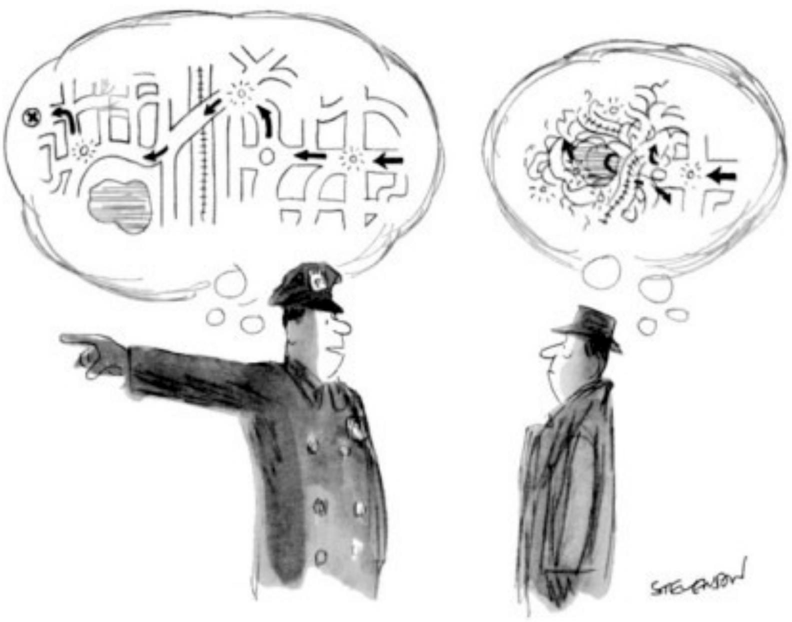

Revisiting Route Choice Modeling: A Multi-Level Modeling Framework for Route Choice Behavior

Evanthia Kazagli

Michel Bierlaire

TRANSP-OR, EPFL

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Evanthia Kazagli
Transport and Mobility Laboratory,
School of Architecture, Civil &
Environmental Engineering
École Polytechnique Fédérale de Lausanne
CH-1015 Lausanne
phone: +41 21 693 24 35
fax: +41 21 693 80 60
evanthia.kazagli@epfl.ch

Michel Bierlaire
Transport and Mobility Laboratory,
School of Architecture, Civil &
Environmental Engineering
École Polytechnique Fédérale de Lausanne
CH-1015 Lausanne
phone: +41 21 693 25 37
fax: +41 21 693 80 60
michel.bierlaire@epfl.ch

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Abstract

The use of random utility models for route choice analysis involves challenges stemming from the large size of the choice set and the physical overlap of paths, the latter resulting in complex correlation structures, but also from the high requirements in data. These factors increase the complexity of the models significantly. Given the difficulty and complexity of designing and estimating route choice models, it is desirable to try to simplify them and facilitate their estimation in large-scale applications. The modeling framework proposed in this paper strives to satisfy this need while maintaining a behaviorally realistic approach. Within the proposed framework, the trade-off between complexity and realism can be explicitly controlled by the analyst, depending on the availability of data and the needs of the application. The innovation and the importance of the approach lies in the potential to break down the combinatorial complexity of the route choice models by replacing the current route *representation* –and subsequently modeling– which is based on *paths* consisting in sequences of links on the network, with an aggregate and more abstract representation. The key feature of the framework is the concept of the *Mental Representation Item* (MRI). This concept is employed to support the new approach for representing the routes in a practical and realistic manner. We argue that the new representation simplifies the choice set problem and reduces the complexity with respect to the correlation among the alternatives. We provide an illustration of the framework using the city of Borlänge in Sweden as a case study.

Keywords

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

1 Introduction

Route choice analysis consists in identifying the route that a given traveler would take to go from one location (origin of the trip) to another (destination of the trip) in a transportation network by means of a certain mode of transport[1]. In practise, route choice depends on attributes of the alternative routes such as the length of the path and the number of traffic lights along it, the characteristics and individual preferences of the traveler –a piece of information that is usually hard to obtain and incorporate in the model, as well as the awareness of the traveler about the available routes [see Ramming (2002) for modeling network knowledge], which is also inaccessible information to the analysts.

Discrete choice models (DCM)[2], formulated within the random utility framework, consist the most common modeling approach in route choice analysis. Probabilistic models are formed on the basis of the utility maximisation decision rule and statistical methods, with maximum likelihood being the most common one, are used for the estimation of the models.

Several issues need to be addressed in order to render discrete choice models (DCM), and consequently route choice models (RCM) as well, operational; starting from the acquisition and processing of data, the generation of the choice set given an origin-destination (OD) pair, the specification of the utility functions and finally the selection of the appropriate type of choice model. Route choice is conspicuously challenging with respect to each and every of these issues.

The objective of this work is to deal with the challenges related to route choice analysis while keeping the models simple and behaviorally realistic. The ultimate goal is to develop a flexible framework for analysing and predicting route choice, that is also operational for large-scale networks. At this stage the scope of the work encompasses car route choice in static deterministic networks, but as soon as the framework is operational it can be adjusted to accommodate dynamic approaches and adaptive route choice.

The remainder of the paper is organized as follows. Section 2 provides a literature review following each one of the challenges associated with route choice modeling. In Section 3 we present a new route choice modeling approach using the concept of Mental Representation Item (MRI), which serves as the backbone to structure the proposed framework. In Section 3 we illustrate the framework, using the city of Borlänge in Sweden as a case study, and we identify the necessary steps for its operationalisation. The last section summarises the findings of the present study and identifies the future steps of research.

[1] A comprehensive review of the route choice modeling problem can be found in Bovy and Stern (1990).

[2] Ben-Akiva and Lerman (1985) is the most prominent textbook for discrete choice theory.

2 Literature Review

All of the models proposed in the existing literature, model the routes as link-by-link paths on the transportation network model. Obtaining this resolution of information is a challenging task. As Frejinger (2008) points out, the data in each original format, either it comes from traditional surveys (respondents reporting their trips), or from GPS records, rarely corresponds to path definitions. The observations need to be matched to the network that the modeler uses and the required processing entails a high risk of introducing biases in the later steps of estimation.

A solution to this issue is proposed by Bierlaire and Frejinger (2008). The developed framework compounds network-free data with a network based model. The core of the idea is that since the underlying route choices, as represented in the models, 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 exploited this approach to develop a probabilistic map-matching algorithm[3] tackling with the inaccuracy and sparseness of the GPS data by proposing several candidate paths, each associated with a likelihood to be the true one, corresponding to the same observed sequence of records.

The second indispensable component for the estimation of RCMs is the choice set[4]. The choice set consists in the group of alternatives, out of all the *possible* alternatives that are *available*, from which the traveler chooses. This is denoted as the universal choice set. The challenge with respect to modeling the choice set is twofold. It concerns both its size, as well as its composition. With respect to the size, the choice set is too large. It comprises of all of the possible paths connecting a given OD pair. This fact renders the full enumeration of paths a difficult task[5]. With respect to the composition, the choice set is latent –meaning that the analyst lacks information about what are the exact alternatives that are known to, and considered by, the traveler.

Subsets of the choice set are generated using path generation algorithms under the assumption that the actual choice set is reproduced –which is not always the case [see for example Ramming (2002) and Prato and Bekhor (2006)]. These algorithms employ various methods starting from the simplest deterministic approaches, e.g. shortest path approaches such as the labelling approach proposed by Ben-Akiva *et al.* (1984), link elimination by Azevedo *et al.* (1993), link

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

[4]Bovy (2009) provides an exhaustive review of the choice set generation problem in route choice.

[5]The enumeration of paths is necessary for the computation of the normalising constant of the sampling distribution, where sampling of a subset of alternatives is needed due to the impractically large size of the full choice set.

penalty by de la Barra *et al.* (1993), and constrained k-shortest path by van der Zijpp and Fiorenzo Catalano (2005), as well as constrained enumeration approaches based on branch-and-bound [see Friedrich *et al.* (2001); Hoogendoorn-Lanser (2005); Prato and Bekhor (2006)].

Works adopting stochastic approaches based on simulation can be found in Ramming (2002) and Bovy and Fiorenzo Catalano (2007). Most recent works on stochastic path generation employ importance sampling algorithms [Frejinger *et al.* (2009); Flötteröd and Bierlaire (2013)]. The idea is that in order to avoid biases, introduced due to an erroneous choice set when modeled in a separate step and resulting in misspecification of the models and bad prediction, the choice set should contain all the paths connecting the OD pairs. This entails great computational burden and this is where the importance sampling comes to play. Importance sampling has been proved to be one of the most adequate techniques for generating sampling correction [Frejinger *et al.* (2009); Chen (2013)] and assure consistent estimation of RCMs.

Regarding the correlation, the problem arises from the way that the routes are represented and modeled. It consists in the significant physical overlap of paths and has as a result very complex correlation structures. Various approaches have been proposed to deal with correlation either in i) the deterministic part [e.g. C-logit [Cascetta *et al.* (1996)] and Path Size Logit (PSL) [Ben-Akiva and Bierlaire (1999)]], which is the simpler approach but not appropriately capturing the correlation, or ii) the stochastic part of the utility function [Generalized Extreme Value (GEV) models: Paired Combinatorial Logit and Cross Nested Logit [Vovsha and Bekhor (1998)]; Non-GEV models: Probit [Daganzo and Sheffi (1977)], Logit Kernel [Bekhor *et al.* (2002)]], which significantly increases the model complexity and entails difficulties with respect to the estimation, especially for large networks. Frejinger and Bierlaire (2007) appropriately captured correlation without increasing the model complexity, by introducing the behaviourally realistic concept of subnetworks within a factor analytic specification of an error componen (EC) model. Yet, the estimation of such a model for large networks is cumbersome.

3 Mental Representation Items

3.1 Behavioral hypothesis and key concepts

As discussed in the previous section, in route choice analysis the notion of path is used to represent and model the routes that travelers choose to go from the origin to the destination of their trips. A path is defined as a chain of consecutive links in the network model, and there exists a huge number of alternative chains, connecting a given origin to a given destination, from which a traveler can presumably choose.

The concept of path is evidently hard to handle due to the large number of alternatives (operational limitations), but also due to the fact that drivers, as planners and decision makers, do not actually use the concept of path (behavioral limitations) [Flötteröd and Bierlaire (2013)].

> "As the accessible space is larger than the space that they can perceive and since most destinations are located beyond the perceptual boundaries, people need to break down the complexity and form representations of the surrounding space in order to move effectively and efficiently in the environment." [Büchner (2011)]

Intuitively speaking, if a traveler was to be asked to describe her itinerary from home to work she wouldn't start enumerating links in sequence. A path, as such, is just the manifestation of the route choice –i.e. the way the traveler implements her decision to take a specific route. In the present work, an alternative representation of the route, facilitating the analysis and at the same time exploiting the behavioral intuition, is intended. We argue that the choice takes place in a higher conceptual and more abstract level or, more precisely, that there are various levels of abstraction and importance on the basis of which we can represent the decision. Hence, a more aggregate representation can be justified.

Following this reasoning, path alternatives are replaced by sequences of geo-marked items elicited from the network. The concept of *Mental Representation Item* (MRI) is used to denote the abstracted items. An MRI can be a highway or the city center[6], and a hierarchical ordering of the MRIs is hypothesized. The hierarchy is related to varying levels of abstraction. Each layer in the hierarchy corresponds to a list of MRIs, and a route is then a proposition of these representation items. The problem begins at the higher conceptual level and works down to the details –that is back to the path on the network. The interest lies in capturing individual's decision in the various levels within the hierarchy, starting from the higher and more intuitive ones.

A concept akin to this of the MRI is the one of the *subnetwork*, proposed by Frejinger and Bierlaire (2007). In that work, the concept of subnetwork is used to capture perceptual correlation. The authors argue that paths sharing a subnetwork component are correlated. They 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)].

In this work we use such kind of abstract components to represent and model routes in a

[6]See Sec. 4 for more details.

behaviorally realistic way. The model is designed in the basis of MRI choice sets that are significantly simplified in this context. As we are going to discuss in the next section, a consequent advantage is the simplification in the correlation structure as well.

3.2 Illustration of the MRI hierarchical structure

Figure 1 exhibits a hypothetical observed route and its potential representation in each layer using the concept of MRI. In *layer 1* the choice is represented as an MRI that corresponds to going around the city center. Alternative MRIs in this layer, not illustrated in the figure, would be to go through the city center, or to avoid it. *Layer 2*, introduces additional detail in the representation of choice. That is, going around the city center may correspond to following a clockwise or a counter-clockwise trajectory. Finally, *layer n* corresponds to the path representation (current approach) with the maximum level of detail. Several such paths may correspond to the aggregate alternative of going around the city center in the higher layer.

The dots in the figure represent data of different nature and precision, accordingly for each layer. Different kinds of data can be employed in each layer, e.g. Wi-Fi records for more abstract layers and GPS map-matched paths for the lower layer[7].

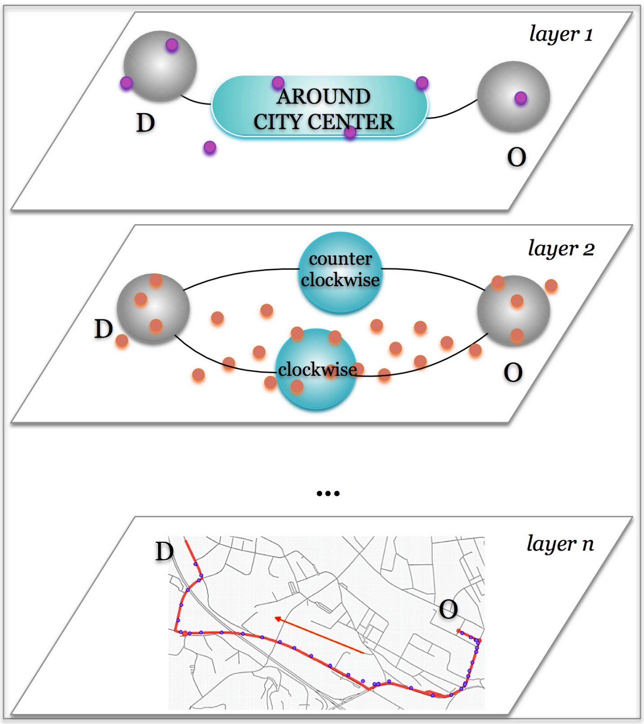

Figure 1: Hierarchical ordering of MRIs depending on the level of abstraction.

[7]See Sec. 4 for the use of data and the construction of measurement equations accounting for the errors.

Obviously, there might be only one source of data to be used for all the layers. We point out the possibility of using different data in each layer, bearing in mind the recent advances in the availability of diverse data coming from smartphones. The more detailed the data is, the more the detail it is possible, if necessary, to incorporate in the representation.

According to the above, conditional on the decision in the higher level –denoted hereafter as layer ℓ– there are several possible lower level alternatives in each of the layers of the hierarchy that correspond to the same higher alternative. The goal is to derive a recursive definition of route choices relating to different layers[8] and subsequently establish the links among the layers.

Each layer represents a choice model of the same process but using the elements of that particular layer only, starting from the most abstract level in the top of the hierarchy and ending to the more detailed and concrete lower level. This approach enables modeling route choice in the various layers of the hierarchy. The choice probabilities corresponding to the same choice can then be obtained from each one of the different layers.

3.3 Modeling framework

Within the proposed framework route choice can be approached and analyzed in each of the layers of the underlying hierarchy. The definition of the layers is driven by modeling considerations, in order to balance between model complexity and tractability, and by the availability of data as illustrated in Fig. 1 above. For instance, in some cases although map-matched trajectories are available, the needs of the application are such that allow us to maintain a more abstract representation and keep the complexity of the model low.

Each layer is characterized by a choice set comprising of MRIs with increasing level of detail from the top to the bottom layers, yet all referring to the same choice. Starting from the top layer ℓ, corresponding to choice set C_ℓ, the probability of choosing MRI (or MRI sequence) r given the set of MRIs C_ℓ is:

$$P_\ell(r|C_\ell;\beta^\ell) \tag{1}$$

where β is the vector of parameters to be estimated. Moving one step down, on layer $\ell + 1$, additional detail is incorporated. The choice set in this layer is denoted as $C_{\ell+1}$ and the probability of choosing MRI sequence r is then:

$$P_{\ell+1}(r|C_{\ell+1};\beta^{\ell+1}) \tag{2}$$

[8] In what follows the terms level and layer are used interchangeably.

This process can be repeated for all the layers up to the lower one (back to the path representation) and route choice models can be estimated in each of the intermediate layers. Different types of route choice models, depending on the data availability and the level of complexity, can be used.

3.4 Arising issues

3.4.1 Consistency

The first arising issue is how to underpin the links among these layers in order to ensure consistency with respect to the probabilities and the estimated parameters resulting from the various layers. Ensuring consistency is very important as the aim is to use the framework for prediction. Exploiting the hierarchy of the framework the choice probability in the top layer ℓ (see equation 1) can also be derived from (linked to) layer $\ell + 1$ as follows:

$$\bar{P}_{\ell}(r|C_{\ell};\beta^{\ell}) = \sum_{k \in C_{\ell+1}} P(r|k, C_{\ell};\beta^{\ell})P(k|C_{\ell+1};\beta^{\ell+1}) \tag{3}$$

where $P(r|k)$ is the probability that representation r in layer ℓ is consistent with representation k in layer $\ell + 1$, and $P(k|C)_{\ell+1}$ is the choice model in layer $\ell + 1$. An illustrative example is provided in Sec. 4. The consistency of the framework can be evaluated on the basis of the choice probabilities derived from the different layers.

3.4.2 Definition of MRIs

The second arising issue is the definition and operationalization of the MRIs. The items need to be behaviorally realistic but also appropriate to keep the model simple. For the terminology and definition of the MRIs –as well as for better understanding of travelers' representation of large-scale environment and spatial behavior– literature review on cognitive science, environmental psychology and geography, helps to draw insights and grasp ideas [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)]. It is in this research fields and in their attempt to answer questions such as how people perceive and process information while moving in spatial networks, that the concepts of *mental map*, *mental representation* and *anchor point* are met. A review on these research fields is avoided in the present document, since contrary to the research conducted in these disciplines, this work does not look at how the representations of space are formed or learned. It rather exploits the intuition gained from this literature in the effort to build a flexible and operational framework for route choice analysis.

The next section provides an illustrative example of the framework described above along with the first steps for its operationalization.

4 Illustrative Example

In this section we illustrate the model presented above and delineate the necessary steps for the operationalisation of the framework. We use the Swedish city of Borlänge as a case study to provide tangible examples[9]. Figure 2 depicts the road network of the city.

Figures 3 and 4 show the result of, Google Maps Directions API, route options for two randomly selected OD pairs. In these figures the city center of Borlänge has been marked with a red-shaded polygon. By inspecting several such examples we notice that, independently of the given OD pair, the suggested routes share in all cases some very distinct common features. That is, very often they take the perimeter of the city center (Fig. 3, 4) or make long detours to avoid the center (3), while seldom they actually go through it (green route in Fig. 4).

Similar features for the alternative routes came up when getting directions in two big cities; Athens and Stockholm. Two simple experiments have been conducted for these two cities. The experiments were formed as simple questionnaires, where 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.

Figure 2: The Borlänge road network.

[9] A GPS dataset collected in Borlänge is available for the estimation of the model (next stage of work). We refer to Axhausen *et al.* (2003) and Frejinger and Bierlaire (2007) for a description of the Borlänge dataset.

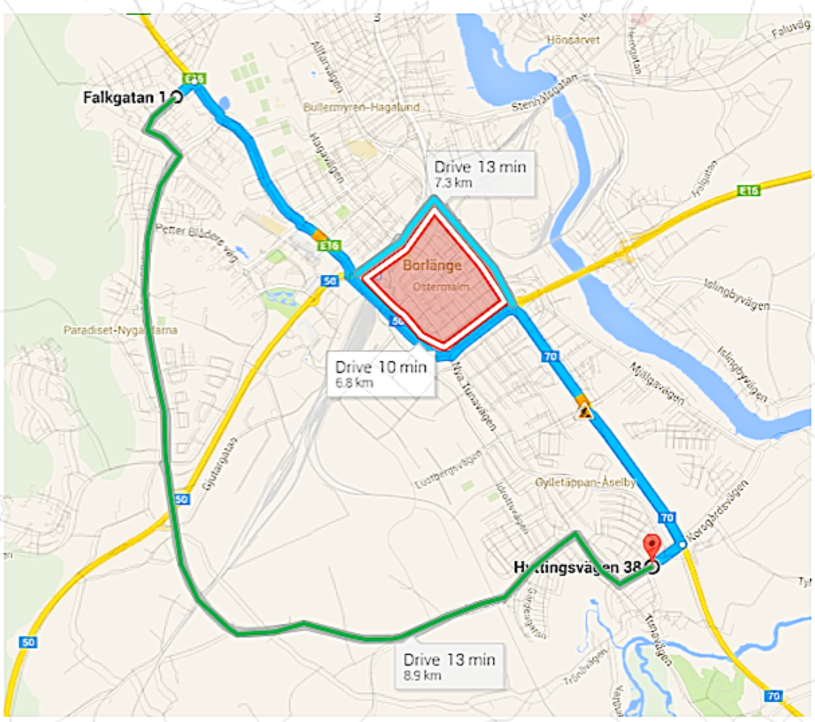

Figure 3: Example of route options provided by Google Maps Directions for a given OD pair.

Figure 4: Example of route options provided by Google Maps Directions for a given OD pair.

The answers revealed that people use elements such as the *city center*, the *highway H*, the *neighborhood N* to describe their routes and identify alternatives. A characteristic answer that came up was: "*I have two options. I either go through the city center or I take the peripheral.*". The attributes that in most cases they associate with the alternatives that they choose are e.g. longer but faster, with less traffic lights, higher speed etc. For instance, regarding the latter statement, the alternative corresponding to the peripheral, although it is longer, might be actually faster than the city center alternative during specific times of the day.

4.1 MRI choice set and type of model

The examples presented above justify the idea to form a very simple choice set in the higher layer of the hierarchy. In accordance with the illustration provided in Section 3 (see also Fig. 1), we start with the higher, and most abstract with respect to the representation, layer and we define the MRI choice set as $C_\ell = \{\text{avoid } CC, \text{ around } CC, \text{ through } CC\}$, where CC denotes the city center. Figure 5 illustrates this choice set, followed by possible choice sets incorporating additional detail in the lower layers, and the underlying hierarchy that goes back down to the current approach with link-by-link sequences.

Layer $l + 1$ introduces additional detail in the representation of choice in comparison with the one in *layer* l. Given that a traveller chooses to avoid the city center, she can either take one of the shortest routes or one of the long detours. Equivalently, given that she goes around the city center, possible routes go either clockwise or counter-clockwise of the perimeter. And lastly, given that the traveler chooses to go through the city center, we can reasonably assume that she takes one of the shortest paths. Subsequently, the choice set in *layer* $l + 1$ is defined as $C_{\ell+1} = \{\text{shortest path}^{avoid\_CC}, \text{ long detour}^{avoid\_CC}, \text{ clockwise}^{around\_CC}, \text{ counter-clockwise}^{around\_CC}, \text{ shortest path}^{through\_CC}\}$. Note that in all the cases described in this paragraph, we talk about shortest/ longest routes, as intuitively it wouldn't make much sense to distinguish among very similar paths that are close to the shortest. Instead we bundle them in a unique aggregate alternative. Finally, *layer n* corresponds to the path representation. Several such paths may correspond to each of the aggregate alternatives in each of the higher layers.

The way the choice set is specified in layers l and $l + 1$ simplifies significantly the modeling steps. There is no need for choice set generation, as we practically impute a common choice set, independent of OD[10]. In addition, a simple logit model can be used for this upper layer as we can reasonably assume that the IIA[11] property holds in this context.

[10] Note that although the abstract choice set is independent of OD, assigning the attributes to the abstract alternatives is OD specific.

[11] Independence from Irrelevant Alternatives. See Train (2003) for a comprehensive discussion on the IIA property and its implications on the choice models.

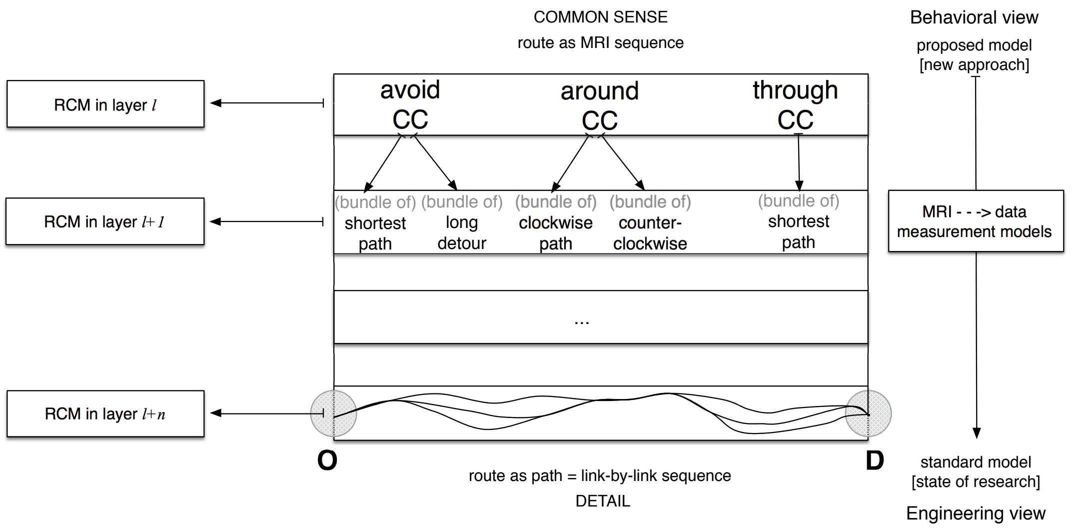

Figure 5: Illustation of the MRI choice sets as opposed to the current approach.

Depending on the definition of the choice set in the lower layers, alternative types of models can be investigated (e.g. the PSL or the EC model with subnetworks could be appropriate). The framework could capture correlation with nested or cross-nested models as well, but this is something we want to avoid for the reasons described in the previous sections. The aim is to keep the models as simple as possible.

4.2 Assigning attributes to MRIs

For the operationalization of the choice set, it is necessary to assign attributes in the abstract alternatives that comprise it, i.e. avoid CC, around CC, through CC. In order to do that, we compute the *expected maximum utility* of each MRI. An MRI is an aggregate alternative, comprising of all the possible paths passing through it. The expected maximum utility of an MRI may be computed as the *logsum* of the utilities of all these paths.

4.2.1 Computing the logsum

One way to derive the logsum is to follow the process of choice set generation. That is, we need to enumerate all paths passing through each MRI and then compute the logsum of the MRI. The enumeration can be accomplished using the Metropolis-Hastings sampling of paths algorithm proposed by Flötteröd and Bierlaire (2013). This approach though brings back the computational burden that we try to avoid. The challenge that arises is that the logsum is cumbersome to compute, due to the high number of paths. A solution to this problem has been proposed by Lai and Bierlaire (2006) (forthcoming). The authors use an expansion factor to avoid the enumeration. This approach will be adopted by the present in order to tackle the computation of the logsum.

4.2.2 Deterministic apporach

Alternative ways to operationalize the choice set, avoiding the enumeration of paths, are also possible. As a simple example, it is feasible to assume that given the choice in the upper layer the corresponding action for its implementation is the shortest, the fastest, or the most usual path, and then elicit the attributes from this path solely.

We point out again that the approach may be adjusted accordingly, to accommodate the trade-offs between complexity/ realism and tractability of the model. The evaluation of the outcome from the two approaches will indicate if it is actually necessary to use the logsum for assigning the attributes.

4.3 Model specification

The objective is to estimate the unknown parameters β^{ℓ} of the route choice model $P_{\ell}(r|C_{\ell};\beta^{\ell})$. As discussed in Sec. 3 the framework is flexible and the choice probabilities can be derived either in each layer or by exploiting the hierarchy (see equation [3]).

The issue that we are facing at this point is the identification of the actual MRI alternative corresponding to each observation. This may be either a straightforward or a very challenging task, depending on the nature of the available data. Equivalently to the approach presented by Bierlaire and Frejinger (2008), in the case of reported trips it is possible to employ a simple measurement equation taking the value of 1 if the MRI corresponds to the reported location, and zero otherwise. For instance, we can expect that the respondent is capable of indicating if she went through or if she avoided the city center.

The task becomes more complicated when it comes to raw GPS or Wi-Fi records, due to the inaccuracy of the data introducing uncertainty. Each observation i, that in this case is a sequence of points, might be relevant to more than one MRI alternatives. In this case more advanced measurement equations need to be investigated. The Domain of Data Relevance approach introduced by Bierlaire and Frejinger (2008), taking into account the distance between the observation and the path (here MRI), would be appropriate in to assist the derivation of the measurement equation.

Whatever the nature of the data is, the model specification should accommodate the measurement errors. The probability of reproducing observation i^{ℓ} given the set C_{ℓ} of MRI sequences in layer

ℓ is given as:[12]

$$P_\ell(i^\ell|C_\ell) = \sum_{r\in C_\ell} P(i^\ell|r)P_\ell(r|C_\ell;\beta^\ell) \tag{4}$$

where $P(i^\ell|r)$ is the measurement equation, giving the probability of observing i if the actual MRI is r, and $P_\ell(r|C_\ell;\beta^\ell)$ is the choice model in layer l. Equivalent process can be followed for each layer by employing different kinds of available data.

Assuming that we have derived the probabilities in each layer, potentially using different kinds of data, it is then possible to test the consistency of the framework, by using input (data and choice set) from the lower layers to derive the probabilities in the higher ones. Employing equation [3] that establishes the links among the layers, the probability of reproducing observation $i^{\ell+1}$ given the set C_ℓ of MRI sequences in layer ℓ is given as:

$$\begin{aligned} P_\ell(i^{\ell+1}|C_\ell) &= \sum_{r\in C_\ell} P(i^{\ell+1}|r)\bar{P}_\ell(r|C_\ell;\beta^\ell) && (5)\\ &= \sum_{k\in C_{\ell+1}}\sum_{r\in C_\ell} P(i^{\ell+1}|r)P(r|k,C_\ell;\beta^\ell)P(k|C_{\ell+1};\beta^{\ell+1}) && (6)\end{aligned}$$

where $P(r|k)$ is the probability that representation r in layer ℓ is consistent with representation k in layer $\ell+1$, $P(k|C_{\ell+1})$ is the choice model in layer $\ell+1$, and $P(i^{\ell+1}|r)$ is the measurement equation, giving the probability that observation i, generated by data in layer $l+1$, belongs to MRI r in layer l.

Thereafter, the framework can be evaluated on the basis of the consistency of the choice probabilities and estimated parameters derived from the direct and indirect approaches, accordingly. For this purpose it is necessary to formulate appropriate *measurement equations* according to the nature of the data used in each layer.

4.3.1 Borlänge case study

In this paragraph, we present a first concrete example of the model for the city of Borlänge. We focus on the MRI choice set of the higher layer as demonstrated above, i.e. $C_\ell = \{\text{avoid } CC, \text{around } CC, \text{through } CC\}$, and we provide the measurement equation and the specification of the utility functions for the estimation of the model. These are the two necessary components for the estimation of the model as illustrated in equation 4.

[12]Note that for simplicity reasons we omit the notation for traveler n.

Available data and measurement equation The available data consists in map-matched trajectories of 24 vehicles that were equipped with dedicated GPS sensors [see Axhausen *et al.* (2003) and Frejinger and Bierlaire (2007) for more details on tho dataset]. The transportation network of the city (Fig. 2) comprises of 3077 nodes and 7459 unidirectional links.

We define the three MRIs –avoid *CC*, around *CC*, through *CC*– using the links of the network. The around the *CC* item is easy to define based on the links that form the perimeter of the city center. The through *CC* item comprises of all the links that are enclosed in the perimeter. Finally, we define the avoid *CC* as the one that does not include any of the links corresponding to the other two MRIs.

It is then possible to associate the map-matched trajectories with the MRI alternatives in layer l, in order to derive $P(i^{\ell}|r)$ of equation 4:

$$\mathrm{P(i \mid r)}= \begin{cases} 1 & \text{if } i \text{ corresponds to } r \\ 0 & \text{otherwise} \end{cases}$$

denoting the probability of reproducing observation i of the actual MRI is r –the former corresponding to a map-matched trajectory. In this example, observation i, composed of links (l_1, ..., l_P), corresponds to r if there exist at least one link in i in common with the ones comprising MRI r. We need to pay attention to the following possible cases: $P(i|r)$ may receive the value of 1 for more than one r.

1. $P(i|r)$ may receive the value of 1 for more than one r. $P(i|around) = 1$ with several links of i coinciding with links demarcating *around CC* and at the same time $P(i|through) = 1$ with only one link of i belonging to the set of links demarcating *through CC*[13]. In this case, it
2. Obviously it is not possible that $P(i|r) = 1$ for all r, as if i corresponds to *avoid CC* by definition it cannot correspond to any of the other two alternatives. Yet, it is possible that $P(i|avoid) = 1$ and the observed route passes very close to the perimeter of the center. In this case, it could be reasonably assumed that i might have been generated by the *around CC* alternative[14].

With respect to the latter case, it would be appropriate to define distance thresholds and formulate $P(i|r)$ as a function of distance of the trajectory from the perimeter of the center. Then $P(i|avoid)$ can receive values greater than 0 even if there is no link correspondence. With respect to the former case, the ratio of the number of links enclosed in the perimeter to the number of links on

[13]This case is equivalent to encountering $P(i|through) = 1$ with several links and $P(i|around) = 1$ with only one link.

[14]This case is equivalent to encountering $P(i|around) = 1$ with only one link and $P(i|avoid) = 0$.

the perimeter could be used for the calculation of the probabilities. In both cases a distributional assumption on the distance and the ratio accordingly needs to be made in order to derive $P(i|r)$.

Note that in this analysis we assume that map-matched trajectories are deterministic and error-free. This is important as if we had also taken into account errors in i would complicate things even more.

Finally, we should underline that, the measurement equation in this specific example is directed towards capturing perceptions rather than measurement errors, which is the case of GPS or Wi-Fi records mentioned above.

Route choice with MRIs We specify here the utility functions for the estimation of a simple logit model for the higher layer of the hierarchy[15]. The deterministic part of the utility for alternative r is:

$$V_r = \beta_{TT} EstimatedTime_r + \beta_{SB} nbSpeedBumps_r + \beta_{LT} nbLeftTurns_r + \beta_{LL} avgLinkLenght_r$$

We use here the same specification as the one of the models presented in Frejinger and Bierlaire (2007), so that we have a direct comparison of the estimation and forecasting results of the proposed model with these models. The variables include the estimated travel time, the number of speed bumps, the number of left turns and the average link length (associated with few crossing along the route)[16]. The travel time attribute is associated with the fact that travelers intend to reach their destination as fast as possible, while the latter three attributes represent our expectation that driver have a preference towards simple and less tiresome routes.

The attributes presented here can be transferred from the path to the MRI level following either of the two approaches described in subsection 4.2. Alternatively, more aggregate attributes, consistent with the definition of the MRI alternatives, could be considered. Examples of such attributes could be congestion indexes for the city center and the other parts of the network, accordingly, depending on the time of day when the trip takes place, or ratings denoting how scenic an MRI is.

[15]Estimation results based on the model specification presented in this paragraph are not yet available.
[16]We refer to Frejinger and Bierlaire (2007) for details on the estimation of the travel times and the description of the remaining attributes.

5 Conclusion

The prominent feature of the framework presented in this paper consists in its flexibility to model the route decision, depending on the needs of the application and the availability of data. The proposed structure aims at simplifying route choice models, ensures consistency, and offers adjustability of the framework in different contexts/ cities. Although the examples are case study specific, they can be generalised easily.

Based on the proposed modeling approach the requirements in data accuracy diminish. Several possible paths connecting the origin and the destination on the transportation network are bundled under MRIs while transferring from a lower to an upper layer. Hence, the choice set size decreases and its composition is simplified. At the same time, the correlation among the alternatives gets simplified as well. These characteristics of the framework are important as they can render the application in large networks operational.

Concepts akin to this of the MRI –like anchor point, mental map, mental representation– have been researched and discussed before in disciplines such as cognitive science and geography, but never investigated or applied in route choice modeling.

The next step of the work concerns the application of the model in the city of Borlänge in order to obtain the first estimation and forecasting results illustrating the framework and its capabilities.

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