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Junji Urata (✉ urata@bin.t.u-tokyo.ac.jp)  
University of Tokyo

Muhammad Zeeshan  
University of Tokyo

Babar Abbasi  
Meridian Quality Management Professionals

Eiji Hato  
University of Tokyo

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A practical approach to sample destination alternatives using machine leaning technique for applying dynamic activity-based travel demand model

Junji Urata¹ *, Muhammad Zeeshan¹, Babar Abbasi², Eiji Hato¹

* corresponding author

1 Department of Civil Engineering, the University of Tokyo, Tokyo, Japan
2 Meridian Quality Management Professionals, Dammam, Saudi Arabia

ABSTRACT

This paper focuses on sequential and forward-looking behavior in destination choices of full-day. We can model the forward-looking behavior in the activity chain using a β-scaled recursive logit model that cannot calculate future utility if the number of destination candidates is too large. Our primary objective is to construct a practical approach to sample destination alternatives. We propose a machine learning-based (ML) sampling approach by applying McFadden correction for choice set limitation to a β-scaled recursive logit model. Our supervised/unsupervised ML models are constructed using the activity history and enumerate among realistic alternatives considering the time-space prism constraint. We propose two sampling protocols: the supervised approach that samples using the decision tree rule constructed by observed choices by time and space; the unsupervised approach that samples from the constructed clusters using features of destinations. Our numerical test showed the estimability under the destination choice set by prism restriction and the proposed sampling. Our empirical case study using actual behavior data observed by smartphone-based GPS validated that our approaches improve the estimation stability of the time discount parameter. Our rule-based sampling protocol increased demand predictability compared to a simple random sampling protocol. The proposed method is practical because we can train the ML models using only observation data.

Keywords: Destination choice, Activity-based travel demand, Recursive logit model, Machine learning

1. Introduction

Progressive traffic growth on the transportation networks has brought urban planners to consider more sophisticated demand forecasting tools for traffic management and the formulation of acceptable transportation policies. The underlying theory of such tools is to model the decision-making process of tourists and its application to travel demand forecasting. Within the conventional planning framework, travel demand forecasting has been dominated by a modeling approach that is referred to as traditional four-step modeling (McNally (2007)). The traditional four-step modeling integrates sub-group models: trip generation, trip distribution, modal split, and route assignment. Another traditional approach for demand forecasting is Origin-Destination (OD) matrix estimation, which is a reverse process of estimation in which the OD matrix is retrieved from the traffic count data and some preliminary information such as historical or target OD matrix. The early work in this context includes the estimation using entropy maximization principles (Van Zuylen & Willumsen (1980)), least-square estimation (Cascetta (1984) and Bell (1991)), Bayesian inference approach (Maher (1983)), and maximum likelihood estimation (Spiess (1987)). It is helpful in that it can be predicted by connecting the information of individual observations. However, these traditional aggregated approaches have been criticized in literature due to a lack of behavioral mechanisms. Disaggregate models, a destination choice model, can include multiple variables that affect individual behavior. In addition, they can evaluate policy-sensitive variables flexibly. Recently, the destination choice model has become increasingly popular for demand forecasting (Zhu and Ye, 2018; Clifton et al., 2016; Yang et al., 2010; Bekhor and Prashker, 2008; Bhat and Guo, 2004). From collecting behavioral data, prevailing technologies make it easy to
collect spatiotemporal data with high accuracy. In these two decades, mobile sensors equipped with a global positioning system (GPS) facilitate to get real-time observations of travel behavior, such as probe person/vehicle technology. Using the probe technology, we can observe the path of the travelers together with the purpose and mode used for traveling in space as well as time dimensions.

Travel demand forecasting models have evolved from integrated trip-based models through tour-based models to activity-based models in the last few decades. The motivation behind activity-based modeling is that the decision-makers travel to participate in different activities by considering the entire day or more extended activity schedule and some spatial-temporal constraints. The activity-based models can be broadly classified into two main components: activity agenda and activity scheduling (Habib (2009)). An activity agenda represents a sequence of different activity episodes scheduled in a specific time span with activity type and specific attributes such as duration, mode, and destination. The second component represents when a particular activity episode is scheduled in the activity agenda. Unification of these two components is necessary to capture the trade-off involved in time allocation decisions. The modeling approaches in the development of activity-based models can be distinguished as a) Constraint-based models, b) Computational process models, and c) Random utility maximization models (Rasouli & Timmermans (2014)). The first approach was more oriented to checking the feasible activity program in specific time-space constraints rather than predicting the activity or travel patterns. The second computational process model generally focuses on the activity scheduling process and considers the generation of activity episodes and their attributes as exogenous variables. Subsequently, travel patterns are assumed to be arising from the activity scheduling process. The early work in schedule models includes the STARCHILD (Simulation of travel/ Activity responses to complex household interactive logistic decisions) model system (Recker et al. (1986a), Recker et al. (1986b)). The key focus of the STARCHILD model was a generation of activity patterns only, lacking in defining attributes of activity episodes and their interdependency. ALBATROSS (a learning-based transportation-oriented simulation system) is an advanced and comprehensive activity-based traveling demand model system (Arentze et al. (2000)). This model was sequential, and for each sequential choice stage, the heuristic rule determines the following action. This approach, however, lacks in incorporating future utilities of time. In the third random utility maximization-based model, Bowman and Ben-Akiva (2000) developed a nested logit structure that treats the tours as sequences of activities conditioned on their importance to the decision-maker. In this method, the secondary tours and subsequent activities are independent, possibly lacking in the establishment of sequential interdependency among activities. In addition, the duration and departure time model has been combined with the tour model and not integrated into the nested structure, lacking in the unification of two components of the activity model (Vovsha & Bradley (2004)). Habib (2011) proposed a discrete-continuous random utility maximization approach for weekend activity patterns. Destination and mode by maximizing the combined utility of all choices in the sequential continuous time frame when decision-makers choose an activity. This model was promising in defining the sequential decision-making process. However, only the following activity episodes are maximized rather than maximizing the full activity pattern. Other methods can also be found in the literature based on standard logit and nested logit form, but most models fail to fully represent the decision-maker choices and activity schedules in a cohesive framework.

People's behavioral choices of their destinations in their activity tours are sequential and forward-looking. The choice of current destination depends on the choices of future destinations in the activity chain as well. In order to capture this sequential and forward-looking choice behavior, a sequential choice model is needed. An approach by the recursive logit (RL) model (Fosgerau et al. (2013), Zimmermann & Freijinger (2020)) has the potential to describe activity patterns in a dynamic network as paths. The RL model and developed RL models are mainly applied to path choice problems (Mai et al. (2015), Mai (2016), Zimmermans et al. (2017), Oyama & Hato (2017), Ramos et al. (2020)). Zimmermann et al. (2018) and Vastberg et al. (2020) developed the RL model to illustrate people's activity in a day by regarding their activity-travel scheduling as they choose their behaviors in an activity-travel network. In the previous studies, the links in the dynamic network can describe the multi-dimensional choices such as choice of the activity, mode, time, and destinations. This model structure formulates all components of an agent's choices in an integrated fashion without explicit enumeration of activity patterns by introducing the stay-
travel network. In this setting, people can make simultaneous decisions in multiple dimensions, including the choice of departure time implicitly in the dynamic network. The decision-makers choose each link by maximizing the instantaneous utility, which depends on their previous actions, and the expected maximum downstream utility up to the last state. However, these RL model-based activity models are built under the presumption that the agents' decisions are always global by taking the time discount rate equals one. On the contrary, Habib (2011) has almost the same structure, but decisions are assumed to be myopic by considering that the time discount rate equals zero. It is typical to assume that the utilities of decisions at the time and in the future are not always equivalent. Oyama & Hato (2017) validated that the time discount in path choice is less than one under an even ordinary situation by their β-scaled RL (β–SRL) model. The developed model allows the inclusion of decision-making dynamics of the agents in the activity path by estimating the value of the time discount rate. The protocol of this work is the extension of the β–SRL model to destination choices which is a sub-model of activity-based travel demand modeling.

Constructing a destination choice model always has a problem with a large number of choice sets. People have candidates for destinations by depending on self-recognition when they choose. However, observers cannot know their correct choice set, and an easy method for estimation analysis is to set all areas as the candidates. RL-based activity model is affected by the number of destination candidates largely because the size of the dynamic network is proportional to the candidates' number squared. A sampling of locations is necessary to estimate and simulate the RL-based activity model for computational efficiency, as Vastberg et al. (2020) mentioned in their future work. The previous RL-based activity model (Zimmermann et al. (2018), Vastberg et al. (2020)) applies simple time-space constraints in mandatory activities and dependencies on previous modes and activities. Crompton & Ankomah (1993) and Decrop (2010) suggest that the choice set generation process is essential in developing the destination choice model. However, choice set generation studies for destination choice are less compared to those for route choice (see Prashker & Bekhor (2004) and Bovy (2009) for reviews). Probabilistic choice set models for destination choice, for example, Morikawa (1995), and Basar & Bhat (2004), do not work for our problem because the models do not eliminate destination candidates. In studies of destination choice with a developed choice set generation approaches, Auld & Mohammadian (2011) and Yoon et al. (2012) applied a time-space prism to generate the choice sets. Hassan et al. (2019) proposed a rule-based fuzzy logic model to sample a latent destination choice set. These approaches have applied to a static destination choice, not to a dynamic choice.

Moreover, the evolution of machine learning (ML) and deep learning (DL) methods, which can mine hidden data patterns, is becoming popular in this Big-Data era. Implementations of ML and DL methods are increasing in the field of transportation (Wang et al. (2019), Van Cranenburgh et al. (2021), for recent reviews), such as the identification of different travel modes (see Hillel et al. (2021), for a recent review) and prediction of travel times (see Varghese et al. (2020), for a recent review). Several studies combine traditional discrete choice models and ML/DL techniques to improve the goodness of fit of models (Wong et al. (2018), Tribby et al. (2017), Sifringer et al. (2020), Zhao et al. (2020)). To the best of our knowledge, few papers apply the ML model for a choice set generation. Yao & Bekhor (2020) form a choice set for a route choice model using a combination of ML approaches that include route characteristic clustering, random forest for feature selection, and data-driven sampling using the route's features.

This study proposes a Markovian choice-based sequential destination choice model, a well-known technique of activity-based travel demand modeling. It accounts for the sequential decision-making process of decision-makers in a discretized time-space network. To analyze sequential decision choices in the activity chain, we estimated the dynamic discounted recursive logit model, also called β–SRL model. The time discount rate β, which is estimated as a parameter, represents the forward-looking decision-making dynamics of decision-makers in the activity chain. However, destination choice on activity-base travel demand models often suffers from the curse of dimensionality due to a large choice set that either makes the model computationally inefficient or unstable. The destination choice set must be restricted to ensure the model's stability and efficiency. This study aims to propose methods of restricting the destination choice set using the ML technique. First, we introduce the concept of time-space prism constraints to restrict the destination zone accessibility at each time interval through inter-zonal distance. Second,
the ML-based methodologies are proposed to sample destination alternatives from the accessible zones defined by
time-space prism constraints. This research assists in predicting the time-dependent destination choices of travelers,
which eventually helps in predicting a dynamic origin-destination (OD) matrix. In addition, we train the ML model
for sampling of destination candidate using only observation data. Since it does not require additional survey, it is
easy to contribute to practical planning using simulation predictions.

This paper is organized as follows: Section 2 discusses the β-SRL model framework and overall research
methodology, including time-space constraints and machine-learning sampling protocols. In Section 3, simulation
analyses evaluate the proposed model estimability and performance. In Section 4, a case study assesses model
performance with real activity diary data. The last section presents the conclusions and discussion.

2. Methodology

2.1. Model Framework

This study introduces the Markovian choice-based sequential destination choice model for activity-based travel
demand forecasting. In order to analyze sequential destination choice behavior together with moving and staying
actions of decision-makers in a definite time, the β-scaled recursive logit model, originally developed in route choice
context (Oyama & Hato (2017)), needs to be extended to the time-space framework where the path represents the
sequence of destination choices. The framework of sequential destination choice analysis with destination choice set
generation is presented in Figure 1. We compose the destination choice set using a sampling method from a time-
space prism and then apply the generated choice set to the β-scaled recursive logit model.

Figure 1 Framework of sequential destination choice analysis with destination choice set generation problem
In the time-space sequential destinations choice network, first we define the set of zones $Q = \{q_1, q_2, \ldots, q_J\}$ and the choice stages $\mathcal{T} = \{0, 1, \ldots, T\}$ as a set of discretized time intervals. The grid can be presented as a direct connected graph $G = (S, A)$, where $S$ is a set of states and $A$ is a set of actions (moving/staying). More precisely, the set of states characterize the destinations chosen by the decision-makers at each discretized time interval, and the set of actions describes expected actions that can be made at each state, referred to as the choice stage, either staying at the same destination or moving to the next destination. For ease, dealing with states, the state can be defined as $S = \{s_0, s_1, \ldots, s_T\}$ and each state is a vector with entities $s_t(q_t, t)$; where $q_t \in Q$, $t \in \mathcal{T}$, and $s_t \in S$. Hence, the attributes and resultant utility of each action is defined by the state pair $(s_t, s_{t+1})$. Each state pair $(s_t, s_{t+1})$ has a deterministic utility component defined as $v(s_t|s_{t+1})$, based on its attributes $x(s_t|s_{t+1})$. Considering a decision-maker $n$ moving in the dynamic network, the instantaneous utility of state $s_t$ being on state $s_{t-1}$ is defined as:

$$u(s_t|s_{t-1}) = v(s_t|s_{t-1}) + \mu \epsilon(s_t).$$

The $\epsilon(s_t)$ is the independent and identical distributed (IID) random error term with zero mean and $\mu$ is the fixed scale parameter. The total utility of state $s_t$ being on state $s_{t-1}$ is calculated by the sum of instantaneous utility and maximum expected downstream utility up to the final state denoted by $V(s_t)$ defined by Bellman’s equation (Bellman (1957). Rust (1987)) with time discount rate ($\beta$) can be expressed as:

$$V(s_t) = E\left[\max_{s_{t+1} \in S} \{v(s_{t+1}|s_t) + \beta V(s_{t+1}) + \mu \epsilon(s_{t+1})\}\right], \quad \forall s_t \in S. \quad (3)$$

The analytical form of Bellman’s equation can be expressed in log-sum function:

$$V(s_t) = \left\{ \begin{array}{ll} 0, & s_t = [q_d, T], \\ \frac{1}{\mu} \log \sum_{s_{t+1} \in S} \delta(s_{t+1}|s_t) e^{v(s_{t+1}|s_t) + \beta V(s_{t+1})}, & \text{otherwise}, \quad \forall s_t \in S, \end{array} \right. \quad (4)$$

where $q_d \in Q$ is last zone in the sequential destinations choice network and there is no leaving state from $s_t = [q_d, T]$. The term $\delta(s_{t+1}|s_t)$ is a connection dummy equals to 1 if the state $s_{t+1}$ is directly connected with state $s_t$. The probability of choosing state $s_t$ being on state $s_{t-1}$ can be expressed in multinomial logit model:

$$P(s_t|s_{t-1}) = \frac{e^{\frac{1}{\mu}v(s_{t+1}|s_{t-1}) + \beta V(s_t)}}{\sum_{s_{t+1} \in S} e^{\frac{1}{\mu}v(s_{t+1}|s_{t-1}) + \beta V(s_t)}}, \quad (5)$$

Choice of state $s_t$ is choice of destination zone at discretized time $t$. It can be understood that the staying pattern cannot be defined only in the spatial network. By virtue of the time-space network, it became easy to include a staying pattern and evaluate time and space simultaneously. Figure 2 shows the sequential destination choices in the time-space framework, where the total choice stages are $|\mathcal{T}| = 5$ and the total number of zones are $|Q| = 4$. The day path $P_{0.5}$ shown in the figure comprises $s_0 = [q_1, 0]$, $s_1 = [q_2, 1]$, $s_2 = [q_3, 2]$, $s_3 = [q_4, 3]$, $s_4 = [q_4, 4]$, and $s_5 = [q_1, 5]$.

### 2.2. Defining Time-space Constraints

It is presumed that the decision-maker can pick any zone from the current destination; hence, destination choices in the time-space network result in vast alternatives. The calculation with many destinations necessitates a large memory and computation cost or, under some situations, may unstable the model. To avoid this problem, we introduce choice-stage constraints (Oyama & Hato (2019)).

Based upon transportable distance between two destination zones, accessibility of one destination zone to another at each discretized time $t$ can be restricted spatially in a sequential destination choice problem. We further assume that the decision-maker essentially travels from the current state $s_{t-1}$ to the next state $s_t$ at every discretized time-step with fixed initial and final states $s_0 = [q_o, 0]$ and $s_T = [q_d, T]$ respectively; where $q_o, q_d \in Q$ are the start and end zones in sequential destination choices. Hence, the choice stage constraints restrict the choices based on fixed initial and final
The governing key parameter of constraints is $T$, which specifies the maximum number of choice stages decision-maker experiences in an activity web.

Given the start and end zones $q_o, q_d \in Q$ and considering initial and final states $s_0 = [q_o, 0]$ and $s_T = [q_d, T]$, two variables are introduced $D^{q_o}(q_n)$ and $D^{q_d}(q_n)$ which define the minimum number of sequential choice stages from zone $q_o$ to zone $q_n$ and from zone $q_n$ to $q_d$ respectively. Defined by dynamic programming, these variables are

$$D^{q_o}(q_n) = \min_{q_i \in Q_{n-}} [D^{q_o}(q_i) + 1],$$

$$D^{q_d}(q_n) = \min_{q_j \in Q_{n+}} [D^{q_d}(q_j) + 1],$$

where $Q_{n-}$ and $Q_{n+}$ are the set of upstream and downstream zones directly connected to zone $q_n$ respectively. Given these variables, the state at $t$ for zone $q_n$, $s_t$, can be expressed as

$$s_t = \{(q_n, t) | I_t(q_n) = 1\},$$

where

$$I_t(q_n) = \begin{cases} 1, & \text{if } D^{q_o}(q_n) \leq t, D^{q_d}(q_n) \leq T - t, \\ 0, & \text{otherwise.} \end{cases}$$

Then, the two adjacent states $s_t = [q_n, t]$ and $s_{t+1} = [q_n, t+1]$ are connected to each other only if

$$\Delta(s_{t+1}|s_t) = I_{t+1}(q_n)I_t(q_n) = 1.$$  

The $\Delta$ is the state connection indicator shows the change in two consecutive states. Using the connection indicator, transition probability of the chosen state using Equation (5) can be reformulated as

$$P(s_t|s_{t-1}) = \frac{\Delta(s_t|s_{t-1})e^{\frac{1}{\beta}(V(s_t|s_{t-1})+\beta V(s_t))}}{\Sigma_{s_{t+1}}\Delta(s_{t+1}|s_{t-1})e^{\frac{1}{\beta}(V(s_{t+1}|s_{t-1})+\beta V(s_{t+1}))}}.$$  

### Figure 2

Day-path $\Psi_{0.5} = \{[q_1, 0], [q_3, 1], [q_3, 2], [q_4, 3], [q_4, 4], [q_4, 5]\}$
Sequential destination choice network typically considers that all zones are connected, unlike the route choice problem where the links are spatially connected based on the existing network. The choice stage constraints assist in restricting the universal choice set at each discretized time $t$. Figure 3 shows an example of choosing zone alternatives before and after defined restriction where accessibility of the next zone is restricted to four distance units.

### 2.3. Applying McFadden Correction

A familiar problem in destination choice modeling is the curse of dimensionality that limits the estimability of a model (McFadden (1978), Guevara & Ben-Akiva (2013), Vastberg et al. (2020)). This situation can be sidestepped by introducing some sampling protocol to choose a subset out of destination choices at each choice stage. McFadden (1978) established a sampling approach by introducing modifications to the multinomial logit (MNL) model. McFadden (1978) demonstrated that if the choice process follows MNL structure, consistent estimate under-sampling of alternatives can be possible by applying a simple correction to the log-likelihood function. The correction is extended to $\beta$-SRL, as the model is formulated using MNL before using machine learning (ML) sampling protocols.

The choice stage $s_t$ is the choice of zone $q_i$ at discretized time interval $t$. For simplicity, without considering the staying behavior and connection indicator $\Delta$ in Equation (10) the probability of choosing $q_i$ being on zone $q_{i-1}$ can be formulated as

$$P(q_i|q_{i-1}, Q) = \frac{e^{\mu v(q_i|q_{i-1}, Q) + \beta V(q_i)}}{\sum_{q_i \in Q} e^{\mu v(q_i|q_{i-1}, Q) + \beta V(q_i)}}.$$  \hspace{1cm} (11)

It can be concluded that at any choice stage, a decision-maker faces the universal choice set $Q$ of cardinality $|Q|=J_Q$ as set of alternatives. In order to make model estimable, the subset $D \subset Q$ of cardinality $|D|=J_D$ can be chosen so that it must include the observed choice $q_i$; otherwise estimation is impossible and the log-likelihood function becomes unbounded. The term $\pi(D|q_i)$ shows the joint probability of drawing subset $D$, which includes the observed choice $q_i$. According to the Bayes’ theorem, this joint probability is formulated as

$$\pi(q_i,D) = \pi(D|q_i)P(q_i) = \pi(q_i|D)\pi(D).$$ \hspace{1cm} (12)

The terms $\pi(D|q_i)$ and $\pi(q_i|D)$ represent the conditional probabilities respectively of drawing subset $D$ conditioned on the decision-maker will choose the alternative $q_i$ and vice versa. As the choice of alternative $q_i$ from the choice
set $Q$ is mutually exclusive and collectively exhaustive, the probability of drawing the subset $\pi(D)$ is defined by the total probability theorem (Bertsekas & Tsitsiklis (2002)) as under

$$\pi(D) = \sum_{q \in Q} \pi(D|q_j)P(q_j) = \sum_{q \in D} \pi(D|q_j)P(q_j).$$  \hspace{1cm} (13)

By substituting Equation (11) and (13) into Equation (12), we get

$$\pi(q_i|D) = \frac{\pi(D|q_i)P(q_i)}{\pi(D)} = \frac{\pi(D|q_i)P(q_i)}{\sum_{q \in D} \pi(D|q_j)P(q_j)} = \frac{\pi(D|q_i)e^{\frac{1}{\mu}(v(q_i)+\beta V(q_i))}}{\sum_{q \in D} \pi(D|q_j)e^{\frac{1}{\mu}(v(q_j)+\beta V(q_j))}} \hspace{1cm} (14)$$

The term $\pi(D|q_i)$ is referred to as a sampling correction term by McFadden (1978) that must be greater than zero; stated as Positive Conditioning (PC) property, and the sampling methods are referred to as PC sampling. If the PC property is satisfied for all $q_j$ in $D$ and the probabilities are defined by the logit model, we can apply the quasi log-likelihood function, which McFadden (1978) proposed, as

$$QL = \sum_{n=1}^{N} \ln \left( \frac{e^{\frac{1}{\mu}(v(q_i)+\beta V(q_i))}}{\sum_{q \in D} e^{\frac{1}{\mu}(v(q_j)+\beta V(q_j))}} \right) \hspace{1cm} (15)$$

where $N$ is the total number of observations. If the sampling correction term $\ln(\pi(D|q_i))$ is the same for all alternatives included in subset $D$, it reduces into standard log-likelihood function. This situation happens when the subset $D$ is explicitly defined, and it contains some alternatives without replacement of observed choice. This property is known as Uniform Conditioning (UC) property. Our sampling protocols, which are proposed in the next Section 3.4, introduce destination choice subset $D$ explicitly for each sequential observation $n$. The protocols predefine the sequential destination choice network in time-space to the model subsequently for parameter estimation likewise to sequential links network in route choice context. The predefinition does not violate the UC property and sampling correction term in log-likelihood.

2.4. Machine Learning Sampling Protocols

To accomplish uniformity, random sampling protocol is commonly recognized because without altering the log-likelihood function parameter estimation, choosing alternatives and randomly drawn non-chosen alternatives from the universal choice set to the subset $D$ for each observation $n$ (Angelo Guevera & Ben-Akiva (2013)). However, there is a criticism correspondingly following the fact that, particularly in decision choices, some adjacent zones/alternatives are more likely to be chosen than distant zones (Daly et al. (2014)). The situation where the model of McFadden (1978) with unequal $\pi$ value would be more efficient. Parsons & Kealy (1992) show that random sampling could perform well when the subset is drawn from the decision-maker’s opportunity set within some limited area.

In our study, decision-makers weigh their preferences by examining characteristics of decision zones such as zone attraction, type of activity to be completed, and so forth. Therefore, postulating that a decision-maker typically chooses their destinations by preferring the destination zones with comparable attributes. Furthermore, if the number
of drawn alternatives in subset D is more than the accessible zones (accessibility constraints defined using discretized time $t$ and inter-zonal distance), the zone accessibility constraints will prevail.

Machine learning (ML) algorithms are broadly used to divide the data into groups with identical attributes and forecast the class of objects accordingly. This study aims to produce the destination choice subset D using the ML algorithms, subsequently restricting the zone accessibility in discretized time $t$ to compare their performance with conventional random sampling approaches. We propose two ML-based sampling techniques, i.e., rule-based sampling (supervised learning method) and cluster-based sampling (unsupervised learning method). Both methods use the observed destinations as the training data and learn the model from the observed data only. In other words, no additional survey is required. Unsupervised learning with clustering is a simple method that allows unobserved destinations to be included in the clusters. On the other hand, supervised learning with decision trees contributes to the enumeration of more likely alternatives by learning in each space and time.

The generation of destination choice subset D through sorting or clustering is only possible in the ML sampling methods when the dataset has some destination attributes. Instead of destination zones attributes data, this study has travel diary data where everyone reported his/her activity, activity time, type of mode, departure time, and chosen zones. The activity diary data can be utilized in the ML algorithms to describe the class of destination zones through classified or clustered trips of the respective destination zones because the zone identity number cannot be used directly as an attribute.

2.4.1. Rule-based Sampling Protocol

We apply a decision tree classifier for the classification of similar destination zones. A decision tree generates a rule by recursive partitioning of nodes to arrive at a particular decision. Decision links to a target class or response variable, which is a time of the day when trips are performed, describes the class of a trip. All other attributes in the data set, i.e., trip purpose, travel mode, activity time, and distance traveled for the trips, are referred to as decision variables that help the tree classify the target class.

Our rule-based sampling protocol assumes that the decision-makers set their preferences for destination zones by the time of the day. Their trips are performed as target classes or response variables in the form of discretized time intervals and trip attributes in the decision tree algorithm conditioned to predict and classify the trips by the time of day. The destination zones chosen for those trips are directed to the time-dependent destination choice subset D by changing the network at each time interval. Conversely, in random sampling, sequential choices in the network remain the same throughout in time-space framework. After formulating subset D, the observed choices are added in the subset if the algorithm misclassifies them and does not include the observed one in the subset; otherwise, the log-likelihood function becomes unbound, and estimation is impossible. Some portion of activity data can be randomly picked for the generation of binary tree rule and then applied to an actual data set for the generation of time-dependent destination choice subsets D. The proposed sampling protocol has the advantage that it is compatible with our main time-space model structure. At each time interval $t$, the decision tree rule draws the time-dependent destination choice subset D. It is difficult to access the type and size of destinations included in subset D because the decision tree decides rigidly, unlike the random alternatives where we can control the size of each subset. Figure 4 shows the stepwise procedure of applying the rule-based sampling protocol in the sequential generation of destination choice subset D. First, a decision tree is generated for activity classification. For each observed sojourn, a choice set of destinations in the time-space prism is enumerated sequentially using the decision tree. Then, the enumerated choice sets are used to construct a $\beta$-SRL model.

2.4.2. Cluster-based Sampling Protocol

Clustering segregates a data set into homogeneous clusters or groups (Klosgen & Zytkow (1996)) and is advantageous in unsupervised classification (Cormack (1971)) when the data is unlabeled and the target class is unknown. The clustering algorithm divides a data set into different classes such that objects in the same class are more similar on some specified criteria. This study applies k-prototype clustering for the classification of similar
Figure 4 Stepwise procedure of rule-based sampling protocol in sequential generation of destination choice subset $D$.

zones to draw subset $D$, which is a type of partitioning clustering where each data object must be in a separate cluster. The k-prototype clustering algorithm is an integration of k-means (MacQueen (1967)) and the k-mode algorithm to process the data with mixed numeric and categorical attributes (Huang (1997), Huang (1998)). The k-prototype can be a more efficient algorithm to segregate data set into the same classes because most of the real data set contain mixed type of attributes.

Our proposed formation process of destination choice subset $D$ in cluster-based sampling is almost similar to the decision tree, except that the target class with the time of the day is not defined in the cluster formation. Instead, the trips in the activity diary data are partitioned into different clusters using attributes such as trip purpose, travel mode, activity time, distance traveled, and time of the day of the trips. The respective destination zones where the trips have been made are assigned to the cluster class of those trips. The number of destination choice subsets becomes equal to the number of clusters. We can select the subset to enumerate alternatives at each sequential choice only after examining the clusters to which the observed destination belongs. The subsets cannot be introduced to the model explicitly because it is hard to pre-determine which subsets need to be introduced at every choice stage. The benefit of cluster-based sampling is that the target class is not obligatory to classify the destination zones as in the case of the decision trees. Hence the initial hypothesis about the target class can be avoided. It is logical in most cases, as we assumed that the trips and their respective zones are time-dependent, which is not always the case because each decision-maker has preferences. In that case, clustering is beneficial to notice the hidden and intrinsic
Fig. 5 Stepwise procedure of cluster-based sampling protocol in sequential generation of destination choice subset $D$. 

2.5. Resolving Bellman’s Equation and Assignment Algorithm

With the purpose of calculating maximum expected downstream utility of each destination zone which will be different depending upon its state (space and time), the bellman’s equation can be solved using retrograde induction method as per following steps:

Step 1: set the initial state $s_0=[q_o,0]$, final state $s_t=[q_d,T]$, and $V(s_0)=0$; calculate $I$ and $A$.

Step 2: initialize with $t=T$ and $V(s_t)=0, \forall s_t \in S$.

Step 3: backward calculation: set $t=T-1$ and calculate $V(s_t)$ by equation (4).

Step 4: if $t=0$; finish the calculation or return to step 3 otherwise.

In assignment algorithm we define the state pair flows $g_{st, s_{t-1}}$ and $f_{st, s_{t-1}}$ respectively for the same (staying) and different (moving) destinations at two states. The flow $g_{st, s_{t-1}}$ can be calculated using the following formulation:

$$g_{st, s_{t-1}} = \begin{cases} \sum_{s_j \in S(s_{t-1})} f_{st, s_{t-1}} & ; t \neq 0 \\ 0 & ; t = 0, T \land q_j = q_o, q_d \\ f_{od} & ; t = 0, T \land q_j \neq q_o, q_d \end{cases} \quad (16)$$
Where \( f_{od} \) is the generating flow from the starting zone \( q_o \) to the ending zone \( q_d \). The set \( S(s_{t-1}) \) includes all the states \( s_{t-1} \) connected to the state \( s_t \). The state pair flow \( f_{s_{t-1},s_{t-2}} \) can be calculated using transition probabilities as:

\[
f_{s_{t-1},s_{t-2}} = g_{s_{t-1},s_{t-2}} P(s_t | s_{t-1})
\]

By means of equation (16) and (17), the assignment algorithm is given as:

1. **Step 1:** set the generating flow \( g_{S0=[o,0]} = f_{od} \).
2. **Step 2:** calculate the state pair flow at \( t=1 \) using the equation (17).
3. **Step 3:** calculate the state pair flow at \( t=2 \) using the equation (16).
4. **Step 4:** terminate the algorithm if \( t=T \), go to step 3 otherwise.

### 3. Numerical test

#### 3.1. Sensitivity of Time Discount Rate-\( \beta \)

To validate the sensitivity of time discount rate-\( \beta \) and to observe the effectiveness of time-space prism constraints, an evaluation of the sequential destination choice network of Fig. 3 is carried out through an example. The time parameter is set as \( T=5 \) through fixing initial and final states \( s_0 = [q_1,0] \) and \( s_T = [q_1,T] \) with pre-defined demand at the initial stage as 1000. Defining the instantaneous utility of state \( v(s_t|s_{t-1}) = \theta_d d_{ij} + \theta_s s_{ii} \), where \( d_{ij} \) is the distance between zones \( i \) and \( j \) and \( s_{ii} \) is the stay dummy of zone \( i \). The stay dummy can be linked with intermediate destination zones \( q_2, q_3, \) and \( q_4 \); the parameters are \( \theta_d = -0.2 \) and \( \theta_s = 1 \). Further, staying and moving flows are evaluated at each destination choice stage with different \( \beta \) values, i.e., 1, 0.5, and 0 before and after interzonal accessibility restriction. The results of the assignment are shown in Appendix 1.

It can be authenticated from Table 1 when time discount rate-\( \beta \) is 1, staying and moving flows at zone \( q_2 \) are higher, as the time discount rate-\( \beta \) goes down, the proportion of flows decreases at zone \( q_2 \). Conversely, at zone \( q_1 \) at \( t=1 \), stay flow increases as the time discount rate-\( \beta \) goes down because a decision-maker, at the lower value of \( \beta \), tends to maximize instantaneous utility only, which is higher for staying at \( q_1 \). Further, the performance of time-space constraints can also be realized from the assignment results. When the zone accessibility is not restricted, moving flow can be observed at \( q_4 \) as an alternative state; however, no flow is observed after restricting accessibility by time-space constraints as \( q_4 \) becomes an unfeasible alternative due to its greater distance from zone \( q_1 \).

The restriction of zone accessibility presented here is to elaborate on the perception of the time-space constraints. In a real-world problem, this restriction is based on the length of discretized time \( t \) and traveling speed of the decision-maker based on the mode used. In an actual data set where destination patterns have mixed modes, the constraints can be set based on the maximum distance traveled in the data set in a single trip.

#### 3.2. Model Estimability using Accessibility Restriction

To confirm the estimability of the proposed model structure and sensitivity of discretized time parameter \( t \), simulation analysis on hypothetical data consisting of 50 zones network is carried out. The zones are supposed to be successively far from one another by unit distance from 1 to 50. A number of decision-makers is 50, and 10 decision-makers are to start and end their trips at zone 1, 10, 20, 30, and 40, respectively, aiming to uniformity inflow distribution and reduction in path overlapping. Eight hours day-path time equivalent to 400 distance units is presumed with the model parameters \( \theta_d = -0.2, \theta_s = 1 \) and \( \beta = 1 \). Four data sets are generated and re-estimated in the following cases:

**Case-I:** The discretized time \( t \) is supposed to be 1 hour; total choice stages become 8. The zone-to-zone accessibility is assumed 50 distance units which are equivalent to the universal destination choice set.
Table 1 Proportion of total travel demand at zone q₁, q₂, and q₄ in different time intervals

<table>
<thead>
<tr>
<th>Zone accessibility</th>
<th>Time discount rate β</th>
<th>Zone q₁</th>
<th>Zone q₂</th>
<th>Zone q₄</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Staying</td>
<td>Moving</td>
<td>Staying</td>
</tr>
<tr>
<td>Not restricted</td>
<td>β = 1</td>
<td>0.239</td>
<td>0.397</td>
<td>0.266</td>
</tr>
<tr>
<td></td>
<td>β = 0.5</td>
<td>0.343</td>
<td>0.302</td>
<td>0.189</td>
</tr>
<tr>
<td></td>
<td>β = 0</td>
<td>0.407</td>
<td>0.296</td>
<td>0.182</td>
</tr>
<tr>
<td>Restricted</td>
<td>β = 1</td>
<td>0.255</td>
<td>0.456</td>
<td>0.321</td>
</tr>
<tr>
<td></td>
<td>β = 0.5</td>
<td>0.375</td>
<td>0.384</td>
<td>0.249</td>
</tr>
<tr>
<td></td>
<td>β = 0</td>
<td>0.453</td>
<td>0.329</td>
<td>0.196</td>
</tr>
</tbody>
</table>

Table 2 Model estimability and sensitivity of discretized time parameter

<table>
<thead>
<tr>
<th>Case No.</th>
<th>Discretized time parameter (hrs.)</th>
<th>Total choice stages</th>
<th>Zone accessibility (units)</th>
<th>Sample size</th>
<th>Estimated parameters</th>
<th>RMSE</th>
<th>ρ²</th>
<th>Calculation time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>1</td>
<td>8</td>
<td>50</td>
<td>400</td>
<td>-0.027</td>
<td>1.320</td>
<td>0.402</td>
<td>0.392</td>
</tr>
<tr>
<td>II</td>
<td>0.8</td>
<td>10</td>
<td>40</td>
<td>500</td>
<td>-0.209</td>
<td>1.162</td>
<td>0.471</td>
<td>0.320</td>
</tr>
<tr>
<td>III</td>
<td>0.4</td>
<td>20</td>
<td>20</td>
<td>1000</td>
<td>-0.199</td>
<td>1.080</td>
<td>0.507</td>
<td>0.289</td>
</tr>
<tr>
<td>IV</td>
<td>0.2</td>
<td>40</td>
<td>10</td>
<td>2000</td>
<td>-0.202</td>
<td>1.038</td>
<td>0.545</td>
<td>0.264</td>
</tr>
</tbody>
</table>

Case-II: The discretized time t is reduced to 0.8 times of the case I, so the choice stages become 8/0.8 = 10 (path length/ time step parameter) for the eight-hour pattern. The zone-to-zone accessibility is reduced to 0.8 times of case I, which becomes 50x0.8 = 40 distance units.

Case-III: The discretized time t is decreased to 0.4 times of the case I; subsequently, the choice stages become 20, and zone accessibility is restricted to 20 distance units.

Case-IV: The discretized time t is further reduced to 0.2 times of case I. The total choice stages become 40, and the zone-to-zone accessibility is reduced to 10 distance units.

It can be noticed in Table 2 that bias and RMSE are high with the higher discretized time parameter due to flexible zone accessibility restrictions and a large number of destination alternatives. With the discretized time parameter reduction, the zone accessibility decreases accordingly with a lesser number of destination alternatives at each choice stage, and then we obtain the lower RMSE. However, the low discretized time parameter increases the total number of choice stages and consequently the sample size when the total time span is unchanged. The large sample size increases the computational cost. A higher value of log-likelihood ρ² corresponds to the high fitness of the model. It is interesting to observe that the model fitness reduces with the reduction in discretized time parameter, which is due to two probable reasons: first, the number of choices become too high, there is moving as well as staying behaviors that lead to immense choice alternatives which eventually decrease the model fitness. Second, it is difficult to obtain each zone's alternative specific constant (ASC), representing the frequency of choosing and staying off that zone. Elimination of ASC from the utility term might be one possibility of low model fitness.

There might be many real-world problems with the lower discretized time parameter, especially in sequential destination choice analysis. First, in full-day, the order of destination choices typically extends over more than 10 hours, and the trip lengths may vary from several minutes to several hours, depending on the trip type and decision-maker. If we set the discretized time parameter based on minimum trip length (Oyama & Hato (2019)), the total number of choice stages becomes very large, and the calculation cost would become very high. Second, the normalization of trips with lengths more than the discretized time parameter and specified inter-zonal distance is required, which is quite a monotonous try-and-error task in a sequential destination choice context. A possible solution to this problem might be the restriction of zone accessibility based on the actual distribution of trip length.
Table 3 Statistical results showing stability of parameters and model fitness in repeated sampling protocols

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Random sampling</th>
<th>Rule-based sampling</th>
<th>Cluster-based sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_d = -0.2$</td>
<td>-0.09</td>
<td>0.0001</td>
<td>-0.08</td>
</tr>
<tr>
<td>$\theta_s = 1$</td>
<td>1.77</td>
<td>0.0271</td>
<td>2.08</td>
</tr>
<tr>
<td>$\beta = 1$</td>
<td>0.59</td>
<td>0.0267</td>
<td>0.84</td>
</tr>
<tr>
<td>Average $\rho^2$</td>
<td>0.347</td>
<td></td>
<td>0.815</td>
</tr>
<tr>
<td>Average RMSE</td>
<td>0.510</td>
<td></td>
<td>1.080</td>
</tr>
<tr>
<td>MCE</td>
<td>-</td>
<td></td>
<td>0.293</td>
</tr>
</tbody>
</table>

and travel time in the whole data set. This method would limit the choice set partially, but when the cardinality of the choice set is high, restriction in zone accessibility is not enough for the model estimation. This fact is well described while dealing with actual data in our case study of Chap. 4.

3.3. Model Estimability using Machine Learning Sampling Protocols

In order to overcome the problem of a large set of destination alternatives in the real world despite restricting the zone accessibility, simulation is performed on hypothetical data described earlier by introducing rule-based and cluster-based machine learning (ML) sampling protocols along with random sampling techniques to ensure the estimability and stability of parameters. Simulation is carried out considering Case-II with the same network, parameters, sample size, zone accessibility, and the discretized time interval $t$, where the destination zone accessibility is restricted to 40 distance units at each discretized time interval. However, the destination choice set changes in the data generation process based on applied sampling techniques elaborated under Heading 3.4 of methodology. The working of each sampling protocol is explained in the subsequent paragraphs.

First, using random sampling protocol, five random destination alternatives at each choice stage are generated, and subsequently, model parameters were estimated in nine repetitions through different destination choice subset D in each repetition. It was observed that $t$-statistics of all the parameters in each reiteration was more than 1.96 presenting their significance; also, model fitness $\rho^2$ was higher, which means model in each recurrence performed well. The statistical results show in Table 3 that the variance of distance parameter $\theta_d$ in the nine repetitions is less than stay dummy $\theta_s$ and time discount rate $\beta$. The reason might be that the distance is a global variable associated with each destination zone pair. The broader variance of stay dummy, which represents the importance of the destination zone as alternative specific, is affected by the high dependence on the destination zones allocated with stay dummy in the destination choice subset D. The variance of time discount rate is also high due to the dependency on not only the destination types at each choice stage but the destination sequences in all choice stages.

Second, using rule-based sampling protocol, randomly selected 80% data was utilized as training data set to obtain time-dependent destination choice subsets. It is assumed that the preferences are time-dependent, and the destination choice subset D varies at each discretized time interval $t$. Nine repetitions through changing the training data randomly at each repetition are performed to check the stability of the parameters. The outcomes indicated that parameters in each repetition were significant, and the model performed well. Table 3 shows similar results of the above random sampling protocol; the variance in distance parameter $\theta_d$ is less as compared to the dummy parameter $\theta_s$ and time discount rate $\beta$. The rule-based sampling results in over-restriction of destination choice subset because of low-flexible rule by less training data volume. The estimated value of $\theta_s$ is biased. The bias ultimately leads to high RMSE. However, the model fitness is good in this case as compared to the random sampling. The misclassification error (MCE) shows the misclassification of the destination zone class by the decision tree rule. In other words, MCE means imprecision in our initial hypothesis that the preferences are time-dependent based on attributes of trips or zones. The result is not bad here.

Third, by utilizing cluster-based sampling protocol, the assumed trip data was partitioned into ten clusters, meaning the destination choice set was divided into ten subsets. As mentioned earlier, assigning alternatives to the model in
cluster-based sampling without having observed choice is difficult, so alternatives are drawn based on observed choice. In the same way as random and rule-based sampling protocols, model parameters were estimated in nine repetitions to check the consistency of the cluster-based sampling protocol. The results indicated that parameters in all repetitions were significant, and the model performed well. The statistical results presented in Table 3 demonstrate that the variances of $\theta_d$ and $\theta_s$ are broader than the other protocols, and RMSE is also higher. Also, the differences from the setting value of the parameter $\theta_d$ and $\beta$ are higher than the other sampling protocols. The first reason is that the initialization of clusters is highly random, which contributes to the randomness in the subsequent subsets, and second, there are chances of over-restriction of subsets similar to the rule-based sampling. However, the model fitness is high against random sampling. The proposed sampling approach contributes to improving the prediction accuracy.

Model fitness is very high in both proposed rule-based sampling and cluster-based sampling as compared to the random sampling protocol. Our proposed approaches sample likely destinations that are accessible and selectable from a current zone. Although their RMSEs are higher than the random sampling approach, the zone accessibility constraints would be needed to estimate the significant parameters in case of a real-world problem consisting of many alternatives.

4. Case Study

4.1. Survey Data and Processing

Predicting actual travel behavior is essential for urban space design and transportation management. We analyze the actual activity diary data of the Kansai region, where the second-largest metropolitan area in Japan, collected over one-month time in May 2011. The trips of the respondents were recorded every day with some trip attributes or identified information, i.e., type of activity, start and end time, travel time, and mode used. In addition, the travelers' GPS courses of the selected path were also recorded through probe person technology to prevent incorrect records by allowing easy access to trip-activity logs. The total numbers of respondents in the data set are 55, and the numbers of trips recorded are 4,793.

The GPS coordinates at the start and end of each trip are mandatory to know about the origin and destination zone of each trip. Therefore, the trip without GPS trajectories is emitted from the data set. This study supposed that the decision-makers plan their activity pattern only for one day, from morning 6:00 am to midnight, for convenience of analysis. The activity patterns duration extended from the abovementioned time are also excluded from the data set. After excluding specious and unnecessary data, the remaining respondents left in the data set is 45, with 3,252 trips. Activity time or stay time at destination zones in the activity pattern is a significant attribute of the trip and is used as a stay time of destination in the time-space framework of the model. Stay time at the destination zone for every trip is calculated from the difference between the stop time of the current trip and the start time of the next trip. The GPS coordinates at the end of each trip represent the trip's destination location, so they are extracted from the GPS data. It is also ensured that the GPS coordinates of the destination of the current trip must be the starting GPS coordinates of the next trip in one activity chain to maintain the continuity of the entire trip chain. The weekday and weekend activity pattern of the randomly picked respondent is shown in Figure 6.

The network data of the Kansai region of Japan that the Ministry of Land and Infrastructure has established is utilized to represent the traffic analysis zones (TAZ). Each zone has a unique identity number with the size of 500m2. The total number of zones in the study area is 17,971. The destination zones are assigned to the trips of activity diary data by minimizing the distance between the destination GPS coordinates of each trip and the zone centroids. The total number of destination zones that the respondents have chosen over the period of one month is 720, which are used as a set of alternatives in our model. Figure 7 shows the starting and ending GPS coordinates of trips and zones in the study area.
The parameter estimation of the sequential destination choice model in the activity chain requires the sequential choices of destinations for one day. As the total number of choice stages \( T \) are required to define the time-space graph, the total time span of 18 hours starting from 6 am to midnight is hypothesized. In addition, a time step \( t \), which must be the same for the entire network, is set based on the 90% distribution of the travel time of trips of the activity diary data. 90% of the trips have traveling time less than or equal to 90 minutes, so the length of time step \( t \) is set as 90 minutes. Hence, the total number of choice stages \( T \) in the day path becomes 12. The action is checked at each time interval, whether the respondent moves to the next destination or stays at the current location. If the two moving actions are undertaken within the same time interval \( t \), the intermediate choices are eliminated from the data set. Similarly, the zone accessibility can be restricted at each time step by zone to zone distance, as discussed before. In order to restrict the zone accessibility, we have analyzed the distribution of the traveling distance of each trip recorded in the activity data, likewise to the traveling time. 90% of the trips have been made within 30km. So, this study hypothesized that the decision-maker could choose the destination zone within 30km from the current zone at each time step \( t \).
4.2. Model Performance with Accessibility Restriction

Sequential time discount rate-$\beta$ together with travel distance variable parameter $\theta_d$ is estimated using $\beta$-SRL model for one-day sequential destination choices data set randomly selected from one month. The recursive logit model can estimate the parameters without enumerating the path, but when the number of alternatives becomes too high, the model tends towards instability, and parameter estimation becomes impossible. We estimated the parameters using the universal choice set having 720 destination zones to evaluate this fact. It is assumed that at each choice stage, every decision maker faces 720 destination zones as a set of alternatives. The results shown in Table 4 indicate that the model is unstable as it is unable to estimate the time discount rate and significance of parameters (t-statistics) of both parameters. In order to estimate the significant parameters, the choice set must be restricted to a viable cardinality.

The parameters of the same data set are re-estimated by restricting the zone accessibility under the above-mentioned criteria. At each choice stage, it is assumed that the decision-maker faces the choices of destination zones that are accessible from the current zone. The results shown in Table 4 are quite better than unrestricted zone accessibility. The distance variable parameter $\theta_d$ is significant. However, the time discount rate-$\beta$ variable is insignificant, indicating high uncertainty in the sequential destination choices of the decision-makers. Now, there can be two feasible options to estimate the significant parameters. First, we reduce the zone-to-zone accessibility further, and second, we apply some sampling protocols for reducing alternatives. In the current setting, the time step parameter and zone accessibility are restricted based on a 90% distribution of travel time and travel distance of the trips. In case of further reduction in zone accessibility, the computation time will increase, and many choice stages might affect the model performance. Therefore, we have adopted sampling protocols in order to reduce the choice set for the parameter estimation.

4.3. Model Performance with ML Sampling Protocols

This chapter compares the ML sampling protocols using three repetitive estimation. First, the estimation is carried out in 3 repetitions by sampling 60 random alternatives at each choice stage. In each repetition, the alternatives are changed in order to check the stability of the parameters within the same destinations choice subset size D. Results indicated that parameters were 5% significant in all the estimations. The estimation results in left side of Table 5 in-

<table>
<thead>
<tr>
<th>Sampling Protocol</th>
<th>Random sampling</th>
<th>Rule-Based sampling</th>
<th>Cluster-Based sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Repetition/Parameter</td>
<td>$\omega$</td>
<td>$\beta$</td>
<td>$\omega$</td>
</tr>
<tr>
<td>1</td>
<td>-0.569</td>
<td>0.172</td>
<td>-0.528</td>
</tr>
<tr>
<td>2</td>
<td>-0.575</td>
<td>0.393</td>
<td>-0.554</td>
</tr>
<tr>
<td>3</td>
<td>-0.572</td>
<td>0.298</td>
<td>-0.496</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.572</td>
<td>0.288</td>
<td>-0.526</td>
</tr>
<tr>
<td>Variance</td>
<td>0.00001</td>
<td>0.01229</td>
<td>0.00084</td>
</tr>
<tr>
<td>St. Deviation</td>
<td>0.003</td>
<td>0.111</td>
<td>0.029</td>
</tr>
<tr>
<td>Average $\rho^2$</td>
<td>0.285</td>
<td>0.405</td>
<td>0.264</td>
</tr>
</tbody>
</table>
-icate that changing the alternatives of destination at each choice stage with the random sampling protocols affects the stability of the parameter estimation. However, the variance and standard deviation indicate that changing the alternatives has less impact on the distance variable parameter \( \theta_d \) as compared to time discount rate-\( \beta \). This is quite intuitive because the time discount rate measures a decision-making dynamic at each choice stage and accordingly depends on future alternatives. Therefore, the sequential sampling of destination alternatives has a considerable impact on the time discount rate. Second, the stability of parameters is analyzed through rule-based sampling protocol in 3 repetitions by changing the training data set at each repetition. Decision tree rule changes with the change in training data set in each repetition. Subsequently, the time dependent destinations choice subsets at each choice stage changes which affects the stability of parameters. We have randomly picked 80% data for training and generation of rule in 3 repetitions by fixing the minimum split of 1 because we obtained less misclassification error and high model fitness with minimum split 1. Increasing the minimum split leads to the reduction in the tree size which consequently increase the misclassification error. Results of each repetition indicated that the parameters were 5% significant. As far as the stability of parameters is concerned, the variance of both parameters is very less in the case of rule-based sampling shown in the center of Table 5. Third, the optimum number of clusters should be known for data partitioning through cluster-based sampling. We performed 39 iterations by changing the number of clusters from 2 to 40 and observing the resultant total sum of square error against each iteration. The elbow method criterion is utilized to find the appropriate number of clusters. There is no more significant reduction in the sum of square errors with the increase in the number of clusters after the elbow points (Syakur (2018)). The parameter estimation is carried out in 3 repetitions with 7 clusters that are optimized through the elbow method. The results of each repetition indicated that the parameters were at a 5% significant level. As far as the stability of parameters is concerned, the variance of time discount rate-\( \beta \) is higher in the case of cluster-based sampling, as shown in Table 5. The comparison in characteristics of the random sampling and our proposed machine learning-based sampling is difficult as the protocol of each sampling method is different. It is worth mentioning that the characteristics of the machine learning-based protocols are challenging to know because the size and type of alternatives in subset D at each choice stage is defined by the machine learning algorithms. We cannot control them since we have performed all analyses using the same data set by only changing the sampling protocols. The comparison can be made based on final model outputs, i.e., stability of estimated parameters and model performances. In Table 5, the variations in the distance variable parameter \( \theta_d \) are low with the random sampling protocol followed by the rule-based and the cluster-based sampling protocols. The variations of \( \theta_d \) are not high in all sampling protocols. The variations in the time discount rate-\( \beta \) are very high in the cluster-based sampling followed by the random sampling. In addition, the performance of the sampling protocols is evaluated through their log-likelihood ratio \( \rho^2 \). It is appropriate to mention that the two models estimated with different alternatives cannot be compared through log-likelihood ratios generally. We compare these sampling protocols through the final model fitness than the behavior model itself to understand the priority of the sampling protocols. Their log-likelihood ratios indicate the goodness of fit of the model, and their values above 0.20 can be considered satisfactory. The model fitness with the rule-based sampling significantly supersedes the other sampling protocols in all three repetitions with a mean value of 0.405. The model's performance with random and cluster-based sampling is almost similar, with average log-likelihood ratios of 0.285 and 0.264, respectively.

5. Conclusion and Discussion

In this study, destination choice behavior in the activity chain is investigated over a specified time period. In order to assess the sequential and somewhat forward-looking decision-making dynamics of tourists in a specific time frame, we developed a \( \beta \)-scaled recursive logit model (\( \beta \)-SRL) where time discount rate \( \beta \) measures the degree of forward-looking decisions and generalizes the decision-making dynamics between global and myopic decisions. Moreover, to address the issue of model instability and unpredictability due to a large number of destination choices, we proposed a two-stage destination choice set restriction methodology. In the upper stage, the zone-to-zone accessibility is restricted by time-space constraints based on discretized time interval t and inter-zone distance. At
the lower stage, we proposed ML-based sampling protocols for the classification of similar destination zones that are accessible from the current zone. The stability of estimated parameters and model fitness are evaluated for each sampling protocol and compared with the conventional random sampling protocol. The results indicate that the estimation stability and model performance is greatly improved by our rule-based sampling protocol with a decision tree classifier.

In the sequential destination choice analysis over a specified time period, the discretized time $t$ is considered equal for all populations and all subsequent trips. However, it varies between individuals and their subsequent trips in a full day depending on the class of decision maker and type of activity for which the trip is being made. Therefore, a more rational solution can be ascertained by changing the discretized time $t$ for each trip. Analysis of destination choices in a continuous time frame might be one possible solution to this limitation. In estimation, we use only one exogenous variable, that is, the inter-zonal distance together with time discount rate $\beta$. The other variables, such as zone attraction and alternative specific constants for destination zones, would reduce the biases in the estimation results. Moreover, only destination choices are analyzed in the activity chain. However, in the supposition of activity-based travel demand modeling, decision-makers make decisions based on the combined utility of activity type, mode, and destination, collectively referred to as activity episode. Therefore, analysis of the total activity episodes is another consideration for future work.

Declarations

Ethical Approval

Not applicable

Competing interests

The authors declare that they have no conflict of interest.

Authors' contributions

Conceptualization: B. Abbasi, J. Urata; Methodology: B. Abbasi, E. Hato; Formal analysis and investigation: B. Abbasi, M. Zeeshan; Writing - original draft preparation: B. Abbasi, M. Zeeshan, J. Urata; Writing - review and editing: M. Zeeshan, J. Urata; Funding acquisition: E. Hato; Resources: E. Hato; Supervision: E. Hato.

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Availability of data and materials

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy reason.

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Appendix 1 Detailed results of numerical examples on section 4.1: Sensitivity of time discount $\beta$ before and after interzonal accessibility restriction

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Stay flow</th>
<th>Moving flow</th>
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<sup>1</sup>Accessibility restriction is shown by blue line

Figure A1 Sensitivity of $\beta$ before and after restriction of zone accessibility (a,c,e) stay flows (b,d,f) moving flow