

## STA414 hw2

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$$1. \text{ A) } \sum_d [x_d \ln \theta_{cd} + (1 - x_d) \ln(1 - \theta_{cd})] = 0$$

$$\Rightarrow \sum_d \left( \frac{x_d}{\theta_{cd}} - \frac{1-x_d}{1-\theta_{cd}} \right) = 0$$

$$\Rightarrow \sum_d (1 - \theta_{cd}) x_d = \sum_d (1 - x_d) \theta_{cd}$$

$$\Rightarrow \sum_d \left( \frac{1}{\theta_{cd}} - 1 \right) x_d = \sum_d (1 - x_d)$$

$$\Rightarrow \sum_d^{784} x_d = \sum_d^{784} \theta_{cd}$$

$$\Rightarrow \widehat{\theta_{cd}} = \frac{1}{784} \sum_d^{784} x_d$$

$$\text{B) } p(\theta|\beta) = \frac{p(\beta|\theta)p(\theta)}{p(\beta)} = p(\beta|\theta)p(\theta)$$

only need to consider this since  $p(\beta)$  doesn't contain theta

$$\ln p(\theta_{cd}|x_d) = \sum_d \ln p(x_d|\theta_{cd}) + \ln p(\theta_{cd}|2,2)$$

$$\frac{\partial}{\partial \theta_{cd}} \ln p(\theta_{cd}|x_d) = \frac{\partial}{\partial \theta_{cd}} \sum_d \ln p(x_d|\theta_{cd}) + \frac{\partial}{\partial \theta_{cd}} \ln \text{Beta}(\theta_{cd}|2,2)$$

$$\Rightarrow 0 = \frac{1}{\theta_{cd}} \sum_d x_d - \frac{1}{1-\theta_{cd}} \sum_d (1 - x_d) + \frac{1}{\theta_{cd}} - \frac{1}{1-\theta_{cd}}$$

$$\Rightarrow \theta_{cd} [\sum_d (1 - x_d) + 1] = (1 - \theta_{cd}) [\sum_d x_d + 1]$$

$$\Rightarrow \theta_{cd} [\sum_d^{784} 1 + 2] = \sum_d x_d + 1$$

$$\Rightarrow \widehat{\theta_{cd}}_{MAP} = (\sum_d x_d + 1) / 786$$

C)

```

97 def fit_MAP(train_images, train_labels):
98     #train_images = binarize(train_images)
99     c = 10
100    n, d = train_images.shape
101    x = np.zeros((c, d))
102    for i in range(n):
103        for j in range(c):
104            if train_labels[i][j] == 1:
105                x[j] += train_images[i]
106    #number of c's
107    total_c = np.reshape(np.sum(train_labels, axis=0), (c, 1))
108    theta = (x+1)/(total_c+2)
109    plot_images(theta, plt)
110    return theta

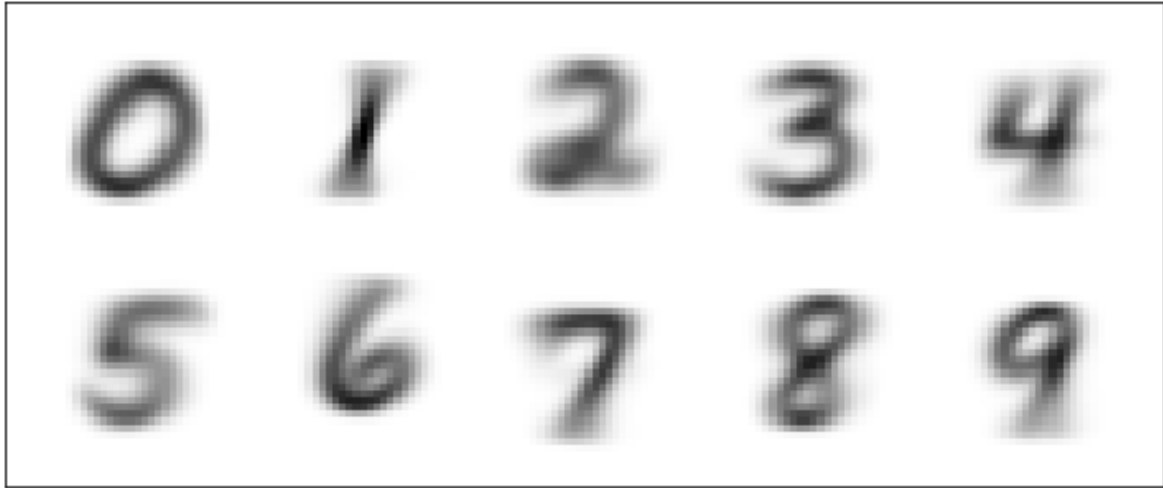
```

```

112 def binarize(train_images):
113     return np.where(train_images > 0.5, 1, 0)

208 if __name__ == "__main__":
209     N_data, train_images, train_labels, test_images, test_labels = load_mnist()
210     train_images = binarize(train_images)
211     #test_images = binarize(test_images)
212     #l_c
213     theta = fit_MAP(train_images, train_labels)

```



$$\begin{aligned}
 \text{D) } p(c|x) &= \frac{p(x|c)p(c)}{p(x)} \\
 &= (\pi_c \prod_{d=1}^{784} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d}) / (\sum_{c=0}^9 \pi_c \prod_{d=1}^{784} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d}) \\
 &= (\pi_c \prod_{d=1}^{784} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d}) / (\sum_{c=0}^9 \exp(\ln(\pi_c \prod_{d=1}^{784} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d}))) \\
 \ln p(c|x) &= \ln(\pi_c) + \sum_d^{784} [x_d \ln \theta_{cd} + (1 - x_d) \ln(1 - \theta_{cd})] \\
 &\quad - \ln \sum_{c=1}^9 \exp(\ln(\pi_c \prod_{d=1}^{784} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d}))
 \end{aligned}$$

E)

```

115 def log_likelihood(x, theta, pi, top=False):
116     bern = np.where(x > 0.5, theta, 1-theta)
117     #for calculating p(c|x_top)
118     if (top):
119         bern = bern[:392]
120     #sum all the pixels
121     numer = np.log(pi) + np.sum(np.log(bern), axis=1)
122     denom = logsumexp(numer)
123     return numer - denom
124
125 def avg_log_likelihood(images, theta, labels, pi=0.1):
126     N = len(images)
127     summ = 0
128     for i in range(N):
129         likelihood = log_likelihood(images[i], theta, pi)
130         t_i = np.argmax(labels[i])
131         summ += likelihood[t_i]
132     return summ/N
133
134 def accuracy(images, theta, labels, pi=0.1):
135     score = 0
136     N = len(images)
137     for i in range(N):
138         likelihood = log_likelihood(images[i], theta, pi)
139         c_i = np.argmax(likelihood)
140         t_i = np.argmax(labels[i])
141         if (c_i == t_i):
142             score += 1
143
144     return score/float(N)
145

```

```

208 if __name__ == "__main__":
209     N_data, train_images, train_labels, test_images, test_labels = load_mnist()
210     train_images = binarize(train_images)
211     test_images = binarize(test_images)
212     #l_c
213     theta = fit_MAP(train_images, train_labels)
214     #l_e
215     print(avg_log_likelihood(train_images, theta, train_labels))
216     print(accuracy(train_images, theta, train_labels))
217     print(avg_log_likelihood(test_images, theta, test_labels))
218     print(accuracy(test_images, theta, test_labels))

```

Average log likelihood for training data: -3.354047795346782

Accuracy of training data: 0.835883333333

Average log likelihood for test data: -3.180015171715445

Accuracy of test data: 0.8426

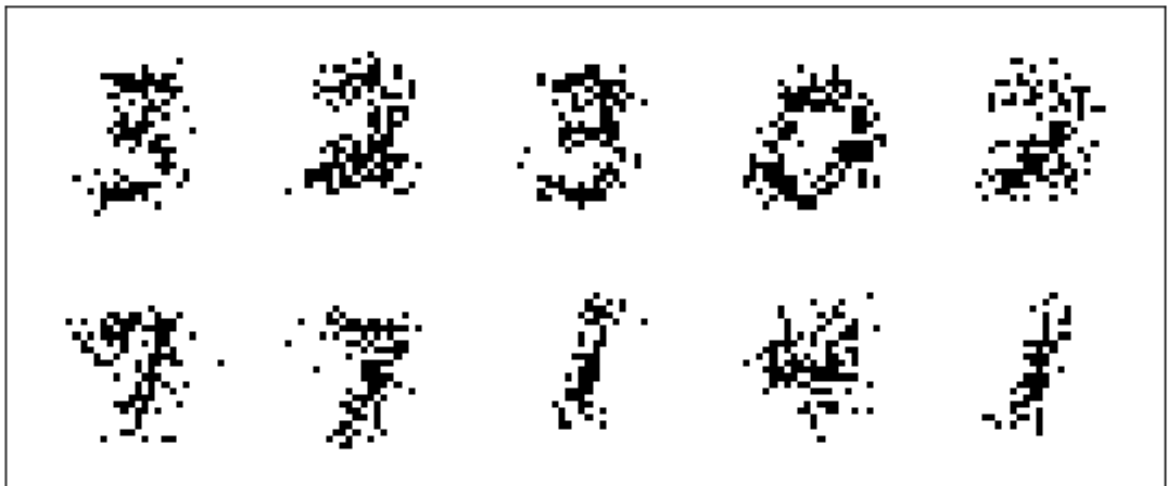
2. A) True

B) False

C)

```
146 def random_image_samples(images, theta, labels, size):
147     d = theta.shape[1]
148     #Distribution of digits
149     prob = np.sum(labels, axis=0)
150     prob = prob/float(labels.shape[0])
151     classes = np.array(range(10))
152     sample_c = np.random.choice(classes, size, p=prob)
153     result = []
154     for digit in sample_c:
155         image = []
156         for i in range(d):
157             P = [1-theta[digit][i], theta[digit][i]]
158             random_pixel = np.random.choice([0,1],1, p=P)
159             image.append(random_pixel)
160         image = np.round(image)
161         result.append(image)
162     plot_images(np.array(result), plt)

208 if __name__ == "__main__":
209     N_data, train_images, train_labels, test_images, test_labels = load_mnist()
210     train_images = binarize(train_images)
211     test_images = binarize(test_images)
212     #1_c
213     theta = fit_MAP(train_images, train_labels)
214     #1_e
215     #print(avg_log_likelihood(train_images, theta, train_labels))
216     #print(accuracy(train_images, theta, train_labels))
217     #print(avg_log_likelihood(test_images, theta, test_labels))
218     #print(accuracy(test_images, theta, test_labels))
219     #2_c
220     random_image_samples(train_images, theta, train_labels, 10)
```



$$\begin{aligned}
 \text{D) } p(x_{i \in \text{bottom}} | x_{\text{top}}, \theta, \pi) &= \sum_{c=0}^9 p(c | x_{\text{top}}) p(x_{i \in \text{bottom}} | c) \\
 &= \sum_{c=0}^9 (\pi_c \prod_{d=1}^{392} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d} / \sum_{c'=0}^9 \pi_{c'} \prod_{d=1}^{392} \theta_{c'd}^{x_d} (1 - \theta_{c'd})^{1-x_d}) (\prod_{d=392}^{784} \theta_{cd}^{x_d} (1 - \theta_{cd})^{1-x_d})
 \end{aligned}$$

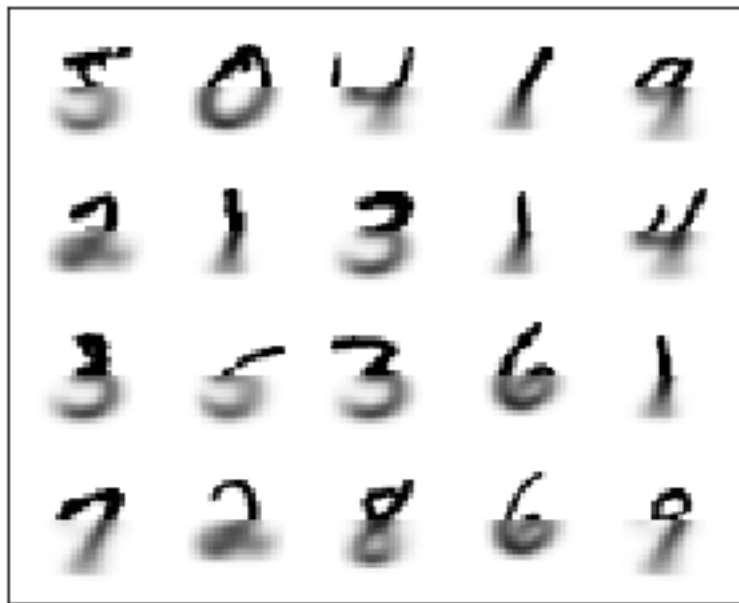
E)

```

164 def marginal_dist(images, theta, size):
165     c, d = theta.shape
166     pi = 0.1
167     result = []
168     for i in range(size):
169         top_half = images[i, :392]
170         #getting rid of log
171         p_cx = np.exp(log_likelihood(images[i], theta, pi, top=True))
172         image = []
173         for j in range(392, d):
174             pixel = 0
175             for digit in range(c):
176                 pixel += theta[digit][j]*p_cx[digit]
177             image.append(pixel)
178         bottom_half = np.array(image)
179         full_image = np.concatenate((top_half, bottom_half))
180         result.append(full_image)
181     plot_images(np.array(result), plt)

208 if __name__ == "__main__":
209     N_data, train_images, train_labels, test_images, test_labels = load_mnist()
210     #train_images = binarize(train_images)
211     #test_images = binarize(test_images)
212     #1_c
213     theta = fit_MAP(train_images, train_labels)
214     #1_e
215     #print(avg_log_likelihood(train_images, theta, train_labels))
216     #print(accuracy(train_images, theta, train_labels))
217     #print(avg_log_likelihood(test_images, theta, test_labels))
218     #print(accuracy(test_images, theta, test_labels))
219     #2_c
220     #random_image_samples(train_images, theta, train_labels, 10)
221     #2_e
222     marginal_dist(train_images, theta, 20)

```



3. A) 2 parameters:  $w$  and  $x$

$$B) \log(p(c|x, w)) = w_c^T x - \log(\sum_{c'=0}^9 \exp(w_{c'}^T x))$$

$$\nabla_w \log p(c|x, w) = x_c - x_c \exp(w_c^T x) / \sum_{c'=0}^9 \exp(w_{c'}^T x)$$

C)

```

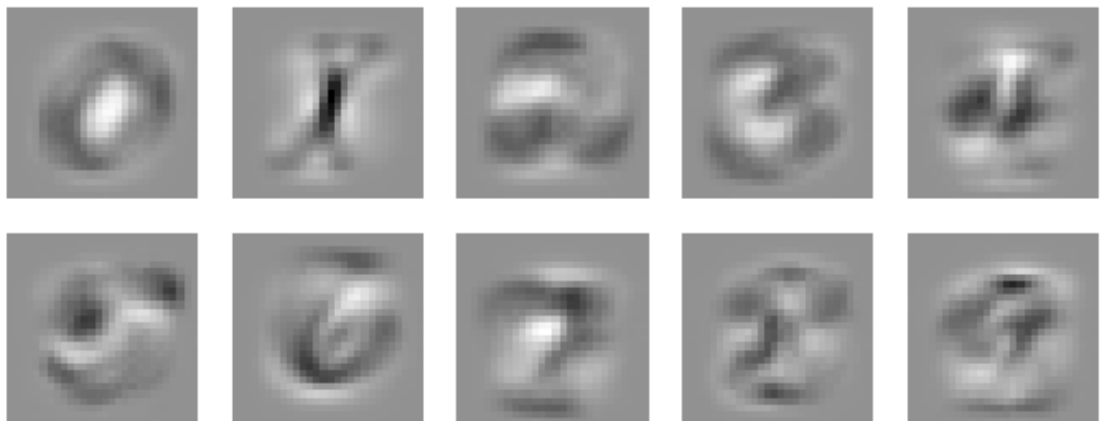
183 def stochastic(w, x, t):
184     wx = np.dot(x, w)
185     N = x.shape[0]
186     y = (np.exp(wx).T / np.sum(np.exp(wx), axis=1)).T
187     return (-1/N)*np.dot(x.T, y-t)

```

```

207 if __name__ == "__main__":
208     N_data, train_images, train_labels, test_images, test_labels = load_mnist()
209     train_images = binarize(train_images)
210     test_images = binarize(test_images)
211     #1_c
212     theta = fit_MAP(train_images, train_labels)
213     #1_e
214     #print(avg_log_likelihood(train_images, theta, train_labels))
215     #print(accuracy(train_images, theta, train_labels))
216     #print(avg_log_likelihood(test_images, theta, test_labels))
217     #print(accuracy(test_images, theta, test_labels))
218     #2_c
219     #random_image_samples(train_images, theta, train_labels, 10)
220     #2_e
221     #marginal_dist(train_images, theta, 20)
222
223     c = 10
224     d = 784
225     weights = np.zeros((d, c))
226     max_iter = 100
227     lr = 0.00001
228     iteration = 0
229     EPS = 1e-4
230     prev_w = weights-10*EPS
231     while(norm(weights - prev_w) > EPS and iteration < max_iter):
232         prev_w = weights.copy()
233         g = stochastic(weights, train_images, train_labels)
234         weights += lr*g
235         iteration += 1
236         print("iteration: ", iteration, "\nw is ", weights)
237     a, v = accuracyAndlikelihood(weights, train_images, train_labels)
238     print("accuracy: ", a, "avg: ", v)
239     weights = weights.transpose()
240     plot_images(weights, plt)

```



d) Accuracy on training data: 0.894316666667

Average log likelihood of training data: -0.3864147759252905

Accuracy on test data: 0.9005

Average log likelihood of test data: -0.3694515017335679

The result was better than Naïve Bayes result.

```
207 if __name__ == "__main__":
208     N_data, train_images, train_labels, test_images, test_labels = load_mnist()
209     train_images = binarize(train_images)
210     test_images = binarize(test_images)
211     #1_c
212     theta = fit_MAP(train_images, train_labels)
213     #1_e
214     #print(avg_log_likelihood(train_images, theta, train_labels))
215     #print(accuracy(train_images, theta, train_labels))
216     #print(avg_log_likelihood(test_images, theta, test_labels))
217     #print(accuracy(test_images, theta, test_labels))
218     #2_c
219     #random_image_samples(train_images, theta, train_labels, 10)
220     #2_e
221     #marginal_dist(train_images, theta, 20)
222
223     c = 10
224     d = 784
225     weights = np.zeros((d, c))
226     max_iter = 100
227     lr = 0.00001
228     iteration = 0
229     EPS = 1e-4
230     prev_w = weights-10*EPS
231     while(norm(weights - prev_w) > EPS and iteration < max_iter):
232         prev_w = weights.copy()
233         g = stochastic(weights, train_images, train_labels)
234         weights += lr*g
235         iteration += 1
236         print("iteration: ", iteration, "\nw is ", weights)
237     a, v = accuracyAndlikelihood(weights, train_images, train_labels)
238     print("train_accuracy: ", a, "train_avg: ", v)
239     a, v = accuracyAndlikelihood(weights, test_images, test_labels)
240     print("test_accuracy: ", a, "test_avg: ", v)
241     weights = weights.transpose()
242     plot_images(weights, plt)
```