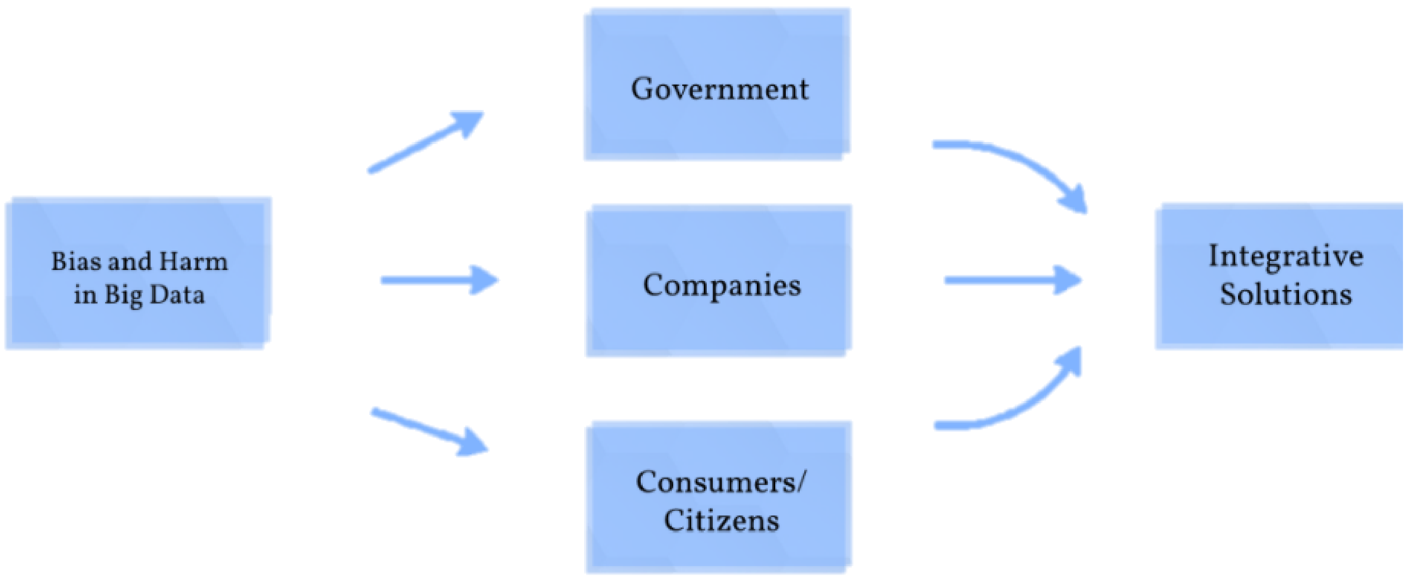

ALGORITHMIC ACCOUNTABILITY

Dorothy L. Andrews, ASA, MAAA, CSPA, FCA
Chief Behavioral Data Scientist
Actuarial & Analytics Consortium, LLC

NAIC Insurance Summit
June 28, 2021
2:00 to 3:20 pm

ALGORITHMIC ACCOUNTABILITY ACT OF 2019

Status: Died in a previous Congress
This bill was introduced on April 10, 2019, in a previous session of Congress, but it did not receive a vote.

116TH CONGRESS
1ST SESSION

H. R. 2231

To direct the Federal Trade Commission to require entities that use, store, or share personal information to conduct automated decision system impact assessments and data protection impact assessments.

IN THE HOUSE OF REPRESENTATIVES

APRIL 10, 2019

Ms. CLARKE of New York introduced the following bill; which was referred to the Committee on Energy and Commerce

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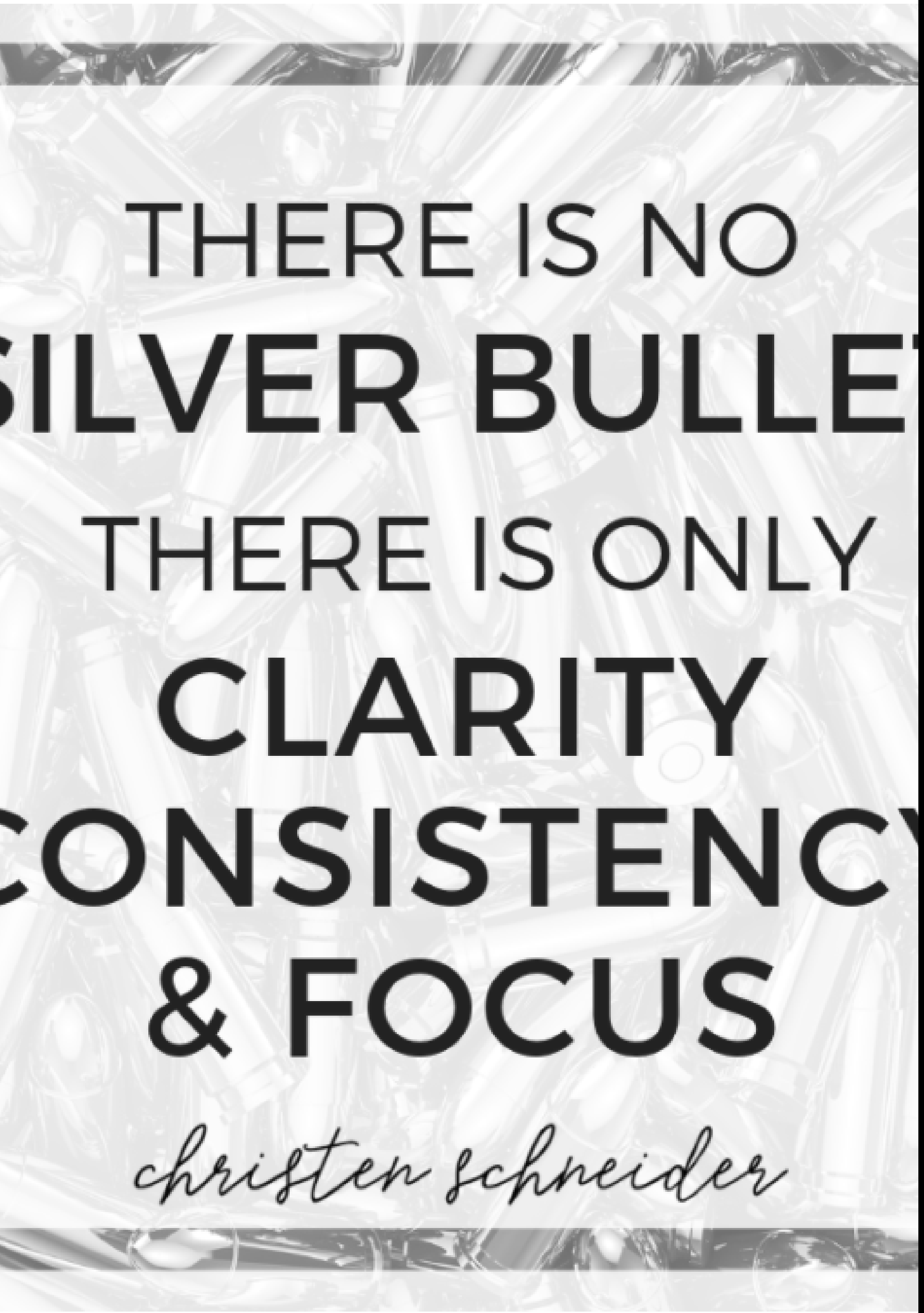
A BILL

To direct the Federal Trade Commission to require entities that use, store, or share personal information to conduct automated decision system impact assessments and data protection impact assessments.

Emerging Observations:

- More than Model Validation
- Analysis of Data Suitability
- Independent Data Testing
- Interdisciplinary Analysis
- Biased Variable Identification
- Independent Audit Resources
- Social Impact Analysis
- Embedded Bias DM Analysis
- Algorithmic Learning Analysis



IS RACE THE SILVER BULLET FOR REMOVING DISCRIMINATION FROM MODELS?

Neither race nor ethnicity is a risk factor.

- Philip M. Alberti, PhD

WIRED BACKCHANNEL BUSINESS CULTURE GEAR IDEAS SCIENCE SECURITY

SETH NEEL BUSINESS 11.09.2016 07:00 AM

Facebook's Race-Targeted Ads Aren't as Racist As You Think

Opinion: Sometimes there are good reasons for using race in algorithms.

BERNHARD LANG/GETTY IMAGES

"Fairness Through Awareness" makes the observation that sometimes, in order to be fair, it is important to make use of sensitive information while carrying out the classification task.

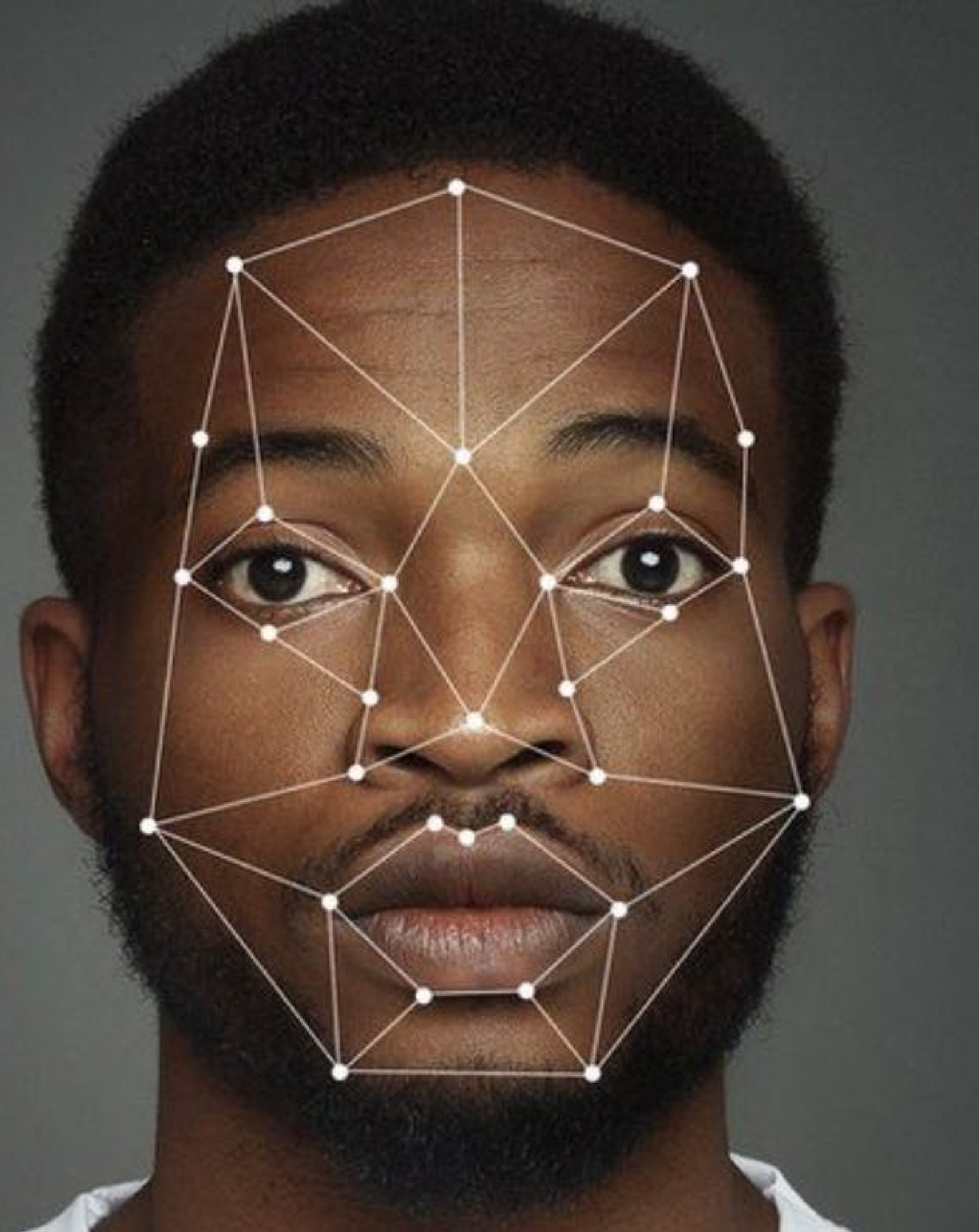
- Cynthia Dwork, Computer Scientist at Microsoft Research.
She says, there are "trade-offs between fairness and privacy."
Algorithms and Bias: Q. and A. With Cynthia Dwork
The New York Times, August 10, 2015

Considerations Controlling for Race:

- Modeling is NOT a Perfect Science
- Statistical Variable Order Matters
- Training Data is Easily Skewed
- Selection Bias of Insurance Data
- Lack of Diversity Among Modelers
- Confounding Effects of Proxies for Race
- Discriminatory Effects Despite Best Efforts
- Qualitative v. Quantitative Measurement
- Don't Forget About Deployment Effects
- Protecting Data from Nefarious Use
- Data Set Size Does Not Guarantee Diversity

"Race is a social construct and as such is difficult to pin down even when you intend to, as any person of mixed race can tell you."

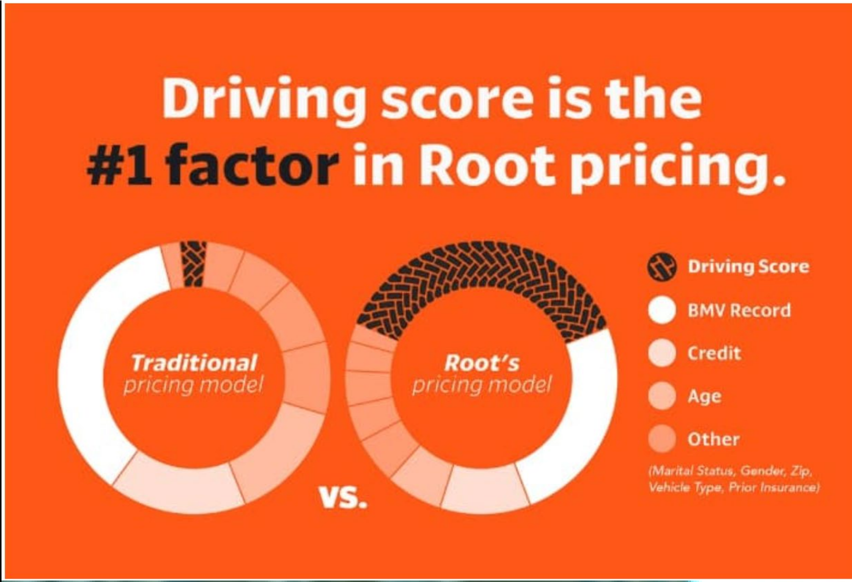
- Cathy O'Neil, Weapons of Math Destruction

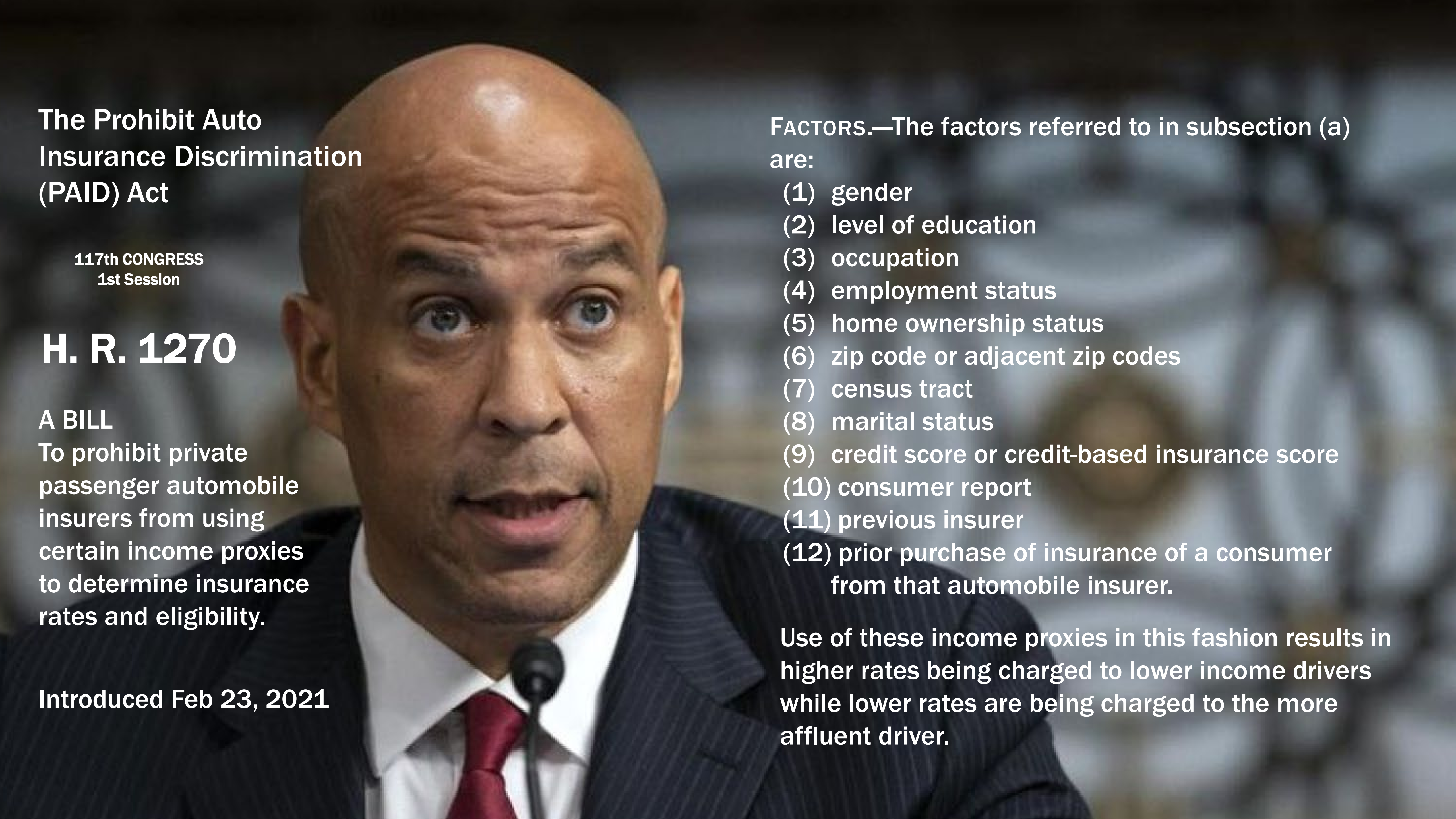


IS ROOT GETTING IT RIGHT?

Eva is a good driver and is in need of auto insurance that puts her in control. Most insurance companies rely on age, education level, zip code and more to determine your rate, but Root Insurance says your driving is the number one factor it uses to find your price.

The Fine Print: The other factors include BMV Record, Credit, Age, Marital Status, Gender, Zip, Vehicle Type, and Prior Insurance.




The Prohibit Auto Insurance Discrimination (PAID) Act
117th CONGRESS
1st Session
H. R. 1270
A BILL
To prohibit private passenger automobile insurers from using certain income proxies to determine insurance rates and eligibility.
Introduced Feb 23, 2021
FACTORS.—The factors referred to in subsection (a) are:
(1) gender
(2) level of education
(3) occupation
(4) employment status
(5) home ownership status
(6) zip code or adjacent zip codes
(7) census tract
(8) marital status
(9) credit score or credit-based insurance score
(10) consumer report
(11) previous insurer
(12) prior purchase of insurance of a consumer from that automobile insurer.
Use of these income proxies in this fashion results in higher rates being charged to lower income drivers while lower rates are being charged to the more affluent driver.

The Risks of Third-Party Data

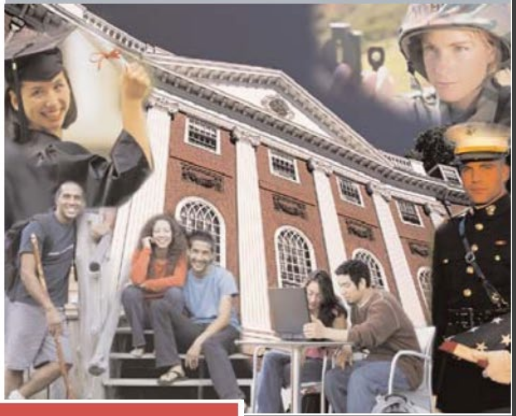
- Unregulated
- Redundant Encodings
- Nearly Un-Auditable
- Design Constraints
- Survey Based Data
- May Lack Veracity
- Mismatched Time Period
- Growing Reliance

Group A: Affluent Suburbia

Group B: Upscale America

Group K: Urban Essence

Group L: Varying Lifestyles



A 3rd Party Data

Disparate Impact?

Unfairly Discriminatory?

Group H: Aspiring Contemporaries

Group I: Rural Villages and Farms

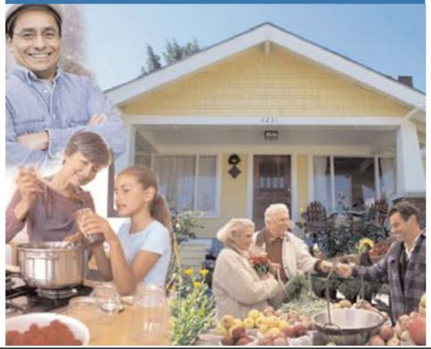
Group J: Struggling Societies

Hidden Biases?

Racial Overtones?

Group C: Small-town Contentment

Group D: Blue-collar Backbone

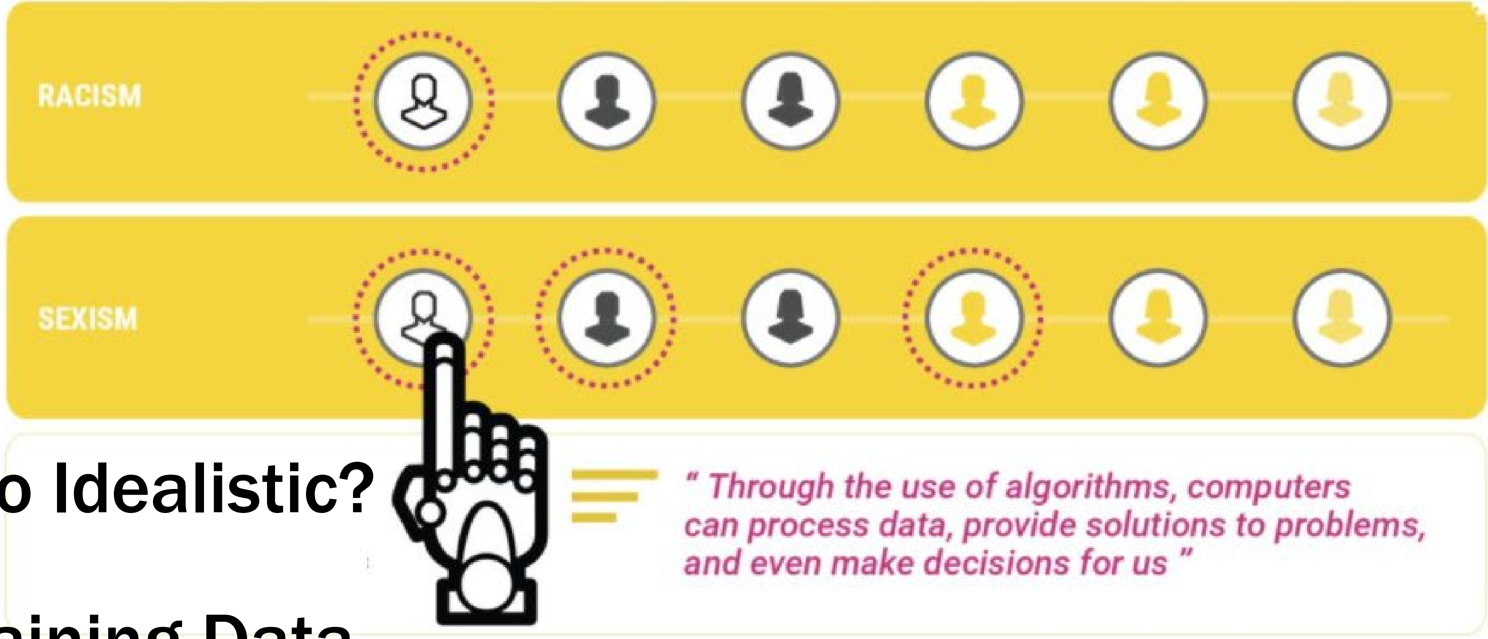


Group E: American Diversity

Group F: Metro Fringe

Group G: Remote America

ALGORITHMIC DISCRIMINATION



How Do We Prevent It?

- End Discrimination – Too Idealistic?
- Remove Biases From Training Data
- Embed Diversity in Training Data
- Diversify Modeling Teams
- Conduct Independent Valuation with Independent Data Sets
- Conduct Algorithmic Audits
- Monitor Implementation
- Hire a Media Ethicist

The Modelers' Hippocratic Oath

I will remember that I didn't make the world, and it doesn't satisfy my equations.

Though I will use models boldly to estimate value, I will not be overly impressed by mathematics.

I will never sacrifice reality for elegance without explaining why I have done so.

Nor will I give the people who use my model false comfort about its accuracy. Instead, I will make explicit its assumptions and oversights.

I understand that my work may have enormous effects on society and the economy, many of them beyond my comprehension.

– Emanuel Derman and Paul Wilmott