

## A METHOD OF PROOF FOR THE RANGE OF CONFIDENCE INTERVALS

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### 1. Introduction

Consider the one-factor nested Components-of-Variance model with equal numbers in the subclass

$$(1.1) \quad y_{i,j} = \mu + A_i + B_{i,j}$$

where  $i=1, 2, \dots, I$ ,  $j=1, 2, \dots, J$  and  $\mu$  is a constant common to all observations.  $A_i, B_{i,j}$  are normally and independently distributed random variables with mean zero and finite variances  $\sigma_A^2$  and  $\sigma_B^2$  respectively.

There is no known method for determining exact confidence limit for  $\sigma_A^2$ . Several approximations are available. Satterthwaite (1948) approximates the distribution of the estimate of a linear combination of variances by Chi-square distribution times a constant. Welch(1956) offers a series approximation for setting approximation is given by Moriguti(1954) are repeated by Bulmer(1957). They derive a confidence interval on  $\sigma_A^2$  by assuming the confidence limit is a certain form and solving for it by forcing the confidence coefficient to be exact under certain limiting conditions.

Tukey(1951) and Williams(1962) constructed an approximate confidence interval for  $\sigma_A^2$  with a guaranteed lower confidence coefficient of  $1-\alpha$  by a geometrical projection. Howe(1974) derives confidence limits on  $\sigma_A^2$  through a modified Cronish-Fisher expansion.

Then, in this case we don't know whether the range is quite fit for  $1-\alpha$  or not. If it is not fit, we don't know how close to  $1-\alpha$  the range is, either. Therefore, we need to find out the closer confidence interval to  $1-\alpha$ .

So in this paper the writer intend to show the new method of proof by the calculus of integration and the change of the random variables.

## 2. The range of confidence interval on $\sigma_A^2$

Let

$$\bar{y}_{i.} = \frac{\sum_{j=1}^J y_{ij}}{J}, \quad \bar{y}_{..} = \frac{\sum_{i=1}^I \sum_{j=1}^J y_{ij}}{IJ},$$

$$S_1^2 = \frac{\sum_{i=1}^I \sum_{j=1}^J (\bar{y}_{i.} - \bar{y}_{..})^2}{I-1}, \quad S_2^2 = \frac{\sum_{i=1}^I \sum_{j=1}^J (y_{ij} - \bar{y}_{i.})^2}{I(J-1)}.$$

It is well known that

$$E(S_1^2) = \theta_1 = \sigma_B^2 + J\sigma_A^2,$$

$$E(S_2^2) = \theta_2 = \sigma_B^2,$$

$$\frac{n_1 S_1^2}{\theta_1} \sim \chi_{n_1}^2 \quad \text{and} \quad \frac{n_2 S_2^2}{\theta_2} \sim \chi_{n_2}^2$$

where

$$n_1 = I - 1, \text{ and } n_2 = I(J - 1).$$

The Tukey-Williams(TW) upper confidence interval on  $\sigma_A^2$  is

$$(2.1) \quad \frac{S_1^2 - S_2^2 F_{\frac{\alpha}{2}; n_1, n_2}}{F_{\frac{\alpha}{2}; n_1, \infty}} \leq \theta_1 - \theta_2 \leq \frac{S_1^2 - S_2^2 F_{1 - \frac{\alpha}{2}; n_1, n_2}}{F_{1 - \frac{\alpha}{2}; n_1, \infty}}$$

THEOREM 1. The probability of TW upper confidence interval on  $\sigma_A^2$  is

$$(2.2) \quad P, \left[ \frac{S_1^2 - S_2^2 F_{\frac{\alpha}{2}; n_1, n_2}}{F_{\frac{\alpha}{2}; n_1, \infty}} \leq \theta_1 - \theta_2 \right] \geq 1 - \frac{\alpha}{2}.$$

PROOF.

$$\begin{aligned} (S_1^2 - S_2^2 F_{\frac{\alpha}{2}; n_1, n_2}) / F_{\frac{\alpha}{2}; n_1, \infty} &\leq \theta_1 - \theta_2 \\ \frac{S_1^2}{\theta_1} - \frac{S_2^2}{\theta_1} F_{\frac{\alpha}{2}; n_1, n_2} &\leq \left(1 - \frac{\theta_2}{\theta_1}\right) F_{\frac{\alpha}{2}; n_1, \infty} \\ \frac{n_1 S_1^2}{\theta_1} &\leq n_1 F_{\frac{\alpha}{2}; n_1, \infty} + n_1 \rho \left( \frac{S_2^2}{\theta_2} F_{\frac{\alpha}{2}; n_1, n_2} - F_{\frac{\alpha}{2}; n_1, \infty} \right). \end{aligned}$$

Let  $\rho = \frac{\theta_2}{\theta_1}$ ,  $U_i = \frac{n_i S_i^2}{\theta_i}$  for  $i = 1, 2$  and  $n_1 F_{\frac{\alpha}{2}; n_1, \infty} = a_1$ .

$$\begin{aligned} U_1 &\leq a_1 + n_1 \rho \left( \frac{U_2}{n_2} F_{\frac{\alpha}{2}; n_1, n_2} - F_{\frac{\alpha}{2}; n_1, \infty} \right), \\ (2.3) \quad P\left(\frac{\alpha}{2}\right) &= P, \left[ U_1 \leq a_1 + n_1 \rho \left( \frac{U_2}{n_2} F_{\frac{\alpha}{2}; n_1, n_2} - F_{\frac{\alpha}{2}; n_1, \infty} \right) \right]. \end{aligned}$$

And let

$$\begin{aligned} n_1 \rho \left( \frac{U_2}{n_2} F_{\frac{\alpha}{2}; n_1, n_2} - F_{\frac{\alpha}{2}; n_1, \infty} \right) &= Y_1, \\ P\left(\frac{\alpha}{2}\right) &= P, [U_1 \leq a_1 + Y_1]. \end{aligned}$$

$U_1$  and  $U_2$  is independent Chi-square distributed with

degree of freedom  $n_i$  for  $i=1, 2$ ,

$$(2.4) \quad P\left(\frac{\alpha}{2}\right) = \int_{-\infty}^{\infty} \left\{ \int_0^{a_1+y_1} f_1(x) dx \right\} f_2(y_1) dy_1.$$

Let  $F$  is cumulative distribution function (c. d. f.) of  $f_1$ .

$$\begin{aligned} \int_0^{a_1+y_1} f_1(x) dx &= \int_0^{a_1} f_1(x) dx + \int_{a_1}^{a_1+y_1} f_1(x) dx \\ &= \int_0^{a_1} f_1(x) dx + [F_1(x)]_{a_1}^{a_1+y_1} \\ &= \int_0^{a_1} f_1(x) dx + \{F_1(a_1+y_1) - F_1(a_1)\}. \end{aligned}$$

$$\begin{aligned} P\left(\frac{\alpha}{2}\right) &= \int_{-\infty}^{\infty} \int_0^{a_1} f_1(x) f_2(y_1) dx dy_1 + \int_{-\infty}^{\infty} \{F_1(a_1+y_1) \\ &\quad - F_1(a_1)\} f_2(y_1) dy_1. \end{aligned}$$

i) If  $Y_1 = 0$ ,

$$\begin{aligned} P\left(\frac{\alpha}{2}\right) &= P\{U_1 \leq a_1 + Y_1\} \\ &= \int_{-\infty}^{\infty} \int_0^{a_1} f_1(x) f_2(y_1) dx dy_1 \\ &= P\{U_1 \leq a_1\} \\ &= 1 - \frac{\alpha}{2}. \end{aligned}$$

ii) If  $Y_1 \neq 0$ ,

$$\begin{aligned} P\left(\frac{\alpha}{2}\right) &= P\{U_1 \leq a_1 + Y_1\} \\ &= \int_{-\infty}^{\infty} \int_0^{a_1} f_1(x) f_2(y_1) dx dy_1 \\ &\quad + \int_{-\infty}^{\infty} \frac{F_1(a_1+y_1) - F_1(a_1)}{y_1} y_1 f_2(y_1) dy_1. \end{aligned}$$

There exists a constant  $\xi_1$  such that

$$\begin{aligned}
 P\left(\frac{\alpha}{2}\right) &= P\{U_1 \leq a_1 + Y_1\} \\
 &= \int_{-\infty}^{\infty} \int_0^{a_1} f_1(x) f_2(y_1) dx dy_1 \\
 &\quad + \frac{F_1(a_1 + \xi_1) - F_1(a_1)}{\xi_1} \int_{-\infty}^{\infty} y_1 f_2(y) dy_1.
 \end{aligned}$$

Using the mean value theorem, there exists constants  $\eta_1$  for  $0 < |\eta_1| < |\xi_1|$  such that

$$\begin{aligned}
 P\left(\frac{\alpha}{2}\right) &= P[U_1 \leq a_1 + Y_1] \\
 &= \int_{-\infty}^{\infty} \int_0^{a_1} f_1(x) f_2(y_1) dx dy_1 \\
 &\quad + f_1(a_1 + \eta_1) \int_{-\infty}^{\infty} y f_2(y_1) dy_1 \\
 &= P[U_1 \leq a_1] + f_1(a_1 + \eta_1) EY_1.
 \end{aligned}$$

Since

$$\begin{aligned}
 f_1(a + \eta) EY_1 &\geq 0, \\
 P\left(\frac{\alpha}{2}\right) &= P\{U_1 \leq a_1\} + f_1(a + \eta) EY_1 \geq P\{U_1 \leq a_1\} \\
 &= 1 - \frac{\alpha}{2}.
 \end{aligned}$$

**THEOREM 2.** The probability of TW lower confidence interval on  $\sigma_A^2$  is

$$P_r\left[\theta_1 - \theta_2 \leq \frac{S_1^2 - S_2^2 F_{1-\frac{\alpha}{2}; n_1, n_2}}{F_{1-\frac{\alpha}{2}, n_1, \infty}}\right] \leq 1 - \frac{\alpha}{2}.$$

**PROOF.**

$$\begin{aligned}
 P\left(1 - \frac{\alpha}{2}\right) &= P\left[\theta_1 - \theta_2 \leq \frac{S_1^2 - S_2^2 F_{1-\frac{\alpha}{2}; n_1, n_2}}{F_{1-\frac{\alpha}{2}, n_1, \infty}}\right] \\
 &= 1 - P_r\left[\frac{S_1^2 - S_2^2 F_{1-\frac{\alpha}{2}; n_1, n_2}}{F_{1-\frac{\alpha}{2}, n_1, \infty}} < \theta_1 - \theta_2\right]
 \end{aligned}$$

$$\begin{aligned}
&= 1 - P\left(1 - \frac{\alpha}{2}\right) \\
&= 1 - P\left[U_1 < n_1 F_{1-\frac{\alpha}{2}, n_1, \infty} \right. \\
&\quad \left. + n_1 \rho(F_{1-\frac{\alpha}{2}, n_1, n_2} - F_{1-\frac{\alpha}{2}, n_1, \infty})\right] \\
&= 1 - P\left[U_1 < n_1 F_{1-\frac{\alpha}{2}, n_1, \infty} \right. \\
&\quad \left. - n_1 \rho(F_{1-\frac{\alpha}{2}, n_1, \infty} - F_{1-\frac{\alpha}{2}, n_1, n_2})\right] \\
&= 1 - P[U_1 < a_2 - Y_2],
\end{aligned}$$

where

$$\begin{aligned}
a_2 &= n_1 F_{1-\frac{\alpha}{2}, n_1, \infty} \geq 0 \\
Y_2 &= n_1 \rho(F_{1-\frac{\alpha}{2}, n_1, \infty} - F_{1-\frac{\alpha}{2}, n_1, n_2}) \geq 0. \\
P\left(1 - \frac{\alpha}{2}\right) &= 1 - P[U_1 < a_2] + P[a_2 - Y_2 < U_1 < a_2] \\
&= P[a_2 \leq U_1] + P[a_2 - Y_2 < U_1 < a_2].
\end{aligned}$$

i) If  $Y_2 = 0$ ,

$$\begin{aligned}
P\left(1 - \frac{\alpha}{2}\right) &= P[a_2 \leq U_1] \\
&= 1 - \frac{\alpha}{2}.
\end{aligned}$$

ii) If  $Y_2 \neq 0$ ,

$$\begin{aligned}
P\left(1 - \frac{\alpha}{2}\right) &= P[a_2 \leq U_1] + P[a_2 - Y_2 < U_1 < a_2] \\
&= P[a_2 \leq U_1] \\
&\quad + \int_{-\infty}^{\infty} \left\{ \int_{b_1 - y_2}^{b_1} f_1(x) dx \right\} f_2(y_2) dy_2 \\
&= P[a_2 \leq U_1] \\
&\quad + \int_{-\infty}^{\infty} \{F(a_2) - F(a_2 - y_2)\} f_2(y_2) dy_2.
\end{aligned}$$

And there exist constants  $\xi_2$  and  $\eta_2$  such that

$$\begin{aligned}
 P\left(1 - \frac{\alpha}{2}\right) &= P_r[a_2 \leq U_1] \\
 &\quad + \frac{F(a_2) - F(a_2 - \xi_2)}{\xi_2} \int_{-\infty}^{\infty} y_2 f_2(y_2) dy_2 \\
 &= P_r[a_2 \leq U_1] + f_1(a_2 - \xi_2) EY_2.
 \end{aligned}$$

Since

$$\begin{aligned}
 f_1(a_2 - \xi_2) EY_2 &\geq 0, \\
 P\left(1 - \frac{\alpha}{2}\right) &= P_r[a_2 \leq U_1] + f_1(a_2 - \xi_2) EY_2 \\
 &= 1 - \frac{\alpha}{2} + f_1(a_2 - \xi_2) EY_2 \\
 &\geq 1 - \frac{\alpha}{2}.
 \end{aligned}$$

THEOREM 3. The probability of TW confidence intervals on  $\sigma_A^2$  is

$$\begin{aligned}
 P_r\left[\frac{S_1^2 - S_2^2 F_{\frac{\alpha}{2}, n_1, n_2}}{F_{\frac{\alpha}{2}, n_1, \infty}} \leq \theta_1 - \theta_2 \leq \frac{S_1^2 - S_2^2 F_{1 - \frac{\alpha}{2}, n_1, n_2}}{F_{1 - \frac{\alpha}{2}, n_1, \infty}}\right] \\
 \geq 1 - \alpha.
 \end{aligned}$$

PROOF.

$$\begin{aligned}
 P(\alpha) &= P_r\left[\frac{S_1^2 - S_2^2 F_{\frac{\alpha}{2}, n_1, n_2}}{F_{\frac{\alpha}{2}, n_1, \infty}} \leq \theta_1 - \theta_2 \leq \frac{S_1^2 - S_2^2 F_{1 - \frac{\alpha}{2}, n_1, n_2}}{F_{1 - \frac{\alpha}{2}, n_1, \infty}}\right] \\
 &= P_r\left[\frac{S_1^2 - S_2^2 F_{\frac{\alpha}{2}, n_1, n_2}}{F_{\frac{\alpha}{2}, n_1, \infty}} \leq \theta_1 - \theta_2\right] \\
 &\quad - P_r\left[\frac{S_1^2 - S_2^2 F_{1 - \frac{\alpha}{2}, n_1, n_2}}{F_{1 - \frac{\alpha}{2}, n_1, \infty}} < \theta_1 - \theta_2\right] \\
 &= P_r[U_1 \leq a_1 + Y_1] - P_r[U_1 < a_2 - Y_2],
 \end{aligned}$$

where

$$b_1 = n_1 F_{1 - \frac{\alpha}{2}; n_1, \infty},$$

$$\begin{aligned}
 Y_2 &= n_1 \rho \left( F_{1-\frac{\alpha}{2}; n_1, \infty} - \frac{U_2}{n_2} F_{1-\frac{\alpha}{2}; n_1, n_2} \right). \\
 P(\alpha) &= P_r[U_1 \leq a_1] + P_r[a_1 < U_1 \leq a_1 + Y_1] \\
 &\quad - P_r[U_1 \leq a_2] + P_r[a_2 - Y_2 < U_1 < a_2] \\
 &= P_r[a_2 \leq U_1 \leq a_1] \\
 &\quad + P_r[a_1 < U_1 \leq a_1 + Y_1] + P_r[a_2 - Y_2 < U_1 < a_2].
 \end{aligned}$$

Then

$$\begin{aligned}
 \text{i) } P_r[a_2 \leq U_1 \leq a_1] &= P_r[n_1 F_{1-\frac{\alpha}{2}; n_1, \infty} \leq U_1 \leq n_1 F_{\frac{\alpha}{2}; n_1, \infty}] \\
 &= 1 - \alpha, \\
 \text{ii) } P_r[a_1 < U_1 \leq a_1 + Y_1] + P_r[a_2 - Y_2 < U_1 < a_2] &= f_1(a_1 + \eta_1) EY_1 + f_1(a_2 - \eta_2) EY_2.
 \end{aligned}$$

Therefore

$$\begin{aligned}
 P\left(1 - \frac{\alpha}{2}\right) &= P_r[a_2 \leq U_1 \leq a_1] \\
 &\quad + f_1(a_1 + \eta_1) EY_1 + f_1(a_2 - \eta_2) EY_2 \\
 &\geq P_r[a_2 \leq U_1 \leq a_1] \\
 &= 1 - \alpha.
 \end{aligned}$$

Though we succeeded in-devising the new method of proof, we don't know exactly the possibility of its application.

### References

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