Abstract
The World Health Organisation (WHO) states that: “There is no health without mental health”. Health population studies show that the most common mental disorders are anxiety disorders. Nowadays, Virtual Reality Exposure Therapy (VRET) is used to help people manage their anxiety. The next step forward, is personalisation of VRET to further improve therapy and patient motivation. The effects of VRET would even be more increased by automating this personalisation by taking background and data from wearables into account. In the ongoing PATRONUS project, we aim at designing such a system that provides truly personalised VRET. In light of this project, this paper discusses the current shortcomings of Contextual Multi-Armed Bandits and related challenges in personalisation. Future research areas are proposed, namely the use of semantics in reinforcement learning and Contextual Multi-Armed Bandits for personalisation as well as clustering patients based on background information in order to train better models.

Introduction
According to (Kessler and Wang 2008), around 25% of the population can be diagnosed with one or more mental disorders in their lifetime. Anxiety is the most common disabling disorder, it accounts for 6% of all disorders in Belgium according to (Bruffaerts et al. 2004). When anxiety begins interfering with daily activities it forms a significant problem. Anxiety disorders not only have an impact on an individual’s ability to operate normally in society, but they also have implications on the economy. In Europe, the costs related to anxiety disorders were calculated at €74.4 billion (Olesen et al. 2012).

Exposure Therapy (ET) is the most successful treatment for anxiety disorders and is often used for post-traumatic stress disorder (Beck et al. 2007). The therapy consists of confrontation with the context that triggers the fear or anxiety of the individual in order to learn how to manage it. Therefore, the therapist needs access to special facilities in order to expose the patient to his fears. For example, fear of flying is treated by flying in a real airplane. These facilities can often be very expensive. Because the patient needs constant supervision and guidance of the therapist, it is also a time consuming job. Additionally, there are significant transportation times needed for in vivo ET. Virtual Reality Exposure Therapy (VRET) is an extension of exposure therapy. The therapy is based on the same principle as normal ET. The patient is exposed to situations that trigger his anxiety. However, instead of real life situations, the patient is confronted with simulated Virtual Environments (VE). VRET is currently used in order to reduce the cost of this treatment while still maintaining the effectiveness (Krijn et al. 2004). Because the therapy does not require special facilities for each individually treated phobia, costs are significantly reduced. Potentially every phobia could be treated in the offices of the therapist. The VE are viewed through a Head Mounted Display (HMD), offering the needed immersive experience. Platforms such as Psious® and CleVR® already offer tools for VRET. However, therapy is a personal process that needs to be tailored to the requirements of the patient. Existing tools allow very little possibilities for adapting the VE in an easy and intuitive ways. Therefore, these tools indeed reduce cost but do not reduce the time needed for therapy.

Automatic personalisation can make such a VRET system much more attractive. A patient is more likely to engage in a personalised and adaptive therapy than in static exercises (Triantafyllidis et al. 2015). A system that incorporates a feedback loop, allowing for (semi-)automatic updates of the VE based on both, physiologic sensor readings and patient background, could improve current solutions. In addition, a mobile application allowing patients to perform homework exercises can further extend the therapy. Based on experiences of anxiety in daily life and the progress of the VRET with the therapist, personalised homework exercises are suggested that improve the effectiveness of the treatment. Coaching the patient outside of the office in daily life situations is also a big advantage. Such a system is designed within the PATRONUS project. It includes the use of wearables such as the Chill Band® to perform anxiety level analysis in order to dynamically adapt the therapy. This project offers a use case in which to position future research.

This paper continues with a brief discussion on the cur-
rent state of the art and indicates some challenges regarding personalisation in healthcare. In the next section, a motivation is given for using the PATRONUS project as a use case in future research. The following section proposes three contributions for research in personalisation for healthcare. The paper concludes with a short discussion.

Current State of the Art

In general, the problem of providing personalised content such as ads on web-pages is represented as a Contextual Multi-Armed Bandit (C-MAB) problem (Langford and Zhang 2008). An extensive and formal description of the C-MAB problem will not be given in this paper, however intuitively, the C-MAB problem is defined as an agent that chooses actions from a fixed set based on context information. The context can be background information about a patient and real-time physiological data. Upon execution of an action, the agents receive a reward indicating the favourability of the action. This reward is defined by the specific problem, for example, a measure for the effectiveness of the treatment can be used. The agent solves the C-MAB problem by selecting actions that maximise the accumulated rewards for all actions.

This formulation is frequently used in literature for its simplicity. Additionally, solutions for C-MAB are often interpretable, and thus provide insights for the therapist into the decision rules of the solution. However, C-MABs have some shortcomings as they do not completely characterise the personalisation problem in healthcare (Zhu and Liao 2017). Specifically, two problems are observed. Firstly, solutions for bandits cannot handle delayed rewards (Zhu and Liao 2017). A bandit only defines a direct relationship between the current context, the action chosen for that context and the immediate reward, not for rewards that will be received multiple time steps later. Secondly, C-MABs illustrate systems where actions are chosen at fixed decision points because bandits do not allow continuous evaluations of the context (Lei, Tewari, and Murphy 2014). Once an action is chosen, the intervention or exercise for that action is executed until completion and the next actions do not depend on the previous action. One bandit cannot include actions for both the initialisation and premature termination of an intervention. This means that bad decisions by the agent can have a big impact on the actual experience of the user.

It can be argued that because of these shortcomings, the problem should be represented as an Markov Decision Process (MDP). The context information could be extended with information about the current progress during an intervention, and the set of possible actions for each state can differ, resulting in a much more flexible systems. These MDPs can be solved using more general reinforcement learning (RL) methods. Such methods would also take delayed rewards into account which are very important for healthcare applications (Zhu and Liao 2017). However, RL algorithms are much more complex than bandits. Therefore, they often require much more computing power and design effort. A comparative study will indicate their benefit over C-MABs.

Naive implementations of personalisation systems with self-learning algorithms bring some additional challenges with them. Firstly, these algorithms need data to learn from. However, the amount of data sampled for one specific person is typically very small (Nguyen and Lauw 2014). With insufficient data it is difficult to build personalised models. Smart initialisation for models is a challenging topic with room for further research. Secondly, but associated with the first challenge, is the transferability of a model for one person to another person. Although personalisation is inherently connected to one person, a model that works for one person could also be used for another person with some potential changes. How to perform this transfer of knowledge is a topic for additional research. A last challenge for personalisation, specifically in healthcare, is exploration of actions. For most self-learning algorithms exploration is an important step. Typically this results in the selection of actions for which no evidence is present that suggest the reward will be positive. In healthcare, such uncontrolled actions are not acceptable (Zhu and Liao 2017). However, exploration is an important and necessary step to find good models.

Use case

The PATRONUS project aims to develop a light-weight and scalable blended care solution for virtual reality exposure therapy. The tool is to be used by therapists and offers a low-cost solution for qualitative therapy. The project focuses on incorporating a feedback loop that allows for easy and personalised adaptation of the virtual environment. Physiological data will be collected through a Chill Band, which is a wrist band equipped with sensors to measure skin conductance, heart rate, body temperature and acceleration in 3 dimensions. On the collected data, personalised and objective anxiety assessment is performed to extract a reliable measurement for the anxiety level. Based on this assessment, adaptations of the VE can be proposed to the therapist. Easy personalisation of the therapy allows for an emotion-aware and patient-centric approach to anxiety therapy. Figure 1 illustrates the general approach of the PATRONUS project.

First, a user profile is created containing relevant information about the patient, for example, age, occupation and health conditions. From this profile, a semantic knowledge model is constructed. This model is extended and linked with additional real-time background information, this includes measurements of anxiety levels. Reasoning and processing is applied on this data graph in order to make decisions on adaptations of the VE. A patient will show a physiological response on the VR experience, which is processed to extract the anxiety measurement. This data provides new information for further personalisation of the exposure therapy.

Included in the scope of PATRONUS is the development of a longitudinal follow-up and coaching mobile application. This app will help with daily life situations by providing personalised guidance and allows the patient to do homework exercises with a light-weight VR set-up. The therapist is absent in the home setting, which makes automatic personalisation a key functionality. Based on background information of the patient and physiological data collection from the wearable sensors, exercises are suggested. These suggestions are provided without supervision of the therapist.
Two proof of concepts are envisioned, one for claustrophobia and one for panic disorder. These PoCs are developed in close collaboration with user researchers and domain experts to ensure they are of high quality. Focus groups are organised to build the knowledge model and personalisation algorithms and to perform subjective user tests with real potential patients to evaluate usability of the system.

Contributions

We suggest research on three topics concerning personalisation. Firstly, a comparative study of C-MABs and more general RL solutions is proposed. Secondly, research on clustering individuals based on their user profile in order to provide personalised therapy for people in each cluster is suggested. Lastly, techniques for applying semantics on intelligent personalising systems to increase performance are studied. The following subsections discuss each area of contribution in more detail, followed by a subsection on the evaluation of the research in the context of PATRONUS.

Comparison

As seen from literature, C-MABs are very popular for representing personalisation problems. However, as stated before, it has some shortcomings. Namely, the lack of integration for delayed rewards and the inability to perform continuous evaluations of the context where an action depends on the previous action. MDPs could describe the problem more accurately. Both problem descriptions have advantages and disadvantages. To our knowledge, a comparative study between solutions for C-MABs and MDPs that describe the problem in as much the same way as possible has not yet been conducted. Such a study could provide insight into the requirements for personalisation in healthcare applications. Because the challenges of healthcare are different from personalisation in other applications, one approach could potentially provide better results over the other. Future research would mainly focus on the resulting family of algorithms from this study.

Clustering

Providing personalised exercises to a large group of users is challenging, because some exercises will have a better effect on some people than on others. In (Nguyen and Lauw 2014), the question of how many bandit agents are needed for a group of users is investigated. Figure 2a illustrates the simplest approach, one agent that gives recommendations for every user. However, such a system might not provide truly personalised content. In the other extreme, there would be exactly one personalisation agent for each user as depicted in figure 2b. While such agents could be completely personalised, typically there would not be enough data to train these agents. A better approach is to construct one agent that serves multiple users. This is possible, because users can often be divided into clusters where every user in the cluster has similar preferences and behaviour. Figure 2c shows that the last approach requires to find a clustering over all users in order to train one agent for each cluster. Ideally, a dynamic clustering algorithm is used such that user can move from one cluster to another as their user profile changes.
Semantics

Semantics in combination with different areas of artificial intelligence is only recently becoming more popular. It allows us to structure data in order to get better insights and could increase the performance of personalisation systems. For example, the context information can be captured in an ontology (Ongenae et al., 2013), which allows the extraction of additional information and extends the context knowledge. Semantics can also be used for efficient feature selection (Ringsquandl et al. 2015). We will also look into data generation based on a semantic representation of a patient, as shown in figure 3. That way, models could further be improved without having to sample data from real patients. These techniques could allow learning from fewer data samples from real patients.

Figure 3: A semantic model is build from a user in order to generate additional data, extract features and help with feature selection.

Evaluation

The evaluation of the conducted research will be performed in the context of the PATRONUS project. Specifically, proposed techniques can be validated by integrating them into the personalised exercise selection mechanism. In the initial stages, the algorithms will simply assist the therapist by providing suggestions for exercises. In later stages, the techniques will be used in a completely autonomous system that generates personalised treatment plans for patients.

Following the design and evaluation of potentially new personalisation techniques for exercise selection, it will be investigated if the proposed solutions can be adapted in order to use them for the generation of personalised VE for VRET. Personalised VE would improve the effectiveness of the therapy.

Discussion

Personalisation in healthcare is still in an early stage and allows for many research opportunities. A comparative study of the performance and benefits of solutions for C-MABs and general RL solutions will help to clarify the landscape of personalisation solutions. With the knowledge of that study we proceed with improve on the current state-of-the-art solutions by using clustering techniques based on user profiles and semantics for data expansion.

The PATRONUS project, which is a collaboration between multiple partners, offers a use case in which personalisation can be evaluated for VRET. Primarily, the selection of homework exercises based on the observed behaviour through wearables is investigated.

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References


