

# Biostatistics II: Hypothesis testing

## Categorical data: McNemar test

### Multiple testing problem

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## In this Section

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- ▶ McNemar test
- ▶ Examples
- ▶ Multiple testing

# McNemar test: Theory

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## Assumptions

- ▶ The variables should be categorical
- ▶ Matched data (pairs)
- ▶ Pairs are independent of one another
- ▶ The levels (or categories) of the variables are mutually exclusive

# McNemar test: Theory

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## Scenario

Is there a difference in the percentage of patients with asthma between the placebo and the drug group (matched data)?

	Drug (asthma)	Drug (no asthma)	Total
Placebo (asthma)	a	b	a + b
Placebo (no asthma)	c	d	c + d
Total	a + c	b + d	n

## Hypothesis

$$H_0 : p_a + p_b = p_a + p_c \text{ and } p_c + p_d = p_d + p_b$$

$$H_1 : p_a + p_b \neq p_a + p_c \text{ and } p_c + p_d \neq p_d + p_b$$

$$H_0 : p_b = p_c$$

$$H_1 : p_b \neq p_c$$

# McNemar test: Theory

## Connection with regression

Conditional logistic model with one binary covariate

$$\pi = \frac{\Pr(Y_{s,drug}=asthma \mid Y_{s,placebo}=no\ asthma)}{\Pr(Y_{s,drug}=asthma \mid Y_{s,placebo}=no\ asthma) + \Pr(Y_{s,drug}=no\ asthma \mid Y_{s,placebo}=asthma)} = \frac{p_c}{p_c + p_b}$$

## Hypothesis

$$H_0: \beta = 0$$

$$\beta = \text{logit}(\pi) = 0$$

if we know that  $\text{logit}(\pi) = \log\left(\frac{\pi}{1-\pi}\right) \Rightarrow$

$$\beta = \log\left(\frac{\frac{p_c}{p_c+p_b}}{1 - \frac{p_c}{p_c+p_b}}\right) = \log\left(\frac{\frac{p_c}{p_c+p_b}}{\frac{p_c+p_b-p_c}{p_c+p_b}}\right) = \log\left\{\frac{p_c(p_c+p_b)}{p_b(p_c+p_b)}\right\} = \log\left(\frac{p_c}{p_b}\right)$$

$$\beta = 0 \Rightarrow \log\left(\frac{p_c}{p_b}\right) = 0 \Rightarrow \frac{p_c}{p_b} = 1 \Rightarrow p_c = p_b$$

# McNemar test: Theory

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## Test statistic

$$\chi^2 = \frac{(b-c)^2}{b+c}$$

When the values in the contingency table are fairly small a “correction for continuity” may be applied to the test statistic:

$$\chi^2 = \frac{(|b-c|-1)^2}{b+c}$$

# McNemar test: Theory

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## Sampling distribution

- ▶  $\chi^2$ -distribution with  $df = 1$
- ▶ Critical value and p-value

## Type I error

- ▶ Normally  $\alpha = 0.05$

## Draw conclusions

- ▶ Compare test statistic ( $X^2$ ) with the critical value or the p-value with  $\alpha$

# McNemar test: Application

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## Scenario

Is there a difference in the percentage of patients with asthma between the placebo and the drug group (matched data)?

## Hypothesis

$$H_0 : p_b = p_c$$

$$H_1 : p_b \neq p_c$$



# McNemar test: Application

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## Collect and visualize data

	Drug (asthma)	Drug (no asthma)	Sum
Placebo (asthma)	8	13	21
Placebo (no asthma)	18	11	29
Sum	26	24	50

## Test statistic

$$\chi^2 = \frac{(b-c)^2}{b+c} = \frac{(13-18)^2}{13+18} = 0.81 \text{ (with no continuity correction)}$$

## Degrees of freedom

$$df = 1$$

## Type I error

$$\alpha = 0.05$$

# McNemar test: Application

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## Critical values

Using R we get the critical values from the  $\chi^2$ -distribution:  
critical value $_{\alpha}$  = critical value $_{0.05}$

```
qchisq(p = 0.05, df = 1, lower.tail = FALSE)
```

```
[1] 3.841459
```

# McNemar test: Application

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## Draw conclusions

We reject the  $H_0$  if:

- ▶  $\chi^2 > \text{critical value}_\alpha$

We have  $0.81 < 3.84 \Rightarrow$  we do not reject the  $H_0$

Using R we obtain the p-value from the  $\chi^2$ -distribution:

```
pchisq(q = 0.81, df = 1, lower.tail = FALSE)
```

```
[1] 0.3681203
```

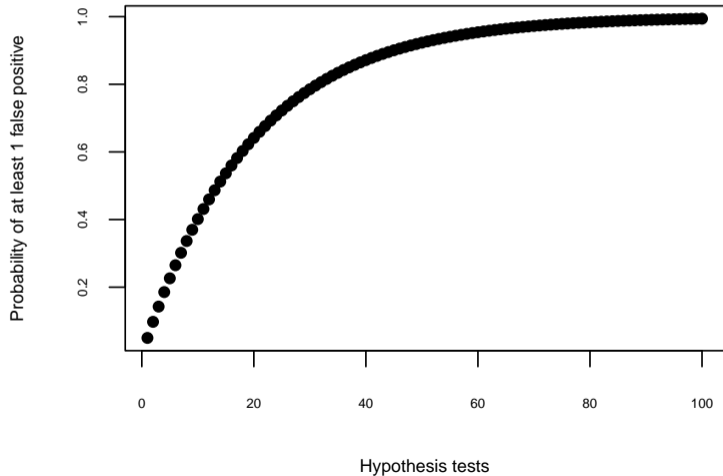
# Multiple testing

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- ▶ A single statistical test is rarely assumed
- ▶ If we perform  $m$  independent tests, what is the probability of at least 1 false positive?
  - ▶  $P(\text{Making an error}) = \alpha$
  - ▶  $P(\text{Not making an error}) = 1 - \alpha$
  - ▶  $P(\text{Not making an error in } m \text{ tests}) = (1 - \alpha)^m$
  - ▶  $P(\text{Making at least 1 error in } m \text{ tests}) = 1 - (1 - \alpha)^m$

# Multiple testing

Visualize this...



# Multiple testing

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Methods to adjust for multiple testing:

- ▶ **Bonferroni adjustment:** multiply the number of simultaneously tested hypothesis, e.g.  $p - value = \min(p - value * m, 1)$  or adjust the significant level to  $\alpha = \alpha/m$
- ▶ **Holm adjustment:**  $\alpha_i = \frac{\alpha}{m-i+1}$ , where  $i$  is the order of the hypothesis - we start from the smallest to the largest p-value
- ▶ **Hochberg adjustment:**  $\alpha_i = \frac{\alpha}{m-i+1}$ , where  $i$  is the order of the hypothesis - we start from the largest p-value

# Multiple testing

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## *It is not as easy as you think*

- ▶ What about the other institutions analyzing data from the same experiment?
- ▶ What about previous papers that were published on the same data?

## **Be transparent about what you have done!**

- ▶ Report effect sizes, confidence intervals, and p-values (avoid arbitrary bounds, e.g  $P < 0.05$ ;  $P > 0.4$ )
- ▶ Report whether you have adjusted for multiple testing or not

# Multiple testing

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## Note that...

- ▶ In studies with a clear primary hypothesis, adjustment is not necessary
- ▶ If in one manuscript one or more secondary outcomes are presented, then adjustment for multiple comparisons may be considered

**Take care:** Strict rules such as always adjust for all comparisons will motivate authors to remove/ignore non significant results to decrease the number of comparisons



## Further reading

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- ▶ Althouse AD. Adjust for multiple comparisons? It's not that simple. *The Annals of thoracic surgery*. 2016 May 1;101(5):1644-5.
- ▶ Chen SY, Feng Z, Yi X. A general introduction to adjustment for multiple comparisons. *Journal of thoracic disease*. 2017 Jun;9(6):1725.