Multi-Modal Route Choice Modeling in a Dynamic Schedule-Based Transit Network

**Maëlle Zimmermann
Kay Axhausen
Emma Frejinger**

August 2018

CIRRELT-2018-36

Multi-Modal Route Choice Modeling in a Dynamic Schedule-Based Transit Nework

Maëlle Zimmermann[1],[*], Kay Axhausen[2], Emma Frejinger[1]

[1] Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT) and Department of Computer Science and Operations Research, Université de Montréal, P.O. Box 6128, Station Centre-Ville, Montréal, Canada H3C 3J7

[2] Institut für Verkehrsplanung, Transporttechnik, Strassen-und Eisenbahnbau, ETH, Zürich, Switzerland

Abstract. Route choice behavior has predominantly been analyzed from the angle of a single mode, most often the car. Considering route choice in the broader context of multi-modal networks yet opens the way to more complex policy analysis and wider applications. The main modeling challenges in this context are the limited availability in time of public transport services and the definition of alternatives to the observed path. This paper tackles these challenges by applying the recursive logit to model the choice of transit modes and route in a real network. The model is based on the assumption of a full available schedule. The approach presents numerous advantages. First, route choice preferences can be consistently estimated without generating choice sets of paths. Second, the model can be used to predict fast and accurately path choices in real network by sampling from estimated link choice probabilities. Although the network is much larger than previous applications of the RL model with over 1 million links, we obtain reasonable computational times. Third, the approach allows to include all transit services without restriction in one large-scale network, providing the possibility to estimate realistic rates of substitution between different attributes.

Keywords: Transit route choice, multi-modal, recursive logit, time-expanded network.

* Corresponding author Maelle.Zimmermann@cirrelt.ca

1 Introduction

Route choice behavior has predominantly been analyzed from the angle of a single mode, most often the car. Considering route choice in the broader context of multi-modal networks yet opens the way to more complex policy analysis and wider applications. In particular, multi-modal traffic assignment models (Lo et al., 2004) and advanced traveler information systems (Zhang et al., 2011) can analyze the effect of fares on congestion or answer routing queries involving several modes. Their mechanisms rely on sound knowledge of traveler's preferences for attributes of multi-modal trips, such as travel time, waiting time or number of transfers.

On many levels, the behavior of travelers in multi-modal networks is more complex to model than that of car drivers. Traditional models of route choice analysis in traffic networks are not directly applicable in this context. To represent a multi-modal trip as a path, it is necessary to combine the networks of available modes via transfer, waiting and/or access links into a so-called supernetwork (Sheffi, 1985). An additional difficulty is the limited availability of public transport services. Indeed transit lines are subject to a frequency or a schedule, which imposes constraints on the route choice and calls for an appropriate treatment of time. To get around this problem, some studies have attempted to simplify the network representation or the level of detail, focusing on schematic networks (e.g. Raveau et al., 2011). Another challenge is related to the definition of alternatives to the observed path. Not only is it more complex to generate realistic path alternatives in a multi-modal network, but there may be a bias in parameter estimates induced by the selection of a restricted choice set (Frejinger et al., 2009).

This paper tackles these challenges by applying the recursive logit to model the choice of transit modes and route in a real network. The model is based on the assumption of a full available schedule. The approach presents numerous advantages. First, route choice preferences can be consistently estimated without generating choice sets of paths. Second, the model can be used to predict fast and accurately path choices in real network by sampling from estimated link choice probabilities. Although the network is much larger than previous applications of the RL model with over 1 million links, we obtain reasonable computational times. Third, the approach allows to include all transit services without restriction in one large-scale network, providing the possibility to estimate realistic rates of substitution between different attributes.

2 Literature review

There is a large body of literature which reports route choice preferences of travelers in a multi-modal network, most of which are based on stated preference (SP) data (e.g. Arentze and Molin, 2013, Fosgerau et al., 2007, Vrtic et al., 2010). Such studies are simpler to implement as the modeler can entirely define the choice situation and its alternatives according to convenience. However SP data has notable disadvantages, in particular the potential disparity between answers given to hypothetical choice situations

and behavior exhibited in reality. In addition, although such studies can provide an interpretation of estimated parameters in terms of policy implications, the models cannot directly be applied to predict route choices in a real network.

Route choice models based on revealed preference (RP) data are congruent with observed behavior in actual choice situations, but face other challenges. The modeler must define a restricted set of path choice alternatives for each observation, as the many possibilities to connect an origin-destination pair are too numerous to enumerate in a real network. In multi-modal networks, there is not only a large number of paths confined to each single mode, but also nearly unlimited transfer possibilities as well as different runs of parallel lines, resulting in a very large number of alternatives. Most studies avoid dealing with the full inherent complexity of the problem. For example, Bovy and Hoogendoorn-Lanser (2005) consider a multi-modal interurban corridor between two Dutch cities which is a schematic network of small size, where some modes only serve as access or egress modes to train. Raveau et al. (2011) restricts the number of modes by considering only the Santiago metro network, a schematic public transport network with no time dimension. While other studies examine larger and more realistic networks with several modes (e.g. Anderson et al., 2014, Eluru et al., 2012, in Montreal and Copenhagen respectively), there also exists limitations regarding how the issue of choice sets is addressed. In Eluru et al. (2012) the observed trip is compared only with few alternatives (between one and six) generated via Google Maps. Anderson et al. (2014) and Bovy and Hoogendoorn-Lanser (2005) generate more alternatives using respectively doubly stochastic and constraint enumeration algorithms, however treat the generated choice sets as the actual alternatives. This implies that the validity of estimation results is questionable due to the bias induced by choice set selection (Frejinger et al., 2009). Finally we also note that there is ongoing research from Montini et al. (2016) to estimate mode and route choice models from a sample of GPS traces collected in Zürich.

The current study fills a gap in the literature by estimating a multimodal transit route choice model with unrestricted choice sets based on RP data collected in a complex network. The approach has the advantage of yielding consistent estimates and can also be used for prediction in a real network without generating choice sets of paths.

3 Model

We assume that the transit system can be described by a static and deterministic network representing the transit lines of each mode, and a timetable which lists the arrival and departure time of each run at each station for a whole day. The complete set of available transit services can be represented as a time-expanded network $G = (\mathcal{A}, \mathcal{V})$ in which each node $v \in \mathcal{V}$ corresponds to a transit stop location l and a time t, and links move through time and/or space. Links belong to one of the following categories:

Transit arc: The arc corresponds to an in-vehicle trip on a transit line (e.g. a bus or a metro line) between two consecutive stations at a specific time.

Transfer arc: The arc corresponds to a walking trip between two geographically close

stations.

Waiting arc: The arc corresponds to waiting at the same station for the arrival of another vehicle.

Contrarily to other time-expanded networks (e.g. Hamdouch and Lawphongpanich, 2008), we do not discretize the day into equally spaced points in time. Instead, time is continuous and the nodes of the static network are expanded according to the schedule. In other words, the nodes $v = (l, t)$ in the time-expanded network are defined only for times t corresponding to the arrival or departure of a transit line. This network representation is similar to what has been called a diachronic graph in the literature (Nuzzolo et al., 2012) and it is at the core of several assignment models.

The network must be extended to include absorbing links without successors to represent destinations. In the model, we assume that travelers have a fixed departure time and must arrive to the destination stop l within a certain time interval T. To represent the destination of an individual traveling in this network, we must define absorbing links outgoing from node (l, t) for all valid times t within the time window T for arrival. Thus in this model the destination of an individual n is represented as a set of absorbing links D_n.

The RL model can be used for the multimodal transit route choice problem by defining states and actions as links $k, a \in \mathcal{A}$ in the dynamic network previously defined. From a state k, the traveler reaches the next state by choosing an action a in the set of outgoing links $A(k)$ in order to maximize instantaneous link utility $u(a|k) = v(a|k) + \mu \epsilon(a)$ and expected maximum utility to destination $V_n(a)$, which is the solution of a dynamic programming problem given by the Bellman equation. The value function V_n is defined for the set of links D_n corresponding to the arrival stop and time window of individual n and is given as follows

$$V_n(k) = \begin{cases} \mu \ln \sum_{a \in A(k)} e^{\frac{1}{\mu} v_n(a|k) + V_n(a)} & \forall k \in \mathcal{A} \\ 0 & \forall k \in D_n \end{cases} \qquad (1)$$

The random terms $\epsilon(a)$ are assumed i.i.d. Gumbel with scale parameter μ, resulting in the multinomial logit model's conditional probability of choosing action a in state k:

$$P_n(a|k) = \frac{e^{u_n(a|k) + V_n(a)}}{\sum_{a' \in A(k)} e^{u_n(a'|k) + V_n(a')}} \qquad (2)$$

The model can be estimated using an approach similar to the nested fixed point algorithm and link choice probabilities in (2) can be used to predict path choices link by link without generating any choice sets.

4 Data

We use a real network in the city of Zürich and we estimate the model based on GPS trajectories of travelers collected in that network by Montini et al. (2013). There are

5'276 stop locations, 724 transit lines and 40'031 runs over a day, for which the exact arrival and departure time at each station along the line is known. Some lines have very frequent services while others are only available at sparse times. Each transit lines corresponds to one of the 6 available modes (bus, train, tram, boat, taxi, cable car). Representing the transit service for one day with a time-expanded network requires over one million links.

We have 302 observations of trips in the transit network. The observations are described as a sequence of stops, line IDs, and a departure time. Since we do not have access to arrival and departure time at each stop, we reconstruct the trip assuming that the first available vehicle matching the observed stops was taken (i.e. individuals did not wait for a subsequent run of the same line). This is a realistic assumption if the observed trips did not take place in a congested network. We obtain a sequence of transit, waiting and/or transfer links in the time-expanded network.

5   Results

We note that link utilities in the RL model must be defined as a function of additive link attributes (Fosgerau et al., 2013). Therefore, dummy variables for link types cannot be directly incorporated in the utility function, since their sum over links in a path cannot be interpreted as a measure of path utility. As an example, the number of tram links contained in a given path is not representative of how much the tram was used, since some links have longer travel time than others. Thus in this model we interact dummy variables for the mode of a link with the travel time of that link.

We retain a model specification with 6 attributes, consisting of the in-vehicle time, the waiting time, a dummy for a transfer between two stations, a link constant, and the in-vehicle time attribute interacted with a dummy for the tram and bus modes. Table 1 displays the estimations results of the chosen utility specification. Following Zimmermann et al. (2017), we note that we may interpret the results as letting the value of the travel time coefficient depend on the mode. Indeed, by adding the in-vehicle time coefficient with each interaction coefficient, we obtain that the value of travel time is -18.81 on a tram and -24.48 on a bus. We note that the observed trips only used the tram, bus and train modes, thus the travel time coefficient on a train would be -12.57.

The model is expensive to estimate, since the state space is large and the value function needs to be solved for each individual. In order to speed up computational time, the value functions are only solved for a subset of links in the time-dependent network. More precisely, for an individual n with observed departure time t_o and latest possible arrival time t_d, we only compute the value function for links (l, t) with $t \in [t_o, t_d]$. As a result, the linear systems which need to be solved to obtain V_n for each observation n have a maximum size of 255,369 for this dataset. The total estimation time is then less than a day.

Model	RL	
Link attribute	$\hat{\beta}$	t-test
In-vehicle time [1/1000s]	-12.57	-5.66
Waiting time [1/1000s]	-8.57	-9.82
Transfer dummy	-5.67	-5.84
Link constant	-0.10	-4.16
Tram dummy $\cdot$ in-vehicle time [1/1000s]	-6.24	-3.42
Bus dummy $\cdot$ in-vehicle time [1/1000s]	-11.91	-5.41
Log likelihood at $\hat{\beta}$	-783.87	

Table 1: Estimation results

Bibliography

Anderson, M. K., Nielsen, O. A., and Prato, C. G. Multimodal route choice models of public transport passengers in the greater copenhagen area. *EURO Journal on Transportation and Logistics*, pages 1–25, 2014.

Arentze, T. A. and Molin, E. J. Travelers' preferences in multimodal networks: design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice*, 58:15–28, 2013.

Bovy, P. H. and Hoogendoorn-Lanser, S. Modelling route choice behaviour in multi-modal transport networks. *Transportation*, 32(4):341–368, 2005.

Eluru, N., Chakour, V., and El-Geneidy, A. M. Travel mode choice and transit route choice behavior in montreal: insights from mcgill university members commute patterns. *Public Transport*, 4(2):129–149, 2012.

Fosgerau, M., Hjorth, K., and Lyk-Jensen, S. V. The danish value of time study. *Danmarks Transport Forskning Report*, 2007.

Fosgerau, M., Frejinger, E., and Karlström, A. A link based network route choice model with unrestricted choice set. *Transportation Research Part B*, 56:70–80, 2013.

Frejinger, E., Bierlaire, M., and Ben-Akiva, M. Sampling of alternatives for route choice modeling. *Transportation Research Part B*, 43(10):984–994, 2009.

Hamdouch, Y. and Lawphongpanich, S. Schedule-based transit assignment model with travel strategies and capacity constraints. *Transportation Research Part B: Methodological*, 42(7):663–684, 2008.

Lo, H. K., Yip, C.-W., and Wan, Q. K. Modeling competitive multi-modal transit services: a nested logit approach. *Transportation Research Part C: Emerging Technologies*, 12(3):251–272, 2004.

Montini, L., Rieser-Schüssler, N., and Axhausen, K. W. One-week GPS-based travel survey in the Greater Zurich area. In *13th Swiss Transport Research Conference (STRC 2013)*. 13th Swiss Transport Research Conference (STRC 2013), 2013.

Montini, L., Antoniou, C., and Axhausen, K. W. Route and mode choice models using gps data. *Arbeitsberichte Verkehrs-und Raumplanung*, 1204, 2016.

Nuzzolo, A., Crisalli, U., and Rosati, L. A schedule-based assignment model with explicit capacity constraints for congested transit networks. *Transportation Research Part C: Emerging Technologies*, 20(1):16–33, 2012.

Raveau, S., Muñoz, J. C., and De Grange, L. A topological route choice model for metro. *Transportation Research Part A: Policy and Practice*, 45(2):138–147, 2011.

Sheffi, Y. Urban transportation network. *Equilibrium analysis with mathematical programming methods, Prentice Hall*, 1985.

Vrtic, M., Schuessler, N., Erath, A., and Axhausen, K. W. The impacts of road pricing on route and mode choice behaviour. *Journal of Choice Modelling*, 3(1):109–126, 2010.

Zhang, J., Liao, F., Arentze, T., and Timmermans, H. A multimodal transport network model for advanced traveler information systems. *Procedia-Social and Behavioral Sciences*, 20:313–322, 2011.

Zimmermann, M., Mai, T., and Frejinger, E. Bike route choice modeling using gps data without choice sets of paths. *Transportation research part C: emerging technologies*, 75:183–196, 2017.