

Branching particle models in environmental studies

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Nonlinear finite state space models

Individuals with type $\in E = \{1, \dots, d\}$ at time $t \in \mathbb{N}$ or \mathbb{R}_+

$\eta_t = [\eta_t(1), \dots, \eta_t(d)] \in \text{Proportion space} = \text{Probab. on } E$

Types : predators-preys, species, colonies, etc.

- **Discrete time** $\eta_{t+1}(j) = \sum_{i=1}^d \eta_t(i) K_{t,\eta_t}(i,j)$
with a nonlinear Markov chain \bar{X}_t :

$$\mathbb{P}(\bar{X}_{t+1} = j \mid \bar{X}_t = i) := K_{t,\eta_t}(i,j) \quad \text{with} \quad \eta_t = \text{Law}(\bar{X}_t)$$

- **Continuous time** (Logistic, Lotka Volterra type, simplex syst.)

$$\frac{d}{dt} \eta_t(j) = \sum_{i=1}^d \eta_t(i) (K_{t,\eta_t}(i,j) - \delta_j(i))$$

with a nonlinear Markov process $\eta_t = \text{Law}(\bar{X}_t)$

Duality model

- $\eta := (\eta(1), \dots, \eta(d))$

$$f := \begin{pmatrix} f(1) \\ \vdots \\ f(d) \end{pmatrix} \quad \text{and} \quad K = \begin{pmatrix} K(1,1) & \cdots & K(1,d) \\ \vdots & \ddots & \vdots \\ K(d,1) & \cdots & K(d,d) \end{pmatrix}.$$

$$\Downarrow (f = 1_i)$$

$$\eta(f) = \sum_{j=1}^d \eta(j) f(j) = \eta(i) , \quad K(f)(j) = \sum_{k=1}^d K(j,k) f(k) = K(j,i)$$

$$\begin{aligned} \text{and } \eta(K(f)) &= \sum_{i=1}^d \eta(i) \left[\sum_{j=1}^d K(i,j) f(j) \right] \\ &= \sum_{j=1}^d \left[\sum_{i=1}^d \eta(i) K(i,j) \right] f(j) := (\eta K)(f) \end{aligned}$$

Weak equations \rightsquigarrow Individual based & mean field particle models

- Weak sol. of nonlinear and discrete generation dyn. syst. :

$$\forall j \quad \eta_{t+1}(j) = \sum_{i=1}^d \eta_t(i) K_{t,\eta_t}(i,j) \iff \forall f \quad \eta_{t+1}(f) = \eta_t K_{t,\eta_t}(f)$$

- Weak solutions of nonlinear PDE :

$$\forall j \quad \frac{d}{dt} \eta_t(j) = \sum_{i=1}^d \eta_t(i) (K_{t,\eta_t}(i,j) - \delta_j(i))$$

$$\iff \forall f \quad \frac{d}{dt} \eta_t(f) := \eta_t(K_{t,\eta_t} - Id)(f) = \eta_t L_{t,\eta_t}(f)$$

- Stochastic processes : Branching, birth and death, cloning, jumps, free evolution, historical processes , genealogical tree evolutions, etc.
- State space examples :

$$E = \mathbb{R}^d, \mathbb{N}^{d_1} \cup \mathbb{R}^{d_2}, \cup_{d \geq 0} S^d, \text{path spaces, excursion spaces}$$

- Duality models:

$$\begin{aligned}\eta(K(f)) &= \int \eta(dx) \left[\int K(x, dy) f(y) \right] \\ &= \int \left[\int \eta(dx) K(x, dy) \right] f(y) = (\eta K)(f)\end{aligned}$$

Weak equations \rightsquigarrow Individual based & mean field particle models

- Weak sol. of nonlinear and discrete generation dyn. syst. :

$$\eta_{t+1}(f) = \eta_t K_{t,\eta_t}(f)$$

- Weak solutions of nonlinear PDE :

$$\frac{d}{dt} \eta_t(f) = \eta_t L_{t,\eta_t}(f)$$

Example : Feynman-Kac path models \rightsquigarrow Genetic type particle models

$$\eta_t(f) \propto \mathbb{E} \left(f(X_t) \prod_{0 \leq s \leq t} G_s(X_s) \right) \text{ or } \mathbb{E} \left(f(X_t) \exp \int_{0 \leq s \leq t} V_s(X_s) ds \right)$$

Not excluded path space models $X_t = (X'_s)_{0 \leq s \leq t}$

Tools \rightsquigarrow Dynamical Syst. \cap Partial differential eq. \cap Probability

Individual based & mean field particle models

- Discrete time \rightsquigarrow **Markov chain** $\xi_t = (\xi_t^1, \dots, \xi_t^N) \in E^N$ s.t.

$$\eta_t^N := \frac{1}{N} \sum_{1 \leq i \leq N} \delta_{\xi_t^i} \simeq_{N \uparrow \infty} \eta_t$$

Approximate local transitions :

$$(\forall 1 \leq i \leq N) \quad \xi_{t-1}^i \rightsquigarrow \xi_t^i \sim K_{t, \eta_{t-1}^N}(\xi_{t-1}^i, dx_t)$$

- Some advantages :

- Microscopic-individual interpretations, historical processes,...
- Mean field particle=stoch. perturbation-linearization model:

$$\eta_t^N = \eta_{t-1}^N K_{t, \eta_{t-1}^N} + \frac{1}{\sqrt{N}} W_t^N$$

with $W_t^N \simeq W_t$ i.i.d. centered gaussian fields.

- $\eta_t = \eta_{t-1} K_{t, \eta_{t-1}}$ stable \Rightarrow non propagation local errors.

Individual based & mean field particle models

- **Continuous time** \rightsquigarrow **Markov process** $\xi_t = (\xi_t^1, \dots, \xi_t^N) \in E^N$ s.t.

$$\eta_t^N := \frac{1}{N} \sum_{1 \leq i \leq N} \delta_{\xi_t^i} \simeq_{N \uparrow \infty} \eta_t$$

Infinitesimal generators :

$$\mathcal{L}_t(F)(x^1, \dots, x^N) := \sum_{i=1}^N L_{t, \frac{1}{N} \sum_{i=1}^N \delta_{x^i}}^{(i)} F(x^1, \dots, x^i, \dots, x^N)$$

- **stoch. perturbation-linearization model**

$$d\eta_t^N(f) = \eta_t^N L_{t, \eta_t^N}(f) dt + \frac{1}{\sqrt{N}} dM_t^N(f)$$

with

$$\langle M^N(f) \rangle_t = \int_0^t \eta_s^N \Gamma_{L_s, \eta_s^N}(f, f) ds$$

Description of the models

Free N -diffusion models (between branching-death-jump events)

- 1-dim SDE :

$$dX_t = a_t(X_t)dt + b_t(X_t)dW_t$$

- 1-dim infinitesimal generator :

$$df(X_t) = L_t(f)(X_t)dt + dM_t(f)$$

- N independent free L_t -evolutions

$$\begin{cases} d\xi_t^i &= a_t(\xi_t^i)dt + b_t(\xi_t^i)dW_t \\ i &= 1, \dots, N \end{cases}$$

- N -dim infinitesimal generator :

$$\mathcal{L}_t^{\text{free}}(F)(x^1, \dots, x^N) := \sum_{i=1}^N L_t^{(i)} F(x^1, \dots, x^i, \dots, x^N)$$

Free N -diffusion models

- $\xi_t = (\xi_t^1, \dots, \xi_t^N) \rightsquigarrow dF(\xi_t) = \mathcal{L}_t^{\text{free}}(F)dt + d\mathcal{M}_t(F)$ with

$$\frac{d}{dt} \langle \mathcal{M}(F) \rangle_t = \Gamma_{\mathcal{L}_t^{\text{free}}}(F, F)(\xi_t) := \mathcal{L}_t^{\text{free}} \left([F - F(\xi_t)]^2 \right) (\xi_t)$$

- **Empirical processes** : $F(\xi_t) = m(\xi_t)(f) := \frac{1}{N} \sum_{i=1}^N f(\xi_t^i)$

$$\mathcal{L}_t^{(i)} F(\xi_t) = \frac{1}{N} \mathcal{L}_t(f)(\xi_t^i) \Rightarrow dm(\xi_t)(f) = m(\xi_t)(\mathcal{L}_t f) dt + dM_t^N(f)$$

and

$$\begin{aligned} \mathcal{L}_t^{\text{free}} \left([F - F(\xi_t)]^2 \right) (\xi_t) &= \frac{1}{N^2} \sum_{i=1}^N \mathcal{L}_t \left([f - f(\xi_t^i)]^2 \right) (\xi_t^i) \\ &= \frac{1}{N} m(\xi_t) (\Gamma_{\mathcal{L}_t}(f, f)) = \frac{d}{dt} \langle M^N(f) \rangle_t \end{aligned}$$

- \rightsquigarrow LLN : $m(\xi_t) \simeq_{N \uparrow \infty} \eta_t = \text{Law}(X_t)$ 1-diff. \mathcal{L}_t -model.

Description of the models

Branching mean field particle models

Stochastic processes $\in \cup_{N \geq 0} E^N$, $E^0 := \{c\}$ cemetery-coffin stateBirth and death type infinitesimal generator ($N_0 = \text{initial pop. size}$)

$$\forall x = (x^1, \dots, x^N) \in \cup_{N \geq 1} E^N \rightsquigarrow m(x) := \frac{1}{N_0} \sum_{i=1}^N \delta_{x^i}$$

$$\mathcal{L}_t^{b,d}(F)(x^1, \dots, x^N)$$

$$:= \sum_{i=1}^N L_{t,m(x)}^{(i)} F(x^1, \dots, x^i, \dots, x^N)$$

$$= \sum_{i=1}^N \lambda_t(m(x), x^i)$$

$$\times \int_{\cup_{d \geq 0} E^d} (F(x^1, \dots, x^{i-1}, \textcolor{red}{u}, x^{i+1}, \dots, x^N) - F(x^1, \dots, x^N)) B_{t,m(x)}(x^i, du)$$

Death $u = c$, jump $x^i \rightsquigarrow u \in E$, d -birth $x^i \rightsquigarrow u = (u^1, \dots, u^{d+1})$, cloning $x^i \rightsquigarrow u = (x^i, \dots, x^i), \dots$

Feynman-Kac particle models with $N_0 = N_t$

$$\eta_t(f) \propto \mathbb{E} \left(f(X_t) \exp \left\{ - \int_{0 \leq s \leq t} V_s(X_s) ds \right\} \right) \quad \text{with} \quad X_t = L_t - \text{motion}$$

$$\rightsquigarrow \mathcal{L}_t = \mathcal{L}_t^{\text{free}} + \mathcal{L}_t^{\text{jump}}$$

$$\mathcal{L}_t(F)(x^1, \dots, x^N)$$

$$:= \sum_{i=1}^N L_t^{(i)} F(x^1, \dots, x^i, \dots, x^N)$$

$$+ \sum_{i=1}^N V_t(x^i)$$

$$\times \int_{\color{red} E} (F(x^1, \dots, x^{i-1}, \color{red} u, x^{i+1}, \dots, x^N) - F(x^1, \dots, x^N)) \ m(x)(du)$$

\rightsquigarrow LLN-Propagation of chaos : $m(\xi_t) \simeq_{N \uparrow \infty} \eta_t.$

Empirical processes

1-Birth $\rightsquigarrow u = (x^i, y)$ with rate $= \lambda_t^b(x^i)$

$$F(x) = m(x)(f) = \frac{1}{N_0} \sum_{i=1}^N f(x^i)$$

\Downarrow

$$\mathcal{L}_t^b(F)(x^1, \dots, x^N)$$

$$= \sum_{i=1}^N \lambda_t^b(x^i)$$

$$\times \int_{\cup_{d \geq 0} E^d} (F(x^1, \dots, x^{i-1}, \textcolor{red}{u}, x^{i+1}, \dots, x^N) - F(x^1, \dots, x^N)) B_{t,m(x)}(x^i, du)$$

$$= \frac{1}{N_0} \sum_{i=1}^N \lambda_t^b(x^i) \int f(y) B'_{t,m(x)}(x^i, dy) = m(x) \left(\lambda_t^b B'_{t,m(x)}(f) \right)$$

and

$$\Gamma_{\mathcal{L}_t^b}(F, F)(x) = \frac{1}{N_0} m(x) \left(\lambda_t^b B'_{t,m(x)}(f^2) \right)$$

1-Death $\rightsquigarrow u = c$ with rate $= \lambda_t^d(x^i)$

$$F(x) = m(x)(f) = \frac{1}{N_0} \sum_{i=1}^N f(x^i)$$

$$\mathcal{L}_t^d(F)(x^1, \dots, x^N)$$

$$= \sum_{i=1}^N \lambda_t^d(x^i)$$

$$\times \int_{\cup_{d \geq 0} E^d} (F(x^1, \dots, x^{i-1}, \textcolor{red}{u}, x^{i+1}, \dots, x^N) - F(x^1, \dots, x^N)) B_{t, m(x)}(x^i, du)$$

$$= -\frac{1}{N_0} \sum_{i=1}^N \lambda_t^d(x^i) f(x^i) = -m(x) (\lambda_t^d f)$$

and

$$\Gamma_{\mathcal{L}_t^d}(F, F)(x) = \frac{1}{N_0} m(x) (\lambda_t^d f^2)$$

Free evolution+1-birth+1-death

$$\mathcal{L}_t = \mathcal{L}_t^{\text{free}} + \mathcal{L}_t^b + \mathcal{L}_t^d \quad \text{and} \quad \Gamma_{\mathcal{L}_t} = \Gamma_{\mathcal{L}_t^{\text{free}}} + \Gamma_{\mathcal{L}_t^b} + \Gamma_{\mathcal{L}_t^d}$$

$$F(x) = m(x)(f) = \frac{1}{N_0} \sum_{i=1}^{N_0} f(x^i)$$

↓

$$\begin{aligned} \mathcal{L}_t(F)(x) &= m(x)(\mathcal{L}_t(f)) + m(x) \left(\lambda_t^b B'_{t,m(x)}(f) \right) - m(x) (\lambda_t^d f) \\ &:= m(x)(\mathcal{L}_{t,m(x)}(f)) \end{aligned}$$

↓

$$dm(\xi_t)(f) = m(\xi_t)(\mathcal{L}_{t,m(\xi_t)}(f))dt + dM_t^{N_0}(f)$$

$$\frac{d}{dt} \langle M^{N_0}(f) \rangle_t = \frac{1}{N_0} m(\xi_t) \left[\Gamma_{\mathcal{L}_t}(f, f) + \lambda_t^b B'_{t,m(x)}(f^2) + \lambda_t^d f^2 \right]$$

Empirical processes

$$f = 1 \Rightarrow \frac{dN_t}{N_0} = m(\xi_t) ([\lambda_t^b - \lambda_t^d]) dt + dM_t^{N_0}(1)$$

and

$$\frac{d}{dt} \langle M^{N_0}(1) \rangle_t = \frac{1}{N_0} m(\xi_t) [\lambda_t^b + \lambda_t^d]$$

Observations :

- $\lambda_t^b - \lambda_t^d = \Delta = Cte \rightsquigarrow \mathbb{E}(N_t) = N_0 e^{t\Delta}$ (explosion or extinction)
- $\lambda_t^b = \lambda_t^d = \lambda$ bounded $\rightsquigarrow N_t/N_0 = M_t^N(1)$ and

$$\mathbb{E} \left(\left[\frac{N_t}{N_0} - 1 \right]^2 \right) = \frac{2}{N_0} \int_0^t (m(\xi_s)(\lambda_s)) ds \leq \frac{2\|\lambda\|t}{N_0}$$

\rightsquigarrow Mean field interpretation model :

$$m(\xi_t) \sim_{N_0 \uparrow \infty} \eta_t \text{ s.t. } \frac{d}{dt} \eta_t(f) = \eta_t(L_{t,\eta_t}(f))$$

- Otherwise \rightsquigarrow an avenue of open problems

- **Mean field and Feynman-Kac type particle models :**

- **[Discrete time]** Feynman-Kac formulae. Genealogical and interacting particle systems, P. Del Moral, Springer (2004) \oplus **Refs.**
- **[Continuous time]** P. Del Moral & L. Miclo. A Moran particle system approximation of Feynman-Kac formulae. *Stochastic Processes and their Applications*, Vol. 86, 193-216 (2000).

- **Branching and genetic type models :**

- P. Del Moral & L. Miclo Asymptotic Results for Genetic Algorithms with Applications to Non Linear Estimation. *Proceedings Second EvoNet Summer School on Theoretical Aspects of Evolutionary Computing*, Ed. B. Naudts, L. Kallel. Natural Computing Series, Springer (2000).