Comparing Apples to Apples

- Main topics this week:
  - Potential outcomes (FE 2.1)
  - Average treatment effects (FE 2.2)
  - Random sampling and expectations (FE 2.3)
  - Random assignment and unbiased inference (FE 2.4–5)
  - Biased results in observational data (FE 2.6)
  - Measuring the effects of online advertising (Lewis and Reiley, 2014)

Why Experimentation?

- Experimentation delivers much more reliable causal inference than any observational method.
  - Allows us to compare two identical populations in which all that varies is treatment of interest
- Conducting experiments correctly isn't easy.
- Concept of "potential outcomes" shows us what can go right and wrong.

Potential Outcomes Defined

- Theoretical concepts useful for thinking about what an experiment could show
- Example: Table 2.1
  - Could never be derived from real data
  - Assumes an impossible amount of information
- In practice: only treatment group observed in treatment, and only control group observed in control
- In theory: can imagine a group in two counterfactual states, but can actually observe only one

Potential Outcomes Notation

- $Y_i(1)$ = outcome if you were to be in treatment
- $Y_i(0)$ = outcome if you were to be in control
- $\tau_i = Y_i(1) - Y_i(0)$ = treatment effect
- In village (i) only, how many more budget percentage points would be devoted to water sanitation if you were in treatment versus control?
  - Not directly observable, but useful to think about hypothetically

No Causation Without Manipulation

- If you can't imagine a manipulation that answers your question, it may not have a causal answer.
- What would the same person do if in one treatment versus another?
- Intervention is required to generate needed data, but sometimes imagining an intervention is impossible.

Fundamentally Unanswerable Questions

- Example: What is the effect on mortality rates of being born in Africa?
  - What does this even mean for a particular person?
  - $Y_i(1)$ = outcome if person born in Africa
  - $Y_i(0)$ = outcome if same person born in the United States
  - Born in African hospital?
  - Lived entire life in Africa?
  - Question not posed well (FUQ'd)
- What is the ideal experiment?
- What is the implied manipulation?

FE 2.2: Reading Guidelines

- d_i = treatment "dosage"
- Box 2.1: D_i versus d_i
    - Should remind you of statistics: a realization x_i of a random variable X_i
- Equation 2.2
    - Uses multiplication to express conditionals
    - $Y_i(1)$ if in treatment [where $d_i = 1$ and $(1 - d_i) = 0$]
    - $Y_i(0)$ if in control [where $d_i = 0$ and $(1 - d_i) = 1$]

Brand Image Advertising

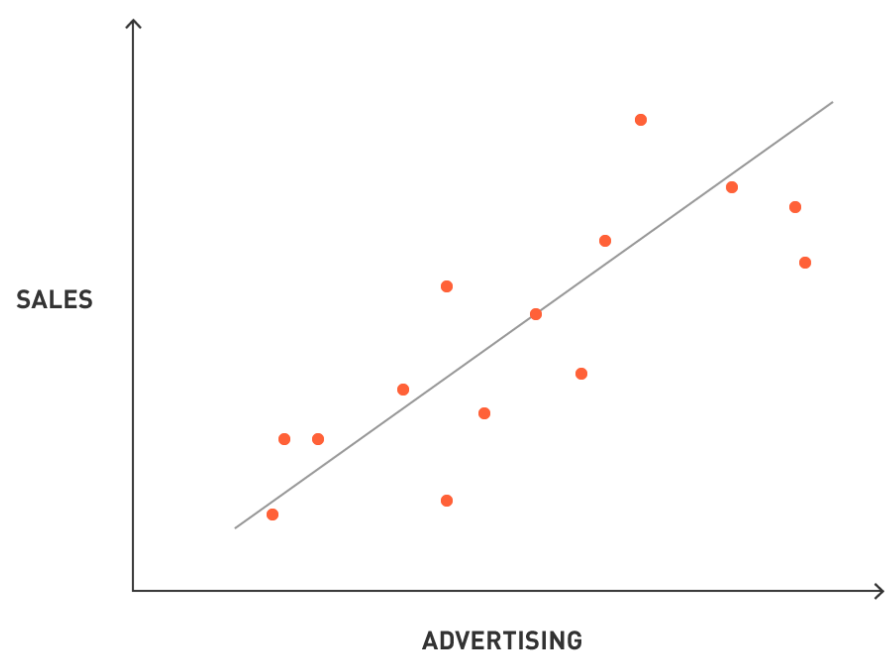
- Difficult to measure the effects of brand image advertising
    - Advertisements that don't solicit direct response; rather, increase awareness of and positive association with a particular brand
- Consider observational methodology published in *Harvard Business Review*by founder and president of ComScore (Abraham, 2008)
    - Panel of one million people.
    - Compare buying behavior of people who did and did not see a given ad campaign.
    - Is treated population more likely to shop at Victoria's Secret than those not exposed to the ad?
    - Potential problem: Two samples don't come from same population.

Search Advertising: E*Trade Example

- Increases sales by over 200%, according to ComScore's analysis.
- Comparing people who did and did not see an E*Trade ad on Google search results.
    - People who see the ad have searched keywords such as "online brokerage."
    - Could there be other differences between those who did and did not execute such searches, aside from seeing the ad?
    - Problem: Group who sees the ad *already interested in* online brokerage.
- Correlation not the same as causality.

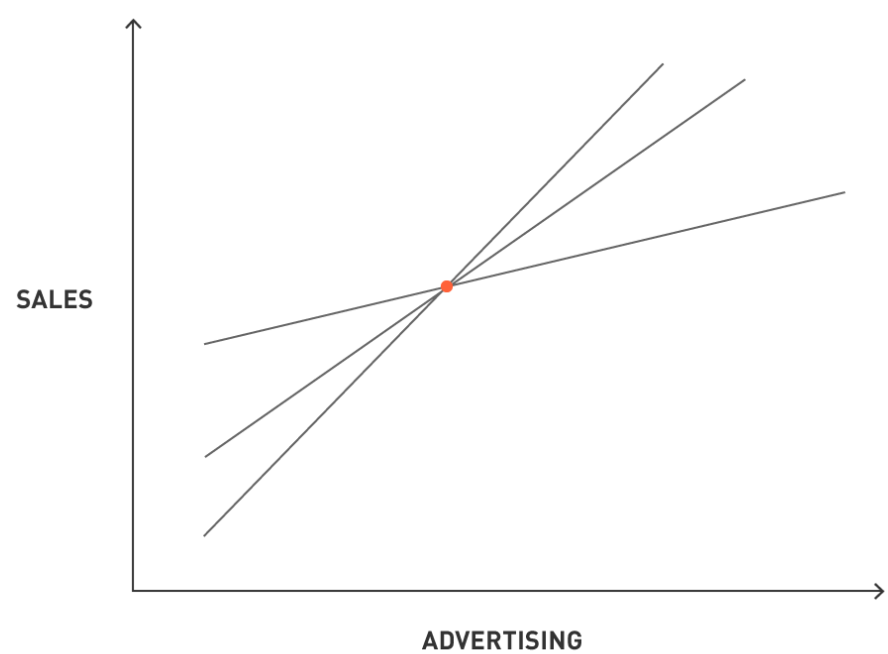
The Marketing Two-Step

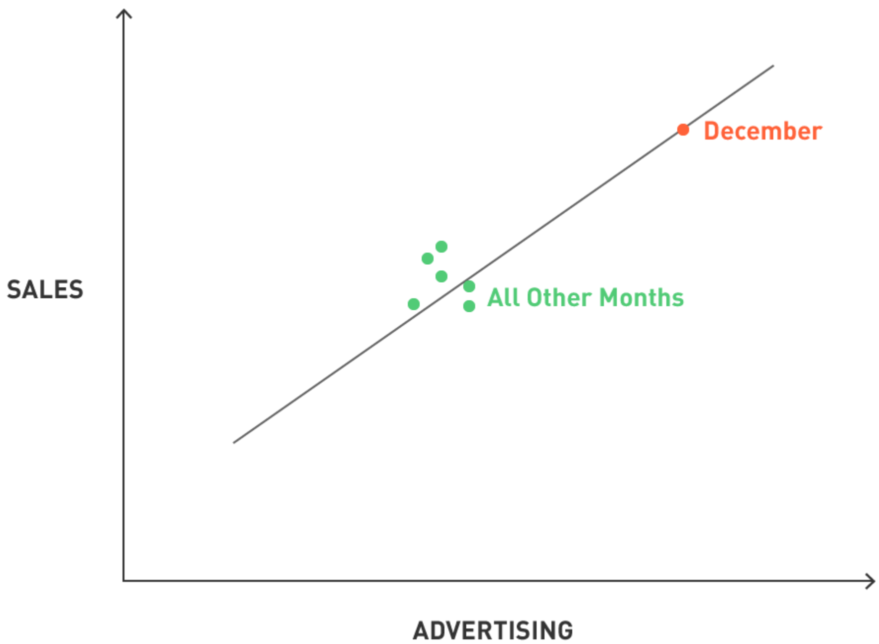
- How is advertising effectiveness measured?
- Online ad firm shows ads only to people most likely to buy a company's product.
- Determining effect of the campaign:
    - Comparing behavior of those who saw ads with those who didn't is not apples-to-apples.
    - Choosing who gets the treatment often has a lot to do with the very outcome we're intending to measure.
- Beware of bias in measuring effects.



Measuring Effects of Advertising on Sales

- Econometric regressions of aggregate sales versus advertising
- "Endogeneity" problem
  - Amount of advertising not randomly determined.
  - Sales and advertising both influence each other.
  - Potential for reverse causality.
- Need a situation where advertising varies independently of other factors that could cause sales
  - I.e., an experiment





Experimentation vs. Observational Data

- Regressing sales on advertising:
  - If advertising doesn't vary, regression doesn't convey much useful information.
  - Experiments generate variation.
- Advertising must vary somehow or slope of regression wouldn't be measurable.
  - More advertising in December
  - More likely to overestimate or underestimate effects of increased advertising in December?

Conclusions: Christmas Advertising Example

- Key question in measuring causal effects of X on Y: How does X vary?
    - Omitted variable—Christmas—causes increased advertising and increased sales.
    - Blindly running regression on observational data implicitly assumes advertising to be only variable responsible for increased sales.
- Effects of advertising overestimated due to omitted-variable bias.
    - Using observational data; not comparing apples to apples.

Review

Three examples of observational data providing inaccurate results:

- Aggregate time-series data
    - Advertising doesn't vary systematically over time.
    - **Reverse causality** problem.
    - **Omitted-variable bias.**
- Individual cross-sectional data
    - **Selection bias**: type of people who see ads not the same population as those who don't.
    - Even in absence of ads, shopping behavior might be different.

Rudimentary Understanding

- Advertising today = physics in the 1500s
- Galileo: "Do heavy bodies fall at faster rates than light ones?"
    - *Manipulate* mass while keeping shape and size constant.
    - Used experimental method to prove objects fell at same rate despite different masses.
    - Huge advance over observational data.

Online-Advertising Field Experiment

- Lewis and Reiley, "Online Ads and Offline Sales," *Quantitative Marketing and Economics*, 2014.
- One of largest field experiments ever conducted.
- Read through Section III.B.

Positive Increase in Sales Due to Ads

	During campaign (2 weeks)
Control	R$1.84 (0.03)
Treatment	1.89 (0.02)

- 1.2 million in treatment group; 400,000 in control
- Effect not statistically significant
    - Confidence intervals overlap considerably.
    - 36% dilution of treatment group.

Observational Comparison:
Treatment-group Members Exposed vs. Not Exposed to Ads

	During campaign (2 weeks)
Control	R$1.84 (0.03)
Treatment	1.89 (0.02)
Exposed to retailer's ads (64% of treatment group)	1.81 (0.02)
Unexposed to retailer's ads (36% of treatment group)	2.04 (0.03)

- Could conclude that advertising reduced sales by R$0.23
    - Not comparing apples to apples

Nonexperimental Sales Differences Unrelated to Ad Exposure

	Before campaign (2 weeks)	During campaign (2 weeks)
Control	R$1.95 (0.04)	R$1.84 (0.03)
Treatment	1.93 (0.02)	1.89 (0.02)
Exposed to retailer's ads (64% of treatment group)	1.81 (0.02)	1.81 (0.02)
Unexposed to retailer's ads (36% of treatment group)	2.15 (0.03)	2.04 (0.03)

- Selection effect
    - Those who browse enough to see ads also have lower baseline propensity to purchase from the retailer.
    - Potential mistake solved with experiment.

Experiments Eliminate Selection Bias

- To measure effect of X on Y, we compare Y among units with different values of X.
    - **Why do units have different values of X?**
- With no experiment, inference difficult because units obtain different values of X for reasons related to Y.
- Experiments generate variation in X independent of Y.
    - Populations should be identical in all ways other than the value of X.
- Random assignment generates apples-to-apples comparison.
- Always ask yourself how group divisions came to be.

Example: Does Playing Outside Improve Eyesight?

- Study conducted by Australian doctors
  - Kids who play outside are less likely to need glasses.
- Possible explanation:
  - More sunlight exposure causes better retinal development?
- Better question:
  - Why do kids choose to play outside or inside in the first place?
    - Maybe kids with worse eyesight don't like to play outside.
  - Need an experiment to establish causality.

Abstracting from the Example

- Read Sections 2.3–2.6.
  - Bring any questions to this week's live session.

Key Points to Remember

- Observational data can easily compare apples to oranges.
- **Selection bias:**Without a clean experiment, other factors can seem like treatment effects.
  - Those who select treatment often differ in other ways.
- In Lewis-Reiley advertising study, naive observational measurement has wrong sign and is three times larger than estimate given by experiment.
- Experimentation more reliably estimates causal effects than observation.
  - Random assignment is gold standard.
- Measuring effect of X on Y.
  - What are the potential outcomes for a given person?
  - What is the ideal experiment?
  - What causes the variation in X?