Untitled

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Contents

- Binary outcomes and proportions
- Comparative parameters of risks and their estimation
- Binomial regression models and comparative parameters
- Adjustment for confounding and evaluation of modification by binomial regression

Main R functions covered:

- twoby2() (Epi package)
- ▶ glm()
- ci.lin() (Epi package)

Outcomes in epidemiologic research

Epidemiologic studies address the occurrence of diseases and other health related phenomena:

(a) cross-sectional: **prevalence** of diseases,

(b) longitudinal: disease incidence, and mortality

Often we want to compare the prevalence or incidence of disease between two groups defined by a binary $risk\ factor\ X$

ightharpoonup X = 1: exposed X = 0: unexposed

Types of outcome variables

- ightharpoonup Binary (0/1) variables at individual level
 - disease status at a time point
 - change of status, event or transition ({e.g.} from healthy to diseased)
- Proportions at group level
 - prevalence
 - incidence proportion or cumulative incidence,
- Rates of events
 - incidence or mortality rate (per 1000 y)
 - car accidents (per million km)
- Time to event
 - survival time (often censored)

Incidence and prevalence proportions}

▶ Incidence proportion (R) of a binary (0/1) outcome (disease, death etc.) over a fixed risk period is defined

$$R = \frac{D}{N} = \frac{\text{number of new cases during period}}{\text{size of population-at-risk at start}}$$

Also called {cumulative incidence} (or even "risk").\ NB.

This formula requires complete follow-up, i.e. no {censorings}, and absence of {competing risks}.

Prevalence (proportion) P of disease at time point t

$$P = \frac{\text{no. of existing cases at t}}{\text{total population size at t}}.$$

Two-group comparison

- ▶ Binary risk factor X: exposed vs. unexposed.
- Summarizy results from cohort study with fixed risk period and no losses:

Exposure	Cases	Non-cases	Group size
yes	D_1	C_1	N_1
no	D_0	C_0	N_0
total	D_+	<i>C</i> ₊	N_+

▶ Incidence proportions in the two exposure groups

$$R_1 = \frac{D_1}{N_1}, \qquad R_0 = \frac{D_0}{N_0}.$$

▶ These are crude *estimates* of the true *risks* π_1 , and π_0 of outcome in the two exposure categories.

Example: Observational clinical study

Treatment failure in two types of operation for renal calculi (Charig et al. 1986. BMJ 292: 879-882)

- ► OS = open surgery (invasive)
- ► PN = percutaneous nephrolithotomy

Treatment	Failure	Success	Patients	Failure-%
$group\;(j)$	(D_j)	(C_j)	(N_j)	(R_j)
OS $(j = 1)$	77	273	350	22.0
PN $(j = 0)$	60	290	350	17.1

Crude incidence proportions of treatment failure:

$$R_1 = 77/350 = 22.0\%, \qquad R_0 = 60/350 = 17.1\%$$

Risks and their comparative parameters

The **risk** or **probability** of binary outcome (e.g. new case of disease) in the exposed π_1 and in the unexposed π_0 as to binary risk factor X (values 1 and 0) are typically compared by

- risk difference $\theta = \pi_1 \pi_0$
- lacktriangledown risk ratio $\phi=\pi_1/\pi_0$
- odds ratio (risk odds ratio)

$$\psi = \frac{\pi_1/(1-\pi_1)}{\pi_0/(1-\pi_0)}$$

The odds ratio is close to the risk ratio when the risks are small (less than 0.1 – the rare-disease assumption).

Odds and Odds Ratio (OR)

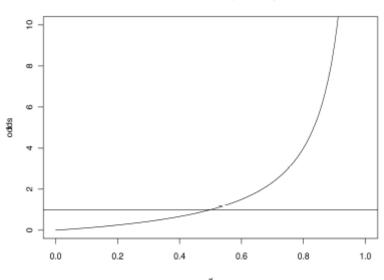
The **odds** (Ω) is the probability of binary outcome $P(Y=1)=\pi$ divided by the the probability of binary outcome $P(Y=0)=1-\pi$.

$$\Omega = \frac{\pi}{1-\pi}$$

- ▶ Odds of 2.5 means that the probability of Y=1 (success) is two and half times higher than the probability of Y=0 (failure)
- Odds 0.5 means that success probability of success is 50% of the probability of failure
- Odds of 1 implies that probability of both outcomes 0.5 (equal)

Probability and odds

Odds as function of probability



Risks and comparative parameters estimated

The risks π_1 and π_0 are estimated by empirical incidence proportions $R_1 = D_1/N_1$, and $R_0 = D_0/N_0$.

Crude estimates of comparative parameters

- ▶ incidence proportion difference $RD = R_1 R_0$
- ▶ incidence proportion ratio $RR = R_1/R_0$
- incidence odds ratio

$$OR = \frac{R_1/(1-R_1)}{R_0/(1-R_0)}$$

NB. To remove *confounding*, the estimated must be adjusted for relevant *confounders*.

Example: OS vs. PN (cont'd)

Crude estimates of true risk difference θ , risk ratio ϕ , and \setminus odds ratio ψ between OS and PN:

RD =
$$\frac{77}{350} - \frac{60}{350} = 0.22 - 0.171 = +0.049 (+4.9\%)$$

RR = $\frac{77/350}{60/350} = \frac{77/60}{350/350} = \frac{0.22}{0.171} = 1.283$
OR = $\frac{77/273}{60/290} = \frac{0.22/(1 - 0.22)}{0.171/(1 - 0.171)} = 1.363$

PN appears more successful than OS.

Is this (a) true, (b) due to bias, or (c) due to chance?

Example: OS vs. PN (cont'd)

Standard error of log(RR), 95% error factor (EF) of RR, and 95% CI for true risk ratio ϕ :

SEL =
$$\sqrt{\frac{1}{73} + \frac{1}{60} - \frac{1}{350} - \frac{1}{350}}$$

= **0.1547**
EF = $\exp\{1.96 \times 0.1547\}$
= **1.3543**
CI = $[1.2833/1.3543, 1.2833 \times 1.3543]$
= $[\mathbf{0.9476}, \mathbf{1.7380}]$.

Estimating comparative parameters in R

- ► A multitude of R functions in several packages are readily available for point estimation and CI calculation using either "exact" or/and various approximative methods.
- We shall here demonstrate the use of function twoby2() in the Epi package. It applies the simple Wald approximations as described above, but for
 - risk difference: the Newcombe method is used, and
 - odds ratio: the exact conditional method is also available.
- ► Hence, similar results are expected as obtained above.

Use of function twoby2()

Loading the Epi package:

```
library(Epi)
```

▶ Reading the counts of the 2 x 2-table into a matrix:

```
counts <- c(77, 273, 60, 290)
tab <- matrix( counts, nrow=2, byrow=T)</pre>
```

▶ Viewing the contents of the matrix/table:

tab

```
[,1] [,2]
[1,] 77 273
[2,] 60 290
```

Make 2 by 2 table

Calling the function with tab as its argument:

```
twoby2(tab)
2 by 2 table analysis:
Outcome · Col 1
Comparing: Row 1 vs. Row 2
     Col 1 Col 2 P(Col 1) 95% conf. interval
                 0.2200 0.1797 0.2664
       77 273
Row 1
Row 2
        60 290
                 0.1714 0.1355 0.2146
                                95% conf. interval
            Relative Risk: 1.2833
                                  0.9476 1.7380
        Sample Odds Ratio: 1.3632 0.9362 1.9851
Conditional MLE Odds Ratio: 1.3626 0.9206 2.0237
   Probability difference: 0.0486 -0.0103 0.1071
            Exact P-value: 0.1272
       Asymptotic P-value: 0.1061
```

Analyses based on binary regression model

Crude estimates and CIs for the comparative parameters can also be obtained by fitting appropriate **binary regression models** for the numbers D_j or proportions R_j .

Special cases of generalized linear models (GLM) with

- (i) random part: D_j is assumed to obey the binomial distribution or {family} with index N_j and probability π_j ,
- (ii) systematic part: {linear predictor} $\eta_j = \alpha + \beta X_j$, in which $X_j = 0$ for unexposed and $X_j = 1$ for exposed,
- **| (iii) link function**: g(.) that connects the probability π_j and the systematic part η_i by:

$$g(\pi_j) = \eta_j = \alpha + \beta X_j$$