

# *Correlation vs. Causation*

## Clarifying the Differences & Implications

Presentation to the National Association of Insurance Commissioners (NAIC) Casualty Actuarial and Statistical (C) Task Force (CASTF) “Book Club”

By Members of the P/C Racial Equity Task Force (RETF) and Data Science and Analytics Committee (DSAC) of the American Academy of Actuaries



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This presentation is based on the *An Actuarial View of Correlation and Causation—From Interpretation to Practice to Implications* issue brief.



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# Presenters

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- Dorothy L. Andrews, Chairperson, DSAC
- Dave Heppen, Member, RETF
- Steven Armstrong, Member, RETF
- Julia Romero, Member, DSAC



# Agenda

- Establishing Causation—Dorothy Andrews
- Correlation v. Causation—Dave Heppen
- Rational Explanations Explained—Steve Armstrong
- Unintended Consequences—Dorothy Andrews
- Spurious Correlations—Julia Romero
- Next Steps—Dorothy Andrews



# Purpose

- Distinguish correlation from causation
- Identify the limitations of predictive models to demonstrate causation
- Discuss challenges of relying only on correlations for evaluating rating variables
- Examine the use of rational explanations as an alternative to demonstrating causation



# Why Is This Issue Important?

- ▣ Rise of big data in risk classification
- ▣ Correlation without demonstrable causation
- ▣ Lack of intuitive relationships in big data to risk
- ▣ Potential to create unfair pricing outcomes
- ▣ Regulatory tools for ensuring fair outcomes
- ▣ Continued industry and regulatory collaboration



# Why Not Just Establish Causation?

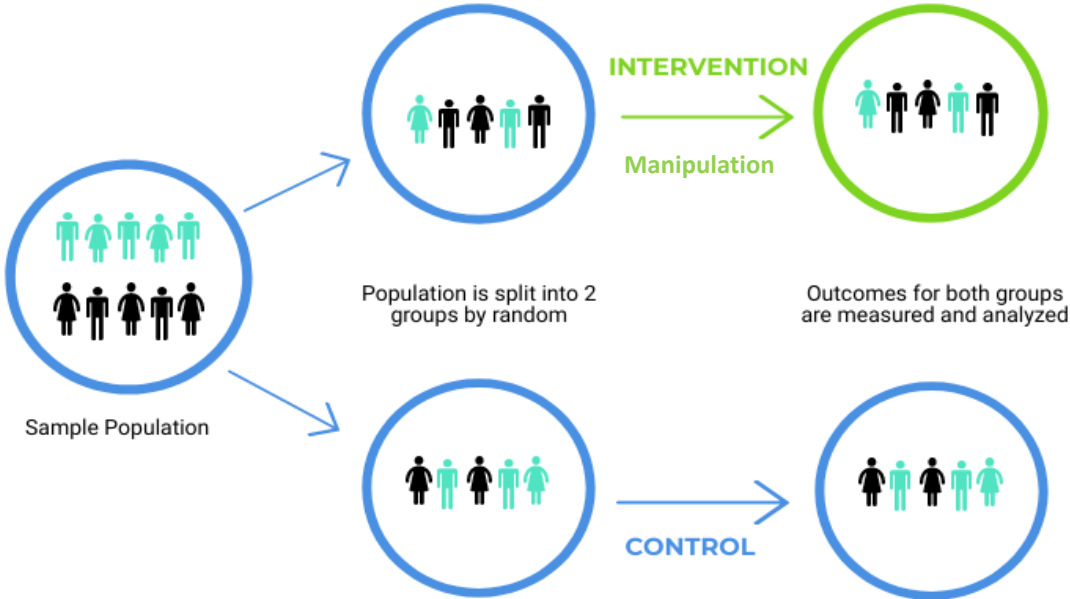
- The simple answer is

**We Can't!**



# Establishing Causation

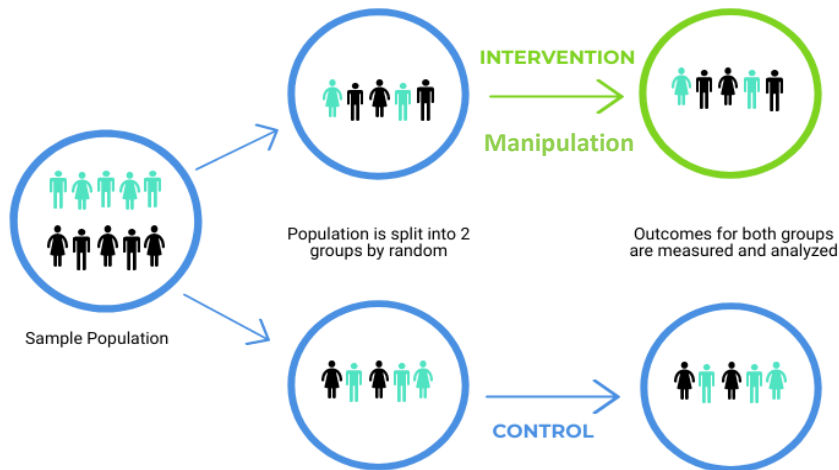
## The Randomized Control Trial (RCT)—**The Gold Standard!**





# Establishing Causation

## Applying RCTs to Auto Insurance—An Example



- ❑ Sample: Drivers
- ❑ Manipulation Variable: Slippery Roads
- ❑ Outcome of Interest: Do Slippery Roads Cause Auto Crashes?

**Are RCTs practical in insurance pricing?**

**Would this be an ethical experiment to perform?**



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# Establishing Causation

## □ Predictive Models vs. RCTs

### Similarities:

- Large number of participants and attributes
- Random sampling: Training, validation & test data sets
- Metrics comparing outcomes on data sets for model fit

### Big Difference:

- No manipulation or intervention. Purely correlation!



# Understanding Correlation Better

## Mediating vs. Moderating Variables

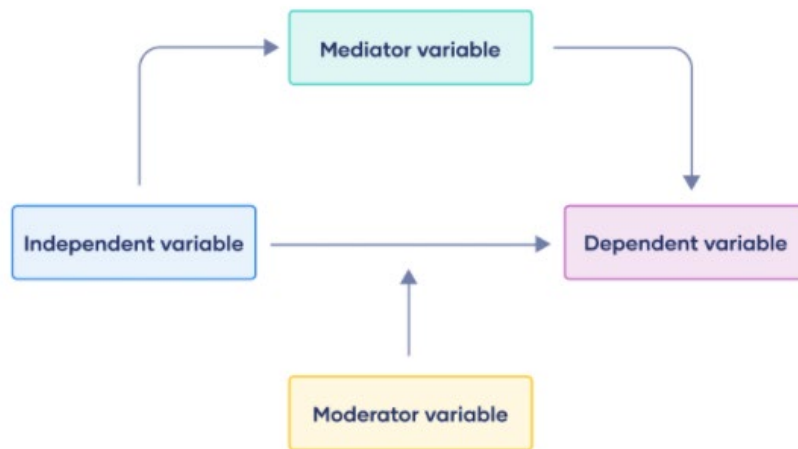
### Mediating (aka Third) Variable

Explains the how or why of an (observed) relationship between an independent variable and its dependent variable. It's part of the causal pathway of an effect, and it tells you how or why an effect takes place. For example, sleep quality (an independent variable) can affect academic achievement (a dependent variable) through the mediator of alertness.

### Moderating Variable

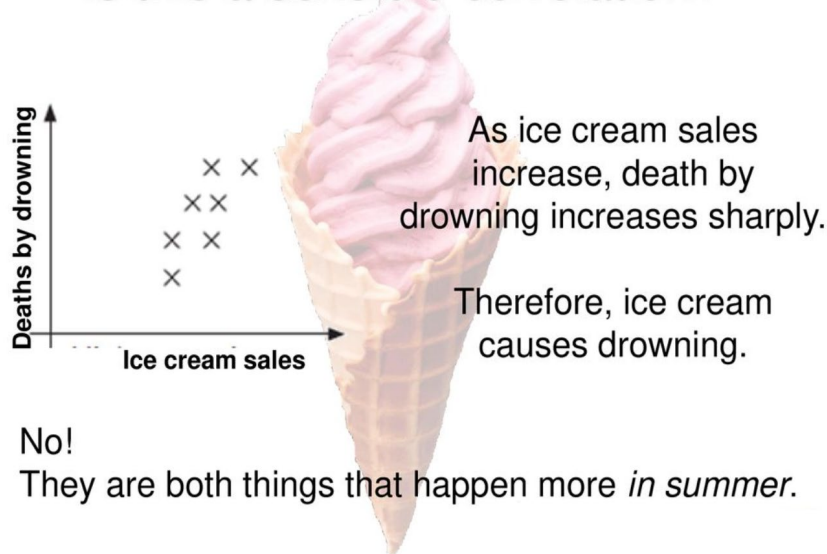
Affects the strength and direction of that relationship. For example, mental health status may moderate the relationship between sleep quality and academic achievement: the relationship might be stronger for people without diagnosed mental health conditions than for people with them.

## Mediator and moderator variables



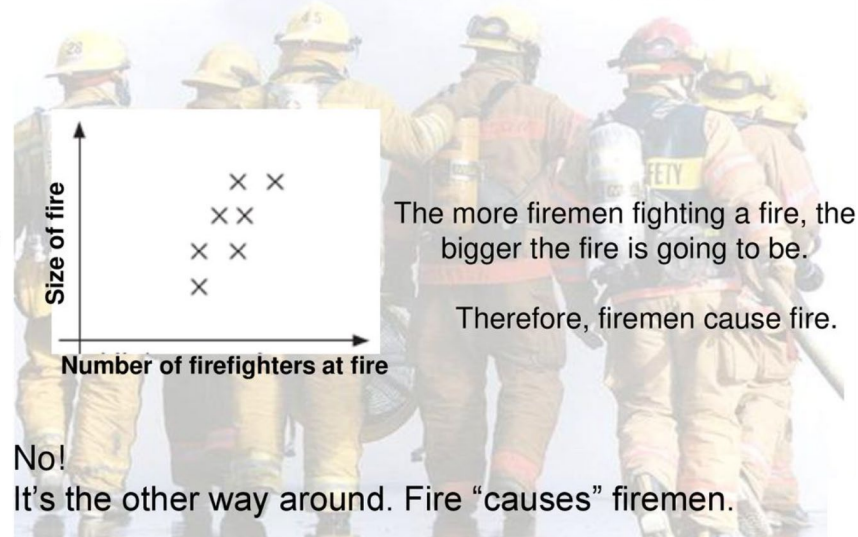
# Correlation or Causation?

Is this a sensible correlation?



No!  
They are both things that happen more *in summer*.

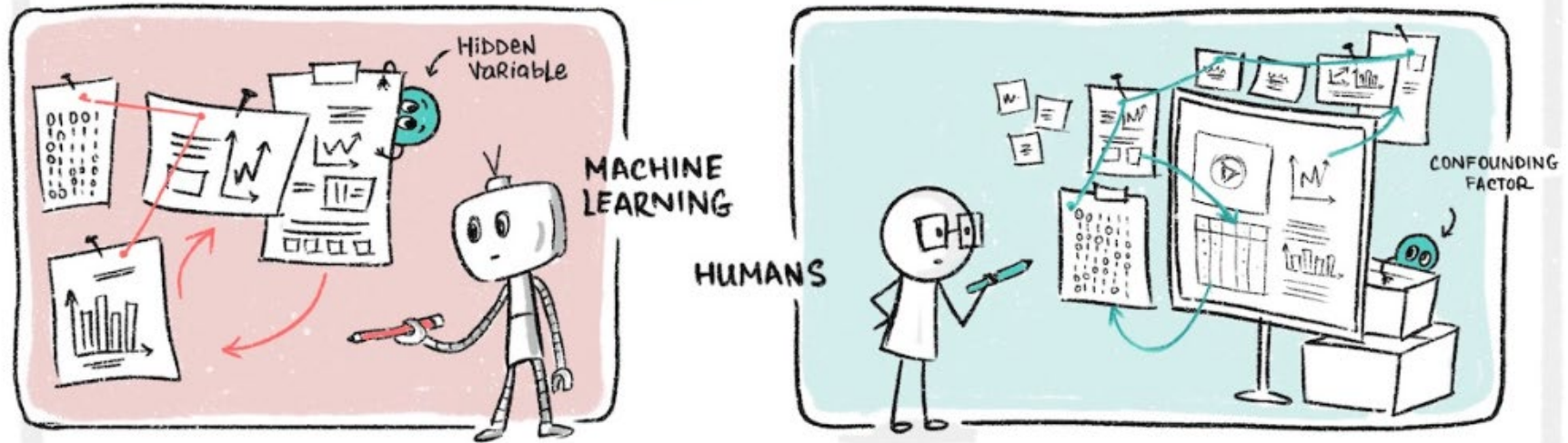
Is this a sensible correlation?



No!  
It's the other way around. Fire "causes" firemen.



# Lurking & Confounding Variables



A Spurious correlation happens when LURKING VARIABLES OR CONFOUNDING FACTOR is Ignored. cognitive Biases force an individual to oversimplify the relationship between two completely unrelated incidents.

# Correlation Operatives

## Variables to look for:

- ❑ Mediating Variables
- ❑ Moderating Variables
- ❑ Lurking Variables
- ❑ Confounding Variables

Is it safe to eat ice cream? Hmmm...



# Correlation v. Causation in Risk Selection

- There are well-established techniques for determining the correlation between a rating variable and the risk of insurance losses
- However, there are no accepted approaches to establishing causation for insurance risk classification
- Actuarial Standard of Practice No. 12, *Risk Classification*, provides guidance to the effect that actuaries should select risk characteristics that are related to expected outcomes, but it is not necessary to establish that the risk characteristics are causal



# Correlation v. Causation in Risk Selection

- Auto insurance: hypothetical example
  - A 17-year-old driver loses control of the car, at night, in rainy conditions, leading to a collision with another vehicle
  - Many factors may have contributed to the accident: weather conditions, time of day, driver inexperience
  - All of these factors will correlate to higher risk of accidents
  - None can be shown to be causal in a statistical model





# Correlation v. Causation in Risk Selection

- Balancing the desire to demonstrate causality with the limitations of models
  - Though not required by ASOP No. 12, public interest may be best served if actuaries assist in demonstrating that there are logical connections between rating variables and outcomes, in addition to demonstrating that a statistical relationship exists between rating variables and outcomes
  - There are both quantitative and non-quantitative approaches that could support this goal while also recognizing the limitations of models



# Correlation v. Causation in Risk Selection

- Balancing the desire to demonstrate causality with the limitations of models
  - An example of a quantitative approach that may support this goal is requiring a minimum amount of correlation between the rating variable and outcomes
  - An example of a non-quantitative approach that may support this goal has been put forth by the NAIC and is termed “rational explanation”



# Rational Explanations Explained

- “Rational explanation” is defined within NAIC publications\* as
  - ▣ “A plausible narrative connecting the variable and/or treatment in question with real world circumstances or behaviors that contribute to the risk of insurance loss in a manner that is readily understandable to a consumer or other educated layperson.”



# Rational Explanations Explained

- Encouraging actuaries to use the concept of “rational explanation” as a bridge between solely focusing on correlation and proving causation has merit
  - ▣ Rational explanations can enhance the actuary’s work product
- Recognition that this principle will evolve and be refined over time



# Unintended Consequences

## Unforeseen Consequences of Model Variables:

- Unintentional bias
- Blinding algorithms to protected class attributes
  - “*Laundering human biases through software*”
- Less intuitive proxies for protected class attributes when algorithms are deprived of directly predictive traits



# Unintended Consequences

Question: Will including protected class attributes remove discriminatory effects from algorithms?



# Legislative Activity—P&C Insurance

- Restrictions—California, Hawaii, Michigan, and Massachusetts restrict one or more of the following in auto insurance pricing: gender, age, credit history, education, occupation, employment status, years of driving experience, and residential status.
- Colorado Bill 21-169; Oklahoma House Bill 3186; Rhode Island House Bill 7230; others...



# Legislative Activity—Life Insurance

- Regulatory focus on accelerated underwriting
- New York & Colorado are focused on
  - External data sources
  - Predictive models
  - Consumer confidence & transparency
- Oklahoma and Rhode Island similar to Colorado





# Spurious vs. “real” correlations

- Non-spurious (“real”) correlations are “amenable to a proper causal interpretation”\*
  - Direct causation—*asbestos exposure causes mesothelioma* \*\*
  - Indirect causal structure—*family history of breast cancer is correlated with an increased mortality risk* \*\*\*
- Spurious correlations have no direct or indirect explanation for the apparent relationship between the variables
  - In many cases, the apparent relationship between the variables is simply an artifact of issues in the actual modeling approach \*\*\*\*

\* *Encyclopedia of measurement and statistics, Vol 3.*

\*\* *Journal of Public Health research, 2018 Dec 20.*

\*\*\* *Breast Cancer Facts & Figures 2019-2020*; American Cancer Society; 2019.

\*\*\*\* *Encyclopedia of measurement and statistics, Vol 3.*



# Testing the validity of a correlation

There are several ways to test whether a given correlation represents a valid relationship:

- Direct causation—causal relationships are non-spurious, so establishing causation is a valid means of demonstrating the validity of a given correlation
  - ▣ Directionality
  - ▣ Residual testing
  - ▣ Literature
- Indirect relationship—this can be more challenging but is far more frequently encountered in practice
  - ▣ Durability of correlation in the presence of other variables
  - ▣ Literature
  - ▣ Dependence and out of sample testing



# Next Steps

- Potential Areas for Regulatory & Industry Collaboration:
  - Criteria for judging an acceptable rational explanation
  - Acceptable thresholds for variable correlations
  - Alternate method to RCTs for examining causation
  - Regulatory sandboxes for bias testing with protected class characteristics



# Questions?

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