Randomized Trials (SOC 412)

Week 1 Lecture 2

Sherrerd Hall 306

J. Nathan Matias

@natematias

civilservant.io

jmatias@princeton.edu

Department of Psychology

PRINCETON UNIVERSITY

CITP

mit media lab

What we will cover today

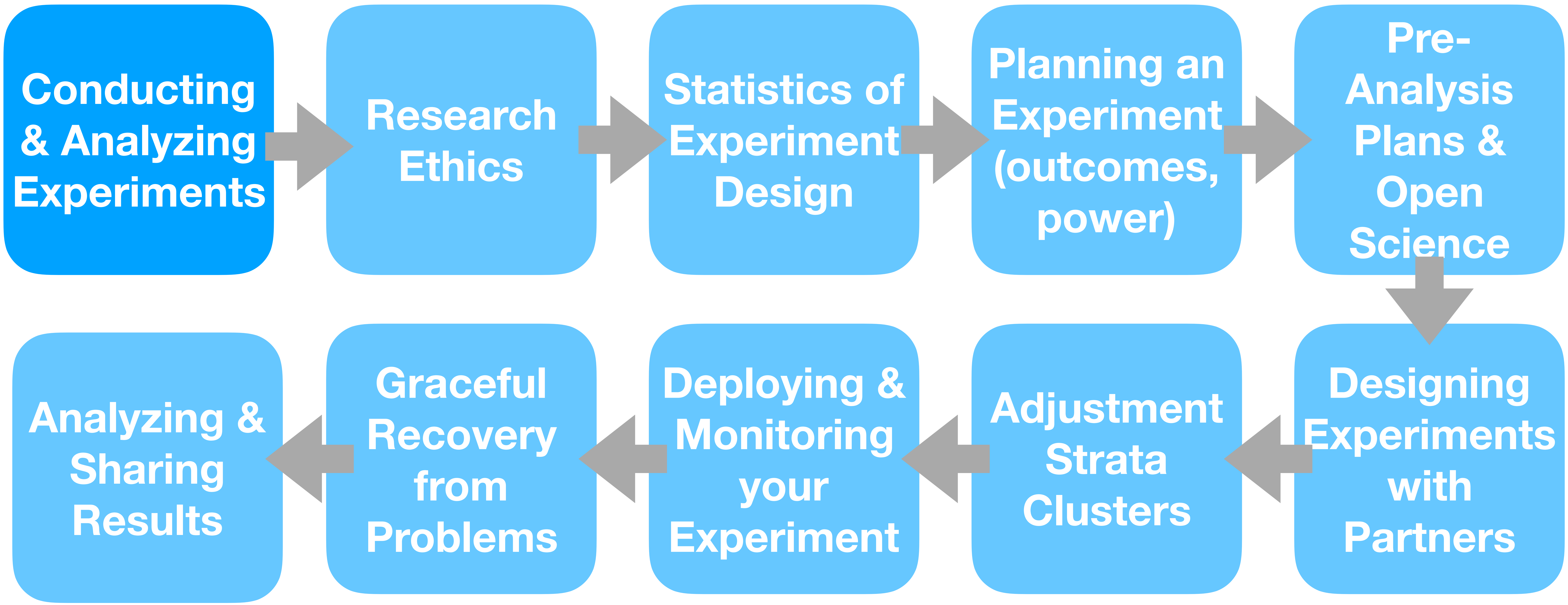
Discuss reading

Introduction to randomized trials

Discuss assignment

Questions about Assignments

- Project Assignments: Due Tuesday 9pm


Conducting & Analyzing Experiments
Research Ethics
Statistics of Experiment Design
Planning an Experiment (outcomes, power)
Pre-Analysis Plans & Open Science
Designing Experiments with Partners
Adjustment Strata Clusters
Deploying & Monitoring your Experiment
Graceful Recovery from Problems
Analyzing & Sharing Results

ARCHIVES | 2002

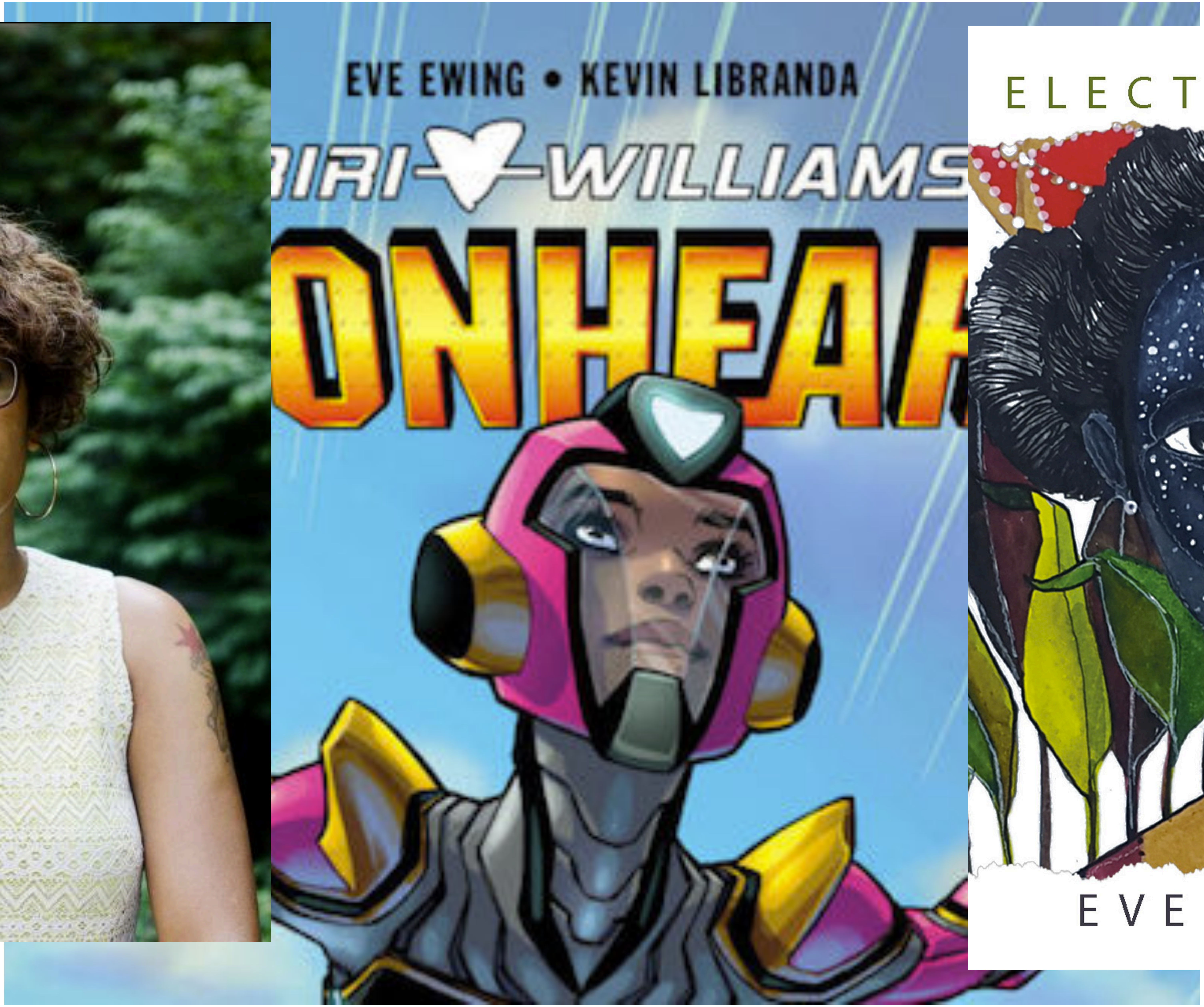
Lilly Heir Makes $100 Million Bequest to Poetry Magazine

By STEPHEN KINZER NOV. 19, 2002

An ailing heir who tried but failed to have her poems published in a small literary journal has given that journal an astonishing bequest that is likely to be worth more than $100 million.

Ruth Lilly, 87, an heir to the Eli Lilly pharmaceutical fortune, submitted several poems to Poetry magazine in the 1970's and was rewarded only with handwritten rejection notes from the editor, Joseph Parisi. Evidently she did not take the rejections to heart. Mr. Parisi announced her gift at the magazine's 90th-anniversary dinner on Friday.

"Its a real mind-blower," said the United States' poet laureate, Billy Collins, who was at the dinner. "Poetry has always had the reputation as being the poor little match girl of the arts. Well, the poor little match girl just hit the lottery."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POETRY FOUNDATION

POEM OF THE DAY

And Day Brought Back My Night

BY GEOFFREY BROCK

COLLECTION

Celebrating Black History Month

COLLECTION

An Introduction to the Harlem Renaissance

PROSE FROM *POETRY* MAGAZINE

From "Fiends Fell"

BY TOM PICKARD

A diary of a secluded place.

How should the Poetry Foundation Share Poetry On Facebook?

Reviewing Historical Data (Simulated)

```r
head(all.poems[c("author", "title", "sim.interactions",  "length",  "name.sex", "color")], 15)
```

author	title	sim.interactions	length	name.sex	color
Aaron Shurin	The Bride of Frank	100	12	male	TRUE
Aaron Shurin	Plume	32	856	male	TRUE
Aaron Poochigian	The Vigil	34	147	male	TRUE
Aaron Shurin	Cool Dust	12	1082	male	FALSE
Aaron Shurin	Then	39	1552	male	FALSE
Abid B Al-Abras	Last Simile	13	554	male	TRUE
Abigail Deutsch	Twenty-Two	60	803	female	TRUE
Abigail Deutsch	After the Disaster	25	814	female	TRUE
Abraham Cowley	Platonic Love	17	1077	male	FALSE
Abraham Lincoln	To Rosa	50	277	male	TRUE

Reviewing Historical Data (Simulated)

```
## SHOW THE DIFFERENCE IN MEANS
aggregate(sim.interactions ~ color,
          data=all.poems, mean)
```

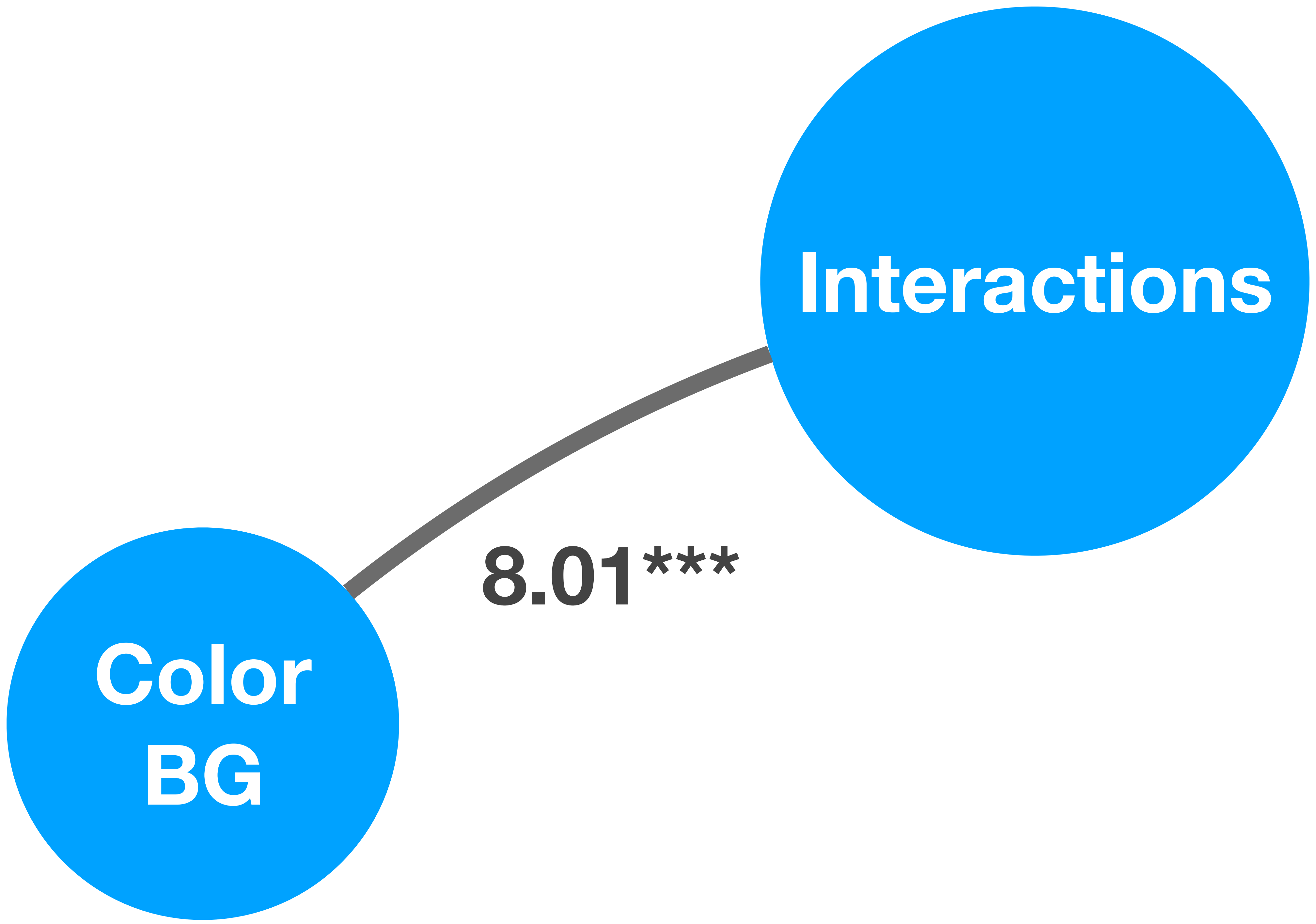
color	sim.interactions
FALSE	25.75
TRUE	33.76

Reviewing Historical Data (Simulated)

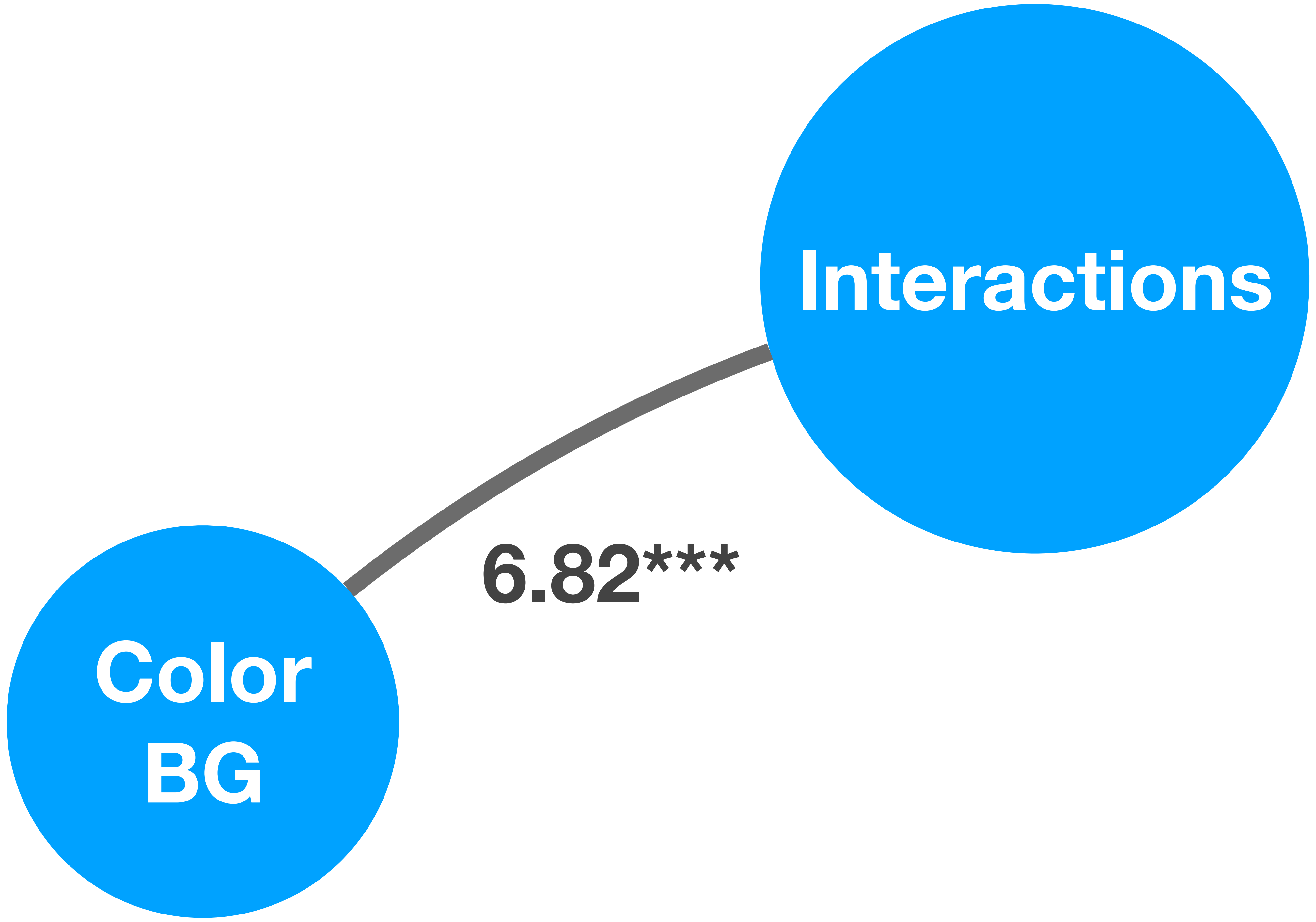
```r
## CONDUCT A T-TEST BETWEEN COLOR AND PLAIN
print(t.test(all.poems$sim.interactions ~ all.poems$color))
```

```
        Welch Two Sample t-test

data:  all.poems$sim.interactions by all.poems$color
t = -26, df = 11000, p-value <2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -8.621 -7.393
sample estimates:
mean in group FALSE  mean in group TRUE
              25.75               33.76
```

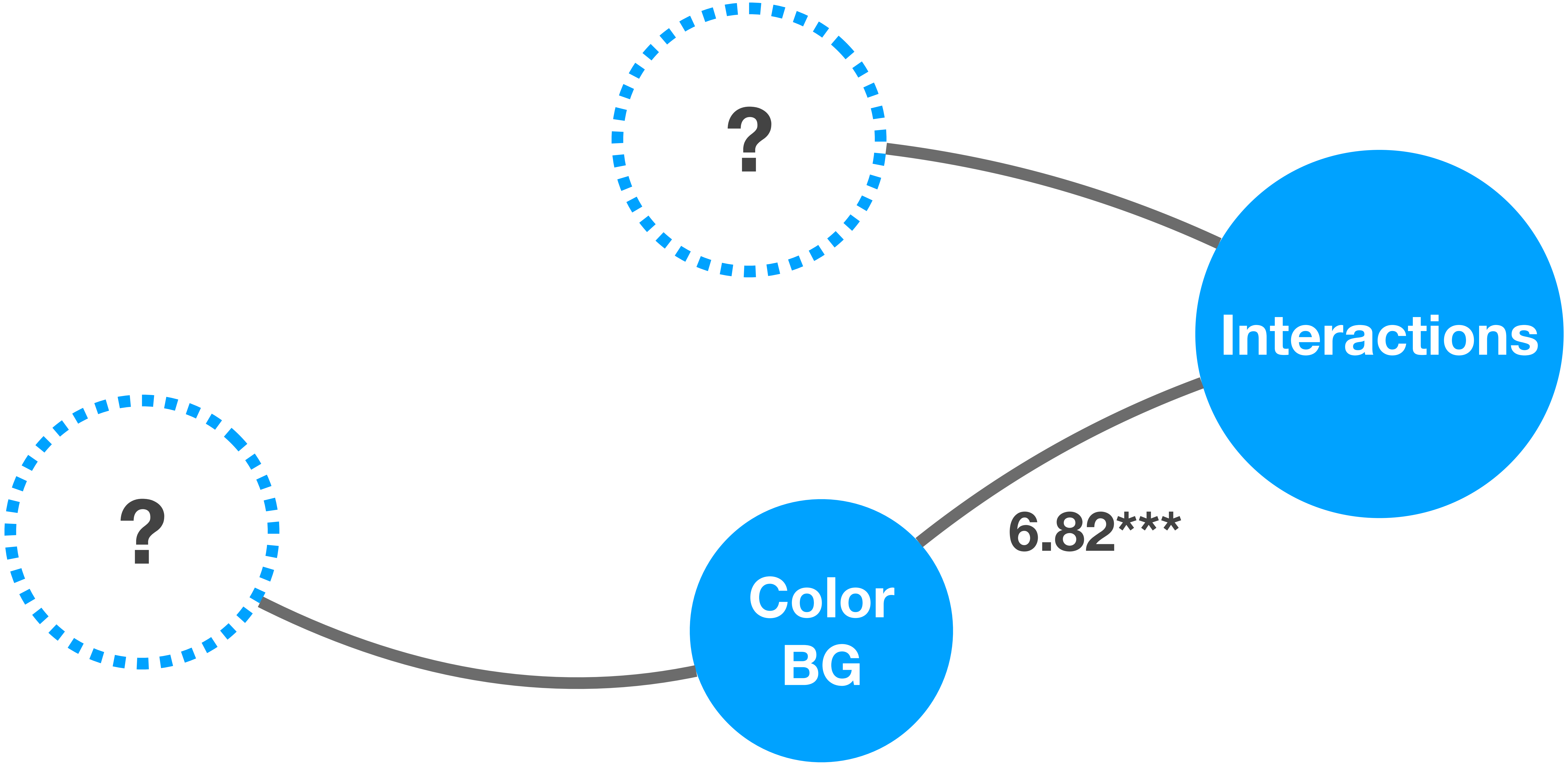
Path Diagram



What Do We Mean by Correlation != Causation?



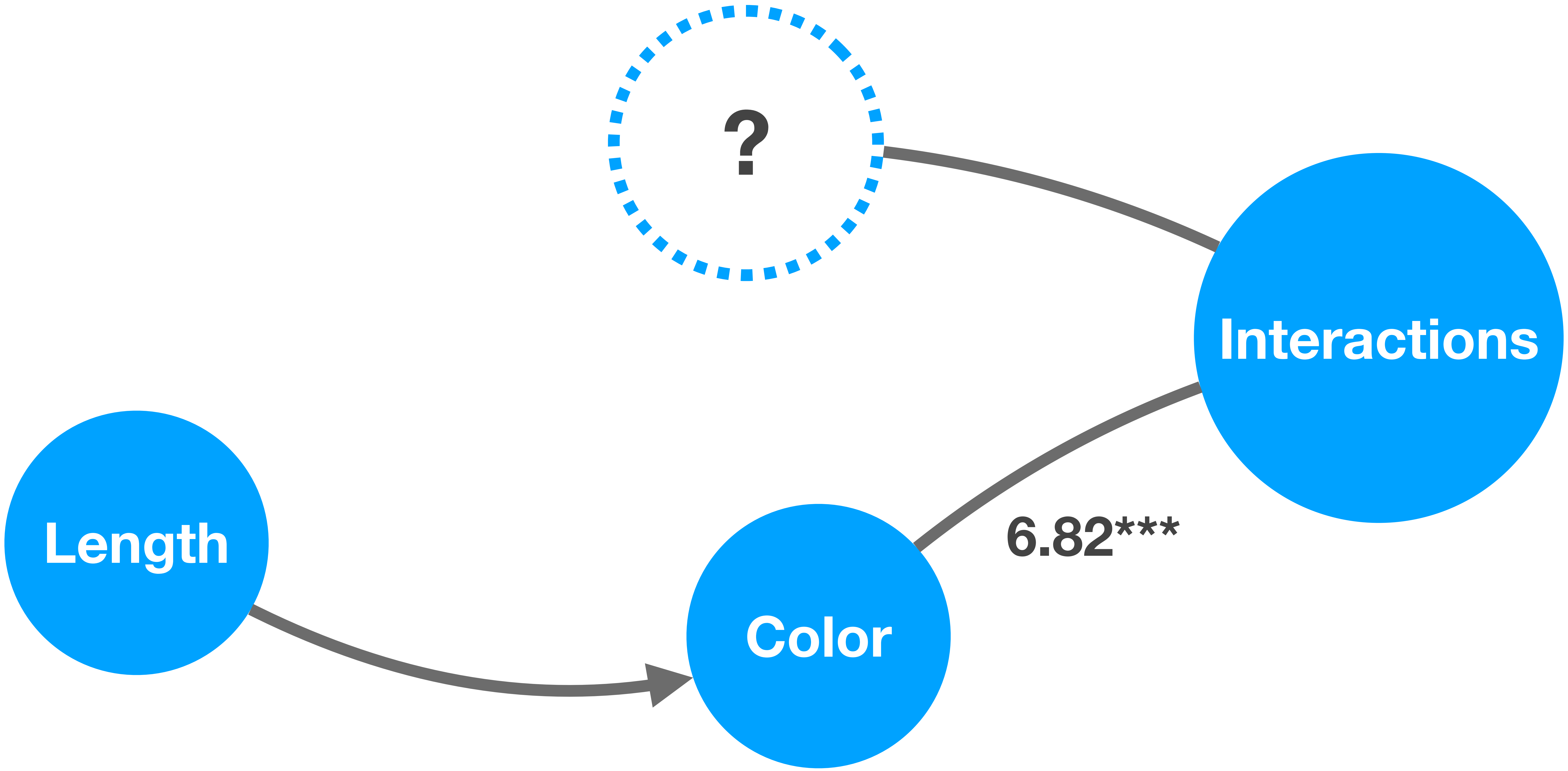
Unobserved Confounders



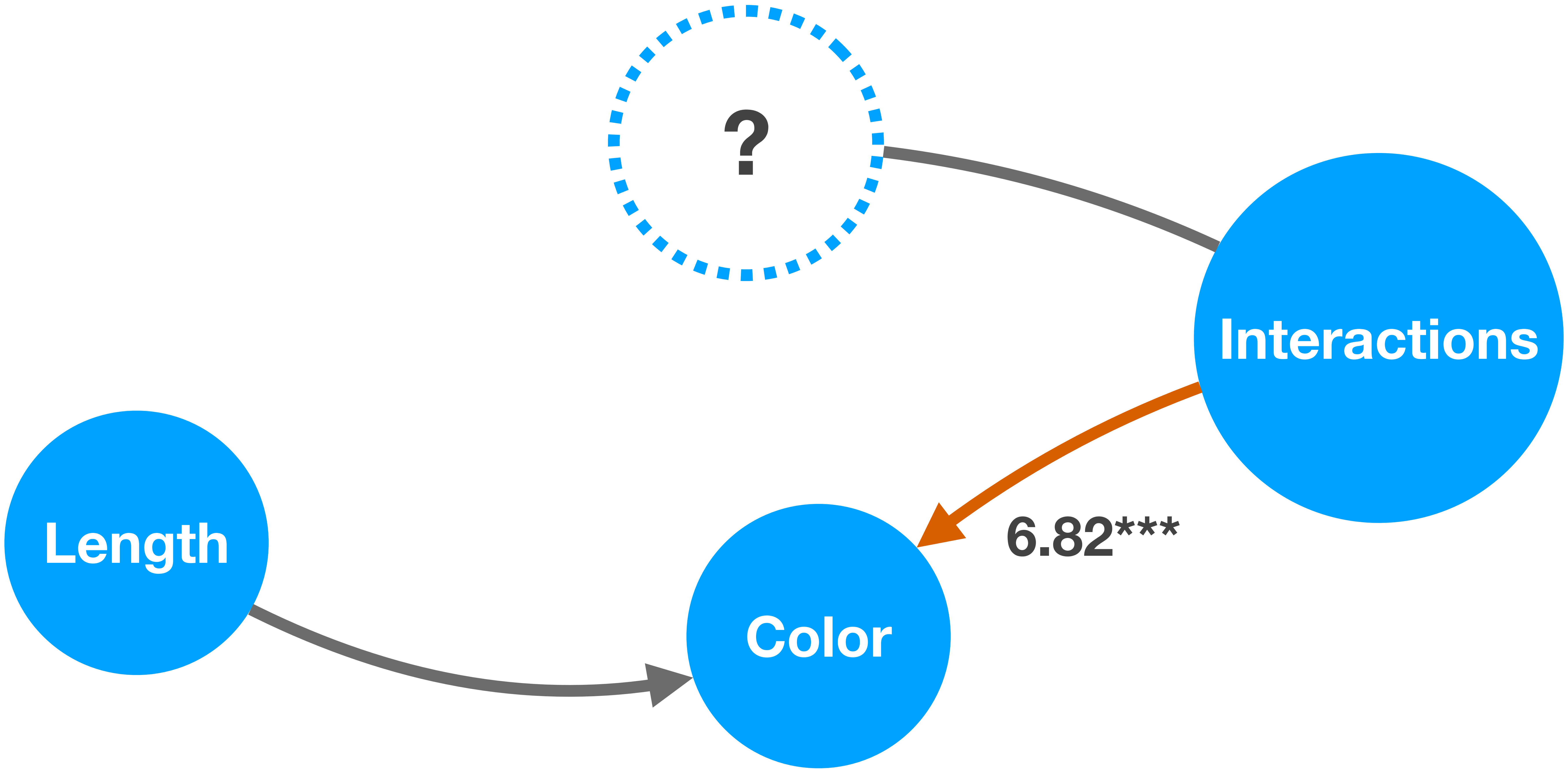
Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among US adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, *6*(1), 3-17.

Problem: Facebook Has a Character Limit for Color Backgrounds

Confounder: Longer Poems are Less Popular, and Longer Poems Can't Have Color BGs



Direction of Causality



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)

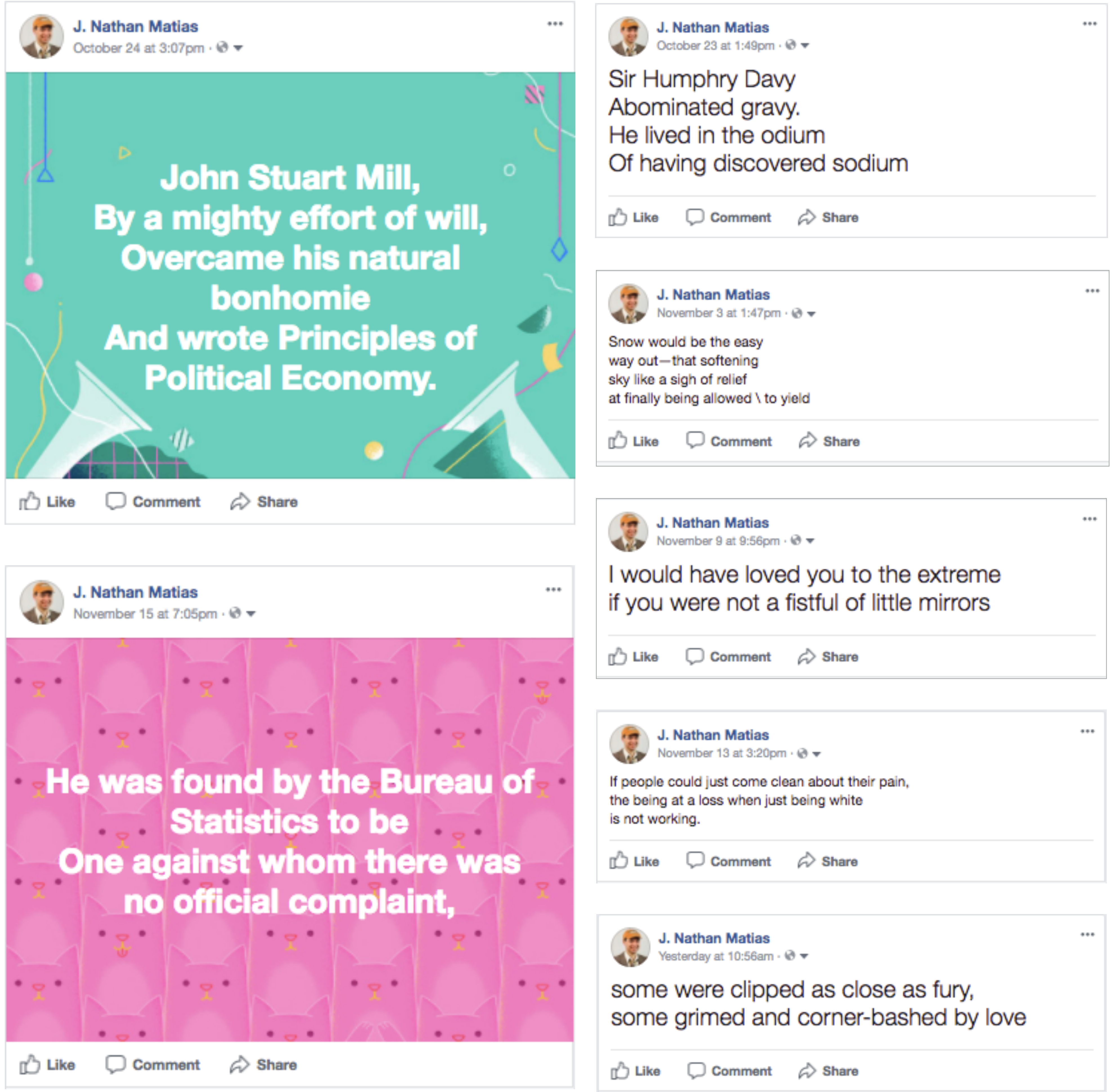
“ When the skies opened and **dumped $185 million on an obscure Chicago poetry journal** in 2002, it was as much a burden as a gift…

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

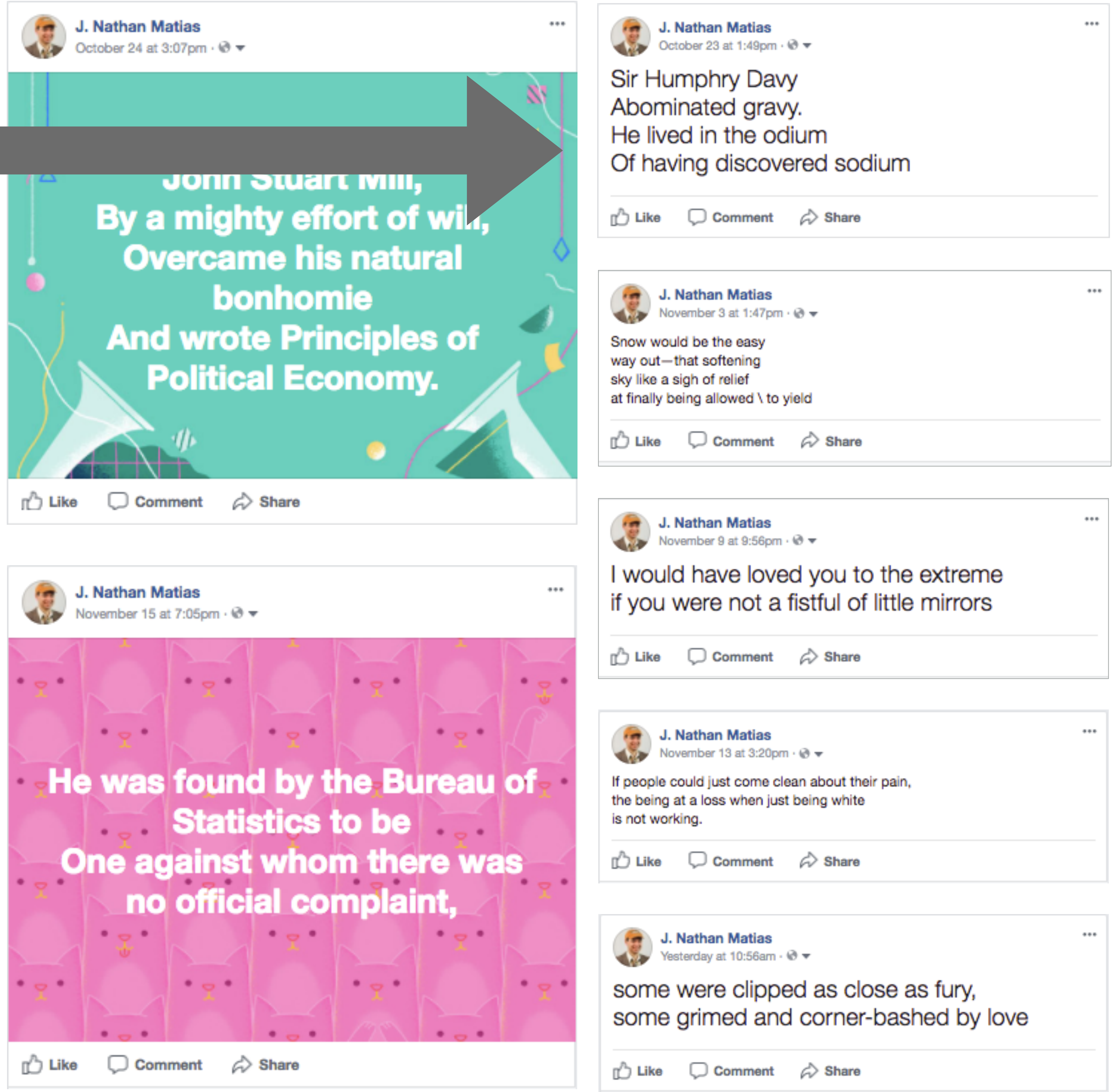
Background Color

?

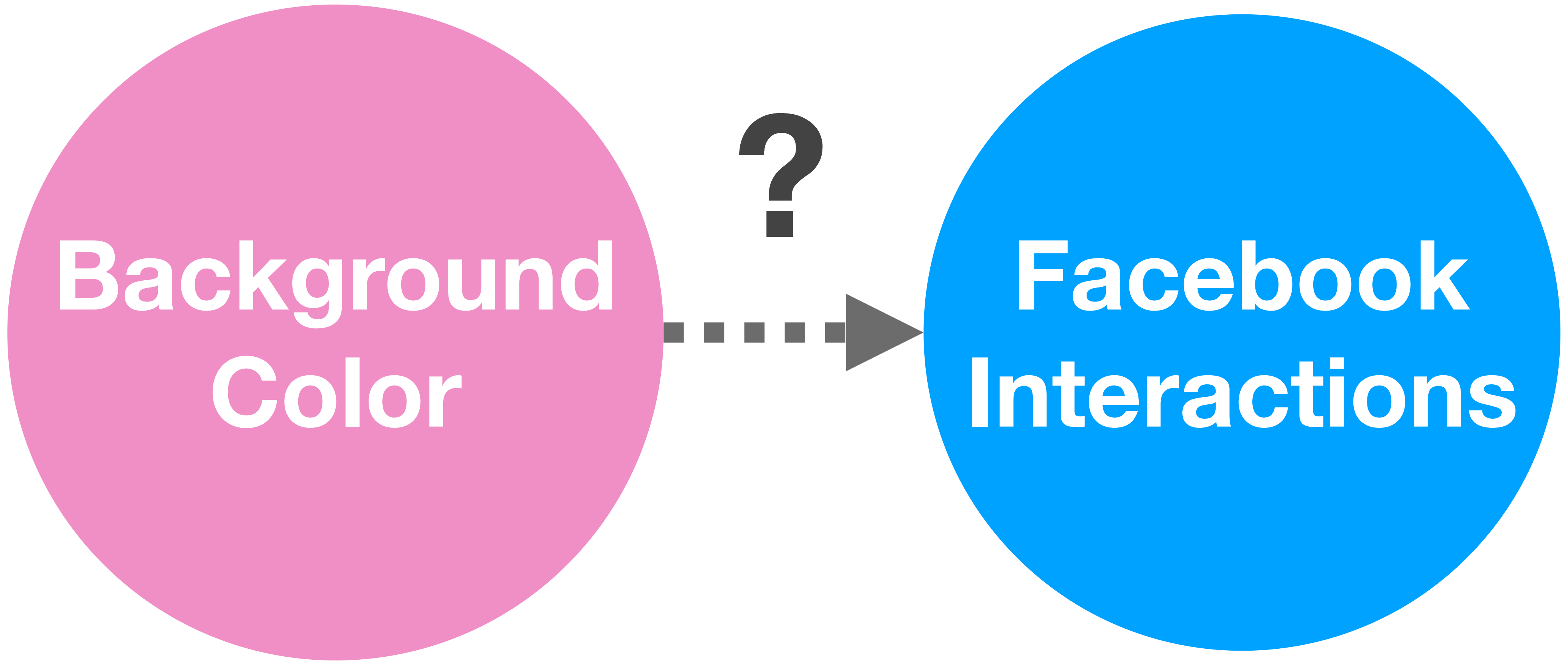
Comparison
(control)
(placebo)

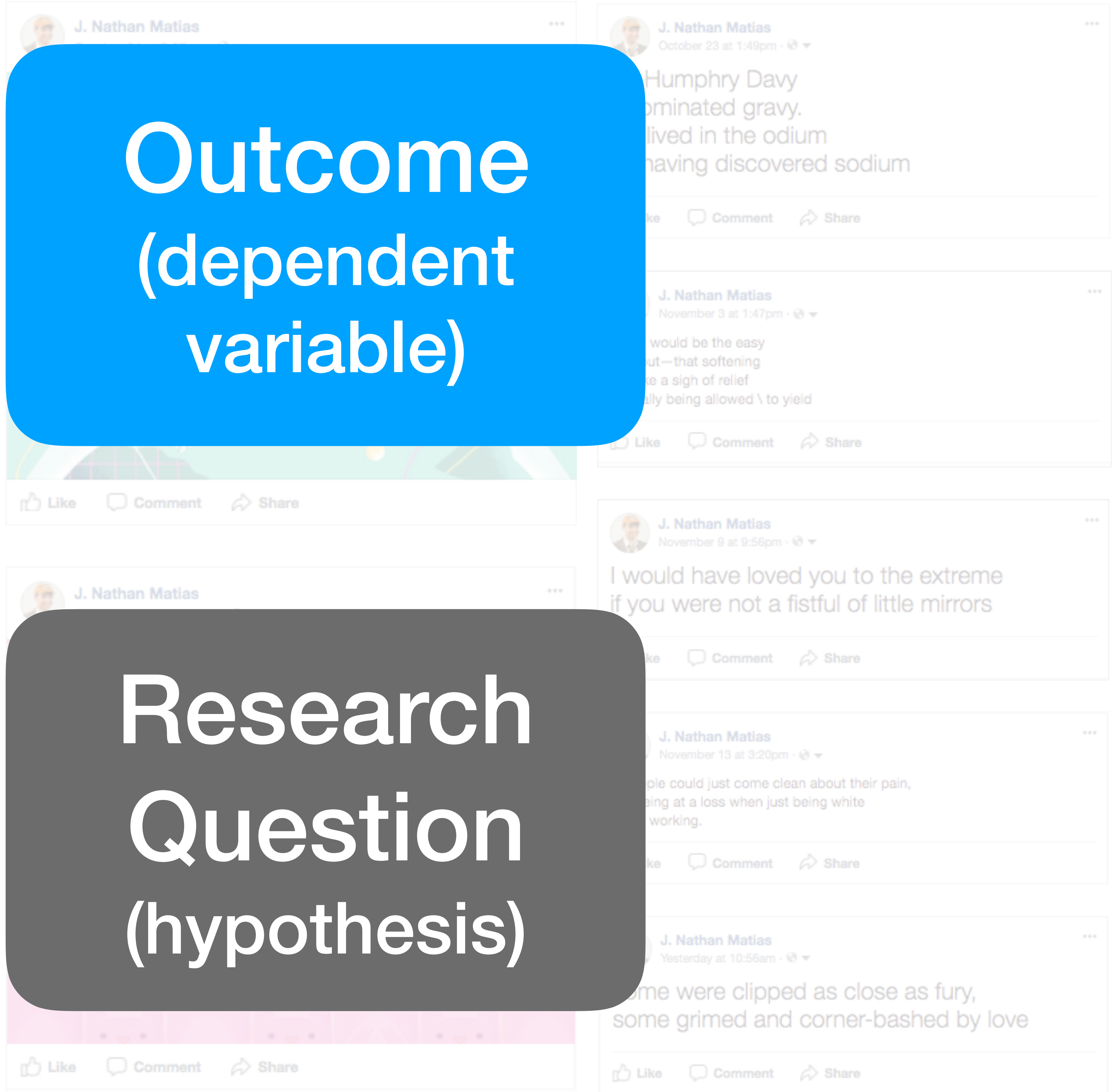
1. Does A Colored Background Increase Facebook Interactions on average?
2. If so, by how

Intervention
(treatment)



Parts of an Experiment

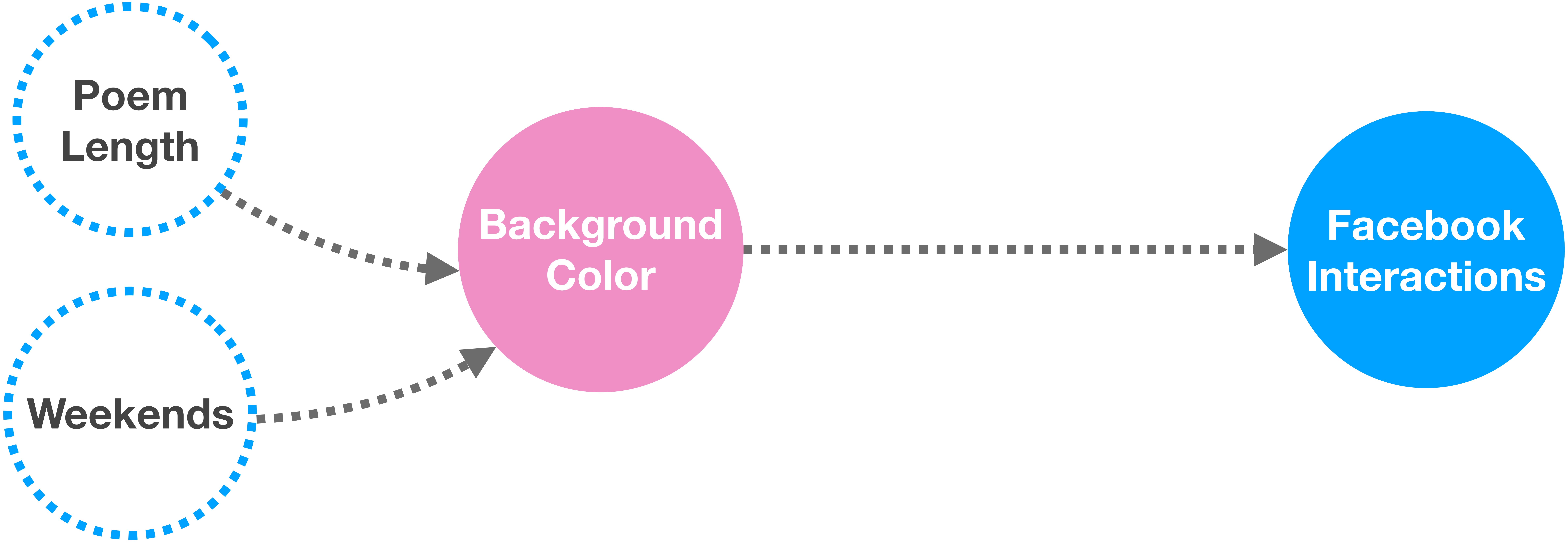




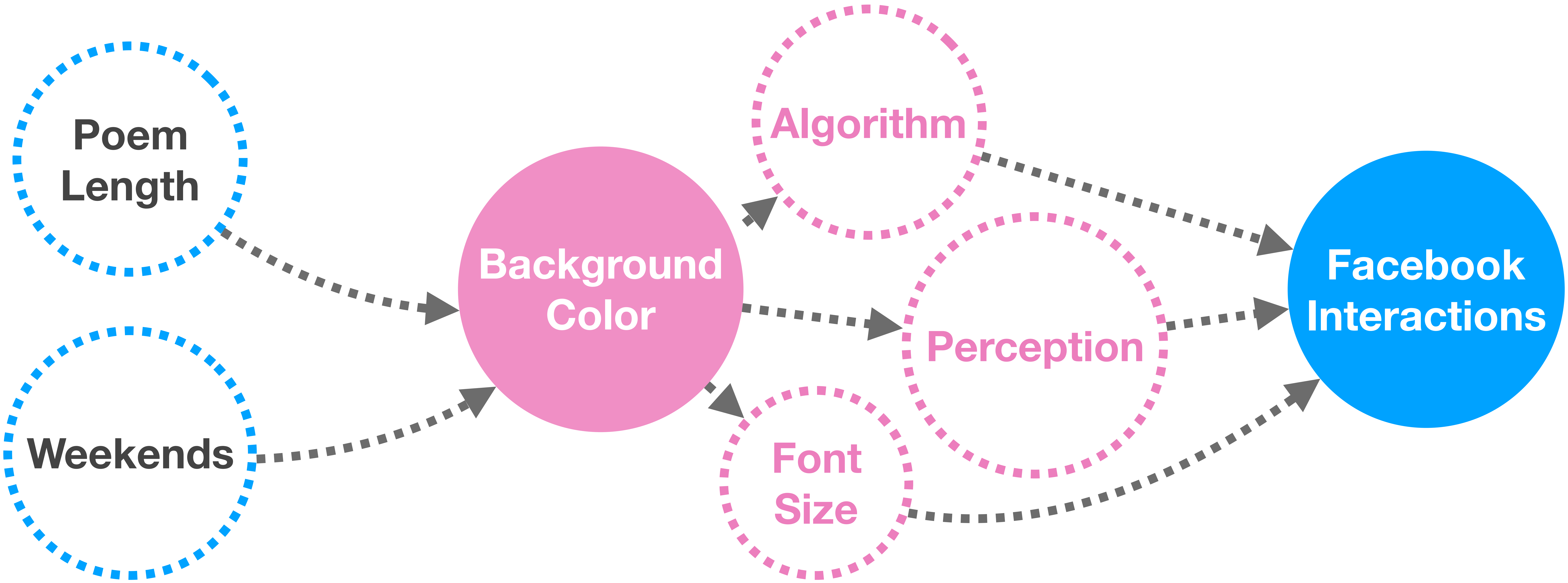
1. Does A Colored Background **Increase** Facebook Interactions on average?
2. If so, **by how much** on average?

Unobserved Confounders

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

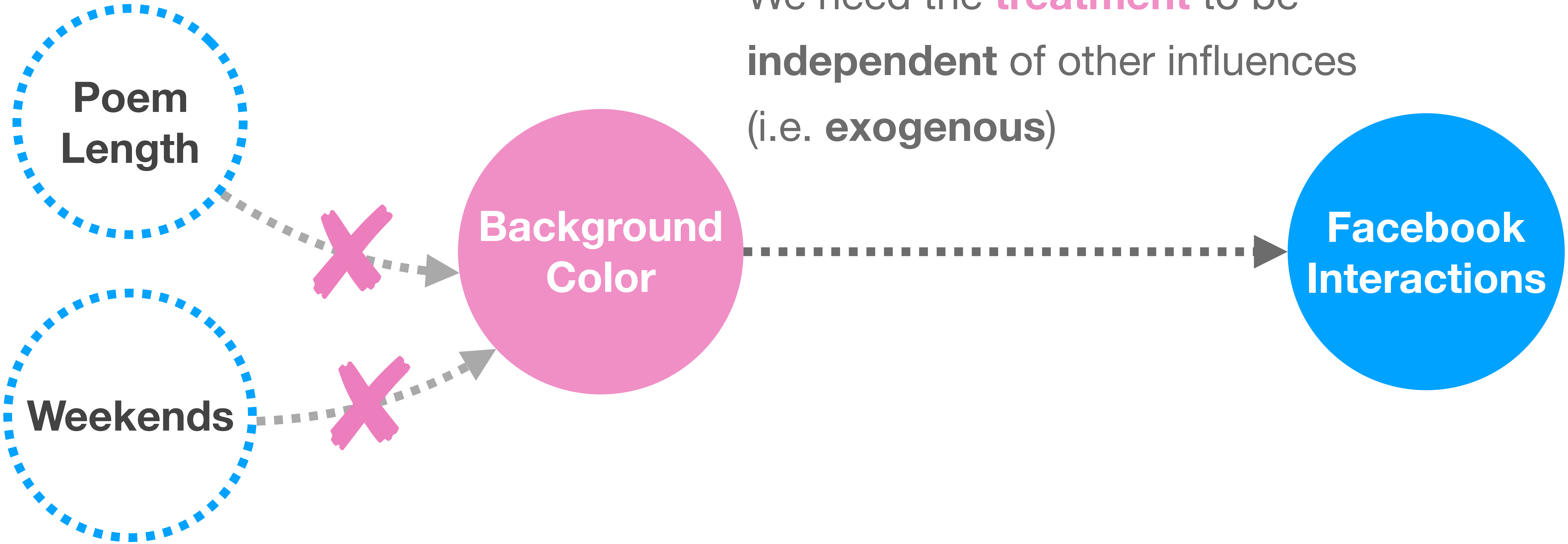


Unobserved Confounders



Independence of the Treatment

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



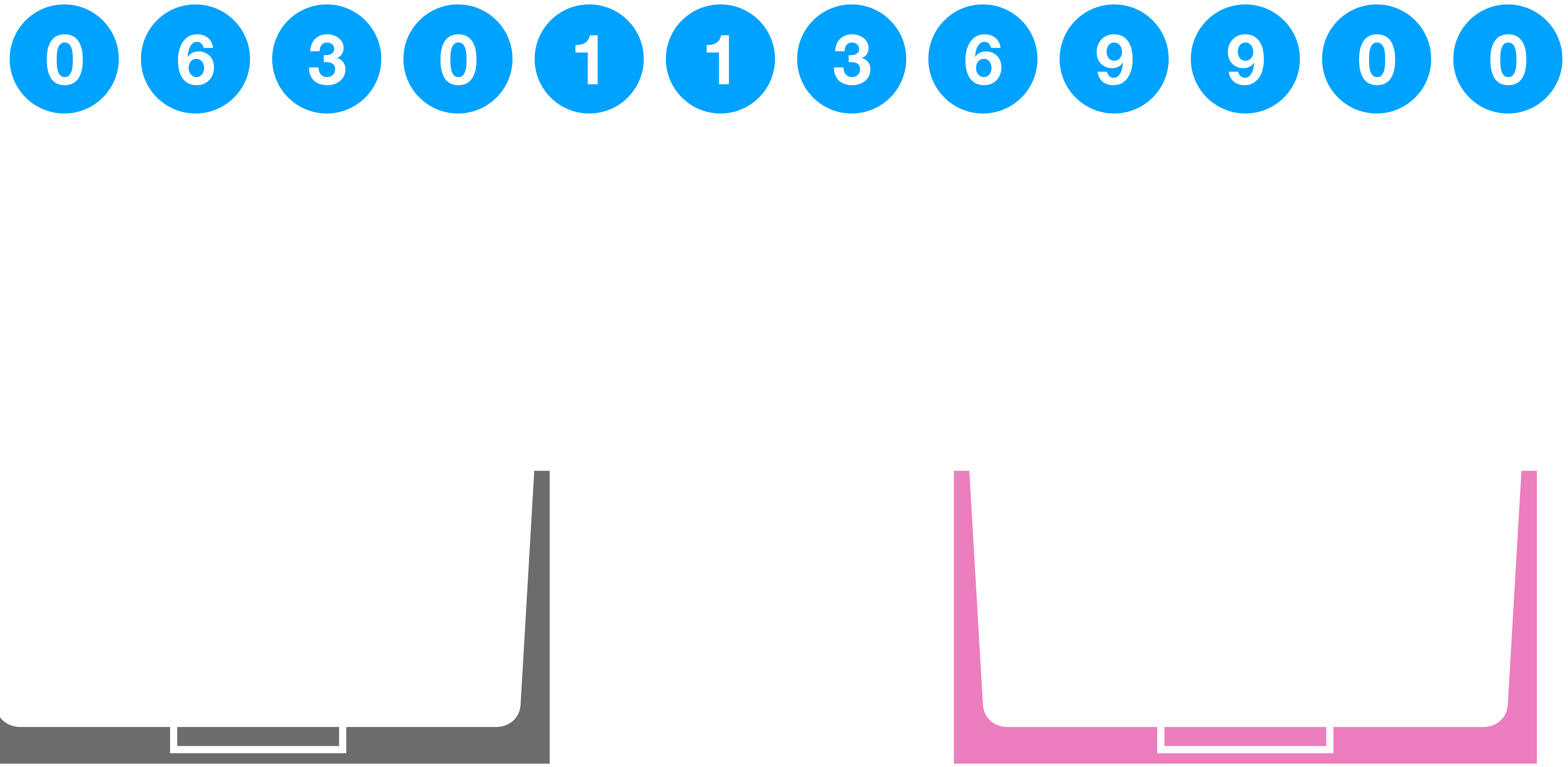
Random Assignment

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**

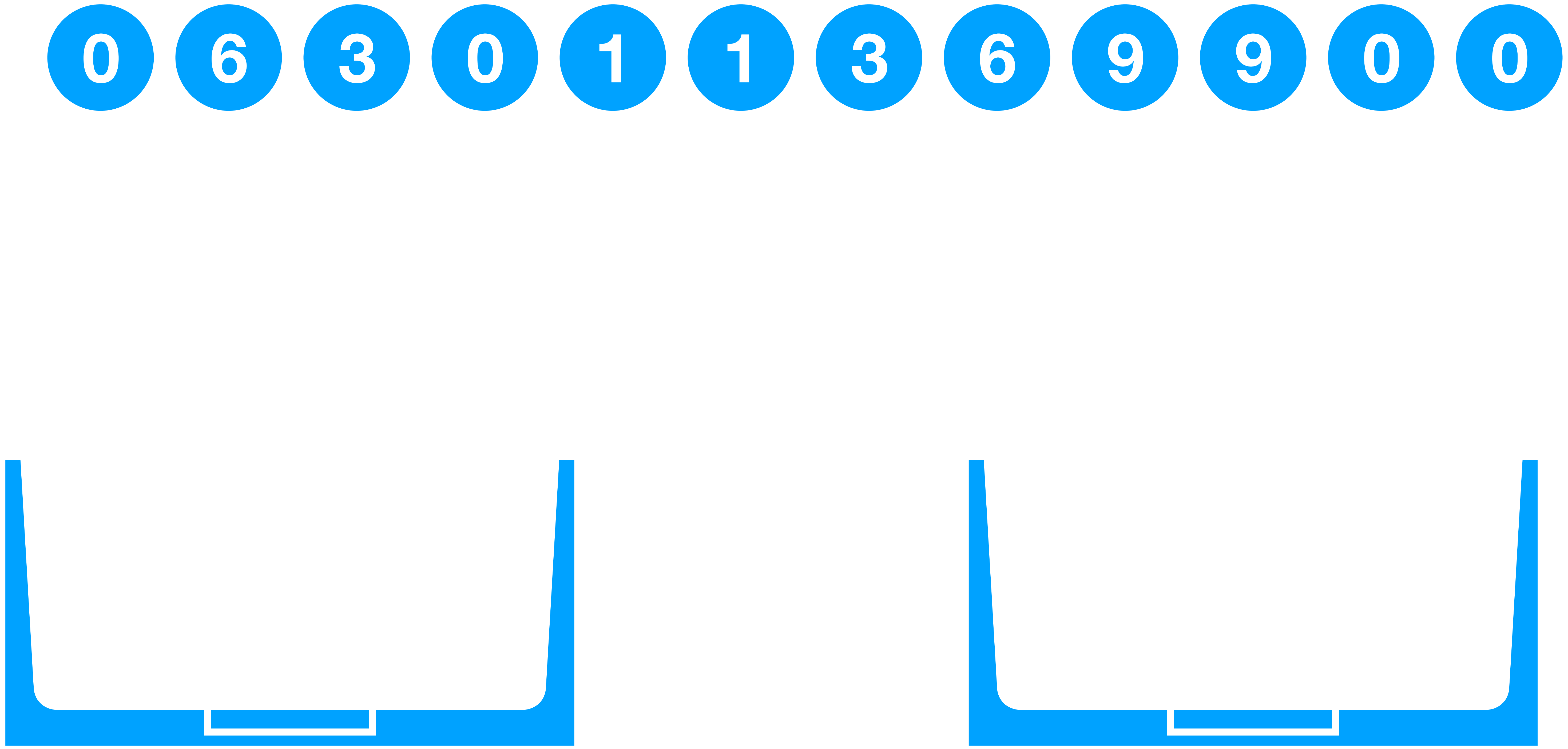
Understanding Randomization via Sampling

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



Understanding Randomization via Sampling

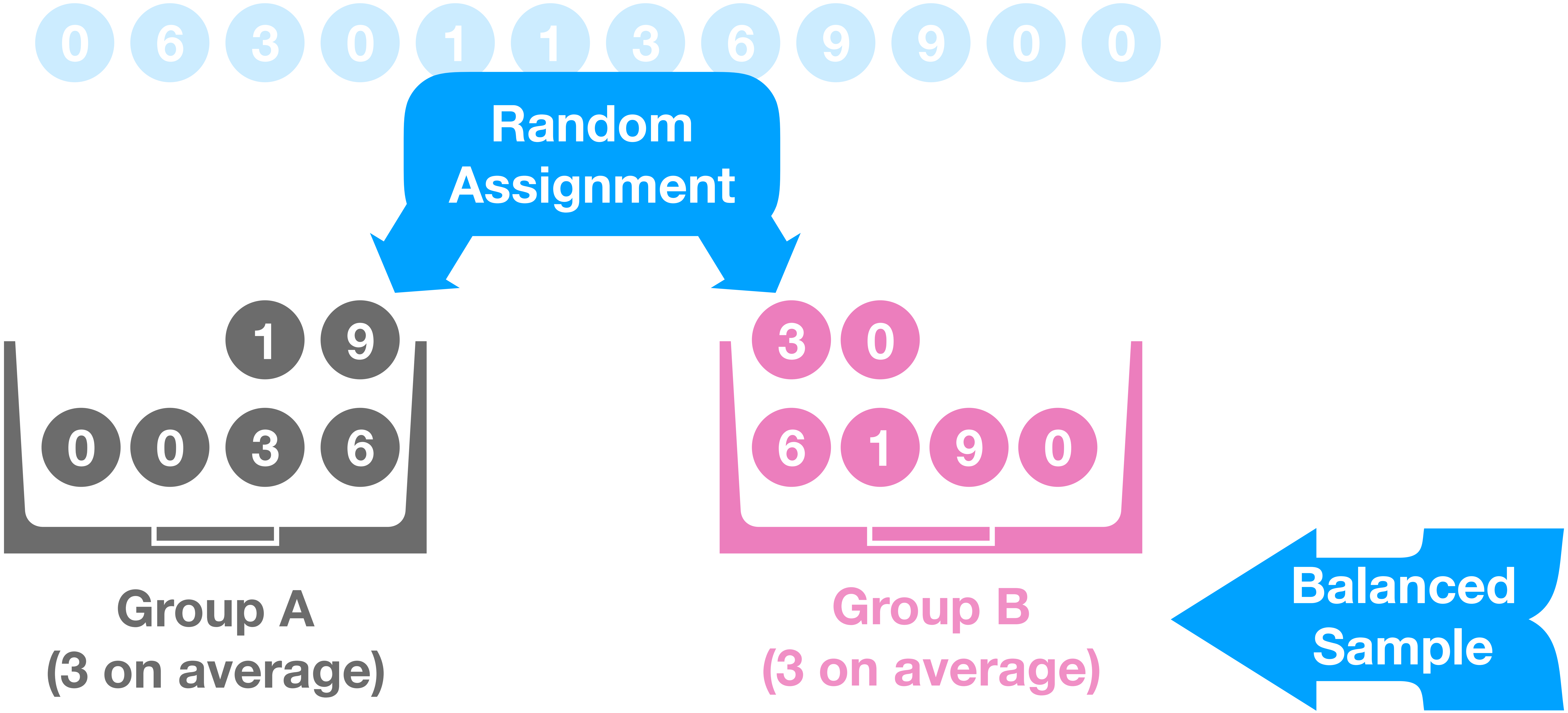
Now imagine that we allocate poems into groups based on a random sample



3 interactions on average

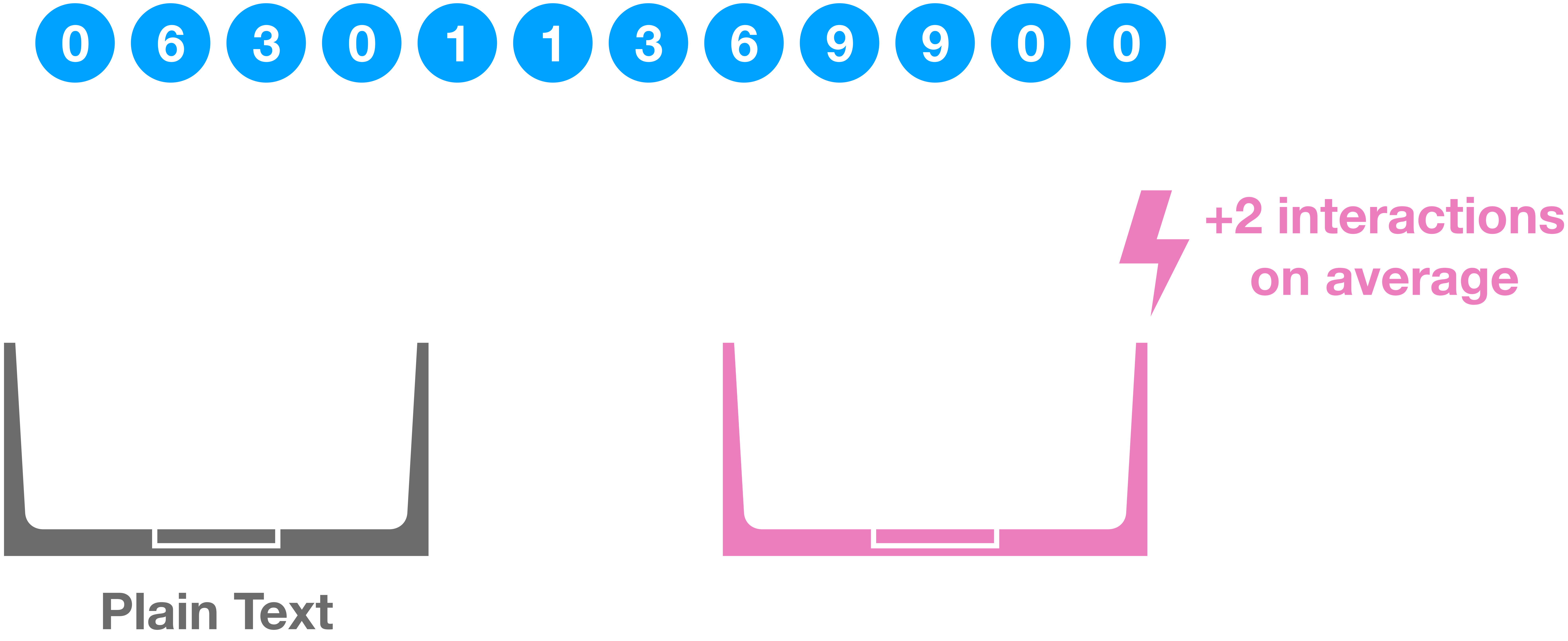
Understanding Randomization via Sampling

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



Potential Outcomes (ATE = 2)

ID (Units)	CONTROL	TREATMENT	Effect
1	0	2	2
2	6	8	2
3	3	5	2
4	0	2	2
5	1	3	2
6	1	3	2
7	3	5	2
8	6	8	2
9	9	11	2
10	9	11	2
11	0	2	2
12	0	2	2

Potential Outcomes (ATE = 2.15)

ID (Units)	CONTROL	TREATMENT	Effect
1	0	1	1.592
2	6	8	2.486
3	3	4	1.599
4	0	2	2.179
5	1	2	1.531
6	1	3	2.507
7	3	5	2.282
8	6	8	2.283
9	9	11	2.992
10	9	11	2.088
11	0	1	1.041
12	0	3	3.261

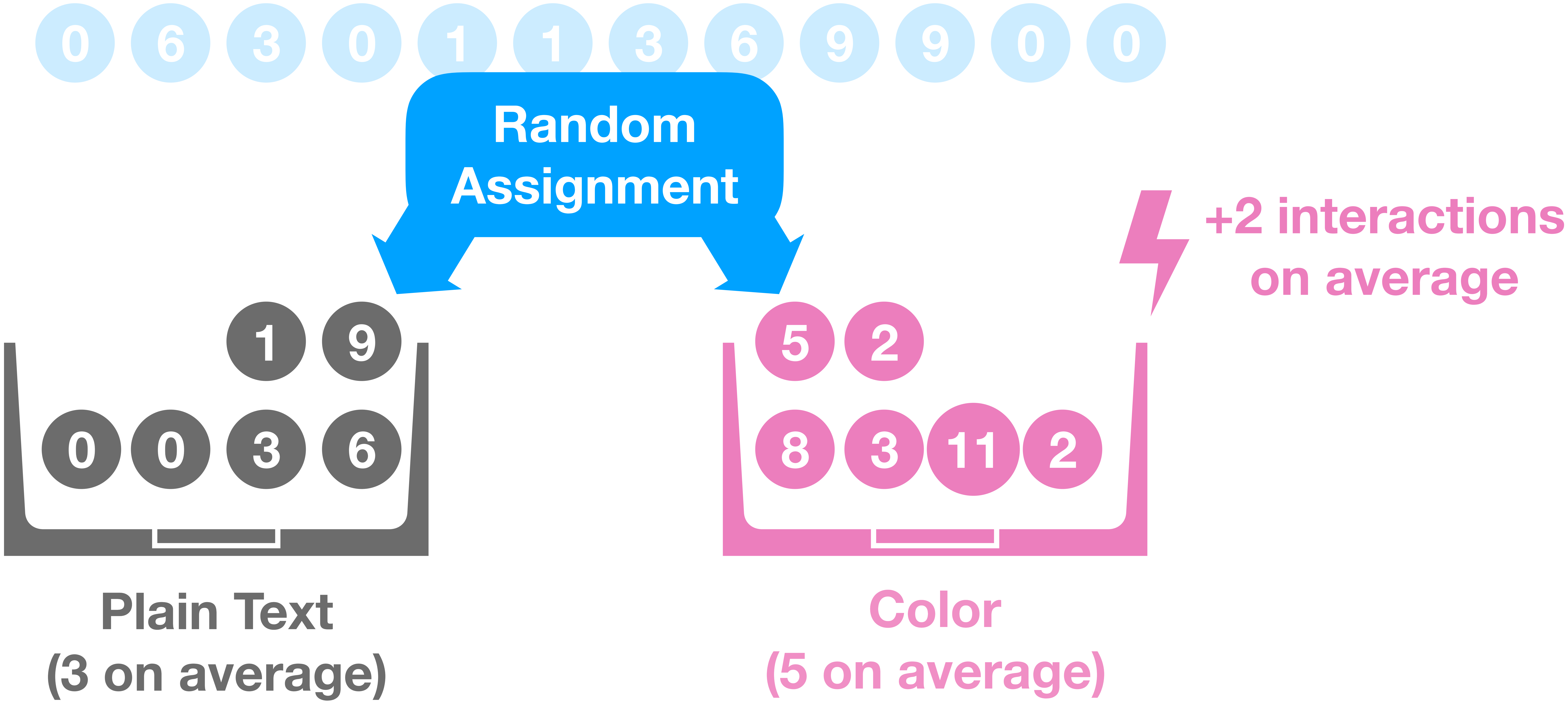
Problem of Causal Inference:

we can observe, at most,
one of the potential outcomes
for each unit

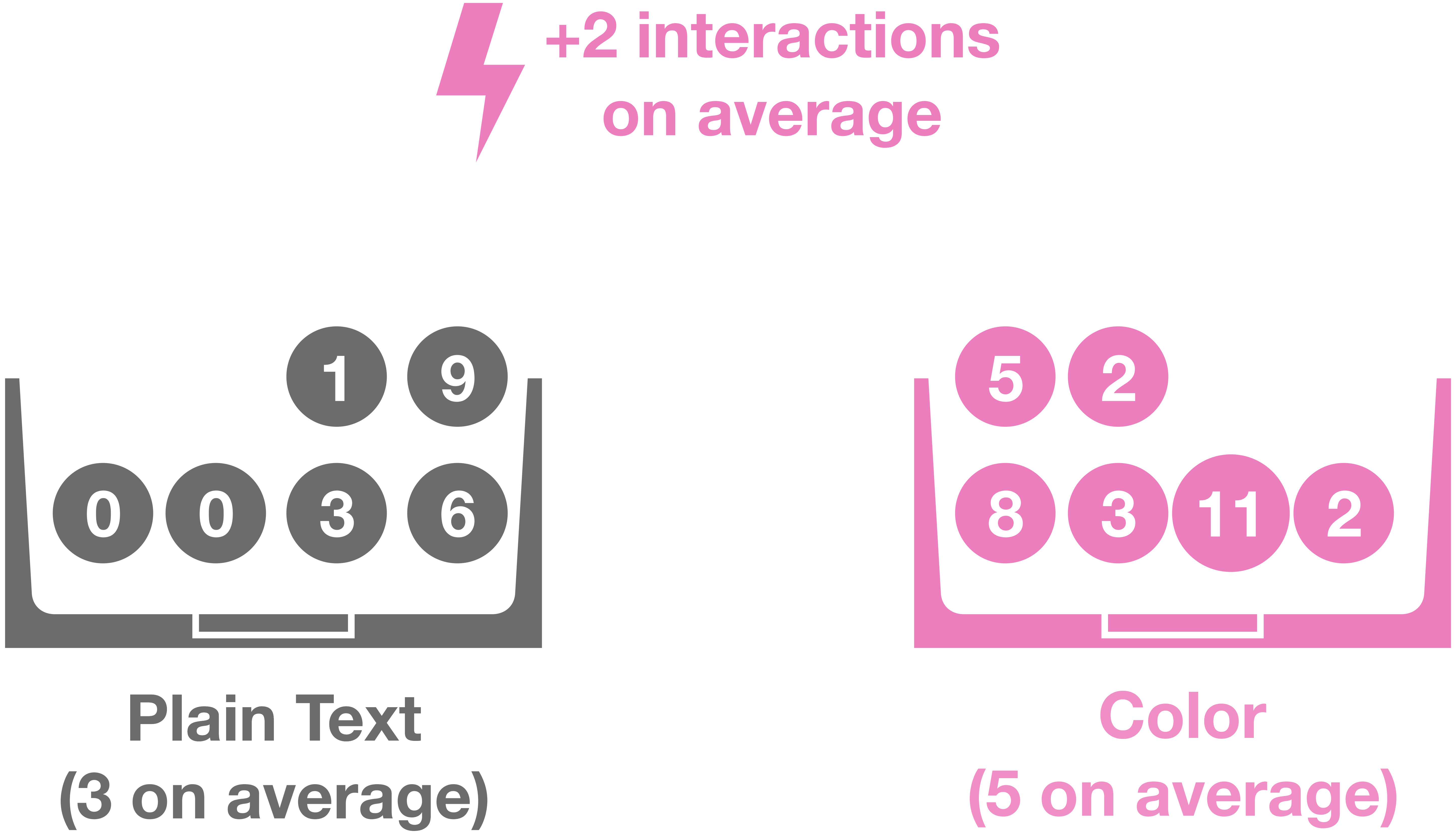
Rubin, D. B. (2003). **Basic concepts of statistical inference for causal effects in experiments and observational studies.** Cambridge, MA: Harvard University, Department of Statistics.

Understanding Randomization via Sampling

Now imagine that posting the colored background has an effect



Average Treatment Effect (ATE)



Average Treatment Effect (ATE)

APPLIES TO POPULATIONS **NOT TO INDIVIDUALS**

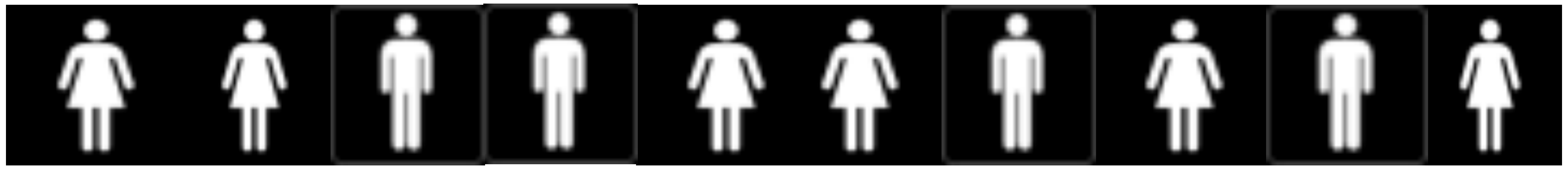
+2 interactions
on average

Plain Text
(3 on average)

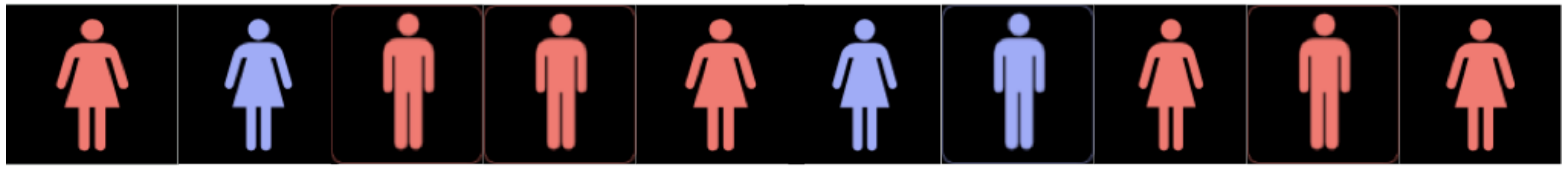
Color
(5 on average)

Simple Randomization

Sample:



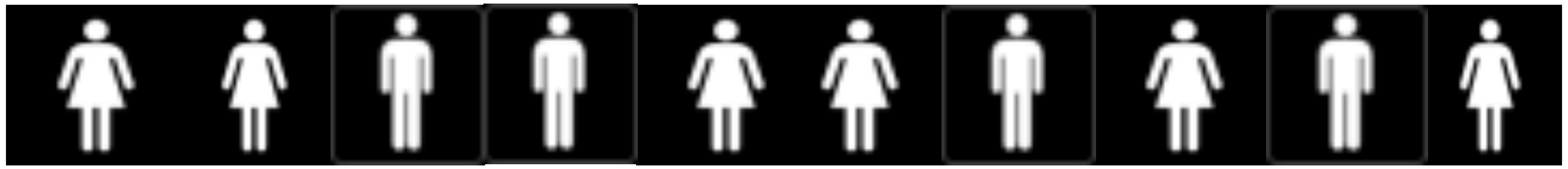
Iteration 1:



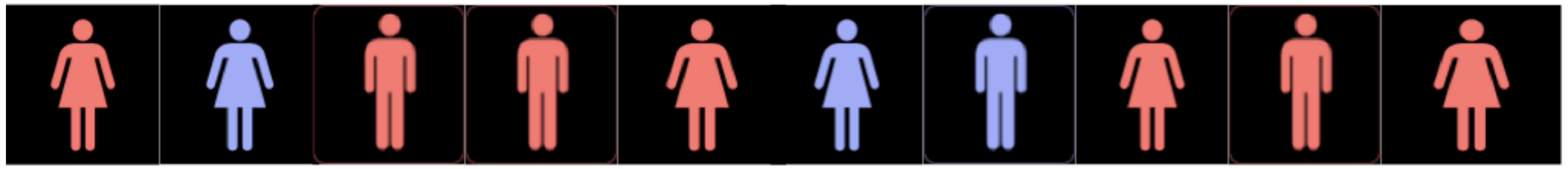
Simple Randomization

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

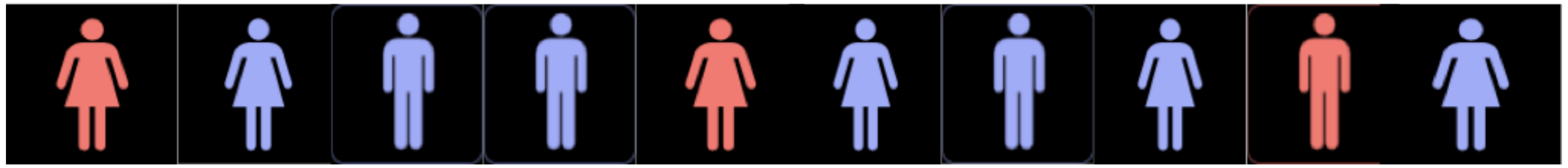
Sample:



Iteration

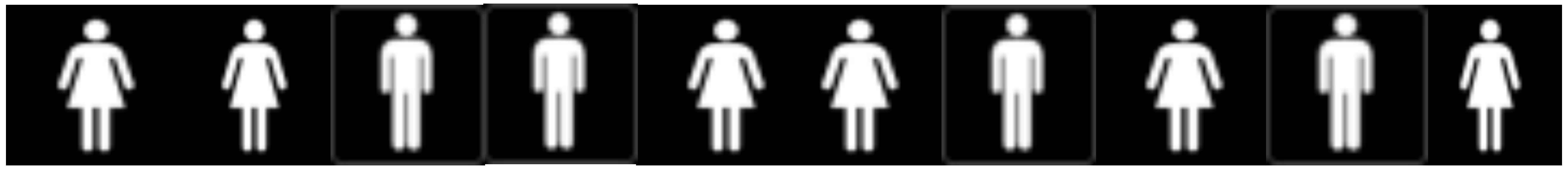


Iteration

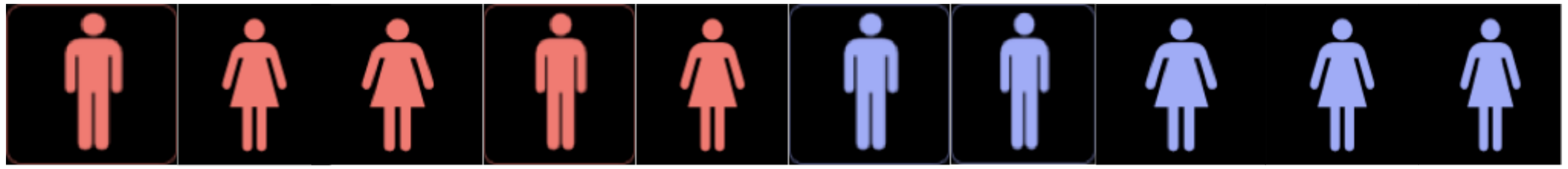


Complete Randomization

Sample:



Iteration



Average Treatment Effect (ATE)

(log-transformed dependent variable)

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

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

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

Average Treatment Effect (ATE)

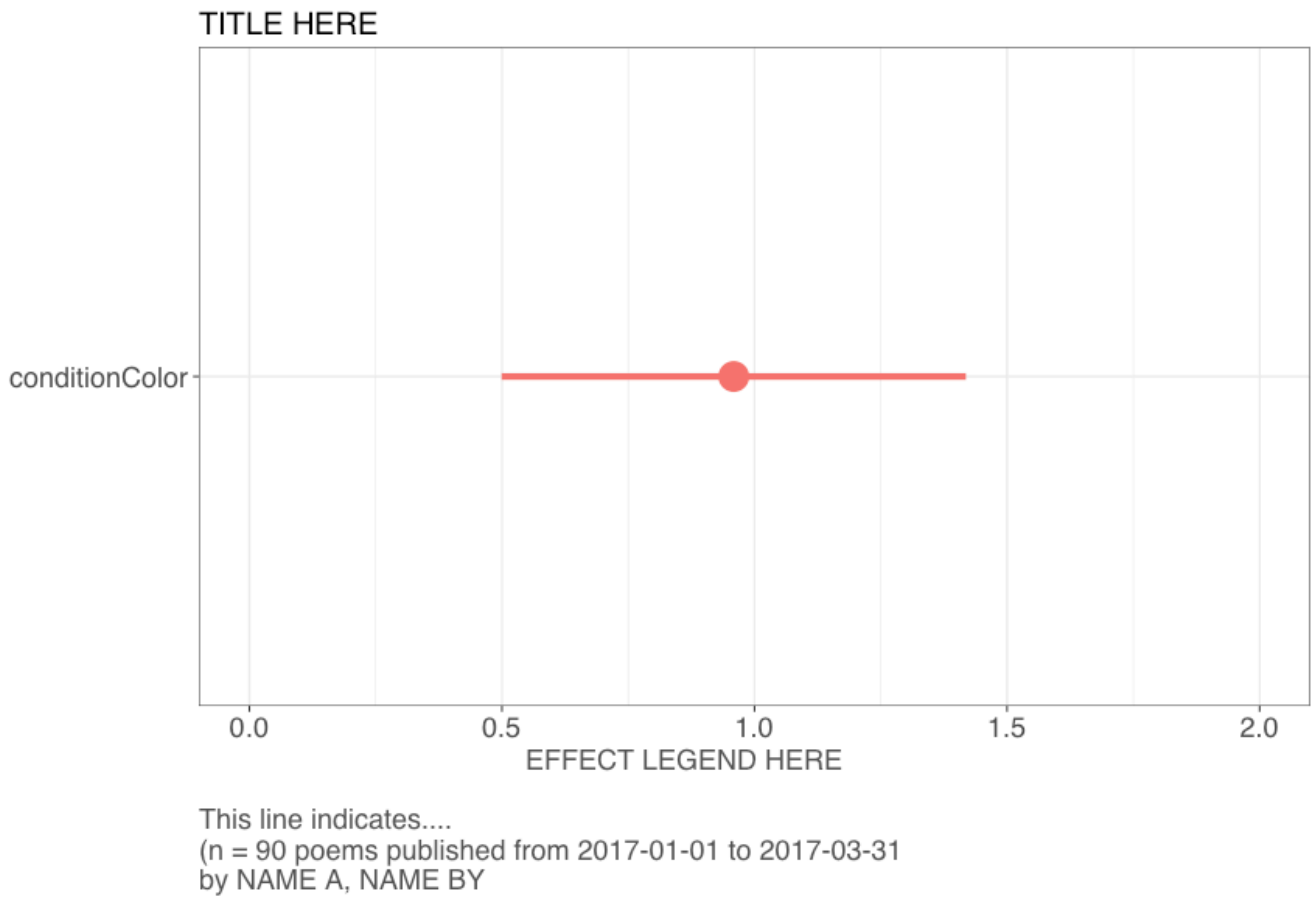
(log-transformed dependent variable)

```
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)



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

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