On Explainable Negotiations via Argumentation

Victor Contreras[1][0000−0002−6189−0217], Reyhan Aydoğan[2,3][0000−0002−5260−9999], Amro Najjar[4][0000−0001−7784−6176], and Davide Calvaresi[1][0000−0001−9816−7439]

[1] University of Applied Sciences Western Switzerland, Switzerland
name.surname@hevs.ch
[2] University of Luxembourg, Luxembourg
amro.najjar@uni.lu
[3] Department of Computer Science, Özyegin University, Istanbul, Turkey
reyhan.aydogan@ozyegin.edu.tr
[4] Interactive Intelligence Group, Delft University of Technology, Netherlands

1 Introduction & Background

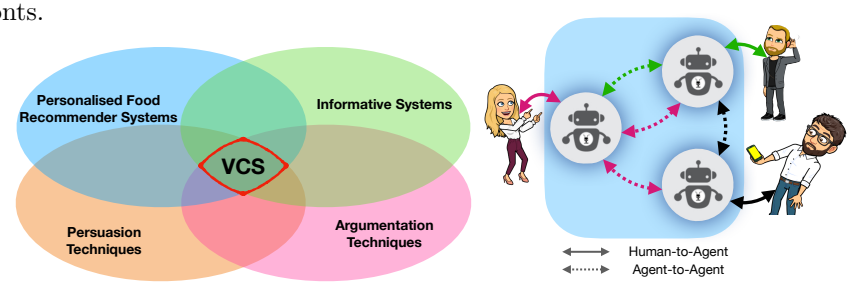
Modern society performs countless choices affecting all sorts of needs daily. Both industry and academia are intensifying their effort to both extend the plethora of possible alternatives and narrow down the most significant ones to be suggested to the user [1]. Thus, it would maximize the possibility of the services consumption and user satisfaction. Recommender systems (RS) [2] have reached remarkable accuracy and efficacy in several domains [3]. Nevertheless, more sensitive areas (i.e., nutrition) demand more complex dynamics beyond conventional RS' capabilities. For example, virtual coaching systems (VCS) leverage persuasion techniques, argumentation, informative systems, and RS (see Figure 1a). However, their efficacy is still far from the one achieved by human coaches, even considering the limitations of the case (see [4]). In particular, the major setbacks are the lack of explanations supporting a given suggestion, the impossibility of "discussing" it with the VCS, and the lack of significant explorations for new out-of-the-box solutions.

Therefore, this work suggests the following negotiation schema for nutrition VCS: $1 - to - 1(-to - \sigma)$ with $\sigma = 0, ..., N$ and N being the number of virtual VCs in the system. In particular, it leverages human-to-agent $(1 - to - 1)$ and agent-to-agent $(1 - to - \sigma)$ joint problem solving via negotiation to generate recommendations and arguments to support them.

2 Personalized Health Coach: Vision & Challenges

Our approach envisions a one-to-one user-agent mapping. Nevertheless, the VCS can consist of multiple agents (assisting users possibly characterized by partially shared traits/features). Therefore, the possibility of extending the agent's knowledge and range of recommendations leveraging other agents' knowledge is more than tangible. Let us assume a user is interacting with the associate agent who has insufficient data to provide accurate suggestions (i.e., cold start). To avoid less appealing and possibly wrong assumptions/suggestions, the agent must profit from inter-agent negotiations to convene more accurate support (see

Figure 1b). With such interactions, the freshman agents produce a series of negotiations equipped with proper argumentations. Once an agreement is reached, new knowledge can be generated, or the old one can be revised. This framework can be formulated as a team negotiation [5]. The team representative (e.g., a freshman agent) can negotiate with the user while, at the same time, it can negotiate with other expert agents. The features used in the agent-to-agent negotiation [6] can exploit or explore solutions leveraging the agents' understanding over personal information (without ever disclosing the actual personal data) and previous interactions. To do so, the first challenges to be overcome are:
CH1 - Effective Interaction: Both structured and natural language-based interactions need to define common ground. Therefore, the challenge is to establish shared syntax, semantic, and knowledge representations. **CH2 - Generating Explainable Arguments:** Comprehensive, personalized, and well-structured explanations can enhance the recommendations' acceptability. The challenge is to create techniques to dynamically generate interpretable explanations (e.g., in natural language or images) w.r.t. their interests and background. **CH3 - Explainable Negotiations:** The interactions must produce sound outcomes (i.e., the decision should be supported by interpretable arguments and suggestions) [7–9]. The challenge is to design agents capable of reasoning over the negotiation, handling information requests, users' demands/interests dynamically, and accordingly generating an offer (i.e., recommendation) equipped with the breakdown of the reasoning process. In addition, the agent should be able to process and learn from users' feedback/comments (e.g., why a given offer is not acceptable). **CH4 - Simultaneous negotiations:** If short on resources/data, agents can help each other sharing their experiences. It can be formulated as group negotiation(s), exchanging aggregated (explainable) understandings on multiple fronts.



(a) VCS Overview. (b) Explainable Team Negotiation

Fig. 1: Vision and Negotiation Framework

Acknowledgments

This work has been partially supported by the CHIST-ERA grant CHIST-ERA-19-XAI-005, and by *(i)* the Swiss National Science Foundation (G.A. 20CH21_195530), *(ii)* the Italian Ministry for Universities and Research, *(iii)* the Luxembourg National Research Fund (G.A. INTER/CHIST/19/14589586 and INTER/Mobility/19/13995684/DLAl/van), *(iv)* the Scientific and Research Council of Turkey (TÜBİTAK, G.A. 120N680).

References

1. Davide Calvaresi, Giovanni Ciatto, Amro Najjar, Reyhan Aydoğan, Leon Van der Torre, Andrea Omicini, and Michael Schumacher. Expectation: Personalized explainable artificial intelligence for decentralized agents with heterogeneous knowledge. In *International Workshop on Explainable, Transparent Autonomous Agents and Multi-Agent Systems*, pages 331–343. Springer, 2021.
2. Jesús Bobadilla, Fernando Ortega, Antonio Hernando, and Abraham Gutiérrez. Recommender systems survey. *Knowledge-based systems*, 46:109–132, 2013.
3. Mouzhi Ge, Francesco Ricci, and David Massimo. Health-aware food recommender system. In *Proceedings of the 9th ACM Conference on Recommender Systems*, pages 333–334, 2015.
4. Bart A Kamphorst. E-coaching systems. *Personal and Ubiquitous Computing*, 21(4):625–632, 2017.
5. Victor Sanchez-Anguix, Reyhan Aydoğan, Vicente Julian, and Catholijn M. Jonker. Intra-Team Strategies for Teams Negotiating Against Competitor, Matchers, and Conceders. In Ivan Marsa-Maestre, Miguel A. Lopez-Carmona, Takayuki Ito, Minjie Zhang, Quan Bai, and Katsuhide Fujita, editors, *Novel Insights in Agent-based Complex Automated Negotiation*, pages 3–22. Springer Japan, Tokyo, 2014.
6. Shaheen Fatima, Sarit Kraus, and Michael Wooldridge. *Principles of Automated Negotiation*. Cambridge University Press, New York, NY, USA, 1st edition, 2014.
7. Sarit Kraus, Katia Sycara, and Amir Evenchik. Reaching agreements through argumentation: a logical model and implementation. *Artificial Intelligence*, 104(1):1 – 69, 1998.
8. Iyad Rahwan, Sarvapali D Ramchurn, Nicholas R Jennings, Peter Mcburney, Simon Parsons, and Liz Sonenberg. Argumentation-based negotiation. *The Knowledge Engineering Review*, 18(4):343–375, 2003.
9. Onat Güngör, Umut Çakan, Reyhan Aydoğan, and Pinar Özturk. Effect of awareness of other side's gain on negotiation outcome, emotion, argument, and bidding behavior. In Reyhan Aydoğan, Takayuki Ito, Ahmed Moustafa, Takanobu Otsuka, and Minjie Zhang, editors, *Recent Advances in Agent-based Negotiation*, pages 3–20, Singapore, 2021. Springer Singapore.