

Mean Field Inference

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1 Introduction

In this project, I used the MNIST dataset to implement Mean Field Inference. I performed 3 operations on each image: 1. Binarize by mapping any value below 0.5 to -1 and any value above to 1 2. Add noise randomly by flipping 2% of the bits 3. Denoise using Boltzman machine model and mean field inference.

2 Average accuracy

The accuracy for each denoised image is obtained by calculating the ratio of pixels with correct value. The average accuracy on first 500 images is 0.9836.

3 Sample images

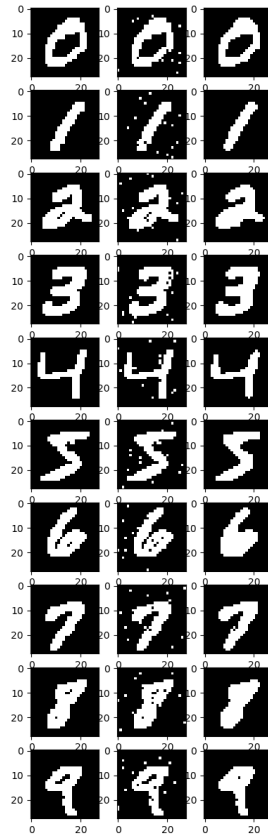


Figure 1: Sample images for each digit. The first column is sample image, the second column is noised version, and the third column is denoised version.

4 Best reconstruction

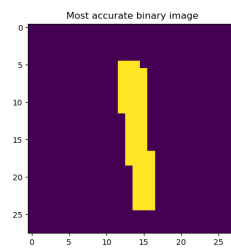


Figure 2: Original image of the best reconstruction

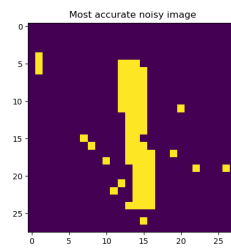


Figure 3: Noised version of the best reconstruction

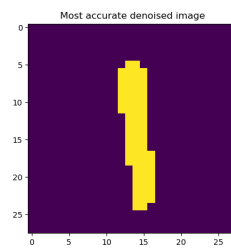


Figure 4: Denoised version of the best reconstruction

5 Worst reconstruction

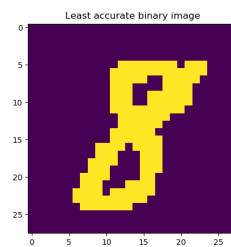


Figure 5: Original image of the worst reconstruction

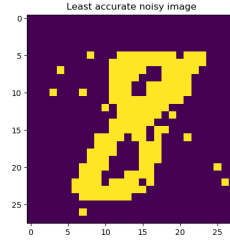


Figure 6: Noised version of the worst reconstruction

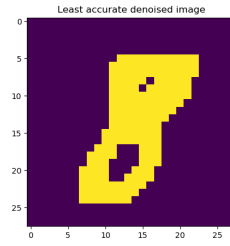


Figure 7: Denoised version of the worst reconstruction

6 ROC Curve

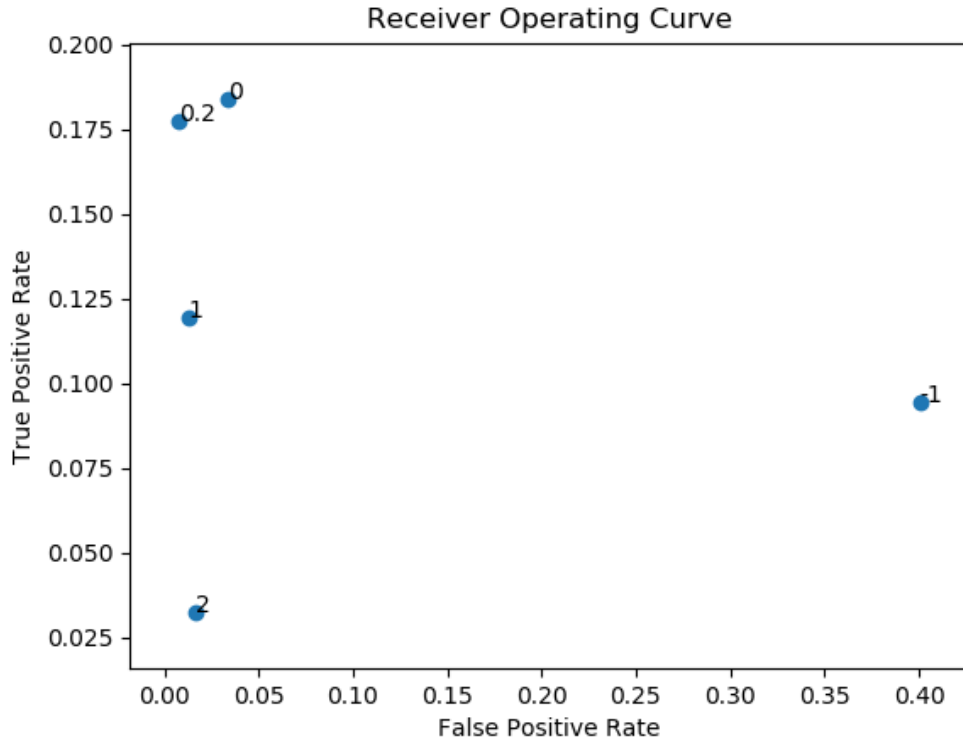


Figure 8: Receiver operating curve. The label for each data point is the value of θ_{ij} for the H_i , H_j terms.

7 Code

7.1 Helper functions

```
1 import numpy as np
2 import gzip
3 import struct
4 import matplotlib.pyplot as plt
5 from mlxtend.data import loadlocal_mnist
6
7 def binarize(images):
8     bi_images = np.zeros(images.shape)
9     for k in range(images.shape[0]):
10         for i in range(images.shape[1]):
11             for j in range(images.shape[2]):
12                 if images[k,i,j] >= 0.5:
13                     bi_images[k,i,j] = 1.0
14                 else:
15                     bi_images[k,i,j] = -1.0
16     return bi_images
17
18 def create_noisy(images):
19     noisy_images = np.copy(images)
20     size = images.shape[1] * images.shape[2]
21     flip_size = (int)(size*0.02)
22     for k in range(images.shape[0]):
23         choice = np.random.permutation(np.arange(size))[:flip_size].tolist()
24         for i in range(size):
25             if i in choice:
26                 noisy_images[k, i//images.shape[1], i%images.shape[1]] \
27                     = -images[k, i//images.shape[1], i%images.shape[1]]
28     return noisy_images
29
```

```

30 def denoise(noisy_images, theta_hh=0.2):
31     # theta_hh = 0.2
32     theta_hx = 0.2
33     epsilon = 0.001
34     num_epochs = 20
35     # Initialize diff list
36     diff = [[] for _ in range(noisy_images.shape[0])]
37     for i in diff:
38         i.append(0)
39     length = noisy_images.shape[1]
40     images = np.copy(noisy_images)
41     for k in range(images.shape[0]):
42         # Initialize edge weights pi
43         pi = np.random.rand(length, length)
44         prev_pi = np.copy(pi)
45         for epoch in range(num_epochs):
46             exponent = np.zeros((length, length))
47             for i in range(images.shape[1]):
48                 for j in range(images.shape[2]):
49                     if i is not 0: # Not on the top edge
50                         exponent[i,j] += theta_hh*(2*pi[i-1,j]-1) + theta_hx*noisy_images[k,i-1,j]
51                     if i is not images.shape[1]-1: # Not on the bottom edge
52                         exponent[i,j] += theta_hh*(2*pi[i+1,j]-1) + theta_hx*noisy_images[k,i+1,j]
53                     if j is not 0: # Not on the left edge
54                         exponent[i,j] += theta_hh*(2*pi[i,j-1]-1) + theta_hx*noisy_images[k,i,j-1]
55                     if j is not images.shape[1]-1: # Not on the right edge
56                         exponent[i,j] += theta_hh*(2*pi[i,j+1]-1) + theta_hx*noisy_images[k,i,j+1]
57                     # Update edge weights
58                     pi[i,j] = np.exp(exponent[i,j]) / (np.exp(exponent[i,j]) + np.exp(-exponent[i,j]))
59                     if pi[i,j] < 0.5:
60                         images[k,i,j] = -1.0
61                     else:
62                         images[k,i,j] = 1.0
63
64                 # diff[k].append(np.linalg.norm(pi-prev_pi,2))
65                 diff[k].append(np.sum(np.power(pi-prev_pi,2)))
66                 prev_pi = np.copy(pi)
67                 if diff[k][-1] < epsilon:
68                     break
69     return images

```

```

71 def accuracy(binary_images,denoise_images):
72     accuracy_list = np.zeros((binary_images.shape[0],1))
73     for k in range(binary_images.shape[0]):
74         n_incorrect = np.count_nonzero(binary_images[k,:,:]-denoise_images[k,:,:])
75         accuracy_list[k] = 1 - (n_incorrect / (binary_images.shape[1]*binary_images.shape[2]))
76     return accuracy_list
77
78 def confusion(binary_images, denoise_images):
79     true_positive_list = np.zeros((binary_images.shape[0],1))
80     false_positive_list = np.zeros((binary_images.shape[0],1))
81     for k in range(binary_images.shape[0]):
82         true_positive = 0
83         false_positive = 0
84         for i in range(binary_images.shape[1]):
85             for j in range(binary_images.shape[2]):
86                 if denoise_images[k,i,j] == 1.0:
87                     if binary_images[k,i,j] == 1.0:
88                         true_positive += 1
89                     else:
90                         false_positive += 1
91         true_positive_list[k] = true_positive / (binary_images.shape[1]**2)
92         false_positive_list[k] = false_positive / (binary_images.shape[1]**2)
93     return np.mean(true_positive_list), np.mean(false_positive_list)

```

7.2 Main function

```
95 ~ def main():
96 ~     # img_filename = 'train-images-idx3-ubyte.gz'
97 ~     # images = extract_images(img_filename, 500)
98 ~     images, labels = loadlocal_mnist(images_path='train-images-idx3-ubyte', labels_path='train-labels-idx1-ubyte')
99 ~     images = images.reshape((-1,28,28)[:500,:,:])
100 ~     labels = labels[:500]
101 ~     label_img_dict = {}
102 ~     for i in range(labels.shape[0]):
103 ~         if labels[i] not in label_img_dict.keys():
104 ~             label_img_dict[labels[i]] = images[i,:,:].reshape((-1,28,28))
105 ~         else:
106 ~             label_img_dict[labels[i]] = np.concatenate((label_img_dict[labels[i]], images[i,:,:].reshape((-1,28,28))), axis=0)
107
108 ~     # Sample images for each digit
109 ~     plt.figure(figsize=(4.5,15))
110 ~     for num in range(10):
111 ~         orig_img = label_img_dict[num]
112 ~         binary_img = binarize(orig_img)
113 ~         plt.subplot(10,3,num*3+1)
114 ~         plt.imshow(binary_img[0,:,:), cmap='gray')
115 ~         noisy_img = create_noisy(binary_img)
116 ~         plt.subplot(10,3,num*3+2)
117 ~         plt.imshow(noisy_img[0,:,:), cmap='gray')
118 ~         denoise_img = denoise(noisy_img)
119 ~         plt.subplot(10,3,num*3+3)
120 ~         plt.imshow(denoise_img[0,:,:), cmap='gray')
121 ~     plt.savefig('samples.png')
122
123 ~     binary_images = binarize(images)
124 ~     noisy_images = create_noisy(binary_images)
125 ~     denoise_images = denoise(noisy_images)
126 ~     accuracy_list = accuracy(binary_images, denoise_images)
127 ~     avg_accuracy = sum(accuracy_list[:500]) / 500
128 ~     print('Average accuracy on the first 500 images: {}'.format(avg_accuracy))

138 ~     # Most accurate
139 ~     max_idx = np.argmax(accuracy_list)
140 ~     plt.figure()
141 ~     plt.imshow(binary_images[max_idx,:,:])
142 ~     plt.title('Most accurate binary image')
143 ~     plt.savefig('most_accurate_binary_image.png')
144 ~     plt.figure()
145 ~     plt.imshow(noisy_images[max_idx,:,:])
146 ~     plt.title('Most accurate noisy image')
147 ~     plt.savefig('most_accurate_noisy_image.png')
148 ~     plt.figure()
149 ~     plt.imshow(denoise_images[max_idx,:,:])
150 ~     plt.title('Most accurate denoised image')
151 ~     plt.savefig('most_accurate_denoised_image.png')
152
153 ~     # Least accurate
154 ~     min_idx = np.argmin(accuracy_list)
155 ~     plt.figure()
156 ~     plt.imshow(binary_images[min_idx,:,:])
157 ~     plt.title('Least accurate binary image')
158 ~     plt.savefig('least_accurate_binary_image.png')
159 ~     plt.figure()
160 ~     plt.imshow(noisy_images[min_idx,:,:])
161 ~     plt.title('Least accurate noisy image')
162 ~     plt.savefig('least_accurate_noisy_image.png')
163 ~     plt.figure()
164 ~     plt.imshow(denoise_images[min_idx,:,:])
165 ~     plt.title('Least accurate denoised image')
166 ~     plt.savefig('least_accurate_denoised_image.png')
```

```

168     # ROC
169     denoise_images_list = []
170     accuracies = []
171     true_positive_list = []
172     false_positive_list = []
173     for theta_hh in [-1,0,0.2,1,2]:
174         denoise_images_list.append(denoise(noisy_images, theta_hh))
175         accuracies.append(accuracy(binary_images, denoise_images))
176         true_positive, false_positive = confusion(binary_images, denoise_images_list[-1])
177         true_positive_list.append(true_positive)
178         false_positive_list.append(false_positive)
179
180     txt_list = [-1,0,0.2,1,2]
181     fig, ax = plt.subplots()
182     ax.scatter(false_positive_list, true_positive_list)
183     for i, txt in enumerate(txt_list):
184         ax.annotate(txt, (false_positive_list[i], true_positive_list[i]))
185     ax.set_xlabel('False Positive Rate')
186     ax.set_ylabel('True Positive Rate')
187     plt.title('Receiver Operating Curve')
188     plt.savefig('roc.png')

```