

# Report

Baoyi Shi

## Case 1: Continuous Outcome and Continuous Mediator

### Data simulation

#### Simulation Procedures

1. Simulate the exposure variable A from  $\text{Binom}(1, P(A=1))$ .
2. Simulate the covariate C from  $N(\mu_C, \sigma_C^2)$ .
3. Simulate the mediator M from  $N((\beta_0 + \beta_1 * A + \beta_2 * C), \sigma_M^2)$ .
4. When there exists interaction between the exposure and the mediator, simulate the outcome Y from  $N(\theta_0 + \theta_1 A + \theta_2 M + \theta_3 AM + \theta_4 C, \sigma_Y^2)$ ; When there doesn't exist interaction between the exposure and the mediator, simulate the outcome Y from  $N(\theta_0 + \theta_1 A + \theta_2 M + \theta_4 C, \sigma_Y^2)$ .

#### True Parameters

Table 1: True Model Parameters for Data Simulation

Sample Size	$\theta_0$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\beta_0$	$\beta_1$	$\beta_2$	P(A=1)	$\mu_C$	$\sigma_C$	$\sigma_M$	$\sigma_Y$
10000	-3.2	0.1	0.1	0.1	0.1	-0.25	0.3	0.2	0.4	1	1	1	1

#### True Models and True Causal Effects

True model for the mediator:

$$E[M|a, c] = \beta_0 + \beta_1 a + \beta_2 c$$

True model for the outcome:

$$E[Y|a, m^*, c] = \theta_0 + \theta_1 a + \theta_2 m^* + \theta_3 am + \theta_4 c$$

True Causal Effects with  $m^* = 0$ ,  $a^* = 0$  and  $a = 1$ :

Table 2: True Causal Effects from 3 Way Decomposition for Cont Y and Cont M

cde	pnde	tnde	pnle	tnle	total effect	proportion mediated
0.100	0.095	0.125	0.030	0.060	0.155	0.240

Table 3: True Causal Effects from 4 Way Decomposition for Cont Y and Cont M

cde	intref	intmed	pie	total effect	cde prop	intref prop
0.100	-0.005	0.030	0.030	0.155	0.645	-0.032
intmed prop	pie prop	overall pm	overall int	overall pe		
0.194	0.194	0.387	0.161	0.355		

## Estimated Causal Effects and Standard Errors from 3 Different Estimation Method

### Delta Method

```
causal_mediation(data = df, method="delta", outcome = "Y_cont_int", treatment = 'A',  
  mediator = 'M_cont', covariates = "C", interaction = TRUE,  
  yreg = "linear", mreg = "linear")
```

```
## $decomp3way  
##      cde      cde_se      pnde      pnde_se      tnde  
## 0.150057809 0.020812692 0.148260878 0.020952001 0.158773634  
##      tnde_se      pnle      pnle_se      tnle      tnle_se  
## 0.020811504 -0.004000957 0.003675867 0.006511799 0.004416459  
##      te      te_se      pm      pm_se  
## 0.154772677 0.020483227 0.021488708 0.015166838  
##  
## $decomp4way  
##      cde      cde_se      intref      intref_se      intmed  
## 0.150057809 0.020812692 -0.001796931 0.001082501 0.010512756  
##      intmed_se      pie      pie_se      te      te_se  
## 0.005726149 -0.004000957 0.003675867 0.154772677 0.020483227  
##      cde_prop      cde_prop_se      intref_prop      intref_prop_se      intmed_prop  
## 0.969536817 0.024403084 -0.011610130 0.007167604 0.067923851  
##      intmed_prop_se      pie_prop      pie_prop_se      overall_pm      overall_pm_se  
## 0.038068903 -0.025850537 0.023994251 0.042073314 0.029070863  
##      overall_int      overall_int_se      overall_pe      overall_pe_se  
## 0.056313720 0.031520362 0.030463183 0.024403084
```

### Bootstrapping

```
causal_mediation(data = df, method="bootstrap", outcome = "Y_cont_int", treatment = 'A',  
  mediator = 'M_cont', covariates = "C", interaction = TRUE,  
  yreg = "linear", mreg = "linear")
```

```
## $decomp3way  
##      cde      cde_se      pnde      pnde_se      tnde  
## 0.150057809 0.021005858 0.148260878 0.021152805 0.158773634  
##      tnde_se      pnle      pnle_se      tnle      tnle_se  
## 0.021004507 -0.004000957 0.003832570 0.006511799 0.004450841  
##      te      te_se      pm      pm_se  
## 0.154772677 0.020476516 0.021488708 0.016128239  
##  
## $decomp4way  
##      cde      cde_se      intref      intref_se      intmed  
## 0.150057809 0.021005858 -0.001796931 0.001123203 0.010512756  
##      intmed_se      pie      pie_se      te      te_se  
## 0.005734305 -0.004000957 0.003832570 0.154772677 0.020476516  
##      cde_prop      cde_prop_se      intref_prop      intref_prop_se      intmed_prop  
## 0.969536817 0.025668536 -0.011610130 0.007703325 0.067923851  
##      intmed_prop_se      pie_prop      pie_prop_se      overall_pm      overall_pm_se  
## 0.039408811 -0.025850537 0.025725582 0.042073314 0.030600136  
##      overall_int      overall_int_se      overall_pe      overall_pe_se  
## 0.056313720 0.032458974 0.030463183 0.025668536
```

## Simulation-based Approach

```
causal_mediation(data = df, method="simulation", outcome = "Y_cont_int", treatment = 'A',
  mediator = 'M_cont', covariates = "C", interaction = TRUE,
  yreg = "linear", mreg = "linear")[1:2]
```

```
## $decomp3way
##      cde      cde_se      pnde      pnde_se      tnde
## 0.150565806 0.020267799 0.148765030 0.020424241 0.159198925
##      tnde_se      pnle      pnle_se      tnle      tnle_se
## 0.020324403 -0.003926874 0.003676045 0.006507022 0.004470166
##      te      te_se      pm      pm_se
## 0.155272052 0.020037178 0.021975249 0.015852597
##
## $decomp4way
##      cde      cde_se      intref      intref_se      intmed
## 0.150565806 0.020267799 -0.001800776 0.001108824 0.010433895
##      intmed_se      pie      pie_se      te      te_se
## 0.005743927 -0.003926874 0.003676045 0.155272052 0.020037178
##      cde_prop      cde_prop_se      intref_prop      intref_prop_se      intmed_prop
## 0.969275763 0.025330106 -0.011813042 0.007586155 0.068324969
##      intmed_prop_se      pie_prop      pie_prop_se      overall_pm      overall_pm_se
## 0.039024586 -0.025787690 0.024668001 0.042537279 0.030220100
##      overall_int      overall_int_se      overall_pe      overall_pe_se
## 0.056511927 0.032241912 0.030724237 0.025330106
```

## Case 2: Continuous Outcome and Binary Mediator

### Data simulation

#### Simulation Procedures

1. Simulate the exposure variable A from  $\text{Binom}(1, P(A=1))$ .
2. Simulate the covariate C from  $N(\mu_C, \sigma_C^2)$ .
3. Simulate the mediator M from  $\text{Binom}(1, \text{expit}(\beta_0 + \beta_1 * A + \beta_2 * C))$ .
4. When there exists interaction between the exposure and the mediator, simulate the outcome Y from  $N(\theta_0 + \theta_1 A + \theta_2 M + \theta_3 AM + \theta_4 C, \sigma_Y^2)$ ; When there doesn't exist interaction between the exposure and the mediator, simulate the outcome Y from  $N(\theta_0 + \theta_1 A + \theta_2 M + \theta_4 C, \sigma_Y^2)$ .

#### True Parameters

Table 4: True Model Parameters for Data Simulation

Sample Size	$\theta_0$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\beta_0$	$\beta_1$	$\beta_2$	P(A=1)	$\mu_C$	$\sigma_C$	$\sigma_Y$
10000	-3.2	0.1	0.1	0.1	0.1	-0.25	0.3	0.2	0.4	1	1	1

#### True Models and True Causal Effects

True model for the mediator:

$$\text{logit}E[M|a, c] = \beta_0 + \beta_1 a + \beta_2 c$$

True model for the outcome:

$$E[Y|a, m^*, c] = \theta_0 + \theta_1 a + \theta_2 m^* + \theta_3 a m + \theta_4 c$$

True Causal Effects with  $m^* = 0$ ,  $a^* = 0$  and  $a = 1$ :

Table 5: True Causal Effects from 3 Way Decomposition for Cont Y and Bin M

cde	pnde	tnde	pnie	tnie	total effect	proportion mediated
0.100	0.149	0.156	0.007	0.015	0.107	0.058

Table 6: True Causal Effects from 4 Way Decomposition for Cont Y and Bin M

cde	intref	intmed	pie	total effect	cde prop	intref prop
0.100	0.049	0.008	0.007	0.107	0.935	0.052
intmed prop	pie prop	overall pm	overall int	overall pe		
0.075	0.065	0.140	0.533	0.598		

## Estimated Causal Effects and Standard Errors from 3 Different Estimation Method

### Delta Method

```
causal_mediation(data = df, method="delta", outcome = "Y_cont_int", treatment = 'A',
  mediator = 'M_bin', covariates = "C", interaction = TRUE,
  yreg = "linear", mreg = "logistic")
```

```
## $decomp3way
##      cde      cde_se      pnde      pnde_se      tnde      tnde_se
## 0.116548012 0.030021402 0.144033806 0.020567413 0.147947728 0.020528597
##      pnle      pnle_se      tnle      tnle_se      te      te_se
## 0.006977980 0.002085807 0.010891901 0.002748639 0.154925707 0.020490896
##      pm      pm_se
## 0.036432697 0.010583705
##
## $decomp4way
##      cde      cde_se      intref      intref_se      intmed
## 0.116548012 0.030021402 0.027485794 0.020216468 0.003913922
##      intmed_se      pie      pie_se      te      te_se
## 0.002934491 0.006977980 0.002085807 0.154925707 0.020490896
##      cde_prop      cde_prop_se      intref_prop      intref_prop_se      intmed_prop
## 0.752283235 0.145829678 0.177412736 0.132586567 0.025263216
##      intmed_prop_se      pie_prop      pie_prop_se      overall_pm      overall_pm_se
## 0.019189662 0.045040812 0.014542562 0.070304029 0.019705412
##      overall_int      overall_int_se      overall_pe      overall_pe_se
## 0.202675952 0.151424572 0.247716765 0.145829678
```

### Bootstrapping

```
causal_mediation(data = df, method="bootstrap", outcome = "Y_cont_int", treatment = 'A',
  mediator = 'M_bin', covariates = "C", interaction = TRUE,
  yreg = "linear", mreg = "logistic")
```

```
## $decomp3way
##      cde      cde_se      pnde      pnde_se      tnde      tnde_se
## 0.116548012 0.030131769 0.144033806 0.020667617 0.147947728 0.020600265
##      pnle      pnle_se      tnle      tnle_se      te      te_se
```

```
## 0.006977980 0.002070357 0.010891901 0.002733369 0.154925707 0.020466233
##          pm          pm_se
## 0.036432697 0.011185787
##
## $decomp4way
##          cde          cde_se          intref          intref_se          intmed
## 0.116548012 0.030131769 0.027485794 0.020221868 0.003913922
##          intmed_se          pie          pie_se          te          te_se
## 0.002942273 0.006977980 0.002070357 0.154925707 0.020466233
##          cde_prop          cde_prop_se          intref_prop          intref_prop_se          intmed_prop
## 0.752283235 0.150527116 0.177412736 0.136624504 0.025263216
## intmed_prop_se          pie_prop          pie_prop_se          overall_pm          overall_pm_se
## 0.019779627 0.045040812 0.015078600 0.070304029 0.020677206
##          overall_int          overall_int_se          overall_pe          overall_pe_se
## 0.202675952 0.155872464 0.247716765 0.150527116
```

### Simulation-based Approach

```
causal_mediation(data = df, method="simulation", outcome = "Y_cont_int", treatment = 'A',
  mediator = 'M_bin', covariates = "C", interaction = TRUE,
  yreg = "linear", mreg = "logistic")[1:2]
```

```
## $decomp3way
##          cde          cde_se          pnide          pnide_se          tnide          tnide_se
## 0.117851509 0.029486437 0.144438425 0.020277479 0.148146818 0.020256660
##          pnide          pnide_se          tnide          tnide_se          te          te_se
## 0.006830306 0.002004824 0.010538699 0.002788934 0.154977124 0.020176533
##          pm          pm_se
## 0.035927992 0.011223360
##
## $decomp4way
##          cde          cde_se          intref          intref_se          intmed
## 0.117851509 0.029486437 0.026586916 0.019970695 0.003708393
##          intmed_se          pie          pie_se          te          te_se
## 0.002869513 0.006830306 0.002004824 0.154977124 0.020176533
##          cde_prop          cde_prop_se          intref_prop          intref_prop_se          intmed_prop
## 0.756414865 0.149608858 0.174445540 0.135441820 0.024299507
## intmed_prop_se          pie_prop          pie_prop_se          overall_pm          overall_pm_se
## 0.019325292 0.044840087 0.014616120 0.069139594 0.020725818
##          overall_int          overall_int_se          overall_pe          overall_pe_se
## 0.198745047 0.154232914 0.243585135 0.149608858
```

## Case 3: Binary Outcome and Continuous Mediator

### Data simulation

#### Simulation Procedures

1. Simulate the exposure variable A from  $\text{Binom}(1, P(A=1))$ .
2. Simulate the covariate C from  $N(\mu_C, \sigma_C^2)$ .
3. Simulate the mediator M from  $N((\beta_0 + \beta_1 * A + \beta_2 * C), \sigma_M^2)$ .

4. When there exists interaction between the exposure and the mediator, simulate the outcome Y from  $Binom(1, expit(\theta_0 + \theta_1 A + \theta_2 M + \theta_3 AM + \theta_4 C, \sigma_Y^2))$ ; When there doesn't exist interaction between the exposure and the mediator, simulate the outcome Y from  $Binom(1, expit(\theta_0 + \theta_1 A + \theta_2 M + \theta_4 C, \sigma_Y^2))$ .

## True Parameters

Table 7: True Model Parameters for Data Simulation

Sample Size	$\theta_0$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\beta_0$	$\beta_1$	$\beta_2$	P(A=1)	$\mu_C$	$\sigma_C$	$\sigma_M$
10000	-3.2	0.1	0.1	0.1	0.1	-0.25	0.3	0.2	0.4	1	1	1

## True Models and True Causal Effects

True model for the mediator:

$$E[M|a, c] = \beta_0 + \beta_1 a + \beta_2 c$$

True model for the outcome:

$$logitE[Y|a, m^*, c] = \theta_0 + \theta_1 a + \theta_2 m^* + \theta_3 am + \theta_4 c$$

True Causal Effects with  $m^* = 0$ ,  $a^* = 0$  and  $a = 1$ :

Table 8: True Causal Effects from 3 Way Decomposition for Bin Y and Cont M

RRcde	RRpnde	RRtnde	RRpnie	RRtnie	RRte	proportion mediated
1.105	1.116	1.150	1.030	1.062	1.185	0.373

Table 9: True Causal Effects from 4 Way Decomposition for Bin Y and Cont M

ERRcde	ERRintref	ERRintmed	ERRpie	ERRte	ERRcde prop
0.105	0.011	0.039	0.030	0.185	0.568
ERRintref prop	ERRintmed prop	ERRpie prop	overall pm	overall int	overall pe
0.059	0.211	0.162	0.373	0.270	0.432

## Estimated Causal Effects and Standard Errors from 3 Different Estimation Method

### Delta Method

```
causal_mediation(data = df, method="delta", outcome = "Y_bin_int", treatment = 'A',
  mediator = 'M_cont', covariates = "C", interaction = TRUE,
  yreg = "logistic", mreg = "linear")
```

```
## $decomp3way
##      cde_rr  cde_rr_se    pnde_rr pnde_rr_se    tnde_rr tnde_rr_se
## 1.13871962 0.10460652 1.13869927 0.10449607 1.14378078 0.10409356
##      pnle_rr pnle_rr_se    tnle_rr tnle_rr_se      te_rr  te_rr_se
## 1.01116135 0.01689346 1.01567371 0.01903890 1.15654691 0.10365767
##          pm      pm_se
## 0.11400824 0.15181425
##
## $decomp4way
##      cde_err      cde_err_se      intref_err
## 0.1388758602 0.1047243981 -0.0001765893
##      intref_err_se      intmed_err      intmed_err_se
## 0.0008261387 0.0066862930 0.0270062967
##      pie_err      pie_err_se      total_err
```

```
##      0.0111613452      0.0168934556      0.1565469090
##      total_err_se      cde_err_prop      cde_err_prop_se
##      0.1036576731      0.8871197844      0.1549166451
##      intref_err_prop intref_err_prop_se      intmed_err_prop
##      -0.0011280283      0.0052215818      0.0427111148
##      intmed_err_prop_se      pie_err_prop      pie_err_prop_se
##      0.1735731513      0.0712971292      0.1173597233
##      overall_pm      overall_pm_se      overall_int
##      0.1140082440      0.1518142517      0.0415830864
##      overall_int_se      overall_pe      overall_pe_se
##      0.1741984955      0.1128802156      0.1549166451
```

## Bootstrapping

```
causal_mediation(data = df, method="bootstrap", outcome = "Y_bin_int", treatment = 'A',
  mediator = 'M_cont', covariates = "C", interaction = TRUE,
  yreg = "logistic", mreg = "linear")
```

```
## $decomp3way
##      cde_rr      cde_rr_se      pnde_rr pnde_rr_se      tnde_rr tnde_rr_se
##      1.13871962 0.10325142 1.13869927 0.10331939 1.14378078 0.10393623
##      pnle_rr pnle_rr_se      tnle_rr tnle_rr_se      te_rr      te_rr_se
##      1.01116135 0.01783798 1.01567371 0.01896028 1.15654691 0.10355903
##      pm      pm_se
##      0.11400824 1.33602577
##
## $decomp4way
##      cde_err      cde_err_se      intref_err
##      0.1388758602 0.1031704940      -0.0001765893
##      intref_err_se      intmed_err      intmed_err_se
##      0.0048919072      0.0066862930      0.0268792926
##      pie_err      pie_err_se      total_err
##      0.0111613452 0.0178379849      0.1565469090
##      total_err_se      cde_err_prop      cde_err_prop_se
##      0.1035590323      0.8871197844      1.2227667882
##      intref_err_prop intref_err_prop_se      intmed_err_prop
##      -0.0011280283      0.2027446924      0.0427111148
##      intmed_err_prop_se      pie_err_prop      pie_err_prop_se
##      1.7646989191      0.0712971292      0.8671367695
##      overall_pm      overall_pm_se      overall_int
##      0.1140082440      1.3360257697      0.0415830864
##      overall_int_se      overall_pe      overall_pe_se
##      1.6028120779      0.1128802156      1.2227667882
```

## Simulation-based Approach

```
causal_mediation(data = df, method="simulation", outcome = "Y_bin_int", treatment = 'A',
  mediator = 'M_cont', covariates = "C", interaction = TRUE,
  yreg = "logistic", mreg = "linear")[1:2]
```

```
## $decomp3way
##      cde_rr      cde_rr_se      pnde_rr pnde_rr_se      tnde_rr tnde_rr_se
##      1.13873710 0.10020762 1.13837171 0.10079788 1.14275168 0.09884837
##      pnle_rr pnle_rr_se      tnle_rr tnle_rr_se      te_rr      te_rr_se
```

```
## 1.01056843 0.01710824 1.01466656 0.01858656 1.15461539 0.09924886
##          pm          pm_se
## -0.09433172 5.74500280
##
## $decomp4way
##          cde_err      cde_err_se      intref_err      intref_err_se      intmed_err
## 0.1388919926 0.1003323161 -0.0005202874 0.0029598833 0.0056752491
## intmed_err_se      pie_err      pie_err_se      total_err      total_err_se
## 0.0262753513 0.0105684346 0.0171082370 0.1546153890 0.0992488564
##          cde_prop      cde_prop_se      intref_prop      intref_prop_se      intmed_prop
## 1.0681615747 4.8872020654 0.0261701436 0.9163436907 -0.1758702410
## intmed_prop_se      pie_prop      pie_prop_se      overall_pm      overall_pm_se
## 6.2023791284 0.0815385228 1.9467290664 -0.0943317183 5.7450028016
##          overall_int      overall_int_se      overall_pe      overall_pe_se
## -0.1497000975 5.2894831343 -0.0681615747 4.8872020654
```

## Case 4: Binary Outcome and Binary Mediator

### Data simulation

#### Simulation Procedures

1. Simulate the exposure variable A from  $\text{Binom}(1, P(A=1))$ .
2. Simulate the covariate C from  $N(\mu_C, \sigma_C^2)$ .
3. Simulate the mediator M from  $\text{Binom}(1, \text{expit}(\beta_0 + \beta_1 * A + \beta_2 * C))$ .
4. When there exists interaction between the exposure and the mediator, simulate the outcome Y from  $\text{Binom}(1, \text{expit}(\theta_0 + \theta_1 A + \theta_2 M + \theta_3 AM + \theta_4 C, \sigma_Y^2))$ ; When there doesn't exist interaction between the exposure and the mediator, simulate the outcome Y from  $\text{Binom}(1, \text{expit}(\theta_0 + \theta_1 A + \theta_2 M + \theta_4 C, \sigma_Y^2))$ .

#### True Parameters

Table 10: True Model Parameters for Data Simulation

Sample Size	$\theta_0$	$\theta_1$	$\theta_2$	$\theta_3$	$\theta_4$	$\beta_0$	$\beta_1$	$\beta_2$	P(A=1)	$\mu_C$	$\sigma_C$
10000	-3.2	0.1	0.1	0.1	0.1	-0.25	0.3	0.2	0.4	1	1

#### True Models and True Causal Effects

True model for the mediator:

$$\text{logit}E[M|a, c] = \beta_0 + \beta_1 a + \beta_2 c$$

True model for the outcome:

$$\text{logit}E[Y|a, m^*, c] = \theta_0 + \theta_1 a + \theta_2 m^* + \theta_3 am + \theta_4 c$$

True Causal Effects with  $m^* = 0$ ,  $a^* = 0$  and  $a = 1$ :

Table 11: True Causal Effects from 3 Way Decomposition for Bin Y and Bin M

RRcde	RRpnde	RRtnde	RRpnie	RRtnie	RRte	proportion mediated
1.105	1.165	1.173	1.007	1.015	1.182	0.095



```

total_err <- te_rr - 1
cde_err_prop <- cde_err/total_err

intmed_err_prop <- intmed_err/total_err

intref_err_prop <- intref_err/total_err

pie_err_prop <- pie_err/total_err

overall_pm <- (pie_err+intmed_err)/total_err

overall_int <- (intref_err+intmed_err)/total_err

overall_pe <- (intref_err+intmed_err+pie_err)/total_err

```

Table 12: True Causal Effects from 4 Way Decomposition for Bin Y and Bin M

ERRcde	ERRintref	ERRintmed	ERRpie	ERRte	ERRcde prop
0.100	0.065	0.010	0.007	0.182	0.549
ERRintref prop	ERRintmed prop	ERRpie prop	overall pm	overall int	overall pe
0.357	0.055	0.038	0.093	0.412	0.451

## Estimated Causal Effects and Standard Errors from 3 Different Estimation Method

### Delta Method

```

causal_mediation(data = df, method="delta", outcome = "Y_bin_int", treatment = 'A',
  mediator = 'M_bin', covariates = "C", interaction = TRUE,
  yreg = "logistic", mreg = "logistic")

```

```

## $decomp3way
##      cde_rr      cde_rr_se      pnde_rr      pnde_rr_se      tnde_rr      tnde_rr_se
## 1.070674124 0.147922338 1.139560468 0.102689391 1.148802668 0.103349182
##      pnle_rr      pnle_rr_se      tnle_rr      tnle_rr_se      te_rr      te_rr_se
## 1.007258248 0.008353451 1.015427435 0.009929004 1.157140963 0.103731519
##      pm      pm_se
## 0.111877227 0.095093026
##
## $decomp4way
##      cde_err      cde_err_se      intref_err
##      0.067071753      0.138608685      0.072488715
##      intref_err_se      intmed_err      intmed_err_se
##      0.234102594      0.010322247      0.013779512
##      pie_err      pie_err_se      total_err
##      0.007258248      0.008353451      0.157140963
##      total_err_se      cde_err_prop      cde_err_prop_se
##      0.103731519      0.426825393      0.728317698
##      intref_err_prop      intref_err_prop_se      intmed_err_prop
##      0.461297381      1.490895417      0.065687817
##      intmed_err_prop_se      pie_err_prop      pie_err_prop_se
##      0.093252723      0.046189410      0.061074187
##      overall_pm      overall_pm_se      overall_int
##      0.111877227      0.095093026      0.526985198
##      overall_int_se      overall_pe      overall_pe_se
##      1.583613441      0.573174607      1.568779594

```

## Bootstrapping

```
causal_mediation(data = df, method="bootstrap", outcome = "Y_bin_int", treatment = 'A',
  mediator = 'M_bin', covariates = "C", interaction = TRUE,
  yreg = "logistic", mreg = "logistic")
```

```
## $decomp3way
##      cde_rr      cde_rr_se      pnde_rr pnde_rr_se      tnde_rr tnde_rr_se
## 1.070674124 0.153887088 1.139560468 0.104791250 1.148802668 0.105526244
##      pnle_rr pnle_rr_se      tnle_rr tnle_rr_se      te_rr      te_rr_se
## 1.007258248 0.008424789 1.015427435 0.010470995 1.157140963 0.105694307
##      pm      pm_se
## 0.111877227 2.067042460
##
## $decomp4way
##      cde_err      cde_err_se      intref_err
##      0.067071753      0.143059374      0.072488715
##      intref_err_se      intmed_err      intmed_err_se
##      0.101202423      0.010322247      0.014695141
##      pie_err      pie_err_se      total_err
##      0.007258248      0.008424789      0.157140963
##      total_err_se      cde_err_prop      cde_err_prop_se
##      0.105694307      0.426825393      11.534222842
##      intref_err_prop intref_err_prop_se      intmed_err_prop
##      0.461297381      9.622170852      0.065687817
##      intmed_err_prop_se      pie_err_prop      pie_err_prop_se
##      1.495825263      0.046189410      0.932138097
##      overall_pm      overall_pm_se      overall_int
##      0.111877227      2.067042460      0.526985198
##      overall_int_se      overall_pe      overall_pe_se
##      11.114862947      0.573174607      11.534222842
```

## Simulation-based Approach

```
causal_mediation(data = df, method="simulation", outcome = "Y_bin_int", treatment = 'A',
  mediator = 'M_bin', covariates = "C", interaction = TRUE,
  yreg = "logistic", mreg = "logistic")[1:2]
```

```
## $decomp3way
##      cde_rr      cde_rr_se      pnde_rr pnde_rr_se      tnde_rr
## 1.069969325 0.143926543 1.126434420 0.099231735 1.135078591
##      tnle_rr_se      pnle_rr      pnle_rr_se      tnle_rr      tnle_rr_se
## 0.098415922 1.006879350 0.007588974 1.014750073 0.009534537
##      te_rr      te_rr_se      pm      pm_se
## 1.142860400 0.099097267 0.649132850 18.880240410
##
## $decomp4way
##      cde_err      cde_err_se      intref_err intref_err_se      intmed_err
##      0.063535110      0.135314176      0.062899310      0.084140056      0.009546630
##      intmed_err_se      pie_err      pie_err_se      total_err      total_err_se
##      0.012778463      0.006879350      0.007588974      0.142860400      0.099097267
##      cde_prop      cde_prop_se      intref_prop intref_prop_se      intmed_prop
##      -2.519777916      105.450931999      2.870645066      86.597219400      0.415636396
##      intmed_prop_se      pie_prop      pie_prop_se      overall_pm      overall_pm_se
##      12.366628516      0.233496454      6.554594066      0.649132850      18.880240410
```

##	overall_int	overall_int_se	overall_pe	overall_pe_se
##	3.286281462	98.962509406	3.519777916	105.450931999