

Using principal stratification to address post-randomization events: A case study

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PSI Webinar**

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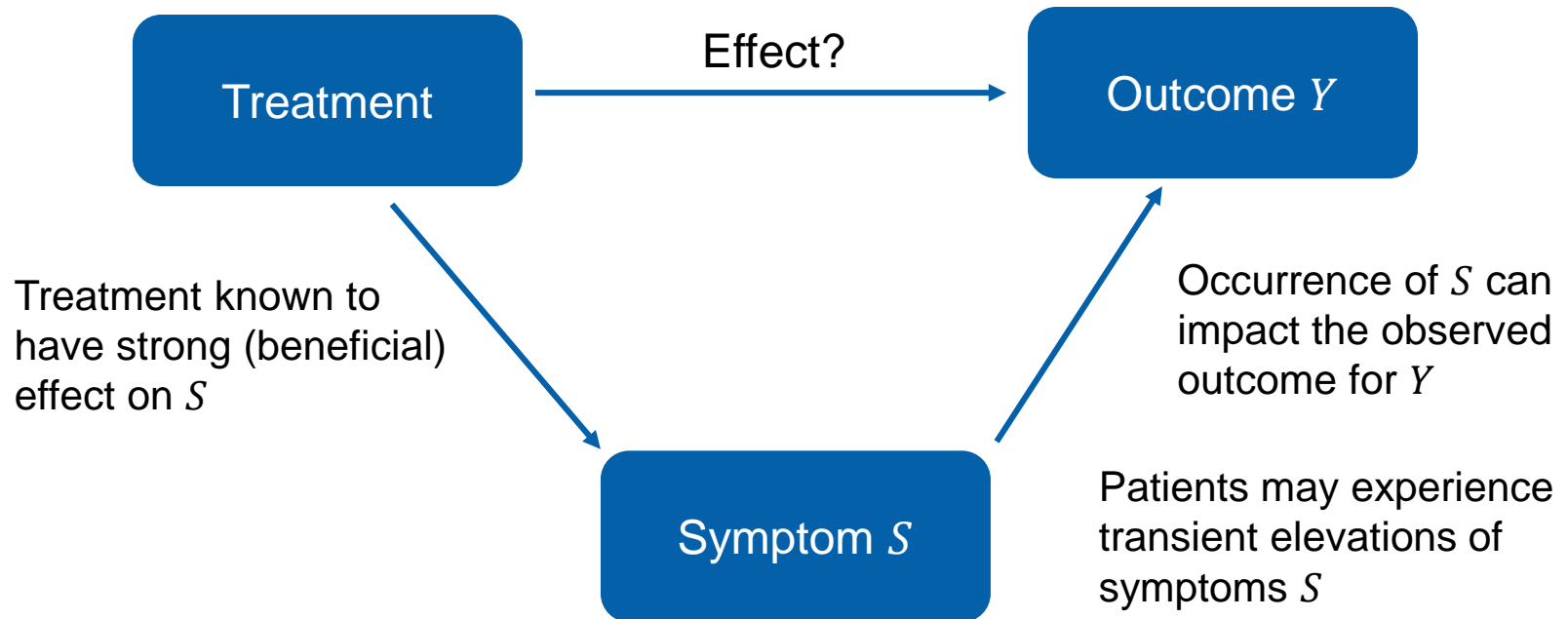
Outline

- Context
- Principal stratification
- Estimand of interest
- A glance at the Bayesian model
- Conclusions

Context

Phase 3 study with randomization to active or control

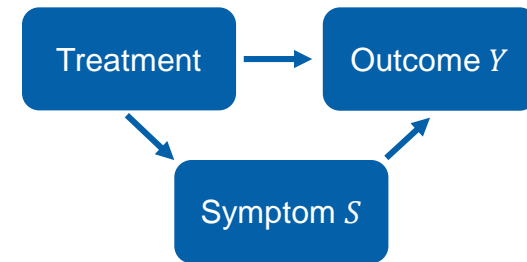
Primary question: What is the effect of treatment on outcome Y ?



Question for this presentation:

How do we account for S on the **estimand** and the **estimator** level?

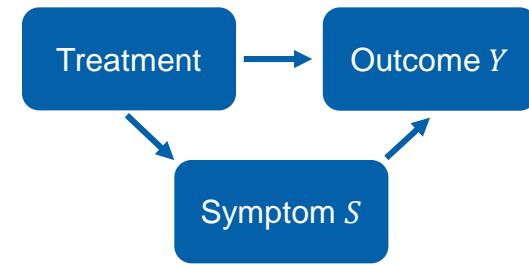
Context



Question for this presentation:

How do we account for S on the estimand and the estimator level?

- Answer depends on the scientific **question of interest**...
- In our example: want to know the effect of treatment on Y among patients for whom S is **very unlikely to occur**
- How to reflect “very unlikely to occur” in our estimand?
- Focus on treatment effect in subgroup of patients who would not experience S **regardless of treatment assignment**
- This is the **principal stratification** estimand discussed in ICH E9 (R1)



Other estimands

As implied by common analyses

- Occurrence of S is irrelevant (treatment policy)
- Effect in population of patients without **pre-study** S
 - Not useful if pre-study S is not predictive of on-study S
 - Does not acknowledge the treatment effect on S
- Effect in the population of patients without **on-study** occurrence of S
 - Conditions on a post-randomization outcome affected by treatment
 - Estimate of treatment effect on Y would not have a causal interpretation
- Effect in a world where S would not occur
 - Hypothetical estimand since S cannot be intervened on
- None of these estimands are appropriate for our situation

Principal stratification

- Notation:
 - $S(z)$ = symptom indicator under treatment $z \in \{0,1\}$
 - That is, $S(z) = 1$ for patients who experience S if assigned to z
 - $Y(z)$ = outcome indicator under treatment $z \in \{0,1\}$
 - That is, $Y(z) = 1$ for patients who experience Y if assigned to z
- $S(z)$ and $Y(z)$ are **potential outcomes**
 - Every patient has a potential outcome for both $z = 0$ and $z = 1$
 - Only observe one potential outcome per patient
 - Considered as fixed attributes (baseline characteristics)
- We use S and Y to denote **observed outcomes**

Principal stratification

- Stratify patients as belonging to one of:
 - **Immune**: No symptom regardless of treatment
 - **Doomed**: Symptom occurs regardless of treatment
 - **Benefiter**: Symptom occurs only on placebo
 - **Harmed**: Symptom occurs only on active

		$S(1)$	
		0	1
$S(0)$	0	Immune	Harmed
	1	Benefiter	Doomed

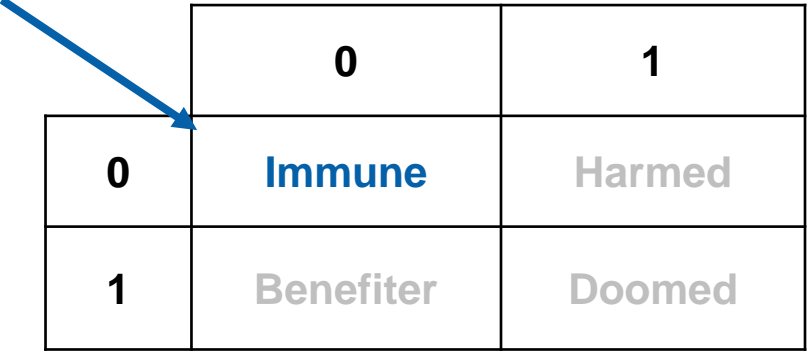
- Stratum membership **not directly observable**
- Observe outcome on **actual treatment received**
- E.g. active arm patient ($z = 1$) with $S = 0$ could be either immune or benefiter

Estimand of interest

- Interested in the difference in proportions of Y in the immune principal stratum

$S(1)$

		0	1
$S(0)$	0	Immune	Harmed
	1	Benefiter	Doomed



- Principal stratum causal effect:

$$P[Y(1) = 1 \mid S(1) = 0, S(0) = 0] / P[Y(0) = 1 \mid S(1) = 0, S(0) = 0]$$

$$= \frac{P[Y(1) = 1 \mid \text{Immune}]}{P[Y(0) = 1 \mid \text{Immune}]}$$

Identifying the estimand

Assumptions

- In practice, only **observe the margins** from this table
- Need **identifying assumptions** in order to link estimand to ‘observables’

		S(1)		
		0	1	Sum
S(0)	0	??		✓
	1	??	??	✓
	Sum	✓	✓	

- **Monotonicity assumption:**
There are no harmed patients
 - A patient not experiencing S on placebo **will not** experience S on active
 - That is, $S(0) = 0 \Rightarrow S(1) = 0$
 - A patient experiencing S on active **will** experience S on placebo
 - That is, $S(1) = 1 \Rightarrow S(0) = 1$

Identifying the estimand

Principal strata proportions

		$S(1)$	
		0	1
$S(0)$	0	Immune	
	1	Benefiter	Doomed

- Monotonicity allows **some patients to be classified**
 - Placebo patient with $S(0) = 0$ must be immune
 - Treated patient with $S(1) = 1$ must be doomed
- Some patients remain not classifiable
 - A treated patient who does not experience a symptom, i.e. $S(1) = 0$, could be immune or a benefiter
- We can now **estimate** the strata proportions
 - $P[\text{Doomed}] = P[S = 1 | Z = 1]$
 - $P[\text{Immune}] = P[S = 0 | Z = 0]$
 - $P[\text{Benefiter}] = 1 - P[\text{Doomed}] - P[\text{Immune}]$

Identifying the estimand

- Estimand of interest:

$$\frac{P[Y(1) = 1 \mid \text{Immune}]}{P[Y(0) = 1 \mid \text{Immune}]}$$

✘
✔

- **Randomization and monotonicity** allow us to identify the denominator:

$$P[Y(0) = 1 \mid \text{Immune}] = P[Y = 1 \mid Z = 0, S = 0]$$

- Because $S(1) = 0$ could imply immune *or* benefiter, the **numerator is not identifiable**
- However, bounds on the numerator can be derived leading to a **range of feasible values** for the estimand

Identifying the estimand

- Using the law of total probability and **without further assumptions**:

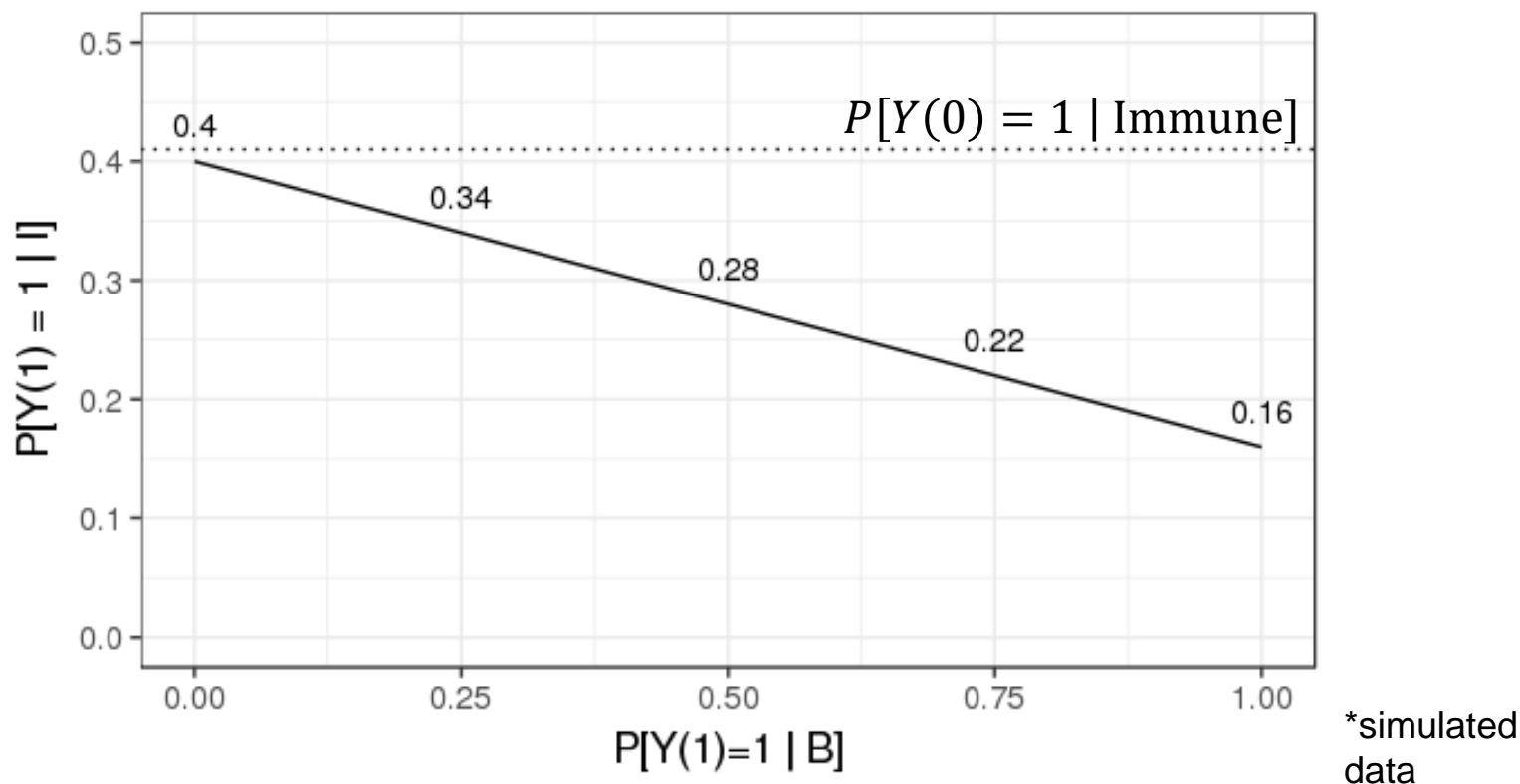
$$P(Y(1) = 1|I) = \underbrace{\frac{P(Y(1) = 1|I \text{ or } B)}{P(I|I \text{ or } B)}}_{\text{Intercept}} - \underbrace{\frac{P(B|I \text{ or } B)}{P(I|I \text{ or } B)}}_{\text{Slope}} P(Y(1) = 1|B)$$

- Intercept and slope can be calculated from the data
 - $P[Y(1) = 1 | \text{Immune or Benefiter}] = P[Y = 1 | Z = 1, S = 0]$
 - $P[I | I \text{ or } B]$ is a function of strata proportions
- $P[Y(1) = 1 | \text{Benefiter}]$ cannot be identified
 - Known to be between 0 and 1
 - Could make further assumptions, e.g.
$$P[Y(1) = 1 | \text{Benefiter}] \leq P[Y(1) = 1 | \text{Doomed}]$$

Identifying the estimand

Visualizing a range of feasible values

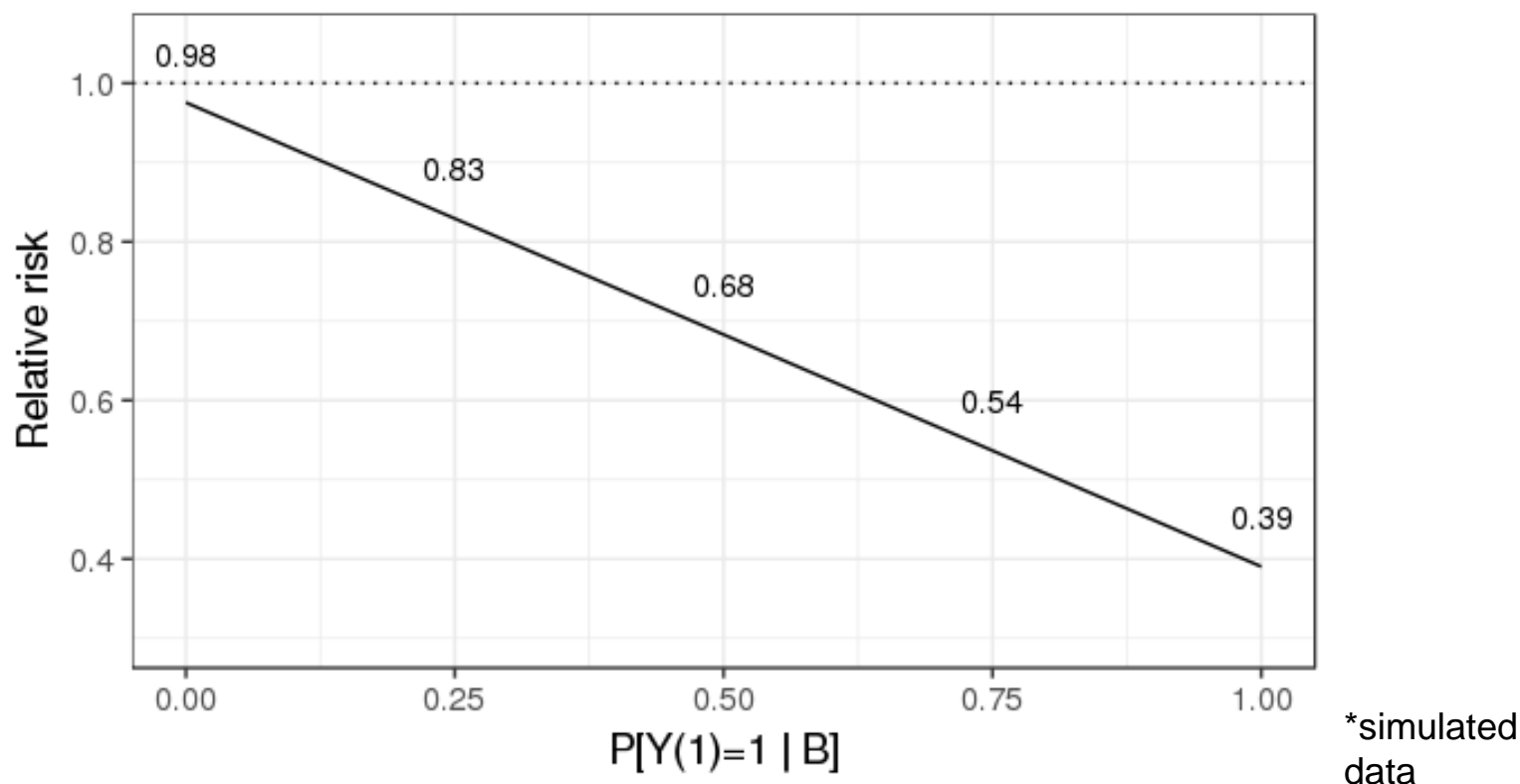
- We can calculate $P[Y(1) = 1 \mid \text{Immune}]$ for a range of values of $P[Y(1) = 1 \mid \text{Benefiter}]$



Identifying the estimand

Visualizing a range of feasible values

- We can also calculate the **range of feasible values** for the estimand of interest



Estimation

- So far... no estimation, no uncertainty
- It is straightforward to estimate the parameters in the Bayesian framework (e.g. using Stan)
- Could use the equation for $P[Y(1) = 1 \mid \text{Immune}]$:

$$P(Y(1) = 1|I) = \underbrace{\frac{P(Y(1) = 1|I \text{ or } B)}{P(I|I \text{ or } B)}}_{\text{Intercept}} - \underbrace{\frac{P(B|I \text{ or } B)}{P(I|I \text{ or } B)}}_{\text{Slope}} P(Y(1) = 1|B)$$

- May result in negative values, so preferable to code the likelihood directly

Estimation

Simplified glance at the Bayesian model

- Principal strata proportions:

- $S | Z = 0 \sim \text{Bernoulli}(1 - \pi_{\text{Immune}})$
- $S | Z = 1 \sim \text{Bernoulli}(\pi_{\text{Doomed}})$
- $\pi_{\text{Benefiter}} = 1 - \pi_{\text{Immune}} - \pi_{\text{Doomed}}$

- Outcome model:

- $Y | S = 0, Z = 0 \sim \text{Bernoulli}(\theta_{\text{Immune, placebo}})$
- $Y | S = 0, Z = 1 \sim \frac{\pi_{\text{Immune}}}{\pi_{\text{Immune}} + \pi_{\text{Benefiter}}} \text{Bernoulli}(\theta_{\text{Immune, active}})$
 $+ \frac{\pi_{\text{Benefiter}}}{\pi_{\text{Immune}} + \pi_{\text{Benefiter}}} \text{Bernoulli}(\theta_{\text{Benefiter, active}})$

- Results summarized by examining the posterior distribution of

$$\theta_{\text{Immune, active}} / \theta_{\text{Immune, placebo}}$$

- Sensitivity analyses:

- Partially relax monotonicity assumption (e.g. through a strongly informative prior)
- Explore various informative priors for $\theta_{\text{Benefiter, active}}$

Estimation

Covariates and missing data

- Due to variable follow-up time, not all patients have available S and Y data in the time period of interest
- Address this using **standardization**
- Write standardized probability of interest as

$$P(\text{Doomed}) = P(S(1) = 1)$$
$$= \int \underbrace{P(S = 1 \mid Z = 1, X = x, M = 0)}_{\text{Model}} dF(x)$$

Baseline covariates

Missingness indicator

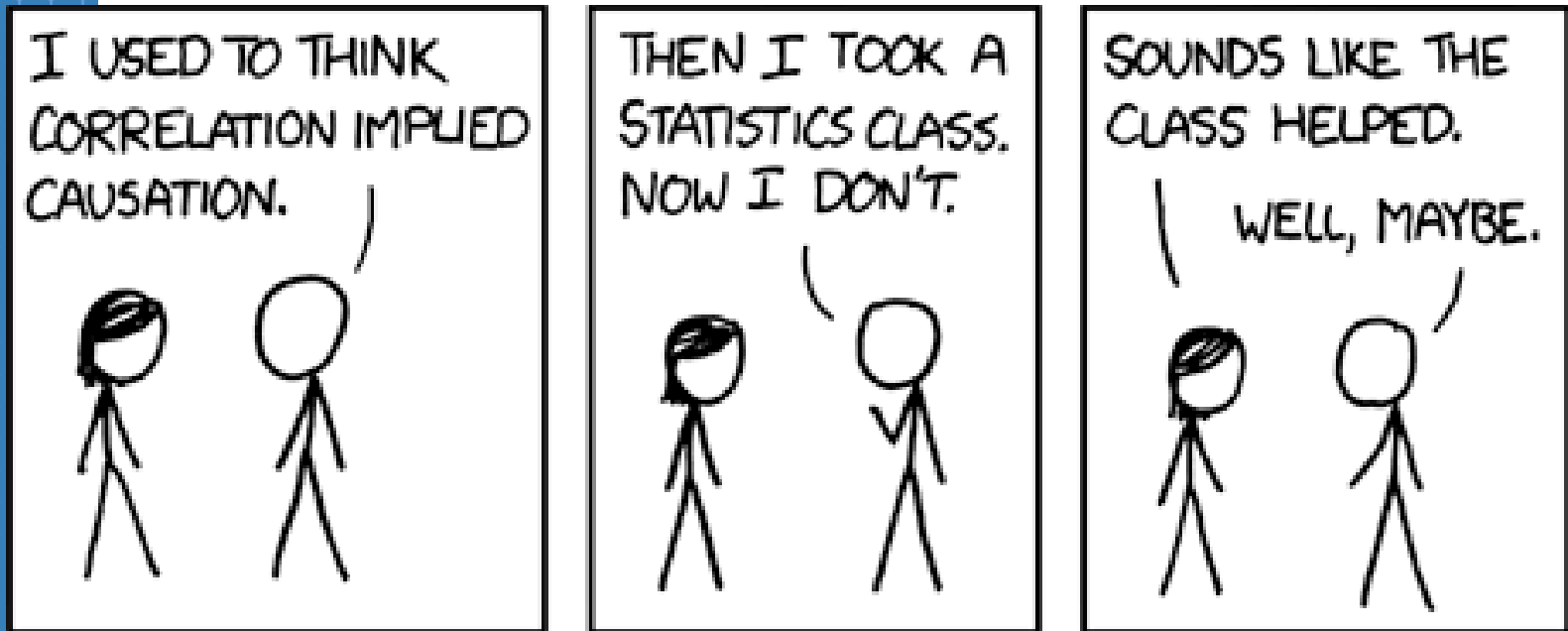
Empirical covariate distribution

Conclusions

- Causal inference framework (potential outcomes) provides a natural way of defining the estimand of interest
- Principal stratification is not the *only* way to approach this type of problem...
 - The appropriate estimand depends on the specific scientific objectives
- Monotonicity assumption is critical
 - Substantive rather than statistical – ideally backed by strong clinical rationale
- Bayesian framework is appealing in this setting:
 - Straightforward to model principal strata proportions
 - Use of mixture distribution to handle lack of identifiability in the active arm
 - Can explicitly encode our (lack of) knowledge about certain parameters using prior distributions

Acknowledgments

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<https://xkcd.com/552/>

Thank you