CENTER for ECONOMIC JUSTICE | FAIR ACCESS FAIR TREATMENT

Comments for the Center for Economic Justice

To the National Council of Insurance Legislators

Proposed Changes to Market Conduct Surveillance Model Law

July 10, 2019

The Center for Economic Justice (CEJ) welcomes NCOIL's consideration of improvements in the Market Conduct Surveillance Model Law to improve the efficiency and effectiveness of state-based insurance market regulation. Such improvements are needed more than ever due to insurers' use of Big Data and complex algorithms for all facets of insurance sales and administration processes. Moreover, the opportunities for greater efficiencies and effectiveness in market analysis are greater than ever due to the regulatory use of new data and new data analysis tools. In addition, there is also much greater opportunity for insurance regulators to interact with and obtain information from insurance consumers to aid the regulators' efforts to monitor consumer market outcomes. In our view, the goal should be to move market conduct surveillance away from an audit-type framework to an analytic framework.

Unfortunately, the proposal by NAMIC is a misguided effort that further bureaucratizes market regulation, hamstrings insurance regulators and further distances insurers from accountability to regulators and consumers. We strongly oppose the NAMIC proposals. We oppose NAMIC's attempt to hamstring regulators through a variety of new hurdles for regulators to jump over before the regulator can take the action necessary to monitor consumer market outcomes and/or protect consumers. NAMIC's proposal consists of additional hurdles and barriers, but offers no new tools. In contract, CEJ suggests that there are a number of actions to improve regulatory capability, including:

<u>Improve Market Regulation Data Collection</u>

Enhancements to market regulation data collection to provide insurance regulators with more data – similar in scope and detail to that provided for financial analysis – to allow regulators to employ more advanced data analytics to better identify market problems.

Improve Consumer Information about Insurer Treatment of Consumers[1]

Public disclosure of individual company market conduct annual statements (MCAS) to allow consumers and third parties to assess insurance company performance on dimensions other than price. Insurance remains one of the few products for which there is no consumer information about how well the product performs. By making individual company MCAS available to the public, consumer organizations or third party organizations (like a Consumers Union) could assemble comparative statistics on consumer market outcomes, Such product/company comparisons would promote more competitive markets by encouraging insurers to improve market performance with the critical added benefit of enabling consumers to shop on dimensions other than price.[2]

Standards for Ethical Algorithms, Including Disparate Impact as Unfair Discrimination

Establish requirements for ethical development and use of algorithms by insurers, including establishment of disparate impact as a type of unfair discrimination. In an era of insurers' use of all manner of personal consumer information coupled with complex algorithms, the potential for discrimination against protected classes by proxy variables is great. Ethical standards for insurers' use of Big Data and algorithms will have a number of benefits including:

- Minimizes Disparate Impact – Stop the Cycle of Perpetuating Historical Discrimination.
- Promotes Availability and Affordability for Underserved Groups
- Improves Cost-Based Insurance Pricing Models
- Improve Price Signals to Insureds for Loss Mitigation Investments
- Help Identify Biases in Data and Modelers / Improve Data Insights
- Improve Consumer Confidence of Fair Treatment by Insurers

Modernize the Consumer Complaint System

The state-based insurance consumer complaint system is not really about complaints. Rather, the system is about insurance departments helping some consumers get fair treatment by insurers. The current system only counts something as a "complaint" if it is confirmed, which means that the insurer is found to be at fault. In contrast, if a number of consumers complain about a certain treatment because the consumers failed to understand the policy provisions, these complaints are not counted because the consumers is "at fault" for failing to understand the policy – regardless of how easy or hard the policy is to understand. Consequently, the

[1] Attached to these comments is a recent presentation by CEJ to insurance regulators regarding regulatory review of complex insurance pricing and claim settlement models. That presentation discusses this topic in greater detail.
[2] Industry will offer a number of meritless objections to this proposal, including bogus claims of trade secret and increased litigation. These red herring arguments are without basis.

complaints system removes critical information – information about routine consumer misunderstanding or misperceptions or feelings of unfair treatment.

The complaints system should be modernized to gather and compile all complaints – not just "confirmed" complaints. In addition, the complaints systems should be modernized to facilitate consumes filing complaints and getting more timely responses. Attached is a recent announcement by the Texas Department of Insurance about their efforts to encourage consumers to file complaints and the salutary effect of consumer complaints for insurance markets.

NAMIC Proposals Go In the Wrong Direction

In contract to utilizing new data sources and methods to improve the efficiency and effectiveness of insurance market surveillance, the NAMIC proposals are directed only at restricting regulators to untested standards, such as "material violations" and requiring regulators to consider insurer self-evaluations despite no offer of proof that such a requirement is justified.

NAMIC also seeks to import the procedure for financial examinations – acceptance by insurers in one state of a financial examination by another state – for market conduct examinations. There is no rationale for such a provision for at least three reasons. First, unlike the financial condition of an insurer which doesn't vary from state to state, market conduct can and will vary state by state due to differences in legal requirements and insurer practices. Second, unlike financial examinations, there are no standards – accreditation or otherwise – for market conduct resources for a state. Third, for market conduct issues which do cross state lines, state insurance regulators already have a tool called multi-state examinations.

Purposes of the Model

NAMIC offers a number of edits and additions to the purposes of the model. We oppose these proposals and offer the following in place of the first current purpose:

> Processes and systems for monitoring insurance markets and consumer market outcomes to identify actual or potential harm to consumers, policyholders and claimants, including harm to competition;

Conclusion

CEJ appreciates NCOIL's review of the Market Conduct Surveillance Model Act because there is great need and great opportunity to modernize market surveillance for more accurate and more timely identification of consumer and market problems. There is great opportunity for regulators to leverage new data and new technologies to achieve these improved results. But, the NAMIC proposal offers nothing to improve regulatory skills, capacity or resources. Instead, the NAMIC proposal simply adds further restrictions and hurdles to an already-sluggish market conduct regulatory system. The efforts to modernize should be oriented towards moving market regulation away from an auditing approach to an analytic approach. NAMIC's proposals fails spectacularly and, consequently, we strongly oppose the NAMIC proposals

Subject: Commissioner Sullivan: Let’s help people complain
From: "Texas Department of Insurance" <TXDeptofInsurance@public.govdelivery.com>
Date: 7/9/2019, 10:31 AM
To: birny@birnybirnbaumconsulting.net

TDI | Texas Department of Insurance

Let’s help people complain

By Kent Sullivan
Insurance Commissioner

If helping people complain sounds like an odd business tactic, consider this: The [Harvard Business Review] found that customers whose complaints were handled quickly were willing to pay even more for services from that company in the future.

For the Texas Department of Insurance, consumer protection is our core business. Everything we do – reviewing insurers’ financial solvency, licensing agents, investigating fraud – is ultimately about protecting consumers. That’s why addressing the agency’s [complaint backlog] was a priority when I took over as Insurance Commissioner 18 months ago.

TDI’s technology and processes had remained essentially unchanged over many years as the number of complaints increased. The result: A backlog developed in 2015 that grew as the gap between the number of complaints received and the number resolved widened. We’re now closing that gap.

We modernized our business operations, increased automation, and emphasized processing center best practices to increase the number of complaints we can process. We assigned more staff to health complaints, which make up 75% of all complaints. We also improved the [information on our website] to help consumers understand what types of complaints we can help with and their other appeal options.

TDI can help consumers when insurance companies fail to comply with state law or the terms of their policies. But some issues require the courts or another dispute resolution process. For example, TDI can’t determine who’s at fault in an accident or how much roof damage was caused by a storm instead of normal wear. We recently developed a list of free and low-cost legal resources to help consumers with these types of disputes.

We plan to do more to help consumers understand their rights and connect them to legal resources. My focus on improving access to justice began long before I joined TDI. I've long encouraged expanding access to legal resources to help consumers represent themselves in court proceedings.

As Insurance Commissioner, I hear too many stories about consumers who have trouble finding out what they can do to protest a company's decision. Failing to provide clear, easy-to-find information about how to complain only leads to more calls and costly disputes in the long-run. Helping people complain – and resolving disputes fairly – is a good business practice. It's also the right thing to do.

More to come...

CENTER for ECONOMIC JUSTICE | FAIR ACCESS FAIR TREATMENT

Public Policy Issues for Insurers' Predictive Models

NAIC Insurance Summit

June 6, 2019

Birny Birnbaum
Center for Economic Justice

The Center for Economic Justice

CEJ is a non-profit consumer advocacy organization dedicated to representing the interests of low-income and minority consumers as a class on economic justice issues. Most of our work is before administrative agencies on insurance, financial services and utility issues.

On the Web: www.cej-online.org

About Birny Birnbaum

Birny Birnbaum is the Director of the Center for Economic Justice, a non-profit organization whose mission is to advocate on behalf of low-income consumers on issues of availability, affordability, accessibility of basic goods and services, such as utilities, credit and insurance.

Birny, an economist and former insurance regulator, has authored reports and testimony for numerous public agencies and consumer organizations, covering a wide variety of topics, including analysis of insurance markets, insurers' use of big data, market regulation, force-placed insurance, homeowners and flood insurance, consumer credit insurance, title insurance and insurance credit scoring. He has served for many years as a designated Consumer Representative at the National Association of Insurance Commissioners. He is a member of the Federal Advisory Committee on Insurance, chairing the Subcommittee on Affordability and Availability of Insurance.

Birny served as Associate Commissioner for Policy and Research and the Chief Economist at the Texas Department of Insurance. In that role, Birny was responsible for review and approval of rate filings, the development of data collection programs for market surveillance and the analysis of competition in numerous insurance markets.

Prior to his work at the TDI, Birny served as Chief Economist at the Texas Office of Public Insurance Counsel where he provided expert testimony in rate and rule hearings on behalf of insurance consumers before the TDI. While at OPIC, Birny performed the first auto insurance redlining study in Texas.

Birny was educated at Bowdoin College and the Massachusetts Institute of Technology. He holds the AMCM certification.

Why CEJ Works on Insurance Issues

Insurance Products Are Financial Security Tools Essential for Individual and Community Economic Development:

CEJ works to ensure ***fair access*** and ***fair treatment*** for insurance consumers, particularly for low- and moderate-income consumers.

Insurance is the Primary Institution to Promote Loss Prevention and Mitigation, Resiliency and Sustainability:

CEJ works to ensure insurance institutions maximize their role in efforts to reduce loss of life and property from catastrophic events and to ***promote resiliency and sustainability*** of individuals, businesses and communities.

Personal Consumer Information in Big Data

- Telematics – Auto, Home, Wearable Devices
- Social Media
- Shopping Habits/Purchase History
- Hobbies and Interests
- Demographics/Household Data/Census Data
- Government Records/Property Records
- Web/Mobile Phone Tracking/GPS/Data Harvesting
- Vehicle Registration and Service Records
- Facial Analytics
- Mainstream Credit Files: Loans, Credit Cards
- Alternative Credit Data: Telecom, Utility, Rent Payment

Sources of Data include consumers (via telematics or wearable devices), government, social media platforms, web sites, mobile devices, e-mail/text, data brokers, online data aggregators, aircraft/satellite photos and many others.

Examples of Insurer Big Data Algorithms

Pricing/Underwriting:

- Price Optimization/Demand Models
- Customer Value Scores
- Telematics,
- Social Media Scores
- Credit Scores
- Criminal History Scores,
- Vehicle Scores,
- FireLine Rating
- Facial Analytics

Claims:

- Claim Optimization/Demand Models
- Fraud Scores
- Facial Analytics
- Severity Scores
- Telematics

Big Data Algorithms as Insurance Market Gatekeepers

- Marketing: web searches and web advertising that pre-score and channel consumers to particular products, providers and price-levels.

- Pricing: pre-fill applications and pricing without the consumer providing information, pricing based not just on risk but on price optimization / consumer demand models, real-time competitive options and/or socio-economic characteristics

- Claims: automated, instant claim settlement proposals based on data generated by a vehicle, home telematics or wearable device and utilizing price optimization/consumer demand models to determine amount of claim settlement offer a particular consumer is likely to accept based on his or her personal data.

- Common characteristics – opaque algorithms, little or no disclosure or transparency to consumer, great potential to penalize most vulnerable consumers, limiting loss mitigation role of insurance

What's So Big about Big Data?

1. Insurers' use of Big Data has huge potential to benefit consumers and insurers by transforming the insurer-consumer relationship and by discovering new insights into and creating new tools for loss mitigation.

2. Insurers' use of Big Data has huge implications for fairness, access and affordability of insurance and for regulators' ability to keep up with the changes and protect consumers from unfair practices

3. The current insurance regulatory framework generally does not provide regulators with the tools to effectively respond to insurers' use of Big Data. Big Data has massively increased the market power of insurers versus consumers and versus regulators.

4. Market forces alone – "free-market competition" – cannot and will not protect consumers from unfair insurer practices. So-called "innovation" without some consumer protection and public policy guardrails will lead to unfair outcomes.

Big Data Example 1: Facial Analytics

From "The Why and What of Accelerated Underwriting"[1]

Accelerated underwriting with new data sources . . . can cause movement of between risk classes of existing insured/applicant pool.

Multiple new data sources to address the full UW space: Wearable technology, Credit profiles, Criminal histories, Smarter App & Candor Analytics

Acceleration without Automation may leave companies falling short of the ultimate potential to change the paradigm.

Most of the new, emerging commonly suggested alternative data sources can be used to predict/stratify mortality:

Criminal History, Credit Mortality Risk Score, Facial Analytics

[1] https://www.acli.com/-/media/ACLI/Files/Events/MED2018/Mon021918TheWhyandWhatofAcceleratedUnderwritingMaryBahnaNolanonlineversion.ashx?la=en

Facial Analytics is one emerging technology that may be used to verify smoker status, BMI, other diseases and reduce the sentinel effect

Technological advances allow the combining of facial analytics with constantly evolving bio-demographic data to provide insurers with more insight, speed and accuracy than ever before.

While insurance companies have traditionally used chronological age for estimating lifespan, this technology provides a new, scientifically proven method of forecasting mortality based on estimates of the rate at which someone is aging. As no two people age at the same rate, by taking each user's individual traits into account, facial recognition provides more realistic and reliable results.

AINow, "Discriminating Systems: Gender, Race and Power in AI"[2]

The use of AI systems for the classification, detection, and prediction of race and gender is in urgent need of re-evaluation.

The histories of 'race science' are a grim reminder that race and gender classification based on appearance is scientifically flawed and easily abused. Systems that use physical appearance as a proxy for character or interior states are deeply suspect, including AI tools that claim to detect sexuality from headshots, predict 'criminality' based on facial features, or assess worker competence via 'micro-expressions.' Such systems are replicating patterns of racial and gender bias in ways that can deepen and justify historical inequality. The commercial deployment of these tools is cause for deep concern.

[2] https://ainowinstitute.org/discriminatingsystems.pdf

“Facing Up to Bias in Facial Recognition,” *American Banker*[3]

Last week the American Civil Liberties Union demanded that Amazon stop selling its Rekognition program to government agencies and police departments. The ACLU said the technology is flawed and that it is worried law enforcement agencies will use the system to track protesters and immigrants.

Recent studies have shown facial recognition systems tend to have higher error rates for women and minorities than white men.

Antony Haynes, associate dean for strategic initiatives and information systems at Albany Law School, pointed out that all artificial intelligence systems have the potential for bias.

“One assumption we make as human beings is that putting something in software makes it somehow objective or neutral or unbiased,” he said. “That couldn’t be further from the truth because a human being has to write the software, provide the training data, and tell the system when it succeeds or fails.”

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[3] https://www.americanbanker.com/news/facing-up-to-bias-in-facial-recognition, May 29, 2018

Big Data Example 2: Genetic Information

SwissRe SONAR 2019

The major challenge for life insurers is to obtain adequate and risk-relevant information during the underwriting process, since existing regulation was mostly enacted before the widespread distribution of direct-to-consumer (DTC) genetic tests. Generally, regulation disallows the use of genetic information in underwriting life insurance.[4] This raises the prospect of more customers at higher risk of disease or mortality applying for life insurance, leading to adverse selection. Customers in the know may also fear being denied life cover due to some genetic conditions, leading the insured to withhold such information from the insurer.

Regulation that stimulates genetic information asymmetry will significantly impact insurers' ability to offer attractively priced coverage, and may challenge the way in which insurance risk is considered and managed. Insurers must be able to evaluate relevant consumer information when underwriting, and that includes risk-relevant data from genetic tests.

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[4] Not in the U.S.

Currently, there seem to be three broad regulatory approaches to access and use of genetic data for risk assessment: none/self-regulation, limitations by law, and outright legal ban. This lack of uniform approach shows the need for ***industry groups and regulators to work together to agree on reasonable self-regulation***, one that balances the interests of consumers while maintaining the ability of insurers to underwrite sustainable products.

As with any new innovation, there will be a challenging transition period in which insurers will need to develop the know-how of capturing and managing the data, design systems to incorporate the data and implement new underwriting approaches. As the results yielded by genetic tests become more accurate and their use becomes more widespread, the way insurers traditionally pool risk to differentiate individual risks may no longer be suitable.

American Council of Life Insurers, *Understanding Risk Classification*

Put simply, it makes sense for the applicant and insurer to be "on the same page," sharing vital information. If someone knows a risk factor about themselves and are applying for coverage, the insurers should know as well.

From the *Position Paper on Genetic Information* U.S. Council for Responsible Genetics from 1996.

Unlike infectious diseases, genetic conditions exist at a fairly stable incidence in our society. There is no epidemic of genetic conditions. Thus, they are already reflected in the actuarial tables used by insurers to establish rates. It is misleading for insurers to suggest that their financial solvency **will be** jeopardized if they are obligated to insure people at risk for genetic conditions. In fact, insurers have always insured people at risk for genetic conditions.

The insurance industry has offered no compelling reason to specifically exclude this group from the insured pool now. Early identification of risk status may actually lead to insurer cost savings as a result of preventative care and longer life spans during which premiums can be collected.

Recent developments in human genetic science and the technology of testing are not identifying new costly diseases which were not previously accounted for by the insurance industry's' actuarial data. Rather, these developments are only facilitating the identification of those individuals who carry disease-associated genes at earlier times; many of these people will never have a related illness, or will experience a lifetime of the asymptomatic, presymptomatic or minimally symptomatic phases of the condition. It is not, therefore, the cost of financing the care of genetic conditions which is driving the call for access and inclusion of genetic information in insurance practices. There is no reason for insurers to begin to use this new predictive information now, merely because it is available.

GENETIC DISCRIMINATION SETS A DANGEROUS PRECEDENT

Genetic testing is not only a medical procedure. It is also a way of creating social categories. As a basic principle, we believe that people should be evaluated based on their individual merits and abilities, and not based on stereotypes and predictions about their future performance or health status. In most cases, genetic testing can only reveal information about probabilities, not absolute certainties. We believe that individuals should not be judged based on stereotypes and assumptions about what people in their class or status are like. Insurance or employment practices which employ these stereotypes in underwriting inadvertently reinforce them in other arenas as well.

There is a strong public policy precedent for avoiding the negative social consequences of such a practice. For example, statistics demonstrate that African Americans do not live as long as· Americans of Northern European descent, even when one controls for socio-economic factors. And yet no life insurance company in the country rates applicants differentially on the basis of race. To do so would violate deeply held community values about equality and equal access. Skin color, like other genetic traits, is mediated by genes. These lie entirely outside the individual's control. Whereas individuals can exercise choices about whether to smoke, how much exercise they get, and how much fat is in their diets, they cannot change the contents of their genes. To make employment or insurance decisions on the basis of genetic characteristics determined at the moment of conception is to discard cherished beliefs in justice and equality.

Big Data Example 3: Aerial Photography at Granular Detail

Geospatial Intelligence Center[5]

“Our Metro-Maps collection is based on versatile, high-resolution aerial systems and offer deep insight into top US metropolitan areas through 7.5cm GSD vertical and 360° oblique views. Mobile mapping sensors provide street-level intelligence through 360° imagery along with elevation data produced through high-density point clouds. Collections are repeated on an annual basis and more frequently for high growth locations.”

Keener Insight Into Property Conditions

The GIC offers the most comprehensive, diverse and detailed imagery collection along with tools and analytics for keener insight into property condition. Combined with historical data of a surrounding area, predictive analysis can be made for deeper understanding of underwriting risk. The result is streamlined underwriting, allowing you to better serve your customers while reducing operating costs.

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[5] http://geointel.org/annual-imagery-program/

Rapid & Effective Disaster Response

GIC high-resolution aerial imagery is rapidly accessible to first responders, humanitarian organizations, and federal and state agencies, providing them with actionable insight into the situation on the ground.

Funded by the GIC consortium of insurers, this support is provided to help responders assist those in need and save lives during and after disaster

The GIC is a National Insurance Crime Bureau (NICB) initiative in partnership with Vexcel Imaging that is focused on building a national database of high resolution imagery to be used by its member companies that write almost 80 percent of all property/casualty insurance and over 94 percent of all auto insurance in the country, as well as public sector and non-governmental organizations. The Geospatial Intelligence Center has previously mapped the areas hardest hit by hurricanes and disasters and those views are also available through the web map portal.

Big Data Example 4: Criminal History

"TransUnion recently evaluated the predictive power of court record violation data (including criminal and traffic violations)

"Also, as court records are created when the initial citation is issued, they provide insight into violations beyond those that ultimately end up on the MVR—such as violation dismissals, violation downgrades, and pre-adjudicated or open tickets."

What is the likelihood that TU Criminal History Scores have a disparate impact against African-Americans? Consider policing records in Ferguson, Missouri.

US DOJ Investigation of the Ferguson Police Department

Ferguson’s approach to law enforcement both reflects and reinforces racial bias, including stereotyping. ***The harms of Ferguson’s police and court practices are borne disproportionately by African Americans, and there is evidence that this is due in part to intentional discrimination on the basis of race.***

Ferguson’s law enforcement practices overwhelmingly impact African Americans. Data collected by the Ferguson Police Department from 2012 to 2014 shows that African Americans account for 85% of vehicle stops, 90% of citations, and 93% of arrests made by FPD officers, despite comprising only 67% of Ferguson’s population.

US DOJ Investigation of the Ferguson Police Department (2)

FPD appears to bring certain offenses almost exclusively against African Americans. For example, from 2011 to 2013, African Americans accounted for 95% of Manner of Walking in Roadway charges, and 94% of all Failure to Comply charges.

Our investigation indicates that this disproportionate burden on African Americans cannot be explained by any difference in the rate at which people of different races violate the law. Rather, our investigation has revealed that these disparities occur, at least in part, because of unlawful bias against and stereotypes about African Americans.

Big Data Algorithms Can Reflect and Perpetuate Historical Inequities

Barocas and Selbst: *Big Data's Disparate Impact*[6]

Advocates of algorithmic techniques like data mining argue that they eliminate human biases from the decision-making process. But an algorithm is only as good as the data it works with. Data mining can inherit the prejudices of prior decision-makers or reflect the widespread biases that persist in society at large. Often, the "patterns" it discovers are simply preexisting societal patterns of inequality and exclusion. Unthinking reliance on data mining can deny members of vulnerable groups full participation in society.

[6] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2477899

Virginia Eubanks, *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*

America's poor and working-class people have long been subject to invasive surveillance, midnight raids, and punitive public policy that increase the stigma and hardship of poverty. During the nineteenth century, they were quarantined in county poorhouses. During the twentieth century, they were investigated by caseworkers, treated like criminals on trial. Today, we have forged what I call a digital poorhouse from databases, algorithms, and risk models. It promises to eclipse the reach and repercussions of everything that came before.

Algorithmic Bias

Steve Bellovin, “Yes, ‘algorithms’ can be biased. Here’s why. A computer scientist weighs in on the downsides of AI.”[7]

This is what's important: machine-learning systems—"algorithms"—produce outputs that reflect the training data over time. If the inputs are biased (in the *mathematical* sense of the word), the outputs will be, too. Often, this will reflect what I will call "sociological biases" around things like race, gender, and class.

One thing is to exercise far more care in the selection of training data. Failure to do that was the likely root cause of Google Images labeling two African-Americans as gorillas. Sometimes, fixing the training data can help.

Of course, this assumes that developers are even aware of the bias problem. Thus, another thing to do is to test for biased outputs—and some sensitive areas, such as the criminal justice system, simply do not use these kinds of tools.

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[7] https://arstechnica.com/tech-policy/2019/01/yes-algorithms-can-be-biased-heres-why/

Given that ML systems (including facial recognition systems) can produce biased output, how should society treat them? Remember that, often, the choice is not between algorithmic output and perfection but between algorithmic decisions and human ones—and humans are demonstrably biased, too. That said, there are several reasons to be wary of the "algorithmic" approach.

One reason is that people put too much trust in computer output. Every beginning programmer is taught the acronym "GIGO:" garbage in, garbage out. To end users, though, it's often "garbage in, gospel out"—if the computer said it, it must be so. (This tendency is exacerbated by bad user interfaces that make overriding the computer's recommendation difficult or impossible.) We should thus demand less bias from computerized systems precisely to compensate for their perceived greater veracity.

The second reason for caution is that computers are capable of doing things—even bad things—at scale. There is at least the perceived risk that, say, computerized facial recognition will be used for mass surveillance. Imagine the consequences if a biased but automated system differentially misidentified African-Americans as wanted criminals. Humans are biased, too, but they can't make nearly as many errors per second.

Our test, then, should be one called disparate impact. "Algorithmic" systems should be evaluated for bias, and their deployment should be guided appropriately. Furthermore, the more serious the consequences, the higher the standard should be before use.

Amazon Created a Hiring Tool Using A.I. It Immediately Started Discriminating Against Women.[8]

All of this is a remarkably clear-cut illustration of why many tech experts are worried that, rather than remove human biases from important decisions, artificial intelligence will simply automate them. An investigation by ProPublica, for instance, found that algorithms judges use in criminal sentencing may dole out harsher penalties to black defendants than white ones. Google Translate famously introduced gender biases into its translations. The issue is that these programs learn to spot patterns and make decisions by analyzing massive data sets, which themselves are often a reflection of social discrimination. Programmers can try to tweak the AI to avoid those undesirable results, but they may not think to, or be successful even if they try.

[8] Jordan Wasserman at, https://slate.com/business/2018/10/amazon-artificial-intelligence-hiring-discrimination-women.html

"The Real Reason Tech Struggles with Algorithmic Bias"[9]

These are mistakes made while trying to do the right thing. But they demonstrate why tasking untrained engineers and data scientists with correcting bias is, at the broader level, naïve, and at a leadership level insincere.

No matter how trained or skilled you may be, it is 100 percent human to rely on cognitive bias to make decisions. Daniel Khaneman's work challenging the assumptions of human rationality, among other theories of behavioral economics and heuristics, drives home the point that human beings cannot overcome all forms of bias. But slowing down and learning what those traps are—as well as how to recognize and challenge them—is critical. As humans continue to train models on everything from stopping hate speech online to labeling political advertising to more fair and equitable hiring and promotion practices, such work is crucial.

[9] Yael Eisenstat at https://www.wired.com/story/the-real-reason-tech-struggles-with-algorithmic-bias/

Becoming overly reliant on data—which in itself is a product of availability bias—is a huge part of the problem. In my time at Facebook, I was frustrated by the immediate jump to “data” as the solution to all questions. That impulse often overshadowed necessary critical thinking to ensure that the information provided wasn't tainted by issues of confirmation, pattern, or other cognitive biases.

There is not always a strict data-driven answer to human nature. The belief that simply running a data set will solve for every challenge and every bias is problematic and myopic. To counter algorithmic, machine, and AI bias, human intelligence must be incorporated into solutions, as opposed to an over-reliance on so-called “pure” data.

Insurers' / Producers' Use of Personal Consumer Data – the Role of Supervisors

Step 1: Establish Values and Principles

"Before we choose our tools and techniques, we must first choose or dreams and values, for some tools serve them while others make them unobtainable." Tom Bender

CEJ’s Principles/Values for Ethical AI

- Cost-Based Pricing: Protect insurer financial condition, provide proper investment risk / mitigation benefit price signals, fair treatment of consumers entering into contracts of adhesion

- Loss Prevention / Mitigation / Sustainability / Resilience: Enhance, not undermine the loss prevention potential of insurance

- Risk Pooling: Protect risk diversification, availability and affordability of insurance

- Availability / Affordability – Address the protection gap for low- and moderate-income consumers and small businesses. Most important tool for individual, business and community recovery and resilience.

- Fair Competition – Antitrust enforcement for emerging types of collective pricing and claim settlement practices facilitated by big data algorithms

- Fair Competition – Empower consumers by more symmetric sharing of information between insurers and consumers

- Digital Rights – consumer ownership and consent to identified uses, protection of consumer data, contestability, disclosure of and remediation following data breaches

- Transparency, Explainability and Accountability – ethical and accountable algorithms

- Regulatory and Legal Compliance – compliance with the letter of and the intent of the law

Values to Guide Ethical Use of AI

Artificial Intelligence: Australia's Ethics Framework[10]

Core Principles for AI

1. Generate Net-Benefits
2. Do No Harm
3. Regulatory and Legal Compliance
4. Privacy Protection
5. Fairness
6. Transparency and Explainability
7. Contestability
8. Accountability

[10] https://consult.industry.gov.au/strategic-policy/artificial-intelligence-ethics-framework/

Values to Guide Ethical Use of AI

Transatlantic Consumer Dialogue

Resolution on Fintech: http://tacd.org/wp-content/uploads/2018/11/TACD_resolution_fintech_final.pdf

Resolution on Competition, Privacy and Consumer Welfare: http://tacd.org/wp-content/uploads/2018/12/TACD-Resolution_Comp_Dec2018_final.pdf

European Commission Consultation: FinTech –A more competitive and innovative European Financial Sector

http://tacd.org/wp-content/uploads/2017/06/TACD-response-to-the-European-Commission-consultation-on-Fintech.pdf

Supervisory Oversight of Insurers'/Producers' Use of Personal Consumer Data

Educate

- Establish and publish consumer digital rights
- Declare Values / Establish Principles for Insurers' / Producers' Fair Treatment of Consumers

Investigate

- Survey insurers/producers on types, sources and uses of personal consumer data – what data from what sources is used for marketing, pricing, sales, claims settlement/anti-fraud
- Collect data on consumer market outcomes

Evaluate

- Are insurers/producers using certain data for impermissible purposes?
- Are consumer outcomes showing disparate impact against protected classes or otherwise contrary to public policy?

Prevent Consumer Harm

- Establish guidelines for ethical collection, use, protection of personal consumer data
- Establish guidelines for ethical algorithm development and use
- Promote / celebrate best practices / outcomes consistent with core values

Redress Consumer Harm

- Identify consumer harm resulting from inappropriate use of consumer personal information / big data algorithms / machine learning / AI
- Stop harmful practices / remediate consumer harm

Operationalize

- Identify and secure necessary human and digital resources

Ethical Algorithms:
Minimizing Disparate Impact in Insurance Models

One Tool: Consider Prohibited Risk Classes in Model Development

Step 1: Include race, religion and national origin – or proxies for these characteristics if actual individual characteristic unknown – as independent variables – control variables – in the model.

By using the characteristics as independent variables in the development of the model, the remaining independent variables' contribution (to explaining the dependent variable) is shorn of that part of their contribution that is a function of correlation with the prohibited characteristics. For the independent variables other than race, religion and national origin, what remains is a more accurate picture of the remaining independent variables' contribution to the target outcome.

Step 2: Omit race, religion and national origin when the model is deployed.

New York Times, August 10, 2015: Algorithms and Bias: Q. and A. With Cynthia Dwork

Q: Some people have argued that algorithms eliminate discrimination because they make decisions based on data, free of human bias. Others say algorithms reflect and perpetuate human biases. What do you think?

A: Algorithms do not automatically eliminate bias. . . .Historical biases in the . . .data will be learned by the algorithm, and past discrimination will lead to future discrimination.

Fairness means that similar people are treated similarly. ***A true understanding of who should be considered similar for a particular classification task requires knowledge of sensitive attributes, and removing those attributes from consideration can introduce unfairness and harm utility.***

Q: Should computer science education include lessons on how to be aware of these issues and the various approaches to addressing them?

A: Absolutely! First, students should learn that design choices in algorithms embody value judgments and therefore bias the way systems operate. They should also learn that these things are subtle: For example, designing an algorithm for targeted advertising that is gender neutral is more complicated than simply ensuring that gender is ignored. They need to understand that classification rules obtained by machine learning are not immune from bias, especially when historical data incorporates bias.

Illustration of One Technique to Minimize Disparate Impact

Let's create a simple model to predict the likelihood of an auto claim:

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + e = y$$

Say that $X_{1,}$ X_2 + X_3 are miles driven, driving record and credit score and we are trying to predict y – the frequency of an auto claim.

Let's assume that all three Xs are statistically significant predictors of the likelihood of a claim and the b values are how much each X contributes to the explanation of claim.

b_0 is the "intercept" – a base amount and e is the error term – the portion of the explanation of the claim not provided by the independent variables.

What Happens When We Explicitly Consider A Variable For Race?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \mathbf{b_4R_1} + e = y$$

R_1 is a control variable – by including race in the model development, the correlation of the Xs to race is statistically removed and the new b values are now the contribution of the Xs, independent of their correlation to race, to explaining the likelihood of a claim

When the model is deployed, the variable for race is removed – the Xs remain, but the b values now minimize disparate impact.

Why is a Statistical Test for Disparate Impact Consistent with Actuarial Justification Used by Insurers?

Actuarial justification is a statistical test – that a particular characteristic of the consumer, vehicle, property or environment is correlated with a particular outcome, like pure premium (average claim cost). The same statistical test can be used to evaluate and minimize disparate impact. Stated differently – if a particular correlation and statistical significance is used to justify, say, insurance credit scoring, those same standards of correlation and statistical significance are reasonable evidence of disparate impact and unfair discrimination on the basis of prohibited factors.

Ethical Algorithms: Reasonable and Necessary for Insurance Pricing and Claims Settlement Models

1. Minimizes Disparate Impact – Stop the Cycle of Perpetuating Historical Discrimination.
2. Promotes Availability and Affordability for Underserved Groups
3. Improves Cost-Based Insurance Pricing Models
4. Improve Price Signals to Insureds for Loss Mitigation Investments
5. Help Identify Biases in Data and Modelers / Improve Data Insights
6. Improve Consumer Confidence of Fair Treatment by Insurers

Flawed Premise: Greater Risk Segmentation Equals More Accurate Pricing, Better Matching of Price to Risk.

Micro risk segmentation is a function of greater reliance on more complex predictive algorithms. Greater segmentation – more variables, more data sources – introduces new risks – modeling risk, data bias risk, unfair discrimination risk. Greater segmentation does not create greater "accuracy," where "accuracy" purports to be better matching price to risk.

The concept of ever more "accurate" and granular risk segmentation must mean greater and greater disparity between the most and least favored consumers with great implications for availability and affordability of insurance and likely burdens on consumers in already-underserved communities under the guide of "matching price to risk" or "fighting fraud."

Antitrust and Competition Concerns With Data Brokers and Vendors of Algorithms

Increased antitrust scrutiny and reinvigorated competition analysis is needed to address the market power and potential collusion mechanisms of data and algorithm vendors.

Dozens or hundreds of companies are engaging in practices that have historically required supervisory oversight to exempt the practices from antitrust laws, including the collection and sharing of insurers' experience and the provision of collective pricing guidance. Vendors that collect exposure and claims data from insurers, combine these data with other, non-insurance data to provide pricing or claim settlement tools present mechanisms for collective pricing and claim settlement valuations, also known as collusion.

Ethical Algorithms -- Sources

Pauline T. Kim, "Auditing Algorithms for Discrimination"
https://www.pennlawreview.com/online/166-U-Pa-L-Rev-Online-189.pdf
Claire Whitaker, "Ethical Algorithms"
https://www.kdnuggets.com/2019/03/designing-ethical-algorithms.html
Erin Russel, "The Ethical Algorithm"
https://www.cognitivetimes.com/2019/01/the-ethical-algorithm/
Barocas and Selbst
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2477899
Kroll, et al, "Accountable Algorithms:
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2765268
Virginia Eubanks, *Automating Inequality: How High Tech Tools Profile, Police and Punish the Poor*
Selbst and Barocas, "The Intuitive Appeal of Explainable Machines
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3126971
Levy and Barocas, "Designing Against Discrimination in Online Markets
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3084502
New York Times, "Algorithms and Bias, Q and A with Cynthia Dwork," 10 August 2015
https://www.nytimes.com/2015/08/11/upshot/algorithms-and-bias-q-and-a-with-cynthia-dwork.html
Martin, Kirsten E. M., What Is an Ethical Algorithm (And Who Is Responsible for It?) (October 21, 2017). Available at SSRN: https://ssrn.com/abstract=3056692 or http://dx.doi.org/10.2139/ssrn.3056692
Kirsten Martin, "Ethical Implications and Accountability of Algorithms"
http://kirstenmartin.net/wp-content/uploads/2013/11/Martin-JBE-Ethics-and-Accountability-of-Algorithms.pdf
Kirsten Martin, DATA AGGREGATORS, BIG DATA, & RESPONSIBILITY ONLINE
http://kirstenmartin.net/wp-content/uploads/2013/11/AAPOR-Martin-Info-Value-Chain-v2.pdf
AIandBigData:Ablueprintforahumanrights,socialandethicalimpactassessmentAlessandroMantelero
https://reader.elsevier.com/reader/sd/pii/S0267364918302012?token=3836947F0CAD3C145A1F273E3CBE6C38F67E777DD7E4D590548F481916130DAACA8D57BED4667BD1FE1F4D8FC80E7C56