INTRODUCTION TO CAUSAL INFERENCE

Michael Kühhirt

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Direct and indirect effects I

PREVIOUSLY...IN CAUSAL INFERENCE

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   Q: What are the possible sources of group differences/associations/correlations?
   A: Specific causal relations between variables (causal effect, common causes, conditioning on a common effect) that can be notated using directed acyclic graphs.

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   A: By separating association through the causal effect of interest from association from noncausal sources (using randomization, covariate adjustment, or a quasi-experimental design between these two most “extreme” strategies).

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   - Q: How can we calculate the effect of interest from empirical data?
   - A: With different nonparametric and parametric methods that calculate the (covariate-adjusted) group contrasts that identify the effect of interest.

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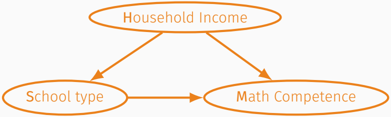
We used the roadmap by Petersen and van der Laan (2014) as a guide for learning about total effects, e.g., with the toy data `07estte1b.dta`:

1. Specify the causal model:



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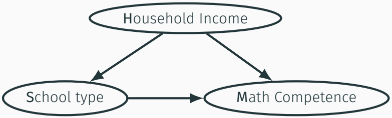

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$$\mathrm{ATE}_{S \to M} = E(M^{S=\text{private}}) - E(M^{S=\text{public}})$$

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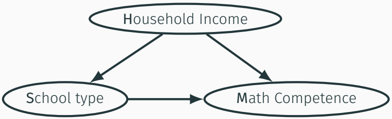

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   All covariates measured in the data; no conditioning on additional variables.

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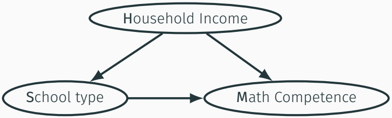

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3. Link the causal model to the available empirical data:

   All covariates measured in the data; no conditioning on additional variables.

4. Assess whether the causal parameter of interest can be identified with the available data and define the respective statistical parameter, δ:

   The $\text{ATE}_{S\to M}$ can be identified by the difference in mean math competence between private and public school students adjusted for $Z = \{H\}$.

   $$\delta = \sum_h E(M|S=\text{private}, H=h)P(H=h) - \sum_h E(M|S=\text{public}, H=h)P(H=h)$$

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7. Interpret the results and discuss assumptions:

   Statistical interpretation: *On average, private school students have a 4.12 [95% CI: -4.31,-3.93] points lower math competence than public school students after adjusting for differences in household income using the regression model. The respective estimate after adjustment by IPT weighting is -3.78 [95% CI: -4.07,-3.48].*

   Counterfactual interpretation: *Attending private school instead of public school leads to an average decrease in math competence by 4.12 [95% CI: -4.31,-3.93] points using regression adjustment. The respective estimate after adjustment by IPT weighting is -3.78 [95% CI: -4.07,-3.48].*

   The statistical interpretation rests on the assumption of no misspecification of the regression model or the IPT weight model, respectively. The counterfactual interpretation rests on the assumptions of positivity and that adjusting for household income d-separates every noncausal path, didn't d-separate any causal path, and didn't d-connect any noncausal path between school type and math competence.

   The distribution of the SIPTW and overlap in the covariate distributions didn't provide any evidence for severe model misspecification or positivity violations.

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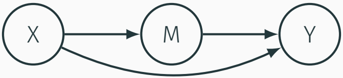
TODAY:
DEFINITION AND IDENTIFICATION OF DIRECT & INDIRECT EFFECTS

1. Terminology and goals
2. Definition of direct and indirect effects
3. Identification of direct and indirect effects

TERMINOLOGY AND GOALS

MEDIATION (ANALYSIS)

Mediation is the phenomenon that a variable X (i.e., the treatment, exposure, independent variable, cause, determinant) affects a variable Y (i.e., outcome, dependent variable, effect) through at least one other variable M (i.e., mediator, mechanism, intermediate, intervening variable).



The total effect of X on Y can then potentially be decomposed into a direct effect and an indirect effect through M. Note that the direct effect is always defined relative to M, such that there may always be other mechanisms that bring it about.

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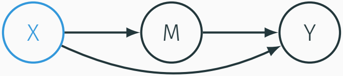

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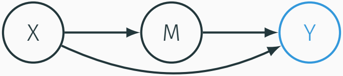

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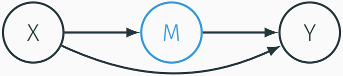

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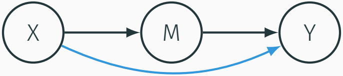

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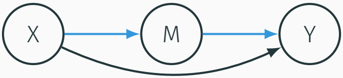

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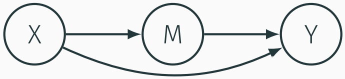

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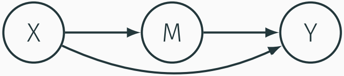

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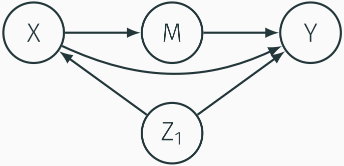

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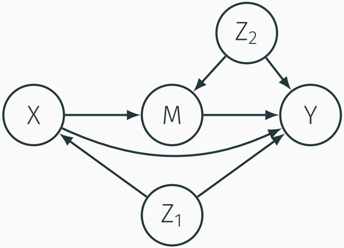
Z_1 e.g., parental income

(Wodtke and Parbst, 2017)

EXAMPLE



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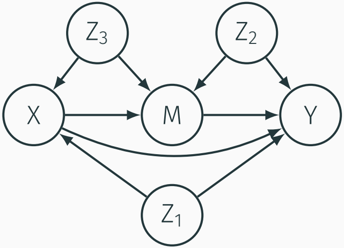

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Z_3 e.g., local government

(Wodtke and Parbst, 2017)

WHY ARE WE INTERESTED IN MEDIATION?

Theory	– explaining and understanding total effects (opening the "black box") – test of alternative theories regarding mechanisms underlying total effect
Practice	– improvement of specific component(s) of interventions/programs – intervention on X not feasible but on M
Methodology	– alternative identification strategy for total effect when some noncausal paths between X and Y cannot be d-separated by simple covariate adjustment ("frontdoor identification", see Pearl et al., 2016, Ch. 3.4) – but stronger (and also untestable) assumptions needed than for simple covariate adjustment

(VanderWeele, 2015, Ch. 1.3.1.)

DEFINITION OF DIRECT AND INDIRECT EFFECTS

JOINT INTERVENTIONS AND NESTED COUNTERFACTUALS

Remember, totel effects correspond to a *single* (hypothetical) intervention on one variable, X.

(Robins and Greenland, 1992; Pearl, 2005)

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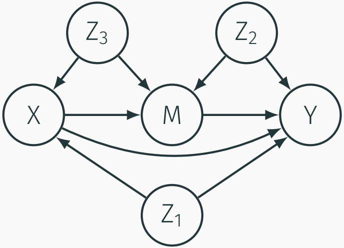
The natural direct and the natural indirect effect thus create *nested counterfactuals* for Y as we use a (natural) counterfactual for M (under specific x) which is then used to create a counterfactual for Y.

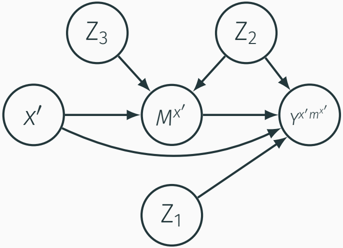
(Robins and Greenland, 1992; Pearl, 2005)

FROM INTERVENTION TO EFFECT



Intervention:

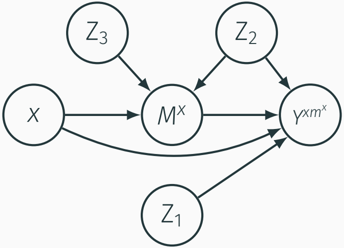
Set X to x’



FROM INTERVENTION TO EFFECT

Intervention:

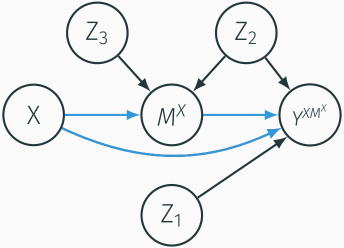
Set X to x



FROM INTERVENTION TO EFFECT

Intervention:

Change X



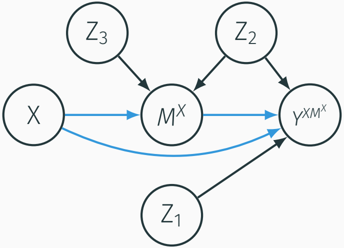
Average total effect

$$\text{ATE} = E(Y^{xm^x}) - E(Y^{x'm^{x'}}) = E(Y^x) - E(Y^{x'})$$

FROM INTERVENTION TO EFFECT

Intervention:

Change X



Example:
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School resources — M
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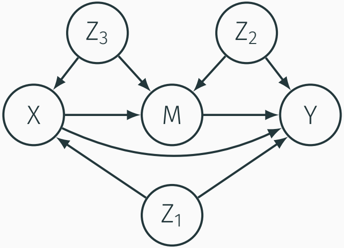
Average total effect

$$\text{ATE} = E(Y^x) - E(Y^{x'})$$

$$\text{ATE} = E(\text{Achievement}^{\text{poor}}) - E(\text{Achievement}^{\text{nonpoor}})$$

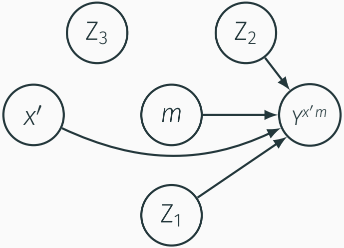
FROM INTERVENTION TO EFFECT



FROM INTERVENTION TO EFFECT

Joint intervention:

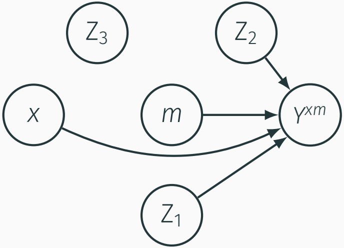
Set X to x’ and M to m



FROM INTERVENTION TO EFFECT

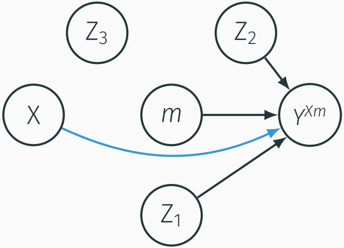
Joint intervention:

Set X to x and M to m



Joint intervention:

Change X and fix M at m



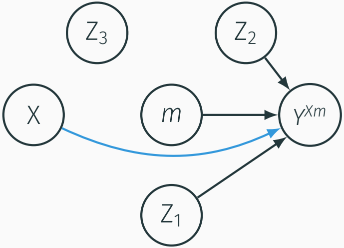
Average controlled direct effects

$$\text{ACDE(m)} = E(Y^{xm}) - E(Y^{x'm})$$

FROM INTERVENTION TO EFFECT

Joint intervention:

Change X and fix M at m



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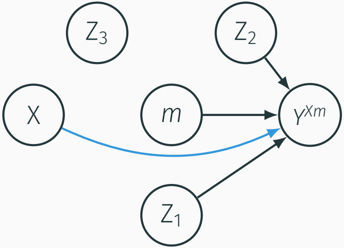
Average controlled direct effects

$$\text{ACDE(m)} = \quad E(Y^{xm}) \;-\; E(Y^{x'm})$$

$$\text{ACDE(low)} = \; E(\text{Achievement}^{\text{poor,low}}) \;-\; E(\text{Achievement}^{\text{nonpoor,low}})$$

Joint intervention:

Change X and fix M at m



Example:
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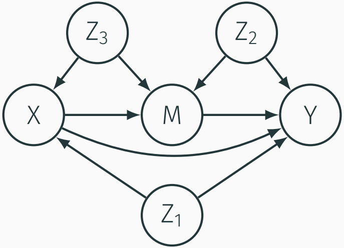
Average controlled direct effects

$$\text{ACDE(m)} = E(Y^{xm}) - E(Y^{x'm})$$

$$\text{ACDE(high)} = E(\text{Achievement}^{\text{poor,high}}) - E(\text{Achievement}^{\text{nonpoor,high}})$$

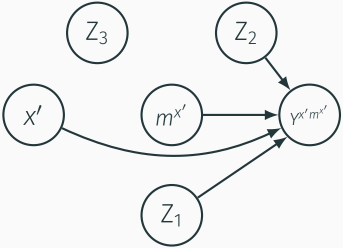
FROM INTERVENTION TO EFFECT



FROM INTERVENTION TO EFFECT

Joint intervention:

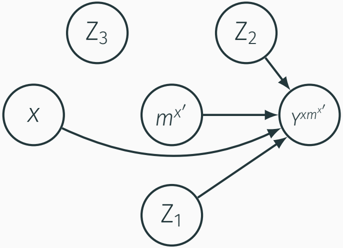
Set X to x' and M to $m^{x'}$



FROM INTERVENTION TO EFFECT

Joint intervention:

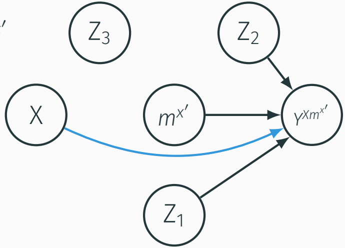
Set X to x and M to $m^{x'}$



FROM INTERVENTION TO EFFECT

Joint intervention:

Change X and fix M at $m^{x'}$



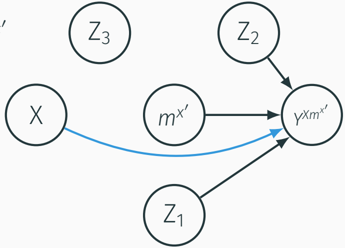
Average natural direct effect

$$\text{ANDE} = E(Y^{xm^{x'}}) - E(Y^{x'm^{x'}})$$

FROM INTERVENTION TO EFFECT

Joint intervention:

Change X and fix M at $m^{x'}$



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Average natural direct effect

$$\text{ANDE} = E(Y^{xm^{x'}}) - E(Y^{x'm^{x'}})$$

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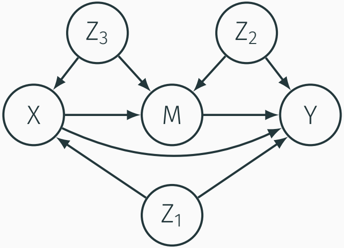
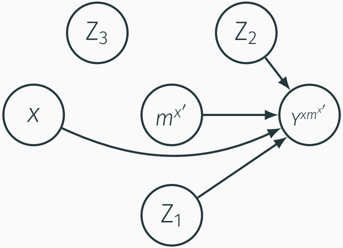

Z_3
Z_2
X
M
Y
Z_1

Joint intervention:

Set X to x and M to $m^{x'}$



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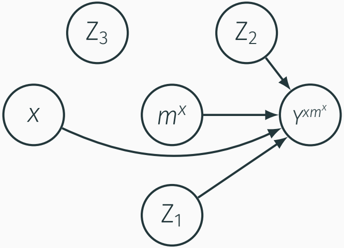
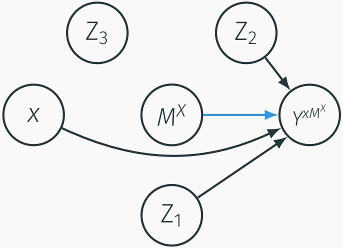
Joint intervention:

Set X to x and M to m^x



FROM INTERVENTION TO EFFECT

Joint intervention:
Fix X at x and
change M from $m^{x'}$ to m^{x}

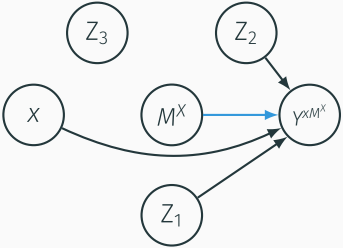


Average natural indirect effect

$$\text{ANIE} = E(Y^{xm^X}) - E(Y^{xm^{X'}})$$

FROM INTERVENTION TO EFFECT

Joint intervention:
Fix X at x and
change M from $m^{x'}$ to m^{x}



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Average natural indirect effect

$$\text{ANIE} = E(Y^{xm^{X}}) - E(Y^{xm^{x'}})$$

$$\text{ANIE} = E(\text{Achievement}^{\text{poor},\text{Resources}^{\text{poor}}}) - E(\text{Achievement}^{\text{poor},\text{Resources}^{\text{nonpoor}}})$$

Quiz 9.1. Definition of direct and indirect effects

Suppose you want to know to what degree the effect of living in a poor (vs. a nonpoor) neighborhood on children's academic achievement is mediated by school resources.

1. Provide the substantive definition of an average controlled direct effect!
2. Provide the substantive definition of the average natural direct effect!
3. Provide the substantive definition of the average natural indirect effect!

Please complete the quiz on Ilias.

EFFECT DECOMPOSITION

$$\text{ATE} = \text{ANIE} + \text{ANDE}$$

- Intuition: The ATE captures the effect of X on Y while M runs its "natural course".

(VanderWeele, 2015, p. 23)

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- Therefore: $\text{ATE} \neq \text{ANIE} + \text{ACDE(m)}$ if there is an X-M interaction (i.e., it matters for the direct effect of X on Y which value M takes on).

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- Therefore: $\text{ATE} \neq \text{ANIE} + \text{ACDE(m)}$ if there is an X-M interaction (i.e., it matters for the direct effect of X on Y which value M takes on).
- Without X-M interaction: $\text{ANDE} = \text{ACDE}$

(VanderWeele, 2015, p. 23)

EFFECT DECOMPOSITION: EXAMPLE

X and M are binary here:

u	M^0	M^1	Y^{00}	Y^{01}	Y^{10}	Y^{11}
1	0	1	18	18	20	25
2	1	0	45	43	40	48
3	1	0	34	40	41	38
4	0	0	30	20	23	25
...	...	...	...	...	...	...

For unit 2:

$\text{TE} = Y^1 - Y^0 = Y^{1m^1} - Y^{0m^0} = Y^{10} - Y^{01} = 40 - 43 = -3$

$\text{CDE}(1) = Y^{11} - Y^{01} = 48 - 43 = 5$

$\text{CDE}(0) = Y^{10} - Y^{00} = 40 - 45 = -5$

$\text{NDE} = Y^{1m^0} - Y^{0m^0} = Y^{11} - Y^{01} = 48 - 43 = 5$

$\text{NIE} = Y^{1m^1} - Y^{1m^0} = Y^{10} - Y^{11} = 40 - 48 = -8$

Calculate the effects for unit 1!

INTERPRETATION AND RELEVANCE

ACDE(m)
- effect of intervention that changes X and sets M to the same value for all *u*
- intervention (theoretically) feasible
- particularly relevant for practice/policy

ANDE/ANIE
- effect of interventions that set X to the same value for all *u* and M to unit-specific counterfactual values
- akin to disabling/switching off indirect causal path through M (for ANDE) or direct causal path not through M (for ANIE)
- unit-specific intervention on M unfeasible (even theoretically), because each unit's M only observable under one x.
- particularly relevant for theory, explanation, effect decomposition

(VanderWeele, 2015, p. 23)

INTERPRETATION AND RELEVANCE: EXAMPLE

Labor market discrimination (e.g., Bertrand and Mullainathan, 2004):

Much empirical social research studies how much labor market inequality by ethnicity (or gender, or class, or parenthood status, ...) can be explained by employer discrimination (i.e., the effect of ethnicity that is not mediated by qualifications).

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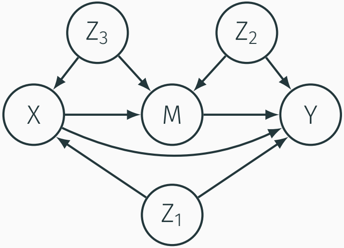
- If we're interested in how much inequality would be reduced by getting rid of discrimination we're asking about the ANDE of ethnicity (i.e., disabling the causal path through qualifications).
- A popular research design to investigate labor market discrimination is to conduct a field experiment which consists of sending applications to real-world employers in which ethnicity varies but qualifications are equal over applications.
- Is this research design able to capture the ANDE (if ethnic inequality in the labor market varies by qualification level)?

IDENTIFICATION OF DIRECT AND INDIRECT EFFECTS

IDENTIFICATION CONDITIONS FOR DIRECT AND INDIRECT EFFECTS

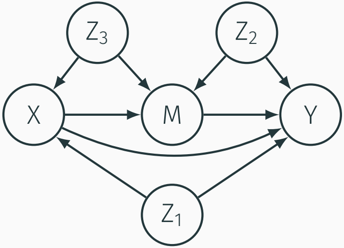


Example:
NH poverty — X
School resources — M
Achievement — Y
(Wodtke and Parbst, 2017)

IDENTIFICATION CONDITIONS FOR DIRECT AND INDIRECT EFFECTS

Assumptions:

i. X⟶Y identifiable
ii. X⟶M identifiable
iii. M⟶Y identifiable
iv. No effect X⟶C



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ACDE(m), ANDE and ANIE can be identified with empirical data under specific substantive assumptions.

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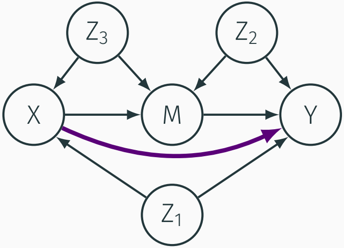

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IDENTIFICATION CONDITIONS FOR DIRECT AND INDIRECT EFFECTS

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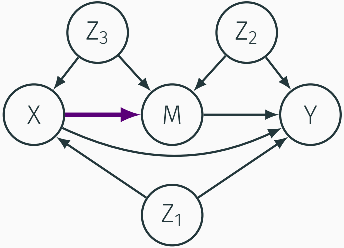

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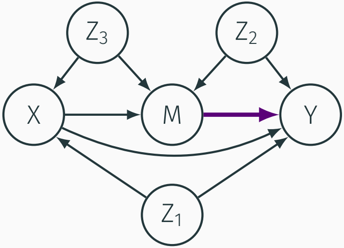

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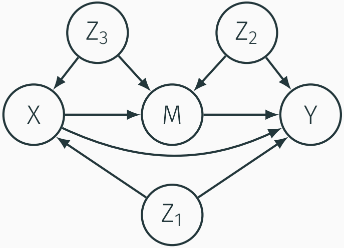

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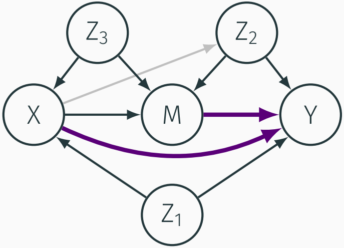

Example:
NH poverty — X
School resources — M
Achievement — Y
(Wodtke and Parbst, 2017)

Average controlled direct effect

$$\text{ACDE(m)} = E(Y^{x,m}) - E(Y^{x',m})$$

Assumptions:

i. X→Y identifiable
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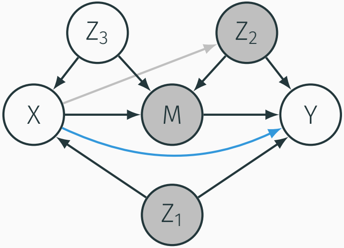

Example:
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Average controlled direct effect

$$\text{ACDE}(m) = E(Y^{x,m}) - E(Y^{x',m})$$
$$= \sum_z [E(Y|X = x, M = m, Z = z) - E(Y|X = x', M = m, Z = z)]P(Z = z)$$

Adjustment of Z={Z_1, Z_2, M} (or Randomization of X and Assignment of M)

IDENTIFICATION CONDITIONS FOR DIRECT AND INDIRECT EFFECTS

Assumptions:

i. $X \rightarrow Y$ identifiable
ii. $X \rightarrow M$ identifiable
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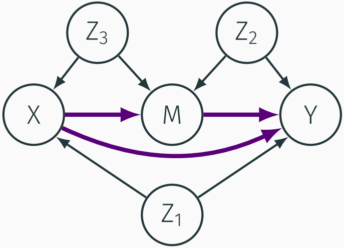

Example:
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(Wodtke and Parbst, 2017)

Average natural direct effect

$$\text{ANDE} = E(Y^{x m^{x'}}) - E(Y^{x' m^{x'}})$$

IDENTIFICATION CONDITIONS FOR DIRECT AND INDIRECT EFFECTS

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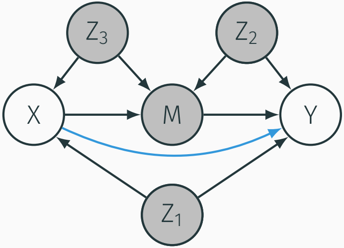

Example:
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(Wodtke and Parbst, 2017)

Average natural direct effect

$$\text{ANDE} = E(Y^{xm^{x'}}) - E(Y^{x'm^{x'}})$$
$$= \sum_m \sum_z [E(Y|X = x, M = m, Z = z) - E(Y|X = x', M = m, Z = z)]$$
$$\times P(M = m|X = x', Z = z)P(Z = z)$$

Adjustment of Z={Z_1, Z_2, Z_3, M} (or Randomization of X and Adjustment of Z={Z_2, M})

Assumptions:

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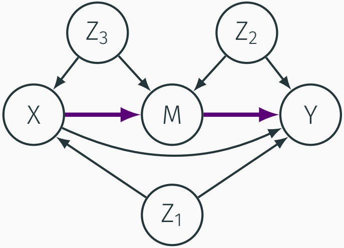

Example:
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Average natural indirect effect

$$\text{ANIE} = \quad E(Y^{x,m^X}) \; - \; E(Y^{x,m^{X'}})$$

Assumptions:

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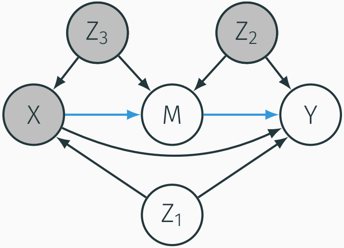

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Average natural indirect effect

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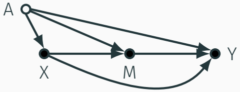
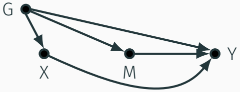
$$\times [P(M = m|X = x, Z = z) - P(M = m|X = x', Z = z)]$$

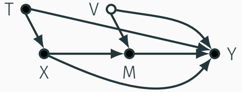
Adjustment of Z={Z_2, Z_3, X} (or Randomization of X and Adjustment of Z={Z_2, X})

Quiz 6.2. Identification of direct and indirect effects

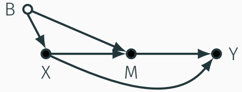
For which of each of the three scenarios is it possible to identify ACDE(m), ANDE, and ANIE by covariate adjustment (i.e., assumptions i.-iv. hold)?

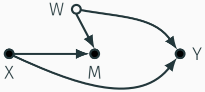


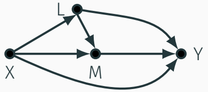




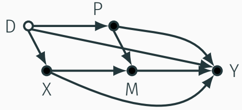
1)
i. ii. iii.

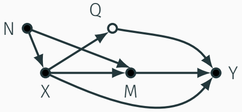


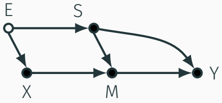




2)
i. ii. iii.







3)
i. ii. iii.

SUMMARY

Mediation is important for both theory (i.e., effect decomposition) and practice (i.e., refinement of policies).

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The conditions to identify direct and indirect effects are stronger than for total effects (e.g., randomization of X is not sufficient).

Unlike for identifying total effects, the causal model for mediation must also consider noncausal paths from M to Y.

If assumptions i.-iv. hold, direct and indirect effects can be identified by covariate adjustment (or a combination of randomization of X and covariate adjustment).

ROADMAP FOR CAUSAL INFERENCE

1. Specify the causal model
2. Define the causal parameter of interest
   (along with the target population)
3. Link the causal model to the available empirical data
4. Assess whether the causal parameter of interest can be identified with the available data and define the respective statistical parameter
5. Specify the statistical model used to estimate the statistical parameter
6. Estimate the statistical parameter
7. Interpret the results and discuss assumptions

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NEXT WEEK:
ESTIMATION OF DIRECT & INDIRECT EFFECTS USING REGRESSION

1. Nonparametric estimators
2. Flexible regression estimators
3. Classic regression estimators

THANK YOU FOR YOUR ATTENTION!

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