Lessons Learned from Machine Learning Researchers about the Terms "Artificial Intelligence" and "Machine Learning"

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The hype around artificial intelligence (AI) can be overwhelming. From administrative histrionics over plagiarism to the actual equations used by complex machine learning (ML) algorithms, it's easy to get confused. Even the terms are difficult to keep straight. As Dr. Stevie Chancellor told me, "The media will tell you that [AI and ML] are the same and everything that is ML the media describes as AI. And it drives me nuts."[1] To help tackle some of these issues, I report here on a study of people involved with using or creating machine learning who self-identified as machine-learning researchers. In this study (IRB #21072), I had two goals: (1) to learn machine learning techniques and advice straight from the experts and (2) to study their writing processes. While several research questions guide this study, I report on a single question here: what are the definitions of AI and ML according to these researchers? To summarize my findings: AI is a flexible, ambiguous, generalized term whereas ML is a set of computational techniques for accomplishing specific tasks with a large amount of data. AI has associations with grant funding, too, and tends to be more of a marketing term with fanciful associations, such as with the movie *The Terminator*. It tends to be a term about which my participants were critical, although many expressed a similar concern about the overuse of the term ML in public discourse. Many described ML as a subset of AI, which computer science textbooks affirm.

The exigence of this Where We Are piece—the *why*—is to provide writing studies with a critical look at the terms AI and ML (and the ideas that comprise them) from people with perspectives closer to the technical details of AI writing technologies. Knowing how individuals in these field think of and use these terms may provide Writing Studies practitioners with strategies for choosing or addressing AI or ML in our research and pedagogies. This choice, and commitments from this choice, are vital because our research trajectories and pedagogies will likely be transformed radically by AI writing technologies.

The Study

I conducted this study from October of 2020 to August of 2022.[2] I interviewed 108 participants across 126 interviews (123 over zoom; 3 over the phone), generating over 93 hours of audio recording.[3] The composition of the interviewee group is described as follows: 98 of the 108 participants hold a PhD, although these degrees vary between computer science, physics, biology, engineering, and others. Computer science is the most dominant degree, followed by physics. Two participants use they/them pronouns, one chose not to use pronouns, 25 use she/her pronouns, and 80 use he/him pronouns. 94 participants are primarily academic, while 14 are primarily industry. However, as I learned, the divide between academia and industry is not as rigid in ML-related fields as other academic disciplines I've encountered. Many participants had extensive experience working for technology corporations, including Google, YouTube, Microsoft, and Ansys, as well as social media companies.

What the Experts Told Me

From my interviews, AI is generally understood to be about automating tasks, such as playing chess or object identification, using computational means. Four main themes around the term AI emerged in my conversations. First, as mentioned in the beginning of this article, AI is a much broader term than ML. ML is typically defined as a subset of AI. As an anonymous participant with a PhD in Sociology who works in a major technology company told me: "Artificial intelligence is often … technically seen as a super category in machine learning, where it's trying to make machines that do some mimicry of human learning or human behavior." Second, AI is an ambiguous term that can describe everything from artificial general intelligence (AGI) to task specification. When speaking to non-specialist audiences, participants reported trying to explain how their work was more related to task specification rather than AGI. Third, AI has economic and marketing connotations. The US government invested billions of dollars in AI, such as the NSF AI institute program. This investment encouraged researchers to write their grant proposals with the term AI. AI thus has a "glossy" marketing association to many of my participants. For example, multiple participants told the same joke without my prompting: "Machine learning is written in Python. AI is written in PowerPoint." To me, this joke means that machine learning is a technical term whereas AI is for presentations that are more encompassing of non-expert audiences. It's important to emphasize that AI can be highly rigorous in its own right. Fourth, AI is capacious. Many participants I talked with understood that researchers and scientists studying AI were numerous and many heterogeneous projects could fall within this term. As Dr. John Laird told me:

> Artificial intelligence is when we think about that in terms of artifacts that we develop. It's not meaning it's artificial like artificial flowers that are fake, it's just that we are the designers of it as opposed

to that coming from nature. It's a broad field, and it includes a lot of different techniques.[4]

Thus, machine learning is a subset of artificial intelligence with a focus on learning from data. There are three categories of machine learning: supervised, unsupervised, and semi-supervised. Three themes around the use of ML emerged. First, there is a particular focus on data. As Dr. Matthew Guzdial told me, "machine learning [is] non-human decision making…where the agent, the decision maker, has changed its decision-making process through experience or by looking at data."[5] Dr. Donald Williamson told me machine learning is specifically a "data-driven" approach.[6] Many participants recounted the importance of collecting, wrangling (processing), and analyzing data. Neal Fultz told me, "80% of the time [of working on ML] is actually getting good data in the first place."[7] Other participants estimated similar percentages. Second, ML has much more math associated with it than with AI. Several participants spoke of how machine learning is a type of rebranded statistics that develops models from data. As Dr. Jeremias Sulam told me, "Machine learning is the use of applied statistics and computational models to inform how to make better predictions about an observable, or to make inferences (learn something new) about the world that we didn't know."[8] The third theme, which follows from the previous two and will feel most familiar to non-expert audiences, involves predictions from that data. Dr. Derek Hoiem[9] said:

> Machine learning is solving for the parameters of a system to make predictions based on data. The requirements are that you have some data that you want to learn from and some task or tasks that you want to perform, and the system tunes its parameters to better perform those tasks based on the data.

Implications

I lay out these definitions and themes here, in a very cursory way, to show that when Writing Studies researchers and instructors use these terms, we may invoke certain connotations.

Choosing the terms "AI" or "ML" creates specific impressions on audiences, may generate genre signals of our writing, and indicates alignments with certain ideologies. Using the term "AI writing technology," for example, may suggest more alignment with a marketed, corporate stance than the term "ML writing technology" or simply writing with large language models (LLMs). The use of ML may underscore an emphasis on a research approach (with a statistical or programming approach) whereas AI may be more related to administrative or bureaucratic needs.

These themes may help those of us in writing studies grapple with discussions of automated writing technologies (e.g., OpenAI GPTs and Google's Bard). From a classroom perspective, the themes above could help facilitate discussions with our students about the degree to which the terms AI or ML are applicable to these technologies. AI may be useful for discussions related to hype in the media, whereas ML could be useful for readings and discussions related to data collection and processing, as well as biased data. Deliberation about these choices may be beneficial, too, for initiating and sustaining scholarly collaborations with colleagues in Computer Science working on related technologies. For example, finding collaborations about AI may be more related to robots and task specifications, whereas ML collaborations may be more related to statistics and computation. In my view, using AI for grant proposals would seem like an effective use of the term, unless the grant involves more technical details, which would then necessitate ML.

Conclusion

Though these themes are not exhaustive, they offer a starting point for understanding nuances between AI and ML. While I would prefer that we use the term ML, AI seems to have won out as preferred terminology regarding these conversations in writing studies, perhaps because writing studies tends to be responsive to current events[10] or due to the hype of AI in our present moment. As writing studies researchers and educators continue to engage with AI writing technologies, it is crucial to consider the implications of the terms we use and to conduct empirical research that investigates the impact of these terminologies on our work and in our field. By doing so, we can better equip ourselves for the transformative impacts of AI writing technologies in the coming years.

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Notes

1. Dr. Stevie Chancellor builds, and critically evaluates, human-centered machine learning (HCML) for high-risk health behaviors in online communities. She holds degrees in both Computer Science and Media Studies and comes to machine learning to make it more rigorous and ethical while meeting the needs of users and communities.

2. I began this project at the height of COVID19 lockdowns. I conducted 12 interviews in the fall 2020 but did not have a good response rate, so I stopped in December 2020 and began anew in Fall 2021. I conducted one straggling interview in December 2022.

3. The interview protocol of the initial interview is available via request. To prepare for the initial interviews, I read through the three most cited articles published by each participant, according to Google Scholar. The second interview was a discourse-based interview (Odell, Goswami, and Herrington). To prepare for second interviews, I asked participants to supply me with two texts that were indicative or emblematic of their writing processes. I then made and edited notes on these two documents.

4. Dr. John E. Laird received his Ph.D. from Carnegie Mellon University working with Allen Newell. His research interests spring from a desire to understand the nature of the architecture underlying artificial and natural intelligence. He is the Co-Director of the Center for Integrated Cognition and the John L. Tishman Professor Emeritus of Engineering at the University of Michigan. In his writing, he tries to engage the reader by describing the challenges of creating AI systems that have the cognitive capabilities and generality of humans.

5. Dr. Matthew Guzdial is an Assistant Professor in the Department of Computing Science at the University of Alberta and a Canada CIFAR AI Chair at the Alberta Machine Intelligence Institute (Amii). His research focuses on the intersection of machine learning, creativity, and human-computer interaction, primarily in the domain of games.

6. Dr. Donald Williamson (Ph.D. in computer science and engineering from The Ohio State University) is a faculty member of Computer Science and Engineering at The Ohio State University. His research focuses on sound-processing algorithms that learn from user and environmental data in real-world environments while preserving user privacy. He is the director of the Audio, Speech and Perceptually-Inspired Research (ASPIRE) group. Williamson is the recipient of two NSF awards, including an NSF CRII and NSF CAREER award.

7. Neal Fultz is the Principal Data Scientist at njnm consulting, a boutique ML and analytics consultancy serving the Los Angeles area. He is also a Data Scientist in Residence at UCLA Social Sciences and a recovering software engineer. In the past he's held various roles at System1, Factual, Korn Ferry, and Zest AI. He is enthusiastic about open-source software and maintains a few dozen R and Python packages. He has consulted on more than 400 studies.

8. Jeremias Sulam is an Assistant Professor at Johns Hopkins University. He received his biomedical engineering degree from the Universidad Nacional de Entre Rios and his PhD in Computer Science at the Technion-Israel Institute of Technology. He is the recipient of the Best Graduates awards of the National Academy of Engineering of Argentina and the Early Career award of the National Science Foundation (NSF). While always interested in biomedical problems, his work has centered on representation learning, matrix factorization, and more recently on robustness

and interpretability in machine learning. Jeremias believes "that the communication of ideas is at the center of the advancement of science, and as a result it should be a core component of the training of anyone working in science and technology. Far from being a final-stage component of publishing new ideas, writing is crucial to the creative process itself: one can hardly have a clear idea in mind if one is not able to clearly articulate it on paper."

9. Derek Hoiem is a Professor in Computer Science at the University of Illinois Urbana-Champaign, co-founder and Chief Science Officer of Reconstruct, and IEEE Fellow. His research focuses on 3D vision and general-purpose multimodal learning. In terms of writing, he advises, "Give it time, and remember: Impact = Idea x Evidence x Writing."

10. See the corpus project that I conducted with several graduate students in statistics: "Analyses of seven writing studies journals, 2000–2019, Part II: Data-driven identification of keywords" (Gallagher et al.) and "Analyses of seven writing studies journals, 2000–2019, Part I: Statistical trends in references cited and lexical diversity" (Gallagher et al.

Work Cited

Gallagher, John R., et al. "Analyses of Seven Writing Studies Journals, 2000–2019, Part I: Statistical Trends in References Cited and Lexical Diversity." *Computers and Composition*, vol. 67, Mar. 2023, pp. 1-18.

—. "Analyses of Seven Writing Studies Journals, 2000–2019, Part II: Data-Driven Identification of Keywords." *Computers and Composition*, vol. 67, Mar. 2023, pp. 1-20.