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ESTIMATING FUNCTIONS: NONPARAMETRIC AND ROBUSTNESS PERSPECTIVES[†]

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In nonparametric and robust inference, explicit or implicit estimating functions are based on suitable statistical functionals. There is a need to critically appraise the interplay of robustness and asymptotic efficiency properties of such usually nonlinear estimators. This picture is examined here by reference to some problems that crop up in various biomedical statistical applications.

1. Introduction. In a parametric setup, parameters generally appear as algebraic constants associated with the underlying distribution functions (d.f.) of assumed functional form(s). The *maximum likelihood estimators* (MLE) have generally some optimal properties, at least asymptotically. The situation is different in a nonparametric setup. There estimable parameters are defined as suitable functionals of the underlying d.f.'s which are not of assumed functional form(s). This formulation automatically shifts the emphasis on validity for a broad class of distributions wherein good efficiency and robustness properties dominate the scenario. The *U-statistics* (Hoeffding, 1948) are the precursors of such nonparametric estimators; they are of the *kernel estimator* type, and enjoy good efficiency (and unbiasedness) properties but may not be generally very robust. Moreover not all parameters in a nonparametric setup are *estimable* or *regular functionals* in the sense of Hoeffding(1948); the median or a percentile of a distribution belonging to a broad class is a classical example of such a nonregular functional. The past three decades have witnessed significant developments in nonparametric and robust estimation theory covering both kernel type and *estimating equation* (EE) type estimating functions. Among the various classes of estimators, three important sectors relate to

- (i) *L-estimators* based on linear functions of order statistics;
- (ii) *M-estimators* allied to the classical MLE;
- (iii) *R-estimators* based on suitable rank statistics.

There has also been a drive to unify these estimators in terms of *differentiable statistical functionals*, although the end product lacks the complete generality to

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cover all such estimators. A good deal of discussion of such estimators with due attention to their robustness and asymptotic properties has appeared in various contemporary research publications; we may refer to Jurečková and Sen (1996) for a treatise of this subject matter in the context of general (*fixed-effects*) linear models. Whereas L-estimators are explicit statistical functionals, M- and R-estimators are defined implicitly (as is generally the case with the parametric MLE). *Conditional statistical functionals* particularly arising in *mixed-effects* and *multivariate models* have added new dimensions to the scope of study of (asymptotic) properties of such nonparametric estimators, where even the very linearity of the model has been challenged (on the grounds of validity and robustness), and hence, *nonparametric regression functions* have emerged in a better perspective than before. Yet, study of their robustness properties needs further scrutiny with special emphasis on their finite sample behavior. In the current study, more emphasis will be placed on such estimating function(al)s.

The basic motivation for estimating functions in some simple nonparametric models is presented in Section 2. We examine the picture in a more general (linear model) setup in Section 3. Some nonstandard models arising in functional estimation problems are introduced in Section 4. The concluding section deals with some general remarks.

2. Nonparametric estimating functions. We may remark that the very formulation of the *Fisher-consistency* criterion of statistical estimators brings the relevance of functionals of empirical measures in estimation theory. In a simple setup, given n independent and identically distributed random variables (i.i.d.r.v.) X_1, \dots, X_n from a distribution function (d.f.) F , a statistical parameter $\theta = \theta(F)$ is interpreted as a functional of F , and a natural (i.e., plug-in) estimator of this parameter is its sample counterpart

$$(2.1) \quad T_n = T(X_1, \dots, X_n) = \theta(F_n),$$

where F_n is the sample (*empirical*) d.f. The empirical d.f. F_n is known to possess some optimality properties in a traditional setup, and if $\theta(F)$ is a linear functional, these properties are shared by T_n as well. The ingenuity of Hoeffding (1948) lies in covering a more general class of functionals where $\theta(F)$ can be expressed as

$$(2.2) \quad \begin{aligned} \theta(F) &= E_F\{g(X_1, \dots, X_m)\} \\ &= \int \cdots \int g(x_1, \dots, x_m) dF(x_1) \cdots dF(x_m), \end{aligned}$$

where $g(\cdot)$ is a *kernel* of *degree* $m (\geq 1)$, and without loss of generality, we assume that $g(\cdot)$ is a symmetric function of its m arguments. Hoeffding (1948) introduced the *U-statistic* as an (unbiased) estimator of $\theta(F)$:

$$(2.3) \quad U_n = \binom{n}{m}^{-1} \sum_{\{1 \leq i_1 < \cdots < i_m \leq n\}} g(X_{i_1}, \dots, X_{i_m}), \quad n \geq m.$$

A closely related estimator is the von Mises (1947) functional

$$\begin{aligned}
 V_n &= \theta(F_n) = \int \cdots \int g(x_1, \dots, x_m) dF_n(x_1) \cdots dF_n(x_m) \\
 (2.4) \quad &= n^{-m} \sum_{i_1=1}^n \cdots \sum_{i_m=1}^n g(X_{i_1}, \dots, X_{i_m}).
 \end{aligned}$$

For $m = 1$, U_n and V_n are the same (and average of i.i.d.r.v.s). But for $m \geq 2$, they are generally not the same; whereas U_n is an unbiased estimator, V_n is generally not so. Nevertheless, under quite general regularity conditions, $|V_n - U_n| = O_p(n^{-1})$, so that asymptotically they share the same optimality properties, studied in detail by various researchers; Sen (1981) contains a systematic account of this work.

We may note that the above formulation is pivoted to a suitable kernel $g(\cdot)$, and the optimality properties, interpreted in a nonparametric fashion, rest on the adoption of the classical Rao-Blackwell theorem along with the sufficiency and completeness of sample order statistics. Nevertheless, from a robustness perspective the choice of the kernel is very important. Generally, if $g(\cdot)$ is unbounded, neither of these two estimators may be very robust. For illustration consider the simple situation where $\theta(F)$ is the variance of the d.f. F . In this case, the kernel $g(\cdot)$ is given by

$$(2.5) \quad g(x_1, x_2) = \frac{1}{2}(x_1 - x_2)^2, \quad m = 2,$$

so that if F does not have a compact support, the estimators are vulnerable to error contamination, gross errors or outliers. A similar situation arises with the mean functional (where $m = 1$ and $g(x) = x$), although there it may be possible to introduce the location parameter by imposing symmetry of F around its median and bypassing some of these technical difficulties. The degree of nonrobustness is likely to be more with dispersion than location measures. Robust estimation of location (and regression) parameters has its genesis in this feature, and we will discuss this briefly later on. There has been some attempts to introduce more robust dispersion functionals, such as the *mean absolute deviation* and *interquartile range*, although they may not belong to the class of estimable parameters in the sense of Hoeffding (1948) and may also lack some generality prevailing in the case of location parameters; we refer to Jurečková and Sen (1996) for some discussion.

For both location and dispersion measures, linear functions of order statistics, known as *L-statistics*, have been used extensively in the literature; they are generally efficient, adaptable in parametric as well as nonparametric setups, and generally possess good robustness properties. The EE for L-estimators of location and scale parameters in (parametric) location-scale family of distributions has its genesis in the theory of (BLUE) *best linear unbiased estimators* which incorporates the *weighted least squares* (WLS) methodology on the set of order statistics. This genesis paved the way for nonparametric adaptations in a fruitful way. In this setup, a parameter $\theta(F)$ is expressed as a functional

$$(2.6) \quad \theta(F) = \int_{-\infty}^{\infty} g(x) J(F(x)) dF(x),$$

where $g(\cdot)$ is real valued, and $J = \{J(u), u \in (0, 1)\}$ is a weight-function defined on the unit interval $(0, 1)$. It is easy to see that the corresponding sample counterpart $\theta(F_n)$, given by

$$(2.7) \quad n^{-1} \sum_{i=1}^n g(X_{n:i}) J_n(i/n),$$

is an L-estimator; here the $X_{n:i}, i = 1, \dots, n$ stand for the order statistics, and $J_n(\cdot)$ is a suitable version converging to $J(\cdot)$ (as n increases) almost everywhere. The flexibility of this approach stems from the choice of $g(\cdot)$ and $J(\cdot)$, for which $\theta(F)$ remains invariant, in such a way that retaining robustness to a greater extent, not much is compromised on (asymptotic) efficiency of an estimator of $\theta(F_n)$. For example, in the location model, the *trimmed mean*, a member of this class of L-estimators, for a small amount of trimming (at both ends) combines robustness with good efficiency properties in a nonparametric setup. The theory of (asymptotically) ABLUE is geared to this direction; it covers both the cases of smooth weight functions and a combination of a selected number of order statistics. For this location model, whenever F is assumed to be symmetric about its median (θ), one may take $g(x) = x$ a.e., and for nonnegative $J_n(i/n)$ (adding upto n), we have a convex combination of the order statistics as an estimator of θ . Within this class, one may like to choose the weight-function in such a way that robustness can be fruitfully combined with high efficiency properties. Generally smoother weight functions are used in this context. For the location-scale problems, the sample quantiles and interquartile range are particular cases of such L-estimators. It is often possible to express an L-statistic as a U-statistic, and in an asymptotic setup, a first order approximation for L-estimators in terms of U-statistics works out well [viz., Sen (1981, ch.7)]. A notable example in this context is the *rank-weighted mean* $T_{n,k}$ which is a U-statistic (the average of all the subsample medians of size $2k + 1$ from the given sample of size n), and as in Sen (1964), we may write this as an L-statistic:

$$(2.8) \quad T_{n,k} = \binom{n}{2k+1}^{-1} \sum_{i=1}^n \binom{i-1}{k} \binom{n-i}{k} X_{n:i}, \quad k \geq 0;$$

for $k = 0$, we have the sample mean, and for $k = [(n-1)/2]$, we have the sample median. Incidentally, this example, for a $k \geq 1$, provides an illustration for the robustness of U-statistics even when the kernel is possibly unbounded.

In order to introduce the salient features of the estimating functions for R- and M-estimators it may be more convenient to start with the conventional MLE when the assumed (location) model is not necessarily the true one. Assume that X_1, \dots, X_n are drawn from a population with an absolutely continuous density function $f(x-\theta)$ where $f(\cdot)$ is symmetric about the origin, while the true density function, given by $g(x-\theta)$, is also absolutely continuous and symmetric about the origin. Then the EE for obtaining the assumed model MLE $\hat{\theta}_n$ is given by

$$(2.9) \quad \sum_{i=1}^n \{-f'(X_i - \theta)/f(X_i - \theta)\} = 0.$$

Note that under the assumed conditions (on f and g),

$$(2.10) \quad \int \{-f'(x - \theta)/f(x - \theta)\}g(x - \theta)dx = 0,$$

so that the assumed model MLE remains pertinent to the entire class of g satisfying the above symmetry condition. Let us denote by

$$(2.11) \quad \begin{aligned} A^2(f, g) &= \int \{-f'(x)/f(x)\}^2 g(x) dx, \\ \gamma(f, g) &= \int \{-f'(x)/f(x)\}g'(x) dx, \\ I(g) &= \int \{-g'(x)/g(x)\}^2 g(x) dx. \end{aligned}$$

Then following standard asymptotics for the MLE, it can be shown that

$$(2.12) \quad n^{1/2}(\tilde{\theta}_n - \theta) \rightarrow_{\mathcal{D}} \mathcal{N}(0, A^2(f, g)/\gamma^2(f, g)).$$

Let the true model MLE be denoted by $\hat{\theta}_n$. Then we have the following result:

$$(2.13) \quad n^{1/2}(\hat{\theta}_n - \theta) \rightarrow_{\mathcal{D}} \mathcal{N}(0, [I(g)]^{-1}).$$

Next note that by the Cauchy-Schwarz inequality,

$$(2.14) \quad \gamma^2(f, g) \leq A^2(f, g)I(g),$$

where the equality sign holds only when $\{-f'(x)/f(x)\} = \{-g'(x)/g(x)\}$ almost everywhere. Thus, if both f and g belong to the same location-scale family of densities for which the logarithmic derivative is *scale-equivariant*, as is the case when g is Laplace or normal, then $\hat{\theta}_n$ and $\tilde{\theta}_n$ are isomorphic, and there is no loss of efficiency due to incorrect model assumption; this is the usual *parametric orthogonality* condition referred to in the literature. This orthogonality condition may not always hold; the Cauchy density is a classical example toward this point. On the other hand, we may define the *asymptotic relative efficiency* (ARE) of $\tilde{\theta}_n$ with respect to $\hat{\theta}_n$ as

$$(2.15) \quad e(f, g) = \gamma^2(f, g)/\{I(g)A^2(f, g)\} (\leq 1).$$

This ARE can be quite low depending on the divergence of f and g . For example if g is Cauchy while f is taken to be normal, $A^2(f, g) = \infty$, and hence, $e(f, g) = 0$. In the above development, we have tacitly assumed that (2.10) holds. Sans the assumed symmetry of f and g this may not be generally true, and therefore in such a case, the MLE $\tilde{\theta}_n$ may have serious bias, and this in turn may make it inconsistent too. In any case, it is clear that with an incorrect model, the derived MLE can not attain the Cramér-Rao information bound for its asymptotic mean square error, and hence, loses its (asymptotic) optimality properties.

The above picture turns out to be far more complex in a general parametric model where θ may not be the location parameter or the density may not be symmetric, and as such it reveals the grave nonrobustness aspects of the classical MLE

to plausible model departures. The situation in a nonparametric setup is more complex in the sense that f and g may not simply differ in nuisance parameters, and their separability is generally defined in terms of more general metrics. As such, the wealth of methodology developed for parametric estimating functions in the presence of nuisance parameters may not be of much use in this more general setup. In the classical *robust inference* setup, Huber (1964) introduced various measures of departures from the assumed model, such as the *Levi-distance*, *Kolmogorov-distance* and *Prokhorov-distance*, and has exhibited the possible lack of robustness of the classical MLE. Following his ground-breaking work, we may therefore conceive of a suitable *score function* $\psi(t)$, $t \in \mathcal{R}$, and for the location model, consider the EE:

$$(2.16) \quad \sum_{i=1}^n \psi(X_i - \theta) = 0,$$

and in order to have good robustness properties of the derived (M-)estimator, generally the *influence function* ψ is taken to be bounded almost everywhere. In order that the above estimating equation provides a consistent solution, we need that

$$(2.17) \quad \int \psi(x)g(x)dx = 0,$$

and a sufficient condition for this is the skew-symmetry of ψ and symmetry of g (both about 0). Within this broad class, specific choice of ψ can be made to achieve local efficiency, and we may refer to Hampel et al. (1986) and Jurečková and Sen (1996) for details.

The estimating functions for R-estimators have a greater appeal from *global robustness* perspectives. It stems from the basic fact that under suitable hypotheses of invariance, a rank statistic is genuinely distribution-free, so that whenever it has some monotonicity properties with respect to an *alignment* in the direction of alternative hypotheses, we have a robust estimating function. For example in the location model, assuming that the underlying d.f. G is symmetric, we may consider a signed rank statistic

$$(2.18) \quad \sum_{i=1}^n \text{sign}(X_i) a_n(R_{ni}^+) = S_n \text{ say,}$$

where $a_n(1) \leq \dots \leq a_n(n)$ are suitable *scores*, and R_{ni}^+ is the rank of $|X_i|$ among $|X_1|, \dots, |X_n|$, for $i = 1, \dots, n$. Note that under the null hypothesis that the location parameter θ is null, S_n has a known, symmetric distribution. Moreover, if we replace the X_i by $X_i - a$, for some real a , and denote the corresponding (aligned) signed rank statistic by $S_n(a)$, then it is easy to verify that

$$(2.19) \quad S_n(a) \text{ is nonincreasing in } a \in \mathcal{R}.$$

Therefore, the estimating function in this case is $S_n(a)$, and the corresponding EE is $S_n(a) = 0$, where, in view of the usual step-function nature of $S_n(a)$, "=" is

defined precisely by letting

$$(2.20) \quad \begin{aligned} \hat{\theta}_{n,1} &= \sup\{a : S_n(a) > 0\}, \\ \hat{\theta}_{n,2} &= \inf\{a : S_n(a) < 0\}; \\ \hat{\theta}_n &= \frac{1}{2}[\hat{\theta}_{n,1} + \hat{\theta}_{n,2}]. \end{aligned}$$

Although in the case of the sign statistic $\hat{\theta}_n$ turns out to be the sample median, and for the Wilcoxon signed rank statistic, it is the median of the mid-ranges, in general, an algebraic expression may not be available, and an iterative solution has to be prescribed. Such R-estimators are distribution-free in the sense that they remain valid for the entire class of symmetric distributions, and unlike the case of the MLE, here the absolute continuity of the density function need not be a part of the regularity assumptions.

Let us have a close look into the ranks $R_{n,i}^+$, which assume the integer values $1, \dots, n$. Thus, if an observation is moved to the extreme right, it continues to have the rank n , no matter how far it is shifted. A similar picture holds for shifting to the extreme left. In that way, the rank scores have good robustness properties for error contaminations and outliers. Under general regularity conditions, R-estimators are *translation-invariant*, robust, consistent and *median-unbiased*, and their asymptotic properties have been extensively studied in the literature; viz., Jurečková and Sen (1996). Under appropriate regularity conditions, we have

$$(2.21) \quad n^{1/2}(\hat{\theta}_n - \theta) \rightarrow_{\mathcal{D}} \mathcal{N}(0, \nu^2),$$

where

$$(2.22) \quad \nu^2 = \left\{ \int \phi^2(u) du \right\} / \left\{ \int \phi(u) \{-g'(G^{-1}(u))/g(G^{-1}(u))\} du \right\}^2,$$

and $\phi(\cdot)$ is the score generating function for the $a_n(k)$. As such, we may conclude that the nonparametric and robustness aspects of R-estimators are prevailed as long as the score function $\phi(\cdot)$ is square integrable inside $(0, 1)$; unlike the case of M-estimators, here we need not confine ourselves to bounded score functions. Within this broad class of score functions, one may choose specific members such that the ARE at a given G is a maximum, so that robustness can also be combined with local optimality.

In passing we may remark that for both M- and R-estimators, the d.f. G is largely treated as a nuisance (functional) parameter, so that the situation differs drastically from the parametric situation where one has generally a finite (and small) number of nuisance parameters. Further, looking at the last equation, we gather that

$$(2.23) \quad \nu^2 \geq [I(g)]^{-1}, \quad \forall \phi \in \mathcal{L}_2(0, 1),$$

where the equality sign holds only when $\phi(u) = K\{-g'(G^{-1}(u))/g(G^{-1}(u))\}$, $\forall u \in (0, 1)$, where K is a nonzero constant. In this way, the situation is quite comparable to the case of M-estimators (sans the boundedness condition). As a matter of fact, both M- and R-estimators have certain asymptotic equivalence properties

(with congruent score functions), and such general equivalence results for L-, M- and R-estimators have been studied in detail in Jurečková and Sen (1996). It follows from their general discussion that all of them are expressible in terms of *statistical functionals*; whereas L-estimators are defined explicitly, M- and R-estimators are implicitly defined functionals. For such statistical functionals, suitable modes of *differentiability* have been incorporated to provide convenient means for the study of general asymptotic properties of such estimators. Among these, the *Hadamard differentiability* property has been exploited mostly. It turns out [viz., Sen, 1996a] that U-statistics for unbounded kernels may not be Hadamard differentiable, although they possess nice (reverse) martingale properties which provide access to various probabilistic tools that can be used to study related asymptotics. Likewise for L-, M- and R-estimators in a functional mold, one needs bounded score (weight) functions to verify the desired Hadamard differentiability property. For L- and M-estimators, such a boundedness condition does not pose any serious threat (as robustness considerations often prompt bounded influence functions), but bounded scores for R-estimators exclude some important statistics (such as the classical *normal scores* and *log-rank scores* statistics), and hence, the adoption of this differentiability approach for R-estimators is not totally appropriate. Fortunately, there are alternative methodologies, studied in detail in Jurečková and Sen (1996, ch.6), which provide a better resolution, and hence, we should not be very concerned about Hadamard differentiability of estimating functions for R-estimators.

For all the types of estimators considered above there is a basic query: Treating the underlying density g to be a nuisance functional belonging to a general class \mathcal{G} , is it possible to formulate some estimating function which yields asymptotically optimal estimators in the sense of attainment of the information bound to its asymptotic mean square error in a semi-parametric setup? The answer is affirmative, under fairly general regularity conditions. We illustrate this point with adaptive R-estimators of location (Hušková and Sen, 1986), and a similar situation holds for other functionals as well (Sen, 1996a). Let us define the Fisher-information score generating function by

$$(2.24) \quad \phi_g(t) = \{-g'(G^{-1}(t))/g(G^{-1}(t))\}, t \in (0, 1),$$

and assume that $I(g) = \int_0^1 \phi_g^2(t) dt < \infty$. Then we may consider a Fourier series expansion

$$(2.25) \quad \phi_g(t) \equiv \sum_{k \geq 0} \gamma_k P_k(t), t \in (0, 1)$$

where the $\{P_k(\cdot), k \geq 0\}$ form a complete orthonormal system [on $(0, 1)$] and the Fourier coefficients γ_k are defined as

$$(2.26) \quad \gamma_k = \int_0^1 \phi_g(t) P_k(t) dt, \text{ for } k = 0, 1, \dots$$

For adaptive R-estimators, Hušková and Sen (1985, 1986) advocated the use of the *Legendre polynomial system* on $(0, 1)$, where for each $k (= 0, 1, 2, \dots)$,

$$(2.27) \quad P_k(t) = (2k + 1)^{1/2} (-1)^k (k!)^{-1} (d^k / dt^k) \{t(1 - t)\}^k, t \in (0, 1),$$

so that $P_0(t) = 1$, $P_1(t) = \sqrt{3}(2t - 1)$, $P_2(t) = \sqrt{5}\{1 - 6t(1 - t)\}$ and so on. Thus $P_1(\cdot)$ is a variant of the Wilcoxon scores, and when g is a logistic density, it is easy to see that $\phi(\cdot) \equiv P_1(\cdot)$, while for a symmetric g , it follows from the above that $\gamma_{2k} = 0$, $\forall k \geq 0$. In general the Fourier series is an infinite one, though convergent. The basic idea is to truncate this infinite series at a suitable *stopping number*, say, K_n , and for such a truncated version $\sum_{k \leq K_n} \gamma_k P_k(t)$, to estimate the Fourier coefficients γ_k by the classical Jurečková-linearity method. If we denote these estimates by $\hat{\gamma}_{k,n}$, $k \leq K_n$, then our adaptive version of the Fisher score function is

$$(2.28) \quad \hat{\phi}_{g,n}(t) = \sum_{k \leq K_n} \hat{\gamma}_{k,n} P_k(t), \quad t \in (0, 1).$$

One may then define a (signed-) rank statistic as in before with the scores $\hat{a}_n(k)$, $k = 1, \dots, n$ generated by the adaptive score generating function $\hat{\phi}_{g,n}(\cdot)$, and, based on the same alignment principle, obtain adaptive R-estimators of location. These estimators are robust and asymptotically efficient for the class of densities with finite Fisher information. Hušková and Sen (1986) considered a suitable sequential version to formulate suitable stopping numbers $\{K_n\}$ for which there are suitable rate of convergence; a more simple algorithm without appealing to such a sequential scheme has been worked out in Sen (1996a).

3. Estimating functions for linear models. Linear models pertain to observations which may not be i.i.d., though the error components are assumed to be i.i.d.r.v.'s. Conventionally, we define a vector of observable random variables $\mathbf{Y}_n = (Y_1, \dots, Y_n)'$ by letting

$$(3.1) \quad \mathbf{Y}_n = \mathbf{X}_n \boldsymbol{\beta} + \mathbf{e}_n; \quad \mathbf{e}_n = (e_1, \dots, e_n)',$$

where \mathbf{X}_n is a given (nonstochastic) $n \times p$ matrix, $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)'$ is a vector of unknown regression parameters, and the errors e_i are assumed to be i.i.d.r.v.'s. In the classical parametric case the errors are assumed to be normal, so that the ML estimating equations are linear in \mathbf{Y}_n , and they agree with the LSE. Specifically, we have

$$(3.2) \quad \hat{\boldsymbol{\beta}}_n = \{\mathbf{X}_n' \mathbf{X}_n\}^{-1} \mathbf{X}_n' \mathbf{Y}_n.$$

In a general parametric model with an assumed density f for the error, the ML estimating function is given by

$$(3.3) \quad \sum_{i=1}^n \mathbf{x}_i' \{-f'(Y_i - \mathbf{x}_i' \mathbf{b})/f(Y_i - \mathbf{x}_i' \mathbf{b})\} = 0,$$

where $\mathbf{X}_n' = (\mathbf{x}_1', \dots, \mathbf{x}_n')$. The situation is quite comparable to the i.i.d. case presented in (2.9) through (2.15), although the ARE properties are isomorphic, possible lack of robustness would be more accentuated here because of the nonidentity of the \mathbf{x}_i . Moreover, for f not belonging to an exponential family, the resulting MLE in (3.3) may not be linear estimators, and hence, a trial and error solution may be necessary.

The usual M-estimators for such linear models are based on estimating functions which resemble (3.3) along the same line as in Section 2: One would use a score function $\psi(\cdot) : \mathcal{R} \rightarrow \mathcal{R}$ satisfying the same regularity conditions as in Section 2, and consider the estimating equations:

$$(3.4) \quad \sum_{i=1}^n \mathbf{x}_i' \psi(Y_i - \mathbf{x}_i' \mathbf{b}) = 0.$$

Jurečková and Sen (1996, ch.5) contains an extensive treatment of first and second order asymptotic distributional representations for M-estimators in linear models; their treatise exploits mostly the uniform asymptotic linearity results of M-statistics (in the regression parameters). Another approach to this type of representation is based on the Hadamard differentiability of extended statistical functionals, and this has been considered in detail by Ren and Sen (1991, 1994, 1995). As in the case of location models, such M-estimators have good robustness and local optimality properties, but are not genuinely nonparametric in nature.

R-estimators of regression parameters are based on suitable linear rank statistics, and they are globally robust and asymptotically optimal for suitable subfamilies of underlying densities. For a given $\mathbf{b} \in \mathcal{R}^p$, we define the residuals by

$$(3.5) \quad Y_i(\mathbf{b}) = Y_i - \mathbf{x}_i' \mathbf{b}, \quad i = 1, \dots, n,$$

and denote the aligned ranks by

$$(3.6) \quad R_{ni}(\mathbf{b}) = \left[\sum_{j=1}^n I(Y_j(\mathbf{b}) \leq Y_i(\mathbf{b})) \right], \quad i = 1, \dots, n.$$

Then a vector of aligned rank statistics is defined by

$$(3.7) \quad \mathbf{L}_n(\mathbf{b}) = \sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}}_n) a_n(R_{ni}(\mathbf{b})), \quad \mathbf{b} \in \mathcal{R}^p,$$

where the scores $a_n(1) \leq \dots \leq a_n(n)$ are defined as in the location case, and $\bar{\mathbf{x}}_n = n^{-1} \sum_{i=1}^n \mathbf{x}_i$. Note that if we take the design matrix in the conventional form with the first column vector as $\mathbf{1}_n$, then β_1 is the intercept parameter. In this case, in the last equation, the contribution of the first coordinate of the \mathbf{x}_i and \mathbf{b} will be null (as the ranks are translation-invariant). Thus, we would have $p - 1$ elements in $\mathbf{L}_n(\mathbf{b})$, while for the first element, we need to use suitable signed rank statistics. In the case of real valued b , for monotone scores, $L_n(b)$ is a monotone step-function, so an estimator of β can be obtained by "equating $L_n(b)$ to 0"; uniform asymptotic linearity of $L_n(b)$ in a shrinking neighborhood of β provides access to the asymptotic properties of the estimator. In the case of vector valued \mathbf{b} , unlike the case of LSE, these aligned linear rank statistics are not linear in \mathbf{b} ; typically for monotone scores, for each $j (= 1, \dots, p)$, the j th coordinate of $\mathbf{L}_n(\mathbf{b})$ is monotone in b_j , but the picture is somewhat complex with respect to the remaining components of \mathbf{b} where the monotonicity may not hold. In addition, we have a nonlinear estimating

function. There are various approaches to motivate such estimating functions, and a detailed account of these is given by Jurečková and Sen (1996, ch.6). Jaeckel (1972) introduced a rank dispersion measure

$$(3.8) \quad D_n(\mathbf{b}) = \sum_{i=1}^n (Y_i - \mathbf{x}_i' \mathbf{b}) a_n(R_{ni}(\mathbf{b})), \quad \mathbf{b} \in \mathcal{R}^p,$$

and proposed to minimize $D_n(\mathbf{b})$ with respect to \mathbf{b} to obtain an estimator of β . Since the ranks are translation-invariant, it can be shown easily that $D_n(\mathbf{b})$ is non-negative, piecewise linear (and hence, continuous) and convex function of \mathbf{b} . Thus, $D_n(\mathbf{b})$ is almost everywhere differentiable with respect to \mathbf{b} and $(\partial/\partial \mathbf{b})D_n(\mathbf{b}) = -L_n(\mathbf{b})$ at any point of differentiability. Therefore 'equating $L_n(\mathbf{b})$ to $\mathbf{0}$ ' in a suitable norm (such as the \mathcal{L}_1 norm) yields a convenient R-estimator of β . In this context too, the uniform asymptotic linearity of $L_n(\mathbf{b})$ in \mathbf{b} in a shrinking neighborhood of the true β provides access to the variety of asymptotic results pertaining to robustness and asymptotic representations for R-estimators.

R-estimators in linear models are closely related to *regression rank scores* (RRS) estimators, developed mostly due to Gutenbrunner and Jurečková (1992). To introduce such estimators, we make use of some related estimating functions, due to Koenker and Bassett (1978), termed the *regression quantiles* (RQ), which possess a basic regression-equivariance property and are variants of L-estimators in linear models. For a given $\alpha : 0 < \alpha < 1$, define

$$(3.9) \quad \rho_\alpha(x) = |x| \{ (1 - \alpha) I\{x < 0\} + \alpha I\{x > 0\} \}, \quad x \in \mathcal{R},$$

and define the α -RQ estimator $\hat{\beta}_n(\alpha)$ by

$$(3.10) \quad \hat{\beta}_n(\alpha) = \arg \min \left\{ \sum_{i=1}^n \rho_\alpha(Y_i - \mathbf{x}_i' \mathbf{b}) : \mathbf{b} \in \mathcal{R}^p \right\}.$$

Following Koenker and Bassett (1978), it can also be shown that an α -RQ can be characterized as optimal solution ($\beta(\alpha)$) of the *linear programming* problem

$$(3.11) \quad \begin{aligned} \alpha \sum_{i=1}^n r_i^+ + (1 - \alpha) \sum_{i=1}^n r_i^- &= \min \\ \sum_{i=1}^n x_{ij} \beta_j + r_i^+ - r_i^- &= Y_i, \quad i = 1, \dots, n; \\ \beta_j \in \mathcal{R}, \quad j = 1, \dots, p; \quad r_i^+ \geq 0, \quad r_i^- \geq 0, \quad i = 1, \dots, n; \end{aligned}$$

where r_i^+ (r_i^-) is the positive (negative) part of the residual $Y_i - \beta' \mathbf{x}_i$, $i = 1, \dots, n$. Thus, for a given $\alpha : 0 < \alpha < 1/2$, usually small, if we define a diagonal matrix $C_n = \text{diag}(c_{n1}, \dots, c_{nn})$ by letting

$$(3.12) \quad c_{ni} = I\{\mathbf{x}_i' \beta(\alpha) < Y_i < \mathbf{x}_i' \beta(1 - \alpha)\}, \quad i = 1, \dots, n,$$

then an α -trimmed (T)LSE of β can be defined as

$$(3.13) \quad \mathbf{T}_n(\alpha) = (\mathbf{X}_n' C_n \mathbf{X}_n)^{-1} \mathbf{X}_n' C_n \mathbf{Y}_n.$$

Here the estimating function in (3.9)-(3.10) is primarily used to obtain the matrix \mathbf{C}_n , so that robustness and efficiency considerations are to be related to this basic choice. We refer to Jurečková and Sen (1996, ch.4) for some detail discussion of these aspects of RQ and related TLSE. For introducing the RRS estimators, for a given $\alpha \in (0, 1)$, we define the vector of regression ranks (RR) $\hat{\mathbf{a}}_n(\alpha) = (\hat{a}_{n1}(\alpha), \dots, \hat{a}_{nn}(\alpha))'$ as the optimal solution of the linear programming problem:

$$(3.14) \quad \sum_{i=1}^n Y_i \hat{a}_{ni}(\alpha) = \max \quad ; \quad \sum_{i=1}^n x_{ij} \hat{a}_{ni}(\alpha) = (1 - \alpha) \sum_{i=1}^n x_{ij}, \quad j = 1, \dots, p;$$

$$\hat{a}_{ni}(\alpha) \in [0, 1], \quad i = 1, \dots, n; \quad \alpha \in (0, 1).$$

Let $\phi(u)$, $u \in (0, 1)$ be a nondecreasing, square integrable score generating function, and let

$$(3.15) \quad \begin{aligned} \phi_n(u) &= \phi(\alpha^*)I(0 < u \leq \alpha^*) + \phi(u)I(\alpha^* < u < 1 - \alpha^*) \\ &+ \phi(1 - \alpha^*)I(1 - \alpha^* \leq u < 1), \end{aligned}$$

where $\alpha \in (0, 1/2)$ and is usually chosen small. Then the RRS, generated by the score function ϕ , are taken as

$$(3.16) \quad \hat{b}_{ni} = - \int_0^1 \phi_n(\alpha) d\hat{a}_{ni}(\alpha), \quad i = 1, \dots, n.$$

We can then consider a regression rank measure of dispersion:

$$(3.17) \quad D_n^*(\mathbf{b}) = \sum_{i=1}^n (Y_i - \mathbf{b}'\mathbf{x}_i) [\hat{b}_{ni}(\mathbf{Y} - \mathbf{X}\mathbf{b}) - \bar{\phi}],$$

where the RRS $(\hat{b}_{ni}(\mathbf{Y} - \mathbf{X}\mathbf{b}), i = 1, \dots, n)$ are computed from the aligned observations $\mathbf{Y} - \mathbf{X}\mathbf{b}$. Then the derived RRS estimator is defined as

$$(3.18) \quad \tilde{\beta}_n = \text{Arg. min}\{D_n^*(\mathbf{b}) : \mathbf{b} \in \mathcal{R}^p\}.$$

A similar estimating function works out for the estimation of a subvector of β . The interesting fact is that under fairly general regularity conditions and based on a common score function $\phi(\cdot)$, the classical R-estimator and the RRS estimator are asymptotically equivalent upto the order $(n^{-1/2})$; we refer to Section 6.8 of Jurečková and Sen (1996) for details. Robustness aspects of both these type of rank estimators can therefore be studied in a unified manner, without requiring a bounded score generating function. We conclude this section with a note that as in the case with the semi-parametric location model, here in the semi-parametric linear models whenever the density f admits a finite Fisher information $I(f)$, we may construct adaptive estimating functions based on adaptive rank scores statistics, and these yield asymptotically optimal estimators of the parameters involved in the parametric part of the model [viz., Hušková and Sen, 1985; Sen, 1996a]. Thus, adaptive estimating functions in semi-parametric linear models, though computationally more complex, yield robust and asymptotically efficient estimators.

4. Estimating functionals. In traditional and generalized linear models, as well as in other specific forms of nonlinear models, we essentially encounter a finite dimensional parameter space, so that estimating functions are essentially vector valued. Robustness and nonparametric perspectives often prompt us not to advocate such finite dimensional models; the conditional mean or quantile regression functions in a multivariate nonparametric setup are simple and classical examples of such functionals. While the basic motivations for estimating functions remain essentially the same in such a functional case, in view of the infinite dimensional nature of such functionals, technical manipulations are usually more extensive. For this reason, robustness and efficiency considerations are to be assessed in a somewhat different manner.

In a multivariate setup, let $(Y_i, \mathbf{X}_i), i = 1, \dots, n$, be i.i.d.r.v.'s with a d.f. F defined on \mathcal{R}^{p+1} , and let $G(y|\mathbf{x})$ be the conditional d.f. of Y , given $\mathbf{X} = \mathbf{x}$. Then typically a regression functional of Y on \mathbf{x} is a location functional of the conditional d.f. $G(\cdot|\mathbf{x}), \mathbf{x} \in \mathcal{R}^p$. Therefore as long as this conditional d.f. can be estimated in a consistent and efficient nonparametric fashion, suitable sample counterparts of such location functionals (based on, for example, appropriate L-, M- and R-statistics) can be constructed in a robust manner. Sans multi-normality of F , such regression functionals may not be generally linear (in \mathbf{x}), and moreover a specific nonlinear form in turn calls for a specific form of F , though in general such functionals may otherwise exhibit good smoothness properties. Therefore in a nonparametric or semiparametric setup, it seems quite plausible to incorporate appropriate smoothness conditions on such conditional functionals and estimate them in a robust, consistent and efficient manner. Of course, one has to pay a little penalty for choosing an infinite dimensional parameter space when actually a finite dimensional one prevails, but, in the opposite case, a finite dimensional model based statistical analysis may be totally inadequate when an infinite dimensional parameter space prevails.

Among various possibilities, we mention specifically the two popular approaches to this problem. They are (i) the *nearest neighbor* (NN) method, and (ii) *kernel smoothing* methods. In a NN-method, corresponding to a set pivot \mathbf{x}_o , usually lying in a convex set $\mathcal{C} \in \mathcal{R}^p$, we define the *pseudovariables*

$$(4.1) \quad Z_i = d(\mathbf{X}_i, \mathbf{x}_o), i = 1, \dots, n,$$

where $d(\cdot)$ is a suitable metric on \mathcal{R}^p (which may as well be taken as the Euclidean norm), and denote the corresponding order statistics by $Z_{n:1} \leq \dots \leq Z_{n:n}$; note that they specifically depend on the base sample as well as the chosen pivot. Also we define a nondecreasing sequence $\{k_n\}$ of positive integers such that $k_n \rightarrow \infty$ but $n^{-1}k_n \rightarrow 0$ as $n \rightarrow \infty$. Further, we set the antiranks S_i by letting $Z_{n:i}$ correspond to \mathbf{X}_{S_i} , for $i = 1, \dots, n$. Then a k_n -NN empirical d.f. at the pivot \mathbf{x}_o is defined by

$$(4.2) \quad G_{n,k_n}(y|\mathbf{x}_o) = k_n^{-1} \sum_{i=1}^{k_n} I(Y_{S_i} \leq y), y \in \mathcal{R}.$$

Estimating functionals are then based on the entire set $G_{n,k_n}(\cdot|\mathbf{x}_o), \mathbf{x}_o \in \mathcal{C}$. Naturally robustness considerations dominate the choice of such functionals (viz., Sen

1996b). In a kernel method, we choose a known density $\phi(\mathbf{x})$ possessing some smoothness properties such as unimodality and symmetry around $\mathbf{0}$, compact support and differentiability upto a certain order, and define a smooth conditional empirical d.f. by integrating $\phi(\mathbf{x} - \mathbf{x}_o)$ with respect to the empirical d.f. F_n . This conditional measure is then incorporated in the formulation of suitable robust functionals. These two methods compare favorably with respect to their *asymptotic bias* and *asymptotic mean squares* and robustness pictures. There is, however, a common concern that stems from the fact that such conditional functionals span an infinite dimensional parameter space, and hence, in setting suitable confidence sets, a prescription in terms of a finite number of pivots may not suffice. Weak convergence approaches [viz., Sen 1993, 1995a, 1996b] provide viable alternatives, yet retaining robustness to a certain extent.

5. General remarks. Estimating functions in the context of (generalized) linear models and possibly involving nuisance parameters have received a good deal of attention in the recent past, and these developments constitute a major advancement in the research literature. There is, however, a point worth mentioning in this context. By the very motivation to retain the flavor of exponential family of densities by skillful choice of (canonical) *link functions*, the associated (generalized) estimating functions retain to a greater extent nonrobustness properties as are generally attributed to MLE and other highly parametric estimators. In most biomedical applications the response variate is nonnegative and has typically a positively skewed distribution. Thus, there may be a need to use some (Box-Cox type) transformation to induce more symmetry (if not normality); however, this may also distort the inherent linearity or other parametric structure of the underlying dose-response relations. Hence generalized linear models [viz., McCullagh and Nelder, 1989] may not be universally advocated in such studies. Considerations of model robustness naturally call for nonparametrics or semiparametrics, and as such L-, M- and R-estimating functions along with their siblings come into the picture. In this context, the dimension of nuisance parameters is often of large dimension, if not infinite, and the estimation parameter space may also be large. The semi-parametric formulations usually allow a finite dimensional estimable parameter space retaining the infinite dimensionality of the nuisance parameter space. As such, compared to pure nonparametrics, such semi-parametrics may yield more efficient estimators when the postulated model is correct, but is naturally more nonrobust to plausible departures from such assumed models. One other advantage of semi-parametrics is that the finite dimensionality of the estimable parameter space usually permits the adoption of adaptive procedures which are asymptotically optimal with respect to the postulated model. we refer again to the semi-parametric linear models for which adaptive R- or M-estimators which are asymptotically efficient [viz., Hušková and Sen (1985,1986)]. In a relatively more general setup of statistical functionals, under a similar semi-parametric modeling, such adaptive estimating functions have also been discussed in Sen (1996a). From this perspective it is clear that modeling part is

a vital task in formulating the estimation space, and estimating functions are to be considered in the light of dimensionality and structure of this setup. In this context, robustness and (asymptotic) efficiency considerations are of utmost importance. In most biomedical, clinical and environmental studies, generally this modeling is far more complex, and conventional parametric (generalized) linear models may not be that appropriate even following suitable transformations. Therefore, there is a genuine need to focus on the appropriateness of suitable semi-parametric and non-parametric models, and model flexibility often favors the latter choice. We refer to Sen (1996c) for some discussion of estimating functions in generalized linear models in biomedical statistical applications.

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