Remarkable AI

ANONYMOUS

The enemy

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

In HCI there is a long-standing tradition for debate around dichotomies regarding to what extend the inner workings and/or values of technologies should be exposed to users. One of these discussions surrounded the notion of Remarkable [24] and unremarkable [29] computing. As an approach to ubiquitous computing in the home, Unremarkable Computing aimed "to make computational resources that can be unremarkably embedded into routines and augment action" [29, p. 404] referencing Weiser's [31] seminal view on *the computer for the 21st century*. In response to this, Petersen [24] suggested *Remarkable Computing* as a complimentary approach, arguing that as much as digital technologies are able to support people's routines, they are also increasingly becoming "objects of lifestyle and identity" [24, p. 1446], and that such objects are and should be remarkable in the home. In the context of education, Eisenberg et al. [12] went so far as to call unremarkable computing counterproductive, arguing that technologies which disappear into the background are unlikely to spur learners' curiosity, and that they, generally, are more suited for contexts where ease-of-use, productivity, etc., are considered highly important, e.g., in work settings.

In 2019, Yang et al. [32] presented an argument similar to that of Tolmie et al., namely the notion of *Unremarkable AI*; an approach to designing AI systems, specifically for supporting clinical decision making, that aims for them to be "subservient to the day-to-day decision-making" of their users or, in order words, to be unremarkable. The connection between AI and ubiquitous computing makes sense, since they share a central tenet, namely the "interest in building technologies that make sense and respond in a sensible way to the complex dynamics of human environments" [19], and (as least in regards to machine learning) a dependence on data collection and analysis. However, this also leaves Unremarkable AI subject to similar critiques to those delivered by Petersen and Eisenberg et al. to Unremarkable Computing.

AI systems are now a large part of most people's every lives, driving technologies that we use multiple times a day, such as social media, search engines, music and video streaming services, and so on. It is safe to say, that AI systems too have become (at least part of) "objects of lifestyle and identity". Such systems are increasingly part of using our everyday technologies, and they has been severely influential across areas as diverse as medicine [6, 28], criminal justice [23] terrorism prevention [33], communication and transportation [27], etc. However, with their proliferation has followed concerns on how AI systems are affecting our societies negatively [21] in ways that are opaque and difficult to understand [1].

With the promise of great progress and the great risk of the increasing usage of AI-system, there is a need for raising public understanding of what these AI-systems are, how they work and how they can affect us. In agreeance with Eisenberg et al. [12], we find that the notion making such systems unremarkable is counterproductive to education to this need. *Comment:* Do I need an explicit research question here?

In this paper, we present Remarkable AI; an approach to designing AI systems, but one that is focused on making users aware that they are interacting with an AI system and on exposing what the AI system is doing, how it is doing it, and why. This approach is based on Petersen's [24] notion of Remarkable Computing, and further developed through a case study analysis of three, to us intimately familiar, research projects that all aim at opening up the black boxes of AI systems and do so through the design of an AI-system. The remainder of the paper is structured as follows; first, we present background on the remarkable/unremarkable debate and on AI-systems design approaches. Second, we present Remarkable AI as a design approach to AI-systems that aim to expose their inner workings to their users. Next, we present the three cases and the results from their analysis, focusing on how they embody the Remarkable AI approach. Finally, we discuss the implications of this approach as well as its future work.

2 BACKGROUND

At the beginning of the century, the HCI community found itself drifting in focus, towards not only considering the use of computer systems in the workplace, and including the home as well [5]. Previously, the HCI field had moved from the studies of "human factors" towards treating humans as actors the their design processes, by, e.g., including them in design processes and moving beyond the singular "user", towards considering the use context as a whole [3]. It was in this context, Weiser [31] presented his vision of "The Computer for the 21st Century"; a vision in which computers weaved ubiquitously into our lives — work lives, that is. Building from Weisers ideas, Tolmie et al. [29] proposed Unremarkable Computing as a strategy for successfully integrating ubiquitous computing in a domestic context. They argued, that systems should be designed to seamlessly and unremarkably fit into daily routines in the home. Tolmie et al. distinguish between perceptual visibility and invisibility and invisibility in use arguing, that they are not the same, and that rather than becoming perceptually invisible, systems should aim for invisibility in use, echoing the heideggerian idea of tools that become *ready-at-hand*, allowing their users to see past them, focusing instead on the task at hand.

In response to this Petersen [24] argued *Comment: ...* "That is when the metaphor makes the user question the technology at hand, start investigating it, become motivated to exploring it, and looking upon it in new ways. The metaphor then provides new horizons of use."

Comment: Some other approaches to design aimed for reflection (or similar): Reflective Design [26], critical design is where a critique is embodied in the designed artefact, questioning current values.. [11], speculative design [2], Value fiction [10, 13] . Even Constructionism [22] could be considered a "design" approach.

Comment: Examples of exposing inner workings of AI: xAI (e.g., [1], others???), AI curriculum [20, 30] and learning tools (e.g., [4, 17, 18, 25]) Those are just my own...

3 REMARKABLE AI

Remarkable AI is an approach to designing AI applications that aims to amplify the potential for making AI present for the user, where the notion of presence refers to that used by Hallnäs and Redström [15], namely "not the mere physical existence of things in someone's surroundings, but rather the existence of things in our everyday life based on an act of acceptance". However, as we will explore below, there are several obstacles affecting the presence of AI and AI systems.

First, there are many things that, on a functional level, exist in our lives and affect it without being, on the existential level of Hallnäs and Redström, present in our lives; things we do not know exist or that are being purposefully hidden from us. This is especially common with software, where we only see the front-end, and where companies often deploy "dark patterns" to hide aspects of their software that does not have the best interests of the users in mind [7, 14]. *Comment:* gap in argument here.. Thus, it stands to reason that to become present, something must first be perceptible. In Unremarkable Computing, this is addressed through routines; "artefacts that are implicated in routines can be perceptually available yet practically invisible in use" [29]. In other words, in Unremarkable Computing the perceptibility of an artefact does not matter; what is important is its perceptibility *in use*. As a response to this, Petersen [24] points out, that no interactive technology is inherently invisible in use; they must first be appropriated and learned, and then they can fade to the background. However, as the proliferation of AI-systems has shown us, that can no longer be said to be true. Surely, the front-end of an interactive system is not inherently invisible, but the back-end might be, and this is where AI is most-often situated.

This leaves two opportunities for AI to become present for the users of systems that integrate it; first, the front-end of AI-systems can be designed in ways that make their AI component perceptible. As in the case of the clinical decision support tools designed by Yang et al. [32] this does not exclude AI systems that invisible in use (or unremarkable). Second, we might teach users how to tell if an AI-system is being deployed behind the scenes and to understand what it's doing, and why.

To do so, Remarkable AI is inspired by the notion of Computational Empowerment [8, 16], an approach to designing learning experiences for children that aim to empower children "to make critical and informed decisions about the role of technology in their lives". Dindler et al. [8] argue that there are two main ways of engaging with technology when trying to understand it, namely through *coding* (i.e., constructing, making, etc.) and through *decoding* (i.e., observing, analysing, etc.). Engaging with technology in this way makes it *present at hand*; it makes users focus on the technology itself instead of what can be accomplished with the technology [9]. For example, consider how we typically interact with a search engine: We enter a search query (most likely in our web-browsers' search bar, i.e. not on the web site of the search engine), scroll through the results of the query and click any link that spark our interest. If we instead try to code (in the broadest of meanings) our own, we become aware of how they work behind the scenes; how queries are interpreted, how web-sites are crawled and indexed to become available for searching and, crucially, how results are ordered (often using AI to personalise them), and which data are collected about the users. These aren't issues that we usually think about when using a search engine, but when coding one, confronting them is a necessity. After doing so we become, arguably, better equipped to make decisions about our choice and use of search engines. Thus, moving from using a technology to coding/decoding it also involves moving from it being ready at hand to becoming present at hand. *Comment:* Am I spending too much time explaining something trivial here, or does it work?

Thus, Remarkable AI aims to move AI systems to be present at hand, so that when you encounter such systems in the wild, you will notice them (also other systems, that the ones designed through this approach). It aims to do so be

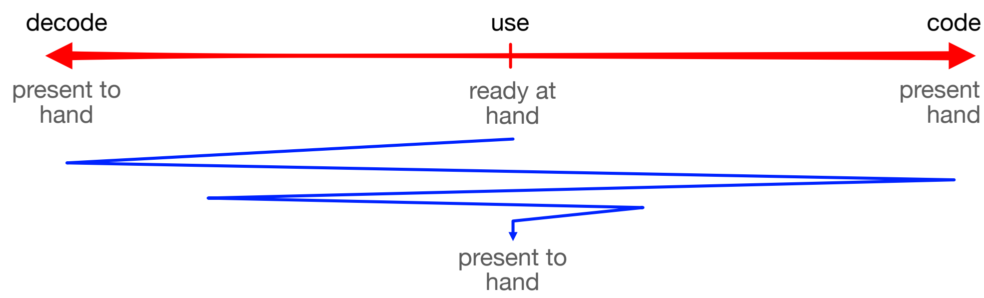

Fig. 1. Remarkable AI framework

presenting opportunities for users to code and decode AI systems (in Dindler et al.'s sense), making them present-at-hand for users, and then referring back to the use of these systems (see Figure 1).

In the following section, we analyse three cases of tools that aim to make AI remarkable to identify different ways of doing so.

4 CASE STUDIES

Comment: In this section I will go through each of these prototypes/cases and analyse them using the Remarkable AI framework presented above. The idea here is to both develop and validate the framework by analysing a set of cases very familiar with me.

4.1 VotestratesML

Comment: See [17]

4.2 The Machine Learning Machine

Comment: See [18]

4.3 ML Ethics Cards

Comment: See [4]

5 DISCUSSION

Comment: In this section I want to discuss the design considerations/sensitivities devised from the analysis above, and what they might mean for the Remarkable AI framework

5.1 Remarkable AI Learning Tools

5.2 Remarkable AI Beyond Education

6 CONCLUSION

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REFERENCES

[1] Ashraf Abdul, Jo Vermeulen, Danding Wang, Brian Y. Lim, and Mohan Kankanhalli. 2018. Trends and Trajectories for Explainable, Accountable and Intelligible Systems: An HCI Research Agenda *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–18. https://doi.org/10.1145/3173574.3174156

[2] James Auger. 2013. Speculative design: crafting the speculation. *Digital Creativity* 24, 1 (Mar 2013), 11–35. https://doi.org/10.1080/14626268.2013.767276

[3] Liam J. Bannon. 1995. *From Human Factors to Human Actors: The Role of Psychology and Human-Computer Interaction Studies in System Design.* Elsevier, 205–214. https://doi.org/10.1016/B978-0-08-051574-8.50024-8

[4] Karl-Emil Kjær Bilstrup, Magnus H. Kaspersen, and Marianne Graves Petersen. 2020. Staging reflections on ethical dilemmas in machine learning: A card-based design workshop for high school students. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference.* 1211–1222.

[5] Susanne Bødker. 2006. When second wave HCI meets third wave challenges. In *Proceedings of the 4th Nordic conference on Human-computer interaction changing roles - NordiCHI '06.* ACM Press, 1–8. https://doi.org/10.1145/1182475.1182476

[6] Po-Hsuan Cameron Chen, Yun Liu, and Lily Peng. 2019. How to develop machine learning models for healthcare. *Nature materials* 18, 5 (2019), 410.

[7] Michael Chromik, Malin Eiband, Sarah Theres Völkel, and Daniel Buschek. 2019. Dark Patterns of Explainability, Transparency, and User Control for Intelligent Systems. In *Joint Proceedings of the ACM IUI 2019 Workshops.* 6.

[8] Christian Dindler, Rachel Smith, and Ole Sejer Iversen. 2020. Computational empowerment: participatory design in education. *CoDesign* 16, 1 (2020), 66–80. https://doi.org/10.1080/15710882.2020.1722173 arXiv:https://doi.org/10.1080/15710882.2020.1722173

[9] Paul Dourish. 2004. *Where the Action is: The Foundations of Embodied Interaction.* MIT Press. Google-Books-ID: DCIy2zxrCqcC.

[10] Anthony Dunne. 2008. *Hertzian tales: electronic products, aesthetic experience, and critical design* (1. mit press paperback ed ed.). MIT Press.

[11] Anthony Dunne and Fiona Raby. 2013. *Speculative everything: design, fiction, and social dreaming.* The MIT Press.

[12] Michael Eisenberg, Ann Eisenberg, Leah Buechley, and Nwanua Elumeze. 2006. Invisibility Considered Harmful: Revisiting Traditional Principles of Ubiquitous Computing in the Context of Education. In *2006 Fourth IEEE International Workshop on Wireless, Mobile and Ubiquitous Technology in Education (WMTE'06).* IEEE, 103–110. https://doi.org/10.1109/WMTE.2006.261355

[13] Bill Gaver and Heather Martin. 2000. Alternatives: exploring information appliances through conceptual design proposals. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems (CHI '00).* Association for Computing Machinery, 209–216. https://doi.org/10.1145/332040.332433

[14] Colin M. Gray, Yubo Kou, Bryan Battles, Joseph Hoggatt, and Austin L. Toombs. 2018. *The Dark (Patterns) Side of UX Design.* Association for Computing Machinery, 1–14. https://doi.org/10.1145/3173574.3174108

[15] Lars Hallnäs and Johan Redström. 2002. From use to presence: on the expressions and aesthetics of everyday computational things. *ACM Transactions on Computer-Human Interaction* 9, 2 (Jun 2002), 106–124. https://doi.org/10.1145/513665.513668

[16] Ole Sejer Iversen, Rachel Charlotte Smith, and Christian Dindler. 2018. From computational thinking to computational empowerment: a 21st century PD agenda. In *Proceedings of the 15th Participatory Design Conference: Full Papers-Volume 1.* 1–11.

[17] Magnus Høholt Kaspersen, Karl-Emil Kjær Bilstrup, Maarten Van Mechelen, Arthur Hjort, Niels Olof Bouvin, and Marianne Graves Petersen. 2021. VotestratesML: A High School Learning Tool for Exploring Machine Learning and its Societal Implications. In *FabLearn Europe / MakeEd 2021 - An International Conference on Computing, Design and Making in Education (FabLearn Europe / MakeEd 2021).* ACM, New York, NY, USA, 14. https://doi.org/10.1145/3466725.3466728

[18] Magnus Høholt Kaspersen, Karl-Emil Kjær Bilstrup, and Marianne Graves Petersen. 2021. The Machine Learning Machine: A Tangible User Interface for Teaching Machine Learning. In *Proceedings of the Fifteenth International Conference on Tangible, Embedded, and Embodied Interaction (TEI '21).* Association for Computing Machinery, 1–12. https://doi.org/10.1145/3430524.3440638

[19] Lucian Leahu, Phoebe Sengers, and Michael Mateas. 2008. Interactionist AI and the promise of ubicomp, or, how to put your box in the world without putting the world in your box. In *Proceedings of the 10th international conference on Ubiquitous computing - UbiComp '08.* ACM Press, 134. https://doi.org/10.1145/1409635.1409654

[20] Duri Long and Brian Magerko. 2020. What is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20).* Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3313831.3376727

[21] Cathy O'Neil. 2016. *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy.* Crown. Google-Books-ID: cbwvDwAAQBAJ.

[22] Seymour Papert. 1990. Children, computers and powerful ideas.

[23] Walt L Perry. 2013. *Predictive policing: The role of crime forecasting in law enforcement operations.* Rand Corporation.

[24] Marianne Graves Petersen. 2004. Remarkable computing: the challenge of designing for the home. In *Extended abstracts of the 2004 conference on Human factors and computing systems - CHI '04.* ACM Press, 1445. https://doi.org/10.1145/985921.986086

[25] Marie-Monique Schaper, Rachel Charlotte Smith, Mariana Aki Tamashiro, Maarten Van Mechelen, Mille Skovhus Lunding, Karl-Emil Kjær Bilstrup, Magnus Høholt Kaspersen, Kasper Løvborg Jensen, Marianne Graves Petersen, and Ole Sejer Iversen. 2022. *Principles for Teenagers' Learning About Emerging Technologies and Their Societal Impact: Machine Learning and Augmented Reality in K-12 Education.* Number ID 4013380. https://doi.org/10.2139/ssrn.4013380

[26] Phoebe Sengers, Kirsten Boehner, Shay David, and Joseph "Jofish" Kaye. 2005. Reflective design. In *Proceedings of the 4th decennial conference on Critical computing between sense and sensibility - CC '05*. ACM Press, 49. https://doi.org/10.1145/1094562.1094569

[27] Ben Shneiderman, Catherine Plaisant, Maxine Cohen, Steven Jacobs, Niklas Elmqvist, and Nicholoas Diakopoulos. 2016. Grand Challenges for HCI Researchers. *Interactions* 23, 5 (Aug. 2016), 24–25. https://doi.org/10.1145/2977645

[28] Jenni AM Sidey-Gibbons and Chris J Sidey-Gibbons. 2019. Machine learning in medicine: a practical introduction. *BMC medical research methodology* 19, 1 (2019), 64.

[29] Peter Tolmie, James Pycock, Tim Diggins, Allan MacLean, and Alain Karsenty. 2002. Unremarkable computing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '02)*. Association for Computing Machinery, 399–406. https://doi.org/10.1145/503376.503448

[30] David Touretzky, Christina Gardner-McCune, Fred Martin, and Deborah Seehorn. 2019. Envisioning AI for K-12: What Should Every Child Know about AI? *Proceedings of the AAAI Conference on Artificial Intelligence* 33, 0101 (Jul 2019), 9795–9799. https://doi.org/10.1609/aaai.v33i01.33019795

[31] Mark Weiser. 1991. The Computer for the 21 st Century. *SCIENTIFIC AMERICAN* (1991), 13.

[32] Qian Yang, Aaron Steinfeld, and John Zimmerman. 2019. Unremarkable AI: Fitting Intelligent Decision Support into Critical, Clinical Decision-Making Processes. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, 1–11. https://doi.org/10.1145/3290605.3300468

[33] Tal Z Zarsky. 2012. Automated prediction: Perception, law, and policy. *Commun. ACM* 55, 9 (2012), 33–35.