

Continuous treatments: Brief introduction

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Soc 212C

Learning goals

1. Define causal effects with continuous treatments
2. Understand an outcome modeling estimator
3. Select a causal estimand involving credible counterfactuals

Why continuous treatments are hard

Why continuous treatments are hard

Person 1

Person 2

Person 3

Person 4

Why continuous treatments are hard

| | Outcome under treatment value | |
|----------|-------------------------------|---------|
| | Untreated | Treated |
| Person 1 | ○ | ○ |
| Person 2 | ○ | ○ |
| Person 3 | ○ | ○ |
| Person 4 | ○ | ○ |

Why continuous treatments are hard

| | Factual treatment | Outcome under treatment value | |
|----------|----------------------|-------------------------------|---------|
| | | Untreated | Treated |
| Person 1 | Untreated | ○ | ○ |
| Person 2 | Treated | ○ | ○ |
| Person 3 | Treated | ○ | ○ |
| Person 4 | Untreated | ○ | ○ |

Why continuous treatments are hard

| | Factual treatment | Outcome under treatment value | |
|----------|-------------------|-------------------------------|---------|
| | | Untreated | Treated |
| Person 1 | Untreated | ● | ○ |
| Person 2 | Treated | ○ | ● |
| Person 3 | Treated | ○ | ● |
| Person 4 | Untreated | ● | ○ |

Why continuous treatments are hard

| | Factual treatment | Outcome under treatment value | | | | | |
|----------|----------------------|-------------------------------|---|---|---|---|-----|
| | | 1 | 2 | 3 | 4 | 5 | ... |
| Person 1 | 3 | ○ | ○ | ● | ○ | ○ | ○ |
| Person 2 | 2 | ○ | ● | ○ | ○ | ○ | ○ |
| Person 3 | 5 | ○ | ○ | ○ | ○ | ● | ○ |
| Person 4 | 4 | ○ | ○ | ○ | ● | ○ | ○ |

Why continuous treatments are hard

| | Factual treatment | Outcome under treatment value | | | | | |
|----------|----------------------|-------------------------------|---|---|---|---|-----|
| | | 1 | 2 | 3 | 4 | 5 | ... |
| Person 1 | 3 | ○ | ○ | ○ | ○ | ○ | ○ |
| Person 2 | 2 | ○ | ○ | ○ | ○ | ○ | ○ |
| Person 3 | 5 | ○ | ○ | ○ | ○ | ○ | ○ |
| Person 4 | 4 | ○ | ○ | ○ | ○ | ○ | ○ |

Solution: Parametric outcome model

$$E(Y^a \mid \vec{X}) = E(Y \mid A = a, \vec{X}) \quad \text{by causal assumptions} \quad (1)$$

$$= \alpha + \beta a + \vec{X}'\vec{\gamma} \quad \text{by a statistical model} \quad (2)$$

Procedure:

- ▶ Model Y given A and \vec{X}
- ▶ Set A to the value of interest a
- ▶ Predict for all units
- ▶ Average to estimate $E(Y^a)$

Additive shift esitmands for credible counterfactuals

For some units, some treatment values are implausible

- ▶ \vec{X} = child has two parents with college degrees
- ▶ A = family income of \$10,000 per year
- ▶ A never occurs given $\vec{X} = \vec{x}$

Additive shift estimands for credible counterfactuals

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Additive shift estimands are plausible:

$$\tau_i = E(Y^{A_i+\delta} - Y^{A_i})$$

Predict counterfactual outcome if treatment increases by δ

Recap: Continuous treatments are

- ▶ the same as categorical treatments in these ways
 - ▶ assume conditional exchangeability
 - ▶ model Y given A, \vec{X}
 - ▶ predict under counterfactual $A = a$
- ▶ different from categorical treatments in these ways
 - ▶ huge number of treatment values and thus potential outcomes
 - ▶ may require careful choice of a credible counterfactual