Class 10 Randomized Controlled Trials

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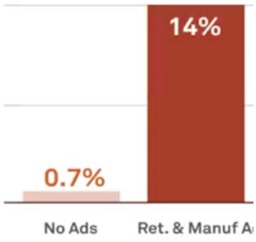
Section 1

Gold Standard of Causal Inference

Revisit of ATE, ATT, and ATU in BMW Case: Targeted Ads

If BMW ads are not randomized to consumers but targeted at interested consumers

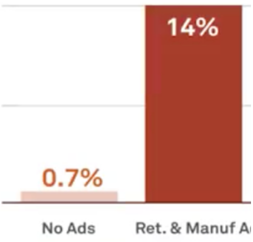


- Observed outcomes in data
  - $E[Y^1|D=1] = 14\%$
  - $E[Y^0|D=0] = 0.7\%$
- Counterfactual outcomes in parallel universe
  - $E[Y^0|D=1] = 5\%$
  - $E[Y^1|D=0] = 2.7\%$

- Average outcome for treated - Average outcome for untreated
  - $= E[Y^1|D=1] - E[Y^0|D=0] =$ 13.3%
  - $= (E[Y^1|D=1] - E[Y^0|D=1]) + (E[Y^0|D=1] - E[Y^0|D=0])$
  - $=$ ATT $+$ Selection Bias
- ATT $= E[Y^1|D=1] - E[Y^0|D=1] =$ 14% - 5% $=$ 9%
- ATU $= E[Y^1|D=0] - E[Y^0|D=0] =$ 2.7% - 0.7% $=$ 2%
- Selection Bias $= E[Y^0|D=1] - E[Y^0|D=0] =$ 5% - 0.7% $=$ 4.3%
- ATE $=$ 0.5 * ATT $+$ 0.5 * ATU $=$ 5.5%

Revisit of ATE, ATT, and ATU in BMW Case: Randomized Ads

If BMW ads are randomized to consumers



- Observed outcomes in data
  - $E[Y^1|D=1] = 14\%$
  - $E[Y^0|D=0] = 0.7\%$
- Counterfactual outcomes in parallel universe
  - $E[Y^0|D=1] = 0.7\%$
  - $E[Y^1|D=0] = 14\%$

- Average outcome for treated - Average outcome for untreated
  - $= E[Y^1|D=1] - E[Y^0|D=0] =$ 13.3%
  - $= (E[Y^1|D=1] - E[Y^0|D=1]) + (E[Y^0|D=1] - E[Y^0|D=0])$
  - $=$ ATT $+$ Selection Bias
- ATT $= E[Y^1|D=1] - E[Y^0|D=1] =$ 14% - 0.7% = 13.3%
- ATU $= E[Y^1|D=0] - E[Y^0|D=0] =$ 14% - 0.7% = 13.3%
- Selection Bias $= E[Y^0|D=1] - E[Y^0|D=0] =$ 0.7% - 0.7% = 0%
- ATE = 0.5 * ATT + 0.5 * ATU = 13.3%

Revisit of Basic Identity of Causal Inference

- After assigning individuals into the treatment group and control group, we also observe the outcome for each individual in both groups.
- We can decompose the **observed** outcome of a treatment into two effects

Basic Identity of Causal Inference

Average outcome for treated - Average outcome for untreated
= [Average outcome for treated - Average counterfactual outcome for treated] + [Average counterfactual outcome for treated - Avereage outcome for untreated]
= **ATT** + **Selection Bias**

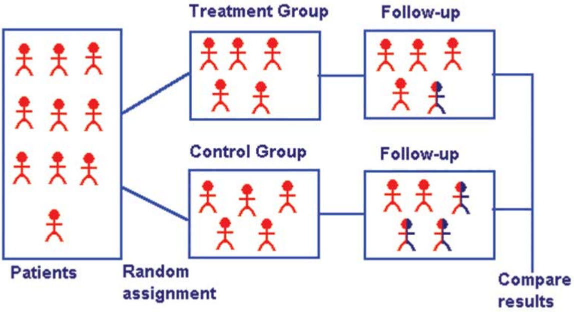
Random Assignment of Individuals

- Basic Identity of Causal Inference shows why randomized controlled trials are the **gold standard for causal inference**: If the treated group is a random sample of the population,
    - the first term is an estimate of the causal impact of the treatment on the population
    - the second term has an expected value of zero.
- Then by computing the average difference between the treatment group and control group, we obtain the **average treatment effect**!

Randomized Controlled Trials

Randomized Controlled Trials

A **randomized controlled trial** (RCT) is an experimental form of impact evaluation in which the population receiving the program or policy intervention is chosen *at random* from the eligible population, and a control group is also chosen *at random* from the same eligible population.



Types of RCTs in Marketing: Based on Location

	Lab Experiment	Field Experiment
Location	In a controlled, laboratory environment	In the field
Internal validity	High	Low
External validity	Low (Hawthorne effect)	High

Types of RCTs in Marketing: Univariate Testing

We only vary the level of a single treatment variable (e.g., loyalty program)

- A/B testing (treatment group + control group)
  1. Loyalty program
  2. No loyalty program
- A/B/N testing (multiple treatment groups + control group)
  1. Point-based loyalty program; points can be redeemd for price vouchers
  2. Point-based loyalty program; points can be redeemd for gifts
  3. Point-based loyalty program; points can be redeemd for free top ups
  4. No loyalty program

Types of RCTs in Marketing: Multivariate Testing

We are interested in multiple treatment variables and their interaction effects.

- 2-by-2 factorial design
  - treatment group 1: LP Yes + Promo Yes
  - treatment group 2: LP Yes + Promo No
  - treatment group 3: LP No + Promo Yes
  - control group: LP No + Promo No

Section 2

Steps to Run a RCT

Motivating Example

- Tom is considering whether or not to introduce a loyalty program for his bubble tea business. This decision is essentially a cost-benefit analysis
  - Cost: it takes money and time to develop the loyalty program
  - Benefit: it may increase spending and retention rate, and hence future CLV
- Cost can be estimated through budgeting, but how to estimate the benefit from introducing LP?
- How you design the experiment is more an art than a science.

Step 1: Decide on the Unit of Randomization

In the first step, we decide the level of granularity random assignment should occur at.

- individual/household/store/city level

Step 1: Proposal I

Proposal 1: It decides at random to test 'No' in West London and 'Yes' in East London.

- Do you expect the "at random" to be true randomization?

Step 1: Proposal II

Proposal 2: It randomizes each individual customer to either the 'No' condition or 'Yes' pricing condition.

- Is this true randomization?
- What problems can we still have?

Step 1: Pros and Cons of Granularity

Disadvantages of granularity:

- Costs and logistics
- Spillovers and crossovers

Advantages of granularity:

- Reduces the chance that the unobserved factors matter ex ante
- Reduces the chance that there might be a systematic error/unbalance of covariates

Additional Questions:

- How can we randomize individualized price discounts to customers?

Step 2: Ensure No Spillover and Crossover Effects

- **Crossover Effects**: A crossover occurs when an individual who was supposed to be assigned to one treatment is accidentally exposed to another treatment.
  - Solution: Make sure that the same unit receives the same treatment throughout the experiment
- **Spillover effects**: The behavior of the treatment group can affect control group as well
  - Solution: Randomize at the level of plausibly isolated social networks such as a community, rather than individual level.

Step 2: Ensure No Spillover and Crossover Effects

Proposal: How should Tom mitigate spillover and crossover effects

Step 3: Decide on Randomization Allocation Scheme

- **Complete Randomization**: individuals (or the relevant unit of randomization) are simply allocated at random into a treatment.
  - Most commonly used; easy to implement; no data required ex ante
- **Stratified Randomization**: individuals are first divided into subsamples based on certain characteristics, and then randomization is conducted in each subsample
  - This stratified technique is useful if a covariate is strongly correlated with an outcome.
  - Limitations: reliable data that would allow such stratification may not be present

Proposal: We can use complete randomization as customer purchase history data may not be available.

Step 4: Collect Data

- Any field experiment should be aware of the potential need for a large sample size
  - The larger sample size, the higher statistical power for the experiment
  - run a power calculation [link for tutorial] if there is a budget
- Collect both data on the outcome variables of interest and consumer characteristics data

Proposal: We need to collect customers' retention rate data and link the retention data with their treatment assignment.

Step 5: Interpreting Results from a Field Experiment

Step 5.1: Randomization check

- We need to check if the treatment group and control group are indifferent and well-balanced in terms of their **pre-treatment** characteristics.

Step 5.2: Analyze the data and estimate the ATE

- **t-test** to examine the difference in the average outcome between the treatment group and control group. In R, we can use `t.test()`
- **Regression analysis** (next week)

After-Class Readings

- (optional) Varian, Hal R. 'Causal Inference in Economics and Marketing'. Proceedings of the National Academy of Sciences 113, no. 27 (5 July 2016): 7310–15.
- (optional) Angrist, Joshua & Pischke, Jörn-Steffen. (2009). Mostly Harmless Econometrics: An Empiricist's Companion.