Proceedings of the CSCW 2021 Workshop – Investigating and Mitigating Biases in Crowdsourced Data

At the 24th ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW 2021) October 23, 2021, Virtual.

ORGANISED BY
Danula Hettiachchi, RMIT University, Australia
Mark Sanderson, RMIT University, Australia
Jorge Goncalves, The University of Melbourne, Australia
Simo Hosio, University of Oulu, Finland
Gabriella Kazai, Microsoft Research, UK
Matthew Lease, U. of Texas at Austin, USA & Amazon, USA
Mike Schaekermann, Amazon, Canada
Emine Yilmaz, University College London, UK & Amazon, UK
## POSITION PAPERS

1. *Managing Bias in Human-Annotated Data: Moving Beyond Bias Removal.*  
   Gianluca Demartini, Kevin Roitero and Stefano Mizzaro.  
   Page 1

2. *Introducing the Cognitive-Biases-in-Crowdsourcing Checklist.*  
   Tim Draws, Alisa Rieger, Oana Inel, Ujwal Gadiraju and Nava Tintarev.  
   Page 5

3. *Bias Mitigation through ML pipeline in Crowd-based Knowledge Creation.*  
   Caifan Du.  
   Page 9

4. *The Productivity Paradox: Understanding Tooling Biases in Crowdwork.*  
   Senjuti Dutta, Rhema Linder, Doug Lowe, Matthew Rosenbalm, Anastasia Kuzminykh and Alex Williams.  
   Page 13

5. *Designing and Optimizing Cognitive Debiasing Strategies for Crowdsourcing Annotation.*  
   Chien-Ju Ho and Ming Yin.  
   Page 17

6. *CrowdRL: A Reinforcement Learning Framework for Human Error Mitigation in Crowdsourcing-based Stream Processing.*  
   Rahul Pandey and Hemant Purohit.  
   Page 23

7. *Demographic Biases of Crowd Workers in Key Opinion Leaders Finding.*  
   Hossein A. Rahmani and Jie Yang.  
   Page 27
Managing Bias in Human-annotated Data: Moving Beyond Bias Removal

GIANLUCA DEMARTINI, The University of Queensland, Brisbane, Australia
KEVIN ROITERO, University of Udine, Udine, Italy
STEFANO MIZZARO, University of Udine, Udine, Italy

Due to the widespread use of data-powered systems in our everyday lives, the notions of bias and fairness gained significant attention among researchers and practitioners, in both industry and academia. Such issues typically emerge from the data, which comes with varying levels of quality, used to train systems. With the commercialization and employment of such systems that are sometimes delegated to make life-changing decisions, a significant effort is being made towards the identification and removal of possible sources of bias that may surface to the final end-user. In this position paper, we instead argue that bias is not something that should necessarily be removed in all cases, and the attention and effort should shift from bias removal to the identification, measurement, indexing, surfacing, and adjustment of bias, which we name bias management. We argue that if correctly managed, bias can be a resource that can be made transparent to the users and empower them to make informed choices about their experience with the system.

1 TO REMOVE BIAS OR NOT TO REMOVE BIAS: THAT IS THE QUESTION

Different humans have diverse experiences and backgrounds which lead to them having different points of views. Each having a subjective view of the world, behavioral sciences agreed that humans are subject to systematic biases and errors [13]. Our society has been delegating more and more tasks and decisions to data-driven algorithms and to automatic or semi-automatic computational systems. Despite efforts to keep the algorithms behind data-driven computational systems neutral and unbiased, joint with the fact that such systems are often trained on human-annotated data, popular incidents made people realize that algorithms and datasets are not free from biases [2, 21]. Famous examples include the case where an algorithm designed to predict the likelihood of a criminal offending was found to be racially biased, and, according to the system, black people where predicted to have a higher risk of recidivism then their true one, and the reverse for white people [9]. Another example is the study which found that facial recognition technology software used for law enforcement was correct 99% of the times for white men, while for dark-skinned women the accuracy was less than 35% [20]. Another study showed that the search results of a search engine for the keyword “CEO” and for highly paid jobs were gender biased [3, 18]. As we can also see with the recent case of Facebook needing to apologize as black men were labeled ‘primates’¹, even large internet platforms are still prone to such bias-driven mistakes.

To address these issues, the study of bias in data and algorithms gained popularity [1, 12, 16, 19, 21, 23], both in disciplines that study fully-automatic systems such as machine and deep learning [14, 15] and in those that study and develop crowdsourcing-based or hybrid human-in-the-loop systems [4, 5, 7, 8]. Analyzing the recent literature, a clear trend that emerges is that algorithmic and human biases are depicted as negative and undesirable, and that bias should be removed from data and systems thus enforcing a, perhaps utopian, completely un-biased system and output [10, 11, 17].

In this position paper, we argue that (i) bias removal could be harmful, as it can lead to users being presented with a reality which is different from that in the off-line world, and (ii) if properly managed, bias can be not only harmless but even useful, as it could be a valuable source of information for the end user. Therefore, we claim that the aim should

¹“Facebook apology as AI labels black men ‘primates’ “. 7 Sep 2021. https://www.bbc.com/news/technology-58462511
not be to remove bias a-priori; instead, bias should be identified, measured, indexed, surfaced to users, and treated as a feature of the system, delegating to the users the choice of whether and how to adjust for it. Note that item (i) is consistent with Ullman’s view that “we should not blame data if it reflects the world as it is, rather than as we would like it to be” [22], but item (ii) goes beyond that.

2 BIAS MANAGEMENT VS. BIAS REMOVAL

We present two use cases for which we envision a scenario where bias removal may be undesirable and potentially harmful and where we think that, instead, bias management would be a more effective approach.

2.1 Example 1: Search Engine

Consider the case where a user needs to manually annotate or label a set of images to create a dataset; it is reasonable to assume that such a dataset may then be used to train an automatic system to independently perform a specific task. Suppose that the user issues the gender-neutral query “nurse” on a search engine and searches for images. The user will see on the page of results the vast majority of images of female nurses. While this might appear as an indication that the ranking algorithm of the search engine has a gender bias, this might also reflect the real gender distribution in this profession, that is, for example, female nurses are statistically more frequent than male nurses. While a traditional approach might propose to resolve this bias by forcing the algorithm to show male and female nurses in the same percentage, we argue that an alternative, less invasive approach might be more useful to the user. We make the following proposal to address the issue in this use case. The search engine might display on the result page a set of additional metadata which may be useful to the user to have a complete understanding of the magnitude of bias in the result set; for example, the search engine might show a label indicating that “the search results appear to be highly imbalanced in terms of gender: in the top 1000 results, 870 of them are of female nurses and 130 of them are of male nurses”. This information makes the user informed and aware of the statistical distribution of the search results with respect to a specific group (in this case, gender). Then, ideally, the user should be asked if they would like to maintain the current result ranking or whether they would prefer to inspect the results after a fairness policy is applied to the data (in this case, for example, forcing the number of male and female nurses to be roughly the same in the search result list).

We argue that not employing an explicit and transparent bias removal intervention might be potentially harmful to the user. In fact, if the task of the user was to investigate something related to or influenced by the percentage of male and female nurses, the implicit application of the fairness policy might leave the user with an inaccurate perception of the real gender distribution in the nursing profession. Taking this concept to the extreme, the user might even erroneously think, somehow paradoxically, that gender bias is not present in the nursing profession, and that male and female nurses are equally present in the job market.

2.2 Example 2: Recommender System

Consider a recommender system with a highly unbalanced set of users; for the sake of simplicity, let us suppose that there are just two groups of users: A, which constitutes 90% of the system userbase, and B, which constitutes the remaining 10% of the userbase (e.g., A could correspond to male and B to female users). Let us also suppose that A and B have very different tastes, and that a product which is good for users belonging to group A is generally not appreciated by users belonging to group B (e.g., the product could be a movie). Let us suppose that the recommender system in production is trained to maximize for user engagement. Given the unbalanced userbase composition, the recommender system will probably serve most of the times items that are likely to be enjoyed by group A users and disliked by users
from group B (in an ideal case, the system should learn to recommend different items to users in A and B, but let us also assume that this cannot be done, for example for privacy/anonymity reasons or to remove group belonging information from the model for fairness purposes). In this case, enforcing a fairness policy would mean to serve 50% A-liked items and 50% B-liked items. However, this might be extremely harmful: the risk is that many users will be not satisfied with the product being served. Notice that if the majority of the users (in this case, group A) is served with an item that they do not like, this will result in a loss of effectiveness of the whole recommender system. On the contrary, we argue that in this case either the users should have a clear overview of the rationale behind being recommended with a particular item (i.e., an explainable system), or the designers of the recommender system should identify a fairness-effectiveness trade-off. Note that imbalanced labeled datasets like the one presented in this use case commonly lead to unknown unknown errors, that is, to trained models that result in high-confidence errors. These errors are very difficult to identify as the model is highly confident of having made an accurate classification decision [6].

3 THE BIAS MANAGEMENT WORKFLOW

The two examples described above serve to support our position that the answer to the question “should bias always be removed and fairness always enforced” is not as straightforward as it might seem at a first glance. Our proposal alternative to removal consists of different steps, which are detailed in the following.

(1) Identification: identify if the data or system being used is subject to bias or fairness issues.

(2) Measurement: quantify with an appropriate metric the magnitude of different types of bias present in the data or system which is under consideration.

(3) Indexing: collect, parse, structure, and store bias metadata and fairness policies aimed at facilitating a subsequent fast and effective retrieval and system adjustments.

(4) Surfacing: present in an appropriate way to the user the bias present in the underlying data and/or any fairness policy that have been applied to the data or system under consideration.

(5) Adjustment: provide the user with a set of tools which allows them to interact with existing bias and to adjust for it in their preferred ways. This enables them to make informed decisions. Giving control to the user is essential since for some tasks they may benefit from fairness (e.g., a job application scenario) while for some others they may not (e.g., understanding the gender distribution in a specific profession).

We argue that bias is part of human nature, and that it should be managed rather than removed. We believe that the ideas detailed in this position paper can lead to a more sound, informed, and transparent decision making process which will impact algorithm and system design.

In the future we plan to categorize use cases across different domains, to design a bias management system implementing (maybe with a human-in-the-loop approach) the above five-step pipeline, and to evaluate the impact of such an approach in terms of effectiveness, user satisfaction, and user engagement.
REFERENCES

[1] Ricardo Baeza-Yates. 2018. Bias on the web. Commun. ACM 61, 6 (2018), 54–61.
[2] David Dankis and Alex John London. 2017. Algorithmic Bias in Autonomous Systems. In IJCAI, Vol. 17. 4691–4697.
[3] Amit Datta, Michael Carl Tschantz, and Anupam Datta. 2015. Automated Experiments on Ad Privacy Settings. Proc. Priv. Enhancing Technol. 2015, 1 (2015), 92–112.
[4] Gianluca Demartini, Djellel Eddine Difallah, Ujwal Gadiraju, and Michele Catasta. 2017. An introduction to hybrid human-machine information systems. Foundations and Trends in Web Science 7, 1 (2017), 1–87.
[5] Gianluca Demartini, Stefano Mizzaro, and Damiano Spina. 2020. Human-in-the-loop Artificial Intelligence for Fighting Online Misinformation: Challenges and Opportunities. The Bulletin of the Technical Committee on Data Engineering 43, 3 (2020).
[6] Xiao Dong, Huaxiang Zhang, and Gianluca Demartini. 2020. A Region Selection Model to Identify Unknown Unknowns in Image Datasets. In ECAI 2020. IOS Press, 474–481.
[7] Carsten Eickhoff. 2018. Cognitive Biases in Crowdsourcing. In Proceedings of WSDM. 162–170.
[8] Boi Faltings, Radu Jurca, Pearl Pu, and Bao Duy Tran. 2014. Incentives to counter bias in human computation. In Second AAAI conference on human computation and crowdsourcing.
[9] Jeff Larson, Surya Mattu, Lauren Kirchner and Julia Angwin. 2016. How We Analyzed the COMPAS Recidivism Algorithm. https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm accessed on 2021-09-07.
[10] Christopher Jung, Michael Kearns, Seth Neel, Aaron Roth, Logan Stapleton, and Zhewei Steven Wu. 2019. Eliciting and enforcing subjective individual fairness. arXiv e-prints (2019), arXiv–1905.
[11] Michael Kearns, Seth Neel, Aaron Roth, and Zhewei Steven Wu. 2019. An empirical study of rich subgroup fairness for machine learning. In Proceedings of the Conference on Fairness, Accountability, and Transparency. 100–109.
[12] Keith Kirkpatrick. 2016. Battling algorithmic bias: how do we ensure algorithms treat us fairly? Commun. ACM 59, 10 (2016), 16–17.
[13] Arie W Kruglanski and Ick Ajzen. 1983. Bias and error in human judgment. European Journal of Social Psychology 13, 1 (1983), 1–44.
[14] Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. A survey on bias and fairness in machine learning. ACM Computing Surveys (CSUR) 54, 6 (2021), 1–35.
[15] Peter A Noseworthy, Zachi I Attia, LaPrincess C Brewer, Sharonne N Hayes, Xiaoji Yao, Suraj Kapa, Paul A Friedman, and Francisco Lopez-Jimenez. 2020. Assessing and mitigating bias in medical artificial intelligence: the effects of race and ethnicity on a deep learning model for ECG analysis. Circulation: Arrhythmia and Electrophysiology 13, 3 (2020), e007988.
[16] Ziad Obermeyer, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. 2019. Dissecting racial bias in an algorithm used to manage the health of populations. Science 366, 6464 (2019), 447–453.
[17] Luca Oneto and Silvia Chiappa. 2020. Fairness in machine learning. Recent Trends in Learning From Data (2020), 155–196.
[18] Jahna Otterbacher, Alessandro Checco, Gianluca Demartini, and Paul Clough. 2018. Investigating user perception of gender bias in image search: the role of sexism. In The 41st International ACM SIGIR conference on research & development in information retrieval. 933–936.
[19] Pedro Saleiro, Kit T Rodolfa, and Rayid Ghani. 2020. Dealing with bias and fairness in data science systems: A practical hands-on tutorial. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 3513–3514.
[20] Timothy Revell. 2018. Face-recognition software is perfect – if you’re a white man. https://www.newscientist.com/article/2161028-face-recognition-software-is-perfect-if-youre-a-white-man/ accessed on 2021-09-07.
[21] Tatiana Tommasi, Novi Patricia, Barbara Caputo, and Tinne Tuytelaars. 2017. A deeper look at dataset bias. In Domain adaptation in computer vision applications. Springer, 37–55.
[22] Jeffrey D Ullman. 2020. The Battle for Data Science. IEEE Data Eng. Bull. 43, 2 (2020), 8–14.
[23] Tian Xu, Jennifer White, Sinan Kalkan, and Hatie Gunes. 2020. Investigating bias and fairness in facial expression recognition. In European Conference on Computer Vision. Springer, 506–523.
Introducing the Cognitive-Biases-in-Crowdsourcing Checklist

TIM DRAWS, ALISA RIEGER, OANA INEL, and UJWAL GADIRAJU, TU Delft, The Netherlands
NAVA TINTAREV, Maastricht University, The Netherlands

Additional Key Words and Phrases: crowdsourcing, cognitive biases, data quality

1 INTRODUCTION

Previous research has shown that cognitive biases (i.e., general human tendencies towards irrationality when making decisions under uncertainty [19]) such as the confirmation bias or anchoring effect can negatively affect the quality of crowdsourced data labels [5, 13]. Despite this empirical knowledge, crowdsourcing tasks are usually conducted without explicitly considering the influence of crowd workers’ cognitive biases on the quality of their annotations. One reason for this lack of consideration of cognitive biases may be complexity: a plethora of cognitive biases have been identified to date [12] and it may often be unclear which of them affect crowd workers in a particular task. Requesters need a practical tool that can help them assess which specific cognitive biases may affect crowd workers in a given task at hand so that targeted assessment and mitigation strategies for these biases can be implemented.

We have recently proposed a 12-item checklist, adapted from business psychology [14], for combating commonly occurring cognitive biases in crowdsourcing [3]. Each item in this checklist targets a different cognitive bias that may affect crowd workers when labeling data. Requesters may use the checklist to identify which particular cognitive biases may affect crowd workers in the tasks they design. In this position paper, we argue that such an assessment could inform the assessment, mitigation, and documentation of cognitive biases in crowdsourcing tasks and thereby strongly improve the quality of human-labeled data. We present our proposed checklist including a running example of a typical relevance judgment task and discuss how the checklist should ideally be used.

2 COGNITIVE-BIASES-IN-CROWDSOURCING CHECKLIST

(1) Self-interest Bias. Does my task offer any room for motivated errors? That is, could crowd workers have some financial, social, or other self-interest-related incentive to judge particular items differently than others? Crowd workers may (subconsciously) fall prey to self-interest bias due to inadvertent incentives and pricing schemes. For example, if workers receive a financial bonus for each “paella pan”-relevant product they find. Other examples include social desirability (i.e., when crowd workers are more likely to make incorrect decisions because other people may examine them; Antin and Shaw 1) and satisficing (i.e., exerting only the minimum required amount of effort into conducting a task to save time or resources; Kapelner and Chandler 15).

(2) Affect Heuristic. Could crowd workers be swayed by the degree to which they ‘like’ the items they annotate? For example, crowd workers may be more likely to judge products of a particular brand they like as relevant, independent from the products’ true relevance to “paella pan”. Phenomena such as priming effects (i.e., responding differently depending on a previously presented stimulus) and the familiarity bias (i.e., greater favorability towards familiar things or concepts) can play a role here [17].

An up-to-date version of the checklist and other material related to this research is publicly available: https://osf.io/rbucj.
(3) **Groupthink or Bandwagon Effect.** Does my task design give crowd workers some notion of other people’s evaluation of the items they annotate? For example, crowd workers may judge products as more likely to be relevant to “paella pan” when they see that a majority of other crowd workers have judged this product as being relevant or if it has received high ratings from consumers [5].

(4) **Salience Bias.** Could crowd workers’ judgments be affected by the salience of particular information? For example, crowd workers may be more likely to judge products as relevant to “paella pan” if they stand out in an unrelated way (e.g., caps lock titles or high-quality images).

(5) **Confirmation Bias.** Could crowd workers be overly influenced by preconceived notions of the items they annotate? For example, crowd workers who have a false preexisting idea of what a paella pan is may exhibit confirmation bias if they conduct the task by looking specifically for information that confirms this belief.

(6) **Availability Bias.** Does my task involve judgments related to concepts or people that are likely to elicit stereotypical associations? For example, crowd workers may be more likely to judge Spanish products as relevant to “paella pan” because they can easily recall numerous examples of the paella dish in Spanish contexts.

(7) **Anchoring Effect.** Is there a possibility that crowd workers overly focus on a specific reference point (i.e., an anchor) when making judgments? For example, if the first of several products that crowd workers are exposed to are clearly not paella pans (e.g., products unrelated to kitchenware), the first item that somewhat resembles a paella pan (e.g., a regular saucepan) may be more likely to be judged as relevant compared to when the same item was shown in a sequence of actual paella pans. Note that the anchoring effect can also occur within a single human intelligence task (HIT); e.g., when workers are overly influenced by the first information they see (i.e., primacy effect), such as the product title, or the last information they see before making their judgment (i.e., recency effect).

(8) **Halo Effect.** Does my task involve judgments that could be influenced by irrelevant pieces of information? For example, crowd workers may be more likely to judge products as relevant to “paella pan” if these products seem suitable for similar dishes (e.g., risotto). This encompasses related biases such as the decoy effect, where the choice between two options is affected by the introduction of a (potentially irrelevant) third choice, or the ambiguity effect, where (potentially irrelevant) missing information affects crowd workers’ decision-making [5].

(9) **Sunk Cost Fallacy.** Is the time required to complete my task and what it requires from crowd workers clear at the onset? The more time and effort crowd workers invest in a task, the more they may want to complete it, despite potentially already having lost interest in the task. This is undesirable as uninterested crowd workers may abandon a task after investing efforts or complete the task with sub-optimal performance [11]. For example, assuming that crowd workers have to annotate the relevance of 50 different products before completing the task but are not aware of the task length beforehand, their performance may deteriorate in the later stages.

(10) **Overconfidence or Optimism Bias.** Is there a possibility that crowd workers overestimate their ability to perform my task? For example, it arguably takes a particular level of cooking knowledge to distinguish a paella pan from a regular frying pan or wok. Crowd workers who have never learned about these distinctions may not perceive the task of assigning “paella pan”-relevance judgments to products as hard but may actually not be skilled enough to give high-quality annotations here. This is related to the Dunning-Kruger effect, which posits that people with low ability concerning a task tend to be overconfident about their projected performance in it [7, 16].

(11) **Disaster Neglect.** Have crowd workers who commit to my task, been properly informed about the consequences of their participation? The task selection process is often fairly arbitrary, which means that workers may not realize potential negative effects of committing to a task that they don’t have expertise on [4]. For example, crowd workers who commit to annotate products as relevant to “paella pan” may later realize that their expertise is not sufficient and may switch to annotate other products or abandon the task altogether.
workers may commit to doing “paella pan”-relevance judgments for products on a whim without considering the potential reputation loss and bad annotation quality that could follow if they do not perform well.

(12) Loss Aversion. Does my task design give crowd workers a reason to suspect that they may not get paid (fairly) after executing my task? Due to loss aversion, crowd workers may not select such tasks or abandon them early, leading to a skewed distribution of participants or task starvation [6]. For example, if a crowd worker suspects that annotating products in a task will only earn them money if they perform at a particular level, they may abandon the task early to avoid wasting their time and effort [10].

How to Use the Cognitive-Biases-in-Crowdsourcing Checklist

Suppose a requester has created a crowdsourcing task to collect viewpoint annotations for search results on several debated topics (i.e., to identify per search result whether it expresses a supporting or opposing opinion). The requester may now apply the cognitive-biases-in-crowdsourcing checklist to determine which cognitive biases may affect crowd workers in this context. For example, after going through the checklist with the task at hand, the requester could conclude that crowd workers may exhibit salience bias (i.e., judging search results as more extreme when they stand out more) and confirmation bias (i.e., annotating search results in line with their personal opinion).

Having identified potential cognitive biases that may affect crowd workers in the task at hand, the requester can do at least three different things to improve the reliability and quality of the resulting data. First, they can try to assess the influence of the identified biases; e.g., in this case, by analyzing whether crowd workers judge search results with capslock titles as more extreme or whether their annotations correlate with their personal opinions. Note that such an assessment may require implementing additional items into the task (e.g., to measure crowd workers’ personal opinion). Second, the requester can try to mitigate the potential problematic cognitive biases. Several studies have already shown how to mitigate some cognitive biases in the crowdsourcing context [5, 13]. Third, the requester may document the potentially impactful cognitive biases in the relevant research outputs (e.g., paper or data documentation). This helps researchers and practitioners who use the data to decide to what degree they want to rely on its correctness.

3 CONCLUSION

The cognitive-biases-in-crowdsourcing checklist we propose is a practical tool that requesters can use to combat cognitive biases in crowdsourcing. Ideally applied before any data collection, requesters may use the checklist to (1) identify which particular cognitive biases could affect crowd workers in the task at hand, (2) assess whether these biases actually take place, (3) attempt to mitigate these biases wherever possible, and (4) thoroughly describe potential influences of cognitive biases in the documentation of the data sets they publish. We discuss the intended use of the cognitive-biases-in-crowdsourcing checklist in the paper where we originally proposed it [3]. Furthermore, this work features a case study in which we describe how to use the checklist step-by-step and a retrospective analysis of related literature that shows that the checklist is widely applicable. We hope that our proposed checklist can meaningfully contribute to general efforts towards more reliable human-labeled data [2, 8, 9, 18].

ACKNOWLEDGMENTS

This activity is financed by IBM and the Allowance for Top Consortia for Knowledge and Innovation (TKI’s) of the Dutch ministry of economic affairs.
REFERENCES

[1] Judd Antin and Aaron Shaw. 2012. Social desirability bias and self-reports of motivation: a study of Amazon Mechanical Turk in the US and India. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. 2925–2934.

[2] Alec Burmania, Srinivas Parthasarathy, and Carlos Busso. 2016. Increasing the Reliability of Crowdsourcing Evaluations Using Online Quality Assessment. IEEE Transactions on Affective Computing 7, 4 (2016), 374–388. https://doi.org/10.1109/TAFFC.2015.2493525

[3] Tim Draws, Alisa Rieger, Oana Inel, Ujwal Gadiraju, and Nava Tintarev. 2021. A Checklist to Combat Cognitive Biases in Crowdsourcing. Proceedings of the Ninth AAAI Conference on Human Computation and Crowdsourcing (2021). https://timdraws.net/files/papers/A_Checklist_to_Combat_Cognitive_Biases_in_Crowdsourcing.pdf

[4] Tom Edishoven, Sihang Qin, Lucie Kuiper, Olivier Dikken, Gwennan Smitskamp, and Ujwal Gadiraju. 2021. Improving Reactions to Rejection in Crowdsourcing Through Self-Reflection. In 13th ACM Web Science Conference 2021. 74–83.

[5] Carsten Eickhoff. 2018. Cognitive biases in crowdsourcing. WSDM 2018 - Proceedings of the 11th ACM International Conference on Web Search and Data Mining 2018-February (2018), 162–170. https://doi.org/10.1145/3159652.3159654

[6] Siamak Faradani, Bjorn Hartmann, and Panagiotis G Ipeirotis. 2011. What’s the right price? pricing tasks for finishing on time. In Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence.

[7] Ujwal Gadiraju, Besnik Fetahu, Ricardo Kawase, Patrick Saebenhel, and Stefan Dietze. 2017. Using worker self-assessments for competence-based pre-selection in crowdsourcing microtasks. ACM Transactions on Computer-Human Interaction (TOCHI) 24, 4 (2017), 1–26.

[8] Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé, and Kate Crawford. 2018. Datasheets for Datasets. (2018). arXiv:1803.09010 http://arxiv.org/abs/1803.09010

[9] R Stuart Geiger, Kevin Yu, Yanlai Yang, Mundy Dai, Jie Qin, Rebekah Tang, and Jenny Huang. 2020. Garbage In, Garbage Out? Do Machine Learning Application Papers in Social Computing Report Where Human-Labeled Training Data Comes From ?. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (FAccT ’20) Association for Computing Machinery, New York, NY, USA, 325–336. https://doi.org/10.1145/3350995.3372862

[10] Lei Han, Kevin Roitero, Ujwal Gadiraju, Cristina Sarasua, Alessandro Checco, Eddy Maddalena, and Gianluca Demartini. 2019. All those wasted hours: On task abandonment in crowdsourcing. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. 321–329.

[11] Lei Han, Kevin Roitero, Ujwal Gadiraju, Cristina Sarasua, Alessandro Checco, Eddy Maddalena, and Gianluca Demartini. 2019. The impact of task abandonment in crowdsourcing. IEEE Transactions on Knowledge and Data Engineering (2019).

[12] Martin Hilbert. 2012. Toward a synthesis of cognitive biases: how noisy information processing can bias human decision making. Psychological bulletin 138, 2 (2012), 211.

[13] Christoph Hube, Besnik Fetahu, and Ujwal Gadiraju. 2019. Understanding and mitigating worker biases in the crowdsourced collection of subjective judgments. Conference on Human Factors in Computing Systems - Proceedings (2019). https://doi.org/10.1145/3290605.3300637

[14] Daniel Kahneman, Dan Lovallo, and Olivier Sibony. 2011. Before you make that big decision... Harvard business review 89, 6 (2011).

[15] Adam Kapelner and Dana Chandler. 2010. Preventing satisficing in online surveys. Proceedings of CrowdConf (2010).

[16] Justin Kruger and David Dunning. 1999. Unskilled and unaware of it: how difficulties in recognizing one’s own incompetence lead to inflated self-assessments. Journal of personality and social psychology 77, 6 (1999), 1121.

[17] Robert R Morris, Mira Dornich, and Elizabeth M Gerber. 2012. Priming for better performance in microtask crowdsourcing environments. IEEE Internet Computing 16, 5 (2012), 13–19.

[18] Jorge Ramírez, Burcu Sayin, Marcos Baer, Fabio Casati, Luca Cernuzzi, Boualem Benatallah, and Gianluca Demartini. 2021. On the state of reporting in crowdsourcing experiments and a checklist to aid current practices. In Proceedings of the ACM on Human-Computer Interaction (PACM HCI), presented at the 24th ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW 2021). October 2021.

[19] Amos Tversky and Daniel Kahneman. 1974. Judgment under Uncertainty: Heuristics and Biases. Science 185 (Sept. 1974), 1124–1131. https://doi.org/10.1126/science.185.4157.1124
This position paper seeks to motivate a systematic approach to mitigating bias in crowdsourced annotation for machine learning (ML) purposes. Crowd annotation is often one single stage through a complete ML pipeline. Yet the antecedents of crowdsourced data biases could emerge from different stages, bearing cascading and systematic consequences on system output and its application domain. In this tailored discussion, I specifically focus on design strategies for organizing crowd annotation, considering bias mitigation. These strategies particularly engage with the knowledge and cognitive processes of annotators.

Additional Key Words and Phrases: crowd annotation, bias mitigation, cognitive process

This position paper seeks to motivate a systematic approach to mitigating bias in crowdsourced annotation for machine learning (ML) purposes. Crowd annotation is often one single stage through a complete ML pipeline. Yet the antecedents of crowdsourced data biases could emerge from different stages, bearing cascading and systematic consequences on system output and its application domain [10]. It is critical to recognize that crowdsourced data annotation has become an important source of knowledge, fueling ML-driven algorithmic systems with scaled impacts on knowledge discovery and creation across various activity domains. Thus, mitigating biases in crowd annotation is a task that matters not only for social justice and welfare but also for a fair, common repertoire of human knowledge. From this perspective, I will discuss strategies to mitigate biases in crowd annotation situated in the whole ML pipeline, highlighting levers for key design decisions.

Figure 1 is a simplified illustration of an ML pipeline based on crowdsourced training data in its broader application context. Such a pipeline itself is a complex sociotechnical system of problem-solving [12]. The system-level goal is to generate useful knowledge informing the solution of a broader problem—it could be resource allocation, risk assessment, learning analytics, business planning, or academic research. The problem formulation links expected system output to the higher-level goal, and thus conditions model selection, training, fine-tuning, and evaluation and the expected annotated data as the model input. Problem formulation for the whole ML system solution also matters for the series of decisions to be made for the crowd annotation task design. Even though the problem is formulated in a harmless manner, the subsequent design decisions throughout the pipeline could still induce biases in its output. But first of all, the problem, to which the system is a solution, either is formulated for promoting social welfare or is at least articulated in a manner avoiding discriminating implications [2, 7].

The last three stages of the ML pipeline, annotation aggregation, model training, tuning, and evaluation, and demonstration and interpretation of the system output also have to tackle specific tasks of bias mitigation. In the following discussion, I focus on the crowd annotation stage. There are three main design choices to be considered for crowd annotation; each design choice has implications on annotation data biases. These three design choices are annotator selection, annotator organization, and workflow arrangement.

**Annotator selection.** Annotator selection concerns who has the best knowledge to complete the annotation task in the least biased manner. This question matters for bias mitigation because it is relevant to whose views and knowledge will be represented in the annotated data [1]. This choice is closely tied to the overall problem formulation. Taking the example discussed in Fazelpour & De-Arteaga’s work, to annotate a dataset of multi-lingual hate speech, we might think the absence of labels in the Spanish subset renders it biased. But we could also consider the absence of labels
from hate speech victims’ perspective is a more concerning bias because they are the very ones holding an in-depth understanding of what is counted as hate speech. On what dimensions biases are evaluated should be deliberated against the problem definition—Do we want to mitigate language bias or bias of under-representativeness? Which one is more relevant to our holistic goal, or both are indispensable dimensions?

The system-level problem formulation helps clarify what kind of knowledge we are seeking to collect in data annotation tasks. Then it is reasonable to design selection mechanisms that enlist crowd annotators who possess the knowledge sought. Test tasks can be designed according to this criterion for qualifying crowd workers for the annotation task. Selecting annotators based on their knowledge is to build a knowledge repertoire that will be imported into the annotated data. Thus, the cognitive diversity of the crowd annotators is an important antecedent for mitigating biases in annotation results [4].

**Annotator organization.** Data annotation is essentially a cognitive activity that requires knowledge and reasoning. After assembling the initial knowledge repertoire, the next step is to design a task process that elicits more diverse, fair, and/or representative knowledge from crowd annotators [13]. Thus, the annotation task design should engage with the annotators’ thinking process. Certain components that can be built into the task process include training, deliberation [11], and discussion [8]. The essential idea is to increase the knowledge of annotators in a limited time and activate more reflective, deliberate cognitive processes of annotators [6].

It is worth noting that the form of organization and mode of interaction matters for collective processes during annotation tasking. A recent experimental study reveals discussion group size and composition could affect crowd performance in forecasting tasks [8]. Other existing studies also demonstrate that more diverse groups tend to engage more with deliberation [3, 5]. Simply put, interaction and communication during annotation tasks can grow the knowledge that interacting participants possess; more diverse members deliberate more during interactional processes. Thus, it is another design choice that is worth consideration: whether and how to organize interactional sessions between crowds during annotation tasks.

**Workflow arrangement.** Workflow arrangement in crowd annotation concerns whether the raw annotation results will be aggregated computationally or will go through group resolution or adjudication processes. It is also possible that an iterative, human-in-the-loop process is applied, such as by active learning (e.g., [9]). The critical choices here that matter for the crowd participants’ cognitive processes include who will engage in more reflexive thinking such as adjudication and whether annotators will be repeatedly exposed to similar tasks. The central mechanism at play is that annotators will constantly learn through reflexive and/or long-time engagement. The learning will shift their individual knowledge repertoire and change the dynamics of the collective knowledge repertoire of all participating...
crowds. Thus, workflow arrangements put the collective knowledge of crowd annotators in motion and have an impact on the annotation biases.

Another way that workflow arrangement can affect bias mitigation is not through tasking but task redesigning. This means feedback can be collected from crowd annotators regarding task design and how the annotation task can be improved to reduce biased input [14].

In this short discussion, my primary focus is on bias mitigation through organizing crowd workers for annotation tasks. Task interface design is another aspect during crowd annotation that has a cognitive effect on the knowledge to be encoded into data annotation. But it is not the focus of this tailored discussion. Bias mitigation mechanisms abound such as various annotation aggregation techniques to date. It is worthwhile to consider all these techniques along the full ML pipeline as well as the problem context to reduce the risk of bias propagation across the ML pipeline.

ACKNOWLEDGMENTS

The author appreciates the constructive comments from the Crowd Bias Workshop reviewers.

REFERENCES

[1] Sina Fazelpour and Maria De-Arteaga. 2021. Diversity in Sociotechnical Machine Learning Systems. arXiv preprint arXiv:2107.09163 (2021).
[2] Batya Friedman and Helen Nissenbaum. 1996. Bias in computer systems. ACM Transactions on Information Systems (TOIS) 14, 3 (1996), 330–347.
[3] Sarah E Gaither, Evan P Apfelbaum, Hannah J Burnbaum, Laura G Rabbitt, and Samuel R Sommers. 2018. Mere membership in racially diverse groups reduces conformity. Social Psychological and Personality Science 9, 4 (2018), 402–410.
[4] Lu Hong and Scott E Page. 2004. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. Proceedings of the National Academy of Sciences 101, 46 (2004), 16385–16389.
[5] Sheen S Levine, Evan P Apfelbaum, Mark Bernard, Valerie L Bartelt, Edward J Zajac, and David Stark. 2014. Ethnic diversity deflates price bubbles. Proceedings of the National Academy of Sciences 111, 52 (2014), 18524–18529.
[6] Matthew D Lieberman, Ruth Gaunt, Daniel T Gilbert, and Yaacov Trope. 2002. Reflection and reflection: a social cognitive neuroscience approach to attributional inference. (2002).
[7] Samir Passi and Solon Barocas. 2019. Problem formulation and fairness. In Proceedings of the Conference on Fairness, Accountability, and Transparency. 39–48.
[8] Niccolò Pescetelli, Alex Rutherford, and Iyad Rahwan. 2021. Modularity and composite diversity affect the collective gathering of information online. Nature communications 12, 1 (2021), 1–10.
[9] Md Mustafizur Rahman, Dinesh Balakrishnan, Dhiraj Murthy, Mucalid Kutlu, and Matthew Lease. 2021. An Information Retrieval Approach to Building Datasets for Hate Speech Detection. arXiv preprint arXiv:2106.09775 (2021).
[10] Nithya Sambasivan, Shivani Kapania, Hannah Higfill, Diana Akrong, Praveen Paritosh, and Lora M Aroyo. 2021. "Everyone wants to do the model work, not the data work". Data Cascades in High-Stakes AI. In proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. 1–15.
[11] Mike Schaekermann, Joslin Goh, Kate Larson, and Edith Law. 2018. Resolvable vs. irresolvable disagreement: A study on worker deliberation in crowd work. Proceedings of the ACM on Human-Computer Interaction 2, CSCW (2018), 1–19.
[12] Andrew D Selbst, Danah Boyd, Sorelle A Friedler, Suresh Venkatasubramanian, and Janet Vertesi. 2019. Fairness and abstraction in sociotechnical systems. In Proceedings of the conference on fairness, accountability, and transparency. 59–68.
[13] Michael Veale, Max Van Kleek, and Reuben Binns. 2018. Fairness and accountability design needs for algorithmic support in high-stakes public sector decision-making. In Proceedings of the 2018 chi conference on human factors in computing systems. 1–14.
[14] Allison Woodruff, Sarah E Fox, Steven Rousso-Schindler, and Jeffrey Warshaw. 2018. A qualitative exploration of perceptions of algorithmic fairness. In Proceedings of the 2018 chi conference on human factors in computing systems. 1–14.
The Productivity Paradox: Understanding Tooling Biases in Crowdwork

SENJUTI DUTTA, University of Tennessee, USA
RHEMA LINDER, University of Tennessee, USA
DOUG LOWE, University of Tennessee, USA
MATTHEW ROSENBALM, University of Tennessee, USA
ANASTASIA KUZMINYKH, University of Toronto, Canada
ALEX C. WILLIAMS, University of Tennessee, USA

Crowdwork is facilitated by an ecology of software tools that aid crowdworkers in finding and managing human intelligence tasks. Prior studies of tooling have reinforced the importance of the software, noting that the vast majority of tooling is engineered by crowdworkers themselves. We report a small subset of findings from an online survey that suggests that the landscape of tooling in crowdwork has greatly expanded in recent years. We also observe a trend that suggests newer tools are not only introducing more advanced capabilities, but also becoming more payment-oriented. We conclude by presenting a research agenda centered around the nature of tooling in crowdwork as it relates to data quality, worker efficiency, and well-being.

Additional Key Words and Phrases: Crowdwork, Tooling, Productivity, Attention.

1 INTRODUCTION: THE ROLE OF TOOLING IN CROWDWORK

Crowdwork is an emergent work practice that centers around finding, managing, and completing human intelligent tasks (HITs). Crowdsourcing marketplaces (e.g., Amazon Mechanical Turk) allow requesters to arbitrarily create HITs that are deployed to an on-demand workforce of crowdworkers for completion. Modern practices for finding and “catching” HITs are largely augmented by software tools that are engineered by crowdworkers to drastically enhance their productivity [3], but this creates a tooling bias. Studies have shown that multitasking and divided attention contexts are common due to the work practice’s on-demand nature [2, 4]. Despite being designed to facilitate productivity, additional research has found that the software tooling used in crowdwork is “designed to interrupt” and can affect how people engage with their work in a number of negative ways (e.g., being repeatedly disrupted, keeping them tethered to work, etc) [10]. In this paper, we describe a paradox in which the productivity tools used by crowdworkers may, by design, introduce new barriers to being productive. We motivate our position with preliminary findings regarding the tools that crowdworkers use today and conclude by presenting a research agenda aimed at understanding the tooling biases in crowdwork through the lens of data quality, worker efficiency, and worker well-being.

2 ONLINE SURVEY

We conducted an IRB-approved Mechanical Turk survey aimed to understand the challenges and opportunities of engaging with crowdwork on mobile devices. Our settings required workers to have a 98% percent acceptance rate and have completed at least 10,000 HITs successfully. In other words, our study did not target casual workers, but those with advanced Mechanical Turk experience. Here, we report findings from the 151 responses to one of its questions:

_Briefly describe the primary tools, scripts, etc. that you use as a crowdworker (e.g. MTurk Suite, Turkinator, etc). If you do not use tools or scripts, type “None”._

CSCW 2021 Workshop – Investigating and Mitigating Biases in Crowdsourced Data, October 23, 2021, Virtual.
©2021 Copyright held by the author(s).
Fig. 1. An overview of (a) tool counts and percentages and (b) a stacked-bar chart of tools with and without subscription-tier models.

Responses were analyzed by enumerating unique tools, verifying the tool’s identity (e.g., online), classifying its target platform, and categorizing whether the tool requires payment. We then used each tools as a label to code each response.

2.1 Preliminary Findings

Our analysis of responses (see Figure 1 (a)) yielded 16 unique actively-used tools reported by participants. Kaplan et al. [3] surveyed and and Williams et al. interviewed [10] MTurk workers, showing that they use various strategies and tools. Our preliminary results echo their findings of a growing trend towards a multiplicity of tool use, both paid and unpaid (see Figure 1 (b)). One of the most striking details in our findings is that 85.4% of respondents use at least one tool. From Figure 1 we see that MTurk Suite (66.2%) and PandaCrazy (22.5%) are the most actively used tools. TurkerView (17.9%) and HITForker (10.6%) are the next most prominent tools utilized by workers. Our preliminary review of these tools indicate that many the features they offer are largely the same: tools for finding and catching “good” HITs. These features create multi-tasking environments and may interrupt users. While 14.6% participants did not use a tool, 48.3% used only one tool and 37.1% of respondents use more than one tool. Our data shows 19.9% use 2 tools, 4.0% use 3, 1.3% use 4, 1.3% use 5, and one participant uses 6 tools. The ecosystem of tooling practice exacerbates multitasking and interruption issues like memory failures [8], attention shifting [7], disruption [6]. Benbuan et al. [1] showed from the analysis 76% of computer based task switching centered on distracting activities. Additionally, it makes it difficult to research because of the potential interaction among tools. It is unclear whether adding additional tools and customization for HIT catchers and finders creates more opportunities for workers at an individual level or overwhelms them.
3 A RESEARCH AGENDA FOR UNDERSTANDING TOOLING BIAS

Our use of the term tooling bias refers to the issues caused by using software tools that augment the work practices and outputs of crowdwork. Our preliminary analysis suggests that more recent tools are not only more sophisticated in their capabilities and features, but their potential for advanced configuration may discourage use by less technically adept crowdworkers. Upon identifying a new work opportunity, HIT-finding tools notify crowdworkers about an opportunity (e.g., with an audio alert), which requires crowdworkers to make an immediate judgement about whether they should accept the opportunity or leave it. Williams et al. reported that the notification can be cognitively challenging to manage under specific circumstances (e.g., when a crowdworker’s HIT queue is already at capacity). In summary, we hypothesize that by using tools that are designed to become increasingly more disruptive, aspects of crowdworkers’ work practices are not benefiting, but rather being harmed by these tools. Given this context, we discuss three important directions for understanding tooling biases in crowdwork: (1) Data Quality, (2) Worker Efficiency, and (3) Worker Well-being:

3.1 Understanding Tooling Bias and Data Quality

Characterizing the reliability of crowdworkers and the data that they subsequently produce is a central and on-going problem of interest for crowdsourcing researchers, practitioners (e.g., requesters), and crowdsourcing marketplaces. Researchers can explore how specific tool designs (i.e., with unique notification approaches) affect the quality of data produced by crowdworkers. Potentially, notification approaches may create a sampling bias. Participants with HIT Catchers may be over represented in surveys that offer a reasonable reward.

3.2 Understanding Tooling Bias and Worker Efficiency

Understanding how crowdworkers’ time and attention can be optimized is of interest to requesters and crowdworkers alike. Prior studies of information work theorize that people are most productive (i.e., efficient) when they are experience fewer interruptions [5]. Researchers should examine the extent to which tool-based interruptions impact the efficiency of crowdworkers not only at the task-level, but also at the level of their work practice.

3.3 Understanding Tooling Bias and Worker Well-being

Recent advances in productivity tooling in information work suggest that efficiency and well-being are intertwined [9]. Therefore, understanding how tools can be redesigned with notification policies that incorporate notions of well-being (e.g., notifications limited to the crowdworker’s standard work hours) is an important pathway for consideration. As these systems are relatively new in information work at large, there is significant opportunity for innovation.

4 CONCLUSION

Crowdwork is facilitated by an ecology of software tools that aid crowdworkers in finding and managing human intelligence tasks. Prior studies of tooling has reinforced the importance of the software, noting that the vast majority of tooling is engineered by crowdworkers themselves. We report a small subset of findings from an online survey that suggests that the landscape of tooling in crowdwork has greatly expanded in recent years. We also observe a trend that suggests newer tools are not only introducing more advanced capabilities, but also becoming more payment-oriented. We conclude by presenting a research agenda centered around the nature of tooling in crowdwork as it relates to data quality, efficiency, and worker wellbeing.
REFERENCES

[1] Raquel Benbunan-Fich and Gregory E Truman. 2009. Technical opinion Multitasking with laptops during meetings. Commun. ACM 52, 2 (2009), 139–141.

[2] Sandy JJ Gould, Anna L Cox, and Duncan P Brumby. 2016. Diminished control in crowdsourcing: An investigation of crowdworker multitasking behavior. ACM Transactions on Computer-Human Interaction (TOCHI) 23, 3 (2016), 1–29.

[3] Toni Kaplan, Sustumu Saito, Kotoaro Hara, and Jeffrey P Bigham. 2018. Striving to earn more: a survey of work strategies and tool use among crowd workers. In Sixth AAAI Conference on Human Computation and Crowdsourcing.

[4] Laura Lascau, Sandy JJ Gould, Anna L Cox, Elizaveta Karmannaya, and Duncan P Brumby. 2019. Monotasking or multitasking: Designing for crowdworkers’ preferences. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 1–14.

[5] Gloria Mark, Daniela Gudith, and Ulrich Klocke. 2008. The cost of interrupted work: more speed and stress. In Proceedings of the SIGCHI conference on Human Factors in Computing Systems. 107–110.

[6] Gloria Mark, Shamsi T Iqbal, Mary Czerwinski, and Paul Johns. 2015. Focused, aroused, but so distractible: Temporal perspectives on multitasking and communications. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. 903–916.

[7] Gloria Mark, Shamsi T Iqbal, Mary Czerwinski, Paul Johns, and Akane Sano. 2016. Neurotics can’t focus: An in situ study of online multitasking in the workplace. In Proceedings of the 2016 CHI conference on human factors in computing systems. 1739–1744.

[8] Brid O’Conaill and David Frohlich. 1995. Timespace in the workplace: Dealing with interruptions. In Conference companion on Human factors in computing systems. 262–263.

[9] Alex C Williams, Harmanpreet Kaur, Gloria Mark, Anne Loomis Thompson, Shamsi T Iqbal, and Jaime Teevan. 2018. Supporting workplace detachment and reattachment with conversational intelligence. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. 1–13.

[10] Alex C Williams, Gloria Mark, Kristy Milland, Edward Lank, and Edith Law. 2019. The perpetual work life of crowdworkers: How tooling practices increase fragmentation in crowdwork. Proceedings of the ACM on Human-Computer Interaction 3, CSCW (2019), 1–28.
Designing and Optimizing Cognitive Debiasing Strategies for Crowdsourcing Annotation

CHIEN-JU HO*, Washington University in St. Louis, United States
MING YIN*, Purdue University, United States

As artificial intelligence (AI) gets increasingly involved in our daily life, the biases in AI and the downstream negative social impacts have also become a pressing concern. In this position paper, we focus on one important source of AI biases—the biases in crowdsourcing annotations that AI is trained on—and advocate for leveraging cognitive debiasing strategies developed in the psychological literature to mitigate biases in crowdsourced annotations.

1 INTRODUCTION

Data has been the secret sauce for the rapid progress of artificial intelligence (AI), and crowdsourcing—the act of outsourcing a task to the crowd—has been one of the most ubiquitous paradigm for obtaining data from humans to enhance machine intelligence in a scalable and cost-effective manner [1, 11, 15, 23, 24, 30, 33]. Meanwhile, humans are notorious for being prone to various kinds of biases, which may lead to systematic deviations between the data collected from them and the ideal [10, 14, 18]. Even worse, these biases could have downstream effects and lead to negative and discriminatory outcomes that hurt the society [2, 3, 36]. Given the critical role that data plays in AI, the need for developing effective and practical methods to mitigate the biases in crowdsourced data is pressing.

In this position paper, we advocate for addressing this challenge by leveraging the cognitive debiasing strategies developed in psychological literature to mitigate the biases in crowdsourced annotation. In particular, we highlight two important research themes: (1) designing cognitive debiasing strategies for crowdsourcing annotation and understanding their empirical effects, and (2) optimizing the use of cognitive debiasing strategies with algorithmic frameworks. In addition to the research themes, we also advocate for the importance of having public, anonymized annotation datasets for performing future research on biases in crowdsourced data, as well as tools for researchers and practitioners to easily incorporate cognitive debiasing strategies during the data collection process.

2 THEORETICAL BACKGROUND: ORIGIN OF BIASES AND COGNITIVE DEBIASING

Decades of psychological studies have identified a wide variety of human biases that would lead to deviation from rationality and result in suboptimal decision-making [22]. The dual process theory (DPT) of reasoning provides a plausible account of the origination of these biases [5, 12, 21]. In particular, DPT specifies two processes through which thoughts may arise—Type 1 and Type 2 processing. Type 1 processing is fast, automatic, instinctive, and unconscious. On the other hand, Type 2 processing is slower, deliberate, rule-based, and conscious. While people usually utilize some combination of both intuitive and analytical processing during their decision making, it is believed that the default processing mode human brains would select is Type 1 processing. However, Type 1 processing is largely associated with the use of heuristics. Thus, excessive reliance of Type 1 processing would override Type 2 processing, trigger bias from humans, and lead to insufficient deliberation and unexamined decisions. Moreover, the risk of overusing Type 1 processing is particularly high when humans suffer from fatigue, sleep deprivation, and cognitive overload [5].

*Both authors contributed equally.
Based on DPT, a premise for “debiasing” is to enable people to decouple from their own automatic responses in decision-making that are resulted from Type 1 processing. In other words, the key to mitigate human biases is to have people actively engage in Type 2 processing and override Type 1 processing as needed. Addressing this key requirement, the concept of “cognitive debiasing” [31, 35] is proposed in the clinical and forensic domains. A variety of cognitive debiasing strategies have been proposed and evaluated, including raising people’s awareness of bias and motivating people to correct bias, enabling people to use situational cues to recognize the need of debiasing, instructing people to inhibit heuristic responses and analyze alternative solutions, etc [4, 5, 13, 19, 20, 27, 29, 32].

3 DESIGNING COGNITIVE DEBIASING STRATEGIES FOR CROWDSONCING ANNOTATION

As a first step towards mitigating biases in crowdsourced data, established cognitive debiasing strategies can be adapted into the crowdsourcing contexts so that their effectiveness can be empirically evaluated. Based on when these strategies will be applied during a data annotator’s annotating process, a design space can be defined as the following:

- **Pre-annotation debiasing**: Debiasing elements can be designed before an annotator starts the annotating process. These elements could serve two main goals: First, increase annotators’ awareness of the existence and risks of their own biases, and promote their initiation in combating these biases (e.g., [18]). Second, help annotators to establish a physical and mental condition that is less vulnerable to biases (e.g., via short breaks and meditation [16, 26]).

- **In-annotation debiasing**: Debiasing elements can be designed to influence the annotators while they are determining the annotation. The main goal of these elements is to nudge annotators to consciously adopt Type 2 processing by, for example, formalizing their thinking process (e.g., as a checklist of actions or if-then rules) and grounding their annotations on sound data [25, 28].

- **Post-annotation debiasing**: Finally, debiasing elements can be designed after the annotator provides an annotation in a task to help annotators reflect upon and critique their own annotations. These interventions aim to both enable annotators to identify any potential biases that they have been subject to in their annotations, and allow annotators to re-examine their annotations comprehensively and systematically (e.g., via examinations of competing hypothesis, feedback, interactions between annotators, etc. [8, 9, 33]).

We highlight a few steps to take in order to establish a comprehensive understanding of the effectiveness of various debiasing strategies on reducing biases in the crowdsourced annotations: (1) identify a few “model annotation tasks,” i.e., tasks that we are aware of that annotators tend to suffer from different kinds of biases; (2) for each model task, explore how to operationalize each element in the design space of debiasing strategies into its specific context; (3) conduct randomized controlled experiments on crowdsourcing platforms to understand the empirical effects of various combinations of debiasing strategies for each of the model tasks. We note that in the empirical evaluations, not only the “benefits” brought by the debiasing strategies (e.g., reduction in data bias) should be measured, but also the potential “cost,” such as the change on annotation expense, annotation time, and annotator burnout. The collection of these information will serve as the foundation for optimally controlling the use of cognitive debiasing strategies in crowdsourcing data collection. We also advocate for sharing the datasets of human annotations that are collected through these empirical evaluations to allow the research community to perform further research on analyzing biases in these annotations.

4 OPTIMIZING COGNITIVE DEBIASING STRATEGIES FOR CROWDSONCING ANNOTATION

With the understanding of the effects of cognitive debiasing strategies for crowdsourced data, the natural next question is how to optimally decide when and which strategies to use. To address this question, we lay out a general framework...
for optimizing cognitive debiasing strategies for crowdsourced data and identify specific challenges that need to be addressed. Formally, let $d_t \in D$ be the parameters of debiasing strategies deployed at time $t$ (e.g., $d_t$ could specify the type of the debiasing strategy, the parameters of the strategy, etc), $S(d_t)$ be the set of data collected with this strategy (which could be a set of answers from workers), and $c(d_t)$ be the cost of deploying this strategy. The requester has a budget $B$ and time $T$ to make decisions. Let $L(S(d_t))_{t=1 \ldots T}$ be the loss the requester suffers from data $(S(d_1), \ldots, S(d_T))$, collected with debiasing strategies $\{d_1, \ldots, d_T\}$. The goal of the requester can be formulated as the following constrained optimization problem.

$$\min_{d_1, \ldots, d_T} L(S(d_t))_{t=1 \ldots T} \text{ subject to } \sum_{t=1}^{T} c(d_t) \leq B \quad (1)$$

We identify the following challenges in optimizing biasing strategies for mitigating biases in crowdsourced data.

- **Aggregate data collected with cognitive debiasing strategies:** The loss function in the optimization objective often depends on the ground truth of annotations, which are not known a priori. One approach is to leverage the techniques in truth discovery [6, 7, 17, 34, 37] to simultaneously infer the ground truth of annotations and the biases associated with the process from the collected data. To achieve this, in the literature, it is often assumed that data is independently drawn from some distribution characterized by given generative models. However, when we deploy debiasing strategies, we might alter the generative model and might even break the independence assumption. Therefore, to address the optimization problem, it is important to develop novel algorithms for aggregating data collected with debiasing strategies.

- **Design online optimization algorithms:** In practice, the requester often needs to decide whether and when to deploy debiasing strategies without having full access to the parameters in the optimization problem (e.g., the ground truths of labeling tasks are not known in advance). To approach this question, the requester needs to adaptively update the estimate of those parameters and make online decisions to optimize the overall loss. Therefore, developing online algorithms that can simultaneously optimize the objective and infer the latent parameters are important for solving this optimization problem.

- **Determine the objective of the optimization with participatory design:** There are various bias definitions, which are known to be incompatible with each other. In our optimization problem for bias mitigation, how should we decide on the optimization objective? Given the social-sensitive nature, we believe it is important to include relevant stakeholders in the loop to shape the objective of the problem. Therefore, developing participatory design approaches to elicit and aggregate stakeholders’ opinions in problem formulation is essential for this line of research.

- **Develop tools for requesters to deploy the debiasing strategies:** In order to maximize the outreach of the research outcomes, we need to make the research results easily applicable by requesters. Therefore, we argue developing easy-to-use tools for requesters to incorporate the debiasing strategies and the optimization algorithms during crowdsourced data collection is critical to maximize the impacts for this line of research.

5 CONCLUSION

In this position paper, we advocate to leverage cognitive debiasing strategies developed in psychological literature to mitigate biases in crowdsourced annotation. We highlight two important research themes on the design and optimization debiasing strategies. In particular, we highlight a few steps to take in order to establish a comprehensive understanding of the effectiveness of various debiasing strategies. We also layout an algorithmic framework for optimizing debiasing strategies and identify the technical challenges.
REFERENCES

[1] Omar Alonso and Stefano Mizzaro. 2012. Using crowdsourcing for TREC relevance assessment. Information processing & management 48, 6 (2012), 1053–1066.

[2] Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In Advances in neural information processing systems. 4349–4357.

[3] Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. Science 356, 6334 (2017), 183–186.

[4] Pat Croskery. 2003. Cognitive forcing strategies in clinical decisionmaking. Annals of emergency medicine 41, 1 (2003), 110–120.

[5] Pat Croskery, Geeta Singhal, and Silvia Mamede. 2013. Cognitive debiasing 1: origins of bias and theory of debiasing. BMJ quality & safety 22, Suppl 2 (2013), i58–i64.

[6] A. P. Dawid and A. M. Skene. 1979. Maximum likelihood estimation of observer error-rates using the EM algorithm. Applied Statistics 28 (1979), 20–28.

[7] Arthur P. Dempster, Nan M. Laird, and Donald B. Rubin. 1977. Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society: Series B 39 (1977), 1–38.

[8] Ryan Drapeau, Lydia B. Chilton, Jonathan Bragg, and Daniel S. Weld. 2016. MicroTalk: Using Argumentation to Improve Crowdsourcing Accuracy. In Fourth AAAI Conference on Human Computation and Crowdsourcing (HCOMP).

[9] Xiaoni Duan, Chien-Ju Ho, and Ming Yin. 2020. Does Exposure to Diverse Perspectives Mitigate Biases in Crowdwork? An Explorative Study. In Proceedings of the AAAI Conference on Human Computation and Crowdsourcing, Vol. 8. 155–158.

[10] Carsten Eickhoff. 2018. Cognitive biases in crowdsourcing. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining. ACM, 162–170.

[11] Maxine Esekenzi, Gina-Anne Leow, Helen Meng, Gabriel Parent, and David Suendermann. 2013. Crowdsourcing for speech processing: Applications to data collection, transcription and assessment. John Wiley & Sons.

[12] Jonathan St BT Evans and Keith Ed Frankish. 2009. In two minds: Dual processes and beyond. Oxford University Press.

[13] Rebecca Jean Featherston, Aron Shlonsky, Courtney Lewis, My-Linh Luong, Adam P Vogel, Catherine Granger, Bridget Hamilton, and Karyn Galvin. 2019. Interventions to mitigate bias in social work decision-making: A systematic review. Research on Social Work Practice 29, 7 (2019), 741–752.

[14] Meric Altug Gemalmaz and Ming Yin. 2021. Accounting for Confirmation Bias in Crowdsourced Label Aggregation. In Proceedings of the 30th International Joint Conference on Artificial Intelligence (IJCAI).

[15] Yvette Graham, Timothy Baldwin, Alistair Moffat, and Justin Zobel. 2017. Can machine translation systems be evaluated by the crowd alone. Natural Language Engineering 23, 1 (2017), 3–30.

[16] Andrew C Hafenbrack, Zoe Kinias, and Sigal G Barsade. 2014. Debiasing the mind through meditation: Mindfulness and the sunk-cost bias. Psychological science 25, 2 (2014), 369–376.

[17] Chien-Ju Ho, Shahin Jabbari, and Jennifer Wortman Vaughan. 2013. Adaptive Task Assignment for Crowdsourced Classification. In The 30th International Conference on Machine Learning (ICML).

[18] Christoph Hube, Beunik Fetahu, and Ujwal Gudreya. 2019. Understanding and mitigating worker biases in the crowdsourced collection of subjective judgments. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. ACM, 407.

[19] Milos Jenicek. 2010. Medical error and harm: Understanding, prevention, and control. CRC Press.

[20] Melissa M Jenkins and Eric A Youngstrom. 2016. A randomized controlled trial of cognitive debiasing improves assessment and treatment selection for pediatric bipolar disorder. Journal of consulting and clinical psychology 84, 4 (2016), 323.

[21] Daniel Kahneman. 2011. Thinking, fast and slow. Macmillan.

[22] Daniel Kahneman, Stuart Paul Slovic, Paul Slovic, and Amos Tversky. 1982. Judgment under uncertainty: Heuristics and biases. Cambridge university press.

[23] Matthew Lease and Emine Yilmaz. 2012. Crowdsourcing for information retrieval. In ACM SIGIR Forum, Vol. 45. ACM, 66–75.

[24] Jin Ha Lee. 2010. Crowdsourcing Music Similarity Judgments using Mechanical Turk. In ISMIR. 183–188.

[25] Joseph J Lockhart and Saty Satya-Murti. 2017. Diagnosing crime and diagnosing disease: bias reduction strategies in the forensic and clinical sciences. Journal of forensic sciences 62, 6 (2017), 1534–1541.

[26] Adam Lopez and Bryan Gibson. 2015. Mindfulness meditation reduces implicit age and race bias: The role of reduced automaticity of responding. Social Psychological and Personality Science 6, 3 (2015), 284–291.

[27] Tess Neal and Stanley L Brodsky. 2016. Forensic psychologists’ perceptions of bias and potential correction strategies in forensic mental health evaluations. Psychology, Public Policy, and Law 22, 1 (2016), 58.

[28] Dennis Rosen. 2010. The checklist manifesto: How to get things right. JAMA 303, 7 (2010), 670–673.

[29] Michelle Derion, Irene Scopelliti, and Carey K Morewedge. 2019. Debiasing training improves decision making in the field. Psychological science 30, 9 (2019), 1371–1379.

[30] Rion Snow, Brendan O'Connor, Daniel Jurafsky, and Andrew Y Ng. 2008. Cheap and fast—but is it good?: evaluating non-expert annotations for natural language tasks. In Proceedings of the conference on empirical methods in natural language processing. Association for Computational
Designing and Optimizing Cognitive Debiasing Strategies for Crowdsourcing Annotation

Linguistics, 254–263.

[31] Keith E Stanovich and Richard F West. 2008. On the relative independence of thinking biases and cognitive ability. Journal of personality and social psychology 94, 4 (2008), 672.

[32] Carl Symborski, Meg Barton, Mary Quinn, C Morewedge, K Kassam, James H Korris, and CA Hollywood. 2014. Missing: A serious game for the mitigation of cognitive biases. In Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC). Citeseer, 1–13.

[33] Wei Tang, Ming Yin, and Chien-Ju Ho. 2019. Leveraging Peer Communication to Enhance Crowdsourcing. In The World Wide Web Conference. ACM, 1794–1805.

[34] Jacob Whitehill, Tingfan Wu, Jacob Bergsma, Javier R. Movellan, and Paul L. Ruvolo. 2009. Whose vote should count more: Optimal integration of labels from labelers of unknown expertise. In Advances in Neural Information Processing Systems (NIPS).

[35] Timothy D Wilson and Nancy Brekke. 1994. Mental contamination and mental correction: unwanted influences on judgments and evaluations. Psychological bulletin 116, 1 (1994), 117.

[36] Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. 2017. Men also like shopping: Reducing gender bias amplification using corpus-level constraints. arXiv preprint arXiv:1707.09457 (2017).

[37] Yudian Zheng, Guoliang Li, Yuanbing Li, Caihua Shan, and Beynold Cheng. 2017. Truth inference in crowdsourcing: Is the problem solved? Proceedings of the VLDB Endowment 10, 5 (2017), 541–552.
CrowdRL: A Reinforcement Learning Framework for Human Error Mitigation in Crowdsourcing-based Stream Processing

RAHUL PANDEY and HEMANT PUROHIT, George Mason University, USA

Efficient data collection and annotation for training are becoming more and more prominent issues in building successful Artificial Intelligence (AI) systems. Among such systems, the real-time streaming data-based systems pose more significant challenges to continually annotate data to update models for filtering out relevant information, such as calls for help during crises. Crowdsourcing provides one approach to incorporate human intelligence in filtering relevant information from the streaming data. Recent crowdsourcing applications use a Hybrid Stream Processing based-approach, where an active learning-driven streaming model is also trained and continuously updated for automatic filtering of relevant data with the previously annotated data from the crowd. However, due to biases such as recall bias (annotators forgetting the initial concepts) and availability bias (annotators learning concepts from recent examples), crowdsourcing workers can become prone to errors in the annotation. As a result, this phenomenon can alter the performance of the streaming model. Hence, minimizing the availability and recall bias in the AI systems can improve the quality of the streaming model, resulting in efficient and rapid collection of high-quality labeled data to update the model. In this paper, we propose an efficient sampling-based framework called ‘CrowdRL’ for hybrid stream processing systems. The framework design aims to reduce availability and recall bias and, thus, human errors in labeling while increasing the performance of the streaming model. CrowdRL framework uses a Reinforcement Learning-based problem formulation to sample incoming instances for crowdsourced labeling efficiently. We describe the framework components as well as discuss their advantages and limitations.

Additional Key Words and Phrases: Human-centered Computing, Active Learning, Annotation Schedule, Memory Decay

1 INTRODUCTION

There is an influx of streaming data collected in various domains such as journalism, public health, and crisis management. For brevity, we illustrate the challenges using examples in the crisis management domain, where filtering social media message streams can be crucial for acquiring situational awareness[7]. Volunteer groups often support such information filtering activities to aid crisis response agencies during an ongoing crisis event. Crowdsourcing volunteers annotate messages in the social media streams to filter out relevant messages of different classes. However, given the high velocity and volume of social media streams, as well as the limited availability of volunteers, most of these crowdsourcing-based annotation systems work as a hybrid stream processing system (HSPS). HSPS includes an active learning-based streaming model that is actively trained with the prior annotated instances, which helps in filtering out the incoming instances to address issues of concept drift and improving model performance [4, 6]. In this setting of HSPS, volunteers are given clear instructions about the concept of the class labels at the beginning of the annotation tasks. However, due to the high influx of streaming messages during an ongoing event, volunteers may forget the class labels’ concepts appearing early in the stream but not infrequently afterward. Thus, they face recall bias1. Moreover, due to the open and free-to-all nature of social media communication, many messages contain noise, inducing incorrect learning of the class labels’ concepts in the volunteers’ memory. This situation gives rise to the availability bias2. These biases can affect the annotation quality and increase the chances of annotation error, which in turn hamper the continual updating of the streaming model and its performance.

1https://catalogofbias.org/biases/recall-bias/
2https://catalogofbias.org/biases/availability-bias/
Fig. 1. The proposed CrowdRL framework. The input to the RL model is the batch of instances and the time last seen of each class label by the oracle. The agent predicts the action of picking or discarding the instances. The selected instances are passed to the oracle to get the annotation and update the streaming model.

Prior research in crowdsourcing are focused on task assignments [3, 8, 10], improving the speed of crowdsourcing [5], or how to get most of collaborative crowdsourcing [1]. However, there is little work on understanding the cause of the human error or providing mitigation strategies to help crowd workers avoid errors from availability and recall biases. The memory decay behavior of humans is widely studied in psychology literature [2], which shows that memory retention decreases exponentially with time. Prior work validates this behavior in the case of crowdsourcing tasks [7]. More specifically, previous work discusses two types of serial-ordering-based human errors: Mistakes and Slips. Mistakes are the error caused when the class labels’ concept is not acquired yet by the crowd annotator. Slips are the error caused by an imbalance presence of a particular class in the annotation data. It creates an implicit bias of selecting the specific class label only.

This research aims to mitigate the serial ordering-based human error while improving the streaming model performance in HSPS. Given a stream of incoming instances from social media, we focus on creating an optimal sampling strategy to generate a sequence of instances to annotate, called annotation schedule. A popular way to sample instances in HSPS is uncertainty sampling, i.e., sample instances that are uncertain to predict by the streaming model. However, it does not focus on minimizing the serial ordering error. We can reduce serial ordering errors by reordering the instances at each time period. However, this is impossible in systems with real-time performance requirements, such as filtering information for crisis response agencies due to time sensitivity. Instead, an optimal sampling algorithm needs to decide in real-time. Moreover, the choice of picking or discarding instances is affected by the past decisions made on all previous instances. Reinforcement Learning (RL) is a branch of machine learning that enables an agent to learn in an interactive environment by trial and error using feedback from its actions and experiences[9]. Since RL does not require the correct set of actions to perform a task, it is an appropriate methodology to continually learn to pick and discard instances by using rewards and penalties for the chosen actions. Finally, through inference of an RL model, we generate the optimal annotation schedule.

2 CROWD-RL FRAMEWORK

2.1 Problem Formulation

The goal of the proposed CrowdRL framework is to generate an annotation schedule for an annotation task in HSPS. The annotation task consists of annotating social media messages into \( N \) classes. The oracle provides the annotation, which is a simulation of human and human behavior of memory decay. Given a batch of incoming instances, the goal is...
to decide either picking or discarding the instances to get the annotations and update the streaming model. In this way, at every time period, we generate a dynamic annotation schedule. The picked instances should improve the performance of the streaming model. Also, the order of instances in the annotation schedule should be determined so that all class instances appear in repetition frequently with almost equal delays. Thus, no class concepts could be forgotten by the oracle or a human annotator agent, leading to the mitigation of labeling errors.

2.2 Framework Overview

We model this problem as a Reinforcement Learning (RL) problem to generate the annotation schedule given a batch of incoming instances. Our approach is motivated by prior works on dynamic task arrangement in crowdsourcing[8]. We define the RL environment as an annotator, a sequence of incoming instances, and a streaming model, while the agent is the platform. The oracle annotates the picked instances from the agent, and along with the forthcoming instances, they both add uncertainty to the environment.

The action is to sample the instances from the batch of incoming instances at every time period. The current state of the environment is the embedding representation of all incoming instances in the batch and a counter, which keeps a record of the time last seen of each class label. The RL model learns the policy on which instances to pick or discard to generate the optimal annotation schedule in terms of machine performance and human performance. The architecture and flow of the proposed CrowdRL framework are given in Figure 1.

There are different reward functions based on the action taken by the agent, which either rewards or penalizes the action based on improving both human and machine performance. We discuss some of the reward functions below.

**Uncertainty Reward:** The agent should be rewarded if it picks the instance that belongs to the uncertain region (high uncertainty score) of model prediction and penalized otherwise. Similarly, the agent should be rewarded if it discards the instances from the certain region (low uncertainty score) and penalizes otherwise. The uncertainty score can be calculated using the entropy of the prediction probability scores from the streaming model.

**Retaining Reward:** The agent should be rewarded if it picks the instance whose potential class’ concept is prone to be forgotten by the oracle. It can be calculated based on an exponential decay function[7] using each class label’s time last seen. The time last seen is changed when new instances are picked and given to the oracle to annotate.

**Performance Reward:** The agent should be rewarded if the streaming model performance is increased when the new instance is picked. If the instance is discarded, the previous performance score is used to compute the reward.

3 DISCUSSION AND FUTURE DIRECTION

The advantage of our CrowdRL framework is its ability to consider both performance elements – human factors and machine/model factors when making the decision of sampling instances in HSPS. We can apply this framework to any annotation task of crowdsourcing applications and not just social media message labeling. The framework could be instrumental in system designs with many class labels, and it is challenging to keep track of different class concepts for the crowdsourcing annotators. However, we don’t consider all the human factors involved during the crowdsourcing task. For example, our model assumes the crowdsourcing annotators to present during the entire duration of the task. Moreover, we assume that the annotator regains the class label definitions and understandings if they observe even one example while annotating, which belongs to that class label. We are planning to share the details of RL modeling in future work.

ACKNOWLEDGEMENT

We thank National Science Foundation Grants (1815459 and 2029719) for partially supporting this research.
REFERENCES

[1] Joseph Chee Chang, Saleema Amershi, and Ece Kamar. 2017. Revolt: Collaborative Crowdsourcing for Labeling Machine Learning Datasets. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, New York, NY, USA, 2334–2346. https://doi.org/10.1145/3025453.3026044

[2] Hermann EBBINGHAUS. 1885. Memory: A Contribution to Experimental Psychology. Classics in the History of Psychology (1885).

[3] Umair Ul Hassan and Edward Curry. 2014. A Multi-armed Bandit Approach to Online Spatial Task Assignment. In 2014 IEEE 11th Intl Conf on Ubiquitous Intelligence and Computing and 2014 IEEE 11th Intl Conf on Autonomic and Trusted Computing and 2014 IEEE 14th Intl Conf on Scalable Computing and Communications and Its Associated Workshops. 212–219. https://doi.org/10.1109/UIC-ATC-ScalCom.2014.68

[4] Muhammad Imran, Ioanna Lykourentzou, Yannick Naudet, and Carlos Castillo. 2013. Engineering crowdsourced stream processing systems. arXiv preprint arXiv:1310.5463 (2013).

[5] Ranjay A. Krishna, Kenji Hata, Stephanie Chen, Joshua Kravitz, David A. Shamma, Li Fei-Fei, and Michael S. Bernstein. 2016. Embracing Error to Enable Rapid Crowdsourcing. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, New York, NY, USA, 3167–3179. https://doi.org/10.1145/2858036.2858115

[6] Christoph Lofi and Kinda El Maarry. 2014. Design Patterns for Hybrid Algorithmic-Crowdsourcing Workflows. In 2014 IEEE 16th Conference on Business Informatics, Vol. 1. 1–8. https://doi.org/10.1109/CBI.2014.16 ISSN: 2378-1971.

[7] Rahul Pandey, Carlos Castillo, and Hemant Purohit. 2019. Modeling human annotation errors to design bias-aware systems for social stream processing. In Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. 374–377.

[8] Caihua Shan, Nikos Mamoulis, Reynold Cheng, Oushiang Li, Xiang Li, and Yuqiu Qian. 2020. An End-to-End Deep RL Framework for Task Arrangement in Crowdsourcing Platforms. In 2020 IEEE 36th International Conference on Data Engineering (ICDE). IEEE, 49–60.

[9] Richard S Sutton and Andrew G Barto. 2018. Reinforcement learning: An introduction. MIT press.

[10] Man-Ching Yuen, Irwin King, and Kwong-Sak Leung. 2015. TaskRec: A Task Recommendation Framework in Crowdsourcing Systems. Neural Processing Letters 41, 2 (April 2015), 223–238. https://doi.org/10.1007/s11063-014-9343-z
Demographic Biases of Crowd Workers in Key Opinion Leaders Finding

HOSSEIN A. RAHMANI, University College London, United Kingdom
JIE YANG, Delft University of Technology, The Netherlands

Key Opinion Leaders (KOLs) are people that have such a strong social and professional status that their recommendations and opinions are listened to when making important decisions. For instance, in the field of medical and health informatics, KOLs are the people who can influence public opinion and lead the medical community through their research papers, clinical practices, and early acceptance of new technologies. Traditionally, consulting companies provide services for identifying KOLs by conducting user surveys. The problems of these solutions are that they use only a limited number of information resources and focus on a small number of involved clients. Therefore, they are not very effective in the real scenarios as well as sensitive domains. Existing studies [9, 13] address these problems using Machine Learning (ML) approaches that are scalable and are able to deal with a large number of candidate KOLs. However, ML approaches require large amount of labeled training data. The datasets are hand-labeled by people who are domain experts and usually very hard to gather. Finding KOLs is a time-consuming and typically difficult process even for domain experts. Consequently, training models based on such datasets makes them highly dependent and limited to expert labels. By allowing to reach to large number of online crowds, crowdsourcing has recently become one of the most promising approaches in collecting data for training ML models for different tasks such as political ideology detection, detecting biased statements, and finding social influencer [1, 3, 4, 7, 11]. However, in many tasks, like KOL mapping, the annotation data are usually affected by the biases of the crowd workers.

In this paper, we consider a crowdsourcing task where the crowd workers are asked to name as many as KOLs as possible in a specific domain. We propose an approach to measure how biased a crowd worker is, through which we can mitigate worker biases and clean the collected data from biased crowd workers.

1 RELATED WORK

Recent works have explored the mitigating crowd worker biases, for example, Hube et al. [6] focused on the subjective task and tried to understand the influence of worker’s preferences on their performance. To do this, they examine the annotations of crowd workers on different topics to see the effect of worker’s opinions on their annotations. Their findings show that crowd workers with strong opinions produce biased annotations. The proposed approach is promising to mitigate such bias and can improve the quality of the data collected. Chakraborty et al. [2] analyzed the demographics of people who suggest the recommendation of contents to understand the demographic distribution of
content promoters in social networks. This distribution can show whether these people are representative of the social network population or there is a bias to the groups of people. To this end, they collect extensive data from Twitter of trending topics and study the demographic biases of trends. Their analysis indicates that a large part of the demographic information of crowds who promoted the trends is significantly different from the overall Twitter population. In [5], the authors extensively analyzed the effect of crowd worker’s opinions on the quality of the annotated data. They proposed an approach that relies on the labels of the statements and the worker’s personal opinion on each statement’s topic. Using this additional information, they are able to measure how biased a crowd worker is and how they can mitigate the measured bias. Raykar et al., in [12], proposed an approach based on the combination of labels provided by different types of crowd workers, i.e., experts and beginners. Therefore, to acquire the final labels of the task they can evaluate the different labels from both experts and beginners then give an estimate of the actual labels. Few researchers [8, 10] have addressed the problem of crowd workers’ biases by assuming different experts between the crowd workers and based on that they proposed the label aggregation models. These approaches usually improve the collected labels by the majority voting among the workers. However, the idea is suitable when there is no agreement between the workers; in subjective tasks such as KOLs, there may be biases also with complete agreement labels due to the varying ideological backgrounds of workers.

3 PROPOSED APPROACH

We propose an approach for collecting data and measuring crowd worker biases for the task of mapping candidate/potential KOLs as either KOL or non-KOL. Our approach can be used for other similar tasks.

Our approach automates the finding and suggesting of potential candidate KOLs. To achieve this, we will prepare a crawling module that collects information using different APIs and scraping different sources. In this study, we target two different aspects of KOLs related to their professionalism in their topics (i.e., scientific aspect) as well as their socialites’ expertise in organizing events and conferences (i.e., social aspect). In particular, we consider Google Scholar\(^1\), PubMed\(^2\), and ClinicalTrials.gov\(^3\). But our crawling module is not limited only to these sources and it is able to be applied to different information sources on various domains. In the next step, we ask crowd workers to suggest as many candidate KOLs as possible. Here, the KOL is about “influence”, and crowds are the target who are directly addressed. The crawling module provides useful information which helps crowd workers to carefully indicate the candidate KOLs. For example, in the category of scientific information, the number of citations of the potential KOLs can be a good parameter to evaluate the quality of candidate KOLs. To this end, we will present the set of collected features representing a candidate KOL, namely, demographic, scientific, and social information to a crowd worker. The KOL mapping task is to predict the likelihood of a candidate KOL to be a potential KOL on a rating scale based on the collected features. Then, we will ask each crowd worker to label \(k\) out of \(N\) candidate KOLs where \(N\) is the number of all candidate KOLs. In this step, to consider the crowd worker bias, we generate the counterfactual of the features for those \(k\) candidate KOLs.

In this study, what we are considering is a simple yet effective class of counterfactual which can be generated by changing the value of demographic information such as age, sex, and race of candidate KOLs. For example, if we want to deal with gender bias what can we do is generating counterfactual information of candidate KOLs when we change

\(^1\)https://scholar.google.com/
\(^2\)https://pubmed.ncbi.nlm.nih.gov/
\(^3\)https://clinicaltrials.gov/
Demographic Biases in KOLs

As shown in Eq. 1, we compute biases of crowd workers using the mean absolute difference of rating score provided for all $k$ pairs of the main candidate KOL and the counterfactual candidate KOL as follows:

$$\text{WorkerBias} = \frac{1}{k} \sum_{i=1}^{k} |M_K - C_K|$$

where the $M_K$ and $C_K$ are the rating score for the main and counterfactual candidate KOL, respectively. Future work will concentrate on extend Eq. 1 to a weighted biased crowd workers that consider all feature categories, i.e., demographic, scientific, and social aspects. In this case, crowd workers will assign rating scores for each dimension and we compute the bias score as follows:

$$\text{WorkerBias} = \alpha \left( \frac{1}{k} \sum_{i=1}^{k} |M_K^d - C_K^d| \right) + \beta \left( \frac{1}{k} \sum_{i=1}^{k} |M_K^c - C_K^c| \right) + (1 - \alpha - \beta) \left( \frac{1}{k} \sum_{i=1}^{k} |M_K^s - C_K^s| \right)$$

where the $M_K^d$ and $C_K^d$ are the rating score related to the demographic aspect, $M_K^c$ and $C_K^c$ are correspond to the scientific aspect, and $M_K^s$ and $C_K^s$ are related to the social aspect.

The final score indicates how biased is a crowd worker; the lower the WorkerBias score, the lower unbiased behavior of crowd worker, and in contrast, the higher values of the WorkerBias score shows a more biased behavior of crowd workers. Therefore, we can use this information of crowd workers bias in conjunction with the crowd worker responses to collect fairer labels and achieve a better dataset. For instance, we can define a threshold based on the biased scores of crowd workers and filter out the labels from those crowd workers whose biased score is beyond the threshold. There may be an issue with generating counterfactual sensitive attributes when a crowd worker relates a previously rated candidate KOL with its counterfactual. This makes a problem to understand is really a crowd worker biased when the crowd worker realized she rated a very similar candidate KOL just before. To address this issue we can consider several solutions: (1) we can play with the order of the candidate KOL information which will be presented to the crowd worker, we should place the candidate information far from each other; (2) we can add noise to some features, for instance, we can change the age of the candidate KOL; (3) we can change the irrelevant and unimportant attributes that those attributes will not have any effects on the crowd worker’s rate, for example, first name, last name, email or phone number, etc.

4 CONCLUSION AND FUTURE WORK

In this position paper, we propose a simple yet effective method to measure the demographic biases of crowd workers using a counterfactual approach. Although introduce this approach on the key opinion leaders finding problem, our proposed method can be applied to any social computing problem, when crowd workers classify data based on the social or demographic information. In our future work, we first plan to evaluate this approach using an empirical study by comparing the dataset obtained using our approach and other reported results. Next, we want to extend this approach with a polynomial regression approach when we can consider different weights for each attribute. Finally, we plan to explore how the existing methods fare against different fairness metrics.

REFERENCES

[1] Ines Arous, Jie Yang, Mourad Khayati, and Philippe Cudrè-Mauroux. 2020. Opencrowd: A human-ai collaborative approach for finding social influencers via open-ended answers aggregation. In Proceedings of The Web Conference 2020. 1851–1862.
[2] Abhijnan Chakraborty, Johnnatan Messias, Fabricio Benevenuto, Saptarshi Ghosh, Nilay Ganguly, and Krishna Gummadi. 2017. Who makes trends? understanding demographic biases in crowdsourced recommendations. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 11.

[3] Ujwal Gadiraju and Jie Yang. 2020. What Can Crowd Computing Do for the Next Generation of AI Systems? In *NeurIPS 2020 Crowd Science Workshop*: Remoteness, Fairness, and Mechanisms as Challenges of Data Supply by Humans for Automation. http://ceur-ws.org/Vol-2736/paper2.pdf

[4] Christoph Hube and Besnik Fetahu. 2018. Detecting biased statements in wikipedia. In *Companion proceedings of the the web conference 2018*. 1779–1786.

[5] Christoph Hube, Besnik Fetahu, and Ujwal Gadiraju. 2018. LimitBias! Measuring Worker Biases in the Crowdsourced Collection of Subjective Judgments (short paper). In *SAD/CrowdBias@HCOMP* (CEUR Workshop Proceedings, Vol. 2276). CEUR-WS.org, 78–82. http://dblp.uni-trier.de/db/conf/hcomp/sad2018.html#HubeFG18

[6] Christoph Hube, Besnik Fetahu, and Ujwal Gadiraju. 2019. Understanding and mitigating worker biases in the crowdsourced collection of subjective judgments. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–12.

[7] Mohit Iyyer, Peter Enns, Jordan Boyd-Graber, and Philip Resnik. 2014. Political ideology detection using recursive neural networks. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 1113–1122.

[8] David R Karger, Sewoong Oh, and Devavrat Shah. 2011. Iterative learning for reliable crowdsourcing systems. In *Advances in Neural Information Processing Systems 24: 25th Annual Conference on Neural Information Processing Systems*. Neural Information Processing Systems, 1953–1961. http://papers.nips.cc/paper/4396-iterative-learning-for-reliable-crowdsourcing-systems

[9] Yanyan Li, Shaoqian Ma, Yonghe Zhang, Ronghuai Huang, et al. 2013. An improved mix framework for opinion leader identification in online learning communities. *Knowledge-Based Systems* 43 (2013), 43–51.

[10] Qiang Liu, UC ICS, Jian Peng, and Alexander Ibler. 2012. Variational inference for crowdsourcing. sign 10 (2012), 701–709. http://papers.nips.cc/paper/4627-variational-inference-for-crowdsourcing

[11] Kalpana Parshotam. 2013. Crowd computing: a literature review and definition. In *Proceedings of the South African Institute for Computer Scientists and Information Technologists Conference*. 121–130.

[12] Vikas C Raykar, Shipeng Yu, Linda H Zhao, Anna Jerebko, Charles Florin, Gerardo Hermosillo Valadez, Luca Bogoni, and Linda Moy. 2009. Supervised learning from multiple experts: whom to trust when everyone lies a bit. In *Proceedings of the 26th Annual international conference on machine learning*. 889–896.

[13] Hua Xu, Shane F Stenner, Son Doan, Kevin B Johnson, Lemuel R Waitman, and Joshua C Denny. 2010. MedEx: a medication information extraction system for clinical narratives. *Journal of the American Medical Informatics Association* 17, 1 (2010), 19–24.