Managing Things You Cannot Control (SOC 412)

Week 10 Lecture 7

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What we will cover today

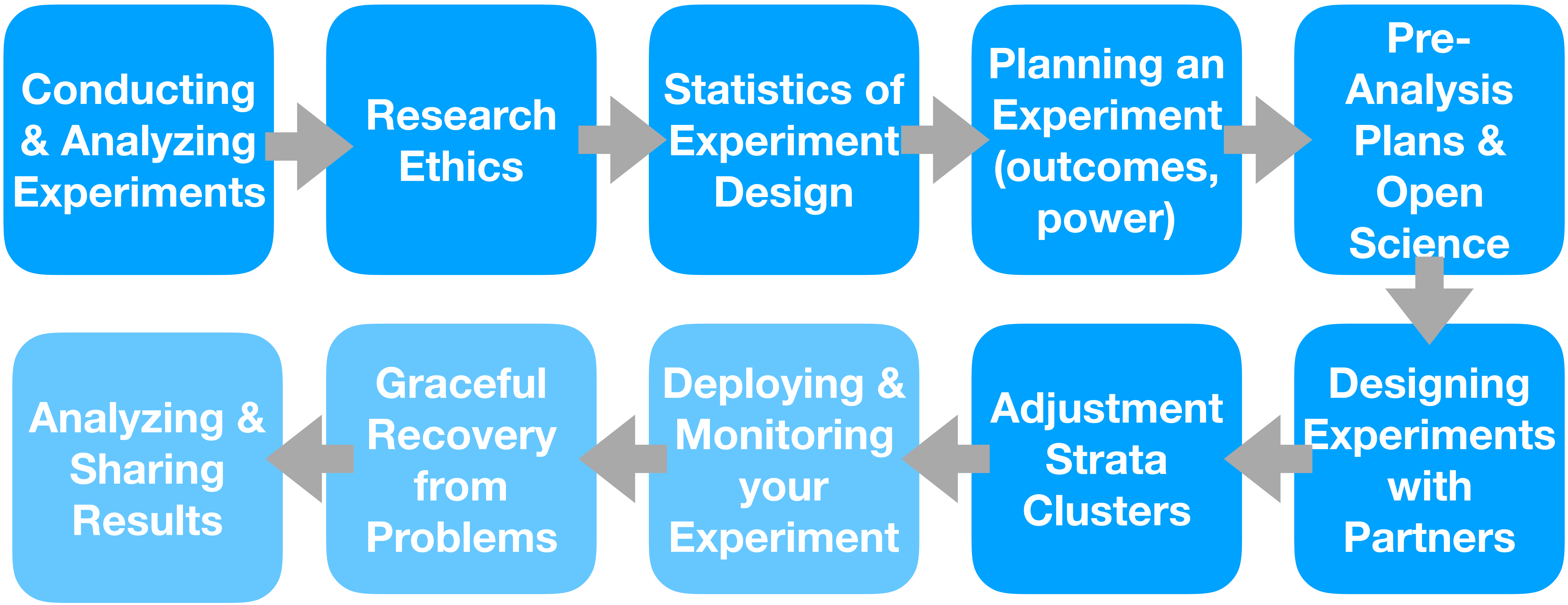
Cluster randomization

Block randomization

Regression adjustment

Bonferroni Adjustment

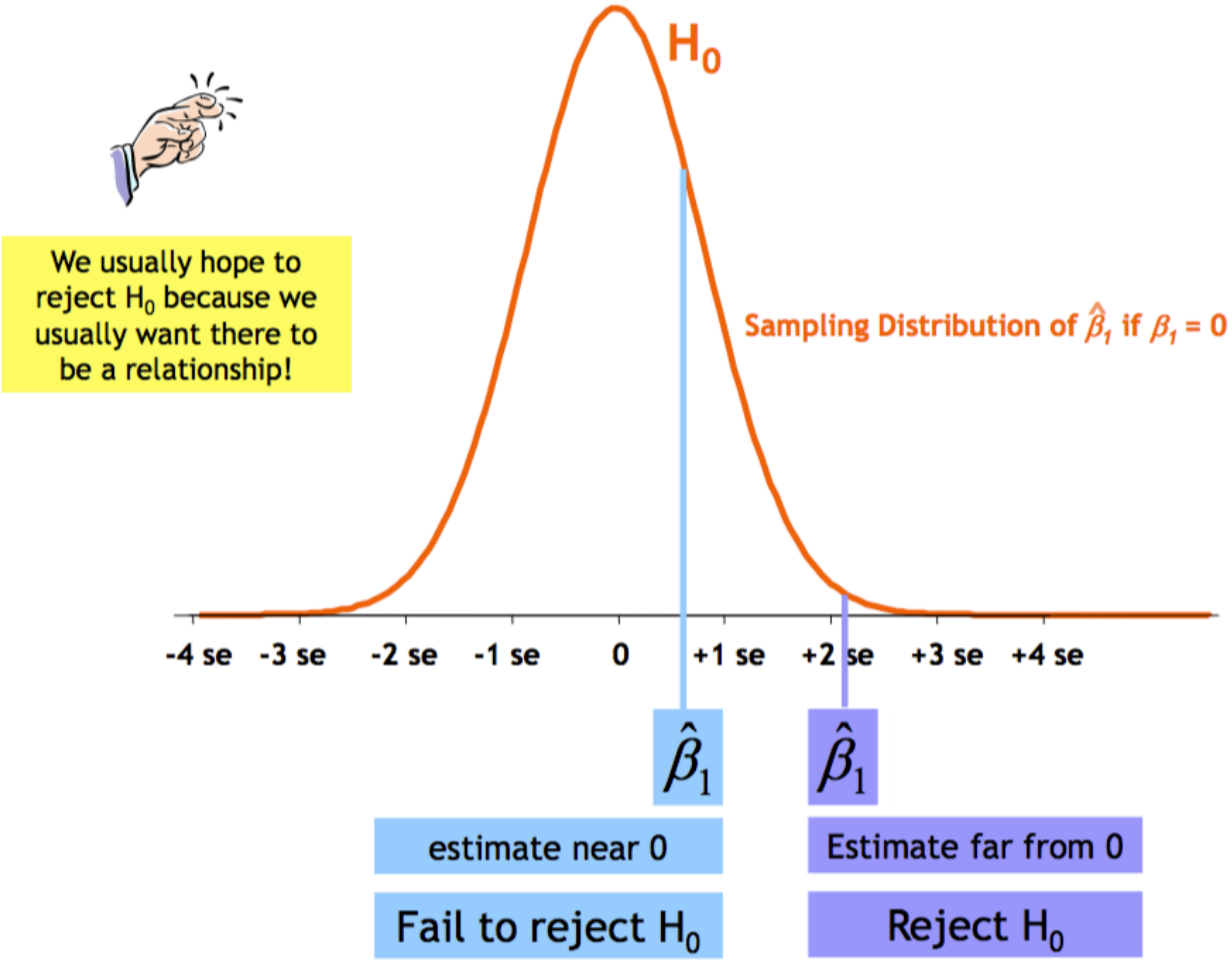
Final Projects
Experiment Plan



Week 10: Managing Things You Cannot Control

Null Hypothesis Testing

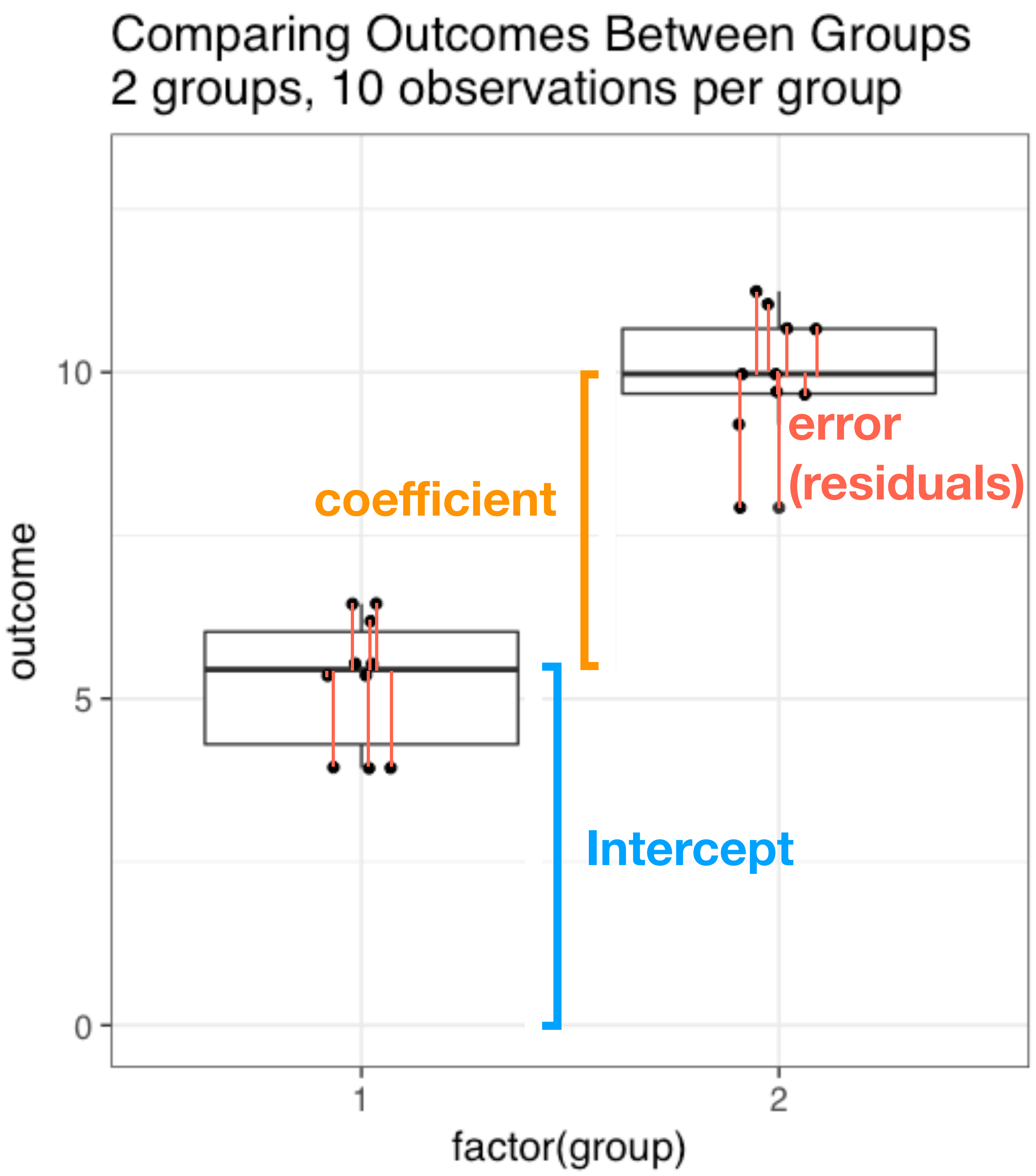
revisiting basics of OLS linear regression



 (plot © James Kim, Harvard Graduate School of Education)

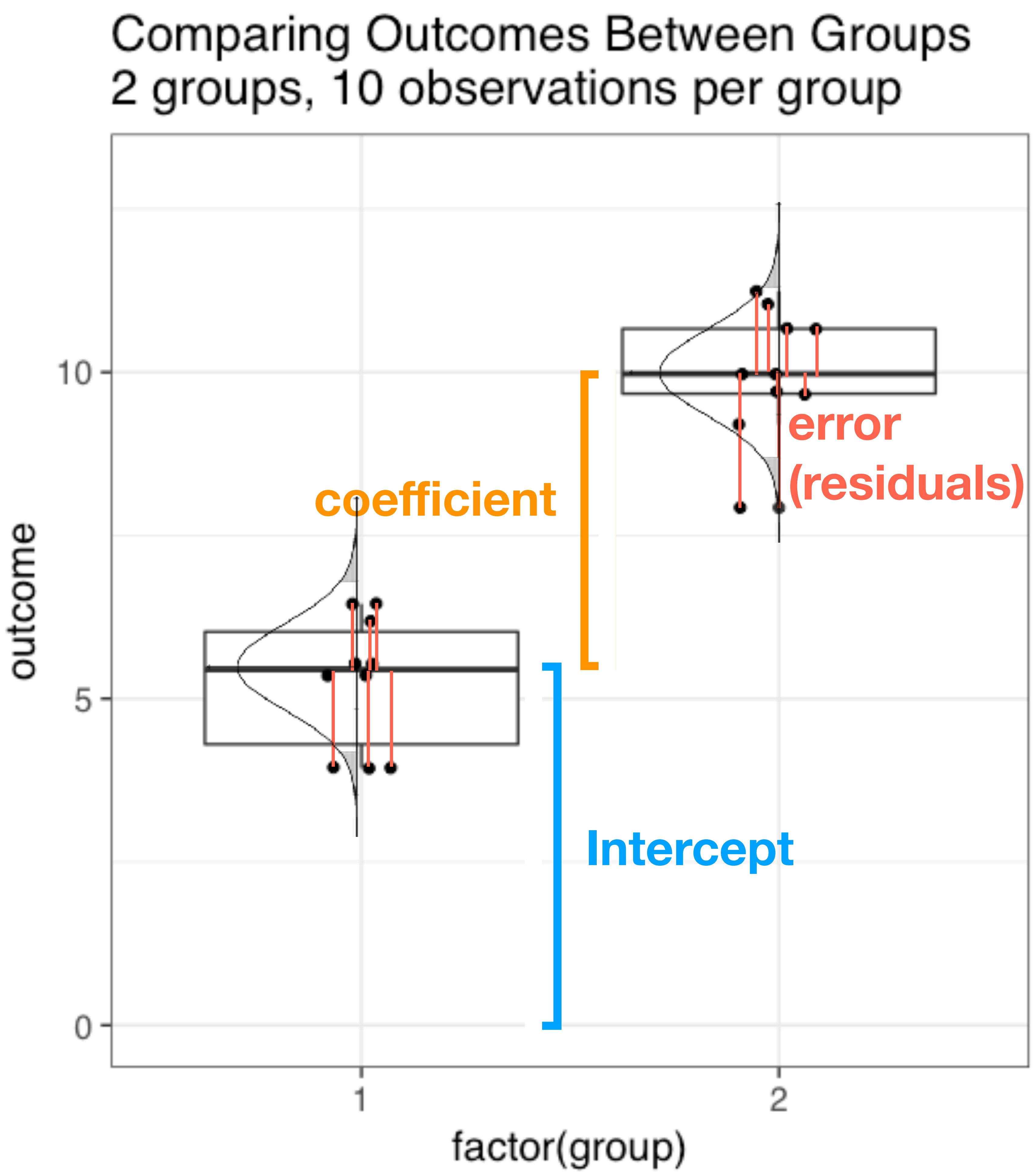
Error

revisiting basics of OLS linear regression



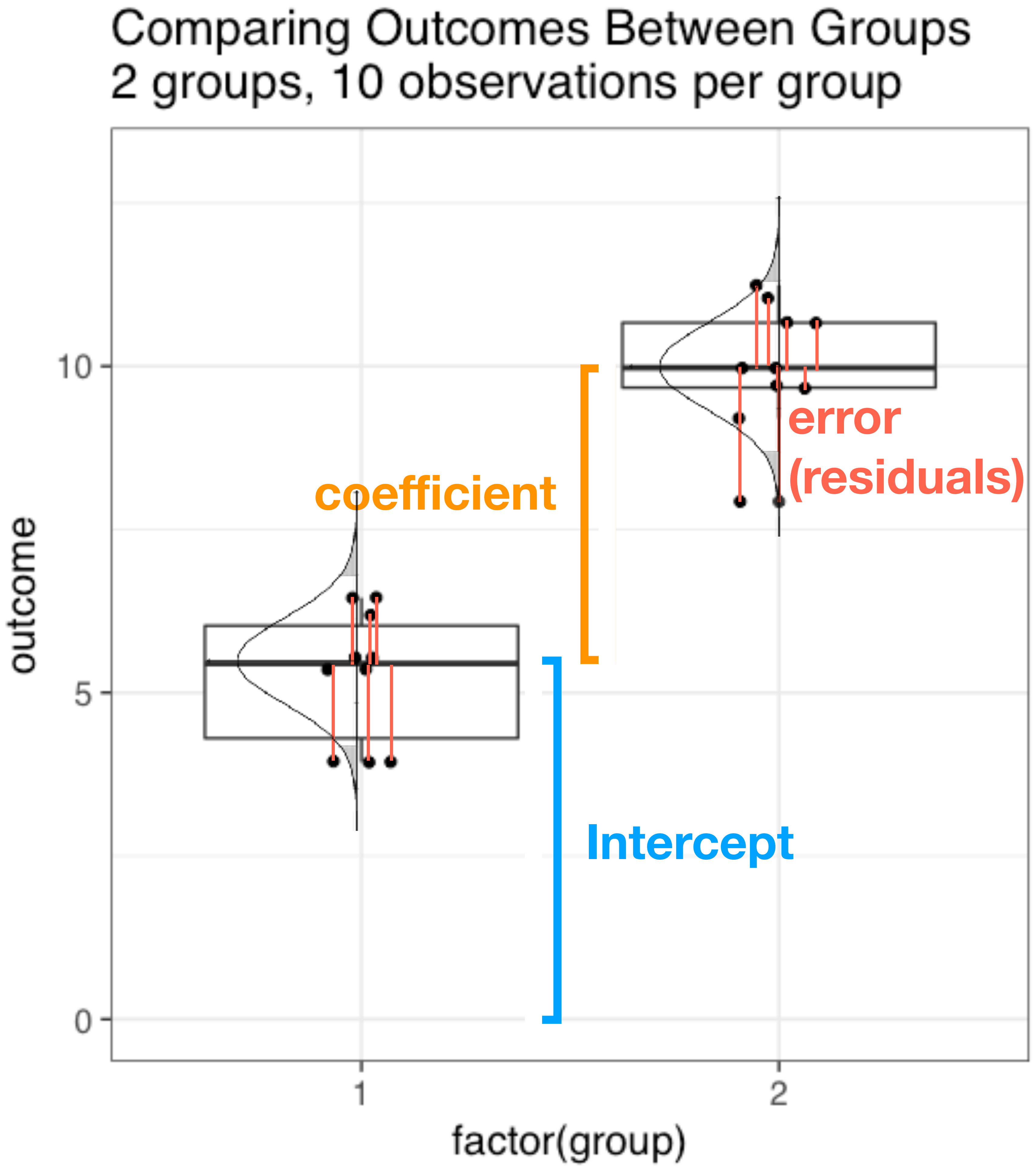
Distribution of Errors

assumption of OLS: error is normally distributed & homoscedastic



Root Mean Square Error

the estimated standard deviation of the residuals

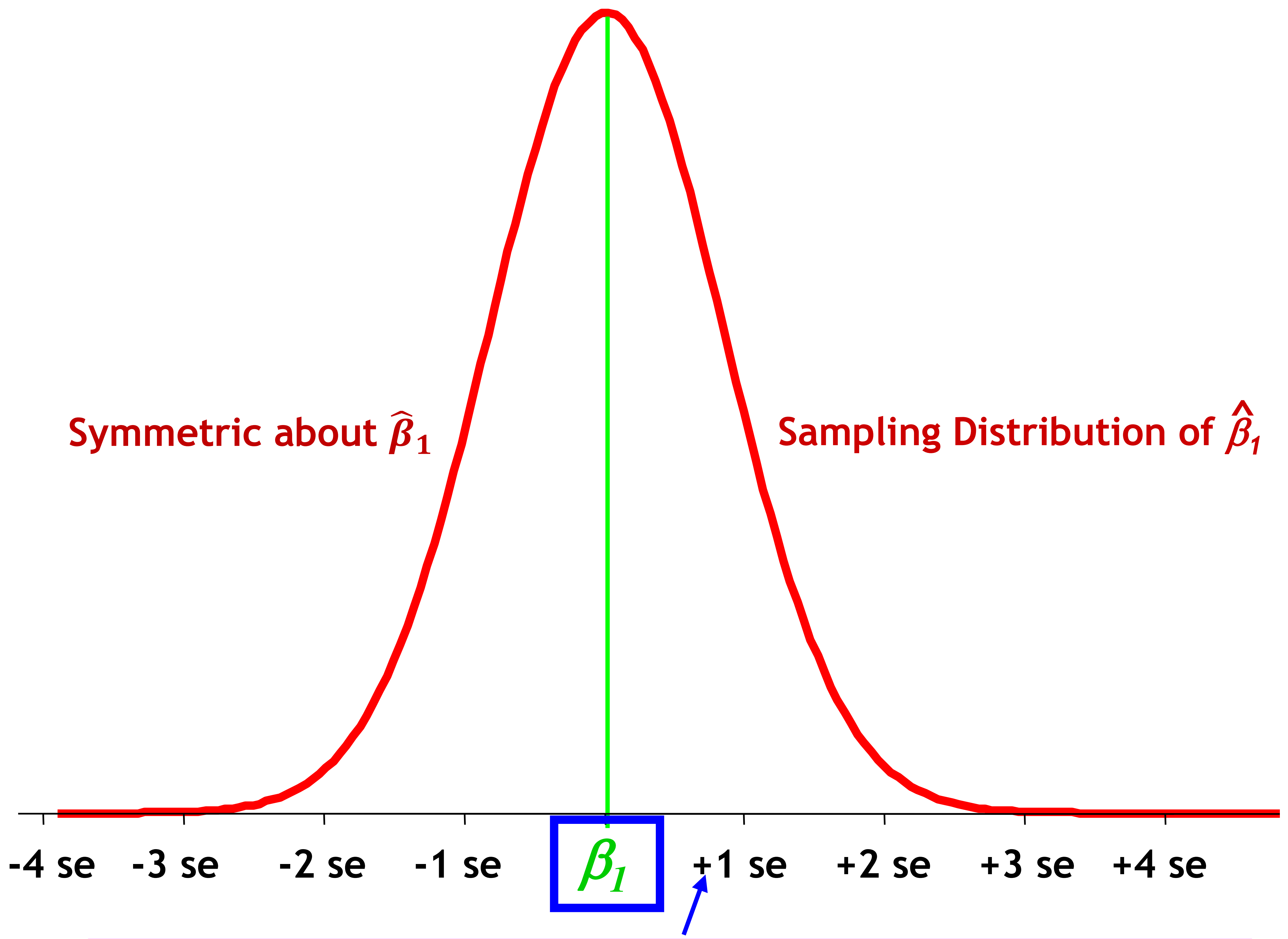



```
m1 <- lm(outcome ~
          group == 2 ,
          data=posts)
```

```
rmse <- sqrt(
 sum(m1$residuals^2) /
    length(m1$residuals)
)
```

Standard Error

The standard deviation of the sampling distribution (of a particular statistic)



Definition: The *standard deviation of a sampling distribution* is known as a "standard error," commonly abbreviated as "se"

$$se(\hat{\beta}) = \frac{\sigma}{\sqrt{(n-1) \times Var(X)}}$$

$\sigma = RMSE$

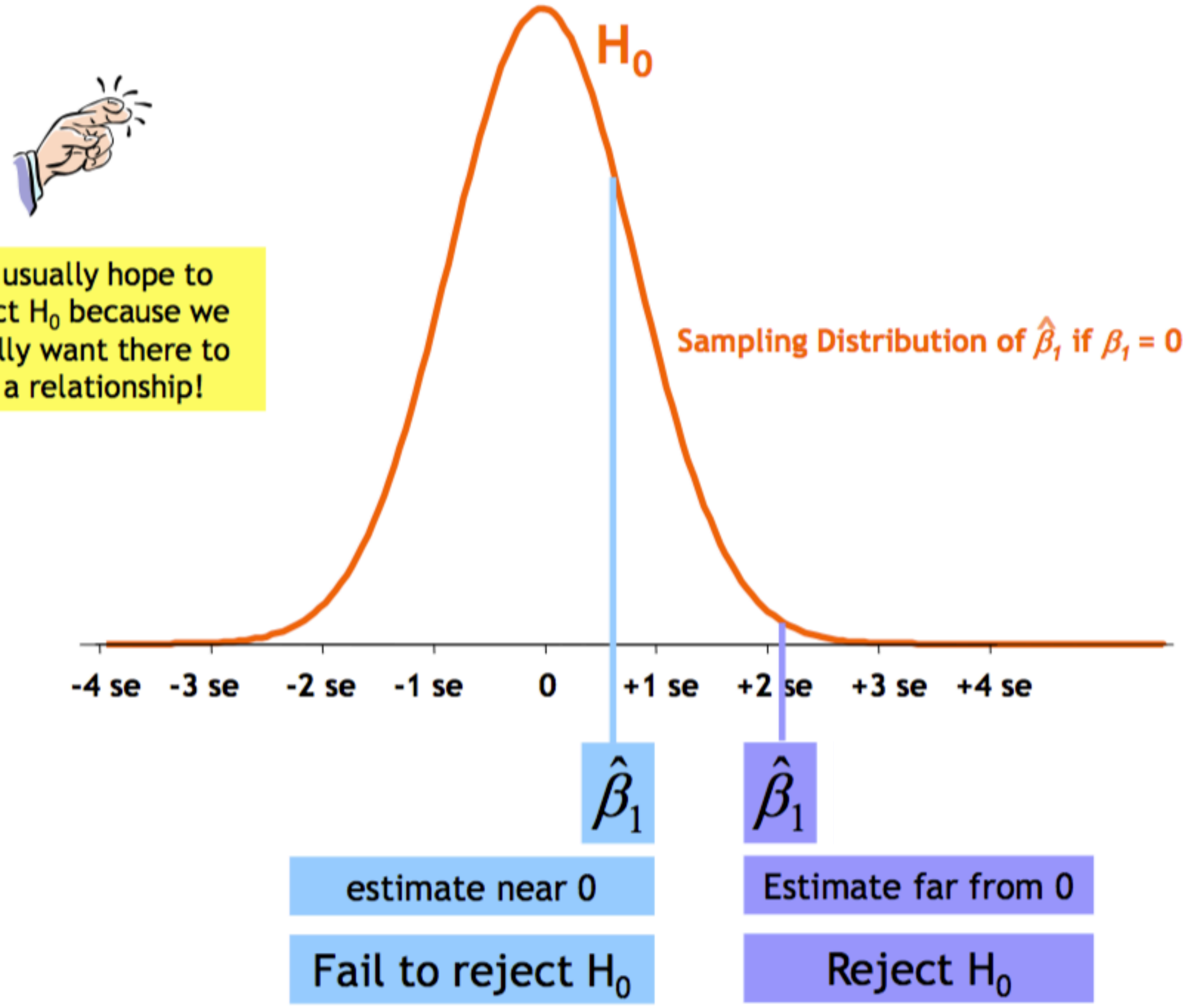
$n = num\ of\ observations$

$Var(X) = variance\ of\ predictor\ (TREAT)$

Null Hypothesis Testing

revisiting basics of OLS linear regression

We usually hope to reject H_0 because we usually want there to be a relationship!



t-statistic

revisiting basics of OLS linear regression

$$t_{obs} = \frac{\hat{\beta} - \beta}{se(\hat{\beta})} \quad where\ H_0: \beta = 0$$

So t_{obs} tells us how many standard errors away from 0 our sample estimate is.

There's nothing magical about $H_0: \beta_1 = 0$, it could be anything (e.g., $H_0: \beta_1 = 1$)

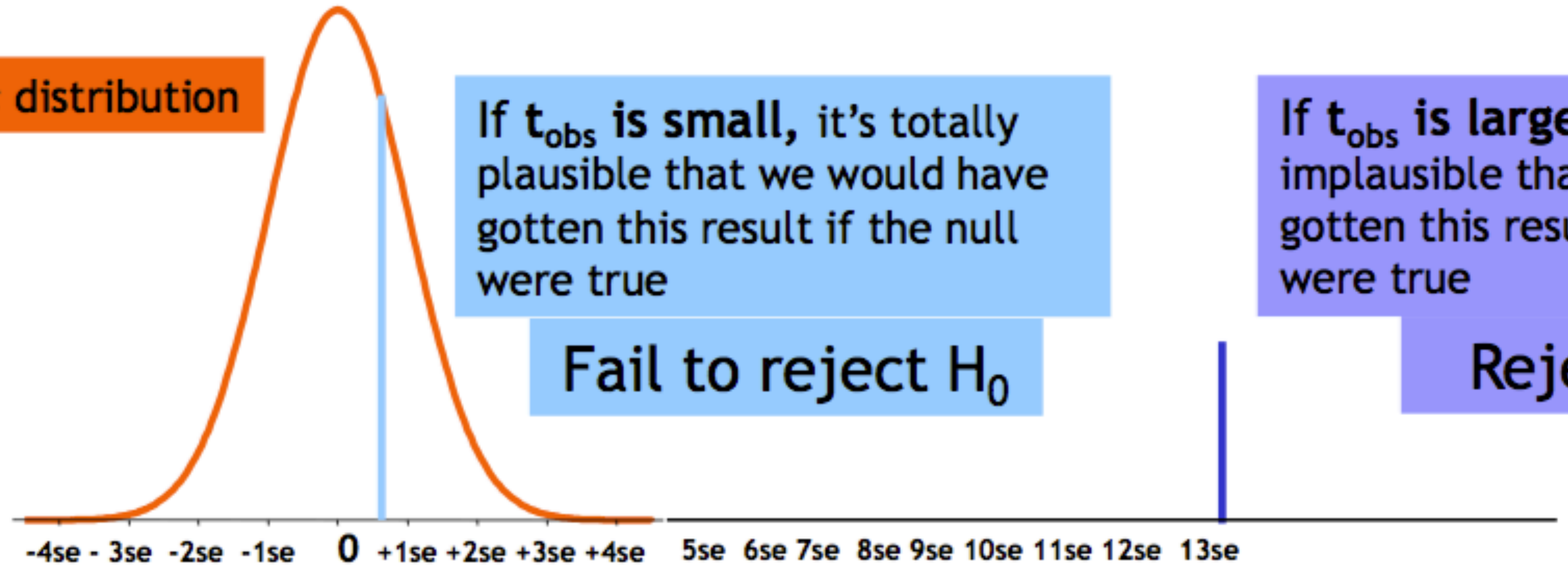
This is a *t* distribution

If t_{obs} **is small,** it's totally plausible that we would have gotten this result if the null were true

Fail to reject H_0

If t_{obs} **is large,** it's highly implausible that we would have gotten this result if the null were true

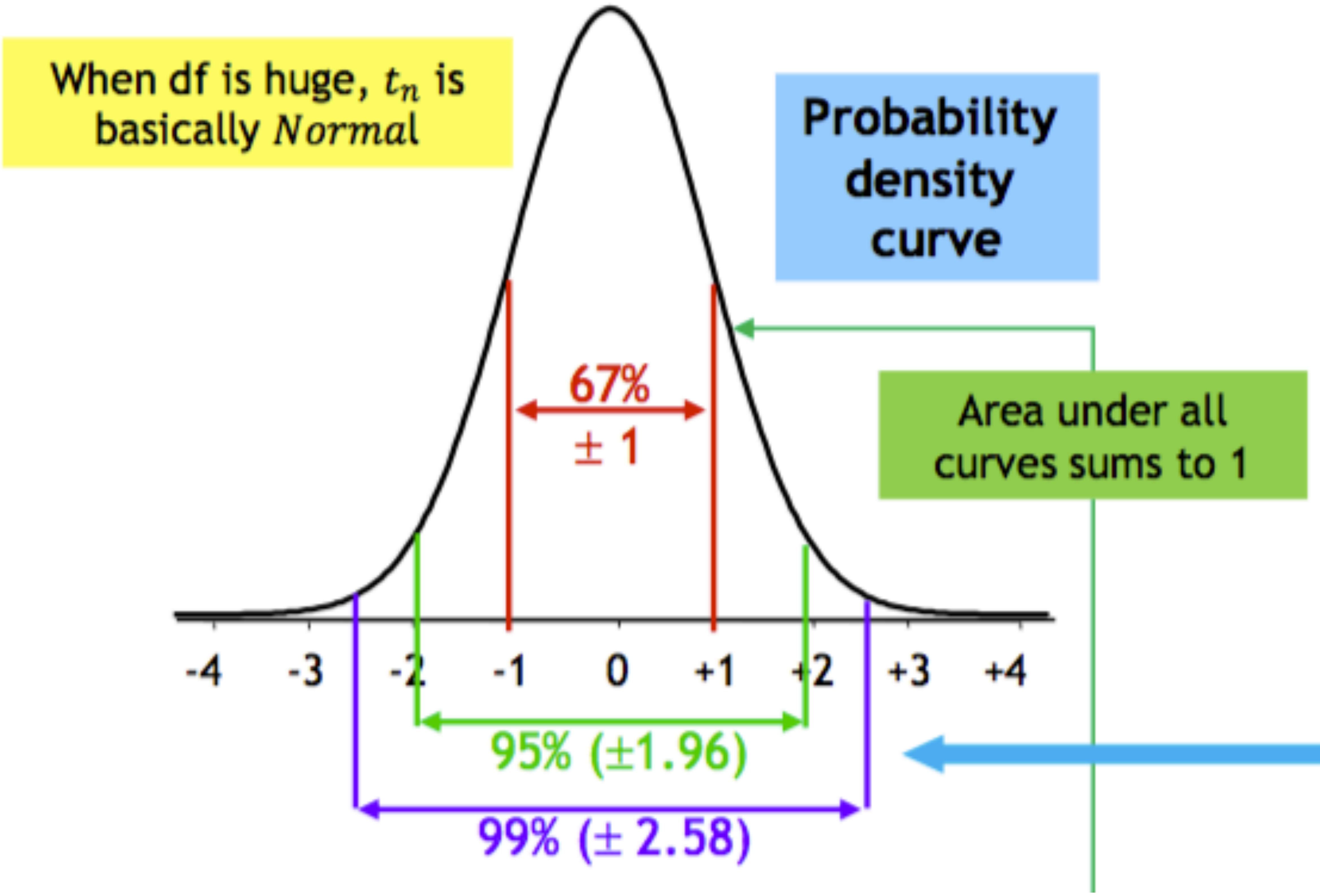
Reject H_0



t-distribution

revisiting basics of OLS linear regression

$$t_{obs} = \frac{\hat{\beta} - \beta}{se(\hat{\beta})} \quad where\ H_0{:}\ \beta = 0$$



How large is large? Critical values of $t_{observed}$			
df	Two-sided probability level, p		
	0.10	0.05	0.01
10	1.81	2.23	3.17
20	1.72	2.09	2.85
30	1.70	2.04	2.75
50	1.68	2.01	2.68
100	1.66	1.98	2.63
infinite	1.64	1.96	2.58

confidence intervals

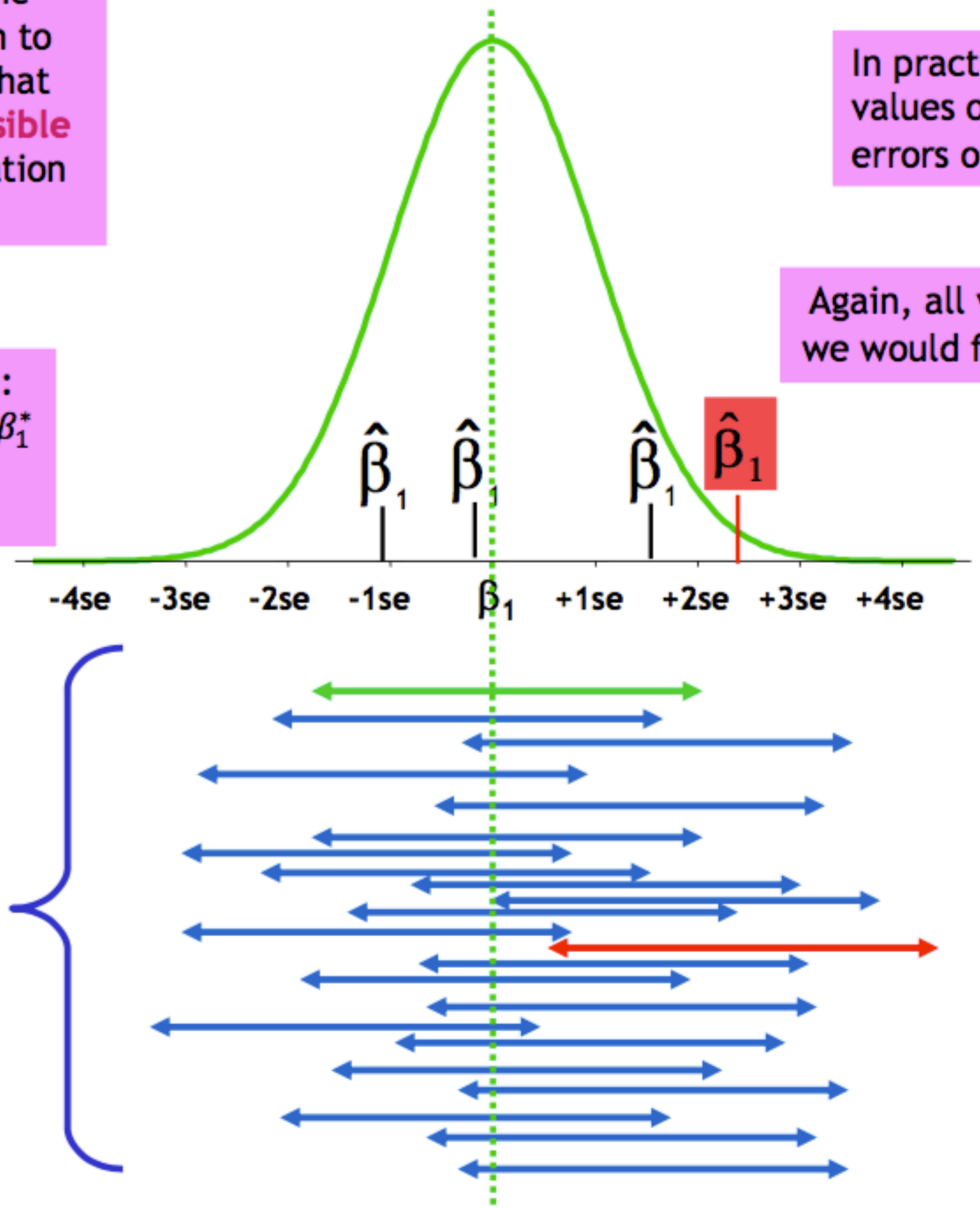
Idea: Can we use the sampling distribution to construct intervals that offer a **range of plausible values** for the population parameter?

Yes!

Confidence interval: Set of all values of β_1^* for which we would reject $H_0: \beta_1 = \beta_1^*$

In practice: Take all possible values of β_1 within ~2 standard errors of $\hat{\beta}_1$

Again, all values of $\beta_{possible}$ for which we would fail to reject $H: \beta = \beta_{possible}$



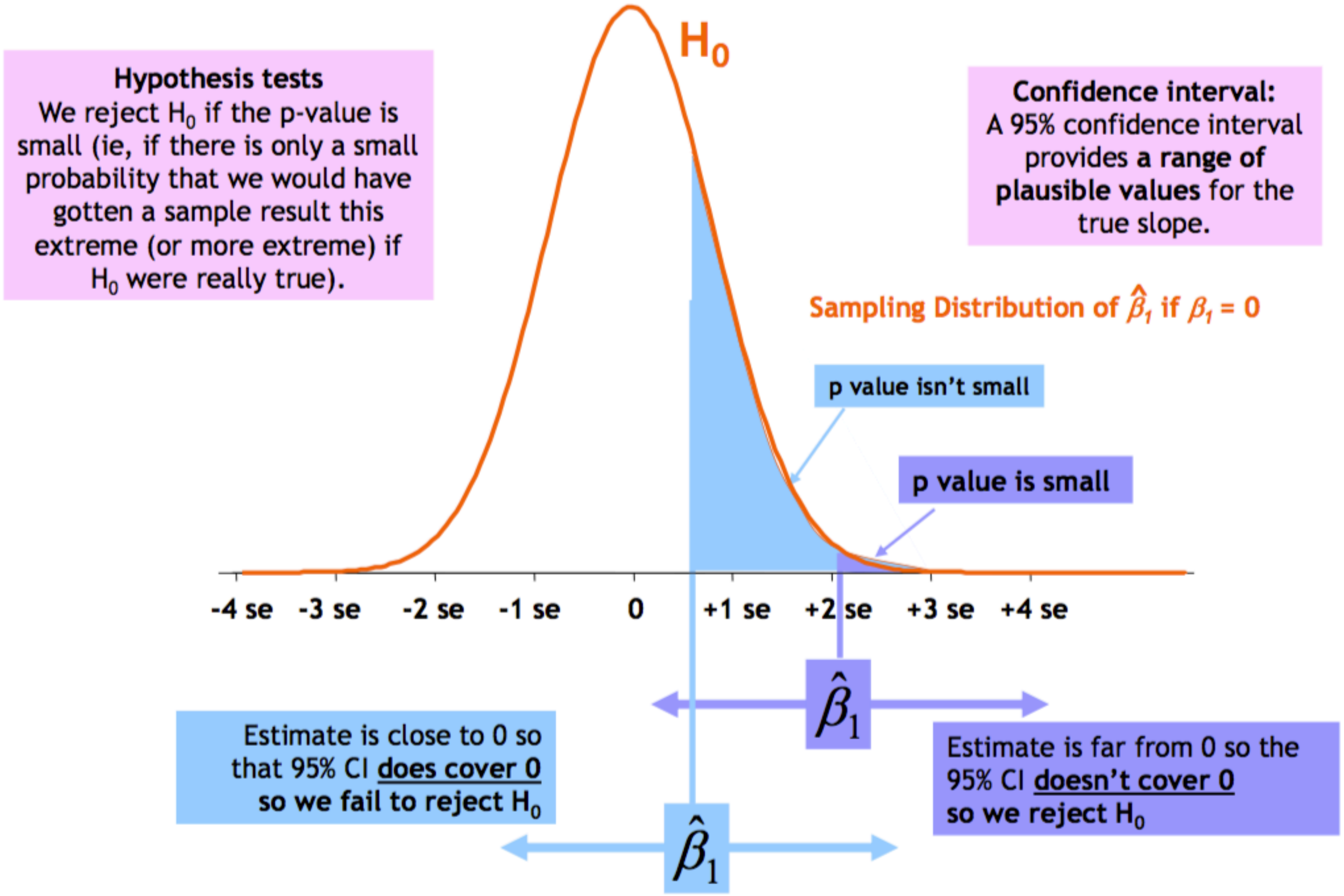
$$95\%\ conf\ interval = \hat{\beta} \pm 1.96\ se(\hat{\beta})$$

For every 20 95% confidence intervals we construct, we estimate that an average of 1 won't cover the true value of β_1

We don't know whether this is one of the lucky 95% that do cover the true value or the unfortunate 5% that don't

p-value

probability of observing a coefficient this extreme if the null hypothesis were true



Clustered Randomization: Class

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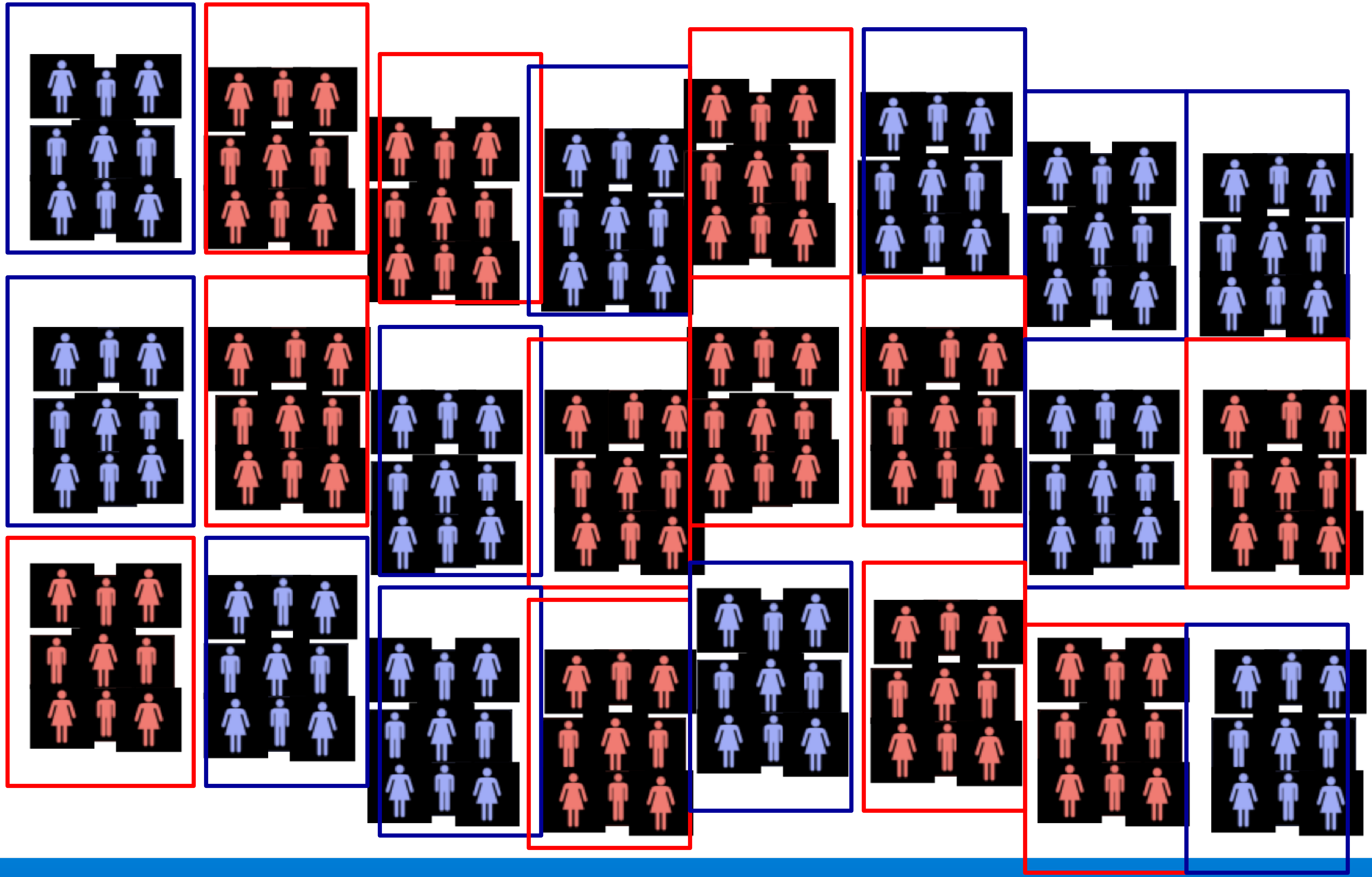
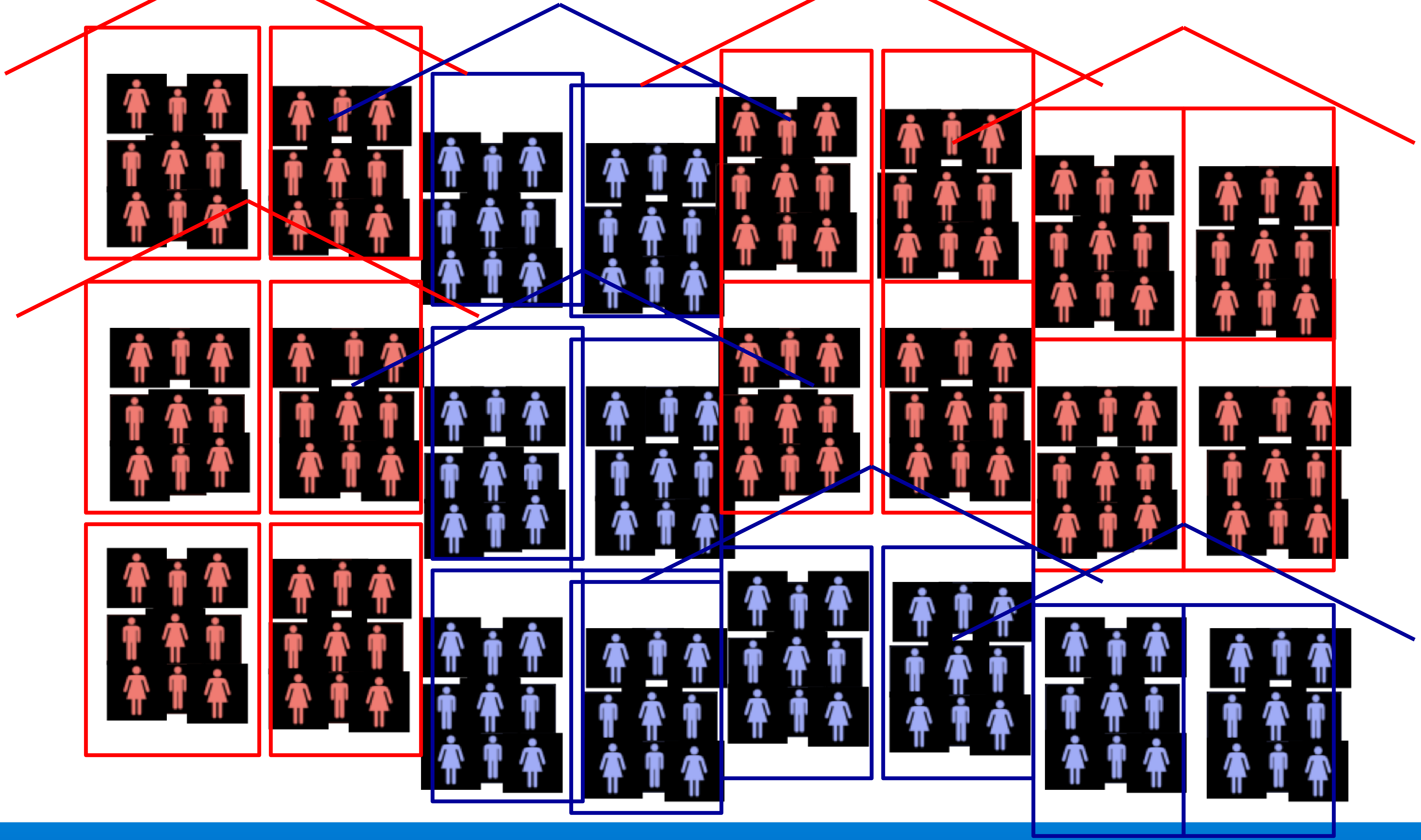


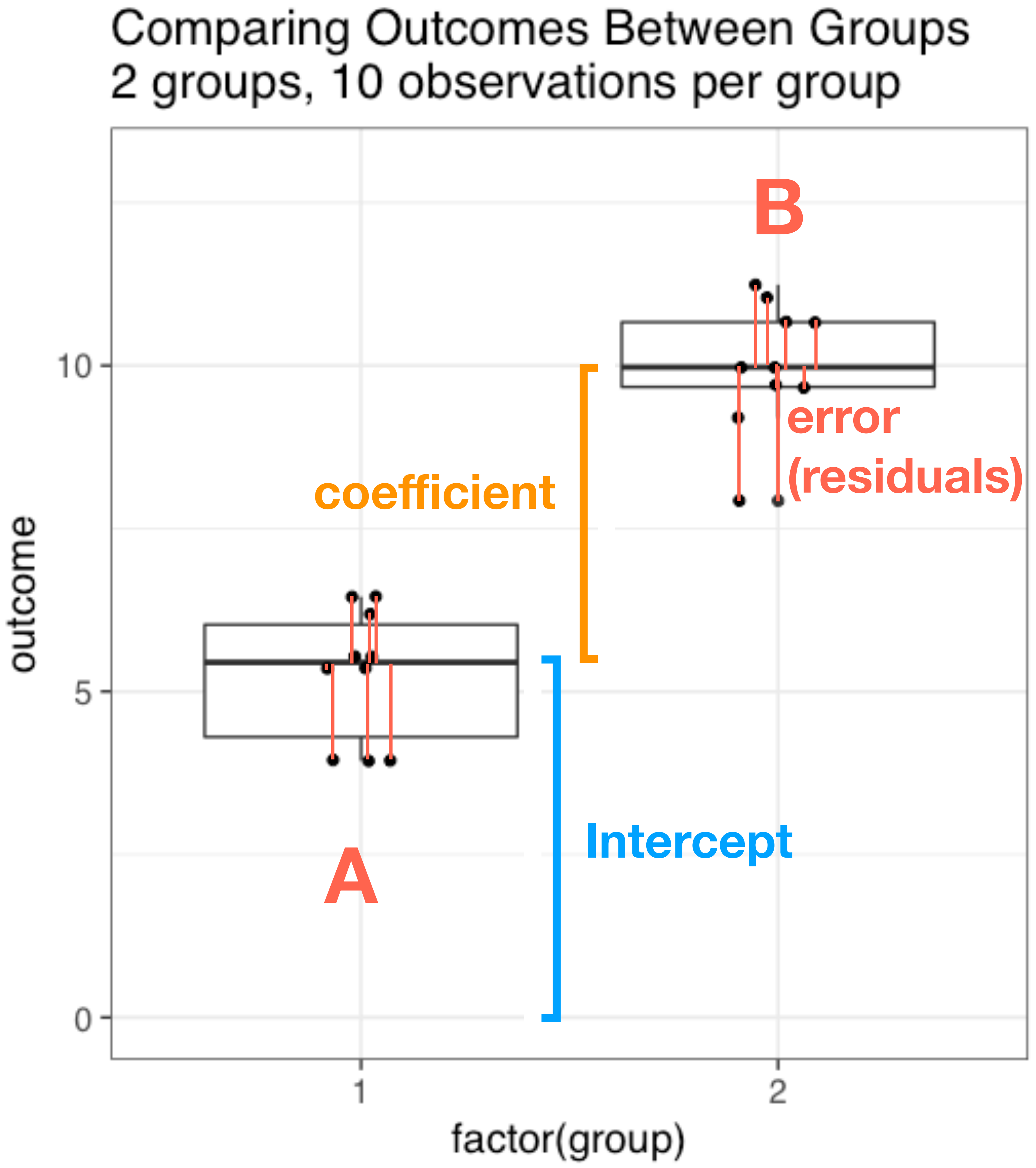
Clustered Randomization: School

Clustered Randomization: School



Estimating ATE from Cluster Randomization

we are estimating the ATE, *not* looking for correlations



Standard Error

$$se(\hat{\beta}) = \frac{\sigma}{\sqrt{(n - 1) \times Var(X)}}$$

$\sigma = RMSE$

$n = \boxed{num\ of\ observations}$

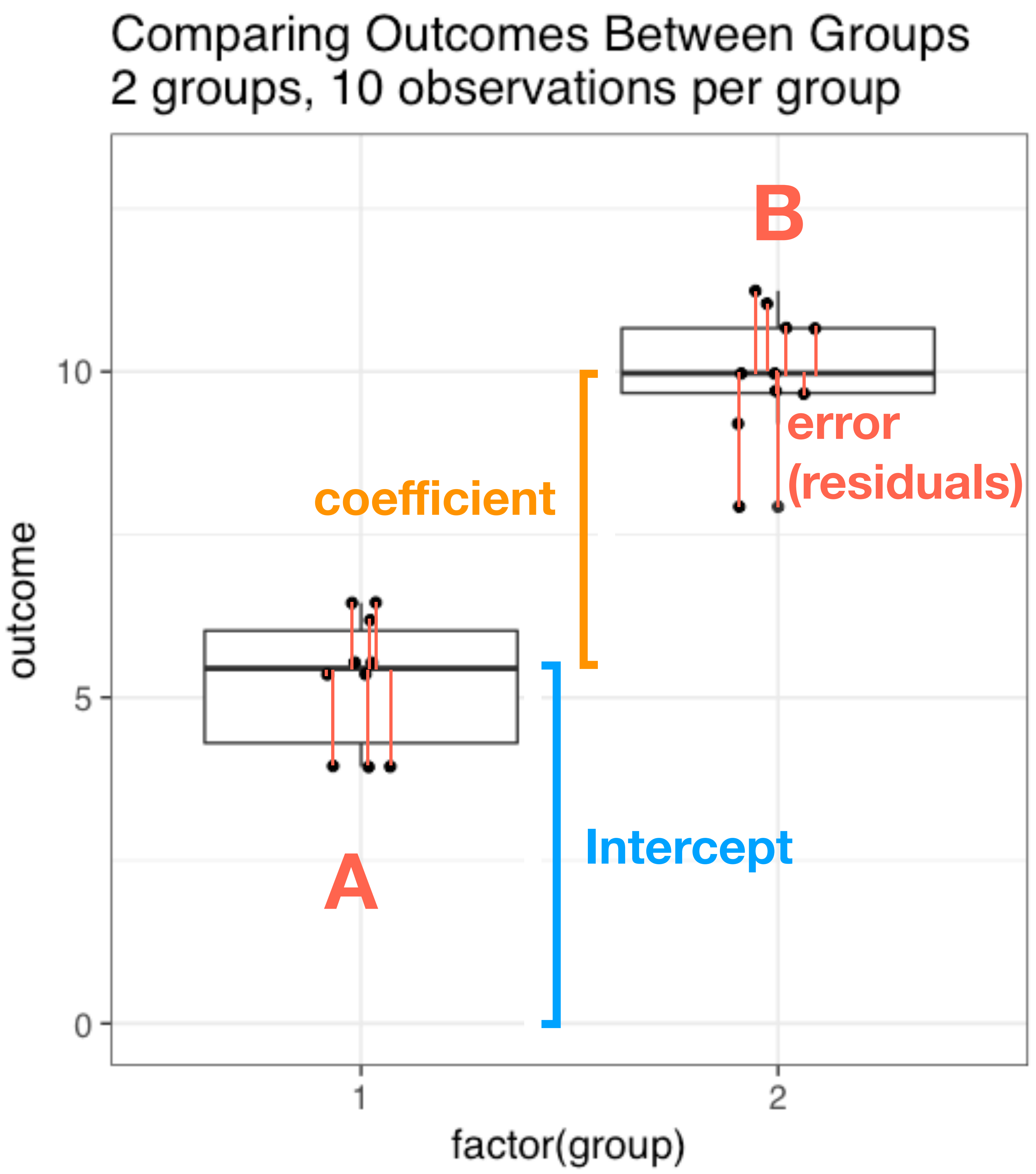
$Var(X) = variance\ of\ predictor\ (TREAT)$

How many observations do we *really* have?

20 observations or 2?

Estimating ATE from Cluster Randomization

we are estimating the ATE, *not* looking for correlations

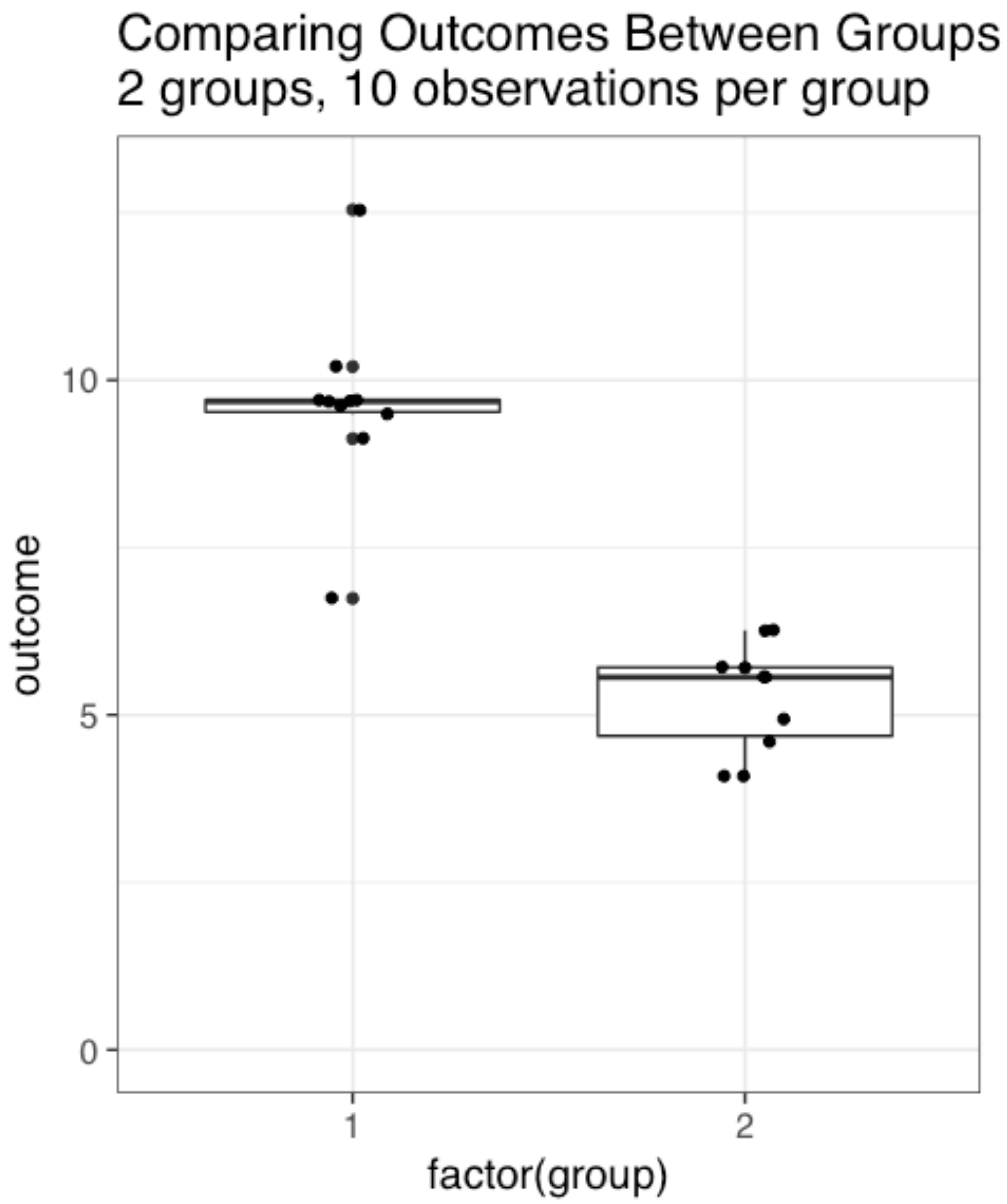


Assumptions of Linear Regression

- Linearity of residuals
- ~~**Independence of Outcomes**~~
- Homoscedasticity
- Normality of errors

Simulating Group Randomization

(examples in R at simulated-cluster-randomization-example.R)



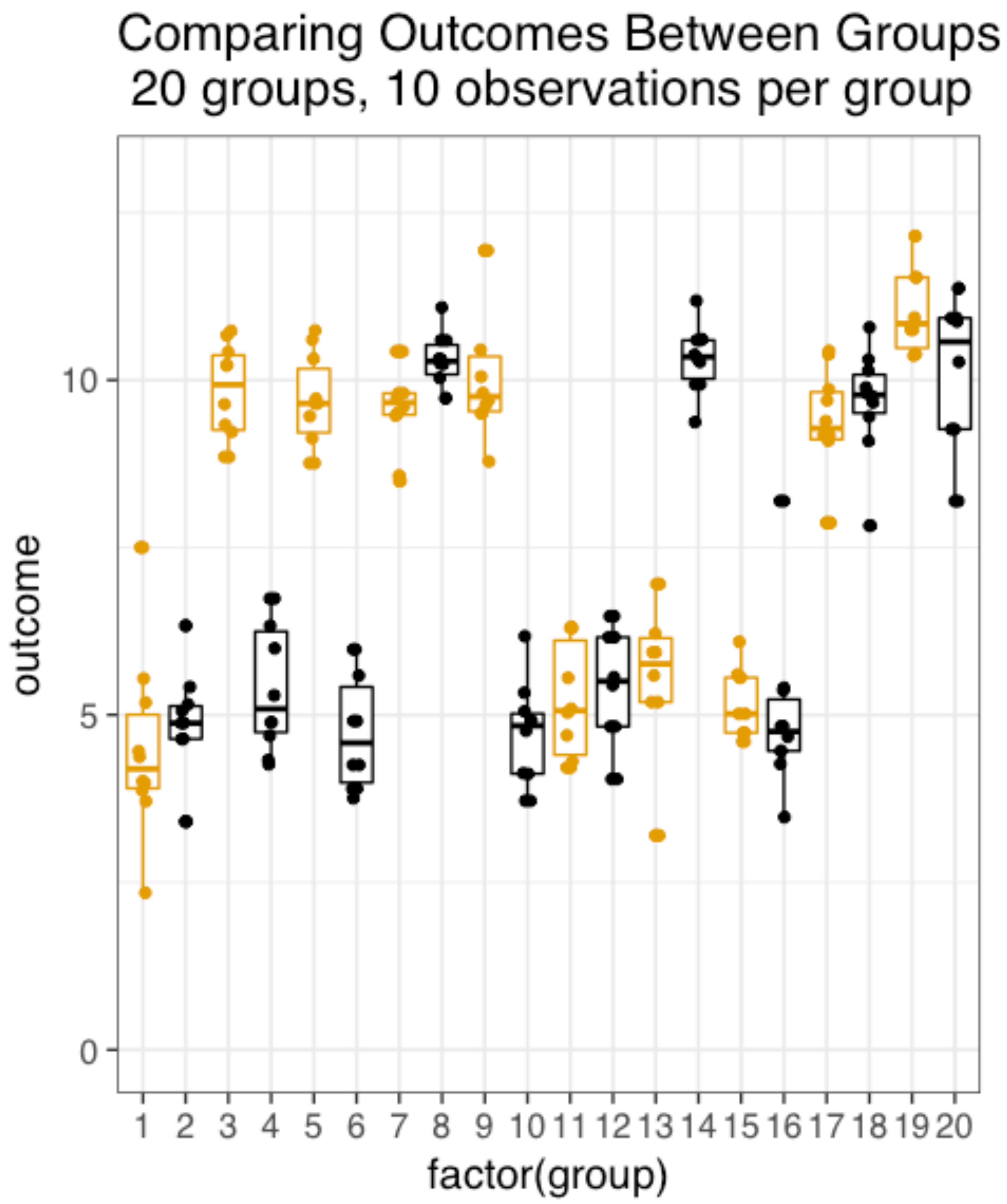

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   5.2787     0.3599  14.666 1.88e-11 ***
group%%2      4.3698     0.5090   8.585 8.85e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.138 on 18 degrees of freedom
Multiple R-squared:  0.8037, Adjusted R-squared:  0.7928
F-statistic:  73.7 on 1 and 18 DF,  p-value: 8.845e-08
```

Simulated 50x: mean treatment effect: 0.59

Simulating Group Randomization

(examples in R at simulated-cluster-randomization-example.R)



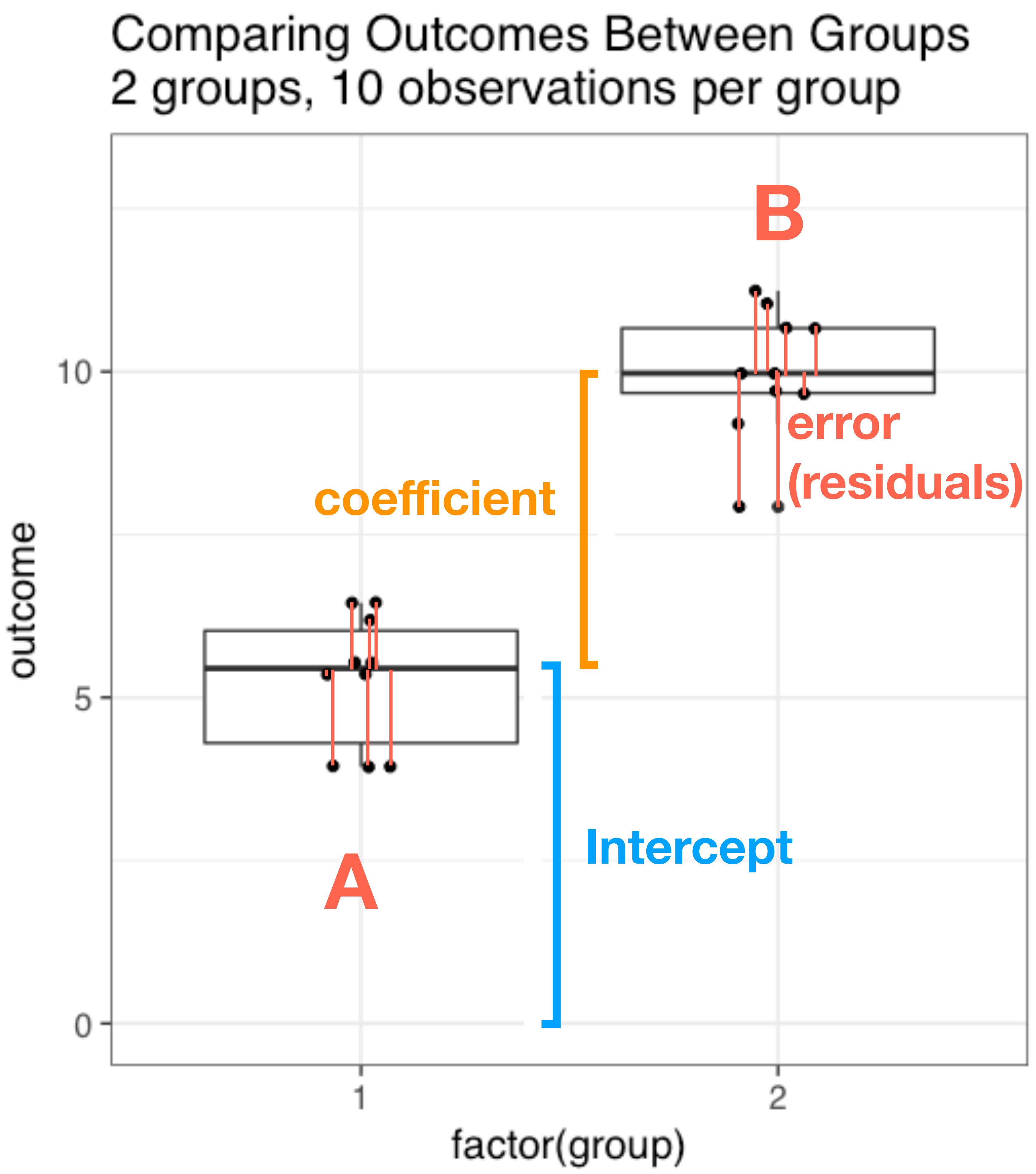

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.0362     0.2629  26.766   <2e-16 ***
group%%2      0.9522     0.3718   2.561   0.0112 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.629 on 198 degrees of freedom
Multiple R-squared:  0.03207,   Adjusted R-squared:  0.02718
F-statistic:  6.56 on 1 and 198 DF,  p-value: 0.01117
```

Simulated 50x: mean treatment effect: 0.13

Estimating ATE for Group Randomization

Random Intercepts Models and Clustered Standard Errors



Strategies

- Random Intercepts model
  - Especially useful for comparing individuals ***and*** groups
- Clustered standard errors (useful for getting point estimates)
  - Without specifying groups
  - With specifying groups

Random Intercepts Model

Random Intercepts Models

- Very specific assumptions
- Useful when comparing blocked randomization in a cluster randomized design (such as different kinds of posts or schools)
- Multilevel & hierarchical modeling could be its own entire semester. As always, take the time to familiarize yourself with a modeling approach before using it regularly

Example R code:

```
library(lme4)
library(lmerTest)
summary(glmer(outcome ~ group.treat + (1|group), data=posts))
```

Clustered Standard Errors

Huber White Standard Errors

- Useful when you want a single point estimate & standard errors
- Ongoing discussion about the best methods to cluster standard errors (Green’s lab now uses Bell & McCaffrey clustered SEs)
- Here we will use Huber White

Example code:

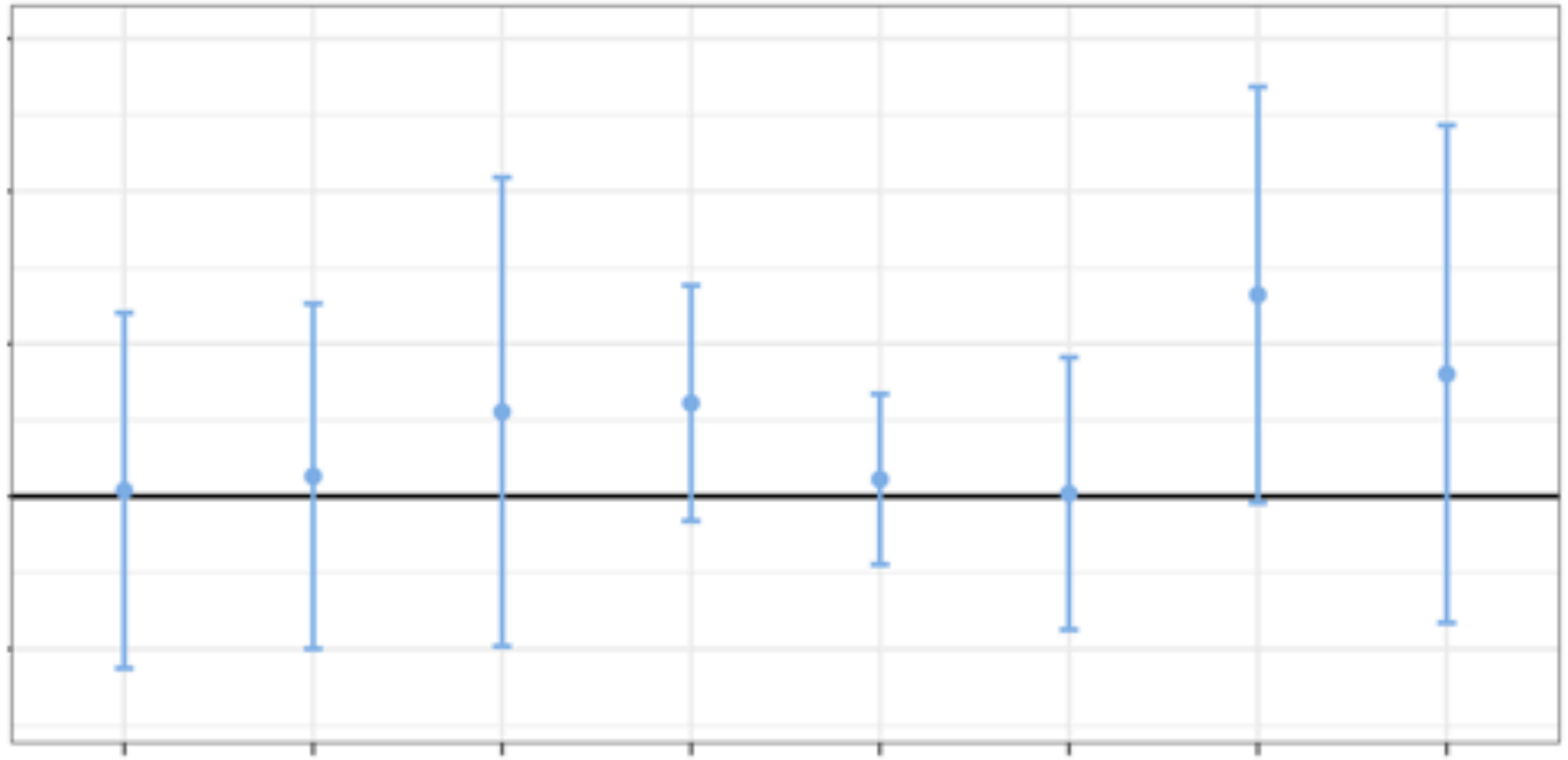
```
library(rms)
r1 = ols(outcome ~ group.treat, data=posts, x=TRUE)
r1.adjusted <- robcov(r1, cluster=factor(posts$group), method=‘huber')
screenreg(list(r1))
```

https://www.rdocumentation.org/packages/rms/versions/5.1-2/topics/robcov

Regression Adjustment

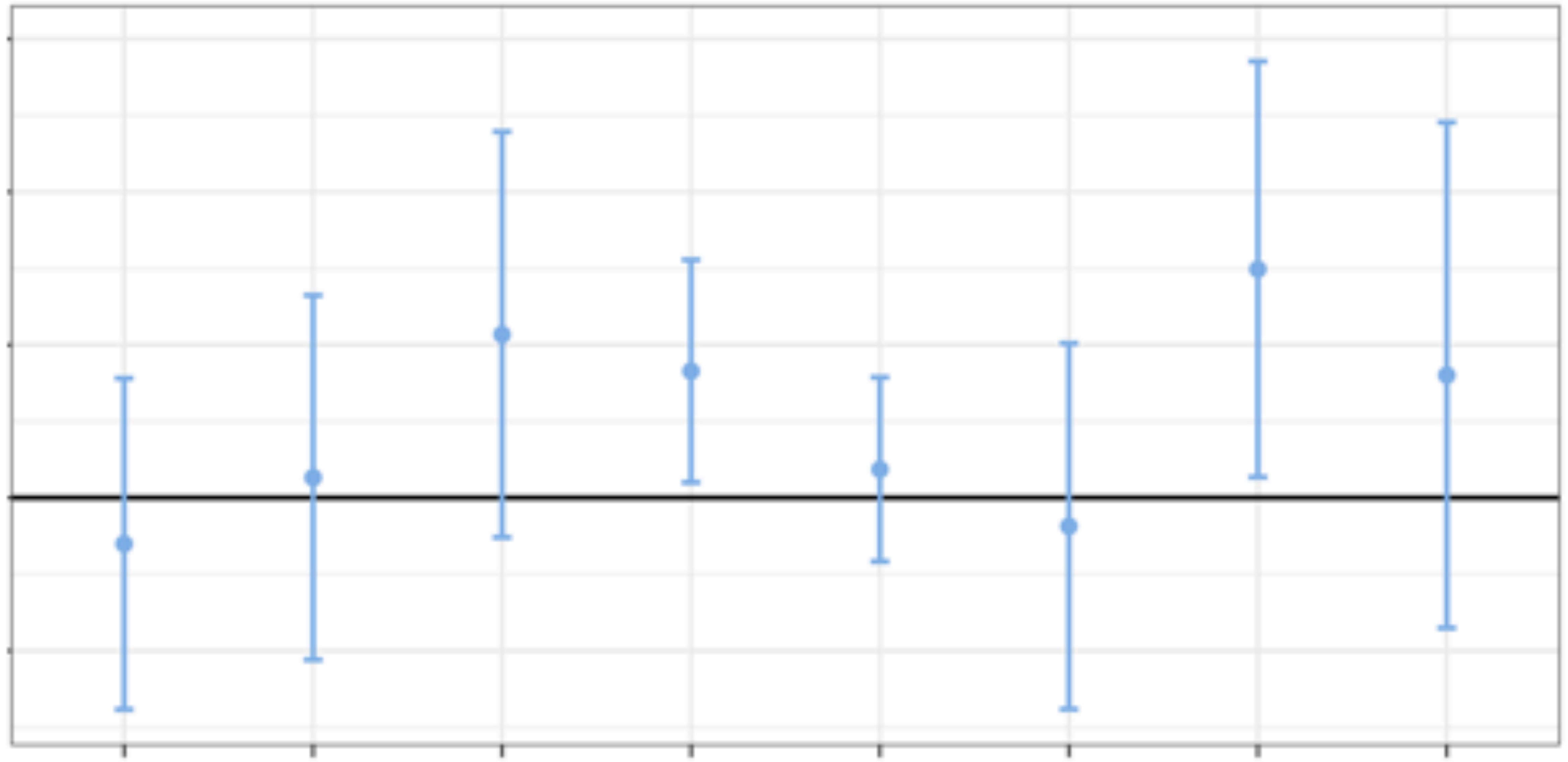
Improving the precision of standard errors

$$\ln Interactions = \beta_0 + \beta_1 TREAT + \epsilon$$



(n=8 experiments conducted on Facebook)
Linear models estimating effect on log-transformed interactions.
Experiment by SOC 412: github.com/natematias/SOC412

$$\ln Interactions = \beta_0 + \beta_1 TREAT + \beta_2 Weekend + \epsilon$$



(n=8 experiments conducted on Facebook)
Linear models estimating effect on log-transformed interactions, adjusted by weekend. Experiment by SOC 412: github.com/natematias/SOC412

Regression Adjustment

Avoid conditioning on post-treatment variables

scholars often unwittingly **distort treatment effect estimates** by conditioning on **variables** that could be **affected by** their experimental **manipulation**.

Montgomery, J. M., Nyhan, B., & Torres, M. (2016, November). **How conditioning on post-treatment variables can ruin your experiment and what to do about it.** In Annual meeting of the Midwest Political Science Association, Chicago, IL, April.

Block Randomization

Preventing Problems From Introducing Selection Bias

Bonferroni Adjustment

Adjusting p-values for multiple comparison

Note: Bonferroni is the most conservative, so you may choose others

```
num.comparisons <- 2
m1 <- lm(outcome ~ group.treat, data=posts)
p.adjust(summary(m1)$coefficients['(Intercept)',][['Pr(>|t|)']],
         method="bonferroni",
         n=num.comparisons)
```