Location-based decision support for user groups

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The ongoing progression of mobile communication devices, in particular with respect to positioning capabilities, has enabled the development of a new generation of location-based services (LBS). One of the most important aspects of current research on LBS is personalisation but it has been treated primarily for individual users. This article presents a first step towards personalised LBS that support user groups in their everyday decision-making, such as deciding where and when to meet for a common activity. The principles behind location-based group decision processes are outlined and a formal model for supporting such processes using methods of multi-criteria decision-making, time geography and similarity measurement is defined. This model is then implemented in the LBS prototype mediatrix. The prototype is used for simulating a location-based decision process aimed at finding an optimal restaurant for a user group in a city.

Keywords: location-based service; multi-criteria decision-making; time geography; similarity measurement; group decision-making

1. Introduction

The capabilities of mobile navigation and communication devices are rapidly improving. On the one hand, mobile routing services based on global positioning system (GPS) support people during wayfinding. On the other hand, the advent of mobile communication technologies such as general packet radio service (GPRS) and universal mobile telecommunications system (UMTS) has enabled users of mobile devices to access the internet anywhere at any time. The integration of both within single devices has led to the development of a new generation of location-based services (LBS). Knowing the position of the user, as well as the location of available information sources allows for increasing the benefits of mobile services dramatically.

Personalisation of services is a critical factor for improving the utility of LBS to help people in making good decisions in their mobile everyday lives (Raper et al. 2007a). Recent research activities have focussed on various aspects of personalisation, that is, the customisation and adaptation of LBS to their users. This trend to use highly specialised LBS has been intensified by people’s increased need to acquire and use spatial and temporal information. In today’s world of vast mobility and change we frequently face new situations in unfamiliar environments, such as finding
one’s way in an unfamiliar city. So far, the focus of research on personalised LBS has been targeted at individual users, their situational and personal context and with regard to mobile map applications (Schmidt et al. 1999, Raubal and Panov 2009). However, location-based decisions are not only made by individuals but also by groups of users (Golledge and Stimson 1997), which requires some kind of mediation process among them.

The objective of this article is to investigate group decision-making in a mobile context and provide a framework for the implementation of LBS, which support groups of people in their everyday decision-making based on spatio-temporal constraints and user preferences. According to the list of significant LBS research issues presented by Raper et al. (2007b) we do not strive for presenting ad-hoc solutions for improving LBS but to give an insight into the possibilities for future services arising from the combination of several areas of research, such as time geography, multi-criteria decision analysis (MCDA) and similarity measurement.

Location-based decision services (LBDSs) (Rinner and Raubal 2004) serve as the foundation for this work. This idea and related research to personalised LBS are outlined in the following section. In addition, a brief summary of time geography and human decision-making is given. In Section 3 we introduce our use case for location-based group decisions, that is, choosing a restaurant in the city of Münster. Section 4 defines the optimal decision outcome of location-based group decision-making (LBGDM) according to the scenario. Based on this definition we define a formal multi-criteria decision making (MCDM) model that allows for the calculation and retrieval of such outcomes. In Section 5, the design and implementation of a prototypical location-based group decision service realising the previously defined MCDM model is described. This prototype is used for a simulation of a decision-making process according to the given scenario. The simulation and an evaluation of the results are given in Section 6. The final section presents conclusions and directions for future research.

2. Related work

The presented research focusses on two aspects of personalising LBS for groups of users: optimising location-based information retrieval using methods of multi-criteria evaluation and integrating spatio-temporal constraints using principles of time geography. This section portrays the theoretical background for the LBGDM model developed here. We start with a brief overview of human decision-making, introduce the concept of a LBDS, and describe the principles of time geography.

2.1. Human decision-making

There is still insufficient knowledge about how mobile location-based decision-making is different from generic decision-making (Raper et al. 2007b). General decision theory covers a wide range of models with different foci on describing how decisions could or should be made, and on specifying decisions that are made (Golledge and Stimson 1997, Amedeo et al. 2009). Human decision-making is not strictly optimising in an economical and mathematical sense (Simon 1955), such as proposed by the algorithms of classical decision-making theories, therefore
behavioural decision theory has been emphasised in the cognitive literature. In this article, we implement a criterion-based judgment approach but several others exist. A classification of decision-making models in terms of rationality is presented in Todd and Gigerenzer (2000). They distinguish between unbounded rationality, optimisation under constraints, satisfying, and their own approach of fast and frugal heuristics.

In order to investigate whether principles of generic decision-making can be transferred to mobile decision-making and find potential differences, researchers have developed tools to study the interaction between environments, individuals and mobile devices. Most case studies focus on pedestrian navigation in various settings, such as urban environments (Li and Longley 2006). Raubal et al. (2004) proposed a user-centred theory of LBS, which specifically focuses on individuals’ mobile decision-making. It integrates spatial, temporal, social (using affordances) and cognitive (using decision-making theory) aspects of LBS.

2.2. Location-based decision services

LBDSs are tools for supporting everyday decision-making in a mobile context. These services are based on the integration of MCDA and can therefore provide analytic evaluations of the attractiveness of alternative destinations and choices being offered (Rinner 2008). MCDA methods had been introduced to geographic information systems in the 1990s for applications, such as site suitability analysis (Malczewski 1999). Rinner and Raubal (2004) designed a service called Hotel Finder by integrating the ordered weighted averaging (OWA) decision rule (Yager 1988). This software features multi-criteria decision support for the task of finding suitable hotels in an unfamiliar environment depending on the user’s location and preferences. The usefulness of the Hotel Finder was demonstrated through a comprehensive user test showing that MCDM-based decision support can be employed for optimising location-based decision processes (Bäumer et al. 2007). The results confirmed that applying the multi-criteria decision strategy enhances people’s decision support in unfamiliar environments. Until now, LBDS were restricted to single users and did not support groups of users in making location-based decisions. Research in the field of spatial decision support systems (SDSS) has shown that multi-criteria evaluation methods can also be applied to supporting group decision processes that depend on spatial information (Jankowski 1997). Such systems have been referred to as collaborative SDSS (Jankowski et al. 2006).

2.3. Time geography

An important aspect of personalised LBS is the integration of the users’ spatio-temporal constraints. Recent work has shown that principles of time geography (Hägerstrand 1970) can be utilised to model spatio-temporal constraints in LBS (Raubal et al. 2004). Time geography defines the space-time mechanics of people and their environment by considering different constraints for people’s ability to be present at a particular location in time – the capability, coupling and authority constraints (Hägerstrand 1970). The possibility of being present at a specific location and time is determined by people’s ability to trade time for space, supported by
transportation and communication services. Space–time paths depict the movement of individuals in space over time. Such paths are available at various spatial (e.g. house, city, country) and temporal granularities (e.g. decade, year, day) and can be represented through different dimensions. All space–time paths must lie within space–time prisms (STPs) (Figure 1). These are geometrical constructs of two intersecting cones and their boundaries limit the possible locations a path can take based on people’s abilities to trade time for space. The inside of a STP is usually referred to as potential path space (PPS), the projection of STPs onto geographic space is called potential path area (PPA).

The graph-related adaptation of the STPs described by Miller (1991a) can be applied to compute network time prisms (NTPs) for mobile agents in an urban network. This was implemented (Raubal et al. 2007), realising a filtering technique for selecting feasible host–client combinations in a shared-ride trip planning scenario based on the intersection of potential path trees (PPT), which are the network equivalents to PPAs.

3. Use case

The possibility for location-based group decisions occurs, if there is a group of users whose STPs overlap for a specific time interval. To address such decision processes we introduce the notion of LBGDM. LBGDM can deal with a variety of different location-based tasks. The core question is thereby the same: ‘What is the best place to perform a specific task?’

LBGDM addresses all components of geographic information (Goodchild et al. 1999): temporal, spatial and thematic components. The selection of places for location-based tasks greatly depends on the local knowledge of the decision maker. This work focusses on cases of ad-hoc LBGDM in which the decision makers have

Figure 1. STP including PPS and PPA, according to Miller (1991b).
little knowledge of their environment and there are only limited resources for a
detailed investigation of the decision alternatives, for example, using a location-
aware search engine, such as Google™. The presented idea of LBGDM is based
on the concept of friend-finder services, which visualise the location of contacts on a
mobile map. These services enable groups of users to spontaneously meet to
perform common tasks, such as having dinner. The selection of a meeting point, as
well as a place for performing the task, for example, a restaurant, requires a group
decision process. In the following, we introduce the scenario for LBGDM to be used
for this work.

Alice is visiting the city of Münster (Germany) to attend a business meeting in the
area of the harbour. She has a free time slot in the evening and queries her friend-
finder service to check whether any of her contacts are located in Münster. The
friend-finder service shows her the position of two of her contacts: Bob and Charlie.
Bob is currently attending a conference in the University castle and Charlie is in his
hotel room. Alice sends a short message to both and invites them to go out for
dinner. She has little knowledge of the city and its places. Therefore, she suggests
meeting at the train station and then discussing where to go. Each of the three
persons has different constraints and preferences. These can be summarised as user
profiles (Table 1). Alice likes Chinese food, but for her it is most important not to
pay too much for dinner. Bob and Charlie like Mexican food. While Bob has no
particular priority, it is very important for Charlie to have Mexican food.

They meet at the train station at 7:00 pm. Now they have to find out which
restaurants are nearby and meet their requirements. They start by querying the
search engines on their mobile web browsers and then discuss the results that are
retrieved. Alice has no more appointments this evening, but Bob has to catch a train
at 8:30 pm, and Charlie has to be back at the hotel in order to attend a conference
call at 8:15 pm. Deciding where to go takes longer than expected, by this time there is
only 1 h left until Charlie has to start back to his hotel. They decide to go to a nearby
rather expensive Italian restaurant to save time for dinner. What they missed was
that there are several nice restaurants close to Charlie’s hotel, which they could have
easily reached if they had met there directly and not at the train station. Decision
processes as described above can be time consuming and do not guarantee satisfying
outcomes. In addition, such processes are always influenced by the discussion
behaviour of the group. Each of the available options, for example, the restaurants in
the case described above, vary in suitability with respect to the overall set of
constraints and preferences. The larger the gap between individual interests, the
harder it is to find an overall satisfying solution. We argue here that such decision
processes can be supported by methods of MCDM.

<table>
<thead>
<tr>
<th>Group member</th>
<th>Priority</th>
<th>Choice</th>
<th>Location</th>
<th>Time limit (destination)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice</td>
<td>Price</td>
<td>Chinese</td>
<td>Harbour</td>
<td>–</td>
</tr>
<tr>
<td>Bob</td>
<td>–</td>
<td>Mexican</td>
<td>University castle</td>
<td>8:30 pm (train station)</td>
</tr>
<tr>
<td>Charlie</td>
<td>Cuisine</td>
<td>Mexican</td>
<td>Hotel</td>
<td>8:15 pm (back to hotel)</td>
</tr>
</tbody>
</table>
4. A formal model of LBGDM

Before defining a MCDM model for any kind of decision support the objectives of the decision process must be identified. The objective of the location-based decision described in the previous section is to find the optimal place to have dinner. We use the notion of optimal decision outcome to address this objective of LBGDM.

4.1. Optimal decision outcome

The optimal outcome of location-based decisions as illustrated in this work is defined as the place that (1) does not violate any individual constraint, (2) is the best match of the individual preferences and (3) is not a disadvantage for any group member. The definition of the optimal decision outcome places requirements upon the model to be developed:

1. It must allow decision makers to formulate constraints, in particular, spatio-temporal constraints. Within MCDM constraints are sometimes considered hard selection criterion (Rinner and Raubal 2004), in common language they are often called K.O. criteria.
2. It must provide quantitative methods for analysing decision alternatives with respect to user preferences.
3. It requires mediation functionality to ensure that no group member is disadvantaged. If an alternative performs well for a majority of group members but badly for a minority, it has to be considered less optimal than an alternative that ensures that each group member is at least satisfied, even if the performance is worse for the majority.

4.2. Spatio-temporal screening

In an area, such as the city of Münster the multitude of restaurants and bars provide many alternatives for decision processes, such as illustrated earlier. The more identifiable alternatives there are, the more complex the decision problem becomes. The first step of the proposed analysis aims at screening those alternatives that are not feasible with respect to spatio-temporal constraints. As mentioned in Section 2.3, Hägerstrand (1970) identified three categories of spatio-temporal constraints: capability, coupling and authority constraints. Capability constraints limit the activity possibilities of an individual due to available resources. Depending on the mode of transportation an individual can have different capability constraints. In our scenario, capability constraints are defined by the walking speed of the individual group members. Coupling constraints limit the activity possibilities of an individual by requiring the concurrent presence with other individuals at one place for a specific time interval. In LBGDM, coupling constraints are set by the personal schedule, for example, meetings or departure times, and the stops that allocate a task for a given time in a specific place. Authority constraints limit the accessibility of places for specific time intervals. Restaurants, for example, impose authority constraints on their guests through their opening hours.

To account for spatio-temporal constraints we adopt the network-based algorithmic solution presented in Raubal et al. (2007). It optimises the selection of
shared rides in a transportation network depending on the clients and hosts’ STPs. The underlying problems of determining the set of feasible hosts in shared-ride trip planning and determining the set of feasible alternatives in LBGDM are similar. In both cases an assessment whether a particular location, either a host’s position or a place alternative, is reachable within a given time must be made. For LBGDM such a filtering mechanism should yield those nodes of a street network for the area of interest at which feasible places are located. The particular method involves the computation of PPT conceptualised as the network equivalents of the se (start, earliest)-cone and the dl (destination, latest)-cone (Winter and Raubal 2006). The overlap of both trees results in a NTP (Wu and Miller 2001), the network equivalent of the general STP. To adopt this approach for LBGDM the relevant se- and dl-cones must be identified. If a group decides to perform a location-based task, its members typically agree on a start time, for example, dinner at 7:00 pm. This article focusses on such cases, in which the individual group members are not co-present at one location, but spread across an urban area. For LBGDM the se-cone is defined as the part of the space–time continuum that is reachable from the start point in space (and time) and the time difference from this start point and the beginning of the first task (Figure 2a). If the task starts at 7:00 pm and a group member can start travelling at 6:30 pm, the se-cone for this member is the sub-tree of the street network that is reachable within 30 min from the start node. The dl-cone for LBGDM has to be considered if a group member has a particular destination she must reach by a given time after meeting with the group (Figure 2b). She might, for example, need to catch a train at 8:30 pm. Destinations in space and time are the basis for creating the dl-cone. The size of the dl-cone is determined by the time that goes by between the end
time of the task and the time limit. If dinner ends at 8:00 pm there are 30 min left to
get from the restaurant to the train station. With a sequence of tasks, the end of the
final task must be considered for creating the \( dl \)-cone. The overlap of both cones
leads to a NTP to be used for filtering the feasible places with respect to one group
member’s individual constraints. Overlapping the individual NTPs yields the feasible
places with respect to the group’s overall constraints (Figure 2c).

4.3. Stop assessment

After the set of feasible places has been determined the viability of each place with
respect to the users’ preferences and non-spatio-temporal constraints must be
assessed. Besides dealing with constraints, such as price limits, this process also
requires scores for the relevant decision criteria, based on compensatory MCDM
techniques. In the case of the task ‘going out for dinner’ the criteria may be prices,
place ratings and cuisine. To fulfill the second definition of the optimal decision
outcome for LBGDM it must be assessed how well each alternative performs with
respect to the user preferences. This requires the use of a decision rule. Decision rules
are compensatory procedures for ordering decision alternatives according to their
performance with respect to the objective (Malczewski 1999). In this case the
objective is characterised by the definition of the optimal decision outcome. Compensatory MCDM techniques require numerical and standardised decision
variables (Jankowski 1995). Depending on the scale of the criteria the application of
such techniques requires transformations. Ratio scales, the scale of choice for
modelling price, generally are not standardised. The standardisation of ratio
variables can be achieved by applying linear scale transformation. For this purpose
we use the score range procedure, which ensures that the whole range between 0 and 1
is used. In the case of benefit criteria, such as place ratings, raw values are
standardised by dividing the difference between the raw value and the minimum
value by the range (F 1). Since place ratings are modelled using ordinal scales, the
raw values for applying formula 1 refer to the position (index) of a particular value
within the given range. In the case of cost criteria, such as price limits this formula
needs to be modified slightly (F 2).

\[
F1: \quad v_{\text{norm}} = \frac{v_{\text{raw}} - v_{\text{min}}}{v_{\text{max}} - v_{\text{min}}}, \quad F2: \quad v_{\text{norm}} = \frac{v_{\text{max}} - v_{\text{raw}}}{v_{\text{max}} - v_{\text{min}}}
\]

In both cases a value of 0 is given to the worst possible score, whereas a value of 1
is given to the best possible score. To account for the spatial distribution of
alternatives, minimum and maximum values are taken from those alternatives within
the NTP that is determined by the group’s spatio-temporal constraints. The
assessment of each variable is therefore relative to the other variables of the same
type provided by the surrounding alternatives.

Integrating attributes on nominal scales, for example, cuisines into a compensatory
MCDM approach is not straightforward. In general, nominal scales only
provide information on whether two values are identical or not. We therefore
propose the use of similarity measurement methods for integrating nominal data into
a compensatory MCDM process. If people discuss where to go for dinner they often
decide about the cuisine that is offered by a place, for example, they like Chinese or
Mexican food. According to the first law of geography (Tobler 1970) ‘everything is related to everything else, but near things are more related than distant things’. This can also be assumed for cuisines on a world-region scale. The Japanese and the Chinese cuisines are more related than the Japanese and the Mexican cuisines. Such relatedness can be derived by the common sense classification of world regions, which can be used to classify restaurants according to the region whose cuisine they provide. The open directory project uses a similar classification for structuring recipes on their web portal. To quantify the relatedness of two cuisines, we utilise the hierarchical structure provided by those classifications. Hierarchies can be modelled as concept graphs consisting of nodes that are connected via *is-a* links (sub-concept relations). The semantic distance between concepts in a hierarchy can be employed to assess the semantic similarity of two concepts (Rada et al. 1989). Figure 3 shows a graphical view of the cuisine hierarchy used in this model.

This article presents an approach to measure the similarity between a cuisine objective \( c_{obj} \) and a cuisine alternative \( c_{alt} \) based on the distance measure \( \text{dist}(c_{obj}, c_{alt}) \) between the nodes that allocate the cuisines in the hierarchy (F 3).

\[
\text{sim}(c_{obj}, c_{alt}) = \begin{cases} 
1 & \text{if } c_{obj} \text{ subsumes } c_{alt} \\
0 & \text{if } \text{lub}(c_{obj}, c_{alt}) = \text{top} \\
1/\text{dist}(c_{obj}, c_{alt}) + 1 & \text{else}
\end{cases}
\]

If the cuisine alternative is subsumed by the cuisine objective (e.g. Chinese cuisine is subsumed by Asian) the similarity value is 1. Hence, the proposed similarity measure is asymmetric in the way that a super concept is considered equal to its sub concepts, which is inverse to the way asymmetry is usually considered (Tversky 1977). The proposed understanding of asymmetry is reasonable, since people may want to select different levels of the hierarchy. If a person wants an Asian dinner she does not bother whether the restaurant provides Chinese or Indian food. If the most specific common super concept or least upper bound (lub) (Rodriguez and Egenhofer 2003) of \( c_{obj} \) and \( c_{alt} \) is the top-concept, the similarity score is 0 (e.g. Chinese to German). Similarity is a decaying function of distance, therefore the inverse distance is taken as input for the decision analysis. This leads to a value range between 0 and 1, which is

![Figure 3. Taxonomy for measuring similarity between cuisines (subtree).](image)
an implicit standardisation. Additionally, the distance is always incremented by 1 to ensure that a distance of 0 leads to a similarity value of 1. The resulting similarity values are strongly influenced by the weights that are assigned to the links of the hierarchy. We choose here a value of 0.5 to achieve reasonable results. Table 2 shows selected similarity scores for measuring similarity between cuisines.

After the relevant criteria scores have been computed, the decision alternatives can be assessed by considering the user preferences. We use the point allocation weighting method, which allows each group member to allocate 100 points to the set of decision criteria, that is, price, rating and cuisine. The scores combined with the individual weights are aggregated via the simple additive weighting (SAW) technique, an additive decision rule based on weighted arithmetic mean computation. SAW is sometimes called scoring or weighted linear average and is one of the most frequently used techniques for spatial multiple attribute decision-making. SAW scores each decision alternative \( A \) with respect to a user \( j \) by summing up the product of each criterion score \( C_i \) and the associated weight \( w_i \) for \( m \) relevant decision criteria (F4).

\[
(F4) \quad A_j = \sum_{i=1}^{m} w_i C_i.
\]

The input for SAW is typically specified via decision tables that store the criterion scores for each alternative. Applying SAW results in a ranked list of place alternatives for each alternative. Applying SAW results in a ranked list of place alternatives for each user.

### 4.4. Mediation

To assess the performance of a stop for the whole group the individual stop scores have to be aggregated. One could simply use arithmetic means, as done by the SAW method. However, the application of arithmetic means for assessing group stops does not guarantee optimal decision outcomes. Arithmetic means can lead to a violation of the third requirement (Section 4.1), namely that no group member is disadvantaged. If one place provides high scores for two of the group members (e.g. 0.8 and 0.9) but a low score for a single one (e.g. 0.2), the arithmetic mean gives the relatively high value of 0.63. The result implies that this alternative performs well with respect to the group’s interests. It conceals that the third group member may not be satisfied by this selection. If there is another alternative that achieves scores of 0.6 for each user, the arithmetic mean will be 0.6, which is lower than the score assigned to the first alternative. According to the definition of the optimal decision outcome, the latter alternative should be preferred. In other words, a mediation process

<table>
<thead>
<tr>
<th>Objective</th>
<th>Alternative</th>
<th>Similarity score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chinese</td>
<td>Chinese</td>
<td>1</td>
</tr>
<tr>
<td>Chinese</td>
<td>East-Asian</td>
<td>0.67</td>
</tr>
<tr>
<td>Chinese</td>
<td>Japanese</td>
<td>0.5</td>
</tr>
<tr>
<td>Chinese</td>
<td>Indian</td>
<td>0.25</td>
</tr>
<tr>
<td>Chinese</td>
<td>German</td>
<td>0</td>
</tr>
<tr>
<td>Asian</td>
<td>Chinese</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2. Selected similarity scores.
between user preferences is required. Therefore, we suggest another aggregation technique for stop assessment of groups: the computation of harmonic means (Bullen 2003). The score of one stop \( S \) is the harmonic mean of all alternative scores \( A \) for each of \( n \) users (F5).

\[
(F5) \quad S = \frac{n}{\sum_{j=1}^{n} \frac{1}{A_j}}.
\]

Using harmonic means leads to a larger impact of low scores on the result. In the example mentioned above the harmonic mean of the first alternative is 0.48, whereas the score of the second alternative is still 0.6.

After the mediation process has been performed the alternatives are ranked so that the best alternative fulfils the requirements of the optimal decision outcome. Taking it a step further, location-based group decision support service (LBGDS) could also be designed to account for multiple tasks, for example, start with dinner and continue with going to the movies or having some drinks. Single user decision support for such task combinations was realised in the project utopian.\(^7\) To keep the possibility for supporting multiple tasks open, we refer to the result of the decision process as a tour. A tour can comprise one or more stops that allocate particular tasks to given places, as well as the paths the users have to follow to get to the stops and their potential destinations.

Figure 4 summarises the methods presented in this section for the case of two users and shows how they can be combined into a model that supports the retrieval
of the optimal decision outcome in a location-based group decision process as defined in Section 4.1.

5. Prototype

In the following, the presented model will be realised and evaluated in a prototypical LBGDS called mediatrix.8

The classic approach for developing LBS is to deploy the whole application on the mobile device without requiring network access (fat-client). An example for a fat-client is the first version of the Hotel Finder (Raubal and Rinner 2004). This solution is suitable for simple problems involving a small data set, but not for LBS used to answer complex spatio-temporal queries. Recent developments of mobile devices, in particular with respect to their communication capabilities, have offered the possibility to develop LBS that also involve server components to be accessed over a network. The latest version of the Hotel Finder (Bäumer et al. 2007) is an example of such distributed LBS. These systems still require the installation of service-specific client software on the mobile device. In the context of mobile applications this requirement is especially critical. The market for personal digital assistants (PDAs) and Smartphones has become highly dynamic and is competitive with contenders offering ambitious platforms, such as the Apple™ iPhone, Google™ Android, Windows™ Mobile and Symbian™ (S60). Software providers have to adjust their applications to each platform they want to support, which can be a time consuming task. A novel approach for designing LBS is to utilise web browsers as client components. This has recently gained importance in the Internet community and benefited from the evolution of web browser technology. One of the most important results was the creation of the AJAX – pattern (asynchronous javascript and XML) (Garrett 2005). AJAX describes the development of web applications unifying the benefits of classical web and desktop applications. They provide sophisticated functionality and a dynamic user interface with only a web-browser on the client. At the core of AJAX is the asynchronous XMLHttpRequest that allows reloading only specific parts of a web page instead of the whole page as done by classic web applications. Prominent examples for current AJAX-applications are Google Maps™ and Flickr™.

5.1. Client

For the implementation of mediatrix we followed the AJAX-approach. The client is realised using hypertext markup language (HTML), cascading style sheets (CSS) and JavaScript. The server component is based on Java™ Servlet Technology and the Apache Wicket web application framework. The user interface is optimised for a resolution of 240*320 pixels, which is the de facto standard for displays of current mobile communication devices. Apache Wicket has been extended by some AJAX-enabled components, such as drop-down choices and links that allow reacting to user input by dynamically reloading other page components. This allows the development of a dynamic web front-end with the look-and-feel of a fat-client. To access mediatrix the user must visit the homepage and log in. After the log-in, the user gets to the
index page, where she can create a tour request, join an existing tour request, edit her profile or view computed tour proposals. One of the advantages of using current AJAX applications is the possibility to combine various online data sources to one hybrid application, called mash-ups (Scharl 2007). Google Maps™ has proven useful for mash-ups that require the visualisation of geographic information. For mediatrix the localisation of the users, their destinations and the visualisation of the computed tour have been realised this way. The client component has been tested on a PDA equipped with Mozilla Minimo which is a mobile browser that supports AJAX-based web applications.

5.2. Data

LBGDS require several types of data: network data, user data, place data and request data. The network data are provided by TeleAtlas® and stored in a relational database (RDB) consisting of node and edge tables. User profiles and their inputs are mapped onto a RDB schema and also stored in a RDB. The RDB further stores the place data, which consists of spatio-temporal and thematic data. The thematic data include information on different scales. Ratio and ordinal data (e.g. prices and ratings) are stored using standard structured query language (SQL) data types. These are not sufficient to store the nominal data required for the decision analysis. Section 4.3 demonstrated how nominal data can be standardised using similarity measurement. This requires data that is structured hierarchically. For this purpose, the cuisine data is stored in the RDB, but also linked to a cuisine hierarchy that is defined using resource description framework-schema (RDFS). RDFS extends resource description framework (RDF) by a standard vocabulary and some core semantics. In particular, it provides the possibility to model hierarchies that are required for similarity measurement.

The current version of mediatrix supports group decision processes for up to three users with respect to the task of going out for dinner. The prototype accounts for spatio-temporal and price constraints, as well as for the opening hours of places. The integration of further data for planning tasks, such as going to the movies or having a drink, and the possibility to combine tasks is left for future work. The user interface has been designed to select more than one task.

6. Evaluation

This section discusses the model and prototype that have been presented in the previous sections. It includes a simulation of mediatrix with respect to the scenario described in Section 3. The results of this simulation are evaluated and used to assess whether the proposed model is able to achieve optimal decision outcomes.

6.1. Simulation

The scenario underlying this work presents an example for a group decision problem in which a group of three people with limited spatio-temporal resources tries to find a restaurant in the city of Münster. The group is characterised by three user profiles (Table 2). These profiles are now taken as user inputs for running a decision process supported by mediatrix. According to the scenario, Alice starts the group task.
She wants to invite two of her friends, Bob and Charlie, to have dinner at 7:00 pm. Therefore, she logs on to mediatrix and creates a tour request with the required parameters start time, invited users and task type (Figure 5).

After the request is registered by the service, it gets published to the invited users. At the current state of the prototype the users have to log in to check for tours they are invited to. For future versions it would be reasonable to integrate a notification service, for example, a short message service (SMS), which directly contacts users after they have been invited to a tour. To join a tour request the invited users can select the tour name and view its details. They can either join the tour or decline the invitation. Figure 6 shows how Bob reacts to the invitation by Alice.

After joining a tour request the user must submit her personal input to the service, that is, the relevant constraints and preferences (Figure 7). Figure 8 shows the Google Maps™ mash-up that is used for setting the start and destination. The input for a tour request is enriched by the personal user profiles that store static and request-independent data, such as weights (Figure 9). The profiles are loaded from the RDB. To perform the decision analysis, each user must submit her constraints and preferences.9 Table 3 summarises the concrete user inputs for the tour request created by Alice.

After the group’s input is complete it is analysed with respect to the area of interest. According to Section 4.2, the analysis starts with spatio-temporal screening resulting in a group NTP that contains the set of feasible places. Table 4 lists the feasible places for the given request and the place data that is important for the decision analysis. To assess the price level of restaurants, the minimum and the
Figure 6. Join tour.

Figure 7. Set input.
maximum price for a single dish are taken to calculate an average price. This is a simple, but plausible approximation of the price level which could be extended by taking all offers provided by a place into account.

Next, the relevant decision criteria are scored including normalisation and similarity measurement. In this case the similarity measurement affects the cuisines provided by the feasible places and the choices made by each group member. The raw values have to be normalised and then aggregated with respect to the user weights using the SAW method. The results are shown in Table 5.

Finally, the place scores are aggregated to stop scores including the input of the whole group. The decision strategy proposed here utilises harmonic mean computations for this step (Section 4.4). Table 6 shows the stop scores computed with harmonic mean compared to the geometric mean computation. The Enchilada achieves the highest score using arithmetic mean, whereas the Ipanema scores best with respect to the harmonic mean. China Corner and Altes Gasthaus Leve achieve a score of 0 using harmonic mean. The resulting tour is shown in Figure 10.

6.2. Results
The results of the simulation are now analysed in the context of the definition of the optimal decision outcome. The optimal decision outcome of location-based group
decisions is defined in Section 4.1 as the outcome that does not violate any individual constraints and matches the preferences best without causing disadvantage to any group member. The first requirement, no violation of user constraints, is achieved by each feasible place. In order to confirm the second requirement the place scores have

Table 3. User profiles for the task ‘having dinner’.

<table>
<thead>
<tr>
<th>User</th>
<th>Choice</th>
<th>Price weight</th>
<th>Rating weight</th>
<th>Choice weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alice</td>
<td>Chinese</td>
<td>80</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Bob</td>
<td>Mexican</td>
<td>30</td>
<td>30</td>
<td>40</td>
</tr>
<tr>
<td>Charlie</td>
<td>Mexican</td>
<td>0</td>
<td>0</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 4. Feasible places and their attributes.

<table>
<thead>
<tr>
<th>Name</th>
<th>Cuisine</th>
<th>Rating</th>
<th>Min price (€)</th>
<th>Max price (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altes Gasthaus</td>
<td>LeveGerman</td>
<td>4.38</td>
<td>8</td>
<td>22</td>
</tr>
<tr>
<td>China Corner</td>
<td>Chinese</td>
<td>4.75</td>
<td>3.50</td>
<td>8</td>
</tr>
<tr>
<td>Enchilada</td>
<td>Mexican</td>
<td>3.75</td>
<td>8.90</td>
<td>15.30</td>
</tr>
<tr>
<td>Ipanema</td>
<td>Latin American</td>
<td>2.5*</td>
<td>4.5</td>
<td>12</td>
</tr>
</tbody>
</table>

Note: *No rating available on www.restaurant-kritik.de (2.5 is the default rating).
to be considered. Due to its Mexican cuisine the Enchilada achieves high scores for Bob and Charlie but because of the high price level a low score for Alice. Taking the arithmetic mean for aggregating the user-specific place scores, the Enchilada achieves the highest score and accordingly fulfills the second requirement. However, Alice would not be happy with this solution and therefore the Enchilada violates the third requirement. Using harmonic mean computation yields the Ipanema as the best result. Since the Ipanema is less expensive, Alice can be quite satisfied with having dinner there. For Charlie it is very important to have Mexican food. The Ipanema provides Latin American cuisine, which is not the same but similar. For Bob both places provide rather satisfying results. Taking everything into account it can be concluded that the Ipanema is the best compromise that could be achieved for the given decision problem and is therefore considered as the optimal decision outcome.

It follows that the proposed MCDM model allows for finding optimal decision outcomes for location-based group decision processes.

### 6.3. Discussion

Several challenges remain for realizing LBGDS according to the model presented. First, one must investigate how closely human decision-making behaviour in scenarios as described in this work can be approximated by the proposed model. This requires a user-centred focus to investigate particular needs of the user, how they interact with other users in a group, and how they make judgments and trade these off. Such research has a long tradition and has been applied within the area of LBS with a focus on individual users and user groups (Wealands et al. 2007, Raubal 2009) for different scenarios, such as mobile guides (Baus et al. 2005). In particular and regarding the work presented here, this affects the definition of the optimal decision outcome, which has not yet been verified with respect to human judgements. The identified decision criteria require further investigation. According to Malczewski (1999), a set of MCDM criteria has to be comprehensive, measurable, complete, operational, decomposable, non-redundant and minimal. Verification that these
characteristics are provided by the set of MCDM criteria utilised in this work has not yet been achieved. We must also assume that some additional criteria, such as ambiance or place size, may play important roles for location-based decisions.

The dynamic aspects of LBGDS need further investigation, as well. Currently, constant travel velocity is assumed and transportation networks, such as for buses have not been regarded yet. Positioning via self-localisation in the current version of mediatrix should be replaced by automated positioning techniques and geocoding services. Finally, it has to be stated that our approach does not strive for guaranteed perfect results, that is, very high scores for each user in general. The outcome of location-based decision processes can rarely be perfect, because user interests vary and the set of alternatives is strongly restricted by the spatio-temporal context. Hence, the underlying notion of optimal should rather be understood in terms of best possible. One of the core advantages of mediatrix is that it only requires asynchronous telepresence of group members (Harvey and Macnab 2000). There is no need for direct interaction as in a standard discussion process since the service maintains requests that have been created until all users have submitted their input.

7. Conclusions and future work
This article presented a formal model and prototypical implementation for LBGDM. It provides a foundation for the future development of personalised LBS that...
support groups of users in their everyday planning of shared activities. Such applications include any location search for common activities, collaborative emergency response operations, mobile guides and the broad range of social network functions. We outlined examples and basic principles of personalisation in LBS, and presented a use case for LBGDM dealing with a group of people searching for a restaurant in the city of Münster. A definition of the optimal decision outcome for LBGDM was given. The formal MCDM model aimed at obtaining such outcomes depending on personal constraints and preferences. Principles of time geography were used to develop a screening method that accounts for spatio-temporal constraints. Similarity measurement methods were employed to integrate nominal decision criteria into decision rules. We proposed using harmonic means to avoid individual group members being disadvantaged. By simulating a decision process using the prototypical LBGDS mediatrix we demonstrated that the proposed model can be employed to achieve optimal decision outcomes for location-based group decisions.

There are several areas for future research with regard to improving the model presented in this work: spatio-temporal attributes have been considered as non-compensatory so far. Allowing compensatory spatio-temporal attributes would enable users to express preferences with respect to spatial-temporal criteria, for example, some users may prefer short travel distances. The proposed MCDM model utilises a series of simple techniques. More sophisticated methods are available, for example, the OWA method. OWA allows for selecting between different personal decision strategies and has already been implemented in LBDS for single users (Rinner and Raubal 2004). Using OWA the user can select optimistic, pessimistic and moderate decision strategies. An optimistic strategy puts higher weights on criteria with high scores, whereas a pessimistic strategy puts higher weights on criteria with low scores. Another MCDM technique that could be utilised for LBGDM is sensitivity analysis (SA) (Malczewski 1999, Ligmann-Zielinska and Jankowski 2008). Using SA in a LBGDS could provide helpful feedback for decision makers by showing how sensitive the selected criteria are with respect to changes in user input. It could be combined with a voting mechanism offering several well-performing tour alternatives. For both MCDM techniques, OWA and SA, the high cognitive workload demanded from the user seems to be a major obstacle for employing them for location-based group decision support. As described in Section 6.3, a user-centred focus will bring more insight to these questions.

The similarity measure proposed here has not been evaluated with respect to its correspondence to human similarity judgements. Considering the semantic distance method employed for measuring cuisine similarity it may be reasonable to include further similarity measures, for example, to exploit information contents as proposed by Resnik (1995). Resnik suggests using probabilities of encountering an instance of a concept for measuring similarity in taxonomies. He defines information content as the negative logarithm of this probability. The similarity between two concepts \( C_1 \) and \( C_2 \) is measured using the information content of the most specific class, or least upper bound, subsuming \( C_1 \) and \( C_2 \). For the top-class of the taxonomy the probability of encountering an instance is 1, which leads to a similarity measure of 0. This is the result of comparing two concepts located in different main-branches of the taxonomy, for example, Chinese to German cuisine. The probability computation depends on empirical, instance-based information. In the case of measuring
cuisine similarity, this translates to restaurant data. If there were many East-Asian restaurants (40% probability) and few African restaurants (5% probability) there would be a higher similarity between African restaurants, for example, sim (Tunisian, Egyptian), than between East-Asian restaurants, for example, sim (Japanese, Chinese), which seems plausible. A combination of the approach used in this work and the information content may improve the decision analysis.

Our major objective was to define a formal, computational model for enabling location-based decision support for user groups. This strongly influenced the development of the prototype, which was developed to demonstrate and analyse this model. As a next step, an evaluation of how such a service could be embedded in the service-oriented architecture provided by the Open-LS specifications is necessary. Mediatrix has been designed and implemented as a stand-alone web application in the Web 2.0 style and does not provide interfaces to connect to other services. Aligning mediatrix to the Open-LS specification would allow accessing other services, such as geocoding and navigation services, which are appropriate extensions for a LBGDS.

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Notes

1. We define location-based tasks as activities that are bound by space and time. For example, eating is an activity, whereas having dinner is a task.
3. For reasons of simplicity a constant travel velocity (5 km/h) is assumed for each group member.
4. We assume a standard duration of 1 h for the task of having dinner.
7. http://www.youtube.com/watch?v=m0zD_n3zEYk
8. mediatrix (Latin): female troubleshooter.
9. This simulation focusses on quantitative methods. Thus, no additional constraints, such as price limits are set.

References


