Adjustment Criteria for Generalizing Experimental Findings

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Causal Effects and Experiments

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- Inferring and reasoning with causal relations are central for decision-making, explainability, and reinforcement learning.

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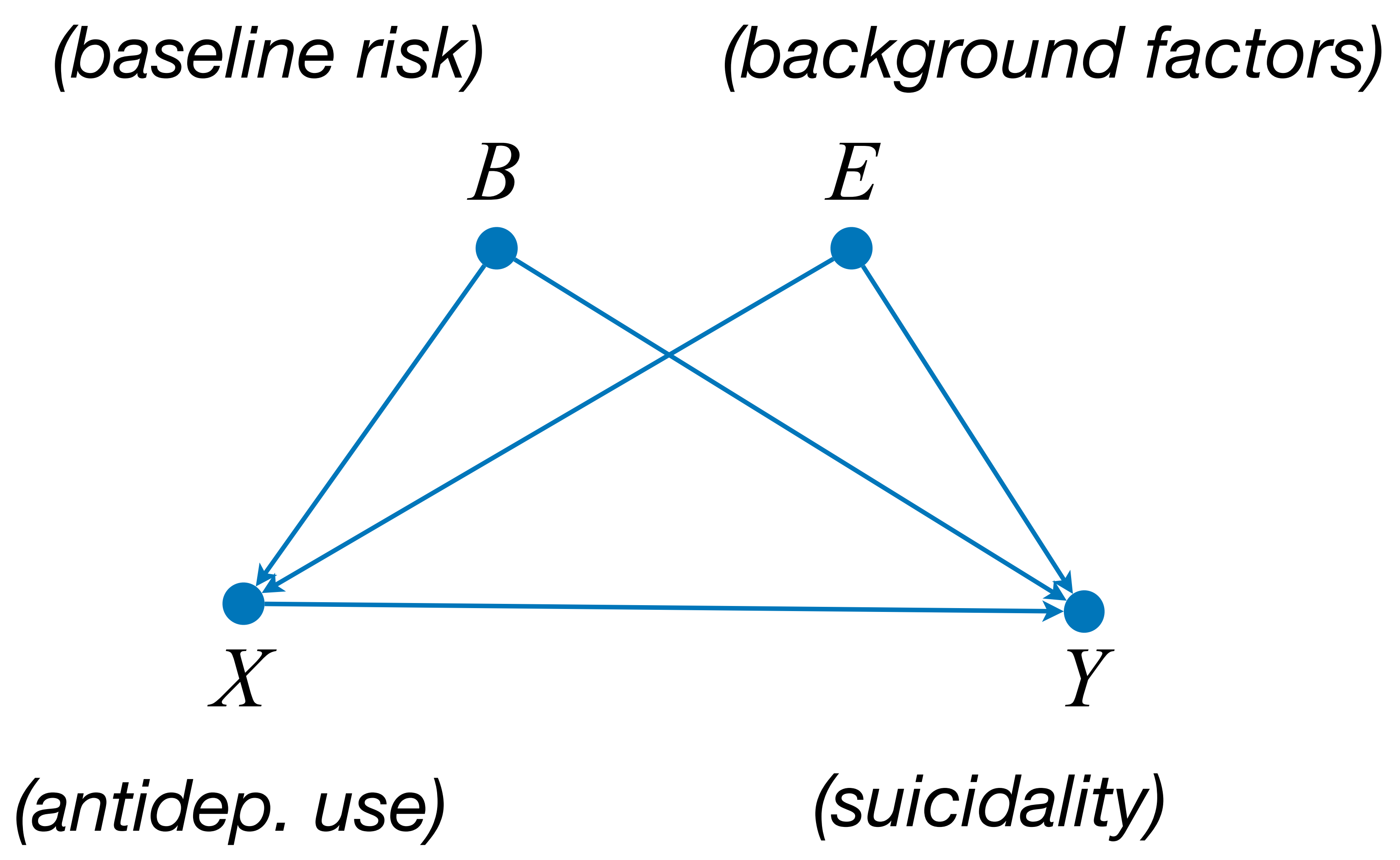
- The FDA was interested in assessing the effect of antidepressant drugs on suicidality.
- Historically, drugs had been prescribed by doctors taking into account background information of the patients and the assessment of their baseline risk.
- Since the prescription and the outcome are both affected by the background factors, a controlled experiment is used to identify the unconfounded effect of the antidepressants.

Controlled Experimentation — Randomization

Natural world (confounded)



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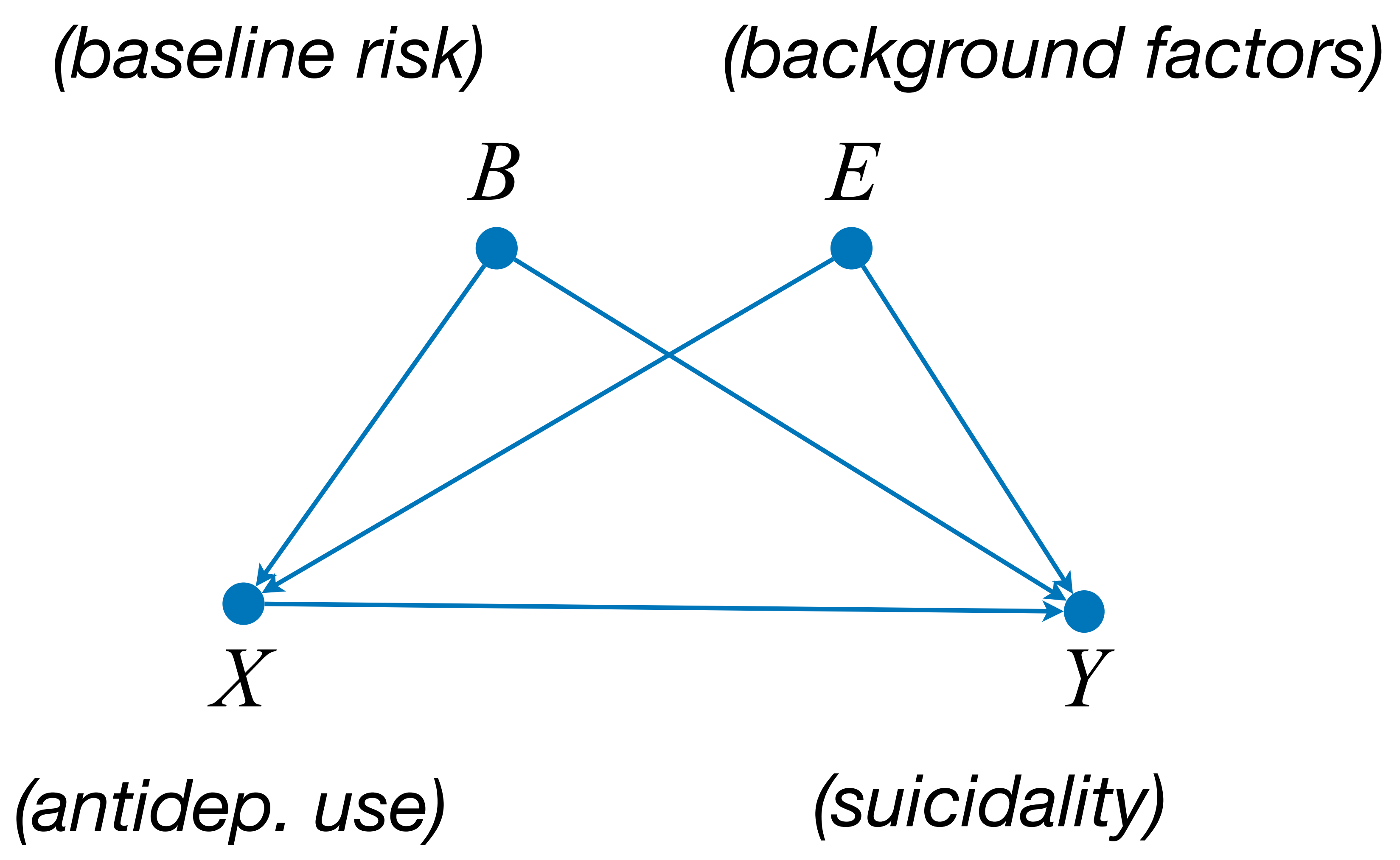

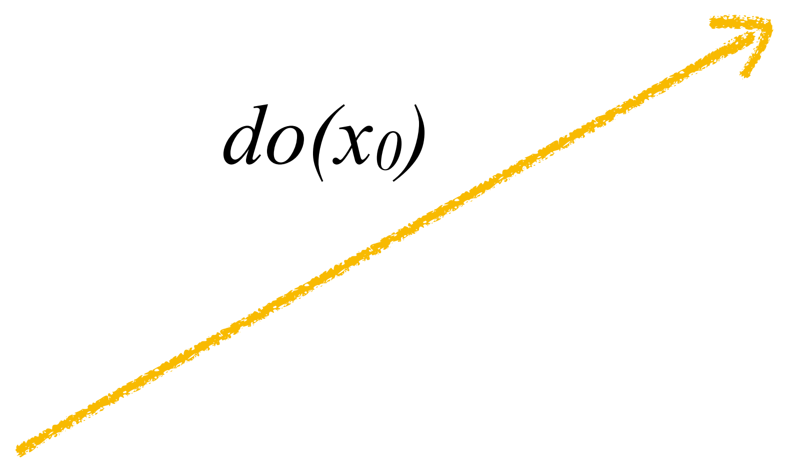

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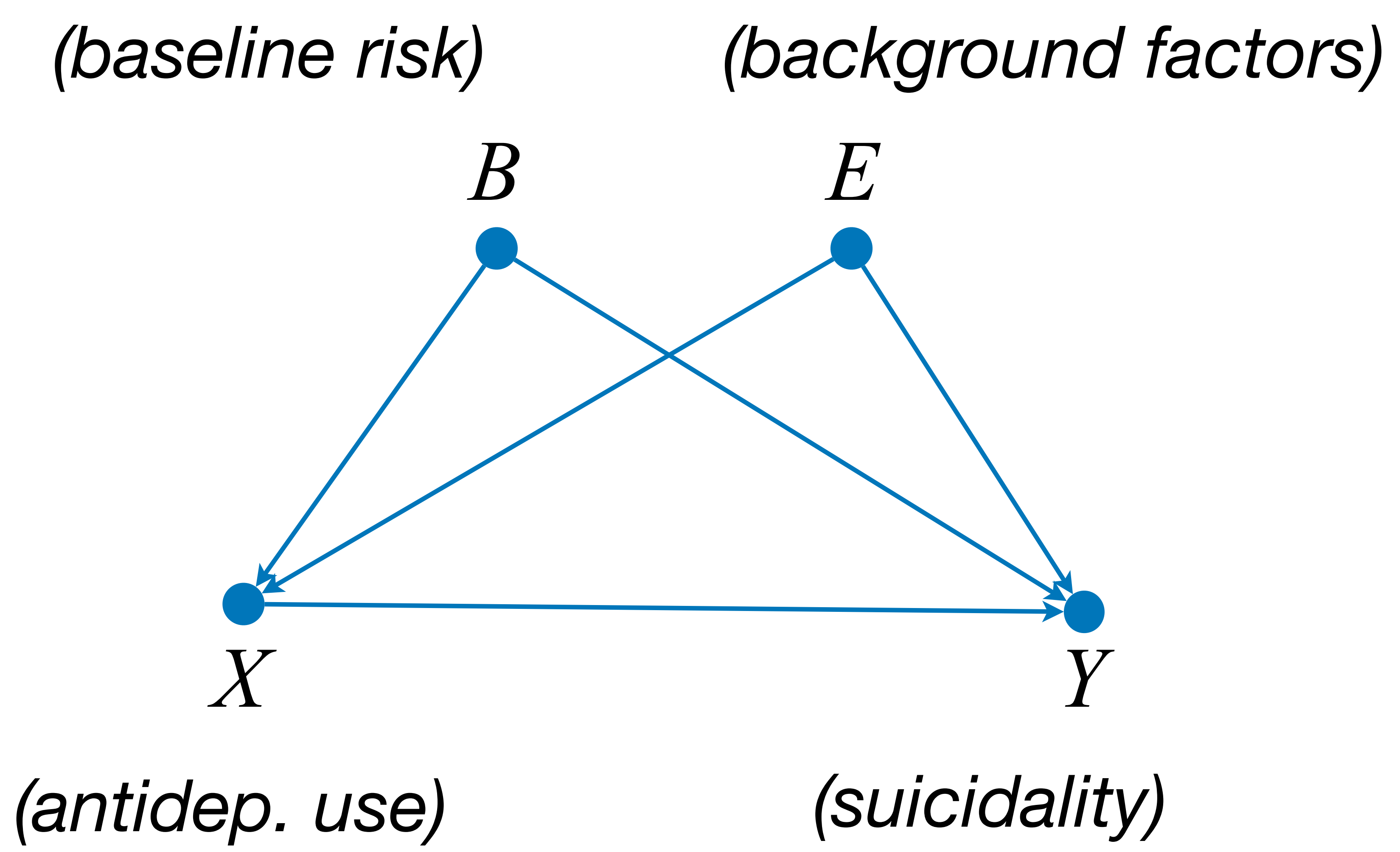
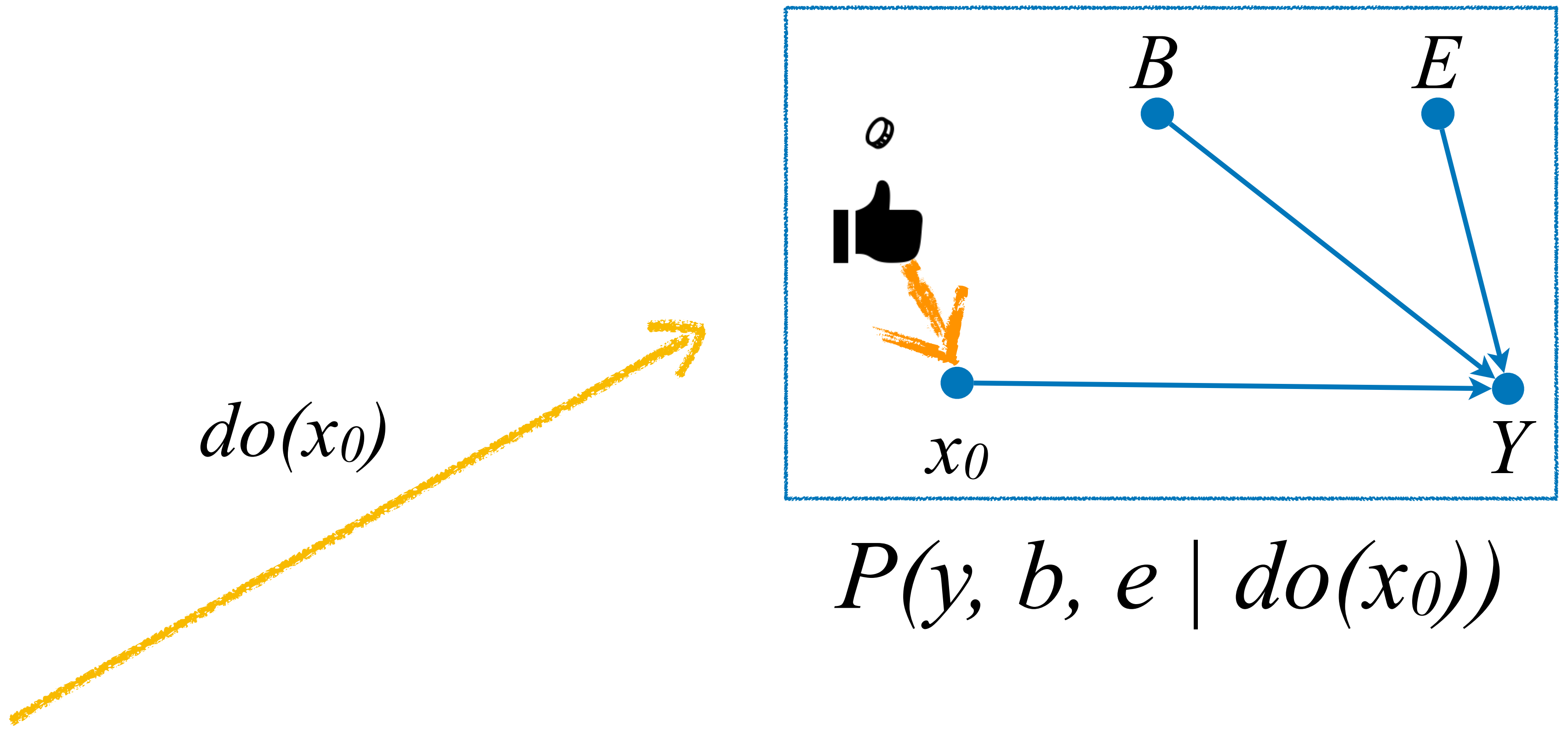
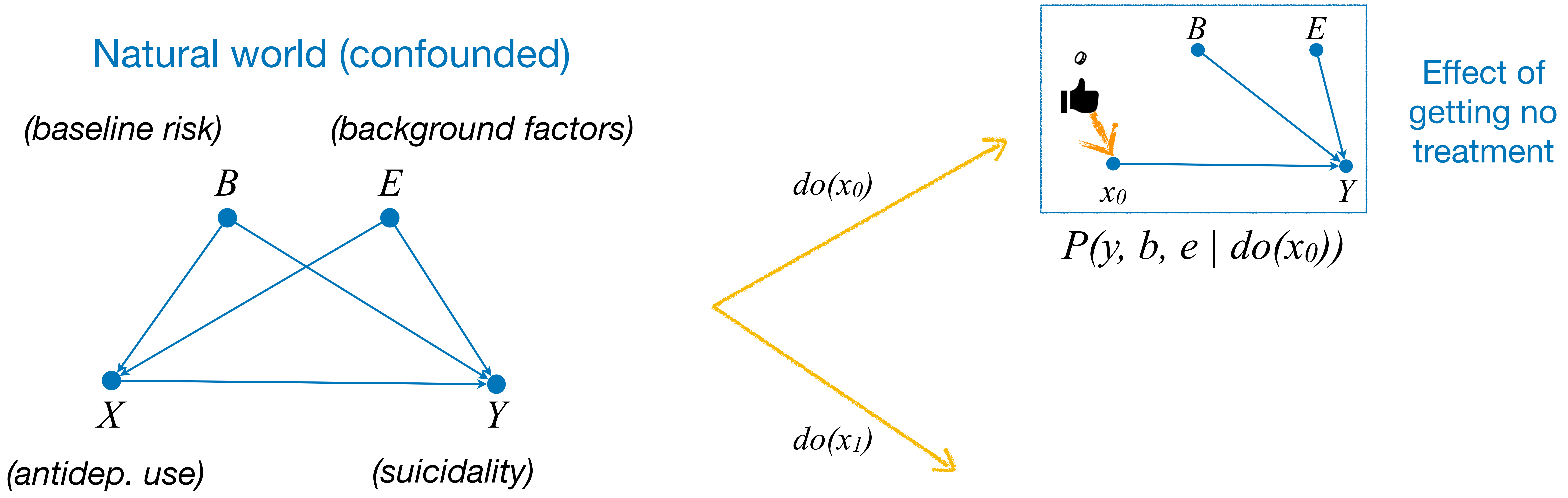




$P(y, b, e \mid do(x_0))$

Effect of getting no treatment

Controlled Experimentation — Randomization



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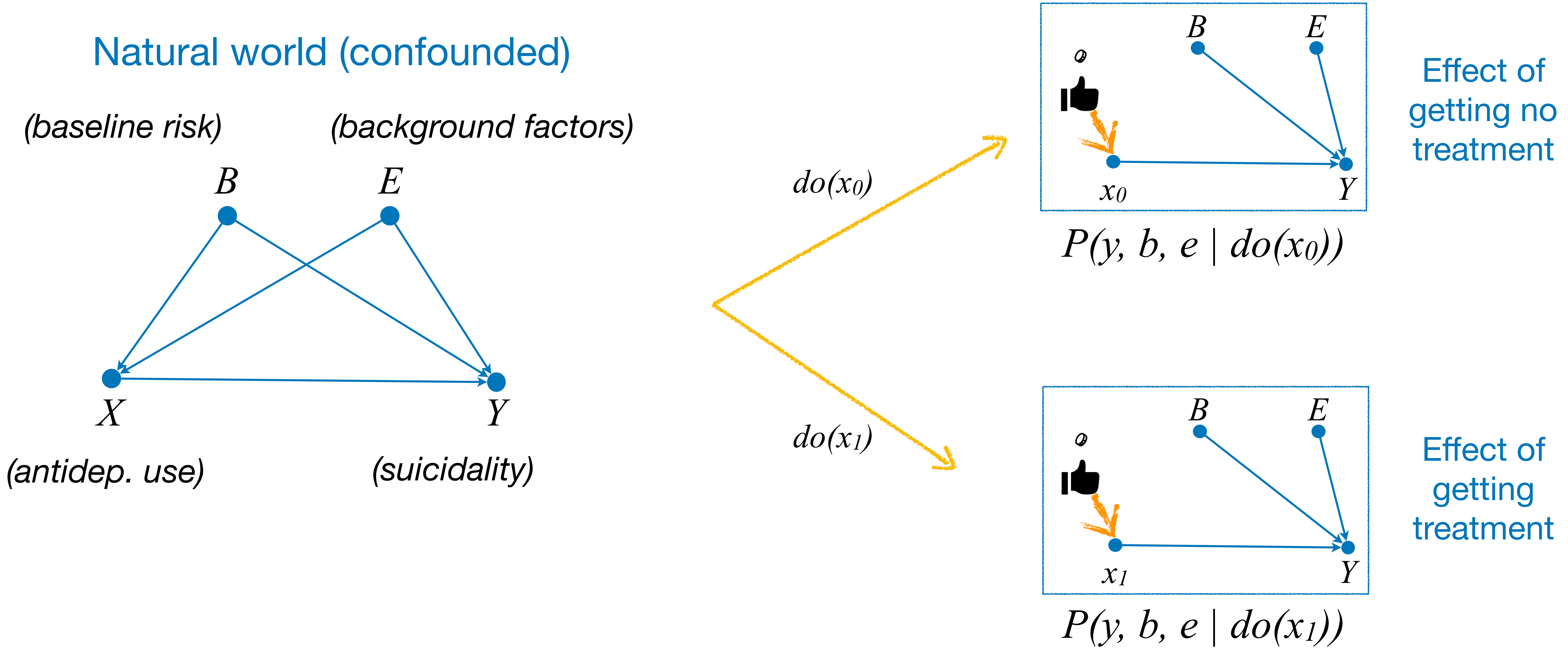

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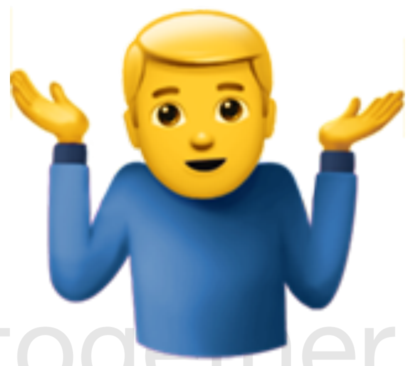

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- Randomization guarantees internal validity, that is, causal conclusions are true for the population that was studied.
- Most experimental findings are intended to be generalized to a broader, or even different, target domain (in other words, population, setting, environment).

Two Challenges

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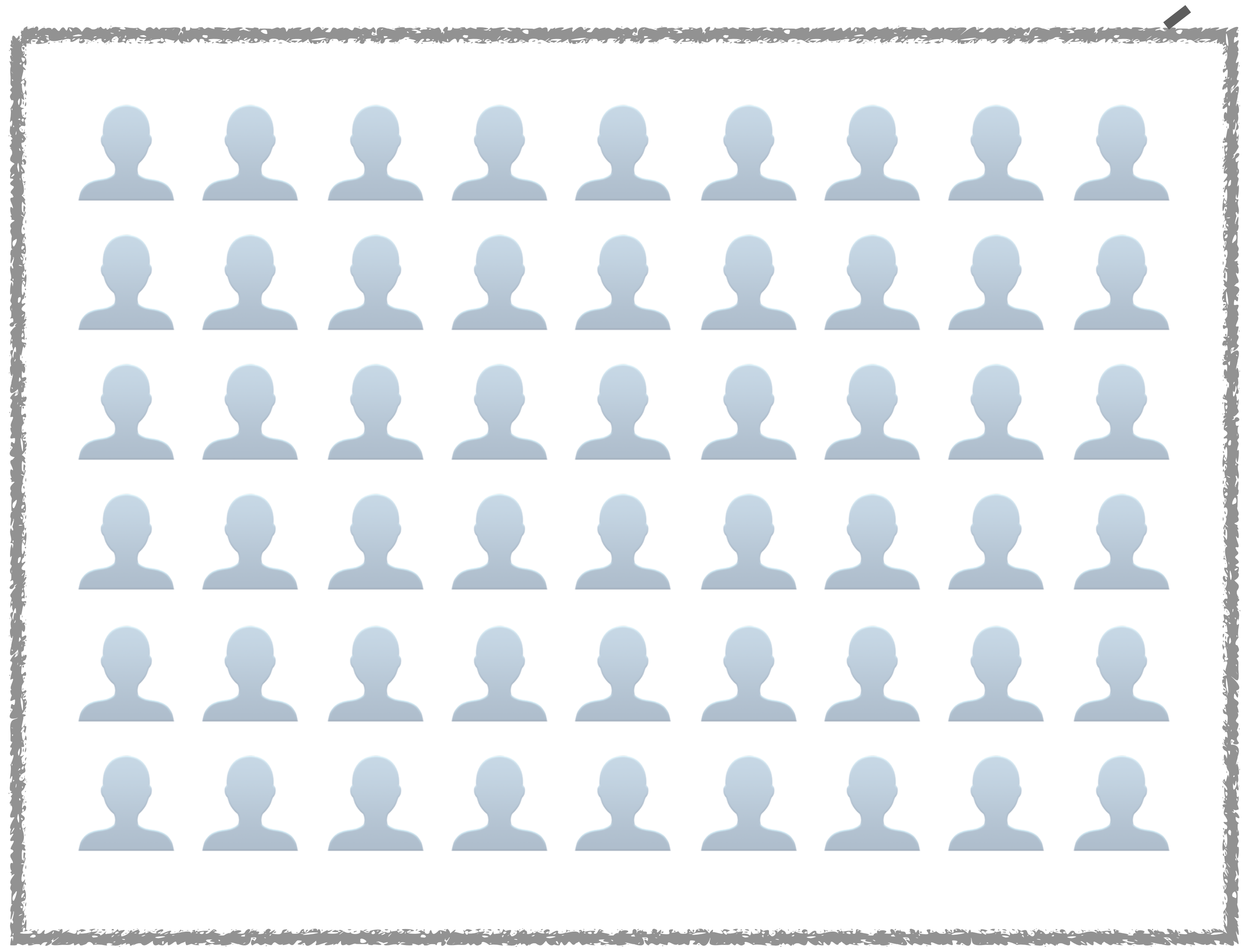

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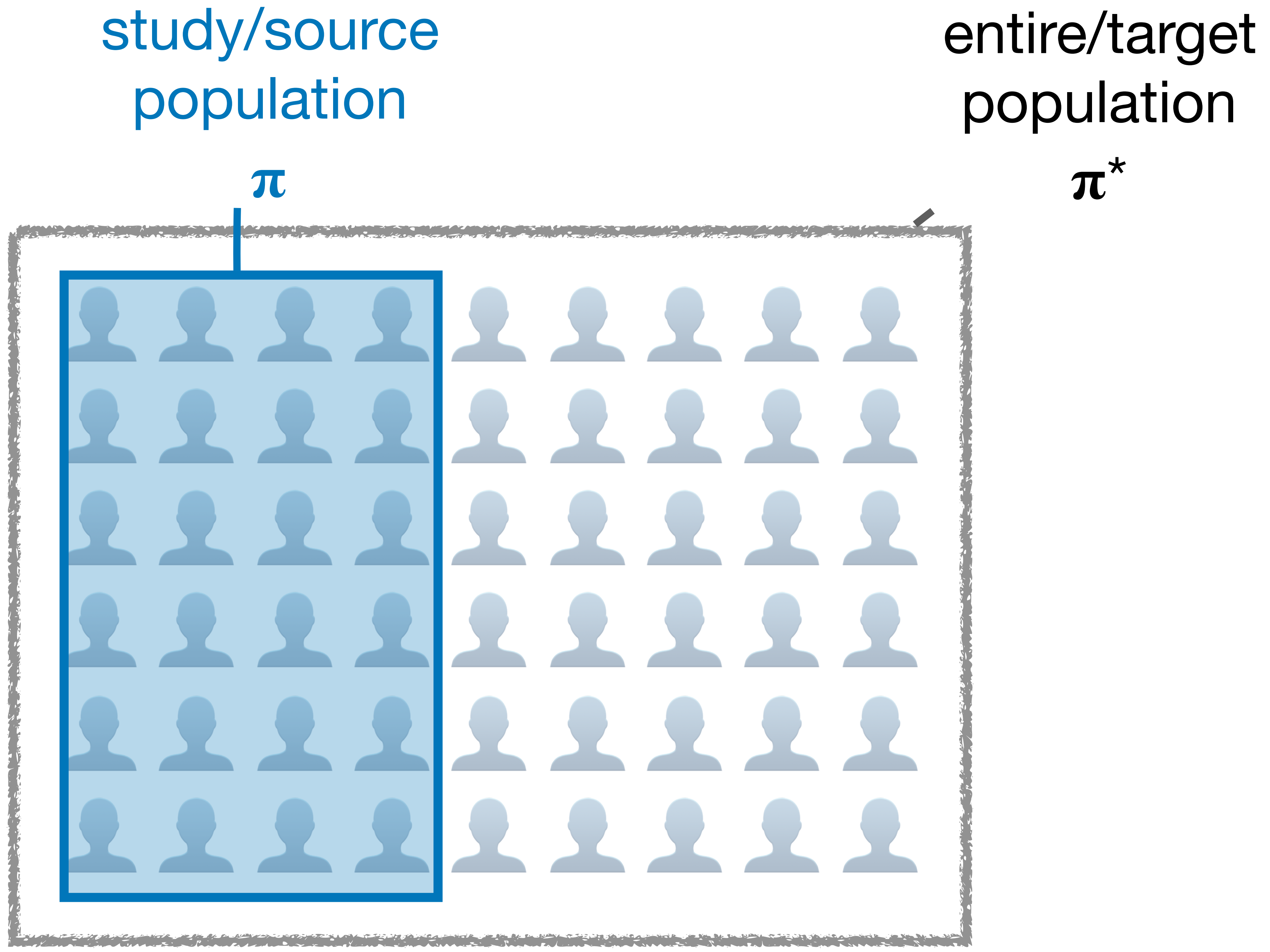

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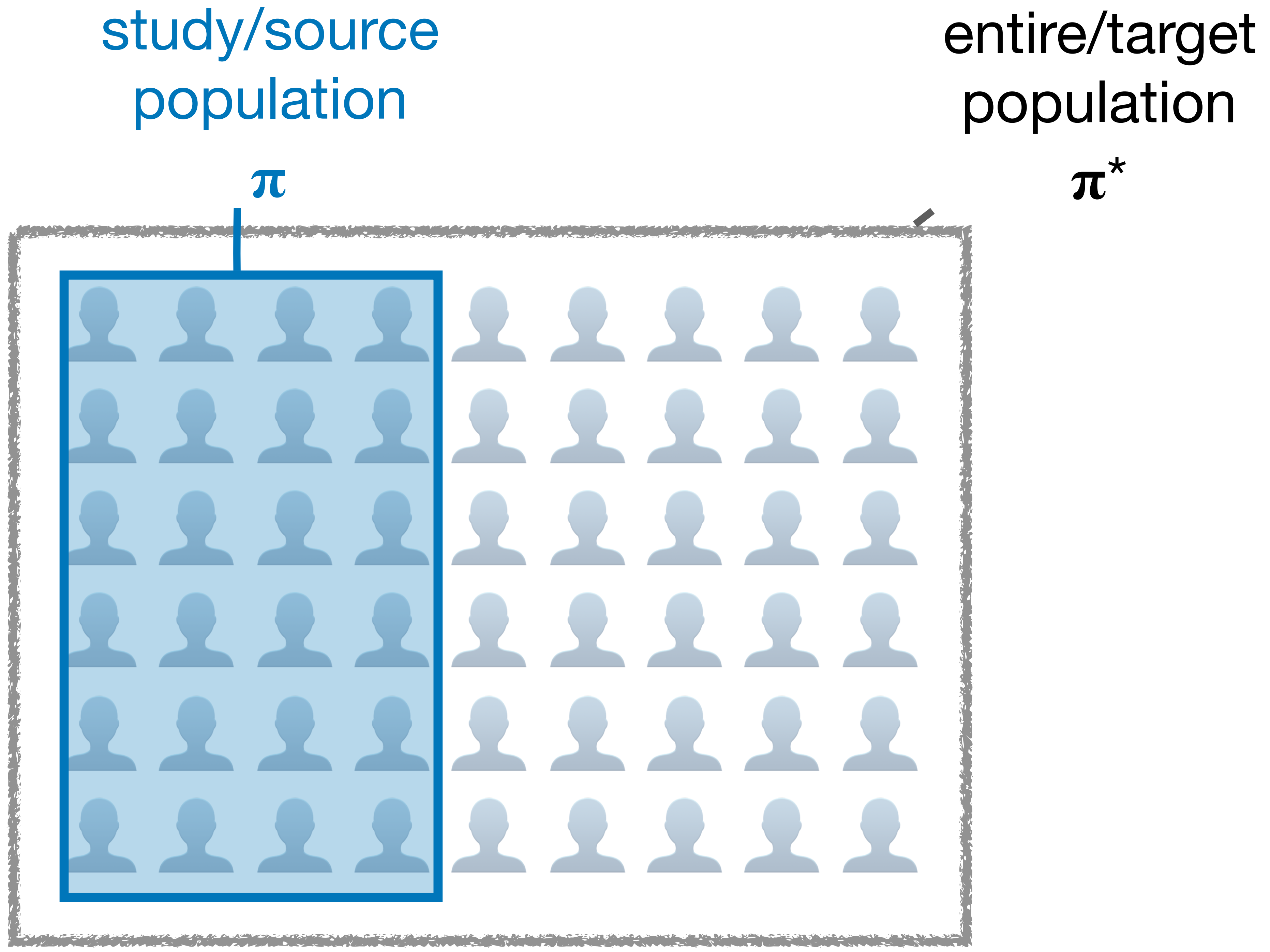

$$P^*(e) \neq P(e)$$

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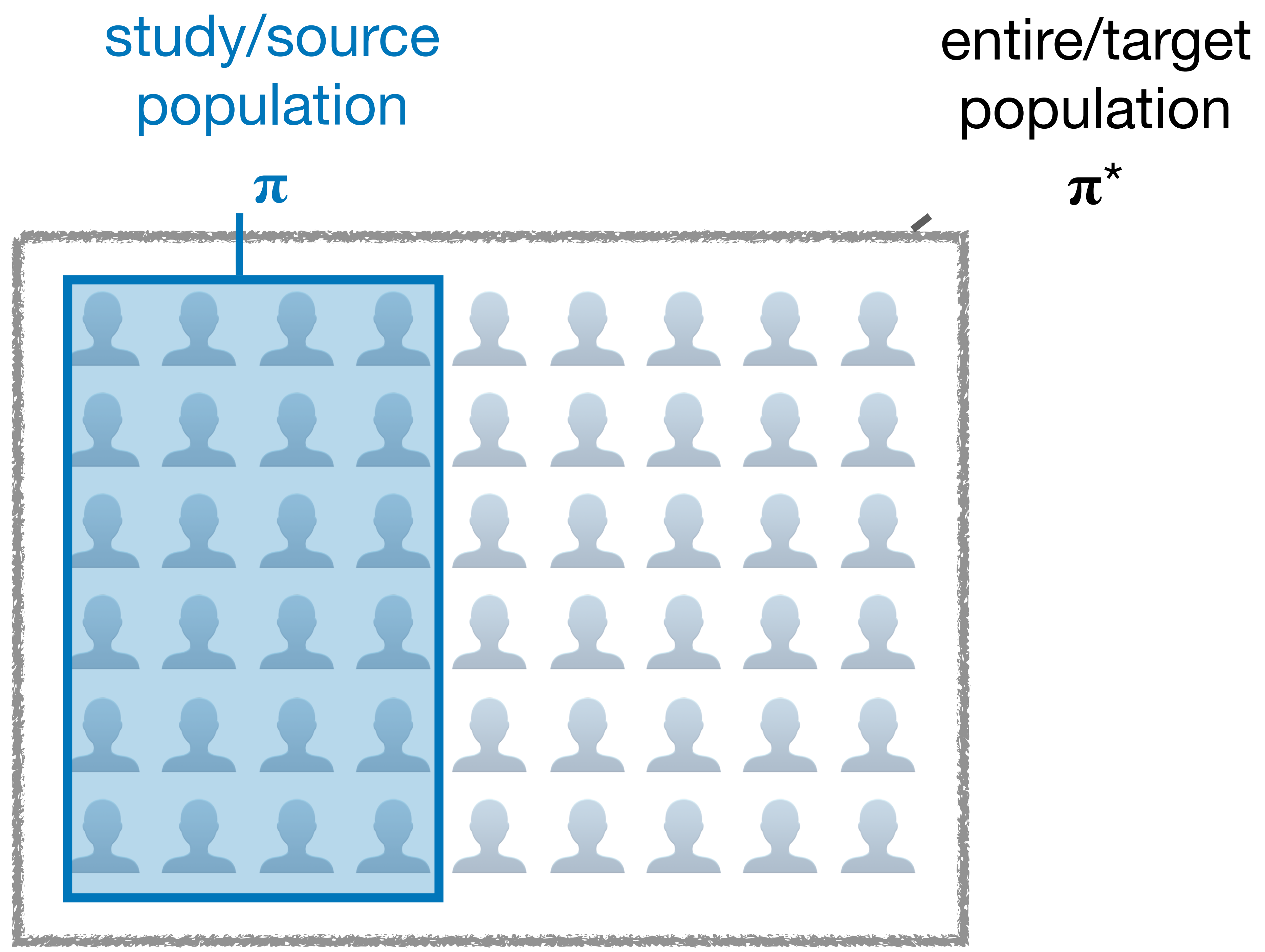

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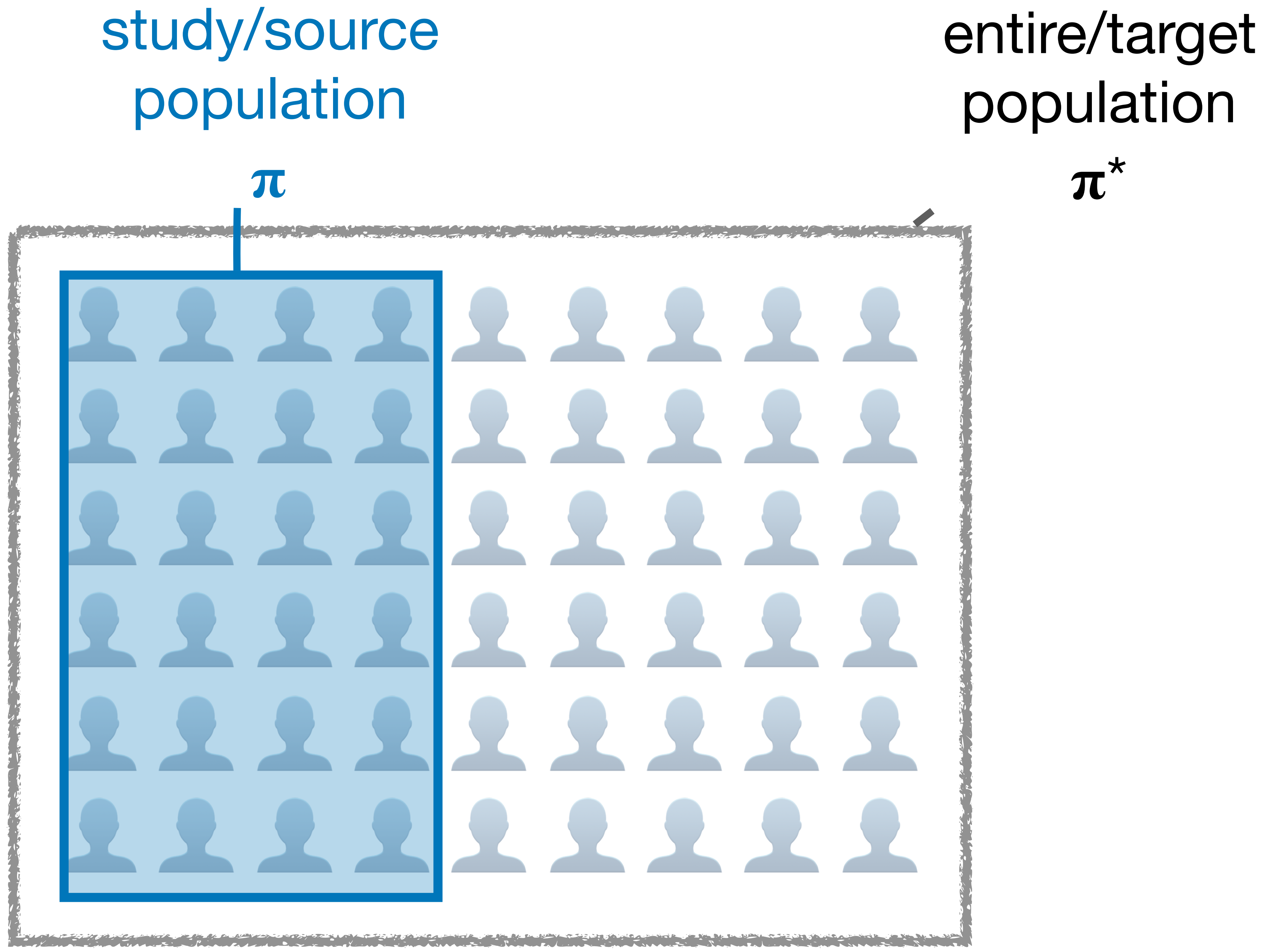
FDA's studies sampled from a distinct population by excluding youths with elevated baseline risk for suicide (B) from their cohorts.



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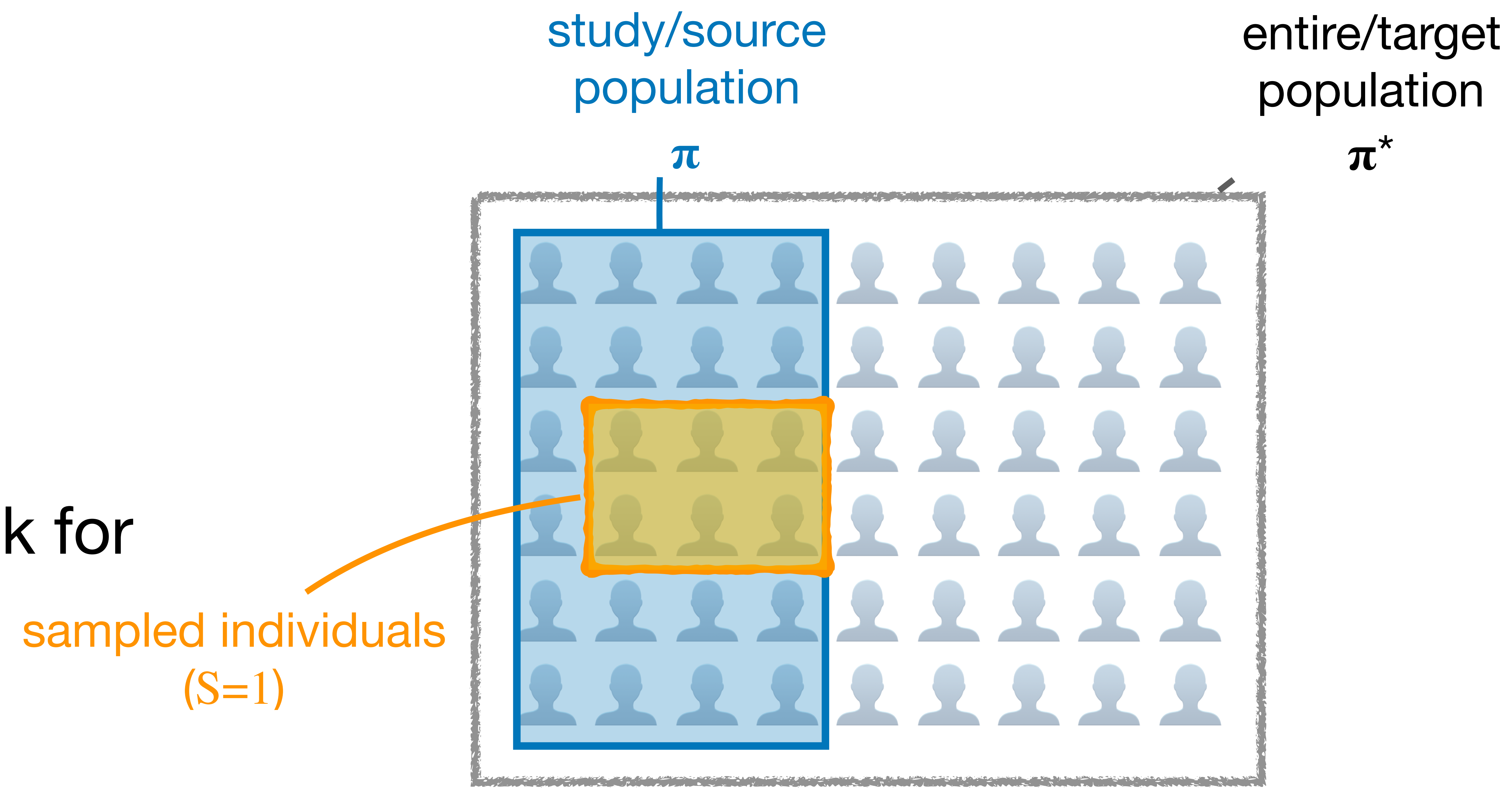

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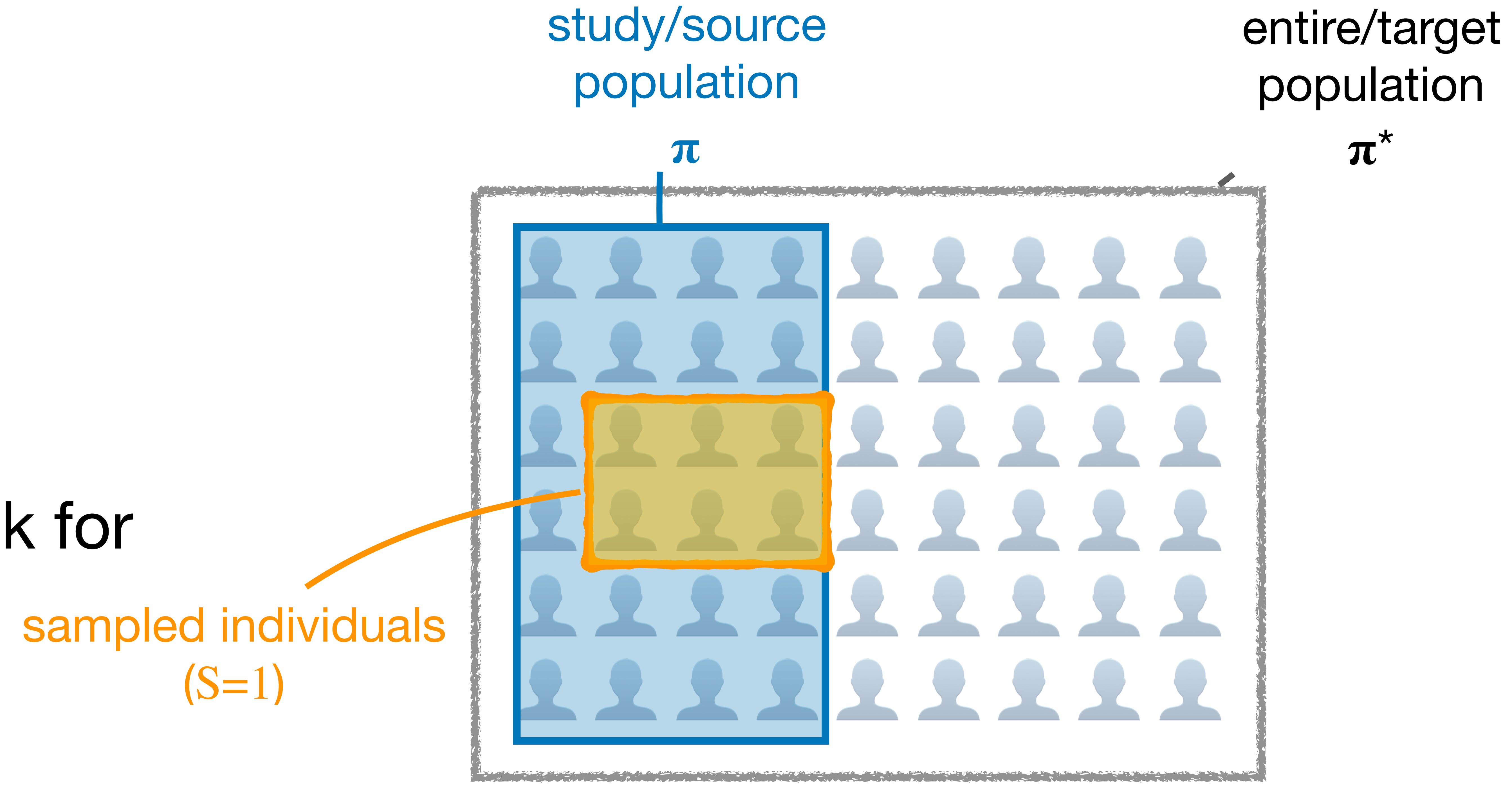

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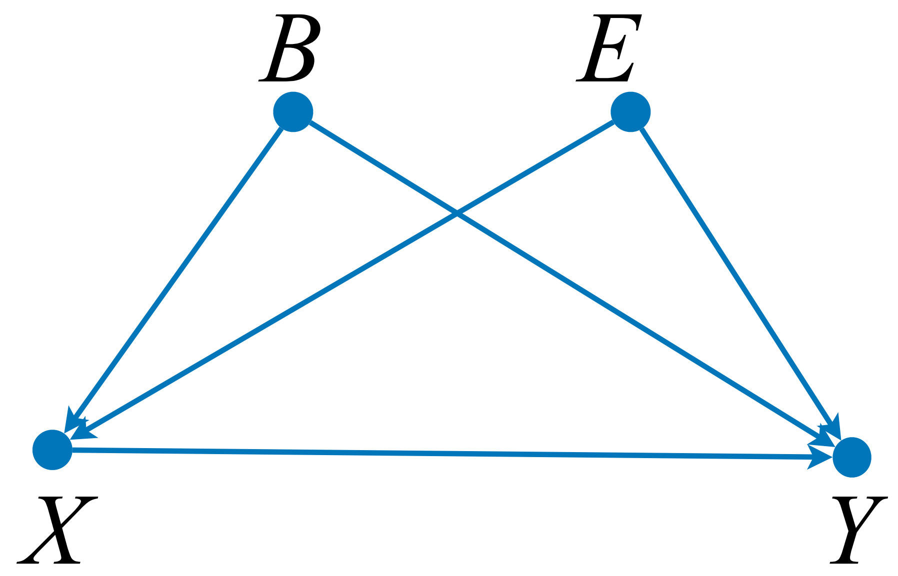
Formalizing the Problem



Formalizing the Problem

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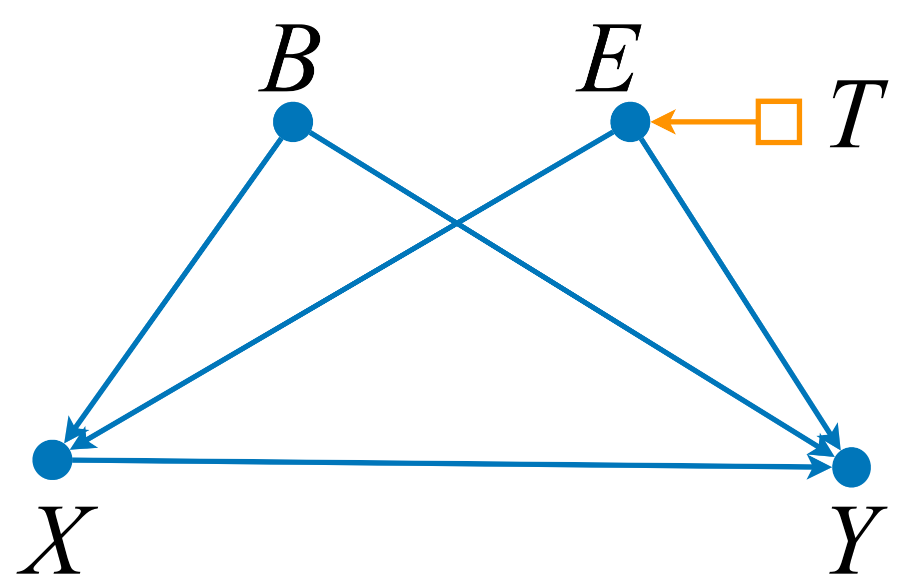

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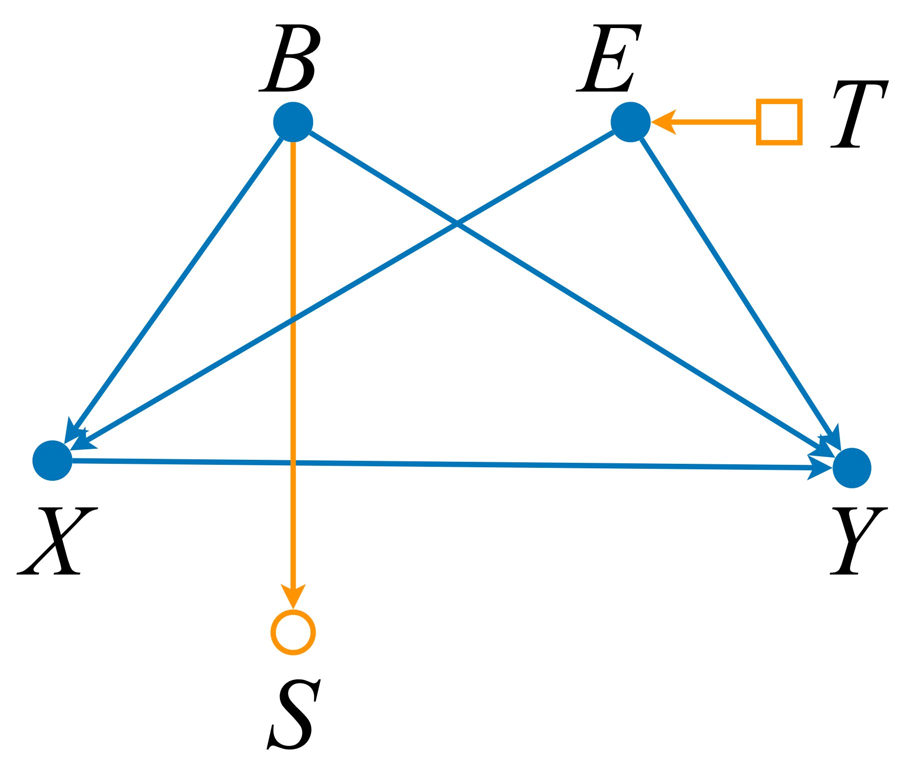

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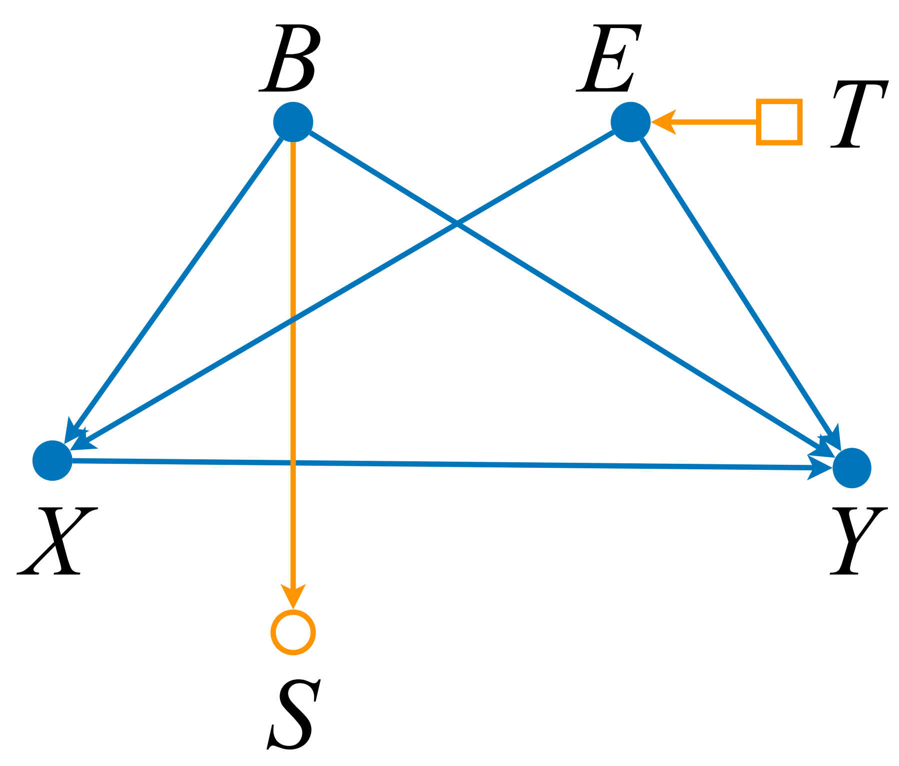

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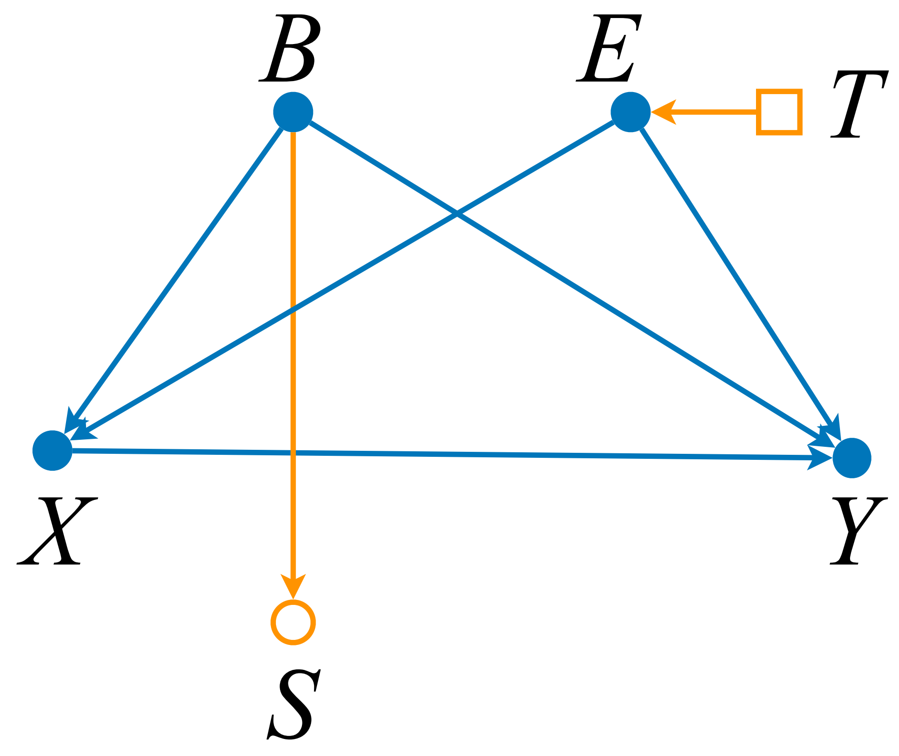

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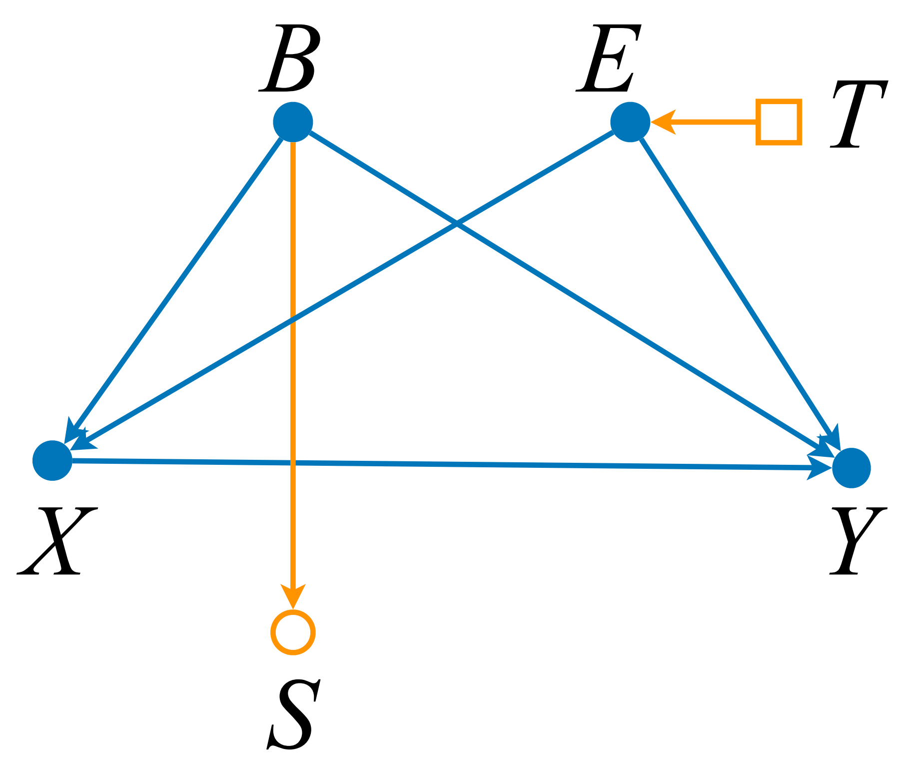

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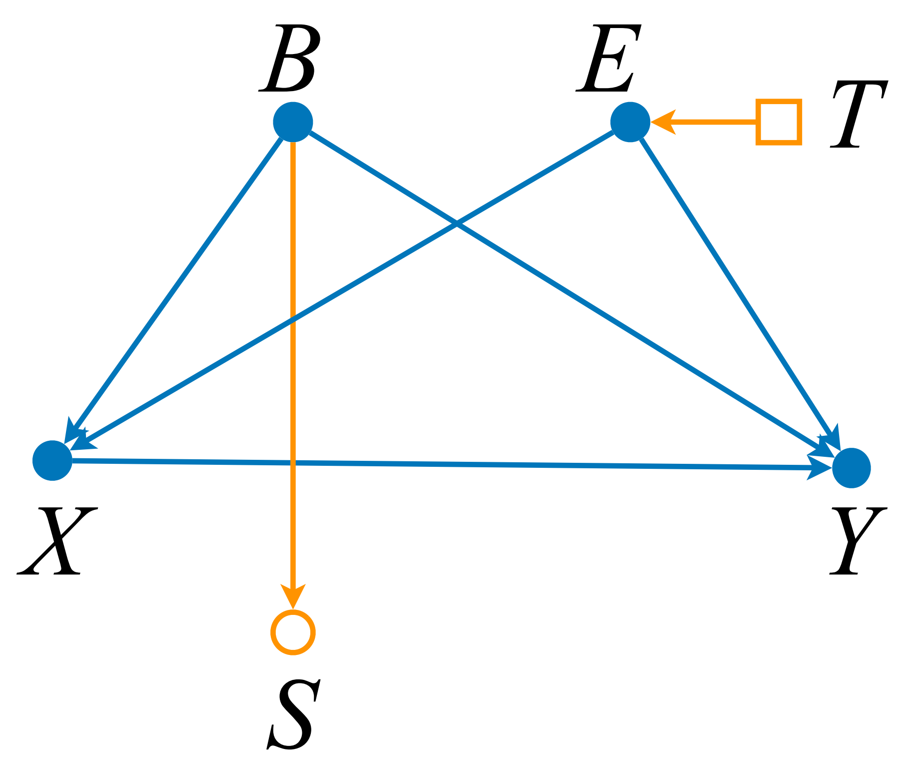

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experimental data from the
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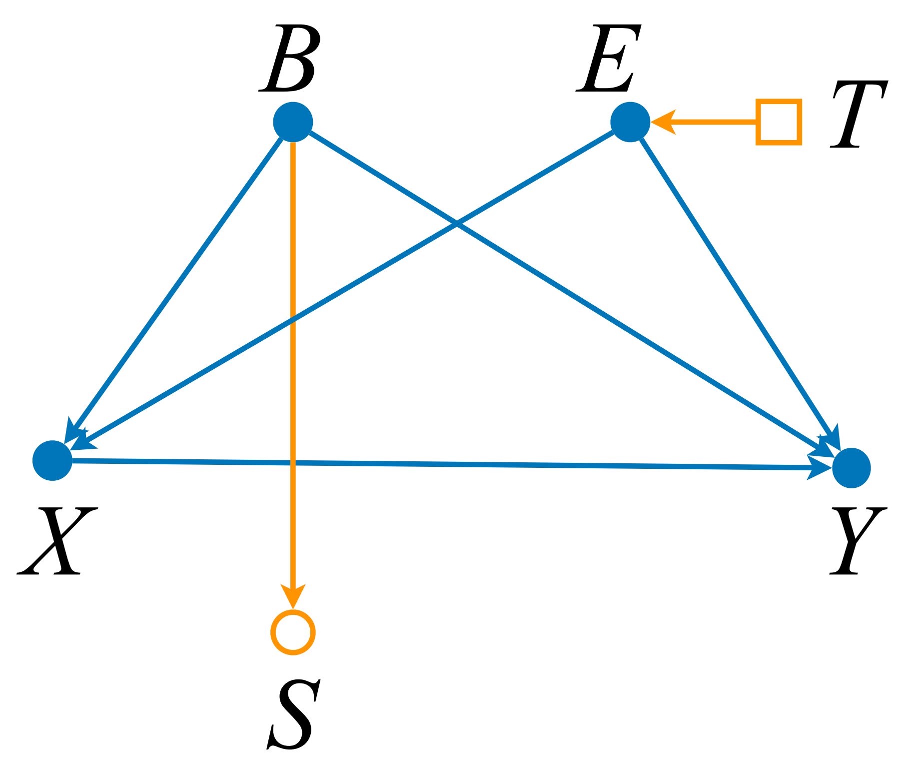

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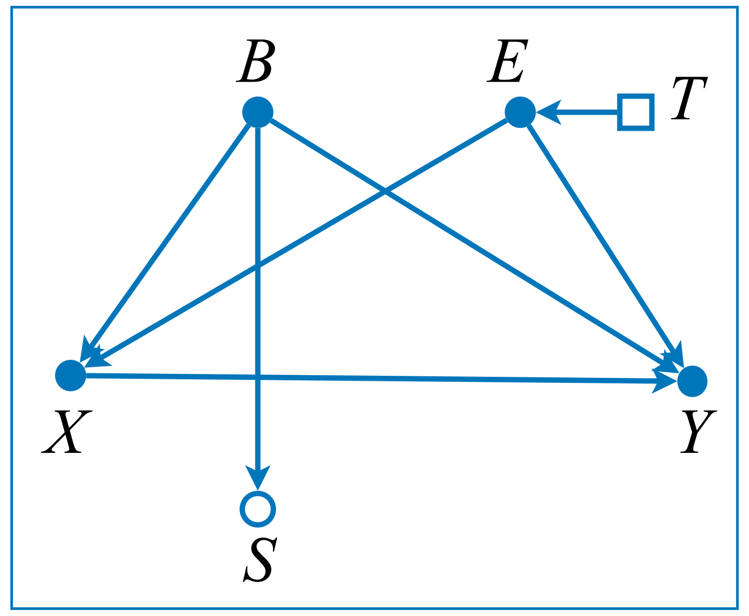

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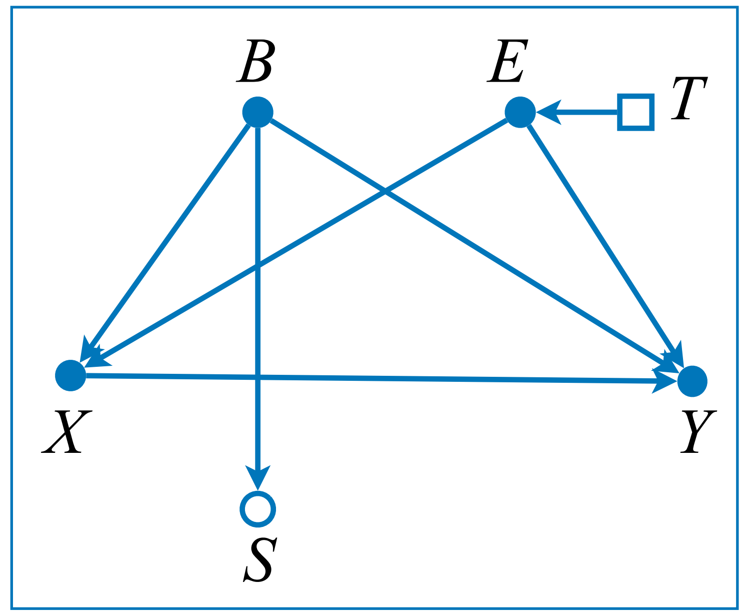

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$P(\mathbf{v} \mid do(x), S = 1)$			

Selection-biased Exp.
Distribution P_1 from $\boldsymbol{\pi}$

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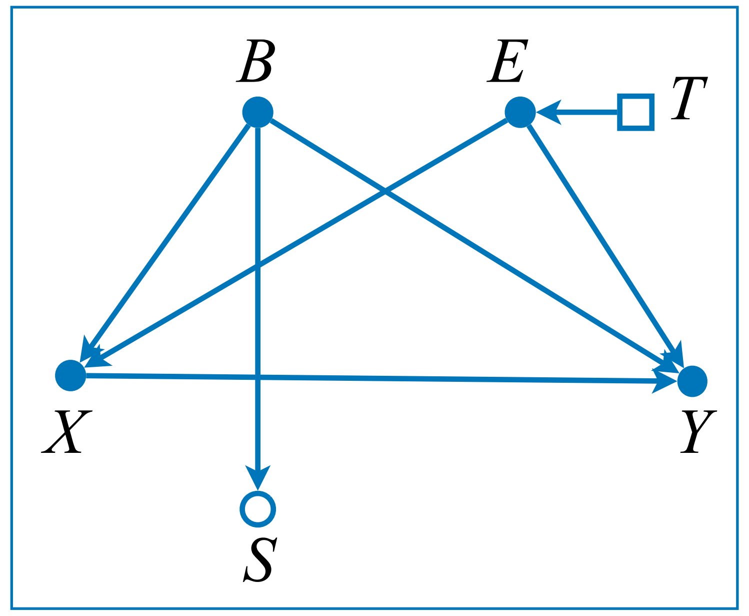

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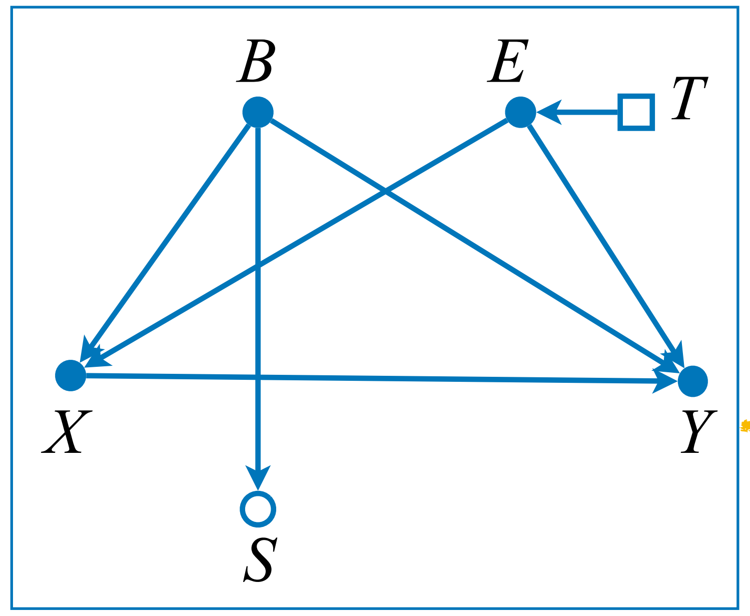

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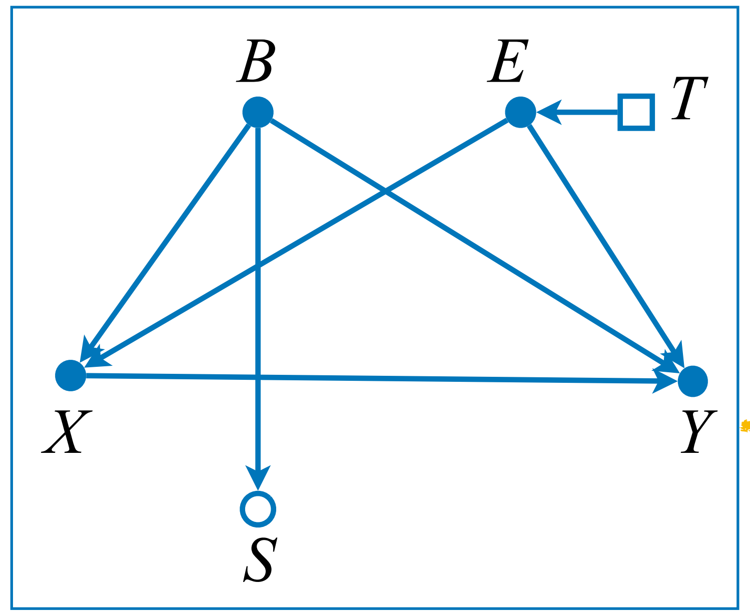

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yes (f) **/** **no**

😀 ☹️

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st-Adjustment Criterion [Correa, Tian and Bareinboim ’19]	–	exp.	✔	✔	✔

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1. How to determine if *st-adjustment* holds for a set of covariates $\mathbf{Z}$?

Solution: Covariate *st*-Adjustment

- Strategy: Recalibrate the results from experiments in the the studied population using observations from the target population.

$$\underbrace{P^*(y \mid do(x))}_{\text{unbiased target effect in } \boldsymbol{\pi}^*} = \sum_{\mathbf{z}} \underbrace{P(y \mid do(x), \mathbf{z}, S = 1)}_{\text{experiment results in source domain } \boldsymbol{\pi}} \underbrace{P^*(\mathbf{z})}_{\text{observations from the target domain } \boldsymbol{\pi}^*}$$

- Questions:

1. How to determine if *st-adjustment* holds for a set of covariates $\mathbf{Z}$?
2. How to find admissible covariate sets?

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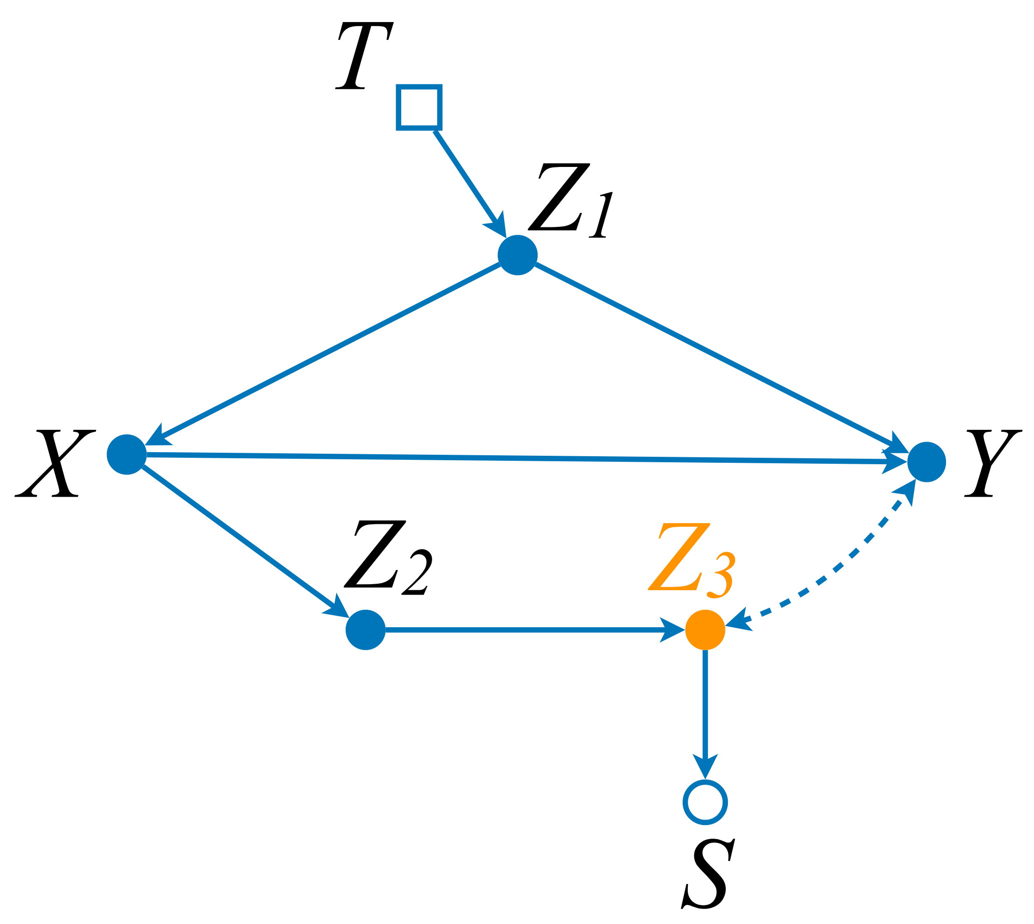

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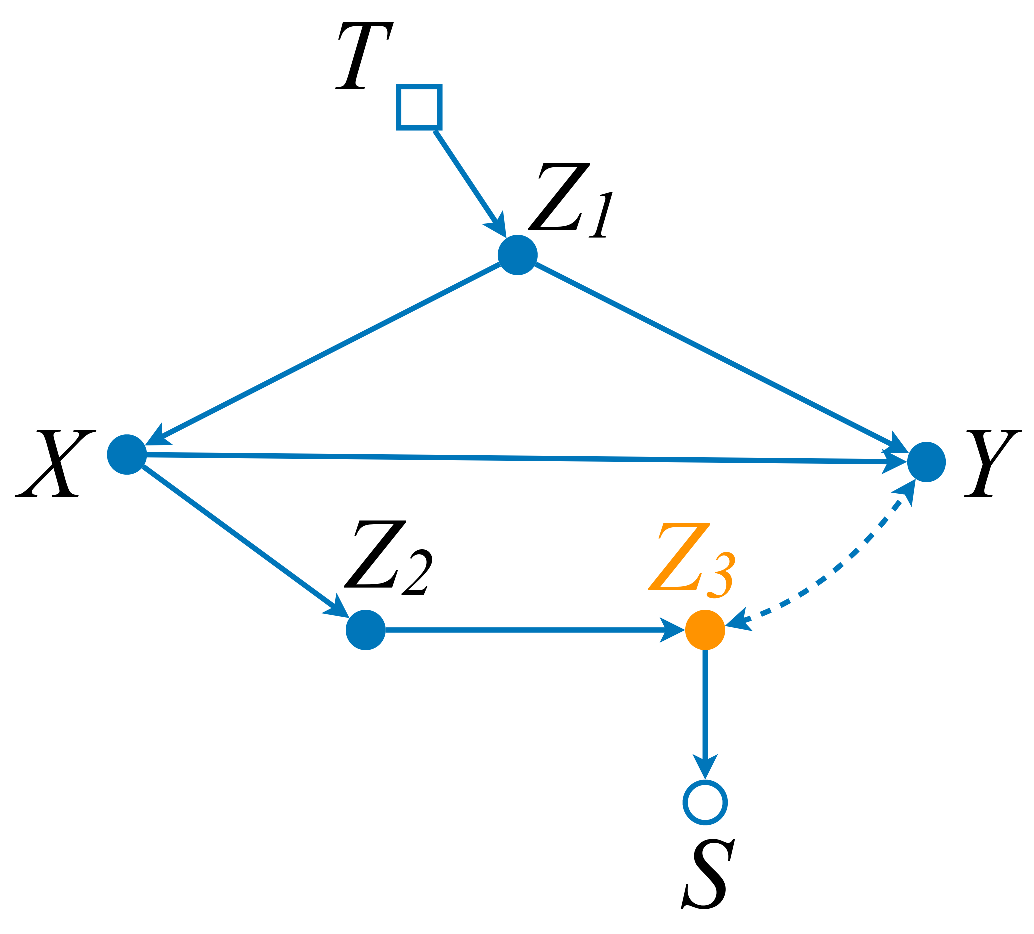

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Thm. The causal effect $\mathrm{P}^*(\mathrm{y} \mid \mathrm{do}(\mathrm{x}))$ is identifiable by *st-adjustment* on a set $\mathbf{Z}$ with D if and only if the conditions above hold for $\mathbf{Z}$ relative to X and Y.

Understanding the criterion

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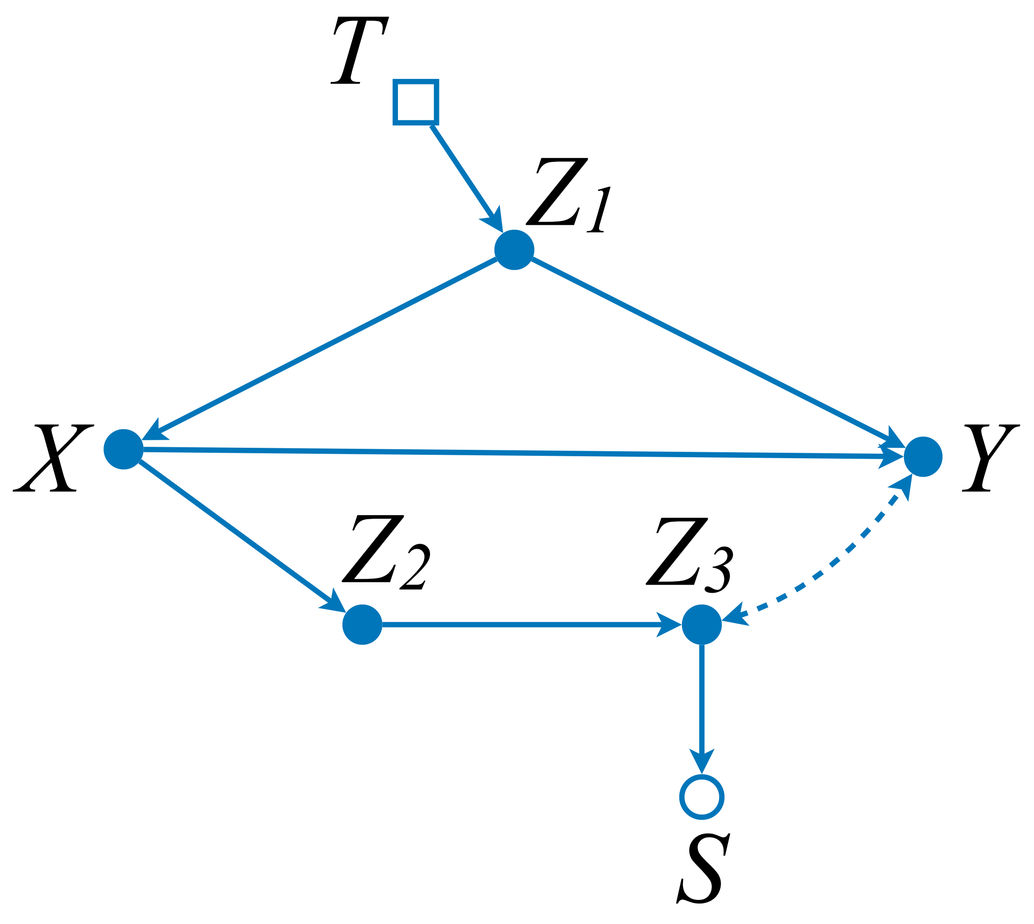

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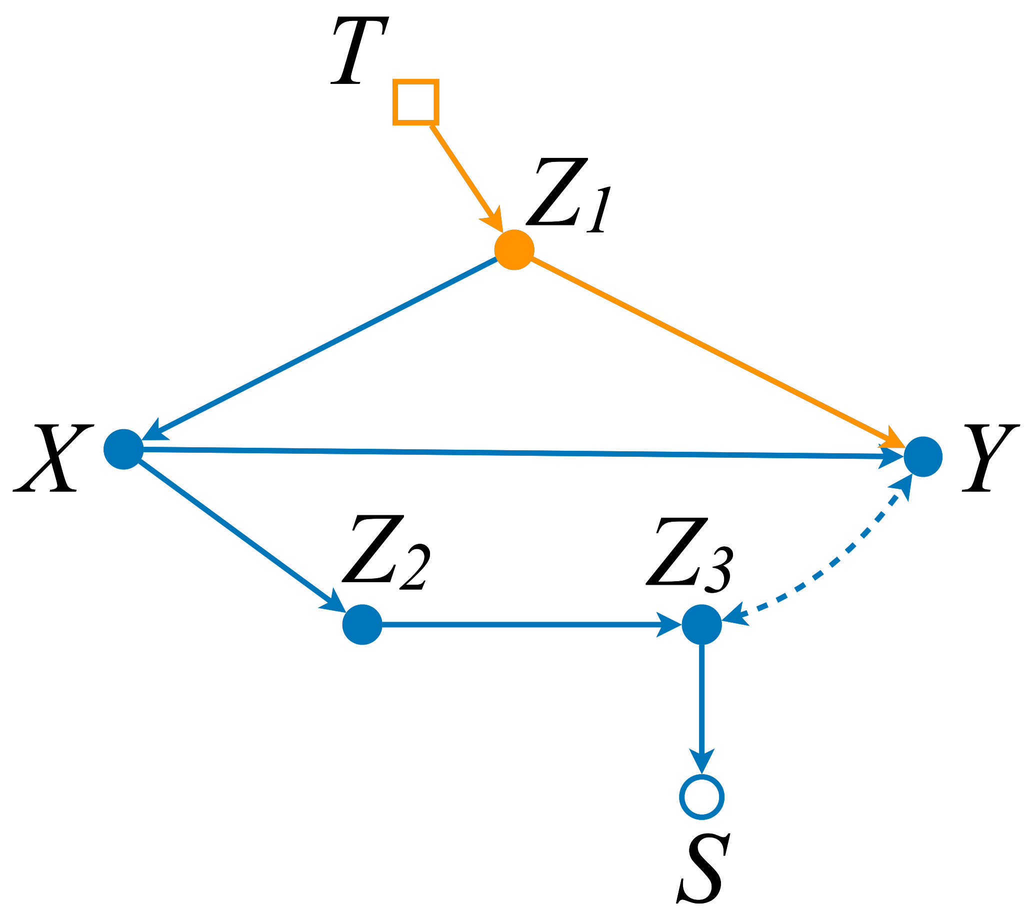

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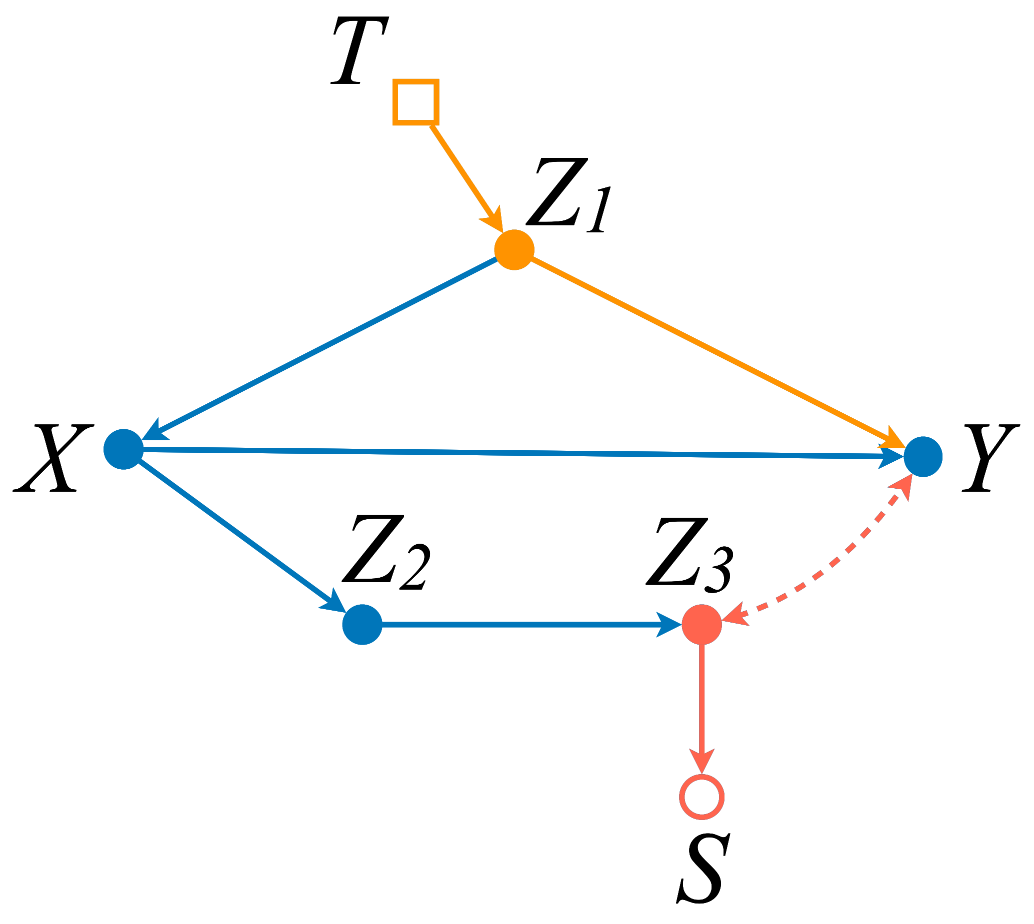

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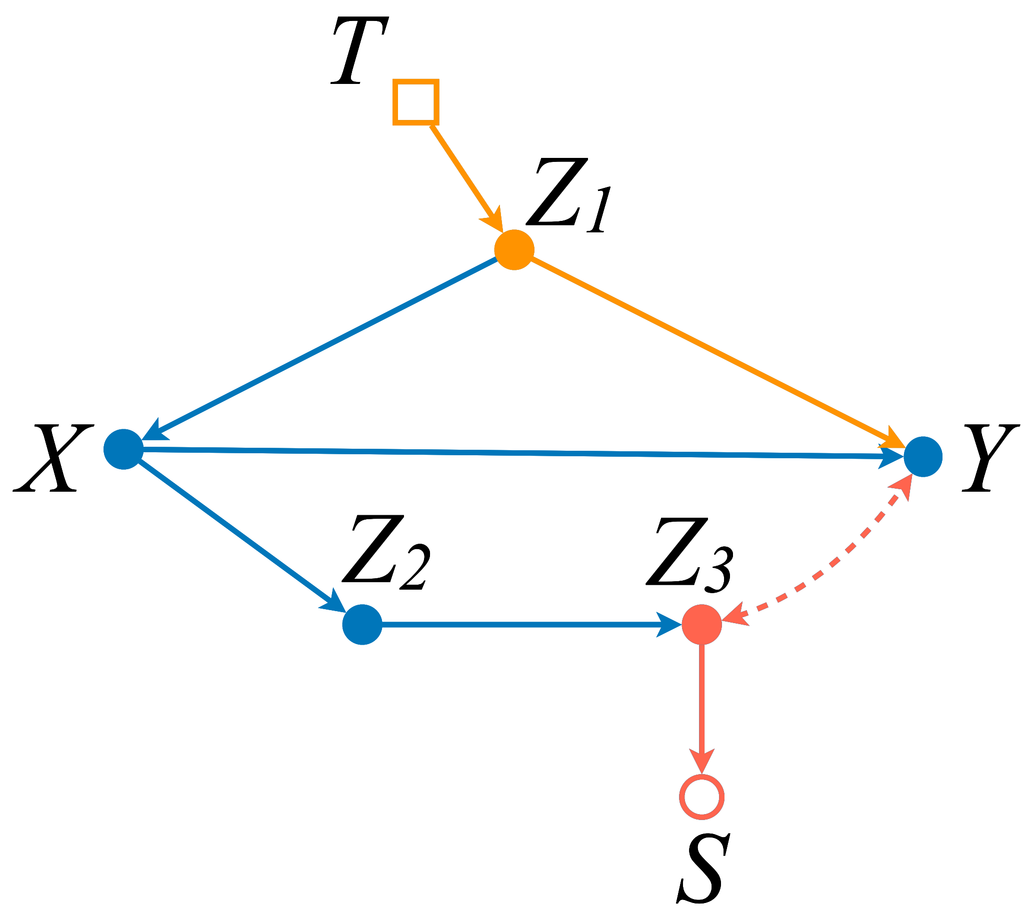

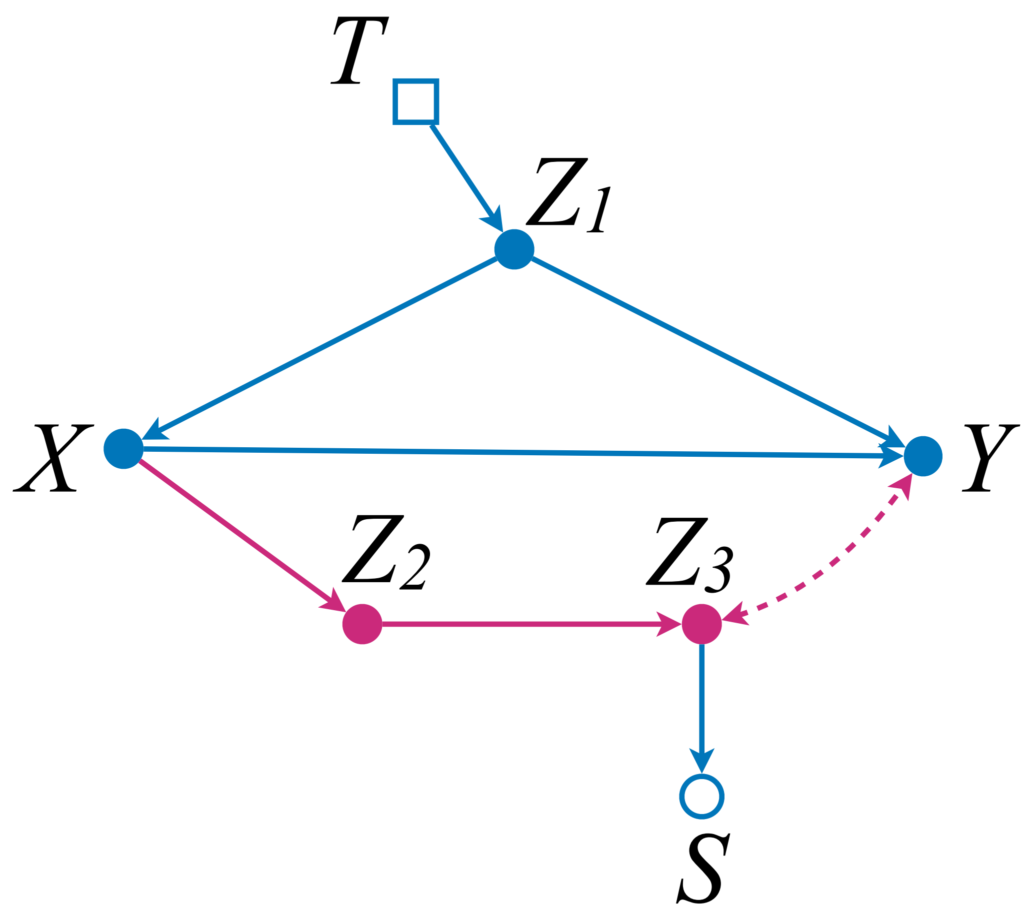

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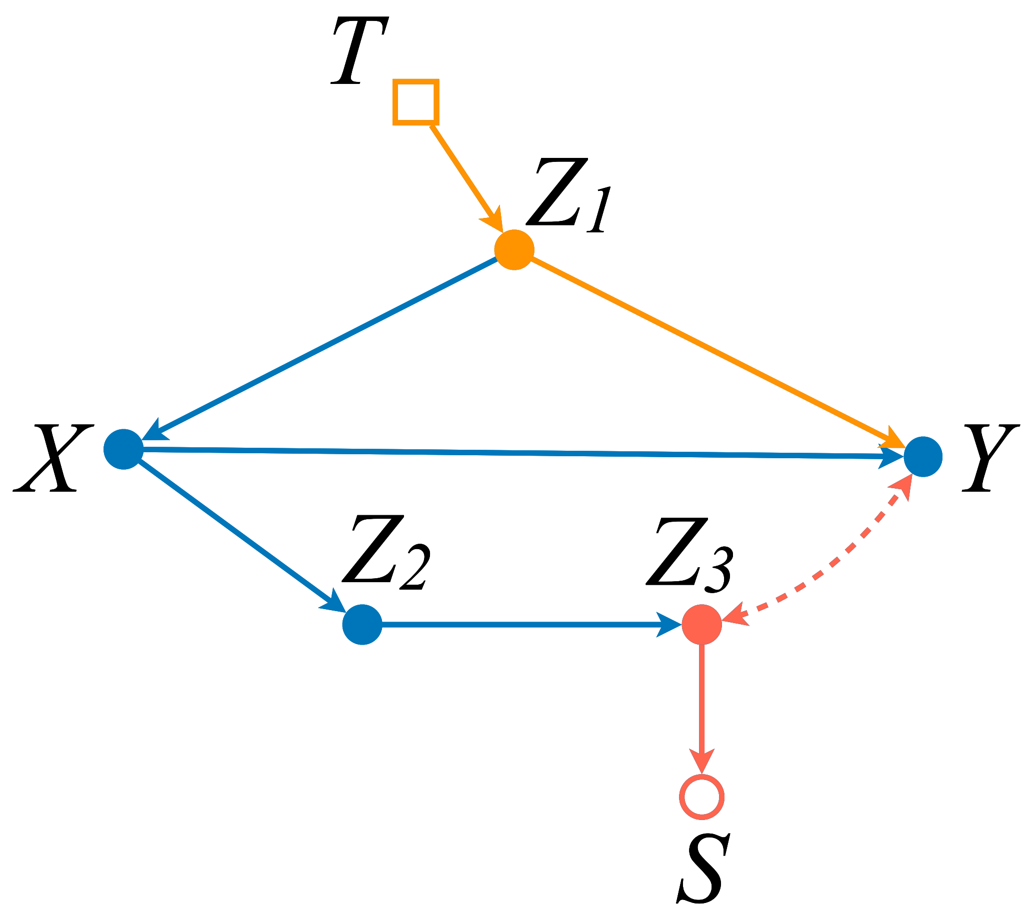

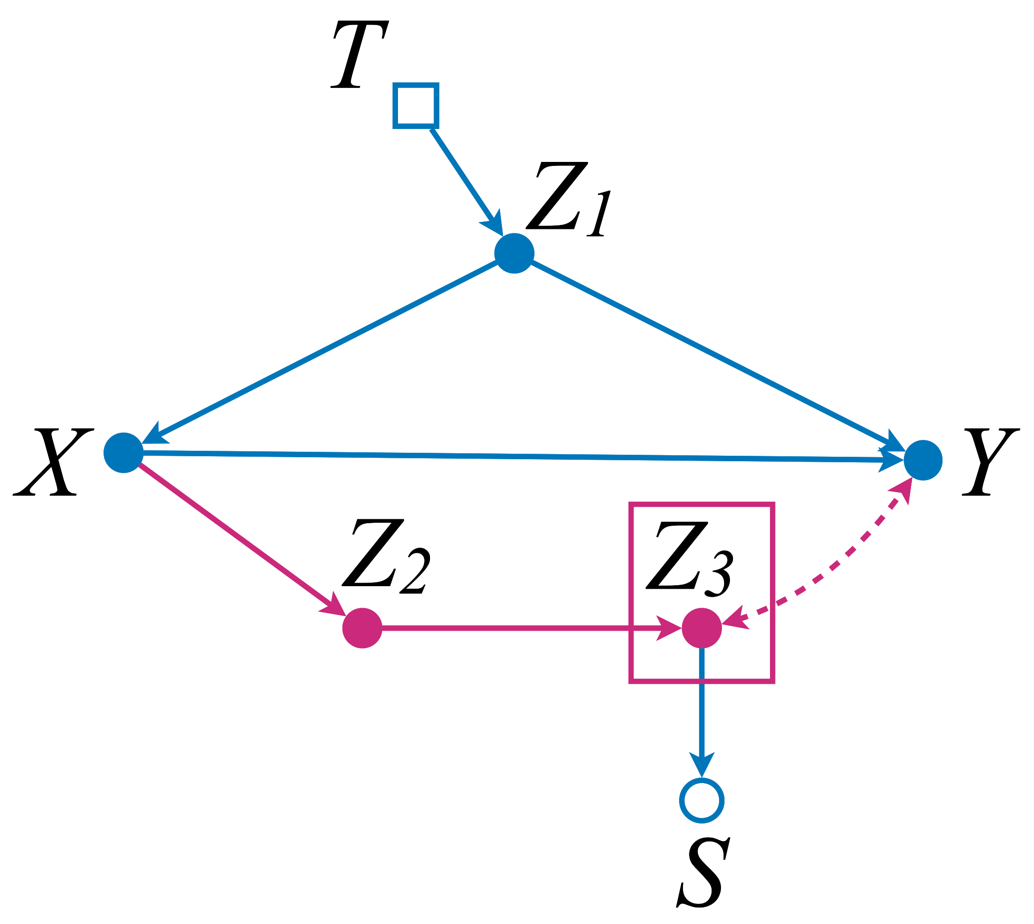

Getting the intuition behind the rules
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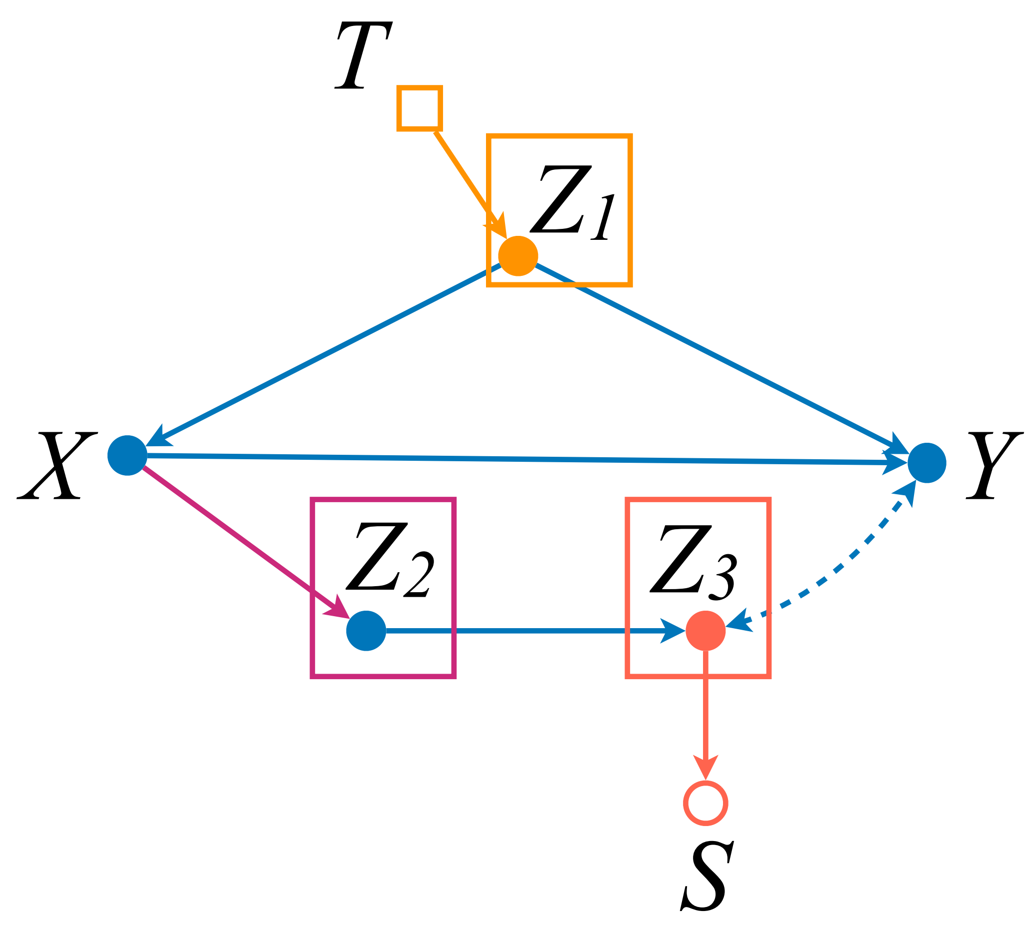

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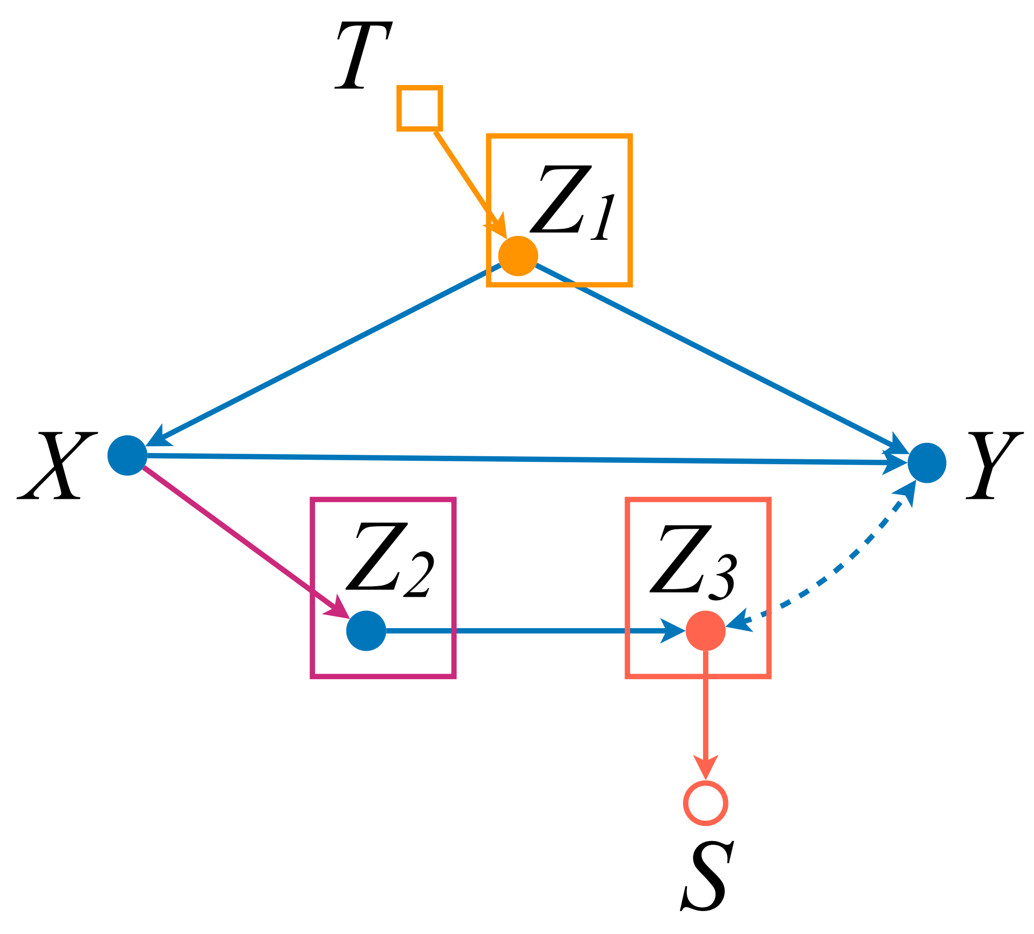

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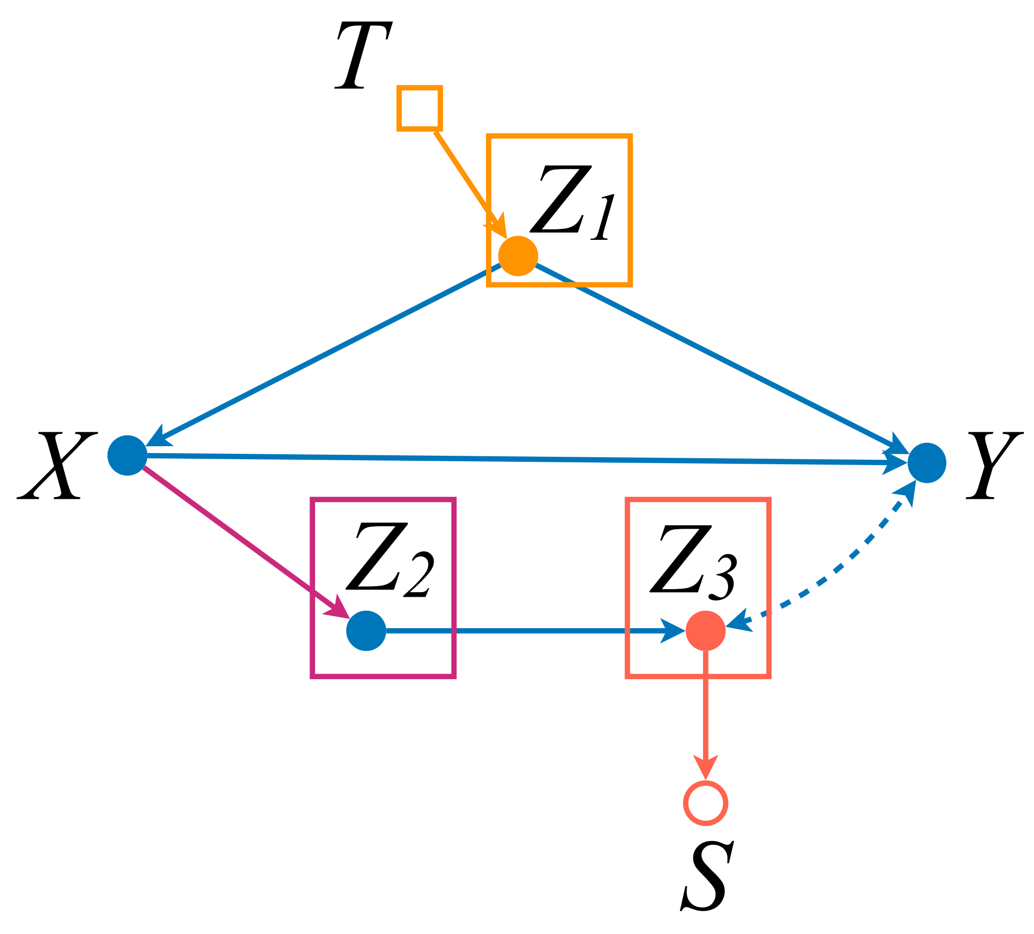

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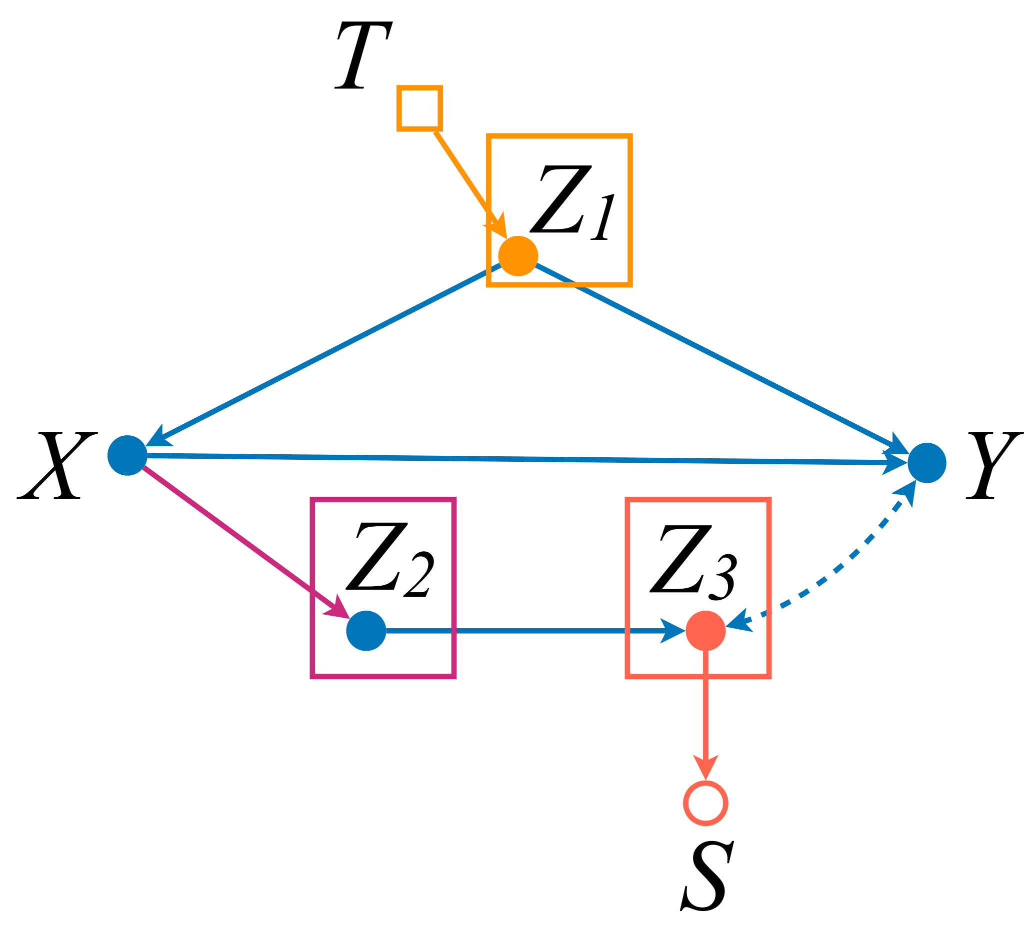

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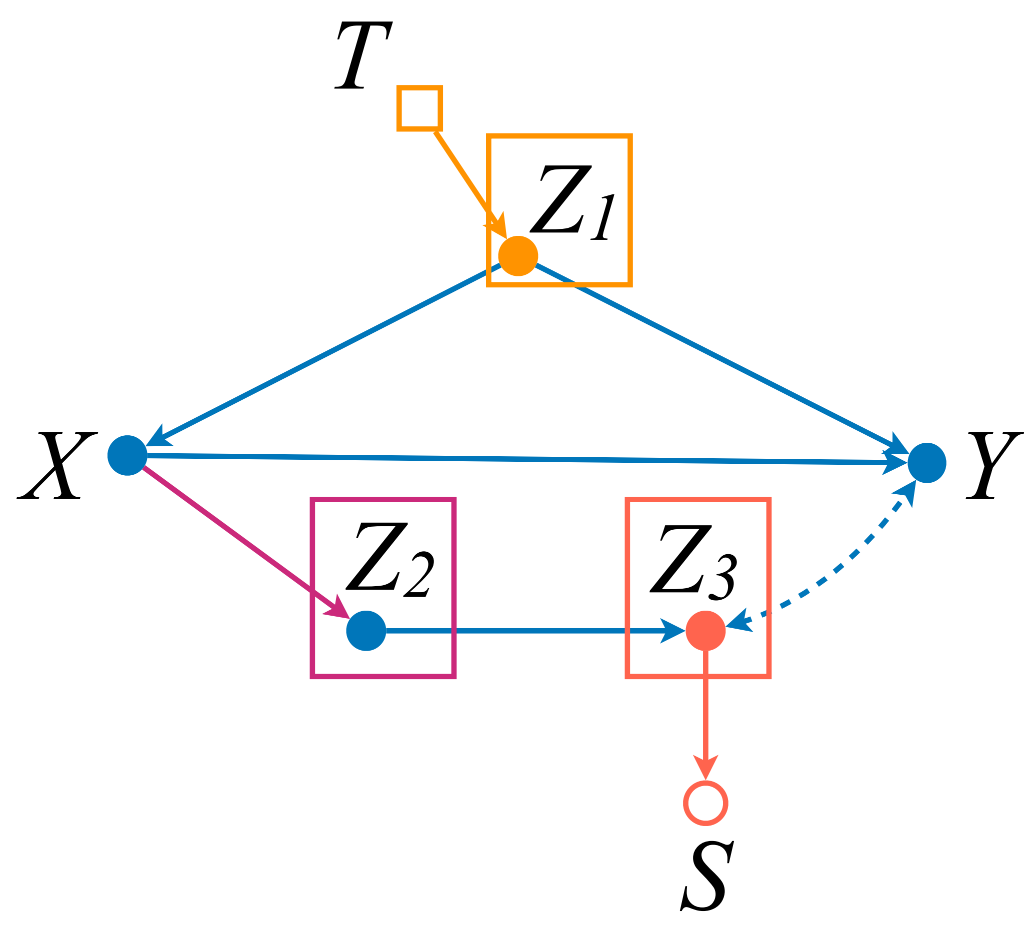

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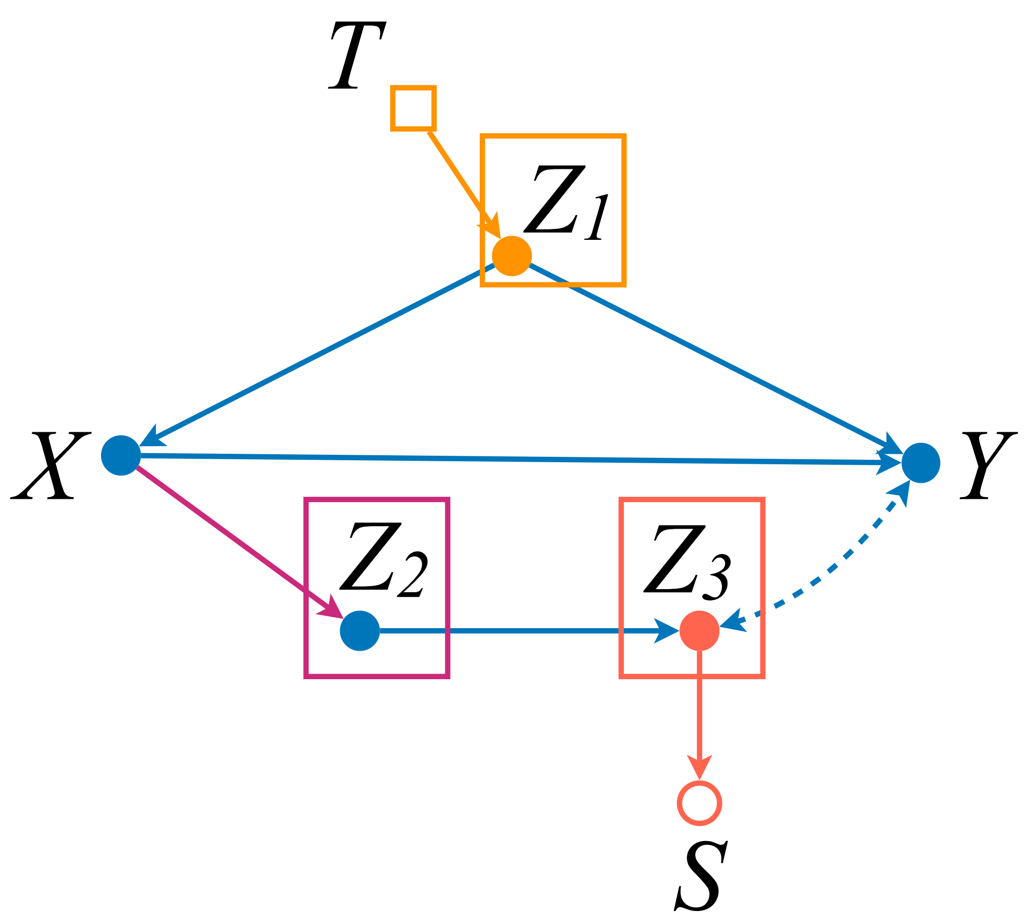

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- There are sets that could be preferred among other admissible ones due to certain properties (e.g., cost, variance).

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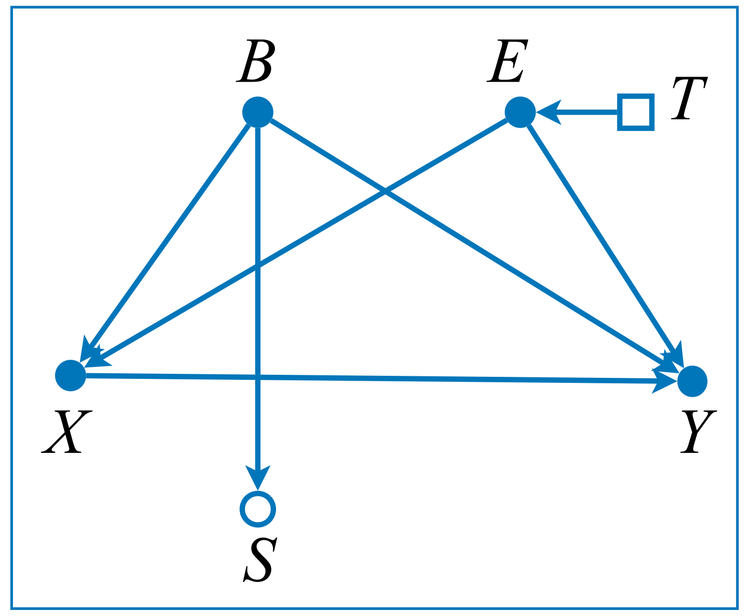

Selection Diagram D

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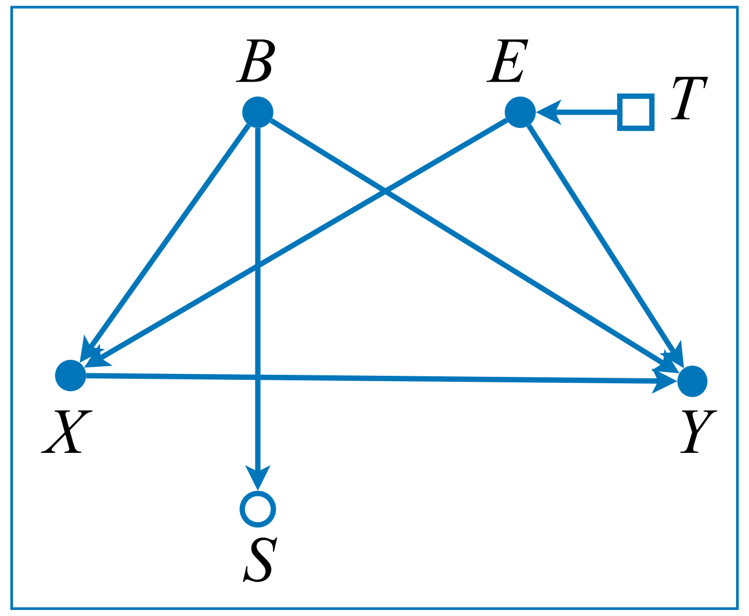

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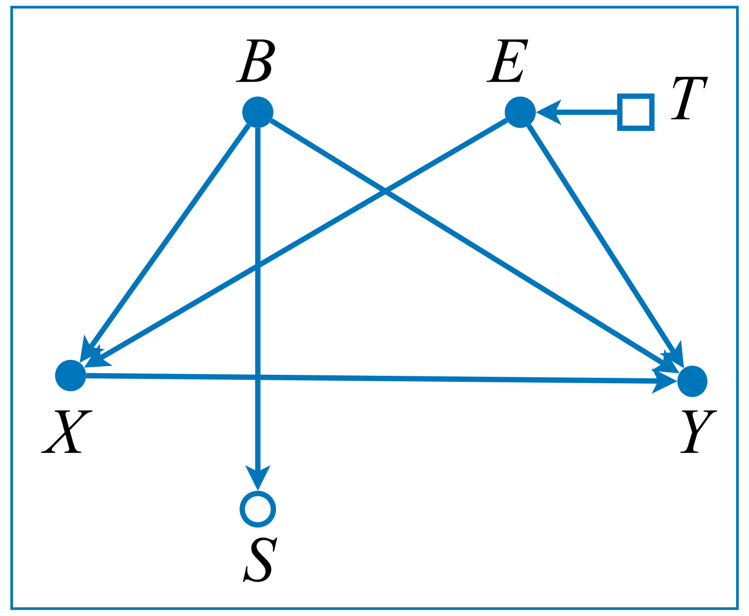

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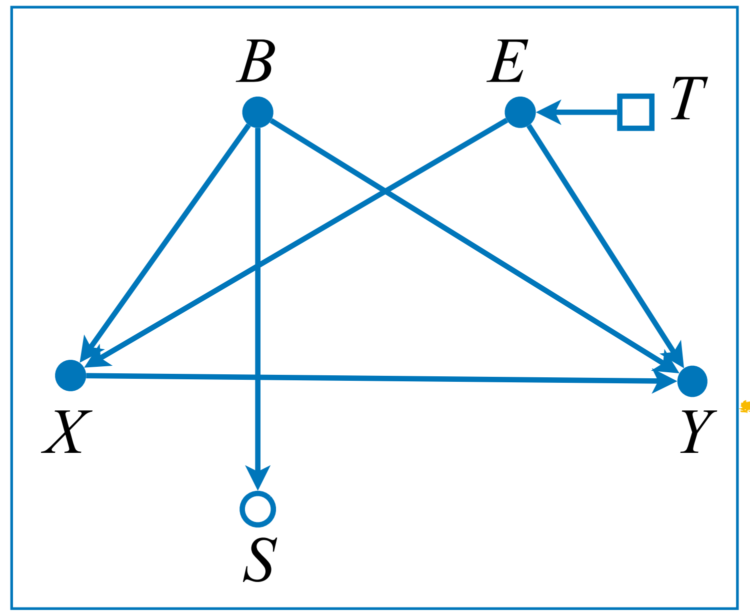

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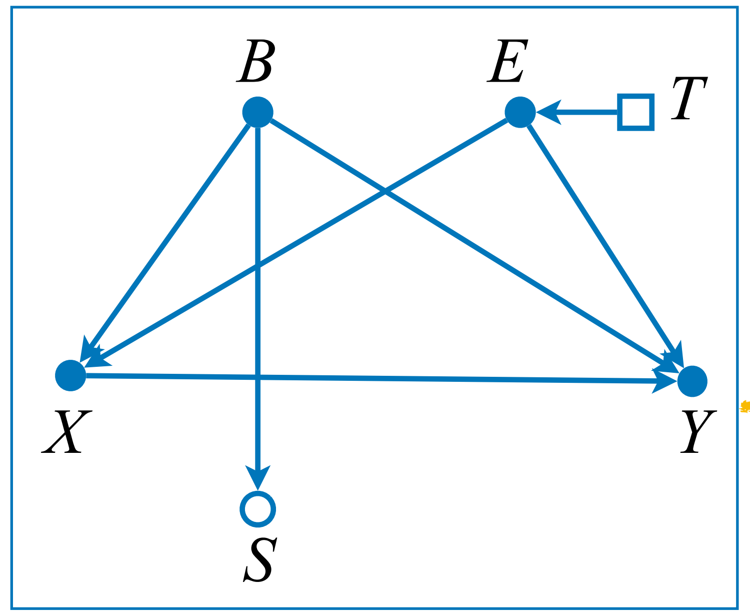

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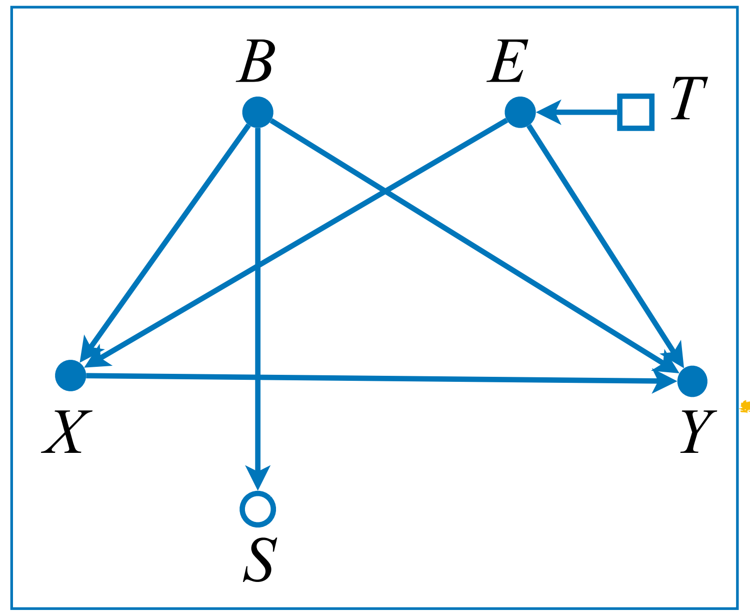

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We provide an algorithm (Alg. 2) that works with polynomial delay (Thm. 6)

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- We hope the formal and transparent dressing given to the problem by our results can help researchers in health sciences, econometrics, reinforcement learning, marketing and others where extrapolating experimental results is crucial.

Thank you!

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Poster

Polynomial delay [Takata ’10]

- Time passing between the start of the execution and first output or failure is polynomial.
- Time between outputs is also polynomial.