Reinforcement Learning-Based Persuasion by a Conversational Agent for Behavior Change

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1 Introduction

There is certainly some behavior that you want to change. Maybe you want to become more physically active, call your mother more often or snack less when watching TV at night. Let's assume that you want to quit smoking. You are not doing this alone, but are supported by your coach Hannah. Hannah constantly persuades you to stick to your intervention. How does she decide how to do that? First, Hannah has a lot of theoretical expertise. Moreover, you are not Hannah's first client, so she can draw upon her experience with other and especially similar clients. Third, Hannah considers your current situation - are you confident or stressed about a deadline? In addition, she will persuade you in such a way that she can persuade you again in the future. And lastly, Hannah will keep adapting her strategy over time. Now, let's suppose that you have another coach, Sam. Unlike Hannah, Sam is a virtual coach. Can Sam do what Hannah can?

Changing personal behavior is a very promising way to improve health and reduce premature death. For example, nearly 40% of deaths in the United States are caused by behavior [21][26], and smoking alone contributes to 19,000 annual deaths in the Netherlands [22][29]. To support such behavior change, recent years have seen a surge of eHealth applications [4][8][17][18]. Yet, while such interventions have the advantage that they are available at all times, scalable, cost-effective and can facilitate tailoring [16], adherence to them remains low [4][15]. We thus aim at developing persuasive communication for a virtual coach that aids people in adhering to their intervention. Previous work has shown that data gathered on other people [13][14], similar people [11][30] or an individual [12][13][14][20][25] can be used to choose a persuasion type. Yet, little work has also incorporated the context of a persuasive attempt, which has been supposed to have an important impact on the effectiveness of different persuasion types [2][3][24]. In addition, persuasion types also differ in their impact on the context of future persuasive attempts [28]. We thus propose a reinforcement learning approach to persuading people that considers a person's current and future states as well as the similarity of people. We test this approach based on persuading people to do small preparatory activities for smoking cessation and physical activity increase such as listing reasons for wanting to quit smoking.

2 Approach

We created a text-based virtual coach that attempts to persuade people to do small activities. For each persuasive attempt, the virtual coach selects a persuasion type based on its learned policy. After a certain time interval, the user provides the virtual coach with feedback by reporting the effort they put into their suggested activity. This feedback is used by the agent to update its policy. Formally, we can define our approach as a Markov Decision Process $\langle S, A, R, T, \gamma \rangle$. The action space A thereby consists of different persuasion types, which include a subset of Cialdini's persuasion types [6], action planning [5][10][27], and the option to not persuade. The reward function $R : S \times A \rightarrow [-1, 1]$ is determined by the self-reported effort, $T : S \times A \times S \rightarrow [0, 1]$ describes the transition function, and the discount factor γ is set to 0.85 to favor rewards obtained in the near future over rewards obtained in the more distant future. The finite state space S is defined by answers to questions that are based on the COM-B Model for Behavior Change [19] and capture a person's capability, opportunity and motivation to perform an activity (e.g. "I feel that I need to do the activity"). To further incorporate the similarity of people, the agent maintains a policy π_i for each user i. When updating π_i, an observed sample from user j is weighted based on how similar i and j are with regards to their personality [9] and stage of change for becoming more physically active based on [23].

3 Experiment

To gather data for and test our approach, we have conducted an experiment with more than 500 daily smokers who planned or contemplated to quit smoking [7]. Participants interacted with the virtual coach Sam in five conversational sessions. In each session, the virtual coach suggested a new activity, together with a persuasion type. The first two sessions thereby served as training sessions in which participants were persuaded by a random persuasion type, whereas the last three sessions were used to test the algorithm components. To this end, participants were randomly split into four groups after session 2. Based on the data gathered in sessions 1 and 2, participants in the four groups were subsequently persuaded based on 1) a persuasion type with the highest immediate reward average, 2) a persuasion type with the highest immediate reward average in their state, 3) a persuasion type with the highest Q-value in their state, and 4) a persuasion type with the highest similarity-weighted Q-value in their state. The data from the experiment will be analyzed according to our Open Science Framework (OSF) pre-registration [1]. We will also share our collected data in anonymized form.

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References

1. Albers, N., Brinkman, W.P.: Perfect fit - experiment to gather data for and test a reinforcement learning-approach for motivating people (May 2021). https://doi.org/10.17605/OSF.IO/K2UAC, osf.io/k2uac
2. Alslaity, A., Tran, T.: On the impact of the application domain on users' susceptibility to the six weapons of influence. In: International Conference on Persuasive Technology. pp. 3–15. Springer (2020). https://doi.org/10.1007/978-3-030-45712-9_1
3. Bertolotti, M., Carfora, V., Catellani, P.: Different frames to reduce red meat intake: The moderating role of self-efficacy. Health Communication **35**, 475 – 482 (2019)
4. Beun, R.J., Brinkman, W.P., Fitrianie, S., Griffioen-Both, F., Horsch, C., Lancee, J., Spruit, S.: Improving adherence in automated e-coaching - A case from insomnia therapy. In: International Conference on Persuasive Technology. pp. 276–287. Springer (2016). https://doi.org/10.1007/978-3-319-31510-2_24
5. Chapman, J., Armitage, C.J., Norman, P.: Comparing implementation intention interventions in relation to young adults' intake of fruit and vegetables. Psychology and Health **24**(3), 317–332 (2009)
6. Cialdini, R.B.: Influence: the psychology of persuasion, revised edition. New York: William Morrow (2006)
7. DiClemente, C.C., Prochaska, J.O., Fairhurst, S.K., Velicer, W.F., Velasquez, M.M., Rossi, J.S.: The process of smoking cessation: an analysis of precontemplation, contemplation, and preparation stages of change. Journal of consulting and clinical psychology **59**(2), 295 (1991)
8. Fadhil, A., Gabrielli, S.: Addressing challenges in promoting healthy lifestyles: the al-chatbot approach. In: Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare. pp. 261–265. ACM (2017). https://doi.org/10.1145/3154862.3154914
9. Gosling, S., Rentfrow, P., Swann, W.: A very brief measure of the big-five personality domains. Journal of Research in Personality **37**, 504–528 (2003)
10. Hagger, M.S., Luszczynska, A.: Implementation intention and action planning interventions in health contexts: State of the research and proposals for the way forward. Applied Psychology: Health and Well-Being **6**(1), 1–47 (2014)
11. Hors-Fraile, S., Malwade, S., Luna-Perejon, F., Amaya, C., Civit, A., Schneider, F., Bamidis, P., Syed-Abdul, S., Li, Y.C., De Vries, H.: Opening the black box: Explaining the process of basing a health recommender system on the i-change behavioral change model. IEEE Access **7**, 176525–176540 (2019). https://doi.org/10.1109/ACCESS.2019.2957696
12. Kang, Y., Tan, A., Miao, C.: An adaptive computational model for personalized persuasion. In: Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, IJCAI. pp. 61–67. AAAI Press (2015)
13. Kaptein, M., Markopoulos, P., De Ruyter, B., Aarts, E.: Personalizing persuasive technologies: Explicit and implicit personalization using persuasion profiles. International Journal of Human-Computer Studies **77**, 38–51 (2015). https://doi.org/10.1016/j.ijhcs.2015.01.004
14. Kaptein, M., McFarland, R., Parvinen, P.: Automated adaptive selling. European Journal of Marketing **52** (2018)
15. Kelders, S.M., Van Zyl, L.E., Ludden, G.D.: The concept and components of engagement in different domains applied to ehealth: a systematic scoping review. Frontiers in psychology **11**, 926 (2020)

16. Liao, Y., Wu, Q., Tang, J., Zhang, F., Wang, X., Qi, C., He, H., Long, J., Kelly, B.C., Cohen, J.: The efficacy of mobile phone-based text message interventions ('happy quit') for smoking cessation in china. BMC Public Health **16**(1), 1–11 (2016)
17. Ly, K.H., Ly, A.M., Andersson, G.: A fully automated conversational agent for promoting mental well-being: a pilot rct using mixed methods. Internet interventions **10**, 39–46 (2017)
18. Meijer, E., Korst, J.S., Oosting, K.G., Heemskerk, E., Hermsen, S., Willemsen, M.C., van den Putte, B., Chavannes, N.H., Brown, J.: "at least someone thinks i'm doing well": a real-world evaluation of the quit-smoking app stopcoach for lower socio-economic status smokers. Addiction science & clinical practice **16**(1), 1–14 (2021)
19. Michie, S., Atkins, L., West, R., et al.: The behaviour change wheel. A guide to designing interventions. 1st ed. Great Britain: Silverback Publishing (2014)
20. Mintz, Y., Aswani, A., Kaminsky, P., Flowers, E., Fukuoka, Y.: Nonstationary bandits with habituation and recovery dynamics. Operations Research **68**(5), 1493–1516 (2020)
21. Mokdad, A.H., Marks, J.S., Stroup, D.F., Gerberding, J.L.: Actual causes of death in the united states, 2000. Jama **291**(10), 1238–1245 (2004)
22. Nationaal Expertisecentrum Tabaksontmoediging: Kerncijfers roken 2017: De laatste cijfers over roken, stoppen met roken, meeroken en het gebruik van elektronische sigaretten (2018)
23. Norman, G., Benisovich, S., Nigg, C., Rossi, J.: Examining three exercise staging algorithms in two samples. In: 19th annual meeting of the Society of Behavioral Medicine (1998)
24. Oinas-Kukkonen, H., Harjumaa, M.: Persuasive systems design: Key issues, process model, and system features. Communications of the Association for Information Systems **24**(1), 28 (2009)
25. Roy, S., Crick, C., Kieson, E., Abramson, C.: A reinforcement learning model for robots as teachers. In: 27th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN. pp. 294–299. IEEE (2018). https://doi.org/10.1109/ROMAN.2018.8525563
26. Schroeder, S.A.: We can do better—improving the health of the american people. New England Journal of Medicine **357**(12), 1221–1228 (2007)
27. Sniehotta, F.F., Scholz, U., Schwarzer, R., Fuhrmann, B., Kiwus, U., Völler, H.: Long-term effects of two psychological interventions on physical exercise and self-regulation following coronary rehabilitation. International journal of behavioral medicine **12**(4), 244–255 (2005)
28. Steward, W.T., Schneider, T.R., Pizarro, J., Salovey, P.: Need for cognition moderates responses to framed smoking-cessation messages 1. Journal of Applied Social Psychology **33**(12), 2439–2464 (2003)
29. Trimbos Instituut: Richtlijn behandeling van tabaksverslaving en stoppen met roken ondersteuning: Herziening 2016 (2016)
30. de Vries, R.A.J.: Theory-based and tailor-made: Motivational messages for behavior change technology. PhD Thesis (2018)