Online Experiments for Computational Social Science

ICWSM Tutorial

Eytan Bakshy
Sean J. Taylor
Facebook Core Data Science

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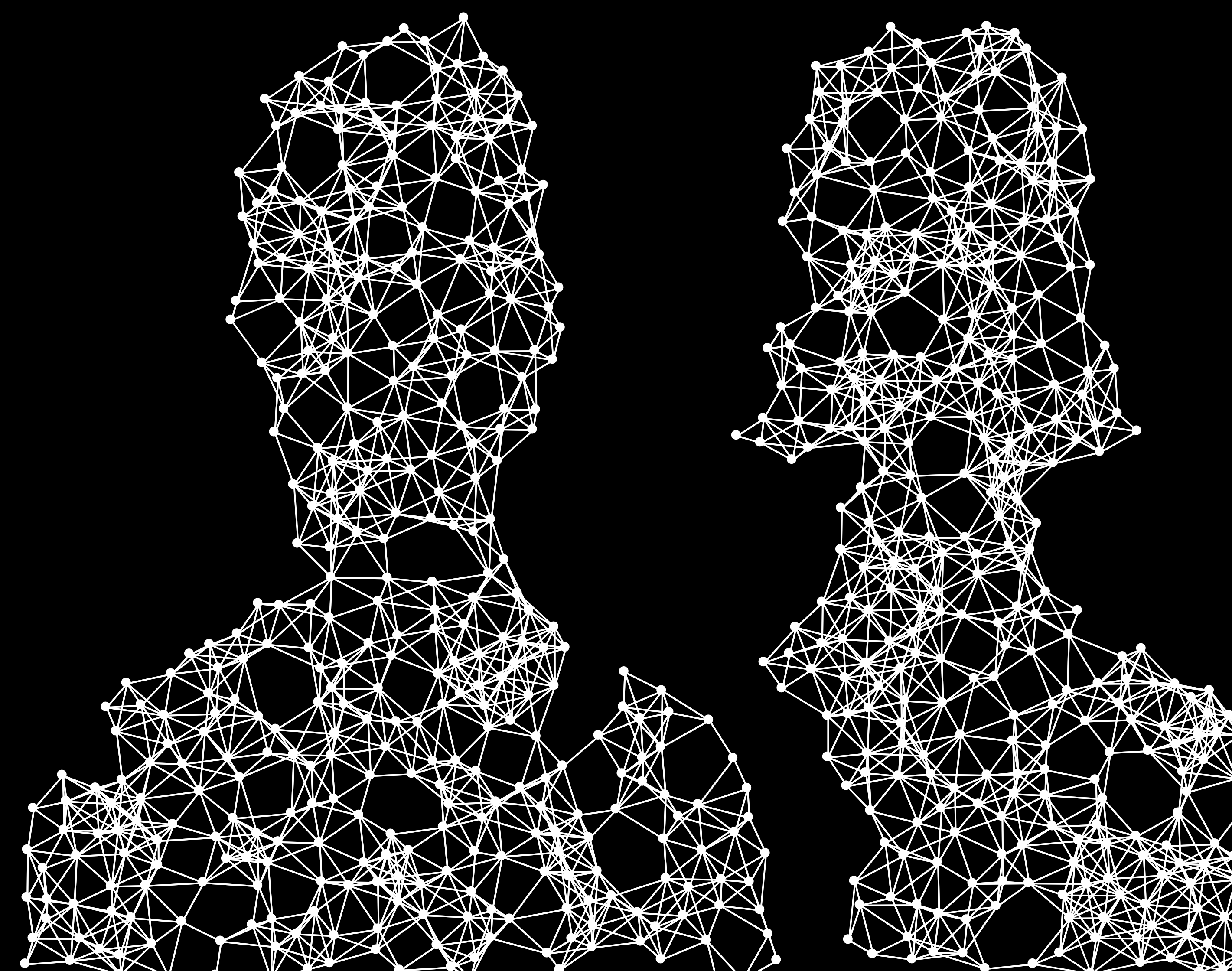


Outline

1. Introduction and Causal Inference (30 minutes)

2. Planning Experiments (30 minutes)

   ‹30 minute break›
   Discussion + analysis exercise (15 minutes)

3. Designing and Implementing Experiments (45 minutes)

4. Analyzing Experiments (30 minutes)

Everything we assume

- Minimum requirements
  - Some basic knowledge of statistics
  - The ability to follow code
- Necessary to understand 90%
  - Intermediate knowledge of R and beginner knowledge of Python
- Necessary to understand 100%
  - Advanced knowledge of R, intermediate Python, intermediate stats, design of experiments

Don’t panic!

Don’t panic!

Buddy up!
Group learning is good for you!

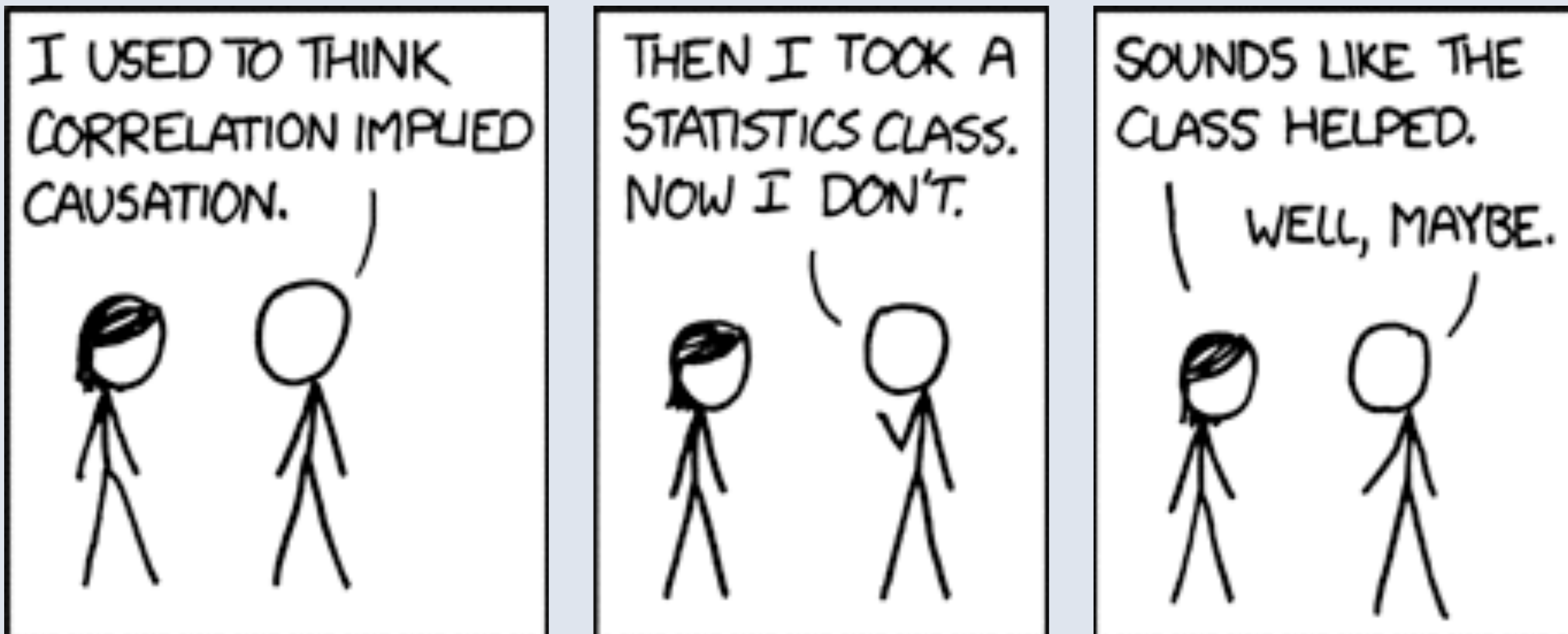
Software requirements

http://bit.ly/icwsm14_experiments

- If you are the kind of person who wants to tinker with code yourself, here are the software requirements
  - Section 1: None
  - Section 2: R
  - Part 3: IPython + PlanOut
  - Part 4: R
- Can't install the software? Buddy up

Section 1:
Introduction and Causal Inference

Obligatory


I USED TO THINK CORRELATION IMPLIED CAUSATION.
THEN I TOOK A STATISTICS CLASS. NOW I DON'T.
SOUNDS LIKE THE CLASS HELPED.
WELL, MAYBE.

Associations

$$(X_i, Y_i)$$

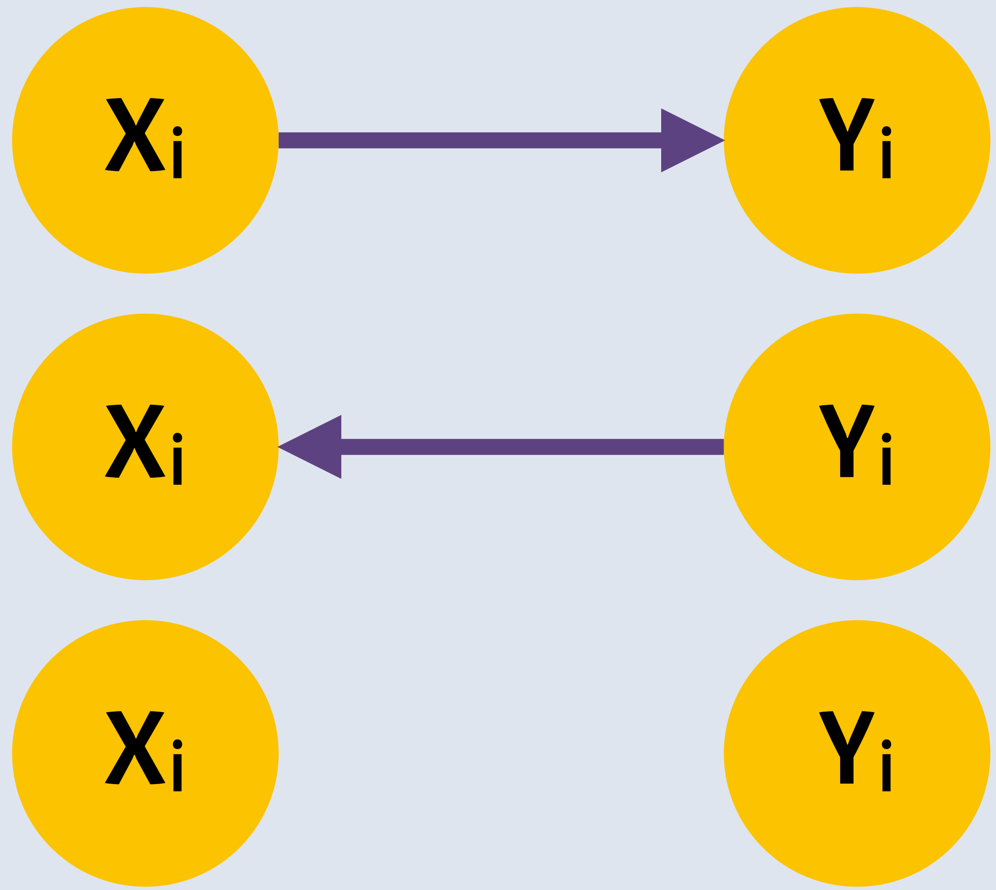
- Health: (smoking, cancer)
- Sports: (running the ball, winning games)
- Education: (completes MOOC course, gets a promotion)
- Social Media: (likes a page on Facebook, buys a product)

Possible Relationships

- $Pr(Y_i \mid X_i) = Pr(Y_i)$ (independence)
- $Pr(Y_i \mid X_i) \neq Pr(Y_i)$ (dependence)

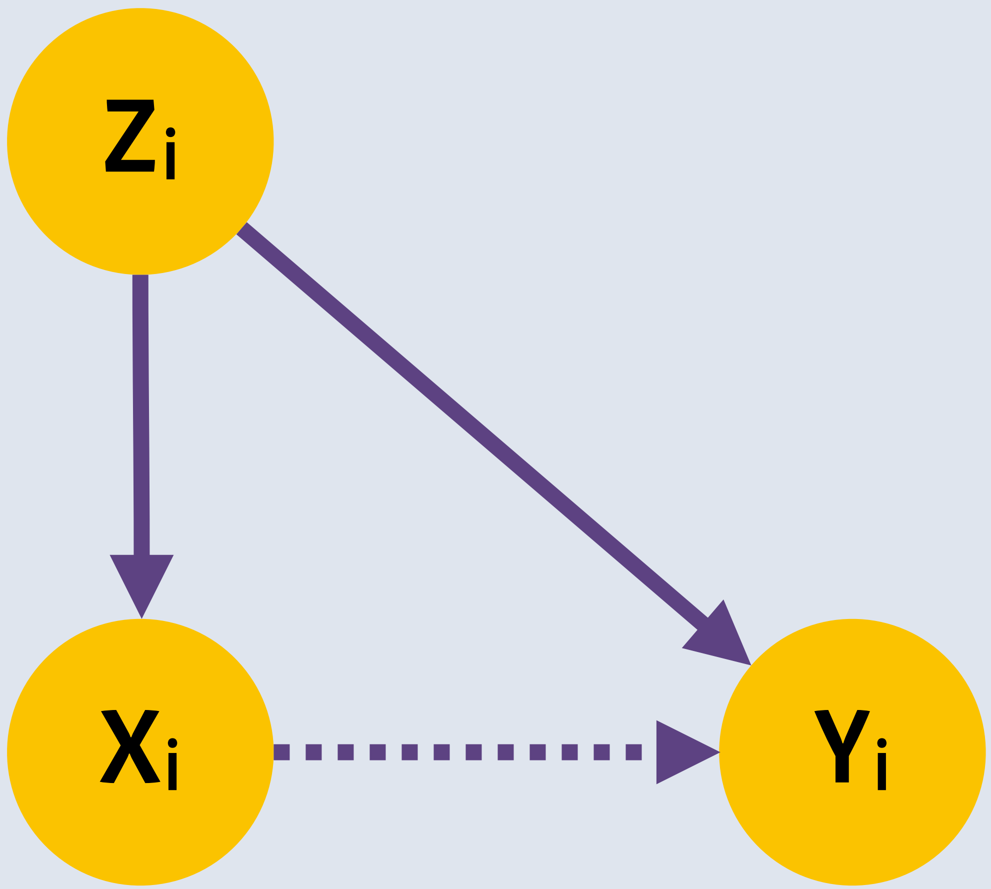
Dependence between variables is useful, but interpretation of this relationship can often be tricky.

Possible Causal Relationships



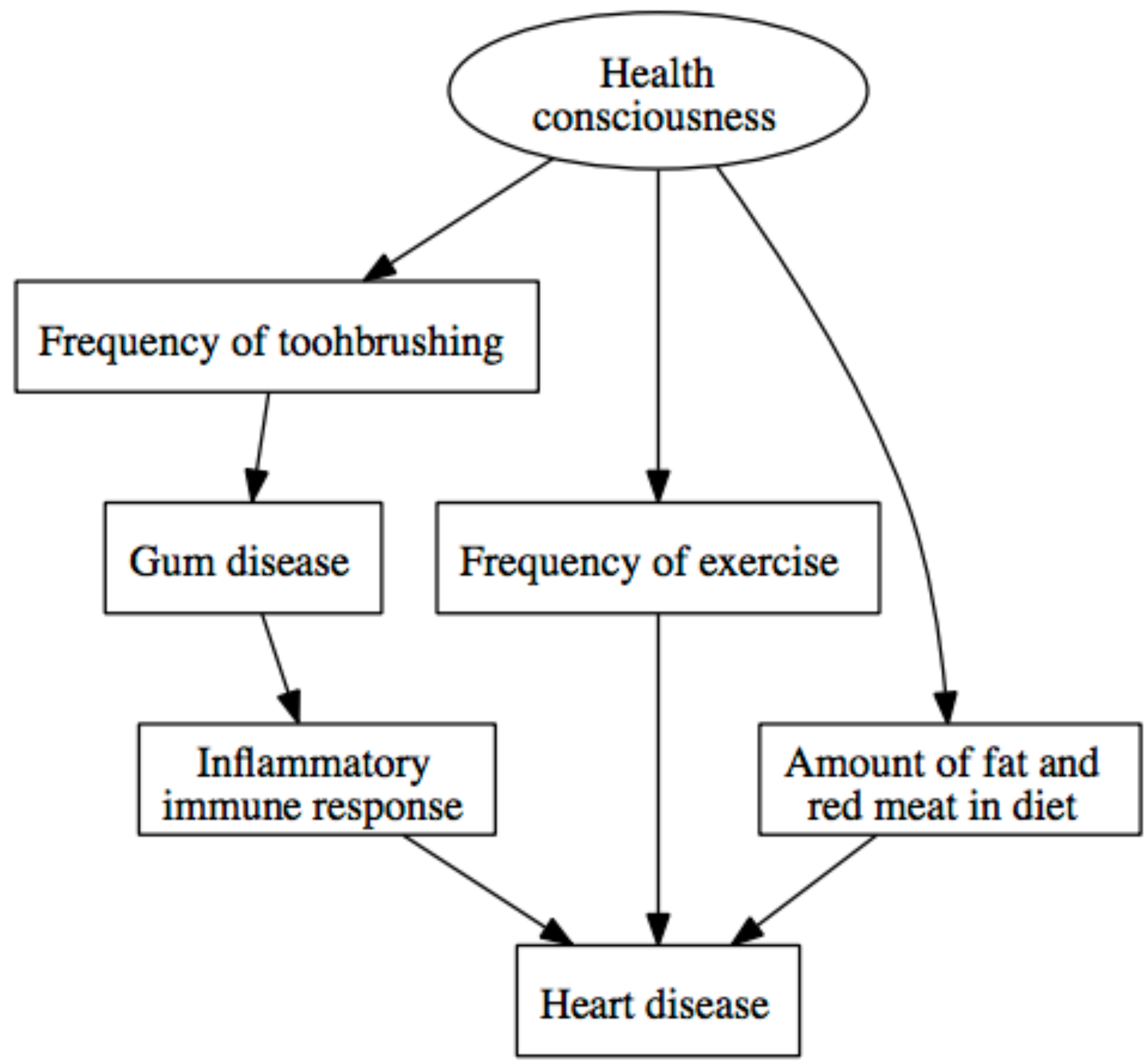
All three causal relationships are possible when there's a dependency between variables.

Correlation without Causation: Introducing Z_i



- Smoking causes cancer (genetics)
- Running the ball causes winning games (having a lead)
- Completing a MOOC causes a promotion (self-motivation)
- Liking a page on Facebook causes a person to buy a product (brand loyalty)

Bigger Example



Why Causal Inference?

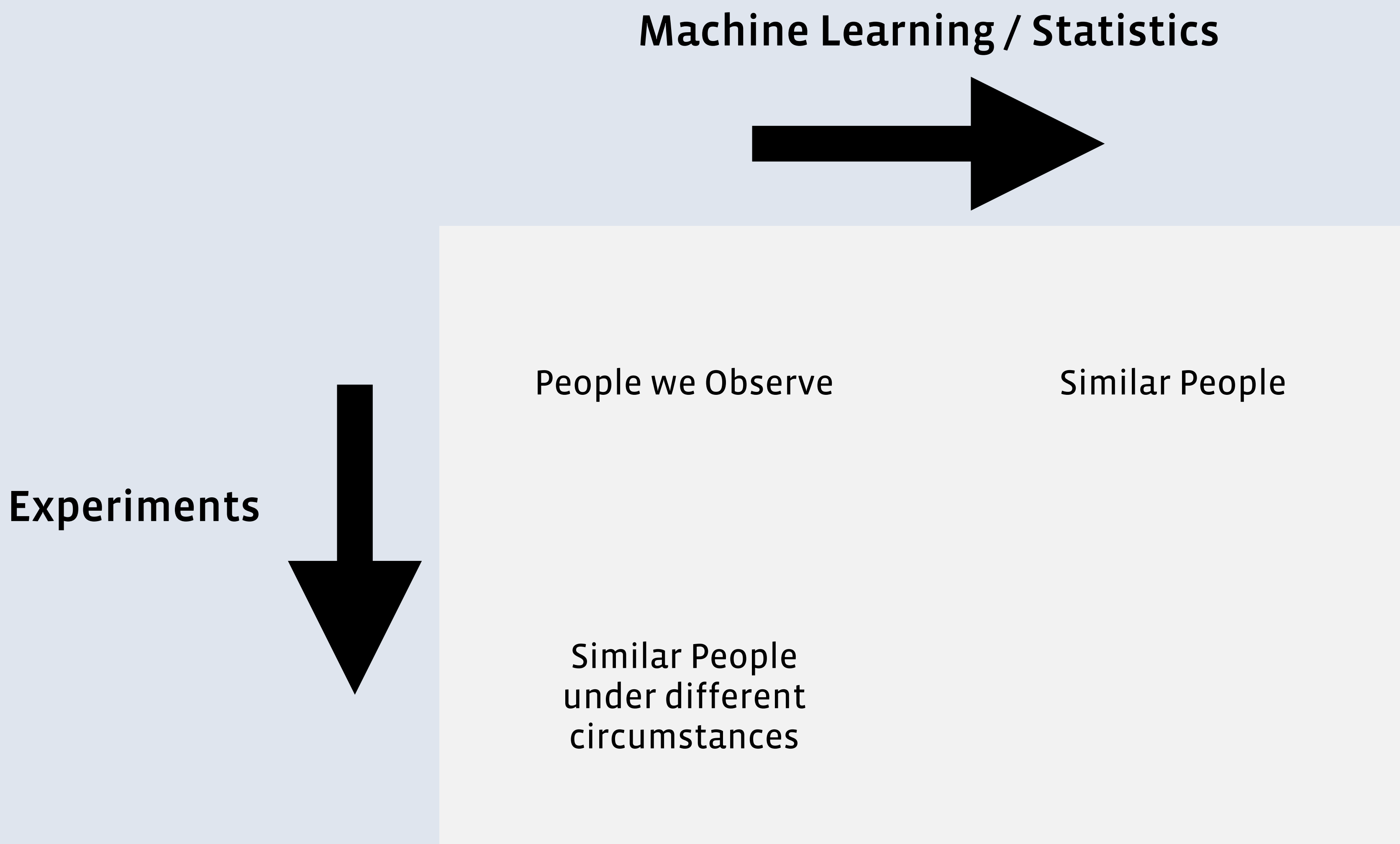
1. **Science:**
   Why did something happen?
2. **Decisions:**
   What will happen if I change something?

Causal Inference for Science

1. Associations between two variables are always more interesting when they're causal.
2. Understanding a phenomenon is different from predicting it.

Explanatory Modeling	**Predictive Modeling**
model captures causal function	model captures association
model carefully constructed from theory	models constructed from data
retrospective	forward-looking
minimize bias	minimize variance
basic science	applied science
make better data	make better features

Two Kinds of Out-of-Sample



Attribute Outcomes to Causes

non-social ad

social ad

Social Influence in Social Advertising: Evidence from Field Experiments.
Bakshy, Eckles, Yan, Rosenn. EC 2012.

Attribute Outcomes to Causes

1 liking friend
0 friends shown

1 liking friend
1 friend shown

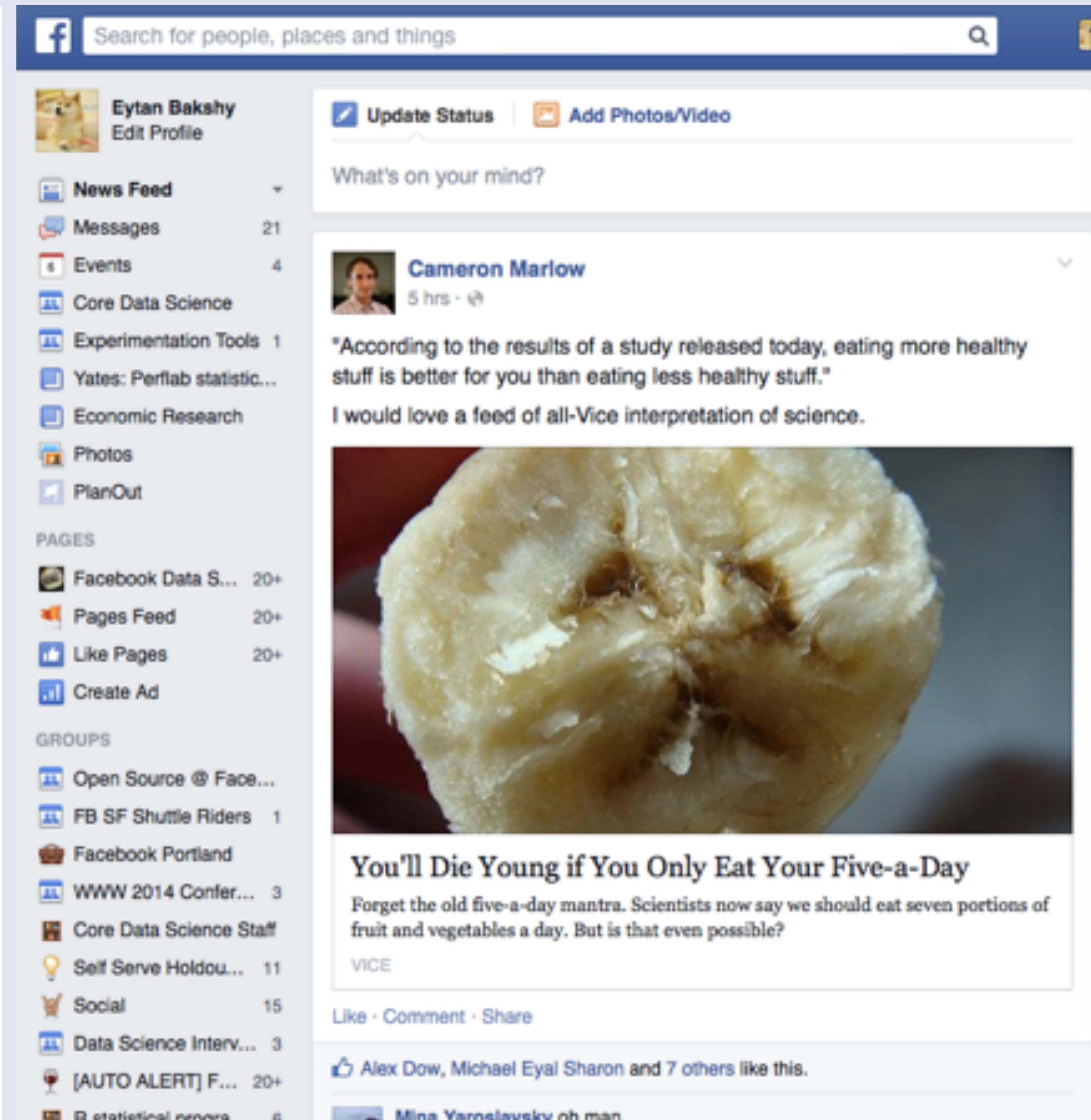
Social Influence in Social Advertising: Evidence from Field Experiments.
Bakshy, Eckles, Yan, Rosenn. EC 2012.

Causal Inference for Decisions

- Health: Quit smoking? Brush your teeth? :)
- Sports: run the ball more?
- Social media: recruit more Facebook fans for my page?
- Advertising: purchase ads?
- Education: invest time in completing a MOOC?

Test complete alternatives

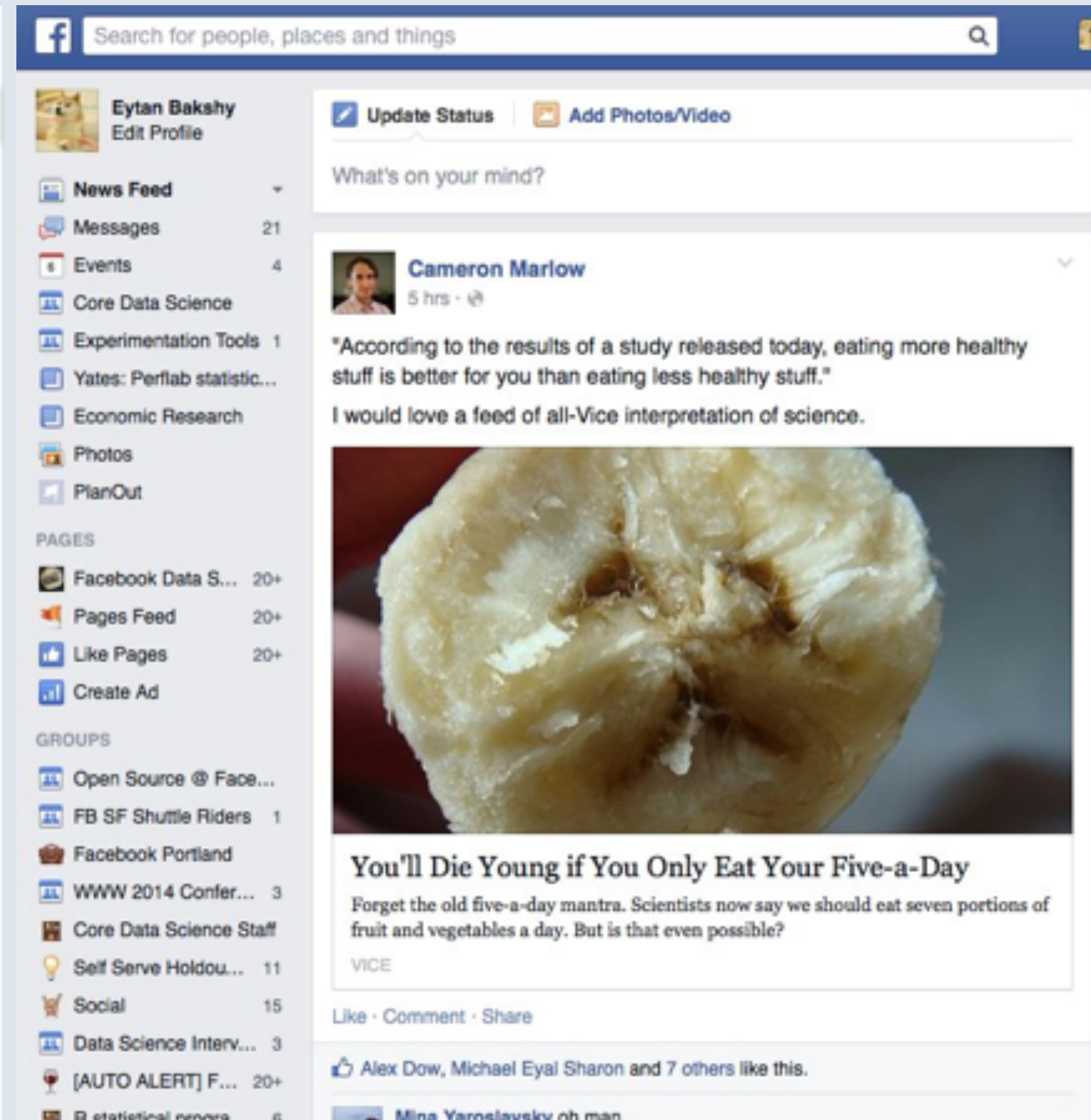
News Feed (2011)



News Feed (2014)

Explore a design space

News Feed (2011)



News Feed (2014)

A Social Science Problem

Causal inference is easy for the natural sciences:

- Manipulation is easy!
- Molecules, cells, animals, plants are exchangeable!

For people, there's always something we may not be observing perfectly.

- Latent traits provide alternative explanations that we often cannot rule out.
- Experiments are often the only way of ruling them out.

Potential Outcomes Framework

	Y	Y	D	Effect
Eytan	10	-5		15
Anna	0	5		-5
Gary	-20	5		-25
Linda	-10	10		-20
Edna	-5	0		-5
Sean	10	5		5
Mean	**-2.14**	**2.86**		**-5**

$Y_i(1)$ is the outcome under treatment
$Y_i(0)$ is the outcome under control

Fundamental Problem of Causal Inference

	Y	Y	D	Effect
Eytan	10		1	?
Anna		5	0	?
Gary		5	0	?
Linda		10	0	?
Edna		0	0	?
Sean	10		1	?
Mean				

We only ever observe a unit in either treatment or control.
Individual level effects are never defined.

Confounding

	Y	Y	D	Effect
Eytan	10		1	?
Anna		5	0	?
Gary		5	0	?
Linda		10	0	?
Edna		0	0	?
Sean	10		1	?
Mean	**10**	**5**	**0.29**	**5**

Here we assumed they selected D_i to maximize their outcome.

Randomization

	Y	Y	D	Effect
Eytan		-5	0	?
Anna	0		1	?
Gary	-20		1	?
Linda		10	0	?
Edna		0	0	?
Sean	10		1	?
Mean	**-3.33**	**1.67**	**0.5**	$\boxed{\textbf{-5}}$

With randomly assigned D_i, we get unbiased effect estimates.
The difference in means is called the **Average Treatment Effect**

The Average Treatment Effect

$$\text{ATE} = \delta = \mathbb{E}[Y_i(1) - Y_i(0)] = \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)]$$

- Due to the linearity of expectations, we can separate the ATE into two measurements.
- In practice, we *estimate* these expectations using the means in our treatment and control groups.

$$\widehat{\text{ATE}} = \frac{1}{N}\sum_{i \in T} Y_i(1) - \frac{1}{M}\sum_{i \in C} Y_i(0)$$

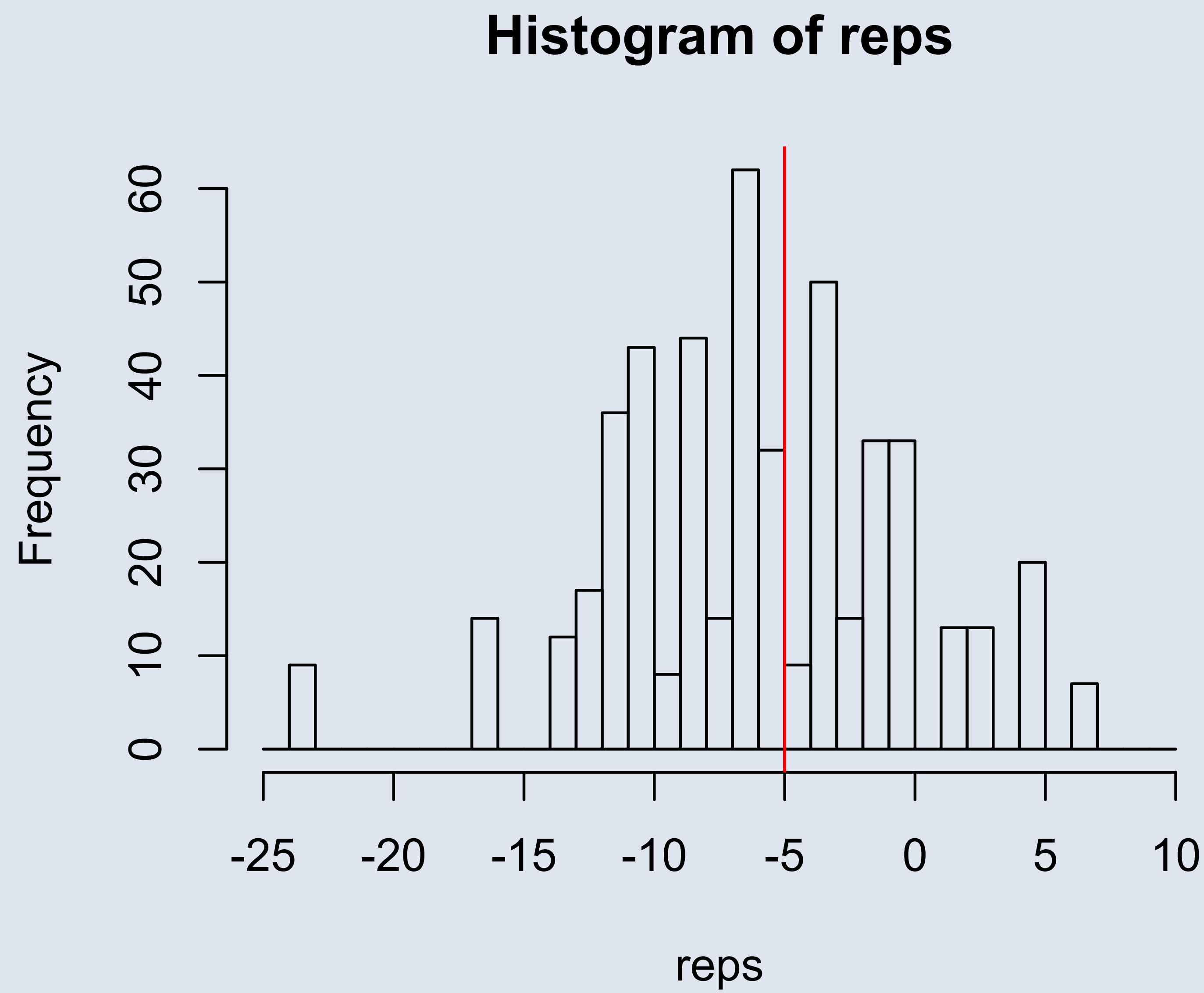
Uncertainty

- How sure are we about the ATE we measured?

Variability in ATE estimates comes from:

1. variation in random assignment
2. variation in subjects

Variation due to Random Assignment



For a given set of potential outcomes and a randomization, we may not always arrive at the right estimate, but it will not be biased.

Standard Errors

- How can we quantify uncertainty about ATEs we measure?

$$\widehat{\mathrm{SE}}(\widehat{\mathrm{ATE}}) = \sqrt{\frac{1}{n_0+n_1}}\sqrt{\frac{n_1}{n_0}\mathrm{Var}(Y_i(0)) + \frac{n_0}{n_1}\mathrm{Var}(Y_i(1))}$$

- SE decreases with √N
- SE is smaller when variances of potential outcomes are smaller
- want n_0 and n_i to be similar if the variances are the same
- want more observations for higher variance conditions

Confidence Intervals

- 95% confidence interval is 1.96 times $\widehat{\mathrm{SE}}(\widehat{\mathrm{ATE}})$

- SEs shrink with the square root of the number of observations, so to double the precision of your experiment you need four times the number of subjects.

Confidence Intervals vs p-values

- Often easy to get statistical significance with big data. Most things have effects!
- Harder to get big, <u>practically significant</u>, effects!
- CIs make uncertainty about an estimate more credible.
- Should favor reporting CIs.

Section 2:
Planning Experiments

The Routine

The routine

- **Step 1: Formulate a research hypothesis**
- Step 2: State an expected effect size
- Step 3: Design your experiment
- Step 4: Power analysis
- Step 5: Write up analysis plan
- Step 6: Collect data
- Step 7: Analyze data according to plan

- A specific hypothesis:
  - Population
  - Empirical context
  - Treatment(s)
  - Subgroups
  - Outcomes

The routine

- Step 1: Formulate a research hypothesis
- **Step 2: State an expected effect size**
- Step 3: Design your experiment
- Step 4: Power analysis
- Step 5: Write up analysis plan
- Step 6: Collect data
- Step 7: Analyze data according to plan

- Use prior literature
- Use existing data
- Collect your own observational data
- Small effects need big data

The routine

- Step 1: Formulate a research hypothesis
- Step 2: State an expected effect size
- **Step 3: Design your experiment**
- Step 4: Power analysis
- Step 5: Write up analysis plan
- Step 6: Collect data
- Step 7: Analyze data according to plan

- Follows from step 1
- Identify:
  - Constraints
  - Threats to validity
  - Ways to increase precision

The routine

- Step 1: Formulate a research hypothesis
- Step 2: State an expected effect size
- Step 3: Design your experiment
- **Step 4: Power analysis**
- Step 5: Write up analysis plan
- Step 6: Collect data
- Step 7: Analyze data according to plan

- Simulate experiment with posited effects and design
- You should feel comfortable that you'll find a clinically significant effect

The routine

- Step 1: Formulate a research hypothesis
- Step 2: State an expected effect size
- Step 3: Design your experiment
- Step 4: Power analysis
- **Step 5: Write up analysis plan**
- Step 6: Collect data
- Step 7: Analyze data according to plan

- Makes it easier to communicate your study
- Helps catch problems with plan
- Keeps you honest as a scientist

The routine

- Step 1: Formulate a research hypothesis
- Step 2: State an expected effect size
- Step 3: Design your experiment
- Step 4: Power analysis
- Step 5: Write up analysis plan
- **Step 6: Collect data**
- Step 7: Analyze data according to plan

- Collect pre-treatment data (if applicable)
- Implement
- Collect experiment data
  - Log sane data

The routine

- Step 1: Formulate a research hypothesis
- Step 2: State an expected effect size
- Step 3: Design your experiment
- Step 4: Power analysis
- Step 5: Write up analysis plan
- Step 6: Collect data
- **Step 7: Analyze data according to plan**

- Wrangle data to get it into a format that you can analyze in R
- Apply appropriate statistical procedures
- Analysis should be easy!

Planning Experiments using Simulation

open: power_part1.R

In-class Exercise

open: power_part2.R

Power analysis for peer effects study

facebook

Section 3: Designing and Implementing Experiments with PlanOut

Be a subject in a linguistic alignment study

http://icwsm.seanjtaylor.com
(3 minutes)

PlanOut

PlanOut scripts are high-level descriptions of randomized parameterizations

The PlanOut Idea

- **User experiences are parameterized by experimental assignments**
- **PlanOut scripts describe assignment procedures**
- Experiments are PlanOut scripts plus a population
- Parallel or follow-on experiments are centrally managed

Sample PlanOut script

```
button_color = uniformChoice(
 choices=["#ff0000", "#00ff00"],
 unit=userid);

button_text = uniformChoice(
 choices=["I'm voting", "I'm a voter”],
 unit=userid);
```

2x2 factorial design

Compiled PlanOut Code

```
{
  "op": "seq",
  "seq": [
    {
      "op": "set",
      "var": "button_color",
      "value": {
        "choices": {
          "op": "array",
          "values": [
            "#ff0000",
            "#00ff00"
          ]
        },
        "unit": {
          "op": "get",
          "var": "userid"
        },
        "op": "uniformChoice"
      }
    },
    {
      "op": "set",
      "var": "button_text",
      "value": {
        "choices": {
          "op": "array",
          "values": [
            "I'm voting",
            "I'm a voter"
          ]
        },
        "unit": {
          "op": "get",
          "var": "userid"
        },
        "op": "uniformChoice"
      }
    }
  ]
```

Using PlanOut

$ ipython notebook --pylab inline

open: 0-planout-intro.ipynb

Selective Exposure Experiment

- Communication literature has shown people tend to choose news sources that align with their political ideologies.
- This experiment was designed to test this hypothesis.
- News source icons were randomly applied to the sample set of stories, and presented in a random order.

Python Web Application Walkthrough

open: webapp/app.py

Extracting Data from Logs

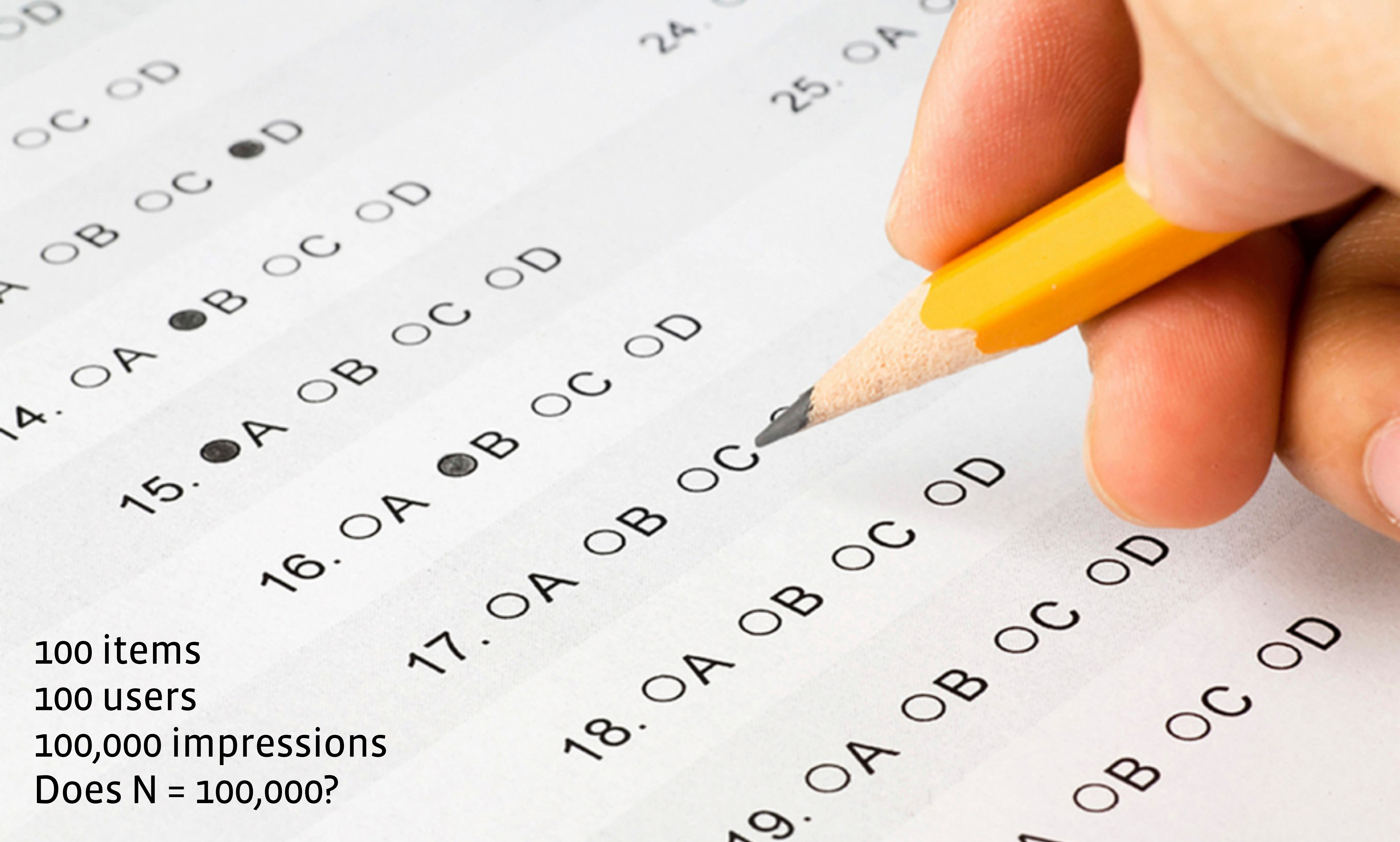
open: webapp/extract_data.py

facebook

Section 4:
Analyzing Experimental Data

Outline

1. Dependence (non- i.i.d. data)
2. The bootstrap
3. Using covariates
4. Data reduction
5. “Big Data Guide”
6. Example in R



100 items
100 users
100,000 impressions
Does N = 100,000?

http://www.tucsonsentinel.com/local/report/062712_az_students/state-natl-rankings-vary-widely-az-student-performance/

Dependence

- Most formulas for confidence intervals assume that each individual data point is independent of all the others.
- In practice, we often have repeated observations of users or content items.
- Ignoring this fact in inference will tend to make confidence intervals anti-conservative.

See Bakshy and Eckles, "*Uncertainty in Online Experiments with Dependent Data*" (KDD 2013)

The Bootstrap

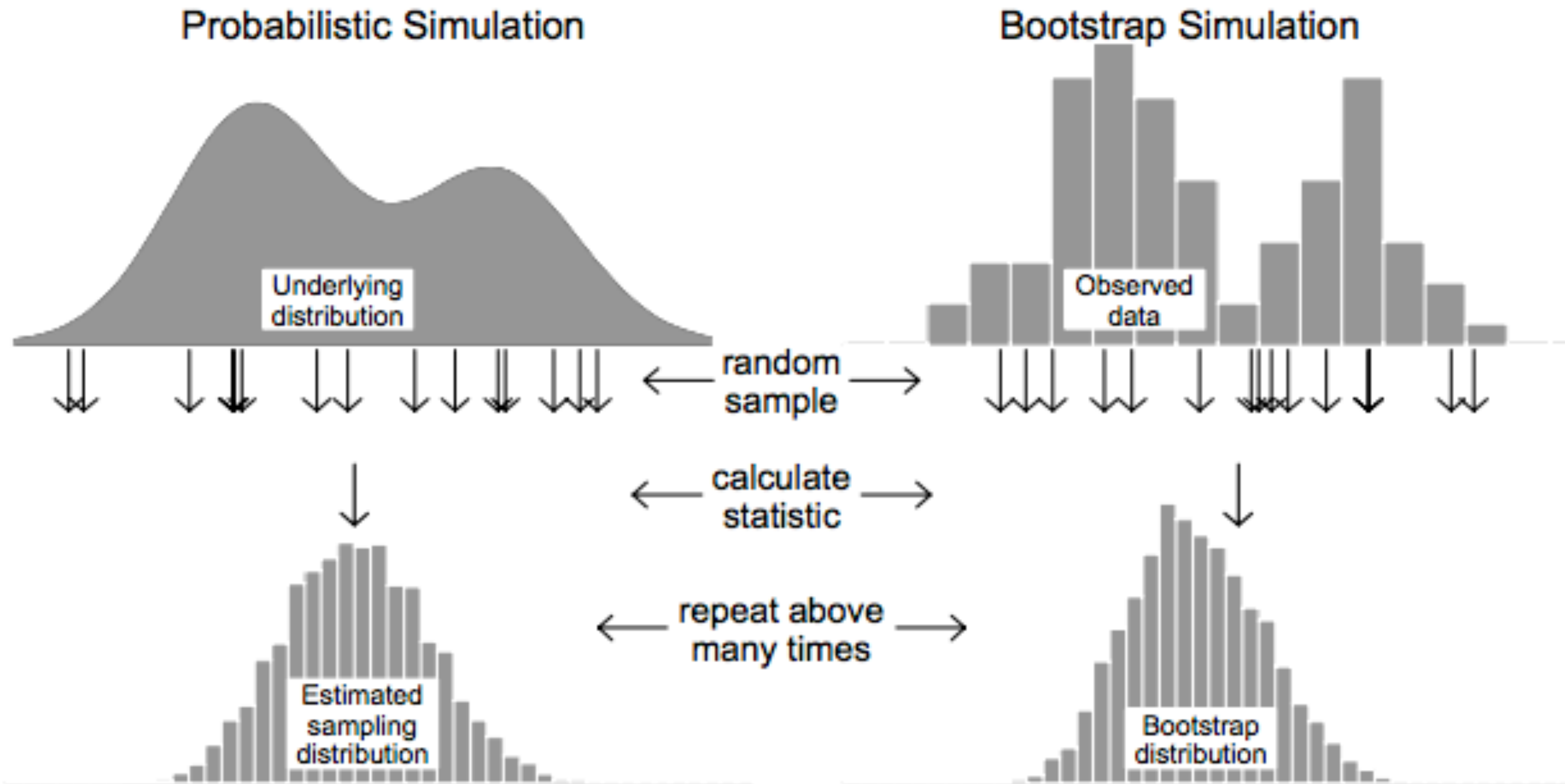
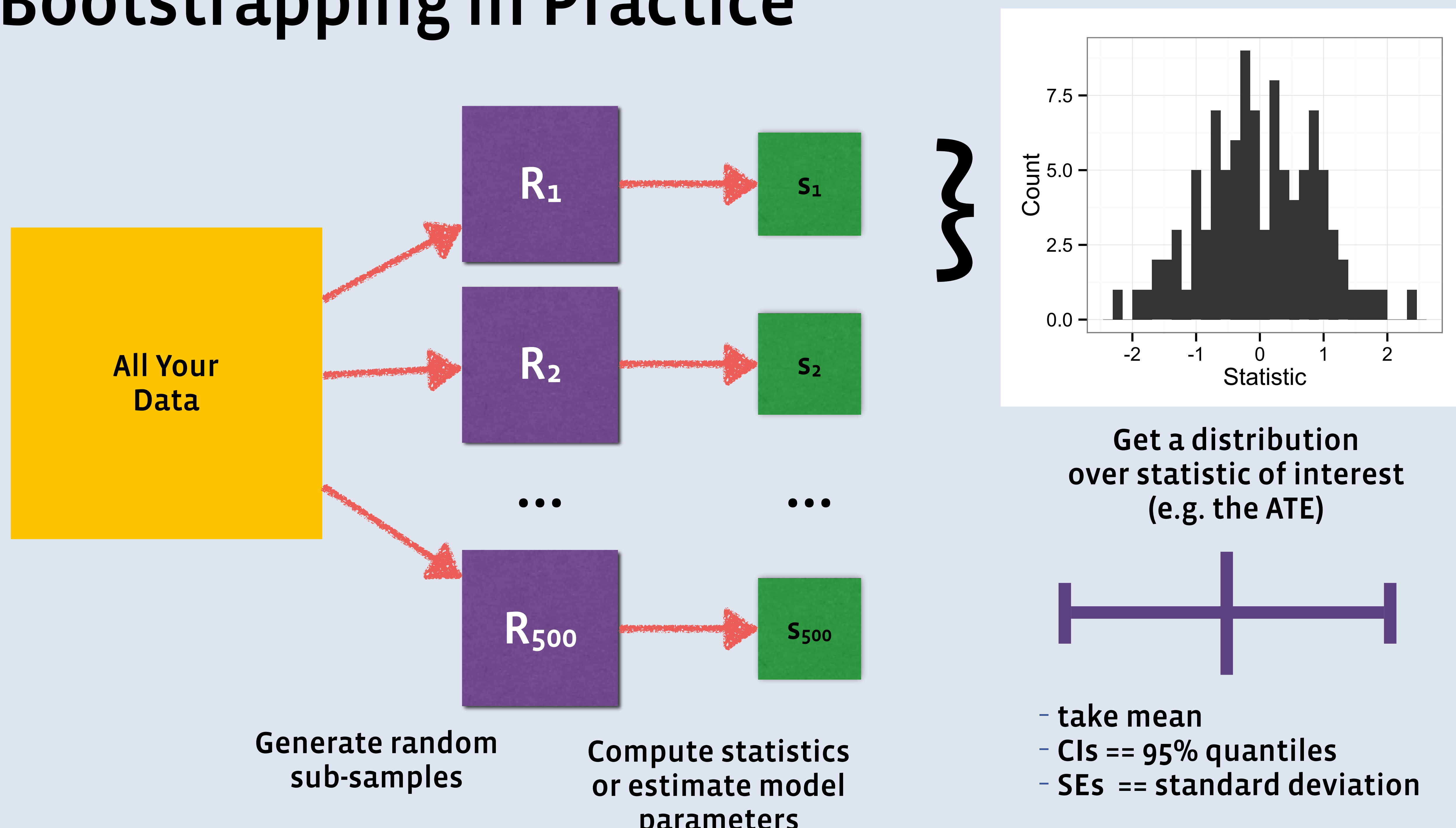


Figure 3: Diagram of probabilistic simulation and bootstrap sampling estimates of sampling distributions.

Bootstrapping in Practice



Using Covariates

- With simple random assignment, using covariates is **not necessary.**
- However, you can improve precision of ATE estimates if covariates explain a lot of variation in the potential outcomes.
- Can be added to a linear model and SEs should decrease if they are helpful.
- Should always at least report results <u>without</u> using covariates.

Data Reduction

Subject	D	Y
Evan	0	1
Ashley	0	1
Greg	1	0
Leena	1	0
Ema	0	0
Seamus	1	1

N

D	Y=1	Y=0
0	2	1
1	1	2

treatments

Data Reduction with Covariates

Subject	X	D	Y
Evan	M	0	1
Ashley	F	0	1
Greg	M	1	0
Leena	F	1	0
Ema	F	0	0
Seamus	M	1	1

N

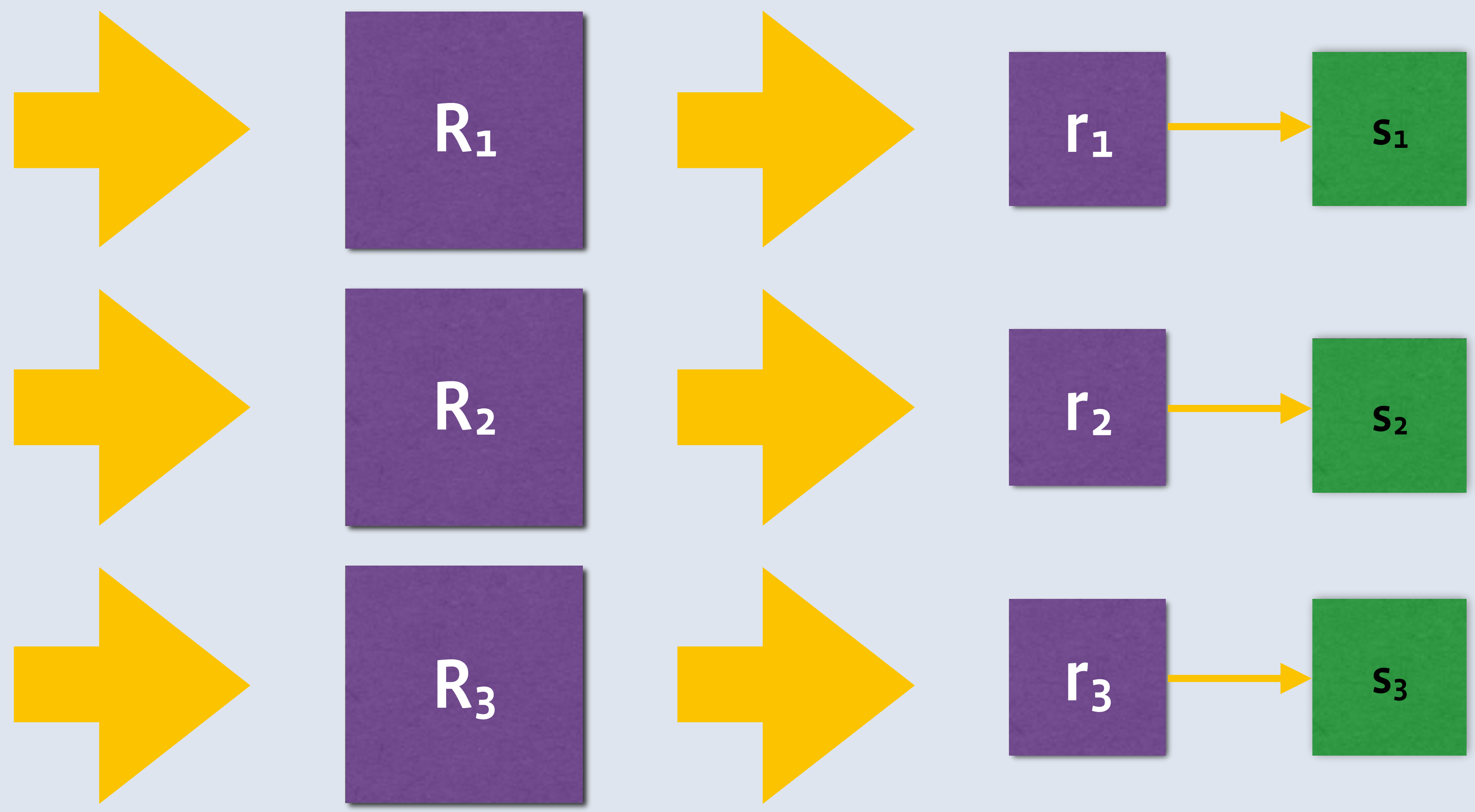
X	D	Y=1	Y=0
M	0	1	0
M	1	1	1
F	0		
F	1		

treatments X # groups

Can analyze the reduced data using a weighted linear model.

Data Reduction with Dependent Data

Subject	D	Y
Evan	1	1
Evan	1	0
Ashley	0	1
Ashley	0	1
Ashley	0	1
Greg	1	0
Leena	1	0
Leena	1	1
Ema	0	0
Seamus	1	1



Create bootstrap replicates

reduce the replicates as if they're i.i.d.

compute statistics on reduced data

Experiment Analysis (i.i.d. data)

Data Size	Fits in memory < 2M rows	Doesn't fit in memory
Using Covariates	linear regression	data reduction + weighted linear models
No Covariates	t-test	data reduction

Experiment Analysis (dependent data)

Data Size	Fits in memory < 2M rows	Doesn't fit in memory
Using Covariates	random effects models or bootstrap + linear models	bootstrap + data reduction + weighted linear models
No Covariates	random effects models or bootstrap in R	bootstrap + data reduction

Analyzing our Experimental Data

open: analyzing_experiments.R

facebook