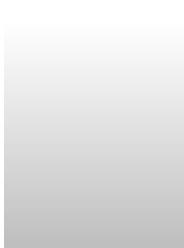
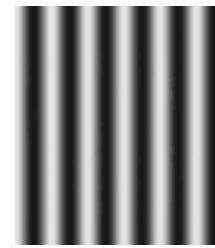
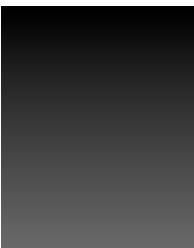
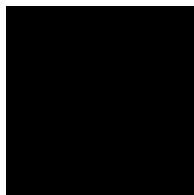
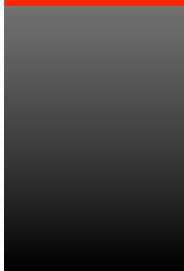
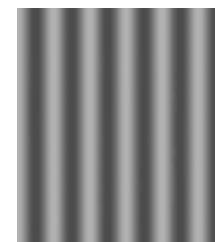
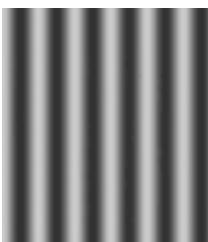
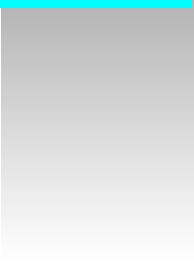


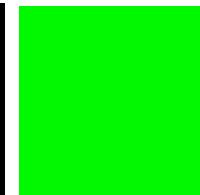
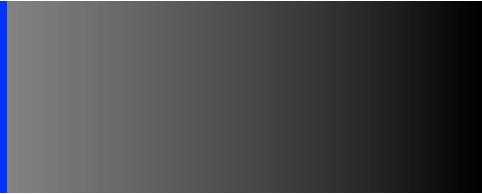
Smallest font



Calibration slide

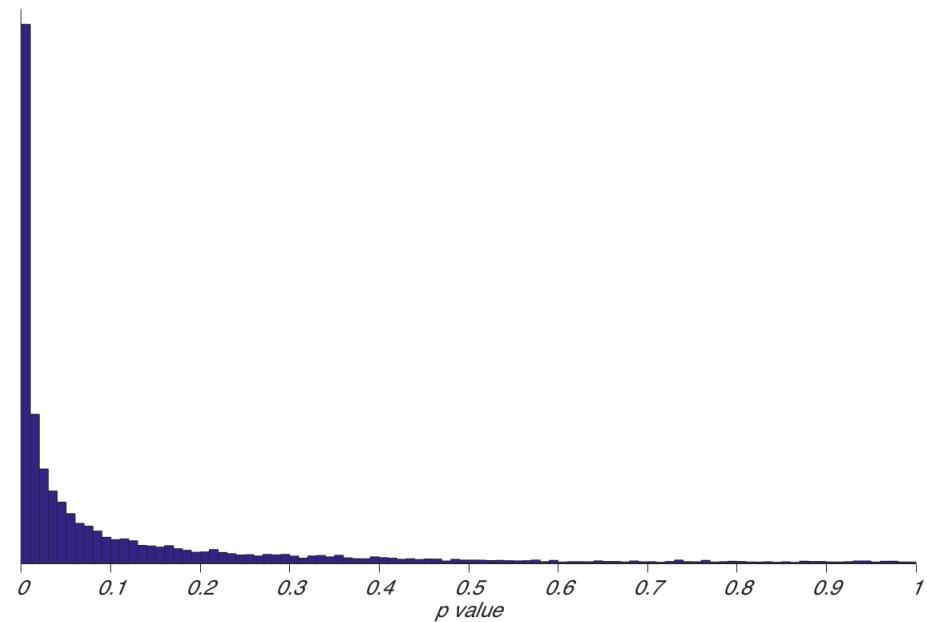


Smallest font

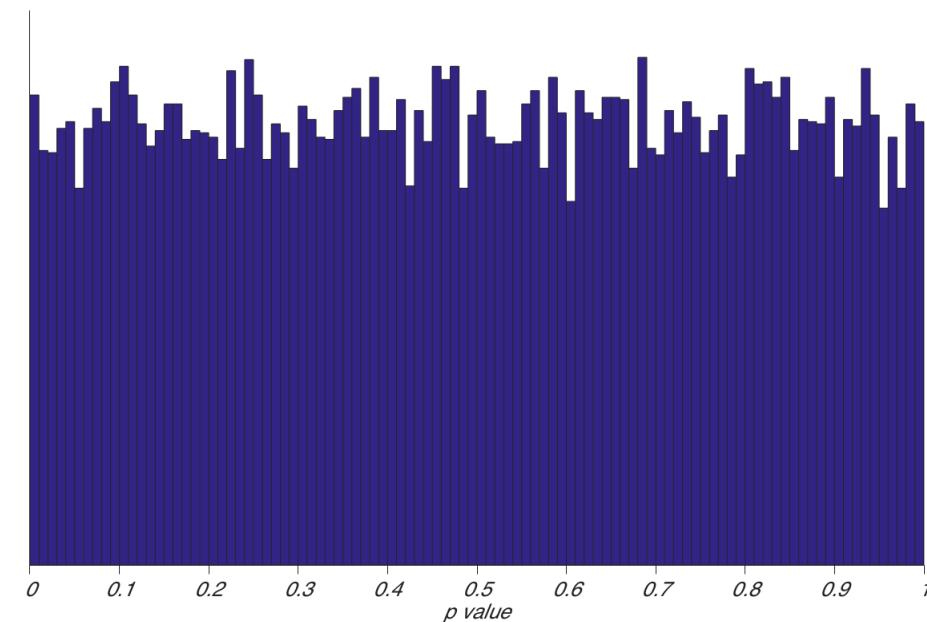


Distribution of p values

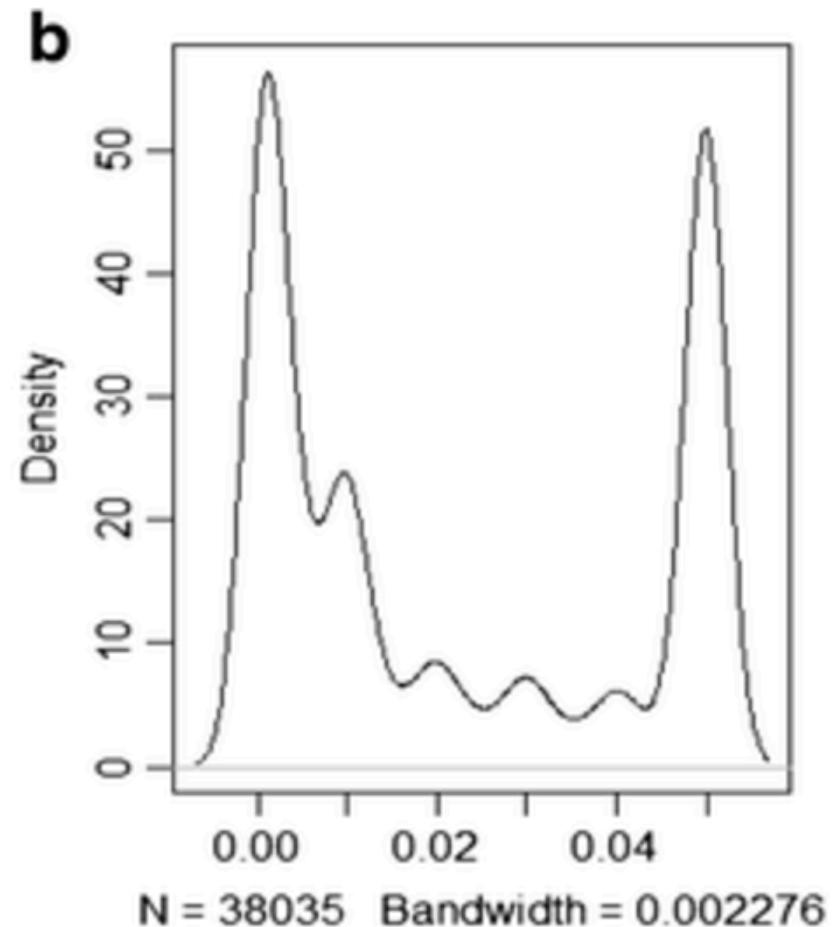
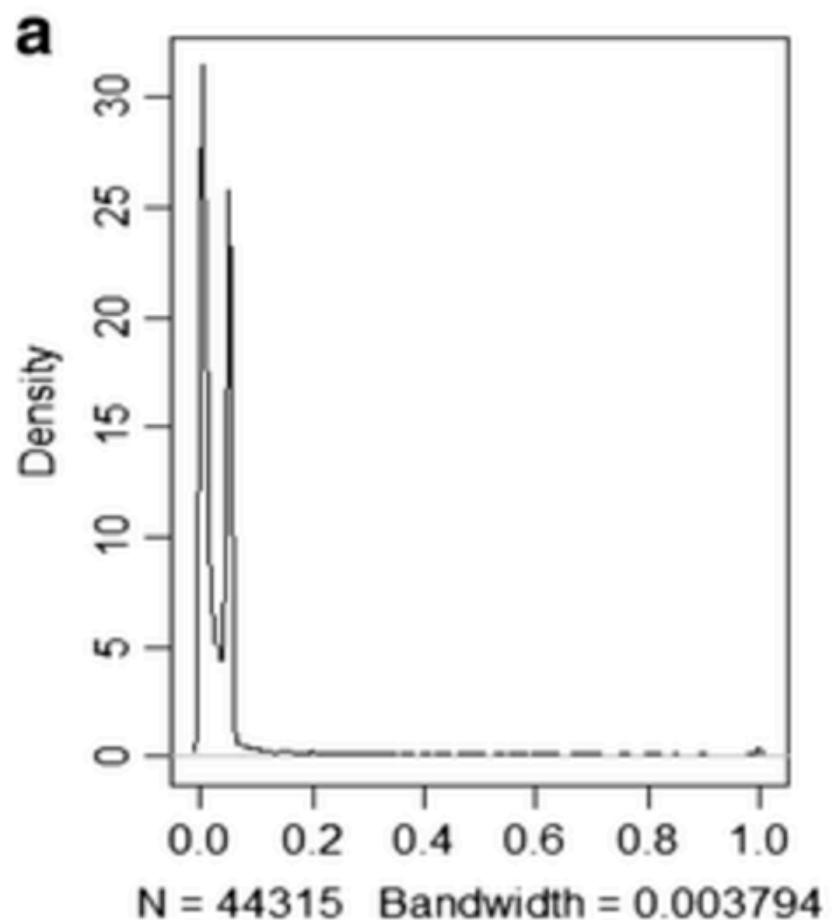
If H_0 is false:



If H_0 is true:



Not just neuroscience and psychology: Evidence of p-hacking in oral health



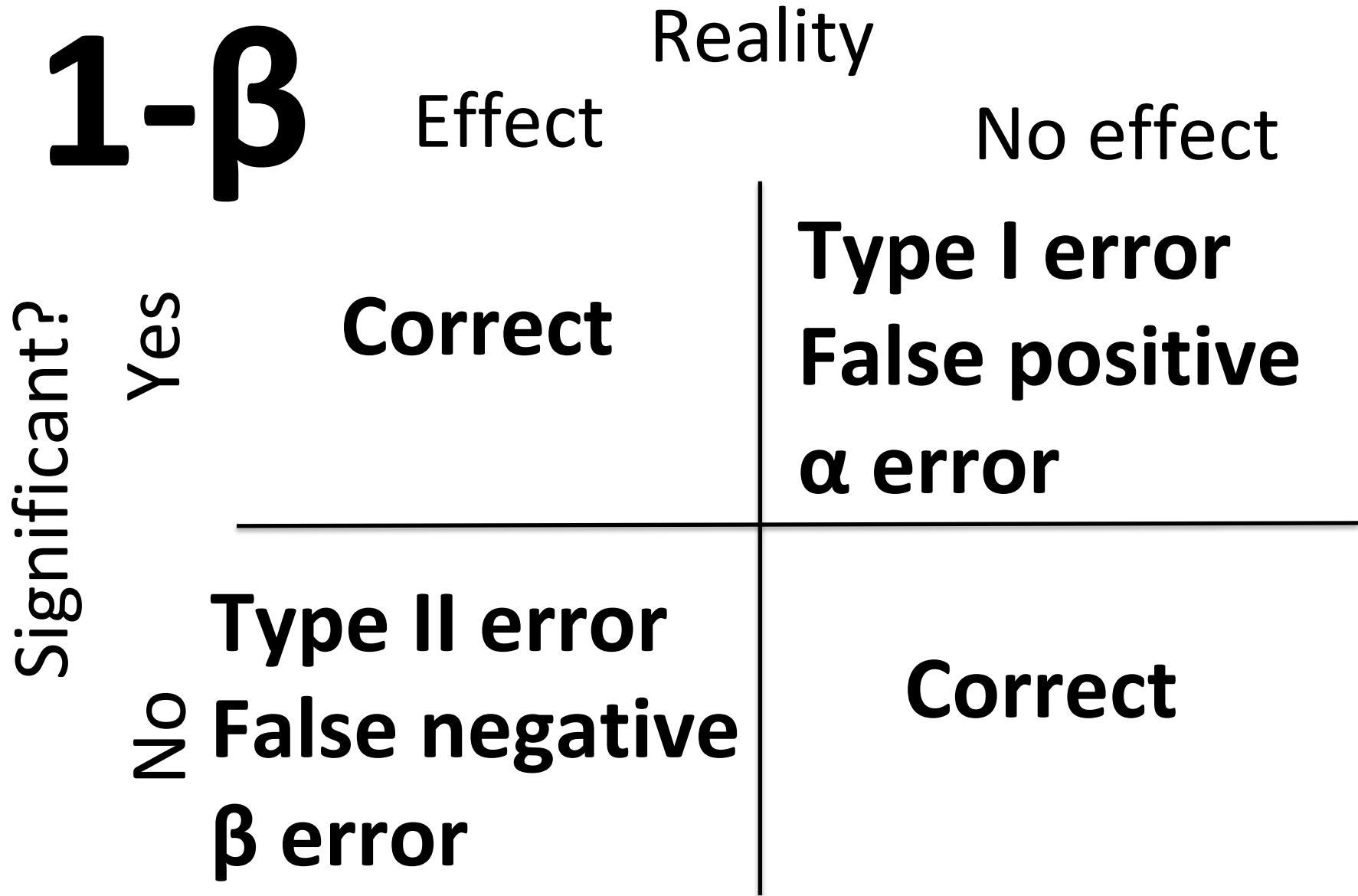
Kagereki et al., 2016

Power

&

Confidence

What is (statistical) power?



What is power really?

Why does it matter so much?

Pearl Harbor 12/1941

Wake Island 12/1941

Hong Kong 12/1941

Malaya 01/1942

Darwin Raid 02/1942

Singapore 02/1942

Borneo 03/1942

Java 03/1942

Sumatra 03/1942

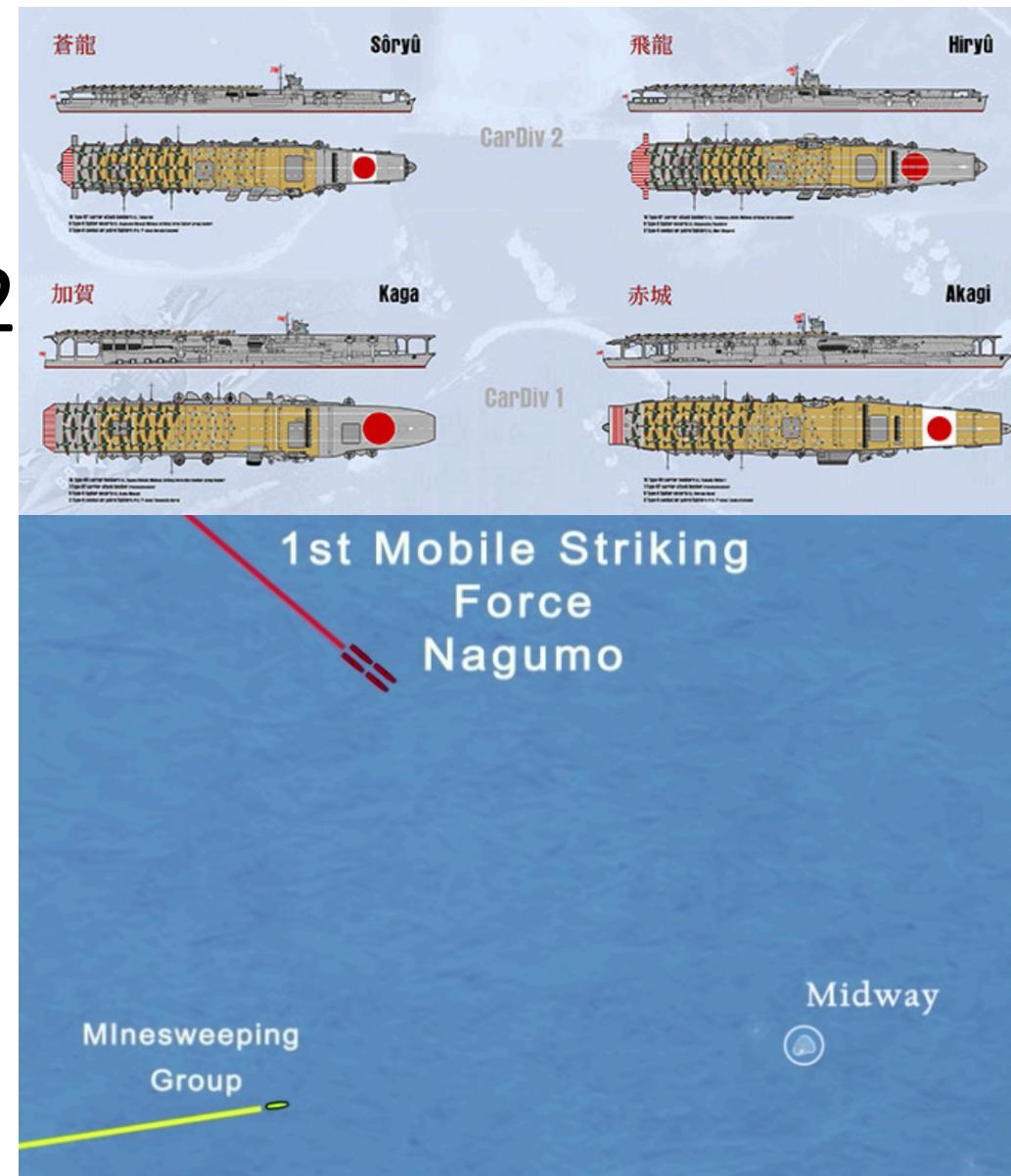
Bataan 04/1942

Mandalay 05/1942

Philippines 05/1942

Kidō Butai

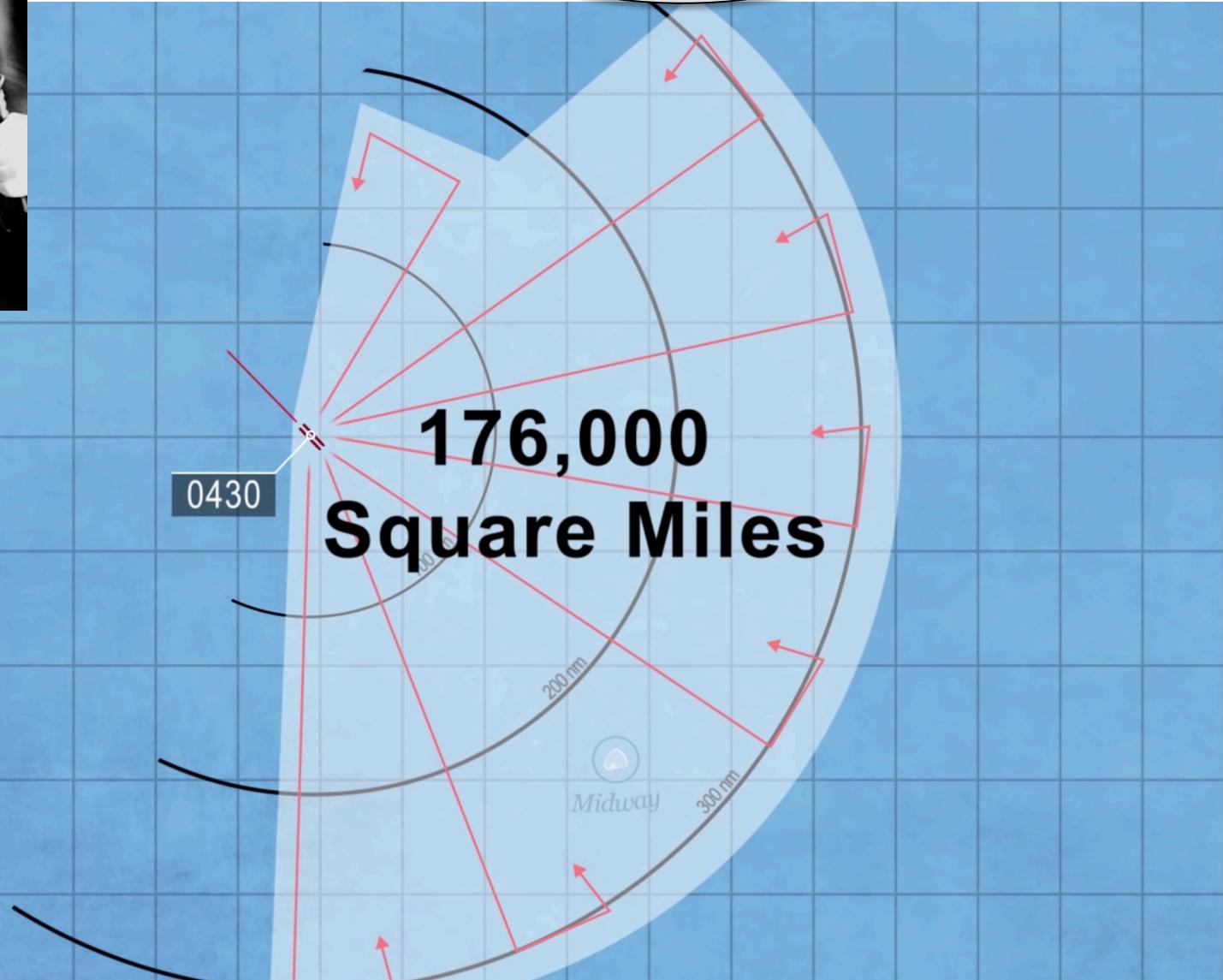
(Mobile Striking Force)



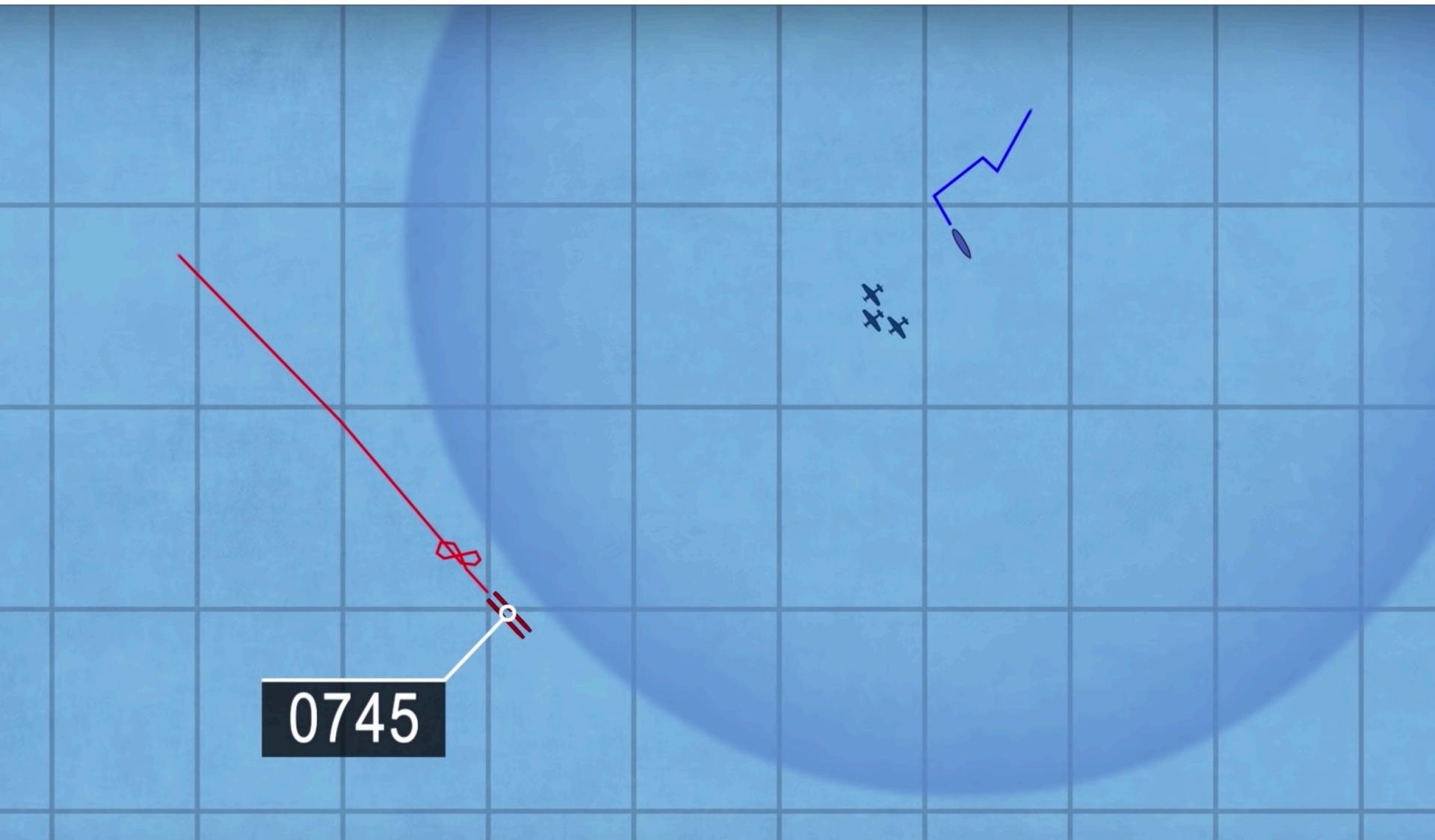


No US carriers spotted =
evidence of absence

Nagumo



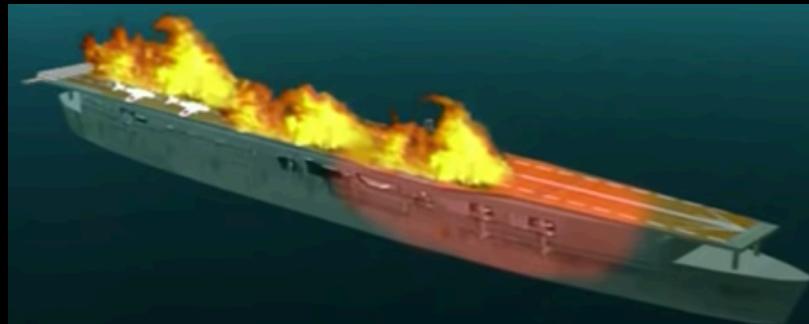
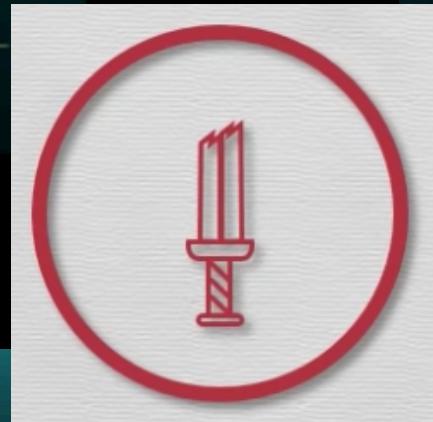
Reality: Absence of evidence!



Lack of power can be devastating



 **KAGA**



 **SORYU**



 **AKAGI**



 **HIRYU**

The link to confidence (intervals)

- Higher power shrinks confidence intervals
- CI = interval estimate of a population parameter
- If we repeated a study often, x% (usually 95 or 99%) of the CIs would contain the population parameter.

How to calculate a confidence interval

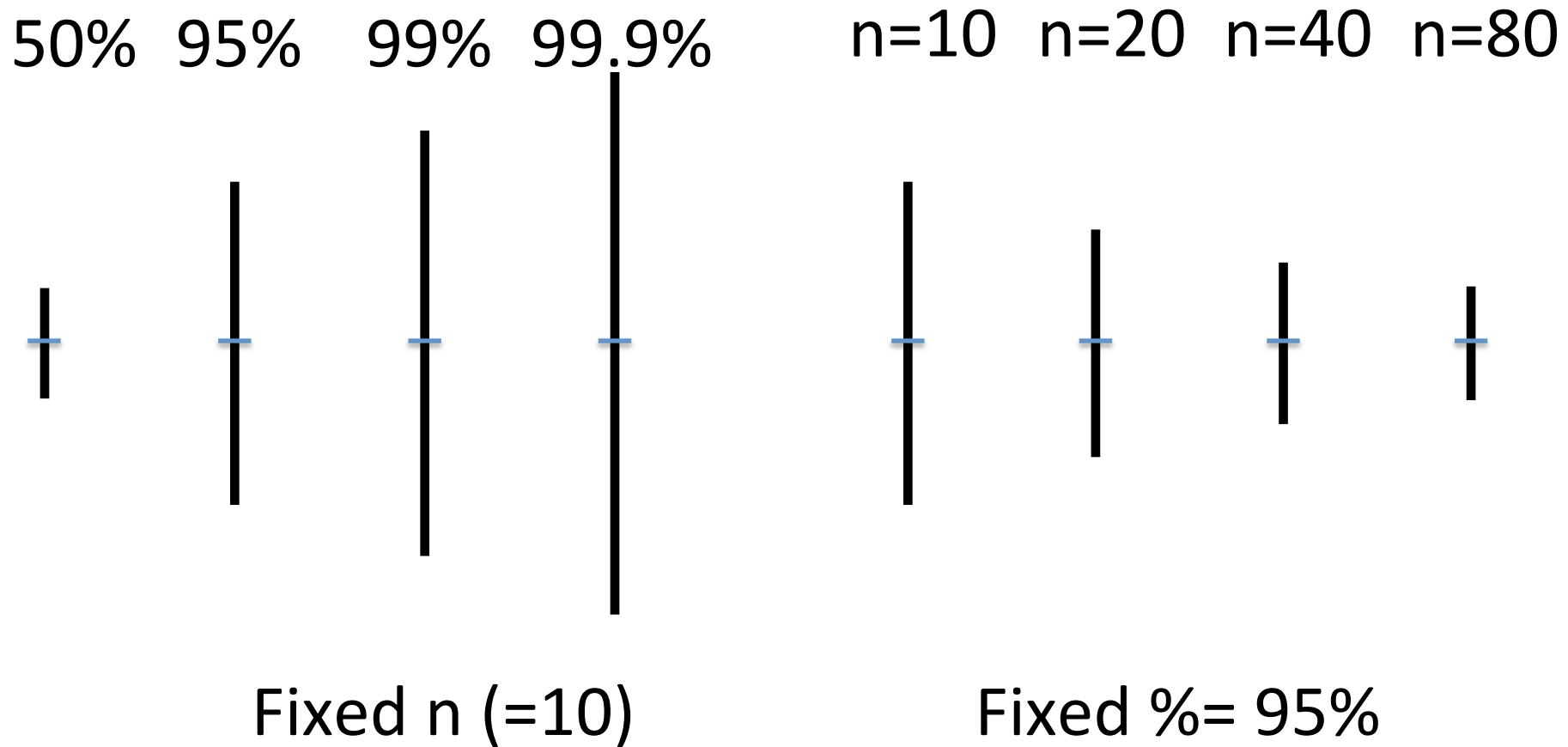
- The idea is to multiply a critical z value with the SEM.

$$SEM = \frac{\sigma}{\sqrt{n}}$$

- Critical z-value:** Found by taking the confidence level (e.g. 95%) and looking it up in a z-table: $z_{a/2}$
- | | |
|-------|------|
| 50% | 0.67 |
| 95% | 1.96 |
| 99% | 2.58 |
| 99.9% | 3.29 |

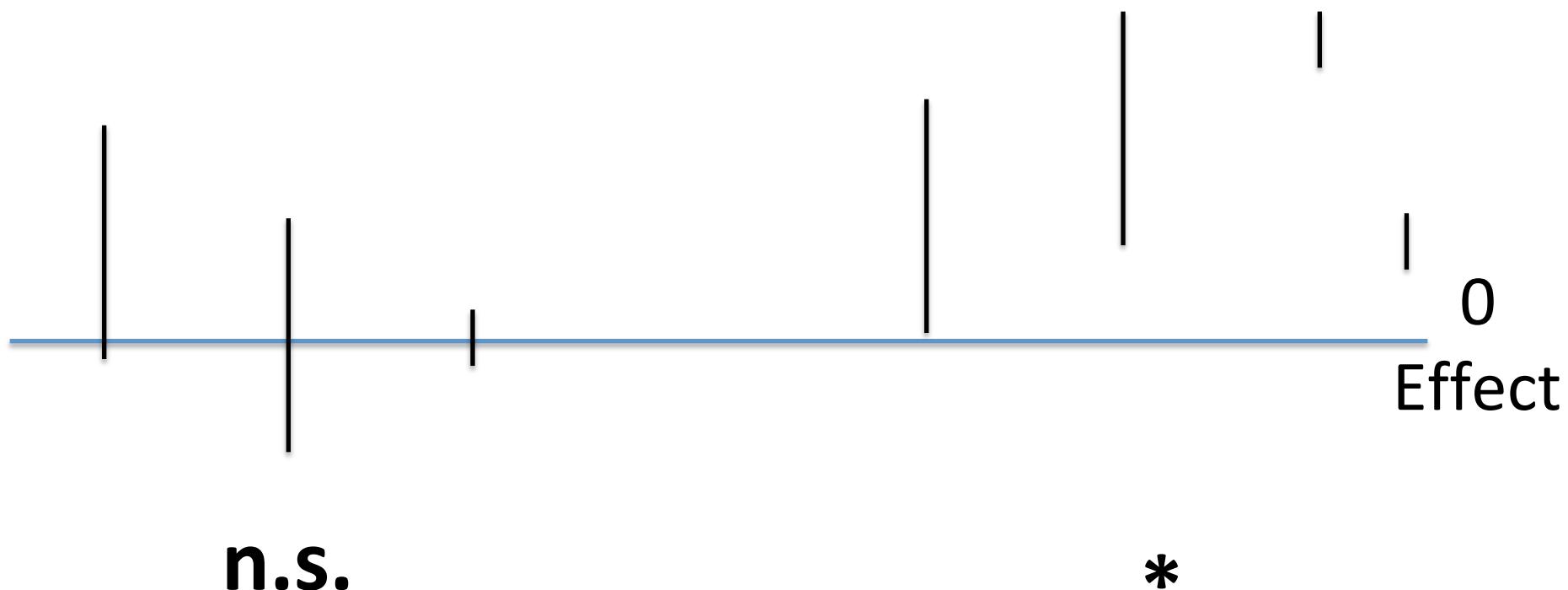
$$CI = \bar{x} \pm z_{a/2} * \frac{\sigma}{\sqrt{n}}$$

Clamped confidence intervals



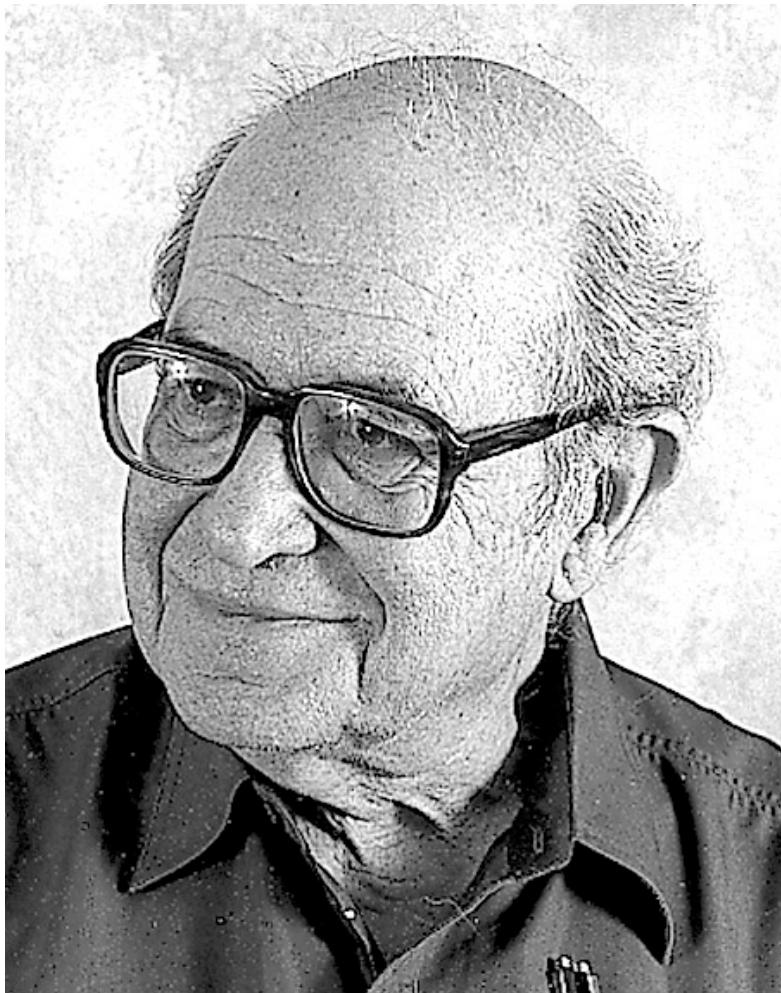
Why is CI a more informative measure than significance alone?

- It allows to distinguish absence of evidence from evidence of absence



The link to effect sizes

- We need to talk about effect sizes



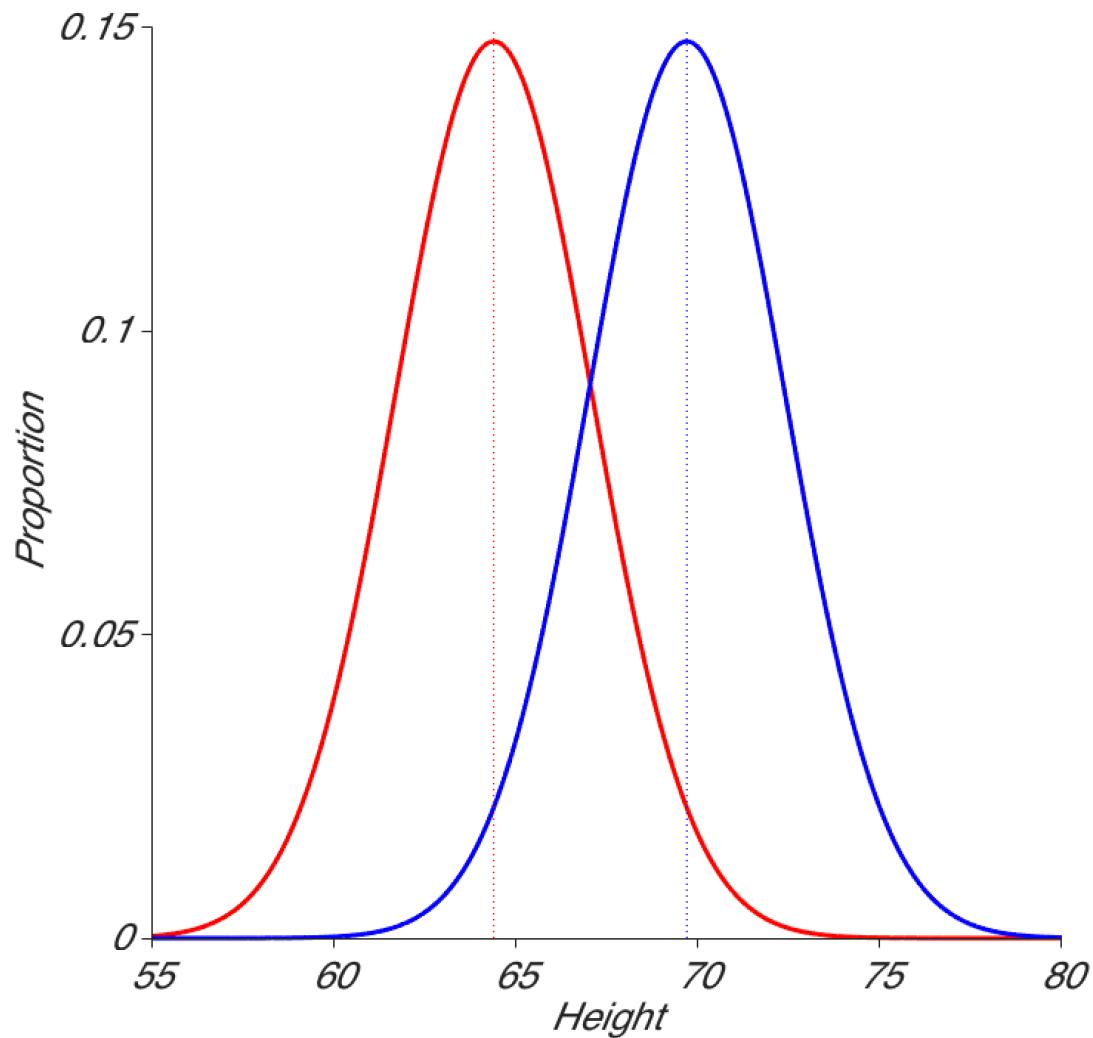
Cohen's d:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{\text{SD}}$$

Jacob Cohen

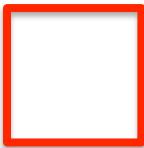
Effect sizes are counterintuitive

- Undiscovered big effects are rare.
- The average size of asteroids discovered annually shrinks by 2.5 percent each year (Arbesman, 2012)
- Similar things are true for effects – the probability of discovering them is not independent of their size.

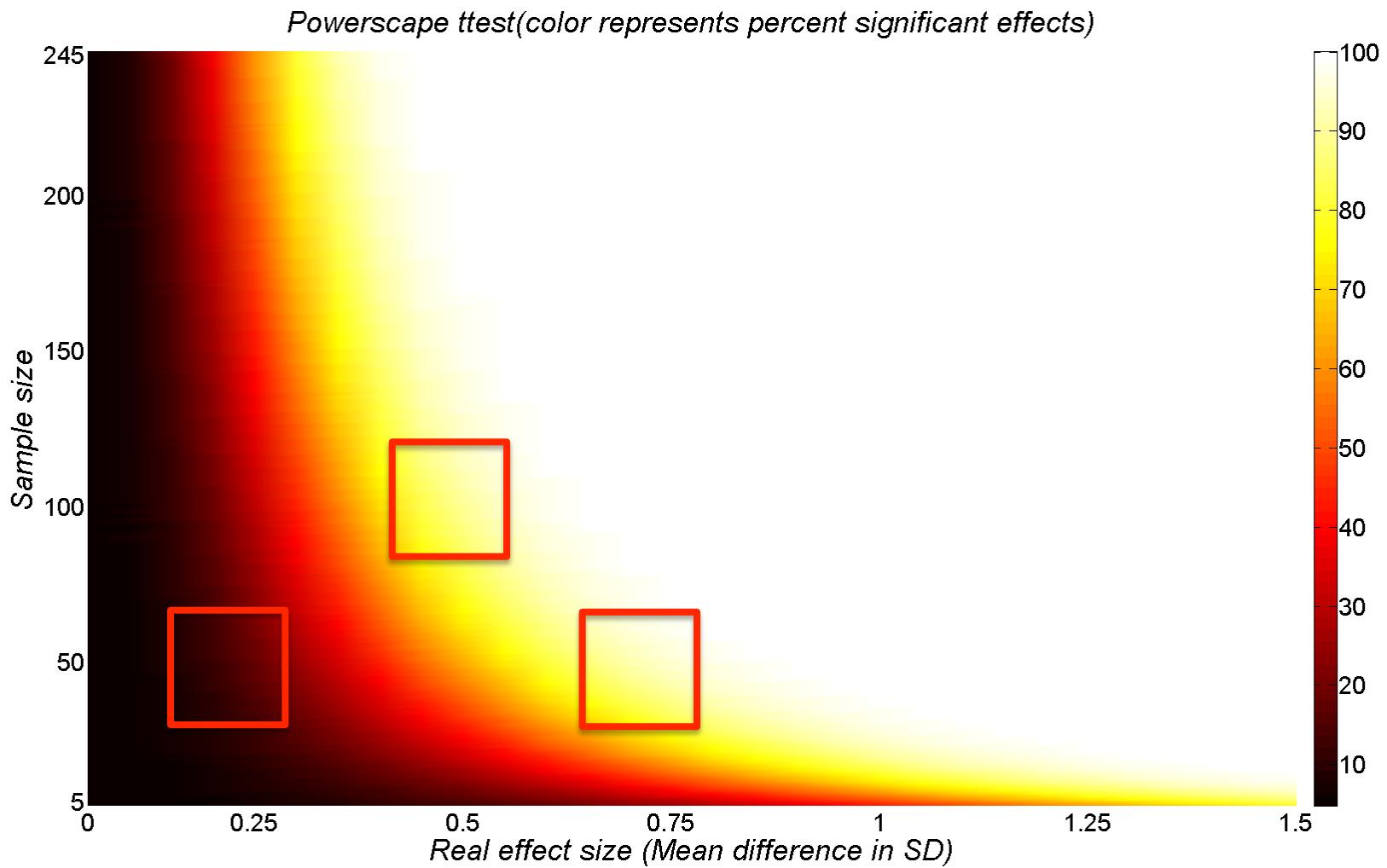


Large effects are rare

- Average pygmy height = 4 ft, 11"
- Average NBA player height = 6 ft, 7"
- Cohen's d = 8
- The effect size of SSRI antidepressants is
 - on average – 0.30. (Cipriani et al., 2018).
- The effect size of psychotherapy is – on average – 0.30 (Hoyt et al., 2017).

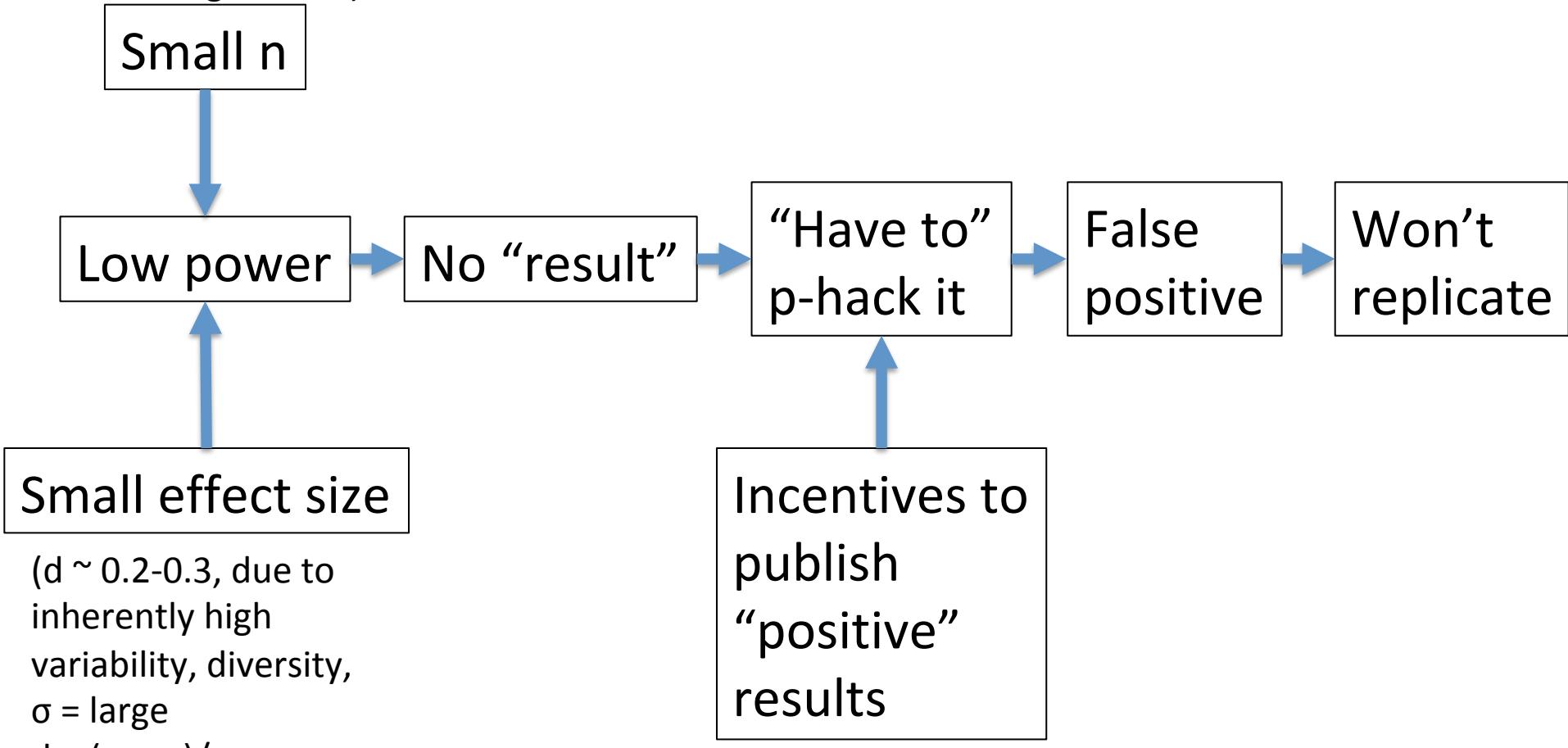


Why does this matter? The powerscape



The replication crisis as a result of power failure

(SEM = σ / \sqrt{n} ,
diminishing returns)

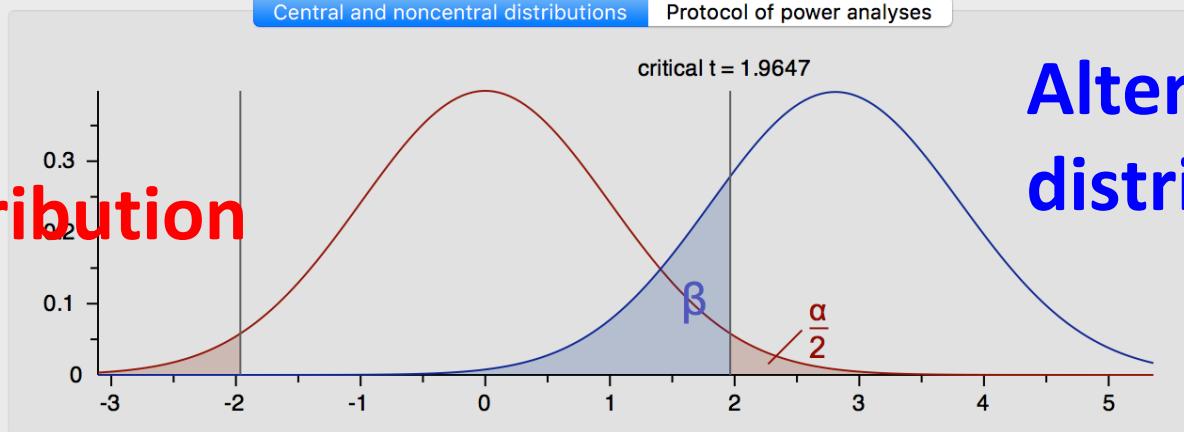


What to do?

- *A priori* (before the study) power analyses.
- Recommended tool: G*Power (free)

Null distribution

Alternative distribution



Test family

Statistical test

t tests

Means: Difference between two independent means (two groups)

Type of power analysis

A priori: Compute required sample size - given α , power, and effect size

Input parameters

Tail(s) Two

Determine

Effect size d 0.25

 α err prob 0.05Power (1- β err prob) 0.8

Allocation ratio N2/N1 1

Output parameters

Noncentrality parameter δ 2.8118055

Critical t 1.9646820

Df 504

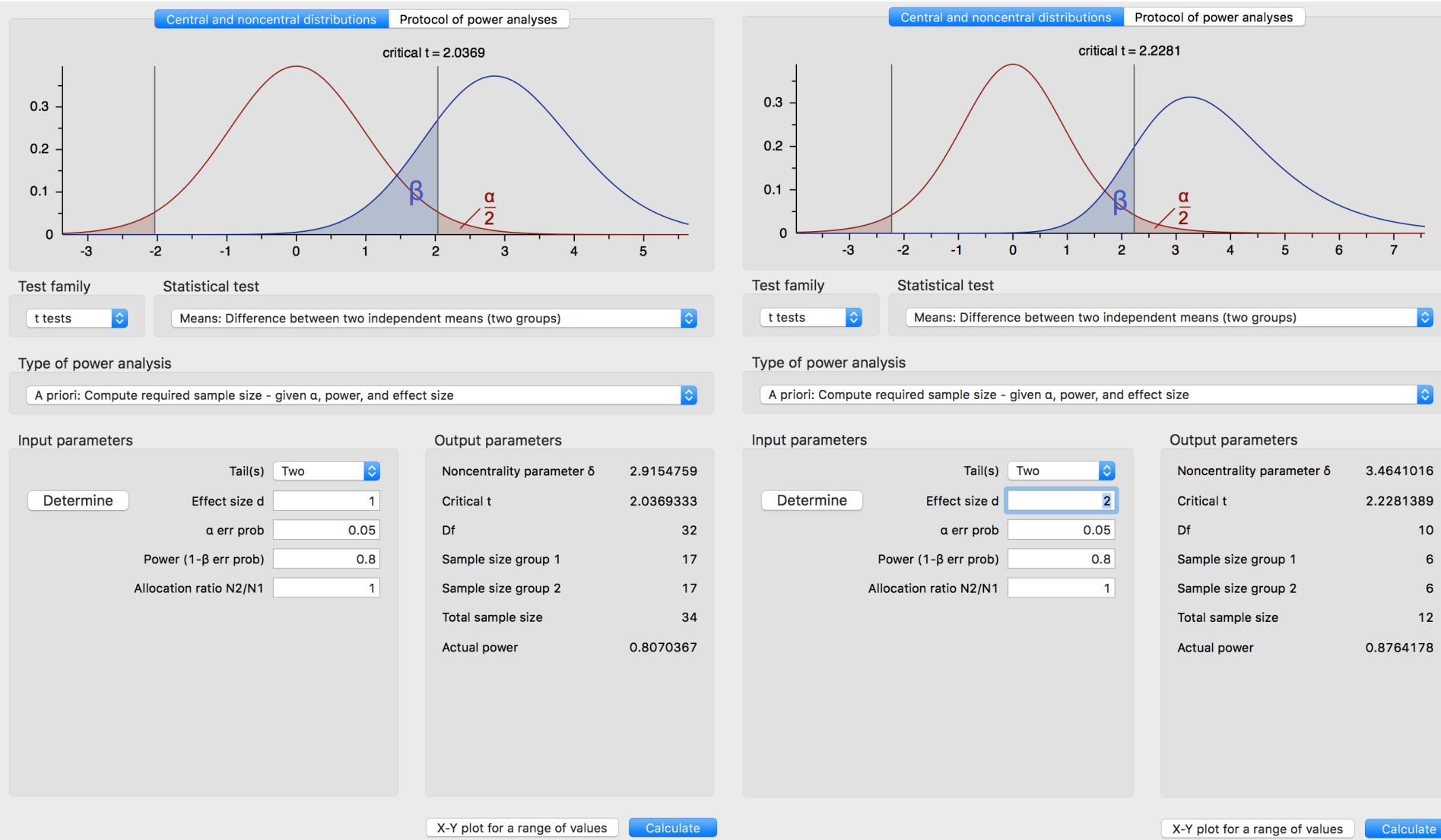
Sample size group 1 253

Sample size group 2 253

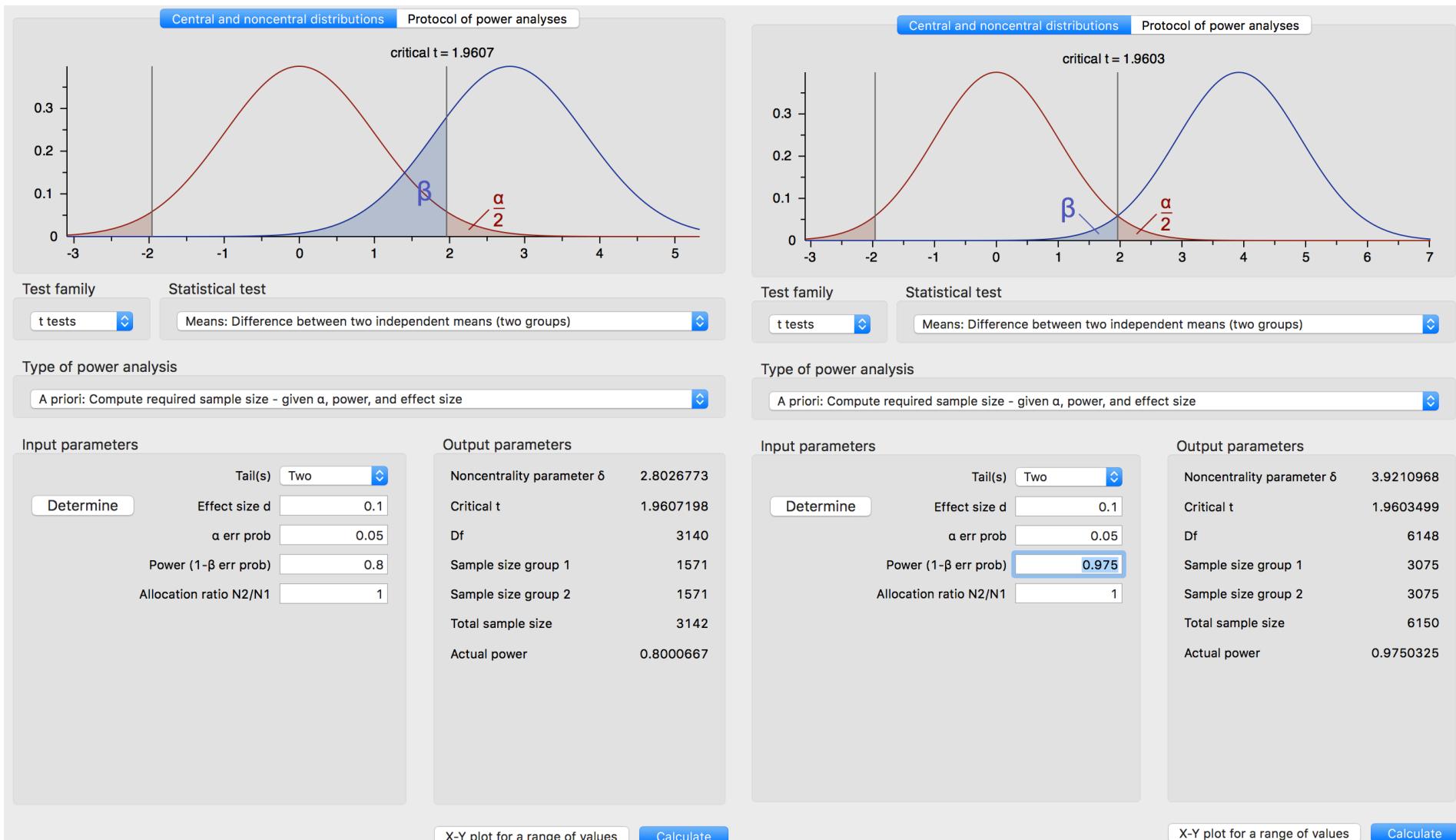
Total sample size 506

Actual power 0.8013584

Large effects are easy to find

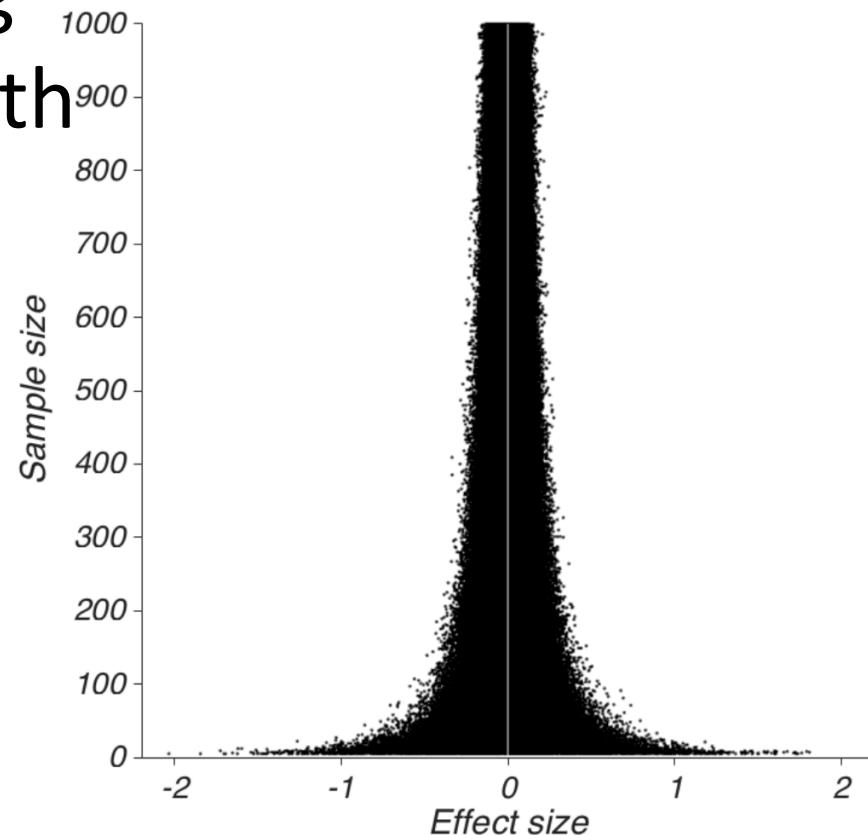


Small effects are not – particularly if you want to be sure



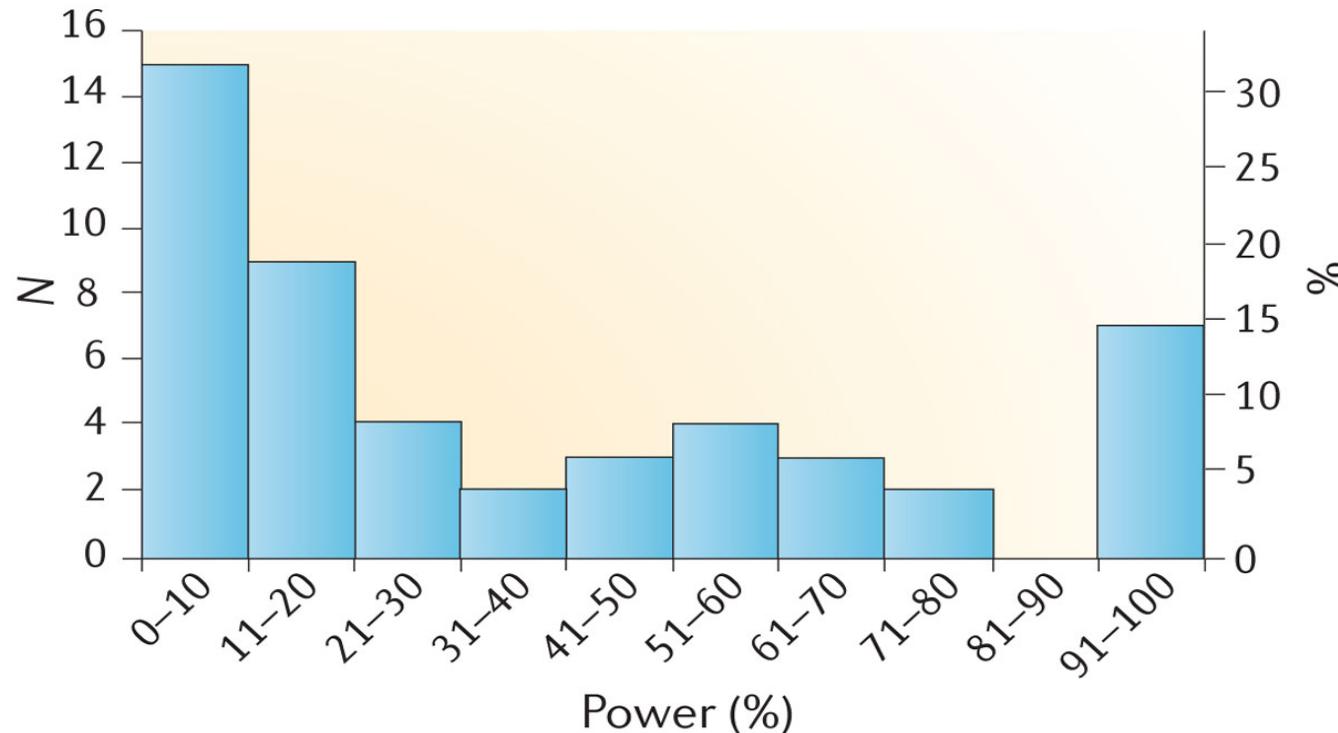
Only a priori power is real power

- Why?
- Because if one runs an underpowered study, one will likely have large sampling errors, in combination with publication bias, this overstates post-hoc or “observed” power.
- Observed power can be misleading:
- Witness the funnel plot

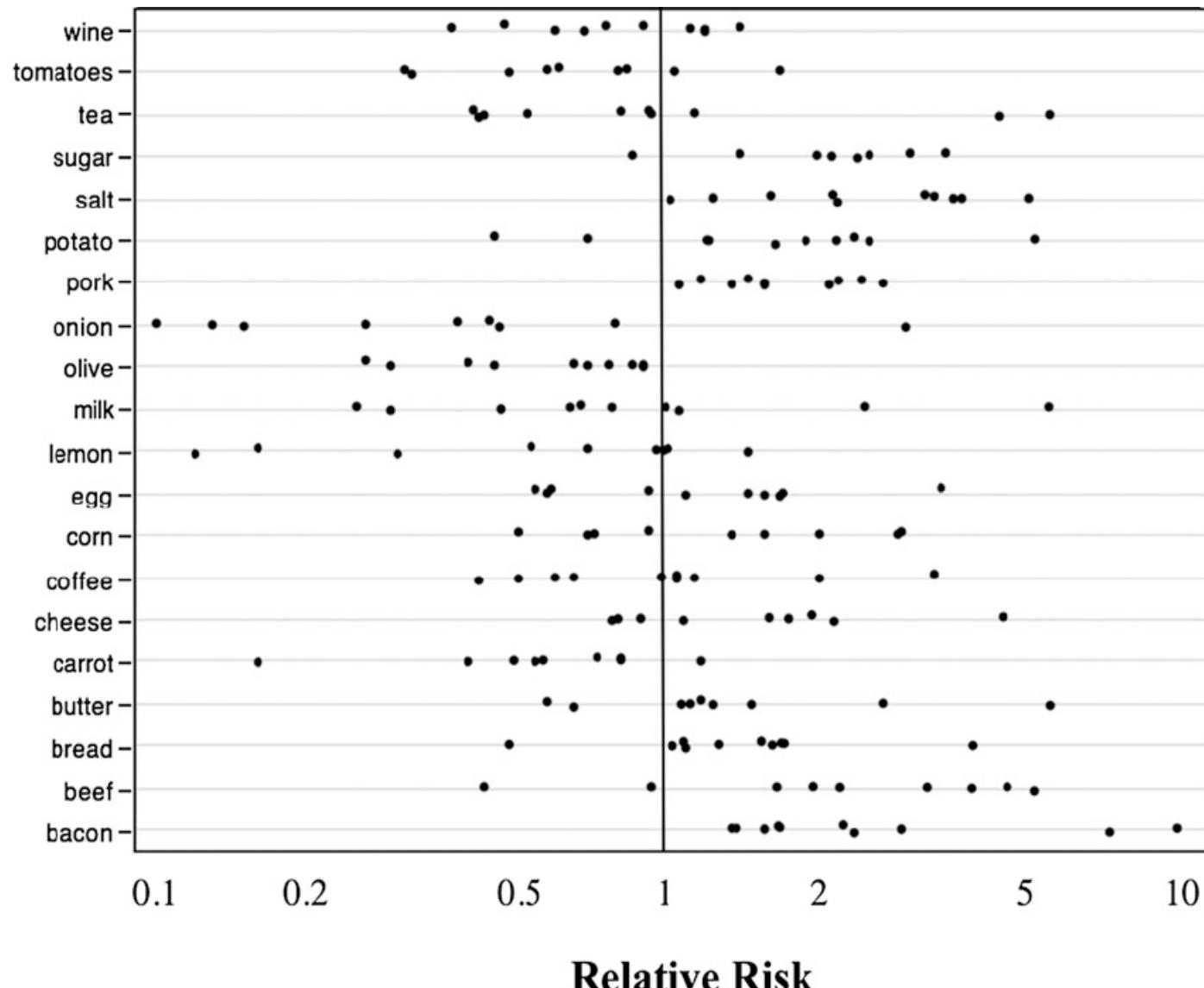


How is neuroscience doing, power-wise?

- Neuroscience research has an average power of between 8% and 31%. (Button et al., 2013).
- Median power is 21%



It's not just us: “Is everything we eat associated with cancer?” (Schoenfeld & Ioannidis 2013)



Why power is linked to confidence

- What is the probability that a published result is actually true?
- If we set the significance level α to 0.05, does this mean that the false positive rate in the field is 5%?
- No!

Why most published research findings are false (Ioannidis, 2005)

- It also depends on the prior probability of a true effect in a given field as well as power.
- PPV = “positive predictive value” – *post* study probability that a result is true:
- R: Ratio of true to false effects in a field.
- PPV links power, alpha and R.

$$PPV = (1 - \beta)R / (R - \beta R + \alpha)$$

$$PPV = (1 - \beta)R / ((1 - \beta)R + \alpha)$$

Deriving PPV

RESEARCH/REALITY	TRUE	FALSE	TOTAL
SIG	$1-\beta$	α	$1-\beta + \alpha$
NONSIG	β	$1-\alpha$	$\beta + 1-\alpha$
TOTAL	1	1	2

RESEARCH/REALITY	TRUE	FALSE	TOTAL
SIG	$N_T (1-\beta)$	$N_F \cdot \alpha$	$N_T (1-\beta) + N_F \cdot \alpha$
NONSIG	$N_T \cdot \beta$	$N_F (1-\alpha)$	$N_T \cdot \beta + N_F (1-\alpha)$
TOTAL	N_T	N_F	$N_T + N_F = c$

$$R = N_T/N_F \quad R \cdot N_F = c - N_F \quad R = N_T/N_F \quad N_T = c \cdot R / (R+1)$$

$$N_T = R \cdot N_F \quad R \cdot N_F + N_F = c \quad R/(R+1) = (N_T/N_F)/c/N_F$$

$$N_T = c - N_F \quad R + 1 = c/N_F \quad R/(R+1) = N_T/c \quad N_F = c/(R+1)$$

Deriving PPV

RESEARCH/REALITY	TRUE	FALSE	TOTAL
SIG	$N_T (1-\beta)$	$N_F \cdot \alpha$	$N_T (1-\beta) + N_F \cdot \alpha$
NONSIG	$N_T \cdot \beta$	$N_F (1-\alpha)$	$N_T \cdot \beta + N_F (1-\alpha)$
TOTAL	N_T	N_F	$N_T + N_F = c$

$$R = N_T / N_F \quad R \cdot N_F = c - N_F \quad R = N_T / N_F \quad N_T = c \cdot R / (R+1)$$

$$N_T = R \cdot N_F \quad R \cdot N_F + N_F = c \quad R / (R+1) = (N_T / N_F) / c / N_F$$

$$N_T = c - N_F \quad R + 1 = c / N_F \quad R / (R+1) = N_T / c \quad N_F = c / (R+1)$$

RESEARCH/REALITY	TRUE	FALSE	TOTAL
SIG	$c(1-\beta) \cdot R / (R+1)$	$c \cdot \alpha / (R+1)$	$c \cdot (R \cdot (1-\beta) + \alpha) / (R+1)$
NONSIG	$c \cdot \beta \cdot R / (R+1)$	$c \cdot (1-\alpha) / (R+1)$	$c \cdot (1 + R \cdot \beta - \alpha) / (R+1)$
TOTAL	$c \cdot R / (R+1)$	$c / (R+1)$	c

Deriving PPV

RESEARCH/REALITY	TRUE	FALSE	TOTAL
SIG	$c(1-\beta) \cdot R/(R+1)$	$c \cdot \alpha/(R+1)$	$c \cdot (R \cdot (1-\beta) + \alpha)/(R+1)$
NONSIG	$c \cdot \beta \cdot R/(R+1)$	$c \cdot (1-\alpha)/(R+1)$	$c \cdot (1 + R \cdot \beta - \alpha)/(R+1)$
TOTAL	$c \cdot R/(R+1)$	$c/(R+1)$	c

$$PPV = p(\text{effect true} \mid \text{significant}) = p(\text{true})/p(\text{sig}) \cdot p(\text{sig} \mid \text{true})$$

$$p(\text{true}) = N_T/c = R/(R+1)$$

$$p(\text{sig} \mid \text{true}) = 1-\beta$$

$$p(\text{sig}) = p(\text{sig} \mid \text{true}) \cdot p(\text{true}) + p(\text{sig} \mid \text{false}) \cdot p(\text{false})$$

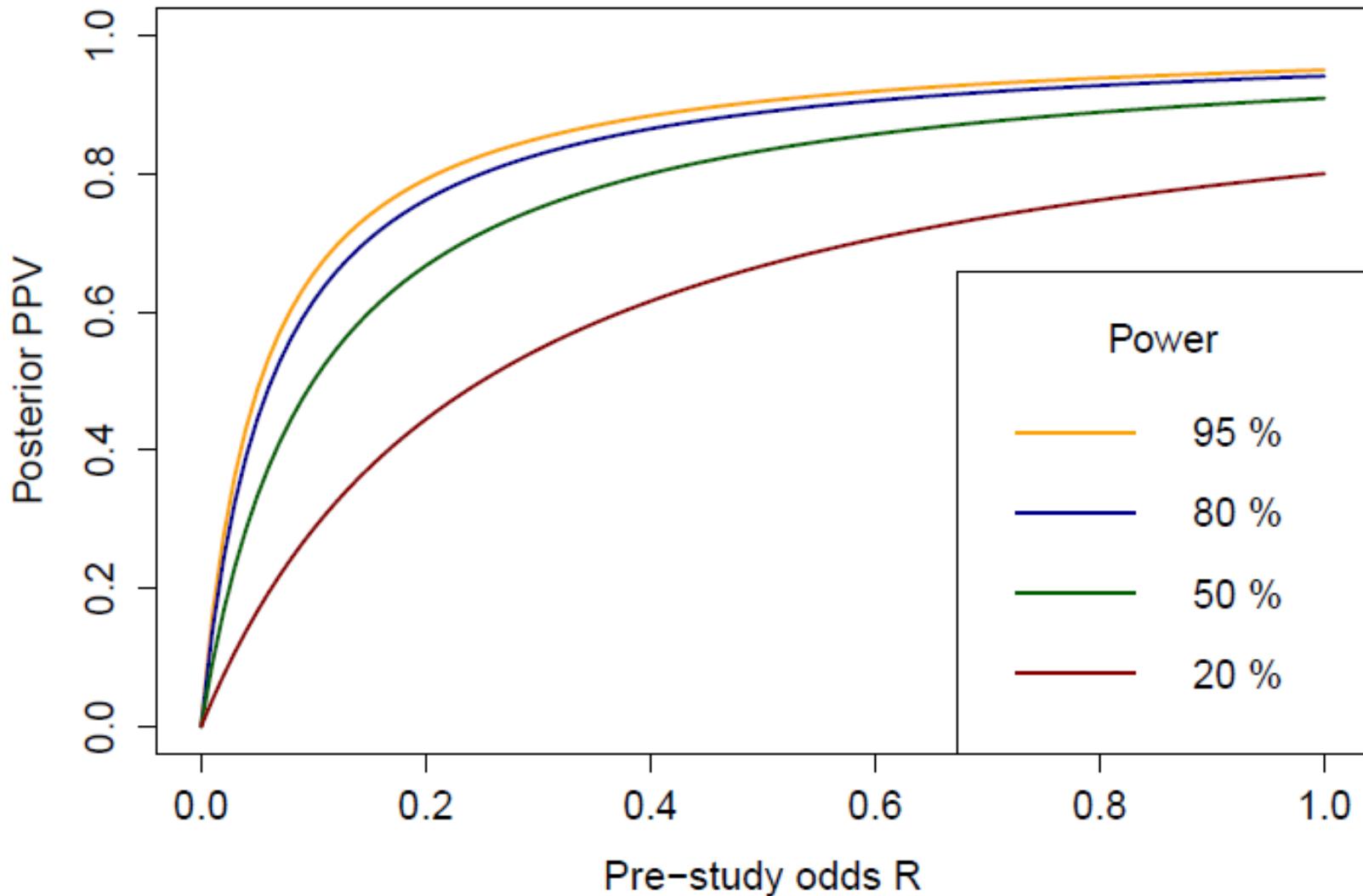
$$p(\text{sig}) = 1-\beta \cdot R/(R+1) + \alpha \cdot N_F/c$$

$$p(\text{sig}) = 1-\beta \cdot R/(R+1) + \alpha \cdot (R+1)$$

$$PPV = R/(R+1) / 1-\beta \cdot R/(R+1) + \alpha \cdot (R+1) \cdot 1-\beta$$

$$PPV = (1-\beta) \cdot R / ((1-\beta) \cdot R + \alpha)$$

Power critically affects PPV at low R



Higher power makes everything better

- Less misses (beta/type II errors)
- Less false positives (alpha/type I errors)
- Makes publication of null results legitimate (evidence of absence of an effect)
- Makes confidence intervals narrower
- Higher PPV