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ON ITERATIVE PROCEDURES OF ASYMPTOTIC INFERENCE

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On iterative procedures of asymptotic inference*)

by

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ABSTRACT

An informal discussion is given on performing unconstrained maximization or solving non-linear equations of statistics by iterative methods with quadratic termination property. It is shown that if a maximized function, e.g. likelihood, is asymptotically quadratic, then for asymptotic efficient inference finitely many iterations are needed.

KEY WORDS & PHRASES: *methods of Newton-Raphson, scoring, quasi-Newton, Davidon-Fletcher-Powell, conjugate gradient; quadratic termination; asymptotically differentiable; asymptotically quadratic*

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In this paper we briefly discuss some applications of modern iteration methods of numerical analysis to the problems of mathematical statistics.

Certain applications of the most basic iteration method of *Newton-Raphson* (or its stochastic modification - *the scoring method*) are well-known since Fisher, and nowadays they are included in many statistical textbooks (see, e.g., Kendall and Stuart (1961), Section 18.31; Rao (1965), Section 5g; Zacks (1971), Section 5.2).

Although *the Newton-Raphson method* is theoretically very attractive, it may turn out to be highly unsuitable in practice, especially when the number of unknown parameters, involved in the statistical model under study, is large.

In order to mitigate some of the computational difficulties, unavoidable in *the Newton-Raphson method*, various developments of this method are intensively discussed in the literature on numerical analysis. The most important are the so-called *quasi-Newton* methods, and their alternatives, the *conjugate gradient methods*.

We intend to demonstrate here that the application of certain stochastic modifications of this kind of methods will, in general, lead to a statistical inference which is at least as efficient as that of the Newton method. It should be noted, however, that the considerations presented below are highly informal, as they are in fact aimed at showing why the above conjecture whould be true, rather then at proving strict mathematical results (te be found, in principle, in the enclosed references).

Returning to Fisher's ideas let us recall that he has applied the Newton-Raphson method to the classical problem of estimating the unknown parameter θ involved in the distribution F_θ, when a sample

(1) $$X_1,\dots,X_n$$

is drawn from a population specified by this distribution function F_θ.

Assuming that the population is of the continuous type and f_θ is the density of F_θ, Fisher (1925) used the Newton-Raphson method for maximizing the likelihood function

(2) $$L_n(X_1,\dots,X_n;\theta) = \sum_{i=1}^{n} \log f_\theta(X_i).$$

Attractiveness and universality of the maximum likelihood method is justifiable by the existence, under fairly wide conditions, of the value of θ that renders the likelihood (2) as large as possible, at least when the sample size n is sufficiently large. Conditions under which the maximizing value of θ - the maximum likelihood estimator $\hat{\theta}_n$ - is $\sqrt{n}$-consistent are also fairly broad.

Under $\sqrt{n}$-consistency of $\hat{\theta}_n$ we mean that the sequence of the distributions

$$(3) \qquad L\{\sqrt{n}(\hat{\theta}_n-\theta)\},\ n = 1,2,\ldots$$

converges to a non-degenerate distribution.

Moreover, some additional conditions guarantee that the limit of (3) is Gaussian with zero mean and variance, being the reciprocal of Fisher's information amount I_θ per single observation, that is

$$(4) \qquad L\{\sqrt{n}(\hat{\theta}_n-\theta)\} \Rightarrow N(0,I_\theta^{-1}).$$

After Fisher, we can therefore call $\hat{\theta}_n$ asymptotically (as $n\to\infty$) efficient. These and some further theoretical properties determine "*a quasi-hypnotic attraction the m.l. estimates seem to exert*" [LeCam (1960), p.94].

However in practice complications may arise when one starts to maximize the likelihood (2) by, for instance, looking for roots of the corresponding likelihood equation

$$(5) \qquad (\partial/\partial\theta)L_n(X_1,\ldots,X_n;\theta) = 0$$

(if there is any for fixed n), especially if this equation turns out to be highly non-linear (as it frequently happens in practice).

The additional task of choosing an appropriate root among several of them is also difficult.

Of course, these problems (as well as Newton's method for the iterative solution of nonlinear equations) were familiar to Fisher. So he has suggested to apply Newton's iterative procedure to the equation (5):

(6) $$\theta_n^{i+1} = \theta_n^i - \left(\frac{\partial^2 L_n}{\partial\theta^2}\right)^{-1}_{\theta_n^i} \left(\frac{\partial L_n}{\partial\theta}\right)_{\theta_n^i}, \quad i = 0,1,\ldots,$$

or, observing that

(7) $$-\frac{1}{n} \frac{\partial^2 L_n}{\partial\theta^2} \to I_\theta \text{ in probabilistic sense,}$$

the asymptotically equivalent procedure of scoring

(8) $$\theta_n^{i=1} = \theta_n^i + \frac{1}{n} (I_\theta^{-1})_{\theta_n^i} \left(\frac{\partial L_n}{\partial\theta}\right)_{\theta_n^i}, \quad i = 0,1,\ldots$$

He also pointed out that if the starting value θ_n^0 is any $\sqrt{n}$-consistent estimator for θ (for instance, constructed by using the method of moments), then the result of the very first iteration, θ_n^1, is an estimator for θ as fine asymptotically as the maximum likelihood estimator $\hat{\theta}_n$.

Indeed, Fisher did not worry about the mathematical accuracy of his statements. The first careful treatment of the subject (provided with the further study of asymptotic properties of the estimator θ_n^1), is due to LeCam (1956).

Later, LeCam (1960) extended his studies to a considerably more general class*) of experiments than those generated by independent identically distributed (i.i.d.) observations: the function $L_n(X_1,\ldots,X_n;\theta)$ was treated as a general loglikelihood function and not necessarily that of the i.i.d. observations (as in (2)). He observed that for a sufficiently large n Taylor's expansion of L_n involves terms which are related to the first and second order derivatives of L_n only, because all other terms become asymptotically negligible when $n\to\infty$. That is,

(9) $$L_n(\theta+h/\sqrt{n}) - L_n(\theta) = h\Delta_n(\theta) - \frac{1}{2}h^2 I_\theta + \ldots$$

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*) Deviating from the i.i.d. case, one often encounters situations in which the formulae (9)-(11) hold with some differential $\delta_n > 0$ such that $\delta_n \to 0$, different from $1/\sqrt{n}$, and this is taken into account in the later works of LeCam (1969,1974).
It should be noted also, that in the case of a vector-valued parameter θ the normalization of each component by $\sqrt{n}$ (to be discussed below) often fails: these components even may have different rates of convergence, and then the normalization by some positive definite matrix with a vanishing (as $n\to\infty$) norm is needed (see Ibragimov and Has'minskii (1981) where an excellent treatment of estimating problems can be found, in the spirit akin to that of LeCam).

where

$$\Delta_n(\theta) = \frac{1}{\sqrt{n}} \frac{\partial L_n}{\partial \theta} + \text{a term asymptotically negligible}^{*)}, \tag{10}$$

and I_θ is the stochastic limit of the second derivative of L_n with opposite sign (recall (7)).

Further under fairly wide conditions the random variable $\Delta_n(\theta)$ is asymptotically normal:

$$L(\Delta_n(\theta)) \Rightarrow N(0, I_\theta) \tag{11}$$

and asymptotically differentiable in the sense, that if θ_n^0 is any $\sqrt{n}$-consistent estimator for θ, then

$$\Delta_n(\theta_n^0) - \Delta_n(\theta) = I_\theta \sqrt{n}(\theta_n^0 - \theta) + \dots \tag{12}$$

(here, as in (9) or anywhere below, the omitted terms are asymptotically negligible in the sense that they tend to 0 stochastically as $n\to\infty$).

Note that in the case of i.i.d. observations (11) is a simple consequence of the central limit theorem and the well-known fact that

$$E\left(\frac{\partial L_n}{\partial \theta}\right)^2 = I_\theta .$$

(But in general this last equation holds only when $n\to\infty$).

Equation (12) also has a natural interpretation in terms of the derivatives of L_n.

The equations (11) and (12) have a very important consequence.

PROPOSITION 1. *If* (11) *and* (12) *hold, the estimator*

$$\theta_n^1 = \theta_n^0 + \frac{1}{\sqrt{n}} I_{\theta_1^0}^{-1} \Delta_n(\theta_n^0) \tag{13}$$

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*) Generally the explicit expression of $(\partial/\partial\theta)L_n$ involves certain terms which are negligible as $n\to\infty$ in comparison with other-principal-ones retained in $\Delta_n(\theta)$. Indeed, the latter quantity has to be chosen among asymptotically equivalent candidates as plain and smooth as possible to ensure, in particular, asymptotic relations of type (12).

is asumptotically normal

(14) $$L(\sqrt{n}(\theta_n^1 - \theta)) \Rightarrow N(0, I_\theta^{-1}).$$

Note the similarity of (13) and (8) with i = 0, and also the coincidence of the right-hand sides of (5) and (14).

PROOF is very simple: By (12) and (13),

$$\sqrt{n}(\theta_n^1 - \theta) = \sqrt{n}(\theta_n^0 - \theta) + I_{\theta_n^0}^{-1} [\Delta_n(\theta) - I_\theta \sqrt{n}(\theta_n^0 - \theta)] + \text{a term asymptotically negligible.}$$

If we now replace θ_n^0 in $I_{\theta_n^0}^{-1}$ by θ (this is justifiable if I_θ is continuous in θ), then

$$\sqrt{n}(\theta_n^1 - \theta) = I_\theta^{-1} \Delta_n(\theta) + \ldots$$

Hence (14) is the immediate consequence of (11).

According to this proposition the estimator $\hat{\theta}_n$ has the same asymptotic properties as the maximum likelihood estimator. In other words, instead of looking for the maximum likelihood estimators $\hat{\theta}_n$ one can use, without loss of efficiency at least for samples of large size n, the following two step*) procedure:

(i) construct a rough estimator θ_n^0 of θ satisfying $\sqrt{n}$-consistency, and then,

(ii) defining for the particular problem under study $\Delta_n(\theta)$ and Γ_θ from a corresponding likelihood function $L_n(\theta)$, construct θ_n^1 as indicated in (13).

It should be noted that, in principle, this alternative procedure "*applies also to cases that certain authors may deem pathological - cases in which m.l. estimates do not behave or do not exist. This is somewhat*

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*) Obviously, this procedure can be used iteratively by continuing as in (8). That is why Fisher called the method of estimation by formula (8) the *scoring method* (the word *scoring* is used here to stress that the procedure scores iteratively the corrections). Considerations as simple as those used in proving Proposition 1 lead to the conclusion that in general the

irrelevant. What is relevant is that statistical life is plagued with situations involving dependent variables or other more or less complicated situations in which it seems to be a waste of time to try to prove that m.l. estimates do behave. Even in cases in which the m.l. estimates are asymptotically well behaved it may be preferable not so use them" [LeCam (1960), Appendix II].

That is why the just cited "*author is firmly convinced that a recourse to maximum likelihood is justifiable only when one is dealing with families of distributions that are extremely regular. The cases in which m.l. estimates are easily obtainable and have been proved to have good properties are extremely restricted. One of the purposes of this paper* [LeCam (1960)] *is precisely to deëmphasize the role of m.l. estimates*".

"*The drawback in having a liberal amount of flexibility in the choice of the estimates is that one is likely to have to choose between radically different formulas which all lead to the same asymptotic properties. From a practical point of view, it should be emphasized that a purely asymptotic theory does not say anything about a particular problem. The standard practice of letting a parameter tend to infinity is a mathematical device which leads to fairly simple theorems . . .*"

The reason for such an extensive quotation should become clear below, for we shall now follow "*the standard practice of letting the sample size* n *tend to infinity*", and define alternative procedures of estimation which lead to the same asymptotic properties as that of m.l. or Newton-Raphson (scoring).

Observe meanwhile that the considerations which are followed above can be easily extended to the s vector-valued parameter case when $\Delta_n(\theta)$ is an s vector-valued random variable and I_θ is a positive definite (s×s)-matrix

In this case the application of fomula (13) (or the iterative procedures of type (6) abd (8) requires the inversion of (s×s)-matrices. This may be difficult, when the number of unknown parameters, s, is large.

Naturally, the question arises on trying other methods for unconstrained

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repetition of the procedure should draw the result somewhat nearer to the m.l. estimator $\hat{\theta}$, since $n^{\kappa/2}(\theta_n^{\kappa} - \hat{\theta}_n) \to 0$ in probabilistic sense, provided that $\kappa + 1$th order differential of L_n is sufficiently smooth in θ, and that this differential divided by n is stochastically bounded.

maximization (or solving essentially nonlinear system of corresponding equations) provided by modern numerical analysis.

The justification of nearly all such methods is based on the presumption that the maximized quantity, in a neighborhood of a maximum point, can be well approximated by a quadratic function. Thus a number of methods are advanced in numerical analysis which efficiently maximize quadratic functions, in the hope that they do perform on more general functions at least in a neighborhood of a maximum point. This motivation leads in the first place to the derivation of Newton's method which gives the maximum of a quadratic function*), $c + b^T x - \frac{1}{2}x^T Ax$ say, after the very first iteration, $x^1 = A^{-1}b$, for any initial value x^0.

Also, the developments of the classical Newton method mentioned in the beginning of this paper, such as the quasi-Newton methods and conjugate gradient methods, possess a special property with respect to quadratic functions: the maximum is found in at most s iterations where s is the number of unknowns. Therefore, it is often said that these methods possess the property of *quadratic termination*.

On the other hand, in view of the asymptotic relation (9) the function L_n can be regarded as "*asymptotically quadratic*".

Basically, this determines the fine asymptotic properties of the first iteration in (6) (or (8)) as an estimator of θ. Realizing these facts one should come to the conjecture that the *quadratic termination* property of a utilized method ought to guarantee the same asymptotic properties for the result of at most s iterations treated as the estimator for θ.

An attempt in this direction is made in Beinicke and Dzhaparidze (1982), where our conjecture is confirmed for a couple of methods. The first one is *the Davidon-Fletcher-Powell* (DFP) method, which is one of a family of quasi-Newton methods.

The concept of a quasi-Newton method for the solution of the system (5) with $(\partial/\partial\theta)$ to be understood now as the gradient vector (or for the

*) As for the maximization of a general function, the nice feature of Newton's method consists in the fact that when the iterations do converge, the rate of convergence is quadratic. However, Newton's iterations often fail to converge - when the results are far from a maximum point difficulties may arise. Nevertheless, the attraction of the quadratic convergence, in a neighborhood of a maximum, keeps all methods as close to Newton's iterations as possible, only introducing modifications to gain more reliability.

maximization of $L_n(\theta)$), consists of an algorithm which proceeds as follows. Choosing the *initial value* (any $\sqrt{n}$- consistent estimator for θ) θ_n^0 beforehand, along with a symmetric positive definite matrix H_n^0 (for instance, H_n^0 can be chosen as the s×s unit matrix), at iteration j, define

$$\text{(15)} \qquad \theta_n^{j+1} = \theta_n^j + \frac{1}{\sqrt{n}} a_n^j H_n^j \Delta_n(\theta_n^j)$$

where a_n^j is determined by an *exact line search*, that is, it is chosen as the value a that maximizes the function

$$L_n(\theta_n^j + \frac{1}{\sqrt{n}} a H_n^j \Delta_n(\theta_n^j)).$$

Neglecting again the omitted terms in (9) and replacing $I_{\theta_n^j}$ by a consistent estimator I_n^* for I_θ (by $I_{\theta_n^0}$, say), we get

$$\text{(16)} \qquad a_n^j = \frac{\Delta_n^T(\theta_n^j) H_n^j \Delta_n(\theta_n^i)}{\Delta_n^T(\theta_n^j) H_n^j I_n^* H_n^j \Delta_n(\theta_n^j)}$$

(Δ_n^T denotes the traspose of Δ_n).

As for the matrices H_n^j, j = 1,2,... in (15) and (16), they have to possess the property

$$\text{(17)} \qquad H_n^{j+1} q_n^j = r_n^j$$

where $r_n^j = \sqrt{n}\,(\theta_n^{j+1} - \theta_n^j)$, $q_n^j = -[\Delta_n(\theta_n^{j+1}) - \Delta_n(\theta_n^j)]$.

The following specific choice of the matrices H_n^j, j = 1,2,..., satisfying (17) determines the DFP method (see, e.g. Ortega and Rheinboldt (1970));

$$\text{(18)} \qquad H_n^{j+1} = H_n^j + \frac{r_n^j (r_n^j)^T}{(r_n^j)^T q_n^j} - \frac{H_n^j q_n^j (H_n^j q_n^j)^T}{(q_n^j)^T H_n^j q_n^j} .$$

The assertion of Theorem 1 below shows the ability of such stochastic modification of the DFP method to perform asymptotically efficient estimation.

THEOREM 1. *If* (11) *and* (12) *are met, then the estimator* θ_n^s *defined by* (15), (16) *and* (18) (s *being the number of unknowns*) *is asymptotically normal, specifically*

$$\mathcal{L}(\sqrt{n}(\theta_n^s - \theta)) \Rightarrow N(0, I_\theta^{-1}). \tag{19}$$

Besides H_n^s *is a consistent estimator for the inverse of Fisher's information matrix* I_θ *per single observation.*

PROOF of this result can be found in Beinicke and Dzhaparidze (1982). Note that the considerations of this paper are based on the definition (18) of the matrices H_j, $j = 1,2,\ldots$, while, in general, results of Dixon (1972) allow extensions on the full *Broyden family* (see, e.g. Brodlie (1977)).

Following considerations similar to those of Beinicke and Dzhaparidze (1982), the former author has shown in his Ph.D. thesis at Tbilisi State University (1979) that the *conjugate gradient* method, appropriately modified, leads to an analoguous result. Specifically, the following theorem holds.

THEOREM 2. *Define the stochastic modification of the conjugate gradient iterations:*

$$\theta_n^{i+1} = \theta_n^i - \frac{1}{\sqrt{n}}\,\alpha_n^i\, p_n^i$$

where

$$\alpha_n^i = \frac{(\Delta_n(\theta_n^i))^T p_n^i}{(p_n^i)^T I_n^* \, p_n^i},$$

$$p_n^0 = \Delta_n(\theta_n^0), \quad p_n^{i+1} = \Delta_n(\theta_n^{i+1}) - \beta_n^i p_n^i, \quad \beta_n^i = \frac{\Delta_n(\theta_n^{i+1})^T I_n^* \, p_n^i}{(p_n^i)^T I_n^* \, p_n^i}.$$

Then under the conditions of Theorem 1 the estimator θ_n^s *has property* (19).

In conclusion, a couple of brief remarks on further statistical applications.

The first of it is concerned with certain situations in which a recourse to the likelihood methods is unjustifiable for that or another reason like quoted above. Moreover, in many applications statistical models under study are not (or rather cannot be) fully defined.

Aiming, under these circumstances, at solving, specifically, estimation problems, one has to look for a suitable criterion function (in place of the undefined likelihood $L_n(\theta)$) which is, essentially, free from any kind of nuisance quantities and thus depends only on θ (and on observations). Of course, this function, say $U_n(\theta) = U_n(X_1,\ldots,X_n;\theta)$, has to be chosen so as to prove the sensibility of the estimator for θ defined as the value of θ that maximizes (or minimizes) $U_n(\theta)$. As an illustrative example of such kind of practice, the utilization in various settings of the *least squares* method should be mentioned.*)

The demands on $U_n(\theta)$ made above are usually met with the requirement of its *asymptotical differentiability* in the sense that for the difference $U_n(\theta+h/\sqrt{n}) - U_n(\theta)$ there exists a (multivariate) relation analoguous to (9) with some (s vector-valued) random variable $\Delta_n(\theta)$ and positive definite matrix I_θ. Besides, these quantities are usually related as in (12). Often the asymptotic normality of $\Delta_n(\theta)$ can also be provided, although the covariance matrix, say W_θ, appearing in the limiting distribution, may, in general, differ from I_θ.

It might be clear now that under these circumstances the considerations followed above remain, in general, valid for $U_n(\theta)$ in place of the likelihood function $L_n(\theta)$, although in the conclusions (namely in (14) and (19)) I_θ^{-1} has to be replaced by $W_\theta^{-1} I_\theta W_\theta^{-1}$ (Beinicke and Dzhaparidze (1982)).

Observe, finally, that the result $H_n^s \to I_\theta^{-1}$ (stochastically), claimed in Theorem 1, can be used, for example, in constructing test statistics for certain tests-of-fit based on χ^2-distribution. For, structurally, these kind of test statistics are describable as quadratic forms in random variables, generated by the inverse of their covariance matrix. Under condition (11), for instance, the statistics

$$\Delta_n^T(\theta_0) I_{\theta_0}^{-1} \Delta_n(\theta_0) \approx \Delta_n^T(\theta_0) H_n^s \Delta_n(\theta_0)$$

can be used for testing the hypothesis: $\theta = \theta_0$.

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*) See, e.g., Jennrich (1969) on non-linear regression, or Kohn (1978), Dzhaparidze and Yaglom (1982) on time series analysis.

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