

Exponential ergodicity of branching processes with competition and immigration

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(第17届马氏过程及相关领域研讨会)

Feller's branching diffusion

[Galton–Watson 1874] established branching process from i.i.d. \mathbb{N} -valued r.v. :

$$X(n) = \sum_{i=1}^{X(n-1)} \xi_{n,i}, \quad n \geq 1.$$

Let $m = \mathbb{E}[\xi_{n,i}]$ and $2c = \text{Var}[\xi_{n,i}]$. Then ($b := 1 - m$)

$$\begin{aligned} X(n) - X(n-1) &= \sum_{i=1}^{X(n-1)} (\xi_{n,i} - m) + (m-1)X(n-1) \\ &= \sqrt{2cX(n-1)} \sum_{i=1}^{X(n-1)} \frac{(\xi_{n,i} - m)}{\sqrt{2cX(n-1)}} - bX(n-1). \end{aligned}$$

A Feller's branching diffusion may arise as the scaling limit [Feller 1951]:

$$X_t = \lim_{k \rightarrow \infty} \frac{1}{k} X(\lfloor kt \rfloor), \quad t \geq 0.$$

Feller's branching diffusion

The Feller's branching diffusion can be constructed as the solution to

$$x(t) = x + \int_0^t \sqrt{2cx(s)} dB_s - \int_0^t bx(s) ds,$$

where $b \in \mathbb{R}$ and $c, x \geq 0$. This equation is *weakly* equivalent to

$$x(t) = x + \int_0^t \int_0^{x(s)} W(ds, du) - \int_0^t bx(s) ds,$$

where $W(ds, du)$ is a time-space Gaussian white noise based on $2cdsdu$.

The corresponding transition semigroup $(P_t)_{t \geq 0}$ satisfies the **(branching property)**:

$$P_t(x, \cdot) * P_t(y, \cdot) = P_t(x + y, \cdot), \quad x, y \in \mathbb{R}_+,$$

This means different individuals act independently.

In general, a **continuous-state branching process (CB-process)** is a càdlàg $[0, \infty]$ -valued Markov process satisfying the **branching property** and it solves the **stochastic equation** [Bertoin–Le Gall 2006; Dawson–Li 2006/2012]:

$$X_t = X_0 + \int_0^t \int_0^{X_s} L(ds, du).$$

Here $L(ds, du)$ is a **one-sided** Lévy white noise given by

$$L(ds, du) = W(ds, du) - bdsdu + \int_0^1 z\tilde{M}(ds, dz, du) + \int_1^\infty zM(ds, dz, du),$$

where $M(ds, dz, du)$ is a Poisson random measure on $(0, \infty)^3$.

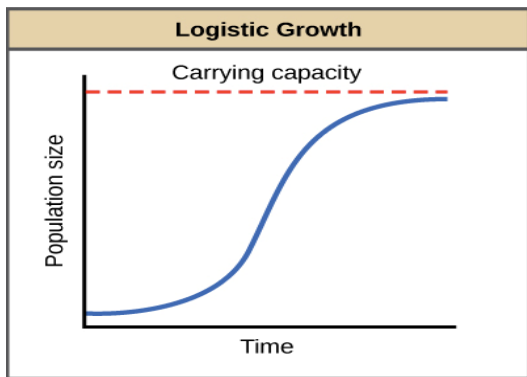
- $Z_t := Z_0 + \int_0^t \int_0^1 L(ds, du)$ is a one-sided Lévy process.
- When $M(ds, dz, du) \equiv 0$, the solution reduces to a Feller's branching diffusion.
- The process either goes to ∞ or goes to 0 as $t \rightarrow \infty$.

A deterministic model

A **logistic growth model** can be constructed as the solution to:

$$X_t = X_0 - \int_0^t (bX_s + dX_s^2) ds,$$

where $-b > 0$ is the rate for each individual to reproduce offspring and $d > 0$ describes competition between each pair of individuals.



[Berestycki et al. 2018] introduced the **branching processes with competition**

$$X_t = x + \int_0^t \int_0^{X_s} L(ds, du) - \int_0^t g(X_{s-}) ds.$$

where g is a nondecreasing continuous function satisfying $g(0) = 0$.

- When $g(x) \equiv 0$, the solution reduces to a CB-process.
- When $g(x) = dx^2$, for some $d > 0$, the solution reduces to the **logistic branching process** introduced by [Lambert 2005].
- Since 0 is absorbing, it usually **doesn't have a stationary distribution**.

The generator of a CBC-process is given by

$$Lf(x) = [-bx - g(x)]f'(x) + cx f''(x) + x \int_0^\infty [f(x+z) - f(x) - z f'(x) \mathbf{1}_{\{z \leq 1\}}] \mu(dz).$$

Theorem [Lambert 2005]

Assume the following:

- (1) $g(x) = dx^2$ for some $d > 0$;
- (2)

$$\int_1^\infty \log z \mu(dz) < \infty.$$

Then $\lim_{t \rightarrow \infty} X_t = 0$ a.s.

Question: How to construct a stationary model?

Let $\eta(t)$ be a subordinator given by

$$\eta(t) = \beta t + \int_0^t \int_0^\infty z N(ds, dz).$$

where $N(ds, dz)$ is a Poisson random measure on $(0, \infty)^2$ with intensity $ds\nu(dz)$. The **continuous-state branching process with immigration and competition (CBIC-process)** is defined as the solution to

$$X_t = \int_0^t \int_0^{X_s} L(ds, du) - \int_0^t g(X_{s-}) ds + \eta_t, \quad (1)$$

The generator of a CBIC-process is given by

$$\begin{aligned} Lf(x) &= [-bx - g(x)]f'(x) + cx f''(x) \\ &\quad + x \int_0^\infty [f(x+z) - f(x) - zf'(x)\mathbf{1}_{\{z \leq 1\}}] \mu(dz) \\ &\quad + \beta + \int_0^\infty [f(x+z) - f(x)] \nu(dz). \end{aligned}$$

Branching processes with immigration and competition

The distribution property of a CBIC-process is completely determined by (Ψ, Φ, g) .

- The **branching mechanism** Ψ is a function on $[0, \infty)$ with *Lévy–Khintchine type representation*:

$$\Psi(\lambda) = b\lambda + c\lambda^2 + \int_0^\infty (e^{-\lambda z} - 1 + \lambda z 1_{\{z \leq 1\}}) \mu(dz),$$

where $b \in \mathbb{R}$ and $c \geq 0$ are constants and $(1 \wedge z^2)\mu(dz)$ is a finite measure on $(0, \infty)$.

- The **immigration mechanism** Φ is a function on $[0, \infty)$ with *Lévy–Khintchine type representation*:

$$\Phi(\lambda) = \beta\lambda + \int_0^\infty (1 - e^{-z\lambda}) \nu(dz),$$

where $\beta \geq 0$ and $(1 \wedge z)\nu(dz)$ is a finite measure on $(0, \infty)$.

- The **competition mechanism** g is a nondecreasing and continuous function on $[0, \infty)$ satisfying $g(0) = 0$.

- Coupling method: Chen ('04, 05'), Chen and Wang ('93, 95')
- For Markov processes with **additive Lévy noises**: Luo–Wang ('16,'19), Schilling–Wang ('12), Majka ('17).
- For **CBI-processes** (without competition, mainly **subcritical branching**): Pinsky ('72), Li–Ma ('15), Friesen et al. ('20).
- For nonlinear CBI-processes: Li–Wang ('20).

Previous work

Consider the CBI-process ($g(x) \equiv 0$)

$$Lf(x) = (\beta - bx)f'(x) + cx f''(x) + \int_0^\infty [f(x+z) - f(x)] \nu(dz) \\ + x \int_0^\infty [f(x+z) - f(x) - z f'(x) \mathbf{1}_{\{z \leq 1\}}] \mu(dz),$$

for any $f \in C_b^2(\mathbb{R}_+)$.

Theorem [Pinsky 1972]

Assume that $-b + \int_1^\infty zm(dz) < 0$. Then the CBI process is ergodic if and only if

$$\int_1^\infty \log z \nu(dz) < \infty.$$

(If $-b + \int_1^\infty zm(dz) > 0$, then the CBI-process is transient.)

Theorem [Li–Ma 2015]

Suppose that $-b + \int_1^\infty z\mu(dz) < 0$, $\nu(dz) = 0$, $\beta > 0$ and

$$\int^{\infty-} \frac{d\lambda}{\Psi(\lambda)} < \infty,$$

where

$$\Psi(\lambda) = b\lambda + c\lambda^2 + \int_0^\infty (e^{-z\lambda} - 1 + z\lambda\mathbb{1}_{\{z \leq 1\}})\mu(dz), \quad \lambda \geq 0.$$

Then the CBI process is exponentially ergodic in total variation distance.

Remark:

- The integral condition doesn't hold when $b > 0$, $c = 0$ and $\mu(dz) = \mathbb{1}_{\{0 < z \leq 1\}}z^{-2}dz$. In fact we have $\lim_{\lambda \rightarrow \infty} \frac{\lambda \log(1+\lambda)}{\Phi(\lambda)} = 1$.

Weighted total variation distance

We study the **exponential ergodicity** of the CBIC-process. For a suitable nonnegative function V , we define the metric on \mathbb{R}_+ by

$$d_V(x, y) = [2 + V(x) + V(y)]\mathbb{1}_{\{x \neq y\}}, \quad x, y \in \mathbb{R}_+. \quad (2)$$

The **V -weighted total variation distance** W_V is given by

$$\begin{aligned} W_V(\mu, \nu) &= \sup_{\|f/(1+V)\| \leq 1} \int_{\mathbb{R}_+} f(x) |\mu(dx) - \nu(dx)| \\ &= \inf_{\pi \in \mathcal{C}(\mu, \nu)} \int_{\mathbb{R}_+^2} d_V(x, y) \pi(dx, dy), \quad \mu, \nu \in \mathcal{P}(\mathbb{R}_+), \end{aligned}$$

where $\mathcal{C}(\mu, \nu)$ is the set of probabilities on \mathbb{R}_+^2 with marginals μ and ν .

The CBIC-process is said to be **exponentially ergodic** in W_V with rate $\lambda > 0$ if its transition semigroup $(P_t)_{t \geq 0}$ has a unique stationary distribution μ and

$$W_V(\mu, P_t(x, \cdot)) \leq C(x)e^{-\lambda t}, \quad t \geq 0, x \geq 0.$$

Condition 1:

- (i) The diffusion parameter $c > 0$ or there is a constant $\kappa > 0$ such that

$$\inf_{0 \leq x \leq \kappa} \mu \wedge (\delta_x * \mu)(\mathbb{R}_+) > 0.$$

- (ii) There are a C^2 -function $V : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ and constants $\lambda, C > 0$ such that,

$$\lim_{x \rightarrow \infty} V(x) = \infty$$

and

$$LV(x) \leq -\lambda V(x) + C, \quad x \in \mathbb{R}_+.$$

Theorem 1

Suppose that [Condition 1](#) holds true. Then the CBIC-process is exponentially ergodic in W_V with rate λ' .

(The expression of λ' is very complex, so we omit it.)

Main results

The general result applies to the Lyapunov functions V_1 defined by

$$V_1(x) = x.$$

Theorem 2

Suppose that $\mu(dz) = \sigma z^{-\alpha-1} \mathbb{1}_{\{z \geq 0\}} dz$ for some $\sigma > 0$ and $\alpha \in (1, 2)$. In addition, assume that

$$\int_1^\infty z \nu(dz) < \infty$$

and

$$\liminf_{x \rightarrow \infty} \frac{g(x)}{x} > \frac{\sigma}{\alpha - 1} - b.$$

Then the CBIC-process is exponentially ergodic in the V_1 -weighted total variation distance.

Main results

The general result applies to the Lyapunov functions V_{\log} defined by

$$V_{\log}(x) = \log(1 + x), \quad x \geq 0.$$

Theorem 3

Suppose that $\mu(dz) = \sigma z^{-\alpha-1} \mathbb{1}_{\{z \geq 0\}} dz$ for some $\sigma > 0$ and $\alpha \in (0, 1]$. In addition, assume that

$$\int_1^{\infty} \log(1 + z) \nu(dz) < \infty$$

and

$$\begin{cases} \liminf_{x \rightarrow \infty} \frac{g(x)}{x^{2-\alpha}} > \frac{\sigma \pi \sin(\alpha \pi)}{\alpha} & \text{for } 0 < \alpha < 1, \\ \liminf_{x \rightarrow \infty} \frac{g(x)}{x \log x} > \sigma & \text{for } \alpha = 1. \end{cases}$$

Then the CBIC-process is exponentially ergodic in the V_{\log} -weighted total variation distance.

Remark: This condition is sharp in some sense.

Coupling method

An operator \tilde{L} is called a *coupling operator* of L if for $h(x, y) = f(x) + g(y)$ for $f, g \in C_b^2(\mathbb{R}_+)$

$$\tilde{L}h(x, y) = Lf(x) + Lg(y) \quad x, y \in \mathbb{R}_+.$$

The Markov process $(X_t, Y_t)_{t \geq 0}$ generated by \tilde{L} is called coupling process.

The *coupling time* $T = \inf\{t \geq 0 : X_t = Y_t\}$ is the first time that the two marginal processes meet each other.

Notice that:

- $(X_t)_{t \geq 0}$ and $(Y_t)_{t \geq 0}$ have the same transition semigroup $(P_t)_{t \geq 0}$.
- $\mathbb{P}(X_t = Y_t | t \geq T) = 1$.

Coupling method

- Step1: Construct a **Markov coupling** $\{(X_t, Y_t) : t \geq 0\}$ of CBIC-processes;
- Step2: Find a nonnegative (nonsymmetric) **control function** $G_0(x, y) = \phi(x)f(x - y)$ such that

$$\tilde{L}G_0(x, y) \leq -\lambda G_0(x, y)$$

The function should control the distance d_V in the sense:

$$c_1 G_0(x, y) \leq d_V(x, y) \leq c_2 G_0(x, y), \quad (x, y) \in D.$$

- Step3: By Gronwall's Lemma, we have

$$W_V(P_t(x, \cdot), P_t(y, \cdot)) \leq K e^{-\lambda t} d_V(x, y), \quad t \geq 0,$$

which immediately leads to the desired result.

Refined basic coupling

Refined basic coupling was established in [Luo and Wang 2019].

Similarly, in our situation, when $x > y \geq 0$, this coupling is described by

$$(x, y) \longrightarrow \begin{cases} (x + z, y + z + (x - y)), & \frac{1}{2}y\mu_{-(x-y)}(dz), \\ (x + z, y + z - (x - y)), & \frac{1}{2}y\mu_{(x-y)}(dz), \\ (x + z, y + z), & y \left[\mu(dz) - \frac{1}{2}\mu_{-(x-y)}(dz) \right. \\ & \left. - \frac{1}{2}\mu_{(x-y)}(dz) \right] + \nu(dz), \\ (x + z, y), & (x - y)\mu(dz), \end{cases}$$

where $\mu_x = [\mu \wedge (\delta_x * \mu)](dz)$.

Refined basic coupling

Let $W_0(ds, du)$ be a Gaussian white noise based on $2cdsdu$. Let $M_0(ds, dz, du, dv)$ be a Poisson random measure with intensity $ds\mu(dz)du dv$ and compensated measure $\tilde{M}_0(ds, dz, du, dv)$. Let

$$L_0(ds, du) = W_0(ds, du) - bdsdu + \int_{\{0 < z \leq 1\}} \int_{\{0 < v \leq 1\}} z \tilde{M}_0(ds, dz, du, dv) \\ + \int_{\{1 < z < \infty\}} \int_{\{0 < v \leq 1\}} z M_0(ds, dz, du, dv)$$

and

$$L_0^*(ds, du) = -W_0(ds, du) - bdsdu + \int_{\{0 < z \leq 1\}} \int_{\{0 < v \leq 1\}} z \tilde{M}_0(ds, dz, du, dv) \\ + \int_{\{1 < z < \infty\}} \int_{\{0 < v \leq 1\}} z M_0(ds, dz, du, dv).$$

Refined basic coupling

For any $x \geq y \geq 0$ a Markov coupling $\{(X_t, Y_t) : t \geq 0\}$ of CBIC-processes is defined by the pathwise uniqueness solution to the system of stochastic equations:

$$X_t = x + \int_0^t \int_0^{X_{s-}} L_0(ds, du) - \int_0^t g(X_s)ds + \eta_t \quad (3)$$

and

$$Y_t = y + \int_{t \wedge T}^t \int_0^{X_{s-}} L_0(ds, du) - \int_0^t g(Y_s)ds + \eta_t \\ + \int_0^{t \wedge T} \int_0^{X_{s-}} L_0^*(ds, du) + \xi_t,$$

where $T = \inf\{t \geq 0 : X_t \leq Y_t\} = \inf\{t \geq 0 : X_t = Y_t\}$ and $(0 \leq \rho_i, \gamma_i \leq 1)$

$$\xi_t = \int_0^{t \wedge T} \int_0^\infty \int_0^{Y_{s-}} \int_0^{\rho_1(Y_{s-} - X_{s-}, z)} (X_{s-} - Y_{s-})M_0(ds, dz, du, dv) \\ + \int_0^{t \wedge T} \int_0^\infty \int_0^{Y_{s-}} \int_0^{\rho_2(X_{s-}, Y_{s-}, z)} (Y_{s-} - X_{s-})M_0(ds, dz, du, dv).$$

Thank you!