A Collaborative Recommender System Based on Space-Time Similarities

Collaboration-based recommenders in an Internet of Things environment rely on user-to-object, space-time interaction patterns. This extension of that idea takes into account user location and interaction time to recommend scattered, pervasive context-embedded networked objects.

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As mobile personal devices and pervasive technologies for interacting with networked objects in smart environments continue to proliferate, there's an unprecedented world of scattered pieces of contextualized information available to mobile users. A simple touch of a user's mobile device to a near-field communication (NFC) tag at the entrance of a cinema, for example, can give the user instant information about similar users' opinions about the films being shown.[1] Finding relevant content in this "Internet of Things" (IoT) brings challenges for extending traditional Internet-based recommender systems to the real world of pervasive networked objects.

The IoT concept promises a world of interconnected devices that offers relevant content to users.[2] Such environments also offer unique challenges, however.[3] On one hand, the contents are typically provided locally to mobile users, who interact directly with the networked objects. Space is therefore important as it relates to user location. On the other hand, using mobile devices allows for physical reorganizations of users and objects in the environment. Therefore, the time in which users interact with the information is also important.

Recommender systems attempt to estimate a particular resource's relevance to a particular user on the basis of

- similar users' rating of that resource (collaborative methods),
- the particular user's ratings of other similar resources (content-based methods), or
- a combination of the two (hybrid methods).

Researchers have used recommender systems in various scenarios, including those in cognitive sciences, approximation theory, information retrieval, forecasting theories, management sciences, and consumer-choice modeling in marketing.[4] We propose using time and location as the basis for finding similar users for our IoT-based collaborative recommender system. Here, we explain our approach and our experiment to test it against more traditional correlation-based methods.[4]

Context-Aware Recommender Systems

Context-aware recommender systems use data such as interaction times and user locations together with other context-related information to recommend products, services, tasks, or events.[5] The context of a particular recommendation might include information about the user's location, the identity of nearby people and objects,[6]

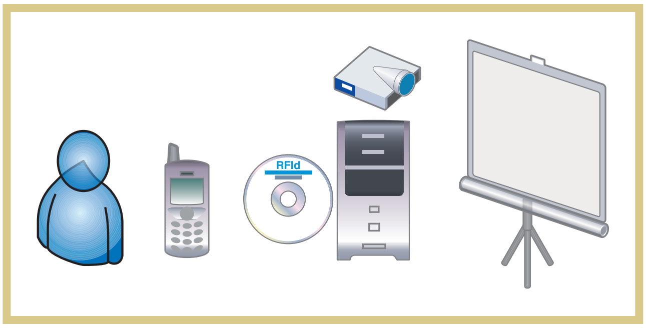

Figure 1. A simple example of a tagged object in an Internet of Things scenario. Product-promotion videos at a technology fair include RFID tags so users can touch the tag to get recommendations about the videos on offer.

the date, the season and temperature,[7] the physical and conceptual statuses of interest to a user,[8] or any information relevant to a user's interaction with an application.[5,9]

Previous work on context-aware recommender systems for mobile users include

- using the user's location to recommend applications to download,[10]
- defining a way to find generic context similarities,[11] and
- using Bayesian networks to accurately identify the minimal set of context important to a particular user for a particular task.[12]

Although our work also uses context-related information in a mobile, context-aware recommender system, it does so while accounting for an IoT's particularities. That is, it considers an environment in which the recommended information is associated with physical objects located at a particular place, in a particular moment, but that can also be mobile and change location over time.

As the "Related Work in Context-Aware Systems" sidebar describes, the use of mobile devices to sense what, when, and where a user does something is the foundation for emerging forms of people-centric sensing systems. To find similarities among users and make recommendations accordingly, our system uses NFC-sensed social networking information from users who are in the same place, at the same time.

Associating content to IoT objects requires a mechanism to identify networked objects and link the physical world with virtual Web resources.[13,14] Typically, object identifiers are embedded into physical objects using bar codes, RFID tags, or infrared beacons.[13] We chose to use RFID tags because they can be read and written using mobile devices that support NFC technologies.[3]

A Social-Centric Collaborative Recommender System

Traditional collaborative recommender systems don't typically consider information about where and when a particular user accesses (consumes) a particular Web resource.[4] Here, we focus on the value of such information as it plays out in an example scenario: a technology fair.

In this scenario, visitors with mobile devices can access location-dependent information from tagged objects to enhance their experiences. For example, presentation rooms might be tagged to inform users about the next scheduled lecture, the cafeteria could provide current menu information, and exhibition halls could have tags for each featured exhibit that offered current and detailed information. Moreover, users' mobile devices could also participate in the scenario, providing information about user-to-user communications. Visitors could thus receive personalized recommendations about relevant exhibits to visit or lectures to attend on the basis of their interests and the plans of similar attendees.

Figure 1 shows a simple example of a tagged object in our IoT scenario. The product-promotion projection system shows videos about different products at different times throughout the fair's duration. Users arriving at the projection room can get recommendations about the current presentations by touching the related RFID tag. Users who rate the promotion videos at similar times are likely to be interested in similar products.

Collaborative recommender systems try to predict an item's value to the user by aggregating similar users' ratings of that item. There are two main approaches for estimating user similarity. The first one is based on the Pearson correlation coefficient:

$$sim(x,y) = \frac{\sum_{s \in S_{xy}} \left(r_{x,s} - \bar{r}_x\right)\left(r_{y,s} - \bar{r}_y\right)}{\sqrt{\sum_{s \in S_{xy}} \left(r_{x,s} - \bar{r}_x\right)^2 \sum_{s \in S_{xy}} \left(r_{y,s} - \bar{r}_y\right)^2}}, \quad (1)$$

where S_{xy} are the items rated by both users x and y, and $sim(x, y)$ is the similarity function between x and y. The second approach uses the ratings of users x and y for common items S_{xy} as vectors and calculates the similarity between two users by computing the cosine of the angle between their rating vectors:

$$sim(x,y) = \cos(\vec{x},\vec{y}) = \frac{\vec{x} \cdot \vec{y}}{\left\|\vec{x}\right\|_2 \times \left\|\vec{y}\right\|_2} = \frac{\sum_{s \in S_{xy}} r_{x,s} r_{y,s}}{\sqrt{\sum_{s \in S_{xy}} \left(r_{x,s}\right)^2 \sum_{s \in S_{xy}} \left(r_{y,s}\right)^2}}, \quad (2)$$

Figure 2. Proof-of-concept scenario. More than 75 objects were tagged with readable RFID tags in the Campus of Leganes at Carlos III University of Madrid. Here, a student interacts with and rates three of those objects: (a) an NFC-based conference panel, (b) a tagged room, and (c) a tagged drawer.

where $\vec{x} \cdot \vec{y}$ denotes the dot-product between the vectors $\vec{x}$ and $\vec{y}$.

We can define similar equations for users and nomadic content by using location and interaction times instead of user ratings. We can therefore define the similarity function based on the Pearson correlation coefficient as

$$sim(x,y) = \frac{\sum_{s \in S_{xy}} \left(t_{x,s} - \bar{t}_x\right)\left(t_{y,s} - \bar{t}_y\right)}{\sqrt{\sum_{s \in S_{xy}} \left(t_{x,s} - \bar{t}_x\right)^2 \sum_{s \in S_{xy}} \left(t_{y,s} - \bar{t}_y\right)^2}}, \tag{3}$$

where S_{xy} are the colocated items—that is, those in the same location (such as the same room, classroom, or office)—that are accessed by both users x and y, and $t_{x,s}$ is the time at which user x accesses resource s. We can define a similar equation for the cosine of the angle between user vectors based on access times of colocated resources using an analogous transformation from Equation 2.

Using Equation 3 to measure similarities between users accounts for the order and time pattern in which each user accesses different resources. Equation 3 focuses on users' relative time patterns, independent of the mean time in which they consumed resources. We could also define other access-time-dependent similarity functions that account for the absolute time differences in which different users consume colocated objects. We can, for example, define the inverse of the access time differences between users x and y:

$$sim(x,y) = \frac{1}{\dfrac{\sum_{s \in S_{xy}} abs\left(t_{x,s} - t_{y,s}\right)}{num(S_{xy})} + 1}, \tag{4}$$

where $num(S_{xy})$ is S_{xy}'s number of elements. In the following scenario, we present results from our experiences with 15 students at Carlos III University of Madrid interacting with more than 75 RFID-tagged objects. To compare the recommendation results of applying the similarity functions of Equations 1 through 4, we calculate the recommendations as

$$r_{c,s} = \bar{r}_c + k \sum_{c' \in C} sim\left(c,c'\right) \times \left(r_{c',s} - \bar{r}_c\right), \tag{5}$$

where C is the set of similar users, the multiplier k serves as a normalizing factor

$$k = 1 / \sum_{c' \in C} \left|sim\left(c,c'\right)\right|,$$

and we define the average rating of user c, $\bar{r}_c$, as

$$\bar{r}_c = (1/|S_C|) \sum_{s \in S_C} r_{c,s},$$

where $S_C = \left\{s \in S \mid r_{c,s} \neq \varnothing\right\}$.[4]

Implemented Scenario

We implemented a proof-of-concept scenario to test the effectiveness of similarity functions based on access times for colocated resources compared to collaborative recommender methods based on user ratings. To do this, we compared the results of applying Equations 1 through 4 to provide predictive ratings in Equation 5 with the real ratings provided by users.

We tagged more than 75 objects in the Campus of Leganes at Carlos III University of Madrid using NFC-readable RFID tags. The tags provided links to external information resources[15] that participants could access using a Nokia 6131 NFC mobile phone. We asked users to rate the content associated with each object. These ratings were stored in a personal user profile in the mobile device, along with the date, time, and an object ID that identified both a particular object and its location. We deployed an external recommender system to receive the user profiles and compute recommendations for other users. Figure 2 shows a student interacting with three different objects.

We recruited 15 students with degrees in engineering and computer sciences (to minimize the learning curve

Related Work in Context-Aware Systems

The evolution of mobile technology is pushing unprecedented computing capabilities into mobile users' pockets. Mobile devices can sense information from the physical environment using either embedded sensors, such as microphones, cameras, or GPS receivers, or external intelligent Internetworked devices providing local access to external contents and services through technologies such as near-field communication (NFC) devices, Bluetooth, or Zigbee. Applications can process the information that mobile devices sense to create sensor-based social networks.

People-Centric Sensing

Using mobile devices to sense what, when, and where a user does something is the foundation for emerging forms of people-centric sensing systems such as Campaignr (www.campaignr.com), CenceMe,[1] and Micro-Blog.[2] CenceMe uses cell-phone embedded sensors (a camera, microphone, and an accelerometer) to provide a stream of high-level inferred states about users, such as whether they're running, at a party, or conversing. The inferred states compose the user's sensed presence, which can enhance IM client information. Micro-Blog aims to design a "virtual information telescope" with users' mobile phones acting as the metaphorical "lens." Users are encouraged to record multimedia blogs on the fly, enriched with inputs from other physical sensors. The blogs are geotagged and uploaded to a remote server that positions them on a spatial platform (such as a map). Distributed clients can zoom in to any part of the map and query selected regions for desired information.

Other researchers have studied the integration of mobile users' sensed information in Web applications that guide mobile users between locations in a city using information sensed by other mobile users.[3] We analyze the use of user-sensed information—such as a user's location when consuming information resources from an environment's objects and user-to-object interaction times—to create sensor-based social networks. Such networks attempt to find similar users and apply their recommendations about a particular object in an Internet of Things (IoT) in collaborative recommendation systems.

Recommender Systems

To estimate the relevance or utility of a particular resource for a particular user, recommender systems must define a utility function to apply to each item and a similarity function to group users and resources. Utility values tend to be manually introduced by users and incorporate subjective user information (such as preferences), but in general, you can use any arbitrary function (such as a profit function). Recommender systems must also define a similarity function. In collaborative recommender systems, the similarity function aims to find similar users or users giving similar recommendations. One early recommender system proposed the use of stereotypes.[4] Another early system had users manually identify other like-minded users.[5] More recent systems typically use correlation or cosine-based approaches,[6] such as the Pearson correlation coefficient[7] described in the main text. Our approach is based on users' space-time interaction patterns. It considers as "similar" two users interacting with the same objects in the same place at the same time in an IoT context. We compare our similarity function's performance to a similarity function based on the calculation of the Pearson correlation index between user rating vectors.

Some researchers have already applied sensed user patterns or manually introduced user profiles to find similar users. Bluedating[8] uses Bluetooth to discover and transfer user profiles in nearby devices to find users who meet a particular search criterion. This application requires users to manually create a personal profile and only finds users within a few meters. Blueaware[9] detects Bluetooth devices in a user's proximity and sends this information to an external server that automatically builds a list of these devices, letting the user find similar users by matching intersections among nearby devices. The application assumes that users who've been near other users share something in common. Another research effort[10] proposed a system that uses either Bluetooth or NFC to exchange address book information to build a common ground for face-to-face interactions. This application is again restricted to nearby users.

Near-Field Communications

Interactions among mobile users and smart networked objects in the environment can use different local connectivity proto-

on the recommender application). Students participated voluntarily and received no compensation in terms of grades; the main incentive was the opportunity to use a new technology and a new system. The students interacted with the tagged objects throughout an entire day (while attending lectures and going to labs, the cafeteria, the library, and even to a job fair). All objects were identified with an NFC tag. Most tags were associated with objects representing physical places (and therefore with the location's activities). We placed the tags behind the room identifier (see Figure 2b).

To simplify the experiment, we calculated the recommendations using the similarity functions in Equations 1 through 4 offline after the experiment was over and the cols. We use NFC technologies to read embedded content in the physical environment because it's easy: users can select an object to communicate with by simply touching it. NFC technologies allow mobile devices to interact with other NFC devices in peer-to-peer mode or to read and write RFID tags (with globally unique identifiers).

NFC is viewed as a major IoT component.[11] Developed in 2002 by Philips and Sony, NFC was adopted as a standard the same year by Ecma International and the following year by both the International Organization for Standardization and the International Electrotechnical Commission. Along with Nokia, Philips and Sony founded the NFC Forum (www.nfc-forum.org/home) in 2004; as of October 2007, the forum had more than 130 members. Sixto Ortiz Jr. produced an interesting study about current and future NFC technologies,[12] citing market analysis results from ABI Research that predict 672 million shipments of NFC-enabled devices as of 2010.

The state of the art in NFC research initiatives shows interesting scenarios, pilots, and trials that use NFC for controlling access, payments, and user identification. One effort proposes using NFC to solve how users are identified.[13] Liberty Alliance (www.projectliberty.org), Microsoft's CardSpace (http://msdn2.microsoft.com/en-us/library/aa480189.aspx), and OpenID (http://openid.net) each propose authentication alternatives. The Stolpan-European consortium is currently defining a framework for deploying NFC-enabled mobile applications across a range of vertical markets, regardless of phone type and services.[14] Erkki Siira carried out a pilot test in which participants used an NFC-based catering services system.[15] Others have proposed using NFC for payments using virtual coupons.[16]

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recommender system had all of the participants' data. The user interface required students to touch the NFC tag associated with an object and provide a rating for the related content or activity (for example, students touching the tag at the "information servers" classroom's door had to give their opinion on the lecture, while students who touched the tag at the cafeteria entrance rated the day's menu). We offered the students a simple demonstration on how to use the application at the beginning of the experiment.

Results

To calculate the results, we defined an error value $d_{x,s}$ as the difference between the recommender system's predicted value for user x and resource s and the real value that user x

TABLE 1
Mean and standard deviation values for d_g.

Equation	Mean	Standard deviation
1	0.83	0.75
2	0.97	0.68
3	0.76	0.64
4	0.80	0.67

TABLE 2
Mean value for the Pearson correlation index for V_X and V_X'.

Equation	Mean
1	0.62
2	0.54
3	0.72
4	0.67

introduced after having consumed the resource *s*. We also defined V_X as the vector containing user *x*'s ratings for all rated resources and V_X' as the vector containing the system's recommended values for user *x*. Finally, we defined an error variable d_g as the absolute value of the difference between recommended values and real values (this is a random variable; we estimated its distribution using the values of $d_{x,s}$ for all users and for each resource).

Table 1 shows d_g's mean and standard deviation values when we use the similarity functions defined by Equations 1 through 4 (each resource's rating is an integer value between 0 and 10). The maximum number of objects students provided ratings for was 16; the minimum was 5. The mean of the number of items rated by each person was 11.8 and the standard deviation was 2.9.

As Table 1 shows, we obtained the best values for Equation 3, which defines a similarity function based on the Pearson correlation coefficient via user location and interaction times (rather than user ratings, as in Equation 1). Equation 4's modifications didn't provide results as good as Equation 3, but they still did better than Equations 1 and 2. One reason might be that students rating the same objects at the same time were often either friends or at least classmates, which likely made their recommendations similar.

We also computed the similarity between the predicted vectors V_X and the vectors containing the real ratings by users V_X'. Table 2 captures the mean value for the Pearson correlation index for V_X and V_X' for all students using Equations 1 through 4. High correlation values measure how the differences between real and predicted rankings evolve relative to their means. Table 2's results complement and thus should be interpreted along with those in Table 1, which capture the magnitudes of the differences between real and predicted rankings. As Table 2 shows, Equation 3 again provides the best value, showing the most similar evolution between the real and predictive rankings relative to their means.

As our experiment shows, contextualized information can improve recommender system recommendations. In the case of an IoT, this is even more important because users obtain the information for providing recommendations directly through interactions with the physical objects in the environment.

After analyzing these results, we conclude that sensed user-location patterns and user-to-object interaction times are better than user-provided ratings for finding similar users in an IoT environment. Moreover, we can automatically access sensed data, such as the user's location, without requiring the user to intervene. However, our approach does require the user's explicit acceptance, which might be a bar too high for some users.

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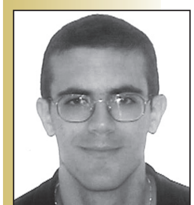

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