

A Fleming-Viot process driven by sub-critical branching: a selection principle.

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Joint work with
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Absorbing processes

$Z = (Z_t, t \geq 0)$, a pure jump Markov process in $\Lambda \cup \{0\}$

$Q = (q(x, y), x, y \in \Lambda \cup \{0\}$ the rates.)

Λ is an irreducible class.

μ is the initial distribution.

0 is absorbing (i.e. $q(0, y) = 0$ for all $y \in \Lambda$)

Absorption is certain: $\mathbb{P}_\mu(Z_t = 0, \text{ for some } t > 0) = 1$.

Unique invariant distribution: δ_0 . In this case we study the conditioned evolution

$$\varphi_t^\mu(x) = \frac{\mathbb{P}_\mu(Z_t = x)}{\mathbb{P}_\mu(Z_t \neq 0)}$$

Quasi-stationary distributions

φ^μ is the unique solution to the Kolmogorov forward equations

$$\frac{d}{dt}\varphi_t^\mu(x) = \sum_{y \in \Lambda} q(y, x) \varphi_t^\mu(y) + \sum_{y \in \Lambda} q(y, 0) \varphi_t^\mu(y) \varphi_t^\mu(x).$$

The *Yaglom limit* for the measure μ is defined by

$$\lim_{t \rightarrow \infty} \varphi_t^\mu(y), \quad y \in \Lambda,$$

if the limit exists and is a probability on Λ .

A *quasi-stationary distribution* (QSD) for Q is a probability measure ν on Λ that is invariant under $\{\varphi_t, t \geq 0\}$, that is

$$\varphi_t^\nu = \nu, \quad \text{for all } t \geq 0.$$

If the Yaglom limit exists, it is known to be a QSD (and a QSD is a Yaglom limit).

Some difficulties

Non-linear semigroup.

It is non-attractive, even if Z is.

Markov process theory can not be applied.

In particular: the number of quasi-stationary distributions can be 0, 1 or ∞ .

There is no obvious way to simulate neither the QSD nor the conditioned evolution for large times.

Example: linear birth and death process

$$q(x, x + 1) = px, \quad q(x, x - 1) = (1 - p)x$$

There is a one parameter family of QSD if $p < \frac{1}{2}$, and no one if $p = \frac{1}{2}$. (Seneta-Vere-Jones, 1966. Cavender, 1978)

Some intuition

Let T be the absorption time and assume $\Lambda = \mathbb{N}$.

Theorem (Ferrari, Kesten, Martínez and Picco 1995):

Assume $\lim_{x \rightarrow \infty} \mathbb{P}_{\delta_x}(T < t) = 0$, then

There exists a QSD $\iff \mathbb{E}(e^{\theta T}) < \infty$, for some $\theta > 0$.

The Fleming-Viot process (FV) driven by Q

We have N particles, each particle moves independently of the others as a continuous time Markov process with rates Q , but when it attempts to jump to state 0, it comes back immediately to Λ by jumping to the position of one of the other particles chosen uniformly at random.

Denote

$\xi_t = \xi_t^{N, \xi^0} = (\xi_t(1), \dots, \xi_t(N)) \in \Lambda^N$ the state of the process at time t .

$\eta(\xi, x)$ the number of ξ particles at site x .

$m_x(\xi) = \frac{\eta(\xi, x)}{N}$, $x \in \Lambda$ the empirical measure.

The Fleming-Viot process (FV) driven by Q

Generator

$$\mathcal{L}^N f(\xi) = \sum_{i=1}^N \sum_{x \in \mathbb{N} \setminus \{\xi(i)\}} \left[q(\xi(i), x) + q(\xi(i), 0) \frac{\sum_{j \neq i}^N \mathbf{1}_{\{\xi(j)=x\}}}{N-1} \right] (f(\xi^{i,x}) - f(\xi)),$$

$$\xi^{i,x}(j) = \begin{cases} x & j = i, \\ \xi(j) & j \neq i, \end{cases}$$

FV as an approximation of the conditioned evolution and QSD

We have

$$\frac{d}{dt} \mathbb{E} \frac{\eta_t(x)}{N} = \sum_{y \in \Lambda} q(y, x) \mathbb{E} \frac{\eta_t(y)}{N} + \sum_{y \in \Lambda} q(y, 0) \mathbb{E} \left[\frac{\eta_t(y)}{N} \frac{\eta_t(x)}{N-1} \right].$$

Recall

$$\frac{d}{dt} \varphi_t^\mu(x) = \sum_{y \in \Lambda} q(y, x) \varphi_t^\mu(y) + \sum_{y \in \Lambda} q(y, 0) \varphi_t^\mu(y) \varphi_t^\mu(x).$$

FV as an approximation of the conditioned evolution and QSD

Introduced by Burdzy, Holyst, Ingemar and March with Brownian Motion in a bounded domain as driving process (1996, 2000).

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Villemonais

Bieniek, Finch (general diffusions).

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In the countable state space setting

Ferrari, Marić, Asselah, Jonckheere

Problems (some)

1. Convergence of $\frac{\eta_t(x)}{N}$ to $\varphi_t^\mu(x)$ as $N \rightarrow \infty$ in finite time intervals.

2. Existence of an invariant measure λ^N for FV and convergence to equilibrium for each N .

3. $\int \left| \frac{\eta(\xi, x)}{N} - \nu(x) \right| d\lambda^N(\xi) \rightarrow 0$, ν a QSD. (which?)

Remark: FV inherits the difficulties of the conditioned process.

Problem 1: Particles correlations

Evolution of the empirical profile

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$$\frac{d}{dt} \varphi_t^\mu(x) = \sum_{y \in \Lambda} q(y, x) \varphi_t^\mu(y) + \sum_{y \in \Lambda} q(y, 0) \varphi_t^\mu(y) \varphi_t^\mu(x).$$

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So $e_t(x) = \mathbb{E} \frac{\eta_t(x)}{N} - \varphi_t^\mu(x)$ verifies

$$\frac{d}{dt} e_t^\mu(x) = \sum_{y \in \Lambda} q(y, x) e_t(y) + \sum_{y \in \Lambda} q(y, 0) (a_y e_t(y) + b_x e_t(x)) + R(\xi; x, t).$$

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$$R(\xi; x, t) = \sum_{y \in \Lambda} q(y, 0) \left[\frac{N}{N-1} \mathbb{E} [m_y(\xi_t) m_x(\xi_t)] - \mathbb{E} m_y(\xi_t) \mathbb{E} m_x(\xi_t) \right].$$

Proposition (Ferrari-Marić, 2006)

For each $t > 0$, and any $x, y \in \Lambda$

$$\sup_{\xi \in \Lambda^N} |\mathbb{E}^\xi[m_x(\xi_t)m_y(\xi_t)] - \mathbb{E}^\xi[m_x(\xi_t)]\mathbb{E}^\xi[m_y(\xi_t)]| \leq \frac{e^{Ct}}{N}.$$

Proposition (Ferrari-Marić, 2006)

For each $t > 0$, and any $x, y \in \Lambda$

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Proof. Follows from

$$|\mathbb{P}(\xi_t(i) = x, \xi_t(j) = y) - \mathbb{P}(\xi_t(i) = x)\mathbb{P}(\xi_t(j) = y)| \leq \frac{e^{Ct}}{N}.$$

which can be proved by coupling.

Coming back to the conditioned evolution...

$$e_t(x) = \mathbb{E} \frac{\eta_t(x)}{N} - \varphi_t^\mu(x)$$

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Subcritical branching

Let $\{p(n), n \in \mathbb{N}\}$ be the offspring distribution. We consider $\Lambda = \mathbb{N}$ and $\{q(x, y); x, y \in \mathbb{N}\}$ of the form

$$q(x, x + i - 1) = xp(i), \quad i \neq 1, \quad q(x, x) = -x,$$

and $q(x, y) = 0$ otherwise.

We assume

$$-v := \sum_{i=-1}^{\infty} ip(i+1) < 0 \quad (\text{and exponential moments})$$

There is a one parameter family of QSD! (Seneta-Vere-Jones 1966, Cavender 1978, Van Doorn 1991)

Subcritical branching

The **minimal QSD** ν_{\min} has generating function given by

$$G(\nu_{\min}; z) = 1 - \exp\left(-v \int_0^z \frac{du}{\sum_{i \geq 0} p(i)u^i - z}\right),$$

and is the Yaglom limit of every initial distribution μ with finite mean.

Subcritical branching

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and is the Yaglom limit of every initial distribution μ with finite mean.

Also it has the minimum expected absorption time.

Subcritical branching

Theorem. (Asselah, Ferrari, G., Jonckheere)

For each $N \geq 1$, the Fleming-Viot process driven by subcritical branching is ergodic with invariant measure λ^N and for each $x \in \mathbb{N}$ we have

$$\lim_{N \rightarrow \infty} \int |m_x(\xi) - \nu_{\min}(x)| d\lambda^N(\xi) = 0.$$

Strategy of proof

$$\int |m_x(\xi) - \nu_{\min}(x)| d\lambda^N(\xi) = \int |m_x(\xi_t^\xi) - \nu_{\min}(x)| d\lambda^N(\xi)$$

Strategy of proof

$$\begin{aligned} \int |m_x(\xi) - \nu_{\min}(x)| d\lambda^N(\xi) &= \int |m_x(\xi_t^\xi) - \nu_{\min}(x)| d\lambda^N(\xi) \\ &= \int_{K(\alpha)} |m_x(\xi_t^\xi) - \nu_{\min}(x)| d\lambda^N(\xi) + 2\lambda^N(K(\alpha)^c) \end{aligned}$$

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$$\leq \sup_{K(\alpha)} |m_x(\xi_t^\xi) - \varphi_t^{m(\xi)}(x)| + \sup_{K(\alpha)} |\varphi_t^{m(\xi)}(x) - \nu_{\min}(x)| + 2\lambda^N(K(\alpha)^c)$$

$\lambda^N(K(\alpha))$

Let

$$K(\alpha) := \{\xi : \psi(\eta) \leq \alpha\} \quad \psi(\eta(\xi, x)) := \frac{\sum x^2 \eta(\xi, x)}{\sum x \eta(\xi, x)}$$

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$$(i) \int \psi d\lambda^N(\xi) \leq C_1 + C_2 \int \frac{\max_i \xi^2(i)}{N} d\lambda^N(\xi)$$

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Corollary.

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Large deviations, another coupling and drift inequalities

Proposition. *The Fleming-Viot process can be embedded in a Multitype Branching Markov Chain (MBMC) driven by Z but avoiding the jumps to 0 (\tilde{Z}).*

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Large deviations, another coupling and drift inequalities

Proposition. *The Fleming-Viot process can be embedded in a Multitype Branching Markov Chain (MBMC) driven by Z but avoiding the jumps to 0 (\tilde{Z}).*

Corollary. The bounds obtained for the (reflected) driving process \tilde{Z} also hold for the Fleming-Viot process but with a factor e^{Ct} .

Graphical construction II

The Multitype Branching Markov Chain

We have a marked PP ω_i^V with rate $C := \sup q(x, 0)$ for each particle. The marks are uniform in $[0, 1] \times \{1, \dots, N\} \setminus \{i\}$

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If ω_i^V rings and the mark points to j , then every type j individual dies and has two children: one of type i and one of type j .

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Individuals evolve spatially according to \tilde{Z} .

Graphical construction II

The embedded Fleming-Viot

Particle i follows the trajectory of the unique type i individual. If ω_i^V rings and the mark $U \leq q(\xi(i), 0)/C$ then particle i (is absorbed and) jumps over the type i individual branched at that time from particle j .

Large deviations for \tilde{Z} and

Proposition. Let $\delta \geq 1$ and a time T such that $T\rho(0) \leq \delta/4$. Then

$$\mathbb{P} \left(\sup_{s < T} |\tilde{Z}(x; s) - e^{-vs}x| \geq \delta \right) \leq e^{-C_T \frac{\delta^2}{\max\{x, \delta\}}}$$

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Corollary.

- (i) Fleming-Viot driven by subcritical branching is ergodic for each N .
- (ii) We have drift inequalities for $\max_i \xi_t^2(i)$

