

CE 530 Molecular Simulation

Lecture 22

Chain-Molecule Sampling Techniques

David A. Kofke

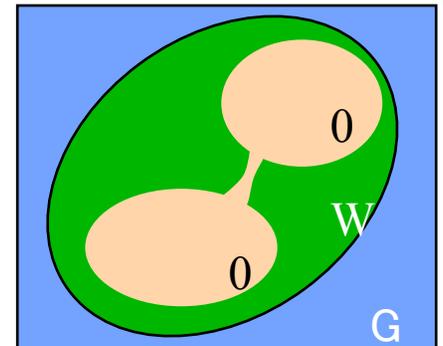
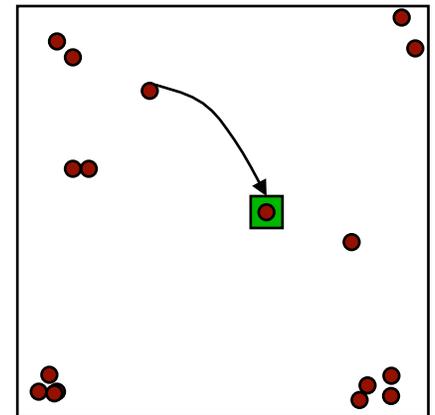
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Monte Carlo Sampling

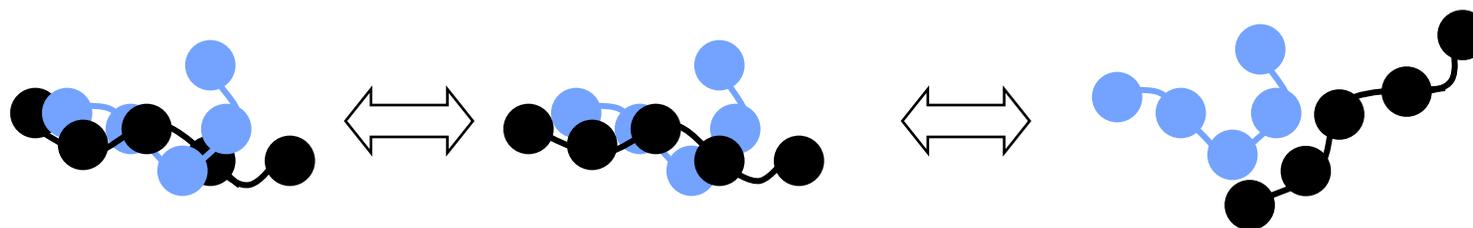
- MC method permits great flexibility in developing improved sampling methods
- Biasing methods improve sampling without changing the limiting distribution
 - *Modification of trial probabilities compensated by changes in acceptance and reverse-trial probabilities*
- Non-Boltzmann sampling methods modify the limiting distribution
 - *Desired ensemble average obtained by taking a weighted average over the non-Boltzmann sample*



$$\langle M \rangle_0 = \frac{\langle M e^{-\beta(U_0 - U_W)} \rangle_W}{\langle e^{-\beta(U_0 - U_W)} \rangle_W}$$

Simulating Chain Molecules

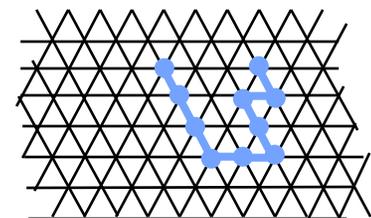
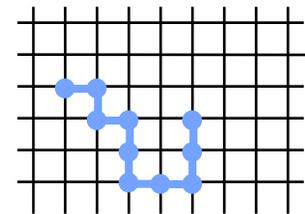
- Slow to explore different parts of phase space
- Concerted moves needed to detangle chains



- Algorithms based solely on single-atom moves may be non-ergodic

Modeling Chain Molecules

- Detailed models use full array of potentials discussed previously
 - *LJ atoms, with torsion, bend, stretch intramolecular potentials*
- Other models try to explain qualitative features of polymer behavior
 - *hard- or soft-sphere atoms, only stretch*
 - *bead-spring; tangent spheres; finitely-extensible nonlinear elastic (FENE)*
 - *each unit of model might represent a multi-unit segment of the true polymer*
 - *the only feasible approach for very long chains*
 - *>10³ units*
- Lattice models are very helpful
 - *discretize space*
 - *various choices for lattice symmetry*
 - *chain occupies contiguous sites on lattice*
 - *one chain unit per site*

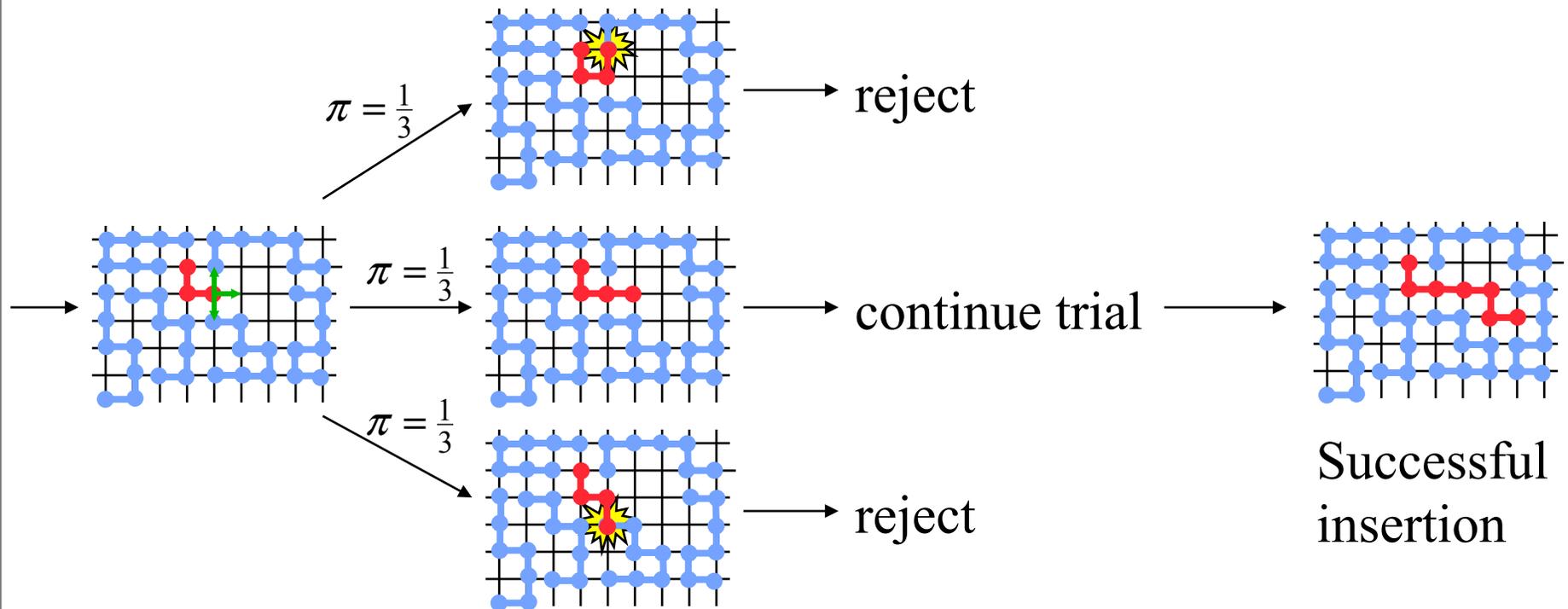


Generating Configurations of Chains

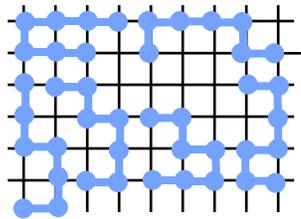
- Open ensembles (grand-canonical) often preferred
 - *insertion and removal of chains enhances sampling of configurations*
- Insertions and removals are difficult!
- We'll examine three approaches
 - *Simple sampling*
 - *Configurational bias*
 - *Pruned-enriched sampling*
- Consider methods in the context of a simple hard-exclusion model (no attraction, no bending energy)
 - *All non-overlapping chain configurations are weighted uniformly*

Simple Sampling

- Molecules are inserted and deleted in an unbiased fashion
 - *Stepwise insertion: after j segments have been inserted, the $(j + 1)$ th segment is placed at random at one of the sites adjoining the last segment*
 - *Any attempt that leads to an overlap with an existing segment causes the whole trial to be immediately discarded*

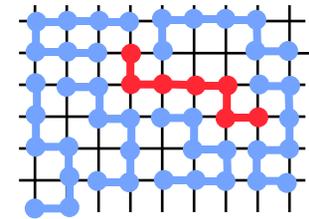


Simple Sampling: Insertion Likelihood



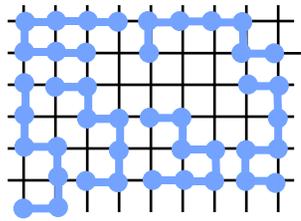
63 sites

- What is the probability that this trial will occur using simple insertion?



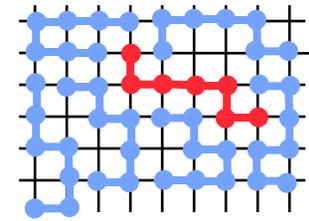
- *In-class assignment 1*
figure it out

Simple Sampling: Insertion Likelihood



63 sites

- What is the probability that this trial will occur using simple insertion?



- Insertion probability for first unit
 - $1/63$

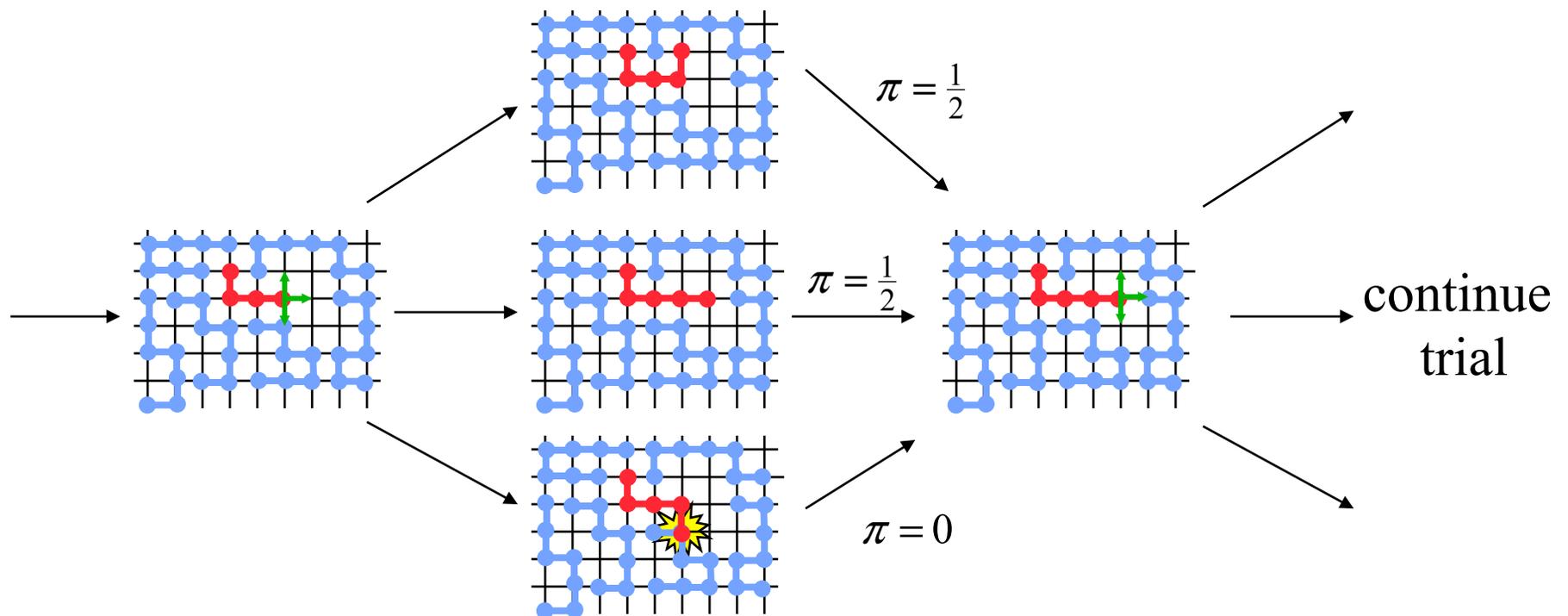
- Insert six more units, each with probability $1/3$ going in the “right” spot
 - $1/3^6$

- Could begin on either end of chain
 - *multiply by 2*

- Total probability is product $\tau_{ij} = \frac{1}{63} \times \frac{1}{3^6} \times 2 = 0.000044$
 $= 4.4 \times 10^{-5}$

Configurational Bias Monte Carlo

- Based on 1955 idea of Rosenbluth & Rosenbluth
- Apply bias during growth of chain, so that overlaps do not lead to rejection of entire trial
- Remove bias during acceptance of complete trial
 - Accumulate “Rosenbluth weight” during course of trial



Configurational-Bias Insertion/Deletion Trial. Analysis of Trial Probabilities

- Detailed specification of trial moves and and probabilities

Event [reverse event]	Probability [reverse probability]
Select insertion trial [select deletion trial]	$\frac{1}{2}$ [$\frac{1}{2}$]
Place molecule at $\{\mathbf{r}\}$ [delete molecule N+1]	$1/W(\{\mathbf{r}\})$ [$1/(N+1)$]
Accept move [accept move]	$\min(1, \chi)$ [$\min(1, 1/\chi)$]

Forward-step trial probability $\frac{1}{2} \times \frac{1}{W} \times \min(1, \chi)$

Reverse-step trial probability $\frac{1}{2} \times \frac{1}{N+1} \times \min(1, \frac{1}{\chi})$

We'll work this out later

Configurational-Bias Insertion/Deletion Trial. Analysis of Detailed Balance

*Forward-step
trial
probability*

$$\frac{1}{2} \times \frac{1}{W} \times \min(1, \chi)$$

*Reverse-step
trial
probability*

$$\frac{1}{2} \times \frac{1}{N+1} \times \min(1, \frac{1}{\chi})$$

Detailed balance

$$\pi_i \pi_{ij} = \pi_j \pi_{ji}$$

*Limiting
distribution*

$$\pi(\mathbf{r}^N) = \frac{1}{\Xi} q(T) e^{-\beta U(\mathbf{r}^N) + \beta \mu N}$$

Configurational-Bias Insertion/Deletion Trial. Analysis of Detailed Balance

*Forward-step
trial
probability*

$$\frac{1}{2} \times \frac{1}{W} \times \min(1, \chi)$$

*Reverse-step
trial
probability*

$$\frac{1}{2} \times \frac{1}{N+1} \times \min(1, \frac{1}{\chi})$$

Detailed balance

$$\pi_i \pi_{ij} = \pi_j \pi_{ji}$$

$$\frac{e^{-\beta U^{old} + \beta \mu N}}{\Xi q^{-N}} \left[\frac{1}{2} \times \frac{1}{W} \times \min(1, \chi) \right] = \frac{e^{-\beta U^{new} + \beta \mu (N+1)}}{\Xi q^{-(N+1)}} \left[\frac{1}{2} \times \frac{1}{N+1} \times \min(1, \frac{1}{\chi}) \right]$$

Energy is zero in both
configurations

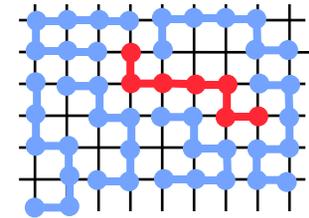
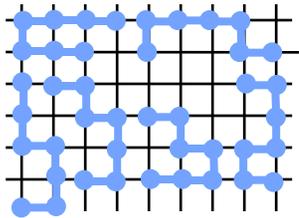
$$\frac{1}{W} \chi = \frac{q(T)}{N+1} e^{+\beta \mu}$$

$$\chi = \frac{q(T)}{N+1} W e^{+\beta \mu}$$

Acceptance probability

Rosenbluth Weight

- What is W ?
- $1/W$ is the probability that the chain would be inserted into the given position



- Each placement of a unit in the chain is selected with probability

$$\pi_j = \frac{1}{w_i}$$

where w_i is the number of non-overlap “sibling” alternatives available at generation i of the overall insertion

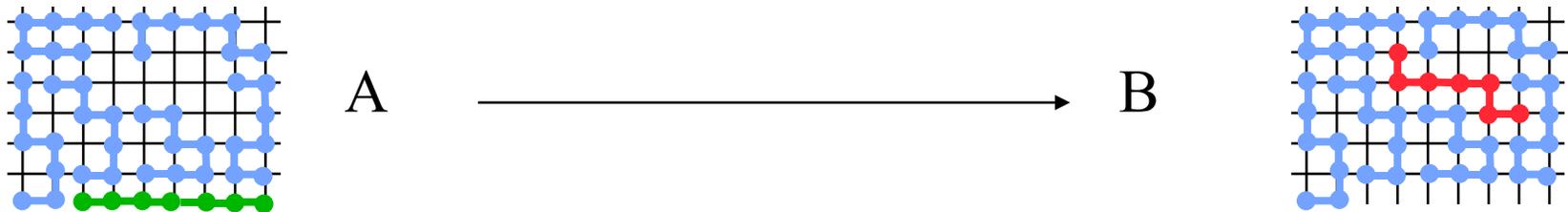
- Probability of making this particular insertion is

$$\tau = \frac{1}{63} \times \frac{1}{1} \times \frac{1}{1} \times \frac{1}{1} \times \frac{1}{2} \times \frac{1}{2} \times \frac{1}{1} = 0.004$$

$$W = 63 \times 1 \times 1 \times 1 \times 2 \times 2 \times 1 = 252$$

NVT Configuration Sampling

- CBMC is also used to generate new configurations of present molecules



- Acceptance of any move is based on Rosenbluth weight for given move and the reverse move
 - $W_A = 63$
 - $W_B = 252$
 - *The move $A \rightarrow B$ is accepted with probability 1*
 - *The move $B \rightarrow A$ is accepted with probability $63/252 = 1/4$*

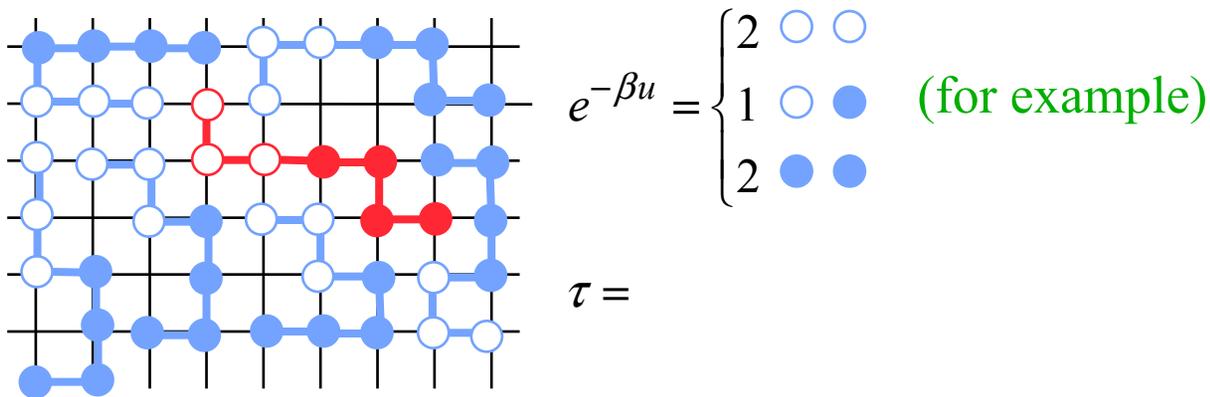
Attractive Interactions

○ Molecules with attraction

- *Generalization uses Boltzmann factor to formulate Rosenbluth weight*

- *At each step weight is $w_i = \sum_{j=1}^k e^{-\beta u_i(j)}$ Before, this was a sum of terms either zero or one*

- *And probability of selecting site j is $\pi_j = \frac{e^{-\beta u_j}}{w_i}$*



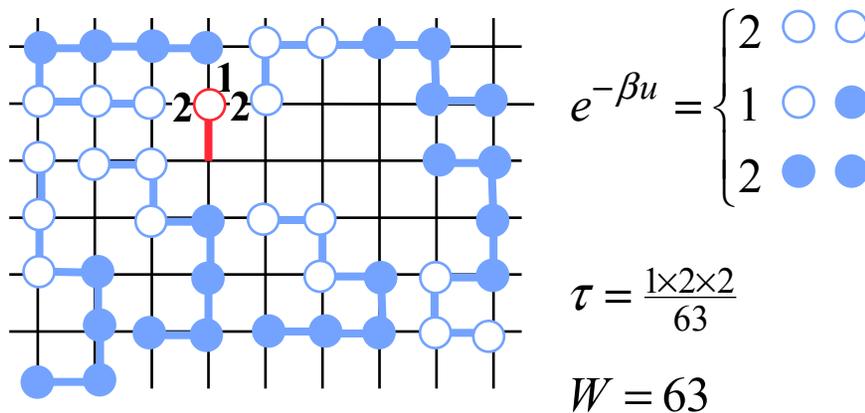
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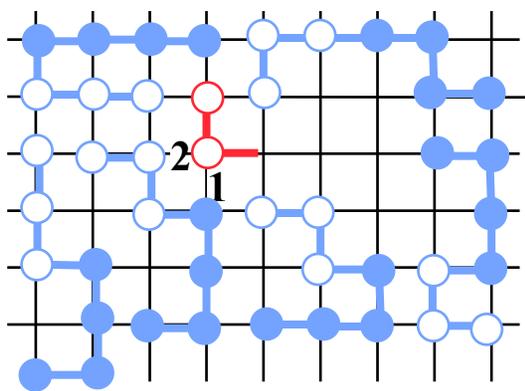
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$$e^{-\beta u} = \begin{cases} 2 & \text{○ ○} \\ 1 & \text{○ ●} \\ 2 & \text{● ●} \end{cases}$$

$$\tau = \frac{4}{63} \times \frac{2 \times 1}{2+0+0}$$

$$W = 63 \times 2$$

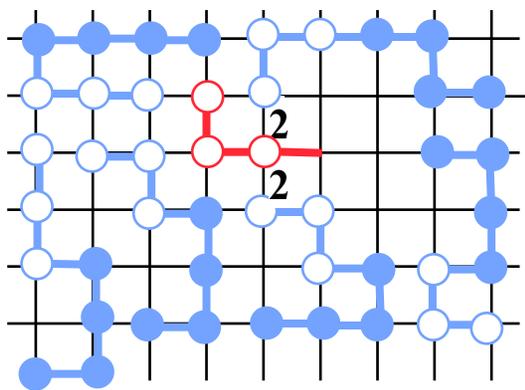
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$$\tau = \frac{4}{63} \times \frac{2}{2} \times \frac{2 \times 2}{4+0+0}$$

$$W = 63 \times 2 \times 4$$

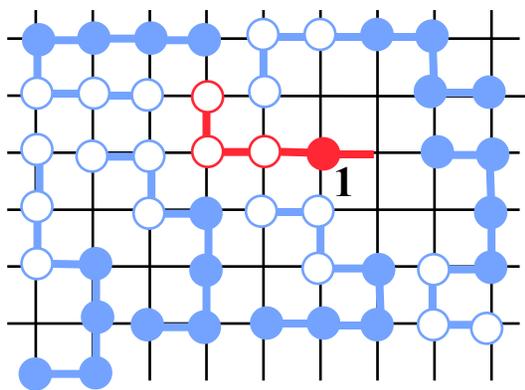
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$$\tau = \frac{4}{63} \times \frac{2}{2} \times \frac{4}{4} \times \frac{1}{1+0+0}$$

$$W = 63 \times 2 \times 4 \times 1$$

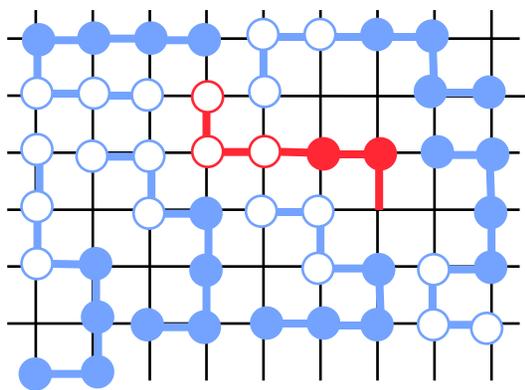
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$$\tau = \frac{4}{63} \times \frac{2}{2} \times \frac{4}{4} \times \frac{1}{1} \times ?$$

$$W = 63 \times 2 \times 4 \times 1 \times ?$$

In-class assignment 2
Get the next term

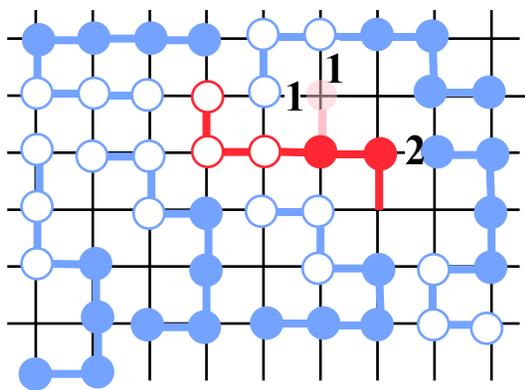
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$$\tau = \frac{4}{63} \times \frac{2}{2} \times \frac{4}{4} \times \frac{1}{1} \times \frac{2}{2+1 \times 1+0}$$

$$W = 63 \times 2 \times 4 \times 1 \times 3$$

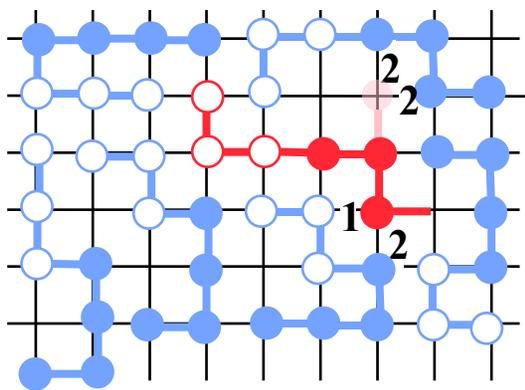
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$$W = 63 \times 2 \times 4 \times 1 \times 3 \times 6$$

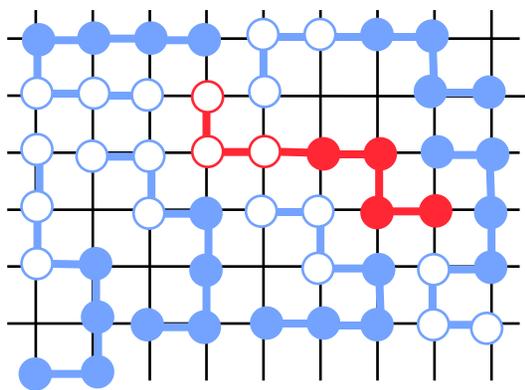
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$$W = 63 \times 2 \times 4 \times 1 \times 3 \times 6 \times 4$$

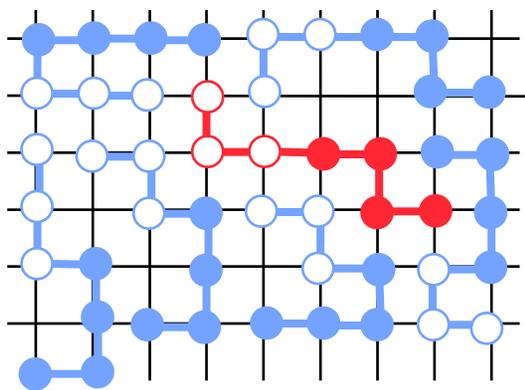
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$$\tau = \frac{4}{63} \times \frac{2}{2} \times \frac{4}{4} \times \frac{1}{1} \times \frac{2}{3} \times \frac{2}{6} \times \frac{4}{4} = 0.014$$

$$W = 63 \times 2 \times 4 \times 1 \times 3 \times 6 \times 4 = 36288$$

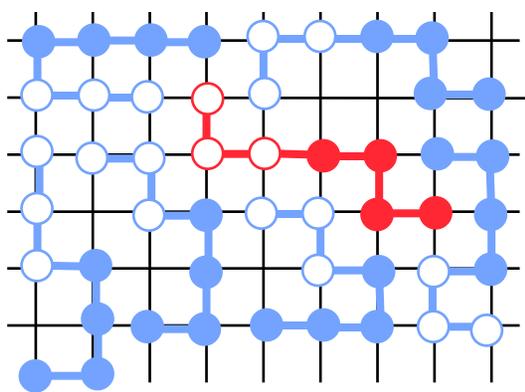
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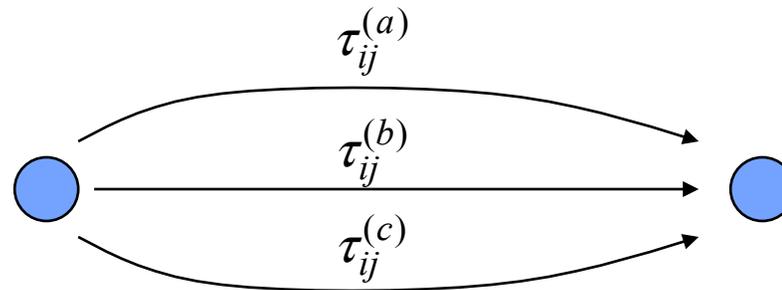
$$W = 63 \times 2 \times 4 \times 1 \times 3 \times 6 \times 4 = 36288$$

○ W is used just as before: accept with proby $\min[1, W_{\text{new}}/W_{\text{old}}]$

- energy contribution is built-in: $\prod \tau_i = \prod \frac{e^{-\beta u_i}}{w_i} = \frac{e^{-\beta U}}{W}$

A General Result for Markov Processes 1.

- Consider a process in which there are several ways to generate each trial $i \rightarrow j$



- To enforce detailed balance, all routes should be considered in formulating acceptance probability

$$\pi_i \left[\tau_{ij}^{(a)} + \tau_{ij}^{(b)} + \tau_{ij}^{(c)} \right] \min[1, \chi] = \pi_j \left[\tau_{ji}^{(a)} + \tau_{ji}^{(b)} + \tau_{ji}^{(c)} \right] \min[1, 1/\chi]$$

- If there are many ways to generate the trial, this can pose difficulties

A General Result for Markov Processes 1.

○ Consider the following recipe for a single-step trial

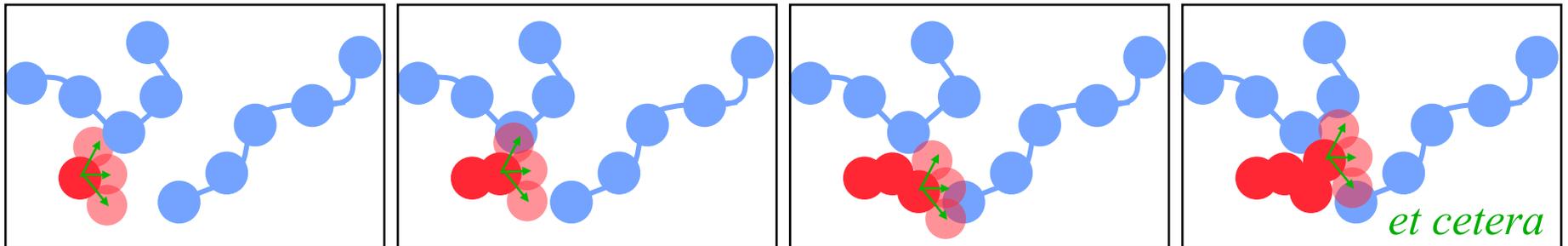
- *Generate the trial $i \rightarrow j$ via route (a), with probability $\tau_{ij}^{(a)}$*
- *Choose a reverse trial $j \rightarrow i$ via one of the routes, say (b)*
Choose it with probability that it would occur as the $j \rightarrow i$ route
Probability = $\tau_{ji}^{(b)}/\tau_{ji}$
- *Accept the (forward) trial as if (a) and (b) were the only routes*

$$\pi_i \tau_{ij}^{(a)} \min[1, \chi^{ab}] = \pi_j \tau_{ji}^{(b)} \min[1, 1/\chi^{ab}]$$

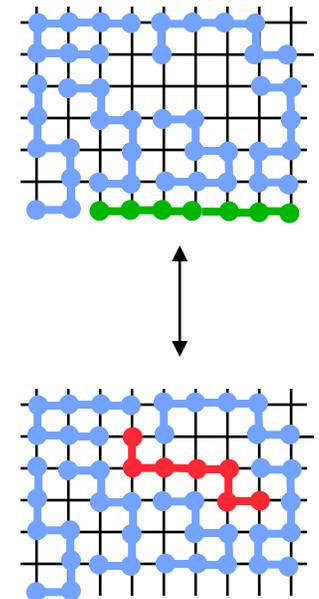
○ This recipe satisfies detailed balance for the overall transition $i \rightarrow j$

Off the Lattice

- CBMC can be extended to off-lattice models
- Choose a set of trial orientations at random for each atom insertion



- Once a chain is generated in new position, perform same operation tracing out its original location
- Compile Rosenbluth weight for new and original chains to use in acceptance $W = \prod_i \sum_j e^{-\beta u_i(j)}$
- Note that each insertion may be accomplished via multiple routes, differing in the discarded atom trials



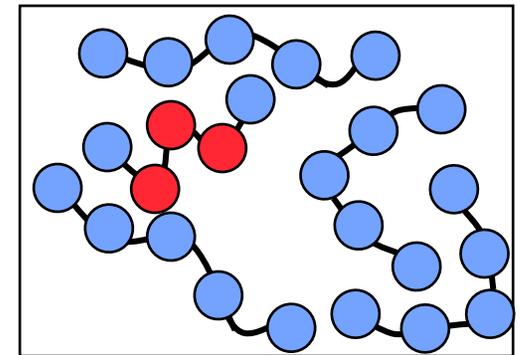
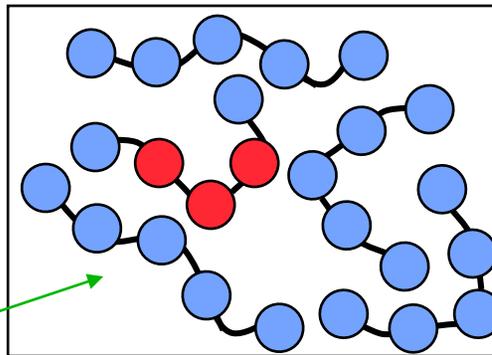
CBMC General Comments

○ Method begins to fail for sufficiently long chains

- *maybe as few as 10 atoms*

○ Extensions of method

- *Gibbs ensemble*
- *Branched polymers*
- *Partial chain regrowth*
- *Chemical-potential calculation*

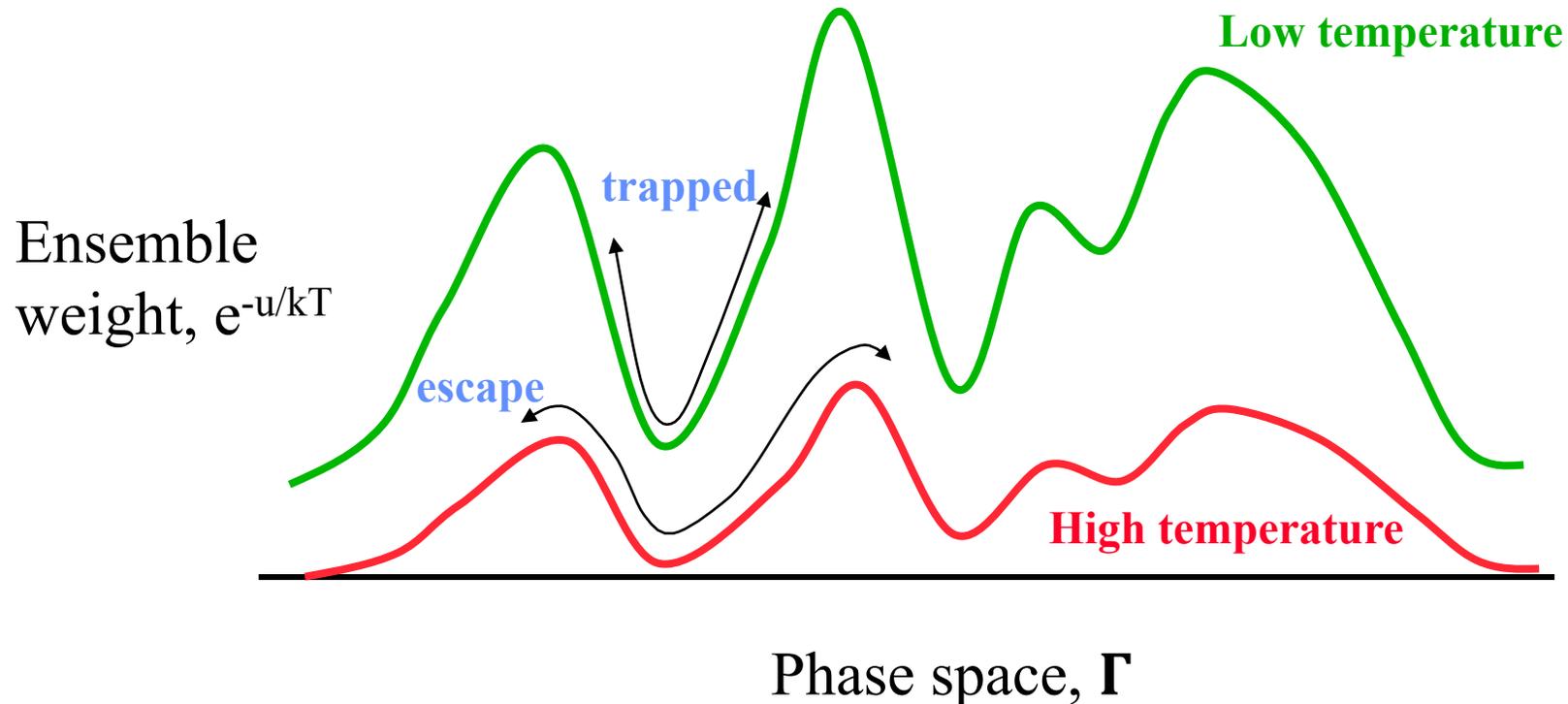


○ General idea can be applied in other ways

- *Multi-step trial broken into smaller decisions, with acceptance including consideration of the choices not taken*

Parallel Tempering 1.

- At high temperature a broader range of configurations is sampled
- Barriers to transitions are lowered

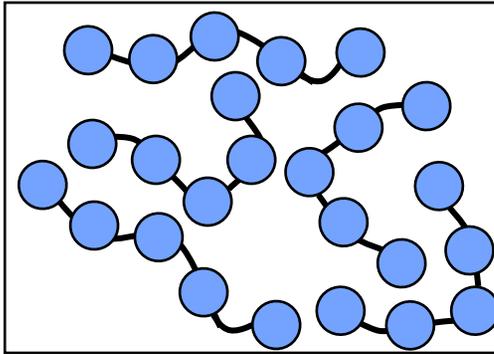


- How to simulate a low-temperature system with high-temperature barrier removal?

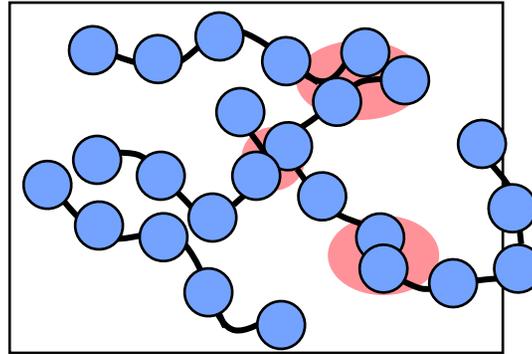
Parallel Tempering 2.

- Simulate loosely coupled high- and low-temperature systems in parallel

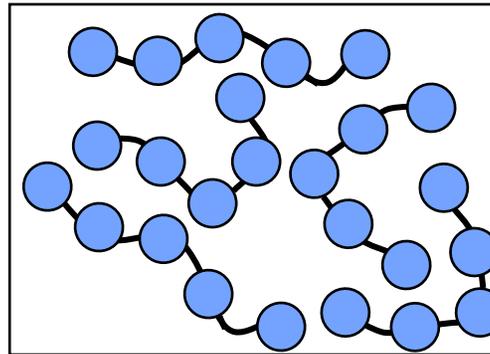
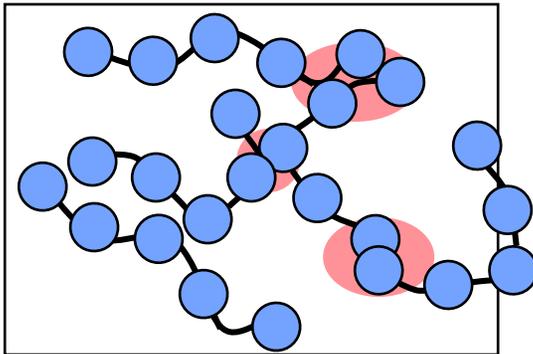
Low temperature



High temperature



- Perform moves in which two systems swap configurations



- Accept based on $e^{-\beta_H(U_2-U_1)}e^{-\beta_L(U_1-U_2)} = e^{-(\beta_H-\beta_L)(U_2-U_1)} = e^{-\Delta\beta\Delta U}$

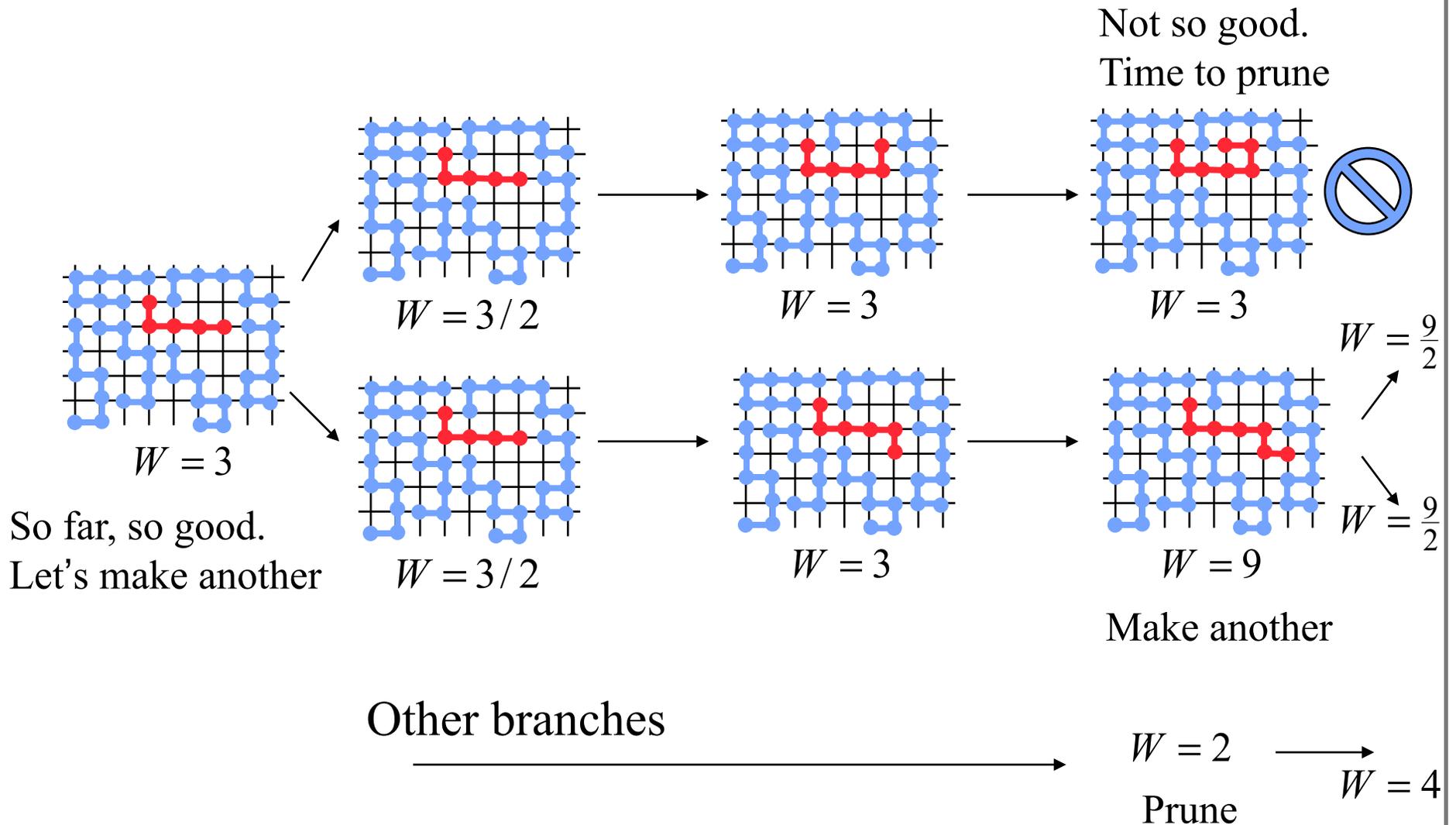
Parallel Tempering 3.

- To get reasonable acceptance rate, temperatures should not be too different
- Can be extended to include any number of systems simulated in parallel
- Can be extended to do “tempering” in other variables, such as the chemical potential
- Very well suited for use in conjunction with histogram reweighting

Pruned-Enriched Rosenbluth Method

- At some point along the growth process it may become clear that
 - *the chain is doomed, or*
 - *the chain is really doing well*
- We'd like to enrich the presence of the good ones, while pruning out the ones that look bad
- Use a criterion based on partial Rosenbluth weight

Pruned-Enriched Rosenbluth Method



Pruned-Enriched Rosenbluth Method

○ Set cutoffs for intermediate Rosenbluth weights

- *duplicate any configuration having $W > W^>$, halving weights of new duplicates*
- *prune configurations having $W < W^<$, taking every-other such configuration, and doubling the weight of those not taken*