

# Assorted Topics in the Monte Carlo Simulation of Polymers

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- Conclusion

# Self-avoiding walk model

- A walk on a lattice, step to neighbouring site provided it has not already been visited.



Simple random walk



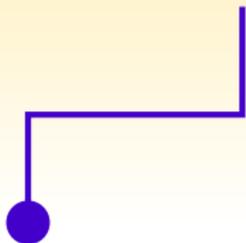
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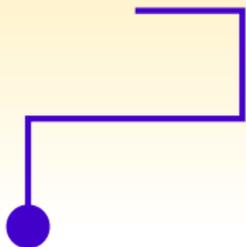
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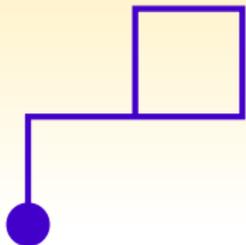
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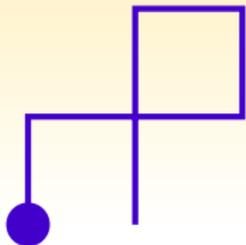
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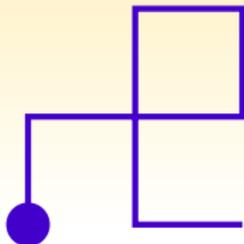
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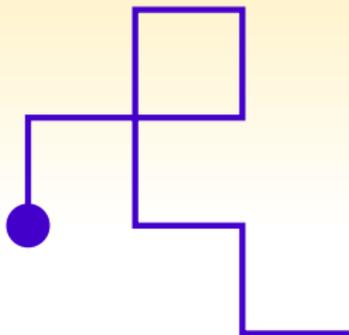


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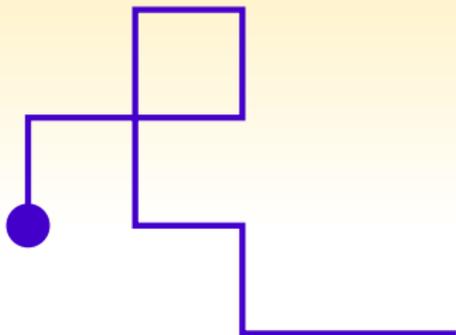


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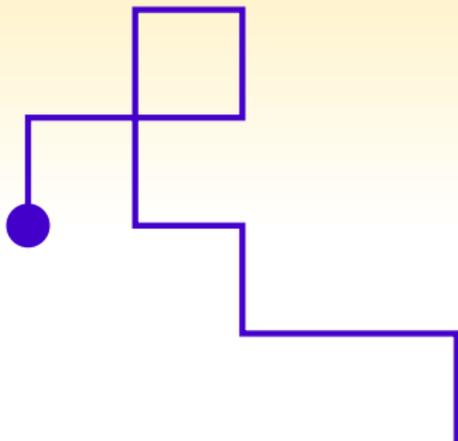




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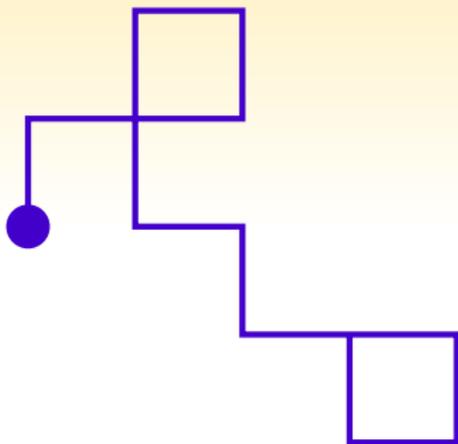


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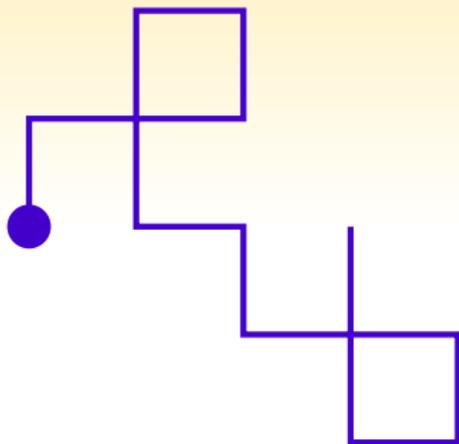
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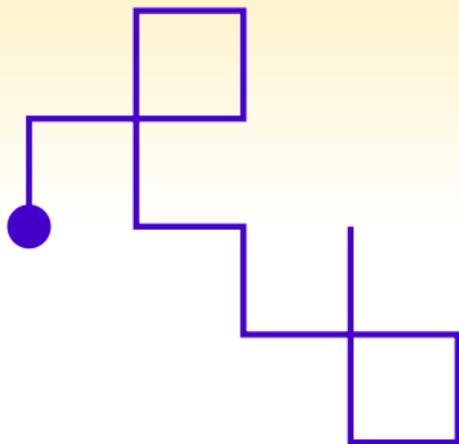




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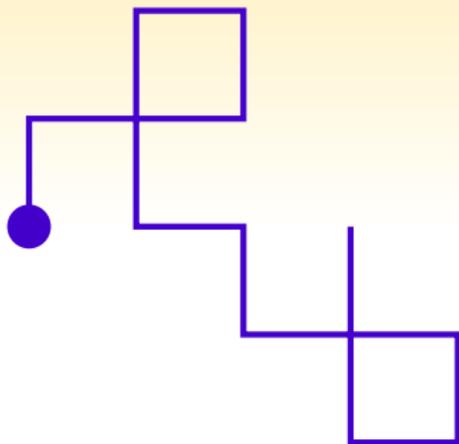


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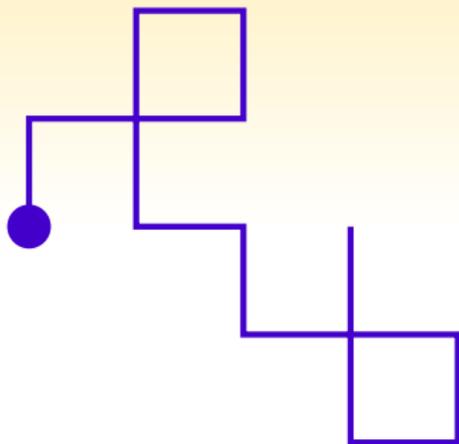


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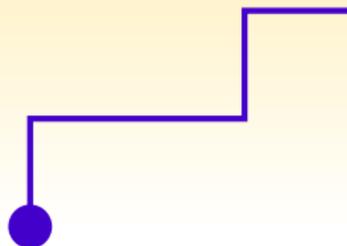


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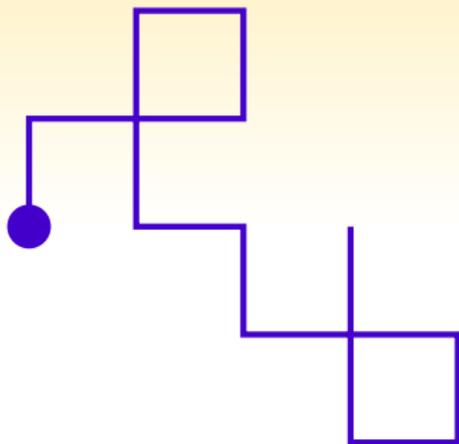


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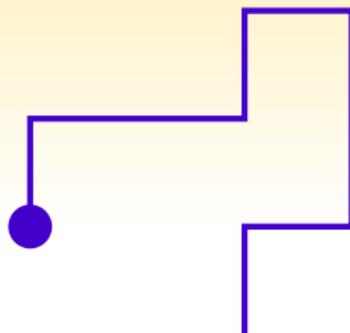




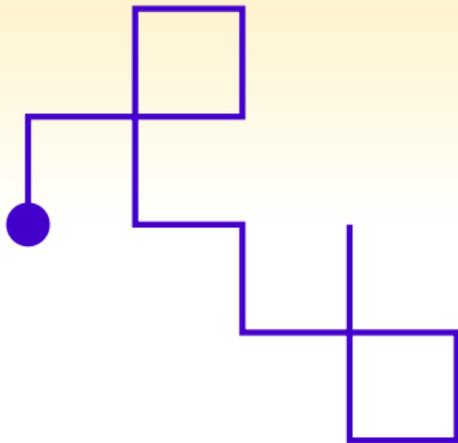




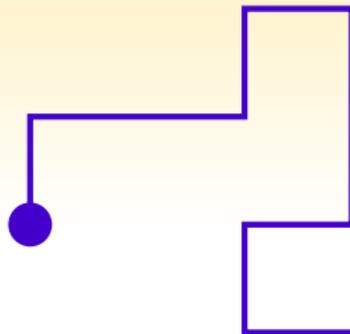
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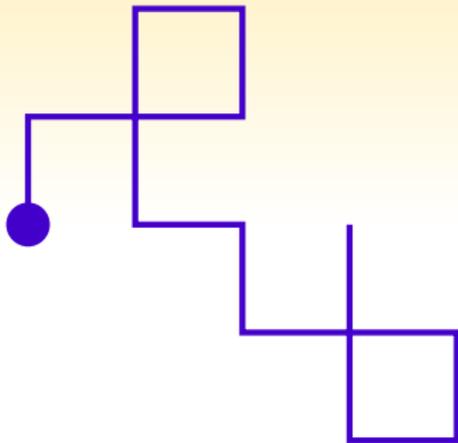
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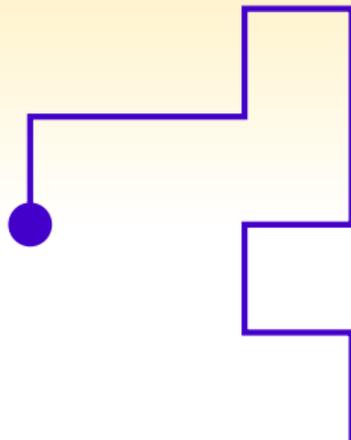
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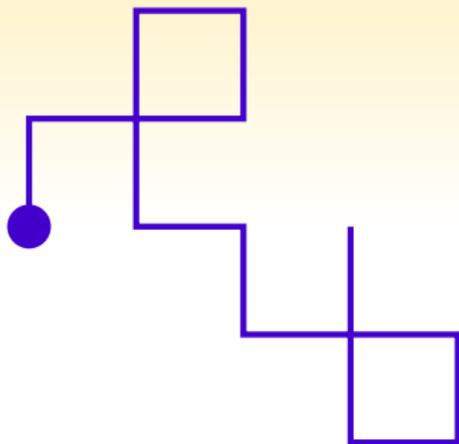


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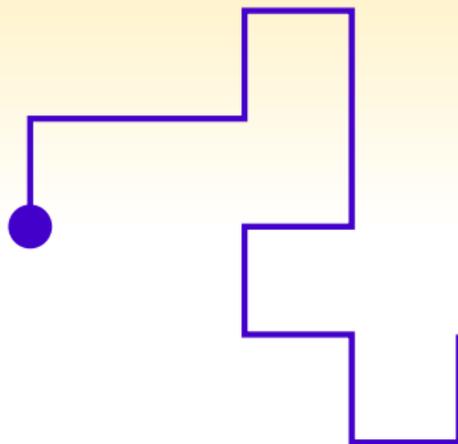


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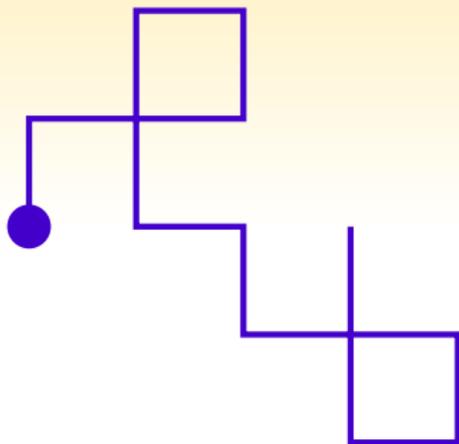




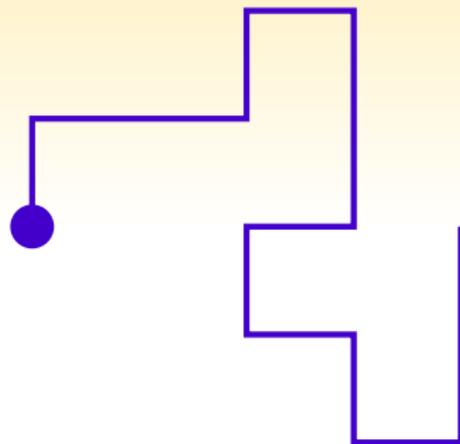
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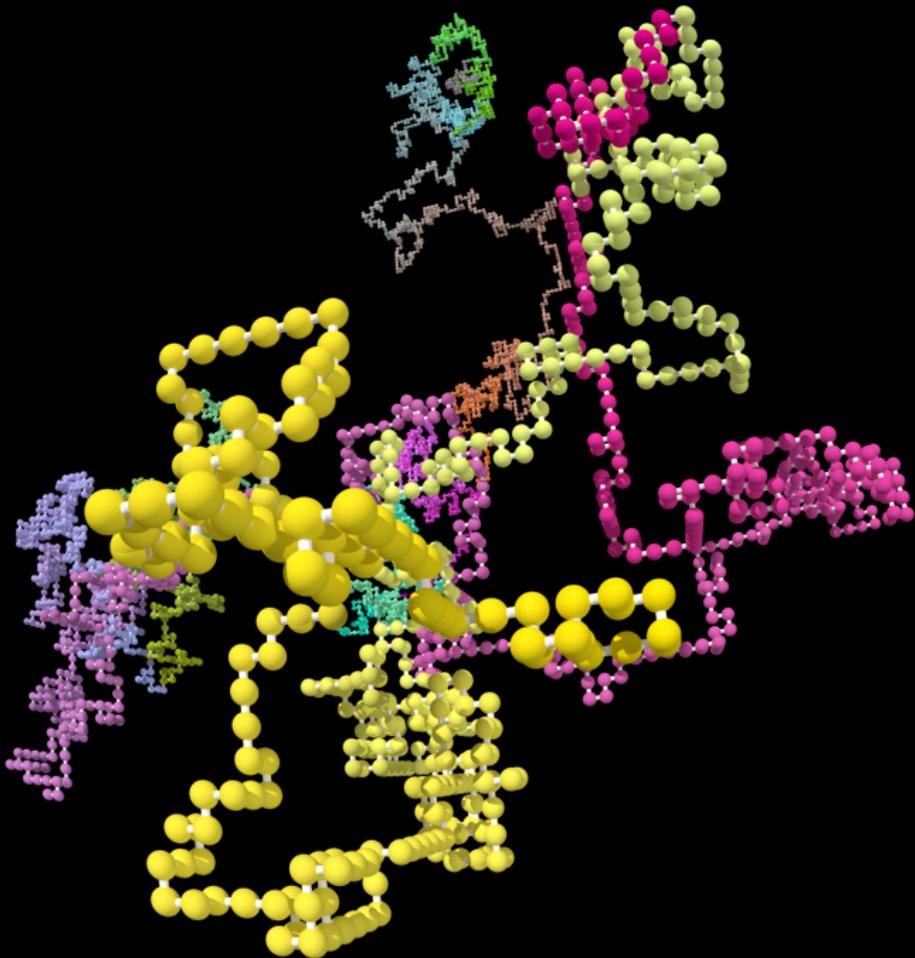


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Self-avoiding walk

A typical SAW of 5000 steps on the simple cubic lattice:



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- $D$  is model dependent, but the critical exponent  $\nu$  is a universal quantity.

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- Estimate physical properties of system by sampling from all possible configurations (state space).
- Basic idea: generate new configurations by deforming current configuration via a “move”.

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- Lal (1969) invented pivot algorithm, but key paper is by Madras and Sokal (1988).

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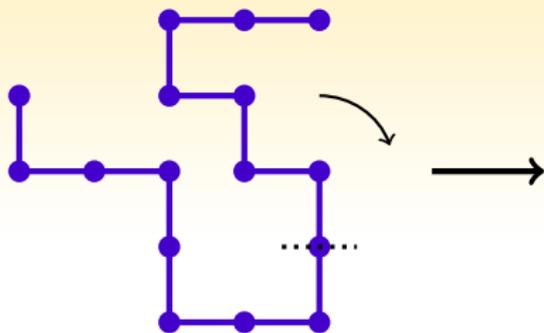
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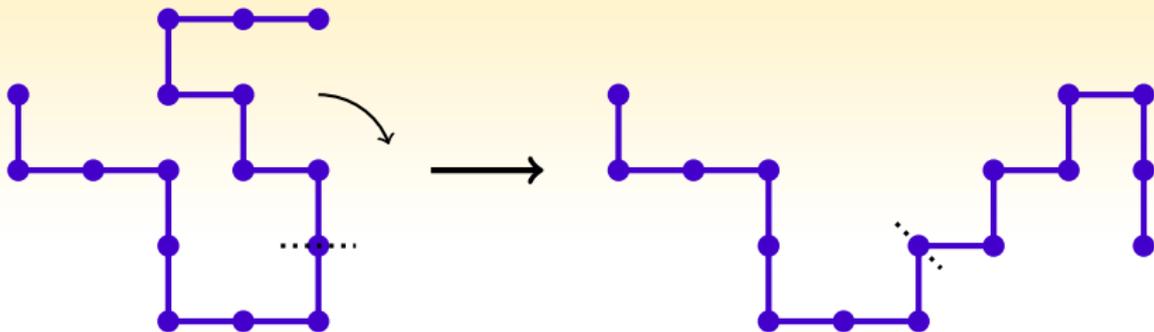
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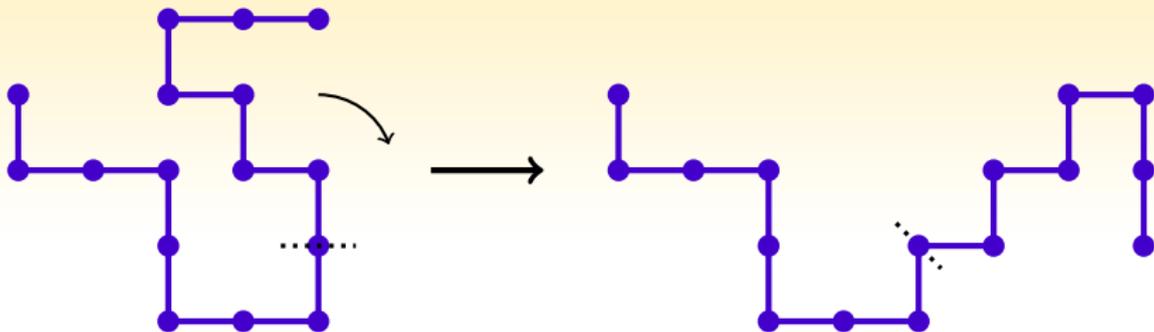
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- Ergodic, samples SAWs uniformly at random.



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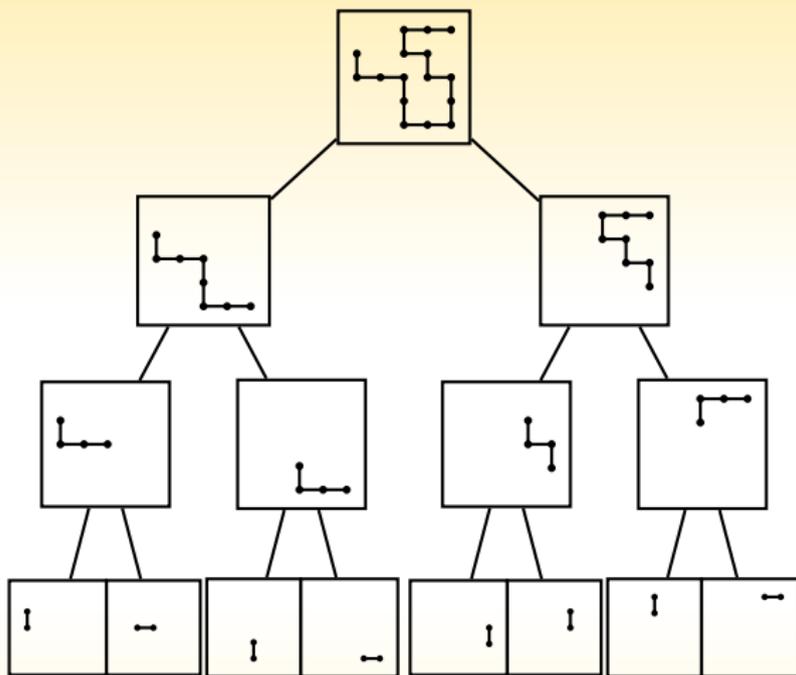
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Run simulation

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- In fact, don't need to write down!  $\Rightarrow o(N)$  (Kennedy, 2002)
- Bookkeeping can be handled efficiently in binary tree structure.  $\Rightarrow O(\log N)$  (C., 2010)



SAW-tree representation of a walk.

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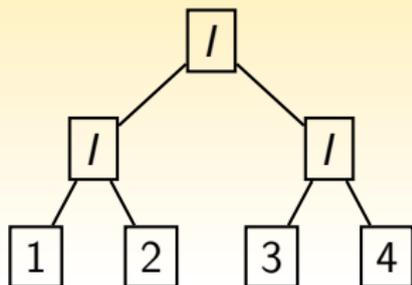
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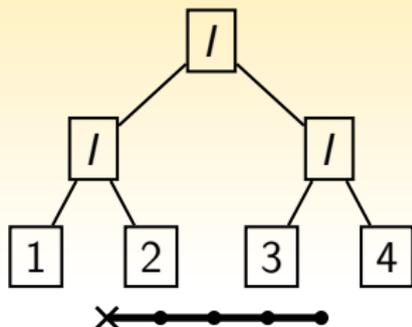
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- Binary tree has typical height  $O(\log N)$ .

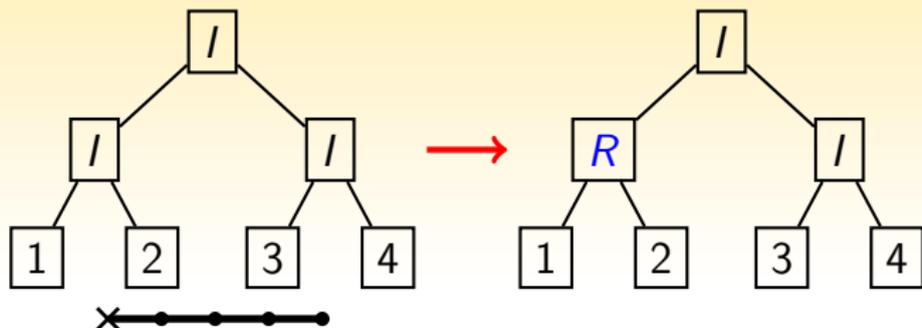
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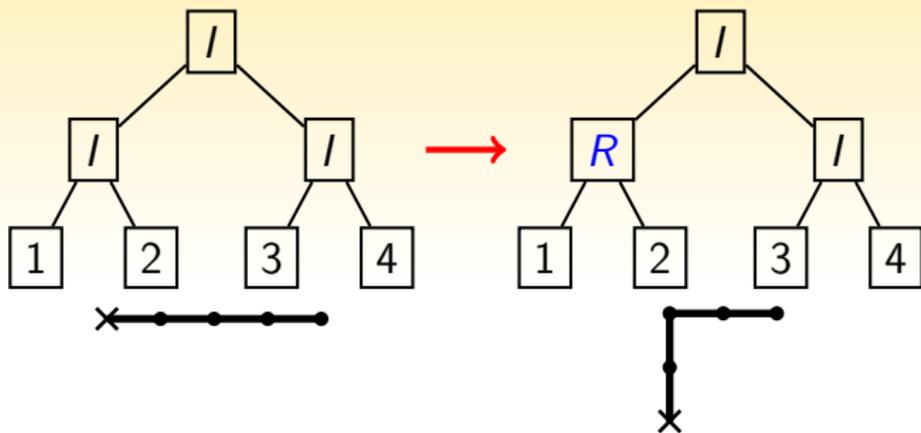
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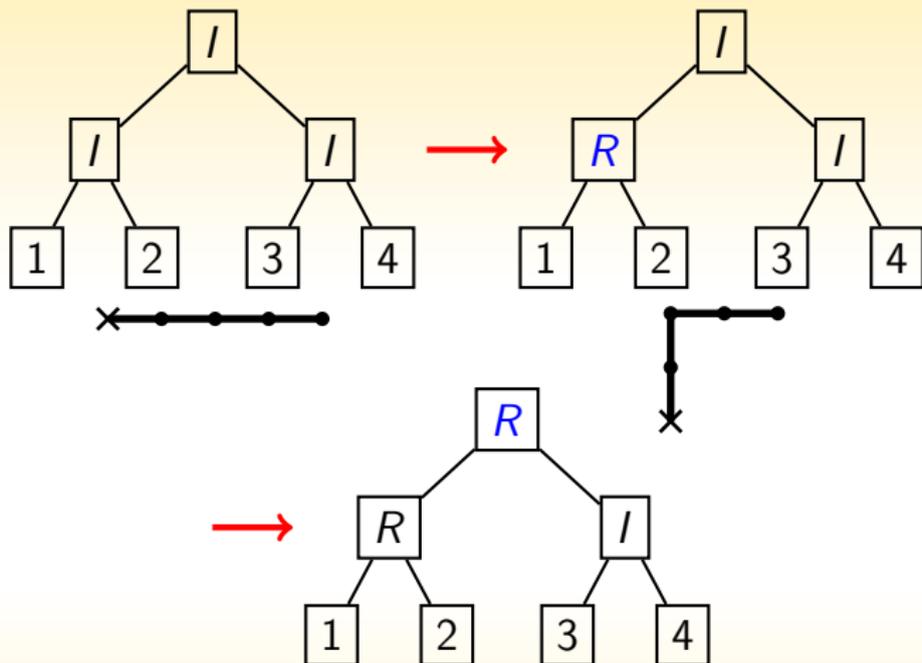
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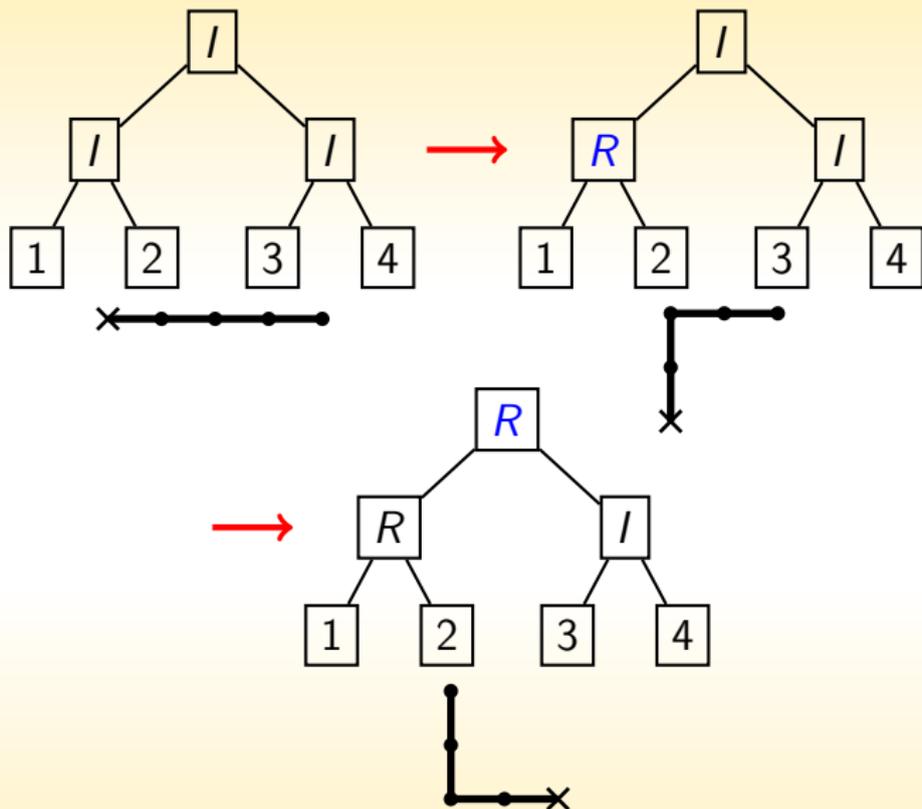
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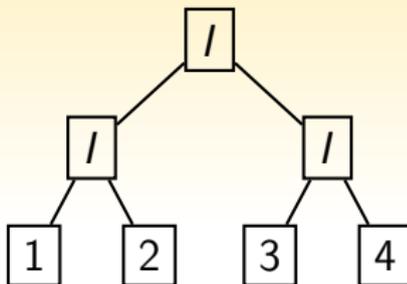
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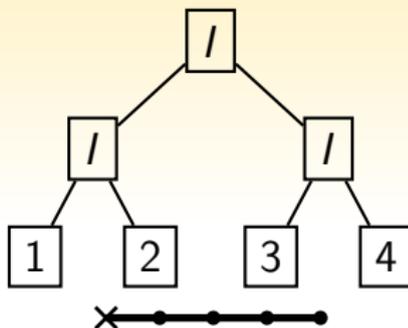
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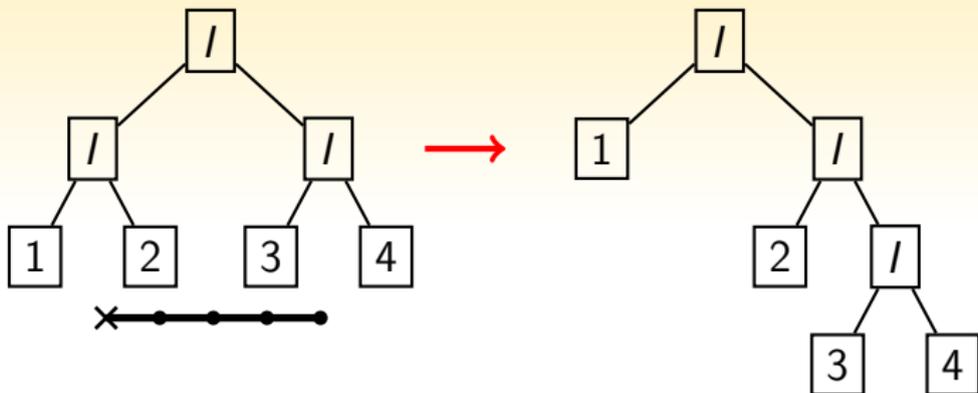
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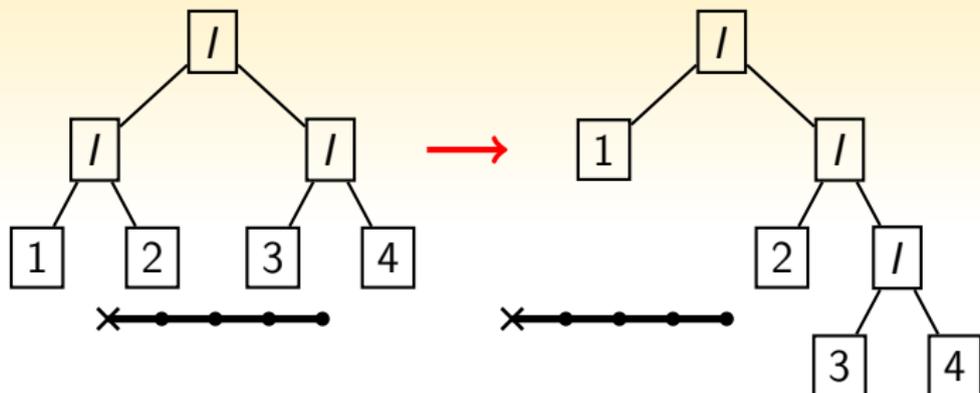
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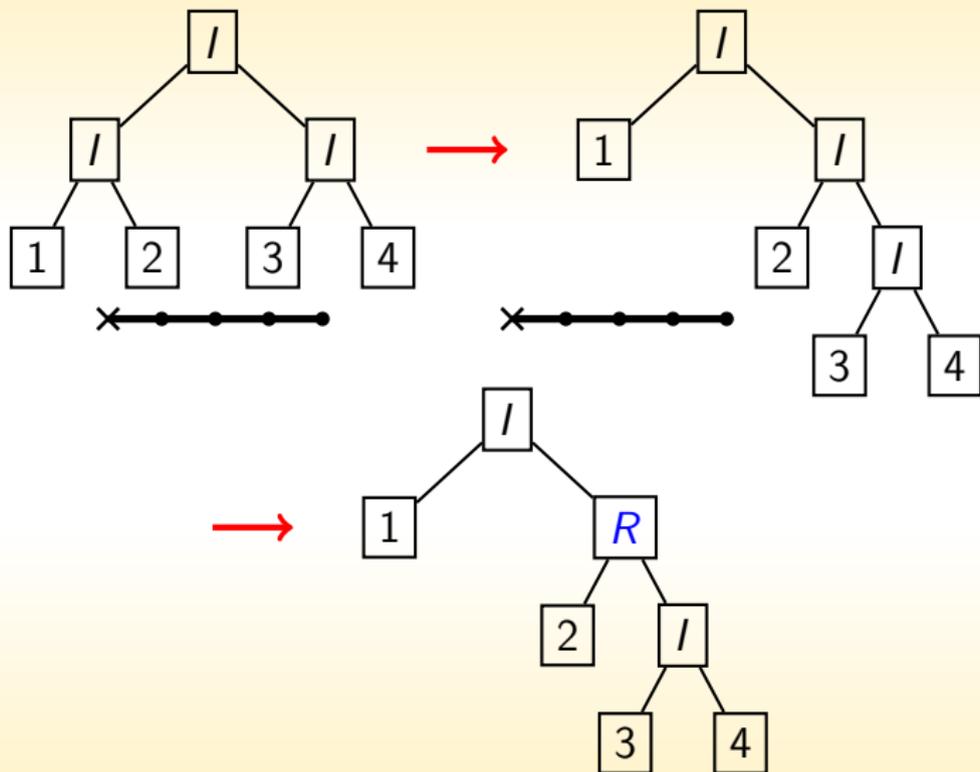
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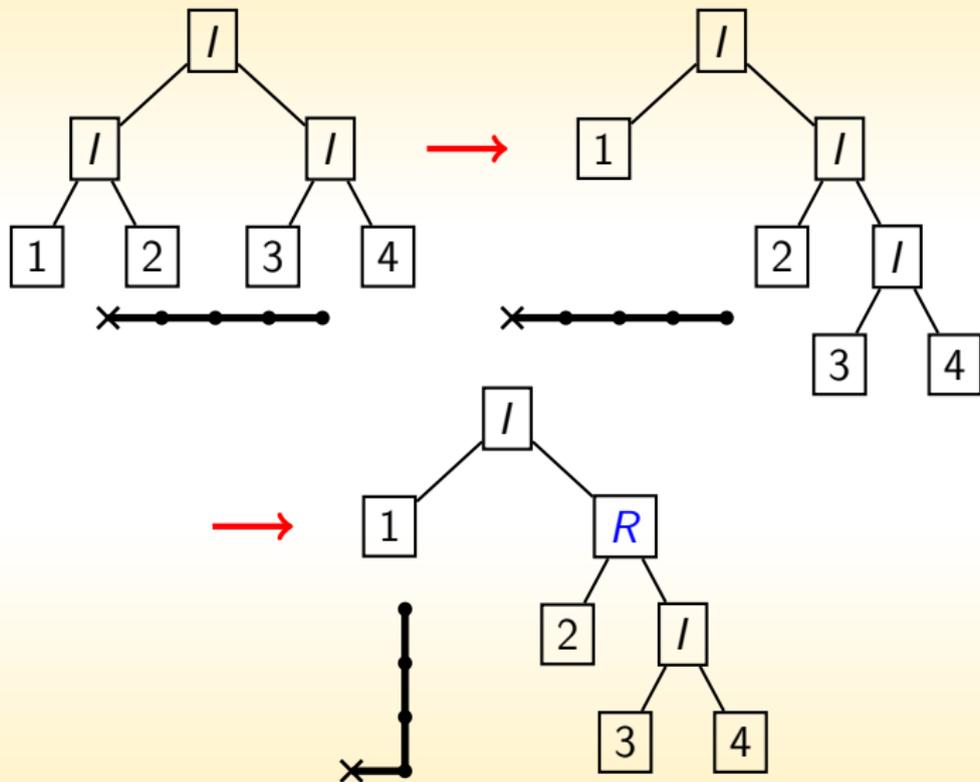
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- How can we extend this key idea - fast global moves - to other models?

# Hamiltonian paths

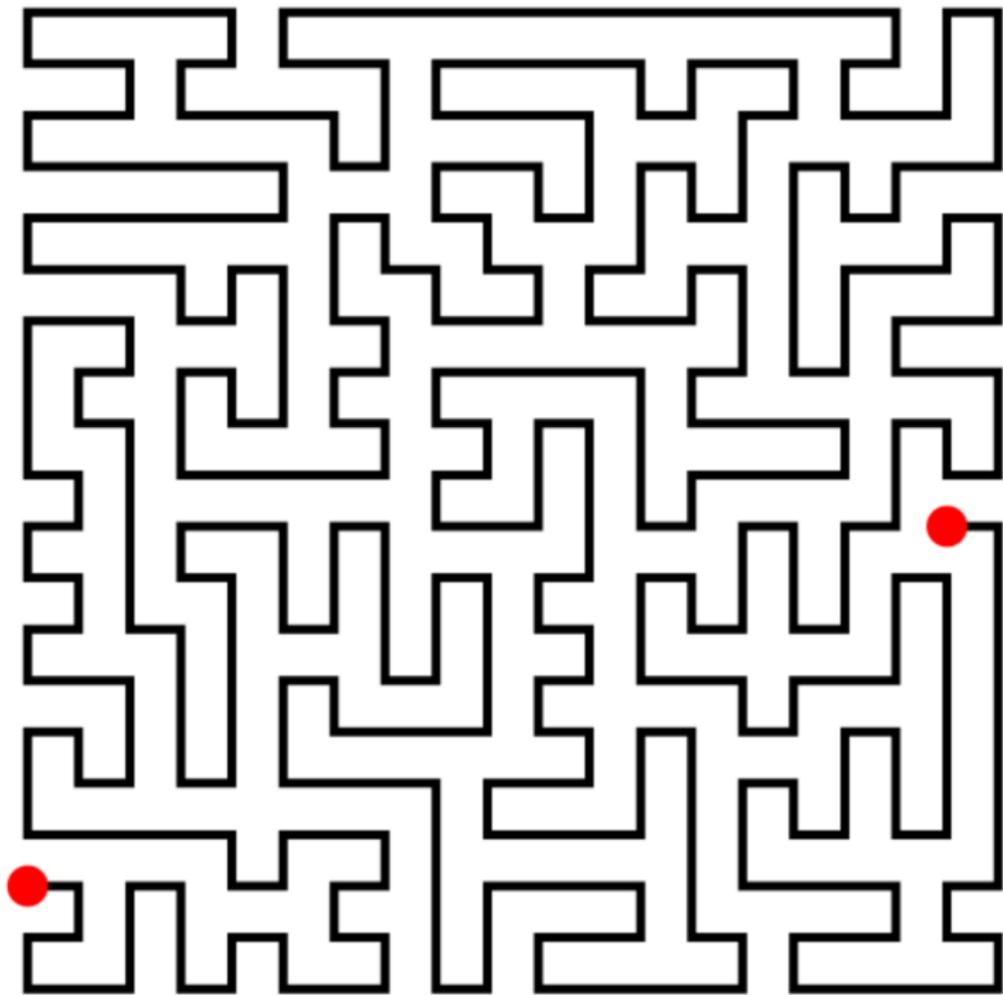
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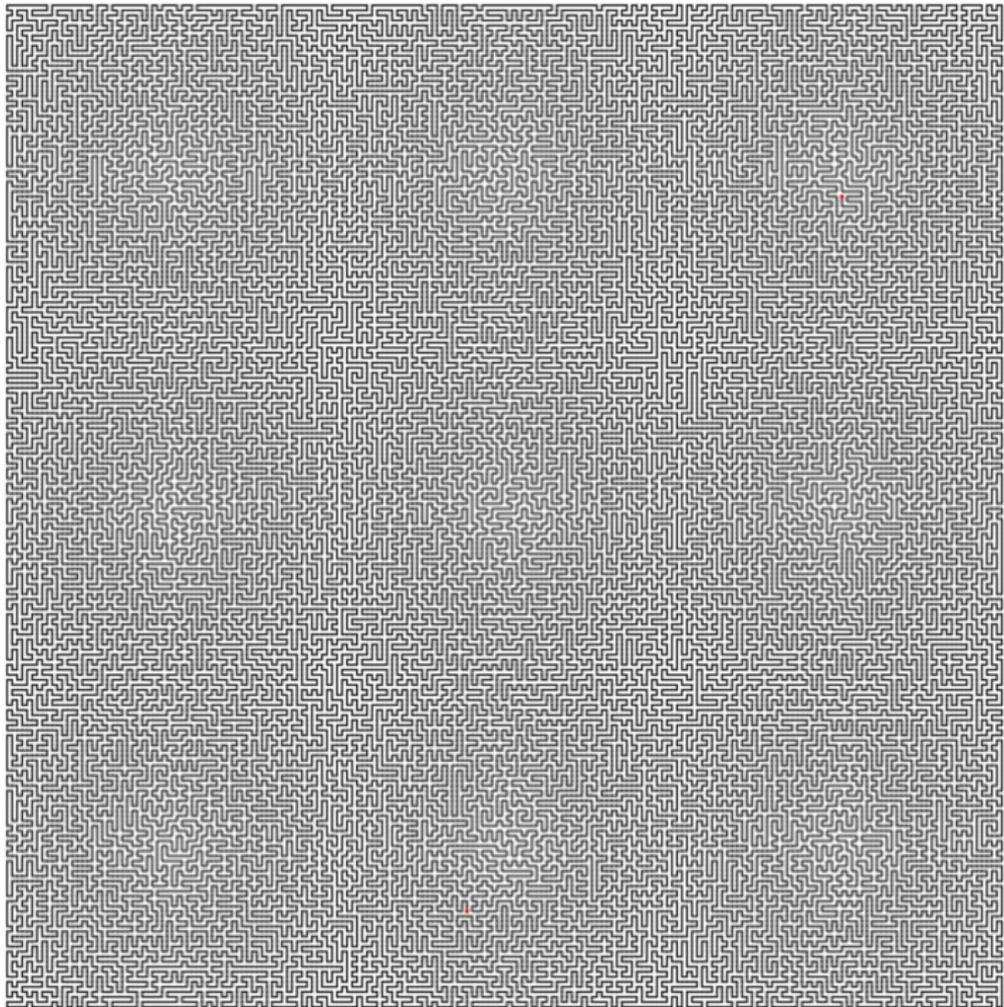
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- Examples on  $20 \times 20$  and  $200 \times 200$  lattice (from generator at:  
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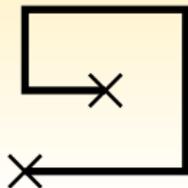
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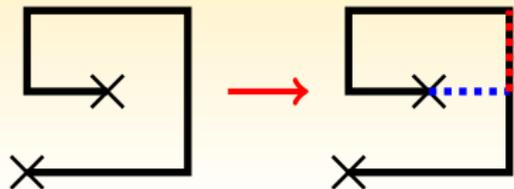
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- One example: backbite move, which is likely to be ergodic for the simple cubic lattice.

Backbite moves for sampling Hamiltonian paths.

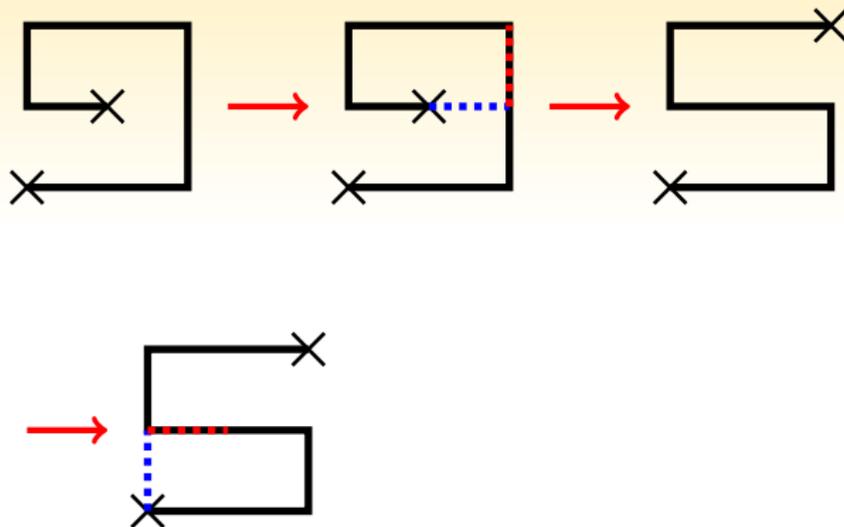


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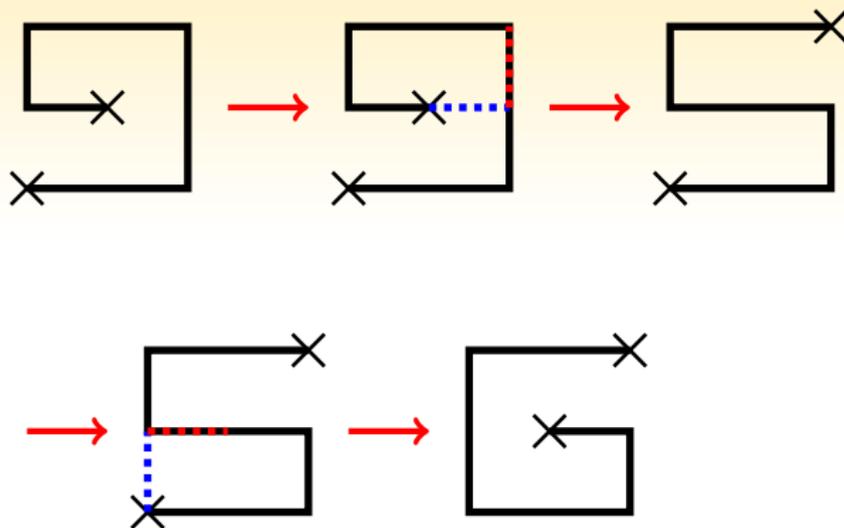




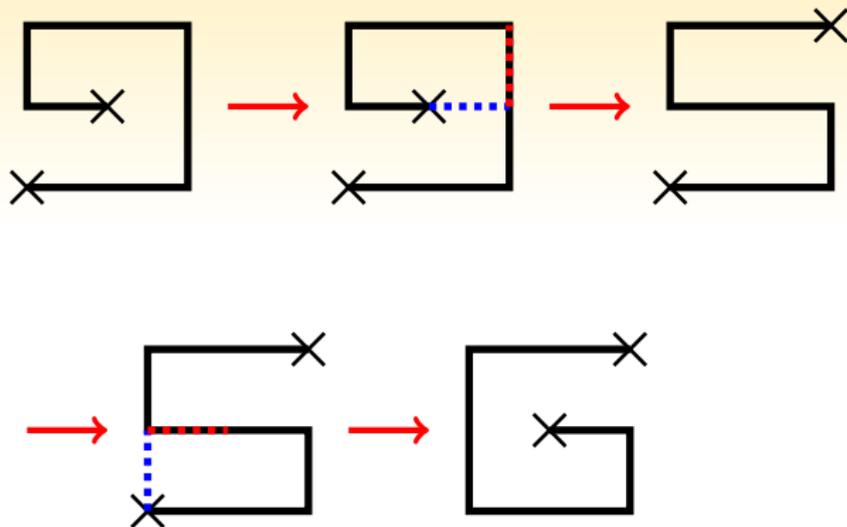
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Each time we make a backbite move we create a loop, delete the edge which completes the loop, and *reverse* the orientation of the remaining edges of the loop.

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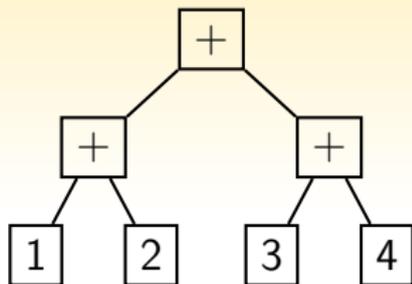
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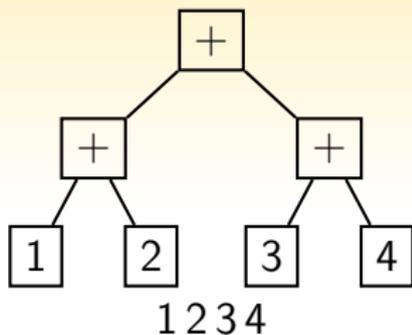
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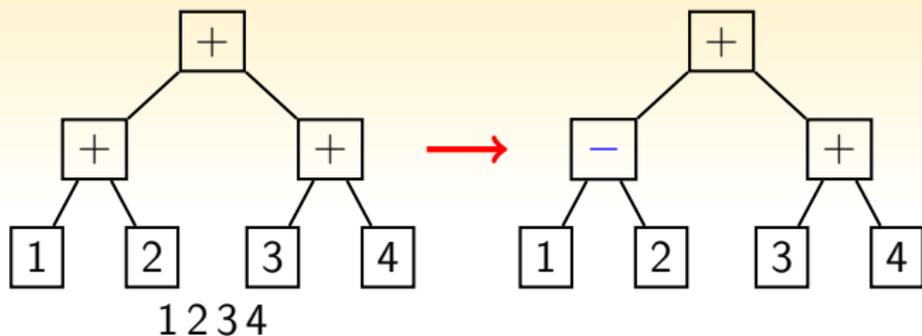
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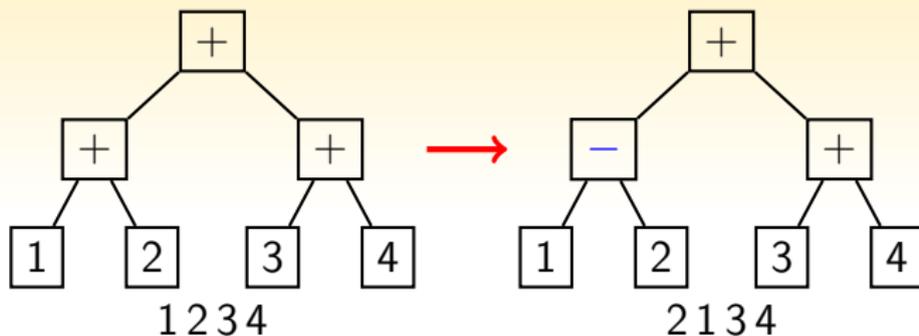
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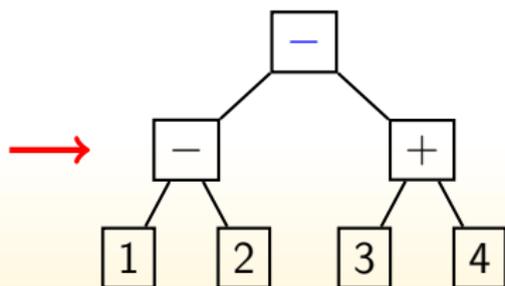
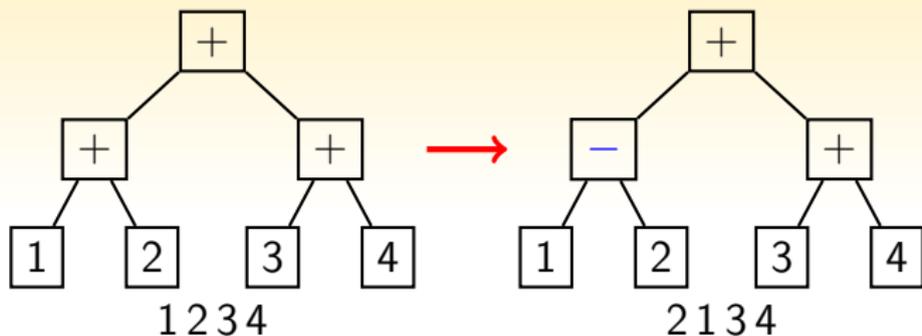
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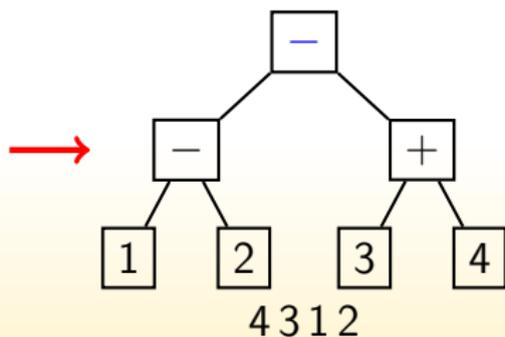
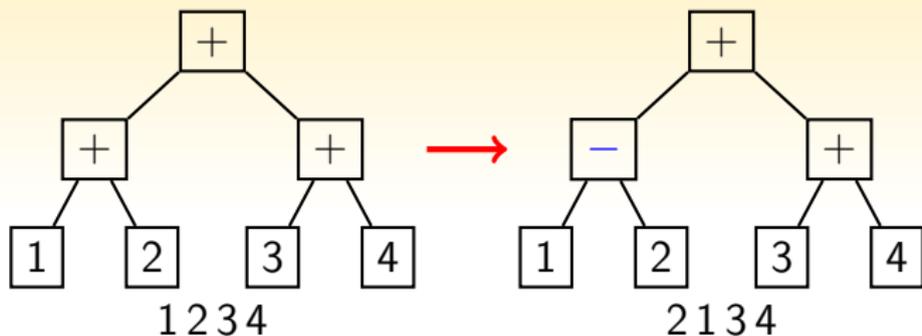
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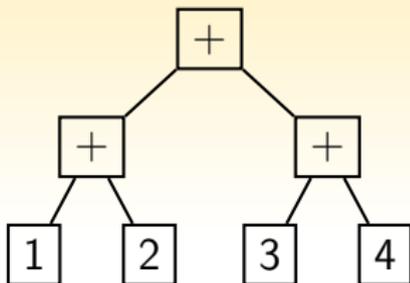
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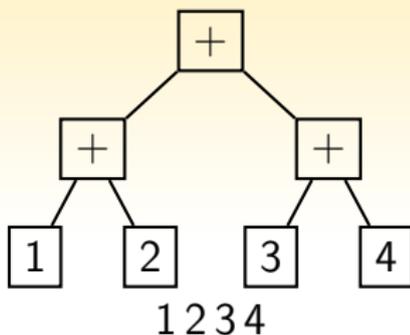
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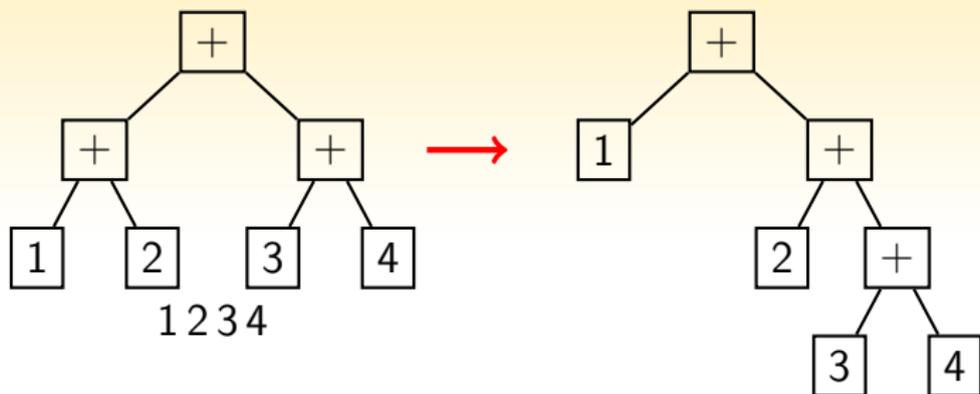
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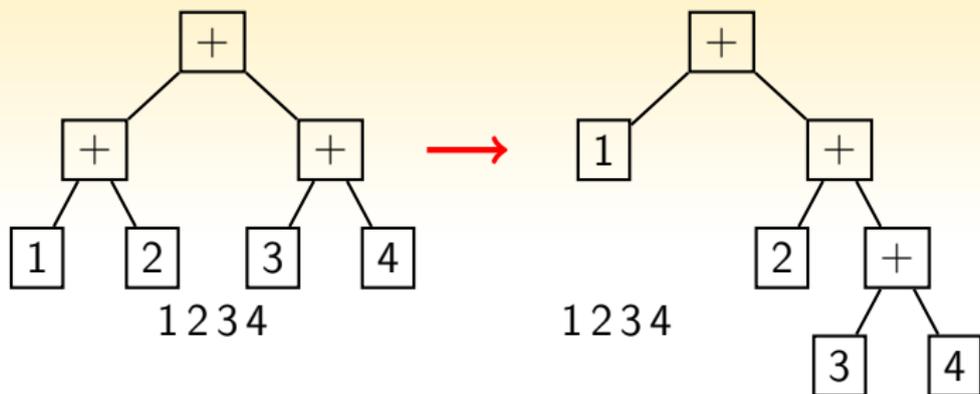
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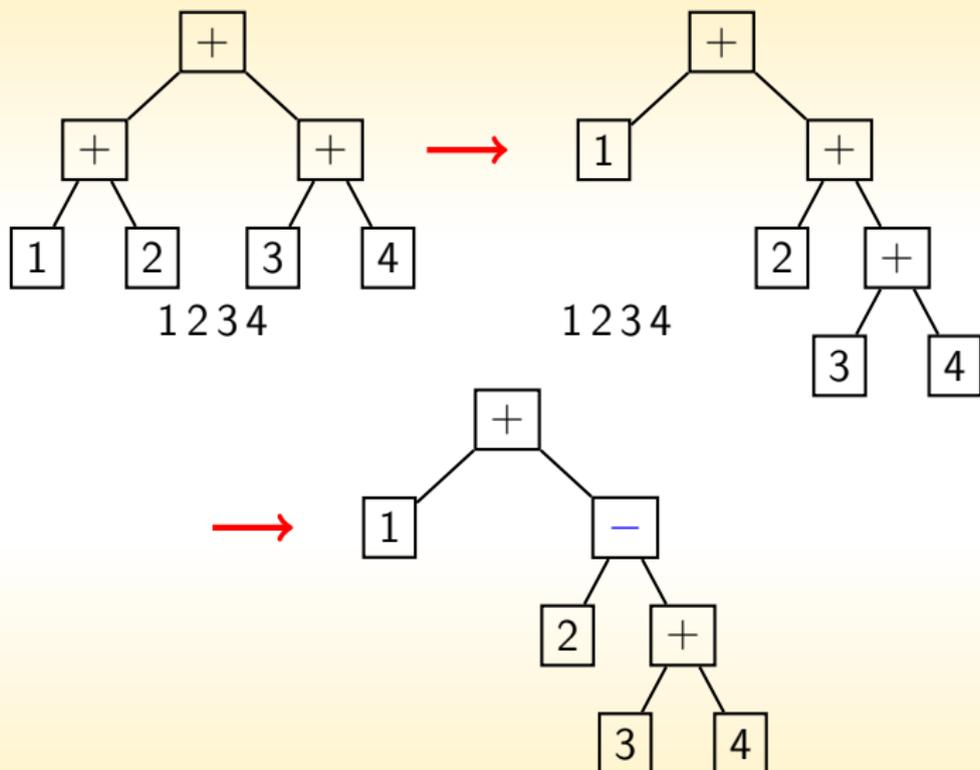
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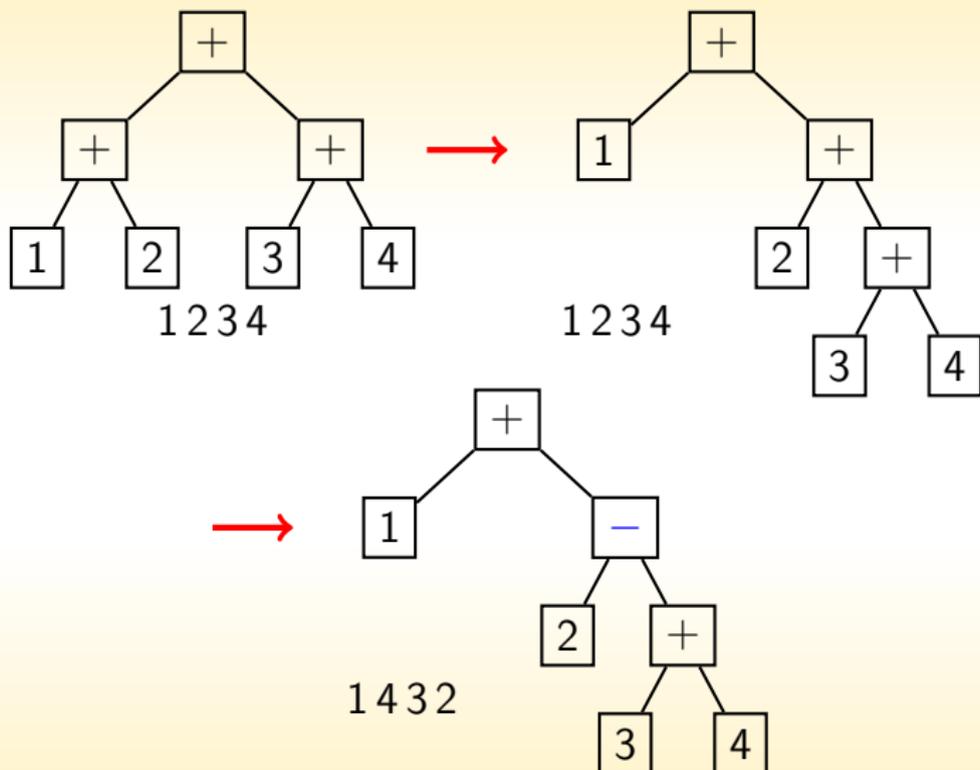
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  - $L = 512$ ,  $N = 134\,217\,728$ : 46 million steps, versus 20.6 tree rotations.

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- Strong corrections to scaling, large  $N$  should make a big difference.

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- Our estimator is a weighted version of  $1/r_{ij}$ , monomers  $i$  and  $j$  chosen at random.
- $1.591 \pm 0.007$ , (Dünweg et al., 2002), vs  $1.58040 \pm 0.00002$ .

# Counting SAW

- Number of SAW of length  $N$ ,  $c_N$ , tells us about how many conformations are available to SAW of a particular length:

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$$c_N = \frac{c_N}{c_{N/2}^2} \left( \frac{c_{N/2}}{c_{N/4}^2} \right)^2 \cdots c_k^{N/k}.$$



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- This idea can be applied to other systems with additional length scales: confined polymers, bridges, star polymers, perhaps  $\theta$ -polymers.

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- Confined polymers, novel observables, dense polymers,  $\theta$ -polymers, bridges, co-polymers,  $\dots$ ?
- Pivot algorithm only part of the story.