



## **NAIC Insurance Summit**

# **Ethical Considerations of Big Data Analytics in Insurance: Challenges and Opportunities for Regulators**

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## 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.

## Big Data Defined

Insurers' use of Big Data has transformed the way they do marketing, pricing, claims settlement and their approach to risk management. For purposes of my talk, Big Data means:

- Massive databases of information about (millions) of individual consumers
- Associated data mining and predictive analytics applied to those data
- Scoring models produced from these analytics.

The scoring models generated by data mining and predictive analytics are algorithms. Algorithms are lines of computer code that rapidly execute decisions based on rules set by programmers or, in the case of machine learning, generated from statistical correlations in massive datasets.

**With machine learning**, the models change automatically. Coupled with the increased volume and granularity of data is the digital technology to generate, access, process, analyze and deploy big data and big data algorithms in real time

# 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/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, data brokers, online data aggregators 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
- Accelerated Life Insurance Underwriting

## 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.

## Ethical Algorithms and Disparate Impact

Many states prohibit insurance discrimination on the basis of race, religion or national origin – for underwriting, pricing or claims settlement regardless of actuarial justification. For other rating factors, at a minimum, actuarial justification is required.

What is actuarial justification? A showing of a statistical relationship (correlation) between a particular characteristic of the consumer, vehicle, property or environment and the designated outcome – e.g., claim frequency, claim severity, pure premium, loss ratio, fraudulent claim, of a claim, likelihood of a fraudulent claim, loss ratio, retention, cross-sales, demand models.



## Intentional Discrimination vs. Disparate Impact

Insurers argue that states' unfair discrimination laws prohibit intentional discrimination based on race – the explicit use of race in pricing or claims settlement.

Disparate Impact refers to practices that, while not explicit discrimination on the basis of, say, race, have the same effect as if race was the basis for the discrimination.

Insurers also argue that Disparate Impact is not recognized as unfair discrimination in state insurance laws. (Disparate impact in homeowners insurance is specifically recognized as a violation of the federal Fair Housing Act).

## Industry Trade Arguments against Disparate Impact in Insurance:

- Insurers don't consider race, religion or national origin, so there can be no unfair discrimination on the basis of these factors.
- Regulators have no authority to consider disparate impact:

*Absent discriminatory treatment or failing to match price to the risk, the issue is whether they are even appropriate inquiries to apply to insurance rating. This is especially the case since some states prohibit even asking about the applicant's or policyholder's race or some other protected class status. As a result, the rating for a particular risk is truly color blind.*

AIA and NAMIC Comments to NAIC Big Data Working Group, January 26, 2018

## Why is Discrimination on the Basis of Race Considered Unfair Discrimination

Why are race, religion and national origin considered suspect classifications by the Supreme Court?

- (1) there is a history of discrimination against the group in question;
- (2) the characteristics that distinguish the group bear no relationship to the group members' ability to contribute to society;
- (3) the distinguishing characteristics are immutable; and
- (4) the subject class lacks political power.

Avraham, Ronen; Logue, Kyle D.; and Schwarcz, Daniel Benjamin, "Understanding Insurance Anti-Discrimination Laws" (2013). *Law & Economics Working Papers*.  
[http://repository.law.umich.edu/law\\_econ\\_current/52](http://repository.law.umich.edu/law_econ_current/52)

## Industry Arguments on Disparate Impact Flawed

The industry claim that their algorithms are “color blind” is, of course, nonsense to anyone familiar with algorithms because algorithms can reflect and perpetuate the historical biases of the data and the developers.

Further – if intentional discrimination against protected classes is prohibited, why would we ignore or permit unintentional discrimination that has the same effect be permitted?

Given that states (for auto insurance) and lenders (for auto and property insurance) require the purchase of insurance, and

That states (fines, loss of civil rights, imprisonment) and lenders (force-placed insurance) penalize consumers who fail to maintain required insurance, then

It is reasonable and necessary for insurance regulators to effectively monitor availability, affordability and actual market outcome on, among other reasons, the basis of protected classes.

## ***Big Data Algorithms Can Reflect and Perpetuate Historical Inequities***

Barocas and Selbst: *Big Data's Disparate Impact*

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.

## **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.

# Why Is Disparate Impact Relevant for Insurance Pricing?

## TransUnion Criminal History Score

**“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

## Potential for Disparate Impact of Anti-Fraud Models

Algorithms reflect bias in data and bias in modelers. Consider data used in anti-fraud models. These models tap a variety of data sources to identify characteristics of the consumer and/or the claim correlated with a fraudulent or suspicious claim. But what is the source of the claims identified as fraudulent used in the development of the models? Do the set of claims identified as fraudulent reflect historical bias in anti-fraud and claim settlement practices? Do the modelers have unintentional biases based on cultural backgrounds?

## Example: Propensity for Fraud

“Unstructured data has become an opportunity instead of a problem. Many insurers have the ability to change unstructured information into structured data and actively mine this for the opportunities available therein.”

“This [propensity] modelling is used to determine the likelihood of a new policy holder to commit a fraudulent act and it can be done in real-time ... Fraud detection has changed in its location relative to the insured. Insurers are now able to run predictive and entity analytics during multiple touch points, essentially as each new piece of information is added. This not only improves detection capabilities in the event of fraud, but it also allows an insurer to assess a fraud-risk. Some have begun providing risky policy holders with high-priced policies in order to drive them to other service providers.”

*“The Role of Data and Analytics in Insurance Fraud Detection,”*  
[www.insurancenexus.com](http://www.insurancenexus.com), June 2016 (UK)

## **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  $X$ s 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?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$$

$R_1$  is a control variable – by including race in the model development, the correlation of the  $X$ s to race is statistically removed and the new  $b$  values are now the contribution of the  $X$ s, 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  $X$ s 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