# You Are Not Alone: Path Search Models, Traffic, and Social Costs

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## Abstract

Existing cognitively motivated path search models ignore that we are hardly ever alone when navigating through an environment. They neither account for traffic nor for the social costs that being routed through certain areas may incur. In this paper, we analyse the effects of "not being alone" on different path search models, in particular on fastest paths and least complex paths. We find a significant effect of aiming to avoid traffic on social costs, but interestingly only minor effects on path complexity when minimizing either traffic load or social costs. Further, we find that ignoring traffic in path search leads to significantly increased average traffic load for all tested models. We also present results of a combined model that accounts for complexity, traffic, and social costs at the same time. Overall, this research provides important insights into the behavior of path search models when optimizing for different aspects, and explores some ways of mitigating unwanted effects.

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## 1 Introduction

We are not alone in this world. This is not a new or surprising insight. However, if we look at cognitively motivated path-search models published in the literature (e.g., [4, 6, 7, 16]), there seems to be an underlying assumption that we are. They seem to take roads to be empty. These models account for all kinds of aspects that may cause navigation to become difficult, aiming for the least complex paths. But they ignore fellow travelers on the road. They do not account for varying degrees of traffic and the complexity such traffic may add to the navigation process – let alone the potentially significant increase in travel time.

Commercial navigation systems, which usually calculate the shortest or fastest route, do account for traffic and the delays it may cause. They adapt suggested routes according to changing situations on the road. Thus, they do not make the same "empty roads" assumption. However, they might make other assumptions of "being alone." Namely, they might ignore that for some parts of the road network social conventions tell that they are not meant for the general public to drive (or even walk) through even if there are no legal restrictions preventing this [9]. Ignoring these social conventions is a deficit commercial systems share with the research models.

In this paper, we will explore the effects of these assumptions of "being alone." That is, we will analyze what effects taking into account traffic and social costs have on the computed routes. In particular, we will test how the fastest and the least complex routes may change under avoiding traffic in terms of their complexity and violation of said social costs. We will also present results of a combined model, i.e., a model that accounts for complexity, traffic, and social costs at the same time. Accordingly, this paper offers important insights into the behavior of path search algorithms when optimizing for different aspects, and explores some ways of mitigating unwanted effects.

In the next section, we discuss relevant related work. We will then introduce the different path search models used in our analysis in Section 3. Methods and results of the analysis are presented in Section 4 and discussed in Section 5. Section 6 concludes the paper with suggesting some future work.

## 2 Related work: Cognitively motivated path search algorithms

Several different models have been proposed in the literature that adapt path search to factors of human cognition, preferences, and environmental layout in order to reduce navigation complexity. Roughly, these models can be divided into three categories: 1) choosing routes that are easiest to describe; 2) integration of and routing along landmarks; 3) adaptation to environmental structure.

The main focus of the first category is on simplifying the instructions needed to guide a wayfinder from origin to destination. These models are inspired by the fact that people often prefer to direct wayfinders along routes that are easy to describe instead of the shortest ones [13, 20], aiming to simplify (or minimize) the amount of information these wayfinders need to remember. For example, Duckham and Kulik [4] proposed the simplest paths algorithm, which essentially implements Mark's complexity model [13]. Mark's model assigns to each wayfinding action a number of required so-called slots to represent said action. Richter and Duckham [16] then took this approach further by employing more realistic instruction generation mechanisms – including references to landmarks and spatial chunking [10].

Models in the second category specifically focus on the integration of landmarks in calculated paths. They aim to exploit the importance of landmarks for human navigation in reducing wayfinding complexity. Richter and Klippel [17] proposed a methodology for generating easier-to-remember wayfinding instructions. For a given route through an environment, their method finds the minimal number of chunks, i.e., the minimal number of instructions, required to fully describe the route. The chunking mechanisms heavily rely on landmarks to anchor actions in space. Caduff and Timpf [1] introduced the landmark spider approach, which calculates paths through a network using edge weights that account for the presence of landmarks. Weights are computed based on the distance between landmark and wayfinder, the direction between landmark and wayfinder, and the salience of the landmark itself. As a consequence, the "shortest landmark spider" path, i.e., the one with the lowest costs, is a path that passes many relevant landmarks.

The third category of models focuses on the complexity of the environment, in particular the structure of decision points and the path network. Such models aim to avoid complex parts of an environment, and also to avoid ambiguity resulting from its structure. For example, Haque, Kulik and Klippel's model [7] computes instruction equivalence for the different turns at an intersection (e.g., two different turns may be both seen as "left"). In path search, the model minimizes ambiguity (or unreliability). Richter [15] proposed a regionalized path planning algorithm based on environmental structure and decision point complexity.

This model computes a complexity measure for each node of the path network. Then nodes are clustered into different regions based on complexity threshold values (a complex region and an easy region in the simplest case). The model allows different cost functions for each region, for example, shortest path for the easy region and simplest paths [4] for the complex one. Manley, Orr and Cheng [12] proposed a hierarchical route choice model using heuristic selection processes. Based on the idea of regionalized path planning [19], among others, the model first determines which regions to travel through. In a second step, this gets refined to major nodes to path through, and then which actual roads to take in the third step. The different selection processes make use of "human" heuristics, such as minimization of angular deviation.

As stated in the introduction, none of these approaches accounts for other people on the road, i.e., traffic, nor for social costs, i.e., avoiding to route through areas that are residential and not meant for higher traffic volumes. In an earlier study, Johnson et al. [9] found that scenic routing and – to a lesser degree – safe routing, i.e., optimizing paths for scenic routes or to avoid "unsafe" regions, leads to these routes becoming more complex, but also to redirecting traffic into areas that are not supposed to take high traffic volume, for example, parks or slower neighborhood roads. In a similar vein, in this paper we explore what it means that we are not alone in the world for different path search optimization criteria, particularly for fastest and least complex paths.

## 3 Path search models

In this section, we will present the different models that are used to calculate paths of varying kind. Specifically, we present a model that accounts for different aspects of wayfinding complexity (inspired by [6]). In addition, we present a model simulating different traffic loads in a road network, thus, allowing for calculating the least-traffic path, and a model that accounts for the previously discussed social costs of navigating urban environments. These different models can then be integrated into a combined model that allows for flexibly using just one, some, or all of these aspects (to varying degree) in computing the costs of traversing a road network. They are all based on Dijkstra's shortest path algorithm [3].

We are aware that some of these models use relatively simple heuristics. This is done because we are interested in showing the principal effects of the various parameters, rather than providing the most realistic modeling possible. Since all of the models, as well as the combined model, are modular it would be straightforward to replace some of the aspects with more complex models in the future.

### 3.1 Complexity model

In order to make paths as easy to follow or remember as possible, we need to know about the complexity of a path's components, particularly its decision points as here decisions about how to continue need to be made. Following [6], there are three categories of complexity factors (see Figure 1): 1) environmental complexity; 2) those related to how instructions are provided; 3) factors inherent to the wayfinders. Some of these factors are assigned to the decision points (nodes), some to the road segments (edges).

#### 3.1.1 Environmental complexity

Already Lynch [11] considered environmental complexity, or legibility, an important factor for the ease of navigating an environment. In his empirical studies, Weisman [18] found a direct relationship between environmental legibility and wayfinding behavior. However, while

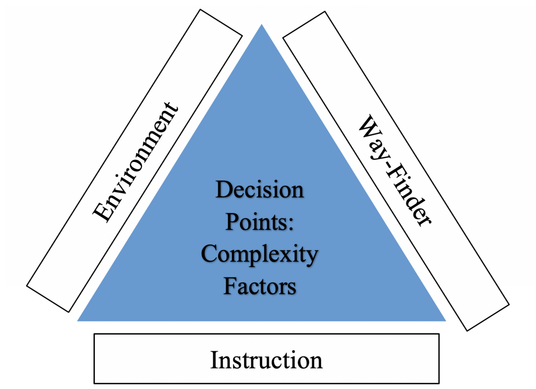



**Figure 1** Three different categories of wayfinding complexity factors: environmental complexity; instruction complexity; factors inherent in the wayfinder.

environmental legibility is arguably the richest factor for environmental complexity, it is also the most poorly understood [14]. In our model, we approximate this factor by using three parameters based on [15] to capture environmental complexity:

- *Number of branches* is the number of road segments that meet at a decision point, i.e., the node degree in network terms. With an increasing number of branches it becomes more likely that a wayfinder takes a wrong turn at a decision point. Node degree is inherent to the nodes and, thus, a parameter assigned to the decision points.
- *Deviation from prototypical angles* is the deviation of a turn from 45 and 90 degree turns. Humans conceptualize turns usually as these prototypical angles. The larger the deviation from these prototypes, the more difficult it may become to identify the correct turn. We assign the mean deviation, i.e., the average over all turn angles between a decision point's branches, as a decision point parameter.
- *Road length* is the length of a road segment originating at the decision point at hand. With longer road segments, wayfinders travel further till the destination without the need to make decisions (i.e., until the next decision point), compared to many short segments, and consequently, the fewer chances they have to take a wrong turn. Length is inherent to a road segment and, thus, stored with an edge.

These factors are calculated as in the following. The number of branches at a decision point is simply the node degree of the corresponding node in the road network. The deviation from prototypical angles is computed as the difference of the *bearing* between the decision point at hand and the decision points at the other end of each branch:

$$\begin{aligned} bearing &= atan2(x, y) \\ x &= \cos(lat_1) * \sin(lat_2) - \sin(lat_1) * \cos(lat_2) * \cos(lon_2 - lon_1) \\ y &= \sin(lon_2 - lon_1) * \cos(lat_2) \end{aligned}$$

with $lat_1$, $long_1$ the latitude and longitude of the start node and $lat_2$, $long_2$ the latitude and longitude of the end node. Road length is the distance between the two nodes forming an edge (branch). It is computed as the following:

$$\begin{aligned} x &= \sin^2((lat_2 - lat_1)/2) + \cos(lat_1) * \cos(lat_2) * \sin^2((long_2 - long_1)/2) \\ y &= 2 * atan2(\sqrt{x}, \sqrt{1 - x}) \\ distance &= radius * y \end{aligned}$$

where *radius* is earth's radius (mean radius = 6,371km).

### 3.1.2 Complexity related to instructions

Wayfinding instructions can be more or less helpful in finding the way, i.e., they may differ in their understandability and interpretability. Our model utilizes three factors to compute this complexity related to instructions: 1) instruction equivalence according to [7]; 2) the number of items to remember according to [4, 13]; 3) the presence of relevant landmarks according to [1].

- *Instruction equivalence* means how many turns at a decision point can be described with the same linguistic label. For example, in historic city centers with 6-way intersections, the instruction "turn right" may apply to several turns; there may be several roads that lead to the "right." Instruction equivalence is calculated by checking the bearing of all branches at a decision point for whether they are in the same quadrant of the bearing coordinate system, which we take as being instruction equivalent. We use quadrants instead of half-planes to allow for distinguishing different linguistic turn direction concepts (e.g., "veer left" vs. "sharp left"). This parameter is assigned to the decision points.
- *Instruction complexity* corresponds to the slot values as in [4]. These slot values reflect the complexity of performing (correctly) different navigation maneuvers, such as going straight (1 slot) vs. turning at a t-intersection (6 slots) vs. turning at a four-way (or more) intersection (5 + node degree slots). We compute the average instruction complexity for all possible turns at a decision point and assign this value to the corresponding node.
- *Landmark complexity* is computed as a combination of the distance between landmark and wayfinder, and the salience of the landmark itself (cf. [1]). All landmark objects in a radius of 50 meters or half of the length of the longest road segment – whichever is smaller – around a decision point are extracted. The distance to the decision point is multiplied by the landmark's salience value. The mean value for all landmarks is stored as the landmark complexity with the decision point at hand. The smaller this value, the more wayfinding is supported by landmarks at this decision point.

### 3.1.3 Wayfinder-related factors

Individual characteristics and differences among wayfinders is another important factor in wayfinding [2]. This factor relates to an individual's ability to, for example, stay oriented, build up a mental representation of an environment, or to understand instructions. In our model, we represent these individual differences with the Santa Barbara Sense of Direction (SBSOD) scale [8]. This self-report measure reliably captures people's spatial abilities. For people with a lower score, wayfinding is more difficult and, thus, their ability to correctly navigate complex decision points reduces. The SBSOD score is a number between 1 and 7, where 7 indicates high spatial abilities. We normalize the score to lie between 0 and 1 and take $1 - SBSOD$ as the complexity value, i.e., the higher somebody's spatial abilities, the less complex navigation is for them.

### 3.1.4 The final model

Table 1 provides a summary of the different parameters used in calculating the complexity of decision points.

All of these parameters get normalized to values between 0 and 1 in their computation. They are then combined in a weighted sum model as follows:

$$C_c = \frac{w_e * Complexity_e + w_w * Complexity_w + w_i * Complexity_i}{w_e + w_w + w_i}$$

**Table 1** Parameters for computing decision point complexity.

| Complexity factor | Parameters |
|---|---|
| **Environment** | Number of branches (node degree), Deviation from prototypical angles, Road length |
| **Instruction** | Instruction equivalence, Instruction complexity, Landmark complexity |
| **Wayfinder** | Santa Barbara Sense Of Direction |

where $w_e, w_w, w_i$ are the weights of the environmental complexity factor, wayfinder-related factor, and factor related to instructions, respectively. The environmental complexity $Complexity_e$ is computed as another weighted sum of its individual parameters:

$$Complexity_e = \frac{w_{nd} * nd + w_{dv} * dv + w_l * (1 - length)}{w_{nd} + w_{dv} + w_l}$$

with $nd$ being the node degree of the decision point at hand, $dv$ the deviation from prototypical angles, and $length$ the normalized length of a branch; $w_{nd}, w_{dv}, w_l$ are the according weights. The instruction complexity is computed accordingly:

$$Complexity_i = \frac{w_{ie} * ie + w_{ic} * ic + w_{lm} * lm}{w_{ie} + w_{ic} + w_{lm}}$$

, with $ie$ being the number of instruction equivalent turns, $ic$ the complexity of describing the turn to take, and $lm$ the complexity of landmarks. Finally, in the current model wayfinder-related factors are only the (normalized) SBSOD score, thus:

$$Complexity_w = 1 - SBSOD$$

## 3.2 Social model

This model accounts for the social costs of traveling certain roads. Since it is difficult (if not impossible) to know these costs for each and every place just based on road network data, we use a simple heuristics. We employ road category as a stand-in for social costs, with the higher the category the lower the social costs (see Table 2). For example, motorways as the highest category would have a cost of 1, while residential roads would have significantly higher costs – for example, when using parts of the OpenStreetMap (OSM) road hierarchy as we do in our evaluation (see Section 4) these costs may be 6. The higher the costs of a road, the less socially appropriate it is to use it. Thus, the social model aims at using higher category roads since these roads have less social costs associated with them.

## 3.3 Traffic model

We use a simple heuristic algorithm to assign traffic load to the different roads in a road network. We create a breadth-first search tree to traverse all the roads based on how they connect. The root of the tree is selected randomly from the list of all decision points. At depth zero (the root level) we randomly assign a number between 0 and 1, with 0 corresponding to "no traffic" and 1 to "heavy traffic". Values in the range of [0,0.3) correspond to slight traffic, the range [0.3,0.7) to moderate traffic. Heavy traffic is defined by the range [0.7,1].

We traverse the tree level by level, assigning to each edge the average traffic of the preceding connected roads, plus a variation factor in the range [-0.4,0.4], which is randomly chosen. The variation factor includes negative numbers because otherwise traffic load would only ever increase for roads further down in the tree. Accordingly, we take the maximum of 0 and the calculated traffic load as the actual value, to avoid negative numbers as traffic load. This traffic load is then used as the costs for traversing an edge in "least traffic" path search.

### 3.4 Combined model

The models presented so far all account for different single factors important in navigation. It seems reasonable to assume that they are independent from each other, thus, they can all be combined using a weighted sum. This way, different factors can be assigned higher weight, i.e., taken to be more important, but the default assumes equal weight, and hence equal importance, of all factors. This results in the following *costs* for traversing an edge in the combined model:

$$costs = \frac{w_c * C_c + w_s * C_s + w_t * C_t}{w_c + w_s + w_t} \tag{1}$$

with $w_c, w_s, w_t = 1$ as a default. Here, $w_c, w_s, w_t$ are the different weights for complexity, social costs, and traffic, respectively. Accordingly, the different $C$ are the respective costs for traversing an edge in the different models.

### 3.5 Fastest path model

The fastest path model computes the fastest path between some origin and destination, as the name implies. To that end, it calculates the time it takes to traverse a road segment based on its length and an assumed average speed, which depends on the road type. This time is then the costs for an edge used in the "fastest path" search.

### 3.6 Shortest path model

In some of our experiments, we also use the shortest path (shortest distance) in the comparisons. This is simply computed using the standard Dijkstra algorithm [3].

## 4 Analysis

In this section, we detail the analysis of the effects of not "being alone" on the various path search models. We first explain the methods employed in the analysis, and then present the results.

### 4.1 Methods

#### 4.1.1 Data

We extract road network data from OpenStreetMap[1] (OSM). OSM data has three main elements, namely *nodes*, *ways* and *relations*. To form a road network, we identify decision points (intersections), which are those *nodes* shared by two or more *ways* elements [5]. Figure 2 shows decision points for a part of New York. The decision points correspond to the nodes and the ways to the edges in the road network, resulting in a directed graph.

[1] `https://www.openstreetmap.org/`

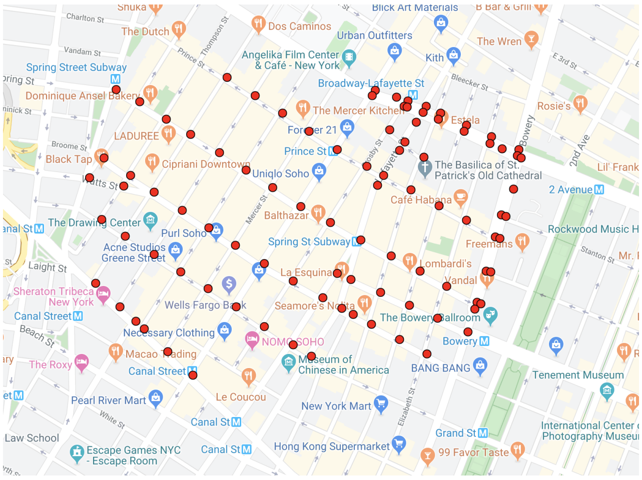



**Figure 2** Identified decision points as red circles for a part of New York, defined by the bounding box $(-74.00433, 40.72038, -73.99263, 40.72545)$.

For our analysis, we selected four different city environments: (parts of) New York, Stockholm, London, and Paris. These cities have been chosen because they differ in their structure, but also because they provide good OSM data quality. Whereas New York exhibits a (well-known) grid structure, Stockholm is similar in the eastern part, but less structured towards the west. The road network of Paris is almost radial with connecting roads forming a "spider web". Finally, London has several areas of local roads loosely connected via some major roads. Figure 3 shows the road networks for the four cities. Here, width and color of the edges represent the road type and traffic load, respectively. The wider an edge, the higher the road type (i.e., residential roads are the thinnest). Slight, moderate, and heavy traffic are shown as green, yellow, and red edges, respectively.

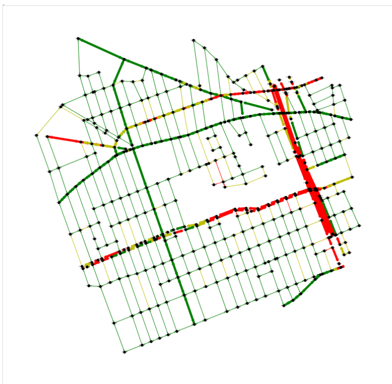
### 4.1.2 The implemented models

Section 3 presented the principal, generic models. For the analysis, they need to be implemented based on the available data. Thus, certain restrictions and simplifications may be made, as well as specific parametrizations for some of the factors. For all models, all parameter weights are set to 1, which makes them all equally important. At this point, we do not have any indications otherwise, and we are interested in the models' general behavior.

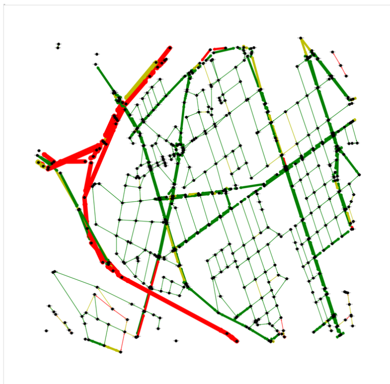
The implemented model for least complex paths does not account for wayfinder-related factors, i.e., SBSOD scores. There are no actual wayfinders involved in the analysis, and as said we are interested in general behavior. To account for landmarks in the model, we use all OSM objects tagged as *amenity* as a stand-in[2]. For reasons of simplicity, each landmark has a salience of 1. We use OSM's API to find all landmarks around a decision point using the procedure explained in Section 3.

The social, traffic, and fastest path models refer to the OSM road type hierarchy, identified via the *highway* tag of the different *ways* objects[3] to distinguish road types. We use six types of *ways* (see Table 2): motorway, trunk, primary, secondary, tertiary, and residential. The higher the category (motorway being the highest), the more social it is to use this road (i.e., the lower the social costs), and the higher the average speed to traverse it.

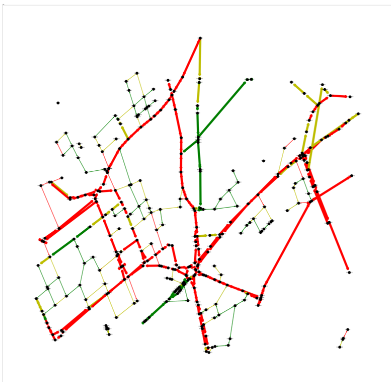
[2] `https://wiki.openstreetmap.org/wiki/Category:Amenities`
[3] `https://wiki.openstreetmap.org/wiki/Key:highway`



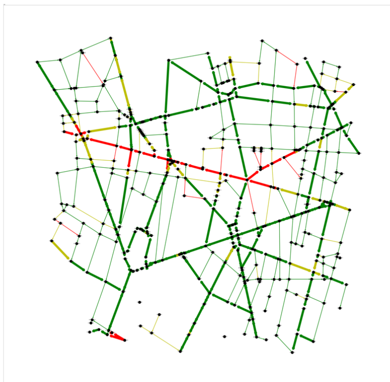
**(a)** New York.



**(b)** Stockholm.



**(c)** London.



**(d)** Paris.

**Figure 3** Road networks for the four different city areas used in the analysis. The width of an edge represents the road type; the color the traffic load.

**Table 2** The different road types used in the analysis, the average speed assigned to them, and their social costs. "Road type" corresponds to OSM *highway* tag value.

| Road Type | Speed (km/h) | Social costs |
|---|---|---|
| **Motorway** | 100 | 1 |
| **Trunk** | 80 | 2 |
| **Primary, Secondary** | 60 | 3, 4 |
| **Tertiary** | 50 | 5 |
| **Residential** | 30 | 6 |

### 4.1.3 Procedure

For each of the four different road networks (city environments), we randomly chose 100 origin / destination pairs, between which we compute the various different path types under investigation. In other words, for each of the different path search models, we compute 100 paths in each of the four different environments. We perform three analysis steps:

1. We compare paths between five different models, namely the complexity model, the traffic model, the social model, the combined model, and – in addition – the shortest path model. Over all 100 different paths for each model, we average path length, paths' complexity value, paths' traffic load and paths' social costs.
2. We investigate the effects of accounting for traffic on the complexity and social costs of the fastest paths. In order to add the effects of traffic to this model, we modify the (assumed) average speed (see Table 2) along a road segment by a "traffic" factor. We multiply this speed by 1, 0.75, and 0.4 for slight, moderate, and heavy traffic, respectively. We average the paths' complexity value and social costs over all 100 different paths.
3. We investigate the effects of accounting for traffic on the complexity and social costs of the least complex paths. To add traffic as a factor to the least complex paths, we use the combined model with according weight settings: $w_c = 1, w_t = 0, w_s = 0$ for paths without traffic; $w_c = 1, w_t = 1, w_s = 0$ for those with traffic. Again, we average the paths' complexity value and social costs over all 100 different paths.

## 4.2 Results

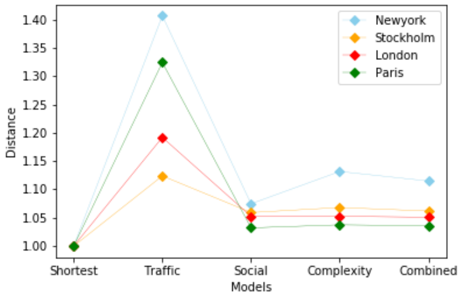
In the following, we present the results of the three analysis steps. These are then further discussed in Section 5.

### 4.2.1 Effects of the different path search models

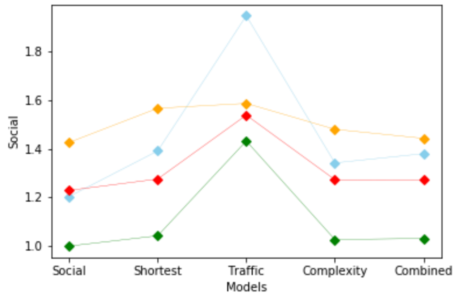
Table 3 and Figure 4 illustrate the effects the different path search models have on distance (a), social costs (b), traffic (c), and complexity (d), for each of the four environments. In each figure, the absolute lowest value is used as a reference value, set to 1, and all others are scaled relative to this reference value. That is, a value of 1.5 would mean that the respective value is 50% higher than the reference value. This is done globally, i.e., across the four environments, except for distance, where for each environment the respective average shortest path is used as a reference value. This is done to more clearly show relative increase of path length when accounting for other factors than distance.

We can see that the traffic model, which finds paths with the least traffic load, results in potentially large detours compared to the shortest path, with the increase depending on the environment (for London on average about 20% longer paths, for Paris more than 30%, for New York more than 40%). The other three models (social, complexity, combined) only lead to minor increases of path length (15% or less on average).

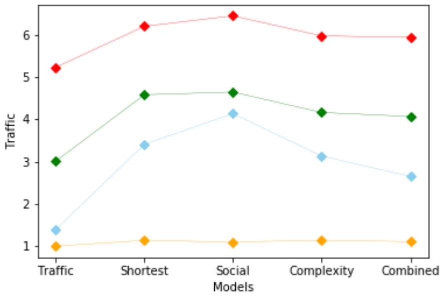
Figures 4b and 4c show the relation between social costs and traffic load for the paths calculated by the different models. First, we can observe that there are differences in the "baseline" between the different environments. For example, traffic load is approximately five times higher in London compared to New York or Stockholm even in the optimal cases, and the paths calculated with the social model have significantly lower social costs in Paris compared to the most social paths in Stockholm. That is, again we see an impact of the environment, but also of the distribution of traffic, on path search behavior. Further, the traffic model results in the paths with the highest social costs (Figure 4b), whereas the social



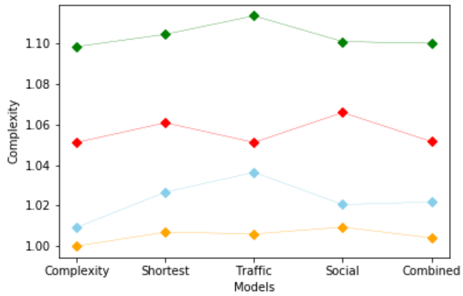

**(a)** Average path length of the different models.




**(b)** Average social costs of the paths computed by the different models.




**(c)** Average traffic load of the paths computed by the different models.




**(d)** Average path complexity of the paths computed by the different models.

**Figure 4** Relative increase of the different factors under investigation depending on the applied path search model, for the four different environments: (a) average distance, (b) average social costs, (c) average traffic load, (d) average complexity. The different colors always represent the same environment across the diagrams.

model results in paths with the most traffic load (Figure 4c). For all other models, there seems to be a rather low increase in the social costs, however, (except for Stockholm) they all suffer a rather drastic increase in traffic load, even if it is lower than for the social model.

In Figure 4d we can see that complexity also depends on the environment, i.e., the least complex path in Stockholm is less complex on average than that in Paris, for example. These differences are less pronounced than for the environments' impact on the social and traffic model, though. Generally, the differences in complexity across the different models are small.

### 4.2.2 Effects on fastest paths

Figure 5a shows the effects accounting for traffic has on the (average) social costs of the fastest paths, whereas Figure 5b shows the same for the average complexity. Table 4 presents the average and standard deviation values. Similar to the previous analysis step, we can see that the social costs increase when accounting for traffic. In terms of path complexity, there is hardly an observable difference of paths with or without traffic for Stockholm and Paris. However, for New York and London complexity decreases slightly when avoiding traffic. Thus, again, the structure of the environment has an impact on the results.

**Table 3** Average (Avg, and standard deviation; Std) path length (a), social costs (b), traffic load (c), and complexity (d) of the different path search models for the four different environments, as relative values (i.e., scaled to the lowest one).

**(a)** Path length.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Shortest | 1.0 | 0.0 | 1.0 | 0.0 | 1.0 | 0.0 | 1.0 | 0.0 |
| Traffic | 1.406 | 0.398 | 1.123 | 0.151 | 1.191 | 0.257 | 1.324 | 0.416 |
| Social | 1.074 | 0.113 | 1.059 | 0.098 | 1.052 | 0.101 | 1.032 | 0.079 |
| Complexity | 1.131 | 0.216 | 1.068 | 0.106 | 1.052 | 0.127 | 1.03 | 0.092 |
| Combined | 1.114 | 0.182 | 1.061 | 0.096 | 1.050 | 0.129 | 1.035 | 0.090 |

**(b)** Social costs.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Shortest | 1.392 | 1.602 | 1.567 | 1.687 | 1.276 | 1.214 | 1.042 | 1.04 |
| Traffic | 1.948 | 2.253 | 1.587 | 1.712 | 1.539 | 1.686 | 1.432 | 1.866 |
| Social | 1.203 | 1.192 | 1.426 | 1.380 | 1.229 | 1.169 | 1.0 | 1.0 |
| Complexity | 1.342 | 1.391 | 1.481 | 1.499 | 1.273 | 1.224 | 1.026 | 1.035 |
| Combined | 1.380 | 1.519 | 1.443 | 1.412 | 1.272 | 1.23 | 1.031 | 1.037 |

**(c)** Traffic.

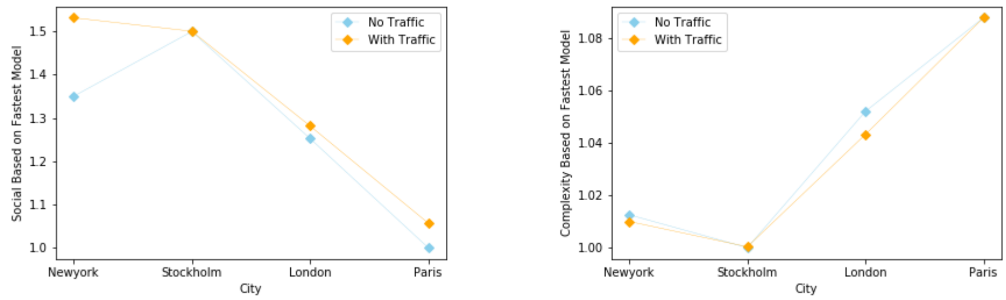
| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Shortest | 3.409 | 13.524 | 1.133 | 1.134 | 6.205 | 10.376 | 4.583 | 12.047 |
| Traffic | 1.391 | 4.713 | 1.0 | 1.178 | 5.232 | 9.763 | 3.008 | 8.839 |
| Social | 4.137 | 12.9 | 1.097 | 1.065 | 6.453 | 9.104 | 4.648 | 11.325 |
| Complexity | 3.131 | 11.744 | 1.137 | 1.058 | 5.978 | 10.333 | 4.163 | 11.259 |
| Combined | 2.65 | 10.928 | 1.106 | 1.0 | 5.945 | 10.374 | 4.068 | 11.394 |

**(d)** Complexity.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Shortest | 1.026 | 1.014 | 1.006 | 1.295 | 1.06 | 1.122 | 1.104 | 1.281 |
| Traffic | 1.036 | 1.133 | 1.005 | 1.297 | 1.051 | 1.129 | 1.113 | 1.331 |
| Social | 1.02 | 1.0 | 1.009 | 1.309 | 1.066 | 1.165 | 1.101 | 1.288 |
| Complexity | 1.009 | 1.001 | 1.0 | 1.292 | 1.051 | 1.167 | 1.098 | 1.282 |
| Combined | 1.021 | 1.083 | 1.004 | 1.31 | 1.051 | 1.179 | 1.1 | 1.28 |

### 4.2.3 Effects on least complex paths

Figures 6a and 6b show the effects of accounting for traffic on average social costs and path complexity, respectively, when computing paths using the least complex paths model (see Table 5 for average and standard deviation values). Again, aiming to reduce traffic load increases social costs. However, average path complexity essentially remains the same.




**(a)** The effects of accounting for traffic on social costs, for the four environments.

**(b)** The effects of accounting for traffic on path complexity, for the four environments.

**Figure 5** Effects of accounting for traffic on (a) social costs and (b) path complexity for the fastest paths.

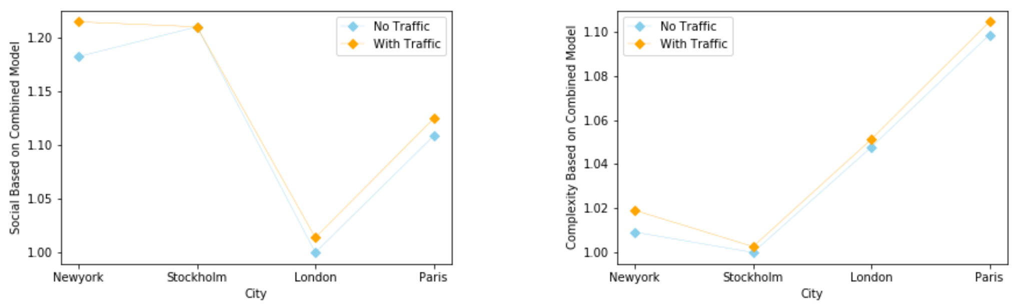
**Table 4** Average and standard deviation of accounting for traffic on (a) social costs and (b) path complexity for the fastest paths.

**(a)** Social costs.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Fastest Model (Without Traffic) | 1.349 | 1.521 | 1.499 | 1.353 | 1.252 | 1.137 | 1.0 | 1.0 |
| Fastest Model (With Traffic) | 1.531 | 1.796 | 1.5 | 1.347 | 1.281 | 1.201 | 1.056 | 1.009 |

**(b)** Complexity.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Fastest Model (Without Traffic) | 1.012 | 1.131 | 1.0 | 1.02 | 1.052 | 1.101 | 1.087 | 1.186 |
| Fastest Model (With Traffic) | 1.009 | 1.145 | 1.0 | 1.0 | 1.04 | 1.081 | 1.087 | 1.186 |




**(a)** Effects of accounting for traffic on social costs for the least complex paths, for the four environments.

**(b)** Effects of accounting for traffic on path complexity for the least complex paths, for the four environments.

**Figure 6** Effects of accounting for traffic on (a) average social costs and (b) average path complexity for the least complex paths, for the four environments.

**Table 5** Average and standard deviation of accounting for traffic on (a) social costs and (b) path complexity for the least complex paths.

**(a)** Social costs.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Combined Model (Without Traffic) | 1.182 | 1.387 | 1.21 | 1.0 | 1.0 | 1.489 | 1.108 | 1.506 |
| Combined Model (With Traffic) | 1.214 | 1.326 | 1.21 | 1.0 | 1.013 | 1.496 | 1.124 | 1.503 |

**(b)** Complexity.

| | New York | | Stockholm | | London | | Paris | |
|---|---|---|---|---|---|---|---|---|
| | Avg | Std | Avg | Std | Avg | Std | Avg | Std |
| Combined Model (Without Traffic) | 1.009 | 1.159 | 1.0 | 1.0 | 1.047 | 1.104 | 1.098 | 1.243 |
| Combined Model (With Traffic) | 1.019 | 1.105 | 1.002 | 1.003 | 1.051 | 1.138 | 1.104 | 1.27 |

## 5 Discussion

The results of our analysis show that accounting for traffic in path search has a clear negative effect on social costs. In avoiding traffic, wayfinders may easily end up in small, residential roads, thus, being redirected into areas that are not built for taking larger amounts of traffic. In some ways, such a result was to be expected, and it confirms similar unwanted consequences as discovered in [9]. This effect goes both ways, i.e., accounting for social costs drastically increases average traffic load. On the other hand, all other tested models mostly have only minor impact on social costs, i.e., seem to implicitly avoid these small, residential roads. Such roads are often rather short and residential areas may involve many turns, thus, navigating through them increases complexity (according to our model) and would often not provide the most direct connection, i.e., increase distance traveled. But ignoring traffic in computing paths may well mean that you end up being stuck in it. In other words, the average traffic load for all other models is also significantly higher than that for the least traffic model, even if this impact is smaller than for the social model. Thus, these results clearly show that assuming to "being alone" is problematic for path search models.

Interestingly, accounting for traffic hardly seems to influence path complexity. In fact, for the fastest path it decreases for some environments, which might be explained by some "simpler", but generally slower, roads becoming now faster to traverse due to lower traffic load. Still, this result seems to contradict the findings in [9]. But they used other path search criteria (scenic and safety) and also their path complexity measure is simpler than ours, only using node degree and turn/no turn, which might explain some of these differences.

The combined model does not lead to much of an increase of either complexity or social costs – at least for most environments. Only for New York the social costs increase from about 1.2 to nearly 1.4. Traffic load does increase significantly, though (except for Stockholm). But this increase is smaller than for any of the other models, so adding traffic as a parameter into the combined model does have the wanted effect. Increasing the weight and, thus, importance of this parameter would help to reduce the increase in traffic load further, though likely with increased social costs as a consequence. It would take a careful calibration of weights to find the ideal balance here, which would also depend on the context.

We observe a major impact of environmental structure on our results. And this impact is amplified by the distribution of traffic. For example, in Stockholm heavy traffic is restricted to the major roads to the west, thus, does not impact paths through the regular, grid-like area to the east. On the other hand, in London all major roads that connect the somewhat dispersed local areas have heavy traffic load, which results in significantly higher traffic load for all paths compared to, for example, Stockholm. And in Paris there is a relatively dense, “spider-web”-like network of major roads interwoven with residential roads, which allows for largely avoiding these small roads in optimizing for social costs, while there are significantly fewer of these major roads in Stockholm, for example.

While our analysis provides some important insights into the effects of “not being alone” it also has some limitations. Notably, the environments we used are fairly small. Larger environments may amplify the differences between the different path search models, but also the effects of traffic on the resulting paths. Further, the model for least complex paths combines several parameters in an overall complexity measure. Arguably, all of them are relevant for wayfinding complexity, but in their combination they may also mask each other to some degree. Thus, a more systematic analysis of their individual impact may be interesting.

## 6 Conclusions and future work

In this paper, we analyse different path search models with respect to the fact that we are not alone while navigating through road networks. “Not being alone” is an aspect that has been neglected so far in most existing models. Overall, we find a significant effect of accounting for traffic, in particular on social costs (and vice versa), however, interestingly, hardly any changes of wayfinding complexity when accounting for either traffic or social costs.

Future work includes analysing further environments to gain more insights into the effects of environmental structure, and in particular, using larger areas in this analysis. We also plan to incorporate individual differences in the analysis, i.e., SBSOD scores but also preferences for certain road types, to evaluate their effects on path search results, in particular complexity and social costs. Finally, looking at real traffic patterns would be interesting to gain better insights into the actual, real-world effects of this parameter.

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