knn

March 28, 2022

1 k-Nearest Neighbor (kNN) exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the assignments page on the course website.

The kNN classifier consists of two stages:

- During training, the classifier takes the training data and simply remembers it
- During testing, kNN classifies every test image by comparing to all training images and transfering the labels of the k most similar training examples
- The value of k is cross-validated

In this exercise you will implement these steps and understand the basic Image Classification pipeline, cross-validation, and gain proficiency in writing efficient, vectorized code.

[ ]:
```
from google.colab import drive
drive.mount('/content/drive' , force_remount=True)



#enter your foldername assignments/assignement1
FOLDERNAME = 'Practical_Learning_in_Computer_Vision/Assignments/assignment1/'

assert FOLDERNAME is not None , "[!] Enter the foldername"

import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

#this will download the CIFAR-10 dataset to your drive
#if it isnt already there

%cd drive/My\ Drive/$FOLDERNAME/CV7062610/datasets/
!bash get_datasets.sh
%cd /content
```

```
Mounted at /content/drive
/content/drive/My Drive/Practical_Learning_in_Computer_Vision/Assignments/assign
ment1/CV7062610/datasets
--2022-03-22 19:20:21--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
```

```
Resolving www.cs.toronto.edu (www.cs.toronto.edu)… 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80…
connected.
HTTP request sent, awaiting response… 200 OK
Length: 170498071 (163M) [application/x-gzip]
Saving to: 'cifar-10-python.tar.gz'

cifar-10-python.tar 100%[===================>] 162.60M  40.3MB/s    in 4.1s

2022-03-22 19:20:25 (40.0 MB/s) - 'cifar-10-python.tar.gz' saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

[ ]:
```
# Run some setup code for this notebook.

import random
import numpy as np
from CV7062610.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# This is a bit of magic to make matplotlib figures appear inline in the␣
↪notebook
# rather than in a new window.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# Some more magic so that the notebook will reload external python modules;
# see http://stackoverflow.com/questions/1907993/
↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

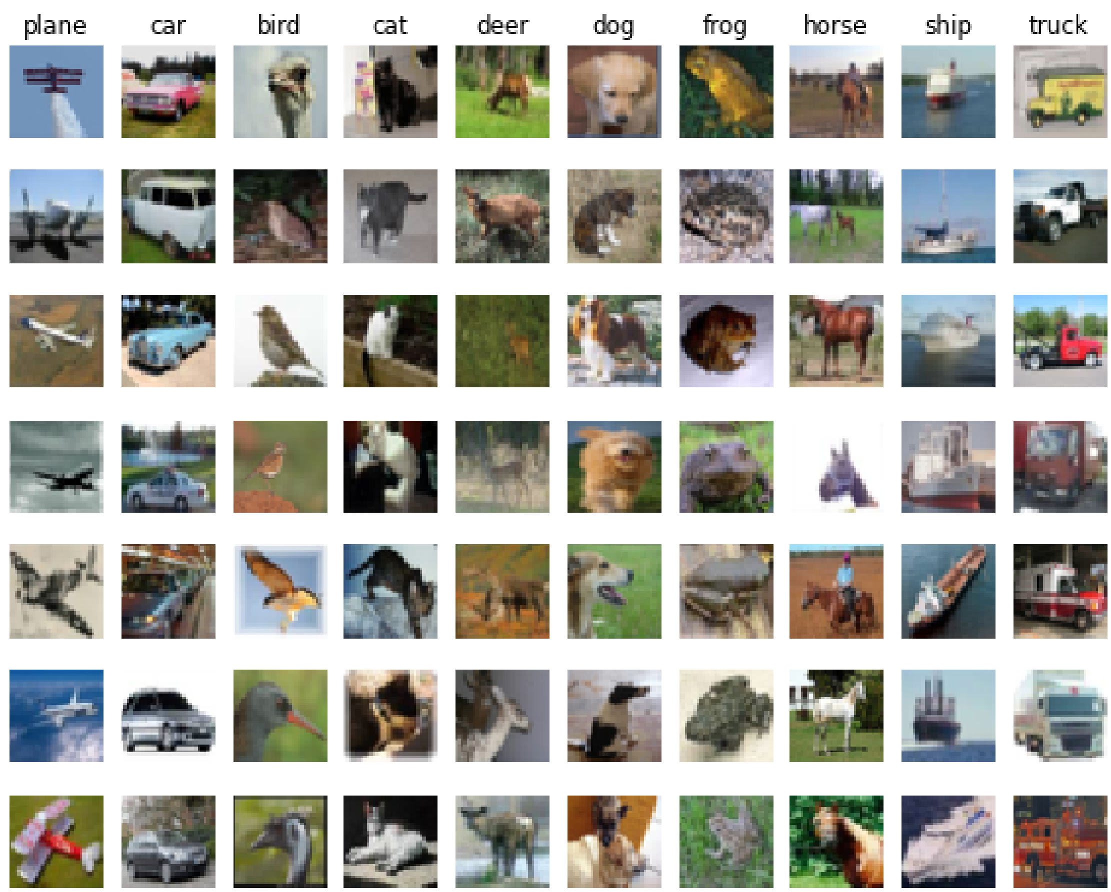
[ ]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = '/content/drive/MyDrive/' + FOLDERNAME + '/CV7062610/datasets/
↪cifar-10-batches-py'
```

```
# Cleaning up variables to prevent loading data multiple times (which may cause␣
↪memory issue)
try:
   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

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,)
```

[ ]:

```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
num_classes = len(classes)
samples_per_class = 7
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].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls)
plt.show()
```



[ ]:
```python
# Subsample the data for more efficient code execution in this exercise
num_training = 5000
mask = list(range(num_training))
X_train = X_train[mask]
y_train = y_train[mask]

num_test = 500
mask = list(range(num_test))
X_test = X_test[mask]
y_test = y_test[mask]

# Reshape the image data into rows
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
print(X_train.shape, X_test.shape)
```

```
(5000, 3072) (500, 3072)
```

[ ]:
```python
from CV7062610.classifiers import KNearestNeighbor

# Create a kNN classifier instance.
# Remember that training a kNN classifier is a noop:
# the Classifier simply remembers the data and does no further processing
classifier = KNearestNeighbor()
classifier.train(X_train, y_train)
```

We would now like to classify the test data with the kNN classifier. Recall that we can break down this process into two steps:

1. First we must compute the distances between all test examples and all train examples.
2. Given these distances, for each test example we find the k nearest examples and have them vote for the label

Lets begin with computing the distance matrix between all training and test examples. For example, if there are **Ntr** training examples and **Nte** test examples, this stage should result in a **Nte x Ntr** matrix where each element (i,j) is the distance between the i-th test and j-th train example.

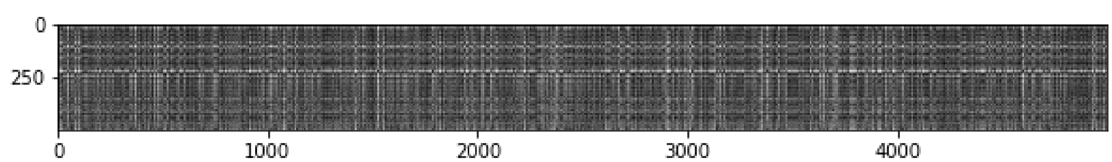
Note: For the three distance computations that we require you to implement in this notebook, you may not use the np.linalg.norm() function that numpy provides.

First, open `cs231n/classifiers/k_nearest_neighbor.py` and implement the function `compute_distances_two_loops` that uses a (very inefficient) double loop over all pairs of (test, train) examples and computes the distance matrix one element at a time.

[ ]:
```python
# Open CV7062610/classifiers/k_nearest_neighbor.py and implement
# compute_distances_two_loops.

# Test your implementation:
dists = classifier.compute_distances_two_loops(X_test)
print(dists.shape)
```

```
(500, 5000)
```

[ ]:
```python
# We can visualize the distance matrix: each row is a single test example and
# its distances to training examples
plt.imshow(dists, interpolation='none')
plt.show()
```



Inline Question 1

Notice the structured patterns in the distance matrix, where some rows or columns are visible brighter. (Note that with the default color scheme black indicates low distances while white indicates high distances.)

- What in the data is the cause behind the distinctly bright rows?
- What causes the columns?

$\color{blue}{\textit{Your Answer}:}$ *fill this in.*

There are bright rows when there is an image in the test set that does not fit any of the label categories, specifically the categories that correspond with the images the training set, or is very disimilar to each of them.

The columns are caused by images in the training set that are disimilar to all the categories; dissimilar to the test set.

[ ]:
```
# Now implement the function predict_labels and run the code below:
# We use k = 1 (which is Nearest Neighbor).
y_test_pred = classifier.predict_labels(dists, k=1)

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

```
Got 137 / 500 correct => accuracy: 0.274000
```

You should expect to see approximately `27%` accuracy. Now lets try out a larger `k`, say `k = 5`:

[ ]:
```
y_test_pred = classifier.predict_labels(dists, k=5)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 139 / 500 correct => accuracy: 0.278000
```

You should expect to see a slightly better performance than with `k = 1`.

Inline Question 2

We can also use other distance metrics such as L1 distance. For pixel values $p_{ij}^{(k)}$ at location (i, j) of some image I_k,

the mean μ across all pixels over all images is

$$\mu = \frac{1}{nhw} \sum_{k=1}^{n} \sum_{i=1}^{h} \sum_{j=1}^{w} p_{ij}^{(k)}$$

And the pixel-wise mean μ_{ij} across all images is

$$\mu_{ij} = \frac{1}{n} \sum_{k=1}^{n} p_{ij}^{(k)}.$$

The general standard deviation σ and pixel-wise standard deviation σ_{ij} is defined similarly.

Which of the following preprocessing steps will not change the performance of a Nearest Neighbor classifier that uses L1 distance? Select all that apply. 1. Subtracting the mean μ ($\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu$.) 2. Subtracting the per pixel mean μ_{ij} ($\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu_{ij}$.) 3. Subtracting the mean μ and dividing by the standard deviation σ. 4. Subtracting the pixel-wise mean μ_{ij} and dividing by the pixel-wise standard deviation σ_{ij}. 5. Rotating the coordinate axes of the data.

$\textit{Your Answer}$:

{1,2,3,5}

$\textit{Your Explanation}$:

1. If we subtract the mean (which is constant) from every pixel, then the pixel-wise difference between two pixels will not change. It is like changing the operation (x-y) to (x-a-(y-a)) .
2. In this case, we are subtracting the same value from every picture with the same coordinates, and therefore the pixel-wise subtraction operation will yield the same results.
3. The mean divided by the standard deviation is a constant and so is the same for each pixel-wise subtraction. Since we are dividing all the pixels by the standard deviation, we can ignore the denominator, just as in the case x is smaller then y if and only if x/z is less then y/z, when x, y and z are all positive.
4. This would change the result because the pixel-wise standard deviation is different for each pair of coordinates. This means that if we have very large or very small values for the pixel-wise standard deviation, the distance will be greatly impacted.

If for example, we have two images m and n, where the pixels in coordinates i and j have the same value. That means the distance is zero. Let's say you have an image a pixel in coordinates i and j that woud normally have a very large distance from the other two images' pixel. Now assume that the pixel-wise deviation and mean are very large. This would bring the distance between the third pixel and the other two to a value approaching zero. 5. This would not change the outcome since each image's coordinates will be changed in the same way and therefore we will be subtracting the same values.

[ ]:
```
# Now lets speed up distance matrix computation by using partial vectorization
# with one loop. Implement the function compute_distances_one_loop and run the
# code below:
dists_one = classifier.compute_distances_one_loop(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('One loop difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
```

```python
else:
    print('Uh-oh! The distance matrices are different')
```

```
One loop difference was: 0.000000
Good! The distance matrices are the same
```

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

# check that the distance matrix agrees with the one we computed before:
difference = np.linalg.norm(dists - dists_two, ord='fro')
print('No loop 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')
```

```
No loop difference was: 0.000000
Good! The distance matrices are the same
```

[ ]:
```python
# Let's compare how fast the implementations are
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, X_test)
print('Two loop version took %f seconds' % two_loop_time)

one_loop_time = time_function(classifier.compute_distances_one_loop, X_test)
print('One loop version took %f seconds' % one_loop_time)

no_loop_time = time_function(classifier.compute_distances_no_loops, X_test)
print('No loop version took %f seconds' % no_loop_time)

# You should see significantly faster performance with the fully vectorized␣
 ↪implementation!

# NOTE: depending on what machine you're using,
# you might not see a speedup when you go from two loops to one loop,
```

```
# and might even see a slow-down.
```

```
Two loop version took 121.291729 seconds
One loop version took 104.115649 seconds
No loop version took 0.957423 seconds
```

1.0.1 Cross-validation

We have implemented the k-Nearest Neighbor classifier but we set the value k = 5 arbitrarily. We will now determine the best value of this hyperparameter with cross-validation.

[ ]:
```
num_folds = 5
k_choices = [1, 3, 5, 8, 10, 12, 15, 20, 50, 100]

X_train_folds = []
y_train_folds = []
################################################################################
# TODO:                                                                        #
# Split up the training data into folds. After splitting, X_train_folds and    #
# y_train_folds should each be lists of length num_folds, where                #
# y_train_folds[i] is the label vector for the points in X_train_folds[i].     #
# Hint: Look up the numpy array_split function.                                #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
X_train_folds = np.array_split(X_train,num_folds)
y_train_folds = np.array_split(y_train,num_folds)
pass
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# A dictionary holding the accuracies for different values of k that we find
# when running cross-validation. After running cross-validation,
# k_to_accuracies[k] should be a list of length num_folds giving the different
# accuracy values that we found when using that value of k.
k_to_accuracies = {}


################################################################################
# TODO:                                                                        #
# Perform k-fold cross validation to find the best value of k. For each        #
# possible value of k, run the k-nearest-neighbor algorithm num_folds times,   #
# where in each case you use all but one of the folds as training data and the #
# last fold as a validation set. Store the accuracies for all fold and all     #
# values of k in the k_to_accuracies dictionary.                               #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
#np.concatenate(a)
#arr = np.array([5,10,15,20,25,30,35,40])
```

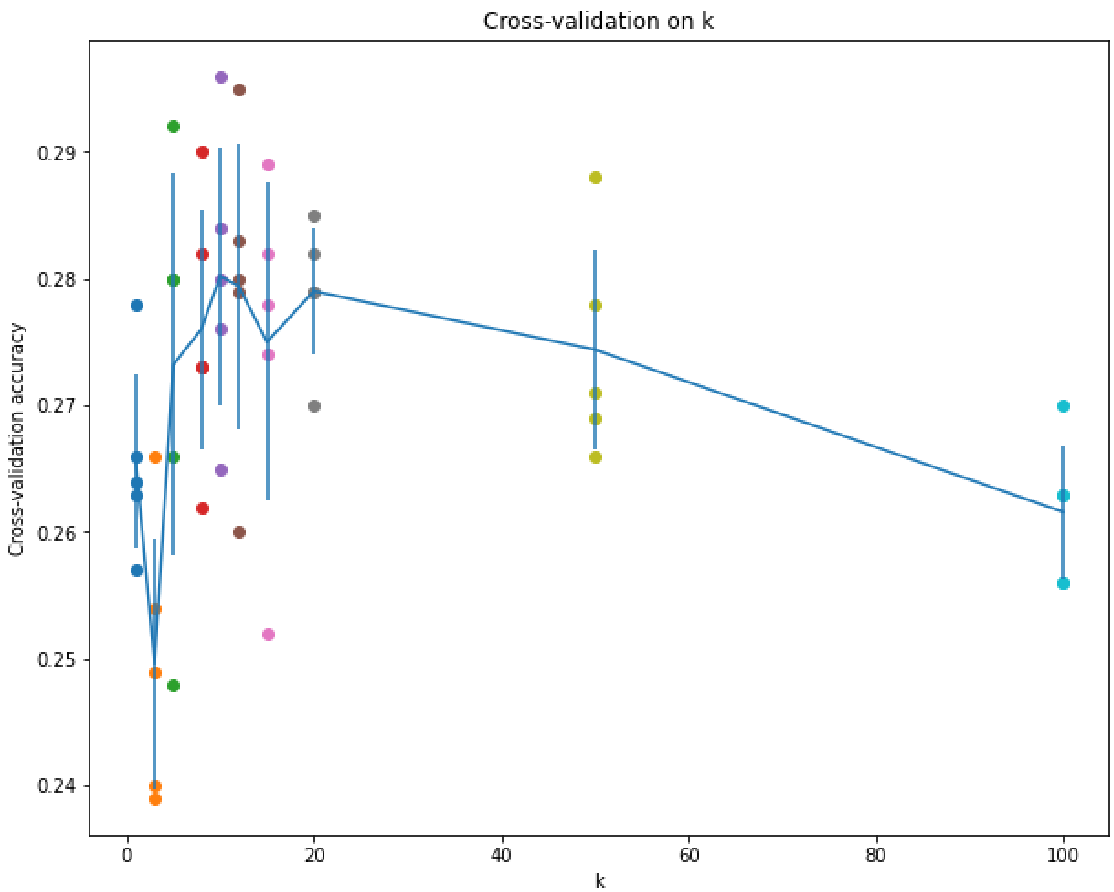
```python
#arr = arr[np.array([1,3,4])]
#a_dict["a"].append("hello")

def create_k_choice(kayla, i):
  #print("i is: ",i)
  arr_train_x = X_train_folds
  arr_train_x = np.delete(arr_train_x,i,0)
  #arr_train_x.pop(i)
  arr_train_x =np.concatenate(arr_train_x, axis=0)
  #print(arr_train_x.shape)

  arr_train_y = y_train_folds
  #arr_train_y.pop(i)
  arr_train_y = np.delete(arr_train_y,i,0)
  arr_train_y =np.concatenate(arr_train_y, axis=0)
  #print(arr_train_y.shape)

  classifier = KNearestNeighbor()
  classifier.train(arr_train_x, arr_train_y)
  dists = classifier.compute_distances_no_loops(X_train_folds[i])
  y_test_pred = classifier.predict_labels(dists, k=kay)
  num_correct = np.sum(y_test_pred == y_train_folds[i])
  accuracy = float(num_correct) / len(y_train_folds[i])
  #print(kayla)
  if kayla not in k_to_accuracies.keys():
    k_to_accuracies[kayla] = []
  k_to_accuracies[kayla].append(accuracy)

def create_all_k_choices(kayler):
  for i in range(5):
    create_k_choice(kayler,i)

for kay in k_choices:
  create_all_k_choices(kay)


pass

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out the computed accuracies
for k in sorted(k_to_accuracies):
    for accuracy in k_to_accuracies[k]:
        print('k = %d, accuracy = %f' % (k, accuracy))
```

```
k = 1, accuracy = 0.263000
k = 1, accuracy = 0.257000
```

```
k = 1, accuracy = 0.264000
k = 1, accuracy = 0.278000
k = 1, accuracy = 0.266000
k = 3, accuracy = 0.239000
k = 3, accuracy = 0.249000
k = 3, accuracy = 0.240000
k = 3, accuracy = 0.266000
k = 3, accuracy = 0.254000
k = 5, accuracy = 0.248000
k = 5, accuracy = 0.266000
k = 5, accuracy = 0.280000
k = 5, accuracy = 0.292000
k = 5, accuracy = 0.280000
k = 8, accuracy = 0.262000
k = 8, accuracy = 0.282000
k = 8, accuracy = 0.273000
k = 8, accuracy = 0.290000
k = 8, accuracy = 0.273000
k = 10, accuracy = 0.265000
k = 10, accuracy = 0.296000
k = 10, accuracy = 0.276000
k = 10, accuracy = 0.284000
k = 10, accuracy = 0.280000
k = 12, accuracy = 0.260000
k = 12, accuracy = 0.295000
k = 12, accuracy = 0.279000
k = 12, accuracy = 0.283000
k = 12, accuracy = 0.280000
k = 15, accuracy = 0.252000
k = 15, accuracy = 0.289000
k = 15, accuracy = 0.278000
k = 15, accuracy = 0.282000
k = 15, accuracy = 0.274000
k = 20, accuracy = 0.270000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.282000
k = 20, accuracy = 0.285000
k = 50, accuracy = 0.271000
k = 50, accuracy = 0.288000
k = 50, accuracy = 0.278000
k = 50, accuracy = 0.269000
k = 50, accuracy = 0.266000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.270000
k = 100, accuracy = 0.263000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.263000
```

[ ]:

```python
# plot the raw observations
for k in k_choices:
    accuracies = k_to_accuracies[k]
    plt.scatter([k] * len(accuracies), accuracies)

# plot the trend line with error bars that correspond to standard deviation
accuracies_mean = np.array([np.mean(v) for k,v in sorted(k_to_accuracies.
 ↪items())])
accuracies_std = np.array([np.std(v) for k,v in sorted(k_to_accuracies.
 ↪items())])
plt.errorbar(k_choices, accuracies_mean, yerr=accuracies_std)
plt.title('Cross-validation on k')
plt.xlabel('k')
plt.ylabel('Cross-validation accuracy')
plt.show()
```



[ ]:

```python
# Based on the cross-validation results above, choose the best value for k,
# retrain the classifier using all the training data, and test it on the test
# data. You should be able to get above 28% accuracy on the test data.
```

```
best_k = 10

classifier = KNearestNeighbor()
classifier.train(X_train, y_train)
y_test_pred = classifier.predict(X_test, k=best_k)

# Compute and display the accuracy
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 141 / 500 correct => accuracy: 0.282000
```

Inline Question 3

Which of the following statements about k-Nearest Neighbor (k-NN) are true in a classification setting, and for all k? Select all that apply. 1. The decision boundary of the k-NN classifier is linear. 2. The training error of a 1-NN will always be lower than that of 5-NN. 3. The test error of a 1-NN will always be lower than that of a 5-NN. 4. The time needed to classify a test example with the k-NN classifier grows with the size of the training set. 5. None of the above.

$\color{blue}{\textit{Your Answer :}}$ 1. false 2. false 3. false 4. true 5. false

$\color{blue}{\textit{Your Explanation :}}$

1. If it were linear, then there would be no misclassifications.
2. There is no training error.
3. In the graph above, we see a case where that isn't true.
4. For each image in the test set, we need to find the distance between the images. We also need to compare the distances. Therefore the classifcation running-time is O($3mnrc$), where m and n are these respective sizes of the training and test sets, and r and c are the size of the rows and columns of the images.

softmax

March 28, 2022

1 Softmax exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the assignments page on the course website.

This exercise is analogous to the SVM exercise. You will:

- implement a fully-vectorized **loss function** for the Softmax classifier
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** with numerical gradient
- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

[15]:
```
from google.colab import drive
drive.mount('/content/drive' , force_remount=True)


#enter your foldername assignments/assignement1
FOLDERNAME = 'Practical_Learning_in_Computer_Vision/Assignments/assignment1/'

assert FOLDERNAME is not None , "[!] Enter the foldername"

import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

#this will download the CIFAR-10 dataset to your drive
#if it isnt already there


%cd drive/My\ Drive/$FOLDERNAME/CV7062610/datasets/
!bash get_datasets.sh
%cd /content
```

```
Mounted at /content/drive
/content/drive/My Drive/Practical_Learning_in_Computer_Vision/Assignments/assign
ment1/CV7062610/datasets
--2022-03-28 21:19:23--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
```

```
Resolving www.cs.toronto.edu (www.cs.toronto.edu)… 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80…
connected.
HTTP request sent, awaiting response… 200 OK
Length: 170498071 (163M) [application/x-gzip]
Saving to: ‘cifar-10-python.tar.gz’

cifar-10-python.tar 100%[===================>] 162.60M  23.0MB/s    in 6.2s

2022-03-28 21:19:29 (26.0 MB/s) - ‘cifar-10-python.tar.gz’ saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

[16]:

```
import random
import numpy as np
from CV7062610.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading extenrnal modules
# see http://stackoverflow.com/questions/1907993/
↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

2 New Section

[17]:
```python
def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000,␣
↪num_dev=500):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the linear classifier. These are the same steps as we used for the
    SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = '/content/drive/MyDrive/' + FOLDERNAME + '/CV7062610/datasets/
↪cifar-10-batches-py'

    # Cleaning up variables to prevent loading data multiple times (which may␣
↪cause memory issue)
    try:
        del X_train, y_train
        del X_test, y_test
        print('Clear previously loaded data.')
    except:
        pass

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

    # subsample the data
    mask = list(range(num_training, num_training + num_validation))
    X_val = X_train[mask]
    y_val = y_train[mask]
    mask = list(range(num_training))
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = list(range(num_test))
    X_test = X_test[mask]
    y_test = y_test[mask]
    mask = np.random.choice(num_training, num_dev, replace=False)
    X_dev = X_train[mask]
    y_dev = y_train[mask]

    # Preprocessing: reshape the image data into rows
    X_train = np.reshape(X_train, (X_train.shape[0], -1))
    X_val = np.reshape(X_val, (X_val.shape[0], -1))
    X_test = np.reshape(X_test, (X_test.shape[0], -1))
    X_dev = np.reshape(X_dev, (X_dev.shape[0], -1))

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis = 0)
    X_train -= mean_image
```

```
    X_val -= mean_image
    X_test -= mean_image
    X_dev -= mean_image

    # add bias dimension and transform into columns
    X_train = np.hstack([X_train, np.ones((X_train.shape[0], 1))])
    X_val = np.hstack([X_val, np.ones((X_val.shape[0], 1))])
    X_test = np.hstack([X_test, np.ones((X_test.shape[0], 1))])
    X_dev = np.hstack([X_dev, np.ones((X_dev.shape[0], 1))])

    return X_train, y_train, X_val, y_val, X_test, y_test, X_dev, y_dev


# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test, X_dev, y_dev =␣
 ↪get_CIFAR10_data()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
print('dev data shape: ', X_dev.shape)
print('dev labels shape: ', y_dev.shape)
```

```
Train data shape:  (49000, 3073)
Train labels shape:  (49000,)
Validation data shape:  (1000, 3073)
Validation labels shape:  (1000,)
Test data shape:  (1000, 3073)
Test labels shape:  (1000,)
dev data shape:  (500, 3073)
dev labels shape:  (500,)
```

2.1 Softmax Classifier

Your code for this section will all be written inside `CV7062610/classifiers/softmax.py`.

[18]:
```
# First implement the naive softmax loss function with nested loops.
# Open the file CV7062610/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from CV7062610.classifiers.softmax import softmax_loss_naive
import time

# Generate a random softmax weight matrix and use it to compute the loss.
W = np.random.randn(3073, 10) * 0.0001
```

```
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 0.0)

# As a rough sanity check, our loss should be something close to -log(0.1).
print('loss: %f' % loss)
print('sanity check: %f' % (-np.log(0.1)))
```

```
loss: 2.318364
sanity check: 2.302585
```

Inline Question 1

Why do we expect our loss to be close to -log(0.1)? Explain briefly.**

$\color{blue}{\textit{Your Answer:}}$ W selcted randomly in the initialization and sum of classes is 10 so the probability of predict correctly is 1/10 then loss would be -log0.1

[19]:
```
# Complete the implementation of softmax_loss_naive and implement a (naive)
# version of the gradient that uses nested loops.
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 0.0)

# As we did for the SVM, use numeric gradient checking as a debugging tool.
# The numeric gradient should be close to the analytic gradient.
from CV7062610.gradient_check import grad_check_sparse
f = lambda w: softmax_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad, 10)

# similar to SVM case, do another gradient check with regularization
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 5e1)
f = lambda w: softmax_loss_naive(w, X_dev, y_dev, 5e1)[0]
grad_numerical = grad_check_sparse(f, W, grad, 10)
```

```
numerical: -1.319020 analytic: -1.319020, relative error: 3.390069e-09
numerical: -1.874284 analytic: -1.874284, relative error: 1.305433e-08
numerical: 1.344135 analytic: 1.344135, relative error: 4.271538e-08
numerical: -0.098143 analytic: -0.098143, relative error: 1.083870e-07
numerical: 3.091417 analytic: 3.091416, relative error: 1.022752e-08
numerical: 2.323603 analytic: 2.323603, relative error: 1.538105e-08
numerical: 2.367387 analytic: 2.367387, relative error: 1.399357e-08
numerical: -0.116979 analytic: -0.116979, relative error: 8.063883e-08
numerical: -0.210734 analytic: -0.210734, relative error: 9.873194e-08
numerical: -1.672645 analytic: -1.672645, relative error: 2.430378e-09
numerical: -0.297251 analytic: -0.294439, relative error: 4.752791e-03
numerical: -1.785274 analytic: -1.779194, relative error: 1.705871e-03
numerical: -1.848513 analytic: -1.853651, relative error: 1.387981e-03
numerical: -3.818065 analytic: -3.814045, relative error: 5.267330e-04
numerical: 1.999599 analytic: 1.998979, relative error: 1.549415e-04
numerical: 1.086114 analytic: 1.083531, relative error: 1.190558e-03
numerical: 4.494518 analytic: 4.489883, relative error: 5.159879e-04
numerical: -1.132909 analytic: -1.135289, relative error: 1.049220e-03
```

```
numerical: 2.278554 analytic: 2.275955, relative error: 5.708280e-04
numerical: 0.013133 analytic: 0.008547, relative error: 2.115030e-01
```

[20]:
```python
# Now that we have a naive implementation of the softmax loss function and its␣
↪gradient,
# implement 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, X_dev, y_dev, 0.000005)
toc = time.time()
print('naive loss: %e computed in %fs' % (loss_naive, toc - tic))

from CV7062610.classifiers.softmax import softmax_loss_vectorized
tic = time.time()
loss_vectorized, grad_vectorized = softmax_loss_vectorized(W, X_dev, y_dev, 0.
↪000005)
toc = time.time()
print('vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic))

# 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)
```

```
naive loss: 2.318364e+00 computed in 10.679791s
vectorized loss: 2.318364e+00 computed in 0.013410s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[30]:
```python
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of over 0.35 on the validation set.

from CV7062610.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None

################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# save the best trained softmax classifer in best_softmax.                     #
################################################################################
```

```
# Provided as a reference. You may or may not want to change these␣
↪hyperparameters
learning_rates = [1e-8, 1e-7, 2e-7]
regularization_strengths = [1e4, 2e4, 3e4, 4e4, 5e4, 6e4, 7e4, 8e4, 1e5]

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
iters = 2000
for lr in learning_rates:
    for rs in regularization_strengths:
        softmax = Softmax()
        print(X_train.shape)
        softmax.train(X_train, y_train, learning_rate=lr, reg=rs,␣
↪num_iters=iters)

        y_train_pred = softmax.predict(X_train)
        acc_train = np.mean(y_train == y_train_pred)
        y_val_pred = softmax.predict(X_val)
        acc_val = np.mean(y_val == y_val_pred)

        results[(lr, rs)] = (acc_train, acc_val)

        if best_val < acc_val:
            best_val = acc_val
            best_softmax = softmax

pass

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out results.
for lr, reg in sorted(results):
    train_accuracy, val_accuracy = results[(lr, reg)]
    print('lr %e reg %e train accuracy: %f val accuracy: %f' % (
                lr, reg, train_accuracy, val_accuracy))

print('best validation accuracy achieved during cross-validation: %f' %␣
↪best_val)
```

```
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
```

```
(49000, 3073)
(49000, 3073)
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(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
(49000, 3073)
lr 1.000000e-08 reg 1.000000e+04 train accuracy: 0.177980 val accuracy: 0.180000
lr 1.000000e-08 reg 2.000000e+04 train accuracy: 0.181796 val accuracy: 0.170000
lr 1.000000e-08 reg 3.000000e+04 train accuracy: 0.174163 val accuracy: 0.180000
lr 1.000000e-08 reg 4.000000e+04 train accuracy: 0.194980 val accuracy: 0.193000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.201612 val accuracy: 0.219000
lr 1.000000e-08 reg 6.000000e+04 train accuracy: 0.208286 val accuracy: 0.201000
lr 1.000000e-08 reg 7.000000e+04 train accuracy: 0.220061 val accuracy: 0.210000
lr 1.000000e-08 reg 8.000000e+04 train accuracy: 0.246510 val accuracy: 0.254000
lr 1.000000e-08 reg 1.000000e+05 train accuracy: 0.230163 val accuracy: 0.242000
lr 1.000000e-07 reg 1.000000e+04 train accuracy: 0.354939 val accuracy: 0.369000
lr 1.000000e-07 reg 2.000000e+04 train accuracy: 0.357122 val accuracy: 0.367000
lr 1.000000e-07 reg 3.000000e+04 train accuracy: 0.348082 val accuracy: 0.363000
lr 1.000000e-07 reg 4.000000e+04 train accuracy: 0.335898 val accuracy: 0.347000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.330102 val accuracy: 0.346000
lr 1.000000e-07 reg 6.000000e+04 train accuracy: 0.317837 val accuracy: 0.336000
lr 1.000000e-07 reg 7.000000e+04 train accuracy: 0.316367 val accuracy: 0.337000
lr 1.000000e-07 reg 8.000000e+04 train accuracy: 0.312408 val accuracy: 0.329000
lr 1.000000e-07 reg 1.000000e+05 train accuracy: 0.310082 val accuracy: 0.323000
lr 2.000000e-07 reg 1.000000e+04 train accuracy: 0.373388 val accuracy: 0.387000
lr 2.000000e-07 reg 2.000000e+04 train accuracy: 0.352469 val accuracy: 0.372000
lr 2.000000e-07 reg 3.000000e+04 train accuracy: 0.351653 val accuracy: 0.364000
lr 2.000000e-07 reg 4.000000e+04 train accuracy: 0.337816 val accuracy: 0.334000
lr 2.000000e-07 reg 5.000000e+04 train accuracy: 0.332286 val accuracy: 0.345000
lr 2.000000e-07 reg 6.000000e+04 train accuracy: 0.320673 val accuracy: 0.338000
lr 2.000000e-07 reg 7.000000e+04 train accuracy: 0.323265 val accuracy: 0.334000
lr 2.000000e-07 reg 8.000000e+04 train accuracy: 0.314531 val accuracy: 0.330000
lr 2.000000e-07 reg 1.000000e+05 train accuracy: 0.303980 val accuracy: 0.328000
best validation accuracy achieved during cross-validation: 0.387000
```

[31]:

```
# evaluate on test set
# Evaluate the best softmax on test set
y_test_pred = best_softmax.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('softmax on raw pixels final test set accuracy: %f' % (test_accuracy, ))
```

```
softmax on raw pixels final test set accuracy: 0.375000
```

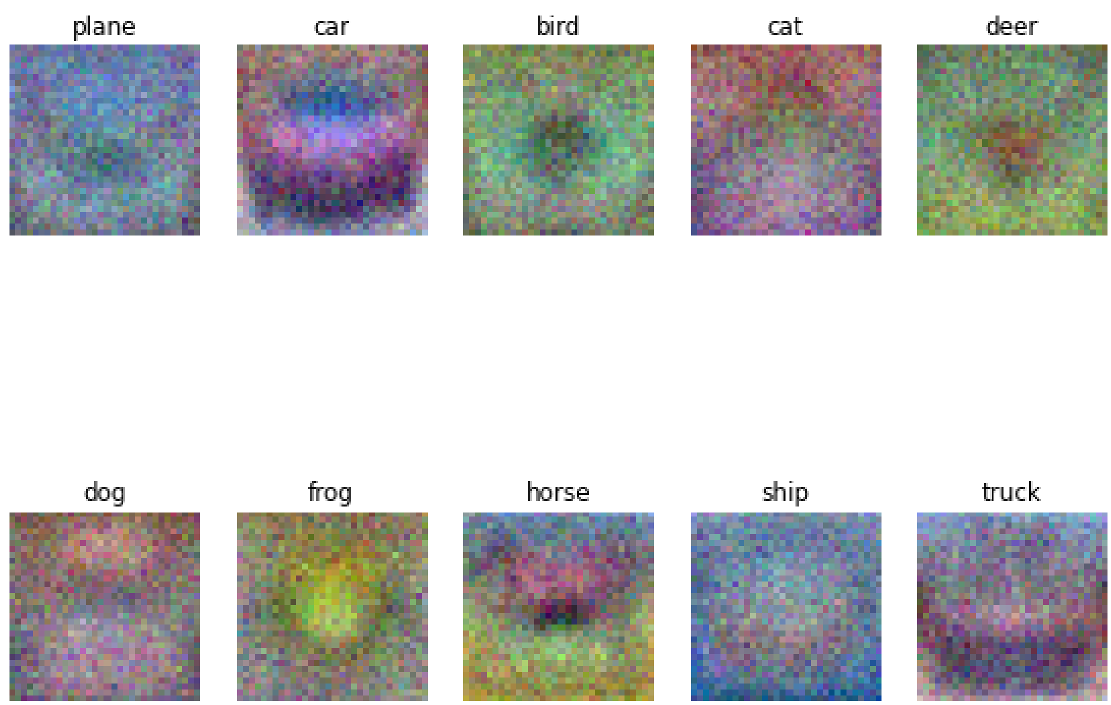
[32]:

```
# Visualize the learned weights for each class
w = best_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])
```



```
[ ]:
```

two_layer_net

March 28, 2022

1 Implementing a Neural Network

In this exercise we will develop a neural network with fully-connected layers to perform classification, and test it out on the CIFAR-10 dataset.

[ ]:
```
# A bit of setup

import numpy as np
import matplotlib.pyplot as plt

from cs231n.classifiers.neural_net import TwoLayerNet

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

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))))
```

We will use the class `TwoLayerNet` in the file `cs231n/classifiers/neural_net.py` to represent instances of our network. The network parameters are stored in the instance variable `self.params` where keys are string parameter names and values are numpy arrays. Below, we initialize toy data and a toy model that we will use to develop your implementation.

[ ]:
```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
hidden_size = 10
num_classes = 3
```

```python
num_inputs = 5

def init_toy_model():
    np.random.seed(0)
    return TwoLayerNet(input_size, hidden_size, num_classes, std=1e-1)

def init_toy_data():
    np.random.seed(1)
    X = 10 * np.random.randn(num_inputs, input_size)
    y = np.array([0, 1, 2, 2, 1])
    return X, y

net = init_toy_model()
X, y = init_toy_data()
```

2 Forward pass: compute scores

Open the file `cs231n/classifiers/neural_net.py` and look at the method `TwoLayerNet.loss`. This function is very similar to the loss functions you have written for the SVM and Softmax exercises: It takes the data and weights and computes the class scores, the loss, and the gradients on the parameters.

Implement the first part of the forward pass which uses the weights and biases to compute the scores for all inputs.

[ ]:
```python
scores = net.loss(X)
print('Your scores:')
print(scores)
print()
print('correct scores:')
correct_scores = np.asarray([
  [-0.81233741, -1.27654624, -0.70335995],
  [-0.17129677, -1.18803311, -0.47310444],
  [-0.51590475, -1.01354314, -0.8504215 ],
  [-0.15419291, -0.48629638, -0.52901952],
  [-0.00618733, -0.12435261, -0.15226949]])
print(correct_scores)
print()

# The difference should be very small. We get < 1e-7
print('Difference between your scores and correct scores:')
print(np.sum(np.abs(scores - correct_scores)))
```

3 Forward pass: compute loss

In the same function, implement the second part that computes the data and regularization loss.

```
[ ]: loss, _ = net.loss(X, y, reg=0.05)
correct_loss = 1.30378789133

# should be very small, we get < 1e-12
print('Difference between your loss and correct loss:')
print(np.sum(np.abs(loss - correct_loss)))
```

4 Backward pass

Implement the rest of the function. This will compute the gradient of the loss with respect to the variables `W1`, `b1`, `W2`, and `b2`. Now that you (hopefully!) have a correctly implemented forward pass, you can debug your backward pass using a numeric gradient check:

```
[ ]: from cs231n.gradient_check import eval_numerical_gradient

# Use numeric gradient checking to check your implementation of the backward␣
↪pass.
# If your implementation is correct, the difference between the numeric and
# analytic gradients should be less than 1e-8 for each of W1, W2, b1, and b2.

loss, grads = net.loss(X, y, reg=0.05)

# these should all be less than 1e-8 or so
for param_name in grads:
    f = lambda W: net.loss(X, y, reg=0.05)[0]
    param_grad_num = eval_numerical_gradient(f, net.params[param_name],␣
↪verbose=False)
    print('%s max relative error: %e' % (param_name, rel_error(param_grad_num,␣
↪grads[param_name])))
```

5 Train the network

To train the network we will use stochastic gradient descent (SGD), similar to the SVM and Softmax classifiers. Look at the function `TwoLayerNet.train` and fill in the missing sections to implement the training procedure. This should be very similar to the training procedure you used for the SVM and Softmax classifiers. You will also have to implement `TwoLayerNet.predict`, as the training process periodically performs prediction to keep track of accuracy over time while the network trains.

Once you have implemented the method, run the code below to train a two-layer network on toy data. You should achieve a training loss less than 0.02.

```
[ ]: net = init_toy_model()
     stats = net.train(X, y, X, y,
                 learning_rate=1e-1, reg=5e-6,
                 num_iters=100, verbose=False)

     print('Final training loss: ', stats['loss_history'][-1])

     # plot the loss history
     plt.plot(stats['loss_history'])
     plt.xlabel('iteration')
     plt.ylabel('training loss')
     plt.title('Training Loss history')
     plt.show()
```

6 Load the data

Now that you have implemented a two-layer network that passes gradient checks and works on toy data, it's time to load up our favorite CIFAR-10 data so we can use it to train a classifier on a real dataset.

```
[ ]: from cs231n.data_utils import load_CIFAR10

     def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
         """
         Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
         it for the two-layer neural net classifier. These are the same steps as
         we used for the SVM, but condensed to a single function.
         """
         # Load the raw CIFAR-10 data
         cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

         # Cleaning up variables to prevent loading data multiple times (which may␣
      ↪cause memory issue)
         try:
            del X_train, y_train
            del X_test, y_test
            print('Clear previously loaded data.')
         except:
            pass

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

         # Subsample the data
         mask = list(range(num_training, num_training + num_validation))
         X_val = X_train[mask]
         y_val = y_train[mask]
```

```
    mask = list(range(num_training))
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = list(range(num_test))
    X_test = X_test[mask]
    y_test = y_test[mask]

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis=0)
    X_train -= mean_image
    X_val -= mean_image
    X_test -= mean_image

    # Reshape data to rows
    X_train = X_train.reshape(num_training, -1)
    X_val = X_val.reshape(num_validation, -1)
    X_test = X_test.reshape(num_test, -1)

    return X_train, y_train, X_val, y_val, X_test, y_test


# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

7 Train a network

To train our network we will use SGD. In addition, we will adjust the learning rate with an exponential learning rate schedule as optimization proceeds; after each epoch, we will reduce the learning rate by multiplying it by a decay rate.

[ ]:
```
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
net = TwoLayerNet(input_size, hidden_size, num_classes)

# Train the network
stats = net.train(X_train, y_train, X_val, y_val,
            num_iters=1000, batch_size=200,
            learning_rate=1e-4, learning_rate_decay=0.95,
```

```
            reg=0.25, verbose=True)

# Predict on the validation set
val_acc = (net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

8 Debug the training

With the default parameters we provided above, you should get a validation accuracy of about 0.29 on the validation set. This isn't very good.

One strategy for getting insight into what's wrong is to plot the loss function and the accuracies on the training and validation sets during optimization.

Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

[ ]:
```
# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Classification accuracy')
plt.legend()
plt.show()
```

[ ]:
```
from cs231n.vis_utils import visualize_grid

# Visualize the weights of the network

def show_net_weights(net):
    W1 = net.params['W1']
    W1 = W1.reshape(32, 32, 3, -1).transpose(3, 0, 1, 2)
    plt.imshow(visualize_grid(W1, padding=3).astype('uint8'))
    plt.gca().axis('off')
    plt.show()

show_net_weights(net)
```

9 Tune your hyperparameters

What's wrong?. Looking at the visualizations above, we see that the loss is decreasing more or less linearly, which seems to suggest that the learning rate may be too low. Moreover, there is no gap between the training and validation accuracy, suggesting that the model we used has low capacity, and that we should increase its size. On the other hand, with a very large model we would expect to see more overfitting, which would manifest itself as a very large gap between the training and validation accuracy.

Tuning. Tuning the hyperparameters and developing intuition for how they affect the final performance is a large part of using Neural Networks, so we want you to get a lot of practice. Below, you should experiment with different values of the various hyperparameters, including hidden layer size, learning rate, numer of training epochs, and regularization strength. You might also consider tuning the learning rate decay, but you should be able to get good performance using the default value.

Approximate results. You should be aim to achieve a classification accuracy of greater than 48% on the validation set. Our best network gets over 52% on the validation set.

Experiment: You goal in this exercise is to get as good of a result on CIFAR-10 as you can (52% could serve as a reference), with a fully-connected Neural Network. Feel free implement your own techniques (e.g. PCA to reduce dimensionality, or adding dropout, or adding features to the solver, etc.).

Explain your hyperparameter tuning process below.

$\color{blue}{\textit{Your Answer :}}$

[ ]:
```
best_net = None # store the best model into this

##################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained␣
↪#
# model in best_net.                                                            ␣
↪#
#                                                                               ␣
↪#
# To help debug your network, it may help to use visualizations similar to the ␣
↪#
# ones we used above; these visualizations will have significant qualitative    ␣
↪#
# differences from the ones we saw above for the poorly tuned network.          ␣
↪#
#                                                                               ␣
↪#
# Tweaking hyperparameters by hand can be fun, but you might find it useful to ␣
↪#
# write code to sweep through possible combinations of hyperparameters          ␣
↪#
```

```
# automatically like we did on the previous exercises.
 ↪#
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

pass

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

[ ]:
```
# Print your validation accuracy: this should be above 48%
val_acc = (best_net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

[ ]:
```
# Visualize the weights of the best network
show_net_weights(best_net)
```

10 Run on the test set

When you are done experimenting, you should evaluate your final trained network on the test set; you should get above 48%.

[ ]:
```
# Print your test accuracy: this should be above 48%
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

Inline Question

Now that you have trained a Neural Network classifier, you may find that your testing accuracy is much lower than the training accuracy. In what ways can we decrease this gap? Select all that apply.

1. Train on a larger dataset.
2. Add more hidden units.
3. Increase the regularization strength.
4. None of the above.

Your Answer :

Your Explanation :