knn

October 8, 2023

[1]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cs231n/assignments/assignment1/'
FOLDERNAME = 'enpm809k fall 2023/assignment1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/My\ Drive/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/enpm809k fall 2023/assignment1/cs231n/datasets
/content/drive/My Drive/enpm809k fall 2023/assignment1
```

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:

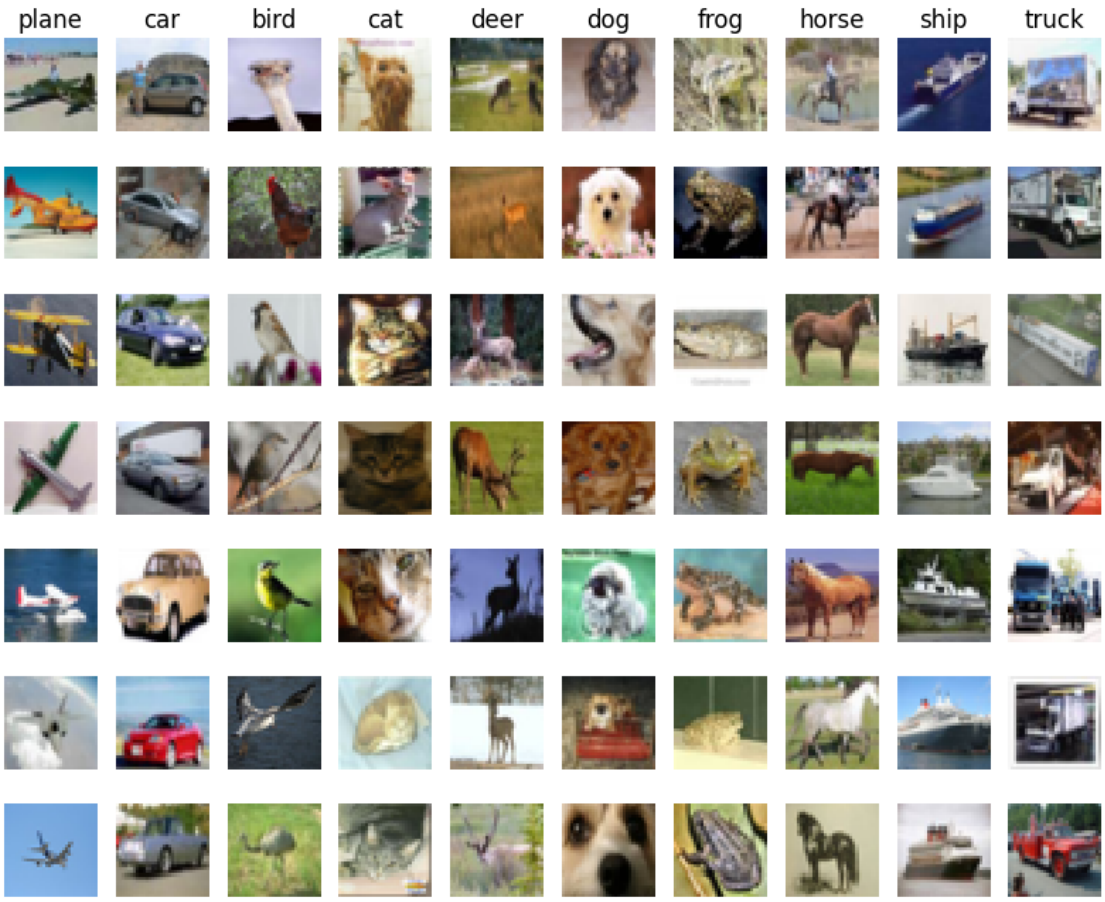
- During training, the classifier takes the training data and simply remembers it
- During testing, kNN classifies every test image by comparing to all training images and transfering the labels of the k most similar training examples
- The value of k is cross-validated

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.

[2]:
```
# Run some setup code for this notebook.

import random
import numpy as np
from cs231n.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
```

[3]:
```
# 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)

# As a sanity check, we print out the size of the training and test data.
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
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)
# PLEASE DO NOT MODIFY THE MARKERS
print('````````````````````````````````````````````````')
```

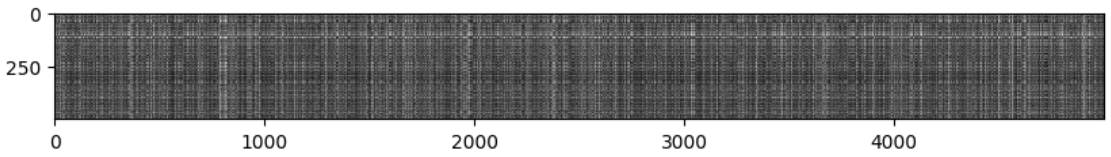
```
||||||||||||||||||||||||||||||||||||||||||||||||
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
``````````````````````````````````````````````````
```

[4]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
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()
print('``')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||
```
```




```
```

[5]:
```
# 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))
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
print(X_train.shape, X_test.shape)
```

```
print('``````````````````````````````````````````````')
```

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

[6]:
```
from cs231n.classifiers import KNearestNeighbor
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||')
# 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)
print('``')
```

```
||||||||||||||||||||||||||||||||||||||||||||||
``````````````````````````````````````````````
```

[7]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

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.

[8]:
```
# Open cs231n/classifiers/k_nearest_neighbor.py and implement
# compute_distances_two_loops.
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')

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

```
print(dists.shape)
# PLEASE DO NOT MODIFY THE MARKERS
print('~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||||
(500, 5000)
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
```

[9]:
```
# We can visualize the distance matrix: each row is a single test example and
# its distances to training examples
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||||')
plt.imshow(dists, interpolation='none')
plt.show()
# PLEASE DO NOT MODIFY THE MARKERS
print('~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||||
```




```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
```

**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?

*Your Answer :*

1) Each row corresponds to single test example and its distances to training examples so the bright rows are caused due to mismatch between test samples and training samples.

2) Each column corresponds to training sample and bright columns indicate the mismatched training samples.

[10]:
```
# 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
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
# PLEASE DO NOT MODIFY THE MARKERS
print('````````````````````````````````````````````````')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||
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`:

[11]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
y_test_pred = classifier.predict_labels(dists, k=5)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
# PLEASE DO NOT MODIFY THE MARKERS
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
print('``')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||
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 $\mu$ 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 $\mu_{ij}$ across all images is

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

The general standard deviation $\sigma$ and pixel-wise standard deviation $\sigma_{ij}$ 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 $\mu$ ($\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu$.) 2. Subtracting the per pixel mean $\mu_{ij}$ ($\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu_{ij}$.) 3. Subtracting the mean $\mu$ and dividing by the standard deviation $\sigma$. 4. Subtracting the pixel-wise mean $\mu_{ij}$ and dividing by the pixel-wise standard deviation $\sigma_{ij}$. 5. Rotating the coordinate axes of the data.

*YourAnswer* : preprocessing steps 1,2,3,4 will not change the performance of a Nearest Neighbor classifier that uses L1 distance

*YourExplanation* :

1) Subtracting the mean:

Subtracting a constant from every pixel of every image will shift all points by the same amount. The relative distances between points will remain unchanged. So, this will not change the performance of the Nearest Neighbor classifier.

2) Subtracting the per pixel mean:

Subtracting the mean of each pixel position from the corresponding pixel of every image will shift all points in a consistent manner. The relative distances between points will remain unchanged. So, this will not change the performance.

3) Subtracting the mean and dividing by the standard deviation:

This is a standard normalization step. While it scales the data, the relative distances between the data points remain the same. So, this will not change the performance.

4) Subtracting the pixel-wise mean and dividing by the pixel-wise standard deviation:

This normalization is done on a per-pixel basis. It scales each pixel's values across all images by its standard deviation. The relative distances between the data points remain the same. So, this will not change the performance. Rotating the coordinate axes of the data:

5) Rotation will change the L1 distances between points. For instance, consider two points on the x-axis. Their L1 distance is just the difference in their x-coordinates. If we rotate the axis, they will have non-zero y-coordinates, and the L1 distance will change. So, this will change the performance of the Nearest Neighbor classifier.

[12]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('|||||||||||||||||||||||||||||||||||||||||||||||||')
# 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')
else:
```

```
    print('Uh-oh! The distance matrices are different')
# PLEASE DO NOT MODIFY THE MARKERS
print('``````````````````````````````````````````````')
```

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

[13]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||')
# 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')
# PLEASE DO NOT MODIFY THE MARKERS
print('``````````````````````````````````````````````')
```

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

[14]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||')
# 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.
# PLEASE DO NOT MODIFY THE MARKERS
print('``````````````````````````````````````````````````')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||
Two loop version took 42.513562 seconds
One loop version took 46.154830 seconds
No loop version took 0.666368 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.

[15]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
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)

*****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)*****

for k in k_choices:
    k_to_accuracies[k] = []
    for i in range(num_folds):
        # Use all except the i-th fold as training data
        X_train_cross = np.vstack(X_train_folds[:i] + X_train_folds[i+1:])
        y_train_cross= np.hstack(y_train_folds[:i] + y_train_folds[i+1:])

        # Use the i-th fold as validation data
        X_val_cross = X_train_folds[i]
        y_val_cross = y_train_folds[i]

        # Initializing and training the k-nearest neighbors classifier
        classifier = KNearestNeighbor()
        classifier.train(X_train_cross, y_train_cross)
        y_val_pred = classifier.predict(X_val_cross, k=k)

        # Compute the accuracy
        accuracy = np.mean(y_val_pred == y_val_cross)
        k_to_accuracies[k].append(accuracy)

# *****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))
# PLEASE DO NOT MODIFY THE MARKERS
print('`````````````````````````````````````````````````')
```

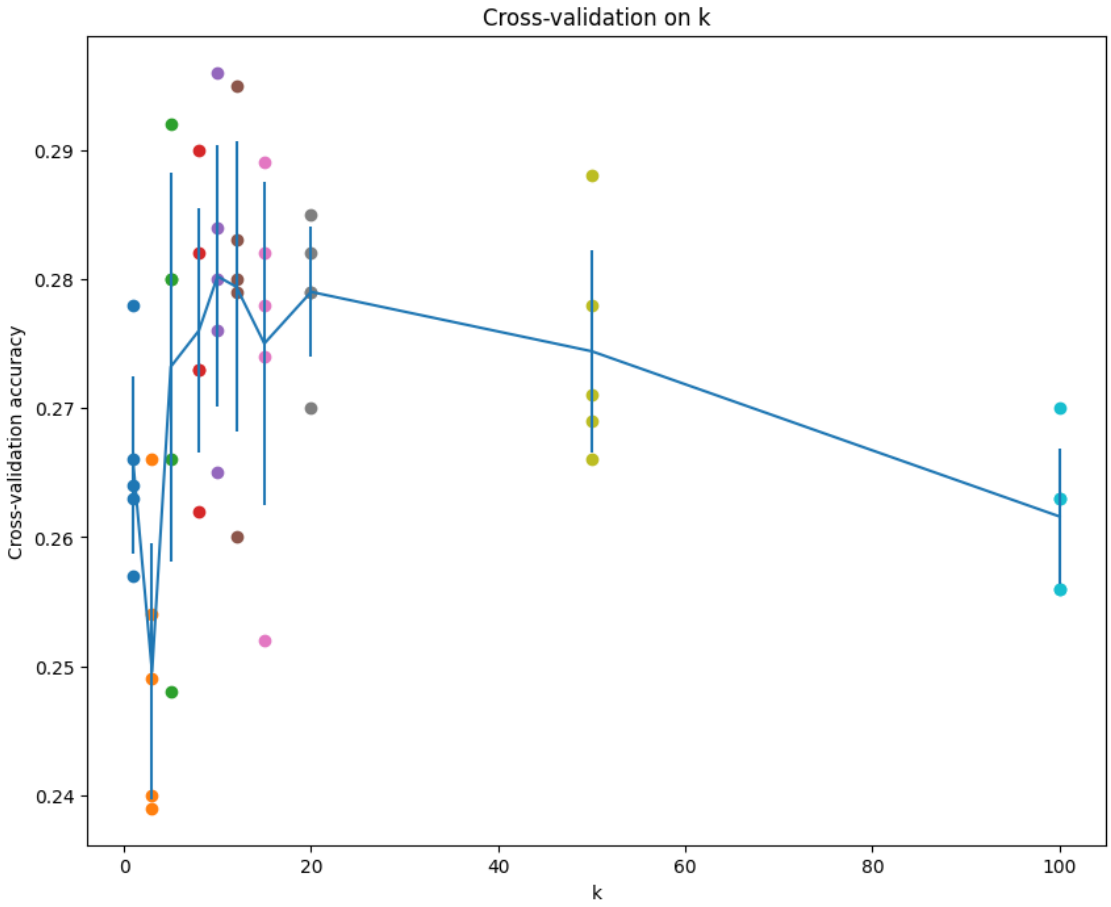
```
|||||||||||||||||||||||||||||||||||||||||||||
k = 1, accuracy = 0.263000
```

```
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
```

[16]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||')
# 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()
# PLEASE DO NOT MODIFY THE MARKERS
print('````````````````````````````````````````````````')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||
```




```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
```

[17]:
```
# PLEASE DO NOT MODIFY THE MARKERS
print('||||||||||||||||||||||||||||||||||||||||||||||||||')
# 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))
# PLEASE DO NOT MODIFY THE MARKERS
print('~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~')
```

```
||||||||||||||||||||||||||||||||||||||||||||||||||
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 or equal to 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.

*YourAnswer* : 2 and 4

*YourExplanation* :

1. False. k-NN can produce non-linear decision boundaries.
2. True. 1-NN's training error is 0 because each training point is its own nearest neighbor.
3. False. Test error varies with data; 1-NN can be more sensitive to noise than 5-NN.
4. True. Classification time increases with more training data due to distance computations.
```

svm

October 8, 2023

[ ]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cs231n/assignments/assignment1/'
FOLDERNAME = 'enpm809k fall 2023/assignment1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/My\ Drive/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/enpm809k fall 2023/assignment1/cs231n/datasets
/content/drive/My Drive/enpm809k fall 2023/assignment1
```

1 Multiclass Support Vector Machine 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.

In this exercise you will:

- implement a fully-vectorized **loss function** for the SVM
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** using 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

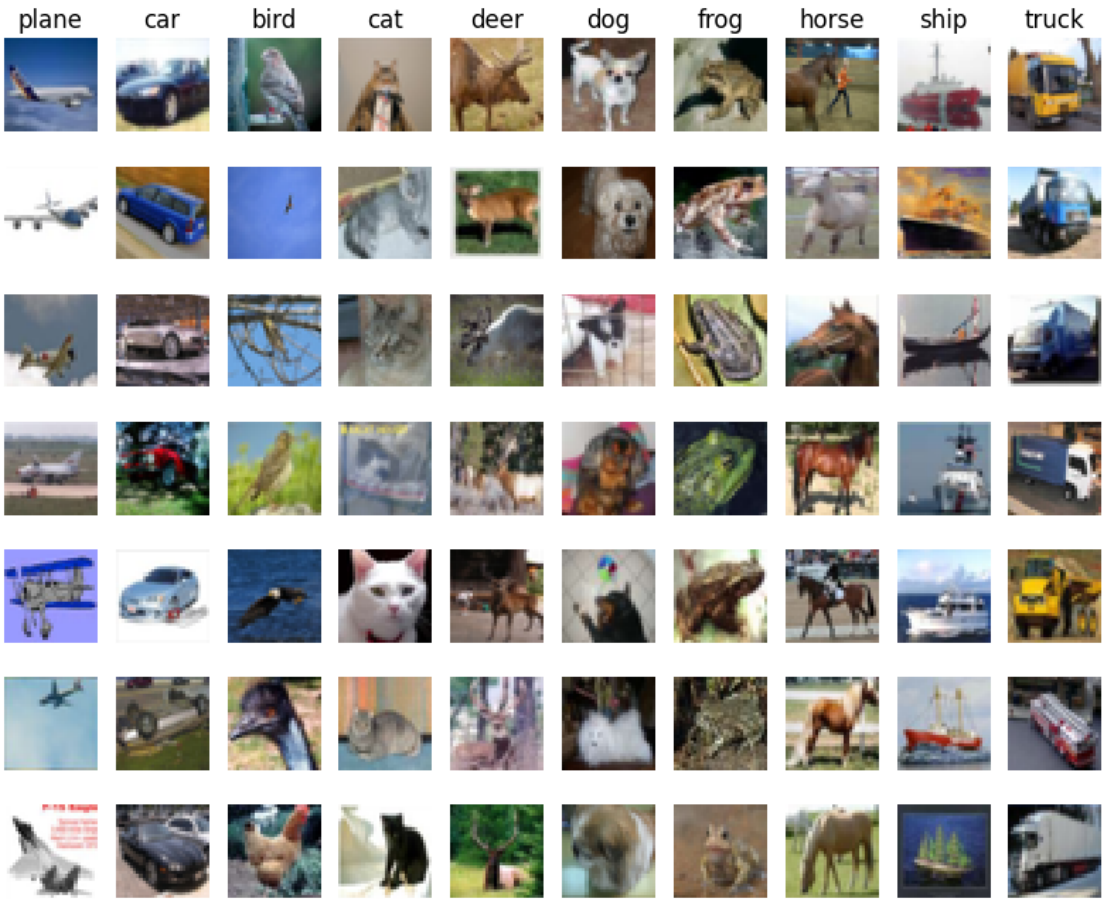
[ ]:
```
# Run some setup code for this notebook.
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# 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
```

1.1 CIFAR-10 Data Loading and Preprocessing

[ ]:
```
# 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)

# 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()
```



[ ]:
```
# Split the data into train, val, and test sets. In addition we will
# create a small development set as a subset of the training data;
# we can use this for development so our code runs faster.
num_training = 49000
num_validation = 1000
num_test = 1000
num_dev = 500

# Our validation set will be num_validation points from the original
# training set.
mask = range(num_training, num_training + num_validation)
X_val = X_train[mask]
y_val = y_train[mask]

# Our training set will be the first num_train points from the original
# training set.
mask = range(num_training)
X_train = X_train[mask]
y_train = y_train[mask]

# We will also make a development set, which is a small subset of
# the training set.
mask = np.random.choice(num_training, num_dev, replace=False)
X_dev = X_train[mask]
y_dev = y_train[mask]

# We use the first num_test points of the original test set as our
# test set.
mask = range(num_test)
X_test = X_test[mask]
y_test = y_test[mask]

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)
```

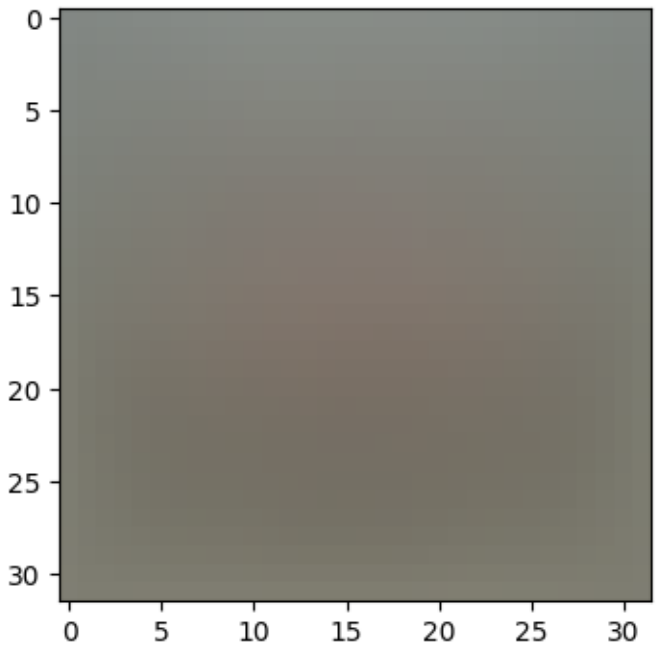
```
Train data shape:  (49000, 32, 32, 3)
Train labels shape:  (49000,)
Validation data shape:  (1000, 32, 32, 3)
Validation labels shape:  (1000,)
Test data shape:  (1000, 32, 32, 3)
Test labels shape:  (1000,)
```

[ ]:
```
# 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))

# As a sanity check, print out the shapes of the data
print('Training data shape: ', X_train.shape)
print('Validation data shape: ', X_val.shape)
print('Test data shape: ', X_test.shape)
print('dev data shape: ', X_dev.shape)
```

```
Training data shape:  (49000, 3072)
Validation data shape:  (1000, 3072)
Test data shape:  (1000, 3072)
dev data shape:  (500, 3072)
```

[ ]:
```
# Preprocessing: subtract the mean image
# first: compute the image mean based on the training data
mean_image = np.mean(X_train, axis=0)
print(mean_image[:10]) # print a few of the elements
plt.figure(figsize=(4,4))
plt.imshow(mean_image.reshape((32,32,3)).astype('uint8')) # visualize the mean␣
 ↪image
plt.show()

# second: subtract the mean image from train and test data
X_train -= mean_image
X_val -= mean_image
X_test -= mean_image
X_dev -= mean_image

# third: append the bias dimension of ones (i.e. bias trick) so that our SVM
# only has to worry about optimizing a single weight matrix W.
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))])

print(X_train.shape, X_val.shape, X_test.shape, X_dev.shape)
```

```
[130.64189796 135.98173469 132.47391837 130.05569388 135.34804082
 131.75402041 130.96055102 136.14328571 132.47636735 131.48467347]
```




```
(49000, 3073) (1000, 3073) (1000, 3073) (500, 3073)
```

1.2 SVM Classifier

Your code for this section will all be written inside `cs231n/classifiers/linear_svm.py`.

As you can see, we have prefilled the function `svm_loss_naive` which uses for loops to evaluate the multiclass SVM loss function.

[ ]:
```
# Evaluate the naive implementation of the loss we provided for you:
from cs231n.classifiers.linear_svm import svm_loss_naive
import time

# generate a random SVM weight matrix of small numbers
W = np.random.randn(3073, 10) * 0.0001

loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.000005)
print('loss: %f' % (loss, ))
```

```
loss: 9.081122
```

The `grad` returned from the function above is right now all zero. Derive and implement the gradient for the SVM cost function and implement it inline inside the function `svm_loss_naive`. You will find it helpful to interleave your new code inside the existing function.

To check that you have correctly 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:

[ ]:
```
# Once you've implemented the gradient, recompute it with the code below
# and gradient check it with the function we provided for you

# Compute the loss and its gradient at W.
loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.0)

# 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.
from cs231n.gradient_check import grad_check_sparse
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad)

# do the gradient check once again with regularization turned on
# you didn't forget the regularization gradient did you?
loss, grad = svm_loss_naive(W, X_dev, y_dev, 5e1)
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 5e1)[0]
grad_numerical = grad_check_sparse(f, W, grad)
```

```
numerical: 19.910379 analytic: 19.910379, relative error: 3.792731e-12
numerical: -1.583564 analytic: -1.600910, relative error: 5.447184e-03
numerical: 0.291462 analytic: 0.347375, relative error: 8.752250e-02
numerical: 3.765578 analytic: 3.817588, relative error: 6.858640e-03
numerical: 7.441814 analytic: 7.465623, relative error: 1.597134e-03
numerical: -33.274750 analytic: -33.274750, relative error: 1.679477e-12
numerical: -5.776102 analytic: -5.776102, relative error: 3.132535e-11
numerical: 13.541943 analytic: 13.541943, relative error: 2.450011e-12
numerical: 17.172447 analytic: 17.172447, relative error: 2.371693e-11
numerical: -43.333538 analytic: -43.333538, relative error: 1.570757e-12
numerical: -0.414672 analytic: -0.414672, relative error: 8.690674e-10
numerical: 8.512655 analytic: 8.508094, relative error: 2.679457e-04
numerical: -40.726586 analytic: -40.814990, relative error: 1.084165e-03
numerical: 1.274972 analytic: 1.274972, relative error: 6.444433e-10
numerical: 4.282296 analytic: 4.282296, relative error: 9.797184e-12
numerical: 0.773356 analytic: 0.773356, relative error: 7.344900e-10
numerical: 10.474130 analytic: 10.474130, relative error: 6.298687e-11
numerical: 5.224578 analytic: 5.224578, relative error: 2.017977e-11
numerical: -6.229857 analytic: -6.229857, relative error: 5.082251e-11
numerical: -18.509443 analytic: -18.509443, relative error: 2.574029e-11
```

Inline Question 1

It is possible that once in a while a dimension in the gradcheck will not match exactly. What could such a discrepancy be caused by? Is it a reason for concern? What is a simple example in one dimension where a gradient check could fail? How would change the margin affect of the frequency of this happening? *Hint: the SVM loss function is not strictly speaking differentiable*

YourAnswer : The SVM loss function, due to the hinge loss component, isn't strictly differentiable

everywhere, specifically at points where the margin is exactly met. This non-differentiability can cause discrepancies during gradient checking, where the numerical gradient might not align with the analytical gradient.

Concern: Typically, this isn't alarming as such discrepancies are usually minor and infrequent, and optimization algorithms generally perform well despite these.

Example: For instance, in a function (f(x) = max(0, x)), discrepancies might occur at (x = 0) during gradient checking, as the function isn't differentiable at that point.

Margin Alteration: Modifying the margin can influence the frequency of non-differentiability points; a larger margin might increase such points, whereas a smaller one might reduce them, contingent also on the data and model weights.

Solution: To mitigate, one might employ a smooth approximation like the squared hinge loss or logistic loss, which are differentiable everywhere, but in practice, standard hinge loss usually suffices with standard subgradient methods.

[ ]:
```
# Next implement the function svm_loss_vectorized; for now only compute the loss;
# we will implement the gradient in a moment.
tic = time.time()
loss_naive, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss: %e computed in %fs' % (loss_naive, toc - tic))

from cs231n.classifiers.linear_svm import svm_loss_vectorized
tic = time.time()
loss_vectorized, _ = svm_loss_vectorized(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic))

# The losses should match but your vectorized implementation should be much faster.
print('difference: %f' % (loss_naive - loss_vectorized))
```

```
Naive loss: 9.081122e+00 computed in 0.109371s
Vectorized loss: 9.081122e+00 computed in 0.014300s
difference: 0.000000
```

[ ]:
```
# Complete the implementation of svm_loss_vectorized, and compute the gradient
# of the loss function in a vectorized way.

# The naive implementation and the vectorized implementation should match, but
# the vectorized version should still be much faster.
tic = time.time()
_, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss and gradient: computed in %fs' % (toc - tic))
```

```
tic = time.time()
_, grad_vectorized = svm_loss_vectorized(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Vectorized loss and gradient: computed in %fs' % (toc - tic))

# The loss is a single number, so it is easy to compare the values computed
# by the two implementations. The gradient on the other hand is a matrix, so
# we use the Frobenius norm to compare them.
difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('difference: %f' % difference)
```

```
Naive loss and gradient: computed in 0.090544s
Vectorized loss and gradient: computed in 0.024904s
difference: 0.000000
```

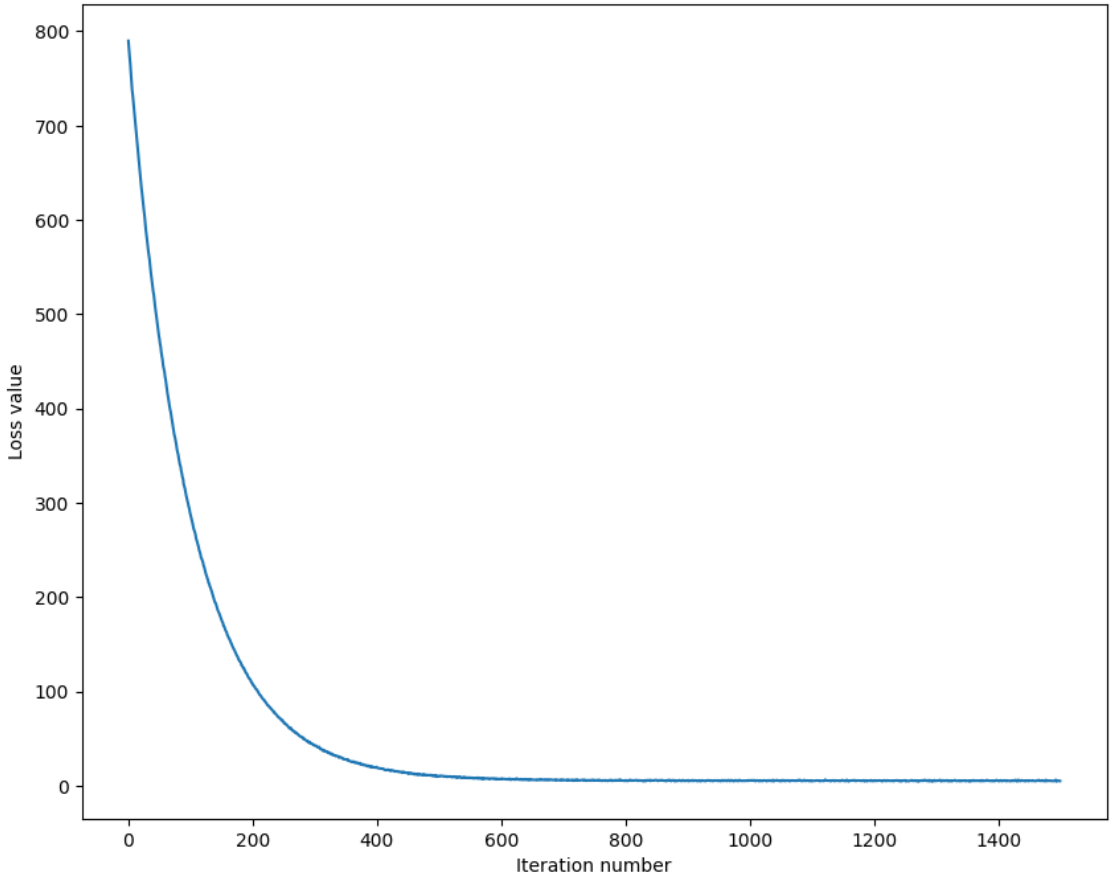
1.2.1 Stochastic Gradient Descent

We now have vectorized and efficient expressions for the loss, the gradient and our gradient matches the numerical gradient. We are therefore ready to do SGD to minimize the loss. Your code for this part will be written inside `cs231n/classifiers/linear_classifier.py`.

[ ]:
```
# In the file linear_classifier.py, implement SGD in the function
# LinearClassifier.train() and then run it with the code below.
from cs231n.classifiers import LinearSVM
svm = LinearSVM()
tic = time.time()
loss_hist = svm.train(X_train, y_train, learning_rate=1e-7, reg=2.5e4,
                      num_iters=1500, verbose=True)
toc = time.time()
print('That took %fs' % (toc - tic))
```

```
iteration 0 / 1500: loss 789.770163
iteration 100 / 1500: loss 287.282042
iteration 200 / 1500: loss 107.520315
iteration 300 / 1500: loss 42.464215
iteration 400 / 1500: loss 19.203731
iteration 500 / 1500: loss 10.047074
iteration 600 / 1500: loss 7.059641
iteration 700 / 1500: loss 5.771827
iteration 800 / 1500: loss 5.844742
iteration 900 / 1500: loss 5.112252
iteration 1000 / 1500: loss 5.251426
iteration 1100 / 1500: loss 5.101679
iteration 1200 / 1500: loss 5.063355
iteration 1300 / 1500: loss 5.322347
iteration 1400 / 1500: loss 4.946179
That took 11.165065s
```

[ ]:
```
# 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()
```



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

```
training accuracy: 0.370633
validation accuracy: 0.374000
```

[ ]:
```
# 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 about 0.39 on the validation set.

# Note: you may see runtime/overflow warnings during hyper-parameter search.
# This may be caused by extreme values, and is not a bug.

# results is dictionary mapping tuples of the form
# (learning_rate, regularization_strength) to tuples of the form
# (training_accuracy, validation_accuracy). The accuracy is simply the fraction
# of data points that are correctly classified.
results = {}
best_val = -1   # The highest validation accuracy that we have seen so far.
best_svm = None # The LinearSVM object that achieved the highest validation␣
 ↪rate.

################################################################################
# TODO:                                                                        #
# Write code that chooses the best hyperparameters by tuning on the validation #
# set. For each combination of hyperparameters, train a linear SVM on the      #
# training set, compute its accuracy on the training and validation sets, and  #
# store these numbers in the results dictionary. In addition, store the best   #
# validation accuracy in best_val and the LinearSVM object that achieves this  #
# accuracy in best_svm.                                                        #
#                                                                              #
# Hint: You should use a small value for num_iters as you develop your         #
# validation code so that the SVMs don't take much time to train; once you are #
# confident that your validation code works, you should rerun the validation   #
# code with a larger value for num_iters.                                      #
################################################################################

# Provided as a reference. You may or may not want to change these␣
 ↪hyperparameters
#learning_rates = [1e-7, 5e-5]
#regularization_strengths = [2.5e4, 5e4]
learning_rates = [1e-7, 5e-7, 1e-6, 5e-6, 1e-5, 5e-5]
regularization_strengths = [1e3, 5e3, 1e4, 5e4, 1e5, 5e5]

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

# Iterate over the hyperparameters
for lr in learning_rates:
    for reg in regularization_strengths:
        # Create a new SVM instance
        svm = LinearSVM()
        # Train the SVM
        loss_hist = svm.train(X_train, y_train, learning_rate=lr, reg=reg,␣
 ↪num_iters=5000)
```

```
        # Predict on the training set
        y_train_pred = svm.predict(X_train)
        train_accuracy = np.mean(y_train == y_train_pred)

        # Predict on the validation set
        y_val_pred = svm.predict(X_val)
        val_accuracy = np.mean(y_val == y_val_pred)

        # Store the results
        results[(lr, reg)] = (train_accuracy, val_accuracy)

        # Check if this is the best validation accuracy so far
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm

# *****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)
```

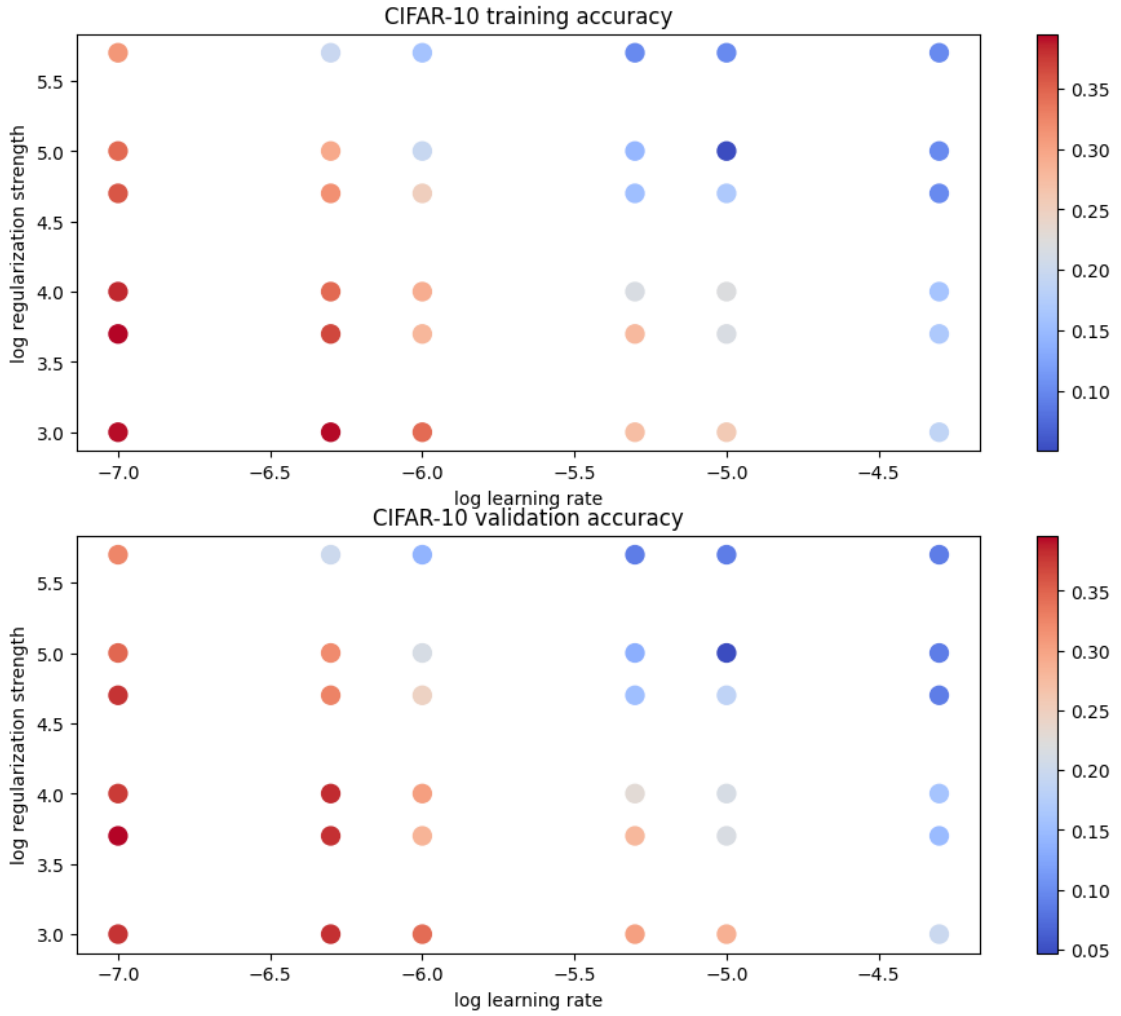
```
/content/drive/My Drive/enpm809k fall
2023/assignment1/cs231n/classifiers/linear_svm.py:94: RuntimeWarning: overflow
encountered in subtract
  margins = np.maximum(0, scores - correct_class_scores + 1)
```

```
lr 1.000000e-07 reg 1.000000e+03 train accuracy: 0.391796 val accuracy: 0.379000
lr 1.000000e-07 reg 5.000000e+03 train accuracy: 0.395286 val accuracy: 0.396000
lr 1.000000e-07 reg 1.000000e+04 train accuracy: 0.383469 val accuracy: 0.375000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.358184 val accuracy: 0.379000
lr 1.000000e-07 reg 1.000000e+05 train accuracy: 0.346286 val accuracy: 0.347000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.310755 val accuracy: 0.325000
lr 5.000000e-07 reg 1.000000e+03 train accuracy: 0.393122 val accuracy: 0.380000
lr 5.000000e-07 reg 5.000000e+03 train accuracy: 0.367816 val accuracy: 0.380000
lr 5.000000e-07 reg 1.000000e+04 train accuracy: 0.345959 val accuracy: 0.383000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.316388 val accuracy: 0.327000
lr 5.000000e-07 reg 1.000000e+05 train accuracy: 0.294898 val accuracy: 0.321000
lr 5.000000e-07 reg 5.000000e+05 train accuracy: 0.197898 val accuracy: 0.201000
lr 1.000000e-06 reg 1.000000e+03 train accuracy: 0.344714 val accuracy: 0.343000
lr 1.000000e-06 reg 5.000000e+03 train accuracy: 0.281082 val accuracy: 0.284000
lr 1.000000e-06 reg 1.000000e+04 train accuracy: 0.290408 val accuracy: 0.304000
```

```
lr 1.000000e-06 reg 5.000000e+04 train accuracy: 0.251653 val accuracy: 0.245000
lr 1.000000e-06 reg 1.000000e+05 train accuracy: 0.195898 val accuracy: 0.213000
lr 1.000000e-06 reg 5.000000e+05 train accuracy: 0.160082 val accuracy: 0.139000
lr 5.000000e-06 reg 1.000000e+03 train accuracy: 0.273653 val accuracy: 0.302000
lr 5.000000e-06 reg 5.000000e+03 train accuracy: 0.278898 val accuracy: 0.280000
lr 5.000000e-06 reg 1.000000e+04 train accuracy: 0.216469 val accuracy: 0.229000
lr 5.000000e-06 reg 5.000000e+04 train accuracy: 0.154245 val accuracy: 0.153000
lr 5.000000e-06 reg 1.000000e+05 train accuracy: 0.144980 val accuracy: 0.134000
lr 5.000000e-06 reg 5.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
lr 1.000000e-05 reg 1.000000e+03 train accuracy: 0.258898 val accuracy: 0.287000
lr 1.000000e-05 reg 5.000000e+03 train accuracy: 0.216592 val accuracy: 0.216000
lr 1.000000e-05 reg 1.000000e+04 train accuracy: 0.220673 val accuracy: 0.213000
lr 1.000000e-05 reg 5.000000e+04 train accuracy: 0.169000 val accuracy: 0.186000
lr 1.000000e-05 reg 1.000000e+05 train accuracy: 0.050061 val accuracy: 0.047000
lr 1.000000e-05 reg 5.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 1.000000e+03 train accuracy: 0.188327 val accuracy: 0.198000
lr 5.000000e-05 reg 5.000000e+03 train accuracy: 0.169918 val accuracy: 0.147000
lr 5.000000e-05 reg 1.000000e+04 train accuracy: 0.161816 val accuracy: 0.160000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 1.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 5.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.396000
```

[ ]:
```python
# Visualize the cross-validation results
import math
import pdb

# pdb.set_trace()

x_scatter = [math.log10(x[0]) for x in results]
y_scatter = [math.log10(x[1]) for x in results]

# plot training accuracy
marker_size = 100
colors = [results[x][0] for x in results]
plt.subplot(2, 1, 1)
plt.tight_layout(pad=3)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 training accuracy')

# plot validation accuracy
colors = [results[x][1] for x in results] # default size of markers is 20
plt.subplot(2, 1, 2)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
```

```
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 validation accuracy')
plt.show()
```

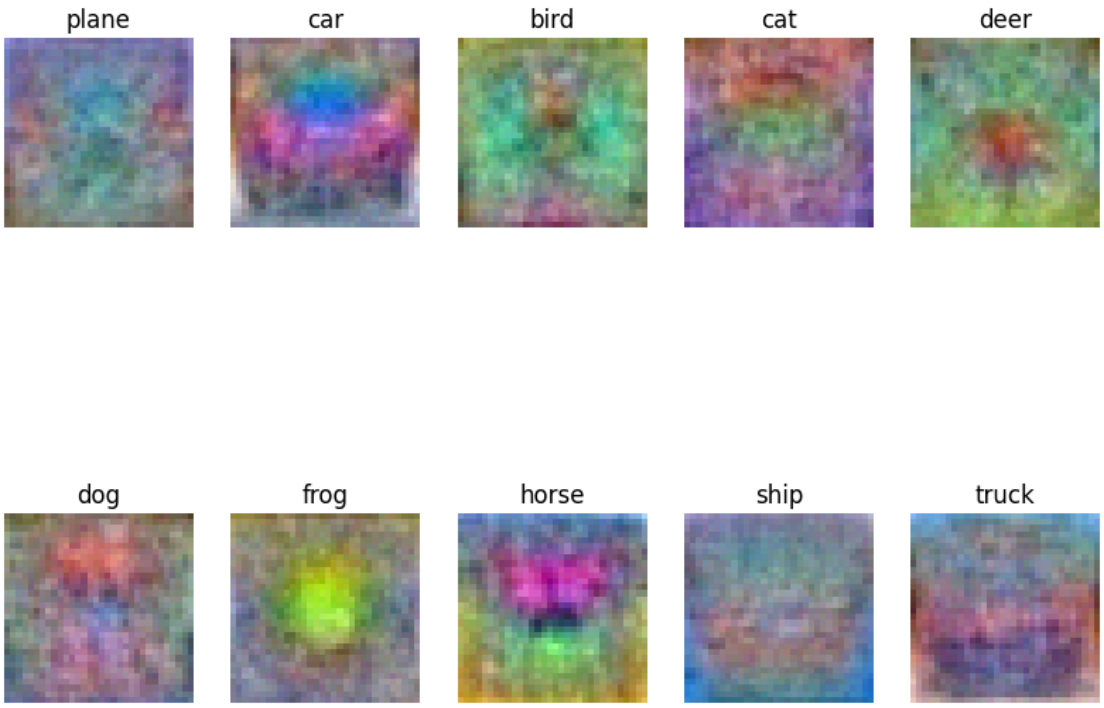


[ ]:
```
# Evaluate the best svm on test set
y_test_pred = best_svm.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('linear SVM on raw pixels final test set accuracy: %f' % test_accuracy)
```

```
linear SVM on raw pixels final test set accuracy: 0.385000
```

[ ]:
```
# Visualize the learned weights for each class.
# Depending on your choice of learning rate and regularization strength, these␣
↪may
```

```
# or may not be nice to look at.
w = best_svm.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])
```



Inline question 2

Describe what your visualized SVM weights look like, and offer a brief explanation for why they look they way that they do.

YourAnswer : Description:

The visualized weights for each class in SVM appear to amalgamate various images corresponding to that class, presenting as generalized, abstract representations of the features identified by the subset of weights for each category. They resemble fuzzy outlines or templates for each class.

Interpretation: The SVM seems to have learned to recognize the unique attributes of each class. For instance, it identifies the prominent feature of a car as its front window and recognizes the color green typically associated with a frog. Given that SVM is a linear classifier, it is unable to create an exact decision boundary to accommodate the diverse shapes each image within a class can have. This is why the visualized weights often appear symmetric, as they are trained to generalize optimally, leading to instances like the depiction of a horse with two heads.

The benefit of linear classification is its ability to yield understandable visualizations, allowing insights into what features the model is focusing on to make decisions.

softmax

October 8, 2023

[1]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cs231n/assignments/assignment1/'
FOLDERNAME = 'enpm809k fall 2023/assignment1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/My\ Drive/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/enpm809k fall 2023/assignment1/cs231n/datasets
/content/drive/My Drive/enpm809k fall 2023/assignment1
```

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

[3]:
```
import random
import numpy as np
from cs231n.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
```

[4]:
```
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 = '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]
```

```
    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,)
```

1.1 Softmax Classifier

Your code for this section will all be written inside `cs231n/classifiers/softmax.py`.

[6]:
```
# First implement the naive softmax loss function with nested loops.
# Open the file cs231n/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from cs231n.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: 2.434746
sanity check: 2.302585
```

Inline Question 1

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

Your Answer : We anticipate that the initial loss must be close to -log(0.1) as we are not using a learning process and are simply computing the softmax based on some initial random weights. This is because initially, all classes have an equal likelihood of being chosen. Since there are 10 classes in CIFAR-10, the probability of selecting the correct class is 0.1, and the softmax loss is the negative log of the probability of selecting the correct class, it is -log (0.1).

[7]:
```
# 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 cs231n.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: 0.025898 analytic: 0.025898, relative error: 1.242005e-06
numerical: 2.473608 analytic: 2.473608, relative error: 1.670912e-08
numerical: 0.478169 analytic: 0.478169, relative error: 9.054572e-08
```

```
numerical: -3.518485 analytic: -3.518486, relative error: 2.160331e-08
numerical: 0.934178 analytic: 0.934178, relative error: 2.547294e-08
numerical: -0.878112 analytic: -0.878112, relative error: 4.845514e-08
numerical: -3.007328 analytic: -3.007328, relative error: 1.530741e-08
numerical: -4.656557 analytic: -4.656557, relative error: 8.772232e-09
numerical: 3.363522 analytic: 3.363522, relative error: 1.670204e-08
numerical: 1.944260 analytic: 1.944260, relative error: 3.002241e-08
numerical: -0.098283 analytic: -0.098283, relative error: 1.616906e-07
numerical: -0.135952 analytic: -0.135952, relative error: 9.716274e-08
numerical: -0.182486 analytic: -0.182486, relative error: 3.307948e-07
numerical: -0.353443 analytic: -0.353443, relative error: 9.182921e-08
numerical: -0.018891 analytic: -0.018891, relative error: 2.801399e-06
numerical: 2.195135 analytic: 2.195135, relative error: 2.277097e-08
numerical: 1.243850 analytic: 1.243850, relative error: 6.993023e-08
numerical: -0.453525 analytic: -0.453525, relative error: 1.366026e-07
numerical: 2.487887 analytic: 2.487887, relative error: 2.348788e-08
numerical: 2.539859 analytic: 2.539859, relative error: 2.540943e-08
```

[8]:
```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 cs231n.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: 2.434746e+00 computed in 0.138312s
vectorized loss: 2.434746e+00 computed in 0.037977s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[15]:
```
# 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 cs231n.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None

################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# This should be identical to the validation that you did for the SVM; 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-7, 5e-7]
#regularization_strengths = [2.5e4, 5e4]
learning_rates = [1e-7, 5e-7, 1e-6, 5e-6, 1e-5, 5e-5]
regularization_strengths = [1e3, 5e3, 1e4, 5e4, 1e5, 5e5]

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

for lr in learning_rates:
    for reg in regularization_strengths:
        # Create a Softmax classifier instance
        softmax = Softmax()

        # Train the Softmax classifier
        loss_hist = softmax.train(X_train, y_train, learning_rate=lr, reg=reg,␣
 ↪num_iters=1500)

        # Predict values for training set and compute accuracy
        y_train_pred = softmax.predict(X_train)
        train_accuracy = np.mean(y_train == y_train_pred)

        # Predict values for validation set and compute accuracy
        y_val_pred = softmax.predict(X_val)
        val_accuracy = np.mean(y_val == y_val_pred)

        # Store the results
        results[(lr, reg)] = (train_accuracy, val_accuracy)

        # Update best validation accuracy and corresponding Softmax object
```

```
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_softmax = softmax


# *****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)
```

```
lr 1.000000e-07 reg 1.000000e+03 train accuracy: 0.260837 val accuracy: 0.265000
lr 1.000000e-07 reg 5.000000e+03 train accuracy: 0.332776 val accuracy: 0.337000
lr 1.000000e-07 reg 1.000000e+04 train accuracy: 0.352429 val accuracy: 0.373000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.308000 val accuracy: 0.325000
lr 1.000000e-07 reg 1.000000e+05 train accuracy: 0.296408 val accuracy: 0.309000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.253857 val accuracy: 0.261000
lr 5.000000e-07 reg 1.000000e+03 train accuracy: 0.390755 val accuracy: 0.393000
lr 5.000000e-07 reg 5.000000e+03 train accuracy: 0.372265 val accuracy: 0.387000
lr 5.000000e-07 reg 1.000000e+04 train accuracy: 0.359082 val accuracy: 0.376000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.306490 val accuracy: 0.321000
lr 5.000000e-07 reg 1.000000e+05 train accuracy: 0.289224 val accuracy: 0.303000
lr 5.000000e-07 reg 5.000000e+05 train accuracy: 0.242245 val accuracy: 0.252000
lr 1.000000e-06 reg 1.000000e+03 train accuracy: 0.400776 val accuracy: 0.395000
lr 1.000000e-06 reg 5.000000e+03 train accuracy: 0.368204 val accuracy: 0.381000
lr 1.000000e-06 reg 1.000000e+04 train accuracy: 0.333612 val accuracy: 0.347000
lr 1.000000e-06 reg 5.000000e+04 train accuracy: 0.304490 val accuracy: 0.318000
lr 1.000000e-06 reg 1.000000e+05 train accuracy: 0.287408 val accuracy: 0.290000
lr 1.000000e-06 reg 5.000000e+05 train accuracy: 0.221184 val accuracy: 0.232000
lr 5.000000e-06 reg 1.000000e+03 train accuracy: 0.349184 val accuracy: 0.360000
lr 5.000000e-06 reg 5.000000e+03 train accuracy: 0.279041 val accuracy: 0.276000
lr 5.000000e-06 reg 1.000000e+04 train accuracy: 0.297429 val accuracy: 0.286000
lr 5.000000e-06 reg 5.000000e+04 train accuracy: 0.142857 val accuracy: 0.154000
lr 5.000000e-06 reg 1.000000e+05 train accuracy: 0.146347 val accuracy: 0.134000
lr 5.000000e-06 reg 5.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
lr 1.000000e-05 reg 1.000000e+03 train accuracy: 0.280388 val accuracy: 0.268000
lr 1.000000e-05 reg 5.000000e+03 train accuracy: 0.160449 val accuracy: 0.145000
lr 1.000000e-05 reg 1.000000e+04 train accuracy: 0.192898 val accuracy: 0.194000
lr 1.000000e-05 reg 5.000000e+04 train accuracy: 0.139531 val accuracy: 0.142000
lr 1.000000e-05 reg 1.000000e+05 train accuracy: 0.102837 val accuracy: 0.103000
lr 1.000000e-05 reg 5.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 1.000000e+03 train accuracy: 0.166694 val accuracy: 0.160000
```

```
lr 5.000000e-05 reg 5.000000e+03 train accuracy: 0.121490 val accuracy: 0.143000
lr 5.000000e-05 reg 1.000000e+04 train accuracy: 0.145510 val accuracy: 0.137000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 1.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 5.000000e+05 train accuracy: 0.100265 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.395000
```

[16]:
```
# 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: 0.385000
```

Inline Question 2 - *True or False*

Suppose the overall training loss is defined as the sum of the per-datapoint loss over all training examples. It is possible to add a new datapoint to a training set that would leave the SVM loss unchanged, but this is not the case with the Softmax classifier loss.

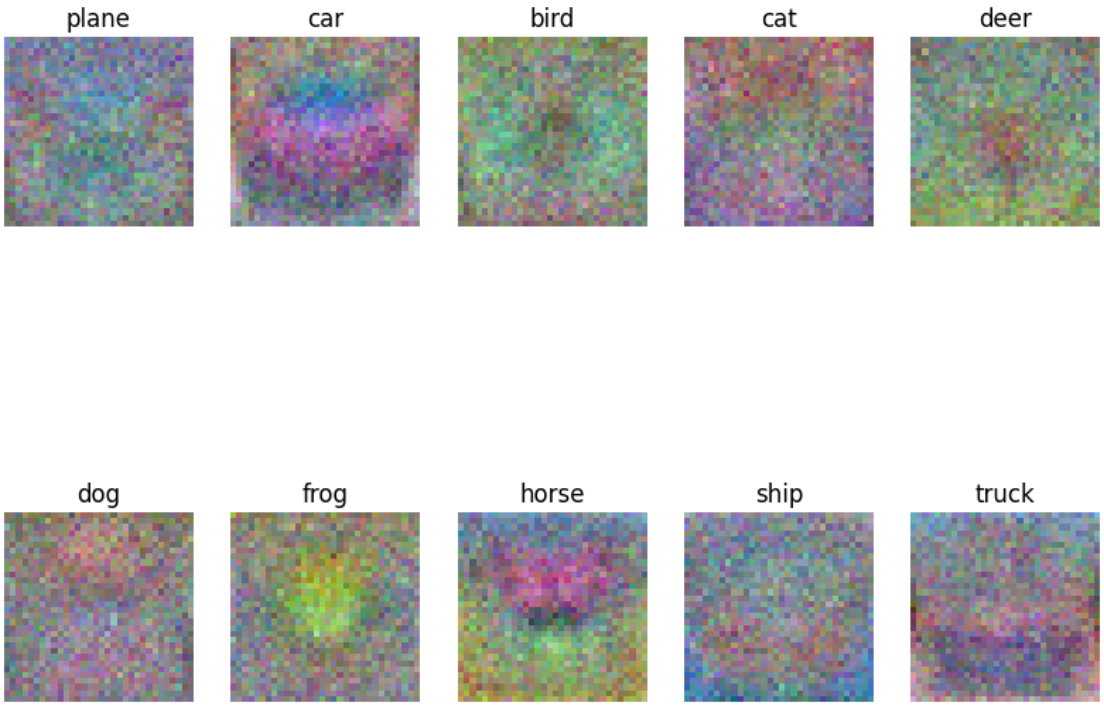
YourAnswer : Above stament is correct.

YourExplanation : SVM Loss: In SVMs, using Hinge Loss, it's possible to add a data point that doesn't change the overall loss, provided the scores for all incorrect classes are below the correct class score by at least the margin, resulting in a loss of zero for that point.

Softmax Classifier Loss: In Softmax Classifiers, using Cross-Entropy Loss, every new data point will always contribute positively to the overall loss, as it involves the negative log of the probability assigned to the correct class, which is always a positive value.

In Short: You can add a data point without affecting the SVM loss, but not the Softmax loss.

[17]:
```
# 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])
```


plane
car
bird
cat
deer
dog
frog
horse
ship
truck

[ ]:

two_layer_net

October 8, 2023

[1]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cs231n/assignments/assignment1/'
FOLDERNAME = 'enpm809k fall 2023/assignment1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/My\ Drive/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/enpm809k fall 2023/assignment1/cs231n/datasets
/content/drive/My Drive/enpm809k fall 2023/assignment1
```

1 Fully-Connected Neural Nets

In this exercise we will implement fully-connected networks using a modular approach. For each layer we will implement a `forward` and a `backward` function. The `forward` function will receive inputs, weights, and other parameters and will return both an output and a `cache` object storing data needed for the backward pass, like this:

```
def layer_forward(x, w):
  """ Receive inputs x and weights w """
  # Do some computations ...
  z = # ... some intermediate value
  # Do some more computations ...
  out = # the output
```

```
  cache = (x, w, z, out) # Values we need to compute gradients

  return out, cache
```

The backward pass will receive upstream derivatives and the `cache` object, and will return gradients with respect to the inputs and weights, like this:

```
def layer_backward(dout, cache):
  """
  Receive dout (derivative of loss with respect to outputs) and cache,
  and compute derivative with respect to inputs.
  """
  # Unpack cache values
  x, w, z, out = cache

  # Use values in cache to compute derivatives
  dx = # Derivative of loss with respect to x
  dw = # Derivative of loss with respect to w

  return dx, dw
```

After implementing a bunch of layers this way, we will be able to easily combine them to build classifiers with different architectures.

[2]:
```
# As usual, a bit of setup
from __future__ import print_function
import time
import numpy as np
import matplotlib.pyplot as plt
from cs231n.classifiers.fc_net import *
from cs231n.data_utils import get_CIFAR10_data
from cs231n.gradient_check import eval_numerical_gradient,␣
 ↪eval_numerical_gradient_array
from cs231n.solver import Solver

%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))))
```

[3]:
```
# Load the (preprocessed) CIFAR10 data.

data = get_CIFAR10_data()
for k, v in list(data.items()):
  print(('%s: ' % k, v.shape))
```

```
('X_train: ', (49000, 3, 32, 32))
('y_train: ', (49000,))
('X_val: ', (1000, 3, 32, 32))
('y_val: ', (1000,))
('X_test: ', (1000, 3, 32, 32))
('y_test: ', (1000,))
```

2 Affine layer: forward

Open the file `cs231n/layers.py` and implement the `affine_forward` function.

Once you are done you can test your implementaion by running the following:

[4]:
```
# Test the affine_forward function

num_inputs = 2
input_shape = (4, 5, 6)
output_dim = 3

input_size = num_inputs * np.prod(input_shape)
weight_size = output_dim * np.prod(input_shape)

x = np.linspace(-0.1, 0.5, num=input_size).reshape(num_inputs, *input_shape)
w = np.linspace(-0.2, 0.3, num=weight_size).reshape(np.prod(input_shape),␣
  ↪output_dim)
b = np.linspace(-0.3, 0.1, num=output_dim)

out, _ = affine_forward(x, w, b)
correct_out = np.array([[ 1.49834967,  1.70660132,  1.91485297],
                        [ 3.25553199,  3.5141327,   3.77273342]])

# Compare your output with ours. The error should be around e-9 or less.
print('Testing affine_forward function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing affine_forward function:
difference:  9.769849468192957e-10
```

3 Affine layer: backward

Now implement the `affine_backward` function and test your implementation using numeric gradient checking.

[5]:
```
# Test the affine_backward function
np.random.seed(231)
x = np.random.randn(10, 2, 3)
w = np.random.randn(6, 5)
b = np.random.randn(5)
dout = np.random.randn(10, 5)

dx_num = eval_numerical_gradient_array(lambda x: affine_forward(x, w, b)[0], x,␣
 ↪dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_forward(x, w, b)[0], w,␣
 ↪dout)
db_num = eval_numerical_gradient_array(lambda b: affine_forward(x, w, b)[0], b,␣
 ↪dout)

_, cache = affine_forward(x, w, b)
dx, dw, db = affine_backward(dout, cache)

# The error should be around e-10 or less
print('Testing affine_backward function:')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing affine_backward function:
dx error:  5.399100368651805e-11
dw error:  9.904211865398145e-11
db error:  2.4122867568119087e-11
```

4 ReLU activation: forward

Implement the forward pass for the ReLU activation function in the `relu_forward` function and test your implementation using the following:

[6]:
```
# Test the relu_forward function

x = np.linspace(-0.5, 0.5, num=12).reshape(3, 4)

out, _ = relu_forward(x)
correct_out = np.array([[ 0.,          0.,          0.,          0.,        ],
                        [ 0.,          0.,          0.04545455,  0.13636364,],
                        [ 0.22727273,  0.31818182,  0.40909091,  0.5,       ]])
```

```
# Compare your output with ours. The error should be on the order of e-8
print('Testing relu_forward function:')
print('difference: ', rel_error(out, correct_out))
```

```
Testing relu_forward function:
difference:  4.999999798022158e-08
```

5 ReLU activation: backward

Now implement the backward pass for the ReLU activation function in the `relu_backward` function and test your implementation using numeric gradient checking:

[7]:
```
np.random.seed(231)
x = np.random.randn(10, 10)
dout = np.random.randn(*x.shape)

dx_num = eval_numerical_gradient_array(lambda x: relu_forward(x)[0], x, dout)

_, cache = relu_forward(x)
dx = relu_backward(dout, cache)

# The error should be on the order of e-12
print('Testing relu_backward function:')
print('dx error: ', rel_error(dx_num, dx))
```

```
Testing relu_backward function:
dx error:  3.2756349136310288e-12
```

5.1 Inline Question 1:

We've only asked you to implement ReLU, but there are a number of different activation functions that one could use in neural networks, each with its pros and cons. In particular, an issue commonly seen with activation functions is getting zero (or close to zero) gradient flow during backpropagation. Which of the following activation functions have this problem? If you consider these functions in the one dimensional case, what types of input would lead to this behaviour? 1. Sigmoid 2. ReLU 3. Leaky ReLU

5.2 Answer:

Sigmoid: Experiences vanishing gradients for very high or low input values, leading to nearly zero gradient at these extremes.

ReLU: Has a gradient of 0 for negative inputs, potentially causing dying ReLU problem where some neurons get "stuck" outputting 0.

Leaky ReLU: Addresses ReLU's issue by having a small, non-zero gradient for negative inputs, thus avoiding zero gradient problem.

In summary, both the sigmoid and standard ReLU activation functions can suffer from zero (or near zero) gradient flow during backpropagatio. Leaky ReLU is designed to mitigate this issue by

allowing a small gradient when the input is negative.

6 "Sandwich" layers

There are some common patterns of layers that are frequently used in neural nets. For example, affine layers are frequently followed by a ReLU nonlinearity. To make these common patterns easy, we define several convenience layers in the file `cs231n/layer_utils.py`.

For now take a look at the `affine_relu_forward` and `affine_relu_backward` functions, and run the following to numerically gradient check the backward pass:

[8]:
```
from cs231n.layer_utils import affine_relu_forward, affine_relu_backward
np.random.seed(231)
x = np.random.randn(2, 3, 4)
w = np.random.randn(12, 10)
b = np.random.randn(10)
dout = np.random.randn(2, 10)

out, cache = affine_relu_forward(x, w, b)
dx, dw, db = affine_relu_backward(dout, cache)

dx_num = eval_numerical_gradient_array(lambda x: affine_relu_forward(x, w,␣
 ↪b)[0], x, dout)
dw_num = eval_numerical_gradient_array(lambda w: affine_relu_forward(x, w,␣
 ↪b)[0], w, dout)
db_num = eval_numerical_gradient_array(lambda b: affine_relu_forward(x, w,␣
 ↪b)[0], b, dout)

# Relative error should be around e-10 or less
print('Testing affine_relu_forward and affine_relu_backward:')
print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
Testing affine_relu_forward and affine_relu_backward:
dx error:  2.299579177309368e-11
dw error:  8.162011105764925e-11
db error:  7.826724021458994e-12
```

7 Loss layers: Softmax and SVM

Now implement the loss and gradient for softmax and SVM in the `softmax_loss` and `svm_loss` function in `cs231n/layers.py`. These should be similar to what you implemented in `cs231n/classifiers/softmax.py` and `cs231n/classifiers/linear_svm.py`.

You can make sure that the implementations are correct by running the following:

[9]:
```
np.random.seed(231)
num_classes, num_inputs = 10, 50
x = 0.001 * np.random.randn(num_inputs, num_classes)
y = np.random.randint(num_classes, size=num_inputs)

dx_num = eval_numerical_gradient(lambda x: svm_loss(x, y)[0], x, verbose=False)
loss, dx = svm_loss(x, y)

# Test svm_loss function. Loss should be around 9 and dx error should be around␣
 ↪the order of e-9
print('Testing svm_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))

dx_num = eval_numerical_gradient(lambda x: softmax_loss(x, y)[0], x,␣
 ↪verbose=False)
loss, dx = softmax_loss(x, y)

# Test softmax_loss function. Loss should be close to 2.3 and dx error should␣
 ↪be around e-8
print('\nTesting softmax_loss:')
print('loss: ', loss)
print('dx error: ', rel_error(dx_num, dx))
```

```
Testing svm_loss:
loss:  8.999602749096233
dx error:  1.4021566006651672e-09

Testing softmax_loss:
loss:  2.302545844500738
dx error:  9.483503037636722e-09
```

8 Two-layer network

Open the file `cs231n/classifiers/fc_net.py` and complete the implementation of the `TwoLayerNet` class. Read through it to make sure you understand the API. You can run the cell below to test your implementation.

[10]:
```
np.random.seed(231)
N, D, H, C = 3, 5, 50, 7
X = np.random.randn(N, D)
y = np.random.randint(C, size=N)

std = 1e-3
model = TwoLayerNet(input_dim=D, hidden_dim=H, num_classes=C, weight_scale=std)

print('Testing initialization ... ')
```

```
W1_std = abs(model.params['W1'].std() - std)
b1 = model.params['b1']
W2_std = abs(model.params['W2'].std() - std)
b2 = model.params['b2']
assert W1_std < std / 10, 'First layer weights do not seem right'
assert np.all(b1 == 0), 'First layer biases do not seem right'
assert W2_std < std / 10, 'Second layer weights do not seem right'
assert np.all(b2 == 0), 'Second layer biases do not seem right'

print('Testing test-time forward pass ... ')
model.params['W1'] = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
model.params['b1'] = np.linspace(-0.1, 0.9, num=H)
model.params['W2'] = np.linspace(-0.3, 0.4, num=H*C).reshape(H, C)
model.params['b2'] = np.linspace(-0.9, 0.1, num=C)
X = np.linspace(-5.5, 4.5, num=N*D).reshape(D, N).T
scores = model.loss(X)
correct_scores = np.asarray(
  [[11.53165108,  12.2917344,   13.05181771,  13.81190102,  14.57198434, 15.
 ↪33206765,  16.09215096],
   [12.05769098,  12.74614105,  13.43459113,  14.1230412,   14.81149128, 15.
 ↪49994135,  16.18839143],
   [12.58373087,  13.20054771,  13.81736455,  14.43418138,  15.05099822, 15.
 ↪66781506,  16.2846319 ]])
scores_diff = np.abs(scores - correct_scores).sum()
assert scores_diff < 1e-6, 'Problem with test-time forward pass'

print('Testing training loss (no regularization)')
y = np.asarray([0, 5, 1])
loss, grads = model.loss(X, y)
correct_loss = 3.4702243556
assert abs(loss - correct_loss) < 1e-10, 'Problem with training-time loss'

model.reg = 1.0
loss, grads = model.loss(X, y)
correct_loss = 26.5948426952
assert abs(loss - correct_loss) < 1e-10, 'Problem with regularization loss'

# Errors should be around e-7 or less
for reg in [0.0, 0.7]:
  print('Running numeric gradient check with reg = ', reg)
  model.reg = reg
  loss, grads = model.loss(X, y)

  for name in sorted(grads):
    f = lambda _: model.loss(X, y)[0]
    grad_num = eval_numerical_gradient(f, model.params[name], verbose=False)
    print('%s relative error: %.2e' % (name, rel_error(grad_num, grads[name])))
```

```
Testing initialization …
Testing test-time forward pass …
Testing training loss (no regularization)
Running numeric gradient check with reg =  0.0
W1 relative error: 1.83e-08
W2 relative error: 3.31e-10
b1 relative error: 9.83e-09
b2 relative error: 4.33e-10
Running numeric gradient check with reg =  0.7
W1 relative error: 2.53e-07
W2 relative error: 2.85e-08
b1 relative error: 1.56e-08
b2 relative error: 7.76e-10
```

9 Solver

Open the file `cs231n/solver.py` and read through it to familiarize yourself with the API. You also need to imeplement the `sgd` function in `cs231n/optim.py`. After doing so, use a `Solver` instance to train a `TwoLayerNet` that achieves about `36%` accuracy on the validation set.

[11]:
```
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
model = TwoLayerNet(input_size, hidden_size, num_classes)
solver = None

################################################################################
# TODO: Use a Solver instance to train a TwoLayerNet that achieves about 36% #
# accuracy on the validation set.                                              #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
# Create a Solver instance
solver = Solver(model, data,
                optim_config={
                  'learning_rate': 1e-4
                },

                print_every=100)

# Train the network
solver.train()

# Now the Solver object will have a trained model which can be accessed as␣
 ↪follows:
trained_model = solver.model
```

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

```
(Iteration 1 / 4900) loss: 2.300089
(Epoch 0 / 10) train acc: 0.138000; val_acc: 0.138000
(Iteration 101 / 4900) loss: 2.240327
(Iteration 201 / 4900) loss: 2.113574
(Iteration 301 / 4900) loss: 2.026074
(Iteration 401 / 4900) loss: 2.048385
(Epoch 1 / 10) train acc: 0.297000; val_acc: 0.300000
(Iteration 501 / 4900) loss: 1.978907
(Iteration 601 / 4900) loss: 1.832621
(Iteration 701 / 4900) loss: 1.862299
(Iteration 801 / 4900) loss: 1.788405
(Iteration 901 / 4900) loss: 1.763286
(Epoch 2 / 10) train acc: 0.358000; val_acc: 0.359000
(Iteration 1001 / 4900) loss: 1.712420
(Iteration 1101 / 4900) loss: 1.733109
(Iteration 1201 / 4900) loss: 1.747407
(Iteration 1301 / 4900) loss: 1.788008
(Iteration 1401 / 4900) loss: 1.785752
(Epoch 3 / 10) train acc: 0.404000; val_acc: 0.383000
(Iteration 1501 / 4900) loss: 1.707665
(Iteration 1601 / 4900) loss: 1.750729
(Iteration 1701 / 4900) loss: 1.697952
(Iteration 1801 / 4900) loss: 1.675512
(Iteration 1901 / 4900) loss: 1.776410
(Epoch 4 / 10) train acc: 0.403000; val_acc: 0.426000
(Iteration 2001 / 4900) loss: 1.655020
(Iteration 2101 / 4900) loss: 1.624574
(Iteration 2201 / 4900) loss: 1.844418
(Iteration 2301 / 4900) loss: 1.447170
(Iteration 2401 / 4900) loss: 1.617801
(Epoch 5 / 10) train acc: 0.408000; val_acc: 0.431000
(Iteration 2501 / 4900) loss: 1.567472
(Iteration 2601 / 4900) loss: 1.674657
(Iteration 2701 / 4900) loss: 1.560354
(Iteration 2801 / 4900) loss: 1.703828
(Iteration 2901 / 4900) loss: 1.466214
(Epoch 6 / 10) train acc: 0.451000; val_acc: 0.447000
(Iteration 3001 / 4900) loss: 1.574692
(Iteration 3101 / 4900) loss: 1.521753
(Iteration 3201 / 4900) loss: 1.599726
(Iteration 3301 / 4900) loss: 1.504628
(Iteration 3401 / 4900) loss: 1.390429
```

```
(Epoch 7 / 10) train acc: 0.469000; val_acc: 0.451000
(Iteration 3501 / 4900) loss: 1.714735
(Iteration 3601 / 4900) loss: 1.386743
(Iteration 3701 / 4900) loss: 1.828679
(Iteration 3801 / 4900) loss: 1.548596
(Iteration 3901 / 4900) loss: 1.448461
(Epoch 8 / 10) train acc: 0.462000; val_acc: 0.467000
(Iteration 4001 / 4900) loss: 1.433746
(Iteration 4101 / 4900) loss: 1.635513
(Iteration 4201 / 4900) loss: 1.449076
(Iteration 4301 / 4900) loss: 1.535322
(Iteration 4401 / 4900) loss: 1.376167
(Epoch 9 / 10) train acc: 0.489000; val_acc: 0.457000
(Iteration 4501 / 4900) loss: 1.580567
(Iteration 4601 / 4900) loss: 1.423031
(Iteration 4701 / 4900) loss: 1.545790
(Iteration 4801 / 4900) loss: 1.458274
(Epoch 10 / 10) train acc: 0.449000; val_acc: 0.476000
```

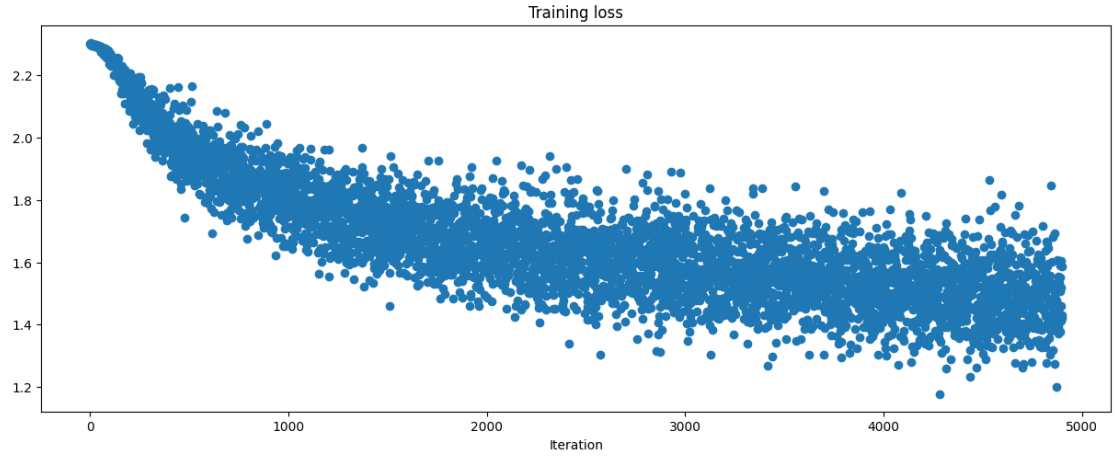
10 Debug the training

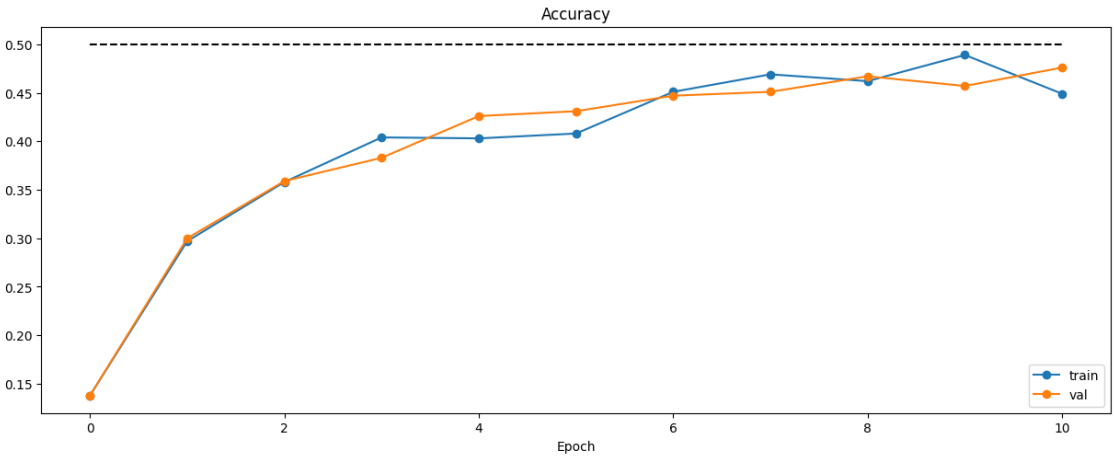
With the default parameters we provided above, you should get a validation accuracy of about 0.36 on the validation set. This isn't very good.

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.

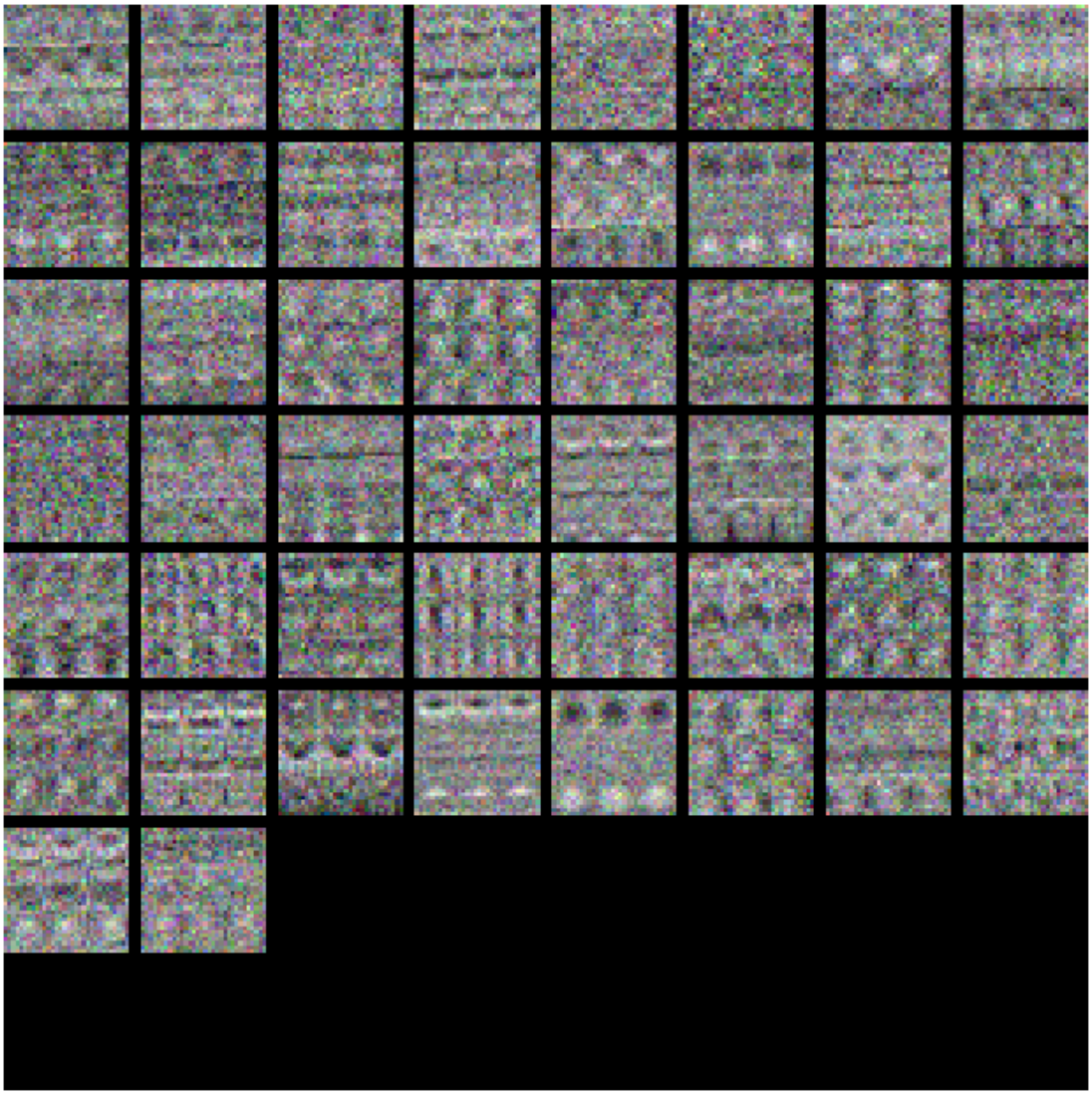
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

[12]:
```
# Run this cell to visualize training loss and train / val accuracy

plt.subplot(2, 1, 1)
plt.title('Training loss')
plt.plot(solver.loss_history, 'o')
plt.xlabel('Iteration')

plt.subplot(2, 1, 2)
plt.title('Accuracy')
plt.plot(solver.train_acc_history, '-o', label='train')
plt.plot(solver.val_acc_history, '-o', label='val')
plt.plot([0.5] * len(solver.val_acc_history), 'k--')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.gcf().set_size_inches(15, 12)
plt.show()
```





[13]:
```python
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(model)
```



11 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.).

[14]:
```
best_model = None


################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained␣
 ↪#
# model in best_model.                                                         ␣
 ↪#
#                                                                              ␣
 ↪#
# 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 thexs previous exercises.                       ␣
 ↪  #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

from itertools import product

best_accuracy = -1
# Define the dimensions and other constants related to the model and training␣
 ↪process
input_size = 32 * 32 * 3
num_classes = 10
hidden_size = 50
num_epochs = 5
batch_size = 200
```

```
# Define the hyperparameters and their possible values for tuning
params = {
    "learning_rates" : [2.5e-3, 2e-3, 1.5e-3],
    "lr_decay" : [0.25, 0.5]
}
key, values = zip(*params.items())
param_prods= list(product(*values))
# Iterate through all combinations of hyperparameters to find the best model
for lr, dec in param_prods:
    print("lr={}, dec={}".format(lr, dec))
    model = TwoLayerNet(input_size, hidden_size, num_classes)
    solver = Solver(model, data,
                    update_rule='sgd',
                    optim_config={
                        'learning_rate': lr,
                    },
                    lr_decay=dec,
                    num_epochs=num_epochs, batch_size=batch_size,
                    print_every=100)
    solver.train()
    # Check if the validation accuracy of the current model is the best so far
    if solver.val_acc_history[-1] > best_accuracy:
        best_params = (lr, dec)
        best_model = model
        best_accuracy = solver.val_acc_history[-1]

print(f'best accuracy:', best_accuracy)
print('best params:', best_params)

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

```
lr=0.0025, dec=0.25
(Iteration 1 / 1225) loss: 2.302457
(Epoch 0 / 5) train acc: 0.145000; val_acc: 0.125000
(Iteration 101 / 1225) loss: 1.708024
(Iteration 201 / 1225) loss: 1.756552
(Epoch 1 / 5) train acc: 0.415000; val_acc: 0.414000
(Iteration 301 / 1225) loss: 1.532449
(Iteration 401 / 1225) loss: 1.410428
(Epoch 2 / 5) train acc: 0.503000; val_acc: 0.495000
(Iteration 501 / 1225) loss: 1.414517
(Iteration 601 / 1225) loss: 1.401694
(Iteration 701 / 1225) loss: 1.348926
(Epoch 3 / 5) train acc: 0.514000; val_acc: 0.486000
```

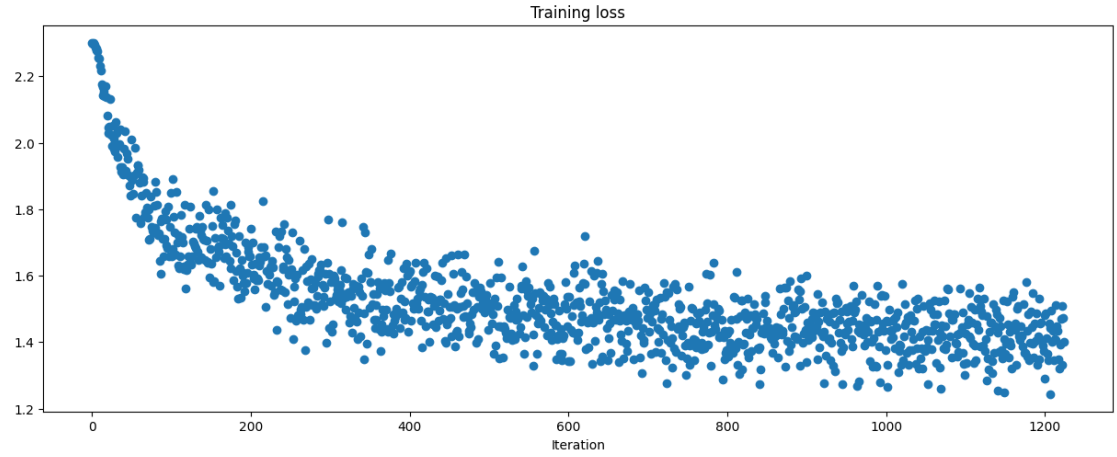
```
(Iteration 801 / 1225) loss: 1.394554
(Iteration 901 / 1225) loss: 1.368546
(Epoch 4 / 5) train acc: 0.525000; val_acc: 0.488000
(Iteration 1001 / 1225) loss: 1.284439
(Iteration 1101 / 1225) loss: 1.405491
(Iteration 1201 / 1225) loss: 1.395928
(Epoch 5 / 5) train acc: 0.502000; val_acc: 0.489000
lr=0.0025, dec=0.5
(Iteration 1 / 1225) loss: 2.303150
(Epoch 0 / 5) train acc: 0.151000; val_acc: 0.171000
(Iteration 101 / 1225) loss: 1.653706
(Iteration 201 / 1225) loss: 1.634409
(Epoch 1 / 5) train acc: 0.423000; val_acc: 0.419000
(Iteration 301 / 1225) loss: 1.547781
(Iteration 401 / 1225) loss: 1.471391
(Epoch 2 / 5) train acc: 0.460000; val_acc: 0.456000
(Iteration 501 / 1225) loss: 1.281432
(Iteration 601 / 1225) loss: 1.383330
(Iteration 701 / 1225) loss: 1.379202
(Epoch 3 / 5) train acc: 0.509000; val_acc: 0.474000
(Iteration 801 / 1225) loss: 1.340378
(Iteration 901 / 1225) loss: 1.378613
(Epoch 4 / 5) train acc: 0.514000; val_acc: 0.478000
(Iteration 1001 / 1225) loss: 1.217226
(Iteration 1101 / 1225) loss: 1.403340
(Iteration 1201 / 1225) loss: 1.347540
(Epoch 5 / 5) train acc: 0.527000; val_acc: 0.482000
lr=0.002, dec=0.25
(Iteration 1 / 1225) loss: 2.300344
(Epoch 0 / 5) train acc: 0.144000; val_acc: 0.163000
(Iteration 101 / 1225) loss: 1.758798
(Iteration 201 / 1225) loss: 1.591019
(Epoch 1 / 5) train acc: 0.408000; val_acc: 0.421000
(Iteration 301 / 1225) loss: 1.588336
(Iteration 401 / 1225) loss: 1.481856
(Epoch 2 / 5) train acc: 0.497000; val_acc: 0.473000
(Iteration 501 / 1225) loss: 1.508328
(Iteration 601 / 1225) loss: 1.351851
(Iteration 701 / 1225) loss: 1.449898
(Epoch 3 / 5) train acc: 0.485000; val_acc: 0.475000
(Iteration 801 / 1225) loss: 1.458120
(Iteration 901 / 1225) loss: 1.515169
(Epoch 4 / 5) train acc: 0.486000; val_acc: 0.484000
(Iteration 1001 / 1225) loss: 1.558023
(Iteration 1101 / 1225) loss: 1.517393
(Iteration 1201 / 1225) loss: 1.391498
(Epoch 5 / 5) train acc: 0.480000; val_acc: 0.484000
lr=0.002, dec=0.5
```

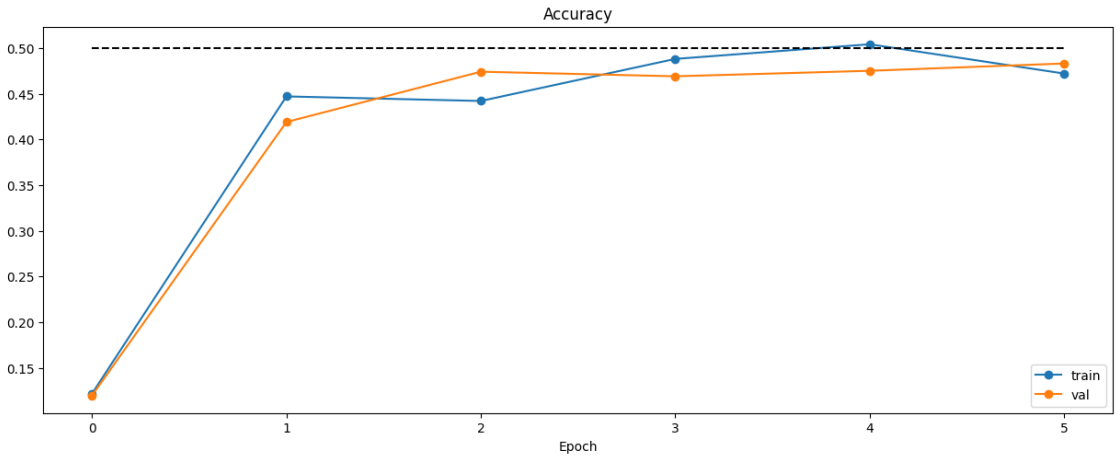
```
(Iteration 1 / 1225) loss: 2.301225
(Epoch 0 / 5) train acc: 0.205000; val_acc: 0.170000
(Iteration 101 / 1225) loss: 1.636559
(Iteration 201 / 1225) loss: 1.656372
(Epoch 1 / 5) train acc: 0.411000; val_acc: 0.413000
(Iteration 301 / 1225) loss: 1.549097
(Iteration 401 / 1225) loss: 1.390145
(Epoch 2 / 5) train acc: 0.470000; val_acc: 0.498000
(Iteration 501 / 1225) loss: 1.513689
(Iteration 601 / 1225) loss: 1.388294
(Iteration 701 / 1225) loss: 1.566693
(Epoch 3 / 5) train acc: 0.509000; val_acc: 0.505000
(Iteration 801 / 1225) loss: 1.337419
(Iteration 901 / 1225) loss: 1.377591
(Epoch 4 / 5) train acc: 0.534000; val_acc: 0.505000
(Iteration 1001 / 1225) loss: 1.426391
(Iteration 1101 / 1225) loss: 1.561939
(Iteration 1201 / 1225) loss: 1.415381
(Epoch 5 / 5) train acc: 0.526000; val_acc: 0.506000
lr=0.0015, dec=0.25
(Iteration 1 / 1225) loss: 2.303073
(Epoch 0 / 5) train acc: 0.119000; val_acc: 0.108000
(Iteration 101 / 1225) loss: 1.778826
(Iteration 201 / 1225) loss: 1.608245
(Epoch 1 / 5) train acc: 0.441000; val_acc: 0.422000
(Iteration 301 / 1225) loss: 1.546055
(Iteration 401 / 1225) loss: 1.588463
(Epoch 2 / 5) train acc: 0.474000; val_acc: 0.453000
(Iteration 501 / 1225) loss: 1.419195
(Iteration 601 / 1225) loss: 1.554925
(Iteration 701 / 1225) loss: 1.571671
(Epoch 3 / 5) train acc: 0.474000; val_acc: 0.460000
(Iteration 801 / 1225) loss: 1.585131
(Iteration 901 / 1225) loss: 1.417261
(Epoch 4 / 5) train acc: 0.482000; val_acc: 0.458000
(Iteration 1001 / 1225) loss: 1.558033
(Iteration 1101 / 1225) loss: 1.474134
(Iteration 1201 / 1225) loss: 1.399437
(Epoch 5 / 5) train acc: 0.467000; val_acc: 0.457000
lr=0.0015, dec=0.5
(Iteration 1 / 1225) loss: 2.300730
(Epoch 0 / 5) train acc: 0.122000; val_acc: 0.120000
(Iteration 101 / 1225) loss: 1.658206
(Iteration 201 / 1225) loss: 1.740057
(Epoch 1 / 5) train acc: 0.447000; val_acc: 0.419000
(Iteration 301 / 1225) loss: 1.524109
(Iteration 401 / 1225) loss: 1.612814
(Epoch 2 / 5) train acc: 0.442000; val_acc: 0.474000
```

```
(Iteration 501 / 1225) loss: 1.499367
(Iteration 601 / 1225) loss: 1.343120
(Iteration 701 / 1225) loss: 1.549070
(Epoch 3 / 5) train acc: 0.488000; val_acc: 0.469000
(Iteration 801 / 1225) loss: 1.425149
(Iteration 901 / 1225) loss: 1.599676
(Epoch 4 / 5) train acc: 0.504000; val_acc: 0.475000
(Iteration 1001 / 1225) loss: 1.463685
(Iteration 1101 / 1225) loss: 1.426407
(Iteration 1201 / 1225) loss: 1.481035
(Epoch 5 / 5) train acc: 0.472000; val_acc: 0.483000
best accuracy: 0.506
best params: (0.002, 0.5)
```

[14]:

[15]:
```
# Run this cell to visualize training loss and train / val accuracy

plt.subplot(2, 1, 1)
plt.title('Training loss')
plt.plot(solver.loss_history, 'o')
plt.xlabel('Iteration')

plt.subplot(2, 1, 2)
plt.title('Accuracy')
plt.plot(solver.train_acc_history, '-o', label='train')
plt.plot(solver.val_acc_history, '-o', label='val')
plt.plot([0.5] * len(solver.val_acc_history), 'k--')
plt.xlabel('Epoch')
plt.legend(loc='lower right')
plt.gcf().set_size_inches(15, 12)
plt.show()
```





[16]:
```
model = best_model
lr, dec = best_params
solver = Solver(model, data,
                update_rule='sgd',
                optim_config={
                    'learning_rate': lr,
                },
                lr_decay = dec,
                num_epochs=15, batch_size=200,
                print_every=100)
solver.train()
```

```
(Iteration 1 / 3675) loss: 1.406927
(Epoch 0 / 15) train acc: 0.483000; val_acc: 0.461000
(Iteration 101 / 3675) loss: 1.490469
(Iteration 201 / 3675) loss: 1.710703
(Epoch 1 / 15) train acc: 0.477000; val_acc: 0.475000
(Iteration 301 / 3675) loss: 1.329301
(Iteration 401 / 3675) loss: 1.478445
```

```
(Epoch 2 / 15) train acc: 0.485000; val_acc: 0.500000
(Iteration 501 / 3675) loss: 1.372860
(Iteration 601 / 3675) loss: 1.361532
(Iteration 701 / 3675) loss: 1.210646
(Epoch 3 / 15) train acc: 0.547000; val_acc: 0.504000
(Iteration 801 / 3675) loss: 1.341524
(Iteration 901 / 3675) loss: 1.244241
(Epoch 4 / 15) train acc: 0.561000; val_acc: 0.522000
(Iteration 1001 / 3675) loss: 1.270717
(Iteration 1101 / 3675) loss: 1.327483
(Iteration 1201 / 3675) loss: 1.270596
(Epoch 5 / 15) train acc: 0.551000; val_acc: 0.522000
(Iteration 1301 / 3675) loss: 1.287347
(Iteration 1401 / 3675) loss: 1.262714
(Epoch 6 / 15) train acc: 0.563000; val_acc: 0.512000
(Iteration 1501 / 3675) loss: 1.231987
(Iteration 1601 / 3675) loss: 1.426297
(Iteration 1701 / 3675) loss: 1.278062
(Epoch 7 / 15) train acc: 0.545000; val_acc: 0.528000
(Iteration 1801 / 3675) loss: 1.218640
(Iteration 1901 / 3675) loss: 1.178881
(Epoch 8 / 15) train acc: 0.566000; val_acc: 0.524000
(Iteration 2001 / 3675) loss: 1.195324
(Iteration 2101 / 3675) loss: 1.407953
(Iteration 2201 / 3675) loss: 1.299578
(Epoch 9 / 15) train acc: 0.577000; val_acc: 0.523000
(Iteration 2301 / 3675) loss: 1.356139
(Iteration 2401 / 3675) loss: 1.229525
(Epoch 10 / 15) train acc: 0.566000; val_acc: 0.524000
(Iteration 2501 / 3675) loss: 1.248466
(Iteration 2601 / 3675) loss: 1.297031
(Epoch 11 / 15) train acc: 0.568000; val_acc: 0.524000
(Iteration 2701 / 3675) loss: 1.352975
(Iteration 2801 / 3675) loss: 1.325135
(Iteration 2901 / 3675) loss: 1.321299
(Epoch 12 / 15) train acc: 0.553000; val_acc: 0.524000
(Iteration 3001 / 3675) loss: 1.291014
(Iteration 3101 / 3675) loss: 1.155285
(Epoch 13 / 15) train acc: 0.581000; val_acc: 0.524000
(Iteration 3201 / 3675) loss: 1.296765
(Iteration 3301 / 3675) loss: 1.394165
(Iteration 3401 / 3675) loss: 1.137992
(Epoch 14 / 15) train acc: 0.550000; val_acc: 0.524000
(Iteration 3501 / 3675) loss: 1.399793
(Iteration 3601 / 3675) loss: 1.214795
(Epoch 15 / 15) train acc: 0.550000; val_acc: 0.524000
```

12 Test your model!

Run your best model on the validation and test sets. You should achieve above 48% accuracy on the validation set and the test set.

[17]:
```
y_val_pred = np.argmax(best_model.loss(data['X_val']), axis=1)
print('Validation set accuracy: ', (y_val_pred == data['y_val']).mean())
```

```
Validation set accuracy:  0.528
```

[18]:
```
y_test_pred = np.argmax(best_model.loss(data['X_test']), axis=1)
print('Test set accuracy: ', (y_test_pred == data['y_test']).mean())
```

```
Test set accuracy:  0.51
```

12.1 Inline Question 2:

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.

YourAnswer : 1 and 3

YourExplanation : 1. **Train on a larger dataset**: Yes, training on a larger dataset can help the model generalize better to unseen data, potentially decreasing the gap between training and testing accuracy. 2. **Add more hidden units**: Not always beneficial. While it may increase the model's capacity to learn, it could also lead to overfitting if not managed correctly, possibly widening the gap between training and testing accuracy. 3. **Increase the regularization strength**: Yes, increasing regularization can prevent overfitting, helping to narrow the gap between training and testing accuracy.

[18]:
```

```

features

October 8, 2023

[1]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cs231n/assignments/assignment1/'
FOLDERNAME = 'enpm809k fall 2023/assignment1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This downloads the CIFAR-10 dataset to your Drive
# if it doesn't already exist.
%cd drive/My\ Drive/$FOLDERNAME/cs231n/datasets/
!bash get_datasets.sh
%cd /content/drive/My\ Drive/$FOLDERNAME
```

```
Mounted at /content/drive
/content/drive/My Drive/enpm809k fall 2023/assignment1/cs231n/datasets
/content/drive/My Drive/enpm809k fall 2023/assignment1
```

1 Image features 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.

We have seen that we can achieve reasonable performance on an image classification task by training a linear classifier on the pixels of the input image. In this exercise we will show that we can improve our classification performance by training linear classifiers not on raw pixels but on features that are computed from the raw pixels.

All of your work for this exercise will be done in this notebook.

[2]:
```
import random
import numpy as np
from cs231n.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
```

1.1 Load data

Similar to previous exercises, we will load CIFAR-10 data from disk.

[3]:
```
from cs231n.features import color_histogram_hsv, hog_feature

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    # 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]

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

X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
```

1.2 Extract Features

For each image we will compute a Histogram of Oriented Gradients (HOG) as well as a color histogram using the hue channel in HSV color space. We form our final feature vector for each image by concatenating the HOG and color histogram feature vectors.

Roughly speaking, HOG should capture the texture of the image while ignoring color information, and the color histogram represents the color of the input image while ignoring texture. As a result, we expect that using both together ought to work better than using either alone. Verifying this assumption would be a good thing to try for your own interest.

The `hog_feature` and `color_histogram_hsv` functions both operate on a single image and return a feature vector for that image. The extract_features function takes a set of images and a list of feature functions and evaluates each feature function on each image, storing the results in a matrix where each column is the concatenation of all feature vectors for a single image.

[4]:
```
from cs231n.features import *

num_color_bins = 10 # Number of bins in the color histogram
feature_fns = [hog_feature, lambda img: color_histogram_hsv(img,␣
 ↪nbin=num_color_bins)]
X_train_feats = extract_features(X_train, feature_fns, verbose=True)
X_val_feats = extract_features(X_val, feature_fns)
X_test_feats = extract_features(X_test, feature_fns)

# Preprocessing: Subtract the mean feature
mean_feat = np.mean(X_train_feats, axis=0, keepdims=True)
X_train_feats -= mean_feat
X_val_feats -= mean_feat
X_test_feats -= mean_feat

# Preprocessing: Divide by standard deviation. This ensures that each feature
# has roughly the same scale.
std_feat = np.std(X_train_feats, axis=0, keepdims=True)
X_train_feats /= std_feat
X_val_feats /= std_feat
X_test_feats /= std_feat

# Preprocessing: Add a bias dimension
X_train_feats = np.hstack([X_train_feats, np.ones((X_train_feats.shape[0], 1))])
X_val_feats = np.hstack([X_val_feats, np.ones((X_val_feats.shape[0], 1))])
X_test_feats = np.hstack([X_test_feats, np.ones((X_test_feats.shape[0], 1))])
```

```
Done extracting features for 1000 / 49000 images
Done extracting features for 2000 / 49000 images
Done extracting features for 3000 / 49000 images
Done extracting features for 4000 / 49000 images
Done extracting features for 5000 / 49000 images
Done extracting features for 6000 / 49000 images
Done extracting features for 7000 / 49000 images
Done extracting features for 8000 / 49000 images
Done extracting features for 9000 / 49000 images
Done extracting features for 10000 / 49000 images
Done extracting features for 11000 / 49000 images
Done extracting features for 12000 / 49000 images
Done extracting features for 13000 / 49000 images
Done extracting features for 14000 / 49000 images
Done extracting features for 15000 / 49000 images
Done extracting features for 16000 / 49000 images
Done extracting features for 17000 / 49000 images
Done extracting features for 18000 / 49000 images
Done extracting features for 19000 / 49000 images
Done extracting features for 20000 / 49000 images
Done extracting features for 21000 / 49000 images
Done extracting features for 22000 / 49000 images
Done extracting features for 23000 / 49000 images
Done extracting features for 24000 / 49000 images
Done extracting features for 25000 / 49000 images
Done extracting features for 26000 / 49000 images
Done extracting features for 27000 / 49000 images
Done extracting features for 28000 / 49000 images
Done extracting features for 29000 / 49000 images
Done extracting features for 30000 / 49000 images
Done extracting features for 31000 / 49000 images
Done extracting features for 32000 / 49000 images
Done extracting features for 33000 / 49000 images
Done extracting features for 34000 / 49000 images
Done extracting features for 35000 / 49000 images
Done extracting features for 36000 / 49000 images
Done extracting features for 37000 / 49000 images
Done extracting features for 38000 / 49000 images
Done extracting features for 39000 / 49000 images
Done extracting features for 40000 / 49000 images
Done extracting features for 41000 / 49000 images
Done extracting features for 42000 / 49000 images
Done extracting features for 43000 / 49000 images
Done extracting features for 44000 / 49000 images
Done extracting features for 45000 / 49000 images
Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
```

```
Done extracting features for 49000 / 49000 images
```

1.3 Train SVM on features

Using the multiclass SVM code developed earlier in the assignment, train SVMs on top of the features extracted above; this should achieve better results than training SVMs directly on top of raw pixels.

[5]:
```
# Use the validation set to tune the learning rate and regularization strength

from cs231n.classifiers.linear_classifier import LinearSVM

learning_rates = [1e-9, 1e-8, 1e-7]
regularization_strengths = [5e4, 5e5, 5e6]

results = {}
best_val = -1
best_svm = None

################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# This should be identical to the validation that you did for the SVM; save    #
# the best trained classifer in best_svm. You might also want to play          #
# with different numbers of bins in the color histogram. If you are careful    #
# you should be able to get accuracy of near 0.44 on the validation set.       #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

import numpy as np
from itertools import product
from sklearn.model_selection import ParameterGrid
# Use itertools.product to get all combinations of learning_rates and␣
 ↪regularization_strengths
param_prods = product(learning_rates, regularization_strengths)

# Iterate through all the combinations of hyperparameters
for lr, reg in param_prods:

    # Create and train the SVM
    svm = LinearSVM()
    svm.train(X_train_feats, y_train, learning_rate=lr, reg=reg, num_iters=1000)

    # Evaluate the SVM
    y_train_pred = svm.predict(X_train_feats)
    train_accuracy = np.mean(y_train == y_train_pred)

    y_val_pred = svm.predict(X_val_feats)
```

```
    val_accuracy = np.mean(y_val == y_val_pred)

    # Store the results and update the best model if necessary
    results[(lr, reg)] = (train_accuracy, val_accuracy)

    if best_val < val_accuracy:
        best_val = val_accuracy
        best_svm = svm


# *****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: %f' % best_val)
```

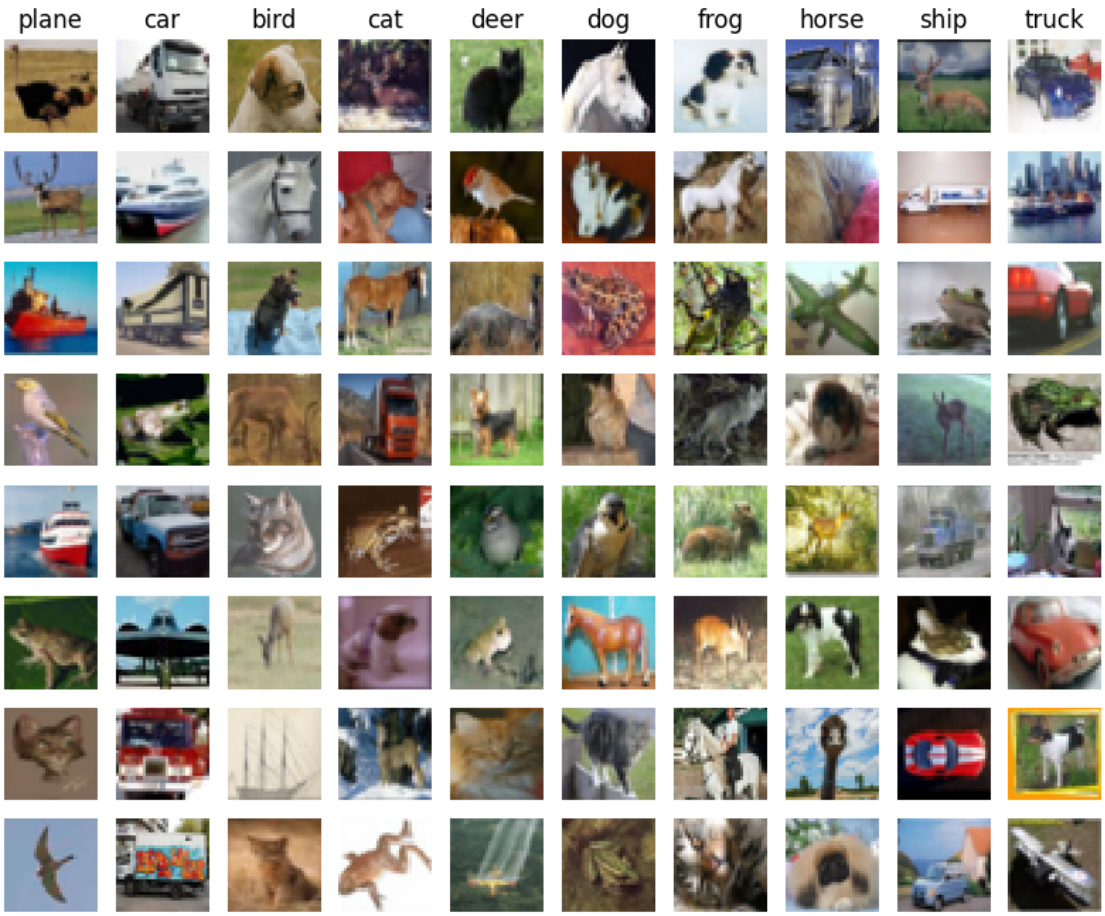
```
lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.107082 val accuracy: 0.118000
lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.101490 val accuracy: 0.096000
lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.297347 val accuracy: 0.264000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.089184 val accuracy: 0.080000
lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.410918 val accuracy: 0.412000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.410592 val accuracy: 0.422000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.416204 val accuracy: 0.408000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.405673 val accuracy: 0.397000
lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.307020 val accuracy: 0.308000
best validation accuracy achieved: 0.422000
```

[6]:
```
# Evaluate your trained SVM on the test set: you should be able to get at least␣
 ↪0.40
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print(test_accuracy)
```

```
0.41
```

[7]:
```
# An important way to gain intuition about how an algorithm works is to
# visualize the mistakes that it makes. In this visualization, we show examples
# of images that are misclassified by our current system. The first column
# shows images that our system labeled as "plane" but whose true label is
# something other than "plane".

examples_per_class = 8
```

```
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
for cls, cls_name in enumerate(classes):
    idxs = np.where((y_test != cls) & (y_test_pred == cls))[0]
    idxs = np.random.choice(idxs, examples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt.subplot(examples_per_class, len(classes), i * len(classes) + cls +␣
 ↪1)
        plt.imshow(X_test[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls_name)
plt.show()
```



1.3.1 Inline question 1:

Describe the misclassification results that you see. Do they make sense?

YourAnswer : The feature extraction methods used, capturing texture via HOG and color via

histograms, may lead to misclassifications among images with similar color or shape traits. For instance, animals with four legs, tails, and brown color might be confused. Likewise, planes or ships might be misidentified based on background colors rather than shape. However, in classes like car, truck, and frog, misclassifications occur despite no apparent shared features, indicating that the HOG and color histogram methods might have fallen short in extracting distinguishing features for these images.

1.4 Neural Network on image features

Earlier in this assigment we saw that training a two-layer neural network on raw pixels achieved better classification performance than linear classifiers on raw pixels. In this notebook we have seen that linear classifiers on image features outperform linear classifiers on raw pixels.

For completeness, we should also try training a neural network on image features. This approach should outperform all previous approaches: you should easily be able to achieve over 55% classification accuracy on the test set; our best model achieves about 60% classification accuracy.

[8]:
```
# Preprocessing: Remove the bias dimension
# Make sure to run this cell only ONCE
print(X_train_feats.shape)
X_train_feats = X_train_feats[:, :-1]
X_val_feats = X_val_feats[:, :-1]
X_test_feats = X_test_feats[:, :-1]

print(X_train_feats.shape)
```

```
(49000, 155)
(49000, 154)
```

[15]:
```
from cs231n.classifiers.fc_net import TwoLayerNet
from cs231n.solver import Solver

input_dim = X_train_feats.shape[1]
hidden_dim = 500
num_classes = 10

net = TwoLayerNet(input_dim, hidden_dim, num_classes)
best_net = None

################################################################################
# TODO: Train a two-layer neural network on image features. You may want to    #
# cross-validate various parameters as in previous sections. Store your best   #
# model in the best_net variable.                                              #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

learning_rates = [0.1, 0.105]
regularization_strengths = [2e-5 ,3e-5]
```

```
lr_decay = [0.9, 1.0]

results = {}
best_val = -1


data = {
    'X_train': X_train_feats,
    'X_val': X_val_feats,
    'X_test': X_test_feats,
    'y_train': y_train,
    'y_val': y_val,
    'y_test': y_test
}

import itertools

for lr, reg in itertools.product(learning_rates, regularization_strengths):
    # Create Two Layer Net and train it with Solver
    model = net
    solver = Solver(model, data, optim_config={'learning_rate': lr},␣
 ↪num_epochs=20, verbose=False)
    solver.train()

    # Compute validation set accuracy and append to dictionary
    results[(lr, reg)] = solver.best_val_acc

    # Save if validation accuracy is the best
    if results[(lr, reg)] > best_val:
        best_val = results[(lr, reg)]
        best_net = model

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

print('best validation accuracy achieved during cross-validation: %f' %␣
 ↪best_val)
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

```
lr 1.000000e-01 reg 2.000000e-05 val accuracy: 0.604000
lr 1.000000e-01 reg 3.000000e-05 val accuracy: 0.602000
lr 1.050000e-01 reg 2.000000e-05 val accuracy: 0.607000
lr 1.050000e-01 reg 3.000000e-05 val accuracy: 0.593000
best validation accuracy achieved during cross-validation: 0.607000
```

[16]:
```
# Run your best neural net classifier on the test set. You should be able
# to get more than 55% accuracy.

y_test_pred = np.argmax(best_net.loss(data['X_test']), axis=1)
test_acc = (y_test_pred == data['y_test']).mean()
print(test_acc)
```

```
0.589
```