

# E14 BP Algorithm (C++/Python)

---

20214966 Yangkai Lin 20214810 Suixin Ou

December 6, 2020

## Contents

<b>1</b>	<b>Horse Colic Data Set</b>	<b>2</b>
<b>2</b>	<b>Reference Materials</b>	<b>2</b>
<b>3</b>	<b>Tasks</b>	<b>7</b>
<b>4</b>	<b>Codes and Results</b>	<b>7</b>

# 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](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 each training case
37     def train(self, training_inputs, training_outputs):
38         self.feed_forward(training_inputs)
39
40         # 1. Output neuron deltas
41         #Your Code Here
42         # E / z
43
44         # 2. Hidden neuron deltas

```

```

45     # We need to calculate the derivative of the error with respect to the
        output of each hidden layer neuron
46     #  $dE/dy = E/z * z/y = E/z * w$ 
47     #  $E/z = dE/dy * z /$ 
48     #Your Code Here
49
50     # 3. Update output neuron weights
51     #  $E/w = E/z * z/w$ 
52     #  $w = * E / w$ 
53     #Your Code Here
54
55     # 4. Update hidden neuron weights
56     #  $E/w = E/z * z/w$ 
57     #  $w = * E / w$ 
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                 print('└└Bias:', self.bias)
81
82         def feed_forward(self, inputs):
83             outputs = []
84             for neuron in self.neurons:

```

```

85         outputs.append(neuron.calculate_output(inputs))
86     return outputs
87
88     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 neuron
106         # The result is sometimes referred to as 'net' [2] or 'net' [1]
107     def squash(self, total_net_input):
108         #Your Code Here
109
110         # Determine how much the neuron's total input has to change to move closer to
111         the expected output
112
113         #
114         # Now that we have the partial derivative of the error with respect to the
115         output (  $E / y$  ) and
116         # the derivative of the output with respect to the total net input (  $dy / dz$  ) we can calculate
117         # the partial derivative of the error with respect to the total net input.
118         # This value is also known as the delta ( ) [1]
119         #  $= E / z = E / y * dy / dz$ 
120
121         #
122     def calculate_pd_error_wrt_total_net_input(self, target_output):
123         #Your Code Here
124
125         # The error for each neuron is calculated by the Mean Square Error method:
126     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  $\# y = 1 / (1 + e^{(-z)})$ 
141 # Note that where represents the output of the neurons in whatever layer
    we're looking at and 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  $\# = z = net = x w + x w \dots$ 
150  $\#$ 
151 # The partial derivative of the total net input with respect to a given
    weight (with everything else held constant) then is:
152  $\# = z / w = some\ constant + 1 * x w ^{(1-0)} + some\ constant \dots$ 
     $= x$ 
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],
159                  hidden_layer_bias=0.35, output_layer_weights=[0.4, 0.45, 0.5, 0.55],
160                  output_layer_bias=0.6)
161
162 for i in range(10000):
163     nn.train([0.05, 0.1], [0.01, 0.99])
164
165     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