```
1 import numpy as np
 2 from nndl.layers import *
 3 import pdb
 4
 5
 6 This code was originally written for CS 231n at Stanford University
  (cs231n.stanford.edu). It has been modified in various areas for use in the
8 ECE 239AS class at UCLA. This includes the descriptions of what code to
9 implement as well as some slight potential changes in variable names to be
10 consistent with class nomenclature. We thank Justin Johnson & Serena Yeung for
11 permission to use this code. To see the original version, please visit
12 cs231n.stanford.edu.
13 """
14
15 def conv_forward_naive(x, w, b, conv_param):
16
17
    A naive implementation of the forward pass for a convolutional layer.
18
19
    The input consists of N data points, each with C channels, height H and width
    W. We convolve each input with F different filters, where each filter spans
20
    all C channels and has height HH and width HH.
21
22
23
    Input:
24
    - x: Input data of shape (N, C, H, W)
25
    - w: Filter weights of shape (F, C, HH, WW)
26
    - b: Biases, of shape (F,)
27
    - conv_param: A dictionary with the following keys:
      - 'stride': The number of pixels between adjacent receptive fields in the
28
29
       horizontal and vertical directions.
30
      - 'pad': The number of pixels that will be used to zero-pad the input.
31
32
    Returns a tuple of:
    - out: Output data, of shape (N, F, H', W') where H' and W' are given by
33
      H' = 1 + (H + 2 * pad - HH) / stride
34
35
      W' = 1 + (W + 2 * pad - WW) / stride
36
    - cache: (x, w, b, conv_param)
37
38
39
    pad = conv_param['pad']
40
    stride = conv_param['stride']
41
    # ----- #
42
43
    # YOUR CODE HERE:
44
    # Implement the forward pass of a convolutional neural network.
45
        Store the output as 'out'.
46
       Hint: to pad the array, you can use the function np.pad.
    47
48
    (N, C, H, W) = x.shape
49
    (F, C, HH, WW) = w.shape
    H_new = 1 + (H + 2 * pad - HH) / stride
50
    \overline{W}_new = 1 + (W + 2 * pad - WW) / stride
51
52
    xpad = np.pad(x, ((0,0), (0,0), (pad,pad), (pad,pad)), mode='constant')
    out = np.zeros((N,F,H_new, W_new))
53
54
55
    for n in range(N):
56
      for f in range(F):
57
        for h in range(H_new):
          for wd in range(W new):
58
59
           h1 = h*stride
           h2 = h1+HH
60
61
           w1 = wd*stride
62
           w2 = w1+WW
           window = xpad[n,:,h1:h2, w1:w2] * w[f,:,:,:]
63
64
            sumWindow = np.sum(window)
65
            out[n,f,h,wd] = sumWindow + b[f]
66
67
68
69
    70
    # END YOUR CODE HERE
    # ----- #
71
72
73
    cache = (x, w, b, conv_param)
    return out, cache
```

```
75
 76
 77 def conv backward naive(dout, cache):
78
     A naive implementation of the backward pass for a convolutional layer.
79
80
81
     Inputs:
     - dout: Upstream derivatives.
82
83
     - cache: A tuple of (x, w, b, conv param) as in conv forward naive
84
85
     Returns a tuple of:
     - dx: Gradient with respect to x
86
87
     - dw: Gradient with respect to w
88
     - db: Gradient with respect to b
89
90
     N, F, out_height, out_width = dout.shape
     x, w, b, conv_param = cache
91
92
     dx, dw, db = None, None, None
93
     dx = np.zeros_like(x)
94
     dw = np.zeros_like(w)
95
     db = np.zeros_like(b)
96
97
     N, C, H, W = x.shape
98
     F, _, HH, WW = w.shape
99
100
     stride, pad = [conv_param['stride'], conv_param['pad']]
101
     xpad = np.pad(x, ((0,0), (0,0), (pad,pad), (pad,pad)), mode='constant')
102
     dxpad = np.pad(dx, ((0,0), (0,0), (pad,pad), (pad,pad)), mode='constant')
103
     num_filts, _, f_height, f_width = w.shape
104
105
     for n in range(N):
106
       for f in range(F):
107
         for ht in range(out_height):
108
          for wd in range(out width):
109
            h1 = ht*stride
110
            h2 = h1+HH
            w1 = wd*stride
111
112
            w2 = w1+WW
113
            dxpad[n,:,h1:h2, w1:w2] += w[f,:,:,:] * dout[n,f,ht,wd]
            dw[f,:,:,:] += xpad[n,:,h1:h2, w1:w2] * dout[n,f,ht,wd]
114
            db[f] += dout[n,f,ht,wd]
115
116
       dx[n,:,:,:] = dxpad[n,:, pad:-pad, pad:-pad]
117
118
119
120
     121
     # YOUR CODE HERE:
122
     # Implement the backward pass of a convolutional neural network.
     # Calculate the gradients: dx, dw, and db.
123
     # ------ #
124
125
126
127
     # ------ #
128
     # END YOUR CODE HERE
     # ------ #
129
130
131
     return dx, dw, db
132
133
134 def max pool forward naive(x, pool param):
135
     A naive implementation of the forward pass for a max pooling layer.
136
137
138
139
     - x: Input data, of shape (N, C, H, W)
     - pool_param: dictionary with the following keys:
140
141
       - 'pool height': The height of each pooling region
       - 'pool_width': The width of each pooling region
142
       - 'stride': The distance between adjacent pooling regions
143
144
145
     Returns a tuple of:
146
     - out: Output data
147
     - cache: (x, pool param)
148
149
     out = None
```

```
150
    N, C, H, W = x.shape
    pool_height = pool_param['pool_height']
151
    pool_width = pool_param['pool_width']
152
153
     stride = pool_param['stride']
    H_new = 1 + (H - pool_height) / stride
154
155
    W new = 1 + (W - pool width) / stride
156
    out = np.zeros((N,C,H_new, W_new))
                     ______ #
157
158
    # YOUR CODE HERE:
159
    # Implement the max pooling forward pass.
    # ------ #
160
    for n in range(N):
161
      for c in range(C):
162
163
        for h in range(H_new):
164
         for wd in range(W new):
165
           h1 = h*stride
           h2 = h1+pool_height
166
167
           w1 = wd*stride
           w2 = w1+pool_width
168
169
           window = np.max(x[n,c,h1:h2, w1:w2])
170
           out[n,c,h,wd] = window
171
    # ------ #
172
173
    # END YOUR CODE HERE
    # ------#
174
175
    cache = (x, pool_param)
176
    return out, cache
177
178 def max_pool_backward_naive(dout, cache):
179
180
    A naive implementation of the backward pass for a max pooling layer.
181
182
    Inputs:
183
     - dout: Upstream derivatives
184
     - cache: A tuple of (x, pool_param) as in the forward pass.
185
186
    Returns:
187
     - dx: Gradient with respect to x
188
189
    dx = None
190
    x, pool param = cache
    pool_height, pool_width, stride = pool_param['pool_height'], pool_param['pool_width'], pool_param['stride']
191
192
193
    # ----- #
194
     # YOUR CODE HERE:
195
    # Implement the max pooling backward pass.
196
    # ----- #
197
    N, F, out_height, out_width = dout.shape
198
    dx = np.zeros_like(x)
199
200
    N, C, H, W = x.shape
201
202
203
    for n in range(N):
204
      for c in range(C):
205
        for ht in range(out height):
206
         for wd in range(out_width):
207
           h1 = ht*stride
208
           h2 = h1+pool_height
209
           w1 = wd*stride
210
           w2 = w1+pool width
           window = x[n,c,h1:h2, w1:w2]
211
212
           window2 = np.reshape(window,(pool height*pool width))
           window3 = np.zeros like(window2)
213
214
           window3[np.argmax(window2)] = 1
215
           dx[n,c,h1:h2, w1:w2] = np.reshape(window3,(pool_height, pool_width)) * dout[n,c,ht,wd]
216
217
218
219
220
     # ----- #
221
     # END YOUR CODE HERE
222
     # ------ #
223
224
    return dx
```

```
225
226 def spatial_batchnorm_forward(x, gamma, beta, bn_param):
227
228
     Computes the forward pass for spatial batch normalization.
229
230
231
     - x: Input data of shape (N, C, H, W)
232
     - gamma: Scale parameter, of shape (C,)
233
     - beta: Shift parameter, of shape (C,)
234
     - bn_param: Dictionary with the following keys:
235
      - mode: 'train' or 'test'; required
      - eps: Constant for numeric stability
236
237
      - momentum: Constant for running mean / variance. momentum=0 means that
238
        old information is discarded completely at every time step, while
        momentum=1 means that new information is never incorporated. The
239
240
        default of momentum=0.9 should work well in most situations.
      - running mean: Array of shape (D,) giving running mean of features
241
242
      - running var Array of shape (D,) giving running variance of features
243
244
     Returns a tuple of:
245
     - out: Output data, of shape (N, C, H, W)
246
     - cache: Values needed for the backward pass
247
248
     out, cache = None, None
     N, C, H, W = x.shape
249
250
     XTranspose = x.transpose(0,2,3,1)
251
     x_reshape = np.reshape(XTranspose,(N*H*W, C))
252
     253
     # YOUR CODE HERE:
254
      Implement the spatial batchnorm forward pass.
255
256
     # You may find it useful to use the batchnorm forward pass you
257
     # implemented in HW #4.
258
     259
     out1, cache = batchnorm_forward(x_reshape, gamma, beta, bn_param)
260
261
     out = out1.reshape((N,H,W,C)).transpose(0,3,1,2)
262
263
     264
     # END YOUR CODE HERE
265
     266
267
     return out, cache
268
269
270 def spatial_batchnorm_backward(dout, cache):
271
272
     Computes the backward pass for spatial batch normalization.
273
274
     Inputs:
275
     - dout: Upstream derivatives, of shape (N, C, H, W)
276
     - cache: Values from the forward pass
277
278
     Returns a tuple of:
279
     - dx: Gradient with respect to inputs, of shape (N, C, H, W)
280
     - dgamma: Gradient with respect to scale parameter, of shape (C,)
281
     - dbeta: Gradient with respect to shift parameter, of shape (C,)
282
283
     dx, dgamma, dbeta = None, None, None
284
285
     # ------ #
     # YOUR CODE HERE:
286
287
     # Implement the spatial batchnorm backward pass.
288
     # You may find it useful to use the batchnorm forward pass you
289
     #
290
        implemented in HW #4.
291
     # ----- #
292
     dx = np.zeros_like(dout)
     N, C, H, W = dout.shape
293
294
     doutTranspose = dout.transpose((0, 2, 3, 1))
295
     dout_reshape = np.reshape(doutTranspose, (-1, C))
     dx_flat, dgamma, dbeta = batchnorm_backward(dout_reshape, cache)
296
297
     dx = dx_{\text{flat.reshape}}((N, H, W, C)).transpose(0, 3, 1, 2)
298
```