Customer Heterogeneity in Purchasing Habit of Variety Seeking Based on Hierarchical Bayesian Model

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Agenda

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3. **Analyzed model**

   a mixture normal-multinomial logit model in a hierarchical Bayesian framework
4. **Result1** ＜latent class VS hierarchical Bayesian ＞
5. **Result2** ＜Bawa model Vs proposed model ＞
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Research Review

- A product choice behavior is called as **"inertia"** if a customer chooses the same product as the previously purchased and **"variety seeking"** if it is a different product from the previous one. (Givon(1984), Lattin et al. (1985))
- These kinds of behaviors are frequently observed in the product category of **"low involvement"** (Dick and Basu (1994), Peter and Olson (1999)).

Research Review

- Consumers tend to purchase a "low involvement" product such as beverage or cake based solely on experience, inertia, or atmosphere. In addition to "inertia" or "variety seeking", **Bawa (1990)** proposed a model for segmentation purposes.
- It has an additional segment of **"hybrid"** customer, of which purchasing tendency changes from **"inertia"** to **"variety seeking"** or vice versa.

Illustration of purchase history by customer type

- Inertia : AAAAAAAAA
- Variety seeking : ABCDCFGAFE
- Hybrid : AAABBBCCC

Research Objective

Research Objective

1. To express product choice behavior in terms of **Inertia** / **Variety Seeking** toward product attribute by customer.
2. To explore effective marketing strategy.
3. To compare results with those by Latent class model.

model

- a mixture normal-multinomial logit model in a hierarchical Bayesian framework

Analyzed Data

Analyzed store：

5 super market stores around Tokyo

Analysis period： 2000.1.1～2001.5.31

Analysis subcategory：

Japanese tea・Chinese tea

①extract 7000 customers by **random sampling** from all of 13238panels.

Analyzed Data

< latent class model vs hierarchical Bayesian model >

② screening

A. exclude **simultaneous** purchase opportunities

B. include customers who purchased **once or more** in 3 periods （2000.1.1～6.30; 7.1～12.31; 2001.1.1～5.31）

C. include customers with **24 times or more purchases** (**only heavy users**)

D. exclude customers with **once or less brand switching**

E. exclude customers with **3 times or less** purchases on **hold-out samples** (in the third period)

Multinomial Logit Model (MNL)

U_{ijt} : utility of product j for customer i in period t

v_{ijt} : fixed utility

ε_{ijt}: random utility (double exponential distribution)

X_{ijt} : explanatory variable of product j for customer i in period t

β_i : parameter for customer i

$$U_{ijt} = v_{ijt} + \varepsilon_{ijt} \qquad v_{ijt} = X_{ijt}\beta_i$$

Explanatory Variable

Inertia / Variety seeking

- repeat purchasing times r of a brand and r^2

  (Bawa(1990,1995), Sakamaki(2005))

  let the latest brand switching time as period **S**

$$r_{itj} = \sum_{t=s}^{t-1} y_{itj} \qquad Z = -\frac{\exp(\text{purchasing interval} - a)}{1+\exp(\text{purchasing interval} - a)} + 1$$

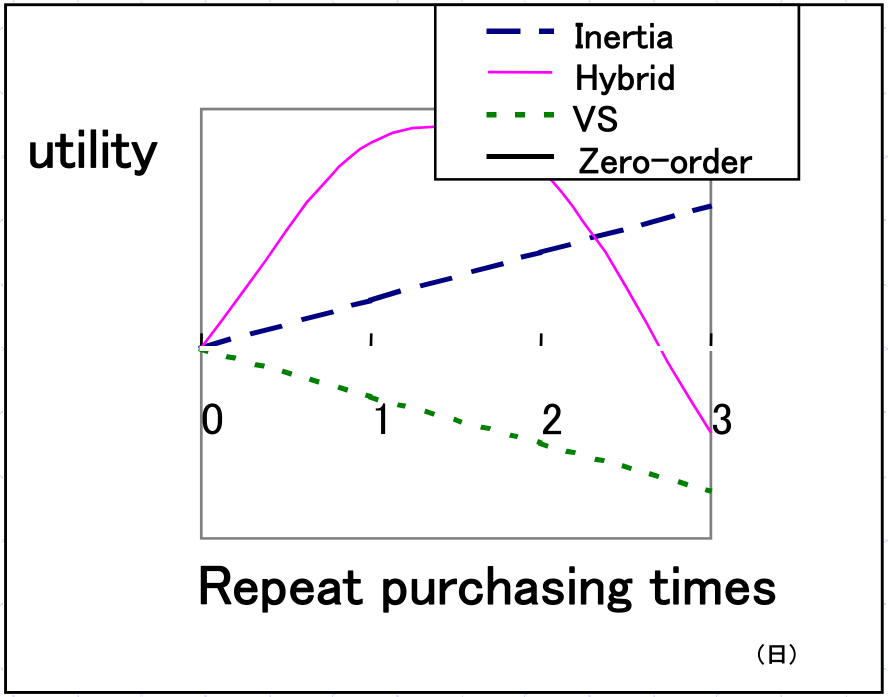
- r × Z and (r^2) × Z

Promotion variable(Seetharamann et al(1998),Kawabata(2004))

- **discount rate**; **displays**; **flyers** for each subcategories of Japanese or Chinese tea
- **Constant term**

Explanatory Variable
<repeat purchasing times **r** & **r^2** >

$$v_{1ijt} = \beta_{i1} r_{ijt} + \beta_{i2} r_{ijt}^{2}$$



v_{1ijt} : fixed utility of inertia / varietysee king for customer i in period t brand j

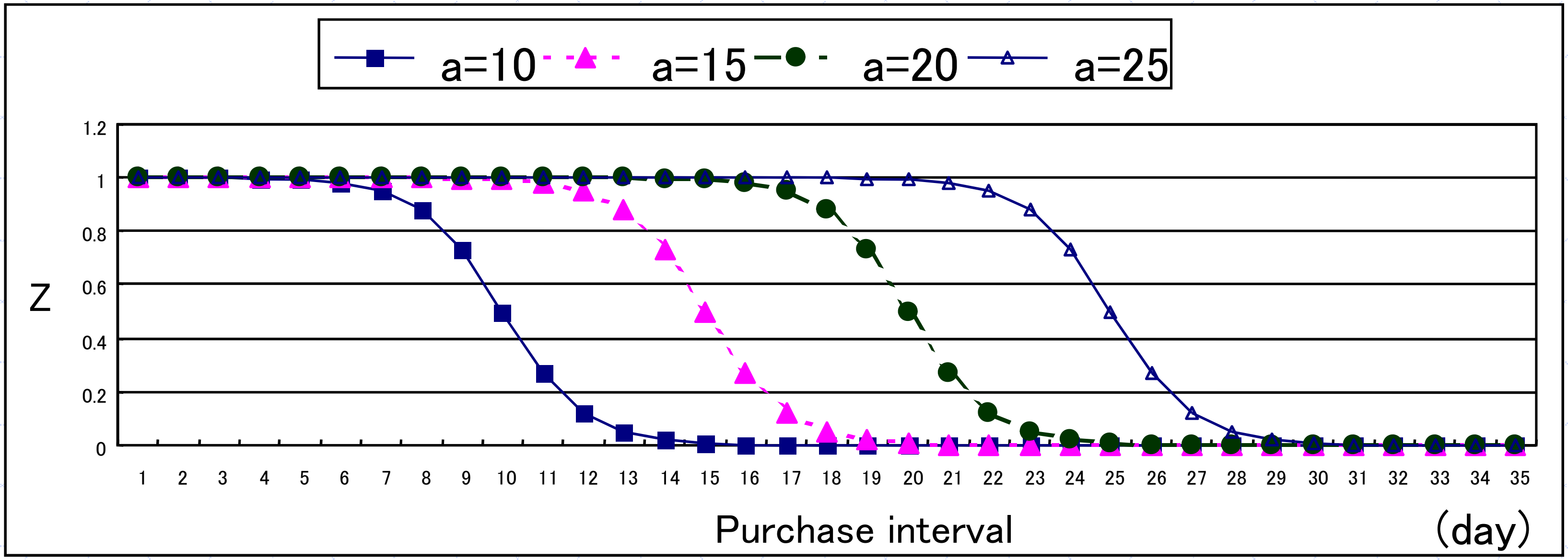
r_{ijt}: repeat purchasing timesfor customer i in period t brand j

r_{ijt}^{2}: the second power of r_{ijt}

β_{i1}, β_{i2}: parameters

Explanatory Variable
<purchasing interval>

$$Z = -\frac{\exp(\text{purchasing interval} - a)}{1 + \exp(\text{purchasing interval} - a)} + 1$$



Latent class model

π_s: probability of segemnt s

$p_{it}(j \mid \alpha_s)$: choice probability of product j beloging segemnt s

$$p_{it}(j \mid \pi, \beta) = \sum_{s=1}^{S} p_{it}(j \mid \beta_s)\pi_s$$

$$where \quad \sum_{s=1}^{S} \pi_s = 1 \quad (\pi_s \geq 0, \forall s = 1, \cdots, S),$$

$$\pi = [\pi_1, \cdots, \pi_s], \beta = [\beta_1, \cdots, \beta_s]$$

A mixture normal-multinomial logit model in a hierarchical Bayesian framework (Rossi et al.(2005))

$$y_{ijt} \sim MNL\left(P_{it}\left(X_{ijt}, \beta_i\right)\right)$$

(MNL:multinomial logit model)

$$\beta_i \sim N(\mu_{ind_i}, \Sigma_{ind_i})$$

$$\mu_k \sim N\left(\bar{\mu}, \Sigma_k \otimes a_\mu^{-1}\right)$$

$$\Sigma_k \sim IW\left(v, V\right)$$

$$ind_i \sim Multinomial_K(pvec)$$

$$pvec \sim Dirichelet(\alpha)$$

$P_{it}(X_{ijt}, \beta_i)$: choice probability of product j for customer i in period t

X_{ijt} : explanatory variable of product j for customer i in period t

β_i : parameters for customer i

Parameter Distribution Estimation Methods& Information Criterion

- Parameter Distribution Estimation Methods
  - ・latent class model： Maximum Log-likelihood
  - ・hierarchical Bayesian model：MCMC method
- Information Criterion
  - ・AIC(Akaike)
  - ・BIC(Schwarz)
  - ・CAIC(Bozdogan)
  - ・DIC(Spiegelhalter et al., 2002)

The smaller value of information criterion, the better model.

Analysis Result 1

＜ latent class model: for heavy users of 63 panel ＞

-Determination of No. of Segments-

	AIC	BIC	CAIC
1segment	3892.91	3988.52	3988.52
2segment	3910.15	4106.97	4106.99
3segment	3925.08	4223.13	4223.16

- Hypothesis A（2 segments ）：VS・Inertia & Hybrid
- Hypothesis B（3 segments）：VS・Inertia・Hybrid

For 1 segment, the model was the best with the minimum value for all of Information Criterions

Analysis Result2

＜comparison of 3 models : for heavy users of 63 panel ＞
-hit rate & Information Criterion-

model	Log-L	DIC	Hit rate1	Hit rate2
Latent class model	------	------	0.749	0.624
H. Bayes model (1 normal dist.)	−958	5425	0.798	0.680
H. Bayes model (3 normal dist.)	−942	5333	0.811	0.734

- Two hierarchical Bayesian models that can estimate parameters for each customer are better than latent class model in terms of hit rate.

- a mixture normal (3 dist.)-multinomial logit model in a hierarchical Bayesian framework is selected as the best model for all of critera.

Analyzed Result3

<Bawa model vs proposed model:
for heavy users of 129 panel > -hit rate & DIC-

	Log-L	DIC	Likelihood	Hit rate1	Hit rate2
Bawa model	−2147	12251	−2210	0.856	0.713
Model A	−2151	12287	−2227	0.860	0.756
Model B	−2139	12223	−2206	0.863	0.750
Model C	−2145	12230	−2210	0.860	0.736

- Bawa model : no purchase interval considered
- Proposed model A : a=10
- Proposed model B : a=15
- Proposed model C : a=20

Proposed model B is the best model than Bawa model in terms of DIC and hit rate1.

Analysis Result4<model B>
-response to promotion for Japanese tea-

		j-discount	j-display	j-flyers	No. customers
Japanese tea	Inertia	1.55	−0.21	0.13	41
	VS	1.05	0.37	0.34	10
	Hybrid	1.14	−0.49	0.59	26
	Zero-order	3.79	0.08	0.21	52

- Zero-order: high response to discounts
- Inertia・ VS ・Hybrid：low response to discounts
- A strategy different from usual discounts for the customers of Variety Seekers are necessary!

Summary

- Latent class model

  No valid segmentation was possible.

- Hierarchical Bayesian Models

  ▪It is possible to estimate parameters for all customers.

  ▪It is possible to do the optimum promotion for each Hybrid customer.

  ▪For VS customers, it may be also necessary to consider brand choices of previous 2 purchases.

Future Research Topics

- Analysis on data on different shop type with different customer characteristics or on different usage scenes
- To vary the decreasing speed of tendency of Inertia or Variety seeking by customer accompanying with purchasing interval.

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Thank you for patience!