Enhancing Individual Mobility: A Multistage Personalization Approach for Itinerary Planning in Multimodal Networks

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Keywords: Mobility, Itinerary Planning, Personalisation, Routing, Multimodal Networks.

Abstract: Individual mobility is an essential element of a prosperous society. Multimodal transportation can offer greater time, cost, and environmental efficiency than relying on a single mode of transport. Personalized itinerary planning is crucial to enhance the appeal of multimodal transport. Our proposed approach for recommending personalized itineraries tailors them by integrating diverse mobility preferences, routing services, and calibrating parameters of these services to provide individualized options. We optimize itineraries within the existing routing services and available data. The aim of this approach is to enhance travel experiences, making them more efficient, cost-effective, and aligned with each traveler's unique needs and preferences. The approach was evaluated in a mid-sized German city by analyzing real-world mobility preferences, available routing services, and mobility providers. Personalization criteria relevant to the evaluation area were selected. A simulation was conducted, which demonstrated a 10.48% increase in travel utility when compared to the shortest path itinerary recommendation.

1 INTRODUCTION

Individual mobility is essential in advancing societal well-being, particularly in promoting work-life balance. Multimodal transportation can be a cost-effective and time-efficient alternative to a reliance on a single transport mode in urban areas, reducing traffic congestion and enhancing overall travel satisfaction. Personalized travel suggestions can improve the appeal of multimodal transportation by incorporating the diverse preferences individuals consider when selecting a route. These preferences, which may change based on situational context or travel purpose, can also vary throughout the day or within a route.

When choosing a route, individuals take into account a variety of mobility preferences, whether consciously or unconsciously. However, the routing recommendation systems can only integrate preferences that it can evaluate and interpret. For example, preferences such as the "behavior of cyclists" may be important for car drivers, but their integration depends on available data, which may not be uniformly collected in all regions of the world. Incorporating such preferences will not enhance personalization if the system cannot assess them. In addition, each preference introduces a new optimization criterion, which requires an estimation of its importance to the individual users.

This paper addresses these challenges by conducting an analysis of mobility preferences and proposing a unified itinerary recommendation system with a multi-stage personalization strategy that integrates diverse preferences, transport modes, and routing services. To achieve this, we propose a strategic selection process for integrating multiple routing services into a unified system. The proposed approach aims to incorporate a specific subset of routing services that maximizes the overall number of supported personalization options and travel modes. Furthermore, the paper presents an algorithm for identifying utility-maximizing parameterization of the selected routing services. Finally, our proposed approach addresses the issue of overchoice, where individuals are faced with too many options, making the decision-making process overwhelming. This is achieved by dynamically estimating the optimal routes for individual users based on their mobility preferences and presenting the user with only the top three routes.

We evaluate our approach in a medium-sized German city, where we analyze travelers' mobility preferences, available routing services, and mobility providers. As an example, we identify a specific sub-

Wins, A., Becker, C., Alpers, S., Kneis, L. and Oberweis, A.
Enhancing Individual Mobility: A Multistage Personalization Approach for Itinerary Planning in Multimodal Networks.
DOI: 10.5220/0012637500003702

In *Proceedings of the 10th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2024)*, pages 319-326
ISBN: 978-989-758-703-0; ISSN: 2184-495X

set of mobility preferences and routing services that can be integrated into the travel planner in the evaluation region. Finally, we integrate the selected services into a unified itinerary recommendation platform and perform simulations on a real-world transport network using real-time travel information to evaluate the effectiveness of our proposed approach.

2 RELATED WORK

Recently, multiple frameworks for personalized routing have been developed. In (Nuzzolo and Comi, 2016), researchers proposed a utility-based approach for path suggestions that considers individual mobility preferences, improving path advice performance over using average preferences. The FAVOUR framework, which offers personalized route recommendations based on situational awareness, has been introduced in (Campigotto et al., 2016). This method consists of three stages: the initialization stage, which chooses one of a few initial profiles based on general user information; the second stage, which personalizes the profile further through a stated preference survey; and the third stage, where the profile is continuously updated through analysis of actual choices the users make. The method proposed in (Lathia et al., 2012) focuses on personalized user experiences by utilizing a hypernetwork that interconnects private and public transport networks. It optimizes advice based on individual preferences and for different modes of transport. The system generates customized routes for users based on factors such as speed, cost-effectiveness, convenience, and environmental impact. Personalized parameters are loaded to the network to generate routes for each individual case and user.

While the approaches mentioned above focus on developing a personalized itinerary recommendation framework, our approach suggests an alternative method for offering extensive personalization options within a single platform without requiring the development of a new routing service. This can be achieved by integrating multiple services into a unified platform. A similar system has been introduced in (Spitadakis and Fostieri, 2012). A WISETRIP planner is an innovative multimodal journey planner that integrates multiple journey planners by providing a communication interface to connect heterogeneous planners. The approach introduced in (Esztergár-Kiss et al., 2022) aims to create mobility solutions and establish multimodal transport networks that connect different systems. This is achieved by identifying appropriate exchange points between separate networks to implement the routing algorithm using various local journey planners. In contrast to the approach presented in this paper, the aforementioned approaches do not address the issue of the parameters calibration of the integrated services.

3 PERSONALIZED ITINERARY RECOMMENDATION SYSTEM

In order to integrate a wide range of mobility preferences, transport modes, and routing services in a unified platform, we propose a personalized itinerary recommendation system with a multi-stage personalization approach, as depicted in Figure 1. In the initial step, user preferences are obtained through simple surveys and choice experiments. Subsequently, in the preprocessing phase, relevant data is gathered from external sources. Personalization rules, derived from user preferences and gathered data (e.g., avoiding cycling if it is raining), are applied to prune possible travel options. In the following phase, external routing services are requested using the start and destination addresses specified by the user and a utility-maximizing parameterization that is tailored specifically to individual user preferences. In the final post-processing phase, routes are prioritized based on their utility for a specific user and preference profile. The best three options are then selected and visualized to the user. Subsequent sections will provide a detailed description of each stage, including the necessary initialization and implementation steps, as well as a description of the functionality and workflow for each stage.

3.1 Creation of Preference Profile

The preference profile enables the definition and estimation of individual mobility preferences of the users. These preferences can vary depending on the region of operation.

3.1.1 Initialization and Configuration

The prerequisite for implementing the preference profile is the analysis of the accessibility of single preferences in the region of operation. To achieve effective personalization, it is crucial for the system to filter out inaccessible preferences, such as the compliant behavior of other road users, and focus solely on preferences with relevant available data. To identify such preferences, one must first establish their interpretation and then the source of the data for that preference. Attributes like safety need interpretation spe-

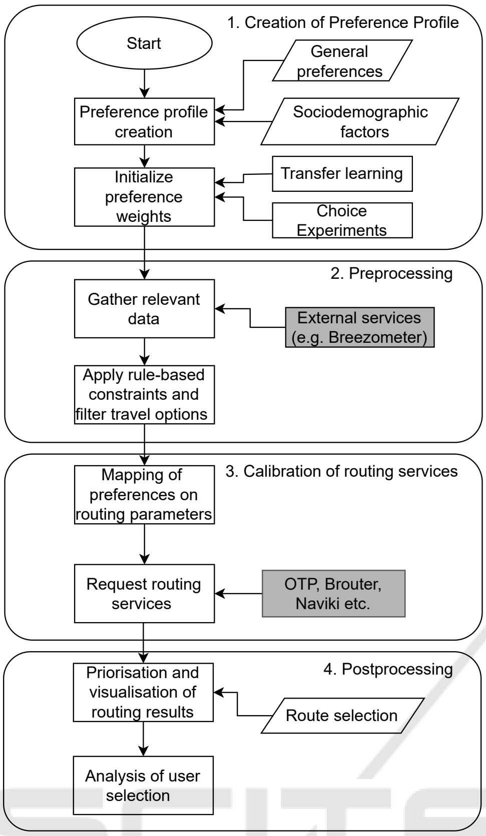

Figure 1: Multi-stage Personalisation Process.

cific to each mode. For instance, safety while cycling can be interpreted as the number of left turns, distance traveled along motorized roads, or the number of accidents on a specific route. Preferences should be considered in the personalization process if one of the following conditions is met:

- The preference can be used as a means of preselecting a transportation option, such as avoiding biking in the rain.
- At least one routing service provides the necessary personalization option, such as wheelchair accessibility.
- Preference can be evaluated by utilizing available data sources, such as user input (e.g., the presence of a driver's license) or open data (e.g., air quality).

3.1.2 Workflow and Functionality

In our itinerary recommendation system, users first register by providing basic sociodemographic information and static preferences that remain constant across different trip contexts, such as mobility impairment. Users can then create separate preference profiles for different situational contexts, incorporating dynamic preferences that adjust based on these contexts. For example, a profile labeled as "travel" may require the accommodation of luggage, while a profile labeled as "night travel" may prioritize illuminated paths. Static preferences are set during registration but can be modified within situational preference profiles to reflect changes, such as traveling with someone who has a mobility impairment. The system proposed in (Nuzzolo and Comi, 2016) distinguishes between rule-based preferences, which can be easily defined by users through simple surveys (such as a maximum number of transfers), and more complex preferences (such as "security" or "reliability") that lack a direct rule-based application and require prioritization or comparison for optimization. Furthermore, these preferences may conflict with each other. Utility theory can be used to represent conflicting objectives by quantifying the importance of each preference (Campigotto et al., 2016; Nuzzolo and Comi, 2016). The utility of a route is calculated as the sum of weighted utilities for each route attribute, addressing conflicting criteria. The utility function of a route r is illustrated in Equation 1, where β is a baseline utility, α_{a_i} is a binary value, depicting the relevance of the attribute a_i to the mode of the route (e.g., traffic is irrelevant for the train routes; therefore α will take the value of 0), β_{a_i} is the weight of the corresponding attribute a_i. The utility of a route $U(r)$ is the sum of weighted attributes a_i.

$$U(r) = \beta + \sum_{i=1}^{N} a_i * \beta_{a_i} * \alpha_{a_i} \tag{1}$$

Quantifying the importance of a wide variety of preferences can be complicated and time-consuming for a user. Therefore, we propose the iterative approach for learning individual user preferences based on the approach outlined in (Campigotto et al., 2016). The initial sociodemographic data is employed to establish default weights of the preferences. For example, the speed parameter could be determined based on the average speed for a specific gender and age. A more sophisticated strategy involving transfer learning, as suggested in (Campigotto et al., 2016), can be employed to initialize user preferences. An alternative method for initializing the default weights is to utilize the weights obtained from surveys conducted in the operation region. These default weights can be further adjusted for each individual user using choice experiments (Campigotto et al., 2016). The method used in this study for generating choice experiments and estimating individual utility functions based on the results of these experiments is described in (Wins et al., 2024) and follows the method outlined in (Louviere et al., 2008).

3.2 Preprocessing

The preprocessing phase is responsible for filtering travel options before the actual optimization process. The filter criteria are derived from the available data and rule-based constraints defined in the preference profile.

3.2.1 Initialization and Configuration

In order to customize the route, data needs to be gathered from different services, such as Breezometer for weather and air quality. The choice of these services depends on the travel region. To enable preprocessing, the analysis and integration of the available services in the operational region must be conducted during implementation.

3.2.2 Workflow and Functionality

Based on the selected preference profile and travel demand, the travel options and requested routing services are filtered in the preprocessing phase. In the first step, data required for the personalization (e.g., weather) is requested from various services available in the region of operation. In the subsequent step, appropriate transport modes and routing services are determined based on the user preferences and available data (including real-time data). For instance, if a user prefers not to cycle during pollination, modes involving cycling (bike, bike-sharing, bike and ride) will be eliminated from further consideration. Furthermore, routing services are selected based on the required personalization options and available data. For instance, if a user prefers public transport and wheelchair accessibility, only services with these options are chosen. However, preferences relying on real-time data, such as weather and pollination, may not be used if information is unavailable at the request time. Therefore, service selection should consider not only feature support, like avoiding specific streets when computing the route but also data availability.

3.3 Calibration of Routing Services

The third phase of our proposed approach to computing personalized itineraries involves requesting routing services that support the specified personalization options and desired travel modes and cover the required areas. To achieve route personalization, mapping of the mobility preferences from the selected profile to the routing request parameters of each requested routing service is essential.

3.3.1 Initialization and Configuration

The first prerequisite for the implementation of the routing calibration stage is the selection of the routing services to integrate into the itinerary recommendation platform. Routing services such as Brouter and OpenTripPlanner(OTP) offer extensive customization of algorithm parameters to cater to diverse user needs. However, due to their complexity, integrating these services requires time to understand their features through documentation and source code. In contrast, services like Naviki offer predefined profiles, such as leisure and mountain biking, without the option to adjust internal parameters. This simplifies use but limits personalization.

To identify the most effective combination of routing services for a specific region, an analysis should be conducted to determine the intersection of routing services that maximize the support for preferences, modes, and region coverage without causing a negative impact on performance. Although routing services can be requested concurrently, prolonged processing time for a single service may adversely affect the overall system performance. Thus, routing services should be selected under consideration of the trade-off between supporting additional features and maintaining optimal performance.

The second prerequisite for the implementation of the routing calibration stage is the integration of various routing services in the system. We propose using the Adapter Pattern (Gamma, 1995) for this purpose. This pattern assists in adapting the interface of the itinerary planner to various routing service interfaces. Each newly added routing service requires an adapter implementation that supports routing requests and provides information on the supported preferences, transport modes, and regions. This data is utilized during the preprocessing stage to determine the suitable routing services. Additionally, the adapter consolidates routing responses and returns them to the itinerary planner in a unified data format.

3.3.2 Workflow and Functionality

The personalization of routing can be achieved through the utility-maximizing calibration of the parameters of routing services. In this process, users' mobility preferences are mapped onto the technical parameters of the respective routing services. These mappings can be complex due to variations in parameter value ranges, data types and sensitivities. To overcome these issues, we suggest a parameter calibration approach based on simulated annealing and utility theory.

The proposed approach, which is based on the method described in (Teodoro et al., 2017), involves identifying and pruning non-influential parameters while simultaneously auto-tuning influential parameters. To enhance calibration performance, a sensitivity analysis is conducted to prune non-influential parameters - those with minimal or no impact on the routes - and exclude them from further analysis. This pruning step can substantially reduce the search space. Parameter calibration is performed individually for each preference profile and transportation mode. This is necessary because certain parameters may only be relevant for specific modes and preference profiles. For example, preferences such as bicycle speed are only relevant to modes such as biking, bike-sharing, and bike-and-ride. It is also crucial to consider the interactions between parameters to ensure accurate calibration. For instance, giving equal weight to conflicting parameters such as "scenic route" and "fastest route" may lead to unsatisfactory outcomes. Resolving conflicting parameterization often relies on the internal algorithms of the routing service being used. To address this problem, it is crucial to identify an appropriate parameter mapping.

For sensitivity analysis, we propose using the Morris Method (Morris, 1991) to evaluate the impact of changes in individual parameters on routing. Assessing the impact based on a single route can be misleading due to route variability, including the availability of direct public transport connections. Therefore, we propose a systematic selection of multiple routes across the evaluation region, aiming for comprehensive coverage that considers the trade-off between high-quality results and the computational efficiency of the analysis. These routes form a test set T. We consider parameters that affect at least one route as influential, recognizing that changes to parameters can affect routes differently.

To assess the elementary effect of a parameter p_i, routes are generated for start and destination using the default parametrization of a routing service $P_a = \{p_0, ...p_{i_a}...p_n\}$. Subsequently, routes are computed with an alternative parametrization $P_b = \{p_0, ...p_{i_b}...p_n\}$, where $p_{i_a} \neq p_{i_b}$, generated based on the Morris Method, while keeping all other parameter values unchanged. The resulting routes R_a and R_b under parametrizations P_a and P_b are then compared. Initially, the comparison is based on spatial factors, particularly the area enclosed by the two routes R_a and R_b (see Figure 2). Subsequently, the comparison focuses on temporal factors. The temporal factors considered are:

- Difference in the start times of routes R_a and R_b.
- Difference in the end times of routes R_a and R_b.
- Duration of routes R_a and R_b

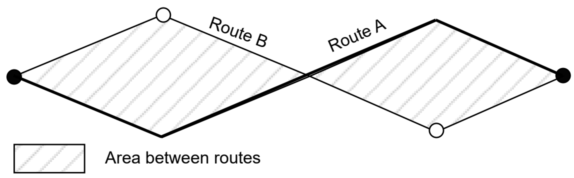

Figure 2: Area between two routes.

Input: $P_{default}$ = default parametrization
T = set of start/end coordinates
$U(x)$ = utility function
N = maximum iterations
Result: utility-maximizing parametrization P_{max}
$P_{max} \leftarrow null$;
$P_{current} \leftarrow P_{default}$;
while $i \leftarrow 0$ **to** N **do**
  if $(P_{max} \neq null)$ **then**
    $p_i \leftarrow random(\{p_0, ..p_j, ..p_n\} \in P_{current})$
    $val \leftarrow random(set\ of\ possible\ p_i\ values)$
    $P_{current}.p_i \leftarrow val$
  end
  $sum \leftarrow 0$
  forall $t\ in\ T$ **do**
    $r \leftarrow computeRoute(t, P_{current})$
    $u \leftarrow U(r)$
    $sum \leftarrow sum + u$
  end
  $f(P_{current}) \leftarrow sum/T.size()$
  if $P_{max} = null\ or\ f(P_{current}) > f(P_{max})$ **then**
    $P_{max} \leftarrow P_{current}$;
  end
end

Algorithm 1: Simulated Annealing.

After completing the sensitivity analysis and pruning non-influential parameters, the subsequent step is auto-tuning the remaining parameters. Similar to the sensitivity analysis, the auto-tuning process is carried out for a selected mode, preferences profile, and test set T. We suggest employing Simulated Annealing for the auto-tuning process. The pseudocode of the used algorithm is outlined in Algorithm 1. Neighbours are generated by randomly choosing a parameter p_i and then randomly selecting a value from the value range associated with that parameter p_i. The fitness function is determined by the utility function of a chosen preference profile, as defined in Equation 1. To compute the fitness of a new parametrization $P_{current}$, routes are requested for every combination of start and destination coordinates from the test set

T using the parametrization $P_{current}$. The utility of each calculated route is then evaluated using the utility function $U(x)$ corresponding to the selected preference profile. The fitness of the new parametrization $f(P_{current})$ is calculated as the mean of the utilities across all generated routes from test set T.

Once the utility-based parametrization is computed, it can be used to request personalized routes for individual users and preference profiles.

3.4 Postprocessing

In the postprocessing phase routes are consolidated and rated based on user preferences. Postprocessing begins with the consolidation of responses: these are transformed into a single format whereby duplicates are eliminated. The remaining routes are rated and prioritised based on the selected preference profile. To avoid overchoice, the user is presented with only three routes with the highest utilities. The actual route choice of a user can be used to update the utility function of the preferences profile using the method described in (Campigotto et al., 2016).

4 EVALUATION

The evaluation of the proposed approach was carried out in a mid-sized city in Germany. Initially, we created training and validation sets T and T' by dividing the evaluation region into 30 equal grids. We have defined the geofence of the evaluation region as a quadrangle with the following coordinates: (49.08144; 8.34344), (49.08189; 8.55081), (48.95559; 8.54806), (48.95491; 8.25967). The overall area of the evaluation region is 254 km^2, which we divided into 30 grid areas of approximately 8.5 km^2 each. From each grid, two coordinates t_i and t_j are selected and added to coordinate lists T_i and T_j, respectively. The training set T is subsequently formed by considering all potential combinations of coordinates from the list T_i, excluding those where the start and end destinations are the same. The divergent validation set T' is formed analogously from the coordinates from the list T_j.

Regional routing services and mobility and data providers were analyzed to select the mobility preferences that can be integrated into itinerary planning based on relevant data availability. Our proposed itinerary planner considers several static preferences, such as mobility impairment, subscriptions, payment methods, favorite places and routes, and type of private vehicle (e.g., electric or diesel car). This information is gathered through a general survey, along with basic sociodemographic data. The itinerary planner allows for the definition of multiple situational preference profiles, which incorporate further preferences of two types: those with and without rule-based application, as suggested in (Nuzzolo and Comi, 2016). The following preferences with rule-based applications have been integrated: luggage, maximum number of transfers, minimum transfer time, car park time, car pickup time, speed, maximum distance for walking and cycling, and environmental friendliness. The user can directly adjust the default values of these preferences, which are based on the default values of OTP (OpenTripPlanner, 2024).

The user's utility function (see Equation 1) incorporates more complex preferences without rule-based application. In our itinerary planner, we have incorporated the following preferences into the utility function: travel mode preference, travel time reluctance, travel cost reluctance, waiting time reluctance, access and egress walk time reluctance, access and egress mode preference, and elevation reluctance. These preferences can be accessed through choice experiments, as described in section 3.1, or learned by the system based on the user's previous choices (Arentze, 2013) or transfer learning (Campigotto et al., 2016). The preferences are then incorporated through parameterization and calibration of routing services, followed by prioritization of routes during the postprocessing phase.

It is important to note that the preferences involved in routing parametrization and post-processing may be different. For example, cycling speed is only relevant for routing parametrization, not for evaluating route utility in the postprocessing phase. When selecting preferences for routing parametrization, it is important to examine the available routing services in the evaluation region thoroughly. In our analysis, we have considered the following routing services: BlaBlaCar, Brouter, Cycle.travel, Graphhopper, HERE, Mapbox, MAPQUEST, Naviki, OpenRouteService, OpenTripPlanner, Trassenfinder, Trias, TripGo, TomTom. An analysis of the personalization options and supported modes provided by each routing service has been conducted. This analysis identifies the preferences applicable during the calibration phase of routing services, which are detailed in Table 1. The selection of OTP, Valhalla, and TomTom constitutes a minimal set of routing services that collectively maximize the range of personalization options in the evaluation region.

The route planning in this study focuses on integrating parameters aligned with individual mobility preferences, neglecting those that could influence the performance of routing algorithms. For instance, such parameters as "search window" have not been incor-

Table 1: Routing parametrization.

Preference	Routing Services	Type
Mobility impairment	OTP, Valhalla, Trias, TripGo, Graphhopper	RB
Travel time	all	F
Number of transfers	OTP	RB
Transfer time	OTP	RB
Transfer	OTP	F
Waiting time	OTP	F
Board with bike	OTP	F
Mode reluctance	OTP	F
Car park time, cost	OTP	RB
Car pickup time	OTP	RB
Speed	OTP, Valhalla, Brouter, Graphhopper, TomTom	RB
Distance (walking/cycling)	all	RB, F
Elevation	Brouter, Valhalla, OTP	F
Road type (e.g. highway)	Brouter, Valhalla	F
Road condition (e.g. paved)	Valhalla	F
Existence of a cycling path	Brouter, Valhalla	F
Existence of a sideway	Brouter, Valhalla	F
Safety	OpenTripPlanner	F
Environmental friendliness	TomTom	RB
Windigness	TomTom	F
Hilligness	TomTom	F
Barriers	Brouter, OTP	F

porated. Routing services commonly employ both rule-based preferences (e.g., speed) with direct assignments and preferences that can be calibrated to match a user's specific preferences or situational context (e.g., walk reluctance). The latter type of parameters is flexible and lacks universal values across different routing services, requiring identification for each specific service. The "Type" column in Table 1 specifies whether a preference is rule-based (RB) or flexible (F).

After selecting the routing services and defining the utility function, the routing services calibration, detailed in section 3.3, has been evaluated for OTP (version 2.2). Considering space constraints, we will solely present the results acquired for OTP for the bicycle mode. The parameters "Car reluctance", "Car pickup cost" were not considered during the calibration for the bicycle mode. The sensitivity analysis results, both spacial and temporal, showed that the parameters "Bike switch cost" and "Optimize type" appeared to have the most influence on the course of the route. To account for this, the simulated annealing algorithm was adjusted to modify this parameter more frequently than the others. None of the parameters was be excluded from further consideration.

To evaluate the effectiveness of the utility-based auto-tuning approach in the bicycle scenario, we have generated 100 utility functions $u \in U$. The values of the weights of route attributes have been randomly selected from the range [-1; 0.1]. This range was selected based on the results of the travel preferences studies, such as (Arentze and Molin, 2013). As we are conducting a simulation, we have set the base utility β to zero for all utility functions. Subsequently, we have performed calibration of OTP with each utility function $u \in U_{bike}$, for bicycle mode and a previously defined training set T to obtain a utility-maximizing parametrization for each particular utility function $u \in U_{bike}$.

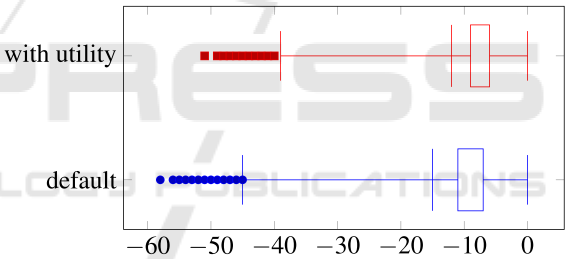

Figure 3: Average utility distributions of bicycle itineraries with and without personalization.

To comprehensively evaluate the calibration results, we use a validation set T'. Routes for the mode bicycle are computed with OTP for each combination of coordinates from the validation set T' using the default parametrization $P_{default}$ and the personalized parametrization P_u obtained from the calibration with the utility function u. For each route r_u computed using parametrization P_u and a route $r_{default}$ computed using parametrization $P_{default}$, we employ the utility functions u to estimate the utilities of these routes, denoted as $U(r_u)$ and $U(r_{default})$ respectively. The difference in utilities $U(r_{default})$ and $U(r_u)$ is then compared to assess the enhancement in satisfaction with the proposed route when utilizing the calibrated parametrization. On average, there is a 10.48% improvement in utility. Figure 3 visually presents the utility distributions for routes computed with and without parameter calibration for OTP bicycle mode. Finally, a carried-out paired t-test with a resulting p-value of 2.2e-16 ensured the statistical significance of the observed differences, affirming that it cannot be attributed to random fluctuations. However, it is essential to evaluate each routing service separately to ensure that routing results based on calibrated parametrizations improve travel satisfaction.

5 CONCLUSIONS

Individual mobility is pivotal for societal well-being, and multimodal transportation offers an efficient alternative to exclusive car use in urban areas. The process of personalizing travel suggestions based on diverse preferences can enhance the attractiveness of multimodal transportation. The proposed multi-stage personalization approach exhibits the capability to efficiently integrate a broad range of mobility preferences and routing services. Leveraging the adapter pattern makes it highly adaptable for different regions worldwide. New operational regions can be integrated by including additional routing services and data sources in the system. The proposed routing calibration approach helps establish utility-maximizing mapping rules for each preference profile and routing service, which is particularly important for efficiently exploiting the personalization capabilities of highly customizable routing services. Additionally, a utility-based comparison of routing options tailored to individual users promises an enhanced user experience. However, challenges persist, including managing extensive preferences, estimating their significance, and ensuring data availability. An additional critical issue is the quality of data, which can be addressed through crowdsensing. The platform's route recommendation quality will improve with more users, mitigating the need for a physical route assessment. Despite these complexities, our proposed approach has the potential to enable the transition towards more personalized and efficient itinerary recommendations in the realm of mobility services.

ACKNOWLEDGEMENTS

The content of this paper is the result of the project "MobAPlan - Mobility and Activity-based Planning Assistant". This research and development project is funded by the Vector Stiftung (Vector Foundation).

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