

HOMework 1

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Perceptron

Problem 1

Decision Boundary:

$$w_1x_1 + w_2x_2 - \theta = 0 \rightarrow w^T x = \theta$$

Distance Proof - The unit vector for weights w shows the perpendicular relationship of the decision boundary to the origin. Therefore for any x the dot product of the unit vector w will result in l :

$$l = \frac{\theta}{\|w\|}$$

$$\theta = w^T x$$

$$l = \frac{w^T x}{\|w\|}$$

Problem 2

Learning Rule:

$$w_i(t+1) = w_i(t) + \alpha(\text{teacher} - \text{output})x_i$$

Learning Pattern:

x_1	x_2	w_1	w_2	Net	Output	Teacher	Threshold (θ)
1	1	0	0	0	1	0	0
0	0	-1	-1	0	0	1	1
0	1	-1	-1	-1	0	1	0
1	1	-1	0	-1	1	0	-1
1	0	-2	-1	-2	0	1	0
		-1	-1				-1

Note : $\alpha = 1$

The solution is not unique. There are three possible solutions that result in convergence. The possible solutions respectively are:

$$w_1 \rightarrow -1, -1, -2$$

$$w_2 \rightarrow -1, -2, -1$$

$$\theta \rightarrow -1, -2, -2$$

Problem 3

Z-Score - The z-score is used to normalize the data. By doing so it allows for a more consistent learning rate when training the weights. In cases where the data sets contain a wider range of values this can help a lot. See attached code for z-score calculation (`flower_classifier.py - findZScore()`)

Plots - The data is linearly separable relative to the flower type. This is clear by looking at the graphs due to the two clusters of data points. See attached files for graph images.

Average Error Rate - 0.0

Learning Rate - My learning rate is set to 1. By altering it you can scale the weights differently. In this case altering the learning rate does not have much of an impact on the outcome.

Code - Code for this problem can be found in the appendix and in the attached file `flower_classifier.py`.

Regression

Problem 1

Logistic Regression

$$E(\theta) = - \sum_{i=1}^N y^{(i)} \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)}))$$

$$E(\theta) = - \sum_{i=1}^N y^{(i)} \log\left(\frac{1}{1 + e^{-\theta^T x^{(i)}}}\right) + (1 - y^{(i)}) \log\left(1 - \frac{1}{1 + e^{-\theta^T x^{(i)}}}\right)$$

$$E(\theta) = \sum_{i=1}^N \log(1 + e^{-\theta^T x^{(i)}}) - y^{(i)} \theta^T x^{(i)}$$

$$\frac{\partial E(\theta)}{\partial \theta} = \sum_{i=1}^N \frac{x^{(i)}}{1 + e^{-\theta^T x^{(i)}}} - y^{(i)} x^{(i)}$$

$$\frac{\partial E(\theta)}{\partial \theta} = \sum_{i=1}^N x^{(i)} (h_{\theta}(x^{(i)}) - y^{(i)})$$

Problem 2

Softmax Regression

$$E(\theta) = - \sum_{i=1}^N \sum_{j=1}^K 1\{y^{(i)} = j\} \log \frac{e^{\theta^{(j)T} x^{(i)}}}{\sum_{l=1}^K e^{\theta^{(l)T} x^{(i)}}}$$

$$E(\theta) = - \sum_{i=1}^N \sum_{j=1}^K 1\{y^{(i)} = j\} (\log(e^{\theta^{(j)T} x^{(i)}}) - \log \sum_{l=1}^K e^{\theta^{(l)T} x^{(i)}})$$

$$E(\theta) = - \sum_{i=1}^N \sum_{j=1}^K 1\{y^{(i)} = j\} (\theta^{(j)T} x^{(i)} - \log \sum_{l=1}^K e^{\theta^{(l)T} x^{(i)}})$$

$$\nabla_{\theta^{(k)}} E(\theta) = - \sum_{i=1}^N 1\{y^{(i)} = k\} (x^{(i)} - \frac{x^{(i)} e^{\theta^{(j)T} x^{(i)}}}{\sum_{j=1}^K e^{\theta^{(j)T} x^{(i)}}})$$

$$\nabla_{\theta^{(k)}} E(\theta) = - \sum_{i=1}^N x^{(i)} (1\{y^{(i)} = k\} - \frac{e^{\theta^{(j)T} x^{(i)}}}{\sum_{j=1}^K e^{\theta^{(j)T} x^{(i)}}})$$

$$\nabla_{\theta^{(k)}} E(\theta) = - \sum_{i=1}^N x^{(i)} (1\{y^{(i)} = k\} - P(y^{(i)} = k | x^{(i)}; \theta))$$

Problem 3

See code in Appendix or attached file regression.py

Problem 4

I implemented Logistic Regression with Stochastic Batch Gradient Descent. The default parameters results in a run with 100 learning iterations on random batch sets of size 1000. The learning rate defaults to $1e-4$.

Logistic Regression Overall Accuracy: 0.8725

Label 0 Accuracy: 0.977142857143

Label 1 Accuracy: 0.961538461538

Label 2 Accuracy: 0.835616438356

Label 3 Accuracy: 0.850241545894

Label 4 Accuracy: 0.861751152074

Label 5 Accuracy: 0.821229050279

Label 6 Accuracy: 0.921348314607

Label 7 Accuracy: 0.819512195122

Label 8 Accuracy: 0.822916666667

Label 9 Accuracy: 0.855670103093

Problem 5

See attached file for graph image

I implemented Softmax Regression with Stochastic Batch Gradient Descent. The default parameters results in a run with 100 learning iterations on random batch sets of size 1000. The learning rate defaults to $1e-4$.

Softmax Regression Overall Accuracy: 0.881

Label 0 Accuracy: 0.988571428571

Label 1 Accuracy: 0.974358974359

Label 2 Accuracy: 0.826484018265

Label 3 Accuracy: 0.869565217391

Label 4 Accuracy: 0.898617511521

Label 5 Accuracy: 0.832402234637

Label 6 Accuracy: 0.910112359551

Label 7 Accuracy: 0.853658536585

Label 8 Accuracy: 0.817708333333

Label 9 Accuracy: 0.835051546392

The accuracy of softmax does seem to consistently be slightly better. This could be due to it working by training weights for each individual case.

Appendix

Listing 1: Perceptron – Flower Classifier

```
1 import random
2 import numpy as np
3 import matplotlib.pyplot as plt
4 from scipy import stats
5
6 def findZScore(data):
7     """
8     Predicts Z-Scores of data
9     :param data: List of x vectors and labels ex: [[array[], label],...]
10    :return: data with x vectors normalized to Z-Scores
11    """
12    for col in range(4):
13        temp = []
14        for row in range(len(data)):
15            temp.append(data[row][0][col])
16        zScores = stats.zscore(np.array(temp))
17        for row in range(len(data)):
18            data[row][0][col] = zScores[row]
19    return data
20
21 def plotData(data, x, y, name, zScore):
22     """
23     Scatter plots two columns in data
24     :param data: List of x vectors and labels ex: [[array[], label],...]
25     :param x: column in data
26     :param y: column in data
27     :param name: list of attribute name for x, y
28     :param zScore: flag if data has been normalized to Z-Scores
29     """
30     xAxis, yAxis = name
31     figure = plt.figure()
32     ax = figure.add_subplot(1,1,1)
33     xSet, ySet, xVer, yVer = [], [], [], []
34     for line in data:
35         if line[1] == 0:
36             xSet.append(line[0][x])
37             ySet.append(line[0][y])
38         else:
39             xVer.append(line[0][x])
40             yVer.append(line[0][y])
41     ax.scatter(xSet, ySet, color='red')
42     ax.scatter(xVer, yVer, color='blue')
43     if zScore:
44         ax.set_title('Z Scores: ' + xAxis + ' vs. ' + yAxis +
45                     '(Setosa=Red, Versicolor=Blue)')
46     else:
47         ax.set_title(xAxis + ' vs. ' + yAxis +
48                     '(Setosa=Red, Versicolor=Blue)')
49     ax.set_xlabel(xAxis)
50     ax.set_ylabel(yAxis)
51     if zScore:
52         figure.savefig('ScatterPlots/ZScore/ZScore_' + xAxis + '_' +
53                       yAxis + '.png')
54     else:
55         figure.savefig('ScatterPlots/' + xAxis + '_' + yAxis + '.png')
56     return
57
```

```

58 def generatePlots(inputFile, zScore):
59     """
60     Builds all possible column vs. column plots
61     :param inputFile: filename
62     :param zScore: flag if data has been normalized to Z-Scores
63     """
64     name = {0: 'Sepal Length',
65             1: 'Sepal Width',
66             2: 'Pedal Length',
67             3: 'Pedal Width'}
68     data = parseData(inputFile)
69     if zScore:
70         data = findZScore(data)
71     for i in range(4):
72         for j in range(i+1, 4):
73             if i != j:
74                 plotData(data, i, j, [name[i], name[j]], zScore)
75     return
76
77 def classLabel(label):
78     """
79     Determines label of attributes
80     :param label: flower name
81     :return: binary label
82     """
83     if 'setosa' in label:
84         return 0
85     else:
86         return 1
87
88 def parseData(trainFile):
89     """
90     Parses data out of input file
91     :param trainFile: filename
92     :return: List of x vectors and labels ex: [[array[], label],...]
93     """
94     file = open(trainFile)
95     lines = file.readlines()
96     for x in range(len(lines)):
97         line = lines[x].strip().split(',')
98         xVector = np.array([float(line[x]) for x in range(4)])
99         lines[x] = [xVector, classLabel(line[4])]
100     file.close()
101     return lines
102
103 def trainPerceptron(trainFile, zScore):
104     """
105     Trains w vector and threshold
106     :param trainFile: filename
107     :param zScore: flag if you want the data to be normalized to Z-Scores
108     :return: w and threshold
109     """
110     a = random.randint(1, 1000)
111     train = parseData(trainFile)
112     if zScore:
113         train = findZScore(train)
114     w = np.array([0] * 4)
115     threshold = 0
116     randRange = len(train) - 1
117     limit = 0
118     while (limit < 100):
119         rand = random.randint(0, randRange)

```

```

120         x, teacher = train[rand]
121         net = np.dot(x, w)
122         if net >= threshold:
123             output = 1
124         else:
125             output = 0
126         w = w + a * (teacher - output) * x
127         threshold = threshold + (teacher - output)
128         limit += 1
129     return w, threshold
130
131 def predict(w, threshold, testFile, zScore):
132     """
133     Predicts type of flower and prints error rate
134     :param w: vector of weights
135     :param threshold: threshold constant
136     :param testFile: filename
137     :param zScore: flag if w and threshold were generated based on Z-Scores
138     """
139     test = parseData(testFile)
140     if zScore:
141         test = findZScore(test)
142     error = 0
143     for x, label in test:
144         net = np.dot(x, w)
145         if net >= threshold:
146             output = 1
147         else:
148             output = 0
149         if output != label:
150             error += 1
151     print('Error Rate: ', end='')
152     print(error / len(test))
153     return
154
155 #Builds scatter plots
156 generatePlots('iris_train.data', False)
157 #Builds Z-Score scatter plots
158 generatePlots('iris_train.data', True)
159 #Trains perceptron
160 w, threshold = trainPerceptron('iris_train.data', False)
161 #Predicts results with perceptron
162 predict(w, threshold, 'iris_test.data', False)

```

```

1  import os, struct
2  import numpy as np
3  from array import array as pyarray
4  from numpy import append, array, int8, uint8, zeros
5  from scipy import stats
6  import math
7  import random
8  import matplotlib.pyplot as plt
9
10
11 def loadMNIST(dataset="training", digits=np.arange(10), path="."):
12     """
13     Loads MNIST files into 3D numpy arrays
14
15     Adapted from: http://abel.ee.ucla.edu/cvxopt/\_downloads/mnist.py
16     """
17     if dataset == "training":
18         fname_img = os.path.join(path, 'train-images.idx3-ubyte')
19         fname_lbl = os.path.join(path, 'train-labels.idx1-ubyte')
20     elif dataset == "testing":
21         fname_img = os.path.join(path, 't10k-images.idx3-ubyte')
22         fname_lbl = os.path.join(path, 't10k-labels.idx1-ubyte')
23     else:
24         raise ValueError("dataset must be 'testing' or 'training'")
25
26     flbl = open(fname_lbl, 'rb')
27     magic_nr, size = struct.unpack(">II", flbl.read(8))
28     lbl = pyarray("b", flbl.read())
29     flbl.close()
30
31     fimg = open(fname_img, 'rb')
32     magic_nr, size, rows, cols = struct.unpack(">IIII", fimg.read(16))
33     img = pyarray("B", fimg.read())
34     fimg.close()
35
36     ind = [ k for k in range(size) if lbl[k] in digits ]
37     N = len(ind)
38
39     images = zeros((N, rows, cols), dtype=uint8)
40     labels = zeros((N, 1), dtype=int8)
41     for i in range(len(ind)):
42         images[i] = array(img[ ind[i]*rows*cols : (ind[i]+1)*rows*cols ]).reshape(←
43             ((rows, cols))
44         labels[i] = lbl[ind[i]]
45
46     return images, labels
47
48 #Lambda function to only grab first 20000 training set
49 trainingData = lambda : (x[0:20000] for x in loadMNIST())
50 #Lambda function to only grab first 2000 testing set
51 testingData = lambda : (x[0:2000] for x in loadMNIST('testing'))
52
53 def setupData(dataType):
54     """
55     Computes the Z-Scores for the images and adds the intercept term
56     :param dataType: either training or testing
57     :return: images, labels
58     """
59     if dataType != 'training' and dataType != 'testing':
60         raise ValueError('dataType must be training or testing')

```

```

60     if dataType == 'training':
61         images, labels = trainingData()
62     else:
63         images, labels = testingData()
64     images = [np.insert(stats.zscore(np.concatenate(x)), 0, 1.0) for x in images]
65     return images, labels
66
67 class logisticRegression:
68
69     def __init__(self, learn=1, iterations=100, subset=1000):
70         """
71         Creates a logistic regression object and performs a gradient descent
72         :param self: logisticRegression object
73         :param learn: learning rate factor, defaults=1
74         :param iterations: number of weight training iterations, default=100
75         :param subset: size of random stochastic batch sampling, default=1000
76         :attribute trainImages: vectorized zscores of training images
77         :attribute trainLabels: vectorized labels of training images
78         :attribute testImages: vectorized zscores of testing images
79         :attribute testLabels: vectorized labels of testing images
80         :attribute weights: vector matrix of pixel weights by classifications 785↵
81                             x10
82         :attribute labels: 10x10 identity matrix used for label processing
83         :attribute learn: learning rate, learn / (subset * 10)
84         :attribute error: vector of testing errors on each label
85         :attribute totals: vector of the number of each label in the testing set
86         """
87         self.trainImages, self.trainLabels = setupData('training')
88         self.testImages, self.testLabels = setupData('testing')
89         self.weights = np.array([[0.0] * len(self.trainImages[0]) for x in range↵
90                                 (10)])
91         self.labels = np.array([[1 if x == y else 0 for x in range(10)] for y in ↵
92                                 range(10)])
93         self.learn = learn / (subset * 10)
94         self.iterations = iterations
95         self.subset = subset
96         self.error = np.array([0] * 10)
97         self.totals = np.array([0] * 10)
98         for k in range(10):
99             for _ in range(self.iterations):
100                 self.gradient(k)
101                 self.predict()
102
103     def probability(self, x, k):
104         """
105         Determines probability of a label for an image
106         :param x: image vector
107         :param k: label
108         :return: probability
109         """
110         dot = np.dot(self.weights[k], x)
111         return 1 / (1 + math.exp(-1 * dot))
112
113     def gradient(self, k):
114         """
115         Gradient descent learning algorithm, updates weights
116         :param k: label
117         """
118         subset = random.sample(range(len(self.trainImages)), self.subset)
119         temp = sum((self.probability(self.trainImages[i], [k]) - self.labels[k][↵
120                                self.trainLabels[i]])
121                   * self.trainImages[i] for i in subset)

```



```

118         self.weights[k] = self.weights[k] - self.learn * temp
119
120     def predict(self):
121         """
122         Predicts testImages labels
123         """
124         for x, y in zip(self.testImages, self.testLabels):
125             guess = 0
126             best = 0
127             self.totals[y] += 1
128             for k in range(10):
129                 if best < self.probability(x, k):
130                     guess = k
131                     best = self.probability(x, k)
132             if y != guess:
133                 self.error[y] += 1
134
135     class softmaxRegression:
136
137     def __init__(self, learn=1, iterations=100, subset=1000):
138         """
139         Creates a softmax regression object and performs a gradient descent
140         :param self: softmaxRegression object
141         :param learn: learning rate factor, defaults=1
142         :param iterations: number of weight training iterations, default=100
143         :param subset: size of random stochastic batch sampling, default=1000
144         :attribute trainImages: vectorized zscores of training images
145         :attribute trainLabels: vectorized labels of training images
146         :attribute testImages: vectorized zscores of testing images
147         :attribute testLabels: vectorized labels of testing images
148         :attribute weights: vector matrix of pixel weights by classifications 785↵
149                             x10
150         :attribute labels: 10x10 identity matrix used for label processing
151         :attribute learn: learning rate, learn / (subset * 10)
152         :attribute error: vector of testing errors on each label
153         :attribute totals: vector of the number of each label in the testing set
154         """
155         self.trainImages, self.trainLabels = setupData('training')
156         self.testImages, self.testLabels = setupData('testing')
157         self.weights = np.array([[0.0] * len(self.trainImages[0]) for x in range↵
158                                 (10)])
159         self.labels = np.array([[1 if x == y else 0 for x in range(10)] for y in ↵
160                                range(10)])
161         self.learn = learn / (subset * 10)
162         self.iterations = iterations
163         self.subset = subset
164         self.error = np.array([0] * 10)
165         self.totals = np.array([0] * 10)
166         for _ in range(self.iterations):
167             self.gradient()
168             self.predict()
169
170     def probability(self, x):
171         """
172         Determines probability of a label for an image
173         :param x: image vector
174         :return: probability vector 10x1
175         """
176         numerator = np.array([(math.exp(np.dot(self.weights[i], x))) for i in ↵
177                               range(10)])
178         denominator = sum(math.exp(np.dot(self.weights[i], x)) for i in range(10)↵
179                            )

```

```

175         return numerator / denominator
176
177     def gradient(self):
178         """
179         Gradient descent learning algorithm, updates weights
180         """
181         subset = random.sample(range(len(self.trainImages)), self.subset)
182         for k in range(10):
183             temp = sum(self.trainImages[i] * (self.labels[k][self.trainLabels[i]]
184                 - self.probability(self.trainImages[i])[k]) for i in ←
185                 subset)
186             self.weights[k] = self.weights[k] - self.learn * (-1 * temp)
187
188     def predict(self):
189         """
190         Predicts testImages labels
191         """
192         for x, y in zip(self.testImages, self.testLabels):
193             self.totals[y] += 1
194             if y != self.probability(x).argmax():
195                 self.error[y] += 1
196
197     def plotData():
198         """
199         Plots softmax accuracy relative to iterations of gradient descent
200         """
201         x = []
202         y = []
203         for iterations in range(10, 101, 10):
204             sr = softmaxRegression(iterations=iterations)
205             x.append(iterations)
206             y.append(1 - sum(sr.error) / 2000)
207         figure = plt.figure()
208         ax = figure.add_subplot(1,1,1)
209         ax.scatter(x, y)
210         ax.set_title('Iterations vs. Test Accuracy')
211         ax.set_xlabel('Iterations')
212         ax.set_ylabel('Test Accuracy')
213         figure.savefig('SoftmaxPlotAccuracy.png')
214
215
216
217 #builds logisticRegression object with default params
218 lr = logisticRegression()
219 #prints number of errors for each label type
220 print(lr.error)
221 #prints overall test accuracy
222 print('Logistic Regression Overall Accuracy: ', end='')
223 print(1 - sum(lr.error) / 2000)
224 count = 0
225 for x, y in zip(lr.error, lr.totals):
226     print('Label ' + str(count) + ' Accuracy: ' + str(1 - x / y))
227     count += 1
228 print(' ')
229
230 #Plots softmax accuracy data
231 plotData()
232
233 #build softmaxRegression object with default params
234 sr = softmaxRegression()
235 #prints number of errors for each label type

```

```
236 print(sr.error)
237 #prints overall test accuracy
238 print('Softmax Regression Overall Accuracy: ', end='')
239 print(1 - sum(sr.error) / 2000)
240 count = 0
241 for x, y in zip(sr.error, sr.totals):
242     print('Label ' + str(count) + ' Accuracy: ' + str(1 - x / y))
243     count += 1
```
