On Proactive Human-Al Systems

Jasmin Grosinger^{1,*}

¹Örebro University, Fakultetsgatan 1, 70182 Örebro, Sweden

Abstract

With a growing number of AI systems and robots sharing the environment of humans, the need to define and investigate the particular topic of artificial proactivity is greater than ever. This position paper advocates the importance of this endeavor and starts the work by giving an initial definition of proactivity for artificial agents, analyzing the cognitive abilities necessary to create proactive agent behavior and suggests a categorization of approaches in different types of proactivity.

Keywords

Proactivity, Proactive AI systems, Proactive agents, Proactive robots, Hybrid Human-AI systems, Human-Machine-Interaction.

1. Introduction

As AI systems increasingly share environments with humans, become our companions and colleagues, we expect them to be equipped with similar cognitive capabilities as us. Suppose you have two working colleagues, Mr. Slow-witted and Ms. Heavy-handed. Both are knowledgeable and skilled in their specific work task, but they do have important shortcomings. Mr. Slowwitted needs to be told every single step of the working process. You cannot expect him to understand what is best to do and when, nor to act on own initiative. Ms. Heavy-handed sometimes imposes her will on others. She stubbornly pursues verbatim single pursuits without common sense and without taking into account the perspective of her co-workers. These sound like impossible colleagues to work with. Yet this description fits the capabilities offered by today's typical AI solutions. We expect co-workers to understand what is going on around us, to reason about it and to act on own initiative. We expect them to do so based on understanding what is desirable considering different perspectives in current and future situations, and taking into account the consequences of their actions. In one word, we expect our co-workers to be proactive. A proactive version of Mr. Slow-witted would take own initiative and understand when and how to act; a proactive version of Ms. Heavy-handed would take into account her co-workers' perspectives and preferences.

Research in cognitive AI can be a great contributor for collaboration in hybrid human-AI systems in complex environments [1]. The recent rise of social robots that share environments with humans necessitates behavior that is human-like and proactivity adds more utility to such robots [2]. AI machines will have to exhibit proactive behavior if they are to be accepted in

*Corresponding author.

CEUR Workshop Proceedings (CEUR-WS.org)

AIC 2022, 8th International Workshop on Artificial Intelligence and Cognition

jngr@aass.oru.se (J. Grosinger) ⊘

D 0000-0003-3726-4176 (J. Grosinger)

^{© 0 2022} Copyright for this paper by its authors. Use permitted under Creative Commons License Attribution 4.0 International (CC BY 4.0).

human-centered environments [3, 4]. Humans prefer proactive AI systems [5] and build trust more easily to them [6].

In this position paper, I highlight the topic of proactivity and proactive behavior in AI systems, artificial agents and intelligent robots, and call for a *general theory of proactivity*. Literature does not provide one distinct definition of proactivity — Section 2 proposes one. I investigate some cognitive abilities that are necessary or useful when creating proactive behavior, and how they interact in Section 3. Depending on their focus, there can be different *types* of proactivity, covered in Section 4. The paper finishes with concluding remarks, future directions and challenges in Section 5.

2. Definition of Proactivity

Proactivity is a feature that is characteristic for humans. Humans can predict and understand what others will do. In behavioral sciences it has been claimed that this ability gives humans an evolutionary advantage compared to other species, enabling us to engage in collaborative and proactive behavior [7]. In organizational psychology, the term *proactive behavior* refers to

- anticipatory, self-initiated action,
- meant to impact people and/or their environments.

[8]. This is opposed to *reactive* behavior which merely is responding to explicit requests or external events. Most of today's AI systems and robots are not proactive according to this definition but reactive. However, there is an emerging tendency *towards* creating proactive systems. Yet we lack a distinct common definition of what it means for an AI system to be proactive and we lack a clear scope of the field. Many current works on proactivity do not define the term but rely on the reader's intuitive understanding. Many sources [9, 10, 11, 12] implicitly understand proactivity to be *self-initiated* acting, but neglect the predictive part of the human proactivity definition. Some researchers (including ourselves) [13, 14, 15, 16] do integrate prediction into their understanding of artificial proactivity, together with self-initiated acting. I propose a definition of artificial proactivity that bases on the definition of human proactivity:

Proactivity is the ability to autonomously initiate anticipatory action based on reasoning, meant to impact people and/or their environments.

Note that to *reason* goes beyond using "hard-wired" rules for acting which are based on some external trigger. This would classify as a reactive, not a proactive approach. Rather one may be able to take Dennett's *Intentional stance* [17] and ascribe 'rationality', 'intentions', 'beliefs', etc., to the reasoning proactive agent. Note also that the outcome of reasoning might be proactive action but might also be deliberate inaction. Thus, the proactive agent does not only decide when and how to act but also when not to act.

3. Cognitive Abilities for Proactivity

A number of cognitive abilities interacting jointly are required to achieve proactive behavior. Here I discuss some, however, a complete list is an open question.

Context. To be able to reason and self-initiate actions, an AI system needs to to understand the world around it. Fields such as context-awareness and situation assessment make perceptions of the environment, using sensors, and infer the current state which is one of the factors for proactive action. A large number of works base proactivity on reasoning on current context only, neglecting prediction [9, 10, 11, 12]. I argue that context awareness is a necessary requirement for proactivity, but it is not sufficient.

Prediction. The definitions of human and artificial proactivity comprise *anticipation* (see Section 2). The proactive agent is able to reason beyond the current state and can deliberate on how the future might evolve. An agent that reasons just about the present, takes actions that are beneficial just for the present, and misses alternative acting behaviors that may be better when considering a wider time horizon. For example, a robot companion might decide to bring the backpack to the human to assist in their current task of preparing for a hiking trip. On the other hand, when the robot also takes into account the future development of states, it can predict that there is a high chance for a thunderstorm in the human's hiking destination. Therefore the robot may choose a different action than bringing the backpack, that is, a communicative action to inform the human about the expected thunderstorm. Some works on proactivity exist that take prediction into account [13, 14, 15, 16].

Mental simulation. For making a deliberate acting decision the proactive agent may need to compare the consequences of different acting alternatives. To be able to do this, the agent needs to simulate possible proactive behaviors and compute their effects. Inherent to such computations is uncertainty which the proactive agent needs to be able to handle. Note that mental simulation is different from prediction; the latter makes forecasts about the development of the world by itself, that is, without robot acting, while the former makes forecasts of the consequences of different robot acting. For example, a robot companion may consider acting alternative 1, to bring the ringing phone to the human now, or choose alternative 2, to inform the human later about the missed call. The effects of option 1 include that the human does not miss the phone call while in option 2 the human misses the phone call. Which of the options is *better* depends on other factors of proactivity. Option 2 may be preferable if the human is currently busy, whereas option 1 may be better otherwise. Examples of works that include mental simulation are [18, 14].

Preference. The question when and how a proactive agent should act may be informed by human preference, of both single and multiple humans, short- or long-term. Russell [19] calls for completely altruistic robots which base their actions solely on human preferences. Human preferences are dynamic and uncertain. An intelligent agent should be aware of its own uncertainty about the human's preferences. This will prevent robots from behaving like Ms. Heavy-handed following a verbatim single-minded pursuit without a chance for the human to confirm that this is what they *actually* want (see Section 1). Example works inferring proactive behavior by reasoning on preferences or user needs are [10, 14].

Epistemic reasoning. An AI agent may reason about the mental states of other agents (the human) to make proactive acting decisions. In philosophy and psychology *Theory of Mind*

(*ToM*) is the study of ascribing another individual particular mental states (beliefs, intentions, desires) [20]. ToM and epistemic reasoning has also gained attention within AI. It can be employed to initiate proactive action based on false beliefs, intentions, or desires of the human. For example, the human's belief that the weather will be nice in their hiking destination is false; the robot companion can decide to proactively approach the human and inform that the human's belief is false and the weather will be bad. Based on the recognized intention that the human wants to go hiking, the robot can either assist in packing or inform about an upcoming thunderstorm, depending on weather forecasts. There are several recent approaches which have taken up the work of creating agents that can reason on ToM and this way enabling proactive behavior [21, 22, 13, 5].

4. Types of Proactivity

To the best of my knowledge, no one has made the effort to group approaches on creating proactive agent behavior into different types. The attempt here is intended to start this work but makes no claim of completeness.

Proactivity to Support the Human to Achieve their Intention. Proactivity of this type is seen as the problem of helping the human fulfill their intention by self-initiated anticipatory acting. This makes necessary to have the ability to do intention recognition in order to understand the human's intention which the artificial agent should help them to achieve. Examples of such an approach are [5, 13]. Harman and Simoens [5] employ action graphs, that enable them to model action dependencies and predict the human's next actions in a plan; then they compute which of these the robot can take over in a domestic scenario. Liu et al. [13] use a probabilistic Markov model to do both human intention inference and intention learning and let a robotic arm proactively assist the human in a table-top task of assembling different cube configurations.

<u>Summary</u>: This type of proactivity is based on: human intention recognition; the ultimate aim is to: support the human in achieving their intention/goal.

Proactivity with a Goal Given. In this category we find approaches that create proactive behavior but only when an explicit goal is given first (by the human, or by an external trigger). One example in this category in the field of proactivity is Bremner et al. [18]. They propose an architecture for a robot system that includes an ethical layer (using BDI) to 'moderate' the robot's actions, simulate behavior alternatives and do anticipation. First, external goals are provided to the robot controller. Then it computes behavioral alternatives and simulates their outcomes. The ethical module evaluates them and proactively initiates a new cycle of computing different plans for behavior alternatives and simulating them, that are more ethical. The ethical module does a final evaluation and the 'most ethical' behavior alternative is dispatched and executed.

<u>Summary</u>: This type of proactivity is based on: one or multiple given goal(s); the ultimate aim is to: employ proactive behavior to achieve the given goal(s).

Proactivity from First Principles. There exist approaches that attempt to create proactive agent behavior by reasoning on first principles. Works in this category aim to understand what the factors and cognitive abilities are that create proactive behavior, and how these interact.

One example of this type is Martins et al. [23]. The authors employ a variant of a POMDP to inform the acting decision of a user-adaptive social robot. They achieve to maintain the user in positive states encoded by value functions while being able to learn the robot's actions' impact on the user 'on-the-fly'. My own work (together with colleagues) [14] is part of this category. We model change in the environment including change induced by the human, and controllable change (actions by a robot), which we set into different relations in formal concepts called *opportunity types*. A *desirability* function to model preference is also used in these opportunity types which enables us to evaluate different acting alternatives.

<u>Summary</u>: This type of proactivity is based on: first principles or fundamentals; the ultimate aim is to: understand the factors and their interaction in proactive decision making; generate proactive behavior from it.

5. Concluding Remarks, Future Directions and Challenges

This paper emphasizes the need to define and study the field of proactivity of AI systems and artificial agents. A definition and scope is suggested, derived from the human proactive process. Cognitive abilities that are necessary (to varying degrees) are presented and put into the context of examples. The author defines types of proactivity and what characterizes them.

Proactivity is a promising emerging field of interest in the AI community. There is still a long list of open issues, and we are just starting to define this field (which this paper intends to contribute to). Many approaches call their work 'proactive' while this 'proactivity' depends on hard-coded rules for when the artificial agent should act. Approaches might not take anticipation into account. This is not corresponding with the definition in the current paper which calls for *anticipatory* acting based on *reasoning*. Another problem with many works within proactivity is they often present domain-specific and/or ad-hoc solutions, meaning, they lack an underlying general theory. Finally, there are numerous aspects that are necessary or useful when trying to create proactive agent behavior (see Section 3). It will be a future milestone to integrate most (or all) of them to achieve artificial agent proactivity.

Proactivity implies a high degree of autonomy, which demands a high degree of responsibility. Bremner et al. [18]'s work is one step in the direction of creating proactive robots that are conforming with human ethical values. This in turn can create *trust*, which is a necessary basis for human-robot interactions in social contexts. Bremner et al. [18] further point out, the early *Laws of Robotics* by Asimov [24] are demanding a robot to be proactive. The first law starts with "A robot should not harm a human...", for this it is enough to have *reactive* robots. But then the law resumes, "... or, through inaction, allow a human to come to harm", which, in fact, demands robots that are *proactive*.

Acknowledgments

This research was funded by the Swedish Research Council (Vetenskapsrådet), No. 2021-05542. The content of this work benefited from discussions with (alphabetical order) Thomas Bolander, Sera Buyukgoz, Mohamed Chetouani, Federico Pecora and Alessandro Saffiotti.

References

- [1] A. Lieto, Cognitive design for artificial minds, Routledge, 2021.
- [2] U. KC, J. Chodorowski, A case study of adding proactivity in indoor social robots using belief-desire-intention (bdi) model, Biomimetics 4 (2019) 74.
- [3] A. K. Pandey, Socially intelligent robots, the next generation of consumer robots and the challenges, in: Proc of the Int Conf on ICT Innovations, 2016, pp. 41–46.
- [4] SPARC partnership, SPARC partnership, https://www.eu-robotics.net/sparc/about/ roadmap, 2016. Multi-Annual Roadmap for Robotics in Europe, release B 02/12/2016. (Sec 5.7 "Cognition"). Accessed: 2020-04-05.
- [5] H. Harman, P. Simoens, Action graphs for proactive robot assistance in smart environments, Journal of Ambient Intelligence and Smart Environments 12 (2020) 1–21.
- [6] M. Kraus, M. Schiller, G. Behnke, P. Bercher, M. Dorna, M. Dambier, B. Glimm, S. Biundo, W. Minker, "Was that successful?" On integrating Proactive Meta-Dialogue in a DIY-Assistant using Multimodal Cues, in: Proceedings of the 2020 International Conference on Multimodal Interaction, 2020, pp. 585–594.
- [7] M. Tomasello, M. Carpenter, J. Call, T. Behne, H. Moll, Understanding and sharing intentions: The origins of cultural cognition, Behavioral and Brain Sciences 28 (2005) 675–735.
- [8] A. M. Grant, S. J. Ashford, The dynamics of proactivity at work, Research in Organizational Behavior 28 (2008) 3–34.
- [9] M. L. Nicora, R. Ambrosetti, G. J. Wiens, I. Fassi, Human-robot collaboration in smart manufacturing: Robot reactive behavior intelligence, Journal of Manufacturing Science and Engineering 143 (2021) 031009.
- [10] A. Umbrico, A. Cesta, G. Cortellessa, A. Orlandini, A holistic approach to behavior adaptation for socially assistive robots, International Journal of Social Robotics (2020) 1–21.
- [11] C. Sirithunge, A. B. P. Jayasekara, D. Chandima, Proactive robots with the perception of nonverbal human behavior: A review, IEEE Access 7 (2019) 77308–77327.
- [12] F. Pecora, M. Cirillo, F. Dell'Osa, J. Ullberg, A. Saffiotti, A constraint-based approach for proactive, context-aware human support, J. of Ambient Intelligence and Smart Environments 4 (2012) 347–367.
- [13] T. Liu, E. Lyu, J. Wang, M. Q.-H. Meng, Unified intention inference and learning for humanrobot cooperative assembly, IEEE Transactions on Automation Science and Engineering (2021).
- [14] J. Grosinger, F. Pecora, A. Saffiotti, Robots that maintain equilibrium: Proactivity by reasoning about user intentions and preferences, Pattern Recognition Letters 118 (2019) 85–93. Cooperative and Social Robots: Understanding Human Activities and Intentions.
- [15] Z. Peng, Y. Kwon, J. Lu, Z. Wu, X. Ma, Design and evaluation of service robot's proactivity in decision-making support process, in: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 2019, pp. 1–13.
- [16] J. Baraglia, M. Cakmak, Y. Nagai, R. P. Rao, M. Asada, Efficient human-robot collaboration: when should a robot take initiative?, The International Journal of Robotics Research 36 (2017) 563–579.

- [17] D. C. Dennett, Intentional systems, The Journal of Philosophy 68 (1971) 87-106.
- [18] P. Bremner, L. A. Dennis, M. Fisher, A. F. Winfield, On proactive, transparent, and verifiable ethical reasoning for robots, Proceedings of the IEEE 107 (2019) 541–561.
- [19] S. Russell, Human compatible: Artificial intelligence and the problem of control, Penguin, 2019.
- [20] D. Premack, G. Woodruff, Does the chimpanzee have a theory of mind?, Behavioral and brain sciences 1 (1978) 515–526.
- [21] S. Buyukgoz, J. Grosinger, M. Chetouani, A. Saffiotti, Two ways to make your robot proactive: reasoning about human intentions, or reasoning about possible futures, arXiv preprint arXiv:2205.05492 (2022).
- [22] M. Shvo, T. Q. Klassen, S. A. McIlraith, Resolving misconceptions about the plans of agents via Theory of Mind, in: Proceedings of the Thirty-Second International Conference on Automated Planning and Scheduling (ICAPS 2022), 2022. To appear.
- [23] G. S. Martins, H. Al Taír, L. Santos, J. Dias, αPOMDP: POMDP-based user-adaptive decisionmaking for social robots, Pattern Recognition Letters 118 (2019) 94–103. Cooperative and Social Robots: Understanding Human Activities and Intentions.
- [24] I. Asimov, Runaround, Astounding science fiction 29 (1942) 94–103.