A New Confidence Interval for the Odds Ratio

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Abstract We consider the problem of interval estimation of the odds ratio. An asymptotic confidence interval is widely applied in medical research. Unfortunately that confidence interval has a poor coverage probability: it is significantly smaller than the nominal confidence level. In this paper a new confidence interval is proposed. The construction needs only information on sample sizes and sample odds ratio. The coverage probability of the proposed confidence interval is at least the nominal confidence level.

Keywords confidence interval, odds ratio

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1. Introduction

In medical research, we often need to compare two treatments using binary data. Three parameters are commonly used: the difference of two proportions (the risk difference), the ratio of two proportions (the relative risk), and the odds ratio. The risk difference is an absolute measurement of effect, while the relative risk and the odds ratio are relative measurements for comparing outcomes. The odds ratio has a direct relationship with the regression coefficient in logistic regression.

The odds ratio is one of the parameters commonly used in such comparisons, especially in two-arm binomial experiments. This indicator was firstly applied by Cornfield (1951). The literature devoted to the analysis of odds ratio and its estimators is very rich, see e.g. Encyclopedia of Statistical Sciences Volume 9, pp. 5722-5726 (http://www.mrw.interscience.wiley.com/ess) and the literature therein.
The problem is in the interval estimation. There are two approaches to the problem. The first one consists of the analysis of $2 \times 2$ tables (Edwards 1963, Gart 1971, Thomas 1971). The second approach is based on logistic model in which the odds ratio has a direct relationship with the regression coefficient (Gart 1971, McCullagh 1980, Morris & Gardner 1988). That approach is commonly applied in applications and an asymptotic interval for odds ratio derived from logistic model is widely used (formula (S) in Section 3). This interval is applied in different statistical packages. There are also many internet scripts for calculating an asymptotic confidence interval (see e.g. http://www.hutchon.net/ConfidOR.htm). Unfortunately this confidence interval has some statistical disadvantages discussed in Section 3. To avoid those disadvantages a new confidence interval is proposed. The idea of construction is similar to the idea of construction of the confidence interval for the difference of two probabilities of success (the risk difference) proposed by Zieliski (2018).

In Section 2 a new confidence interval is constructed. In Section 3 some disadvantages of the asymptotic confidence interval are discussed. Final conclusions are given in Section 4.

2. A new confidence interval

Consider two independent r.v.’s $\xi_A$ and $\xi_B$ distributed as $\text{Bin}(n_A, p_A)$ and $\text{Bin}(n_B, p_B)$, respectively. The problem is in estimating the odds ratio:

$$OR = \frac{(p_A/(1-p_A))}{(p_B/(1-p_B))} = \frac{p_A}{1-p_A} \cdot \frac{(1-p_B)}{p_B}.$$  

Let $n_{A1}$ and $n_{B1}$ be observed numbers of successes. The data are usually organized in a $2 \times 2$ table:

|       | success | failure |
|-------|---------|---------|
| Group A | $n_{A1}$ | $n_{A0}$ | $n_A$ |
| Group B | $n_{B1}$ | $n_{B0}$ | $n_B$ |
|        | $n_1$   | $n_0$   | $n$   |

The standard estimator of $OR$ is as follows:

$$\hat{OR} = \frac{n_{A1}}{n_A - n_{A1}} \cdot \frac{n_B - n_{B1}}{n_{B1}} \quad (\ast)$$

Usually the problem of estimating an odds ratio is considered in the following statistical model:

$$\{(0, 1, \ldots, n_A) \times \{0, 1, \ldots, n_B\}, \{\text{Bin}(n_A, p_A) \cdot \text{Bin}(n_B, p_B) \cdot (p_A, p_B) \in (0, 1) \times (0, 1)\}\).$$

Since we are interested in estimating the odds ratio $r$, consider now a new statistical model. This model is the one-parameter model: the odds ratio is an unknown parameter

$$\mathcal{X}, \{F_r, 0 \leq r \leq +\infty\},$$
where
\[ \mathcal{X} = \left\{ \frac{n_{A1}}{n_A - n_{A1}} \frac{n_B - n_{B1}}{n_{B1}} : n_{A1} \in \{0, 1, \ldots, n_A\}, n_{B1} \in \{0, 1, \ldots, n_B\} \right\}. \]

The cumulative distribution functions \( F_r(\cdot) \) are defined as follows.

Note that the estimator \( \hat{OR} \) given by the formula (\( \star \)) is undefined for \( n_{A1} = 0 \) or \( n_{A1} = n_A \) and \( n_{B1} = 0 \) or \( n_{B1} = n_B \). We extend the definition of \( \hat{OR} \) in the following way:

\[ \hat{OR} = \begin{cases} 0, & \text{for } (n_{A1} = 0, n_{B1} \geq 1) \text{ or } (n_{A1} \leq n_A - 1, n_{B1} = 0) \\ +\infty, & \text{for } (n_{A1} = n_A, n_{B1} \geq 1) \text{ or } (n_{A1} \leq n_A - 1, n_{B1} = 0) \\ 1, & \text{for } (n_{A1} = 0, n_{B1} = 0) \text{ or } (n_{A1} = n_A, n_{B1} = n_B) \\ \text{formula } (\star), & \text{elsewhere} \end{cases} \]

To find the distribution of \( \hat{OR} \), note that for a given odds ratio equal to \( r > 0 \)
\[ p_B = \frac{p_A}{p_A + r(1 - p_A)}, \quad 1 - p_B = \frac{r(1 - p_A)}{p_A + r(1 - p_A)}. \]

The probability of observing \( \xi_A = n_{A1} \) and \( \xi_B = n_{B1} \) equals
\[ P_{p_A,p_B} \{n_{A1}, n_{B1}\} = \binom{n_A}{n_{A1}} p_A^{n_{A1}} (1 - p_A)^{n_A - n_{A1}} \binom{n_B}{n_{B1}} p_B^{n_{B1}} (1 - p_B)^{n_B - n_{B1}}. \]

Equivalently
\[ P_{r,p_A} \{n_{A1}, n_{B1}\} = r^{n_B - n_{B1}} \binom{n_A}{n_{A1}} \binom{n_B}{n_{B1}} \frac{p_A^{n_{A1} + n_{B1}} (1 - p_A)^{n_A + n_{B1} - n_{A1} - n_{B1}}}{(p_A + r(1 - p_A))^n_B}. \]

The probability \( p_A \) is eliminated by an appropriate integration
\[ P_r \{n_{A1}, n_{B1}\} = \int_0^1 P_{p_A,p_B} \{n_{A1}, n_{B1}\} dp_A = n! \binom{n_A}{n_{A1}} \binom{n_B}{n_{B1}} \binom{1}{r}^{n_{B1}} 2F_1 \left[ n_B, n_1 + 1; n + 2; 1 - \frac{1}{r} \right], \]

where
\[ 2F_1 [x, y; z; t] = \frac{1}{\Gamma(z - y)\Gamma(y)} \int_0^1 u^{y-1} (1 - u)^{z-y-1} (1 - ut)^{-x} du \text{ (for } z > y > 0) \]

is the regularized confluent hypergeometric function. The cdf of \( \hat{OR} \) equals (for \( t \geq 0 \))
\[ F_r(t) = P_r \left\{ \hat{OR} \leq t \right\} = \sum_{n_{A1}=0}^{n_A} \sum_{n_{B1}=0}^{n_B} P_r \{n_{A1}, n_{B1}\} 1 \left( \hat{OR} (n_{A1}, n_{B1}) \leq t \right), \]

where \( 1 (q) = 1 \) when \( q \) is true and \( = 0 \) elsewhere.

The family \( \{F_r, r \geq 0\} \) is stochastically ordered, i.e. for a given \( t > 0 \)
\[ F_{r_1}(t) \geq F_{r_2}(t) \text{ for } r_1 \leq r_2. \]

It follows from the fact that for a given \( n_{A1}, n_{B1} \) and \( p_A \) the probability \( P_{r,p_A} \{n_{A1}, n_{B1}\} \) is the decreasing function of odds ratio \( r \) and hence \( P_r \{n_{A1}, n_{B1}\} \) is also decreasing in \( r \).

Let
\[ G_r(t) = P_r \left\{ \hat{OR} < t \right\} = \sum_{n_{A1}=0}^{n_A} \sum_{n_{B1}=0}^{n_B} P_r \{n_{A1}, n_{B1}\} 1 \left( \hat{OR} (n_{A1}, n_{B1}) < t \right). \]
Let $\gamma$ be the given confidence level and let $\hat{r}$ be the observed odds ratio. The confidence interval for $r$ takes on the form

$$(Left (\hat{r}), Right (\hat{r})),$$

where

$$Left (\hat{r}) = \begin{cases} 0, & \hat{r} = 0, \\ 0, & \text{if } \lim_{r \to 0} G_r (\hat{r}) < (1 + \gamma)/2, \\ r^*, & r^* = \max \{r : G_r (\hat{r}) \geq (1 + \gamma)/2\}, \end{cases}$$

and

$$Right (\hat{r}) = \begin{cases} \infty, & \hat{r} = \infty, \\ \infty, & \text{if } \lim_{r \to \infty} F_r (\hat{r}) > (1 - \gamma)/2, \\ r^*, & r^* = \min \{r : F_r (\hat{r}) \leq (1 - \gamma)/2\}, \end{cases}$$

Theorem. For $n_A > \frac{2}{1 - \gamma} - 1$ the confidence interval for the odds ratio is two-sided and is one-sided otherwise.

For the proof see Appendix 1.

If $\hat{r}$ is the observed odds ratio then the confidence interval for $r$ takes on the following form:

for $\hat{r} \in [0, 1)$:

$$\begin{cases} (0, r^*), & \text{for } n_A \leq \frac{2}{1 - \gamma} - 1, \\ (r^*, r^*), & \text{for } n_A > \frac{2}{1 - \gamma} - 1, \end{cases}$$

for $\hat{r} \in [1, +\infty)$:

$$\begin{cases} (r^*, +\infty), & \text{for } n_A \leq \frac{2}{1 - \gamma} - 1, \\ (r^*, r^*), & \text{for } n_A > \frac{2}{1 - \gamma} - 1, \end{cases}$$

where $r^*$ and $r^*$ are given by the formula $(M)$.

Minimal sample sizes $n_A$ for which two-sided confidence interval exists are given in Table 1.

| $\gamma$ | 0.9 | 0.95 | 0.99 | 0.999 |
|---|---|---|---|---|
| $n_A$ | 20 | 40 | 200 | 2000 |

For a given $r > 0$ the coverage probability, by construction, equals at least $\gamma$. In Figure 1 there is shown the coverage probability for $n_A = 60$ and $n_B = 70$. On the $x$-axis the value $r$ of the odds ratio is given and on the $y$-axis the probability of coverage is shown. The coverage probabilities are calculated, not simulated.
Remark. The above considerations are made for A versus B. It is obvious that
\[ OR(A \text{ vs } B) = \frac{1}{OR(B \text{ vs } A)} . \]
It is easily seen that the new confidence interval has the following natural property:
\[ \text{Left}(A \text{ vs } B) = \frac{1}{\text{Right}(B \text{ vs } A)} \quad \text{and} \quad \text{Right}(A \text{ vs } B) = \frac{1}{\text{Left}(B \text{ vs } A)}. \]
In case of considering B versus A in the Theorem the sample size \( n_A \) should be changed to \( n_B \).

3. **Standard confidence interval**

Estimating the odds ratio is one of the crucial problems in medicine, biometrics etc. The most widely used confidence interval at the confidence level \( \gamma \) is of the form
\[
\left( \hat{OR} \cdot \exp \left( u_{1-\gamma} \sqrt{ \frac{1}{n_{A1}} + \frac{1}{n_{A0}} + \frac{1}{n_{B1}} + \frac{1}{n_{B0}} } \right), \hat{OR} \cdot \exp \left( u_{1+\gamma} \sqrt{ \frac{1}{n_{A1}} + \frac{1}{n_{A0}} + \frac{1}{n_{B1}} + \frac{1}{n_{B0}} } \right) \right), \quad (S)
\]
where \( u_\delta \) denotes the \( \delta \) quantile of \( N(0,1) \) distribution. In the above formula the estimator \( \hat{OR} \) is given by (*). Unfortunately this confidence interval has at least three disadvantages. They are as follows.

1. **Confidence interval (S) does not exist if at least one of** \( n_{A0}, n_{A1}, n_{B0} \) or \( n_{B1} \) equals zero.

2. **The coverage probability of c.i. (S) is less than the nominal one.** In Figure 2 the coverage probability is shown for \( n_A = 60, n_B = 70 \) and \( \gamma = 0.95 \) (the value \( r \) of odds ratio is given on the x-axis and the coverage probability is given on the y-axis).

![Figure 2. Coverage probability of (S).](image)

The probability of wrong conclusion, i.e. of overestimation or underestimation is greater than the assumed 0.05. Of course it is in contradiction to Neyman (1934, p. 562) definition of a confidence interval.

3. **The standard asymptotic confidence interval requires the knowledge of sample sizes as well as sample proportions in each sample.** Unfortunately it may lead to misunderstandings. Namely, suppose that six
experiments were conducted. In each experiment two samples of sizes sixty and seventy respectively, were drawn ($n_1 = 60$, $n_2 = 70$). The resulting numbers of successes are shown in Table 2 (the first two columns). It is seen that the sample odds ratio (the third column) is the same in all experiments, but the confidence intervals are quite different. Moreover, for example in the first experiment it may be claimed that the population odds in groups $A$ and $B$ may be treated as equal, while in the fourth one such a conclusion should not be drawn.

4. Conclusions

In this paper a new confidence interval for the odds ratio is proposed. The confidence interval is based on the exact distribution of the sample odds ratio, hence it works for large as well as for small samples. The coverage probability of that confidence interval is at least the nominal confidence level, in contrast to asymptotic confidence intervals known in the literature. It must be noted that the only information needed to construct the new confidence interval are the sample sizes and the sample odds ratio. Unfortunately, no closed formulae for the ends of the confidence interval are available. However, for given $n_A$, $n_B$ and observed $\hat{OR}$ the ends may be easily numerically computed with the aid of the standard software such as R, Mathematica etc (see Appendix 2).

Since the proposed confidence interval may be applied for small as well as for large sample sizes, it may be recommended for practical use.

References

Cornfield, J. (1951). A Method of Estimating Comparative Rates from Clinical Data. Applications to Cancer of the Lung, Breast, and Cervix. JNCI: Journal of the National Cancer Institute. 11:1269-1275, DOI: 10.1093/jnci/11.6.1269

Edwards, A. W. F. (1963). The Measure of Association in a $2 \times 2$ Table. Journal of the Royal Statistical Society. Ser. A. 126: 109-114. DOI: 10.2307/2982448.

Gart, J. J. (1971). The comparison of proportions: a review of significance tests, confidence intervals, and adjustments for stratification. Review of the International Statistical Institute. 39: 148-169.

Lawson, R. (2004). Small Sample Confidence Intervals for the Odds Ratio. Communications in Statistics - Simulation and Computation. 33: 1095-1113, DOI: 10.1081/SAC-200040691.

Morris, J. A., Gardner M. J. (1988). Calculating confidence intervals for relative risks (odds ratios) and standardised ratios and rates. British Medical Journal. 296: 1313-6. DOI: 10.1136/bmj.296.6632.1313.
McCullagh, P. (1980). Regression Models for Ordinal Data. Journal of the Royal Statistical Society. Ser. B. 42: 109-142.

Neyman, J. (1934). On the Two Different Aspects of the Representative Method: The Method of Stratified Sampling and the Method of Purposive Selection, Journal of the Royal Statistical Society. 97: 558-625.

Thomas, D. G. (1971). Algorithm AS-36: exact confidence limits for the odds ratio in a 2 × 2 table. Applied Statistics. 20: 105-110.

Wang, W., Shan G. (2015). Exact Confidence Intervals for the Relative Risk and the Odds Ratio. Biometrics. 71: 985-995 DOI: 10.1111/biom.12360.

Zieliński, W. (2018). A new exact confidence interval for the difference of two binomial proportions. REVSTAT-Statistical Journal. (https://www.ine.pt/revstat/pdf/ANewExactConfidenceInterval.pdf)

Appendix 1

A few remarks before the proof.

**Remark 1.** \( P_r \{ n_{A1}, n_{B1} \} \to \begin{cases} 0, & \text{as } r \to 0 \\ 0, & \text{as } r \to +\infty \end{cases} \) for \( 1 \leq n_{A1} \leq n_A - 1 \) and \( 1 \leq n_{B1} \leq n_B - 1 \)

**Proof of Remark 1.** For \( 1 \leq n_{A1} \leq n_A - 1 \) and \( 1 \leq n_{B1} \leq n_B - 1 \)

\[
P_{r,PA} \{ n_{A1}, n_{B1} \} \propto p_A^{n_{A1}} (1-p_A)^{n_A-n_{A1}} \cdot \left( \frac{p_A}{p_A + r(1-p_A)} \right)^{n_{B1}} \left( \frac{r(1-p_A)}{p_A + r(1-p_A)} \right)^{n_B-n_{B1}}
\]

\[
\to \begin{cases} 0, & \text{as } r \to 0 \\ 0, & \text{as } r \to +\infty \end{cases}
\]

Hence \( P_r \{ n_{A1}, n_{B1} \} \to 0 \) as \( r \to 0 \) or \( r \to \infty \).

**Remark 2.** \( P_r \{ \hat{OR} = 0 \} \to \begin{cases} \frac{n_A}{n_A + 1}, & \text{as } r \to 0 \\ 0, & \text{as } r \to +\infty \end{cases} \)

**Proof of Remark 2.** Note that \( \hat{OR} = 0 \) iff \( (n_{A1} = 0 \text{ and } n_{B1} \geq 2) \) or \( (1 \leq n_{A1} \leq n_A - 1 \text{ and } n_{B1} = n_B) \).

Hence

\[
P_{r,PA} \{ \hat{OR} = 0 \} = (1-p_A)^{n_A} \sum_{n_{B1} \geq 1} \frac{n_{B1}}{n_{B1}} p_B^{n_{B1}} (1-p_B)^{n_B-n_{B1}} + p_B^{n_B} \sum_{n_{A1}=1}^{n_A-1} \frac{n_{A1}}{n_{A1}} p_A^{n_{A1}} (1-p_A)^{n_A-n_{A1}}
\]

\[
= (1-p_A)^{n_A} \left( 1 - \left( \frac{r(1-p_A)}{p_A + r(1-p_A)} \right)^{n_B} \right) + \left( \frac{p_A}{p_A + r(1-p_A)} \right)^{n_B} (1-p_A^{n_A} - (1-p_A)^{n_A})
\]

\[
\to \begin{cases} (1-p_A)^{n_A} + (1-p_A^{n_A} - (1-p_A)^{n_A}) = 1 - p_A^{n_A}, & \text{as } r \to 0 \\ 0, & \text{as } r \to +\infty \end{cases}
\]

We obtain

\[
P_r \{ \hat{OR} = 0 \} = \int_0^1 P_{r,PA} \{ \hat{OR} = 0 \} dp_A \to \begin{cases} \frac{n_A}{n_A + 1}, & \text{as } r \to 0 \\ 0, & \text{as } r \to +\infty \end{cases}
\]

**Remark 3.** \( P_r \{ \hat{OR} = 1 \} \to \begin{cases} \frac{1}{n_A + 1}, & \text{as } r \to 0 \\ \frac{1}{n_A + 1}, & \text{as } r \to +\infty \end{cases} \)
Proof of Remark 3. Note that $\hat{O}R = 1$ iff $n_A A_B = n_B A_B$. Hence

$$P_{r,p_A}\{\hat{O}R = 1\} = (1 - p_A)^n_A (1 - p_B)^n_B + \sum_{n_A = 1}^{n_A - 1} P_{r,p_A}\{n_A, n_B\}$$

$$= (1 - p_A)^n_A \left( \frac{r(1 - p_A)}{p_A + r(1 - p_A)} \right)^{n_B} + \sum_{n_A = 1}^{n_A - 1} P_{r,p_A}\{n_A, n_B\}$$

$$\rightarrow \begin{cases} p_A^n_A, & as \ r \rightarrow 0 \\ (1 - p_A)^n_A, & as \ r \rightarrow +\infty \end{cases}$$

We obtain

$$P_{r,\{\hat{O}R = 1\}} = \int_0^1 P_{r,p_A}\{\hat{O}R = 1\} dp_A \rightarrow \begin{cases} \frac{1}{n_A + 1}, & as \ r \rightarrow 0 \\ \frac{1}{n_A + 1}, & as \ r \rightarrow +\infty \end{cases}$$

Theorem. For $n_A > \frac{2}{1 - \gamma} - 1$ the confidence interval for $r$ is two-sided and is one-sided otherwise.

Proof.

For $0 < t < 1$ we have

$$P_r\{\hat{O}R \leq t\} = P_r\{\hat{O}R = 0\} + P_r\{0 < \hat{O}R \leq t\} \rightarrow \begin{cases} \frac{1}{n_A + 1}, & as \ r \rightarrow 0 \\ 0, & as \ r \rightarrow +\infty \end{cases}$$

If $\frac{n_A}{n_A + 1} > \frac{1 + \gamma}{2}$, i.e. $n_A > \frac{2}{1 - \gamma} - 1$, the confidence interval is two-sided. Otherwise the c.i. is one sided with the left end equal to 0.

For $1 \leq t < +\infty$ we have

$$P_r\{\hat{O}R \leq t\} = P_r\{\hat{O}R < 1\} + P_r\{\hat{O}R = 1\} + P_r\{1 < \hat{O}R < +\infty\} \rightarrow \begin{cases} 1, & as \ r \rightarrow 0 \\ \frac{1}{n_A + 1}, & as \ r \rightarrow +\infty \end{cases}$$

If $\frac{1}{n_A + 1} < \frac{1 + \gamma}{2}$, i.e. $n_A > \frac{2}{1 - \gamma} - 1$, the confidence interval is two-sided. Otherwise the c.i. is one sided with the right end equal to $+\infty$.

Appendix 2

An exemplary R code for calculating the confidence interval for odds ratio is enclosed.

```r
OR=function(n,m){
  ifelse(m[1]==0 & m[2]==0,0,
    ifelse(m[1]==n[1] & m[2]==n[2],2*(n[1]-1)*(n[2]-1),
      ifelse(m[2]==0,2*(n[1]-1)*(n[2]-1),
        ifelse(m[1]==n[1],2*(n[1]-1)*(n[2]-1),m[1]*(n[2]-m[2])/(n[1]-m[1])/m[2])))
  )
}
f=function(rr,k1,k2,pA){dbinom(k1,n[1],pA)*dbinom(k2,n[2],pA/(pA+rr*(1-pA)))}
nieostar=function(rr,tt){
  line<0
  prawd<0
  for (k1 in 0:n[1])
    for (k2 in 0:n[2])
      {
        mrob=c(k1,k2)
        if(OS(n,mrob)<tt)
          line=line+1;
      }
```

8
ostra=function(rr,tt)
{
line<-0
prawd=c()
for (k1 in 0:n[1])
for (k2 in 0:n[2])
{krob=c(k1,k2)
if(OR(n,mrob)<tt)
{line=line+1;
prawd[line]=integrate(f,0,1,rr=rr,k1=k1,k2=k2,subdivisions = 1000000L,stop.on.error = FALSE)$value;}}
tg=sum(prawd)
}
CI=function(n,m,level)
{
orobs<-OR(n,m)
eps=1e-6
ifelse(orobs<1,
{
L=0;
P=uniroot(function(t){ostra(t,orobs)-(1-level)/2}, lower = orobs, upper = 2*(n[1]-1)*(n[2]-1),
tol = eps)$root,
{L=uniroot(function(t){nieostra(t,orobs)-(1+level)/2}, lower = 0.00000001, upper = orobs,
tol = eps)$root;
P=uniroot(function(t){ostra(t,orobs)-(1-level)/2}, lower = orobs, upper = 2*(n[1]-1)*(n[2]-1),
tol = eps)$root});
}{ifelse(n[1]<=2/(1-level)-1,
{L=uniroot(function(t){nieostra(t,orobs)-(1+level)/2}, lower = 0.00000001, upper = orobs, tol = eps)$root;
P=Inf,
{L=uniroot(function(t){nieostra(t,orobs)-(1+level)/2}, lower = 0.00000001, upper = orobs, tol = eps)$root;
P=uniroot(function(t){ostra(t,orobs)-(1-level)/2}, lower = orobs, upper = 2*(n[1]-1)*(n[2]-1),
tol = eps)$root});
)
print(paste("Confidence interval for odds ratio (",round(L,5),",",round(P,5),") at the confidence level ",
level,sep=""),quote=FALSE)
}
print(paste("Sample odds ratio equals ",round(orobs,4), "; n1="n[1],", n2="n[2],sep=""),quote=FALSE)

#Example of usage
n=c(60,70) # input n_A and n_B
m=c(7,63) # input n_A1 and n_B1
CI(n,m,level=0.95)