Uniform Consistency of Some
Estimates of a Density Function

Ъу

D.S. Moore and E.G. Henrichon

Department of Statistics

Division of Mathematical Sciences

Mimeograph Series No. 168

August, 1968

Uniform Consistency of Some
Estimates of a Density Function

bу

D. S. Moore and E. G. Henrichon Purdue University

- 1. Introduction and summary. Let X_1, \ldots, X_n be independent random variables identically distributed with absolutely continuous distribution function F and density function f. Loftsgaarden and Quesenberry [2] propose a consistent nonparametric point estimator $\hat{f}_n(z)$ of f(z) which is quite easy to compute in practice. In this note we introduce a step-function approximation f_n^* to \hat{f}_n , and show that both \hat{f}_n and f_n^* converge uniformly (in probability) to f, assuming that f is positive and uniformly continuous in $(-\infty, \infty)$. For more general f, uniform convergence over any compact interval where f is positive and continuous follows. Uniform convergence is useful for estimation of the mode of f, for it follows from our theorem (see [3], section 3) that a mode of either \hat{f}_n of f_n^* is a consistent estimator of the mode of f. The mode of f is particularly tractable; it is applied in [1] to some problems in pattern recognition.
- 2. The result. Choose a non-decreasing sequence of positive integers, $\{k(n)\}$, such that $k(n) \to \infty$ but k(n) = o(n). For any real number z, let $r_{k(n)}(z)$ be the distance from z to the k(n)th closest of the observations X_1, \ldots, X_n . Then the univariate form of the Loftsgaarden-Quesenberry estimator is

$$f_n(z) = \{(k(n) - 1) / n\} \{1/2r_{k(n)}(z)\}$$

We define also the random step-function f_n^* as follows: let $X_{ln} \leq X_{2n} \leq \cdots \leq X_{nn}$ be the order statistics from X_1, \ldots, X_n . Then

$$f_n^*(z) = 0$$
 $z < X_{ln}$ or $z \ge X_{nn}$
= $\hat{f}_n(X_{in})$ $X_{in} \le z < X_{i+1,n}$ $i = 1,..., n-1$.

THEOREM. If f(z) is uniformly continuous and positive on $(-\infty, \infty)$ and $(\log n) / k(n) \rightarrow 0$, then for every $\varepsilon > 0$

(2.1)
$$P[\sup_{-\infty < z < \infty} |\hat{f}_{n}(z) - f(z)| > e] \to 0$$

and

(2.2)
$$P[\sup_{-\infty < z < \infty} |f_n^*(z) - f(z)| > \epsilon] \to 0 .$$

<u>Proof.</u> We will abbreviate (2.1) by $\hat{f}_n \rightarrow f$ (UP) and denote convergence in probability by $a_n \rightarrow a(P)$. Define

$$U_{k(n)}(z) = F(z + r_{k(n)}(z)) - F(z-r_{k(n)}(z)).$$

We show first that

(2.3)
$$\{n/(k(n)-1)\} \ U_{k(n)}(z) \to 1(UP) .$$

By definition of $r_{k(n)}(z)$, the interval $[z-r_{k(n)}(z), z+r_{k(n)}(z)]$ contains exactly k(n) observations, one of which falls at an endpoint of the interval. Suppose the order statistic X_{qn} is the lower endpoint. Then

(2.4)
$$\sum_{j=1}^{k(n)-1} \{F(X_{q+j,n}) - F(X_{q+j-1,n})\} \le U_{k(n)}(z)$$
$$\le \sum_{j=1}^{k(n)} \{F(X_{q+j,n}) - F(X_{q+j-1,n})\}$$

with the conventions $F(X_{0,n}) = 0$ and $F(X_{n+1,n}) = 1$. Upper and lower bounds having the same distribution as those in (2.4) exist when X_{qn} is on upper endpoint. (It is stated in [2] that $U_{k(n)}$ has the beta distribution of one of the sums of elementary coverages in (2.4). This is false, since w.p.l only one endpoint of the interval coincides with an observation; the modifications required to correct the proof of [2] are trivial.)

It is well known that

$$F(X_{ln}), F(X_{2n}) - F(X_{ln}), ..., 1-F(X_{nn})$$

have the same joint distribution as

$$Y_1 / S_{n+1}, ..., Y_{n+1} / S_{n+1}$$

where Y_1, \ldots, Y_{n+1} are independent exponential random variables with mean 1 and $S_{n+1} = Y_1 + \ldots + Y_{n+1}$. So the upper and lower bounds in (2.4) will converge to 1 (UP) if we can prove that

(2.5)
$$\max_{0 \le i \le n-k(n)+1} \left| \left\{ \frac{1}{k(n)} \sum_{j=i+1}^{i+k(n)} Y_j / \frac{1}{n} S_{n+1} \right\} - 1 \right| \to 0 (P) .$$

Since $n^{-1}S_{n+1} \to 1$ w.p.l by the law of large numbers, (2.5) will follow if we can show that the sums $\{k(n)^{-1}_j\}_{j+1}^{j+k(n)}Y_j$ are uniformly near 1 in probability. For any $\epsilon > 0$,

(2.6)
$$P_{n} = P[for some i, |\sum_{j=i+1}^{i+k(n)} (Y_{j}-1)| > k(n) \in]$$

$$\leq \sum_{i=1}^{n+1} P[\sum_{j=i+1}^{i+k(n)} (Y_{j}-1) > k(n) \in] + \sum_{i=1}^{n+1} P[\sum_{j=i+1}^{i+k(n)} (Y_{j-1}) < -k(n) \in].$$

Using the fact that $P[X>0] \leq E[e^{tX}]$ for any random variable X and t>0 such that the right side is finite, we obtain

$$\begin{split} \text{Pf} & \sum_{j=i+1}^{i+k(n)} (Y_{j}-1) > k(n)_{\varepsilon}] \leq \text{Ef } e^{-t(\Sigma Y_{j}-k(n)-k(n)_{\varepsilon})} \\ & = \{e^{-t(1+\varepsilon)}/(1-t)\}^{k(n)} \qquad 0 < t < 1 . \end{split}$$

(Recall that a sum of k(n) Y_j's has the gamma distribution with parameter k(n).) Choosing the minimizing value $t = 1 - (1 + \epsilon)^{-1}$ gives the bound $\{(1 + \epsilon)e^{-\epsilon}\}^{k(n)}$. A similar bound holds for each term of the second sum on the right side of (2.6). Therefore $P_n \leq (n+1) a(\epsilon)^{-k(n)}$, where $a(\epsilon) > 1$ for $\epsilon > 0$. Since $(\log n) / k(n) \to 0$, $P_n \to 0$ and (2.5) is proved.

It follows from (2.3) that $U_{k(n)} \to 0$ (UP) and hence, since f is everywhere positive, that $r_{k(n)} \to 0$ (UP).

To conclude (2.1) we need only (2.3) and the fact that $U_{k(n)}/2r_{k(n)} \rightarrow f$ (UP). Since f is uniformly continuous and $r_{k(n)} \rightarrow 0$ (UP), this is immediate from the estimate

(2.7)
$$|\frac{U_{k(n)}(z)}{2r_{k(n)}(z)} - f(z)| = |\frac{1}{2r_{k(n)}(z)} \int_{z-r}^{z+r} |f(t)-f(z)| dt |$$

$$\leq \max \{|f(t)-f(z)| : z-r_{k(n)}(z) \leq t \leq z + r_{k(n)}(z)\} .$$

The argument for (2.2) is slightly longer. Let i(z) be the index such that

$$X_{i(z),n} \leq z < X_{i(z)+1,n}$$

For any compact interval I, the probability that $X_{\rm ln}$ and $X_{\rm nn}$ fall outside I approaches 1 as $n\to\infty$, by positivity of f. Thus i(z) is defined for all $z_{\rm c}I$ with probability approaching 1 for large n. The Glivenko-Cantelli theorem and uniform continuity of ${\bf F}^{-1}$ on $[\alpha, 1-\alpha]$ for any $\alpha>0$ give that

(2.8)
$$\sup_{z \in I} |X_{i(z),n} - z| \rightarrow 0 (P).$$

From (2.8) and the fact that $r_{k(n)} \rightarrow 0$ (UP), we can conclude by an estimate analogous to (2.7) that

$$\sup_{z \in I} \left| \frac{U_{k(n)}(X_{i(z),n})}{2r_{k(n)}(X_{i(z),n})} - f(z) \right| \to 0 (P)$$

and hence, using (2.3), that for any compact interval I and any $\epsilon > 0$,

(2.9)
$$\lim_{n\to\infty} P[\sup_{z\in I} | f_n^*(z) - f(z) | > \varepsilon] = 0$$

If we can establish that for any $_{\varepsilon}>0\,$ there is a compact interval I such that

(2.10)
$$\lim_{n\to\infty} \Pr[\sup_{z\not\in I_{\epsilon}} | f_n^*(z) - f(z) | >_{\epsilon}] = 0,$$

this with (2.9) will imply (2.2).

Since $f(z) \to 0$ as $z \to \pm \infty$, we can choose a compact interval $I^* = [a,b]$ such that $f(z) < \epsilon/2$ outside I^* . Then by (2.1), $\hat{f}_n(z) < \epsilon$ for all $z \not\in I^*$ with probability approaching 1 as $n \to \infty$. Let I = [a,b+c] for some c > 0. Then by (2.8) and the fact that $P(X_{ln} < a, X_{nn} > b + c] \to 1$, we have that

$$P[X_{i(z),n} \not\in I^* \text{ for all } z \not\in I_{\varepsilon} \text{ with } X_{in} \leq z < X_{nn}] \rightarrow 1.$$

Thus with probability approaching 1, $f_n^*(z)$ is either 0 or $\hat{f}_n(X_{in})$ for some $X_{in} \not\in I^*$, for all $z \not\in I_{\varepsilon}$. This establishes (2.10).

References

- Henrichon, E.G. and Fu, K.S. (1968). On mode estimation for pattern recognition. Submitted to <u>IEEE Trans. Information Theory</u>.
- [2] Loftsgaarden, D.O. and Quesenberry, C.P. (1965). A nonparametric estimate of a multivariate density function. Ann. Math. Statist. 36 1049-1051.
- Parzen, Emanuel (1962). On estimation of a probability density function and mode. Ann. Math. Statist. 33 1065-1076.