

## Reweighting

Suppose that a MC simulation generates samples  $x_t \sim \pi_\beta(x_t) = \frac{1}{Z} e^{-\beta E(x)}$  from a canonical distribution at temperature  $T = \frac{1}{\beta}$ .

Using these we can estimate expectation values  $\langle A \rangle_\beta = \int A(x) \pi_\beta(x) dx \approx$

$$\approx \bar{A}_\beta = \frac{1}{N} \sum_t A(x_t)$$

But we can also use the samples to estimate expectation values at different  $\beta'$ :

$$\begin{aligned} \langle A \rangle_{\beta'} &= \int A(x) \pi_{\beta'}(x) dx = \int A(x) \frac{\pi_{\beta'}(x)}{\pi_\beta(x)} \pi_\beta(x) dx = \\ &= \langle A \hat{W} \rangle_\beta \approx \frac{1}{N} \sum_t A(x_t) \hat{W}(x_t) \end{aligned}$$

$$\approx \bar{A}_{\beta'} = \frac{1}{N} \sum_t A(x_t) \hat{W}(x_t) \approx$$

$$\approx \frac{\sum_t A(x_t) W(x_t)}{\sum_t W(x_t)}$$

The last self-normalized version has the advantage that we don't need to know the normalization constants  $Z_\beta, Z_{\beta'}$ .

Thus, we can extrapolate the simulation at  $\beta$  to nearby  $\beta'$ .

The extrapolation only works in a rather small region around  $\beta$ , since the samples from  $\pi_\beta$  must contribute significantly to  $\pi_{\beta'}$ .



the overlap needs to be large.

If not the fluctuations in the weight  $w(x) = e^{-(\beta' - \beta)E(x)}$  becomes too large.

Mathematically we must require that  $\pi_{\beta'}(\cdot)$  is absolutely continuous with respect to  $\pi_\beta(\cdot)$ .

### Single histogram reweighting

In practice one may collect a histogram of the energies encountered in the simulation,

$$H(E) = \sum_{t=1}^N \delta_{E, E(x_t)} \quad \text{and} \quad A(E) = \sum_{t=1}^N A(x_t) \delta_{E, E(x_t)}$$

$$\text{Then } \langle A \rangle_{\beta'} \approx \bar{A}_{\beta'} = \frac{\sum_E A(E) e^{-(\beta' - \beta)E}}{\sum_E e^{-(\beta' - \beta)E} H(E)}$$

## WHAM

To extrapolate over a wider range one can use the multiple histogram method, a.k.a. WHAM, Weighted Histogram Analysis Method (see also MBAR, which is a binless method working with the time series instead of histograms.)

Recall that  $\pi_\beta(x) = \frac{e^{-\beta E(x)}}{Z}$

$$\pi_\beta(E) = \int \delta(E - E(x)) \pi_\beta(x) dx = \underbrace{\Omega(E)}_{\text{Density of states}} \frac{e^{-\beta E}}{Z}$$

From a single histogram  $H_{\beta_i}(E)$  collected at  $\beta_i$  we can estimate

$$\Omega_i(E) = Z_i e^{\beta_i E} \frac{H_{\beta_i}(E)}{N_i} = e^{\beta_i(E - F_i)} \frac{H_{\beta_i}(E)}{N_i}$$

Since  $\Omega(E)$  does not depend on  $\beta$  we can combine the estimates  $\Omega_i$  taken at different  $\beta_i$  into

$$\bar{\Omega}(E) = \sum_i \alpha_i(E) \Omega_i(E)$$

Choose  $\alpha_i(E)$  to minimize the variance of  $\bar{\Omega}(E)$  under the constraint  $\sum \alpha_i(E) = 1$ .

Natural to assume  $\text{Var } H_i(E) \approx \langle H_i(E) \rangle$  (Poisson distr)

$$\text{Var } \bar{\Omega} = \sum_i \alpha_i^2(E) \left( \frac{e^{\beta_i(E - F_i)}}{N_i} \right)^2 N_i e^{\beta_i(F_i - E)}$$

$$\text{Min Var } \bar{\Omega} \rightarrow \sum_i \alpha_i \Rightarrow \alpha_i(E) = \frac{N_i e^{\beta_i(F_i - E)}}{\sum_j N_j e^{\beta_j(F_j - E)}}$$

⇒ the WHAM eqs

$$\bar{\Omega}(E) = \frac{\sum_i H_i(E)}{\sum_i N_i e^{\beta_i(F_i - E)}}$$

The unknown free energies  $F_i$  may be solved for selfconsistently

$$e^{-\beta F} = \sum_E \bar{\Omega}(E) e^{-\beta E} = \sum_E \frac{\sum_i H_i(E) e^{-\beta E}}{\sum_i N_i e^{\beta_i(F_i - E)}}$$

The temperatures  $\beta_i$  should be chosen so that the neighboring distributions overlap

