Comparing Apples to Apples

1. Potential Outcomes: theoretical concepts useful for thinking about what an experiment could show; in practice, only treatment group observed in treatment and only control group observed in control, whereas in theory, can imagine a group in two counterfactual states, but can actually observe only one.
   1. Potential outcomes notation
      1. = outcome if you were in treatment; potential outcomes to treatment
      2. = outcome if you were in control; potential outcomes to control
      3. = treatment effect for individual *i*
         1. Average treatment effect
      4. = treatment “dosage”
      5. if in treatment; and
      6. if in control; and
   2. No causation without manipulation. What would the same person do if in one treatment vs. another?
      1. Fundamentally unanswerable questions: Intervention is required to generate needed data, but sometimes imagining an intervention is impossible.
      2. Random Sampling and expectations
         1. Random assignment and unbiased inference
         2. Biased results in observational data
      3. Lewis and Reiley, “Online Ads and Offline Sales,” Quantitative Marketing and Economics, 2014. One of the largest field experiments ever conducted. See a positive increase in sales due to ad but not statistically significant.
         1. Design: 1.2 million in treatment group; 400,000 in control; over 2 weeks.
         2. People who are shopping are not online enough to see the ads.
         3. Those who browse enough to see ads also have lower baseline propensity to purchase from the retailer.
         4. Using the methodology of an observational study would suggest the effect was negative and 3x larger (statistically significant).
      4. Experiments eliminate selection bias. To measure effect of X on Y, we compare Y among units with different values of X.
         1. With no experiment, inference difficult because units obtain different values of X for reasons related to Y.
            1. Experiments generate variation in X independent of Y.
            2. Population should be identical in all ways other than the value of X.
         2. Random assignment generates apples-to-apples comparison.
         3. Always ask yourself how group decisions came to be.
   3. Measuring the Effects of Advertising
      1. Difficult to measure the effects of brand image advertising because ads don’t solicit a direct response, rather increasing awareness of and positive association with a particular brand.
      2. Observational Methodology published in the HBR by found and president of ComScore (Abraham, 2008): panel of 1 million people, compare buyer behavior of people who did and did not see a given ad campaign. Is treated population more likely to shop at the retailer than those not exposed to the ad?
         1. Problem: two samples don’t come from the same population.
         2. Search advertising increased sales by over 200% according to ComScore’s analysis. Compared people who did and did not see the E\*Trade ad on Google search results (searched keywords such as “online brokerage”). Were there other differences between those who did and did not execute such searches, aside from seeing the ad?
            1. Group who saw the ad were already interested in online brokerage. Correlation does not equal causation.
      3. Marketing Two-Step: online ad firm shows ads only to people most likely to buy a company’s product.
         1. Trying to determine the effect of campaign, but comparing behavior of those who saw ads with those who didn’t isn’t the same.
         2. Choosing who gets the treatment often has a lot to do with the very outcome we’re intending to measure.
         3. Beware of bias in measuring effects.
      4. Econometric regressions of aggregate sales versus advertising
         1. “Endogeneity” problem: amount of advertising is not randomly determined. Sales and advertising both influence each other. Potential for reverse causality.
         2. Need a situation where advertising varies independently of other factors that could cause sales. Needs an experiment.
   4. Observational effects can produce inaccurate results. Even in absence of ads, shopping behavior might be different.
      1. Aggregate time-series data
         1. Advertising doesn’t vary systematically over time
         2. Reverse causality problem: we only have draws from the joint distribution, not directions
         3. Omitted-variable bias problem: there are other variables that might confound relationships that naïve regressions estimate exist.
      2. Individual cross-sectional data
         1. Selection bias problem: type of people who see ads are not the same population as those who don’t.