CS5340: Uncertainty Modeling in AI

Coding Assignment 2

Deadline: April 19th, 2019

Problem 1. (Image Recovery using Hopfield Network)

Hopfield Networks

A Hopfield network (HopNet) is a fully-connected Ising model with a symmetric weight matrix, i.e., the weight matrix has the following properties:

- $\mathbf{W}_{ii} = 0$
- $\mathbf{W}_{ij} = \mathbf{W}_{ji}$

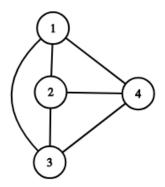


Figure 1: A Hopfield Network with 4 nodes.

A HopNet also has a bias vector b. The parameters ($\theta = [\mathbf{W}, b]$) can be learned from data. HopNets can be used as an associative memory. We train the HopNet on a fully observed set corresponding to some patterns that we want to memorize. At test time we present a partial or corrupted pattern and the network attempts to complete the pattern. Once the parameters are learned, pattern completion can be performed using iterated conditional modes or ICM (similar to image denoising example).

The conditional probability of a node taking the value 1 is given by:

$$p(x_i = 1 | \mathbf{x}_{-i}, \theta) = \sigma(\mathbf{W}_{i,:}^{\top} \mathbf{x}_{-i} + b_i)$$

where σ is the sigmoid function, i.e., $\sigma(x) = \frac{1}{1 + \exp(-x)}$.

For a more detailed description, refer "Machine Learning – A Probabilistic Perspective", Kevin Murphy (Chapter 19, 19.4.2) and the Wikipedia article: Hopfield Network.

Goal

You are expected to implement a Hopfield network for image recovery. Given a set of binary images, your goal is to:

- Learn the parameters θ using a set of training images.
- Predict the most likely assignment of pixel values for the corrupted versions of training images using ICM.

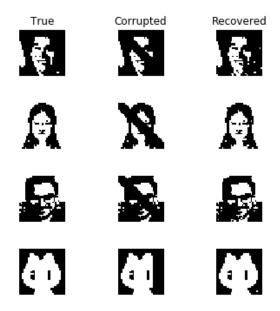


Figure 2: Example result.

Parameter Learning (15 Marks)

Your task is to learn the parameters using two methods:

1. Hebbian Learning Rule (5 Marks): This rule is often stated as, "Neurons that fire together, wire together. Neurons that fire out of sync, fail to link". Complete the function learn_hebbian(imgs) in the skeleton code. The function takes a numpy array of shape (n,32,32) where n is the number of 32 × 32 binary images. The function should return a tuple (W, b) where W is the learned 1024 × 1024 weight matrix and b is the 1024 dimensional bias vector.

Allowed libraries: numpy and scipy.

2. Maximum Pseudo-likelihood (10 Marks): The parameters can also be learned by using gradient-based methods to maximize the *pseudo-likelihood* which is given by

$$PL(\theta) = \prod_{k=1}^{N} \prod_{i=1}^{D} p(x_i^k | \mathbf{x}_{-i}^k, \theta)$$

Note that this is not the actual likelihood which is given by:

$$L(\theta) = \prod_{k=1}^{N} p(\mathbf{x}^k | \theta)$$

Complete the function learn_maxpl(imgs) in the skeleton code. The function takes a numpy array of shape (n,32,32) as the input, where n is the number of 32×32 binary images. The function should return a tuple (W, b), where W is the learned 1024×1024 weight matrix and b is the 1024 dimensional bias vector.

Allowed libraries: numpy and scipy. Libraries torch, autograd, etc., are also allowed for automatic gradient computation, if required.

Image Recovery (5 Marks)

Complete the function recover(cimgs, W, b) in the skeleton code. The function takes a numpy array of shape (n,32,32) and W and b as the input, where n is the number of 32×32 corrupted binary images, and W and b are the learned weight matrix and bias vector respectively. The function should return a numpy array of shape (n,32,32) which contains the images recovered using the HopNet.

Submission Format

Submit only the python (.py) file renamed to YourMatricNumber-PartnerMatricNumber.py on IVLE. If your matric number is A0174067B and your partner's is A0175067A, then the file should be named A0174067B-A0175067A.py. If you're doing the assignment as an individual, name it as YourMatricNumber.py. Submit only one python file per group.

Code Skeleton

You are only allowed to modify the functions learn_hebbian(imgs), learn_maxpl(imgs), and recover(cimgs, W, b) in the code skeleton. Adding helper functions is allowed but modifying main() in any way is not allowed.

```
Description: CS5340 - Hopfield Network

Name: Your Name, Your partner's name

Matric No.: Your matric number, Your partner's matric number

'''

matplotlib
matplotlib.use('Agg')
miport numpy as np
import glob
miport matplotlib.pyplot as plt
```

```
from PIL import Image, ImageOps
13
14
15
  def load_image(fname):
      img = Image.open(fname).resize((32, 32))
17
      img_gray = img.convert('L')
18
      img_eq = ImageOps.autocontrast(img_gray)
19
      img_eq = np.array(img_eq.getdata()).reshape((img_eq.size[1], -1))
20
      return img_eq
21
22
  def binarize_image(img_eq):
      img_bin = np.copy(img_eq)
25
      img_bin[img_bin < 128] = -1
26
      img_bin[img_bin >= 128] = 1
27
      return img_bin
28
29
30
  def add_corruption(img):
31
      img = img.reshape((32, 32))
32
      t = np.random.choice(3)
33
      if t == 0:
34
         i = np.random.randint(32)
35
         img[i:(i + 8)] = -1
36
      elif t == 1:
37
         i = np.random.randint(32)
         img[:, i:(i + 8)] = -1
      else:
40
         mask = np.sum([np.diag(-np.ones(32 - np.abs(i)), i)
41
                      for i in np.arange(-4, 5)], 0).astype(np.int)
42
         img[mask == -1] = -1
43
      return img.ravel()
44
45
  def learn_hebbian(imgs):
47
      img_size = np.prod(imgs[0].shape)
48
      49
      50
      weights = np.zeros((img_size, img_size))
51
      bias = np.zeros(img_size)
52
      # Complete this function
      # You are allowed to modify anything between these lines
      # Helper functions are allowed
55
      56
      57
```

```
return weights, bias
58
59
60
   def learn_maxpl(imgs):
      img_size = np.prod(imgs[0].shape)
62
      63
      64
      weights = np.zeros((img_size, img_size))
65
      bias = np.zeros(img_size)
66
      # Complete this function
67
      # You are allowed to modify anything between these lines
      # Helper functions are allowed
      70
      71
      return weights, bias
72
73
74
   def plot_results(imgs, cimgs, rimgs, fname='result.png'):
75
76
      This helper function can be used to visualize results.
77
78
      img_dim = 32
79
      assert imgs.shape[0] == cimgs.shape[0] == rimgs.shape[0]
80
      n_imgs = imgs.shape[0]
81
      fig, axn = plt.subplots(n_imgs, 3, figsize=[8, 8])
      for j in range(n_imgs):
83
         axn[j][0].axis('off')
         axn[j][0].imshow(imgs[j].reshape(img_dim, img_dim), cmap='Greys_r')
85
      axn[0, 0].set_title('True')
86
      for j in range(n_imgs):
87
         axn[j][1].axis('off')
88
         axn[j][1].imshow(cimgs[j].reshape(img_dim, img_dim), cmap='Greys_r')
89
      axn[0, 1].set_title('Corrupted')
90
      for j in range(n_imgs):
         axn[j][2].axis('off')
         axn[j][2].imshow(rimgs[j].reshape((img_dim, img_dim)), cmap='Greys_r')
93
      axn[0, 2].set_title('Recovered')
94
      fig.tight_layout()
95
      plt.savefig(fname)
96
97
98
   def recover(cimgs, W, b):
      img_size = np.prod(cimgs[0].shape)
100
      101
      102
```

```
rimgs = []
103
       # Complete this function
104
       # You are allowed to modify anything between these lines
105
       # Helper functions are allowed
       107
       108
       return rimgs
109
110
111
   def main():
112
       # Load Images and Binarize
113
       ifiles = sorted(glob.glob('images/*'))
114
       timgs = [load_image(ifile) for ifile in ifiles]
115
       imgs = np.asarray([binarize_image(img) for img in timgs])
116
117
       # Add corruption
118
       cimgs = []
119
       for i, img in enumerate(imgs):
120
           cimgs.append(add_corruption(np.copy(imgs[i])))
121
       cimgs = np.asarray(cimgs)
123
       # Recover 1 -- Hebbian
124
       Wh, bh = learn_hebbian(imgs)
125
       rimgs_h = recover(cimgs, Wh, bh)
126
       np.save('hebbian.npy', rimgs_h)
127
128
       # Recover 2 -- Max Pseudo Likelihood
       Wmpl, bmpl = learn_maxpl(imgs)
130
       rimgs_mpl = recover(cimgs, Wmpl, bmpl)
131
       np.save('mpl.npy', rimgs_mpl)
132
133
134
   if __name__ == '__main__':
135
       main()
136
```