

# Quantitative methods for small data

RSP unit OU28

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# Who's still working with small data?

HCI, social science, medicine

- Small number of human subjects

Natural language processing (NLP)

- Small number of corpora

Causal machine learning (fit a model across data from multiple domains)

- Small number of domains

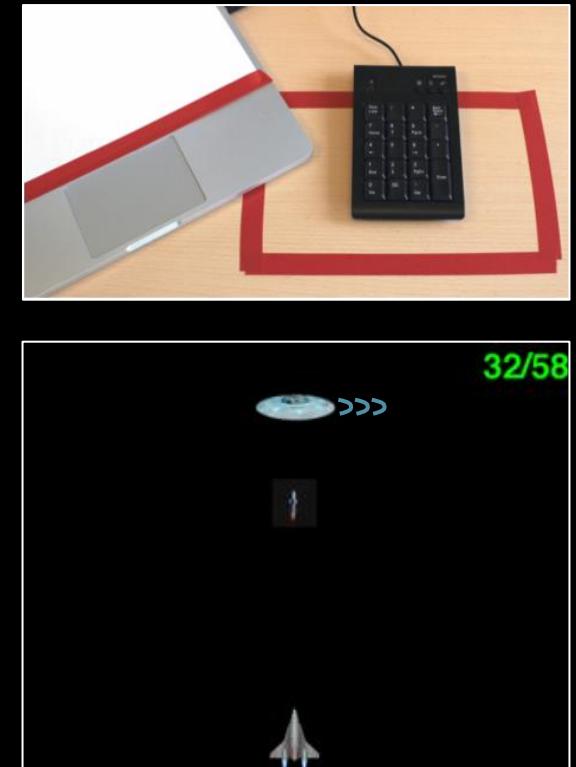
# A typical small-data HCI experiment

SubjectID	Device	HitRate
1	touchpad	0.939
2	touchpad	0.975
3	button	0.940
4	button	1.000
5	button	0.915
:	:	:

Subjects played a game in which they have to shoot at a moving UFO.

- For firing, some subjects were told to tap a touchpad, and others were asked to press a button.
- Subjects have one shot per UFO. Their hit rate over a 3-minute game was measured.

Sense of Agency and User Experience: Is There a Link?  
(Bergström, Knibbe, Pohl, Hornbæk.  
ACM Trans. HCI. 2022)



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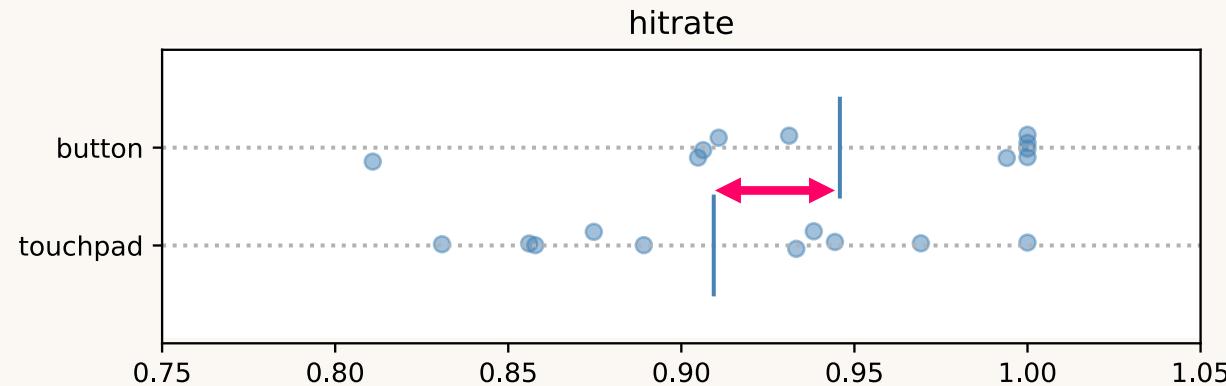
response /  
outcome metric /  
dependent variable

condition /  
independent variable

experimental unit

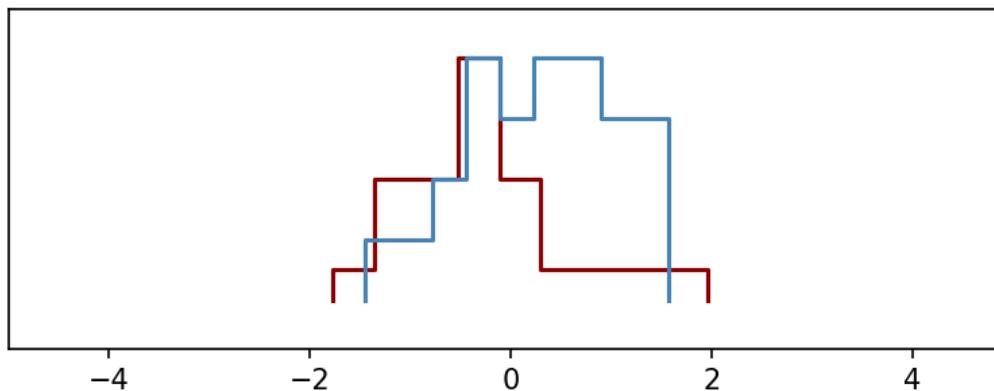
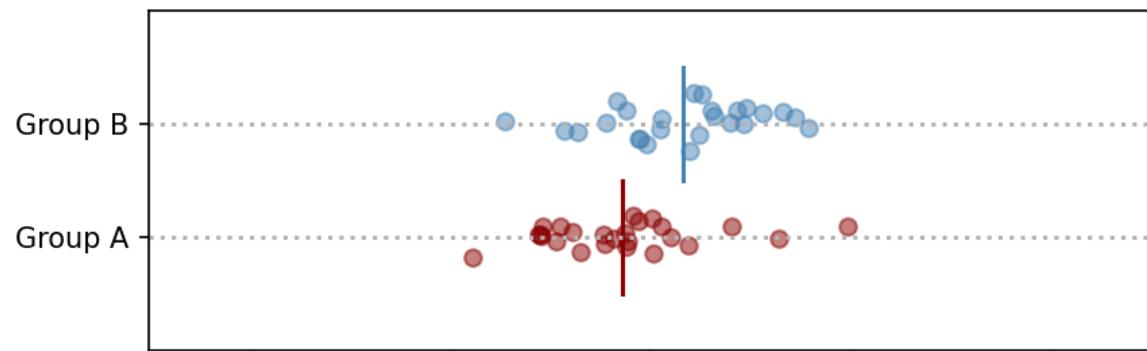
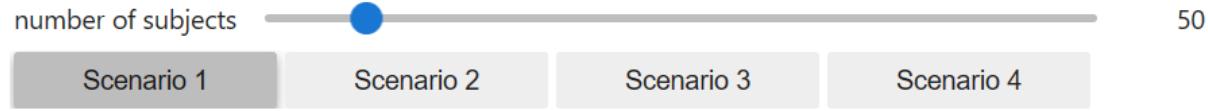
We want to learn  
**“How does the  
response depend  
on the condition?”**

# With small datasets, it's hard to untangle signal from noise



Button-users are 0.036 percentage points more accurate, on average.  
But is this “real”, or is it just noise?

The  $p$ -value is a way to measure how confident we can be that the signal is real.



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“The two groups have significantly different HitRate (t-test,  $p = 0.020$ ).”

- ❖ Don’t confuse *significant* with *meaningful*
- ❖ Don’t use the word *significant* in any other context!

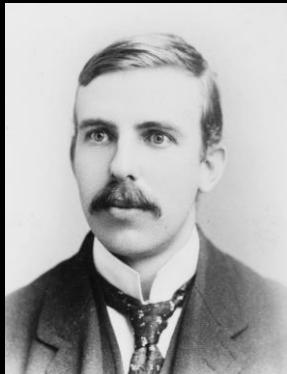
(With only two groups I think it’s more helpful to report a confidence interval for the difference, rather than a  $p$ -value.)

# The conceptual foundation of hypothesis testing

or

what type of statement am I making  
when I report a *p*-value?

## GENERALIZATION



“All science is either physics or stamp-collecting.”

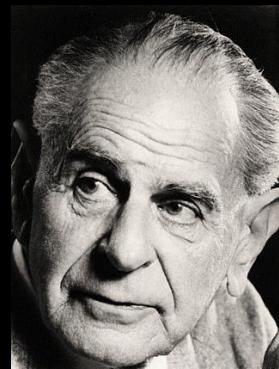
Ernest Rutherford (1871-1937)

LAWS OF NATURE

dataset

in-the-wild

## FALSIFICATION



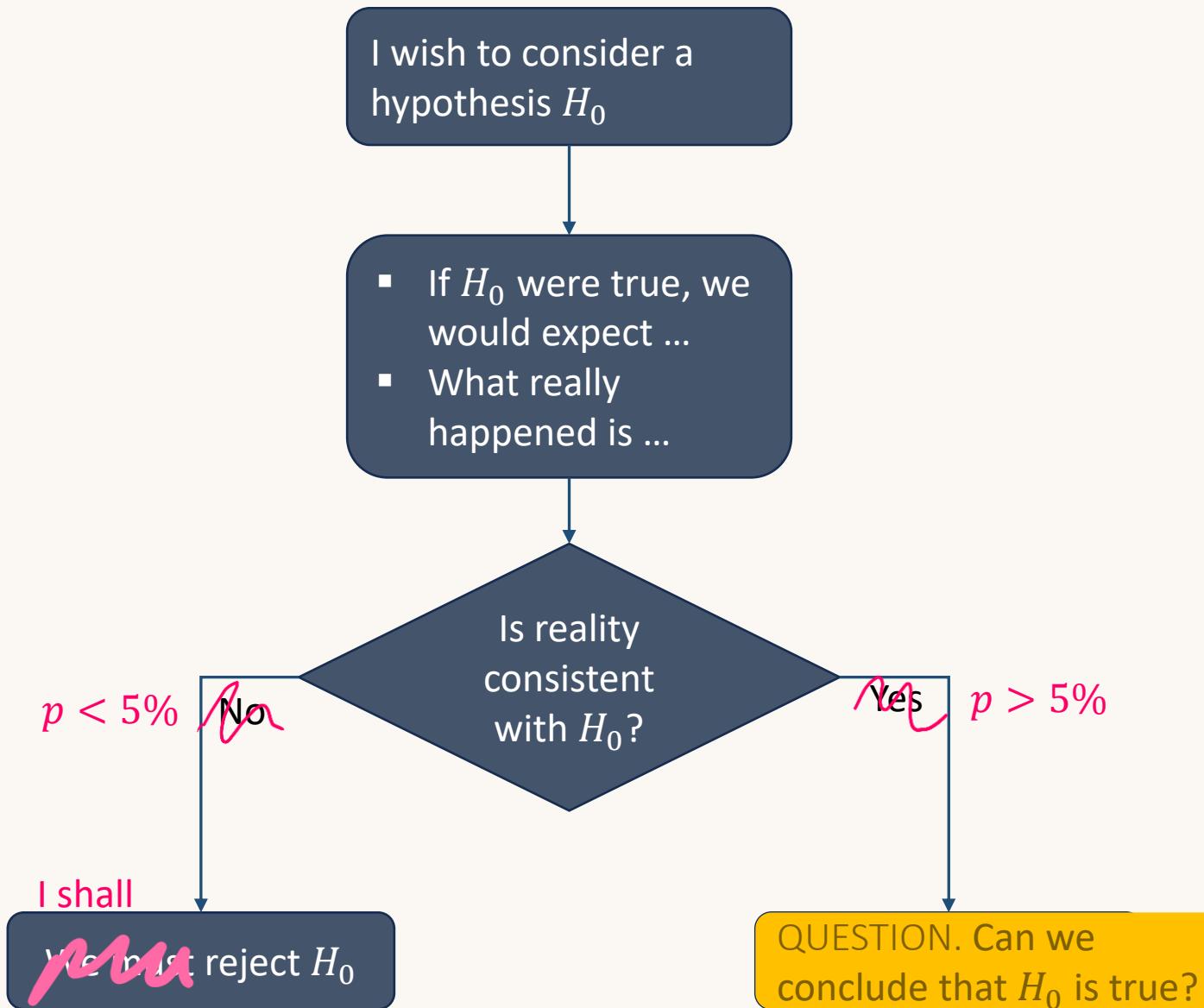
“Every genuine scientific theory must be falsifiable.”

Karl Popper (1902-1994)

- ❖ Scientists propose models for Nature a.k.a. hypotheses
- ❖ Data may make us reject a model, but it cannot prove a model true

I gathered a dataset and I modelled it.  
What can I usefully say about future data?  
i.e. about Nature?

# Popper's hypothetico-deductive approach



Because of noise, it's not yes/no, it's a question of *how* consistent reality is with  $H_0$ . We measure this with the  $p$ -value.

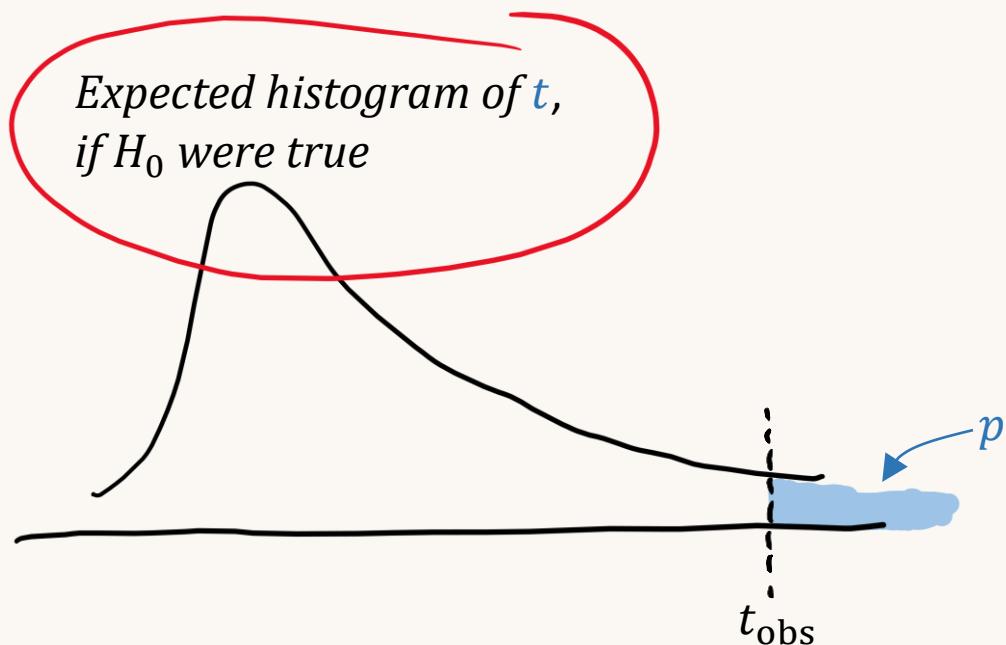
# The mechanics of hypothesis testing

[explained fully in IB Data Science videos & lecture notes]

1. Decide on your null hypothesis,  $H_0$
2. Choose a test statistic  $t$ ,  
e.g. " $t$  = average difference between group A and group B"
3. Assuming  $H_0$  to be true, what distribution would I expect to see for  $t$ ?

The  $p$ -value is defined to be  $p = \mathbb{P}(t \text{ as extreme or more so than } t_{\text{obs}} \mid H_0)$

the value of  $t$  that we  
actually saw



QUESTION. Which of these is a correct interpretation of the  $p$ -value?

1. "If  $p \approx 0$  then  $H_0$  is super-duper unlikely, and if  $p \approx 1$  then it's likely." X

$p$  measures the likelihood of the data, not of the hypothesis.

There is no such thing as "probability that a hypothesis is true"

Even if  $p \approx 1$ ,  $H_0$  may be false.  
e.g. very small amount of data.

2. "The  $p$ -value lets me select between models. I'll test  $H_0$  against an alternative,  $H_1$ . Since  $p < \text{MAGIC\_CONST}$ ,  $H_1$  is better." X

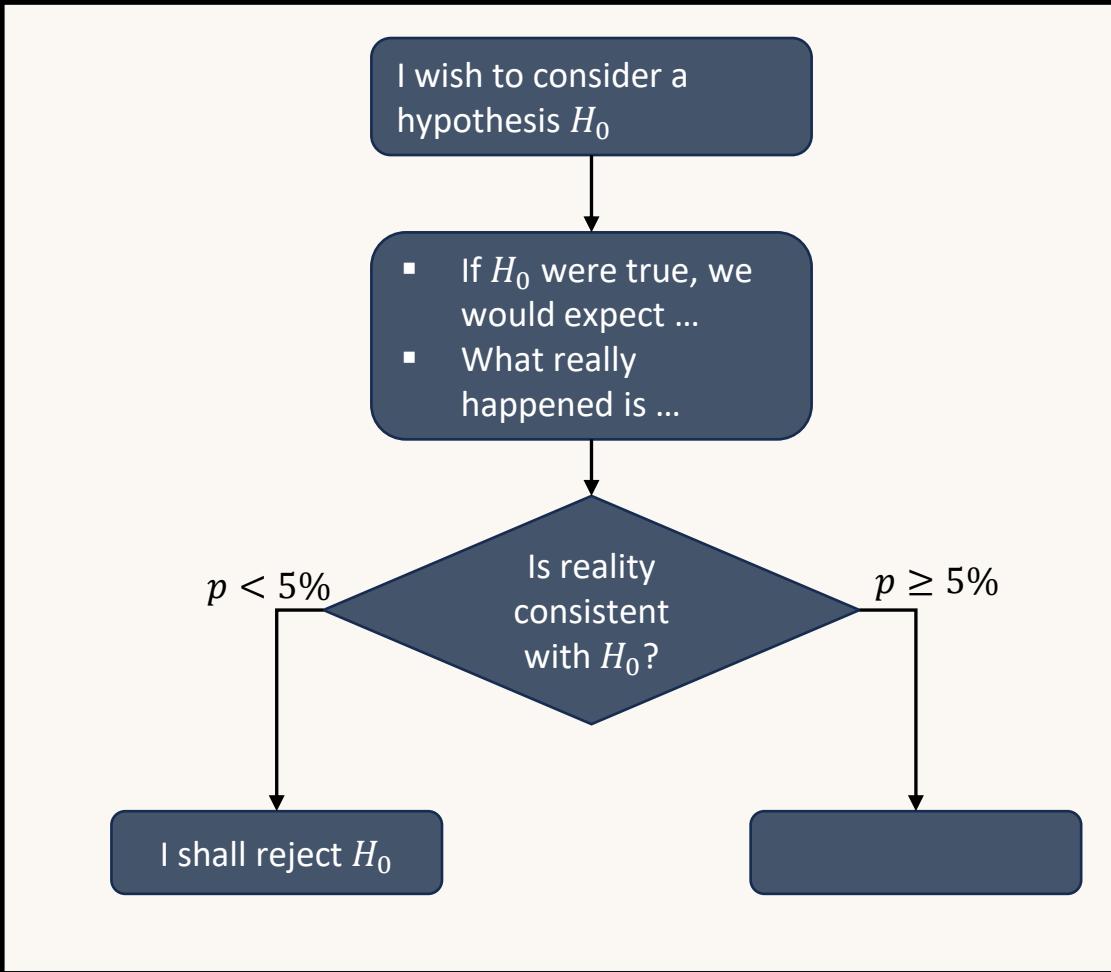
The  $p$ -value is only for evaluating a SINGLE hypothesis.

Holdout set evaluation is THE best way to choose between models.

In small-data world, use AIC  $\equiv$  leave-one-out cross-validation.

3. "Since  $p < \text{MAGIC\_CONST}$  we should reject  $H_0$ ."  
*I shall*

What makes a good  
hypothesis test?



## RHETORICAL ANALYSIS

We only get a definite publishable conclusion if we reject  $H_0$ .

Anything we want to argue, we have to phrase it as “reject  $H_0$ ” for a suitable  $H_0$ .

Our  $H_0$  should match the research question we want to answer, and not bring in contentious subclaims.

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:	:	:

*Composite hypothesis*

$H_0$ : the readings from both groups are all independent Gaussian random variables with identical mean and variance

*This is the null hypothesis that is tested by the standard t-test*

*means not identical*

*OR variance not identical*

*OR distributions might not be Gaussian*

*OR readings might not be independent*

QUESTION. What might you conclude by rejecting this  $H_0$ ?

# Multiple testing

Eight algorithms

	R-1	R-2	R-L	R-SU4
<i>Abstract generation from propositions</i>				
OurAbs (A)	0.364	0.088	0.340	0.131
<i>Sentence extraction with compression</i>				
X + Cl	0.361	0.090	0.335	0.132
X + Co	0.340	0.074	0.321	0.113
L + Cl	0.356	0.077	0.325	0.126
L + Co	0.336	0.067	0.314	0.110
<i>Sentence extraction</i>				
OurExt (X)	0.376	0.122	0.345	0.154
LexRank (L)	0.349	0.087	0.316	0.129
<i>Token extraction for propositions</i>				
OurTok (T)	0.356	0.088	0.336	0.130

Four metrics

#tests = 112

	A	X+Cl	X+Co	L+Cl	L+Co	X	L	
x+Cl	=	<<	<<					
x+Co	<<	=	=	>				
L+Cl	=	=	=	=				
L+Co	<<	<<	=	<<	=			
x	=>	>>	>>	=>	=>	>>		
L	=	=	=	=>	=>	=>	<<	
T	<<	=	>>	=	>>	<<	=>	=>

1 2  
L SU4

Table 2: ROUGE F-scores and statistical significance of the differences. The four positions in the significance table correspond to ROUGE-1, 2, L and SU4, respectively. “>>” means row statistically outperforms column at  $p < 0.01$  significance level; “>” at  $p < 0.05$  significance level, and “=” means no statistical difference detected.

QUESTION. What  $H_0$  do you think the authors have in mind?

$H_0$ : “All models are equally good across all 4 metrics”

$P\text{-value} \leq \# \text{tests} \times \min p_i$   $\leftarrow \min p\text{-value across all tests.}$

# Attendance question

What question strikes fear into the heart of a simple-minded experimentalist?

And if they're bold enough to answer you, follow it up with

*“Have you corrected for multiple testing?”*

Our  $H_0$  should be credible to our audience.

If we propose a non-credible  $H_0$  and then reject it — who cares?

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:	:	:

“The touchpad and button groups have significantly different HitRate (t-test,  $p = 0.020$ ).”

QUESTION. What's the implied  $H_0$ , and is it credible?

Not credible.  $H_0$  includes “readings are independent” and no one will believe that.

<b>SubjectID</b>	<b>Device</b>	<b>HitRate</b>	
1	touchpad	0.939	I want to test if the results are higher with the button than with the touchpad.
	button	0.975	
2	touchpad	0.940	How can I account for the grouping structure in my dataset?
	button	1.000	
3	touchpad	0.915	
:	:	:	

There's an art to designing tests that make minimal assumptions.  
Such tests are highly credible.  
But they often involve condensing the data.

SubjectID	button	touchpad	difference	1[button better]
1	0.975	0.939	+0.036	1
2	1.000	0.940	+0.060	1
3	0.905	0.915	-0.010	0
:	:	:	:	
$n$ subjects				

### PAIRED t-TEST

$H_0$ : the within-subject differences are independent  $\text{Normal}(0, \sigma^2)$  for some  $\sigma$

**Test statistic:** let  $t$  be the average of within-subject differences

[If  $H_0$  is true then  $t \sim N(0, \hat{\sigma}^2/n)$  and we can calculate the  $p$ -value on this basis.]

### SIGN TEST

$H_0$ : the two devices are equally as good

**Test statistic:** let  $t$  be the number of trials in which button is better

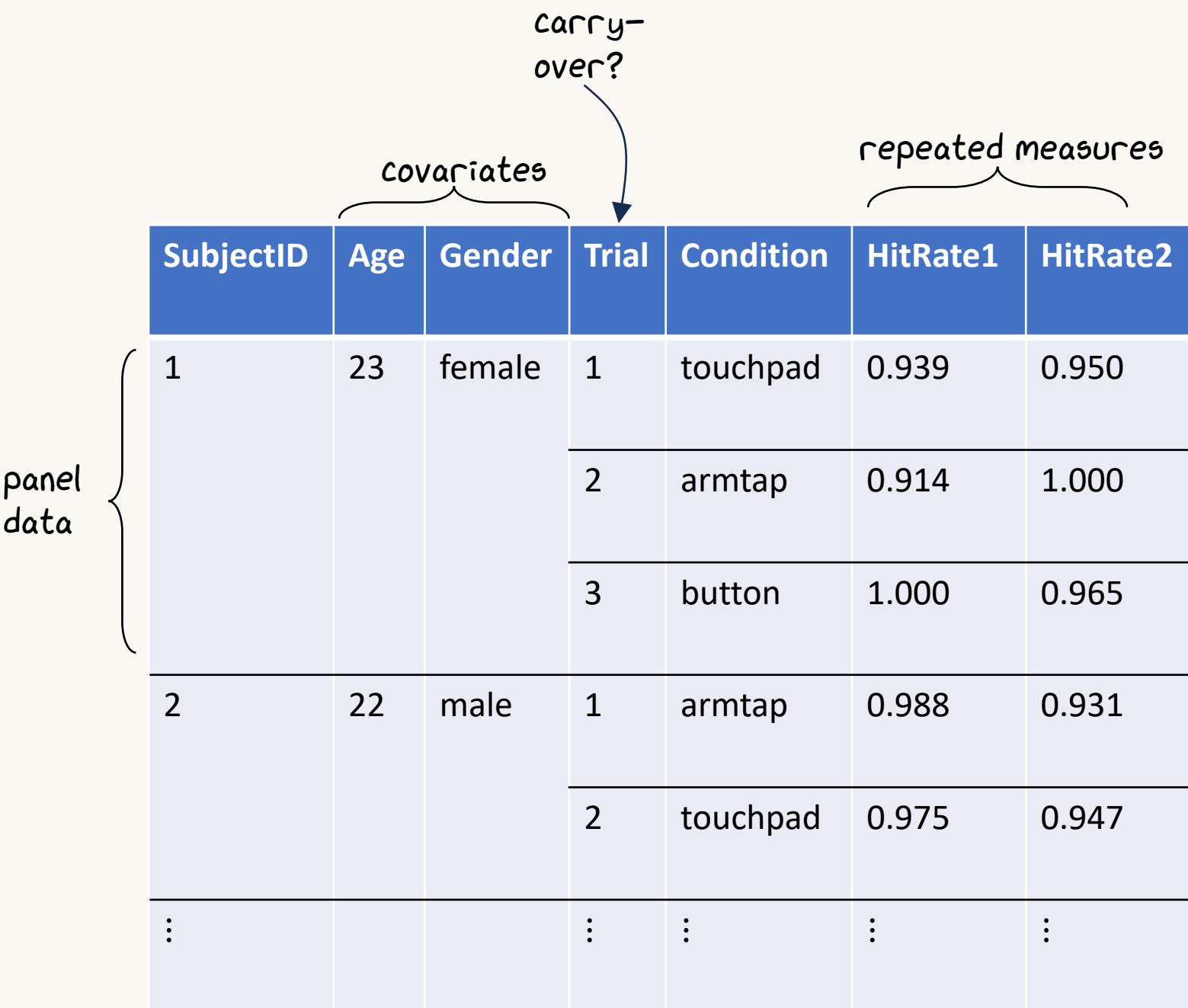
[If  $H_0$  is true then  $t \sim \text{Bin}(n, 1/2)$  and we can calculate the  $p$ -value on this basis.]

# Grouped data

To make full use of a rich dataset, we typically have to propose an “anti-minimal” detailed probability model for  $H_0$  that incorporates all the grouping structure.

And the covariates too.

When you describe your data and tests, be very clear about the grouping structure. It has a huge impact on the analysis.



The diagram illustrates a grouped data structure. A large curly brace on the left, labeled "panel data", groups rows for different subjects. Above the table, a bracket labeled "covariates" groups "SubjectID", "Age", and "Gender". An arrow labeled "carry-over?" points from "Trial" to "Condition", indicating a dependency between these two variables. Another bracket labeled "repeated measures" groups "HitRate1" and "HitRate2".

SubjectID	Age	Gender	Trial	Condition	HitRate1	HitRate2
1	23	female	1	touchpad	0.939	0.950
			2	armtap	0.914	1.000
			3	button	1.000	0.965
2	22	male	1	armtap	0.988	0.931
			2	touchpad	0.975	0.947
:			:	:	:	:

# Where to go for help:

The screenshot shows the University of Cambridge Statistics Clinic website. The header includes the University of Cambridge logo, navigation links for Study at Cambridge, About the University, Research at Cambridge, Quick links, a search bar, and a login link. The main title is "The Statistics Clinic". The page features a large central image of a word cloud related to statistics, including terms like classification, time series, logistic regression, linear regression, hypothesis testing, survey data, and various statistical methods. Below the word cloud, text describes the clinic's purpose, services, and booking information. A sidebar on the right lists forthcoming clinics.

UNIVERSITY OF CAMBRIDGE

Study at Cambridge About the University Research at Cambridge Quick links Search Login

## The Statistics Clinic

Home How the Clinic Works Useful Statistical Resources Future Clinic Dates Testimonials Our Team Areas of Expertise Travel Information

bootstrap Cox model

correlation causal inference

t-test cross-validation model selection

ANOVA Categorical cluster analysis

mixed effect model contingency table

classification survival analysis

time series meta-analysis

PCA p-value

multiple testing chi-squared test

likelihood SEM

ordinal extreme value

linear regression Mann-Whitney U test

hypothesis testing R panel data

survey data missing data

Established in 2009, the **Statistics Clinic** aims to offer **free** statistical consulting services to all members of the broader research community within the University of Cambridge (and its affiliated institutes and hospitals). Eligible university members, including, but not limited to, faculty members, staff, postdocs and graduate students, are all welcome to use our service for advice at any stage of their research and data analysis.

Students taking statistics courses should understand that **this is NOT a teaching/supervision service**.

Our clinic sessions happen fortnightly during term time and around every third week during summer. See [our timetable](#) for the dates and information concerning how to sign-up. **Signing up is required to take part in a session.** Please meet our excellent Statistics Clinic team [here](#) and read more about our [areas of expertise](#). The team is based in the [Statistical Laboratory](#) at the [Centre for Mathematical Sciences](#), which is also where consultations take place.

While we offer the option of a remote consultation, we **strongly** encourage clients to sign up for an in-person session when possible.

*If you are unsure whether your query is appropriate for the clinic, feel free to drop us an email at [camstatslabclinic@gmail.com](mailto:camstatslabclinic@gmail.com) to check. However, please note that we are unable to answer scientific questions by email.*

Forthcoming clinics

16:30 - 18:00: Statistics Clinic Michaelmas 2024 IV MR5 at the CMS **20 NOV**

16:30 - 18:00: Statistics Clinic Michaelmas 2024 V MR5 at the CMS **04 DEC**