

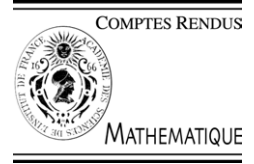


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Statistics/Probability Theory

Estimation of the offspring mean of a supercritical or near-critical size-dependent branching process

Nadia Lalam^a, Christine Jacob^b

^a EURANDOM, P.O. Box 513, 5600 MB Eindhoven, The Netherlands

^b Unité de biométrie, INRA, 78352 Jouy-en-Josas cedex, France

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Abstract

We consider a single-type supercritical or near-critical size-dependent branching process $\{N_n\}_n$ such that the offspring mean converges to a limit $m \geq 1$ with a rate of convergence of order N_n^α as the population size N_n grows to ∞ and the variance may change at the rate N_n^β , where $\alpha > 0$ and $-1 \leq \beta < 1$. The offspring mean depends on an unknown parameter θ_0 that we estimate on the non-extinction set by using the conditional least squares method. We prove the strong consistency of the estimator of θ_0 as $n \rightarrow \infty$ under some general conditions on the asymptotic behavior of the process. We also give its asymptotic distribution for a certain class of size-dependent branching processes. **To cite this article:** *N. Lalam, C. Jacob, C. R. Acad. Sci. Paris, Ser. I 339 (2004).*

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Résumé

Estimation de la descendance moyenne d'un processus de branchement taille-dépendant supercritique ou presque-critique. On considère un processus de branchement taille-dépendant unitype $\{N_n\}_n$ supercritique ou presque-critique tel que sa descendance moyenne converge vers une limite $m \geq 1$ à une vitesse de l'ordre de N_n^α lorsque l'effectif de la population N_n tend vers l'infini et tel que sa variance évolue à la vitesse N_n^β où $\alpha > 0$ et $-1 \leq \beta < 1$. La descendance moyenne dépend d'un paramètre inconnu θ_0 que l'on estime sur l'ensemble de non-extinction du processus à l'aide de la méthode des moindres carrés conditionnels. On démontre la consistance forte de l'estimateur de θ_0 quand $n \rightarrow \infty$ sous des hypothèses générales concernant le comportement asymptotique du processus. On donne aussi sa distribution asymptotique pour une certaine classe de processus taille-dépendants. **Pour citer cet article :** *N. Lalam, C. Jacob, C. R. Acad. Sci. Paris, Ser. I 339 (2004).*

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E-mail addresses: lalam@eurandom.tue.nl (N. Lalam), cj@banian.jouy.inra.fr (C. Jacob).

1. Introduction

We are concerned with the estimation of the offspring mean of a supercritical or near-critical size-dependent single-type branching process in discrete time. For a survey of inference for branching processes, see [1]. The size N_{n+1} of the population at generation $n + 1$ is defined by

$$N_{n+1} = \sum_{i=1}^{N_n} Y_{n+1,i}, \tag{1}$$

where $Y_{n+1,i}$ is the offspring size at generation $n + 1$ of the i -th individual from generation n . The initial size N_0 is given and we assume that, conditionally to $F_n = \sigma(N_0, \dots, N_n)$, the $\{Y_{n+1,i}\}_i$ are independently and identically distributed (i.i.d.) with $0 < p_{N0} + p_{N1} < 1$, for all $N \geq 1$, where $\{p_{Nj}; j \in \mathbb{N}\}$ is the offspring distribution, when the population size equals N , and with the offspring mean $m(N)$ and variance $\sigma^2(N)$ when the population size equals N satisfying:

A1: for all $N \geq 1$, $m(N) = m + f(N)$; $|f(N)| \leq KN^{-\alpha}$, $K < \infty$, $\alpha > 0$, $m \geq 1$;

A2: for all $N \geq 1$, $\sigma^2(N) \leq \sigma^2 N^\beta$; $0 < \sigma^2 < \infty$, $-1 \leq \beta < 1$;

A3: when $m = 1$, for all $N \geq 1$, $m(N) > 1$, the function $N \mapsto m(N)$ decreases to 1, $N \mapsto \sigma^2(N)/(N^2(m(N) - 1))$ is ultimately decreasing and satisfies $\int_1^\infty \sigma^2(x)/(x^2(m(x) - 1)) dx < \infty$.

The size-dependent branching process is called supercritical when $m > 1$ and near-critical when $m = 1$.

We assume that $m(\cdot)$ depends on a finite dimensional and identifiable parameter θ_0 that we estimate and on a nuisance part depending on a parameter v_0 that may be of infinite dimension. Denote $m(N)$ by $m_{\theta_0, v_0}(N)$.

The estimator $\hat{\theta}_{h,n,\gamma,v}$ will minimize over θ the conditional least squares based on $n - h + 1$ successive observations:

$$\tilde{S}_{h,n,\gamma,v}(\theta) = \sum_{k=h+1}^n (N_k - m_{\theta,v}(N_{k-1})N_{k-1})^2 N_{k-1}^{-\gamma}, \tag{2}$$

where $m_{\theta,v}(\cdot)$ is the offspring mean in which θ is unknown, v has a given value that may depend on n , and $\gamma \in \mathbb{R}$. One of the advantage of conditional least squares methodology is that it does not require the knowledge of the exact law of $\{Y_{n,i}\}_{i,n}$ unlike methods based on the likelihood. The asymptotic properties of $\{\hat{\theta}_{h,n,\gamma,v}\}_n$ will be studied on the set of non-extinction $\varepsilon_\infty = \{\overline{\lim}_{n \rightarrow \infty} N_n \neq 0 \text{ a.s.}\}$ by increasing n to ∞ , with either h or $n - h$ fixed.

From Eq. (1), $\{N_n\}_n$ follows the stochastic nonlinear regressive model $N_{n+1} = m(N_n)N_n + \eta_{n+1}$, where the noise $\eta_{n+1} = \sum_{i=1}^{N_n} [Y_{n+1,i} - m(N_n)]$ is a martingale difference satisfying $E(\eta_{n+1}^2 | F_n) \leq \sigma^2 N_n^{1+\beta}$. Estimation in this setting has been studied by Lai [5] and Skouras [8] but their methods require conditions that are difficult to check in practice. In order to get the consistency, we will rather rely on a minimum contrast method [9] and the rate of convergence will be obtained thanks to a central limit theorem [7].

2. Strong consistency of $\{\hat{\theta}_{h,n,\gamma,v}\}_n$ in the general model (A1, A2, A3)

Let $(\theta_0, v_0) \in \Theta \times \mathbb{R}^{d_2}$, where Θ is a compact set in \mathbb{R}^{d_1} , $d_1 \in \mathbb{N}$, $d_2 \in \mathbb{N}$ when v is of finite dimension or $d_2 = \mathbb{N}$ when v is of infinite dimension.

Let $B_\delta^c = \{\theta = (\theta_1, \dots, \theta_{d_1}) \in \Theta : \sum_{k=1}^{d_1} |\theta_k - \theta_{0,k}| \geq \delta\}$, where $\delta > 0$.

Let $v(N) = N^\psi$, where $\psi \in \mathbb{R}$ and define the two semi-norms $\|u(\cdot)\|_{n,\infty} = \sup_{h+1 \leq k \leq n} |u(N_{k-1})|$ and $\|u(\cdot)\|_n^2 = \sum_{k=h+1}^n u^2(N_{k-1}) N_{k-1}^{2(1-\psi)-\gamma} [\sum_{k=h+1}^n N_{k-1}^{2(1-\psi)-\gamma}]^{-1}$ for some function $u(\cdot)$.

Theorem 2.1. *Assume the following conditions on the non-extinction set ε_∞ :*

(1) B1: for all $\delta > 0$, $\underline{\lim}_{n \rightarrow \infty} \inf_{\theta \in B_\delta^c} \|(m_{\theta_0,v}(\cdot) - m_{\theta,v}(\cdot))v(\cdot)\|_n \stackrel{\text{a.s.}}{\neq} 0$;

B2: $\overline{\lim}_{n \rightarrow \infty} \sup_{\theta \in B_\delta^c} \|(m_{\theta_0, v}(\cdot) - m_{\theta, v}(\cdot))v(\cdot)\|_{n, \infty} < \infty$ a.s. B1 and B2 imply that θ_0 is uniformly asymptotically identifiable in $m_{\theta_0, v}(\cdot)$ at the exact rate $v(\cdot)$ for the semi-norm $\{\|\cdot\|_n\}_n$;

(2) B3: $\overline{\lim}_{n \rightarrow \infty} \|(m_{\theta_0, v_0}(\cdot) - m_{\theta_0, v}(\cdot))v(\cdot)\|_n \stackrel{a.s.}{=} 0$, i.e. $(m_{\theta_0, v_0}(\cdot) - m_{\theta_0, v}(\cdot))v(\cdot)$ is asymptotically negligible;

(3) B4: (i) $\{\sum_{k=h+1}^n N_{k-1}^{2(1-\psi)-\gamma}\}_n$ increases a.s. to ∞ , as $n \rightarrow \infty$;

(ii) there exists h_0 such that $\sum_{k=h_0+1}^\infty N_{k-1}^{2[2(1-\psi)-\gamma]} N_{k-1}^{\beta+2\psi-1} (\sum_{l=h+1}^k N_{l-1}^{2(1-\psi)-\gamma})^{-2} < \infty$ a.s. (take $h_0 = h$ when h is fixed);

(4) B5: for all $\delta > 0$, for all N , $\sup_{\theta \in B_\delta^c} (m_{\theta_0, v}(N) - m_{\theta, v}(N))$ is attained for some θ_N^{sup} (respectively, $\inf_{\theta \in B_\delta^c} (m_{\theta_0, v}(N) - m_{\theta, v}(N))$ is attained for some θ_N^{inf}).

Then, $\{\hat{\theta}_{h, n, \gamma, v}\}_n$ is strongly consistent.

Proof. The proof (detailed in [6]) relies on a sufficient condition concerning the minimum contrast method [9] and on the martingale difference property of $\{N_k - m_{\theta_0, v_0}(N_{k-1})N_{k-1}\}_k$ [2]. \square

Remark 1. Let $a_0 = 1$ and for $n \geq 1$, $a_n = m^n$ in the supercritical case, $a_n = a_{n-1}m(a_{n-1})$ in the near-critical case and let $W_n = N_n a_n^{-1}$. Under A1, A2 and A3, there exists an integrable random variable W such that

$$\lim_{n \rightarrow \infty} W_n \stackrel{a.s.}{=} W; \quad P(W > 0) > 0; \quad \varepsilon_\infty = \{W > 0 \text{ a.s.}\} = \left\{ \lim_{n \rightarrow \infty} N_n \stackrel{a.s.}{=} \infty \right\}. \tag{3}$$

In the near-critical case, $W \stackrel{a.s.}{=} 1$ (see Klebaner [4] for the proof in the supercritical case and Kersting [3] in the near-critical one). Thanks to Toeplitz lemma, relationship (3) implies that we can replace $\{N_{k-1}\}_k$ by $\{a_{k-1}\}_k$ in assumption B4.

Remark 2. When $\gamma = 1 + \beta$ and h is fixed, B4(ii) is always satisfied (see page 158 of [2]).

3. Strong consistency and rate of convergence in a subclass of model (A1, A2, A3)

We study the properties of $\hat{\theta}_{h, n, \gamma, v} - \theta_0$ properly normalized under the more accurate model

($\widetilde{A1}$, $\widetilde{A2}$, $\widetilde{A3}$) which is a particular case of (A1, A2, A3), where $\widetilde{A1}$: for all $N \geq 1$, $m_{\theta, v}(N) = m + \theta N^{-\alpha} + r_{\theta, v}(N)$, where m and α are assumed known and $r_{\theta, v}(N) = o(N^{-\bar{\alpha}})$ with $\bar{\alpha} > \alpha$;

$\widetilde{A2}$: when $m > 1$, for all $N \geq 1$, $\sigma^2(N) = \sigma^2 N^\beta - r_+(N)$, and when $m = 1$, for N large enough, $\sigma^2(N) = \sigma^2 N^\beta - r_+(N)$, $r_+(N) \geq 0$, $r_+(N) = o(N^\beta)$, $0 < \sigma^2 < \infty$ and $-1 \leq \beta < 1$.

Let $B_n = \sqrt{\sum_{k=h+1}^n a_{k-1}^{1+\beta+2(1-\alpha)-2\gamma}}$, $D_n = \sum_{k=h+1}^n a_{k-1}^{2(1-\alpha)-\gamma}$ and $\Phi_{h, n, \gamma} = B_n D_n^{-1}$.

Let the assumptions

C1: (i) $\overline{\lim}_{N \rightarrow \infty} \sup_\theta |r_{\theta, v}(N)|N^{\bar{\alpha}} < \infty$;

(ii) B5, i.e. for all $\delta > 0$, for all N , $\sup_{\theta \in B_\delta^c} (m_{\theta_0, v}(N) - m_{\theta, v}(N))$ is attained for some θ_N^{sup} (respectively $\inf_{\theta \in B_\delta^c} (m_{\theta_0, v}(N) - m_{\theta, v}(N))$ is attained for some θ_N^{inf});

C2: (i) $\{\sum_{k=h+1}^n a_{k-1}^{2(1-\alpha)-\gamma}\}_n$ increases to ∞ , as $n \rightarrow \infty$;

(ii) there exists h_0 such that $\sum_{k=h_0+1}^\infty a_{k-1}^{2[2(1-\alpha)-\gamma]+[\beta+2\alpha-1]} (\sum_{l=h+1}^k a_{l-1}^{2(1-\alpha)-\gamma})^{-2} < \infty$;

C3: (i) for all N , $\theta \mapsto r_{\theta, v}(N)$ is twice continuously differentiable in a neighborhood of θ_0 and there exist $M' < \infty$, $M'' < \infty$ such that $\sup_\theta |r'_{\theta, v}(N)|N^{\bar{\alpha}} \leq M'$ and $\sup_\theta |r''_{\theta, v}(N)|N^{\bar{\alpha}} \leq M''$, for all N ;

(ii) for all N , $\sup_\theta r''_{\theta, v}(N)$ is attained for some θ_N^{sup} (resp. $\inf_\theta r''_{\theta, v}(N)$ is attained for some θ_N^{inf});

C4: when h is fixed, $\lim_{n \rightarrow \infty} B_n = \infty$;

C5: if $v \neq v_0$, $\lim_{n \rightarrow \infty} [\sum_{k=h+1}^n a_{k-1}^{2-\gamma-\bar{\alpha}-\alpha}] B_n^{-1} = 0$;

C6: for all $x \in \mathbb{R}$, $\lim_{H \rightarrow \infty} \lim_{n \rightarrow \infty} \sup_{H+1 \leq k \leq n} E(R_k^2 1_{\{R_k^2 \geq B_{k,n}^2 x^2\}} | F_{k-1}) \stackrel{\text{a.s.}}{=} 0$, where $R_k = [Y_{k,1} - m_{\theta_0, v_0}(N_{k-1})] \times m'_{\theta_0, v}(N_{k-1}) W_{k-1}^{1-\gamma} a_{k-1}^{\frac{1}{2}(-\beta+2\alpha)}$ and $B_{k,n} = B_n a_{k-1}^{\frac{1}{2}[-\beta-2(1-\alpha)+2\gamma]}$ (Lindeberg condition type).

According to the linear Taylor series expansion applied to the first derivative of the contrast (2):

$$\Phi_{h,n,\gamma}^{-1}(\hat{\theta}_{h,n,\gamma,v} - \theta_0) = P_{h,n,\gamma,v} [Q_{h,n,\gamma,v}]^{-1}, \quad (4)$$

where $P_{h,n,\gamma,v} = [\sum_{k=h+1}^n \sum_{i=1}^{N_{k-1}} [Y_{k,i} - m_{\theta_0, v}(N_{k-1})] m'_{\theta_0, v}(N_{k-1}) N_{k-1}^{1-\gamma}] B_n^{-1}$, $Q_{h,n,\gamma,v} = [m'_{\theta_n, v}(N_{k-1}) + m_{\theta_n, v}(N_{k-1}) m''_{\theta_n, v}(N_{k-1}) - N_k N_{k-1}^{-1} m''_{\theta_n, v}(N_{k-1})] N_{k-1}^{2-\gamma} D_n^{-1}$ and $\theta_n \in]\min(\hat{\theta}_{h,n,\gamma,v}, \theta_0), \max(\hat{\theta}_{h,n,\gamma,v}, \theta_0)[$; the symbol ' designates the derivative with respect to θ .

Theorem 3.1. Under C1 and C2 on ε_∞ , $\lim_{n \rightarrow \infty} \hat{\theta}_{h,n,\gamma,v} \stackrel{\text{a.s.}}{=} \theta_0$. Assume in addition C3 to C6 on ε_∞ , then

$$\lim_{n \rightarrow \infty} P_{h,n,\gamma,v} \stackrel{d}{=} P, \quad E[\exp(itP)] = E\left[\exp\left(-\frac{t^2}{2} \sigma^2 W^{1+\beta+2(1-\alpha)-2\gamma}\right)\right],$$

$$\lim_{n \rightarrow \infty} Q_{h,n,\gamma,v} \stackrel{\text{a.s.}}{=} W^{2(1-\alpha)-\gamma}.$$

The best rate of convergence is attained for $\gamma = 1 + \beta$, and for this value of γ , under $\beta + 2\alpha < 1$, in the supercritical case, $\Phi_{h,n,\gamma}^{-1} = 0(a_n^{\frac{1-\beta-2\alpha}{2}})$, and in the near-critical case, $\Phi_{h,n,\gamma}^{-1} > a_h^{\frac{1-\beta-2\alpha}{2}} \sqrt{n-h}$. Under $\beta + 2\alpha = 1$, $\Phi_{h,n,\gamma}^{-1} = \sqrt{n-h}$.

Proof. Strong consistency is a consequence of Theorem 2.1 and Remark 1. We establish that the asymptotic distribution of $\{P_{h,n,\gamma,v}\}_n$ is a mixture of Gaussian laws by using the asymptotic behavior of the process (3) and a central limit theorem for random sums (Rahimov [7]). The proof of the a.s. limit of $\{Q_{h,n,\gamma,v}\}_n$ relies on (3) and a strong law of large numbers (Hall and Heyde [2]). Details are given in [6]. \square

Remark 3. Following the same reasoning, Theorem 3.1 also holds when estimating the unknown limit parameter m in the supercritical model $m(N) = m + 0(N^{-\alpha})$. The only amendment to make is to replace α (respectively $\bar{\alpha}$) by 0 (respectively α) in conditions C1–C6 and in the statement of the theorem. Since (m, θ) is not asymptotically identifiable, we cannot estimate simultaneously m and θ (see [6]).

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