



# DS-UA 112

## Introduction to Data Science

Week 3: Lecture 1

Tables - Arranging Data in Rows and Columns





How can tables help us  
to summarize data?

# DS-UA 112

## Introduction to Data Science

### Week 3: Lecture 1

### Tables - Arranging Data in Rows and Columns

*Adapted from Nolan, Hug, and Salganik*



# Announcements

- ▶ Please check Week 3 agenda on NYU Classes
  - ▶ Homework 1
  - ▶ Lab 3
  - ▶ Grader Office Hours
- ▶ Remember to post to Piazza

Check the Calendar linked to NYU Classes for important dates

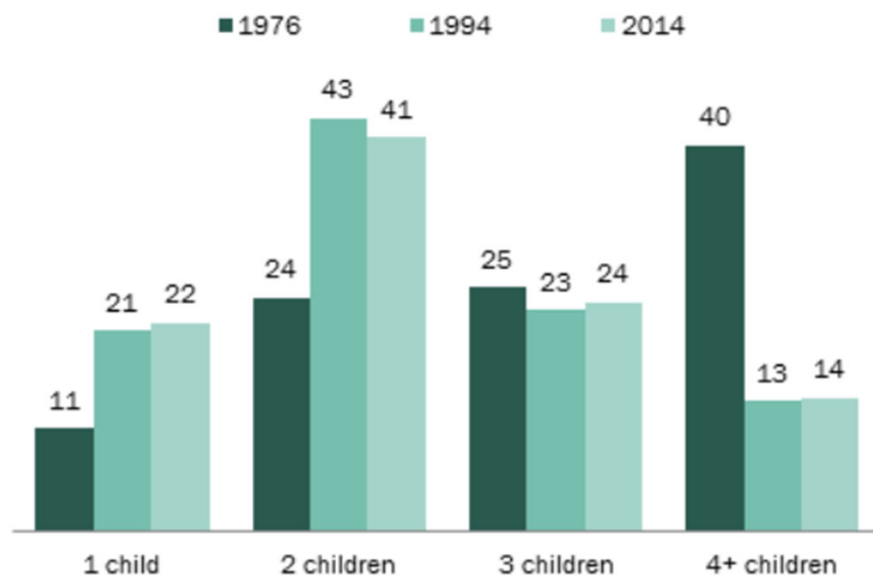
ed m don't standing deep ning field clean lot idea skill job code world tool large hope method analyze practical library help create expand actual knowledge real python application basic class making experience project good gain work data science

# Review

Pew Research Study  
Fertility and Education

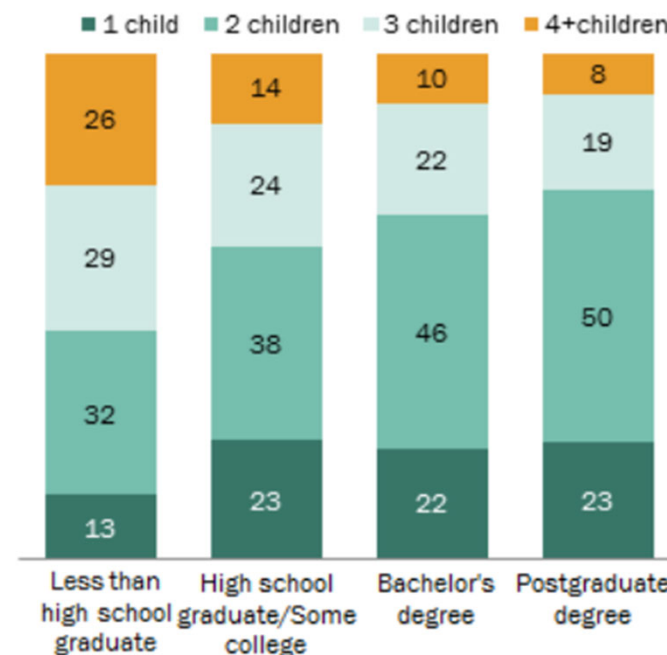
## Among Mothers, Family Size is Shrinking

% of mothers ages 40 to 44 with...



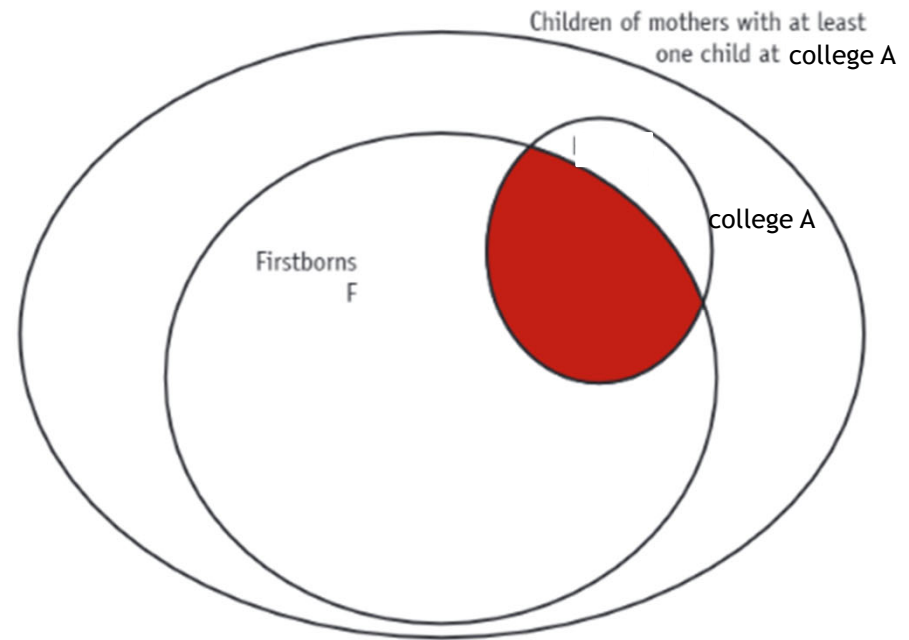
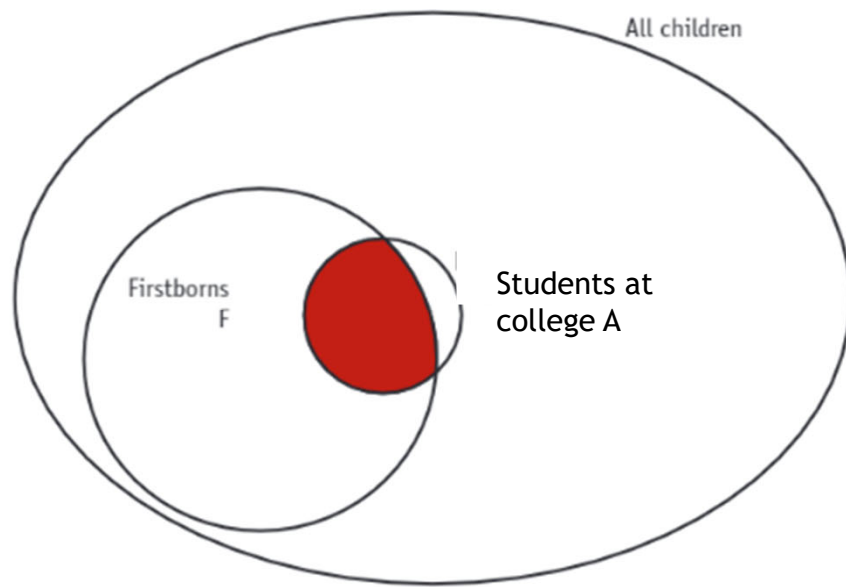
## Moms with Less Education Have Bigger Families

% of mothers ages 40 to 44 with ...

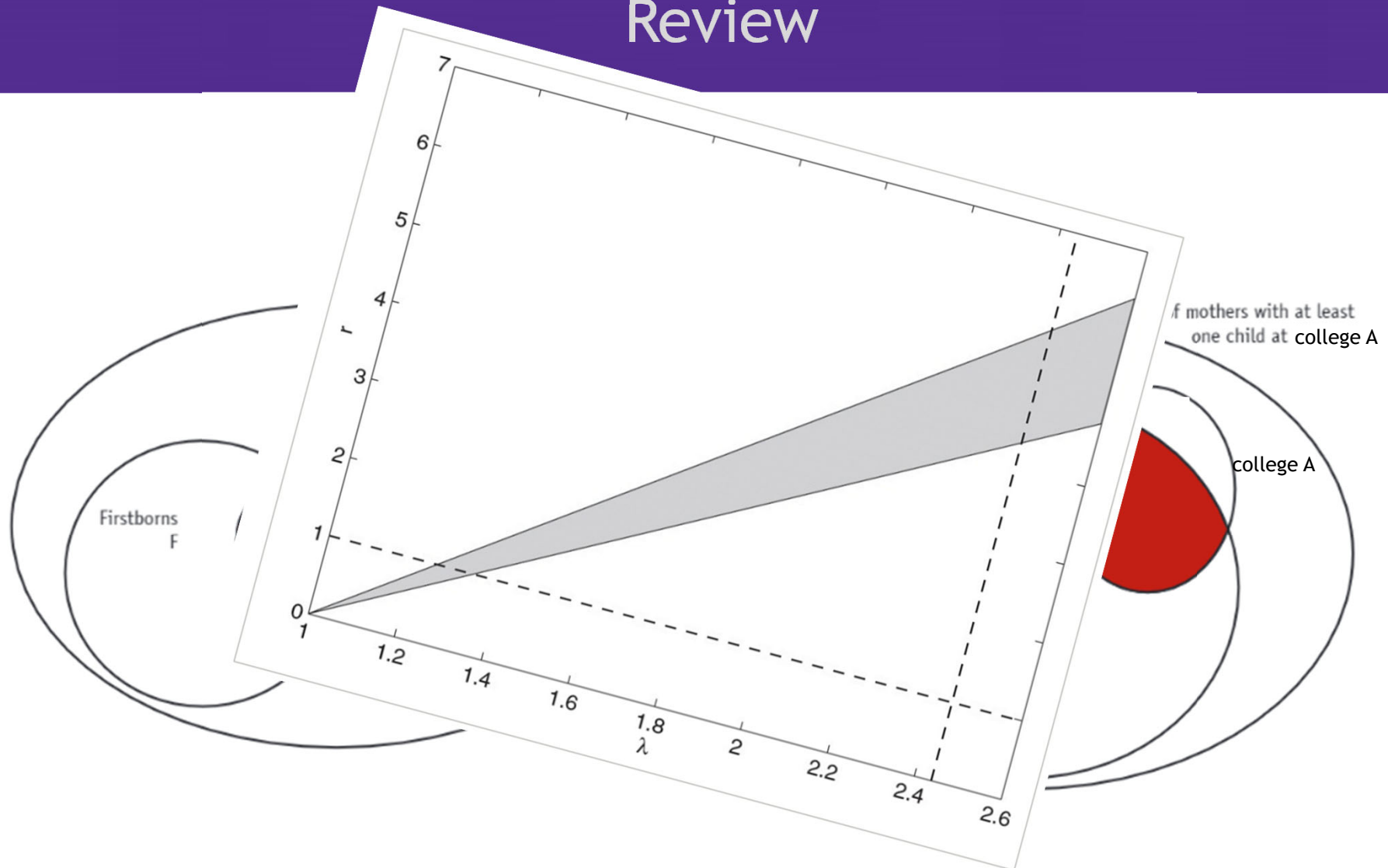


# Review

Base Rate Fallacy



# Review



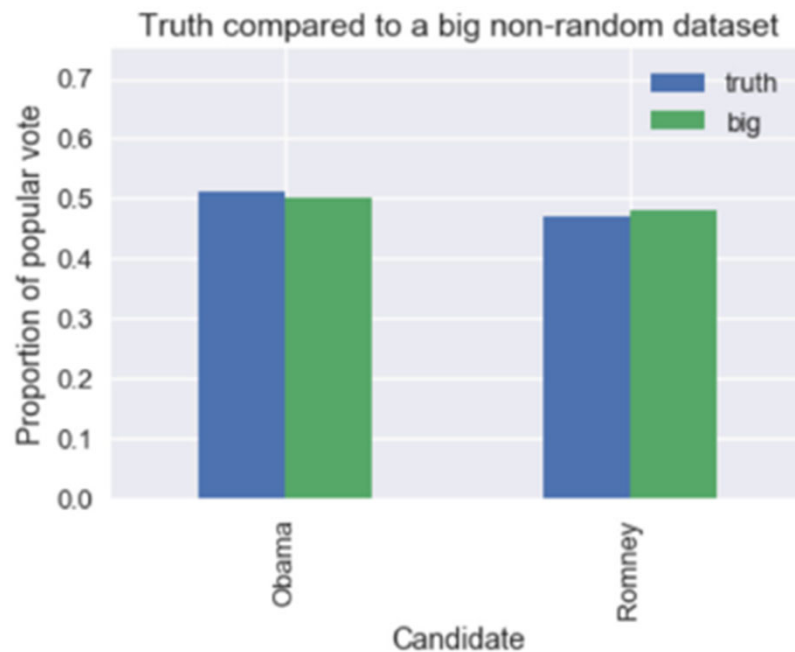
# Agenda

- ▶ Probability
  - ▶ Addition, Multiplication, Complement Rules
  - ▶ Summarize with average value
- ▶ Confounded Data
  - ▶ Adjusting for Bias
- ▶ Messy Data
  - ▶ Arranging into Rows and Columns

## References

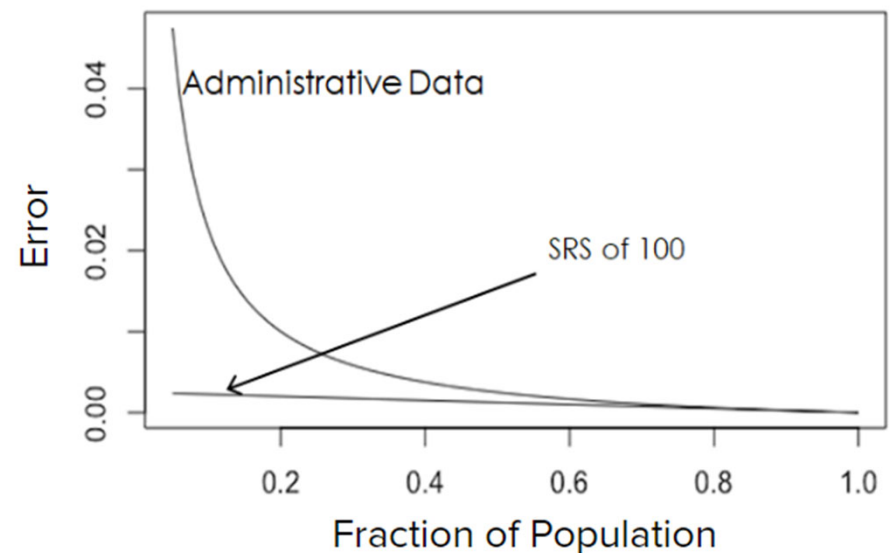
- ▶ Nolan, Lau, Gonzalez (Chapter 2, 3.1)
  - ▶ <https://cp71.github.io/textbook>
- ▶ Salganik (Chapter 3)

# Not Representative



Approach to data collection could indicate bias to us.

If a dataset is not representative, then it may or may not be suitable for a study. Sometimes it causes bias in the analysis.





# Not Representative

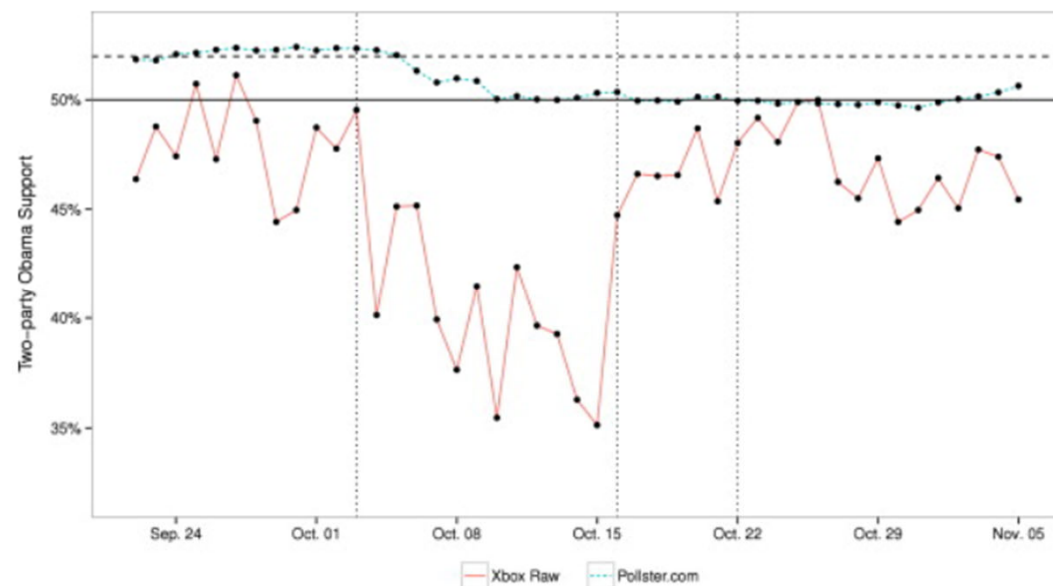
Sampling Frame may not  
lie in the Population

## Abstract

Election forecasts have traditionally been based on representative polls, in which randomly sampled individuals are asked who they intend to vote for. While representative polling has historically proven to be quite effective, it comes at considerable costs of time and money. Moreover, as response rates have declined over the past several decades, the statistical benefits of representative sampling have diminished. In this paper, we show that, with proper statistical adjustment, non-representative polls can be used to generate accurate election forecasts, and that this can often be achieved faster and at a lesser expense than traditional survey methods. We demonstrate this approach by creating forecasts from a novel and highly non-representative survey dataset: a series of daily voter intention polls for the 2012 presidential election conducted on the Xbox gaming platform. After

## Forecasting elections with non-representative polls

Wei Wang<sup>a</sup>, David Rothschild<sup>b</sup>, Sharad Goel<sup>b</sup>, Andrew Gelman<sup>a, c</sup>



# Not Representative

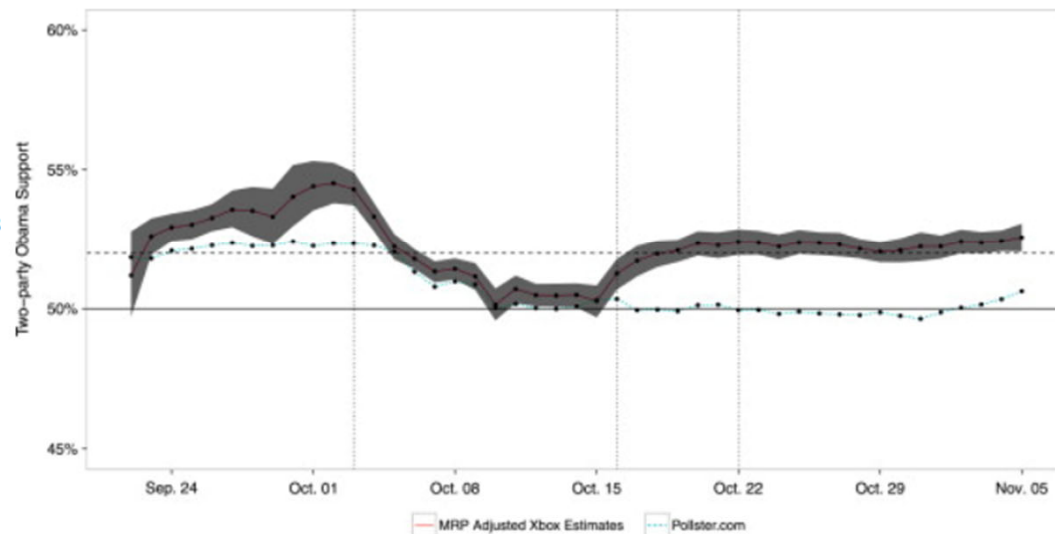
Adjustments made by  
stratifying following the  
data collection

## Abstract

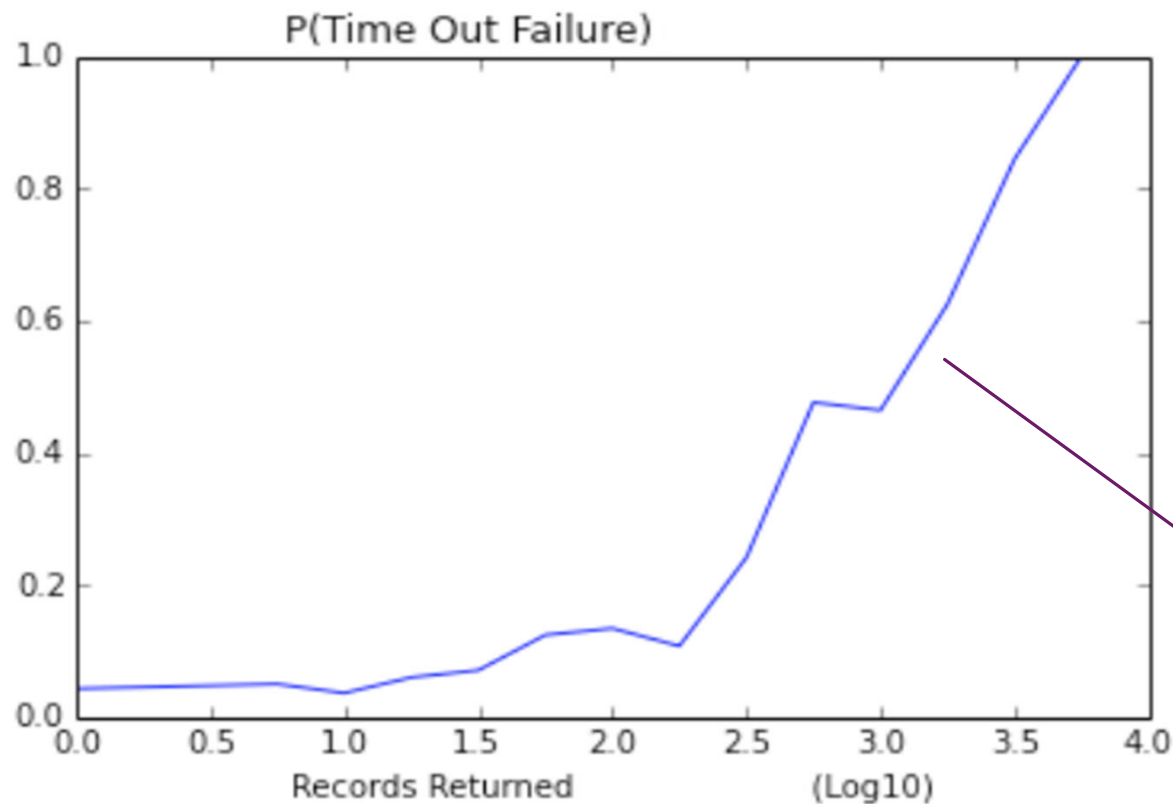
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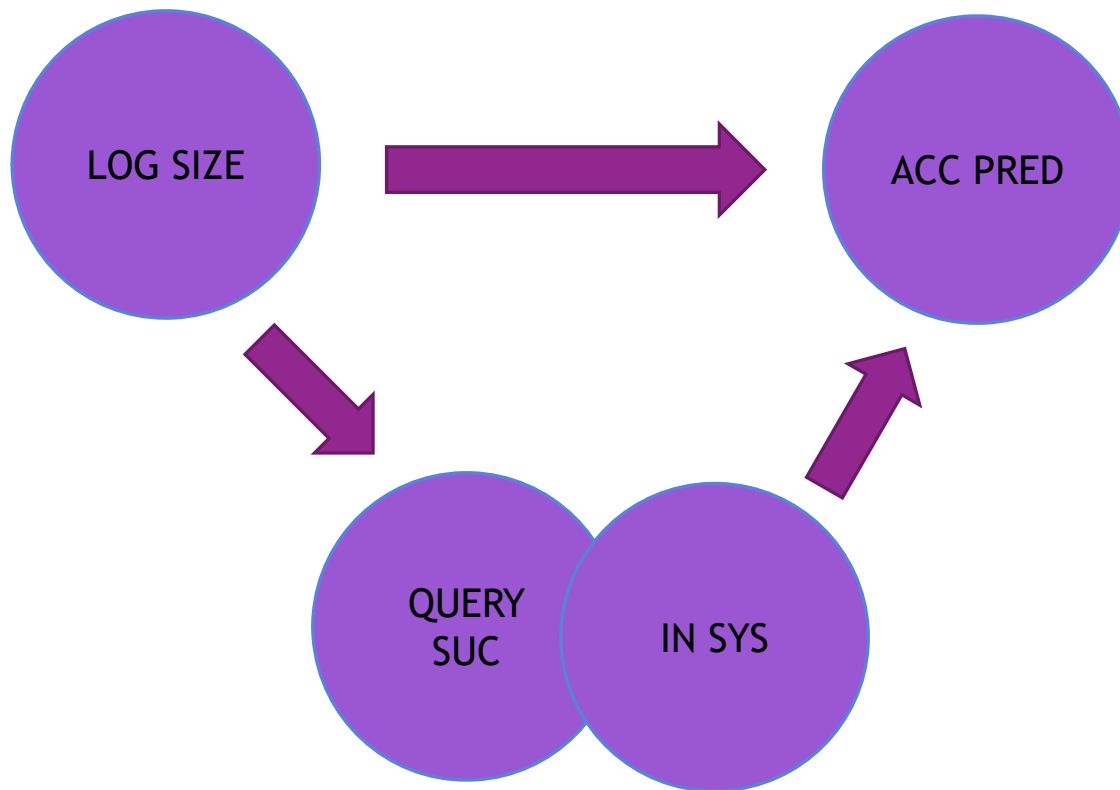
# Confounded Data



Here the probability of inclusion of the record in the sample changes depending on the size of the record

How could this lead to bias? In particular, why might predictions reflect habits of new customers

# Confounded Data



ACC PRED

Accurate Prediction of  
Least Popular

LOG SIZE

Size of Database Record

QUERY SUC

Whether Query  
Returned Successfully

IN SYS

Whether Record in the  
System

## Confounded Data

How to adjust the probabilities?

$$P(\text{ACC PRED} \mid \text{LOG SIZE}) =$$

$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{QUERY SUC}) \times P(\text{QUERY SUC} \mid \text{LOG SIZE})$$

+

$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{NOT QUERY SUC}) \times P(\text{NOT QUERY SUC} \mid \text{LOG SIZE}) =$$

# Confounded Data

How to adjust the probabilities?

$$P(\text{ACC PRED} \mid \text{LOG SIZE}) =$$

$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{QUERY SUC}) \times P(\text{QUERY SUC} \mid \text{LOG SIZE})$$

+

$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{NOT IN SYS}) \times P(\text{NOT QUERY SUC} \mid \text{LOG SIZE}) =$$

# Confounded Data

How to adjust the probabilities?

$$P(\text{ACC PRED} \mid \text{LOG SIZE})$$

=

$$P(\text{ACC PRED} \mid \text{LOG SIZE, QUERY SUC}) \times P(\text{QUERY SUC} \mid \text{LOG SIZE})$$

+

$$P(\text{ACC PRED} \mid \text{LOG SIZE, NOT IN SYS}) \times P(\text{NOT QUERY SUC} \mid \text{LOG SIZE})$$

=

$$P(\text{ACC PRED} \mid \text{LOG SIZE, QUERY SUC})P(\text{QUERY SUC} \mid \text{LOG SIZE})$$

+

$$(0) P(\text{NOT QUERY SUC} \mid \text{LOG SIZE})$$

# Confounded Data

How to adjust the probabilities?

$$P(\text{ACC PRED} \mid \text{LOG SIZE})$$
$$=$$
$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{QUERY SUC}) \times P(\text{QUERY SUC} \mid \text{LOG SIZE})$$

Without this quantity  
the two sides would  
not be equal.



# Confounded Data

How to adjust the probabilities?

$$P(\text{ACC PRED} \mid \text{LOG SIZE})$$

=

$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{QUERY SUC}) \times P(\text{QUERY SUC} \mid \text{LOG SIZE})$$

$$\frac{P(\text{ACC PRED} \mid \text{LOG SIZE})}{P(\text{QUERY SUC} \mid \text{LOG SIZE})}$$

=

$$P(\text{ACC PRED} \mid \text{LOG SIZE}, \text{QUERY SUC})$$

Without this quantity the two sides would not be equal.

# Confounded Data

## Gender Achievement Gaps in U.S. School Districts

**Author/s:** Sean F. Reardon , Erin Fahle , Demetra Kalogrides , Anne Podolsky , Rosalía C. Zárate

**Year of Publication:** 2018

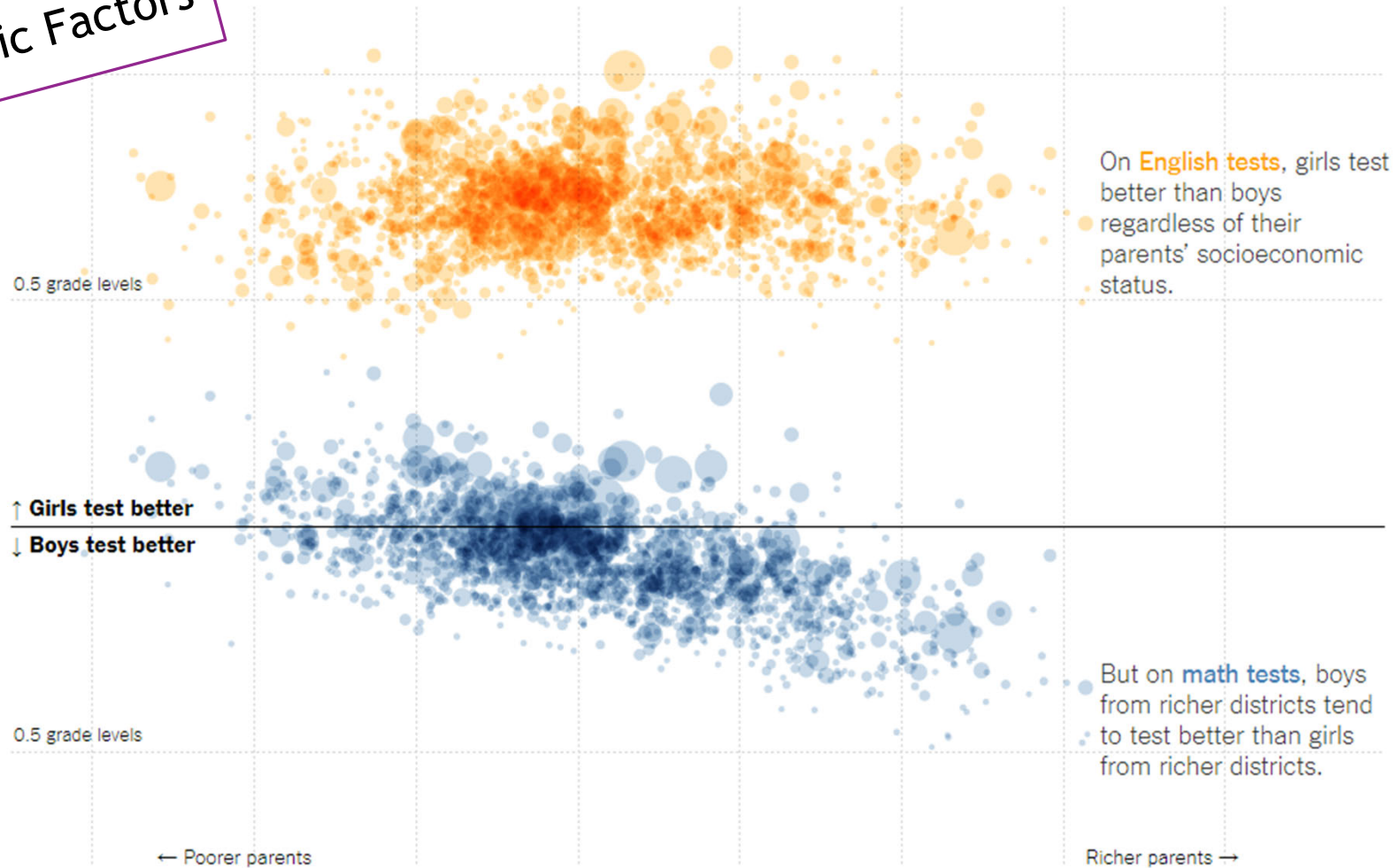
In the first systematic study of gender achievement gaps in U.S. school districts, we estimate male-female test score gaps in math and English Language Arts (ELA) for nearly 10,000 school districts in the U.S. We use state

- ▶ What is the population?
- ▶ What is the question under study?

- ▶ What is the sampling frame?
- ▶ What could lead to confounded data?

# Confounded Data

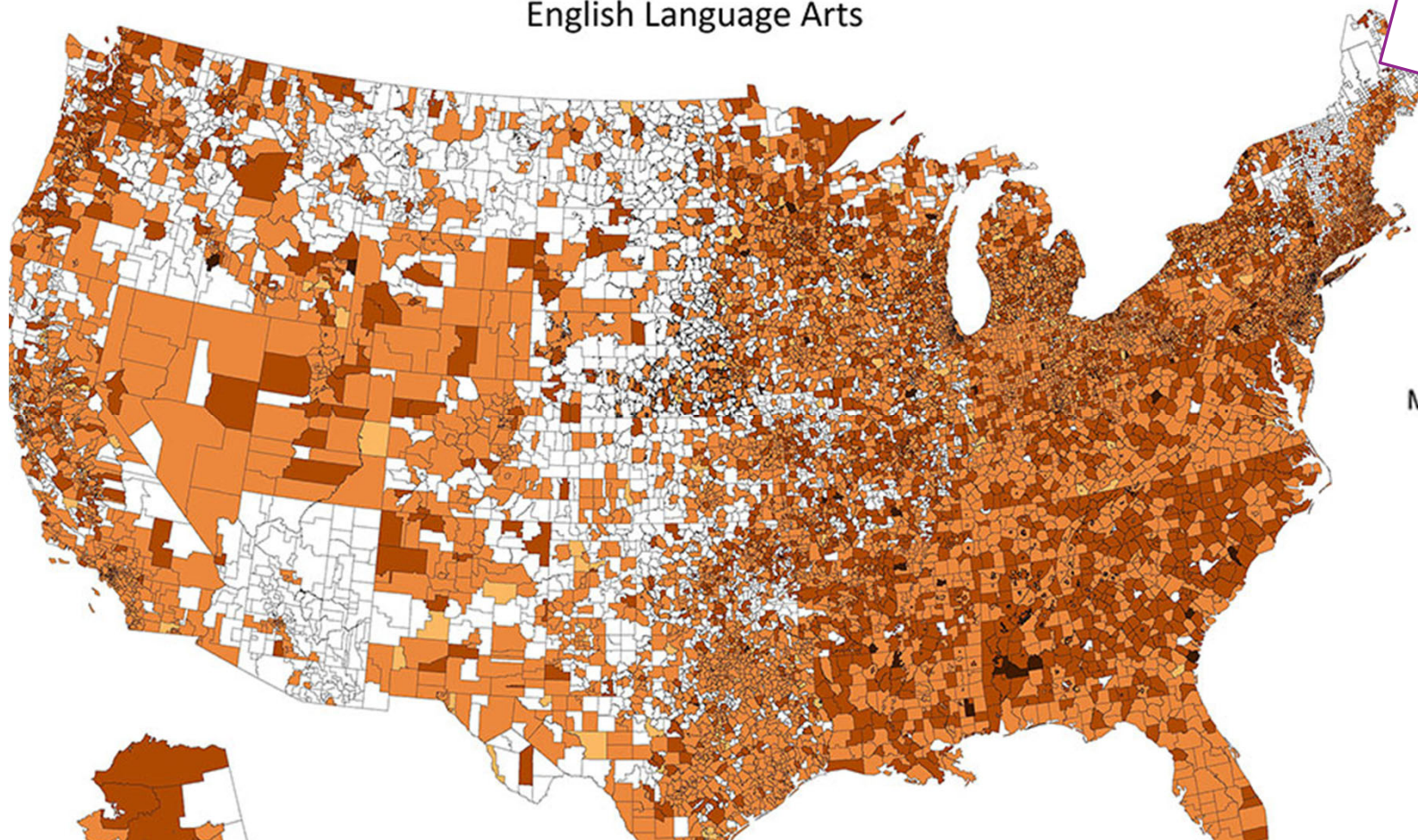
Economic Factors



# Confounded Data

English Language Arts

Geographic  
Factors



Male-Female Gap, NS Scale

- More than 0.25 SDs
- 0.15 to 0.25 SDs
- 0.05 to 0.15 SDs
- -0.05 to 0.05 SDs
- -0.15 to -0.05 SDs
- -0.25 to -0.15 SDs
- -0.35 to -0.25 SDs
- Less than -0.35 SDs
- missing



# Questions

- ▶ Questions on Piazza?
- ▶ Question for You!

Should the word data be understood as singular or plural?

*In Latin, data is the plural of datum and, historically and in specialized scientific fields, it is also treated as a plural in English, taking a plural verb, as in the data were collected and classified. In modern non-scientific use, however, despite the complaints of traditionalists, it is often not treated as a plural. Instead, it is treated as a mass noun, similar to a word like information, which cannot normally have a plural and which takes a singular verb. Sentences such as data was (as well as data were) collected over a number of years are now widely accepted in standard English.*

# Questions

- ▶ Questions on Piazza?
- ▶ Question for You!

# Should the word data be understood as singular or plural?

[illegible]