```
import numpy as np
import pdb

"""
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
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    #   set margins, and then normalize the loss by the number of
          #       training examples.)
    # ================================================================
#
      for j in np.arange(num_classes):
        if y[i] != j:
            loss += max(0, 1 + self.W[j].dot(X[i]) -
self.W[y[i]].dot(X[i]))

    loss /= num_train

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

    return loss

  def loss_and_grad(self, X, y):
    """
        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.
    # ================================================================
#
      for j in np.arange(num_classes):
        if y[i] != j:
          zj = 1 + self.W[j].dot(X[i]) - self.W[y[i]].dot(X[i])
          loss += max(0, zj)
          grad[j] += 0 if zj <= 0 else X[i]
          grad[y[i]] += 0 if zj <= 0 else -X[i]
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    # =================================================================
#
    # 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

    # =================================================================
#
    # YOUR CODE HERE:
        #   Calculate the SVM loss WITHOUT any for loops.
    # =================================================================
#
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    scores = X.dot(self.W.T)
    num_train = X.shape[0]

    losses = np.ones_like(scores) + scores -
scores[np.arange(num_train), y].reshape(scores.shape[0], 1)
    losses[losses < 0] = 0
    losses[np.arange(num_train), y] = 0
    loss = np.sum(losses) / num_train

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

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

    selector = losses.T
    selector[selector > 0] = 1
    selector[y, np.arange(num_train)] = np.sum(selector, axis=0) *
(-1)
    grad = selector.dot(X) / 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
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    - 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
    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.
      #
================================================================ #

      indices = np.random.choice(num_train, batch_size)
      X_batch, y_batch = X[indices], y[indices]

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

      # evaluate loss and gradient
      loss, grad = self.fast_loss_and_grad(X_batch, y_batch)
      loss_history.append(loss)
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      #
================================================================ #
      # YOUR CODE HERE:
      #   Update the parameters, self.W, with a gradient step
      #
================================================================ #

      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.
    # ================================================================
#

    scores = X.dot(self.W.T)
    y_pred = np.argmax(scores, axis=1)

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

    return y_pred
```