CSDS 452 Causality and Machine Learning

Lecture 6: Unobserved confounders

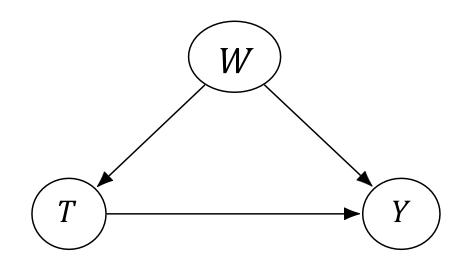
Instructor: Jing Ma

Fall 2024, CDS@CWRU

Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

Recap: Adjusting for Confounders



$$E[Y(1) - Y(0)] = E_W[E[Y|T = 1, W] - E[Y|T = 0, W]]$$

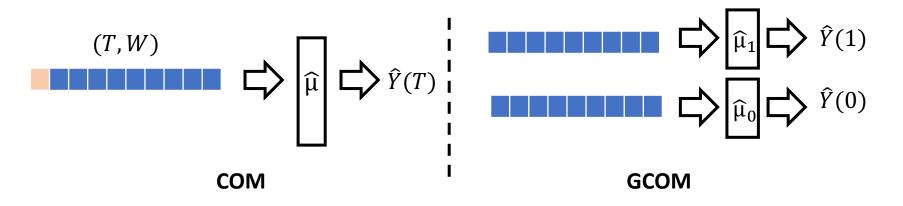
Recap: COM/GCOM estimation

COM Estimator:

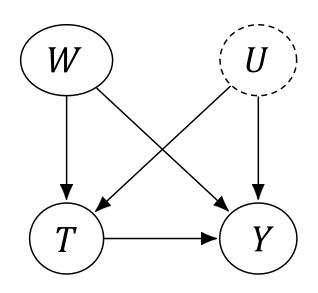
$$\hat{\tau} = \frac{1}{n} \sum_{i} (\widehat{\mu}(1, w_i) - \widehat{\mu}(0, w_i))$$

GCOM Estimator

$$\hat{\tau} = \frac{1}{n} \sum_{i} (\widehat{\mu}_1(w_i) - \widehat{\mu}_0(w_i))$$

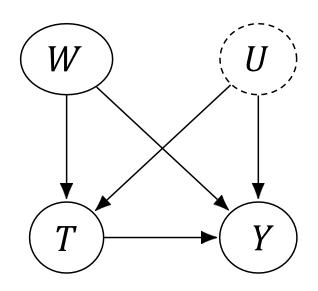


Unobserved Confounders



$$E[Y(1) - Y(0)] = E_{W,U}[E[Y|T = 1, W, U] - E[Y|T = 0, W, U]]$$

Unobserved Confounders



$$E[Y(1) - Y(0)] = E_{W,U}[E[Y|T = 1, W, U] - E[Y|T = 0, W, U]]$$

How different is it compared to $E_W[E[Y|T=1, W] - E[Y|T=0, W]]$?

Unconfoundedness assumption is often violated in real world

- Unobserved confounders are ubiquitous!
 - E.g., when study the causal effect of face mask on COVID infection, many confounders (culture background, personality, lifestyles, ...) are unmeasured.
- "The Law of Decreasing Credibility: The credibility of inference decreases with the strength of the assumptions maintained" (Manski, 2003).

Can we make weaker assumption?

Unconfoundedness assumption

$$E[Y(1) - Y(0)] = E_W[E[Y|T = 1, W] - E[Y|T = 0, W]]$$

Identify a "Point"

Can we make weaker assumption?

Unconfoundedness assumption

$$E[Y(1) - Y(0)] = E_W[E[Y|T = 1, W] - E[Y|T = 0, W]]$$

Identify a "Point"

- Weaker assumption
 - Allow the existence of some unobserved confounders
 - Instead of a point, identify an interval
 - "Partial identification" or "set identification"

Now, let's try to throw out the unconfoundedness assumption!

Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

Bounded Potential Outcomes

• Example: Suppose that we know the potential outcomes are within a range [0, 1].

$$0 \le Y(0), Y(1) \le 1$$

Bounded Potential Outcomes

• Example: Suppose that we know the potential outcomes are within a range [0, 1].

$$0 \le Y(0), Y(1) \le 1$$



$$0 - 1 \le Y_i(1) - Y_i(0) \le 1 - 0$$

Bounded Potential Outcomes

• Example: Suppose that we know the potential outcomes are within a range [0, 1].

$$0 \le Y(0), Y(1) \le 1$$



$$0 - 1 \le Y_i(1) - Y_i(0) \le 1 - 0$$



$$-1 \le Y_i(1) - Y_i(0) \le 1$$

An interval with length 2

More general cases

• Example: Suppose that we know the potential outcomes are within a range [a, b].

$$a \le Y(0), Y(1) \le b$$

More general cases

• Example: Suppose that we know the potential outcomes are within a range [a, b].

$$a \le Y(0), Y(1) \le b$$



$$a - b \le Y_i(1) - Y_i(0) \le b - a$$

More general cases

• Example: Suppose that we know the potential outcomes are within a range [a, b].

$$a \le Y(0), Y(1) \le b$$



$$a - b \le Y_i(1) - Y_i(0) \le b - a$$



$$a - b \le E[Y(1) - Y(0)] \le b - a$$

Trivial bound: an interval with length 2(b-a)

$$E[Y(1) - Y(0)]$$

$$E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)]$$

$$E[Y(1) - Y(0)]$$

= $E[Y(1)] - E[Y(0)]$ Conditioning and marginalization
= $P(T = 1)E[Y(1)|T = 1] + P(T = 0)E[Y(1)|T = 0]$
 $-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y(0)|T = 0]$

$$E[Y(1) - Y(0)]$$
= $E[Y(1)] - E[Y(0)]$
Consistency

= $P(T = 1)E[Y(1)|T = 1] + P(T = 0)E[Y(1)|T = 0]$
 $-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y(0)|T = 0]$

= $P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$
 $-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$

```
E[Y(1) - Y(0)]
= E[Y(1)] - E[Y(0)]
= P(T = 1)E[Y(1)|T = 1] + P(T = 0)E[Y(1)|T = 0]
-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y(0)|T = 0]
= P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]
-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]
```

Observational

```
E[Y(1) - Y(0)]
= E[Y(1)] - E[Y(0)]
= P(T = 1)E[Y(1)|T = 1] + P(T = 0)E[Y(1)|T = 0]
-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y(0)|T = 0]
= P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]
-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]
```

Observational

Counterfactual

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$
$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$

$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$

$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$E[Y(1) - Y(0)] \le ?$$

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$

$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$
 Counterfactual

$$E[Y(1) - Y(0)] \le ?$$

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$

$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$
 Counterfactual

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$

$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$
 Counterfactual

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$
$$E[Y(1) - Y(0)] \ge ?$$

$$E[Y(1) - Y(0)] = P(T = 1)E[Y|T = 1] + P(T = 0)E[Y(1)|T = 0]$$

$$-P(T = 1)E[Y(0)|T = 1] - P(T = 0)E[Y|T = 0]$$

$$= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$
 Counterfactual

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$

$$E[Y(1) - Y(0)] \ge e \cdot E[Y|T = 1] + (1 - e)a - eb - (1 - e)E[Y|T = 0]$$

No-Assumptions Interval Length

Trivial bound:

$$a - b \le E[Y(1) - Y(0)] \le b - a$$

Length: 2(b-a)

No-Assumptions Interval Length

Trivial bound:

$$a - b \le E[Y(1) - Y(0)] \le b - a$$

Length: 2(b-a)

No-assumption bound:

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$

$$E[Y(1) - Y(0)] \ge e \cdot E[Y|T = 1] + (1 - e)a - eb - (1 - e)E[Y|T = 0]$$

$$Length: (1 - e)b + eb - ea - (1 - e)a = b - a$$

Questions

 What kind of bounds can we get on the ATE if the potential outcomes are unbounded?

Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

Nonnegative Monotone Treatment Response (MTR)

Assume treatment always helps. Mathematically,

$$\forall i, Y_i(1) \geq Y_i(0)$$

Nonnegative Monotone Treatment Response (MTR)

Assume treatment always helps. Mathematically,

$$\forall i, Y_i(1) \geq Y_i(0)$$

• Intuition: ITE is nonnegative, so lower bound for ITE comes up from a-b to 0

$$\forall i, Y_i(1) \geq Y_i(0)$$

- Intuition: ITE is nonnegative, so lower bound for ITE comes up from a-b to 0
- Proof: (Observational-Counterfactual Decomposition)

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\forall i, Y_i(1) \geq Y_i(0)$$

- Intuition: ITE is nonnegative, so lower bound for ITE comes up from a-b to 0
- Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$
$$\ge e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(0)|T = 0] - e \cdot E[Y(0)|T = 0$$

$$\forall i, Y_i(1) \geq Y_i(0)$$

- Intuition: ITE is nonnegative, so lower bound for ITE comes up from a-b to 0
- Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(0)|T = 0] - e \cdot E[Y(1)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\forall i, Y_i(1) \geq Y_i(0)$$

- Intuition: ITE is nonnegative, so lower bound for ITE comes up from a-b to 0
- Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y|T = 0] -$$

$$e \cdot E[Y|T = 1] - (1 - e) \cdot E[Y|T = 0]$$
consistency

$$\forall i, Y_i(1) \geq Y_i(0)$$

- Intuition: ITE is nonnegative, so lower bound for ITE comes up from a-b to 0
- Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y|T = 0] - e \cdot E[Y|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$= 0$$

• Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2

- No-assumption bound: ?
- Nonnegative MTR lower bound: ?

• Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2

No-assumption bound:

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$
$$= 0.3 * 0.9 + 0.7 - 0 - 0.7 * 0.2 = 0.83$$

Nonnegative MTR lower bound:

• Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2

No-assumption bound:

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$

$$= 0.3 * 0.9 + 0.7 - 0 - 0.7 * 0.2 = 0.83$$

$$E[Y(1) - Y(0)] \ge e \cdot E[Y|T = 1] + (1 - e)a - eb - (1 - e)E[Y|T = 0]$$

$$= 0.3 * 0.9 + 0 - 0.3 - 0.7 * 0.2 = -0.17$$

Nonnegative MTR lower bound:

• Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2

• No-assumption bound:

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$

$$= 0.3 * 0.9 + 0.7 - 0 - 0.7 * 0.2 = 0.83$$

$$E[Y(1) - Y(0)] \ge e \cdot E[Y|T = 1] + (1 - e)a - eb - (1 - e)E[Y|T = 0]$$

$$= 0.3 * 0.9 + 0 - 0.3 - 0.7 * 0.2 = -0.17$$

Nonnegative MTR lower bound:

$$E[Y(1) - Y(0)] \ge 0$$

• Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2

• No-assumption bound:

$$E[Y(1) - Y(0)] \le e \cdot E[Y|T = 1] + (1 - e)b - ea - (1 - e)E[Y|T = 0]$$

$$= 0.3 * 0.9 + 0.7 - 0 - 0.7 * 0.2 = 0.83$$

$$E[Y(1) - Y(0)] \ge e \cdot E[Y|T = 1] + (1 - e)a - eb - (1 - e)E[Y|T = 0]$$

$$= 0.3 * 0.9 + 0.0 - 0.3 - 0.7 * 0.2 = -0.17$$

Nonnegative MTR lower bound:

$$E[Y(1) - Y(0)] \ge 0$$

• Combine them together: $0 \le E[Y(1) - Y(0)] \le 0.83$

Nonpositive Monotone Treatment Response

Assume treatment always cannot help.
 Mathematically,

$$\forall i, Y_i(1) \leq Y_i(0)$$

Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

 Treatment groups' potential outcomes are no worse than control groups':

$$E[Y(1)|T = 1] \ge E[Y(1)|T = 0]$$

 $E[Y(0)|T = 1] \ge E[Y(0)|T = 0]$

 Treatment groups' potential outcomes are no worse than control groups':

$$E[Y(1)|T = 1] \ge E[Y(1)|T = 0]$$

 $E[Y(0)|T = 1] \ge E[Y(0)|T = 0]$

Under the MTS assumption, ATE is bounded by:

$$E[Y(1) - Y(0)] \le E[Y|T = 1] - E[Y|T = 0]$$

Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

 Treatment groups' potential outcomes are no worse than control groups':

$$E[Y(1)|T = 1] \ge E[Y(1)|T = 0]$$

 $E[Y(0)|T = 1] \ge E[Y(0)|T = 0]$

• Under the MTS assumption, ATE is bounded by: $E[Y(1) - Y(0)] \le E[Y|T = 1] - E[Y|T = 0]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\leq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 1] -$$

 Treatment groups' potential outcomes are no worse than control groups':

$$E[Y(1)|T = 1] \ge E[Y(1)|T = 0]$$

 $E[Y(0)|T = 1] \ge E[Y(0)|T = 0]$

• Under the MTS assumption, ATE is bounded by: $E[Y(1) - Y(0)] \le E[Y|T = 1] - E[Y|T = 0]$

Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\leq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 1] -$$

$$e \cdot E[Y(0)|T = 0] - (1 - e) \cdot E[Y|T = 0]$$

 Treatment groups' potential outcomes are no worse than control groups':

$$E[Y(1)|T = 1] \ge E[Y(1)|T = 0]$$

 $E[Y(0)|T = 1] \ge E[Y(0)|T = 0]$

Under the MTS assumption, ATE is bounded by:

$$E[Y(1) - Y(0)] \le E[Y|T = 1] - E[Y|T = 0]$$

Proof:

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\leq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y|T = 1] - e \cdot E[Y|T = 0] - (1 - e) \cdot E[Y|T = 0]$$

$$= E[Y|T = 1] - E[Y|T = 0]$$

Example: MTS and MTR

- Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2
- No-assumption bound:

$$-0.17 \le E[Y(1) - Y(0)] \le 0.83$$

MTR lower bound:

$$E[Y(1) - Y(0)] \ge 0$$

Example: MTS and MTR

- Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2
- No-assumption bound:

$$-0.17 \le E[Y(1) - Y(0)] \le 0.83$$

MTR lower bound:

$$E[Y(1) - Y(0)] \ge 0$$

• MTS upper bound:

$$E[Y|T=1] - E[Y|T=0] = 0.9 - 0.2 = 0.7$$

Example: MTS and MTR

- Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2
- No-assumption bound:

$$-0.17 \le E[Y(1) - Y(0)] \le 0.83$$

MTR lower bound:

$$E[Y(1) - Y(0)] \ge 0$$

MTS upper bound:

$$E[Y|T=1] - E[Y|T=0] = 0.9 - 0.2 = 0.7$$

Bound together:

$$0 \le E[Y(1) - Y(0)] \le 0.7$$

Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

Optimal Treatment Selection (OTS) Assumption

 Individuals always receive the treatment that is best for them:

$$T_i = 1 \Rightarrow Y_i(1) \ge Y_i(0)$$
$$T_i = 0 \Rightarrow Y_i(0) > Y_i(1)$$

Optimal Treatment Selection (OTS) Assumption

 Individuals always receive the treatment that is best for them:

$$T_i = 1 \Rightarrow Y_i(1) \ge Y_i(0)$$

$$T_i = 0 \Rightarrow Y_i(0) > Y_i(1)$$



$$E[Y(1)|T=0] \le E[Y(0)|T=0] = E[Y|T=0]$$
$$E[Y(0)|T=1] \le E[Y(1)|T=0] = E[Y|T=1]$$

• Based on OTS, we have $E[Y(1)|T=0] \le E[Y|T=0]$

• Based on OTS, we have $E[Y(1)|T=0] \le E[Y|T=0]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

• Based on OTS, we have $E[Y(1)|T=0] \le E[Y|T=0]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\leq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

• Based on OTS, we have $E[Y(1)|T=0] \le E[Y|T=0]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\leq e \cdot E[Y|T = 1] + \frac{(1 - e) \cdot E[Y|T = 0]}{e \cdot E[Y(0)|T = 1]} - \frac{(1 - e) \cdot E[Y|T = 0]}{e \cdot E[Y|T = 0]}$$

• Based on OTS, we have $E[Y(1)|T=0] \le E[Y|T=0]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\leq e \cdot E[Y|T = 1] + \frac{(1 - e) \cdot E[Y|T = 0]}{e \cdot E[Y(0)|T = 1]} - \frac{(1 - e) \cdot E[Y|T = 0]}{e \cdot E[Y|T = 1]} - eE[Y(0)|T = 1]$$

$$\leq e \cdot E[Y|T = 1] - eE$$

• Based on OTS, we have $E[Y(0)|T=1] \le E[Y|T=1]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

• Based on OTS, we have $E[Y(0)|T=1] \le E[Y|T=1]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

• Based on OTS, we have $E[Y(0)|T=1] \le E[Y|T=1]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] -$$

$$e \cdot E[Y|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

• Based on OTS, we have $E[Y(0)|T=1] \le E[Y|T=1]$

$$E[Y(1) - Y(0)] = e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - e \cdot E[Y|T = 1] - (1 - e) \cdot E[Y|T = 0]$$

$$= (1 - e) \cdot E[Y(1)|T = 0] - (1 - e) \cdot E[Y|T = 0]$$

• Based on OTS, we have $E[Y(0)|T=1] \le E[Y|T=1]$

$$\begin{split} E[Y(1) - Y(0)] &= e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - \\ &= e \cdot E[Y(0)|T = 1] - (1 - e) \cdot E[Y|T = 0] \\ &\geq e \cdot E[Y|T = 1] + (1 - e) \cdot E[Y(1)|T = 0] - \\ &= e \cdot E[Y|T = 1] - (1 - e) \cdot E[Y|T = 0] \\ &= (1 - e) \cdot E[Y(1)|T = 0] - (1 - e) \cdot E[Y|T = 0] \\ &\geq (1 - e) \cdot a - (1 - e) \cdot E[Y|T = 0] \end{split}$$

OTS Complete Bound

- $E[Y(1) Y(0)] \ge (1 e) \cdot a (1 e) \cdot E[Y|T = 0]$
- $E[Y(1) Y(0)] \le e \cdot E[Y|T = 1] ea$
- Interval length:

$$e \cdot E[Y|T = 1] - a + (1 - e) \cdot E[Y|T = 0]$$

Example: OTS

- Potential outcome bounded [a=0, b=1] e = 0.3, E[Y|T = 1] = 0.9, E[Y|T = 0] = 0.2
- OTS Bound 1:

$$-0.14 \le E[Y(1) - Y(0)] \le 0.27$$

Outline

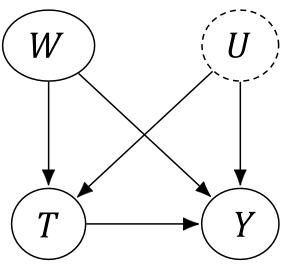
- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

Sensitivity Analysis

 We completely threw out the unconfoundedness assumption just now.

 Now, we assume that there are observed confounders W and unobserved confounders U

again:

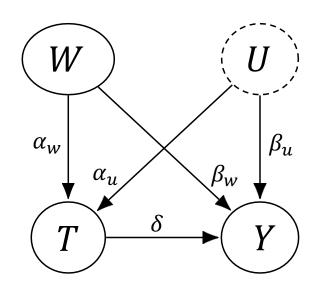


$$E[Y(1) - Y(0)] = E_{W,U}[E[Y|T = 1, W, U] - E[Y|T = 0, W, U]]$$

Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

Bias in Simple Linear Setting



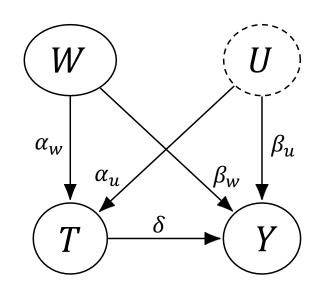
$$T \coloneqq \alpha_w W + \alpha_u U$$
$$Y \coloneqq \beta_w W + \beta_u U + \delta T$$

$$E[Y(1) - Y(0)] = E_{W,U}[E[Y|T = 1, W, U] - E[Y|T = 0, W, U]]$$

What is the bias of this estimator?

$$E_W[E[Y|T=1, W] - E[Y|T=0, W]]$$

Bias in Simple Linear Setting

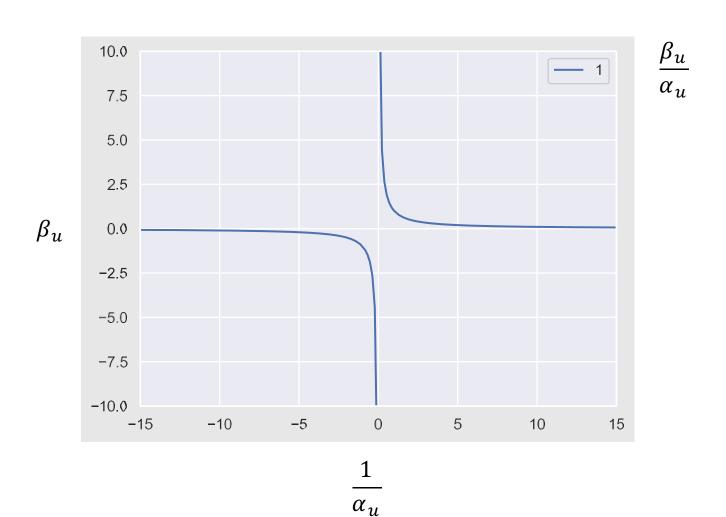


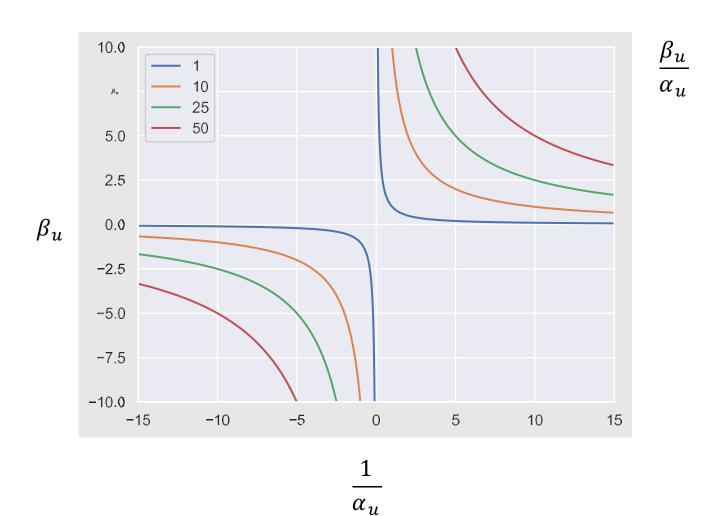
$$T \coloneqq \alpha_w W + \alpha_u U$$
$$Y \coloneqq \beta_w W + \beta_u U + \delta T$$

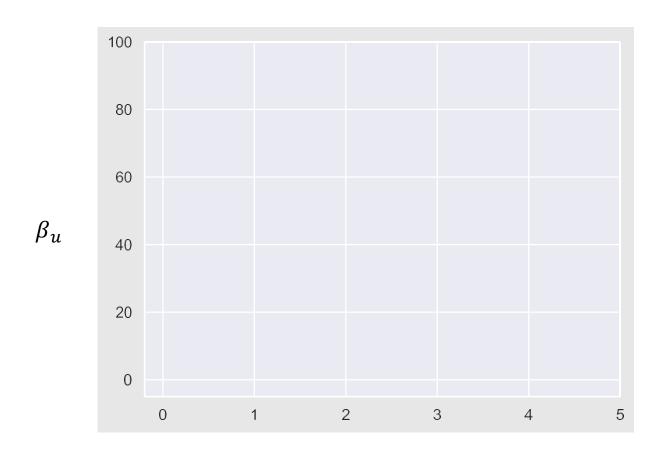
$$E[Y(1) - Y(0)] = E_{W,U}[E[Y|T = 1, W, U] - E[Y|T = 0, W, U]] = \delta$$

$$E_W[E[Y|T=1, W] - E[Y|T=0, W]] = \delta + \beta_u/\alpha_u$$

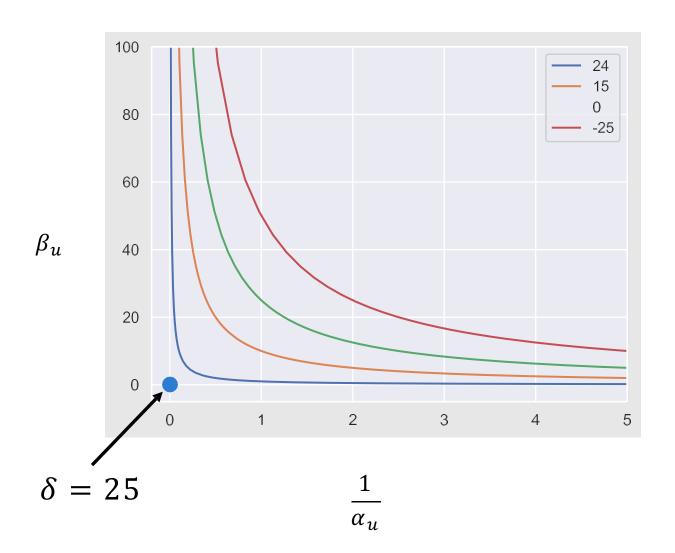
Bias of only adjusting for
$$W: \delta + \frac{\beta_u}{\alpha_u} - \delta = \frac{\beta_u}{\alpha_u}$$







 $\frac{1}{\alpha_u}$



Outline

- Bounds without unconfoundedness
 - No-assumption bound
 - Monotone treatment response
 - Monotone treatment selection
 - Optimal treatment selection
- Sensitivity analysis
 - Linear single confounder
 - More general settings

More General Cases

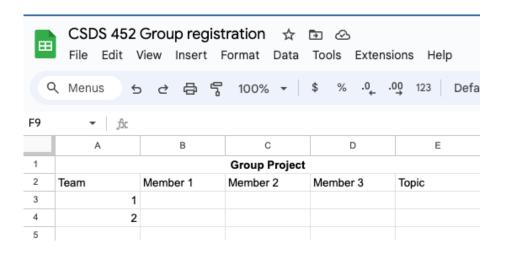
- Arbitrary graphs with linear structural equations
 - Cinelli C, Kumor D, Chen B, et al. Sensitivity analysis of linear structural causal models[C]//International conference on machine learning. PMLR, 2019: 1252-1261.

Binary cases

- Rosenbaum P R, Rubin D B. Assessing sensitivity to an unobserved binary covariate in an observational study with binary outcome[J]. Journal of the Royal Statistical Society: Series B (Methodological), 1983, 45(2): 212-218.
- Imbens G W. Sensitivity to exogeneity assumptions in program evaluation[J]. American Economic Review, 2003, 93(2): 126-132.
- Treatment mechanism and the outcome mechanism can be modeled with arbitrary machine learning models
 - Veitch V, Zaveri A. Sense and sensitivity analysis: Simple post-hoc analysis of bias due to unobserved confounding[J]. Advances in Neural Information Processing Systems, 2020, 33: 10999-11009.

Register your group

- Once you have formed a group, please register in
 - https://docs.google.com/spreadsheets/d/1laxOBGnUDNzJq8v7RvirW5iT1wJRPdHV9GCTnHvD64/edit?usp= sharing



	A	В	С	D
1	Paper Presentation			
2	Team	Member 1	Member 2	Paper title
3				
4				
5				

Thank you! Q&A