Personality Diagnosis for Personalized eHealth Services

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Abstract. In this paper we present two different approaches to personality diagnosis, for the provision of innovative personalized services, as used in a case study where diabetic patients were supported in the improvement of physical activity in their daily life. The first approach presented relies on a *static clustering* of the population, with a specific motivation strategy designed for each cluster. The second approach relies on a *dynamic population* clustering, making use of recommendation systems and algorithms, like Collaborative Filtering. We discuss pro and cons of each approach and a possible combination of the two, as the most promising solution for this and other personalization services in eHealth.

Keywords: Personalization, Personality Diagnosis, Motivation Strategy, Collaborative Filtering, Natural Language Processing, Contextualization, Dynamic Clustering.

Introduction

According to the World Health Organization, modifiable behaviours, including specific aspects of diet, overweight, inactivity, and smoking, account for over 70% of stroke and colon cancer, over 80% of coronary heart disease, and over 90% of adult onset diabetes [1]. Intervention trials recently showed that a correct diet in combination with exercise programs can reduce the risk of developing diabetes by 60% in subjects with impaired glucose tolerance [2]. Also, great emphasis has recently been put on improving quality of life for diabetic patients, especially in terms of physical activity [3]. Most people are aware of healthy recommendations (e.g., about diet, physical activity), but they often find them very difficult to put into practice in their daily life, or fail to associate daily micro-behaviours (e.g., driving to work, rather than cycling or walking) with long-term health consequences. It is therefore important to understand how to promote a behaviour, like physical activity, taking into account the psychological determinants of such behaviour.

The European research project PIPS (Personalised Information Platform for Health and Life Services) [4] investigated the use of a eHealth platform for health promotion. In an intervention aimed at promoting physical activities among diabetic patients, a

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platform was designed, together with a methodology, which used a feedback based support system for the improvement of personal performances in physical activity [9]. This methodology relies on a pedometer for correctly assessing the patient's daily activity, and on a motivational strategy to provide a personalized support. The designed strategy is specific for a particular cluster of population (that have in common a specific *health personality* or, in the specific case, a common *motivational status*), which was *statically* determined by San Raffaele Hospital psychologists. During the PIPS project, some attempts to introduce a *dynamic* clustering have been proposed with promising, yet partial, results. This paper will present first the static clustering approach, describing the Motivational Strategy implemented in PIPS, then it presents a possible improvement using Recommendation Systems, and how it these could be implemented in PIPS. Finally the paper discusses some possible combination and comparison of the two approaches.

Static Clustering: Motivation Strategy

The motivational strategy designed in the context of PIPS was personalized along several dimensions and delivered through ICT solutions and devices, allowing to constantly support the patients during their daily lives; the proposed strategy has been designed with the aim of exploring the effectiveness of an e-health platform jointly with appropriate motivational tools for health promotion.

The level of personalization in the support tools has been implemented including socio-demographic and individual characteristics. PIPS introduces a motivation assessment determining the stage of behaviour change the user is at, as well as a detailed profiling and medical assessment. PIPS then provides a personalized and incremental target in terms of number steps, walking time, speed and caloric consumption and gives the patient a pedometer, that has been demonstrated to be a valid monitoring and motivation tool. With the pedometer, walking data are constantly updated and corrective, motivational messages are delivered just-in-time to the user mobile phone, thus supporting patient compliance with a real time response.

Motivational Messages are sent, with the aim to give feedback on the performance and to motivate to improve, giving advice to support their walking activity.

During the course of the program the patients receive several kinds of motivational message: a standard message is sent Monday to Thursday; a Friday *Special* message includes suggestions for the weekend; a Sunday *Summary* provides an overall judgement on the week performance. Moreover, a *Recover* message is sent when the patients significantly underachieve the daily target, around the time when they are supposed to have completed the activity they committed to: this message is an alert but also contains advice on how to achieve the target before the end of the day.

Messages are personalized along several dimensions: motivational stage of change, performance level, emotional status, how far is the patient in the programme, and other user's features as indicated in the profile (e.g. dog owner, drive to work, etc), location (e.g. weather forecast), perceived obstacles, as indicated by the patients when they fail to achieve their targets.

On the last day of the month the patient also receives a report of the month, which is intended to provoke some thoughts on the reasons of success/failure, so as to increase self awareness and eventually modify personal strategies, and the patient can comment on the system's deductions. Finally, the system sends a message containing a proverb related to the positive/negative factors that influenced the target achievements or a suggestion/encouragement for the next month.

A message structure was identified consisting of segments, each of which related to personalization factors and/or communicative goals [10]. The generation of the messages is achieved by means of a composition algorithm using constraint satisfaction techniques, selecting among around 1000 canned text segments, which are filled in with data from the database.

The PIPS Walking Program underwent different validation phases throughout the whole implementation process. In a first, informal evaluation, diabetes medical doctors and psychologists were asked to comment on the pilot. A second evaluation involved about 50 patients selected within the Outpatients Diabetes Care Centre of San Raffaele Hospital aged between 45 and 70. Patients had the opportunity to wear the pedometer for 15 minutes, to see the graphical representation of their walking performance and to see examples of the personalized messages composed after entering some selected information (e.g. diary, preferences, habits). Users were asked to feedback about the presented services: e.g. usability, information effectiveness, messages motivational level and understanding, exercise plan usefulness, etc. Of the patients interviewed, 75% said they were more inclined to increase their physical activity and to use technological devices as a support to the diabetes management.

Currently, a National, mono-centric (Diabetes, Endocrinology and Metabolism Department, FCSR, Milan), randomized, open-label, intervention study is ongoing enrolling patients from San Raffaele Diabetes Outpatient department. The study protocol, approved by San Raffaele Ethical Committee, sees the enrolment of 60 patients for a duration of 6 months each (2 run-in weeks, 3 months intervention period, 3 months control period), randomized according to two branches: the control group receives PIPS Pedometer as monitoring tool and standard diet/exercise care, the intervention group receives PIPS pedometer and mobile phone, a personalized walking target path (steps/min and total minutes) and information and motivation feedback. Inclusion criteria consider patients with Diabetes Type 2, aged 35-70, with no physical or psychological impairment and with a BMI<35. The primary objective of the study is to demonstrate the effectiveness of PIPS, which integrates a technological platform and a personalized motivation strategy, to achieve a personalized exercise target and to improve patient compliance. Patients were profiled according to the stage of behaviour change both towards exercise and towards technology [11]. First results report an improvement in the metabolic profile of the patients after 3 months of physical activity supported by PIPS strategy. Feedback from users indicates that the tool overall increases their willingness to walk. With respect to the messages, they are considered relevant to the actual target achievement, but sometimes too repetitive, so they were read with less interest over time.

Towards A More Effective Solution: Dynamic Clustering

One of the shortcomings of the aforementioned solution is that the choice of a message among a set of equally relevant ones does not take into account the projected outcome of this message in terms of improving the patients' performances. While an accurate measure of the message effectiveness would require a very sophisticated user model, including also emotional and cognitive factors, some prediction could be achieved by using knowledge coming from other users, or the same user in other similar situations. Our proposal is therefore to apply to the choice of which message to present the user with, techniques coming from works on recommender systems. In particular, our assumption relies on a Personality Diagnosis [12], that is the probability that a user is of the same "personality type" as other users, influences the probability that the user will adopt a behaviour (e.g. like an item, buy a product, etc).

The typical recommender system has the aim of predict user's preferences towards some products to buy or examine, on the basis of information acquired on the community of the system's users. Algorithms in use can be of various sorts [5][7][8], and come from diverse areas, like information retrieval, information filtering, data mining, or machine learning. Recommender systems can use collaborative filtering (based on the relationships among users), association rules (based on the relationships among products) or classifiers (based on the content of the knowledge base).

For example, in a system recommending books there usually are two sets, a set of users U (e.g. the readers) and a set of items I (e.g. the books), and a utility function r between the two sets (e.g. the rating the users gives to the books). In its most common formulation, the recommendation problem is reduced to the problem of estimating ratings for the items that have not been seen by a user, selecting for each user $u \in U$ the item $i' \in I$ that maximizes the defined user's utility.

In our specific case the set U of users is the set of diabetic patients, while the set of items I is formed by the set of all the possible messages to be sent to the patients. The relationship between the two sets, instead of being a rating, is a "success" function. The hypothesis is that, if a motivational message was "successful" we would expect performances to improve. The success function is therefore determined by the walking results, measured as the percentage of achievement of the target on the following day of walk.

Messages, as well as the patient profile, can be considered as vectors, described by a set of parameters. For example for the message we can consider the parameters:

- type (messages can give a strong o a mild encouragement),
- subject (some of them are related to the body, other to health in general, other to social aspect of physical activity, etc.),
- length (different person may like short messages, other complete information),
- value (some messages are more positive, e.g. "if you walk you will feel the benefit", other are more negative, e.g. "if you don't do you physical activity you will have complications…", etc),
- attitude (some message can be more friendly, other more formal).

In this case we can present each message $i \in I$ as:

$$i = (i_1, i_2, \dots, i_m)$$

For the patient, we can consider the dimensions explained in the previous section, for example motivational stage, performance level, preferences, perceived obstacles, etc.

In this way we can consider each element $u \in U$ as a vector described by its dimensions:

$$u = (u_1, u_2, \dots, u_n)$$

With this model, two recommendation services are possible:
1. the patient will be provided with messages similar to the ones that worked better in the past (content-based recommendations);
2. the patient will be provided with messages that worked with people with similar characteristics and preferences in the past (collaborative recommendations).

In content-based recommendations systems the goal is to identify similarities between items, and that's the final purpose. In collaborative recommendation this is just an intermediate step used to identify similarities of "tastes" between users. In our case study, the first service model seems preferable, because it has the advantage that the cold start problem, typical of the recommendation systems, is limited: the patient receives at least one message per day (more if underperforming), a Friday special, a Sunday special, and the monthly report. In average we can consider from 40 to 70 messages per month, or 480 to 840 messages per year, which makes a lot of data available to the system.

To calculate similarity, a recommendation systems typically takes into account all items that are co-rated by two different users. In our case we will choose the subset of I, $I_{xy} = I_x \cap I_y$, where I_x are all the items rated by patient x and I_y are all the items rated by user y. Collaborative Filtering algorithm can determine the nearest neighbours of user x without computing I_{xy} for all users y. In the correlation-based approach, the Pearson correlation is used to calculate the similarity [7][8]:

$$sim_{Pearson}(x, y) = \frac{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r_x})(r_{y,i} - \bar{r_y})}{\sqrt{\sum_{i \in I_{xy}} \left(r_{x,i} - \bar{r_x}\right)^2}}$$

In the cosine-based approach, the two users x and y are treated as two vectors in m-dimensional space, where $m = |I_{xy}|$. Then, the similarity between two vectors can be measured by computing the cosine of the angle between them:

$$sim_{cos}(x, y) = \cos(\vec{x}, \vec{y}) = \frac{\sum_{i \in I_{xy}} r_{x,i} r_{y,i}}{\sqrt{\sum_{i \in I_{xy}} r_{x,i}^2} \sqrt{\sum_{i \in I_{xy}} r_{y,i}^2}}$$

The best similarity function has not been identified yet, because of the lack of sufficient data in the study to compare the two approaches.

Implementation Of The Personality Diagnosis Method In PIPS

The basic idea is, as said above, to consider the appropriate message to present to a patient as the most "recommendable" message, on the basis of how the message to propose (or others in a similar class) was evaluated in the past either by the same patient or by other patients in the same situation of the user. A good evaluation is considered, broadly speaking, one when, after receiving the message, a user did improve his performances: so when the target patient has similar characteristics and similar past performances, one can assume the same message may provide the same outcome. The interaction of a user with a typical recommender system is however explicit: the user browses some products, or purchases them, or provides an evaluation for them. In our case, the only way in which a patient can interact with the system is by providing the daily performance, or updating his data. The approach used, therefore, is the one of creating a relationship among the performance and its derivative, the messages, and other data collected about on the users.

In PIPS, the characteristics of the message to recommend come from an ontology [10], so relevant classes in the ontology are used as parameters. The message itself is of course not the only factor that influences the performance of the patient: the context like the weather for the day or how good was the day at work, can be determinant of the performance no matter how good the motivational message was. It made therefore sense to consider, in computing the evaluation, both the *message* and the *context*. Thus, $I' = I \times C$ is the new extended item set for our recommendations, where I is the set of all the possible messages and C is the set of all the possible contexts. Formally we can say that each element $i' \in I'$ has the following components:

$$i' = (i_1, i_2, \dots, i_m, c_1, c_2, \dots, c_p)$$

The idea of extending the recommendation by including contextual information was proposed also for a movie recommendation system [5], where the suggestions showed meaningful improvement by adding contextual information, such as when, where, and with whom a movie is seen. In our preliminary implementation we considered as context the parameters that the patient inputs on a daily "diary". The patients can input aspects related to their day as emoticons, choosing to comment on the level of gratification at work on that day, their perception on the social relationships on the day, the weather, and an overall emotional orientation, or "mood". This is a simple solution, but one can think, assuming to be able to rely on monitoring system and on internet public services, of adding more descriptive contextual variables, such as environment (e.g. pollens concentration), physical parameters like blood pressure; social interactions, from events in the user's day, etc.

In the current implementation, the system considers the performance of the day, in relation to the one on the previous day. If the performance improves, the message of the day before is "promoted", otherwise it is "demoted", of a factor depending on the context, given by entries in the user's diary. Entries in the diary with a positive orientation (e.g. a good day at work) cause a lesser increase in the value of the message when the performance improves (the idea being that the user might have been motivated by the positive experience, rather than the message), and cause a greater decrease when the performance deteriorates (representing the fact that the message was not effective in spite of the positive attitude). Similarly, entries in the diary with a negative orientation (e.g. a bad day at work) cause a greater increase in the value of the message when the performance improves, and a lesser decrease in the value of the message if the performance deteriorates.

The work on fine tuning the formulae is still ongoing, and is based on the result of preliminary questionnaires where patients were asked to evaluate the messages produced with the original method. The objective of this analysis, for our purposes, is to obtain some *a priori* values for starting the system up, and possibly a set of benchmark values for evaluation.

Final Considerations

In this paper we presented two possible approaches for determining the health personality of patients, with the purpose of tailoring specific personalized strategies and services. The case study presented, in particular, describes a service for physical activity support, where (diabetic) patient receives motivational feedbacks to improve their performances. Static and dynamic clustering are important bases for providing personalized services. Both approaches present advantages and disadvantages.

The Static clustering has the advantage that the reference model (e.g. the motivational status psychological theory) is known a priori. Correlation between relevant factors is identified from the start and the support feedback is designed to maximise effectiveness. On the other hand, if the model is not descriptive enough of the process, or if many uncontrolled variables influences the final results, the static approach is less personalised and contextualised, and may become repetitive.

In dynamic clustering the correlations between relevant variables are not known a priori, but, on the other hand, they become clear during the processing and can change when new data is taken into account. The ability to cluster the population based on patients' behaviour makes this approach very promising to predict future behaviours, thus to provide the proper support feedback. The dynamic clustering suffers from all the problems typical of recommendation systems, in particular from the *cold start*, when there are not enough data about the users or about messages.

PIPS started the clinical trial described above making large use of a Static Clustering approach, that classified the patients' health personality based on their *motivational status* and provided specific messages, validated by psychologists, to bring a change in the patient's motivation and actions. A first attempt was also made to use also the dynamic clustering and, even if results are still very preliminary, they seems very promising. The lesson learned is that probably the best solution would be a combination of the two clustering. This, in our case study, can be done in two ways:

1. Using the static clustering when a new user enters the system, until there are sufficient data about him to start using the dynamic clustering. This approach has the advantage to reduce the problem of the cold start of the recommendation system, and that in the second phase it will fully adapt to the behaviour of the user. On the other hand, messages provided to the user in the second phase are *uncontrolled* by medical personnel, thus a patient may receive a message that would not have been selected for the same patient by the static, controlled method, so a message which could not have been pre-approved by the medical experts.
2. Using the dynamic clustering on a set of messages that have been preselected to be appropriate to the static cluster to which the user belongs. In other words, we apply first the static clustering, preselecting the subset $I_x \, c \, I$, of all the items (messages) appropriate for user x based on the users' motivational status. We can then use this subset of messages to calculate the new item set $I'_x = I_x \times C$, as the item set to which apply the collaborative (finding similar users) or content based (finding similar messages) recommendations. This approach is safer from the point of view of medical validation, but will lead to less variability.

In both cases, it is crucial to ensure that the monitored variables are descriptive enough of the factors impacting on user's decisions and behaviours, and are as complete as possible.

The two approaches were compared in terms of complexity and effectiveness with respect to the case study. A formal evaluation of the first approach is currently under way with a randomized trial, while for the second it is envisaged a less formal evaluation, due to the experimental nature of the approach.

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