Linking cognition, spatial syntax and network use: a bivariate ordered probit for link memory fluency and use frequency

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Abstract

Understanding the role of spatial cognition and mental maps in route choice behavior is critical for efficient and behaviorally rigorous transport simulation models. We investigate the relationship between spatial network characteristics, collective memory, and link consideration in navigation. Using a survey involving spatial recall, spatial memory strategies, and navigation tasks, we quantify link use fluency and collective street memory. Network data and spatial syntax indices (centralities) are incorporated to analyze their association with recalled link frequencies and link use in route choice. Results reveal that collective spatial memory is related to road hierarchy, points of interest, and spatial syntax indices, while link consideration depends on collective street memory, shortest path consideration, and navigation landmarks. These findings validate the hypothesis that mental maps mediate between urban networks and route choice, and the usefulness of leveraging spatial syntax to generate link availability weights in choice set generation and recursive route choice models.

1. Introduction

The mathematical representation of routes is a cornerstone of strategic transport simulation models, allowing to represent traffic flows and to calculate network level of service. Two important challenges were widely addressed: (i) decision rules, and (ii) choice set reproduction Human path finding is limited in terms of the awareness set, the consideration set, and accounting for similarity in distinguishable alternatives (Prato 2009)[1] ,(Bovy 2009)[2] ,(Kaplan & Prato 2012)[3]. Previous studies generated the consideration set with a variety of methods (e.g., stochastic methods, branch-and-bound), covering 70-80% of the chosen route. Recent studies, (i.e., Mai et al., 2015)[4], assume recursive route choice, bypassing the need for choice set generation. Yet, network availability remains challenging in both approaches. Bekhor and Yao (2022)[5] suggested the use of link weights representing the perceived link availability. A remaining gap is understanding the association rule between the urban network and its mental representation as a cognitive map.

Recent studies suggested using mental maps to simplify the network. Manely et al.(2015)[6], show that network links, such as bridges, serve as anchor points, attracting many routes. Their study establish the importance of network mental considerations. The approach aligns with studies (e.g., Foo et al (2005)[7]) showing that people are likely to navigate using landmarks. Kazagli et al (2016)[8] proposed to simplify route choice models by mimicking the mental network representation. They propose to reduce the network complexity by referring to mental maps defined as the spatial and travel related information used and stored in human memory. Their idea includes spatial reduction by referring to mental representation items (MRIs) which are significant landmarks, areas, and route sections that people think of specifically when they are thinking of routes. According to their idea MRI's can be used in the choice set generation process to adjust the probability of route inclusion in the consideration set based on navigation landmarks. Their choice-set generation process includes defining the landmarks and generating alternative routes based on their MRI transversal. The model is verified by a case study of representing the city center as an MRI and generating routes traversing it, avoiding it, or traveling its perimeter. The approach has the advantage in that it does not necessitate full knowledge regarding mental maps to be applied, rather, it relies on spatial syntax elements such as landmarks, points, axes and edges.

While MRI's are useful in historical cities, the majority of network links may not carry distinct features or MRI's, in particular in cities following new urbanism principles and grid-link networks. The current study explores the role of spatial cognition or mental maps as mediator between the urban network and link availability underlying the construction of consideration sets. We hypothesize that in addition to spatial anchors, landmarks and MRI's, people remember network fragments and structures, which are useful for navigation. We hypothesize that spatial syntax underlies both link memory and navigation. While existing studies assumed that such a relationship exists, limited attempts have been conducted to observe this relationship due to challenges related to information recall, unstructured cognitive spatial perceptions, distorted spatial cognitions containing non-Euclidean geometry, and goal-driven retrieval of mental spatial representations.

The current study explores the association between spatial network characteristics and awareness sets, with the aim of creating availability weights serving to simplify the network structure underlying route choice. In the effort, we offer to retrieve a collective spatial memory, to associate it with spatial syntax and to show that it also underlies link use frequency in route choice. First, we create a visual representation of collective mental maps and see whether people's mental maps of a specific area match. Then we associate the collective memory with network-based spatial indices. Last, we associate link use frequency both to the recalled routes and spatial syntax indices, to establish the hypothesis that mental maps underline route choice, even in the era of navigation aids. By understanding people's view of the universal realm, we can increase computational efficiency and behavioral realism of existing models by decreasing the weight of less probable links. We show that collective memory can be a useful tool for revealing systematic link availability.

2. Research question and hypothesis

This study explores the connection between spatial cognition, as reflected in collective memory and mental maps, and route choice behavior in urban networks. Specifically, the research investigates whether a statistically significant relationship exists between link use in route choice, link memory fluency (the frequency of link recall), landmark data, and spatial syntax indices such as closeness, betweenness, and straightness centrality. We test the following hypotheses:

H1: Collective memory, characterized by the frequency of link recall, is not evenly or randomly distributed across urban networks. Rather, it is significantly associated with network characteristics.

H2: People overt specification of network recall strategies is useful for generating statistically significant relationships between collective memory and urban network characteristics.

H3: The collective memory serves as a proxy to implicit spatial cognition. Namely, the collective memory mediates between urban networks and route choice. Link consideration in route choice is influenced by the collective memory of link fluency, in addition to navigation landmarks and shortest path considerations.

H4: The collective memory and navigation are related both to explicit MRI's and to implicit spatial syntax indices such as centrality closeness, betweenness and straightness.

3. Methods

The workflow is provided in Figure 1.

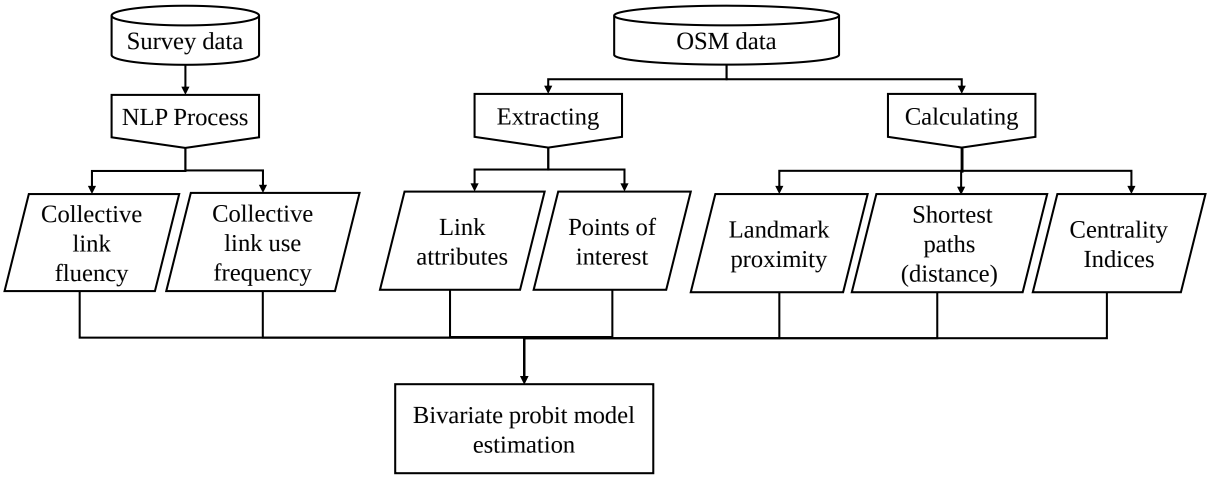


Figure 1. Workflow

2.1 Data collection

Choice data for this study was collected with an online experiment to retrieve link memory-based fluency and use frequency. The experiment included two recall tasks (i.e., street name, landmarks) to elicit link memory-based fluency, two navigation tasks (i.e., habitual and non-habitual) to elicit link use frequency, and questions related to navigation and spatial memory strategies. In the memory tasks the participants were given a “blind map” of a well-known and easy to identify 40 minutes walking square in the city center within defined boundaries. The chosen study area was the central area of the city of Tel-Aviv, which has a grid structure and applying early concepts of New Urbanism and “super blocks”, - large blocks bounded by major roads, and threaded with narrow residential streets, which apply also to 15-minutes cities. The respondents were asked to name from memory between 10-30 familiar landmarks, points of interest, and activity locations, and 10-30 street names, traffic circles or intersections. To encourage the participants, the survey reward was calculated according to the number of correctly remembered names. The survey participants were instructed to do the experiment based on memory alone, and each survey entry had a time stamp to detect the use of a navigation app. In the navigation tasks, the participants were provided with a regular map of the same area and were asked to provide one primary route and two alternatives. In both tasks, the participants chose their preferred transport mode for the task. In the habitual navigation task, the participants provided three routes between self-selected habitually frequented origin-destination pair. In the non-habitual task, the participants had to indicate three routes between a selected origin destination pair, from a predefined randomized list. The routes were indicated by a list of street names to encourage a natural recall process by mimicking map-based drivers’ indications. In the questions regarding memory/navigation strategies, the participants indicated memorable street characteristics (e.g., vegetation, commercial front, main road, traffic lights, landmarks). At the data analysis phase, the generated routes were checked for inconsistencies and missing links, map-matched and verified. The experiment was administered among 150 participants. To control for place familiarity, the participants had either at least two-year city work/residence experience, or frequent visits (at least 4 times weekly) to the city in the last year.

2.2 Network data

Network data (road hierarchy, landmarks) were retrieved from the Open Street Map (OSM). Link proximity to landmarks was calculated separately for single point landmarks (e.g., local businesses, activity locations), and for large landmarks with distinctive geometric size. Point-based landmarks satisfying one of the following OSM tags: 'tourism', 'historic', 'leisure', 'amenity', 'natural', 'manmade', 'building', 'place', 'square', 'shop', and were noted as a point rather than a polygon. These were either businesses or visual landmarks like statues that do include natural geometric shape on the map. Because of the prevalence of shops in this category, the landmarks can also indicate a commercial front.

Geometry-based landmarks were defined as map polygons satisfying one of the tags. Notably, they mainly include plazas, public open spaces, large buildings and shopping malls. Regarding the former, the landmark was assigned to the nearest link within a 15 meters radius. Regarding the latter, the landmark was associated with all the links within 15 meters from its edges. Figure 2 shows the OSM-landmarks and road hierarchy (i.e., main versus non-main streets). 2196 links and 1116 nodes were identified.

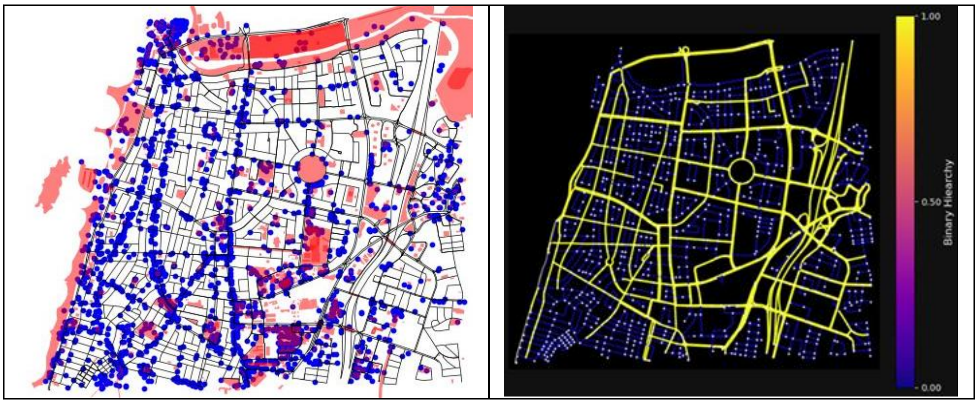


Figure 2. Point (blue) and polygon (pink) landmarks (left), street hierarchy (right)

2.3. Spatial syntax

We calculated node-based closeness, betweenness and straightness centrality indices (see Figure 3) as follows in equations 1-3 from Wang (2011)[9]. Link values were obtained by calculating the corresponding node averages. Distance-based shortest paths were generated with the Dijkstra algorithm.

Closeness centrality:

$$C_i^{closeness} = \frac{N-1}{\sum_{j=1;\, j\neq i}^{N} d_{ij}}$$

Where N is the total number of nodes in a network and d_{ij} is the shortest distance between nodes i and j.

Betweenness centrality:

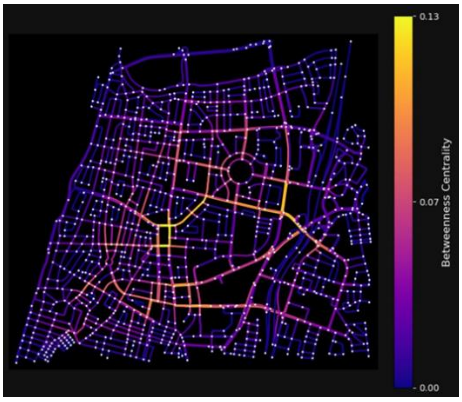
$$C_i^{Betweenness} = \frac{1}{(N-1)(N-2)} \sum_{j=1;k=1,\, j\neq k\neq i}^{N} \frac{n_{jk}(i)}{n_{jk}}$$

Where n_{jk} is the number of shortest paths from j to k, and $n_{jk}(i)$ is the number of shortest paths from j to k that pass i.

Straightness Centrality:

$$C_i^{Straighness} = \frac{1}{(N-1)} \sum_{j=1;\, j\neq i}^{N} \frac{d_{ij}^{Eucl}}{d_{ij}}$$

Where d_{ij}^{Eucl} and d_{ij} are the euclidian and the route distance, respectively, between i and j.



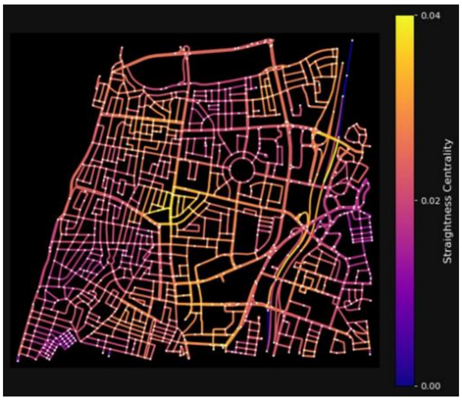


Figure 3 The calculated betweenness (left) and straightness (right) centrality indices.

2.4. Shortest route calculations:

OD Pairs were extracted for the routes analized. Those ODs were used in OSM's built-in shortest route function. It makes use of the djikstra shortest route algorithm and for simplicity the algorithm was set to minimize route length.

2.5. Model Estimation

We estimated a generalized structural equations model with two dependent variables: i) link recall frequencies representing the collective memory, and ii) link inclusion in consideration set of the population. Link recall incidents, were represented with a count response model, choosing between Poisson, Negative Binomial and Zer-inflated negative binomial. In the estimation process we tested and rejected the poisson hypothesis (equal mean and variance) and the zero inflation hypothesis. The most suitable was the negative binomial model. Link inclusion in the consideration set is a binary variable, representing whether the link was considered by at least one participants. This is due to the fact that while the collective memory refers to the entire netwrok in the study area, the consideration sets are specific to origin-destination pairs. Following the hypotheses that the collective memory and the consideration set are related (i.e., links with more recall incidents have a higher probability to be in the considered choice set), and that both can be associated with spatial attributes, a recursive model was chosen. The model was estimated by using the Stata **gsem** command.

3. Results

Among the 150 participants, the majority are highly familiar with the study area. 17% and 45% have a residential experience of 5-10 years and over 10 years, respectively. 81% of the sample has at least two years of working experience in the city. 33% of the sample reside in the area corresponding to the provied map. The respondents are multi-modal travellers. 35% drive a car, 39% ride public transportation and 52% walk at least twice weekly. The preffered travel modes for the self-defined route choice task were car and public tranpsport with equal shares (38.7%). For the pre-defined route choice task, the proportions were 26.7% and 47.3% for car and public transport, respectively.

In the memory task people identified 197 unique streets, of which 26% had over 10 recall episodes. 40% of the respondents identified 30 or more streets with the maximum number allowed in the survey being 60. The respondents identified 877 unique landmarks, of which 30% had less than 10 recall episodes, 29% recalled 30 which was the maximum number allowed. The self-reported spatial neumonic strategies were location-based (55%), directional screening (23%), hirearchical (19%), tree structure (19%) and route-based (18%). 49% of the respondents used more than one strategy. 33% of the respondents inidcated that recency plays a role in their spatial recall. Only 14% used time-base strategy (i.e., chronoogical order) for the network recall task. Figure 4 shows the street attributes that make the street memorable and desirable attributes for street consideration in route choice and Figure 4b shows the top ranked route choice considerations.

The three most prevalent spatial chatacretistics for link recall are main roads, landmarks, and storefronts. The most prevalent spatial characteristics for recall in route choice (considering all the transport modes) are traffic lights, main streets, vegetation and parking. Route directness and shortest route distance were ranked as the most impoprtant criterion for 28.7% and 40.0% of the respondents. The number of traffic lights was the top criteria only for 8.7% of the people.

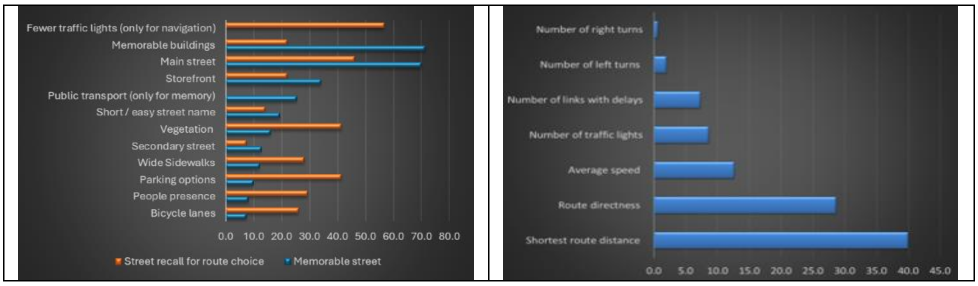


Figure 4. (a) Memorable streets (blue) and street recall for route choice (red), (b) The most important attribute for route selection

Figure 5 shows the collective network memory represented by the recalled street frequencies.

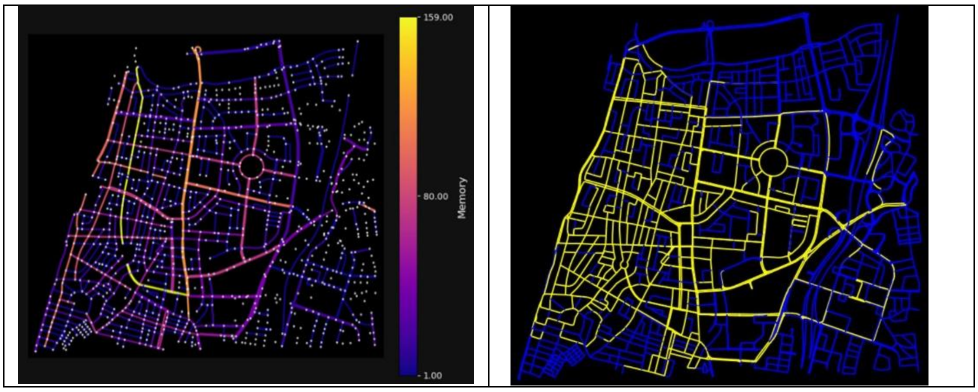


Figure 5. Collective network memory (left), collective link consideration for navigation (right)

The estimated GSEM resuls are shown in table 1. The explanatory variables reflect the self-reported strategies, with main roads and points of interest effect on memory and with distance-based shortest path for inclusion in the consideration set. Alpha is greater than unity and statistically significant, which indicates the existence of overdisperssion and the suitability of the negative binomial model over the null hypothesis of a poisson process. The model results show that the number of link recall incidents is related to road hierarchy, points of interest (POI), the betweenness and straightness centrality indices. Link consideration probabilities are related to the number of link recalls, POI, closeness centrality and the links considered for the shortest -path. Replacing the points of interests with geographical landmarks resulted insignificant in both equations. The model results support the research hypotheses H1-H4.

Table 1: model results

	Coefficient	Std. err.	z	P>z	[95% conf.	interval]
Collective memory (Negative binomial)						
Main_road	1.669705	0717447	23.27	0.000	1.529088	1.810322
Points of interest	.2450831	.0323696	7.57	0.000	.1816398	.3085264
C_straightness	27.45432	7.276613	3.77	0.000	13.19242	41.71622
C_betweenness	13.04508	1.71254	7.62	0.000	9.688563	16.4016
Constant	.6392051	.1883308	3.39	0.001	.2700835	1.008327
Link consideration in routes (Logit)						
Collective memory	.0361041	.0034007	10.62	0.000	.0294388	.0427695
Points of interest	.1690012	.0692714	2.44	0.015	.0332319	.3047706
C_closeness	46.02358	8.255926	5.57	0.000	29.84226	62.2049
Shortest path choice set	2.500565	.173881	14.38	0.000	2.159765	2.841366

_cons	-3.911775	.4400152	-8.89	0.000	-4.774189	-3.049362
/memory						
lnalpha	.8457468	.0339649			.7791769	.9123167

4. Conclusions

The results validate the reseach hypotheses by demonstrating that (i) colletive memory of urban networks can be meaningfully quantified and related to network characteristics; (ii) link consideration for navigation is related to the collective memory set, shortest path considerations, and navigation landmarks. While the relationship between collective memory and link consideration for navigation may seem trivial, this study is the first to show the statistical relationship using a large scale survey data of memory retrieval and route choice. The fact that both memory and link consieration are related to spatial syntax support the use of the latter for filtering or weighting the universal realm used as a basis for choice set generation or recursive route choice models.

These results are from a preliminary pilot study, the next phase of the survey will adress mode choice more sigificantly as well as increase number of participants.

5. References

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