```python
import numpy as np
import pdb
import copy
from sklearn.model_selection import train_test_split
"""
This code was based off of code from cs231n at Stanford University, and modified
for ECE C147/C247 at UCLA.
"""
class SVM(object):

  def __init__(self, dims=[10, 3073]):
    self.init_weights(dims=dims)

  def init_weights(self, dims):
    """
        Initializes the weight matrix of the SVM.  Note that it has shape (C, D)
        where C is the number of classes and D is the feature size.
        """
    self.W = np.random.normal(size=dims)

  def loss(self, X, y):
    """
    Calculates the SVM loss.

    Inputs have dimension D, there are C classes, and we operate on minibatches
    of N examples.

    Inputs:
    - X: A numpy array of shape (N, D) containing a minibatch of data.
    - y: A numpy array of shape (N,) containing training labels; y[i] = c means
      that X[i] has label c, where 0 <= c < C.

    Returns a tuple of:
    - loss as single float
    """

    # compute the loss and the gradient
    num_classes = self.W.shape[0]
    num_train = X.shape[0]
    loss = 0.0

    for i in np.arange(num_train):
    # ================================================================ #
    # YOUR CODE HERE:
        #   Calculate the normalized SVM loss, and store it as 'loss'.
    #   (That is, calculate the sum of the losses of all the training
    #   set margins, and then normalize the loss by the number of
        #       training examples.)
    # ================================================================ #

      score = np.dot(X[i],self.W.T)
      for j in range(num_classes):
        if j == y[i]:
          continue
        margin = score[j] - score[y[i]] + 1
        loss = loss + max(np.max(margin),0)
    loss = loss / num_train

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

    return loss

  def loss_and_grad(self, X, y):
    """
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        Same as self.loss(X, y), except that it also returns the gradient.

        Output: grad -- a matrix of the same dimensions as W containing
                the gradient of the loss with respect to W.
        """

    # compute the loss and the gradient
    num_classes = self.W.shape[0]
    num_train = X.shape[0]
    loss = 0.0
    grad = np.zeros_like(self.W)

    for i in np.arange(num_train):
    # ================================================================ #
    # YOUR CODE HERE:
        #   Calculate the SVM loss and the gradient.  Store the gradient in
    #   the variable grad.
    # ================================================================ #
      score = np.dot(X[i],self.W.T)
      for j in range(num_classes):
        if j != y[i]:
          margin = score[j] - score[y[i]] + 1
          loss = loss + max(np.max(margin),0)
          if margin > 0:
            grad[j] = grad[j] + X[i].T
            grad[y[i]] = grad[y[i]] - X[i].T

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

    loss /= num_train
    grad /= num_train

    return loss, grad

  def grad_check_sparse(self, X, y, your_grad, num_checks=10, h=1e-5):
    """
    sample a few random elements and only return numerical
    in these dimensions.
    """

    for i in np.arange(num_checks):
      ix = tuple([np.random.randint(m) for m in self.W.shape])

      oldval = self.W[ix]
      self.W[ix] = oldval + h # increment by h
      fxph = self.loss(X, y)
      self.W[ix] = oldval - h # decrement by h
      fxmh = self.loss(X,y) # evaluate f(x - h)
      self.W[ix] = oldval # reset

      grad_numerical = (fxph - fxmh) / (2 * h)
      grad_analytic = your_grad[ix]
      rel_error = abs(grad_numerical - grad_analytic) / (abs(grad_numerical) + abs
(grad_analytic))
      print('numerical: %f analytic: %f, relative error: %e' % (grad_numerical,
grad_analytic, rel_error))

  def fast_loss_and_grad(self, X, y):
    """
    A vectorized implementation of loss_and_grad. It shares the same
        inputs and ouptuts as loss_and_grad.
    """
    loss = 0.0
    grad = np.zeros(self.W.shape) # initialize the gradient as zero
```

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    num_classes = self.W.shape[0]
    num_train = X.shape[0]

    # ================================================================ #
    # YOUR CODE HERE:
        #   Calculate the SVM loss WITHOUT any for loops.
    # ================================================================ #

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

    #loss = np.sum([np.sum([1 - ((np.dot(X[i],self.W[y[i]].T) - np.dot(X[i],self.W
[j].T)) if y[i]!=j and (np.dot(X[i],self.W[y[i]].T) - np.dot(X[i],self.W[j].T)) <
1 else 1) for j in range(num_classes)]) for i in range(num_train)])
    score = np.dot(X,self.W.T)
    #y_belong = np.argwhere(y == 0).T.tolist() + np.argwhere(y == 1).T.tolist() +
np.argwhere(y == 2).T.tolist() + np.argwhere(y == 3).T.tolist() + np.argwhere(y ==
4).T.tolist() + np.argwhere(y == 5).T.tolist() + np.argwhere(y == 6).T.tolist() +
np.argwhere(y == 7).T.tolist() + np.argwhere(y == 8).T.tolist() + np.argwhere(y ==
9).T.tolist()
    margin_total = (score + 1 - score[:,y].diagonal().reshape(num_train,1))#.T

    np.put_along_axis(margin_total,y.T.reshape(num_train,1),0,axis=1)
    #for i in range(num_classes):
    #  margin_total[i,y_belong[i]] = 0
    margin_total[margin_total<0] = 0
    loss = np.sum(margin_total)


    margin_total[margin_total>0] = 1
    coef_neg = np.zeros((num_train,num_classes))
    coef_neg[range(num_train),y] = np.sum(margin_total,axis=1)
    grad = np.dot(margin_total.T,X) - np.dot(coef_neg.T,X)

        # ================================================================ #
    # YOUR CODE HERE:
        #   Calculate the SVM grad WITHOUT any for loops.
    # ================================================================ #
    loss /= num_train
    grad /= num_train
    # ================================================================ #
    # END YOUR CODE HERE
    # ================================================================ #

    return loss, grad

  def train(self, X, y, learning_rate=1e-3, num_iters=100,
            batch_size=200, verbose=False):
    """
    Train this linear classifier using stochastic gradient descent.

    Inputs:
    - X: A numpy array of shape (N, D) containing training data; there are N
      training samples each of dimension D.
    - y: A numpy array of shape (N,) containing training labels; y[i] = c
      means that X[i] has label 0 <= c < C for C classes.
    - learning_rate: (float) learning rate for optimization.
    - num_iters: (integer) number of steps to take when optimizing
    - batch_size: (integer) number of training examples to use at each step.
    - verbose: (boolean) If true, print progress during optimization.

    Outputs:
    A list containing the value of the loss function at each training iteration.
    """
    num_train, dim = X.shape
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    num_classes = np.max(y) + 1 # assume y takes values 0...K-1 where K is number
of classes

    self.init_weights(dims=[np.max(y) + 1, X.shape[1]]) # initializes the weights
of self.W

    # Run stochastic gradient descent to optimize W
    loss_history = []

    for it in np.arange(num_iters):
      X_batch = None
      y_batch = None

      # ================================================================ #
      # YOUR CODE HERE:
      #   Sample batch_size elements from the training data for use in
      #   gradient descent.  After sampling,
      #     - X_batch should have shape: (dim, batch_size)
            #     - y_batch should have shape: (batch_size,)
            #   The indices should be randomly generated to reduce correlations
            #   in the dataset.  Use np.random.choice.  It's okay to sample with
            #   replacement.
      # ================================================================ #
      _, X_batch,_, y_batch = train_test_split(X,y,test_size=batch_size/num_train,
random_state=int(np.random.randint(0,2**32-1,size=1)))
      # ================================================================ #
      # END YOUR CODE HERE
      # ================================================================ #

      # evaluate loss and gradient
      loss, grad = self.fast_loss_and_grad(X_batch, y_batch)
      loss_history.append(loss)

      # ================================================================ #
      # YOUR CODE HERE:
      #   Update the parameters, self.W, with a gradient step
      # ================================================================ #
      self.W = self.W - learning_rate * grad
            # ================================================================ #
      # END YOUR CODE HERE
      # ================================================================ #

      if verbose and it % 100 == 0:
        print('iteration {} / {}: loss {}'.format(it, num_iters, loss))

    return loss_history

  def predict(self, X):
    """
    Inputs:
    - X: N x D array of training data. Each row is a D-dimensional point.

    Returns:
    - y_pred: Predicted labels for the data in X. y_pred is a 1-dimensional
      array of length N, and each element is an integer giving the predicted
      class.
    """
    y_pred = np.zeros(X.shape[1])


    # ================================================================ #
    # YOUR CODE HERE:
    #   Predict the labels given the training data with the parameter self.W.
    # ================================================================ #
    y_pred = np.argmax(X.dot(self.W.T), axis=1)
    # ================================================================ #
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    # END YOUR CODE HERE
    # ================================================================ #

    return y_pred
```