Personalized, Context-aware Intermodal Travel Information

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Abstract: The integration of heterogeneous mobility services increases the number of itinerary choices exponentially. To support travelers with the selection of such an intermodal itinerary this work proposes the use of a recommendation system. The developed framework rates intermodal itineraries supplied by an external travel information system based on learned personal preferences and user context (e.g. weather). This rating can be used by the client application (e.g. a mobile app) for sorting or a five-star rating. The framework realizes a set of interfaces to extract feature data of the user context and the possible itineraries and applies a combination of item-based and context-based recommendation algorithms. As evaluation an online questionnaire (n = 101) applying the framework was conducted to assess the feasibility of the approach. The number of participants preferring the personalized and context-aware itinerary presentation compared to the traditional departure time-based presentation was significant. Furthermore it could be verified that a mobility self-assessment is suitable as initial training data.

1 INTRODUCTION

Recent technological and socio-economical developments changed personal mobility significantly. Recent examples are the growth in car sharing (Shaheen and Cohen, 2007), bike sharing services (Shaheen et al., 2010) and services like Uber (Cusumano, 2015). The advent of such transport modalities and the combination with ordinary modalities give travelers more choices regarding their itineraries. Although this improves the service coverage and is potentially more environmentally friendly, the rising complexity in travel planning is problematic. Modern intermodal travel information systems (TIS) might offer dozens of different itineraries for a fixed journey. These itineraries differ from each other in terms of duration, price, modality, number of changes, environmental friendliness, and many more aspects. Comprehending these differences and hereafter selecting the appropriate itinerary can therefore be a hard task.

This work proposes to enhance travel information systems by rehashing the available itineraries to better suit the traveler, based on his personal preferences, context information (e.g. weather), and popular selections. In practice, this could improve the selection in following ways:

- For persons who tend to select cheap itineraries, the cheapest one is shown first.
- In case of rain, itineraries containing bikesharing are presented less prominently.
- If multiple people avoid a specific bus line (maybe it's overcrowded), it is presented less prominently.

Systems implementing such tasks, are called *Recommender Systems*. Recommender Systems are information systems which suggest one or more items from a set of items to a user, based on similarities. The best known recommendation methods are collaborative filtering (operates on user similarity), item-based filtering (item similarity), and context-aware filtering (context similarity).

The remainder of this paper is structured as follows: In Section 2, related research and existing applications are discussed. Section 3 describes the proposed approach on a conceptual level, whereas Section 4 presents details of the technical realization of the prototype. The evaluation methodology and results are presented in Section 5 followed by Section 6 concluding the paper.

2 RELATED WORK

This Section gives an overview on production appli-

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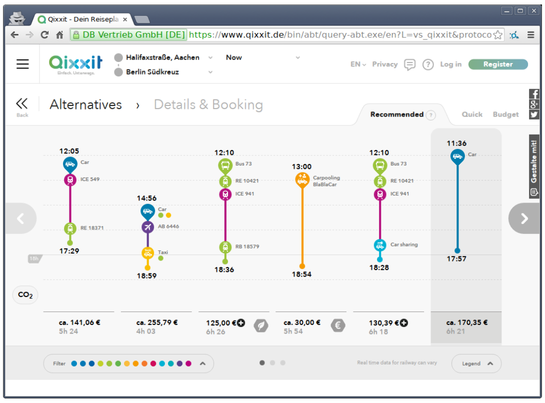

Figure 1: The Qixxit travel information web-platform.

cations and current scientific work with focus on intermodality and personalization.

Travel Information Systems have been scientifically investigated and technically improved in several aspects in recent years. Modern travel information applications like Transit App[1], Moovel[2] or Qixxit[3] have different strength and weaknesses (Beutel and Krempels, 2014). Qixxit (see Figure 1) is the newest travel information platform provided by Deutsche Bahn. It offers an extensive variety of different modalities provided by different operators accompanied by a state-of-the-art user experience. Crucial for the success of TISes are two main factors: a) the quality of the provided information in terms of comprehensiveness and completeness and b) the systems' usability (Beul-Leusmann et al., 2014). (Papangelis et al., 2013) state that travelers are highly frustrated when using public transportation because of lacking information provided. The problem of information and data integration of heterogeneous mobility services is currently under investigation (Beutel et al., 2014; Kluth et al., 2015). A taxonomy of the public transport context is presented in (Krömker and Wienken, 2015). In (Digmayer et al., 2015) the authors identify and model the phases of an intermodal journey to distinguish user requirements, whereas in (Vogelsang et al., 2015) a literature-based study on requirements on information systems is presented. (Keller et al., 2011) observed that creating an ideal representation of public transit trip information on a mobile device is a difficult task. Using paper prototypes, different approaches to display intermodal travel chains are compared. The authors of (Wienken et al., 2014) embedded a mobility planning model hierarchically into an agenda planning model and identified common information needs. (Stopka et al., 2015) conducted an empirical study of current intermodal mobility applications using Apple AppStore and Google Playstore data as well as an online survey. The work identifies different user types (e.g. "The Open-Minded Planner") as well as different operation modes, e.g. "Route Search".

[1]http://transitapp.com
[2]https://www.moovel.com/en
[3]http://www.qixxit.de/en

The framework proposed in (Pessemier et al., 2014) detects the current context and activity of the user by analyzing data retrieved from different sensors available on mobile devices and recommends activities. In (Yang et al., 2015) the authors present an algorithmic framework for personalized and context-aware driving routing based on trajectories. The driving behavior (e.g. fuel consumption) is modeled as context and new routes or rather trajectories are personalized accordingly. The work presented in (Codina et al., 2015) was conducted in project SUPER-HUB. A contextual user model was applied to recommend multi-modal journey plans. The system supports the modalities walk, bike, public and private transportation, as well as combinations. Sharing services are not considered. Ten types of contextual factors are identified as relevant, e.g. purpose of journey and weather. To evaluate the users had to rate journeys using a 5-star scale with regard to a manually entered context.

3 APPROACH

This section presents the theoretical approach used to construct itinerary recommendations.

3.1 Modeling Users, Context and Itineraries

To calculate similarities between items (i.e., itineraries) or users (i.e., travelers) it is required to model them accordingly. These initial models are kept as simple as possible to allow a reasonable implementation and to only rely on available data.

For the first implementation we opt for a simple *user model* only consisting of sex and age group. The age groups are aligned to the age groups used in (Follmer et al., 2010).

The *context model* is simplistic as well. Related work, e.g. (Pessemier et al., 2014), put a strong focus on thorough user context detection (e.g., using hardware sensors). This was intentionally not done for this work, because the context while planning is likely to differ from the context of the actual travel. Instead the probable context of time and place of the journey is processed. That is the time of day and weather of both start and destination. Temperature is clustered in weather conditions (sunny, rainy, etc.) and by temperature in $5°C$ intervals. Time is clustered in six hour intervals.

In contrast, the *itinerary model* is bit more sophisticated. A itinerary can be described by numerous features, obviously important ones are overall duration and price. Lesser important but sometimes mentioned might be the slope of a bike leg. For this work we aimed for a compromise of deemed important and available information. In literature (Vogelsang et al., 2015) duration and price are identified as main features for decision making. The price was unfortunately not available through public APIs, but is still part of the model for a later integration. The similarity s of two durations (d, d') (for prices analog) is calculated as:

$$s(d, d') = \frac{1}{1 + |d - d'|}. \tag{1}$$

The reason for this transformation, is that similarity is usually denoted normalized to $[-1, 1] \subseteq \mathbb{R}$, whereas -1 denotes opposite and 1 equality. Also relevant for most travelers are the modalities used. Two itineraries are considered similar iff the dominant, that is timewise longest used, modalities match.

3.2 Creating Recommendations

The essence of this work is recommending itineraries for travelers. To create recommendations a combination of different techniques, i.e., algorithms, is utilized. These algorithms have no inter-dependencies and are therefore both replaceable and extensible.

As already mentioned the itinerary *duration* is one of the most important decision factors. It is safe to assume that travelers will always select the faster itinerary of otherwise identical ones. Accordingly, we use the travel duration for an initial score. The list of itineraries $i \in I$ is sorted ascending by duration and then rated (r_i) using:

$$\begin{aligned} r_i &= \left(1 - \frac{k}{|I| - 1}\right) * 0.5 \\ with \quad i_k &\in (i_1, ..., i_{|I|}), \quad 1 \leq k \leq |I|. \end{aligned} \tag{2}$$

The actual duration is not used here, but instead the ordering of possible itineraries. The weight is modified using the factor 0.5, so the impact on overall recommendation score is lower compared to the following recommender.

The way *carsharing* services work, it is advisable to treat it specially regarding recommendations. Carsharing requires a formal registration with the operator to check the travelers drivers license. Based on the fact that the majority of traveler are not registered, we assume that only traveler who already used carsharing want recommendations containing carsharing legs.

Let p_{cs} be the frequency of carsharing travels, where as let p_c be the frequency of non-carsharing travels.

$$r_i = \begin{cases} \frac{p_{cs}}{p_{cs} + p_c}, & p_{cs}, p_c \neq 0 \\ 0, & p_{cs} = 0 \\ 1, & p_c = 0 \end{cases} \tag{3}$$

For the following recommendations the *overall similarity* between itineraries is required. We already introduced feature similarity in Section 3.1 but still need a way of combining them. For combined similarity only features present in both sets are considered. The similarity between itineraries is defined as $s(f, f')$. Let F be the set of features of $i \in I$, and let F' be the set of features of $i' \in I$.

$$s(i, i') = \frac{\sum_{\forall f, f' \in F_c} s(f, f')}{|F_c|}, \; with \; F_c = F \cap F'. \tag{4}$$

The weighting of feature similarities is conceivable but was not used for this work.

To enrich the similarity with *context-based* information we extend the used function with context at the origin (C_o) and the context at the destination (C_d) of itinerary $i \in I$. C'_o, C'_d likewise for itinerary $i' \in I$.

$$\begin{aligned} &s(i, i') = \\ &\frac{\sum_{\forall \zeta, \zeta' \in Z} s(\zeta, \zeta') + \sum_{\forall \gamma, \gamma \in \Gamma_o} s(\gamma, \gamma') + \sum_{\forall \gamma, \gamma \in \Gamma_d} s(\gamma, \gamma')}{|Z| + |\Gamma_o| + |\Gamma_d|} \\ &with \quad Z = F \cap F', \quad \Gamma_o = C_o \cap C'_o, \quad \Gamma_d = C_d \cap C'_d. \end{aligned} \tag{5}$$

The final personal *item-based* rating, is calculated by multiplying the personal preference $p_{u,i'}$ for item i' by the similarity $s(s, s')$ whereby $P \subseteq I$ ist the set of learned preferences. Additionally we only consider items with similarity values of 0.75 or more (P'). Initial tests of systems showed that lower similarities denote completely unrelated itineraries.

$$\begin{aligned} P' &= \{i' | i' \in P \wedge s(i, i') > 0.75\}, \\ r_i &= \sum_{i' \in P'} p_{u,i'} * s(i, i'). \end{aligned} \tag{6}$$

Combining Equation (5) and Equation (6) results in the final item-based and context-aware recommender. The algorithm is designed to deal with adding or removing of itinerary and context features by only calculating similarities if the respective feature exist for both items.

3.3 Filtering Results

As final step the results are filtered depending on the configuration, i.e., the request. It is possible to filter the results based on a score threshold or to filter

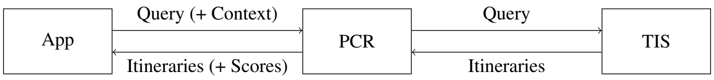

Figure 2: Information Exchange with PCR.

results qualitatively. For example, a filter could eliminate itineraries with pedestrian legs longer then 5km, as suggested in (Follmer et al., 2010).

4 REALIZATION

In this section the actual implementation of the proposed framework is described. The system was developed in Java Enterprise Edition 7, as application container Red Hat Wildfly 8[4] is used. To enable easy modularization, Java Context and Dependency Injection (CDI) is employed. As data storage MongoDB is used. For build and deployment Maven[5], Vagrant[6] and Puppet[7] are used.

4.1 System Architecture

To simplify the integration into existing travel information systems, the personalized, context-aware recommendation (PCR) system can also transparently work between an existing (mobile) travel information application and an existing backend as shown in Figure 2.

4.2 Data Acquisition and Feature Extraction

Itineraries or rather routing information, are the most important input data. The creation of itineraries using routing algorithms for public transport and such, is not in the scope of this work, instead the PCR system relies on existing travel information systems. The PCR supports the integration of multiple routing services by offering a plugin API. Currently, Google Directions[8] and MapQuest[9] are supported via respective RESTful API clients. Both services offer itineraries consisting of pedestrian legs, public transport legs, private car legs as well as combinations. To enhance the variety, it is appropriate to include more uncommon modes of transportation, e.g. carsharing, as mentioned earlier. Unfortunately, TISes like Qixxit (see Section 2) or MobilityBroker (Beutel et al., 2014) supporting holistic intermodal itineraries did not offer an open API at the time the system was developed. To still allow such itineraries, the itineraries supplied by Google Directions and MapQuest were augmented with realistic carsharing legs for the evaluation.

The *Context Data* injection is modularized. For testing and demonstration of the PCR system, time of day and weather data supplied by OpenWeatherMap[10] is supported. For start and destination of itineraries the corresponding weather information are fetched and cached for follow-up requests. Besides weather information various other context information sources are conceivable to use.

4.3 Recommendation System

The Recommendation Engine is built on top of Apache Mahout[11], which is a framework for developing scalable machine learning and recommendation applications. Mahout can be used in conjunction with Apache Hadoop[12] and/or Apache Spark[13] for distributed computing, but the use is optional. For the relatively small data pool and number of users, we opted to not use any kind of distributed computing.

4.4 Test and Evaluation Client

To test the server-based framework an Android mobile application was developed for demonstration. Because the graphical user interface was not in scope of this work, the application only uses a text based interface. For information on the design of mobile travel information application, refer to Section 2. The application allows registration, login, as well as the main functionality: the actual travel query. After the input of start, destination and departure time the user is presented with a list of possible itineraries sorted by the recommendation rating. He or she can select one of them as usual to train the system. In case of anonymous usage, which is also possible, personalized information is not considered.

To evaluate the system, a special web client was developed using AngularJS (Figures 3 and 4). The

[4] http://www.wildfly.org
[5] http://maven.apache.org
[6] http://www.vagrantup.com
[7] http://puppetlabs.com/puppet/what-is-puppet
[8] https://www.google.com/maps/dir/
[9] http://www.mapquest.com
[10] http://openweathermap.org
[11] http://mahout.apache.org
[12] http://hadoop.apache.org
[13] http://spark.apache.org

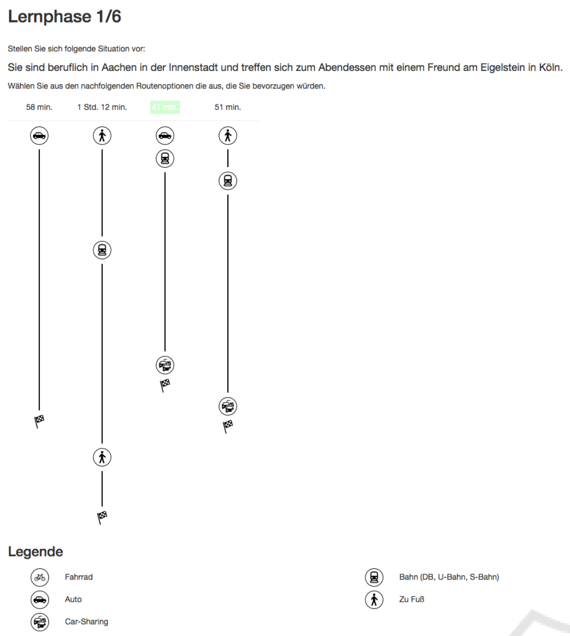

Figure 3: User-Study Learning Phase.

collected data is saved in a MongoDB database for later analysis. The evaluation component is modularized so it can be easily removed for production operation.

5 EVALUATION

Aim of the user study is to decide whether the approach is feasible and to gain general insight. The methodology for the evaluation is described in Section 5.1 and the results are presented in Section 5.2.

5.1 Methodology

The user study was developed as a web based application. The application consists of three phases:

1. Collection of demographic data and mobility self-assessment,
2. Training phase (6 selections),
3. Evaluation phase (3 selections).

Demographic data questions are the usual reference data (e.g., age, sex, professional and educational background). The mobility self-assessment consists of questions whether the participants consider themselves as “car-person”, “train-person” or “bike-person” (multiple answers possible).

Both the training and evaluation phase do not allow the traveler to query arbitrary journeys but instead query a fixed set of scenarios. A scenario consists of a start and destination, fixed contextual information and description for the participant, e.g.: “You are in city A work-related and want to meet for dinner in city C. The weather is sunny. Please select your preferred itinerary.” The graphical representation resembles a state-of-the-art TIS with a time-scaled, vertical, icon-based visualization of travel chains (Vogelsang et al., 2015).

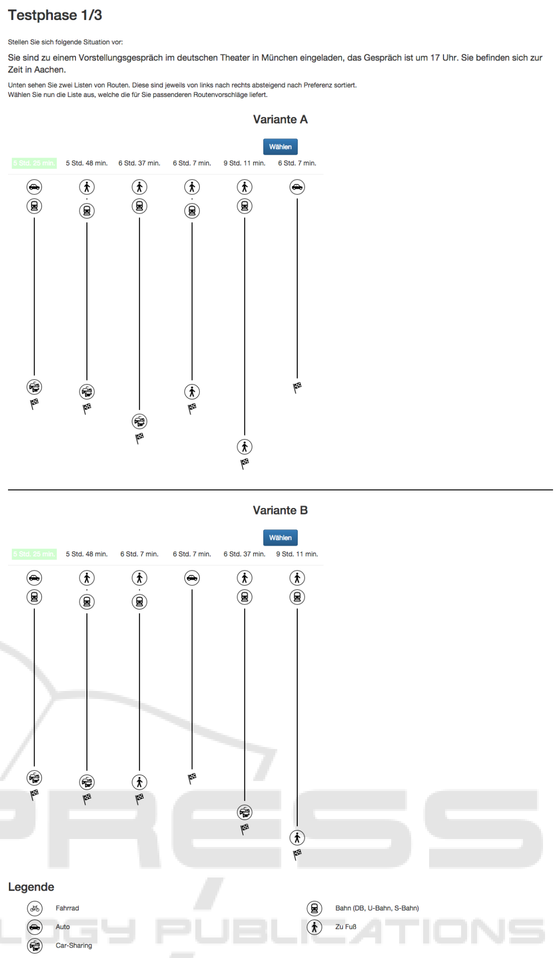

Figure 4: User-Study Evaluation Phase.

In the *training phase* the participant selects a suitable itinerary out of the presented ones, based on e.g. duration, used modal types or number of changes, just as in the real world (see Figure 3). The selection for each question is then used to train the recommender system. Unfortunately, prices are not shown, as none of the supported travel information systems offer price information. This would be a major concern for the productive operation of the system but does not limit the evaluation as the price information is just an additional itinerary feature similar to the duration.

In the *evaluation phase* (see Figure 4) the partici-

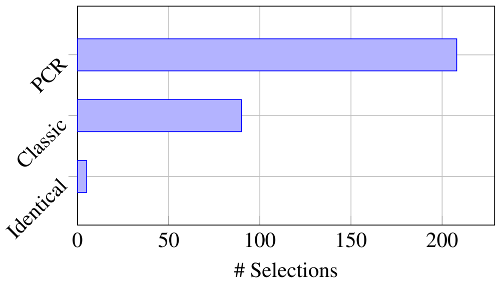

Figure 5: Total variant selection.

pant can select his or her preferred itineraries sorting. He or she can select between the PCR-based sorting and a traditional sorting (departure time-based). The position of both variants is randomized.

The recommendation knowledge base is freshly initialized for every participant to allow independent and reproducible results.

Of 101 participants who completed the questionnaire, 52 were female. Participants ages ranged from 18 to 82 with an average of 33.6 years. 95% of the participants own a drivers license, 50.5% hold a least college degree. The overall answer time per person was around 10-15 minutes.

5.2 Results

The central question of this evaluation is, whether travelers prefer a personalized, context-aware itinerary presentation compared to the traditional, departure-time based presentation. To answer, participants could choose between these variants in the evaluation phase of the questionnaire. The results, in number of selections, are shown in Figure 5. Identical means that both variants (PCR and traditional) had identical sorting, so no improvement was gained by PCR. With a significance level of 95%, 65% of the selections are for PCR, which proves that travelers prefer a personalized, context aware itinerary selection. The number of selections is three times the number of participants because every participant had three choices.

A common problem for recommendation systems is the *cold start* problem, which is to give meaningful recommendations to novel users for whom the system has not learned any preferences (Lam et al., 2008). For productive use, it is impractical to let new users go through a lengthy learning phase of six selections as carried out in the evaluation questionnaire. Instead we assume answering a few self-assessment questions to be more suitable usability-wise and enough information for initialization. In Figure 6 the modality selection and the respective modality self-assessment is depicted. Travelers, who consider themselves as

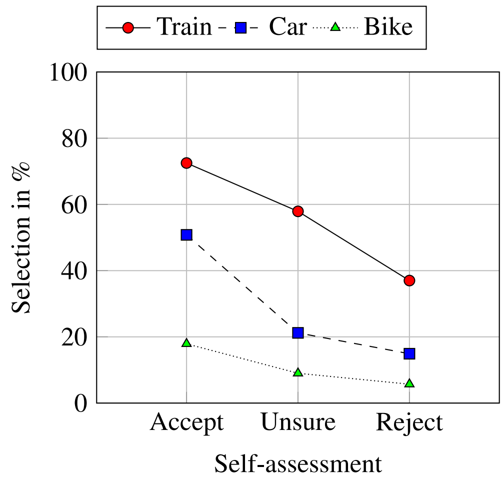

Figure 6: Modal use for respective self-assessment.

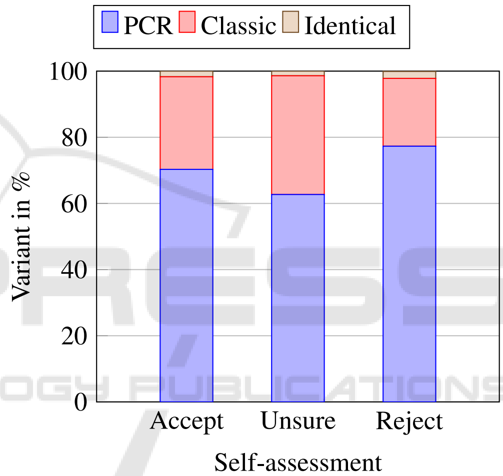

Figure 7: Relative variant selection per self-assessment.

"train-person", selected a train connection in 72.5% of the cases, whereas travelers who rejected this, only selected a train connection with a likelihood of 37%. The relative high number of car and train selections compared bike selections is caused by the nature of the scenarios. Four out of six trips cover a long distance (50km - 600km) and one of the remaining two is a job interview which generally discourages to use a bike. Based on the correlation of the mobility self-assessment and actual selection, one can assume that self-assessment is usable as initial personal training data. That is, the recommender systems behave as if the new user had chosen a respective itinerary previously based on his self-assessment.

Figure 7 shows the relation between the share of selections of PCR vs. the traditional presentation and the self-assessment answer. The interesting result is the bend for the answer "unsure"; Travelers, who are unsure about their own mobility profile, are less likely to select PCR. That leads to the conclusion, that travelers with a volatile travel behavior are harder to predict and therefore harder to present with satisfying recommendations. This is somewhat expected, but still noteworthy.

6 CONCLUSION

This work presented a system for enhancing the itinerary selection by employing personalized and context-aware recommendations. The system was implemented as a web service with a modular architecture to easily extend existing travel information systems. The recommendation engine is based on Apache Mahout and uses item-based, context-aware scoring. To evaluate the system an online questionnaire with both a learning and testing phase was used. The questionnaire results ($n = 101$) showed that participants prefer a personalized and context-aware sorted itinerary selection.

Discussion and Outlook

Although the presented evaluation showed that the approach is technically working and the enhanced itinerary selection is superior, some aspects are not fully covered. Not all mobility services, most notably flights and carpooling, are currently supported. Even more important, price information is not covered, because of the lack of public APIs that offer this information. We can assume that these features are required for productive operation of such systems to be on par with existing TISes.

The system in its current form does utilize collaborative filtering, i.e., population data. Also the employed models are simple compared to models used in established recommender systems domains like eCommerce. Extending the models and algorithms used, can improve the recommendation results fruther, but requires a significant amount of data, which was not available for evaluation. Because of the modular design of the system, the implementation of enhanced models and algorithms is straightforward.

A potential gap in the current implementation is the way that travelers explicitly state that they are using a specific itinerary. For an occasional travel, this is conceivable. But for a daily commute, travelers might not interact with a travel information system at all and instead opt for an itinerary purely based on experience. Still, these information might be valuable both for the personal profile of the traveler and for population data. To solve this, an automatic tracking, potentially combined with a travel assistance system (Samsel et al., 2015), is required.

Personalization (and tracking even more) always has implications towards privacy. Travelers have to be informed about the workings of such a system and should always have the option to use it anonymously. This way a traveler can make a distinct decision if he or she wants to trade privacy for comfort (Kowalewski et al., 2015).

Last but not least, the presented evaluation was conducted based on hypothetical scenarios without any actual travel conducted. It is still unknown how such a system performs in productive operation and if traveler actually considered it useful in the long run.

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