

Proximo, Location-Aware Collaborative Recommender

Eoghan Parle and Aaron Quigley

UCD School of Computer Science & Informatics
University College Dublin
Belfield, Dublin 4, Ireland.
{eoghan.parle, aquigley}@ucd.ie

Abstract. Pervasive computing systems typically rely on a range of context data, from user preference and interaction through to the sensed environment. In Proximo we propose an approach to combine a collaborative recommendation system, with location-aware technology to provide personalised, dynamic and domain-driven paths through work and social spaces. For our purposes, context includes user preferences, current location, importance measures for digital artifacts and a community of other users' measures. We report on an ethnographic study of two art galleries, the architecture of a privacy-centric proximation and recommendation system, an exploratory user study and results from a gallery tour application.

1 Introduction

The selection of relevant information for a person is constrained by the ability of the system to determine that person's context. Typically we provide *explicit* "context" through preferences, selection or search criteria. Examples of implicit actions (context) include selecting a particular file or opening a specific website. Context includes information from the sensed environment (environmental state) and computational environment (computational state) which is provided to alter an application's behavior in relation to the context. However, the context for ones human computer interaction includes *implicit context* in addition to users interactions and their peer's (within a given community) interactions.

Context-aware computing aims to leverage the entire gamut of physical and digital interactions people and their peers have with computer systems. A major factor for systems that are context-aware is the ability to know users' location as this dictates much for the systems understanding about current activity. However, location is but one small part of a context-aware system. We propose Proximo; a system that merges location-aware computing and recommendation techniques to create socially minded applications (guides) for use within buildings such as museums, art galleries or hospitals.

2 Background

One aspect of context aware computing is *location-awareness*. Location or positioning systems operate within a clearly defined area of operability with a resolution and performance usually defined by the characteristics of the technology supporting the system. Location-aware applications include finding services such as printing or telephones or tracking individuals [2,11,16]. Here we would like to focus on systems that support context-aware use within buildings such as museums, art galleries or hospitals.

A range of approaches to indoor location use specially designed infrastructure. These include approaches using Infrared in the Active-Badge [8], 802.11 RADAR [5] and RF/Ultrasound in Cricket [6]. Each approach can locate a user quite accurately within an indoor environment but would not work outside or in any area not fitted with a plethora of sensors. Approaches such as BlueStar [12] attempt to utilize existing infrastructures to realize indoor location-awareness (proximation). Location is deduced by handset/PDA-resident (mobile terminal) applications that have two sources of information, passive sniffing of existing wireless infrastructure (Bluetooth or 802.11b) and details of the local wireless infrastructure provided based on the GSM knowledge of the user's approximate location from the networks positioning system.

2.1 Recommendation-Based Systems

Recommendation systems provide tailored suggestions to the user based on an understanding of the content or from a view of the collective group or community which this user fits into or even a hybrid "boosted" approach. Content-based recommendation uses similar techniques to information retrieval. A comparison between the user profile and the content of the objects is the basis of a recommendation. If it can be seen that a user has rated highly a set of objects with similar content then it may be determined that that particular user would probably be interested in anything which contains more similar content. NewsWeeder [3] and InfoFinder [4] are examples of purely content-based recommendation systems.

Collaborative recommendation differs from content-based recommendation in that it recommends items based on what similar users liked rather than what the individual user liked. These systems sometimes define a set of 'nearest neighbour' users for each user based on the correlation of past likes and/or dislikes. Ratings for unseen items are based on a combination of the ratings from these neighbours. Pure collaborative recommendation systems such as GroupLens [10,11] know nothing about the items themselves, only about what users think of them. Collaborative recommendation systems address some of the problems associated with content-based systems as these systems can cope with any kind of content whether it is a web page, a piece of art or a DVD. This is because these systems examine user ratings rather than content. They can recommend items that are totally dissimilar to any seen before – as long as other users have rated them.

These systems do have their own shortcomings. If a new item is added to the database then it will not be recommended until a user rates it. This might prove difficult, as the user might not be able to find it unless it is recommended. If there are a large number of items and a small number of users then a lot of items could end up not being rated. Users with unusual tastes might also have problems with this type of system as they might not have anyone close enough to their own tastes to give good recommendations.

3 Ethnographic & Online Studies

To help explore our research questions on socially minded electronic guides [2] we have adopted a domain-driven approach to our study. Our research involved a small ethnographic study involving the curator of a family-run gallery (Cherrylane Fine Arts Ireland) and two of archivists from the National Gallery of Ireland. These people were questioned about a number of aspects of the day-to-day activities in their respective galleries using a questionnaire. This questionnaire focused on who, what, when, where & why questions to help elicit details on the ways people wish to interact with the media (i.e. paintings) beyond simply looking at them. This work was supplemented with an online study of many major art galleries such as the Tate Modern London and the Louvre Paris, using a similar series of measures.

Our findings show that a majority of people, from a diverse set of backgrounds, visiting either a small or major gallery tend to want more information about some of the paintings they are viewing. There is an interest in leaving messages in both galleries but at the moment these must be left on message cards or a message book. These current methods do not allow for messages to be left in the vicinity of the paintings and can not be accessed whilst viewing a painting. Online access to galleries affords the opportunity to plan visits in the future where half of all visitors to the Tate Gallery website do so to plan a visit [1]. This shows that there is an interest in using emerging technologies to help personalise visits to art galleries.

4 Proximo

Proximo consists of a PC-based recommendation system (Figure 1b) using sample paintings and a rating system in addition to an application running on a Java-enabled Bluetooth a mobile phone as shown in Figure 1. The recommendation system collects & stores data from multiple user interactions that is used to create user profiles based on a weighted nearest neighbors algorithm [1]. The items with the highest predicted ratings are those, which will be recommended to the user. Once the user has given an initial rating the location and other domain-specific information relevant to these items are transferred to the handset-resident application.

The indoor positioning of BlueStar works by 'sniffing out' the fixed Bluetooth devices or low-cost beacons deployed in the area of use [12]. This room-level accuracy means improved precision and is accurate enough for a certain class of trail-

based applications such as a tour guide. The mapping service on the mobile handset displays a map of the intended area of use which can be manipulated in a variety of ways including ZoomZones, Scrolling, Zooming and toggle selection. Items provided by the recommendation system are displayed as icons over the map of the active area on the mobile application. This provides both location information and an interface for the user to select between the different items. The user can scroll between the icons to view information about the corresponding item.

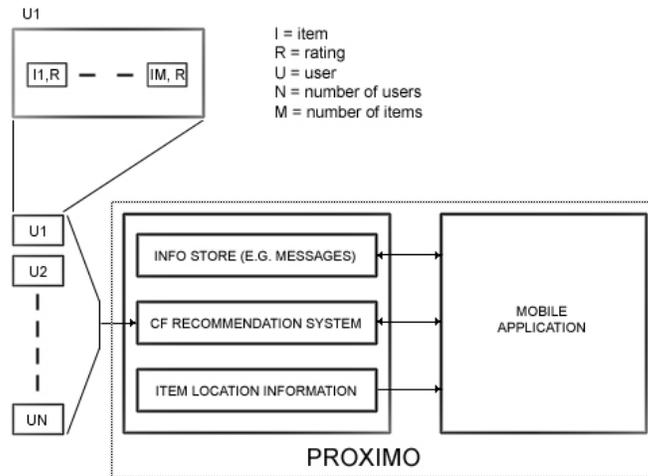


Figure 1: Proximo architecture

The mobile application constantly monitors the users location and displays the active areas of the building (the area they are in) accordingly. The paintings on the tour are also displayed in a different colour that highlights them from the others. The first step in taking any action relating to a particular painting is to first select it. Any action performed now will relate to the painting which is selected. To further aid the users of the system a small image of the item is displayed in the top-right corner of the map. Scrolling clockwise and anti-clockwise navigates around the group of items (paintings).

When a painting is selected there are a number of actions which a user can take. There is a facility for the user to provide a rating for the painting. Our messaging feature akin to Stick-e Notes [7] and GeoNotes [9] where messages can be left at a specific location and can only be accessed from that location within a certain context. Proximo allows users to leave and receive messages at each painting they visit on their tour (and those not on the tour too).

5 User Study

A user study of the Proximo system was conducted to determine usability, assess acceptance of the system and to measure the effectiveness of the recommendation system. ‘The CSI Gallery’ was set up on the ground floor of the U.C.D. School of Computer Science and Informatics building. Seven users were asked to complete a tour of the gallery, each visiting a number of paintings which were suggested by the recommendation system. The tour provided for each user was created by the recommendation system. Each user was asked to rate (between 1 & 5) ten paintings which were displayed in the gallery. These ratings were entered into the collaborative recommendation system, that created the tour for each user.

Users were asked to complete fully their tour of the CSI Gallery answering each question on a given question sheet. They were also asked to leave a rating for each painting on their tour and leave at least three messages themselves (about anything they liked) whilst on their tour. The last two tasks were to be completed using the application running on the mobile phone. When the tour was completed each user was asked to fill in a questionnaire which consisted of 28 multiple-choice questions which were split up into three sections.

5.1 Results and Evaluation

In our user study we asked users to evaluate a range of aspects of the system including, usability, recommendation quality and workload. The recommendation system was tested by examining the predicted rating and actual rating for the paintings on each users tour. The absolute difference or error between these two values is used to measure the success of the predictions. The overall success of the system is calculated by finding the mean absolute error over all the predictions made. In this case the mean absolute error was 1.19.

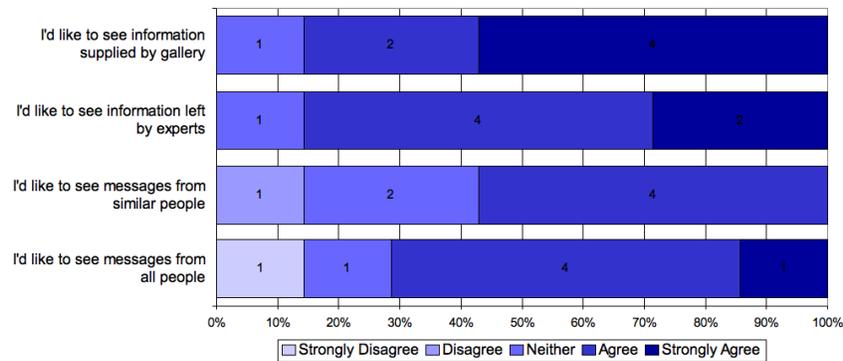


Figure 2: User Interest in Information

Contrary to expectations there was a marginally better response to seeing messages left by all users rather than just by similar users. It was suggested by one user (obviously before he got to the question about similar users) that there be an option to view messages left by only similar people. One user thought it would be “hard to say if they would be helpful or not”. In general the users thought that having the ability to see information left by different sources was a good idea. Information left by more learned people are considered more desirable than information left by just anyone.

6 Conclusions

We have explored the use of Proximo, a location-aware recommendation-driven system for use within indoor environments such as museums and art galleries. Our user study suggests that small amounts of both explicit and implicit context data can enhance the quality of the users experience in trails through a physical space. The notion that collective wisdom can guide a mobile experience based on the suggestions of others has been demonstrated.

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