

A new class of interacting Markov Chain Monte Carlo methods

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Outline

- 1 Introduction
 - Stochastic sampling problems
 - Some stochastic engineering models
 - Interacting sampling methods
- 2 Some classical distribution flows
 - Feynman-Kac models
 - "Static" Boltzmann-Gibbs models
- 3 Interacting stochastic sampling technology
 - Mean field particle methods
 - Interacting Markov chain Monte Carlo models (i-MCMC)
- 4 Functional fluctuation & comparisons
- 5 Some references

Stochastic sampling problems

- "Nonlinear" distribution flow with \uparrow level of complexity.

$$\eta_n(dx_n) = \frac{\gamma_n(dx_n)}{\gamma_n(1)} \quad \text{Time index } n \in \mathbb{N} \quad \text{State var. } x_n \in E_n$$

- Two objectives :

- 1 \sim "Sampling independent" random variables w.r.t. η_n
- 2 Computation of the normalizing constants $\gamma_n(1)$
(= \mathcal{Z}_n Partition functions).

Stochastic engineering \rightsquigarrow Conditional & Boltzmann-Gibbs' measures

- **Filtering:** Signal-Observation (X_n, Y_n) [Radar, Sonar, GPS, ...]

$$\eta_n = \text{Law}(X_n \mid (Y_0, \dots, Y_n))$$

- **Rare events:** [Overflows, ruin processes, epidemic propagations, ...]

$$\eta_n = \text{Law}(X_n \mid n \text{ intermediate events}) \ \& \ \mathcal{Z}_n = \mathbb{P}(\text{Rare event})$$

- **Molecular simulation:** [ground state energies, directed polymers...]

$$\eta_n := \text{Feynman-Kac/Boltzmann-Gibbs}$$

$$\sim \text{Free Markov motion in an absorbing medium}$$

- **Combinatorial counting, Global optimization, HMM**

$$\eta_n = \frac{1}{\mathcal{Z}_n} e^{-\beta_n V(x)} \lambda(dx) \quad \text{or} \quad \eta_n = \frac{1}{\mathcal{Z}_n} 1_{A_n}(x) \lambda(dx)$$

Two simple ingredients

- Find or Understand the probability mass transformation

$$\eta_n = \Phi_n(\eta_{n-1})$$

~ Cooling schemes, temp. variations, constraints sequences, subset restrictions, observation data, conditional events,...

- Natural interacting sampling idea :

Use η_{n-1} or its empirical approx. to sample w.r.t. η_n

- Monte-Carlo/ Mean Field models :

$$\eta_n = \text{Law}(\bar{X}_n) \quad \text{with} \quad \text{Markov} : \bar{X}_{n-1} \xrightarrow{\sim \eta_{n-1}} \bar{X}_n$$

- Interacting MCMC models :

$$\left\{ \begin{array}{l} \text{Use the occupation measures} \\ \text{of an MCMC with target } \eta_{n-1} \end{array} \right\} \rightsquigarrow \text{MCMC target } \eta_n$$

Feynman-Kac distribution flows

- **Weak representation:** $[f_n$ test funct. on a state space $E_n]$

$$\eta_n(f_n) = \frac{\gamma_n(f_n)}{\gamma_n(\mathbf{1})} \quad \text{with} \quad \gamma_n(f_n) = \mathbb{E} \left(f_n(X_n) \prod_{0 \leq p < n} G_p(X_p) \right)$$

- **A Key Formula:** $Z_n = \mathbb{E} \left(\prod_{0 \leq p < n} G_p(X_p) \right) = \prod_{0 \leq p < n} \eta_p(G_p)$
- **Path space models** $X_n = (X'_0, \dots, X'_n)$

Examples

- $G_n \in [0, 1] \rightsquigarrow$ particle absorption models.
- $G_n =$ Observation likelihood function \rightsquigarrow Filtering models.
- $G_n = 1_{A_n} \rightsquigarrow$ Conditional/Restriction models.

Nonlinear distribution flows

Evolution equation:

$$\eta_{n+1} = \Phi_{n+1}(\eta_n) = \Psi_{G_n}(\eta_n)M_{n+1}$$

With the only 2 transformations :

- **X-Free Markov transport eq.** : $[M_n(x_{n-1}, dx_n)$ from E_{n-1} into $E_n]$

$$(\eta_{n-1}M_n)(dx_n) := \int_{E_{n-1}} \eta_{n-1}(dx_{n-1}) M_n(x_{n-1}, dx_n)$$

- **Bayes-Boltzmann-Gibbs transformation** :

$$\Psi_{G_n}(\eta_n)(dx_n) := \frac{1}{\eta_n(G_n)} G_n(x_n) \eta_n(dx_n)$$

Boltzmann-Gibbs distribution flows

- Target distribution flow : $\eta_n(dx) \propto g_n(x) \lambda(dx)$
- Product hypothesis :

$$g_n = g_{n-1} \times G_{n-1} \implies \eta_n = \Psi_{G_{n-1}}(\eta_{n-1})$$

Running Ex.:

$$\begin{aligned} g_n &= 1_{A_n} & \text{with } A_n \downarrow & \implies G_{n-1} = 1_{A_n} \\ g_n &= e^{-\beta_n V} & \text{with } \beta_n \uparrow & \implies G_{n-1} = e^{-(\beta_n - \beta_{n-1})V} \end{aligned}$$

- **Problem** : $\eta_n = \Psi_{G_{n-1}}(\eta_{n-1}) = \text{unstable equation.}$

Feynman-Kac modeling

- Choose $M_n(x, dy)$ s.t. local fixed point eq. $\rightarrow \eta_n = \eta_n M_n$
(Metropolis, Gibbs,...)

- Stable equation :

$$g_n = g_{n-1} \times G_{n-1} \implies \eta_n = \Psi_{G_{n-1}}(\eta_{n-1})$$

$$\implies \eta_n = \eta_n M_n = \Psi_{G_{n-1}}(\eta_{n-1}) M_n = \text{FK-model}$$

- Feynman-Kac "dynamical" formulation (X_n Markov M_n)

$$\int f(x) g_n(x) \lambda(dx) \propto \mathbb{E} \left(f(X_n) \prod_{0 \leq p < n} G_p(X_p) \right)$$

- \rightsquigarrow Interacting Metropolis/Gibbs/... stochastic algorithms.

Mean field interpretation

- **Nonlinear Markov models** : Always $\exists K_{n,\eta}(x, dy)$ Markov s.t.

$$\eta_n = \Phi_n(\eta_{n-1}) = \eta_{n-1} K_{n,\eta_{n-1}} = \text{Law}(\bar{X}_n)$$

i.e. :

$$\mathbb{P}(\bar{X}_n \in dx_n \mid \bar{X}_{n-1}) = K_{n,\eta_{n-1}}(\bar{X}_{n-1}, dx_n)$$

Mean field particle interpretation

- **Markov chain** $\xi_n = (\xi_n^1, \dots, \xi_n^N) \in E_n^N$ s.t.

$$\eta_n^N := \frac{1}{N} \sum_{1 \leq i \leq N} \delta_{\xi_n^i} \underset{N \uparrow \infty}{\simeq} \eta_n$$

- Particle approximation transitions ($\forall 1 \leq i \leq N$)

$$\xi_{n-1}^i \rightsquigarrow \xi_n^i \sim K_{n,\eta_{n-1}^N}(\xi_{n-1}^i, dx_n)$$

Discrete generation mean field particle model

Schematic picture : $\xi_n \in E_n^N \rightsquigarrow \xi_{n+1} \in E_{n+1}^N$

$$\begin{array}{ccc}
 \xi_n^1 & \xrightarrow{K_{n+1, \eta_n^N}} & \xi_{n+1}^1 \\
 \vdots & & \vdots \\
 \xi_n^i & \longrightarrow & \xi_{n+1}^i \\
 \vdots & & \vdots \\
 \xi_n^N & \longrightarrow & \xi_{n+1}^N
 \end{array}$$

Rationale :

$$\begin{aligned}
 \eta_n^N \simeq_{N \uparrow \infty} \eta_n &\implies K_{n+1, \eta_n^N} \simeq_{N \uparrow \infty} K_{n+1, \eta_n} \\
 &\implies \xi_n^i \text{ almost iid copies of } \bar{X}_n
 \end{aligned}$$

Ex.: Feynman-Kac distribution flows

- **FK-Nonlinear Markov models :**

$\epsilon_n = \epsilon_n(\eta_n) \geq 0$ s.t. η_n -a.e. $\epsilon_n G_n \in [0, 1]$ ($\epsilon_n = 0$ not excluded)

$$K_{n+1, \eta_n}(x, dz) = \int S_{n, \eta_n}(x, dy) M_{n+1}(y, dz)$$

$$S_{n, \eta_n}(x, dy) := \epsilon_n G_n(x) \delta_x(dy) + (1 - \epsilon_n G_n(x)) \Psi_{G_n}(\eta_n)(dy)$$

- **Mean field genetic type particle model :**

$$\xi_n^i \in E_n \xrightarrow{\text{accept/reject/selection}} \widehat{\xi}_n^i \in E_n \xrightarrow{\text{proposal/mutation}} \xi_{n+1}^i \in E_{n+1}$$

- **Examples :**

- $G_n = 1_A \rightsquigarrow$ killing with uniform replacement.
- M_n -Metropolis/Gibbs moves \rightsquigarrow G_n -interaction function (subsets fitting or change of temperatures)

Mean field genetic type particle model :

$$\begin{bmatrix} \xi_n^1 \\ \vdots \\ \xi_n^i \\ \vdots \\ \xi_n^N \end{bmatrix} \xrightarrow{S_{n,\eta_n^N}} \begin{bmatrix} \widehat{\xi}_n^1 & \xrightarrow{M_{n+1}} & \xi_{n+1}^1 \\ \vdots & & \vdots \\ \widehat{\xi}_n^i & \xrightarrow{\quad\quad\quad} & \xi_{n+1}^i \\ \vdots & & \vdots \\ \widehat{\xi}_n^N & \xrightarrow{\quad\quad\quad} & \xi_{n+1}^N \end{bmatrix}$$

Accept/Reject/Selection transition :

$$S_{n,\eta_n^N}(\xi_n^i, dx)$$

$$:= \epsilon_n G_n(\xi_n^i) \delta_{\xi_n^i}(dx) + (1 - \epsilon_n G_n(\xi_n^i)) \sum_{j=1}^N \frac{G_n(\xi_n^j)}{\sum_{k=1}^N G_n(\xi_n^k)} \delta_{\xi_n^j}(dx)$$

Ex. : $G_n = 1_A$, $\epsilon_n = 1 \rightsquigarrow G_n(\xi_n^i) = 1_A(\xi_n^i)$

Path space models

- $X_n = (X'_0, \dots, X'_n) \rightsquigarrow$ genealogical tree/ancestral lines

$$\eta_n^N := \frac{1}{N} \sum_{1 \leq i \leq N} \delta_{\xi_n^i} = \frac{1}{N} \sum_{1 \leq i \leq N} \delta_{(\xi_{0,n}^i, \xi_{1,n}^i, \dots, \xi_{n,n}^i)} \simeq_{N \uparrow \infty} \eta_n$$

- **Unbias particle approximations :**

$$\gamma_n^N(1) = \prod_{0 \leq p < n} \eta_p^N(G_p) \simeq_{N \uparrow \infty} \gamma_n(1) = \prod_{0 \leq p < n} \eta_p(G_p)$$

- **Ex.** $G_n = 1_A :$

$$\Rightarrow \gamma_n^N(1) = \prod_{0 \leq p < n} (\text{success \% at } p)$$

- **FK-Mean field particle models** = sequential Monte Carlo, population Monte Carlo, particle filters, pruning, spawning, reconfiguration, quantum Monte carlo, go with the winner...

Objective

- Find a series of MCMC models $X^{(n)} := (X_k^{(n)})_{k \geq 0}$ s.t.

$$\eta_k^{(n)} = \frac{1}{k+1} \sum_{0 \leq l \leq k} \delta_{X_l^{(n)}}$$

$$\simeq_{k \uparrow \infty} \eta_n$$

\Rightarrow Use $\eta_k^{(n)} \simeq \eta_n$ to define $X^{(n+1)}$ with target η_{n+1}

Advantages

- Using η_n the sampling η_{n+1} is often easier.
- Improve the proposition step in any Metropolis type model with target η_{n+1} (\rightsquigarrow enters the stability prop. of the flow η_n)
- Increases the precision at every time step.
But CLT variance often \geq CLT variance mean field models.
- Easy to combine with mean field stochastic algorithms.

Interacting Markov chain Monte Carlo models

- Find M_0 and a collection of transitions $M_{n,\mu}$ s.t.

$$\eta_0 = \eta_0 M_0 \quad \text{and} \quad \Phi_n(\mu) = \Phi_n(\mu) M_{n,\mu}$$

- $(X_k^{(0)})_{k \geq 0}$ Markov chain $\sim M_0$.
- Given $X^{(n)}$, we let $X_k^{(n+1)}$ with Markov transitions $M_{n+1, \eta_k^{(n)}}$

Rationale :

$$\begin{aligned} \eta_k^{(n)} \simeq \eta_n &\implies \begin{cases} \Phi_{n+1}(\eta_k^{(n)}) \simeq \Phi_{n+1}(\eta_n) = \eta_{n+1} \\ M_{n+1, \eta_k^{(n)}} \simeq M_{n+1, \eta_n} \end{cases} \text{ with fixed point } \eta_{n+1} \\ &\implies \eta_k^{(n+1)} \simeq \eta_{n+1} \end{aligned}$$

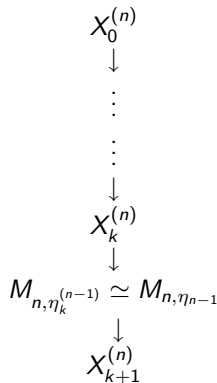
Example : $M_{n,\mu}(x, dy) = \Phi_n(\mu)(dy) \rightsquigarrow X_k^{(n+1)}$ r.v. $\sim \Phi_{n+1}(\eta_k^{(n)})$

$((n-1)$ -th chain)



$$\xrightarrow{\eta_k^{(n-1)} \simeq \eta_{n-1}}$$

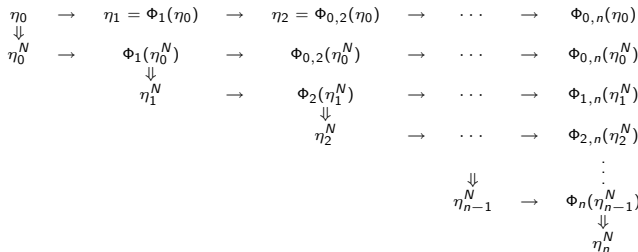
$(n$ -th chain)



[MEAN FIELD PARTICLE MODEL] **Nonlinear semigroup** $\longrightarrow \Phi_{p,n}(\eta_p) := \eta_n$

Local fluctuation theorem : $W_n^N := \sqrt{N} [\eta_n^N - \Phi_n(\eta_{n-1}^N)] \simeq W_n \perp$ Centered Gaussian field

Local transport formulation :



\rightsquigarrow **Key decomposition formula :**

$$\begin{aligned}
 \eta_n^N - \eta_n &= \sum_{q=0}^n [\Phi_{q,n}(\eta_q^N) - \Phi_{q,n}(\Phi_q(\eta_{q-1}^N))] \\
 &\simeq \frac{1}{\sqrt{N}} \sum_{q=0}^n W_q^N D_{q,n} \leftrightarrow \text{First order decomp. } \Phi_{p,n}(\eta) - \Phi_{p,n}(\mu) \simeq (\eta - \mu)D_{p,n} + (\eta - \mu)^{\otimes 2} \dots
 \end{aligned}$$

\Rightarrow **Example Functional CLT :** $\sqrt{N} [\eta_n^N - \eta_n] \simeq \sum_{q=0}^n W_q D_{q,n}$

[i-MCMC] **Nonlinear** sg $\Phi_{p,n}(\eta_p) = \eta_n$ with a first order decomp. :

$$\Phi_{p,n}(\eta) - \Phi_{p,n}(\mu) \simeq (\eta - \mu)D_{p,n} + (\eta - \mu)^{\otimes 2} \dots$$

↓

Functional CLT for correlated/interacting MCMC models :

$$\sqrt{k} [\eta_k^{(n)} - \eta_n] \simeq \sum_{q=0}^n \frac{\sqrt{(2(n-q))!}}{(n-q)!} V_q D_{q,n}$$

with $(V_q)_{q \geq 0} \perp$ Centered Gaussian field

$$\mathbb{E} \left(V_q(f)^2 \right) = \eta_q \left[(f - \eta_q(f))^2 \right] + 2 \sum_{m \geq 1} \eta_q \left[(f - \eta_q(f)) M_{q, \eta_{q-1}}^m (f - \eta_q(f)) \right]$$

"Comparisons" : **[Mean field case]** $(W_q)_{q \geq 0} \perp$ Centered Gaussian field

$$\mathbb{E} \left(W_q(f)^2 \right) = \eta_{q-1} \left\{ K_{q, \eta_{q-1}} (f - K_{q, \eta_{q-1}}(f))^2 \right\}$$

Case : $K_{q, \eta}(x, dy) = M_{q, \eta}(x, dy) = \Phi_q(\eta)(dy) \implies (V_q = W_q) \implies$ **[Mean field] > [i-MCMC]**

Some references

Interacting stochastic simulation algorithms

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Interacting stochastic simulation algorithms

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