A Route Choice Model based on Mental Representations

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Abstract

We present a new approach for modeling and analyzing route choice behavior. It is inspired by the rationale that people break down the complexity of the environment by forming representations of their surrounding space. The proposed framework is based on aggregate elements for the representation of the choice set, denoted as *Mental Representation Items* (*MRIs*). This key feature of the framework allows us to reduce the complexity of the model and is more behaviorally realistic than the conventional assumption of *path* alternatives. In this paper, we focus on the operationalization of the *MRIs* and we develop a simple procedure to generate the attributes of the *MRI* alternatives in order to assess the methodology. We further discuss the application of the model in traffic assignment and route guidance systems.

Keywords
Route choice, Random utility models, Aggregate route representation, Mental representation item (MRI)

1 Introduction

We are interested in modeling and forecasting the route choice behavior of individuals. Route choice (RC) is one of the key questions in travel demand analysis and the core of traffic assignment. Discrete choice models (DCM) provide a powerful and flexible methodological framework, where a great deal of explanatory variables can be considered, and the heterogeneity of behavior across the population can be explicitly captured. The use of DCMs for route choice analysis involves challenges as compared to standard choice models, e.g. mode choice. The challenges concern the demanding requirements in data collection and processing, the combinatorial nature of the choice set, and the structural correlation due to the physical overlap of paths (Ben-Akiva and Bierlaire (2003)).

Route choice models (RCMs) aim at predicting the route that a given traveler would take to go from the origin of her trip to the destination. A comprehensive review of the route choice modeling problem can be found in Bovy and Stern (1990) and Frejinger (2008). The conventional representation of routes is based on paths that are constructed as sequences of oriented arcs on a connected graph. In addition to the above mentioned challenges for the modeler, the complexity of the path approach is not consistent with the actual behavior of travelers. The general trend in the literature is to propose more and more complex models to deal with this complexity (Fosgerau *et al.* (2013); Yang and Juang (2014); Lai and Bierlaire (2014); Ramos (2015)).

In this work, we are investigating in the opposite direction, i.e. we attempt to simplify the problem. This is accomplished by modeling the strategic decisions of the users, instead of the operational ones, through aggregated choice sets. We show that the simplification in the choice set allows us to estimate a model and it is useful for fusion and comparison with other models.

The paper is organized as follows. Section 2 is a literature review about the challenges in route choice modeling. Section 3 motivates the proposed framework. Section 4 is devoted to the methodology. In Section 5 we illustrate the application of the model in traffic assignment and we discuss its potential in the development of route guidance systems. The last section summarises the findings of the present study and identifies the future steps of the research.

2 Literature review

The literature review is organized along the three challenges identified above, i.e. data, choice set composition, and physical overlap of paths.

Route choice data, either collected through traditional surveys or from global positioning system (GPS) records, needs to be matched to the network that the modeler uses (Wolf *et al.* (1999); Marchal *et al.* (2005); Schuessler and Axhausen (2009)). Bierlaire and Frejinger (2008) argue that the required processing entails a high risk of introducing biases in later steps of estimation. The authors propose a methodology in order to tackle the inaccuracy of the observations. It is based on the concept of network-free data. The idea is that since the underlying route choices are based on paths on the physical network –while the observations are not– there is a need to establish a link between them. This is accomplished by determining physical areas in the network, denoted as Domains of Data Relevance (DDR), where each piece of data, e.g. a reported location along a trip or a GPS point, is relevant. Later work by Bierlaire *et al.* (2013) further exploits this approach to develop a probabilistic map-matching algorithm[1] dealing with the inaccuracy and sparseness of the GPS records by proposing several candidate paths, each one associated with a likelihood to be the true one, corresponding to the same observed sequence of records.

The size and the composition of the choice set are also challenging issues. The definition of the choice set is of utmost importance in the estimation of route choice models. The choice set consists in the group of alternatives that are *available* to the traveler. Three approaches are proposed in the literature. The first one tries to reconstruct the choice set actually considered by the travelers (Bovy and Fiorenzo Catalano (2007); Prato and Bekhor (2007)). However, Bekhor *et al.* (2006) showed that all methods fail to generate a set that includes the observed routes.

The second approach assumes that the choice set contains all feasible paths between the origin and the destination. To make this approach operational, sampling techniques have been proposed (Frejinger *et al.* (2009); Flötteröd and Bierlaire (2013)). The third approach does not explicitly build the choice set. Fosgerau *et al.* (2013) introduce the recursive logit (RL) model. It is a link-choice-based model that follows a dynamic setting which does not require choice set generation and, therefore, no sampling.

Finally, various approaches have been established to address the correlation of the path utilities. They can be generally divided in two categories; those dealing with the correlation in the deterministic part of the utility function, and those dealing with it in the stochastic part. Examples of the former include the C-logit proposed by Cascetta *et al.* (1996) and the Path Size Logit (PSL) proposed by Ben-Akiva and Bierlaire (1999). Examples of the latter include the Generalized Extreme Value (GEV) models, such as the Paired Combinatorial Logit and Cross Nested Logit (CNL) (Vovsha and Bekhor (1998); Lai and Bierlaire (2014)), and Non-GEV models, such as the Probit (Daganzo and Sheffi (1977)) and the Logit Kernel model (Bekhor *et al.* (2002);

[1]Technique from which the actual paths of the users which are the input to RCMs are reconstructed by means of the GPS records. Refer to Quddus *et al.* (2007) for a comprehensive review of map-matching algorithms.

Frejinger and Bierlaire (2007)).

Mai *et al.* (2014) exploited the RL model by Fosgerau *et al.* (2013) and extended it to the nested recursive logit (NRL). The NRL model builds on the RL model, where no choice set generation is needed, and improves it by relaxing the independence from irrelevant alternatives (IIA) property in order to accommodate the correlation of path utilities. The first work to use a GEV model with sampling of alternatives is the one by Lai and Bierlaire (2014). The authors specify a CNL model and adopt the Metropolis-Hastings algorithm proposed by Flötteröd and Bierlaire (2013) with a new expansion factor inspired by Guevara and Ben-Akiva (2013) in order to avoid the enumeration of paths.

3 Motivation and Key Concepts

The concept of path is evidently hard to handle due to the operational limitations discussed in the previous sections, but also due to the fact that drivers, as planners and decision makers, do not actually use the concept of path to make decisions (Flötteröd and Bierlaire (2013)). The latter entails behavioral limitations. Intuitively speaking, if a traveler is asked to describe her itinerary from home to work, she wouldn't report sequences of links. In this work we argue that a path is solely the manifestation of the route choice; the way the traveler implements her decision to take a specific route. The route choice takes place at a higher conceptual level that can be supported by an aggregate route representation (ARR). The alternatives that are considered by the traveler are short sequences of specific landmarks, or pieces of infrastructure.

In order to investigate how this observation could be exploited for modeling purposes, we have performed simple qualitative case studies in the cities of Athens and Stockholm. We have performed interviews involving a total of three drivers in each city. Respondents were asked to give a description of the routes that they follow to go from home to work, or to a relative's place. The answers revealed that elements such as the *city center*, the *highway H*, the *neighborhood N* are used to describe the routes and identify alternatives. Also, the attributes that in most cases are associated with the alternatives are in the form of longer but faster, with less traffic lights etc.

The literature that assisted in gaining insights into the representation of large-scale environments and spatial behavior includes Tolman (1948), Lynch (1960), Suttles (1972), Chase (1983), Couclelis *et al.* (1987), Golledge (1999), Golledge and Gärling (2003), Arentze and Timmermans (2005), Hannes *et al.* (2008). A review on these research fields is avoided in the present document, since contrary to the research conducted in these disciplines, this project does not look at how the representations of space are formed or learned. It rather exploits the intuition gained from these fields in the effort to build a flexible and operational framework. Indeed, both the literature and the case studies were used as inspiration and both support the *ARR* assumption.

In this context, our objective is to derive a modeling framework with a level of complexity consistent with the one actually handled by the travelers. To do so, we introduce the concept of *Mental Representation Item (MRI)*. The *MRIs* are elements used in daily language to describe a route. The exact definition of the *MRI* is context dependant, and must be designed such that (i) it has a meaningful behavioral interpretation, and (ii) its level of aggregation is high enough for the model to be simple and operational, and low enough for the model to be useful.

A concept akin to this of the *MRI* is the one of the *subnetwork*, proposed by Frejinger and Bierlaire (2007). The concept of subnetwork is used to capture perceptual correlation without increasing the model complexity. The authors define a subnetwork component as a *"sequence of links corresponding to a part of the network which can be easily labeled, and is behaviorally meaningful in actual route descriptions"*. Hence, even paths that do not physically overlap are assumed to be correlated. As an example, *"paths going through the city center may share unobserved attributes, even if they do not share any link"* (Frejinger and Bierlaire (2007)). The motivation of this work is similar, but extend this idea to the choice set itself. We would like to derive a model where "common sense" concepts actually used by the travelers to describe their routes are the main modeling elements.

4 Definition of the Choice Model

In this section, we outline the methodology for the definition of a route choice model based on aggregated choice sets that are composed of *MRI* elements. The two main elements that need to be defined for the development of a discrete choice model are (i) the alternatives among which the individuals can choose (choice set), and (ii) the attributes of the available alternatives, such as travel time, length, etc..

The difference of the present work with the regular route choice models is that the alternative routes are represented as *MRI* sequences, instead of *link* sequences. We build on this feature to simplify the definition of the choice set. We start by providing the definition of what an *MRI* is. Then, we define alternatives on the basis of *MRI* elements, we discuss how to relate the *MRI* elements with the data, and we propose ways to assign attributes to them in order to make them operational. We conclude with the definition of the choice model based on the proposed aggregated choice set.

4.1 Definition of the *MRI*

An *MRI* is an item characterizing the mental representation of an itinerary. Each *MRI* is characterized by a *name*, a *description*, a *geographical span*, and a *representative geocoded point*. A typical example is "the city center". Its description would roughly explain the boundaries of the zone, while the geographical span would describe exactly these boundaries. The representative point may be the most important central intersection in the center. Another example would be a highway or bridge. The description in this case would be a toponym, while the geographical span would be a set of arcs. The representative point may be the middle point of the span in each case.

The definition of the *MRIs* should be specific to the given context and appropriate to keep the model simple and at the same time behaviorally realistic. A process equivalent to the one discussed in Section 3, taking into consideration the characteristics of the city and fusing information from surveys where people talk about their itineraries, is the most appropriate approach for the definition of the *MRI* elements in a given context.

4.2 Definition of the alternatives

Following the definition of the *MRI*, the choice set consists in either one-*MRI* or sequence-of-*MRI*-alternatives. The composition of the choice set depends on the size and nature of the city but also on the needs of the application. It is possible that for a simple network we are able to identify a common choice set of one-*MRI*-alternatives for all individuals, e.g. {go through the city center, avoid the city center}. On the other hand, for bigger networks we may identify different aggregate choice sets depending on the origin and the destination of the trip that consist in sequence-of-*MRI*-alternatives.

In this work, we start with the simplest case, this of one-*MRI* alternatives, and a common choice set for all individuals, denoted as C_n. We acknowledge the potential complexity in the case of large networks, and we are going to investigate it in future work.

The aggregation of the choice set enables us to avoid the cumbersome step of choice set generation. The issues that arise are (i) how to relate the available data to *MRI* alternatives, and (ii) how to assign attributes to the *MRI* alternatives and render an aggregated choice set, such as {go through the city centre, avoid the city center}, operational for the estimation of the model. For this step we rely on the paths. Different heuristics can be considered and evaluated. We discuss two approaches to elaborate this step in the following paragraphs.

4.2.1 From data to *MRIs*

Collecting route choice data for an *MRI* model is relatively easy using interviews and surveys, as the level of aggregation of the data is similar to the level of the model. Nowadays, route choice data coming from GPS devices or smartphones are more and more available. In the same way that the classical path-based models require some map-matching procedures, we need to relate the *MRI* alternatives with the GPS data.

The *MRIs* are geo-marked on the network model as sets of arcs. Let's consider two examples of aggregated choice sets: (i) {go through the city center, avoid the city center}, and (ii) {north bridge, south bridge, ferry boat}. For the first problem, we can define the *go through the city center MRI* as the set of arcs that fall into the boundaries of the core of the city (*geographical span*) in the network model. The remaining arcs are assigned to the *avoid the city center*. Same reasoning can be followed for the bridge choice problem, where each bridge corresponds to a specific set of arcs, and the ferry can also be assigned to implicit arcs.

Subsequently, each observation is replaced by an *MRI* depending on the arcs that the GPS records traverse; it reads like: $P(GPS|MRI) = 1$, if the GPS records traverse at least one arc of the *MRI* span, and *zero* otherwise.

Measurement equations It is possible that either because (i) the boundaries among the *MRIs* are not as distinct as in the examples presented above, or (ii) due to the inaccuracy of the records, that we cannot assign each observation to solely one *MRI* alternative deterministically. Measurement equations taking into account the fuzziness among the various *MRI* alternatives should be investigated in that case, depending on the nature of the data.

4.2.2 Generation of attributes

A deterministic approach with representative paths As soon as the list of *MRI* elements in the choice set is defined, we follow a deterministic approach that assumes a *representative path* for each abstract element in the list. The representative path passes through the *representative geocoded point* of the *MRI*. We make use of these paths to derive link additive attributes, such as the travel time for the *MRIs*. The representative path may be the shortest or the fastest path satisfying the criterion of the representative point for the *MRI*.

Expected maximum utility with path enumeration An *MRI* is an aggregate alternative, i.e. several paths connecting the OD of a trip may correspond to the same *MRI*. An *MRI* may be any of the possible paths satisfying the criterion of the *representative geocoded point*. Therefore, it makes sense to assume the expected maximum utility of each *MRI*. The expected maximum utility of an *MRI* can be computed as the *logsum* of the utilities of all the valid paths.

One way to derive the logsum is to follow the process of choice set generation; i.e. to enumerate all paths satisfying an *MRI* and compute the logsum. The enumeration can be accomplished using the *Metropolis-Hastings* sampling of paths algorithm proposed by Flötteröd and Bierlaire (2013). This approach brings back the computational burden that we try to avoid though. The challenge that arises is that the logsum is cumbersome to compute due to the high number of paths.

Remarks Evidently, the latter approach is more complex. The former approach is a feasible and operational way to start with simple, and specific to the case study, criteria. The decision of which procedure to follow for the generation of the attributes of the alternatives should take into consideration the trade-off between the flexibility and the complexity.

4.3 Specification of the model

After defining the choice set, relating the observations to $MRIs$ alternatives, and making the *MRI* alternatives operational by assigning attributes to them, we are able to specify a route choice model, and estimate the choice probabilities for each *MRI* alternative. *Utility maximization* assumes that the individual n will choose the alternative i (in this case an *MRI*) that maximizes her utility[2]. Each *MRI* alternative is associated with a utility which is a function of the attributes of the alternatives x_{in} and the characteristics of the individual z_n (if available). The choice model is then:

$$P(i|C_n;\beta) \tag{1}$$

defining the probability of choosing *MRI* (or *MRI* sequence) i given C_n. β is the vector of parameters to be estimated.

It is expected that the number of alternatives will be low due to the aggregation in the representation of the routes. Given this, it is possible to estimate alternative specific constants ($ASCs$)

[2] $\mathcal{P}(i|C_n) = Pr(U_{in} \geq U_{jn} \forall j \in C_n)$, where C_n is the choice set.

for the *MRI* alternatives[3]. In addition, a logit model should be sufficient. Alternative types of models can be investigated, but our first priority is to keep the model as simple as possible.

4.4 Model estimation

The estimation of the model is accomplished by means of the *maximum likelihood estimation* technique. The likelihood function is:

$$\mathcal{L}^* = \prod_{n=1}^{N} \prod_{i \in C_n} \mathcal{P}_n(i)^{y_{in}} \tag{2}$$

where y_{in} is 1 if *MRI* alternative is chosen, and 0 otherwise. For a logit model we have:

$$\mathcal{P}_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{\mathcal{V}_{jn}}} \tag{3}$$

where V_{in} is the deterministic part of the utility which is expressed as a function of the observed variables (x_{in} and z_n).

5 Model Application

It is very important to ensure the feasibility of the use of the proposed model in practical applications. There are two main applications that we ask the proposed model to be useful for: (i) traffic assignment, and (ii) design of route guidance systems. In this section we discuss these operational aspects of using the model and we introduce a multi-level framework where different models can be used.

5.1 Traffic assignment

To make the model operational for traffic assignment we need to transfer from the aggregate alternatives back to paths. We propose to use the *Metropolis-Hastings* sampling of paths that has been introduced by Flötteröd and Bierlaire (2013) to sample paths from the network. The

[3] $ASCs$ cannot be estimated in typical route choice models due to the high number of *path* alternatives.

probability of each *path* p to be selected, given the OD and the choice set C_n, is then:

$$\mathcal{P}(p|C_n) = \sum_i \mathcal{P}(p|i) \cdot \mathcal{P}(i|C_n) \tag{4}$$

where $\mathcal{P}(p|i)$ gives the probability of path p to be selected given the MRI alternative i. To perform the assignment, we need to define an indicator function $\delta(p, i)$, which is 1 if the sampled path p is consistent with MRI i, and 0 otherwise. $P(i|C_n)$ is the choice model, the parameters of which has to be estimated.

Equation [4] has two components: (i) $\mathcal{P}(p|i)$ consists the operational component for assignment, and (ii) $\mathcal{P}(i|C_n)$ is the behavioural component represented by the choice model. The assumption is that the decision has been made in the MRI level based on $\mathcal{P}(i|C_n)$, while $\mathcal{P}(p|i)$ is just the implementation of this decision. We want to keep $\mathcal{P}(p|i)$ as simple as possible. A reasonable assumption is to compute the probability of each path in the bundle of paths under each MRI, as the ratio of the length of the path by the length of the representative path, being it the shortest or the fastest path, of the MRI.

5.2 Route guidance

We believe that the proposed approach has potential in the development of route guidance systems, where the provision of information is in an aggregate manner, instead of instructions to follow specific itineraries. A key advantage of the approach in this case, is that the $MRIs$ can be used for guidance on variable message signs (VMS), radio announcements or oral instructions in in-vehicle navigation systems.

In-vehicle navigation systems could be adjusted according to the needs of the driver. As an example, drivers with good knowledge of the network do no always need step-by-step instructions to reach their destination, rather suggestions that would help them to avoid congestion in specific parts of the network (e.g. avoid the city center). In this context, the navigation systems could provide the option to choose between detailed itineraries –in case of new destinations– or aggregate route suggestions in case of everyday trips, such as the trip to work, according to the current traffic conditions.

5.3 A multi-level hierarchical structure of the MRI approach

From the analysis of the case studies, we have delineated a hierarchical ordering of the decisions of travelers, following varying levels of detail in the representation (Fig. 1). This ordering can

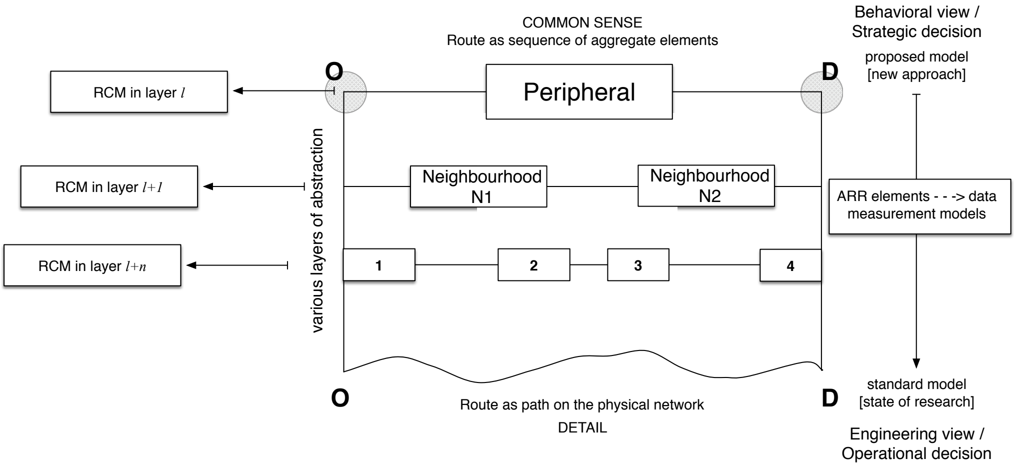

Figure 1: Outline of the hierarchical ordering of the decision process.

be parallelised to the *Normative Pedestrian Flow Theory* introduced by Hoogendoorn (2001) to describe pedestrian dynamics at three levels: i) the strategic (most aggregate representation), ii) the tactical (intermediate representations), and iii) the operational (path representation).

The decision on which layer the analysis should be conducted in rests on the needs of the application and the data availability. The model that we have presented in this paper corresponds to the highest layer of this hierarchical structure. The lowest level of aggregation corresponds to the conventional path representation as a sequence of arcs and nodes, i.e. to the traditional route choice model. Subsequently, the interconnection of the layers consists a matter of consistency of the hierarchical framework that should be investigated.

Exploiting the hierarchy the choice probability in the top layer ℓ, given by $P_\ell(i|C_\ell;\beta^\ell)$, can also be derived from layer $\ell+1$ as follows:

$$\bar{P}_\ell(i|C_\ell;\beta^\ell) = \sum_{j\in C_{\ell+1}} P(i|j,C_\ell;\beta^\ell)P(j|C_{\ell+1};\beta^{\ell+1}) \tag{5}$$

where $P(i|j)$ is the probability that representation i in layer ℓ is consistent with representation j in layer $\ell+1$, and $P(j|C_{\ell+1})$ is the choice model in layer $\ell+1$.

This structure can be exploited for data fusion. Data of different nature and precision, depending on the level of abstraction, can be used in each layer.

6 Conclusion

In this paper we present a new approach for route choice analysis. The proposed framework builds on solid ground of the current state of the art and adds on it by suggesting a new approach that reduces the complexity of the model and brings flexibility to the analyst. The approach tackles with the large size of the choice set and is behaviorally realistic. We further illustrate the plausibility of the approach for traffic assignment.

On the other hand, the challenges pertaining to the approach concern involved modeling and data processing. We also point out the importance of survey and interview data (i) for the definition and justification of the mental representations, and (ii) to understand how drivers use the information systems. The former concerns modeling purposes, while the latter is important for effective design of navigation and travel information systems, based on the *MRI* approach.

There are several steps underway for the completion and the extension of the framework introduced in this paper. At first, it is important to investigate the use of the aggregate model for traffic assignment as proposed in Section 5. As discussed in the same section, the exploitation of the multi-layer framework for data fusion is a natural and interesting extension of the model. The hierarchical structure allows the model to be complementary to the existing ones and compatible with them through the consistency equations. Along these lines, it is also necessary to investigate ways to test and ensure the consistency within the proposed hierarchical structure. Another interesting extension of the work is the generation of attributes based on the idea of computing the expected maximum utility of *MRIs* by means of path enumeration. Finally, the application of the methodology in a bigger network and the investigation of the additional complexity that alternatives consisting in sequences of *MRI* may bring to the model is also an important add-on to the current state of work.

To conclude the discussion, we are aware that the performance and efficiency of the model need to be compared with those of the current state of the art models. The next step of work consists in the use of the RL model by Fosgerau *et al.* (2013) with a dual objective. At a first stage in order to compare the two models in terms of performance and efficiency, and at a second stage to explore the potential gains of combining them for the simulation of large networks.

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