2/11/2021 optim.py

```
1 import numpy as np
 2
 3 | """
 4 This code was originally written for CS 231n at Stanford University
 5 (cs231n.stanford.edu). It has been modified in various areas for use in the
 6 ECE 239AS class at UCLA. This includes the descriptions of what code to
 7 implement as well as some slight potential changes in variable names to be
 8 consistent with class nomenclature. We thank Justin Johnson & Serena Yeung for
 9 permission to use this code. To see the original version, please visit
10 cs231n.stanford.edu.
11 """
12
13 """
14 This file implements various first-order update rules that are commonly used for
15 training neural networks. Each update rule accepts current weights and the
16 gradient of the loss with respect to those weights and produces the next set of
17 weights. Each update rule has the same interface:
18
19 def update(w, dw, config=None):
20
21 Inputs:
22
    - w: A numpy array giving the current weights.
     - dw: A numpy array of the same shape as w giving the gradient of the
24
       loss with respect to w.
25
     - config: A dictionary containing hyperparameter values such as learning rate,
26
       momentum, etc. If the update rule requires caching values over many
       iterations, then config will also hold these cached values.
27
28
29 Returns:
    - next w: The next point after the update.
31
     - config: The config dictionary to be passed to the next iteration of the
32
       update rule.
33
34 NOTE: For most update rules, the default learning rate will probably not perform
35 well; however the default values of the other hyperparameters should work well
36 for a variety of different problems.
38 For efficiency, update rules may perform in-place updates, mutating w and
39 setting next w equal to w.
40 """
41
42
43 def sgd(w, dw, config=None):
44
45
       Performs vanilla stochastic gradient descent.
46
47
       config format:
48
       - learning rate: Scalar learning rate.
49
50
       if config is None:
51
           config = {}
52
       config.setdefault('learning rate', 1e-2)
53
       w -= config['learning rate'] * dw
54
55
       return w, config
56
57
58 def sgd_momentum(w, dw, config=None):
59
       Performs stochastic gradient descent with momentum.
```

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```
61
62
      config format:
63
      - learning rate: Scalar learning rate.
      - momentum: Scalar between 0 and 1 giving the momentum value.
64
65
        Setting momentum = 0 reduces to sgd.
66
      - velocity: A numpy array of the same shape as w and dw used to store a moving
67
        average of the gradients.
68
69
      if config is None:
70
         config = {}
71
      config.setdefault('learning_rate', 1e-2)
72
      # set momentum to 0.9 if it wasn't there
73
      config.setdefault('momentum', 0.9)
74
      # gets velocity, else sets it to zero.
75
      v = config.get('velocity', np.zeros_like(w))
76
77
      78
      # YOUR CODE HERE:
79
         Implement the momentum update formula. Return the updated weights
80
         as next w, and the updated velocity as v.
      81
      v = config['momentum'] * v - config['learning rate'] * dw
82
83
      next w = w + v
84
      # ============ #
85
      # END YOUR CODE HERE
      # ------ #
86
87
88
      config['velocity'] = v
89
90
      return next_w, config
91
92
93 def sgd_nesterov_momentum(w, dw, config=None):
94
95
      Performs stochastic gradient descent with Nesterov momentum.
96
97
      config format:
98
      - learning rate: Scalar learning rate.
99
      - momentum: Scalar between 0 and 1 giving the momentum value.
100
        Setting momentum = 0 reduces to sgd.
101
      - velocity: A numpy array of the same shape as w and dw used to store a moving
102
        average of the gradients.
103
      if config is None:
104
105
         config = {}
      config.setdefault('learning rate', 1e-2)
106
107
      # set momentum to 0.9 if it wasn't there
108
      config.setdefault('momentum', 0.9)
109
      # gets velocity, else sets it to zero.
110
      v = config.get('velocity', np.zeros_like(w))
111
112
      # ========== #
113
      # YOUR CODE HERE:
         Implement the momentum update formula. Return the updated weights
114
         as next_w, and the updated velocity as v.
115
      116
      v_old = v
117
      v = config['momentum'] * v - config['learning rate'] * dw
118
      next_w = w + v + config['momentum'] * (v-v_old)
119
      120
```

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```
121
      # END YOUR CODE HERE
122
      123
      config['velocity'] = v
124
125
126
      return next_w, config
127
128
129 def rmsprop(w, dw, config=None):
130
131
      Uses the RMSProp update rule, which uses a moving average of squared gradient
132
      values to set adaptive per-parameter learning rates.
133
134
      config format:
135
      - learning rate: Scalar learning rate.
136
       - decay_rate: Scalar between 0 and 1 giving the decay rate for the squared
137
        gradient cache.
138
      - epsilon: Small scalar used for smoothing to avoid dividing by zero.
139
       - beta: Moving average of second moments of gradients.
140
141
      if config is None:
142
          config = {}
      config.setdefault('learning rate', 1e-2)
143
144
       config.setdefault('decay_rate', 0.99)
145
       config.setdefault('epsilon', 1e-8)
       config.setdefault('a', np.zeros_like(w))
146
147
148
      next w = None
149
150
      # ============= #
151
      # YOUR CODE HERE:
152
         Implement RMSProp. Store the next value of w as next w. You need
153
          to also store in config['a'] the moving average of the second
154
          moment gradients, so they can be used for future gradients. Concretely,
155
          config['a'] corresponds to "a" in the lecture notes.
156
      a = config['a']
157
158
      eps = config['epsilon']
159
      beta = config['decay_rate']
160
      a = beta * a + (1-beta) * dw * dw
      next w = w - config['learning rate'] * dw / (np.sqrt(a) + eps)
161
162
      config['a'] = a
163
      # _____ # #
      # END YOUR CODE HERE
164
165
       166
167
      return next_w, config
168
169
170 def adam(w, dw, config=None):
171
172
      Uses the Adam update rule, which incorporates moving averages of both the
173
       gradient and its square and a bias correction term.
174
175
      config format:
      - learning rate: Scalar learning rate.
176
177
      - beta1: Decay rate for moving average of first moment of gradient.
178
      - beta2: Decay rate for moving average of second moment of gradient.
179
       - epsilon: Small scalar used for smoothing to avoid dividing by zero.
180
      - m: Moving average of gradient.
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```
config = {}
config.setdefault('learning_rate', 1e-3)
config.setdefault('beta1', 0.9)
config.setdefault('beta2', 0.999)
config.setdefault('epsilon', 1e-8)
config.setdefault('v', np.zeros_like(w))
config.setdefault('a', np.zeros_like(w))
config.setdefault('t', 0)
next w = None
# YOUR CODE HERE:
# Implement Adam. Store the next value of w as next w. You need
  to also store in config['a'] the moving average of the second
   moment gradients, and in config['v'] the moving average of the
   first moments. Finally, store in config['t'] the increasing time.
# =========== #
b1 = config['beta1']
b2 = config['beta2']
eps = config['epsilon']
a = config['a']
v = config['v']
config['t'] += 1
v = b1 * v + (1-b1) * dw
a = b2 * a + (1-b2) * dw * dw
vu = v / (1-b1**config['t'])
au = a / (1-b2**config['t'])
next_w = w - config['learning_rate'] * vu / (np.sqrt(au) + eps)
config['a'] = a
config['v'] = v
# END YOUR CODE HERE
return next_w, config
```

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