## A NOTE ON CONSERVATIVE CONFIDENCE REGIONS FOR THE MEAN OF A MULTIVARIATE NORMAL

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1. Introduction. Suppose  $x_i = (x_{li}, \dots, x_{mi})'$   $(i = 1, \dots, n)$  are independent observations from a *m*-variate normal population with mean vector  $\mu$  and covariance matrix  $\Sigma$ . Let  $\bar{x}_{i.} = \sum_{j} x_{ij}/n$  and  $s_i^2 = \sum_{j} (x_{ij} - \bar{x}_{i.})^2/(n-1)$ . If  $\Sigma$  is a diagonal matrix, a confidence region for  $\mu$  can be constructed from

(1) 
$$\Pr\{|z_i| \le c_i, i = 1, \dots, m\} = \prod_{i=1}^m \Pr\{|z_i| \le c_i\}$$

with  $z_i = n^{\frac{1}{2}}(\bar{x}_i - \mu_i)/\sigma_i$  if the diagonal elements,  $\sigma_i^2$ , of  $\Sigma$  are known, and  $z_i = n^{\frac{1}{2}}(\bar{x}_i - \mu_i)/s_i$  otherwise. Dunn [1] conjectured that, for any  $\Sigma$ ,

(2) 
$$\Pr\{|z_i| \leq c_i, i = 1, \dots, m\} \geq \prod_{i=1}^m \Pr\{|z_i| \leq c_i\}.$$

She proved the conjecture when  $\Sigma$  is of a special form, and in general for m=2 and m=3, and used the relation to construct conservative confidence limits for  $\mu$ . The purpose of this note is to provide a general proof of the conjecture. When the variances are known, the conjecture has been proved with a different method by Sidak [2].

2. Diagonal elements of  $\Sigma$  kown. In this case  $z=(z_1,\cdots,z_m)'$  has a normal distribution with  $E(z_i)=0$ ,  $E(z_i^2)=1$  and covariance matrix AA' say ( $\sum_j a_{ij}^2 a_{ij}$ 

LEMMA 1. Pr  $\{y \in R_m\} \geq [\Phi(c_1) - \Phi(-c_1)] \Pr \{y \in R_{m-1}\}$ 

PROOF. The Lemma has been proved essentially by Dunn for m = 2. If m > 2, it is enough to show that

(3) 
$$\Pr\{R_m \mid y \in P\} \ge [\Phi(c_1) - \Phi(-c_1)] \Pr\{R_{m-1} \mid y \in P\}$$

for every plane P containing the  $x_1$  – axis.

Choose such a plane P. By an orthogonal transformation of  $(y_2, \dots, y_m)'$ , P can be taken to be the co-ordinate plane  $\{y: y_i = 0, i = 3, \dots, m\}$ . Then equation (3) becomes

(4) 
$$\Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1, |y_2| \le c_2'\} \ge [\Phi(c_1) - \Phi(-c_1)] \Pr\{|y_2| \le c_2'\}.$$

But this follows immediately from the case for m=2 [since  $a_{11}^2+a_{12}^2\leq 1$ ]. Now

$$\Pr\{|z_i| \leq c_i, i = 1, \cdots, m\} = \Pr\{y \in R_m\}.$$

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and

$$\Pr\{|z_i| \leq c_i\} = \Phi(c_i) - \Phi(-c_i).$$

Theorem 1 then follows from Lemma 1 by induction.

Theorem 1. If the diagonal elements of  $\Sigma$  are known

$$\Pr\{|z_i| \le c_i, i = 1, \dots, m\} \ge \prod_{i=1}^m \Pr\{|z_i| \le c_i\}$$

3. Diagonal elements of  $\Sigma$  unknown. Let A and y be as in the preceding section.

Lemma 2. Pr 
$$\{|\sum_{i} a_{ij}y_{i}| \geq c_{i}, i = 1, \dots, m\} \geq \prod_{i=1}^{m} \Pr\{|y_{i}| \geq c_{i}\}$$
 Proof. Suppose  $m = 2$ ,

$$\Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1\} = \Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1, |y_2| \le c_2\}$$

$$+ \Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1, |y_2| \ge c_2\}$$

$$\ge \Pr\{|y_1| \le c_1, |y_2| \le c_2\}$$

$$+ \Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1, |y_2| \ge c_2\}$$

by Theorem 1.

But

$$\Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1\} = \Pr\{|y_1| \le c_1\} \qquad (a_{11}^2 + a_{12}^2 = 1) \\
= \Pr\{|y_1| \le c_1, |y_2| \le c_2\} + \Pr\{|y_1| \le c_1, |y_2| \ge c_2\}$$

Therefore

$$\Pr\{|a_{11}y_1 + a_{12}y_2| \le c_1, |y_2| \ge c_2|\} \le \Pr\{|y_1| \le c_1, |y_2| \ge c_2\}$$

so that

$$\Pr \left\{ \left| a_{11} y_1 \, + \, a_2 y_2 \right| \, \ge \, c_1 \, , \, \left| y_2 \right| \, \ge \, c_2 \right\} \, \ge \, \Pr \left\{ \left| y_1 \right| \, \ge \, c_1 \, , \, \left| y_2 \right| \, \ge \, c_2 \right\}$$

The proof for m > 2 proceeds just as the proof of Theorem 1.

Let V be the matrix with elements  $v_{ij} = (x_{ij} - \mu_i)/\sigma_i$  let H be an  $n \times n$  orthogonal matrix with nth column equal to  $(1/n^{\frac{1}{2}}, 1/n^{\frac{1}{2}}, \dots, 1/n^{\frac{1}{2}})'$  and let U = VH. Then the columns of U are independent and identically distributed with  $E(u_{ij}) = 0$  and  $E(u_{ij}^2) = 1$ . Moreover  $z_i = (n-1)^{\frac{1}{2}}u_{in}/(\sum_{j=1}^{n-1}u_{ij}^2)^{\frac{1}{2}}$ . Let the covariance matrix of each column vector be BB' with B chosen so that  $b_{i1} = 0$   $(i = 2, \dots, m)$ , and let  $Y = B^{-1}U$ . Then

$$\Pr\{|z_{i}| \leq c_{i}, i = 1, \dots, m\} = \Pr\{u_{ni}^{2} \leq [c_{i}^{2}/(n-1)] \sum_{j=1}^{n-1} u_{ji}^{2}, i = 1, \dots, m\}$$

$$= \Pr\{\left[\sum_{k} b_{ik} y_{kn}\right]^{2} \leq \left[c_{i}^{2}/(n-1)\right] \sum_{j=1}^{n-1} \left[\sum_{k} b_{ik} y_{kj}\right]^{2}, i = 1, \dots, m\}$$

$$\geq \Pr\{y_{in}^{2} \leq \left[c_{i}^{2}/(n-1)\right] \sum_{j=1}^{n-1} \left[\sum_{k} b_{ik} y_{kj}\right]^{2}, i = 1, \dots, m\}$$

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by Theorem 1

$$\geq \Pr\{y_{in}^{2} \leq [c_{i}^{2}/(n-1)][\sum_{j=1}^{n-2}(\sum_{k}b_{ik}y_{kj})^{2} + y_{in-1}^{2}],$$

$$i = 1, \dots, m\}$$

$$\vdots$$

$$\geq \Pr\{y_{in}^{2} \leq [c_{i}^{2}/(n-1)]\sum_{j=1}^{n-1}y_{ij}^{2}, i = 1, \dots, m\}$$
by repeated application of Lemma 2
$$= \prod_{1}^{n}\Pr\{|y_{in}| \leq [c_{i}/(n-1)^{\frac{1}{2}}][\sum_{j=1}^{n-1}y_{ij}^{2}]^{\frac{1}{2}},$$

$$i = 1, \dots, m\}$$

$$= \prod_{1}^{n}\Pr\{|z_{i}| \leq c_{i}\}.$$

This proves:

THEOREM 2. If  $z_i = n^{\frac{1}{2}}(m_i - \mu_i)/s_i$ , then

$$\Pr\{|z_i| \le c_i, i = 1, \dots, m\} \ge \prod_{i=1}^m \Pr\{|z_i| \le c_i\}$$

4. Acknowledgment. I would like to thank the referee for pointing out reference [2].

#### REFERENCES

- Dunn, Olive Jean. (1958). Estimation of the means of dependent variables. Ann. Math. Statist. 29 1095-1111.
- [2] Sidak, Zbynek (1965). Rectangular confidence regions for means of multivariate normal distributions. 35th Session of the International Statistical Institute, Belgrade.

### **CORRECTION NOTE**

#### CORRECTION TO

# CALCULATION OF EXACT SAMPLING DISTRIBUTION OF RANGES FROM A DISCRETE POPULATION

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Correction to page 530, Ann. Math. Statist. 26, 530-532, the lower limit on the summation in equation (2) should read j = i not j = 1, as it was printed.