief introduction of the design and analysis method. A learn-based approach by E.T. Bradlow, Y.Hu and T. H. is introduced. There is also a brief introduction of MNL models.

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Week 9

Qingzhao Yu (Statistics)

I will present a method of using splitting data to build models. I will use Kentucky Derby data as an example to show how this method works and compare the result with the automatically selected model.