

# Travel Recommendations in a Mobile Tourist Information System

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**Abstract:** An advanced mobile tourist information system delivers information about sights and events on a tourists travel route. The system should be personalized in its interaction with the tourist. Data that can be used for personalization are: the tourists interest profile, an analysis of their travel history, and the tourists feedback about sights. Existing mobile information systems for tourists do not tailor their information delivery to the tourists interests.

In this paper, we propose the use of personalised recommendations that consider all of the personal information a tourist provides. We adopt and modify techniques from recommender systems to the new application area of mobile tourist information. We propose a number of methods for personalised recommendations; and select a subset of these for implementation. This paper then presents the implemented recommender component of our TIP system for mobile tourist information.

## 1 Introduction

Advanced tourist information systems should deliver more than static information. Instead, semantically-rich information about sights should be delivered to the mobile users, based on their preferences and travel history. The system should also recommend sights that match the user's context and interest. User context may be their location, the weather at their current position, their means of travel, and the current time. The user's interests are captured in their profile, their travel history, and by giving feedback about items in their travel history.

Currently, no tourist information system considers the personal background of a traveller for recommending routes and sights. Typically, the recommendations are base on rudimentary information such as the opening time or the physical proximity of sights to the user. Research areas that evaluate methods for user recommendations are recommender systems. These systems use a database about user preferences to predict additional topics or products a new user might like. Travel decision-making is one of the most comprehensively investigated areas in tourism research. As pointed out by Ricci [RdM04], only a very limited number of contributions have dealt with the topic of integrating decision models into travel recommender systems. One reason might be that the focus is traditionally not on interactive travel aids but on off-line decision making. Consequently, these studies do not take into account the unique characteristics of a mobile recommendation system.

Our approach is to combine the findings from these research areas with personalised and context-based information delivery in the tourist application. This paper describes the design and prototypical implementation of a *recommender engine for a mobile tourist information system*. The design is based on a combination of three recommendation paradigms: content-based recommendation, collaborative filtering and knowledge-based recommendation. The engine is implemented as a part of our tourist information system TIP [HV02].

The contributions of this paper are: (1) a thorough requirements analysis for recommendations in a traveller's mobile environment; (2) a comprehensive analysis of the state of the art in tourist information systems and research in recommender systems; (3) the design of new travel recommendation methods by using a variety of personalised information sources and sight-related information as context; and (4) implementation and first cut qualitative analysis of the proposed recommendation methods.

The remainder of this paper is organised as follows: Section 2 defines requirements for the system design. Section 3 evaluates related work; Section 4 discusses special considerations for recommendations in a mobile tourist environment. In Section 5, we propose hybrid recommendation methods for the mobile traveller context. In Section 6, we introduce our implementation and the results of the practical and theoretical analyses. We conclude the paper in Section 7 with a summary and outlook for future research.

## 2 Scenario and Requirements

To give a picture of the usage of the recommender engine within the TIP system, we describe a simple example for two users. Daniel and Audrey are in Whitianga. Audrey arrived here two days ago while Daniel just arrived. They both use a mobile TIP system and have defined swimming and fishing as personal profile. Audrey has travelled around the area and has given her feedback about the places she visited to the system. She prefers swimming and walking along the beach and is impressed by the scenic Cathedral Cove and Opito Bay. Daniel starts his journey early in the morning at the hot water beach; afterwards he would like to explore other beaches. He asks the TIP system where to go further. The system gives details of Hahei beach and Cathedral Cove. He is also overwhelmed by the beauty of the Cathedral Cove so he gives positive feedback to the system. While he is heading back to the hotel the system suggests him to go to Opito Bay based on his preference, the information given by Audrey two days ago and information from other users who have been here before and have similar preferences.

We identify the following information (recommendation data - *RD*) that can beneficially influence the recommendations given to a user (see Figure 1):

*RD1* The personal preferences stated in the user's profile.

*RD2* The personal travel history of the user: A user might want to see more sights that are similar to the ones they have seen already, e.g., buildings by the same architect. Additionally, the user may or may not be directed back to places where they have

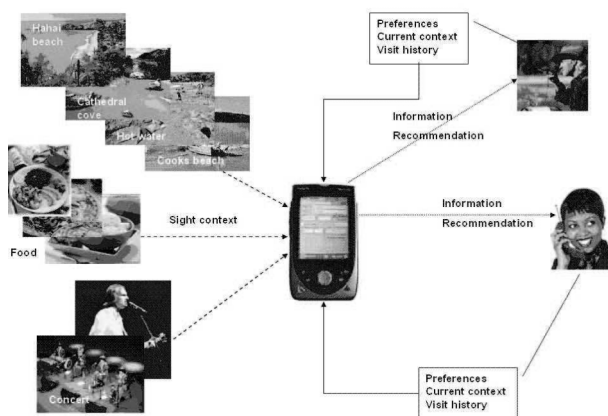


Figure 1: Data that might be used to shape the recommendations given to a user

been on previous travels and that they enjoyed. They may also be interested in new places to discover, e.g., to satisfy an interest which has not been addressed so far.

*RD3* Current context of the user: e.g., location, time, weather, and means of travel. The current context refers to the accessibility of the recommended sights, e.g., based on distance and time to travel, opening hours.

*RD4* Context of the sights: Sights do have a context that includes, e.g., their location, opening hours, and wether preferences. In addition, sights may belong to semantic groups: Sights that are in a semantic group share certain features; we assume that a user who has seen several sights in a group is interested in seeing more.

*RD5* User feedback for similar sights: Information about past experiences of the user may give indication as to whether the user would enjoy visiting similar sights. The user may also have stated a certain preference in the personal profile but their travel history might indicate that the profile was not sufficient.

*RD6* Travels of similar users: Information about the preferences of users with similar interests (indicated in a similar travel history or in similar user feedback regarding the sights) may be used to create recommendation for the individual user.

We believe that all available information sources should be used to create recommendations for a tourist. We will show that using only selected sources hinders fluid and traceable recommendations, which are important for the user's acceptance of a mobile system. We therefore define the following qualitative criteria for designing a recommender system for a mobile tourist information system:

**Viability** This is the basic functional test for a recommender engine: Is all required information available so that a recommendation can be computet. That is, recommendation based on user interest cannot be given if the user enters the system the first

time and did not have any interaction with the system yet (e.g., no profile, history, or feedback). The same applied for methods depending on other users feedback. The fulfilment of this criterium can be reasoned by analyzing the methods.

**Acceptability** We see this as the qualitative functional test for a recommender engine: the provided recommendations are similar to the ones that a user would choose. We believe this criterium to be necessary but not sufficient for a mobile system. The reason is that the interaction with the system is not a one-off situation, but rather a continuous way that slowly adapts the system's behaviour to the user. In addition, the user context and location changes but the system reacts based on a history of user interactions (i.e., long term and short term preferences need to be balanced). The fulfilment of this criterium can be tested using user test groups and exemplary recommendation lists; it can also be reasoned based on previous studies.

**Tractability** This is a long term qualitative functional test regarding user acceptance. The system's reasoning, i.e., the basis for the recommendations, must be transparent to the user so that they are able to control and manipulate the system's reactions. Otherwise the users will not accept the system for a long term usage. The fulfilment of this criterium has to be evaluated in a longitudinal user study. A set of reasonable expectations can be argued for in a first-cut analysis; these need further validation based on a user study.

In this paper, we are concentrating on designing and evaluating our system according to all three criteria of Viability, Acceptability, and Tractability. The design will be evaluated based on the first two criteria. Successful Tractability of our design will also be discussed here, but thoroughly analyzed in a later stage of the project.

### 3 State of the Art

This section analyzes the state of the art in creating recommendations for both tourist information systems and recommender systems. We show that sophisticated recommendations are barely supported in existing mobile tourist information systems (they mainly focus on the mobile component and the information delivery). We therefore turn to recommender system for methodically related approaches regarding recommendations. Both the tourist information provider systems and the recommender systems are compared in turn against *RD1* to *RD6* as identified in the previous section.

**Recommendations in Tourist Information Systems** We analyzed several tourist information systems in detail; Table 1 shows a selected comparison against the six requirements for recommendations in a mobile system.

GUIDE [CMD02] is a mobile context-aware tourist guide facilitates city visitors while they are travelling around the city of Lancaster. The GUIDE system offers a personalised 'Nearby Attractions' page on which it recommends sights that are near by the users current location and that match the user's interests (with a lower ranking for those sights that

System	Information delivery (○)/Recommendation (+) based on					
	User Profiles	User	Sight	User History	Similarity in feedback to other users	this user
Guide	○ –	○ +	○ +	– –	– –	– –
Tourist Guide	– –	○ –	○ –	– –	– –	– –
CyberGuide	– –	○ –	– –	○ –	– –	– –
CRUMPET	○ –	○ –	– –	○ –	– –	– –
AccessSights	– –	○ –	○ –	– –	– –	– –

Table 1: Comparison of five tourist information systems on six requirements for the production of the TIP recommendation component. (Symbols: +/○ system addresses requirement, – system does not fulfill the requirement)

the user has already seen). The GUIDE system focuses on providing tourist information according to a user’s current location and sight information e.g. sight location, sight opening and closing time, and user’s visit histories. The system gives recommendations to the user by asking the user for a selection of attractions they want to go to. Subsequently, the system recommends a sequence for visiting those attractions.

TouristGuide [SHT03] is a location based tourist guide application for the visitors to the Adelaide city center. The system is implemented on a pen based mobile computing device with a GPS sensor. The system provides three modes of operation: map mode, guide mode, and attraction mode. The map mode lets the user know where they are in relation to other tour attractions. In guide mode, a trail is marked on the map showing a set of related attractions. The attraction mode acts as a digital tourist guide, supplying users with sound, images and textual tourism information. TouristGuide system concentrates mainly on sight contexts; no user preferences are used and no recommendations are provided.

CyberGuide [AAH<sup>+</sup>97] is a mobile system that assists a visitor in a tour of Georgia Tech Lab. The system mainly focuses on investigating context-sensitive computing so that only limited support for tourists’ information and recommendations is provided. CyberGuide supports users when exploring the lab therefore their context of use is not wide enough to take user interests into account.

CRUMPET [PLM<sup>+</sup>01] is a mobile that provides personalized and location-aware services to tourists. To interact with the system, a user first provides their demographic information. Then the system learns more specific user preferences while they are traveling and interacting to the system. This information is used to revise the user’s profiles. CRUMPET provides tourist information to their user according to the user’s location.

AccessSights [KKB04] is a multimodal location-aware mobile tourist information system that provides tourist information to both normally sighted users and visually impaired people. AccessSights consists of three phases: orientation, movement and information perception. Both visual display and auditory information is given to users. Normally sighted users perceive the point of interests via both senses and follow a guide map whereas blind people listen to information. The system uses loudness to indicate distance between users’ current location and attraction spots. A route to point of interests is provided when user is further away while site information is given when user reaches a point of interest.

In summary (see Table 1), these five systems provide information via hand-held devices based on the user's location. None of the evaluated tourist information systems supports user feedback about neither visited sights nor information about the interests of similar users. In most cases, a user's history is used only for ranking of sight information in order to exclude items that have already been visited.

**Recommender Systems** A recommender system is a system that provides a recommendation, prediction, opinion, or user configured list of items that assists the user in evaluating items. Three different types of recommendation approaches are distinguished [Bur99]: (a) content-based, (b) collaborative-filtering, and (c) knowledge-based.

a) *Content-based recommendation* use machine learning techniques to classify items (e.g., sights) for a particular user based on the feedback of the user; items that are similar to the users preferences are recommended. This approach has the advantage of immediate recommendations, i.e., no feedback from other users about the items is necessary. Moreover, users with unique interests (i.e., unlike other users) can also be served. However, users can only get recommendations about items that are similar to the ones they visited before. In addition, the classifier needs to learn with a sufficient amount of data.

b) *Collaborative filtering* gives recommendations to users based on the preferences of similar users. Rather than determining the similarity between item and user preferences (as in Content-based recommendations), this approach computes the similarities among the users based on their feedback. Here, the users are not restricted to recommendations about items similar to what they preferred in the past; recommendations cover a wider range. The system needs to be initialized with a large amount of user-related data. Additionally, the accuracy depends on the number of items (i.e., sights) that can be associated with a certain user.

c) *Knowledge-based recommenders* do not depend on user rating for items or on information about individual users. They use information about users and products to (interactively) generate recommendations. The system leads a user through an information catalog using qualitative ratings as navigation aids. The users typically have to complete several navigation steps, their interactions and choices are recorded as their current preferences. Each recommendation is immediate, user data is not stored for later sessions.

We evaluated five recommender systems regarding our six requirements, see Table 2.

CBCF [MMN02] (Content-Boosted Collaborative Filtering) is a framework for combining content-based and collaborative recommendations. To recommend a movie to an active user, CBCF uses a content-based predictor to enhance the user's data by predicting their rating based on past ratings. They then provide personalized suggestions through collaborative filtering using the predicted ratings. This approach avoids the drawbacks of a sparse coverage of ratings in the system.

Fab [BS97] is a recommender system for the Web that uses a hybrid content-based and collaborative approach. Each user receives pages matching their profile from a personal collection agent. When user has requested, received and looked over their recommendations, they assign an appropriate rating. The user's ratings are used to update their personal selection agent's profiles and forwarded to the originating collection agents. The collection

System	Recommendation based on					
	User Profiles	User	Sight	User History	Similarity in feedback to other users	this user
CBCF	+	–	–	++	++	++
Fab	+	–	–	+	++	++
LIBRA	+	–	–	++	–	++
MRS	+	–	–	+	+	+
FindMe	+	–	–	–	–	++

Table 2: Comparison of five recommender systems on five requirements for the production of the TIP recommendation component. (Symbols: + system addresses requirement, ++ system addresses requirement and the recommendation is truly influenced by the requirement, - system does not fulfill the requirement)

agents then adapt their profiles in accordance with the users’ rating.

LIBRA [MR00] is a content-based book recommending system that utilizes information extraction and machine-learning algorithm on text categorization. It gives recommendations for books based on individual user’s preferences. A user selects and rates a set of books. A machine learning algorithm is used to build a user profile from their given ratings. Once a profile is learned, it is used to predict the ranking of the remaining books, and the top-scoring recommendations are presented to the user. After reviewing the recommendations, the users may assign their own rating to what they consider to be incorrectly provided and keep the system to improve the given recommendations.

MRS [CC01] provides a personalized service of music recommendations. The systems extracts representative tracks of an individual MIDI music object; six features are extracted to classify each track. The access histories of users (which are referred to as a user profile) are analyzed to derive users’ interests. Both content-based and collaborative filtering methods are implemented for producing recommendations. In addition, the system uses statistic-based recommendations from the list of overall most-accessed music objects.

FindMe [BHY97] is a knowledge-based recommender systems that helps people find items of interest, e.g., restaurants or movies, by providing a guided interactive search called similarity retrieval. The user selects a given item from a list provided by the system and requests items similar to it. To perform this retrieval, a large set of candidate entities is initially retrieved from the database. This set is sorted and a selection of top candidates is returned to the user. The system lets the user browse through the catalog using qualitative ratings as navigation aids. Each navigation step informs the system about the user’s preferences. The similarity metrics in FindMe determine what counts as similar when two items are being compared; retrieval strategies determine how important different aspects of similarity are to the overall calculation.

In summary (see Table 2), the recommender systems evaluated here do not focus on providing recommendation to moving devices like mobile phone or PDA. None of the systems utilizes *RD2* (travel history) nor *RD3* (context) for producing their recommendations. Note that each of the systems defines the meaning of ‘user profiles’ differently. To avoid the drawbacks of the collaborative filtering and content-based recommendation methods,

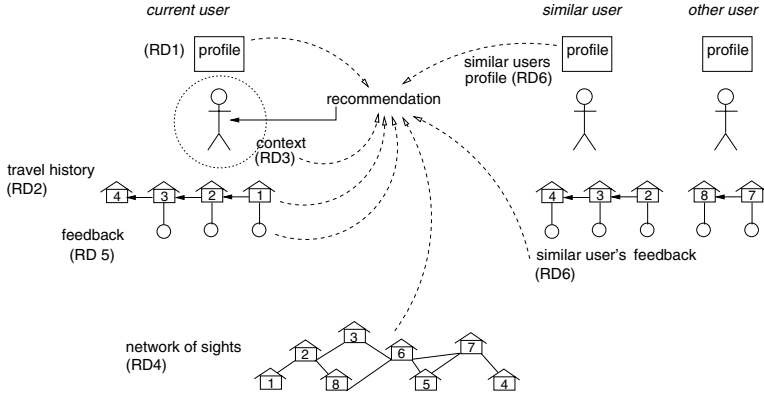


Figure 2: Input recommender data ( $RD1 - RD6$ ) used for personalised recommendations. Note that  $RD6$  - information about the preferences of similar users can be drawn from their feedback or their profiles.

CBCF, Fab, and MRS use hybrid approaches. User profiles ( $RD1$ ) and user histories ( $RD4$ ) as well as similarities to other users ( $RD5$ ) are used. Similarity to other users and similarity to users' feedback ( $RD5$  and  $RD6$ ) have a strong impact in CBCF and Fab because these two systems expand their sparse ratings by projecting users' ratings from their past ratings or profiles.

## 4 Discussion: Recommendations in a Mobile Traveller Environment

The recommendation engine in the TIP system Version 1.0 used a pure knowledge-based recommendation approach based on semantically-related sights using the semantic network of sight-related information in combination with user profiles, user history, and current context (e.g., location) [HLV04]. The event notification component of TIP (e.g., notifying about external events like theater performances) already provides a content-based filter component for external events.

For sophisticated recommendations in TIP Version 2.0, we aim at effectively combining the different recommender methods described above using the recommender data ( $RD1 - RD6$ ) identified in Section 2. One of the central questions was how to best combine the given information sources in order to achieve Viability, Acceptability, and Tractability. Note that if a recommender does not meet these users requirements, superior or inferior performance is of little or no consequence. Thus, our first aim was to assess recommendation methods from a user perspective, before proceeding to a thorough analysis of alternative implementations for efficiency and performance.

We will now discuss the options and restrictions for recommendations in a mobile tourist environment. For illustrations see Figure 2. As discussed in Section 3, research in recommender systems has already combined some of the described three pure approaches. In the



context of a tourist information system, the available information is more heterogeneous than the information used in recommender systems and a larger number of influential factors are to be considered (*RD1-RD6*). In addition, the application area imposes the challenge of users not continuously following stable long term interests but being influenced by the immediate context (*RD3*), e.g., Audrey might like swimming and beaches only in the north of New Zealand but not in colder regions. Also, Daniel might prefer going to museums when being overseas instead of walking on the beach.

Ricci [RdM04] points out that collaborative filtering works well for items that are purchased frequently and reflect a continuous interest of the user. The algorithms cannot take into account session-specific needs such as temporary interest of a user (e.g., induced by travel partners) or the restrictions of a particular context (e.g., interest in sailing might only be satisfied when close to the sea). Travel recommendations based purely on collaborative filtering are therefore not to be advised. Our use of additional data as a basis for the recommender engine can be compared to Pazzani [Paz99] creation of user profiles based on positive training and then directly applying the CF algorithms, instead of applying it to the ratings.

The preferences of the user may be derived from the user's feedback (*RD5*) - the classical machine learning approach - or from information about visited sights in the travel history (*RD2*) or based on the personal profile (*RD1*). Again, the classifier needs to be trained with sufficient data. Using a nearest neighbour classifier can decrease the amount of data required. Here, the personal user profile (*RD1*) can again be used to select appropriate neighbours. Using information about the travels of similar users (*RD6*) requires collaborative filtering methods. For collecting user-related data, the system may use feedback (*RD5* and *RD6*), or information about travel histories (*RD2*) and predefined personal preferences in the users' profiles (*RD1*).

Note that the current user context (*RD3*) such as location and weather may be used simply as additional filter or ranking information. It may also be used as input for the recommender algorithms, e.g., on a sunny day tourists prefer Restaurant X (large windows and nice view) and in autumn when it rains, tourists prefer Restaurant Y (cosy and has heating).

Using information about the semantic relations between sights (*RD4*) would support the usage of a knowledge-based recommender.

## 5 Design of Travel Recommendations

Considering possibilities of combinations of different recommendation data and recommender approaches as discussed in the previous section and the existing recommender engine in the TIP system, we propose the analysis of the following approaches.

**Pure approaches** These approaches are direct implementations, they form the basis for further combinations of data sources and recommendation methods.

- A1. Content-based: this approach gives recommendations based on a particular user's feedback. Sights similar to what they liked in the past are recommended (*RD5*).
- A2. Collaborative Filtering: this approach recommends sights that users liked which are similar to a particular user. This information is based on their previous feedbacks (*RD5* and *RD6*): Sights that these similar users liked are recommended.
- A3. Knowledge-based: this approach recommends sights based on the context; it recommends sights that are semantically-related to sights this user has visited in the past (*RD2* and *RD4*). For example, a user receives recommendations about further beaches after they visited two beaches.
- A4. Must-see sights: this approach recommends preset places that are the point of interests in a particular area e.g. sky tower in Auckland. These points of interests can be defined based on the feedback of a large set of users (*RD5* and *RD6*).
- A5. Nearby sights: this approach takes users context, sight context and user history into account (*RD3* and *RD4* and *RD2*). The user context is user's current location, time and means of their travel. User who travels by car will get recommendation on farther point of interests or up coming activities than users who travel by bike or on foot. Then the system suggests their user to go to the place which they can conveniently visited and have never been before.
- A6. User profile: this approach gives recommendations on sights that match this user's profiles (*RD1*).

**Compound approaches** These approaches use combinations of base data as input for recommendation methods, either boolean combinations or extensions. They combine *A5* and *A6*, and extend *A6* by this users feedback or other user's profile information and feedback (*RD6*).

- B1. Nearby sight and user profile: this approach extends approach *A5* by filtering the results of *A5* according to a particular user's profile before giving a final recommendation. The user is required to explicitly define their interests when they register to the system.
- B2. Revise profile: When using recommendations based on the user's profile (see *A5*), their profile may be revised according to the feedback they give to the system (*RD5*).
- B3. Extend profile: This approach gives recommendations on sights that matches this user's (extended) profile. The user's profile is extended using information about other users. After determining similar users, information in their profiles is added to this user's profile (*RD6*).

**Extended Content-based approaches** These approaches use combinations of the content-based method with other information sources.

- C1. Implicit feedback: this approach is based on the principles of content-based recommendation but the users do not need to explicitly give their feedback to the system. Their feedback is created from the information in their user profile (*RD1*) and on what they have done in the past, which is recorded in their user history (*RD2*).
- C2. Content-boosted: This approach is a combination of content-based recommendation and collaborative filtering. The user may not yet have given enough feedback: Missing feedback is simulated based on the feedback of similar users. In this way the data set for content-based filtering is enlarged.
- C3. Context-aware Feedback: This approach uses content-based recommendation where the user gives their feedback according to circumstances of their context, e.g., the user prefers going to Restaurant X when it is raining or the user likes going to café Y on a sunny day because it is near the beach.
- C4. Implicit Context-aware Feedback: This method uses content-based recommendation based on this user's feedback (*RD5*) that are recorded according to sight context (*RD4*) and user history (*RD2*). The user do not need to explicitly give their feedback to the system but it is created from the information in their user history (*RD2*) and the sight context (*RD4*).
- C5. User information and feedback: This method uses this user's available information and their feedback for content-based recommendations. This approach takes user profile (*RD1*), user context (*RD3*), sight context (*RD4*), user history (*RD2*) and their feedback (*RD5*) to verify the final recommendation to a particular user. However, user context may or may not be considered.

**Extended Knowledge-based approach** These approaches use extension to the knowledge base of the system with other information sources.

- D1. Supplementary Sight context: This approach updates the sight context (*RD4*) according to the feedback of the users (*RD5* and *RD6*). Recommendations are given based on the information stored about the sights, e.g., the semantic groups they belong to. Feedback of users given about the sights may create new groups.

**Extended Collaborative Filtering approaches** These approaches extend the data set used for collaborative filtering.

- E1. User profile: If no feedback (*RD5* and *RD6*) is available from a number of users, the feedback is simulated by creating synthetic feedback data based on the user's profile data (*RD1*). It can be assumed that the users like items that match their user profile, thus, a positive synthetic feedback is created for these items. These synthetic feedbacks are then used as input for collaborative filtering.
- E2. User history: Similar to E1, synthetic feedback is created based on the information in the users' histories (*RD2*).

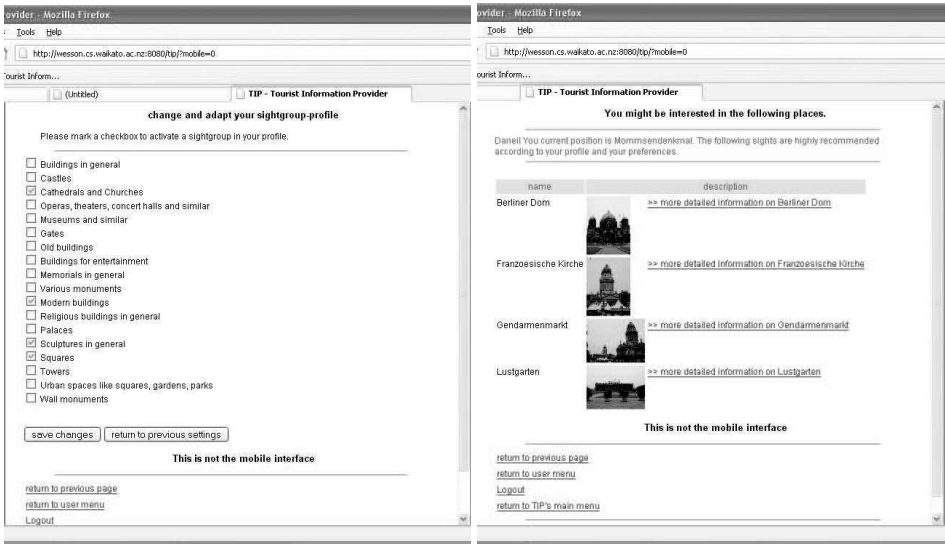


Figure 3: Screenshots: left - profile interface for selecting semantic groups, right - recommendations based on location, personal profile, and earlier feedback for similar sights

E3. User profile and history: This approach is a combination of E1 and E2: synthetic feedback is created for a group of similar users based on information from their profiles (*RD1*) and user histories (*RD2*).

## 6 Implementation and First-cut Analysis

Selected methods from the ones proposed on the previous section were implemented in our mobile tourist information system TIP Version 2.0. For more detail about the information delivery methods in TIP Version 1.0 refer to [HLV04]. Here, we concentrate on the recommendations in TIP Version 2.0. Figure 3 (left) shows the interface for defining a user profile using semantic groups (another part of the profile contains information topics). For clarity, we do not use the mobile interface for this paper's screenshots and only show selected parts of the interface.

As a proof of concept, we implemented approaches A2, A3, A5, A6, B1, and C5; further implementations are under way. Thus, the system uses all identified recommendation data *RD1* to *RD6*. When arriving at a certain point (based on the GPS data), users receive information about the sights they are facing. The given information depends on the user profile and the user history. Users can give feedback about the sights; user feedback is given using a scale from 1 to 10.

The users can select different recommendation options out of a list. Following the link

to a specific recommendation option results in displaying a new page with recommended sights. For simplicity, we do not show screenshots of the information delivery pages here, but focus on the recommendations. Figure 3 (right) shows the recommendations given about sights nearby that are interesting to the user Daniel according to his profile and his feedback and which are in the same semantic group. Note that we use German locations in our prototype; a database with New Zealand locations is being assembled. The screenshot shows the recommendations given to Daniel based on the fact that he gave high scores for similar sights.

We now discuss the results of our theoretical and practical qualitative analysis of the proposed recommendation methods. We start by analyzing the pure approaches and then move on to the various extensions.

*Pure Approaches:* Both content-based recommendations A1 and collaborative filtering A2 heavily rely on the availability of significant amounts of user feedback data. If the users are new or reluctant to give feedback, no viable recommendations can be given. Knowledge-based recommendations A3 do not take personal contexts and long-term interests of the user into account. The list of must-see sights A4 depends on the preferences of the majority of users; individual interests are not catered for. Near-by sights A5 describe valid recommendations, but with a low degree of personalization. Recommendations based on user profiles A6 suffer from the limitations in the users' abilities and their willingness to describe their interests. In addition, all pure methods A1 to A6 suffer from poor consideration of user and sights contexts; they are all limited by the restrictions of the underlying static sight information.

*Compound Approaches:* Approach B1 addresses the limitations of A5 by introducing personalization. Methods B2 and B3 both address the limitations of A6 by releasing the user from the burden of initially defining their profiles.

*Extended Content-based Approaches:* These approaches are variations of recommendations based on a single user's feedback. The implicit feedback in C1 solves the problems of reluctant users in giving feedback (as in A1). C2 addresses the problem of new users that do not have visited a sufficient number of sights yet to create recommendations. C3 allows for much richer context data to be considered, but opens the problem of extensive and burdening feedback. C4 addresses these problems by implicitly collecting data about the user. This, of course, might create trust and security problems. C5 describes a rich method for user recommendations. A drawback is the focus on data by a single user (closeness): new interests or sights are less likely to be discovered by this user, which may lead to frustration.

*Extended Knowledge-based Approach:* The extension of the sight data set as proposed in D1 solves the problem from which all approaches discussed so far suffered: the limitation of a static set of sight information.

*Extended Collaborative Filtering Approaches:* These are variations of recommendations based on a multiple user's feedback that are similar. All of the methods proposed here address the problems of reluctant users in giving feedback (as in A1 and A2).

The viability of each recommendation method strongly depends upon the availability of the base data. For example, A6 cannot be used where there are no user profiles. Rely-

ing on a single form of base data results in the system being overly dependent on that form. Conversely, where a system can utilize a variety of base data forms and methodologies it is more likely to deliver good quality recommendations. Acceptability depends on issues of initial personalization costs (e.g., for creating user profiles), privacy and trust, and finally the quality of the recommendations themselves. Most of the existing mobile tourist information systems rely on very simple recommendations; it is obvious that under these circumstances, no sophisticated personalized recommendations can be given. Such requirements again support a decision to employ advanced recommendation methods and also to be able to function based on a variety of base data. In the case of initial costs, avoiding a requirement for explicit user profiles is desirable. Privacy and trust require at least openness about the data held on a user; in addition, there are other complex issues which we will address in future work. Using recommendation methods that are closer to the present state of the art in recommender systems while taking into account the specific needs of the application area, should result in a superior perceived quality when compared to existing mobile tourist systems.

## 7 Conclusion

In this paper, we analyzed current methods for recommendation in traveller system. We have shown that existing systems do only rudimentarily support personalised recommendations. Inspiration can be found in the area of recommender systems. We discussed that typical pure recommender approaches are not directly applicable for mobile traveller system. We proposed, implemented, and evaluated a number of variations that use a range personal data sources.

As a result of our theoretical and practical analysis of extended recommendation methods, we propose a combination of six data sources with three base methods for recommendations. The data sources can be used to address problems such as user reluctance or inability to define personal profiles or insufficient feedback for recommendations. User feedback may extend the sight database and be used to create synthetic feedback.

The advantages of our approach are: (1) Our hybrid system can start with no personal user data. This is especially useful for users whose data is insufficient. Our approach also addresses the problems of (2) users not being able to define their interest appropriately or (3) users having changing short term interests (as is typical for travellers). (4) We believe that it is important to offer a clearly laid out variety of recommender choices to the user that does not hide the mechanics of recommendations as a 'black box'.

In our practical and theoretical qualitative analysis, we have discussed the viability and acceptability of the proposed approaches. The system supports tractability by offering a clear variety of choices to the user. We are planning further qualitative and quantitative studies of the recommendations in TIP to evaluate the tractability and efficiency of the implementation, respectively. We will also address the open problem of security and trust in personalised systems by introducing trust-measures. The inclusion of rich context remains an interesting challenge, which we plan to address in our further studies.

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