

Equilibrium computation of free-energy differences using non-equilibrium methods

Mathias ROUSSET¹, Gabriel STOLTZ^{2,3}

¹ LSP, Université Paul Sabatier (Toulouse, France)

² CERMICS, ENPC (Marne-la-Vallée, France)

³ CEA/DAM (Bruyères-le-Châtel, France)

<http://cermics.enpc.fr/~stoltz/>

References

- Strategy inspired by the Sequential Monte Carlo philosophy
- M. Rousset and G. Stoltz, *An interacting particle approach for molecular dynamics*, submitted to *M3AS* (2005)
- Presentation and preprints available at the URL
<http://cermics.enpc.fr/~stoltz/>

Jarzynski's equality: a simulated annealing strategy

References

- Jarzynski's seminal papers:
 - Nonequilibrium equality for free-energy differences, *Phys. Rev. Lett.*, 78 (14) (1997) 2690-2693.
 - Equilibrium free energy differences from nonequilibrium measurements: a master equation approach, *Phys. Rev. E* 56(5) (1997) 5018–5035.
- A recent re-derivation (Jarzynski, *J. Stat. Mech.*, 2004)
- Improvements
 - Jarzynski's formula as a special case of a fluctuations/dissipation relation (Crooks, *PRE*, 1999 and *PRE*, 2000).
 - Path sampling method (Sun, *J. Chem. Phys.*, 2003)
- Pedagogical example: the ideal gas case (Lua/Grosberg, *J. Phys. Chem. B*, 2005)
- Many studies comparing different free-energy methods, the method is still a matter of debate among physicists!

The simulated annealing setting

- Family of Hamiltonian functions H_λ , parameter $\lambda \in [0, 1]$ (change of temperature, 'alchemical transition')
- Irreducible Markovian dynamics $t \mapsto X_t^{\lambda(t)}$, $X_0^{\lambda(0)} \sim \mu_0$
- Smooth schedule $t \mapsto \lambda(t)$ ($\lambda(1) = 0$ and $\lambda(T) = 1$)
- Canonical measure $d\mu_\lambda$ **invariant**
- Examples
 - Hypo-elliptic Langevin dynamics
 - Overdamped Langevin dynamics
 - Hamiltonian case (NVE) can also be considered (non irreducible)

Jarzynski's equality

- Differentiation of the *non-normalized* Boltzmann path $t \mapsto e^{-\beta H_{\lambda(t)}(x)} dx$

$$\partial_t \Pi_{\lambda(t)}(f) = \Pi_{\lambda(t)} \left(L_{\lambda(t)}(f) - \beta \frac{\partial H_{\lambda(t)}}{\partial \lambda} \lambda'(t) f \right).$$

- Free-energy $F(\lambda) = -\beta^{-1} \ln Z_\lambda$ (partition function Z)
- Feynman-Kac formula (with $f = 1$):

$$\mathbb{E}(e^{-\beta W_t}) = e^{-\beta(F(\lambda(t)) - F(0))}$$

- Work defined as $W_t = \int_0^t \frac{\partial H_{\lambda(s)}}{\partial \lambda} (X_s^{\lambda(s)}) \lambda'(s) ds$
- Jensen's inequality $\mathbb{E}(W_t) \geq F(\lambda(t)) - F(0) \rightarrow$ use the virtual work W_t to perform a **selection** between replicas

Re-interpreting the dynamics as a jump-diffusion process

Derivation of the jump-diffusion process

- Differentiation of the *normalized Boltzmann* (with $\mathcal{F}_\lambda = \mu_\lambda \left(\frac{\partial H_\lambda}{\partial \lambda} \right)$)

$$\partial_t \mu_{\lambda(t)}(f) = \mu_{\lambda(t)} \left(L_{\lambda(t)}(f) + \beta \left(\mathcal{F}_{\lambda(t)} - \frac{\partial H_{\lambda(t)}}{\partial \lambda} \right) \lambda'(t) f \right),$$

- Rewritten as a **nonlinear Markovian evolution**

$$\partial_t \mu_{\lambda(t)}(f) = \mu_{\lambda(t)} (L_{\lambda(t)}(f) + J_t(f))$$

- **Jump generator**

$$J_t(f)(x) = \int_{\mathcal{M}} (f(y) - f(x)) (\alpha_t^-(x) + \alpha_t^+(y)) \mu_{\lambda(t)}(dy)$$

with transition intensities

$$\alpha_t^- = \beta \lambda'(t) \left(\mathcal{F}_{\lambda(t)} - \frac{\partial H_{\lambda(t)}}{\partial \lambda} \right)^-, \quad \alpha_t^+ = \beta \lambda'(t) \left(\mathcal{F}_{\lambda(t)} - \frac{\partial H_{\lambda(t)}}{\partial \lambda} \right)^+$$

The jump-diffusion process

• Jump-diffusion process

Process 1 $Y_0 \sim d\mu_0(x)$, $(\tau_n^b, \tau_n^d)_{n \geq 1} \sim \mathcal{E}(1)$, $T_0^d = 0, T_0^b = 0$.

- Between each jump time, $t \mapsto Y_t$ evolves according to the chosen dynamics;

- At random times T_{n+1}^d defined by $\int_{T_n^d}^{T_{n+1}^d} \alpha_s^-(Y_s) ds = \tau_{n+1}^d$, the process jumps to a configuration y , chosen according to the probability measure $d\mu_{\lambda(T_{n+1}^d)}(y)$ [death];

- At random times T_{n+1}^b defined by $\int_{T_n^b}^{T_{n+1}^b} \mu_{\lambda(s)}(\alpha_s^+) ds = \tau_{n+1}^b$, the process jumps to a configuration y , chosen according to the probability measure $\sim \alpha_{T_{n+1}^b}^+(y) d\mu_{\lambda(T_{n+1}^b)}(y)$ [birth].

- For all $t \geq 0$, the law of Y_t is $\mu_{\lambda(t)}$.

Discretizing the process
using an Interacting Particle System
approach

Discretizing the process

- M replicas of the system
- Evolution in a **mean-field** sense: **empirical** mean force

$$\mathcal{F}_{\lambda(t)}^M = \frac{1}{M} \sum_{k=1}^M \frac{\partial H_{\lambda(t)}}{\partial \lambda}(X_t^k)$$

and **empirical** Boltzmann distribution

$$d\mu_{\lambda(t)}^M(x) = \frac{1}{M} \sum_{k=1}^M \delta_{X_t^k}(dx),$$

- Selection mechanism favors replicas sampling lower virtual works \rightarrow 'self-organization' to keep closer to a quasi-static transformation
- Convergence properties as $M \rightarrow \infty$

The IPS algorithm

Process 2 Initial distribution $(X_0^1, \dots, X_0^M) \sim d\mu_0(x)$, times $\tau_1^{k,b}, \tau_1^{k,d} \sim \mathcal{E}(1)$, initial jump times $T_0^{k,d} = 0, T_0^{k,b} = 0$.

- Between each jump time, evolve independently the replicas X_t^k according to the chosen dynamics;
- At random times $T_{n+1}^{k,d}$ defined by

$$\beta \int_{T_n^{k,d}}^{T_{n+1}^{k,d}} \left(\mathcal{F}_{\lambda(s)}^M - \frac{\partial H_{\lambda(s)}}{\partial \lambda}(X_s^k) \right)^- \lambda'(s) ds = \tau_{n+1}^{k,d},$$

pick at random $l \in \{1, \dots, M\}$, replace k -th replica by the l -th. New time $\tau_{n+2}^{k,d} \sim \mathcal{E}(1)$ [death];

- At random times $T_{n+1}^{k,b}$ defined by

$$\beta \int_{T_n^{k,b}}^{T_{n+1}^{k,b}} \left(\mathcal{F}_{\lambda(s)}^M - \frac{\partial H_{\lambda(s)}}{\partial \lambda}(X_s^k) \right)^+ \lambda'(s) ds = \tau_{n+1}^{k,b},$$

pick at random $l \in \{1, \dots, M\}$, replace l -th replica by the k -th. New time $\tau_{n+2}^{k,b} \sim \mathcal{E}(1)$ [birth].

Some numerical results

- IPS generates **canonical distributions for all $\lambda(t)$** , and allows computation of all free-energy differences in this range
- **Jarzynski's estimators** (rely on the tails of the work distributions)

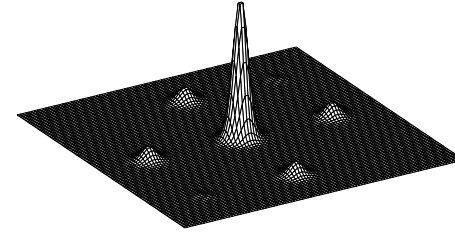
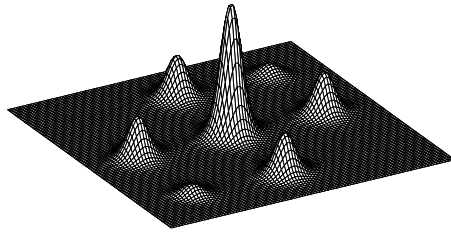
$$\Delta \hat{F}_J = -\frac{1}{\beta} \ln \left(\frac{1}{M} \sum_{k=1}^M e^{-\beta W_1^k} \right), \quad \Delta \hat{F}'_J = \int_0^T \mathcal{F}_{\lambda(t)}^{M_{\text{ind}}} \lambda'(t) dt,$$

where $\mathcal{F}_{\lambda(t)}^{M_{\text{ind}}} = \mu_{\lambda(t)}^{M_{\text{ind}}} \left(\frac{\partial H_{\lambda(t)}}{\partial \lambda} \right)$ with $\mu_{\lambda(t)}^{M_{\text{ind}}}(dx) = \frac{\sum_{k=1}^M \delta_{X_t^k}(dx) e^{-\beta W_t^i}}{\sum_{k=1}^M e^{-\beta W_t^i}}$.

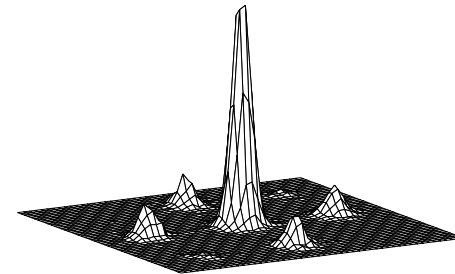
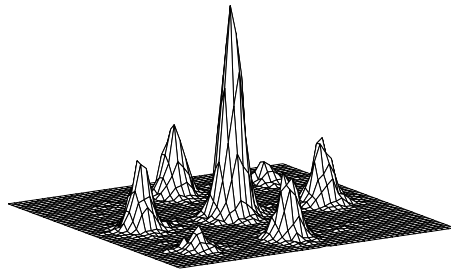
- **IPS estimator** ($e^{-\beta \Delta \hat{F}_{\text{IPS}}}$ unbiased estimator of $e^{-\beta \Delta F}$, $\Delta \hat{F}_{\text{IPS}}$ asymptotically normal with bias and variance of order M^{-1})

$$\Delta \hat{F}_{\text{IPS}} = \int_0^T \mathcal{F}_{\lambda(t)}^M \lambda'(t) dt.$$

Computation of canonical distributions

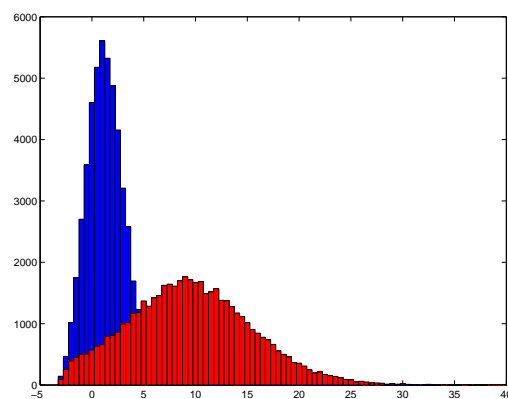
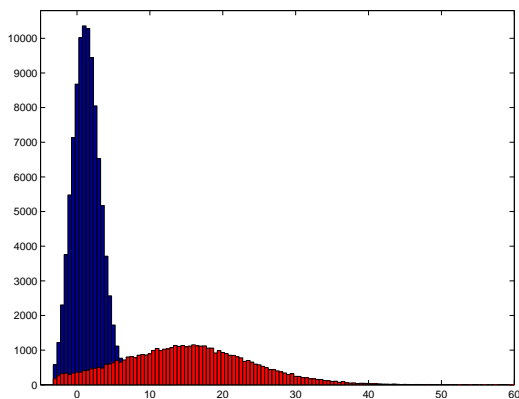


Empirical probability distribution of the dihedral angles (ϕ_1, ϕ_2) of the pentane molecule, for $T = 300$ K (Left) and $T' = 150$ K (Right) [Importance sampling, $M = 10^9$ points].



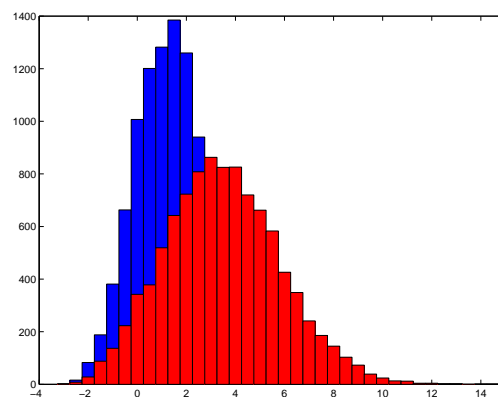
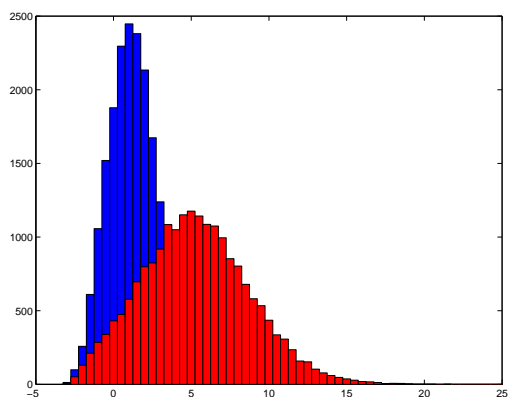
Empirical probability distributions at $T = 150$ K, generated with simulated annealing (Left), and IPS (Right), starting from $T = 300$ K, with sample size $M = 10,000$.

Computing free-energy differences: Widom insertion (Langevin dynamic



Left: $\mu_{\text{IPS}} = 1.37$ (blue), $\mu_{\text{SA}} = 1.32$ (red), $\tau = 1$. Right: $\mu_{\text{IPS}} = 1.35$, $\mu_{\text{SA}} = 1.29$ ($\tau = 2$).

Reference (Zwanzig, 10^8 points): $\mu_{\text{ex}} = 1.31$.



Left: $\mu_{\text{IPS}} = 1.29$, $\mu_{\text{SA}} = 1.33$ ($\tau = 5$). Right: $\mu_{\text{IPS}} = 1.34$, $\mu_{\text{SA}} = 1.36$ ($\tau = 10$).