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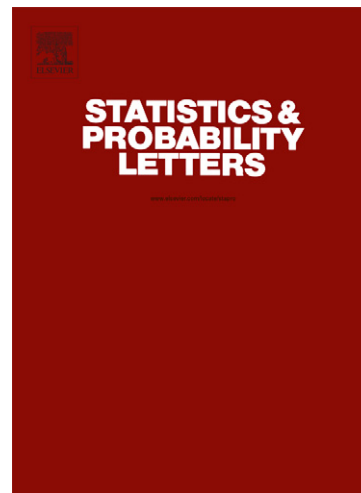
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The uniqueness of extremum estimation

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Abstract

Let W denote a family of probability distributions with parameter space Γ , and W_G be a subfamily of W depending on a mapping $G : \Theta \rightarrow \Gamma$. Extremum estimations of the parameter vector $\vartheta \in \Theta$ are considered. Some sufficient conditions are presented to ensure the uniqueness with probability one. As important applications, the maximum likelihood estimation in curved exponential families and nonlinear regression models with independent disturbances as well as the maximum likelihood estimation of the location and scale parameters of Gumbel distributions are treated.

KEYWORDS: Extremum estimation, Sard's theorem, nonlinear regression, curved exponential families, Gumbel distributions.

AMS CLASSIFICATION 62F10, 62F11

JEL CLASSIFICATION C13, C16

1 Introduction

Extremum estimation designates a principle often used for estimating unknown parameters: Starting from data those parameter vectors are selected which maximize or minimize a certain function defined over the parameter space. Some estimation methods currently applied in practical situations of estimation are subsumed under the principle of extremum estimation, for example the maximum likelihood and least squares estimation. Employing the extremum estimation in practice causes the problem to choose some parameter vector if the related maximization (or minimization) problem has more than one solution. Under general conditions the question of the uniqueness of extremum estimation seems to be still open. A known result of some special cases was presented by Pazman (cf. [8]). He showed that in some curved exponential families the maximum likelihood method has at most one

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solution with probability one.

The present paper is an attempt to generalize the result of Pazman to a greater variety of applications, with respect to the extremum estimation.

Since there is no essential difference between maximization and minimization, we shall restrict ourselves to estimation that maximizes a certain function which is dependent on the parameters. After introducing some general notations we shall present in section 3 our main result. We shall deal with the estimation of parameter vectors of distributions which are dominated by Lebesgue measures. The fundamental idea is to employ Sard's theorem to ensure that almost surely the estimation has at most one solution, adapting the line of reasoning that Pazman followed in the above mentioned paper. It may be simplified when considering uniqueness of nonlinear least squares estimation. So the reader is referred to Pazman's monograph on nonlinear regression (cf. [9]) to get a first idea.

The main result of the paper relies on the assumption that for almost every observation from the sample space the respective objective function has only non degenerated critical points. In section 4 this assumption will be replaced by some conditions to restate the main result. The obtained criteria to ensure uniqueness of extremum estimation almost surely will be applied to the maximum likelihood estimation in nonlinear regression models with independent disturbances (section 5) as well as curved exponential families (section 6), and also to maximum likelihood estimation of the location and scale parameter of a Gumbel distribution (section 7). Appendix A provides a crucial auxiliary result, whereas appendix B deals with the proof of the main theorem. Finally appendix C reviews Lindelöf's theorem and useful special versions of Sard's theorem.

2 Notations and preliminaries

For a differentiable mapping $f : H \rightarrow \mathbf{R}^t$ defined on an open subset H of \mathbb{R}^s , the Jacobian of f at x will be denoted by $J_x(f)$, its rank will be symbolized by $rank(J_x(f))$. As usual f will be called a C^r -mapping ($r \in \mathbb{N}$) if it is r times continuously differentiable. f is said to be a C^r -immersion/ C^r -submersion ($r \in \mathbb{N}$) if it is a C^r -mapping with $rank(J_x(f)) = s/rank(J_x(f)) = t$ for all $x \in H$. If $t = n$, and if f is an homeomorphism from H onto the open subset $f(H)$ such that $f : H \rightarrow f(H)$ and its inverse $f^{-1} : f(H) \rightarrow H$ are C^r -immersions, then f is called a C^r -diffeomorphism onto $f(H)$. The Jacobians of a C^r -diffeomorphism are nonsingular. In the case of $t = 1$ $\nabla_x f$ stands for the gradient of f at x , whereas $\nabla \nabla_x f$ will be used for the Hessian of f at x if f is twice differentiable. If $\nabla_x f = 0$, then we shall speak of x as a critical point, which will be called degenerated provided that $\nabla \nabla_x f$ is singular.

For $m \in \mathbb{N}_0$ and $r \in \mathbb{N}$ a subset $A \subseteq \mathbb{R}^s$ is called a m -dimensional C^r -submanifold of \mathbb{R}^s if for any $x \in A$ there exists a C^r -diffeomorphism f from an open neighbourhood U of x in \mathbb{R}^s onto the open subset $f(U)$ of \mathbb{R}^s such that $f(U \cap A) = f(U) \cap \{(x_1, \dots, x_s) \in \mathbb{R}^s \mid x_{m+1} = \dots = x_s = 0\}$ (cf. [1], Definition 2.1.1). Note that in view

of Lindelöf's theorem (cf. appendix C, Proposition C.2) a 0-dimensional C^r -submanifold of \mathbb{R}^s is an at most countable set. If $g : U \rightarrow \mathbb{R}^t$ denotes a C^r -submersion from an open subset U of \mathbb{R}^s into \mathbb{R}^t , then we know by the regular value theorem (cf. [4], p.14 or p.22, Theorem 3.2) that for each $y \in \mathbb{R}^t$ the fibre $g^{-1}(\{y\})$ is empty or a $(s - t)$ -dimensional C^r -submanifold of \mathbb{R}^s .

The transpose of a vector \underline{x} in a standard euclidean space or a matrix M will be indicated by \underline{x}' and M' respectively. Furthermore the notation λ^t will be employed for the Lebesgue measure on \mathbb{R}^t .

Throughout the paper we shall consider the following setting of extremum estimation: Let Y be a random vector with measurable space $(\mathcal{X}, \mathcal{B}(\mathcal{X}))$, where \mathcal{X} is an open subset of \mathbb{R}^n , and $\mathcal{B}(\mathcal{X})$ denotes the σ -algebra of Borel subsets of \mathcal{X} . We suppose that the distribution Q_Y of Y may be parameterized by a mapping $G : \Theta \rightarrow \mathbb{R}^m$, i.e. it belongs to a family $W_G = \{P_{G(\vartheta)} \mid \vartheta \in \Theta\}$ of probability distributions, which in addition we assume to be dominated by $\lambda^n \mid \text{Borel}(\mathcal{X})$. Of course the parameter ϑ should be identified, which implies

(2.1) G is injective.

Starting from a realisation y of the random vector Y , we are interested in estimating the (unknown) vector ϑ by maximizing the mapping $l(y; \cdot) \circ G =: l_G(y; \cdot)$ defined by a given mapping $l(\cdot; \cdot) : \mathcal{X} \times \Gamma \rightarrow \mathbf{R}$, where Γ stands for an open subset of \mathbb{R}^m enclosing $G(\Theta)$. Additionally, it will be assumed

(2.2) $G(\Theta) = \bigcup_{j=1}^{\infty} G^j(\Theta^j)$, where G^j denotes a C^2 -mapping defined on an open subset Θ^j of \mathbf{R}^{r_j} ,

(2.3) $l(\cdot; \cdot)$ is a C^2 -mapping.

3 Statement of the main result

The main result relies on the following additional assumptions.

(3.1) Under (2.2), (2.3) the set L_j , consisting of all $y \in \mathcal{X}$ such that $l(y, \cdot) \circ G^j$ has degenerated critical points, is a λ^n -null set for each $j \in \mathbb{N}$.

(3.2) Under (2.2), (2.3) every set L_{ij} ($i, j \in \mathbb{N}$) of all $y \in \mathcal{X}$ with $\nabla_{\vartheta^i} l(y, \cdot) \circ G^i = 0$, $\nabla_{\vartheta^j} l(y, \cdot) \circ G^j = 0$ and $\nabla_y l(\cdot, G^i(\vartheta^i)) = \nabla_y l(\cdot, G^j(\vartheta^j))$ for some $(\vartheta^i, \vartheta^j) \in \Theta^i \times \Theta^j$, $G^i(\vartheta^i) \neq G^j(\vartheta^j)$, is a λ^n -null set.

Later on we shall replace (3.1) by some sufficient conditions.

Theorem 3.1 *Let the assumptions (2.1) - (2.3) be fulfilled. If the mappings G^j ($j \in \mathbb{N}$) are C^2 -immersions, and if the conditions (3.1), (3.2) are valid, then*

$$K := \{y \in \mathcal{X} \mid l_G(y; \vartheta) = l_G(y; \tilde{\vartheta}) = \max_{\vartheta \in \Theta} l_G(y; \vartheta) \text{ for some different } \vartheta, \tilde{\vartheta} \in \Theta\} \in \mathcal{B}(\mathcal{X})$$

with $Q_Y(K) = 0$.

The proof is delegated to appendix B.

In the following we try to substitute condition (3.1). Our main tool will be provided by Lemma A.1 (cf. appendix A). Unfortunately, it can be applied directly only in the case that the dimension n of the sample space \mathcal{X} coincides with the dimension m of the parameter space Γ . But if we are in the position to modify the maximization problem in a suitable way we would be able to draw on Lemma A.1. We shall treat the cases $n \geq m$ and $m \geq n$ separately.

4 Specializations

In the case of $n \geq m$ we can use Lemma A.1 if we may reduce the dimension of the sample space by the following condition:

(4.1) There exist a C^2 -submersion $T : \mathcal{X} \rightarrow \mathbf{R}^m$ and a real-valued C^2 -mapping l^* on $T(\mathcal{X}) \times \Gamma$ such that $l(y; \cdot) = l^*(T(y); \cdot)$ holds for arbitrary $y \in \mathcal{X}$.

Since T is a C^1 -submersion, $T(\mathcal{X})$ is an open subset of \mathbb{R}^m , and moreover, $\lambda^n(T^{-1}(B)) = 0$ if $\lambda^m(B) = 0$ (cf. [8], Proposition A3). Then a direct application of Theorem 3.1 with Lemma A.1 leads to the following result concerning the uniqueness of the extremum estimation of ϑ .

Theorem 4.1 *Let the condition (4.1) as well as the assumptions (2.1) - (2.3) be valid, let the mappings G^j ($j \in \mathbb{N}$) be C^2 -immersions, and let condition (3.2) be fulfilled. If there exist some C^1 -diffeomorphism g from an open subset U of \mathbb{R}^m onto an open subset $g(U)$ of \mathbb{R}^m and a C^1 -mapping $\phi : \Gamma \rightarrow \mathbb{R}^m$ such that $t - \phi(\gamma) \in U$ and $\nabla_\gamma l^*(t; \cdot) = g(t - \phi(\gamma))$ hold for $(t, \gamma) \in T(\mathcal{X}) \times \Gamma$, then*

$$K := \{y \in \mathcal{X} \mid l_G(y; \vartheta) = l_G(y; \tilde{\vartheta}) = \max_{\vartheta \in \Theta} l_G(y; \vartheta) \text{ for some different } \vartheta, \tilde{\vartheta} \in \Theta\} \in \mathcal{B}(\mathcal{X})$$

with $Q_Y(K) = 0$.

Remark 4.2 *If $n = m$, condition (4.1) is satisfied, choosing for T the restriction of the identity mapping on \mathbb{R}^n to \mathcal{X} . Therefore we may restate in this case Theorem 4.1 without condition (4.1).*

Now let $m \geq n$. For reduction of the dimension of Γ we want to assume:

(4.2) Under (2.2), (2.3) there exist an open subset H of $\mathcal{X} \times \mathbb{R}^n$ with nonvoid $H_y := \{x \in \mathbb{R}^n \mid (y, x) \in H\}$ ($y \in \mathcal{X}$), a C^2 -mapping $l^* : H \rightarrow \mathbb{R}$ and a sequence $(F^j)_j$ of mappings $F^j : A^j \rightarrow \mathbb{R}^n$ such that the following properties are satisfied

- a) F^j is a C^2 -immersion on an open subset of \mathbb{R}^{p_j} for every $j \in \mathbb{N}$.
- b) If for $y \in \mathcal{X}$ and arbitrary $j \in \mathbb{N}$ the mapping $l(y, \cdot) \circ G^j$ has a degenerated critical point, then the mapping $l^*(y, \cdot) \circ F^j|(F^j)^{-1}(H_y)$ has a degenerated critical point too.

Under condition (4.2) the combination of Theorem 3.1 and Lemma A.1 (cf. appendix A) reads as follows.

Theorem 4.3 *Let the condition (4.2) as well as the assumptions (2.1) - (2.3) be valid, let the mappings G^j ($j \in \mathbb{N}$) be C^2 -immersions, and let condition (3.2) be fulfilled. If there exist some C^1 -diffeomorphism g from an open subset U of \mathbb{R}^n onto an open subset $g(U)$ of \mathbb{R}^n , an open subset V of \mathbb{R}^n with $V \supseteq \bigcup_{y \in \mathcal{X}} H_y$, and a C^1 -mapping $\phi : V \rightarrow \mathbb{R}^n$ such that $y - \phi(\gamma) \in U$ and $\nabla_\gamma l^*(y; \cdot) = g(y - \phi(\gamma))$ hold for $(y, \gamma) \in H$, then*

$$K := \{y \in \mathcal{X} \mid l_G(y; \vartheta) = l_G(y; \tilde{\vartheta}) = \max_{\vartheta \in \Theta} l_G(y; \vartheta) \text{ for some different } \vartheta, \tilde{\vartheta} \in \Theta\} \in \mathcal{B}(\mathcal{X})$$

with $Q_Y(K) = 0$.

Proof: Due to Lindelöf's theorem (cf. appendix C, Proposition C.2) we may find a sequence $(U_l \times V_l)_l$ of open subsets of $\mathbb{R}^n \times \mathbb{R}^n$ with $\bigcup_{l=1}^{\infty} U_l \times V_l = H$. In view of Lemma A.1 (cf. appendix A) the set B_{lj} of all $y \in U_l$ with $l^*(y, \cdot) \circ F^j | (F^j)^{-1}(V_l)$ having a degenerated critical point is a λ^n -null set for $l, j \in \mathbb{N}$. Then, condition (4.2) implies condition (3.1), and the statement of Theorem 4.1 follows from Theorem 3.1. ■

5 Maximum likelihood estimation in nonlinear regression models

Let $Y = F(\alpha) + U$ be a nonlinear regression model with nonstochastic regressors, where

(6.1) Y denotes the random vector of the endogenous variables,

(6.2) $F : A \rightarrow \mathbf{R}^n$ stands for the regression function defined on a subset A of \mathbf{R}^r , $r \leq n$,

(6.3) $U = (U_1, \dots, U_n)'$ symbolizes the random vector of the disturbances U_i which are supposed to be independently and normally distributed with

$$EU = 0, (\text{Var}(U_1), \dots, \text{Var}(U_n)) =: \tilde{F}(\beta), \quad \tilde{F} : (]0, \infty[)^q \rightarrow \mathbf{R}^n, \beta \mapsto (\beta_{i_1}, \dots, \beta_{i_n})$$

(i_1, \dots, i_n fixed values with $\{i_1, \dots, i_n\} = \{1, \dots, q\}$).

It is easy to see that the parameter vector (α, β) is identified if and only if

(6.4) the injectivity of the regression function F is supposed.

Moreover, we assume that

(6.5) a sequence $(p_j)_j$ of positive integers $p_j \leq n$, a sequence $(A^j)_j$ of open subsets A^j of \mathbf{R}^{p_j} and a sequence $(F^j)_j$ of mappings $F^j : A^j \rightarrow \mathbf{R}^n$ exist with

$$F(A) = \bigcup_{j=1}^{\infty} F^j(A^j).$$

W denotes the family of normal distributions with independent marginal distributions. $\Gamma := \mathbf{R}^n \times (]0, \infty[)^n$ is a parameter space of W . We can now apply our results of extremum estimation to the maximum likelihood estimation of (α, β) .

Theorem 5.1 *Let us retake assumptions (6.1)-(6.5), let $l(y, \cdot)$ denote the log likelihood function w.r.t. W and the realization y of Y . Furthermore let $G : A \times (]0, \infty[)^q \rightarrow \Gamma$ be defined by $G(\alpha, \beta) := (F(\alpha), \tilde{F}(\beta))$.*

If the mappings F^j are C^2 -immersions, then

$$K := \{y \in \mathbb{R}^n \mid l_G(y; \vartheta) = l_G(y; \tilde{\vartheta}) = \max_{\vartheta \in \Theta} l_G(y; \vartheta) \text{ for some different } \vartheta, \tilde{\vartheta} \in \Theta\} \text{ is a Borel subset of } \mathbb{R}^n$$

with $Q_Y(K) = 0$.

Proof:

Let for a positive integer j the mapping $G^j : A^j \times (]0, \infty[)^q \rightarrow \Gamma$ be defined by $G^j(\vartheta^j, \beta) = (F^j(\vartheta^j), \tilde{F}(\beta))$. Then by assumption G fulfills the conditions (2.1), (2.2).

Next let us introduce the open subset $H := \{(y, \mu) \in \mathbb{R}^n \times \mathbb{R}^n \mid \sum_{t \in T_i} (y_t - \mu_t)^2 \neq 0 \text{ for all } i \in \{1, \dots, q\}\}$ of $\mathbb{R}^n \times \mathbb{R}^n$, where $T_i := \{t \in \{1, \dots, n\} \mid \tilde{F}_t(\beta) = \beta_i\}$ for $i \in \{1, \dots, q\}$. Furthermore let us consider the mappings $h : H \rightarrow (]0, \infty[)^q$, defined by $h(y, \mu) = (\frac{1}{\#T_1} \sum_{t \in T_1} [y_t - \mu_t]^2, \dots, \frac{1}{\#T_q} \sum_{t \in T_q} [y_t - \mu_t]^2)$, and the mapping $l^* : H \rightarrow \mathbb{R}$, defined by

$$l^*(y, \mu) := l(y, \mu, \tilde{F} \circ h(y, \mu)) = -\frac{1}{2} \left(n(\ln(2\pi) + 1) + \sum_{i=1}^q \#T_i [\ln(\sum_{t \in T_i} (y_t - \mu_t)^2) - \ln(\#T_i)] \right).$$

By routine procedures it can be shown that l^* and $(F^j)_j$ satisfy condition (4.2). Note that we have

$$\nabla_{\beta} l(y; \mu, \cdot) \circ \tilde{F} = 0 \Leftrightarrow \beta = \left(\frac{1}{\#T_1} \sum_{t \in T_1} [y_t - \mu_t]^2, \dots, \frac{1}{\#T_q} \sum_{t \in T_q} [y_t - \mu_t]^2 \right), \text{ for all } (y, \mu) \in H.$$

Moreover we can define on $U := \{x \in \mathbb{R}^n \mid \sum_{t \in T_i} x_t^2 \neq 0 \text{ for all } i \in \{1, \dots, q\}\}$ the mapping $g : U \rightarrow \mathbf{R}^n$ by

$$g(x) = \sum_{i=1}^q \sum_{t \in T_i} \frac{\#T_i x_t}{\sum_{s \in T_i} x_s^2} e_t, \text{ where } \{e_1, \dots, e_n\} \text{ denotes the standard basis of } \mathbb{R}^n. \text{ We get for arbitrary } (y, \mu) \in H$$

$$y - \mu \in U, \nabla_{\mu} l^*(y; \cdot) = g(y - \mu), \nabla_y l^*(\cdot; \mu) = -g(y - \mu),$$

g is a bijective indefinitely differentiable function from U onto U with $g^{-1} = g$. Thus $\nabla_y l^*(\cdot; \mu) \neq \nabla_y l^*(\cdot; \tilde{\mu})$ for arbitrary $\mu \neq \tilde{\mu}$, which means that condition (3.2) is fulfilled. The statement of the theorem follows from Theorem 4.3. ■

6 Maximum likelihood estimation in curved exponential families

Let ν be a σ -finite measure on the σ -algebra $\mathcal{B}(\mathbb{R}^n)$ of Borel subsets of \mathbb{R}^n which is dominated by the Lebesgue measure on \mathbb{R}^n . Additionally, let $\mathcal{N} := \{\gamma \in \mathbb{R}^n \mid 0 < \int_{\mathbb{R}^n} \exp(\gamma'y)\nu(dy) < \infty\}$ and Γ be an open subset of \mathbb{R}^n enclosed in \mathcal{N} . Introducing $\psi : \mathcal{N} \rightarrow [-\infty, \infty]$, $\gamma \mapsto \ln(\int_{\mathbb{R}^n} \exp(\gamma'y)\nu(dy))$ we consider a minimal exponential family $W := \{P_\gamma \mid \gamma \in \Gamma\}$ of probability distributions having densities

$$f_\gamma : \mathbb{R}^n \rightarrow \mathbb{R}, y \mapsto \exp(\gamma'y - \psi(\gamma)) \quad (\gamma \in \Gamma)$$

with respect to ν . The parameter vector γ is identified since W is a minimal exponential family with parameter space $\Gamma \subseteq \mathcal{N}$ (cf. [2], Theorem 1.13). $G : \Theta \rightarrow \Gamma$ denotes an injective mapping which induces the subfamily $W_G := \{P_{G(\vartheta)} \in W \mid \vartheta \in \Theta\}$ of W . Now we may consult Theorem 4.1 concerning the uniqueness of the maximum likelihood estimation of the parameter vector ϑ .

Theorem 6.1 *Let the mapping G satisfy the conditions (2.1), (2.2), let Y be a random vector with distribution $Q_Y \in W_G$, and let $l(y; \cdot) : \Gamma \rightarrow \mathbb{R}$ denote the log likelihood function with respect to W and $y \in \mathbb{R}^n$. If the mappings G^j ($j \in \mathbb{N}$) are C^2 -immersions, then*

$$K := \{y \in \mathbb{R}^n \mid l_G(y; \vartheta) = l_G(y; \tilde{\vartheta}) = \max_{\vartheta \in \Theta} l_G(y; \vartheta) \text{ for some different } \vartheta, \tilde{\vartheta} \in \Theta\} \text{ is a Borel subset of } \mathbb{R}^n$$

with $Q_Y(K) = 0$.

Proof:

$\psi|_\Gamma$ is indefinitely differentiable (cf. [11], Satz 1.164), which implies that $\phi : \Gamma \rightarrow \mathbb{R}^n, \gamma \mapsto \nabla_\gamma \psi$, and $l(\cdot; \cdot) | \mathcal{X} \times \Gamma : \mathcal{X} \times \text{int}(\Gamma) \rightarrow \mathbb{R}$, defined by $l(y; \gamma) = \gamma'y - \psi(\gamma)$, are indefinitely differentiable. Moreover, for arbitrary $y \in \mathcal{X}$ and different $\gamma, \tilde{\gamma} \in \Gamma$ we may observe $\nabla_y l(\cdot; \gamma) = \gamma \neq \tilde{\gamma} = \nabla_y l(\cdot; \tilde{\gamma})$, and furthermore $\nabla_\gamma l(y; \cdot) = y - \nabla_\gamma \psi$. Thus the statement is a direct consequence of Theorem 4.1. \blacksquare

Remark:

Theorem 6.1 retains the result of Pazman (cf. [8], Theorem) mentioned in the introduction, which in turn also encompasses Pazman's criterion concerning the uniqueness of nonlinear least squares estimation in nonlinear regression models with nonstochastic regressors and i.i.d. disturbances (cf. [7], Theorem 3 and [9], Corollary 4.4.6).

7 Maximum likelihood estimation of location and scale parameter of a Gumbel distribution

Gumbel distributions build a subfamily of the so called extreme value distributions which play an important role in extreme value theory. The Gumbel distribution with location parameter $\mu \in \mathbb{R}$ and scale parameter $\sigma > 0$ is

defined by the Lebesgue density

$$f_{\mu,\sigma} : \mathbb{R} \rightarrow \mathbb{R}, \quad z \mapsto \frac{1}{\sigma} \exp\left(-\frac{z-\mu}{\sigma} - \exp\left(-\frac{z-\mu}{\sigma}\right)\right)$$

(cf. [5], p. 76). We want to investigate the uniqueness of the maximum likelihood estimation of (μ, σ) based on a random sample $Y := (Y_1, \dots, Y_n)$ ($n \geq 2$) from a Gumbel distribution.

For this purposes let us introduce the mapping

$$l(\cdot; \cdot) : \mathbb{R}^n \times (\mathbb{R} \times]0, \infty[) \rightarrow \mathbb{R}, \quad ((y_1, \dots, y_n); (\gamma_1, \gamma_2)) \mapsto n \ln(\gamma_2) + \sum_{i=1}^n \ln \circ f_{(0,1)}(\gamma_2 y_i - \gamma_1)$$

Since $\phi : \mathbb{R} \times]0, \infty[\rightarrow \mathbb{R} \times]0, \infty[$, $(\mu, \sigma) \mapsto (\frac{\mu}{\sigma}, \frac{1}{\sigma})$ is bijective, we may check easily that for every realization (y_1, \dots, y_n) of (Y_1, \dots, Y_n) the maximum likelihood estimation of (μ, σ) has at most one solution if and only if the mapping $l((y_1, \dots, y_n); \cdot)$ has at most one maximizing point. Therefore we might try to apply Theorem 3.1 to $l(\cdot; \cdot)$ and the identity mapping G on $\mathbb{R} \times]0, \infty[$. Obviously, both mappings together satisfy the assumptions (2.1) - (2.3), and G is a C^2 -immersion.

Observing that $\frac{df_{(0,1)}}{dz}(z) = f_{(0,1)}(z)(\exp(-z) - 1)$ holds for $z \in \mathbb{R}$, routine calculations lead to the following partial derivatives of first and second order for $l((y_1, \dots, y_n); \cdot) \circ G$ ($(y_1, \dots, y_n) \in \mathbb{R}^n$)

$$\begin{aligned} \frac{\partial l((y_1, \dots, y_n); \cdot) \circ G}{\partial \gamma_1}(\gamma_1, \gamma_2) &= n - \exp(\gamma_1) \sum_{i=1}^n \exp(-\gamma_2 y_i) \\ \frac{\partial l((y_1, \dots, y_n); \cdot) \circ G}{\partial \gamma_2}(\gamma_1, \gamma_2) &= \frac{n}{\gamma_2} - \sum_{i=1}^n y_i + \exp(\gamma_1) \sum_{i=1}^n y_i \exp(-\gamma_2 y_i) \\ \frac{\partial^2 l((y_1, \dots, y_n); \cdot) \circ G}{\partial \gamma_1^2}(\gamma_1, \gamma_2) &= -\exp(\gamma_1) \sum_{i=1}^n \exp(-\gamma_2 y_i) \\ \frac{\partial^2 l((y_1, \dots, y_n); \cdot) \circ G}{\partial \gamma_1 \partial \gamma_2}(\gamma_1, \gamma_2) &= \exp(\gamma_1) \sum_{i=1}^n y_i \exp(-\gamma_2 y_i) \\ \frac{\partial^2 l((y_1, \dots, y_n); \cdot) \circ G}{\partial \gamma_2^2}(\gamma_1, \gamma_2) &= -\frac{n}{\gamma_2^2} - \exp(\gamma_1) \sum_{i=1}^n y_i^2 \exp(-\gamma_2 y_i) \end{aligned}$$

Now let $(\hat{\gamma}_1, \hat{\gamma}_2)$ be a critical point of the function $l((y_1, \dots, y_n); \cdot) \circ G$. Then $\exp(\hat{\gamma}_1) = \frac{n}{\sum_{i=1}^n \exp(-\hat{\gamma}_2 y_i)}$ as well as

$$\frac{n}{\hat{\gamma}_2} = \sum_{i=1}^n y_i - \exp(\hat{\gamma}_1) \sum_{i=1}^n y_i \exp(-\hat{\gamma}_2 y_i), \text{ and hence}$$

$$\det \nabla \nabla_{(\hat{\gamma}_1, \hat{\gamma}_2)} l((y_1, \dots, y_n); \cdot) \circ G = \frac{\sum_{i=1}^n \exp(-\hat{\gamma}_2 y_i) (n y_i - \sum_{j=1}^n y_j)^2}{\sum_{i=1}^n \exp(-\hat{\gamma}_2 y_i)}$$

Thus the set L of all $(y_1, \dots, y_n) \in \mathbb{R}^n$ with $l((y_1, \dots, y_n); \cdot) \circ G$ having a degenerated critical point coincides with the subvector space of all $(y_1, \dots, y_n) \in \mathbb{R}^n$ with $n y_i = \sum_{j=1}^n y_j$ for $i = 1, \dots, n$. In particular L is a λ^n -null set.

Let us now consider for $(y_1, \dots, y_n) \in \mathbb{R}^n$ different critical points $(\hat{\gamma}_1, \hat{\gamma}_2)$ and $(\tilde{\gamma}_1, \tilde{\gamma}_2)$ of $l((y_1, \dots, y_n); \cdot) \circ G$ satisfying $\nabla_{(y_1, \dots, y_n)} l(\cdot; (\hat{\gamma}_1, \hat{\gamma}_2)) = \nabla_{(y_1, \dots, y_n)} l(\cdot; (\tilde{\gamma}_1, \tilde{\gamma}_2))$. This means that for each $i \in \{1, \dots, n\}$ the equation $\hat{\gamma}_2(\exp(\hat{\gamma}_1) \exp(-\hat{\gamma}_2 y_i) - 1) = \tilde{\gamma}_2(\exp(\tilde{\gamma}_1) \exp(-\tilde{\gamma}_2 y_i) - 1)$ is valid. Hence $\hat{\gamma}_2 \neq \tilde{\gamma}_2$, say $\hat{\gamma}_2 > \tilde{\gamma}_2$, and additionally $\hat{\gamma}_2 \exp(\hat{\gamma}_1) = (\hat{\gamma}_2 - \tilde{\gamma}_2) \exp(\hat{\gamma}_2 y_i) + \tilde{\gamma}_2 \exp(\tilde{\gamma}_1) \exp((\hat{\gamma}_2 - \tilde{\gamma}_2) y_i)$ for $i = 1, \dots, n$, which in turn implies $(\hat{\gamma}_2 - \tilde{\gamma}_2) \exp(\hat{\gamma}_2 y_i) + \tilde{\gamma}_2 \exp(\tilde{\gamma}_1) \exp((\hat{\gamma}_2 - \tilde{\gamma}_2) y_i) = (\hat{\gamma}_2 - \tilde{\gamma}_2) \exp(\hat{\gamma}_2 y_1) + \tilde{\gamma}_2 \exp(\tilde{\gamma}_1) \exp((\hat{\gamma}_2 - \tilde{\gamma}_2) y_1)$ for $i = 1, \dots, n$. The mapping $g : \mathbb{R} \rightarrow \mathbb{R}$, $x \mapsto (\hat{\gamma}_2 - \tilde{\gamma}_2) \exp(\hat{\gamma}_2 x) + \tilde{\gamma}_2 \exp(\tilde{\gamma}_1) \exp((\hat{\gamma}_2 - \tilde{\gamma}_2) x)$, is differentiable, and its derivatives satisfy

$$\frac{dg}{dx}(x) = (\hat{\gamma}_2 - \tilde{\gamma}_2)[\hat{\gamma}_2 \exp(\hat{\gamma}_2 x) + \tilde{\gamma}_2 \exp(\tilde{\gamma}_1) \exp((\hat{\gamma}_2 - \tilde{\gamma}_2) x)] > 0 \quad (x \in \mathbb{R})$$

Therefore g is injective, and we may conclude $y_1 = \dots = y_n$. Then we know that the set \hat{L} of all (y_1, \dots, y_n) such that $\nabla_{(y_1, \dots, y_n)} l(\cdot; (\hat{\gamma}_1, \hat{\gamma}_2)) = \nabla_{(y_1, \dots, y_n)} l(\cdot; (\tilde{\gamma}_1, \tilde{\gamma}_2))$ holds for some couple $(\hat{\gamma}_1, \hat{\gamma}_2)$ and $(\tilde{\gamma}_1, \tilde{\gamma}_2)$ of different critical points of $l((y_1, \dots, y_n); \cdot) \circ G$ is enclosed in the subvector space of all $(y_1, \dots, y_n) \in \mathbb{R}^n$ with $y_1 = \dots = y_n$. In particular \hat{L} is a λ^n -null set.

Altogether we have shown that $l(\cdot; \cdot)$ and G fulfill the conditions (3.1), (3.2), and this yields the following result concerning the uniqueness of the maximum likelihood estimation of (μ, σ) due to Theorem 3.1.

Theorem 7.1 *Let $Y := (Y_1, \dots, Y_n)$ ($n \geq 2$) be a random sample from the Gumbel distribution with the location parameter $\mu \in \mathbb{R}$ and scale parameter $\sigma > 0$, and let $L(y_1, \dots, y_n; \cdot)$ denote the likelihood function w.r.t. the family of Gumbel distributions and the realization (y_1, \dots, y_n) . Furthermore let the distribution of Y be symbolized by \mathbb{Q}_Y . Then*

$$K := \{(y_1, \dots, y_n) \in \mathbb{R}^n \mid L((y_1, \dots, y_n); \cdot) \text{ has at least two maximizing points}\}$$

is a Borel subset of \mathbb{R}^n with $\mathbb{Q}_Y(K) = 0$.

A Appendix

Lemma A.1 *Let H_1, H_2 be open subsets of \mathbb{R}^k , and let $f : H_1 \times H_2 \rightarrow \mathbb{R}$ be a C^2 -mapping. Moreover there exist some C^1 -diffeomorphism g from an open subset U of \mathbb{R}^k onto an open subset $g(U)$ of \mathbb{R}^k and a C^1 -mapping $\phi : H_2 \rightarrow \mathbb{R}^k$ such that $t - \phi(\gamma) \in U$ and $\nabla_\gamma f(t; \cdot) = g(t - \phi(\gamma))$ hold for $(t, \gamma) \in H_1 \times H_2$.*

If F denotes a C^2 -immersion from an open subset A of \mathbb{R}^p into H_2 , then $\lambda^k(B_F) = 0$, where B_F is defined to consist of all $t \in H_1$ such that $\nabla_\alpha f(t, \cdot) \circ F = 0$ and $\det \nabla \nabla_\alpha f(t, \cdot) \circ F = 0$ for some $\alpha \in H_2$.

Proof:

For $p = k$ we have

$$\nabla_\alpha f(t; \cdot) \circ F = 0, \quad \det \nabla \nabla_\alpha f(t; \cdot) \circ F = 0 \quad \Leftrightarrow \quad \nabla_{F(\alpha)} f(t; \cdot) = 0, \quad \det \nabla \nabla_{F(\alpha)} f(t; \cdot) = 0.$$

Thus, defining, $\tilde{\phi} : \tilde{U} \rightarrow \mathbf{R}^k, t \mapsto \phi(t) + g^{-1}(0)$, we may conclude $B_F \subseteq \tilde{\phi}(\{t \in \tilde{U} \mid \det J_t(\tilde{\phi}) = 0\})$. Note that g is a diffeomorphism with

$$\nabla_{F(\alpha)} f(t; \cdot) = g(t - \phi \circ F(\alpha)).$$

Sard's theorem (cf. appendix C, Proposition C.1) leads to $\lambda^k(B_F) = 0$.

Now let $p < k$.

Since F is a C^2 -immersion, we may conclude from the rank theorem together with standard orthonormalization that for an arbitrary $\alpha \in A$ there are C^1 -mappings $h_\alpha^1, \dots, h_\alpha^{k-p}$ defined on an open neighbourhood U_α of α in A satisfying

$$h_\alpha^i(\tilde{\alpha})' J_{\tilde{\alpha}}(F) = 0, \quad h_\alpha^i(\tilde{\alpha})' h_\alpha^i(\tilde{\alpha}) = 1, \quad h_\alpha^i(\tilde{\alpha})' h_{\tilde{g}^j}^q(\tilde{\alpha}) = 0 \quad (i \neq q)$$

for every $\tilde{\alpha} \in U_\alpha$ and arbitrary $i, q \in \{1, \dots, k-p\}$.

By Lindelöf's theorem (cf. appendix C, Proposition C.2) we may select a sequence $(\alpha(s))_s$ in A such that $(U_{\alpha(s)})_s$ is a cover of A . For abbreviation we set $U_s := U_{\alpha(s)}, h_s^i := h_{\alpha(s)}^i$ ($i = 1, \dots, k-p$). Furthermore $x_\nu : \mathbb{R}^k \rightarrow \mathbb{R}$ denotes the projection on the ν -th component ($\nu \in \{1, \dots, k\}$).

We observe for $(t, \alpha) \in H_1 \times A$

$$\nabla_\alpha f(t; \cdot) \circ F = J_\alpha(F)' \nabla_{F(\alpha)} f(t; \cdot)$$

and

$$\begin{aligned} \nabla \nabla_\alpha f(t; \cdot) \circ F &= \sum_{\nu=1}^k \frac{\partial f(t; \cdot)}{\partial x_\nu}(F(\alpha)) \nabla \nabla_\alpha x_\nu \circ F + J_\alpha(F)' \nabla \nabla_{F(\alpha)} f(t; \cdot) J_\alpha(F) \\ &= \sum_{\nu=1}^k x_\nu \circ g(t - \phi \circ F(\alpha)) \nabla \nabla_\alpha x_\nu \circ F - J_\alpha(F)' J_{t - \phi \circ F(\alpha)}(g) J_\alpha(\phi \circ F). \end{aligned}$$

Let for $s \in \mathbb{N}$ the mappings $g^s, \phi^s : W_s \rightarrow \mathbb{R}^k$ be defined by $g^s(\alpha, b) := \sum_{i=1}^{k-p} b_i h_s^i(\alpha)$ and $\phi^s(\alpha, b) := \phi \circ F(\alpha) + g^{-1} \circ g^s(\alpha, b)$, where W_s consists of all $(\alpha, b) \in U_s \times \mathbb{R}^{k-p}$ with $\sum_{i=1}^{k-p} b_i h_s^i(\alpha) \in g(U)$. Notice that W_s is an open subset of \mathbb{R}^k , and that g^s is a C^1 -mapping, which implies that ϕ^s is a C^1 -mapping.

Now let $(\hat{t}, \hat{\alpha}) \in H_1 \times A$ with $\nabla_{\hat{\alpha}} f(\hat{t}; \cdot) \circ F = 0$. Then there exist some $s \in \mathbb{N}$ and a vector $\hat{b} := (\hat{b}_1, \dots, \hat{b}_{k-p})$ from \mathbb{R}^{k-p} with

$$g(\hat{t} - \phi \circ F(\hat{\alpha})) = \nabla_{F(\hat{\alpha})} f(\hat{t}; \cdot) = \sum_{i=1}^{k-p} \hat{b}_i h_s^i(\hat{\alpha}).$$

In particular $(\hat{\alpha}, \hat{b}) \in W_s$, and $g(\hat{t} - \phi \circ F(\hat{\alpha})) = g^s(\hat{\alpha}, \hat{b})$. Hence $\hat{t} = \phi^s(\hat{\alpha}, \hat{b})$.

As a consequence of $J_\alpha(F)' h_s^i(\alpha) = 0$ for $\alpha \in U_s$ as well as $i = 1, \dots, k-p$ we obtain

$$\sum_{\nu=1}^k x_\nu \circ h_s^i(\alpha) \nabla \nabla_\alpha x_\nu \circ F = -J_\alpha(F)' J_\alpha(h_s^i),$$

and therefore

$$\nabla \nabla_{\hat{\alpha}} f(\hat{t}; \cdot) \circ F = -J_{\hat{\alpha}}(F)' J_{\hat{t}-\phi \circ F(\hat{\alpha})}(g) J_{\hat{\alpha}}(\phi^s(\cdot; \hat{b})).$$

Following the rules for determinants of partitioned matrices (cf. [3], p.43, equation (II)), we get

$$\begin{aligned} |\det[J_{\hat{\alpha}}(F), h_s^1(\hat{\alpha}), \dots, h_s^{k-p}(\hat{\alpha})]' J_{\hat{t}-\phi \circ F(\hat{\alpha})}(g) J_{(\hat{\alpha}, \hat{b})}(\phi^s)]| &= |\det J_{\hat{\alpha}}(F)' J_{\hat{t}-\phi \circ F(\hat{\alpha})}(g) J_{\hat{\alpha}}(\phi^s(\cdot; \hat{b}))| \\ &= |\det \nabla \nabla_{\hat{\alpha}} f(\hat{t}; \cdot) \circ F| \end{aligned}$$

$[J_{\hat{\alpha}}(F), h_s^1(\hat{\alpha}), \dots, h_s^{k-p}(\hat{\alpha})]' J_{\hat{t}-\phi \circ F(\hat{\alpha})}(g)$ has rank k since F is an immersion. Therefore we can conclude

$$\det \nabla \nabla_{\hat{\alpha}^j} f(\hat{t}; \cdot) \circ F^j = 0 \Leftrightarrow \det J_{(\hat{\alpha}, \hat{b})}(\phi^s) = 0$$

Thus $B_F \subseteq N := \bigcup_{s=1}^{\infty} \phi^s(\{(\alpha, b) \in W_s \mid \det J_{(\alpha, b)}(\phi^s) = 0\})$. Applying Sard's theorem (cf. appendix C, Proposition C.1), we get N as a set of Lebesgue-measure zero, which completes the proof. \blacksquare

B Appendix

Proof of Theorem 3.1:

Let us retake notations and assumptions from Theorem 3.1. Furthermore let us introduce for positive integer i, j the set M_{ij} consisting of all $y \in \mathcal{X}$ with $\nabla_{\vartheta^i} l(y, \cdot) \circ G^i = 0$, $\nabla_{\vartheta^j} l(y, \cdot) \circ G^j = 0$ and $l(y, G^i(\vartheta^i)) = l(y, G^j(\vartheta^j))$ for some ϑ^i, ϑ^j with $G^i(\vartheta^i) \neq G^j(\vartheta^j)$. Obviously, $K \subseteq \bigcup_{(i,j) \in \mathbb{N} \times \mathbb{N}} M_{ij}$. Therefore it remains to show

- (1) M_{ij} is a λ^n -null set for arbitrary $i, j \in \mathbb{N}$.
- (2) K is a Borel subset of \mathcal{X} .

proof of (1):

Let us define for $i, j \in \mathbb{N}$ the open subset $U := \{(\vartheta^i, \vartheta^j, y) \in \Theta^i \times \Theta^j \times \mathcal{X} \mid G^i(\vartheta^i) \neq G^j(\vartheta^j)\}$ of $\Theta^i \times \Theta^j \times \mathcal{X}$, and the set $Z := h^{-1}(\{0\}) \cap \Theta^i \times \Theta^j \times (\mathbb{R}^n \setminus (L_i \cup L_j \cup L_{ij}))$, where

$$h : U \rightarrow \mathbf{R}^{r_i+r_j+1}, (\vartheta^i, \vartheta^j, y) \mapsto (\nabla_{\vartheta^i} l(y; \cdot) \circ G^i, \nabla_{\vartheta^j} l(y; \cdot) \circ G^j, l(y; G^i(\vartheta^i)) - l(y; G^j(\vartheta^j))).$$

Let $(\hat{\vartheta}^i, \hat{\vartheta}^j, y)$ be an element of Z and $s \in \{1, \dots, n\}$ with $\frac{\partial l(\cdot; G^i(\hat{\vartheta}^i))}{\partial y_s}(y) \neq \frac{\partial l(\cdot; G^j(\hat{\vartheta}^j))}{\partial y_s}(y)$. Using the Laplace-expansion of determinants and the rules of partitioned matrices (cf. [3], p.43, equation (I)), we obtain

$$\begin{aligned} &\det[J_{(\hat{\vartheta}^i, \hat{\vartheta}^j)}(h(\cdot, \cdot, y)), \frac{\partial h}{\partial y_s}(\hat{\vartheta}^i, \hat{\vartheta}^j, y)] \\ &= \det(\nabla \nabla_{\hat{\vartheta}^i} l(y; \cdot) \circ G^i) \det(\nabla \nabla_{\hat{\vartheta}^j} l(y; \cdot) \circ G^j) \left[\frac{\partial l(\cdot; G^i(\hat{\vartheta}^i))}{\partial y_s}(y) - \frac{\partial l(\cdot; G^j(\hat{\vartheta}^j))}{\partial y_s}(y) \right] \neq 0, \end{aligned}$$

noticing $y \notin L_i \cup L_j$. Thus Z is a subset of $\tilde{U} := \{(\vartheta^i, \vartheta^j, y) \in U \mid \text{rank of } J_{(\vartheta^i, \vartheta^j, y)}(h) = r_i + r_j + 1\}$, which is an open subset of $\mathbb{R}^{r_i+r_j+n}$. Therefore $h \mid \tilde{U}$ is a C^1 -submersion and $\tilde{Z} := (h \mid \tilde{U})^{-1}(\{0\})$ is empty or a $(n-1)$ -dim. C^1 -submanifold of $\mathbf{R}^{r_i+r_j+n}$. We have

$$M_{ij} \setminus (L_i \cup L_j \cup L_{ij}) = Pr(Z) \subseteq Pr(\tilde{Z}),$$

where Pr denotes the canonical projection from $\mathbb{R}^{r_i+r_j+n}$ onto \mathbb{R}^n . By Sard's theorem (cf. appendix C, Proposition C.1) we get $\lambda^n(Pr(\tilde{Z})) = 0$ and, due to assumptions (3.1), (3.2),

$$\lambda^n(M_{ij}) = \lambda^n(M_{ij} \setminus (L_i \cup L_j \cup L_{ij})) + \lambda^n(L_i \cup L_j \cup L_{ij}) = 0.$$

proof of (2):

For positive integers i, j we define the open subset $N_{ij} := \{(\vartheta^i, \vartheta^j) \in \Theta^i \times \Theta^j \mid G^i(\vartheta^i) \neq G^j(\vartheta^j)\}$ of $\Theta^i \times \Theta^j$ respectively $\mathbf{R}^{r_i+r_j}$. Applying Lindelöf's Theorem (cf. appendix C, Proposition C.2) and using the local compactness of N_{ij} we get a sequence $(U_\nu \times V_\nu)_\nu$ of compact sets $U_\nu \times V_\nu$ satisfying $N_{ij} = \bigcup_{\nu=1}^{\infty} U_\nu \times V_\nu$. Since each set $U_\nu \times V_\nu$ is sequentially compact, every $y \in \mathcal{X}$ being an accumulation point of the set

$$G_\nu^{ij} := \{y \in \mathcal{X} \mid l(y; G^i(\vartheta^i)) = l(y; G^j(\vartheta^j)) = \max_{\vartheta \in \vartheta} l_G(y; \vartheta) \text{ for some } (\vartheta^i, \vartheta^j) \in U_\nu \times V_\nu\}$$

is also an element of G_ν^{ij} , i.e. the sets G_ν^{ij} are closed in \mathcal{X} and therefore Borel subsets. Then K is a Borel subset because

$$K = \bigcup_{i=1}^{\infty} \bigcup_{j=1}^{\infty} \bigcup_{\nu=1}^{\infty} G_\nu^{ij}$$

Therefore (2) is shown, which completes the proof. ■

C Appendix

Proposition C.1 (Special versions of Sard's theorem) *Let $f : U \rightarrow \mathbb{R}^t$ denote a C^r -mapping ($r \in \mathbb{N}$) from an open subset U of \mathbb{R}^s into \mathbb{R}^t . Then we can state:*

- .1 *If $s = t$, then $f(\{x \in U \mid \det J_x(f) = 0\})$ is a λ^t -null set.*
- .2 *If $A \subseteq U$ is a m -dimensional C^r -submanifold of \mathbb{R}^s with $0 \leq m < t$, then $f(A)$ is a λ^t -null set.*

These versions of Sard's theorem may be found in [1] (Corollary 3.3.17.4 and Theorem 4.3.1) or in [4] (p. 69) or in [10] (remark on Definition 3.3 and Theorem 3.1).

Proposition C.2 (Lindelöf's theorem) *Let (Ω, τ) denote a topological Hausdorff space such that τ has a countable base. Then every open cover of a subset $A \subseteq \Omega$ has a countable subcover.*

For a proof cf. e.g. [6] (p.49).

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