

Notes on Upper and Lower Bounds of Odds Ratio

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Abstract

We shall give upper and lower bounds of the odds ratio of an event by a slight condition of the conditional probability of events.

Key Words and Phrases: odds ratio, conditional probability.

1. Introduction

Throughout, all sets are used as events in the same sample space Ω . Define $\frac{P(A)}{P(A^c)}$ be the odds ratio of an event A, $0 < P(A) < 1$ (see Ross(1998)). And in the Bernoulli trial, the odds ratio of a successive event can be applied to test whether the successive proportion equals to 1 or not. Sasienni(1994) studied confidence intervals and variance estimators of the odds ratio, and small-sample properties of a family of odds ratio estimators were studied by Sasienni(1994) and Ejigou(1990).

Here we shall give upper and lower bounds of the odds ratio of an event by a strongly more informationed condition of the conditional probability.

2. Main results

Let $P(A|M) = \frac{P(A \cap M)}{P(M)}$ be the conditional probability of A given M, $P(M) > 0$.

From definition of the conditional probability and the multiplication rule (Rohatgi (1976)), we can get it:

Fact 1.(Ross(1998)) (a) $P(A|M) = \frac{P(A)}{P(M)} \cdot P(M|A)$, if $P(A) > 0$ and $P(M) > 0$.

(b) $\frac{P(A)}{P(A^c)} = \frac{P(A|M)}{P(A^c|M)} \cdot \frac{P(M|A^c)}{P(M|A)}$, if all denominators are positive.

Proof. (b) comes from (a).

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From the result of Fact 1(a),

Fact 2. Let $0 < P(A) < 1$ and $0 < P(M) < 1$. Then

$$\begin{aligned} P(A|M) = P(M|A) & \quad \text{if } P(A) = P(M) \\ & \quad \text{if } P(A^c) = P(M^c) \\ & \quad \text{if } P(A^c|M^c) = P(M^c|A^c). \end{aligned}$$

It has been well-known in Ross(1998) that

$$\frac{P(M_2|M_1)}{P(M_2)} \geq 1 \quad \text{if } P(M_2|M_1) \geq P(M_2)$$

if, M_1 carries positive information about M_2 .

And the equality holds if, M_1 and M_2 are mutually independent.

It is very interesting that we shall compare the results of Fact 1(b) and Theorem 1.

Theorem 1. Let $0 < P(A) < 1$. Then

The odds ratio of an event A has a lower bound and an upper bound:

$$P(A|M) \cdot \frac{P(M|A^c)}{P(M|A)} < \frac{P(A)}{P(A^c)} < \frac{1}{P(A^c|M)} \cdot \frac{P(M|A^c)}{P(M|A)},$$

if all denominators are positive

Proof. From Bayes' formula, we get it :

$$P(A|M) = \frac{P(A)P(M|A)}{P(A)P(M|A) + P(A^c)P(M|A^c)} \quad (1.1)$$

Since $(1 + \frac{1}{x})^{-1} < x$, for all positive x , then we can obtain the lower bound by letting $x = \frac{P(A)P(M|A)}{P(A^c)P(M|A^c)}$.

While, from Bayes formula (1.1), $P(A|M) = 1 - \frac{P(A^c)P(M|A^c)}{P(A)P(M|A) + P(A^c)P(M|A^c)}$. By the same method, we can obtain the upper bound by letting

$$x = \frac{P(A^c)P(M|A^c)}{P(A)P(M|A)}. \text{ So we have done(a).}$$

Let $P(A) > 0$. Then we define $P_A(\cdot) = P(\cdot|A)$ by the conditional probability function on the sample space(see Ross(1998))

Definition 1. If $P_A(M_2|M_1) = P_A(M_2)$, for $P(A) > 0$ and $P(M_1) > 0$, then M_2 is conditionally independent of M_1 with respect to A.

Example 1. Consider throwing a fair die.

Let $E = \{1, 2, 3, 4\}$, $F = \{2, 4, 6\}$, $A = \{2, 3, 5\}$, $M = \{1, 2, 3, 5\}$, and $G = \{2, 3, 5\}$.

Then E and F are mutually independent, but E and F are not conditionally independent with respect to A , and M and G are conditional independent with respect to M (or G), M and G are not mutually independent.

From definition of the conditional independent, we can obtain:

Fact 3. If $P_A(M_2|M_1) = P_A(M_2)$, then $P_A(M_1M_2) = P_A(M_1)P_A(M_2)$ and so M_1 and M_2 are mutually conditional independent with respect to A .

If an event A is the sure event, then M_1 and M_2 are well-known as mutually independent events, and it is clear that M_1 and M_2 are conditionally independent with respect to $M_i, I = 1, 2$, since $P_{M_i}(M_1M_2) = P_{M_i}(M_1)P_{M_i}(M_2)$ for every $i = 1, 2$.

As we can extend the conditional independence of finite events as like the conditional independence of two events, we can obtain the followings:

Fact 4(Ross(1998)). (a) Let E_1, E_2, \dots, E_n be the conditional independent with respect to a positive event A . Then $P_A(\cup_{i=1}^n E_i) = 1 - \prod_{i=1}^n (1 - P_A(E_i))$.

(b) Let $\{E_n : n \geq 1\}$ and $\{F_n : n \geq 1\}$ be increasing sequences of events which $\lim E_n = E$ and $\lim F_n = F$, and the corresponding E_n and F_n be the conditional independent with respect to a positive event A . Then E and F are the conditional independent with respect to A .

Definition 2. Events M_1 and M_2 are more strongly informationed conditionally given A^c than given A , if $\frac{P_{A^c}(M_2|M_1)}{P_{A^c}(M_2)} \geq \frac{P_A(M_2|M_1)}{P_A(M_2)}$, if all denominators are positive.

From its definition and Fact 3, we can know it easily.

Theorem 2. Events M_1 and M_2 are more strongly informationed conditionally given

$$A^c \text{ than given } A \text{ iff, } \frac{P_{A^c}(M_1M_2)}{P_{A^c}(M_1)P_{A^c}(M_2)} \geq \frac{P_A(M_1M_2)}{P_A(M_1)P_A(M_2)}, \quad (1.2)$$

where all denominators are positive.

Remark. If equality holds in (1.2), then two events M_1 and M_2 are equally informationed conditionally under A^c and A (see Barlow and Proschan(1981)).

Example 2. Consider throwing two fair die.

Let $M_1 = \{(x, y) : y = 3, 4, 5\}$, $M_2 = \{(x, y) : x = 1, 2\}$, $M_3 = M_2 \cup \{(3, 3)\}$, and $A = \{(x, y) : x + y = 7\}$.

Then, (1) M_1 and M_3 are conditionally independent with respect to A , but not mutually independent. M_1 carries positive information about M_3 .

(2) M_1 and M_3 are more strongly informationed conditionally given A^c than given A .

since $\frac{P_{A^c}(M_1M_3)}{P_{A^c}(M_1)P_{A^c}(M_3)} = \frac{12}{11}$, $\frac{P_A(M_1M_3)}{P_A(M_1)P_A(M_3)} = 1$.

(3) M_1 and M_2 are equally informed conditionally under A^c and A ,

since $\frac{P_{A^c}(M_1M_2)}{P_{A^c}(M_1)P_{A^c}(M_2)} = \frac{P_A(M_1M_2)}{P_A(M_1)P_A(M_2)} = 1$.

Definition 3. Events M_1, M_2, \dots, M_k are more strongly informed conditionally given A^c than given A , if

$$\frac{P_{A^c}(\bigcap_{i=1}^k M_i)}{\prod_{i=1}^k P_{A^c}(M_i)} \geq \frac{P_A(\bigcap_{i=1}^k M_i)}{\prod_{i=1}^k P_A(M_i)}, \quad \text{if all denominators are positive.} \quad (1.3)$$

We obtain equally informed conditionally when the equality in (1.3) holds (see Barlow and Proschan(1981))

Theorem 3. If events M_1, M_2, \dots, M_k are more strongly informed conditionally given A^c than given A , and $P(\bigcap_{i=1}^k M_i) > 0$, then the odds ratio of an event $A (0 < P(A) < 1)$ has a lower bound and an upper bound:

$$P(A | \bigcap_{i=1}^k M_i) \cdot \prod_{i=1}^k \frac{P(M_i | A^c)}{P(M_i | A)} < \frac{P(A)}{P(A^c)} < \frac{1}{P(A^c | \bigcap_{i=1}^k M_i)} \cdot \prod_{i=1}^k \frac{P(M_i | A^c)}{P(M_i | A)},$$

if all denominators are positive.

Proof. From Bayes' formula of the conditional probability (Rohatgi(1976)), we obtain

$$P(A | \bigcap_{i=1}^k M_i) = \frac{P(A)P(\bigcap_{i=1}^k M_i | A)}{P(A)P(\bigcap_{i=1}^k M_i | A) + P(A^c)P(\bigcap_{i=1}^k M_i | A^c)}$$

By the same proof method of Theorem 1,

$$P(A | \bigcap_{i=1}^k M_i) < \frac{P(A)P(\bigcap_{i=1}^k M_i | A)}{P(A^c)P(\bigcap_{i=1}^k M_i | A^c)}.$$

From definition of more strongly informed conditionally, that is, (2)-inequality,

$$\frac{P(\bigcap_{i=1}^k M_i | A)}{P(\bigcap_{i=1}^k M_i | A^c)} \leq \frac{\prod_{i=1}^k P(M_i | A)}{\prod_{i=1}^k P(M_i | A^c)}, \quad \text{and so we can obtain the lower bound.}$$

Similarly, from the same proofing method of last part in Theorem 1, we can obtain the upper bound of the odds ratio of an event A .

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