



Automating Inequality

By: Virginia Eubanks

About the Author



- Ph.D. in Science and Technology Studies from Rensselaer Polytechnic Institute
- Virginia Eubanks is an Associate Professor of Political Science at the University at Albany, SUNY
- She has written / edited 3 separate books about technology and social justice and has published in a multitude of magazines.
- She is a co-founder of Popular Technology Workshops, where people come together and discuss the injustices of the information age.
- She is a founding member of the Our Data Bodies Project, a group that studies how “communities’ digital information is collected, stored, and shared by government and corporations”
- She is from Troy, NY.



Introduction

- *Automating Inequality* focuses on the transition of various government assistance programs from solely human decision making to using predictive models and algorithms
- All of the programs discussed have changed drastically over the past decade due to the increase in automated decision making
- Her research was gathered by conducting interviews with many families that have been affected, caseworkers, activists, policy-makers, and more
- Overall, one common factor in these systems is the amount of data that they gather on poor and working-class people, with little regard for privacy or data security
- Additionally, these algorithms often provide less insight and flexibility in the decision making process - for example when an individual is denied assistance based on an algorithm's decision, they cannot easily call a caseworker and determine the cause



History

From Poorhouse to Database

- Before going into the case studies of specific systems, Eubanks provides some background on how poor and working-class people have been discriminated against and had their privacy invaded throughout American history
- First, in the mid 1800s, many cities constructed “poorhouses”, establishments that were meant to house the elderly, disabled, mentally ill, or unable to find work for various reasons. These establishments stripped their inmates of civil rights such as being able to vote, marry, or hold office. The majority had terrible living conditions, and exploited the individuals who lived there.
- Throughout the book, Eubanks compares the data stores for current government assistance algorithmic decision making models to “digital poorhouses”, designed to “profile, police, and punish the poor”



History continued

- Throughout the rest of the history of welfare in America, there have been various attempts to separate the “deserving poor” from the “undeserving” - depending on the time, what qualifies as deserving varies, is it those who need temporary relief to get back on their feet, or those who will require permanent assistance? This is also split based on discrimination based on race, gender, etc., or on moral grounds
- Done with good intentions - there are not enough public resources to help everyone in need, so we attempt to filter people in order to help the most needy
- Some tactics make the process of applying for aid more complicated so that people are diverted along the way
- These human issues appear again with the use of algorithmic decision making



Structure

- Introduction with idea of Digital Poorhouse
- Three case studies that instantiate this idea
 - Indiana - welfare system
 - Los Angeles - electronic registry of the unhoused
 - Allegheny County, PA - child neglect risk model
- Conclusion and Dismantling Digital Poorhouse

Case Study 1: Automating Public Benefits enrollment in Indiana

What happened? Indiana experiments with welfare eligibility automation (SNAP, Medicaid, etc..)

What was it before? Case workers handled all paperwork and eligibility determination

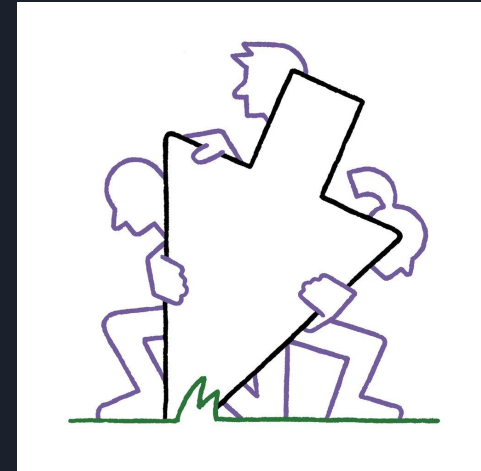


Why did they switch? Believed case workers' time shouldn't be put towards filing paperwork and should focus their energy to more important matters

Aftermath - Told through 3 stories “failure to cooperate”

Consequences of Automation: 12.2% of those applying for food stamps were wrongly denied

- Stipes family’s story - Child with developmental delays gets denied Medicaid after years of care
- Lindsay Kidwell’s story - Mother who submitted all documents appealed decision and won
- Omega Young’s story - Missed appointment to recertify Medicaid, received \$10,000 medical bill, won appeal the day after she died



The System's Failures & What Happened Afterwards

What were the problems?

- Lack of Human Interaction
- Inaccessibility to computers
- High Error Rate

What happened afterwards? Hybrid System

- Brought in 2009
- Allowed for face to face interactions with caseworkers



Case Study 2: Coordinated Entry System

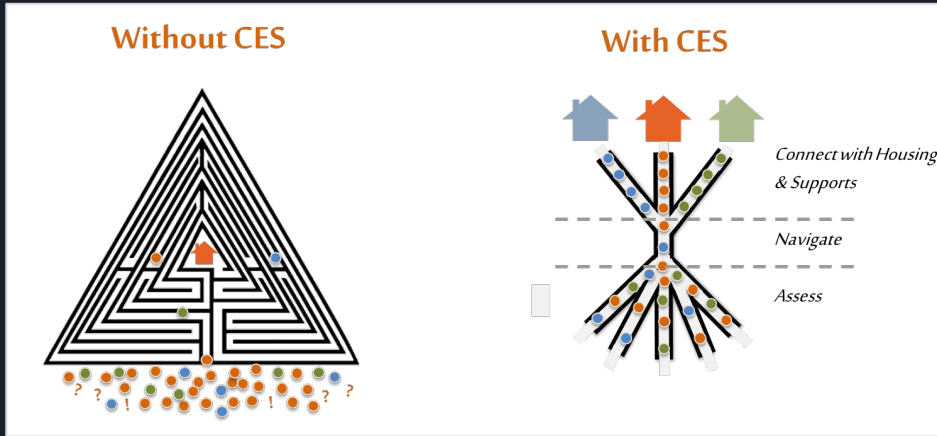
High Tech Homelessness in the City of Angels

Prior to implementation of the system:

- Competition among homeless service providers with limited funding and limited housing
- Severe mismatch between housing supply and demand
- Skid Row
 - Long history of housing poor, working-class individuals
 - Currently houses 2,000 residents in shelter beds, 6,500 in supportive housing for mentally ill, drug addicts, and another 3,000 in encampments
 - Population boom 2006-2013 led to increased vacancy to 12%, median apartment \$2,500



Coordinated Entry System



- Launched in 2013 by Home for Good
- System created to address the “disastrous mismatch between housing supply and demand”
- Philosophies:
 1. Prioritization: Chronic vs Crisis Homelessness
 2. Housing First
- Vulnerability Index - Service Prioritization Decision Assistance Tool (VI-SPDAT)
 - Assessment tool used to collect data
 - Collected very personal data (SSN, Mental Illness History, Legal History...), shared with 168 organizations

With this data, the system:

1. Ranks the unhoused in order of vulnerability on a scale of 1 to 17
2. Uses these ranks to match them to housing opportunities by housing providers

Problems with CES

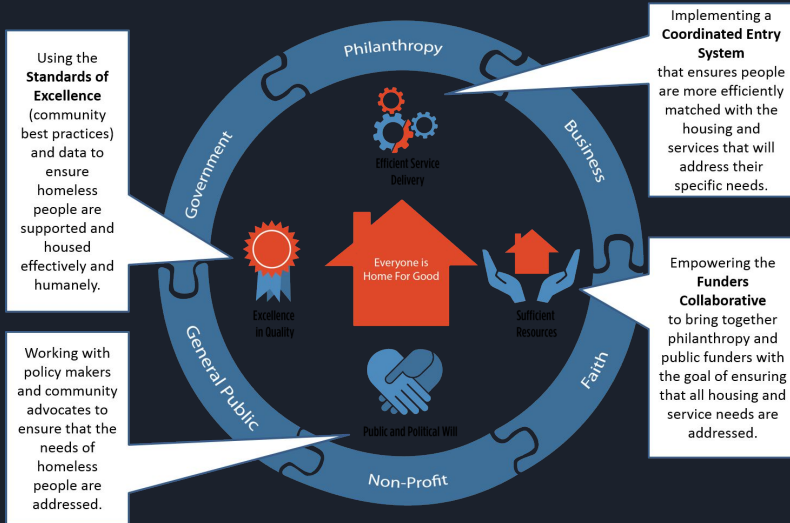



Biggest Problem: Lack of available resources

- Goal was to better manage homelessness, did not provide more housing
- Measures H and HHH in 2016/17

Other Problems:

1. Inconsistent results on the VI-SPDAT survey
2. No guarantees of housing
3. Absence of sufficient public investment
4. Catch 22 in admitting risky/illegal behavior
5. Insufficient long-term solutions: *rapid rehousing*





Case Study 3: Predicting Risk for Child Maltreatment in Allegheny County, PA

- Allegheny County employed a risk model to aid human services case works with estimating a child's risk for maltreatment when an individual calls in a report about a child
 - Is comprised of historical data from a multitude of **public** agencies
 - Used history of family members to calculate risk i.e. if your mother was put into foster care than you are more likely to be predicted as higher risk
- Model is used **EXCLUSIVELY** on choosing to investigate a family, not on choosing when to take someone from the home
- Model was trained on this data labeled with whether a child was taken from the home conditioned on the fact that they were chosen to be investigated
- Risk scores were integer version of a probability score
 - Top scores were automatically chosen to be investigated without manager override



Key Takeaways

- The poor are more likely to be surveilled than the middle class
 - As a result, the standard for their parenting is much higher
 - Allegheny Model only used public data, middle class people are more likely to seek services from private providers unlike poor people
- Researchers who created system seem to mean well, but there are big questions about how system will be used in posterity
 - ““People have concerns about what happens when Marc and Erin leave,”
- There was evidence to suggest that risk scores started dictating case worker actions rather than as just an aid
 - High accuracy is not always what it seems, are workers being trained to agree with the model?
- Sociopolitical - algorithmic systems require political support to operate on public data. The researchers who created this algorithm were originally defeated from doing so in New Zealand before being contracted in Pennsylvania.



Conclusion - What is to be done?

We are in the midst of a violent retrenchment on equality and plurality; the technological revolution that Martin Luther King foresaw as a force for good has instead created a generation of astonishing, sophisticated technologies that automate discrimination and deepen inequality.

Change is possible, but it will take “profound changes to culture, politics, and personal ethics.”

1. Changing how we think, talk, and feel about poverty and the poor
2. Mobilizing interracial, cross-class grassroots movements led by the poor themselves

A return to the economic and social ideas laid forth by Martin Luther King 50 years prior

1. Universal Basic Income and other public assistance programs



Conclusion (cont)

On the technological front - the main concern of this class -- we need to develop basic technological design principles to minimize harm

1. Does the tool increase the self-determination and agency of the poor?
2. Would the tool be tolerated if it was targeted at non-poor people?

A new draft of the Hippocratic oath for data scientists, system engineers, hackers, and administrative officials of the new millennium is needed

Mass Incarceration versus the Digital Poorhouse



Final Thoughts

Dismantling the digital poorhouse will require an interracial and intersectional coalition that encompasses all classes; everyone, from the progressive middle class to the technology professionals are responsible

“Our ethical evolution still lags behind our technological revolutions”

Questions?



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