

14/20

Homework 2

2-D Ising model simulation

Answer 1

Necessary modules

8/10

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import random as r
from random import choice
```

```
# We now work to generalize the Ising model to 2-Dimensions and or
that the lattice size becomes (N_x) X (N_y) where we
# assume periodic boundary conditions in both, x and y, directions. It
is given that we use the same coupling constant in
# both directions.
```

```
# To calculate change in energy after one spin flips at position (x,y)
```

```
def energy_flip(s,J,h,x,y,n):
```

```
# Here, the s is the spin, x and y are th positions of the 2 D
lattice, J,n, and h are the same variables as defined before
```

```
# The function calculates the energy after the spin at one site is
flipped.
```

```
    return 2 * s[x][y]*(J*(s[((x+1)%n)][y] + s[((x-1)%n)][y] + s[x]
[((y+1)%n)] + s[x][((y-1)%n)]) + h)
```

```
# Number of sweeps for thermalization for every value of J,h
```

```
n_therm = 100
```

```
# Number of measurements for each J,h
```

```
n_meas = 100
```

```
def energy(s,J,h,x,y,n):
```

```
    return -J*((s[((x+1)%n)][y] + s[((x-1)%n)][y] + s[x][((y+1)%n)] +
s[x][((y-1)%n)])*s[x][y]) - h*s[x][y]
```

```
def variables(n,J,h,obs):
```

```
# Defining local arrays
```

```
    m = np.array([]) # Magnetization
```

```
    E = np.array([]) # Energy
```

```
    m_absolute = np.array([]) # Absolute value of magnetization
```

Seperate Global and local variable ! Don't define

Global variable in middle of functions !

no. of steps too low
for monte carlo & thermalization we atleast

Don't make such a huge function it makes the code very inefficient adding a lot of if statements make it inefficient

```
prob = np.array([]) # Probability information
# Now we need to assign spins to the site and because this is a 2D lattice, we have to keep in mind the dimensions
# x and y and do that. This has been done as follows:
# The variable (s) is the spin here and n is some random integer
```

```
s = [[choice((+1,-1)) for x in range(n)] for y in range(n)]
```

```
for j in range(n_therm):
    # Assigning a random integer value to x and y
    x = np.random.randint(n)
    y = np.random.randint(n)
```

Don't use list
it takes long time!

```
# We need to define the change of energy after flipping the lattice site (x,y) picked randomly. We call the defined function energy_flip to calculate that.
```

```
delta_energy = energy_flip(s,J,h,x,y,n)
if delta_energy < 0:
    s[x][y] *= -1 # Condition to accept the spin flip
else:
    if np.random.uniform(0,1) <= np.exp(-delta_energy):
        s[x][y] *= -1
```

```
for i in range(n_meas):
    for j in range(n**2): #sweeping the lattice
```

This doesn't help sweep over entire lattice !! run for $n^2=4$

```
x = j % n
y = j // n
delta_energy = energy_flip(s,J,h,x,y,n)
```

if $\text{random}() \leq \min(1, \exp(-\Delta E))$

```
if delta_energy < 0:
    s[x][y] *= -1 # Condition to accept the spin
```

$s[x][y] *= -1$

flip

```
else:
    if np.random.uniform(0,1) <= np.exp(-delta_energy):
        s[x][y] *= -1
        prob = np.append(prob,1.) # Accept.
```

```
else:
    prob = np.append(prob,0.) # We reject the other
```

values.

```
# Measurements
```

```
if obs == "m":
    m = np.append(m, np.mean(s))
    obs = np.mean(m)
```

```
if obs == "E":
    temp = np.array([])
    for x in range(n):
        for y in range(n):
```

These two statements can be combined

Build indent here

Mean has to be performed at indent specified and because of this you have to be in steps

Missing from Code!

Sample after every 10-20 sweeps to reduce auto correlation

```

        temp = np.append(temp,energy(s,J,h,x,y,n))
        E=np.append(E,np.mean(temp))
        obs=np.mean(E)
    if obs == "m_absolute":
        m_absolute=np.append(m_absolute,np.absolute(np.mean(s)))
        obs=np.mean(m_absolute)

return obs

```

Answer 2

The system size, Λ , we have to iterate over all lattice sites and every time keep the number of nearest neighbours constant. ✓



Answer 3

We consider the site and the four neighbours to find the difference in energy because $O(\Lambda)$ is constant.



Calculating ΔS just requires knowing no. of nearest neighbours.

Answer 4

The significance of critical coupling J_c is that it helps us to see when the phase transition will happen because the system starts behaving in an ordered manner with couplings greater than J_c . ✓



Answer 5: $\langle m \rangle$ vs h

Now plotting the required variables

$J = 0.5$ # Keeping J fixed at a certain value

$h_range = np.arange(-1,1,0.01)$

this precision is not required 0.1 or 0.2 is sufficient

We are supposed to take different values of N ($N_x = N_y$), so we define as follows:

```

mag_4 = [variables(4,J,h,"m") for h in h_range]
mag_8 = [variables(8,J,h,"m") for h in h_range]
mag_12 = [variables(12,J,h,"m") for h in h_range]
mag_16 = [variables(16,J,h,"m") for h in h_range]
mag_20 = [variables(20,J,h,"m") for h in h_range]

```

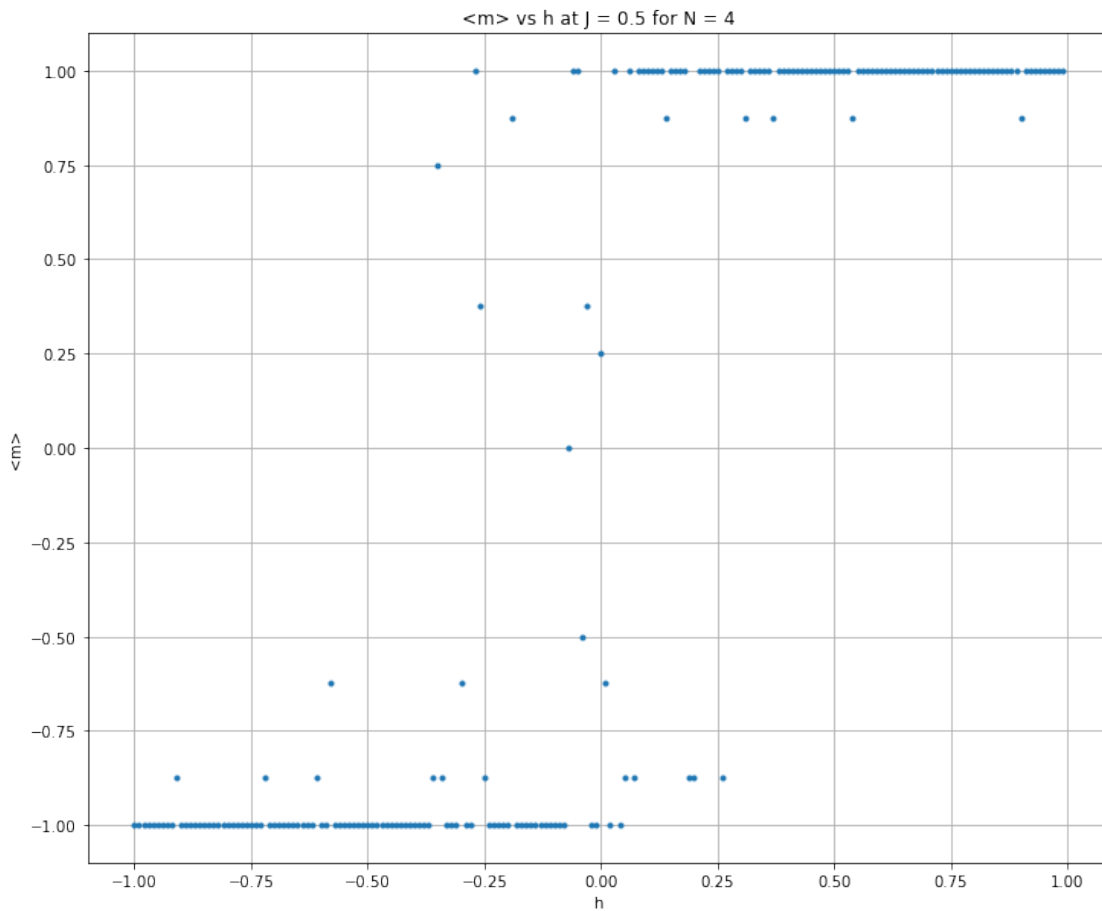
this is increases code time

```

plt.figure(figsize=(12,10))
plt.title("<m> vs h at J = 0.5 for N = 4",fontsize=12)
plt.grid()
plt.xlabel("h")
plt.ylabel("<m>")
plt.plot(h_range,mag_4,'.',label="N=4")
plt.legend()

```

[<matplotlib.lines.Line2D at 0x7f523ec793d0>]

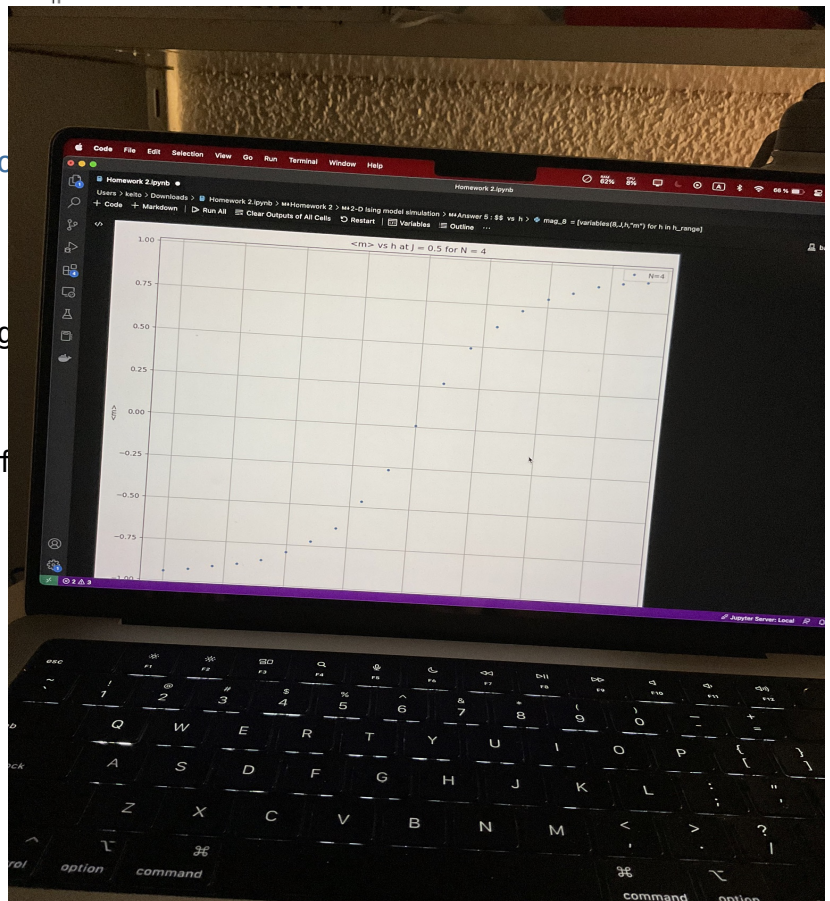


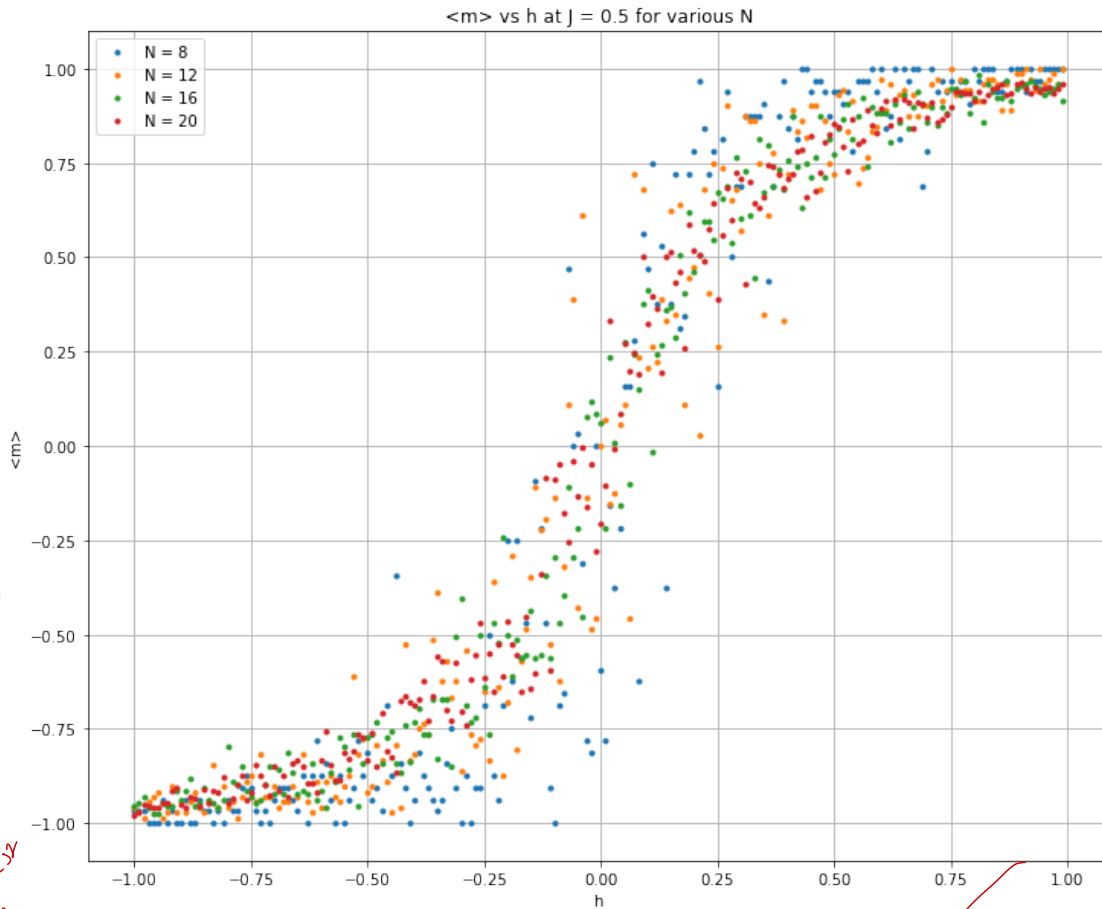
Use the
Values to get
better plot

For different values of N:

```
plt.figure(figsize=(12,10))
plt.title("<m> vs h at J = 0.5 for N = 4")
plt.grid()
# plt.plot(h_range,mag_4)
plt.xlabel("h")
plt.ylabel("<m>")
plt.plot(h_range,mag_8,'.',h_range,mag_12,'.',h_range,mag_20,'.')
plt.legend(("N = 8", "N = 12", "N = 20"))
```

<matplotlib.legend.Legend at 0x7f...





Answer 6: ϵ vs J at $h = 0$
Now

```
import scipy.special as s
```

```
h = 0
```

```
J_range = np.linspace(0.25,2,100)
```

```
# Given average energy epsilon function is defined as follows:
```

```
Eps_th=-J_range*(1/np.tanh(2*J_range))*(1+(2/np.pi)*(2*(np.tanh(2*J_range))**2-1)*s.ellipk(4*(1/np.cosh(2*J_range))**2*(np.tanh(2*J_range))**2))
```

```
avg_4 = [variables(4,J,h,"E") for J in J_range]
avg_8 = [variables(8,J,h,"E") for J in J_range]
avg_12 = [variables(12,J,h,"E") for J in J_range]
avg_16 = [variables(16,J,h,"E") for J in J_range]
avg_20 = [variables(20,J,h,"E") for J in J_range]
```

```
plt.figure(figsize=(12,10))
plt.title("<e> vs J at h = 0",fontsize=12)
plt.grid()
```

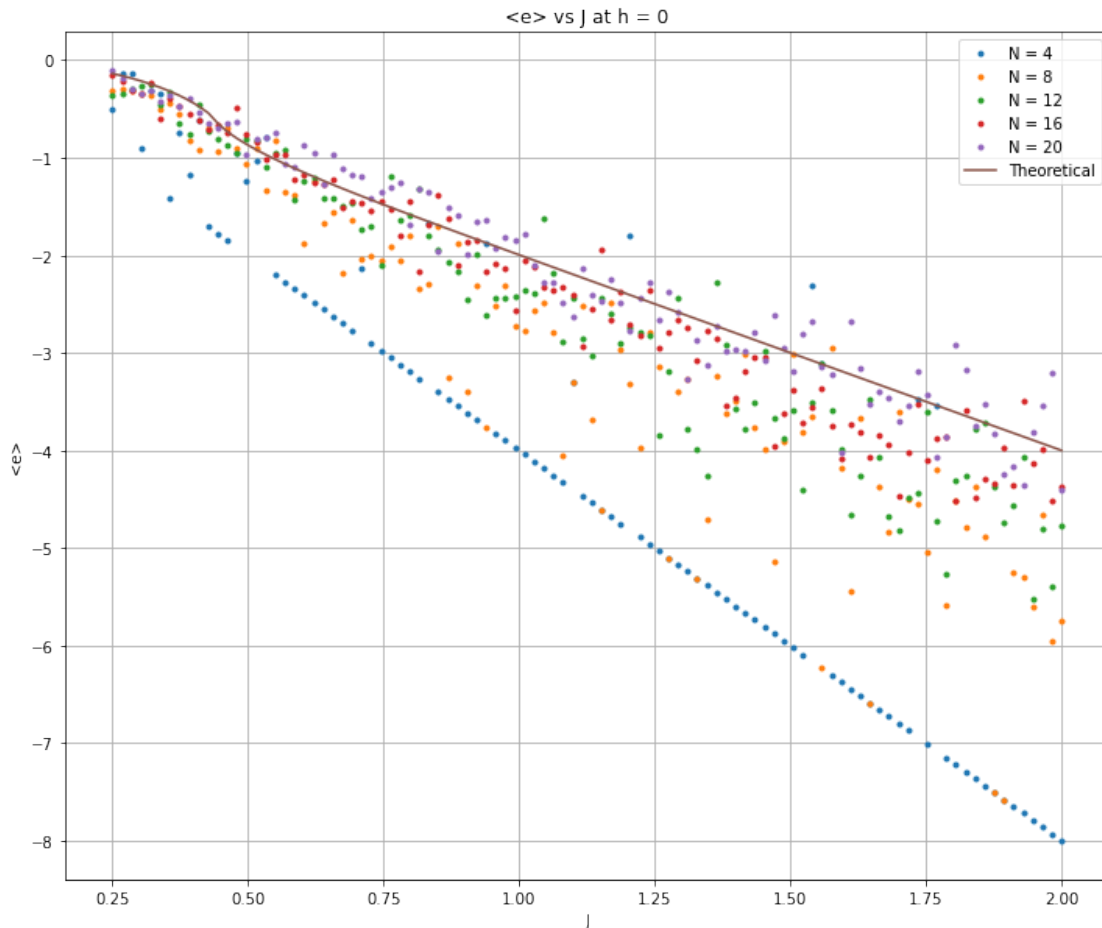
Something
to check
as $\langle m \rangle$ goes
up in steps

```

plt.xlabel("J")
plt.ylabel("<e>")
# plt.plot(J_range, avg_4)
plt.plot(J_range, avg_4, '.', J_range, avg_8, '.', J_range, avg_12, '.', J_range, avg_16, '.', J_range, avg_20, '.')
plt.plot(J_range, Eps_th, label="Theoretical")
plt.legend(("N = 4", "N = 8", "N = 12", "N = 16", "N = 20",
"Theoretical"))

```

<matplotlib.legend.Legend at 0x7f523c0b40d0>



Answer 7: $\langle |m| \rangle$ vs J at $h = 0$

```
J_new = np.linspace(0.25, 1, 50)
```

```
new = np.zeros(len(J_new))
```

```
for i in range(len(J_new)):
```

```
    if(J_new[i] > 0.440686793):
```

```
        new[i] = (1 - 1/(np.sinh(2*J_new[i]))**4)**0.125
```

Again

```
h = 0
```

```

mabs_4 = [variables(4,J,h,"m_absolute") for J in J_new]
mabs_8 = [variables(8,J,h,"m_absolute") for J in J_new]
mabs_12 = [variables(12,J,h,"m_absolute") for J in J_new]
mabs_16 = [variables(16,J,h,"m_absolute") for J in J_new]
mabs_20 = [variables(20,J,h,"m_absolute") for J in J_new]

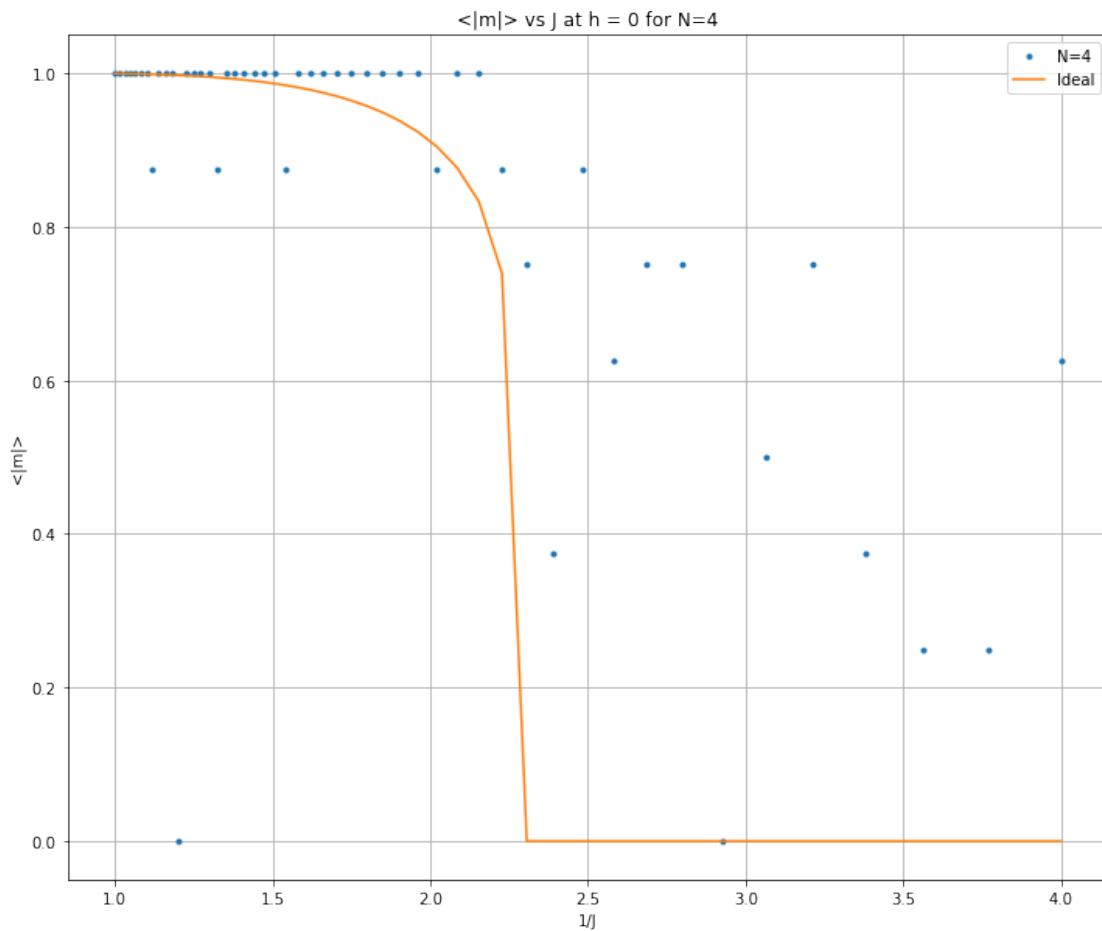
```

```

plt.figure(figsize=(12,10))
plt.title("<|m|> vs J at h = 0 for N=4",fontsize=12)
plt.grid()
plt.xlabel("1/J")
plt.ylabel("<|m|>")
plt.plot(1/J_new,mabs_4,'.',label="N=4")
plt.plot(1/J_new,new,label="Ideal")
plt.legend()

```

<matplotlib.legend.Legend at 0x7f5237f171f0>



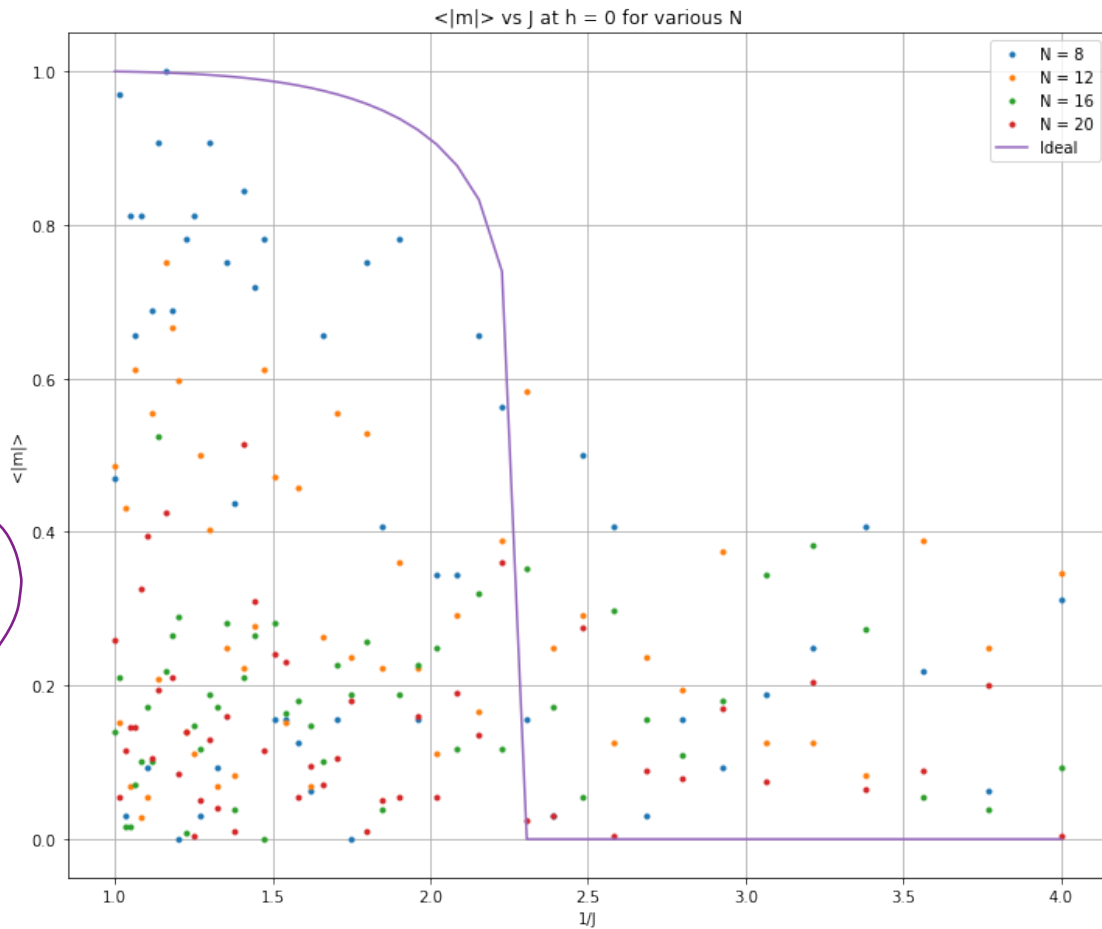
```

plt.figure(figsize=(12,10))
plt.title("<|m|> vs J at h = 0 for various N",fontsize=12)
plt.grid()

```

```
plt.xlabel("1/J")
plt.ylabel("<|m|>")
# plt.plot(1/J_new,mabs_4,'.')
plt.plot(1/J_new,mabs_8,'.',1/J_new,mabs_12,'.',1/J_new,mabs_16,'.',1/J_new,mabs_20,'.')
plt.plot(1/J_new,new,label="Ideal")
plt.legend(("N = 8", "N = 12", "N = 16", "N = 20", "Ideal"))
```

<matplotlib.legend.Legend at 0x7f5237e12580>



Note: For some reason, the plots for $N=4$ seem nicer than the others. I have separated the simulations for $N=4$ and higher N 's

Also, I don't understand the difference in the simulation between $N=4$ and others: In the sense that, for $N=4$, we have some points at 0 but this is not the case for higher N 's

Compare $\langle m \rangle$ & $\langle |m| \rangle$ & significance?