

E14 BP Algorithm (C++/Python)

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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

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_201901@foxmail.com`

4 Codes and Results

```
1  # -*- coding: utf-8 -*-
2  import random
3  import math
4  import pandas as pd
5  import matplotlib.pyplot as plt
6
7  # Shorthand:
8  # "pd_" as a variable prefix means "partial derivative"
9  # "d_" as a variable prefix means "derivative"
10 # "_wrt_" is shorthand for "with respect to"
11 # "w_ho" and "w_ih" are the index of weights from hidden to output layer neurons and
   input to hidden layer neurons respectively
12
13 class NeuralNetwork:
14     LEARNING_RATE = 0.05
15     def __init__(self, num_inputs, num_hidden, num_outputs, hidden_layer_weights = None,
16                 hidden_layer_bias = None, output_layer_weights = None, output_layer_bias = None
17                 ):
18         #Your Code Here
19         self.num_inputs = num_inputs
20         self.num_hidden = num_hidden
21         self.num_outputs = num_outputs
22         self.hidden_layer_weights = hidden_layer_weights
23         self.hidden_layer_bias = hidden_layer_bias
24         self.output_layer_weights = output_layer_weights
25         self.output_layer_bias = output_layer_bias
26
27         self.hidden_layer = NeuronLayer(num_hidden, hidden_layer_bias)
28         self.output_layer = NeuronLayer(num_outputs, output_layer_bias)
29
30         self.init_weights_from_inputs_to_hidden_layer_neurons(hidden_layer_weights)
31         self.init_weights_from_hidden_layer_neurons_to_output_layer_neurons(
32             output_layer_weights)
33
34     def init_weights_from_inputs_to_hidden_layer_neurons(self, hidden_layer_weights):
35         #Your Code Here
36         if not hidden_layer_weights:
37             self.hidden_layer_weights = [random.random() for i in range(self.num_inputs
38                                     * self.num_hidden)]
```

```

35     begin = 0
36     for neuron in self.hidden_layer.neurons:
37         neuron.weights = self.hidden_layer_weights[begin : begin+self.num_inputs]
38         begin += self.num_inputs
39
40
41     def init_weights_from_hidden_layer_neurons_to_output_layer_neurons(self,
42         output_layer_weights):
43         #Your Code Here
44         if not output_layer_weights:
45             self.output_layer_weights = [random.random() for i in range(self.num_hidden
46                 * self.num_outputs)]
47         begin = 0
48         for neuron in self.output_layer.neurons:
49             neuron.weights = self.output_layer_weights[begin : begin+self.num_hidden]
50             begin += self.num_hidden
51
52     def inspect(self):
53         print('_____')
54         print(' * Inputs: {} '.format(self.num_inputs))
55         print('_____')
56         print('Hidden Layer')
57         self.hidden_layer.inspect()
58         print('_____')
59         print(' * Output Layer')
60         self.output_layer.inspect()
61         print('_____')
62
63     def feed_forward(self, inputs):
64         #Your Code Here
65         self.hidden_layer_outputs = self.hidden_layer.feed_forward(inputs)
66         self.output_layer_outputs = self.output_layer.feed_forward(self.
67             hidden_layer_outputs)
68         return self.output_layer_outputs
69
70
71     # Uses online learning, ie updating the weights after each training case
72     def train(self, training_inputs, training_outputs):
73         self.feed_forward(training_inputs)
74
75         # 1. Output neuron deltas
76         # E / z

```

```

73     # Your Code Here
74     output_neuron_deltas = []
75     for j, neuron in enumerate(self.output_layer.neurons):
76         output_neuron_deltas.append(neuron.calculate_pd_error_wrt_total_net_input(
77             training_outputs[j]))
78
79     # 2. Hidden neuron deltas
80     # We need to calculate the derivative of the error with respect to the output of
81     each hidden layer neuron
82     #  $dE/dy = \sum E/z * z/y = \sum E/z * w$ 
83     #  $E/z = dE/dy * z/$ 
84     # Your Code Here
85     hidden_neuron_deltas = []
86     for h, neuron_h in enumerate(self.hidden_layer.neurons):
87         Sum = 0
88         for j, neuron_o in enumerate(self.output_layer.neurons):
89             Sum += neuron_o.weights[h] * output_neuron_deltas[j]
90             tmp = neuron_h.output * (1 - neuron_h.output)
91             hidden_neuron_deltas.append(tmp * Sum)
92
93     # 3. Update output neuron weights
94     #  $E/w = E/z * z/w$ 
95     #  $\Delta w = * E/w$ 
96     # Your Code Here
97     for j, neuron_o in enumerate(self.output_layer.neurons):
98         for h, neuron_h in enumerate(self.hidden_layer.neurons):
99             neuron_o.weights[h] += self.LEARNING_RATE * output_neuron_deltas[j] *
100                 neuron_h.output
101
102     # 4. Update hidden neuron weights
103     #  $E/w = E/z * z/w$ 
104     #  $\Delta w = * E/w$ 
105     # Your Code Here
106     for h, neuron_h in enumerate(self.hidden_layer.neurons):
107         for i, x in enumerate(training_inputs):
108             neuron_h.weights[i] += self.LEARNING_RATE * hidden_neuron_deltas[h] * x
109
110     # 5. update output layer bias
111     # for j, neuron in enumerate(self.output_layer.neurons):
112     #     neuron.bias += -1 * self.LEARNING_RATE * output_neuron_deltas[j]

```

```

111         ## 6. update hidden layer bias
112         # for h, neuron in enumerate(self.hidden_layer.neurons):
113         #     neuron.bias += -1 * self.LEARNING_RATE * hidden_neuron_deltas[h]
114
115     def calculate_total_error(self, training_sets):
116         #Your Code Here
117         total_error = 0
118         for case in training_sets:
119             training_inputs, training_outputs = case
120             self.feed_forward(training_inputs)
121             for i, target_output in enumerate(training_outputs):
122                 total_error += self.output_layer.neurons[i].calculate_error(
123                     target_output)
124         return total_error
125
126 class NeuronLayer:
127     def __init__(self, num_neurons, bias):
128
129         # Every neuron in a layer shares the same bias
130         self.bias = bias if bias else random.random()
131
132         self.neurons = []
133         for i in range(num_neurons):
134             self.neurons.append(Neuron(self.bias))
135
136     def inspect(self):
137         print('Neurons: ', len(self.neurons))
138         for n in range(len(self.neurons)):
139             print('  Neuron', n)
140             for w in range(len(self.neurons[n].weights)):
141                 print('    Weight: ', self.neurons[n].weights[w])
142             print('  Bias: ', self.bias)
143
144     def feed_forward(self, inputs):
145         outputs = []
146         for neuron in self.neurons:
147             outputs.append(neuron.calculate_output(inputs))
148         return outputs
149
150     def get_outputs(self):

```

```

151         outputs = []
152         for neuron in self.neurons:
153             outputs.append(neuron.output)
154         return outputs
155
156 class Neuron:
157     def __init__(self, bias):
158         self.bias = bias
159         self.weights = []
160
161     def calculate_output(self, inputs):
162         self.inputs = inputs
163
164         # Calculate total new input
165         total_net_input = 0
166         for i in range(len(self.weights)):
167             total_net_input += inputs[i] * self.weights[i]
168
169         # Apply the logistic function to squash the output of the neuron
170         # Here we use sigmoid function
171         x = total_net_input - self.bias
172         self.output = 1 / (1 + math.e**(-x))
173
174         return self.output
175
176     # Determine how much the neuron's total input has to change to move closer to the
177     expected output
178     #
179     # Now that we have the partial derivative of the error with respect to the output (E
180     / y) and
181     # the derivative of the output with respect to the total net input (dy/dz) we can
182     calculate
183     # the partial derivative of the error with respect to the total net input.
184     # This value is also known as the delta () [1]
185     # = E / z = E / y * dy / dz
186     #
187     def calculate_pd_error_wrt_total_net_input(self, target_output):
188         #Your Code Here
189         a = self.calculate_pd_error_wrt_output(target_output)
190         b = self.calculate_pd_total_net_input_wrt_input()
191         return -1 * a * b

```

```

189
190 # The error for each neuron is calculated by the Mean Square Error method:
191 def calculate_error(self, target_output):
192     #Your Code Here
193     return 0.5 * (target_output - self.output) ** 2
194
195 # The partial derivate of the error with respect to actual output then is calculated
by:
196 # = 2 * 0.5 * (target output - actual output) ^ (2 - 1) * -1
197 # = -(target output - actual output)
198 #
199 # The Wikipedia article on backpropagation [1] simplifies to the following, but most
other learning material does not [2]
200 # = actual output - target output
201 #
202 # Alternative, you can use (target - output), but then need to add it during
backpropagation [3]
203 #
204 # Note that the actual output of the output neuron is often written as y and target
output as t so:
205 # = E / y = -(t - y)
206 def calculate_pd_error_wrt_output(self, target_output):
207     #Your Code Here
208     return -(target_output - self.output)
209
210 # The total net input into the neuron is squashed using logistic function to
calculate the neuron's output:
211 # y = 1 / (1 + e^(-z))
212 # Note that where represents the output of the neurons in whatever layer we're
looking at and represents the layer below it
213 #
214 # The derivative (not partial derivative since there is only one variable) of the
output then is:
215 # dy/dz = y * (1 - y)
216 def calculate_pd_total_net_input_wrt_input(self):
217     #Your Code Here
218     return self.output * (1 - self.output)
219
220 # The total net input is the weighted sum of all the inputs to the neuron and their
respective weights:
221 # = z = net = xw + xw ...

```



```

222     #
223     # The partial derivative of the total net input with respect to a given weight (
        with everything else held constant) then is:
224     # =  $z/w = \text{some constant} + 1 * xw^{(1-0)} + \text{some constant} \dots = x$ 
225     def calculate_pd_total_net_input_wrt_weight(self, index):
226         #Your Code Here
227         return self.inputs[index]
228
229
230 def get_training_sets(filename):
231     training_sets = []
232     data = pd.read_csv(filename)
233
234     for line in data.values:
235         attr = list(line)
236         target = attr.pop(22)
237         training_output = [0.90 if i == (target-1) else 0.05 for i in range(3)]
238         training_input = attr
239         training_sets.append([training_input, training_output])
240     return training_sets
241
242
243 training_sets = get_training_sets('horse-colic-data.csv')
244 nn = NeuralNetwork(len(training_sets[0][0]), 3, len(training_sets[0][1]))
245 total, correct = 0, 0
246 epoch = 10
247 decay = 0.99
248 x = []
249 y = []
250 for i in range(epoch*300):
251     #x.append(i)
252     training_inputs, training_outputs = training_sets[i%len(training_sets)]
253     nn.train(training_inputs, training_outputs)
254     #y.append(nn.calculate_total_error(training_sets))
255     if i % 300 == 0:
256         print('epoch:', i // 300, 'err:', nn.calculate_total_error(training_sets))
257         nn.LEARNING_RATE *= decay
258     if i >= (epoch-1)*300:
259         output_idx = nn.output_layer_outputs.index(max(nn.output_layer_outputs))
260         target_idx = training_outputs.index(max(training_outputs))
261         total += 1

```

```

262         correct += output_idx == target_idx
263     print("Accuracy on training set:\n" ,correct/total)
264
265     #plt.xlabel("train data")
266     #plt.ylabel("Error")
267     #plt.title('bp algorithm')
268     #plt.plot(x, y, linewidth = 2, label = 'error')
269     #plt.show()
270
271
272 testing_sets = get_training_sets('horse-colic-test.csv')
273 total, correct = 0, 0
274 for i, test_case in enumerate(testing_sets):
275     input, target = test_case
276     output = nn.feed_forward(input)
277     target_idx = target.index(max(target))
278     output_idx = output.index(max(output))
279     total += 1
280     correct += target_idx == output_idx
281 print("Accuracy on testing set:\n" ,correct/total)

```

Results

```

D:\study\Artificial-Intelligence-I
epoch: 0 err: 115.59953176982211
epoch: 1 err: 52.23142678946307
epoch: 2 err: 50.695807786256026
epoch: 3 err: 50.41221918768156
epoch: 4 err: 50.29846171515466
epoch: 5 err: 50.24137961050213
epoch: 6 err: 50.20891600827906
epoch: 7 err: 50.188874736543
epoch: 8 err: 50.17576417859534
epoch: 9 err: 50.16680892866546
Accuracy on training set:
0.6366666666666667
Accuracy on testing set:
0.6029411764705882

```

Figure 1: Result

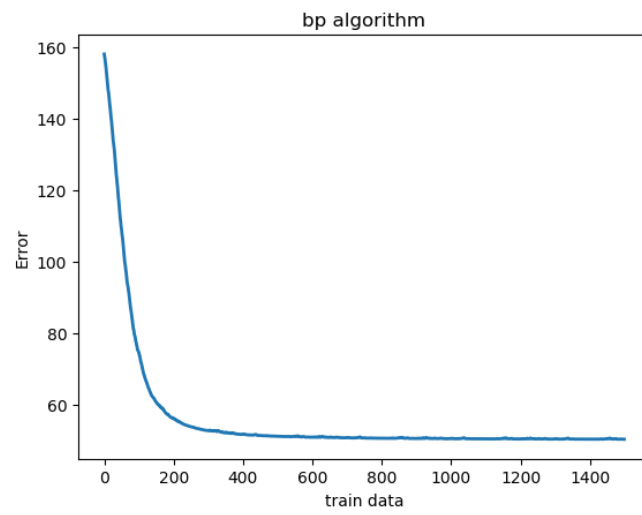


Figure 2: Training curve