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Gradient Projection for Nonparametric Maximum Likelihood Estimation with Interval Censored Data

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A well-known way of computing the nonparametric maximum likelihood estimator (NPMLE) of a distribution function of censored observations is the EM-algorithm, which is known as slow and hence not practicable, especially in simulation studies. In the case of interval censored observations, computing the NPMLE can be considered as a general strictly concave programming problem and a gradient projection method can be used to maximize a concave function subject to a number of constraints. This is worked out for interval censored observations with two or more censoring points. Also some simulation results are given.

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1. INTRODUCTION

Animals, machines or whatever can be observed at random times. In many situations it is only possible to see whether or not the observed object has entered a certain state and the actual entrance (or exit) times cannot be seen. This leads to so-called interval censored observations. One of the estimators of the distribution function of the transition times is the non-parametric maximum likelihood estimator (NPMLE). This situation is quite common in medical research, where only at certain times patients can be checked on whether or not their disease has entered (or left) a certain state, see e.g. Gröger (1986).

When for each observed object only one such observation is available, the NPMLE can be computed by considering the maximization problem as an isotonic regression problem, see Groeneboom (1987). This study will consider the situation with two such observations for each object. The algorithms for computing the NPMLE in this case are easy to extend to the case of three or more observations.

A formal description of the considered model runs as follows. Let X be a non-negative random variable denoting the "unobservable transition time" with d.f. $F_0(x)$ and let T and U be non-negative random variables with $\Pr(T \leq U) = 1$, the observation times with

d.f. $H(t,u)$. The censoring mechanism is such that we only know whether X is less than T , between T and U or greater than U . Let $(X_1, T_1, U_1), \dots, (X_n, T_n, U_n)$ be a sample of random variables distributed as (X, T, U) . The only observations available are (T_i, U_i, A_i, B_i) , with $A_i = 1_{\{X_i \leq T_i\}}$ and $B_i = 1_{\{X_i \leq U_i\}}$.

The NPMLE of the distribution function F_0 is obtained by maximizing the likelihood

$$(1.1) \quad \prod_{i=1}^n F(t_i)^{\alpha_i} (F(u_i) - F(t_i))^{\beta_i - \alpha_i} (1 - F(u_i))^{1 - \beta_i}$$

as a function of F , where $(t_i, u_i, \alpha_i, \beta_i)$ are realizations of the random variables (T_i, U_i, A_i, B_i) .

A well-known way of computing this NPMLE is the EM-algorithm, using the iterations

$$(1.2) \quad F^{(m+1)}(s_i) = \frac{1}{n} \sum_{j=1}^n \Pr^{(m)}\{X_j \leq s_i \mid T_j = t_j, U_j = u_j, A_j = \alpha_j, B_j = \beta_j\}$$

where $s_1 \leq s_2 \leq \dots \leq s_{2n}$ are the ordered observation times t_i and u_i . Unfortunately this algorithm converges very slowly to the solution. Gröger (1986) page 78 used this algorithm. As a convergence criterion he used that the improvement of the estimator (i.e. the maximal change of the estimator values at one iteration step) is less than 0.025. Then the process terminates after about 5 iterations, for a sample of 100 observations. This convergence criterion can lead to big errors, because the convergence of the EM-algorithm is slow and hence an improvement of multiples of 0.025 is possible. For instance in our simulation study we found in a problem with a sample of 20 observations an error w.r.t. the exact solution of 0.012, if the algorithm were stopped after 81 iterations. The last improvement was 0.00035. This does not bode well for bigger samples. Hence one gets the impression that the EM-algorithm cannot be used in this way.

Another way of computing the NPMLE is found by considering the problem as a general concave programming problem. Now a gradient projection method can be used to maximize a concave function subject to a number of linear constraints, see e.g. Rosen (1960) and Luenberger (1973). Before such a method can be used, the likelihood has to be simplified to a strictly concave function on a closed convex space. This guarantees a unique solution of the problem. The gradient projection algorithm in this paper gives the solution of the problem with 20 observations, mentioned above, after 6 iterations with a precision of 0.0002, in about one third of the CP execution time.

One of the purposes of this study is to develop a useful way of computing or estimating the NPMLE, so that it is possible to develop or check theoretical results by simulation.

2. THE GRADIENT PROJECTION METHOD

Maximizing (1.1) is equivalent to maximizing the log likelihood

$$(2.1) \quad \sum_{i=1}^n \alpha_i \log(F(t_i)) + (\beta_i - \alpha_i) \log(F(u_i) - F(t_i)) + (1 - \beta_i) \log(1 - F(u_i))$$

under the restriction that F is a distribution function.

2.1. Some simplifications of the log likelihood

Let $0 < s_1 \leq s_2 \leq \dots \leq s_{2n} < 1$ be the ordered observation times t_i and u_i , and let $s_0 = 0$ and $s_{2n+1} = 1$. Since the values of the function F between the points s_i and s_{i+1} are not relevant, we suppose $F(x) = F(s_i)$ if $s_i \leq x < s_{i+1}$, $i = 0, 1, 2, \dots, 2n$. Let $b_{i,1}$ and $b_{i,2}$ be defined by

$$(2.2) \quad b_{i,1} = \begin{cases} 0 & \text{if } \alpha_i = 1 \\ j & \text{if } \alpha_i = 0, \beta_i = 1 \text{ and } t_i = s_j \\ k & \text{if } \beta_i = 0 \text{ and } u_i = s_k \end{cases},$$

$$(2.3) \quad b_{i,2} = \begin{cases} j & \text{if } \alpha_i = 1 \text{ and } t_i = s_j \\ k & \text{if } \alpha_i = 0, \beta_i = 1 \text{ and } u_i = s_k \\ 2n+1 & \text{if } \beta_i = 0 \end{cases},$$

and let $y_j = F(s_j)$, with $F(0) = 0$ and $F(1) = 1$.

Maximizing (2.1) is the same as maximizing

$$(2.4) \quad \sum_{i=1}^n \log(y_{b_{i,2}} - y_{b_{i,1}})$$

under the restriction that $0 = y_0 \leq y_1 \leq \dots \leq y_{2n} \leq y_{2n+1} = 1$. In this function each variable y_i can occur in at most one term. Hence there is a maximum of $2n$ variables. First the number of variables will be reduced.

THEOREM 2.1. *a.) If $b_{j,2} < b_{i,1}$ for $i \neq j$ and if for all $k \neq j$: $b_{k,2} < b_{j,2}$ or $b_{k,2} > b_{i,1}$, then the maximizing $y = (y_0, y_1, \dots, y_{2n+1})$ has to satisfy*

$$y_m = y_{b_{j,2}} \text{ for } m = b_{j,2} + 1, \dots, b_{i,1}.$$

b.) If $b_{j,2} < b_{k,2}$ and if for all i : $b_{i,1} < b_{j,2}$ or $b_{i,1} > b_{k,2}$, then the maximizing y has to satisfy

$$y_m = y_{b_{j,2}} \text{ for } m = b_{j,2} + 1, \dots, b_{k,2}.$$

REMARK 2.2. We look for pairs of indices $(b_{i,1}, b_{j,2})$ such that $b_{i,1}$ is the biggest index less than $b_{j,2}$. Note that $(b_{i,1}, b_{j,2})$ do not have to be indices of endpoints of one observation interval. This means that when we write down the corresponding signs of the y_i , we give the y_i corresponding to a list of plus signs and the y_i corresponding to the following list of minus signs the same value.

PROOF OF THEOREM 2.1. Consider $\log(y_{b_{i,2}} - y_{b_{i,1}})$. The maximum of this term is reached for $y_{b_{i,2}} = y_{b_{i,2}+1}$ and $y_{b_{i,1}} = y_{b_{i,1}-1}$.

a.) This means that the only indices between $b_{j,2}$ and $b_{i,1}$ are of the form $b_{k,1}$. The maximum of the terms in which these $b_{k,1}$ occur is attained by $y_{b_{k,1}} = y_{b_{k,1}-1}$. Hence $y_{b_{j,2}} = y_{b_{j,2}+1} = \dots = y_{b_{i,1}}$.

b.) This means that the only indices between $b_{j,2}$ and $b_{k,2}$ are of the form $b_{i,2}$. The maximum of the terms in which these $b_{i,2}$ occur is attained by $y_{b_{i,2}} = y_{b_{i,2}+1}$. Hence $y_{b_{j,2}} = y_{b_{j,2}+1} = \dots = y_{b_{k,2}}$. \square

Using theorem 2.1, the problem can be reformulated as the problem of maximizing

$$(2.5) \quad \sum_{i=0}^{k-1} \sum_{j=i+1}^k a_{i,j} \log(y_j' - y_i')$$

with $0 = y_0' < y_1' \leq \dots \leq y_{k-1}' < y_k' = 1$ the values y_i which not have been set equal and $a_{i,j}$ the number of terms of the form $\log(y_j' - y_i')$. The number of variables left is less than n , in practice it is much less.

THEOREM 2.3. *The function defined by (2.5) is strictly concave in the variables y_0', \dots, y_k' .*

PROOF OF THEOREM 2.3. The logarithm is a strictly concave function, hence the function in (2.5) is concave. Suppose $x = (x_0, x_1, \dots, x_k)$ and $y = (y_0, y_1, \dots, y_k)$ are points satisfying the side conditions. Then we have

$$(2.6) \quad \sum_{i=0}^{k-1} \sum_{j=i+1}^k a_{i,j} \log\{\lambda(x_j - x_i) + (1-\lambda)(y_j - y_i)\} \geq \\ \lambda \sum_{i=0}^{k-1} \sum_{j=i+1}^k a_{i,j} \log(x_j - x_i) + (1-\lambda) \sum_{i=0}^{k-1} \sum_{j=i+1}^k a_{i,j} \log(y_j - y_i) \text{ for } \lambda \in (0,1).$$

We shall prove that the equality sign only holds if $x = y$.

For each term we have $\log\{\lambda(x_j-x_i)+(1-\lambda)(y_j-y_i)\} \geq \lambda \log(x_j-x_i) + (1-\lambda) \log(y_j-y_i)$. Since $0 \leq x_i < x_j \leq 1$ and $0 \leq y_i < y_j \leq 1$, equality is only possible if $x_j-x_i=y_j-y_i$. Hence we have for all $a_{i,j} \neq 0$, $x_j-x_i=y_j-y_i$.

The definition of the function ensures that $a_{0,1} \neq 0$ and hence $x_1=y_1$. For all j with $a_{1,j} \neq 0$, we now have $x_j=y_j$. Next for all j and m with $x_j=y_j$ and $a_{j,m} \neq 0$ or $a_{m,j} \neq 0$ we have $x_m=y_m$. This process can be repeated till no more elements are set equal. Since the number of variables is finite, this process terminates.

Let A_1 be the set of indices i of elements x_i which have been set equal to y_i , starting with x_1 . The complement A_1^c contains indices of elements x_i which have no "connection" with x_1 and hence have not been set equal by the algorithm. Let i_0 be the smallest index in A_1^c . Each x_m occurs in a term of the form $\log(x_m-x_j)$ with $a_{j,m} \neq 0$. For all j with $1 \leq j < i_0$ we have $a_{j,i_0} = 0$, since from $x_j \in A_1$ and $a_{j,i_0} \neq 0$ we should have $x_{i_0} \in A_1$, which is a contradiction. The only possibility is that there is a term $\log(x_{i_0})$ with $a_{0,i_0} \neq 0$. This gives $x_{i_0}=y_{i_0}$. We can now enlarge the collection A_1 in the same way as when we started with x_1 to a collection A_2 .

When we repeat the whole process, it terminates with $x_i=y_i$ for all i . Hence the function is strictly concave. \square

2.2. Gradient projection

In more general terms the problem is to maximize a strictly concave function $f(x)$ on a closed convex space K of feasible points, i.e. points which satisfy the side conditions. Hence there is a unique solution. The convex space K is defined by

$$(2.7) \quad K := \{y \in \mathbb{R}^k: 0=y_0 \leq y_1 \leq y_2 \leq \dots \leq y_k=1\}$$

or more general for a feasible point $y \in K$ holds:

$$(2.8) \quad a_i'y \leq 0 \text{ with } a_{i,i-1}=1, a_{i,i}=-1 \text{ and } a_{i,j}=0 \text{ for } j \neq i, j \neq i-1 \text{ and } i=1,2,\dots,k.$$

The latter more general form is used in Luenberger (1973) page 247 and in the algorithm, although the special structure of the constraints makes it possible to simplify some expressions in practice. A constraint $a_i'y \leq 0$ is said to be active at a feasible point y if $a_i'y=0$ and inactive if $a_i'y < 0$.

The algorithm for the gradient projection method given in Luenberger(1973) can be improved as suggested in exercise 14, page 275. The improvement is that the set of active constraints is already changed when the projected gradient vector is small instead of waiting till it is zero. The algorithm now runs as follows:

GRADIENT PROJECTION ALGORITHM

1. Start with a feasible point \mathbf{x} ,
2. Find the subspace of active constraints M and form A_q , defined as composed of the rows of the q active constraints,
3. Calculate the projection matrix $P_q = I - A_q'(A_q A_q')^{-1} A_q$ and the projection \mathbf{d} of the gradient vector $\nabla f(\mathbf{x})'$ onto M , $\mathbf{d} = P_q \nabla f(\mathbf{x})'$,
4. Calculate $\beta = (A_q A_q')^{-1} A_q \nabla f(\mathbf{x})'$ and $\gamma = \max_i (-\beta_i) \vee 0$,
5. If $\mathbf{d} = \mathbf{0}$ and $\gamma = 0$, stop, the solution is found,
- 5a. If $\|\mathbf{d}\|_\infty < \epsilon$ and $\gamma < \epsilon$, where $\|\mathbf{d}\|_\infty = \max_i |d_i|$, stop, we are near the solution,
6. If $\|\mathbf{d}\|_\infty < \gamma$, drop the active constraint corresponding to γ (this is the same as deleting the corresponding row from A_q) and return to 3,
7. If $\|\mathbf{d}\|_\infty \geq \gamma$, find α_1 achieving $\max\{\alpha: \mathbf{x} + \alpha \mathbf{d} \text{ is feasible}\}$,
8. Calculate $r = \nabla f(\mathbf{x} + \alpha_1 \mathbf{d}) \mathbf{d}$, the direction gradient,
9. If $r \geq 0$, f is still increasing in $\mathbf{x} + \alpha_1 \mathbf{d}$ in the direction \mathbf{d} , hence set \mathbf{x} to $\mathbf{x} + \alpha_1 \mathbf{d}$ and return to 2,
10. If $r < 0$, find α_2 achieving $\max\{f(\mathbf{x} + \alpha \mathbf{d}): 0 < \alpha < \alpha_1\}$, set \mathbf{x} to $\mathbf{x} + \alpha_2 \mathbf{d}$ and return to 2.

REMARK 2.4. The special structure of the constraints (2.7) results in the projection $P_q \mathbf{x}$ being just taking averages over the sets of active constraints, see paragraph 2.4. Hence we don't have to invert a big matrix.

REMARK 2.5. The space of feasible points has an extra condition for the terms $\log(y_j - y_i)$ with $a_{i,j} \neq 0$, since in that case we should have: $y_i \neq y_j$. Since the function value tends to $-\infty$ when y_i is close to y_j , the algorithm cannot converge to such a point. If step 7 of the algorithm results in such a point α_1 , a point close to α_1 can be chosen.

REMARK 2.6. It is quite likely that this algorithm always converges, although we have no proof for it. Du and Zhang (1986) give a convergence theorem for a gradient method that is closely related to our algorithm. The main difference is a constant factor c in step 6 and 7. They use $\|\mathbf{d}\|_2 < c \cdot \gamma$ as a criterion for changing the set of active constraints. The conditions on c would cause a very small c in our case. Especially in the initial phase (when we start with a number of constraints which is as small as possible, see paragraph 2.4) this would slow down the process of making active constraints inactive. The risk of "zig-zagging" or "jamming" (i.e. the phenomenon that a constraint is alternately active and inactive without settling down to one of these states) is small. If the set of active constraints does not change any more, the convergence of the algorithm is ensured. Du and Zhang (1986) conjecture that

their algorithm is convergent for any $c > 0$ and have proved this conjecture for problems with three variables.

An explanation of the basic idea of the algorithm is given in Luenberger, we only justify the main steps.

THEOREM 2.7. *Let x_0 be a boundary point of K , which lies in the subspace M of q active constraints. Then the point x_0 is the global maximum of the strictly concave function $f(x)$, subject to the constraints $a_i'x \leq 0$, if, and only if*

$$(2.9) \quad P_q \nabla f(x_0)' = 0,$$

and

$$(2.10) \quad \beta = (A_q A_q')^{-1} A_q \nabla f(x_0)' \geq 0.$$

REMARK 2.8. This theorem justifies step 5 of the algorithm.

PROOF OF THEOREM 2.7. First the sufficiency of these conditions will be shown. Assume x_0 is not a global maximum. Then there is a point $x_1 \in K$ with $f(x_1) > f(x_0)$. Let $d = x_1 - x_0$, then

$$0 < f(x_1) - f(x_0) < d' \nabla f(x_0)',$$

because for a strictly concave function f : $f(x+h) < f(x) + h' \nabla f(x)$.

By

$$(2.11) \quad \nabla f(x_0)' = P_q \nabla f(x_0)' + A_q' \beta$$

and (2.9) we have

$$(2.12) \quad \nabla f(x_0)' = A_q' \beta = \sum_{i=1}^q \beta_i a_i.$$

Hence

$$(2.13) \quad 0 < d' \nabla f(x_0)' = \sum_{i=1}^q \beta_i (d' a_i) = \sum_{i=1}^q \beta_i a_i' d.$$

Because $a_i' x_0 = 0$ and d is a feasible direction of ascent, $a_i' d \leq 0$. Hence $\beta_j < 0$ for some j which contradicts (2.10). Thus that x_0 is the global maximum.

The necessity of the conditions is a result of the Kuhn-Tucker conditions, see e.g. Luenberger (1973) page 233. \square

THEOREM 2.9. *Let x be a feasible point and suppose a component of $\beta=(A_q A_q')^{-1} A_q \nabla f(x)'$ corresponding to an active constraint is negative. If this constraint is set inactive, the projection \hat{d} of the gradient vector onto the remaining subspace of active constraints is a feasible direction of ascent.*

REMARK 2.10. This theorem justifies step 6 of the algorithm.

PROOF OF THEOREM 2.9. Let $g=\nabla f(x)'$ and $d=P_q g=(I-A_q'(A_q A_q')^{-1} A_q)g$. Suppose $\beta_j<0$ and hence $a_j'y\leq 0$ becomes inactive. Let A_{q-1} denote the matrix A_q with the row a_j deleted. We have $A_q x=0$, which leads to $A_{q-1}x=0$ and $a_j'x=0$. Further $P_{q-1}P_q g=P_q g$, because P_q is a projection onto a part of the subspace corresponding to the projection P_{q-1} . We have

$$(2.14) \quad g=P_q g+A_q'\beta$$

and

$$(2.15) \quad (P_{q-1}A_q')_i = \begin{cases} 0 & \text{if } i \neq j \\ P_{q-1}a_j & \text{if } i = j \end{cases}.$$

Hence

$$(2.16) \quad P_{q-1}g=P_q g+P_{q-1}a_j\beta_j.$$

For the new direction $\hat{d}=P_{q-1}g$ we have

$$(2.17) \quad a_j'\hat{d}=a_j'P_{q-1}g=a_j'P_q g+a_j'P_{q-1}a_j\beta_j=a_j'P_{q-1}P_{q-1}a_j\beta_j<0,$$

since $a_j'P_q=0$. This makes \hat{d} a feasible direction. Since $g-\hat{d}$ is orthogonal to \hat{d} ,

$$(2.18) \quad g'\hat{d}=(g-\hat{d}+\hat{d})'\hat{d}=\|\hat{d}\|_2^2>0.$$

Hence it is a direction of ascent. \square

2.3. Parallel tangents

When the set of active constraints does not change, another improvement can be made. In theory the path of ascent is zig-zag in character, because a new search direction is orthogonal to the previous one. This phenomenon suggests an accelerated gradient method

which searches for a maximum on the line connecting a point x_0 and a point y two gradient steps later, see e.g. Luenberger (1973) page 184.

Let k be the total number of variables, q the number of active constraints and $p=k-q$ the number of inactive constraints. Then there are p unequal variables. To solve a problem of p variables, the algorithm for parallel tangents (PARTAN) is defined as:

PARTAN

1. Start with an arbitrary feasible point x_0 ,
2. Set i to 1,
3. Find the point x_1 by a gradient projection step from x_0 . If the set of active constraints is changed in x_1 , set x_0 to x_1 and return to 2,
4. Set i to $i+1$ (start of the partan part),
5. Find the point y by a gradient projection step from x_1 . If the set of active constraints is changed in y , set x_0 to y and return to 2,
6. Calculate $d=y-x_0$ and find α_1 achieving $\max\{\alpha: x_0+\alpha d \text{ is feasible}\}$,
7. Calculate $r=\nabla f(x_0+\alpha_1 d)d$, the direction gradient,
8. If $r \geq 0$, f is still increasing in $x_0+\alpha_1 d$ in the direction d , hence set x_0 to $x_0+\alpha_1 d$ and return to 2,
9. If $r < 0$, find α_2 achieving $\max\{f(x_0+\alpha d): 0 < \alpha < \alpha_1\}$,
10. If i is greater or equal than p , set x_0 to $x_0+\alpha_2 d$ and return to 2,
11. Set x_0 to x_1 , x_1 to $x_0+\alpha_2 d$ and return to 4.

Each step of the process consists of a gradient projection step and an additional move that provides further increase of the objective function, hence the convergence of the PARTAN algorithm is at least as good as the convergence of gradient projection. Restarting the process after p times the partan part (step 10) accelerates the convergence of the algorithm, see Luenberger (1973).

2.4. Application of the gradient projection with PARTAN

The special structure of the constraints (2.7) makes it easy to calculate the projection $P_q x$ and β . The constraints can be written in the form

$$(2.19) \quad \begin{array}{l} 1. \quad -y_1 \leq 0 \\ 2. \quad y_1 - y_2 \leq 0 \\ 3. \quad y_2 - y_3 \leq 0 \\ \quad \quad \quad \vdots \\ k. \quad y_{k-1} - y_k \leq 0 \end{array}$$

The construction of function (2.5) gives $y_1 > 0$ and $y_{k-1} < y_k = 1$. Let $l_1 < l_2 < \dots < l_p$ be the indices of the inactive constraints, then we have $l_1 = 1$ and $l_p = k$. For the projection $\mathbf{d} = \mathbf{P}_q \mathbf{x} = (d_1, d_2, \dots, d_k)$ of a point $\mathbf{x} = (x_1, x_2, \dots, x_k)$ we have $d_{l_i} = d_{l_i+1} = \dots = d_{l_{i+1}-1}$ for $i = 1, 2, \dots, p-1$. The variables $d_{l_i}, d_{l_i+1}, \dots, d_{l_{i+1}-1}$ only depend on $x_{l_i}, x_{l_i+1}, \dots, x_{l_{i+1}-1}$, hence the blocks can be considered separately for the projection. We now have

$$(2.20) \quad d_{l_i} = d_{l_i+1} = \dots = d_{l_{i+1}-1} = \frac{x_{l_i} + x_{l_i+1} + \dots + x_{l_{i+1}-1}}{l_{i+1} - l_i}$$

The projection \mathbf{P}_q is the same as taking averages over a set of active constraints.

For $\beta = (\mathbf{A}_q \mathbf{A}_q')^{-1} \mathbf{A}_q' \nabla f(\mathbf{x})'$ we have

$$(2.21) \quad \mathbf{A}_q' \beta = \nabla f(\mathbf{x})' - \mathbf{P}_q \nabla f(\mathbf{x})'$$

Let β_i belong to the i -th constraint, then

$$(2.22) \quad \beta = (\beta_2, \dots, \beta_{l_2-1}, \beta_{l_2+1}, \dots, \beta_{l_1-1}, \beta_{l_1+1}, \dots, \beta_{l_p-1})'$$

$\mathbf{A}_q' \beta$ can be considered as a vector composed of components of the form

$$(2.23) \quad (\beta_{l_i+1}, -\beta_{l_i+1} + \beta_{l_i+2}, \dots, -\beta_{l_{i+1}-2} + \beta_{l_{i+1}-1}, -\beta_{l_{i+1}-1})', \text{ for } i = 1, 2, \dots, p-1.$$

Since

$$(2.24) \quad \sum_{j=l_i}^{l_{i+1}-1} (\nabla f(\mathbf{x})_j - (\mathbf{P}_q \nabla f(\mathbf{x})')_j) = 0, \text{ for } i = 1, 2, \dots, p-1,$$

we have

$$(2.25) \quad \beta_i = \sum_{j=1}^i (\nabla f(\mathbf{x})_j - (\mathbf{P}_q \nabla f(\mathbf{x})')_j), \text{ for } i = 2, 3, \dots, k,$$

with $\beta_{l_j-1} = 0$ for $j = 2, 3, \dots, p$. Now we have

$$(2.26) \quad \gamma = \max_i (-\beta_i) = \max_i \sum_{j=1}^i ((\mathbf{P}_q \nabla f(\mathbf{x})')_j - \nabla f(\mathbf{x})_j).$$

EXAMPLE: Suppose we have 8 variables and $l_1 = 1$, $l_2 = 5$ and $l_3 = 8$. Note that $x_8 = 1$. Then

$$\mathbf{A}_q = \begin{pmatrix} 1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 \end{pmatrix}$$

and

$$A_q' \beta = A_q' \begin{pmatrix} \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_6 \\ \beta_7 \end{pmatrix} = \begin{pmatrix} \beta_2 \\ -\beta_2 + \beta_3 \\ -\beta_3 + \beta_4 \\ -\beta_4 \\ \beta_6 \\ -\beta_6 + \beta_7 \\ -\beta_7 \end{pmatrix}$$

Hence

$$\begin{aligned} \beta_2 &= g_1 - d_1, \\ \beta_3 &= g_1 - d_1 + g_2 - d_2, \\ \beta_4 &= g_1 - d_1 + g_2 - d_2 + g_3 - d_3 = -(g_4 - d_4), \\ \beta_6 &= g_5 - d_5, \\ \beta_7 &= g_5 - d_5 + g_6 - d_6 = -(g_7 - d_7), \end{aligned}$$

with g defined as in the proof of theorem 2.9.

The algorithm starts with a feasible point x . There are several possibilities to select such a point. The simplest way is to start with only inactive constraints and $x_i = \frac{i}{k}$ for $i=1,2,\dots,k$. From the situation with one observation point we know that for the solution most constraints are active. Hence the initial phase, in which a lot of inactive constraints are made active, will take a lot of time.

One can also start with a number of inactive constraints which is as small as possible. An algorithm to select such a point is given below.

STARTING POINT

1. Start with $l_1=1$ and $m=1$, the first constraint is always active,
2. Set m to $m+1$, ignore all terms $\log(y_j - y_i)$ with $i < l_{m-1}$ and determine the smallest j with $a_{i,j} \neq 0$, set l_m to j ,
3. If l_m is less than k return to 2,
4. Set x_j to $\frac{i}{m}$ for $j=l_i, \dots, l_{i+1}-1$, for $i=1, \dots, m-1$, and x_k to 1.

Unfortunately we have no guarantee that the inactive constraints found this way are also inactive for the solution of the maximizing problem. In our simulation study this need not be the case. Nevertheless this starting point gives a faster rate of convergence than the previous one. For other starting points we need more insight into the behaviour of the NPMLE.

3. SIMULATION RESULTS

The algorithms mentioned in this paper are used in the program NPMLE for simulations, see the appendix. This program is written in Fortran77 (Balfour and Marwick (1979)).

To get an impression for the precision of the NPMLE in seven special cases, we give some results for a sample of 1000 observations (T,U,A,B). The pictures are made with DISSPLA, a graphic library. The numbers correspond with the class numbers in the program NPMLE.

THE NPMLE OF F

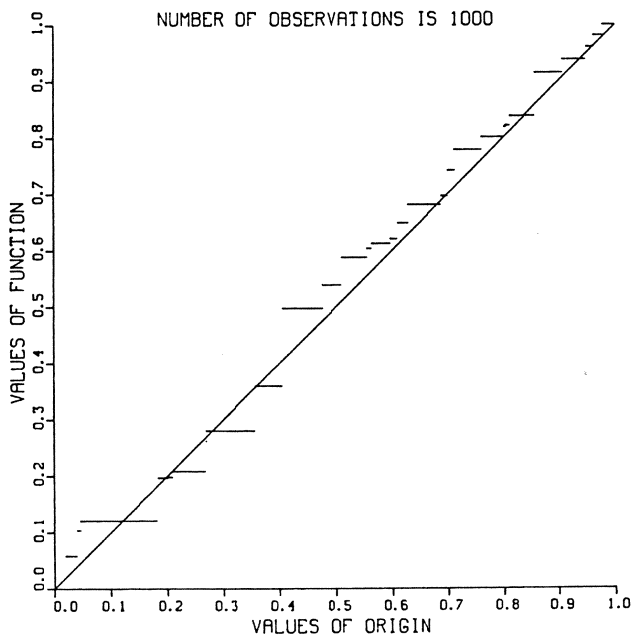


FIGURE 3.1. 1. $F(x) = x$, $h(t,u) = \frac{1}{1-t}$.

THE NPMLE OF F

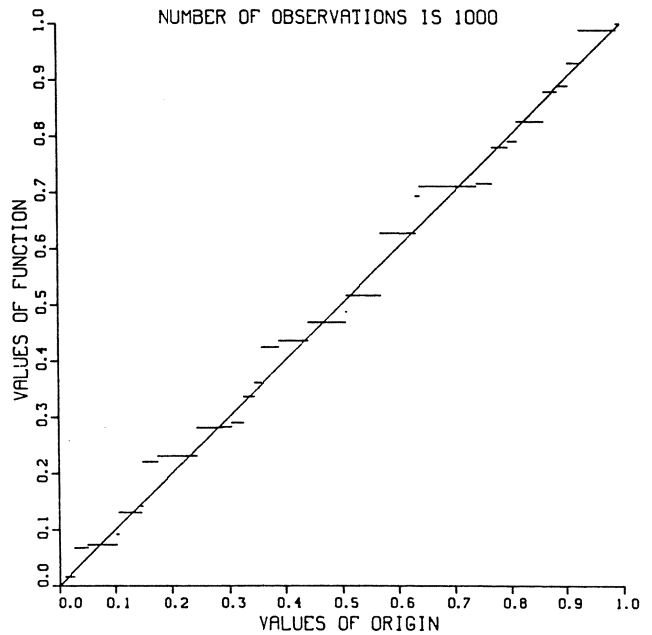
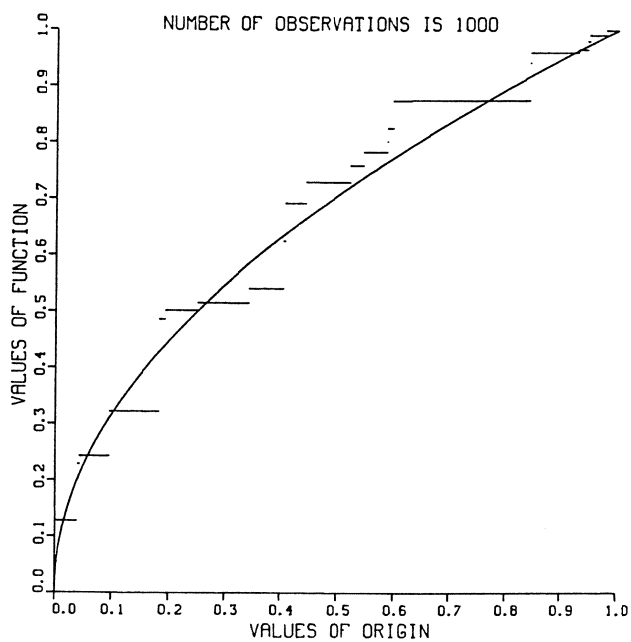
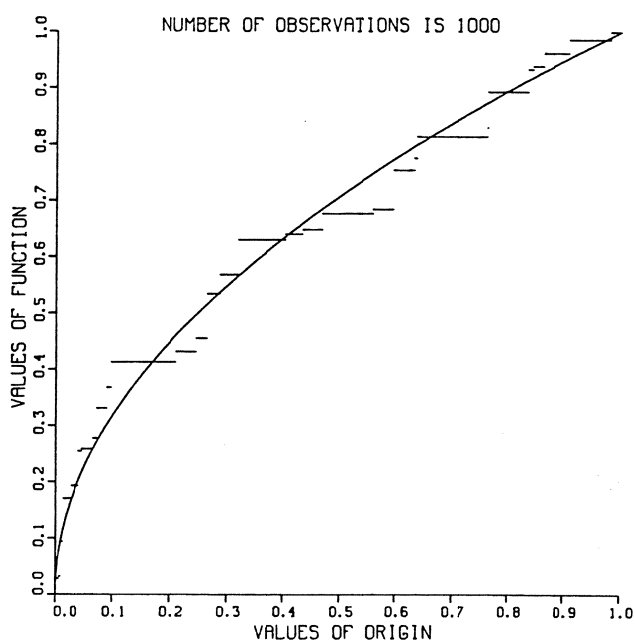
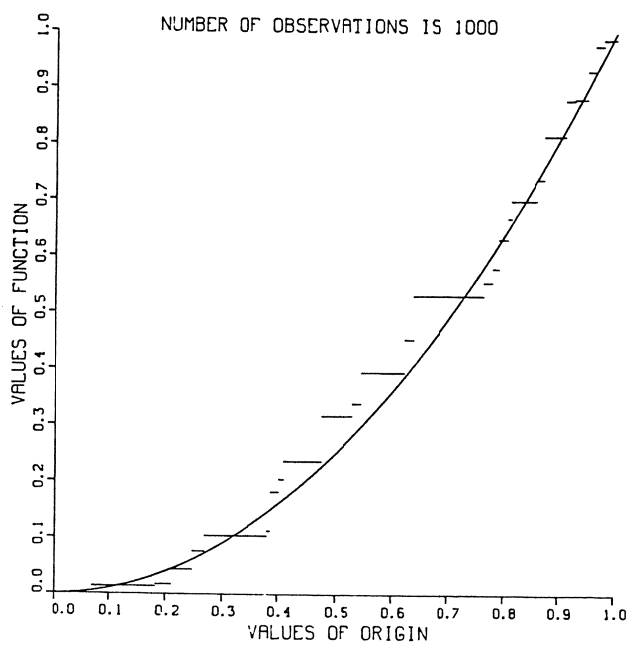
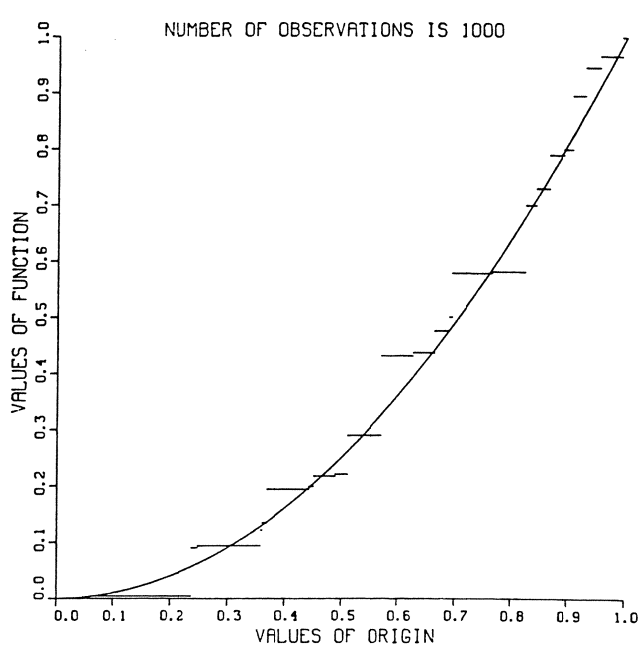


FIGURE 3.2. 2. $F(x) = x$, $h(t,u) = \frac{1}{2\sqrt{t}(1-t)}$

THE NPMLE OF FFIGURE 3.3. 3. $F(x)=\sqrt{x}$, $h(t,u) = \frac{1}{1-t}$.THE NPMLE OF FFIGURE 3.4. 4. $F(x)=\sqrt{x}$, $h(t,u) = \frac{1}{2\sqrt{1-t}}$.THE NPMLE OF FFIGURE 3.5. 5. $F(x)=x^2$, $h(t,u) = \frac{1}{1-t}$.THE NPMLE OF FFIGURE 3.6. 6. $F(x)=x^2$, $h(t,u) = \frac{1}{2\sqrt{1-t}}$.

THE NPMLE OF F

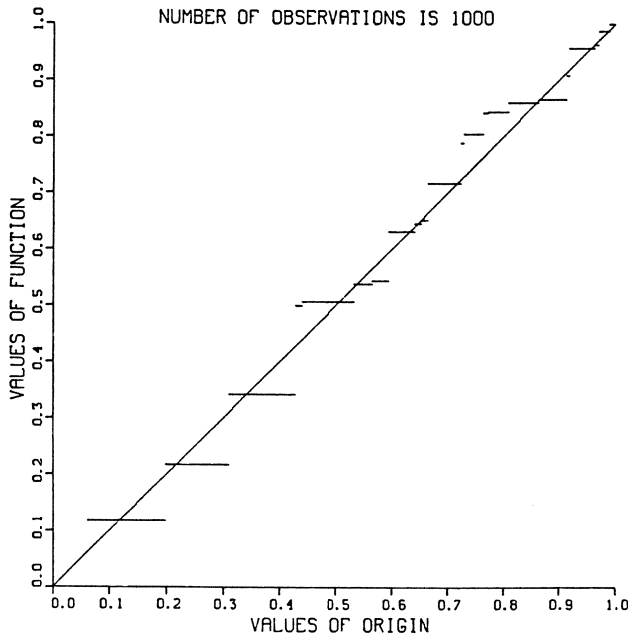


FIGURE 3.7. 7. $F(x)=x$, $h(t,u) = \frac{2t}{1-t}$.

The gradient projection method terminates if the projected gradient is small enough. We have used $\|d\|_{\infty} < 10^{-4}$ as a criterion. The number of references to ZBREN (the IMSL subroutine we used to determine a zero of a function) before the process terminates varies strongly. We took a maximum of 250 and in most cases this is enough. For three different combinations of F_0 and h , corresponding with figure 3.1, 3.5 and 3.7, we have done 100 simulations with 1000 observations. The minimum number of references to ZBREN was 39 in class 1, 40 in class 5 and 41 in class 7. In all three cases there were not more than three simulations which did not terminate before 250 references. The simulations were done at a cyber 995E, and the average CP time to determine a solution was 6.6 seconds.

Acknowledgement

This research was done for a Master's thesis at the department of mathematics of the University of Amsterdam. I want to thank professor Piet Groeneboom for his help and patience. Without his knowledge it would not have been possible for me to do this study.

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```

* NEXT GIVE IXLP (1) THE NUMBER OF JUMPS UPTO AND
* INCLUDING I.
* SPR (K) IS THE VALUE OF CANDIDATE JUMP K.
  IXLP(1)=ISP(1)
  K = 0
  IF (ISP(1).EQ.1) THEN
    K = 1
    SPR(K) = TU(1)
  END IF
  DO 350 I=2,MAXN
    IXLP(I) = IXLP(I-1) + ISP(I)
    IF (ISP(I).EQ.1) THEN
      K = K+1
      SPR(K) = TU(I)
    END IF
  350 CONTINUE
  NV=IXLP(MAXN)
* CHANGE IGRX INTO THE NUMBERS OF THE FIRST AND THE
* LAST JUMP WHICH ARE COVERED BY THE INTERVAL OF X.
  DO 1000 I=1,N
    IF (IGRX(I,1) = IXLP(IGRX(I,1)) + 1
    ELSE
      IGRX(I,1) = 1
    END IF
    IGRX(I,2) = IXLP(IGRX(I,2))
  1000 CONTINUE
  RETURN
  END
* *****
  SUBROUTINE STOFT (NT,IGRX)
* GIVES THE INFORMATION TO RESTART THE ANALYSIS
* IF THE PARAMETERS ARE TOO SMALL.
* *****
  COMMON/size/N,NV,MAXN
  COMMON/SPRBLOCK/SPR(1)
  10 FORMAT(' THE PARAMETER NVART IS TOO SMALL, WE NEED AT LEAST:',I7,
  + /, ' THE ANALYSIS IS STOPPED WITH:')
  20 FORMAT(2I5)
  30 FORMAT(I7,F15.8)
  WRITE(2,10) NV
  WRITE(2,20) (IGRX(I,2),I=1,N)
  WRITE(2,30) (I,SPR(I),I=1,NV)
  RETURN
  END
* *****
  SUBROUTINE MINBLOK (NT,IGRX,NTEBLOK)
* THIS SUBROUTINE DETERMINES A MINIMUM NUMBER OF BLOCKS THAT GIVES
* A FEASIBLE POINT. HENCE WE DETERMINE A JUMP AS RIGHTMOST AS POSSIBLE
* AND IGNORE ALL THE INTERVALS WHICH CONTAIN THIS JUMP WHEN WE
* DETERMINE THE NEXT JUMP.
* *****
* INPUT: IGRX : FIRST AND LAST JUMP COVERED BY THE INTERVAL OF X.
* *****
* OUTPUT: IBLOK,F,NTEBLOK : START VALUES FOR PARTAN.
* *****
  INTEGER IGRX(NT,2),NTEBLOK
  COMMON/size/N,NV,MAXN
  COMMON/FUN/IGRX(NT,2)
  IGLKHD = 0.0
  DO 100 I = 1, N
    IL = IGRX(I,1) - 1
    IR = IGRX(I,2)
    IF (IL.EQ.0) THEN
      IGLKHD = IGLKHD + LOG(F(IR))
    ELSE

```

```

COMMON/size/N,NV,MAXN
COMMON/FELOK/F(1)
COMMON/IBLOCK/IBLOK(1)

```

```

IBLOK(1) = 1
DO 10 I = 2, NV
  10 IBLOK(I) = 0
  NTEBLOK = 1
  NS = 1

```

```

* NS IS THE LATEST JUMP FOUND.
  100 CONTINUE

```

```

* LG THE MINIMUM LEFT LIMIT OF INTERVALS WE CONSIDER.
  LG = NS + 1
  NS = NV

```

```

DO 300 I = 1, N
  IF (IGRX(I,1).GE.IG) THEN
    IF (IGRX(I,2).LT.NS) NS = IGRX(I,2)
  END IF

```

```

  300 CONTINUE
  IBLOK(NS)=1
  NTEBLOK=NTEBLOK+1
  IF (NS.LT.NV) GOTO 100
  NTEBLOK = NTEBLOK

```

```

* START VALUES FOR THE DETERMINED BLOCKS.
  F(1) = 1.0/REAL(NTEBLOK)
  DO 500 I = 2, NV-1
    IF (IBLOK(I).EQ.0) THEN
      F(I)=F(I-1)
    ELSE
      F(I)=F(I-1)+F(1)
    END IF
  500 CONTINUE
  F(NV) = 1.0
  RETURN
  END

```

```

* *****
  SUBROUTINE LOGLIK (NVAR,F,IGLKHD)

```

```

* WE USE F (NVAR)=1.0 .
* *****

```

```

* INPUT: F
* *****

```

```

* OUTPUT: IGLKHD
* *****

```

```

* PARAMETER (NT=1000)
* *****

```

```

  INTEGER NVAR
  REAL IGLKHD,F (NVAR)

```

```

  INTRINSIC LOG

```

```

  COMMON/size/N,NV,MAXN
  COMMON/FUN/IGRX(NT,2)

```

```

  IGLKHD = 0.0
  DO 100 I = 1, N
    IL = IGRX(I,1) - 1
    IR = IGRX(I,2)
    IF (IL.EQ.0) THEN
      IGLKHD = IGLKHD + LOG(F(IR))
    ELSE

```

```

I L K H D = I G L K H D + L O G ( F ( I R ) - F ( I L ) )
END IF
100 CONTINUE
RETURN
END

* *****
SUBROUTINE GRDLGLK (NVAR,F,GRD)
* THE GRADIENT VECTOR OF LOGLIK.
* WE USE F(NVAR)=1.0 .
* *****
* INPUT: F
* *****
* OUTPUT: GRD: THE GRADIENT.
* *****
PARAMETER (NT=1000)
INTEGER NVAR
REAL F (NVAR) , GRD (NVAR)
COMMON/SIZE/N,NV,MAXN
COMMON/FUN/IGRX(NT,2)
DO 100 I = 1 , NV
GRD (I) = 0.0
DO 200 I = 1 , N
IL = IGRX (I,1) - 1
IR = IGRX (I,2)
IF (IL.EQ.0) THEN
GRD (IR) = GRD (IR) + 1.0/F (IR)
ELSE
HLP = 1.0 / ( F (IR) - F (IL) )
GRD (IL) = GRD (IL) - HLP
GRD (IR) = GRD (IR) + HLP
END IF
200 CONTINUE
GRD (NV) = 0.0
RETURN
END

* *****
REAL FUNCTION GRDLBDA (BLABDA)
* THIS FUNCTION GIVES THE DIRECTIONAL DERIVATIVE OF LOGLIK AT
* (F + BLABDA * PG) WITH RESPECT TO THE VECTOR PG.
* *****
* INPUT: BLABDA,F,PG
* *****
* OUTPUT: GRDLBDA
* *****
COMMON/SIZE/N,NV,MAXN
COMMON/FBLOK/F (1)
COMMON/PGBLOK/PG (1)
COMMON/WORK1/Y (1)
COMMON/WORK2/GRD (1)
EXTERNAL GRDLGLK,SDOT
BLBDA = BLABDA
DO 100 I=1,NV
Y (I) = F (I) + BLBDA * PG (I)

```

```

CALL GRDLGLK (NV,Y,GRD)
GRDLBDA = SDOT (NV,GRD,1,PG,1)
RETURN
END

* *****
SUBROUTINE PROJGRD (NV,GRDF,PGNRM)
* THIS SUBROUTINE DETERMINES THE PROJECTION OF THE GRADIENT GRDF
* ONTO THE SPACE RELATED WITH THE ACTIVE CONSTRAINTS IN IBLOK.
* *****
* INPUT: IBLOK,GRDF
* *****
* OUTPUT: PG : PROJECTION OF GRDF
PGNRM: NORM OF PG
* *****
REAL GRDF (NV) , PGNRM
COMMON/PBLOK/PG (1)
COMMON/IBLOK/IBLOK (1)
EXTERNAL ISAMAX
NS=1
* NS IS THE BEGINNING OF THE NEW BLOCK.
100 CONTINUE
I=NS
200 CONTINUE
I=I+1
IF ((IBLOK (I).EQ.0).AND.(I.LT.NV)) GOTO200
* I IS NOW THE BEGINNING OF THE NEXT BLOCK.
* THE LIMITS OF THE BLOCK ARE NS AND I-1.
SOMNS = 0.0
DO 300 J=NS,I-1
SOMNS = SOMNS + GRDF (J)
SOMNS = SOMNS / (I-NS)
DO 400 J=NS,I-1
PG (J) =SOMNS
NS=I
IF (NS.LT.NV) GOTO100
PG (NV) =0.0
IMAX = ISAMAX (NV,PG,1)
PGNRM = ABS (PG (IMAX))
RETURN
END

* *****
SUBROUTINE SPLBDA (NT,IGRX,SPLBDA,ISPLBDA)
* THIS SUBROUTINE DETERMINES THE MAXIMUM VALUE FOR SPLBDA
* IN F + SPLBDA * PG WHICH IS PERMITTED FOR F(I) <= F (I+1)
* ISPLBDA GIVES THE CONSTRAINT THAT CAN BECOME INACTIVE,
* AND BECAME NEGATIVE WHEN THE POINT IS NOT PERMITTED.
* INPUT: IGRX,IBLOK,F,PG
* *****
* OUTPUT: SPLBDA : MAXIMUM VALUE PERMITTED
ISELBA: RELATED CONSTRAINT
* *****
INTEGER ISPLBDA,IGRX (NT,2)
REAL SPLBDA
COMMON/SIZE/N,NV,MAXN

```

```

COMMON/FBLOK/F(1)
COMMON/PGBLOK/PG(1)
COMMON/IBLOCK/IBLOK(1)

SPLBDA = 0.0
ISPLEDA = 0
IF (PG(1).LT.0.0) THEN
  SPLBDA = (1.0/REAL(N) - F(1)) / PG(1)
  ISPLEDA = -1
END IF
DO 100 I=2,NV - 1
  IF (PG(I-1).GT.PG(I)) THEN
    HLP=(F(1)-F(I-1))/PG(I-1)-PG(I)
    IF ((ISPLEDA.EQ.0).OR.(HLP.LT.SPLEDA)) THEN
      SPLBDA=HLP
      ISPLEDA=-I
    END IF
  END IF
100 CONTINUE
IF (PG(NV-1).GT.0.0) THEN
  HLP = (1.0 - 1.0/REAL(N) - F(NV-1)) / PG(NV-1)
  IF ((HLP.LT.SPLEDA).OR.(ISPLEDA.EQ.0)) THEN
    SPLBDA = HLP
    ISPLEDA = -NV
  END IF
END IF
* THEORY GIVES SFLBDA NOT EQUAL 0 WHEN PG NOT EQUAL 0.
* CHECK IF SFLBDA GIVES A PERMITTED POINT.
* SEARCH THE LIMITS OF THE BLOCKS WHICH CAN BE PUT TOGETHER.
IF (ISPLEDA.GT.0) THEN
  IL = ISPLEDA - 1
  IR = ISPLEDA + 1
300 CONTINUE
IF (IBLOK(IL).EQ.0) IL = IL - 1
IF (IBLOK(IR).EQ.0) IR = IR + 1
IF ((IBLOK(IL).EQ.0).OR.(IBLOK(IR).EQ.0)) GOTO 300
IR = IR - 1
* THE BLOCK IS FROM IL UPTO AND INCLUDING IR
DO 500 I = 1, N
  IF ((IGRX(I,1).GT.IL).AND.(IGRX(I,2).LE.IR)) THEN
    THIS INTERVAL IS COMPLETELY IN THE NEW BLOCK,
    HENCE THE POINT IS NOT FEASIBLE.
    SPLBDA = SPLBDA -
      (1.0/REAL(N)) / (PG(ISPLEDA-1) - PG(ISPLEDA))
    ISPLEDA = -ISPLEDA
    GOTO 700
  END IF
500 CONTINUE
END IF
700 CONTINUE
RETURN
900 FORMAT (' F + SFLBDA * PG REACHES NO LIMIT,',
  + ' THIS IS NOT POSSIBLE. THERE MUST BE SOMETHING WRONG',
  + ' IN THE PROGRAM.',
  + ' /', THIS WAS SUBROUTINE SUPLEDA.')
9999 WRITE(2,900)
STOP
END
* *****
SUBROUTINE VERBLOK (NV,NTELBL,GRDF,PGNRM,
  GAMMA,ERROR,NEWBLOK,KLAAR)
+
* WHEN THE IMPROVEMENT OF THE SOLUTION IS TOO SLOW WITH THE
* ACTUAL SET OF ACTIVE CONSTRAINTS, ONE CONSTRAINT WILL BE
* DROPPED DEPENDING ON THE VALUE OF GAMMA.
* WHEN GAMMA AND PGNRM ARE BOTH SMALL ENOUGH, WE ARE CLOSE
* TO THE SOLUTION AND THE SEARCH PROCEDURE WILL TERMINATE.
* *****
* INPUT: IBLOK,NTELBL,GRDF,PG,PGNRM,ERROR
* *****
* OUTPUT: IBLOK,NTELBL,KLAAR,NEWBLOK,GAMMA
* *****
INTEGER NV,NTELBL,KLAAR
REAL GRDF(NV),PGNRM,ERROR,GAMMA
LOGICAL NEWBLOK
COMMON/PGBLOK/PG(1)
COMMON/IBLOCK/IBLOK(1)
NEWBLOK = .FALSE.
IMAX = 0
GAMMA = 0.0
SOM = 0.0
DO 100 J = 1, NV-1
  SOM = SOM + PG(J) - GRDF(J)
  IF (SOM.GT.GAMMA) THEN
    GAMMA = SOM
    IMAX = J + 1
  END IF
100 CONTINUE
IF ((GAMMA.LT.ERROR).AND.(PGNRM.LT.ERROR)) THEN
  IF ((PGNRM.EQ.0.0).AND.(GAMMA.EQ.0.0)) THEN
    KLAAR = 1
  ELSE
    KLAAR = 2
  END IF
ELSE IF (PGNRM.LT.GAMMA) THEN
  IBLOK(IMAX) = 1
  NEWBLOK = .TRUE.
  NTELBL = NTELBL + 1
END IF
RETURN
END
* *****
SUBROUTINE PARTAN (NT,IGRX,NTEBLOK,NTITERA,ERROR,ITMAX,
  ERZBERN,MXZBERN,PGNRM,GAMMA,KLAAR)
+
* THIS SUBROUTINE DETERMINES THE NPMLE WITH MODIFIED
* GRADIENT PROJECTION AND PARALLEL TANGENTS.
* *****
* INPUT: IBLOK,NTEBLOK,F : STARTVALUES FROM MINBLOK.
* KLAAR : 0
* ITMAX : MAXIMUM NUMBER OF REFERENCES TO ZBERN.
* MXZBERN : MAXIMUM NUMBER OF ITERATIONS OF ZBERN.
* ERZBERN : RELATIVE PRECISION OF ZBERN.
* ERROR : MAXIMUM VALUE PERMITTED FOR PGNRM AND GAMMA.
* IGRX : FUNCTION PARAMETERS AS STATED IN MAXBLOK.
* *****
* OUTPUT: F,IBLOK,NTEBLOK,NTITERA,PGNRM,GAMMA,KLAAR
* *****
INTEGER NV,ISLEBDA,ITMAX,ITEL,MAXF,
+ IGRX(NT,2),KLAAR,MXZBERN,NTEBLOK,NTELBL,NTITERA

```

```

REAL PGNRM, SPLBDA, GAMMA, ERROR, ERZBREN,
+   FGRDLBD, BLEDDAO, ERRABS
LOGICAL NEWBLOK

COMMON/SIZE/N, NV, MAXN
COMMON/FBLOK/F (1)
COMMON/PGBLOK/PG (1)
COMMON/IBLOCK/IBLOK (1)
COMMON/WORK2/GRDF (1)
COMMON/F0BLOK/F0 (1)
COMMON/F1BLOK/F1 (1)

EXTERNAL GRDLGK, PROJGRD, VERBLOK, SUPLEBDA,
+   GRDLBDA, ZBREN, SCOPY, SAXPY

ITEL = 0
ERRABS = 0.0
NTELEL = NTEBLOK

100 CALL SCOPY (NV, F, 1, F0, 1)
CALL GRDLGK (NV, F, GRDF)
200 CALL PROJGRD (NV, GRDF, PGNRM)
CALL VERBLOK (NV, NTELEL, GRDF, PGNRM,
+   GAMMA, ERROR, NEWBLOK, KLAAR)
IF (KLAAR.NE.0) GOTO 9990
IF (NEWBLOK) GOTO 200
CALL SUPLEBDA (NT, IGRX, SPLBDA, ISPLEBDA)
* GRDF IS FREE FOR USE IN GRDLBDA !!!!
FGRDLBD = GRDLBDA (SPLBDA)
IF (FGRDLBD.GE.0.0) THEN
  CALL SAXPY (NV, SPLBDA, PG, 1, F, 1)
  IF (ISPLEBDA.GT.0) THEN
    IBLOK (ISPLEBDA) = 0
    NTELEL = NTEBLOK - 1
  END IF
GOTO 100
END IF
ITEL = ITEL + 1
BLEDDAO = 0.0
MAXF = MZXZBREN
CALL ZBREN (GRDLBDA, ERRABS, ERZBREN, BLEDDAO, SPLBDA, MAXF)
CALL SAXPY (NV, SPLBDA, PG, 1, F, 1)
* THE PARTAN STEP.
DO 900 I = 1, NV
  PG (I) = F (I) - F0 (I)
900 CONTINUE
CALL SCOPY (NV, F0, 1, F, 1)
CALL SUPLEBDA (NT, IGRX, SPLBDA, ISPLEBDA)
FGRDLBD = GRDLBDA (SPLBDA)
IF (FGRDLBD.GE.0.0) THEN
  CALL SAXPY (NV, SPLBDA, PG, 1, F, 1)
  IF (ISPLEBDA.GT.0) THEN
    IBLOK (ISPLEBDA) = 0
    NTELEL = NTEBLOK - 1
  END IF
GOTO 100
END IF
ITEL = ITEL + 1
BLEDDAO = 0.0
MAXF = MZXZBREN
CALL ZBREN (GRDLBDA, ERRABS, ERZBREN, BLEDDAO, SPLBDA, MAXF)
CALL SAXPY (NV, SPLBDA, PG, 1, F, 1)
IF (ITEL.GE.ITMAX) THEN
  KLAAR = 3
  CALL GRDLGK (NV, F, GRDF)
  CALL PROJGRD (NV, GRDF, PGNRM)
  CALL VERBLOK (NV, NTELEL, GRDF, PGNRM,
+   GAMMA, ERROR, NEWBLOK, KLAAR)
  ELSE IF (ITPART.LT.NTELEL) THEN
    CALL SCOPY (NV, F1, 1, F0, 1)
    CALL SCOPY (NV, F, 1, F1, 1)
    GOTO 300
  ELSE
    GOTO 100
  END IF
9990 NTEBLOK = NTELEL
NTITERA = ITEL
RETURN
END

+
*****
SUBROUTINE PRINSOL (NTEBLOK, NTITERA, PGNRM, GAMMA, ICLASS, KLAAR)
* PRINT THE RESULTS.
* STATE OF THE SOLUTION ON TAPE2.
* SOLUTION ON TAPES, LAYOUT FOR FURTHER ANALYSIS:
*
* N ICLASS NV NTEBLOK NTITERA
* I SPR (I) F (I)
* IGLKHD PGNRM GAMMA
* *****
INTEGER NTEBLOK, NTITERA, ICLASS, KLAAR
REAL PGNRM, GAMMA, IGLKHD

COMMON/SIZE/N, NV, MAXN
COMMON/FBLOK/F (1)
COMMON/SPRBLOK/SPR (1)
COMMON/IBLOCK/IBLOK (1)

```

```

EXTERNAL LOGLIK, ISUM

* STATE OF THE SOLUTION.
1 FORMAT (/, ' EXACT SOLUTION FOUND.      ')
2 FORMAT (/, ' THE GRADEPOJ. AND GAMMA ARE SMALL ENOUGH. ')
3 FORMAT (/, ' MAXIMUM NUMBER OF REFERENCES TO ZBERN REACHED. ')
4 FORMAT (/, ' NO SOLUTION FOUND. ')
IF (KLAAR.EQ.1) THEN
  WRITE (2,1)
ELSE IF (KLAAR.EQ.2) THEN
  WRITE (2,2)
ELSE IF (KLAAR.EQ.3) THEN
  WRITE (2,3)
ELSE
  WRITE (2,4)
  RETURN
END IF
100 FORMAT (2X,5I7)
200 FORMAT (2X,I6,2X,F8.6,2X,E23.15)
300 FORMAT (2X,3E23.15)
NTBLOK = ISUM(NV,IBLOK,1)
WRITE (3,100) N,ICLASS,NV,NTBLOK,NTITERA
DO 400 I=1,NV
  IF (IBLOK(I).EQ.1) WRITE (3,200) I,SPR(I),F(I)
400 CONTINUE
CALL LOGLIK (NV,F,IGLKHD)
WRITE (3,300) IGLKHD,PGNRM,GAMMA
RETURN
END

```