Estimation of Transit Hyperpaths with Smartcard data

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We use smartcard data from a local Japanese city to estimate route choice sets of bus passengers. We consider that passengers will select a set of attractive lines based on their evaluation of service attributes and then choose "whichever attractive line comes first". We present model properties and show estimation results for different passenger groups. In the conclusions we discuss how smartcard data can advance transit assignment models

Key Words : *Smartcard data, Passenger route choice, hyperpath, transit assignment model*

1. Introduction

Understanding and predicting travel patterns and travel demand is important for transport providers, in particular those of public transport services. Assuming that choice is based on the utility concept, random variation in behaviour is usually dealt with by including stochastic factors into the model, leading to random utility models. In particular in transit networks random variation and route selection are, however, often difficult to distinguish. A passenger might alter his/her route choice on subsequent days not because of any learning process but because of service inherent uncertainties. This random variation can be usefully described with the concept of hyperpaths and strategy[1), 2)]. Whereas for drivers usually a change in route is explained with a (perceived) change in attractiveness of the road conditions[3)]. Though there is ample of literature discussing that different passenger groups attach different values to on-board travel time, waiting time, transfers or seat availability, this issue has not been much reflected in hyperpath based transit assignment models. Obviously, different values will result in different path sets. Generally, passengers will avoid being fixed to a specific line and rather increase their choice set (with some lines that are potentially longer) in order to reduce their expected waiting time. Kurauchi et al[4)] provide evidence for this with a stated preference survey. Fonzone et al[5)] extend this line of research by providing further evidence for differences in hyperpaths among passenger groups based on a survey asking respondents to describe their actual travel patterns as well as asking them to choose their strategy in hypothetical bus networks. It appears that only some passengers choose the hyperpaths predicted by the Spiess and Florian model; a significant number of passengers appear to prefer simple choice sets. Furthermore, the choice of strategy seems to be influenced by the actual experiences made by the passenger during their daily commute.

Both of these studies have used "artificially" collected data for the estimation of hyperpaths, i.e. transit passengers have been asked to recall their travel patterns and to answer hypothetical choice situations. Through the advance in smartcard data nowadays there are improved possibilities though. A large number of cities have introduced such systems offering possibilities for better understanding of passenger behaviour, service planning and evaluation[6]. For our purposes, of importance is that such data store the actual lines boarded by passengers over longer time periods. This allows us to observe their actual choices and make some implications about their strategy. This forms the motivation for this paper. Our objective is to develop a model that estimates the choice set of passengers in dense networks where it is often optimal to form complex choice sets. Since choice sets are latent we assume that we can construct these by observing passengers repeated choice when they travel from the same origin to the same destination. We obtain such time series route choice data from the bus service provider of a local city in Japan and provide some example results for different OD pairs where we could observe that different passengers have taken different routes to reach the same destination.

2. Logit Hyperpath Choice Set Generation with Random Bus Choice

(1) Transit hyperpath characteristics

Hyperpath generation is a dynamic programming approach where the traveller sequentially chooses the shortest path[1]. The advantage is that the choice set at each node becomes, in many cases, manageable. In the context of transit passengers, where choices are made at stops, usually there not more than 5 or 6 lines that one might consider, unless at some major hubs in large metropolitan networks. This means that for our problem the universal choice set is easily obtainable but that generating them by the traveller considered options is the main issue.

In contrast to discrete choice approaches frequency-based transit assignment choice sets are generated truly endogenously. Following the seminal work of Spiess and Florian[2] the above defined hyperpaths are created by solving a linear program at each node. The problem can be solved with a variant of Dijkstra's shortest path algorithm by backward search from the destination. We emphasise two important aspects of choice set generation for high frequency transit networks. These are reflected in the work of Spiess and Florian but are not captured within the above described choice set generation methods.

Transit Choice Characteristic (TCC) 1: Whereas the transit passenger has full control over the selection of the choice set, (s)he might leave the choice of a specific option from among the choice set to some degree "up to nature". Especially in the absence of countdown information passengers might take a strategy of taking whichever bus comes first. This means that the choice depends to some degree on the (unknown) arrival time of the bus and only partly on utility maximisation at this 2nd choice level.

Transit Choice Characteristic (TCC) 2: The utility of a choice within a set is depending on the choice set itself. This is the case for passengers at bus stops due to the expected waiting time effect. The more choices are included in the choice set, the shorter the total expected waiting time becomes. Therefore passengers will include fast but infrequent transit lines into their choice set if the risk of potentially long waiting times can be compensated by including also other buses with potentially longer on-board travel times into their choice set. Focusing on the fast bus only would be too risky.

We develop a model that captures the above two transit characteristics and captures (person group specific) evaluation of the importance of travel time and weighting time already in the choice set generation. As will be shown in the following we therefore take the "opposite approach" compared to Nguyen et al. In the approach presented here the choice set generation is stochastic (based on utilities) and the choice of a line itself is deterministic (based on line frequencies only). In contrast in Nguyen et al[1], the choice set generation is deterministic (based on the efficiency principle) whereas the choice of a line from a choice set is stochastic (based on utilities).

(2) General Framework of choice at a stop

Given our transit characteristic TCC1 and TCC2 we require a joined modelling approach of choice set and choice since the traveller has only control over the choice set. Once the choice set is determined the choice probabilities are given by the service arrivals. Therefore, partly following the decision framework and notation in Swait[7] the choice probability $P(i,n\tau)$ can be described as

$$P(i,n\tau)=\sum_{k\in K_i} P\left(i\tau \middle| C_k\right)\cdot Q_{n\tau}\left(C_k\right) \tag{1}$$

where i denotes the chosen option from a bus stop, n the "person type" and τ the time period in which the traveller departs. Consideration of time is required since we consider that the service level varies during different periods of the day due to changes in the service frequency as well as due to longer travel times by congestion during peak hours. Further, C_k represents the choice set or "nest" and $Q_{n\tau}$ describes the attractiveness of the choice set as explained below. K denotes the number of choice sets and K_i the choice sets that include choice i.

The conditional choice probability for our bus choice problem of an option (i.e. bus line) from the choice set is formulated as

$$P(i|C_k) = \Pr\left(a_i + E(u(i)) < a_j + E(u(j)) \middle| \forall j \in C_k; j \neq i\right) \quad (2)$$

where a_i denotes the waiting time until bus i arrives at the stop and E(u(i)) the expected disutility of choosing option i from the current stop once the bus arrives (i.e. ignoring the waiting time at this stop). This equation hence fulfils our above stated TCC1. The passenger can estimate E(u(i)) according to his/her taste but a_i is out of the passenger's control. Following Spiess and Florian[2] we simplify (2) by assuming that a) buses arrive with exponentially distributed headways and b) that passengers only know the service frequency (no countdown information). In that case, and considering that service headways differ during the day, the above formulation reduces to

$$P(i\tau|C_k) = f_{i\tau} \Big/ \sum_{j \in C_k} f_{j\tau} \quad (3)$$

where $f_{i\tau}$ denotes the service frequency of option i during departure time interval τ. Note that we assume in (1) that this equation is only applied if i is included in C_k. Equation (3) illustrates that the lower choice problem is dependent only on the service frequency and is independent of personal characteristics of the decision maker.

In line with nested choice models as well as Swait's "Generation Logit" we assume that the selection probability of a choice set is determined by a general cost or inclusive value associated with this nest / choice set. We assume a dispersion parameter μ and logit choice structure leading to

$$Q_{n\tau}(C_k) = \exp(\mu I_{kn\tau}) \Big/ \sum_{r=1}^{K} \exp(\mu I_{rn\tau}) \quad (4)$$

Accordingly the inclusive value should reflect the perceived disutility of choosing this choice set C_k. Eq. (5) hence includes on-board travel time, waiting time and expected number of transfers. In line with TCC2, however, one needs to consider that these attributes depend on the choice itself. This is in contrast to other nested discrete choice models where the utility of a nest can be determined as the logsum of the utility of the options within a nest. We therefore obtain the nest specific expected values $T_{k\tau}$, $W_{k\tau}$, and $Y_{k\tau}$ for travel time, waiting time and expected number of transfers respectively. We further include specifically path set size as a value for the inclusive value. This is based on findings in Kurauchi et al[4] that some passenger groups seem to prefer simple hyperpaths *per se*. In other words, even if including an additional line would reduce the overall expected travel time, some passengers might prefer to limit their choice set, possibly to avoid having to track and check the arrival of multiple lines at the stop.

$$I_{kn\tau} = \beta_{tn} T_{k\tau} + \beta_{wn} W_{k\tau} + \beta_{yn} Y_{k\tau} + \beta_{zn} |C_k| \quad (5)$$

(3) Expected values for service attributes

Following our assumption of a frequency-based service we obtain the expected nest specific service attributes as weighted average over the likelihood of taking a service within the choice set as in Equations (6) to (8).

$$T_{k\tau} = \sum_{i \in C_k} t_{i\tau} f_{i\tau} \Big/ \sum_{i \in C_k} f_{i\tau} \quad (6)$$

$$W_{k\tau} = 1 \Big/ \sum_{i \in C_k} f_{i\tau} \quad (7)$$

$$Y_{k\tau} = \sum_{i \in C_k} y_{i\tau} f_{i\tau} \Big/ \sum_{i \in C_k} f_{i\tau} \quad (8)$$

where $t_{i\tau}$ and $y_{i\tau}$ denote the expected travel time and number of transfers respectively if the traveller is boarding line i at the current node. We emphasised that these values are for the whole path from the current boarding point to the destination and not just for the travel time until the next decision point. This implies that our choice problem has to be solved in a network context recursively backward from the destination. Only if the passenger's strategy (choice likelihood of nests) at the downstream nodes is determined the expected travel time and the expected number of transfers can be determined.

(4) Model properties

We note that cross-nested logit models and Swait's "generation logit" model include scale factors μ_k for each nest. These are not included in our model as we assume that the sensitivity to choice on the lower level is not determined by utility but is fixed and given by the bus frequency. Therefore our model only includes the scale parameter μ which can be interpreted as the sensitivity to utility for the hyperpath set choice. As in MNL choice models we can, however, fix one parameter among {μ, $\boldsymbol{\beta}$} and in the following choose this to be μ[8].

Swait[7] notes that the generation logit model collapses to the MNL model in case all μ_k equal μ and if all alternatives appear in the same number of choice sets. In contrast, our model does not collapse to the MNL since the lower choice probability is not determined by the utility. As boundary conditions we can only establish a special case. To better understand the properties of our model in the following we compare the MNL model with our proposed model assuming that only travel time and line frequency influence choice.

Consider choice between three lines at a stop. Line 1 is infrequent but fast (f_1 = 5 services per hour, t_1 = 20 min), Line 3 is frequent but slow (f_3 = 15, t_3 = 30) and Line 2 is a compromise between both ((f_2 = 10, t_3 = 25).

Figure 1 compares the predicted probability of a traveller choosing line 1 as a function of β_{wait} assuming β_{travel_time} = 0. At β_{wait} the MNL predicts that the traveller is equally likely to choose each line, whereas in our proposed "hyperpath logit" model considers that other lines are more frequent so that the choice of the fast line is only 0.25. With increasing importance of waiting time in both models the likelihood of taking Line 1 reduces. Our proposed model is, however, less sensitive to β_{wait}. This is because the likelihood of choosing Line 1 only reduces on the "upper choice" level, i.e. the likelihood of choosing a hyperpath that includes Line 1. Figure 2 shows the similar effect for a decrease in β_{travel_time} assuming that β_{wait} = 0. With increasing importance of travel time in the choice the attractiveness of Line 1 increases, though in our proposed model less fast. Finally Figure 3 shows the effect of increasing the service frequency of Line 1 assuming $\beta_{wait} = \beta_{travel\_time}$ = 1. Our proposed model is more sensitive to an increase in service frequency, as frequency influence choice at the lower level/within the hyperpath as well as on the upper level as it increases the utility of hyperpaths that include Line 1.

(5) Maximising the Likelihood Function

For generality and notational simplicity we refer to the service characteristics that determine the nest attractiveness in (5) as $X_{akn\tau}$ and $Y_{ak\tau}$ where a denotes travel time, waiting time, number of transfers or nest size. $X_{akn\tau}$ hence denote the attributes that are estimated passenger group specific, whereas the values of attributes $Y_{ak\tau}$ are estimated for the whole sample. The estimated probability that line i is chosen by sample s is then (9) where $I_{kn\tau}$ is determined with (10).

$$P(i,n\tau)=\sum_{k\in K_i}\left(\frac{f_i}{\sum\limits_{j\in C_k} f_j}\cdot\frac{\exp\left(\mu I_{kn\tau}\right)}{\sum_{r=1}^{K}\exp\left(\mu I_{rn\tau}\right)}\right) \tag{9}$$

$$I_{kn\tau}=\sum_a \beta_{an}X_{akn\tau}+\sum_b \beta_b Y_{bk\tau} \tag{10}$$

Let us denote the observed choices as set S consisting of samples s. Each sample is associated with a person type n and a travel period τ. With this formulation the likelihood function L in (11) and the log likelihood function L^* (12) can be formulated as follows where $n(s)$ and $\tau(s)$ denote the person types and travel period of sample s respectively. δ_{is} is 1 if sample s chooses option i and 0 otherwise.

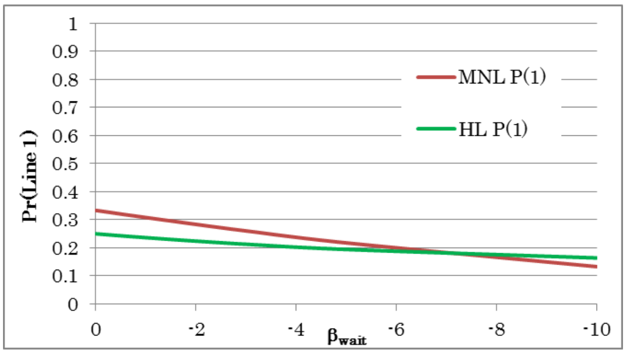


Fig. 1. Influence of waiting time sensitivity on the MNL and our proposed "HL model"

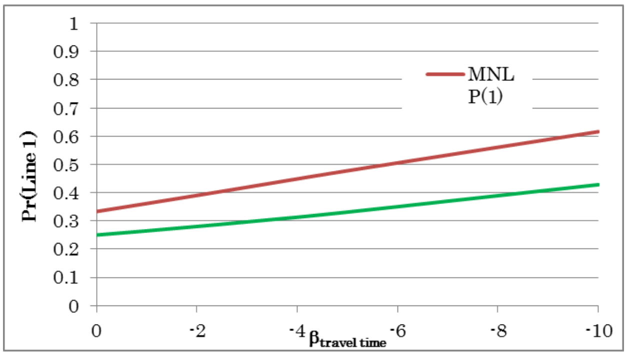


Fig. 2. Influence of travel time sensitivity on the MNL and our proposed "HL model"

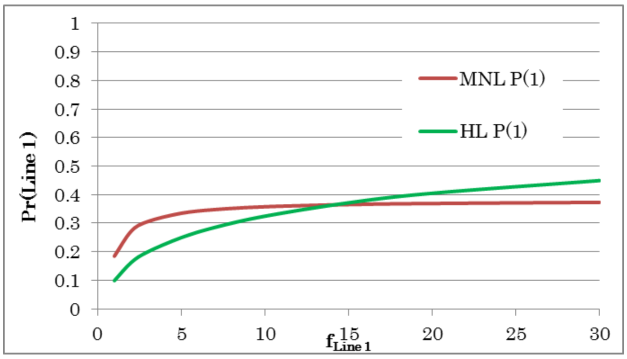


Fig. 3. Influence of service frequency on the MNL and our proposed "HL model"

$$L=\prod_i\prod_s\left(\sum_{k\in K_i}\left(\frac{f_i}{\sum\limits_{j\in C_k} f_j}\cdot\frac{\exp\left(\mu I_{kn(s)\tau(s)}\right)}{\sum_{r=1}^{K}\exp\left(\mu I_{rn(s)\tau(s)}\right)}\right)\right)^{\delta_{is}} \tag{11}$$

$$L^*=\sum_i\sum_s \delta_{is}\ln\left(\sum_{k\in K_i}\left(\frac{f_i}{\sum\limits_{j\in C_k} f_j}\cdot\frac{\exp\left(\mu I_{kn(s)\tau(s)}\right)}{\sum_{r=1}^{K}\exp\left(\mu I_{rn(s)\tau(s)}\right)}\right)\right) \tag{12}$$

We aim to maximise (12) with respect to our parameters β_{an}. For this we establish the gradient and Hessian of this log likelihood function (see Schmöcker et al[9] for details). Unfortunately, especially the Hessian takes a complex nonlinear form. Similar to other cross-nested logit models we cannot establish that our objective function is concave and hence test convergence with different initialisation for our parameters[10].

In the following tests we use Matlab^R for estimation of (12) as well as the calculation of t-values of our parameters and model fit statistics at convergence.

3. Case Study with Smartcard Data

(1) Data overview

To check the validity of the proposed model, we use smartcard data obtained by a bus operator of a local city in Japan. The dataset includes 2,100,285 records made by 82,320 cards over two months from the beginning of September 2011 until the end of October 2011. The smartcard has been used mainly for the route bus services but also for some community-run bus services within this Prefecture. Therefore we picked up the records of route bus services within the city. Consequently, we have 2,005,421 trip records made by 44,310 cards.

The bus company applies a flat-fare system in the central part of the city with a time-independent fixed cost per ride. Once the bus leaves the central area, an additional distance-based fare is applied. For this reason, passengers have to tap the smartcard twice, when boarding and alighting a bus. If passengers make transfer to other bus route, the fare on the subsequent bus is discounted if the transferring time is less than 45 minutes. Because of this fare structure, we can accurately identify the boarding and alighting bus stop. The advantage of our dataset compared to smartcard data from other cities can be summarised as follows;

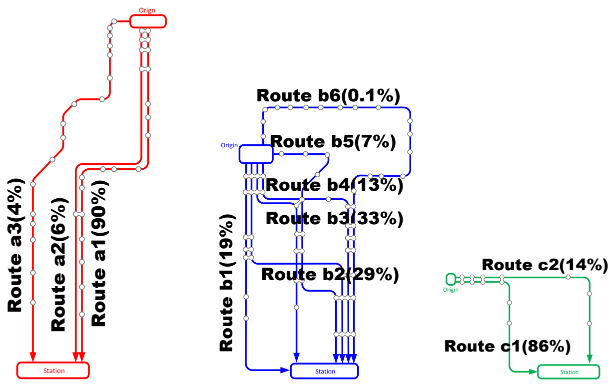
1) Card ID has been kept and individual behaviour can be tracked,
2) the whole city is covered only by the bus services and there is no rail service,
3) More than 70% of travellers use the smartcard data,
4) Boarding and alighting bus stops can be identified since travellers have to tap at boarding as well as alighting,

Since the smartcard data also contain date/time of boarding and alighting as well as route and bus ID we can therefore identify the data needed for our model.

A fifth characteristic is that the bus service is schedule-based. This has the advantage that we can estimate the effect of the delay of service. It has the disadvantage though that our assumptions made in (3) and (5) are possibly too simplistic. If passengers know (and trust) the schedule the experienced traveller will not arrive random at the bus stop but time his/her arrival. This will have an effect on the expected waiting time and line choice probability (see Nökel and Wekeck[11] for a detailed discussion on this.)

(2) Data extraction

From the journey dataset we pick up some OD pairs where there is choice between different routes and where we can observe repeated choices. This limits our data choice for this network fairly stringent as there are few OD pairs for which there are reasonable distinguishable alternatives and a significant number of observations. We pick up the 3 OD pairs and construct the hyperpaths. The destination of all three ODs is the railway station as many passengers arriving here transfer to rail lines. Figures 4 a)-c) illustrate the ODs together with the chosen routes and their passenger share. We note that there are six chosen routes from Origin B to the station, leading to 63 (=2^6-1) choice sets. Table 1 summarises the service characteristics of all lines. For some lines the service attributes differ significantly depending on time of day. In particular line a2 is only operated in the morning peak hour. Limiting our sample further to those timer periods, where passengers face a choice, we obtained 4,033 journeys made by 257 cardholders for OD *a*, 1,589 journeys made by 122 cardholders for the OD *b* and 958 journeys made by 123 cardholders for the OD *c*. Note that on none of these three routes we could find passengers who transfer and hence in the following we cannot estimate β_{yn}. For other OD pairs were one transfer is required there is no reasonable alternative route without transfer (or with more than one transfer) or sample sizes are very small, so that these data are not useful for our illustration. This shows a second disadvantage of our data set as this city is not as big and the bus network not as complex as that of other large metropolitan cities, so that transfer is often not required.



a) OD *a* b) OD *b* c) OD *c*

Fig. 4. Three OD pairs with share of passengers for each route

Table 1. Summary of service characteristics of the lines

OD *a*		*a*1	*a*2	*a*3			
	Serv. /Hour	9-17	4	1-3			
	Opeating Hrs.	5-23	6-7	6-20			
	Travel Time	18-26	18	26-31			
OD *b*		*b*1	*b*2	*b*3	*b*4	*b*5	*b*6
	Serv. /Hour	1-3	7-9	7-8	3-5	2-3	3-4
	Opeating Hrs.	6-20	6-23	6-23	6-22	6-19	6-23
	Travel Time	10-14	14-16	14-23	12-17	17-23	28
OD *a*		*c*1	*c*2				
	Serv. /Hour	4-7	1-4				

	Opeating Hrs.	5-23	6-21
	Travel Time	10-12	10-15

(3) User groups

In a separate analysis we firstly use all bus user data to establish whether we can distinguish some user groups. We use information such as whether the user holds a seasonal ticket, if yes what kind of seasonal ticket, as well as data on his/her "general aggregated" behaviour such as usual day of time travelled and number of trips per month. We further include a characteristic how often they make journeys that include transfers. We employ cluster analysis and find that we can distinguish four passenger groups described in Table 2. Details of this behavioural analysis are reported in Kurauchi et al[4]. With four user groups this means that in total we estimate 12 parameters (β_{tn}, β_{wn} and β_{zn} for all clusters).

Table 2. Characteristics of the four distinguished user groups.

User group	Characteristic of user group
Commuter	Hold commuter pass, travel often and mostly during weekday, include a large number of students.
Elderly	Hold elderly season pass, travel not often, mostly during day time, make almost no trips that include transfers.
Irregular	Passengers that fairly often make journeys that include transfers (23.6% of all journeys). Fairly few total journeys. Irregular OD patterns.
Other	Not passholders, fairly few total journeys, very few journeys that include transfers.

(4) Estimation results

Tables 3 and 4 illustrate our model results for the three OD pairs shown in Figure 5. Travel time and waiting time parameters all have the expected sign. We further note that the model fit varies significantly depending on the OD pair. With larger choice set the model fit reduces as one would expect. In particular for OD *b* there are six lines with often fairly similar travel times so that a passenger arriving at the stop without prior knowledge of the exact departure time will be indeed likely to choose the line whichever comes first explaining our lower ρ^2. (We remind that our model fit measure is an index of the model estimating the specific chosen line correctly, not the choice set, since this is obviously not measureable.)

For OD *a* we estimate two models; in the first one we include a group independent waiting time parameter as well as choice set size. We find that choice set size is not at all significant for this OD pair as well as for all other OD pairs so that we omit it for other estimations. A reason for this is likely the strong correlation with our waiting time parameter. We secondly find that group specific estimates of waiting in general lead to slightly better model fit. Further, we find some fairly consistent differences in the waiting time estimates across the OD pairs. Older persons appear to value waiting time more than commuters. As a result of this we estimate probability for older persons to choose choice sets including more lines higher than for commuters (Table 4). We believe there are two explanations for this, which we cannot distinguish with data available to us. Firstly, older persons might indeed prefer to spend time in the bus than at the bus stop. Secondly, commuters might have more accurate knowledge of the precise departure time of the services. Therefore they target their arrival time at the bus stop to the arrival of the faster bus services, meaning that service frequency is less of a criterion for their line choice.

We finally note that we find that the parameter estimates to some degree vary depending on the starting point of our parameter estimates in the maximisation of our log likelihood function due to the above discussed issue that our optimisation might be trapped in local optima.

Table 3. Model Estimation Results

	OD *a*			
	beta	t-value	beta	t-value
Travel time β_t	**-10.7**	-18.6	**-183.0**	-1062
Waiting time β_{wn}				
Commuter	**-10.8**	-6.83	**-62.7**	-351.1
Elderly			**-75.7**	-862.0
Irregular			-69.7	-173.0
Other			-79.6	-474.9
Choice set size β_{zn}	-1.61	-0.23		-
sample size		4033		4033
ρ^2		0.51		0.51
LL(0)		2385.6		2385.6
L*		1177.7		1174.1

	OD *b*		OD *c*		All OD pairs	
	beta	t-value	beta	t-value	beta	t-value
Travel time β_t	**-43.9**	-57.1	**-65.8**	-441.3	**-87.6**	-218.6
Waiting time β_{wn}						
Commuter	**-3.58**	-5.98	**-1.48**	-3.74	**-33.8**	-219.4
Elderly	**-34.0**	-523.8	**-26.8**	-420.2	**-46.6**	-427.3
Irregular	-0.59	-0.07	-1.20	-1.59	**-34.1**	-35.1
Other	-2.99	-1.16	**-18.5**	-124.7	**-48.1**	-256.2
Choice set size β_{zn}		-		-		-
sample size		1589		958		6580
ρ^2		0.15		0.31		0.27
LL(0)		2701.1		576.9		5663.5
L*		2305.5		394.9		4137.0

Table 4. Examples of Estimated Choice Set Probabilities

OD *a*, 6-7am	(a1)	(a2)	(a3)	(a1, a2)	(a1, a3)	(a2, a3)	(a1,a2,a3)
Commuter	0.01	0.18	0.00	0.64	0.00	0.01	0.17
Elderly	0.00	0.02	0.00	0.75	0.00	0.00	0.22
Irregular	0.01	0.06	0.00	0.73	0.00	0.01	0.20
Other	0.00	0.01	0.00	0.75	0.00	0.00	0.23

OD *c*, 7-8am	(c1)	(c2)	(c1,c2)
Commuter	0.71	0.04	0.25
Elderly	0.34	0.00	0.66

Irregular	0.71	0.04	0.25
Other	0.47	0.01	0.52

4. Conclusions

This paper presented a discrete choice model with explicit choice set generation aimed specifically at transit line choice at stops. A main feature of our model is that it is only on the upper level, the choice set formation, a RUM model. On the lower level the user is assumed to not control his/her choice but simply board which bus from the choice set arrives first. A second aspect of our model is that the inclusive value of the nest considers the "hyperpath effect". For example in the "generation logit" model of Swait (2001) the inclusive value of a nest is estimated as the log sum of the utilities of the options within the nest. We discuss that this is not appropriate in the transit case, in particular due to the reduced expected waiting time when several lines are included in the nest.

Considering these transit characteristics hence leads to a model which cannot be reduced to other simpler discrete choice models easily. We illustrate that we expect passenger's line choice to be more sensitive to service frequency and less sensitive to other factors, given similar user preferences. To estimate our model we establish the log likelihood function and its first and second order derivatives.

Our model formulation was motivated by the common practice in frequency-based transit assignment models to assign passengers to the shortest hyperpath in line with the "take whichever attractive line comes first" assumptions. We believe that our results, despite some shortcomings mentioned below, illustrate that these assumptions are often too simplistic. We present an approach to estimate the relative value of waiting time compared to on-board time in order to find (person-group specific) attractive sets. With such calibrated hyperpaths the model accuracy of transit assignment models might improve.

Smartcard data from a local city in Japan allow us to illustrate choice behaviour. In initial results we find that choice behaviour between passenger groups vary, in particular we find that older persons dislike waiting times relatively more compared to on-board travel time and other person groups. We can observe that some passengers form smaller choice sets than the attractive set proposed if evaluating travel time and waiting time equally. We acknowledge that our model results should be considered with some care as some passengers might perceive the service as schedule-based rather than frequency based and hence our data might not fully fit our model assumptions. In other cities with less reliable bus services we would expect that passengers form larger choice sets, highlighting the need to estimate hyperpaths supply specific.

This research can be continued in several directions. Firstly, a detailed analysis comparing our estimation results with that of other choice models has not been carried out yet. Secondly, convergence of our model estimates and sensitivity to model assumptions such as service regularity assumptions should be investigated in more detail. Thirdly, we do not consider panel effects in our model nor do we consider that users change preferences depending on time of day. Fourthly, we need to discuss about the mathematical properties of the proposed model, especially about the uniqueness of the solution. We believe with nowadays more smartcard data becoming available our estimations could be repeated in more complex networks. This would allow us to also estimate the impact of possible different numbers of transfers to reach the destinations on the choice set formation.

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交通ICカードデータを用いた公共交通hyperpathの推定

シュマッカー ヤンディァク・嶋本寛・倉内文孝

本研究では，交通ICカードデータを用いてバスの乗客の経路選択行動を推定した．乗客は，それぞれの路線系統について，そのサービス特性を元に利用するかどうかを決定し，それら利用してもよいと考える経路の集合（attractive set）のうちで，「最初に到着する系統」を利用するものとした．本稿では，モデルの特性と異なる乗客グループにおけるhyperpath選択の推定結果を示す．その結果から，交通ICカードデータを活用した乗客配分モデルの改良について議論した．