

Course Reminders

Due Sunday (11:59 PM)

- D4
- Q5
- Project Proposal
- [Mid-course survey](#) (*optional for EC, link also on Canvas assignment*)
- [Weekly Project Survey](#) (*optional, link also on Canvas assignment and homepage*)

Notes:

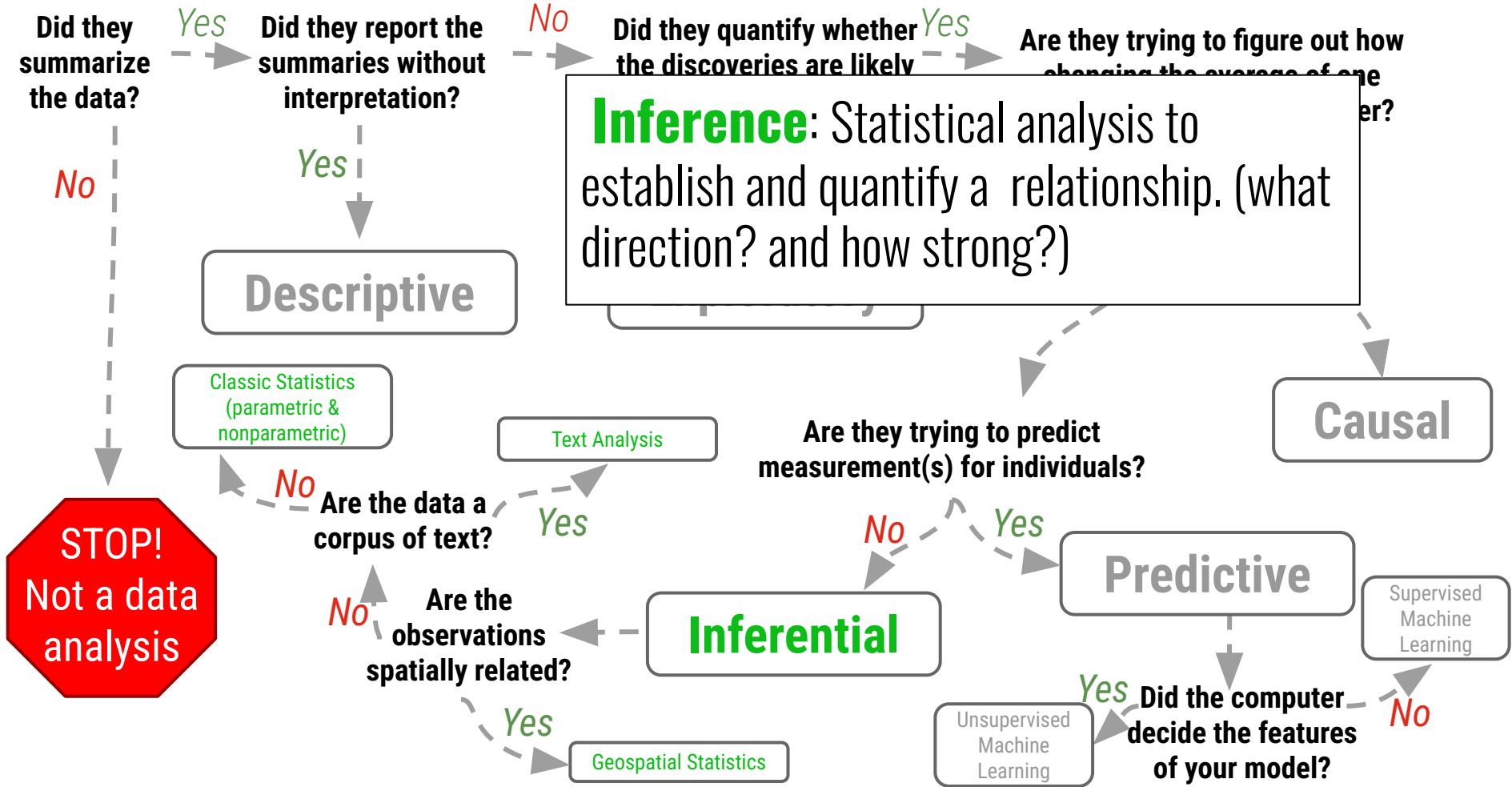
- A3 now available

Inferential Analysis

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Population

All comments on YouTube

During the second quarter of 2020, almost 2.13 billion comments on YouTube videos were removed due to violation of the platform's community guidelines. - J Clement on

We want to learn something about this...

Sampling

Inference

....but we can only *actually* collect data from this

Sample

1 million
comments from 2020

Air pollution
control

??

Lifespan

What is the relationship between air pollution control and lifespan?



The Effect of Air Pollution Control on Life Expectancy in the United States: An Analysis of 545 US counties for the period 2000 to 2007

Andrew W. Correia,

Department of Biostatistics, Harvard School of Public Health, 655 Huntington Avenue, HSPH Building 2, 4th Floor, Boston, MA 02115

C. Arden Pope III,

Department of Economics, Brigham Young University, 142 Faculty Office Building, Provo, UT 84602

Douglas W. Dockery,

Departments of Environmental Health and Epidemiology, Harvard School of Public Health, 655 Huntington Avenue, HSPH Building 1, 1301B, Boston, MA 02115

Yun Wang,

Department of Biostatistics, Harvard School of Public Health, 655 Huntington Avenue, HSPH Building 2, 4th Floor, Boston, MA 02115

Majid Ezzati, and

MRC-HPA Centre for Environment and Health and Department of Epidemiology and Biostatistics, Imperial College London, Norfolk Place, St Mary's Campus, London W2 1PG

Francesca Dominici

Department of Biostatistics, Harvard School of Public Health, 655 Huntington Avenue, HSPH Building 2, 4th Floor, Boston, MA 02115, fdominic@hsph.harvard.edu, P: (617) 432-1056; F: (617)-739-1781

A decrease of 10 $\mu\text{g}/\text{m}^3$ in the concentration of $\text{PM}_{2.5}$ was associated with an increase in mean life expectancy of 0.35 years SD= 0.16 years, $p = 0.033$). This association was stronger in more urban and densely populated counties.

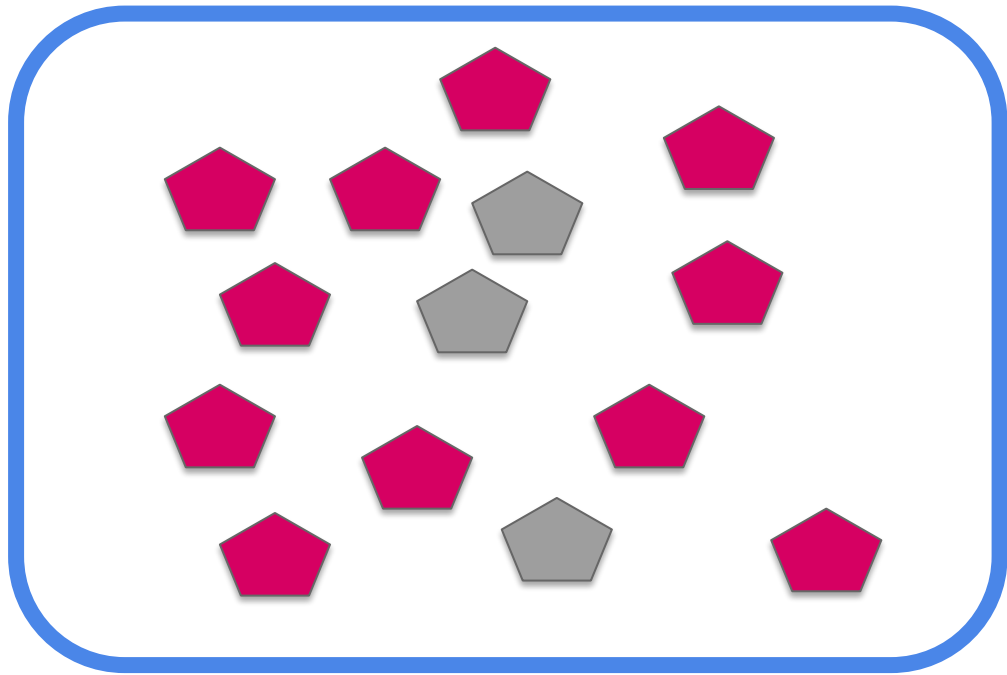
Establishing & Stating Your Null and Alternative Hypotheses Helps Guide Your Analysis

Null Hypothesis:

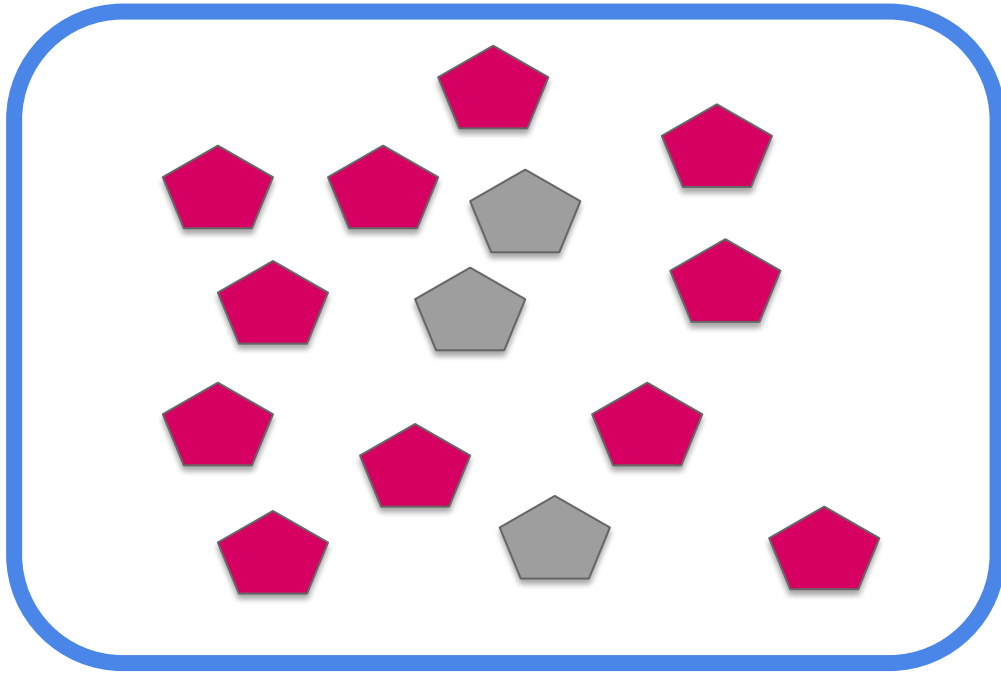
H_0 : Air pollution has no effect on lifespan

Alternative Hypothesis:

H_a : Air pollution has an effect on lifespan

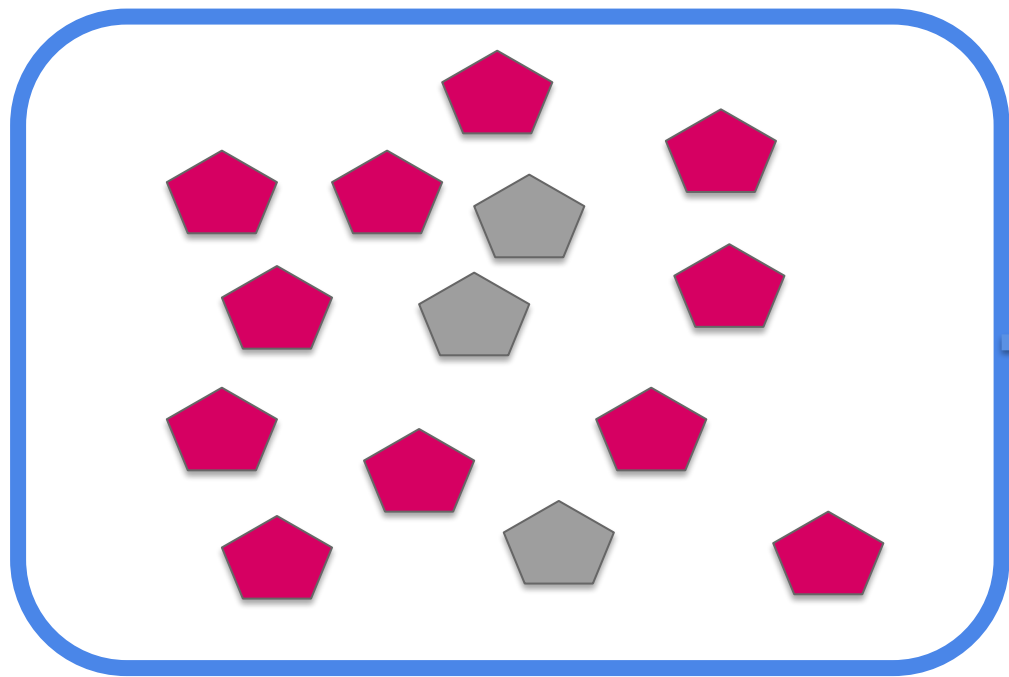


Population

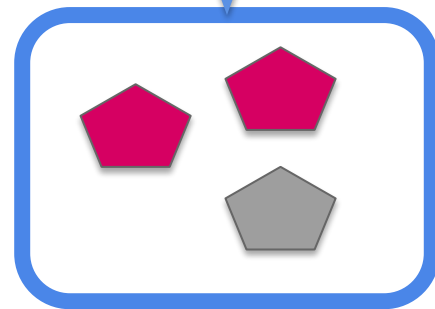


Population

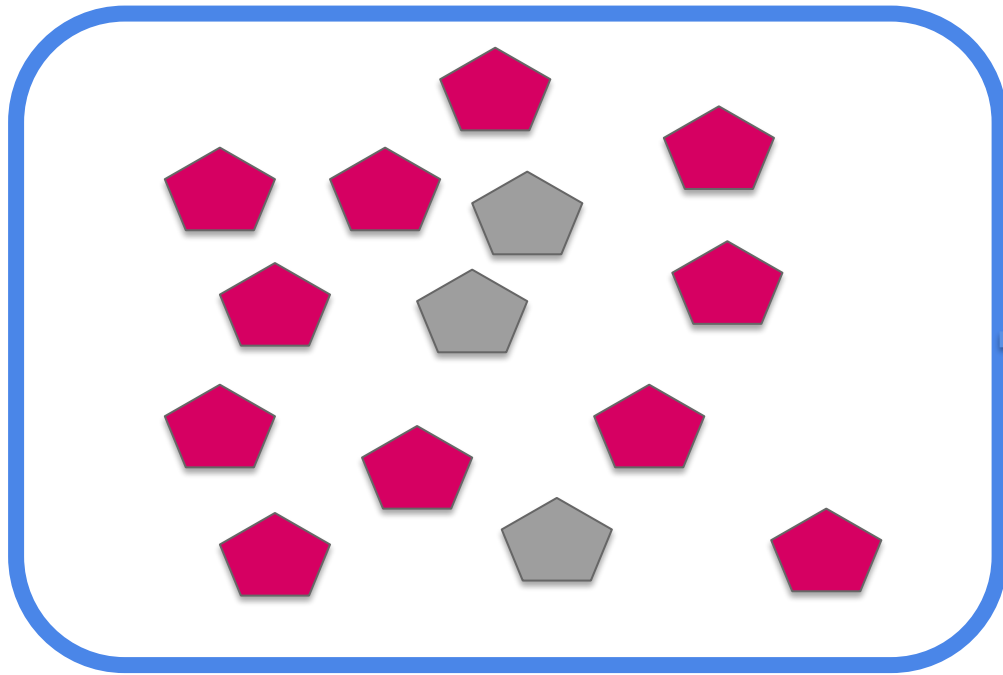
In our air pollution question, the population would be every individual in the US



Population

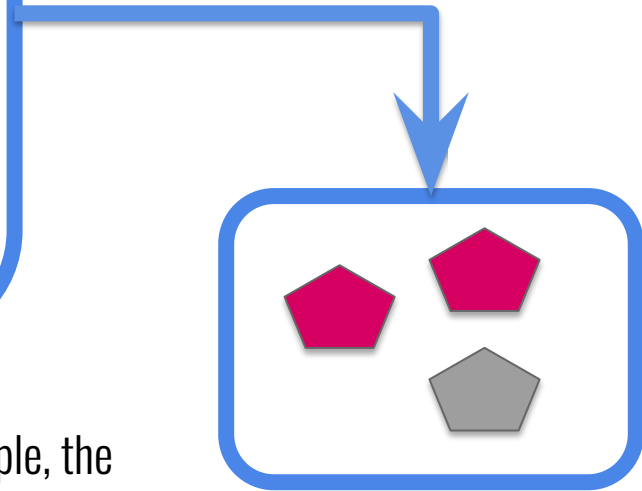


Sample

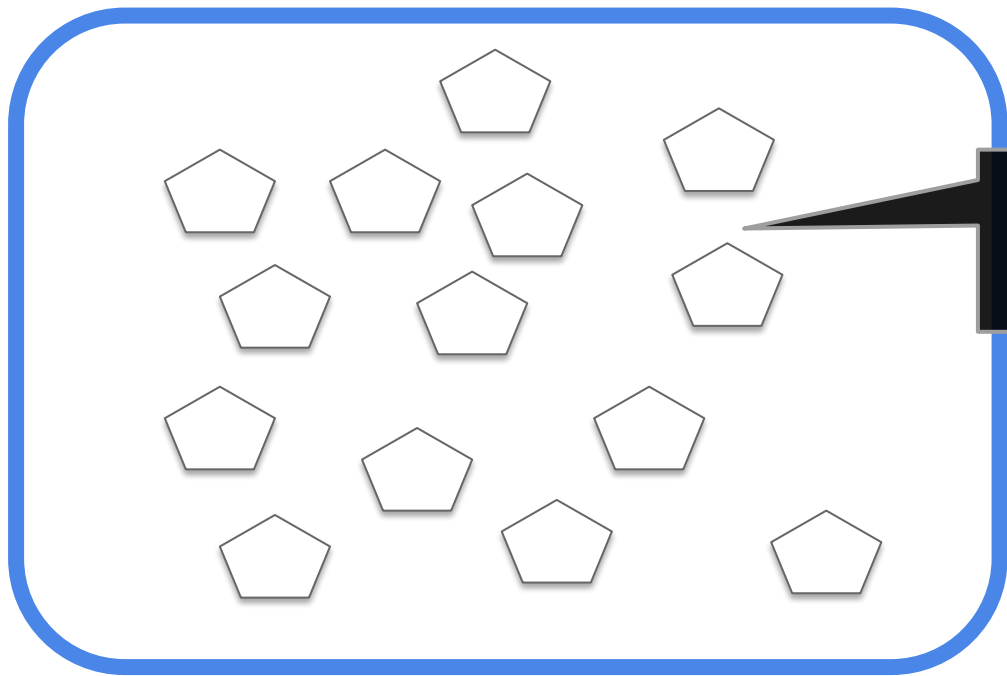


Population

In our air pollution example, the sample would be measurements for some of the US

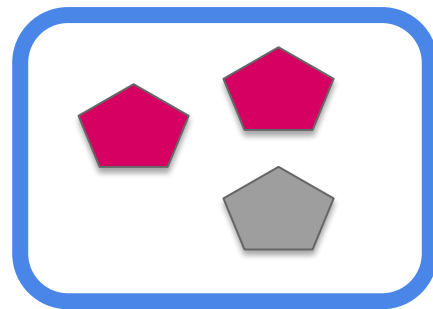


Sample



「_(ツ)_/」

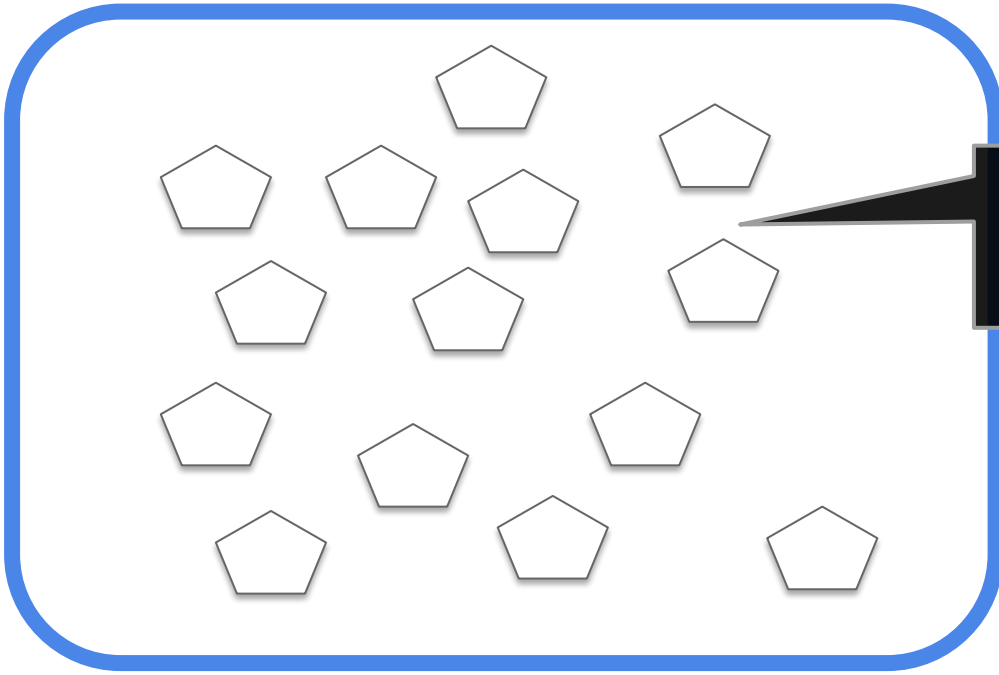
Population



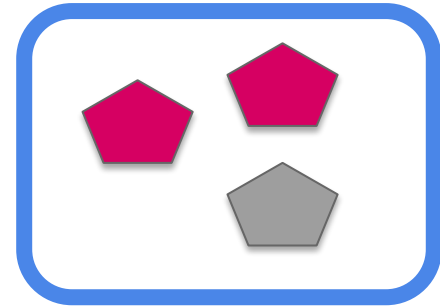
Sample

We don't know how much air pollution each individual is exposed to.

— \ (ツ) / —

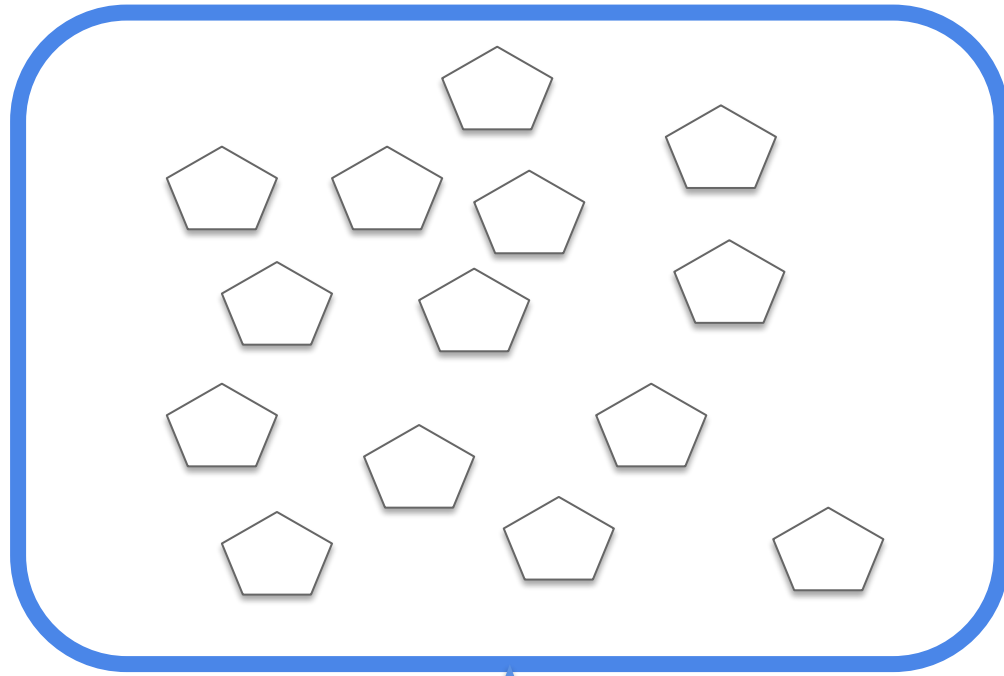


Population

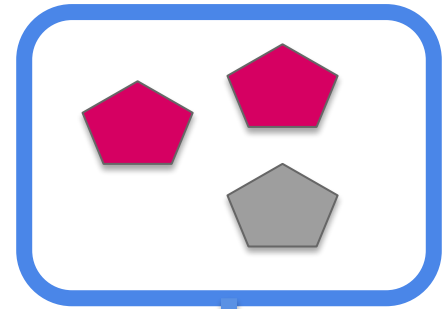


Sample

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



Population

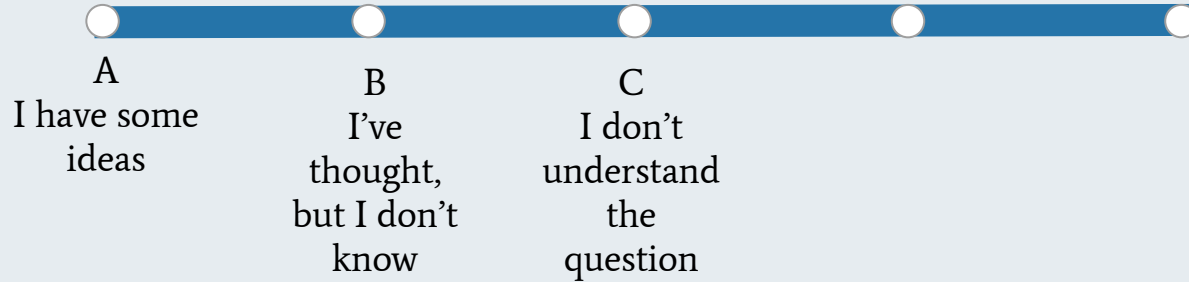


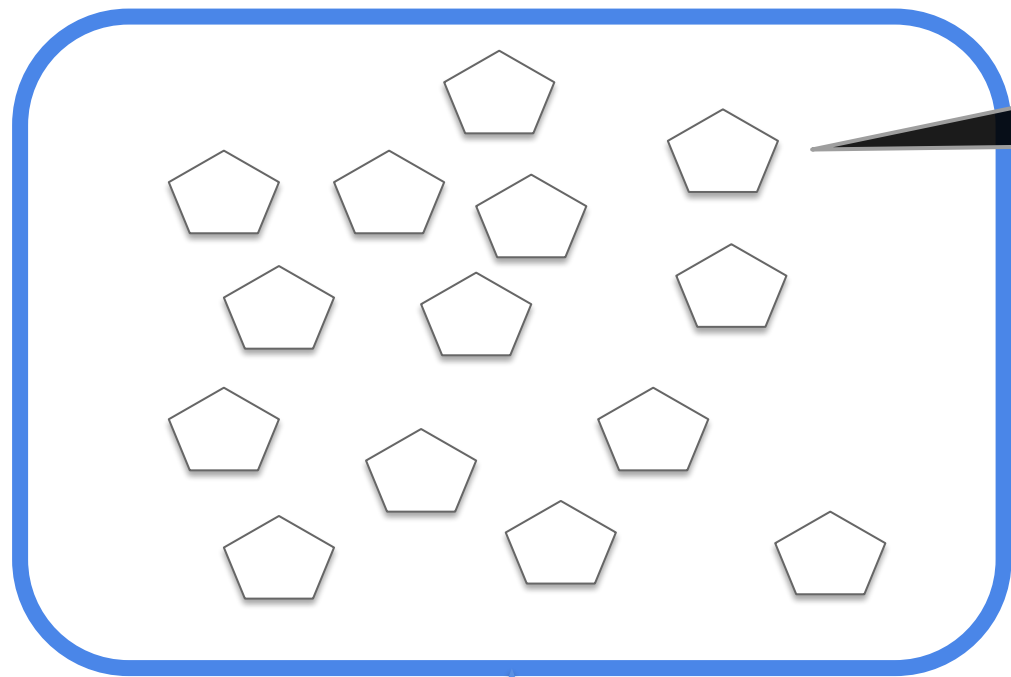
Sample

Inference!



What would you need to consider when sampling air pollution in the US?

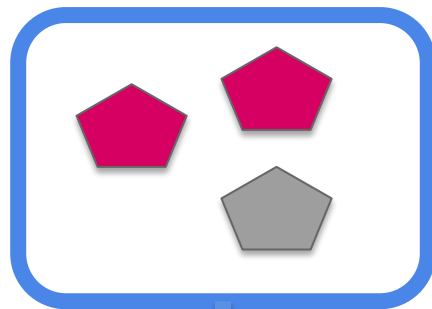




Population

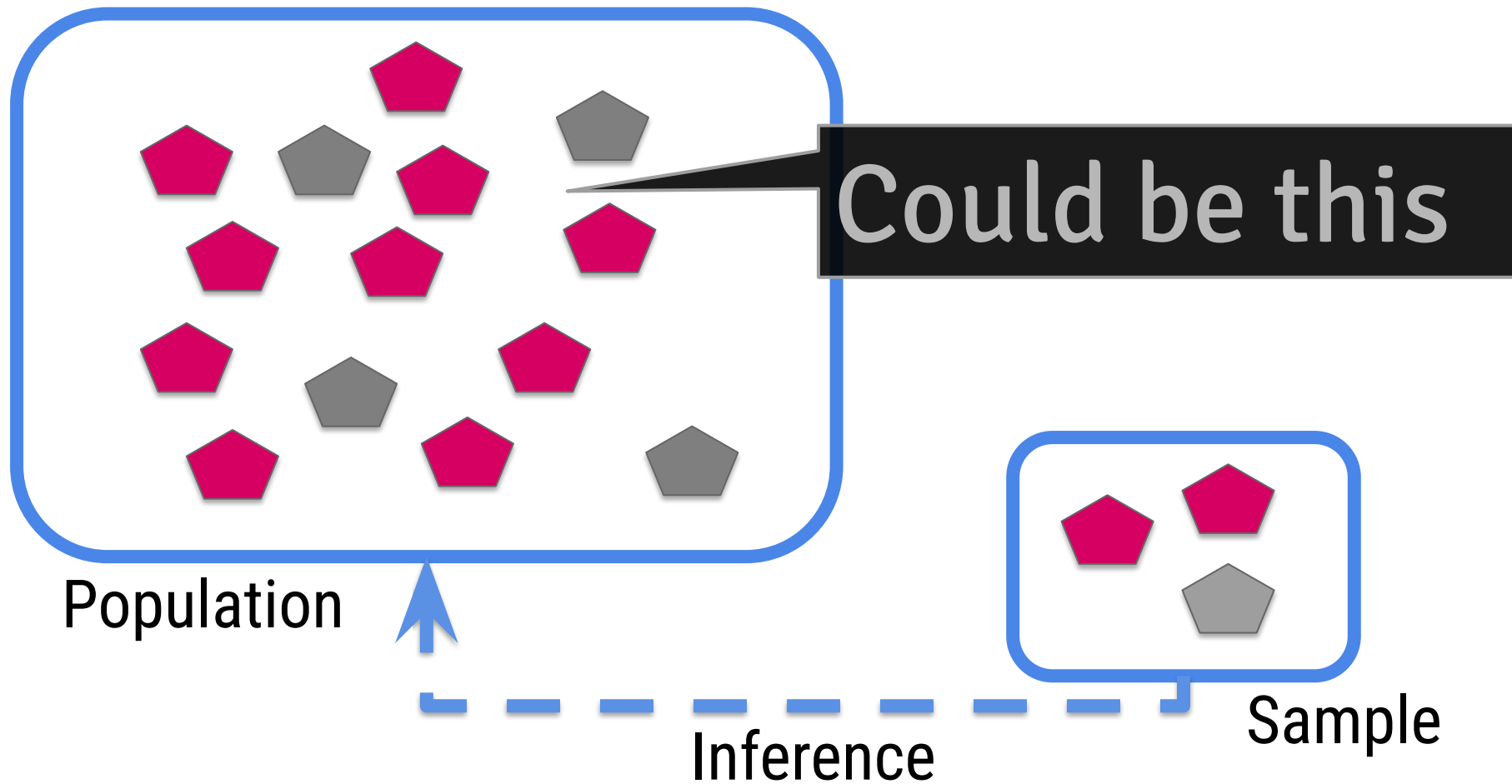
Best guess

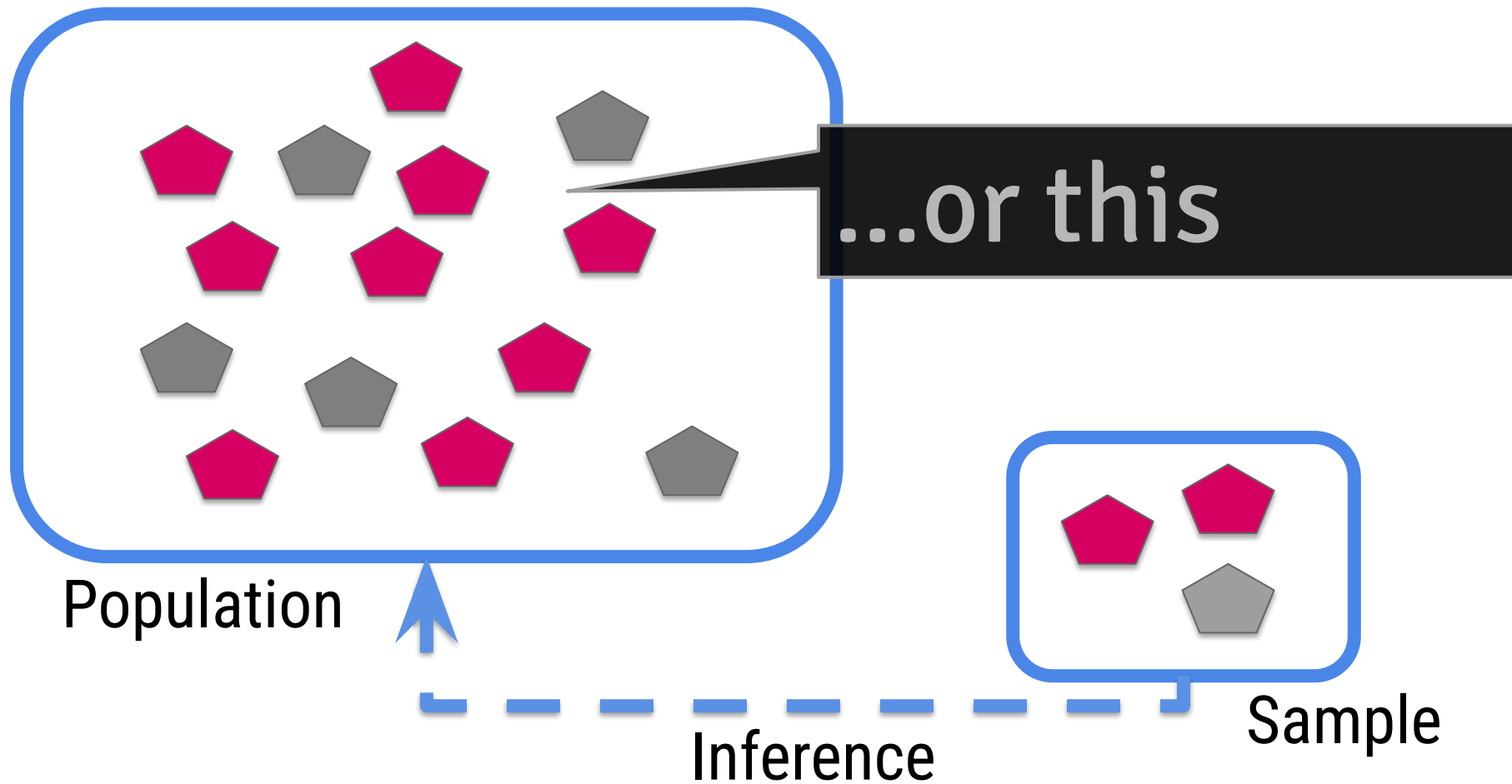
So we measure pollution levels
in a representative sample of
US counties

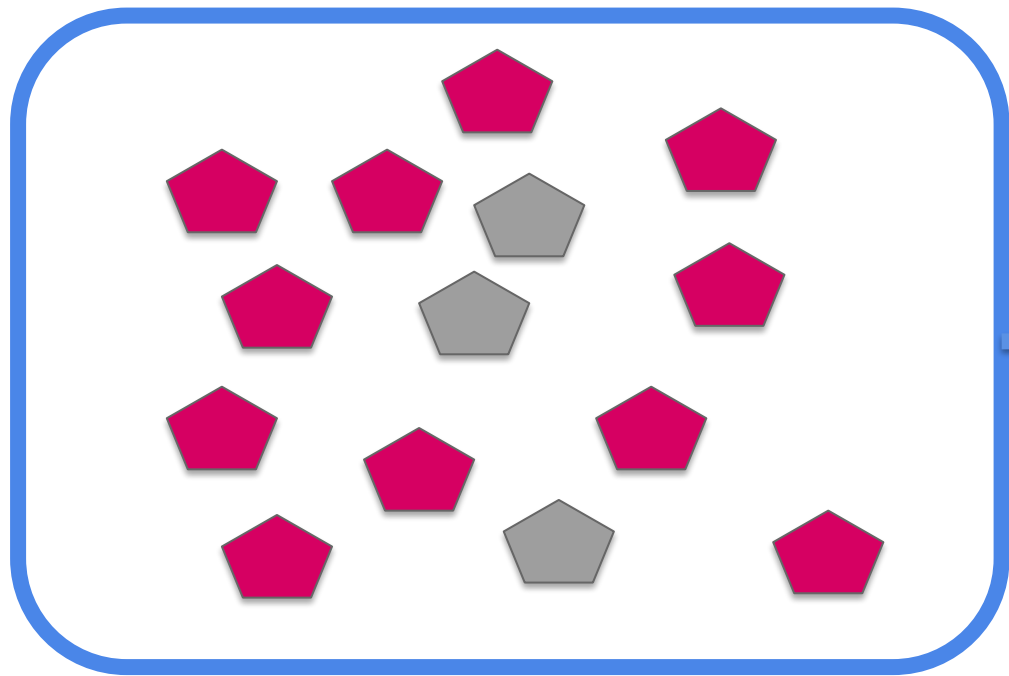


Sample

Inference!

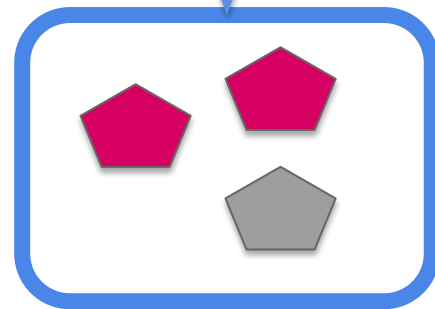




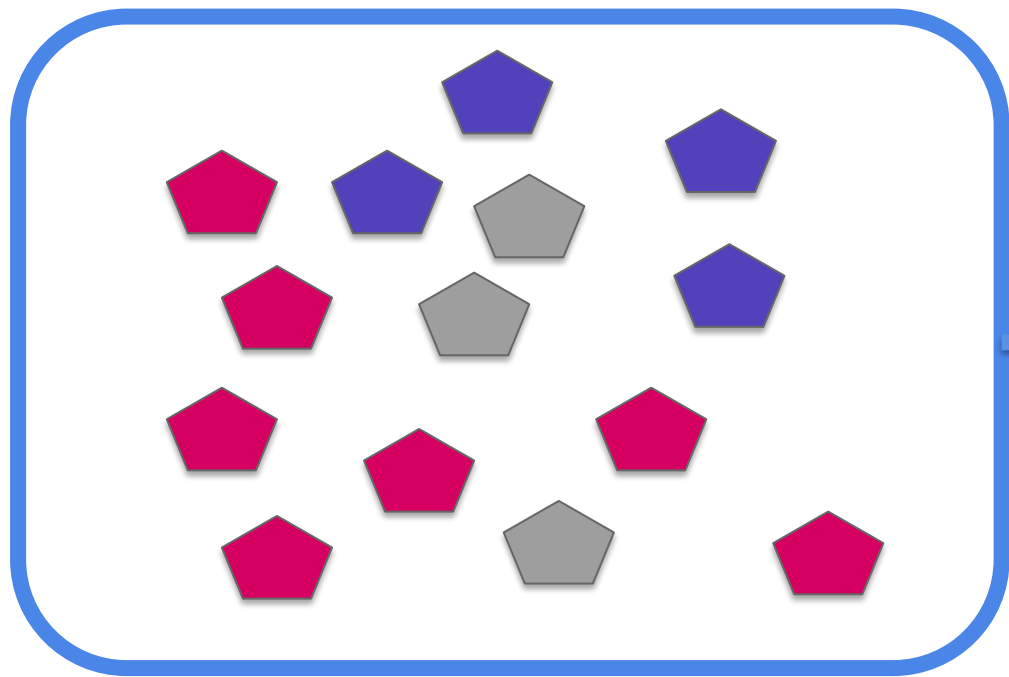


Population

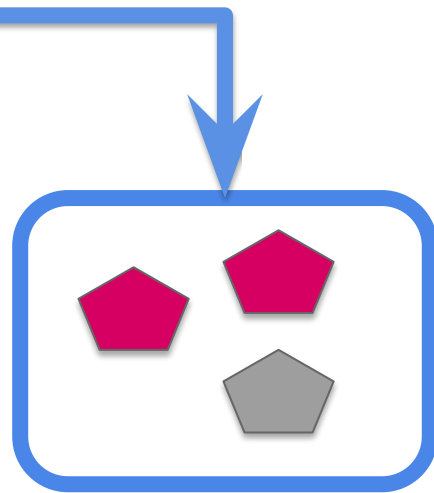
Probability



Sample

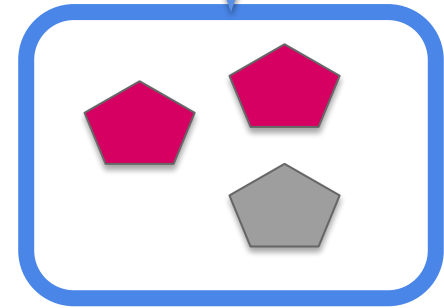
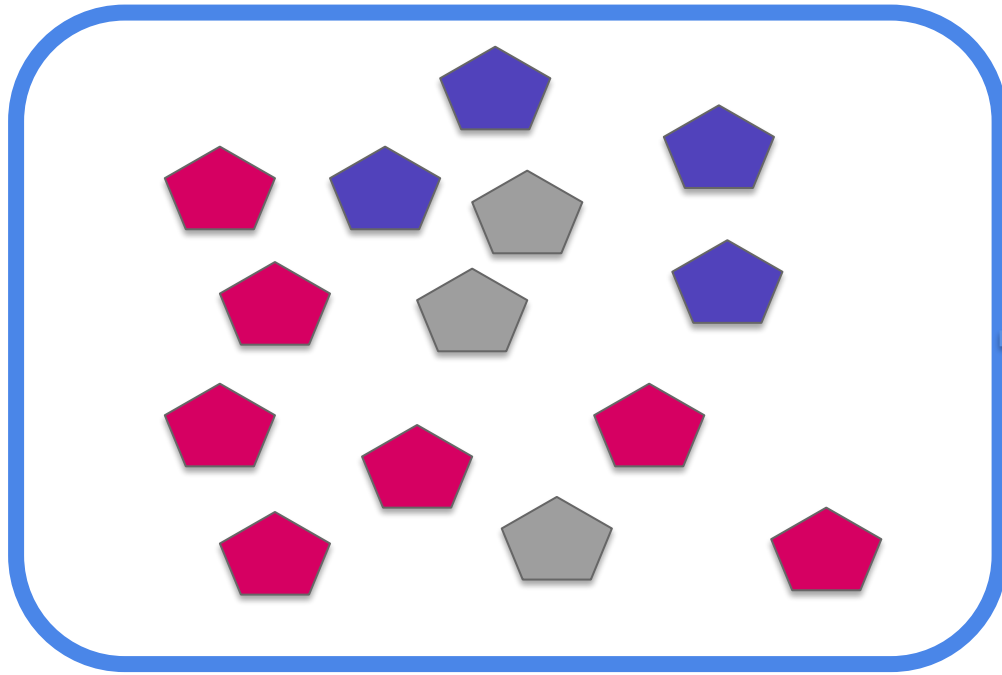


Population



Sample

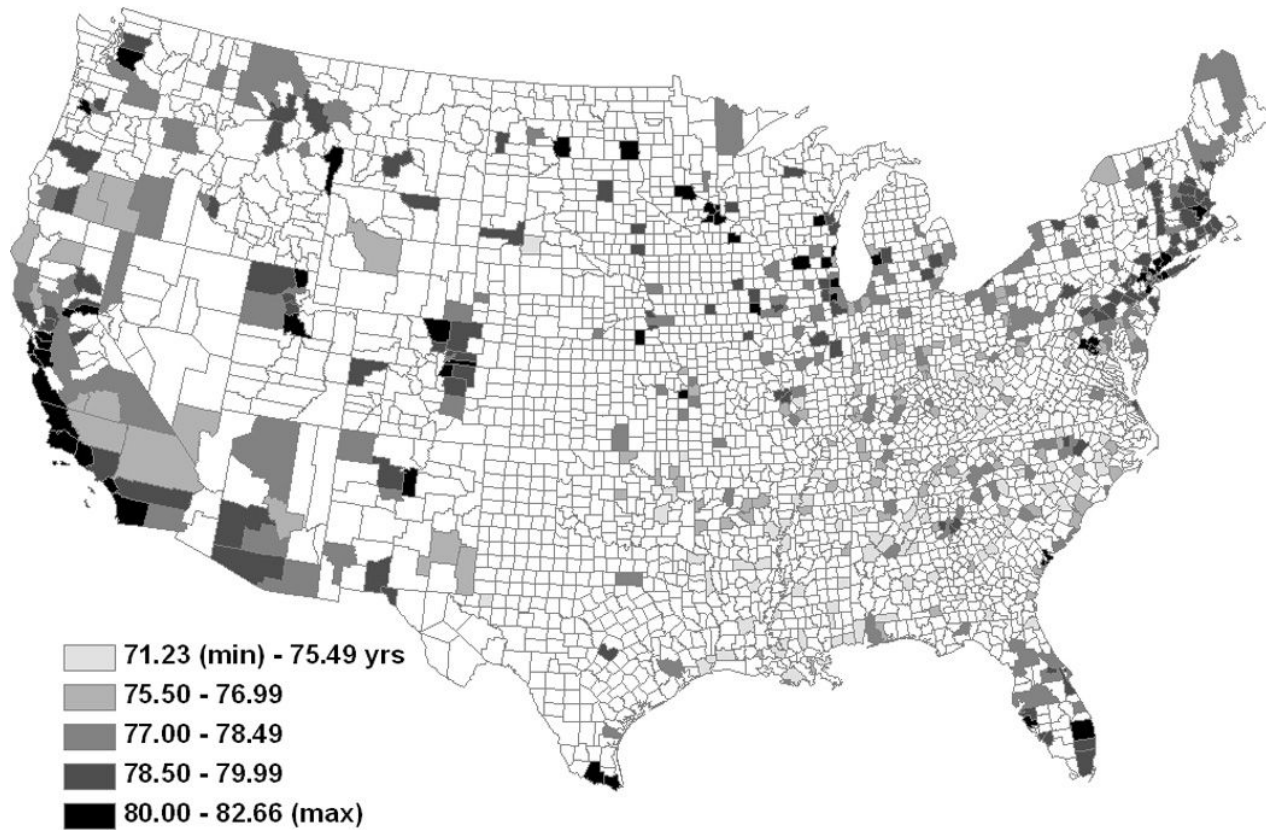
If your sample is *not* representative of your population, you can not do inferential analysis.



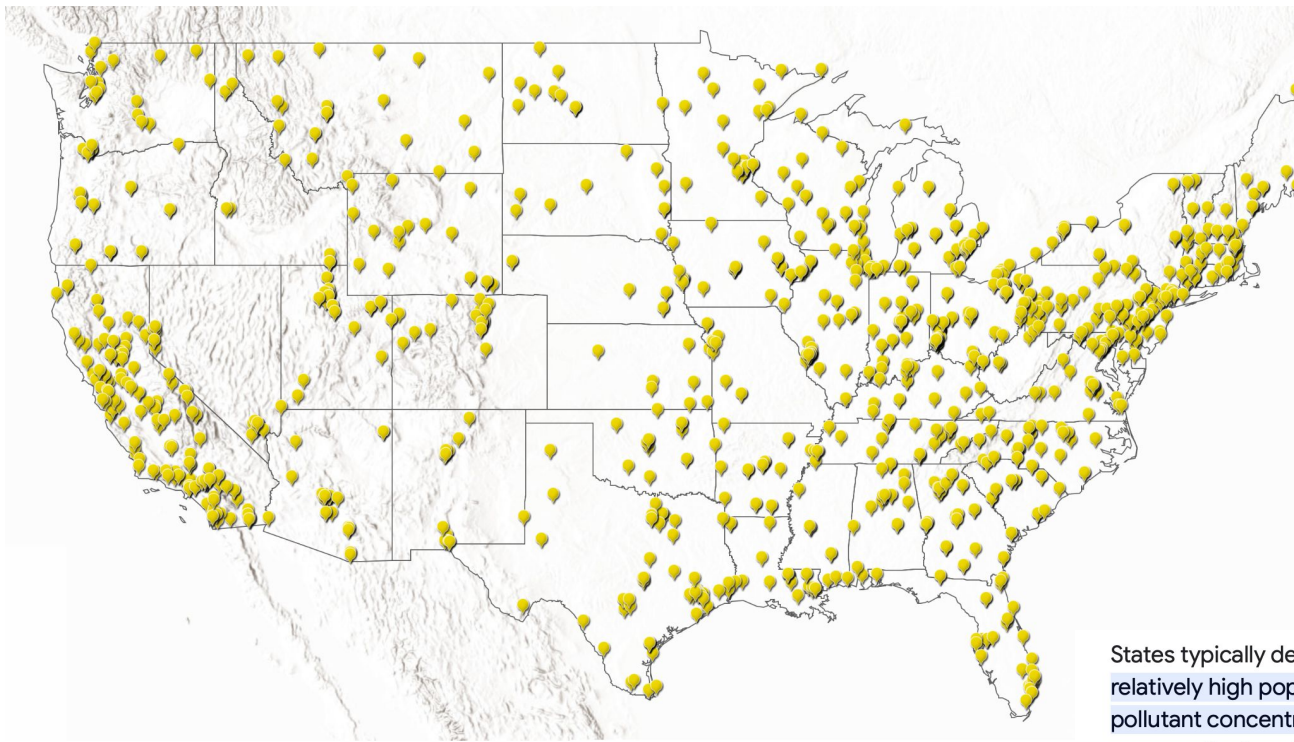
Population

~~Inference~~

Sample



All counties with with available matching PM2.5 data for 2000 and 2007 from the EPA's Air Quality System. Includes both metropolitan and non-metro counties



States typically decide where monitors are placed based on areas of relatively high population and/or areas believed to have relatively higher pollutant concentrations. Each state is responsible for developing its own monitoring plan, which is then reviewed and revised every five years. Aug 28, 2023



United States Environmental Protection Agency (.gov)

<https://www.epa.gov/outdoor-air-quality-data/who-decides-where-monitors-get-placed>



Who decides where monitors get placed? | US EPA

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

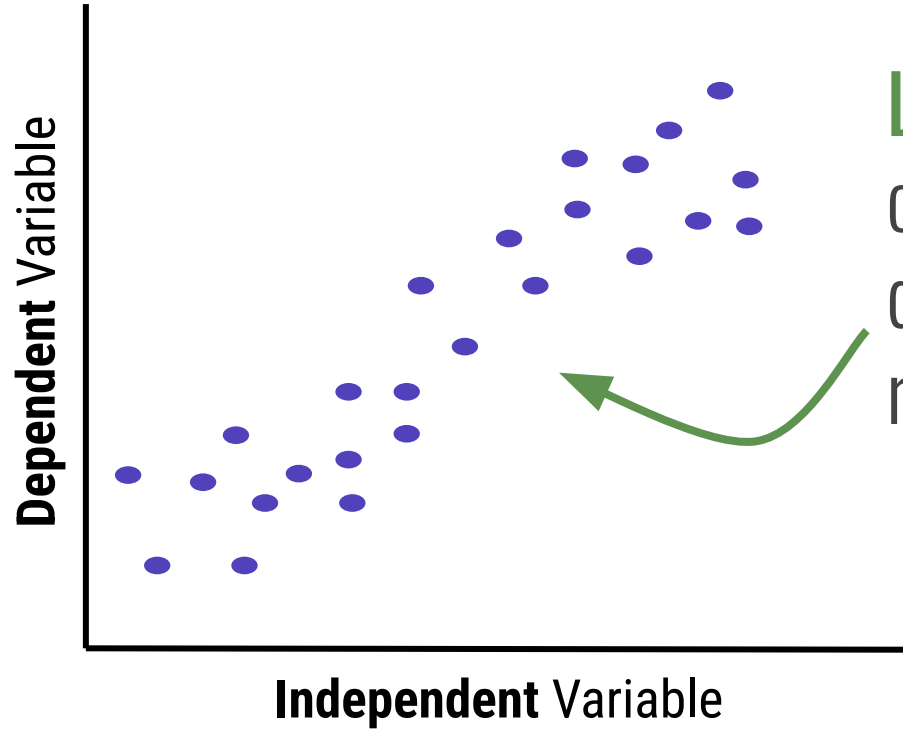
DOES CHANGE IN ONE
VARIABLE MEAN CHANGE IN
ANOTHER?

i.e. simple regression,
multiple regression

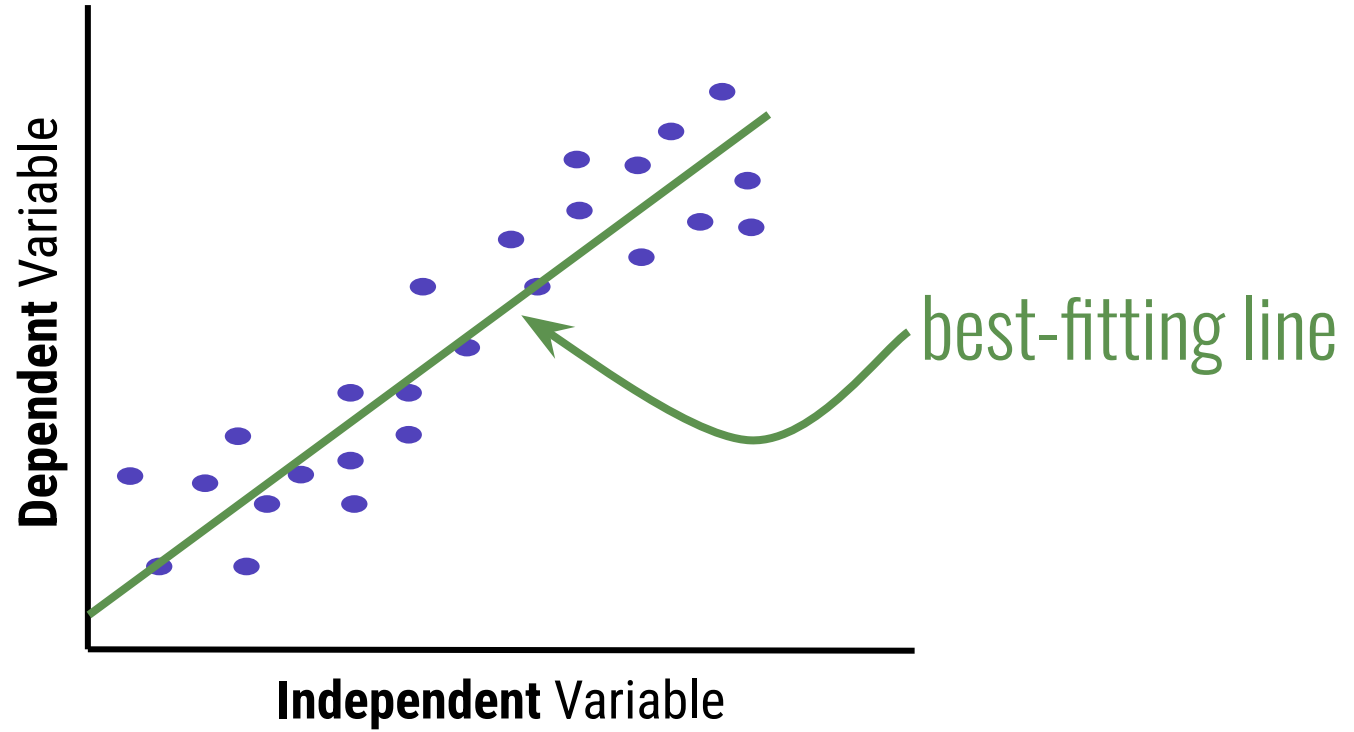
NON-PARAMETRIC TESTS

FOR WHEN ASSUMPTIONS IN
THESE OTHER 3 CATEGORIES
ARE NOT MET

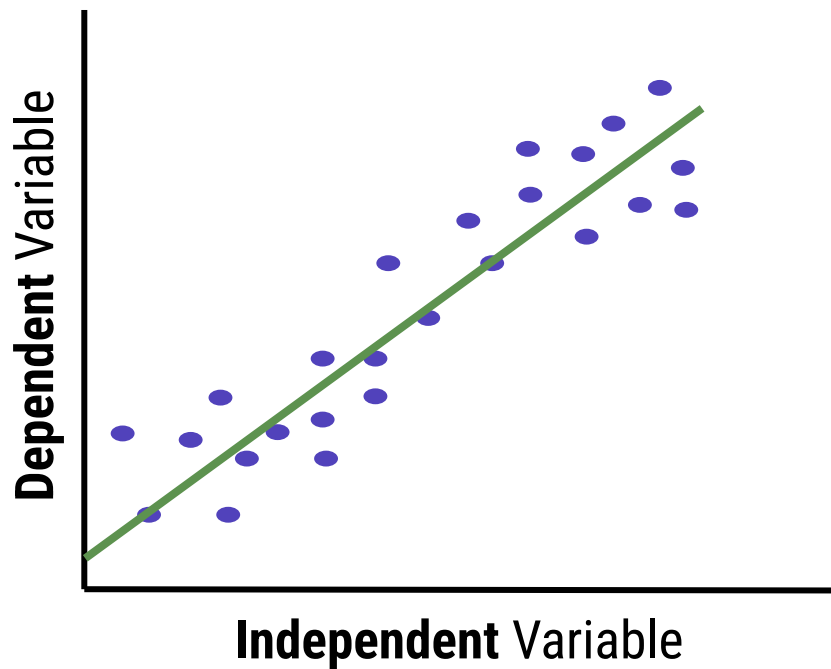
i.e. Wilcoxon rank-sum test,
Wilcoxon sign-rank test,
sign test



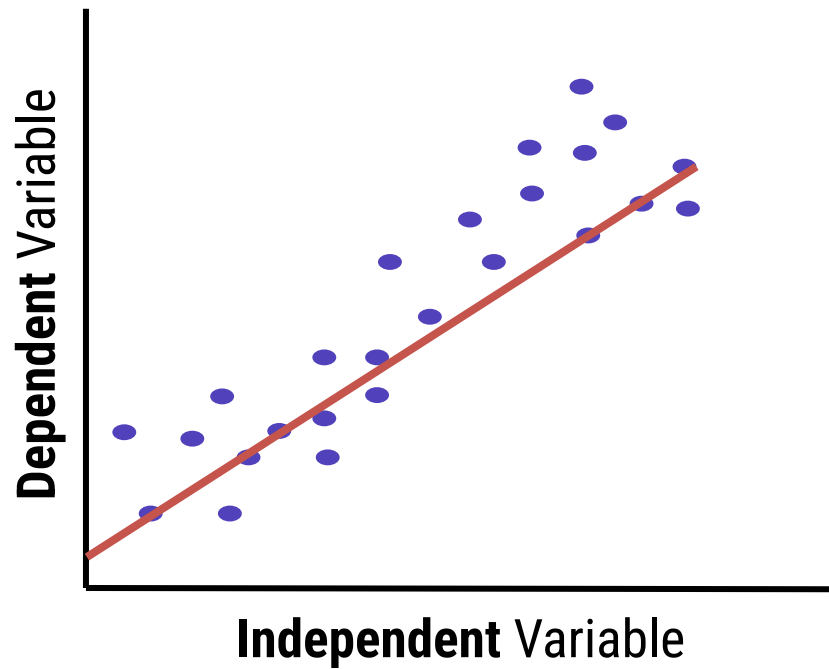
Linear regression
can be used to
describe this
relationship

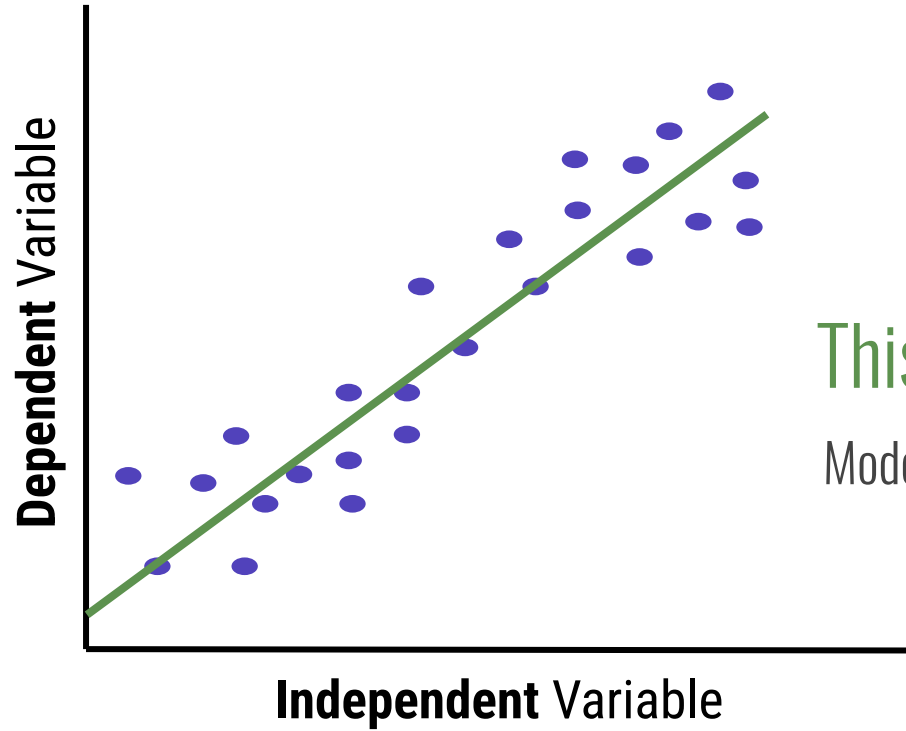


Best-fitting line



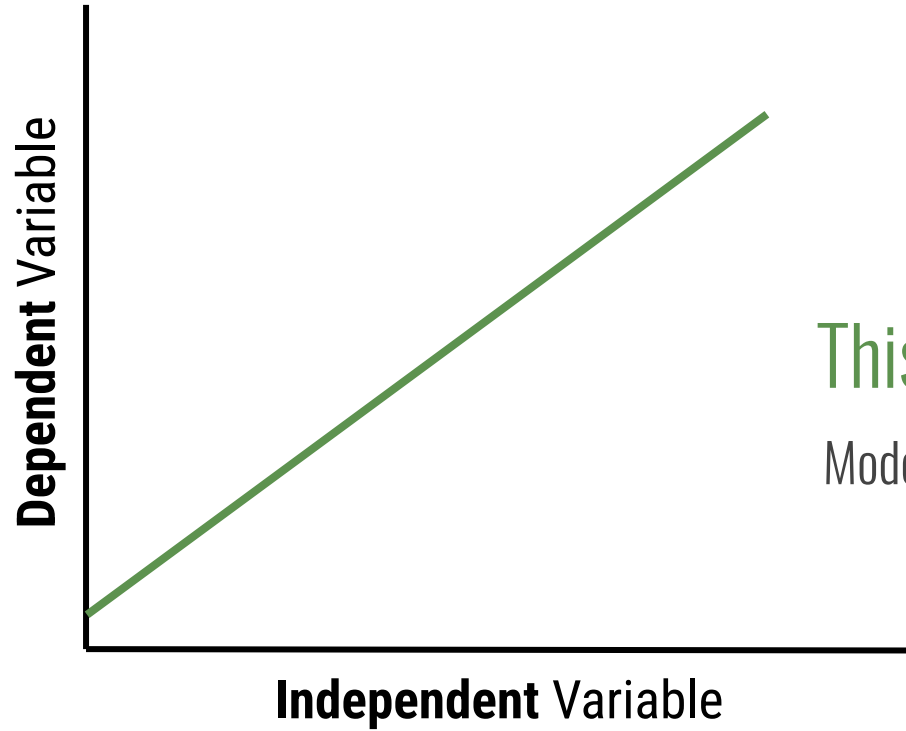
NOT a best-fitting line





This line is a **model** of the data

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

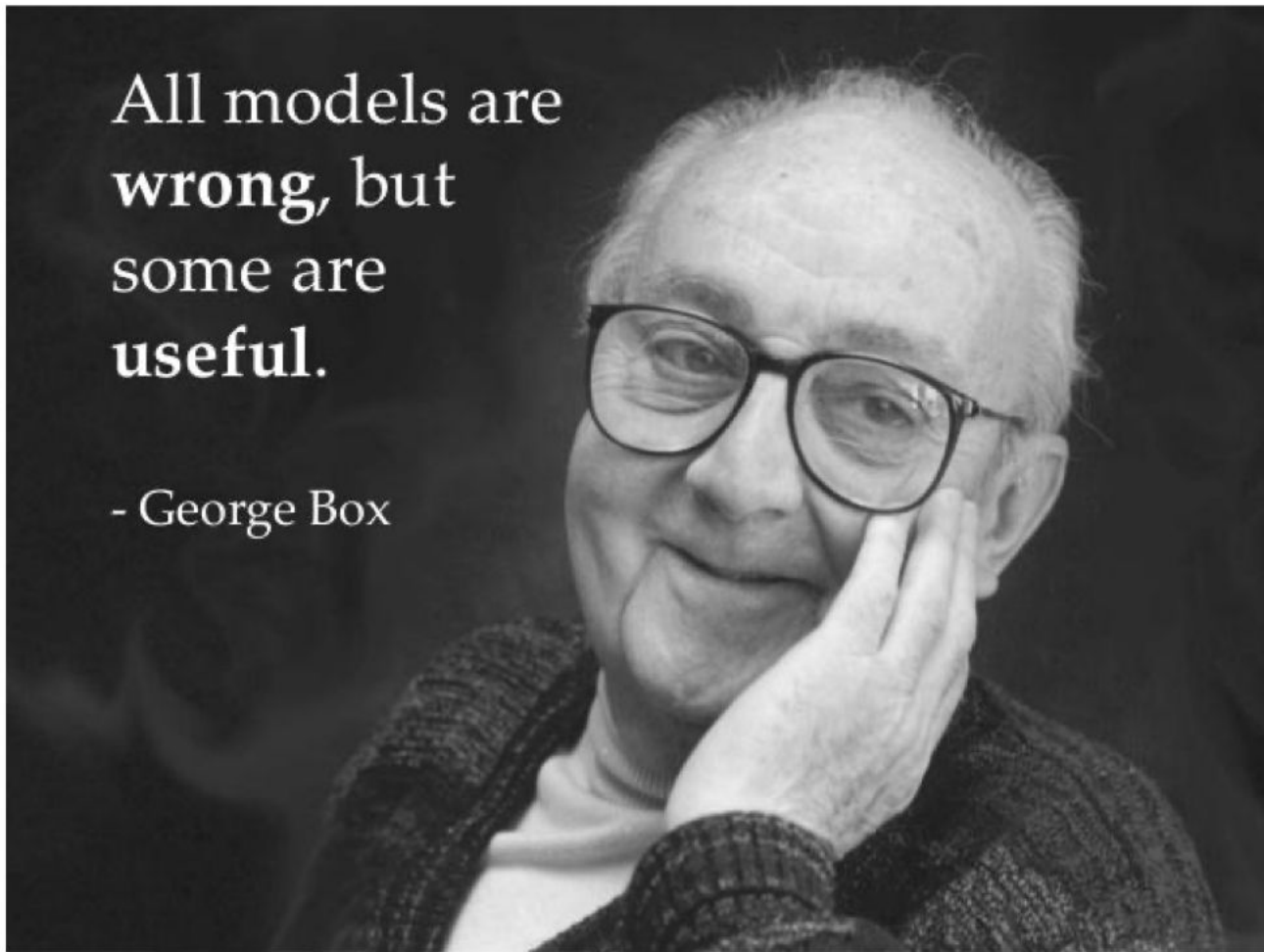


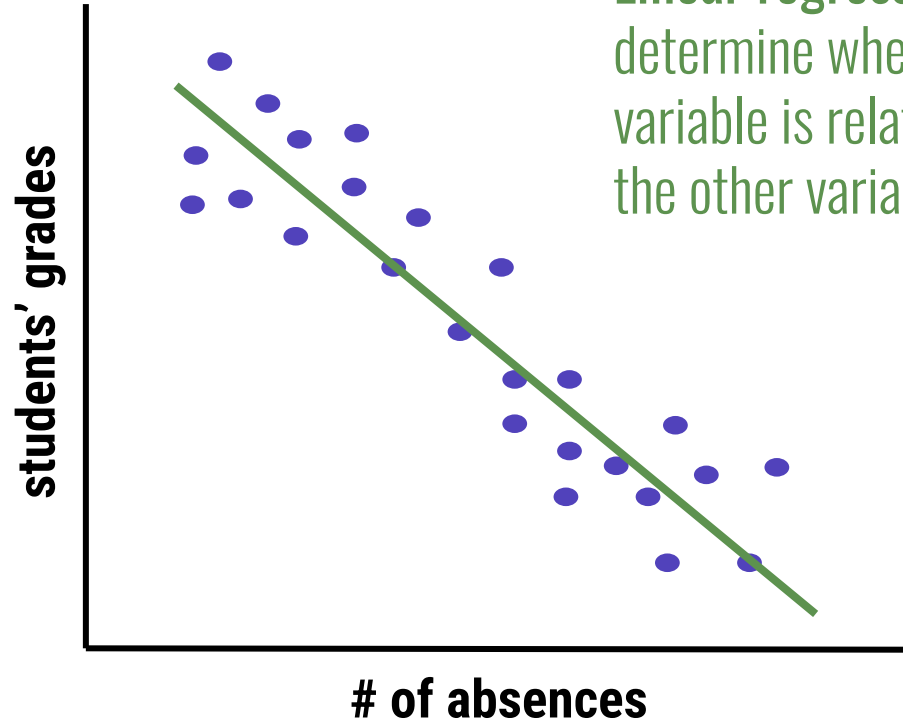
This line is a **model** of the data

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

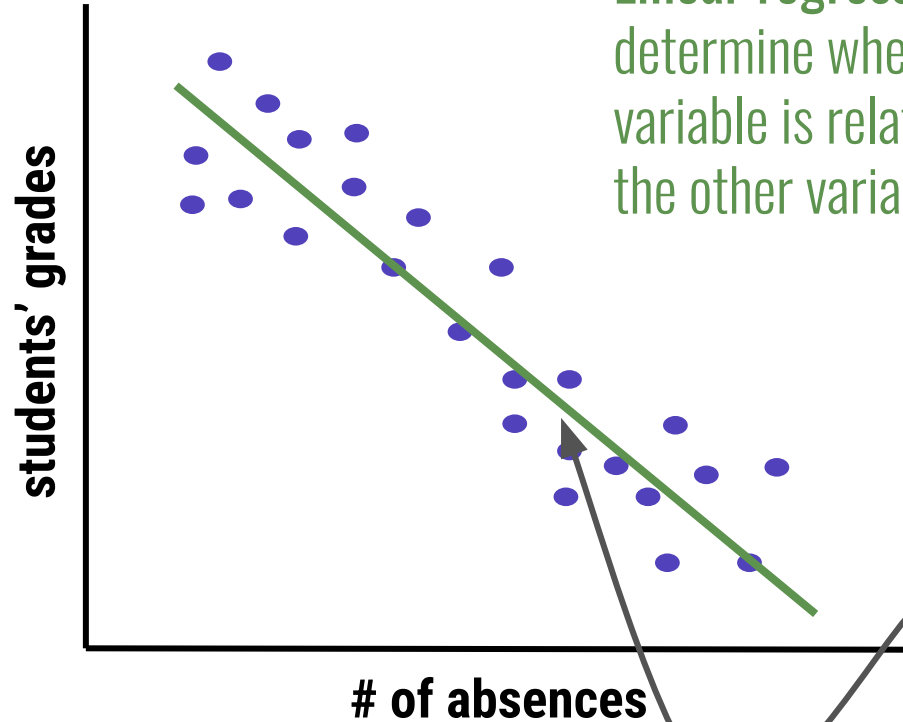
All models are
wrong, but
some are
useful.

- George Box



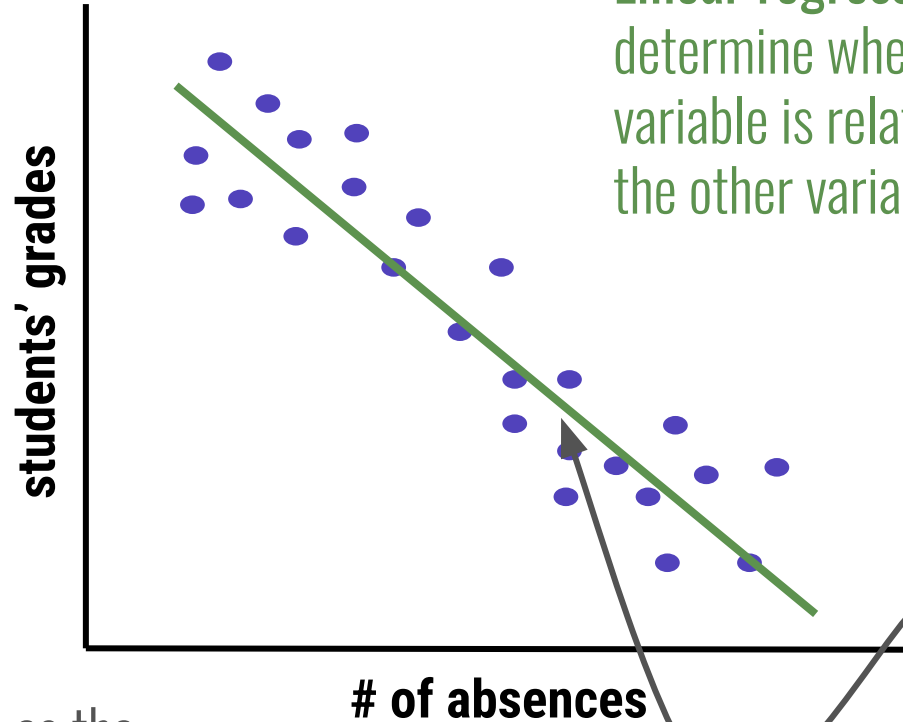


Linear regression can be used to determine whether a change in one variable is related to the change in the other variable



The magnitude of the relationship is measured by the slope of the line

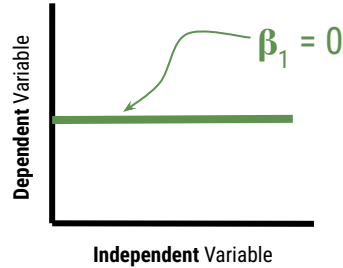
Linear regression can be used to determine whether a change in one variable is related to the change in the other variable



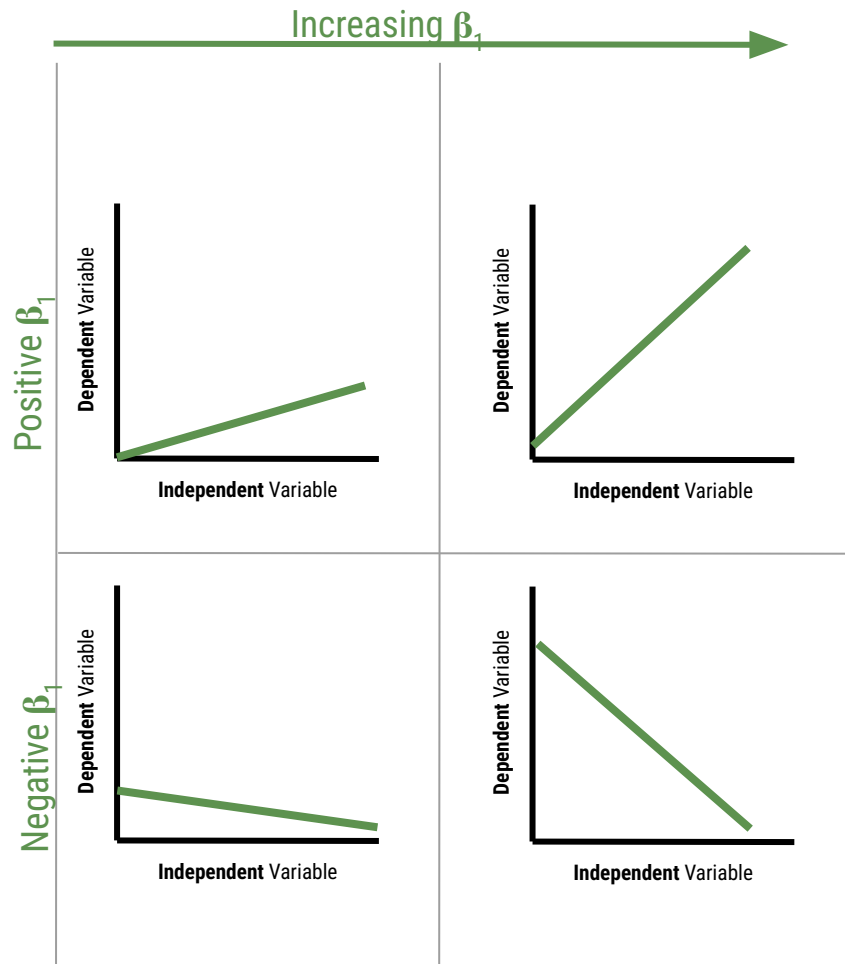
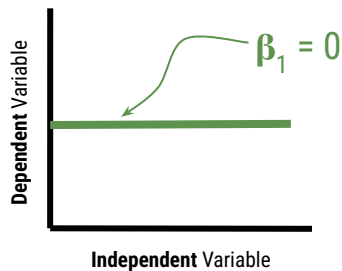
The magnitude of the relationship is measured by the slope of the line

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

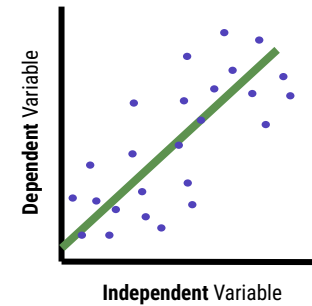
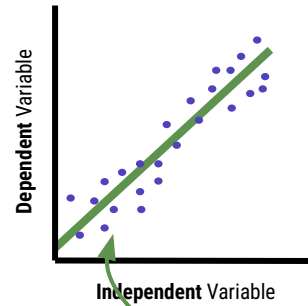
Effect size (β_1) can be estimated using the slope of the line



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



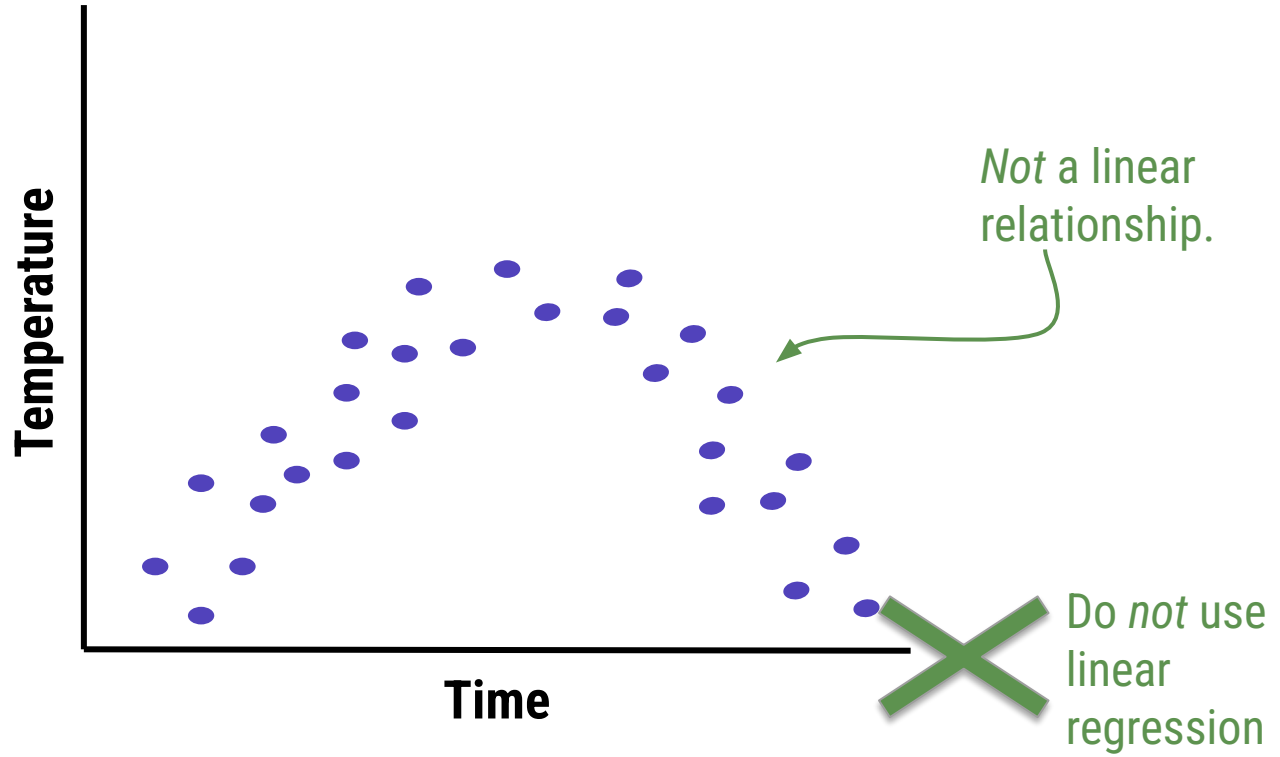
increasing standard error (SE) →



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

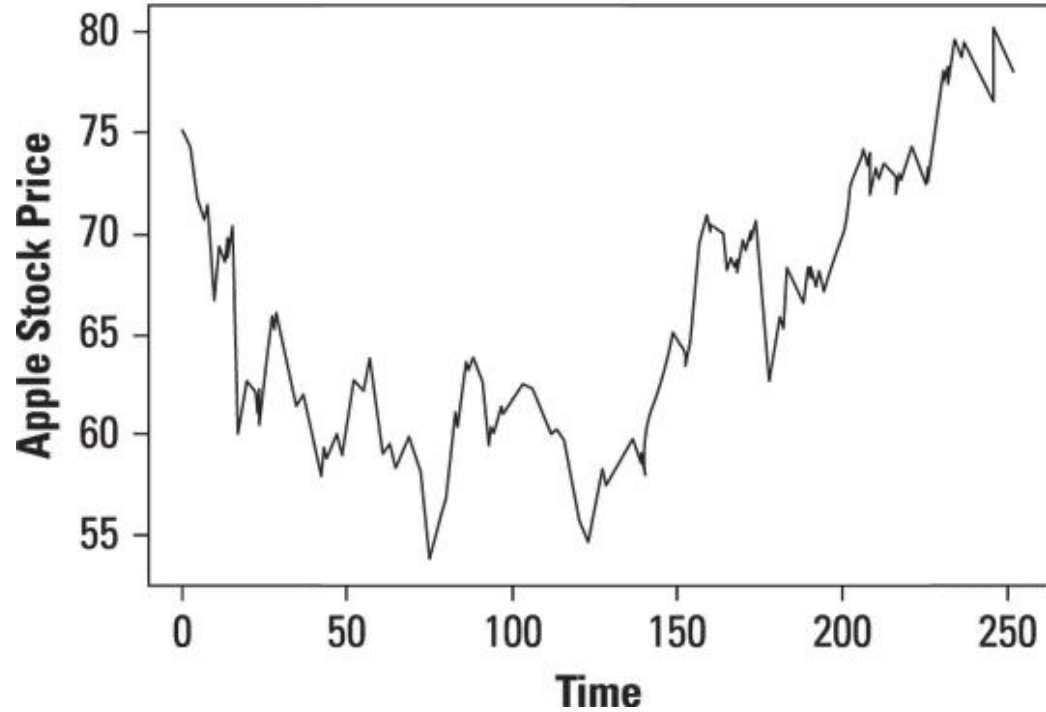
Assumptions of linear regression

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

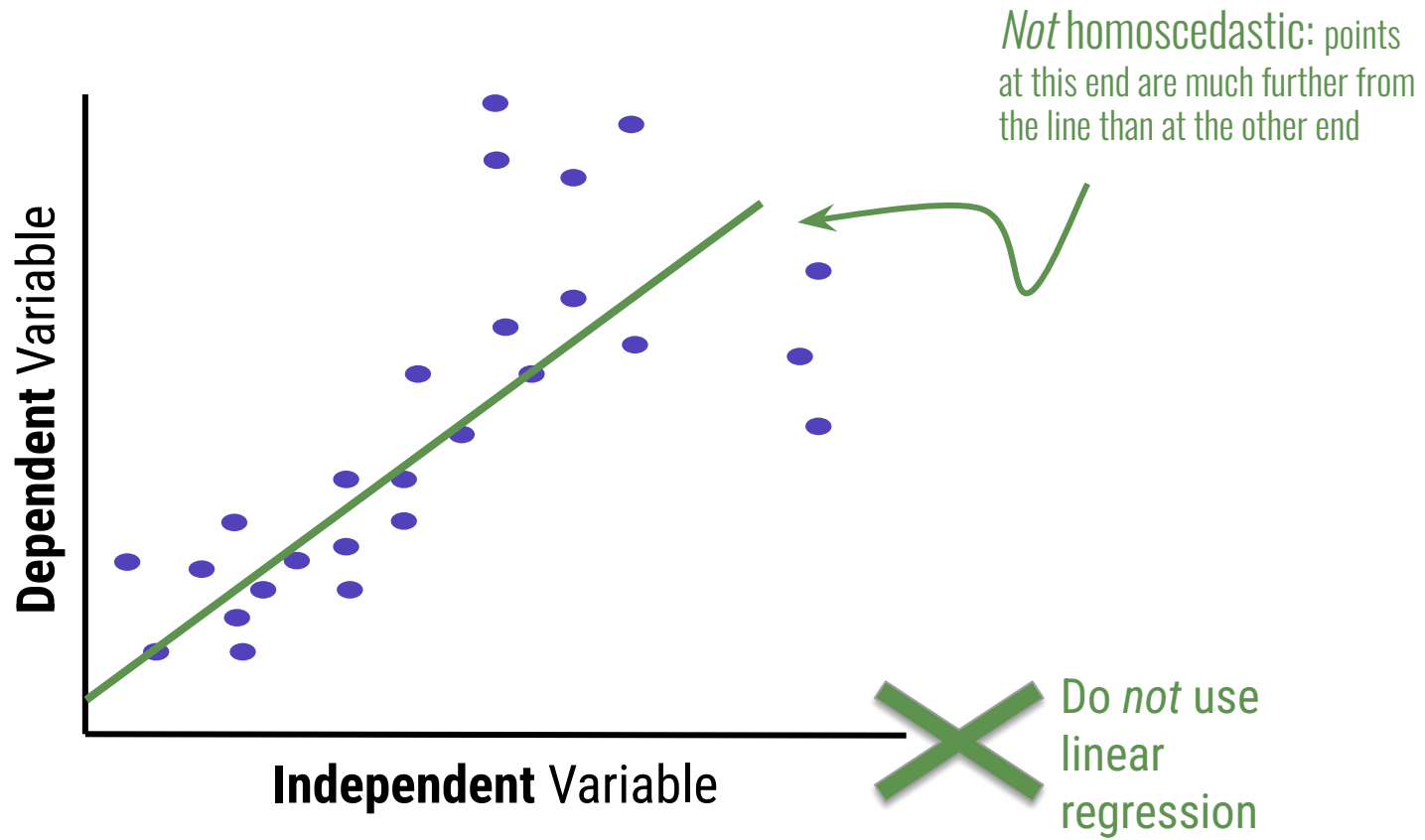


Linear regression assumes no multicollinearity. **Multicollinearity** occurs when the independent variables (in multiple linear regression) are too highly correlated with each other.

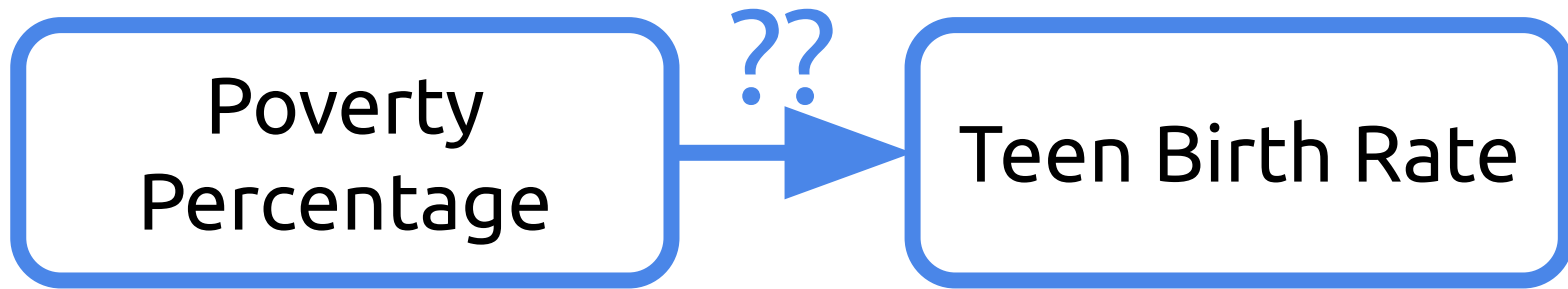
Time Series Plot of Apple Stock Prices



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 ($\beta_1=0$)

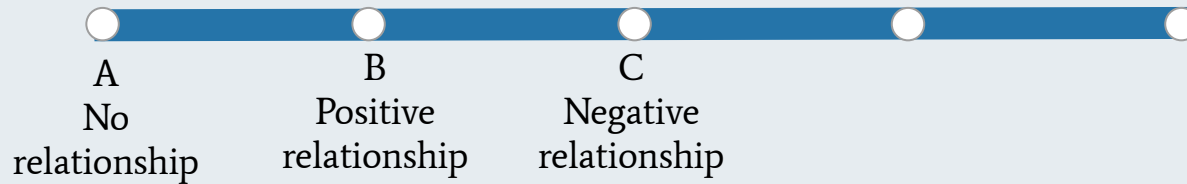
Alternative Hypothesis:

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



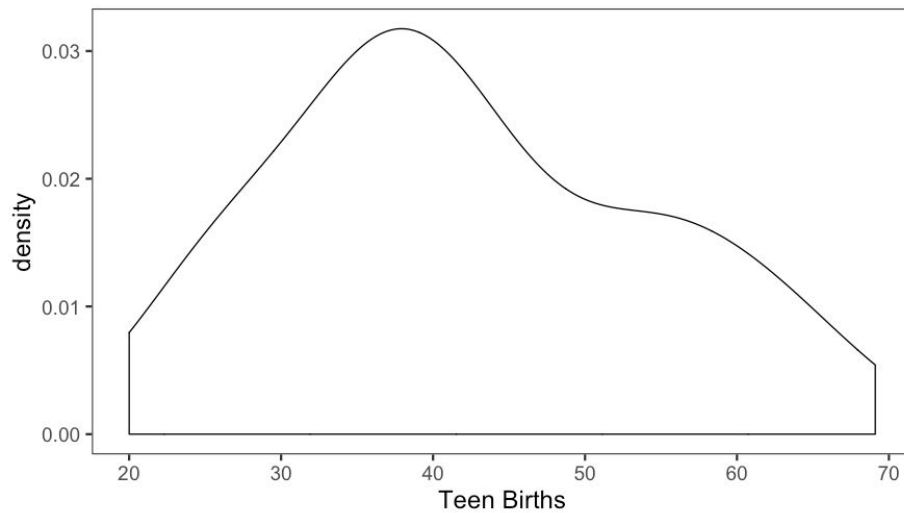
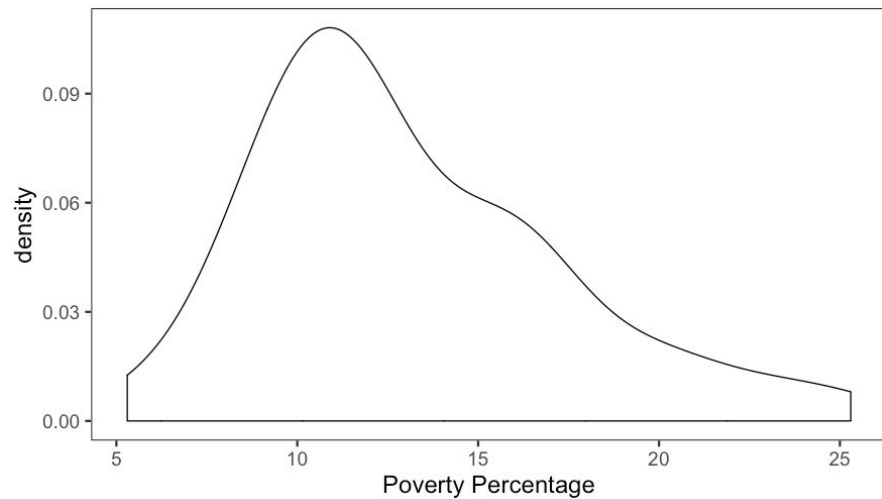
What is the relationship between Poverty Percentage & Teen Birth Rate?

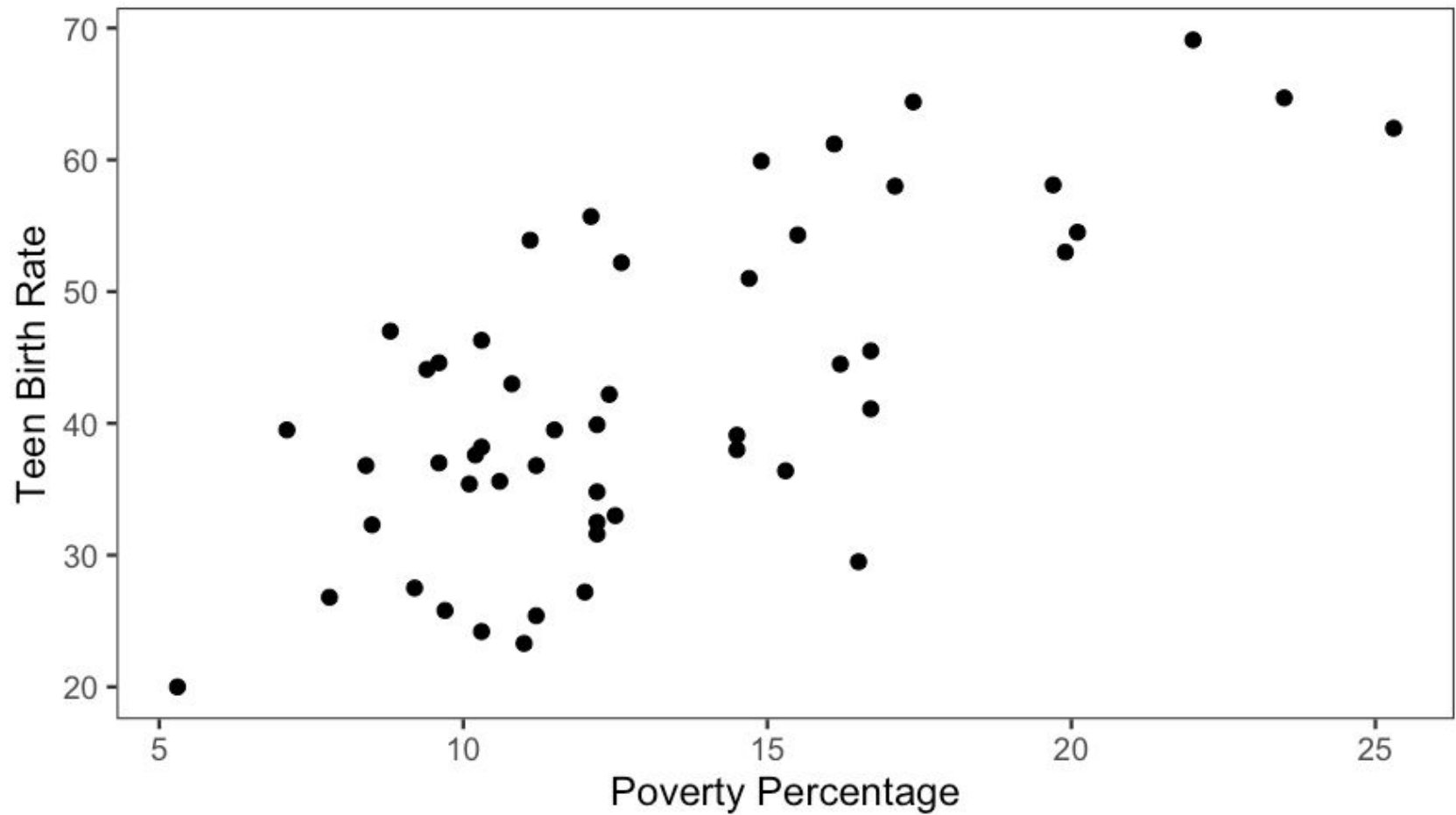
What's your hypothesis?

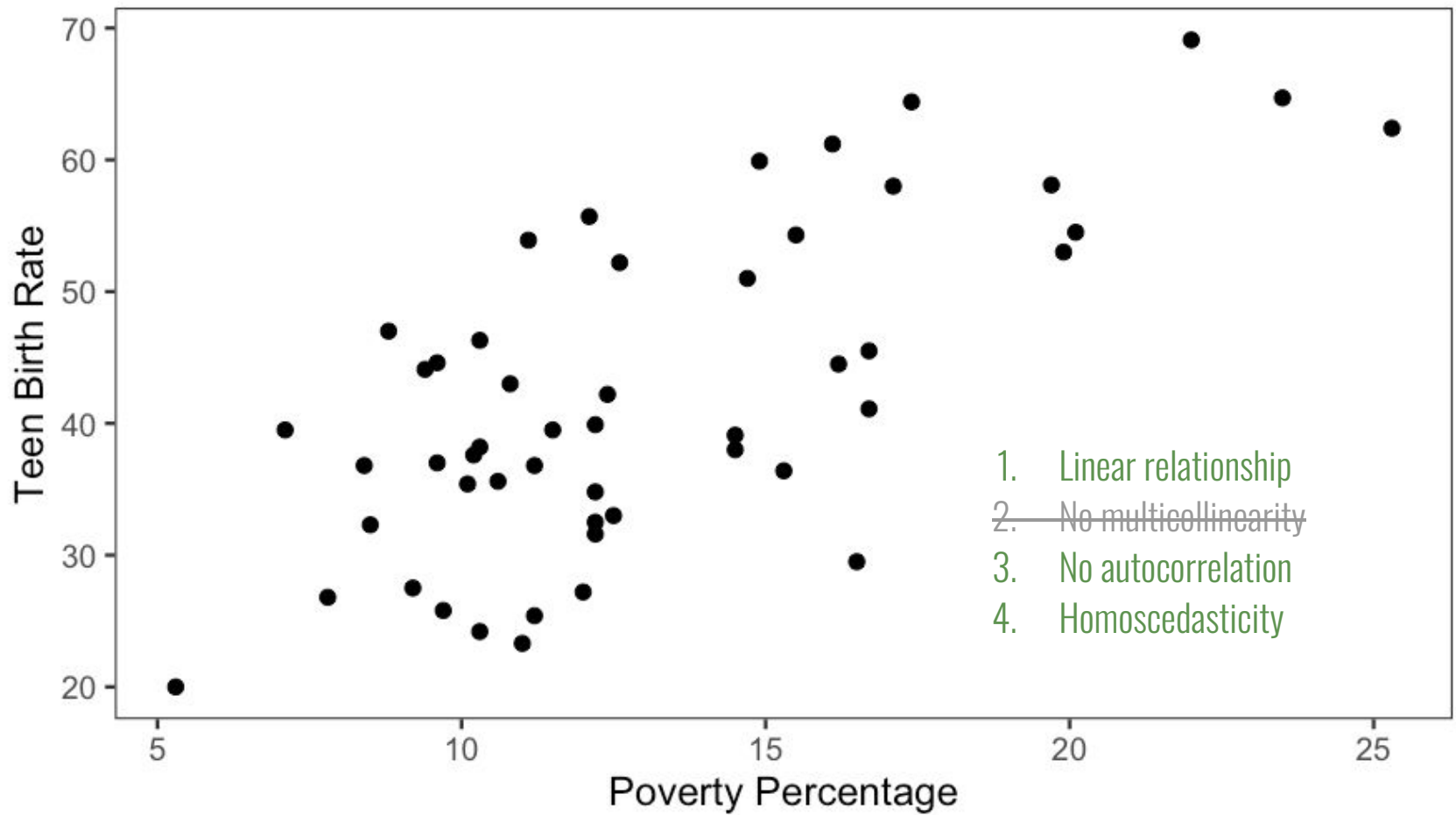


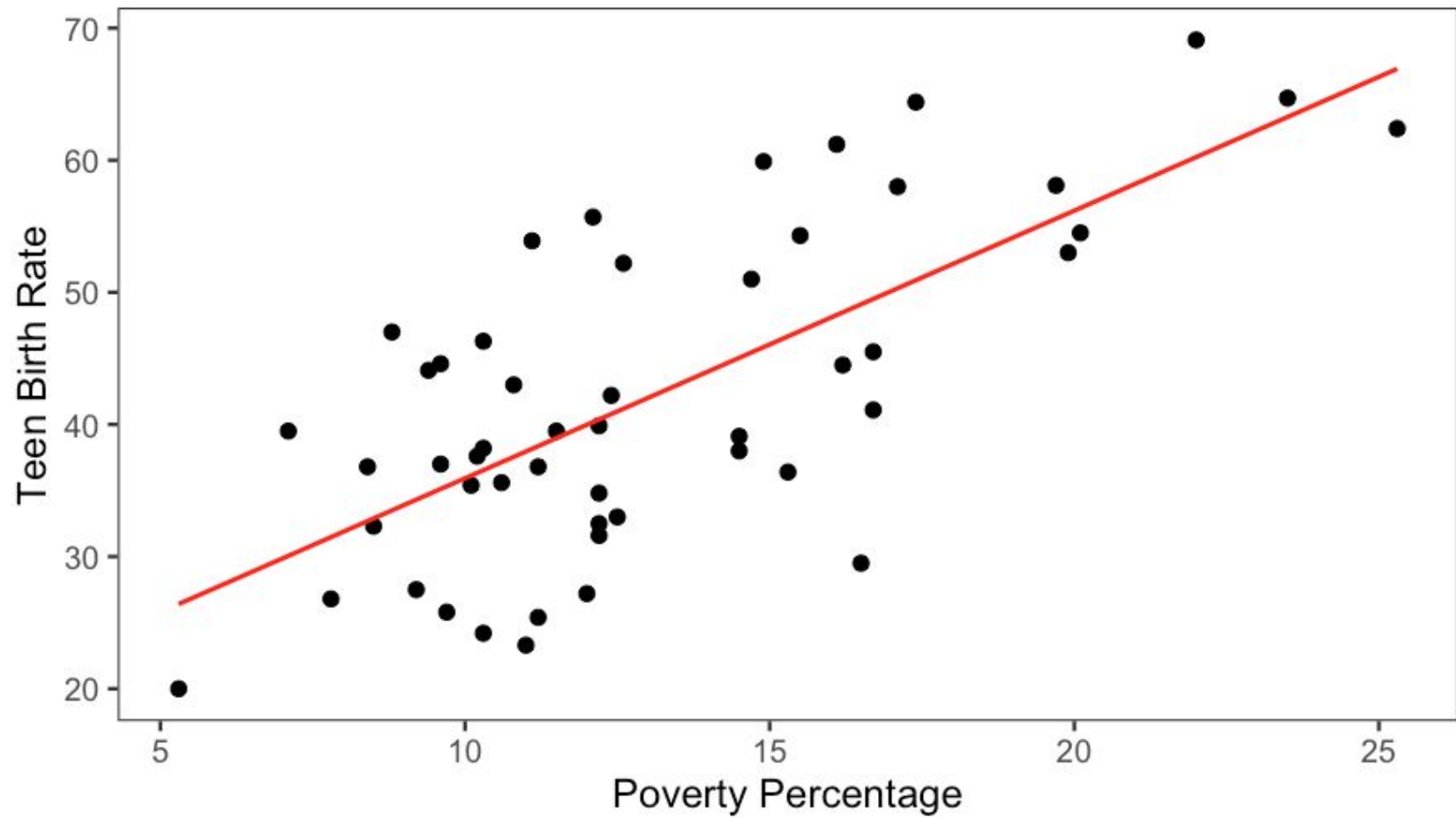
	Location	PovPct	Brth15to17	Brth18to19	ViolCrime	TeenBrth
1	Alabama	20.1	31.5	88.7	11.2	54.5
2	Alaska	7.1	18.9	73.7	9.1	39.5
3	Arizona	16.1	35.0	102.5	10.4	61.2
4	Arkansas	14.9	31.6	101.7	10.4	59.9
5	California	16.7	22.6	69.1	11.2	41.1
6	Colorado	8.8	26.2	79.1	5.8	47.0
7	Connecticut	9.7	14.1	45.1	4.6	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

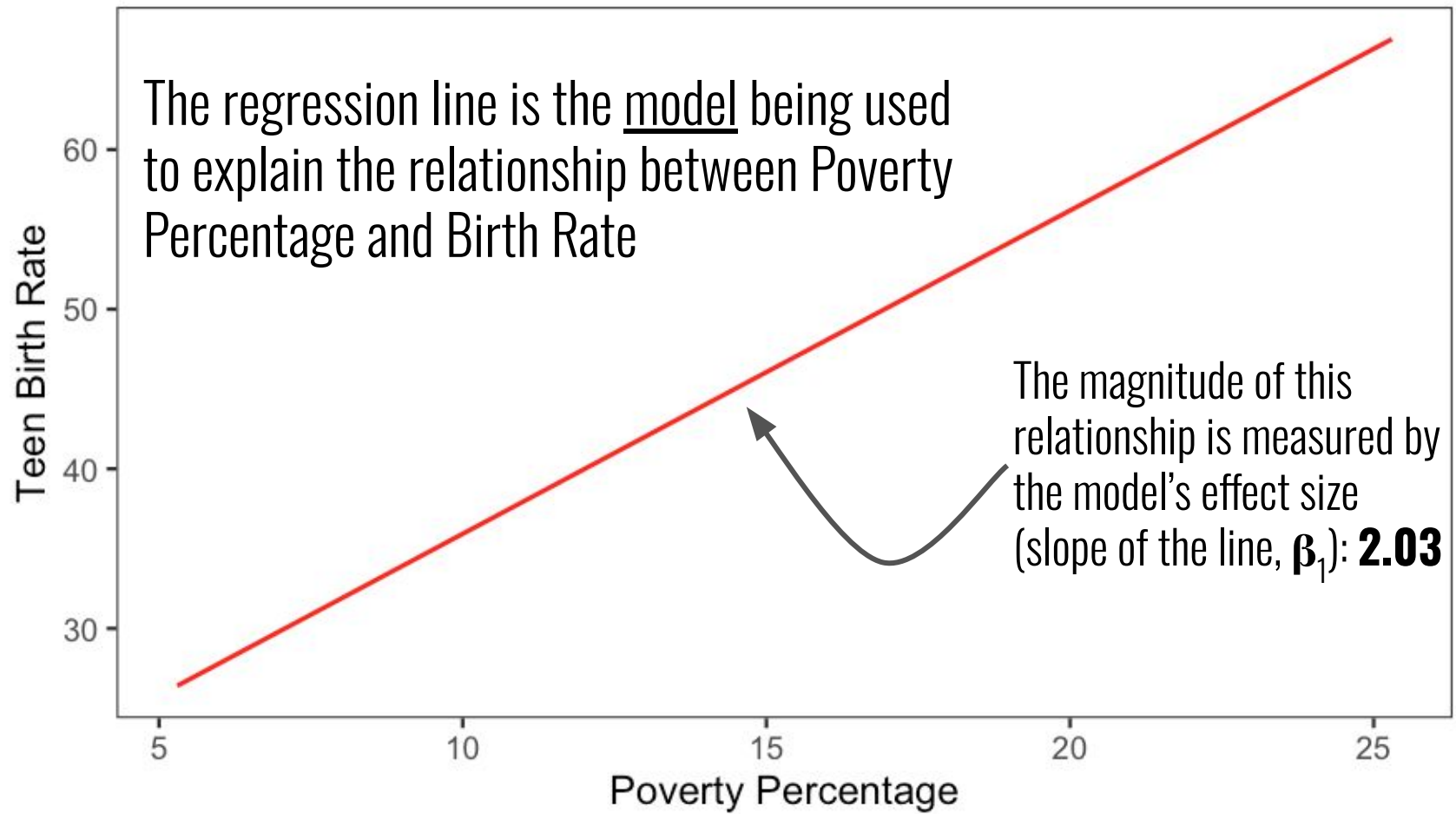
EDA: distributions

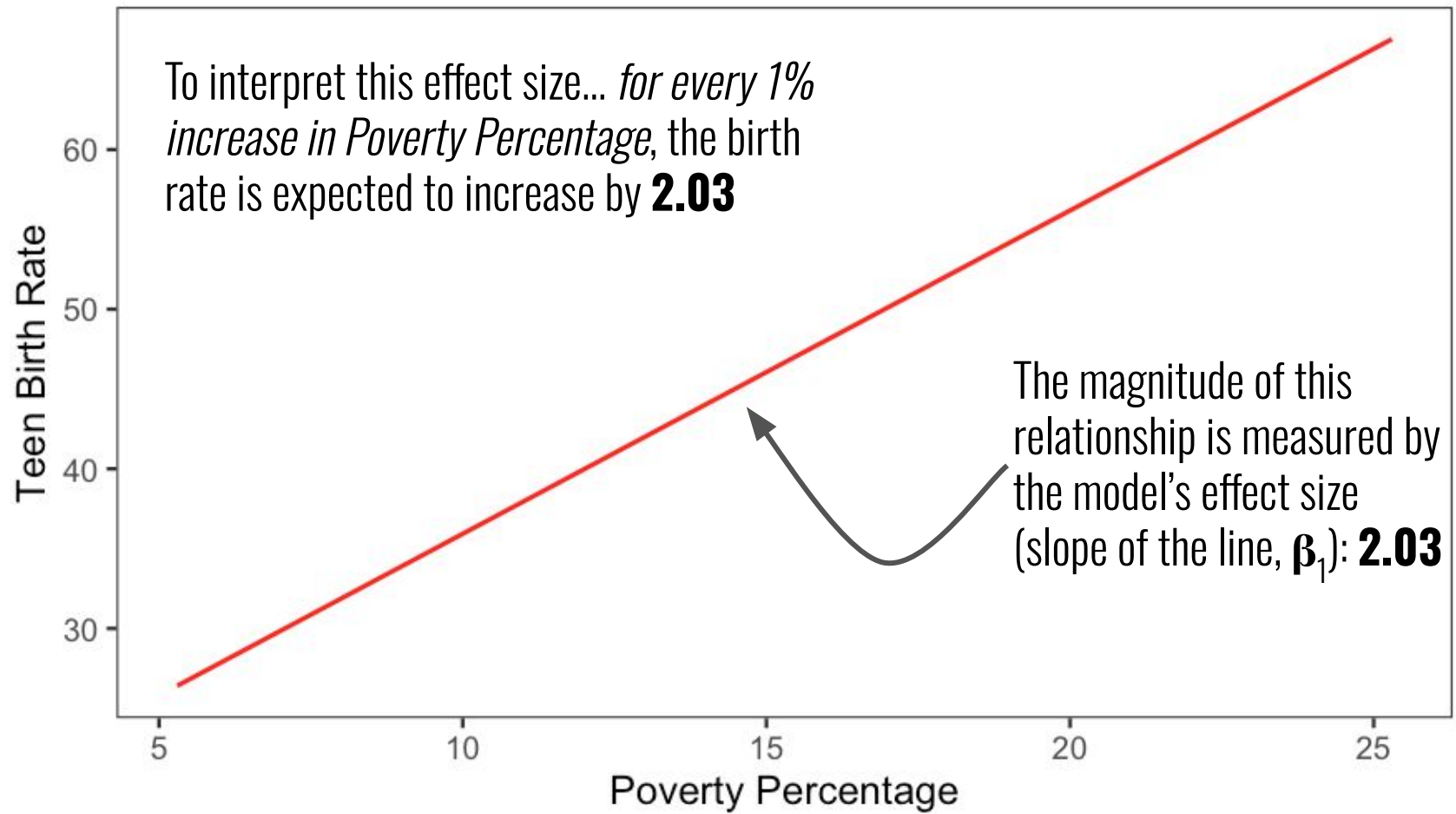












...but *how confident* are we in that estimate of the effect size?

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

Teen Birth Rate

60

50

40

30

5

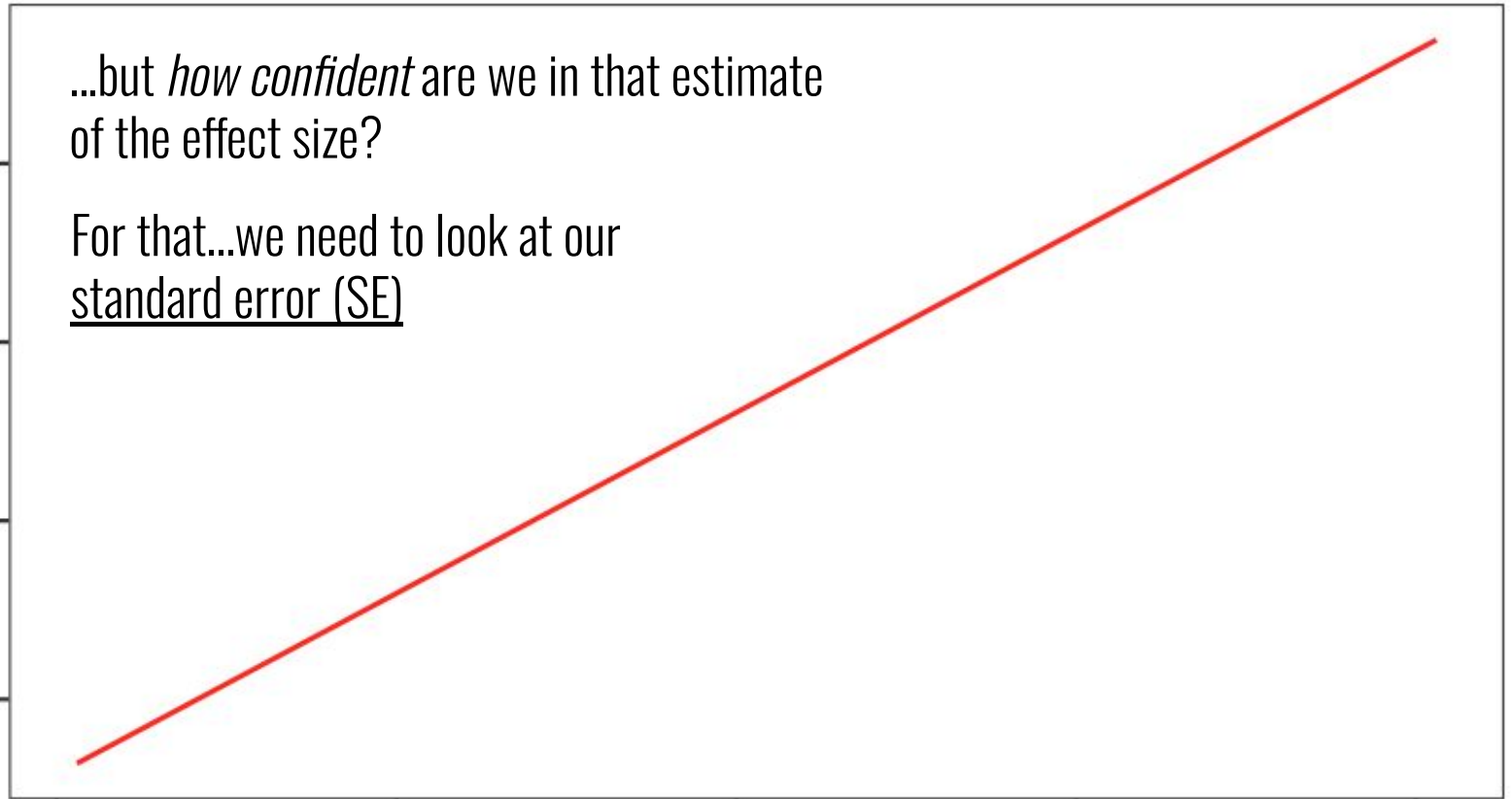
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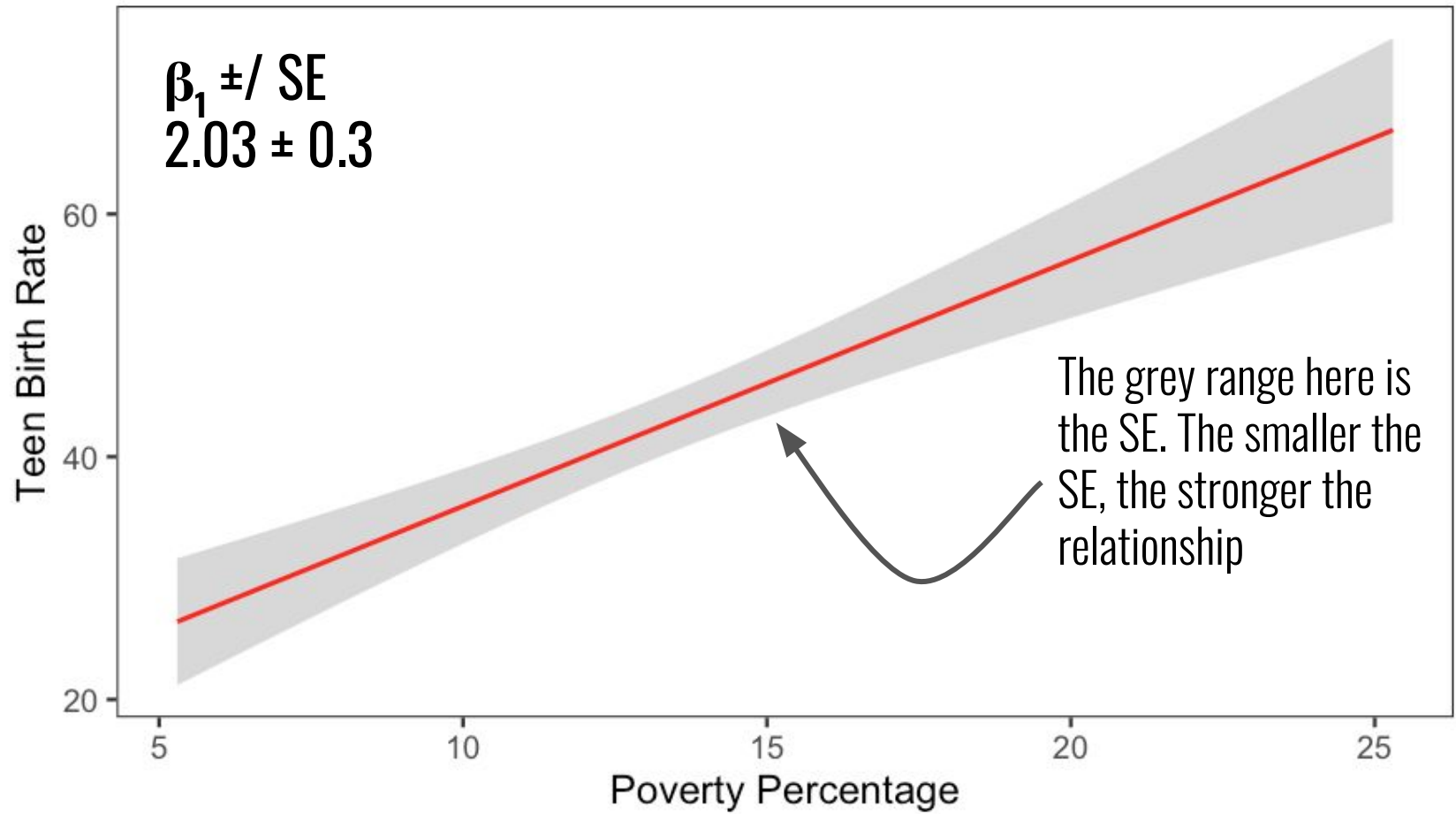
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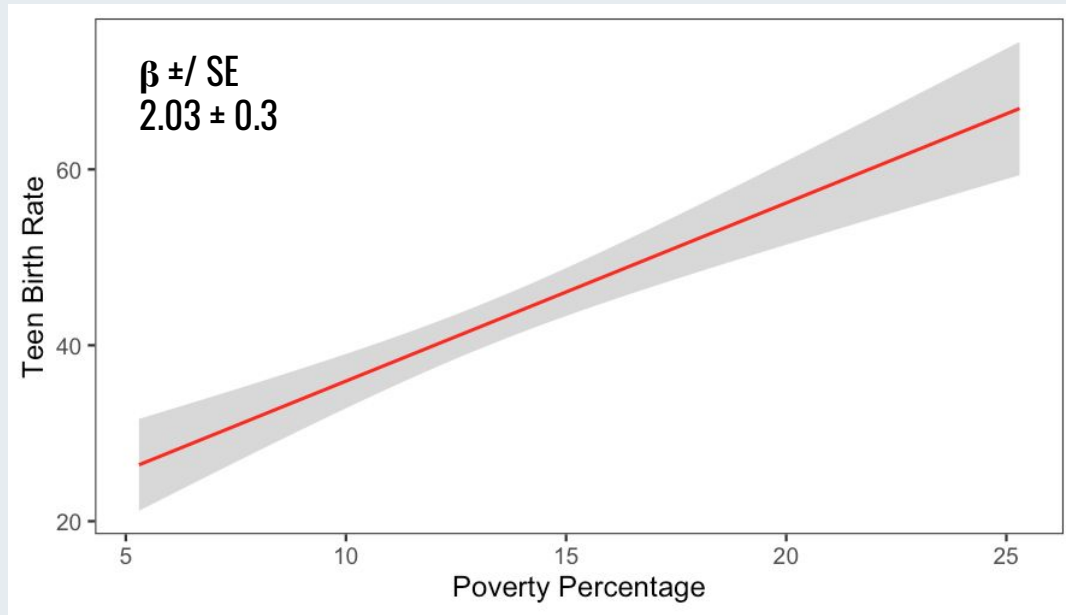
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25

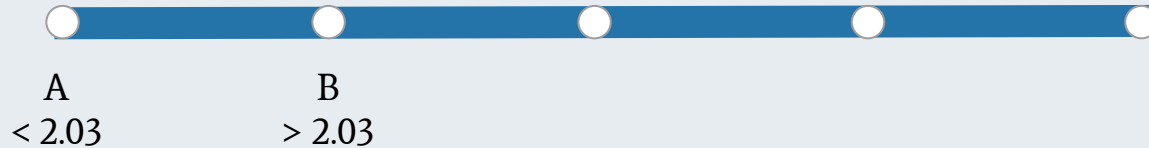
Poverty Percentage

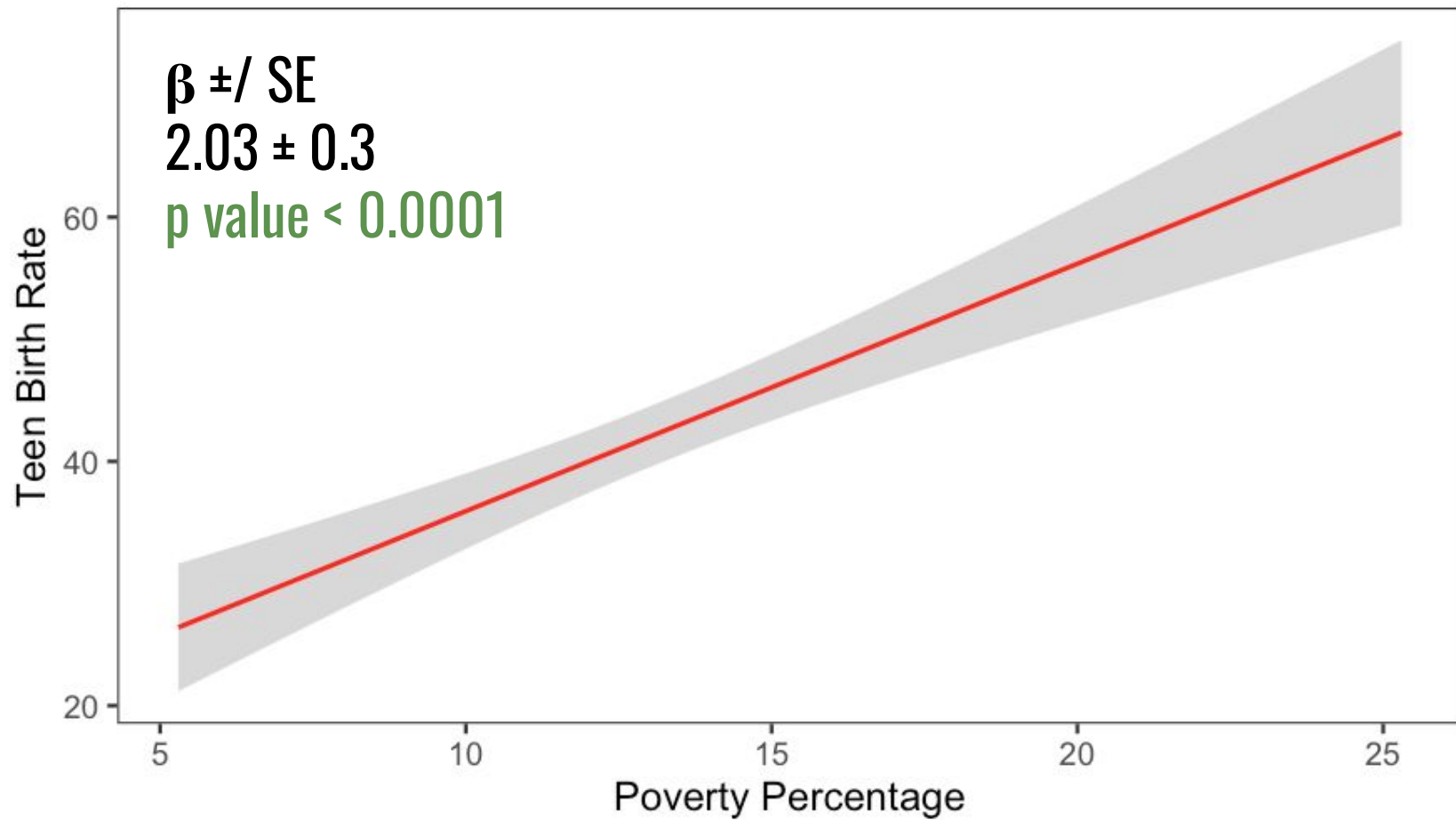




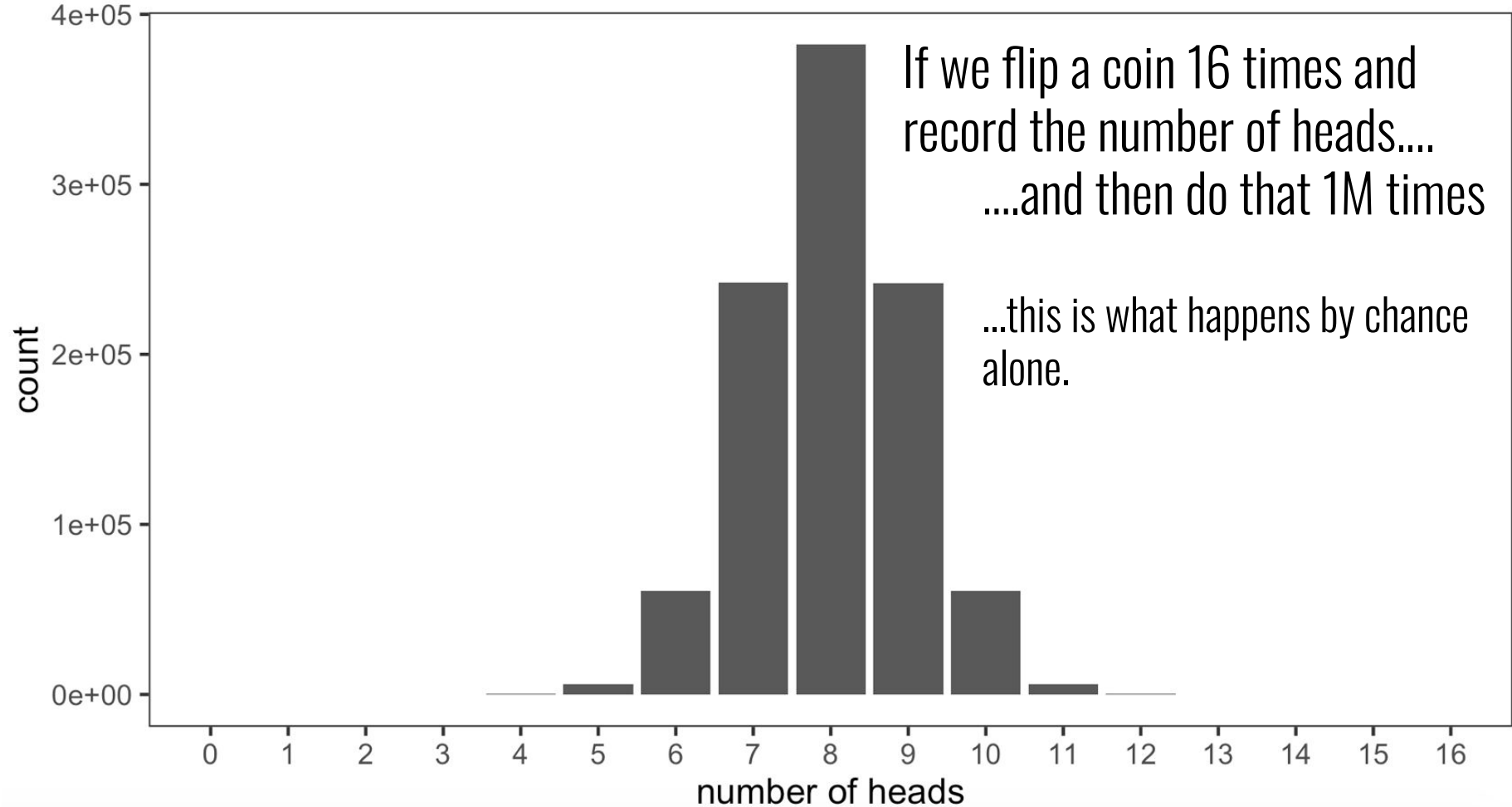


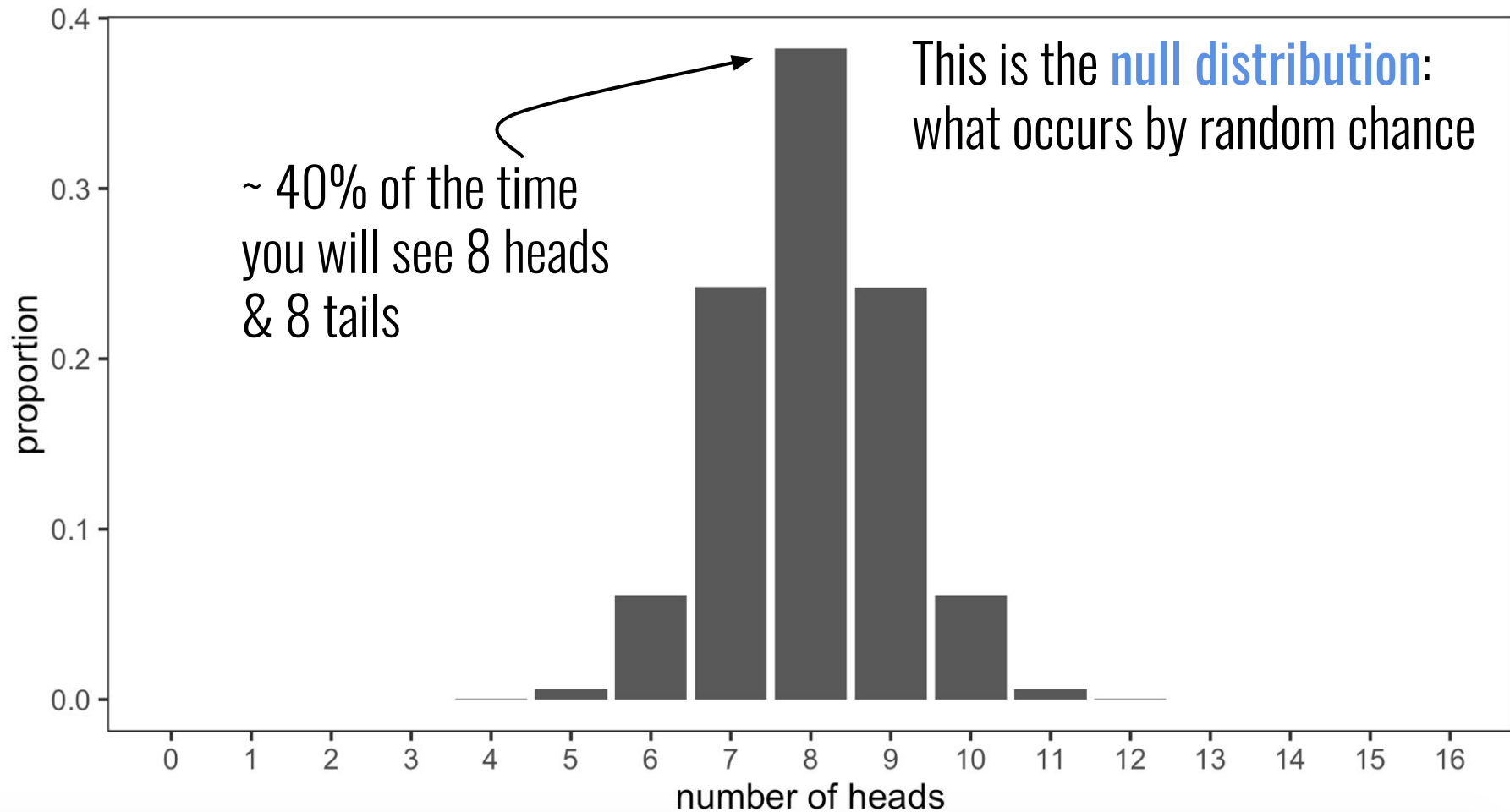
If there were a stronger effect of Poverty on Birth rate, what would β_1 be?

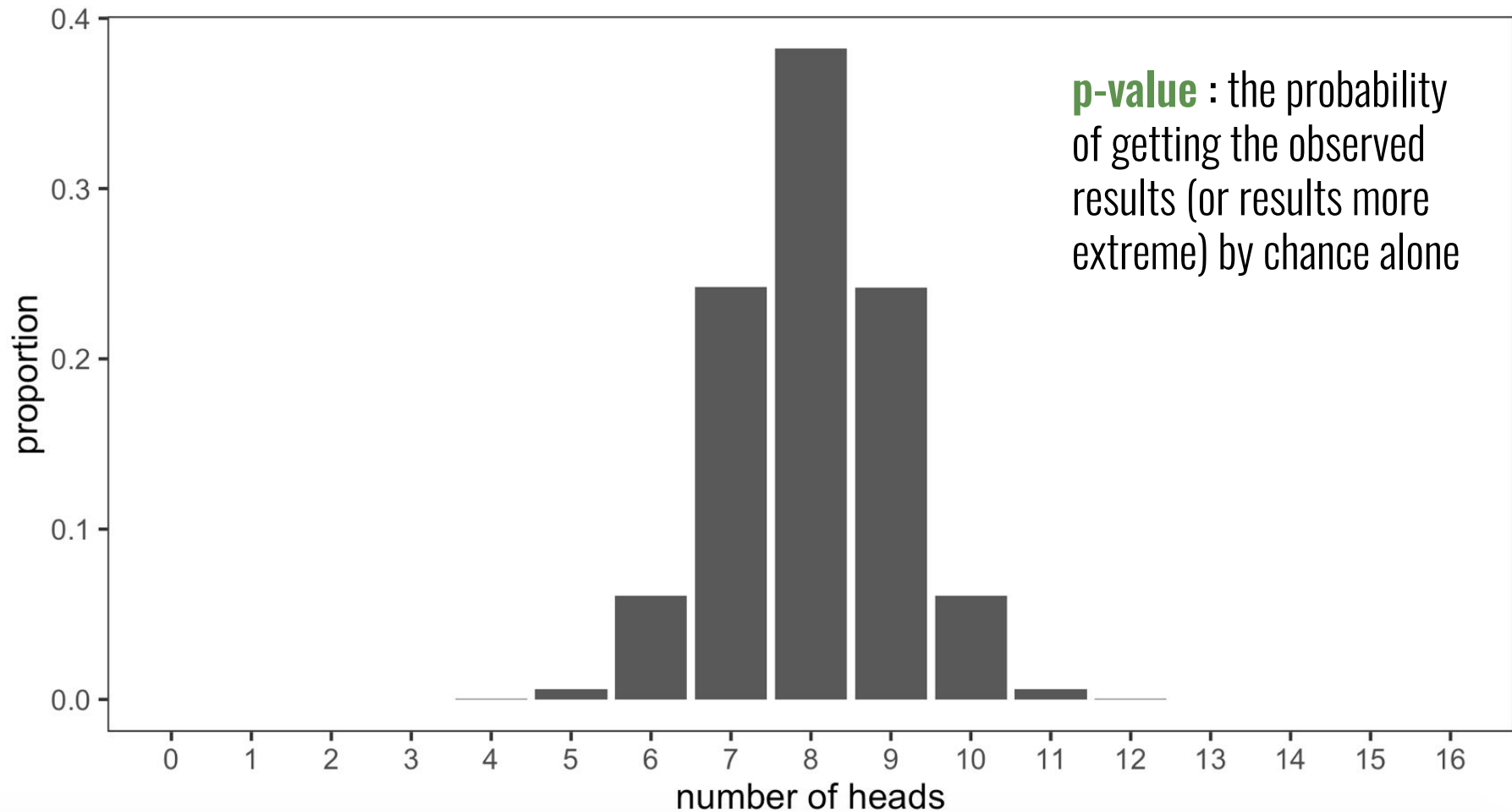




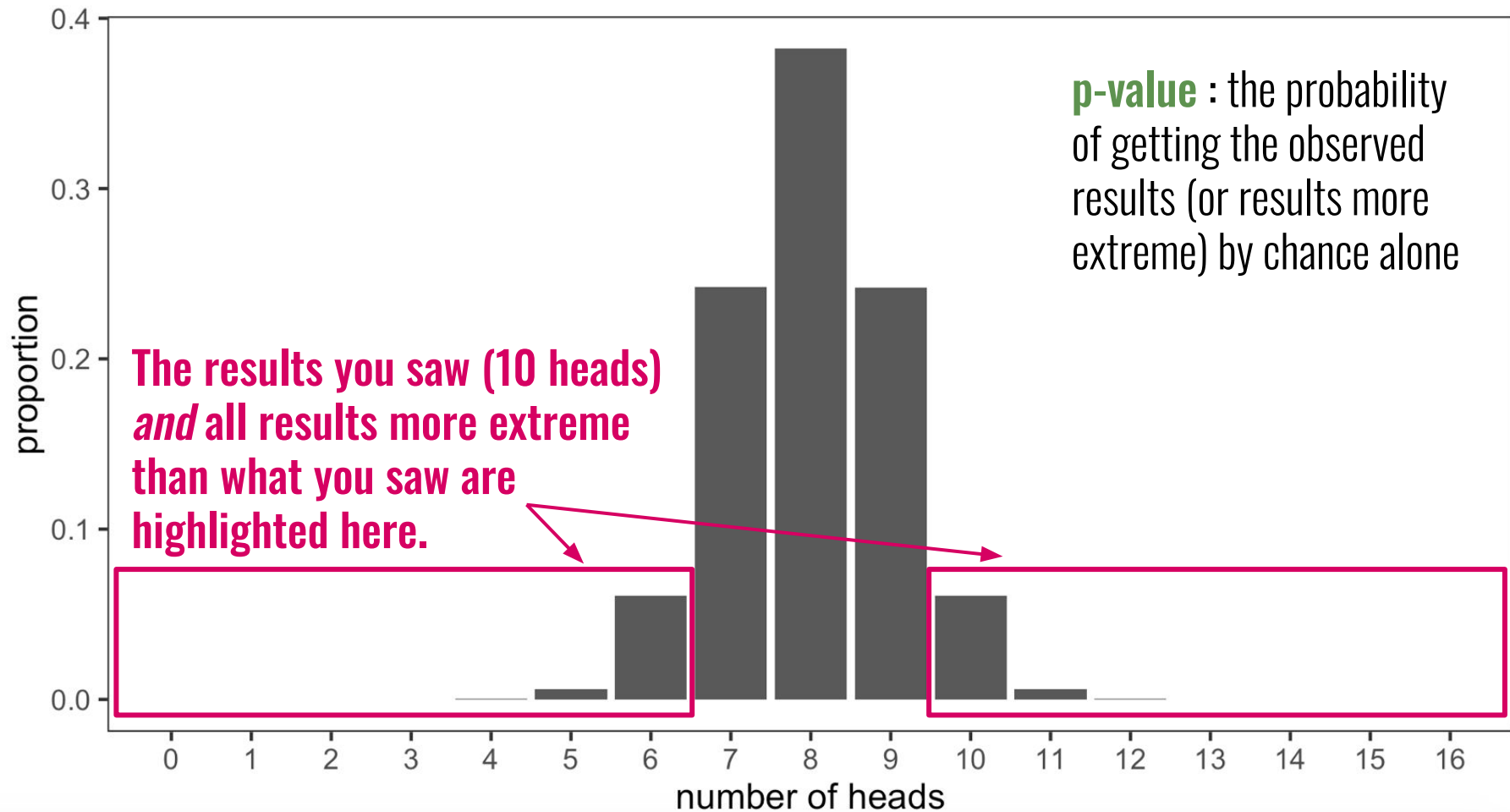
p-value : the probability of getting the observed results (or results more extreme) by chance alone

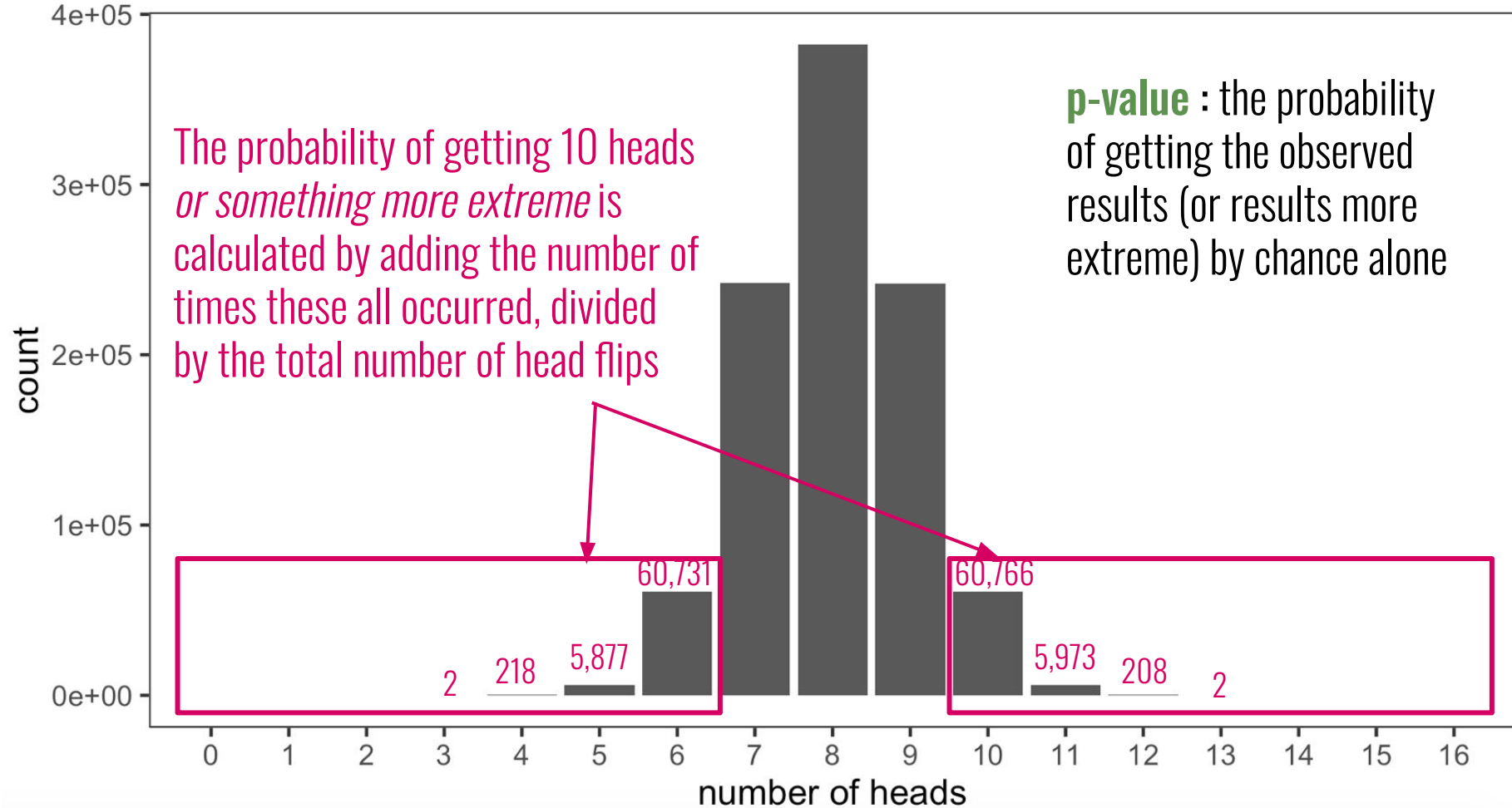


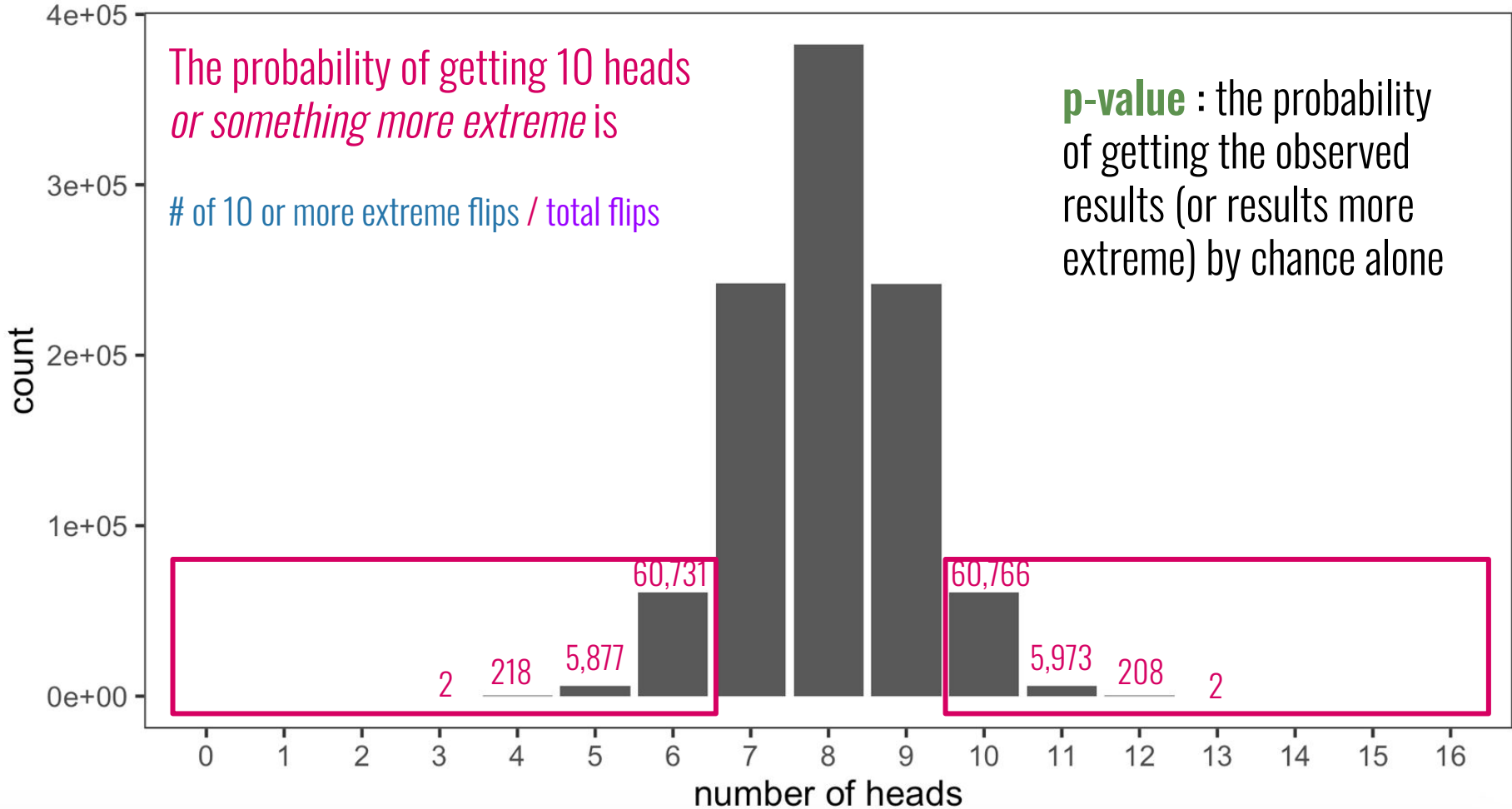


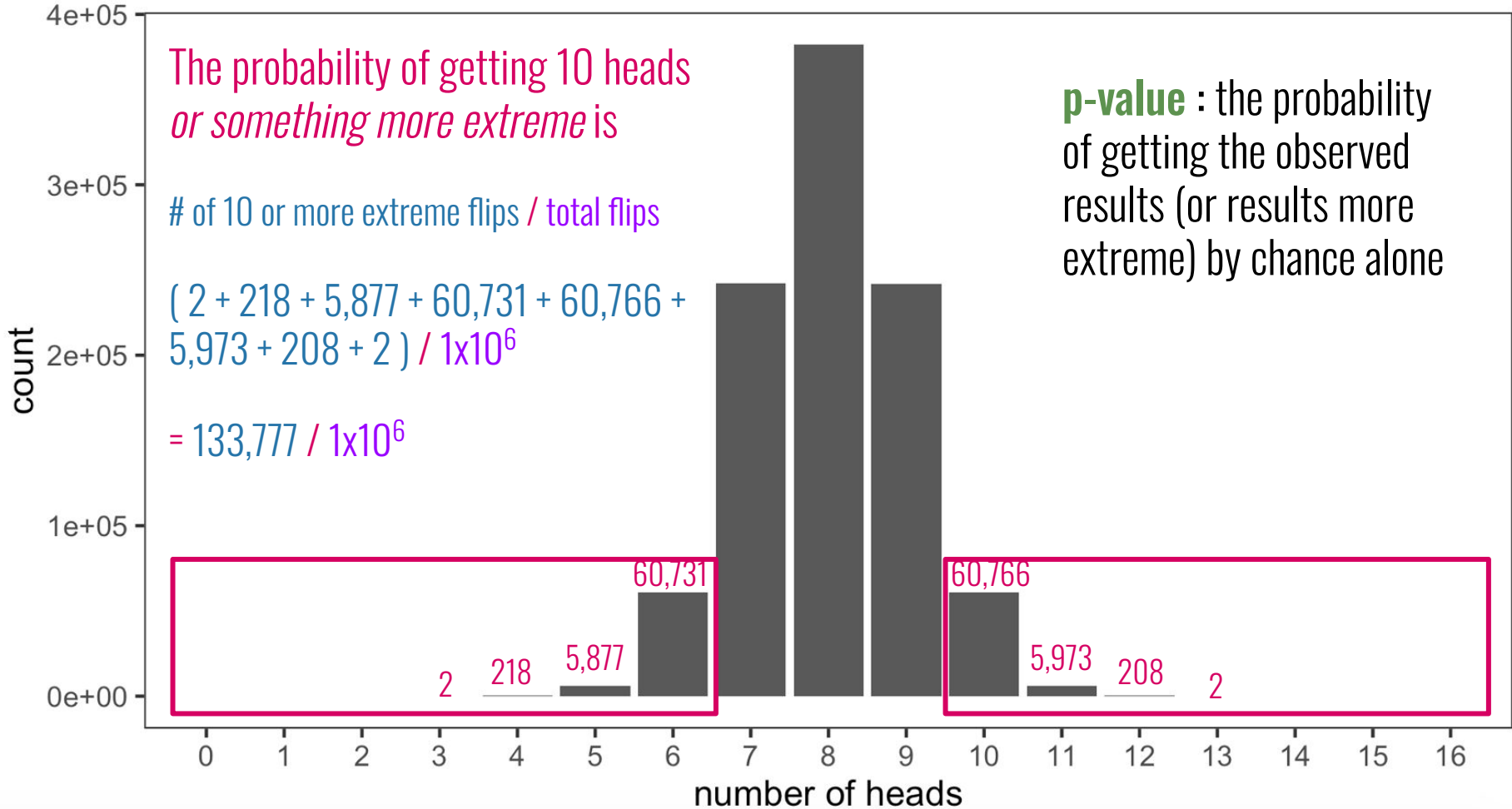


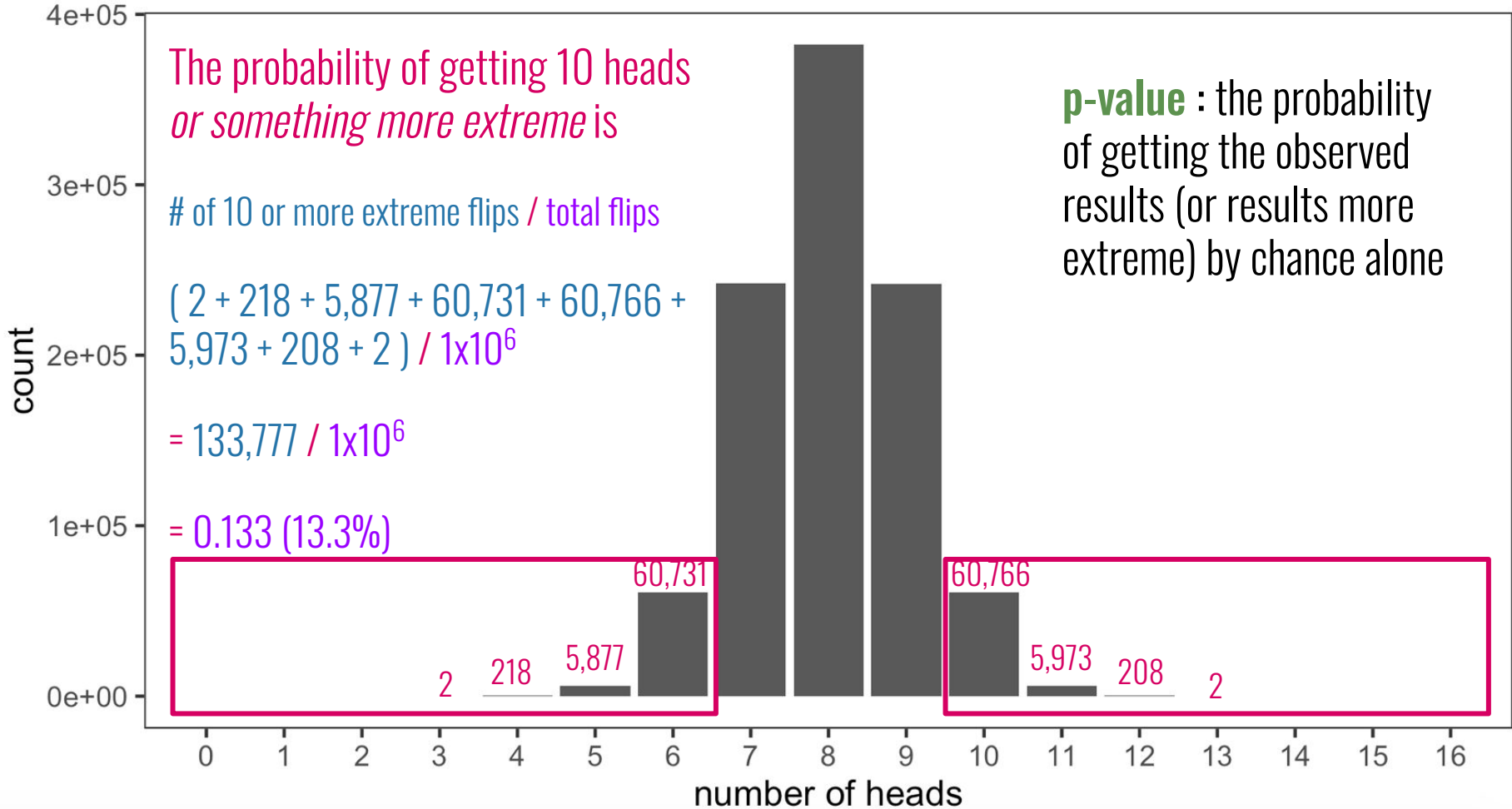


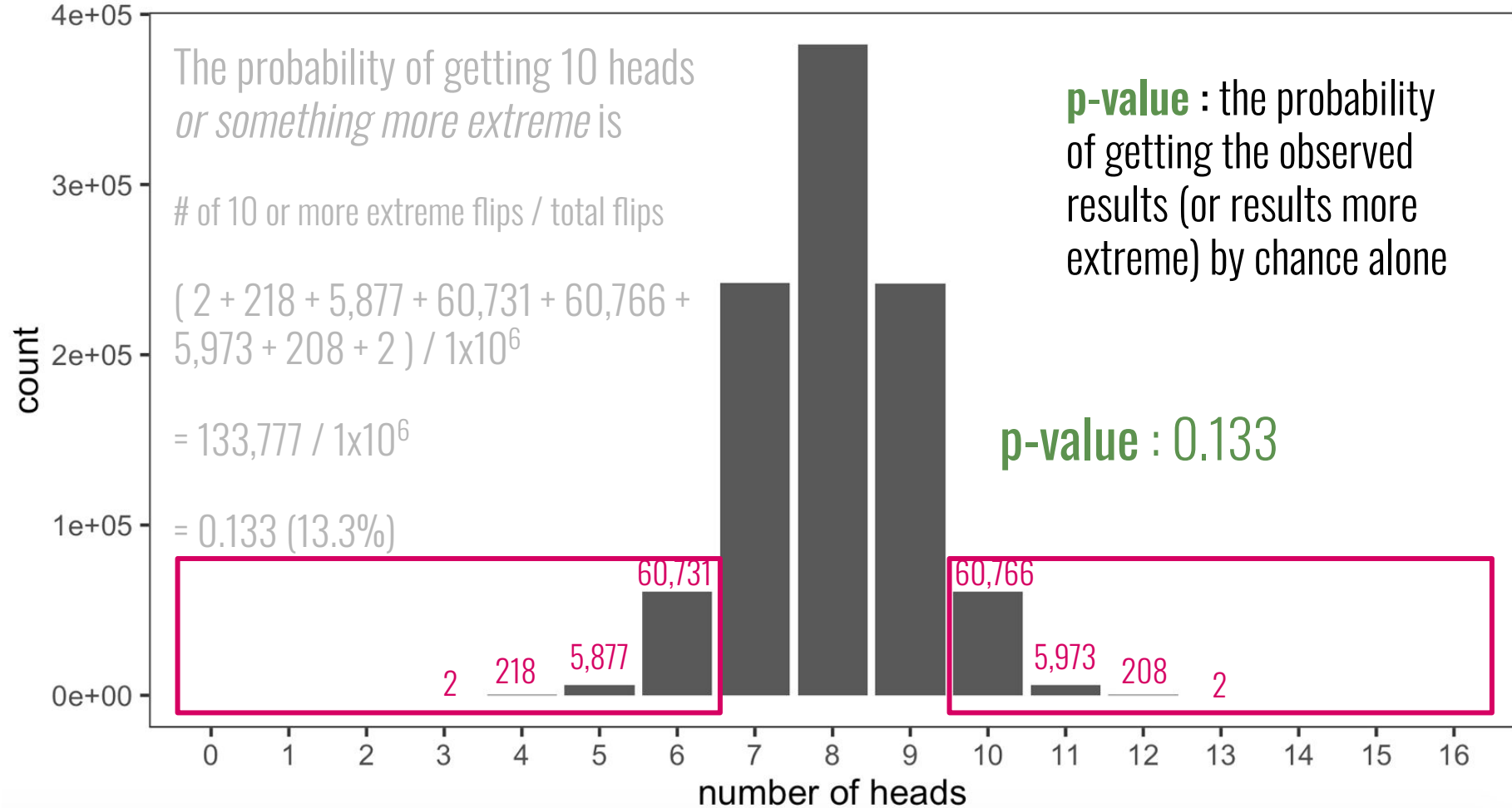


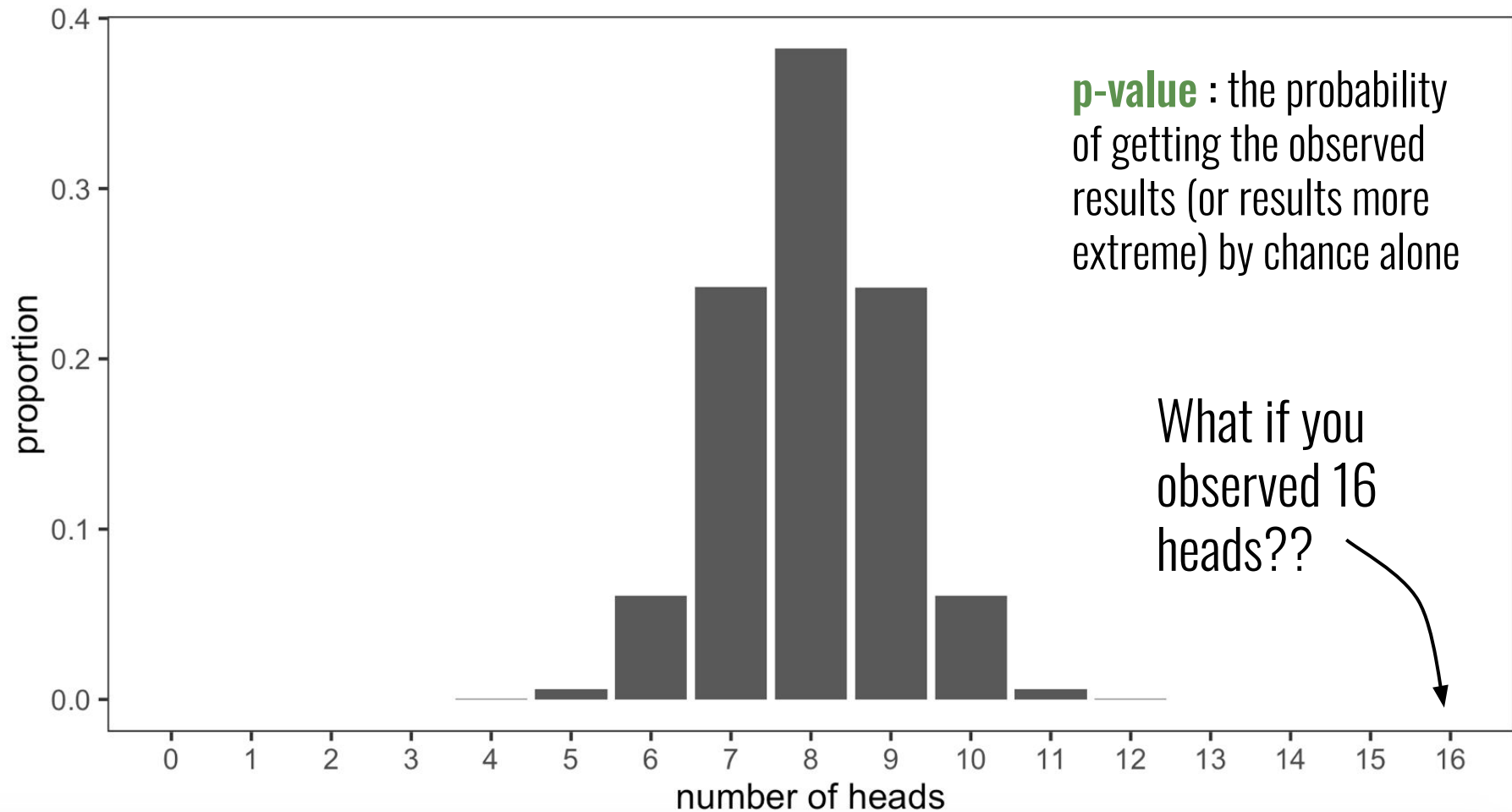


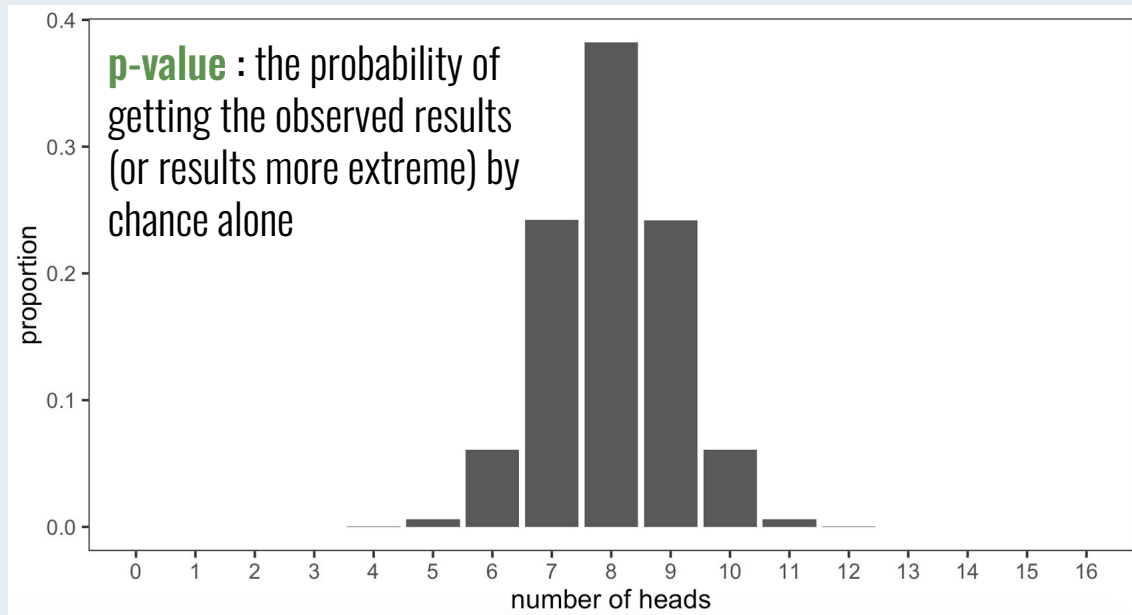




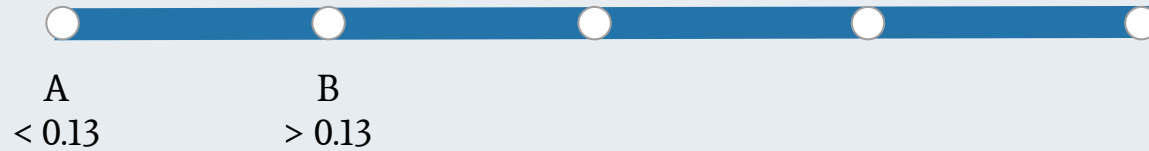


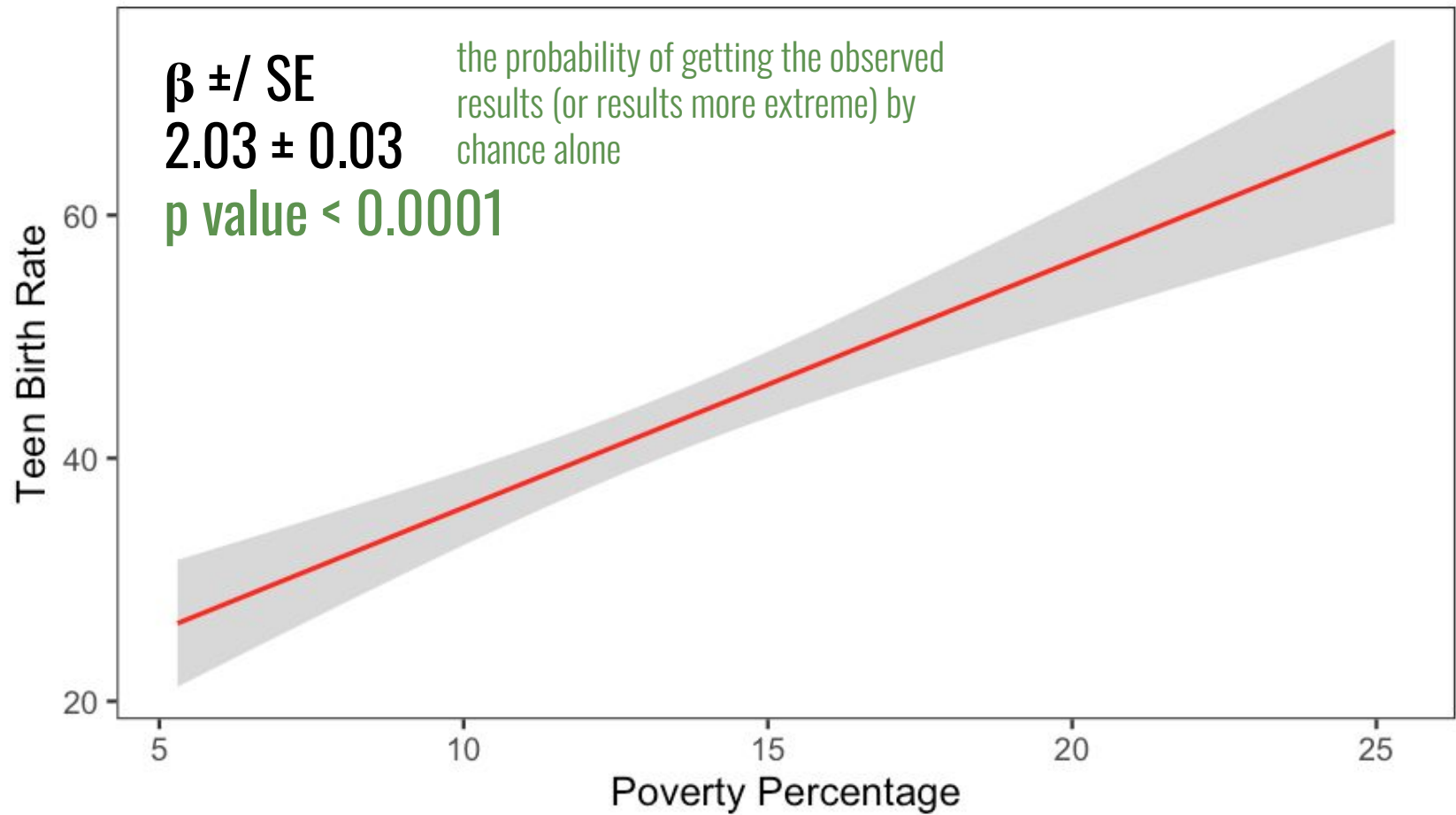




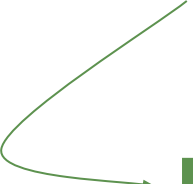


What would be the p-value of you flipping 16 heads?





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

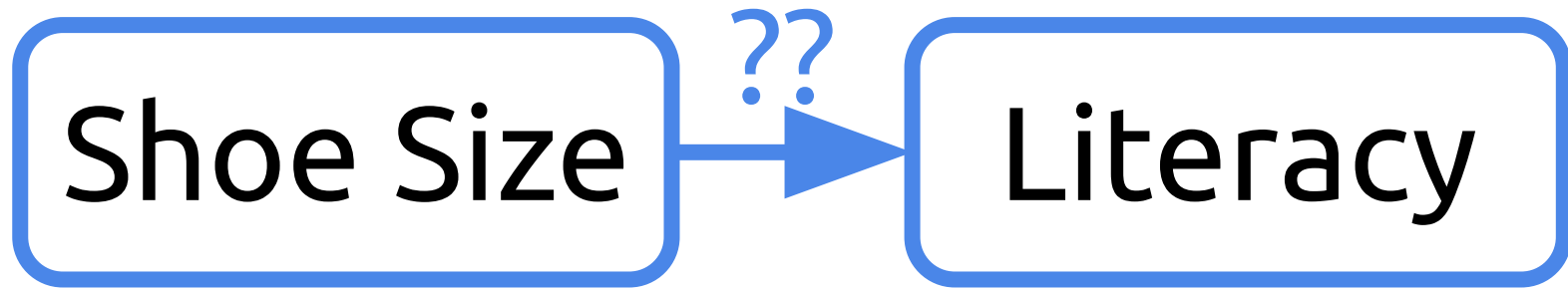
Confounding






Big shoes
Literate

Small shoes
Not literate





Big shoes
Literate
Adults

Small shoes
Not literate
Child

Shoe Size

Literacy

Age

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

The diagram illustrates a relationship where two variables, 'Shoe Size' and 'Literacy', are linked to a third variable, 'Age'. 'Shoe Size' and 'Literacy' are each enclosed in a solid blue rounded rectangle. Arrows from the bottom of these two boxes converge on a dashed blue rounded rectangle labeled 'Age'.

Variable1

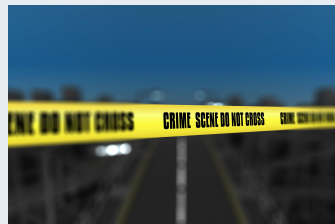
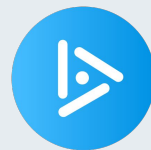
Variable2

Confounder

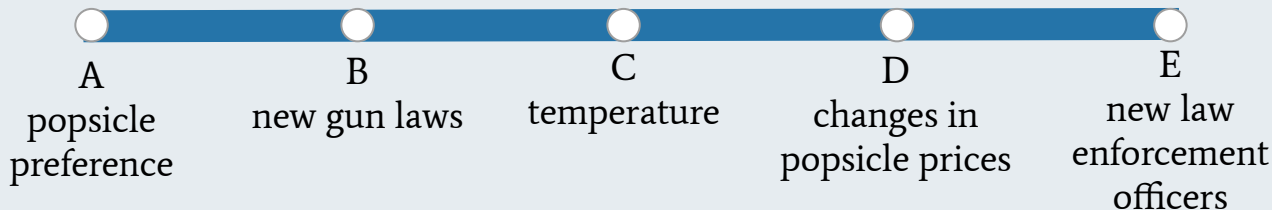
```
graph TD; V1[Variable1] --> C[Confounder]; V2[Variable2] --> C;
```

The diagram illustrates a causal relationship where two variables, Variable1 and Variable2, are influenced by a common factor, the Confounder. Variable1 and Variable2 are represented by solid blue boxes with rounded corners, while the Confounder is represented by a dashed blue box with rounded corners. Two blue arrows point from the bottom of the Variable1 and Variable2 boxes to the top of the Confounder box, indicating that the confounder is the common cause of both variables.

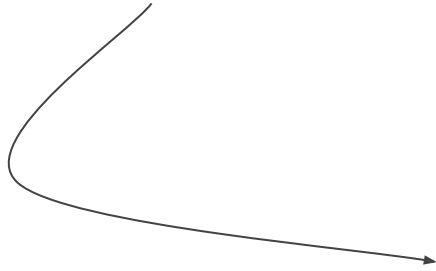
Confounding



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



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

