Casualty Actuarial and Statistical (C) Task Force
CASTF Book Club
October 26, 2021

ALGORITHMIC ACCOUNTABILITY

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Senior Behavioral Data Scientist and Actuary
National Association of Insurance Commissioners

Algorithmic Accountability ultimately refers to the assignment of responsibility for how an algorithm is created and its impact on society; if harm occurs, accountable systems include a mechanism for redress.

– Data & Society

“Algorithms Are Opinions
Embedded In Code”

WHO IS RESPONSIBLE WHEN ALGORITHMS DO HARM?

Mark Bovens: Accountability Model

- Actor-Forum Relationship
- Actor is Judged by forum
- Actor Explains & Justifies Conduct
- Forum Poses Questions
- Forum Passes Judgement
- Actor May Face Consequences

Types of Accountability

Based on the nature of the forum

- Political accountability
- Legal accountability
- Administrative accountability
- Professional accountability
- Social accountability

Based on the nature of the actor

- Corporate accountability
- Hierarchical accountability
- Collective accountability
- Individual accountability

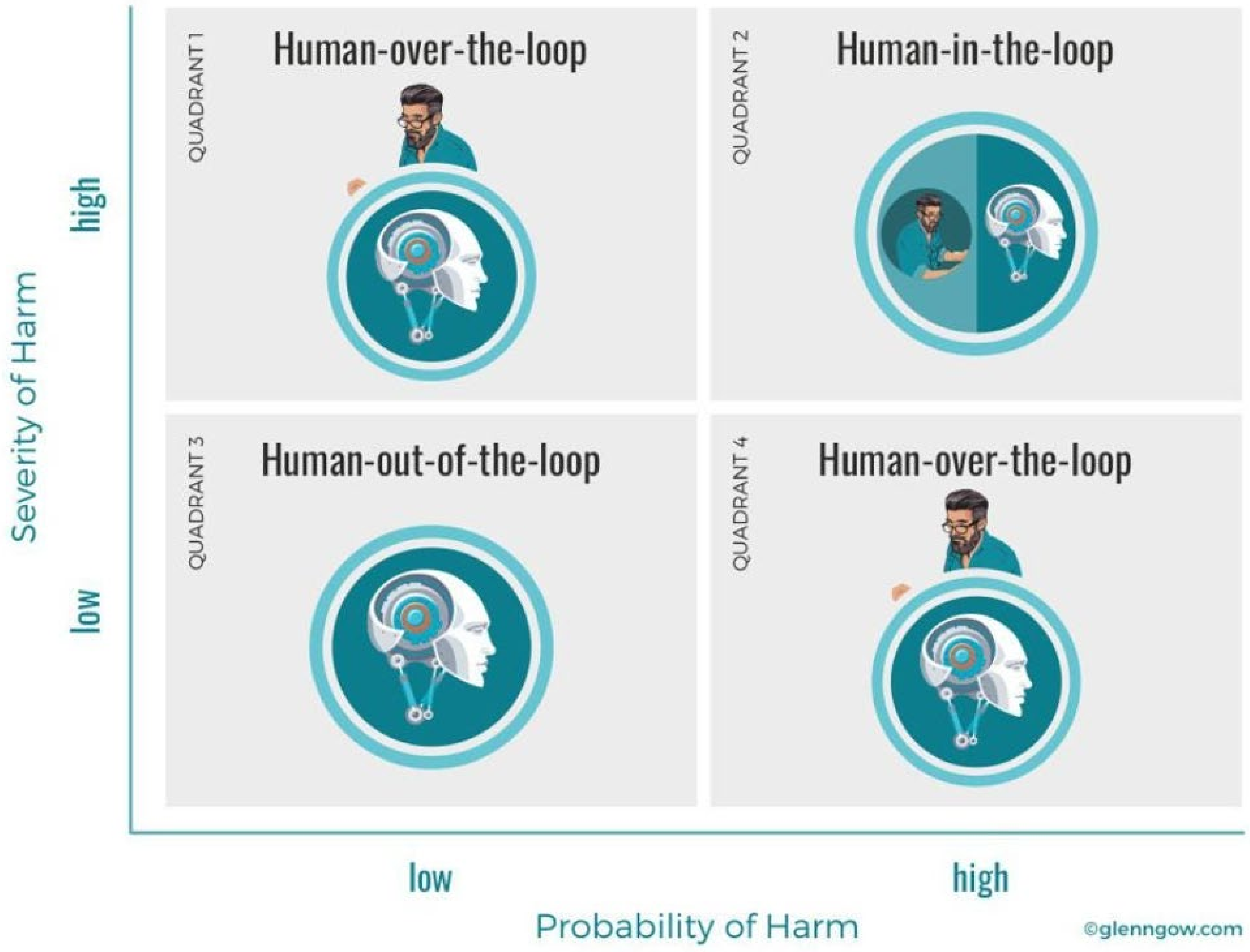
Based on the nature of the conduct

- Financial accountability
- Procedural accountability
- Product accountability

Based on the nature of the obligation

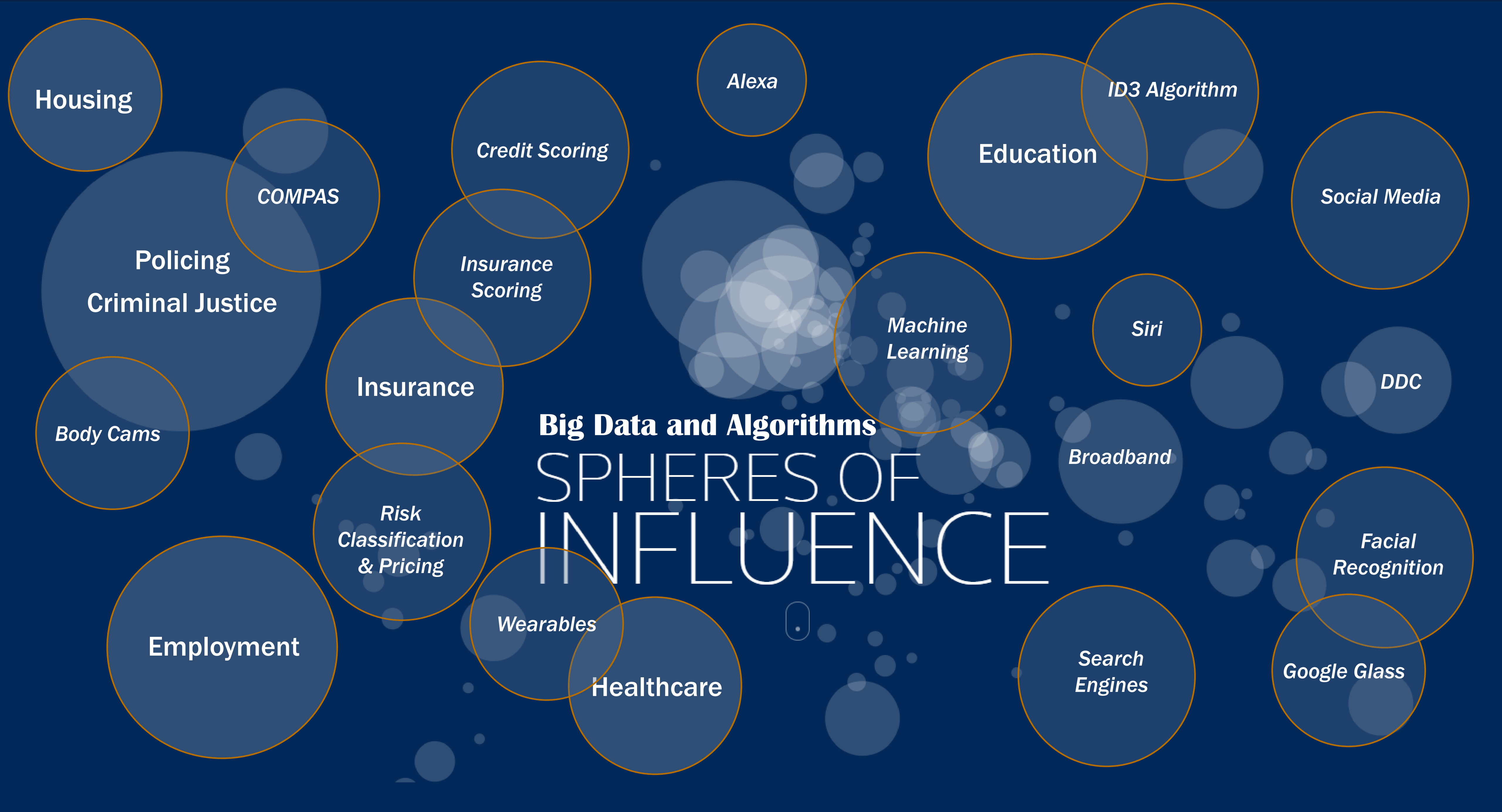
- Vertical accountability
- Diagonal accountability
- Horizontal accountability

A Loop is a system or process the generates, manages and leverages data.



Singapore's Model AI Governance Framework

- The probability of harm caused by AI
- The severity of harm caused by AI


Big Data and Algorithms
SPHERES OF
INFLUENCE
Housing
COMPAS
Policing
Criminal Justice
Body Cams
Credit Scoring
Insurance Scoring
Insurance
Risk Classification & Pricing
Employment
Wearables
Healthcare
Alexa
Machine Learning
Education
ID3 Algorithm
Social Media
Siri
DDC
Broadband
Facial Recognition
Google Glass
Search Engines

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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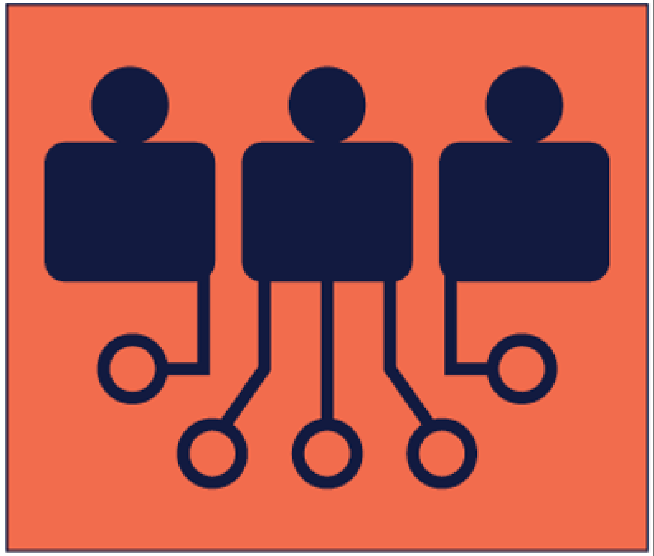
A BILL

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.

Big Data and Algorithmic Impacts



Discrimination by Proxy

An algorithm can have an adverse effect on vulnerable populations even without explicitly including protected characteristics. This often occurs when a model includes features that are correlated with these characteristics.

JDSUPRA®

May 19, 2021

A Rocky Road Ahead for Insurers Using Consumer Data and Models

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The NAIC's development of guiding principles on artificial intelligence seeks to proactively avoid proxy discrimination, safeguard against other unfairly discriminatory outcomes, and apply risk management to address unfair discrimination. Extending the work of the NAIC, two states have introduced proposals that seek to address unfair discrimination in the use of data or algorithms, giving insurers using data or algorithms a steep climb:

- The Colorado legislature proposed SB 21-169 prohibiting the use of any external consumer data and information source, algorithm, or predictive model that unfairly discriminates against an individual based on race, color, national or ethnic origin, religion, sex, sexual orientation, disability, or transgender status.
- The Connecticut Insurance Department issued a notice on April 14, 2021, reminding all entities "to use technology and big data in full compliance with anti-discrimination laws."

WRITTEN BY:

Carlton Fields

Jamie Bigayer

Ann Young Black

PUBLISHED IN:

Algorithms

Anti-Discrimination Policies

Artificial Intelligence

Big Data

Insurance Industry

Protected Class

Public policy recommendations, to mitigate algorithmic bias and reduce harm to consumers:

- Update nondiscrimination and civil rights laws to apply to digital practices with intent is to understand how algorithms trigger discrimination

- Update existing civil rights laws to reflect contributory digital parameters and thresholds.

- Implement regulatory sandboxes to foster anti-bias experimentation and safe harbors to curb online biases.

Nicol Turner Lee, Paul Resnick, and Genie Barton
May 22, 2019

NATIONAL COUNCIL OF INSURANCE LEGISLATORS

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NCOIL Special Committee on Race in Insurance Underwriting Holds Virtual Interim Meeting: Adopted Definition of "Proxy Discrimination"

Atlantic Corporate Center
2317 Route 34, Suite 2B
Manasquan, NJ 08726
732-201-4133
CHIEF EXECUTIVE OFFICER: Thomas B. Considine

For purposes of this Act, as well as for the purpose of any regulatory material adopted by this State, or incorporated by reference into the laws or regulations of this State, or regulatory guidance documents used by any official in or of this State, *"Proxy Discrimination" means the* ***intentional substitution*** *of a neutral factor for a factor based on race, color, creed, national origin, or sexual orientation for the purpose of discriminating against a consumer to prevent that consumer from obtaining insurance or obtaining a preferred or more advantageous rate due to that consumer's race, color, creed, national origin, or sexual orientation.*

Professor Daniel Schwarcz is an award-winning teacher and scholar. His research focuses on a broad range of issues in insurance law and regulation, spanning systemic risk, regulatory federalism, consumer protection, employer-sponsored health insurance, and insurance coverage litigation.

Proxy Discrimination in the Age of Artificial Intelligence and Big Data

Anya Prince & Daniel Schwarcz
105 Iowa Law Review 1257 (2020)

Proxy discrimination occurs when insurers discriminate based on facially-neutral traits that (i) are correlated with membership in a protected groups, AND (ii) are predictive of losses for precisely that reason.

"Unintentional proxy discrimination by AIs is virtually inevitable…"

"AIs use training data to discover on their own what characteristics can be used to predict the target variable."


GENDER- BIASED HIRING TOOL
amazon
NOW DISCARDED

Algorithms & Accountability – Balancing the Tradeoffs

Auditing Algorithms

- 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

Can Auditing Eliminate Bias from Algorithms?

Two Terms, Four Approaches:

- ❑ Algorithm Audit
  - ✓ Bias Audit *(aka Black Box Audits)*
  - ✓ Regulatory Inspection
- ❑ Algorithmic Impact Assessment
  - ✓ Algorithmic Risk Assessment
  - ✓ Algorithmic Impact Evaluation

Algorithm Audit

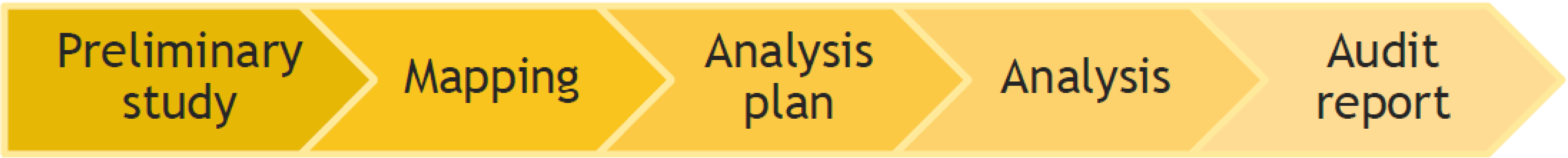
- **Bias Audit:** A targeted, non-comprehensive approach focused on assessing algorithmic systems for bias.

- **Regulatory Inspection:** A broad approach, focused on an algorithmic system's compliance with regulation or norms, necessitating a number of different tools and methods; typically performed by regulators or auditing professionals.

Algorithmic Impact Assessment

- Algorithmic risk assessment: assessing possible societal impacts of an algorithmic system ***before*** the system is in use (with ongoing monitoring often advised).
- Algorithmic impact evaluation: assessing possible societal impacts of an algorithmic system on the users or population it affects ***after*** it is in use.

Five Stages of the Audit Process



- Parties involved
- New/known problem
- Exchange of information
- Audit Journal

- Degree of system development
- List of minimum requirements
- Expectations and main issues to be analyzed

- Definition of audit terms and time frame
- Choice of methodology and audit team
- Consensus on the Analysis Plan

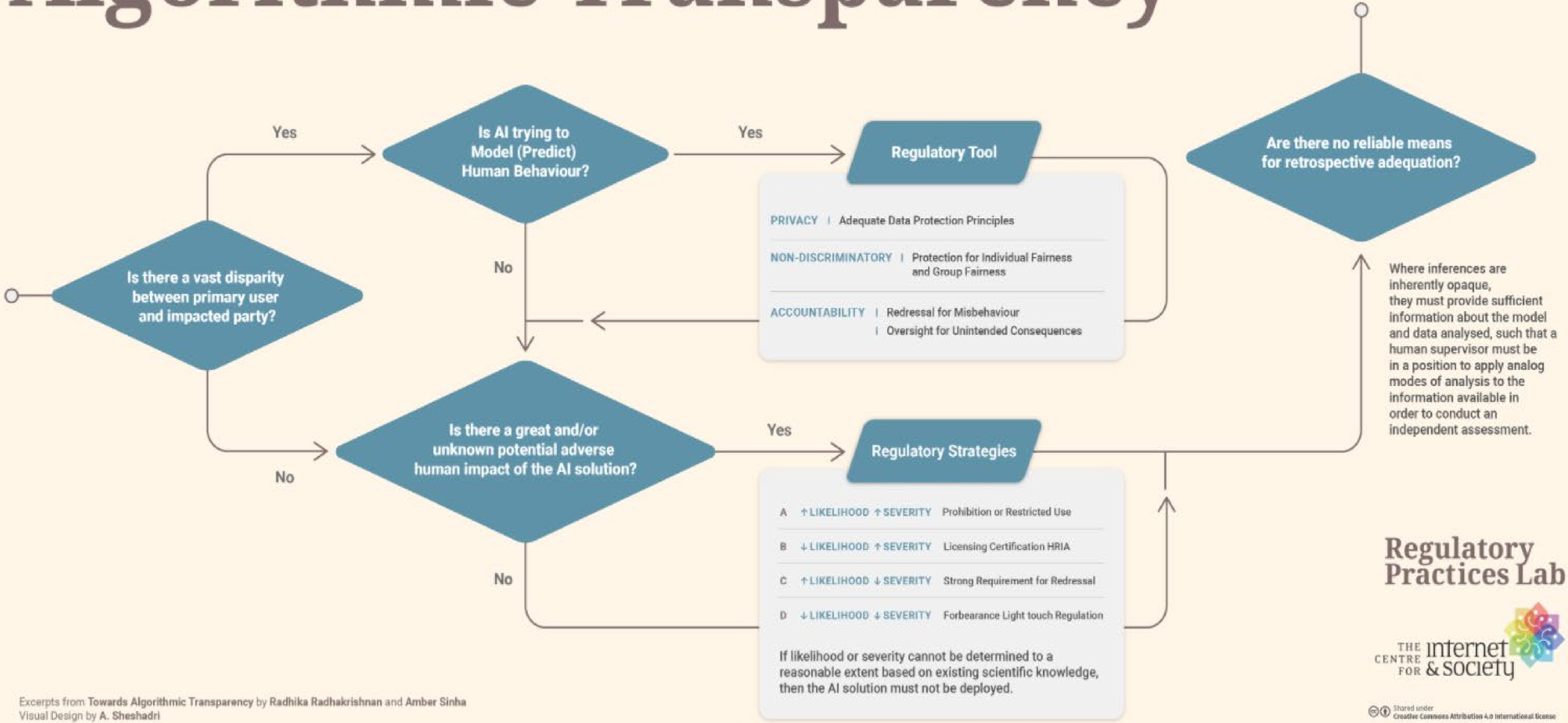
- Research
- Execution, follow-up and readjustment of the Analysis Plan (if applicable)
- Obtaining and analyzing results

- Interpretation
- of results
- Conclusions and final assessment of the system
- Recommendations for improvement

This Guide to Algorithmic Auditing has been developed and reviewed by a research team at Eticas Research and Consulting SL under the commission and supervision of the Spanish Data Protection Agency.

THRESHOLDS FOR REGULATION OF

Algorithmic Transparency



Excerpts from **Towards Algorithmic Transparency** by **Radhika Radhakrishnan** and **Amber Sinha**
Visual Design by **A. Sheshadri**

Regulatory Practices Lab

THE CENTRE FOR internet & society

Major Barriers to Algorithmic Transparency

- ✓ Exposing trade secrets may
  1. Undermine competitive advantage
  2. Impair reputation and ability to do business
  3. Leave company open to gaming and manipulation.

- ✓ Remember Edward Snowden? –The Federal Agency Data Mining Reporting Act of 2007 compels transparency but conflicts with national security!

THE ETHICAL MATRIX, A FRAMEWORK FOR ETHICAL DEBATES

Home > Resources > The Ethical Matrix, a framework for ethical debates

THE ETHICAL MATRIX, A FRAMEWORK FOR ETHICAL DEBATES

The Ethical Matrix is a versatile tool for analysing ethical issues.

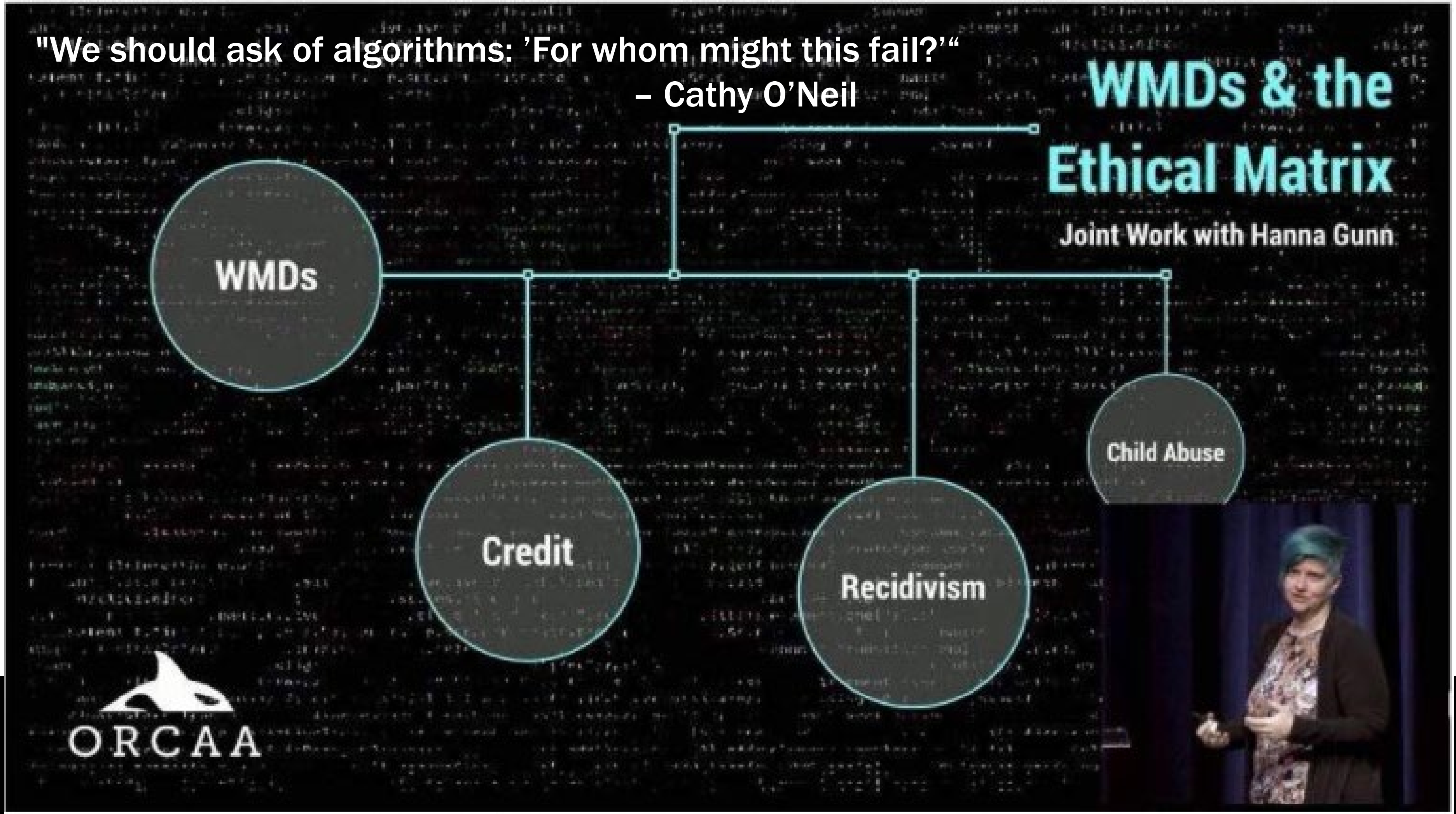
Devised by Professor Ben Mepham, Director of the Centre for Applied Bioethics at the University of Nottingham and a member of the Food Ethics Council, it is intended to help people make ethical decisions, particularly about new technologies.

- Provides a means of examining the ethical positions of all interest groups – ensuring equality of treatment (justice/fairness).
- It helps to identify where one stronger principle might overcome a weaker one or where a compromise should be sought
- Separates well-being, autonomy and fairness

Respect for:	Well-being	Autonomy	Fairness
Interest group 1	Best outcome	Best outcome	Best outcome
Interest group 2	Best outcome	Best outcome	Best outcome
Interest group 3	Best outcome	Best outcome	Best outcome
Interest group 4	Best outcome	Best outcome	Best outcome

"We should ask of algorithms: 'For whom might this fail?'"

– Cathy O'Neil



	Efficiency	Fairness	False +'s	False -'s	Transparency	Predictive Parity	Consistency	Data quality
Court								
Black Defendants								
White Defendants								
Public								
Northpointe								

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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

"Sometimes you actually do need to know these attributes like race and gender in order to measure your fairness.

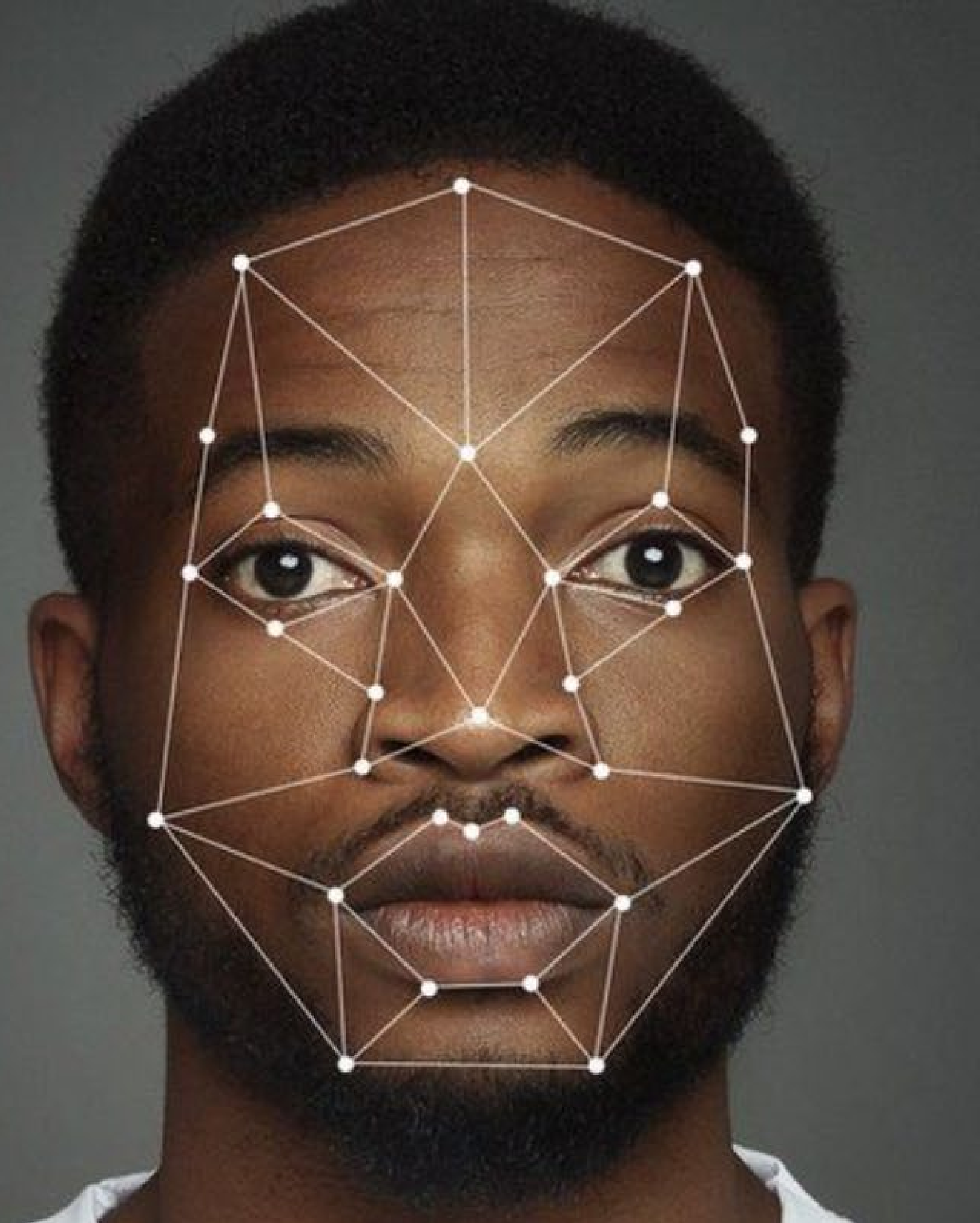
- Cathy O'Neil, Weapons of Math Destruction, Talks at Google
Retrieved from https://www.youtube.com/watch?v=TQHs8SA1qpk
November 2, 2016

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



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

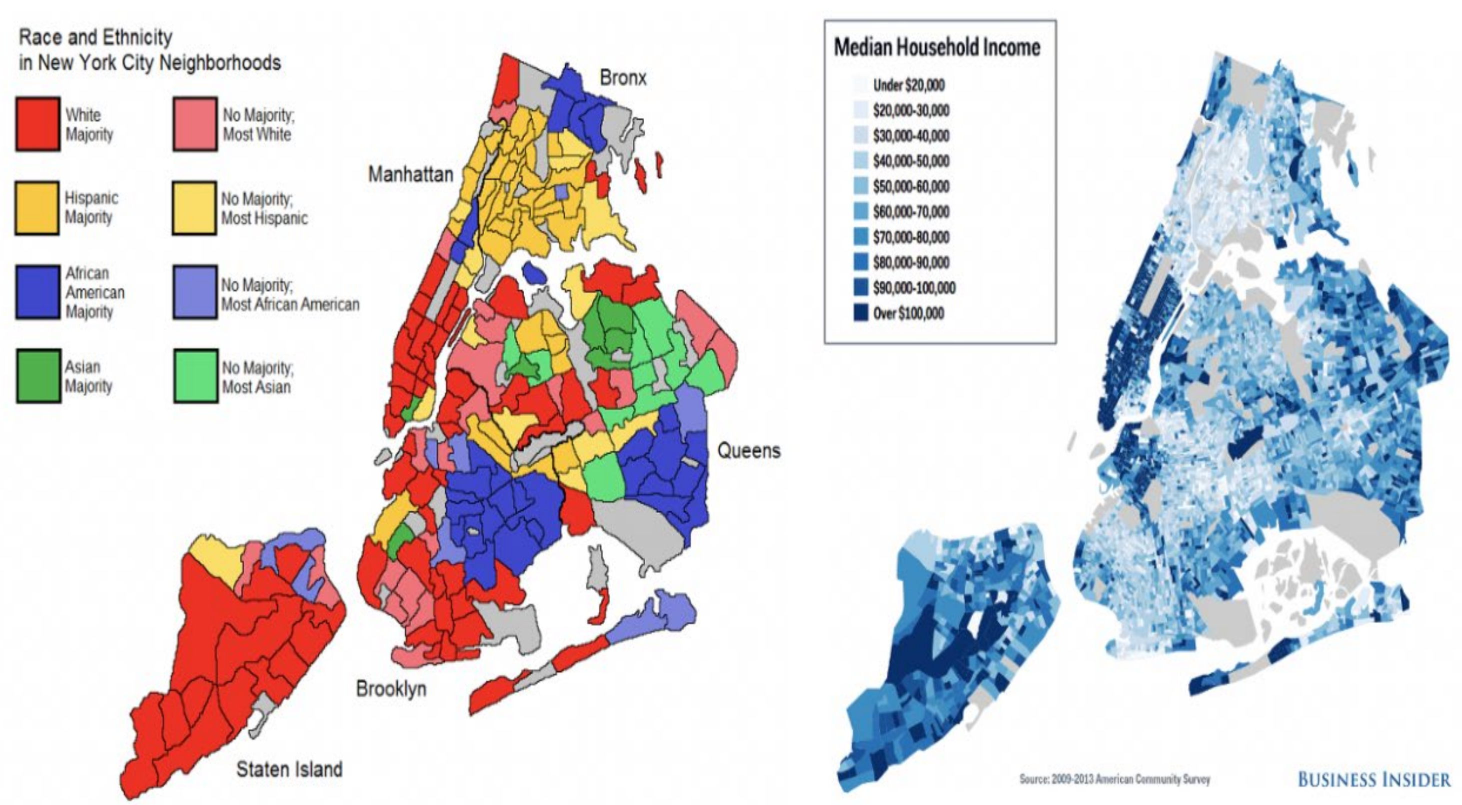
Redundant Encodings:

The protected attribute is encoded across one or multiple features in a dataset, making the removal of the protected attribute useless.

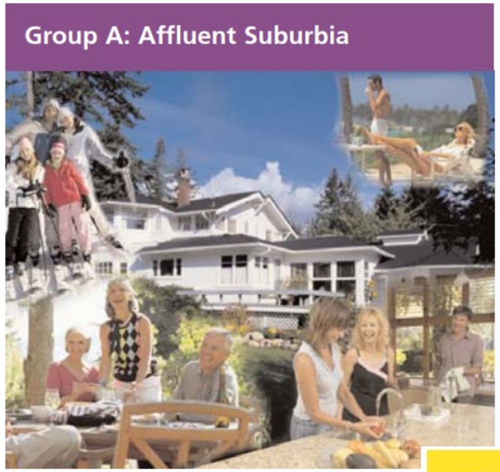
A study by Samuel Yeom, Anupam Datta, and Matt Fredrikson designed to predict the crime rate per community based on 1990 Census data and 1995 FBI Crime Reporting Data.

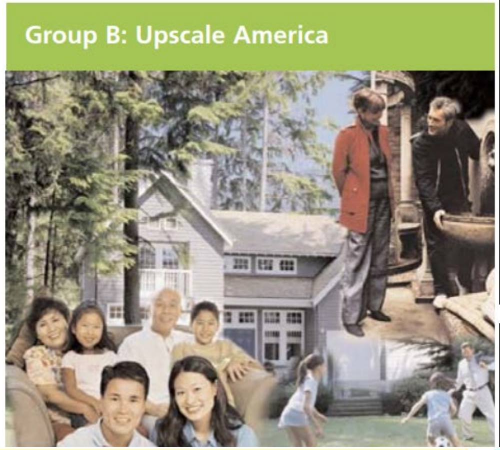
Findings:

- Removed the 32 out of the 122 features explicitly linked to race.
- They found a proxy for race consisting of a combination of ***58 features out of the 90 remaining features***.
- This proxy had an association with race of 0.85, while the single feature with the strongest association in the dataset only had an association of 0.73.

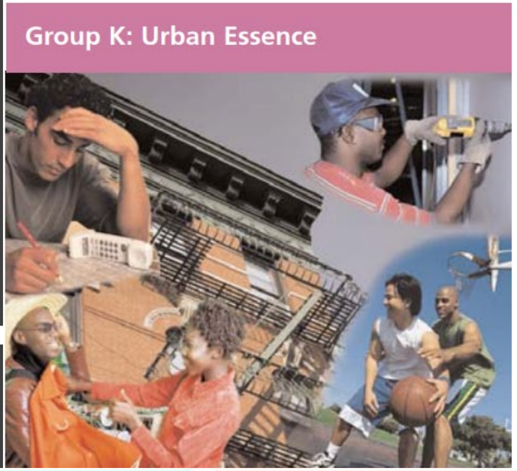


Race and ethnicity vs. median household income in New York City.

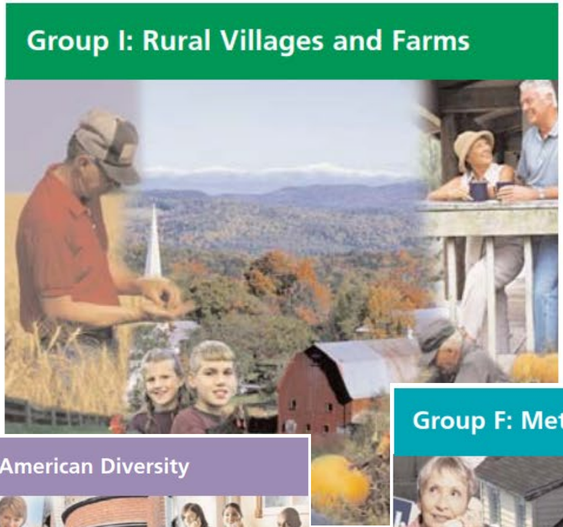


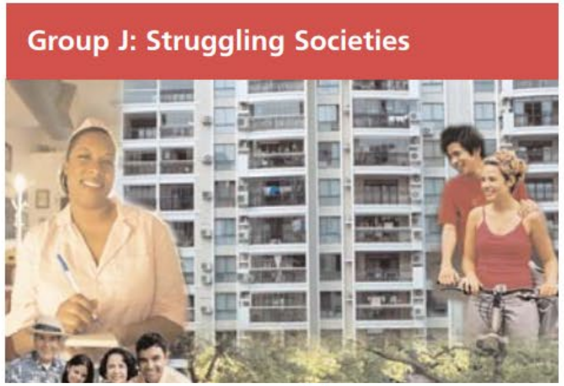


A 3rd Party Data



Disparate Impact?

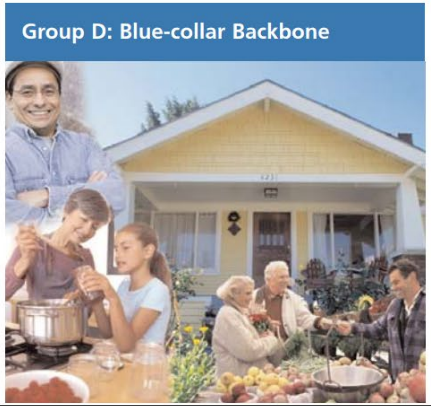


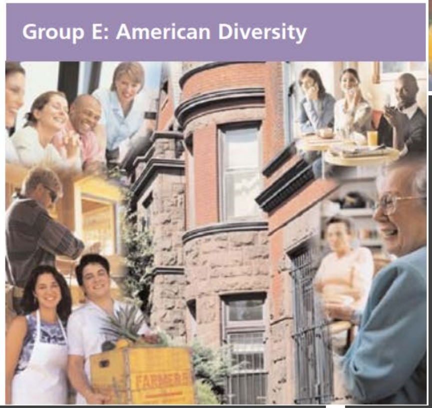


Hidden Biases?

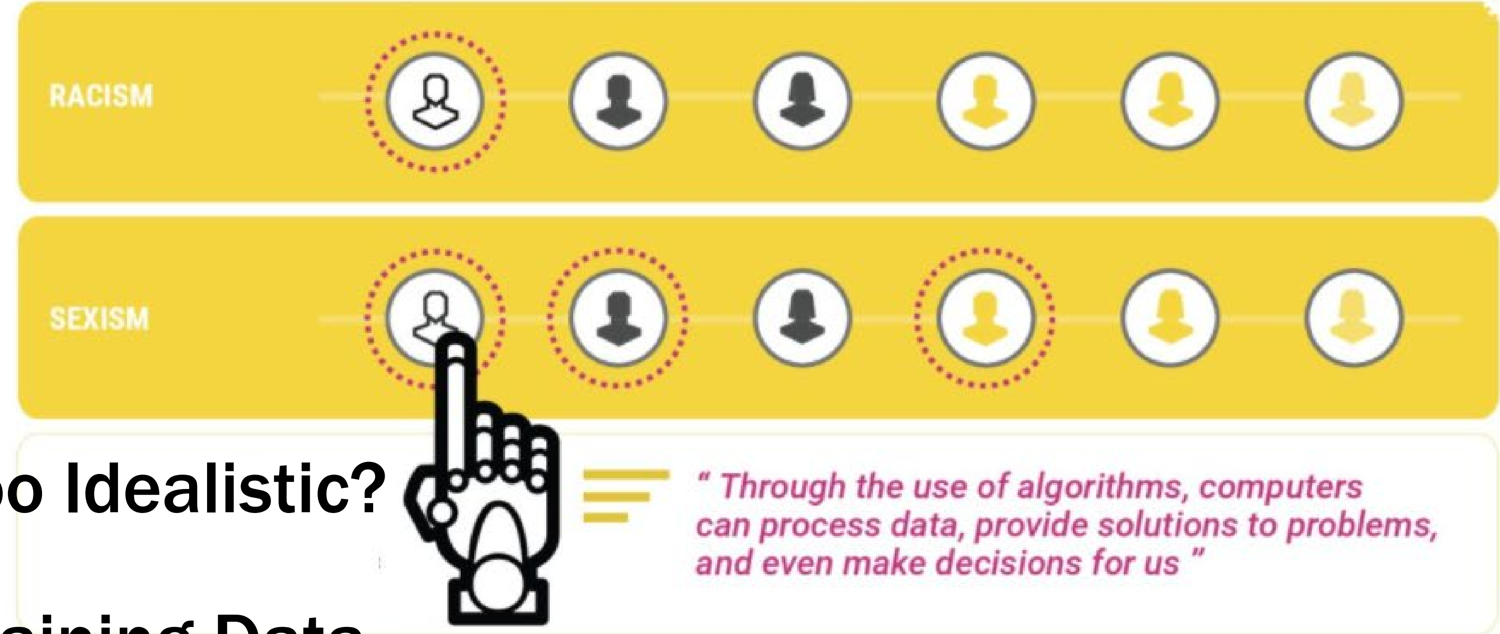
Unfairly Discriminatory?

Racial Overtones?





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.

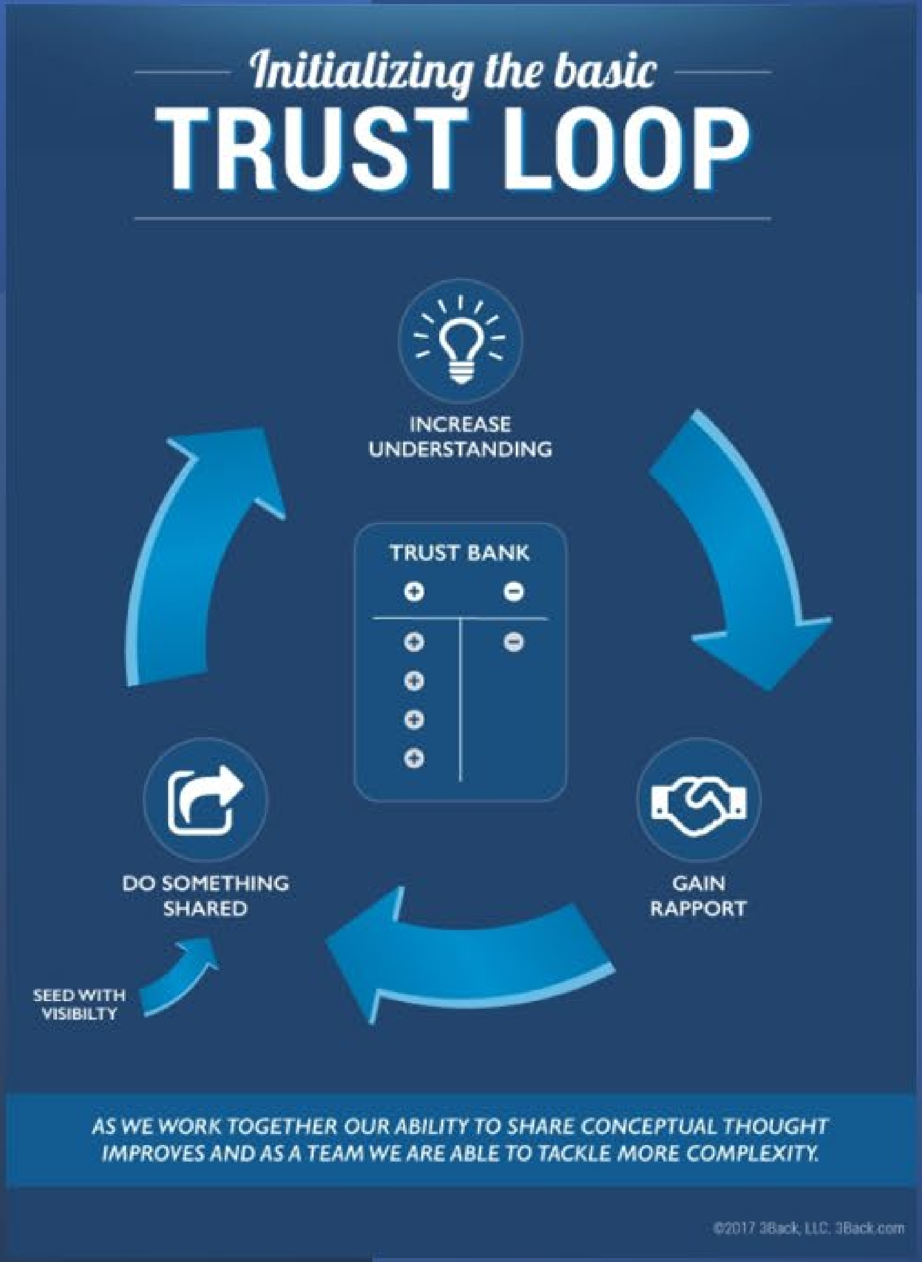
Though I will use models boldly to estimate value, I will not be overly impressed by mathematics.

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



The Rise of Algorithms in Decision-Making

Is This a Threat to Human Autonomy?

Recommended Reading:

1. Algorithms of Oppression - Safiya Noble
2. Automating Inequality - Virginia Eubanks
3. Biased - Jennifer L. Eberhardt
4. Race After Technology - Ruha Benjamin
5. The Ethical Algorithm – Michael Kerns & Aaron North
6. Noise - Daniel Kahneman
7. Tyranny of Metrics - Jerry Z. Muller
8. Weapons of Math Destruction - Cathy O'Neil
9. Innumeracy in the Wild - Ellen Peters

NAIC Model Review Team

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- Property Casualty Rate Modeling Actuary

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- Senior Behavioral Data Scientist and Life Actuary

Eric King, FSA, MAAA
- Senior Health Actuary

What we do for Regulators

- State Requested NAIC Model Reviews

  - ✓ Analyze model data for balance, bias, and appropriateness
  - ✓ Review sub-models relied upon (as requested) used
  - ✓ Assess the appropriateness of the model for the insured risk
  - ✓ Interrogate the model building process for technical competency
  - ✓ Validate derivation of model factors
  - ✓ Certify every model implementation step is clear and documented
  - ✓ Evaluate the data and model for unfair discrimination concerns
  - ✓ Identify procedures for consumer disputations of data and model results

- Model Comparison Reports
- Case Studies
- Shared Model Database
- Education & Training
- CASTF Book Club

NAIC NATIONAL ASSOCIATION OF INSURANCE COMMISSIONERS