fc_net

February 2, 2023

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# %load fc_net.py
import numpy as np

from .layers import *
from .layer_utils import *


class TwoLayerNet(object):
  """
  A two-layer fully-connected neural network with ReLU nonlinearity and
  softmax loss that uses a modular layer design. We assume an input dimension
  of D, a hidden dimension of H, and perform classification over C classes.

  The architecure should be affine - relu - affine - softmax.

  Note that this class does not implement gradient descent; instead, it
  will interact with a separate Solver object that is responsible for running
  optimization.

  The learnable parameters of the model are stored in the dictionary
  self.params that maps parameter names to numpy arrays.
  """

  def __init__(self, input_dim=3*32*32, hidden_dims=100, num_classes=10,
               dropout=0, weight_scale=1e-3, reg=0.0):
    """
    Initialize a new network.

    Inputs:
    - input_dim: An integer giving the size of the input
    - hidden_dims: An integer giving the size of the hidden layer
    - num_classes: An integer giving the number of classes to classify
    - dropout: Scalar between 0 and 1 giving dropout strength.
    - weight_scale: Scalar giving the standard deviation for random
      initialization of the weights.
    - reg: Scalar giving L2 regularization strength.
    """
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        self.params = {}
        self.reg = reg

        # ================================================================ #
        # YOUR CODE HERE:
        #   Initialize W1, W2, b1, and b2.  Store these as self.params['W1'],
        #   self.params['W2'], self.params['b1'] and self.params['b2']. The
        #   biases are initialized to zero and the weights are initialized
        #   so that each parameter has mean 0 and standard deviation weight_scale.
        #   The dimensions of W1 should be (input_dim, hidden_dim) and the
        #   dimensions of W2 should be (hidden_dims, num_classes)
        # ================================================================ #
        self.params['W1'] = np.random.randn(input_dim, hidden_dims) * weight_scale
        self.params['W2'] = np.random.randn(hidden_dims, num_classes) * weight_scale
        self.params['b1'] = np.zeros((1,hidden_dims))
        self.params['b2'] = np.zeros((1,num_classes))
        pass

        # ================================================================ #
        # END YOUR CODE HERE
        # ================================================================ #

    def loss(self, X, y=None):
        """
        Compute loss and gradient for a minibatch of data.

        Inputs:
        - X: Array of input data of shape (N, d_1, ..., d_k)
        - y: Array of labels, of shape (N,). y[i] gives the label for X[i].

        Returns:
        If y is None, then run a test-time forward pass of the model and return:
        - scores: Array of shape (N, C) giving classification scores, where
          scores[i, c] is the classification score for X[i] and class c.

        If y is not None, then run a training-time forward and backward pass and
        return a tuple of:
        - loss: Scalar value giving the loss
        - grads: Dictionary with the same keys as self.params, mapping parameter
          names to gradients of the loss with respect to those parameters.
        """
        scores = None

        # ================================================================ #
        # YOUR CODE HERE:
        #   Implement the forward pass of the two-layer neural network. Store
        #   the class scores as the variable 'scores'.  Be sure to use the layers
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    #   you prior implemented.
    # ================================================================ #
    W1, W2 =  self.params['W1'], self.params['W2']
    b1, b2 = self.params['b1'], self.params['b2']
    output_first_layer, cache_first = affine_relu_forward(X, W1, b1)
    scores, cache_sec = affine_forward(output_first_layer, W2,b2)
    pass
    # ================================================================ #
    # END YOUR CODE HERE
    # ================================================================ #

    # If y is None then we are in test mode so just return scores
    if y is None:
      return scores

    loss, grads = 0, {}
    # ================================================================ #
    # YOUR CODE HERE:
    #   Implement the backward pass of the two-layer neural net.  Store
    #   the loss as the variable 'loss' and store the gradients in the
    #   'grads' dictionary.  For the grads dictionary, grads['W1'] holds
    #   the gradient for W1, grads['b1'] holds the gradient for b1, etc.
    #   i.e., grads[k] holds the gradient for self.params[k].
    #
    #   Add L2 regularization, where there is an added cost 0.5*self.reg*W^2
    #   for each W.  Be sure to include the 0.5 multiplying factor to
    #   match our implementation.
    #
    #   And be sure to use the layers you prior implemented.
    # ================================================================ #
    loss, dout = softmax_loss(scores ,y)
    d_first_hidden, dW2, db2 = affine_backward(dout, cache_sec)
    dx, dW1, db1 = affine_relu_backward(d_first_hidden, cache_first)
    dW1 = dW1 + self.reg * W1
    dW2 = dW2 + self.reg * W2
    grads['W1'], grads['W2'] = dW1, dW2
    grads['b1'], grads['b2'] = db1, db2
    loss = loss + 0.5 * np.sum( self.reg * W1 * W1 ) + 0.5 * np.sum( self.reg *
 ↪W2 * W2 )

    pass

    # ================================================================ #
    # END YOUR CODE HERE
    # ================================================================ #

    return loss, grads
```

```python
class FullyConnectedNet(object):
  """
  A fully-connected neural network with an arbitrary number of hidden layers,
  ReLU nonlinearities, and a softmax loss function. This will also implement
  dropout and batch normalization as options. For a network with L layers,
  the architecture will be

  {affine - [batch norm] - relu - [dropout]} x (L - 1) - affine - softmax

  where batch normalization and dropout are optional, and the {...} block is
  repeated L - 1 times.

  Similar to the TwoLayerNet above, learnable parameters are stored in the
  self.params dictionary and will be learned using the Solver class.
  """

  def __init__(self, hidden_dims, input_dim=3*32*32, num_classes=10,
               dropout=0, use_batchnorm=False, reg=0.0,
               weight_scale=1e-2, dtype=np.float32, seed=None):
    """
    Initialize a new FullyConnectedNet.

    Inputs:
    - hidden_dims: A list of integers giving the size of each hidden layer.
    - input_dim: An integer giving the size of the input.
    - num_classes: An integer giving the number of classes to classify.
    - dropout: Scalar between 0 and 1 giving dropout strength. If dropout=0 then
      the network should not use dropout at all.
    - use_batchnorm: Whether or not the network should use batch normalization.
    - reg: Scalar giving L2 regularization strength.
    - weight_scale: Scalar giving the standard deviation for random
      initialization of the weights.
    - dtype: A numpy datatype object; all computations will be performed using
      this datatype. float32 is faster but less accurate, so you should use
      float64 for numeric gradient checking.
    - seed: If not None, then pass this random seed to the dropout layers. This
      will make the dropout layers deteriminstic so we can gradient check the
      model.
    """
    self.use_batchnorm = use_batchnorm
    self.use_dropout = dropout > 0
    self.reg = reg
    self.num_layers = 1 + len(hidden_dims)
    self.dtype = dtype
    self.params = {}
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    # ================================================================ #
    # YOUR CODE HERE:
    #   Initialize all parameters of the network in the self.params dictionary.
    #   The weights and biases of layer 1 are W1 and b1; and in general the
    #   weights and biases of layer i are Wi and bi. The
    #   biases are initialized to zero and the weights are initialized
    #   so that each parameter has mean 0 and standard deviation weight_scale.
    # ================================================================ #
    self.params['W1'] = np.random.randn(input_dim, hidden_dims[0]) *␣
↪weight_scale
    self.params['b1'] = np.zeros(hidden_dims[0])


    for i in range(self.num_layers - 2):
      j = i + 2
      weights = str('W') + str(j)
      bias = str('b') + str(j)
      # print(weights,bias)
      self.params[weights] = np.random.randn(hidden_dims[j-2],␣
↪hidden_dims[j-1]) * weight_scale
      self.params[bias] = np.zeros((1, hidden_dims[j-1]))


    weight_last = str('W') + str(self.num_layers)
    bias_last = str('b') + str(self.num_layers)
    self.params[weight_last] = np.random.randn(hidden_dims[-1], num_classes)
    self.params[bias_last] = np.zeros(num_classes)
    pass

    # ================================================================ #
    # END YOUR CODE HERE
    # ================================================================ #

    # When using dropout we need to pass a dropout_param dictionary to each
    # dropout layer so that the layer knows the dropout probability and the mode
    # (train / test). You can pass the same dropout_param to each dropout layer.
    self.dropout_param = {}
    if self.use_dropout:
      self.dropout_param = {'mode': 'train', 'p': dropout}
      if seed is not None:
        self.dropout_param['seed'] = seed

    # With batch normalization we need to keep track of running means and
    # variances, so we need to pass a special bn_param object to each batch
    # normalization layer. You should pass self.bn_params[0] to the forward pass
    # of the first batch normalization layer, self.bn_params[1] to the forward
```

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    # pass of the second batch normalization layer, etc.
    self.bn_params = []
    if self.use_batchnorm:
      self.bn_params = [{'mode': 'train'} for i in np.arange(self.num_layers -
↪1)]

    # Cast all parameters to the correct datatype
    for k, v in self.params.items():
      self.params[k] = v.astype(dtype)


  def loss(self, X, y=None):
    """
    Compute loss and gradient for the fully-connected net.

    Input / output: Same as TwoLayerNet above.
    """
    X = X.astype(self.dtype)
    mode = 'test' if y is None else 'train'

    # Set train/test mode for batchnorm params and dropout param since they
    # behave differently during training and testing.
    if self.dropout_param is not None:
      self.dropout_param['mode'] = mode
    if self.use_batchnorm:
      for bn_param in self.bn_params:
        bn_param[mode] = mode

    scores = None
    # ================================================================== #
    # YOUR CODE HERE:
    #   Implement the forward pass of the FC net and store the output
    #   scores as the variable "scores".
    # ================================================================== #
    output = {}
    output[0] = X
    cache = {}
    for i in range(self.num_layers):
      j = i + 1
      weights = str('W') + str(j)
      bias = str('b') + str(j)
      W_j = self.params[weights]
      b_j = self.params[bias]

      if j == self.num_layers:
        output[j], cache[i] = affine_forward(output[i], W_j, b_j)
      else:
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        output[j], cache[i] = affine_relu_forward(output[i], W_j, b_j)

    scores = output[self.num_layers]
    pass

    # ============================================================== #
    # END YOUR CODE HERE
    # ============================================================== #

    # If test mode return early
    if mode == 'test':
      return scores

    loss, grads = 0.0, {}
    # ============================================================== #
    # YOUR CODE HERE:
    #   Implement the backwards pass of the FC net and store the gradients
    #   in the grads dict, so that grads[k] is the gradient of self.params[k]
    #   Be sure your L2 regularization includes a 0.5 factor.
    # ============================================================== #
    loss, dx = softmax_loss(scores, y)
    reg_loss = 0
    for i in range(self.num_layers):
      j = i + 1
      weights = str('W') + str(j)
      W_j = self.params[weights]
      reg_loss = reg_loss + 0.5 * self.reg * np.sum(W_j * W_j)
    loss = loss + reg_loss

    # compute grads
    doutput = {}
    hidden_dims = self.num_layers - 1
    weight_last = str('W') + str(self.num_layers)
    bias_last = str('b') + str(self.num_layers)
    W_last, b_last = self.params[weight_last], self.params[bias_last]
    doutput[hidden_dims], grads[weight_last], grads[bias_last] = affine_backward(dx, cache[hidden_dims])
    grads[weight_last] = grads[weight_last] + self.reg * self.params[weight_last]

    for i in range(hidden_dims):
      weight = str('W') + str(hidden_dims - i)
      bias = str('b') + str(hidden_dims - i)
      doutput[hidden_dims - i -1], grads[weight], grads[bias] = affine_relu_backward(doutput[hidden_dims - i], cache[hidden_dims - i -1])
      grads[weight] = grads[weight] + self.reg * self.params[weight]
```

```
    pass

    # =============================================================== #
    # END YOUR CODE HERE
    # =============================================================== #
    return loss, grads
```