RecFit: A Context-Aware System for Recommending Physical Activities

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Abstract

Many people are bored with their current physical activities and would like individualized recommendations of alternatives. Even users who have favorite exercises may seek recommendations if their context (e.g., bad weather, location) changes. Prior work has focused on tracking user activities and goal-setting, but not on recommendations. In this paper, we describe RecFit, which systematically suggests physical activities based on the user's context (e.g. risk tolerance, budget, location, weather). RecFit works from 137 activities selected from the 2011 compendium of physical activities in order to recommend the 5 most suitable recommendations for each user. We describe our filtering criteria, algorithms, prototype and RecFit's activity database, which augments activities with metadata of ideal performance context (popularity, sociability, risk, location, expense, time, and weather).

Categories and Subject Descriptors

H.3.3 [**Information Storage And Retrieval**]: Information Search and Retrieval—*information filtering, search process, selection process*

General Terms

Design

Keywords

Recommender System, Physical Activity, Fitness, Smartphone Application

1 Introduction

Boredom with their exercises is one of 18 obstacles that exercisers face [17]. Yet if people seek alternative exercises, they can be overwhelmed by existing compendiums listing 100s of physical activities. Very few algorithms exist to systematically recommend individually appropriate physical activities (PA). In our view, providing individualized recommendations for PA is an important next step for promoting health and for extending current PA support apps.

Prior work has focused on smartphone apps for activity tracking (user steps calories spent) and classification (sitting, running, climbing stairs) [6] and providing feedback to users based on their goals [5]. To take the next step toward generating individualized PA recommendations would involve 1) tracking contextual information, and 2) developing algorithms to generate individualized recommendations. While context-awareness on mobile devices has been well studied [4, 9], PA recommender systems have received little attention. PA recommendations from the Centers for Disease Control and Prevention and the American College of Sports Medicine [12] are general, not specific to individual needs. This paper describes "RecFit", a smartphone recommender system that suggests specific PA types to users based on their preferences, profiles and context. We describe our PAs filters, our algorithms to select and refine PAs, and our RecFit prototype.

2 Related Work

Tracking Health Information: Smartphones are now equipped with various sensors including motion sensors, accelerometers, gyroscopes, magnetic field sensors, and GPS. Smartphone apps can use data from these sensors to classify physical activities of the smartphone user, including sleeping, sitting, walking, running, and climbing stairs, steps and PA intensity. Moves [14], ARGUS [3], and Human [8] are examples of smartphone apps that track physical activity. Body-worn activity trackers such as Nike+ FuelBand, Fitbit, and Jawbone UP track and display the users' progress towards their fitness goals.

Behavior Change and Interventions: Smartphone apps such as Fish'n'Steps [11], UbiFit Garden [5] and BeWell [10] integrate behavior change mechanisms, such as highlighting the user's wellbeing, promoting goal-setting, rewarding users for fitness achievements, and facilitating social norming. Apps have not yet addressed the problem of recommending specific physical activities to users.

3 Our General Approach

In selecting suitable exercises, we start with a set large set (a database) of candidate exercises. We then filter out exercises that the user may find unsuitable for a wide variety of reasons including the exercise intensity (METs) level (too intense or not intense enough), expense, risk and sociability

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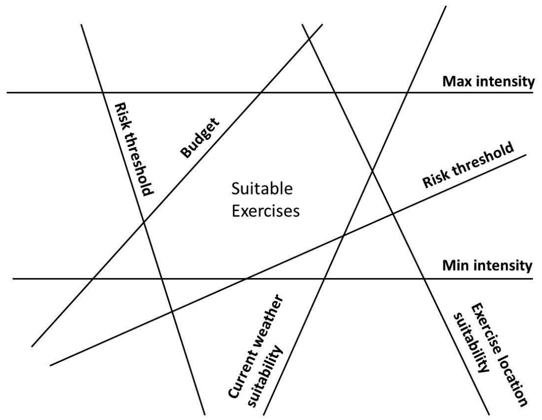

Figure 1. Diagram illustrating exercise constraints and the preferences of users

(number of people required to perform the physical activity) and location where exercise is usually performed (indoor or outdoor). We also filter physical activities using contextual factors such as current weather and the suitability of the exercise at the current time (before work, after work, etc). We can express the selection task and these constraints as:

Find suitable exercise in exercise database s.t.
Exercise intensity $>$ ***User's preferred minimum METs***
Exercise intensity $<$ ***User's preferred maximum METs***
Exercise location $=$ ***User's preferred location***
Exercise expense $<$ ***User's budget***
Exercise risk $<$ ***User's risk threshold***
Current Weather $=$ ***suitable for this exercise***
Current time $=$ ***suitable for this exercise***

These constraints are illustrated diagrammatically in Figure 1. For simplicity the constraints are shown as straight lines. However, in practice the constraints may not be linear. Our contributions include:

1) Identifying constraints: that allow the large set of potential exercises to be filtered meaningfully

2) Synthesizing metrics: that allow specific constraints (e.g. risk) to be computed quantitatively

3) Designing user interfaces: and sliders that allow the user to specify their personal thresholds and preferences

4) Proposing algorithms: that generate a reusable database of suitable physical activities and specific activities that satisfy a user's expressed constraints, and

5) Demonstrating feasibility: by implementing our ideas as a smartphone application

4 Selecting Suitable Physical Activities

We start with the *2011 Compendium of Physical Activities*, a comprehensive list of 821 PAs in 21 categories, with their Metabolic Equivalent of Task (MET) levels [2]. The activity list in the compendium is used in many commercial fitness trackers such as Fitbit. Sample listed activities are shown in Table 2. Physical activities such as bicycling, running and swimming are excellent for maintaining health. However, religious, home and volunteer activities are primarily not for maintaining health and should be filtered. We first eliminate unsuitable activities with the following filters.

4.1 Sedentariness Filter

We eliminated sedentary activities in the compendium (e.g., sitting, lying down), which do not fit our goal of recommending PA that increase calorie burn through moderate to vigorous exercise. We used the definition of "sedentary" as one that does not increase energy expenditure substantially above resting levels, i.e., PA with MET levels ≤ 1.5 [13]. This filter eliminated 52 PAs such as "sleeping" and "meditating".

4.2 Occupation Filter

We removed occupation-specific activities such as "building road", "coal mining", and "farming". Overall, this eliminated 275 PAs.

4.3 Household Activities Filter

While household activities (e.g., "wash dishes") do consume calories, they are not appropriate for recommending as healthy exercises. The household activities filter eliminated 92 PAs.

4.4 Similarity Filter

We group compendium PA that are the same activity but with varying intensities into a single activity (e.g., 18 variants of outdoor bicycling with speeds ranging from 5.5 mph to 12 mph become bicycling). Each PA then has max and min MET values representing the intensity range of the activity group. Applying the sedentariness, occupation and household activity filters, produced 399 PAs. Applying the similarity filter reduced the list to final 137 PA.

5 Adding Contextual Attributes

To facilitate recommendations, we augment each activity in our working set of 137 PAs with contextual metadata about conditions under which each activity is usually performed: (1) popularity; (2) sociability; (3) risk; (4) expense; (5) location; (6) time; and (7) weather (See Table 1).

5.1 Popularity

To quantify the popularity of each PA, we used the number of participants in the *2013 Sports, Fitness and Leisure Activities Topline Participation Report* from the *Sports and Fitness Industry Association* [16]. In future, we shall compute PA popularity for different regions and recommend PAs that are popular in the user's current geographic region.

5.2 Sociability

Sociability refers to the number of people required to perform the PA. We classified each PA into 1 of 3 levels of sociability. Level 1 is activities typically performed by a single individual (e.g., "rope skipping and "stationary rowing"). Level 2 is activities that may be performed either alone or with others (e.g., jogging, swimming), or team sports like basketball and soccer that can also be practiced alone. Level 3 is sports (e.g., team and racket sports) that must be performed by at least 2 people.

Table 1. Sample physical activity database for demonstration

Physical Activity	Min METs	Max METs	Popularity (million)	Sociability	Risk	Expense	Location	Time	Weather
Walking	2.0	9.8	114,029	2	6.46	$0	Home, office, outdoor, mountain, forest	Before work, working time, after work, weekend/holiday	Temp: 10-24C, Humidity: 30-70%, Precipitation: 0-50%, UV: 0-5, PM2.5: 0-50
Fishing	2.0	6.0	56,850	2	3.74	$75	Lake, river, sea	Weekend/holiday	10-24C, 30-70%, 0-25%, 0-5, 0-50
Jogging	4.5	8.0	51,450	2	6.46	$50	Outdoor, track, gym	Before work, after work, weekend/holiday	10-24C, 30-70%, 0-25%, 0-5, 0-50
Bowling	3.0	3.8	48,614	3	0.13	$10	Club	After work, weekend/holiday	-10-40C, 0-100%, 0-100%, 0-10, 0-500
Bicycling, stationary	3.5	14.0	44,464	1	6.46	$10	Gym	After work, weekend/holiday	-10-40C, 0-100%, 0-100%, 0-10, 0-500
Resistance training	3.5	6.0	38,999	1	6.46	$10	Gym	After work, weekend/holiday	-10-40C, 0-100%, 0-100%, 0-10, 0-500
Stretching, mild	2.3		35,873	1	6.46	$0	Home, office, gym	After work, weekend/holiday	10-24C, 30-70%, 0-100%, 0-10, 0-500
Billiards	2.5		34,712	3	0.01	$5	Bar	After work, weekend/holiday	10-24C, 30-70%, 0-100%, 0-10, 0-500
Hiking	5.3	6.0	34,519	2	6.46	$50	Outdoor, mountain, forest	Weekend/holiday	10-24C, 30-70%, 0-25%, 0-5, 0-50
Elliptical trainer	5.0		28,560	1	6.46	$10	Gym	After work, weekend/holiday	-10-40C, 0-100%, 0-100%, 0-10, 0-500

5.3 Risk

For many users, the risk of injury or death is a major factor that influences their PA choices. To capture the risk levels of different PAs, we rate PAs on a scale from minimal risk (risk = 1) (e.g., walking) to high risk (risk = 100) even with protective equipment (e.g., auto racing). We compute the risk (**R**) of each sport based on sports injury statistics provided by the US Consumer Product Safety Commission [18], using the equation:

$$R = \frac{n_{injury}}{N} \cdot C_{injury} \cdot w_{injury} + \frac{n_{death}}{N} \cdot C_{death} \cdot w_{death}$$

where n_{injury} is the number of medically treated injuries, n_{death} is the number of deaths, N is the number of participants, C_{injury} is the medical treated injury costs, and C_{death} is the death costs. Since death is much more serious than injury, we set the weight of death—w_{death}—1000, where the weight of injury (w_{injury}) is set to 1. Finally, the value of risk is normalized to [0, 100] range.

5.4 Expense

Many users avoid expensive activities. For each PA, the expense is estimated in two parts: 1) equipment cost (e.g., shoes or rackets) and 2) facility expense (e.g., gym membership). The equipment cost is retrieved from the bestseller lists on the Walmart and Amazon websites. The facility expense is calculated based on the national average of membership or entrance fees to gyms and sports clubs as reported in the Sports Expense Profile 2013-14 from Roncalli High School [15].

5.5 Location

Some PAs (e.g., basketball) can only be performed at specific places. Other PAs, such as walking and pushups can be performed almost anywhere. We label each PA with a list of locations where it can be performed. We use the following location types: *home, office, outdoor (general), gym, track, field, pool (indoor), pool (outdoor), club, bar, river, lake, sea, mountain, forest, and ski area*.

5.6 Time

We label each PA as most appropriately performed *before work, working time, after work, and weekend/holiday*. Time labels are important because many people prefer not to perform high intensity PAs before work. Weekends also have more flexible hours than weekdays in terms of both PA duration and intensity. PAs that require locations far away from the user's home should generally be recommended during the weekends.

5.7 Weather

The suitability of each PA may depend on the weather. We label each PA with the comfortable and healthy weather ranges for performing it including temperature, humidity, precipitation, ultraviolet (UV), and particulate matter 2.5 (PM2.5). Typically, indoor locations have fewer limitations than outdoor locations.

Table 2. Sample physical activities listed in the 2011 Compendium

CODE	METS	MAJOR HEADING	SPECIFIC ACTIVITIES
01013	5.8	Bicycling	Bicycling, on dirt or farm road, moderate pace
02001	2.3	Conditioning exercise	Activity promoting video game (e.g. Wii Fit) light effort (e.g. balance yoga)
02048	5.0	Conditioning exercise	Elliptical trainer, moderate effort
03038	11.3	Dancing	Ballroom dancing, competitive, general
04020	4.0	Fishing and hunting	Fishing from river bank and walking
05021	3.5	Home activities	Cleaning, mopping, standing, moderate effort
05052	2.5	Home activities	Cooking or food preparation, walking
05092	4.0	Home activities	Laundry, hanging wash, washing clothes by hand, moderate effort
06052	3.8	Home repair	Carpentry, outside house, building a fence
07010	1.0	Inactivity/quiet/light	Lying quietly and watching television
07060	1.3	Inactivity/quiet/light	Reclining, talking or talking on phone
08120	5.0	Lawn and garden	Mowing lawn, power mower, light or moderate
08261	4.0	Lawn and garden	Yard work, general, moderate effort
09010	1.5	Miscellaneous	Card playing, sitting
10070	2.3	Music playing	Piano, sitting
11010	4.0	Occupation	Bakery, general, moderate effort
11375	4.0	Occupation	Garbage collector, walking, dumping bins into truck
12030	8.3	Running	Running, 5 mph (12 min/mile)
12170	15.0	Running	Running, stairs, up
13030	1.5	Self care	Eating, sitting
13050	2.0	Self care	Showering, toweling off, standing
15070	4.5	Sports	Basketball, shooting baskets
15265	4.3	Sports	Golf, walking, carrying clubs
15605	10.0	Sports	Soccer, competitive
16016	1.3	Transportation	Riding bus or train
17012	7.8	Walking	Backpacking, hiking or organized walking with a daypack
17040	7.3	Walking	Climbing hills with 10 to 20 lbs load
17140	5.0	Walking	Using crutches
18100	5.0	Water activities	Kayaking, moderate effort
18265	5.3	Water activities	Swimming, breastroke, recreational
18360	10.0	Water activities	Water polo
19090	9.0	Winter activities	Skiing, cross country, 4.0-4.9 mph, moderate speed and effort
20025	1.3	Religious activities	Kneeling in church or at home, praying
20040	5.0	Religious activities	Praise with dance or run, spiritual dancing in church
21000	1.5	Volunteer activities	Sitting, meeting, general, and/or with talking involved

6 Prototype Design

RecFit and its PA database can be used either as a standalone PA recommendation application or integrated into other smartphone fitness applications [Figure 3]. We demonstrate the prototype version of RecFit system by populating its database with the 10 most popular sports [Table 1]. Given the context, <location, time, weather, need for social interaction, risk tolerance>, RecFit filters and sorts PAs using the logic flow shown in Figure reffig:flow. The utility function we use in RecFit is:

$$u = p \cdot w_p + r \cdot w_r + e \cdot w_e$$

where **p**, **r**, and **e** are normalized popularity, risk, and expense respectively ranging from 0 to 100. The risk value is inverted—higher value means lower risk. In our demonstration prototype, all weight (**w**) values were set to 1.

Table 3 shows the ranking of an example with contextual conditions: <**location** = near gym, **time** = after working, **weather** = temperature between 10°C, 90% chance of raining & UV 5 & PM2.5 20, **sociability** = level 2, **risk tolerance** = low>.

Table 3. Sample RecFit results

Physical Activity	Utility	Ranking
Jogging	70.0	#1
Bicycling, stationary	68.5	#2
Resistance training	61.1	#3
Stretching, mild	58.8	#4
Elliptical trainer	46.9	#5

7 Future Work

In future, RecFit will be integrated into our previously developed smartphone physical activity applicationOn11 [7]. One limitation of our prototype is that it does not consider whether users will like the exercise. In much the same way that online retailers try to determine what goods shoppers will like, determining exercises that users will like based on

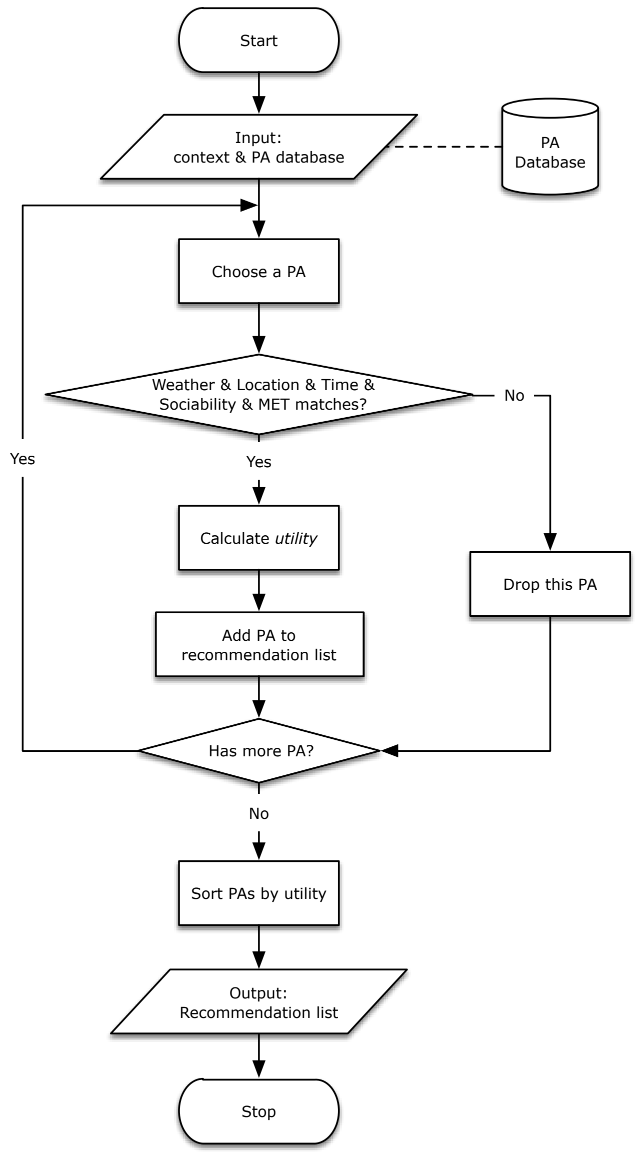

Figure 2. Flow for generating the PA recommendations

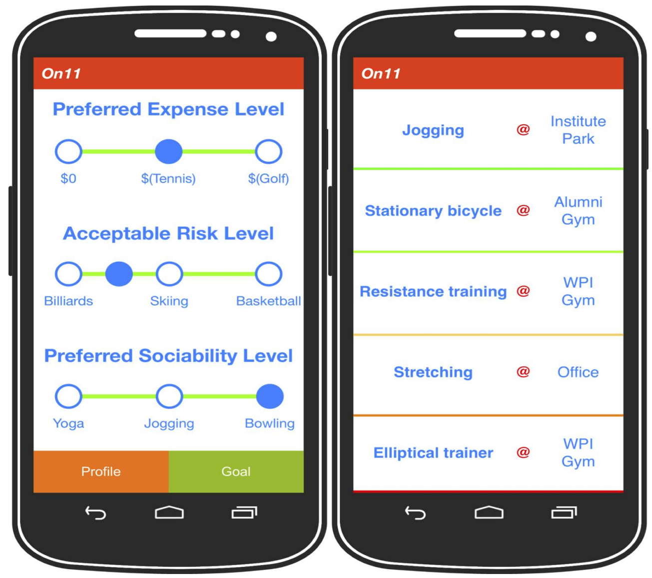

Figure 3. User profile settings (left) and personalized recommendations (right) screens.

their profile is a classic recommender system problem, which we are addressing in future work.

Adomavicius and Tuzhilin [1] describe 3 categories of recommender system, which we shall investigate: (1) *Content-based recommendation*. RecFit will recommend physical activities similar to the ones users have performed and liked in the past. For instance, if a user liked walking, RecFit may recommend low intensity hiking during the weekend, which is similar to walking but with longer distance and in natural environments. (2) *Collaborative recommendation*. RecFit will recommend PAs liked by other users with similar profiles based on clustering users with similar preferences. Another way to implement collaborative recommendations is to use social networking. Friends may be added to groups based on activities they enjoy and perform regularly. For example, RecFit could organize a soccer game and recommend it to a group of soccer players. (3) *Hybrid approaches*. These methods leverage both content-based and collaborative techniques.

8 Conclusion

In this paper, we presented RecFit, a smartphone app that generates individualized PA recommendations for users based on a database developed from the *2011 Compendium of Physical Activities* by excluding unsuitable activities, resulting in 137 PAs selected from the 821 PAs listed in the compendium. To provide information for recommending, we augmented the RecFit's PA database with quantitative contextual metadata from reliable data sources.

In the future, we will try different ranking algorithms and recommendation models [1] in RecFit and evaluate the ranking results with students and staff through on-campus user studies.

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