Here I have outlined the programs used and how to run them on the GPU machine available at TIFR.

## 1.1 Implementation

### 1.1.1 Ising Model

#### **Monte Carlo Algorithm**

To begin with study of samples generated from deep learning models, we require data to train them. This data is generated using the Wolff Cluster algorithm, for various lattice sizes. The following code implements it using parallel processing for faster implementation.

#### **CODE**

```
1 import numpy as np
2 import matplotlib.pyplot as plt
4 import os
5 from tqdm import tqdm
6 import multiprocessing as mp
7 from itertools import repeat
9 train_path = '../../data/Ising/train/'
valid_path = '../../data/Ising/valid/'
11
def makeArray(L):
      array = np.random.randint(0,2,size=(L,L), dtype=int)
     array[array==0] = -1
14
     return array
15
16
17 def cluster_flip(array,cluster):# Flip all spins in a cluster
18
      Parameters:
19
          array: numpy array containing the current spin configuration
20
          cluster: List of spins to be flipped
21
22
     for pair in cluster:
23
          i,j=pair
24
          array[i,j]*=-1
```

```
def Wolff(array,T,calcE=False):
      # Wolff algorithm for a square lattice
28
29
      Parameters:
          array: numpy array containing the current spin configuration
31
          T: Temperature
32
          calcE: Flag to calculate and return the average spin energy for
      the final configuration.
      0.000
34
      L,_ = array.shape
35
      cluster_i = np.zeros((L,L)) # spins already in cluster
36
      i,j = np.random.randint(0,L,size=2)
38
      spin = array[i,j]
39
      stack = [(i,j)]
40
      cluster_i[i,j]=1
42
      cluster = [(i,j)]
43
44
      while len(stack)>0:
          i,j = stack.pop()
          neighbors = [(i,(j+1)%L),(i,(j-1)%L),((i+1)%L,j),((i-1)%L,j)]
46
          for pair in neighbors:
47
               l,m = pair
               if (array[1,m]==spin and cluster_i[1,m]==0 and np.random.
     random() < (1.0-np.exp(-2.0/T))):
                   cluster.append((1,m))
50
                   stack.append((1,m))
51
                   cluster_i[l,m]=1
52
53
      cluster_flip(array,cluster)
54
      if calcE:
56
          avgE=0.0
57
          for i in range(L):
58
               for j in range(L):
                   spin_final = array[i,j]
60
                   neighbor\_sum = array[(i+1)\%L,j] + array[(i-1)\%L,j] + array[
61
     i,(j+1)%L]+array[i,(j-1)%L]
                   E_final = -spin_final*neighbor_sum
62
                   avgE+=float(E_final)
63
64
          avgE/=float(L**2)
65
          return avgE
67
  def sim(array,T,L,steps,step_r,lattice):
68
      #MC simulation for a square lattice, using the Wolff algorithm
69
      for step in range(steps):
70
          Wolff(array,T)
          if step>step_r and step%divide==0:
72
73
             i=int((step-step_r)/divide)
74
             lattice[i]=array
75
76 def save_data(T,L,steps,step_r,lattice):
    array=makeArray(L)
    sim(array,T,L,steps,step_r,lattice)
78
    lattice=np.reshape(lattice,(length,L*L))
```

```
np.savetxt("isingdata_"+str(L*L)+f"{T:.2f}"+".csv",lattice,delimiter=
     ",")
81
82 Temps=np.arange(1.5,3.2,0.1) #in Kelvin
L = 25
85 step_r=200 #configurations to be removed
steps = 200000+step_r
87 divide=20 #autocorrelation tim
88 length=int((steps-step_r)/divide) #size of dataset
89 lattice=np.zeros((len(Temps),length,L,L))
90 #Parallel processing
91 jobs=zip(Temps,repeat(L),repeat(steps),repeat(step_r),lattice)
92 p = mp.Pool(5)
93 p.starmap(save_data, jobs)
94 p.close()
95 p.join()
```

Listing 1.1: isingdata25\_wolff.py

This program saves the data as "isingdata\_ $L^2T\{2 \text{ digits}\}.\text{csv}$ " with  $L^2$  rows and  $steps-step\_r$  columns. The mp.Pool() function is used to implement parallel processing.

To check is the data is generated correctly OR to study the properties of Ising model for various lattice sizes and temperatures, we can plot certain parameters. Here we plot the magnetisation defined as  $M = \frac{1}{N} \times \sum_{N} \{\frac{1}{L^2} \times |\Sigma_{L^2} s_i|\} = \frac{1}{N} \times \sum_{N} s$ , where  $s_i$  is the spin at  $i^{th}$  lattice position, and  $N = steps - step_r$ .

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
5 L=35
6 Size=3000
8 mag=np.zeros((5))
sample = np.genfromtxt('/user1/utkarsh/dataising350', delimiter = ',')
     #changing the file type to .csv format
np.savetxt("dataising350.csv",sample, delimiter = ',')
12 print (sample)
13 df2 = pd.read_csv('/user1/utkarsh/dataising350.csv') #reading the .csv
     file
14 data=df2.to_numpy()
np.savetxt('mag.csv',data)
print(data.shape)
m=np.sum(data,axis=1)
m=np.sum(m)
19 print (m)
20 \text{ mag}[0] = (m/L**2)/Size
22 sample = np.genfromtxt('/user1/utkarsh/dataising352', delimiter = ',')
23 np.savetxt("dataising352.csv",sample, delimiter = ',')
24 df2 = pd.read_csv('/user1/utkarsh/dataising352.csv')
25 data=df2.to_numpy()
m=np.sum(data,axis=1)
m=np.sum(m)
28 mag[1] = (m/L**2)/Size
```

```
sample = np.genfromtxt('/user1/utkarsh/dataising354', delimiter = ',')
np.savetxt("dataising354.csv",sample, delimiter = ',')
32 df2 = pd.read_csv('/user1/utkarsh/dataising354.csv')
data=df2.to_numpy()
m=np.sum(data,axis=1)
m=np.sum(m)
mag[2] = (m/L**2)/Size
sample = np.genfromtxt('/user1/utkarsh/dataising356', delimiter = ',')
39 np.savetxt("dataising356.csv", sample, delimiter = ',')
40 df2 = pd.read_csv('/user1/utkarsh/dataising356.csv')
41 data=df2.to_numpy()
42 m=np.sum(data,axis=1)
m = np.sum(m)
mag[3] = (m/L**2)/Size
46 sample = np.genfromtxt('/user1/utkarsh/dataising358', delimiter = ',')
47 np.savetxt("dataising358.csv", sample, delimiter = ',')
48 df2 = pd.read_csv('/user1/utkarsh/dataising358.csv')
49 data=df2.to_numpy()
m=np.sum(data,axis=1)
m=np.sum(m)
mag[4] = (m/L**2)/Size
54 print(mag)
55 plt.plot(mag)
plt.savefig('mag350_mc.png')
```

Listing 1.2: magplot\_mc\_35.py

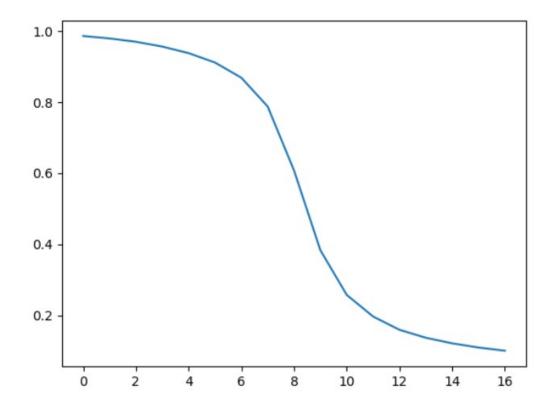


Figure 1.1: Magnetisation v/s Temperature index

The second parameter of interest is the Binder Cumulant given as  $U = 1 - \frac{\langle s^4 \rangle}{3 \langle s^2 \rangle^2}$ .

```
2 import pandas as pd
3 from matplotlib import pyplot as plt
4 import numpy as np
6 nbeta=5 # Number of data points
7 time = 3000 #Number of samples per data point
_{8} L=35 #Lattice size
data=np.zeros((nbeta,time,d**2))
df2 = pd.read_csv('/user1/utkarsh/rbmdata350.csv',header=None) #keep
     the required file name
12 data[0] = df2.to_numpy()
df2 = pd.read_csv('/user1/utkarsh/rbmdata352.csv',header=None)
14 data[1] = df2.to_numpy()
df2 = pd.read_csv('/user1/utkarsh/rbmdata354.csv',header=None)
16 data[2] = df2.to_numpy()
47 df2 = pd.read_csv('/user1/utkarsh/rbmdata356.csv',header=None)
18 data[3] = df2.to_numpy()
19 df2 = pd.read_csv('/user1/utkarsh/rbmdata358.csv',header=None)
20 data[4]=df2.to_numpy()
21
22 mag_4_avg=np.zeros(nbeta) #Mag**4 average
23 mag_sq_avg=np.zeros(nbeta) #Mag**2 average
betas = np.linspace(0.43,0.45,5) #beta values
27 for i in range(nbeta): #Loop over all data points
28
    mag=np.sum(data[i],axis=1)
29
   for o in range(time): #Calculation for each data point
30
      mag_4_avg[i]+=mag[o]*mag[o]*mag[o]*mag[o]
31
      mag_sq_avg[i] += mag[o] * mag[o]
    print("sweep",i)
33
  mag_4_avg[i]=mag_4_avg[i]/time
  mag_sq_avg[i]=mag_sq_avg[i]/time
36 U1=1-(1/3)*(mag_4_avg/(mag_sq_avg*mag_sq_avg))
37
38
39 nbeta=5
40 time = 3000
L = 25
data=np.zeros((nbeta,time,d**2))
44 df2 = pd.read_csv('/user1/utkarsh/rbmdata250_.csv',header=None)
45 data[0]=df2.to_numpy()
46 df2 = pd.read_csv('/user1/utkarsh/rbmdata252_.csv',header=None)
47 data[1] = df2.to_numpy()
48 df2 = pd.read_csv('/user1/utkarsh/rbmdata254.csv',header=None)
49 data[2]=df2.to_numpy()
50 df2 = pd.read_csv('/user1/utkarsh/rbmdata256.csv',header=None)
51 data[3] = df2.to_numpy()
52 df2 = pd.read_csv('/user1/utkarsh/rbmdata258.csv',header=None)
53 data [4] = df2.to_numpy()
55 mag_4_avg=np.zeros(nbeta)
```

```
56 mag_sq_avg=np.zeros(nbeta)
 betas = np.linspace(0.43,0.45,5)
59
 for i in range(nbeta):
    mag=np.sum(data[i],axis=1)
61
62
    for o in range(time):
63
64
      mag_4_avg[i] += mag[o] * mag[o] * mag[o] * mag[o]
65
      mag_sq_avg[i]+=mag[o]*mag[o]
    print("sweep",i)
66
    mag_4_avg[i]=mag_4_avg[i]/time
67
    mag_sq_avg[i]=mag_sq_avg[i]/time
69 U2=1-(1/3)*(mag_4_avg/(mag_sq_avg*mag_sq_avg))
71 plt.plot(betas,U1/U2)
#plt.plot(betas,U2)
73 plt.savefig('UIratio.png')
```

Listing 1.3: BinderCumulant\_Ratio25\_35.py

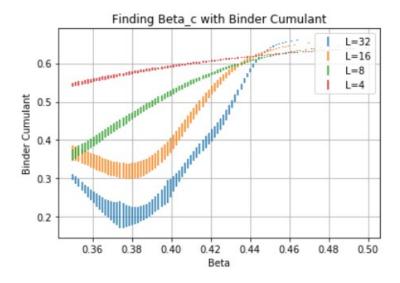


Figure 1.2: Binder Cumulant

Another parameter is  $\chi$  i.e., the susceptibility given by  $\chi = <\frac{s^2}{12}>$ .

```
m=np.sum(data,axis=1)
15 \text{ msq} = \text{m} * \text{m}
m=np.sum(m)
msq=np.sum(msq)
18 print(m)
19 print (msq)
20 \text{ mag}[0] = (m/L**2)/3000
chi[0] = (msq/L**4)/3000
22 sample = np.genfromtxt('/user1/utkarsh/dataising352', delimiter = ',')
23 np.savetxt("dataising352.csv", sample, delimiter = ',')
24 df2 = pd.read_csv('/user1/utkarsh/dataising352.csv')
25 data=df2.to_numpy()
m=np.sum(data,axis=1)
msq=m*m
m=np.sum(m)
29 msq=np.sum(msq)
30 print(m)
31 print (msq)
mag[1] = (m/L**2)/3000
33 chi[1] = (msq/L**4)/3000
sample = np.genfromtxt('/user1/utkarsh/dataising354', delimiter = ',')
np.savetxt("dataising354.csv",sample, delimiter = ',')
36 df2 = pd.read_csv('/user1/utkarsh/dataising354.csv')
37 data=df2.to_numpy()
m=np.sum(data,axis=1)
msq=m*m
m = np.sum(m)
msq=np.sum(msq)
42 print(m)
43 print (msq)
mag[2] = (m/L**2)/3000
45 chi[2] = (msq/L**4)/3000
46 sample = np.genfromtxt('/user1/utkarsh/dataising356', delimiter = ',')
47 np.savetxt("dataising356.csv", sample, delimiter = ',')
48 df2 = pd.read_csv('/user1/utkarsh/dataising356.csv')
49 data=df2.to_numpy()
m=np.sum(data,axis=1)
msq=m*m
m = np.sum(m)
msq=np.sum(msq)
55 print(m)
56 print (msq)
mag[3] = (m/L**2)/3000
sechi[3] = (msq/L**4)/3000
59 sample = np.genfromtxt('/user1/utkarsh/dataising358', delimiter = ',')
60 np.savetxt("dataising358.csv", sample, delimiter = ',')
61 df2 = pd.read_csv('/user1/utkarsh/dataising358.csv')
62 data=df2.to_numpy()
m=np.sum(data,axis=1)
msq=m*m
m=np.sum(m)
msq=np.sum(msq)
68 print(m)
69 print (msq)
mag[4] = (m/L**2)/3000
71 chi[4] = (msq/L**4)/3000
```

```
print(mag)
print(chi)
plt.plot(chi)
plt.savefig('chi350_mc.png')
```

Listing 1.4: chi\_plot\_mc.py

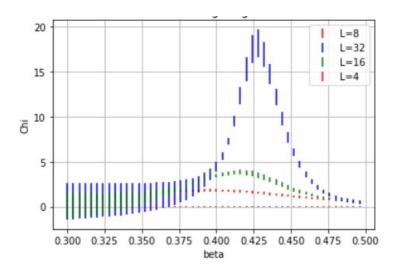


Figure 1.3:  $\chi v/s \beta$ 

#### **Restricted Boltzmann Machine**

A Restricted Boltzmann Machine is trained with dataset generated from the Wolff Cluster Algorithm. We had flatten the dataset to a 2D matrix of shape  $[N, L^2]$  and feed it in the input nodes. The second layer size is a hyperparamter. The following program implements the training for one value of the temperature. The complete code can be found here.

```
1 import numpy as np
2 import random
3 import numpy as np
4 import math
5 import matplotlib
6 import matplotlib.pyplot as plt
7 import pandas as pd
8 import os
10 epoch=25
11 size_h=1500
12 #return the average of h given x
def h_{mean}(x, w, b):
      #x: visible layer. One row is one data
      #w: weight, size_h*784
15
      #b: bias, size_h
16
17
      #return data*size_h
18
      b_shaped=np.reshape(b,(1,b.size))
19
      b_shaped=np.repeat(b_shaped,x.shape[0],axis=0)
20
      y=np.dot(x,w.T)+b_shaped
21
      return 1.0/(np.exp(-y)+1.0)
```

```
23
 def x_mean(h,w,c):
      #h: visible layer. One row is one data
25
      #w: weight, size_h*784
26
      #c: bias, size_h
27
      c_shaped=np.reshape(c,(1,c.size))
29
      c_shaped=np.repeat(c_shaped,h.shape[0],axis=0)
30
      y=np.dot(h,w)+c_shaped
32
      return np.tanh(y),1/(np.exp(-1.0*y)+1.0)
33
34 def gibbs_cd(x,kcd,w,b,c):
     h_p=h_mean(x,w,b)
      rad_h=np.random.rand(h_p.shape[0],h_p.shape[1])
36
      h_samp=np.zeros(h_p.shape)
37
      h_samp[rad_h < h_p] = 1
38
      for i in range(kcd):
          #sample x
40
          _, x_prob=x_mean(h_samp,w,c)
41
          rad_x=np.random.rand(x_prob.shape[0],x_prob.shape[1])
42
          x_samp=-np.ones(x_prob.shape)
          x_samp[rad_x < x_prob] = 1</pre>
44
          #sample h
45
          h_p=h_mean(x_samp,w,b)
          rad_h=np.random.rand(h_p.shape[0],h_p.shape[1])
          h_samp=np.zeros(h_p.shape)
48
          h_samp[rad_h < h_p] = 1
49
      return x_samp
50
51
52 def loss(x_in,x_p):
      1=(x_{in}-x_{p})**2
53
      loss=np.sum(1)/x_in.size
      return loss
55
56
59 df2 = pd.read_csv('/user1/utkarsh/isingdata_6251.50.csv')
60 data=df2.to_numpy()
62 trX=data[0:8000]
63 test_data=data[8000:10000]
65 spin_flatten=trX
67 #learning rate
68 \text{ gamma} = 0.005
69 #momentum
70 beta = 0.0
71 #11 regularization
72 lambd=0
74 #number of hidden units
76 size_v=spin_flatten.shape[1]
77 w=np.reshape(np.random.normal(scale=0.1,size=size_v*size_h),(size_h,
     size_v))
78 b=np.zeros(size_h)
79 c=np.zeros(size_v)
```

```
81 batch=100 #batch size
kcd=20
            #cd number
83
85 train_loss=np.zeros(epoch)
grad_w0=np.zeros(w.shape)
grad_b0=np.zeros(b.shape)
88 grad_c0=np.zeros(c.shape)
  print('start')
90
91
  for i in range(epoch):
      spin_train=np.random.permutation(spin_flatten)
93
      for j in range(math.floor(spin_train.shape[0]/batch)):
94
           x_in=spin_train[j*batch:j*batch+batch,:]
           x_sampling= gibbs_cd(x_in,kcd,w,b,c)
97
           #gradient update
98
           grad_w=np.zeros(w.shape)
99
           for k in range(batch):
100
               x_k=np.reshape(x_in[k,:],(1,x_in[k,:].size))
101
               x_ksample=np.reshape(x_sampling[k,:],(1,x_sampling[k,:].
102
      size))
               grad_w=grad_w+(np.outer( h_mean(x_k,w,b),x_k)-np.outer(
103
     h_mean(x_ksample,w,b),x_ksample))
104
           w=w+gamma*(grad_w-lambd*np.sign(w))
106
           b=b+gamma*np.sum( h_mean(x_in,w,b)- h_mean(x_sampling,w,b),axis
107
      =0)
109
           c=c+gamma*np.sum(x_in-x_sampling,axis=0)
110
111
      print('epoch'+str(i))
113
      #training reconstruction
114
      h_p= h_mean(spin_train,w,b)
115
116
      x_p, = x_{mean}(h_p, w, c)
      train_loss[i] = loss(spin_train,x_p)
117
      print('train'+str(train_loss[i]))
118
119
121 fnamew='w ising'+'6251.50.csv'
np.savetxt(fnamew,w, delimiter=",")
fnameb='b_ising'+'6251.50.csv'
np.savetxt(fnameb,b, delimiter=",")
fnamec='c_ising'+'6251.50.csv'
np.savetxt(fnamec,c, delimiter=",")
```

Listing 1.5: rbmising25.py

Once the model is trained with the data for a given lattice size and temperature, we can generate data from the models with the following code.

```
import pandas as pd

return the average of h given x
```

```
4 def h_mean(x,w,b):
      #x: visible layer. One row is one data
      #w: weight, size_h*784
6
      #b: bias, size_h
      #return data*size_h
      b_shaped=np.reshape(b,(1,b.size))
10
      b_shaped=np.repeat(b_shaped,x.shape[0],axis=0)
11
      y=np.dot(x,w.T)+b_shaped
12
13
      return 1.0/(np.exp(-y)+1.0)
14
def x_mean(h,w,c):
      #h: visible layer. One row is one data
      #w: weight, size h*784
17
      #c: bias, size_h
18
19
      c_shaped=np.reshape(c,(1,c.size))
      c_shaped=np.repeat(c_shaped,h.shape[0],axis=0)
21
      y=np.dot(h,w)+c_shaped
22
      return np.tanh(y),1/(np.exp(-1.0*y)+1.0)
23
25 def gibbs_cd(x,kcd,w,b,c):
      h_p=h_mean(x,w,b)
26
      rad_h=np.random.rand(h_p.shape[0],h_p.shape[1])
27
28
      h_samp=np.zeros(h_p.shape)
      h_{samp}[rad_h < h_p] = 1
29
      for i in range(kcd):
30
          #sample x
31
           _, x_prob=x_mean(h_samp,w,c)
32
          rad_x=np.random.rand(x_prob.shape[0],x_prob.shape[1])
33
          x_samp=-np.ones(x_prob.shape)
34
          x_{samp}[rad_x < x_{prob}] = 1
          #sample h
36
          h_p=h_mean(x_samp,w,b)
37
          rad_h=np.random.rand(h_p.shape[0],h_p.shape[1])
38
           h_samp=np.zeros(h_p.shape)
           h_samp[rad_h < h_p] = 1
40
      return x_samp
41
42
def loss(x_in,x_p):
44
      1 = (x_{in} - x_p) **2
      loss=np.sum(1)/x_in.size
45
      return loss
46
47
48 #sampling from the rbm
49 import numpy as np
50 import math
51 import matplotlib
52 import matplotlib.pyplot as plt
53 #import rbm_xy_fun as rbm_fun
54 import os
55 def generate(n,w,b,c,x_data):
56
      for i in range(n):
57
          rad_x=np.random.rand(1,c.size)
58
           x_sampling=gibbs_cd(rad_x,kcd,w,b,c)
59
          h_p=h_mean(x_sampling,w,b)
60
          x_p,x_dat=x_mean(h_p,w,c)
61
```

```
rad_x=np.random.rand(x_dat.shape[0],x_dat.shape[1])
62
         x_samp=-np.ones(x_dat.shape)
63
         x_samp[rad_x < x_p] = 1
64
         x_shaped=np.reshape(x_samp,(d,d))
65
         x_data[i]=x_shaped
68 d = 16
69 n = 1000
70 \, \text{kcd} = 100
sigma=1
72 m=np.zeros(17)
73 msq=np.zeros(17)
     76 df = pd.read_csv('/user1/utkarsh/b_ising2561.50.csv', header=None)
77 b=df.to_numpy()
78 df = pd.read_csv('/user1/utkarsh/c_ising2561.50.csv', header=None)
79 c=df.to_numpy()
80 df = pd.read_csv('/user1/utkarsh/w_ising2561.50.csv', header=None)
81 w=df.to_numpy()
82
x_{data} = np.zeros((n,d,d))
84 generate(n,w,b,c,x_data)
85
86 x_data=np.reshape(x_data,(n,d**2))
88 mag=np.sum(x_data, axis=1)
89 ms=mag*mag
msq[0] = np.sum(ms)
m[0] = np.sum(abs(mag))
93 np.savetxt("rbmdata2561.5.csv", x_data, delimiter=",")
94 #
     96 df = pd.read_csv('/user1/utkarsh/b_ising2561.60.csv', header=None)
97 b=df.to_numpy()
98 df = pd.read_csv('/user1/utkarsh/c_ising2561.60.csv', header=None)
99 c=df.to_numpy()
df = pd.read_csv('/user1/utkarsh/w_ising2561.60.csv', header=None)
101 w=df.to_numpy()
102
x_{data} = np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
107
mag=np.sum(x_data, axis=1)
109 ms=mag*mag
msq[1]=np.sum(ms)
111 m[1] = np.sum(abs(mag))
np.savetxt("rbmdata2561.6.csv", x_data, delimiter=",")
114 #
```

```
116 df = pd.read_csv('/user1/utkarsh/b_ising2561.70.csv', header=None)
117 b=df.to_numpy()
118 df = pd.read_csv('/user1/utkarsh/c_ising2561.70.csv', header=None)
119 c=df.to_numpy()
120 df = pd.read_csv('/user1/utkarsh/w_ising2561.70.csv', header=None)
121 w=df.to_numpy()
123 x_data=np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
mag=np.sum(x_data, axis=1)
129 ms=mag*mag
msq[2]=np.sum(ms)
m [2] = np.sum(abs(mag))
np.savetxt("rbmdata2561.7.csv", x_data, delimiter=",")
     136 df = pd.read_csv('/user1/utkarsh/b_ising2561.80.csv', header=None)
137 b=df.to_numpy()
138 df = pd.read_csv('/user1/utkarsh/c_ising2561.80.csv', header=None)
139 c=df.to_numpy()
140 df = pd.read_csv('/user1/utkarsh/w_ising2561.80.csv', header=None)
141 w=df.to_numpy()
x_{data} = np.zeros((n,d,d))
144 generate(n,w,b,c,x_data)
145
146 x_data=np.reshape(x_data,(n,d**2))
148 mag=np.sum(x_data, axis=1)
149 ms=mag*mag
msq[3]=np.sum(ms)
m [3] = np. sum(abs(mag))
np.savetxt("rbmdata2561.8.csv", x_data, delimiter=",")
154 #
     156 df = pd.read_csv('/user1/utkarsh/b_ising2561.90.csv', header=None)
157 b=df.to_numpy()
df = pd.read_csv('/user1/utkarsh/c_ising2561.90.csv', header=None)
c=df.to_numpy()
160 df = pd.read_csv('/user1/utkarsh/w_ising2561.90.csv', header=None)
161 w=df.to_numpy()
x_data=np.zeros((n,d,d))
164 generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
167
```

```
mag=np.sum(x_data, axis=1)
169 ms=mag*mag
msq[4]=np.sum(ms)
m[4] = np.sum(abs(mag))
np.savetxt("rbmdata2561.9.csv", x_data, delimiter=",")
174 #
     175
df = pd.read_csv('/user1/utkarsh/b_ising2562.00.csv', header=None)
b=df.to_numpy()
178 df = pd.read_csv('/user1/utkarsh/c_ising2562.00.csv', header=None)
179 c=df.to numpy()
180 df = pd.read_csv('/user1/utkarsh/w_ising2562.00.csv', header=None)
181 w=df.to_numpy()
x_{data} = np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
187
mag=np.sum(x_data, axis=1)
189 ms=mag*mag
msq[5] = np.sum(ms)
191 m [5] = np.sum(abs(mag))
192
np.savetxt("rbmdata2562.0.csv", x_data, delimiter=",")
     196 df = pd.read_csv('/user1/utkarsh/b_ising2562.10.csv', header=None)
197 b=df.to_numpy()
198 df = pd.read_csv('/user1/utkarsh/c_ising2562.10.csv', header=None)
199 c=df.to_numpy()
200 df = pd.read_csv('/user1/utkarsh/w_ising2562.10.csv', header=None)
w=df.to_numpy()
202
x_{data=np.zeros((n,d,d))}
204 generate(n,w,b,c,x_data)
205
x_data=np.reshape(x_data,(n,d**2))
208 mag=np.sum(x_data, axis=1)
209 ms=mag*mag
msq[6]=np.sum(ms)
211 m [6] = np. sum (abs (mag))
212
213 np.savetxt("rbmdata2562.1.csv", x_data, delimiter=",")
     216 df = pd.read_csv('/user1/utkarsh/b_ising2562.20.csv', header=None)
217 b=df.to_numpy()
218 df = pd.read_csv('/user1/utkarsh/c_ising2562.20.csv', header=None)
c=df.to_numpy()
```

```
220 df = pd.read_csv('/user1/utkarsh/w_ising2562.20.csv', header=None)
w=df.to_numpy()
x_data=np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
mag=np.sum(x_data, axis=1)
229 ms=mag*mag
msq[7] = np.sum(ms)
231 m [7] = np.sum(abs(mag))
pp.savetxt("rbmdata2562.2.csv", x_data, delimiter=",")
234 #
     235
236 df = pd.read_csv('/user1/utkarsh/b_ising2562.30.csv', header=None)
b=df.to_numpy()
238 df = pd.read_csv('/user1/utkarsh/c_ising2562.30.csv', header=None)
c=df.to_numpy()
240 df = pd.read_csv('/user1/utkarsh/w_ising2562.30.csv', header=None)
w=df.to_numpy()
x_{data=np.zeros((n,d,d))}
244 generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
247
248 mag=np.sum(x_data, axis=1)
249 ms=mag*mag
250 msq[8]=np.sum(ms)
251 m [8] = np.sum(abs(mag))
pp.savetxt("rbmdata2562.3.csv", x_data, delimiter=",")
254 #
     256 df = pd.read_csv('/user1/utkarsh/b_ising2562.40.csv', header=None)
b=df.to_numpy()
258 df = pd.read_csv('/user1/utkarsh/c_ising2562.40.csv', header=None)
c=df.to_numpy()
260 df = pd.read_csv('/user1/utkarsh/w_ising2562.40.csv', header=None)
w=df.to_numpy()
x_{data} = np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
268 mag=np.sum(x_data, axis=1)
269 ms=mag*mag
270 \text{ msq} [9] = \text{np.sum} (\text{ms})
271 m [9] = np.sum (abs (mag))
273 np.savetxt("rbmdata2562.4.csv", x_data, delimiter=",")
```

```
274 #
     275
276 df = pd.read_csv('/user1/utkarsh/b_ising2562.50.csv', header=None)
b=df.to_numpy()
278 df = pd.read_csv('/user1/utkarsh/c_ising2562.50.csv', header=None)
c=df.to_numpy()
280 df = pd.read_csv('/user1/utkarsh/w_ising2562.50.csv', header=None)
w=df.to_numpy()
282
x_data=np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
287
288 mag=np.sum(x_data, axis=1)
289 ms=mag*mag
msq[10] = np.sum(ms)
291 m [10] = np. sum (abs (mag))
293 np.savetxt("rbmdata2562.5.csv", x_data, delimiter=",")
294 #
     295
296 df = pd.read_csv('/user1/utkarsh/b_ising2562.60.csv', header=None)
297 b=df.to_numpy()
298 df = pd.read_csv('/user1/utkarsh/c_ising2562.60.csv', header=None)
c=df.to_numpy()
300 df = pd.read_csv('/user1/utkarsh/w_ising2562.60.csv', header=None)
w=df.to_numpy()
x_{data} = np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
307
mag=np.sum(x_data, axis=1)
309 ms=mag*mag
msq[11] = np.sum(ms)
311 m [11] = np.sum(abs(mag))
np.savetxt("rbmdata2562.6.csv", x_data, delimiter=",")
314 #
     316 df = pd.read_csv('/user1/utkarsh/b_ising2562.70.csv', header=None)
b=df.to_numpy()
318 df = pd.read_csv('/user1/utkarsh/c_ising2562.70.csv', header=None)
c=df.to_numpy()
320 df = pd.read_csv('/user1/utkarsh/w_ising2562.70.csv', header=None)
w=df.to_numpy()
x_{data} = np.zeros((n,d,d))
generate(n,w,b,c,x_data)
325
```

```
x_data=np.reshape(x_data,(n,d**2))
mag=np.sum(x_data, axis=1)
329 ms=mag*mag
msq [12] = np.sum(ms)
331 m [12] = np.sum(abs(mag))
np.savetxt("rbmdata2562.7.csv", x_data, delimiter=",")
334 #
     335
336 df = pd.read_csv('/user1/utkarsh/b_ising2562.80.csv', header=None)
b=df.to numpy()
338 df = pd.read_csv('/user1/utkarsh/c_ising2562.80.csv', header=None)
339 c=df.to_numpy()
340 df = pd.read_csv('/user1/utkarsh/w_ising2562.80.csv', header=None)
w=df.to_numpy()
342
343 x_data=np.zeros((n,d,d))
344 generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
347
348 mag=np.sum(x_data, axis=1)
349 ms=mag*mag
msq[13] = np.sum(ms)
m[13] = np.sum(abs(mag))
353 np.savetxt("rbmdata2562.8.csv", x_data, delimiter=",")
354 #
     355
356 df = pd.read_csv('/user1/utkarsh/b_ising2562.90.csv', header=None)
357 b=df.to_numpy()
358 df = pd.read_csv('/user1/utkarsh/c_ising2562.90.csv', header=None)
c=df.to_numpy()
360 df = pd.read_csv('/user1/utkarsh/w_ising2562.90.csv', header=None)
361 w=df.to_numpy()
362
x_{data} = np.zeros((n,d,d))
generate(n,w,b,c,x_data)
x_data=np.reshape(x_data,(n,d**2))
367
mag=np.sum(x_data, axis=1)
369 ms=mag*mag
msq[14] = np.sum(ms)
m[14] = np.sum(abs(mag))
np.savetxt("rbmdata2562.9.csv", x_data, delimiter=",")
374 #
     376 df = pd.read_csv('/user1/utkarsh/b_ising2563.00.csv', header=None)
377 b=df.to_numpy()
```

```
378 df = pd.read_csv('/user1/utkarsh/c_ising2563.00.csv', header=None)
379 c=df.to_numpy()
380 df = pd.read_csv('/user1/utkarsh/w_ising2563.00.csv', header=None)
w=df.to_numpy()
x_{data=np.zeros((n,d,d))}
generate(n,w,b,c,x_data)
  x_{data} = np.reshape(x_{data}, (n, d**2))
387
mag=np.sum(x_data, axis=1)
389 ms=mag*mag
msq[15] = np.sum(ms)
391 m[15] = np.sum(abs(mag))
sys np.savetxt("rbmdata2563.0.csv", x_data, delimiter=",")
     395
396 df = pd.read_csv('/user1/utkarsh/b_ising2563.10.csv', header=None)
397 b=df.to_numpy()
398 df = pd.read_csv('/user1/utkarsh/c_ising2563.10.csv', header=None)
399 c=df.to_numpy()
400 df = pd.read_csv('/user1/utkarsh/w_ising2563.10.csv', header=None)
401 w=df.to_numpy()
402
403 x_data=np.zeros((n,d,d))
404 generate(n,w,b,c,x_data)
405
406 x_data=np.reshape(x_data,(n,d**2))
408 mag=np.sum(x_data, axis=1)
409 ms=mag*mag
msq[16] = np.sum(ms)
m[16] = np.sum(abs(mag))
412
413
  np.savetxt("rbmdata2563.1.csv", x_data, delimiter=",")
416 #
     _{417} m=m/d**2
418 \text{ m} = \text{m}/\text{n}
419
420 chi = (msq/d**4)/n
err=np.sqrt(abs(chi-m**2))
x=np.arange(1.5,3.2,0.1)
424
425 plt.errorbar(x,m,err)
plt.savefig("magrbm16_err_new.png")
```

*Listing 1.6: rbmgenerate\_err.py* 

The generated datafile is now used to reproduce the plots for magnetisation, magnetic susceptibility and Binder Cumulant. The following plots present these results.

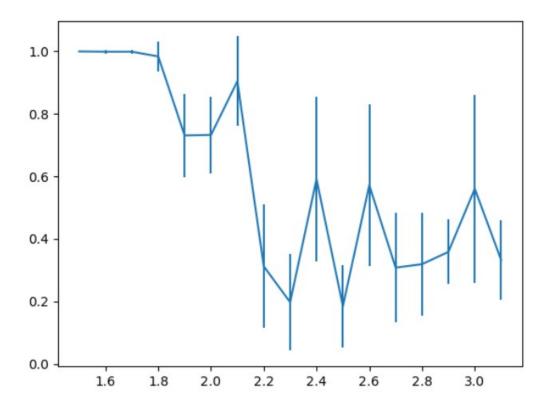


Figure 1.4: Mv/sT(K), L=8

**GPU Programs** 

### **1.1.2 XY Model**

### **Monte Carlo Algorithm**

Here is the code for the Monte Carlo algorithm to generate uncorrelated samples for the classical XY model.

```
# -*- coding: utf-8 -*-
 """dataxy32.ipynb
4 Automatically generated by Colaboratory.
 Original file is located at
      https://colab.research.google.com/drive/1
     IE1vmGDRo25BgQcJ2zuOSWi6ER1B6a-h
 0,0,0
8
9
10 import matplotlib
matplotlib.use('Agg')
12 import numpy as np
13 from numpy import linalg as LA
import matplotlib.pyplot as plt
15
_{16} L = 32
17 \text{ step_r} = 3000
```

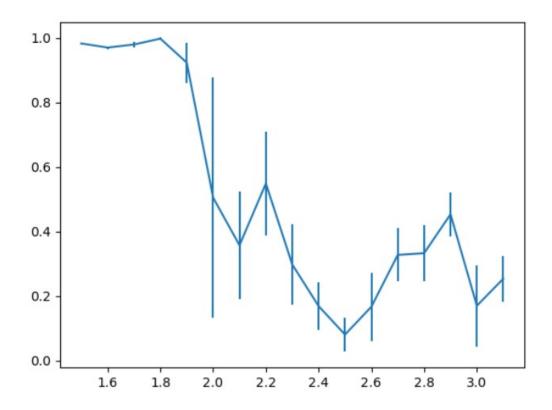


Figure 1.5: Mv/sT(K), L=16

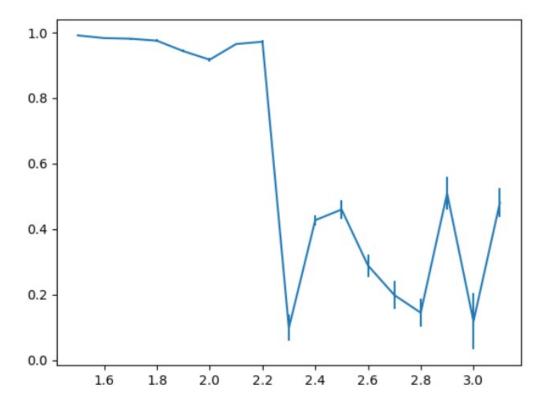


Figure 1.6: Mv/sT(K), L=25

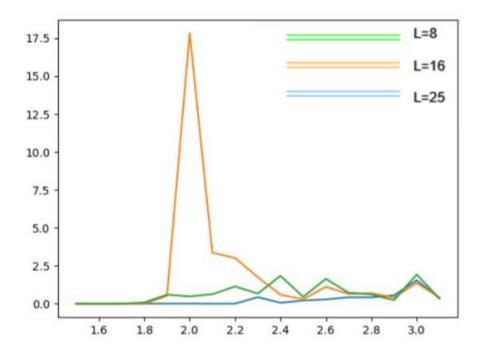


Figure 1.7:  $\chi v/sT(K)$ 

```
18 \text{ step} = 750000
19 \text{ nt} = 10
n_{emove}=30
J = 1 + J>0 to make it ferromagnetic
23
24 # Intitialize the XY network
25 def init():
      return np.random.rand(L, L)*2*np.pi
26
      #return np.ones([L, L])
27
29 # periodic neighbor
 def next(x):
      if x == L-1:
31
           return 0
      else:
33
          return x+1
34
35
 # construct the bond lattice
  def FreezeBonds(Ising,T,S):
37
      iBondFrozen = np.zeros([L,L])
38
      jBondFrozen = np.zeros([L,L])
39
      for i in np.arange(L):
           for j in np.arange(L):
41
               freezProb_nexti = 1 - np.exp(-2 * J * S[i][j] * S[next(i)][
42
     j] / T)
               freezProb_nextj = 1 - np.exp(-2 * J * S[i][j] * S[i][next(j)]
     )] / T)
               if (Ising[i][j] == Ising[next(i)][j]) and (np.random.rand()
44
      < freezProb_nexti):</pre>
                   iBondFrozen[i][j] = 1
```

```
if (Ising[i][j] == Ising[i][next(j)]) and (np.random.rand()
       < freezProb_nextj):
                    jBondFrozen[i][j] = 1
47
       return iBondFrozen, jBondFrozen
48
50 # H-K algorithm to identify clusters
  def properlabel(prp_label,i):
51
       while prp_label[int(i)] != i:
           i = prp_label[int(i)]
54
       return i
55
56 # Swendsen-Wang cluster
57 def clusterfind(iBondFrozen,jBondFrozen):
       cluster = np.zeros([L, L])
58
       prp_label = np.zeros(L**2)
59
       label = 0
60
       for i in np.arange(L):
61
           for j in np.arange(L):
62
               bonds = 0
63
               ibonds = np.zeros(4)
64
               jbonds = np.zeros(4)
65
66
               # check to (i-1,j)
67
               if (i > 0) and iBondFrozen[i-1][j]:
                    ibonds[bonds] = i-1
69
                    jbonds[bonds] = j
                    bonds += 1
               # (i,j) at i edge, check to (i+1,j)
               if (i == L-1) and iBondFrozen[i][j]:
73
74
                    ibonds[bonds] = 0
                    jbonds[bonds] = j
                    bonds += 1
               # check to (i,j-1)
77
               if (j > 0) and jBondFrozen[i][j-1]:
78
                    ibonds[bonds] = i
79
                    jbonds[bonds] = j-1
                    bonds += 1
81
               # (i,j) at j edge, check to (i,j+1)
82
               if (j == L-1) and jBondFrozen[i][j]:
83
84
                    ibonds[bonds] = i
                    jbonds[bonds] = 0
85
                    bonds += 1
86
87
               # check and label clusters
               if bonds == 0:
89
                    cluster[i][j] = label
90
                    prp_label[label] = label
                    label += 1
92
               else:
93
                    minlabel = label
94
95
                    for b in np.arange(bonds):
                        plabel = properlabel(prp_label,cluster[int(ibonds[b
96
      ])][int(jbonds[b])])
                        if minlabel > plabel:
97
                             minlabel = plabel
99
                    cluster[i][j] = minlabel
100
                    # link to the previous labels
101
```

```
for b in np.arange(bonds):
102
                        plabel_n = cluster[int(ibonds[b])][int(jbonds[b])]
103
                        prp_label[int(plabel_n)] = minlabel
104
                        # re-set the labels on connected sites
105
                        cluster[int(ibonds[b])][int(jbonds[b])] = minlabel
      return cluster, prp_label
107
108
  # flip the cluster spins
  def flipCluster(Ising,cluster,prp_label):
      for i in np.arange(L):
111
           for j in np.arange(L):
               # relabel all the cluster labels with the right ones
113
               cluster[i][j] = properlabel(prp_label,cluster[i][j])
114
115
      sNewChosen = np.zeros(L**2)
      sNew = np.zeros(L**2)
116
      flips = 0 # get the number of flipped spins to calculate the Endiff
117
       and Magdiff
      for i in np.arange(L):
118
119
           for j in np.arange(L):
               label = cluster[i][j]
120
               randn = np.random.rand()
121
               # mark the flipped label, use this label to flip all the
      cluster elements with this label
               if (not sNewChosen[int(label)]) and randn < 0.5:</pre>
123
                   sNew[int(label)] = +1
                   sNewChosen[int(label)] = True
               elif (not sNewChosen[int(label)]) and randn >= 0.5:
126
                   sNew[int(label)] = -1
127
                   sNewChosen[int(label)] = True
128
129
               if Ising[i][j] != sNew[int(label)]:
                   Ising[i][j] = sNew[int(label)]
                   flips += 1
132
      return Ising,flips
134
135
    Swendsen-Wang Algorithm in Ising model (with coupling constant
      dependency on sites)
# One-step for Ising
  def oneMCstepIsing(Ising, S):
       [iBondFrozen, jBondFrozen] = FreezeBonds(Ising, T, S)
139
       [SWcluster, prp_label] = clusterfind(iBondFrozen, jBondFrozen)
140
       [Ising, flips] = flipCluster(Ising, SWcluster, prp_label)
141
      return Ising
142
143
144 # Decompose XY network to two Ising networks with project direction
      proj
  def decompose(XY,proj):
145
      x = np.cos(XY)
146
      y = np.sin(XY)
147
      x_rot = np.multiply(x,np.cos(proj))+np.multiply(y,np.sin(proj))
      y_rot = -np.multiply(x,np.sin(proj))+np.multiply(y,np.cos(proj))
149
      Isingx = np.sign(x_rot)
150
      Isingy = np.sign(y_rot)
151
      S_x = np.absolute(x_rot)
      S_y = np.absolute(y_rot)
153
      return Isingx, Isingy, S_x, S_y
154
155
```

```
# Compose two Ising networks to XY network
  def compose(Isingx_new,Isingy_new,proj,S_x, S_y):
       x_rot_new = np.multiply(Isingx_new,S_x)
158
       y_rot_new = np.multiply(Isingy_new,S_y)
159
       x_new = np.multiply(x_rot_new,np.cos(proj))-np.multiply(y_rot_new,
160
      np.sin(proj))
       y_new = np.multiply(x_rot_new,np.sin(proj))+np.multiply(y_rot_new,
161
      np.cos(proj))
       XY_new = np.arctan2(y_new,x_new)
       return XY_new
163
164
  def oneMCstepXY(XY):
165
       proj = np.random.rand()
       [Isingx, Isingy, S_x, S_y] = decompose(XY, proj)
167
       Isingx_new = oneMCstepIsing(Isingx, S_x)
168
       Isingy_new = oneMCstepIsing(Isingy, S_y)
169
       XY_new = compose(Isingx_new, Isingy_new, proj, S_x, S_y)
       return XY_new
171
172
173 # Calculate the energy for XY network
  def EnMag(XY):
174
       energy = 0
175
       for i in np.arange(L):
176
           for j in np.arange(L):
177
                # energy
                \label{eq:energy} \ = \ \operatorname{energy} \ - \ (\operatorname{np.cos}(\texttt{XY[i][j]-XY[(i-1)\%L][j])+np.cos}(
179
      XY[i][j]-XY[(i+1)%L][j])+np.cos(XY[i][j]-XY[i][(j-1)%L])+np.cos(XY[i])
      ][j]-XY[i][(j+1)%L]))
       magx = np.sum(np.cos(XY))
180
       magy = np.sum(np.sin(XY))
181
       mag = np.array([magx,magy])
182
       return energy * 0.5, LA.norm(mag)/(L**2)
184
# Swendsen Wang method for XY model
  def SWang(T):
186
       XY = init()
187
       # thermal steps to get the equilibrium
188
       for step in np.arange(step_r):
189
           XY = oneMCstepXY(XY)
190
191
       # finish with thermal equilibrium, and begin to calc observables
       E_sum = 0
192
       M_sum = 0
193
       Esq_sum = 0
194
       Msq_sum = 0
       lattice_data=np.zeros((step,L,L))
196
       mag = []
197
       for step in np.arange(step):
           XY = oneMCstepXY(XY)
199
           [E,M] = EnMag(XY)
200
           mag=np.append(mag,M)
201
           lattice_data[step]=XY
           E_sum += E
203
           M_sum += M
204
           Esq_sum += E**2
205
           Msq_sum += M**2
207
       E_mean = E_sum/step/(L**2)
208
       M_{mean} = M_{sum}/step
```

```
Esq_mean = Esq_sum/step/(L**4)
      Msq_mean = Msq_sum/step
211
212
      return lattice_data, XY, E_mean, M_mean, Esq_mean, Msq_mean, mag;
213
215 M = np.array([])
216 E = np.array([])
217 M_sus = np.array([])
218 SpcH = np.array([])
220 Trange = np.linspace(0.75, 1.25, nt)
Lattice_XY=np.zeros((step*nt,L,L))
222 Mag=[]
223 for t in range(Trange.shape[0]):
      T=Trange[t]
224
      lattice_data, Ising, E_mean, M_mean, Esq_mean, Msq_mean, mag =
      SWang(T)
      M = np.append(M, np.abs(M_mean))
226
      E = np.append(E, E_mean)
227
      Mag=np.append(Mag,mag, axis=0)
      M_sus = np.append(M_sus, 1/T*(Msq_mean-M_mean**2))
      SpcH = np.append(SpcH, 1/T**2*(Esq_mean-E_mean**2))
      for h in range(step):
           l=t*step+h
           Lattice_XY[1] = lattice_data[h]
234
      print(T)
235
      print(lattice_data.shape)
237 # plot the figures
238 T = Trange
240 plt.figure()
plt.plot(T, E, 'rx-')
242 plt.xlabel(r'Temperature $(\frac{J}{k_B})$')
plt.ylabel(r'$\langle E \rangle$ per site $(J)$')
plt.savefig("E.pdf", format='pdf', bbox_inches='tight')
246 plt.figure()
plt.plot(T, SpcH, 'kx-')
248 plt.xlabel(r'Temperature $(\frac{J}{k_B})$')
plt.ylabel(r'C_V per site (\frac{J^2}{k_B^2}))
250 plt.savefig("Cv.pdf", format='pdf', bbox_inches='tight')
251
252 plt.figure()
253 plt.plot(T, M, 'bx-')
plt.xlabel(r'Temperature $(\frac{J}{k_B})$')
255 plt.ylabel(r'$\langle|M|\rangle$ per site $(\mu)$')
256 plt.savefig("M.pdf", format='pdf', bbox_inches='tight')
257
plt.figure()
259 plt.plot(T, M_sus, 'gx-')
260 plt.xlabel(r'Temperature $(\frac{J}{k_B})$')
261 plt.ylabel(r'$\chi$ $(\frac{\mu}{k_B})$')
262 plt.savefig("chi.pdf", format='pdf', bbox_inches='tight')
264 plt.tight_layout()
265 fig = plt.gcf()
266 plt.show()
```

```
268 np.savetxt('output.data',np.c_[T,E,SpcH,M,M_sus])
269 np.savetxt('mag_data.csv', Mag)
270 \#T = 0.1
#[XY, E_mean, M_mean, Esq_mean, Msq_mean] = SWang(T)
272 \text{ #Cv} = 1 / \text{T**2} * (Esq_mean - E_mean**2)
273 #M_sus = 1 / T * (Msq_mean - M_mean**2)
274 \# [E1,M1] = EnMag(XY)
\#E2 = E1/(L**2)
#print(E_mean, E2, M_mean, M1, Cv, M_sus)
277 ## plot the network cluster
278 #plt.figure()
#plt.matshow(XY,cmap='cool')
#plt.axis('off')
#np.savetxt('latticeXYpredict8_25000.csv',Lattice_XY)
283 num_lattice=nt*step/n_remove
284 num_lattice=int(num_lattice)
285 latticexy=np.zeros((num_lattice,L,L,1))
287 Lattice_XY=Lattice_XY.reshape((nt*step,L,L,1))
288 print(Lattice_XY.shape)
289 k = 0
290 for i in range(Lattice_XY.shape[0]):
    if i%n_remove==0:
      latticexy[k]=Lattice_XY[i]
292
      k += 1
293
295 spin_flatten=np.zeros((Lattice_XY.shape[0],Lattice_XY.shape[1]**2))
296 for i in range(Lattice_XY.shape[0]):
       spin_flatten[i,:]=Lattice_XY[i,:,:].flatten()
pnp.savetxt('latticeXY32.csv',spin_flatten)
```

Listing 1.7: dataxy32.py

#### **Convolutional Neural Network**

The following code implements the CNN to regenerate the transition temperature for the classical XY model for various lattice sizes.

```
# -*- coding: utf-8 -*-
"""Copy of cnnXY.ipynb

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1
    HfqSm4Q3sVTq9yfwMp_tre5QvntrsMVh
"""

# Commented out IPython magic to ensure Python compatibility.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
# %matplotlib inline
import keras
from keras.datasets import mnist
```

```
17 from keras.models import Sequential
18 from keras.layers import Dense, Dropout, Activation, Flatten
19 from tensorflow.keras.optimizers import Adam
20 from keras.layers import BatchNormalization
21 from keras.utils import np_utils
from keras.layers import Conv2D, MaxPooling2D, ZeroPadding2D,
     GlobalAveragePooling2D
23 from keras.layers.advanced_activations import LeakyReLU
24 from keras.preprocessing.image import ImageDataGenerator
25 from tensorflow.keras import datasets, layers, models
27 model = models.Sequential()
28 model.add(layers.Conv2D(12, (3, 3), activation='relu', input_shape
     =(8,8,1))
#model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(8, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
#model.add(layers.Conv2D(64, (3, 3), activation='relu'))
33
model.add(layers.Flatten())
36 model.add(layers.Dense(128, activation='relu'))
model.add(layers.Dense(2))
model.add(Activation('sigmoid'))
40 model.summary()
41
42 model.compile(loss='categorical_crossentropy', optimizer=Adam(),
     metrics=['accuracy'])
44 from google.colab import drive
45 drive.mount('/content/drive', force_remount=True)
47 import pandas as pd
48 import io
49 latticexy = pd.read_csv('/content/drive/MyDrive/
     latticeXYpredict16_25000.csv',delimiter='', header= None)
50 latticexy=latticexy.to_numpy()
52 np.shape(latticexy)
53
54 \text{ nt} = 10
step = 50000
L = 16
x=np.linspace(0.75,1,nt)
temp=np.zeros(step*nt)
59 for j in range(nt):
   for i in range(step):
      temp[j*step+i]=x[j]
61
62
63 latticexy
65 temp
67 ''' k=0
68 for i in range (50000):
69 if temp[i] == 1:
k + = 1
```

```
72 print(k)
  , , ,
73
74
  latticexy=np.reshape(latticexy, (10*step,L,L,1))
77
80
81 print(latticexy.shape)
82 print(temp.shape)
84 latticexy_train=latticexy[0:40000]
print(np.shape(latticexy_train))
86 for i in range(nt):
    if i!=0:
      latticexy_train=np.append(latticexy_train,latticexy[50000*i:50000*i
88
      +40000], axis=0)
      print(np.shape(latticexy_train))
89
90 temp_train=temp[0:40000]
91 for i in range(10):
    if i!=0:
92
      temp_train=np.append(temp_train,temp[50000*i:50000*i+40000],axis=0)
93
      print(temp_train.shape)
95
96 temp_train.shape
98 latticexy_test=latticexy[40000:50000]
99 for i in range (10):
    if i!=0:
100
      latticexy_test=np.append(latticexy_test,latticexy[50000*i
      +40000:50000*i+50000],axis=0)
temp_test=temp[40000:50000]
103 for i in range (10):
    if i!=0:
      temp_test=np.append(temp_test,temp[50000*i+40000:50000*i+50000],
105
      axis=0)
106
  temp_train[temp_train<0.892]=0
107
108
temp_train[temp_train>0.892]=1
110
temp_test[temp_test>0.892]=1
temp_test[temp_test<0.892]=0</pre>
plt.imshow(latticexy_test[1990,:,:,0])
115 plt.show
116
117 temp_train.shape
temperature_train=np.zeros((temp_train.shape[0],2))
temperature_test=np.zeros((temp_test.shape[0],2))
for i in range(temp_train.shape[0]):
    if temp_train[i] == 0:
      temperature_train[i]=[1,0]
123
    else:
124
  temperature_train[i]=[0,1]
```

```
126
for i in range(temp_test.shape[0]):
    if temp_test[i] == 0:
128
      temperature_test[i] = [1,0]
129
    else:
      temperature_test[i]=[0,1]
131
133 latticexy_test/=2*np.pi
134 latticexy_train/=2*np.pi
#model.fit(latticexy_train, temp_train, epochs=5, validation_data=tuple
      (latticexy_test,temp_test))
137 model.fit(latticexy_train, temperature_train, batch_size=64, epochs=50,
      validation_data=(latticexy_test,temperature_test))
138
score = model.evaluate(latticexy_test,temperature_test)
140 print()
print('Test accuracy: ', score[1])
142
predictions = model.predict(latticexy_test)
t = np.linspace(0.75, 1, 10)
y=np.zeros((10,1000,2))
148 for i in range (10):
    y[i]=predictions[1000*i:1000*(i+1)]
149
150
151 y_avg=np.mean(y, axis=1)
152 y_avg_sum=np.mean(y_avg, axis=0)
153
154 y_avg.shape
156 line=np.full(10,0.8935)
y_line=np.linspace(0, 1,10)
159 plt.plot(t,y_avg[:,0])
160 plt.plot(t,y_avg[:,1])
plt.plot(line,y_line)
```

Listing 1.8: cnnxy.py

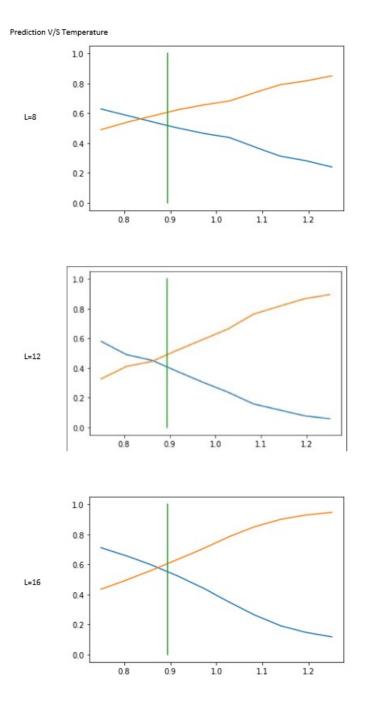


Figure 1.8: Transition temperature with CNN