

AN ALTERNATIVE TO THE SATTERSWAITE-WELCH DEGREES OF FREEDOM AND ITS COMPUTER INTENSIVE CONFIDENCE INTERVALS

By

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Abstract

An alternative to the Satterthwaite-Welch degrees of freedom (df) is developed in this paper based on unbiased estimating equations. The method enables us to evaluate the impact of sample variation due to using estimated df instead of the true df by computer intensive method. It is shown by simulation that the alternative df is close to the Welch df and the method developed could be also used for evaluating the impact of sample variation due to using estimated df in the Welch test.

Key Words and Phrases: Behrens-Fisher problem, heterogeneity of population variances, Satterthwaite test, Student t -test, Welch test

1. Introduction

We express the intention of this paper in a framework of two-sample problem. Let $X_{i1}, X_{i2}, \dots, X_{im_i}$ be a random sample from a population with normal distribution $N(\mu_i, \sigma_i^2)$, $i = 1, 2$. We consider statistical test for testing $H_0: \mu_1 = \mu_2$ against $H_1: \mu_1 \neq \mu_2$. If population variances are homogeneous, routine practice is to apply the Student t -test. The test is based on statistic

$$T_p = (\bar{X}_1 - \bar{X}_2) / S_p \sqrt{\frac{1}{m_1} + \frac{1}{m_2}},$$

where S_p is a pooled estimator of $\sigma = \sigma_1 = \sigma_2$ defined by

$$S_p^2 = \frac{1}{m_1 + m_2 - 2} \left(\sum_{j=1}^{m_1} (X_{1j} - \bar{X}_1)^2 + \sum_{j=1}^{m_2} (X_{2j} - \bar{X}_2)^2 \right).$$

T_p follows a t -distribution with $(m_1 + m_2 - 2)$ degree of freedom (df) under H_0 . If $\sigma_1 \neq \sigma_2$, T_p does not follow a t -distribution. A reasonable alternative is to employ statistic

$$T = (\bar{X}_1 - \bar{X}_2) / \sqrt{\frac{S_1^2}{m_1} + \frac{S_2^2}{m_2}},$$

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where S_i^2 is the group sample variance given by

$$S_i^2 = \frac{1}{m_i - 1} \sum_{j=1}^{m_i} (X_{ij} - \bar{X}_i)^2.$$

The distribution of T was first discovered by Behrens (1929) and later developed by Fisher (1939). The problem of constructing the optimum test for comparing two normal means when the unknown population variances are unequal have been called the Behrens-Fisher problem (Lehman and Romano, 2005).

A common alternative to the Behrens-Fisher sampling distribution that is complicated to apply in practice is to approximate the distribution of T by t -distribution with adjusted df . Smith (1936) and later Welch (1938) found that such adjusted df was given by

$$\nu_w = (U_1 + U_2)^2 / \left(\frac{U_1^2}{m_1 - 1} + \frac{U_2^2}{m_2 - 1} \right),$$

where $U_i = S_i^2/m_i$. The ν_w is often called the Welch df and the test that uses T by considering it follows t -distribution with the adjusted df is called the Welch test. The test is installed in standard statistical packages and suggested to use when $\sigma_1 \neq \sigma_2$. The Welch test is later extended to K -sample problems by Satterthwaite (1946).

In subsequent years the robustness of the Student t -test was studied extensively. It was shown by numerous authors (Boneau, 1960; Box, 1953; Cochran, 1947; Posten, Yeh, and Owen, 1982; Srivastava, 1958 among others) that t -test was robust against considerable departure from its theoretical assumption. In particular, it was shown that if the sample sizes were approximately equal ($m_1 \approx m_2$), the t -test based on T_p was fairly robust against violations of the variance homogeneity up to ratio of variances about 4.0 (Millar, 1986 Section 7.3). Thus the usefulness of the Welch test is limited in the situation where sample sizes are substantially imbalanced and/or ratio of variances is more than 4.

We look at the fact in this study that the Welch df is subject to sampling variation via S_i^2 . We show by simulation in the next section that impact of the variation on p -values of the Welch test could be substantial, even if the sample sizes are not small.

We develop an unbiased estimating equation of the df that approximates the distribution of T by t -distribution. We call the df the tdf and the estimator of tdf from the unbiased estimating equation is called the u-estimator of the tdf . We replace the Welch df with the u-estimator of tdf in this paper and evaluate the impact of its sampling variation, by first constructing computer intensive confidence intervals of tdf and then calculating p -values using the upper and lower limits of the confidence intervals.

In Section 3 we formulate the problem in a framework of K -sample problems and define tdf , the degree of freedom that approximates the distribution of T by t -distribution. In Section 4 we develop an unbiased estimating equation for the tdf based on samples generated in computer by assuming those observed sample means and variances from populations are as if given constants. Also c-intensive approximate 90% confidence intervals of the tdf and p -value are constructed by using the unbiased estimating equation in the same section. The U -test, an alternative to the Welch-Satterthwaite test, is defined in Section 5. Behavior of the c-intensive confidence intervals are studied by simulation in Section 6. Section 7 states the conclusion of the study in this paper and finally discussion is given in Section 8.

2. Impact of sampling variation of Welch df

The Welch df does depend on samples. We conducted simulation to evaluate its impact on the levels of the Welch test in the following way. (i) Construct two samples by generating m_1 random digits that follow normal distribution with mean zero and variance σ_1^2 , and m_2 random digits that follow normal distribution with mean zero and variance σ_2^2 . (ii) Compute the values of Welch df and T based on the two samples. (iii) Repeat (i)~(ii) 10,000 times. (iv) Denoting by (f_i, T_i) the computed values of Welch df and T in the i -th run, stratify (f_i, T_i) , $i = 1, 2, \dots, 10,000$, into four strata by means of the first, second and third quadrants of f 's, and compute empirical tail probabilities of the Welch test by

$$R_i = \frac{1}{2500} \sum_{j=1}^{2500} I(|t_{ij}| > t_{f_{ij}}(0.025)),$$

where $I(A) = 1(0)$, if A is true (false), t_{ij} and f_{ij} are the j -th values of T and df in the i -th stratum, and $t_f(0.025)$ is the upper 2.5% point of the t -distribution with f degrees of freedom. R_i represents empirical tail probabilities of the Welch test under H_0 when the nominal level is 0.05.

Table 1 Tail probabilities of the Welch test when the nominal value is 0.05.

id	σ_1^2	σ_2^2	m_1	m_2	R_1	R_2	R_3	R_4	RSS
1	6	9	5	8	0.024	0.050	0.061	0.055	0.029
2	6	9	15	20	0.046	0.048	0.045	0.056	0.008
3	6	9	50	60	0.047	0.049	0.047	0.050	0.004
4	6	9	8	5	0.012	0.034	0.060	0.101	0.066
5	6	9	20	15	0.032	0.042	0.052	0.068	0.027
6	6	9	60	50	0.044	0.043	0.054	0.053	0.011
7	6	24	5	8	0.047	0.040	0.047	0.058	0.014
8	6	24	15	20	0.039	0.050	0.048	0.066	0.020
9	6	24	50	60	0.042	0.046	0.050	0.061	0.015
10	6	24	5	21	0.013	0.032	0.062	0.083	0.054
11	6	24	15	53	0.036	0.051	0.057	0.069	0.025
12	6	24	50	160	0.043	0.051	0.052	0.066	0.018
13	6	24	8	5	0.008	0.020	0.048	0.146	0.109
14	6	24	20	15	0.026	0.038	0.053	0.080	0.040
15	6	24	60	50	0.036	0.042	0.054	0.070	0.027

Table 1 summarizes values of R_i , $i = 1, 2, 3, 4$, when $(\sigma_1^2, \sigma_2^2) = (6, 9)$, $(6, 24)$ and $(m_1, m_2) = (5, 8)$, $(8, 5)$, $(15, 20)$, $(20, 15)$, $(50, 60)$, $(60, 50)$, $(5, 21)$, $(15, 53)$, $(50, 160)$. Those values should be in the vicinity of 0.05 if the Welch df is valid. The last column of the table gives the value of

$$RSS = \sqrt{\sum_{i=1}^4 (R_i - 0.05)^2}$$

to evaluate it. The table shows that when $\sigma_1^2 < \sigma_2^2$ and $m_1 < m_2$, RSS decreases as the increase of sample sizes, so long as $(\sigma_2^2/\sigma_1^2)/(m_2/m_1)$ is constant; but that it is not the

case when $\sigma_1^2 < \sigma_2^2$ and $m_1 > m_2$, or when $\sigma_1^2 < \sigma_2^2$, $m_1 < m_2$ and $(\sigma_2^2/\sigma_1^2)/(m_2/m_1)$ is not constant; that tail probabilities of the Welch test on the 2nd and 3rd strata are close to the nominal value, 0.05, when (σ_2^2/σ_1^2) is small, but it is not the case when (σ_2^2/σ_1^2) is large; that those probabilities on the first and the fourth strata are far from the nominal level when $\sigma_1^2 < \sigma_2^2$ and $m_1 > m_2$, for example, $R_1 = 0.036$ when $m_1 = 60$, $m_2 = 50$, $\sigma_1^2 = 6$ and $\sigma_2^2 = 24$. Furthermore, when $\sigma_1^2 < \sigma_2^2$ and $m_1 > m_2$ and m_1 and m_2 are small, values of R_1 are far away from 0.05; for example, $R_1 = 0.012$ when $\sigma_1^2 = 6$, $\sigma_2^2 = 9$, $m_1 = 8$, $m_2 = 5$.

3. Mathematical development

3.1. K -sample problem

We shall formulate the problem in a framework of K -sample problem. Suppose that only summary statistics such as sample size, sample mean and variance, denoted by m_i , \bar{X}_i and S_i^2 , $i = 1, 2, \dots, K$, are available. We assume in this paper that these statistics are obtained from the i -th sample from the population with normal distribution $N(\mu_i, \sigma_i^2)$, $i = 1, 2, \dots, K$.

Consider statistical test for testing hypothesis $H_0: c_1\mu_1 + c_2\mu_2 + \dots + c_K\mu_K = 0$ against the alternative hypothesis H_1 that negates H_0 , where c 's are given contrasts such that $\sum_{i=1}^K c_i = 0$. We employ statistic

$$T = \frac{\sum_{i=1}^K c_i \bar{X}_i}{\sqrt{\sum_{i=1}^K c_i^2 S_i^2 / m_i}}$$

for testing the hypothesis. If $\sigma_1 = \sigma_2 = \dots = \sigma_k$, T follows a t -distribution with $\sum_{i=1}^K (m_i - 1)$ df under H_0 . However, if it is not the case T does not follow a t -distribution under H_0 . Satterthwaite (1946), extending the idea of Smith (1936) and Welch (1938), proposed to approximate the distribution of T by t -distribution with adjusted df given by

$$\hat{\nu}_w = \left(\sum_{i=1}^K \frac{c_i^2 S_i^2}{m_i} \right)^2 / \left(\sum_{i=1}^K \frac{1}{m_i - 1} \left(\frac{c_i^2 S_i^2}{m_i} \right)^2 \right). \quad (1)$$

The $\hat{\nu}_w$ is called the Satterthwaite-Welch df . It reduces to the Welch df when $K = 2$.

3.2. Definition of the tdf

We first define tdf , the degree of freedom that approximates the distribution of T by t -distribution. In order for T to follow t -distribution, the squared denominator of T multiplied by constant must follow a chi-squared distribution. We define tdf as the df of chi-squared distribution whose first two moments agree with those moments of the distribution of the statistic. More precisely, putting, $A = \sum_{i=1}^K c_i^2 S_i^2 / m_i$, and letting Q_ν be the statistic that follows a chi-squared distribution with ν df , tdf is defined as ν that satisfies

$$E(A) = E(\xi Q_\nu), \quad Var(A) = Var(\xi Q_\nu), \quad (2)$$

where ξ is an unknown parameter. We need following lemmas to get explicit form of tdf . The proofs of lemmas are straightforward and are omitted.

Lemma 1. Let S_i^2 be the sample variance of data from a population with normal distribution $N(\mu_i, \sigma_i^2)$. Then

$$(i) E(S_i^2) = \sigma_i^2, \quad (ii) V(S_i^2) = \frac{2\sigma_i^4}{(m_i - 1)}, \quad (iii) E(S_i^4) = \frac{(m_i + 1)\sigma_i^4}{(m_i - 1)}.$$

Lemma 2. Assume the assumption of Lemma 1, then (2) is represented by

$$\begin{aligned} \sum_{i=1}^K \frac{c_i^2 \sigma_i^2}{m_i} &= \xi \nu, \\ \sum_{i=1}^K \frac{1}{m_i - 1} \left(\frac{c_i^2 \sigma_i^2}{m_i} \right)^2 &= \xi^2 \nu. \end{aligned}$$

From Lemma 2 and definition, we have

$$tdf = \left(\sum_{i=1}^K \frac{c_i^2 \sigma_i^2}{m_i} \right)^2 \left(\sum_{i=1}^K \frac{1}{m_i - 1} \left(\frac{c_i^2 \sigma_i^2}{m_i} \right)^2 \right)^{-1}, \quad (3)$$

and

$$\xi = \left(\sum_{i=1}^K \frac{1}{m_i - 1} \left(\frac{c_i^2 \sigma_i^2}{m_i} \right)^2 \right) / \left(\sum_{i=1}^K \frac{c_i^2 \sigma_i^2}{m_i} \right). \quad (4)$$

Theorem 1. Assume the assumption of Lemma 1, then the distribution of T under H_0 is approximated by a t -distribution with tdf degree of freedom.

Proof. The proof of the theorem is given in Appendix.

Note that the Satterswaite-Welch df may be obtained by replacing unknown parameter σ^2 in formula (3) with S_i^2 , namely from

$$\left(\sum_{i=1}^K \frac{c_i^2 S_i^2}{m_i} \right)^2 - \nu \sum_{i=1}^K \frac{1}{m_i - 1} \left(\frac{c_i^2 S_i^2}{m_i} \right)^2 = 0. \quad (5)$$

This estimating equation is not unbiased for tdf . An unbiased estimating equation for tdf is given in the following theorem.

Theorem 2. Assume the assumption of Lemma 1, then an unbiased estimating equation for tdf is given by

$$\left(\sum_{i=1}^K \frac{c_i^2 S_i^2}{m_i} \right)^2 - 2 \sum_{i=1}^K \frac{1}{m_i + 1} \left(\frac{c_i^2 S_i^2}{m_i} \right)^2 - \nu \sum_{i=1}^K \frac{1}{m_i + 1} \left(\frac{c_i^2 S_i^2}{m_i} \right)^2 = 0. \quad (6)$$

Proof. The proof of the theorem is given in Appendix.

Note that when $m = m_i$ for all $i = 1, 2, \dots, K$ it follows that

$$\hat{\nu}_u = \hat{\nu}_w + \frac{2}{m-1} \left(\hat{\nu}_w - (m-1) \right),$$

where $\hat{\nu}_u$ and $\hat{\nu}_w$ are solutions of equations (6) and (5), respectively, thus $\hat{\nu}_u \geq \hat{\nu}_w$ since $\hat{\nu}_w \geq m-1$. We target $\hat{\nu}_u$, the estimator of tdf obtained from (6), in this paper. $\hat{\nu}_u$ is called the u -estimator in the introduction. The advantage of unbiasedness of estimating equations is discussed in Yanagimoto and Yamamoto (Chapter 6 in Godambe, 1999).

4. Sampling from population with estimated mean and variance

4.1. Unbiased estimating equation

Generate n_i random digits, denoted by $X_{i1}^*, X_{i2}^*, \dots, X_{in_i}^*$, from $N(\bar{x}_i, s_i^2)$ by assuming that $\bar{X}_i = \bar{x}_i$ and $S_i^2 = s_i^2$ are given constants, where n_i may be different from m_i , $i = 1, 2, \dots, K$. Put

$$\bar{X}_i^* = \frac{1}{n_i} \sum_{j=1}^{n_i} X_{ij}^* \quad \text{and} \quad S_i^{*2} = \frac{1}{n_i-1} \sum_{j=1}^{n_i} (X_{ij}^* - \bar{X}_i^*)^2.$$

Note that \bar{X}_i^* and S_i^{*2} are conditional sample mean and sample variance conditioned on $\bar{X}_i = \bar{x}_i$ and $S_i^2 = s_i^2$. We have the following lemma.

Lemma 3. *Assume the assumption of Lemma 1. Then unconditional expectations of S_i^{*2} and $S_i^{*4} = (S_i^{*2})^2$ are given by*

$$(i) \quad E(S_i^{*2}) = \sigma_i^2, \quad (ii) \quad E(S_i^{*4}) = \frac{(m_i+1)(n_i+1)}{(m_i-1)(n_i-1)} \sigma_i^4.$$

(iii) *Furthermore, the unconditional variance of S_i^{*2} is given by*

$$V(S_i^{*2}) = \frac{2(m_i+n_i)}{(m_i-1)(n_i-1)} \sigma_i^4.$$

Proof. The proof of the lemma is given in Appendix.

Theorem 3. *Assume the assumption of Lemma 1. Then an unbiased estimating equation for tdf based on $\{X_{ij}^*\}_{j=1}^{n_i}$, $i = 1, 2, \dots, K$, is given by*

$$\left(\sum_{i=1}^K \frac{c_i^2 S_i^{*2}}{m_i} \right)^2 - 2 \sum_{i=1}^K \left(\frac{c_i^2 S_i^{*2}}{m_i} \right)^2 \frac{(m_i+n_i)}{(m_i+1)(n_i+1)} = \nu \sum_{i=1}^K \left(\frac{c_i^2 S_i^{*2}}{m_i} \right)^2 \frac{(n_i-1)}{(m_i+1)(n_i+1)}. \quad (7)$$

Proof. The expectation of the left hand side of the equation is

$$\begin{aligned} & E \left(\sum_{i=1}^K \frac{c_i^2 S_i^{*2}}{m_i} \right)^2 - 2 \sum_{i=1}^K \left(\frac{c_i^2}{m_i} \right)^2 \frac{(m_i+n_i)}{(m_i+1)(n_i+1)} E(S_i^{*4}) \\ &= E \left(\sum_{i=1}^K \frac{c_i^2}{m_i} S_i^{*2} \right)^2 - 2 \sum_{i=1}^K \left(\frac{c_i^2}{m_i} \right)^2 \frac{(m_i+n_i)}{(m_i-1)(n_i-1)} \sigma_i^4 \end{aligned}$$

$$\begin{aligned}
&= E\left(\sum_{i=1}^K \frac{c_i^2}{m_i} S_i^{*2}\right)^2 - \sum_{i=1}^K \left(\frac{c_i^2}{m_i}\right)^2 V(S_i^{*2}) \\
&= \left(\sum_{i=1}^K \frac{c_i^2 \sigma_i^2}{m_i}\right)^2.
\end{aligned}$$

On the other hand, the expectation of the right hand side of the equation in the theorem is

$$\begin{aligned}
&\nu \sum_{i=1}^K \left(\frac{c_i^2}{m_i}\right)^2 \frac{(n_i - 1)}{(m_i + 1)(n_i + 1)} E(S_i^{*4}) \\
&= \nu \sum_{i=1}^K \left(\frac{c_i^2}{m_i}\right)^2 \frac{1}{m_i - 1} \sigma_i^4.
\end{aligned}$$

Therefore the expectations of left and right hand sides agree with if ν is equal to the *tdf* given in formula (3). This completes the proof of the theorem.

It follows from Theorem 3 that the *u*-estimator for *tdf* based on $\{X_{ij}^*\}_{j=1}^{n_i}$ is given by

$$\hat{\nu}^* = \left(\left(\sum_{i=1}^K U_i^* \right)^2 - 2 \sum_{i=1}^K (U_i^*)^2 \frac{(m_i + n_i)}{(m_i + 1)(n_i + 1)} \right) \left(\sum_{i=1}^K (U_i^*)^2 \frac{(n_i - 1)}{(m_i + 1)(n_i + 1)} \right)^{-1}, \quad (8)$$

where $U_i^* = c_i^2 S_i^{*2} / m_i$.

4.2. Computer intensive confidence intervals for *tdf* and *p*-value

$\hat{\nu}^*$ is an estimator of *tdf*, but its distribution is not easy to develop. We construct an approximate 90% empirical confidence interval (CI) of *tdf* and *p*-value from the empirical distribution of $\hat{\nu}^*$ in this section.

First, we set up the *true* empirical CI of *tdf* as follows. (1-1) Give the values of μ_i and σ_i^2 , generate random digits of size m_i from $N(\mu_i, \sigma_i^2)$, and compute \bar{x}_i and s_i^2 for $i = 1, 2, \dots, K$. (1-2) Compute $\hat{\nu}_u$ from the unbiased estimating equation given in Theorem 2. (1-3) Repeat this process, get the empirical distribution of $\hat{\nu}$, and obtain 5% and 95% points of the empirical distribution. Denote these points by $\nu_{0.05}$ and $\nu_{0.95}$. We call interval $(\nu_{0.05}, \nu_{0.95})$ the true 90% empirical CI of *tdf*.

Next, we construct the true CI of *p*-value as follows. Let p_{low} and p_{upp} be the values of $P(T > |t|)$ computed by assuming the distribution of T being *t*-distribution with $\nu_{0.05}$ and $\nu_{0.95}$ degrees of freedom, respectively. Then it follows that

$$p_{low} \leq p\text{-value} \leq p_{upp},$$

since when T follows a *t*-distribution with ν df the tail probability $P(|T| > x)$ is a decreasing function of ν for fixed $x > 0$. Furthermore, it follows that (p_{low}, p_{upp}) is a 90% empirical CI of *p*-value given $T = t$. We call it the true empirical conditional 90% CI of the *p*-value given $T = t$. Note that $(\nu_{0.05}, \nu_{0.95})$ and (p_{low}, p_{upp}) are available when μ_i and σ_i^2 are known.

Finally, when μ_i and σ_i^2 are unknown, we construct approximate 90% CIs of the *tdf* and *p*-value based on the empirical distribution of $\hat{\nu}^*$ as follows. (2-1) Putting $n_i = hm_i$ and denoting a given class of h by H , where m_i is the size of the original sample from the i -th population, generate n_i random digits, $X_{i1}^*, X_{i2}^*, \dots, X_{in_i}^*$, from $N(\bar{x}_i, s_i^2)$, using \bar{x}_i and s_i^2 that were given in step (1-1), $i = 1, 2, \dots, K$. (2-2) Compute the estimator given in formula (8). (2-3) Repeat steps (2-1) \sim (2-2) L times and find the 5% and 95% points of the empirical distribution of $\hat{\nu}^*$; denote them by $\hat{\nu}_{low,h}^*$ and $\hat{\nu}_{upp,h}^*$. (2-4) Obtain $\hat{p}_{low,h}^*$ and $\hat{p}_{upp,h}^*$ from $\hat{\nu}_{low,h}^*$ and $\hat{\nu}_{upp,h}^*$ similarly as above. (2-5) Compare $(\hat{p}_{low,h}^*, \hat{p}_{upp,h}^*)$ with the true 90% empirical conditional CI of *p*-value, and select the $h \in H$ that makes $(\hat{p}_{low,h}^*, \hat{p}_{upp,h}^*)$ the closest to the true 90% empirical conditional CI of *p*-values. Since the bounds of the interval changes monotonically with the increase of h , it will not take time to find the best h . The intervals with the best h , denoted by $(\hat{\nu}_{low}^*, \hat{\nu}_{upp}^*)$ and $(\hat{p}_{low}^*, \hat{p}_{upp}^*)$, are called the c-intensive approximate 90% CIs of *tdf* and *p*-value, respectively.

5. U-test

For testing $H_0: c_1\mu_1 + c_2\mu_2 + \dots + c_K\mu_K = 0$ with T , we approximate the distribution of T under H_0 by t -distribution with $\hat{\nu}$ degree of freedom, where $\hat{\nu}$ is the u -estimator of *tdf* obtained from the unbiased estimating function given in Theorem 2. We call this test the U -test. The *p*-value of the U -test is given by $P(|T| > |t||H_0)$, where t is the observed value of T . As the Welch test, the U -test employs the estimated *tdf*, i.e., $\hat{\nu}$, in computing *p*-value and it depends on the variability of both $\hat{\nu}$ and t . We suggest to express the test results by *p*-value with its c-intensive approximate 90% CI. It could be useful for a cautious evaluation of the *p*-value. For example, we may reject H_0 if $\hat{p}_{upp}^* < 0.05$, but not reject, or retain hypothesis H_0 if $\hat{p}_{upp}^* \geq 0.05$, even if *p*-value < 0.05 .

6. Simulation

Simulation was conducted to investigate the behavior of the proposed method when $K = 2$. First we established the true empirical CI of *tdf* as follows. (1) Generating random digits of size m_i from $N(\mu_i, \sigma_i^2)$ for given values of μ_i and σ_i^2 , and computed \bar{x}_i and s_i^2 for $i = 1, 2$ when $\mu_1 = 2.0, 2.25, 2.3, 2.5, 2.75, 2.8, 2.9, 3.3, 3.4, 3.8, 3.9, 4.4$, $\mu_2 = 0$; $\sigma_1^2 = 3, \sigma_2^2 = 6, 12, 18, 24$; $m_1 = 5$ and $m_2 = 7, 10, 20$. (2) Obtained $\hat{\nu}_u$ from the unbiased estimating equation given in Theorem 2. (3) Repeated this process 5,000 times, and obtained the true empirical CI of *tdf*. (4) Then for $H = \{1, 2, 3\}$ generated random digits of size $n_i = hm_i$ from $N(\bar{x}_{ij}, s_{ij}^2)$, $i = 1, 2$ and $h \in H$, where (\bar{x}_{ij}, s_{ij}^2) was the value of (\bar{x}_i, s_i^2) obtained in step (1) in the j -th run, $j = 1, 2, \dots, 5,000$. (5) Repeated the step (4) 1,000 times (i.e. $L = 1,000$) and obtained 90% interval $(\hat{\nu}_{j,low,h}^*, \hat{\nu}_{j,upp,h}^*)$ for each j ($j = 1, 2, \dots, 5000$) and $h \in H$. (6) Finally, $\hat{\nu}_{low,h}^*$ and $\hat{\nu}_{upp,h}^*$ were obtained by averaging those 5,000 lower and upper bounds for each $h \in H$.

Table 2 summarizes the results of the simulation. The first six columns in the table are values of $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, m_1$ and m_2 . The 7th and 8th columns list the values of the true 90% empirical CI. The remaining columns list c-intensive intervals of *tdf* for $h \in H = \{1, 2, 3\}$. Table 3 lists the values of conditional $(\hat{p}_{low}, \hat{p}_{upp})$ and $(\hat{p}_{low,h}^*, \hat{p}_{upp,h}^*)$ given $t = 2.2$ for each $h \in H$. These intervals are computed from corresponding intervals of *tdf* listed in Table 2. Table 3 shows that those conditional lower and upper bounds of *p*-value given $t = 2.2$ are fairly stable throughout the experimental conditions and that

the values of the lower band of the c-intensive CIs for p -value are not decreasing with the increase of h , and those of the upper band do not increase as the increase of h ; that many values of the lower bound listed under $h = 1$, $h = 2$ and $h = 3$ are fairly close to the true bounds; and that those values of the upper bounds listed under $h = 1$ are the closest to those true values among $h = 1, 2, 3$. Thus we suggest to use $(\hat{p}_{low}^*, \hat{p}_{upp}^*)$ obtained when $h = 1$ as the c-intensive approximate 90% CI of p -values.

Table 2 The true CI and c-intensive CI of tdf when $h = 1, 2, 3$

mean, SD and sample size						true CI		c-intensive CI					
μ_1	μ_2	σ_1^2	σ_2^2	m_1	m_2	$\hat{\nu}_{low}$	$\hat{\nu}_{upp}$	$h = 1$		$h = 2$		$h = 3$	
								$\hat{\nu}_{low}^*$	$\hat{\nu}_{upp}^*$	$\hat{\nu}_{low}^*$	$\hat{\nu}_{upp}^*$	$\hat{\nu}_{low}^*$	$\hat{\nu}_{upp}^*$
2.9	0	3	6	5	7	7.00	11.99	6.88	14.58	7.85	12.84	8.29	12.25
3.4	0	3	12	5	7	6.84	11.98	6.93	14.20	7.77	12.38	8.15	11.77
3.9	0	3	18	5	7	6.59	11.94	6.81	13.77	7.49	11.86	7.80	11.23
4.4	0	3	24	5	7	6.45	11.87	6.69	13.35	7.25	11.39	7.51	10.74
2.3	0	3	6	5	10	7.35	14.98	8.61	17.57	9.56	15.77	10.01	15.07
2.8	0	3	12	5	10	9.81	14.99	9.59	17.42	10.63	15.78	11.11	15.23
3.3	0	3	18	5	10	9.98	14.98	9.82	17.15	10.78	15.50	11.22	14.95
3.8	0	3	24	5	10	9.85	14.97	9.84	16.85	10.69	15.17	11.08	14.61
2.0	0	3	6	5	20	6.19	24.27	9.23	26.45	9.81	21.62	10.18	19.49
2.25	0	3	12	5	20	8.52	24.91	12.62	27.45	13.49	24.76	14.02	23.36
2.5	0	3	18	5	20	10.87	24.96	14.87	27.57	15.90	25.60	16.49	24.64
2.75	0	3	24	5	20	13.13	24.98	16.41	27.55	17.52	25.83	18.12	25.10

Table 3 $(\hat{p}_{low}, \hat{p}_{upp})$ and $(\hat{p}_{low}^*, \hat{p}_{upp}^*)$ when $h = 1, 2, 3$

mean, SD and sample size						true CI		c-intensive CI					
μ_1	μ_2	σ_1^2	σ_2^2	m_1	m_2	\hat{p}_{low}	\hat{p}_{upp}	$h = 1$		$h = 2$		$h = 3$	
								\hat{p}_{low}^*	\hat{p}_{upp}^*	\hat{p}_{low}^*	\hat{p}_{upp}^*	\hat{p}_{low}^*	\hat{p}_{upp}^*
2.9	0	3	6	5	7	0.048	0.064	0.044	0.064	0.047	0.060	0.048	0.058
3.4	0	3	12	5	7	0.048	0.065	0.045	0.064	0.047	0.060	0.049	0.058
3.9	0	3	18	5	7	0.048	0.066	0.045	0.065	0.048	0.061	0.050	0.060
4.4	0	3	24	5	7	0.048	0.067	0.046	0.065	0.049	0.062	0.051	0.061
2.3	0	3	6	5	10	0.044	0.062	0.041	0.057	0.043	0.054	0.044	0.052
2.8	0	3	12	5	10	0.044	0.053	0.042	0.054	0.043	0.051	0.044	0.050
3.3	0	3	18	5	10	0.044	0.052	0.042	0.053	0.043	0.051	0.044	0.050
3.8	0	3	24	5	10	0.044	0.053	0.042	0.053	0.044	0.051	0.044	0.050
2.0	0	3	6	5	20	0.038	0.069	0.037	0.055	0.039	0.053	0.040	0.052
2.25	0	3	12	5	20	0.037	0.057	0.036	0.047	0.037	0.046	0.038	0.045
2.5	0	3	18	5	20	0.037	0.050	0.036	0.044	0.037	0.043	0.037	0.042
2.75	0	3	24	5	20	0.037	0.046	0.036	0.042	0.037	0.041	0.037	0.041

7. Conclusion

Results of the simulation suggest that the p -value of the U -test for testing $H_0: c_1\mu_1 + c_2\mu_2 + \dots + c_K\mu_K = 0$ is better to be evaluated by using the c-intensive approximate 90% CI of p -value constructed by the the size of sample $n_i = m_i, i = 1, 2, \dots, K$.

8. Discussion

The u-estimator of tdf is not substantially different from the Welch df . Table 4 lists the values of the Welch df and u-estimator of tdf obtained from the simulation that

was carried out by 5,000 run by generating random samples of size m_1 from $N(\mu_1, \sigma_1^2)$ and of size m_2 from $N(\mu_2, \sigma_2^2)$, where values of $\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, m_1$ and m_2 employed are listed in Table 4. The table shows relatively large differences between the Welch df and u-estimator of the tdf ; for example, 8.71 vs. 10.21 in id 1, or 18.78 vs. 21.46 in id 12. However those differences are not substantial when evaluated by means of the right tail probabilities. Table 5 lists the right tail probabilities of t -distribution in the range of $t \geq 1.0$ when the values of df are 8.71 (id 1 Welch), 10.21 (id 1 u-estimator), 18.78 (id 12 Welch) and 21.46 (id 12 u-estimator). The table indicates that differences of p -values are small between two df 's.

Looking at Table 5 the referee of the present paper pointed out that the tail probabilities of t -distribution with 8.71 df and 21.46 df were not substantially different, indicating the stability of p -values and thus no need of constructing the CI of p -values regardless of the variation of estimated df . Our answer to the comment is as follows. The finding from Table 1 is true; namely, the impact of the variation of estimated df on the level of the test, and also on the p -value, could be substantial. Readers might have the feeling of contradiction between the comment and this statement. To resolve it they are asked to understand that the right tail probability of t -distribution could undergoes significant fluctuation due to small shift of df in the range of small values, for example, when $t = 2.2$ the right tail probabilities of $df = 4$ and $df = 8$ are 0.046 and 0.029, respectively. To express the point more clearly we obtained the empirical distribution of Welch's df by generating 5,000 sets of normal random digits when $\sigma_1^2 = 3$, $\sigma_2^2 = 6$, $m_1 = 5$ and $m_2 = 20$. The summary statistics of the distribution were given as follows.

min = 4.35, max = 23.00, mean=10.82, SD=4.95, 90% CI=(5.47, 21.73).

When $t = 2.00$, the upper tail probabilities of t -test with the df corresponding to the above summary statistics are obtained as

min = 0.029, max = 0.055, mean=0.036 and 90% CI=(0.029, 0.049).

The referee also pointed out that over-all behavior of the Welch test was not so bad. Look at the id.13 in Table 1. The empirical levels of the test on R_1, R_2, R_3 and R_4 are 0.008, 0.020, 0.048, 0.146, respectively; the levels on R_1 and R_4 are far from the nominal level. However, the average of those levels is 0.055, fairly close to 5%, indicating that if we apply the Welch test many times repeatedly, then we get over-all satisfaction. However, we stress that the Welch test is often applied to data that repetition is never conceived. For example, the repetition is not conceived in many clinical studies and yet decision is done based on p -value from each study. Such is the case that a cautious evaluation of the p -values would be absolutely-required.

where tdf and ξ are given in formulae (3) and (4). Now $Z = \sum c_i \bar{X}_i / \sqrt{\sum c_i^2 \sigma_i^2 / m_i}$ follows standard normal distribution under H_0 , and by using formulae (3) and (4) we may represent T^* by $T^* = Z / \sqrt{Q_{tdf} / tdf}$. Thus T^* follows t -distribution with tdf degrees of freedom. This completes the proof of Theorem 1.

Proof of Theorem 2

It follows from Lemma 1 that

$$\begin{aligned} E\left(\sum \frac{c_i^2 S_i^2}{m_i}\right)^2 &= Var\left(\sum \frac{c_i^2 S_i^2}{m_i}\right) + \left(E\left(\sum \frac{c_i^2 S_i^2}{m_i}\right)\right)^2 \\ &= 2 \sum \frac{1}{m_i - 1} \left(\frac{c_i^2 \sigma_i^2}{m_i}\right)^2 + \left(\sum \frac{c_i^2 \sigma_i^2}{m_i}\right)^2 \end{aligned}$$

and

$$\begin{aligned} E\left(\sum \frac{1}{m_i + 1} \left(\frac{c_i^2 S_i^2}{m_i}\right)^2\right) &= \sum \frac{1}{m_i + 1} \left(Var\left(\frac{c_i^2 S_i^2}{m_i}\right) + \left(E\left(\frac{c_i^2 S_i^2}{m_i}\right)\right)^2\right) \\ &= 2 \sum \frac{1}{(m_i + 1)(m_i - 1)} \left(\frac{c_i^2 \sigma_i^2}{m_i}\right)^2 + \sum \frac{1}{m_i + 1} \left(\frac{c_i^2 \sigma_i^2}{m_i}\right)^2. \end{aligned}$$

Therefore the expectation of the left hand side of the equation is

$$\begin{aligned} E\left(\left(\sum \frac{c_i^2 S_i^2}{m_i}\right)^2 - 2 \sum \frac{1}{m_i + 1} \left(\frac{c_i^2 S_i^2}{m_i}\right)^2 - \nu \sum \frac{1}{m_i + 1} \left(\frac{c_i^2 S_i^2}{m_i}\right)^2\right) \\ = \left(\sum \frac{c_i^2 \sigma_i^2}{m_i}\right)^2 - \nu \sum \frac{1}{m_i - 1} \left(\frac{c_i^2 \sigma_i^2}{m_i}\right)^2. \end{aligned}$$

Thus the expectation is zero if $\nu = tdf$, where tdf is given in formula (3). This complete the proof of Theorem 2.

Proof of Lemma 3

(i) From Lemma 1

$$E(S_i^{*2}) = E\left(E(S_i^{*2} | s_i^2)\right) = E(S_i^2) = \sigma^2.$$

(ii) Also from Lemma 1

$$\begin{aligned} E(S_i^{*4}) &= E\left(E(S_i^{*4} | s_i^2)\right) = E\left(\frac{n_i + 1}{n_i - 1} S_i^4\right) \\ &= \frac{(n_i + 1)(m_i + 1)}{(n_i - 1)(m_i - 1)} \sigma_i^4. \end{aligned}$$

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