Socializing Public Transportation
Using Situational Context in Public Transportation to Get in Touch with People Around You

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Abstract: Unexpected delays or long traveling times lead often to people who get bored while using public transport. Whereas some might use their travel time for work or even enjoy the silence, there are still many people that would welcome an opportunity to use the spatio-temporal proximity to get to know others or meet with friends that are in the same train. This paper introduces a novel, smartphone based concept to bring people together while using or waiting for public transport. Based on location and personal preferences, suggestions can be made for getting in touch with nearby persons. We propose a recommendation system, which identifies the concrete public transport vehicle and compares the preferences with other users to create recommendations about people nearby who are also traveling in or waiting for a public transport vehicle.

1 INTRODUCTION

With the megatrend of increasing urbanisation around the world, more and more people are expected to use public transportation in the near future. Due to unexpected delays or problems on public transport lines, frequent use of transportation modes like subways, trains or buses inevitably leads to planned or even unexpected waiting times at stations, bus stops or similar. In particular trips including multiple vehicles or modes of transport can be subject to unexpected waiting times due to the possibility of missing a connection trip. Waiting times of up to 30 minutes are not uncommon, especially when traveling late at late evening. Commonly, most people waiting at e.g. train stations today just try to fight their boredom by playing smartphone games or similar. But the upcoming boredom can not only be observed when waiting on e.g. a train or plane, but also during a trip. While some people might use their travel time for work or even enjoy the silence, there are still many people in e.g. a train that are bored and would welcome an opportunity to use the spatio-temporal proximity to other bored persons to get to know other people or meet with friends that are in the same train. The missing link to bringing together people with the same temporal interests is the uncertainty of the intents of the people around, respectively in the same train. Once this inhibition threshold is overcome by connecting people with same interests travel or waiting times can be used for socializing instead of being bored. Due to overall penetration of smartphones and internet connectivity – even in the subway and on planes – people are always connected to each other anywhere. This is an excellent precondition to bring traveler together. Since built-in smartphone components can be used to track nearby traveler, suggestions can be made about friends or other traveler in the same vehicle, that are available for chatting. This paper introduces a novel, smartphone based concept to bring people together while using or waiting for public transport. Based on location and personal preferences, suggestions can be made for getting in contact with nearby persons. We propose a recommendation system, which compares location data and preferences with other users and creates recommendations about people nearby. This opens up a variety of new possibilities. For instance, a person missing a connecting train can easily experience waiting times of up to 2 hours until the next train to the destination. Finding people in a similar situational context could not only lead to less boredom during waiting time, but also to shared rides to a common destination. Generally speaking, our approach enables the use of random occasions to meet people.

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2 RECOMMENDATION SYSTEM

Almost every second person living in Germany has a smartphone today (data from May 2014, (Statista, 2014)), and generally, the number of smartphone usage is increasing. Most smartphones have various kinds of sensor components built in, which can be used for location tracking. With rising smartphone usage, services like texting, social network apps and app usage in general, provide a good basis for location and preference based recommendation systems (Lenhart, 2012). So there is no need for additional devices, which could be a barrier.

Also the fact that (long distance) public transport is often delayed or even spontaneously canceled confirms that a recommendation system for bored traveler is a promising concept (AFP/woz, 2010), (Bahn, 2014). In addition, different statistics show that ride sharing is growing in North America and in Europe (Chan and Shaheen, 2012), (BlaBlaCar, 2012). Establishing a real time ride sharing network could also reduce CO2 pollution. Mobile apps like *Tinder*, *Lovoo*, *Grindr* and *Cuddlr* demonstrate that geolocation based matchmaking has a huge potential. 11 times a day on average, people use such kind of apps and spent between 7.2 and 8.5 minutes per login using the app (Bilton, 2014). Combining the idea of matchmaking with an recommendation system for travelers, based on short geolocation distance with an intelligent algorithm for finding potential conversation partners with the same transportation route and preferences, a solution for potential boredom during trips can be created.

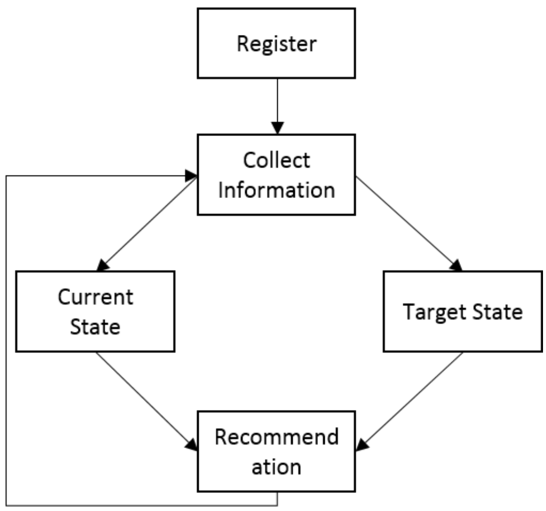

Figure 1: Workflow Recommendation System.

We propose a recommendation system based on the workflow shown in figure 1. First of all the user needs to set some preferences according to the attributes of the desired user group. As soon as the system knows the user, the person can plan routes while the system continuously keeps track of the user's location. By gathering information the system can estimate the current and target state. By merging the states and evaluating the differences, recommendations are made.

2.1 Micro Social Network

One focus of the proposed idea is to connect people considering their personal preferences. To make it work, we need to know who the people are. So every user needs to register at the service and participate within the network. It is also conceivable to offer registration using OAuth / connect APIs of major social networks to be able to collect more information and preferences and reduce configuration costs for the user. Intelligent suggestions can only be made if the service knows the bias of the users.

The intention is not to create another social network where the users maintain their profiles additionally to the existent major social networks but only provide a minimum set of their bias and one or more photos. This micro social network is more provider driven to be able to build graph based databases about social contacts according to users who are friends and potential matches while the user is being tracked.

The way to connect others is to press "Like" on target profile. Only after the user behind the targeted profile also has pressed "Like" they are connected and can start to communicate. The targeted user does not know in advance if he/she was liked.

2.2 Habits

Humans tend to pattern daily actions into sequences which they repeat at particular times in particular places (Townsend and Bever, 2001). Furthermore, most people spend a large proportion of their time at just a few locations, of which the home of a person as well as his/her workplace(s) have a high impact (Herder et al., 2014), (Song et al., 2010), (Gonzalez et al., 2008). Such regularities in persons' mobility patterns can be used to predict likely next locations of a person as well as the corresponding route and mode of transport that is taken to the destination. To perform such predictions, there exist various methods based on heuristics (Froehlich and Krumm, 2008), different variants of Bayesian networks (Simmons et al., 2006) or similar. Most of the approaches use motion tracking data from smartphone sensors and apply different clustering algorithms about commonly visited locations, such as a persons home and workplace. Furthermore, statistical models about spatio-temporal relations between locations are generated to enable predictions of likely next locations of a person as well as the corresponding departure time, mode of transportation and the used routes.

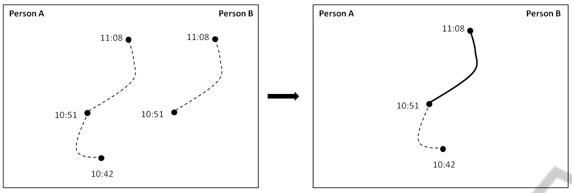

Figure 2: Two different persons traveling the same section at the same time.

Such information about habitual trips of a person can be used to intelligently create recommendations for possible meetings with people, the user is connected with. Figure 2 illustrates a situation in which such a recommendation could be useful. Person A usually leaves his/her home at around 10:51am each Saturday to visit his/her grandmother by train. Person B, to whom person A is connected by the micro social network (as described in section 2.1), joined the same train earlier at 10:42am with the same destination. In this case, our system could inform both persons about a possible meeting opportunity. The same scenario would not only be thinkable for routes with the exact same destination, also routes with partial similarities are possible candidates for meetings.

3 IDENTIFICATION OF CONTEXTUAL DATA

To make our proposed idea work, we need to know two additional things about the person using our system. On the one hand, we need to have a better understanding of the localization of a person who is using public transportation. On the other hand, our system should be aware of the remaining time the particular person will spend traveling in or waiting for bus, train etc. First we will describe, how we can identify the precise localization of a person using different types of public transport. Further we will take a closer look on how we manage to get the remaining travel time.

3.1 Localization

As we suggest a solution, which notifies a person about possible passengers or friends who are also traveling in a particular public transport vehicle and are also looking for a conversational partner, our system should be able to identify the concrete means of transport in which those two people are traveling. For our solution, we assume that we don't need to equip the trains or buses with further hardware, to make the positioning better and that it can work with the sensors of a smartphone. Based on that assumption, current systems lack of functionality, to identify the precise public transport a person is using. Those systems map only low-level sensors to a generalized high-level behaviour, e.g. walking, running or driving, without the concrete distinction between, which public transport vehicle, route and station is actually used (Partzsch and Foerster, 2012), (Patterson et al., 2003), (Reddy et al., 2008). The methodology is mostly based on a classification model made out of mobility patterns based on historically collected data. While it is easy to distinguish between motorized and non-motorized states, it is difficult to differentiate between the various motorized states.

Proximity sensing, trilateration or dead reckoning are the the most common technologies, when it comes to identify the position of a person. During a trip, a person can use different kinds of transportation types, including "on foot", using motorbike, car or public transport. The focus of our proposed system is to identify the concrete public transport vehicle a person is currently using as well as the public transport states. Limitations in areas where for example no GSM or GPS connection exists, makes it almost impossible to identify the concrete public transport a person is currently traveling with just by using the smartphone sensors. That case applies especially in underground transportation systems. But we need that kind of information, to be able to understand whether someone is traveling in a particular subway using which directions and heading towards which station. Current research also shows, that as soon contextual data is used, the success rate is much higher (Patterson et al., 2003). They showed an increase on the prediction accuracy from 60 per cent to 78 per cent with just addition additional bus stops, bus routes and parking lots. Thus, we built a knowledge-based system to overcome these limitations and used context-information to identify the current public transport vehicle, the direction and station a person is heading to.

For our knowledge-based system we built a data base with a representation of a digital map of all kinds of public transport and stations of Munich, Germany. Second, we considered to add additional contextual information like entrances, stairs, elevators to identify a concrete station, but decided to stay with the stations as the only information for better public transport vehicle identification, because it was the only source of contextual data that could be exported from map content databases, which are publicly available (e.g.

Google Maps). we name that contextual information keypoints. The main focus of keypoints is the relations to each other. This information was mapped to a directional graph, wheres every edge is able to represent multiple lines. Figure 3 shows such an sample keypoint representation of Munich, wheras the map represents the real-world example and the graph shows the abstract representation of that real-world example. The yellow points represent tram stations, magenta are bus stations and blue are subway stations. The small blue points are the entries of a particular subway station. If a traveler is close to a subway entrance, the keyoint logic would return a high probability for that subway station.

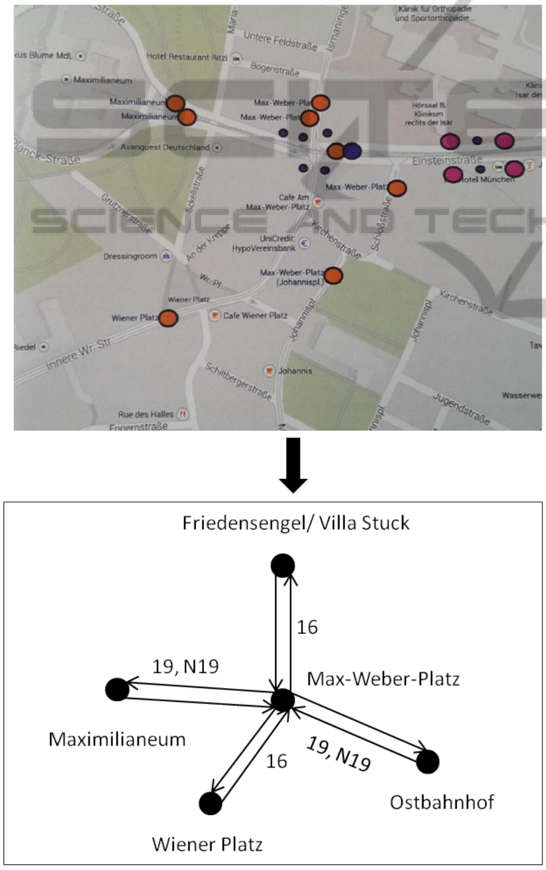

Figure 3: Abstract graph visualization between multiple keypoints.

After the initialization of the digital map, including the contextual information described before, we're tracking, by using smartphone sensors, all targeted key-points, if they are approached by the traveler. When the probability of one targeted key-point falls, then it is sorted out and the key-point resets itself to its initial state. As soon as the traveler gets close enough to the targeted key-point, it switches to the "check if stops"-state (compare figure 4). At this point a decision can be made, and all lines that are assigned on that edge are possible public transportation candidates. With the addition of live departure times at a station, the likelihood of one line can be shifted to the most recent line departed. Without the live information these are excluded as soon as they split up their route. This closeness factor has about four times the size to the nearby factor because the traveler is moving in a faster pace and the algorithm needs to determine if the traveler will indeed slow down and stop. If the traveler stops, an "on public" notification is sent, as shown in figure 4. The next targeted key-point is notified. This is done by an own state to prevent multiple "on public" notifications. Hereby it prioritizes the current possible lines but if additional lines stop at the current station, or there are transitions available, they are also tracked in the background, because the traveler might change the vehicle.

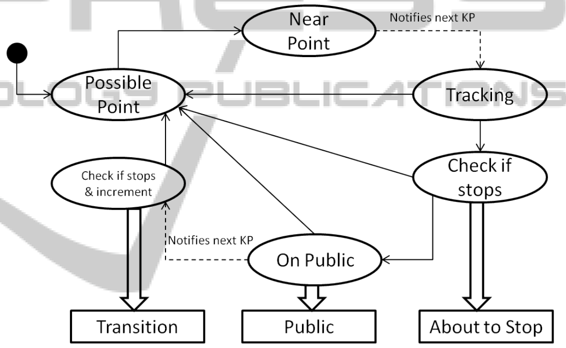

Figure 4: States and transitions in the keypoint logic.

Using this localization methodology, we're now able to recognize with a success rate of 95 per cent the concrete public transport a person is in, the concrete line and direction and at which station the person is currently. If various people use our system, we can identify two people (at least) who are traveling in the same public transport. Having additional information, like if the two people are friends, we can inform these people that there is someone they know in the same train or bus etc. Then they can either ride the rest of the trip together. Thus, we have built a technical solution for bringing friends, who are unknowingly riding the same public transport, together (compare figure 5).

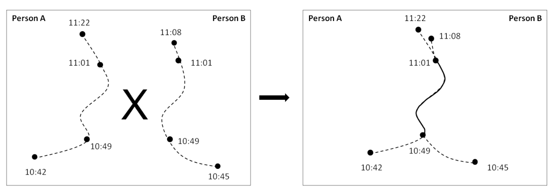

Figure 5: Friends, who are using the same public transport can travel together (Scenario A).

3.2 Deviation Detection

The methodology we use to detect deviations allows us to understand where and for how long a person will need to wait on the chosen route. Basically, a route deviation can happen in two dimensions, active and passive. An active deviation can for example occur if the user didn't left at a predetermined time. Also the user can leave at the right time, but getting lost or going too slow and thus missing the connection. Another example for an active deviation is, if the user accidentally takes the wrong public transport vehicle. These deviations are capable of being influenced so the user can be actively warned or informed about any anomaly to undertake countermeasures.

The passive deviation occurs for example if a public transport delay or even cancellation happened. If the user is traveling by car, then a traffic jam has also a influence on the deviation. The only deviation which is important for our presented system is, if the public transport is late and the person has to wait for or in it. To identify such a deviation, we need the target and current state in regards to public transport. The target state is the time and place a public transport should be according to the schedule. This is what our system gets as the route parameters, which needs to be observed. The current state of the public transport is the time and place the vehicle is in real-time. If we have access to real-time data about the whereabouts of various public transports, we can easily identify deviations by comparing the target with the current state. If we don't posses this real-time data, we have to work with the identification of the whereabouts of the public transport using our knowledge-based system as described above. This can only work, if we have many users who are using our system, so that we know the current states about any public transport without having access to real-time data.

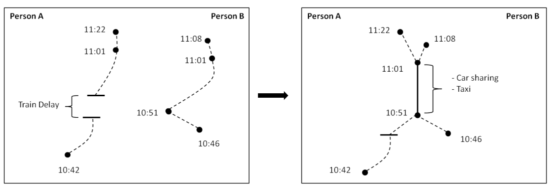

Figure 6: Strangers who want to travel with the same train can get notified if the train delays or gets cancelled so that they can arrange an alternative to travel to the desired destination by using car sharing or taxi (Scenario B).

As can be seen in figure 6, person A and person B want to travel with the same train, which leaves at 10:51 and arrives at 11:01. Person A has another trip before the train and as person A arrives, he/she notes, that the desired train has a delay. Our recommendation system doesn't only know about the train delay but also about the habits of person B. Thus, the system assumes, that person B wants to travel to a destination using the same train. As both, person A and B, had pressed "like" before, the system suggests that both can either share a car, which is near the train station or a taxi to split costs.

4 USE CASE

In the sections before, we have described various technological solutions for different kinds of problems. Now we want to bring all of them together and describe, how they can interact in order to make our proposed system work.

After a user registered on our system and entered preferences concerning the potential co-travelers, the user can now select a route using our system, which should have at least one public transport route segment. If the user selected one of the presented route suggestions, we can start tracking to get a better understanding of the personal mobility patterns. With the help of our knowledge-based system described above, we are able to identify the concrete public transport vehicle, direction and station, at which a person is currently heading to. Based on the preferences towards other people and the connection to existing social networks, we know who the person would like to travel with. If our knowledge-based system for identifying the concrete means of public transport found that, at least, two people are traveling with the same public transport vehicle and if the set preferences towards each other are positive, we can show that there is someone in the public transport whom both probably would like to travel with. If we know, with the access towards various social networks, that those two people are friends, and each other pushed the "like" button in our system when was asked for meeting that friend, we can notify them.

We also collect information about behavioural patterns, like when does the user goes where using which type of transportation. After a while, we have learned the typical destinations and traveling habits and thus can predict future trips. In the event of a public transport deviation, e.g. a train delay, we know that there are people who either also wanted to take the same public transport vehicle or are heading towards the same destination. Depending on the set preferences (either by pressing "like" in our system or via social network connection), our system would pop suggestions like using a car or taxi together in order to pay less.

5 CONCLUSIONS

One possibility to launch this intelligent mobility recommendation system would be in combination with a cloud backend and a mobile app. The system logic and the algorithms would reside in the backend. Therefore it is possible to create thin mobile apps for different mobile OS' with no need for expensive high-power CPUs in mobile phones. The mobile app should be only a client for the cloud backend, which is more like a GUI. The main task is to transmit information for computation, receive the results as well as notifications and visualize these information. Due to this approach no additional devices are needed and the acceptance barrier would be lowered. "Yet another app!" could be a barrier for the user, if this idea is not going to be integrated into existing navigation apps. Another app must be installed and configured (registration, settings etc.) before usage. Moreover privacy is also a valid reason to be concerned to start using this system. The user has to let the system record the tracking information, compute mobility patterns and store personal preferences and relations to other people, who are connected with the user.

If the user is willing to let this happen the system can support him to get a new experience about spare time usage and socializing while traveling. Even in reducing costs and saving the environment in case of delayed or cancelled public transports by sharing non public transport vehicle costs.

We also think about to use the described subsystems in an inter modal navigation system. The focus would be on detecting anomalies of different transportation types, which should be used to arrive at the destination point. The current time and the schedules of the different transportation vehicles must be continuously observed and deviations have to be detected in real time to warn the traveler or do a recalculation, if there is a high risk to miss a connection. This provides a high potential for efficient route planning and time saving especially in todays fast progression of urbanization.

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