Route Choice Behavior Models by Considering Uncertainties

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1.INTRODUCTION

Uncertainties can be divided into two different types: One is randomness due to the non-deterministic nature of travel choice behavior problems and random utility models have been widely employed to deal with the uncertainty. The other is vagueness due to the poor knowledge and the lack of familiarity with network attributes and fuzzy reasoning models have been dealt with the vagueness of uncertainty. For modeling travel choice behaviors, researchers usually use one of the two modeling methodologies with an implicit assumption that travelers in their sample represent a homogeneous population. However, traveler's perceptions may differ at the individual level of familiarity with network attributes, it is called heterogeneity of sample data in this paper. Lotan and Koutshopoulos (1993) instanced that travelers can be divided into familiar and unfamiliar travelers with network attributes, and their choice behaviors can be modeled by using probability (randomness) and possibility distribution (vagueness), respectively. In addition, it is reasonable that both uncertainties exist simultaneously in sample data. Therefore, the heterogeneity in sample data has to be considered for travel choice behavior modeling.

2. LATENT CLASS CLUSTERING

Suppose that the probability density function of a random vector W has a finite mixture of k latent class distribution f_k, then $f(w;f)=\sum_{k=1}^{K} p_k \prod_{l=1}^{L} f_{kl}(w_{il};q_{kl})$. In this paper, we assume the k latent class distributions come from multivariate normal densities with unknown means $m_{1l},\ldots,m_{Kl}$ and variances $s_{1l}^2,\ldots s_{Kl}^2$ of the distribution f_{kl}. The complete-data log likelihood for f has the multinomial form

$$\log L_c(f)=\log\left(\prod_{i=1}^{I}\prod_{k=1}^{K}\left[p_k^{z_{ik}}\left\{\prod_{l=1}^{L} f_{kl}(w_{il};q_{kl})\right\}^{z_{ik}}\right]\right)$$

Keywords Latent class clustering, EM algorithm, Fuzzy Reasoning Model and Uncertainty

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To solve a maximization problem, EM algorithm requires the iterative Expectation (E) and Maximization (M) of the complete log likelihood.

<E-STEP> $$E_{f^t}(z_{ik}\backslash w)=z_{ik}^{(t)}=\frac{p_k^{(t)}\prod_{l=1}^{L} f_{kl}(w_{il};q_{kl}^{(t)})}{\sum_{k=1}^{K}p_k^{(t)}\prod_{l=1}^{L} f_{kl}(w_{il};q_{kl}^{(t)})}$$

<M-STEP> $$p_k^{(t+1)}=\sum_{i=1}^{I} z_{ik}^{(t)}/I,\quad m_k^{(t+1)}=\sum z_{ik}^{(t)} w_{il}\Big/\sum_{i=1}^{I} z_{ik}^{(t)},$$
$$s_k^{(t+1)}=\sum_{i=1}^{I} z_{ik}^{(t)}(w_{il}-m_k^{(t+1)})^2\Big/\sum_{i=1}^{I} z_{ik}^{(t)}.$$

The number of latent classes is decided based on Bayesian Information Criterion.

3. FUZZY REASONING MODEL FRAMEWORK

For fuzzy reasoning models, nine fuzzy inference rules are established as follows:

Rule 1) If HTT is S and LTT is S then P is M

: : : :

Rule 9) If HTT is L and LTT is L then P is M

Note) HTT: Highway travel time, LTT: Local way travel time.

The initial membership functions of the antecedent term and the consequent term of the fuzzy rules are illustrated in Figure 1 and 2, respectively.

Antecedent term: Travel time={S,M,L}={Short, Moderate, Long travel time}

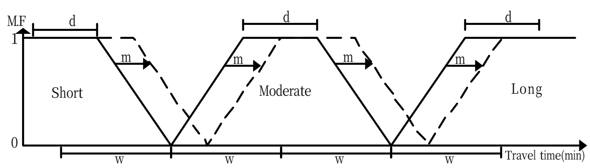

Figure 1. Membership Functions of Travel Time

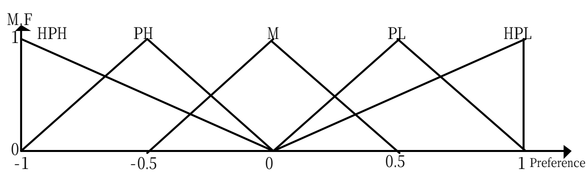

Figure 2. Membership Functions of Preference

Consequent term: Preference={HPH,PH,M,PL,HPL} ={High preference of highway, Preference of highway, Middle preference, Preference of local way, High preference of local way}. In this paper, the optimal fuzzy membership functions are estimated by trial-and-error method in that three indices (d, m, w) are changed from initial membership function ranges by one minute at each iteration step and Min-Max-Centroid of area method is employed as a fuzzy inference process.

4.EMPIRICAL STUDY

The survey was conducted at two intercity roads, Honnam highway and No.22 local way among driving commuters with an objective to examine ordinary perception levels of travel time on the alternative routes and ordinary choice route. To estimate the latent class, we first classify the ordinary perception levels of travel time by using the absolute value of difference of travel time levels, shown in Table 1.

Table 1. Classification of Travel Time Perceptions

Absolute (Highway – Local way travel time) (minutes)					
(0~5): 1	(6~10):2	(11~15):3	(16~20):4	(21~25):5	(25<):6

Table 2 shows the BIC values of latent class clustering. For analyzing we choose the clustering result of 2-latent classes that have the lowest BIC value.

Table 2. Comparison of BIC Values

Num. Of Class	BIC	Num. Of Class	BIC
1-Latent class	3081.9	3-Latent classes	2808.2
2-Latent classes	2614.7	4-Latent classes	7732.9

Table 3. The Result of 2-Latent Classes Clustering

Latent class	Latent class 1(49.2%)		Latent class 2(50.8%)	
Variables	m_1	s_1	m_2	s_2
Short	3.143	1.512	1.595	0.525
Moderate	3.179	1.451	1.449	0.523
Long	3.930	1.629	1.569	0.527
	Randomness class		Vagueness class	

The result shown in Table 3 represents that the drivers of latent class 1 have more distinct perception levels of travel time of alternative routes than those of the drivers of latent class 2. Therefore, it is assumed that the latent class 1 and the latent class 2 correspond to the randomness class and the vagueness class, respectively. Table 4 contains the estimated results of random utility models based on each latent class and whole data. For the travel time variable of random utility models, we employed the average value of three ordinary perception levels of travel time. Moreover, age and willingness to switch by traffic situations are added for modeling.

Table 4. Estimation Results of Route Choice Models

Random Utility Models			
	Whole data	Latent class 1	Latent class 2
Variables	Coefficient (t-value)		
Travel time	-0.044 (-4.32)	-0.045 (-3.95)	-0.055 (-2.01)
Age	-0.024(-2.59)	-0.021(-1.51)	-0.025(-1.97)
Switch	0.640(2.48)	0.714(1.77)	0.570(1.62)
# Of sample	284	139	145
$L(o)-L(b)$	-16.414	-11.816	-5.599
ρ^2	0.083	0.123	0.056
Adjusted ρ^2	0.068	0.092	0.026
%oF right	64.79%	66.91%	62.76%
Fuzzy Reasoning Models			
Variables	Short, Moderate and Long travel time		
%oF right	62.676%	61.871%	63.448%

The best estimation result in random utility models is outputted in the latent class 1 (randomness class), while the worst result is in the latent class 2 (vagueness class). Moreover, the coefficient value of willingness to switch variable shows that respondents of the randomness class are more sensitive to traffic situations than respondents of the vagueness class. The opposite estimation results with random utility models are outputted in fuzzy reasoning models, that is, the estimation result of the latent class 2 is better than that of the latent class 1. These results present that the vagueness of uncertainty is well considered in the fuzzy reasoning model, while the random utility model is applicable to treat the randomness of uncertainty. Accordingly, all results in Table 4 support that the two methodologies can deal the uncertainties with a certain amount of reliability, but the accuracy of route choice behavior model can be reduced, if the heterogeneity of sample data is not considered for modeling.

5.Colclusions

The purposes of this paper are classifying the heterogeneity of sample data into some homogeneous latent classes and estimating the random utility and fuzzy reasoning models with the latent classes. In addition, if the uncertainties are estimated without considering the heterogeneity of data, then the accuracy of route choice behavior model is deteriorated. The result also support the necessity of a new model combining both two models