



## Bias Discussion 2.0: Fairness in Insurance Modeling

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### Agenda

- Introduction
- Methods for Measuring Potential Bias
  - Data Required
  - Analytical Methods
- Parting Thoughts

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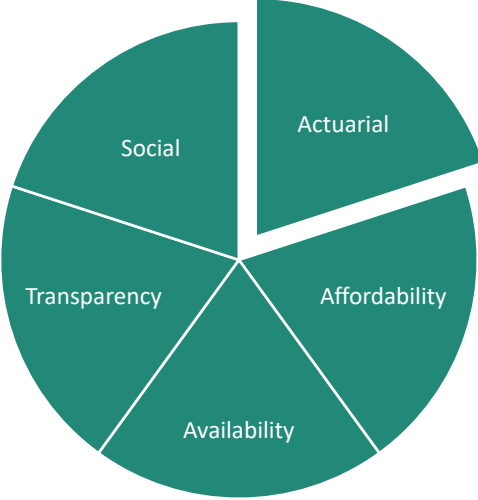
# Introduction




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## Definition of Fairness



Component
Actuarial
Affordability
Availability
Transparency
Social



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## Definitions of Fairness – Actuarial Fairness

- State Rating Laws
- Casualty Actuarial Society Statement of Principles Regarding Property and Casualty Insurance Ratemaking
- Actuarial Standard of Practice No. 53
- American Academy of Actuaries Actuarial Standard of Practice No. 12

A rate is reasonable and not excessive, inadequate, or unfairly discriminatory if it is an **actuarially sound estimate of the expected value of all future costs associated with an individual risk transfer.**

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## Proposed Colorado Regulation 3 CCR 702-4

- Governance and Risk Management Framework Requirements for Life Insurance Carriers' Use of External Consumer Data and Information Sources [ECDIS], Algorithms, and Predictive Models
- Establishes the requirements for a Life Insurance company's internal risk management framework necessary to ensure that the life insurers' use of external consumer data and information sources, algorithms, and predictive models does not result in unfairly discriminatory insurance practices.

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## Methods for Measuring Potential Bias

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### Defining Bias – Discriminatory Effects

#### Prohibited from using protected characteristics in rating

- Even though protected characteristics may be predictive of loss, insurers are prohibited from using them in rating



#### What if I find something that is perfectly correlated to the protected characteristic?

- I am not using the protected characteristic, so technically I am not violating the law
- But I am ending up in the same place as if I used the protected characteristic, so I am violating the spirit of the law

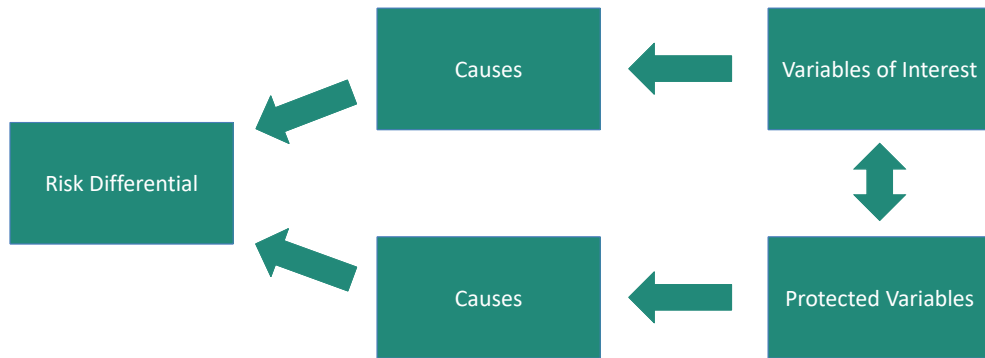


#### What if I am using something that is partially correlated to the protected characteristic?

- How much is too much?

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## Thinking through Variable Relations



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## Exploring Effects via Simulated Data

- Consider the following scenario
  - Two differentiating factors of claim frequency, uniform severity
    - One Well Proxied by Territory (Urban/Rural, Urban has higher freq)
    - One Well Proxied by Race (Black/non-Black, Black has higher freq)
  - Territory and Race are strongly correlated
  - We model using Territory to predict chance of claim arising, and apply the uniform severity to the predictions

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## Model vs. Truth – What is the Territory Relativity

- Each of the two risk differentials: +25%
- Achievable through territory (urban/rural) as proxy, mathematically:
  - Differential 1: +11.8%
  - Differential 2: +5.9%

Territory	Proportion of Book	Pred Pure Prem	Actual Pure Prem - Period 1	Actual Pure Prem - Period 2
Rural	50%	581	581	584
Urban	50%	687	687	683
Total Book	100%	634	634	633
	Urban Relativity	1.183	1.183	1.169

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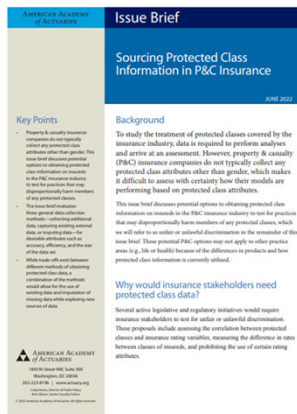
## Implicit Differential by Race

- The implicit differential here is due to
  - Higher representation of Blacks in the urban area
  - The ability of territory to capture some of the “Race related effects”

Race	Proportion of Book	Pred Pure Prem	Actual Pure Prem - Period 1	Actual Pure Prem - Period 2
non-Black	50%	607	580	579
Black	50%	662	688	689
Total Book	100%	634	634	634
	Implicit Racial Relativity	1.091	1.185	1.190

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## Data



- Capture existing external data
  - Postal code or census level
  - Individual level
- Imputation – prediction based on location and name
  - BISG
  - BIFSG
- Collect additional data
  - Ask insured

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## Data Consistency

### Census vs. BISG

	BISG		
Census	Black	Not Black	Total
Black	5.9%	4.7%	10.6%
Not Black	4.9%	84.5%	90.4%
Total	10.9%	89.1%	

### BISG vs. BIFSG

	BIFSG		
BISG	Black	Not Black	Total
Black	3.8%	6.8%	10.6%
Not Black	1.1%	88.3%	89.4%
Total	4.9%	95.1%	

While overall consistency may look good, individual consistency may show different results

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## Playing with BIFSG



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## Data Framework

- The data question can be answered
- The answer is not going to be 100% accurate, but accuracy can grow over time
- The real question will be how the accuracy of each method ultimately impacts the analysis results

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## Model Fairness

The latest research in model fairness and model de-biasing is introducing an additional component to the concept of model bias that transcends the purely statistical context. The central theme in this additional dimension of bias detection and bias mitigation is attempting to provide practitioners of analytics with mechanisms and mathematical constructs to minimize the social inequalities that their models may capture through data, and ensure that the model does not unfairly discriminate against certain protected classes.

Independence	Separation	Sufficiency
$\hat{Y} \perp A$	$\hat{Y} \perp A Y$	$Y \perp A \hat{Y}$

A - protected attribute

Y - observed value of target variable

$\hat{Y}$  - predicted value of target variable

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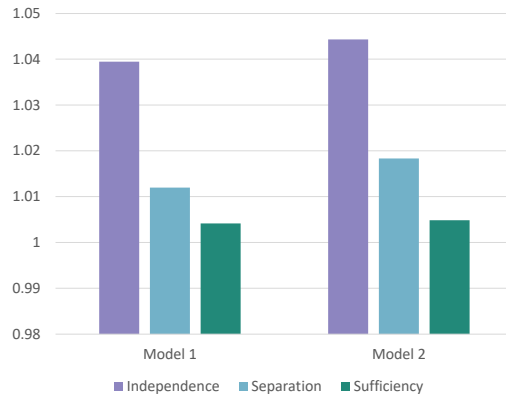
## Model Fairness – Colloquially Speaking

- **Independence**
  - The model should predict equally regardless of the protected attribute
- **Separation**
  - If I look at the good outcomes (or bad), the model should predict equally regardless of the protected attribute
- **Sufficiency**
  - If I look at all the people predicted to have good outcome (or bad), the actual amount of good (or bad) outcome should match regardless of the protected attribute

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## Example – Fairness Metrics

- In the approach described in Steinberg, D., et al. (2020), the authors propose a way of checking this independence.
- The intuition behind this method is that the closer to 1.0 the metrics are the better. When all metrics are close to 1.0 then it means that from the perspective of a predictive model there are no meaningful differences between subgroups.



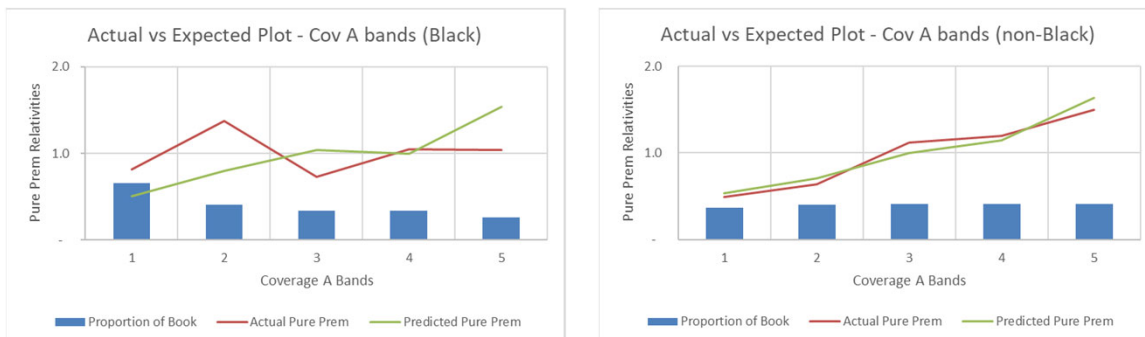
Steinberg, Daniel, Alistair Reid, Simon O'Callaghan. "Fairness Measures for Regression via Probabilistic Classification"

## Exploring Independence

- With respect to independence, the discussion of fairness often pulls in these two directions
  - How much are you predicting for each class
  - How accurate are you in predicting within each class

	Total	Black	non-Black
Proportion of Book	100%	10%	90%
Actual Pure Prem	586	577	588
Predicted Pure Prem	586	512	596

## Exploring Independence – Conditioned on Coverage A Amount

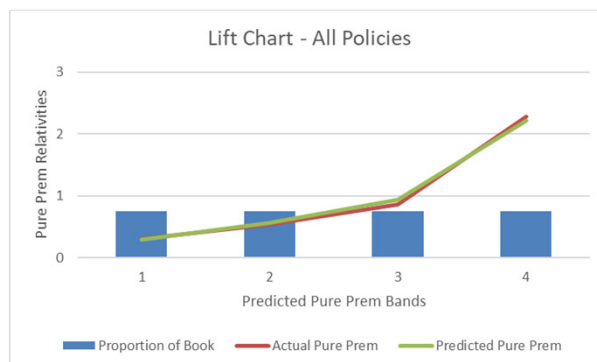


• Exposure proportions are shown relative to Black/non-Black totals, respectively. They do not reflect the 10/90 class split between the two class segments.

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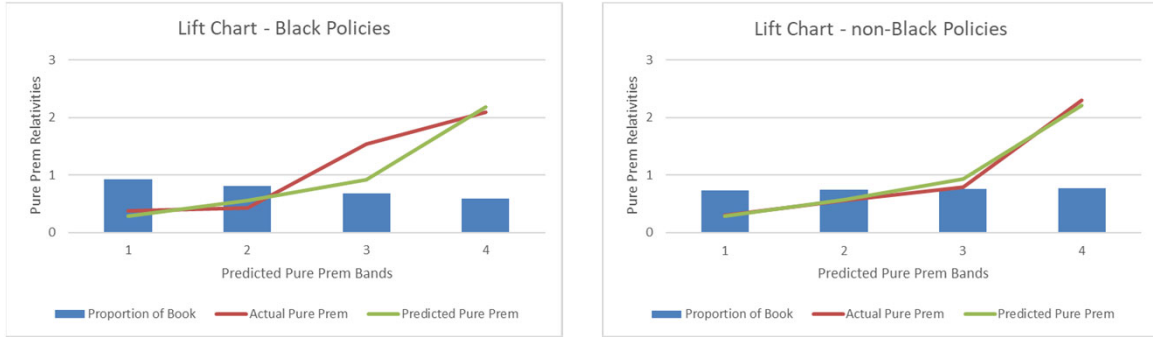
## Exploring Sufficiency – Using the Lift Chart View

- The Lift Chart lines up the data based on predicted values, creating bins of comparable predicted values



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## Exploring Sufficiency – Using the Lift Chart View



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## Exploring Separation

- Here, we start with a comparable actual outcome, and study how the model predicts for each class

Actual Experience	Predicted Pure Premium			Difference
	Total	Black	Non-Black	
No Loss	574	507	582	-13%
Small/Moderate Pure Prem	700	569	718	-21%
Large Pure Prem	1,004	673	1,035	-35%

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## Parting Thoughts

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### Practical Implications of Mitigating Potential Bias

- Impacts the ability to satisfy other fairness criteria (e.g., actuarial)
- There is no black and white answer, there is a gray area and regulators/legislators/judiciary will have to decide what is acceptable
- Will the requirements be industry-wide or company-specific
- There are potential unknown consequences of this decision
  - Impact on individual companies could be different depending on the specifics of the company
  - Broad solutions could create additional challenges

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## A Parting Thought

- **American Academy of Actuaries Actuarial Standard of Practice No. 1** –  
“Introductory Actuarial Standard of Practice”
  - *There are situations where applicable law (statutes, regulations, and other legally binding authority) may require the actuary to deviate from the guidance of an ASOP. Where requirements of law conflict with the guidance of an ASOP, the requirements of law shall govern (3.1.5)*

## Thank You

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