Integrating Route Attractiveness Attributes into Tourist Trip Recommendations

Daniel Herzog
Department of Informatics
Technical University of Munich
85748 Garching bei München, Germany
herzogd@in.tum.de

Sherjeel Sikander
Department of Informatics
Technical University of Munich
85748 Garching bei München, Germany
sherjeel.sikander@tum.de

Wolfgang Wörndl
Department of Informatics
Technical University of Munich
85748 Garching bei München, Germany
woerndl@in.tum.de

ABSTRACT

Tourist trip recommender systems (RSs) support travelers in identifying the most attractive points of interest (POIs) and combine the POIs along a route for single- or multi-day trips. Most RSs consider only the quality of POIs when searching for the best recommendation. In this work, we introduce a novel approach that also considers the attractiveness of the routes between POIs. For this purpose, we identify a list of important attributes of route attractiveness and explain how to implement our approach using three exemplary attributes. We develop a web application for demonstration purposes and apply it in a small preliminary user study with 16 participants. The results show that the integration of route attractiveness attributes makes most people choose the more attractive route over the shortest path between two POIs. This paper highlights how tourist trip RSs can support smart tourism. Our work aims to encourage further discussion on collecting and providing environmental data in cities to enable such applications.

CCS CONCEPTS

• **Information systems → Web applications**; **Recommender systems**.

KEYWORDS

Recommender System, Tourist Trip Design Problem, Route Attractiveness, Environmental Data, User Study

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1 INTRODUCTION

Generally, tourists exploring a city wish to visit as many points of interest (POIs) as possible. However, visiting all POIs is usually not feasible because of constraints, such as the time available for the trip. The problem of designing tourist trips covering multiple POIs along enjoyable routes is called the Tourist Trip Design Problem (TTDP) [22]. In its simplest specification, the TTDP is identical to the Orienteering Problem (OP), a combinatorial optimization problem in which several locations with an associated profit have to be visited within a given time limit. Each location may be visited only once, and the aim is to maximize the overall profit gained on the tour [19]. Practical applications of the TTDP can be integrated in recommender systems (RSs) which help users to identify the most attractive POIs in an area of interest and combine them to devise single- or multi-day trips.

In most tourist trip algorithms and applications, the total profit of a trip is the sum of the profits of the locations. However, we argue that tourists do not always want to take the shortest route between two POIs. Rather, the perceived quality of a tourist trip depends also on the attractiveness of the routes between the POIs. For example, a trip becomes more attractive when the route between two POIs is a relaxing walk in a green area instead of a walk by a loud street, even if this means taking a detour. Furthermore, when too many tourists take the same routes, the recommendations can be adapted to better balance the tourist flows in the city, thereby helping reduce the crowd and pollution in these areas. Consequently, tourist trip RSs should be able to determine the profits of routes by considering all relevant route attractiveness attributes and to adapt the recommendations accordingly.

In this paper, we present a solution to integrate route attractiveness attributes into a tourist trip RSs for walking tourists. Our approach allows the integration of any data influencing the quality of routes and adjusting the importance of each attribute according to the user's needs. We illustrate our approach by explaining the integration of three attributes as an example. In addition, we present a web-based application implementing our approach and evaluate the recommended routes in a user study. A more detailed description of our approach can be found in [16]. The advantages of our system are twofold. Tourists receive recommendations for personalized trips tailored to their needs. Further, cities and tourist spots can promote the development of smart tourism by providing the users with all relevant information about the attractions to visit, how to reach them, and any form of environmental conditions influencing their trip. Hence, our main contribution is an innovative, practical smart tourism application that promises benefits with regard to the economy, environment and mobility in cities. The aim of this paper is to encourage discussion on the environmental data that should be collected in cities to enable these benefits, how to collect these data, and how to make the data accessible to promising applications.

The remainder of this paper is organized as follows: In Section 2 we summarize relevant related work. We define route attractiveness

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and identify relevant attributes for a tourist trip RS in Section 3. In Section, 4 we explain the edge weight calculation of selected attributes. We present the implementation of our approach and our web-based application in Section 5. The preliminary user study we conducted and its results are presented in Section 6. Finally, Section 7 presents the conclusions and suggestions for future work.

2 RELATED WORK

RSs support tourists in finding best travel destinations, POIs, and travel packages combined of multiple travel-related items [1]. Practical applications that solve the TTDP have been developed in the recent years. The City Trip Planner, introduced by Vansteenwegen et al. [20], was the first practical application to solve the TTDP. It provides recommendations for single- or multi-day trips and can include lunch breaks into the recommendation. CompRec-Trip is a RS for sets or sequences of POIs; it has a graphical user interface allowing users to customize the recommended trips [25]. Gavalas et al. [6] developed DailyTRIP, a web and mobile web application that takes into account the opening days and hours. Recently, Herzog et al. [9] presented TourRec, a mobile RS that provides suggestions for personalized trips to individuals and groups.

All of these RSs solve the TTDP by maximizing the sum of POI profits while trying to minimize the distances between the POIs. Only few works have considered the quality of routes between POIs when determining the total value of a trip. Souffriau et al. [17] introduced the Arc Orienteering Problem (AOP), a variant of the OP. The AOP assigns a cost and a non-negative profit to routes (*arcs*) instead of locations. Souffriau et al. presented a greedy randomized adaptive search procedure to solve the AOP and implemented it in a cycle route planner to recommend pleasant routes for cyclists. Verbeeck et al. [23] presented the Cycle Trip Planning Problem (CTPP), an extension of the AOP. In the CTPP, a vertex can be visited twice. Vansteenwegen et al. [21] introduced another extension of the AOP, namely, the Mixed OP; in this problem, scores are assigned to routes as well as locations. Gavalas et al. [5] worked on recommending scenic routes, i.e., walking paths of tourist value. They integrated their approach in a context-aware mobile city guide for Athens, Greece with 18 scenic routes. A user study confirmed that their approach can recommend tours of high quality. Querica et al. [14] introduced a different approach to recommend trips. Their recommendations suggest routes that are perceived as pleasant, thereby trying to maximize the perceived happiness of users while adding only a few extra walking minutes to the trip.

However, to the best of our knowledge, there is no tourist trip RS that considers all types of route attractiveness attributes, such as air pollution, greenery, and street quality, to find the optimal trip. In this paper, we explain how such attributes can be integrated into TTDP algorithms. The novelty of our approach is its flexibility that allows easy addition or removal of attributes and adaption of the route attractiveness calculation to the recommendation's context and the user's needs.

3 ROUTE ATTRACTIVENESS

The influence of environmental attributes on people's decisions to participate in outdoor activities, such as walking or cycling, has been explored earlier. We analyzed previous studies [8], literature reviews [11, 18], developed frameworks [12], and models [2, 15] that dealt with the influence of environmental attributes on the choice of walking routes. It is not possible to directly compare the results of all works as they used different methodologies or were limited to specific target groups, such as elderly people. Based on our findings, we thus devised a novel, subjective list of route attractiveness attributes that should be considered when evaluating routes in a tourist trip RS.

Table 1 lists all route attractiveness attributes that we identified and their impact on the quality of a walking route. The attributes are classified into three categories: attributes that are likely to affect the route, attributes that are somewhat likely to affect the route, and attributes that are less likely to affect the route or for which the data are insufficient to determine the probability. The listed attributes are not ordered.

Table 1: Route attractiveness attributes for tourist trip RSs. The (+) sign following an attribute's name indicates a positive impact on a walking route, and the (−) sign, a negative impact.

Attribute	Probability
Aesthetics: Trees (+)	High
Aesthetics: Pollution (−)	High
Aesthetics: Cleanliness (+)	High
Permeability: Pavements (+)	High
Traffic: Speed (−)	High
Walking Surface: Maintenance (+)	High
Personal Safety: Surveillance (+)	High
Aesthetics: Landscaping (+)	Medium
Permeability: Intersection Distance (−)	Medium
Traffic: Volume (−)	Medium
Personal Safety: Lightening (+)	Medium
Traffic: Crossings (+)	Medium
Traffic: Crossing Aids (+)	Medium
Streets: Width (+)	Medium
Aesthetics: Parks (+)	Medium
Permeability: Slopes (−)	Medium
Permeability: Stairs (−)	Medium
Traffic Control Devices (+)	Low / Unclear
Walking Surface: Continuity (+)	Low / Unclear
Traffic: Verge Width (+)	Low / Unclear
Destination: Shops (+)	Low / Unclear
Traffic: Noise (−)	Low / Unclear
Facilities: Places to rest (+)	Low / Unclear
Environment: Walking Trails (+)	Low / Unclear
Facilities: Shops (+)	Low / Unclear
Personal Safety: Blind Walls (−)	Low / Unclear
Aesthetics: Green strips (+)	Low / Unclear

All the earlier studies that we reviewed agree that aesthetics attributes are the most important route attractiveness attributes. These attributes include the number of trees along the path, pollution, and cleanliness. Traffic speed is an important safety hazard influencing the attractiveness of a route while the impact of traffic noise is unclear. Other important route attractiveness attributes are the presence of pavements, maintenance of the walking surface, and personal safety in form of surveillance (people around, avoiding empty streets, etc.).

We suggest that smart tourism applications, such as tourist trip RSs, should consider all attributes in the first category and examine whether attributes from the secondary category should be considered before recommending routes to people. Further research is necessary to evaluate the impact of the attributes from the last category, and their impact may also highly depend on the use case.

4 EDGE WEIGHT CALCULATION OF EXEMPLARY ATTRIBUTES

Our approach recommends tourist trips by running a shortest path algorithm on a graph of vertices and edges. However, our approach does not use only the distance between two vertices to determine the edge weight (*cost*). It also considers the presence or absence of the relevant route attractiveness attributes listed in Table 1.

In this section, we explain the calculation of the edge weights in such a shortest path algorithm for three examples: trees, pollution, and cleanliness. These are the most relevant attributes for our scenario. We then present the final edge weight calculation taking into account all three attributes. Our goal is to present a flexible and extendable solution for integrating attractiveness attributes. Providers of tourist trip RSs should be able to easily add or replace attributes, depending on the available data sources. Users should be able to individually adjust the importance of each attractiveness attribute while exploring a city.

4.1 Aesthetics: Trees

The tree edge weight is based on the tree density on a route. The greater the number of trees on the edge, the higher is the tree density and vice versa. A higher tree density corresponds to a lower edge weight in the graph.

In order to weight the different tree densities, we utilize a weighting method described by Giles-Corti et al. [7]. For our purpose, we normalize the weights to a scale from 0 to 5 (Table 2).

Table 2: Weights for tree density according to [7] and after normalization (exact values in brackets).

Tree Density	Weight	Normalized Weight
Many trees touching	14.3	5
Some trees touching	11.4	4 (3.986)
Trees close but do not touch	8.6	3 (3.007)
Trees spread apart	5.7	2 (1.993)
Sparse trees	2.86	1
No trees	0	0

We use the horizontal spread of the tree when viewed from the top, i.e., the crown spread, to define tree density. For the sake of simplicity, we use a generic crown radius of 5 m for every tree in our algorithm. This is roughly the average crown size of the *Tilia cordata* Mill. species, which is the species of trees most commonly planted in Berlin, Germany (35 %) [13]. We use the following function to estimate tree density:

$$DensityScore(Edge_i) = \frac{EdgeLength(Edge_i)}{NumberOfTrees(Edge_i)}, \quad (1)$$

where $Edge_i$ is the ith edge in the graph; $EdgeLength$ is the distance of the edge in meters; and $NumberOfTrees$ is the total number of trees assigned to the edge. Using this equation and assuming a generic crowd radius of 5 m, we estimated tree density as specified in Table 3.

Table 3: Tree density categorization based on density score.

Tree Density	Density Score (x)
Many trees touching	$x < 5$
Some trees touching	$5 \leq x < 15$
Trees close but do not touch	$15 \leq x < 25$
Trees spread apart	$25 \leq x < 35$
Sparse trees	$35 \leq x$
No trees	0

The tree edge weight is eventually calculated by dividing the density score by the normalized weight of the respective tree density category in Table 2. When there are no tress, the edge length is divided by 0.5.

4.2 Aesthetics: Pollution

Air quality is measured differently by different countries. Pollutants are measured over a certain defined period, and the density of the pollution is usually measured in micrograms per cubic meter. Some of the most common air pollutants are nitrogen dioxide (NO2), ozone (O3), fine particulate matter (PM2.5), and coarse particulate matter (PM10). In order to standardize the concentration values of different pollutants, we use the Common Air Quality Index (CAQI) (Table 4) [3]. The CAQI is an index that compares air quality across different European countries. It has been used in the data on the website www.airqualitynow.eu since 2006.

Table 4: CAQI values corresponding to different pollutant concentrations [3].

Index Class	Grid	Pollutant (hourly) density in μ/m^3			
		NO2	PM10	O3	PM2.5 (opt.)
Very high	>100	>400	>180	>240	>110
High	75–100	200–400	90–180	180–240	55–110
Medium	50–75	100–200	50–90	120–180	30–55
Low	25–50	50–100	25–50	60–120	15–30
Very low	0–25	0–50	0–25	0–60	0–15

If two or more pollutants have different CAQI values for a region, the higher value is considered to be the overall CAQI value as the worst grid value determines the overall index class.

We use the CAQI values to map air pollution values to edges. The air pollution weight is calculated by dividing the CAQI value of the edge by 25 and multiplying it with the edge length. For very low air pollution CAQI values, we divide the CAQI value of the edge by 50 to reduce the costs of edges with very low pollution even more strongly.

4.3 Aesthetics: Cleanliness

There is no standard way of measuring cleanliness as it greatly depends on the public perception of littering. In this work, we measure cleanliness as littering on a scale of 0 to 10. The littering value could be reported by citizens through mobile applications, for example. Values less than 5 are considered as low or medium littering while values greater than or equal to 5 are considered as high littering. The value of 0 represents either no littering or unavailability of data.

The littering weight for high littering is calculated by multiplying the littering value by the edge length. For low littering values, we divide the littering value by 2 before multiplying it by the edge length. For no littering or no data, we multiply the edge length by 0.1.

4.4 Final Edge Weight

The final edge weight e takes the edge length and the attractiveness attributes into account. Our proposed calculation assigns weights to the attributes:

$$\begin{aligned} e = (x * treesWeight) + (y * airpollutionWeight) \\ + (z * litterWeight), \end{aligned} \tag{2}$$

where x, y, and z determine the importance of each attractiveness attribute. They can either be fixed, provided at runtime by the user, calculated from user preferences, or learned through user behavior. The dynamic nature of these values makes the algorithm adjustable, allowing us to meet the requirement of a flexible and extendable solution to integrate attractiveness attributes. For example, if the presence of trees is more important than no littering for a user, x should be greater than z. If the user wants to completely ignore an attribute, the corresponding value is set to 0. Furthermore, additional attributes with the desired weight can be added at any time. In this work, we initially set x, y, and z to 1. We evaluated the importance of each attribute, as described in Section 6.1.

5 IMPLEMENTATION

The calculated final edge weight can be interpreted as the cost for traveling between two POIs in a tourist trip RS. Shortest path algorithms, such as algorithms based on Dijkstra's algorithm, can be used to incorporate the costs when recommending tourist trips [24]. In this case, the RS first identifies the POIs that the user should visit during a trip. Then, the routing algorithm finds the best routes between the POIs, considering the calculated costs for each route.

In order to execute such an algorithm, we need map data to build a graph of vertices and edges. In the following text, we explain the pre-processing of map data and our example attributes, and the mapping of these attributes to the graph. For our prototype, we used the open source vector map data source OpenStreetMap to access to the required data. We implemented our approach using only a small extract of OpenStreetMaps since loading the entire map data for a large city or region and performing route operations on it is a memory-intensive task. In this work, we used an extract of the city center of Munich, Germany.

In OpenStreetMap, ways are essentially a collection of connected nodes. We can consider ways as edges for simplicity of discussion. A node in OpenStreetMap can be a street intersection, a bench, or any other point specific information. Nodes, such as benches, trees, or ways that are only used to define boundaries of a park, for example, are not connected to other nodes, and hence, they do not specify streets or footpaths. We need to extract only those nodes that are surely connected. We use these ways from our OpenStreetMap extract to eventually build a graph. Given the latitude and longitude information of two neighboring nodes, we can calculate the distance between them to create a weighted graph that is required in our path algorithm.

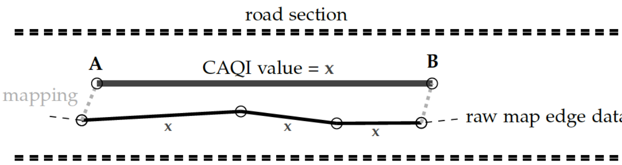

Figure 1: Mapping a CAQI vector to edges.

In the next step, we map the attractiveness attributes to the graph edges so that they can be used in the routing algorithm.

Tree data are available in OpenStreetMap files and are represented by latitudes and longitudes. We assign every tree to the edges of the nearest node. This approach increases the actual number of trees assigned to the graph; however, this tree count is only used to estimate the tree density for an edge.

Air pollution data are represented by a vector line with a start point and an end point. Since we do not have access to real pollution data, we assume the values in this work. First, we find two nodes: the nearest node for the start point and that for the end point of the CAQI vector. Within the length of a single CAQI vector, multiple edges of the graph might be present. The CAQI value needs to be translated to all the edges lying between two points A and B. Hence, we use a shortest path calculation between two nearest nodes to find all such edges. This approach is illustrated in Figure 1. Nodes A and B represent the starting and end points of a CAQI vector. They are mapped to the nearest nodes, and the shortest path between these nodes has three edges. If multiple CAQI values are mapped to the same edge, the highest CAQI value is assigned.

The litter data are also represented as a point; however, the impact is considered to be within a certain radius. Since we do not have access to real littering data, we assume their values in this work. First, we find the nearest node for every litter position. Then, we determine all the edges that are within or intersect with a 10 m radius around this nearest node. For each edge, we add the current litter value to the total litter value of this edge. It is important to note that multiple littering spots near the same edge add up, and hence the final littering value of an edge can be greater than 10.

After assigning all the weights to the edges, the final graph can be created and used by a tourist trip RS or any type of routing application to find routes taking into account the integrated attractiveness attributes. We developed a web application incorporating the aforementioned attractiveness attributes to visualize our approach and the routes that can be generated. The applications is developed using ReactJS, a javascript library for building web applications. Figure 2 shows the recommendation made by

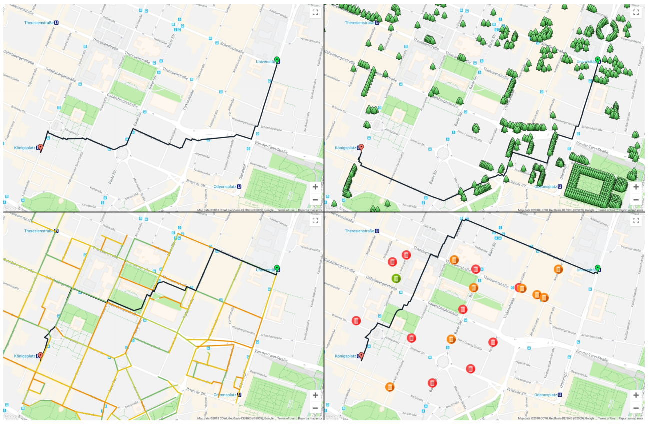

Figure 2: Visualization of route attractiveness attributes in our application and the recommended routes between two POIs. Top left: shortest path, top right: trees, bottom left: air pollution, and bottom right: cleanliness (littering).

our application regarding the shortest path between two POIs and different alternatives depending on the considered attribute.

6 PRELIMINARY USER STUDY

The main goal of the preliminary user study is to determine the impact of route attractiveness attributes on the user's decision of choosing an alternative walking route between two POIs instead of the shortest path. The user study is divided into two parts:

(1) Determination of the impact of the three considered attributes on route attractiveness.
(2) Evaluation of the recommended routes, including the route attractiveness attributes of the examples.

In all, 16 users participated in the user study. Most of the participants were students from Munich in the age range 22 and 29 years.

6.1 Attributes Questionnaire

A relevant route attractiveness attribute either has a positive impact or a negative impact on route attractiveness. We asked the participants about their decision to walk a route between two POIs if an attribute is (a) present and (b) absent.

Table 5 summarizes the results of our questionnaire. Air pollution is obviously a very critical attribute for travelers. In fact, 100% of our participants claimed that they will avoid routes with little air pollution, while the absence of air pollution is the reason for choosing an alternative route over the shortest path. A similar, less unanimous behavior can be observed when asking participants about littering. Greenery, however, seems to be a bonus for travelers. Having no greenery (e.g., no trees) does not influence their decision of choosing an alternative route.

We conclude that air pollution and littering are two dominant factors influencing the choice of a route. Hence, they should receive very high weight in a tourist trip RS. Missing greenery does not necessarily decrease the recommendation probability of a route if the route is clean. However, almost a fifth of travelers prefer routes

Table 5: Influence of the presence or absence of route attractiveness attributes on travel decisions (highest value marked in bold).

	Travel	Avoid	No influence
No air pollution	**100%**	0%	0%
Little air pollution	0%	**100%**	0%
No greenary	12.5%	18.75%	**68.75%**
Greenary	**93.75%**	0%	6.25%
No littering	**87.5%**	0%	12.5%
Littering	6.25%	**81.25%**	12.5%

with greenery when traveling. Greenery can therefore be used to choose between different routes with similar pollution. This also validates our assumption that users should be able to adjust the weights, if necessary.

6.2 Evaluation of the Recommended Trips

The 16 participants of our user study were then asked to use the application. Each participant had to specify two POIs, a starting and ending point, five times. For each POI pair, the shortest path and a route for each of the four test conditions (tree attribute only, air pollution attribute only, litter attribute only, and all the attributes combined) were calculated. For each test condition, the participants saw the attributes visualized on the application's map, as illustrated in Figure 2. Since some of our data were assumed, the participants were asked to assume that all data are real.

After every recommendation, the participants were given a comparison of the time taken in minutes for the detour compared to that for the shortest path and were asked if they would prefer the recommended route over the shortest path.

Table 6 summarizes the results. For each test condition, we conducted a binomial test to find out if the integration of route attractiveness attributes had a significant effect on the users' decision. Results show that integrating trees, air pollution, and all the attributes taken together prompt tourists to significantly more often select the recommended route over the shortest path. Less littering, however, does not seem to make people choose the recommended route more often than the shortest path.

Table 6: Ratio of users choosing the more attractive route over the shortest path (Note: *p<0.05; **p<0.01; ***p<0.001).

Algorithm	Average	Significant
Air pollution only	0.7	Yes ***
Trees only	0.76	Yes ***
Littering only	0.59	No
Combined	0.66	Yes **

7 DISCUSSION AND CONCLUSION

Previous research showed that many environmental factors have a significant influence on the perceived attractiveness of routes. The presence or absence of some of these factors is prompting people to choose routes with the given characteristics even at the cost of taking a detour. For tourists, in particular, route attractiveness plays an important role when planning city trips. Many tourists do not want to only visit as many POIs as possible. The walking time between two locations is also part of the pleasure and can increase a traveler's happiness. Hence, attractive routes are often preferred over the shortest path if they promise a more pleasant journey. RSs for tourists should incorporate route attractiveness attributes to better adapt their recommendations to the users' individual needs.

We presented a list of attributes that influence people's decisions on the choice of walking routes. We demonstrated the integration of three such attributes into a tourist trip RS. In our preliminary user study, a significant majority chose recommended routes considering attractiveness attributes over the shortest path. Future work should provide solutions to integrate all attributes with a large impact on a walking route's quality. A big challenge for the developers of smart tourism and mobility applications is the availability of such data. In this work, we were only able to get real tree data for our test area. For cities, data have to be collected by deploying sensors to measure air pollution, for example. Collecting air pollution data for single routes or tourist spots is a challenging task as air quality is usually monitored using networks of static and sparse measurement stations [10]. More fine-grained measurements can be achieved by involving citizens who use air quality monitoring kits to measure pollution at home [4], or mobile applications to report problems, such as road damages and lack of accessibility. The data should be made public and accessible in real-time to allow developers of smart city applications to integrate them into their services.

We presented one example of an eco-sensitive, smart tourism application, i.e., a tourist trip RS. Route recommendations considering environmental data not only promise improved support of tourists while traveling in cities, but also help cities to become smarter from many perspectives. Recommendations can be made to avoid currently polluted areas until the air quality improves. The congestions of routes and means of transport can be integrated as route attractiveness attributes to support tourists, locals, and commuters, helping them avoid congested areas. Thus, better distribution of travelers and, in turn, a higher satisfaction of all players in a city can be ensured. Furthermore, cities can analyze how people move between POIs and start initiatives to make alternative routes more attractive by adopting measures such as planting more trees and improving pavements along unpopular routes.

As the next step of our research, we will integrate further route attractiveness attributes into our application. Our user study was limited to a small test area with predefined POIs. For a better understanding of the influence of the attractiveness of routes and detours on a traveler's satisfaction with a recommended trip, we want to evaluate our approach in a larger user study with real tourists and a fully working RS to specify own travel goals and preferred POI categories and to adjust the importance of attractiveness attributes.

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