# Variation in Evidence and Simpson's Paradox 

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## Introduction

## Motivation

There are a lot of different models of "variation in evidence" going under various different names: robustness, consilience, unification, coherence, focused correlation, triangulation...

Formal models include those offered by: Bovens and Hartmann (2003), Claveau (2013), Fitelson (2001), Heesen, Bright, and Zucker (2019), Lehtinen (2016, 2018), McGrew (2003), Myrvold (1996, 2003, 2017), Schlosshauer and Wheeler (2011), Schupbach (2005, 2018), Sober (1989), Staley (2004), Stegenga and Menon (2017), Wheeler (2009, 2012), and Wheeler and Scheines (2013), and that list doesn't include applications.

## The project

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Present thought: the connection with Simpson's paradox shows why this sort of analysis is going to get into trouble.

## The plan

1. Why you might want a reliability-based model.
2. The relationship between confirmation and Simpson's paradox.
3. Why this relationship is a problem and not a solution.

## Reliability

## Sources of evidence

Consider:

- Witnesses testifying to the same fact.
- Multiple thermometers.
- Peterson (2003): study shows that global warming trend is robust across changes in location.

Crucial to these examples is that there's a difference between the sources of information.

## The basic picture


$\mathbf{H}$ and $\mathbf{R}$ jointly control $\mathbf{E}$; "varation" can be defined in terms of probabilistic relationships between $\mathbf{R}$ variables.
E.g.:
$V=\frac{\operatorname{Pr}\left(R_{1} \vee R_{2}\right)-\operatorname{Pr}\left(R_{1} \& R_{2}\right)}{\operatorname{Pr}\left(R_{1} \vee R_{2}\right)}$

## How does E affect H?

Suppose we learn $E_{1}$ and $E_{2}$.

1. Direct effect: changes the probability of $H$ given $R_{1}$ and/or $R_{2}$.
2. Indirect effect: changes the probability of $R_{1}$ and/or $R_{2}$.

## The direct effect

Before learning $E_{1} \& E_{2}$ :


After learning $E_{1} \& E_{2}$ :


$$
R_{1} R_{2}
$$

$$
R_{1} \neg R_{2}
$$


$\neg R_{1} R_{2} \quad \neg R_{1} \neg R_{2}$

## The indirect effect

Before learning $E_{1} \& E_{2}$ :


After learning $E_{1} \& E_{2}$ :

$R_{1} R_{2}$
$R_{1} \neg R_{2}$

$\neg R_{1} R_{2}$
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## Three idealizations

IC1: $H$ is probabilistically independent of the reliability of any source: $\operatorname{Pr}(H)=\operatorname{Pr}\left(H \mid R_{i}\right)=\operatorname{Pr}\left(H \mid \neg R_{i}\right)$.

IC2: The posterior probability given by reliable evidence is not affected by the reliability of other sources of evidence:
$\operatorname{Pr}\left(H \mid E_{i}, R_{i}, R_{j}\right)=\operatorname{Pr}\left(H \mid E_{i}, R_{i}, \neg R_{j}\right)$.
EC: there's no conditionalization on unreliable evidence: for all $X$, then $\operatorname{Pr}\left(H \mid E_{i}, \neg R_{i}, X\right)=\operatorname{Pr}\left(H \mid \neg R_{i}, X\right)$.

## The direct effect

Let $\delta(H, E)=\operatorname{Pr}(H \mid E)-\operatorname{Pr}(H)$. Then:

$$
\begin{array}{rlr}
\delta\left(H, E_{1} \& E_{2}\right) & =\operatorname{Pr}\left(R_{1}, R_{2}\right) & \times \delta\left(H, E_{1} \& E_{2} \mid R_{1}, R_{2}\right) \\
& +\operatorname{Pr}\left(R_{1}, \neg R_{2}\right) & \times \delta\left(H, E_{1} \mid R_{1}, \neg R_{2}\right) \\
& +\operatorname{Pr}\left(\neg R_{1}, R_{2}\right) & \\
\times \delta\left(H, E_{2} \mid \neg R_{1}, R_{2}\right)
\end{array}
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& +\operatorname{Pr}\left(\neg R_{1}, R_{2}\right) & \\
\times \delta\left(H, E_{2} \mid \neg R_{1}, R_{2}\right)
\end{array}
$$

The only value that can be negative is $\delta\left(H, E_{1} \& E_{2} \mid R_{1}, R_{2}\right)$ (compare Mayo-Wilson 2011, 2014; Stegenga and Menon 2017).

## The direct results

Result 1: Sufficient condition on confirmation:

$$
-\delta\left(H, E_{1} \& E_{2} \mid R_{1}, R_{2}\right)<\frac{V\left(R_{1}, R_{2}\right)}{1-V\left(R_{1}, R_{2}\right)} \delta(H, E \mid R)
$$

Result 2: (Assuming that the sufficient condition holds:) increasing $\operatorname{Pr}\left(R_{1} \vee R_{2}\right)$ increases the degree of confirmation, ceteris paribus.

## Simpson's Paradox

## The indirect effect

Recall: learning $E_{1}$ and $E_{2}$ has two effects.

1. Direct effect: changes the probability of $H$ given $R_{1}$ and/or $R_{2}$.
2. Indirect effect: changes the probability of $R_{1}$ and/or $R_{2}$.

We've only discussed the direct effect. How does considering the indirect effect change things?

## More complexity!

This is what $\delta\left(H, E_{1} \& E_{2}\right)$ looks like (EC enforced):

$$
\begin{aligned}
& =\operatorname{Pr}\left(R_{1}, R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid E_{1}, E_{2}, R_{1}, R_{2}\right)-\operatorname{Pr}\left(R_{1}, R_{2}\right) \operatorname{Pr}\left(H \mid R_{1}, R_{2}\right) \\
& +\operatorname{Pr}\left(R_{1}, \neg R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid E_{1}, R_{1}, \neg R_{2}\right)-\operatorname{Pr}\left(R_{1}, \neg R_{2}\right) \operatorname{Pr}\left(H \mid R_{1}, \neg R_{2}\right) \\
& +\operatorname{Pr}\left(\neg R_{1}, R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid E_{2}, \neg R_{1}, R_{2}\right)-\operatorname{Pr}\left(\neg R_{1}, R_{2}\right) \operatorname{Pr}\left(H \mid \neg R_{1}, R_{2}\right) \\
& +\operatorname{Pr}\left(\neg R_{1}, \neg R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid \neg R_{1}, \neg R_{2}\right)-\operatorname{Pr}\left(\neg R_{1}, \neg R_{2}\right) \operatorname{Pr}\left(H \mid \neg R_{1}, \neg R_{2}\right)
\end{aligned}
$$

## The same condition identified earlier

Before learning $E_{1} \& E_{2}$ :
After learning $E_{1} \& E_{2}$ :


$R_{1} R_{2}$

$\neg R_{1} R_{2}$

$\neg R_{1} \neg R_{2}$

## Not quite that simple

Recall IC1: $H$ is probabilistically independent of the reliability of any source: $\operatorname{Pr}(H)=\operatorname{Pr}\left(H \mid R_{i}\right)=\operatorname{Pr}\left(H \mid \neg R_{i}\right)$.
What happens if we relax this assumption?

## Not quite that simple

Recall IC1: $H$ is probabilistically independent of the reliability of any source: $\operatorname{Pr}(H)=\operatorname{Pr}\left(H \mid R_{i}\right)=\operatorname{Pr}\left(H \mid \neg R_{i}\right)$.
What happens if we relax this assumption? Same result for $\delta\left(H, E_{1} \& E_{2}\right):$
$=\operatorname{Pr}\left(R_{1}, R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid E_{1}, E_{2}, R_{1}, R_{2}\right)-\operatorname{Pr}\left(R_{1}, R_{2}\right) \operatorname{Pr}\left(H \mid R_{1}, R_{2}\right)$
$+\operatorname{Pr}\left(R_{1}, \neg R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid E_{1}, R_{1}, \neg R_{2}\right)-\operatorname{Pr}\left(R_{1}, \neg R_{2}\right) \operatorname{Pr}\left(H \mid R_{1}, \neg R_{2}\right)$
$+\operatorname{Pr}\left(\neg R_{1}, R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid E_{2}, \neg R_{1}, R_{2}\right)-\operatorname{Pr}\left(\neg R_{1}, R_{2}\right) \operatorname{Pr}\left(H \mid \neg R_{1}, R_{2}\right)$
$+\operatorname{Pr}\left(\neg R_{1}, \neg R_{2} \mid E_{1}, E_{2}\right) \operatorname{Pr}\left(H \mid \neg R_{1}, \neg R_{2}\right)-\operatorname{Pr}\left(\neg R_{1}, \neg R_{2}\right) \operatorname{Pr}\left(H \mid \neg R_{1}, \neg R_{2}\right)$

## A new problem emerges

Before learning $E_{1} \& E_{2}$ :


After learning $E_{1} \& E_{2}$ :


## Simpson's paradox

Pearl (2014): "Simpson's paradox refers to a phenomena whereby the association between a pair of variables ( $\mathrm{X}, \mathrm{Y}$ ) reverses sign upon conditioning of a third variable, $Z$, regardless of the value taken by Z . If we partition the data into subpopulations, each representing a specific value of the third variable, the phenomena appears as a sign reversal between the associations measured in the disaggregated subpopulations relative to the aggregated data, which describes the population as a whole."

What's happened: each worldly "subpopulation" observes an increase in confirmation while confirmation decreases overall.

## A cool result?

Potential upshot: for confirmation from varied evidence, all we need is to (a) avoid Simpson's paradox situations and (b) avoid the reversals discussed by Stegenga and Menon (2017).

And that result would hold in a general setting, with relatively few idealizations.

A problem, not a solution

## Moving forward

What's the next step for a theory of variation in evidence?
Based on the above, an account of how $\mathbf{R}$ is affected by E-i.e., how our the probability of reliability changes with multiple confirming reports.
(That's essentially what Bovens and Hartmann (2003) and Claveau (2013) are both doing.)

## The problem

Notice, however, that E will have both direct and indirect (through $\mathbf{H})$ effects on $\mathbf{R}$.

Bovens and Hartmann (2003) and Claveau (2013) both avoid this problem with IC1.

But IC1 is horribly unrealistic.

## The problem, then

Claim: There's no interesting general relationship between the hypotheses that we're interested in testing and the (un)reliability of our tools.

Means that we're unlikely to be able to use the present tools to say anything more interesting about when these weird reversals occur.

## Thank you

Thank you!

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