



Numerical Calculation for Bose-Hubbard Model

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MODEL INTRODUCTION

Hamiltonian

The Bose-Hubbard model (BHM) gives a description of the physics of interacting spinless Bosons on a lattice[1].

$$\mathcal{H} = -t \sum_{\langle i,j \rangle} \hat{b}_i^\dagger \hat{b}_j + \frac{1}{2} U \sum_i \hat{n}_i (\hat{n}_i - 1) - \mu \sum_i \hat{n}_i. \quad (1.1)$$

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Hopping Term – Superfluid

Bosons move between neighboring sites with amplitude t . The operator \hat{b}_i^\dagger creates a particle at site i , while \hat{b}_j removes one at site j .

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Chemical Potential Term

Controls the average particle number via external field μ . For $\mu = 5$, the system will keep a fixed density of the mean particle number.



STOCHASTIC SERIES EXPANSION FOR BHM

Kernel Formula

Applying the Taylor expansion to the partition function

$$Z = \sum_{m=0}^{\infty} \frac{\beta^m}{m!} \sum_{\{i_1, \dots, i_m\}} \sum_{\{b_1, \dots, b_m\}} \prod_{k=1}^m \langle i_k | -H_{b_k} | i_{k+1} \rangle. \quad (2.1)$$

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Expansion Usage Example Taking the order $m = 3$ in 1D-4site model with the parameters

Parameters	t	U	μ	β	N	
Values	1	2	5	4	4	$\{(t, (1, 2)), (U, 3), (\mu, 4)\}\}$
Notations	/	/	/	/	Total number of particles in the 4-site	Jumping, repulsion, chem- ical potential operators

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The state sequences become

$$1. |i_1\rangle = |2, 1, 1, 0\rangle.$$

$$2. |i_2\rangle = |1, 2, 1, 0\rangle.$$

$$3. |i_3\rangle = |1, 2, 1, 0\rangle.$$

$$4. |i_4\rangle = |2, 1, 1, 0\rangle = |i_1\rangle.$$



NUMERICAL CALCULATION ANALYSIS: 3 SCHEMES

Scheme A: Heat Bath Update

Basic Principle

Weight-Proportional Sampling: Transition probabilities equal normalized weights $\pi_j = w_j / \sum w_k$.
No rejection step, i.e., always accept according to weights.

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Transition Matrix Structure

For 4 scattering processes (bounce, straight, jump, turn)

$$T_A = \begin{bmatrix} \pi_1 & \pi_2 & \pi_3 & \pi_4 \\ \pi_2 & \pi_1 & \pi_4 & \pi_3 \\ \pi_3 & \pi_4 & \pi_1 & \pi_2 \\ \pi_4 & \pi_3 & \pi_2 & \pi_1 \end{bmatrix}, \quad T_{Aii} = \pi_i.$$

The diagonal term $T_{ii} = \pi_i$ allows state stagnation, then causes high autocorrelation.

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The diagonal term $T_{ii} = \pi_i$ allows state stagnation, then causes high autocorrelation.

Simple but inefficient due to frequent bounce moves.

Scheme B: Minimal Bounce Solution

Basic Principle

Linear Programming Optimization: Minimize total bounce probability $\text{Tr}(T_B) = \sum_i T_{Bii}$ subject to

- Normalization: $\sum_j T_{Bij} = 1$.
- Detailed balance: $w_i T_{Bij} = w_j T_{Bji}$.

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Example Matrix

For weights $[0.2, 0.4, 0.3, 0.1]$

$$T_B = \begin{bmatrix} 0.1 & 0.5 & 0.3 & 0.1 \\ 0.5 & 0.1 & 0.1 & 0.3 \\ 0.3 & 0.1 & 0.1 & 0.5 \\ 0.1 & 0.3 & 0.5 & 0.1 \end{bmatrix}.$$

The diagonal term reduced: $T_{B11} = 0.1$, in comparison to $\pi_1 = 0.2$ in Scheme A.

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Reduces wasted bounce moves via constrained optimization.

Scheme C: Locally Optimal Algorithm

Basic Principle

Peskun's theorem + Metropolization: Diagonal elements set to zero for all but the largest weight state

$$T_{Cii} = 0 \quad (i \neq \max).$$

Prohibits lingering in low-weight states; Minimizes autocorrelation.

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Transition Matrix ($\pi_1 \leq \pi_2 \leq \pi_3 \leq \pi_4$)

$$T_C = \begin{bmatrix} 0 & \frac{\pi_2}{1-\pi_1} & \frac{\pi_3}{1-\pi_1} & \frac{\pi_4}{1-\pi_1} \\ \frac{\pi_1}{1-\pi_2} & 0 & \frac{\pi_3}{1-\pi_2} & \frac{\pi_4}{1-\pi_2} \\ \frac{\pi_1}{1-\pi_3} & \frac{\pi_2}{1-\pi_3} & 0 & \frac{\pi_4}{1-\pi_3} \\ \frac{\pi_1}{1-\pi'_4} & \frac{\pi_2}{1-\pi'_4} & \frac{\pi_3}{1-\pi'_4} & \pi'_4 \end{bmatrix}.$$

Only $T_{C44} \neq 0$; All other diagonals are zero.

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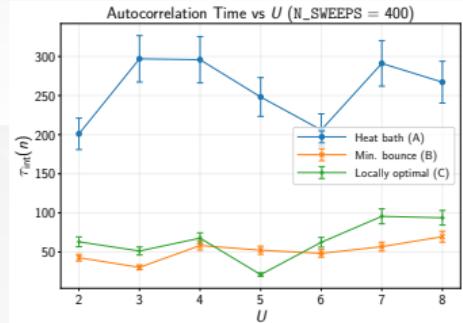
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Optimal for balanced weights; Derived from Peskun's ordering theorem.



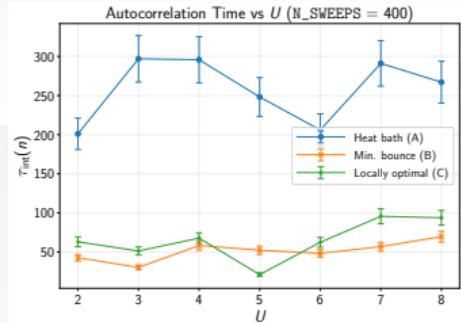
SIMULATION RESULTS

Simulations under different sweep numbers

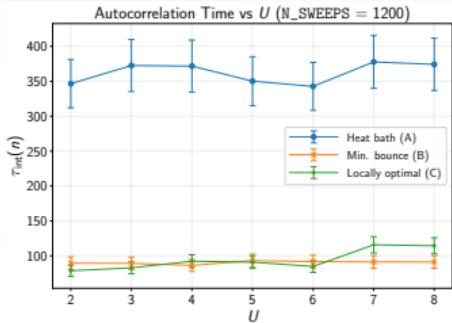


(a) 400 Sweeps

Simulations under different sweep numbers

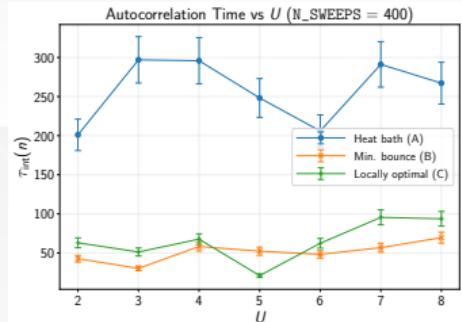


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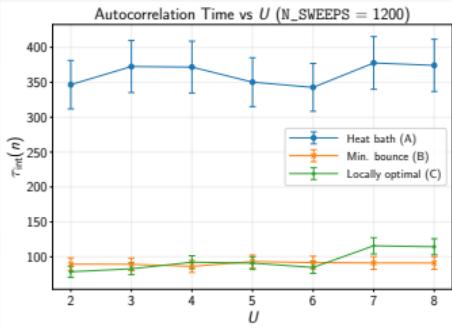


(b) 1200 Sweeps

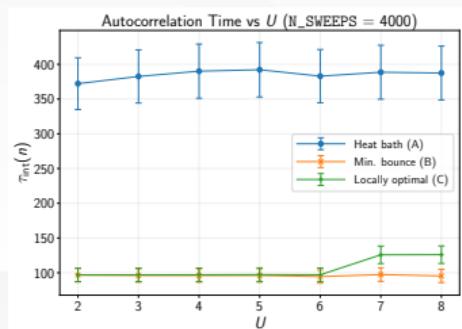
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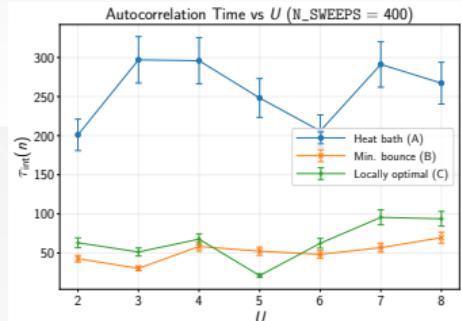


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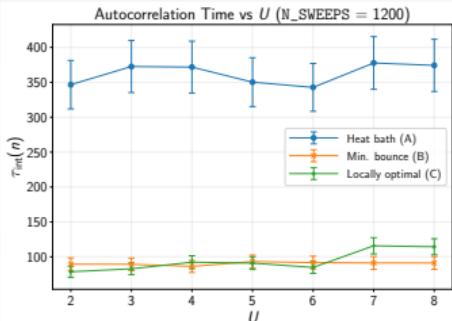


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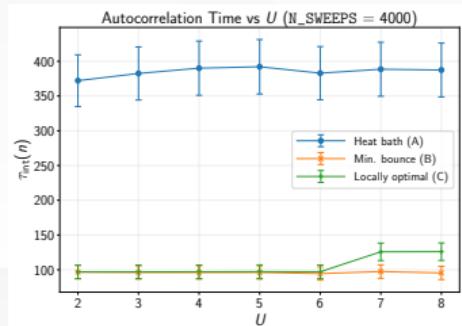
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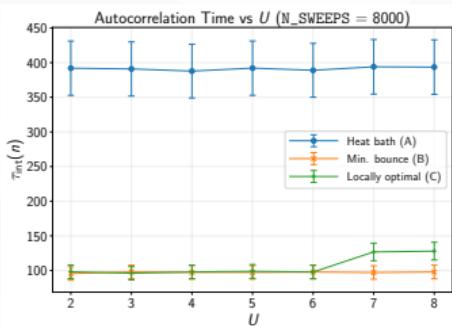
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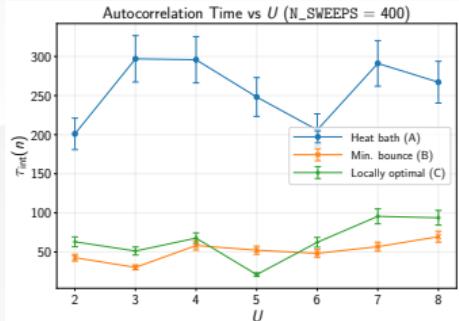


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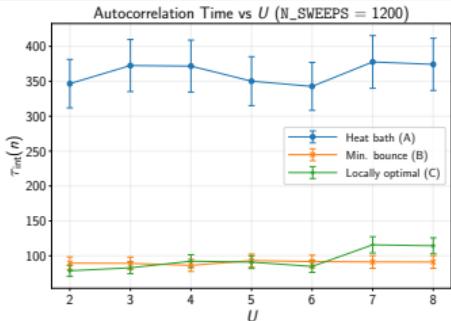


(d) 8000 Sweeps

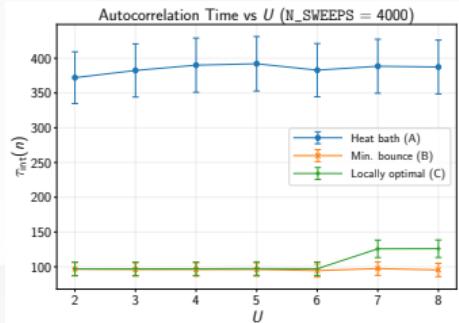
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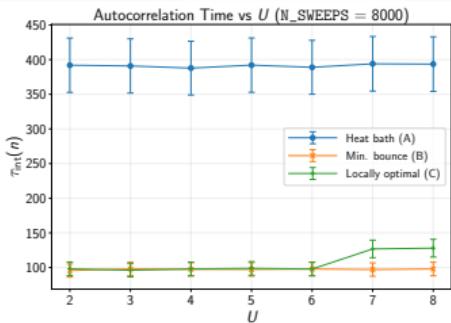
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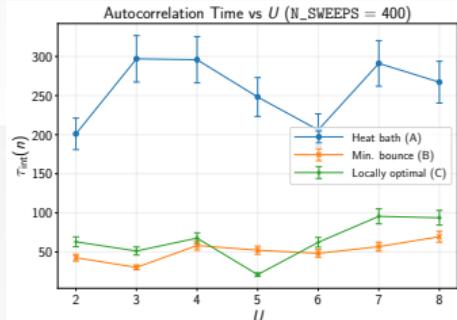


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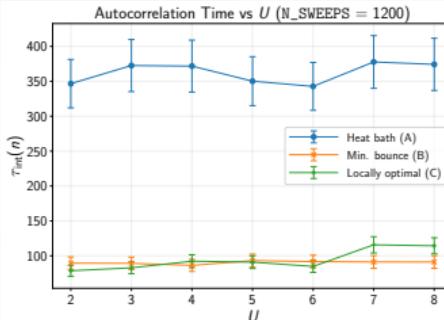


As U increases, the diagonal weights in the SSE configuration space become dominant. Scheme C shows a slight increase in τ in comparison to B.

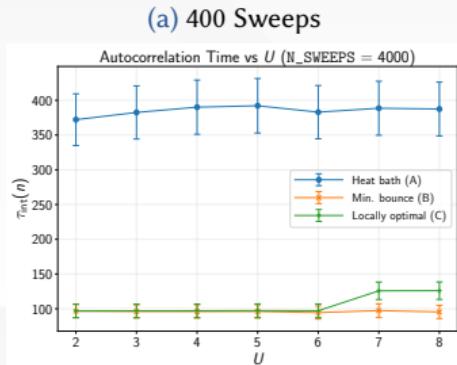
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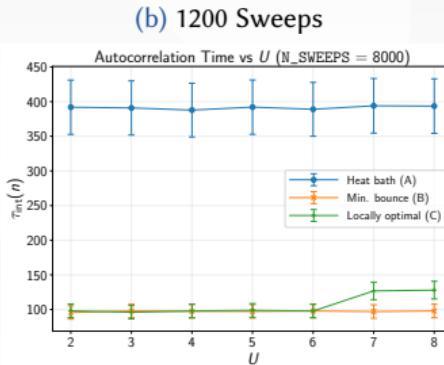
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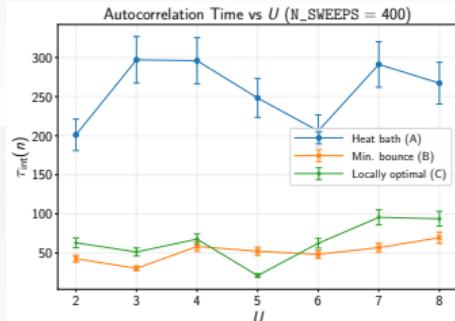


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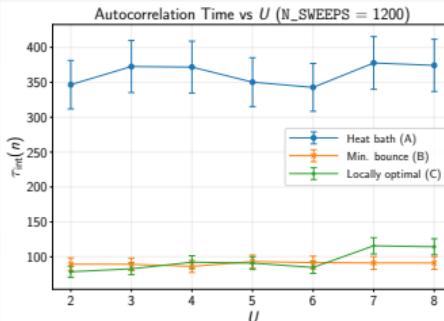
Table. Comparasion under different U

	Phases	Superfluid Transition	Near-Mote
U	$U < 3$	$3 \leq U \leq 6$	$U \rightarrow 9$
(A)	20 ~ 30	30 ~ 45	45 ~ 50
(B)	8 ~ 10	10 ~ 20	15 ~ 20
(C)	7 ~ 9	9 ~ 18	18 ~ 25

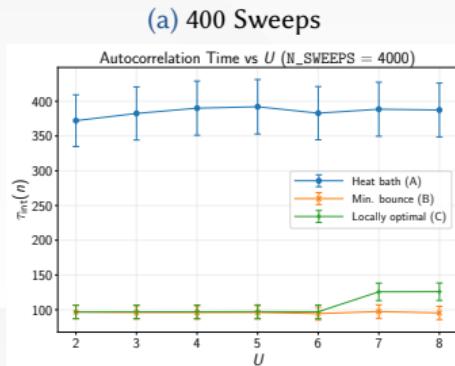
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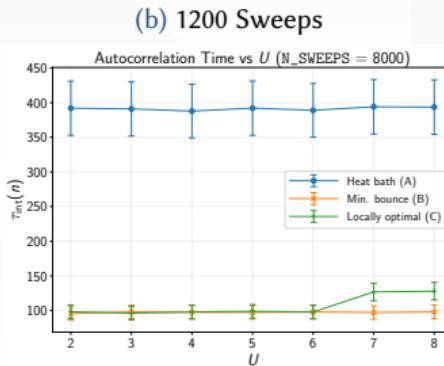
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A fixed random seed is loaded to ensure the fixed result for every time running.



CONCLUSION

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Core Design Principle

For efficient algorithms, the condition “Diagonal elements of non-maximum weight states returning to zero” is necessary (both B and C satisfy this), and the remaining degrees of freedom need to be adapted to the weight distribution.



SIMULATION METHOD

Configuration & Process

Key Parameters

- **Lattice:** 1D chain, $L = 64$, $t = 1$, $\mu = 5$.
- **Thermodynamics:** $\beta = L = 64$ (low- T),
 $U \in [0, 6]$.
- **Algorithm:** A: 16 loops \times 4; B/C: 4 loops.
- **Statistics:** 4000 independent chains, each with 1 million steps.
- **Cutoff:** For efficiency, particle number reduced at $U = 3, 8$.

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Method: SSE + Directed Loop

Stochastic Series Expansion maps quantum problem to $(d + 1)$ D classical graph

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Procedure

- ➊ **Burn-in:** Discard first 10% of samples.
- ➋ **Worm updates:** Collect density series $\{n^{(t)}\}$.
- ➌ **Autocorrelation**

$$\tau_{\text{int}}(n) = \frac{1}{2} + \sum_{t=1}^{\infty} \frac{\langle n^{(i+t)} n^{(i)} \rangle - \langle n^{(i)} \rangle^2}{\langle n^{(i)} \rangle^2 - \langle n^{(i)} \rangle^2}.$$
- ➍ **Average:** Mean over 4000 chains, plot U vs $\tau_{\text{int}}(n)$.



PYTHON IMPLEMENTATION

Class Initialization and State Representation

The class stores the lattice size L , inverse temperature β , and model parameters. The state is represented by an array of occupation numbers \mathbf{n} .

```

1 def __init__(self, L, beta, U, mu, t = 1,
2   ↪ method = 'A'):
3     self.L = L
4     self.beta = beta
5     self.U = U
6     self.mu = mu
7     self.t = t
8     self.method = method # 'A', 'B', 'C'
```

Initialize state: occupation numbers on each

site.

```
8     self.n = np.zeros(L, dtype = int)
```

Starting density roughly μ/U to reach equilibrium faster.

```

9     initial_dens = max(1, int(mu/U + .5)) if
10    ↪ U > 0 else 1
11     self.n[:] = initial_dens
```

Energy shift: Ensures diagonal weights in SSE remain positive. Calculated based on maximum expected local density.

```
11     self.E_shift = .5 * U * 10 * 9 + 20
```

Calculating Vertex Weights

In SSE, the probability of choosing an operator depends on its “weight”. Diagonal weights are related to the local energy, while off-diagonal weights are related to the hopping amplitude t .

```
1 def get_vertex_weight(self, n1, n2, op_type):
2     E1 = .5 * self.U * n1 * (n1 - 1) - self.mu * n1
3     E2 = .5 * self.U * n2 * (n2 - 1) - self.mu * n2
4     H_diag_val = .5 * (E1 + E2)
```

Branches for the Diagonal operator (1) and Off-diagonal: hopping (2).

```
5     if op_type == 1:
6         return max(0, self.E_shift - H_diag_val)
7     elif op_type == 2:
8         return self.t
9     return 0
```

Transition Matrix Schemes I

The core of the “Optimal Monte Carlo” paper is the design of the transition matrix T_{ij} . According to Peskun’s theorem, to minimize the autocorrelation time, one should minimize the diagonal elements T_{ii} (the “bounce” or “stagnation” probability).

```
1 def solve_greedy_min_bounce(self, weights):
2     w0, w1, w2 = weights
3     sw = w0 + w1 + w2
4     pi = np.array(weights) / sw
5     p_out = np.zeros(3)
```

- **Scheme A: Heat Bath** The core of the “Optimal Monte Carlo” paper is the design of the transition matrix T_{ij} . According to Peskun’s theorem, to minimize the autocorrelation time, one should minimize the diagonal elements T_{ii} (the “bounce” or “stagnation” probability).
- **Scheme B and C: Optimization via Peskun’s Theorem** Scheme B (Minimal Bounce) and Scheme C (Locally Optimal) aim to set $T_{ii} = 0$ whenever possible. The code implements this using a “greedy” approach or Metropolized Gibbs sampling.

Transition Matrix Schemes II

Metropolized Gibbs strategy: In [2], Using

$$T_{ij}^{MG} = \begin{bmatrix} 0 & \frac{\pi_2}{1-\pi_1} & \frac{\pi_3}{1-\pi_1} & \cdots & \frac{\pi_n}{1-\pi_1} \\ \frac{\pi_1}{1-\pi_1} & 1 - \dots & \frac{\pi_3}{1-\pi_2} & \cdots & \frac{\pi_n}{1-\pi_2} \\ \frac{\pi_1}{1-\pi_1} & \frac{\pi_2}{1-\pi_2} & 1 - \dots & \cdots & \frac{\pi_n}{1-\pi_3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{\pi_1}{1-\pi_1} & \frac{\pi_2}{1-\pi_2} & \frac{\pi_3}{1-\pi_3} & \cdots & 1 - \dots \end{bmatrix} = \min\left(\frac{\pi_j}{1-\pi_i}, \frac{\pi_i}{1-\pi_j}\right).$$

```

6   for i in [1, 2]:
7       term1 = pi[i] / (1 - pi[0]) if (1 -
    ↪ pi[0]) > 1e-9 else 0
8       term2 = pi[i] / (1 - pi[i]) if (1 -
    ↪ pi[i]) > 1e-9 else 1
9       p_out[i] = min(term1, term2)
10      current_sum = p_out[1] + p_out[2]
11      if current_sum > 1:
12          p_out[1] /= current_sum
13          p_out[2] /= current_sum
14          p_out[0] = 0
15      else:
16          p_out[0] = 1 - current_sum
17      return p_out

```

The Simulation Loop

The run method performs the actual Markov Chain sweeps. Each site is updated based on the calculated transition probabilities.

```

1 def run(self, n_sweeps):
2     densities = []
3     for _ in range(n_sweeps):
4         for i in range(self.L):
5             n_curr = self.n[i]
6             w0 = self.get_vertex_weight(n_curr,
7                 ↪ n_curr, 1)
7
8             w_plus =
9                 ↪ self.get_vertex_weight(n_curr,
10                ↪ n_curr + 1, 2)
10            w_minus =
11                ↪ self.get_vertex_weight(n_curr,
12                ↪ n_curr - 1, 2) if n_curr > 0
13
14             probs = self.solve_scattering([w0,
15                 ↪ w_plus, w_minus], self.method)
16
17             r = np.random.rand()
18             if r < probs[0]:
19                 pass # Stay
20             elif r < probs[0] + probs[1]:
21                 self.n[i] += 1
22             else:
23                 self.n[i] -= 1
24
25             densities.append(np.mean(self.n))
26
27     return densities

```

9 probs = self.solve_scattering([w0,
 ↪ w_plus, w_minus], self.method)

Sample the next state.

10 r = np.random.rand()
11 if r < probs[0]:
12 pass # Stay
13 elif r < probs[0] + probs[1]:
14 self.n[i] += 1
15 else:
16 self.n[i] -= 1

Record average density as the observable.

17 densities.append(np.mean(self.n))
18 return densities



Thanks for Listening! Any Questions?
