

and get the same result, so that we can also reach the point where  $m(x)$  takes its last zero, which can be sometimes important. (By a similar process, we can reach the first zero, when  $m(x) \geq 0$ , for every value of  $x$  exceeding that zero point.)

If we do not know the value of the constant, we can use the next Theorem, which imposes, however, sharper conditions on  $m(x)$ .

THEOREM. *Let the following Conditions be fulfilled.*

$$(14) \quad |m(x+1) - m(x)| < L|x| + K.$$

$$(15) \quad \sigma^2(x) \leq \sigma^2 < \infty.$$

$$(16) \quad \text{If } x < x_0, \text{ then } \bar{D}m(x) = 0; \text{ while if } x > x_0, \text{ then } \underline{D}m(x) > 0.$$

$$(17) \quad \text{For every } \delta > 0, \quad \inf_{\delta < x - x_0 < \infty} \underline{D}m(x) > 0.$$

If we choose  $a_n, c_n, \delta_n$  such that:

$$a_n > 0, \quad \sum a_n = \infty, \quad \sum a_n^2 < \infty, \quad \sum a_n^2/c_n^2 < \infty, \\ \delta_n > 0, \quad \delta_n \rightarrow 0, \quad \sum a_n \delta_n = \infty;$$

and if we define:  $x_{n+1} = x_n - a_n\{[y(x_n + c_n) - y(x_n)]/c_n - \delta_n\}$ , then  $x_n \rightarrow x_0$  w.p.1. and in mean square.

The problem of finding the point where  $m(x)$  stops being a constant, was suggested by Gutmann [3].

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## THE USE OF THE RANGE IN PLACE OF THE STANDARD DEVIATION IN STEIN'S TEST

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A two sample procedure for obtaining a confidence interval of predetermined length for the mean,  $\mu$ , of a normal distribution with unknown variance,  $\sigma^2$ , was devised by Stein [4] and generalized by Wormleighton [5]. In this procedure a first

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sample of size  $n_1$  is taken following which a second sample of size  $n_2$  is taken,  $n_2$  being a function of the standard deviation of the first sample. If the choice of  $n_2$  must be made under field conditions, computation of the standard deviation may not be practical, whereas the range is easily obtained. It is the purpose of this note to present a range-based Stein procedure.

Let  $s$  be any estimate of  $\sigma$  obtained from the first sample which is statistically independent of the mean of that sample,  $\bar{x}_1$ , and for which the distribution of  $s/\sigma$  is independent of  $\sigma$ . (In particular, both standard deviation and range [3] have these properties.) Let

$$(1) \quad u = (\bar{x}_1 - \mu)(n_1)^{\frac{1}{2}}/s,$$

and let  $u_a$  be the  $a$ th quantile of its distribution.

The size of the second sample will be  $n_2 = n(s) - n_1$  where  $n$  is any measurable function of  $s$  for which  $n(s) \geq n_1$ . It will be shown that

$$(2) \quad \text{Prob} \{ \bar{x} - \mu \leq su_a/n(s)^{\frac{1}{2}} \} = a,$$

where  $\bar{x}$  is the mean of the total sample (first and second combined); from this, confidence intervals are immediate, and it is seen that the same tables will be used for the two as for the one sample procedure. (If  $s$  is the range, tables can be found in references [1] and [3].) Proof of (2) follows Wormleighton [5]. For a ratio,  $y/s$ , to be distributed as  $u$  it is sufficient that the conditional distribution of  $y$  given  $s$  be  $N(0, \sigma^2)$ . As the conditional distribution, given  $s$ , of the mean of the first sample is  $N(\mu, \sigma^2/n_1)$ , and the conditional distribution, given  $s$ , of the mean of the second sample, if one be taken, is  $N(\mu, \sigma^2/[n(s) - n_1])$ , the conditional distribution, given  $s$ , of the mean of the total sample is  $N(\mu, \sigma^2/n(s))$ , and that of  $(\bar{x} - \mu)[n(s)]^{\frac{1}{2}}$  is  $N(0, \sigma^2)$ . Equation (2) holds when the distribution of  $s/\sigma$  is dependent on  $\sigma$ , but in such a case  $u_a$  will also depend on  $\sigma$ .

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