responsible operations

data science, machine learning, and ai in libraries

oc.lc/responsibleoperations

thomas padilla, oclc research
sarah shreeves, university of arizona

1. what & how
2. a path
3. next steps

… a library community research agenda that charts a path for (responsible) operationalization of data science, machine learning, and AI.

advisory group

Kenning Arlitsch, Montana State University
Jon Cawthorne, Wayne State University
Karen Estlund, Colorado State University
Josh Hadro, IIIF Consortium
Bohyun Kim, University of Rhode Island
Trevor Owens, Library of Congress
Ben Schmidt, Northeastern University
😎🌵**Sarah Shreeves, University of Arizona**🌵😎
MacKenzie Smith, University of California Davis
Claire Stewart, University of Nebraska Lincoln
Melissa Terras, University of Edinburgh
Diane Vizine-Goetz, OCLC Research
John Wilkin, University of Illinois at Urbana Champaign
Kate Zwaard, Library of Congress

landscape group

Ruth Ahnert, Queen Mary University of London
Taylor Arnold, University of Richmond
Helen Bailey, Massachusetts Institute of Technology
Ted Baldwin, University of Cincinnati
Daina Bouquin, Harvard University and the Smithsonian Institution
Karen Cariani, WGBH
Michelle Cawley, University of North Carolina Chapel Hill
Rumman Chowdhury, Accenture
Jason Clark, Montana State University
Nicole Coleman, Stanford University
Rebecca Dikow, Smithsonian Institution
Quinn Dombrowski, Stanford University
Virginia Dressler, Kent State University
Jon Dunn, Indiana University
Ixchel Faniel, OCLC
Maggie Farrell, University of Nevada Las Vegas
Lisa Federer, National Institutes of Health
Barbara Fister, Gustavus Adolphus College
Kathleen Fitzpatrick, Michigan State University
Themba Flowers, Yale University
Alex Gil, Columbia University
Jean Godby, OCLC
Tiffany Grant, University of Cincinnati
Jane Greenberg, Drexel University
Harriett Green, Washington University St Louis
Umi Hsu, ONE Archives Foundation
Richard Johansen, University of Cincinnati
Bohyun Kim, University of Rhode Island
Lauren Klein, Georgia Tech
Emily Lapworth, University of Nevada Las Vegas
Shari Laster, Arizona State University
Matthew Lincoln, Carnegie Mellon University
Meris Longmeier, The Ohio State University
Dominique Luster, Carnegie Museum of Art
Nandita Mani, University of North Carolina Chapel Hill
And more!

1 year of activity
60 hours of interviews
1 face to face event
3 conferences
144 challenges
150 comments
7 drafts

an ode to big data, GPUs this is not

nor will you hear unfettered enthusiasm for “scale”

MICROSOFT POLICY US & WORLD

Microsoft denied police facial recognition tech over human rights concerns

The company has sold the technology to at least one US prison though

By James Vincent | Apr 17, 2019, 5:16am EDT

Amazon shareholders will vote to ban facial recognition tech

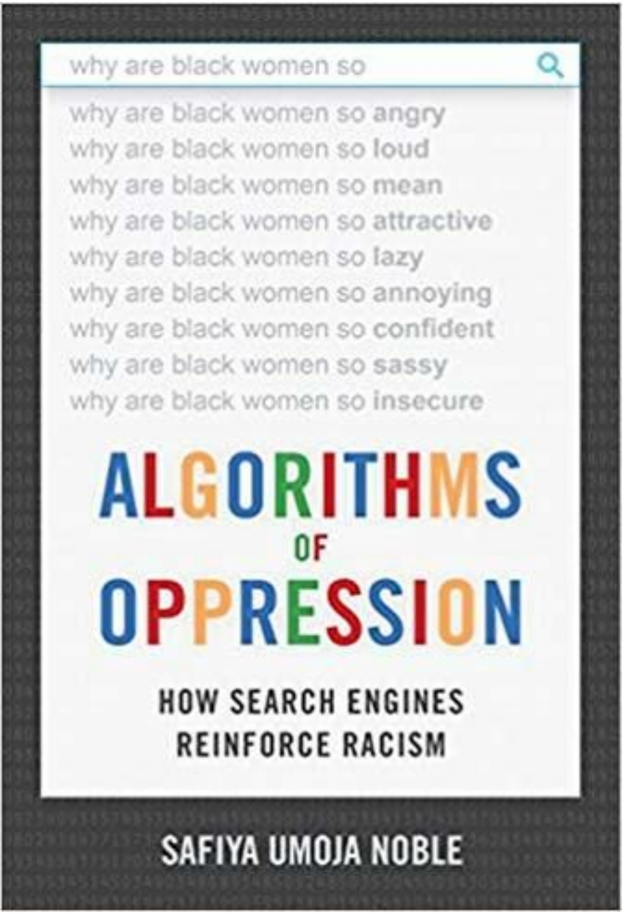
Amazon's board opposes it and wants government regulation instead.

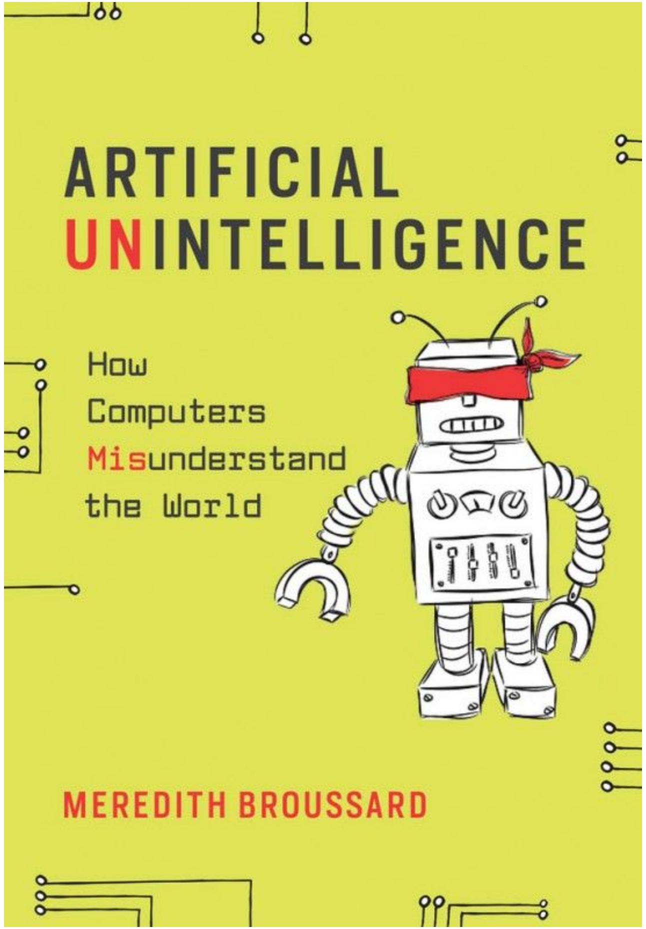
rather

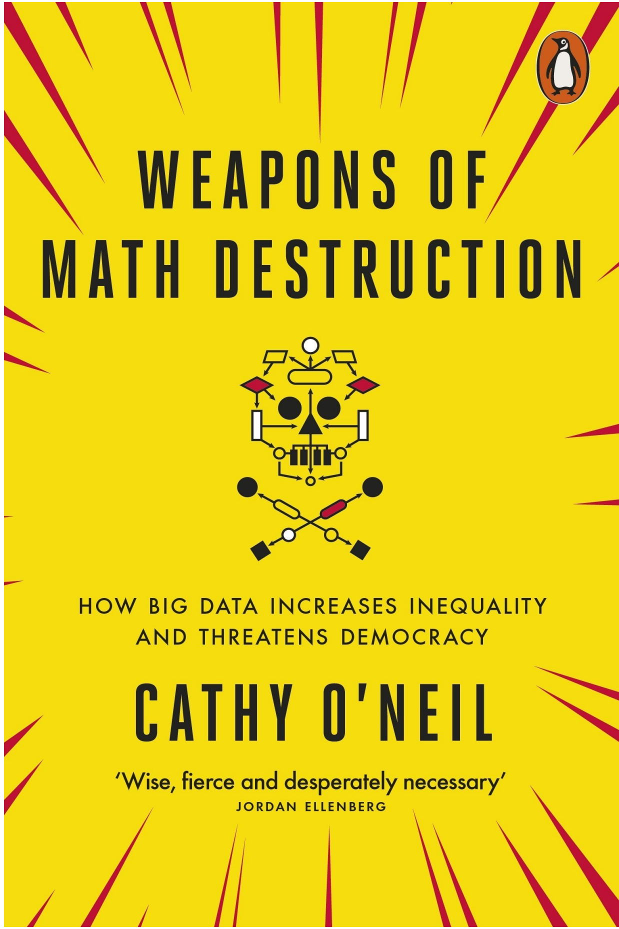
responsible operations

a commitment to fostering individual, organizational, and community capacities for responsible operationalization of data science, machine learning, and AI.

h/t rumman chowdhury for the inspo


why are black women so
why are black women so angry
why are black women so loud
why are black women so mean
why are black women so attractive
why are black women so lazy
why are black women so annoying
why are black women so confident
why are black women so sassy
why are black women so insecure
ALGORITHMS OF OPPRESSION
HOW SEARCH ENGINES REINFORCE RACISM
SAFIYA UMOJA NOBLE


ARTIFICIAL UNINTELLIGENCE
How Computers Misunderstand the World
MEREDITH BROUSSARD


WEAPONS OF MATH DESTRUCTION
HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY
CATHY O'NEIL
'Wise, fierce and desperately necessary'
JORDAN ELLENBERG

getting from concept to operations

Responsible Operations: Data Science, Machine Learning, and AI in Libraries

Thomas Padilla

oc.lc/responsibleoperations

doi.org/10.25333/xk7z-9g97

7 areas of investigation

18 challenges

51 recommendations

1. Committing to Responsible Operations

A. Managing Bias

B. Transparency, Explainability, and Accountability

C. Distributed Data Science Fluency

D. Generous Tools

2. Description and Discovery

A. Enhancing Description at Scale

B. Incorporating Uncertain Description

C. Ensuring Discovery and Assessing Impact

3. Shared Methods and Data

A. Shared Development and Distribution of Methods

B. Shared Development and Distribution of Training Data

4. Machine-Actionable Collections

A. Making Machine-Actionable Collections a Core Activity

B. Broadening Machine-Actionable Collections

C. Rights Assessment at Scale

5. Workforce Development

A. Investigating Core Competencies

B. Commiting to Internal Talent

C. Expanding Evidence-Based Training

6. Data Science Services

A. Modeling Data Science Services

B. Research and Pedagogy Integration

7. Sustaining Interprofessional and Interdisciplinary Collaboration

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1a - managing bias

3a - shared development and distribution of methods

4b - broadening machine actionable collections

5b - committing to internal talent

1a - managing bias

3a - shared development and distribution of methods

4b - broadening machine actionable collections

5b - committing to internal talent

responsible operations call for sustained engagement with human biases manifest in training data, machine learning models, and outputs.

remediation

Bias management activities have precedent and are manifest in collection development, collection description, instruction, research support, and more.

DISCRIMINATING SYSTEMS

Gender, Race, and Power in AI

APRIL 2019

Cite as: West, S.M., Whittaker, M. and Crawford, K. (2019). Discriminating Systems: Gender, Race and Power in AI. AI Now Institute. Retrieved from https://ainowinstitute.org/discriminatingsystems.html.

monoculture cannot effectively manage bias.

diversity is not a nice to have, it is an imperative.

a recommendation

Explore creation of a “practices exchange” that highlights successes as well as notable missteps in cultural heritage use of data science, machine learning, and AI. Commit to transparency as a means to work against repeated community mistakes — a pattern of negative behavior in Silicon Valley that Jacob Metcalf, Emanuel Moss, and danah boyd have referred to as “blinkered isomorphism.”

1a - managing bias

3a - shared development and distribution of methods

4b - broadening machine actionable collections

5b - committing to internal talent


LIBRARIES USING COMPUTER VISION
SO MANY THINGS!
IS GOOD?

venues and mechanisms for refinement are few

impacts assessment
& broader uptake

a recommendation

Develop venues, publication outlets, and funding sources that facilitate the sharing of methods and benchmarks for machine learning and artificial intelligence in the cultural heritage community.

1a - managing bias

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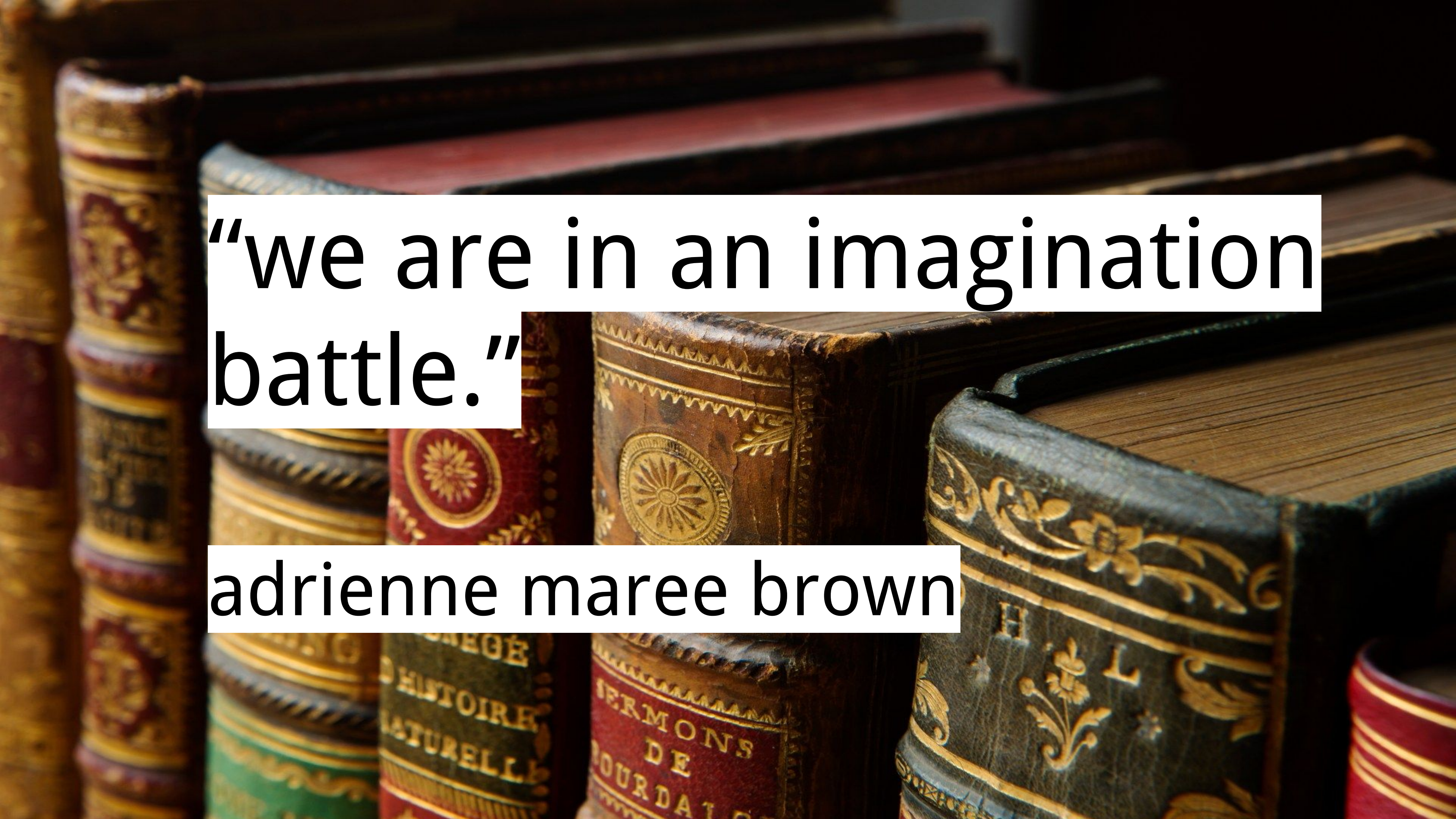


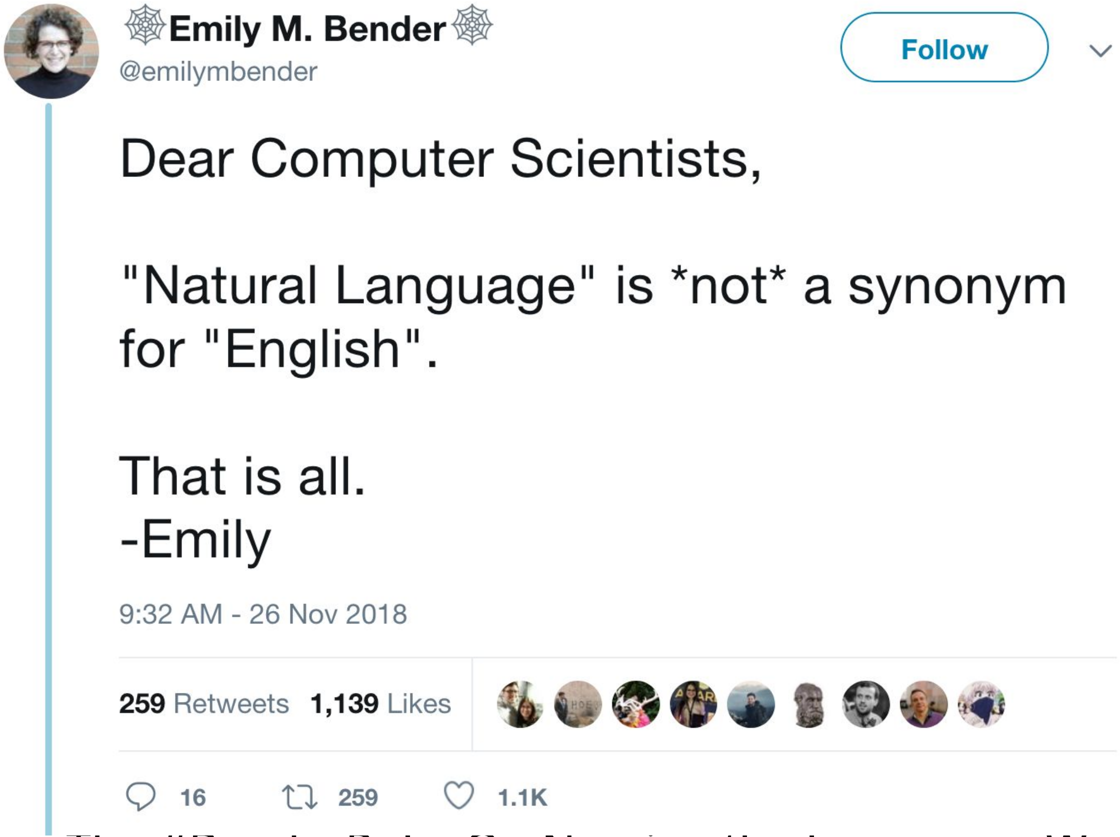
“we are in an imagination battle.”

adrienne maree brown

“Natural Language” Processing Digital Divide

As of Augu

961 resour
121 for Am
216 for Ge
180 for Fre
130 for Spa
103 for Ma
103 for Jap
Remainin **s.**



Emily M. Bender, [The #BenderRule: On Naming the Languages We Study and Why It Matters]

a recommendation

Prioritize the creation of machine-actionable collections that speak to the experience of underrepresented communities. Inform this work through collaborations with community groups that have ties to collections, subject experts, and reference to resources … like *Design for Diversity*. Per community input, decisions to not develop a machine-actionable collection are as positive as decisions to develop a machine-actionable collection.

1a - managing bias

3a - shared development and distribution of methods

4b - broadening machine actionable collections

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SMURFS

a recommendation

Form a working group to investigate the development of organizational models that avoid silos and support hybridity between core and emerging services - models of this kind may encourage natural diversification and/or deepening of skills over time.

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reflections

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