Mobile Recommendations for Leisure Activities

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ABSTRACT
We demonstrate a context-aware mobile system for recommending information about leisure activities (Shopping, Eating, Doing, Seeing, and Reading), codenamed Magitti, which infers the user's leisure activity from context and patterns of behavior. Magitti filters a database of city-guide-style leisure information to find the most relevant items based on the user's profile, history, context, and predicted activity. Users can also customize the profile or dynamically adjust the current preferences if they wish to improve the recommendations further.

Author Keywords
context-aware, mobile recommendation systems.

ACM Classification Keywords
H5.m. Information interfaces and presentation: Misc.

INTRODUCTION

We demonstrate a system, codenamed Magitti, which uses context filtering to narrow down the inevitable overload of leisure time offerings in dense urban areas. It can do so without the user having to explicitly define her profile or preferences. The system infers interests and activities from models that are learned over time, based on individual and aggregate user behavior, such as places visited, web browsing, and communications with friends. More details about the motivation and fieldwork that led to the system design can be found in prior work [2].

USER INTERFACE

Magitti's Main Screen (Figure 1) shows a scrollable list of up to 20 recommended items that match the user's current situation and profile. As the user walks around, the list updates automatically to show items relevant to new locations. Each recommendation is presented in a summary form on the result list, but the user can tap each one to view its Detail Screen on the touch screen (Figure 1). This screen shows the initial text of a summary, a formal review, and user comments, and the user can view the full text of each component on separate screens. The Detail Screen also allows the user to rate the item on a 5-star scale.

To locate recommended items on the Main Screen, users can tap the Map tab to see the partial map (Figure 2), which shows the four items currently visible in the list on the map. A second tap slides the map out to full screen.

The minimal size and one-handed operation requirements have a clear impact on the UI. As can be seen from Figures 1 and 2, large buttons dominate the screen to enable the user to operate Magitti with a thumb while holding the device in one hand. Our design utilizes marking menus on touch-screens to operate the interface, as shown in the right side of Figure 2. The user taps on an item and holds for 400ms to view the menu; then drags her thumb from the center X and releases over the menu item. As the user learns commands and their gestures, she can simply sweep her thumb in that direction without waiting for the menu to appear. Over time, she learns to operate the device without the menus, although they are available whenever needed.

Menu buttons at the bottom of the Main Screen allow the user to adjust the recommendation list if needed. By default, the system is in "Any" mode, meaning it will offer recommendations based on its predictions about the likelihood of each of five classes of user activity; Eat, Buy, See, Do, or Read (these will be explained later). But the user can ask to see recommendations from just one category

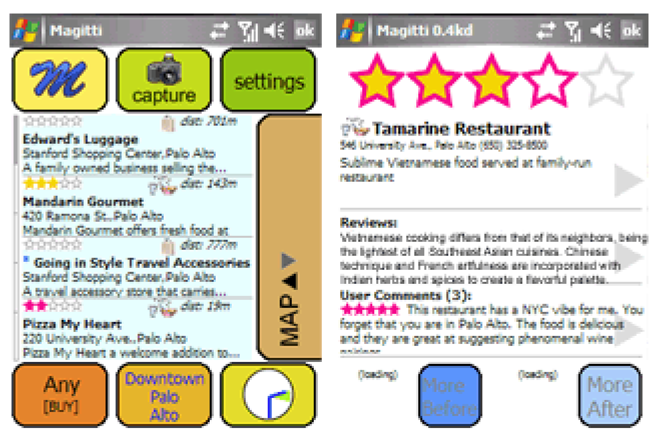

Figure 1. Magitti's Main Screen (left) and Detail Screen (right).

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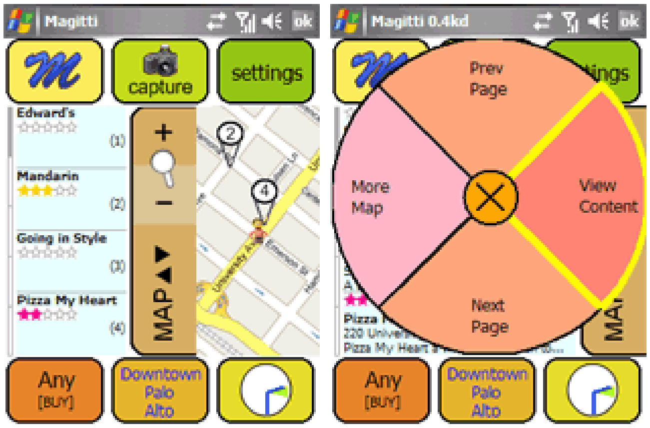

Figure 2: Main Screen with partial map view (left) and Main Screen marking menu (right).

(in so doing, informing the device of their activity interests, thus providing data for learning). The user can also ask for recommendations within a certain distance or time range. For planning purposes, he can ask for items in another location and/or at another time. Additionally, a user can indicate his general preferences for cuisines, shops, activities, events, and other attributes of the information content, which will influence the types of recommendations offered. The user can specify preferences for attributes of places, such as price range, noise level, availability of parking, smoking, and so on. And, finally, he can bookmark recommended items and perform keyword searches.

Recommender System

For a given user and context, the *Recommender* computes the value of each content item by combining results from a variety of recommendation models. When all items have been scored, the top results are returned to fill the slots allocated by the activity model, as illustrated in Figure 3. Following other research on hybrid context-aware recommendations [1], Magitti scores items based on the

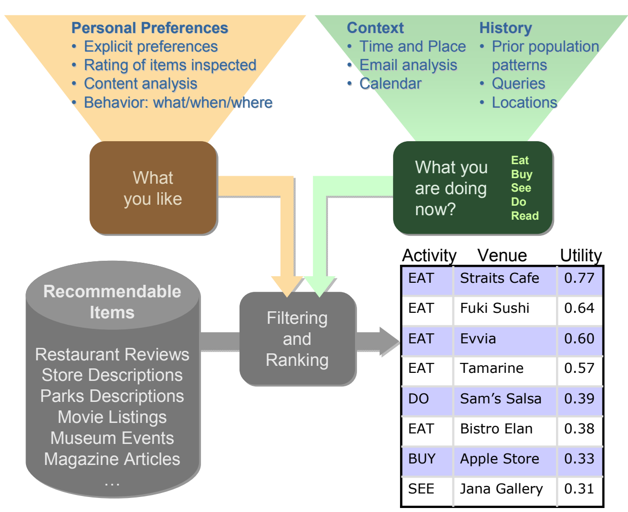

Figure 3. Magitti recommendations combine current activity and personal preferences.

results of an arbitrarily large number of models. In the current incarnation of Magitti we combine eight models (more details are in [3]):

- **Collaborative filtering:** Like others, we utilize ratings to compute similarities between users. This model scores each item, based on how other similar users rated it.
- **Preference query:** Magitti users can express preferences, which might evolve over time.
- **Learned preference query:** This model works similarly to the Preference Query model, but is learned from previous behavior rather than stated preferences.
- **Content preference:** This model measures the similarity of an item's content to a profile of the user's previously viewed content in web pages and documents.
- **Distance:** Given a range (either entered or inferred from location traces), the system scores items within the range and uses an exponential decay function to rate the others.
- **Reading:** The system uses a model of when users are most likely to read, according to data from the fieldwork.
- **Boredom Buster:** This model reduces the scores of items that have previously been seen, providing diversity to the set of recommended items.
- **Future Plans:** This model temporarily raises scores based on evidence of future plans derived from analyzing the contents of the user's messages and appointments.

FUTURE DIRECTIONS

Our research indicates that a large amount of information about leisure activities comes from friends and family. Future research involves using information about the user's social network to enhance recommendations about leisure activities.

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