STAT 8101: Applied Causality (Spring'22)	Week 3: Feb 7, 2022 - Feb 13, 2022

Chapter 1&2 of Causal Inference: What If

Han Lin hl3199@columbia.edu MS in Computer Science

Chapter 1 first introduces the definition of individual causal effect, which is hard to identify in general. Then it defines a more useful definition, which is average causal effects in the population: $P[Y^{a=1} = 1] \neq P[Y^{a=0} = 1]$ (or $E[Y^{a=1}] \neq E[Y^{a=0}]$). There are three measures of causal effect, which are the causal risk difference, risk ratio, and odds ratio, which quantify the causal effect on different scales. However, in practice, there are two sources that could lead to random errors during the computation of such causal effect. The first is random error from sampling variability, which is easy to understand. The second source is nondeterministic counterfactuals: the values of an individual's counterfactual outcomes are not fixed in advance, and these probabilities could also vary across individuals because not all individuals are equally susceptible to develop the outcome.

Section 1.5 provides a great illustration for the difference between causation and association, especially Figure 1.1, which refreshed my understanding a lot. As also mentioned in Section 1 of Chapter 2 in the recommended book "Causal Inference In Statistics: A Primer", when we conditional on a variable Y, we are actually filter the data into groups based on the value of Y. So if we look back the definition for Association: $E[Y|A = a]$, we are filtering the data according to the realized value of A, so that's way it represents the actual world. On the contrary, Causation $E[Y^a]$ asks what if questions in the counterfactual world, so it is an unconditional (or marginal) probability.

Chapter 2 talks about how to estimate the effects measures mentioned in the last chapter in detail. Given that in the real world, only one of the two counterfactual outcomes could be seen, (marginally) randomized experiments provides a way to consistently estimate the causal effect. I understood the definition of random experiments until reached the part talks about exchangeability ($Y^a \perp\!\!\!\perp A, \forall a$). Pointing out the difference wrt $Y \perp\!\!\!\perp A$ is also very useful for understanding. An intuition is that people are just divided into treated/untreated groups randomly, but since they are homogeneous in nature, they will also have the same risk in the counterfactual world. And this is not equivalent to say the treatment is independent of the death rate.

Then starting from section 2.2, the author talks about conditional randomization, and two methods that could compute the average causal effect in the population from conditionally randomized experiments, which are standardization and inverse probability weighting. Because people are randomly assigned, the observed risks = counterfactual risks in each group. Therefore, the first method, standardization, could rewrite the unobserved marginal counterfactual risk $P[Y^a = 1]$ as a weighted average of the observed stratum-specific risks $\sum_l P[Y^a = 1|L = l]P[L = l] = \sum_l P[Y|L = l, A = a]P[L = l]$. Then the author uses a tree structure to illustrate the second method, which is IPW. The illustration for why IPW has such form is quite illuminating. It provides a view by simulating what would happen had all individuals in the population been untreated or treated.