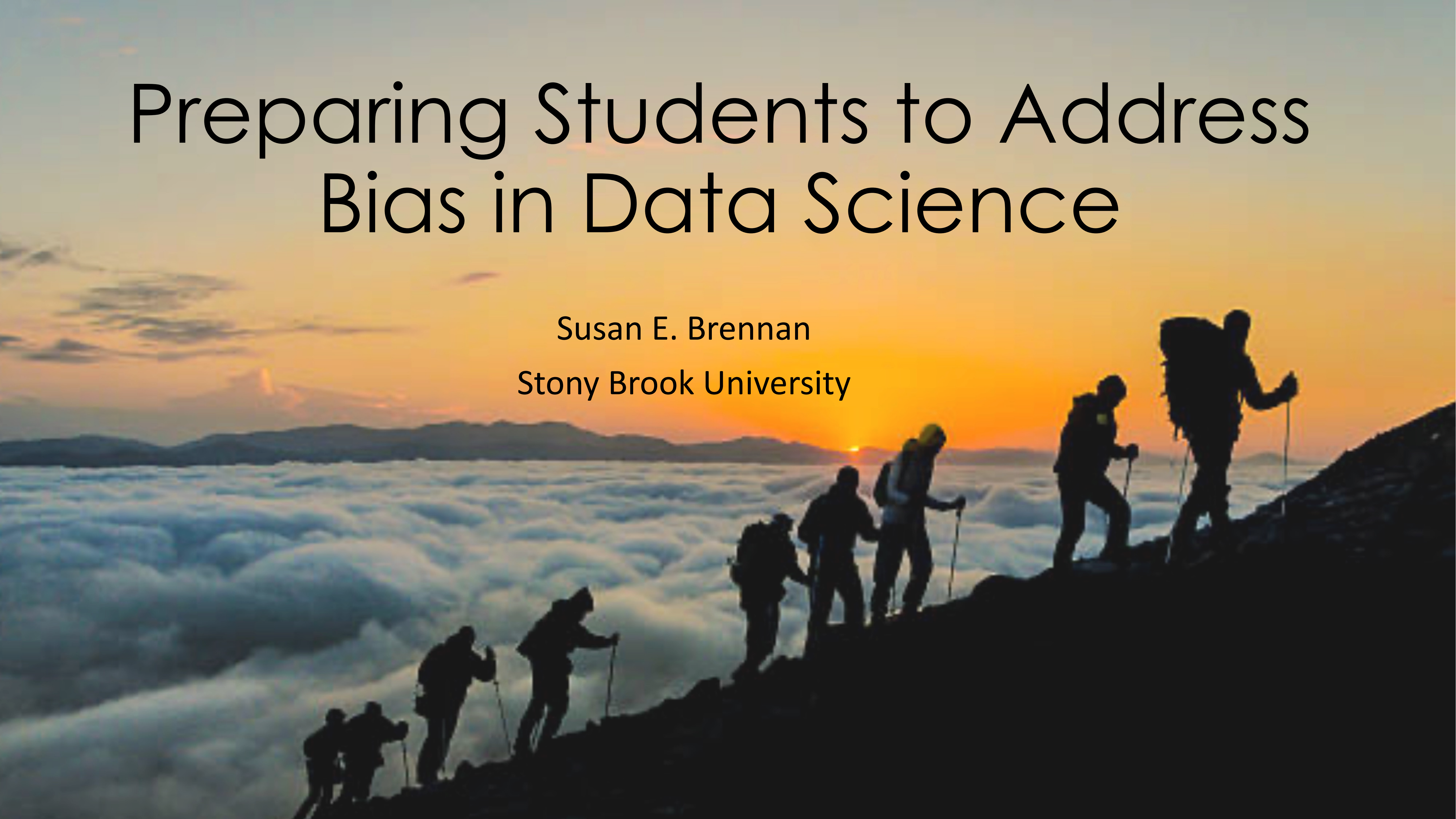


Preparing Students to Address Bias in Data Science

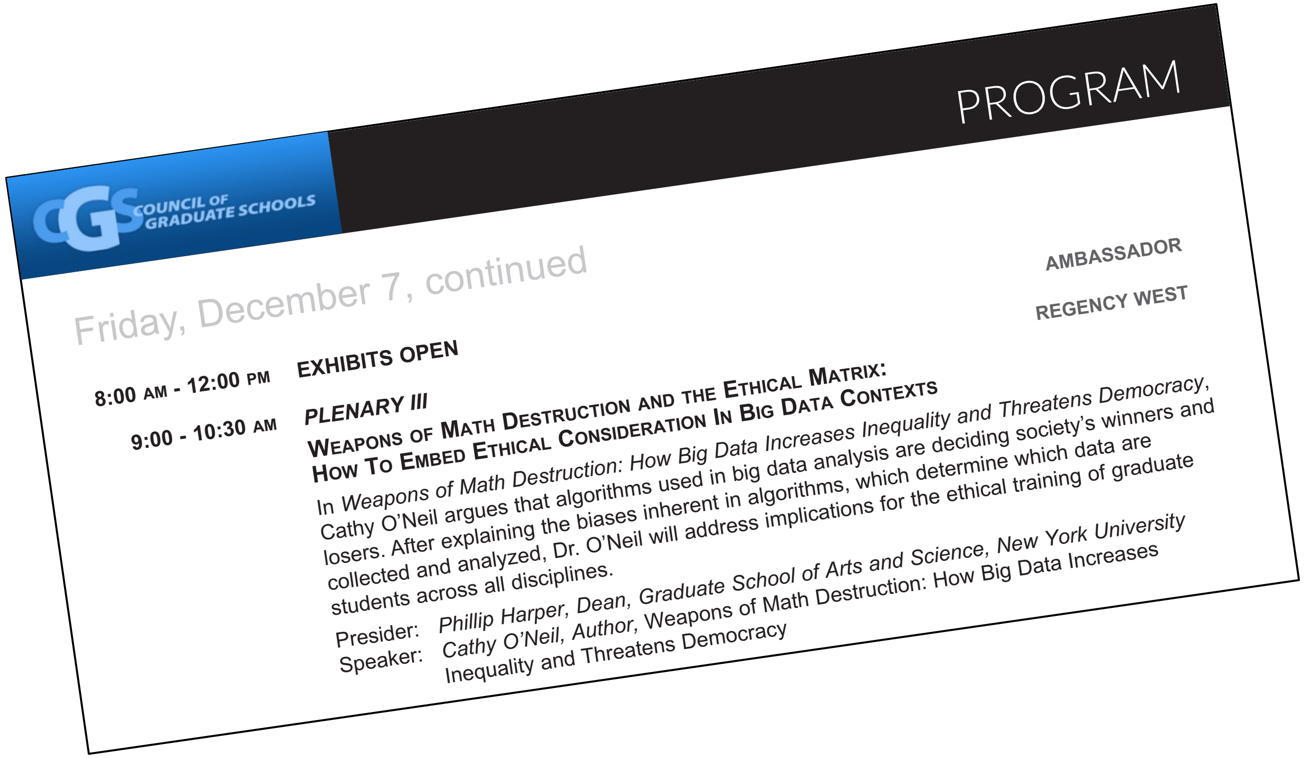
Susan E. Brennan

Stony Brook University

What is a model?

“An opinion, embedded in math”

(Cathy O’Neil, 2016, p. 21)



CGS COUNCIL OF GRADUATE SCHOOLS

PROGRAM

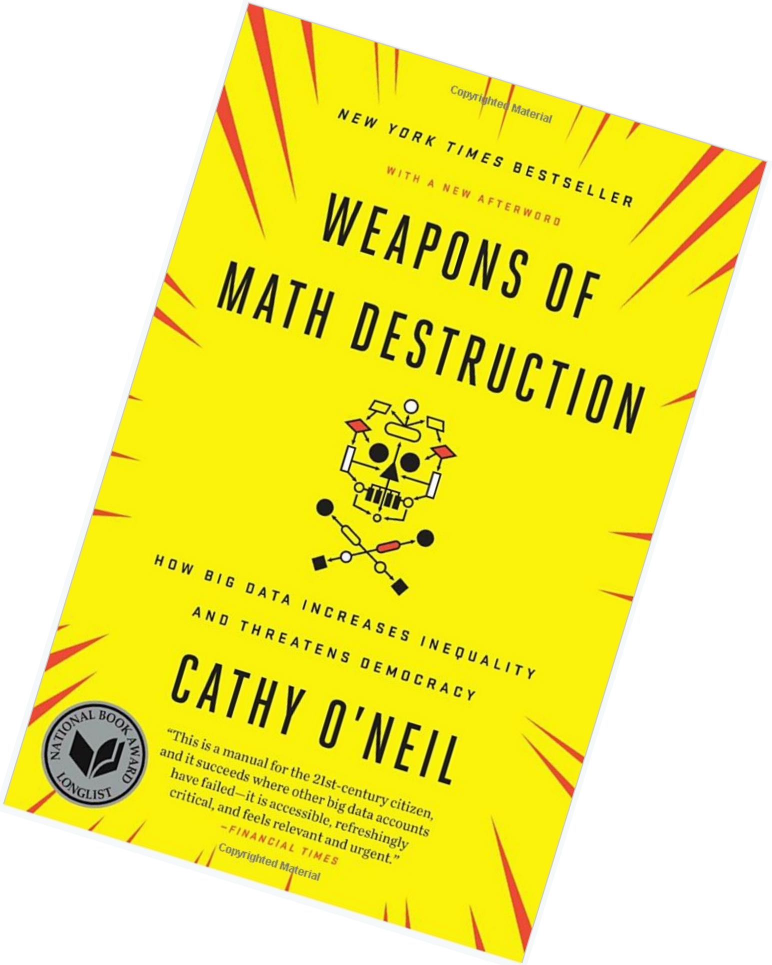
Friday, December 7, continued

8:00 AM - 12:00 PM	EXHIBITS OPEN	AMBASSADOR
9:00 - 10:30 AM	*PLENARY III* WEAPONS OF MATH DESTRUCTION AND THE ETHICAL MATRIX: HOW TO EMBED ETHICAL CONSIDERATION IN BIG DATA CONTEXTS	REGENCY WEST

In *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, Cathy O’Neil argues that algorithms used in big data analysis are deciding society’s winners and losers. After explaining the biases inherent in algorithms, which determine which data are collected and analyzed, Dr. O’Neil will address implications for the ethical training of graduate students across all disciplines.

Presider: *Phillip Harper, Dean, Graduate School of Arts and Science, New York University*

Speaker: *Cathy O’Neil, Author,* Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy


Copyrighted Material
NEW YORK TIMES BESTSELLER
WITH A NEW AFTERWORD
WEAPONS OF MATH DESTRUCTION
HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY
CATHY O'NEIL
NATIONAL BOOK AWARD LONGLIST
"This is a manual for the 21st-century citizen, and it succeeds where other big data accounts have failed—it is accessible, refreshingly critical, and feels relevant and urgent."
—FINANCIAL TIMES
Copyrighted Material

When people use technology for decision-making, where might bias come into play?

The AI Technology Stack *(Moore, 2018)*

DECIDE	Weigh the output, search, plan, predict
LEARN	Deep learning, ML (a black box) or something more transparent
PERCEIVE	Data input (historical data), "Big Data," hardware, the cloud

Example: Bias in Automated Decision Systems

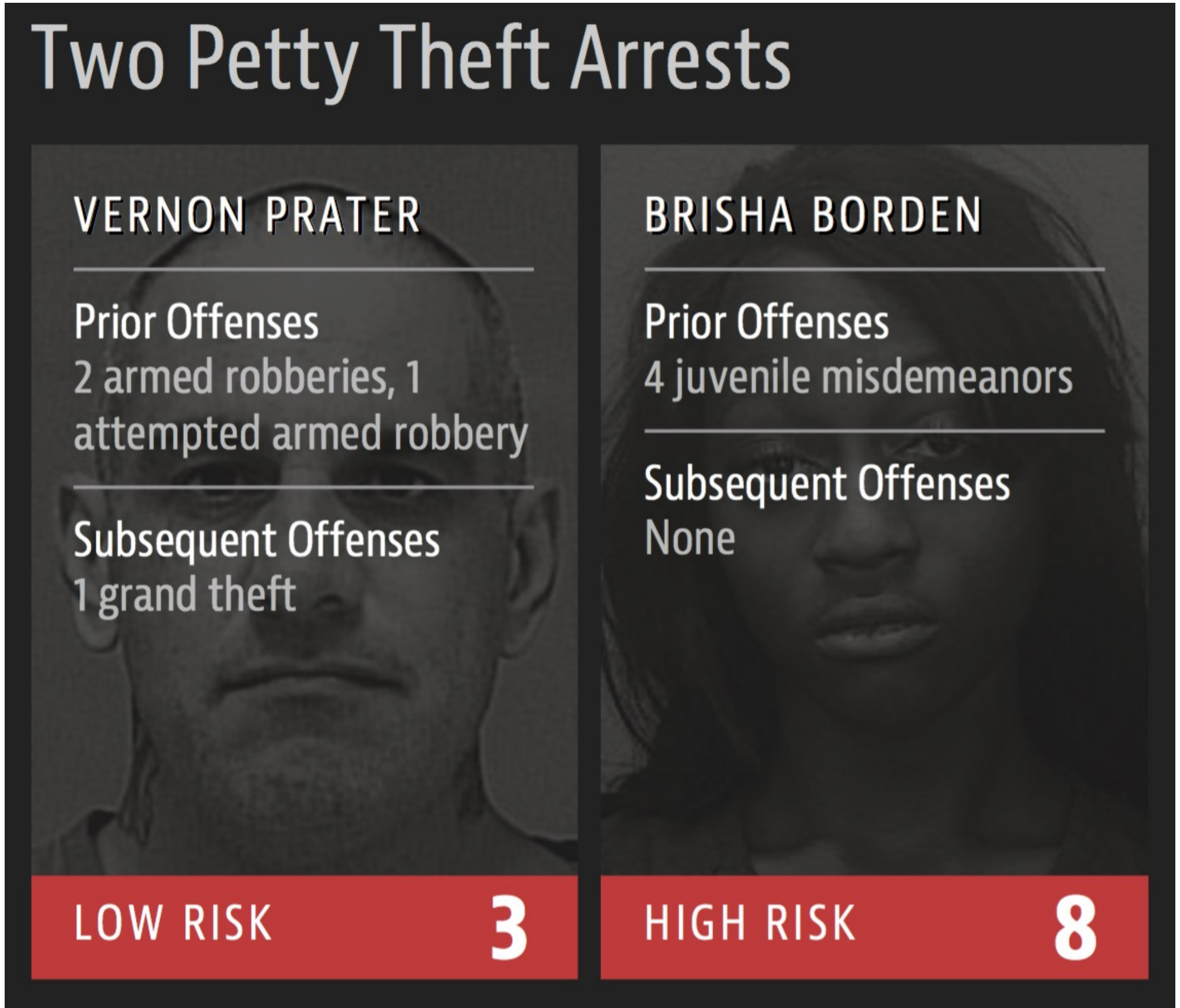
Machine Bias in the

Northpointe COMPAS Algorithm:

What is the likelihood that someone arrested for an $80 misdemeanor) will commit another crime?

by Julia Angwin, Jeff Larson, Surya Mattu & Lauren Kirchner

ProPublica, May 23, 2016



Two Petty Theft Arrests

VERNON PRATER

Prior Offenses
2 armed robberies, 1 attempted armed robbery

Subsequent Offenses
1 grand theft

LOW RISK 3

BRISHA BORDEN

Prior Offenses
4 juvenile misdemeanors

Subsequent Offenses
None

HIGH RISK 8

ProPublica's Method

- Obtained records for 18,000 Broward Cty arrests (2013 & 2014)
- Input data: 137-Q COMPAS questionnaire upon being booked into jail

  Joined these data with individuals' race

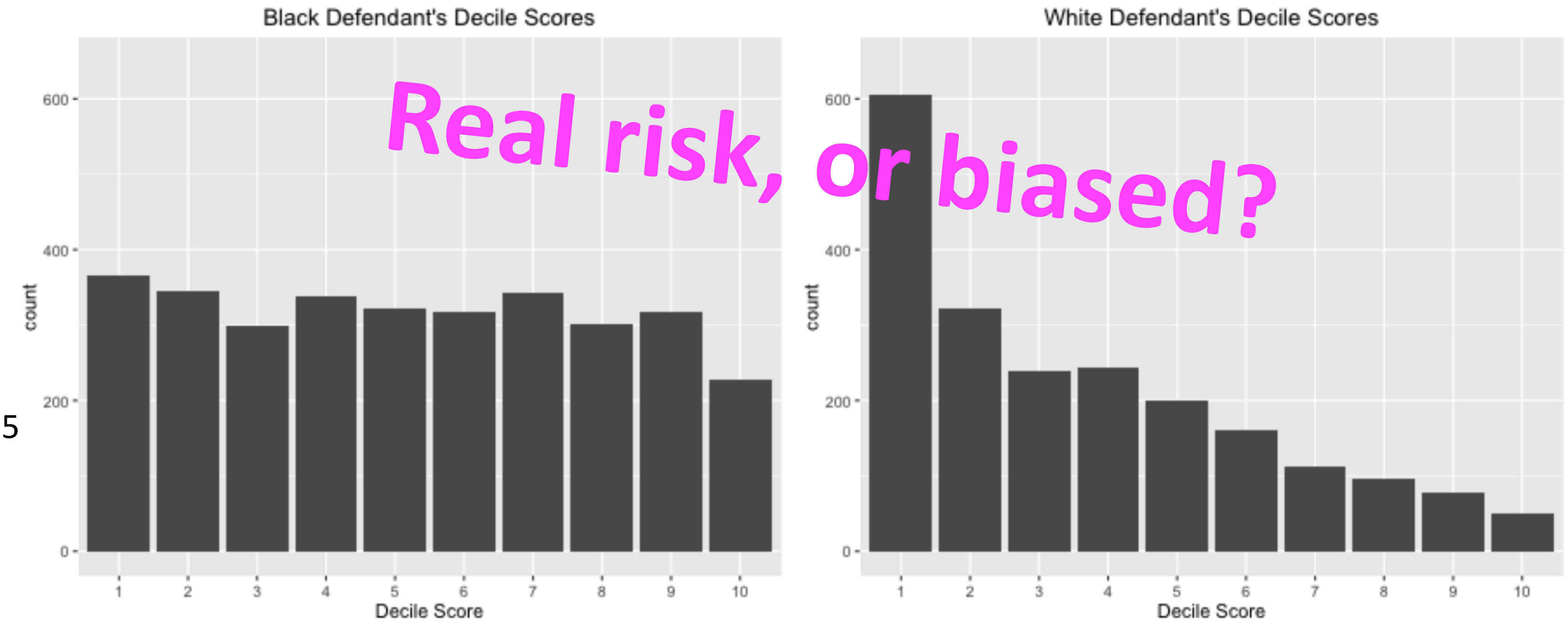
  - Recidivism algorithms do not use race in their ML models (illegal), but *do* use many variables correlated with race or neighborhood
    - When was the first time you were ever involved with the police?
    - Do any of your relatives have criminal records?
    - Are you employed?
    - How long have you lived in your home? How often have you moved?

Proxies!

ProPublica's Method

- Obtained records for 18,000 Broward Cty arrests (2013 & 2014)
- Input data: 137-Q COMPAS questionnaire upon being booked into jail

N=3,175



Real risk, or biased?

N=2,101

ProPublica's Method

- Obtained records for 18,000 Broward Cty arrests (2013 & 2014)
- Input data: 137-Q COMPAS questionnaire upon being booked into jail
- Compared predictions with outcomes (ground truth) over 2 yrs
  - COMPASS was 61% correct in predicting nonviolent recidivism
  - For 7,000 inmates, error rate was roughly equal for Blacks & Whites (39%), so were "well-calibrated"—a common way of defining "fairness"
    - **BUT** **Whites were misclassified as low risk** twice as often as Blacks
    - and **Blacks were misclassified as high risk** twice as often as Whites

		Black Defendants	**White Defendants**
False Positive Rate	(no +crime)	**44.85%**	**23.45%**
False Negative Rate	(+crime)	**27.99%**	**47.72%**

Where *is* the bias in COMPAS?

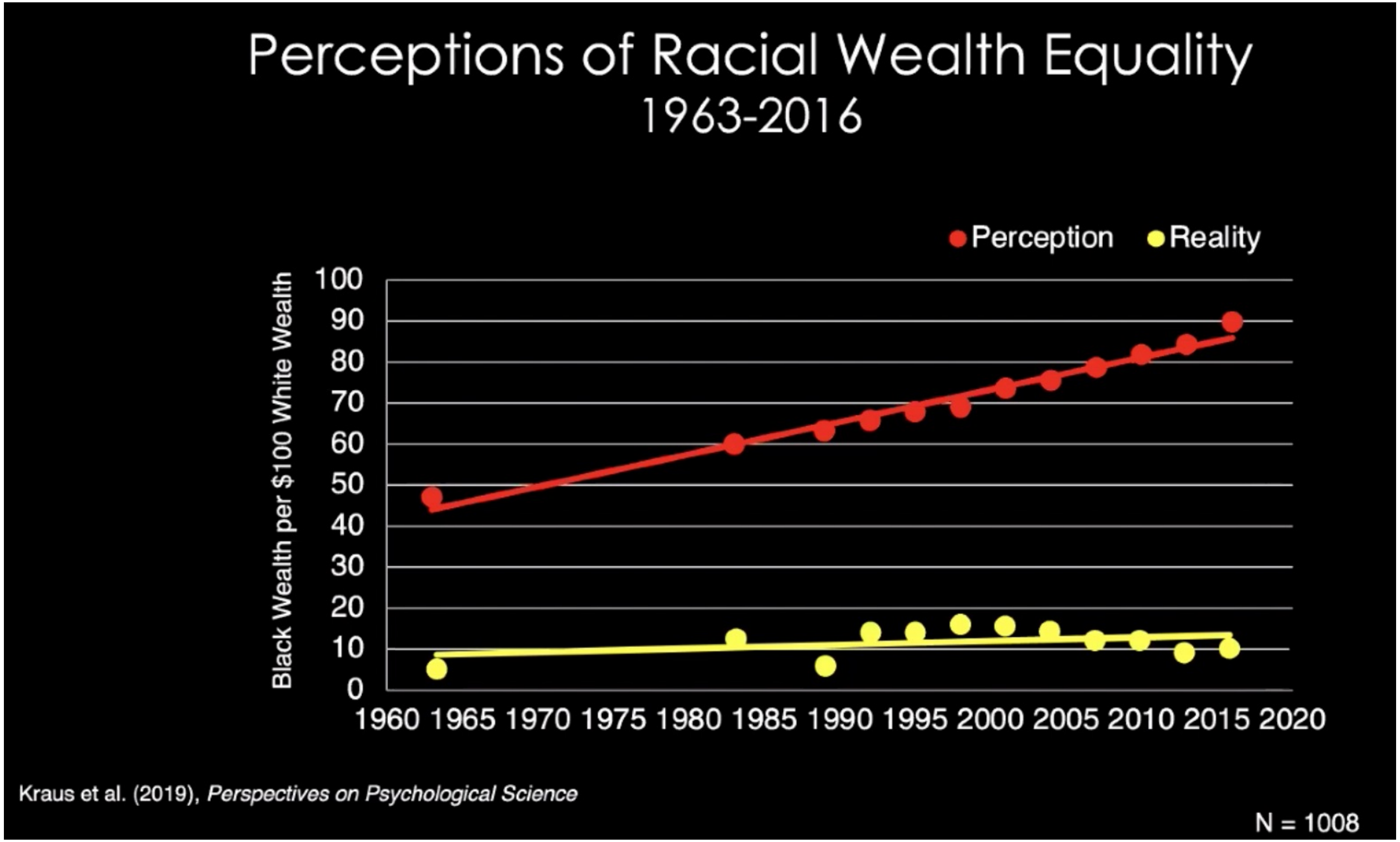
DECIDE

LEARN

PERCEIVE

- In the input data (*PERCEIVE*) – with the use of proxies. *Ignoring* race does not factor it out, but can amount to colorblind racism.
- In the algorithm (*LEARN*) – "well-calibrated" does not mean "fair."
- In its use for decisions – COMPAS was designed to predict recidivism, but has been used for sentencing (even Northpointe agrees this is misguided).
- Policy issue: The biases in COMPAS could be deployed differently:
    - For EVIL: Risk scales filter individuals by a flawed notion of risk to society (unfair).
    - For GOOD: Needs scales can measure the needs of stakeholders, inform case plans, and identify opportunities for intervention and anti-recidivism support

Bias exists simultaneously on multiple levels: *Data* vs. *What People Think about Data*



Kraus et al. (2019), *Perspectives on Psychological Science*

(🡐 The Ground Truth)

Jennifer Richeson & colleagues (2019)

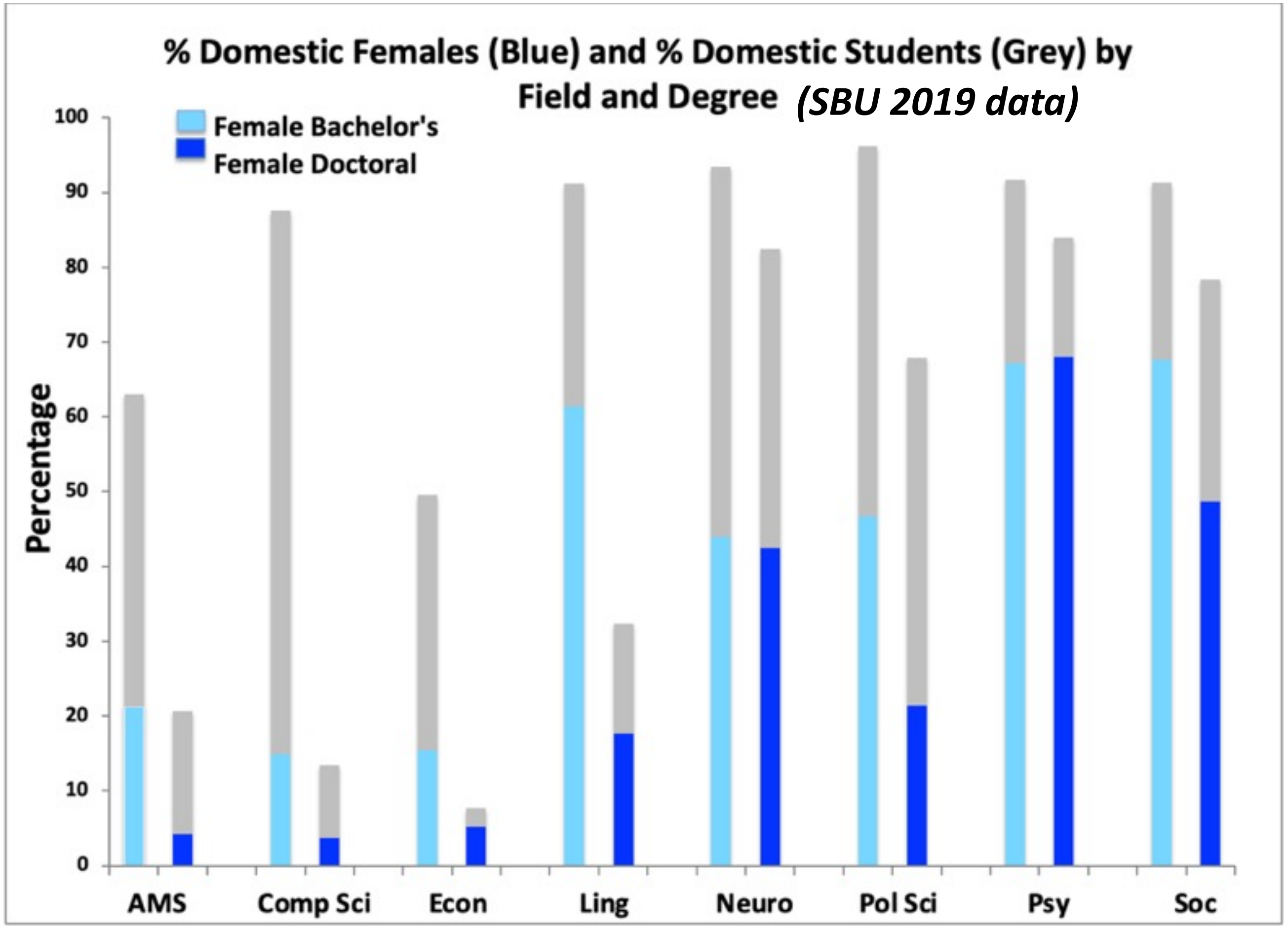
This is why **history** – another word for data – is so very important!

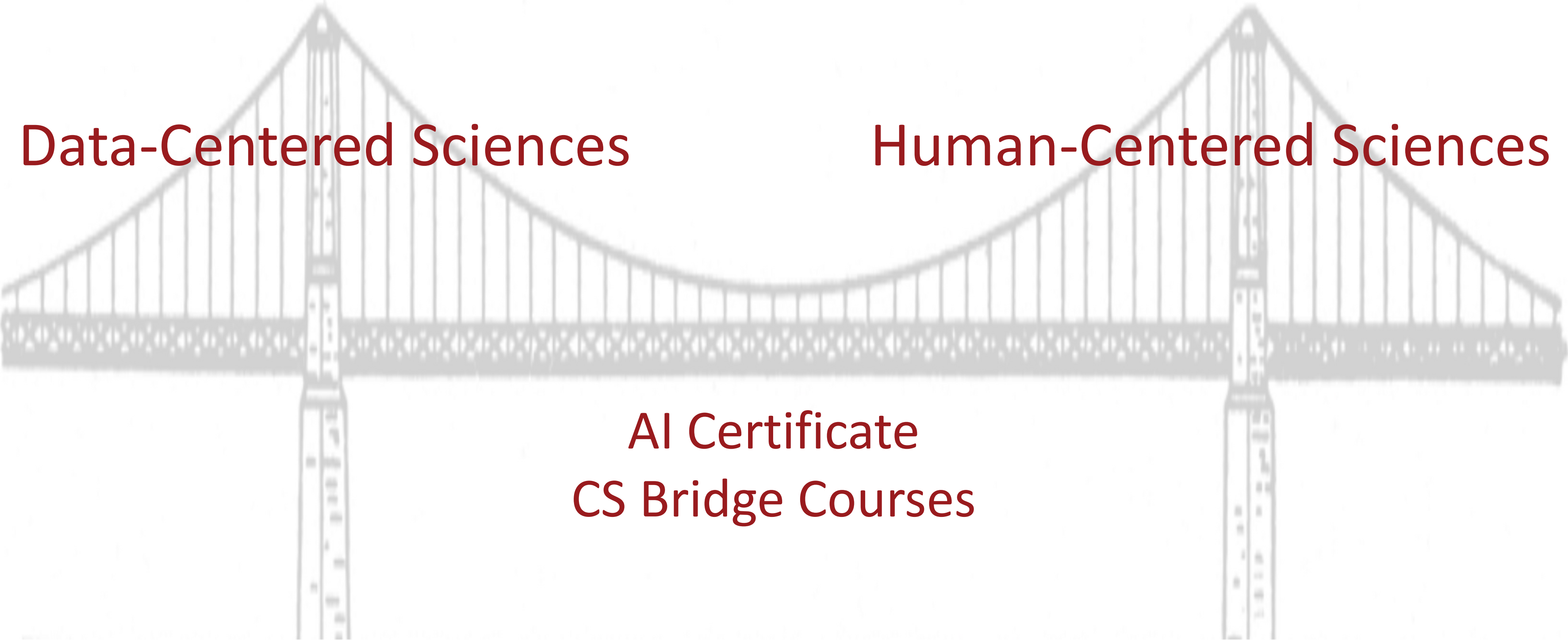
Now, back to the story of our traineeship....

Why are there so few women in our computer science classes?

Where *are* the data scientists?

One program’s challenge can be another program’s solution.





Data-Centered Sciences

Human-Centered Sciences

AI Certificate

CS Bridge Courses

Our NSF Research Traineeship – A timeline

- Feb 6, 2019 – First proposal submitted. Good pedagogical model, but weak theme.
- July 2019 – Declined (encouraging but critical reviews; but proposal was not even discussed)
- Early 2020 competition – Sat this one out; we missed SBU's internal competition deadline

Detecting and Addressing BIAS in Data, Humans, and Institutions

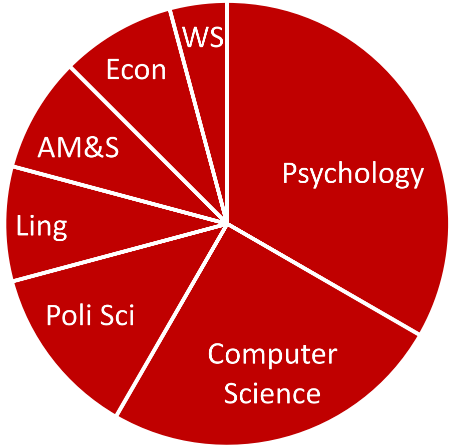
Our NSF Research Traineeship – A timeline

- Feb 6, 2019 – First proposal submitted. Good pedagogical model, but weak theme
- July 2019 – Declined (encouraging but critical reviews; but proposal was not even discussed)
- Early 2020 competition – Sat this one out; we missed SBU's internal competition deadline

- Oct 2020 – With our new (bias) theme, we were selected in SBU's internal competition
- Feb 25, 2021 – Second proposal submitted
- May 27, 2021 (Memorial Day holiday weekend) – We made NSF's short list. With only a week to respond to a set of questions, we were able to flesh out our model and add a Human-Centered Data Science certificate to our curriculum.
- July 12, 2021 – Funding recommended by NSF!
- Sept 1, 2021 – Project start date (unexpectedly, a month early)
- August, 2022 – First cohort of 11 NRT trainees admitted (from 7 graduate programs, 5 depts)
- July, 2023 – Second cohort of 13 NRT trainees admitted (from 9 programs, 7 depts)

Detecting and Addressing
BIAS
in Data, Humans, and Institutions

Features of the Traineeship Model



Convergent Research Practica
Data Science Internships
Cohort-based Training
Bridge Courses
2 Certificates

AI Focus
HCDS Focus

34 Funded Trainees
34 Non-Funded Trainees
Alan Alda Center Courses
Cross-Disciplinary Mentoring
Travel funds

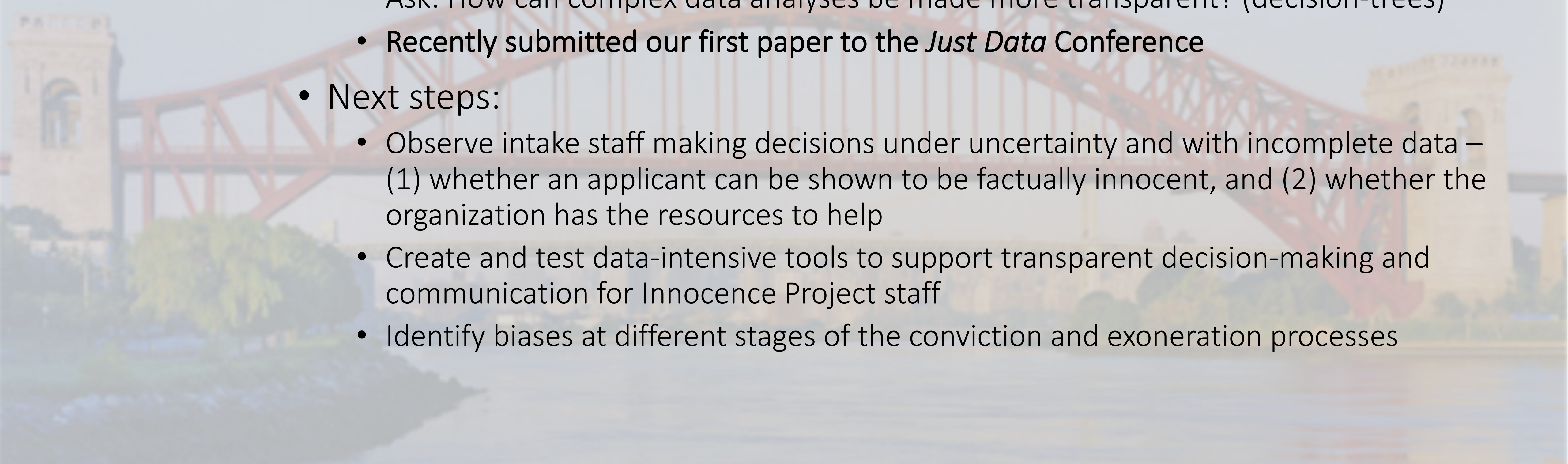
Stony Brook University

This project is based on work supported by NSF Grant #2125295

CONVERGENT RESEARCH PROJECTS

COHORT 1

- *Post-Conviction Project* – with data from the National Registry of Exonerations and advisors from the Innocence Project’s Network
- *Bias in Large Language Models* (especially gender bias; several projects)
- *Bias in Facial Emotion Recognition* (clinical applications)



Post-Conviction Project

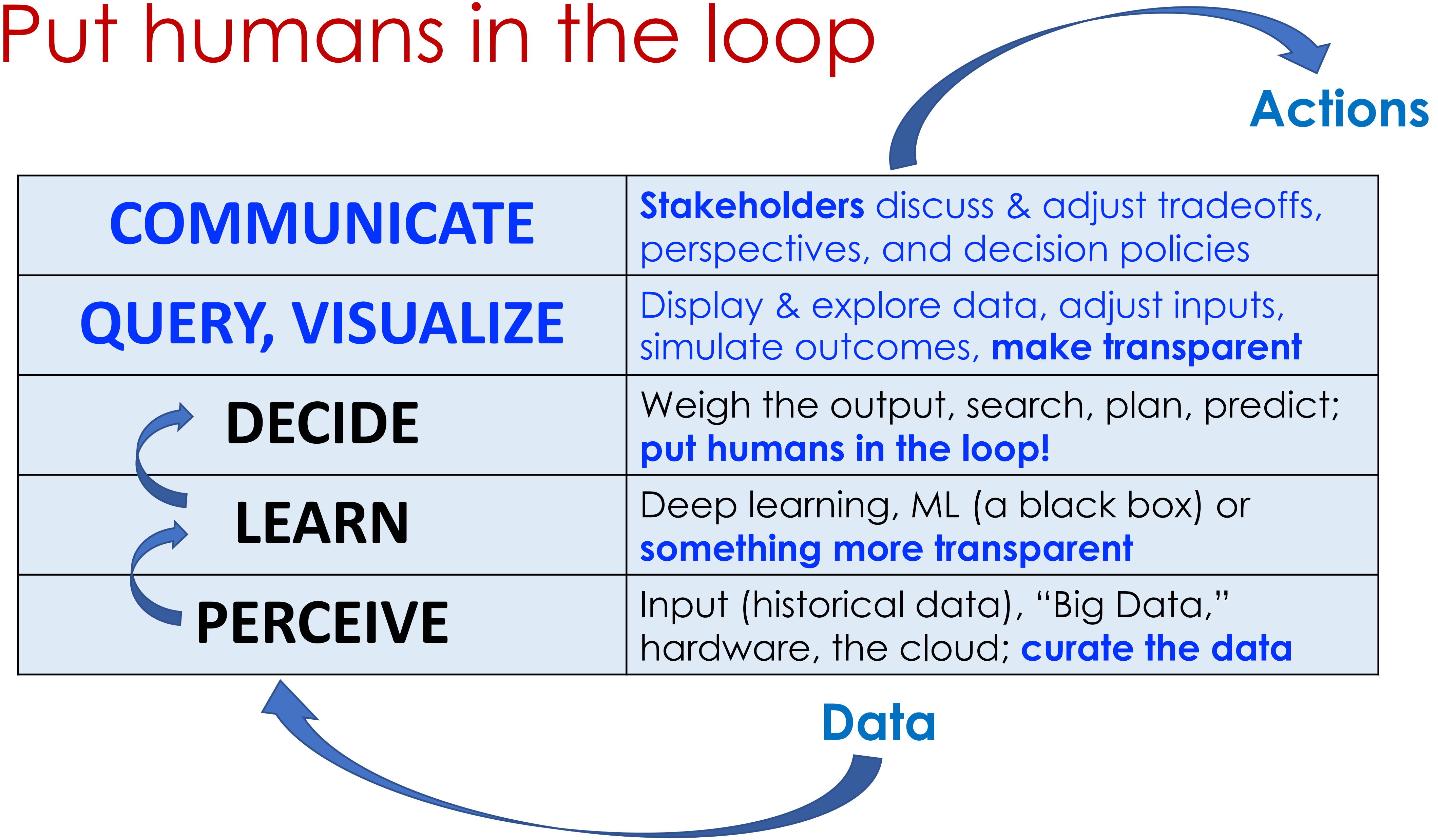
COHORT 1

- Partners: Domain experts (including 4 Innocence Organizations)
- The National Registry of Exonerations – Public facing database with ~3,200 exonerations since 2012; continuously updated
  - Explore factors underlying wrongful conviction and successful exoneration; categorize cases (latent classes) and make predictions
  - Ask: How can complex data analyses be made more transparent? (decision-trees)
  - Recently submitted our first paper to the *Just Data* Conference
- Next steps:
  - Observe intake staff making decisions under uncertainty and with incomplete data – (1) whether an applicant can be shown to be factually innocent, and (2) whether the organization has the resources to help
  - Create and test data-intensive tools to support transparent decision-making and communication for Innocence Project staff
  - Identify biases at different stages of the conviction and exoneration processes

Where is the bias? *In the context of use.* Let’s extend the AI technology stack.

DECIDE	Weigh the output, search, plan, predict
LEARN	Deep learning, ML (a black box) or something more transparent
PERCEIVE	Data input (historical data), “Big Data,” hardware, the cloud

Put humans in the loop



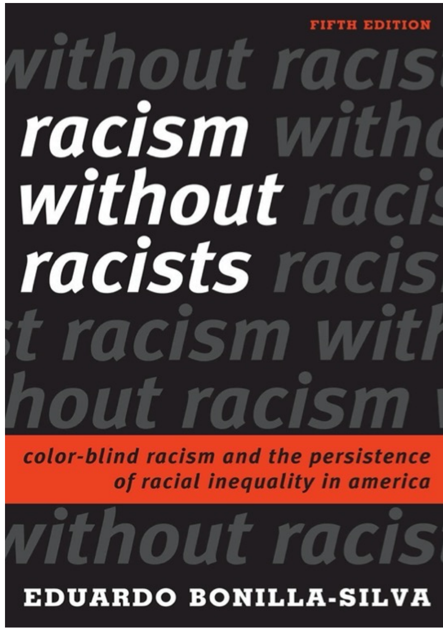
COMMUNICATE	**Stakeholders** discuss & adjust tradeoffs, perspectives, and decision policies
QUERY, VISUALIZE	Display & explore data, adjust inputs, simulate outcomes, **make transparent**
DECIDE	Weigh the output, search, plan, predict; **put humans in the loop!**
LEARN	Deep learning, ML (a black box) or **something more transparent**
PERCEIVE	Input (historical data), "Big Data," hardware, the cloud; **curate the data**

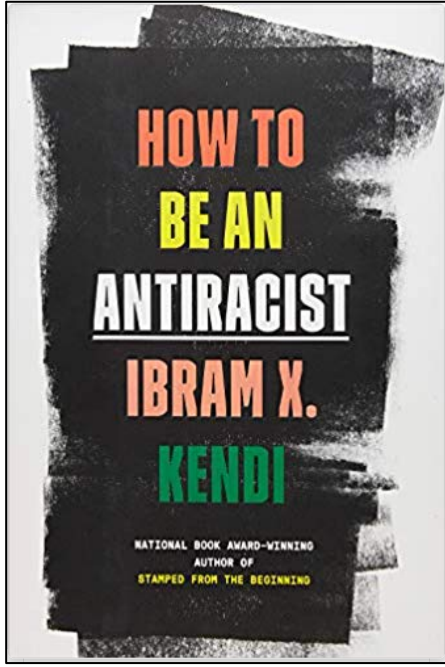
We can’t address bias by ignoring it

- Bias-blindness ignores the strong historical impacts of bias
- Historical impacts are embedded in our institutions and infrastructure (redlining; property tax school funding; healthcare algorithms; and even the LI highway system)
- Color- (or gender-) blindness makes Whiteness (or maleness) the norm, and everyone else, the exception.

Addressing bias is even harder than detecting it.

- As scientists, we’re equipped to *detect* bias w.r.t. a particular context.
- It’s much more difficult to *address* bias; that depends on values, goals, policies, and the ability to effect change.


FIFTH EDITION
racism without racists
color-blind racism and the persistence of racial inequality in america
EDUARDO BONILLA-SILVA


HOW TO BE AN ANTIRACIST
IBRAM X. KENDI
NATIONAL BOOK AWARD-WINNING AUTHOR OF
STAMPED FROM THE BEGINNING

We can’t address bias by ignoring it

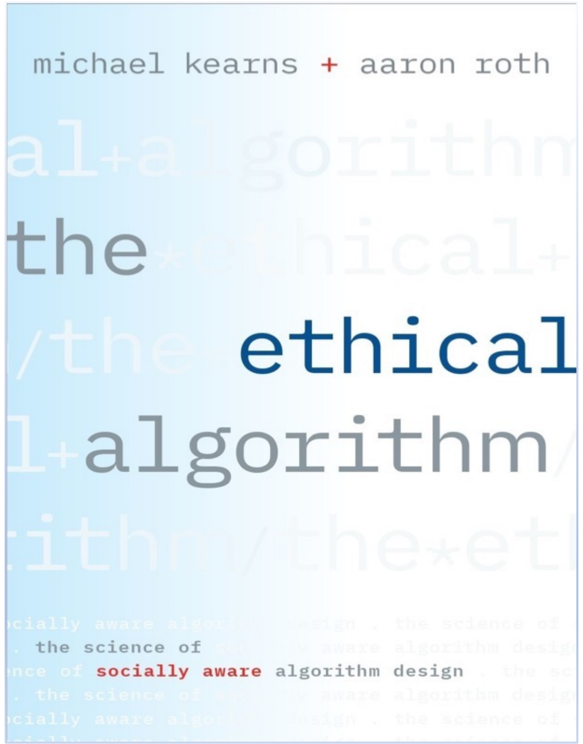
“The only way out of this morass—for all of us—is to stare at racial disparity unblinkingly, and then do what evidence and experts tell us is required to level the playing field and march forward together, collectively striving to achieve true equality for all Americans.”

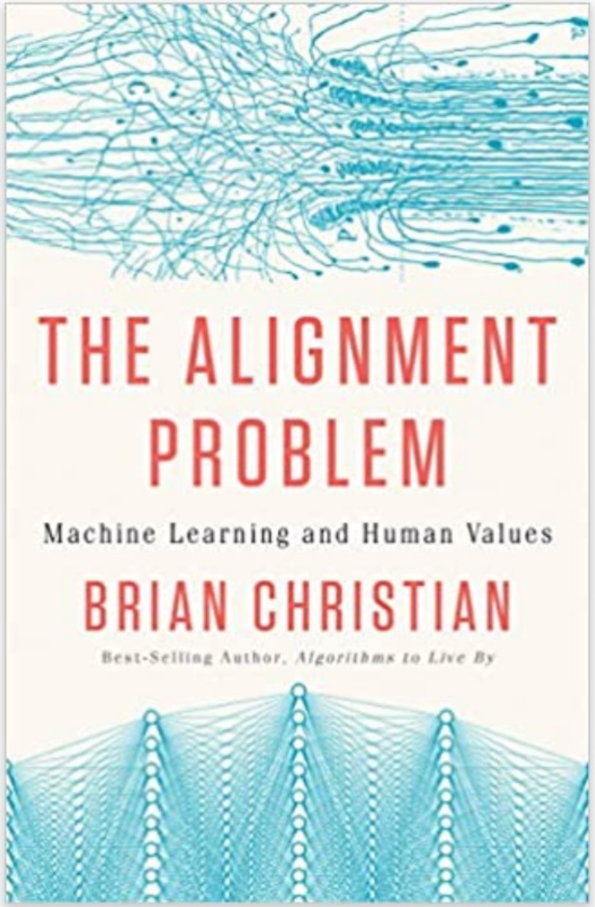
Judge K. B. Jackson’s dissent in 21–707, SFFA Inc. v. UNC, p. 26

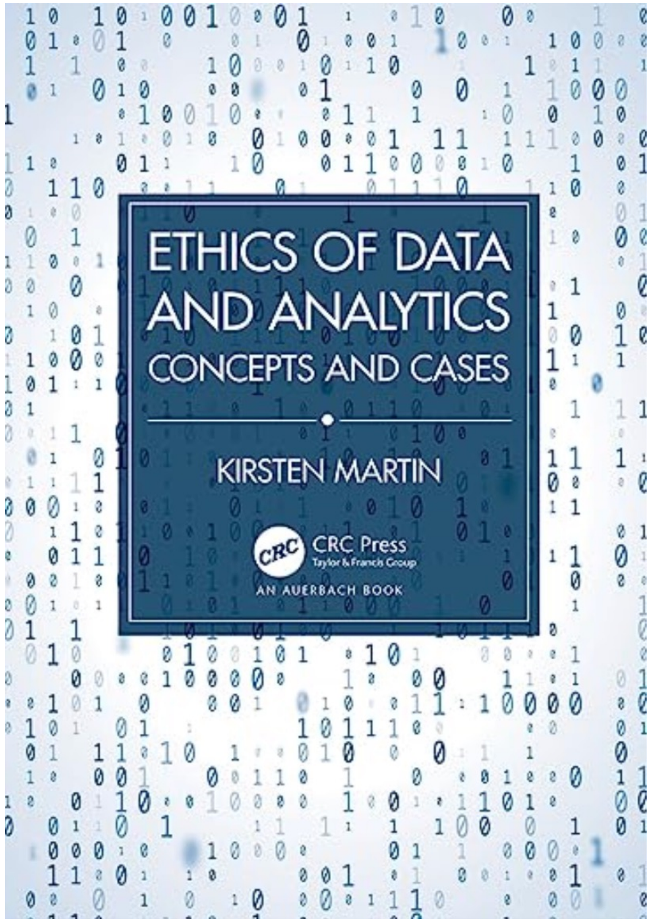
How can we get to **accountability** for AI? Training in data science should include auditing datasets and algorithms for bias

- Auditing for bias should consider the algorithm’s broad contexts of use.
- It should involve stakeholders—not just developers and those with power.
- Establish clear and transparent standards, without COI (tech can’t monitor itself).
- Don’t ask if AI is good or fair—ask how it shifts power (Kalluri, 2020, *Nature*)
- See also Timnit Gebru et al.’s work (incl. *Stochastic Parrot* and *Datasheets* papers)
- Auditing adaptive algorithms is itself quite a research problem! Policy and science need to work together on this.

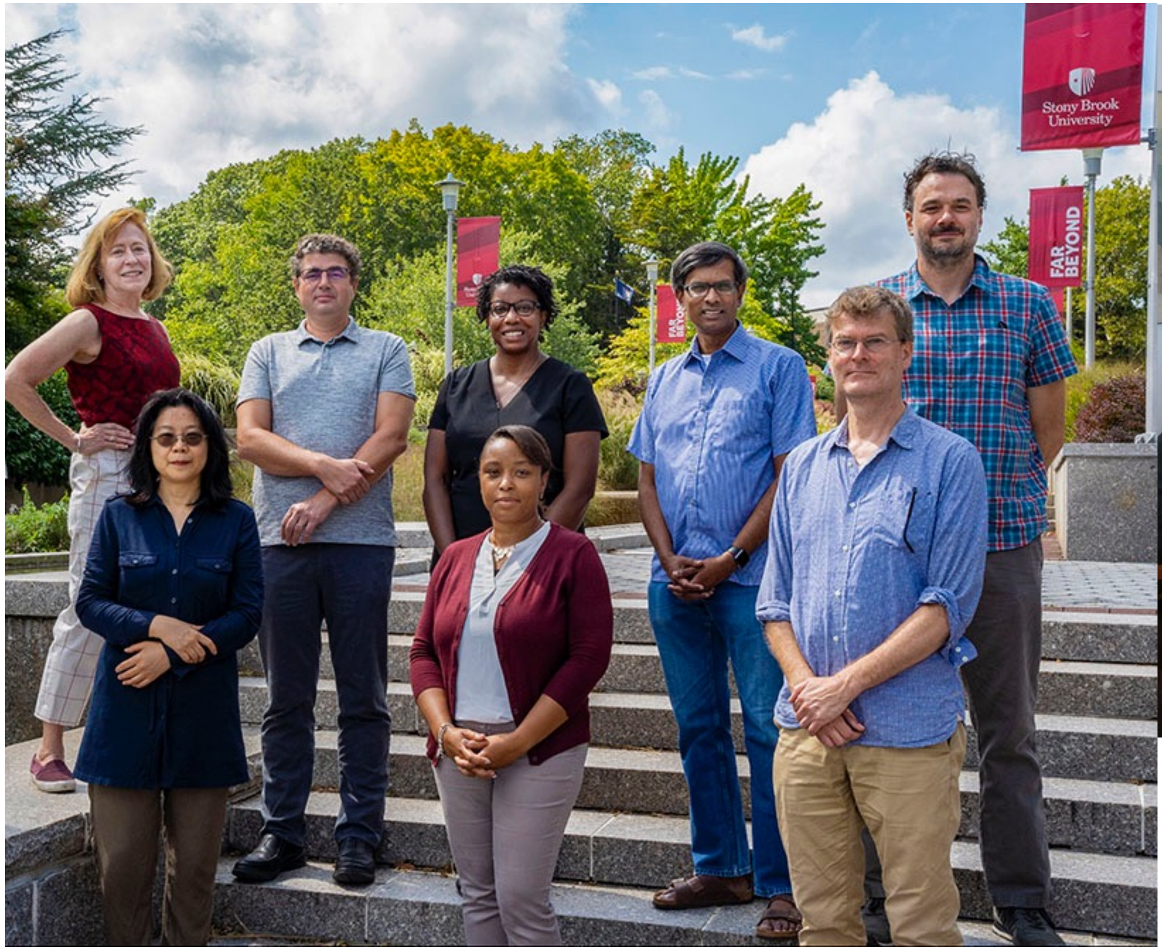
Resources and Inspiration:


michael kearns + aaron roth
the ethical algorithm
the science of socially aware algorithm design


THE ALIGNMENT PROBLEM
Machine Learning and Human Values
BRIAN CHRISTIAN
Best-Selling Author, Algorithms to Live By



Thanks!



Stony Brook University

This project is based on work supported by NSF Grant #2125295