

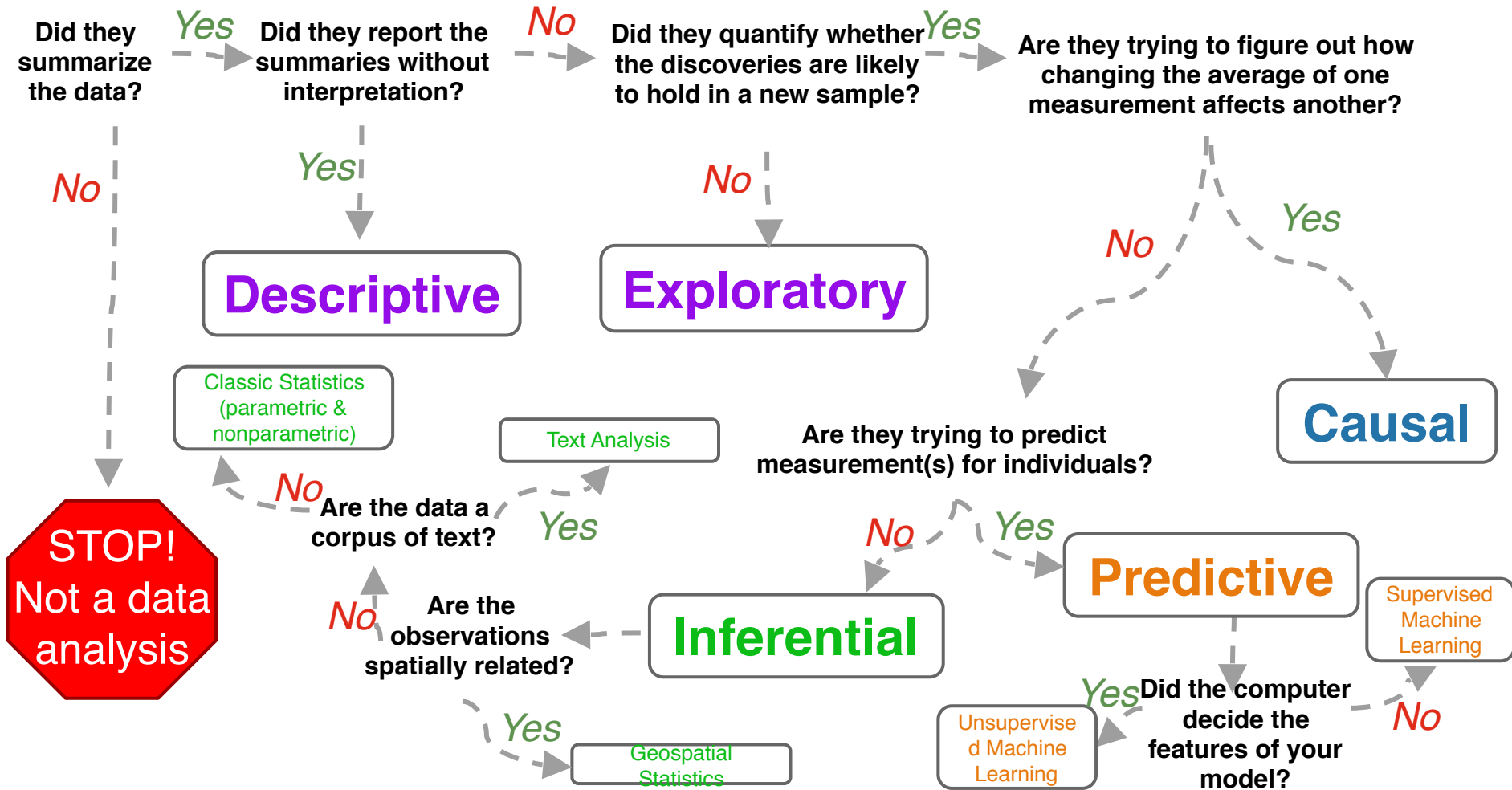
Inferential Analysis

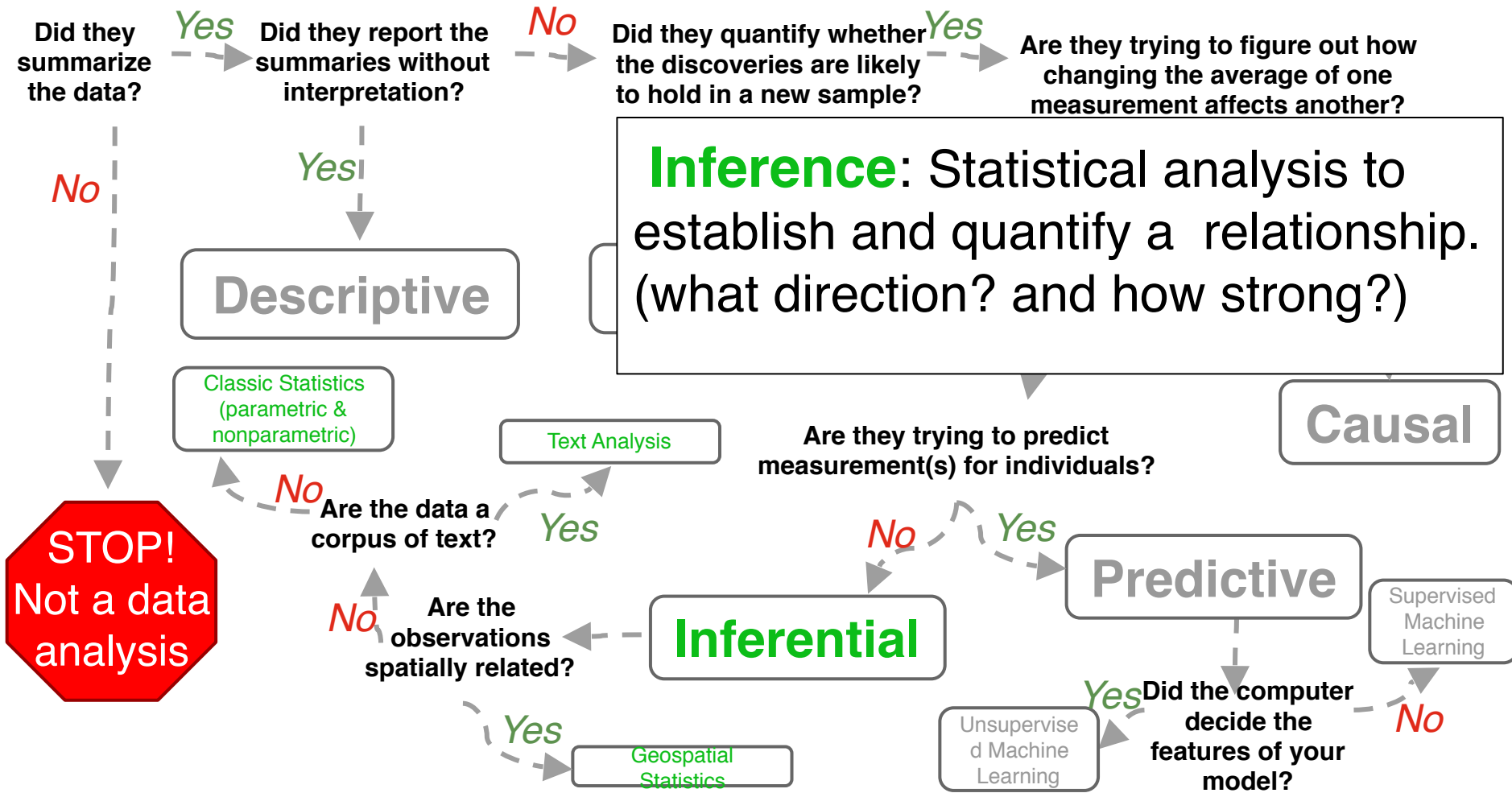
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Lectures : <https://github.com/COGS108/Lectures-Wi23>





- **Problem:** Does Sesame Street affect kids brain development?
- **Data science question:** What is the relationship between watching Sesame Street and test scores among children?
- **Type of analysis:** Inferential analysis



Sesame Street
viewership

??

Test scores

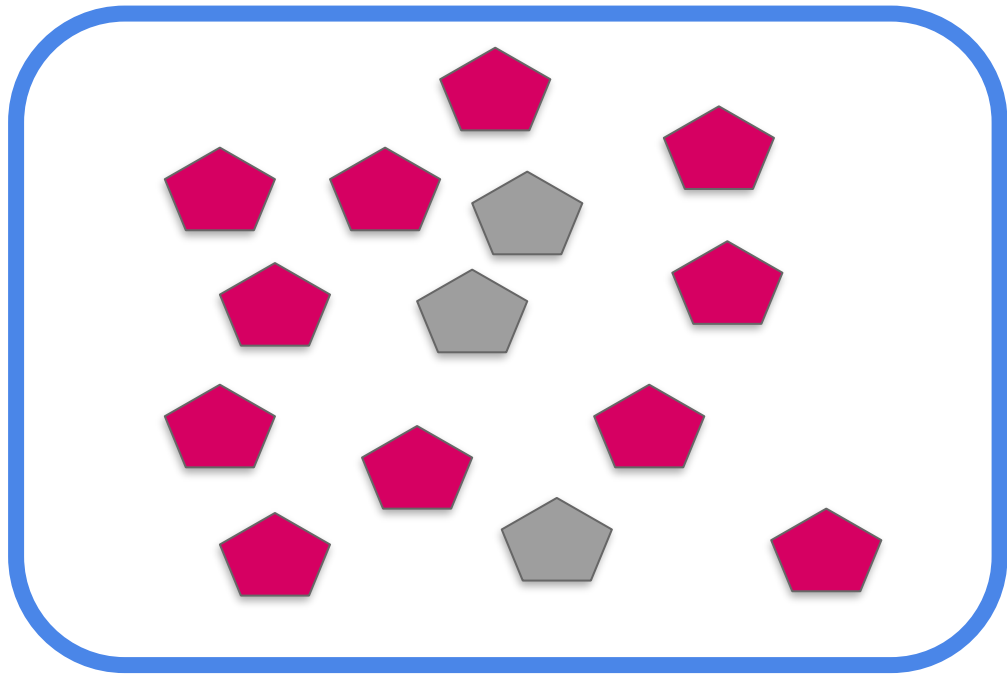
Establishing & Stating Your Null and Alternative Hypotheses Helps Guide Your Analysis

Null Hypothesis:

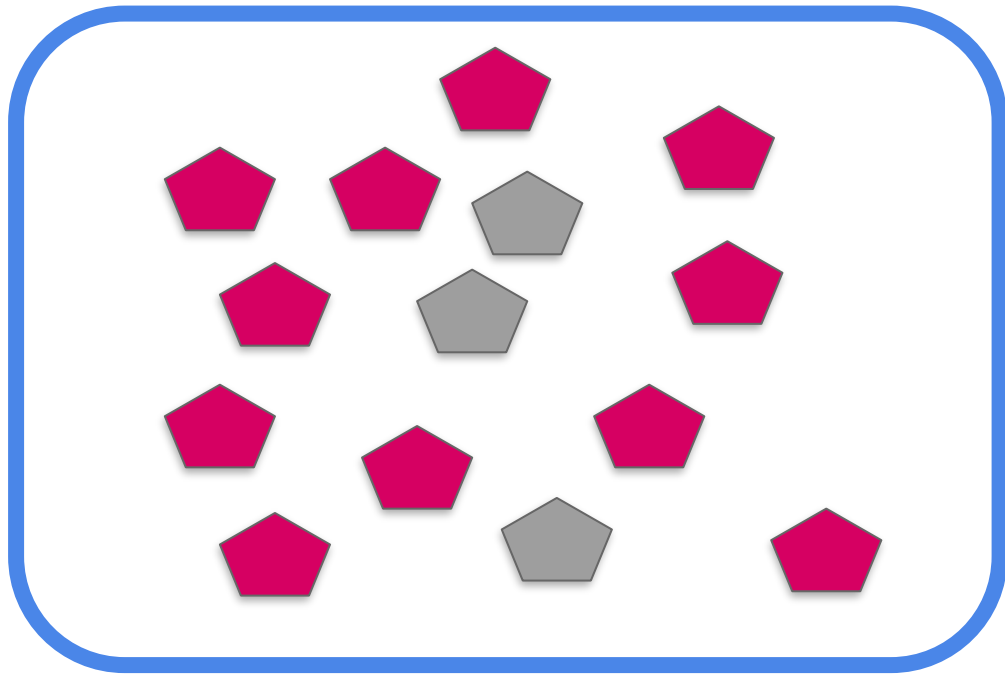
H_0 : Sesame Street has *no effect* on kids brain development

Alternative Hypothesis:

H_a : Watching Sesame Street *has an effect* on kids' brain development



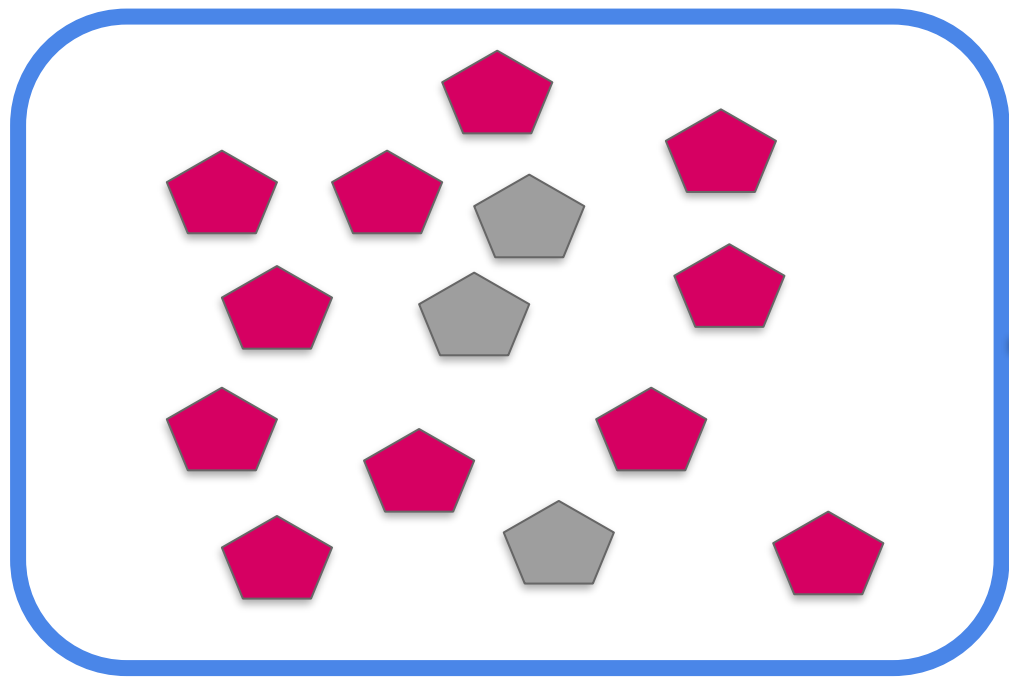
Population



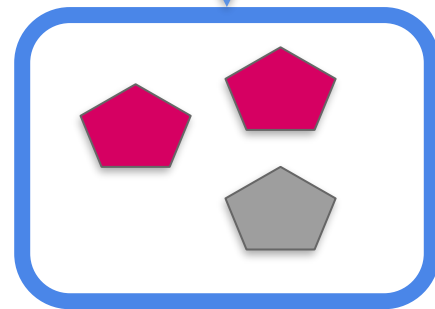
Population



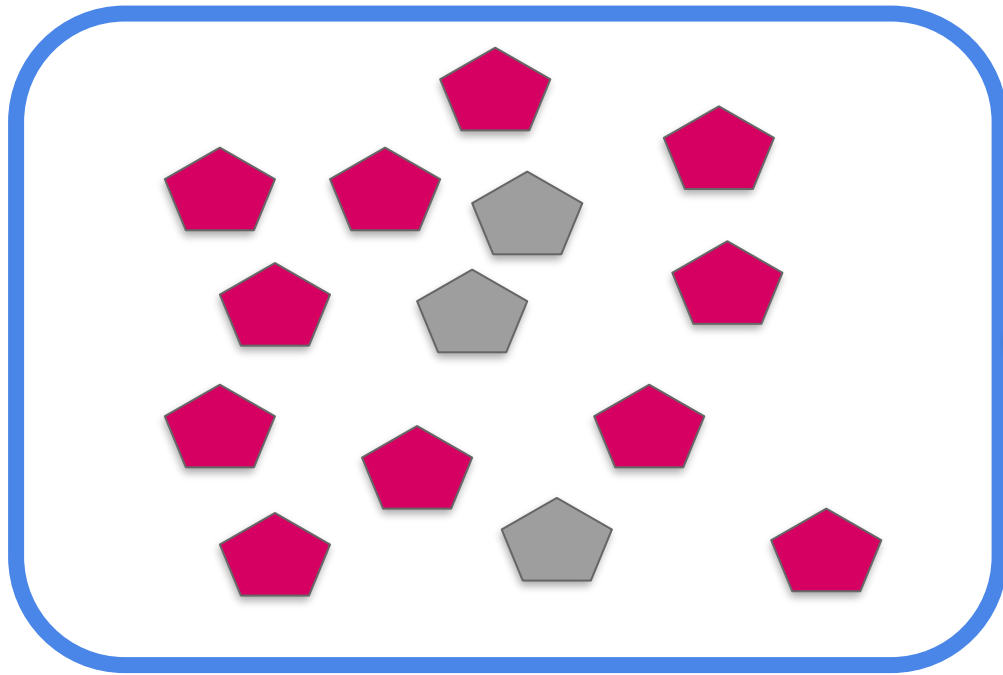
In our Sesame street
example, the
population would be
all children



Population



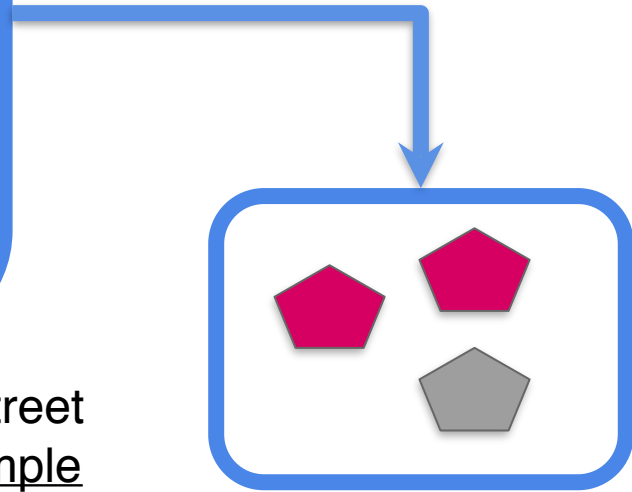
Sample



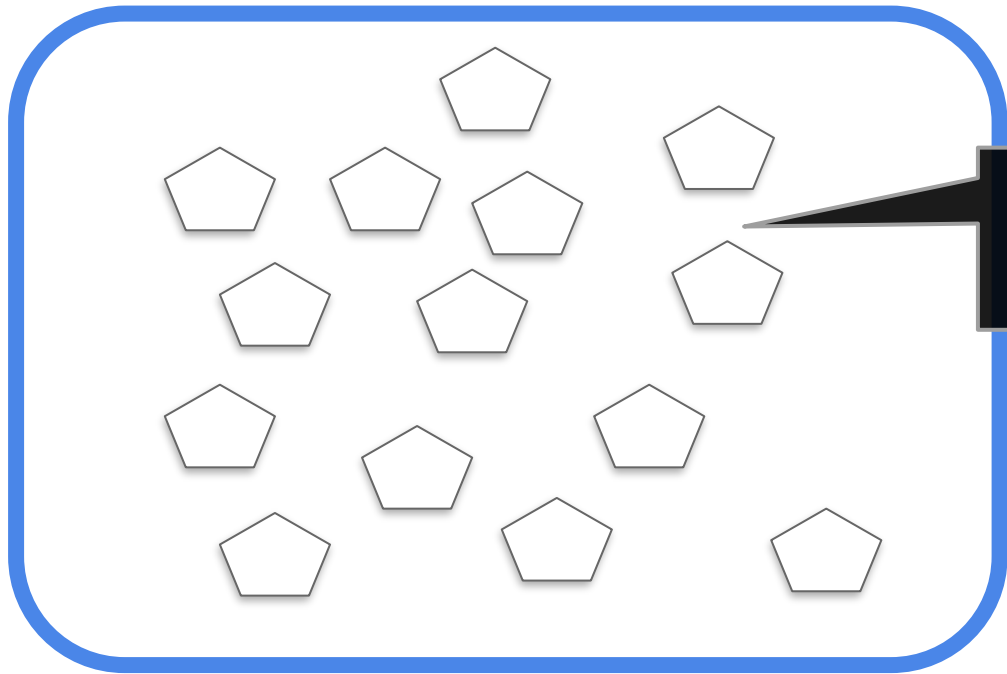
Population



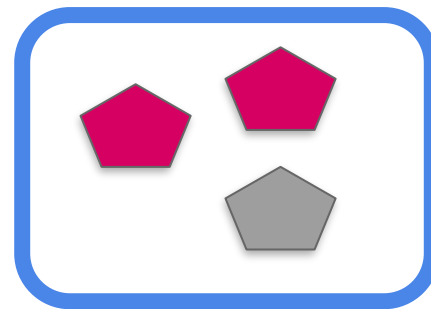
In our Sesame street example, the sample would be the children included in the study



Sample



Population

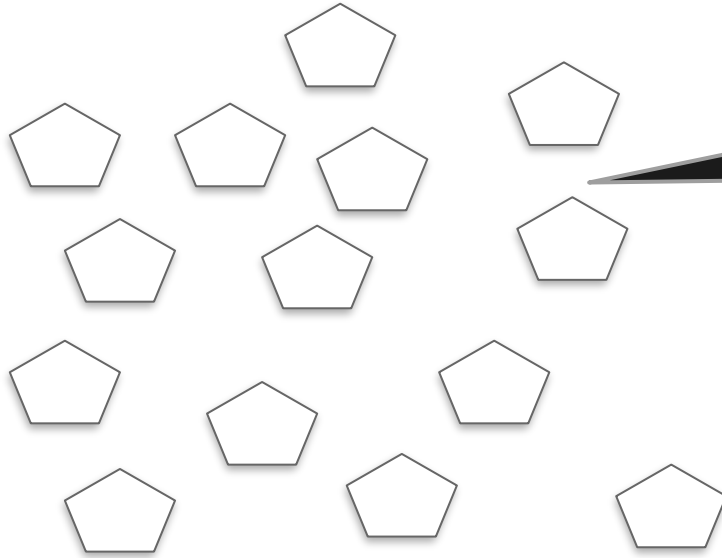


Sample

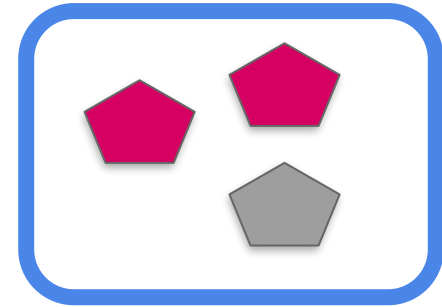


We don't know how
much Sesame street
was watched by or the
tests scores of all kids

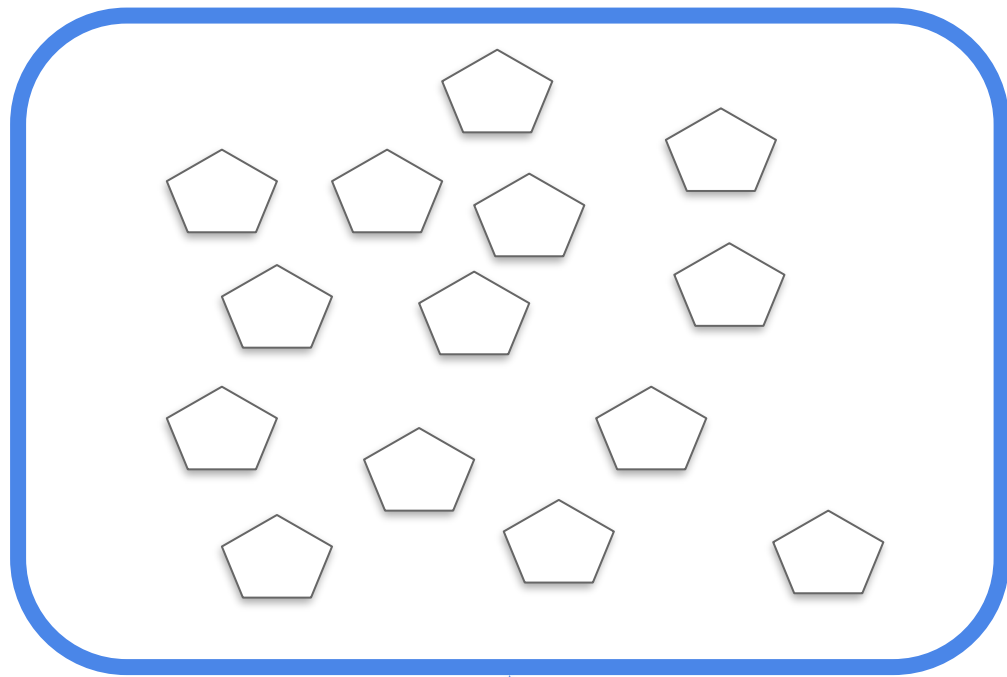
(ツ)



Population

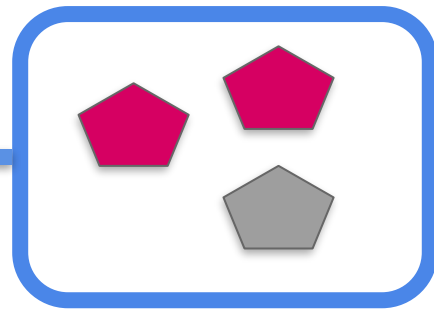


Sample



Population

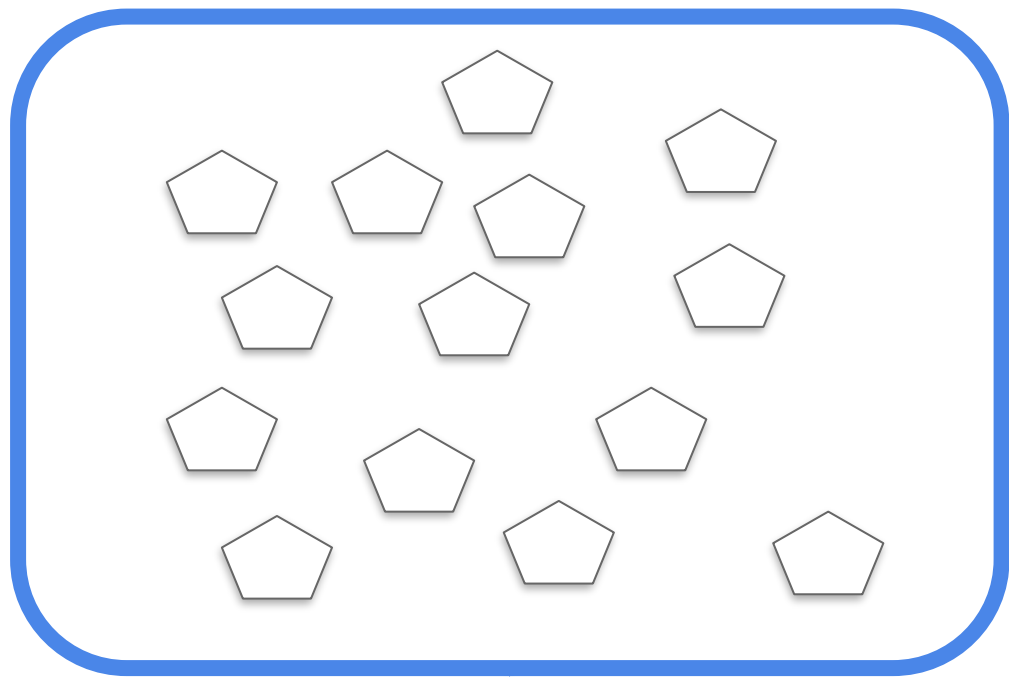
Based on the relationship we see in our sample, we can infer the answer to our question in our population



Sample

Inference

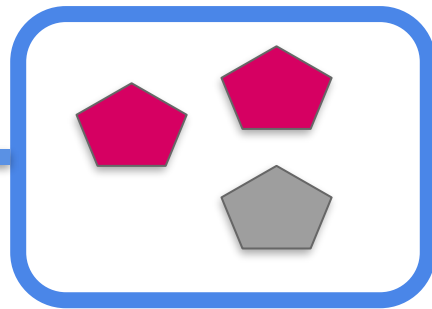




Population



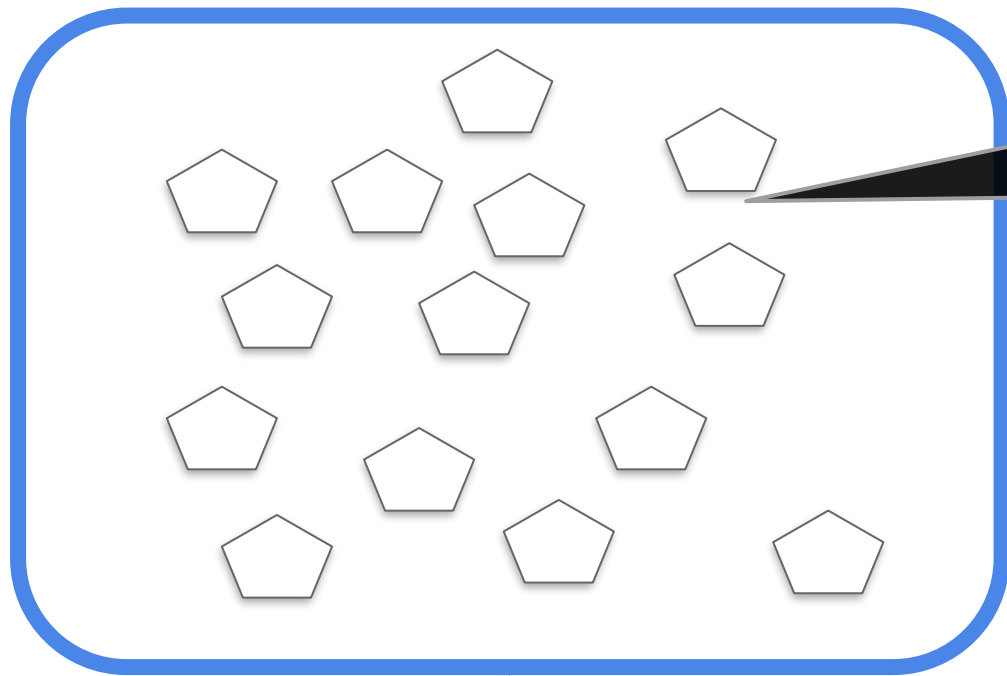
So we look at Sesame
street viewing and test
scores in a representative
sample of kids



Sample

Inference

!

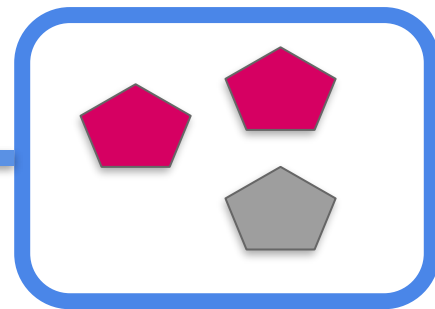


Population

Best guess



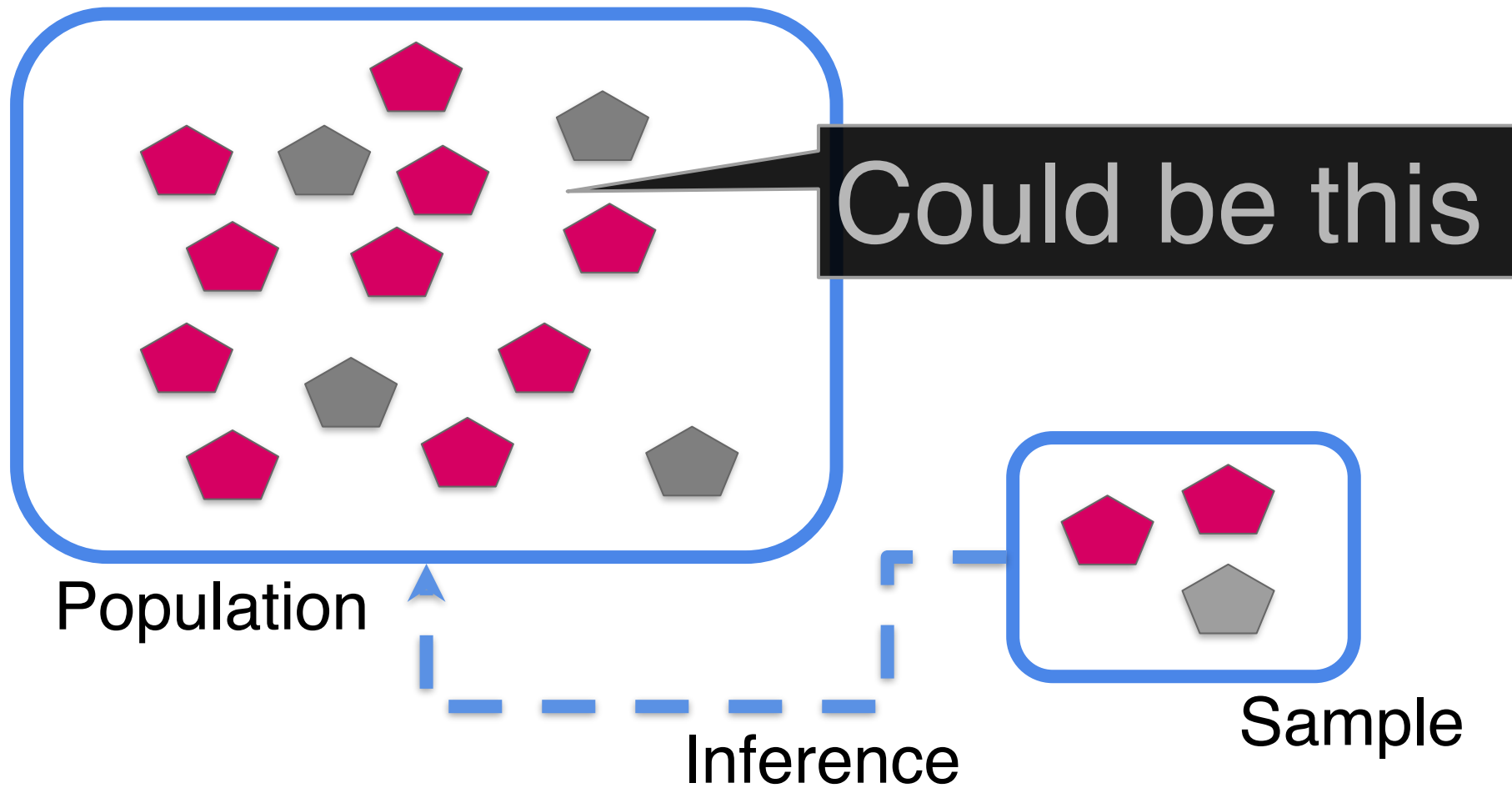
So we look at Sesame street
viewing and test scores in a
representative sample of kids

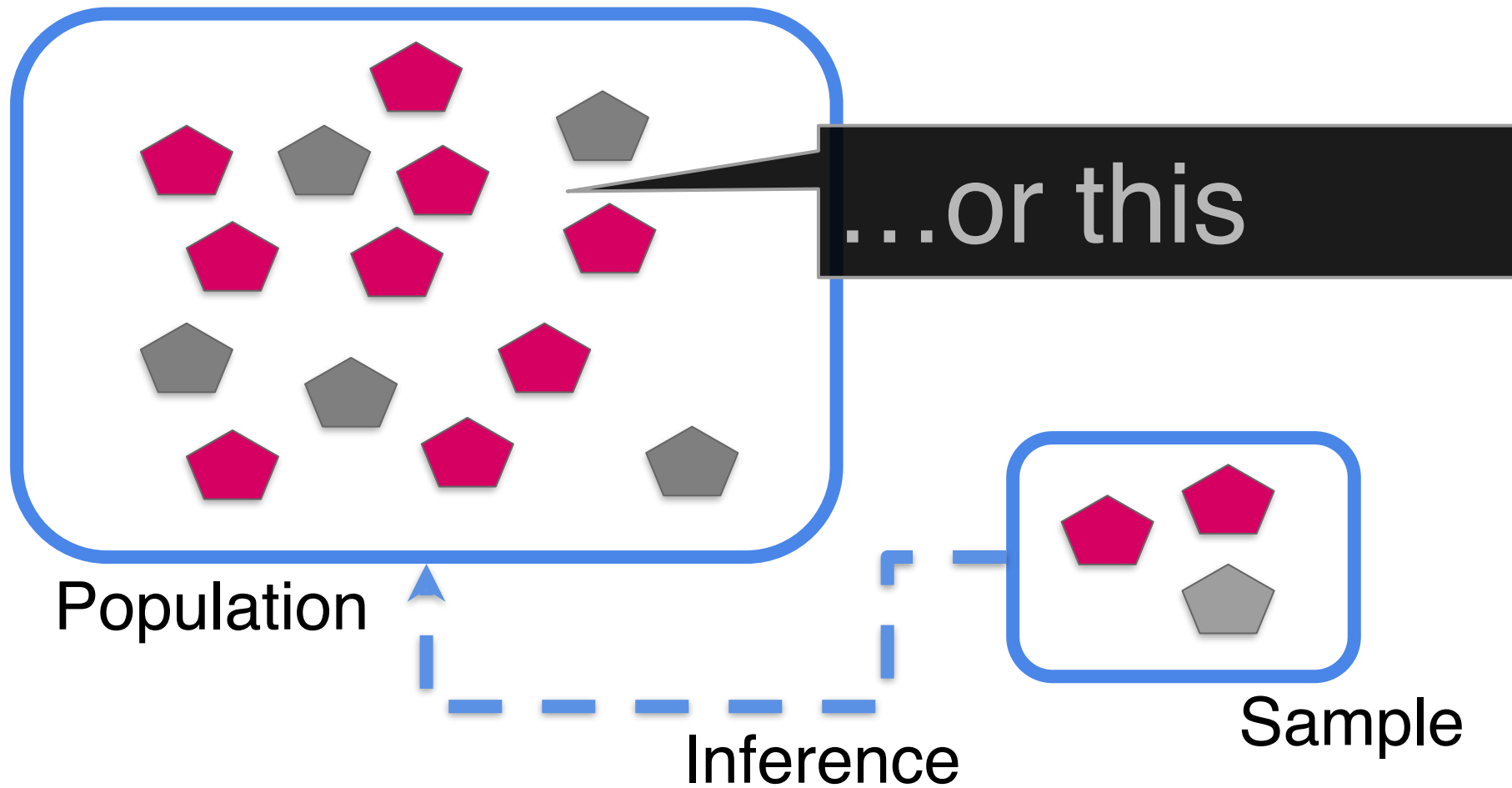


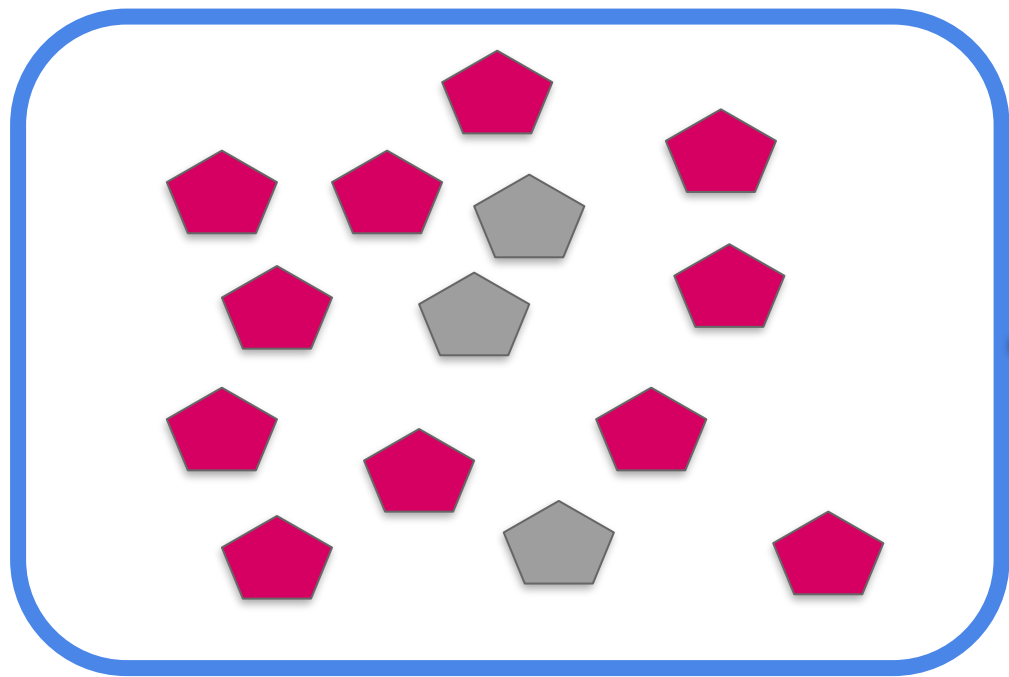
Sample

Inference

!

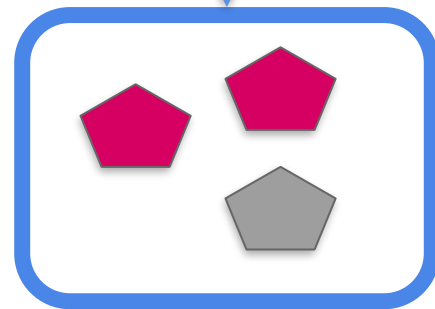




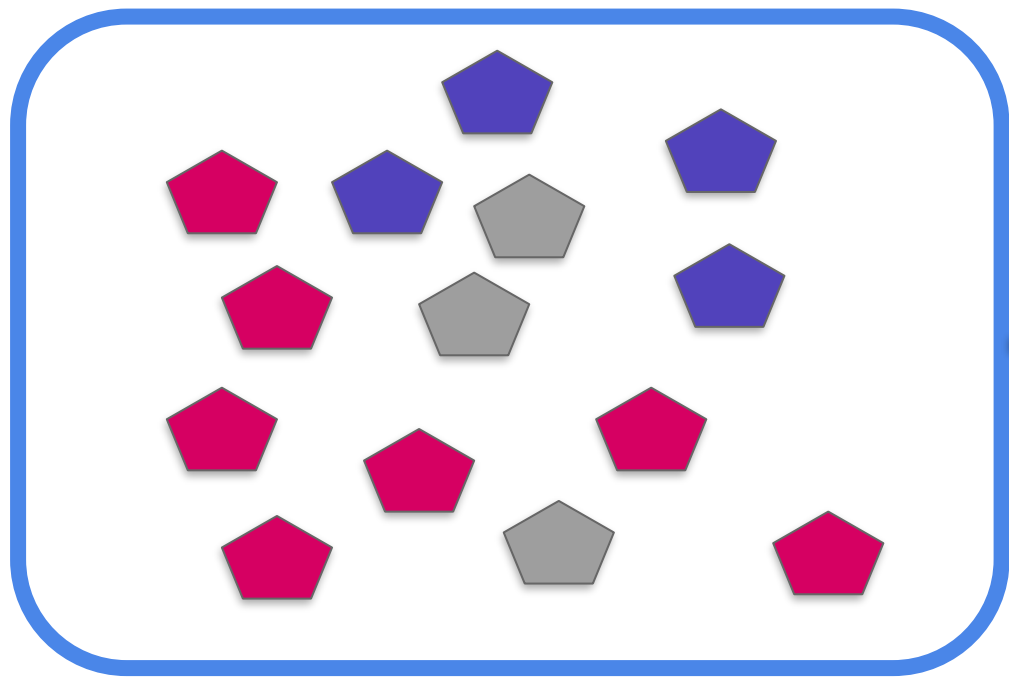


Population

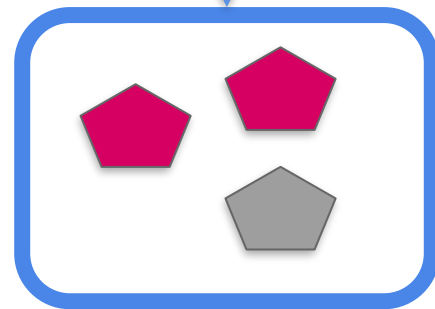
Probability



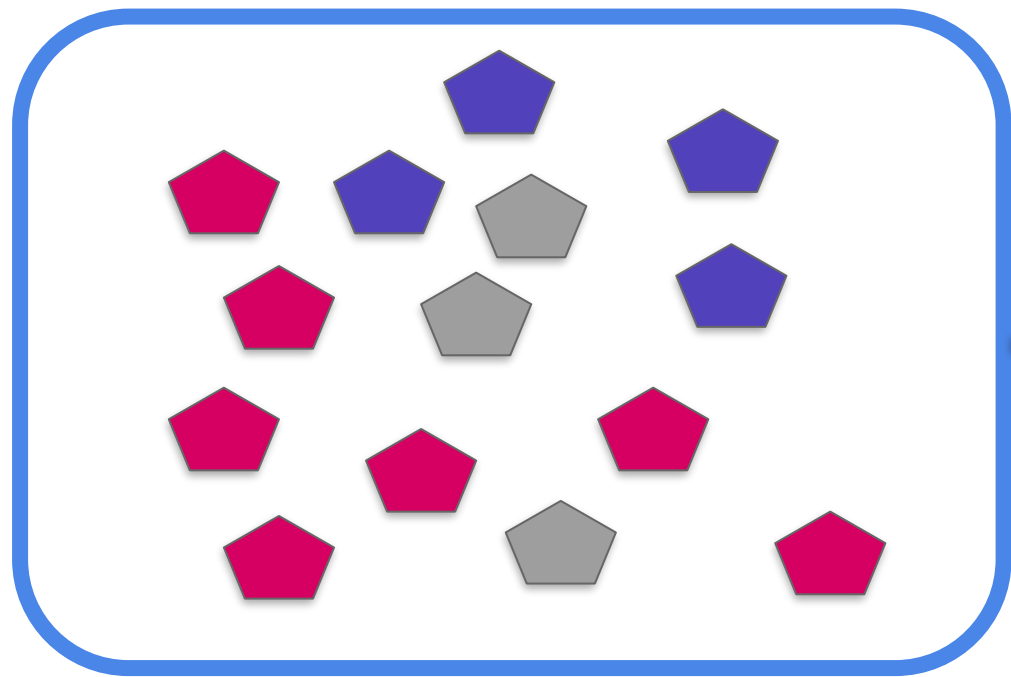
Sample



Population

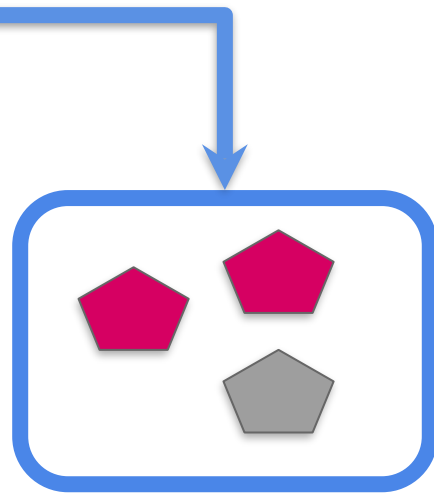


Sample



Population

If your sample is *not* representative of your population, you can not do inferential analysis.



Sample

Inference

Approaches to Inference

CORRELATION

ASSOCIATION
BETWEEN VARIABLES

i.e. Pearson
Correlation,
Spearman
Correlation, chi-
square test

COMPARISON OF MEANS

DIFFERENCE IN MEANS
BETWEEN VARIABLES

i.e. t-test, ANOVA

REGRESSION

DOES CHANGE IN ONE
VARIABLE MEAN
CHANGE IN ANOTHER?

i.e. simple
regression, multiple
regression

NON-PARAMETRIC TESTS

FOR WHEN
ASSUMPTIONS IN
THESE OTHER 3
CATEGORIES ARE NOT
MET

i.e. Wilcoxon rank-
sum test, Wilcoxon
sign-rank test, sign
test

CORRELATION
ASSOCIATION
BETWEEN VARIABLES

i.e. Pearson
Correlation,
Spearman
Correlation, chi-
square test

**COMPARISON OF
MEANS**
DIFFERENCE IN MEANS
BETWEEN VARIABLES

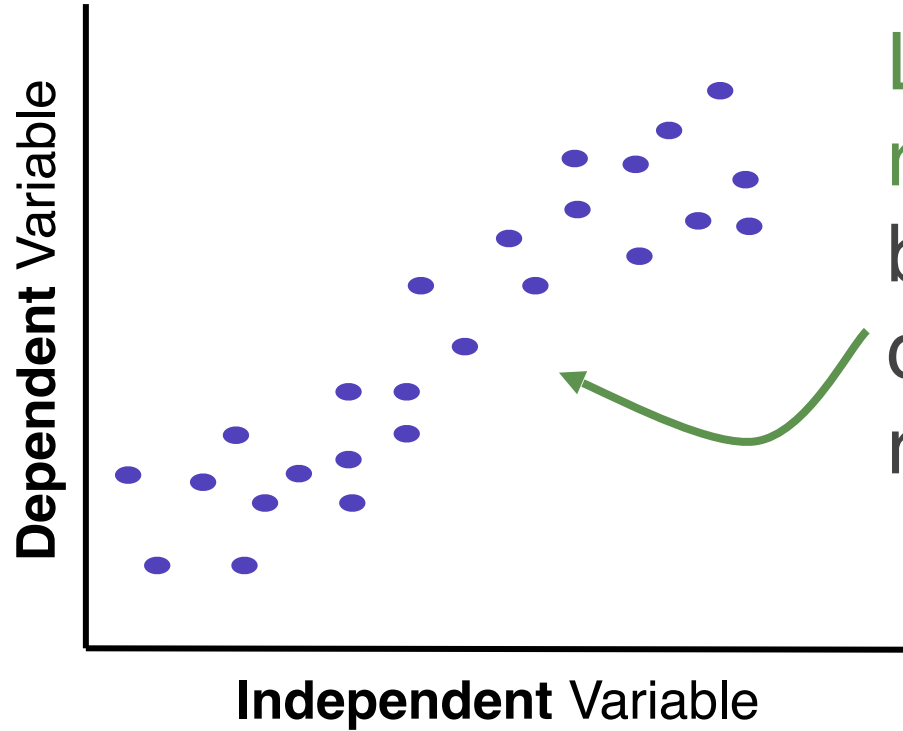
i.e. t-test, ANOVA

REGRESSION
DOES CHANGE IN ONE
VARIABLE MEAN
CHANGE IN ANOTHER?

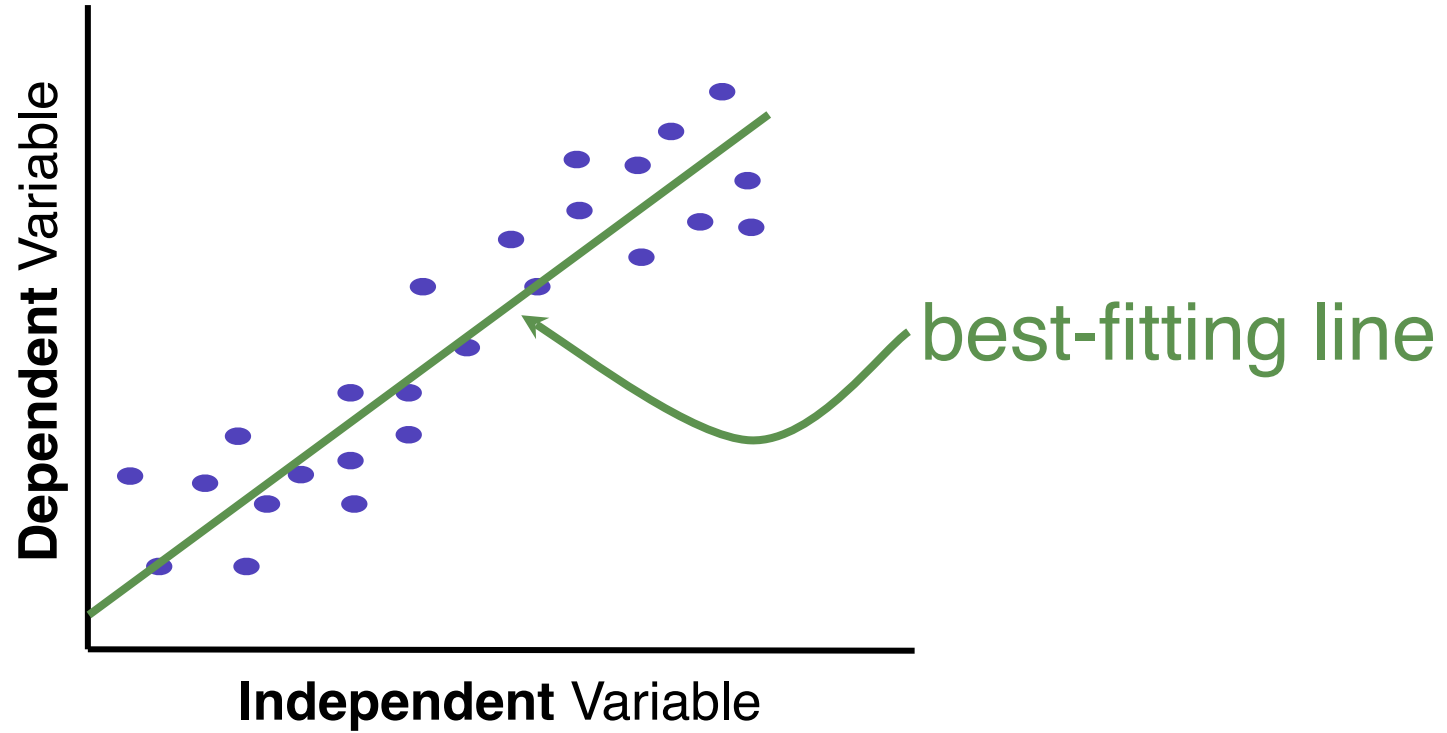
i.e. simple
regression, multiple
regression

**NON-PARAMETRIC
TESTS**
FOR WHEN
ASSUMPTIONS IN
THESE OTHER 3
CATEGORIES ARE NOT
MET

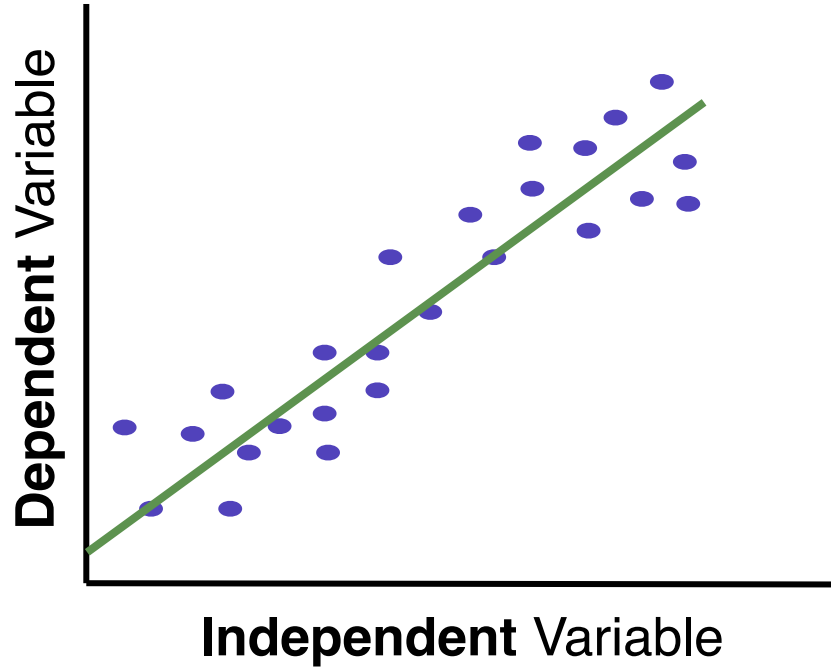
i.e. Wilcoxon rank-
sum test, Wilcoxon
sign-rank test, sign
test



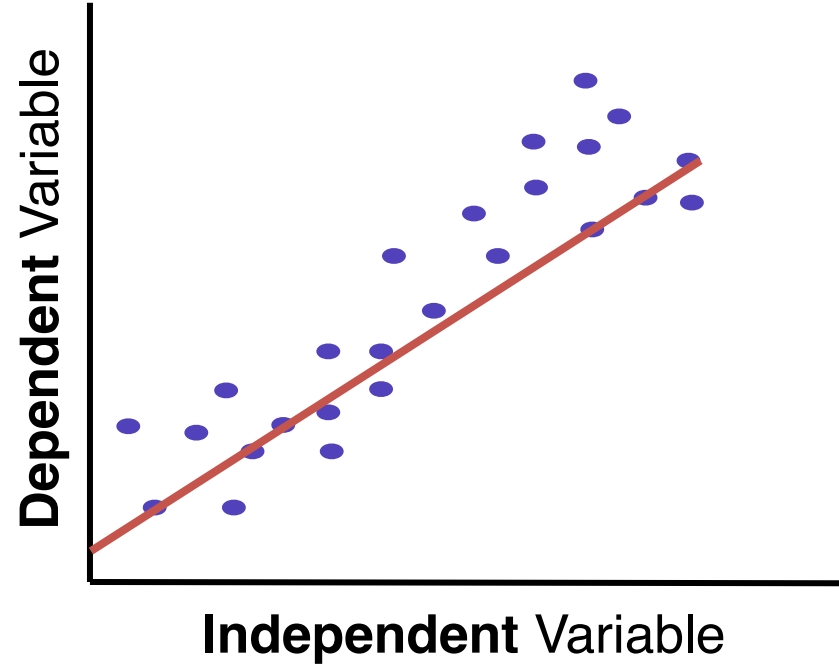
Linear regression can be used to describe this relationship

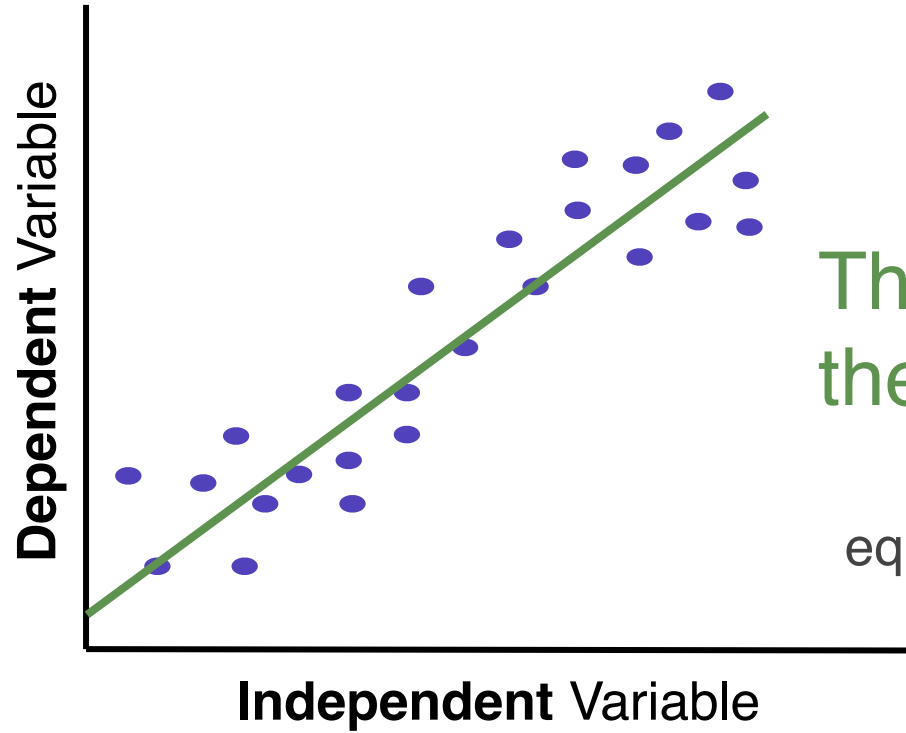


Best-fitting line



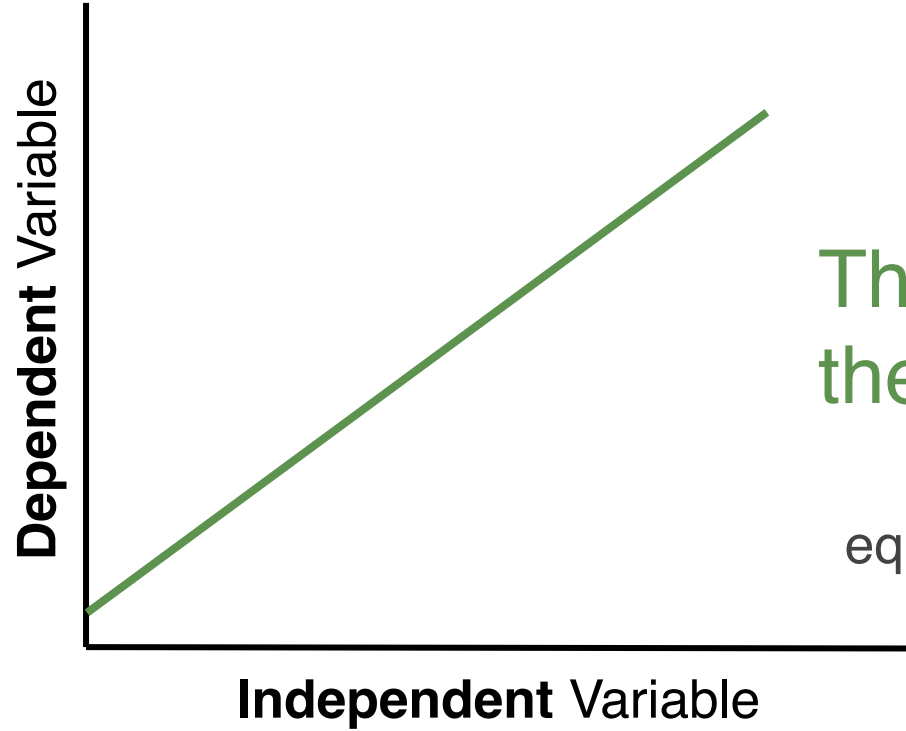
NOT a best-fitting line





This line is a model of the data

Models are mathematical equations generated to *represent* the real life situation

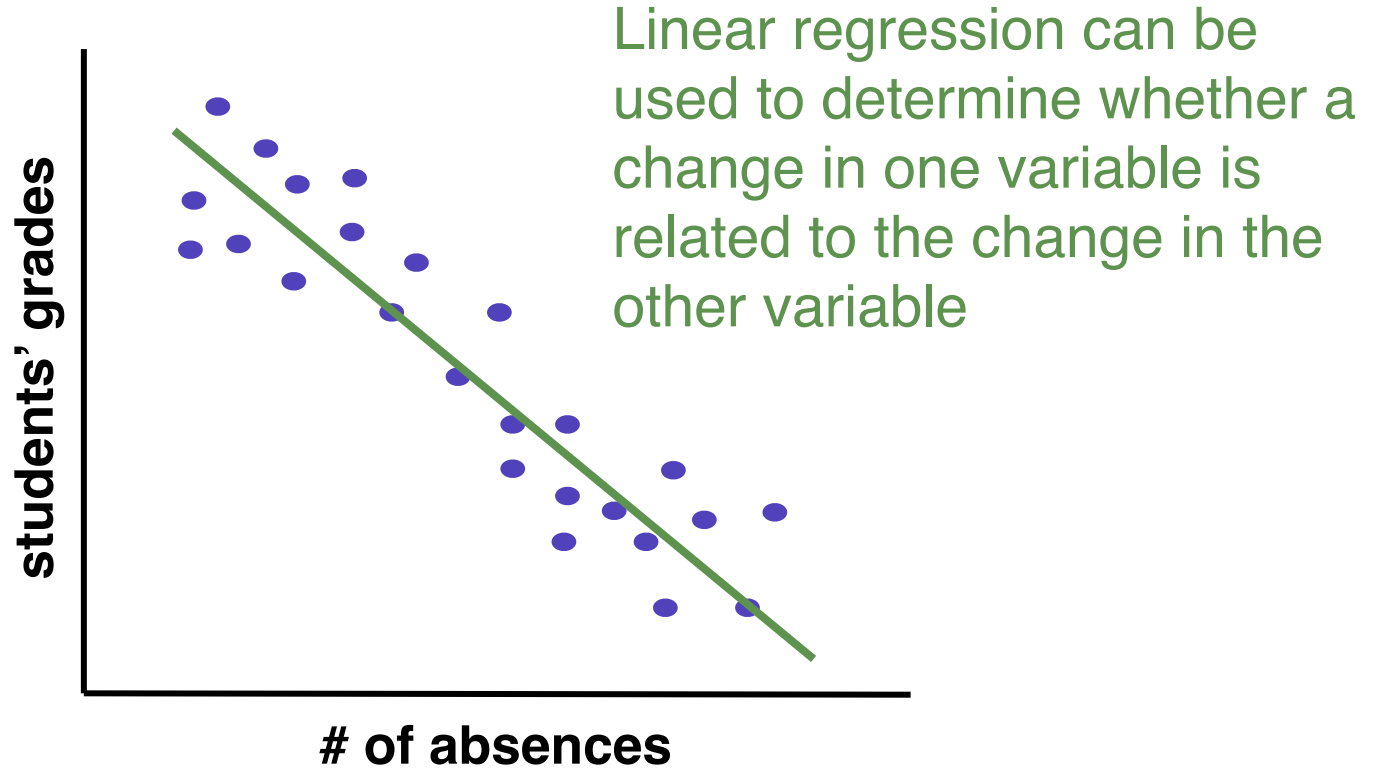


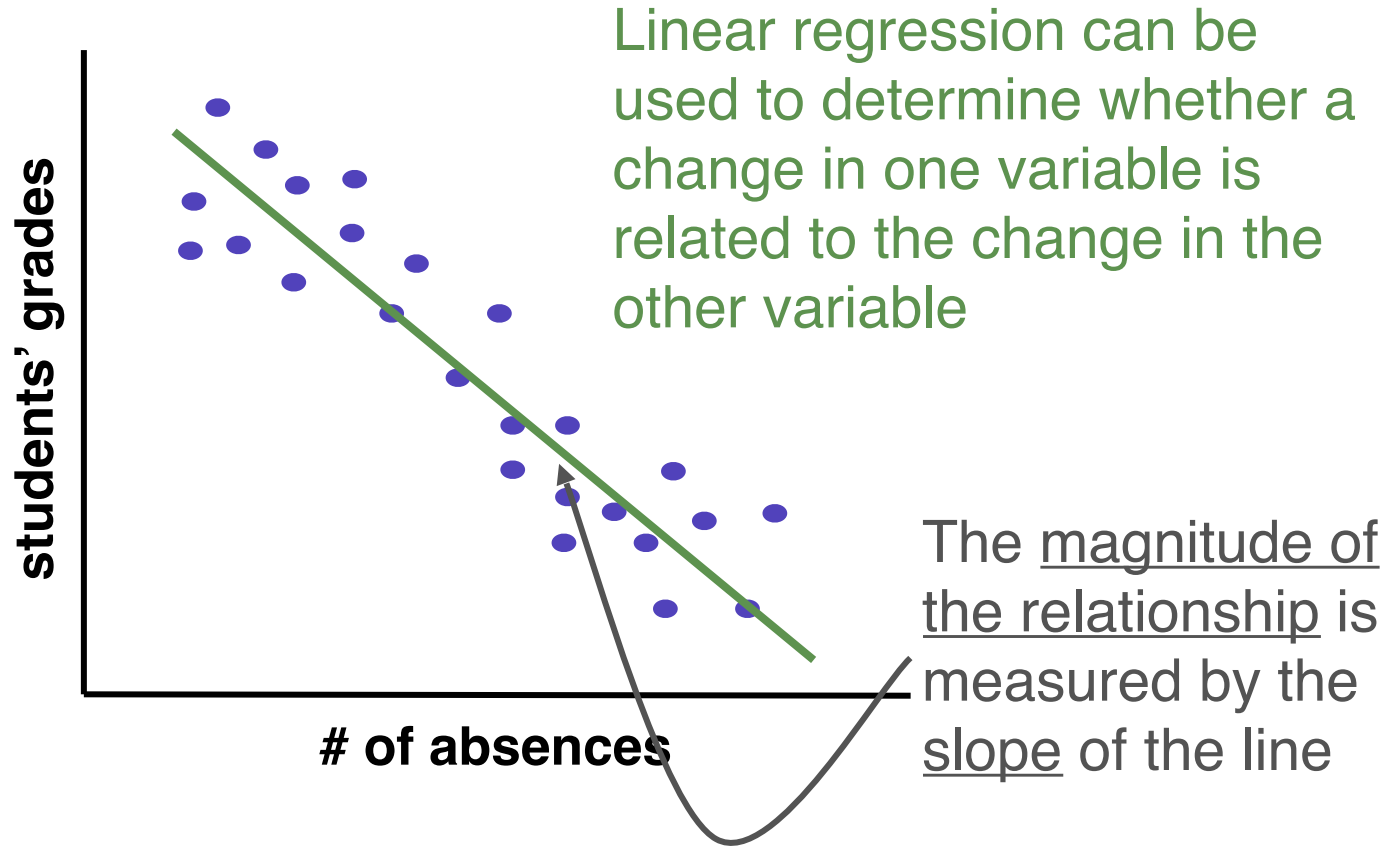
This line is a model of the data

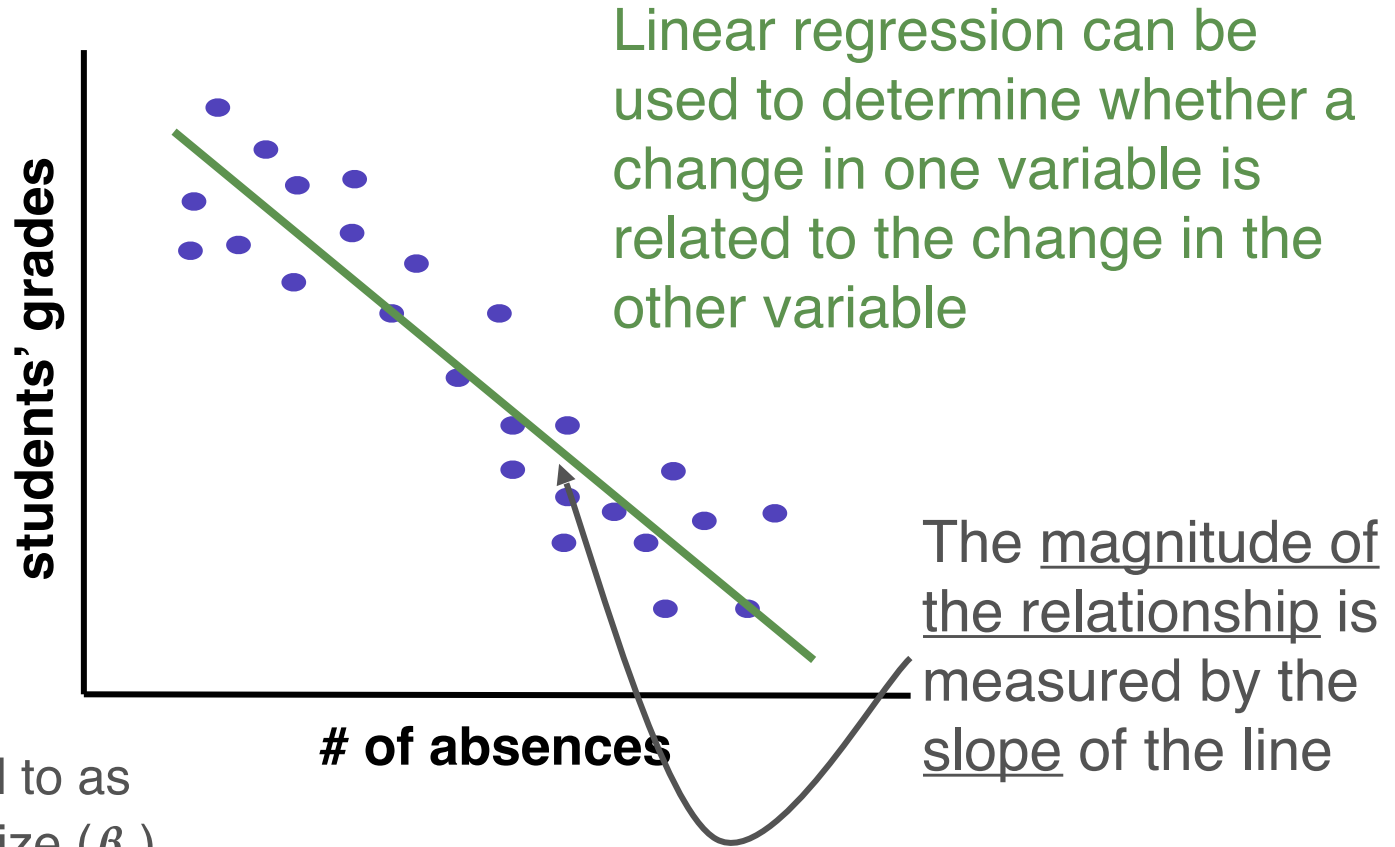
Models are mathematical equations generated to *represent* the real life situation

“All models are wrong, but some are useful”

-George Box (British Statistician, *JASA* 1976)

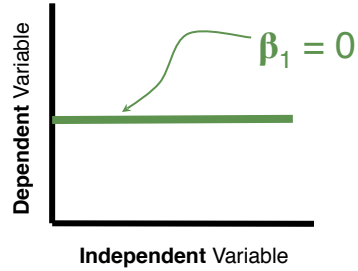




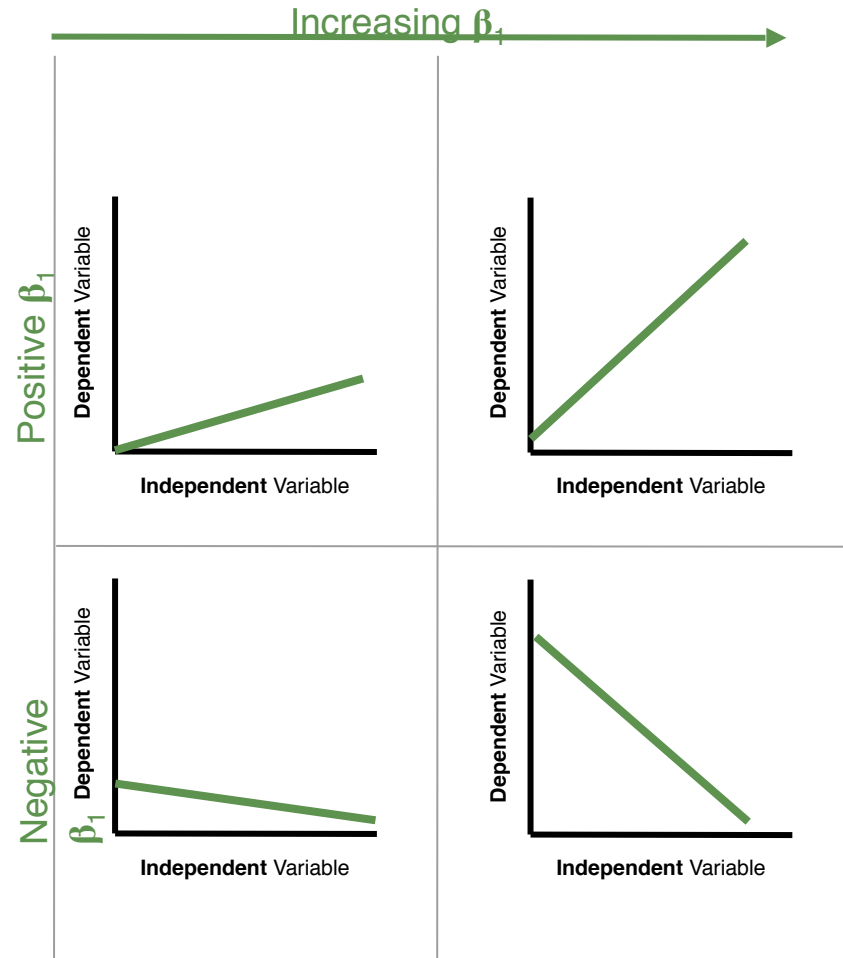
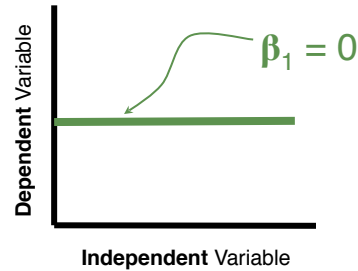


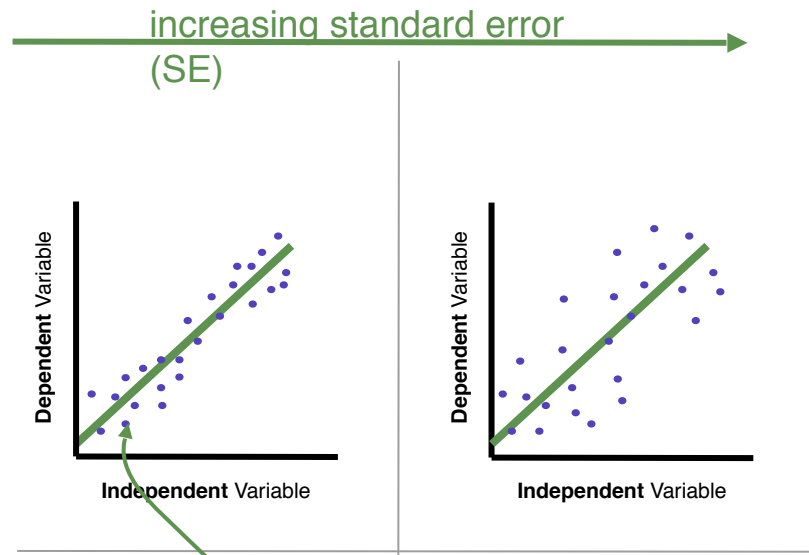
This is also referred to as the model's effect size (β_1)

Effect size (β_1)
can be estimated
using the slope of
the line



Effect size (β_1)
can be estimated
using the slope of
the line

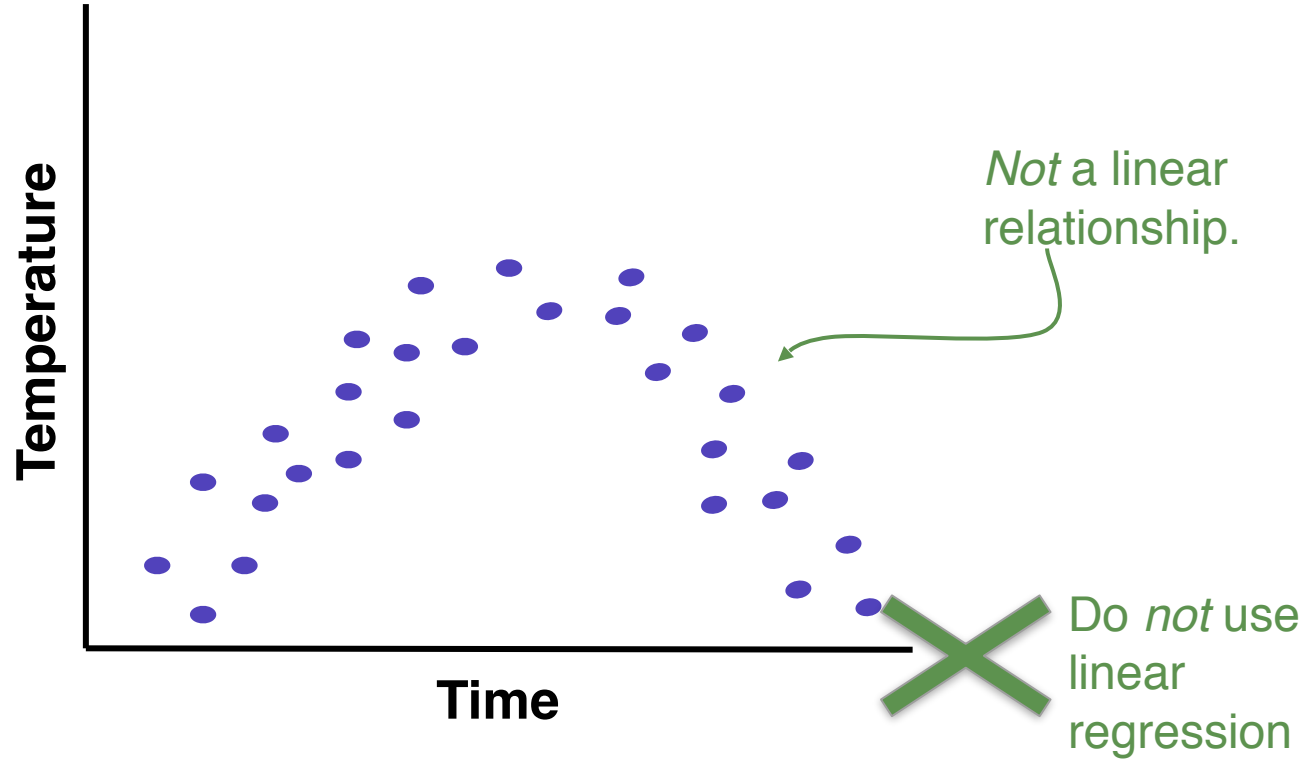




The *closer* the points
are to the regression
line, the *less*
uncertain we are in
our estimate

Assumptions of linear regression

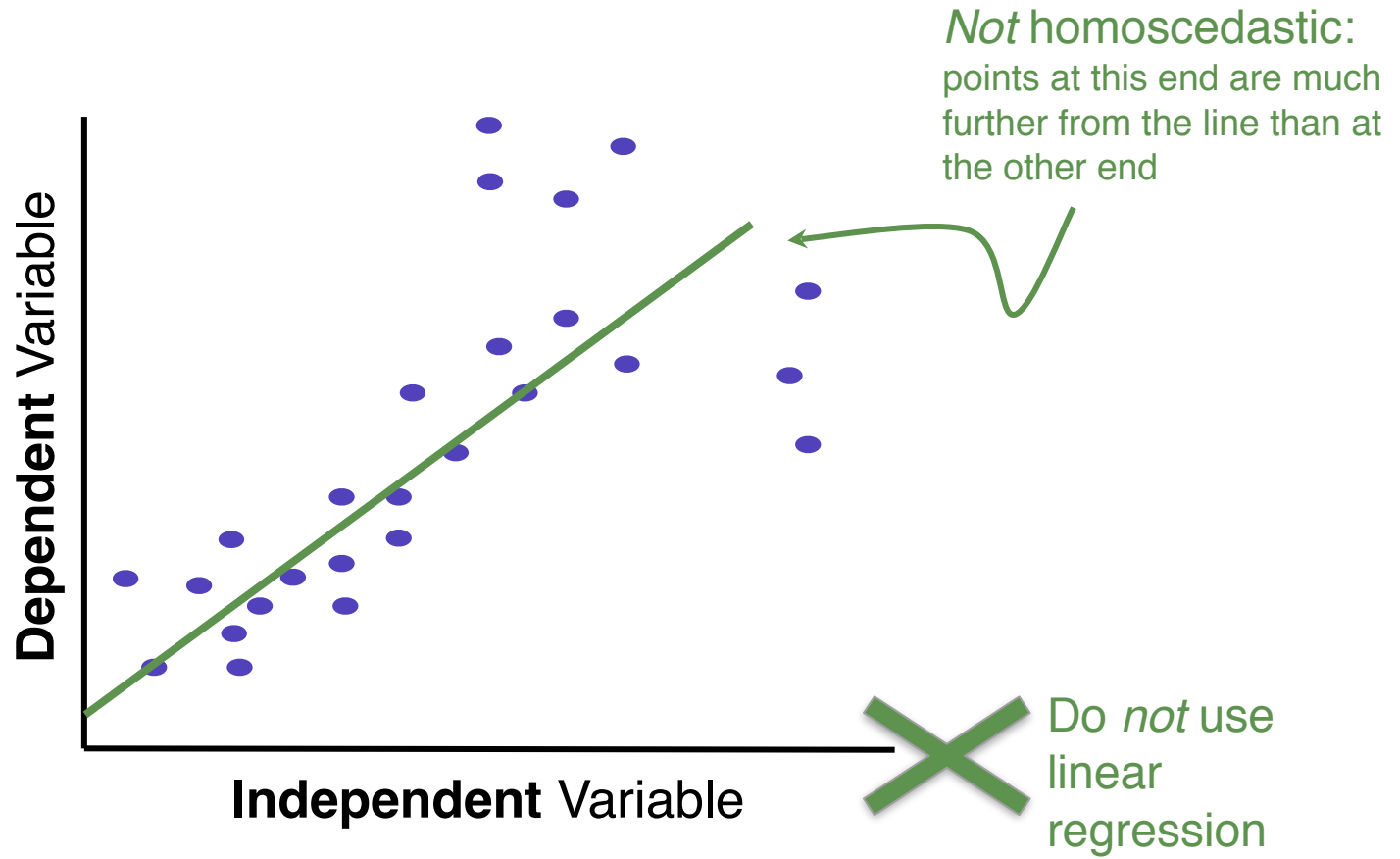
1. Linear relationship
2. No multicollinearity
3. No auto-correlation
4. Homoscedasticity



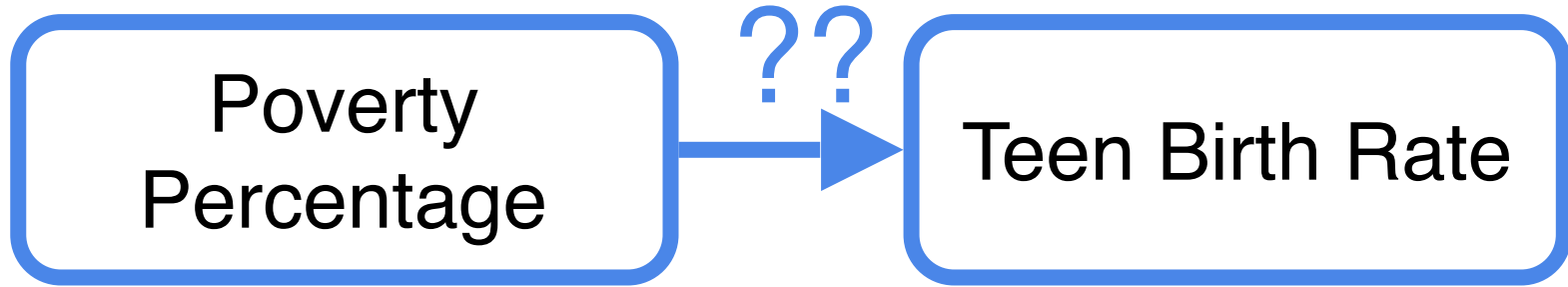
Linear regression assumes no multicollinearity. **Multicollinearity** occurs when the independent variables (in multiple linear regression) are too highly correlated with each other.

Autocorrelation
occurs when the
observations are *not*
independent of one
another (i.e. stock
prices)





Does Poverty
Percentage affect Teen
Birth Rate?



Null Hypothesis:

H_0 : Poverty Rate does not affect Teen Birth Rate ($\beta_1 = 0$)

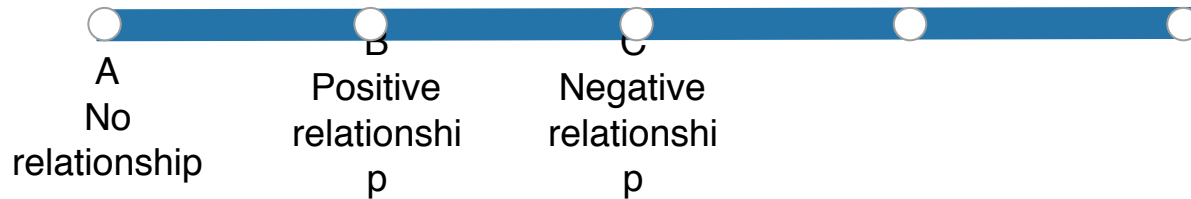
Alternative Hypothesis:

H_a : Poverty Rate affects Teen Birth Rate ($\beta_1 \neq 0$)



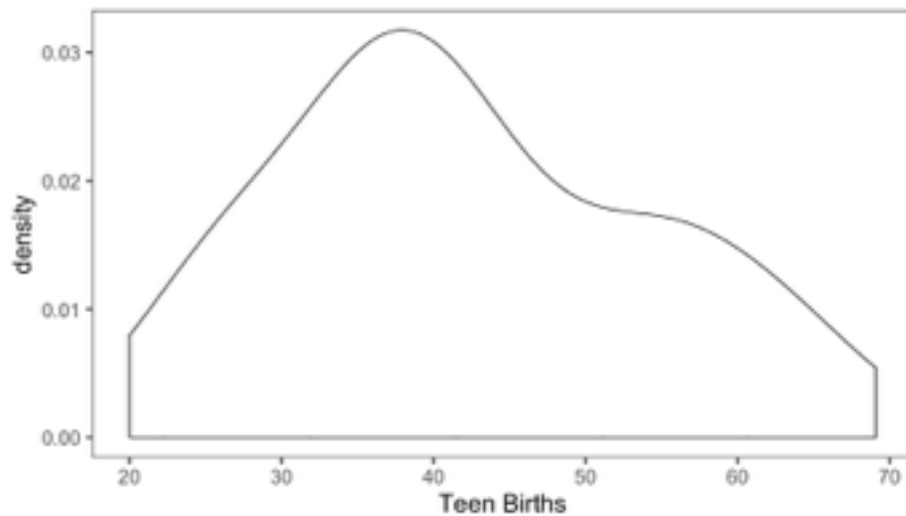
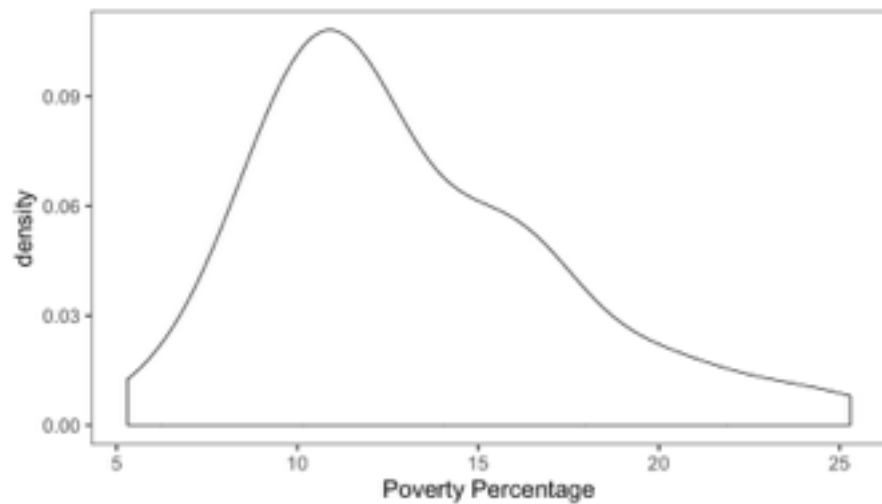
What is the relationship between Poverty Percentage & Teen Birth Rate?

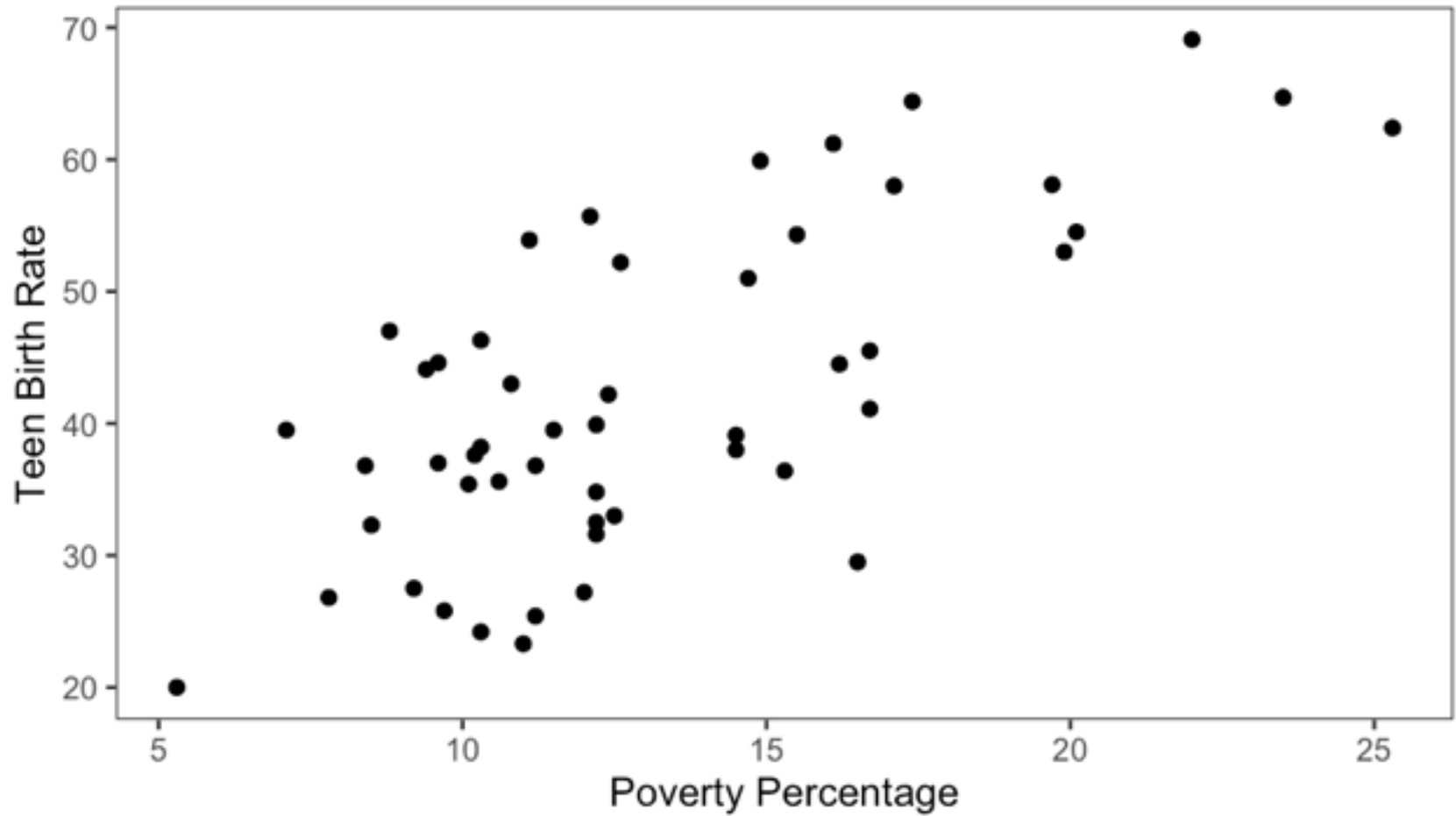
What's your hypothesis?

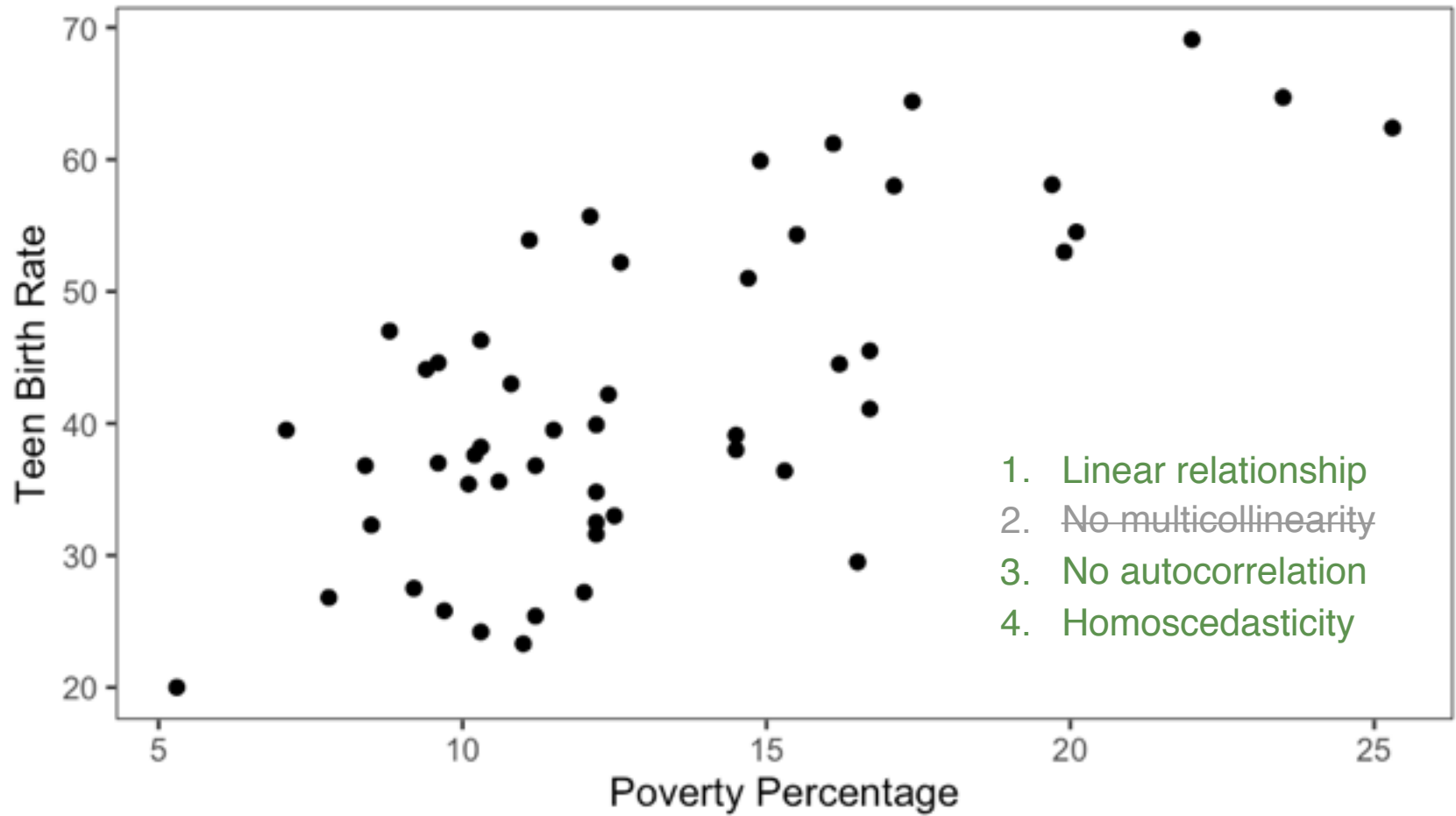


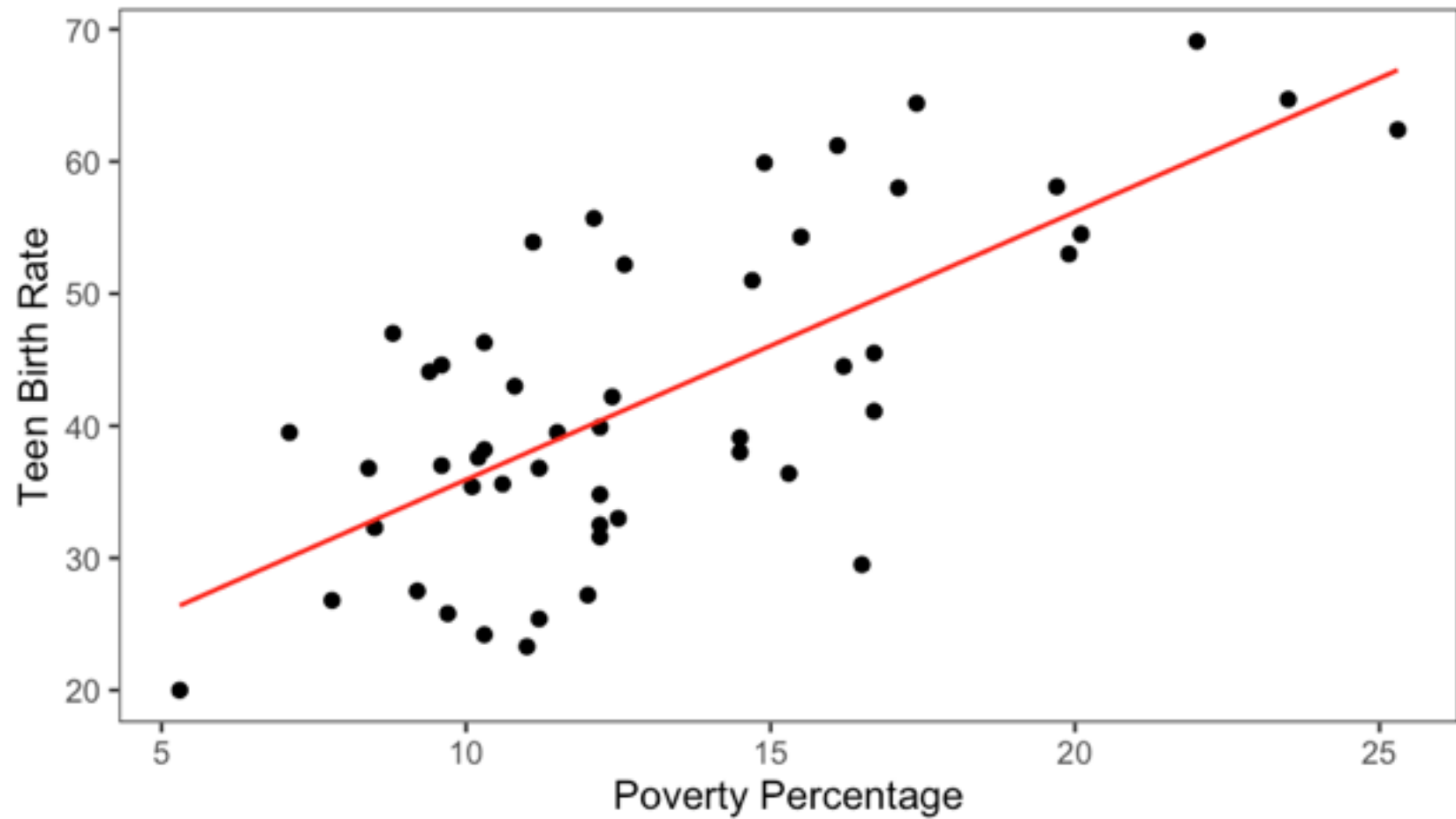
	Location	PovPct	Brth15to17	Brth18to19	ViolCrime	TeenBrth
1	Alabama	20.1	31.5	88.7	11.2	54.5
2	Alaska	7.1	18.9	73.7	9.1	39.5
3	Arizona	16.1	35.0	102.5	10.4	61.2
4	Arkansas	14.9	31.6	101.7	10.4	59.9
5	California	16.7	22.6	69.1	11.2	41.1
6	Colorado	8.8	26.2	79.1	5.8	47.0
7	Connecticut	9.7	14.1	45.1	4.6	25.8
8	Delaware	10.3	24.7	77.8	3.5	46.3
9	District_of_Columbia	22.0	44.8	101.5	65.0	69.1
10	Florida	16.2	23.2	78.4	7.3	44.5
11	Georgia	12.1	31.4	92.8	9.5	55.7
12	Hawaii	10.3	17.7	66.4	4.7	38.2
13	Idaho	14.5	18.4	69.1	4.1	39.1
14	Illinois	12.4	23.4	70.5	10.3	42.2
15	Indiana	9.6	22.6	78.5	8.0	44.6
16	Iowa	12.2	16.4	55.4	1.8	32.5
17	Kansas	10.8	21.4	74.2	6.2	43.0

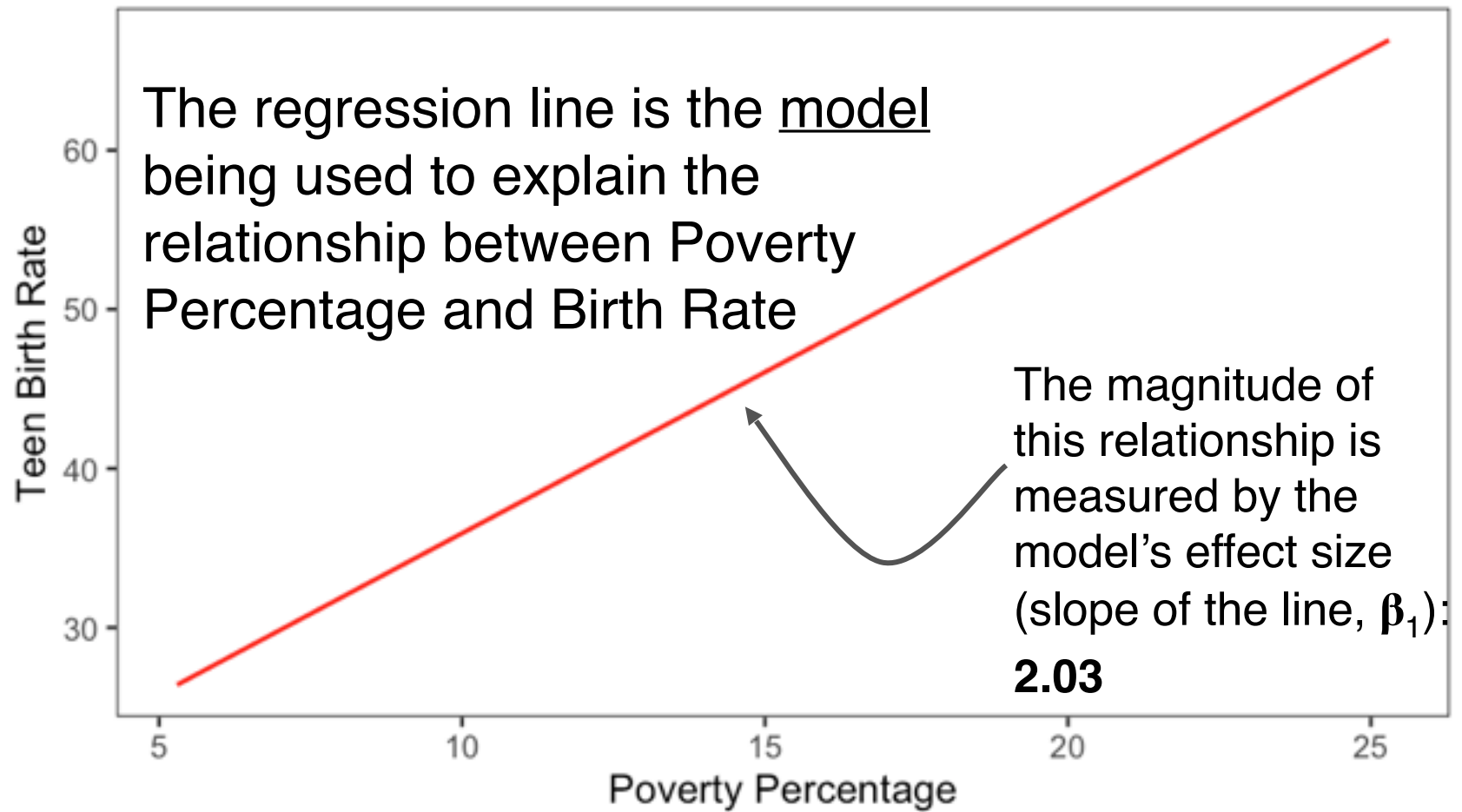
EDA: distributions

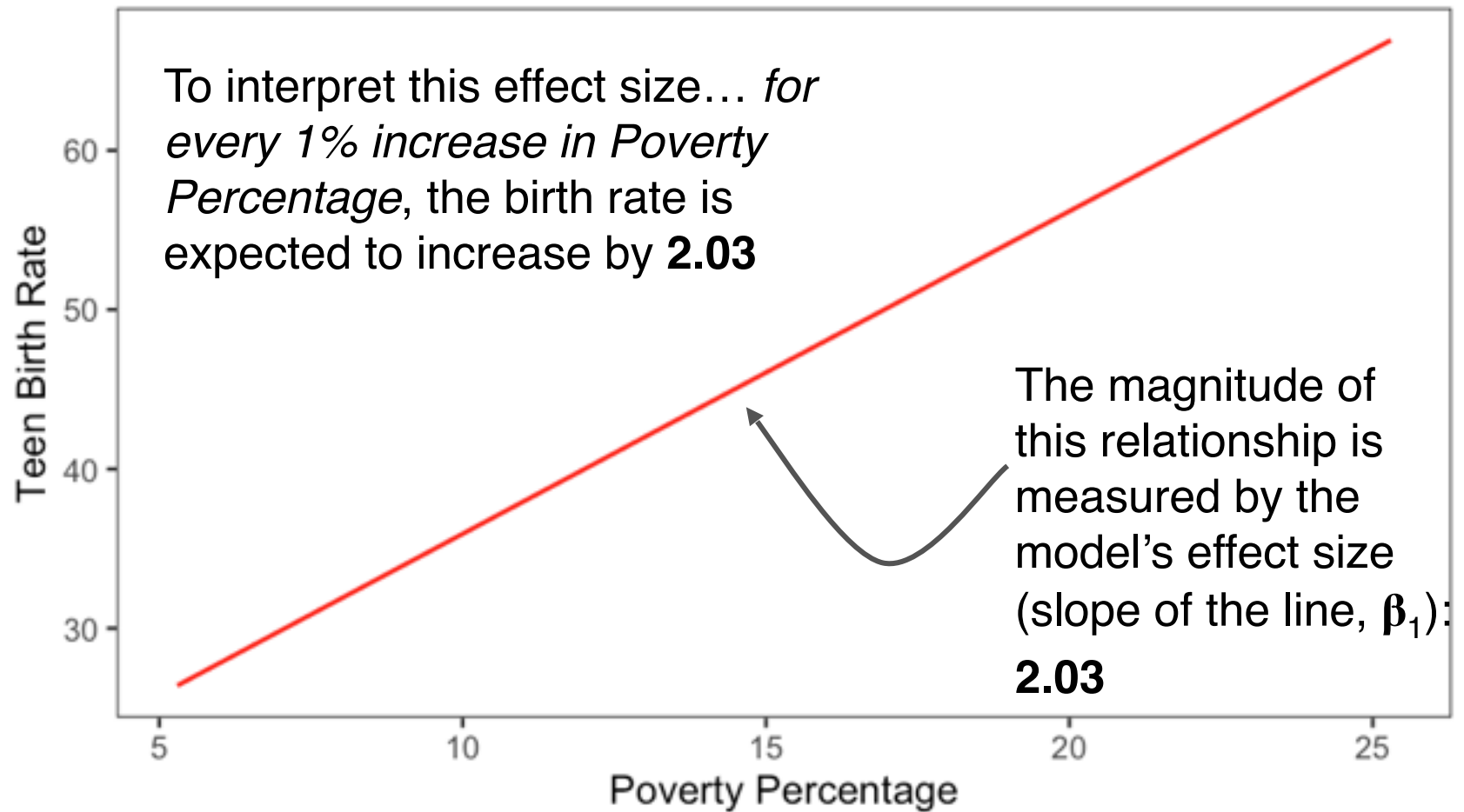






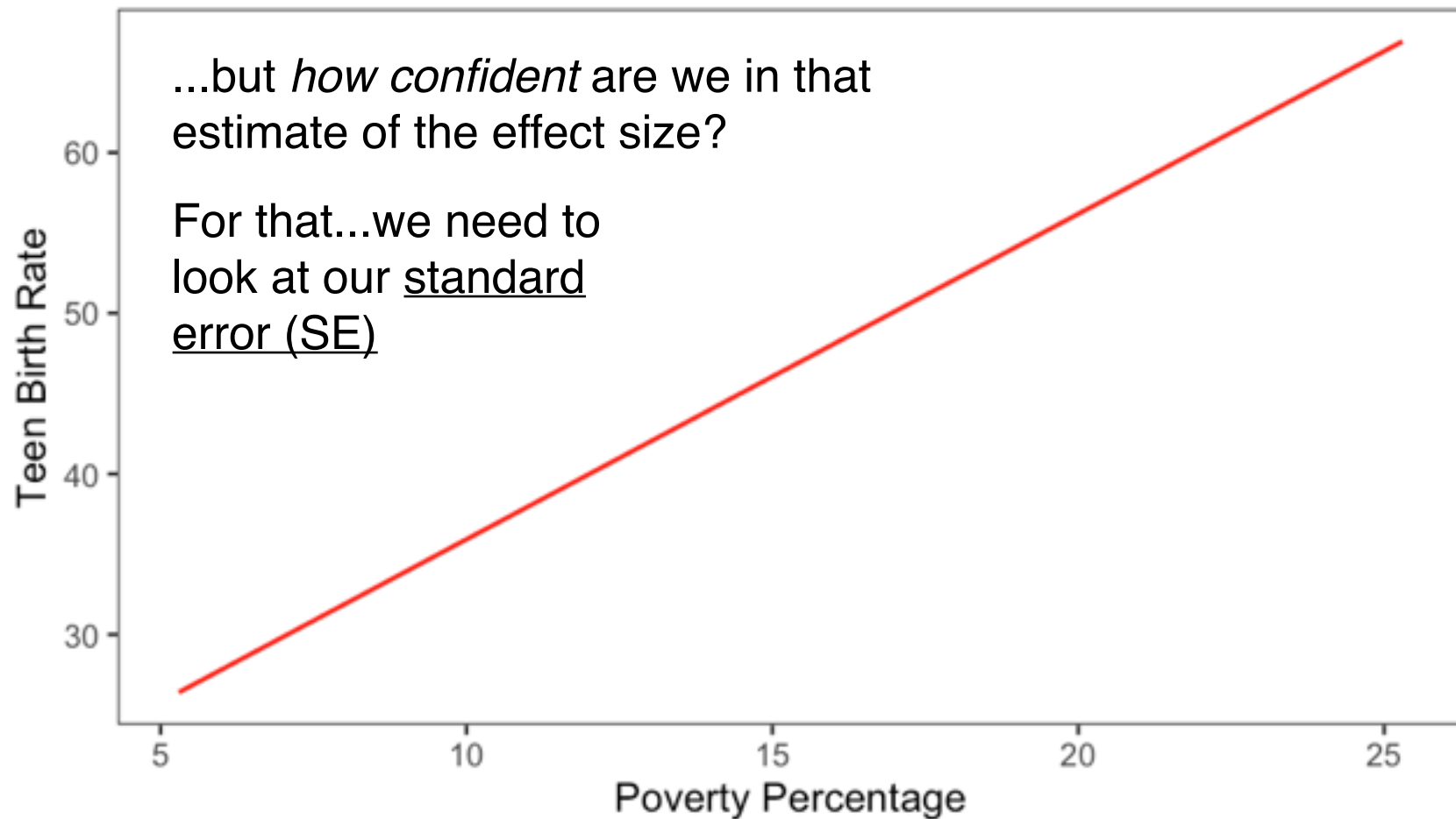


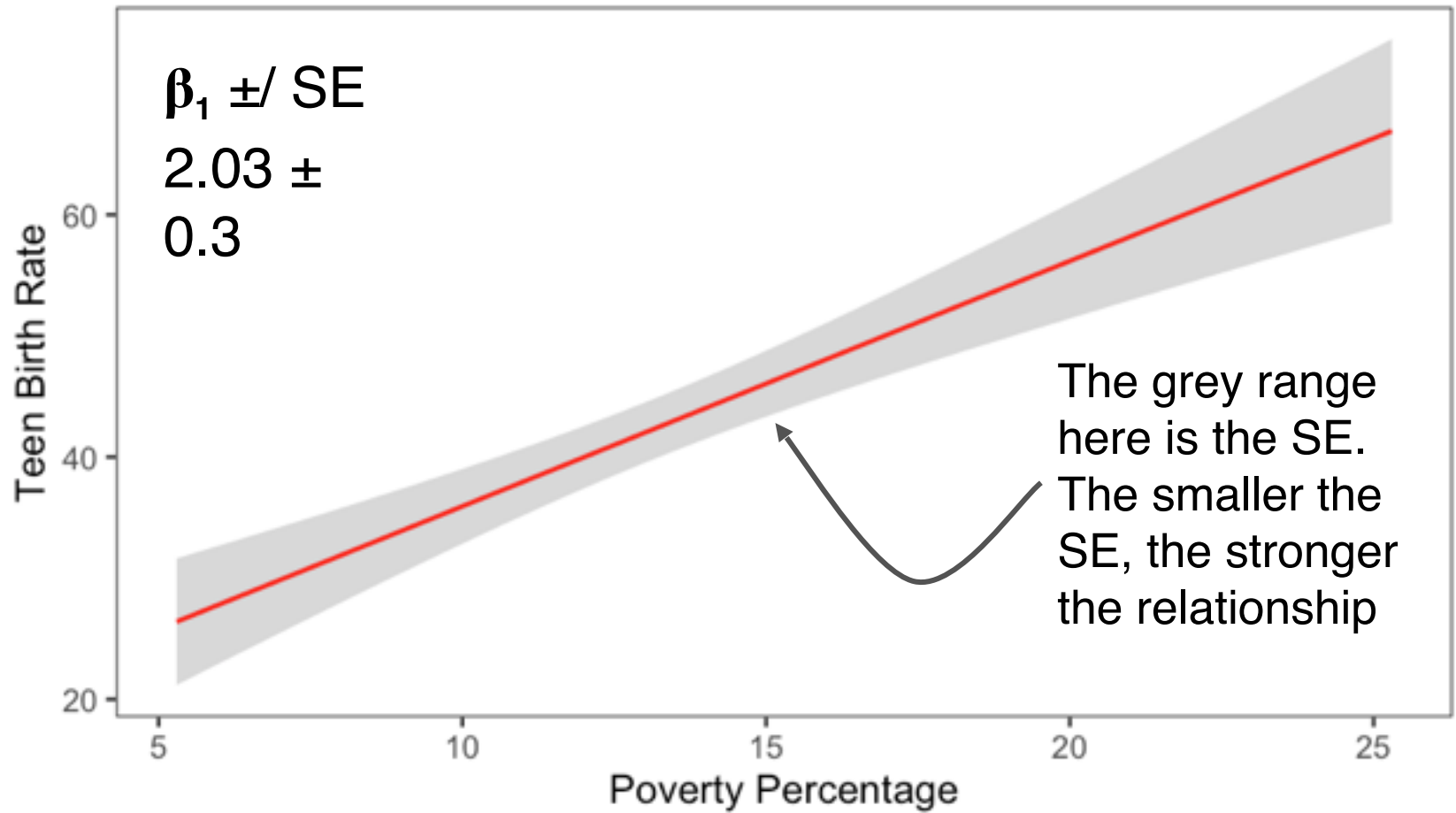


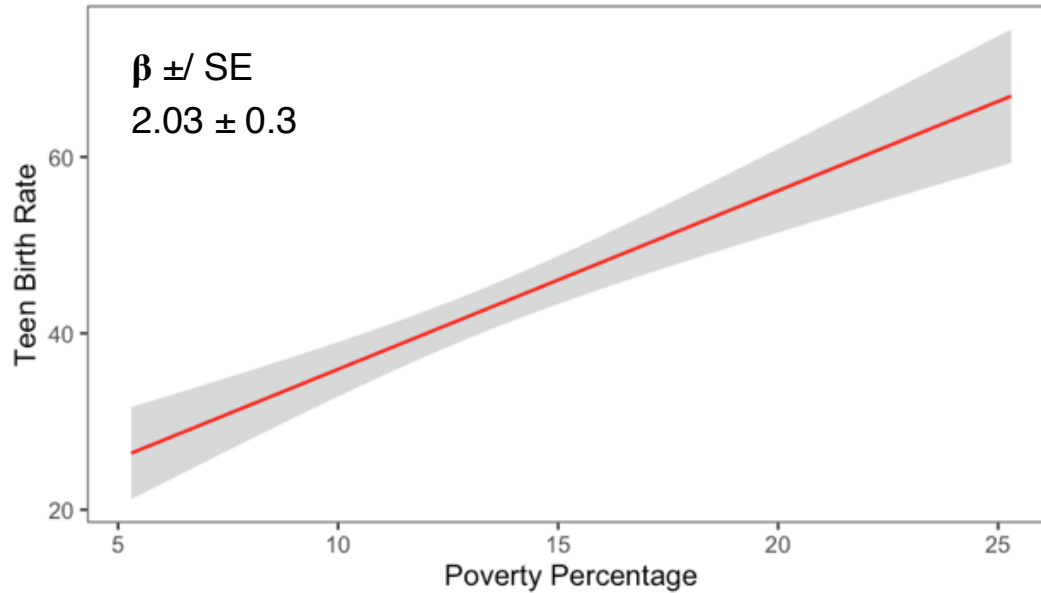


...but *how confident* are we in that estimate of the effect size?

For that...we need to look at our standard error (SE)

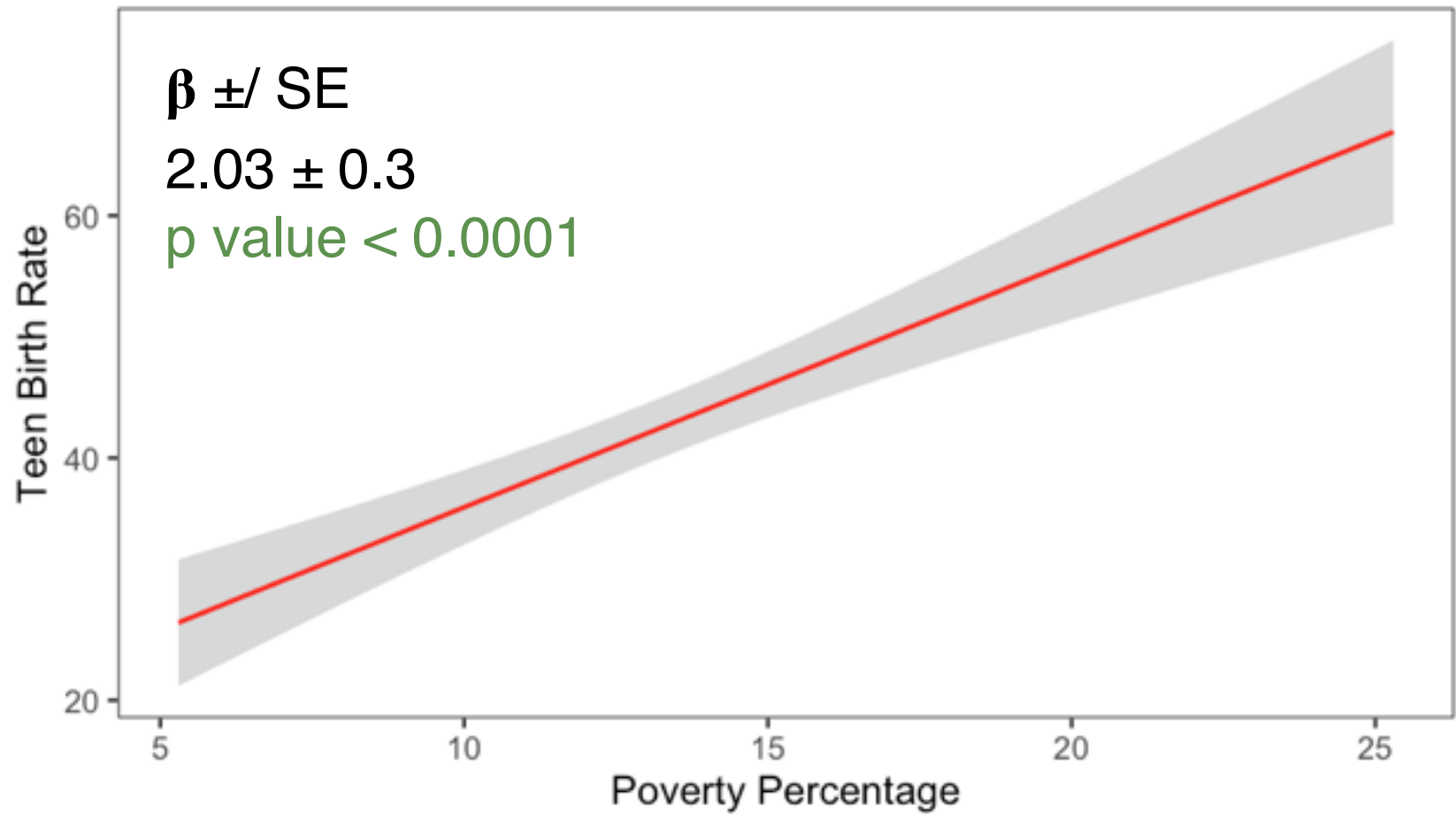




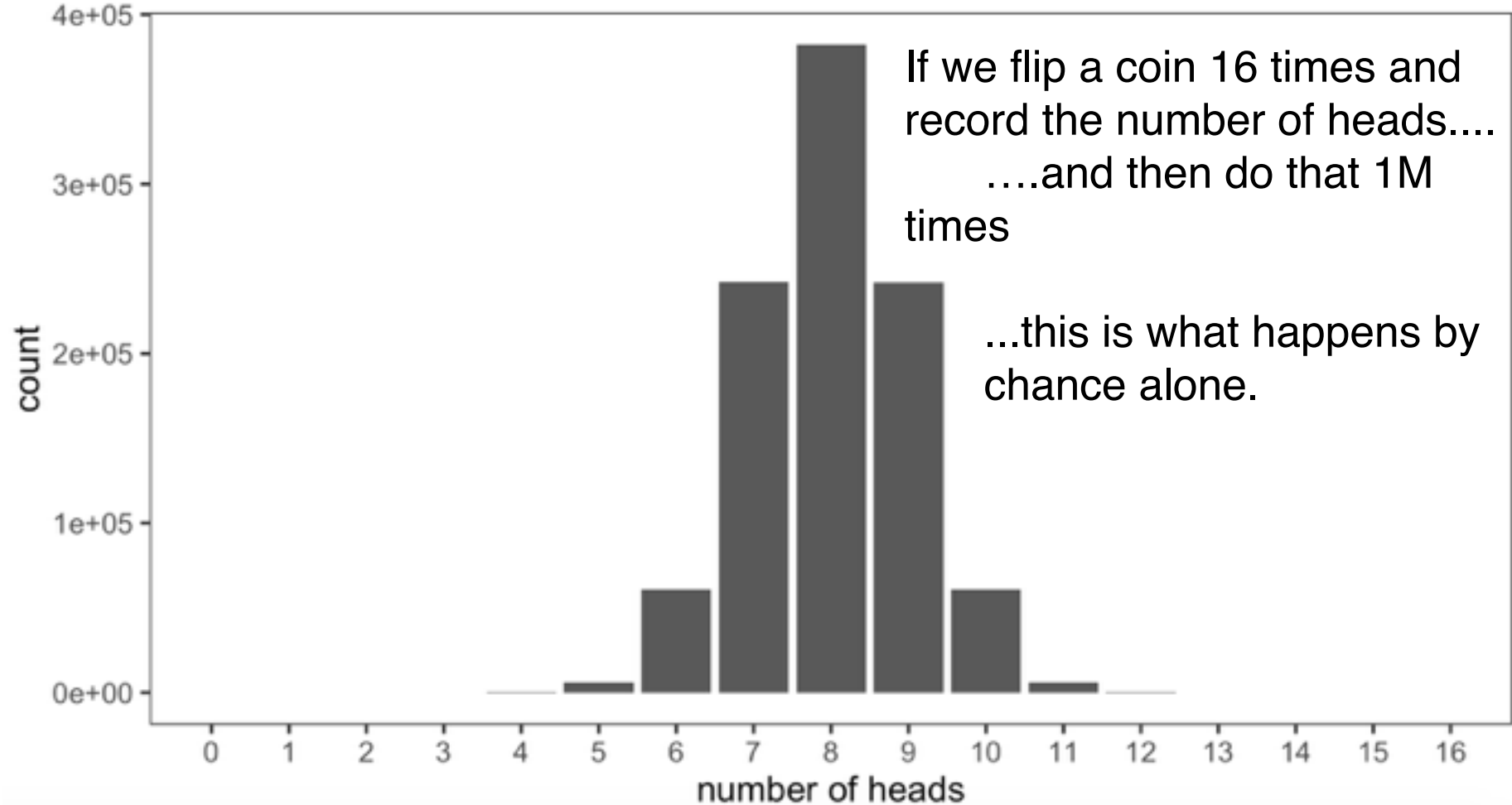


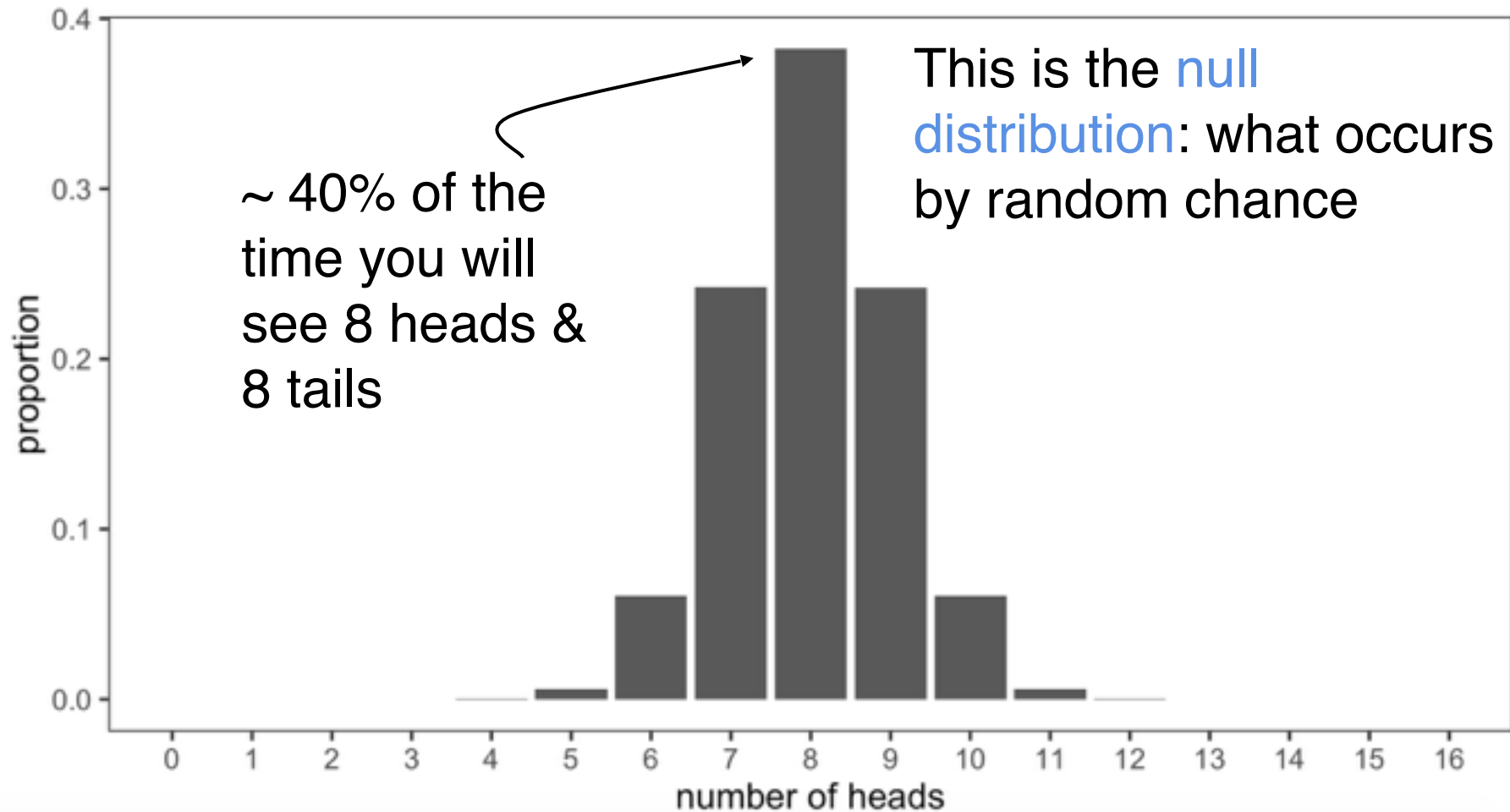
If there were a stronger effect of Poverty on Birth rate, what would β_1 be?

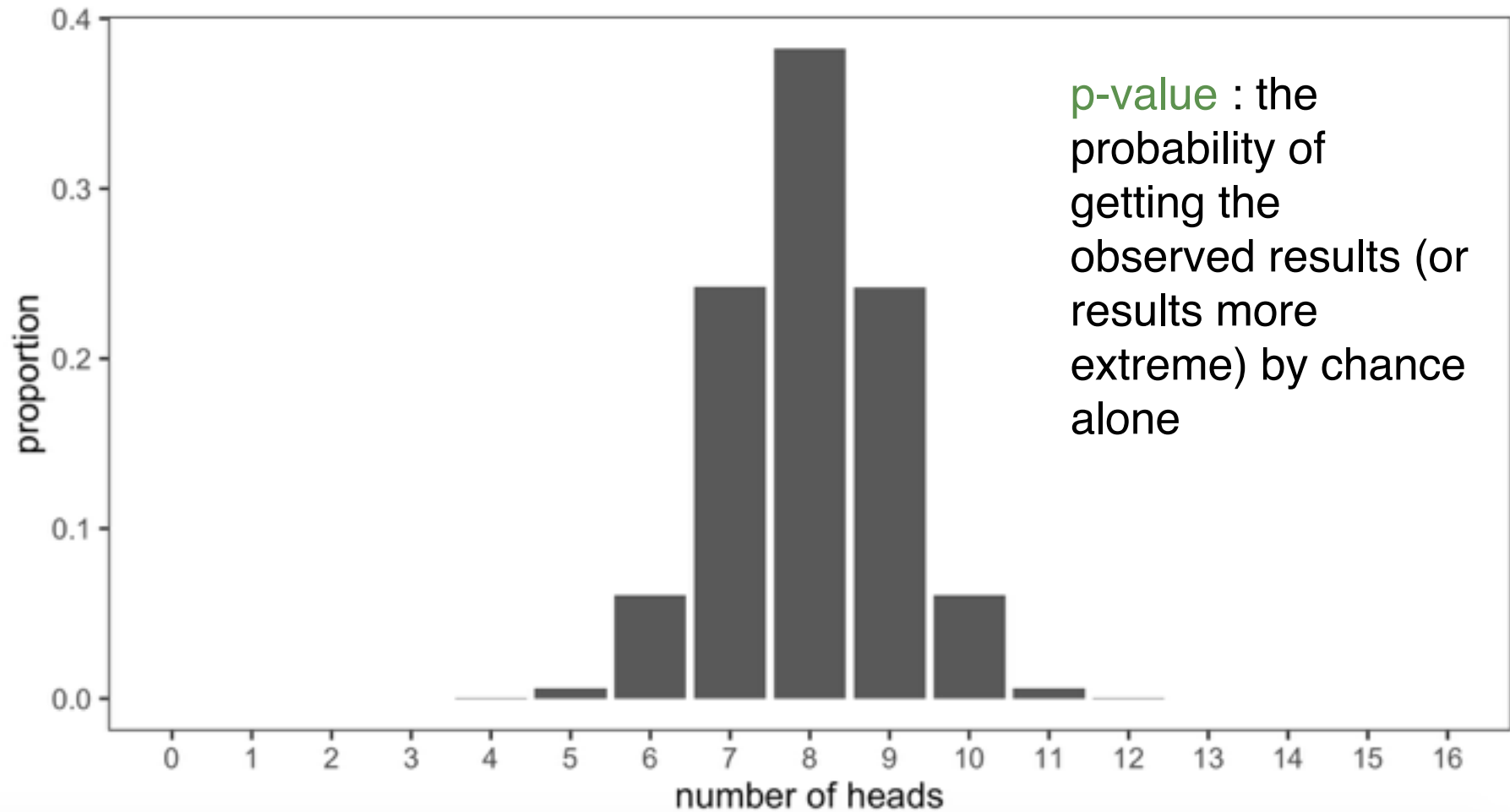


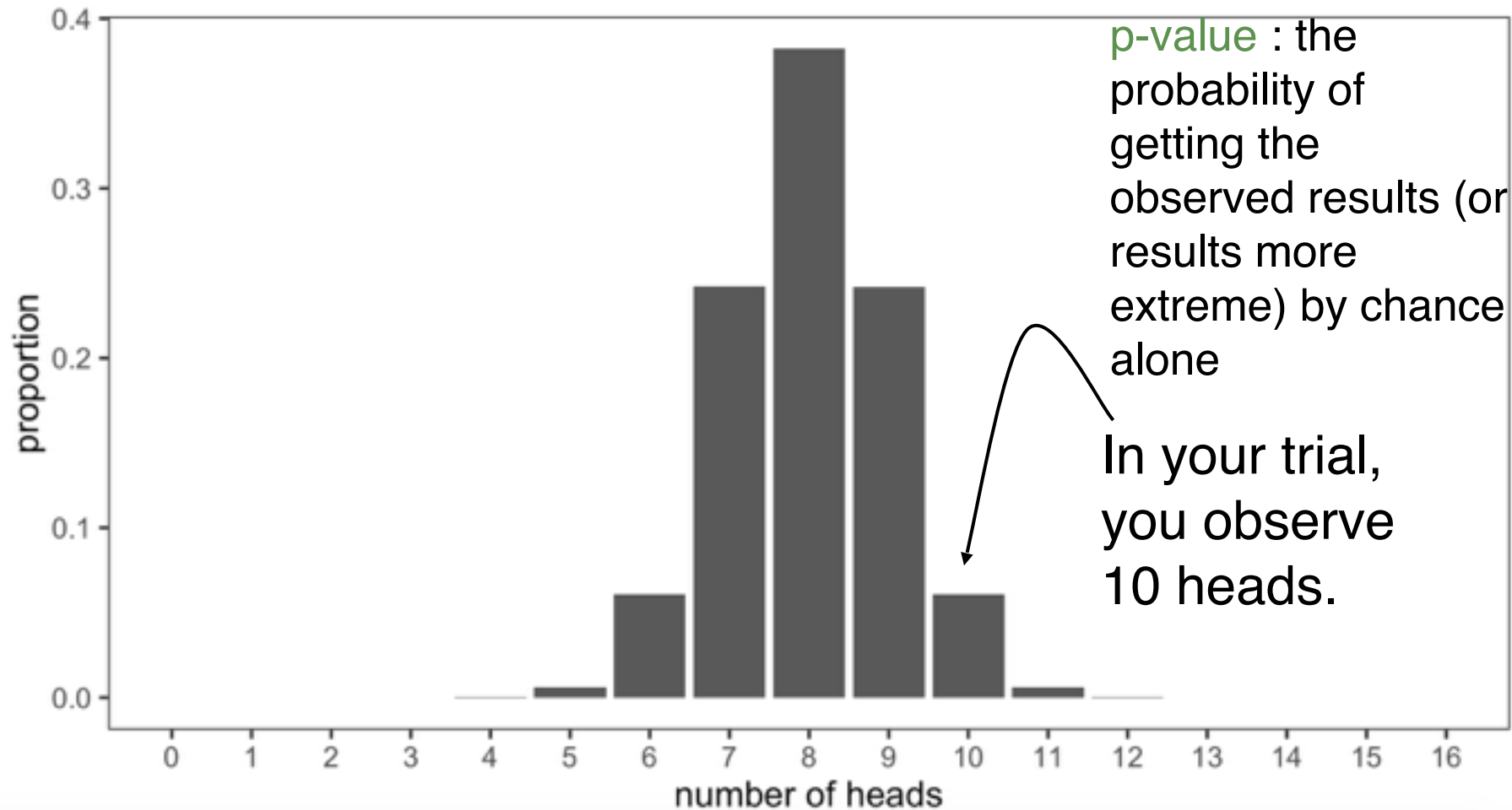


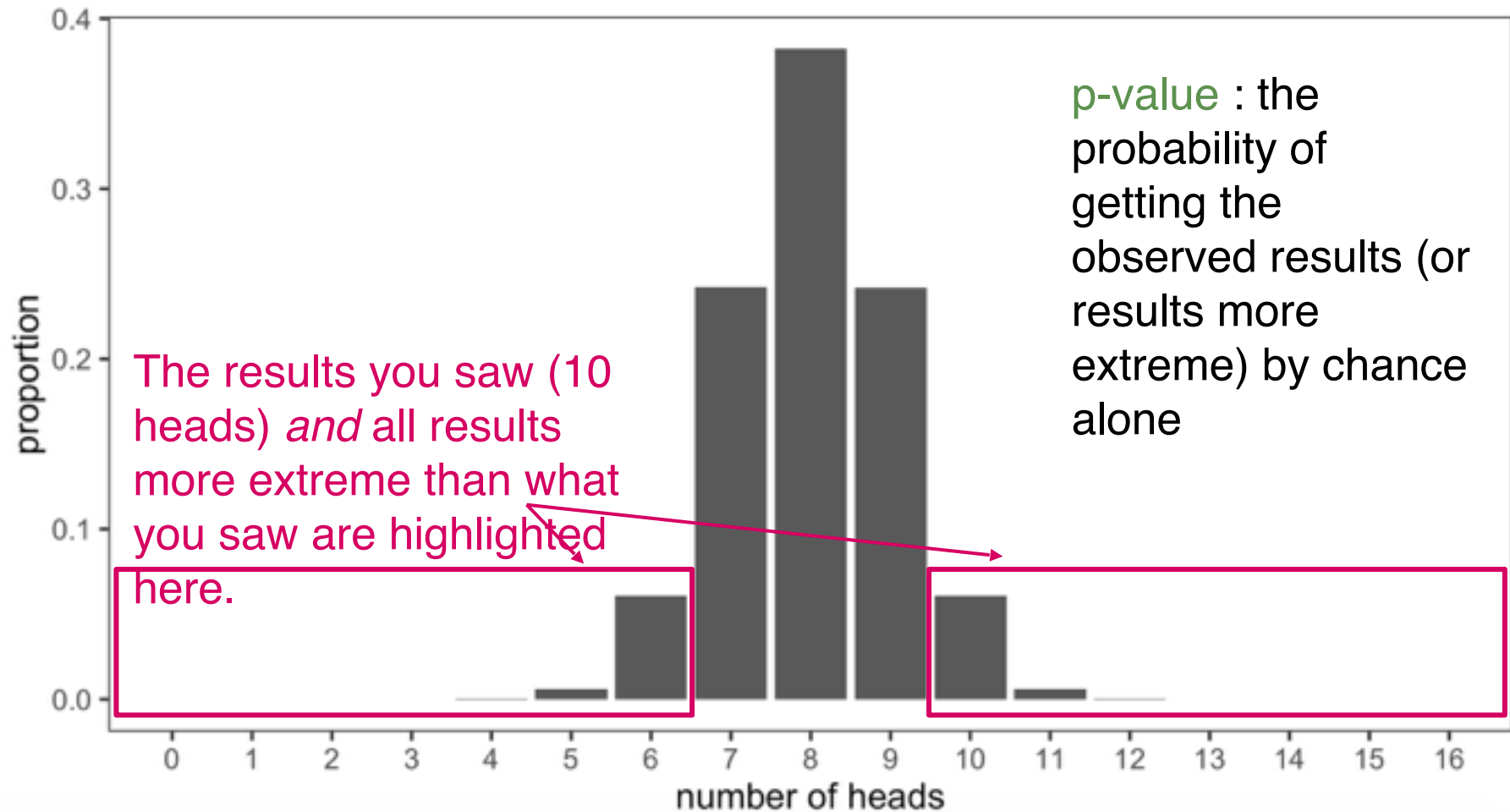
p-value : the probability of getting the observed results (or results more extreme) by chance alone

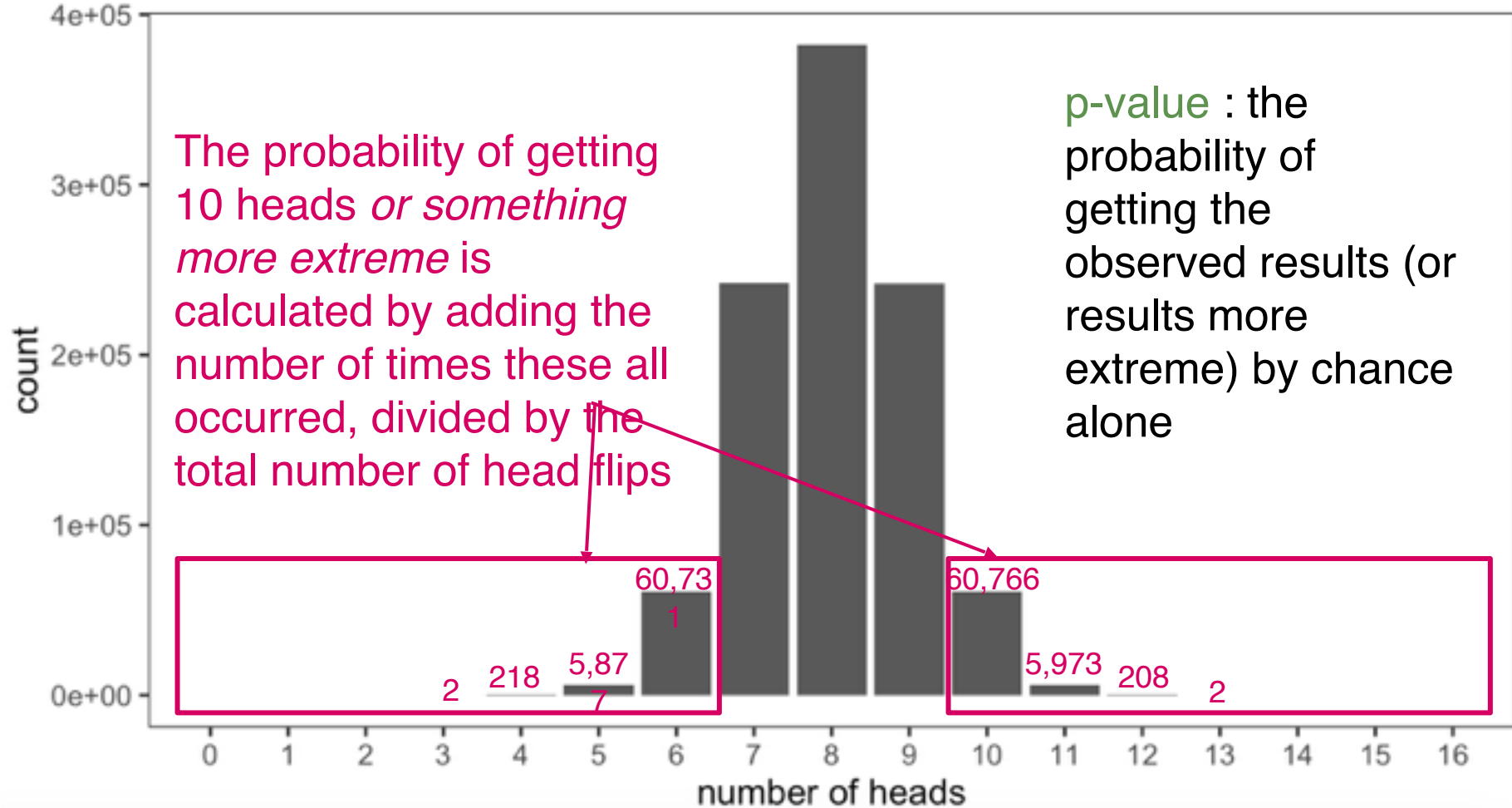


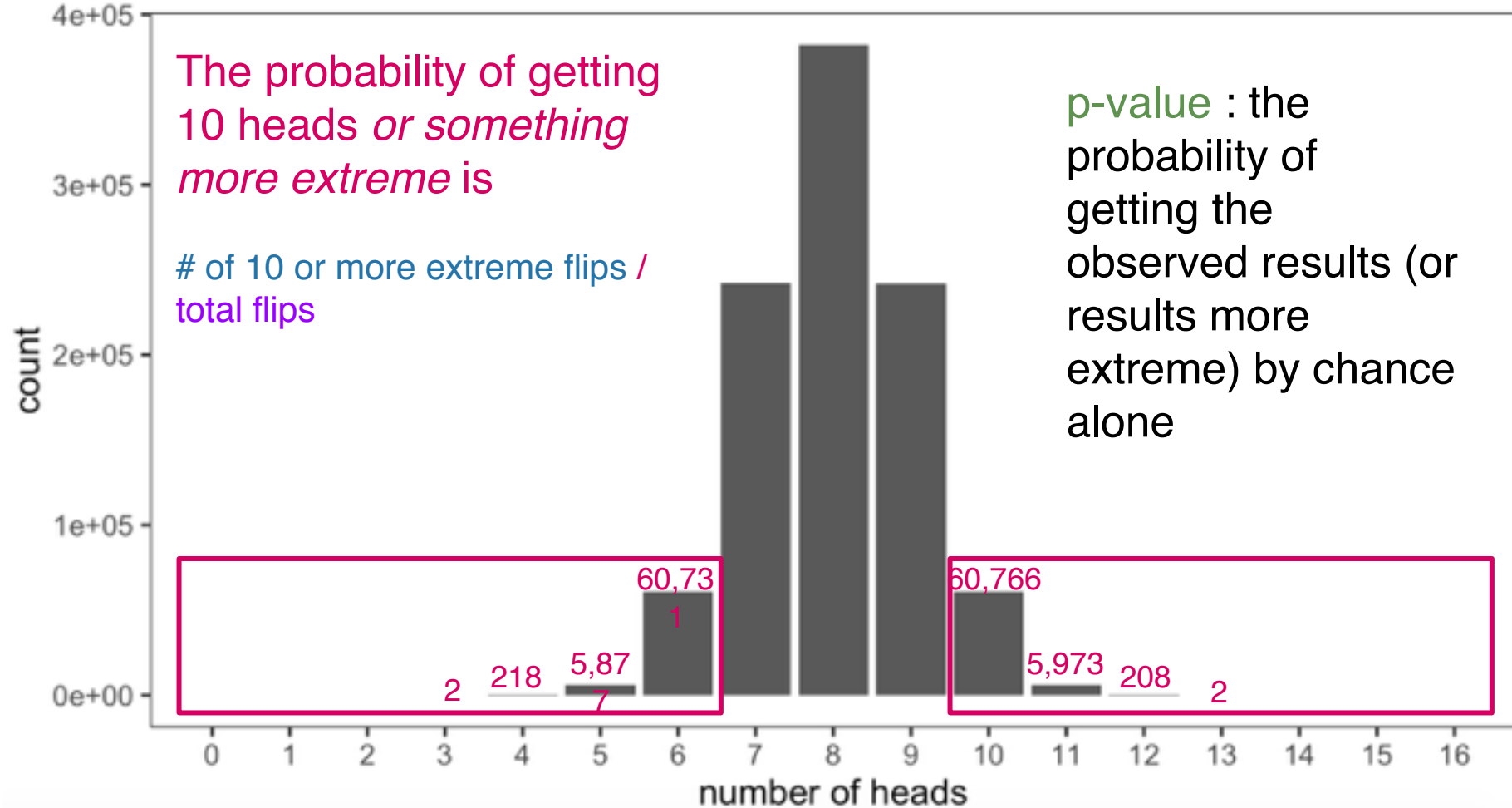


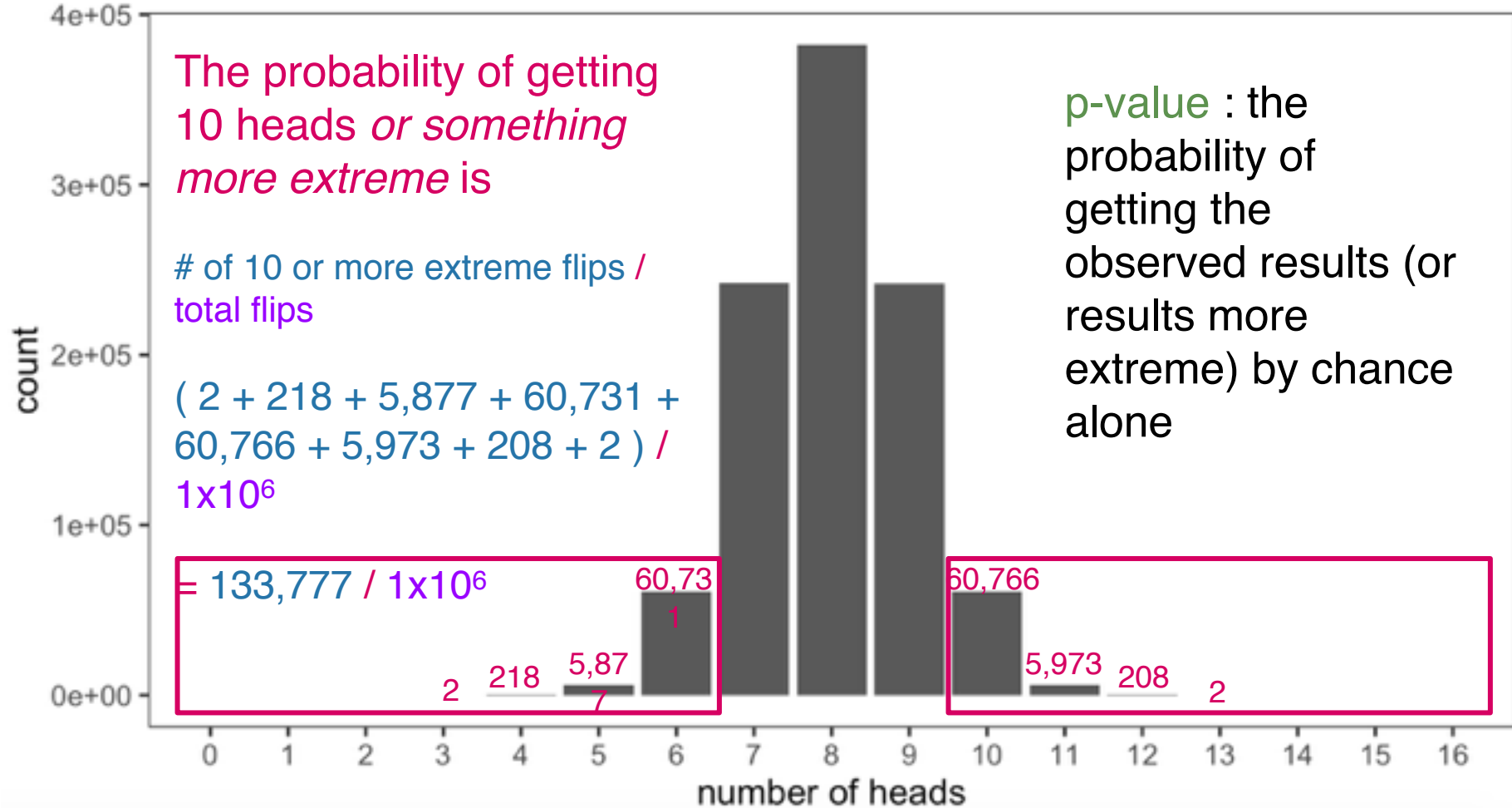


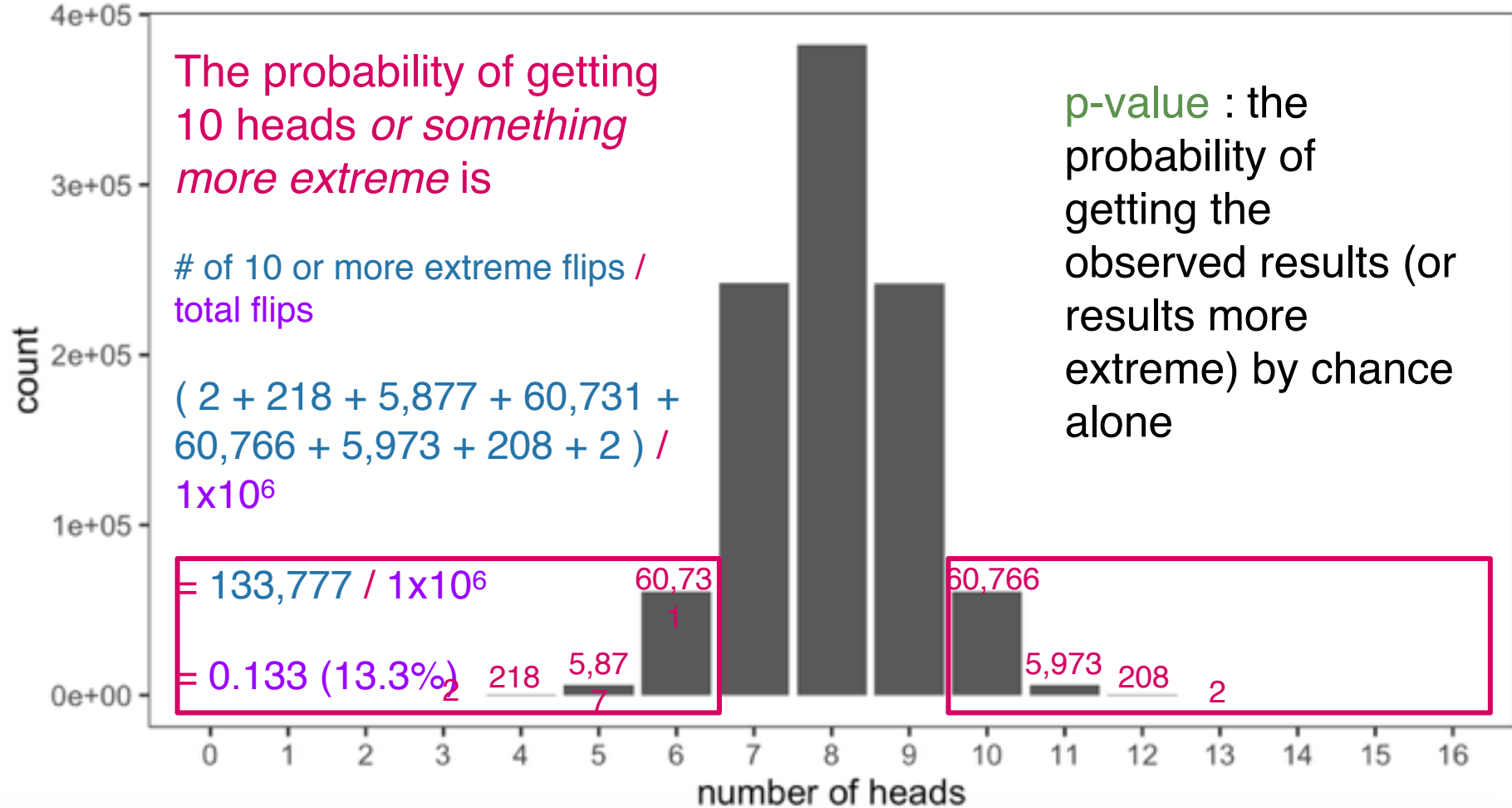


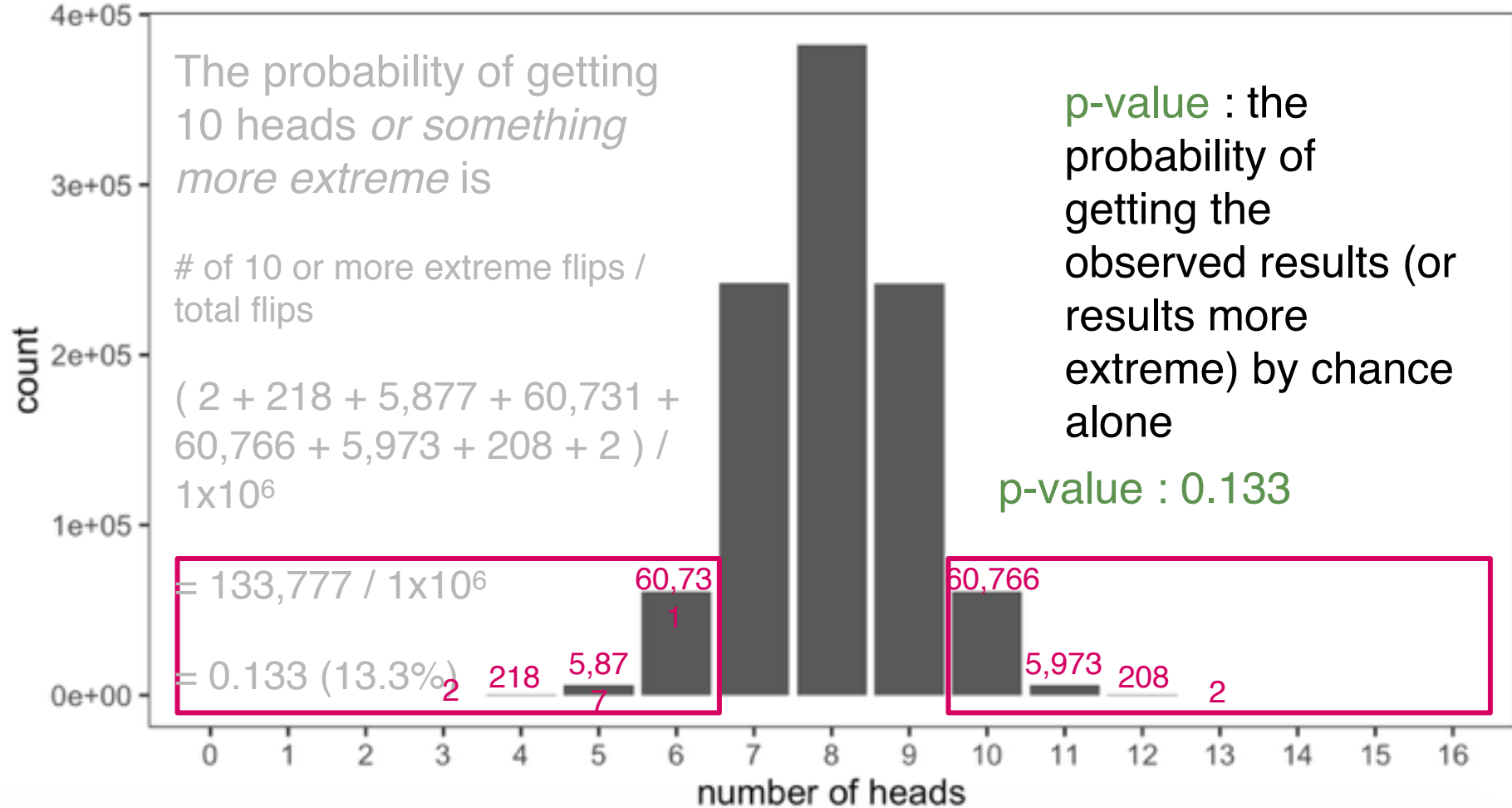


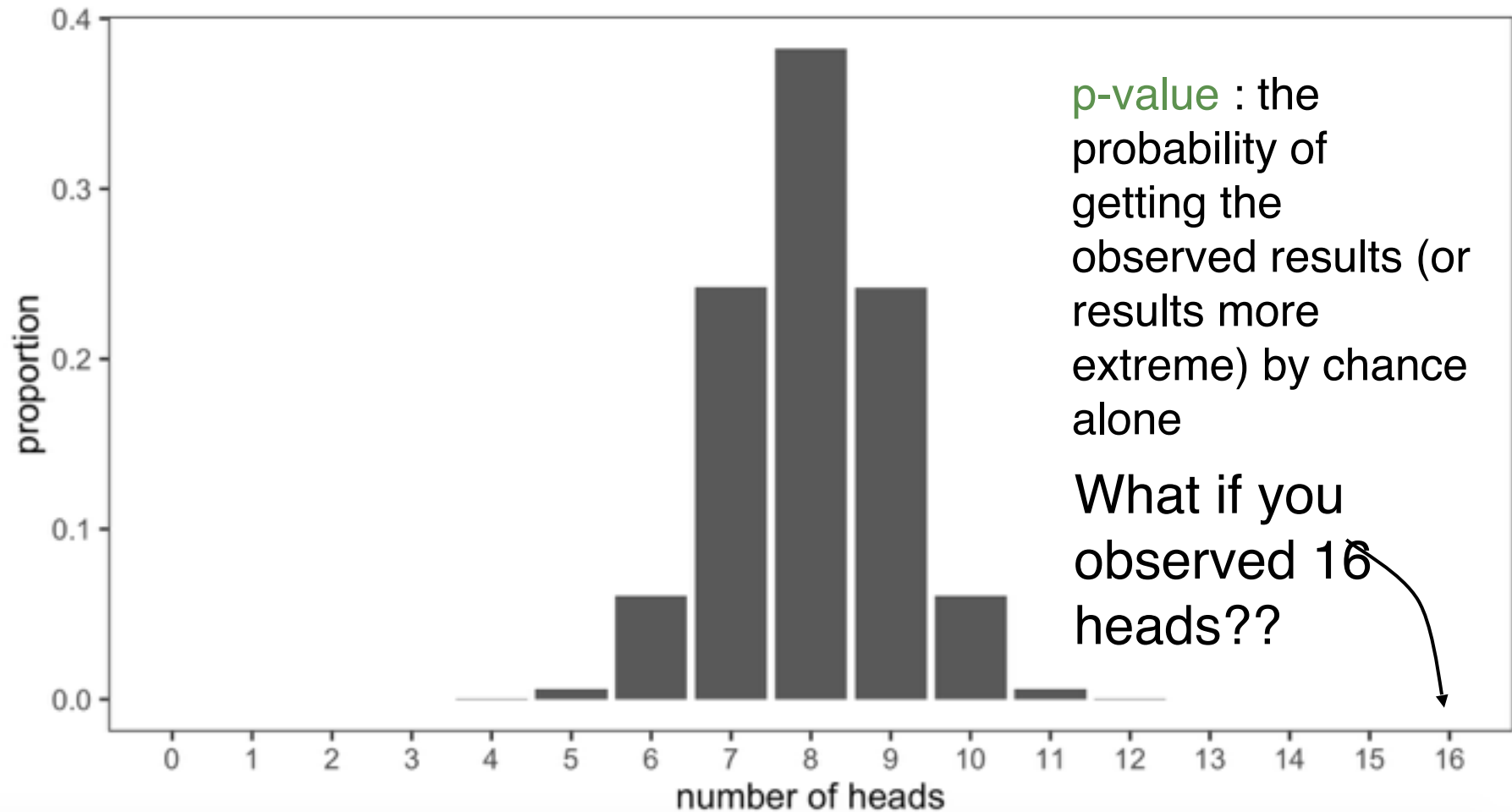


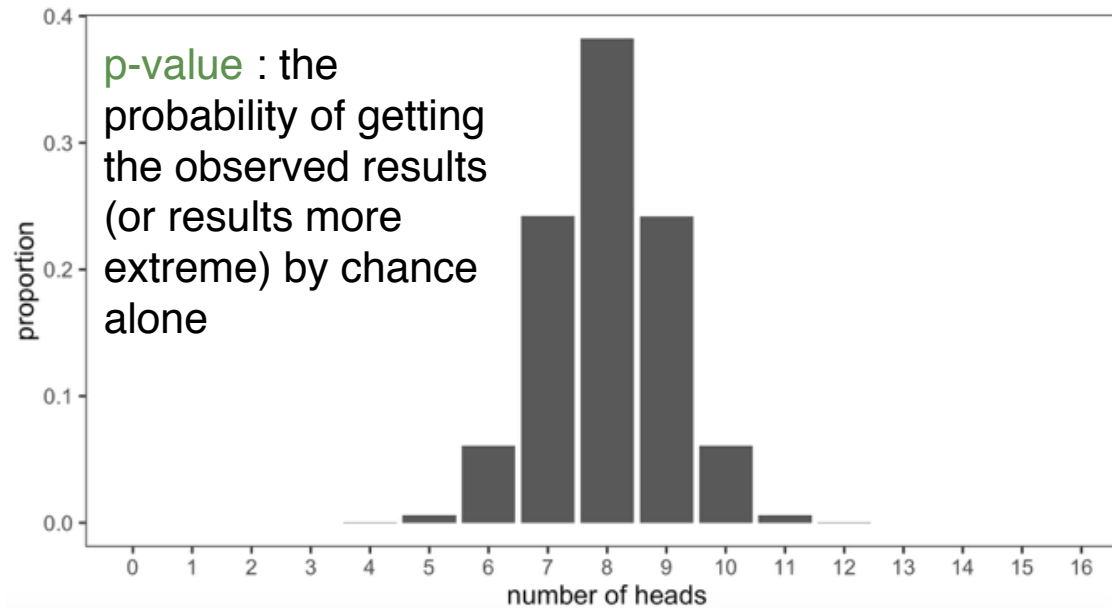




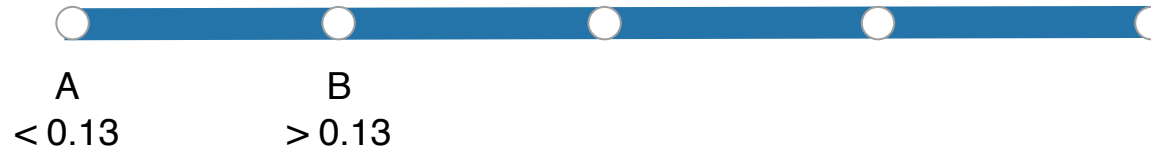


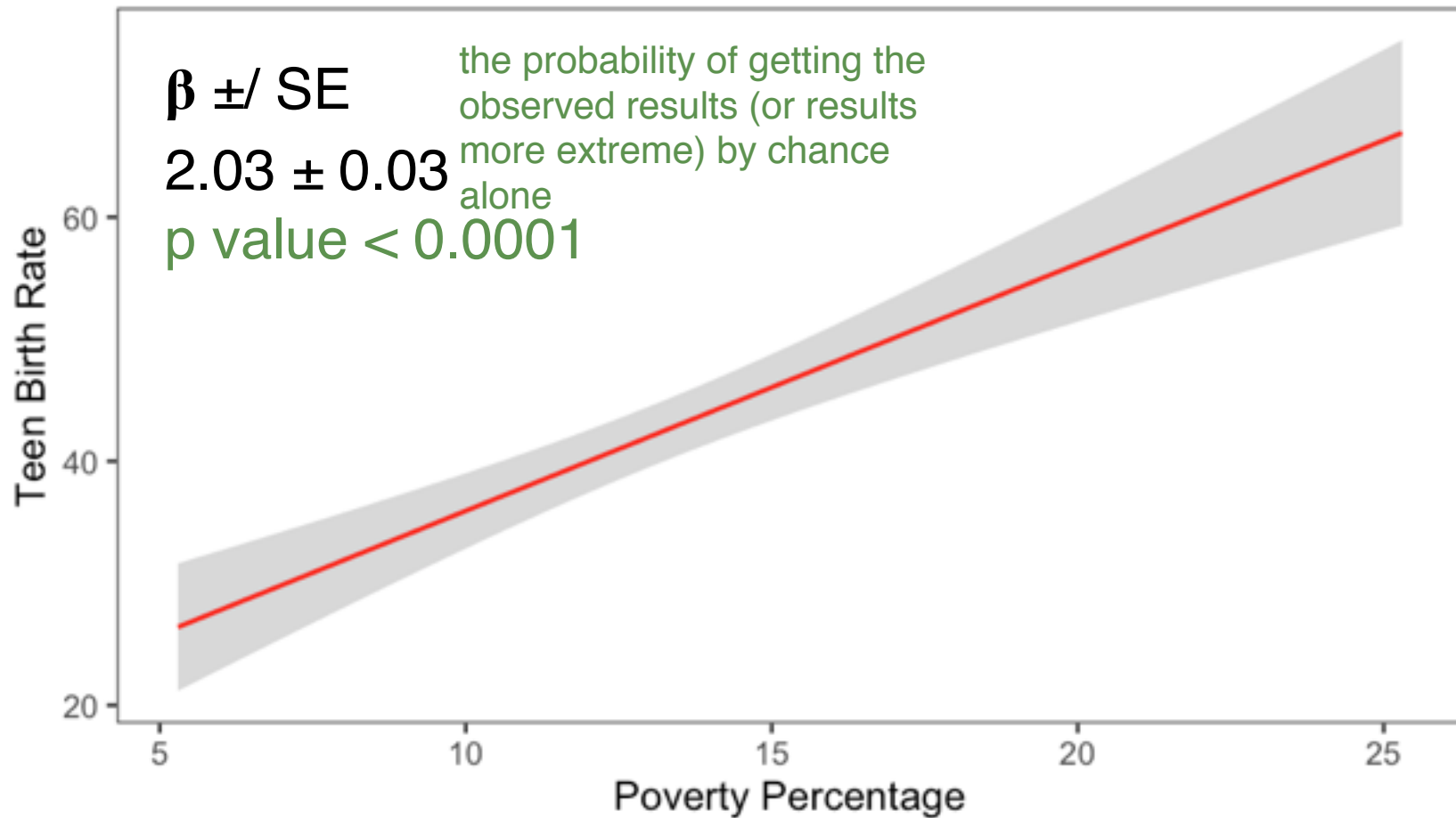







What would be the p-value of you flipping 16 heads?






Takes into account
the effect size (β_1)
and the SE



p-value : the probability of
getting the observed results (or
results more extreme) by
chance alone

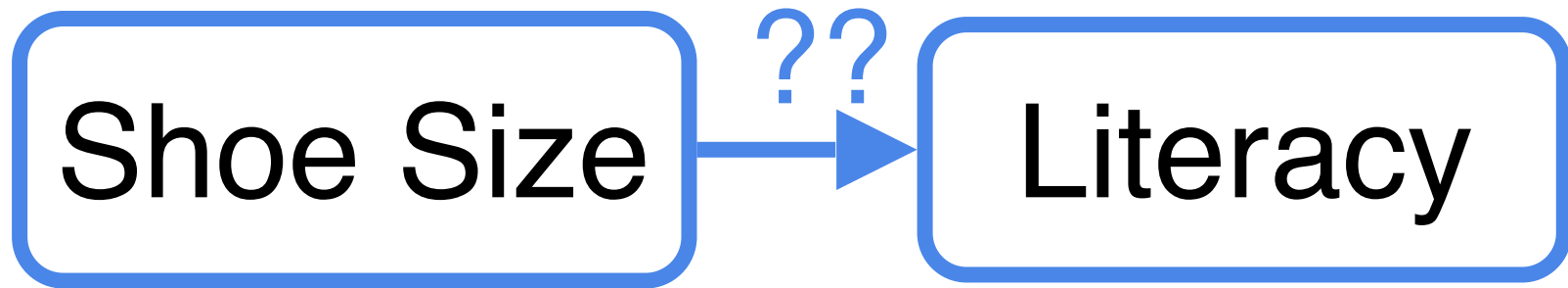
Confounding





Small shoes
Not literate

Big shoes
Literate





Small shoes
Not literate
Child

Big shoes
Literate
Adult

Shoe
Size

Literacy

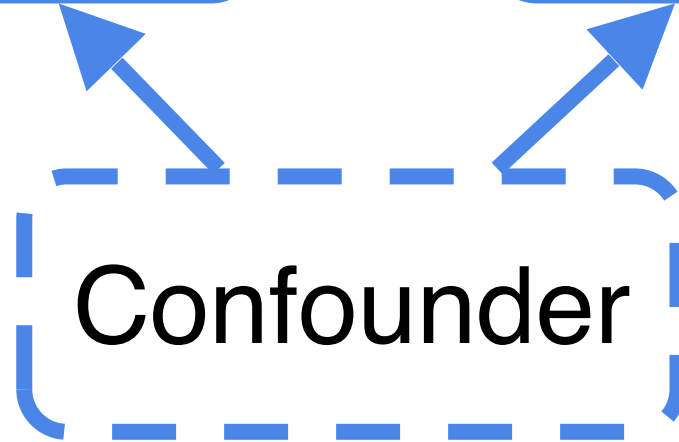
Age

```
graph TD; A[Shoe Size] --> C[Age]; B[Literacy] --> C;
```

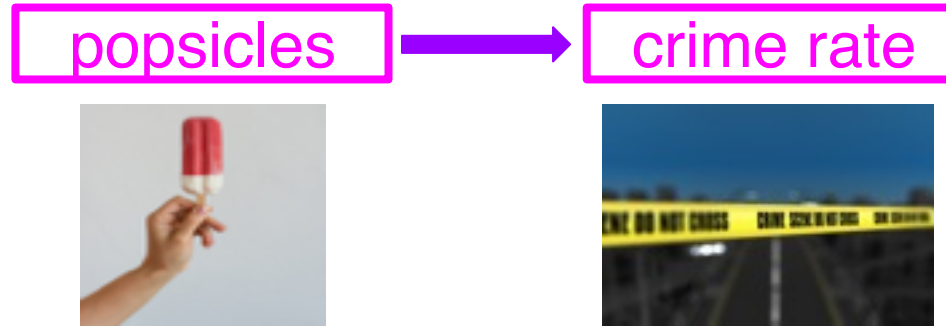
A diagram illustrating a relationship between three variables. At the top, there are two boxes: 'Shoe Size' on the left and 'Literacy' on the right. Both boxes have a solid blue border. Below them, centered, is a box labeled 'Age' with a dashed blue border. Two blue arrows originate from the bottom of the 'Shoe Size' box and the bottom of the 'Literacy' box, both pointing towards the 'Age' box, suggesting that both Shoe Size and Literacy are predictors or related to Age.

Variable1

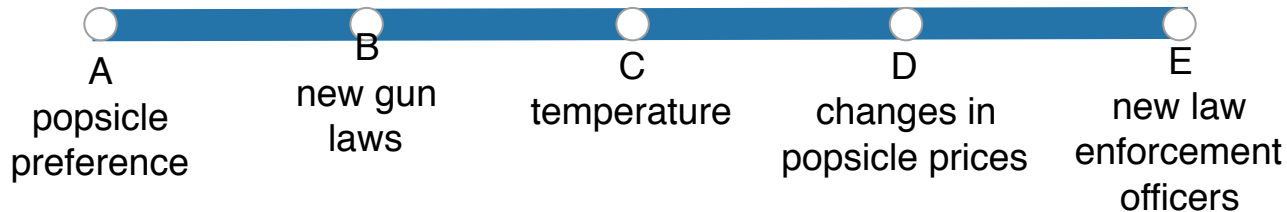
Variable2



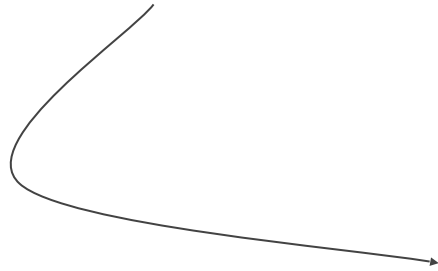
Confounding



Your analysis sees an increase in crime rate whenever popsicle sales increase. What could confound this analysis?



We'll discuss additional approaches of how to account for confounding in your analysis in the next lecture.



Ignoring confounders will
lead you to draw
incorrect conclusions
from your analyses

Spine Surgery Results

Sample: 400 patients with index vertebral fractures

Vertebroplasty	Conservative care	Relative risk (95% confidence interval)
30/200 (15%)	15/200 (7.5%)	2.0 (1.1–3.6)

subsequent fractures



Eek....looks like vertebroplasty was way worse for patients!

But wait...at time of initial fracture...

	Vertebroplasty N = 200	Conservative care N = 200
Age, y, mean \pm SD	78.2 \pm 4.1	79.0 \pm 5.2
Weight, kg, mean \pm SD	54.4 \pm 2.3	53.9 \pm 2.1
Smoking status, No. (%)	110 (55)	16 (8)

Age and weight are similar between groups. **Smoking Status** differs vastly.

So...let's stratify those results real quick

Smoke			No smoke		
Vertebroplasty	Conservative	RR (95% confidence interval)	Vertebroplasty	Conservative	RR (95% confidence interval)
23/110 (21%)	3/16 (19%)	1.1 (0.4, 3.3)	7/90 (8%)	12/184(7%)	1.2 (0.5, 2.9)

Risk of re-fracture is now similar
within group

Confounding



What are possible confounders for our analysis of the effect of poverty on teen birth rate?

