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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
ECE 239AS class at UCLA. This includes the descriptions of what code to
implement as well as some slight potential changes in variable names to be
consistent with class nomenclature. We thank Justin Johnson & Serena Yeung for
permission to use this code. To see the original version, please visit
cs231n.stanford.edu.
from nndl.layers import *
from utils.gradient_check import eval_numerical_gradient, eval_numerical_gradient_array
from nndl.layer utils import affine relu forward, affine relu backward
from nndl.fc net import FullyConnectedNet
def rel error(x, y):
  """ returns relative error """
  return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
def affine forward test():
    # Test the affine forward function
    num inputs = 2
    input shape = (4, 5, 6)
    output dim = 3
    input_size = num_inputs * np.prod(input_shape)
   weight size = output dim * np.prod(input shape)
   x = np.linspace(-0.1, 0.5, num=input size).reshape(num inputs, *input shape)
    w = np.linspace(-0.2, 0.3, num=weight size).reshape(np.prod(input shape), output dim)
   b = np.linspace(-0.3, 0.1, num=output dim)
    out, = affine forward(x, w, b)
    correct out = np.array([[1.49834967, 1.70660132, 1.91485297],
                            [ 3.25553199, 3.5141327, 3.77273342]])
    # Compare your output with ours. The error should be around 1e-9.
   print('If affine forward function is working, difference should be less than 1e-9:')
   print('difference: {}'.format(rel error(out, correct out)))
def affine backward test():
    # Test the affine_backward function
   x = np.random.randn(10, 2, 3)
    w = np.random.randn(6, 5)
   b = np.random.randn(5)
    dout = np.random.randn(10, 5)
   dx num = eval numerical gradient array(lambda x: affine forward(x, w, b)[0], x, dout)
    dw_num = eval_numerical_gradient_array(lambda w: affine_forward(x, w, b)[0], w, dout)
    db num = eval numerical gradient array(lambda b: affine forward(x, w, b)[0], b, dout)
     , cache = affine forward(x, w, b)
   dx, dw, db = affine backward(dout, cache)
    # The error should be around 1e-10
    print('If affine backward is working, error should be less than 1e-9::')
   print('dx error: {}'.format(rel error(dx num, dx)))
   print('dw error: {}'.format(rel error(dw num, dw)))
   print('db error: {}'.format(rel error(db num, db)))
def relu forward test():
    # Test the relu forward function
   x = np.linspace(-0.5, 0.5, num=12).reshape(3, 4)
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out, _ = relu_forward(x)
                                           0.,
                                                                     0.,
    correct_out = np.array([[ 0.,
                                                        0.,
                                                                     0.13636364,],
                            [ 0.,
                                         0.,
                                                        0.04545455,
                            [ 0.22727273, 0.31818182, 0.40909091,
                                                                     0.5,
                                                                                ]])
    # Compare your output with ours. The error should be around 1e-8
    print('If relu forward function is working, difference should be around 1e-8:')
    print('difference: {}'.format(rel error(out, correct out)))
def relu backward test():
    x = np.random.randn(10, 10)
    dout = np.random.randn(*x.shape)
    dx num = eval numerical gradient array(lambda x: relu forward(x)[0], x, dout)
    _, cache = relu forward(x)
    dx = relu backward(dout, cache)
    # The error should be around 1e-12
   print('If relu forward function is working, error should be less than 1e-9:')
    print('dx error: {}'.format(rel error(dx num, dx)))
def affine relu test():
    x = np.random.randn(2, 3, 4)
    w = np.random.randn(12, 10)
    b = np.random.randn(10)
    dout = np.random.randn(2, 10)
    out, cache = affine relu forward(x, w, b)
    dx, dw, db = affine relu backward(dout, cache)
    dx num = eval numerical gradient array(lambda x: affine relu forward(x, w, b)[0], x, dout)
    dw num = eval numerical gradient array(lambda w: affine relu forward(x, w, b)[0], w, dout)
    db num = eval numerical gradient array(lambda b: affine relu forward(x, w, b)[0], b, dout)
   print('If affine relu forward and affine relu backward are working, error should be less
than 1e-9::')
   print('dx error: {}'.format(rel error(dx num, dx)))
   print('dw error: {}'.format(rel error(dw num, dw)))
   print('db error: {}'.format(rel_error(db_num, db)))
def fc_net_test():
   N, D, H1, H2, C = 2, 15, 20, 30, 10
    X = np.random.randn(N, D)
    y = np.random.randint(C, size=(N,))
    for reg in [0, 3.14]:
      print('Running check with reg = {}'.format(reg))
      model = FullyConnectedNet([H1, H2], input dim=D, num classes=C,
                                reg=reg, weight_scale=5e-2, dtype=np.float64)
      loss, grads = model.loss(X, y)
      print('Initial loss: {}'.format(loss))
      for name in sorted(grads):
        f = lambda : model.loss(X, y)[0]
        grad_num = eval_numerical_gradient(f, model.params[name], verbose=False, h=1e-5)
       print('{} relative error: {}'.format(name, rel_error(grad num, grads[name])))
```