Healthy Routes in the Smart City

A Context-Aware Mobile Recommender

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A context-aware recommender system offers personalized recommendations of exercise routes to people according to their medical condition and real-time information from the smart city. Experiments with a simulated dataset and real data verified the system’s usefulness.

The world population’s average age has been increasing gradually over the past 50 years mainly because of medical and healthcare advances. However, millions of people suffer from chronic respiratory diseases, arthritis, and back pain. In addition, exposure to air pollution causes millions of illnesses and premature deaths annually worldwide and harms the health of children, the elderly, and people with chronic diseases.

An active lifestyle can help reduce or even prevent physical issues such as cardiorespiratory problems, musculoskeletal diseases, or morbidity. Moreover, it has positive neurocognitive effects. For instance, increased cardiorespiratory fitness is associated with increased cortical thickness in both healthy adults and the elderly diagnosed with dementia. So, the aging of society and the need to foster healthy habits in society imply a great challenge for public healthcare systems.

To address these issues, the healthcare sector has strived to integrate new technologies that promote healthy habits. Although the deployment of such services implies initial investments, in the long run, their adoption decreases healthcare system costs and improves people’s quality of life.

Healthcare models are steadily shifting toward patient-centric approaches in which patients are not only passive elements but also proactive contributors to their own and their peers’ health. From a much wider perspective, the sharing of information has led to recommender systems, which have evolved and integrated transparently into our daily lives. Such systems exploit collaboration among users and help them make better decisions.

To advance the state of the art, we’ve developed a system that augments mobile health in the context of smart health. It suggests exercise routes in real time, using a context-aware recommender system and a mobile app.

Toward Socially Aware Computing

Many health-related mobile apps are devoted to sports and health monitoring, and research on healthcare applications and ambient-assisted-living solutions is growing. The growth of such applications and systems in conjunction with wearable computing will extend the notion of context awareness to socially aware
Large-scale ensembles of such heterogeneous systems will lead to a new collective intelligence in which users become a part of “massive urban superorganisms.” So, it’s compelling to move toward such next-generation trends and propose solutions that exploit context-aware technology (for example, the sensing infrastructures of smart cities) and collective behavior (for example, the crowdsourcing of information).

Recommender Systems and Collaborative Filtering

Recommender systems evolved from the field of knowledge discovery in databases, which companies use to discover patterns in large collections of data. However, in typical recommender systems, people provide recommendations as input, which the systems then aggregate and direct to the appropriate recipients.7

In particular, collaborative filtering (CF) makes recommendations on a set of items (for example, books, music, films, or routes), based on the preferences of a set of users who have already acquired or rated some of those items.12 CF relies on large databases of user evaluations. CF recommendations assume that similar users are interested in the same items.

CF methods are classified according to the data they use:

- **Memory-based methods** use the data matrix with all the entries, ratings, and relationships.
- **Model-based methods** estimate statistical models and functions on the basis of the data matrix.
- **Hybrid methods** combine the previous two methods with content-based information to enhance recommendations.

Our system uses a memory-based method that employs neighborhood search (to determine groups of similar users) and recommendation or prediction computation, using various techniques.

**Our Approach to Healthy City Routes**

Most people who take up an active lifestyle do so because of medical recommendations based on health issues. So, the activities are usually driven more by emotion and less by facts. Although this approach enables people to choose activities (for example, a sport they like), they don’t receive the proper guidance on how to perform them.

For instance, although jogging might be beneficial, a person must have some baseline to determine when and where to do it. Most people would base these choices on distance, weather, and scenery, neglecting static factors such as a route’s difficulty and dynamic factors such as air pollution and crowd density, which are important for people with a chronic illness.

Our approach considers real-time constraints and information from several sources—for example, real-time information from the smart-city infrastructure and people’s preferences and health conditions. The system has these features:

- It recommends routes that best fit users’ needs and preferences.
- Users can employ commercial smartphones.
- The system is dynamic and collaborative, and it adapts to real-time changes that affect the variables monitored by the city sensors.
- The users act as sensors that contribute their knowledge and experience to the system.
- Users can inform the system about unexpected situations that could affect other users (for example, a rockslide has blocked a route).
- Users can propose new routes so as to enrich the system.

The System Architecture

Figure 1 illustrates our system architecture and its main actors. The Context-Aware Recommender System (CARS) software runs on a server and recommends routes. The recommendation procedure comprises the following five steps, which correspond to the numbers in Figure 1.

First, a user establishes bidirectional communication with CARS and asks for a route recommendation. The user also sends information such as his or her location.

Second, the smart city’s communication infrastructure obtains real-time environmental information (such as air quality, ultraviolet radiation, wind speed, temperature, and precipitation) from sensors and sends that information to CARS. CARS evaluates the information from the nearest sensor from each route in its database, using well-known metrics.13 The system assigns one of three statuses to a route:

- **Danger.** The route might be dangerous to the user’s health.
- **Caution.** Possible risk exists—for example, for users who are more sensitive to environmental factors.
- **Idle.** No evidence of risk exists.

CARS also considers crowdsourced information when determining a route’s status.

Third, CARS checks the user’s preferences and applies CF to the
complete database of routes to produce the top N recommendations.

Fourth, CARS uses healthcare information about the user and information received from the smart city to discard routes that might endanger the user’s health. For instance, for users with respiratory problems, CARS automatically assigns the “caution” status to routes with a lot of greenery. After applying this filter, if no route satisfies the criteria, CARS goes back to the third step and computes a new set of the top N recommendations.

Finally, CARS sends the user a list of the N routes.

Figure 2 depicts CARS’ decision flow. The procedure iterates until CARS produces a recommendation that fits the user’s health and environmental constraints.

SmartRoute

Users can interact with CARS through the SmartRoute mobile app (available through Google Play). The app uses real weather data and air quality measurements (for example, ozone, nitrogen dioxide, or particulate matter) from the Catalan air-quality-monitoring network. (Statistics are available in real time at dtes.gencat.cat/icqa/start.do?lang=en.)

Users log onto the app; from the home screen (see Figure 3a), they can

- go to the closest route and start,
- look for a specific route,
- get the top routes, or
- create a route by adding checkpoints while walking.

The app menu (see Figure 3b) lets users check and manage records.
of different route sessions and update their health conditions or other data in their profiles (see Figure 3c). Additionally, they can check weather and air quality information (see Figure 3d) and check the feedback provided by our app (for example, the background color changes according to the dangerousness or quality of such information).

Once users select a route, the app shows the path to the starting point and additional information such as a description of the route and possible warnings (see Figure 3e). When a route session starts, SmartRoute shows information such as distance, approximate duration, speed, and possible alerts or changes in the route in real time (see Figure 3f). In addition, users can send notifications to warn others of issues with that route. Finally, the app shows the statistics collected during the session (see Figure 3g) and asks the user to rate the route.

### Experimental Results and Discussion

To show our approach’s applicability, we created two datasets for two cities. The Tarragona dataset contained...
11 routes and information on 1,000 simulated users; the Barcelona dataset contained 28 routes and information on 5,000 simulated users. We built the simulated users on the basis of age distribution and medical statistics from the World Health Organization and World Heart Federation. We profiled the users according to their health issues, and CARS rated routes on the basis of the users’ medical conditions and the routes’ features. For more details, see Technical Report: Implementation and Validation of a Smart Health Application.

Using those datasets, we measured our approach’s accuracy and robustness with sparse data. First, we extracted from 10 to 50 percent of the ratings stored in the datasets. Next, we predicted these ratings using the nearest neighbor’s rating. We applied the $k$-nearest-neighbor approach with $k = 1$. Although we could have used larger values of $k$, using $k = 1$ reduced the computational cost and made our approach more practical. We determined the neighbors by using the Euclidean distance between users, considering only their assessments of the same routes. Finally, we computed the mean absolute error (MAE) between the original values and the values that this procedure predicted.

For the Tarragona dataset, we obtained 12.28 MAE with 10 percent of the unknown data and only 13.89 MAE with 50 percent of the data. Clearly, when the percentage of unknown data grew, so did the error, but it remained at low levels, satisfying the users’ preferences on average. For the Barcelona dataset, MAE grew more slowly, and the values were lower. So, the more referrals there were, the higher the chances were of finding similar users.

Finally, we ran a trial with 20 real people in Tarragona using SmartRoute to store their preferences and provide recommendations. Owing to the sample’s small size, we had more difficulty finding similar users when we increased the amount of missing data. However, the recommendations were still accurate; the highest MAE was below 17.81 percent. This signifies that the results with the simulated data were similar to those with the real data.

Our next step will be a double-blind experiment with two groups of users: one that follows our recommendations and one that ignores them. Our long-term study will use data from users, the smart city, and health specialists to determine the benefits of healthy habits combined with efficient use of smart-city information.

The wide deployment of smart sensors in cities will pave the way for the success of tools like SmartRoute and will help promote active lifestyles without compromising people’s health.

We plan to provide more personalized recommendations by fusing the data with information from linked electronic health records. So, we’re collaborating with medical researchers to determine the baseline information needed from the records, to enhance recommendations by proposing alternative activities. Moreover, the system will incorporate wearables and body sensors to determine the users’ condition in real time as they follow a recommended route.

**References**


