

Lecture 5 Monte-Carlo Methods and Diagrammatics

Objective for today:

- brief introduction to Monte-Carlo integration
- continuous time QMC as an example method using diagrams.
- next time, will cover labeled diagrammatic MC.

Disclaimer: there are many other useful MC techniques that I will not touch upon.

- Variational Monte-Carlo
- Diffusion Monte-Carlo
- ...

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Monte-Carlo basics:

- generally, a method to evaluate high-dimensional integrals.
- integral is transformed into a summation over characteristic configurations that are generated from a Markov-chain process.
- expectation values in some distribution with weight / probability $p(\underline{x})$

$$\langle O \rangle_p = \frac{1}{Z} \int \underbrace{d\underline{x}}_{\text{integral over configuration space}} O(\underline{x}) p(\underline{x})$$

with the partition function (total weight)

$$Z = \int \underbrace{d\underline{x}}_c p(\underline{x})$$

A Monte-Carlo process will approximate the observable

$$\langle O \rangle_p \leftarrow \langle O \rangle_{MC} = \frac{1}{M} \sum_{i=1}^M O(\underline{x}_i)$$

where configurations $\underline{x}_i$ are selected with probability $\frac{p(\underline{x}_i)}{Z}$.

By virtue of the central limit theorem, in the limit of many samples, the error between our estimates and the exact value will scale via

$$(\Delta O)^2 = \langle (O_{MC} - O_p)^2 \rangle = \frac{\text{Var } O}{M}$$

$$\text{i.e. } \Delta O \sim \frac{1}{\sqrt{M}}$$

Generating Samples via a Markov-Chain

- transition matrix $T_{x,y}$ between configurations, giving probability to go from $\underline{x}$ to y
- approximate the true distribution by a sequence of configurations drawn from any starting point $\underline{x} = \underline{\sigma}_0$ in C

The transition-matrix needs to satisfy

- $$\sum_j T_{xy} = 1 \quad : \text{ Normalization}$$

2. Ergodicity: any configuration x must be reachable from any other configuration y in a finite number of steps:

$$\forall x, y, \exists N < \infty \mid n \geq N: (T^n)_{x,y} \neq 0.$$

- Balance: probability to reach a certain point = probability to leave it.

$$\int_C d\underline{x} \, p(\underline{x}) \, T_{xy} = p(y)$$

(so: $p(x)$ is a left eigenvector of T_{τ_y})

In general, matrices satisfying balance are difficult to construct, unless requiring

- Detailed Balance:

$$\frac{T_{xy}}{T_{yx}} = \frac{p(y)}{p(x)} \quad \text{or} \quad \overset{\downarrow}{p(x)} T_{xy} = \overset{\downarrow}{p(y)} T_{yx}$$

Metropolis-Hastings algorithm

- particular scheme for constructing a set of moves satisfying detailed balance: in two steps:

- 1) propose a given move to go from $x \rightarrow y$ with the a-priori probability

$$A(x \rightarrow y)$$

- 2) Accept or reject the move with an acceptance ~~probability~~ ~~ratio~~ probability

$$B(x \rightarrow y)$$

such that $T_{xy} = A(x \rightarrow y) B(x \rightarrow y)$

Using detailed balance, we require:

$$p(x) A(x \rightarrow y) B(x \rightarrow y) = p(y) A(y \rightarrow x) B(y \rightarrow x)$$

so

$$\boxed{\frac{B(x \rightarrow y)}{B(y \rightarrow x)} = \frac{p(y) A(y \rightarrow x)}{p(x) A(x \rightarrow y)} \equiv R}$$

Now, Metropolis proposed to resolve this via

$$B(x \rightarrow y) = \min(1, R)$$

$$B(y \rightarrow x) = \min(1, 1/R)$$

i.e. R determines the probability that a given move should be accepted.

Reweighting

the exact distribution $p(x)$ may be difficult/inconvenient to calculate, and we can sample instead with a different probability distribution to estimate

$$\langle O \rangle = \frac{1}{Z} \int dx O(x) p(x)$$

$$= \frac{\int dx O(x) \frac{p(x)}{q(x)} q(x)}{\int dx \frac{p(x)}{q(x)} q(x)}$$

$$= \frac{\langle O \cdot \frac{p}{q} \rangle_q}{\langle \frac{p}{q} \rangle_q}$$

(Cave needs to be taken when estimating the errors on the ratio of these averages, as they are drawn from the same samples of configurations...
 $\Rightarrow$ jackknife / bootstrap procedure, see e.g. Numerical Recipes)

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Quantum Field Theory with Monte Carlo:

- proposed to evaluate the partition function of a quantum problem directly! (at finite T)

$$Z = \text{Tr} \left\{ e^{-\beta(\hat{H} - \mu \hat{N})} \right\}$$

which can be expressed in the interaction representation of a solvable piece $\hat{H}_0$ of the Hamiltonian

$$\text{with } H = H_0 + H_1$$

$$Z = \text{Tr} \left\{ e^{-\beta(\hat{H}_0 - \mu \hat{N})} \mathcal{U}(0, \beta) \right\}$$

$$= \sum_{n=0}^{\infty} \left(-\frac{1}{i}\right)^n \int_0^{\beta} d\tau_1 \int_0^{\beta} d\tau_2 \dots \int_0^{\beta} d\tau_n \underbrace{\text{Tr} \left\{ e^{-\beta(\hat{H}_0 - \mu \hat{N})} H_1(\tau_n) H_1(\tau_{n-1}) \dots H_1(\tau_1) \right\}}_{\rightarrow \text{Feynman diagrams via Wick's theorem.}}$$

$$= \sum_{\substack{n=0 \\ \text{diagrams}}}^{\infty} \sum_{\substack{\gamma \\ \text{topology of diagram}}} \int d\tau_1 \dots \int d\tau_n W(n, \gamma, \tau)$$

Let's call a configuration the ensemble of parameters that classify order, topology and interactions of a diagram.

$$\sigma = (n, \gamma, \tau, \dots)$$

The weight or probability of a given configuration is

$$p(\sigma) = W(\sigma) d\tau_1 d\tau_2 \dots d\tau_n$$

which we assume to be positive for the moment.

Why continuous time is possible:

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Integration over internal momenta proceeds as in a usual MC integration, however, we have a new class of moves which change the diagram order n .

Typically, this move will be of the following form (not thinking about $\hbar$)

$$\sigma_n = (n, \vec{\tau}) = (n, \tau_1, \dots, \tau_n)$$

$\Downarrow$

$$\sigma_{n+1}^1 = (n+1, \vec{\tau}^1) = (n+1, \tau_1^1, \dots, \tau_{n+1}^1)$$

We can draw the time τ_{n+1}^1 of the new vertex uniformly in $[0, \hbar\beta]$, so the ~~prop~~ a-priori possibility to propose the move is

$$A(\sigma_n \rightarrow \sigma_{n+1}^1) = \frac{d\tau}{\hbar\beta}$$

for the reverse move of eliminating one vertex, we can just select one vertex at random

$$A(\sigma_{n+1}^1 \rightarrow \sigma_n) = \frac{1}{k+1}$$

Hence, the acceptance ratio becomes

$$R_{(n, \vec{\tau}; n+1, \vec{\tau}^1)} = \frac{p(\sigma_{n+1}^1) A(\sigma_{n+1}^1 \rightarrow \sigma_n)}{p(\sigma_n) A(\sigma_n \rightarrow \sigma_{n+1}^1)}$$

$$= \frac{W(\sigma_{n+1}^1) d\tau_1^1 \dots d\tau_{n+1}^1}{W(\sigma_n) d\tau_1 \dots d\tau_n} \frac{\frac{1}{k+1}}{d\tau / \hbar\beta}$$

$$= \frac{W(\sigma_{n+1}^1)}{W(\sigma_n)} \frac{\hbar\beta}{k+1} \Rightarrow \text{all factors of the infinitesimal } d\tau \text{ cancel.}$$

$\Rightarrow$ can use continuous τ .

Note on the sign problem:

for a generic fermionic theory, the diagram weight can become negative, so we cannot use $w(\sigma)$ as a sampling probability. Instead, we may use a re-weighting technique and take the sampling probability to be $|w(\sigma)|$

$$Z_f = \sum_{\sigma \in C} \frac{w(\sigma)}{|w(\sigma)|} |w(\sigma)| = \langle \text{sgn}(w) \rangle_{|w|}$$

and we then have to sample observables via

$$\langle O \rangle = \frac{\langle O \text{sgn}(w) \rangle_{|w|}}{\langle \text{sgn}(w) \rangle_{|w|}}$$

The fermionic partition function has a numerically much smaller value than the corresponding bosonic problem with $w_B = |w|$. $Z_B = \int d\tau w_B(\sigma)$. The ratio is related to the free energy difference ΔF .

$$\langle \text{sgn}(w) \rangle = \frac{Z_f}{Z_B} = e^{-\beta \Delta F}$$

Hence, the calculation needs to be run until the variance is of order of the expectation-value.

$$\begin{aligned} \text{Var sgn}(w) &= \langle \text{sgn}(w)^2 \rangle - \langle \text{sgn}(w) \rangle^2 \\ &= 1 - e^{-2\beta \Delta F} \approx 1 \end{aligned}$$

and the relative error grows with decreasing T :

$$\Delta \text{sgn}(w) = \frac{\frac{1}{\sqrt{M}} \sqrt{\text{var sgn}(w)}}{\langle \text{sgn}(w) \rangle} = \frac{e^{\beta \Delta F}}{\sqrt{M}}$$

$\Rightarrow$ computer-time grows exponentially at low T .

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Example application:

Single-impurity Anderson model:

$$H = H_{\text{bath}} + H_{\text{hyb}} + H_u + H_{\text{imp}}$$

$$H_{\text{bath}} = \sum_{k, \sigma} \epsilon_{k, \sigma} \hat{c}_{k\sigma}^\dagger \hat{c}_{k\sigma}$$

$$H_{\text{imp}} = \sum_{\sigma} \epsilon^{\sigma\sigma'} \hat{d}_{\sigma}^\dagger \hat{d}_{\sigma'} \quad ; \quad \text{here: } \epsilon^{\sigma\sigma'} = \epsilon_0 \delta_{\sigma\sigma'}$$

$$H_{\text{hyb}} = \sum_{k, \sigma} (V_k \hat{c}_{k\sigma}^\dagger \hat{d}_{\sigma} + \text{h.c.})$$

$$H_u = U \hat{n}_{\uparrow} \hat{n}_{\downarrow} \quad \hat{n}_{\sigma} = \hat{d}_{\sigma}^\dagger \hat{d}_{\sigma}$$

there is only one interaction-term, while all other parts are free.

The task is to calculate the impurity Green's function

$$\begin{aligned} G_d(\tau) &= \langle T_{\tau} d(\tau) d^\dagger(0) \rangle \\ &= \frac{1}{Z} \text{Tr} \left\{ e^{-(\beta-\tau)H} d e^{-\tau H} d^\dagger \right\} \\ &\quad \uparrow \\ &\quad \text{trace over bath + impurity D.O.F.} \end{aligned}$$

The bath can be integrated out analytically, given that fermions $\hat{c}^{(\sigma)}$ obey a free theory. This yields a renormalized propagator for the $\hat{d}$'s. $\rightarrow$ $d=0$ problem!

$$\begin{aligned} S_0^{\text{eff}} &= \int d\tau d\tau' \sum_{\sigma\sigma'} \hat{d}_{\sigma}^\dagger(\tau) \left[(\partial_{\tau} + \epsilon^{\sigma\sigma'}) \delta(\tau - \tau') \right. \\ &\quad \left. + \Delta^{\sigma\sigma'}(\tau - \tau') \right] \hat{d}_{\sigma}(\tau') \end{aligned}$$

where the hybridization-function derives from the coupling:

$$\Delta^{\sigma\sigma'}(i\omega_n) = \sum_{k\mu} V_k^{*\sigma\mu} (i\omega_n - \epsilon_{k\mu})^{-1} V_k^{\mu\sigma'}$$

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We thus have a bare Green's function for d-el's:

$$(G_d^0)_{\sigma\sigma'} = - \left(\frac{1}{i\omega_n + \underline{E} + \underline{\Delta}} \right)_{\sigma\sigma'} \stackrel{\text{here}}{=} \frac{1}{i\omega_n - \epsilon_0 - \Delta\sigma} \delta_{\sigma\sigma'}$$

In addition, we have the interaction term with the local Hamiltonian H_u , which we treat perturbatively:

$$H_{int}(\tau) = H_u(\tau) = U \hat{n}_r(\tau) \hat{n}_l(\tau)$$

At n^{th} order, we have to consider diagrams arising from

$$\text{Tr} \left\{ e^{-\beta H_0} H_{int}(\tau_n) \dots H_{int}(\tau_1) \right\}$$

$$= U^n \left\langle \left(\hat{n}_r(\tau_n) \hat{n}_l(\tau_n) \right) \left(\hat{n}_r(\tau_{n-1}) \hat{n}_l(\tau_{n-1}) \right) \dots \left(\hat{n}_r(\tau_1) \hat{n}_l(\tau_1) \right) \right\rangle_0$$

$$= \left\langle \underbrace{d_r^\dagger(\tau_n) d_r(\tau_n)}_{\text{}} d_l^\dagger(\tau_n) d_l(\tau_n) \dots d_r^\dagger(\tau_1) d_r(\tau_1) d_l^\dagger(\tau_1) d_l(\tau_1) \right\rangle_0$$

Wick's th.

$$= \det \mathcal{D}_n^r \times \det \mathcal{D}_n^l$$

$$\text{using } - \langle \tau d(\tau_i) d^\dagger(\tau_j) \rangle = G_d^0(\tau_i - \tau_j)$$

$$\Rightarrow \left(\mathcal{D}_n^\sigma \right)_{ij} = G_\sigma^0(\tau_i - \tau_j).$$

and the partition-function has the form:

$$\mathcal{Z} = \mathcal{Z}_0 \sum_{n=0}^{\infty} \frac{(-U)^n}{n!} \int_0^\beta d\tau_n \dots \int_0^\beta d\tau_1 \prod_\sigma (\det \mathcal{D}_n^\sigma).$$

$$\text{and the weight-function is } w(n, \vec{\tau}) = \frac{(-U)^n}{n!} \prod_\sigma (\det \mathcal{D}_n^\sigma)$$

Note: the trivial sign-problem for $U > 0$ can be managed by redefinitions.

E.g.
$$\left\{ \begin{array}{l} d_{\downarrow}^{\dagger} \rightarrow \tilde{d}_{\downarrow} \\ d_{\downarrow} \rightarrow \tilde{d}_{\downarrow}^{\dagger} \end{array} \right\} \quad \text{p-h. conjugate } \downarrow\text{-spins.}$$

$$\Rightarrow \left\{ \begin{array}{l} \epsilon_{0L} \rightarrow -\epsilon_{0L} \\ \epsilon_{0R} \rightarrow \epsilon_{0R} + U \end{array} \right. \quad \begin{array}{l} \Delta_L(\tau) \rightarrow -\Delta_L(-\tau) \\ \underline{U \rightarrow -U} \end{array}$$

(Better approach to do this symmetrically)

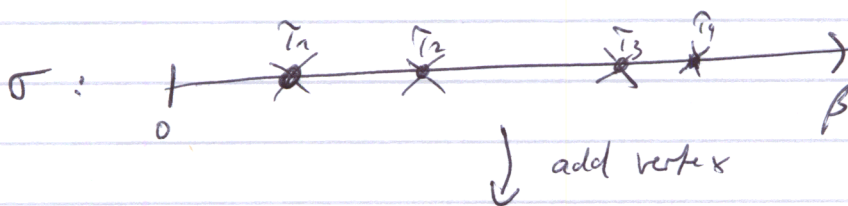
Anyway, we can get a positive weight-function $\omega(\tau, \tau^2)$.

$\Rightarrow$ Updates can proceed as discussed previously

by inserting/removing a single vertex at τ_i

(topology does not occur, as we summed over all contractions of the correlator in form of a determinant!)

$\leadsto (d=0)$



with acceptance ratio
$$R = \frac{t\beta U}{(k+1)} \prod_{\sigma} \frac{\det D_{n+1}^{\sigma}}{\det D_n^{\sigma}}$$

$\uparrow$

can evaluate ratio efficiently!

Measurements:

ultimately, we want to measure observables, such as the propagator

$$G_0(\tau - \tau') = -\frac{z_0}{z} \sum_{n=0}^{\infty} \frac{(u)^n}{n!} \int d\tau_1 \dots d\tau_n \underbrace{\left\langle T_F d\tau(\tau) d\tau^\dagger(\tau') H_1(\tau_1) \dots H_1(\tau_n) \right\rangle}_{g(\tau, \tau'; \vec{\tau})}$$

while we sample a series (with the same summations and integrations) with probability/weight $w(\tau, \vec{\tau})$

the suitable estimator is

$$G_0(\tau - \tau') \leftarrow \frac{\langle g(\tau, \tau'; \vec{\tau}) \rangle_0}{\langle w(\tau, \vec{\tau}) \rangle_0} \Big|_{MC}$$

$\uparrow$ all Wick-contractions in the free theory $\uparrow$ average ~~sum~~ over MC samples.

as previously for $w(\tau, \vec{\tau})$, the expression for $g(\tau, \tau'; \vec{\tau})$ expands to a determinant of Green's / cf.° .

Summary / Outlook:

- we've seen some of the basic ingredients for constructing continuous time / determinant Monte Carlo algorithms.
- there is a considerable body of work on these and similar algorithms. See
 - E. Gull et al. Rev. Mod. Phys. 83 (2011)
 - Philip Wein: Continuous time impurity solvers, Notes (2011)