## mediator

# an R package for conducting causal mediation analyses

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### Mediation analysis

Examines an exposure and outcome through an intermediate variable (mediator)

Causal relationship

- Understanding the mechanics behind an association
- NOT prediction

Goal of mediation analysis: Estimate the direct and indirect effects

Black race → Access / QoC →



### **Diected Acyclic Graphs (DAGs)**





DAGs contain variables of interest and common causes

Quickly assess assocations between variables

Rules for reading DAGs

- Modern Epidemiology Chapter 12
  Causal Inference https://www.hsph.harvard.edu/miguel-hernan/causal-inference-book/

Tool for drawing DAGs: https://apps.gerkelab.com/shinyDAG/

### **Classic mediation analysis**

Baron and Kenny aka the product method

- https://www.sesp.org/files/The%20Moderator-Baron.pdf
- Over 90,000 citations

Criteria to be a mediator:

- Changing the exposure change the mediator (Race -> Access/ QoC)
- The mediator affect the outcome (Access / Qoc -> Lethal outcomes)
- Changing the exposure change the outcome ( 🐸 unless the indirect and direct effects cancel out)
- After controlling for the mediator, the previously significant relationship between the exposure and the outcome is no longer significant ( 😀 unless it partial mediaton)



## Baron and Kenny approach

If A is the exposure, Y the outcome, M the mediator and C the covariates

• Y and M are continuous

Step 1: Fit E[M] =  $\beta_0$  +  $\beta_1 a$  +  $\beta_2 c$ 

Step 2: Fit E[Y] =  $\theta_0$  +  $\theta_1 a$  +  $\theta_2 m$  +  $\theta_4 c$ 

Direct effect =  $\theta_1 a$ 

• Direct effect is the exposure effect on the outcome at a fixed level of the mediator

Indirect effect =  $\theta_2 \beta_1$ 

• Indirect effect is the effect on the outcome of changes of the exposure which operate through the mediator

Does not accommodate exposure-mediator interactions



Causal Inference Methods

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#### Allowing exposure-mediator interactions

Step 1: Fit E[M] =  $eta_0 + eta_1 a + eta_2 c$ 

• same as previously

Step 2: Fit E[Y] =  $heta_0 + heta_1 a + heta_2 m + heta_3 a m + heta_4 c$ 

Assuming a binary exposure changing level  $a^* = 0$  to a = 1

Controlled direct effect =  $( heta_1+ heta_3m)(a-a^*)$ 

Natural direct effect =  $\{ heta_1+ heta_3(eta_0+eta_1a^*+eta_2c)\}(a-a^*)$ 

Natural indirect effect =  $( heta_2eta_1+ heta_3eta_1a)(a-a^*)$ 

 $\leftarrow$  When no exposure-mediator interaction is present,  $\theta_3$  = 0

- CDE = NDE =  $\theta_1$  and NIE =  $\theta_2\beta_1$
- Same as the direct and indirect effects in Baron and Kenny



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#### Interpreting the estimates

Controlled direct effect =  $( heta_1+ heta_3m)(a-a^*)$ 

• How much the outcome would change if exposure changed from a\* to a and the mediator were controlled at level m in the population

Natural direct effect =  $\{ heta_1 + heta_3(eta_0 + eta_1a^* + eta_2c)\}(a-a^*)$ 

• How much the outcome would change if exposure were set at level a versus a\* but for each individual the mediator were kept at the level it would have taken in the absence of exposure

Natural indirect effect =  $( heta_2eta_1+ heta_3eta_1a)(a-a^*)$ 

• How much the outcome would change if exposure were controlled at level a but the mediator were changed from the level it would take with a\* to the level it would take with a

Total effect of A = NDE + NIE

### Mediation or confounding ...

#### **Original Investigation**

May 23, 2019

### Association of Black Race With Prostate Cancer-Specific and Other-Cause Mortality

Robert T. Dess, MD<sup>1</sup>; Holly E. Hartman, MS<sup>2</sup>; Brandon A. Mahal, MD<sup>3</sup>; <u>et al</u>

» Author Affiliations | Article Information JAMA Oncol. 2019;5(7):975-983. doi:10.1001/jamaoncol.2019.0826



Related Articles

#### **Key Points**

**Question** Is black race associated with worse prostate cancer outcomes after controlling for known prognostic variables and access to care?

### Mediation or confounding ...



## Mediation or confounding ...

Second, our approach highlights the challenges of interpreting population-based data.<sup>24</sup> We adjusted for age, insurance, and a newly released validated socioeconomic status variable. Moreover, we adjusted for cancer- and treatment-related confounders, including the newly released quality-assured PSA values, which were a significant limitation in prior SEER analyses.<sup>25</sup> Inclusion of these crucial prognostic factors substan-



## mediator - https://github.com/GerkeLab/mediator

E README.md

#### mediator

#### build passing codecov 86%

The goal of mediator is to conduct causal mediation analysis under the counterfactual framework, allowing interation between the exposure and mediator [Valeri 2013]. Currently, mediator estimates the controlled direct effect (CDE), natural direct effect (NDE), natural indirect effect (NIE), total effect (TE) and proportion mediated (PM) and their 95% confidence intervals.

#### Installation

You can install mediator from github with:

```
# install.packages("devtools")
devtools::install github("gerkelab/mediator")
```

#### ???

Explain the goals for the package, its outputs and installation







## mediator - quick start

**Required arguments** 

- data = the data for performing the analysis
- out.model = fitted model object for the outcome
  - glm, lm or coxph
- med.model = fitted model object for the mediator
  - glm or lm
- treat = character string indicating the name of the treatment/exposure variable

#### Default arguments

- a = numeric value indicating the exposure level
  - default = 1
- a\_star = numeric value indicating the compared exposure level
  - $\circ$  default = 0
- m = numeric value indicating the level of the mediator
  - default = 1
- boot\_rep = numeric value indicating the number of repetitions to use when utalizing bootstrap to calculate confidence intervals
  - deault = 0 (Delta method)

Based on > 500,000 prostate cancer cases in the National Cancer Data Base

- Those who are insured are more likely to receive surgery than those who are uninsured
- Those who are insured have better overall survival than those who are uninsured
- Those who receive surgery have better overall survival than those who do not receive surgery





OS

Full code available at: https://github.com/jhcreed/bsp2020-mediator

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Effect	Estimate	Lower 95% CI	Upper 95% CI
CDE	0.61238	0.56128	0.66814
NDE	0.53448	0.49786	0.57378
NIE	0.92258	0.91319	0.93207
<b>Total Effect</b>	0.49310	0.45907	0.52965
<b>Proportion Mediated</b>	0.08163		

- The number of potential estimates for the CDE is equal to the number of levels that the mediator can take

- CDE of being insured compared to uninsured when forcing surgery not to occur is 0.47 (0.42-0.52)
- CDE of being insured compared to uninsured when forcing surgery to occur is 0.61 (0.56-0.67)

Full code available at: https://github.com/jhcreed/bsp2020-mediator

NDE: the effect of the exposure (insured) on the outcome (overall survival) if the pathway from the exposure to the mediator (surgery) was removed

• HR for being insured compared to uninsured, when each individual's surgical status is kept at the level it would take in the absence of insurance status, is 0.53 (0.50-0.57)



NIE: the effect of the exposure (insured) that operates by changing the mediator (surgery)

• HR for being insured, if surgical status was changed from the level it would take if insurance status was uninsured to the level if insurance status was insured, is 0.92 (0.91-0.93)



TE: the overall effect of the exposure (insured) on the outcome (overall survival)

• HR for insured compared to uninsured, overall, is 0.49 (0.46-0.53)



## SAS, STATA and R - Oh My!

mediator is the sister program of %mediator the SAS/SPSS macro developed by Valeri and VanderWeele

#### **Confidence** Intervals

- %mediator uses hard coded 1.96 and -1.96 while mediator uses c(-1,1)\*qnorm(.975) for the Delta method
- during bootstrapping, *mediator* bootstraps effect estimates and CIs while *mediator* only bootstraps the CIs
- minor differences due to rounding

#### Speed differences

• mediator up to 1000x faster than %mediator when using bootstrapping

#### Covariates

• %mediator uses dummy variables for multi-level factors while mediator allows multi-level and character variables in models

#### mediation R package

- different set of terminology
- different estimation approach

### Package == Reproducibility

Easy to share and implement new methods

R packages are more than just a bundle of code : tests, data, documentation, ...

the average controlled direct effect and the average natural uncer and Fects are given by  $CECDE(m) = \left(\theta_1 + \theta_3 m\right)(a - a^*)$   $CECDE(m) = \left(\theta_1 + \theta_3 m\right)(a - a^*)$  CECDE(m) =ffects are given by  $OR^{NIE} = \frac{\{1 + \exp(\beta_0 + \beta_1 a^* + \beta_2' c)\}\{1 + \exp(\theta_2 + \theta_3 a + \beta_0 + \beta_1 a + \beta_2' c)\}}{\{1 + \exp(\beta_0 + \beta_1 a + \beta_2' c)\}\{1 + \exp(\theta_2 + \theta_3 a + \beta_0 + \beta_1 a^* + \beta_2' c)\}}$ 



#### GitHub

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#### GitHub





## GitHub

<pre>     / R </pre>						≡
Files	=	•		•	Coverage	
delta_method.R	31	31	0	0	1	00.00%
effect_estimates.R	43	43	0	0	1	00.00%
■ gammas.R	156	156	0	0	1	00.00%
mediator.R	112	66	0	46		58.93%
igma.R	20	20	0	0	1	00.00%
■ utils.R	30	25	0	5		83.33%
Folder Totals (6 files)	392	341	0	51		<mark>86.9</mark> 9%
Project Totals (6 files)	392	341	0	51		<mark>86.9</mark> 9%

