

ADVANCED RECOMMENDATIONS IN A MOBILE TOURIST INFORMATION SYSTEM

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Abstract

An advanced tourist information provider system delivers information regarding sights and events on their users' travel route. In order to give sophisticated personalized information about tourist attractions to their users, the system is required to consider base data which are user preferences defined in their user profiles, user context, sights context, user travel history as well as their feedback given to the sights they have visited. In addition to sights information, recommendation on sights to the user could also be provided. This project concentrates on combinations of knowledge on recommendation systems and base information given by the users to build a recommendation component in the Tourist Information Provider or TIP system. To accomplish our goal, we not only examine several tourist information systems but also conduct the investigation on recommendation systems. We propose a number of approaches for advanced recommendation models in a tourist information system and select a subset of these for implementation to prove the concept.

1. Introduction

The development of advanced mobile information systems and Location Based Services (LBS) offer people a new way of information receiving. Nowadays, people can receive their required information by interacting with their hand-held devices from wherever they are. Therefore, it is not a surprise to know that somebody sitting beside us is checking a flight schedule, booking movie tickets or accessing a weather forecast channel from their tiny mobile phone. Delivering information to a user based on their location or context could be used in many information service systems. Tourism is one service area for which new research issues emerged when developing context-aware applications in a mobile environment. Tourist information services present information to tourists based on the tourists' preferences and other contextual information such as sight locations, weather condition or special functions which are arranged during their visit. Consequently, tourists guide books or paper maps will no longer be required. The tourists will carry their hand-held devices such as mobile phone or Personal Digital Assistant (PDA) and will interactively access the required information from service providers.

To have a more clear idea of context-aware applications in the mobile environment of a tourist information system, this section introduces the Tourist Information Provider system or TIP. Subsequently, the objective of this study is explained.

1.1 The Tourist Information Provider System

The Tourist Information Provider (TIP) is an advanced mobile tourist information system. The system is a combination of an event notification service (ENS), a location-based service (LBS) and a context-aware information delivery service. Delivering different types of information based on user interests, their travel routes and sight-related information is the main focus of the system. The users dynamically get information from the system via their handheld devices such as mobile phones or PDA. At the beginning, the users are required to define their preferences to the system as user profiles. In the user profile, the system keeps the user information, for instance, the type of sights they are interested in e.g. cathedral and churches as well as the type of information the users are interested in e.g. history of the sights or a sights' architecture. This information can be changed whenever the users want to revise their interests. The information on the user's current location, their already visited sights and sights' locations are considered before any information is given to the users. Apart from giving the users information about the place they are visiting, the system also supports recommendations about places to go to or interesting activities to do for a particular user. The existing implementation of TIP supports only basic recommendation.

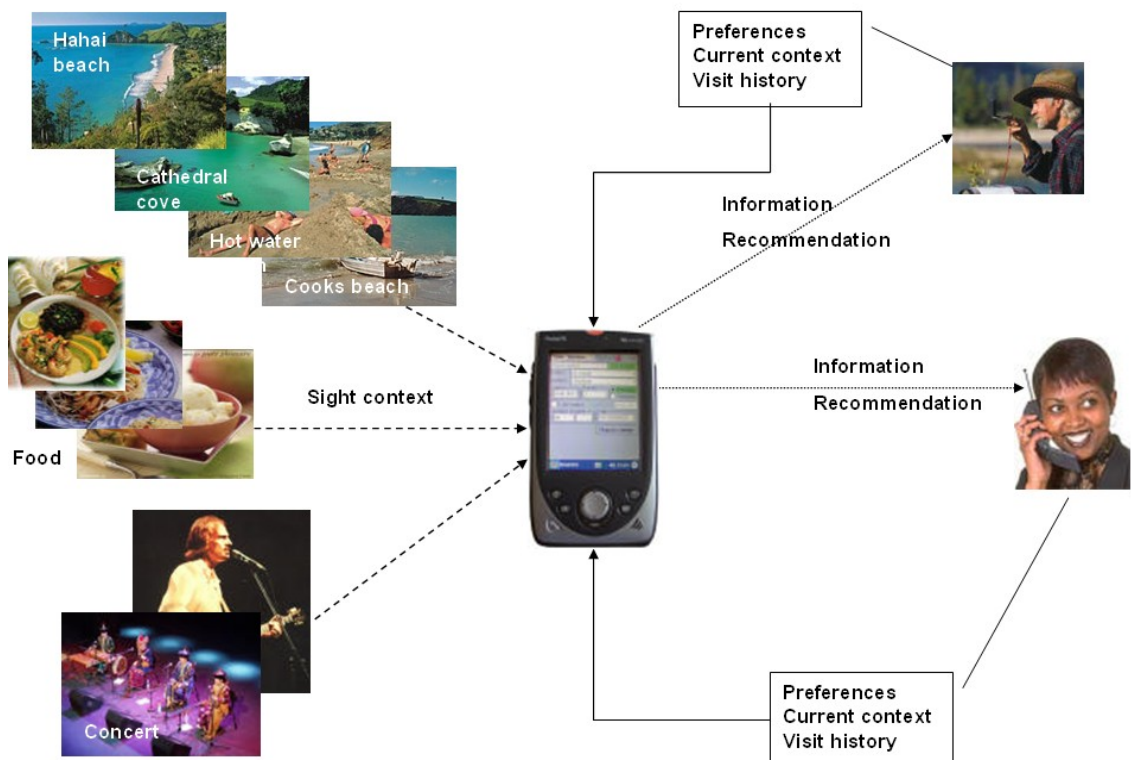


Figure 1 An overview of the data relevant to our advanced recommendation component in the Tourist Information Provider (TIP) system

Recommendations should be given based on user preferences, travel history and location. Figure 1 represents the new concept of recommendations in the TIP system. A tourist provides their personal preferences as well as their current context e.g. their location to the system. Based on these data, sights information or recommendations are given to the tourist by the TIP system.

1.2 Project Objective

In this project, we focus on the idea of giving advanced recommendations about sights to the user.

Therefore, in this project we study and evaluate methods of giving recommendation in a mobile environment. The goal of the project is to find ways of providing recommendations which conform to the users' preferences and can be implemented in the TIP system. The contributions of this project are as follows:

1. *System requirement analysis for the recommendation component in a mobile tourist a mobile tourist information system*
This is to find out requirements needed to take into account for the implementation of a recommendation component in a mobile environment of the TIP system. This study, which is then called the requirement analysis, is conducted in two steps. We first examine the current recommendation feature of the TIP system. This is followed by a user scenario illustrating the extended recommendation component which will be developed for the TIP system. From the user scenario we derive a set of requirements for the new recommendation component.
2. *Review of existing tourist information systems*
This is to study the current tourist information systems and to compare their features against the requirements gained from the requirement analysis. The study concentrates on recommendation features supported by these systems.
3. *Review of existing recommendation systems*
This is to investigate the current recommendation systems in order to examine the approaches which they have used. We compare these systems with the requirements classified. We also evaluate advantages and drawbacks of these recommendation approaches.
4. *Propose viable recommendation methods for TIP*
We propose several methods for creating recommendations in TIP.
5. *Example implementation of the advanced recommendation component in the TIP system*
To show the possibilities for implementing a recommendation component in the mobile environment of the TIP system, selected approaches are implemented as the example models for the advanced recommendation component.

The outcomes of this project lead to initial results for implementing recommendation component in a mobile environment of the TIP system.

1.3 Structure of this Report

The structure of report is arranged as follows: The user scenario and requirement analysis of the TIP's recommendation component are illustrated in Section 2. Section 3 describes our study of the tourist information systems and their comparison against the recommendation component's requirements. In Section 4, an examination of recommendation systems and their comparison against the recommendation component's requirements is discussed. Section 5 proposes recommendation models for the TIP system. Implementation and analysis of the example models is described in Section 6. Finally, a conclusion and an outlook for further work are summarized in Section 7.

2. Requirement Analysis

This section describes a requirement analysis for the recommendation component of the TIP system. The analysis is conducted by creating a user scenario which is then used as the reference scenario of this project. In this scenario, two tourists – Audrey and Daniel are travelling in Coromandel Peninsular. Their behaviour during their sights visit shows interactions between them and the system regarding the recommendation component. Considering this scenario together with a study of the existing features of the TIP system, requirements for the advanced recommendation component are identified.

Before we illustrate the example scenario and describe system requirements, we need to identify the recommendation features of the previous TIP system to make the scenario and analysis more comprehensible.

2.1 Characteristics of the Existing Recommendation Function in TIP

As we have mentioned in Section 1 the previous TIP system has already provided simple recommendations of sights to the users. The system mainly focused on information delivery. The system distinguished type of sights for instances beaches, parks, cathedrals and churches, statues and squares. In addition, sights information is sorted into topic, for example history and architecture. The user is asked to describe their preferences when they first registration; they can define types of sights and types of information they are interested in. Furthermore, for each single sight there is information available which is structured in levels. The information provides more interested users detailed information whereas users with less interest would get just general information about the sight. The user can revise their preferences whenever they want.

The TIP system's current information delivery takes user and their current location into account before giving sights information to the user. For the recommendations, TIP user only information about types of sights. The system recommended sights of the same type as the ones that the user already visited. To improve and extend this simple recommendation component we introduce an example scenario. System requirements will be described in the following section.

2.2 Example Scenario

To give a clear picture of the extended recommendation component which will be implemented in the TIP system, the following scenario is described and it is used as the reference scenario through out the report. Daniel and Audrey are at now Whitianga city, in Coromandel Peninsular, New Zealand. Audrey arrived here two days ago while Daniel just arrived this afternoon. They both love swimming and fishing according to the information they have put into their personal profile for the TIP system registration. They also are fond of technology. Audrey has both mobile phone and PDA and Daniel just bought his new mobile phone a month before he came to New Zealand. They do enjoy interacting with the TIP system.

Audrey has traveled 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 next morning at the hot water beach. He feels very happy and would like to visit other beaches around the area. 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 Cathedral Cove so he gives his positive feedback to the system. 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 as Daniel, the system suggests to him to stop by the Opito bay on his way back to the hostel.

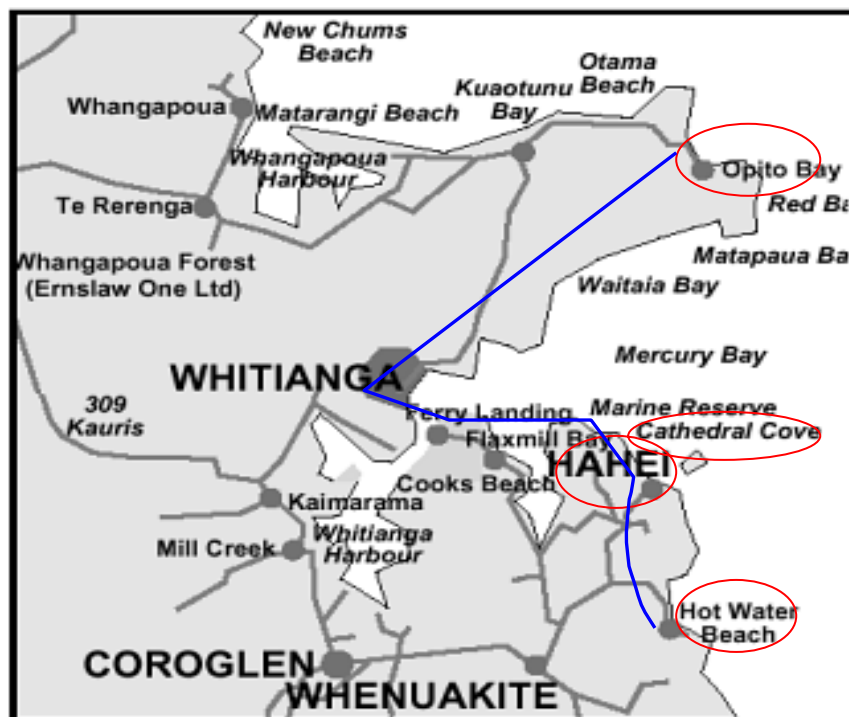


Figure 2 Daniel and Audrey's tracks in beach areas of Whitianga city

Figure 2 describes Daniel's traveling route. The top circle indicates the Opito Bay which is recommended to Daniel by the TIP system based on his preferences together with Audrey's and other similar users' positive feedbacks given to this sight. Other circles indicate further visited places.

2.3 Requirements for the Recommendation Component

As mentioned in Section 2.1, the existing recommender component of the TIP system gives suggestions to users based only on defined similarity of sights (i.e. type). These simple recommendations may or may not be the right one for the user. This restriction of recommended sights could lead the users not use this feature of the system. Obvious attributes that we need to pay attention to are the user profile and the users' past visits. Furthermore, user feedbacks on the places they have visited should also be taken into account as illustrated in Section 2.2. The current naïve recommendation component in the TIP system needs to be enhanced in order to function effectively. We consider the following five factors essential for an enhancement of the recommender component of the TIP system:

R1 User profile

A user's profile specifies information of interest of the user. The system learns user's preferences from the given information and provides recommendations based on the acquired knowledge about the user.

R2 Context of a user

A user's context may specify current location, time, weather, means of travel of a particular user etc. Current context determines the suitability of a sight for instance distance from the users' current location and opening and /or closing time of the sight.

R3 Context of sight

Sight context contains information about groups or types of sights for recommendations, which have certain features in common e.g. churches. Context of sights also cover their location, operating hours and weather conditions. Recommendations might be given on the assumption that users who have visited several sights in a group might be interested in seeing more sights of this group. A sight might not be recommended if it will close within half an hour.

R4 Users' travel history

The user's travel history which includes places, time and location the user has been to. This information is a track of the user movements therefore the system will not recommend places that user has already visited. The system may learn user preferences from what users did in the past and predict what they would like to visit or do in the future.

R5 Users similarity

This requirement is identified in two forms.

- a) Similarity to other users who have similar likes and dislikes.

Sights which other similar users liked may be recommended to the user. As a result, the user gains wider information based not only on their preferences but also their similarity preferences with other users.

b) **Similarity to this users' feedback**

The user receives recommendations based on the similarity of sights to other sights this user gave positive feedback about.

These five requirements will be considered for an improvement of the recommendation component before the systems gives suggestions to the users.

To this point, we have examined the current recommendation of the TIP system and generated an example user scenario. The five requirements user profile, context of a user, context of sight, user's travel history and similarity to other users as well as similarity to this user's feedback are set up. In the next two sections, existing tourist information systems and recommendation systems are examined and compared to these five requirements.

3. State of Art in Tourist Information Systems

In this section we analyze existing tourist information systems. We conduct an investigation on five tourist information provider systems as well as the TIP system. The study compares these systems to the five requirements (R1–R5) which are key factors to build a recommendation component in a mobile tourist information system

There are several tourist information systems implemented by various groups of researchers. This investigation aims to examine the employed techniques and their functions provided to the users. These systems are analyzed for their information delivery and their recommendation function compared to the five requirements defined in Section 2. We first describe each of the system then show the result of our analysis.

3.1 Overview of Tourist Information Systems

- a) **GUIDE** [5] – The GUIDE system is an electronic context-aware tourist guide providing information to city visitors while they are traveling around the city of Lancaster, the U.K. A user interacts with the system via a hand-held device the Fujitsu TeamPad 7600. The system utilizes a high-bandwidth, cell-based, wireless infrastructure which support interactive services and highly dynamic information such as accessing to the web. The user can retrieve web-based information based on his current location as well as create a tailored tour of the city to explore and learn about the city in his own way. He also can access interactive service such as book a seat in a restaurant for dinner and sends message to other users or to the staff of the tourist information center.

- b) **Tourist Guide** [15] – The Tourist Guide system is a location based tourist guide application for the visitors to both the Mawson Lakes campus of the University of South Australia and the North Terrace precinct in the Adelaide city center. The system is implemented in Compaq Aero a pen based mobile computing device which is augmented with Global Positioning System (GPS). The system provides three modes of operation: map mode, guide mode, and attraction mode. The map mode is to let the user know where they are in

relation to the other tour attractions. In the guide mode, a trail is marked on the map with an interesting related set of attractions. These attractions are shown up on the map in red. The attraction mode acts as a digital tourist guide, supplying users with sound, images and textual tourism information.

- c) **Cyberguide** [1] – The Cyberguide is a system proposed by the Future Computing Environments (FCE) Group within the College of Computing and the Graphics, Visualization and Usability (GVO Center) at Georgia Institute of Technology, Atlanta, USA. It is built up on the concept of ubiquitous computing focusing on mobile devices. The initial prototypes were designed to assist a visitor in a tour of GVU Center Lab during the GVU monthly open houses. The system is employed on the Apple MessagePad and it consists of four modules a map component, and information component, communication component and a position component. Combination of these four modes help users to interactively get information about each of the demos in display GVU lab based on their current location. At this point, though there is an attempt to build a Cyberguide prototype for outdoor use still the system focuses mainly on investigating context sensitive computing. So it is limited to support tourist information and recommendations.
- d) **CRUMPET** [13] - Creation of User-Friendly Mobile Services Personalized for Tourism is the EU funded research project. CRUMPET integrates four key technology domains and applies to tourism domain. The system combines personalized services, multi-agent technology, location-aware services and transparent mobile data communication altogether in order to facilitate their users. It is not only giving location-aware information about a user's destination but also providing individualized information and services to him. To manipulate the system a user provides their demographic information at the beginning. Then the system learns more specific user preferences while they are traveling and interacting to the system. To do this the system uses the current position of a user to specify the use's request. The system then filters relevant information. After that if the user is moving in a region this information is used as an index of for his interest to revise his user profiles. For instance if a user has visited a number of parks around the area he is perhaps interested in other parks or other forest.
- e) **AccessSights** [9] - Accessible Sightseeing is a multimodal location-aware mobile tourist information system. The system aims to provide tourist information to both normally sighted users and visually impaired people traveling in the garden. AccessSights consists of three modes: orientation phase, movement phase and information perception phase. 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. Voice signal is getting louder when user comes closer to the point.
- f) **TIP** [6] – Tourist Information Provider is an advanced tourist information provider developed in the University of Berlin. The system combines three knowledge the event notification service (ENS) location-based service (LBS)

and context-awareness in a mobile environment. It delivers different types of information about the sights to the user based on user preferences and their current location. The user defines their preferences when they first login to the system. The system keeps this user information as their user profile. The user dynamically interacts with the system by providing their current location while they are asking for information from the system. TIP also gives recommendation to their user based on the user's current position and information in their user profile. The user gets a list of nearby sights which they might like to visit if they request the system's recommendation.

3.2 Analysis of Tourist Information Systems

Table 1 presents the analysis of the information delivery in the above six tourist information systems and an investigation of the recommendation feature which are provided by these systems. Using CRUMPET and TIP version 1.0, a user needs to provide his personal information which is then kept as his user profile (R1). These two system attempts to match and provide information to their user based on what the user has defined in their user profile. CRUMPET proposes additionally to revise the user profile based on the user's current location and places they have visited. While the other three systems Tourist Guide, Cyberguide and AccessSights do not consider user profiles for delivering information, GUIDE seems to take this requirement into account. GUIDE identifies two broad classed of context which are personal and environmental context. Personal context includes the user's interests; the user's current location and attraction they have already visited. But no information about usage of the user profile is explained in the literature.

Apparently, all of the systems deliver information to the user based on user context (R2) whereas sight context (R3) is not taken into account for information distribution by two of them Cyberguide and CRUMPET. Cyberguide pays more attention to user context than sight context; this might be because the current prototype aims to use in the GVU lab. So there is no information on sight architecture or its opening/closing time involved. Sight context is not precisely defined in the literature about CRUMPET. User history (R4) is used to build a user model while a user is interacting with CRUMPET. The system asks the user to fill in their demographic information which is then used as a typical interest profile. After that, a user's current location as well as information about his visited sights are used together to complete his user profile. For instance if the user has visited three beaches around the area the system would infer that this user likes beaches and would revise his typical user profile.

Even though Cyberguide aims to take record of past locations of a user in order to enhance the service no clear evidence has been given in the literature to support this claim.

GUIDE takes user history (R4) as well as user context (R2) and sight context (R3) to give recommendation for nearby places of interest for their users. TIP version 1.0 considers only the sight context (R3) to recommend sights.

In summary, these six systems provide information via hand-held devices based mostly on the user's location. Most of them pay more attention on the context-awareness and location-based services for the information delivery. Only simple recommendation features have been provided in two out of six systems. None of them has considered taking all requirements (R1 – R5) for their recommendations.

System	Information Delivery based on					Recommendation based on					
	User Profiles (R1)	User Context (R2)	Sight Context (R3)	User History (R4)	Recommendations	R1	R2	R3	R4	other users' feedback (R5a)	this user's feedback (R5b)
Guide	(+)	+	+	+	+		(+)	(+)		-	-
Tourist Guide	-	+	+	-	-	-	-	-	-	-	-
Cyberguide	-	+	-	(+)	-	-	-	-	-	-	-
CRUMPET	+	+	-	+	-	-	-	-	-	-	-
AccessSights	-	+	+	-	-	-	-	-	-	-	-
TIP 1.0	-	-	+	-	+	-	-	+	-	-	-

Table 1 Comparison of six Tourist Information Providers on five requirements and detailed verification of the recommendation components they have provided.

Symbols: + System addresses a requirement.

(+)System indirectly addresses a requirement.

- System does not address a requirement.

From the above study, we concluded that there have been several attempts conducted by the researchers in order to provide mobile tourist information. Most of these systems concentrate on the user's context, for instance their location and their preferences for information delivery. Even if TIP and GUIDE systems have considered almost all of the five requirements for their information delivery, no advanced recommendation component is implemented yet. Consequently, a combination of the recommendation systems and the tourist information provider would be an appealing research area. Having such a system which provides the users with information they require at the right time in the right context would help these users to fulfill their information need while they are traveling. For inspiration about recommendation techniques we turn to the area of recommendation systems in the next section.

4. State of Art in the Recommendation Systems

In this section we conduct an investigation on recommendation systems. We start with a definition of recommendation systems and the three prevailing recommendation paradigms. Then we study five recommendation systems implemented in several areas such as book stores, music, web, movies, restaurants and tourism. After that, each system is evaluated regarding the five system requirements

defined in Section 1 and is also compared to the current recommendation component of the TIP system.

4.1 Definition of Recommendation System and Recommendation Paradigms

A recommendation system is any system which provides recommendation, prediction, opinion, or user configured list of items that assists the user in evaluating items [13]. Recommendation systems have been implemented and become prevailing especially in the E-Commerce. Many of the largest commerce Web sites, for instance Amazon, Levis, are already using recommender systems to help their customers find products to purchase [14]. Meanwhile investigations for effective recommender systems paradigms are still going on among several research groups. Most existing recommender systems have been developed based on the following three paradigms.

- *Content-based recommendation:*

This paradigm uses information about an item and a particular user's likes and dislikes to provide suggestions. This approach suggests items to the user based on a comparison between the items' content and the particular users' profile. So an item that is similar to what the user liked in the past is recommended to the user. It has the advantage of being able to recommend items which match the users' preferences without waiting until the items are rated by other users. Moreover, users with a unique interest can get their information even though what they like is different from others. However it is likely that the user is restricted to recommended items similar to what they have rated before [8, 11, 12].

- *Collaborative filtering:*

This paradigm bases recommendations on other users who have similar preferences to a particular user. Rather than work out the similarity between item and user preferences, this approach computes the similarities among the users. As it collects more ratings from more users, the possibility increases that someone in the system will be a good match for given users. Consequently, the users are not restricted only to items similar to what they preferred in the past. They will get broader information based on other people who have similar likes and dislikes. The shortcoming of collaborative filtering is that it must be initialized with a large amount of data, because a system with a small base of ratings is unlikely to be very useful. The system can be useful for a particular user when sufficient number of ratings on an item have been collected [4, 10]

- *Knowledge-based recommendation:*

This paradigm uses knowledge about users and products to follow a knowledge-based approach to generate recommendations. This approach does not depend on a base of user ratings nor gather information about a particular user. The user needs not to explicitly input their preferences at the beginning. The system lets the user browse through the information catalog using qualitative ratings as navigation aids. Because the user usually makes several navigation steps, then what the user interacts with in the system is implicitly collected as their preference information. Apparently, the knowledge-based recommendation neither needs user feedback nor their preferences. However this advantage is

hindered by a requirement for a knowledge engineering algorithm and that only one static suggestion one gained from the system [4, 5].

Each of these three recommendation paradigms mentioned above have advantages which would be practical to implement in some areas while their drawbacks would impede their implementation in others. The following section presents a closer look at five relevant recommendation projects. Some of them have applied a pure approach based on one paradigm while others have employed a mixture of two paradigms.

4.2 Overview of Recommendation Systems

To gain a more comprehensive overview of recommendation component for the TIP systems, five recommender systems and the TIP system itself have been investigated. These recommender systems have implemented the content-based method, the collaborative filtering method, the hybrid of the two methods or the knowledge-based method. Each system gives suggestions on different items books, music, web, movies, restaurants and point of interests for tourists. This variety of implementations would bring broader notions on advantages and disadvantages of the system which then will be used as guidelines for the enhanced recommendation component of the TIP system.

- a) **CBCF** [10] or Content-Boosted Collaborative Filtering is a framework for combining content-based and collaborative recommendations. To recommend a movie to an active user, this approach uses a content-based predictor to enhance the users' data by predicting their rating of the movies from their past rating profiles and then providing personalized suggestions through collaborative filtering using the predicted ratings. User ratings range from zero to five stars. Zero stars indicate extreme dislike whereas five stars indicate high praise. To avoid the drawbacks of sparse rating in collaborative filtering the system makes use of content-based prediction. If one user provides less rating information the system uses information from other users who have similar ratings but provide more information than that user to calculate their rating.
- b) **Fab** [2] is a recommendation system for the Web and has been operational since 1994. It is a distributed implementation of a hybrid content-based and collaborative system and is part of the Stanford University digital library project. There are three main components: collection agent, selection agent and the central router. The collection agent's profile represents its current topic while a selection agent's profile represents a single user's interests. Collection agents send web pages relevant to a number of topics to the central router. Each user receives pages matching their profile from the collection agents via the central router. Pages that are not seen by many users are regularly weeded out and the best one duplicated to take their place. When user has requested, received and looked over their recommendations, they are required to assign an appropriate rating from a 7-point scale. The user's ratings are used to update their personal selection agent's profiles as well as forwarded back to the originating collection agents. The collection agents then adapt their profiles in accordance with the users' rating. In addition, the users with similar profiles will directly get pages that are highly rated by other similar users.

- c) **LIBRA** [12] or Learning Intelligent Book Recommending Agent 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. The system uses a database of book information extracted from web pages at Amazon.com. A simple pattern-based information extraction system extracts information on title, authors, synopses, published reviews, customer comments, related titles and subject terms from book-description URLs of broadly relevant titles. The user selects and rates a set of books by providing a discrete 1 – 10 rating for each selected title. A user rating of 1 – 5 is interpreted as negative and 6 – 10 as positive. A machine learning algorithm, a bag-of-words simple Bayesian text classifier extended to handle a vector of bags is employed to learn and 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 send these to the system to improve the given recommendations.
- d) **MRS** [8] or Music Recommendation System provides personalized service of music recommendation. The system extracts a representative track for an individual MIDI music object. Then six features mean and standard deviation of the pitch value, pitch density, pitch entropy, tempo degree and loudness, are pulled out. These six features are then used to classify music into groups. The system provides both content-based and collaborative filtering methods as two separate functions to generate a recommendation. In the content-based function, a recommendation is given based on the recent interests of the user. The users' access history are analyzed to derive users' interest. Each transaction in the history archive of the user is assigned a different weight. The latest transaction has the highest weight. Moreover, the music group containing more accessed music objects in a transaction has weight than other groups in the same transaction. These weights are kept as a user profile. After calculating the weight of each music group, the MRS system ranks the entire music group. The music with greater weight takes a higher priority of recommendation. The collaborative filtering method also utilizes the user's access history but in a different view. This method derives the profiles of user interests and their behaviors from their access history. Users with similar profiles of interests and behaviors are identified as relevant users. To make a recommendation for a user, the weights of each music group associated with the relevant users in the same groups are averaged. These averaged weights are kept as associated preferences. The system calculates differences between the weights in a user profile and their associated preferences. A music group with negative or zero differences is not recommended to the user. Besides these two functions, the system proposes the other approach called statistic-based recommendations. When a user chooses the third recommendation method, the 'last' N tracks which this individual user has never accessed is given. Half of them are from the most common music objects in the access histories of all users and the other half are from the most popular music objects in the last five transactions in the access histories of all users.
- e) **FindMe** [3] is a knowledge-based recommender system. It aims to help people finding their items of interest for instance restaurants or movies, by providing a

guide search and search interaction. The technique used in FindMe system is called similarity retrieval. The user selects a given item from the source 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 based on the source and the top few candidates 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 heart of a FindMe system is similarity metrics and retrieval strategies. The similarity metrics determine what counts a similar when two items are being compared; retrieval strategies determine how important different aspects of similarity are to the overall calculation.

- f) **TIP** [6] – Tourist Information Provider gives recommendation to the user based on their current location and their defined user profiles. The system delivers the user a list of nearby sights which match the user preferences while it discards sights that do not meet the user profile.

4.3 Analysis of Recommendation Systems

Table 2 presents a comparison of these five recommendation system to the five requirements which will be used to develop the extended recommendation component of the TIP system. This analysis concentrates on which of the three recommendations paradigm is used in the system as well as which requirements are considered to provide a recommendation to the user. The '+' mark in the table indicates not only if the system employs this requirement but also a degree of influence to the recommendation system this requirement would have.

CBCF and Fab systems apply a hybrid approach which is a combination of the collaborative filtering and content-based recommendation methods. These hybrid systems attempt to incorporate the advantages while avoiding the disadvantages of both methods. Sparse ratings in collaborative filtering recommendation can be filled by user information gained by the content-based method. As a result a user of the collaborative filtering system who has specific preferences can get recommendations even though the system may not be able to find any similar users for him. Meanwhile, a user of the content-based recommendation is no longer restricted to get only information that meets their preferences. He will also get information that other similar users preferred. The LIBRA system implements the content based recommendation paradigm. It employs information extraction and machine-learning algorithm on text categorization to create recommendations. MRS does not apply a hybrid approach but provides three separate modes for recommendations: content-based recommendation, collaborative filtering and statistic-based recommendations. FindMe provides a guided search and search interaction to its users. The system lets the users browse through the catalog using qualitative ratings as navigation. It is therefore considered to employ the knowledge-based recommendation paradigm similar to the TIP system. Consider these systems on the five requirements, despite the TIP system the other five recommendation systems do not yet focus on providing recommendations in a mobile environment. All of them are implemented as Web applications. Therefore none of the five systems utilizes user context (R2) and sight context (R3) for their recommendations. Furthermore, each system defines their user profiles (R1) differently. In CBCF and LIBRA user profiles contain users' past ratings. User profiles of Fab are additionally updated in accordance with ratings given

System	Recommendation based on					
	Knowledge-based				Collaborative Filtering	Content-based
	User Profiles (R1)	User Context (R2)	Sight context (R3)	User history (R4)	Similarity to other users' feedback (R5a)	Similarity to this user's feedback (R5b)
CBCF	+	-	-	++	++	++
Fab	+	-	-	-	++	++
LIBRA	+	-	-	++	-	++
MRS	+	-	-	++	(++)	(++)
FindMe	+	-	-	-	-	(++)
TIP 1.0	-	-	++	-	-	-

Table 2 Comparison of five recommendation systems on five systems for the extended recommendation component of the TIP system. The TIP system is included in the table to indicate what approach has already been implemented in the system itself.

- Symbols:*
- + System addresses a requirement.
 - ++ System addresses a requirement and the recommendation is truly influenced by the requirement.
 - (++) System indirectly addresses a requirement but the requirement has strong impact on the recommendation.
 - System does not address a requirement.

by the user. The MRS defines its user profiles on the users' access history whereas FindMe collects users' preferences and builds users' profiles from user interactions. CBCF, LIBRA and MRS create user profiles from users' past access to the system or their past ratings so user history (R4) has strong influence for their recommendations. However, Fab, FindMe and TIP do not take user history into account for giving recommendation.

Similarity to other users (R5a) is crucial on the systems that employ collaborative filtering paradigm. The systems create groups of relevant users from their given feedbacks. So this requirement is definitely addressed in CBCF and Fab. MRS indirectly sets up groups of relevant users by prioritizing user access history. However the system recommendation definitely depends on this requirement. LIBRA, FindMe and TIP do not consider similarity to other user for their recommendations.

Users are required to explicitly give their feedback (R5b) in CBCF, Fab and LIBRA. Fab utilizes these feedback to update user profiles while CBCF and LIBRA predict rating score of a particular user from there past feedbacks. Since MRS and FindMe generate user feedbacks from users' past accesses to the system, their users need not to provide explicit feedback.

In summary, these recommendation systems have encountered shortcomings of their implemented recommendation paradigms. Several attempts have been made to fix the problems. However, it seems that they could not solve one without creating another. Although the five requirements have been addressed in these

recommendation systems, none of the systems have taken all of them to generate recommendation yet.

Up to now, we have presented the definition of the recommendation and introduced the three recommendation paradigm the content-based recommendation, the collaborative filtering and the knowledge recommendation. From the above study, research projects concerning recommender systems are still searching for an approach to decrease the drawbacks as well as promote the advantages they have found in the implementation of each of these three paradigms. None of these recommendation approaches have been used in the environment of a mobile tourist information system.

5. Recommendation Models for the TIP System

To this point, we have identified the requirements for implementing a recommendation component in the TIP system. We conducted studies of tourist information systems and recommendation systems in Section 3 and 4. The next step is to define recommendation models that are applicable in the TIP system. In this section, we propose several of recommendation models based on the idea of providing personalized suggestions to a user. Some of these models will be selected for implementation as example models in the TIP prototype.

5.1 Approaches for the Recommendation Component of the TIP System

As we have found in our studies in Section 3 and Section 4, while the recommendation systems are trying to find a flawless recommendation approach, the tourist information systems are focusing on an accurate user location, easy to use user interface and appropriate hand-held devices. Therefore, no recommendation function has been fully implemented in tourist information systems yet. In this section we will propose recommendation models for the TIP system.

Considering possibilities of combinations of application requirements, recommendation approaches and the existing recommendation component in the TIP system, we propose the recommendation models in the following approaches.

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

- A1. Content-based Recommendation: this approach gives recommendation based on a particular user's feedback (R5b). Sights similar to what they liked in the past are recommended.
- A2. Collaborative Filtering Recommendation: this approach recommends sights that users liked which are similar to a particular user. This information based on their previous feedbacks (R5a and R5b). Sights that these similar users like are recommended.
- A3. Knowledge-based Recommendation: this approach recommends places based on sight context that are semantically-related to what this user has visited in the past (R2 and R4). For instance, a user gets recommendations about further beaches after they visited two beaches.
- A4. Must-see sights: this approach recommends places that are the point of interests in a particular area e.g. sky tower in Auckland.

- A5. Nearby sights: this approach takes users context, sight context and user history into account (R2 and R3 and R4). 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 profile (R1).

Compound approaches – These approaches use combination of base data as input for recommendation method. They combine A5 and A6, and extend A6 by this user's feedback (R5b) or other users' profile information (R1) and feedback (R5a)

- B1. Nearby sights and user profile: this approach extends approach A5 by filtering the results of A5 according to a particular user's profile before giving recommendation. The user is required to explicitly define their preferences when they first register to the system.
- B2. Revise profile: To recommend up-to-date things to this user, their profile (R1) may be revised according to their feedback they give to the system (R5b).
- B3. Extend profile: This approach gives recommendations on sights that match this user's extended profile. The user's profile is extended using information about other users. After establishing a group of similar users, information in their profiles is added to this user's profile.

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 principle of content-based recommendation but the user need not to explicitly give their feedback to the system. Their feedback is created from the information in their user profile (R1) and the information on what they have done in the past which is recorded in their user history (R4).
- C2. Content-boosted Recommendation – is a combination of the content-based recommendation and the collaborative filtering. If feedbacks given by this user are not yet enough, the dataset for collaborative filtering is extended by simulating missing user feedbacks based on the feedbacks of other similar users. This approach is proposed in [10].
- 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 prefer 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 approach uses content-based recommendation based on this user's feedback (R5b) that are recorded according to sight context (R3) and user history (R4). The user needs not to explicitly give their feedback to the system but it is created from the information in their user history (R4) and the sight context (R3).

C5. User information and feedback: this approach takes user profile (R1), user context (R2), sight context (R3), user history (R4) and their feedback (R5b) to verify recommendation to a particular user. However user context may or may not be considered.

Extended Knowledge-based approach – This approach use extension to the knowledge based of the system with other information sources.

D1. Supplementary Sight Context: this approach updates sight context according to the feedback of the users (R5a and R5b). Recommendations are given based on the information stored about the sights, e.g. the semantic groups they belong to. Feedback of user given about the sights may create new groups.

Extended Collaborative Filtering approaches – These approaches extends the data set used for collaborative filtering.

E1. User profile: this approach assumes that the users like items that match their user profile (R1). Therefore if no feedback (both R5a and R5b) is available from the number of users, the feedback is simulated by creating positive synthetic feedback data based on the user's profile. These synthetic feedbacks are then used as input for collaborative filtering.

E2. User history: this approach is similar to E1. Synthetic feedback is created based on the information in users' histories (R2).

E3. User profile and user 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 user profiles (R1) as well as their user histories (R4).

We have classified recommendation models for the TIP system into five major approaches as mentioned above. Selected approaches from the list are chosen to be applied as example models for TIP recommendation component. The next section describes the selected approaches in more detail.

5.2 Example models for TIP Recommendation Component

To prove the concept, the six approaches A2, A3, A5, A6, B1, and C5 have been selected to implement as example models for the recommendation component of the TIP system. We now describe the concept of the implementation and give more detail in the next section.

- **Collaborative Filtering Approach (A2)**: In this approach, user's feedbacks, which are known as ratings for the sights they have visited, are collected. The rating score from one to four gives negative impressions whereas rating score from seven to ten indicates positive impressions. Rating scores five and six shows the users' indifferent opinions. Other users who share the opinions or have the same taste can use this user feedback to better decide which sights to go to. The approach uses two steps: first identify similar users and then recommend sights that similar users liked.

We will use a pure collaborative filtering component that uses a neighborhood-based algorithm similar to the one in [10] for the identification of similarities. The approach can be summarized into the two following steps:

1. A subset of users is chosen based on their similarity to the current user. These users are considered to be the current user's neighbors. Similarity between two users, a and u , is computed using the Pearson correlation coefficient $P_{a,u}$ defined in the following equation:

$$P_{a,u} = \frac{\sum_{i=1}^m (r_{a,i} - \bar{r}_a) \times (r_{u,i} - \bar{r}_u)}{\sqrt{\sum_{i=1}^m (r_{a,i} - \bar{r}_a)^2 \times \sum_{i=1}^m (r_{u,i} - \bar{r}_u)^2}} \quad (1)$$

Where $r_{a,i}$ is the rating given to sight i by user a
 \bar{r}_a is the mean rating given by user a
 m is the total number of sights

As it is explained in [17], the correlation coefficient measures the strength of a linear relationship between two variables (i.e., the similarity between the users' feedback). It is always between -1 and +1. A typical interpretation of the correlation is as follows:

- -1.0 to -0.7 strong negative association
- -0.7 to -0.3 weak negative association
- -0.3 to + 0.3 little or no association
- +0.3 to + 0.7 weak positive association
- +0.7 to +1.0 strong positive association

According to the interpretation above, in users who have correlation coefficient greater than or equal to 0.7 are considered to be the login user's neighborhood this implementation.

2. A weighted combination of these neighborhoods' rating is used to produce recommendations for the current user. Equation 2 is used to calculate the predicted feedback score $P_{a,i}$ of the current user for a given sight.

$$P_{a,i} = \bar{r}_a + \frac{\sum_{u=1}^n (r_{u,i} - \bar{r}_u) \times P_{a,u}}{\sum_{u=1}^n P_{a,u}} \quad (2)$$

Where $P_{a,i}$ is the prediction for the login user for sight i
 $P_{a,u}$ is the similarity between user a and u
 n is the number of users in the neighborhood.

Our recommendation component prototype filters sight information using the user id and the user's current location. The current user's neighborhood is created by calculating Pearson correlation coefficient from the feedbacks or ratings they have given to their visited sights as mentioned in Equation 1. Those users who have coefficient equal to 0.7 or more are considered to be neighbors of the current user. The predicted feedbacks for the current user are calculated using Equation 2. The sights that have a predicted feedback score greater than or equal to seven are recommended to the current user.

- **Other pure approaches**

- A3:** Recommend sights that are semantically-related to the sights this user has visited in the past (R2 and R4) as used by TIP version 1.0

- A5:** Recommend nearby sights based on user context (R2), sight context (R3) and user history (R4). In this approach we recommend sights based on the user's current location and their past visits information. Sights which are located near the current user's position and the user has not yet visited are recommended.

- A6:** Recommend sights which match this user's profiles. In this approach we recommend sights that are in the same types as defined in the current user's profile.

- **Compound approach B1:** Recommend nearby sights which match a user's profile. The user is required to define their interest when the first register to the system. This approach combines A5 and A6. Nearby sights which are in the same types as defined in the current user's profile and have not been visited by the user are recommended.

- **Extended Content-based approach C5:** This approach take all requirements (R1 and R2 and R3 and R4 and R5) into account for giving recommendation. Other nearby sights, which are in the same type as the sights that the current user has visited and given high feedback scores, are recommended.

In this section, we proposed and classified applicable approaches for the recommendation component of the TIP system in five major groups. The six approaches A2, A3, A5, A6, B1 and C5, have been selected to be implemented in the TIP system as the example models as a proof the concept. The implementation and analysis on these example models are described in the next section.

6. Implementation and Analysis of Example Recommendation Models

This section describes the implementation and analysis of six sample models selected from our list of recommendation models introduced in Section 5. We begin with a brief explanation of the technical details of the TIP system and the test data which we use in this study. We then show in detail the effective use of the

implemented methods through demonstrations of the advanced recommendation models in use.

6.1 Extended TIP System

The TIP system is implemented using the central database approach. The PostgreSQL object-relational database management system and the Java Servlet Technology have been used in the implementation. Jakarta Tomcat 5.0.28 is deployed in order to work as a special servlet engine for the Java servlet technology. The java version 1.4.2.06 Standard Edition is used. Furthermore, the database is PostgreSQL 7.3.4 with a postgis 0.7.5 extension for the spatial or the location coordinator part of the database. For more detail on TIP refer to [7, 10]

The recommendation component has been implemented in Java. For interaction with user we use JSP to build our user interfaces. For capturing user feedback we extended the TIP database by the two tables ‘user_rating’ and ‘mean_rating’. These two tables are rather simple so we do not explain them in a technical detail.

6.2 Test Data

We initially planned to test our example models by using either New Zealand tourist information as we have described in our example scenario in Section 2 or information of the university’s campus area. However, the collection of New Zealand related data is still underway. We therefore decided to use the existing data set for sights in Berlin, Germany. The input of GPS data is simulated by direct insertion of the required data in the user interface and the database.

As introduced earlier, sights in TIP are grouped into semantic clusters of sights or types which are collection of sights that have some characteristics in common. Therefore, there could be clusters of sights that have the same architecture and/or clusters of sights that are close to each other. We use example of clusters that have been built in the TIP system:

- Sights of the same class in a certain area for instance all Cathedrals in Berlin Mitte.
- Sights of the same class having the same value in attribute ‘century’ such as all Cathedrals built in the 18th century
- Sight that have the same value for attribute ‘street’.
- Sight that that are of the class ‘building’ and have the value of attribute year in common.

Figure 6.1 shows a map of example sights data used to test the recommendation component.

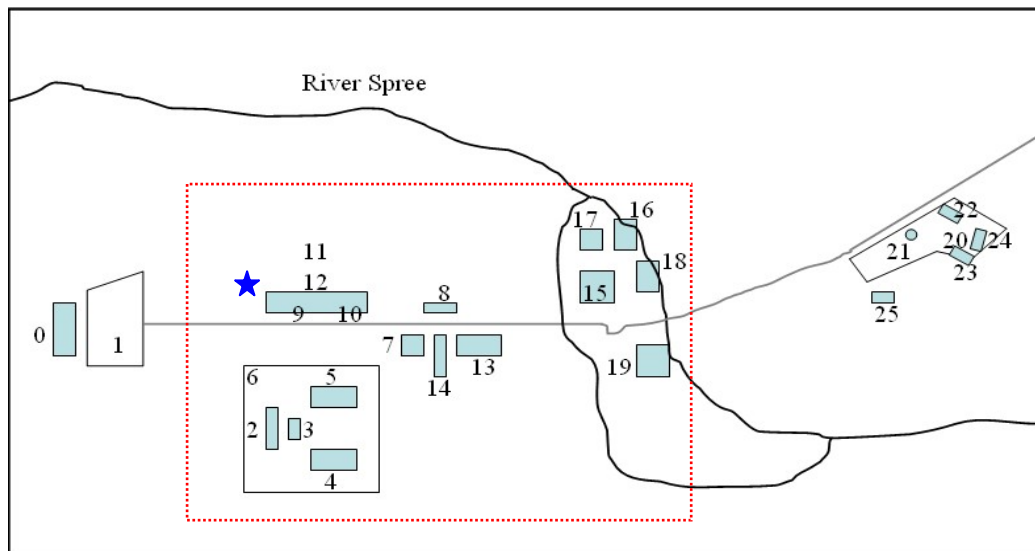


Figure 6.1 An Abstract Map of Example Data Sights. The dashed square describes our area of interest for this section.

The following types of sights are used in our test scenario. The numbers in parenthesis refer to the number of sight in Figure 6.1.

- **Cathedral** : Deutscher Dom (4), Französischer Dom(5), Berliner Dom(18), Nikolaikirche(25)
- **Palace** : Humboldt Universität zu Berlin(12)
Prinzessinnenpalais(13), Kronprinzenpalais(14)
- **Sculptor** : Schillerdenkmal(3), Mommsendenkmal(9),
Humboldtdenkmal(10), Helmholtzdenkmal(11)
- **Square** : Pariser Platz(1),Gendarmenmarkt(6), Lustgarten(15)
- **Modernbuilding** : Palast der Republik(19),Berolina Haus(22),
Alexanderhaus(23), Haus des Lehrers(24)
- **Tower** : Fernsehturm(21)
- **Gate** : Brandenburger Tor (0)
- **Misc Monument** : Weltzeituhr(20)
- **Educational building** : Pergamonmuseum (17), Alte Nationalgalerie(19)

6.3 Analysis of the Implemented Models

For clarity, screen shots of the implementation of the example models are captured from a personal computer (PC) instead of a mobile phone. The coordinates, which have been assigned to the test sights, are used to simulate the signal of the real GPS data in this test setting.

Now we need to get back to our scenario in order to see if implementation of these example models would satisfy Daniel, our current user. Daniel has already defined his interests to the system when he first registered. This is to let the system knows what he is interested in so that the system can provide him with personalized information. Daniel defined in his profile that he is interested in cathedrals and churches, modern buildings, sculptures in general and square as shown in Figure 6.2. He also informed the system about the type of information regarding the sights he is interest in so that he does not receive all available sight information but only selected ones. In general, the system would present a picture of the sights as well as some general information.

Daniel can ask for more detail, for example, the architect who designed the building, the history of the cathedrals, the art style of the monument or the architecture of the sights.

Figure 6.3 illustrates the five topics regarding sight information which Daniel can choose in TIP.

Daniel started his travel track in Mommsendenkmal, indicated by the star sign in the map. He sent his location to the system. From this point he can give his impression of this sight as feedback to the system or he can ask for recommended sights from the system. Daniel decided to give his feedback about the Mommsendenkmal (see Figure 6.4). Rating score ranges from 1 to 10 can be selected from a drop down list. The system keeps the selected score and additionally calculates an average of the feedback scores he has given. Daniel was fairly impressed by the sight history so he selected 10 as his feedback score for the Mommsendenkmal. Figure 6.4 illustrates user rating score which can be given to the user's current visit sight.

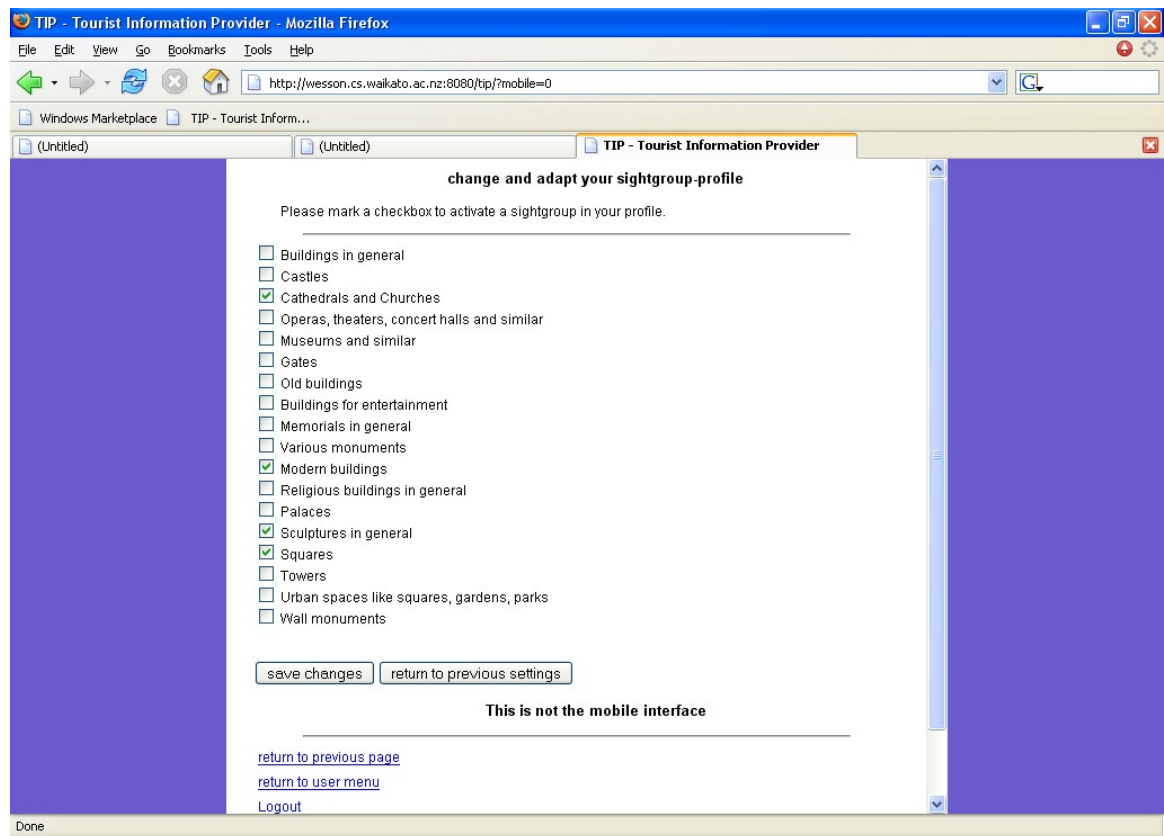


Figure 6.2 Daniel's user profile regarding sight types.

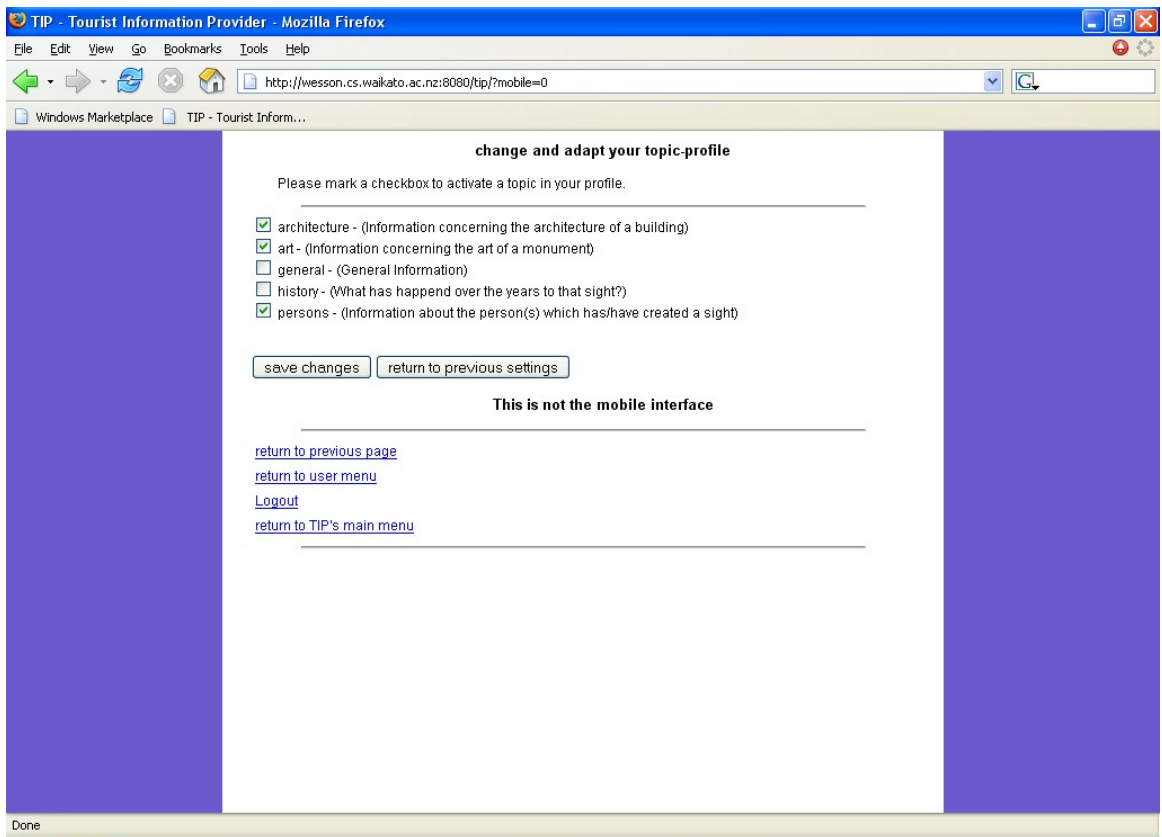


Figure 6.3 Daniel’s user profile regarding information topics

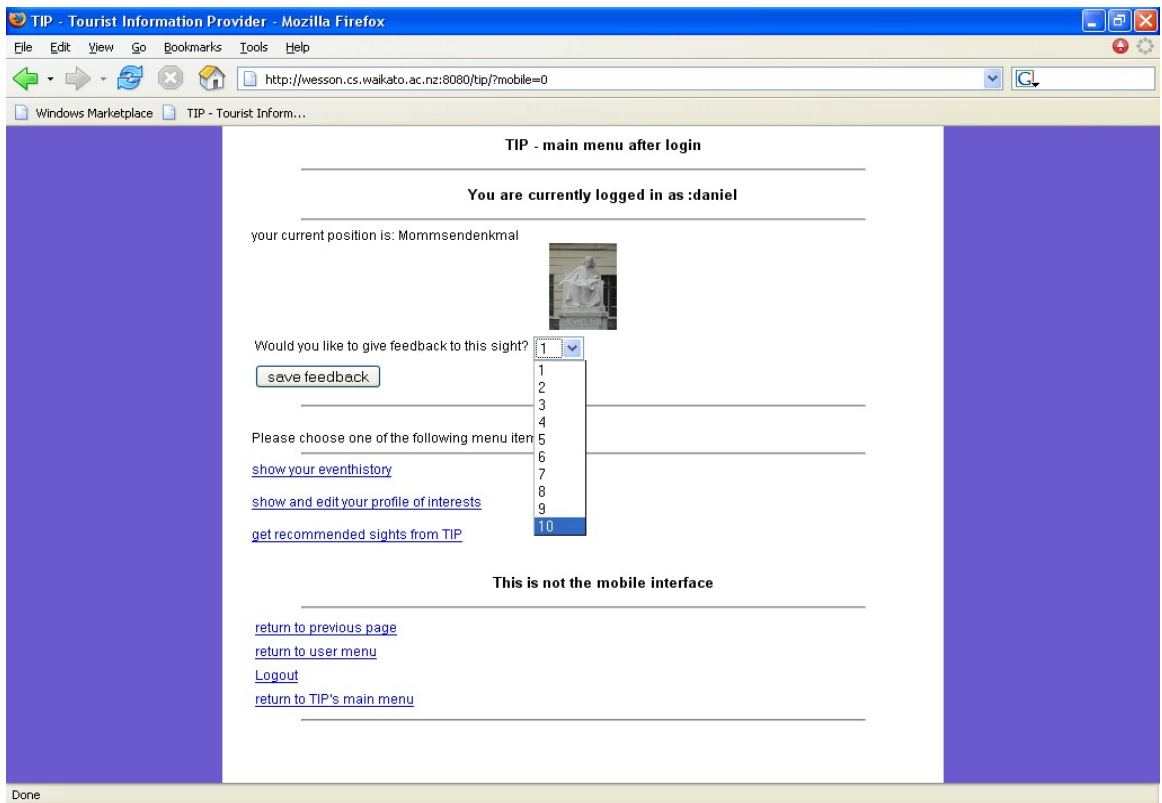


Figure 6.4 Daniel’s user rating page for the Mommssendenkmal

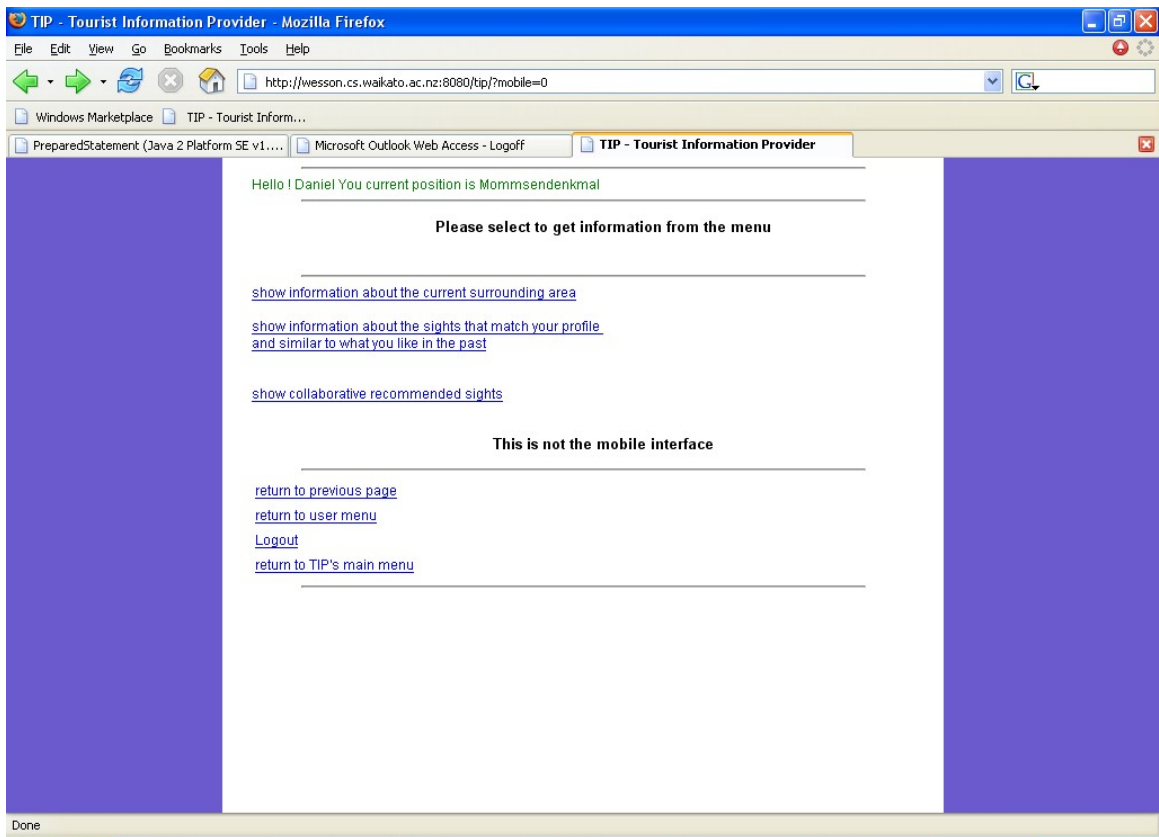


Figure 6.5 Screen for three recommendation methods

Daniel then decided to receive recommendations about sights. In TIP, we have combined the six selected example models A2, A3 A5, A6, B1 and C5 into three recommendation options in the TIP prototype. Hereafter, each of these three options is explained.

Daniel clicked on ‘get recommended sights from tip’ to get recommendation for sights he might interest to visit, he had three options to choose as shown in Figure 6.5. He first decided to get recommendation on sights which are not far from his current location and match his preferences. So he chose ‘show information about the current surrounding area’. In this test setting we define sights that are located no farther 1 kilometer from the current user’s position as nearby sights which can be changed later on. The system took his current location position as well as information he has registered in his user profile. Then the sight information was filtered and a list of matching sights was returned to him.

Consider our area of attention indicated by a dashed rectangular in Figure 6.1; Daniel was traveling at sight number 9 indicated as star sign in the map. When he selected this recommendation option, his current positions together with information about sights he is interested in defined in his user profile are used to filter sights information. The following recommended sights are given to him as shown in Figure 6.6.

- Cathedrals and churches: Deutsche Dom (4), Französischer Dom (5) and Berliner Dom (18)
- Sculpture: Humboldtdenkmal(10) and Helmholtzdenkmal (11)
- Square: Gendarmenmarkt(6) and Lustgarten(15)

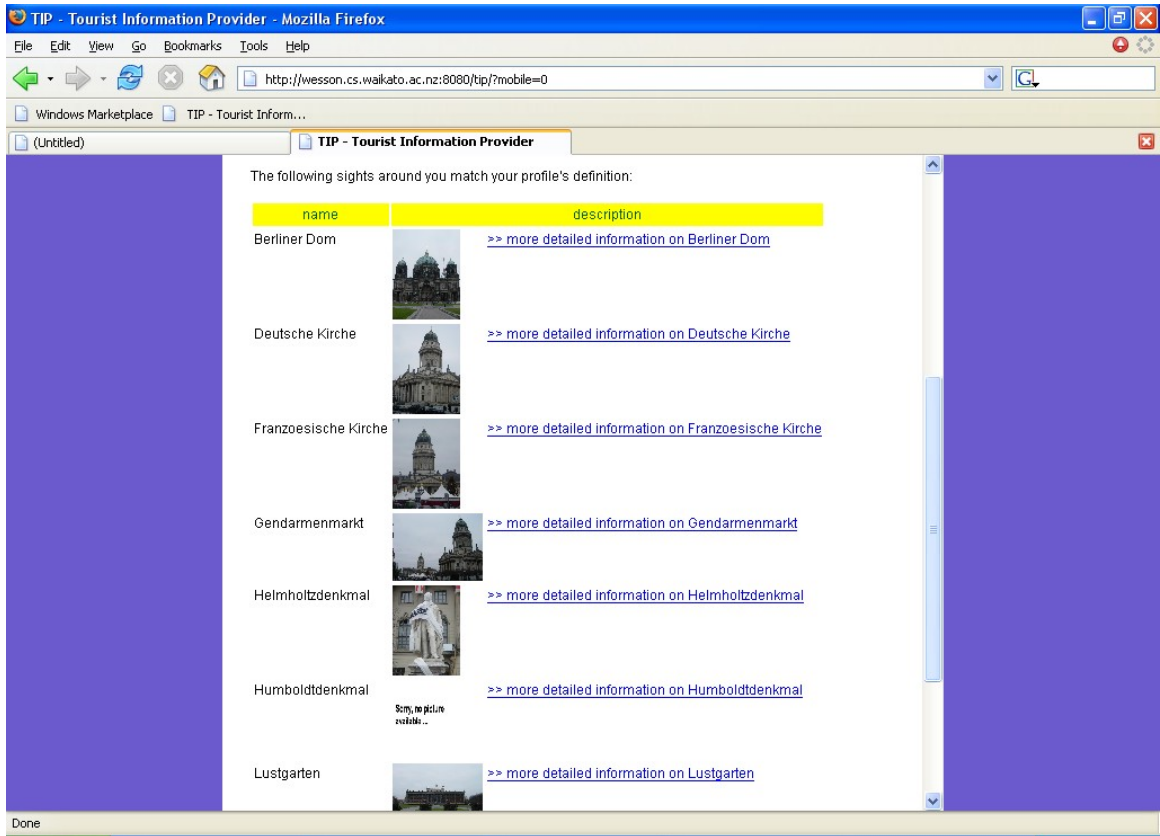


Figure 6.6 A list of nearby sights that Daniel might be interested in

On one hand this approach is very effective because all places he might want to go around this area were suggested. On the other hand, we can obviously see that he would be overwhelmed by a number of recommended sights he got from the system. The number of match sights would be more than seven if he is also interested in other sight groups for instance Palaces because there are two palaces Prinzessinnenpalais(13) and Kronprinzenpalais(14) located near his current location as well. In addition, Daniel might not like some of the sights. Therefore this option could turn to be overwhelming and irritating.

The next recommendation option is proposed to prevent too much information to be selected while matching his favorites (see Figure 6.7). The second option brings his ratings given to his past visit sights into account. Consequently, the system combines his current position and positive rating scores (≥ 7) given to sights in his preferred sight groups and then filters sights that are in the same group and nearby.

This approach is created based on assumption that when people like a particular place they might want to see more similar places. Daniel has visited Pariser Platz (1) and Deutsche Dom (4) before he was at the current position. He liked these two sights so he gave 9 and 10 as his rating score. He later on requested recommended sights from the system by clicking on the second option ‘show information about the sights that match your profile and similar to what you liked in the past’. A list of other two nearby cathedrals, the Berliner Dom (18) and the Französischer Dom (5) as well as the other two nearby square the Lustgarten (15) and the Gendarmenmarkt (6) is given.

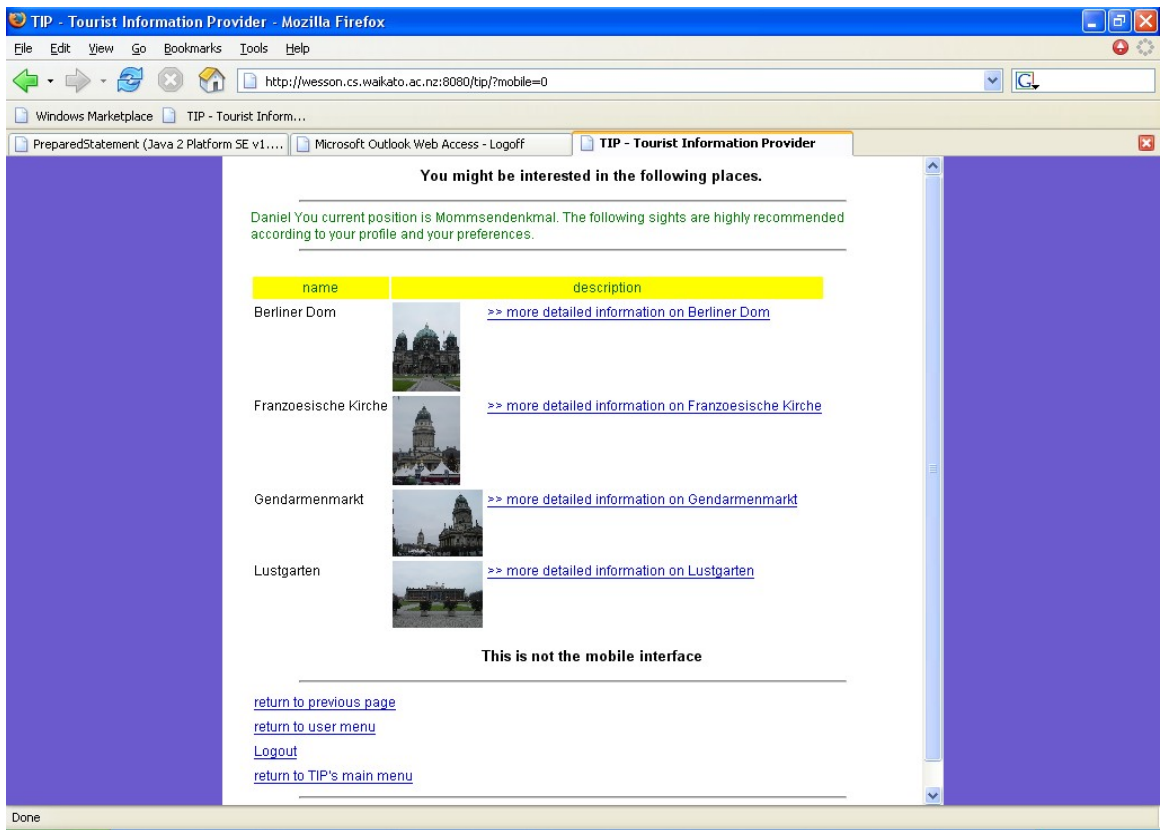


Figure 6.7 A list of recommended nearby sights that Daniel gave high score to other similar sights in the sight group

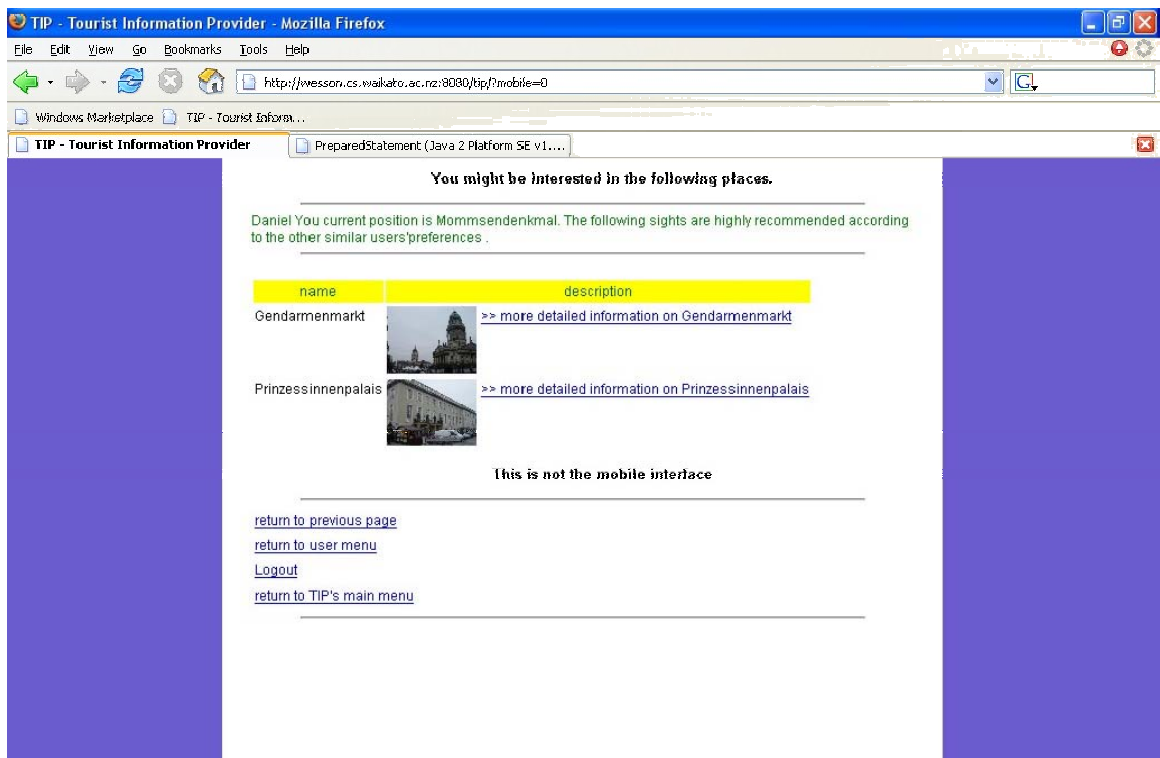


Figure 6.8 The result list of Collaborative Filtering Recommendation option

This approach solves the problem of having too many sights in the returned list because it discards sight groups that the user did not impress in their past visits. However, if Daniel has not either visited any of the sights in the sight group or has forgot to give his positive rating to any of them in his past visits, these ‘must be recommended’ sights are mistakenly discarded by the system. It seems that the second option cannot fully fix the drawback of the first option. Moreover, the user profile used in the filter mechanism of these two options could lead the system to give too restricted information to the users. Because the user will not get any attractive sights which do not match their user profiles, but they might be interested in.

According to these shortcomings, the third option of the recommendation component is to apply collaborative filtering to recommend sights (Figure 6.8). This is to give the users an opportunity to get some sights that they do not define in their user profile but they might like to have a visit. The system calculates the Pearson correlation coefficient of each user in the database and determines the neighborhoods of similar users to the current user. Sights which have been visited and liked by these users are then recommended to the current user.

Let’s get back to our scenario, in order to get collaborative filtering recommendation Daniel selects ‘show collaborative recommended sights’ from the recommendation menu. The result list returned by the system is shown in Figure 6.8. Daniel is suggested to visit nearby square the Gendarmenmarkt (6) and nearby palace the Prinzessinnenpalais (13) which are the sights his neighbors like most. This approach fixes the drawback of restricted sights given by the system. Though he did not define that he likes palace, the system assumes that he might want to visit the Prinzessinnenpalais because the other similar users have given high score to this sight. This approach could be followed if no similar exists or if too little feedback was given.

From our practical analysis based on the example scenario mentioned above, we have found that each approach has its restrictions. For instance, users might be overwhelmed by the sights information recommended based on their user profiles if they have defined many sights of interest. Sight information given based on their user feedback is controlled by their positive score. So it is possible that these users would miss a chance to visit other sights in this sight group they might like. Furthermore, to get sight information that other similar user like requires a number of similar user as well as their given ratings.

In summary, though the three proposed recommendation methods use all identified system requirements (R1- R5), we have found that they still have some drawbacks which are challenging to manage. This is because the practicality of each recommendation approach strongly depends on the availability of the system requirements R1 – R5. For instance, option three of the implemented approaches - the collaborative filtering method - relies heavily on users’ feedback while option one depends and two strongly depends on user profile and user feedback. Therefore, we proposed that the system should utilize a combination of system requirements (R1- R5) and methodologies in order to provide good quality recommendations.

7. Conclusion

In this section, we first summarize what we have accomplished in this project. Then we suggest future work in this area.

7.1 Summary

This report describes the concept of an advanced recommendation component in the Tourist Information Provider (TIP) system.

As motivated in detailed in Section 1, mobile technology is getting more involved in our daily life. Taking pictures, sending or receiving e-mail or booking movie tickets could be done via a tiny mobile phone. We are no longer consuming static information instead we are interactively exchanging the information. In the tourist environment where people usually relocate themselves and acquire sights information, this issue is getting more important. The TIP system is one of several tourist information providers created to contribute sights related information to the users. What we have found appealing in the system is TIP provides not only sights information but also giving recommendation regarding nearby sights which match the users' preferences. However the implemented recommendation approach may or may not agree with the users' requests.

Focusing on providing sights recommendation to the users in TIP, we generated the example scenario in Section 2. In this scenario, the two tourists are visiting Whitianga city, in Coromandel Peninsula, New Zealand. These users' interactions with the system lead to the definition of five requirements needed to take into account for providing recommendations.

- *Requirement 1* – user profiles specifies information of interest of the users.
- *Requirement 2* – user context specifies the users' current location, time, weather as well as their means of traveling.
- *Requirement 3* – sight context contains information of groups of sights that have certain feature in common for instance located on the same street or having the same architecture.
- *Requirement 4* – user travel history contains information of the users' visits which includes places, time and locations.
- *Requirement 5* – similarity is identified in two forms. One is similar to other users and the other is similar to what this user liked in their past. Similarities are retrieved from user feedbacks given to their visited sights.

In Section 3, we have conducted the study on six tourist information provider systems including TIP. We again compared these systems against our five system requirements. The result is that these systems have provided information via hand-held devices based on mostly the user's location. Most of them pay more attention on the context-awareness and location based services so they have tried to accurately locate the user current position and give them information. None of them have considered taking all our five system requirements (R1 – R5) for their information providing and only simple recommendation feature has been provided in two out of six systems.

Investigation on the definition of the recommender system and five recommender systems have been conducted in Section 4. We have analyzed the three main

recommendation paradigms. Content-based recommendation uses information about an item and a particular user's likes and dislikes to provide suggestions. Collaborative filtering bases recommendation on other users who have similar preferences to a particular user. Knowledge-based recommendation uses knowledge about users and products to track a knowledge-based approach to generate recommendations. We then examined five recommender systems and TIP against the five system requirements we have come up with. These five recommenders have been implemented based on the three paradigms in several areas books, web, music, movies, restaurants and points of interests for tourists. The examination result is that these systems have not taken all of the five requirements into account for recommendation yet. The researches on recommender systems are still on going to combine the advantages of each paradigm and get rid of their shortcomings in order to find out a complete system.

To implement an advanced recommendation feature in the TIP system, we find it necessary to enhance the existing tourist information provider with a recommendation system that follows the five system requirements. Consequently, we propose a list of applicable approaches for recommendation models in Section 5. These approaches are grouped into five main recommendation models for TIP system.

- *Pure Approaches* – These approaches are direct implementations; they form the basis for further combinations of data sources and recommendation methods.
- *Compound approaches* – These approaches use a combination of base data as input for the recommendation methods.
- *Extended Content-based Approaches* – These approaches use combinations of the content based recommendation method with other information sources.
- *Extended Knowledge-Based Approaches* – This approach uses extensions to the knowledge based of the system with other information sources.
- *Extended Collaborative Filtering Approaches* – These approaches extend the data set used for collaborative filtering.

As a proof of the concept, we implemented approaches A2, A3, A5, A6, B1, and C5 as example models for recommendation component of TIP system. Screen shots shown in Section 6 describe the analysis of the implementation of these selected models. In this implementation, we did the tests on a personal computer by simulating the signal of the real GPS data from the coordinates which have been assigned to the test sights. Since collecting tourist information about New Zealand in TIP is still undergoing we used the existing database of TIP relating to sights in Berlin. In this implementation, the system used all identified system requirements for recommendation (R1-R5).

Table 3 extends Table 1 to compare the new version of the TIP system after example recommendation models have been implemented to other recommendation systems and TIP version 1.0.

In our test scenario, when a user arrives at some certain point based on his GPS data, he receives information about the sights he is facing. The given sights information depends on his user profile and his travel history. The user can give feedback about the sights which ranges from 1 to 10. The system provides three recommendation options which the user can select out of a list. A new page with recommended sights is given back from the system when the user requests recommendations. From the analysis, though the proposed recommendation methods

System	Recommendation based on					
	Knowledge-based Filtering				Collaborative Filtering	Content-based Filtering
	User Profiles (R1)	User Context (R2)	Sight context (R3)	User history (R4)	Similarity to other users' feedback (R5a)	Similarity to this user's feedback (R5b)
CBCF	+	-	-	++	++	++
Fab	+	-	-	-	++	++
LIBRA	+	-	-	++	-	++
MRS	+	-	-	++	(++)	(++)
FindMe	+	-	-	-	-	(++)
TIP 1.0	+	+	++	-	-	-
TIP 2.0	+	+	++	+	++	+

Table3 Comparison on TIP version 2.0 and other recommender systems and TIP version 1.0

- Symbols:*
- + System addresses a requirement.
 - ++ System addresses a requirement and the recommendation is truly influenced by the requirement.
 - (++)System indirectly addresses a requirement but the requirement has strong impact on the recommendation.
 - System does not address a requirement.

are theoretically promising to implement, practically they still have some drawbacks which are challenging to manage. This is because the practicality of each recommendation approach strongly depends on the availability of the system requirements R1 – R5. Therefore, the system is required to utilize a combination of system data (R1-R5) and methodologies in order to provide good quality recommendations.

7.2 Outlook

In this project, we proposed several recommendation methods. Selected methods were implemented. Future work on the recommendation component of the TIP system is to continue implementing approaches to find out more advantages and shortcomings from the implementation.

We have done some functional tests on the implementation of the example models; still we do need to conduct some qualitative test functions to confirm our test results. We also plan to test various combinations of different methods. Furthermore, our system strongly relies on information provided by the users. Consequently, privacy and trust about the data held on the user are crucial issues which need to be carefully considered.

In conclusion, most of the existing mobile tourist information systems provide only very simple recommendations. Our project is a first step towards advanced

recommendations in mobile tourist information systems. In our future study we plan to extend our initial work while considering privacy and trust issues.

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