Personalization with Latent Confounders

Inspiration for Personalized Marketing

- So let's go through the fundamentals before we dive in. So what is personalized marketing?
- Actually the inspiration for Personalized marketing comes from prescriptive or personalized medicine.
- In the non-personalized medicine paradigm, you have a single treatment that is applied to all patients. The problem with this is that individuals tend to have different response to treatments.
- Personalization is all about trying to identify an exploit this heterogeneity by assigning the treatment to each patient that is expected to maximize the outcome we care about.

Estimating Treatment Effects - Non-Personalized Paradigm

- So when the goal is to estimate the treatment effect in the non-personalized paradigm (goal is to learn the ATE), ideally we would count with experimental data.
- So in this context, A/B Test are gold-standard because they remove the influence of unobserved confounders
- So for example…
- Fisher's very motivation for considering randomize the treatment was to eliminate the influence of unobserved confounders

Estimating Treatment Effects - Personalized Paradigm

- Now, in the personalized paradigm….if there is a single key message from this presentation is that…
- So, in what follows…

Data Generating Process

- Graph is non-parametric. Here's the parametric equations that relate to the graph.

- Profit table observations:
  - The 0.50 and 0.30 represent the profit we get from clients who visited the public site, if they hadn't gotten the incentive (so example, clients who visit the site might get the card regardless of the incentive, and hence we might be losing money on them)
  - Notice that if I don't visit the public site, the client might still get the card by visiting a branch, so there could still be profit (no incentive in this case).This is the highlighted 0.1 and 0.05 in second row. Now, had these clients gotten the incentive, their profit would be higher. This could happen, for example, if this clients are less likely to get the card, but the iPad incentive motivates them to get the card.

Approach #1: Empirical Decision Criterion (EDC)

- My goal here is to to identify the personalized incentive that maximizes this function. Notice that I don't get to see whether you are retired, just married.
- To that end, I compare the expected profit from those who got the incentive and did not get the incentive, and use it to determine who should receive an incentive when visiting the public site.
- Notice that I implement my decision rule on those who visited the site, hence my expected profit for Not Married under No Purchase Incentive is 0.05 (top right), not 0.10.

Approach #2: Post-Visit Randomization (PVR)

- So let's say, I'm a data scientist who understands I cannot just compare those who did and did not get the incentive in the past, because they are not exchangeable.
- So I decide to run an A/B test to determine who receives the incentive.
- No, in addition to whether you visit the public site, I is determined by C.
- No, I'm not basing my decision on observing "I",but doing "I". I need to condition on do(I).

Approach #3: A/B Test on All New-to-RBC clients (ABT)

- In this case, for every prospect I flip a coin to determine whether they receive the incentive (regardless of channel). For example, if a new-to-rbc client walks into a branch an I offer a card, the incentive is also

determined by a coin-flip.
- Notice in this case, I'm not conditioning on V=1.
- Now, the conclusion is exactly the opposite as in the PVR

Approach #4: Regret Decision Criterion (RDC)

- Now, I'll use a regret decision criterion. So condition on whether you got or not the incentive in the current campaign, I'll find the incentive that maximizes profit.
- If a treatment is binary, this counterfactual quantity can be computed by combining experimental data from the A/B test (approach #3) and the observational data from the current campaign.
- Intuitively, conditioning on whether you received the incentive in the current campaign gives me information about the unobserved confounder.

Additional points

- Review Pearl P. 94+. What is the difference between individual level counterfactuals and ETT with conditioning on intent (and observed features)?
    - ETT still represents an average effect conditional on X and intent, it is NOT represent the effect for a specific individual. The latter requires a parametric model (and of course the causal graph). If for example, we have latent counfounders which interact with treatment, and the functional form of that interaction is specific to a given individual, then the Personalization approach I'm describing in this deck cannot recover the individual treatment effect. Again, I can only speak about the average treatment effect on the treated conditional on covariates and intent (see also paper "on the distinction between CATE and ITE".
    - For ETT, I either (i) need the causal graph, so I can use the backdoor criterion for adjustment, or (ii) in the binary treatment case, if I have access to both observational and experimental data, I can get away without the graph.

- What happens with more than 1 latent confounder? I believe I have this in my notes somewhere
    - For example, if I have two unobserved confounders as in the MABUC

paper, in that case RDC still gives me the oracle payout just because of the configuration of the payout table. In my notes (see Notes for white paper - Page A - around page 29, I have an example of a configuration of payout where I cannot get the oracle by conditioning on intent.

- If (i) the goal is to learn optimal personalized actions, and (ii) we have unobserved confounders (very likely!), and (iii) these confounders interact with the action: then Counterfactual-based decision-making may outperform Causal-decision making.
    - \textcolor{red}{But even if the unobserved feature is not technically a confounder, but there is interaction between the unobserved variable and the treatment, Counterfactual-based decision-making may also outperform Causal-decision making}

Notes - Bandits with unobserved confounders

- The existence of unobserved confounders is the most sensible assumption in practice.
- How do we know the existence of unobserved confounders in the example of the presentation? P(Y|do(x)) /neq P(Y|X)
    - The residual difference between these distributions is encoding knowledge about the unobserved confounders, which can lead to improved decision making.
- Fisher's very motivation for considering randomize the treatment was to eliminate the influence of unobserved confounders
- Need to add distribution of P(M) and P(R) = 0.5 in SCM? Yes, an SCM includes the distribution over the exogenous variables.
    - P(r,s) =0.25 (see counterfactual randomization page 2)
- Under the presence of unobserved confounders P(Y|do(X)) does not seem to capture the information required to maximize payout, but rather the average payout to providing the incentive by a coin flip
- For binary case ETT can be computed without knowledge of the causal graph. For the general case, the ETT is not computable without knowledge of the causal graph (see Pearl primer 108-109). This is a sub-population-level counterfactual. For individual level, we need a parametric model (Neil Video #12).

Notes - Counterfactual Randomization

- The controlled of UCs provided by RCTs may yield population-level treatment outcomes, but comes with a cost: Information about unit or patient level effects is lost.