

E14 BP Algorithm (C++/Python)

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2020 年 12 月 10 日

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1 Horse Colic Data Set

The description of the horse colic data set (<http://archive.ics.uci.edu/ml/datasets/Horse+Colic>) is as follows:

Data Set Characteristics:	Multivariate	Number of Instances:	368	Area:	Life
Attribute Characteristics:	Categorical, Integer, Real	Number of Attributes:	27	Date Donated	1989-08-06
Associated Tasks:	Classification	Missing Values?	Yes	Number of Web Hits:	108569

We aim at trying to predict if a horse with colic will live or die.

Note that we should deal with missing values in the data! Here are some options:

- Use the feature's mean value from all the available data.
- Fill in the unknown with a special value like -1.
- Ignore the instance.
- Use a mean value from similar items.
- Use another machine learning algorithm to predict the value.

2 Reference Materials

1. Stanford: **CS231n: Convolutional Neural Networks for Visual Recognition** by Fei-Fei Li, etc.

- Course website: <http://cs231n.stanford.edu/2017/syllabus.html>
- Video website: https://www.bilibili.com/video/av17204303/?p=9&tdsourcetag=s_pctim_aiomsg

2. **Machine Learning** by Hung-yi Lee

- Course website: <http://speech.ee.ntu.edu.tw/~tlkagk/index.html>
- Video website: <https://www.bilibili.com/video/av9770302/from=search>

3. A Simple neural network code template

```
1 # -*- coding: utf-8 -*-
2 import random
```

```

3 import math
4
5 # Shorthand:
6 # "pd_" as a variable prefix means "partial derivative"
7 # "d_" as a variable prefix means "derivative"
8 # "_wrt_" is shorthand for "with respect to"
9 # "w_ho" and "w_ih" are the index of weights from hidden to
    output layer neurons and input to hidden layer neurons
    respectively
10
11 class NeuralNetwork:
12     LEARNING_RATE = 0.5
13     def __init__(self, num_inputs, num_hidden, num_outputs,
        hidden_layer_weights = None, hidden_layer_bias = None,
        output_layer_weights = None, output_layer_bias = None
        ):
14         #Your Code Here
15
16     def init_weights_from_inputs_to_hidden_layer_neurons(self
        , hidden_layer_weights):
17         #Your Code Here
18
19     def
        init_weights_from_hidden_layer_neurons_to_output_layer_neurons
        (self, output_layer_weights):
20         #Your Code Here
21
22     def inspect(self):
23         print('-----')
24         print('* Inputs: {}'.format(self.num_inputs))
25         print('-----')
26         print('Hidden Layer')
27         self.hidden_layer.inspect()

```

```

28         print('-----')
29         print('* Output Layer ')
30         self.output_layer.inspect()
31         print('-----')
32
33     def feed_forward(self, inputs):
34         #Your Code Here
35
36     # Uses online learning, ie updating the weights after
37         each training case
38     def train(self, training_inputs, training_outputs):
39         self.feed_forward(training_inputs)
40
41         # 1. Output neuron deltas
42         #Your Code Here
43         #  $E / z$ 
44
45         # 2. Hidden neuron deltas
46         # We need to calculate the derivative of the error
47             with respect to the output of each hidden layer
48             neuron
49         #  $dE / dy = \sum_w E / z * z / y = \sum E / z *$ 
50
51         #  $E / z = dE / dy * z /$ 
52         #Your Code Here
53
54         # 3. Update output neuron weights
55         #  $E / w = E / z * z / w$ 
56         #  $\Delta w = \alpha * E / w$ 
57         #Your Code Here
58
59         # 4. Update hidden neuron weights
60         #  $E / w = E / z * z / w$ 

```

```

57         #  $\Delta w = \alpha * E / w$ 
58         #Your Code Here
59
60     def calculate_total_error(self, training_sets):
61         #Your Code Here
62         return total_error
63
64 class NeuronLayer:
65     def __init__(self, num_neurons, bias):
66
67         # Every neuron in a layer shares the same bias
68         self.bias = bias if bias else random.random()
69
70         self.neurons = []
71         for i in range(num_neurons):
72             self.neurons.append(Neuron(self.bias))
73
74     def inspect(self):
75         print('Neurons:', len(self.neurons))
76         for n in range(len(self.neurons)):
77             print(' Neuron', n)
78             for w in range(len(self.neurons[n].weights)):
79                 print(' Weight:', self.neurons[n].weights[w
80                     ])
81             print(' Bias:', self.bias)
82
83     def feed_forward(self, inputs):
84         outputs = []
85         for neuron in self.neurons:
86             outputs.append(neuron.calculate_output(inputs))
87         return outputs
88
89     def get_outputs(self):

```

```

89         outputs = []
90         for neuron in self.neurons:
91             outputs.append(neuron.output)
92         return outputs
93
94 class Neuron:
95     def __init__(self, bias):
96         self.bias = bias
97         self.weights = []
98
99     def calculate_output(self, inputs):
100 #Your Code Here
101
102     def calculate_total_net_input(self):
103 #Your Code Here
104
105     # Apply the logistic function to squash the output of the
106     # neuron
107     # The result is sometimes referred to as 'net' [2] or '
108     # net' [1]
109
110     def squash(self, total_net_input):
111 #Your Code Here
112
113     # Determine how much the neuron's total input has to
114     # change to move closer to the expected output
115
116     #
117     # Now that we have the partial derivative of the error
118     # with respect to the output (E / y) and
119     # the derivative of the output with respect to the total
120     # net input ( dy/ dz) we can calculate
121     # the partial derivative of the error with respect to the
122     # total net input.
123
124     # This value is also known as the delta  $\delta$  () [1]

```

```

116 #  $\delta = E / z = E / y * dy / dz$ 
117 #
118 def calculate_pd_error_wrt_total_net_input(self,
        target_output):
119 #Your Code Here
120
121 # The error for each neuron is calculated by the Mean
        Square Error method:
122 def calculate_error(self, target_output):
123 #Your Code Here
124
125 # The partial derivate of the error with respect to
        actual output then is calculated by:
126 #  $= 2 * 0.5 * (target\ output - actual\ output)^{(2 - 1) * -1}$ 
127 #  $= -(target\ output - actual\ output)$ 
128 #
129 # The Wikipedia article on backpropagation [1] simplifies
        to the following, but most other learning material
        does not [2]
130 #  $= actual\ output - target\ output$ 
131 #
132 # Alternative, you can use  $(target - output)$ , but then
        need to add it during backpropagation [3]
133 #
134 # Note that the actual output of the output neuron is
        often written as  $y$  and target output as  $t$  so:
135 #  $= E / y = -(t - y)$ 
136 def calculate_pd_error_wrt_output(self, target_output):
137 #Your Code Here
138
139 # The total net input into the neuron is squashed using
        logistic function to calculate the neuron's output:

```

```

140 #  $y = \Phi = 1 / (1 + e^{(-z)})$ 
141 # Note that where output represents the output of the neurons
    in whatever layer we're looking at and layer represents
    the layer below it
142 #
143 # The derivative (not partial derivative since there is
    only one variable) of the output then is:
144 #  $dy/dz = y * (1 - y)$ 
145 def calculate_pd_total_net_input_wrt_input(self):
146 #Your Code Here
147
148 # The total net input is the weighted sum of all the
    inputs to the neuron and their respective weights:
149 #  $z = net = \sum xw + \text{bias}$  ...
150 #
151 # The partial derivative of the total net input with
    respective to a given weight (with everything else
    held constant) then is:
152 #  $\partial z / \partial w = \text{some constant} + 1 * xw^{(1-0)} + \text{some constant} \dots = x$ 
153 def calculate_pd_total_net_input_wrt_weight(self, index):
154 #Your Code Here
155
156 # An example:
157
158 nn = NeuralNetwork(2, 2, 2, hidden_layer_weights=[0.15, 0.2,
    0.25, 0.3], hidden_layer_bias=0.35, output_layer_weights
    =[0.4, 0.45, 0.5, 0.55], output_layer_bias=0.6)
159 for i in range(10000):
160     nn.train([0.05, 0.1], [0.01, 0.99])
161     print(i, round(nn.calculate_total_error([[[0.05, 0.1],
        [0.01, 0.99]]]), 9))

```


3 Tasks

- Given the training set `horse-colic.data` and the testing set `horse-colic.test`, implement the BP algorithm and establish a neural network to predict if horses with colic will live or die. In addition, you should calculate the accuracy rate.
- Please submit a file named `E14.YourNumber.pdf` and send it to `ai_2020@foxmail.com`
- Draw the training loss and accuracy curves
- (optional) You can try different structure of neural network and compare their accuracy and the time they cost.

4 Codes and Results

code

```
1 """ 孙新梦
2
3     18340149
4     BP.py
5 """
6 import numpy as np
7 import copy
8 from math import exp, tanh, sqrt
9 from collections import Counter
10 import matplotlib.pyplot as plt
11 import random
12
13 # 激活函数
14 activate_functions = {
15     'sigmoid': lambda x: 1 / (1 + exp(-x)),
16     'tanh': lambda x: tanh(x),
17     'relu': lambda x: 0 if x <= 0 else x,
18     'softmax': lambda x, exp_sum_except_x: exp(x) / (
19         exp_sum_except_x + exp(x)),
```

```

19     'linear': lambda x: x
20 }
21
22 # 激活函数的导函数
23 activate_function_derivatives = {
24     'sigmoid': lambda x: exp(-x) / ((1 + exp(-x)) ** 2),
25     'tanh': lambda x: 1 - tanh(x) ** 2,
26     'relu': lambda x: 0 if x <= 0 else 1,
27     'softmax': lambda x, exp_sum_except_x: exp_sum_except_x * exp(
28         x) / ((exp_sum_except_x + exp(x)) ** 2),
29     'linear': lambda x: 1
30 }
31
32 class NeuronNetwork(object):
33     # 初始化神经网络:
34     def __init__(self, layer_dict, weight_init_dict,
35         bias_init_dict, activate_type_ = 'relu'):
36         self.neuron_layer = {}
37         if 'output' in layer_dict:
38             self.derivative = np.zeros((layer_dict['output'][0],
39                 1))
40         if 'softmax' in layer_dict:
41             self.derivative = np.zeros((layer_dict['softmax'][0],
42                 1))
43         for layer_type_, layer_neurons in layer_dict.items():
44             self.neuron_layer[layer_type_] = []
45             for i, num in enumerate(layer_neurons):
46                 self.neuron_layer[layer_type_].append(
47                     NeuronLayer(num, bias_init_dict[layer_type_][i],
48                         activate_type = activate_type_,
49                         layer_type = layer_type_)

```

```

46         if layer_type_ != 'input':
47             self.neuron_layer[layer_type_][i].
                setInputWeight(weight_init_dict[layer_type_
                    ][i])
48
49 # 设置超参数
50 def setHyperparameters(self, learning_rate = 1e-3, alpha =
    0.9, beta = 0.9, epochs = 300):
51     self.learning_rate = learning_rate
52     self.alpha = alpha
53     self.beta = beta
54     self.epochs = epochs
55     self.loss_epochs = [0 for _ in range(epochs)]
56     self.accuracy_epochs = [0 for _ in range(epochs)]
57
58 # 设置验证集
59 def setValidationData(self, val_features, val_labels):
60     self.val_features = val_features
61     self.val_labels = val_labels
62     self.val_accuracy_epochs = [0 for _ in range(epochs)]
63
64 # 设置优化器
65 def setOptimizer(self, optimizer_type = 'simple'):
66     self.optimizer_type = optimizer_type
67
68 def setResultDict(self, res_list):
69     self.res_list = res_list
70
71 # 扩展一层的输出，方便下一层的输入
72 def expandOutput(self, output, n):
73     if output.shape[0] == 1:
74         expanded_output = np.zeros((output.shape[1], n))
75         for i in range(n):

```

```

76         expanded_output[:, i] = output[0, :]
77     else:
78         expanded_output = np.zeros((output.shape[0], n))
79         for i in range(n):
80             expanded_output[:, i] = output[:, 0]
81     return expanded_output
82
83 # 预测一条数据
84 def predictOne(self, feature, label, is_training = True,
85               is_detailed = False):
86     # 计算输入层输出
87     self.neuron_layer['input'][0].setInput(feature)
88     hidden_output = self.neuron_layer['input'][0].calOutput()
89
90     # 计算隐藏层输出
91     for i, x in enumerate(self.neuron_layer['hidden']):
92         expanded_output = self.expandOutput(hidden_output, len
93         (x.neurons))
94         self.neuron_layer['hidden'][i].setInput(
95             expanded_output)
96         hidden_output = self.neuron_layer['hidden'][i].
97             calOutput()
98
99     # 计算输出层输出
100     if 'output' in self.neuron_layer:
101         expanded_output = self.expandOutput(hidden_output, len
102         (self.neuron_layer['output'][0].neurons))
103         self.neuron_layer['output'][0].setInput(
104             expanded_output)
105         hidden_output = self.neuron_layer['output'][0].
106             calOutput()
107
108     # 计算层输出softmax

```

```

102         if 'softmax' in self.neuron_layer:
103             expanded_output = self.expandOutput(hidden_output, len
                (self.neuron_layer['softmax'][0].neurons))
104             self.neuron_layer['softmax'][0].setInput(
                expanded_output)
105             hidden_output = self.neuron_layer['softmax'][0].
                calOutput()
106
107         # 对于每一个样例,  $E = (output - label)^2$ , 计
            算 $dE / d(output)$ 
108         self.derivative += hidden_output - label
109         index = np.argmax(hidden_output, axis = 0)
110         predict = self.res_list[index[0]]
111         index = np.argmax(label, axis = 0)
112         true_res = self.res_list[index[0]]
113
114         # 比较是否正确
115         flag = (predict == true_res)
116         if not is_training:
117             if is_detailed:
118                 print预测(":", predict, end = " ")
119                 print结果(":", true_res, end = " ")
120                 if flag:
121                     print("True")
122                 else:
123                     print("False")
124
125             return 0, flag
126
127         if 'softmax' in self.neuron_layer:
128             return self.neuron_layer['softmax'][0].calLoss(label),
                flag
129         return self.neuron_layer['output'][0].calLoss(label), flag

```

```

130
131 # 预测全部输入数据
132 def predictAll(self, features, labels, is_training = True,
    is_detailed = False):
133     assert(features.shape[0] == labels.shape[0])
134     feature_len = features.shape[1]
135     label_len = labels.shape[1]
136
137     total_loss, total_accuracy = 0, 0
138     for i in range(features.shape[0]):
139         now_loss, now_accuracy = self.predictOne(features[i].
            reshape((1, feature_len)), labels[i].reshape((
                label_len, 1)), is_training, is_detailed)
140         total_loss += now_loss
141         total_accuracy += now_accuracy
142
143     total_loss /= features.shape[0]
144     total_accuracy /= features.shape[0]
145     #  $dE / d(\text{output}) = 1 / n * \sum(\text{output} - \text{label})$ 
146     self.derivative /= features.shape[0]
147
148     return total_loss, total_accuracy
149
150 # 误差逆传播
151 def backPropagation(self, iter_num = None):
152     forward_derivative = self.derivative
153
154     if self.optimizer_type == 'simple':
155         if 'softmax' in self.neuron_layer:
156             forward_derivative = self.neuron_layer['softmax
                '][0].simpleBackwardUpdate(forward_derivative,
                    self.learning_rate)
157         if 'output' in self.neuron_layer:

```

158	<pre> forward_derivative = self.neuron_layer['output '][0].simpleBackwardUpdate(forward_derivative , self.learning_rate) </pre>	<pre> self . learning , </pre>
159	<pre> </pre>	<pre> self . alpha , </pre>
160	<pre> i = len(self.neuron_layer['hidden']) - 1 </pre>	<pre> self . beta) </pre>
161	<pre> while i >= 0: </pre>	<pre> self . beta) </pre>
162	<pre> forward_derivative = self.neuron_layer['hidden'][i].simpleBackwardUpdate(forward_derivative , self .learning_rate) </pre>	<pre> self . beta) </pre>
163	<pre> i -= 1 </pre>	<pre> self . beta) </pre>
164	<pre> else: </pre>	<pre> self . beta) </pre>
165	<pre> if 'softmax' in self.neuron_layer: </pre>	<pre> self . beta) </pre>
166	<pre> forward_derivative = self.neuron_layer['softmax '][0].adamBackwardUpdate(forward_derivative , iter_num , </pre>	<pre> self . beta) </pre>
167	<pre> </pre>	<pre> self . beta) </pre>
168	<pre> if 'output' in self.neuron_layer: </pre>	<pre> self . beta) </pre>
169	<pre> forward_derivative = self.neuron_layer['output '][0].adamBackwardUpdate(forward_derivative , </pre>	<pre> self . beta) </pre>

170	iter_num ,	self
		. learning ,
		self . alpha ,
		self . beta)
171		
172	i = len(self.neuron_layer['hidden']) - 1	
173	while i >= 0:	
174	forward_derivative = self.neuron_layer['hidden'][i]].adamBackwardUpdate(forward_derivative , iter_num ,	
175		self . learning_rat , self . alpha , self


```
.  
beta  
)
```

```
176         i -= 1  
177  
178     # 训练  
179     def train(self, train_features, train_labels):  
180         best_accuracy = 0  
181         best_epoch = 0  
182         for i in range(self.epochs):  
183             if i > 0 and i % 200 == 0:  
184                 self.learning_rate /= 2  
185                 self.loss_epochs[i], self.accuracy_epochs[i] = self.  
186                     predictAll(train_features, train_labels)  
187                 print第(" %d 代, Loss: %.6f"%(i, self.loss_epochs[i]))  
188                 print准确度(" : %.6f"%(self.accuracy_epochs[i]))  
189  
190                 self.backPropagation(i)  
191                 _, self.val_accuracy_epochs[i] = self.predictAll(self.  
192                     val_features, self.val_labels, is_training = False)  
193                 if best_accuracy < self.val_accuracy_epochs[i]:  
194                     best_accuracy = self.val_accuracy_epochs[i]  
195                     best_epoch = i  
196                 print("Val Accuracy:", self.val_accuracy_epochs[i])  
197             print最佳准确  
198                 度(" %.6f 第 %d 代"%(best_accuracy, best_epoch))  
199  
200     # 生成正确率和的图像loss  
201     def plotInfo(self):  
202         x = list(range(0, self.epochs))  
203         plt.figure(1)
```

```

202         plt.xlabel('')
203         plt.ylabel('值loss')
204
205         plt.plot(x, self.loss_epochs, 'b-^', linewidth = 2)
206         plt.savefig('loss.png')
207
208         plt.figure(2)
209         plt.xlabel('epochs')
210         plt.ylabel('accuracy')
211
212         plt.plot(x, self.accuracy_epochs, 'c-x', linewidth = 2)
213         plt.plot(x, self.val_accuracy_epochs, 'r-.', linewidth =
214                 2)
215         plt.legend(['train', 'val'])
216         plt.savefig('accuracy.png')
217
218     def predict(self, test_features, test_labels):
219         _, accuracy = self.predictAll(test_features, test_labels,
220                                     is_training = False, is_detailed = True)
221         print("Test Accuracy:", accuracy)
222
223 class NeuronLayer(object):
224     # 激活函数: 层用, 层用, 隐藏层可自行设定激活函
225     # 数outputsigmoidsoftmaxsoftmax
226     def __init__(self, num_neurons, bias, activate_type = 'relu',
227                 layer_type = 'hidden'):
228         self.bias = bias
229         self.bias_first_moment = np.zeros(bias.shape)
230         self.bias_second_moment = np.zeros(bias.shape)
231         self.layer_type = layer_type
232         if layer_type == 'input':
233             self.neurons = [Neuron(0, 'linear') for i in range(
234                             num_neurons)]

```

```

230         elif layer_type == 'softmax':
231             self.neurons = [Neuron(bias[i, 0], 'softmax') for i in
                               range(num_neurons)]
232         elif layer_type == 'output':
233             self.neurons = [Neuron(bias[i, 0], 'sigmoid') for i in
                               range(num_neurons)]
234         else:
235             self.neurons = [Neuron(bias[i, 0], activate_type) for
                               i in range(num_neurons)]
236         self.input = None
237         self.input_weight = None
238         self.exp_sum = None
239         self.output = np.zeros((num_neurons, 1))
240
241     # inputs: m * n(为上一层神经元数目, 为当前层神经元数目mn)
242     def setInput(self, inputs):
243         assert(inputs.shape[1] == len(self.neurons))
244         self.inputs = copy.deepcopy(inputs)
245         for i in range(len(self.neurons)):
246             self.neurons[i].setInput(inputs[:, i].reshape((inputs.
                                                                shape[0], 1)))
247
248     # 记录入权重: m * n
249     def setInputWeight(self, weights):
250         assert(self.layer_type != 'input')
251         assert(weights.shape[1] == len(self.neurons))
252         self.weights = copy.deepcopy(weights)
253         self.weight_first_moment = np.zeros(weights.shape)
254         self.weight_second_moment = np.zeros(weights.shape)
255         for i in range(len(self.neurons)):
256             self.neurons[i].setInputWeight(weights[:, i].reshape((
                                                                weights.shape[0], 1)))
257

```

```

258 # 计算输出: n * 1
259 def calOutput(self):
260     if self.layer_type == 'input':
261         self.output = copy.deepcopy(self.inputs)
262     else:
263         if self.layer_type == 'softmax':
264             self.exp_sum = 0
265
266             for i, x in enumerate(self.neurons):
267                 self.output[i, 0] = x.calOutput()
268                 # 层计算的和softmaxexp
269                 if self.layer_type == 'softmax':
270                     self.exp_sum += self.output[i, 0]
271
272             if self.layer_type == 'softmax':
273                 for i, _ in enumerate(self.neurons):
274                     self.output[i, 0] /= self.exp_sum
275                     self.neurons[i].output /= self.exp_sum
276         return self.output
277
278 # 计算损失（只有层或层）softmaxoutput
279 def calLoss(self, label):
280     assert(self.layer_type == 'softmax' or self.layer_type ==
281            'output')
282     return 0.5 * (np.linalg.norm(self.output - label, 2) ** 2)
283
284 # 梯度下降（普通的，是上一层传递过来的梯度）GDforward_derivatives
285 def simpleBackwardUpdate(self, forward_derivatives,
286                           learning_rate = 1e-3):
287     exp_sum = self.exp_sum
288     last_layer_shape = self.weights.shape[0]
289     now_derivatives = np.zeros((last_layer_shape, 1))

```

```

289         for i, x in enumerate(self.neurons):
290             bias_derivative, weight_derivative, input_derivative =
                x.calBackwardDerivative(forward_derivatives[i, 0],
                    exp_sum)
291
292         # 层只传播梯度, 不更新权重和softmaxbias
293         if self.layer_type != 'softmax':
294             self.bias[i, 0] -= learning_rate * bias_derivative
295             self.weights[:, i] -= learning_rate *
                weight_derivative[:, 0]
296             self.neurons[i].setBias(self.bias[i, 0])
297             self.neurons[i].setInputWeight(self.weights[:, i].
                reshape((last_layer_shape, 1)))
298
299             now_derivatives += input_derivative
300         else:
301             now_derivatives[i, 0] = bias_derivative
302
303         return now_derivatives
304
305     # 梯度下降(自己实现的) adam
306     def adamBackwardUpdate(self, forward_derivatives, iter_num,
        learning_rate = 1e-3, alpha = 0.9, beta = 0.9):
307         exp_sum = self.exp_sum
308         last_layer_shape = self.weights.shape[0]
309         now_derivatives = np.zeros((last_layer_shape, 1))
310         for i, x in enumerate(self.neurons):
311             bias_derivative, weight_derivative, input_derivative =
                x.calBackwardDerivative(forward_derivatives[i, 0],
                    exp_sum)
312
313         # 层只传播梯度, 不更新权重和softmaxbias
314         if self.layer_type != 'softmax':

```

```

315         first_moment = alpha * self.bias_first_moment[i,
316             0] + (1 - alpha) * bias_derivative
317         second_moment = beta * self.bias_second_moment[i,
318             0] + (1 - beta) * bias_derivative *
319             bias_derivative
320         first_moment_unbias = first_moment / (1 - alpha **
321             (iter_num + 1))
322         second_moment_unbias = second_moment / (1 - beta
323             ** (iter_num + 1))
324         self.bias[i, 0] -= learning_rate *
325             first_moment_unbias / (np.sqrt(
326                 second_moment_unbias) + 1e-7)
327         self.bias_first_moment[i, 0] = first_moment
328         self.bias_second_moment[i, 0] = second_moment
329
330         weight_first_moment = alpha * self.
331             weight_first_moment[:, i] + (1 - alpha) *
332             weight_derivative[:, 0]
333         weight_second_moment = beta * self.
334             weight_second_moment[:, i] + (1 - beta) * (
335                 weight_derivative[:, 0] ** 2)
336         weight_first_moment_unbias = weight_first_moment /
337             (1 - alpha ** (iter_num + 1))
338         weight_second_moment_unbias = weight_second_moment
339             / (1 - beta ** (iter_num + 1))
340         self.weights[:, i] -= learning_rate *
341             weight_first_moment_unbias / (np.sqrt(
342                 weight_second_moment_unbias) + 1e-7)
343         self.weight_first_moment[:, i] =
344             weight_first_moment
345         self.weight_second_moment[:, i] =
346             weight_second_moment

```

```

331         x.setBias(self.bias[i, 0])
332         x.setInputWeight(self.weights[:, i].reshape((
333             last_layer_shape, 1)))
334         now_derivatives += input_derivative
335     else:
336         now_derivatives[i, 0] = bias_derivative
337
338     return now_derivatives
339
340 class Neuron(object):
341     def __init__(self, bias, activate_type = 'relu'):
342         self.bias = bias
343         self.input = None
344         self.input_weight = None
345         self.activate_type = activate_type
346         self.activate_function = activate_functions[activate_type]
347         self.derivative_function = activate_function_derivatives[
348             activate_type]
349         self.output = 0
350         self.linear_output = 0
351
352     # 设置神经元输入: m * (1是上一层神经元数量) m
353     def setInput(self, inputs):
354         self.input = inputs
355
356     # 设置神经元入权重: m * (1是上一层神经元数量) m
357     def setInputWeight(self, weight):
358         self.input_weight = copy.deepcopy(weight)
359
360     # 设置神经元: biasm * (1是上一层神经元数量) m
361     def setBias(self, new_bias):
362         self.bias = new_bias

```

```

362 # 计算单个神经元输出
363 def calOutput(self, exp_sum = None):
364     if self.activate_type == 'linear':
365         self.output = self.input
366     else:
367         #  $y = Wx + b$ 
368         self.linear_output = np.dot(self.input.T, self.
            input_weight) + self.bias
369         if self.activate_type == 'softmax':
370             self.output = exp(self.linear_output)
371         else:
372             self.output = self.activate_function(self.
                linear_output)
373     return self.output
374
375 # 每个神经元计算梯度
376 def calBackwardDerivative(self, forward_derivative, exp_sum =
    None):
377     # 计算  $df / dy$  (是激活函数f, 是线性输出y)
378     if exp_sum == None:
379         function_derivative = self.derivative_function(self.
            linear_output)
380     else:
381         function_derivative = self.derivative_function(self.
            linear_output, exp_sum - self.output)
382     bias_derivative = forward_derivative * function_derivative
383
384     input_len = self.input.shape[0]
385     weight_derivative = np.zeros((input_len, 1))
386     input_derivative = np.zeros((input_len, 1))
387     if self.activate_type != 'softmax':
388         for i in range(input_len):
389             #  $df / dw = df / dy * dy / dw$ 

```



```

390         weight_derivative[i, 0] = bias_derivative * self.
           input[i, 0]
391         # df / dx = df / dy * dy / dx
392         input_derivative[i, 0] = bias_derivative * self.
           input_weight[i, 0]
393
394         return bias_derivative, weight_derivative,
           input_derivative
395
396 class DataHandler(object):
397     def __init__(self, file_road, linear_indexs, ignore_indexs):
398         self.file_road = file_road
399         self.linear_indexs = linear_indexs
400         self.ignore_indexs = ignore_indexs
401         self.features = []
402         self.labels = []
403
404         # [3, 4, 5, 15]
405         def isLinear(self, feature_index):
406             return feature_index in self.linear_indexs
407
408         # [2]
409         def isIgnore(self, feature_index):
410             return feature_index in self.ignore_indexs
411
412         # 读数据
413         def readData(self):
414             with open(self.file_road, 'r') as f:
415                 j = 0
416                 for line in f.readlines():
417                     now_line = line.strip('\n').strip(' ').split(' ')
418                     if now_line[0] == '':
419                         continue

```

```

420         # 只要前列数据（第列是2323）label
421         now_line = now_line[:23]
422         if now_line[-1] == '?':
423             self.labels.append(float(1.0))
424         else:
425             self.labels.append(float(now_line[-1]))
426         self.features.append([])
427         for i, x in enumerate(now_line[:-1]):
428             if x != '?':
429                 if x[0] != '0':
430                     self.features[j].append(float(x))
431                 else:
432                     self.features[j].append(x)
433             else:
434                 self.features[j].append(x)
435         j += 1
436
437     # 处理features
438     def handleFeature(self):
439         valid_feature_len = len(self.features[0]) - len(self.
440             ignore_indexs)
441         features = np.zeros((len(self.features), valid_feature_len
442             ))
443         j = 0
444         for i in range(features.shape[1]):
445             if self.isIgnore(i):
446                 continue
447             feature_col = [feature[j] for feature in self.features
448                 ]
449             no_miss_feature_col = [x for x in feature_col if x !=
450                 '?']
451             update_num = 0
452             if not self.isLinear(i):

```

```

449         update_num = 0
450     else:
451         update_num = sum(no_miss_feature_col) / len(
452             no_miss_feature_col)
453
454     # 对于缺失的数据，若为离散量，补；若为连续量，补均值0
455     for k in range(features.shape[0]):
456         if feature_col[k] == '?':
457             features[k, j] = update_num
458         else:
459             features[k, j] = feature_col[k]
460
461     # 标准化
462     features[:, j] = (features[:, j] - np.mean(features[:,
463         j])) / np.std(features[:, j])
464     j += 1
465
466     self.features = features
467
468     # 处理label
469     def handleLabel(self, classify = 3):
470         counter = Counter(self.labels).most_common()
471
472         res_dict = {}
473         for i, x in enumerate(counter):
474             res_dict[x[0]] = i
475
476         labels = np.zeros((len(self.labels), classify))
477         for i, label in enumerate(self.labels):
478             labels[i, res_dict[label]] += 1
479
480         self.labels = labels
481         return res_dict

```

```

480 # 数据增强（最后没用到）
481 def argumentData(self):
482     data_len = self.features.shape[0]
483     total_add_feature = None
484     total_add_label = None
485     flag = 0
486     for i in range(data_len):
487         index = np.argmax(self.labels[i], axis = 0)
488         add_size = (index + 1)
489         add_feature = np.zeros((add_size, self.features.shape
490                                [1]))
491         add_label = np.zeros((add_size, self.labels.shape[1]))
492
493         for j in range(add_size):
494             add_feature[j, :] = self.features[i, :]
495             add_label[j, :] = self.labels[i, :]
496
497         for j in range(self.features.shape[1]):
498             if self.isLinear(j + 1):
499                 add_feature[:, j] += 0.0001 * np.random.randn(
500                     add_size)
501
502         if flag == 0:
503             total_add_feature = add_feature
504             total_add_label = add_label
505             flag = 1
506         else:
507             total_add_feature = np.concatenate((
508                 total_add_feature, add_feature), axis = 0)
509             total_add_label = np.concatenate((total_add_label,
510                 add_label), axis = 0)
511
512     self.features = np.concatenate((self.features,
513                                     total_add_feature), axis = 0)

```

```

508         self.labels = np.concatenate((self.labels, total_add_label
509                                         ), axis = 0)
510
511     def readAndHandle(self, argument = False, classify = 3):
512         self.readData()
513         self.handleFeature()
514         self.handleLabel(classify)
515         if argument:
516             self.argumentData()
517
518 if __name__ == '__main__':
519     classify_ = 3
520     print("Read And Handle training data ...")
521     train_data_handler = DataHandler('horse-colic.data',
522                                     linear_indexs = [3, 4, 5, 15],
523                                     ignore_indexs = [2])
524     train_data_handler.readAndHandle(classify = classify_)
525     print("Done ...")
526
527     print("Read And Handle testing data ...")
528     test_data_handler = DataHandler('horse-colic.test',
529                                    linear_indexs = [3, 4, 5, 15],
530                                    ignore_indexs = [2])
531     test_data_handler.readAndHandle(classify = classify_)
532     print("Done ...")
533
534     layer_dict = {
535         'input': [21],
536         'hidden': [12],
537         'output': [3]
538         # 'softmax': [3],
539     }
540     weight_init_dict = {

```

```

540         'input': [None],
541         'hidden': [np.random.randn(21, 12) / (sqrt(21 * 12) * 0.5)
542                    ],
543         'output': [np.random.randn(12, 3) / sqrt(12 * 3)]
544         # 'softmax': [np.eye(3)],
545     }
546     bias_init_dict = {
547         'input': [np.zeros((21, 1))],
548         'hidden': [np.zeros((12, 1))],
549         'output': [np.zeros((3, 1))]
550         # 'softmax': [np.zeros((3, 1))],
551     }
552     learning_rate = 2e-3
553
554     # 的两个参数adam
555     alpha = 0.8
556     beta = 0.8
557     epochs = 400
558     # 隐藏层激活函数类型
559     activate = 'relu'
560     # 优化器
561     optimizer = 'adam'
562
563     my_nn = NeuronNetwork(layer_dict, weight_init_dict,
564                           bias_init_dict, activate)
565     my_nn.setHyperparameters(learning_rate, alpha, beta, epochs)
566     my_nn.setOptimizer(optimizer)
567     my_nn.setResultDict([1.0, 2.0, 3.0])
568
569     print("_____")
570     print(" Training ...")
571     train_features = train_data_handler.features
572     train_labels = train_data_handler.labels

```

```

571     val_features = test_data_handler.features
572     val_labels = test_data_handler.labels
573
574     my_nn.setValidationData(val_features, val_labels)
575     my_nn.train(train_features, train_labels)
576     print("Done ...")
577
578     print("_____")
579     print("Plotting ...")
580     my_nn.plotInfo()
581     print("Done ...")
582
583     print("_____")
584     print("Testing ...")
585     my_nn.predict(test_data_handler.features, test_data_handler.
        labels)
586     print("Done ...")

```

result 下面三张图分别说明了我们输出的几个部分：一个是训练的时候输出loss，准确度，之后看到经过400代训练，准确度依次提升，可以达到训练集最佳0.72准确度

之后测试集上进行测试，看到也有0.72的准确度。这两张是程序运行过程中画出的准确度和Loss值的图像，看到准确度刚开始的训练大幅度提升，之后趋于平缓，loss值则有下降的趋势

Training ...

第 0 代, Loss: 0.397882

准确度: 0.170000

Val Accuracy: 0.17647058823529413

第 1 代, Loss: 0.396291

准确度: 0.166667

Val Accuracy: 0.17647058823529413

第 2 代, Loss: 0.394804

准确度: 0.173333

Val Accuracy: 0.17647058823529413

第 3 代, Loss: 0.393394

准确度: 0.186667

Val Accuracy: 0.22058823529411764

第 4 代, Loss: 0.392053

准确度: 0.216667

Val Accuracy: 0.22058823529411764

第 5 代, Loss: 0.390792

准确度: 0.233333

Val Accuracy: 0.25

第 6 代, Loss: 0.389606

准确度: 0.240000

Val Accuracy: 0.2647058823529412

第 7 代, Loss: 0.388490

准确度: 0.256667

Val Accuracy: 0.27941176470588236

Val Accuracy: 0.7205882352941176

第 394 代, Loss: 0.272213

准确度: 0.590000

Val Accuracy: 0.7205882352941176

第 395 代, Loss: 0.272173

准确度: 0.590000

Val Accuracy: 0.7205882352941176

第 396 代, Loss: 0.272141

准确度: 0.590000

Val Accuracy: 0.7205882352941176

第 397 代, Loss: 0.272112

准确度: 0.590000

Val Accuracy: 0.7205882352941176

第 398 代, Loss: 0.272075

准确度: 0.590000

Val Accuracy: 0.7205882352941176

第 399 代, Loss: 0.272040

准确度: 0.590000

Val Accuracy: 0.7205882352941176

最佳准确度 0.720588 第 198 代

Done ...

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 3.0 False

预测: 1.0 结果: 2.0 False

预测: 1.0 结果: 3.0 False

预测: 1.0 结果: 3.0 False

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 3.0 False

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 2.0 False

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 3.0 False

预测: 1.0 结果: 1.0 True

预测: 1.0 结果: 2.0 False

Test Accuracy: 0.7205882352941176

Done ...

Process finished with exit code 0

