Published in final edited form as:

Nat Mach Intell. 2019 February ; 1(2): 70–71. doi:10.1038/s42256-019-0021-8.

Educational strategies to foster diversity and inclusion in machine intelligence

Shannon Wongvibulsin^{1,2,3,*}

¹Johns Hopkins University School of Medicine, Johns Hopkins University, Baltimore, Maryland

²Department of Biomedical Engineering, Johns Hopkins University School of Medicine, Baltimore, Maryland ³Johns Hopkins University Medical Scientist Training Program, Baltimore, Maryland

To attract and retain talent from all backgrounds, new educational models and mentorship programs are needed in machine intelligence, says Shannon Wongvibulsin.

Machine intelligence is making an increasing impact on society in fields such as transportation, sustainability, agriculture, healthcare, and finance.¹ Nevertheless, the diversity of society is not currently represented in the machine intelligence community. Specifically, women and minority groups, including African Americans, Hispanics, Native Americans, and people with disabilities are underrepresented.² Although these groups constitute over half of the population, of the undergraduate computer science degrees awarded at nonprofit institutions, only 20% are to women, 8.3 % to African Americans, 11% to Hispanics, and 0.4% to Native Americans, and within industry, only 26% of entry-level technical positions are women, 8.3% African Americans, and 6.3% Hispanics.^{3,4}

Without the diversity and inclusion of the full range of the population, we risk the development of biased algorithms and a lack of the necessary talent pool required to fill the growing workforce needed to address the expanding impact of this field on research and developments in other disciplines and in society in general.^{5,6} Numerous organizations have recognized the need to foster diversity and inclusion in machine intelligence and have created programs such as CSForAll,⁷ <http://Code.org>,⁸ Girls Who Code,⁹ Black Girls Code,¹⁰ and AI4ALL.¹¹

While these programs have begun to make an impact with the general objective of early exposure to the field to foster interest and provide foundational skills and knowledge, it is clear that the issues surrounding diversity and inclusion remain difficult to address. This Comment shares key proposals concerning an accessible education and mentorship structure

*Corresponding Author: swongvi1@jhmi.edu, Telephone: 410-955-8008, Postal Address: 1830 E. Monument Street, Suite 2-300, Baltimore, Maryland 21205.

Contributions

S.W. conceived the ideas for the manuscript and wrote the Comment article in its entirety.

Competing Interests

S.W. has no competing interests.

to promote a sustainable infrastructure for active participation as well as retention and long-term success within the machine intelligence community for individuals of all backgrounds.

Building a Welcoming Culture

For individuals belonging to groups currently underrepresented in the field, machine intelligence can seem to be an exclusive discipline, open only to those with strong technical backgrounds. Offering introductory courses with no prerequisites can help minimize this impression. Such courses can provide the fundamentals for long-term success in machine intelligence by teaching programming skills, critical thinking, mathematical concepts, and the foundations of machine learning algorithms. Furthermore, these courses can serve as the bridge to excite students with no prior technical background to pursue further education in this area.

For example, at Johns Hopkins University, the Hopkins Engineering Applications & Research Tutorials (HEART) program provides undergraduates with the opportunity to learn about cutting-edge engineering research and its societal impact.¹² These courses are designed and taught by advanced graduate students and postdoctoral fellows and have no prerequisites to ensure that the classes are accessible to entering undergraduates. Additionally, the class sizes are kept small (typically around ten students) to facilitate an interactive learning environment with ample student-instructor interaction. I designed and instructed HEART Foundations of Statistical Machine Learning which introduces both the theoretical foundations of modern statistical machine learning models and the implementation of these algorithms in the R programming language. The class is structured to include lectures, discussions, and R labs. The discussion part provides an opportunity for students to think about the real-world applications of machine learning algorithms, discuss their ideas in smaller groups, and then share with the class. The R labs offer students the chance to practice their programming skills, see the algorithms discussed in action, and obtain feedback on and assistance with their coding from the instructor as well as their peers.

HEART Foundations of Statistical Machine Learning was offered for the first time in the Fall 2018 semester. In a survey at the conclusion of the course, 9 out of 10 students indicated that after taking the course, they were more interested in statistical machine learning and the remaining one student indicated equal interest in statistical machine learning from before the course. The students found the interactive portions of the class and connections to real-world applications most enjoyable. Designing and teaching HEART Foundations of Statistical Machine Learning reinforced for me the importance of offering assessable courses to excite students from diverse backgrounds and further provided insights into possible ways to mitigate some of the challenges associated with fostering a sustainable infrastructure for diversity and inclusion, through pedagogical models that transform the student into the teacher, active learning in a “flipped classroom”, and longitudinal outreach programs.

Pedagogical Models that Transform the Student into the Teacher

Teaching peers can increase confidence and mastery of the material. Furthermore, building constructive relationships with peers can further promote a sense of belonging within the community and help foster inclusivity. Machine intelligence education could benefit from borrowing ideas from pedagogical models such as “see one, do one, teach one” which is common in medical education.¹³ For instance, in medical training, the junior doctor or medical student often learns a new procedure by *seeing one* performed by another healthcare professional and then *doing one* under supervision and then *teaching one* to another trainee. The machine intelligence community could implement a similar strategy by structuring introductory courses to include a *seeing* component (e.g. lecture), a *doing* component (e.g. coding lab), and a *teaching* component (e.g. peer teaching or outreach to teach high school students, etc.). Transforming the student into the teacher offers the potential to reinforce the course material, build strong peer relationships, and amplify the impact of the course through outreach projects.

Active Learning in a “Flipped Classroom”

Rather than using class time for lecture, the “flipped classroom” minimizes lecture-based instruction and promotes active learning in the classroom.¹⁴ Active learning has been shown to increase students’ performance in science, engineering, and mathematics.¹⁵ For instance, HEART Foundations of Statistical Machine Learning facilitates an active learning environment through problem solving activities, discussion, coding exercises, and connections to real-world challenges. This “flipped classroom” structure further encourages students to develop problem-solving skills to address current societal challenges and demonstrates the potential impact that students of all backgrounds can have as members of the machine intelligence community.

Longitudinal Outreach Programs

Outreach programs with leadership or teaching roles at every stage offers the potential to provide a sustainable infrastructure for promoting diversity and inclusion. Peer mentorship program structures offer the opportunity for students to learn from their peers in addition to faculty role models or established leaders in machine intelligence community. As the student progresses in training, the individual student can be both a mentor (of a younger student) and mentee (of an older student). This structure offers the opportunity to get advice from individuals who have recently faced similar challenges and have had recent relatable experiences. Furthermore, this support structure facilitates continuity of mentorship across the different stages of training (e.g. elementary, middle, and high school, college, and beyond). Additionally, pedagogical models such as “see one, do one, teach one” as part of the core curriculum in the science, technology, engineering, and mathematics (STEM) educational system can amplify outreach efforts. For example, college students can provide outreach in high schools to encourage high school students to pursue STEM majors and provide mentorship on college applications; high school students’ outreach efforts can provide middle and elementary school students with exposure to STEM. This structure allows individuals to be involved as valued members of the machine intelligence community

from an early stage as well as increase self-confidence and sense of belonging in the field of machine intelligence to help overcome the retention and inclusivity challenges that women and minority groups often face as underrepresented members of the community.

Conclusion

As machine intelligence increasingly impacts society, diversity and inclusion are issues of growing concern. Expanding HEART-type classes that are accessible and prerequisite-free in college-level education could attract more individuals from a broader range of backgrounds, some of which might consider pursuing a degree and eventual career in machine intelligence. Nevertheless, offering welcoming courses to entering undergraduates is only one small part of the necessary steps to promote active and long-term participation from individuals of all backgrounds. Moving forward, it will also be essential to engage students in primary and secondary education and facilitate a mentorship structure to promote a sustainable infrastructure for diversity and inclusion to ensure the development and implementation of safe, equitable, and impactful applications of machine intelligence.

Acknowledgements

This work was supported by the Johns Hopkins School of Medicine Medical Scientist Training Program (National Institutes of Health: Institutional Predoctoral Training Grant – T32), National Institutes of Health: Ruth L. Kirschstein Individual Predoctoral NRSA for MD/PhD: F30 Training Grant, the Johns Hopkins Individualized Health (inHealth) Initiative, and the Hopkins Engineering Applications & Research Tutorials (HEART) program.

References

1. Horvitz E AI, people, and society. *Science* (New York, N.Y.) 357, 7 (2017).
2. Whitney T & Taylor VJC Increasing Women and Underrepresented Minorities in Computing: The Landscape and What You Can Do. 51, 24–31 (2018).
3. Integrated Postsecondary Education Data Systems (IPEDS), <<https://nces.ed.gov/ipeds>>
4. Commission UEEO (US Equal Employment Opportunity Commission. Retrieved from <https://www.eeoc.gov/eeoc/statistics/reports/hightech/upload/diversity-in-high-tech-report.pdf>, 2016).
5. Ferrini-Mundy J Science education. Driven by diversity. *Science* (New York, N.Y.) 340, 278 (2013).
6. Miller FA, Katz JH & Gans RJ O. P. The OD Imperative to Add Inclusion to the Algorithms of Artificial Intelligence. 50 (2018).
7. CSForAll, <www.csforall.org>
8. Code.org, <<https://code.org>>
9. Girls Who Code, <<https://girlswhocode.com>>
10. Black Girls Code, <www.blackgirlscode.com>
11. AI4All, <<http://ai-4-all.org/>>
12. Hopkins Engineering Applications & Research Tutorials (HEART) Program <<https://engineering.jhu.edu/heart/>>
13. Tuthill JJ T. L See one, do one, teach one. 371, 1906 (2008).
14. Velegol SB, Zappe SE & Mahoney E The Evolution of a Flipped Classroom: Evidence-Based Recommendations. *Advance in Engineering Education* 4, n3 (2015).
15. Freeman S et al. Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences of the United States of America* 111, 8410–8415, 1319030111 (2014). [PubMed: 24821756]