New Opportunities for Dialogue-based Interaction in Behavior Change Domain

Rafal Kocielnik
University of Washington
Seattle, US
rkoc@uw.edu

Gary Hsieh
University of Washington
Seattle, US
garyhs@uw.edu

Abstract
Despite many recent advancements in conversational interaction and personal assistants, relatively little of that revolution have affected behavior change domain. The commercial applications that do use conversational interaction, generally just repackage the already well-supported functionalities in the conversational form (e.g. motivational triggers, reports on self-tracking data, collecting profile information). They do not take advantage of the new possibilities for novel forms of engaging the user that dialogue based interaction enables. In this paper we propose three such unique engagement scenarios: negotiation around relapse, reflection on goal setting, and social coordination. For each we discuss, the unique value of dialogue based approach, propose an example interaction model and discuss challenges. Our work brings conversational assistant revolution to the behavior change domain in a set of use cases that take active advantage of dialogue-based interaction.

Author Keywords
Conversational; dialogue-based; assistant behavior change; motivation; persuasion; interaction

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

Introduction

Thanks to recent advances in machine learning (ML) and natural language processing (NLP), conversational assistants such as Amazon's Alexa, Apple's Siri and Microsoft's Cortana are now robust enough to be in wide practical use. Despite such progress relatively little has been done to bring these conversational capabilities to the behavior change domain [1].

Existing behavior change systems rely on motivational triggers and visualizations of self-tracking data. Yet, some of the most effective practices in non-technology based behavior change interventions rely on personal counseling [2]. Human councilors successfully employ techniques such as motivational interviewing [3] and reflection-based dialogues. Much of the focus of these strategies goes into dialogues that help with identifying and reassessing person's behavior barriers, negotiating around effective methods of overcoming such barriers, dynamically readjusting person's goals and expectations and relapse management [4]. However, a recent review of behavior change apps [5] identified that very few incorporate such aspects.

There are numerous reasons why such strategies have remained rarely supported. First of all, the proper "understanding" of very personal, dynamic and contextual user barriers and motives expressed in natural language is difficult for an algorithmic approach. Thanks, however, to the recent advancements, these limitations are now less strict. Conversational agents are now able to understand user input in natural form and generate appropriate responses in natural language. This opens up opportunities for behavior change systems to engage with users in new ways.

There have been recent attempts at building conversational behavior change assistants, such as Lark[1], HealthyBot[2], and CountIt[3] to name a few. Unfortunately, these solutions still leverage dialogue-based interaction to support user tasks that could already be done quite well, if not better, with non-conversational interaction. For example HealthyBot and CountIt, mainly provide activity triggers along with motivational contents through Slack. This is not different from regular one-sided text-based behavior change triggers sent through SMS or email. User typed input is just used to query information, as a replacement for clicking a button. Lark being arguably the most advanced of these, actually provides some interesting use cases. It actively interviews the user for gathering basic profile information and weaves in reports of user activity into the chat, but the user input part is limited mostly to provided and fixed responses. These solutions do not take any specific advantage of dialogue-based interaction to do something that has not been possible or hard to do.

In our work we explore the new ways of engaging the user in the behavior change domain that make use of the natural strengths of dialogue-based interaction. These scenarios are: 1) relapse handling through **negotiation** 2) **reflection** on goal setting and 3) **coordinated social activity**. We contribute by opening up the design space of behavior change to the new use scenarios that can be uniquely realized through dialogue-based interaction.

---

[1] http://www.web.lark.com/

[2] https://healthybot.io/

[3] https://beta.countit.com/

Example dialogue for negotiation around relapse

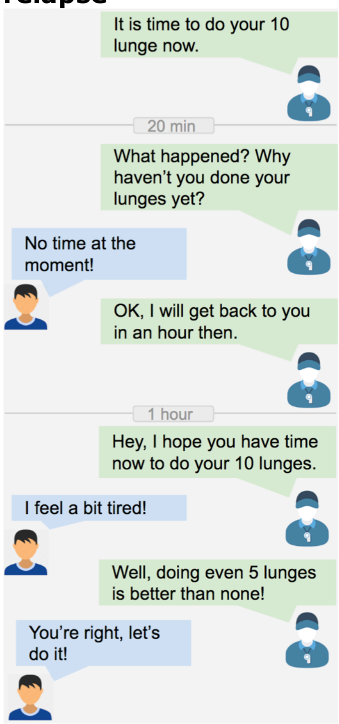

Figure 4: Example dialogue exchange for handling relapse in exercising through negotiation. It is assumed here, that the user has set to perform "10 lunges" at a specific time.

Scenario 1: Negotiation around relapse

Relapse takes place when the person stops following the agreed on actions and reverts back the previous patterns of behavior. Relapse is one of the hardest aspects to handle due to its, often unpredictable, appearance and causes, as well as the difficulty of reestablishing rapport with the user to get back on track [6]. Occasional decreases in motivation, disappointment with progress, unexpected schedule changes, lack of energy, and forgetting can all form dynamic, unexpected barriers [7]. Once the person skips a planned activity, abandoning the plan is likely. Such scenario is quite common, with 50% average dropout for physical activity interventions and even 60% for diet/weight loss interventions [8].

Current approaches

Most common handling of relapse in existing behavior change solutions relies on not noticing it at all and hoping that user will get back on track. Such handling may, however, lead to decreased engagement, as the system does not seem to care about user actions. Other approaches offer a later review of the progress through visualizations or text-based summaries [4]. Such approach do not address non-adherence at the moment, but rather let's the user reflect on non-adherence in the past in hopes of triggering change in future behavior or helping the user adjust the goals. It still does not address the at-the-moment problem and puts additional temporal distance between the problem and the solution. The most advanced approaches try to deal with individual causes of relapse by tailoring motivational contents and forming personalized plans. There are, however, aspects that change dynamically and that are not covered by one-time tailoring. Some approaches have tried to address the dynamic aspects by employing a technique called dynamic tailoring, which extends the simple message triggers with follow-up contents tailored dynamically based on user response [9]. The solution here is a one-time follow up with a, hopefully, more persuasive message.

Proposed approach

In our approach, we use the dialogue-based capabilities to follow-up on user non-adherence with a negotiation tactics. The system tries to prompt the user to understand the particular reason for non-adherence at the moment and adjust the next action in a way that would increase the chance of user doing at least part of the activity. Conceptual dialogue flow for exercising is show in Fig.1.

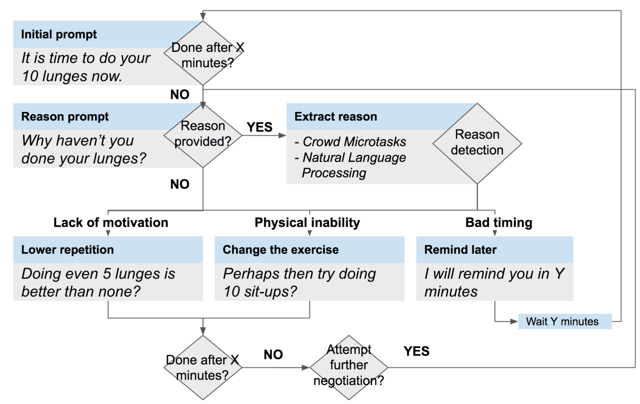

Figure 1: A potential dialogue structure for supporting exercise performance negotiation in response to user-non-adherence. The paths leading to successful accomplishment of the exercise are omitted for clarity.

Based on understanding the reasons given by the user, there could be a number of negotiation strategies employed. For example, when the reason for non-

Example dialogue for reflection on measurable behavior change goals

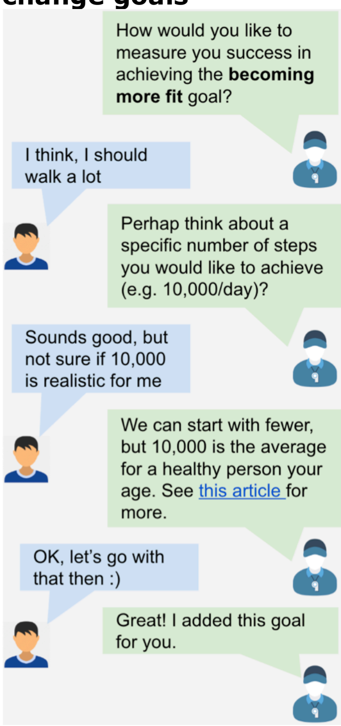

Figure 5: Example dialogue exchange for helping user reflect on and set a measurable behavior change goals. It is assumed here, that the system knows from previous exchanges that the user's high-level goal is "becoming more fit".

adherence is lack of time, the negotiation prompt could offer moving the exercise for a later time. If the reason is due to one-time physical inability the system could offer an alternative exercise or propose a less intense variant. The main idea here is that it is better for the user to complete at least part of the activity. Also expressing interest in users' performance may lead to higher perception of empathy expressed by the system.

Challenges

A number of challenges still persist. First of all, encouraging user to spend additional time on typing non-adherence reasons might be cumbersome. In one solution, the system could offer quick shortcuts, to the most common reasons, somewhat similar to what Lark does, but in a more intelligent form. This might unfortunately lower the feeling of conversation and degrade the reflective aspect of the exchange. Worse yet, it can remove the details of the actual reasons and make users gravitate towards suggested responses (e.g. the user actually feels lack of motivation, but the shortcut reason is lack of time).

Scenario 2: Reflection on goals formulation

Reflection has been identified as one of the key most important aspects of behavior change [10]. Through the process of reflection users form commitments towards their goals, formulate realistic goals and make meaning of the self-tracking data [11]. Yet, despite such importance a recent review identified that still the main approaches present users visualization of data in hope of triggering reflection and behavior change [10].

Current approaches

There have been, however, few noticeable approaches to reflection. In the HealthMashups [12] the system automatically detects strong correlations in stream of data and brings them to user's attention. On the other end, self-experimentation approaches help user test hypotheses about a behavior [13] and reflect on the causes. Commercial tools, however, mostly focus on visualizations and triggers, and don't take specific aims towards reflection. Given such gap, we believe that supporting reflection offers a great opportunity for dialogue-based system to make a real impact in the behavior change domain.

Proposed approach

In general the purpose of reflection is to help people obtain deeper realization and insight, oftentimes without a particular, predefined goal in mind. In behavior change, reflection can be guided towards a specific outcome (e.g. improved health).

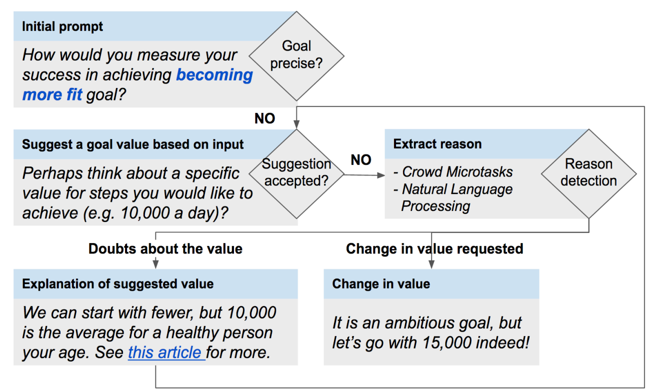

Figure 2: A potential dialogue structure for reflection on formulating measurable goals for exercising behavior change. The paths leading to setting the goals it itself (success) are omitted for clarity.

An approach in behavior change called motivation interviewing uses concepts of reflection to help guide

Example dialogue for social coordination

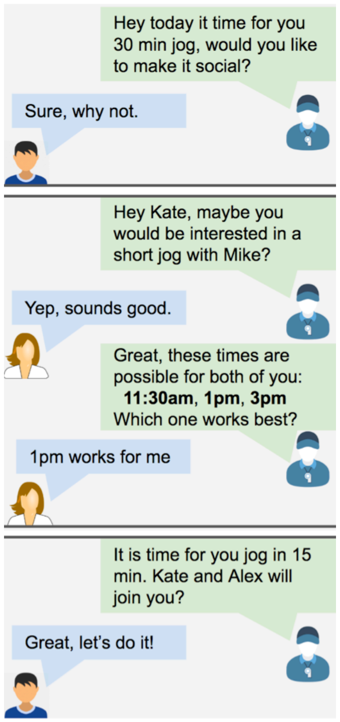

Figure 6: Example dialogue exchange for helping the user perform an exercise activity with others. It is assumed here that the assistant has access to users calendars and that there are co-located groups of people willing to exercise together

people to realize their own behavior change goals and batter formulate their own action plans for achieving the desired behaviors [2]. The power of such approach is that the goals and actionable plans are formulated by people themselves and hence have stronger fit and motivational support for the person than when a goal is given a priori. Dialogue based interaction lends itself well to supporting such reflection as arriving at measurable goals is oftentimes an iterative process. Conceptual interaction flow in Fig.2 exemplifies a possible dialogue.

Challenges
Reflection is a complex concept. There could be a number of reflective purposes and reflective dialogues. These can be geared towards accomplishing a number of things for the user. From better understanding of ones own goals to better understanding the self-tracing data for gaining insights about ones own behavior to understanding barriers and motivations. Helping users reflect and not to overwhelm them with long conversational sessions is one of the key challenges.

Scenario 3: Coordinated social activity

Social support relates to the use of social relations to encourage performing a behavior by leveraging competition or cooperation. Such support is valuable and known to increase motivation and adherence. Most major models of behavior change involve social aspect as a key contributor of behavior [14].

Current realizations
Consequently, many existing behavior change approaches try to leverage social relations. Most of these approaches, however, focus on presenting leader boards, providing access to communities (e.g. runners) or present users social tips generated by others. These apps stop short from actually coordinating an activity giving users access to social support, but leaving it up to them to contact others for anything more than just sharing activity scores.

Approach
In our approach, conversational agent serves as a facilitator and coordinator of social performance of an activity. We want to lower the barrier of performing an activity by connecting users directly. Although social support has been shown to be effective, there is still considerable effort and social anxiety involved in asking others to join an activity even in the same office. These can prevent the user from making an activity social and also reduce user's own motivation.

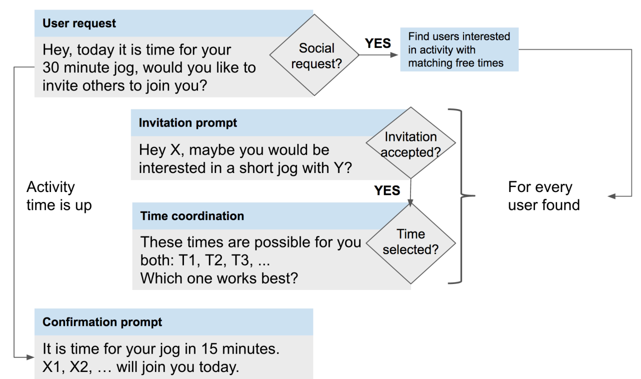

Figure 3: A potential dialogue structure for reflection on formulating measurable goals for exercising behavior change. The paths leading to setting the goals it itself (success) are omitted for clarity.

Although social coordination can be done in multiple different ways, a social agent seems like a natural solution for closed work groups and co-located environments, where users communicate through messengers. Such agent could lower the barrier of setting up a social activity by taking care of the coordination parts. An example dialogue diagram is presented in Fig 3.

Challenges

Coordinating social performance of an activity is not possible and practical in every environment. The major limitation could be the need for physical co-location of participants (e.g. people at the same household, or work office). Not every behavior change domain also requires or makes sense to benefit from social co-performance (e.g. financial savings).

Other aspects of conversational interaction for behavior change

In this paper we focused only on the use cases for behavior change that, we believe, would benefit from dialogue-based interaction. There are, however, many other aspects, unique to dialogue based interaction that can be crucial in behavior change domain. These involve the organization of dialogue navigation. Authors in [15] show that different structure of dialogues tuned to culture can affect user satisfaction. Similar might be true for behavior change. Dialogue based interaction also opens up possibilities for different word use and rhetorical strategies [16]. Finally in case of voice assistants, there is an additional layer of voice type and style of speaking. All these are properties specific to conversational interaction that have only partially been explored for their impact in behavior change domain.

Conclusion

In this short paper we focus on exploring the use cases for dialogue-based interaction in behavior change domain. Despite recent revolution in personal assistants, relatively little has been done to employ this form of interaction in behavior change domain. Consequently, we identify three example use cases where we believe that dialogue based interaction can offer valuable benefits: negotiation around relapse, reflection on goals setting and social coordination.

Acknowledgements

This work was in part supported by National Science Foundation grant #1348543.

References

[1] V. Götzmann, "Towards a Persuasive Dialog System Supporting Personal Health Management," National Research Center, 2015.

[2] C. for S. A. Treatment, *Chapter 3—Motivational Interviewing as a Counseling Style*. Substance Abuse and Mental Health Services Administration (US), 1999.

[3] "Center for Evidence-Based Practices at Case Western Reserve University." [Online]. Available: https://www.centerforebp.case.edu/practices/mi. [Accessed: 10-Jan-2017].

[4] C. Abraham and S. Michie, "A taxonomy of behavior change techniques used in interventions.," *Health Psychol.*, vol. 27, no. 3, p. 379, 2008.

[5] D. E. Conroy, C.-H. Yang, and J. P. Maher, "Behavior change techniques in top-ranked mobile apps for physical activity," *Am. J. Prev. Med.*, vol. 46, no. 6, pp. 649–652, 2014.

[6] M. E. Bouton, “Why behavior change is difficult to sustain,” *Prev. Med.*, vol. 68, pp. 29–36, 2014.
[7] R. S. Myers and D. L. Roth, “Perceived benefits of and barriers to exercise and stage of exercise adoption in young adults.,” *Health Psychol.*, vol. 16, no. 3, p. 277, 1997.
[8] F.-E. Kinnafick, C. Thøgersen-Ntoumani, and J. L. Duda, “Physical Activity Adoption to Adherence, Lapse, and Dropout A Self-Determination Theory Perspective,” *Qual. Health Res.*, vol. 24, no. 5, pp. 706–718, 2014.
[9] M. A. Lewis *et al.*, “Tailored text messaging intervention for HIV adherence: A proof-of-concept study.,” *Health Psychol.*, vol. 32, no. 3, p. 248, 2013.
[10] R. Fleck and G. Fitzpatrick, “Reflecting on reflection: framing a design landscape,” in *Proceedings of the 22nd Conference of the Computer-Human Interaction Special Interest Group of Australia on Computer-Human Interaction*, 2010, pp. 216–223.
[11] I. Li, A. K. Dey, and J. Forlizzi, “Understanding my data, myself: supporting self-reflection with ubicomp technologies,” in *Proceedings of the 13th international conference on Ubiquitous computing*, 2011, pp. 405–414.
[12] K. Tollmar, F. Bentley, and C. Viedma, “Mobile Health Mashups: Making sense of multiple streams of wellbeing and contextual data for presentation on a mobile device,” in *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, 2012, pp. 65–72.
[13] R. Karkar *et al.*, “A framework for self-experimentation in personalized health,” *J. Am. Med. Inform. Assoc.*, p. ocv150, 2015.
[14] I. Ajzen, “The theory of planned behavior,” *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, 1991.
[15] B. Dhillon, R. Kocielnik, I. Politis, M. Swerts, and D. Szostak, “Culture and facial expressions: A case study with a speech interface,” in *IFIP Conference on Human-Computer Interaction*, 2011, pp. 392–404.
[16] A. Shamekhi, M. Czerwinski, G. Mark, M. Novotny, and G. A. Bennett, “An Exploratory Study Toward the Preferred Conversational Style for Compatible Virtual Agents,” in *International Conference on Intelligent Virtual Agents*, 2016, pp. 40–50.