Dynamic evacuation location choice model with risk-responsive survival of alternatives

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1 INTRODUCTION

Location choice in disaster situation follows a dynamic mechanism, where agents consider expected utilities of each location in their choices. However, when the future risks rise, alternatives may easily drop out from agents' choice set. Manski (1977) proposed a semi-compensatory framework which assumes alternatives are reduced to a feasible choice set, and a choice is made from the reduced choice set. Models for choice set formation applying Manski's framework exist in static context, for example in Kaplan *et al.* (2011).

Survival probability is a concept addressed by Rust (2016), which captures the probability that the problem will continue. The concept aligns with the aforementioned mechanism of location choice during a disaster. Utilities brought by a risky candidate which may not survive as a choice must be reduced when they are perceived.

We propose a dynamic location choice model in a heavy rain disaster, which considers realistic choice set formation according to risk. Since choice set formation is probabilistic, dropping out of risky candidates are incorporated as the probability of candidate's survival. Our proposed models are applied to real evacuation behavior data.

2 METHODOLOGY

2.1 Dynamic evacuation location choice model

We formulate a dynamic evacuation location choice model using a time-structured network, based on the discounted recursive logit model presented by Oyama & Hato (2017). The instant utility of state s_{t+1} from state s_t is expressed as:

$$u(s_{t+1}|s_t) = \rho(s_{t+1}|s_t)\ v(s_{t+1}|s_t) + \varepsilon_{s_t,s_{t+1}}, \tag{1}$$

where $\rho(s_{t+1}|s_t)$ is the probability that s_{t+1} survives as a choice of s_t, $v(s_{t+1}|s_t)$ is the utility of transition from s_t to s_{t+1}, and $\varepsilon_{s_t,s_{t+1}}$ is the error term. The expected utility $V(s_t)$ at state s_t is expressed using a discount factor β:

$$V(s_t) = E\left[\max_{s_{t+1}\in C(s_t)} \left[\rho(s_{t+1}|s_t)\{v(s_{t+1}|s_t) + \beta V(s_{t+1})\} + \varepsilon_{s_t,s_{t+1}}\right]\right], \tag{2}$$

where $C(s_t)$ indicates all alternatives from state s_t, from which a realistic choice set is formed. Assuming $\varepsilon_{s_t,s_{t+1}}$ are i.i.d. extreme value type I error terms, Eq.(2) is reformulated as a logsum:

$$V(s_t) = \begin{cases} \log \sum_{s_{t+1} \in C(s_t)} \exp \rho(s_{t+1}|s_t)\{v(s_{t+1}|s_t) + \beta V(s_{t+1})\} & s_t \neq s_T \\ 0 & s_t = s_T, \end{cases} \tag{3}$$

where T is the terminal time considered in the model. The proposed formulation is equivalent to a traditional dynamic model when $\rho = 1$ for all alternatives.

2.2 Example

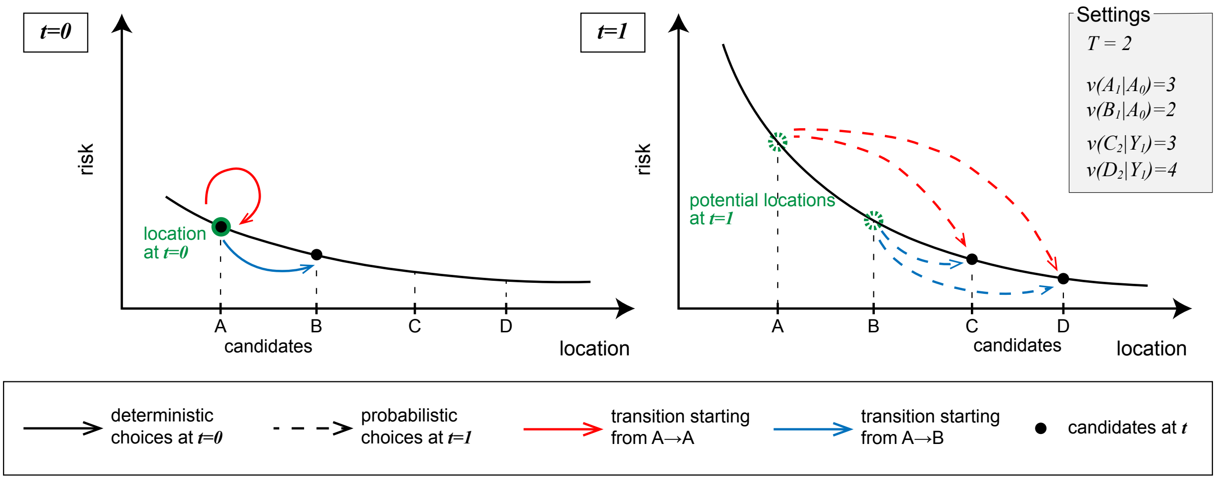

Figure 1 – *Example Network*

To describe what is expressed by incorporating probabilistic choice set formation, we present an example with a simple network shown in Figure 1. Consider a location choice problem at time $t = 0$ in A. Let $U(Y_{t+1}|X_t)$ denote the utility of transition from X to Y at time t, expressed as:

$$U(Y_t|X_t) = \rho(Y_{t+1}|X_t)\{v(Y_{t+1}|X_t) + \beta V(Y_{t+1})\}. \tag{4}$$

The utilities are as shown in Figure 1 and the discount factor $\beta = 0.9$. At $t = 0$, alternatives A and B are considered as next locations. The risk rises at $t = 1$ eliminating A and B, making the safer locations C and D next candidates. A trip to C/D from A is however difficult due to route risk. Moving to B_1 in advance would make them more accessible. Table 1 shows the probabilities of candidates' survival and the utilities of transition to A_1 and B_1, reflecting such conditions.

Table 1 – *Difference in preference when risk-responsive survival probability is considered*

	Y	Z	$\rho(Z\|Y)$	$U(Y\|A_0)$
Traditional	A_1	C_2	1	6.88
		D_2	1	
	B_1	C_2	1	5.88
		D_2	1	
Proposed	A_1	C_2	0.4	4.54
		D_2	0.2	
	B_1	C_2	0.8	4.78
		D_2	0.6	

In the traditional model, A_1 with higher instant utility is more preferred, where as in the proposed model, B_1 that broadens future choices are favored.

2.3 Model for choice set formation

To determine $\rho(s_{t+1}|s_t)$ exogenously, we propose a model for choice set formation with observed choice set, based on Kaplan *et al.* (2011). Two criteria are assumed: (i)Location Risk and (ii)Route Risk. As risk is an unobserved latent variable, both risk and threshold are structured. Threshold θ_{kqt} and risk R_{kt} of household q, time t, criterion k for an alternative is expressed:

$$\theta_{kqt} = \boldsymbol{\alpha}_k' \boldsymbol{Z}_{kqt} + \xi_{kqt}, \tag{5}$$

$$R_k = \boldsymbol{\beta}_k' \boldsymbol{G}_k + \sigma_{kq}, \tag{6}$$

where $\boldsymbol{\alpha}$,$\boldsymbol{\beta}$ are parameters to be estimated, Z is household characteristics or time-dependent rainfall, G is spatial characteristics of location or route, ξ and σ are random terms. When the risk exceeds its threshold, the alternative is considered risky and is eliminated from the choice set. Assuming the random term $\sigma - \xi$ are i.i.d. standard normally distributed, the probability that an alternative will survive in criterion k is:

$$P(R_{kt} < \theta_{kqt}) = P(\sigma_{kt} - \xi_{kqt} < \theta_{kqt} - R_k) = \Phi\left(\theta_{kqt} - R_k\right), \tag{7}$$

where Φ is the cumulative distribution function of the standard normal distribution. An alternative remains in the choice set when it is rejected by neither of the criteria. Thus the probability:

$$\rho(s_{t+1}|s_t) = \prod_{k \in \{\text{location,route}\}} \Phi\left(\theta_{kqt}(s_{t+1}|s_t) - R_k(s_{t+1}|s_t)\right). \tag{8}$$

2.4 Alternatives enumeration algorithm

Since full enumeration of alternatives is computationally demanding, we adopt an enumeration algorithm to efficiently sample alternatives using the risk perception modeled in the previous subsection 2.3. Each household will choose one node $j_{i,k}$ as the corresponding destination of $x_{i,k}$, the k-th alternative for origin node i. $x_{i,k}$ holds multiple nodes that have similar spatial characteristics as seen from i. Below is the enumeration algorithm for a household:

1. Pick an origin node i and an alternative $x_{i,k}$
2. Extract $J_{i,k}$, the set of nodes that are included in $x_{i,k}$
3. Calculate the sampling probability for each node j in the set $J_{i,k}$
4. Generate a random number of uniform distribution, and choose node $j_{i,k}$
5. Repeat steps for all k and i

The sampling probability $P_{\text{sample},i,k}(j)$ in step 3 is normalized by $\rho(s_{t+1}|s_t)$:

$$P_{\text{sample},i,k}(j) = \frac{\rho(j|i)}{\sum_{j \in J_{i,k}} \rho(j|i)}. \tag{9}$$

3 RESULTS

3.1 Evacuation behaviors in the 2018 heavy rain disaster

Kure, Hiroshima was one of the hardest hit in the 2018 heavy rain disaster in western Japan. The heavy rain in early July caused floods and landslides in Hiroshima prefecture, which ranked first in its casualties of 150. Kure had the highest number in the prefecture with 29 deaths.

A survey was conducted among the residents of Kure about their evacuation behaviors and household characteristics. Their choice sets of evacuation location were included in the survey. The results revealed many stayed in their houses instead of sheltering in evacuation sites, and those who evacuated often left their homes when the rainfall was hardest.

The proposed model is implemented on survey data of Tenno, Kure. A zonal network that takes into account spatial barriers such as rivers and elevation difference is used. Zones are smaller when closer to the place of stay, and larger when they are farther away.

3.2 Parameter estimation

Estimation results of the choice set formation model indicated that more the rainfall and higher the elevation of origin, lower the threshold. A lower threshold means small risks will be perceived risky. Higher the elevation of destination and closer the destination from river, higher the location risk will be. Crossing the river and a trip of long distance were considered a route risk. The results align with the fact that damage was caused by flood and landslides.

Table 2 presents estimation results of two dynamic location choice models. Model 1 assumes deterministic choice sets and model 2 is the proposed model. All attributes were significant and had the expected signs. Staying in the same location brings positive utility and staying home was better than staying elsewhere. A transition to relatives' or friends' houses were positive too, though smaller than staying. Evacuation sites with larger capacity were more likely to be chosen, and a long distance was avoided. The two models compared, distance is more important in model 1, because unrealistic options are not dropped out. A likelihood ratio test of the two models proved that the proposed model had better predictive power, where the improvement was significant at 1%, shedding light on the significance of considering choice set formation.

Table 2 – *Estimation result: Dynamic location choice*

	1. Traditional		2. Proposed	
Attributes	Param.	t-Stat.	Param.	t-Stat.
Stay: home[a]	2.47	3.10**	3.08	3.72**
Stay: not home[a]	1.92	2.33*	2.67	2.98**
Not stay: relatives/friends[a]	1.52	3.48**	1.67	3.75**
Capacity of evacuation shelter(persons, ln/10)	0.38	2.14*	0.26	1.70†
Distance: owns car (m, ln)	-0.37	-3.36**	-0.23	-1.93†
Distance: no car (m, ln)	-0.40	-3.50**	-0.20	-1.65†
Discount Factor	0.74	9.20**	0.82	8.10**
Observations	1651		1651	
LL(0)	-2859.91		-2069.44	
LL(C)[b]	-312.55		-283.06	
Final LL	-248.17		-229.78	

*significant at 5%, **significant at 1%
[a]Included as a dummy variable
[b]A model with only a stay-dummy, discount factor is fixed to estimated value

4 DISCUSSION

Extending the works of Rust (2016) and Kaplan *et al.* (2011), we proposed a dynamic evacuation location choice model that incorporates choice set formation by introducing the ρ, the probability of evacuation location candidate's survival. Our simple example demonstrated the update in choice preference when ρ is considered. We collected actual evacuation data that surveys required components in our proposed model, such as households' choice sets, which is rarely surveyed. Estimation results proved that our methodology is superior to traditional models, which does not consider choice set formation.

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