Human-AI Collaboration in Data Science:
Exploring Data Scientists' Perceptions of Automated AI

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Reviewed by: Rishabh Devgon

Critical Review:

Dakuo Wang et al. [1] aim to investigate the current work practices within data science and how that may change with AutoAI. The authors try to provide a description of who constitutes as a data science worker. The paper also elaborates on how Auto AI can be further extended to make artificial intelligence more transparent, explanatory and recommended. The authors also research the role of AutoAI in the data science pipeline and study its implications on data science workers. I really appreciate the section titled "What is AutoAI?" because it provides a comprehensive overview of the subject that the researchers are exploring and the work being done/ already done in this field. Figure 1 does an excellent job of visually representing the data science pipeline for AutoAI, and each process within the pipeline is described well in this section. The authors review related work in Human Intervention in Data Science, Data Science Teams and Disciplinary Diversity, and Data Science Tools.

One particularly interesting reflection that I found was how interdisciplinary insights into data science knowledge could help in improving its current scenario. This makes sense given how AI is being adopted in various interdisciplinary fields and how background knowledge into these fields can benefit AI as a whole. I personally found the results section very intriguing because it makes use of quotes from informants which added another layer to the derived insights and made the paper more human centered. The limitations are an excellent addition to the paper, and they disclose several oversights and restrictions in the paper. The work is novel because it is one of the pioneers in the field of AutoAI evaluated through a lens from data science practitioners. There has been previous work on AutoAI, but they have not adopted this approach.

The authors make use of qualitative insights from interviewing 20 data scientists through semi-structured interviews which is justified because it helps in gaining first hand knowledge about the research question, allowing for probes. I really appreciate the fact that the themes for the interviews were provided for readers, thus increasing the transparency of the interview process. They have explicitly mentioned their selection criteria and have used snowball sampling as a method for recruitment. The authors have used open coding as a method of analysis of the obtained interview data. Open coding is a great method here because it allows the researchers to go in with a blank slate and identify various themes on the basis of what the informants have to say. A research method that I would suggest is a wizard of oz trial of AutoAI system for a data science task. This would add to the authenticity of the experience and generate more candid insights.

The interview study was done within a limited purview with all data scientists interviewed working at IBM and not extended further. So, a case could be made about how the results obtained from the study are not generalisable and could be biased as they come from a singular institution with shared beliefs. Since the recruitment is done within IBM, purposive stratified sampling may have been a better way to recruit participants. The informants, although ranging in their designation and roles, seem fairly homogenous when it comes to socio-cultural and regional aspects. Further additions could also be their confidentiality agreements with the informants and how they maintained the privacy of the recruits. I think a discussion about what method they employed here would add value to their methodology.

The research does not address what effect AutoAI has further down the AI ladder with a lack of focus on data workers. The paper also does not point out which communities are particularly vulnerable with the automation aspect in AI and does not address the fairness of AI automation at all. There is no mention of a regulatory body to keep in check the ramifications of automation, and there is no mention of the agency. The paper could have further explored that in case of any real-world consequences especially in various high stakes domains, be it humanitarian, environmental etc. who is culpable and who can we hold accountable when the AI is involved in decision making. Further, there is a question on sustainability and feasibility of an AutoAI intervention and finding perhaps a dynamic balance for collaboration between humans and AI.

An aspect that felt somewhat missing in this analysis was how the AutoAI could actually help to increase the accessibility to data science and move towards bringing it closer to everyday users and thus enabling them in a way. Yes, it does create a black box, but at the same time, it also makes AI more inclusive of people who lack super specialised technical ability. This is because this ability is also a function of a person's background, conditioning and other socio-cultural factors. The paper overall brings forward a very well balanced discussion about the Human and AutoAI collaboration and thus resonates with the project title.

References:

1. Dakuo Wang, Justin D. Weisz, Michael Muller, Parikshit Ram, Werner Geyer, Casey Dugan, Yla Tausczik, Horst Samulowitz, and Alexander Gray. 2019. Human-AI Collaboration in Data Science: Exploring Data Scientists' Perceptions of Automated AI. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW: 1–24. https://doi.org/10.1145/3359313