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0.1 EECS 442 PS3: Learning

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0.2 Starting

Run the following code to import the modules you'll need. After your finish the assignment, remember to run all cells and save the note book to your local machine as a .ipynb file for Canvas submission.

[294]:
```
import csv
import math
import matplotlib.pyplot as plt
import numpy as np
import os
import pickle
import platform
import random
from random import randrange
from six.moves import cPickle as pickle
from skimage.color import rgb2gray
from skimage.feature import hog
import time
from torchvision.datasets import CIFAR10
from torchvision.utils import make_grid
random.seed(0)
np.random.seed(0)
download = not os.path.isdir('cifar-10-batches-py')
dset_train = CIFAR10(root='.', download=download, train='True')
dset_test = CIFAR10(root='.', train='False')
```

0.3 Debug Flag

Set the debug flag to true when testing. Setting the debug flag to true will let load_CIFAR only use 20% of the training dataset, which makes everything run faster. Please make sure to rerun the cells that call load_cifar after changing the flag. You may want to set the flag to false before reporting the answers. Please also remember to set the flag to false before submitting.

[295]:
```
DEBUG = False
```

Helper functions for data loading and gradient checking

[296]:
```
def load_pickle(f):
    version = platform.python_version_tuple()
    if version[0] == '2':
        return  pickle.load(f)
    elif version[0] == '3':
        return  pickle.load(f, encoding='latin1')
    raise ValueError("invalid python version: {}".format(version))

def load_CIFAR_batch(filename):
  """ load single batch of cifar """
  with open(filename, 'rb') as f:
    datadict = load_pickle(f)
    X = datadict['data']
    Y = datadict['labels']
    X = X.reshape(10000, 3, 32, 32).transpose(0,2,3,1).astype("float")
    Y = np.array(Y)
    return X, Y

def load_CIFAR10(ROOT):
  """ load all of cifar """
  xs = []
  ys = []
  if DEBUG:
    f = os.path.join(ROOT, 'data_batch_1')
    Xtr, Ytr = load_CIFAR_batch(f)
  else:
    for b in range(1,6):
      f = os.path.join(ROOT, 'data_batch_%d' % (b, ))
      X, Y = load_CIFAR_batch(f)
      xs.append(X)
      ys.append(Y)
    Xtr = np.concatenate(xs)
    Ytr = np.concatenate(ys)
    del X, Y
  Xte, Yte = load_CIFAR_batch(os.path.join(ROOT, 'test_batch'))
  return Xtr, Ytr, Xte, Yte

def grad_check_sparse(f, x, analytic_grad, num_checks=10, h=1e-5):
  """
  sample a few random elements and only return numerical
  in this dimensions.
  """

  for i in range(num_checks):
    ix = tuple([randrange(m) for m in x.shape])
```

```
    oldval = x[ix]
    x[ix] = oldval + h # increment by h
    fxph = f(x) # evaluate f(x + h)
    x[ix] = oldval - h # increment by h
    fxmh = f(x) # evaluate f(x - h)
    x[ix] = oldval # reset

    grad_numerical = (fxph - fxmh) / (2 * h)
    grad_analytic = analytic_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))
```

0.4 Load and visualize CIFAR-10

[297]:
```
cifar10_dir = './cifar-10-batches-py'

X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

# As a sanity check, we print out the size of the training and test data.
print('Training data shape: ', X_train.shape)
print('Training labels shape: ', y_train.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

0.4.1 Visualize some examples from the dataset.

[298]:
```
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
samples_per_class = 7

def visualize_data(dataset, classes, samples_per_class):
    num_classes = len(classes)
    for y, cls in enumerate(classes):
      idxs = np.flatnonzero(y_train == y)
      idxs = np.random.choice(idxs, samples_per_class, replace=False)
      for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
```

```
        plt.imshow(X_train[idx].reshape((32, 32, 3)).astype('uint8'))
        plt.axis('off')
        if i == 0:
          plt.title(cls)
    plt.show()

visualize_data(X_train, classes, samples_per_class)
```

0.5 Problem 3.1

0.5.1 (a) Define the KNearestNeighbor class

[299]:
```
from collections import Counter
class KNearestNeighbor(object):
  """ a kNN classifier with L2 distance """

  def __init__(self):
    pass

  def train(self, X, y):
    """
    Train the classifier. For k-nearest neighbors this is just
    memorizing the training data.
    Inputs:
    - X: A numpy array of shape (num_train, D) containing the training data
      consisting of num_train samples each of dimension D.
```

```
    - y: A numpy array of shape (N,) containing the training labels, where
         y[i] is the label for X[i].
    """
    self.X_train = X
    self.y_train = y

  def predict(self, X, k=1, num_loops=0):
    """
    Predict labels for test data using this classifier.
    Inputs:
    - X: A numpy array of shape (num_test, D) containing test data consisting
         of num_test samples each of dimension D.
    - k: The number of nearest neighbors that vote for the predicted labels.
    - num_loops: Determines which implementation to use to compute distances
      between training points and testing points.
    Returns:
    - y: A numpy array of shape (num_test,) containing predicted labels for the
      test data, where y[i] is the predicted label for the test point X[i].
    """
    if num_loops == 0:
      dists = self.compute_distances_no_loops(X)
    elif num_loops == 1:
      dists = self.compute_distances_one_loop(X)
    elif num_loops == 2:
      dists = self.compute_distances_two_loops(X)
    else:
      raise ValueError('Invalid value %d for num_loops' % num_loops)

    return self.predict_labels(dists, k=k)

  def compute_distances_two_loops(self, X):
    """
    Compute the l2 distance between each test point in X and each training␣
↪point
    in self.X_train using a nested loop over both the training data and the
    test data.
    Inputs:
    - X: A numpy array of shape (num_test, D) containing test data.
    Returns:
    - dists: A numpy array of shape (num_test, num_train) where dists[i, j]
      is the Euclidean distance between the ith test point and the jth training
      point.
    """
    num_test = X.shape[0]
    num_train = self.X_train.shape[0]
    dists = np.zeros((num_test, num_train))
    for i in range(num_test):
```

```
      for j in range(num_train):

        # ===== your code here! =====

        # TODO:
        # Compute the l2 distance between the ith test image and the jth
        # training image, and store the result in dists[i, j].

        diff = X[i] - self.X_train[j]
        dists[i, j] = np.linalg.norm(diff)

        # ==== end of code ====

    return dists

  def compute_distances_one_loop(self, X):
    """
    Compute the l2 distance between each test point in X and each training␣
↪point
    in self.X_train using a single loop over the test data.
    Input / Output: Same as compute_distances_two_loops
    """
    num_test = X.shape[0]
    num_train = self.X_train.shape[0]
    dists = np.zeros((num_test, num_train))
    for i in range(num_test):

      # ===== your code here! =====

      # TODO:
      # Compute the l2 distance between the ith test point and all training
      # points, and store the result in dists[i, :].

      tests = np.tile(X[i], (num_train, 1))
      trainers = self.X_train.reshape(num_train, -1)
      diffs = tests - trainers
      sqrs = diffs * diffs
      sums = np.sum(sqrs, axis=1)
      norms = np.sqrt(sums)
      dists[i, :] = norms

      # ==== end of code ====

    return dists

  def compute_distances_no_loops(self, X):
    """
```

```
    Compute the l2 distance between each test point in X and each training␣
↪point
    in self.X_train using no explicit loops.
    Input / Output: Same as compute_distances_two_loops
    """
    num_test = X.shape[0]
    num_train = self.X_train.shape[0]
    dists = np.zeros((num_test, num_train))

    # ===== your code here! =====

    # TODO:
    # Compute the l2 distance between all test points and all training
    # points without using any explicit loops, and store the result in
    # dists.
    #
    # You should implement this function using only basic array operations;
    # in particular you should not use functions from scipy.
    #
    # HINT: ||x - y||^2 = ||x||^2 + ||y||^2 - 2x^T y

    Y = self.X_train.reshape(num_train, X.shape[1])
    norm_X = np.sum(X**2, axis=1)
    norm_Y = np.sum(Y**2, axis=1)
    xTy = -2 * np.dot(X, Y.T)
    dists = np.sqrt(xTy + norm_Y + norm_X[:, np.newaxis])

    # ==== end of code ====

    return dists

  def predict_labels(self, dists, k=1):
    """
    Given a matrix of distances between test points and training points,
    predict a label for each test point.
    Inputs:
    - dists: A numpy array of shape (num_test, num_train) where dists[i, j]
      gives the distance betwen the ith test point and the jth training point.
    Returns:
    - y: A numpy array of shape (num_test,) containing predicted labels for the
      test data, where y[i] is the predicted label for the test point X[i].
    - knn_idxs: List of arrays, containing Indexes of the k nearest neighbors
      for the test data. So, for M classes, it will be a list of length M with
      each element of the list, an array of size 'k'. This will be used for
      visualization purposes later.
    """
    num_test = dists.shape[0]
```

```
    y_pred = np.zeros(num_test)
    knn_idxs = []
    for i in range(num_test):
      # A list of length k storing the labels of the k nearest neighbors to
      # the ith test point.

      closest_y = []

      # ===== your code here! =====

      # TODO:
      # Use the distance matrix to find the k nearest neighbors of the ith
      # testing element, and use self.y_train to find the labels of these
      # neighbors. Store these labels in closest_y.
      # Also, don't forget to apprpriately store indices knn_idxs list.
      # Hint: Look up the function numpy.argsort.

      knn_idxs.append(np.argsort(dists[i])[:k])
      for ik in range(len(knn_idxs[i])):
        closest_y.append(self.y_train[knn_idxs[i][ik]])

      # ==== end of code ====

      # Now that you have found the labels of the k nearest neighbors, the code
      # below finds the most common label in the list closest_y of labels.
      # and stores this label in y_pred[i]. We break ties by choosing the
      # smaller label.
↪

      vote = Counter(closest_y)
      count = vote.most_common()
      y_pred[i] = count[0][0]

    return y_pred, knn_idxs
```

Sample the original dataset to get a smaller dataset for efficient KNN code execution. Note here that, you can use `knn_data_dict` dictionary to access the train/ val / test splits of the data

[300]:
```
# Take a smaller subset of the training set for efficient execution of kNN

X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

if DEBUG:
  knn_num_train = 8000
  knn_num_val = 2000
else:
  knn_num_train = 10000
  knn_num_val = 2000
```

```
knn_num_test =  500

knn_data_dict = {}

knn_data_dict['X_train'] = X_train[:knn_num_train].reshape(knn_num_train, -1)
knn_data_dict['y_train'] = y_train[:knn_num_train]
knn_data_dict['X_val'] = X_train[knn_num_train:knn_num_train+knn_num_val].
 ↪reshape(knn_num_val, -1)
knn_data_dict['y_val'] = y_train[knn_num_train:knn_num_train+knn_num_val]
knn_data_dict['X_test'] = X_test[:knn_num_test].reshape(knn_num_test, -1)
knn_data_dict['y_test'] = y_test[:knn_num_test]


print('Train data shape: ', knn_data_dict['X_train'].shape)
print('Train labels shape: ', knn_data_dict['y_train'].shape)
print('Validation data shape: ', knn_data_dict['X_val'].shape)
print('Validation labels shape: ', knn_data_dict['y_val'].shape)
print('Test data shape: ', knn_data_dict['X_test'].shape)
print('Test labels shape: ', knn_data_dict['y_test'].shape)
```

```
Train data shape:  (10000, 3072)
Train labels shape:  (10000,)
Validation data shape:  (2000, 3072)
Validation labels shape:  (2000,)
Test data shape:  (500, 3072)
Test labels shape:  (500,)
```

Again, Note above that, you can use `knn_data_dict` dictionary to access the train/ val / test splits of the data

0.5.2 (b) Check L2 distance implementation

Now, let's do some checks to see if you have implemented the functions correctly. We will first calculate the distances using ***compute_distance_two_loops*** function and check the accuracies for k=1 and k=3. Then, we will compare the ***compute_distance_one_loop*** and ***compute_distance_no_loop*** functions with it to check their consistency with the ***compute_distance_two_loops*** function.

Initialize the KNN Classifier

[301]:
```
classifier = KNearestNeighbor()
classifier.train(knn_data_dict['X_train'], knn_data_dict['y_train'])
```

Compute the distance between the training and test set. This might take some time to run since we are running the two loops function which is not efficient.

[302]:
```
dists = classifier.compute_distances_two_loops(knn_data_dict['X_test'])
```

Now, let's do some checks to see if you have implemented the functions correctly. We will first calculate the distances using compute_distance_two_loops function and check the accuracies for k=1 and k=3. Then, we will compare the compute_distance_one_loop and compute_distance_no_loop functions with it to check their correctness.

Predict labels and check accuracy for k = 1. You should expect to see approximately 27% accuracy.

[303]:
```
y_test_pred, k_idxs  = classifier.predict_labels(dists, k=1)
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_data_dict['y_test'])
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 138 / 500 correct => accuracy: 0.276000
```

Let's predict the labels and calculate accuracy for k = 3. You should expect to see a slightly better performance than with k=1

[304]:
```
y_test_pred, k_idxs = classifier.predict_labels(dists, k=3)
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_data_dict['y_test'])
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 150 / 500 correct => accuracy: 0.300000
```

[305]:
```
# Implement the function compute_distances_one_loop in KNearestNeighbor class
# and run the code below:
dists_one = classifier.compute_distances_one_loop(knn_data_dict['X_test'])

# To ensure that our vectorized implementation is correct, we make sure that it
# agrees with the naive implementation. There are many ways to decide whether
# two matrices are similar; one of the simplest is the Frobenius norm. In case
# you haven't seen it before, the Frobenius norm of two matrices is the square
# root of the squared sum of differences of all elements; in other words,␣
 ↪reshape
# the matrices into vectors and compute the Euclidean distance between them.
difference = np.linalg.norm(dists - dists_one, ord='fro')
print('Difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
Difference was: 0.000000
Good! The distance matrices are the same
```

[306]:
```
# Now implement the fully vectorized version inside compute_distances_no_loops
# and run the code
dists_two = classifier.compute_distances_no_loops(knn_data_dict['X_test'])
```

```
# check that the dist ance matrix agrees with the one we computed before:
difference = np.linalg.norm(dists - dists_two, ord='fro')
print('Difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
Difference was: 0.000000
Good! The distance matrices are the same
```

[307]:
```
dists_two.shape
```

[307]:
```
(500, 10000)
```

Let's compare how fast the implementations are You should see significantly faster performance with the fully vectorized implementation

[308]:
```
def time_function(f, *args):
    """
    Call a function f with args and return the time (in seconds) that it took␣
 ↪to execute.
    """
    import time
    tic = time.time()
    f(*args)
    toc = time.time()
    return toc - tic

two_loop_time = time_function(classifier.compute_distances_two_loops,␣
 ↪knn_data_dict['X_test'])
print('Two loop version took %f seconds' % two_loop_time)

one_loop_time = time_function(classifier.compute_distances_one_loop,␣
 ↪knn_data_dict['X_test'])
print('One loop version took %f seconds' % one_loop_time)

no_loop_time = time_function(classifier.compute_distances_no_loops,␣
 ↪knn_data_dict['X_test'])
print('No loop version took %f seconds' % no_loop_time)

# you should see significantly faster performance with the fully vectorized␣
 ↪implementation
```

```
Two loop version took 61.741375 seconds
One loop version took 105.979523 seconds
No loop version took 1.233720 seconds
```

0.5.3 (c) Use the validation set for tuning the value of 'K'

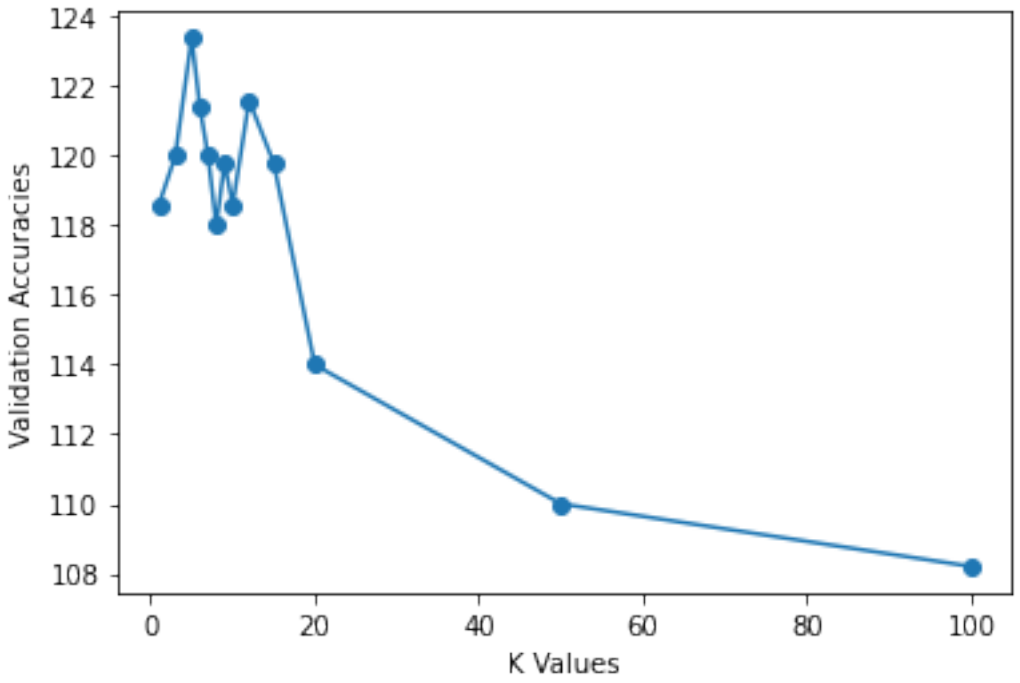
[309]:
```
k_choices = [1, 3, 5, 6, 7, 8, 9, 10, 12, 15, 20, 50, 100]
k_accuracies = np.zeros((len(k_choices), ))
classifier = KNearestNeighbor()
max_accuracy = 0
max_k = 0

classifier.train(knn_data_dict['X_train'], knn_data_dict['y_train'])
dists = classifier.compute_distances_no_loops(knn_data_dict['X_val'])
for ik, k in enumerate(k_choices):

  # ===== your code here! =====

  # TODO:
  # Find the accuracies for all the k values given in k_choices. You need to
  # use the validation set from the dictionary knn_data_dict already defined
  # for prediction and find its k nearest neighbors in the training set.
  # Note: Access the dataset using the knn_data_dict dictinoary defined earlier.

  # HINT: See how we had used the KNearestNeighbor() class
  # functions for k=1 and k=5 in the above cells.

  y_preds, k_idxs = classifier.predict_labels(dists, k)
  num_correct = np.sum(y_preds == knn_data_dict['y_val'])
  k_accuracies[ik] = float(num_correct) / knn_num_test

  # ==== end of code ====

  if(k_accuracies[ik] > max_accuracy):
    max_accuracy = k_accuracies[ik]
    max_k = k
  print("k = %d, accuracy = %f" %(k, k_accuracies[ik]))

print("Maximum validation accuracy obtained is: %f for k = %d"␣
 ↪%(max_accuracy,max_k))
```

```
k = 1, accuracy = 1.186000
k = 3, accuracy = 1.200000
k = 5, accuracy = 1.234000
k = 6, accuracy = 1.214000
k = 7, accuracy = 1.200000
k = 8, accuracy = 1.180000
k = 9, accuracy = 1.198000
k = 10, accuracy = 1.186000
k = 12, accuracy = 1.216000
k = 15, accuracy = 1.198000
k = 20, accuracy = 1.140000
```

```
k = 50, accuracy = 1.100000
k = 100, accuracy = 1.082000
Maximum validation accuracy obtained is: 1.234000 for k = 5
```

[310]:
```
plt.plot(k_choices, 100*k_accuracies, 'o-')
plt.xlabel('K Values')
plt.ylabel('Validation Accuracies')
```

[310]:
```
Text(0, 0.5, 'Validation Accuracies')
```



0.5.4 TODO:

Report the best accuracy and the corresponding k value in this cell below:

Use the best k value you found from the validation set to evaluate you final accuracy on the test set

[311]:
```
# Set the value of best_k to be equal to the 'k' which gave the best accuracy
# for the validation set.

best_k = max_k
classifier = KNearestNeighbor()
classifier.train(knn_data_dict['X_train'], knn_data_dict['y_train'])
dists = classifier.compute_distances_no_loops(knn_data_dict['X_test'])
y_test_pred, k_idxs  = classifier.predict_labels(dists, k=best_k)
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_data_dict['y_test'])
```

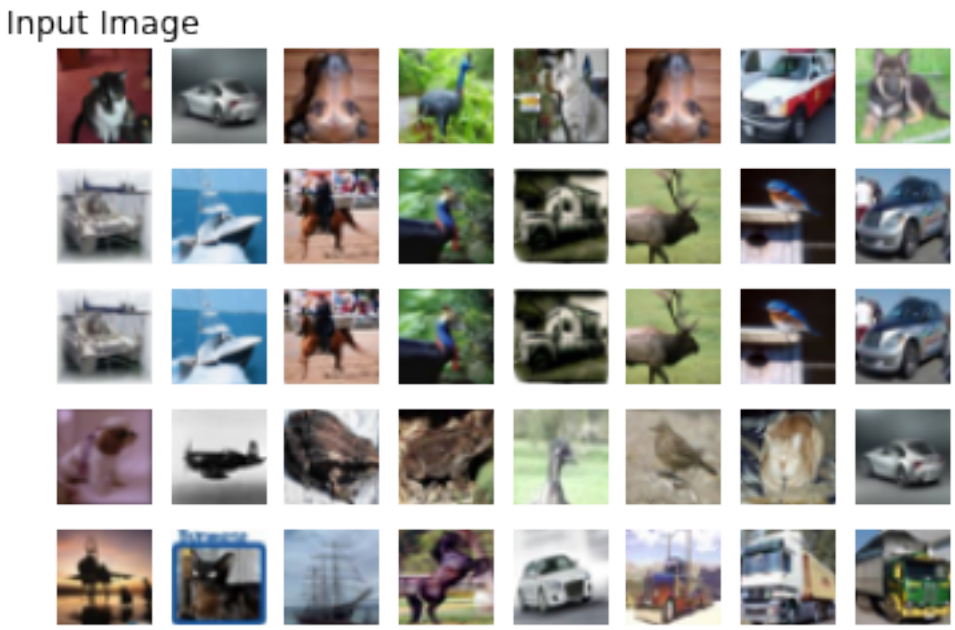
```
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 162 / 500 correct => accuracy: 0.324000
```

0.5.5 Visualize KNN results

Let's visualize the K nearest images for some randomly selected examples from the test set using the k_idxs list you returned in predict_labels

[312]:
```
def visualize_knn(num_examples, K):

  idxs = np.random.choice(500, num_examples)
  vis_im = knn_data_dict['X_test'][idxs]
  _, k_idxs = classifier.predict_labels(dists, k=K)
  vis_labels = np.stack(k_idxs, axis=0)[idxs].astype('uint8')

  num_images = num_examples*K + num_examples
  for i in range(num_images):
    plt.subplot(num_examples,K+1,i+1)
    if (i%(K+1) == 0):
      plt.imshow(vis_im[int(i/(K+1))].reshape(32,32,3).astype('uint8'))
      plt.axis('off')
      if(i==0):
        plt.title('Input Image')
    else:
      plt.imshow(knn_data_dict['X_train'][vis_labels[int(i/(K+1)), i -␣
 ↪(K+1)*int(i/(K+1)) - 1]].reshape(32,32,3).astype('uint8'))
      plt.axis('off')


# Here the leftmost column is the input image from the test set and rest of the
# K columns are the K nearest neighbors from the training set
num_examples = 5
K = 7
visualize_knn(num_examples, K)
```



0.5.6 *(Optional)* Does normalizing the images give better accuracy?

We normalize each image here by subtracting the image by its mean and dividing by its standard deviation.

[313]:
```
X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)
X_instance_mean = np.mean(X_train, axis = (1, 2, 3))
X_instance_std = np.std(X_train, axis = (1, 2, 3))
X_test_instance_mean = np.mean(X_test, axis = (1, 2, 3))
X_test_instance_std = np.std(X_test, axis = (1, 2, 3))
X_train_instance = (X_train - X_instance_mean[:, None, None, None])/
 ↪X_instance_std[:, None, None, None]
X_test_instance = (X_test - X_test_instance_mean[:, None, None, None])/
 ↪X_test_instance_std[:, None, None, None]
```

Store these tensors into a dictionary `knn_norm_data_dict`

[314]:
```
knn_norm_data_dict = {}

knn_norm_data_dict['X_train'] = X_train_instance[:knn_num_train].
 ↪reshape(knn_num_train, -1)
knn_norm_data_dict['y_train'] = y_train[:knn_num_train]
knn_norm_data_dict['X_val'] = X_train_instance[knn_num_train:
 ↪knn_num_train+knn_num_val].reshape(knn_num_val, -1)
knn_norm_data_dict['y_val'] = y_train[knn_num_train:knn_num_train+knn_num_val]
knn_norm_data_dict['X_test'] = X_test_instance[:knn_num_test].
 ↪reshape(knn_num_test, -1)
knn_norm_data_dict['y_test'] = y_test[:knn_num_test]
```

```
print('Train data shape: ', knn_norm_data_dict['X_train'].shape)
print('Train labels shape: ', knn_norm_data_dict['y_train'].shape)
print('Validation data shape: ', knn_norm_data_dict['X_val'].shape)
print('Validation labels shape: ', knn_norm_data_dict['y_val'].shape)
print('Test data shape: ', knn_norm_data_dict['X_test'].shape)
print('Test labels shape: ', knn_norm_data_dict['y_test'].shape)
```

```
Train data shape:  (10000, 3072)
Train labels shape:  (10000,)
Validation data shape:  (2000, 3072)
Validation labels shape:  (2000,)
Test data shape:  (500, 3072)
Test labels shape:  (500,)
```

We calculate the accuracies again using k = 1 and k = 3 and see that the accuracies are much better compared to those we obtained without any preprocessing on the images!

[315]:
```
classifier = KNearestNeighbor()
classifier.train(knn_norm_data_dict['X_train'], knn_norm_data_dict['y_train'])
```

[316]:
```
dists = classifier.compute_distances_no_loops(knn_norm_data_dict['X_test'])
y_test_pred, k_labels  = classifier.predict_labels(dists, k=1)
```

[317]:
```
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_norm_data_dict['y_test'])
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 171 / 500 correct => accuracy: 0.342000
```

[318]:
```
y_test_pred, k_labels = classifier.predict_labels(dists, k=3)
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_norm_data_dict['y_test'])
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 180 / 500 correct => accuracy: 0.360000
```

0.5.7 (d) KNN with HOG

The previous parts all directly used raw pixels from input images to compute distances with k-NN. In this part, you will first compute the Histogram of Oriented Gradients (HOG) features of each image. You can then find the k-NN of the images with the most similar HOG features. Please read the descriptions and fill in the functions below.

[319]:
```
def compute_angles(image):
    """
    Computes the gradients in both x and y directions.
    Computes the magnitudes of the gradients.
    Computes the angles from the gradients and map to range [0, 180 deg].
    Inputs:
    - image: A numpy array of shape (32, 32) containing one grayscaled image.
    Returns:
    - magnitudes: A numpy array of shape (32, 32) where magnitudes[i, j]
      is the magnitude of the gradient at the (i, j) pixel in the input image.
    - angles: A numpy array of shape (32, 32) where angles[i, j]
      is the angle of the gradient at the (i, j) pixel in the input image.
    """

    # ===== your code here! =====

    # TODO:
    # Compute the gradients along the rows and columns as two arrays.
    # Compute the magnitude as the square root of the sum of the squares of both gradients
    # Compute the angles as the inverse tangent of the gradients along the rows and
    # the gradients along the columns, and map them to the range [0, 180 deg]

    x_grad = np.gradient(image, axis=0)
    y_grad = np.gradient(image, axis=1)
    angles = (np.arctan2(y_grad, x_grad) * (180/math.pi)) % 180
    magnitudes = np.sqrt(x_grad**2 + y_grad**2)

    # ==== end of code ====

    return magnitudes, angles
```

[320]:
```
def compute_hog_linear_interp(angles, magnitudes, num_bins, pixels_per_cell, cells_per_block):
    """
    Creates a Histogram of Oriented Gradients (HOG) weighted by gradient
    magnitudes from the orientations and magnitudes of an image
    Inputs:
    - angles: A numpy array of shape (32, 32) where angles[i, j]
        is the angle of the gradient at the (i, j) pixel in the input image.
    - magnitudes: A numpy array of shape (32, 32) where magnitudes[i, j]
        is the magnitude of the gradient at the (i, j) pixel in the input image.
    - num_bins: An int of the number of different bins in the histogram
      representing intervals of different orientations
    - pixels_per_cell: An int representing the number of rows/columns of pixels
```

```
    present in each cell
  - cells_per_block: An int representing the number of rows/columns of cells
    present in each block
  """

  num_cell_rows = angles.shape[0] // pixels_per_cell
  histogram = np.zeros((num_cell_rows, num_cell_rows, num_bins));
  step_size = 180 // num_bins

  # ===== your code here! =====

  # TODO:
  # Iterate through each pixel in every cell
  # Find the index to the bin in histogram for that pixel's orientation
  # Linearly interpolate based on angle to determine the weight of magnitude
  # to the two nearby bins
  # Add the weighted magnitude to the corresponding bins in the histogram

  for r in range(num_cell_rows):
    for c in range(num_cell_rows):
      for i in range(r*pixels_per_cell, (r+1)*pixels_per_cell):
        for j in range(c*pixels_per_cell, (c+1)*pixels_per_cell):
          lower_idx = math.floor(angles[i, j] / step_size - 0.5)
          bin_A = (angles[i, j] - (lower_idx + 0.5) * step_size ) / step_size
          bin_B = ((lower_idx + 1.5) * step_size - angles[i, j]) / step_size
          histogram[r, c, lower_idx] += bin_B * magnitudes[i, j]
          histogram[r, c, (lower_idx + 1) % num_bins] += bin_A * magnitudes[i,␣
↪j]

  # ==== end of code ====

  normalize_histogram(histogram, num_cell_rows, cells_per_block, epsilon=1e-5)
  return histogram.flatten()
```

[321]:
```
def normalize_histogram(histogram, num_cell_rows, cells_per_block,␣
↪epsilon=1e-5):
  """
  Normalizes the histogram in blocks of size cells_per_block.
  Inputs:
  - histogram: A numpy array of shape (num_cell_rows, num_cell_rows, num_bins)
    representing the histogram of oriented gradients of the input image.
    It can be modified in place.
  - num_cell_rows: An int representing the number of rows/columns of cells
    in the input image.
  - cells_per_block: An int representing the number of rows/coluns of cells␣
↪that
    should together be normalized in the same block.
```

```
  - epsilon: A float indicating the small amount added to the denominator when
    normalizing to avoid dividing by zero.
  """

  num_block_rows = num_cell_rows // cells_per_block
  # Block normalization
  for r in range(num_block_rows):
    for c in range(num_block_rows):
      histogram[r : r + cells_per_block, c : c + cells_per_block, :] /= np.
↪sqrt(np.sum(np.square(histogram[r : r + cells_per_block, c : c +␣
↪cells_per_block, :])) + epsilon ** 2)
```

After implementing your HOG functions, please run the cells below to test the results. You should expect to get an accuracy slightly higher than that with unnormalized raw pixels.

[322]:
```
def generate_histogram(image):
  """
  Builds a Histogram of Oriented Gradients (HOG) weighted by gradient␣
↪magnitudes
  from an input image
  Inputs:
  - image: A numpy array of shape (32, 32) containing one grayscaled image.
  Outputs:
  - histogram: A 1D numpy array of shape
    (num_cell_rows * num_cell_rows * num_bins, ) that shows a HOG of an image.
  """
  # Read and reshape input image
  input_image = image.reshape((32, 32, 3)).astype('uint8')
  grayscaled = rgb2gray(input_image)
  magnitudes, angles = compute_angles(grayscaled)
  # 9 bin, histogram with 64 4x4 pixel cells, normalize 4 cells per block
  # Get histogram of 4 quadrants with 9 bins concatenated into a␣
↪8x8x9-dimensional vector
  histogram = compute_hog_linear_interp(angles=angles, magnitudes=magnitudes,␣
↪num_bins=9, pixels_per_cell=4, cells_per_block=4)
  return histogram
```

[323]:
```
X_train_hog = []
for image_index in range(X_train.shape[0]):
  histogram = generate_histogram(X_train[image_index])
  X_train_hog.append(histogram)

X_test_hog = []
for image_index in range(X_test.shape[0]):
  histogram = generate_histogram(X_test[image_index])
  X_test_hog.append(histogram)
```

Store these tensors into a dictionary `knn_hog_data_dict`

[324]:
```
knn_hog_data_dict = {}

knn_hog_data_dict['X_train'] = np.array(X_train_hog[:knn_num_train]).
 ↪reshape(knn_num_train, -1)
knn_hog_data_dict['y_train'] = y_train[:knn_num_train]
knn_hog_data_dict['X_val'] = np.array(X_train_hog[knn_num_train:
 ↪knn_num_train+knn_num_val]).reshape(knn_num_val, -1)
knn_hog_data_dict['y_val'] = y_train[knn_num_train:knn_num_train+knn_num_val]
knn_hog_data_dict['X_test'] = np.array(X_test_hog[:knn_num_test]).
 ↪reshape(knn_num_test, -1)
knn_hog_data_dict['y_test'] = y_test[:knn_num_test]

print('Train data shape: ', knn_hog_data_dict['X_train'].shape)
print('Train labels shape: ', knn_hog_data_dict['y_train'].shape)
print('Validation data shape: ', knn_hog_data_dict['X_val'].shape)
print('Validation labels shape: ', knn_hog_data_dict['y_val'].shape)
print('Test data shape: ', knn_hog_data_dict['X_test'].shape)
print('Test labels shape: ', knn_hog_data_dict['y_test'].shape)
```

```
Train data shape:  (10000, 576)
Train labels shape:  (10000,)
Validation data shape:  (2000, 576)
Validation labels shape:  (2000,)
Test data shape:  (500, 576)
Test labels shape:  (500,)
```

[325]:
```
classifier = KNearestNeighbor()
classifier.train(knn_hog_data_dict['X_train'], knn_hog_data_dict['y_train'])
dists = classifier.compute_distances_no_loops(knn_hog_data_dict['X_test'])
y_test_pred, k_labels  = classifier.predict_labels(dists, k=3)
print(np.stack(k_labels, axis=0)[0].astype('uint8'))
```

```
[198  86  63]
```

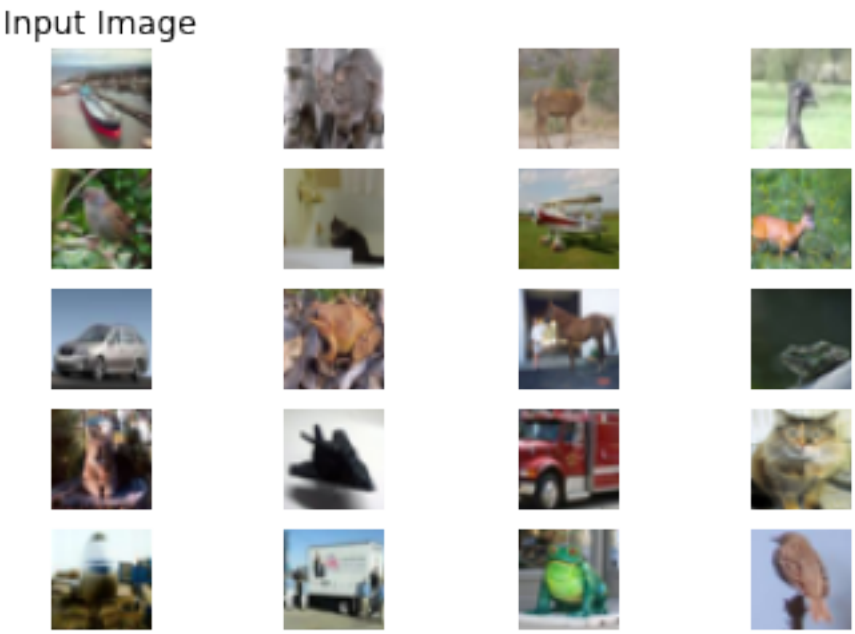
[326]:
```
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_hog_data_dict['y_test'])
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 161 / 500 correct => accuracy: 0.322000
```

You can also visualize the K nearest images for some randomly selected examples from the test set using the k_idxs list you returned in predict_labels trained with HOG descriptors.

[327]:
```
def visualize_knn_sift(num_examples, K):
  idxs = np.random.choice(500, num_examples)
```

```
  vis_im = knn_data_dict['X_test'][idxs]
  vis_labels = np.stack(k_labels, axis=0)[idxs].astype('uint8')

  num_images = num_examples*K + num_examples
  for i in range(num_images):
    plt.subplot(num_examples,K+1,i+1)
    if (i%(K+1) == 0):
      plt.imshow(vis_im[int(i/(K+1))].reshape(32,32,3).astype('uint8'))
      plt.axis('off')
      if(i==0):
        plt.title('Input Image')
    else:
      plt.imshow(knn_data_dict['X_train'][vis_labels[int(i/(K+1)), i -␣
↪(K+1)*int(i/(K+1)) - 1]].reshape(32,32,3).astype('uint8'))
      plt.axis('off')


# Here the leftmost column is the input image from the test set and rest of the
# K columns are the K nearest neighbors from the training set
num_examples = 5
K = 3
visualize_knn_sift(num_examples, K)
```



0.5.8 (*Optional*) Skimage HOG

We have provided the Skimage implementation that computes full HOG features. These features should obtain significantly higher accuracy.

[328]:
```
X_train_skimage_hog = []
for image_index in range(X_train.shape[0]):
  histogram = hog(X_train[image_index], pixels_per_cell=(4, 4),␣
 ↪cells_per_block=(4, 4))
  X_train_skimage_hog.append(histogram)

X_test_skimage_hog = []
for image_index in range(X_test.shape[0]):
  histogram = hog(X_test[image_index], pixels_per_cell=(4, 4),␣
 ↪cells_per_block=(4, 4))
  X_test_skimage_hog.append(histogram)

knn_skimage_hog_data_dict = {}

knn_skimage_hog_data_dict['X_train'] = np.array(X_train_skimage_hog[:
 ↪knn_num_train]).reshape(knn_num_train, -1)
knn_skimage_hog_data_dict['y_train'] = y_train[:knn_num_train]
knn_skimage_hog_data_dict['X_val'] = np.array(X_train_skimage_hog[knn_num_train:
 ↪knn_num_train+knn_num_val]).reshape(knn_num_val, -1)
knn_skimage_hog_data_dict['y_val'] = y_train[knn_num_train:
 ↪knn_num_train+knn_num_val]
knn_skimage_hog_data_dict['X_test'] = np.array(X_test_skimage_hog[:
 ↪knn_num_test]).reshape(knn_num_test, -1)
knn_skimage_hog_data_dict['y_test'] = y_test[:knn_num_test]
```

[329]:
```
classifier = KNearestNeighbor()
classifier.train(knn_skimage_hog_data_dict['X_train'],␣
 ↪knn_skimage_hog_data_dict['y_train'])

dists = classifier.
 ↪compute_distances_no_loops(knn_skimage_hog_data_dict['X_test'])
y_test_pred, k_labels  = classifier.predict_labels(dists, k=3)
```

[330]:
```
# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == knn_skimage_hog_data_dict['y_test'])
accuracy = float(num_correct) / knn_num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, knn_num_test,␣
 ↪accuracy))
```

```
Got 251 / 500 correct => accuracy: 0.502000
```

0.6 Problem 3.2

Linear classifier with Softmax Loss

0.6.1 Preprocess images

If we consider N images, we flatten the `(N, 32, 32, 3)` images into one dimesional arrays of shape `(N, 3072)` and we append a row of ones for each image, to accomodate for the bias when using the bias trick. This makes the shape of the input images `(N, 3073)`. We also normalize the data by subtracting the mean image from the train and test data.

[331]:
```
X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

if DEBUG:
  num_training=9000
  num_validation=1000
else:
  num_training=49000
  num_validation=1000
num_test=10000

# Flatten the images
X_train = X_train.reshape(X_train.shape[0], -1)
X_test = X_test.reshape(X_test.shape[0], -1)

# Normalize the data: subtract the mean image from train and test data
mean_image = np.mean(X_train, axis=0, keepdims=True)
X_train -= mean_image
X_test -= mean_image

# Append the bias dimension of ones (i.e. bias trick) so that our classifier
# only has to worry about optimizing a single weight matrix W.
ones_train = np.ones((X_train.shape[0],1))
X_train = np.concatenate((X_train, ones_train), axis=1)
ones_test = np.ones((X_test.shape[0],1))
X_test = np.concatenate((X_test, ones_test), axis=1)

# Store them in a dictionary.
data_dict={}
data_dict['X_train'] = X_train[0:num_training]
data_dict['y_train'] = y_train[0:num_training]
data_dict['X_val'] = X_train[num_training:num_training+num_validation]
data_dict['y_val'] = y_train[num_training:num_training+num_validation]
data_dict['X_test'] = X_test[0:num_test]
data_dict['y_test'] = y_test[0:num_test]

print('Train data shape: ', data_dict['X_train'].shape)
print('Train labels shape: ', data_dict['y_train'].shape)
print('Validation data shape: ', data_dict['X_val'].shape)
print('Validation labels shape: ', data_dict['y_val'].shape)
print('Test data shape: ', data_dict['X_test'].shape)
print('Test labels shape: ', data_dict['y_test'].shape)
```

```
Train data shape:  (49000, 3073)
Train labels shape:  (49000,)
Validation data shape:  (1000, 3073)
Validation labels shape:  (1000,)
Test data shape:  (10000, 3073)
Test labels shape:  (10000,)
```

0.6.2 (a) Softmax_loss_naive function

[332]:
```python
def softmax_loss_naive(W, X, y):
  """
  Softmax loss function, naive implementation (with loops)
  Inputs have dimension D, there are C classes, and we operate on minibatches
  of N examples.
  Inputs:
  - W: A numpy array of shape (D, C) containing weights.
  - 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: loss as single float
  - dW: gradient with respect to weights W averaged across the whole batch;
     an array of same shape as W
  """
  # Initialize the loss and gradient to zero.
  loss = 0.0
  dW = np.zeros_like(W)

  num_classes = W.shape[1]
  num_train = X.shape[0]

  # ===== your code here! =====

  # TODO:
  # Loop over each example in the batch
  # Calculate the scores
  # Compute the softmax loss
  # Compute gradient dW using explicit loop
  # Average loss and gradient across the whole batch
  # Note: When calculating dW, subtract the maximum score from each scores to
  # avoid infinity (See note in the PSet).

  scores = np.zeros((num_train, num_classes))

  for i in range(num_train):
    x_i = X[i].reshape(X.shape[1], -1)
    scores = W.T.dot(X[i, :])
```

```
    max = np.max(scores)
    scores -= max

    sum_scores = 0.0
    for s in scores:
      sum_scores += np.exp(s)
    loss += -scores[y[i]] + np.log(sum_scores)

    for j in range(num_classes):
      if j != y[i]:
        dW[:, j] += (np.exp(scores[j]) / sum_scores) * X[i, :]
      else:
        dW[:, j] += (np.exp(scores[j]) / sum_scores - 1) * X[i, :]

  loss /= num_train
  dW /= num_train

  # ==== end of code ====

  return loss, dW
```

As a sanity check to see whether we have implemented the loss correctly, run the softmax classifier with a small random weight matrix and no regularization. You should see loss near log(10) = 2.3

[333]:
```
# Generate a random weight matrix of small numbers and use it to compute the␣
 ↪loss
random.seed(0)
np.random.seed(0)
W = np.random.randn(3073, 10) * 0.00001

# For debugging purpose we can calculate the loss with very low W and no␣
 ↪regularization
# The result should be near log(10) (log(#number_class))
loss, grad = softmax_loss_naive(W, data_dict['X_val'], data_dict['y_val'])
print('loss: %f' % (loss))
print('sanity check: %f' % (np.log(10.0)))
```

```
loss: 2.303055
sanity check: 2.302585
```

To check that you have implemented the gradient correctly, you can numerically estimate the gradient of the loss function and compare the numeric estimate to the gradient that you computed. We have provided code that does this for you

(The relative errors should be less than 1e-6).

[334]:
```
# Compute the loss and its gradient at W.
loss, grad = softmax_loss_naive(W, data_dict['X_val'], data_dict['y_val'])
```

```
# Numerically compute the gradient along several randomly chosen dimensions, and
# compare them with your analytically computed gradient. The numbers should match
# almost exactly along all dimensions.
f = lambda w: softmax_loss_naive(w, data_dict['X_val'], data_dict['y_val'])[0]
grad_numerical = grad_check_sparse(f, W, grad)
```

```
numerical: 2.584677 analytic: 2.584677, relative error: 2.774105e-08
numerical: 1.951478 analytic: 1.951478, relative error: 1.706606e-08
numerical: -1.353721 analytic: -1.353721, relative error: 1.605797e-08
numerical: 1.205571 analytic: 1.205571, relative error: 4.109712e-08
numerical: 0.063289 analytic: 0.063289, relative error: 8.720625e-07
numerical: -0.523113 analytic: -0.523114, relative error: 5.703314e-08
numerical: -0.289167 analytic: -0.289167, relative error: 9.598689e-08
numerical: 1.047718 analytic: 1.047718, relative error: 6.574467e-08
numerical: -3.473024 analytic: -3.473024, relative error: 6.339743e-09
numerical: -1.130936 analytic: -1.130936, relative error: 1.881945e-08
```

Next, we implement a vecotrized version of the softmax loss for you, for faster execution, as we quantify the speedup in the below cells. If you want to get a flavor of writing optimized (vectorized) code in the future for Deep Learning systems as well as future homeworks, it might be helpful to go through this function **AFTER** finishing the required parts of the Problem Set

[335]:
```
def softmax_loss_vectorized(W, X, y):
  """
  Softmax loss function, vectorized version.
  Inputs and outputs are the same as softmax_loss_naive.
  """

  dW = np.zeros(W.shape) # initialize the gradient as zero
  loss = 0.0             # initialize the loss as zero

  num_train = X.shape[0]
  scores = X.dot(W)
  scores -= np.max(scores, axis =1, keepdims = True)
  exp_scores = np.exp(scores)
  scores_exp_sum = np.sum(exp_scores, axis=1, keepdims=True)
  norm_scores = exp_scores/(scores_exp_sum + 1e-12)
  loss = np.sum(-np.log(norm_scores[range(num_train),y]))

  norm_scores[np.arange(num_train),y] -= 1
  dW = np.matmul(X.T, norm_scores)

  loss/=num_train
  dW/=num_train
```

```
  return loss,dW
```

[336]:
```
# Now that we have a naive implementation of the softmax loss function and its␣
 ↪gradient,
# we have provided a vectorized version in softmax_loss_vectorized.
# The two versions should compute the same results, but the vectorized version␣
 ↪should be
# much faster.

tic = time.time()
loss_naive, grad_naive = softmax_loss_naive(W, data_dict['X_val'],␣
 ↪data_dict['y_val'])
toc = time.time()
ms_naive = 1000.0 * (toc - tic)
print('naive loss: %e computed in %fs' % (loss_naive, ms_naive))

tic = time.time()
loss_vectorized, grad_vectorized = softmax_loss_vectorized(W,␣
 ↪data_dict['X_val'], data_dict['y_val'])
toc = time.time()
ms_vec = 1000.0 * (toc - tic)
print('vectorized loss: %e computed in %fs' % (loss_vectorized, ms_vec))

# As we did for the SVM, we use the Frobenius norm to compare the two versions
# of the gradient.
grad_difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('Loss difference: %f' % np.abs(loss_naive - loss_vectorized))
print('Gradient difference: %f' % grad_difference)
print('Speedup: %f' %(ms_naive/ms_vec))
```

```
naive loss: 2.303055e+00 computed in 365.529537s
vectorized loss: 2.303055e+00 computed in 28.066874s
Loss difference: 0.000000
Gradient difference: 0.000000
Speedup: 13.023522
```

0.6.3 (b) Define Linear Classifier class

[337]:
```
class LinearClassifier(object):

  def __init__(self):
    self.W = None

  def train(self, X, y,  X_val, y_val, 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
    num_classes = np.max(y) + 1 # assume y takes values 0...K-1 where K is␣
↪number of classes
    if self.W is None:
      # lazily initialize W
      self.W = 0.000001 * np.random.randn(dim, num_classes)

    # Run stochastic gradient descent to optimize W
    loss_history = []
    for it in range(num_iters):
      X_batch = None
      y_batch = None

      # ==== your code here ! ====

      # TODO:
      # Sample batch_size elements from the training data and their
      # corresponding labels to use them as arguments for the loss
      # function. Store the data in X_batch and their corresponding labels
      # in y_batch.

      # Hint: Use np.random.choice to generate indices. Sampling with
      # replacement is faster than sampling without replacement.

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

      # ===== end of code =====

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

```
      # perform parameter update

      # ==== your code here ! ====

      # TODO:
      # Update the weights using the gradient and the learning rate.

      # For each iteration of the update, please subtract the gradient
      # times the learning rate from the weight matrix in the previous
      # iteration, and set that value as the new weight.

      prevW = self.W
      self.W = prevW - learning_rate * grad

      # ===== end of code =====

      if verbose and it % 100 == 0:
        print('iteration %d / %d: loss %f' % (it, num_iters, loss))

      y_val_pred = self.predict(X_val)
      val_accuracy = np.mean(y_val == y_val_pred)

    return loss_history

  def predict(self, X):
    """
    Use the trained weights of this linear classifier to predict labels for
    data points.
    Inputs:
    - X: A numpy array of shape (N, D) containing training data; there are N
      training samples each of dimension D.
    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[0])
    # ==== your code here ! ====

    # TODO:
    # Calculate the scores and store the predicted labels in y_pred.

    sc = X.dot(self.W)
    # print("\nscores =", sc.shape)
    for i in range(sc.shape[0]):
      y_pred[i] = np.argmax(sc[i])
```

```
    # ===== end of code =====
    return y_pred

  def loss(self, X_batch, y_batch):
    """
    Compute the loss function and its derivative.
    Subclasses will override this.
    Inputs:
    - X_batch: A numpy array of shape (N, D) containing a minibatch of N
      data points; each point has dimension D.
    - y_batch: A numpy array of shape (N,) containing labels for the minibatch.
    - reg: (float) regularization strength.
    Returns: A tuple containing:
    - loss as a single float
    - gradient with respect to self.W; an array of the same shape as W
    """
    pass

class LinearSoftmax(LinearClassifier):
  """ A subclass that uses the Multiclass SVM loss function """

  def loss(self, X_batch, y_batch):
    return softmax_loss_vectorized(self.W, X_batch, y_batch)
```

0.6.4 (c) Train and test the classifier

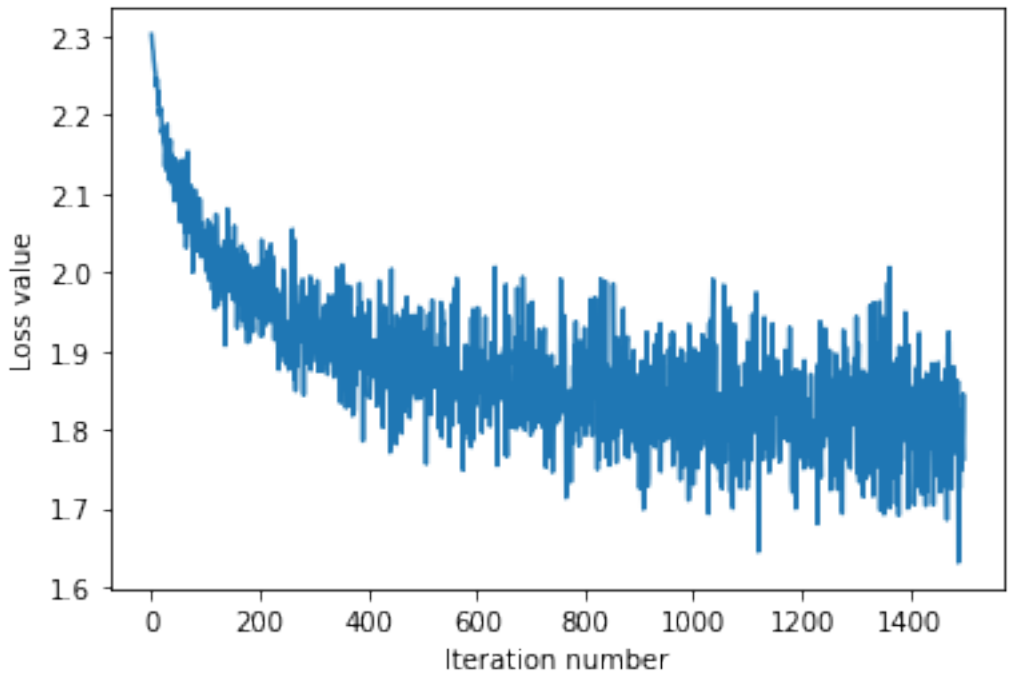
Run the linear classifier and observe the train, validation and test accuracies and see the visualization of the weights.

[338]:
```
softmax = LinearSoftmax()
tic = time.time()
loss_hist = softmax.train(data_dict['X_train'], data_dict['y_train'],␣
 ↪learning_rate=1e-7,
                          num_iters=1500, verbose=True, X_val=data_dict['X_val'],␣
 ↪y_val=data_dict['y_val'])
toc = time.time()
print('That took %fs' % (toc - tic))
```

```
iteration 0 / 1500: loss 2.302404
iteration 100 / 1500: loss 2.001393
iteration 200 / 1500: loss 1.971843
iteration 300 / 1500: loss 1.908188
iteration 400 / 1500: loss 1.871189
iteration 500 / 1500: loss 1.855388
iteration 600 / 1500: loss 1.831074
iteration 700 / 1500: loss 1.792770
iteration 800 / 1500: loss 1.792470
iteration 900 / 1500: loss 1.864091
```

```
iteration 1000 / 1500: loss 1.730051
iteration 1100 / 1500: loss 1.911876
iteration 1200 / 1500: loss 1.789723
iteration 1300 / 1500: loss 1.805863
iteration 1400 / 1500: loss 1.855482
That took 32.175610s
```

[339]:
```
# A useful debugging strategy is to plot the loss as a function of
# iteration number:
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
plt.show()
```



[340]:
```
# Write the LinearSoftmax.predict function and evaluate the performance on both␣
 ↪the
# training and validation set
y_train_pred = softmax.predict(data_dict['X_train'])
print('training accuracy: %f' % (np.mean(data_dict['y_train'] == y_train_pred),␣
 ↪))
y_val_pred = softmax.predict(data_dict['X_val'])
print('validation accuracy: %f' % (np.mean(data_dict['y_val'] == y_val_pred), ))
```

```
training accuracy: 0.387878
validation accuracy: 0.405000
```

[341]:
```
# Evaluate the best softmax on test set
y_test_pred = softmax.predict(data_dict['X_test'])
test_accuracy = np.mean(data_dict['y_test'] == y_test_pred)
print('linear Softmax on raw pixels final test set accuracy: %f' %␣
 ↪test_accuracy)
```

```
linear Softmax on raw pixels final test set accuracy: 0.384000
```

Visualize the learned weights for each class.

[342]:
```
w = softmax.W[:-1,:] # strip out the bias
w = w.reshape(32, 32, 3, 10)
w_min, w_max = np.min(w), np.max(w)
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
for i in range(10):
    plt.subplot(2, 5, i + 1)

    # Rescale the weights to be between 0 and 255
    wimg = 255.0 * (w[:, :, :, i].squeeze() - w_min) / (w_max - w_min)
    plt.imshow(wimg.astype('uint8'))
    plt.axis('off')
    plt.title(classes[i])
```

0.7 Visualize the mean image for each class

[343]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
samples_per_class = 7

for i in range(10):
  plt.subplot(2, 5, i+1)

  idxs = np.flatnonzero(y_train == i)
  mean_img = np.mean(X_train[idxs], axis = 0)
  plt.imshow(mean_img.astype('uint8'))
  plt.axis('off')
  plt.title(classes[i])
```

1 Convert Notebook to PDF

[ ]:
```
# generate pdf
# %%capture
!git clone https://gist.github.com/bc5f1add34fef7c7f9fb83d3783311e2.git
!cp bc5f1add34fef7c7f9fb83d3783311e2/colab_pdf.py colab_pdf.py
from colab_pdf import colab_pdf
# change the name to your ipynb file name shown on the top left of Colab window
# Important: make sure that your file name does not contain spaces!
colab_pdf('cktran_09859713.ipynb')
```

```
fatal: destination path 'bc5f1add34fef7c7f9fb83d3783311e2' already exists and is
not an empty directory.
```