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Connected-Health Algorithm: Development and Evaluation

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Abstract — Nowadays, there is a growing interest towards the adoption of novel ICT technologies in the field of medical monitoring and personal health care systems. This paper proposes design of a connected health algorithm inspired from social computing paradigm. The purpose of the algorithm is to give a recommendation for performing a specific activity that will improve user's health, based on his health condition and set of knowledge derived from the history of the user and users with similar attitudes to him. The algorithm could help users to have bigger confidence in choosing their physical activities that will improve their health. The proposed algorithm has been experimentally validated using real data collected from a community of 1000 active users. The results showed that the recommended physical activity, contributed towards weight loss of at least 0.5 kg, is found in the first half of the ordered list of recommendations, generated by the algorithm, with the probability > 0.6 with 1% level of significance.

Keywords: healthcare information system, connected health, collaborative algorithms, e-Health, recommendations.

Introduction

Rapid development of the information and communication technologies, pose new opportunities and challenges in the healthcare sector. The advances in mobile technologies and wireless sensor networks as well as the social networks have revolutionized the way health information is gathered, disseminated, and used by healthcare providers, patients and citizens. The ubiquities of these technologies have transformed the healthcare services from the services tightly coupled to the ordinations and hospitals into pervasive and mobile connected health services. Activities and services that require physical presence of the patients have now been performed at anytime-anywhere basis. This provides flexibility in patients' everyday life [1]. They are also helping the healthcare providers to focus on preventing diseases and promoting health [2].

On the other hand, connected health services increase the quantity and complexity of healthcare information [3]. Therefore, developing information systems that are capable not only to store and retrieve health data, but offer continuous monitoring of health data is very important for both healthcare providers and patients [4]. Such systems should be equipped with dedicated artificial intelligence algorithms and could support the process of decision making and diagnosing, searching through large amounts of health data and facts, classifying them and identifying issues that directly relate to a given medical condition. In this way they could offer citizens to be directly involved in their health care, providing information that will assist in making decisions about their own health [5]. Patients will have a greater role in the decision making processes related to their health as they could be empowered with the ability to gain access and manage information that fits with their personalized needs. Ultimately, they will be able to shape their health as a reflection of the health model of the whole community.

In healthcare systems most devices and their applications are wireless in nature, so they bear new risks and raise challenges with respect to security and privacy aspects [6, 7]. The main objectives of a secure health information systems are secure exchange of information through wireless devices and preventing improper use of illegal devices for interception of transmitted data, repeating the outdated information or disclose the health status of the patient.

In [8] Culfield et al. defines connected health as: "Connected Health encompasses terms such as wireless, digital, electronic, mobile, and tele-health and refers to a conceptual model for health management where devices, services or interventions are designed around the patient's needs, and health related data is shared, in such a way that the patient can receive care in the most proactive and efficient manner possible. All stakeholders in the process are 'connected' by means of timely sharing and presentation of accurate and pertinent information regarding patient status through smarter use of data, devices, communication platforms and people." While Kvedar et al. [9] examines the concept of connected health as an overarching structure for telemedicine and telehealth that provides examples of its value to professionals as well as patients. Generally, Connected Health involves the use of ICT to improve healthcare quality and outcomes, by developing and delivering healthcare solutions that can increase quality of life and reduce the risk to patients while lowering the overall cost of care [10].

As an example of a connected health system we propose COHESY (Collaborative health care system model). The design of a connected health algorithm, presented in this paper, is inspired from social computing paradigm that generates recommendations and suggestions for preventive intervention supporting emergency care and hospital admissions. The algorithm is part of the COHESY [11], which integrates data from various healthcare levels and sources. It also fosters collaboration between people with similar condition, generates automatic recommendations that should improve quality of care and life to its users, with the confidence that a medical professional is monitoring their health condition.

The proposed algorithm is based on collaborative filtering approach and it tends to find the dependency between health conditions and performed physical activities i.e. the impact of the performed physical activity on health parameters of similar users. Therefore, it is necessary to find out how physical activity, determined by its characteristics (type, duration, path length, etc.), affects the improvement of the users' health condition. The standard recommender systems have easy access to the feedback and they don't work on data that contains time dimension contrary to the proposed algorithm for activity recommendation. This algorithm uses time dimension to find the feedback and afterwards it is used to generate recommendations. The efficiency and correctness of the proposed algorithm has been experimentally validated using real data collected from a community of 1000 active users. The results of the evaluation show that the proposed algorithm generates personalized relevant recommendations with high confidence to the user, helping him to improve his/her health condition.

The next section is a related work. A brief overview of the recommendation algorithm is given in the third section. The fourth section describes the methodology used for the evaluation of the algorithm and discuss it. And the fifth section concludes the paper.

Related work

There are various examples of mobile systems for sending messages and notifications [12-16]. In these systems, the personalization of messages is typically according to the user's health. Although there are examples where generation of messages, despite the health of the user, exploit some prior knowledge of other users, analysis is usually performed by a medical service. The solution that we proposed (COHESY and its recommendation algorithm), in addition to monitoring physical activity also monitors health parameters of the user. Despite the differences of the recommendations generated in COHESY and systems in notifications [12-16] (for example - the proposed collaborative model recommends various activities with different intensity and duration) there is a substantial difference in the evaluation of the recommendation.

Cafazzo et al. [17] examined the impact of mobile applications for diabetes management of patients with diabetes type1. For that purpose they have developed a mobile application called "mHealth diabetes". According to the results of the survey in [17], the usage of the proposed application for monitoring the glucose level in people with diabetes encourages users to measure their glucose level more often. The frequent measurement affects the self-control of the users and encourages them to pay more attention on diet and their lifestyle. That self-control leads to a reduction of the glucose level, or with other words improves their health condition. Although the results of this research cannot be fully generalized, the authors suggest that the use of mobile applications in the diabetes management leads to improvements in behavior and dealing with illness in adolescents with diabetes type1.

Ruiz-Zafra et al. [18] are presenting the m-health cloud-transparent platform called Zappa. Zappa is extensible, scalable and customizable cloud platform for the development of eHealth/mHealth systems. Its main advantage is the ability to operate in the cloud. By using cloud computing, open technologies (open-source software, open hardware, etc.) and additional techniques the platform provides uninterrupted monitoring with the goal of obtaining some information that can be subsequently analyzed by physicians for diagnosing. In order to show the applicability of the platform the authors are introducing two m-health systems, Zappa App and Cloud Rehab, based on the Zappa platform.

Zan et al. [19] are (pilot) testing the iGetBetter system. This system is a cloud-based application that provides patients with clear treatment plans, and remotely monitor each patients' clinical status on a daily basis. The iGetBetter is a solution at lower cost that measure and collect key vital signs. The aim of this study [19] is to evaluate the feasibility and acceptability of use of the iGetBetter telemonitoring system in a group of ambulatory heart failure patients. The findings suggest the potential for improved health outcomes in similar patient populations who use the system. The portability and convenience offered by the consumer-facing digital devices likely contributed to patient satisfaction and high engagement levels, while dissatisfaction with the interactive voice response system and technical difficulties likely affected adoption and engagement in certain patients. Overall, patients reported high acceptability of the iGetBetter system, and found the intervention highly feasible and applicable to their care.

Taking into account research [17-21] it can be noted that the solution we offer is in accordance with the requirements of customers by offering timely recommendations and motivation to improve their health condition.

Recommendation algorithm

The proposed recommendation algorithm [11] is based on the dependence between the values of the health parameters (e.g. heart rate, blood pressure, arrhythmias, blood glucose level) and the users' physical activities (e.g. slow walking, fast walking, running, biking, swimming, hiking). The basic idea is to find out which physical activities affect change (improvement) of the value of health parameters. This dependence continues to be used by the algorithm to recognize the same or similar health situations found in another user with similar characteristics.

The purpose of the recommendation algorithm is to recommend the physical activities that the users should carry out in order to improve their health. The algorithm incorporates collaboration and classification techniques in order to generate recommendations and suggestions for preventive intervention. To achieve this, we consider datasets from the health history of the users and we use classification algorithms on these datasets to group the users by their similarity. The usage of classified data when generating the recommendation provides more relevant recommendations because they are enacted on knowledge from users with similar medical conditions and reference parameters.

In our algorithm, fuzzy sets and fuzzy discretization are considered as a suitable approach that can bridge the gap between the discrete way reasoning in the IT systems and the continuity of biomedical parameters. For the purpose of this paper we will use only one vital parameter – body weight and for this parameter several discretization intervals are considered. Each person has a corresponding membership factors for each of those intervals, depending on his/her parameter value. To improve the efficiency of the algorithm we have incorporated three filtering levels: classification (classifying users according to their diagnosis), collaborative filtering techniques (finding users with similar health conditions), and content-based filtering techniques (finding the best matching activities that would improve the health condition of the given user).

The algorithm for recommendation of physical activities consists of four main phases as shown on Figure1.

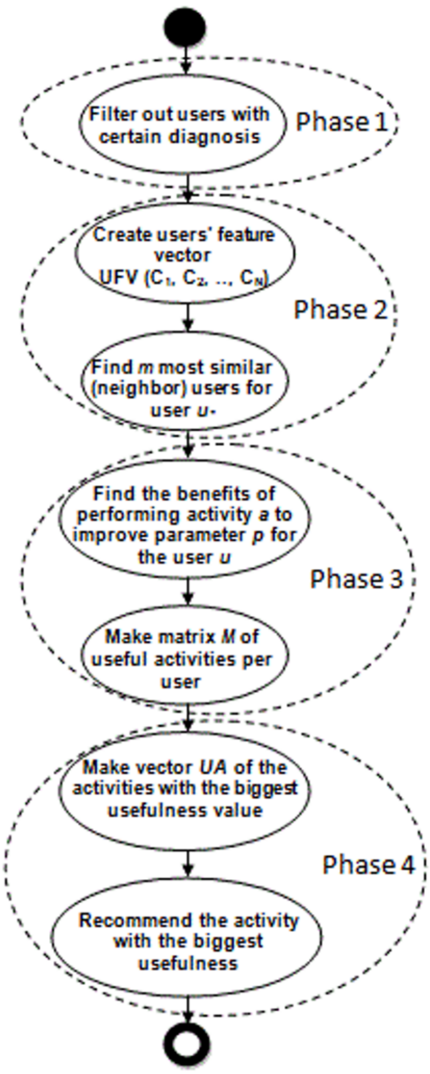

Figure1. UML activity diagram of the recommendation algorithm

Phase 1: Categorization of the users according to their diagnosis and filtering of all users that do not belong to the same category with the active user.

We assume that physical activities have similar effect to the people with the same diagnosis. Categorization of the users is made by grouping the users that have the same diagnosis and the same set of permissible activities. This phase is very important because we cannot treat people with heart problems and people with good physical condition in the same way. Categories of people with different characteristics should be determined with a help from a doctor. Different classification algorithms can be used in this step.

Phase 2: Selection of the users most similar to the active user according to the history of the health profiles by using collaborative filtering.

In this phase we generate the active user's profile. His/her profile is defined as a combination of parameter values in a given moment. We assume that if two users had the same combination of parameter values in the past, there is high probability that similar latent factors affect their health condition. Our system calculates the user's profile in regular time intervals, and if it notices that the current profile is significantly different from his past profiles, than the current profile is added to the database. When we need to find the most similar users to a given user, first we generate his profile, and after that we compare his profile with all saved health profiles of all other users. For calculating the similarity between the users' profiles, Euclidian distance measurement has been applied. Before that, features need to be normalized.

Phase 3: Calculating the usefulness of the activities to the active user and his similar users by using their health history and history of performed activities.

In this phase we use the control parameters and the history of readings and performed activities by each user from the set of similar users. For each performed activity we check its influence on the change of the parameter value. Our main assumption is that the activities that happened in the interval between two measurements influenced the parameter change with intensity that depends on the moment of occurrence. The intensity is proportional to the effort given to complete the activity. If some parameter value is smaller than the normal range of values for that parameter, we penalize all activities that decrease the parameter value.

In this way we create a connected health model that will represent the effect of the activity over the parameter value after its completion. It should not be expected that the activity influenced the parameter to change a lot in very short period of time (few days) and very long period of time (few weeks) after the completion of the activity. The usefulness of the activity for user u is calculated by the sum of the usefulness of the activity for each health parameter.

Phase 4: Generation of recommendations by using the calculated usefulness of the activities.

There are different ways to use the results produced in the previous phase in order to make recommendation. The most useful activity could be recommended by first summarizing the usefulness of the activity for all users, and then choosing the activity with the biggest usefulness. Other method, that can be used, is to recommend the activity which is considered as most useful by the biggest number of similar users. It is worth to mention that if the recommended activity is performed by the user and it improved his/her health condition, then in the subsequent recommendation process the same activity will have larger usefulness. In the other case, the activity will have smaller usefulness and there will be bigger probability that it will not be recommended again.

Evaluation

Proposed algorithm analyzes all types of activities (mentioned in the previous section) from the training set and sorts them according to the measure of usefulness. If some type of activity is associated with larger usefulness, this means that it is more certain that the activities of that type could have positive effect on achieving the previously defined goal. The most useful activity is recommended to the active user.

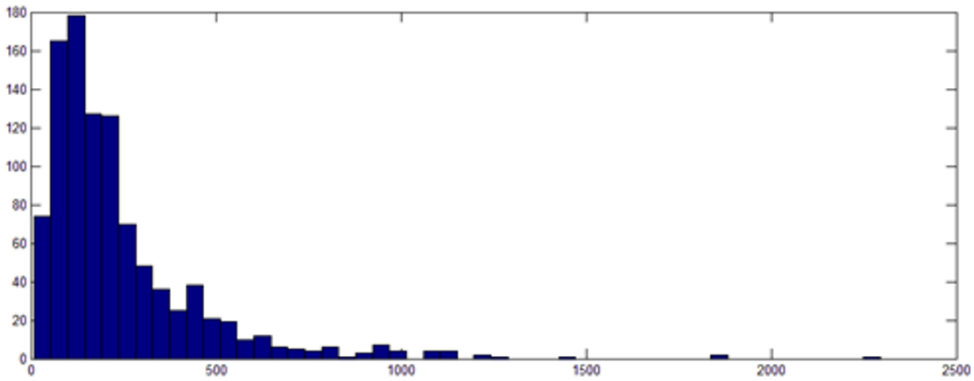

Figure2. Frequency histogram of users according the number of their activities (x axis)

Proposed algorithm is evaluated on the SportyPal dataset. SportyPal [22] is a sports training and tracking application that uses the GPS sensor of the user’s smartphone to track her/his fitness activities. The application is compatible with few types of sensors that measure heart rate, blood glucose level and blood pressure. It also offers the users possibility to enter other types of vital parameters, such as body weight. In our evaluation we will use the outdoor activities and only one vital parameter – body weight. This parameter was chosen because, according to the literature, excessive body weight is associated with various diseases, particularly cardiovascular diseases, diabetes, obstructive sleep apnea, certain types of cancer, osteoarthritis and asthma [23,24]. As a result, obesity has been found to reduce life expectancy.

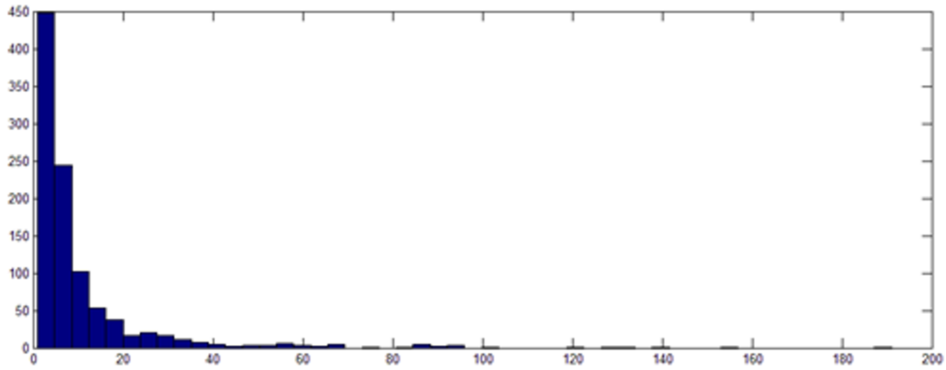

Figure 3. Frequency histogram of users according the number of their measurements (x axis)

The goal of the performed experiment is to show that the algorithm gives relevant recommendations to the active user based only on the history of his performed activities and measurements. This means that evaluation of step 3 of the algorithm is sufficient. This step is the core of the proposed recommendation algorithm. Without losing the generality it was decided to ignore the additional information for each performed activities besides their type. This is reasonable because the goal is to find out whether the algorithm generates relevant recommendations for weight loss.

Methodology

For evaluation of the proposed algorithm, a specific methodology that consists of five steps has been applied:

1) User u and moment m are chosen.
2) All activities and measurements performed by u before m as a local training set are considered.
3) Recommendation algorithm is used to generate recommendations for weight loss. All types of activities are sorted according to the measure of usefulness.
4) The first activity au that happened after moment m and the closest measurements of weight $prev(a_u)$ and $nextp(a_u)$, made before and after a_u respectively, are considered.
5) If the type of a_u exists in the local training set, the difference between the measurement of weight made after and before the activity is recorded.

Few more constraints are added to filter the observations generated according to the above method in order to get more relevant results. For the purpose of the experiment, we decided that there should be at least 5 activities (2 types of activities at least) and 5 measurements in the local training sets of all observations, the period between consecutive measurements $next(a_u)$ and $prev_p(a_u)$ should be at least 5 days and at most 20 days and there should be no more than one activity in this interval. Additionally, a_u should not be performed in the last 5 days of the interval because we want to increase the chances that the activity influenced $next(a_u)$).

Results

Evaluation data set consisted of the activities and measurements of 1,000 SportyPal users. These users had the larger product of the number of activities and the number of measurements. Data anonymization process has been conducted before analysis.

The frequency histograms of users according the number of their activities and measurements are shown on Figure 2 and Figure 3. 90% of the users have performed less than 489 activities. 90% of the users have made less than 24 measurements. One can observe that the amount of measurements is significantly smaller than the amount of activities.

The local training sets on which the recommendation algorithm has been applied contained from 2 to 8 different activities. The ordinal numbers of each analyzed activity au were normalized in the range [0, 1]. For example, if there are 2 different activities in the local training set and au has ordinal number 1, then the normalized ordinal number of au is 0. If there are 6 different activities in the local training set and au has ordinal number 4, then the normalized ordinal number of au is 0,6. The average normalized ordinal numbers for each different number of activities are shown in the fourth column in Table 1.

Table 1. Ordinal numbers

Number of different types of activities	Number of observations where weight loss of at least 0.5kg is noticed	Sum of ordinal numbers	Average normalized ordinal number	Sum of normalized ordinal numbers	Sum of normalized ordinal numbers (the assumption is that the normalized ordinal numbers are 0.5)
nt	ni	z	$\frac{z-ni}{(nt-1)\cdot ni}$	$ni \cdot \frac{z-ni}{(nt-1)\cdot ni}$	$ni \cdot 0.5$
2	43	55	0.27907	12	21.5
3	85	163	0.458824	39	42.5
4	41	81	0.325203	13.33333	20.5
5	30	32	0.016667	0.5	15
6	3	11	0.533333	1.6	1.5
7	0	0	/	0	0
8	17	17	0	0	8.5
Σ	219	359	/	66.43333	109.5

Discussion

In the performed experiment the relevance of the generated recommendations is analyzed. More specifically, the point of interest is the order of the types of activities according to the measure of usefulness and its relevance. Threshold t=−0.5 is defined and all observations for which the difference between the value of the measurement $next_p(a_u)$ and the value of the measurement $prev_p(a_u)$ is smaller or equal to t (observations where weight loss of at least 0.5 kg is noticed) are selected. To each of these observations is associated the ordinal number of au from the list of recommended types of activities sorted according to the measure of usefulness. The ordinal number is from to P where P is the number of different types of activities in the local training set. The expectation is that the types of the activities that had influence on weight loss have smaller ordinal numbers. So, the test is whether there is a larger probability that the type of activity, that contributed to decrease of weight for at least 0.5 kg, is found in the first half of the ordered list of recommendations.

If the algorithm assigns random usefulness value to each type of activity, then the expectation is that the average normalized ordinal number is 0.5. Each value less than 0.5 means that there is a larger probability that the types of activities which contributed towards weight loss of at least 0.5 kg enter in the first half of the ordered list of recommendations. There are 219 observations and this means that the minimum sum of the normalized ordinal numbers is 0 and the maximum sum is 219. If the ordinal numbers are chosen uniformly by random then the expectation is that the sum of these ordinal numbers is half the sum i.e. 109.5. Each sum of the ordinal numbers that is less than 109.5 means that the activities that cause weight loss of at least 0.5 kg probably have smaller ordinal numbers. The sum of the normalized ordinal numbers in the experiment is 66.43 and this is a lot smaller number than 109.5.

In order to find out what is the certainty that the types of activities which contributed towards weight loss are ranked higher by the algorithm (they have smaller ordinal numbers), the random event A is defined as: "The type of the activity a which contributed towards weight loss of at least 0.5 kg is found in the first half of the ordered list of recommendations" and $p=P(A)$. 219 observations are made and obtained that the event A occurred 152 times.

To check if the probability p is greater than 0.6, the null hypothesis

$$H_0\colon p = 0.6 \tag{1}$$

is tested against the alternative hypothesis

$$H_1\colon p > 0.6 \tag{2}$$

with $\alpha = 0.01$ level of significance.

The z-statistics that is used for testing is:

$$Z_0 = \frac{\hat{P} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \tag{3}$$

The critical domain for the hypotheses is $C_{\alpha}=(z_{\alpha}, +\infty)$ such that $P\{Z > z_{\alpha}\}=\alpha$.

The experiment demonstrated that $z_0=2,841$ and $C_{0.01}=(2.3263, +\infty)$. Since $z_0 \in C_{0.01}$, the null hypothesis is rejected and the alternative one is accepted. So, the conclusion is that $p=P(A)>0.6$ with 1% level of significance.

Conclusion

In this paper a recommendation connected health algorithm as a part of a collaborative healthcare system – COHESY has been presented and evaluated. This algorithm tends to find the dependency between health conditions and performed physical activities. We have evaluated the most important phase of the algorithm – the phase where we calculate the usefulness of the activities to the active user. An experiment was made on a real data set and we tested the probability that the type of the activity which contributed towards weight loss of at least 0.5 kg is found in the first half of the ordered list of recommendations. The results showed that this probability is higher than 0.6 which proves that our algorithm generates relevant recommendations.

The future work will focus on evaluation of the other three phases of the algorithm which are designed to improve the quality of the recommendations. The recommendations that are generated by the proposed algorithm as a part of a health care system will help users to have bigger confidence in choosing their activities.

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