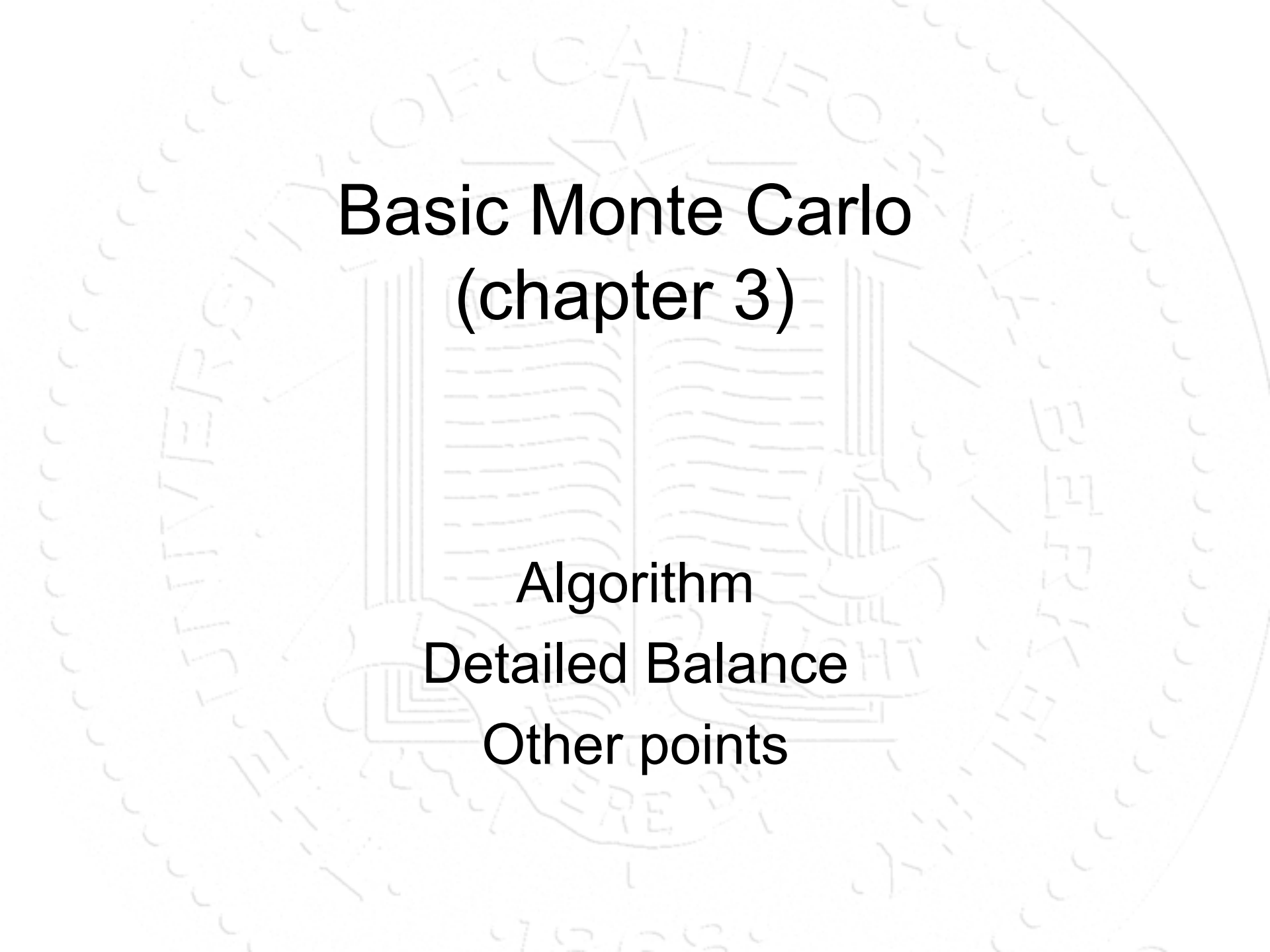


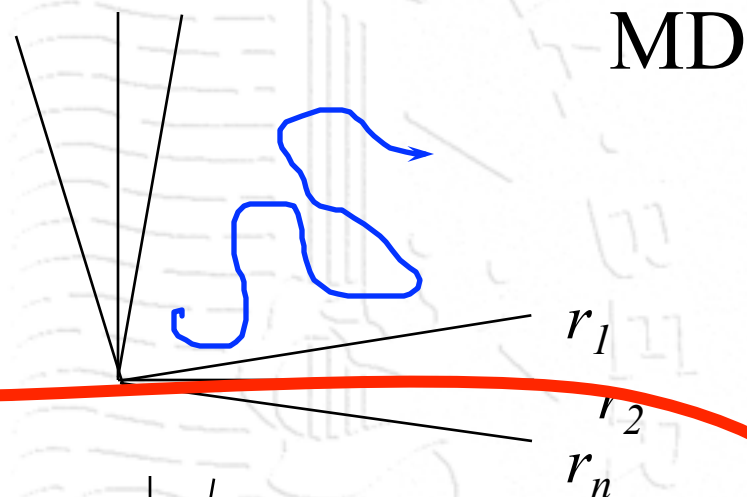
The background of the slide features a large, faint watermark of the University of California seal. The seal is circular and contains the text "UNIVERSITY OF CALIFORNIA" around the top and "1868" at the bottom. In the center of the seal is a shield with a book and a sun, flanked by two figures.

Basic Monte Carlo (chapter 3)

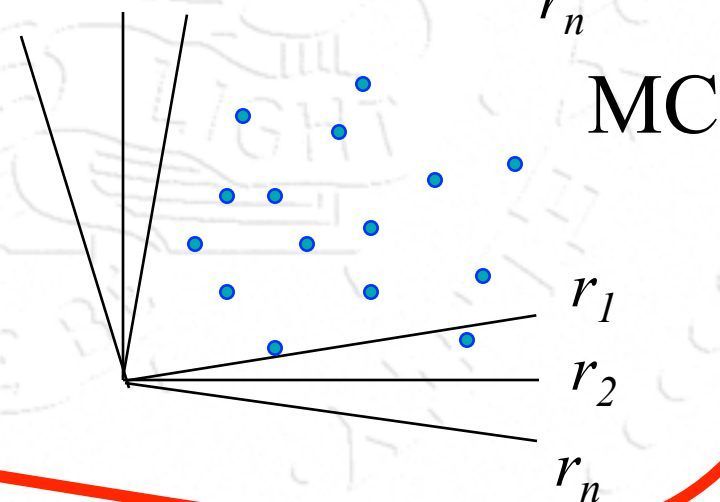
Algorithm
Detailed Balance
Other points

Molecular Simulations

- ◆ Molecular dynamics: solve equations of motion



- ◆ Monte Carlo: importance sampling



Statistical Thermodynamics

Partition function

$$Q_{NVT} = \frac{1}{\Lambda^{3N} N!} \int d\mathbf{r}^N \exp[-\beta U(\mathbf{r}^N)]$$

Ensemble average

$$\langle A \rangle_{NVT} = \frac{1}{Q_{NVT}} \frac{1}{\Lambda^{3N} N!} \int d\mathbf{r}^N A(\mathbf{r}^N) \exp[-\beta U(\mathbf{r}^N)]$$

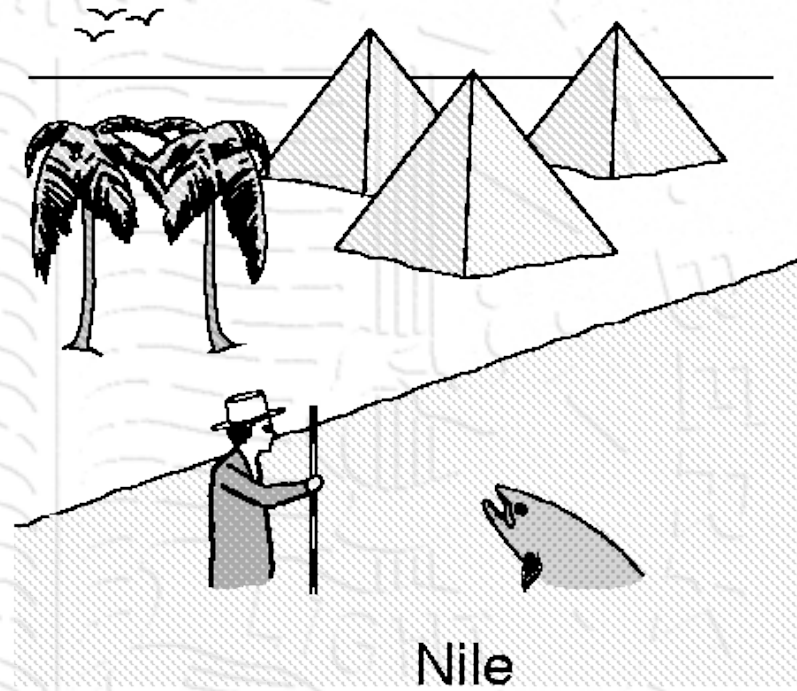
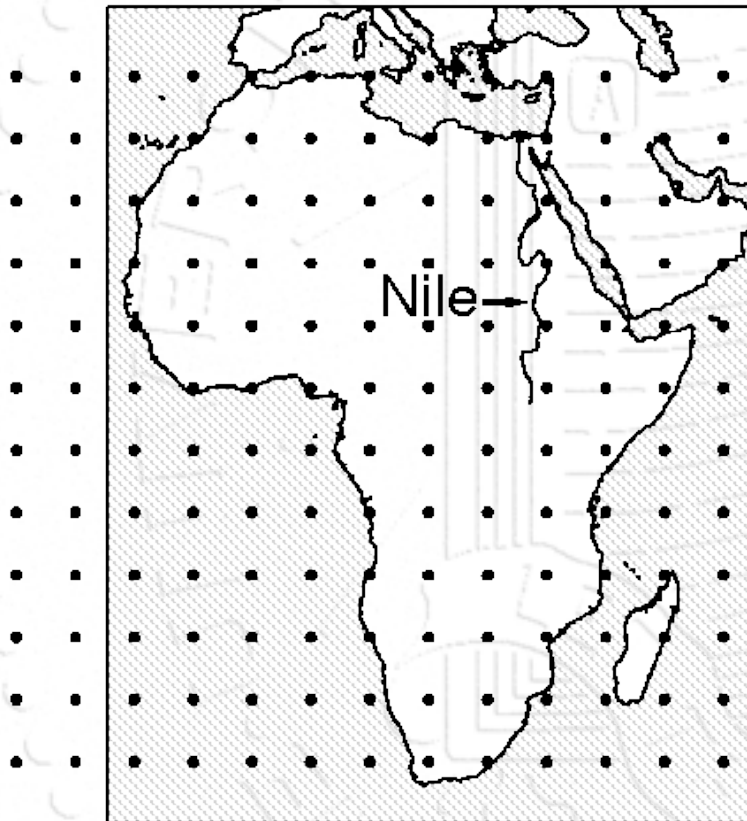
Probability to find a particular configuration

$$N(\mathbf{r}^N) = \frac{1}{Q_{NVT}} \frac{1}{\Lambda^{3N} N!} \int d\mathbf{r}'^N \delta(\mathbf{r}'^N - \mathbf{r}^N) \exp[-\beta U(\mathbf{r}'^N)] \propto \exp[-\beta U(\mathbf{r}^N)]$$

Free energy

$$\beta F = -\ln(Q_{NVT})$$

Monte Carlo simulation



Ensemble average

$$\begin{aligned}
 \langle A \rangle_{NVT} &= \frac{1}{Q_{NVT}} \frac{1}{\Lambda^{3N} N!} \int d\mathbf{r}^N A(\mathbf{r}^N) \exp[-\beta U(\mathbf{r}^N)] \\
 &= \int d\mathbf{r}^N A(\mathbf{r}^N) P(\mathbf{r}^N) = \frac{\int d\mathbf{r}^N A(\mathbf{r}^N) P(\mathbf{r}^N)}{\int d\mathbf{r}^N P(\mathbf{r}^N)} \\
 &= \frac{\int d\mathbf{r}^N A(\mathbf{r}^N) C \exp[-\beta U(\mathbf{r}^N)]}{\int d\mathbf{r}^N C \exp[-\beta U(\mathbf{r}^N)]} = \frac{\int d\mathbf{r}^N A(\mathbf{r}^N) \exp[-\beta U(\mathbf{r}^N)]}{\int d\mathbf{r}^N \exp[-\beta U(\mathbf{r}^N)]}
 \end{aligned}$$

$$P(\mathbf{r}^N) = \frac{\exp[-\beta U(\mathbf{r}^N)]}{Q_{NVT} \Lambda^{3N} N!}$$

Generate configuration using MC:

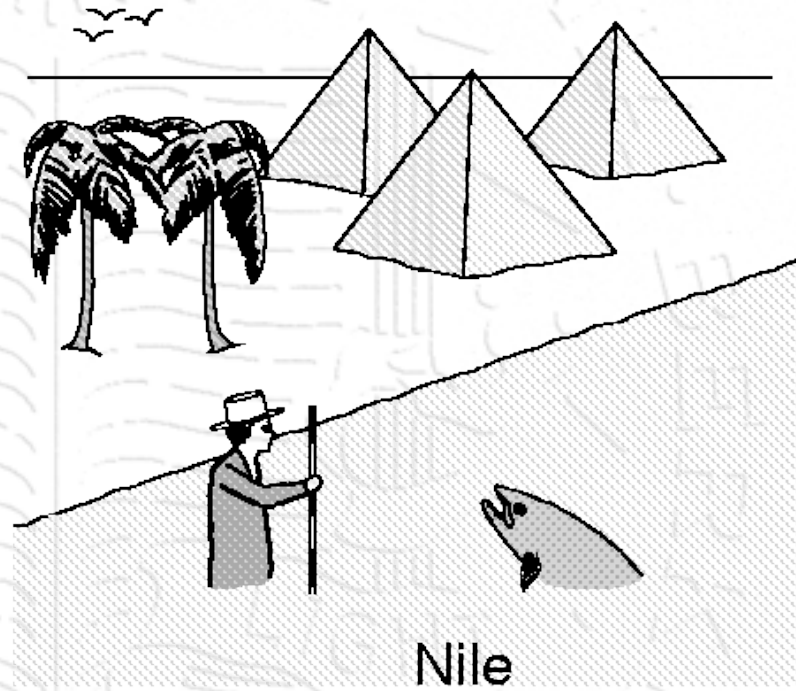
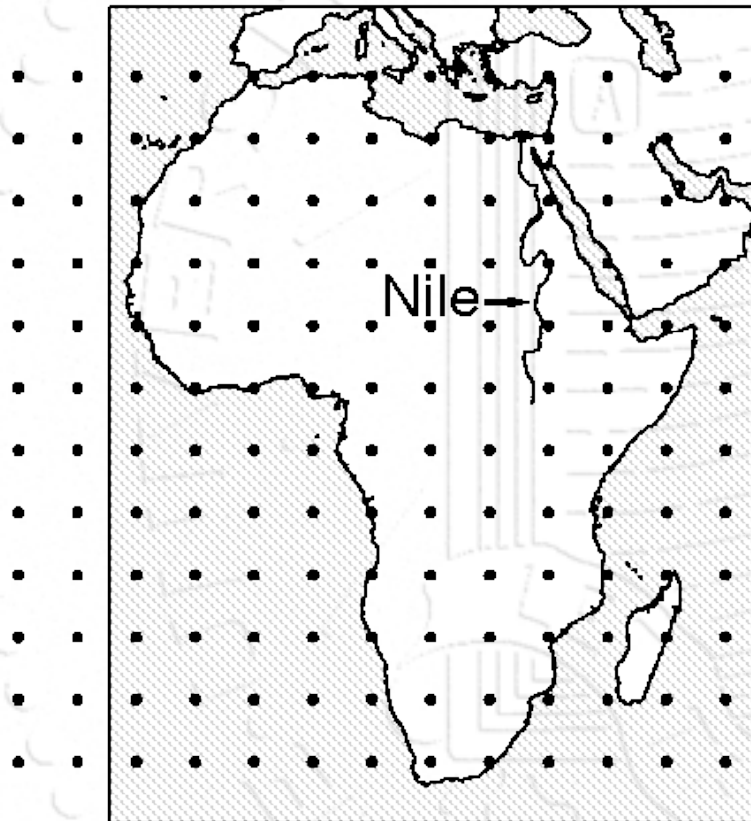
$$\{\mathbf{r}_1^N, \mathbf{r}_2^N, \mathbf{r}_3^N, \mathbf{r}_4^N \dots, \mathbf{r}_M^N\} \quad \bar{A} = \frac{1}{M} \sum_{i=1}^M A(\mathbf{r}_i^N) = \frac{\int d\mathbf{r}^N A(\mathbf{r}^N) P^{MC}(\mathbf{r}^N)}{\int d\mathbf{r}^N P^{MC}(\mathbf{r}^N)}$$

with

$$P^{MC}(\mathbf{r}^N) = C^{MC} \exp[-\beta U(\mathbf{r}^N)]$$

$$\begin{aligned}
 &= \frac{\int d\mathbf{r}^N A(\mathbf{r}^N) C^{MC} \exp[-\beta U(\mathbf{r}^N)]}{\int d\mathbf{r}^N C^{MC} \exp[-\beta U(\mathbf{r}^N)]} \\
 &= \frac{\int d\mathbf{r}^N A(\mathbf{r}^N) \exp[-\beta U(\mathbf{r}^N)]}{\int d\mathbf{r}^N \exp[-\beta U(\mathbf{r}^N)]}
 \end{aligned}$$

Monte Carlo simulation



Algorithm 1 (Basic Metropolis Algorithm)

<pre>PROGRAM mc</pre>	basic Metropolis algorithm
<pre>do icycl=1,ncycl</pre>	perform <code>ncycl</code> MC cycles
<pre> call mcmove</pre>	displace a particle
<pre> if (mod(icycl,nsamp).eq.0)</pre>	
<pre>+ call sample</pre>	sample averages
<pre>enddo</pre>	
<pre>end</pre>	

Comments to this algorithm:

- 1. Subroutine `mcmove` attempts to displace a randomly selected particle (see Algorithm 2).*
- 2. Subroutine `sample` samples quantities every `nsamp`th cycle.*

Algorithm 2 (Attempt to Displace a Particle)

<pre>SUBROUTINE mcmove o=int(ranf()*npart)+1 call ener(x(o), eno) xn=x(o)+(ranf()-0.5)*delx call ener(xn, enn) if (ranf().lt.exp(-beta + *(enn-eno)) x(o)=xn return end</pre>	attempts to displace a particle select a particle at random energy old configuration give particle random displacement energy new configuration acceptance rule (3.2.1) accepted: replace $x(o)$ by xn
---	---

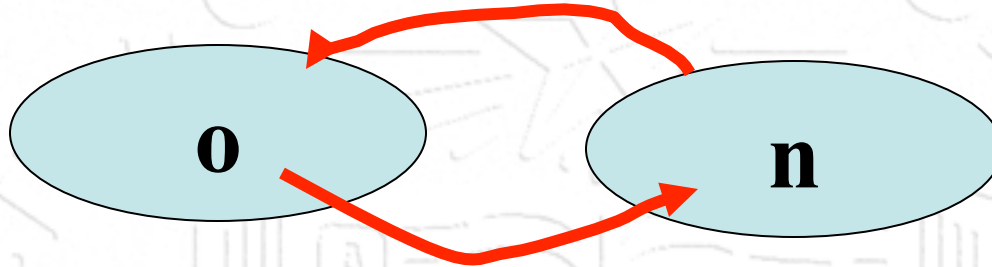
Comments to this algorithm:

1. Subroutine `ener` calculates the energy of a particle at the given position.
2. Note that, if a configuration is rejected, the old configuration is retained.
3. The `ranf()` is a random number uniform in $[0, 1]$.

Questions

- How can we prove that this scheme generates the desired distribution of configurations?
- Why make a random selection of the particle to be displaced?
- Why do we need to take the old configuration again?
- How large should we take: δx ?

Detailed balance



$$K(o \rightarrow n) = K(n \rightarrow o)$$

$$K(o \rightarrow n) = N(o) \times \alpha(o \rightarrow n) \times \text{acc}(o \rightarrow n)$$

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NVT-ensemble

$$N(n) \propto \exp[-\beta U(n)]$$

$$\frac{\text{acc}(o \rightarrow n)}{\text{acc}(n \rightarrow o)} = \frac{N(n)}{N(o)}$$

$$\frac{\text{acc}(o \rightarrow n)}{\text{acc}(n \rightarrow o)} = \exp[-\beta[U(n) - U(o)]]$$

Algorithm 2 (Attempt to Displace a Particle)

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Algorithm 2 (Attempt to Displace a Particle)

<pre>SUBROUTINE mcmove o=int(ranf()*npart)+1 call ener(x(o), eno) xn=x(o)+(ranf()-0.5)*delx call ener(xn, enn) if (ranf().lt.exp(-beta + *(enn-eno)) x(o)=xn return end</pre>	attempts to displace a particle select a particle at random energy old configuration give particle random displacement energy new configuration acceptance rule (3.2.1) accepted: replace $x(o)$ by xn
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- How large should we take: δx ?

Mathematical

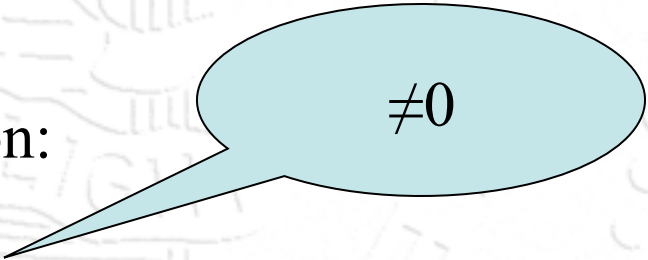
Transition probability:

$$\pi(o \rightarrow n) = \alpha(o \rightarrow n) \times \text{acc}(o \rightarrow n)$$

$$\sum_n \pi(o \rightarrow n) = 1$$

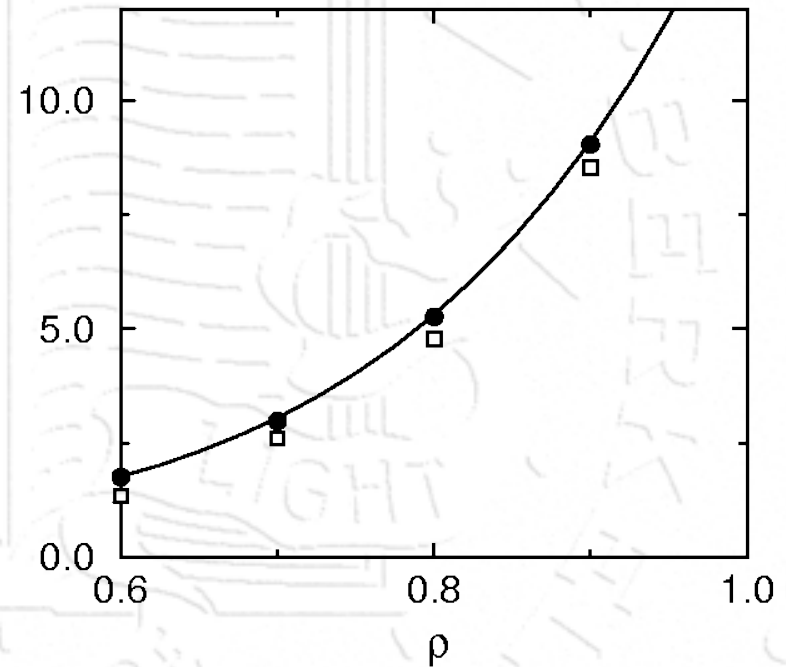
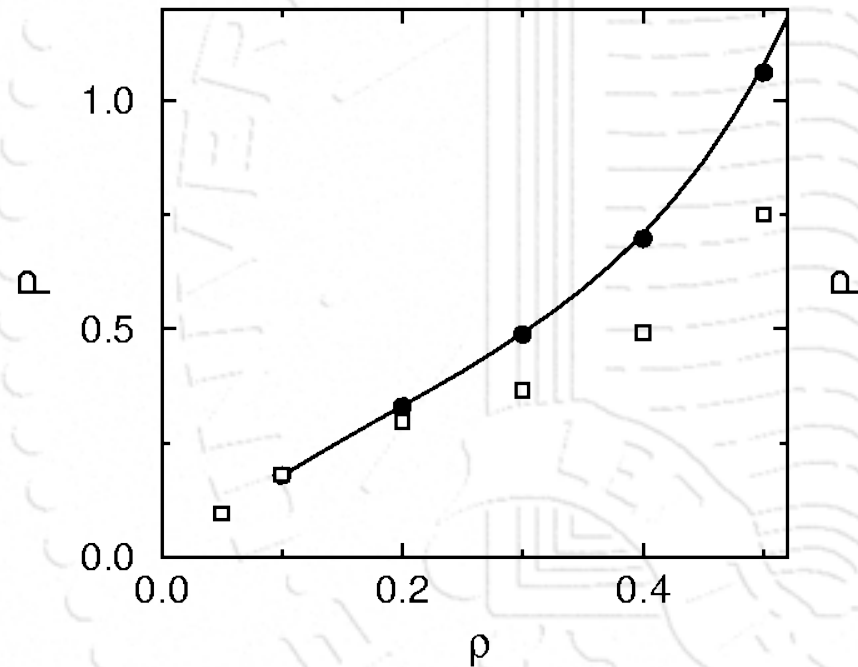
Probability to accept the old configuration:

$$\pi(o \rightarrow o) = 1 - \sum_{n \neq o} \pi(o \rightarrow n)$$



$\neq 0$

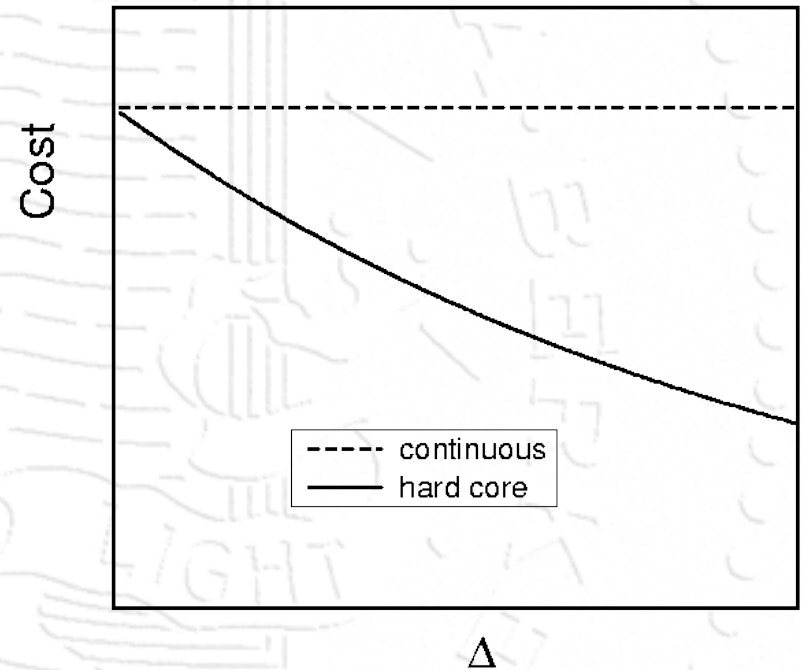
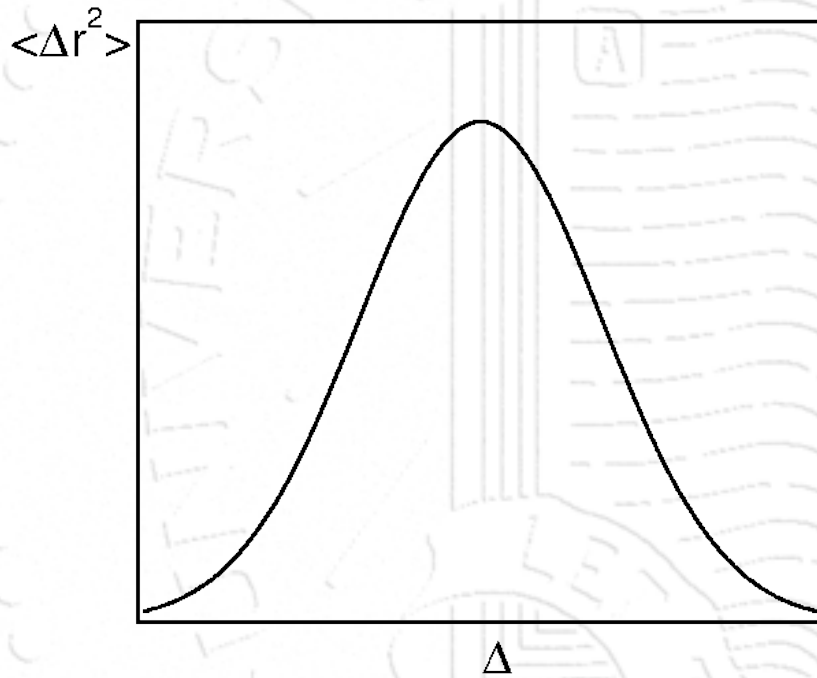
Keeping old configuration?



Questions

- How can we prove that this scheme generates the desired distribution of configurations?
- Why make a random selection of the particle to be displaced?
- Why do we need to take the old configuration again?
- How large should we take: δx ?

Not too small, not too big!



Non-Boltzmann sampling

$$\langle A \rangle_{NVT_1} = \frac{1}{Q_{NVT_1}} \frac{1}{\Lambda^{3N} N!} \int dr^N A(r^N) \exp[-\beta_1 U(r^N)]$$

$$= \frac{\int dr^N A(r^N) \exp[-\beta_1 U(r^N)]}{\int dr^N \exp[-\beta_1 U(r^N)]}$$

T_1 is arbitrary!

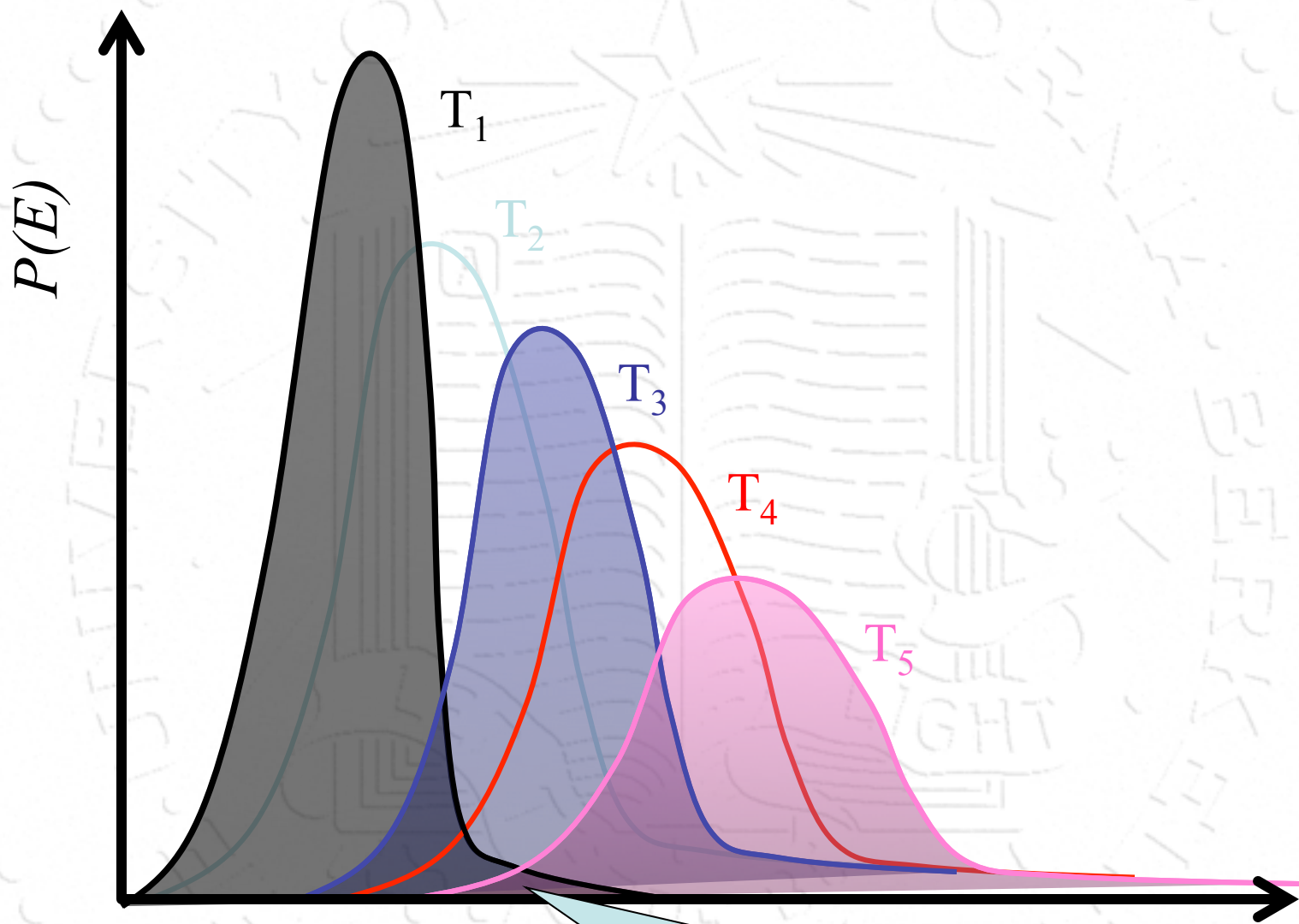
$$= \frac{\int dr^N A(r^N) \exp[-\beta_1 U(r^N)] \exp[\beta_2 U(r^N) - \beta_2 U(r^N)]}{\int dr^N \exp[-\beta_1 U(r^N)] \exp[\beta_2 U(r^N) - \beta_2 U(r^N)]}$$

We only need a
single
simulation!

Why are we not using this?

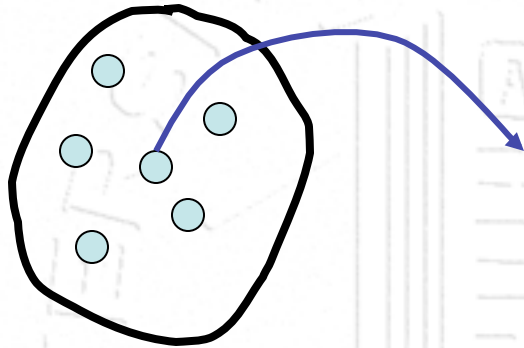
We perform a simulation at $T=T_2$
and
we determine A at $T=T_1$

$$= \frac{\langle A \exp[(\beta_2 - \beta_1)U] \rangle_{NVT_2}}{\langle \exp[(\beta_2 - \beta_1)U] \rangle_{NVT_2}}$$



Overlap becomes very small

How to do *parallel* Monte Carlo



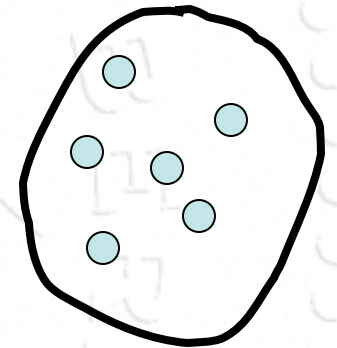
- Is it possible to do Monte Carlo in parallel
 - Monte Carlo is sequential!
 - We first have to know the fate of the current move before we can continue!

Parallel Monte Carlo

Algorithm (**WRONG**):

1. Generate k trial configurations in parallel
2. Select out of these the one with the lowest energy

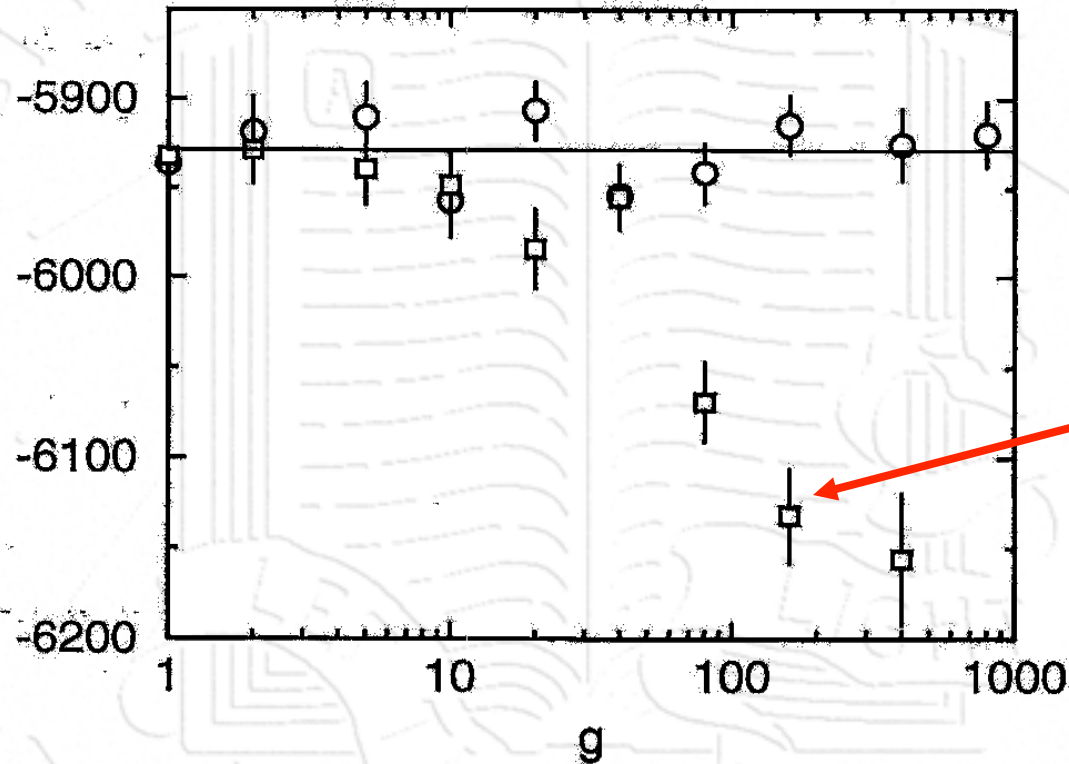
$$P(n) = \frac{\exp[-\beta(U_n)]}{\sum_{j=1}^g \exp[-\beta(U_j)]}$$



3. Accept and reject using normal Monte Carlo rule:

$$\text{acc}(o \rightarrow n) = \exp[-\beta(U_n - U_o)]$$

Conventional acceptance rule



Conventional acceptance rules leads to a *bias*

W

Detailed balance!

$$K(o \rightarrow n) = K(n \rightarrow o)$$

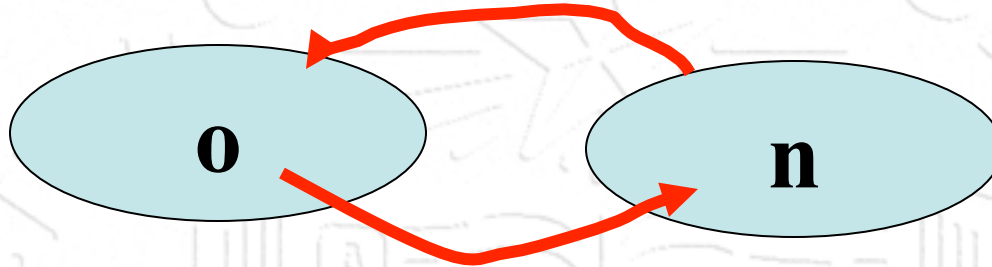
$$K(o \rightarrow n) = N(o) \times \alpha(o \rightarrow n) \times \text{acc}(o \rightarrow n)$$

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Detailed balance



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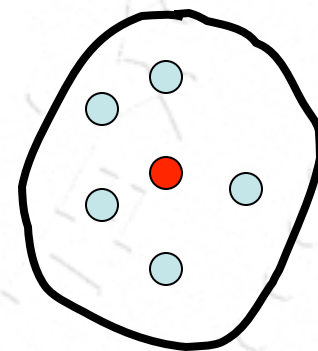
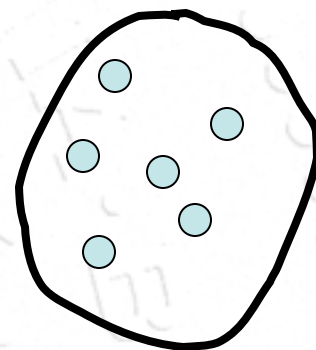
$$K(o \rightarrow n) = N(o) \times \alpha(o \rightarrow n) \times \text{acc}(o \rightarrow n)$$

$$\alpha(o \rightarrow n) = \frac{\exp[-\beta(U_n)]}{\sum_{j=1}^g \exp[-\beta(U_j)]}$$

$$\alpha(o \rightarrow n) = \frac{\exp[-\beta(U_n)]}{W(\textcolor{red}{n})}$$

$$\alpha(n \rightarrow o) = \frac{\exp[-\beta(U_o)]}{\sum_{j=1}^g \exp[-\beta(U_j)]}$$

$$\alpha(n \rightarrow o) = \frac{\exp[-\beta(U_o)]}{W(\textcolor{red}{o})}$$

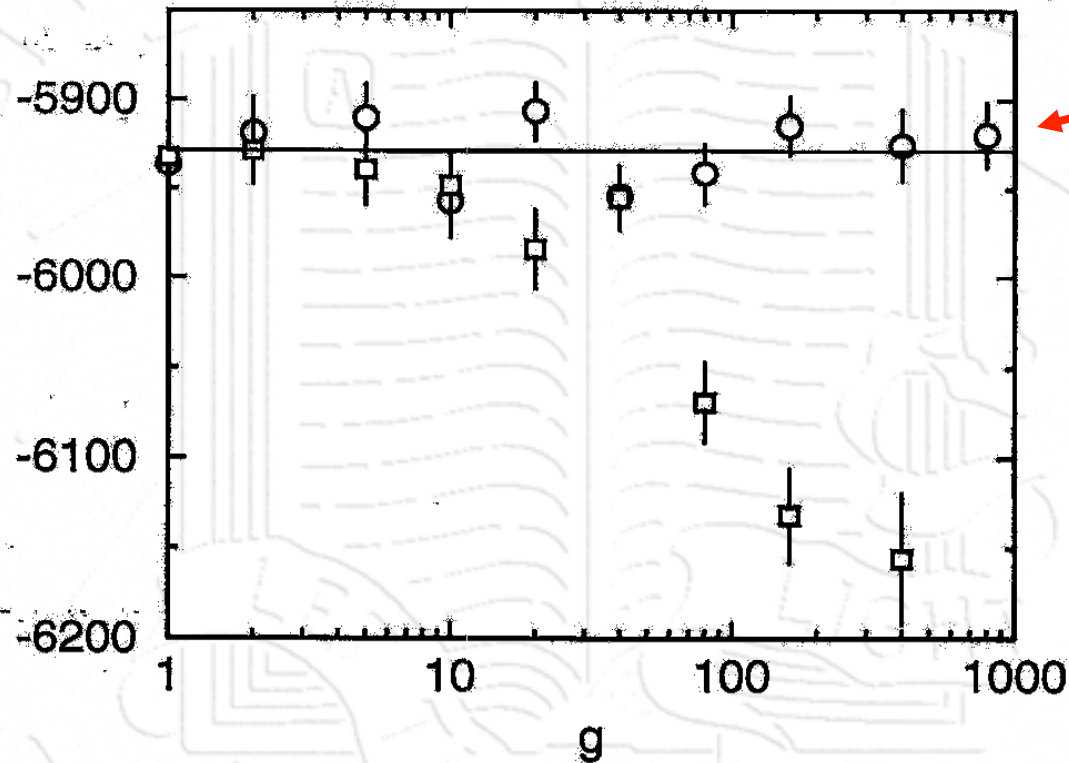


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Modified acceptance rule



Modified acceptance rule remove the *bias* exactly!