# Monte Carlo methods 

## Dénes Sexty

University of Graz

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Here we discuss the Ising-model.

$$
\begin{equation*}
H=-J \sum_{\text {neighbors }} s_{i} s_{j}-h \sum_{i} s_{i} \tag{1}
\end{equation*}
$$

Near $T_{c}$ there are large domains.
Spin-flip Metropolis alg. moves the boundaries of the domains
$\rightarrow$ many sweeps until a new configuration

Autocorrelation: $\tau \sim \xi^{z}$
$z \approx 2.125$ for 2D Ising, $z \approx 2$ for 3D Ising


Close to $T_{c}$ one a $128 \times 128$ lattice

The idea in Swendsen-Wang is to better understand the physical degrees of freedom (the domains) and try to update them.
Given a configuration
1 Visit all links which have the same spins at both ends
2 introduce a bond with probability

$$
\begin{equation*}
P_{\text {bond }}=1-e^{-2 \beta J} \tag{2}
\end{equation*}
$$

3 identify clusters which are connected with bonds
(Use Hoshen-Kopelmann as discussed in connection with percolation)
4 Flip all clusters with probability $\frac{1}{2}$
5 delete all bonds $\rightarrow$ new configuration


## Swendsen-Wang

The algorithm is ergodic
There is a nonzero chance that any spin becomes a cluster on its own and is flipped
$\Longrightarrow$ Any configuration can be reached for any other configuration.

Detailed balance is satisfied $\Longrightarrow$ we get to the correct distribution

Very effiecient As clusters can get broken up and large islands get flipped in one step.

$$
\begin{equation*}
2 \mathrm{D}: \quad z \sim 0.33 \quad 3 \mathrm{D}: z \sim 0.53 \tag{3}
\end{equation*}
$$

Further Advantage: Some observables measured in terms of clusters After identification of the clusters, every cluster could be flipped with $1 / 2$ probability
$\Longrightarrow \quad 2^{N_{c}}$ configurations can be reached, each with the same probability. We can use all of these configurations to measure some observables.

$$
\begin{equation*}
m=\frac{1}{V} \sum_{i} s_{i}=\frac{1}{V} \sum_{k=1}^{N_{c}} n_{k} \operatorname{sign} C_{k} \tag{4}
\end{equation*}
$$

$N_{c}$ is the number of clusters, $n_{k}$ is the number of spins in the $k$-th cluster. $\operatorname{sign}\left(C_{k}\right)$ is the orientation in the $k$-th cluster.

$$
\begin{aligned}
\left\langle m^{2}\right\rangle & =\frac{1}{V^{2}}\left\langle\left(\sum_{k=1}^{N_{c}} n_{k} \operatorname{sign}\left(C_{k}\right)\right)^{2}\right\rangle=\frac{1}{V^{2}}\left\langle\sum_{k, k^{\prime}=1}^{N_{c}} n_{k} n_{k^{\prime}} \operatorname{sign}\left(C_{k}\right) \operatorname{sign}\left(C_{k^{\prime}}\right)\right\rangle(\text { (5) } \\
& =\frac{1}{V^{2}}\left\langle\sum_{k=1}^{N_{c}} n_{k}^{2}\right\rangle+\frac{1}{V^{2}}\left\langle\sum_{k \neq k^{\prime}} n_{k} n_{k}^{\prime} \operatorname{sign}\left(C_{k}\right) \operatorname{sign}\left(C_{k^{\prime}}\right\rangle\right.
\end{aligned}
$$

The second term averages to zero.
also called Wolff algorithm
1 Choose a lattice point randomly (called the "seed" of the cluster)
2 Look for neighbors with the same spin and connect to them via a bond with probability $p_{b o n d}=1-e^{-2 \beta J}$
3 Go to the new elements of the cluster and try their neighbors as before with probability $p_{\text {bond }}$
4 If the cluster's growth is finished, flip it.
No cluster identification is needed, but also no improved estimators are only partly available.
Average cluster size ( $p_{i}=$ prob. of choosing the seed in $i$-th cluster):

$$
\begin{equation*}
\langle n\rangle=\sum_{i} p_{i} n_{i}=\sum_{i} \frac{n_{i}}{V} n_{i}=V\left\langle m^{2}\right\rangle \tag{6}
\end{equation*}
$$

above $T_{c}$ we have $\langle m\rangle=0$ so we have

$$
\begin{equation*}
\chi=V\left\langle m^{2}\right\rangle=\langle n\rangle \tag{7}
\end{equation*}
$$

Generalization of the Swendsen-Wang algorithm for continous spins.
$O(N)$ Spin model

$$
H=-J \sum_{\text {neigh. }} S_{i} S_{j}, \quad S_{i}=\left(\begin{array}{c}
S_{i}^{1}  \tag{8}\\
S_{i}^{2} \\
\vdots \\
S_{i}^{N}
\end{array}\right), \quad S_{i} S_{i}=1
$$

$S$ is invariant under global rotations with $M$ orthogonal matrix

$$
\begin{equation*}
S_{i}^{\prime}=M S_{i}, \quad M^{T} M=1 \quad \Longrightarrow \quad S_{i}^{\prime} S_{j}^{\prime}=S_{i}^{\prime T} S_{j}^{\prime}=S_{i}^{T} M^{T} M S_{j}=S_{i} S_{j} \tag{9}
\end{equation*}
$$

Spins can be decomposed in parallel and perpendicular components given a vector $u$ with $u u=1$

$$
\begin{equation*}
S_{i}^{\|}=\left(S_{i} u\right) u, \quad S_{i}^{\perp}=S_{i}-S_{i}^{\|} \tag{10}
\end{equation*}
$$

$\Longrightarrow \quad S_{i}^{\perp} u=S_{i}^{\perp} S_{j}^{\|}=0$
Scalar products can be decomposed:

$$
\begin{equation*}
S_{i} S_{j}=\left(S_{i}^{\|}+S_{i}^{\perp}\right)\left(S_{j}^{\|}+S_{j}^{\perp}\right)=S_{i}^{\|} S_{j}^{\|}+S_{i}^{\perp} S_{j}^{\perp} \tag{11}
\end{equation*}
$$

we choose a random unit vector $u$

$$
\begin{equation*}
H=-J \sum_{n e i g h} S_{i} S_{j}=-J \sum\left[S_{i}^{\|} S_{j}^{\|}+S_{i}^{\perp} S_{j}^{\perp}\right] \tag{12}
\end{equation*}
$$

We can write the parallel part as $S_{i}^{\|}=\epsilon_{i}\left|S_{i}^{\|}\right| u$ with $\epsilon_{i}= \pm 1$ We than decompose the Hamiltonian:

$$
\begin{align*}
& H=\underbrace{-J \sum\left|S_{i}^{\|}\right|\left|S_{j}^{\|}\right| \epsilon_{i} \epsilon_{j}}_{=H^{\|}} \underbrace{-J \sum S_{i}^{\perp} S_{j}^{\perp}}_{=H^{\perp}}  \tag{13}\\
& H^{\|}=-\sum_{n e i g h} J_{i j} \epsilon_{i} \epsilon_{j}, \quad J_{i j}=J\left|S_{i}^{\|} \| S_{j}^{\|}\right| \tag{14}
\end{align*}
$$

Effective Ising Hamiltonian with bond dependent coupling.

Now we can update $\epsilon_{i}$ with the Swendsen-Wang alg.
1 choose a random $u$ vector with $u u=1$
$\boxed{2}$ insert a bond between neighbors $\epsilon_{i}$ and $\epsilon_{j}$ with probability

$$
p_{\text {bond }}=1-e^{-2 \beta J_{i j}}
$$

3 identify clusters
4 Flip each cluster with probability $\frac{1}{2}$.

$$
\begin{equation*}
S_{i}=S_{i}^{\|}+S_{i}^{\perp} \rightarrow-S_{i}^{\|}+S_{i}^{\perp} \tag{15}
\end{equation*}
$$

5 Delete all bonds

One can show that detailed balance, ergodicity is OK.

## Quantum spins

Consider a spin chain with spin $\frac{1}{2}$ particles. Basis states for one spin:

$$
\begin{equation*}
\text { spin up: }|+1\rangle=\binom{1}{0} \quad \text { spin down: }|-1\rangle=\binom{0}{1} \tag{16}
\end{equation*}
$$

Pauli operators:

$$
\hat{\sigma}^{z}|s\rangle=s|s\rangle, \quad \hat{\sigma}^{z}=\left(\begin{array}{cc}
1 & 0  \tag{17}\\
0 & -1
\end{array}\right), \quad \hat{\sigma}^{x}|s\rangle=|-s\rangle, \quad \hat{\sigma}^{x}=\left(\begin{array}{cc}
0 & 1 \\
1 & 0
\end{array}\right)
$$

We have a chain of $L$ spins. The Hilbert space is given by:

$$
\begin{equation*}
|s\rangle=\left|s_{1}\right\rangle \otimes\left|s_{2}\right\rangle \otimes \ldots\left|s_{L}\right\rangle, \quad s_{n}= \pm 1, \quad\left\langle s \mid s^{\prime}\right\rangle=\prod_{i=1}^{L}\left\langle s_{i} \mid s_{i}^{\prime}\right\rangle \tag{18}
\end{equation*}
$$

Commutation relations:

$$
\begin{array}{r}
\forall n, m:\left[\hat{\sigma}_{n}^{x}, \hat{\sigma}_{m}^{x}\right]=\left[\hat{\sigma}_{n}^{z}, \hat{\sigma}_{m}^{z}\right]=0  \tag{19}\\
\forall n \neq m:\left[\hat{\sigma}_{n}^{x}, \hat{\sigma}_{m}^{z}\right]=0, \quad \forall n:\left[\hat{\sigma}_{n}^{x}, \hat{\sigma}_{m}^{z}\right] \neq 0
\end{array}
$$

one dimensional Ising model in a transverse field

$$
\begin{equation*}
\hat{H}=\underbrace{-J \sum_{i=1}^{N} \hat{\sigma}_{i}^{z} \hat{\sigma}_{i+1}^{z}}_{=\hat{H}_{1}} \underbrace{-h \sum_{i=1}^{N} \hat{\sigma}_{i}^{x}}_{=\hat{H}_{2}} \tag{20}
\end{equation*}
$$

We want to calculate the canonical partition function

$$
\begin{equation*}
Z=\operatorname{Tr}\left(e^{-\beta \hat{H}}\right) \tag{21}
\end{equation*}
$$

Baker-Campbell-Hausdorf:

$$
\begin{equation*}
e^{(A+B) \Delta t}=e^{A \Delta t} e^{B \Delta t} e^{-\frac{1}{2}[A, B] \Delta t^{2}}+O\left(\Delta t^{3}\right) \tag{22}
\end{equation*}
$$

Trotter Formula

$$
\begin{equation*}
e^{A+B}=\lim _{n \rightarrow \infty}\left(e^{A / n} e^{B / n}\right)^{n} \tag{23}
\end{equation*}
$$

$$
\begin{gathered}
e^{A / n}=1+\frac{A}{n}+O\left(\frac{1}{n^{2}}\right) \quad e^{A / n} e^{B / n}=1+\frac{A+B}{n}+O\left(\frac{1}{n^{2}}\right) \\
\left(e^{A / n} e^{B / n}\right)^{n}=\sum_{k=0}^{n}\binom{n}{k}\left(\frac{A+B}{n}\right)^{k}+O\left(1 / n^{2}\right) \\
\binom{n}{k} \frac{1}{n^{k}}=\frac{n(n-1) \ldots(n-k+1)}{n^{k}} \frac{1}{k!}=(1+O(1 / n)) \frac{1}{k!}
\end{gathered}
$$

$$
\lim _{n \rightarrow \infty}\left(e^{A / n} e^{B / n}\right)^{n}=\lim _{n \rightarrow \infty} \sum_{k=0}^{n} \frac{A+B}{k!}(1+O(1 / n))+O\left(1 / n^{2}\right)=e^{A+B}
$$

We can therefore use for small step : $e^{i(A+B) \Delta t}=e^{i A \Delta t} e^{i B \Delta t}+O\left(\Delta t^{2}\right)$
Higher order discretisation: $e^{i(A+B) \Delta t}=e^{i A \Delta t / 2} e^{i B \Delta t} e^{i A \Delta t / 2}+O\left(\Delta t^{3}\right)$ Exercise: Show that

$$
e^{-i H_{1} \Delta t / 2} \ldots e^{-i H_{\llcorner } \Delta t / 2} e^{-i H_{L} \Delta t / 2} \ldots e^{-i H_{1} \Delta t / 2}=e^{-i \sum H_{i} \Delta t}+O\left(\Delta t^{3}\right)
$$

## Partition function

$$
\begin{gathered}
Z_{N}=\operatorname{Tr}\left(e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\right)^{N}=\sum_{s}\langle s|\left(e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\right)^{N}|s\rangle= \\
=\sum_{s^{(0)}, \ldots, s^{(N-1)}\left\langle s^{(0)}\right| e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\left|s^{(1)}\right\rangle\left\langle s^{(1)}\right| e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\left|s^{(2)}\right\rangle \ldots}^{\left\langle s^{(N-1)}\right| e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\left|s^{(0)}\right\rangle}
\end{gathered}
$$

Now we calculate each matrix element:

$$
\langle s| e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\left|s^{\prime}\right\rangle=\langle s| \prod_{i} e^{\frac{\beta J}{N} \hat{\sigma}_{i}^{z} \hat{\sigma}_{i+1}^{z}} \prod_{i} e^{\frac{\beta h}{N} \hat{\sigma}_{i}^{\chi}}\left|s^{\prime}\right\rangle=\prod_{i=1}^{L} e^{\frac{\beta J}{N} s_{i} s_{i+1}} \prod_{i=1}^{L}\left\langle s_{i}\right| e^{\frac{\beta h}{N} \hat{\sigma}_{i}^{\chi}}\left|s_{i}^{\prime}\right\rangle
$$

We can simplify the second factor using $\left(\hat{\sigma}^{x}\right)^{2}=1$

$$
\begin{equation*}
\left\langle s_{i}\right| e^{\frac{\beta h}{N} \hat{\sigma}_{i}^{\times}}\left|s_{i}^{\prime}\right\rangle=\left\langle s_{i}\right| \cosh \frac{\beta h}{N}+\sinh \frac{\beta h}{N} \hat{\sigma}_{i}^{x}\left|s_{i}^{\prime}\right\rangle \tag{25}
\end{equation*}
$$

This means:

$$
\begin{gathered}
\left\langle s_{i}\right| e^{\frac{\beta h}{N} \hat{\sigma}_{i}^{x}}\left|s_{i}^{\prime}\right\rangle=\left\{\begin{array}{l}
\cosh \frac{\beta h}{N} \text { for } s_{i}=s_{i}^{\prime} \\
\sinh \frac{\beta h}{N} \text { for } s_{i} \neq s_{i}^{\prime}=\underbrace{\sqrt{\sinh \frac{\beta h}{N} \cosh \frac{\beta h}{N}}\left(\frac{\sqrt{\cosh (\beta h / N)}}{\sqrt{\sinh (\beta h / N)}}\right)^{s_{i} s_{i}^{\prime}}=}_{=C} \\
=C e^{\frac{\beta}{N} K s_{i} s_{i}^{\prime}} \text { with } K=\frac{N}{2 \beta} \ln \left(\operatorname{coth}\left(\frac{\beta h}{N}\right)\right)
\end{array},\right.
\end{gathered}
$$

## Partition function

$$
\begin{align*}
\langle s| e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\left|s^{\prime}\right\rangle & =\prod_{i=1}^{L} e^{\frac{\beta J}{N} s_{i} s_{i+1}} \prod_{i=1}^{L}\left\langle s_{i}\right| e^{\frac{\beta h}{N} \hat{\sigma}_{i}^{x}}\left|s_{i}^{\prime}\right\rangle=e^{\sum_{i=1}^{L} \frac{\beta J}{N} s_{i} s_{i+1}} \prod_{i=1}^{L} C e^{\frac{\beta}{N} K s_{i} s_{i}^{\prime}}= \\
& =C^{L} e^{\sum_{i=1}^{L} \frac{\beta J}{N} s_{i} s_{i+1}+\sum_{i=1}^{L} \frac{\beta}{N} K s_{i} s_{i}^{\prime}}
\end{align*}
$$

Now we need the product of $N$ such matrices:

$$
\begin{equation*}
Z_{N}=\sum_{s^{(0)}, \ldots, s^{(N-1)}} \prod_{t=0}^{N}\left\langle s^{(t)}\right| e^{-\frac{\beta}{N} \hat{H}_{1}} e^{-\frac{\beta}{N} \hat{H}_{2}}\left|s^{(t+1)}\right\rangle \tag{27}
\end{equation*}
$$

We have periodic boundary conditions in $t$ (and also in the $i$ direction)

$$
\begin{align*}
Z_{N} & =C^{L N} \sum_{s^{(0)}, \ldots, s^{(N-1)}} \prod_{t=0}^{N} e^{\sum_{i=1}^{L} \frac{\beta J}{N} s_{i}^{(t)} s_{i+1}^{(t)}+\sum_{i=1}^{L} \frac{\beta K}{N} s_{i}^{(t)} s_{i}^{(t+1)}}=  \tag{28}\\
& =C^{L N} \sum_{s_{i}^{(t)}= \pm 1} e^{\frac{\beta}{N} \sum_{i, t}\left[J s_{i}^{(t)} s_{i+1}^{(t)}+K s_{i}^{(t)} s_{i}^{(t+1)}\right]}
\end{align*}
$$

Quantum 1D Ising chain $\rightarrow$ 2D classical (anisotropic) Ising model

11 $\hat{H}=\sum \hat{H}_{i}$ terms in each $H_{i}$ should commute with each other.
■ Trotter decomposition:

$$
\begin{equation*}
Z=\lim Z_{N}, \quad Z_{N}=\operatorname{Tr}\left[\left(\prod_{i} e^{-\frac{\beta}{N} \hat{H}_{i}}\right)^{N}\right] \tag{29}
\end{equation*}
$$

B include the unity operator: $1=\sum_{\alpha}\left|\alpha^{(t)}\right\rangle\left\langle\alpha^{(t)}\right|$ between each $\prod_{i} e^{-\frac{\beta}{N} \hat{H}_{i}}$

$$
\begin{equation*}
Z_{N}=\sum_{\alpha}\left\langle\alpha^{(0)}\right| \prod_{i} e^{-\frac{\beta}{N} \hat{H}_{i}}\left|\alpha^{(1)}\right\rangle \ldots\left\langle\alpha^{(N-1)}\right| \prod_{i} e^{-\frac{\beta}{N} \hat{H}_{i}}\left|\alpha^{(0)}\right\rangle \tag{30}
\end{equation*}
$$

4. Calculate the matrix element

$$
\begin{equation*}
\left\langle\alpha^{(t}\right| \prod_{i} e^{-\frac{\beta}{N} \hat{H}_{i}}\left|\alpha^{(t+1)}\right\rangle \tag{31}
\end{equation*}
$$

To get the partition function as a sum over "configurations" $\alpha^{(t)}$
This converts a dimensional quantum system into a $d+1$ dimensional classical statistical system, which can be dealt with using standard Monte Carlo methods.

## Microcanonical simulations

Suppose we want to calculate in the Microcanonical ensemble (should not matter much if the system size is large)
Usually $\rightarrow$ Use the equations of motion calculated e.g. in Hamiltonian formulation $\equiv$ Molecular dynamics. Random sampling through chaotic behaviour. (Not discussed in detail in this lecture).
What to do with e.g. the Ising model, where no time evolution eq. is available?
Alternative: Demon Algorithm for calculating in the Microcanonical ensemble by Creutz. A demon travels on the lattice, and it has a bag which can contain a positive amount of energy

1 initialize a configuration with a given energy $E$, the bag is empty. (or lattice ground state, bag contains all energy)
2 Propose a change in the configuration
3 if the energy change is negative, the demon takes the energy (and puts it into the bag) and the change is carried out.
4 if the energy change is positive, and the demon has enough energy in its bag, it is carried out, substracting the energy from the bag.
5 otherwise the change is rejected.
6 goto 2

From the point of the demon, the system acts a big heat reservoir. $E_{D}$, the energy in the bag is distributed as:
$\Longrightarrow p\left(E_{D}\right) \sim e^{-\beta E_{D}}$
This allows the measurement of a temperature.
Consider e.g. Ising model with zero magnetic field. In this case the

$$
\begin{equation*}
E_{D}=4 k J, \quad k=0,1, \ldots \tag{32}
\end{equation*}
$$

$$
\begin{aligned}
\left\langle E_{D}\right\rangle & \left.=\frac{\sum_{k=0}^{\infty} 4 k J e^{-\beta 4 k J}}{\sum_{k=0}^{\infty} e^{-\beta 4 k J}}=-\frac{\partial}{\partial \beta} \ln \sum e^{-\beta 4 k J}=-\frac{\partial}{\partial \beta} \ln \frac{1}{1-e^{-\beta 4 J}} \neq 33\right) \\
& =\frac{4 J e^{-\beta 4 J}}{1-e^{-\beta 4 J}}=\frac{4 J}{e^{4 \beta J}-1}
\end{aligned}
$$

This implies $\beta=\frac{1}{4 J} \ln \left(1+4 J /\left\langle E_{D}\right\rangle\right)$.
For continous models we have

$$
\left\langle E_{D}\right\rangle=\frac{\int_{0}^{\infty} E_{D} e^{-\beta E_{D}} d E_{D}}{\int_{0}^{\infty} e^{-\beta E_{D}} d E_{D}}=-\frac{\partial}{\partial \beta} \ln \int e^{-\beta E_{D}} d E_{D}=-\frac{\partial}{\partial \beta} \ln \frac{1}{\beta}=\frac{1}{\beta}
$$

We are interested in a system described with

$$
\begin{equation*}
Z=\int d \Phi e^{-S}=\operatorname{Tr}\left(e^{-\beta(\hat{H}-\mu \hat{N})}\right)=\sum_{c} W(c) \tag{34}
\end{equation*}
$$

We have learned about improtance sampling so far:
We build a Markov chain of configurations (Metropolis algorithm, Langevin eq., etc.)

$$
\begin{equation*}
\ldots \rightarrow C_{i-1} \rightarrow C_{i} \rightarrow C_{i+1} \ldots \tag{35}
\end{equation*}
$$

where we arranged the properties of the chain such that $p(C) \sim W(C)$ (probability of visiting $C$ proportional to the weight)

$$
\begin{equation*}
\langle X\rangle=\frac{1}{Z} \operatorname{Tr} X e^{-\beta(\hat{H}-\mu N)}=\frac{1}{Z} \sum_{C} W(C) X(C)=\frac{1}{N} \sum X\left[C_{i}\right] \tag{36}
\end{equation*}
$$

If we have $W[C]$ non positive (or even complex) this strategy breaks down. In that case we have a Sign Problem.

## Sign problems

Sometimes we can solve the Sign problem by changeing the representation:

$$
\begin{equation*}
Z=\sum_{C} W[C]=\sum_{D} W^{\prime}[D] \tag{37}
\end{equation*}
$$

if $Z \geq 0$ we might be able to find a representation with positive terms $W^{\prime}[D] \geq 0$. We can than simulate in terms of $D \Longrightarrow$ We need to find the right variables.

Sometimes $Z$ is non positive, in that case we have a sign problem in every representation (e.g. at complex parameters, in supersymmetry, etc.)

Time evolution operator: $U=e^{-i t \hat{H}}$. e.g.: $|\Psi(x, t)\rangle=e^{-i t \hat{H}}|\Psi(x, t=0)\rangle$. We are interested in the transition amplitude

$$
\begin{equation*}
\left\langle q_{2}\right| e^{-i t \hat{H}}\left|q_{1}\right\rangle \tag{38}
\end{equation*}
$$

We can calculate e.g. using the Schrödinger eq.: $i \partial_{t} \Psi=\hat{H} \Psi$.

Equivalently: Path integral formulation

$$
\begin{equation*}
\left\langle q_{2}\right| e^{-i t \hat{H}}\left|q_{1}\right\rangle=\int_{q_{1}}^{q_{2}} D q e^{i S[q(t)]} \tag{39}
\end{equation*}
$$

path integral is the sum for all functions $q(t)$ with the correct boundary conditions $q\left(t=t_{1}\right)=q_{1}, q\left(t=t_{2}\right)=q_{2}$


## Time evolution and other sign problems

$$
\begin{equation*}
\left\langle q_{2}\right| e^{-i t \hat{H}}\left|q_{1}\right\rangle=\int_{q_{1}}^{q_{2}} D q e^{i S[q(t)]} \tag{40}
\end{equation*}
$$

if we replace: it $\rightarrow \beta$, and do a Trace, we get thermal physics. (this trick is called imaginary time formalism)
If we want to calculate time evolution $\rightarrow$ Hard sign problem.

We sometimes have a sign problem if we introduce fermions. Famous example: Imbalanced Fermi gas

We often have sign problem if we introduce chemical potential. e.g.: Bose Gas, XY model, QCD, etc.

Topological terms in gauge theories also lead to a sign problem

Sometimes you can solve exactly using new variables

$$
\begin{equation*}
Z=\sum_{C} W[C]=\sum_{D} W^{\prime}[D] \tag{41}
\end{equation*}
$$

or using subsets

$$
\begin{equation*}
Z=\sum_{C} W[C]=\sum_{S}\left(\sum_{C \in S} W[C]\right) \tag{42}
\end{equation*}
$$

If you find a good parameter for that, you can use Taylor expansion

$$
\begin{equation*}
Z(\mu)=Z(\mu=0)+\mu \partial_{\mu} Z(0)+\frac{\mu^{2}}{2} \partial_{\mu}^{2} Z(0)+\ldots \tag{43}
\end{equation*}
$$

For this one needs to have no sign problem at $\mu=0$. coefficients are observables such charge density end susceptibility

$$
\begin{equation*}
n=\frac{1}{V Z} \partial_{\mu} Z(\mu), \quad \chi_{q}=\frac{1}{V Z} \partial_{\mu}^{2} Z(\mu) \tag{44}
\end{equation*}
$$

## Reweighting

We want to calculate

$$
\begin{equation*}
\langle X\rangle=\frac{\sum_{c} W[C] X[C]}{\sum_{c} W[C]} \tag{45}
\end{equation*}
$$

Suppose we come up with a modification of the weight $W[C] \rightarrow W^{\prime}[C]$ such that $W^{\prime}[C]>0$. (We can use e.g. $\left.W^{\prime}=|W|\right)$

$$
\begin{align*}
\langle X\rangle_{W} & =\frac{\sum_{c} W[C] X[C]}{\sum_{c} W[C]}=\frac{\sum_{c} W^{\prime}[C]\left(W[C] / W^{\prime}[C]\right) X[C]}{\sum_{c} W^{\prime}[C]\left(W[C] / W^{\prime}[C]\right)}  \tag{46}\\
& =\frac{\frac{1}{Z^{\prime}} \sum_{c} W^{\prime}[C]\left(W[C] / W^{\prime}[C]\right) X[C]}{\frac{1}{Z^{\prime}} \sum_{c} W^{\prime}[C]\left(W[C] / W^{\prime}[C]\right)}=\frac{\left\langle\left(W / W^{\prime}\right) X\right\rangle_{W^{\prime}}}{\left\langle\left(W / W^{\prime}\right)\right\rangle W^{\prime}}
\end{align*}
$$

Where we defined $Z^{\prime}=\sum_{c} W^{\prime}[C]$
if we have $W^{\prime}=|W|$ than $W / W^{\prime}=e^{i \theta}$.
For $\left\langle W / W^{\prime}\right\rangle_{W^{\prime}} \sim O(1)$ we have a mild sign problem,
For $\left\langle W / W^{\prime}\right\rangle_{W^{\prime}} \ll 1$ we have a severe sign problem (and this method fails).

Let's look again at $\left\langle\left(W / W^{\prime}\right)\right\rangle w^{\prime}$

$$
\begin{equation*}
\left\langle\left(W / W^{\prime}\right)\right\rangle_{W^{\prime}}=\frac{\sum_{c} W^{\prime}\left(W / W^{\prime}\right)}{\sum_{c} W^{\prime}}=\frac{\sum_{c} W[C]}{\sum_{c} W^{\prime}[C]}=\frac{Z_{W}}{Z_{W^{\prime}}} \tag{47}
\end{equation*}
$$

Using the free energy: $F=-k_{B} T \ln Z$

$$
\begin{equation*}
\left\langle\left(W / W^{\prime}\right)\right\rangle_{W^{\prime}}=\frac{Z_{W}}{Z_{W^{\prime}}}=e^{-\beta F_{W}} / e^{\beta F_{W^{\prime}}}=e^{-\beta v \Delta f} \tag{48}
\end{equation*}
$$

Where $\Delta f$ is the difference of the free energy density between the two ensembles ( $F$ is extensive).
$\Longrightarrow$ Sign problem is exponentially hard with the volume (and usually we want to have $V \rightarrow \infty)$.

$$
\begin{equation*}
Z=\int_{-\infty}^{\infty} e^{-\left(\sigma x^{2}+i \lambda x\right)} d x, \quad\left\langle x^{2}\right\rangle=\frac{1}{Z} \int_{-\infty}^{\infty} x^{2} e^{-\left(\sigma x^{2}+i \lambda x\right)} d x=? \tag{49}
\end{equation*}
$$

We use random uniform sampling in the region $-a \leq x \leq a$ to estimate integrals

$$
\begin{equation*}
\int_{-a}^{a} f(x) d x \approx \frac{1}{N} \sum_{i} f\left(x_{i}\right) \tag{50}
\end{equation*}
$$



$\sigma=\sqrt{2}, \lambda=0$
We need 100 samples to get $10 \%$ relative error
$\sigma=1+i, \lambda=20$
$Z \approx 10^{-22}$
$\sim 10^{46}$ samples for $10 \%$ relative error

## Solutions to sign problem using analiticity - Complex Langevin

We used Langevin equation before:

$$
\begin{equation*}
\frac{d x_{i}}{d \tau}=-\frac{\partial S}{\partial x_{i}}+\eta_{i} \tag{51}
\end{equation*}
$$

We never had to mention probabilities $\rightarrow$ use it for a complex action.
$x_{i}$ becomes complex
Observables are calculated using complex continuation (with $x \rightarrow x+i y$ )

$$
\begin{equation*}
\langle O[x]\rangle=\frac{1}{T} \int d \tau O[x(\tau)] \rightarrow \frac{1}{T} \int d \tau O[x(\tau)+i y(\tau)] \tag{52}
\end{equation*}
$$

For example:

$$
\begin{equation*}
\left\langle x^{2}\right\rangle \rightarrow\left\langle x^{2}-y^{2}\right\rangle+i 2\langle x y\rangle \tag{53}
\end{equation*}
$$

Using the complex measure $\rho(x)=\frac{1}{Z} e^{-S(x)}$ and the real probability measure $P(x, y)$ on the complex plane this means

$$
\begin{equation*}
\int d x \rho(x) O(x) \rightarrow \int d x d y P(x, y) O(x+i y) \tag{54}
\end{equation*}
$$

## Complex Langevin for toy model

$$
\begin{equation*}
Z=\int_{-\infty}^{\infty} e^{-\left(\sigma x^{2}+i \lambda x\right)} d x, \quad S=\sigma x^{2}+i \lambda x \tag{55}
\end{equation*}
$$

Now we complexify the Langevin equation $S(x) \rightarrow S(z)$, and $x \rightarrow z=x+i y$

$$
\begin{equation*}
\frac{\partial S(z)}{\partial z}=2 \sigma z+i \lambda \tag{56}
\end{equation*}
$$

One can also calculate the derivate first and complexify afterwards (since $S(x)$ is analytic, we get the same).

$$
\begin{align*}
\frac{d x}{d \tau} & =-\frac{\partial S}{\partial z_{i}}+\eta_{i}=-2 \operatorname{Re}(\sigma(x+i y))-\operatorname{Re}(i \lambda)+\eta_{i}  \tag{57}\\
\frac{d y}{d \tau} & =-2 \operatorname{Im}(\sigma(x+i y))-\operatorname{Im}(i \lambda)
\end{align*}
$$

To measure the original $\left\langle x^{2}\right\rangle$ in the complexified theory we measure $x^{2}-y^{2}$.

## Complex Langevin solution of the toy problem

## Gaussian Example

$$
S[x]=\sigma x^{2}+i \lambda x
$$

CLE

$$
\frac{d}{d \tau}(x+i y)=-2 \sigma(x+i y)-i \lambda+\eta
$$

$$
P(x, y)=e^{-a\left(x-x_{0}\right)^{2}-b\left(y-y_{0}\right)^{2}-c\left(x-x_{0}\right)\left(y-y_{0}\right)}
$$

$\left.\begin{aligned} & \begin{array}{l}\text { Gaussian distribution } \\ \text { around critical point }\end{array}\end{aligned} \frac{\partial S(z)}{\partial z}\right|_{z_{0}}=0$




## Complex Langevin

Sometimes Complex Langevin gives a spectacular solution Other times it converges to a wrong result: process wanders to far, fluctuations grow large

When does it give a good solution?

1. Action needs to be analytical (also no poles)
2. $P(x, y)$ needs to vanish fast enough as $x, y \rightarrow \infty$.

Large amount of freedom, reparametrizations, kernels, etc.

## Solutions to sign problem using analiticity 2

We want to calculate the integral

$$
\begin{equation*}
\int_{-\infty}^{\infty} F(x) e^{-S(x)} d x \tag{58}
\end{equation*}
$$

If $S(x)$ and $F(x)$ is analytic, we consider them as complex functions $S(z)$ and $F(z)$. Assuming they have no poles:

$$
\begin{equation*}
\int_{-\infty}^{\infty} F(x) e^{-S(x)} d x=\int_{C} F(z) e^{-S(z)} d z \tag{59}
\end{equation*}
$$

Where the $C$ curve goes from $-\infty$ on the real axis to $\infty$ on the real axis. It can take an arbitrary shape in between. $C$ is parametrized as $z(t)$

$$
\begin{equation*}
\int_{-\infty}^{\infty} F(x) e^{-S(x)} d x=\int d t\left(\frac{d z}{d t}\right) e^{S(z(t))} F(z(t)) \tag{60}
\end{equation*}
$$

it is easier to simulate on the curve $C$ if $e^{\operatorname{ReS}(z(t))}$ has a sharp peak, and $e^{i \operatorname{Im} S(z(t))}$ is a mild sign problem

Constant imaginary part $\Longrightarrow$ no sign problem

$$
\begin{equation*}
\frac{d \operatorname{Im} S}{d t}=\frac{\partial \operatorname{Im} S}{\partial x} \frac{d x}{d t}+\frac{\partial \operatorname{Im} S}{\partial y} \frac{d y}{d t}=0 \tag{61}
\end{equation*}
$$

$$
\begin{equation*}
\frac{\partial \operatorname{ImS} / \partial x}{d y / d t}=-\frac{\partial \operatorname{ImS} / \partial y}{d x / d t} \underbrace{\Longrightarrow}_{\text {Cauchy }- \text { Riemann }} \frac{\partial R e S / \partial y}{d y / d t}=\frac{\partial R e S / \partial x}{d x / d t} \tag{62}
\end{equation*}
$$

Which means the curve will be in the direction of the gradient of the real part of the action $\Longrightarrow$ sharply peaked.

Mild sign problem $\Longleftrightarrow$ sharply peaked action This curve is called the Lefschetz thimble
generally we have multiple contributing thimbles

$$
\begin{equation*}
Z=\sum_{k} m_{k} e^{-i \operatorname{Im} S\left(z_{k}\right)} \int_{C_{k}} d t\left(\frac{d z_{k}}{d t}\right) e^{-\operatorname{ReS}\left(z_{k}(t)\right)} \tag{63}
\end{equation*}
$$

$m_{k}$ is an integer, the intersection number
The Jacobians give a residual sign problem if the thimble is curved


In practice in makes sense to map the real axis somewhere close to the thimbles, but not necceseraly exactly on them: Sign optimized manifolds

