Data Ethics in a Modern Age of Educational Research

Machine Learning Fairness, Considerations for Special Populations, and Current Issues

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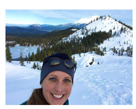
Who Am I? Sondra Stegenga

- B.S. Behavioral Science
- M.S. Occupational Therapy
- M.Ed. Educational Leadership
- Ph.D. Special Education/Early Intervention
- Pediatric Occupational Therapist, Early Interventionist/Home Visitor, Program Administrator, Faculty Member, Teacher, Researcher

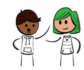
Who Am I? Sondra Stegenga

- Sister, Partner, Aunt, Friend, Daughter, Neighbor, Cat Mom
- Volleyball Player, Hiker, Biker, Scuba Diver, Coffee Lover, Lifelong Learner
- Duck!






Who Are You?



Talk with a partner

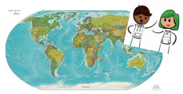
- Who are you?
- How do you introduce yourself in different contexts (e.g. professional events versus events with family/friends), is it different or the same?
- What information might you be missing due to the typical questions you ask when you meet someone?
- How is this similar to the research questions we ask?
- What might we be missing in the data if we begin analyzing and do not understand or consider our own frames of reference and biases?
- Who else do we need to partner with or involve to help us see beyond these lenses?

The Growth of 'Big Data'

Term emerged in 1998 in a presentation by John Mashey – Computer Scientist

- Volume
- Variety
- Velocity

(Ahmadi, Dileepan, & Wheatly, 2016; Baro, Degoul, Beuscart, & Chazard, 2015)

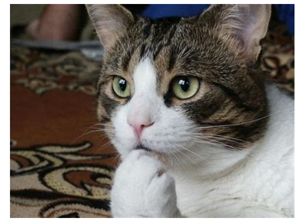




Size/Volume	Data in Numbers	Equivalence Examples
Megabyte (MB)	1,000,000 bytes	1MB=Small Novel 5MB=Complete works of Shakespeare 500MB = Hard Disk of common PCs
Gigabyte (GB)	1,000,000,000 bytes	1GB=Pickup Truck filled with paper 100GB=A floor of academic journals
Terabyte (TB)	1,000,000,000,000 bytes	1TB=All the X-Ray films in a large hospital 10TB=Printed collection of US Library of Congress
Petabyte (PB)	1,000,000,000,000,000 bytes	1PB=7,812 iPhones (128GB) 2PB=All US academic research libraries 200PB=All printed material in the world
Exabyte	1,000,000,000,000,000,000 bytes	5EB=All words ever spoken by humans to date

Information Adapted from Bunn (2012) in Stegenga, Munger, Squires, & Anderson (2018)

Definition?

There is not one agreed upon definition!



Why has 'Big Data' Become So Popular?

"The world's most valuable resource is no longer oil, but data""

(The Economist, 2017; https://www.economist.com/leaders/2017/05/06/the-worlds-most-valuable-resource-is-no-longer-oil-but-data)

- It is constantly changing and updating – in the moment knowledge!
- Powerful business and analytic tool – foundation for understanding and predicting buying habits
- Has helped to improve understanding leading to improved outcomes in some areas of health and society
- Solved problems previously unsolvable due to lack of data or access

Successes!

- Decreased child mortality rates from Sepsis due to use of analytics! https://www.healthcatalyst.com/success_stories/pediatric-sepsis-texas-childrens-hospital
- Decreased mother mortality rates in CA due to use of analytics and discovering bias in practices (Mitchell et al., 2014)
- Identifying mental health concerns and providing supports

Strengths of Big Data (Review by Stegenga et al., 2018 – OSF Preprint)

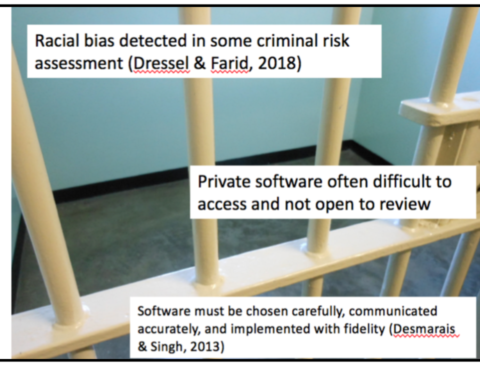
- Availability
- Timeliness/efficiency
- Cost effectiveness
- Decreased subject risk
- New insights
- Increased strength of conclusions
- Broad applicability
- Personalized feedback

Challenges of Big Data (Review by Stegenga et al., 2018 – OSF Preprint)

- Data quality issues
- Data complexity
- Limited scope
- Lack of ability to translate and use the complex data in specialized educational and early childhood/developmental settings
- Structural/systems level barriers to use in education, health, and early childhood settings
- Legal considerations
- Ethical challenges

Increasing Attention to Ethical Challenges with Big Data

- April 2011 – Security researchers identified Apple was recording on iPhones and saving to a hidden file position data
- Feb. 2012 – New York Times reports on Target’s increasing ability to identify when customers are pregnant



Racial bias detected in some criminal risk assessment (Dressel & Farid, 2018)

Private software often difficult to access and not open to review

Software must be chosen carefully, communicated accurately, and implemented with fidelity (Desmarais & Singh, 2013)

Predictive Analytics in Child Welfare? (Hurley, 2018)

The Evolving Conversation on Ethical Use of Big Data

- 2010 – Article by Michael Zimmer, “But the data is already public: On the ethics of research in Facebook”
- 2012 – Book by Kord Davis, “Ethics of Big Data: Balancing Risk and Innovation
- Many others!
- More recent – focus on big data ethics in particular areas of study:
  - Ethics of big data in big agriculture (Carbonell, 2016)
  - Big data, ethics and religion: New questions from a new science (Fuller, 2017)
  - Market research and ethics of big data (Nunan & Domenico, 2017)
  - Ethics of big data in higher education (Johnson, 2014)
  - Etc!

Data Protection Policies Not Keeping Pace

- Varied and often contradictory federal, state, and agency specific policies
- IRBs updating but still not comprehensive

“The extensive use of increasingly more data—often personal, if not sensitive (big data)—and the growing reliance on algorithms to analyse them in order to shape choices and to make decisions (including machine learning, artificial intelligence and robotics), as well as the gradual reduction of human involvement or even oversight over many automatic processes, pose pressing issues of fairness, responsibility and respect of human rights, among others”

- Floridi & Taddeo (2016) p. 2

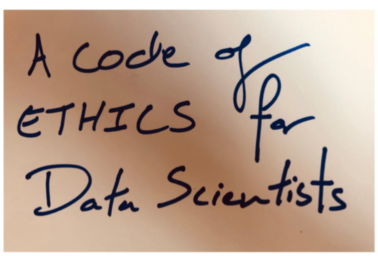
Some things may be legal…but are they ethical??

What is Data Ethics?

- Newer in the conversations in data science
- Ethical codes in many professions (e.g. OT, MD, special education teachers) BUT…No formalized ethical code in data science, yet.
- Why is this just emerging now? Data science is a newer field!
- Building from other ethical codes and work such as Association for Computing Machinery (https://www.acm.org/code-of-ethics) and American Statistical Association (https://www.amstat.org//asa/files/pdfs/EthicalGuidelines.pdf) due to their focus on ethics relative to data (Loukides, Mason, & Patil 2018)

A Code of Ethics for Data Science

dj patil Follow
Feb 1, 2018 · 4 min read



Checklist of Considerations (Loukides, Mason, & Patil 2018)

- Have we listed how this technology can be attacked or abused?
- Have we tested our training data to ensure it is fair and representative?
- Have we studied and understood possible sources of bias in our data?
- Does our team reflect diversity of opinions, backgrounds, and kinds of thought?
- What kind of user consent do we need to collect to use the data?
- Do we have a mechanism for gathering consent from users?
- Have we explained clearly what users are consenting to?

Checklist of Considerations (Loukides, Mason, & Patil 2018)

- Do we have a mechanism for redress if people are harmed by the results?
- Can we shut down this software in production if it is behaving badly?
- Have we tested for fairness with respect to different user groups?
- Have we tested for disparate error rates among different user groups?
- Do we test and monitor for model drift to ensure our software remains fair over time?
- Do we have a plan to protect and secure user data?

Machine Learning Fairness – Principles, Practices, and Issues

"In the context of decision-making, fairness is the *absence of any prejudice or favoritism toward an individual or a group based on their inherent or acquired characteristics"*

– Mehrabi (2019)

However…

We know that the training data we use is inherently biased because it is created and gathered by humans…with biases…

Dangerous because impacts of biased data often compounded over time…For example, training data based on bias in hiring with continue to point to and create more biased hiring patterns.

Other Considerations

- Word embeddings in online news articles (e.g. gendered language about scientists) can lead to more bias in findings
- Sample size disparities – underrepresented groups do not have as much data and hence prediction may not be as accurate
- Skewed or tainted samples
- Lack of understanding of causes of disparities in data

Why Do We Care about ML Fairness?

ML impacts so many aspects of our lives and world!

- Employers using ML for screening applicants
- LinkedIn rating individuals based on ML
- Self-driving cars dependent on ML
- Dating apps using ML to help match
- Health care decisions being impacted by ML algorithms
- Has increased dramatically in the research conversations since 2011!!

Current Debates and Ideas for Improving Fairness

- Preprocessing
- Optimizing at training time
- Post-Processing

Blog with pros and cons and recent research links:
https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb

What we can learn from other fields on ethics relative to fairness and special populations?

Fairness in Machine Learning Lessons from Political Philosophy
by Binns (2017)

- Which measures of fairness are most appropriate in a context?
- When would we give different treatment to particular groups and why?
- Is it about ensuring equal probability or minimizing harms?
- What generalizations are we making about groups to improve fairness? Fails to treat people as individuals…

- Balance of access and privacy
- Authentic partnerships
- Consider mixed methods
- Ensure domain knowledge
- Open data sets
  - Transparency to understand and critically examine algorithms
  - Well-documented data (definitions, collection procedures – what and who is missing?)
- Training in data ethics
- Regular reflection

Balance – Access and Privacy

- Too much access
- Too much privacy/unable to access data

Authentic Partnerships

Looks Like

- **EACH** member is considered an expert and feels equal in the partnership
- All opinions are considered and **purposefully elicited** to ensure each and every voice is heard
- Decisions and ideas **stem from** collaborative discussion
- Requires **trust building over time**
- Aims to **solve a real-world** pressing issue/problem of practice as determined by all partners

Doesn't Look Like

- Researcher/data scientist as expert
- Researcher/data scientist always leading and the main voice in meetings
- Decisions and ideas formed by the researcher/data scientist possibly with approval from families or the community after the ideas have been established (e.g. obtains letters of support from partners but they did not assist in the design or innovation of the idea)
- Researcher/data scientist does not have long standing engagement with the community
- Issue being addressed may not necessarily be a highly rated priority by the community or field

Modified from Stegenga et al. (2020)

Why Do We Need Authentic Partnerships?

- Works to amplify community and stakeholder voices
- Communities know best
- Democratization of data, research, and decision-making
- Move from ~~doing to~~ to ***collaborating with*** from the very beginning and throughout
- Avoid harm from data practices and decisions
- Will never fully understand what works, for whom, and under what conditions without partnering in real world settings under authentic conditions (there remains a lot of unaccounted for variance in our models – hence we must continue to work to identify what this might be!)

Big Data as Theory Versus the End All?

'Some big data fundamentalists argue that at sufficient scale, data is enough; "statistical algorithms find patterns where science cannot" (Anderson, 2008, para. 14), and thus big data represents "the end of theory" (Graham, 2012). But we argue that big data *is* theory. It is an emerging *Weltanschauung* grounded across multiple domains in the public and private sectors, one that is need of deeper critical engagement. '

- Crawford, Gray, & Miltner (2014)

Big Data and Qualitative? Considering Mixed Methods

- Helps to bridge, reveal, and understand gaps in the data
- Decreases misunderstanding resulting in inappropriate conclusions
- Some experts have promoted we need more than big data but also "thick data" – Tricia Wang
- What is Thick Data? "Ethnographic approaches that uncover the meaning behind Big Data visualization and analysis" – Tricia Wang (http://ethnographymatters.net/blog/2013/05/13/big-data-needs-thick-data/)

Considerations in Mixed Methods When Time is an Issue

- Rapid reviews in implementation focused research
- Use of rapidly improving text analysis - Latent Dirilecht Allocation (Nikolenkon et al., 2017)
- Not meant to take the place of traditional qualitative research and rigor but may compliment processes

What Else to Consider - Qualitative Research in an Age of Big Data? Is It Really Needed?

TED Talk by Tricia Wang – Technology Ethnographer

Hint: The answer is YES!

Direct Link:
https://www.ted.com/talks/tricia_wang_the_human_insights_missing_from_big_data/reading-list#t-958603

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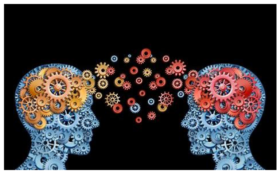
Domain Knowledge

- Know your limitations
- Who should you be partnering with?
- Gather information and learn!
- Collaboration



Open Data Sets and Access to Algorithms

Training and Ongoing Discourse Related to Data Ethics

Regular Reflection on Bias and Frames of Reference

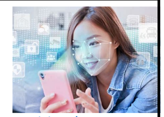
Considerations with COVID-19

- Times of innovation but also danger
- Data sharing
- Using fairness to advance health equity, versus prohibit
- Over sharing and tracking causing some to be wary of testing – may actually provide issues with outcomes/individuals most at risk not getting testing and spreading.
- Many examples of individuals without domain knowledge making charts that do not apply or could be used harmfully…

Considerations with COVID-19

Incorrect charts (y axis) being shown on the news

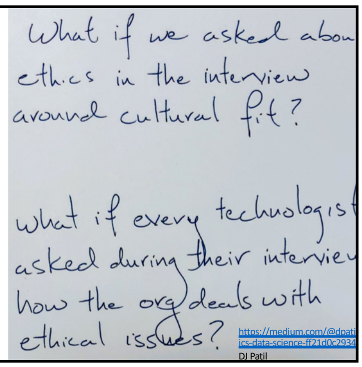
Current Changes & Potential Impacts



- Facial recognition in many cities (https://www.usatoday.com/story/tech/2019/12/17/face-recognition-ban-some-cities-states-and-lawmakers-push-one/2680483001/)
- Facial recognition in our schools (who already have disproportionate suspension expulsion + known issues with facial recognition with people of color) (https://www.nytimes.com/2020/02/07/learning/should-facial-recognition-technology-be-used-in-schools.html)
- Data that was off limits (e.g. health data) is now being pulled in as part of our state of emergency (https://www.tampabay.com/news/health/2020/05/19/covid-19-data-sharing-with-law-enforcement-sparks-concern/)

Data Science for Good in a Field without a Formal Ethical Framework?

- Where do you stand?
- Consider how and where you are using your skills
- Ask Questions
  - What will be required of you with your employer?
  - What is the scope of work? (Remember you are interviewing them too!)



https://medium.com/@dpati
ics-data-science-ff21d0c2934
DJ Patil

What Else to Consider?

- Think ahead – what would you do if put in a situation which you do not feel is ethical?
- Consider formal ethics for the field of data science? (like health and medical professions, teachers, etc.)
- Must have ethics beyond just internal review boards and employers (just because its “legal” or not prohibited, does it mean its ethical?)
- IRBs not keeping up and not in all settings – cannot just count on this process

What Else to Consider?

- Go beyond just “data ethics”
- Continue learning about people, cultures, contexts, systems, our world
- Seek out training in ethics, diversity, bias, anti-racism, etc. to better understand and reflect upon what may be contributing to data collection practices, data use, training procedures, analyses, assumptions, models, theories of change, etc.!!

What Else to Consider?

- Promote & support diversity in the field of data science & research
  - Follow and amplify
  - Listen, learn – follow the conversation
- Support great initiatives and organizations helping to make change (just naming a few – many more!)
  - Black in AI: https://blackinai.github.io
  - Black Girls Code: https://www.blackgirlscode.com
  - Data Science Africa: http://www.datascienceafrica.org
  - LatinX in AI: http://www.latinxinai.org
  - Women in Machine Learning: https://wimlworkshop.org
  - R-Ladies Global (find your local chapter too!): https://rladies.org
  - ResearchHers Code: https://www.researcherscode.com

Resources for Additional Learning/Reading

- Ethics and Data Science (free e-book + quick read) by Loukides, Mason, & Patil 2018 https://www.amazon.com/dp/B07GTC8ZN7/ref=cm_sw_r_cp_ep_dp_fKyLBb0YWVH94
- Ted Talk linked in this presentation
- Blog on a Code of Ethics for Data Science – DJ Patil (Former advisor to the Obama administration) https://medium.com/@dpatil/a-code-of-ethics-for-data-science-cda27d1fac1
- Data & Society – Council for big Data, Ethics, and Society: https://datasociety.net/research/council-for-big-data-ethics-and-society/
- Follow the conversations on Twitter & become part of the community!
- Free course on Coursera on Data Ethics from the University of Michigan: https://www.coursera.org/learn/data-science-ethics?utm_source=umich&utm_medium=institutions&utm_campaign=michigan-online&utm_term=Data+Science+Ethics&utm_content=website


"Numbers have an important story to tell. They rely on you to give them a voice."

Stephen Few – Data Visualization Expert



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