An Introduction to Causal Inference and Sensitivity Analysis
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Throughout this reading program, I have learned methods that allow us to observe the causality of variables whether they be in experimental or observational studies. With the help of my mentor, we also encounter possibilities of determining the causality of variables when some in-between variables are not measured, the unobserved counterfactuals (the "I would do this method instead" thought), and more. I get used to using the directed acyclic graphs (DAGs) that connect the dots in between variables, which later help to see if the association or causality is true or falsified from the dataset.

We started the readings with the reviews of the linear regression models and how they vary from the number of variables being regressed. We further the discussions into ways that the observers could interpret the regression coefficients of the models to find the direct, total, and (possibly) indirect effects of a variable towards the other. From this review, we began to discuss the connections between the probability distributions, structural equations (beyond the regression models), and graphs are all connected to confirm the causality or the noncausality between the variables of interest. While describing what graphs look like, I read through the subchapter of the DAGs which branched out how variables relate to each other. The DAGs' relations might be something like a chain (X→Y→Z), a fork (X←Y→Z), or a collider (X→Y←Z), which are important to note when we progress through the conditional probabilities to see which variable(s) are independent or dependent, conditionally or unconditionally, to the other. By conditioning variables, I also learn the theory of d-separation where we could change the direction of association between variables from the analysis of the DAGs.

Aside from that, I was introduced to the concept of intervention where instead of saying "we are calculating probability (or expected values) of Y, given X certain values", we say "all X would be only a single value of a, find the probability (or expected values) of Y." The intervention contrasts the conditional probabilities and the effects on the independence of the variables. From this, we came back to the fundamentals of the d-separation to introduce concepts of two criteria: the front door criterion and the back door criterion, which are tools in which the observers could block the paths of association between multiple variables to isolate a single direct effect between two chosen variables.

Before wrapping up the meetings for the final project, we did touch briefly on the idea of counterfactuals, which I could repeat as the "I should do this method instead of the one I did" thought. Since the factual and counterfactuals are two different outcomes from two different environments, it is a bit hard to calculate the counterfactuals, altogether with cases where the counterfactuals themselves are non-determinant (the "I should not do what I did but what are the possible alternatives" approach). Though talked briefly about, I am so excited to learn more about the approach with counterfactuals in the future using fundamentals highlighted via this program overall.