# LIKELIHOOD RATIO TESTS FOR COMPARING & POPULATIONS —THE TWO-PARAMETER NONREGULAR MODELS

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### Summary

The null and nonnull distributions of the likelihood ratio statistics for testing the homogeneity of k given populations, each associated with a nonregular density depending on two truncation parameters, are investigated. This generalizes to the two-parameter case the work of Hogg (1956, Ann. Math. Statist., 27, 529-532), Barr (1966, J. Amer. Statist. Assoc., 61, 856-864) and Khatri and Jaiswal (1969, Aust. J. Statist., 11, 79-84; 1969, 1971, Ann. Inst. Statist. Math., 21, 127-136; 23, 199-210).

### 1. Introduction

Let (c, d) be a given (finite or infinite) interval, h(x) a positive integrable function over every closed interval contained in (c, d), and  $\Theta = \{(\theta_1, \theta_2): c < \theta_1 < \theta_2 < d\}$ . Let  $f(x: \theta_1, \theta_2), (\theta_1, \theta_2) \in \Theta$ , be a two-parameter density defined as

(1.1) 
$$f(x: \theta_1, \theta_2) = \begin{cases} h(x)/g(\theta_1, \theta_2) & \theta_1 \leq x \leq \theta_2 \\ 0 & \text{elsewhere ,} \end{cases}$$

where 
$$g(\theta_1, \theta_2) = \int_{\theta_1}^{\theta_2} h(t)dt$$
.

Let k populations be given with  $f(x: \theta_1^i, \theta_2^i)$  as the parent density associated with the i-th population,  $i=1,\dots,k$ . Let  $X_i$  and  $Y_i$  be the minima and maxima, respectively, of a random sample of size  $n_i (\geq 2)$  drawn from  $f(x: \theta_1^i, \theta_2^i)$ ,  $i=1,\dots,k$ , and assume that the k samples are independent. Based on these data and the likelihood ratio test (LRT),

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we test for the homogeneity of the k populations, as given by the following hypotheses:

$$\left\{ \begin{array}{ll} H_1 \colon (\theta_1^i,\,\theta_2^i) \!=\! (\theta_1^0,\,\theta_2^0) & \text{ for every } i \!=\! 1,\cdots,k, \\ & \text{ where } (\theta_1^0,\,\theta_2^0) \in \theta \text{ is specified} \\ \\ K_1 \colon (\theta_1^i,\,\theta_2^i) \!\neq\! (\theta_1^0,\,\theta_2^0) & \text{ for some } i \!=\! 1,\cdots,k \;. \end{array} \right.$$

and

$$\left\{ \begin{array}{ll} H_2 \colon (\theta_1^i,\,\theta_2^i) \!=\! (\theta_1,\,\theta_2) & \text{ for every } i \!=\! 1,\cdots,k, \\ & \text{ where } (\theta_1,\,\theta_2) \text{ is unspecified} \\ \\ K_2 \colon (\theta_1^i,\,\theta_2^i) \!\neq\! (\theta_1^j,\,\theta_2^j) & \text{ for some } i \text{ and } j,\; i \!\neq\! j,\; i,\, j \!=\! 1,\cdots,k \;. \end{array} \right.$$

Hogg [5] analyzed the one-parameter problem for testing the homogeneity of the k populations. For the case in which the  $\theta_1^{ij}$ s are known to be equal to a given constant, Hogg showed that -2 times the logarithm of the LRT statistic has  $\chi^2(2k)$  as its null distribution if the common value of the  $\theta_2^{ij}$ s is specified (under the null hypothesis), and  $\chi^2(2k-2)$  otherwise. Barr [2] and Khatri and Jaiswal ([6]-[8]) derived the nonnull distribution of the LRT statistics.

For the two-parameter problem, let  $\Lambda_i$  be the LRT statistic for  $H_i$  vs  $K_i$ , and set  $l_i = -2 \log \Lambda_i$ , i = 1, 2. In contrast to the one-parameter results obtained by Hogg [5], it is shown in Section 2 that chi-square fails to be the exact null distribution of the  $l_i$ 's. Nevertheless it serves as a limiting distribution since as  $n_i \to \infty$ ,  $i = 1, \dots, k$ , the limiting null distributions of  $l_1$  and  $l_2$  are  $\chi^2(4k)$  and  $\chi^2(4k-4)$ , respectively. The exact nonnull distribution of  $l_1$  is discussed in Section 3. The corresponding distribution of  $l_2$  is quite difficult to derive (even for the two and three population case). Accordingly, it will not be treated here and is left as an open question.

## 2. The limiting null distributions of the LRT statistics

To simplify the presentation of the results we first present a lemma. In what follows we use  $\phi_Q(\cdot)$  and  $f_Q(\cdot)$  to denote the characteristic and density functions, of a r.v. Q.

LEMMA 2.1. Let X and Y be the minima and maxima, respectively, of a random sample of size n drawn from (1.1), and define  $W_1 = g(X, Y)/g(\theta_1, Y)$ ,  $W_2 = g(X, Y)/g(\theta_1, \theta_2)$ ,  $R = g(\theta_1, X)/g(\theta_1, \theta_2)$  and  $S = g(\theta_1, Y)/g(\theta_1, \theta_2)$ . Then, i)  $-2 \log W_1^{n-1} \sim \chi^2(2)$ , ii)  $-2 \log W_2^n \stackrel{\mathcal{D}}{=} Z_1 + (n/(n-1))Z_2$ , where  $Z_1$  and  $Z_2$  are i.i.d. r.v.'s with a common  $\chi^2(2)$  distribution, and iii) the distribution of (R, S) is free of  $(\theta_1, \theta_2)$ .

PROOF. By transforming from (X,Y) to  $(W_1,W_2)$ , we obtain  $f_{W_1,W_2}(w_1,w_2)=n(n-1)w_2^{n-1}/w_1^2$  for  $0< w_2< w_1<1$ . The marginal densities of  $W_1$  and  $W_2$  yield (i) and (ii). (iii) is obtained by transforming from (X,Y) to (R,S). One obtains that  $f_{R,S}(r,s)=n(n-1)(s-r)^{n-2}$  for 0< r< s<1, which is the desired result.

We now consider the LRT's for  $H_i$  vs  $K_i$ , i=1, 2. Using the monotonicity properties of  $g(\cdot, \cdot)$ , we can express  $\Lambda_1$  and  $\Lambda_2$  as

$$(2.1) \quad \varLambda_{1} = \begin{cases} \prod\limits_{j=1}^{k} \{g(X_{j}, Y_{j})/g(\theta_{1}^{0}, \theta_{2}^{0})\}^{n_{j}}, & \theta_{1}^{0} < X_{j} < Y_{j} < \theta_{2}^{0}, \ j = 1, \cdots, k \\ 0, & \text{elsewhere}, \end{cases}$$

where  $\{\Lambda_1=0\}$  is a null event under  $H_1$ , and

(2.2) 
$$\Lambda_2 = \prod_{j=1}^{k} \{g(X_j, Y_j)/g(X^*, Y^*)\}^{n_j},$$

where  $X^* = \min_{1 \le i \le k} X_i$  and  $Y^* = \max_{1 \le i \le k} Y_i$ . The limiting null distributions of  $l_1$  and  $l_2$  are given by the following theorem.

THEOREM 2.1. Let  $n_j \to \infty$  for  $j=1,\dots,k$ , then a)  $l_1 \xrightarrow{\mathcal{D}} \chi^2(4k)$  under  $H_1$ , and b)  $l_2 \xrightarrow{\mathcal{D}} \chi^2(4k-4)$  under  $H_2$ .

PROOF. Assume that  $H_1$  holds.  $\Lambda_1$  can be written as  $\Lambda_1 = \prod_{j=1}^k \nu_j$ , where  $\nu_j = \{g(X_j, Y_j)/g(\theta_1^0, \theta_2^0)\}^{n_j}$ ,  $j=1,\dots,k$ . Because of the independence of the k samples, application of Lemma 2.1 (ii) yields for every t

$$\phi_{\iota_1}(t) \! = \! \prod_{j=1}^k \phi_{-2\log \nu_j}(t) \! = \! (1-2it)^{-k} \prod_{j=1}^k (1-2itn_j/(n_j-1))^{-1} \! \to \! (1-2it)^{-2k}$$
 as  $n_j \! \to \! \infty$ 

 $j=1,\dots,k$ , and this implies a).

Now assume that  $H_2$  holds. We show that the distribution of  $\Lambda_2$  is free of  $(\theta_1, \theta_2)$ , and that  $\Lambda_2$  is independent of  $(X^*, Y^*)$ . We then use Lemma 2.1 (ii) to complete the proof. Define  $R_j = g(\theta_1, X_j)/g(\theta_1, \theta_2)$ ,  $S_j = g(\theta_1, Y_j)/g(\theta_1, \theta_2)$ ,  $j = 1, \dots, k$ ,  $R^* = \min_{1 \le j \le k} R_j$ , and  $S^* = \max_{1 \le j \le k} S_j$ . Then rewriting (2.2) in terms of these quantities, we obtain  $\Lambda_2 = \prod_{j=1}^k \{(S_j - R_j)/(S^* - R^*)\}^{n_j}$ . By Lemma 2.1 (iii), the distribution of  $(R_j, S_j)$  is free of  $(\theta_1, \theta_2)$  for all  $j = 1, \dots, k$ . Since independence of the k samples implies independence of the  $(R_j, S_j)$ 's, it follows that the distribution of the random vector  $(R_j, S_j, j = 1, \dots, k)$  is free of  $(\theta_1, \theta_2)$  and hence the distribution of  $\Lambda_2$  is also free of  $(\theta_1, \theta_2)$ .

Under  $H_2$ ,  $(X^*, Y^*)$  is complete and sufficient for  $(\theta_1, \theta_2)$ . This, the

fact that the distribution of  $\Lambda_2$  is free of  $(\theta_1, \theta_2)$ , and Basu's Theorem (Basu [3], Theorem 2) imply that  $\Lambda_2$  is independent of  $(X^*, Y^*)$ .

Finally, rewrite  $\Lambda_2$  in (2.2) as  $\Lambda_2 = \prod_{j=1}^k \xi_j/\xi^*$ , where  $\xi_j = \{g(X_j, Y_j)/g(\theta_1, \theta_2)\}^{n_j}$ ,  $j=1,\cdots,k$  and  $\xi^* = \{g(X^*, Y^*)/g(\theta_1, \theta_2)\}^{n_j}$ ,  $N=\sum\limits_{j=1}^k n_j$ . Since  $\Lambda_2$  is independent of  $(X^*, Y^*)$ , the r.v.'s  $-2\log\Lambda_2$  and  $-2\log\xi^*$  are independent, so that we have for every t,  $\psi_{-2\log\Lambda_2}(t)\psi_{-2\log\xi^*}(t) = \prod\limits_{j=1}^k \psi_{-2\log\xi_j}(t)$ . Application of Lemma 2.1 (ii) for the r.v.'s  $-2\log\xi^*$  and  $-2\log\xi_j$ ,  $j=1,\cdots,k$ , yields

$$\phi_{-2\log A_2}(t) \!=\! (1-2it)^{-(k-1)} (1-2itN/(N-1)) \prod_{j=1}^k (1-2itn_j/(n_j-1))^{-1} \,.$$

Letting  $n_i \to \infty$ ,  $j=1,\dots,k$ , we obtain b).

*Remark.* If the  $\theta_1^{i}$ 's and the  $\theta_2^{i}$ 's are considered as the structural and incidental parameters, respectively, one may be interested in testing

$$\left\{egin{array}{ll} H_3\colon heta_1^i\!=\! heta_1^0 & ext{for every } i\!=\!1,\cdots,k, ext{ where } heta_1^0 ext{ is specified} \ K_3\colon heta_1^i\!
eq\! heta_1^0 & ext{for some } i\!=\!1,\cdots,k \,. \end{array}
ight.$$

For testing these hypotheses one can use the LRT as well as the conditional likelihood ratio test (CLRT). The CLRT, which is based on the conditional likelihood of the structural parameters, is defined in a manner analogous to the ordinary LRT. Such a conditional test was introduced by Andersen [1], who derived its asymptotic behaviour for a certain regular model.

Let  $\Lambda_3$  and  $\Lambda_3^c$  be the LRT and CLRT statistics, respectively, for testing  $H_3$  vs  $K_3$ . These statistics have the forms

$$arLambda_3 = \left\{egin{array}{ll} \prod\limits_{j=1}^k \left\{g(X_j,\,Y_j)/g( heta_1^0,\,Y_j)
ight\}^{n_j}\,, & & heta_1^0 \!<\! X_j \!<\! Y_j, \;\; j \!=\! 1,\cdots, k \ 0\,, & & elsewhere\,, \end{array}
ight.$$

and

$$arLambda_{3}^{c} = \left\{ egin{array}{ll} \prod_{j=1}^{k} \{g(X_{j},\,Y_{j})/g( heta_{1}^{0},\,Y_{j})\}^{n_{j}-1}\,, & & heta_{1}^{0} \!<\! X_{j} \!<\! Y_{j}, \;\; j \!=\! 1, \cdots, \, k \ & & ext{elsewhere} \;. \end{array} 
ight.$$

If  $l_3 = -2 \log \Lambda_3$  and  $l_3^c = -2 \log \Lambda_3^c$ , then under  $H_3$ ,  $l_3 \xrightarrow{\mathcal{D}} \chi^2(2k)$  as  $n_j \rightarrow \infty$ ,  $j = 1, \dots, k$ , whereas  $l_3^c \sim \chi^2(2k)$ . The derivation of these results is omitted since it is similar to that of Hogg [5] for the one-parameter case.

## 3. The nonnull distribution of $l_1$

Here, we derive the nonnull distribution of  $l_1$  for the k population case. Calculations of standard nature are omitted for the sake of brevity.

We shall find  $P(\Lambda_1 \leq \lambda)$  for all values of the parameters and from this compute the power function of the test. Define the events  $B_j = \{\theta_1^0 \leq X_j \leq Y_j \leq \theta_2^0\}$ ,  $\bar{B}_j$  the complement of  $B_j$ ,  $j=1,\dots,k$ , and the indexing sets  $K = \{1,\dots,k\}$ ,  $A_1 = \{j \in K: \theta_2^j \leq \theta_1^0\}$ ,  $A_2 = \{j \in K: \theta_1^j < \theta_1^0 < \theta_2^j \leq \theta_2^0\}$ ,  $A_3 = \{j \in K: \theta_1^j < \theta_1^0 < \theta_2^0 < \theta_2^j\}$ ,  $A_4 = \{j \in K: \theta_1^0 \leq \theta_2^j < \theta_2^0\}$ ,  $A_5 = \{j \in K: \theta_1^0 \leq \theta_2^0 < \theta_2^0\}$ , and  $A_6 = \{j \in K: \theta_2^0 \leq \theta_2^0\}$ .

If  $\lambda < 0$ , then  $P(\Lambda_1 \le \lambda) = 0$ , while if  $\lambda \ge 0$ ,

(3.1) 
$$P(\Lambda_1 \leq \lambda) = P(\Lambda_1 \leq \lambda, \ \overline{B}_j \text{ occurs for at least one } j=1,\dots,k) + (P(\Lambda_1 \leq \lambda, \ B_j \text{ occurs for all } j=1,\dots,k).$$

Let  $c_1$  and  $c_2$  denote the first and second terms, respectively, on the right hand side of (3.1). Since the occurance of  $\bigcup_{j=1}^{k} \overline{B}_{j}$  implies  $A_1 = 0 \le \lambda$ , we have  $c_1 = P\Big(\bigcup_{j=1}^{k} \overline{B}_{j}\Big) = 1 - \prod_{i=1}^{6} \prod_{j_i \in A_i} P(B_{j_i})$ , where  $P(B_{j_i}) = 0$  for  $j_i \in A_i$ , i = 1, 6,  $P(B_{j_2}) = \{g(\theta_1^0, \theta_2^{j_2})/g(\theta_1^{j_2}, \theta_2^{j_2})\}^{n_{j_2}}, \ j_2 \in A_2, \ P(B_{j_3}) = \{g(\theta_1^0, \theta_2^0)/g(\theta_1^{j_3}, \theta_2^{j_3})\}^{n_{j_3}}, \ j_3 \in A_3, \ P(B_{j_4}) = 1, \ j_4 \in A_4, \ \text{and} \ P(B_{j_5}) = \{g(\theta_1^0, \theta_2^0)/g(\theta_1^{j_5}, \theta_2^{j_5})\}^{n_{j_5}}, \ j_5 \in A_5.$  If  $A_1 \cup A_6 = \phi$  then  $\bigcup_{i=2}^{5} A_i = K$  and  $\bigcap_{i=1}^{k} B_i = \bigcup_{i=2}^{5} \bigcap_{j_i \in A_i} B_{j_i}$ , and hence we have

(3.2) 
$$c_{1} = \begin{cases} 1, & \text{if } A_{1} \cup A_{6} \neq \phi \\ 1 - \prod_{i=2}^{5} \prod_{j_{i} \in A_{i}} P(B_{j_{i}}), & \text{if } A_{1} \cup A_{6} = \phi. \end{cases}$$

Let

$$\begin{split} D_1 &= -2\log\left\{\prod_{j_2\in A_2}\left[\frac{g(X_{j_2},Y_{j_2})}{g(\theta_1^0,\,\theta_2^{j_2})}\right]^{n_{j_2}}\prod_{j_3\in A_3}\left[\frac{g(X_{j_3},\,Y_{j_3})}{g(\theta_1^0,\,\theta_2^0)}\right]^{n_{j_3}}\right.\\ &\times\prod_{j_4\in A_4}\left[\frac{g(X_{j_4},\,Y_{j_4})}{g(\theta_1^{j_4},\,\theta_2^{j_4})}\right]^{n_{j_4}}\prod_{j_5\in A_5}\left[\frac{g(X_{j_5},\,Y_{j_5})}{g(\theta_1^{j_5},\,\theta_2^0)}\right]^{n_{j_5}}\right\}\,, \end{split}$$

and  $d_1 = -2 \log (\lambda b_1)$ , where

$$b_1 \! = \! \prod_{j_2 \in A_2} \! \left[ \frac{g(\theta_1^0,\,\theta_2^0)}{g(\theta_1^0,\,\theta_2^{j_2})} \right]^{n_{j_2}} \prod_{j_4 \in A_4} \! \left[ \frac{g(\theta_1^0,\,\theta_2^0)}{g(\theta_1^{j_4},\,\theta_2^{j_4})} \right]^{n_{j_4}} \prod_{j_5 \in A_5} \! \left[ \frac{g(\theta_1^0,\,\theta_2^0)}{g(\theta_1^{j_5},\,\theta_2^0)} \right]^{n_{j_5}}.$$

Then, we have

$$(3.3) c_2 = \begin{cases} 0, & \text{if } A_1 \cup A_6 \neq \phi \\ P\left(D_1 \ge d_1 \Big| \bigcap_{i=2}^5 \bigcap_{j_i \in A_i} B_{j_i}\right) \prod_{i=2}^5 \prod_{j_i \in A_i} P(B_{j_i}), & \text{if } A_1 \cup A_6 = \phi. \end{cases}$$

Derivation of the distribution of  $(X_{j_i}, Y_{j_i})$  conditional on  $B_{j_i}$  for  $j_i \in A_i$ ,  $i=2,\cdots,5$ , and application of Lemma 2.1 (ii) show that the distribution of  $D_1$  conditional on  $\bigcap\limits_{i=2}^5\bigcap\limits_{j_i\in A_i}B_{j_i}$  equals the distribution of  $\sum\limits_{j=1}^k(Z_{1j}+(n_j/(n_j-1))Z_{2j})$ , where the  $Z_{1j}$ 's and the  $Z_{2j}$ 's are i.i.d. r.v.'s having a common  $\chi^2(2)$  distribution. Letting  $G_{k,n_1,\cdots,n_k}$  denote the distribution of the latter summation, combining (3.2) with (3.3), and noting that  $d_1\leq 0$  is equivalent to  $\lambda\geq b_1^{-1}$ , we obtain for  $\lambda\geq 0$ 

$$(3.4) \quad P(\Lambda_{1} \leq \lambda) = \begin{cases} 1 \text{ , } & \text{if } A_{1} \cup A_{6} \neq \phi \text{ or } A_{1} \cup A_{6} = \phi \text{ and } \lambda \geq b_{1}^{-1} \\ 1 - \int_{0}^{d_{1}} dG_{k, n_{1}, \dots, n_{k}}(x) \cdot \prod_{j_{2} \in A_{2}} \left[ \frac{g(\theta_{1}^{0}, \; \theta_{2}^{j_{2}})}{g(\theta_{1}^{j_{2}}, \; \theta_{2}^{j_{2}})} \right]^{n_{j_{2}}} \\ \times \prod_{j_{3} \in A_{3}} \left[ \frac{g(\theta_{1}^{0}, \; \theta_{2}^{0})}{g(\theta_{1}^{j_{3}}, \; \theta_{2}^{j_{3}})} \right]^{n_{j_{3}}} \prod_{j_{5} \in A_{5}} \left[ \frac{g(\theta_{1}^{j_{5}}, \; \theta_{2}^{0})}{g(\theta_{1}^{j_{5}}, \; \theta_{2}^{j_{5}})} \right]^{n_{j_{5}}}, \\ \text{ if } A_{1} \cup A_{6} = \phi \text{ and } \lambda < b_{1}^{-1}. \end{cases}$$

If  $\alpha \in (0, 1)$  is the significance level, then  $H_1$  is rejected if the given sample value of  $\Lambda_1$  is less than  $\lambda_0$ , the critical value determined by  $1-\alpha=\int_0^{-2\log\lambda_0}dG_{k,n_1,\dots,n_k}(x)$ . The power function of the corresponding LRT is obtained by replacing in (3.4),  $\lambda$  by  $\lambda_0$ . The technical difficulty connected with the derivation of the power function lies with the fact that no simple expression exists for  $G_{k,n_1,\dots,n_k}$ —the distribution of a linear combination of chi-square variates. However, in some special cases it can be given a simpler form. For example, in the case  $n_1=\dots=n_k=n$ , we have for  $t\geq 0$ 

$$egin{aligned} G_{^{k,n,\cdots,n}}\!(t) \!=\! rac{(n\!-\!1)^k}{2^{2k} n^k ((k\!-\!1)!)^2} \sum_{i=0}^{k-1} inom{k-1}{i} (-1)^i \int_0^t w^{k-1-i} e^{-w/2} \\ & \cdot \left[ \int_0^w y^{k-1-i} e^{y/(2n)} dy 
ight] \! dw \; , \end{aligned}$$

which can be evaluated by use of Gradshtein and Ryzhik ([4], p. 92 (2.321)). Hence for k=2, 3, we obtain, respectively,

$$G_{2,n,n}(t) = (1/2)e^{-t/2} \{ ne^{t/(2n)} [-(n-1)t + 2n(2n-3)] - (n-1)^2 (t+4n+2) + 2e^{t/2} \},$$

and

$$\begin{split} G_{3,n,n,n}(t) = & (1/8)e^{-t/2}\{ne^{t/(2n)}[-(n-1)^2t^2 + 4n(n-1)(3n-4)t\\ & -8n^2(6n^2 - 15n + 10)] + (n-1)^3[t^2 + 4(3n+1)t\\ & + 8(6n^2 + 3n + 1)] + 8e^{t/2}\} \ . \end{split}$$

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