



Data Feminism

D'Ignazio, C. & Klein, L. F. (2020).

Autumn 2020:
TGIS 502 Intro to Geospatial Technology
Slides by:
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Crowsa Luxembourg

@quendergeer



It's only toxic masculinity if you
ingest it, otherwise it's venomous
masculinity

5:34 PM · Oct 10, 2020 · Twitter Web App

6.3K Retweets **84** Quote Tweets **38.6K** Likes

#ToxicMasculinity

Ch1 - The Power Chapter

(Examine Power / Matrix of Domination)

Ch2 - Collect, Analyze, Imagine, Teach

(Challenge Power)

Ch3 - On Rational, Scientific, Objective Viewpoints from Mythical, Imaginary Impossible Stanpoints.

(Elevate Emotion and Embodiment)

Ch4 - What Gets Counted Counts

(Rethink Binaries and Hierarchies)

Break-time!

Ch5 - Unicorns, Janitors, Ninjas, Wizards, and Rock Stars

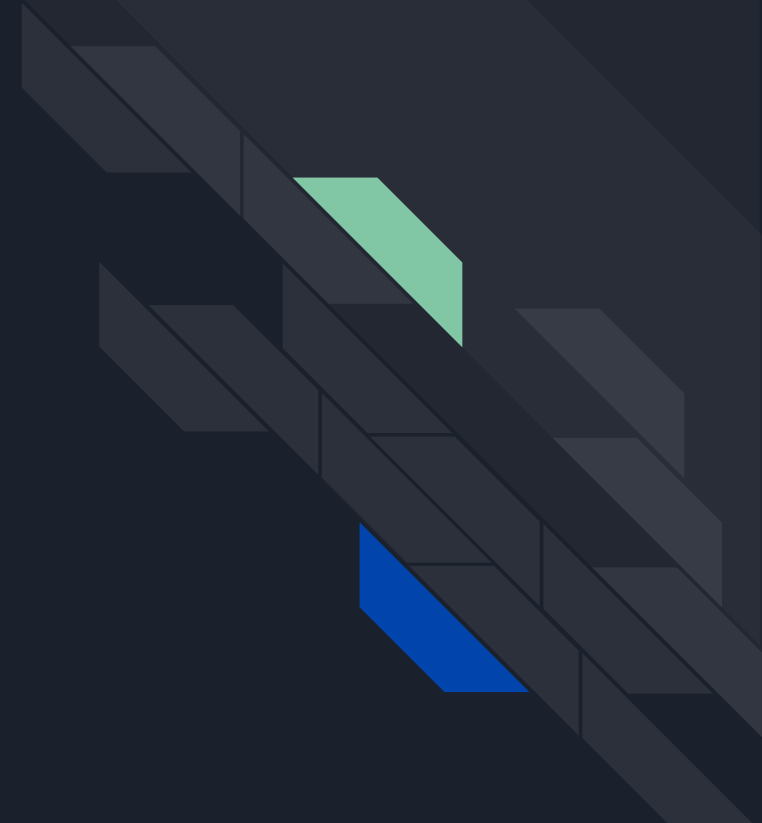
(Embrace Pluralism)

Ch6 - The Numbers Don't Speak for Themselves

(Consider Context)

Ch7 - Show your work

(Make Labor Visible)





Introduction & The Power Chapter

Examine Power / Matrix of Domination

Christine Mann Darden & Serena Williams examples (p. 1/21)

- The importance of Self Advocating
- The importance of Evidence

Disciplinary Domain of Laws and Policy (p. 36)

- Deferral of Responsibility

“Whose goals are prioritized?” (p. 41)

- “...the cloud is not light and it is not airy. And the cloud is not cheap.” (p. 42)
- “The new oil” (p. 45)
- Privilege hazard (p. 47)



Notable Passages/Images:

“What we choose to measure is a statement of what we value in health...We might edit his statement to add that it’s a measure of *who* we value in health, too.” (p. 23)

“...the biggest threat from artificial intelligence systems is not that they will become smarter than humans, but rather that they will hard-code sexism, racism, and other forms of discrimination into the digital infrastructure of our societies.” (p. 29)

“Far too often, the problem is not that data about minoritized groups are missing but the reverse: the databases and data systems of powerful institutions are built on the excessive surveillance of minoritized groups.” (p. 39)

Maximizing Profit over People?



If a main goal for data is for *science, surveillance, and selling*; then what other purposes are going underserved?



Collect, Analyze, Imagine, Teach

Challenging Power

Co-liberation (p. 63)

- “Counterdata” (p. 72)
- “...it is important to remember that minoritized individuals and groups should not have to repeatedly prove that their experiences of oppression are real.” (p. 72)

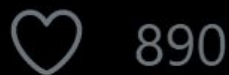
Data Ethics(or Equality?) vs. Data Justice (or Equitable) (p. 61-62)

- What is the significance of observing ‘redlining’ practices, when considering cartographic history? (p. 50)
- “Workplace Sexism” (p. 56)
- “Deficit narratives” (p. 58)



Annabelle 7 @Annabllebitch · 8m

Twitter broken ? Men ain't shit



Jigsaw 7 @FineAssJigsaw · 8m

Ummm... got nothing to do with men but go off 👍





Notable Passages/Images:

“Challenging power requires mobilizing data science to push back against existing and unequal power structures and to work toward more just and equitable futures” (p. 53)

“They had no need to prove to their own communities that structural racism was a factor in these deaths. Rather, their goal in partnering with the DGEI was to prove the structural nature of the problem to those in positions of power.” (p. 57)

“The key to co-liberation is that it requires a commitment to and a belief in mutual benefit, from members of both dominant groups and minoritized groups; that’s the co in the term.” (p. 63)

Risk Assessment Bias

Shoplifted \$86.35 worth of tools

VERNON PRATER

Prior Offenses

2 armed robberies, 1
attempted armed
robbery

Subsequent Offenses

1 grand theft

LOW RISK

3

"Borrowed" bike and scooter, \$80 in worth

BRISHA BORDEN

Prior Offenses

4 juvenile
misdemeanors


Subsequent Offenses

None

HIGH RISK

8

Who was *ranked* Higher Risk by the algorithm?



On Rational, Scientific, Objective Viewpoints from Mythical, Imaginary Impossible Stanpoints.

Embrace Emotion and Embodiment

With whom should we consider the values of “respect, responsibility, and reciprocity” (p. 92)

- Why is “The God Trick” frowned upon by contemporaries? (p. 76)

Data Visualization vs Data Viseralization

- “If there is any single rule in design, it’s that context is queen.” (p. 91)



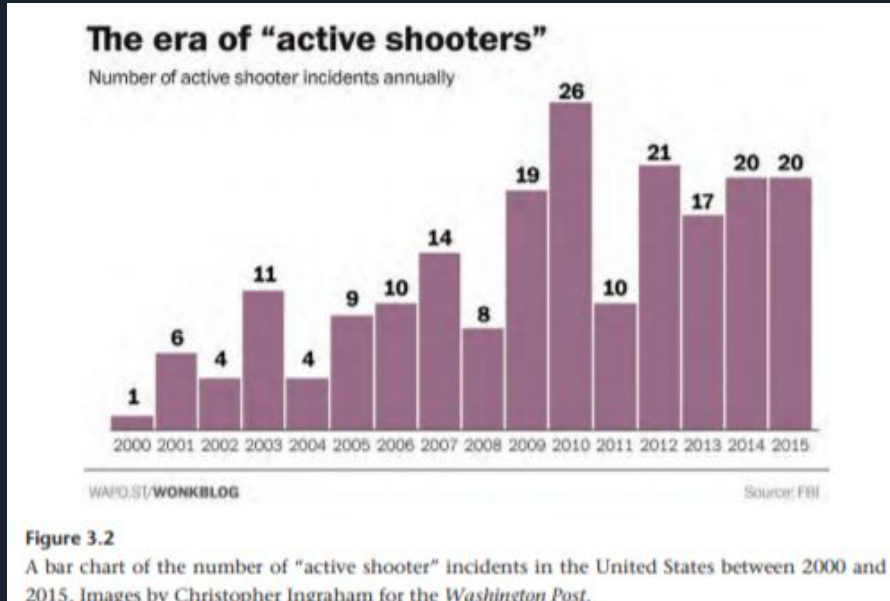
Notable Passages/Images:

“This is largely due to the influence of one man:... Tufte invented a metric for measuring the amount of superfluous information included in a chart. He called it the *data-ink ratio*.” (p. 76)

“...activating emotion, leveraging embodiment, and creating novel presentation forms help people grasp and learn more from data-driven arguments, as well as remember them more fully.” (p. 88)

“...*leverage emotion and affect* so that people experience uncertainty perceptually. Or, to invoke a common refrain from rhetorical training and design schools, ‘show, don’t tell.’ Rather than *telling* people that they are looking at uncertainty while employing a certain-looking graphic style... make them *feel* the uncertainty.” (p. 90)

Data Visualization vs. Data Visceralization



How does Figure 3.1 affect our emotions than more Figure 3.2?



What Gets Counted Counts

Rethinking Binaries and Hierarchies

“Binary choice” (p. 97)

- Is abolition an option? (p. 100)
- Thomas Jefferson “all men” (p. 102)
- Pockets (p. 108)
- Breast pumps (p. 120)

Paradox of Exposure (p. 105)

- Administrative violence (p. 106)
- White Abolitionist and Black Activists (p. 118)



Notable Passages/Images:

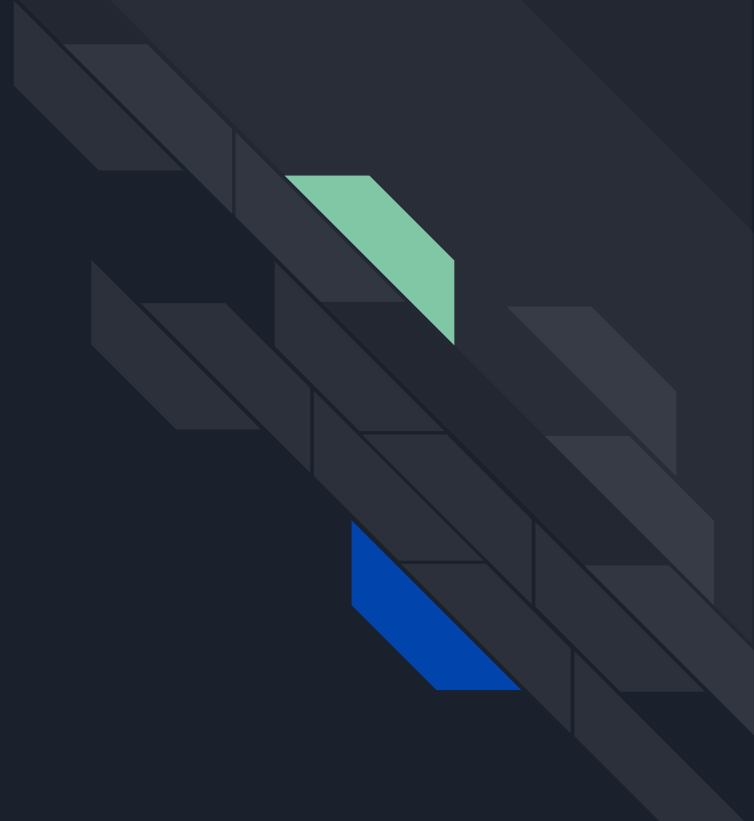
“...they call for ‘hacking’ the Black/white binary that, on the one hand, helps to expose the racism experienced by Black people in the United States and, on the other, erases the other forms of racism experienced by Indigenous as well as Latinx, Asian American, and other minoritized groups. ‘Binary racial discourses elide our struggles for justice,’ (p. 111)

“...undertaken deliberately, tailored to specific goals, and with issues of privacy and potential harms always in mind, counting can be used to support accountability—as one method, among many, of working toward a larger goal.” (p. 122)

“...rethink the assumptions and beliefs behind our classification infrastructure, as well as consistently probe who is doing the counting and whose interests are served. Counting and measuring do not always have to be tools of oppression.” (p. 123)

What does this mean to
you?:

“...creating new
knowledge and new
designs from the
margins.” (p. 139)





jules

@limbobitch


me: i hate boss bitch feminism

me 5 mins later: ME AND THE BESTIE 😊



9:20 AM · Oct 13, 2020 · Twitter for iPhone

Break-time!



Unicorns, Janitors, Ninjas, Wizards, and Rock Stars

Embracing Pluralism

Co-liberation:

“Community science projects” (p. 142)

“grounded in the belief that enduring and asymmetrical power relations among social groups serve as the root cause of many societal problems.” (p. 141)

Data Sets vs. Data Settings (p. 132)

- Epistemic violence (p. 133)
- Transparency and Reflexivity (p. 137)



@tintangdilaw



And while we're still at it, remind ko lang na feminism isn't about loving women then hating men. We seek equal rights for both men and women in this patriarchal society, a society that we actually need to destroy. Twitter feminism really is confusing most of the times.

9:15 PM · Oct 13, 2020 · Twitter for Android

#Co-liberation #Abolition #Patriarchy



Notable Passages/Images:

“ We take this to mean that there is a way to build space for transparency plus reflexivity in data science, rather than undertaking projects that purport to be objective. Transparency and reflexivity allow the people involved in any particular project to be explicit about the methods behind their project, as well as their own identities.” (p. 136)

“Rather than framing acts of technical service as benevolence or charity, the goal of co-liberation requires that those technical workers acknowledge that they are engaged in a struggle for their own liberation as well, even and especially when they are members of dominant groups.” (p. 141)

“This means transferring knowledge from experts to communities and explicitly cultivating community solidarity in data work.” (p. 148)

Implicit-Association Test

Arab-Muslim IAT	<i>Arab-Muslim</i> ('Arab Muslim - Other People' IAT). This IAT requires the ability to distinguish names that are likely to belong to Arab-Muslims versus people of other nationalities or religions.
Sexuality IAT	<i>Sexuality</i> ('Gay - Straight' IAT). This IAT requires the ability to distinguish words and symbols representing gay and straight people. It often reveals an automatic preference for straight relative to gay people.
Disability IAT	<i>Disability</i> ('Disabled - Abled' IAT). This IAT requires the ability to recognize symbols representing abled and disabled individuals.
Presidents IAT	<i>Presidents</i> ('Presidential Popularity' IAT). This IAT requires the ability to recognize photos of Donald Trump and one or more previous presidents.
Gender-Career IAT	<i>Gender - Career</i> . This IAT often reveals a relative link between family and females and between career and males.
Transgender IAT	<i>Transgender</i> ('Transgender People - Cisgender People' IAT). This IAT requires the ability to distinguish photos of transgender celebrity faces from photos of cisgender celebrity faces.
Weapons IAT	<i>Weapons</i> ('Weapons - Harmless Objects' IAT). This IAT requires the ability to recognize White and Black faces, and images of weapons or harmless objects.
Skin-tone IAT	<i>Skin-tone</i> ('Light Skin - Dark Skin' IAT). This IAT requires the ability to recognize light and dark-skinned faces. It often reveals an automatic preference for light-skin relative to dark-skin.
Gender-Science IAT	<i>Gender - Science</i> . This IAT often reveals a relative link between liberal arts and females and between science and males.
Religion IAT	<i>Religion</i> ('Religions' IAT). This IAT requires some familiarity with religious terms from various world religions.
Weight IAT	<i>Weight</i> ('Fat - Thin' IAT). This IAT requires the ability to distinguish faces of people who are obese and people who are thin. It often reveals an automatic preference for thin people relative to fat people.
Native IAT	<i>Native American</i> ('Native - White American' IAT). This IAT requires the ability to recognize White and Native American faces in either classic or modern dress, and the names of places that are either American or Foreign in origin.
Asian IAT	<i>Asian American</i> ('Asian - European American' IAT). This IAT requires the ability to recognize White and Asian-American faces, and images of places that are either American or Foreign in origin.
Age IAT	<i>Age</i> ('Young - Old' IAT). This IAT requires the ability to distinguish old from young faces. This test often indicates that Americans have automatic preference for young over old.
Race IAT	<i>Race</i> ('Black - White' IAT). This IAT requires the ability to distinguish faces of European and African origin. It indicates that most Americans have an automatic preference for white over black.

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How can assessing our own bias be beneficial for transparency and reflexivity in data science?



The Numbers Don't Speak for Themselves

Consider Context

- BDData (p. 151)
- Statistical inference (p. 156)
- Open data & Zombie data (p. 155)

Rape Culture (p. 157)

- Underreporting on campus
- Thomas Jefferson “founding foodie” (p. 160)

“Raw data is an oxymoron” (p. 159)



Notable Passages/Images:

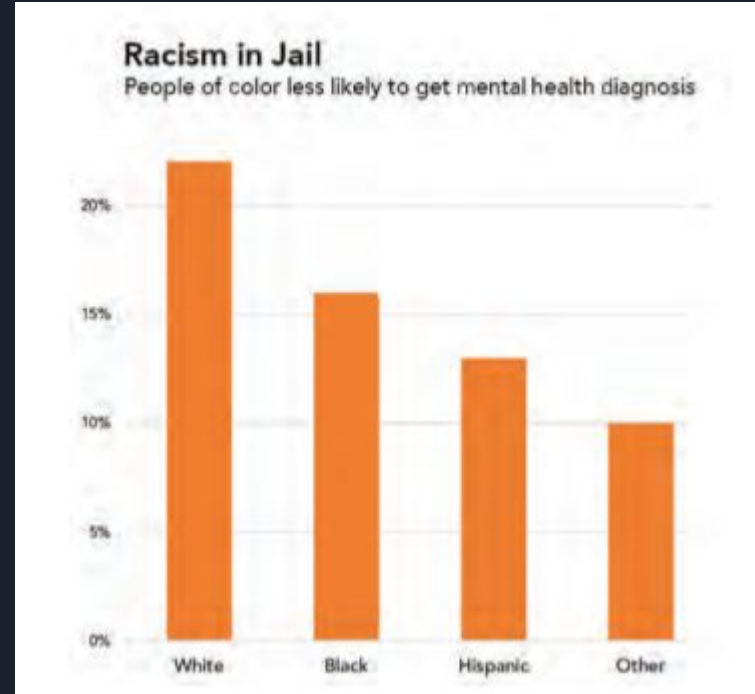
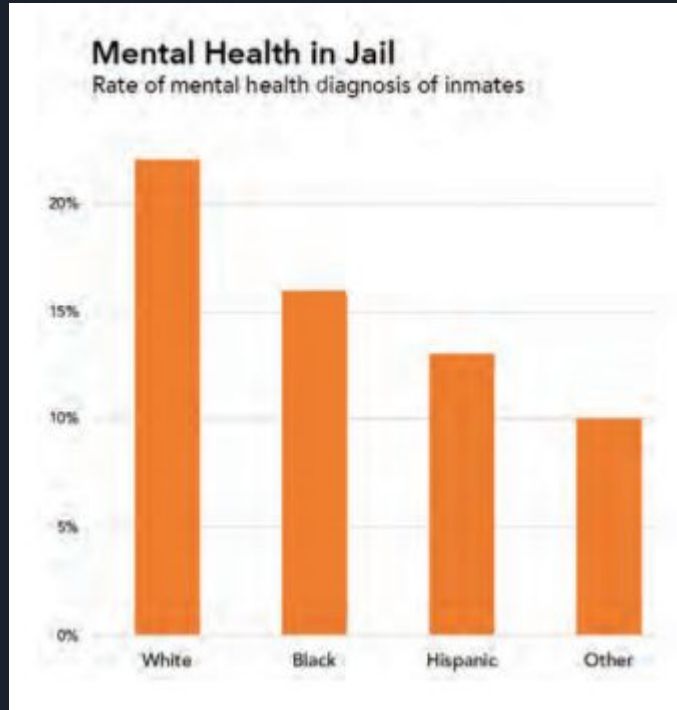
“Exploring and analyzing what is missing from a dataset is a powerful way to gain insight into the cooking process—of both the data and of the phenomenon it purports to represent.” (p. 160)

“Refusing to acknowledge context is a power play to avoid power. It’s a way to assert authoritativeness and mastery without being required to address the complexity of what the data actually represent...” (p. 162)

“Naming these structural forces may be the most effective way to communicate broad context.” (p. 166)

“The energy around context, metadata, and provenance is impressive, but until we fund context, then excellent contextual work will remain the exception rather than the norm.” (p. 172)

Same Data, Different Context



How does these two different portrayals change your *perception of the data*?

WHITE COLLAR CRIME RISK ZONES

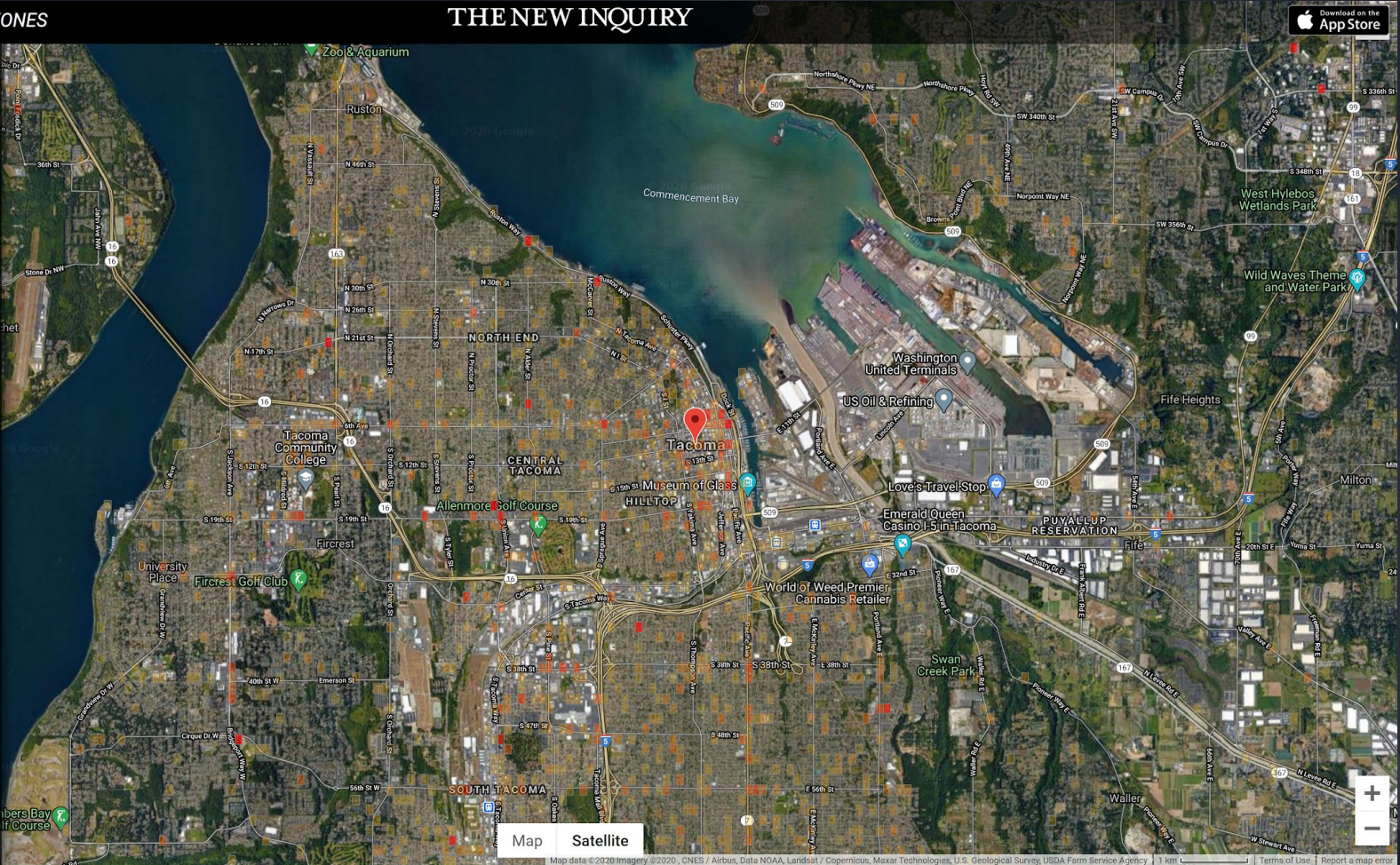
White Collar Crime Risk Zones uses machine learning to predict where financial crimes are most likely to occur across the US. To learn about our methodology, read our [white paper](#).

By [Brian Clifton](#), [Sam Lavigne](#) and [Francis Tseng](#) for *The New Inquiry Magazine*, Vol. 59: [ABOLISH](#).

Tacoma, WA

Search

THE NEW INQUIRY





Show Your Work

Make Labor Visible

“Ghost work” (p. 183)

- The Zong, Capitalism & Slavery (p. 183)
 - Insurance & Money, over human life?

Infor-Maintenance & Care-work: Cultural and Emotional, tolls and costs

- Affective Labor: What does your work show you / what do ‘they’ see? (p. 193)



Notable Passages/Images:

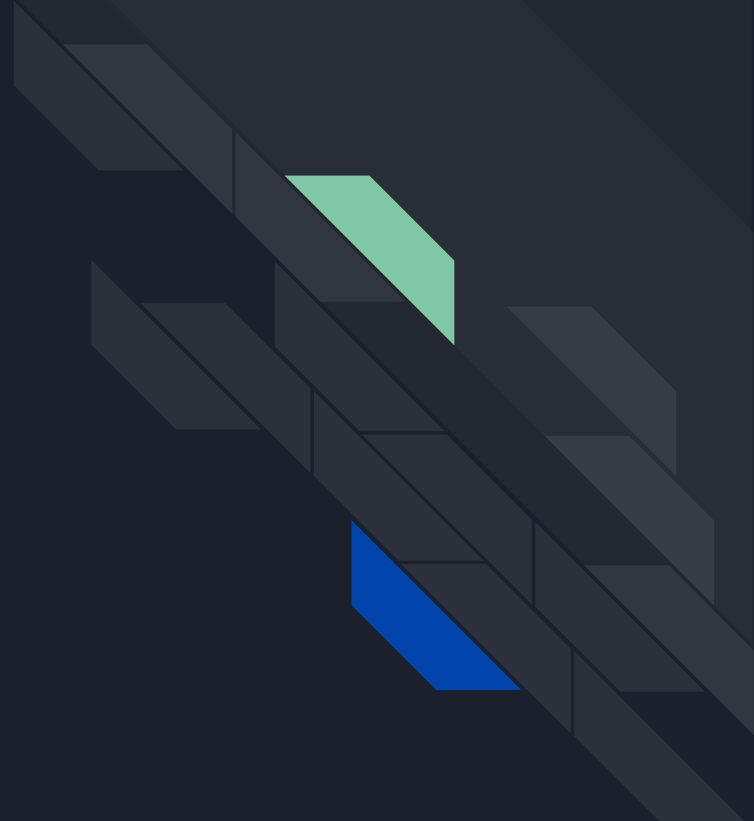
“ The humanitarian and ecological stakes of our attachments to data and technology cannot be higher, nor can their source be any more clear: the capitalist and colonial forces that encourage the exploitation of Black and brown bodies so that white bodies can thrive.” (p. 184)

“...we can also begin to carve out additional space for the scholars, journalists, and other researchers who are explicitly studying the labor of data science—those who are examining and challenging the power by tracing visualizations and algorithms and bots back to their human and material sources.” (p. 184)

“Showing the work is crucial to ensure that undervalued and invisible labor receives the credit it deserves, as well as to understand the true cost and planetary consequences of data work” (p. 201)

What does this mean to
you?:

“...the work of data
entry is profoundly
undervalued in
proportion to the
knowledge it helps to
create.” (p. 181)





Conclusion

“These paltry actions, clearly motivated by the bottom line, underscore the unyielding influence of profit and power and the need for a feminism that is intersectional as a matter of course.” (p. 207)

“We will need all of them for mobilizing resistance to the differentials of power embedded in our current datasets and data systems. ...to imagine what data science and artificial intelligence beyond the matrix of domination might look like.” (p. 214)

Credits / Final Discussion!



D'Ignazio, C. & Klein, L. F. (2020). *Data Feminism*. Cambridge, Massachusetts: The MIT Press.