User-Similarity for Recommending Lifestyle and Behavior Changes

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INTRODUCTION

Users' lifestyle, activities, sleep and work patterns are valuable information contained in the fine-grained sensor data collected from personal devices. The increasing use of wearables in the society enables this data to be collected from a diverse population, varying in physical, cultural and social characteristics. Furthermore analysis of an individual's habits, lifestyles, wellness goals and their achievements and failures allow interventions that are personalized to the needs of the individual. Personalization of health-care by being sensitive to users' medical, biological, cultural and socio-economic characteristics could bring great benefit to the society. Building recommender systems that are designed to support this, is a step in that direction.

In this paper I first briefly summarize some of the work done within the domain of health and wellness recommender systems. I would then propose an approach to leveraging user-user similarity measure to generate recommendations for lifestyle and behavior change. Finally, I highlight some of the important challenges and opportunities that arise when designing a recommender system for supporting health and wellness. I am personally exploring these directions in my research.

Lifestyle Recommendations

Many factors influence our health and wellness, such as physical activity, diet, work and sleep patterns, and social contact. Behavior change research has explored many techniques like metaphors [2], reminders, social influence, goal-setting and self-monitoring [7]. Recommending lifestyle and behavior change is another promising technique that has been shown to be useful for recommending nutritional foods [8] and has been proposed for supporting health and wellness along other dimensions like physical activity [4] and medical treatments [6].

Context-aware recommendation has been of much interest recently. Within the HCI community, its usefulness has been shown in variety of domains including recommendation of activities. Bellotti et al. developed Magitti, a context- and activity-aware system to recommend leisure activities [1]. They used a combination of machine learning models to predict a user's leisure activity and recommend relevant content from data about the user' profile, preferences, location and activity history. Their inferred activities include: Eating, Shopping, Seeing, Doing, or Reading. Their system seemed to work well in guiding people to places based on their interest and their context and activity state.

Hammer et al. (2010) proposed Med-Styler, a lifestyle recommender system for diabetes patients with the goal of personalizing their physical exercise and meals [4]. They proposed the use of an individual's medical status and personal preferences to recommend meals and activities. Their recommendation approach utilized collaborative filters and demographic similarity for finding similar users and making recommendations. Collaborative filtering is however, susceptible to sparse data characterized by diversity in individual characteristics.

Farell et al. (2012) presented the Intrapersonal Retrospective Recommendations (IRR), that is not susceptible to sparsity of data by making recommendations from one's personal history(Text-box below)[3]. Although, IRR looks promising in making lifestyle recommendations that are not sensitive to the limitations of traditional User-User recommendations like collaborative filtering, it suffers from its own limitations- 1) cold start problem that takes a significant amount of time before it gets running, 2) lack of novel recommendations since they are made from a user's own history, 3) limited coverage of only those items that a user has already explored.

The IRR algorithm:

- Finds periods of success and failures within user's history
- Tracks stable patterns in a user's history
- Find potential changes in stable patterns
- Determine if these changes contribute or detract from user's goals
- Recommend changes that potentially have the highest positive impact towards reaching individual goals

Lane et al. presented an approach to activity recognition that takes diversity within population into account and is found to be the most robust approach when compared with other approaches [5]. Their approach utilizes information along three dimensions- physical, lifestyle and sensor-data, for each user, to create a network with each node being a user and the edge weight being the similarity measure between the users. This enables the creation of a personalized model for each user that requires less data than traditional approaches. Such an approach, when applied to making recommendations could overcome the challenge of high dimensionality of users' activity and lifestyle data. The similarity networks effectively reduces the dimensionality of the data and hence overcomes the limitations of collaborative filtering. The following is a hypothetical scenario utilizing such a system:

Louis runs regularly in the morning. He now sets a new goal with the system of gaining muscle mass. However, he doesn't want to change his usual routine of running and given his restrictive schedule, wants to know the easiest and the most efficient way of doing this. The system would find similar users like Louis who have achieved similar goals and share similar features like age and gender. From the most similar users, it would then find successful patterns of behavior that led to an objective goal like "gaining muscle mass", and finally recommend Louis some of these changes. Louis now learns that a user similar to him, gained 10 pounds of muscle mass by combining running with pull-ups everyday. This motivates him to add pull-ups to his routine.

I propose that an effective recommender system for achieving health and wellness goals can be realized by calculating user-user similarity using the Community Similarity Networks approach and recommending lifestyle changes and activities using the IRR algorithm.

DISCUSSION

To evaluate a recommender system, it is required to have a user's data along the dimensions of our consideration- activities, lifestyle, and physical. Moreover, to test the efficacy of recommendations, it is further needed to analyze the feedback of the user. Any system proposed would hence require many users and resources, and a study over a longer period of time. This system opens up various challenges that need to be overcome:

Characteristics of Lifestyle and Activity Data

Research exploring health and wellness recommendations needs to investigate the characteristics of data required to make meaningful recommendations. Characteristics include the kinds of activities, lifestyle patterns, and physical characteristics needed to calculate similarity between users. Given the high dimensionality of this data, the recommendations made along these characteristics need to be explored in more detail as some lifestyle changes are easy to recommend and some are more effective than others. There is a need to show which lifestyle patterns are most useful and effective for being recommended, taking into account individual differences of the users.

Complex Nature of Health and Wellness Recommendations

Traditional recommendations are given mainly over a single dimension (for e.g. movies, books, etc.) that do not critically depend upon other parameters of an individual's needs. In a health and wellness recommender system, the recommendations made are over multiple dimensions of activities and lifestyle (diet, sleeping patterns, etc). Recommendations need to be sensitive towards parameters like diet and lifestyle restrictions. For instance, a diabetic user should never be recommended foods that contains significant amount of sugar. Moreover, the kinds of recommendation made are inter-dependent to each other. For e.g. a recommendation made for increasing one's physical activity would require one to sleep more. This directly affects one's diurnal patterns and hence work patterns. Such recommendations should be carefully made as they could have a cascading impact on one's life.

In addition to the various dimensions of an individual's habits, recommendations are affected by one's personality type, motivation, and perceived benefits. For example, a person who plays sports as a way of social engagement is different from a person who exercises as a way to get fit. Recommendations can be imagined to be different for these two types. Future research could show which recommendations are most effective for which kind of user.

Presentation of Recommendations

The multiple types of recommendations made (diet, activity, etc) or recommending a complete lifestyle opens up significant challenges for the designers of the interfaces of such systems. The designer would need to consider the many different types of recommendations made. Moreover, it should be useful to know the context of such recommendations. For e.g. if its recommended to the user to replace a habitual physical activity with another, it would be necessary to explain why was such a recommendation made.

Temporal Nature of Recommendations

A user might be in different stages of one's fitness goals. For instance, consider a goal like losing weight. A person starting to work towards this goal is in a different stage than a person who has been running for a while and is trying to maintain one's physical activity. Recommendations made to these users might need to be completely different. For e.g. a beginner might benefit from bigger lifestyle changes like changing the diet and diurnal rhythms, whereas a user trying to maintain one's activity might benefit from smaller changes like replacing one activity with another.

CONCLUSION

Activity sensing systems collect data about its users' lifestyles, wellness goals, and their achievements and failures. For this information to be recommended strategically to cause positive behavior change in users, it is necessary to explore research looking at the ways of recommending such lifestyle and activity patterns. This paper proposes one approach that potentially overcomes the limitations of earlier approaches. Furthermore, I discuss some of the many challenges that need to be overcome to effectively make personalized recommendations to users.

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