

Randomized Trials

(SOC 412)

Week 1 Lecture 2

Sherrerd Hall 306



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What we will cover today

Discuss reading

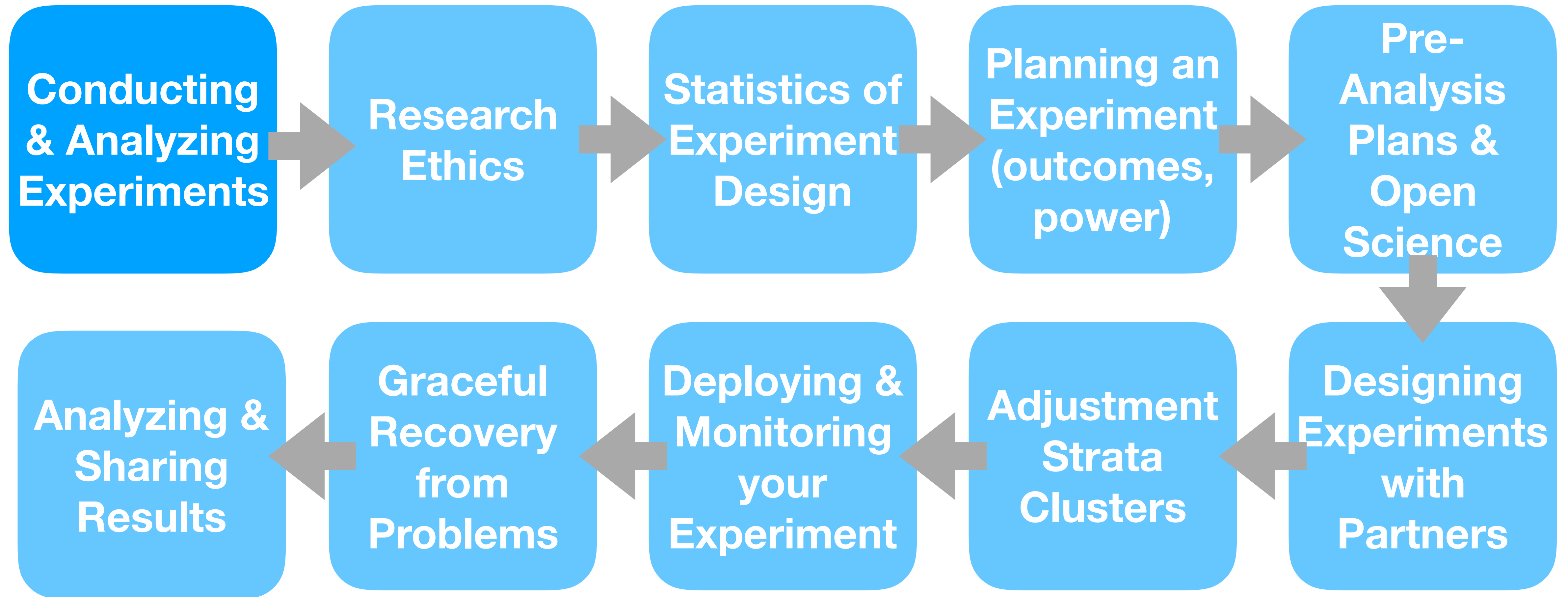
Introduction to randomized trials

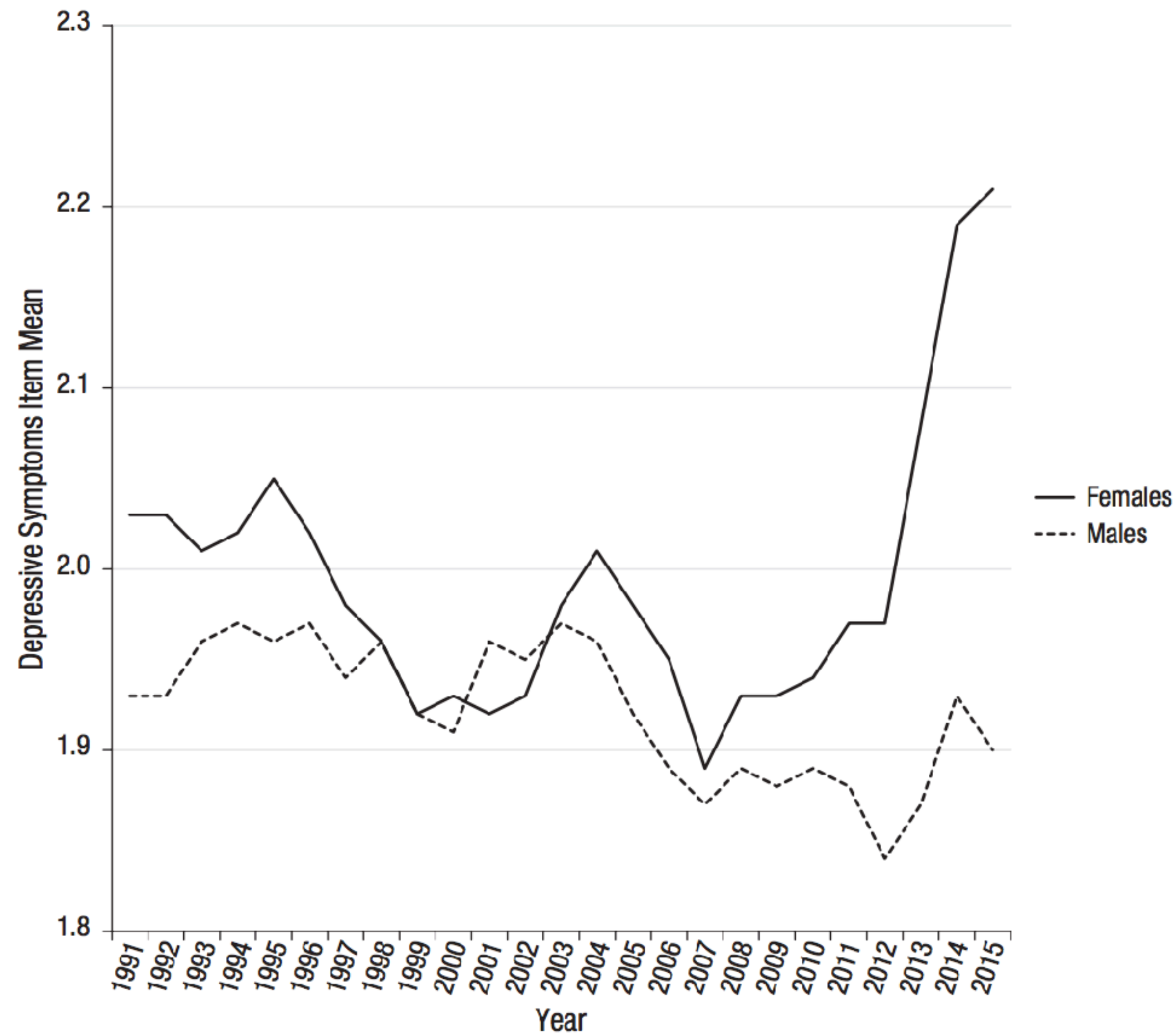
Discuss assignment

Discuss first full field experiment

Questions about Assignments

- **Project Assignments: Due Monday evening?**
- **Reflective Writing Due Friday midday?**





Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.



Next, we examined **possible causes of the increase in depressive symptoms** and suicide-related outcomes among adolescents

When examined individually, the four **suicide-related outcomes** were **all significantly correlated with electronic device use**

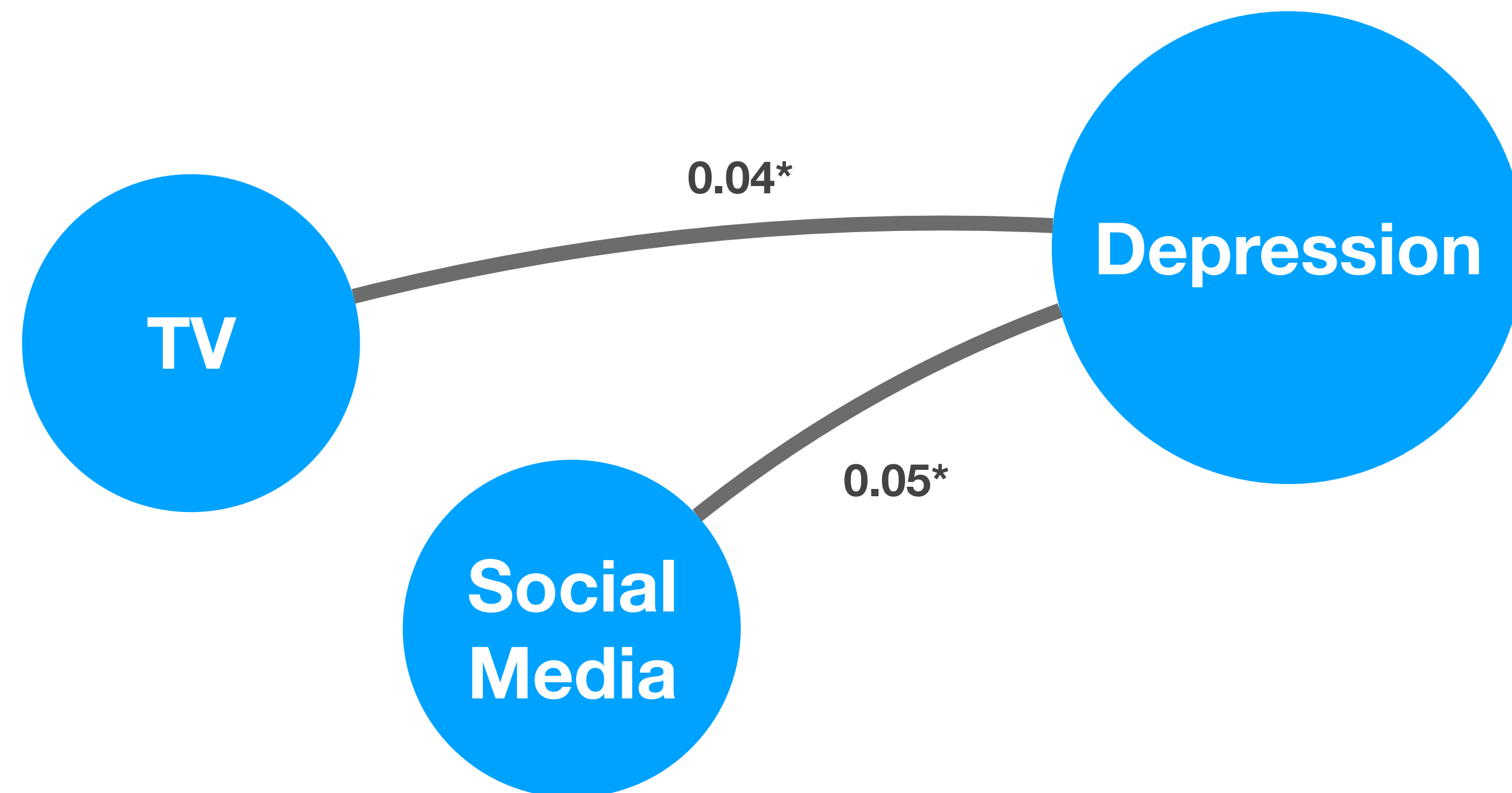
Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

Table 2. Correlations Between Screen and Nonscreen Activities and Depressive Symptoms (8th and 10th Graders, MtF) and Suicide-Related Outcomes (9–12th Graders, YRBSS), 2009–2015 **p* < .001.

	Bivariate <i>r</i>	Controlled for sex, race, SES, grade, and region	Controlled for sex, race, SES, grade, and region and in-person social interaction	Girls (controlled for race, SES, grade, and region)	Boys (controlled for race, SES, grade, and region)
<i>MtF (correlations with depressive symptoms)</i>					
<i>Screen activities</i>					
Social media use	.05*	.03*	.06*	.06*	.01
TV viewing	.04*	.02*	.03*	.03*	.02*
Internet news use	.00	.00	.01*	.01	−.02
<i>Nonscreen activities</i>					
In-person social interaction	−.07*	−.08*	−.09*	−.08*	−.09*
Religious services attendance	−.15*	−.14*	−.14*	−.16*	−.13*
Sports or exercise	−.22*	−.19*	−.18*	−.20*	−.19*
Homework hours	−.06*	−.05*	−.06*	−.06*	−.04*
Print media use	−.11*	−.10*	−.09*	−.12*	−.08*
Having a paid job	.00	.01	.02*	−.01	.02*

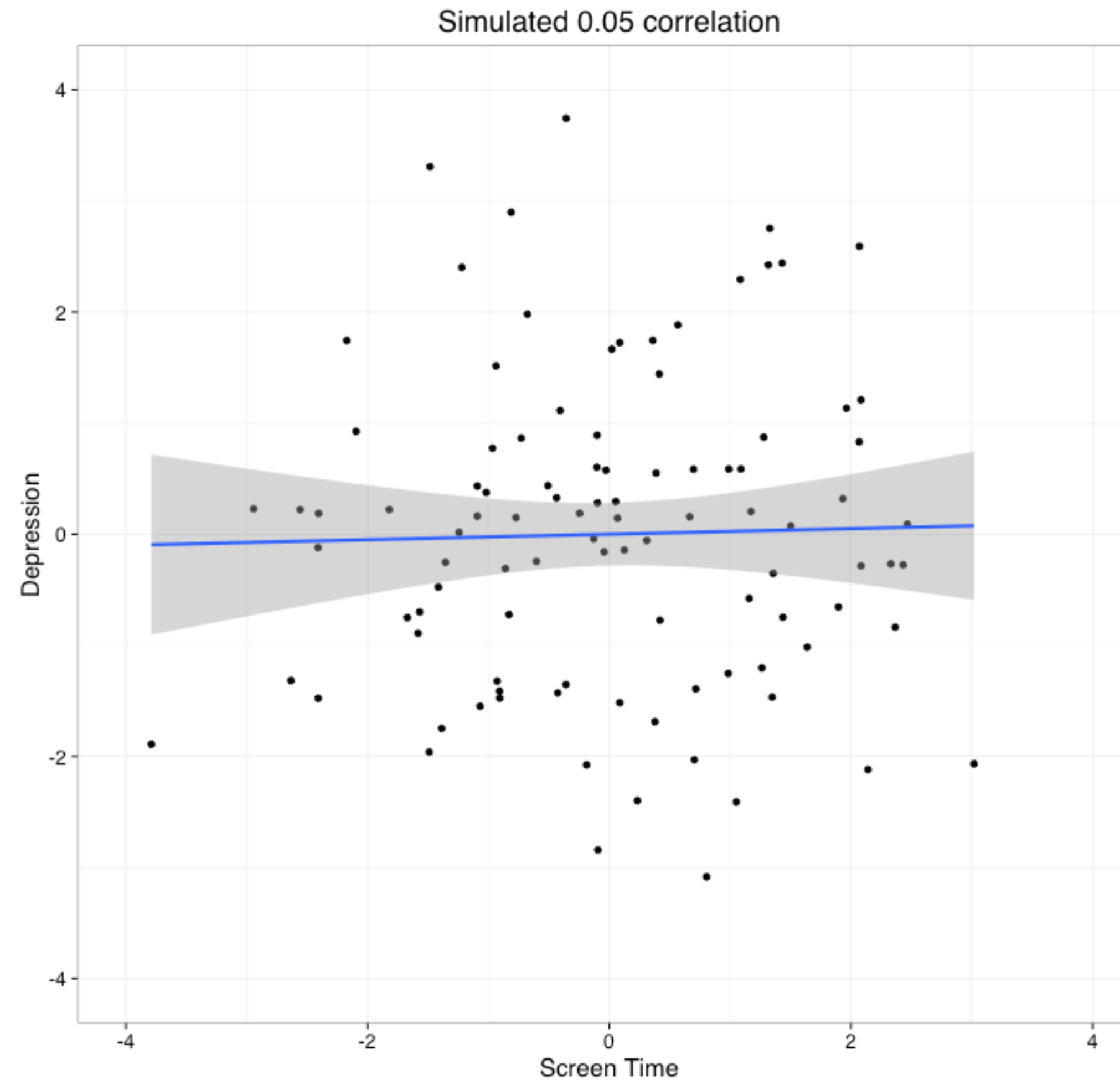
Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

Correlation? Association? Description?



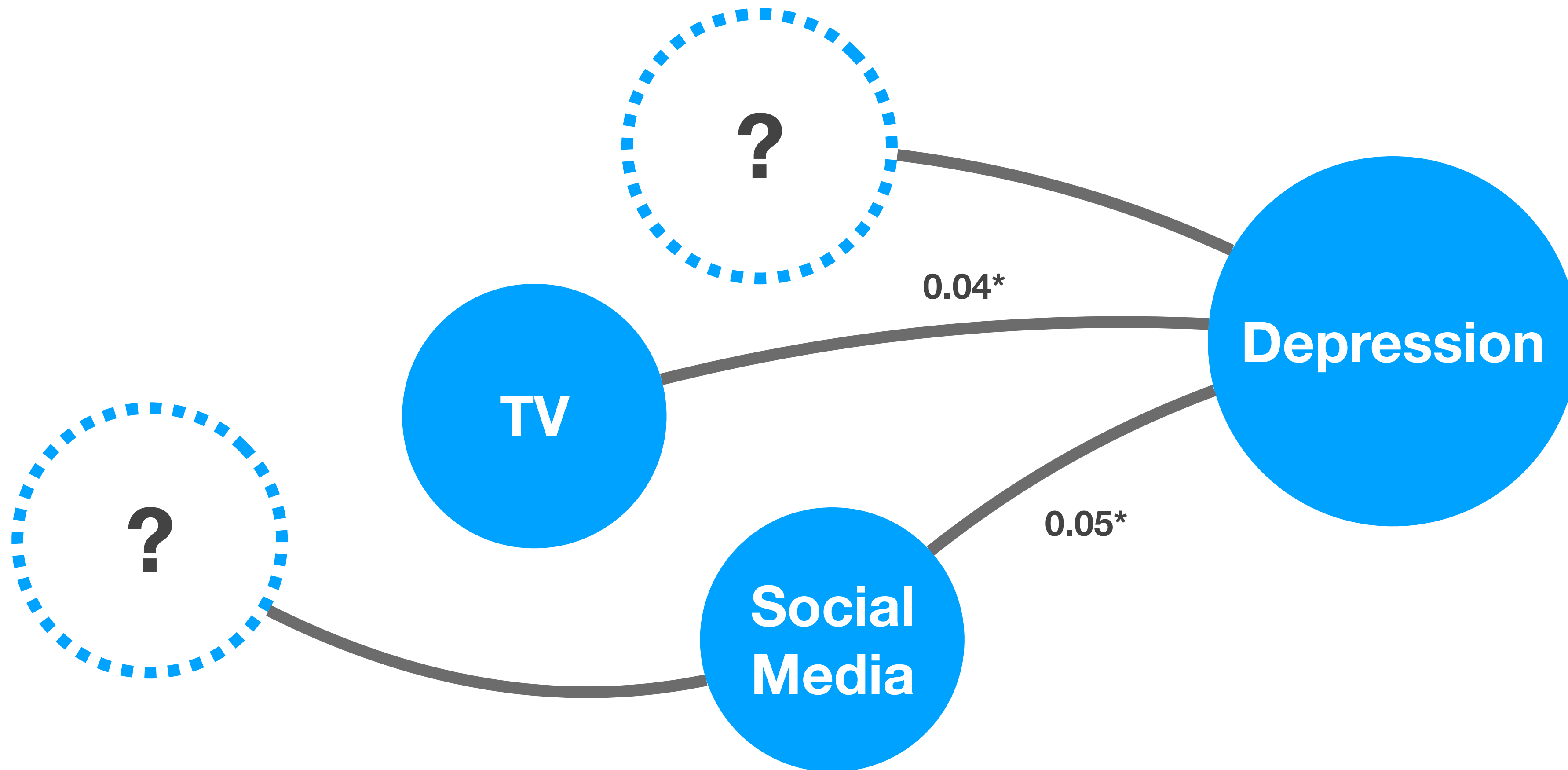
Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

Correlation? Association? Cause?



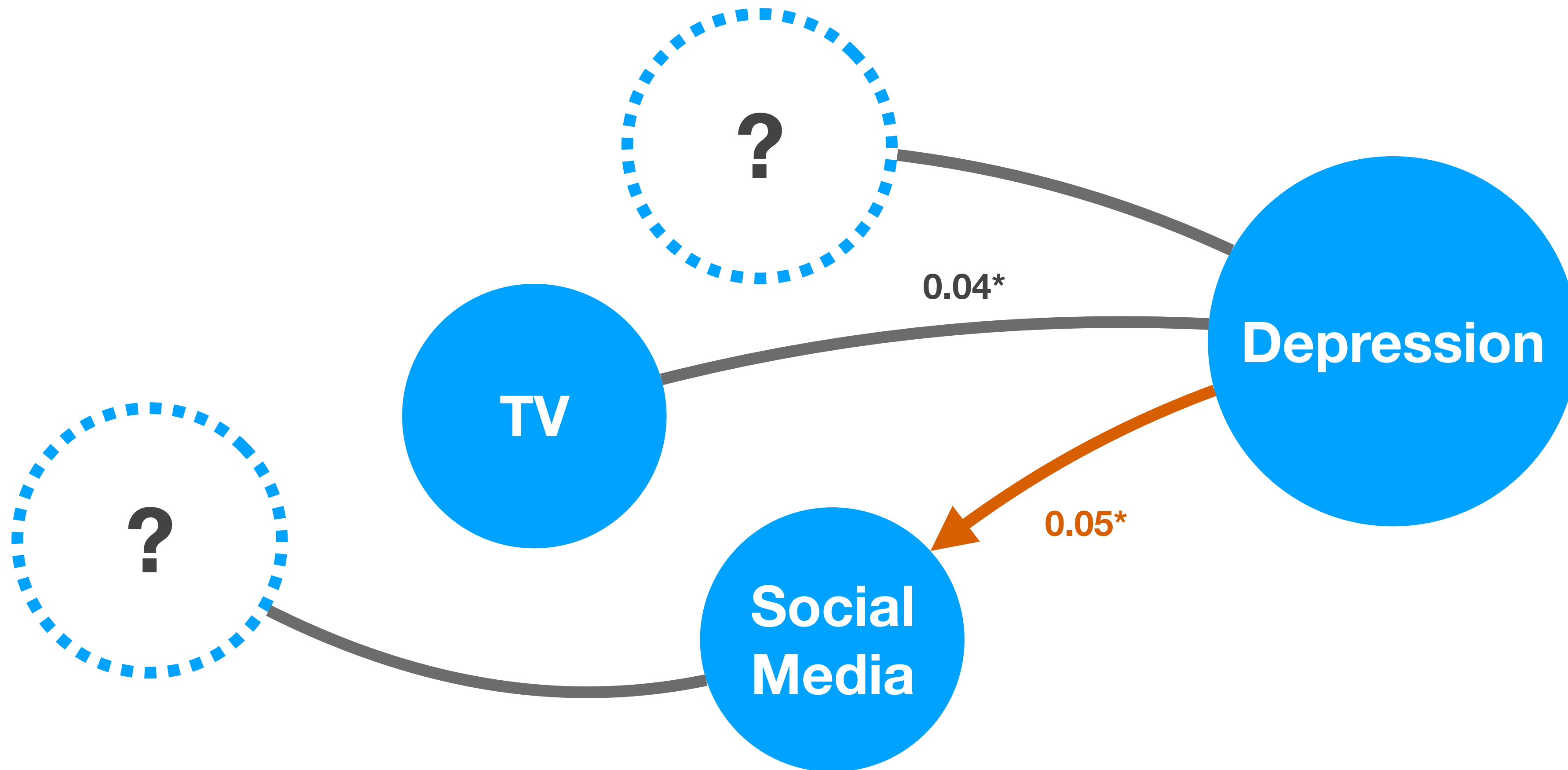
Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

Unobserved Confounders



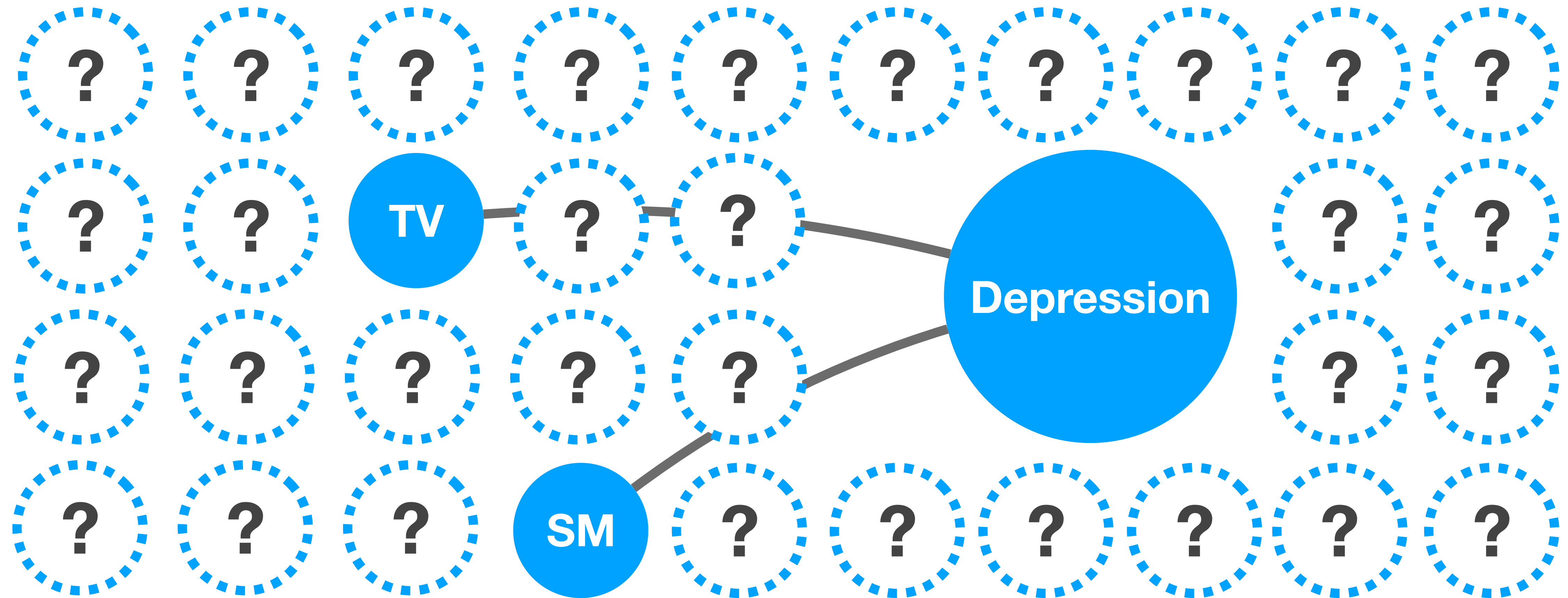
Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

Direction of Causality (Selection Bias)



Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

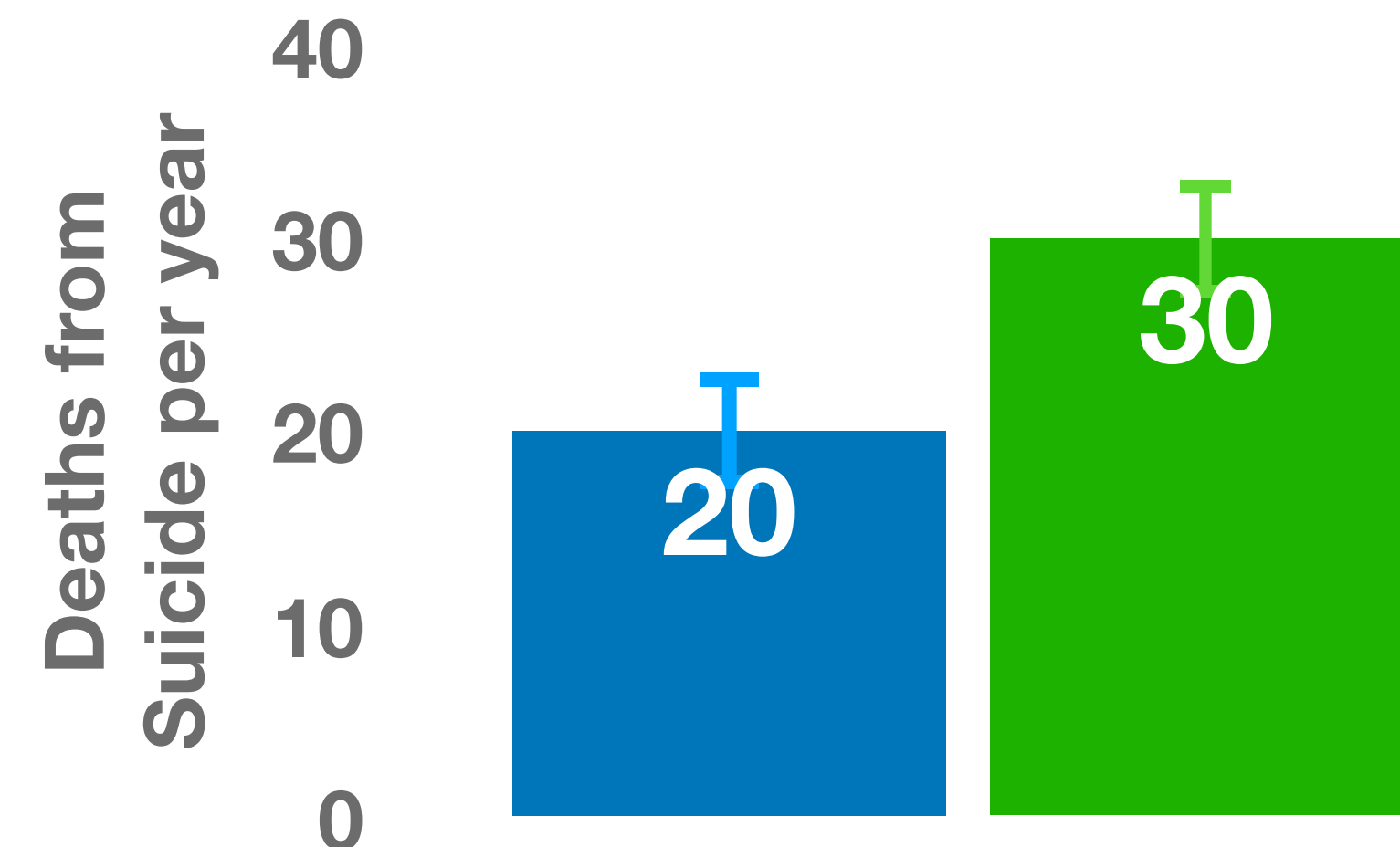
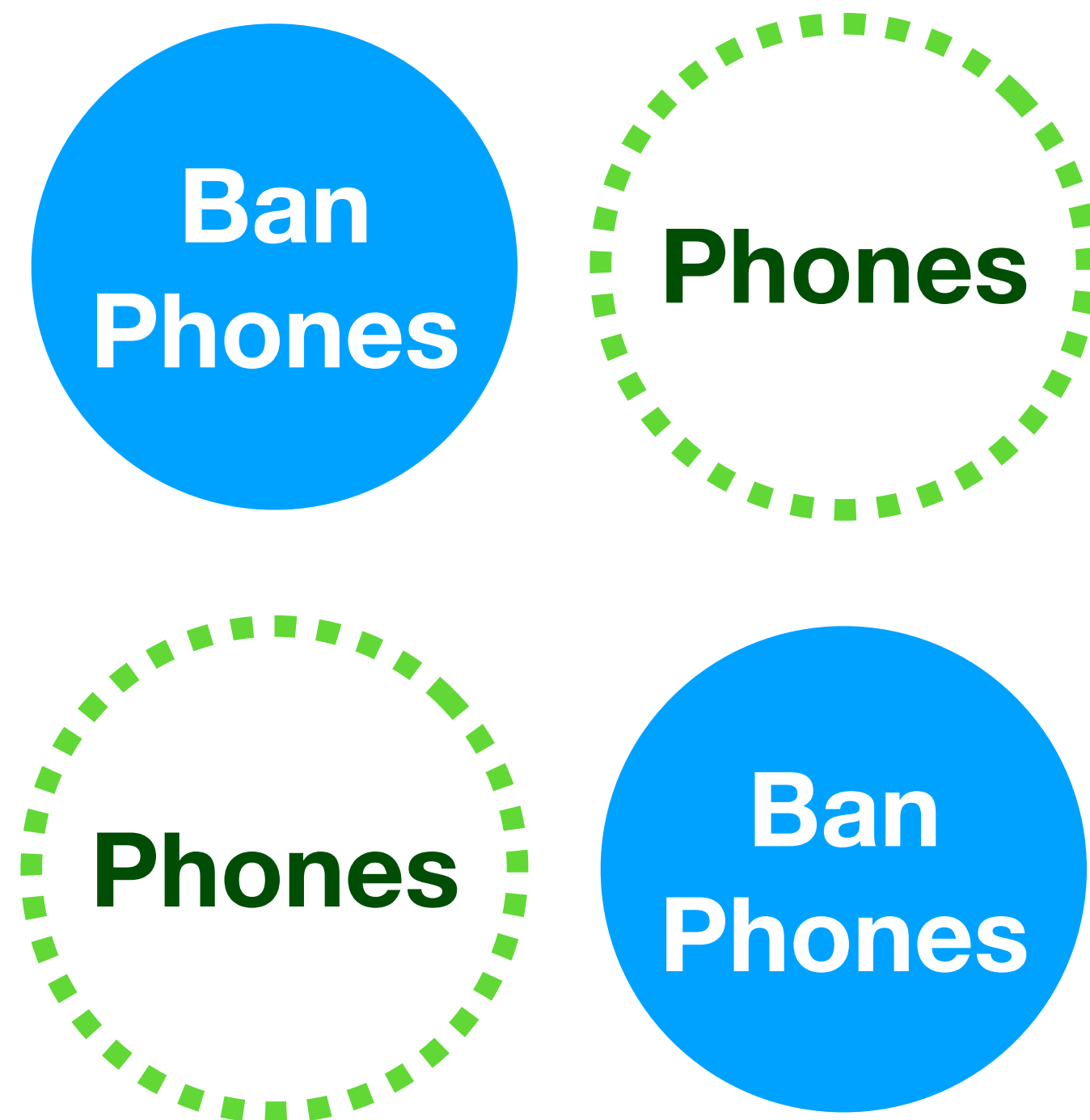
Multiple Comparisons



Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, 6(1), 3-17.

Observational Data Analysis

(imagine a dataset of depression cases)
(for schools that banned phones and those that didn't)



Why Experiment? (methodology)

- **Causal explanation vs description**
- Addresses **unobserved confounders**
- **Unbiased inference** (e.g. if the experiment were replicated an infinite number of times, our model would generate the right answer on average)
- Up-front design (“ex ante”) in principle **limits the analyst’s discretion**

Parts of an Experiment (example)

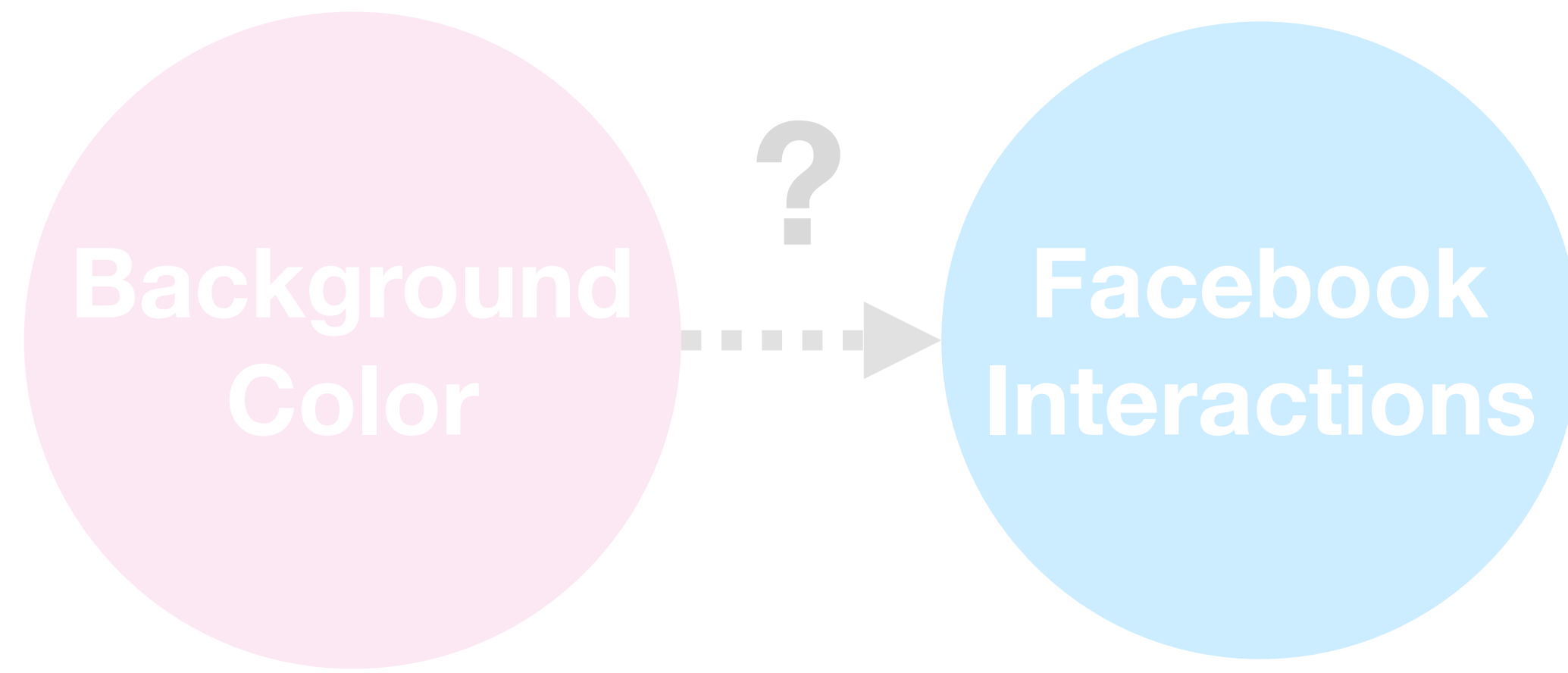


When the skies opened and **dumped \$185 million on an obscure Chicago poetry journal** in 2002, it was as much a burden as a gift...

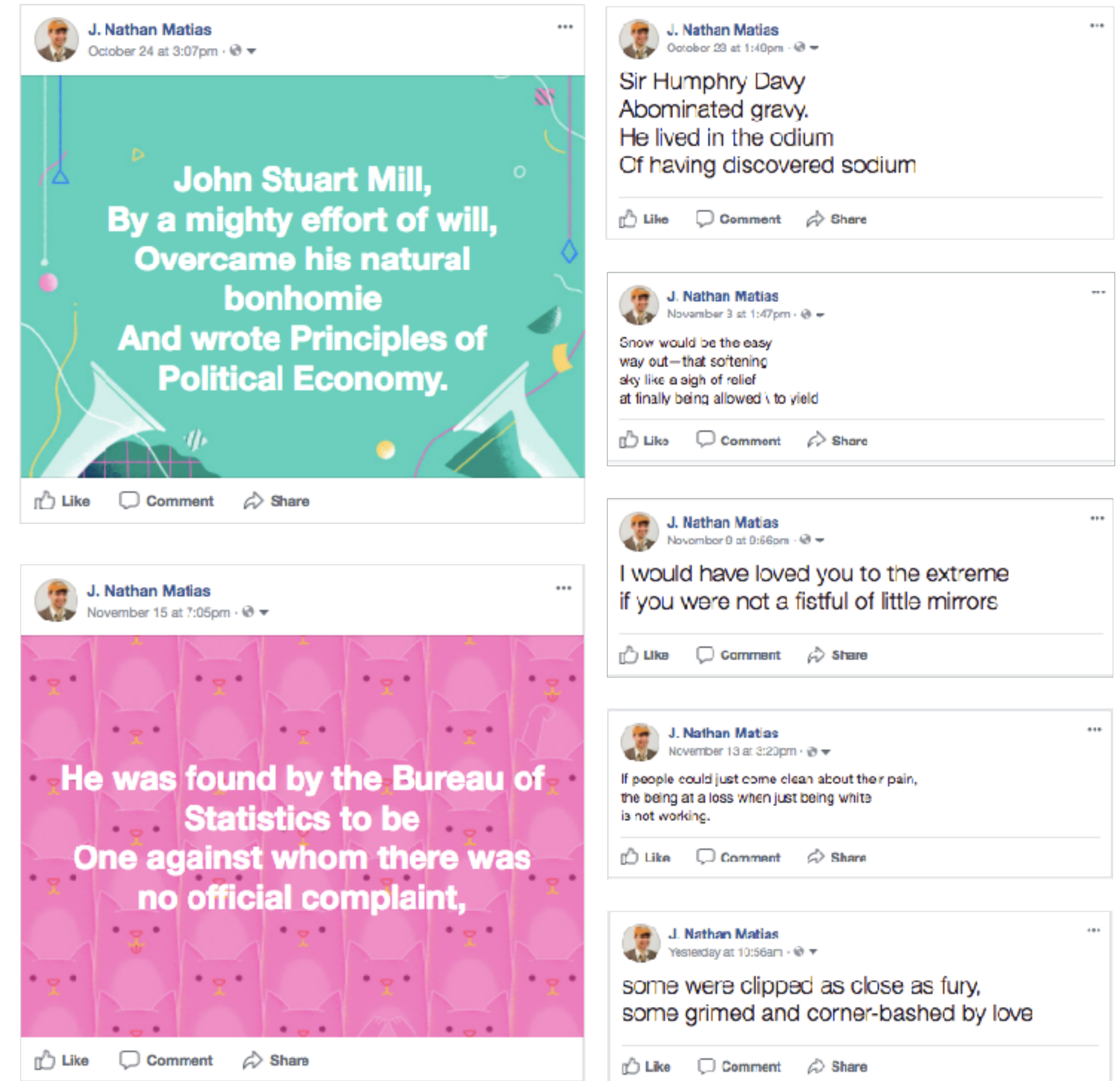
Barr still speaks in unpoetic terms like "cost per impact"

Fisher, Daniel. *No Rhyme or Reason*. Forbes, Jan 7, 2011.

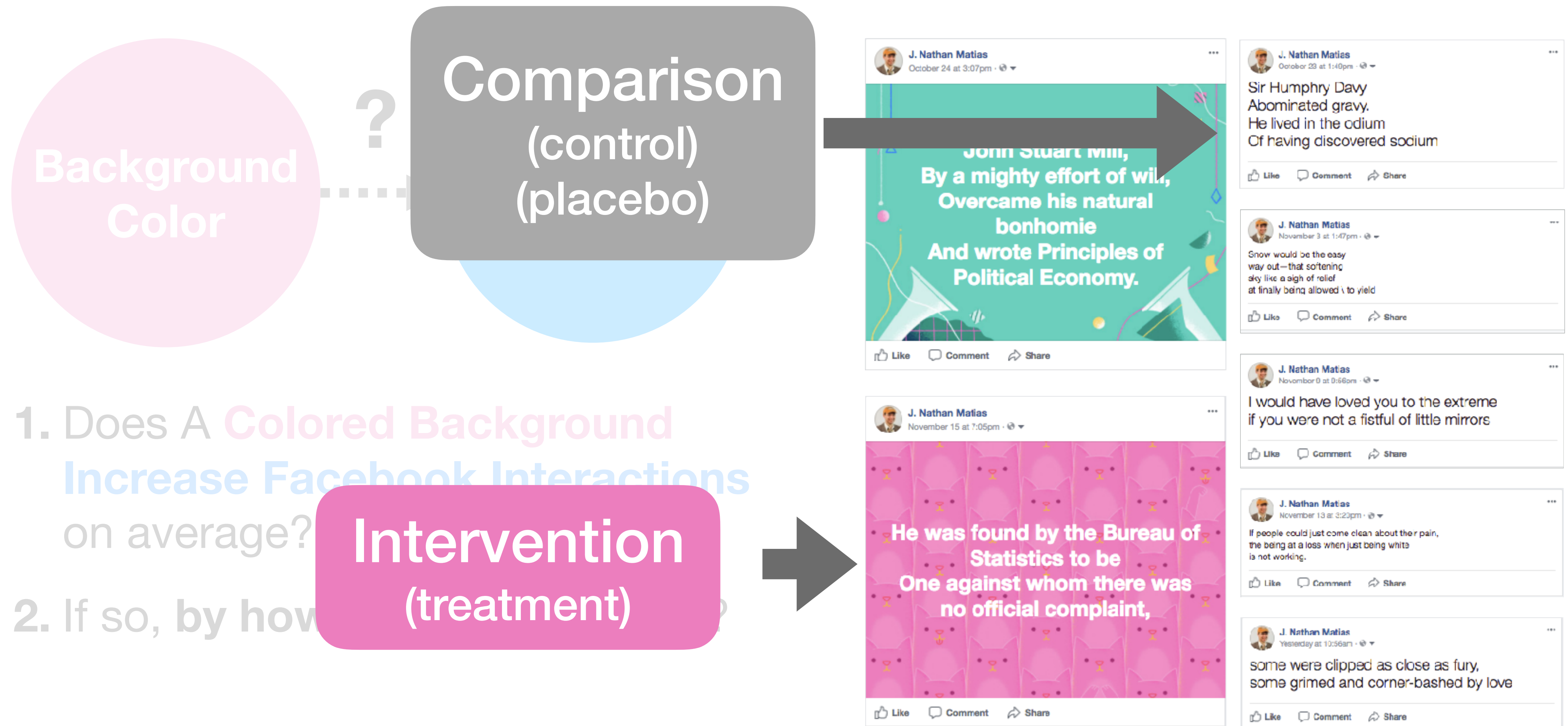
Parts of an Experiment



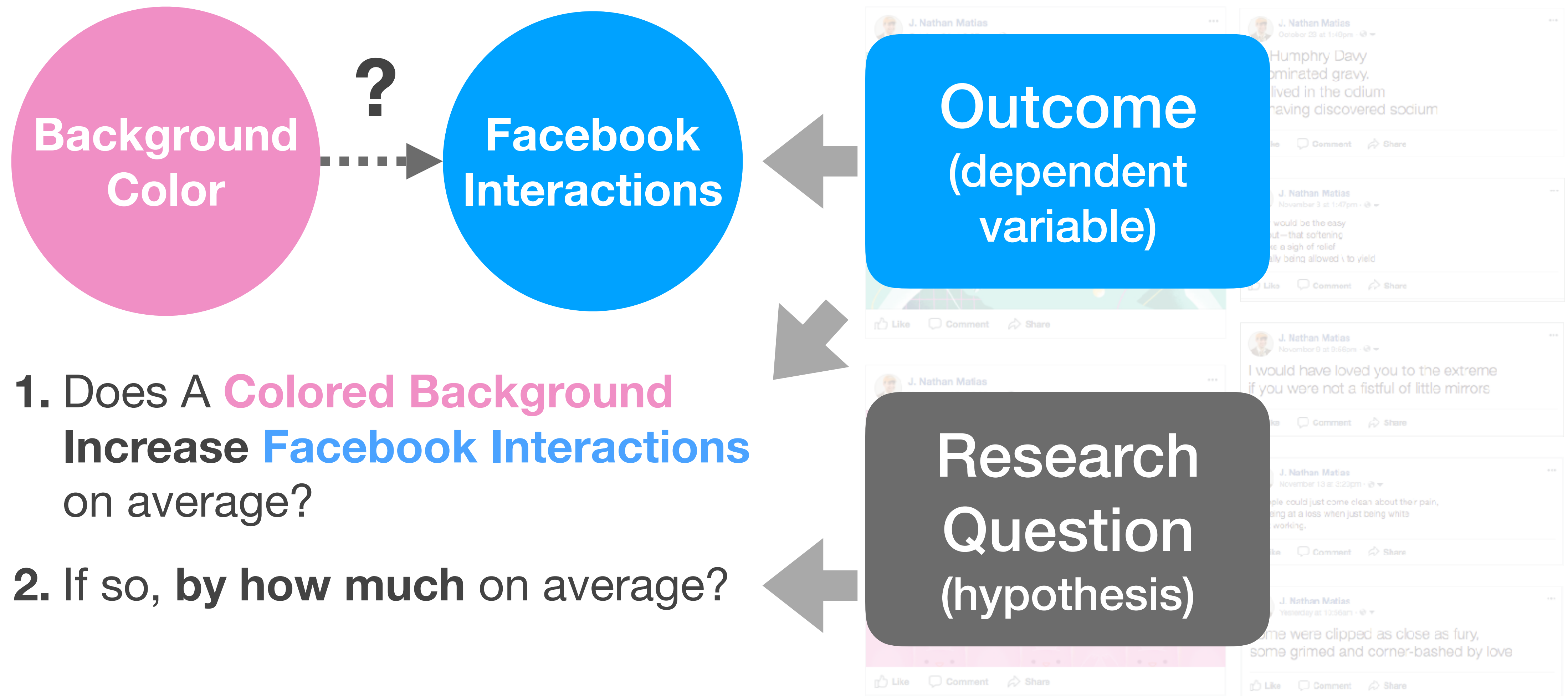
1. Does A **Colored Background** **Increase Facebook Interactions** on average?
2. If so, by how much on average?



Parts of an Experiment

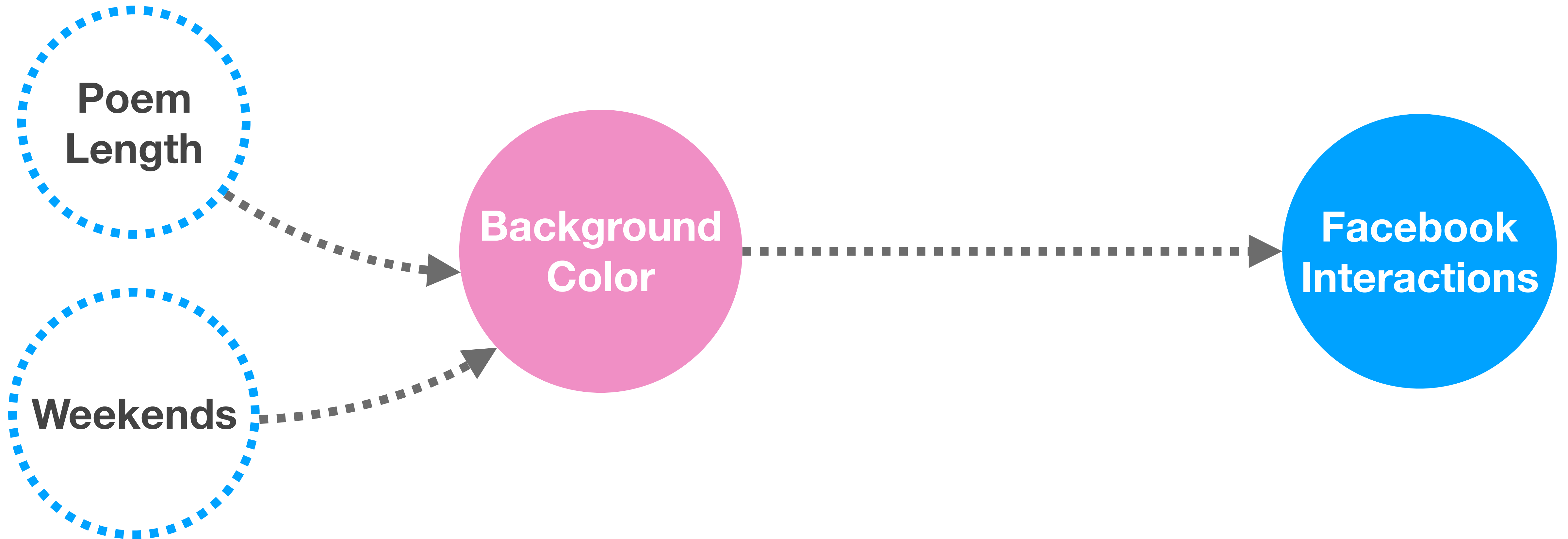


Parts of an Experiment

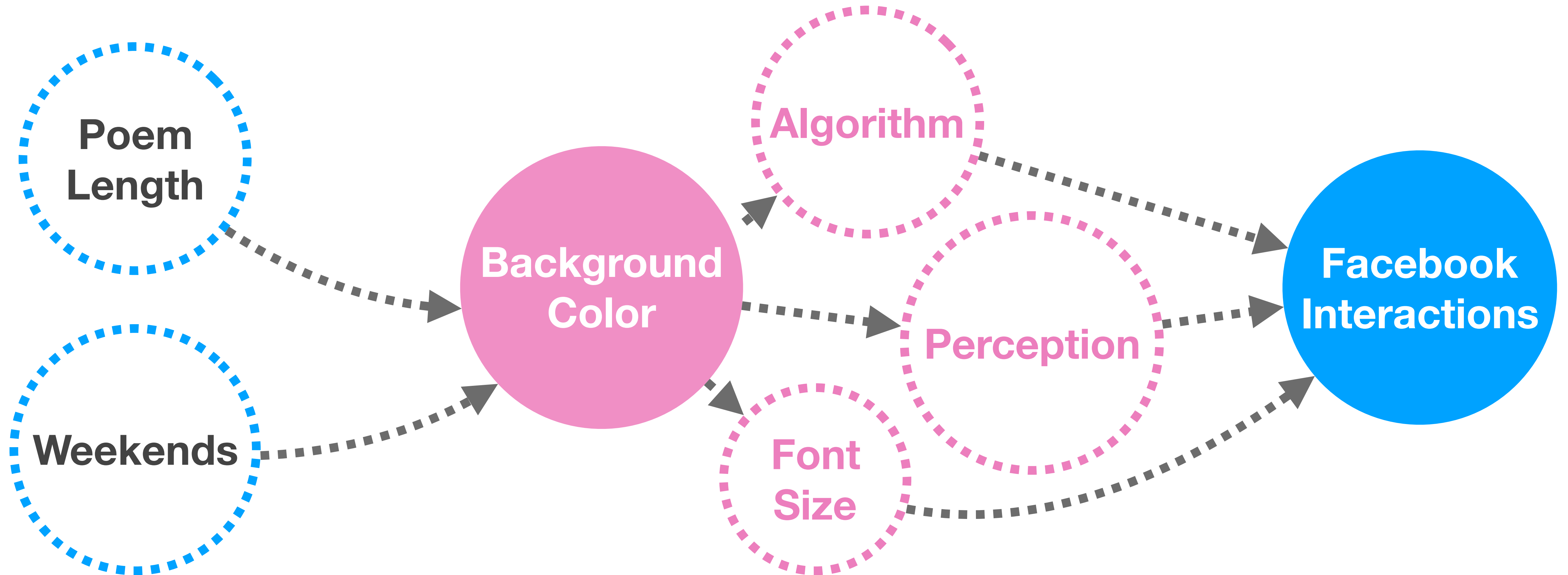


Unobserved Confounders

(by the way, this graph is called a path diagram)

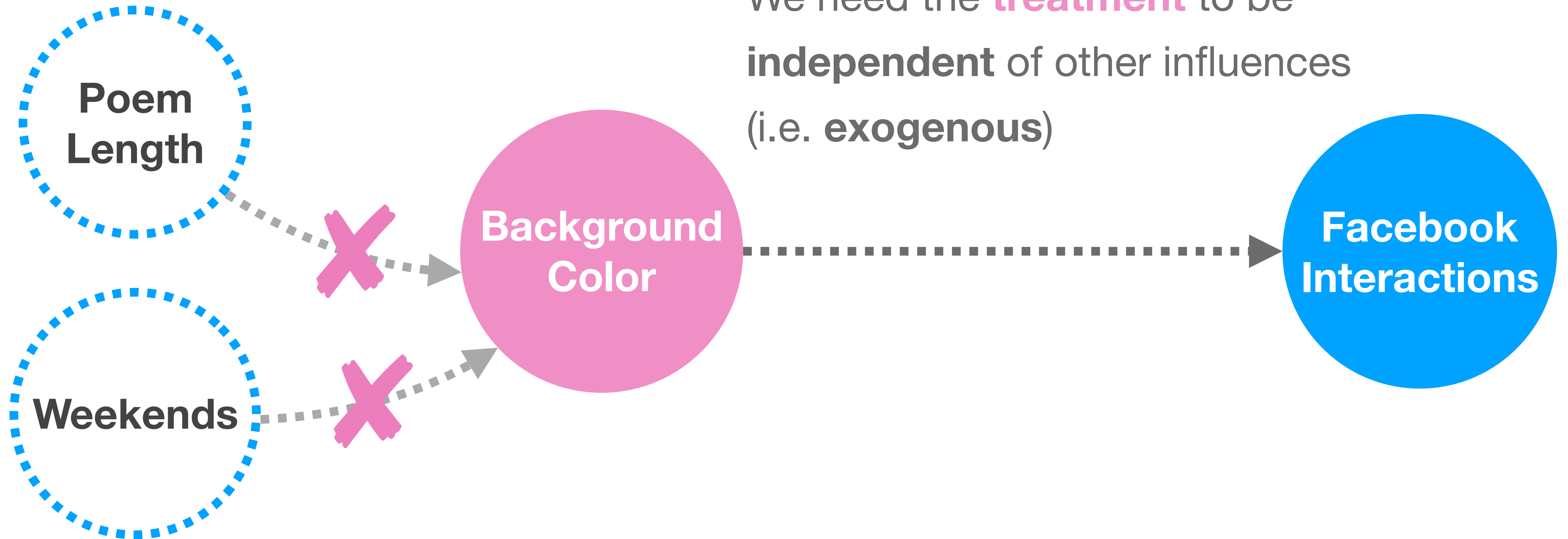


Unobserved Confounders



Independence of the Treatment

We need the **treatment** to be independent of other influences (i.e. **exogenous**)



Random Assignment

By using random assignment to choose between the **treatment** and **control** (conditions)

we ensure that the treatment is **independent** (exogenous) of outside influence, and that any **difference in outcomes** is due to **the effect of the intervention**

Understanding Randomization via Sampling

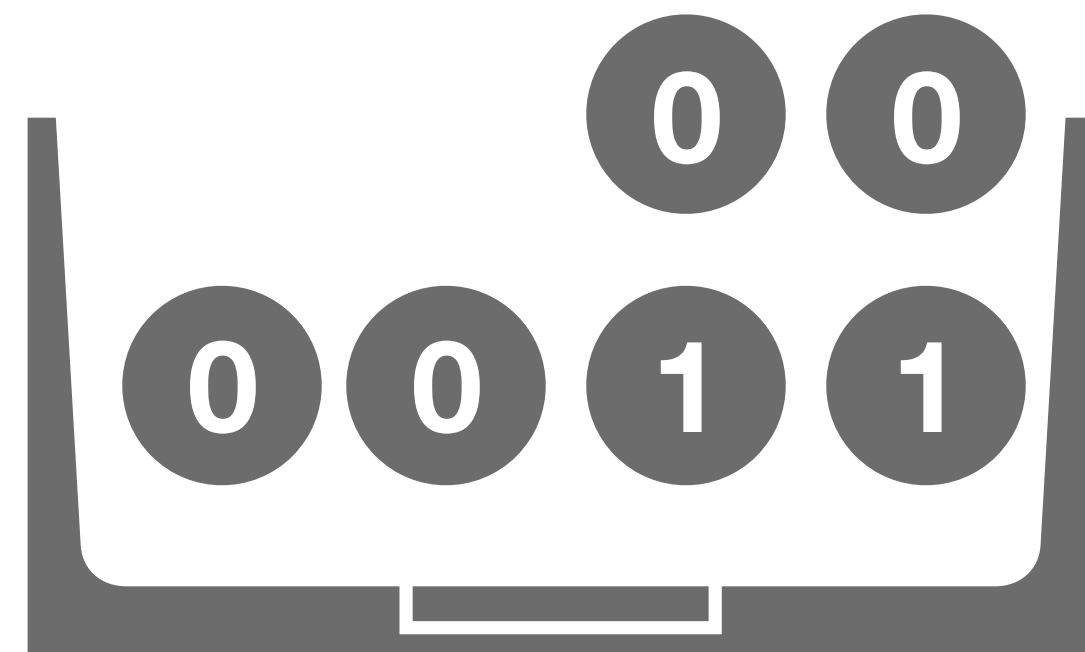
Imagine each poem has a basic potential “interactability” and that the poem-poster unconsciously allocates colors based on that factor

0 6 3 0 1 1 3 6 9 9 0 0

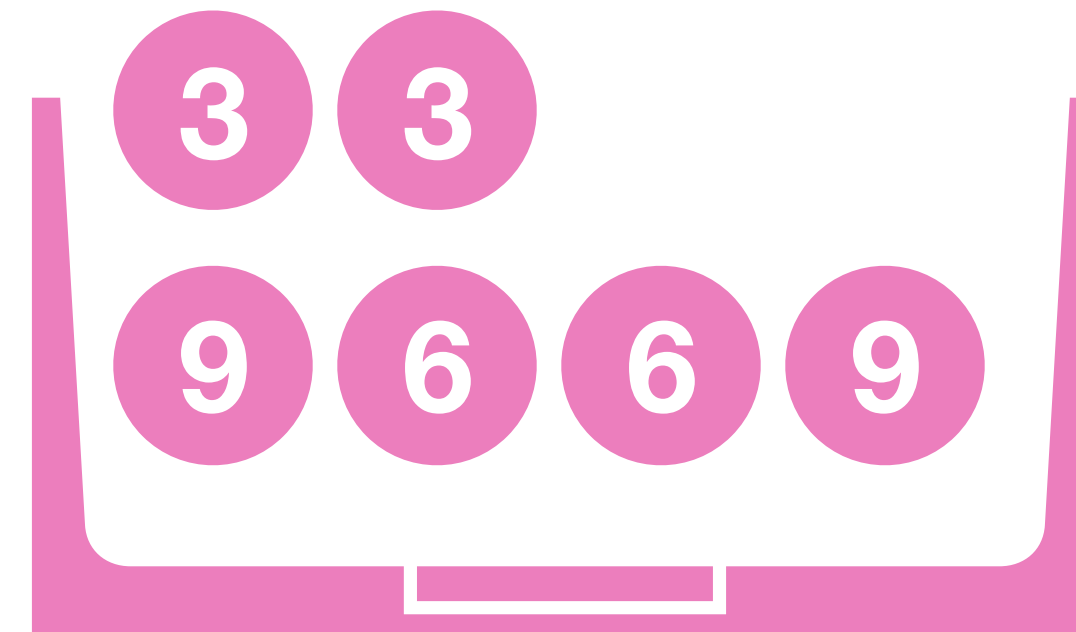


Understanding Randomization via Sampling

Imagine each poem has a basic potential “interactability” and that the poem-poster unconsciously allocates colors based on that factor



No Color
(0 interactions)



Color
(6 interactions)

Understanding Randomization via Sampling

Now imagine that we allocate poems into groups based on a random sample

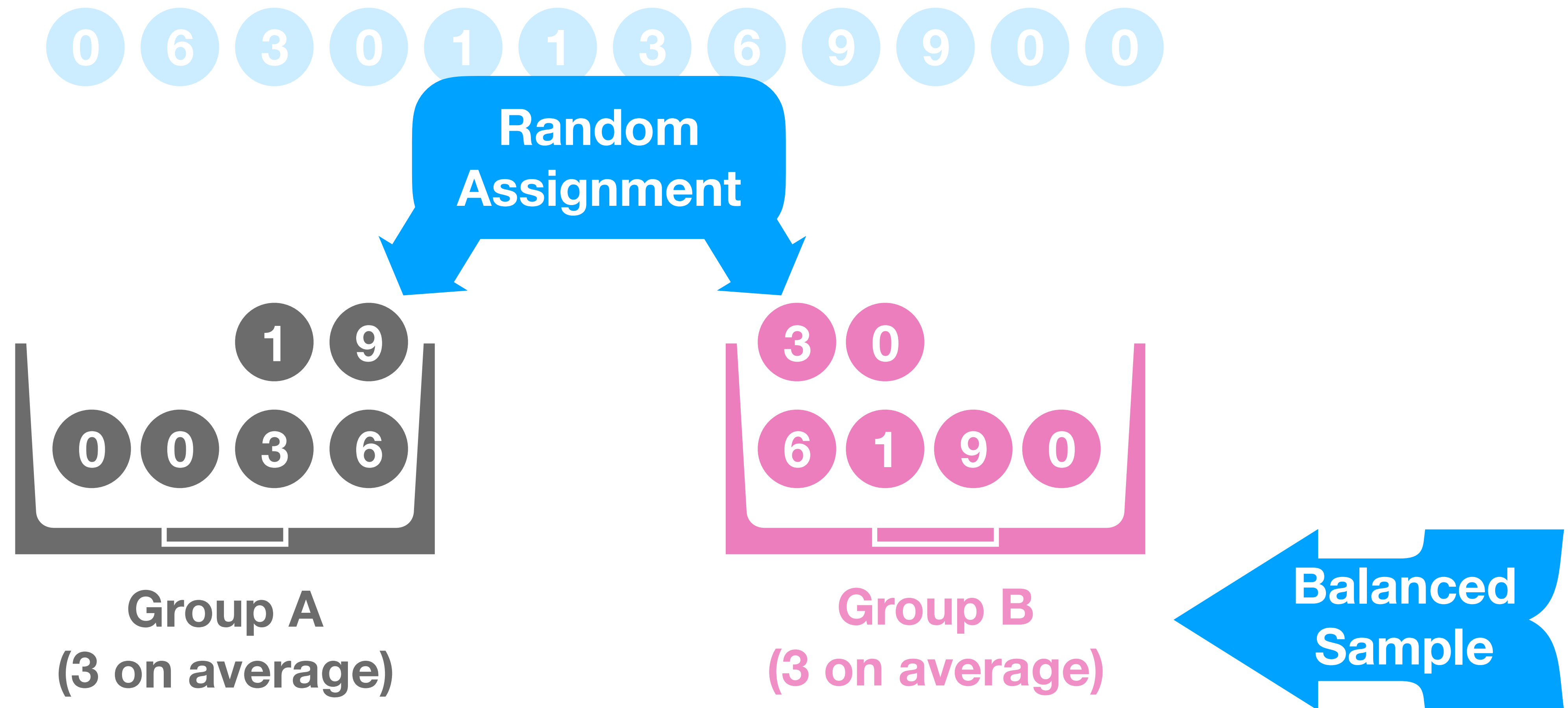
0 6 3 0 1 1 3 6 9 9 0 0

**3 interactions
on average**



Understanding Randomization via Sampling

Now imagine that we allocate poems into groups based on a random sample



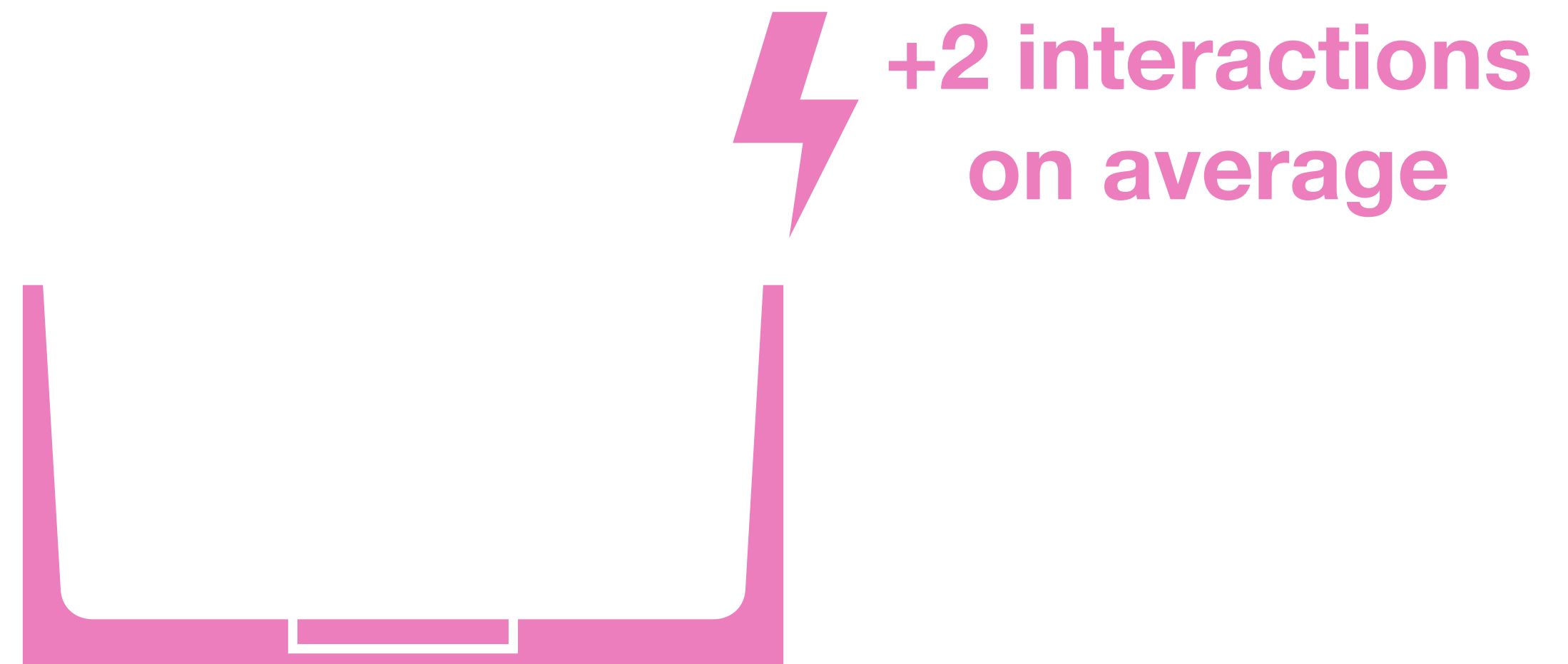
Understanding Randomization via Sampling

Now imagine that posting the colored background has an effect

0 6 3 0 1 1 3 6 9 9 0 0

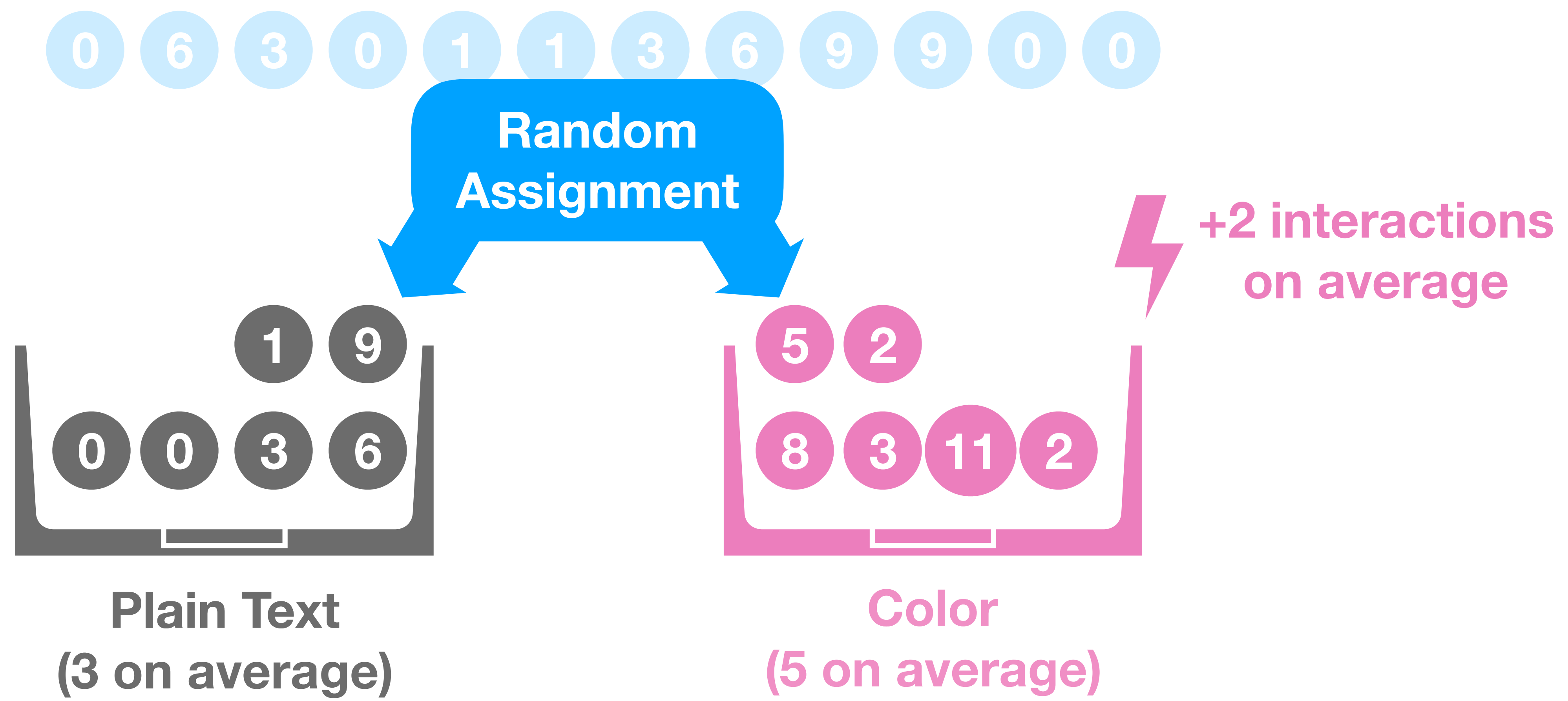


Plain Text



Understanding Randomization via Sampling

Now imagine that posting the colored background has an effect

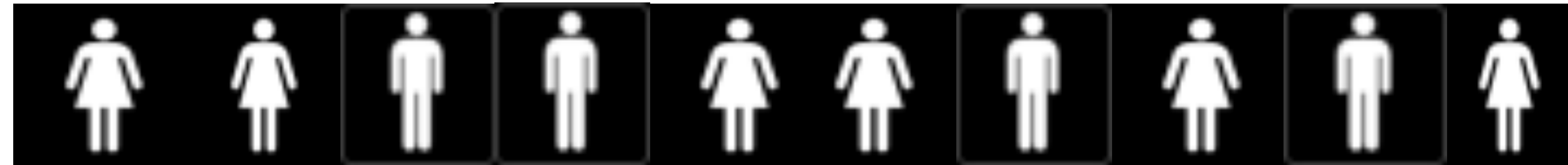


Common Methods of Random Assignment

- **Simple randomization** (coin flips)
 - Problem: it's hard to get equal groups
- **Complete** (equal groups)
 - Example: sorted lists
- **Clustered**: (by group)
 - Randomized students by randomizing schools
- **Blocked**: (within groups)

Simple Randomization

Sample:



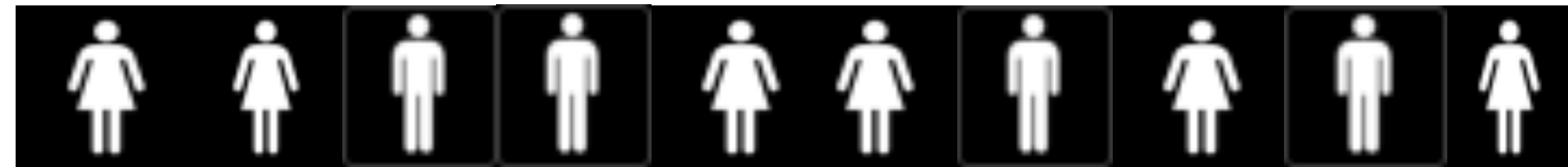
Iteration 1:



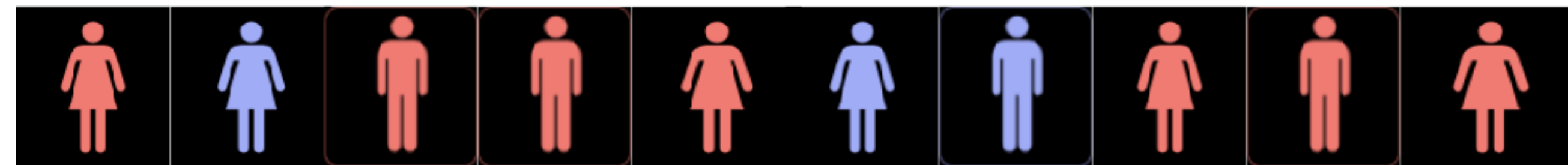
Simple Randomization

May not allocate the expected number of participants to treatment and control

Sample:



Iteration 1:



Iteration 2:

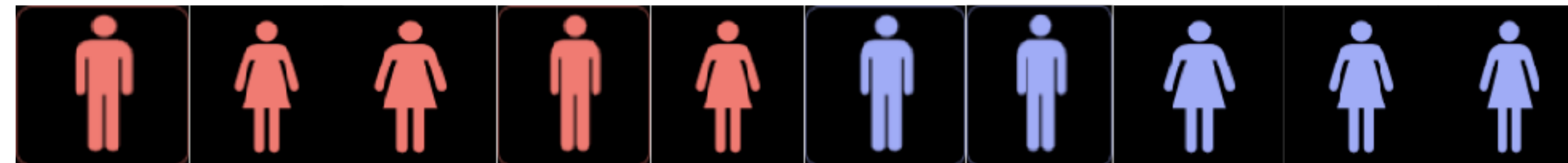


Complete Randomization

Sample:



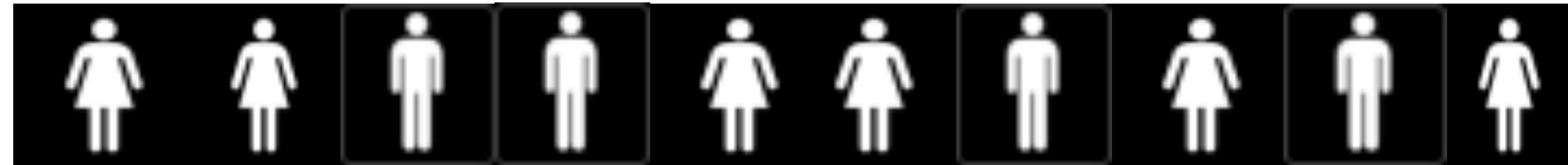
Iteration 1:



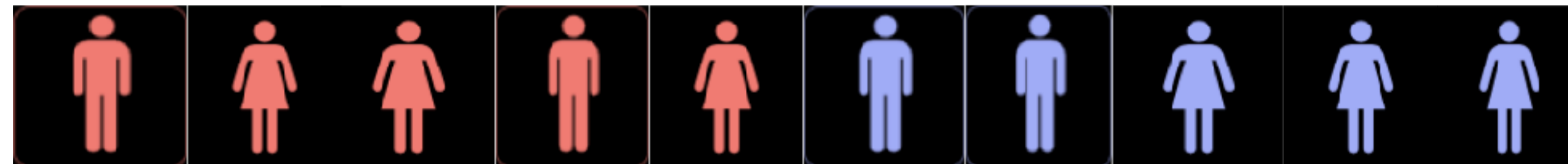
Complete Randomization

Always allocates the expected number of participants to treatment and control

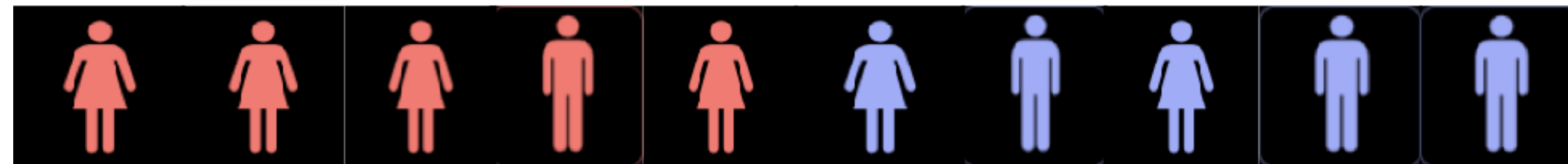
Sample:



Iteration 1:



Iteration 2:

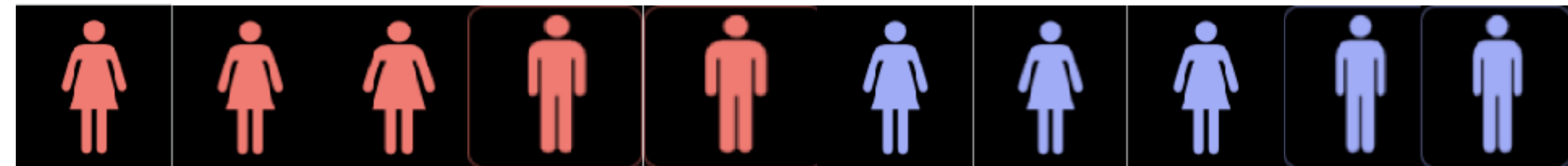


Blocked Randomization

Sample:



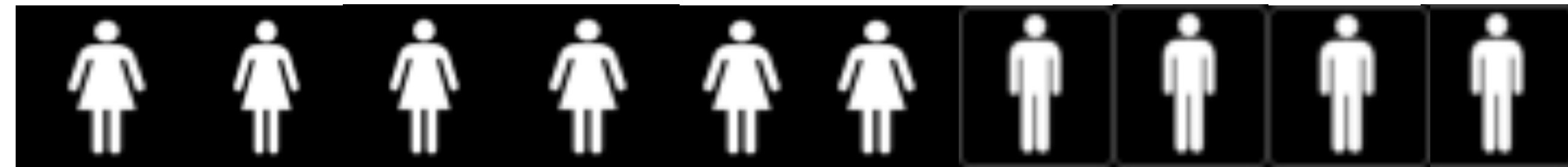
Iteration 1:



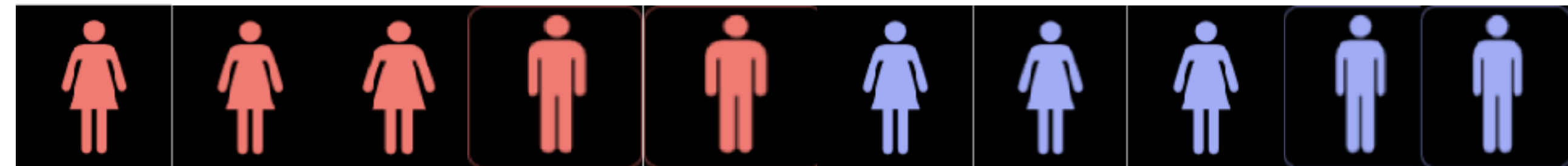
Blocked Randomization

Always maintains balance between characteristics (such as gender)

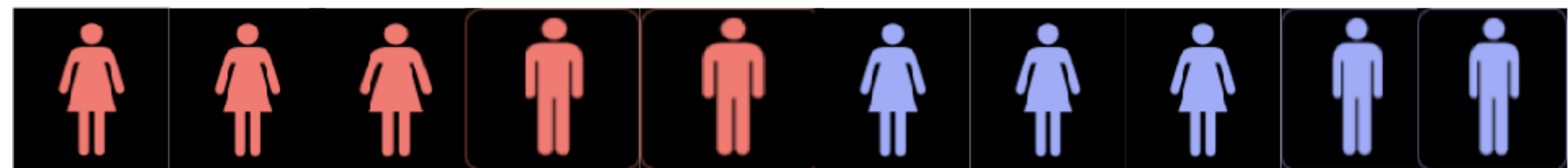
Sample:



Iteration 1:



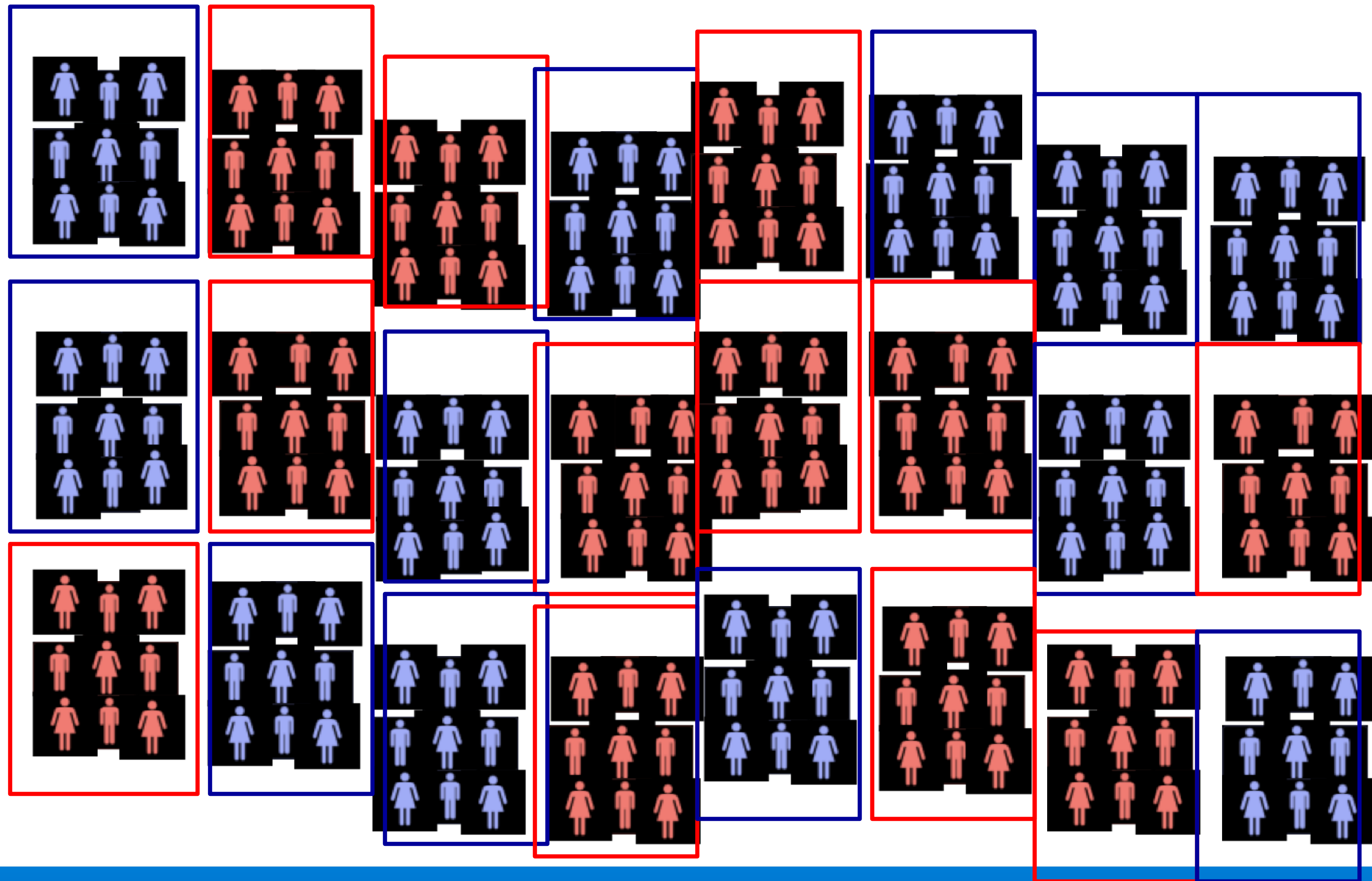
Iteration 2:



Clustered Randomization: Class



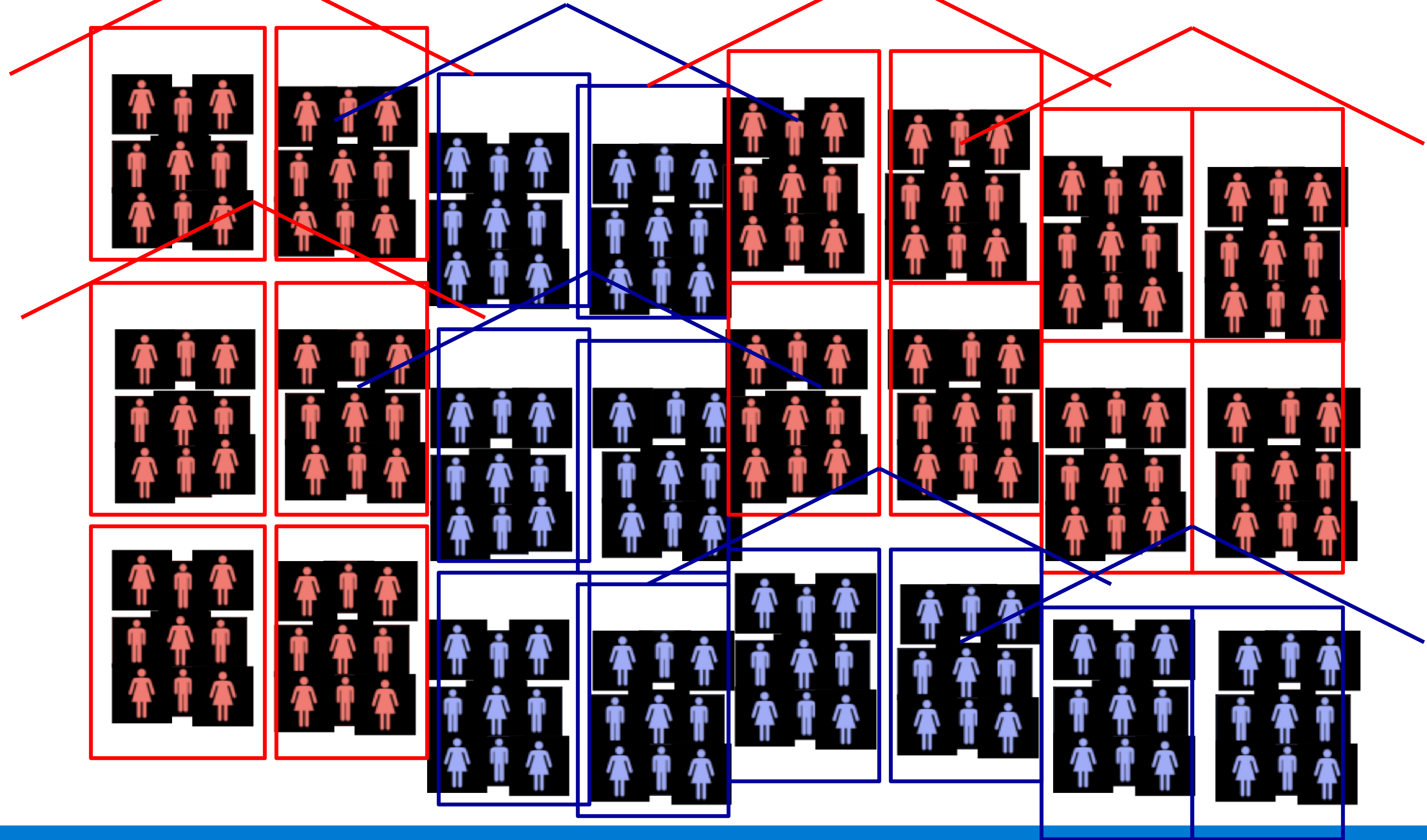
Clustered Randomization: Class



Clustered Randomization: School

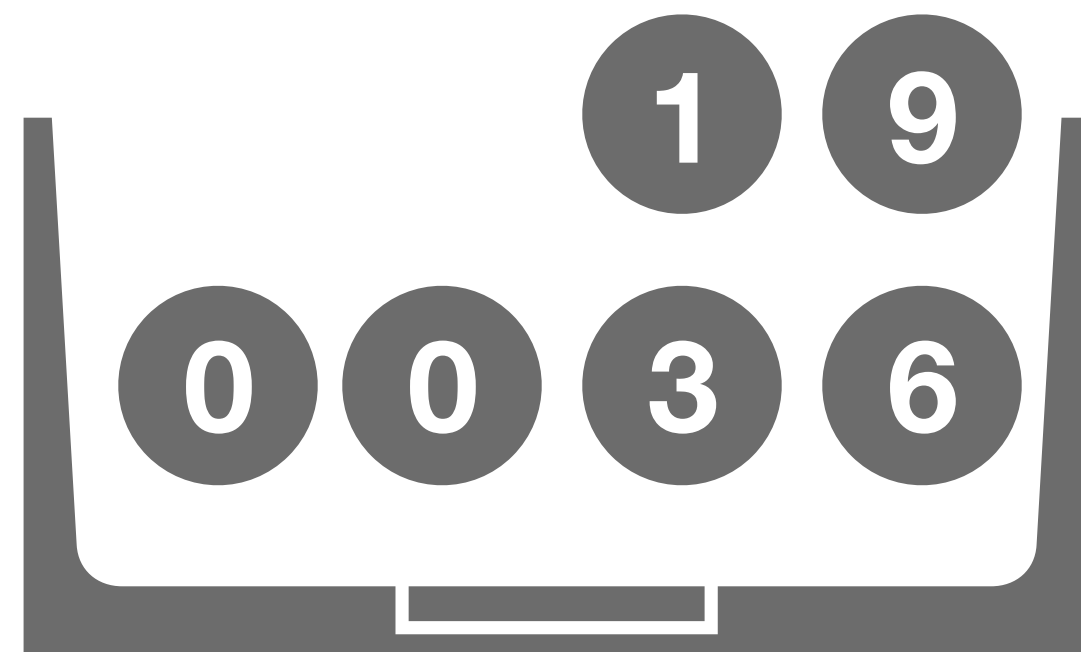


Clustered Randomization: School

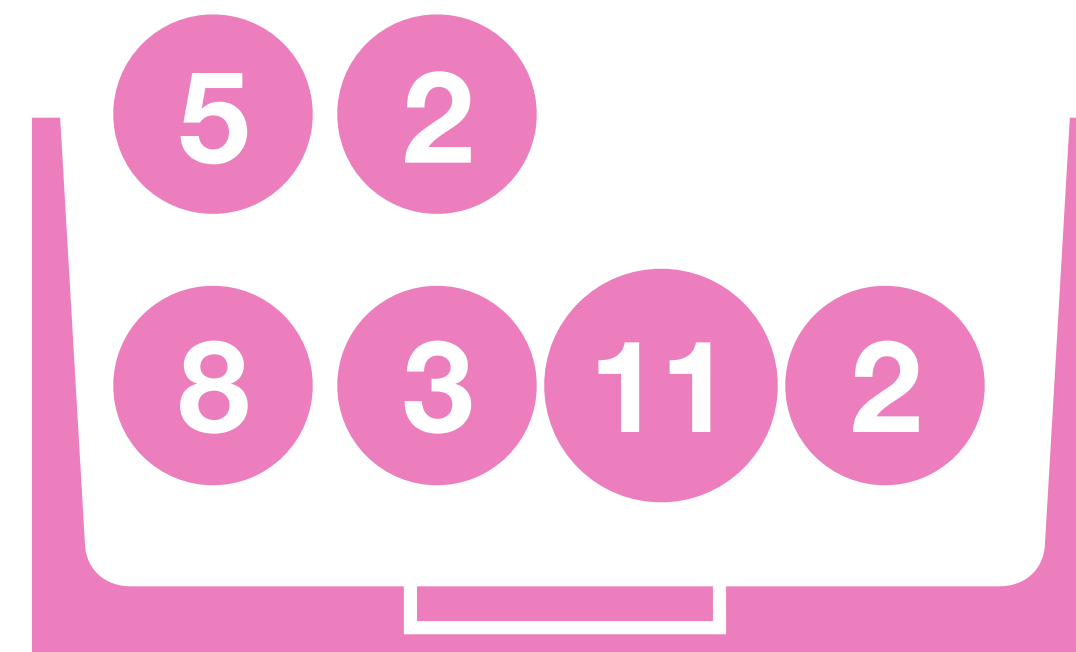


Average Treatment Effect (ATE)

 +2 interactions
on average



Plain Text
(3 on average)



Color
(5 on average)

Average Treatment Effect (ATE)

$$Y = \alpha + \beta_1 X + \epsilon$$

$$\textit{Interactions} = \alpha + \beta_1 \textit{Background} + \epsilon$$

`lm(interactions ~ condition, data=poems)`

Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)

```
Call:
lm(formula = interactions ~ condition, data = poems)

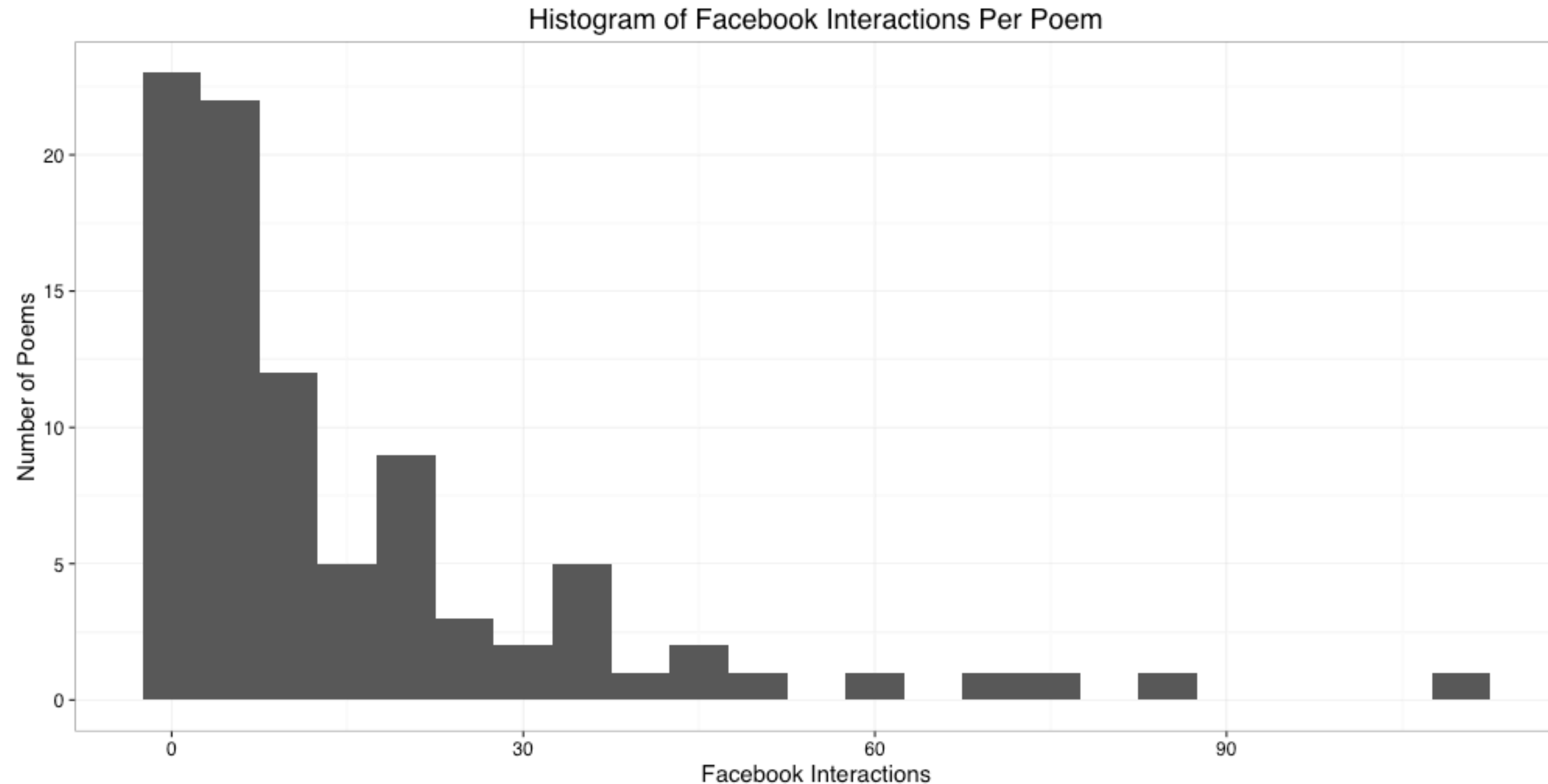
Residuals:
      Min       1Q   Median       3Q      Max
-17.578 -11.578  -8.578   3.922  99.289

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    11.711     3.008   3.893 0.000192 ***
conditionColor    7.867     4.254   1.849 0.067785 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 20.18 on 88 degrees of freedom
Multiple R-squared:  0.03741,    Adjusted R-squared:  0.02647
F-statistic: 3.42 on 1 and 88 DF,  p-value: 0.06778
```

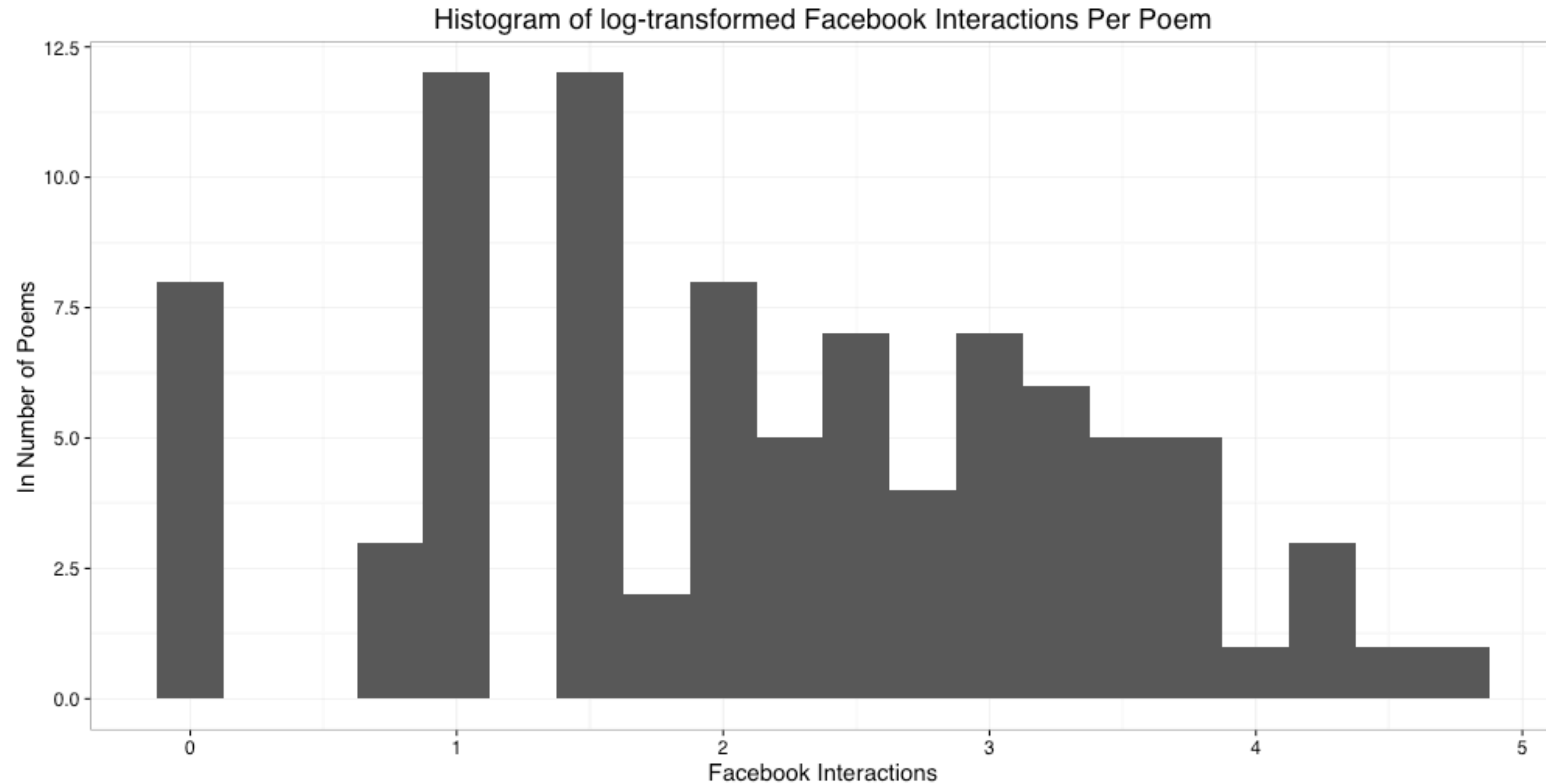
Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)



Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)



Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)

(log-transformed dependent variable)

$$\ln(\textit{Interactions} + 1) = \alpha + \beta_1 \textit{Background} + \epsilon$$

`lm(log1p(interactions) ~ condition, data=poems)`

Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)

(log-transformed dependent variable)

```
Call:
lm(formula = log1p(interactions) ~ condition, data = poems)

Residuals:
    Min       1Q   Median       3Q      Max
-1.6856 -0.5869 -0.1596  0.7456  3.0329

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    1.6856     0.1635  10.309  < 2e-16 ***
conditionColor  0.9589     0.2312   4.147 7.74e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.097 on 88 degrees of freedom
Multiple R-squared:  0.1635, Adjusted R-squared:  0.154
F-statistic: 17.2 on 1 and 88 DF,  p-value: 7.737e-05
```

Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)

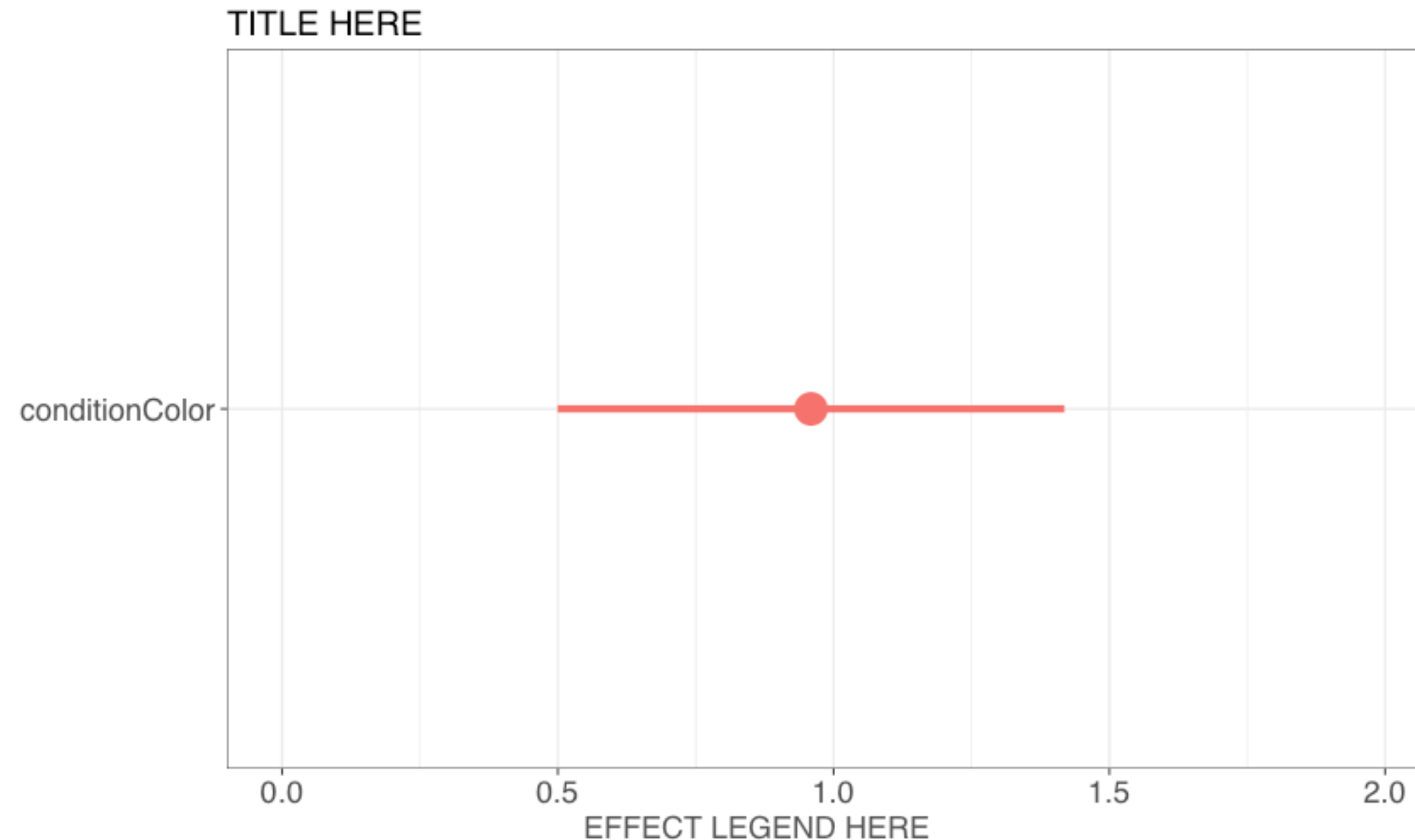
(log-transformed dependent variable)

	Linear	Log-Transformed
Color	7.87	0.96 ***
	(4.25)	(0.23)
(Intercept)	11.71 ***	1.69 ***
	(3.01)	(0.16)
R^2	0.04	0.16
Num. obs.	90	90
RMSE	20.18	1.10
Linear models estimating log-transformed likes, comments, and shares per poem		

Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

Average Treatment Effect (ATE)

(log-transformed dependent variable)



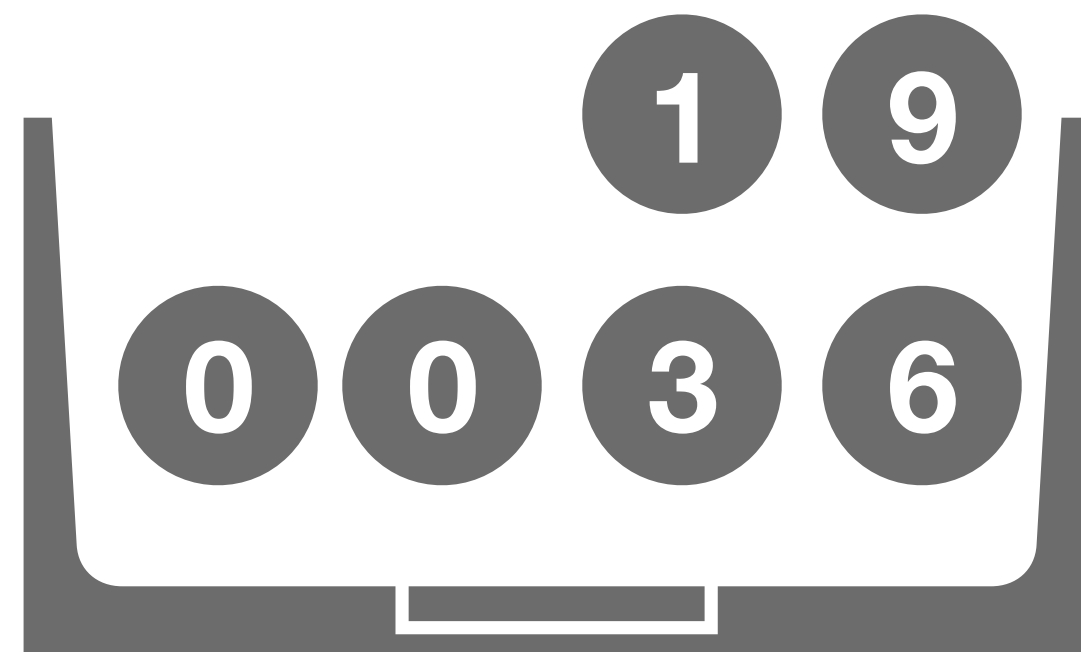
This line indicates....
(n = 90 poems published from 2017-01-01 to 2017-03-31
by NAME A, NAME BY

Example at github.com/natematias/SOC412/tree/master/1-facebook-poem

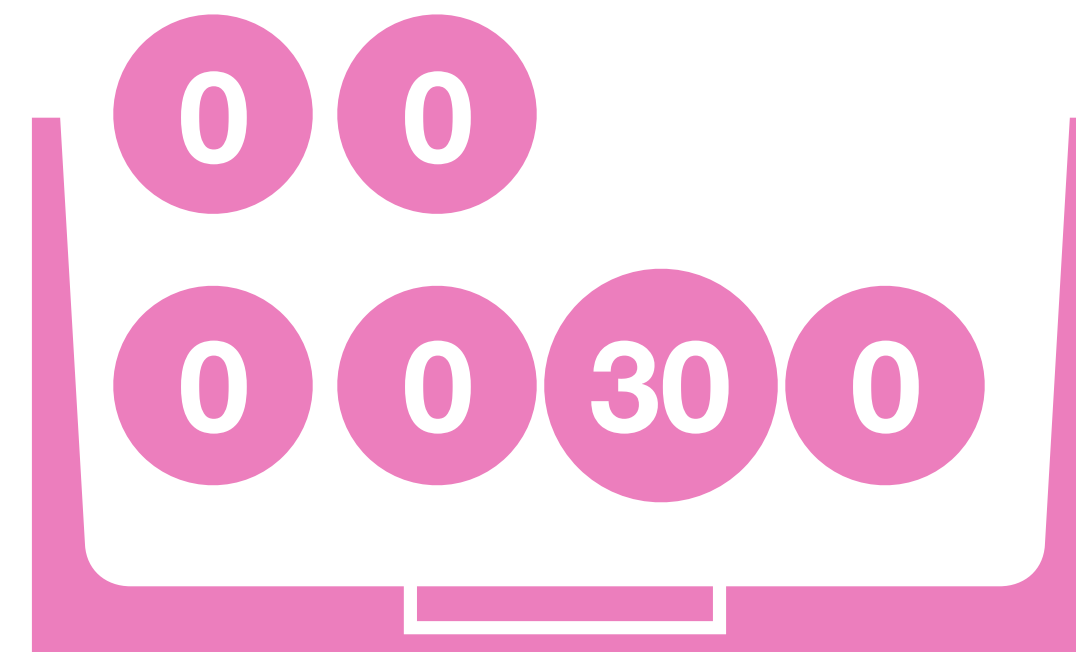
Average Treatment Effect (ATE)

APPLIES TO POPULATIONS **NOT TO INDIVIDUALS**

 +2 interactions
on average



Plain Text
(3 on average)



Color
(5 on average)

Assumptions of ATE

- **Random assignment** of participants to treatment
 - implies that receiving the treatment is statistically independent of participants' potential outcomes
- **Non-interference**: a participant's potential outcomes reflect only whether they receive the treatment themselves (not by others receiving it)

Assumptions of ATE

- **Excludability** a participant's potential outcomes respond only to the defined treatment, not other extraneous factors that may be correlated with treatment
- importance of defining the treatment precisely and maintaining symmetry between treatment and control groups (e.g. through blinding)

Conspicuously Absent Assumptions

- Random sampling of subjects from a larger population is not a core assumption
- The issue of “external validity” is a separate question that relates to the issue of whether the results obtained from a given experiment apply to other subjects, treatments, contexts, and outcomes
- For now, we aim only to estimate the ATE in our subject pool