## Computation Physics II 5640, Spring 2017

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## 1 Master equation and Metropolis dynamics for classical Ising ring

The state of a 1-D classical Ising ring can be defined by an array of binary variable,  $\{\sigma_i\}$ , where we also assume periodic boundary conditions,  $\sigma_{N+1} = \sigma_1$ . The probability of a ring state transitioning to another state, differing by a single spin flip, is given by the Metropolis algorithm:

$$P\left(\left\{\sigma_{i}'\right\} \to \left\{\sigma_{i}\right\}\right) = \frac{1}{N} min \left\{1, e^{\frac{-\left(E\left\{\sigma_{i}\right\} - E\left\{\sigma_{i}'\right\}\right)}{T}}\right\}$$
(1)

Where  $E\{\sigma\}$  is given by the Hamiltonian of the system, which is defined as:

$$\hat{H} = -J \sum_{i=1}^{N} \sigma_i \sigma_{i+1} \tag{2}$$

From this we can construct a  $2^N \times 2^N$  transition matrix  $\mathbb{P}_{\{\sigma_i'\},\{\sigma_i\}} = P\left(\{\sigma_i'\} \to \{\sigma_i\}\right)$ , an example of which, in the N=3 case, is given by Table 1, where  $r=e^{\frac{-(E\{\sigma_i\}-E\{\sigma_i'\})}{T}}$ , the states of which can be seen graphically in figure 1.

	0	1	2	3	4	5	6	7
0	1 - r	1/3	1/3	1/3	0	0	0	0
1	r/3	0	0	0	1/3	1/3	0	0
2	r/3	0	0	0	1/3	0	1/3	0
3	r/3	0	0	0	0	1/3	1/3	0
4	0	1/3	1/3	0	0	0	0	r/3
5	0	1/3	0	1/3	0	0	0	r/3
6	0	0	1/3	1/3	0	0	0	r/3
7	0	0	0	0	1/3	1/3	1/3	1 - r

Table 1: Transition Matrix of N=3 Ising ring, value is probability of transitioning from column state to row state. Note, columns add to 1.

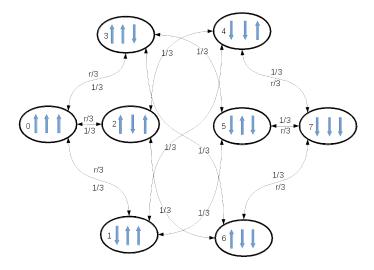


Figure 1: Transition map of N=3 case. Probabilities above transition lines are for transitions to the right, below are to the left. Probabilities on the lines are for both directions.

The eigenvectors,  $\mathbb{U}_{\alpha}$ , and eigenvalues,  $\lambda_{\alpha}$ , of  $\mathbb{P}$  can be used to obtain the Markovian dynamics of the system. This can be seen by taking  $\mathbb{U}_0$ , the eigenvector corresponding to the largest eigenvalue,  $\lambda_0$ , which is always equal to one.  $\mathbb{U}_0$  is the probability distribution of the steady state of the system when normalized by the sum of the vector. We can show this by taking the zero element,  $\mathbb{U}_0\{0\}$ , corresponding to the fully polarized state and plotting its normalized value over the analytical solution, given by equation 3, which can be seen in figure 2.

$$\frac{\mathbb{U}_0\{0\}(T)}{\sum_i \mathbb{U}_0\{i\}(T)} = \frac{exp(-NJ/T)}{Z_N}$$

$$Z_N = (2\cosh\beta J)^N + (2\sinh\beta J)^N$$
(3)

Another behavior that can be determined in this way is the relaxation time,  $\tau$ , of the system.  $\tau$  is how many steps it takes the system to reach the steady state, and it's given by the second largest eigenvalue,  $\lambda_1$ , in such  $\tau(T) = \frac{-1}{\ln \lambda_1(T)}$ . The temperature dependence of which can be seen for several values of N in figure 3.

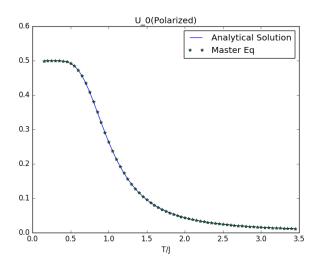


Figure 2: Plot Master Equation over the Analytical Solution, for N=10 case.

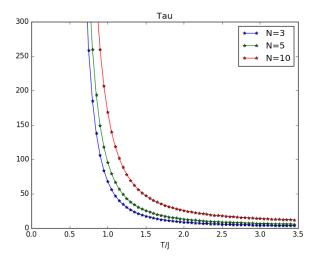


Figure 3: Plot of the temperature dependence of  $\tau$  for several N.

## 2 Appendix: Source Code

```
\#! /usr/bin/python
import numpy as np
import itertools
from matplotlib import pyplot as plt
def get_states(N):
    out = []
    for i in itertools.combinations_with_replacement([0,1],N):
        for j in itertools.permutations(i,N):
            o = list(j)
            o.reverse()
            if not o in out:
                out.append(o)
    return out #returns list of all possible states of N spins
def get_E(state):
    ran = range(len(state))
    out = 0.0
    for i in ran:
        if i != ran[-1]:
            if state[i] = state[i+1]:
                out += -1.0
            else:
                out += 1.0
        else:
            if state[i] = state[0]:
                out += -1.0
            else:
                out += 1.0
    return out
def get_off_diag_P (state1, state2, N,T):
    f l i p s = 0
    for i in range(len(state1)):
        if not state1[i] == state2[i]:
            flips +=1
    if not flips = 1:
        return 0.0
    else:
        return \min([1.0, np.e**(-(get_E(state1) - get_E(state2))/T)])/float(N)
def get_pi_hat(states,N,T):
    ret = np.zeros(shape=(2**N, 2**N))
```

```
for i in range (2**N):
        for j in range (2**N):
             if not i = j:
                 ret[i,j] = get_off_diag_P(states[i],states[j],N,T)
    for k in range (2**N):
        if ret [:,k].sum() != 1.0:
             ret[k,k] = 1.0 - ret[:,k].sum()
    return ret
def analytical_Sol(T,N):
      =((2.0*np.cosh(1.0/T))**N + (2.0*np.sinh(1.0/T))**N)
    return (np.e**(float(N)/T))/Z
if __name__ == '__main__':
    for N in [10]:
        states = get_states(N)
        T=np. arange (0.15, 3.5, 0.05)
        Y = []
        y = []
        for t in T:
             pi_hat = get_pi_hat(states, N, t)
            w, v = np. linalg. eig(pi-hat)
            w = list(w)
            o = v[:, w.index(max(w))]
            Y. append (o[-1]/o.sum())
        y = [analytical\_Sol(t,N) \text{ for } t \text{ in } T]
        plt.plot(T,y,label="Analytical_Solution")
        plt.plot(T,Y,linestyle='',marker='*',label="Master_Eq")
    plt.title("U_0(Polarized)")
    plt.xlabel("T/J")
    plt.legend()
    plt.show()
    for N in [3,5,10]:
        states = get_states(N)
        T=np.arange (0.15,3.5,0.05)
        Y = []
        for t in T:
             pi_hat = get_pi_hat(states, N, t)
            w, v = np. linalg. eig(pi-hat)
            w = list(w)
            w.sort()
            o = v[:, w.index(max(w))]
            Y. append (-1.0/(\text{np.log}(w[-2])))
        plt.plot(T, Y, marker='*', label="N="+str(N))
    plt.title("Tau")
    plt.xlabel("T/J")
```

```
plt.ylim(0.0,300)
plt.legend()
plt.show()
```