

Course at the Joint Research Centre  
of Ispra:

‘Sensitivity analysis,  
sensitivity auditing and  
beyond’  
Part on the p-test

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Ispra March 29–31

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sensitivity analysis, sensitivity auditing, science for policy, impact assessment

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# An investigation of the false discovery rate and the misinterpretation of $p$ -values

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David Colquhoun

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“If you are foolish enough to define ‘statistically significant’ as anything less than  $p=0.05$  then... you have a 29% chance (at least) of making a fool of yourself.

Who would take a risk like that? Judging by the medical literature, most people would. No wonder there is a problem”

## P values by way of an example

- Two groups, one with a placebo, one with the treatment
- Random allocation to groups (+more!)
- The difference  $d$  between the means of the two groups is tested (is it different from zero?)
- $p=0.05$  implies that if there were no effect the probability of observing a value equal to  $d$  or higher would be 5%

“At first sight, it might be thought that this procedure would guarantee that you would make a fool of yourself only once in every 20 times that you do a test”

Colquhoun D. 2014 An investigation of the false discovery rate and the misinterpretation of p-values. R. Soc. Open sci. 1: 140216. <http://dx.doi.org/10.1098/rsos.140216>

“The classical p-value does exactly what it says. But it is a statement about what would happen if there were no true effect. That cannot tell you about your long-term probability of making a fool of yourself, simply because sometimes there really is an effect. In order to do the calculation, **we need to know a few more things**”



## A classic exercise in screening

You test positive for AIDS (one test only). Time for despair?

Only one 1 in 100,000 has AIDS in your population

The test has a 5% false positive rate

Already one can say: in a population of say 100,000 one will have AIDS and 5,000 (5% of 100,000) will test positive

→ Don't despair (yet)

## Another exercise in screening (Colquhoun 2014)

You test positive for mild cognitive impairment (MCI) (one test only).  
Time to retire?

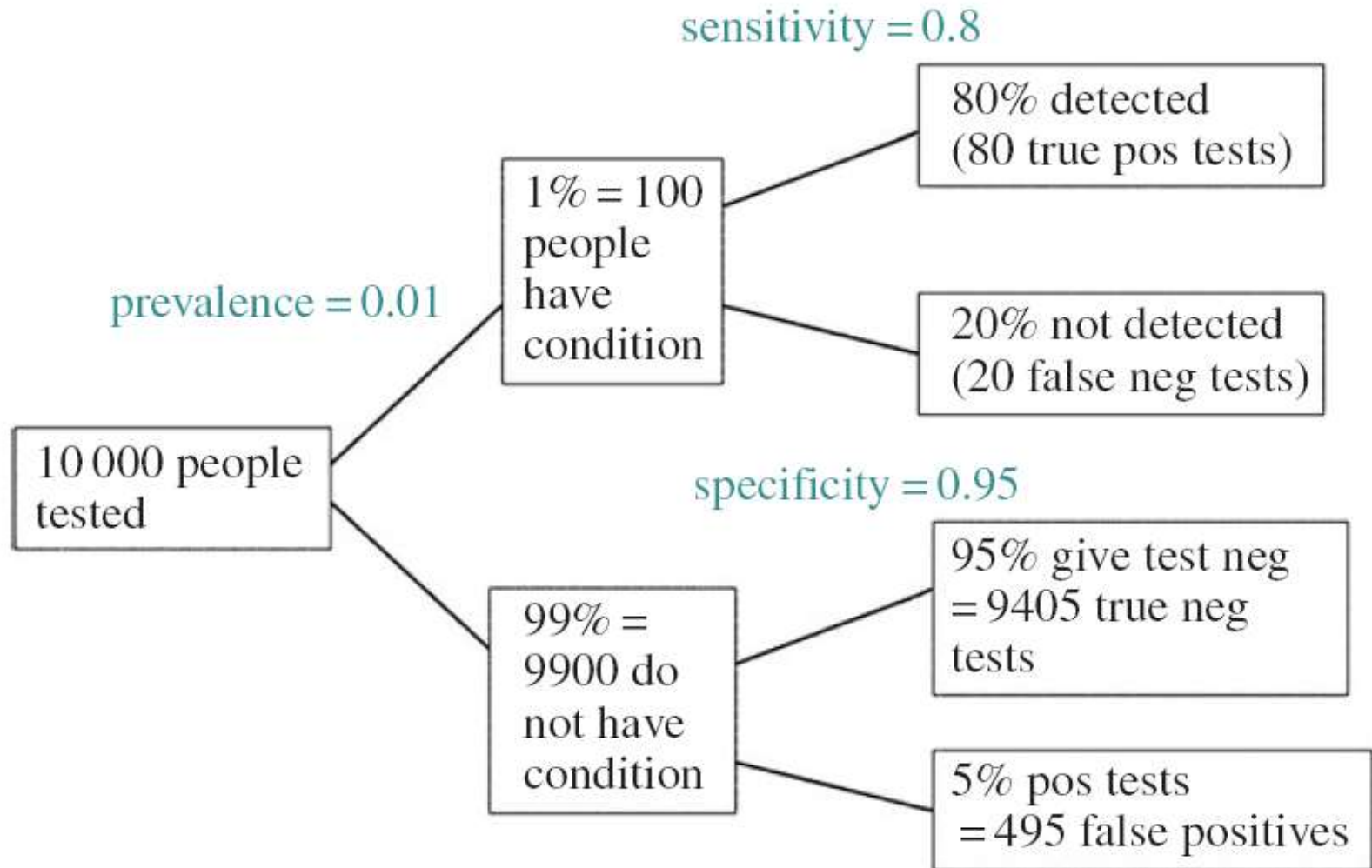
MCI prevalence in the population 1%, i.e. in a sample of 10,000 then 100 have MCI and 9,900 don't

The test has a 5% false positive rate; of the 9,900 who don't have MCI 495 test (false) positive and the remaining 9,405 (true) negative

The test does not pick all the 100 MCI but only 80; there will be 20 false negative. So we see  $80+495=575$  positive of which only 80 (a 14%) are true and the remaining 86% false

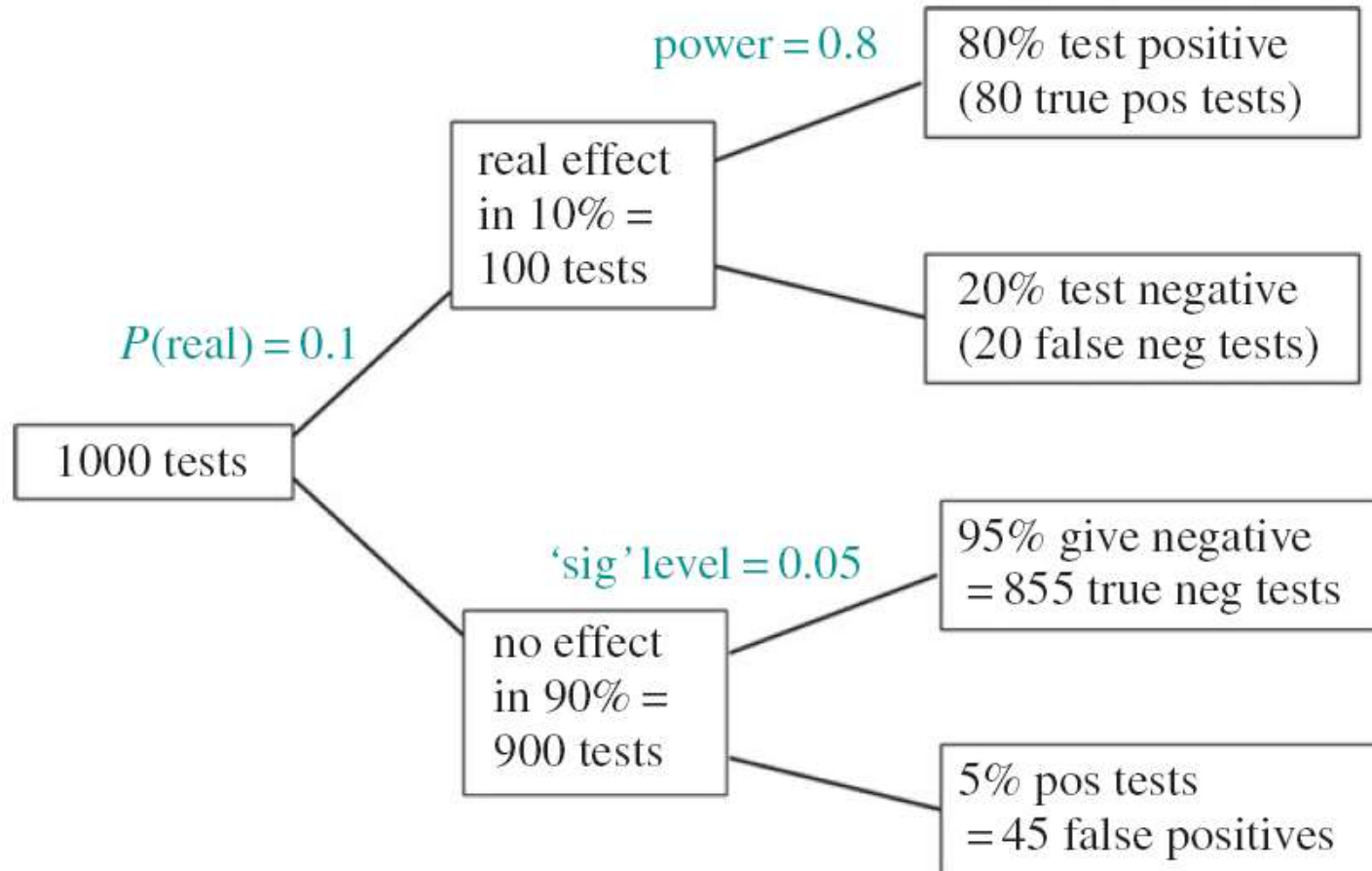
→ It does not make sense to screen the population for MCI!

The number  $86\% = 495 / (495 + 80)$  is our false discovery rate



The same concept of false discovery rate applies to the problem of significance test

# We now consider tests instead of individuals

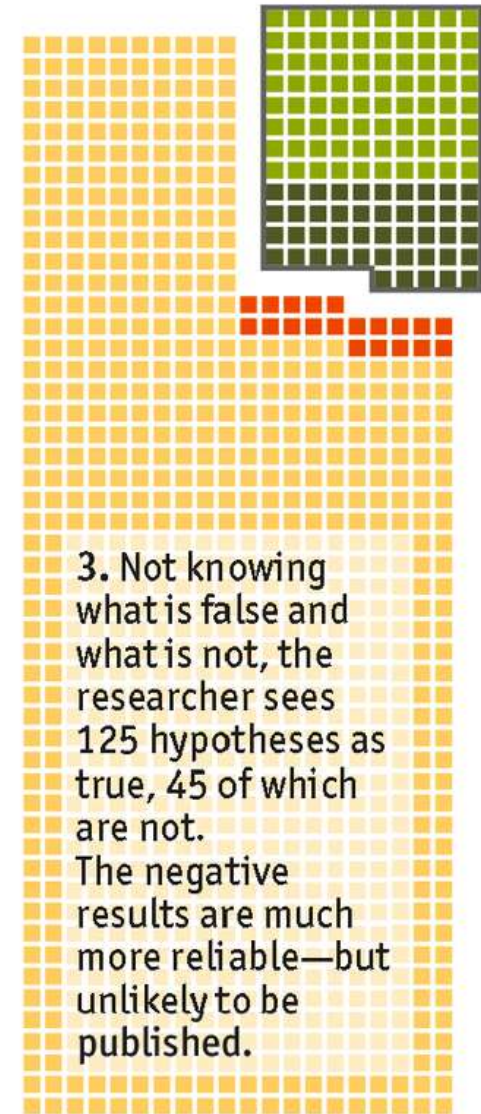
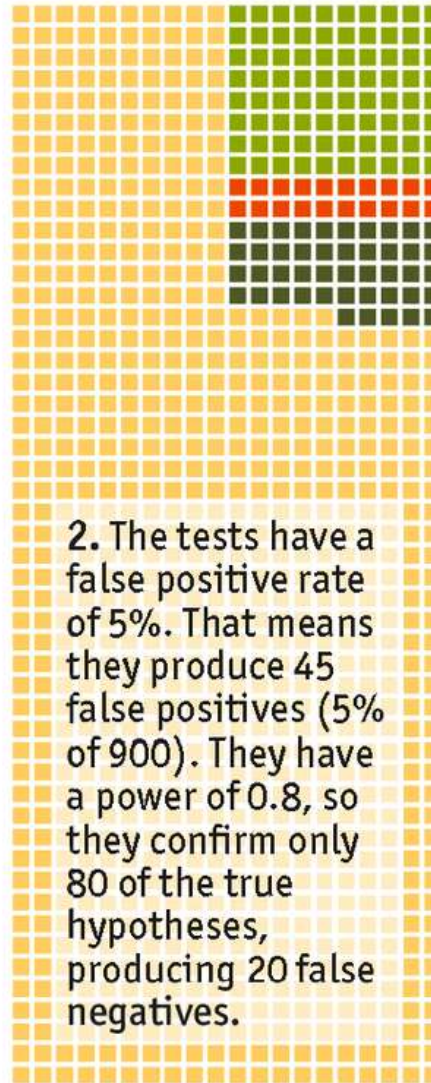
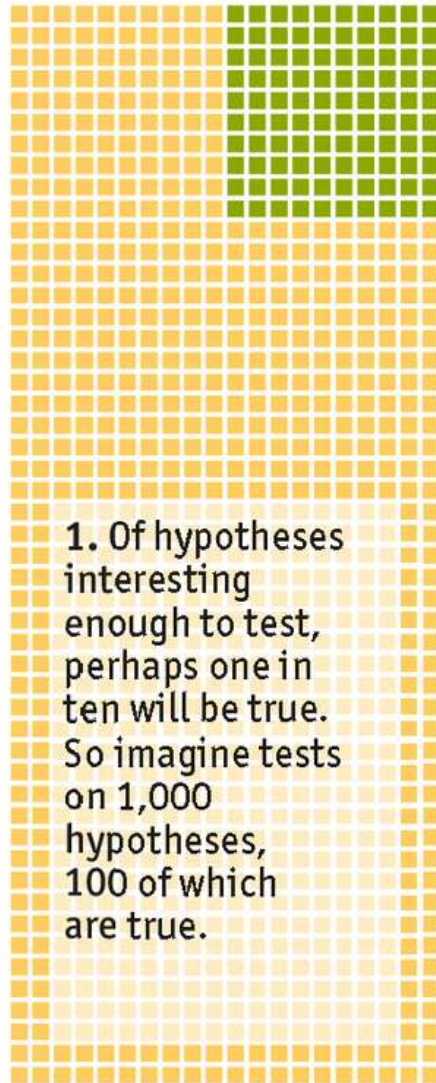


## Unlikely results

How a small proportion of false positives can prove very misleading

False True False negatives False positives

The false discovery rate is  $\sim$  the dark divided by the light green



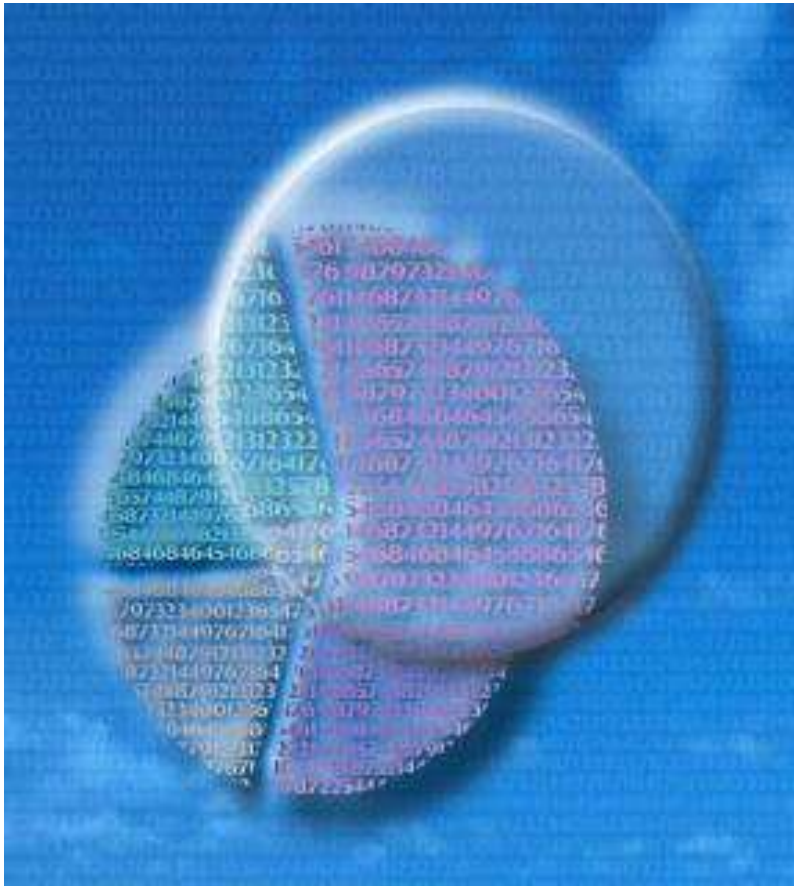
→ We see 125 hypotheses as true 45 of which are not;  
the false discovery rate is  $45/125 = 36\%$

Significance  $p=0.05$  → false discovery rate of 36%

We now know that  $p=0.05$  did not correspond to a  
chance in twenty of being wrong but to one in three

How many numbers did we need to know to reach this  
conclusion?





# END

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