

We want to compute the error on the sample mean, which is again defined as

$$\sigma^2 = \left\langle \left( \frac{1}{N+1} \sum_{n=0}^N f(X_n) - \sum_x \pi_x f(x) \right)^2 \right\rangle_{MC,0}$$

where, the average is taken over all possible histories (MC repetitions) that start at  $X_0$ .

Note: This expression is correct only if there is no bias on the sample mean or if the bias is negligible. For generic  $X_0$  this occurs for large values of  $N$ . The formula is valid for any  $N$  if we start in equilibrium (the only case we will consider, see slide 3).

**THEOREM:** The limit

$$\lim_{N \rightarrow \infty} N \sigma^2$$

is finite and independent of the initial configuration.

Thus, also in the case of dynamic Monte Carlo fluctuations (errors) decrease as  $1/\sqrt{N}$ .

We wish now to estimate  $\sigma^2$  from the data. If

$$F = \sum_x \pi_x f(x)$$

we have

$$\sigma^2 = \frac{1}{(N+1)^2} \sum_{n=0}^N \sum_{m=0}^N \langle (f(X_n) - F)(f(X_m) - F) \rangle_{MC,0}$$

Now we define the **autocorrelation function**  $C_f(n, m, X_0)$  :

$$C_f(n, m, X_0) = \langle (f(X_n) - F)(f(X_m) - F) \rangle_{MC,0}$$

so that

$$\sigma^2 = \frac{1}{(N+1)^2} \sum_{n=0}^N \sum_{m=0}^N C_f(n, m; X_0)$$

The autocorrelation function depends on  $X_0$ , while the large- $N$  limit of  $\sigma$  does not.

**We now assume we start in equilibrium.** From a mathematical point, starting in equilibrium means averaging over the starting point with probability  $\pi$ : we average the behavior of the system with respect to the initial state using the equilibrium distribution.

In practice, starting in equilibrium means considering a **typical configuration** as starting conf (if we choose a configuration with probability  $\pi_x$ , we will obviously select a typical configuration).

In equilibrium, configurations at time  $t = n$  are distributed according to  $\pi$ .

$$\text{prob of } y \text{ at time } n = \sum_{x_0} \pi_{x_0} P_{x_0 y}^n$$

But now we use repeatedly the stationarity relation  $\sum_x \pi_x P_{xy} = \pi_y$  so that

$$\sum_{x_0} \pi_{x_0} P_{x_0 y}^n = \sum_{x_0} \pi_{x_0} \sum_z P_{x_0 z} P_{zy}^{n-1} = \sum_z \left[ \sum_{x_0} \pi_{x_0} P_{x_0 z} \right] P_{zy}^{n-1} = \sum_z \pi_z P_{zy}^{n-1} = \dots = \pi_y$$

Configurations have always the same distribution, independently of time: the system is **time-translation invariant**.

We define the **equilibrium autocorrelation function**:

$$C_f(n, m; \text{eq}) = \sum_x \pi_x C_f(n, m, x)$$

The equilibrium autocorrelation function is time-translation invariant, hence depends only on  $|n - m|$ :  $C_f(n, m; \text{eq}) = C_f(|n - m|)$ . Therefore,

$$\sigma^2 = \frac{1}{(N+1)^2} \sum_{n=0}^N \sum_{m=0}^N C_f(|n - m|)$$

Now, we wish to replace the two sums with a single sum over  $k = n - m$ .

To understand this point, let us imagine  $N = 2$  and compute ( $g(n)$  is a generic function)

$$\sum_{n=0}^N \sum_{m=0}^N g(n-m) = \sum_{n=0}^2 [g(n) + g(n-1) + g(n-2)]$$

Now we make the summation over  $n$  explicit. We obtain

$$g(0) + g(-1) + g(-2)$$

here  $n = 0$

$$g(1) + g(0) + g(-1)$$

here  $n = 1$

$$g(2) + g(1) + g(0)$$

here  $n = 2$

Summing all terms, we get

$$3g(0) + 2g(1) + 2g(-1) + g(2) + g(-2)$$

For generic values of  $N$  we have

$$\sum_{n=0}^N \sum_{m=0}^N g(n-m) = (N+1)g(0) + N[g(1) + g(-1)] + (N-1)[g(2) + g(-2)] + \dots + g(N) + g(-N)$$

that is

$$\sum_{n=0}^N \sum_{m=0}^N g(n-m) = (N+1)g(0) + \sum_{k=1}^N (N+1-k)[g(k) + g(-k)]$$

It follows

$$\begin{aligned} \sigma^2 &= \frac{1}{(N+1)^2} \left[ (N+1)C_f(0) + 2 \sum_{k=1}^N (N+1-k)C_f(k) \right] \\ \sigma^2 &= \frac{1}{(N+1)} \left[ C_f(0) + 2 \sum_{k=1}^N C_f(k) \right] - \frac{2}{(N+1)^2} \sum_{k=1}^N kC_f(k) \end{aligned}$$

The function  $C_f(|k|)$  decays exponentially (not at continuous transitions but we are not discussing this issue here). This guarantees that for  $N \rightarrow \infty$  we have

- (a)  $\sum_{k=1}^N C_f(k) \approx \sum_{k=1}^{\infty} C_f(k)$ , with (exponentially small) corrections that vanish as  $N \rightarrow \infty$ .
- (b)  $\sum_{k=1}^N k C_f(k)$  is finite for  $N \rightarrow \infty$ , so that the last term in the expression of  $\sigma^2$  is of order  $N^{-2}$ .

Hence, we have proved that the error is of order  $1/N$  and obtained the relation

$$\sigma^2 = \frac{1}{N+1} \left[ C_f(0) + 2 \sum_{k=1}^{\infty} C_f(k) \right].$$

**Observation:**  $C_f(0)$  is the variance with respect to  $\pi$   
We use the definition

$$C_f(n, n; X_0) = \langle (f(X_n) - F)^2 \rangle_{MC,0} = \sum_x P_{X_0, x}^n (f(x) - F)^2$$

Now we assume that we are in equilibrium:

$$C_f(0) = \sum_{x_0} C_f(n, n; x_0) \pi_{x_0} = \sum_{x_0} \sum_x \pi_{x_0} P_{x_0, x}^n (f(x) - F)^2 = \sum_x (f(x) - F)^2 \sum_{x_0} \pi_{x_0} P_{x_0, x}^n$$

$$C_f(0) = \sum_x (f(x) - F)^2 \pi_x = \langle (f(x) - F)^2 \rangle_{\pi} = \text{Var}_{\pi} f$$

**Observation.** For static algorithms we obtain the usual formula (do not get confused by the  $N+1$  in the normalization: here we sum from 0 to  $N$  and therefore there are  $N+1$  data).

Indeed, if  $n \neq m$  we have  $\langle f(X_n)f(X_m) \rangle_{MC} = \langle f(X_n) \rangle_{MC} \langle f(X_m) \rangle_{MC}$ . It follows  $C_f(n, m; X_0) = 0$  if  $n \neq m$ .

For **uncorrelated data** the autocorrelation function  $C_f(n)$  vanishes except for  $n = 0$ .

It follows

$$\sigma^2 = \frac{1}{N+1} C_f(0) = \frac{1}{N+1} \text{Var}_{\pi} f$$



# Integrated autocorrelation time

We define an **integrated autocorrelation time**  $\tau_{\text{int},f}$  as

$$\tau_{\text{int},f} = \frac{1}{2} + \sum_{k=1}^{\infty} \frac{C_f(k)}{C_f(0)}.$$

The error becomes

$$\sigma^2 = \frac{C_f(0)}{N+1} 2\tau_{\text{int},f}.$$

The definition of  $\tau_{\text{int},f}$  can be understood by considering the simple case in which  $C_f(k) = C_f(0) \exp(-k/\tau)$ . We use the result for the geometric series  $(1-x)^{-1} = \sum_n x^n$ , so that

$$\sum_{k=1}^{\infty} e^{-k/\tau} = -1 + \sum_{k=0}^{\infty} e^{-k/\tau} = -1 + \frac{1}{1-e^{-1/\tau}}$$

It follows

$$\tau_{\text{int},f} = -\frac{1}{2} + \frac{1}{1-e^{-1/\tau}} \approx \tau$$

where the last equality holds for  $\tau \gg 1$  ( $1/\tau$  is small so that we can expand the expression in powers of  $1/\tau$ ,  $e^{-1/\tau} \approx 1 - 1/\tau$ ). For uncorrelated data  $\tau_{\text{int},f} = 1/2$ .