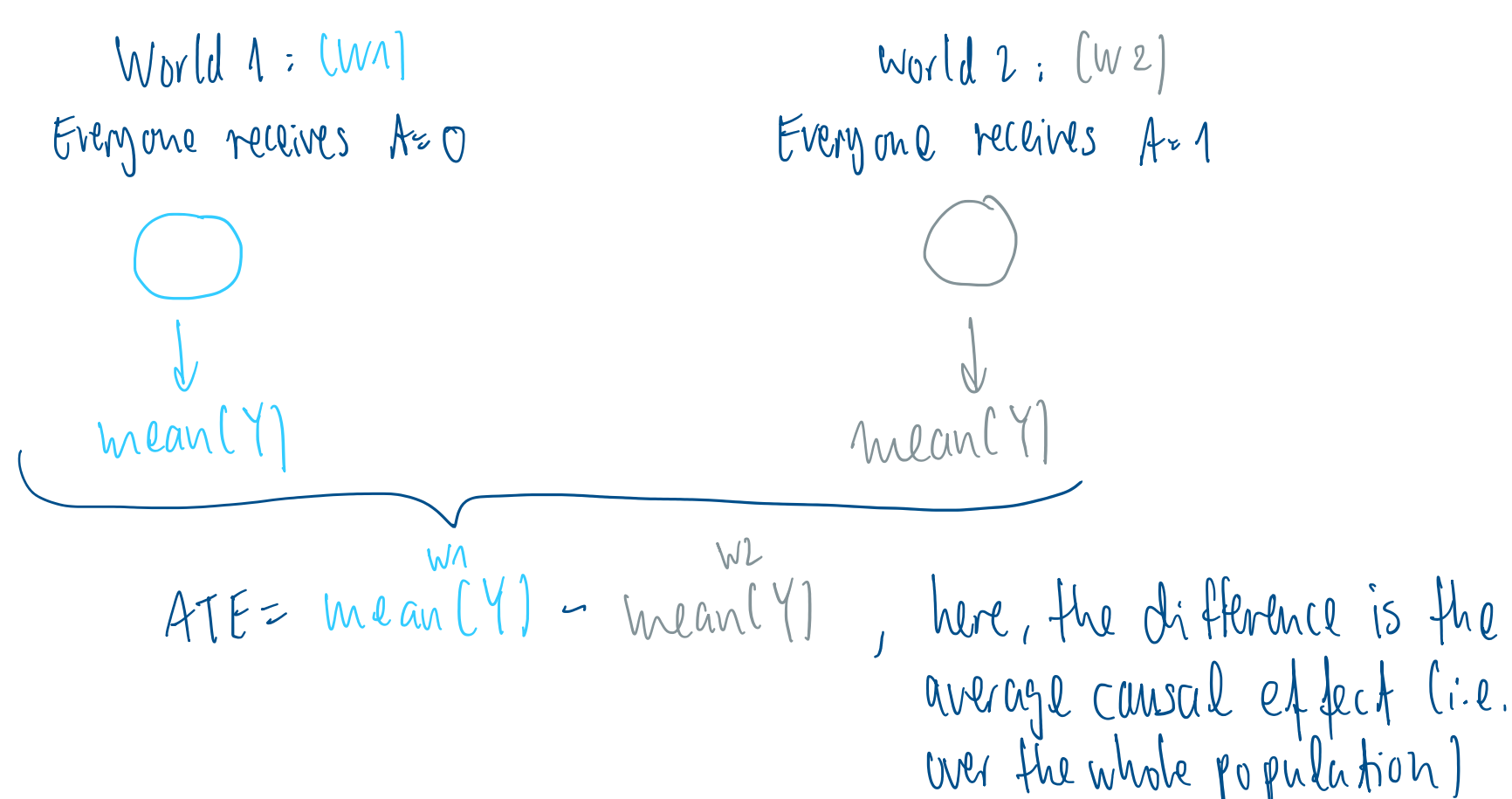


Average Causal Effect (ATE):

pop. of interest



$E(Y^1 - Y^0)$ : if  $Y$  is binary, this would be a risk difference ( $P(Y=1|group1) - P(Y=1|group2)$ ).

Conditioning on versus setting treatment:

based on conditioning outcomes i.e. after data was collected/observed

- in general:  $E(Y^1 - Y^0) \neq E(Y|A=1) - E(Y|A=0)$

based on idea of potential outcomes: i.e. setting treatments

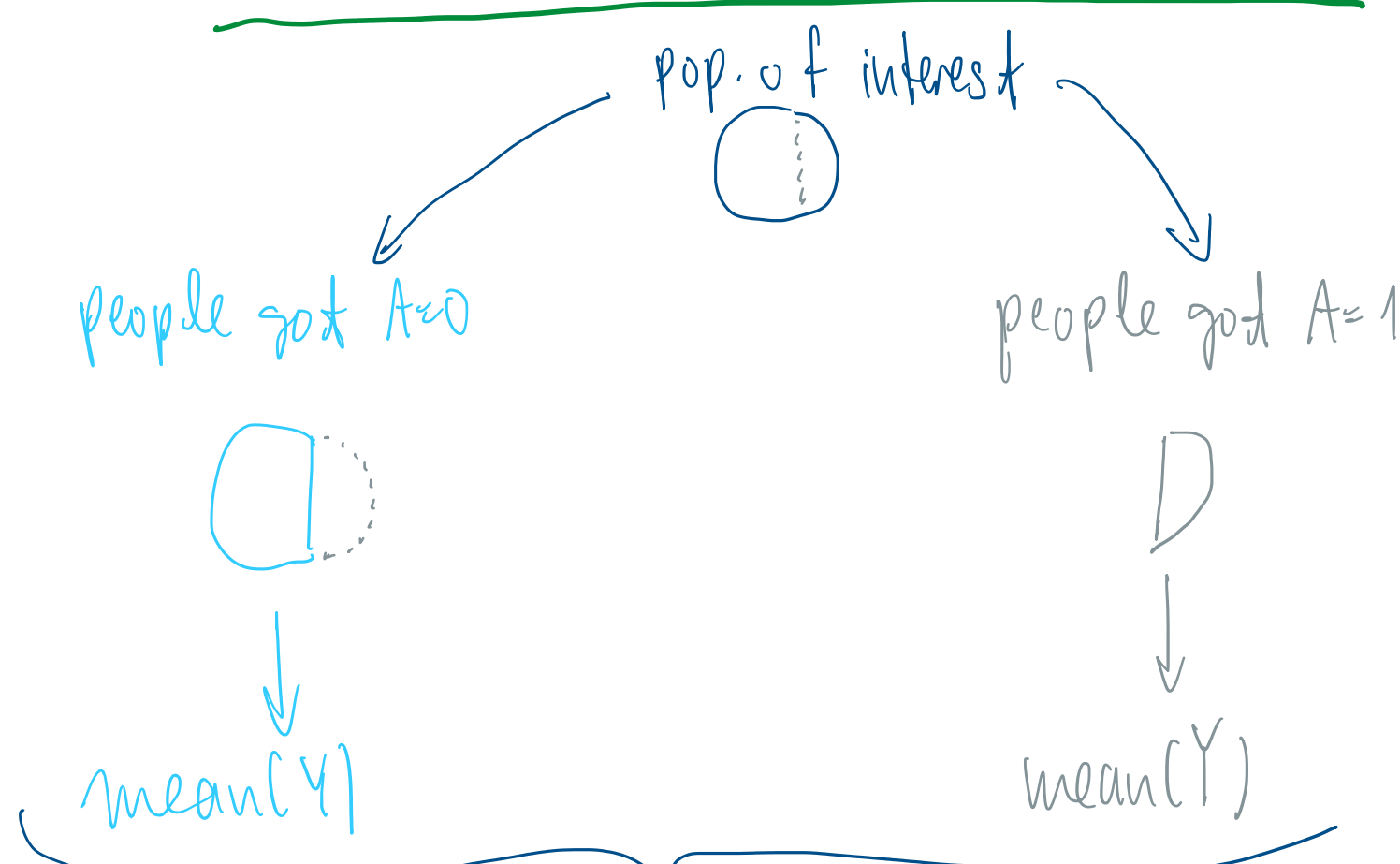
means MANIPULATING

$E(Y^1 - Y^0)$ : average causal effect

$E(Y|A=1) - E(Y|A=0) \neq$  average causal effect b/c:

$\hookrightarrow E(Y|A=a)$  is restricted to subpopulation of people who actually had  $A=a$ .

$\hookrightarrow$  THIS ISN'T INTERVENTIONING!!!

REAL WORLD IS DIFFERENT:

average diff. in outcome between 2 totally different subpopulations defined by treatment group

$\Rightarrow$  this doesn't result in an isolated treatment effect because the minuend ( $E(Y|A=1)$ ) is from a different population than the subtrahend ( $E(Y|A=0)$ )!

$\rightarrow$  causal effect estimates should thus always be based on outcomes from the EXACT SAME POPULATION!!!

Example:

$E(Y|A=1)$ : mean of  $Y$  among people with  $A=1$

$E(Y^1)$ : mean of  $Y$  if the whole population was treated with  $A=1$

$E(Y|A=1) - E(Y|A=0)$  is not a causal effect, because it compares two different populations of people!!!

$E(Y^1 - Y^0)$  ... is a causal effect b/c it compares the same people under different treatments  $A$ .

Other causal effects:

$E(Y^1/Y^0)$ : causal relative risk

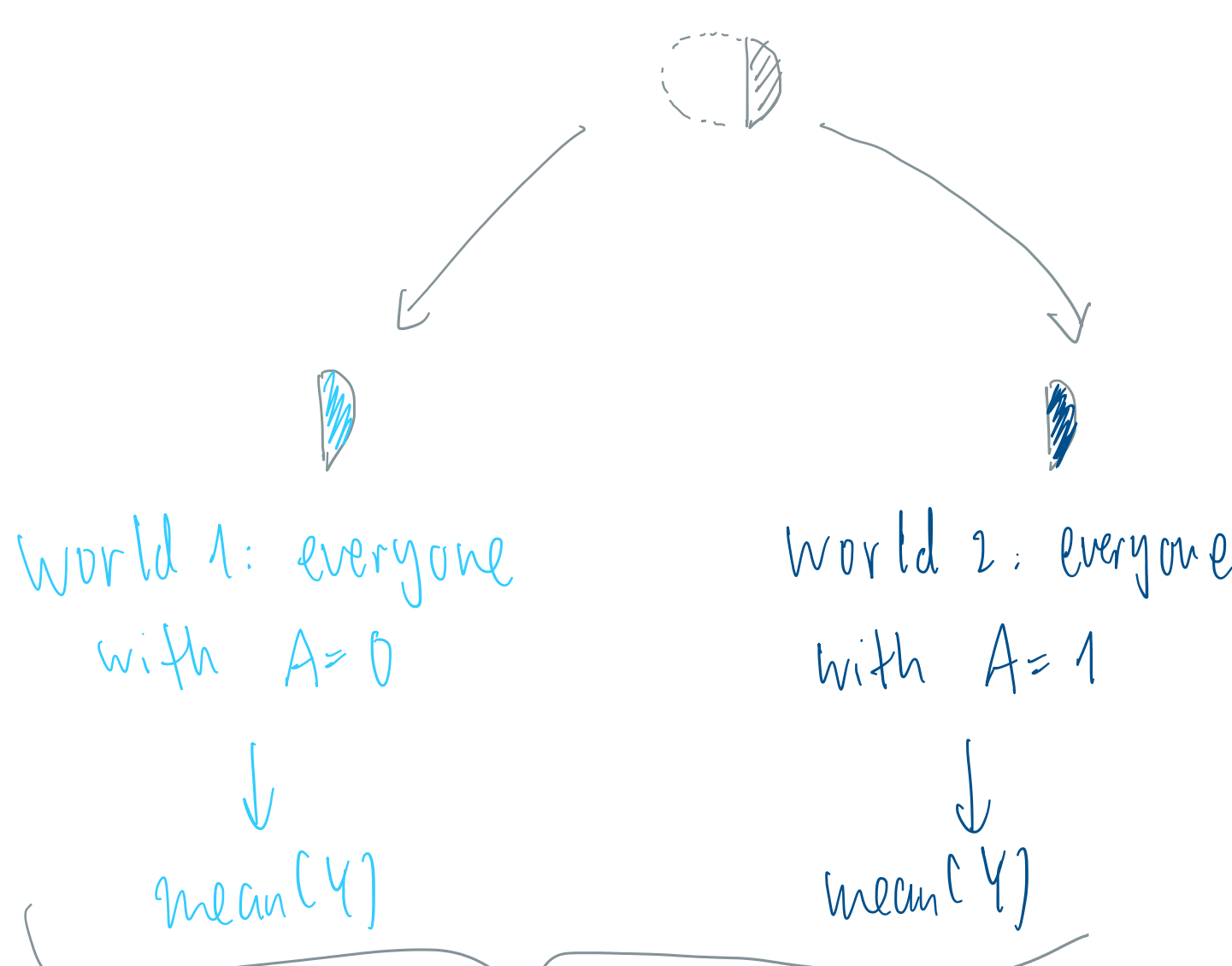
(\*)  $E(Y^1 - Y^0 | A=1)$ : causal effect of treatment on the treated

restrict to subpopulation

$E(Y^1 - Y^0 | V=v)$ : average causal effect in the subpopulation with covariate  $V=v$ .

$\hookrightarrow$  aka heterogeneity of treatment effects

$\hookrightarrow$  ex.:  $V=\text{age}$ ,  $V=\text{race}$ , etc.  $\rightarrow$  defines a subpopulation, where  $V=v$  is true.

(\*) example: CE of treatment on the treated:treated population (20%) ( $A=1$ )

causal effect of treatment on the treated