

Research Methods I

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Scoping



Research

Scoping



Scoping



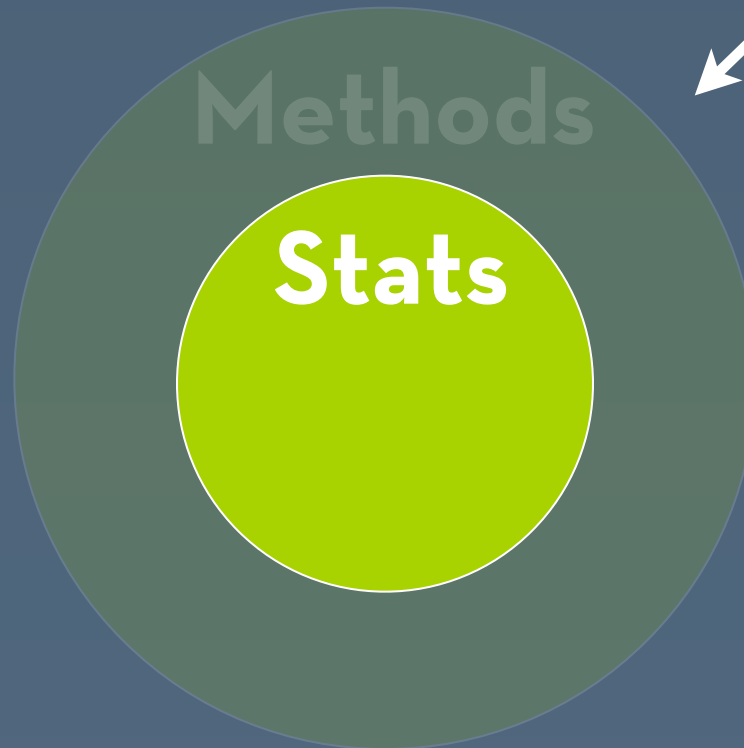
Scoping

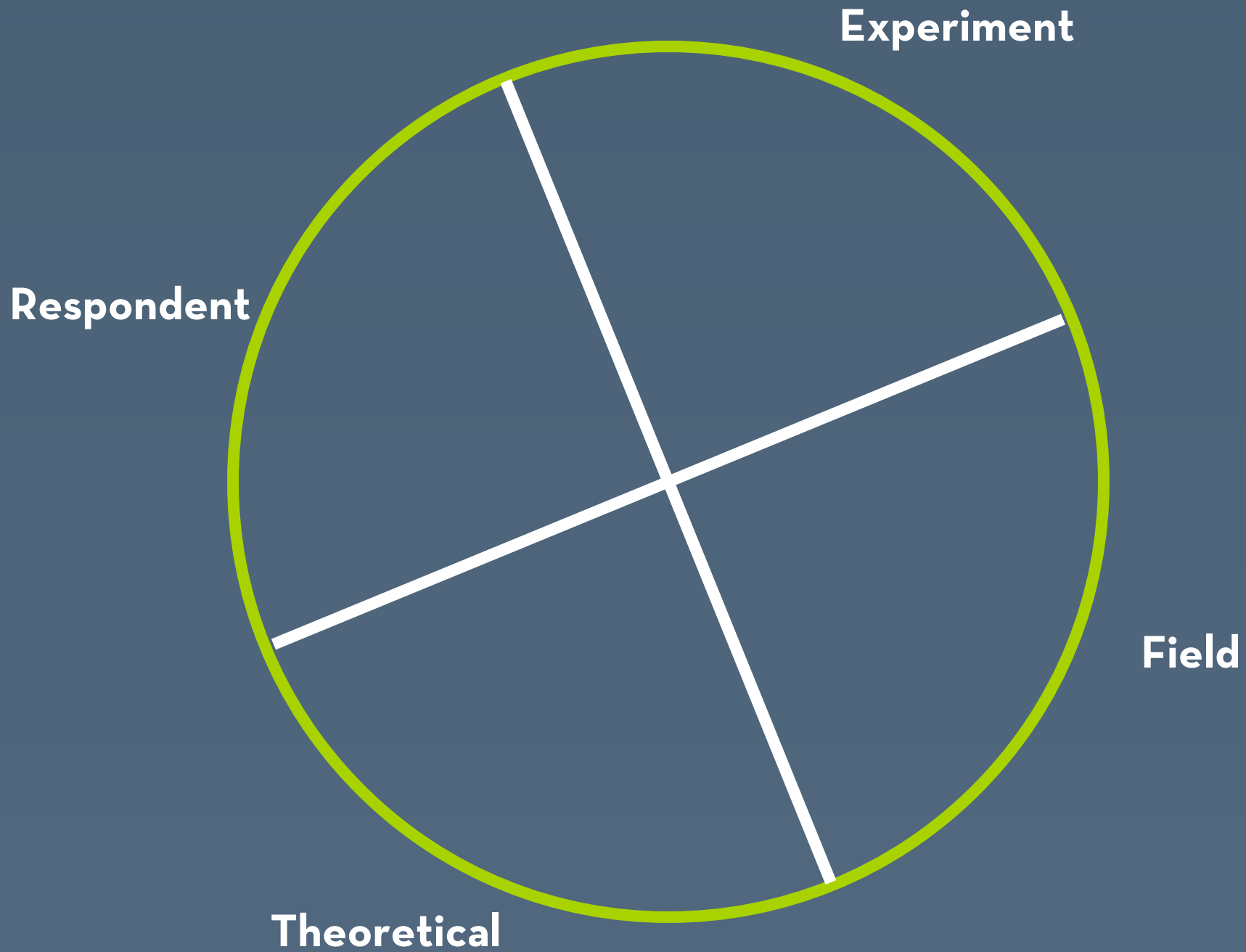
This week's
lectures

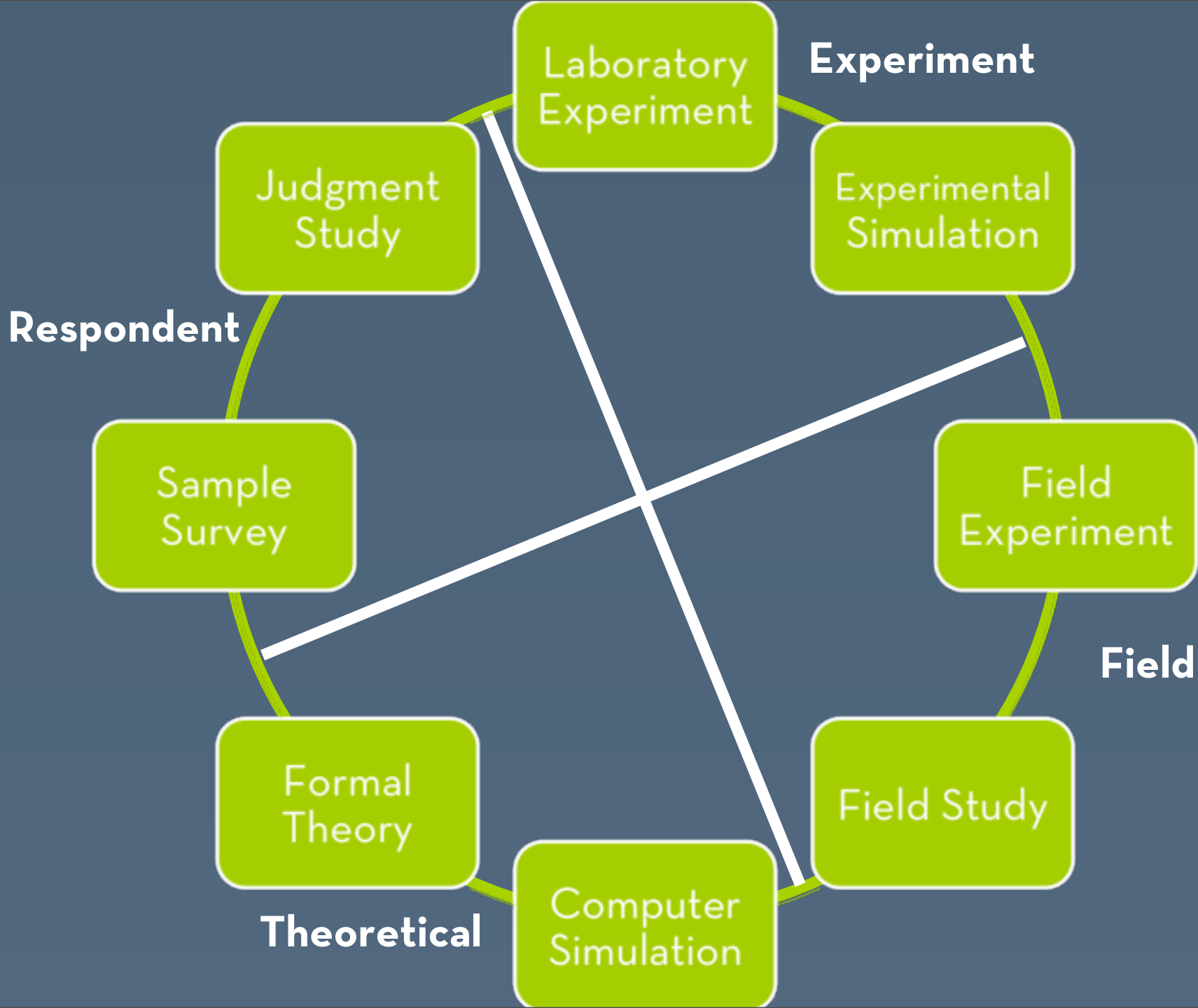


Scoping

This week's
lectures







Method triangulation

- All methods are flawed
- Thus, your argument becomes far stronger if you can demonstrate the same phenomenon using multiple methods
 - Complement your statistics with semi-structured interviews
 - Complement qualitative work with primary source evidence or log data

Objectivity in reporting

- Readers are more cynical if that paper is presenting a one-sided argument
- Which argument do you buy?
 - “Ellipsoidal windows were better for all tasks.”
vs.
“Ellipsoidal windows were better for all tasks we measured. However, users found them to be confusing.”

Framing an evaluation

- The difficulty: defining and isolating the construct that you are trying to maximize
- Tempting to aim for something easy: time, task completion, number of clicks
- But, testing the easily quantifiable often **misses the point.**

Framing an evaluation

- Reflect on your implicit thesis about why your contribution is a good idea.
 - Skinput is a good idea because...
 - Parallel designs are a good idea because...
 - Soylent is a good idea because...
- This thesis can **directly imply the claim that you need to test.** (It may or may not be comparative in nature.)

Example theses

- Enable previously difficult/impossible tasks
- Improve task performance or outcome
- Modify/influence behavior
- Improve ease-of-use, user satisfaction
- User experience

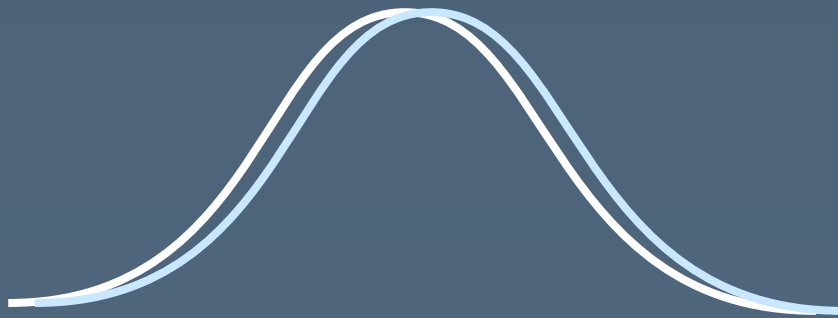
Statistics

Goal: you are more confident in the logic behind the tests you are using

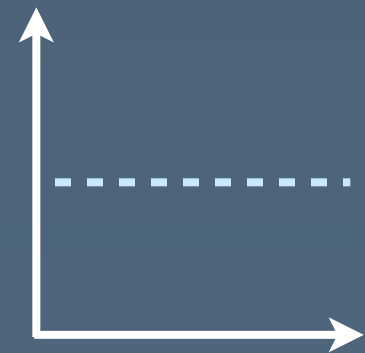
Anatomy of a statistical test

Things you know already

- If your change had no effect, what would the world look like?



No difference in means



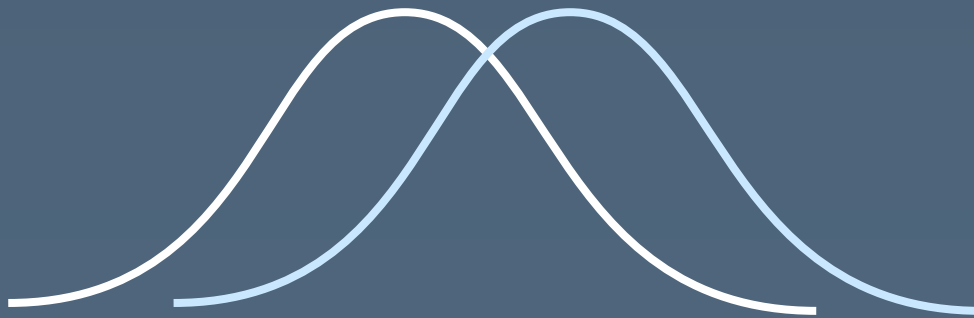
No slope in relationship

- This is known as the **null hypothesis**

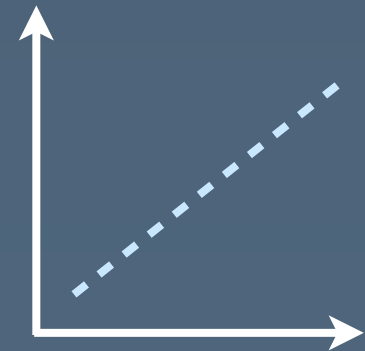
Anatomy of a statistical test

Things you know already

- Given the difference you observed, how likely is it to have occurred by chance?



Probability of seeing a mean difference at least this large, by chance, is 0.012



Probability of seeing a slope at least this large, by chance, is 0.012

Errors

Things you know already

		Difference exists?	
		Y	N
Difference detected?	Y	True positive	Type 1 error (publish false findings)
	N	Type 2 error (get more data)	True negative

p-value

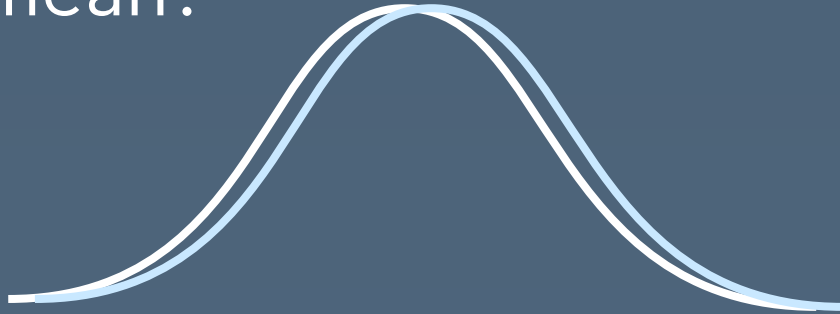
Things you know already

- The probability of seeing the observed difference by chance – e.g., $P(\text{Type I error})$
- Typically accepted levels: 0.05, 0.01, 0.001

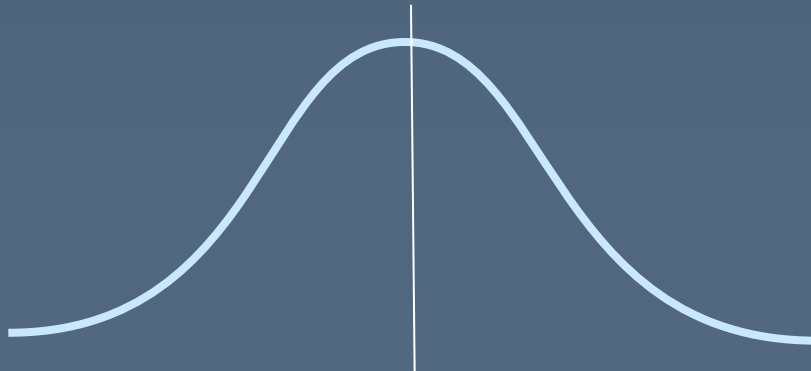
Student's t-test

Things you know already

- Do two normal distributions have the same mean?



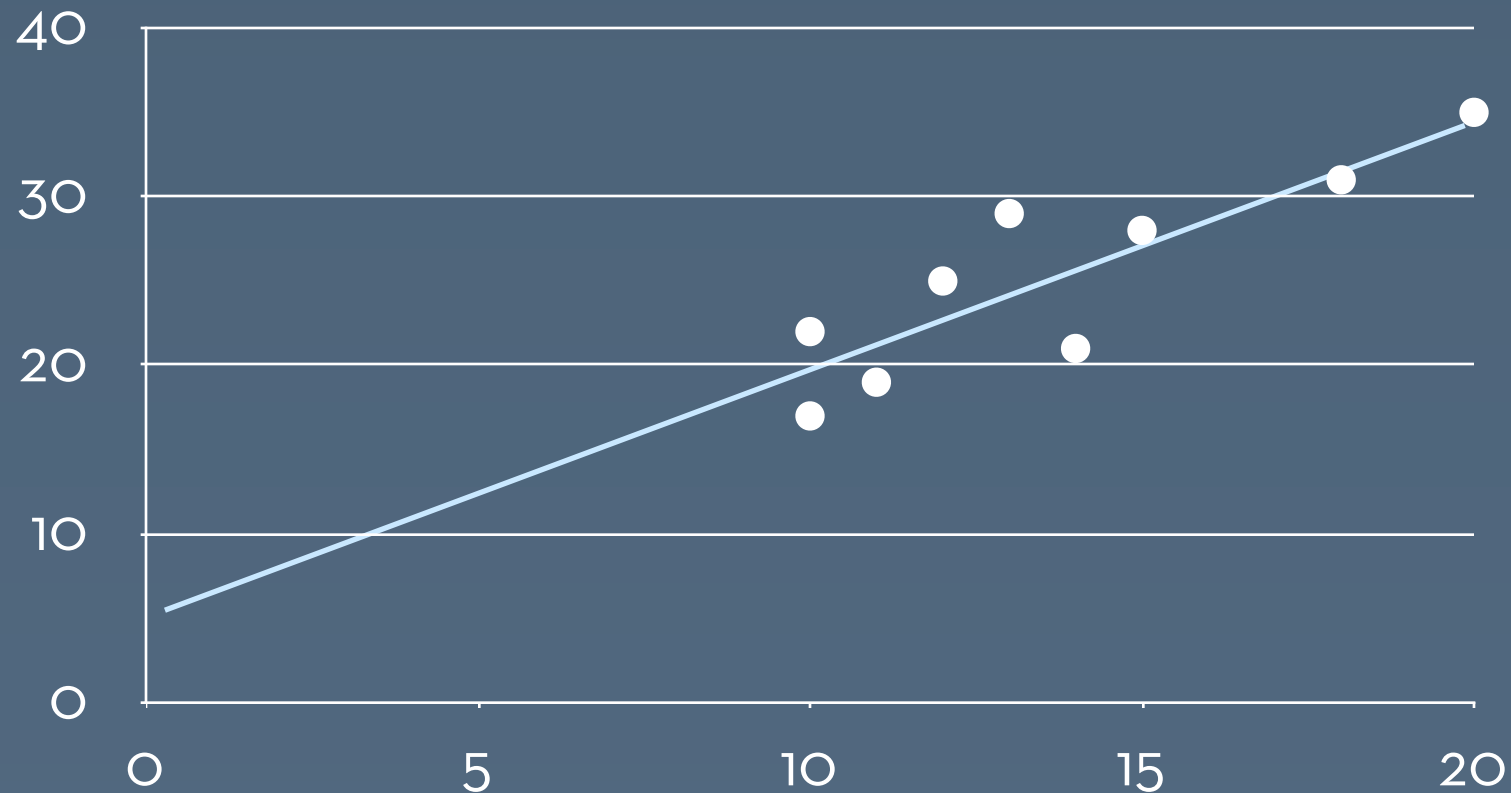
- Paired t-test: does the distribution of (after - before) have mean 0?



Demo

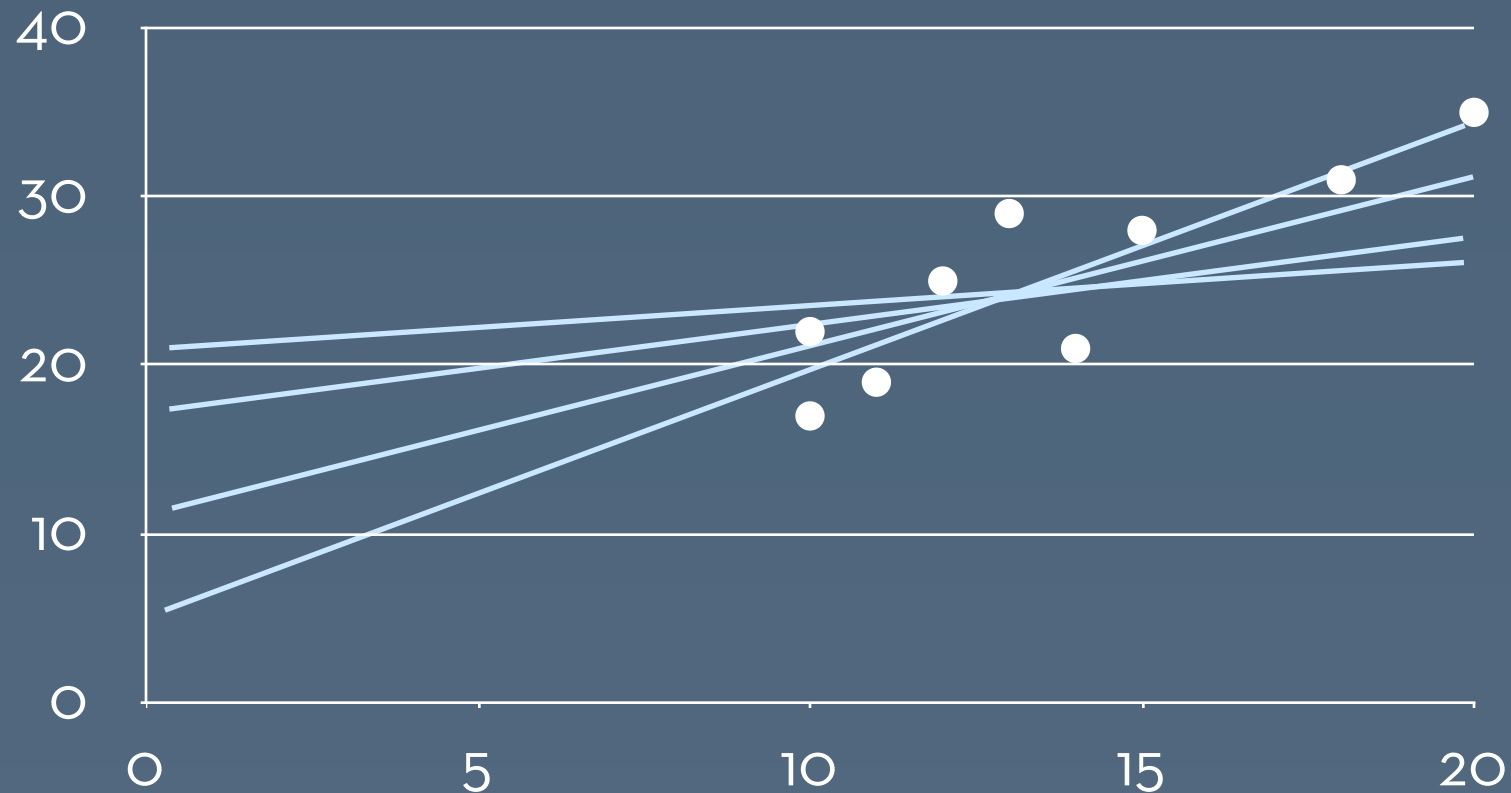
Linear regression

- Is the slope of the relationship between X and Y significantly different than 0?



Linear regression

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Linear regression model

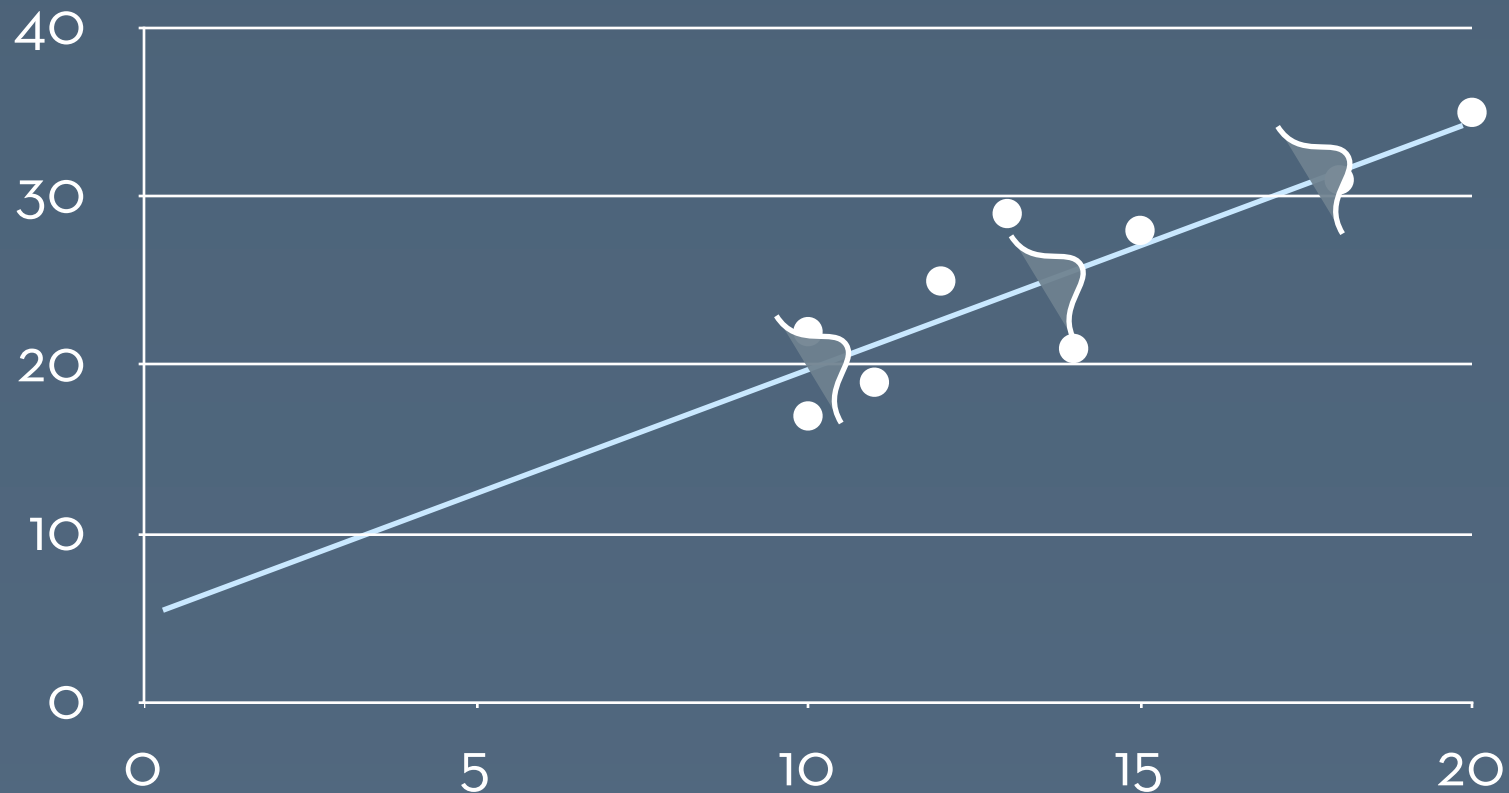
$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

intercept

slope: ΔY for
one-unit ΔX

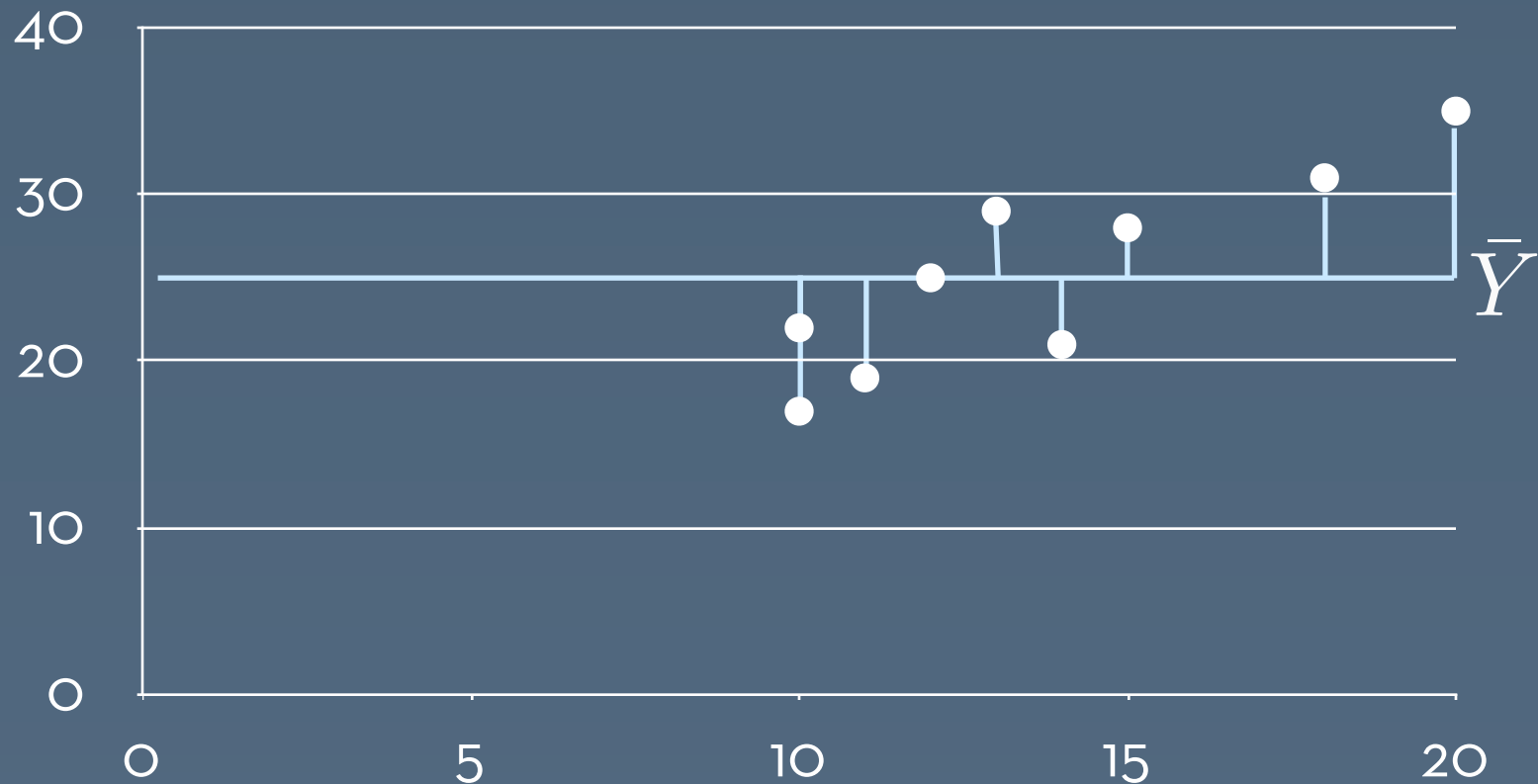
error

n data points



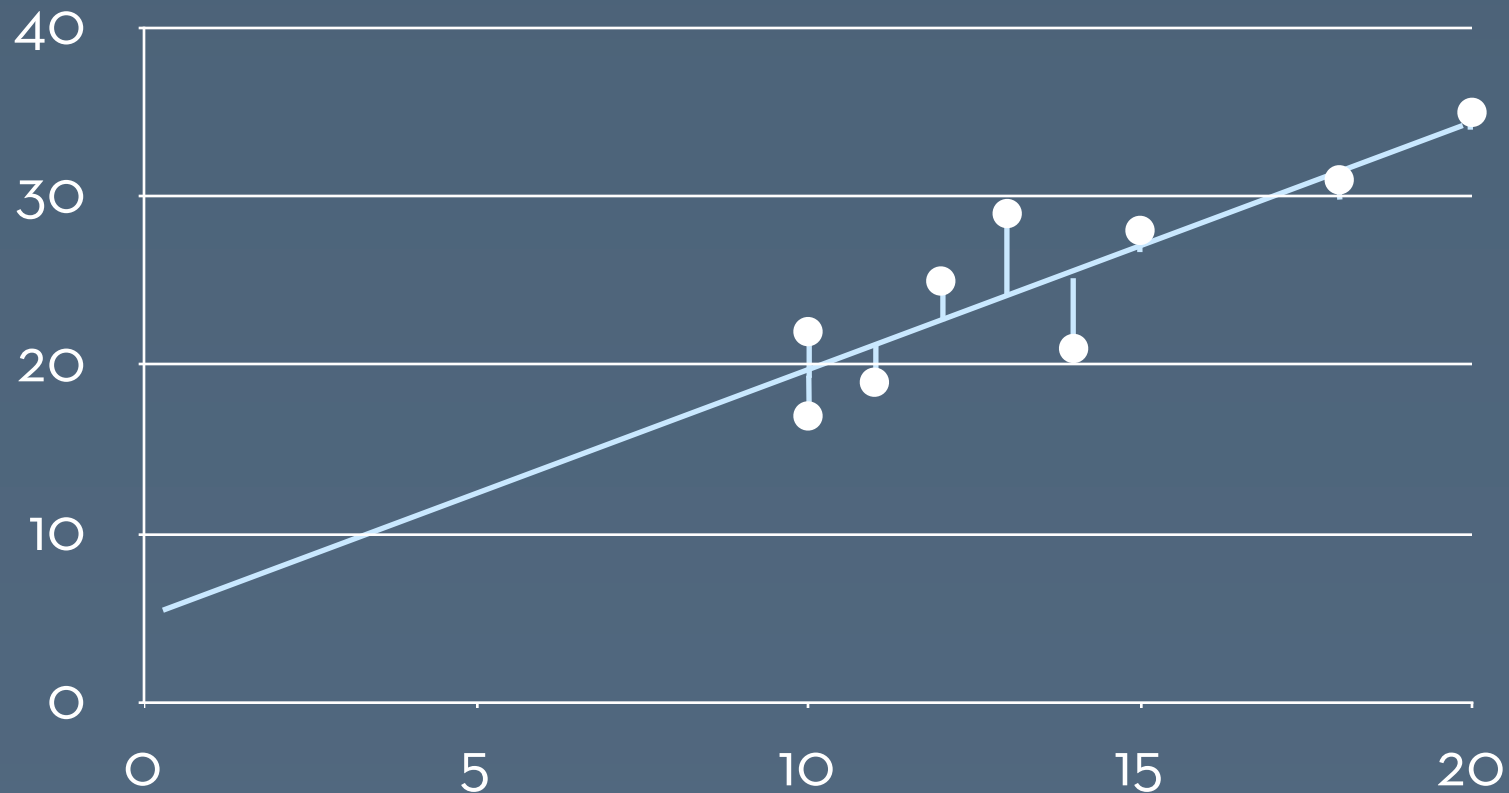
Linear regression model

SSTO: sum of squared deviations versus grand mean \bar{Y}



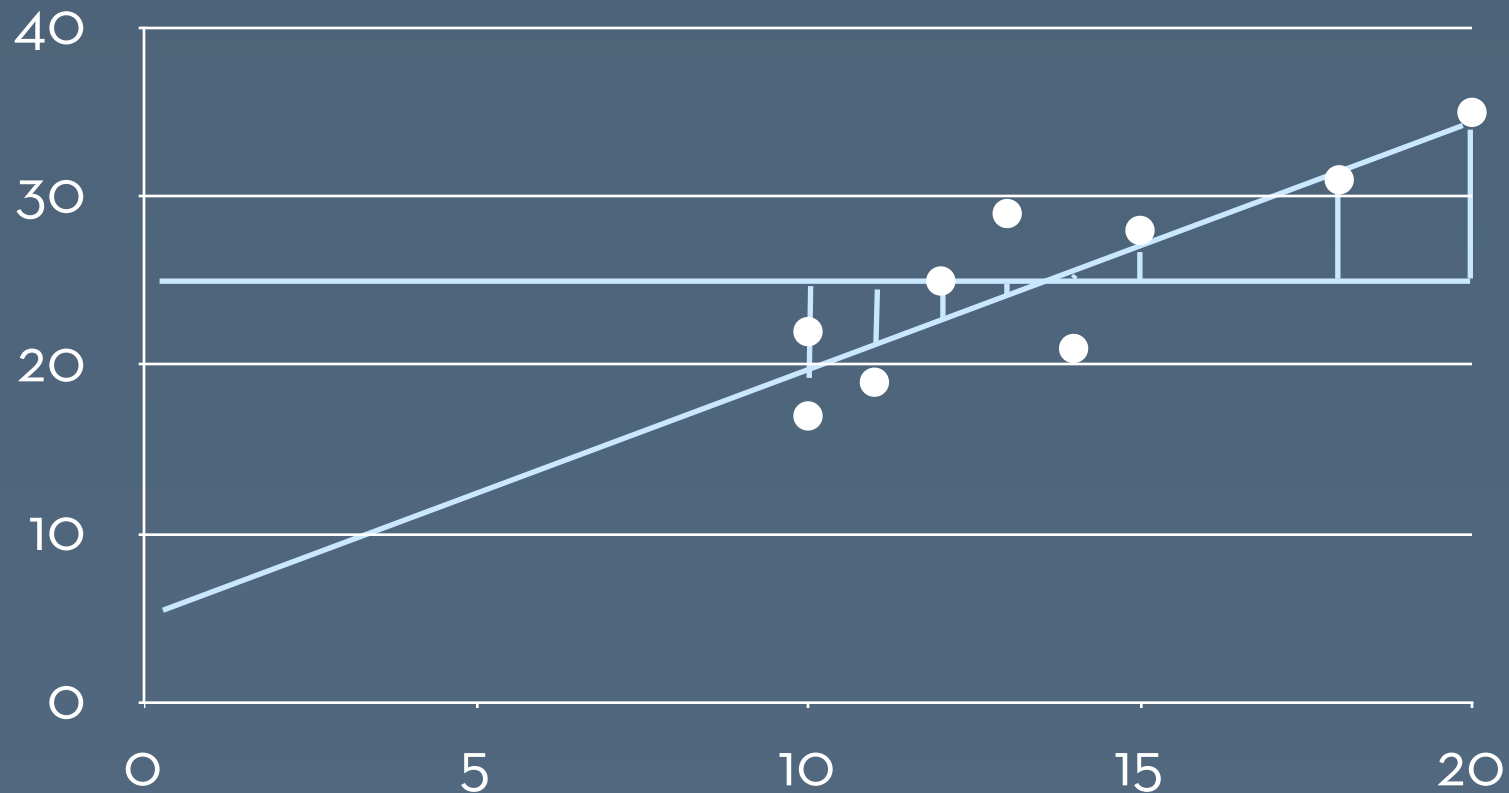
Linear regression model

SSTO: sum of squared deviations versus grand mean \bar{Y}
SSE: sum of squared errors versus regression line



Linear regression model

SSTO: sum of squared deviations versus grand mean \bar{Y}
SSE: sum of squared errors versus regression line
SSR: sum of squared deviations from regression line to the grand mean



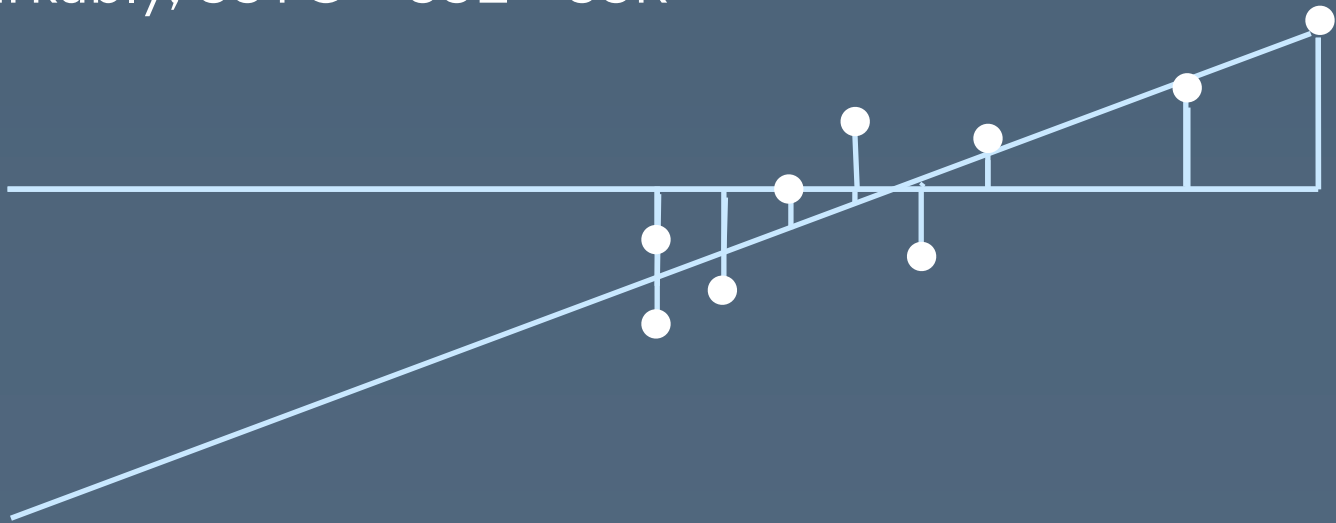
Linear regression model

SSTO: sum of squared deviations versus grand mean \bar{Y}

SSE: sum of squared errors versus regression line

SSR: sum of squared deviations from regression line to the grand mean

Remarkably, $SSTO = SSE + SSR$



Linear regression description

- Coefficient of determination:
how related are X and Y?
- Put another way: what proportion of the variance in Y does a regression line explain?

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

Demo

Linear regression tests

- R^2 does not test the relationship. So, we ask:
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So, test if our sampled b_1 is beyond that range:

$$\left| \frac{b_1}{s\{b_1\}} \right| > t(1 - \alpha/2; n - 2)$$

**standardized
statistic**

t
**confidence
range (.05)**

degrees of freedom

Reporting a linear regression

- “The bonding social capital scale was a significant predictor of sharing volume ($b=1.98$, $t(13)=12.18$, $p<0.01$).

This single predictor explained much of the variance in sharing volume ($R^2=.91$).”

Multiple regression

- More than one predictor variable:
double (or N-tuple) the fun!
- Model:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} \\ + \dots + \beta_m X_{im} + \epsilon_i$$

factor	β	p
Seeking	0.74	< .001
Bridging social capital	0.22	< .05
Bonding social capital	0.01	0.33

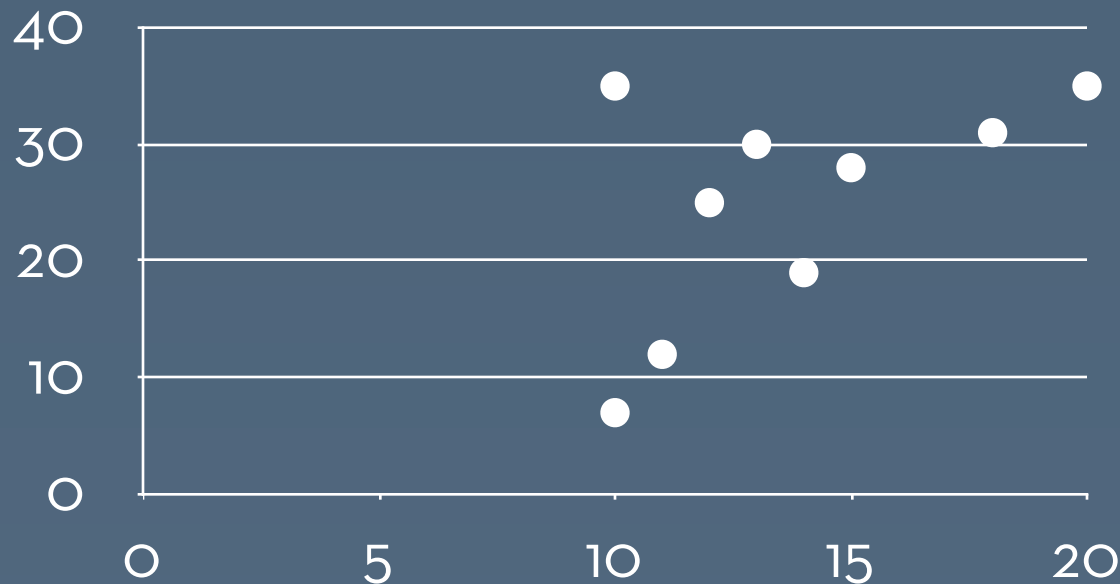
Adj. $R^2 = 0.56$

Multiple regression

- If a predictor is not part of your theory, you can use multiple regression to **control** for it
 - e.g., predict sharing interest by using seeking scale, bridging and bonding social capital, and controlling for age
- This has no impact on the regression mechanics – it is a reflection of your theory

Important assumptions

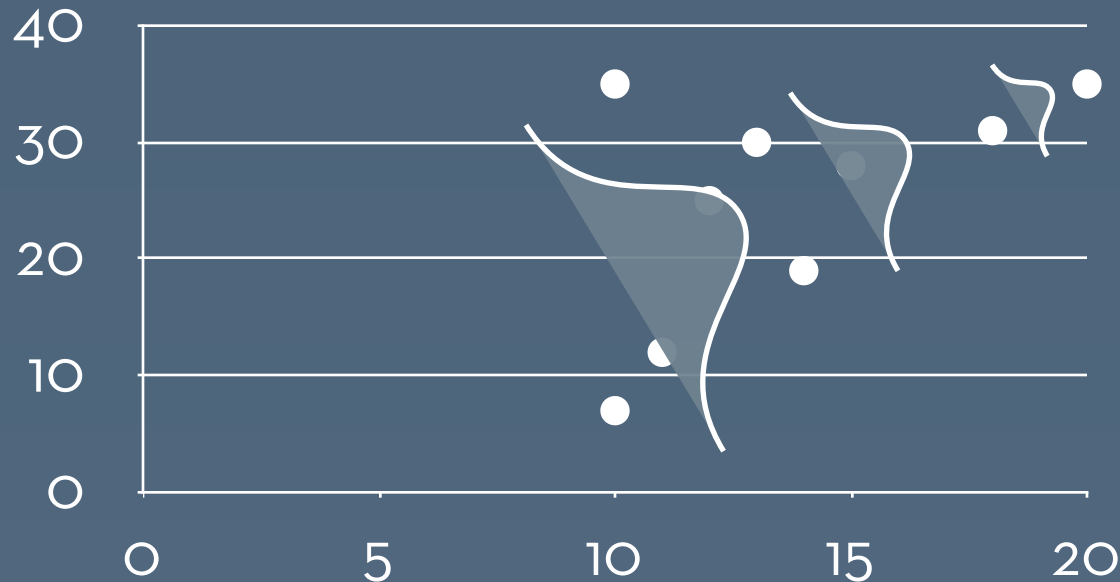
- Errors are normally distributed around regression line
- No heteroskedasticity (use Levene's test)



- Regression predictors are uncorrelated

Important assumptions

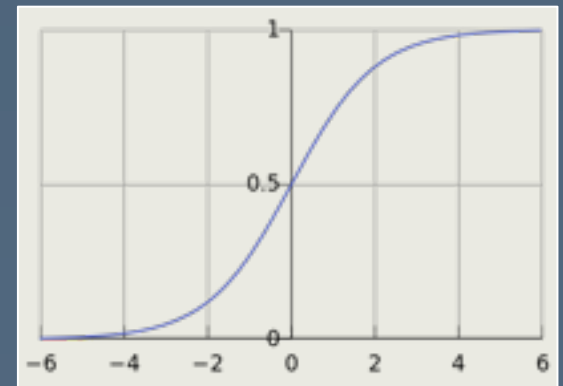
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Logistic regression

- Predicting a **binary** outcome when you are trying to control for other variables
 - e.g., predict user abandonment using training level and age
- Instead of fitting a line, the system fits a **logistic curve**: more weight toward 0 and 1
- Warning: beta coefficient interpretation is now in terms of **odds**



Next: ANOVA