

## ASYMPTOTICALLY OPTIMAL TESTS IN MARKOV PROCESSES

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**1. Introduction and summary.** Let  $(\mathcal{X}, \mathcal{A})$  be a measurable space and let  $\Theta$  be an open subset of the  $k$ -dimensional Euclidean space  $\mathcal{E}_k$ . For each  $\theta \in \Theta$ , let  $P_\theta$  be a probability measure on  $\mathcal{A}$ . Let  $\{X_n, n \geq 0\}$  be a discrete parameter Markov process defined on  $(\mathcal{X}, \mathcal{A}, P_\theta)$ ,  $X_n$  taking values in the Borel real line  $(R, \mathcal{B})$ . Finally, let  $\mathcal{A}_n$  be the  $\sigma$ -field induced by the first  $n+1$  random variables  $X_0, X_1, \dots, X_n$  from the process and let  $P_{n, \theta}$  be the restriction of  $P_\theta$  to the  $\sigma$ -field  $\mathcal{A}_n$ .

Under suitable conditions on the process, the following results are derived. Let  $\theta_0$  be an arbitrary but fixed point in  $\Theta$  and let  $\Delta_n(\theta_0)$  be a  $k$ -dimensional vector defined in terms of the random variables  $X_0, X_1, \dots, X_n$ ;  $\Delta_n^*(\theta_0)$  stands for a certain truncated version of  $\Delta_n(\theta_0)$ . By means of  $\Delta_n^*(\theta_0)$  and  $h \in \mathcal{E}_k$ , one defines a probability measure  $R_{n, h}$ ,  $n \geq 0$ . The first main result is that the sequences  $\{P_{n, \theta}\}$  and  $\{R_{n, h}\}$  of probability measures with  $h = n^{\frac{1}{2}}(\theta - \theta_0)$ ,  $\theta \in \Theta$ , are *differentially equivalent* at the point  $\theta_0$ . (See Definition 5.1.) This is shown in Corollary 5.1. It is also proved in Corollary 5.2 that the sequence  $\{\Delta_n^*(\theta_0)\}$  is *differentially sufficient* at  $\theta_0$  (see Definition 5.2) for the family  $\{P_{n, \theta}; \theta \in \Theta\}$  of probability measures. Next, let  $\{h_n\}$  be a bounded sequence of  $h$ 's in  $\mathcal{E}_k$  and set  $\theta_n = \theta_0 + h_n n^{-\frac{1}{2}}$ . Then for hypotheses testing problems, Theorem 6.1 allows one to restrict oneself to the class of tests depending on  $\Delta_n(\theta_0)$  alone, at least as far as the asymptotic power of the test under alternatives of the form  $P_{n, \theta_n}$  is concerned.

In Section 7, these results are applied to the case of testing hypotheses about a real-valued parameter. More specifically, asymptotically most powerful tests for testing the hypothesis  $\theta = \theta_0$  against one-sided alternatives are constructed. This is covered in Theorem 7.1.1. Also an asymptotically most powerful unbiased test for testing the same hypothesis as above against two-sided alternatives is constructed in Theorem 7.1.2.

The first of these problems was also dealt with in Johnson and Roussas [2] but the approach is different here. The second problem is solved in Wald [8] for the independent identically distributed case. However, both the assumptions and approach are different here in addition to the Markovian character of the random variables involved.

Section 6 treats the general situation where  $\Theta$  is an open subset of  $\mathcal{E}_k$ . Theorem 6.1 together with Theorem 6.3 provide a way for studying the corresponding

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hypothesis testing problem in the  $k$ -dimensional parameter case. Finally, at the end of the last section, an outline is presented of forthcoming results for that case.

These results extend, under substantially weaker conditions, the work of Wald [8], [9] to Markov processes. The method of proof relies heavily on the development in LeCam [3].

Unless otherwise stated, limits will be taken as the sequence  $\{n\}$ , or subsequences thereof, tends to  $\infty$ . Integrals without limits will extend over the entire appropriate space. For  $h \in \mathcal{E}_k$ ,  $h'$  stands for its transpose. All bounding constants will be finite numbers.

**2. Notation and assumptions.** Let  $\Theta$  be an open subset of the  $k$ -dimensional Euclidean space  $\mathcal{E}_k$  and for each  $\theta \in \Theta$ , let  $\{X_n, n \geq 0\}$  be a discrete time parameter real-valued Markov process defined on the probability space  $(\mathcal{X}, \mathcal{A}, P_\theta)$  with initial and transition distributions  $p_\theta(\cdot)$  and  $p_\theta(\cdot, \cdot)$ , respectively. It will be assumed in the following that the probability measures  $\{P_{n, \theta}, \theta \in \Theta\}$ ,  $n \geq 0$  are mutually absolutely continuous, where  $P_{n, \theta}$  stands for the restriction of  $P_\theta$  to the  $\sigma$ -field  $\mathcal{A}_n$  induced by the random variables  $X_0, X_1, \dots, X_n$ . Therefore for any  $\theta, \theta' \in \Theta$ , we will have  $[dP_{0, \theta} / dP_{0, \theta'}] = q(X_0; \theta, \theta')$ ,  $[dP_{1, \theta} / dP_{1, \theta'}] = q(X_0, X_1; \theta, \theta')$ . Furthermore, let  $q(X_1 | X_0; \theta, \theta') = q(X_0, X_1; \theta, \theta') / q(X_0; \theta, \theta')$ ,  $\varphi_j(\theta, \theta') = [q(X_j | X_{j-1}; \theta, \theta')]^{\frac{1}{2}}$  and  $f_j(\theta, \theta') = [q(X_{j-1}, X_j; \theta, \theta')]^{\frac{1}{2}}$ ,  $j = 1, \dots, n$ , so that  $\int \varphi_1^2(\theta, \theta') dP_{1, \theta} = 1$ . There is no loss in generality by assuming that  $\Theta$  contains the origin in the  $\mathcal{E}_k$  space and we will do so.

The results in this paper are derived under the following set of assumptions and an additional one presented in Section 7.

**ASSUMPTION 1.** For each  $\theta \in \Theta$ , the Markov process  $\{X_n, n \geq 0\}$  is stationary and metrically transitive (ergodic). (See, e.g., Doob [1] page 457.)

**ASSUMPTION 2.** The probability measures  $\{P_{n, \theta}, \theta \in \Theta\}$ ,  $n \geq 0$  are mutually absolutely continuous.

**ASSUMPTION 3.** (i) For each  $\theta \in \Theta$ , the random function  $\varphi_1(\theta, \theta')$  is differentiable in quadratic mean (q.m.) with respect to  $\theta'$  at  $(\theta, \theta)$  when  $P_\theta$  is employed.

Let  $\dot{\varphi}_1(\theta)$  be the derivative of  $\varphi_1(\theta, \theta')$  with respect to  $\theta'$  at  $(\theta, \theta)$ . Then,  
(ii)  $\dot{\varphi}_1(\theta)$  is  $\mathcal{A}_2 \times \mathcal{C}$ -measurable, where  $\mathcal{C}$  denotes the  $\sigma$ -field of Borel subsets of  $\Theta$ .

Let  $\Gamma(\theta)$  be the covariance function defined by  $\Gamma(\theta) = 4\mathcal{E}_\theta [\dot{\varphi}_1(\theta) \dot{\varphi}_1'(\theta)]$ . Then,

(iii)  $\Gamma(\theta)$  is positive definite for every  $\theta \in \Theta$ .

**ASSUMPTION 4.** For every  $\theta \in \Theta$ , the random function  $f_1(\theta, \theta')$  is continuous in  $P_{1, \theta}$ -probability at  $(\theta, \theta)$ .

For an arbitrary but fixed  $\theta \in \Theta$ , we will be interested in sequences  $\theta_n \rightarrow \theta$ . Then, from Assumption 2 it follows that  $[dP_{n, \theta_n} / dP_{n, \theta}] = q(X_0; \theta, \theta_n) \prod_{j=1}^n \varphi_j^2(\theta, \theta_n)$  is

well defined outside a  $P_\theta$ -null set for all  $\theta \in \Theta$ . Therefore outside this set we can define the random variable  $\Lambda_n[P_{n, \theta_n}; P_{n, \theta}]$  as follows

$$\Lambda[P_{n, \theta_n}; P_{n, \theta}] = \log [dP_{n, \theta_n}/dP_{n, \theta}] = \log [q(X_0; \theta, \theta_n) \prod_{j=1}^n \varphi_j^2(\theta, \theta_n)].$$

In the sequel the probability measures  $P_{n, \theta}$  and  $P_\theta$  will be used interchangeably.

**3. Preliminary results.** For  $h_n, h \in \mathcal{E}_k$  the following theorem holds true.

**THEOREM 3.1.** *Under Assumptions A1, A2, A3(i), A3(ii) and A4, we have*

- (i)  $\mathcal{L}\{\Lambda[P_{n, \theta_n}; P_{n, \theta}] | P_\theta\} \rightarrow N(-\frac{1}{2}h'\Gamma(\theta)h, h'\Gamma(\theta)h).$
- (ii)  $\mathcal{L}\{\Lambda[P_{n, \theta_n}; P_{n, \theta}] | P_{\theta_n}\} \rightarrow N(\frac{1}{2}h'\Gamma(\theta)h, h'\Gamma(\theta)h),$

where  $\theta_n = \theta + h_n n^{-\frac{1}{2}}$  and  $h_n \rightarrow h$ .

The first conclusion of this theorem is Theorem 3.2.1 in Roussas [6] and the second is Theorem 2 in Roussas [7].

The  $k$ -dimensional random vector  $\Delta_n(\theta)$  is defined by

$$(3.1) \quad \Delta_n(\theta) = 2n^{-\frac{1}{2}} \sum_{j=1}^n \phi_j(\theta).$$

The function  $\Delta_n(\theta)$  plays a central role in the development.

The following theorems are also true.

**THEOREM 3.2.** *Under the same assumptions as those in Theorem 3.1, we have*

$$\mathcal{L}[\Delta_n(\theta) | P_\theta] \rightarrow N(0, \Gamma(\theta)).$$

This is Theorem 3.2.1 in Roussas [6].

**THEOREM 3.3.** *Under the same assumptions as those in Theorem 3.1, we have*

$$\Lambda[P_{n, \theta_n}; P_{n, \theta}] - h'\Delta_n(\theta) \rightarrow -A(h, \theta) \quad \text{in } P_{n_\theta}\text{-probability,}$$

where  $A(h, \theta) = \frac{1}{2}h'\Gamma(\theta)h$ .

This is Theorem 3.1.1 in Roussas [6].

Heuristically, this last theorem states that  $\exp[-A(h, \theta) + h'\Delta_n(\theta)] dP_{n, \theta}$  approximates  $dP_{n, \theta_n}$ . However, the integral of the approximating measure may not even be finite. The next few sections are devoted to the construction of an exponential family which does approximate  $dP_{n, \theta_n}$ .

Now we recall from LeCam [3] two of several equivalent definitions of the concept of contiguity which will be used in this paper.

**DEFINITION 3.1.** Two sequences  $\{P_n\}$  and  $\{Q_n\}$  of probability measures defined on  $(\mathcal{X}, \mathcal{A})$  are said to be *contiguous* if for any sequence  $\{T_n\}$  of random variables we have  $T_n \rightarrow 0$  in  $P_n$ -probability if and only if  $T_n \rightarrow 0$  in  $Q_n$ -probability.

**DEFINITION 3.2.** Let  $\{P_n\}$  be as in Definition 3.1 and  $\{T_n\}$  be a sequence of random variables. Then we say that the sequence  $\{\mathcal{L}(T_n | P_n)\}$  is *relatively compact* if for every  $\{n'\} \subset \{n\}$  there is a further  $\{m\} \subset \{n'\}$  such that  $\{\mathcal{L}(T_m | P_m)\}$  converges (in the weak sense) to a probability distribution.

Now assume that  $\chi_n$  defined by  $\chi_n = \Lambda[Q_n; P_n]$  exists. Then

DEFINITION 3.3. The sequences  $\{P_n\}$  and  $\{Q_n\}$  are said to be *contiguous* if  $\{\mathcal{L}(\chi_n | P_n)\}$  is relatively compact. Furthermore, if  $\{m\} \subset \{n\}$  is such that  $\{\mathcal{L}(\chi_m | P_m)\}$  converges to a probability distribution  $\mathcal{L}(\chi)$ , say, then  $\mathcal{E}(\exp \chi) = 1$ , where the expectation is calculated under  $\mathcal{L}(\chi)$ .

The following result follows from Theorem 3.1(i) and Theorem 2.1(6) in LeCam [3] and is isolated here for easy reference.

PROPOSITION 3.1. *Under the same assumptions as those in Theorem 3.1, we have that the sequences  $\{P_{n, \theta_n}\}$  and  $\{P_{n, \theta}\}$  are contiguous.*

PROOF. By Theorem 3.1(i),  $\{\mathcal{L}\{\Lambda[P_{n, \theta_n}; P_{n, \theta}] | P_\theta\}\}$  is, trivially, relatively compact and the limit law  $\mathcal{L}(\chi)$  is  $N(-\frac{1}{2}h'\Gamma(\theta)h, h'\Gamma(\theta)h)$ . Furthermore it is easily seen that  $\mathcal{E}(\exp \chi) = 1$  and Theorem 2.1(6) in LeCam [3] completes the proof.

**4. Some lemmas.** In this section, some lemmas are collected for use in later sections of the paper. Let  $W$  be a bounded convex symmetric neighborhood of  $\theta_0$  in  $\mathcal{E}_k$ . Without loss of generality—and with conceptual advantages—we may assume that  $W$  is the closed sphere of radius 1 centered at  $\theta_0$ . On  $\mathcal{E}_k$ , define the real-valued function  $\rho$  by  $\rho(t) = \sup \{h't; h \in W\}$ . Then  $\rho(t) = \theta_0't + \sup \{(h - \theta_0)'t; h \in W\} = \theta_0't + \|t\|$ , where  $\|\cdot\|$  is the usual norm in  $\mathcal{E}_k$ . Consequently, there is no restriction if it is assumed that  $\theta_0 = 0$  when defining the function  $\rho$  and we will do so. Thus, it will be assumed that  $W$  is the unit sphere centered at the origin with the function  $\rho$  defined on  $\mathcal{E}_k$  by

$$(4.1) \quad \rho(t) = \|t\|.$$

It follows that  $\rho$  is continuous and therefore Theorem 3.2 implies that

$$(4.2) \quad \mathcal{L}[\rho(\Delta_n) | P_0] \rightarrow \mathcal{L}[\rho(\Delta) | P_0],$$

where  $\Delta$  is a  $k$ -dimensional random vector such that  $\mathcal{L}(\Delta | P_0) = N(0, \Gamma)$ ,  $\Delta_n = \Delta_n(0)$ , and  $\Gamma$  denotes  $\Gamma(0)$ .

Now we are in a position to proceed with the lemmas.

LEMMA 4.1. *For every  $\lambda > 0$ , we have  $\mathcal{E}_0[\exp \lambda \rho(\Delta)] < \infty$ .*

PROOF. Let  $\Delta = (\Delta_1, \dots, \Delta_k)'$ . Then  $\|\Delta\| \leq \sum_{j=1}^k |\Delta_j|$  and therefore

$$\begin{aligned} \mathcal{E}_0[\exp \lambda \rho(\Delta)] &= \mathcal{E}_0[\exp \lambda \|\Delta\|] \leq \mathcal{E}_0[\exp(\lambda \sum_{j=1}^k |\Delta_j|)] \\ &= \mathcal{E}_0(\prod_{j=1}^k \exp \lambda |\Delta_j|) \leq \prod_{j=1}^k \mathcal{E}_0^{1/k}(\exp k\lambda |\Delta_j|) \end{aligned}$$

by a generalized version of the Hölder inequality. But  $\mathcal{E}_0(\exp k\lambda |\Delta_j|) < \infty$  since  $\Delta_j$  is normal,  $j = 1, \dots, k$ . This completes the proof of the lemma.

Consider the random vectors  $\Delta_n, \Delta$  and for each  $\alpha > 0$ , define the following truncated random vectors  $\Delta_n^\alpha, \Delta^\alpha$ .

$$(4.3) \quad \begin{aligned} \Delta_n^\alpha &= \Delta_n, & \text{if } \rho(\Delta_n) < \alpha; & \quad \Delta^\alpha = \Delta, & \text{if } \rho(\Delta) < \alpha; \\ &= 0, & \text{otherwise} & \quad &= 0, & \text{otherwise.} \end{aligned}$$

Then the following lemma is true.

LEMMA 4.2. For every  $\alpha > 0$ , we have  $\mathcal{L}(\Delta_n^\alpha | P_0) \rightarrow \mathcal{L}(\Delta^\alpha | P_0)$ .

PROOF. For every bounded, continuous, real-valued function  $f$  on  $\mathcal{E}_k$ , it is easily seen that  $\int f(t) d\mathcal{L}(\Delta_n^\alpha | P_0) \rightarrow \int f(t) d\mathcal{L}(\Delta^\alpha | P_0)$ , since  $\mathcal{L}(\Delta_n | P_0) \rightarrow \mathcal{L}(\Delta | P_0)$  and the set of discontinuities of  $f\{tI_{[\rho(t) < \alpha]}(t)\}$  is a subset of the surface of the sphere of radius  $\alpha$ , centered at the origin, which is assigned ( $k$ -dimensional) Lebesgue measure zero and hence  $\mathcal{L}(\Delta | P_0)$  measure zero.

Lemma 4.2 and the continuity of  $\rho$  also imply that

$$(4.4) \quad \mathcal{L}[\rho(\Delta_n^\alpha) | P_0] \rightarrow \mathcal{L}[\rho(\Delta^\alpha) | P_0] \quad \text{for every } \alpha > 0.$$

By the definition of  $\rho$  and  $\Delta^\alpha, \Delta_n^\alpha$ , it follows that  $\rho(\Delta^\alpha) \leq \alpha, \rho(\Delta_n^\alpha) \leq \alpha$  for every  $\alpha > 0$  and all  $n$ . Thus whereas  $\mathcal{E}_0[\exp \lambda \rho(\Delta_n)]$  need not be finite, the expectations  $\mathcal{E}_0[\exp \lambda \rho(\Delta^\alpha)]$  and  $\mathcal{E}_0[\exp \lambda \rho(\Delta_n^\alpha)]$  are finite for every  $\alpha, \lambda > 0$  and all  $n$ . What is more, the following lemma holds true.

LEMMA 4.3. For every  $\alpha, \lambda > 0$ , we have

$$\mathcal{E}_0[\exp \lambda \rho(\Delta_n^\alpha)] \rightarrow \mathcal{E}_0[\exp \lambda \rho(\Delta^\alpha)].$$

PROOF. Since the distributions  $\mathcal{L}[\rho(\Delta^\alpha) | P_0]$  and  $\mathcal{L}[\rho(\Delta_n^\alpha) | P_0]$  have support confined to the interval  $[0, \alpha]$ , the result follows from (4.4) and the Helly-Bray lemma.

LEMMA 4.4. For every  $\lambda > 0$ , we have

$$\mathcal{E}_0[\exp \lambda \rho(\Delta^\alpha)] \rightarrow \mathcal{E}_0[\exp \lambda \rho(\Delta)] \quad \text{as } \alpha \rightarrow \infty.$$

PROOF. We have

$$\mathcal{E}_0[\exp \lambda \rho(\Delta^\alpha)] = \mathcal{E}_0\{\exp \lambda \rho(\Delta) I_{[\rho(\Delta) < \alpha]}(\Delta)\}.$$

Now  $\exp\{\lambda \rho(\Delta) I_{[\rho(\Delta) < \alpha]}(\Delta)\}$  is bounded by  $\exp \lambda \rho(\Delta)$  (independent of  $\alpha$ ) which is  $P_0$ -integrable. Also, since  $\exp\{\lambda \rho(\Delta) I_{[\rho(\Delta) < \alpha]}(\Delta)\} \rightarrow \exp[\lambda \rho(\Delta)]$  as  $\alpha \rightarrow \infty$ , the Dominated convergence theorem applies and gives the result.

Now let  $\{\alpha_v\}, \{\varepsilon_v\}$  be two sequences such that  $0 < \alpha_v \uparrow \infty$  and  $0 < \varepsilon_v \downarrow 0$  as  $v \rightarrow \infty$ . Let  $\lambda > 0$  be specified later. For every  $\alpha_v, \varepsilon_v$  and  $\lambda$  as above, there exists a positive integer  $N_v = N(\alpha_v, \varepsilon_v, \lambda)$  such that

$$(4.5) \quad |\mathcal{E}_0[\exp \lambda \rho(\Delta_n^{\alpha_v})] - \mathcal{E}_0[\exp \lambda \rho(\Delta^{\alpha_v})]| \leq \varepsilon_v, \quad n \geq N_v, \quad v = 1, 2, \dots$$

This is possible according to Lemma 4.3. Clearly  $\{N_v\}$  can be chosen so that  $N_v \uparrow \infty$ . Then, we define a sequence  $\{\Delta_n^*\}$  of  $k$ -dimensional random vectors by

$$(4.6) \quad \Delta_n^* = \Delta_n^{\alpha_v} \quad \text{for } n \text{ such that } N_v \leq n < N_{v+1}, \quad v = 1, 2, \dots$$

Clearly,

$$|\mathcal{E}_0[\exp \lambda \rho(\Delta_n^*)] - \mathcal{E}_0[\exp \lambda \rho(\Delta^{\alpha_v})]| \leq \varepsilon_v, \quad N_v \leq n < N_{v+1}, \quad v = 1, 2, \dots$$

by (4.5). Thus

$$\mathcal{E}_0[\exp \lambda \rho(\Delta_n^*)] - \mathcal{E}_0[\exp \lambda \rho(\Delta^{\alpha_v})] \rightarrow 0 \quad \text{as } n \rightarrow \infty (v \rightarrow \infty).$$

But  $\mathcal{E}_0[\exp \lambda \rho(\Delta^{\alpha_v})] \rightarrow \mathcal{E}_0[\exp \lambda \rho(\Delta)]$  as  $v \rightarrow \infty$  by Lemma 4.4. Therefore  $\mathcal{E}_0[\exp \lambda \rho(\Delta_n^*)] \rightarrow \mathcal{E}_0[\exp \lambda \rho(\Delta)]$ .

The following result has been established.

LEMMA 4.5. *Let the sequence  $\{\Delta_n^*\}$  be defined by (4.6). For every  $\lambda > 0$ , we have*

$$\mathcal{E}_0[\exp \lambda \rho(\Delta_n^*)] \rightarrow \mathcal{E}_0[\exp \lambda \rho(\Delta)].$$

From the definition of  $\Delta_n^*$ , we have  $\Delta_n^* = \Delta_n^{\alpha_v} = \Delta_n I_{[\rho(\Delta_n) < \alpha_v]}(\Delta_n)$  for  $n$  such that  $N_v \leq n < N_{v+1}$ . Thus  $(\Delta_n^* \neq \Delta_n) = [\rho(\Delta_n) \geq \alpha_v]$  and

$$(4.7) \quad P_0(\Delta_n^* \neq \Delta_n) = P_0[\rho(\Delta_n) \geq \alpha_v].$$

But  $\mathcal{L}[\rho(\Delta_n) | P_0] \rightarrow \mathcal{L}[\rho(\Delta) | P_0]$  by (4.2) and  $\alpha_v \rightarrow \infty$  as  $v \rightarrow \infty$  (which implies  $n \rightarrow \infty$ ). Therefore, taking the limits in (4.7) as  $v \rightarrow \infty$ , we get

$$(4.8) \quad P_0(\Delta_n^* \neq \Delta_n) \rightarrow 0.$$

Since  $\mathcal{L}(\Delta_n | P_0) \rightarrow N(0, \Gamma)$  by Theorem 3.2, it follows from (4.8) that

$$(4.9) \quad \mathcal{L}(\Delta_n^* | P_0) \rightarrow N(0, \Gamma).$$

Now let  $C_n = (\Delta_n^* \neq \Delta_n)$  and  $Z_n = I_{C_n}$ . Then, for  $\varepsilon > 0$ , we have  $P_0(|Z_n| \geq \varepsilon) = P_0(Z_n = 1) = P_0(C_n) \rightarrow 0$  by (4.8). That is,  $Z_n \rightarrow 0$  in  $P_0$ -probability and this implies that  $Z_n \rightarrow 0$  in  $P_{\theta_n}$ -probability by Proposition 3.1. Here  $\theta_n = h_n n^{-\frac{1}{2}}$ , where  $h_n, h \in \mathcal{E}_k$  and  $h_n \rightarrow h$ . Thus we have the following proposition.

PROPOSITION 4.1. *Let  $\Delta_n, \Delta_n^*$  be as above and set  $\theta_n = h_n n^{-\frac{1}{2}}$ , where  $h_n, h \in \mathcal{E}_k$  and  $h_n \rightarrow h$ . Then*

$$P_0(\Delta_n^* \neq \Delta_n) \rightarrow 0 \quad \text{and} \quad P_{\theta_n}(\Delta_n^* \neq \Delta_n) \rightarrow 0.$$

The following lemma will also be needed.

LEMMA 4.6. *Let  $\{Y_n\}$  be a sequence of  $m$ -dimensional random vectors and let  $\{Z_n\}$  be a sequence of random variables such that  $|Z_n| \leq M$  for all  $n$ . Let  $Q$  be a probability measure on  $\mathcal{A}$  and let  $\mathcal{L}(Y_n | Q) \rightarrow \lambda^*$ , where  $\lambda^*$  is a probability measure on the  $m$ -dimensional Borel  $\sigma$ -field. Then if  $\{\mathcal{L}(Y_n, Z_n | Q)\}$  converges (weakly), it converges to a probability measure on the  $(m+1)$ -dimensional Borel  $\sigma$ -field.*

PROOF. Denote by  $F_n$  the cdf of  $(Y_n, Z_n)$ . Then the proof consists of showing that  $\limsup \{1 - F_n(\alpha, \beta)\} \rightarrow 0$ , where  $F_n(\alpha, \beta]$  denotes the variation of  $F_n$  over the  $(m+1)$ -dimensional interval  $(\alpha, \beta]$ . However, this follows readily from our assumptions.

For simplicity, we set  $\Lambda_n = \Lambda[P_n, \theta_n; P_n, 0]$ , and then recall that  $\theta_n = h_n n^{-\frac{1}{2}}$ ,  $h_n, h \in \mathcal{E}_k$ , and  $h_n \rightarrow h$ . The following lemma will be needed in the sequel.

LEMMA 4.7. *Let  $\{Y_n\}, \{Z_n\}$  be two sequences of random variables and let  $Y, Z$  be random variables such that  $\mathcal{L}(Y_n, Z_n | P_0) \rightarrow \mathcal{L}(Y, Z | P_0)$ . Assume that  $\Lambda_n - Y_n \rightarrow c$ , a constant, in  $P_0$ -probability. Then*

$$\mathcal{L}(Y_n, Z_n | P_{\theta_n}) \rightarrow \exp(y + c)\mathcal{L}(Y, Z | P_0),$$

where here and in the sequel the notation  $f \mathcal{L}$  stands for a probability measure which is absolutely continuous with respect to the probability measure  $\mathcal{L}$  and has density  $f$ .

PROOF. We have  $\mathcal{L}(Y_n, Z_n | P_0) \rightarrow \mathcal{L}(Y, Z | P_0)$  if and only if  $\mathcal{L}(c_1 Y_n + c_2 Z_n | P_0) \rightarrow \mathcal{L}(c_1 Y + c_2 Z | P_0)$  for every  $c_1, c_2$  in  $R$ . Also  $c_1 \Lambda_n - c_1 Y_n \rightarrow c_1 c$  in  $P_0$ -probability. Hence  $\mathcal{L}(c_1 \Lambda_n + c_2 Z_n | P_0) \rightarrow \mathcal{L}[c_1 (Y+c) + c_2 Z | P_0]$  for every  $c_1, c_2$  in  $R$  which is equivalent to  $\mathcal{L}(\Lambda_n, Z_n | P_0) \rightarrow \mathcal{L}(Y+c, Z | P_0)$ . By setting  $Y+c = U$ , we then have  $\mathcal{L}(\Lambda_n, Z_n | P_0) \rightarrow \mathcal{L}(U, Z | P_0)$ . Then Theorem 2.1 in LeCam [3] implies that

$$\begin{aligned} \mathcal{L}(\Lambda_n, Z_n | P_{\theta_n}) &\rightarrow \mathcal{L}(U_0, Z_0 | P_0), && \text{where} \\ dP(U_0 \leq u, Z_0 \leq z) &= \exp u dP(U \leq u, Z \leq z) \\ &= \exp u dP(Y \leq u - c, Z \leq z). \end{aligned}$$

The substitution  $u - c = y$  completes the proof.

**5. Differential equivalence of certain probability measures.** In this section,  $h \in \mathcal{E}_k$  and  $\{h_n\}$  is taken to be a bounded sequence in  $\mathcal{E}_k$ . Then  $\mathcal{E}_0(\exp h' \Delta_n^*)$  is finite as has been seen. Set

$$(5.1) \quad \exp B_n(h) = \mathcal{E}_0(\exp h' \Delta_n^*)$$

and define the probability measures  $R_{n,h}$  on  $\mathcal{A}_n$  as follows

$$(5.2) \quad R_{n,h}(A) = \exp [-B_n(h)] \int_A \exp(h' \Delta_n^*) dP_{n,0}, \quad A \in \mathcal{A}_n.$$

Replacing  $h$  by  $h_n$ , we get  $R_{n,h_n}$  and then the probability measures  $P_{n,\theta_n}$  and  $R_{n,h_n}$  are differentially equivalent. (See Definition 5.1.) More precisely, we have the following theorem.

**THEOREM 5.1.** *For any bounded sequence  $\{h_n\}$  in  $\mathcal{E}_k$  and  $\theta_n$  defined by  $\theta_n = h_n n^{-\frac{1}{2}}$ , we have  $\|R_{n,h_n} - P_{n,\theta_n}\| \rightarrow 0$ , where  $\|\cdot\|$  is the norm associated with convergence in variation; that is,*

$$\|R_{n,h_n} - P_{n,\theta_n}\| = 2 \sup [ |R_{n,h_n}(A) - P_{n,\theta_n}(A)| ; A \in \mathcal{A}_n ].$$

PROOF. The proof is by contradiction. Assume that  $\|R_{n,h_n} - P_{n,\theta_n}\| \not\rightarrow 0$ . Then there exists an  $\varepsilon > 0$ ,  $\{m\} \subseteq \{n\}$  and  $\{h_m\} \subseteq \{h_n\}$  such that  $\|R_{m,h_m} - P_{m,\theta_m}\| > 2\varepsilon$  for all  $m$ . Equivalently,  $\sup \{ |R_{m,h_m}(A) - P_{m,\theta_m}(A)| ; A \in \mathcal{A}_m \} > \varepsilon$  for all  $m$ . Then there exists  $A_m \in \mathcal{A}_m$  such that  $|R_{m,h_m}(A_m) - P_{m,\theta_m}(A_m)| > \varepsilon$  for all  $m$ . Since  $\{h_m\}$  is bounded, there exists  $\{h_r\} \subseteq \{h_m\}$  such that  $h_r \rightarrow h$ , say. Thus we have  $|R_{r,h_r}(A_r) - P_{r,\theta_r}(A_r)| > \varepsilon$  for all  $r$  and  $h_r \rightarrow h$ . By setting  $Z_r = I_{A_r}$ , the last relationship becomes

$$(5.3) \quad \left| \int Z_r dR_{r,h_r} - \int Z_r dP_{r,\theta_r} \right| > \varepsilon \quad \text{for all } r.$$

The remaining part of the proof consists in arriving at a contradiction of (5.3). Since the process of doing so is rather long, it would be more suggestive to break the various auxiliary results into lemmas. Toward this end, we begin.

LEMMA 5.1. *There exists a subsequence  $\{s\}$  of  $\{r\}$  and a random variable  $Z$  with  $0 \leq Z \leq 1$  such that*

$$\int Z_s dP_{s,\theta_s} \rightarrow \int Z \exp(h'\Delta + c) dP_0,$$

where  $c = -A(h, 0)$ , to be shortened to  $A(h)$ , and  $h$  is the limit of  $\{h_s\}$ .

PROOF. Let  $\mu_r = \mathcal{L}(h_r'\Delta_r^*; Z_r | P_0)$ . Then there exists  $\{\mu_s\} \subseteq \{\mu_r\}$  such that  $\mu_s \rightarrow \mu$ . Lemma 4.6 applies with  $m = 1$ ,  $Y_s = h_s'\Delta_s^*$ ,  $Z_s = I_{A_s}$ ,  $Q = P_0$ , and  $\lambda^*$  being the  $N(0, h'\Gamma h)$  measure. Therefore  $\mu$  is a probability measure and we let  $\mu = \mathcal{L}(h'\Delta, Z | P_0)$ , where  $0 \leq Z \leq 1$ . Then

$$(5.4) \quad \mathcal{L}(h_s'\Delta_s^*, Z_s | P_0) \rightarrow \mathcal{L}(h'\Delta, Z | P_0).$$

Now  $\Lambda_s - h_s'\Delta_s \rightarrow c$  in  $P_0$ -probability by Theorem 3.3, while  $h_s'\Delta_s - h_s'\Delta_s^* \rightarrow 0$  in  $P_0$ -probability by (4.8). Thus  $\Lambda_s - h'\Delta_s^* \rightarrow c$  in  $P_0$ -probability and Lemma 4.7 applies and gives

$$(5.5) \quad \mathcal{L}(h_s'\Delta_s^*, Z_s | P_{\theta_s}) \rightarrow \exp(y+c)\mathcal{L}(h'\Delta, Z | P_0).$$

$$\begin{aligned} \text{Next } \int Z_s dP_{\theta_s} &= \int_{[0,1] \times R} z d\mathcal{L}(Z_s | P_{\theta_s}) = \int_{[0,1] \times R} z d\mathcal{L}(h_s'\Delta_s^*, Z_s | P_{\theta_s}) \\ &\rightarrow \int_{[0,1] \times R} z \exp(y+c) d\mathcal{L}(h'\Delta, Z | P_0) \end{aligned}$$

by (5.5) and this is equal to  $\int Z \exp(h'\Delta + c) dP_0$ . The proof is completed.

LEMMA 5.2. *Let  $\{s\}$  be as in Lemma 5.1. Then*

- (i)  $\int (Z_s \exp h_s'\Delta_s^*) dP_0 \rightarrow \int (Z \exp h'\Delta) dP_0$ , and
- (ii)  $\int \exp h_s'\Delta_s^* dP_0 \rightarrow \int \exp h'\Delta dP_0$ .

PROOF. Since  $\{h_n\}$  is bounded, one can choose  $\lambda > 0$  sufficiently large so that  $\lambda^{-1} \|h_n\| \leq 1$  for all  $n$ . Then  $\lambda^{-1} h_n \in W$  for all  $n$ , which implies that  $\lambda^{-1} h_n' t \leq \rho(t)$  for all  $n$ , and this is equivalent to

$$(5.6) \quad h_n' t \leq \lambda \rho(t) \quad \text{for all } n.$$

We may assume that this is the  $\lambda$  used in defining  $\Delta_n^*$  in (4.6). Now let  $B = \{t \in \mathcal{E}_k; \|t\| \leq r\}$ . Then since  $\mathcal{E}_0[\exp \lambda \rho(\Delta)] < \infty$  by Lemma 4.1, one can choose  $r$  sufficiently large so that

$$(5.7) \quad \int_{B^c} \exp[\lambda \rho(t)] d\mathcal{L}(\Delta | P_0) < \varepsilon.$$

Let  $\tau_n = \mathcal{L}(\Delta_n^*, Z_n | P_0)$ . Then, by Lemma 4.6, there exists  $\{\tau_{m'}\} \subseteq \{\tau_n\}$  such that  $\tau_{m'} \rightarrow \tau$  and  $\tau$  is a probability measure. Let  $\tau = \mathcal{L}(\Delta, Z | P_0)$ . Since  $\tau_{m'} \rightarrow \tau$  implies that  $\mathcal{L}(h'\Delta_{m'}^*, Z_{m'} | P_0) \rightarrow \mathcal{L}(h'\Delta, Z | P_0)$ , we may assume that the sequence  $\{s\}$  of Lemma 5.1 is a subsequence of  $\{m'\}$ . Thus we have  $\tau_s \rightarrow \tau$ . Also, since  $\mathcal{L}(\Delta_s^* | P_0) \rightarrow \mathcal{L}(\Delta | P_0)$  and  $I_B(t) \exp \lambda \rho(t)$  is bounded and its discontinuity set is a subset of the surface of  $B$  which is assigned Lebesgue measure zero and hence  $\mathcal{L}(\Delta | P_0)$ -measure zero, we have

$$(5.8) \quad \int_B \exp \lambda \rho(t) d\mathcal{L}(\Delta_s^* | P_0) \rightarrow \int_B \exp \lambda \rho(t) d\mathcal{L}(\Delta | P_0).$$



Now

$$\begin{aligned} \mathcal{E}_0[\exp \lambda \rho(\Delta_s^*)] &= \int \exp \lambda \rho(t) d\mathcal{L}(\Delta_s^* | P_0) \rightarrow \int \exp \lambda \rho(t) d\mathcal{L}(\Delta | P_0) \\ &= \mathcal{E}_0[\exp \lambda \rho(\Delta)] \end{aligned}$$

by Lemma 4.5. This result together with relation (5.8) then imply that

$$(5.9) \quad \int_{B^c} \exp \lambda \rho(t) d\mathcal{L}(\Delta_s^* | P_0) \rightarrow \int_{B^c} \exp \lambda \rho(t) d\mathcal{L}(\Delta | P_0).$$

Relations (5.7) and (5.9) imply that

$$(5.10) \quad \int_{B^c} \exp \lambda \rho(t) d\mathcal{L}(\Delta_s^* | P_0) \leq 2\varepsilon \text{ for } s \text{ sufficiently large.}$$

Next  $|\int_{[0,1] \times B^c} (z \exp h_s' t) d\tau_s - \int_{[0,1] \times B^c} (z \exp h' t) d\tau| \leq \int_{[0,1] \times B^c} \exp \lambda \rho(t) d\tau_s + 2 \int_{[0,1] \times B^c} \exp \lambda \rho(t) d\tau$  by (5.6) and the fact that  $h_s \rightarrow h$ . The bound is equal to  $\int_{B^c} \exp \lambda \rho(t) d\mathcal{L}(\Delta_s^* | P_0) + 2 \int_{B^c} \exp \lambda \rho(t) d\mathcal{L}(\Delta | P_0)$ . Relations (5.7) and (5.10) imply that

$$(5.11) \quad |\int_{[0,1] \times B^c} (z \exp h_s' t) d\tau_s - \int_{[0,1] \times B^c} (z \exp h' t) d\tau| \leq 4\varepsilon$$

for  $s$  sufficiently large.

Now we concentrate on the set  $[0, 1] \times B$ . On this set, we have

$$|z \exp h_s' t - z \exp h' t| \leq |z| |\exp h_s' t - \exp h' t| \leq |\exp h_s' t - \exp h' t| \leq M_1 \|h_s - h\|,$$

where  $M_1$  is a constant. Therefore

$$\begin{aligned} &|\int_{[0,1] \times B} (z \exp h_s' t) d\tau_s - \int_{[0,1] \times B} (z \exp h' t) d\tau| \\ &\leq |\int_{[0,1] \times B} (z \exp h_s' t) d\tau_s - \int_{[0,1] \times B} (z \exp h' t) d\tau_s| \\ &\quad + |\int_{[0,1] \times B} (z \exp h' t) d\tau_s - \int_{[0,1] \times B} (z \exp h' t) d\tau| \\ &\leq M_1 \|h_s - h\| + |\int_{[0,1] \times B} (z \exp h' t) d\tau_s - \int_{[0,1] \times B} (z \exp h' t) d\tau| \rightarrow 0, \end{aligned}$$

since  $h_s \rightarrow h$ ,  $\tau_s \rightarrow \tau$ , and the integrand is bounded and continuous except on a subset of the surface of  $[0, 1] \times B$ , where  $B$  can be chosen so that the surface of  $[0, 1] \times B$  has  $\tau$ -measure zero. Thus we have

$$(5.12) \quad |\int_{[0,1] \times B} (z \exp h_s' t) d\tau_s - \int_{[0,1] \times B} (z \exp h' t) d\tau| \leq \varepsilon$$

for  $s$  sufficiently large. Relations (5.11) and (5.12) then imply that

$$(5.13) \quad \int_{[0,1] \times \mathcal{S}_k} (z \exp h_s' t) d\tau_s \rightarrow \int_{[0,1] \times \mathcal{S}_k} (z \exp h' t) d\tau.$$

Finally, relation (5.13) is rewritten as

$$(5.14) \quad \int (Z_s \exp h_s' \Delta_s^*) dP_0 \rightarrow \int (Z \exp h' \Delta) dP_0$$

which is the first part of the lemma. From an argument entirely similar to that employed to establish relation (5.13) ( $Z$  is merely removed), it is seen that

$$\int_{[0,1] \times B} \exp h_s' t d\tau_s \rightarrow \int_{[0,1] \times B} \exp h' t d\tau$$

which is equivalent to  $\int \exp h_s' \Delta_s^* dP_0 \rightarrow \int \exp h' \Delta dP_0$  and this is the second part of the lemma.

LEMMA 5.3. *Let  $\{s\}$  and  $\{h_s\}$  be as in Lemma 5.1. Then*

$$\int \{Z_s \exp [h_s' \Delta_s^* - A(h_s)]\} dP_0 \rightarrow \int [Z \exp (h' \Delta + c)] dP_0.$$

PROOF. We know that  $\mathcal{L}(h' \Delta | P_0)$  is  $N(0, h' \Gamma h)$  and  $h' \Gamma h = -2c$ . Thus the right-hand side of (ii) in Lemma 5.2, being the moment generating function of  $h' \Delta$  evaluated at  $t = 1$ , is equal to  $\exp(\frac{1}{2} h' \Gamma h) = \exp(-c)$ . That is,  $\int \exp h' \Delta dP_0 = \exp(-c)$ .

It follows that  $A(h_s) \rightarrow -c$ , and  $\exp[-A(h_s)] \rightarrow \exp c$ . This result together with relation (5.14) gives

$$\int \{Z_s \exp [h_s' \Delta_s^* - A(h_s)]\} dP_0 \rightarrow \int [Z \exp (h' \Delta + c)] dP_0$$

as was to be shown.

LEMMA 5.4. *Let  $\{s\}$  and  $\{h_s\}$  be as in Lemma 5.1. Then*

$$\int Z_s dR_{s, h_s} - \int Z_s dP_{s, \theta_s} \rightarrow 0.$$

PROOF. From Lemma 5.1 and Lemma 5.3, one obtains

$$(5.15) \quad \int Z_s dP_{\theta_s} - \int \{Z_s \exp [h_s' \Delta_s^* - A(h_s)]\} dP_0 \rightarrow 0.$$

Now, from the definition of  $R_{s, h_s}$

$$(5.16) \quad \begin{aligned} \int Z_s dR_{s, h_s} &= \int \{Z_s \exp [-B_s(h_s)] \exp h_s' \Delta_s^*\} dP_0 \\ &= \exp [-B_s(h_s)] \int [Z_s \exp h_s' \Delta_s^*] dP_0. \end{aligned}$$

But  $\exp B_s(h_s) = \int \exp h_s' \Delta_s^* dP_0 \rightarrow \int \exp h' \Delta dP_0$  by Lemma 5.2(ii), and  $\int \exp h' \Delta dP_0 = \exp(-c)$  as was seen in the proof of Lemma 5.3. Furthermore  $A(h_s) \rightarrow -c$  and hence

$$(5.17) \quad \exp B_s(h_s) - \exp A(h_s) \rightarrow 0.$$

Employing relation (5.16) and Lemma 5.2(i), together with relation (5.17)

$$(5.18) \quad \int Z_s dR_{s, h_s} - \int \{Z_s \exp [h_s' \Delta_s^* - A(h_s)]\} dP_0 \rightarrow 0.$$

Finally, relations (5.15) and (5.18) imply that

$$\int Z_s dR_{s, h_s} - \int Z_s dP_{s, \theta_s} \rightarrow 0$$

as asserted.

Now we complete the proof of Theorem 5.1 by observing that Lemma 5.4 contradicts relation (5.3) (with  $r$  replaced by  $s$ ).

This theorem has two important corollaries whose formulation requires the following definitions.

DEFINITION 5.1. Let  $\{Q_{n, \theta}^{(1)}\}$  and  $\{Q_{n, \theta}^{(2)}\}$  be two sequences of probability measures on  $\mathcal{A}_n$ . Then we say that these two sequences are *differentially (asymptotically) equivalent* at the point  $\theta_0$  if, for each bounded set  $C$  in  $\mathcal{E}_k$ ,

$$\sup \{ \|Q_{n, \theta}^{(1)} - Q_{n, \theta}^{(2)}\|; \theta \in \Theta, n^{\frac{1}{2}}(\theta - \theta_0) \in C \} \rightarrow 0.$$

**COROLLARY 5.1.** *The sequences  $\{P_{n,\theta}\}, \{R_{n,h_n}\}$  with  $h_n = \theta n^{\frac{1}{2}}$  are differentially (asymptotically) equivalent at the point 0.*

**PROOF.** Let  $R_{n,h_n} = R'_{n,\theta}$ , where  $h_n = \theta n^{\frac{1}{2}}$ , and set  $Q_{n,\theta}^{(1)} = P_{n,\theta}, Q_{n,\theta}^{(2)} = R'_{n,\theta}$ . Assume that for a bounded set  $C$  of  $\mathcal{E}_k$ ,  $\sup \{ \|Q_{n,\theta}^{(1)} - Q_{n,\theta}^{(2)}\|; \theta \in \Theta, \theta n^{\frac{1}{2}} \in C \}$  does not converge to zero. Then there exists  $\{m\} \subseteq \{n\}$  and a sequence  $\{\theta_m\}$  with  $\theta_m m^{\frac{1}{2}} \in C$  such that  $\|Q_{m,\theta_m}^{(1)} - Q_{m,\theta_m}^{(2)}\| > \varepsilon$ , some  $\varepsilon > 0$  and for all  $m$ . Reverting to the original measures, this becomes  $\|P_{m,\theta_m} - R_{m,h_m}\| > \varepsilon$  for all  $m$ , where  $\theta_m = h_m m^{-\frac{1}{2}}$  and  $h_m \in C$  for all  $m$ ; but this contradicts the theorem and completes the proof of the corollary.

**DEFINITION 5.2.** A sequence  $\{V_n\}$  of  $\{\mathcal{A}_n\}$ -measurable functions, or the sequence  $\{\mathcal{B}_n\}$  of the  $\sigma$ -fields induced by them, is said to be *differentially (asymptotically) sufficient* at  $\theta_0$  for the family  $\{P_{n,\theta}; \theta \in \Theta\}$  if there is a family  $\{Q_{n,\theta}; \theta \in \Theta\}$  such that the sequences  $\{P_{n,\theta}\}$  and  $\{Q_{n,\theta}\}$  are differentially equivalent at  $\theta_0$  and for each  $n$ ,  $V_n$ , or the  $\sigma$ -field  $\mathcal{B}_n$ , is sufficient for the family  $\{Q_{n,\theta}; \theta \in \Theta\}$ .

**COROLLARY 5.2.** *The sequence  $\{\Delta_n^*\}$  is differentially (asymptotically) sufficient at 0 for the family  $\{P_{n,\theta}; \theta \in \Theta\}$ .*

**PROOF.** From the definition of  $R_{n,h}$  and for each  $n$ , one has  $[dR_{n,h}/dP_{n,0}] = \exp[-B_n(h)] \exp(h'\Delta_n^*)$ ,  $h \in C_n = \{h \in \mathcal{E}_k; h = \theta n^{\frac{1}{2}}, \theta \in \Theta\}$ ; equivalently

$$[dR'_{n,\theta}/dP_{n,0}] = \exp[-B_n(\theta n^{\frac{1}{2}})] \exp(n^{\frac{1}{2}}\theta'\Delta_n^*), \theta \in \Theta,$$

where  $R'_{n,\theta} = R_{n,h}$  with  $h = \theta n^{\frac{1}{2}}$ . Thus, for each  $n$ ,  $\Delta_n^*$  is sufficient for the family  $\{R'_{n,\theta}; \theta \in \Theta\}$  or, equivalently, for the family  $\{R_{n,h}; h \in C_n\}$ . Since  $\{P_{n,\theta}\}, \{R_{n,h}\}$  are differentially equivalent at the point 0 by Corollary 5.1, the proof is completed.

**6. Asymptotic properties of tests based on  $\Delta_n$  and asymptotic distribution of  $\{\Delta_n\}$ .**  
In this section, two main results are presented. The first asserts that from the asymptotic power viewpoint, any test may be based on  $\Delta_n$  alone. The second provides the asymptotic distribution of  $\{\Delta_n\}$  under the moving measure  $P_{n,\theta_n}$ . More precisely, we have

**THEOREM 6.1.** *Let  $\{Z_n\}$  be a sequence of random variables such that  $|Z_n| \leq 1$ ,  $n \geq 1$  and set  $\bar{Z}_n = \mathcal{E}_{P_{n,0}}(Z_n | \Delta_n)$ . Then*

$$\sup |\mathcal{E}(Z_n | P_{n,\theta_n}) - \mathcal{E}(\bar{Z}_n | P_{n,\theta_n})| \rightarrow 0,$$

where  $\theta_n = hn^{-\frac{1}{2}}$  and the sup is taken over all sequences  $\{Z_n\}$  of random variables bounded by 1 in absolute value and over all  $h$ 's in a bounded set  $C$ .

**PROOF.** We have,  $\mathcal{E}(Z_n | P_{n,\theta_n}) - \mathcal{E}(\bar{Z}_n | P_{n,\theta_n}) = I_1(n, h) + I_2(n, h) + I_3(n, h)$ , where

$$I_1(n, h) = \mathcal{E}(Z_n | P_{n,\theta_n}) - \mathcal{E}(Z_n | R_{n,h})$$

$$I_2(n, h) = \mathcal{E}(Z_n | R_{n,h}) - \mathcal{E}(\bar{Z}_n | R_{n,h})$$

$$I_3(n, h) = \mathcal{E}(\bar{Z}_n | R_{n,h}) - \mathcal{E}(\bar{Z}_n | P_{n,\theta_n}).$$

Now, with the sup as above,  $\sup |I_1(n, h)| \leq \sup \{ \|R_{n,h} - P_{n,\theta_n}\|; h \in C \}$ . If the right-hand side of this last relation does not converge to zero, there exists

$\{m\} \subseteq \{n\}$  and a sequence  $\{h_m\}$  of  $h$ 's in  $C$  such that  $\|R_{m,h_m} - P_{m,\theta_m}\| > \varepsilon$  for all  $m$ ; but this contradicts Theorem 5.1 and thus  $\sup |I_1(n, h)| \rightarrow 0$ . In the same way it is seen that  $\sup |I_3(n, h)| \rightarrow 0$ . Thus we need only show that  $\sup |I_2(n, h)| \rightarrow 0$ . To see this, we observe that

$$\begin{aligned} \mathcal{E}(\bar{Z}_n | R_{n,h}) &= \mathcal{E}[\mathcal{E}_{P_{n,0}}(Z_n | \Delta_n) | R_{n,h}] = \int [\mathcal{E}_{P_{n,0}}(Z_n | \Delta_n)] dR_{n,h} \\ &= \int [\mathcal{E}_{P_{n,0}}(Z_n | \Delta_n)] \exp[-B_n(h)] \exp(h' \Delta_n^*) dP_{n,0} \\ &= \mathcal{E}_{P_{n,0}}\{\mathcal{E}_{P_{n,0}}(Z_n | \Delta_n) \exp[-B_n(h)] \exp(h' \Delta_n^*)\} \\ &= \mathcal{E}_{P_{n,0}}[\mathcal{E}_{P_{n,0}}\{Z_n \exp[-B_n(h)] \exp(h' \Delta_n^*) | \Delta_n\}] \end{aligned}$$

because  $\Delta_n^*$  is a function of  $\Delta_n$ . Thus the last expression reduces to

$$\mathcal{E}_{P_{n,0}}\{Z_n \exp[-B_n(h)] \exp(h' \Delta_n^*)\}$$

and this is equal to  $\mathcal{E}(Z_n | R_{n,h})$ . Therefore  $I_2(n, h) = 0$  and the proof of the theorem is completed.

According to this last result, if  $\{Z_n\}$  is any sequence of tests, where  $Z_n$  has level  $\alpha_n$ , then one can always replace  $Z_n$  by  $\bar{Z}_n = \mathcal{E}_{P_{n,0}}(Z_n | \Delta_n)$  which has the same level. Furthermore, the asymptotic power will remain unchanged. Thus in searching for an optimal test, for example in the sense of maximizing the power under the alternatives considered above, one may restrict attention to tests based only on  $\Delta_n$ .

Next let  $h, h_n \in \mathcal{E}_k$  with  $h_n \rightarrow h$  and, for  $\theta \in \Theta$ , set  $\theta_n = \theta + h_n n^{-\frac{1}{2}}$ . We also set  $\Lambda_n(\theta) = \Lambda[P_{n,\theta_n}; P_{n,\theta}]$ . Then Theorem 3.2 provides the asymptotic distribution of  $\Delta_n(\theta)$  under  $P_{n,\theta}$ . In statistical applications, the asymptotic distribution of  $\Delta_n(\theta)$  under  $P_{n,\theta_n}$  is also needed. With this in mind, we establish the following theorem.

**THEOREM 6.2.** *Let  $h, h_n \in \mathcal{E}_k$  with  $h_n \rightarrow h$  and let  $\theta_n = \theta + h_n n^{-\frac{1}{2}}$ ,  $\theta \in \Theta$ . Then*

$$\mathcal{L}[\Delta_n(\theta) | P_{n,\theta_n}] \rightarrow N(\Gamma(\theta)h, \Gamma(\theta)).$$

**PROOF.** Let  $c' = (c_1, \dots, c_k)$  and  $c_0, c_j \in R, j = 1, \dots, k$ . Then

$$(6.1) \quad c_0 \Lambda_n(\theta) + c' \Delta_n(\theta) = c_0 [\Lambda_n(\theta) - h_n' \Delta_n(\theta)] + [c_0 h_n' + c'] \Delta_n(\theta).$$

By Theorem 3.2, we then have

$$(6.2) \quad \mathcal{L}\{[c_0 h_n' + c'] \Delta_n(\theta) | P_{n,\theta}\} \rightarrow N(0, \Gamma^*(\theta, h)),$$

where  $\Gamma^*(\theta, h) = (c_0 h' + c') \Gamma(\theta) (c_0 h + c)$ . Therefore, relation (6.1), together with Theorem 3.2 and Theorem 3.3, gives

$$(6.3) \quad \mathcal{L}[c_0 \Lambda_n(\theta) + c' \Delta_n(\theta) | P_{n,\theta}] \rightarrow N(-\frac{1}{2} c_0 h' \Gamma(\theta) h, \Gamma^*(\theta, h)).$$

Let  $d' = (c_0, c_1, \dots, c_k)$ . Then

$$c_0 \Lambda_n(\theta) + c' \Delta_n(\theta) = d' \begin{pmatrix} \Lambda_n(\theta) \\ \Delta_n(\theta) \end{pmatrix}$$

while  $-\frac{1}{2}c_0 h' \Gamma(\theta) h = d' \begin{pmatrix} -\frac{1}{2}h' \Gamma(\theta) h \\ 0 \\ \vdots \\ 0 \end{pmatrix}$  and  $\Gamma^*(\theta, h) = d' \begin{pmatrix} h' \Gamma(\theta) h & h' \Gamma(\theta) \\ \Gamma(\theta) h & \Gamma(\theta) \end{pmatrix} d$ .

Thus relation (6.3) states that

$$\mathcal{L} \left[ d' \begin{pmatrix} \Lambda_n(\theta) \\ \Delta_n(\theta) \end{pmatrix} \middle| P_{n, \theta} \right] \rightarrow N \left( d' \begin{pmatrix} -\frac{1}{2}h' \Gamma(\theta) h \\ 0 \\ \vdots \\ 0 \end{pmatrix}, d' \begin{pmatrix} h' \Gamma(\theta) h & h' \Gamma(\theta) \\ \Gamma(\theta) h & \Gamma(\theta) \end{pmatrix} d \right)$$

and this is equivalent to

$$(6.4) \quad \mathcal{L}\{[\Lambda_n(\theta), \Delta_n(\theta)] | P_{n, \theta}\} \rightarrow N \left( \begin{pmatrix} -\frac{1}{2}h' \Gamma(\theta) h \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} h' \Gamma(\theta) h & h' \Gamma(\theta) \\ \Gamma(\theta) h & \Gamma(\theta) \end{pmatrix} \right).$$

Let the distribution on the right-hand side of relation (6.4) be the joint distribution, under  $P_\theta$ , of the random variables  $\Lambda^*$  and  $\Delta$ , that is,  $\mathcal{L}(\Lambda^*, \Delta | P_\theta)$  where  $\mathcal{L}(\Lambda^* | P_\theta) = N(-\frac{1}{2}h' \Gamma(\theta) h, h' \Gamma(\theta) h)$  and  $\mathcal{L}(\Delta | P_\theta) = N(0, \Gamma(\theta))$ . Then relation (6.4) implies, by Theorem 2.1(6) in LeCam [3],

$$(6.5) \quad \mathcal{L}\{[\Lambda_n(\theta), \Delta_n(\theta)] | P_{n, \theta_n}\} \rightarrow \exp(\lambda) \mathcal{L}(\Lambda^*, \Delta | P_\theta).$$

But

$$\int \exp(\lambda) d\mathcal{L}(\Lambda^*, \Delta | P_\theta) = \iint \exp(\lambda) d\mathcal{L}[\Lambda^* | \Delta | P_\theta] d\mathcal{L}(\Delta | P_\theta)$$

and  $\mathcal{L}[\Lambda^* | \Delta | P_\theta]$  is normal with mean

$$\begin{aligned} \mathcal{E}[\Lambda^* | P_\theta] + \Sigma_{12} \Sigma_{22}^{-1} [\Delta - \mathcal{E}(\Delta | P_\theta)] &= -\frac{1}{2}h' \Gamma(\theta) h + h' \Gamma(\theta) \Gamma^{-1}(\theta) \Delta \\ &= -\frac{1}{2}h' \Gamma(\theta) h + h' \Delta \end{aligned}$$

and variance

$$\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} = h' \Gamma(\theta) h - h' \Gamma(\theta) \Gamma^{-1}(\theta) \Gamma(\theta) h = h' \Gamma(\theta) h - h' \Gamma(\theta) h = 0.$$

(See, e.g., Rao [5] page 441(v)). Hence

$$\int_{(-\infty, \lambda']} \exp(\lambda) d\mathcal{L}[\Lambda^* | \Delta | P_\theta] = \exp[-\frac{1}{2}h' \Gamma(\theta) h + h' \Delta] \quad \text{if} \\ \lambda' \geq -\frac{1}{2}h' \Gamma(\theta) h + h' \Delta$$

and zero otherwise. Letting  $(-\infty, t]$  stand for a  $k$ -dimensional interval, relation (6.5) states that

$$P[\Lambda_n(\theta) \leq \lambda', \Delta_n(\theta) \leq t | P_{n, \theta_n}] \rightarrow \int_{(-\infty, t]} \int_{(-\infty, \lambda']} \exp(\lambda) d\mathcal{L}(\Lambda^*, \Delta | P_\theta),$$

which implies that

$$P[\Delta_n(\theta) \leq t | P_{n, \theta_n}] \rightarrow \int_{(-\infty, \infty)} \left[ \int_{(-\infty, t]} \exp(\lambda) d\mathcal{L}(\Lambda^*, \Delta | P_\theta) \right] d\lambda.$$

But the right-hand side of the last relation is equal to

$$\int_{(-\infty, 1]} \exp \left[ -\frac{1}{2} h' \Gamma(\theta) h + h' \delta \right] d\mathcal{L}(\Delta \mid P_\theta)$$

and by taking into consideration that  $\mathcal{L}(\Delta \mid P_\theta) = N(0, \Gamma(\theta))$ , this integral becomes

$$\begin{aligned} & \int_{(-\infty, 1]} \exp \left[ -\frac{1}{2} h' \Gamma(\theta) h + h' \delta \right] (2\pi)^{-k/2} |\Gamma(\theta)|^{-\frac{1}{2}} \exp \left[ -\frac{1}{2} \delta' \Gamma^{-1}(\theta) \delta \right] d\delta \\ &= \int_{(-\infty, 1]} (2\pi)^{-k/2} |\Gamma(\theta)|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} [\delta - \Gamma(\theta)h]' \Gamma^{-1}(\theta) [\delta - \Gamma(\theta)h] \right\} d\delta. \end{aligned}$$

Therefore  $\mathcal{L}[\Delta_n(\theta) \mid P_{n, \theta_n}] \rightarrow N(\Gamma(\theta)h, \Gamma(\theta))$  as was to be seen.

Theorem 6.1 shows that, from an asymptotic power viewpoint, any test can be based on  $\Delta_n$ . Proceeding further along the same path, the next theorem asserts that one can actually base all tests on  $\Delta_n^*$  rather than  $\Delta_n$ . The significance of this fact is apparent: the original family of distributions can be treated asymptotically as if it were an exponential family, where  $\Delta_n^*$  plays the all important role of the statistic appearing in the exponent of an exponential family.

**THEOREM 6.3.** *Let  $\{Z_n\}$ ,  $n \geq 1$  be a sequence of test functions and set  $\theta_n = hn^{-\frac{1}{2}}$ ,  $h \in \mathcal{E}_k$ . Then, we have*

$$\sup \{ |\mathcal{E}_{\theta_n} Z_n(\Delta_n) - \mathcal{E}_{\theta_n} Z_n(\Delta_n^*)|; h \in K \} \rightarrow 0,$$

where  $K$  is any compact subset of  $\mathcal{E}_k$ .

**PROOF.** We recall that  $\Delta_n^*$  is defined as follows

$$\begin{aligned} \Delta_n^* &= \Delta_n, & \text{if } \rho(\Delta_n) < \alpha_v \\ &= 0, & \text{otherwise,} \end{aligned} \quad \text{where } \alpha_v \uparrow \infty.$$

Let  $Q_{1,n}^h(B) = P_{\theta_n}(\Delta_n \in B)$ ,  $Q_{2,n}^h(B) = P_{\theta_n}(\Delta_n^* \in B)$ , where  $B$  varies over the  $k$ -dimensional Borel  $\sigma$ -field  $\mathcal{B}_k$ . Set  $B_n = \{\rho(z) < \alpha_v\} - \{0\}$ . Then  $\Delta_n^* = \Delta_n$  pointwise on  $\Delta_n^{*-1}(B_n) = \Delta_n^{-1}(B_n)$  so that  $P_{\theta_n}(\Delta_n \in B_n) = P_{\theta_n}(\Delta_n^* \in B_n)$ . Next for any  $B \in \mathcal{B}_k$ , we have

$$\begin{aligned} Q_{1,n}^h(B \cap B_n) &= Q_{2,n}^h(B \cap B_n), \\ Q_{1,n}^h(B \cap B_n^c) &\leq Q_{1,n}^h(B_n^c) = P_{\theta_n}(\Delta_n \neq \Delta_n^*) + P_{\theta_n}(\Delta_n = 0), & \text{and} \\ Q_{2,n}^h(B \cap B_n^c) &\leq Q_{2,n}^h(B_n^c) = P_{\theta_n}[\rho(\Delta_n^*) \geq \alpha_v] + P_{\theta_n}(\Delta_n^* = 0) = P_{\theta_n}(\Delta_n^* = 0), \end{aligned}$$

since  $[\rho(\Delta_n^*) \geq \alpha_v] = \emptyset$ .

In terms of these relations,

$$\begin{aligned} (6.6) \quad |Q_{1,n}^h(B) - Q_{2,n}^h(B)| &= |Q_{1,n}^h(B \cap B_n^c) - Q_{2,n}^h(B \cap B_n^c)| \\ &\leq Q_{1,n}^h(B \cap B_n^c) + Q_{2,n}^h(B \cap B_n^c) \\ &= P_{\theta_n}(\Delta_n \neq \Delta_n^*) + P_{\theta_n}(\Delta_n = 0) + P_{\theta_n}(\Delta_n^* = 0). \end{aligned}$$

Clearly,  $(\Delta_n^* = 0) = (\Delta_n \neq \Delta_n^*) + (\Delta_n = 0)$ . Therefore (6.6) becomes

$$|Q_{1,n}^h(B) - Q_{2,n}^h(B)| \leq 2[P_{\theta_n}(\Delta_n \neq \Delta_n^*) + P_{\theta_n}(\Delta_n = 0)]$$

and hence

$$\sup \{ |Q_{1,n}^h(B) - Q_{2,n}^h(B)|; B \in \mathcal{B}_k \} \leq 2 [P_{\theta_n}(\Delta_n \neq \Delta_n^*) + P_{\theta_n}(\Delta_n = 0)].$$

Also

$$\begin{aligned} \sup \{ |Q_{1,n}^h(B) - Q_{2,n}^h(B)|; B \in \mathcal{B}_k, h \in K \} \\ \leq 2 \sup \{ [P_{\theta_n}(\Delta_n \neq \Delta_n^*) + P_{\theta_n}(\Delta_n = 0)]; h \in K \}. \end{aligned}$$

Now the right-hand side of this last relation converges to zero for, if not, there is  $\{m\} \subseteq \{n\}$  and  $h_m \in K$  with  $h_m \rightarrow h$  such that at least one of the sequences  $\{P_{\theta_m^*}(\Delta_m \neq \Delta_m^*)\}, \{P_{\theta_m^*}(\Delta_m = 0)\}$  does not converge to zero. Here  $\theta_m^* = h_m m^{-\frac{1}{2}}$ . This is a contradiction since  $P_0(\Delta_m \neq \Delta_m^*) \rightarrow 0, P_0(\Delta_m = 0) \rightarrow 0$  and the same is true for the above sequences by contiguity. Now

$$|\mathcal{E}_{\theta_n} Z_n(\Delta_n) - \mathcal{E}_{\theta_n} Z_n(\Delta_n^*)| = |\int z(t) d\mathcal{L}(\Delta_n | P_{\theta_n}) - \int z(t) d\mathcal{L}(\Delta_n^* | P_{\theta_n})|,$$

where  $0 \leq z(t) \leq 1, t \in \mathcal{E}_k$ . The right-hand side of this last relation is bounded by  $\|Q_{1,n}^h - Q_{2,n}^h\|$  which converges to zero by the previous result. This completes the proof of the theorem.

**7. Some applications to hypotheses testing problems.** In this section, we further extend the results of Wald [8] along the lines suggested by LeCam [3]. More general hypotheses are considered than in Johnson and Roussas [2] although the null hypothesis is required to be simple. As expected from the terminology of the previous sections, the asymptotically optimal tests may be based on the sequence  $\{\Delta_n\}$ . In the present paper, we treat in detail the one-dimensional parameter situation considered in Johnson and Roussas [2] from the viewpoint of differential (asymptotic) sufficiency. At the end of this section, some preliminary remarks are also made in anticipation of  $k$ -dimensional parameter results.

7.1. *One-dimensional*  $\Theta$ . Modifying slightly the definitions of Wald [8] with respect to the significance level requirement, we have

DEFINITION 7.1.1. A sequence of tests  $\{\lambda_n\}$  with  $\mathcal{E}_{\theta_0} \lambda_n \rightarrow \alpha$  is said to be an *asymptotically most powerful* test of  $H_0: \theta = \theta_0$  against  $H_1: \theta > \theta_0$ , of asymptotic size  $\alpha$ , if for any other sequence of tests  $\{\omega_n\}$  with  $\mathcal{E}_{\theta_0} \omega_n \rightarrow \alpha$ , we have

$$(7.1.1) \quad \limsup [\sup (\mathcal{E}_{\theta} \omega_n - \mathcal{E}_{\theta} \lambda_n; \theta > \theta_0, \theta \in \Theta)] \leq 0.$$

A similar expression is required to hold with  $\theta > \theta_0$  replaced by  $\theta < \theta_0$  if the alternative is  $H_2: \theta < \theta_0$ .

DEFINITION 7.1.2. A sequence of tests  $\{\lambda_n\}$  is defined to be an *asymptotically most powerful unbiased* test of the hypothesis  $H_0: \theta = \theta_0$ , of asymptotic size  $\alpha$ , if  $\mathcal{E}_{\theta_0} \lambda_n \rightarrow \alpha$  with  $\liminf [\inf (\mathcal{E}_{\theta} \lambda_n; \theta \neq \theta_0; \theta \in \Theta)] \geq \alpha$ , and if for any other sequence of tests  $\{\omega_n\}$  satisfying  $\mathcal{E}_{\theta_0} \omega_n \rightarrow \alpha$  and  $\liminf [\inf (\mathcal{E}_{\theta} \omega_n; \theta \neq \theta_0; \theta \in \Theta)] \geq \alpha$ , we have

$$(7.1.2) \quad \limsup [\sup (\mathcal{E}_{\theta} \omega_n - \mathcal{E}_{\theta} \lambda_n; \theta \neq \theta_0, \theta \in \Theta)] \leq 0.$$

Once more, without loss of generality, we take  $\theta_0 = 0$ .

The form of the asymptotic distribution of  $\{\Delta_n\}$ , under  $P_{n,0}$  and  $P_{n,\theta_n}$ , where  $\theta_n = hn^{-\frac{1}{2}}$ , suggests a form for tests based on  $\Delta_n$ . Namely, for a fixed  $\alpha(0 < \alpha < 1)$ , let

$$(7.1.3) \quad \begin{aligned} \varphi_{1,n}(\Delta_n) &= 1, & \text{if } \Delta_n > c_n \\ &= 0, & \text{if } \Delta_n < c_n, \end{aligned}$$

where  $c_n \rightarrow \xi_\alpha$ , the upper  $\alpha$ th quantile of the  $N(0, \Gamma)$ , and  $\mathcal{E}_0 \varphi_{1,n}(\Delta_n) \rightarrow \alpha$ . Further, set

$$(7.1.4) \quad \begin{aligned} \varphi_{2,n}(\Delta_n) &= 1, & \text{if } \Delta_n < a_n \text{ or } \Delta_n > b_n \\ &= 0, & \text{if } a_n < \Delta_n < b_n, \end{aligned}$$

where  $\lim(-a_n) = \lim b_n = \xi_{\alpha/2}$ , so that  $\mathcal{E}_0 \varphi_{2,n}(\Delta_n) \rightarrow \alpha$ .

For both sequences of tests, a critical function may assume any value on the boundary of its critical region.

In order to show that the first and the second tests are optimal in the sense of Definition 7.1.1 and Definition 7.1.2, respectively, we must employ one further assumption which was verified for a number of interesting cases in Johnson and Roussas [2].

**ASSUMPTION 5.** Let  $\{\theta_n\}$  be a sequence of elements of  $\Theta$  with  $\theta_n > 0$  for each  $n$ . The condition  $\lim \theta_n n^{\frac{1}{2}} = \infty$  implies that  $\Delta_n \rightarrow \infty$  in  $P_{\theta_n}$ -probability.

**ASSUMPTION 5'.** Let  $\{\theta_n\}$  be a sequence of elements of  $\Theta$  with  $\theta_n < 0$  for each  $n$ . The condition  $\lim \theta_n n^{\frac{1}{2}} = -\infty$  implies that  $\Delta_n \rightarrow -\infty$  in  $P_{\theta_n}$ -probability.

We first restate the result for one-sided tests from Johnson and Roussas [2] which was established without the concept of differential (asymptotic) sufficiency.

**THEOREM 7.1.1.** *Under Assumptions 1–5, the test  $\varphi_{1,n}$  defined by (7.1.3) is asymptotically most powerful for testing  $H_0: \theta = 0$  against the alternative  $H_1: \theta > 0$ ,  $\theta \in \Theta$ .*

We have an analogous theorem for the alternative  $H_2: \theta < 0$ ,  $\theta \in \Theta$ , under Assumptions 1–5'.

The proof of these results parallels the proof of Theorem 7.1.2 below and therefore will be omitted.

To Theorem 7.1.1, we also have the following Corollary.

**COROLLARY 7.1.1.** *Under Assumptions 1–4, the test  $\varphi_{1,n}$  defined by (7.1.3) is asymptotically locally most powerful. That is, the test satisfies (7.1.1) when the alternatives are further restricted to  $\theta$ 's for which  $n^{\frac{1}{2}}(\theta - \theta_0) \leq C$  for an arbitrary fixed  $C$ .*

Of course, we again have an analogous result for the alternative  $H_2: \theta < 0$ ,  $\theta \in \Theta$ .

The proof of the next theorem requires the results on the differential (asymptotic) sufficiency of the truncated version  $\Delta_n^*$ .



**THEOREM 7.1.2.** *Under Assumptions 1–5, 5', the test  $\varphi_{2,n}$  defined by (7.1.4) is asymptotically most powerful unbiased for testing  $H_0: \theta = 0$  against the alternative  $H_3: \theta \neq 0, \theta \in \Theta$ .*

For the proof of this theorem some auxiliary results will be needed which are formulated below as lemmas. The first is one version of the extended Helly–Bray lemma and the proof is included because it is brief.

**LEMMA 7.1.1.** *Let  $G_n \rightarrow G$ , a continuous cdf of a random variable, and let  $\{g_n\}$ ,  $g$  and  $h$  be continuous functions satisfying*

- (i)  $|g_n(x)| \leq h(x)$  for all  $x$ ,
- (ii)  $g_n(x) \rightarrow g(x)$  uniformly on finite intervals, and
- (iii)  $\int h dG_n \rightarrow \int h dG$ .

Then

$$(7.1.5) \quad \int g_n dG_n \rightarrow \int g dG.$$

Relation (7.1.5) also holds for the modified functions  $g_n^* = I_{(a_n, b_n)} g_n$  and  $g^* = I_{(a, b)} g$ , where  $a_n \rightarrow a, b_n \rightarrow b$  with  $a, b$ , finite or infinite.

**PROOF.** Given an  $\varepsilon > 0$ , select  $c$  and  $d$  such that

$$(7.1.6) \quad \int_{(-\infty, c]} h dG + \int_{(d, \infty)} h dG < \varepsilon. \quad \text{Then}$$

$$(7.1.7) \quad \int_{(-\infty, c]} |g_n| dG_n + \int_{(d, \infty)} |g_n| dG_n \leq \int_{(-\infty, c]} h dG_n + \int_{(d, \infty)} h dG_n$$

and the r.h.s. converges to the l.h.s. of (7.1.6) according to condition (iii) and the Helly–Bray lemma. Then on the interval  $(c, d)$ ,

$$(7.1.8) \quad \left| \int_{(c, d]} g_n dG_n - \int_{(c, d]} g dG \right| \leq \int_{(c, d]} |g_n - g| dG_n + \left| \int_{(c, d]} g dG_n - \int_{(c, d]} g dG \right|$$

and the first term on the r.h.s. converges to zero by condition (ii) and the second by the Helly–Bray lemma.

Note that the bound (7.1.7) also holds for the modified functions  $g_n^*$  and  $g^*$  so that it is clearly sufficient to treat the case where  $a$  and  $b$  are finite. Since  $G$  is continuous, there exist an  $a_0 > 0$  such that

$$(7.1.9) \quad \int_{(a-a_0, a+a_0]} h dG + \int_{(b-a_0, b+a_0]} h dG < \varepsilon.$$

For sufficiently large  $n$ ,  $0 = g_n^* = g^*$  outside the interval  $(a-a_0, b+a_0)$  and  $g_n^* = g_n, g^* = g$  on  $(a+a_0, b-a_0)$ . For the latter interval, use the method leading to (7.1.8). Also

$$\int_{(a-a_0, a+a_0]} |g_n^*| dG_n + \int_{(b-a_0, b+a_0]} |g_n^*| dG_n \leq \int_{(a-a_0, a+a_0]} h dG_n + \int_{(b-a_0, b+a_0]} h dG_n$$

and this converges to the l.h.s. of (7.1.9) which completes the proof.

**LEMMA 7.1.2.** *Consider the sequence of tests  $\{\varphi_n(\Delta_n^*)\}, n \geq 1$ , defined as follows*

$$(7.1.10) \quad \begin{aligned} &= 1, && \text{if } \Delta_n^* < a_n^* \text{ or } \Delta_n^* > b_n^* \\ \varphi_n(\Delta_n^*) &= \gamma_1^* \text{ or } \gamma_2^*, && \text{if } \Delta_n^* = a_n^* \text{ or } \Delta_n^* = b_n^*, \text{ respectively,} \\ &= 0, && \text{if } a_n^* < \Delta_n^* < b_n^*, \end{aligned}$$

where the constants  $a_n^*, b_n^*, \gamma_1^*$ , and  $\gamma_2^*$  are defined through the relations

$$(7.1.11) \quad \mathcal{E}_0 \varphi_n(\Delta_n^*) = \alpha, \quad \mathcal{E}_0[\Delta_n^* \varphi_n(\Delta_n^*)] = \alpha \mathcal{E}_0 \Delta_n^*.$$

Then  $a_n^* \rightarrow -\xi_{\alpha/2}$  and  $b_n^* \rightarrow \xi_p$ , where  $\xi_p$  is the upper  $p$ th quantile of the  $N(0, \Gamma)$ .

PROOF. The proof is by contradiction. In the first place one may neglect asymptotically the contribution due to randomization. In fact, if  $x_n \rightarrow x$ , where  $x$  may be finite or  $\pm \infty$ , one has  $P_0(\Delta_n^* \leq x_n) - \Phi^*(x_n) \rightarrow 0$ ; here  $\Phi^*$  stands for the distribution function of the  $N(0, \Gamma)$  distribution. Thus by continuity of  $\Phi^*$ ,  $P_0(\Delta_n^* \leq x_n) \rightarrow \Phi^*(x)$ . Therefore

$$P_0(\Delta_n^* = x_n) \leq P_0(\Delta_n^* \leq x_n + \varepsilon) - P_0(\Delta_n^* \leq x_n - \varepsilon) \rightarrow \Phi^*(x + \varepsilon) - \Phi^*(x - \varepsilon)$$

and letting  $\varepsilon \rightarrow 0$ , one obtains  $P_0(\Delta_n^* = x_n) \rightarrow 0$ . Now assume that both  $\{a_n^*\}$  and  $\{b_n^*\}$  are unbounded. Then there are three cases to consider: there exist subsequences  $\{a_m^*\}$  and  $\{b_m^*\}$  such that  $a_m^* \rightarrow -\infty$  and  $b_m^* \rightarrow \infty$ , or  $a_m^* \rightarrow \infty$  and  $b_m^* \rightarrow \infty$ , or  $a_m^* \rightarrow -\infty$  and  $b_m^* \rightarrow -\infty$ . In the first case one has, for  $m$  sufficiently large,

$$\begin{aligned} \alpha &\leq \frac{1}{4}\alpha + \left[ \int_{(-\infty, a_m^*+1)} d\mathcal{L}(\Delta_m^* | P_0) + \int_{(b_m^*-1, \infty)} d\mathcal{L}(\Delta_m^* | P_0) \right] \\ &\leq \frac{1}{4}\alpha + \int_{(-\xi_{\alpha/4}, \infty)} d\mathcal{L}(\Delta_m^* | P_0) + \int_{(\xi_{\alpha/4}, \infty)} d\mathcal{L}(\Delta_m^* | P_0) \end{aligned}$$

and this converges to  $\frac{3}{4}\alpha$ . Thus we arrive at a contradiction. For the second case, one has  $\alpha \geq \int_{-\infty}^{a_m^*-1} d\mathcal{L}(\Delta_m^* | P_0)$  and this converges to 1. The third case is treated in a similar fashion. Now let one of the sequences  $\{a_n^*\}$ ,  $\{b_n^*\}$  be unbounded, for example, the sequence  $\{a_n^*\}$  and the other be bounded. Then there exist subsequences  $\{a_m^*\}$  and  $\{b_m^*\}$  such that  $a_m^* \rightarrow -\infty$  and  $b_m^* \rightarrow b$  finite. Thus

$$\begin{aligned} \alpha &= \lim \left[ \int_{(-\infty, a_m^*)} d\mathcal{L}(\Delta_m^* | P_0) + \int_{(b_m^*, \infty)} d\mathcal{L}(\Delta_m^* | P_0) \right] \\ &= 1 - \lim \int_{[a_m^*, b_m^*]} d\mathcal{L}(\Delta_m^* | P_0) = 1 - \Phi^*(b) \end{aligned}$$

so that  $b = \xi_\alpha$ . Next,  $\mathcal{E}_0 \Delta_n^* = \int x d\mathcal{L}(\Delta_n^* | P_0) \rightarrow \int x d\Phi^*$  by Lemmas 7.1.1 and 4.5 and this is equal to zero. On the other hand,  $\lim \mathcal{E}_0[\Delta_m^* \varphi_m(\Delta_m^*)] = \lim \left[ \int_{(-\infty, a_m^*)} x d\mathcal{L}(\Delta_m^* | P_0) + \int_{(b_m^*, \infty)} x d\mathcal{L}(\Delta_m^* | P_0) \right] = \lim \int_{(b_m^*, \infty)} x d\mathcal{L}(\Delta_m^* | P_0)$  by Lemma 7.1.1 and this last limit equals  $\int_{(b, \infty)} x d\Phi^*$  by the same lemma. Therefore, taking the limits of both sides of the second relation in (7.1.11) through the subsequence  $\{m\}$ , one has  $0 = \int_{(b, \infty)} x d\Phi^*$  which is a contradiction. The case that  $\{a_n^*\}$  is bounded and  $\{b_n^*\}$  unbounded is treated similarly. Finally, consider the case that both  $\{a_n^*\}$  and  $\{b_n^*\}$  are bounded and let  $\{a_m^*\}$ ,  $\{b_m^*\}$  be subsequences such that  $a_m^* \rightarrow a$ ,  $b_m^* \rightarrow b$ , where both  $a$  and  $b$  are finite. In the first place,  $\lim \mathcal{E}_0 \Delta_m^* = 0$  as was seen above. Next

$$\begin{aligned} \lim \mathcal{E}_0[\Delta_m^* \varphi_m(\Delta_m^*)] &= \lim \left[ \int_{(-\infty, a_m^*)} x d\mathcal{L}(\Delta_m^* | P_0) + \int_{[b_m^*, \infty)} x d\mathcal{L}(\Delta_m^* | P_0) \right] \\ &= -\lim \int_{[a_m^*, b_m^*]} x d\mathcal{L}(\Delta_m^* | P_0) = -\int_{[a, b]} x d\Phi^* \end{aligned}$$

by Lemma 7.1.1. Therefore, by taking the limits of both sides of the second relation in (7.1.11) through the subsequence  $\{m\}$ , one has  $\int_{[a, b]} x d\Phi^* = 0$  which can happen

only if  $a = -b$ . By taking the limit of the first relation in (7.1.11) through the subsequence  $\{m\}$ , one also has  $\Phi^*(b) - \Phi^*(a) = 1 - \alpha$  or  $\Phi^*(b) - \Phi^*(-b) = 1 - \alpha$  which implies that  $b = \xi_{\alpha/2}$ . The proof of the lemma is completed.

It is worthwhile to remark that the power satisfies

$$(7.1.12) \quad \mathcal{E}_{\theta_m} \varphi_m(\Delta_m^*) \rightarrow \int_{|x| \geq \xi_{\alpha/2}} d\Phi_h,$$

under alternatives  $\theta_m = h_m m^{-\frac{1}{2}}$  with  $h_m \rightarrow h$ , where  $\Phi_h$  denotes the distribution function of  $N(\Gamma h, \Gamma)$ . This follows directly from the last two lemmas.

PROOF OF THEOREM 7.1.2. Let  $\{\varphi_{2,n}\}$  be defined by (7.1.4) and let  $\{\omega_n\} = \{\omega_n(X_0, X_1, \dots, X_n)\}$  be any other sequence of tests with  $\mathcal{E}_0 \omega_n \rightarrow \alpha$  and

$$\liminf \inf (\mathcal{E}_\theta \omega_n; \theta \neq 0, \theta \in \Theta) \rightarrow \alpha.$$

Assume, for contradiction, that the left-hand side of (7.1.2) takes the value  $10\delta > 0$ . That is, there exist sequences  $\{m\} \subseteq \{n\}$  and  $\{\theta_m\}$  with  $\theta_m \in \Theta$  and  $\theta_m \neq 0$  for all  $m$ , satisfying

$$(7.1.13) \quad \lim (\mathcal{E}_{\theta_m} \omega_m - \mathcal{E}_{\theta_m} \varphi_{2,m}) = 10\delta.$$

Passing to a further subsequence if necessary, it is clear that at least one of the following cases must occur: (a)  $\theta_m m^{\frac{1}{2}} \rightarrow \infty$  (or  $-\infty$ ), (b)  $\theta_m m^{\frac{1}{2}} \rightarrow 0$ , or (c)  $\theta_m m^{\frac{1}{2}} \rightarrow h \neq 0$ .

Consider case (c) first. According to Theorem 6.1, we can restrict ourselves to the conditional expectation  $\bar{\omega}_n$  of  $\omega_n$ , given  $\Delta_n$ . Thus, writing  $\theta_m$  for  $h_m m^{-\frac{1}{2}}$  where  $h_m \rightarrow h$ , we have

$$(7.1.14) \quad \mathcal{E}_{\theta_m} \bar{\omega}_m(\Delta_n) - \mathcal{E}_{\theta_m} \varphi_{2,m}(\Delta_m) > 9\delta \quad \text{for } m > N_1.$$

Further, for every test function  $\psi_n(\Delta_n)$ , we have

$$(7.1.15) \quad |\mathcal{E}_{\theta_n} \psi_n(\Delta_n) - \mathcal{E}_{\theta_n} \psi_n(\Delta_n^*)| \leq 2P_{n, \theta_n}(\Delta_n \neq \Delta_n^*).$$

By Proposition 4.1, the right-hand side of (7.1.15) with  $n$  replaced by  $m$  converges to zero.

Specializing this to  $\bar{\omega}_n, \varphi_{2,n}$  and utilizing (7.1.14), we have

$$(7.1.16) \quad \mathcal{E}_{\theta_m} \bar{\omega}_m(\Delta_m^*) - \mathcal{E}_{\theta_m} \varphi_{2,m}(\Delta_m^*) > 8\delta \quad \text{for } m > N_2.$$

By Theorem 6.2 and Proposition 4.1, we have  $\mathcal{L}(\Delta_m^* | P_{m, \theta_m}) \rightarrow N(\Gamma h, \Gamma)$ . Thus

$$(7.1.17) \quad |\mathcal{E}_{\theta_m} \varphi_{2,m}(\Delta_m^*) - \int_{|x| \geq \xi_{\alpha/2}} d\Phi_h| < \delta \quad \text{for } m > N_3,$$

where  $\Phi_h$  denotes the distribution function of  $N(\Gamma h, \Gamma)$ . Select  $\alpha_1 > \alpha$  such that

$$(7.1.18) \quad \left| \int_{|x| \geq \xi_{\alpha/2}} d\Phi_h - \int_{|x| \geq \xi_{\alpha_1/2}} d\Phi_h \right| < \delta.$$

For  $m > N_4$ ,  $\mathcal{E}_0[\bar{\omega}_m(\Delta_m^*)] < \alpha_1$  since  $\mathcal{E}_0 \bar{\omega}_m(\Delta_m^*) \rightarrow \alpha$ .

The test  $\varphi_n(\Delta_n^*)$  defined in (7.1.10) with  $\alpha$  replaced by  $\alpha_1$  is most powerful unbiased of level  $\alpha_1$ . (See, e.g., Lehmann [4] page 126.) Therefore it is most powerful among all unbiased tests of level  $\leq \alpha_1$ . For each  $m$ , any test that does not reject

outside of an interval can be improved, in terms of power, by a test of that form (see Ferguson, T. S. 1967, *Mathematical Statistics*, Academic Press for a specialized version of a more general result due to Karlin). The asymptotic unbiasedness then leads to the inequality  $\mathcal{E}_{\theta_m} \varphi_m(\Delta_m^*) \geq \mathcal{E}_{\theta_m} \bar{\omega}_m(\Delta_m^*)$  for  $m > N_5$ . Also  $\mathcal{E}_{\theta_m} \varphi_m(\Delta_m^*) \rightarrow \int_{|x| \geq \xi_{\alpha/2}} d\Phi_h$  according to the remark following Lemma 7.1.2, so that

$$|\mathcal{E}_{\theta_m} \varphi_m(\Delta_m^*) - \int_{|x| \geq \xi_{\alpha/2}} d\Phi_h| < \delta \quad \text{for } m > N_6.$$

This, together with (7.1.17) and (7.1.18), gives

$$\mathcal{E}_{\theta_m} \varphi_m(\Delta_m^*) - \mathcal{E}_{\theta_m} \varphi_{2,m}(\Delta_m^*) < 3\delta \quad \text{for } m > N_7.$$

Finally combining this result with the fact that  $\mathcal{E}_{\theta_m} \bar{\omega}_m(\Delta_m^*) - \mathcal{E}_{\theta_m} \varphi_m(\Delta_m^*) \leq 0$ , we get

$$\mathcal{E}_{\theta_m} \bar{\omega}_m(\Delta_m^*) - \mathcal{E}_{\theta_m} \varphi_{2,m}(\Delta_m^*) < 3\delta \quad \text{for } m > N_8$$

which contradicts (7.1.16).

If case (a) holds, the contradiction is obtained from Assumptions 5 and 5' since  $\mathcal{E}_{\theta_m} \varphi_{2,m}(\Delta_m^*) \rightarrow 1$ .

If case (b) holds, the argument given in Theorem 4.1 of Johnson and Roussas [2] leads to a contradiction of (7.1.13). Namely, an application of Proposition 3.1 from that paper shows that  $\|P_{m,\theta_m} - P_{m,\theta_0}\| \rightarrow 0$  so that all tests have asymptotic power equal to their level.

The above proof shows that the test (7.1.4) is asymptotically locally most powerful unbiased without Assumptions 5 and 5'. That is,

**COROLLARY 7.1.2.** *Under Assumptions 1–4, the test  $\varphi_{2,n}$  defined by (7.1.4) is asymptotically locally most powerful unbiased. (See also Corollary 7.1.1.)*

**7.2.  $k$ -dimensional  $\Theta$ .** It is also possible to obtain results similar to Wald [9] for testing a simple hypothesis in the multi-parameter situation. On the basis of Theorem 6.1 and Theorem 6.3, one may construct a sequence of tests which is asymptotically optimal. The criterion could be that of best average power over a family of surfaces, best constant power over a family of surfaces, or that of a most stringent test. These problems will be treated in detail in a forthcoming paper.

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