

Fluctuating observation time
ensembles and an analogous
Jarzynski equality in the
thermodynamics of trajectories

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Overview

- Thermodynamics of trajectories
 - s -ensemble
- Fluctuating observation time
 - x -ensemble
 - Relation to s -ensemble
- Transition path sampling
 - Efficiency of the x -ensemble
- Analogous Jarzynski equality

s-ensemble

- Considering stochastic processes described by master equations : $\partial_t \rho(t) = W[\rho(t)]$

- Classical -
$$W \equiv \sum_{C' \neq C} A(C \rightarrow C') |C'\rangle \langle C| - \sum_C R(C) |C\rangle \langle C|$$

- Quantum -
$$W \equiv -i[H, \rho] + \sum_{i=1}^{N_L} L_i \rho L_i^\dagger - \frac{1}{2} \sum_{i=1}^{N_L} \{L_i^\dagger L_i, \rho\}$$

- Observe time record of some event – eg photon emission from an atomic source
- Probability of observing K events has a large-deviation (LD) form in the long time limit :

$$P_\tau(K) \approx e^{-t\varphi(K/\tau)}$$

- Can obtain moment generating function :

$$Z_\tau(s) \equiv \sum_{K=0}^{\infty} P_\tau(K) e^{-sK} \approx e^{\tau\theta(s)}$$

- θ and φ related by a Legendre transform :

$$\theta(s) = -\min_{K/\tau} [\varphi(K/\tau) + sK/\tau]$$

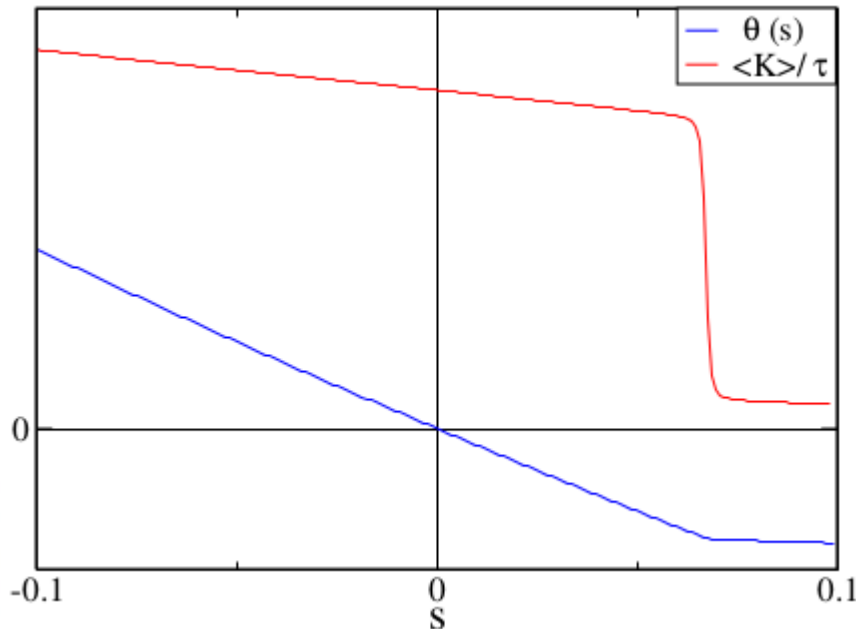
s-ensemble

- Can extract $\theta(s)$ directly from the largest eigenvalue of the *deformed* master operator, \mathbf{W}_s

$$\mathbf{W}_s(\rho_s) = -i[H, \rho] + e^{-s} L_1 \rho L_1^\dagger + \sum_{i=2}^{N_L} L_i \rho L_i^\dagger - \frac{1}{2} \sum_{i=1}^{N_L} \{L_i^\dagger L_i, \rho\}$$

- n -th cumulant of the activity obtained from $\theta(s)$

$$\frac{\langle\langle K^n \rangle\rangle}{\tau} = (-)^n \frac{\partial^n}{\partial s^n} \theta(s) \Big|_{s=0}$$



s defines an *ensemble of trajectories* with probability

$$P_s(\mathbf{X}_\tau) = \frac{e^{-sK} P(\mathbf{X}_\tau)}{Z_\tau(s)}$$

s-ensemble

- s-ensemble: Fixed time, fluctuating event numbers
 - “Grand Canonical Ensemble”
 - Time ~ “Volume”
 - K ~ “Particle Numbers”
 - $\varphi(K/\tau)$ ~ “Entropy density”
 - $\theta(s)$ ~ “Free Energy”
 - s ~ “Chemical Potential”

x-ensemble

- As with thermodynamic ensembles, free to choose which quantities are fixed and which vary
- x-ensemble: fix event numbers, K , allow time to fluctuate

- Probability that observing K events takes a time t :

$$P_K(t) \approx e^{-K\psi(\tau/K)}$$

- Moment Generating Function

$$Z_t(s) \equiv \int_0^{\infty} d\tau P_K(t) e^{-x\tau} \approx e^{Kg(x)}$$

- Again, ψ and g are related by a Legendre transformation:

$$g(x) = -\min_{\tau/K} [\psi(\tau/K) + x\tau/K]$$

- Can define a transfer matrix

$$\mathbf{T}_x \equiv \sum_{C' \neq C} \frac{A_s(C \rightarrow C')}{x + R(C)} |C'\rangle \langle C| \quad \mathbf{T}_x \equiv \sum_{i=1}^{N_L} L_i [(x + \mathbf{R})^{-1}(\rho)] L_i^\dagger \quad ; \quad \mathbf{R} \equiv iH_{\text{eff}}\rho - i\rho H_{\text{eff}}$$

- By relating \mathbf{W}_s and \mathbf{T}_x , can show

$$g(x) = \theta^{-1}(x)$$

$$\theta(s) = g^{-1}(s)$$

Generalised ensembles

- s-ensemble: Fixed time, fluctuating event numbers

- “Grand Canonical Ensemble”
- Time ~ “Volume”
 - fixed
- K ~ “Particle Numbers”
 - fluctuates
- $\varphi(K/\tau)$ ~ “Entropy density”
- $\theta(s)$ ~ “Free Energy”
- s ~ “Chemical Potential”

$$\mathbf{X}_\tau : \begin{array}{cccccc} 0 & t_1 & t_2 & \dots & t_n & \tau \\ \blacksquare & | & | & \dots & | & \blacksquare \\ \mathcal{C}_0 & \mathcal{C}_1 & \mathcal{C}_2 & \dots & \mathcal{C}_n & \end{array} P_s(\mathbf{X}_\tau) = \frac{e^{-sn} P(\mathbf{X}_\tau)}{Z_\tau(s)}$$

$$\mathbf{X}'_\tau : \begin{array}{cccccc} 0 & t'_1 & t'_2 & \dots & t'_{n'} & \tau \\ \blacksquare & | & | & \dots & | & \blacksquare \\ \mathcal{C}'_0 & \mathcal{C}'_1 & \mathcal{C}'_2 & \dots & \mathcal{C}'_{n'} & \end{array} P_s(\mathbf{X}'_\tau) = \frac{e^{-sn'} P(\mathbf{X}'_\tau)}{Z_\tau(s)}$$

⋮

- x-ensemble: Fixed event numbers, fluctuating time

- “Isobaric-isothermal Ensemble”
- Time
 - fluctuates
- K
 - fixed
- $\Psi(\tau/K)$
- $g(x)$ - “Grand Potential”
- x ~ “Pressure”

$$\mathbf{Y}_K : \begin{array}{cccccc} 0 & t_1 & t_2 & \dots & t_{K-1} & \tau \\ \blacksquare & | & | & \dots & | & | \\ \mathcal{C}_0 & \mathcal{C}_1 & \mathcal{C}_2 & \dots & \mathcal{C}_{K-1} & \mathcal{C}_K \end{array} P_x(\mathbf{Y}_K) = \frac{e^{-x\tau} P(\mathbf{Y}_K)}{Z_K(x)}$$

$$\mathbf{Y}'_K : \begin{array}{cccccc} 0 & t'_1 & t'_2 & \dots & t'_{K-1} & \tau' \\ \blacksquare & | & | & \dots & | & | \\ \mathcal{C}'_0 & \mathcal{C}'_1 & \mathcal{C}'_2 & \dots & \mathcal{C}'_{K-1} & \mathcal{C}'_K \end{array} P_x(\mathbf{Y}'_K) = \frac{e^{-x\tau'} P(\mathbf{Y}'_K)}{Z_K(x)}$$

⋮

Transition path sampling (TPS)

- Motivation :
 - Efficiently generate 'rare' events
 - Well suited to the s/x -ensemble description
- TPS is a Metropolis-Hastings algorithm applied to trajectories rather than static configurations
- Method :
 - Simulate systems using continuous-time Monte Carlo
 - Random walk through the space of trajectories
 - Bias the random walk towards the ensemble of trajectories defined by

$$P_s(\mathbf{X}_\tau) = \frac{e^{-sK} P(\mathbf{X}_\tau)}{Z_\tau(s)} \quad ; \quad P_x(\mathbf{Y}_K) = \frac{e^{-x\tau} P(\mathbf{Y}_K)}{Z_K(x)}$$

Transition path sampling (TPS)

- Algorithm :

1. Generate a trajectory, Y , and calculate observables of interest τ , \mathbf{M} ...
2. Propose a new trajectory, $Y'(\tau', \mathbf{M}')$
3. Calculate the change in the observables of interest, $\Delta\tau = \tau' - \tau$, etc...
4. Accept or reject the proposed trajectory with probability

$$P_{accept} = \min \{1, e^{-x\Delta\tau - s\Delta K}\}$$

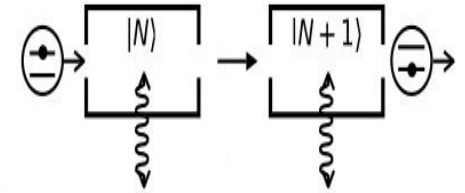
5. Repeat steps 2-4 until the trajectory has “equilibrated” to the desired values of x, s

x-ensemble TPS scheme

- Typically with fixed observation time, use “forwards-backwards shooting/shifting”
 - On average, half of an old trajectory is replaced
- With fixed total event numbers, K , a trajectory is fully described by K sets of random numbers
 - Modifying one (or more) of the sets of random numbers produces a legitimate trajectory
 - Method of Crooks/Chandler
- Furthermore, it is possible to reconstruct the s -ensemble from x -ensemble numerics

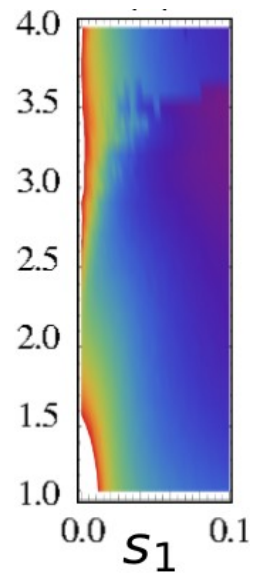
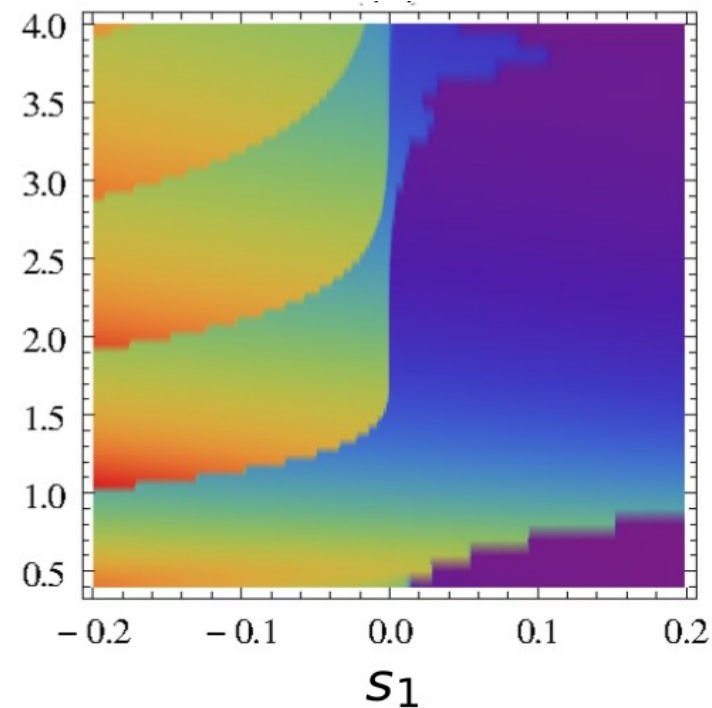
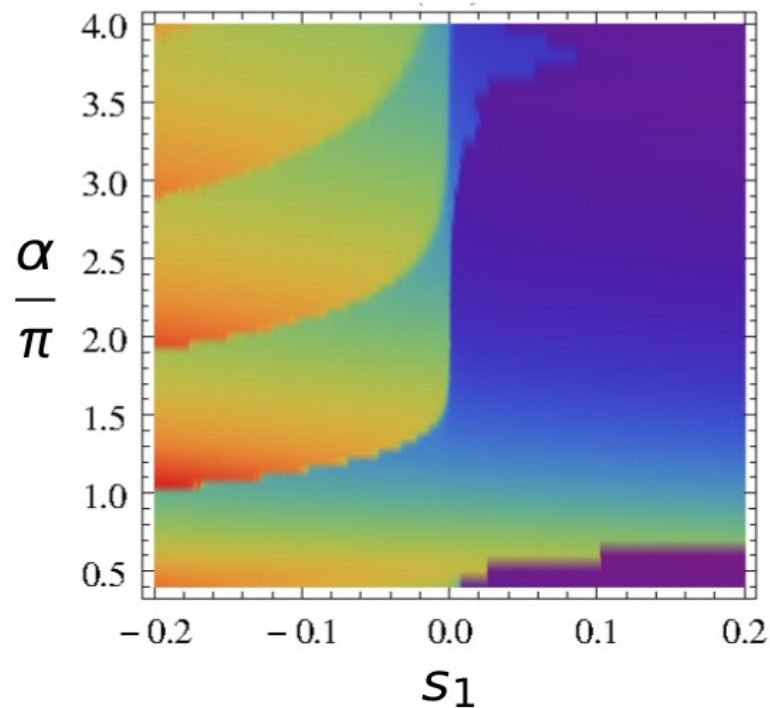
Results : Micromaser

$$L_1 = \sqrt{r} \sin \frac{(\varphi \sqrt{aa^\dagger})}{\sqrt{aa^\dagger}} a \quad L_2 = \sqrt{r} \cos(\varphi \sqrt{aa^\dagger})$$



$$L_3 = \sqrt{\kappa} a$$

$$L_4 = \sqrt{\gamma} a^\dagger$$



$$\alpha \equiv \varphi \sqrt{r / (\kappa - \gamma)}$$

Analogous Jarzynski equality

- Other properties of thermodynamic ensembles should be preserved in the *thermodynamics of trajectories*
- Of particular interest, Jarzynski equality allows for calculation of free-energy differences between two equilibrium states, using non-equilibrium (fast) processes

$$\langle e^{-W/kT} \rangle = e^{-\Delta F/kT}$$

- Important to remember there are two layers to the dynamics: the non-equilibrium trajectory taken by a system, and the *meta-dynamics* of a the trajectory being “equilibrated” to a trajectory typical of the ensemble defined by x , through TPS
- Free-energy difference between two states becomes the difference in the LD function $g(x)$ between two trajectories from ensembles defined by values x_i, x_f

$$\Delta F = g(x_f) - g(x_i)$$

- Need to identify a candidate for “work”

Analogous Jarzynski equality - Method

- Meta-dynamics of trajectories: Move in a series of N TPS steps from some x_i to some x_f
- Identify “meta-work” done in taking the system from x_i to x_f as

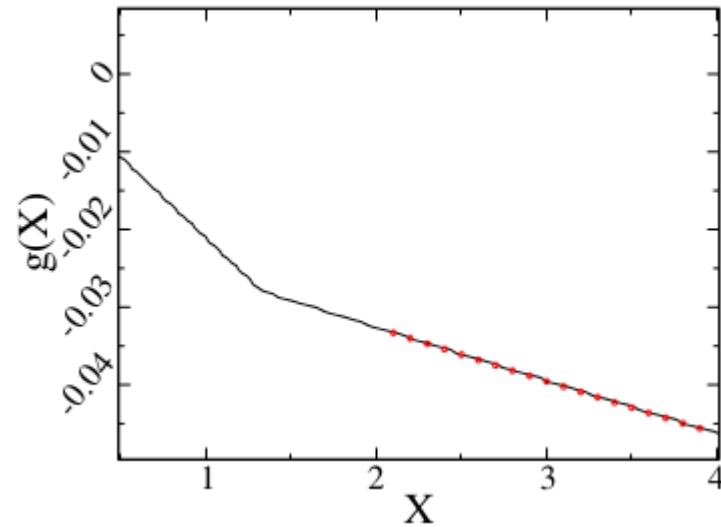
$$W = \sum_{i=1}^{i=N-1} (x_{i+1} - x_i) \tau_i$$

- “Equilibrate” the trajectory to x_f
- Reverse process: move from x_f to x_i
- Repeat the process J times to build a distribution of meta-work done for each of the forward and reverse processes respectively
- x can change quickly - “out of meta-equilibrium” but needs to be some overlap in the work distributions for the forward and reverse processes
- Meta-free-energy difference calculated the iterative Bennets Acceptance Ratio (BAR) method

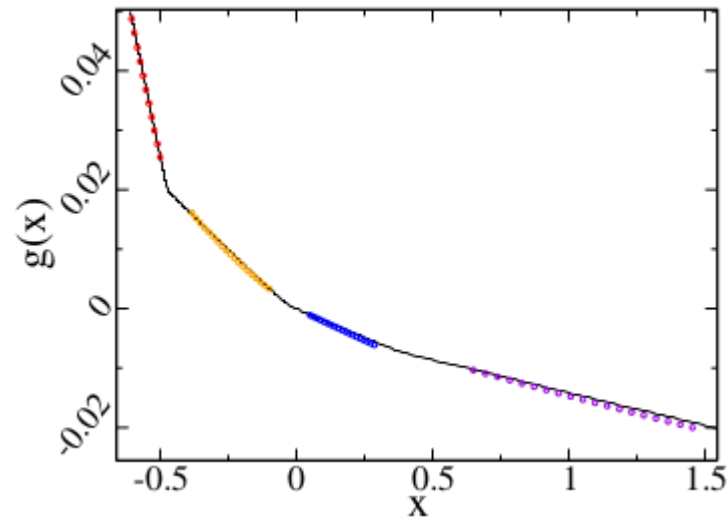
$$\Delta g^{(n+1)} = -\ln \frac{\sum_{j=1}^J [1 + e^{W_{\text{forward},j} - \Delta g^{(n)}}]^{(-1)}}{\sum_{j=1}^J [1 + e^{W_{\text{reverse},j} - \Delta g^{(n)}}]^{(-1)}}$$

Analogous Jarzynski equality

$$\alpha = 1.2 \pi$$

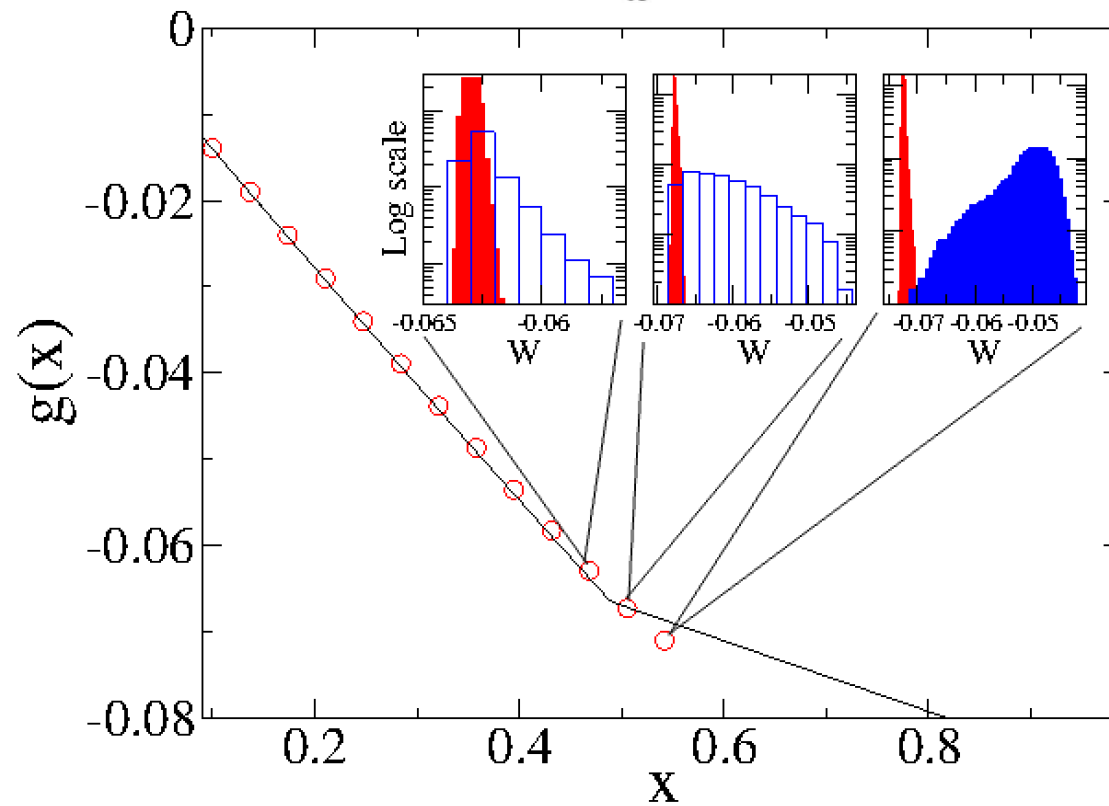
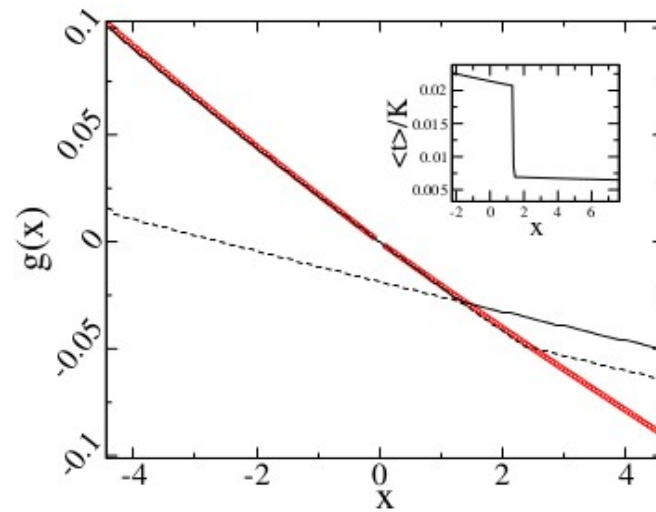


$$\alpha = 4 \pi$$



Analogous Jarzynski equality

$$\alpha = 1.2 \pi$$



Conclusions

- Flexible language – pick the ensemble most suited to the problem
 - Can convert between ensembles at a later stage
- Fluctuating time ensembles can potentially (depending on the system) provide orders of magnitude greater efficiency in the simulation of atypical trajectories
 - Applicable in any case trajectories can be fully described by a sequence of sets of random numbers
 - Can predict sources of efficiency gain for a system
 - Worst case scenario s-ensemble and x-ensemble TPS schemes are roughly equivalent in performance
- Analogous Jarzynski equality provides a direct method of calculating meta-free-energy differences in the thermodynamics of trajectories
- Potential scope to explore useful properties and relations of other thermodynamic ensembles