knn

April 23, 2020

[1]:
```
# from google.colab import drive
#
# drive.mount('/content/drive', force_remount=True)
#
# # enter the foldername in your Drive where you have saved the unzipped
# # 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# # folders.
# # e.g. 'cs231n/assignments/assignment1/cs231n/'
# FOLDERNAME = None
#
# assert FOLDERNAME is not None, "[!] Enter the foldername."
#
# %cd drive/My\ Drive
# %cp -r $FOLDERNAME ../../
# %cd ../../
# %cd cs231n/datasets/
# !bash get_datasets.sh
# %cd ../../
```

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.
```

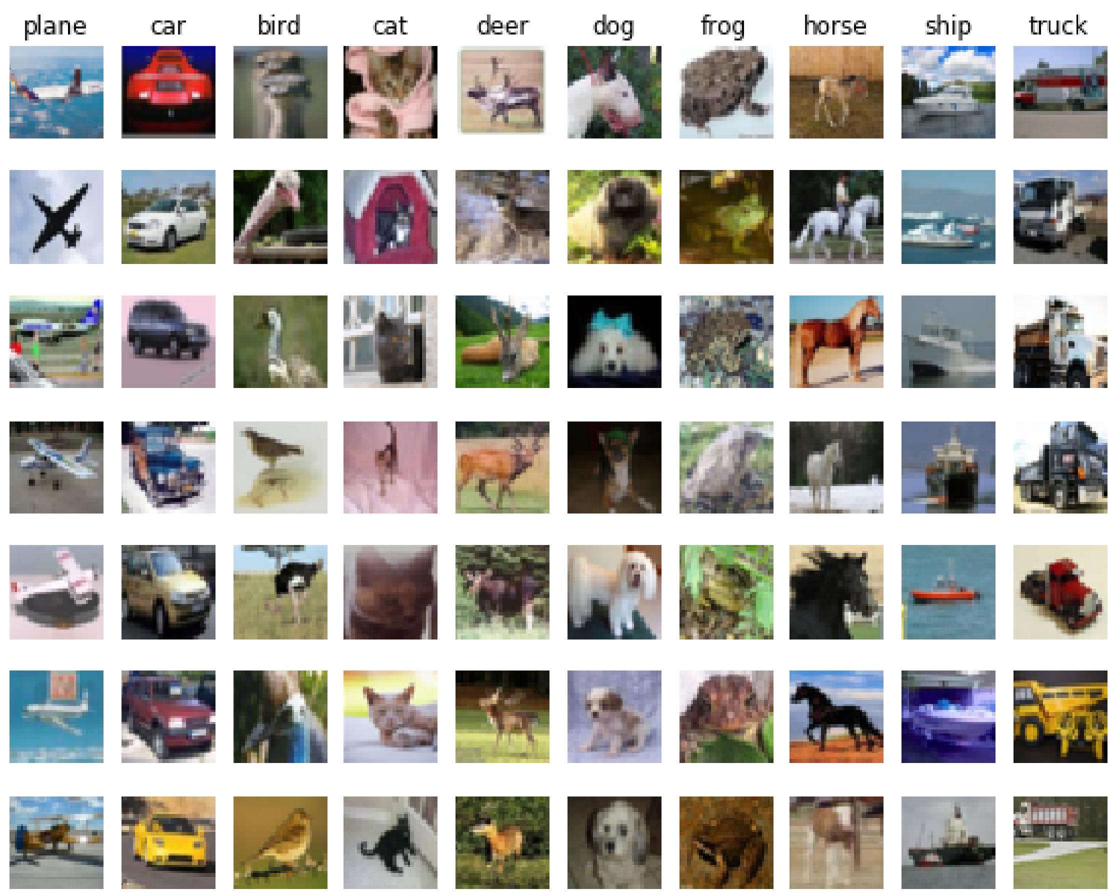
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# 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.
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,)
```

[4]:
```
# 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()
```



[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))
print(X_train.shape, X_test.shape)
```

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

[6]:
```
from cs231n.classifiers import KNearestNeighbor

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

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

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

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

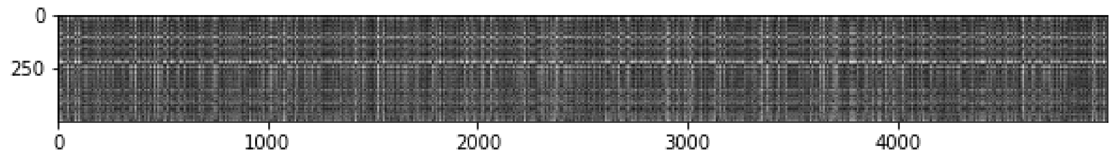
Note: For the three distance computations that we require you to implement in this notebook, you may not use the np.linalg.norm() function that numpy provides.

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

[7]:
```
# Open cs231n/classifiers/k_nearest_neighbor.py and implement
# compute_distances_two_loops.

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

```
(500, 5000)
```

[8]:
```
# We can visualize the distance matrix: each row is a single test example and
# its distances to training examples
plt.imshow(dists, interpolation='none')
plt.show()
```



Inline Question 1

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

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

$\color{blue}{\textit{Your Answer:}}$ - the reason for distinctly bright rows is because one test image raw pixel is very different from all training images - the reason for distinctly bright cols is because one training image raw pixel is very different from all test images

[9]:
```
# Now implement the function predict_labels and run the code below:
# We use k = 1 (which is Nearest Neighbor).
y_test_pred = classifier.predict_labels(dists, k=1)

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

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

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

[10]:
```
y_test_pred = classifier.predict_labels(dists, k=5)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

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

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

Inline Question 2

We can also use other distance metrics such as L1 distance. For pixel values $p_{ij}^{(k)}$ at location (i,j) of some image I_k, the mean μ across all pixels over all images is

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

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

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

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

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

$\color{blue}{\textit{Your Answer}:}$ - 1, 2, 3, 4, 5

$\color{blue}{\textit{Your Explanation}:}$ - subtracting the means and per pixel mean do not change the performance of NN classifier with L1 distance. Mean subtraction makes every point shift in the same direction by the same amount, so the distance between the points remain the same

- subtracting the mean and divided by standard deviation will also not change the performance. Mean subtraction means first shift every poin in same direction, which do not change the distances between points, standard diviation division means the distances between the points are scaled by the same amount, which do not change the relative distance between points. biggest distance remain the biggest distance after scaling.
- rotating the coordinate axes of the data also do not change the distance between different data points, because L1 distance is the summation of abs of element-wise subtraction, so the distance remains the same.

[11]:
```python
# 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')
```

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

[12]:
```
# Now implement the fully vectorized version inside compute_distances_no_loops
# and run the code
dists_two = classifier.compute_distances_no_loops(X_test)

# check that the distance matrix agrees with the one we computed before:
difference = np.linalg.norm(dists - dists_two, ord='fro')
print('No loop difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

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

[13]:
```
# Let's compare how fast the implementations are
def time_function(f, *args):
    """
    Call a function f with args and return the time (in seconds) that it took␣
 ↪to execute.
    """
    import time
    tic = time.time()
    f(*args)
    toc = time.time()
    return toc - tic

two_loop_time = time_function(classifier.compute_distances_two_loops, X_test)
print('Two loop version took %f seconds' % two_loop_time)

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

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

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

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

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

```
Two loop version took 40.291997 seconds
One loop version took 32.690451 seconds
No loop version took 0.232083 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.

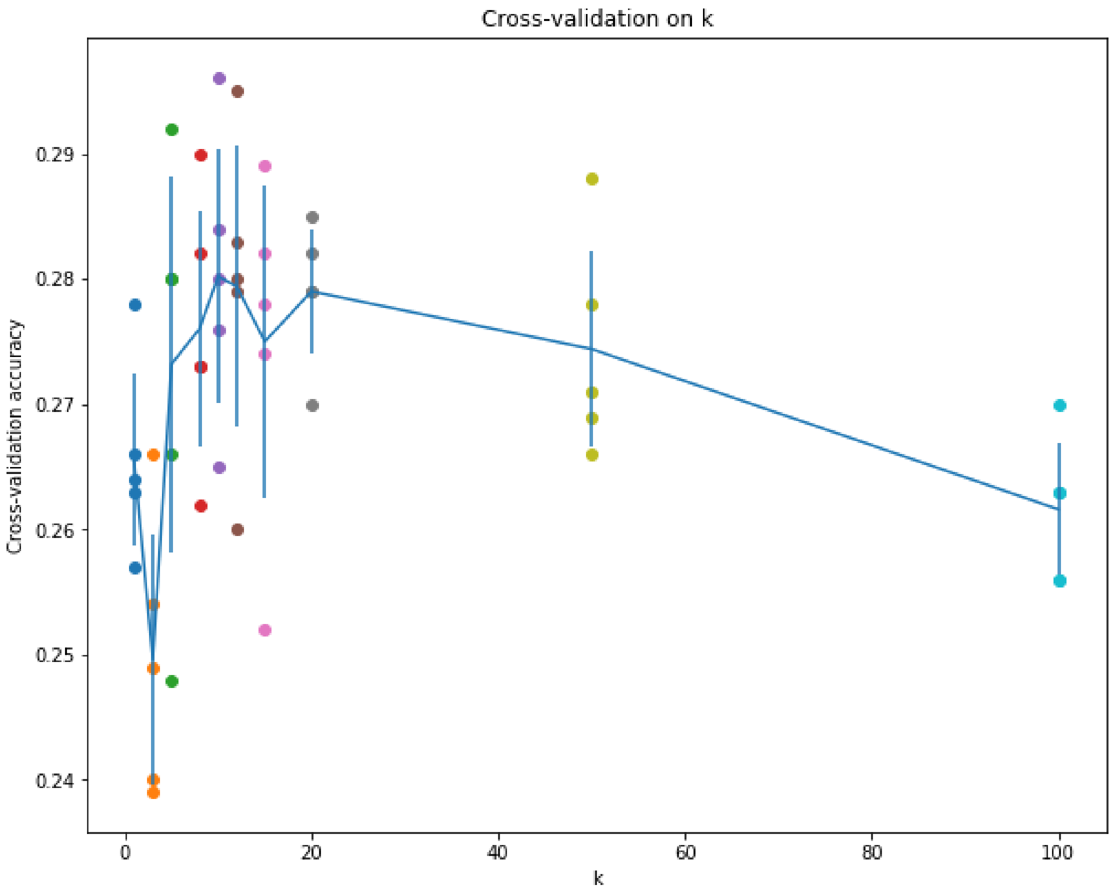
[14]:
```
num_folds = 5
k_choices = [1, 3, 5, 8, 10, 12, 15, 20, 50, 100]

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:
    accuracies = []
```

```
    for j in range(num_folds):
        # prepare dataset
        tmp_x_train = np.concatenate(x_train_folds[:j] + x_train_folds[j+1:])
        tmp_y_train= np.concatenate(y_train_folds[:j] + y_train_folds[j+1:])
        tmp_x_val = x_train_folds[j]
        tmp_y_val = y_train_folds[j]

        # train and evaluate knn
        knn = KNearestNeighbor()
        knn.train(tmp_x_train, tmp_y_train)
        tmp_y_pred = knn.predict(tmp_x_val, k=k, num_loops=0)
        accuracies.append(np.mean(tmp_y_pred == tmp_y_val))
    k_to_accuracies[k] = accuracies




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

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

```
k = 1, accuracy = 0.263000
k = 1, accuracy = 0.257000
k = 1, accuracy = 0.264000
k = 1, accuracy = 0.278000
k = 1, accuracy = 0.266000
k = 3, accuracy = 0.239000
k = 3, accuracy = 0.249000
k = 3, accuracy = 0.240000
k = 3, accuracy = 0.266000
k = 3, accuracy = 0.254000
k = 5, accuracy = 0.248000
k = 5, accuracy = 0.266000
k = 5, accuracy = 0.280000
k = 5, accuracy = 0.292000
k = 5, accuracy = 0.280000
k = 8, accuracy = 0.262000
k = 8, accuracy = 0.282000
k = 8, accuracy = 0.273000
k = 8, accuracy = 0.290000
k = 8, accuracy = 0.273000
k = 10, accuracy = 0.265000
k = 10, accuracy = 0.296000
k = 10, accuracy = 0.276000
```

```
k = 10, accuracy = 0.284000
k = 10, accuracy = 0.280000
k = 12, accuracy = 0.260000
k = 12, accuracy = 0.295000
k = 12, accuracy = 0.279000
k = 12, accuracy = 0.283000
k = 12, accuracy = 0.280000
k = 15, accuracy = 0.252000
k = 15, accuracy = 0.289000
k = 15, accuracy = 0.278000
k = 15, accuracy = 0.282000
k = 15, accuracy = 0.274000
k = 20, accuracy = 0.270000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.282000
k = 20, accuracy = 0.285000
k = 50, accuracy = 0.271000
k = 50, accuracy = 0.288000
k = 50, accuracy = 0.278000
k = 50, accuracy = 0.269000
k = 50, accuracy = 0.266000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.270000
k = 100, accuracy = 0.263000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.263000
```

[15]:
```
# 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()
```



[16]:
```python
# Based on the cross-validation results above, choose the best value for k,
# retrain the classifier using all the training data, and test it on the test
# data. You should be able to get above 28% accuracy on the test data.
best_k = 1

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

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

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

Inline Question 3

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

$\color{blue}{Your Answer:}$ 2, 4

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

1. [False] whether the decision boundary of the K-nn is linear is depend on the distance metrics. For L2 distance the decision boundary is not linear.
2. [True] the training error of a 1-NN will always be 0% because its nearest neighbor is itself, but not necessary for 5-NN
3. [False] 5-nn will tend to be better in most case because it is more robust to outlier data point
4. [True] the testing computational complexity of K-nn is O(n), where n is the size of the training set, because the test data need to be compute distance with all training dataset.

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[17]:
```
# import os

# FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
# FILES_TO_SAVE = ['cs231n/classifiers/k_nearest_neighbor.py']

# for files in FILES_TO_SAVE:
#   with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])),␣
↪'w') as f:
#     f.write(''.join(open(files).readlines()))
```

svm

April 23, 2020

[1]:
```
# from google.colab import drive

# drive.mount('/content/drive', force_remount=True)

# # enter the foldername in your Drive where you have saved the unzipped
# # 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# # folders.
# # e.g. 'cs231n/assignments/assignment1/cs231n/'
# FOLDERNAME = None

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

# %cd drive/My\ Drive
# %cp -r $FOLDERNAME ../../
# %cd ../../
# %cd cs231n/datasets/
# !bash get_datasets.sh
# %cd ../../
```

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

[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
```

1.1 CIFAR-10 Data Loading and Preprocessing

[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.
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,)
```

[4]:
```
# 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()
```

[5]:
```
# 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.
```

```python
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,)
```

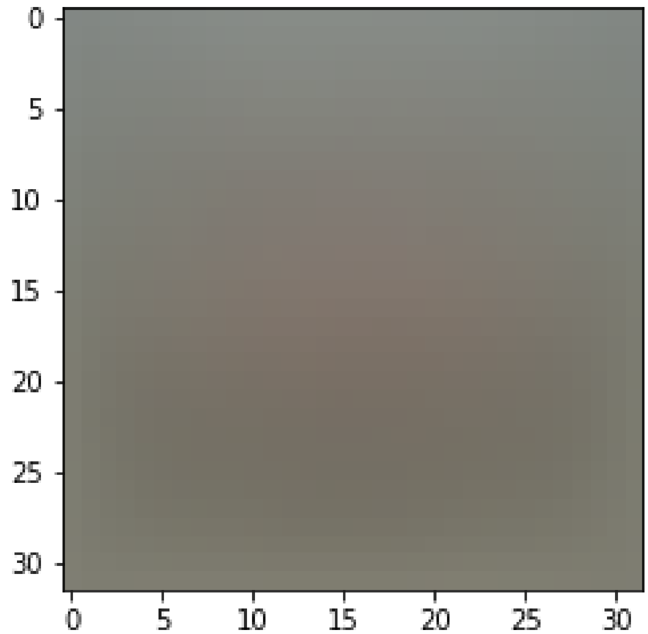
[6]:
```python
# Preprocessing: reshape the image data into rows
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_val = np.reshape(X_val, (X_val.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
```

```
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)
```

[7]:
```
# 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.

[8]:
```python
# 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: 8.672692
```

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:

```
[9]: # 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: -11.749592 analytic: -11.851516, relative error: 4.318611e-03
numerical: -7.653762 analytic: -7.729927, relative error: 4.951029e-03
numerical: 2.261747 analytic: 2.261747, relative error: 3.055124e-11
numerical: 4.374209 analytic: 4.374209, relative error: 4.143304e-11
numerical: -13.883060 analytic: -13.883060, relative error: 3.046715e-12
numerical: -6.628684 analytic: -6.628684, relative error: 2.279581e-11
numerical: -11.249014 analytic: -11.249014, relative error: 1.693372e-12
numerical: -1.370047 analytic: -1.370047, relative error: 7.232035e-11
numerical: 2.828246 analytic: 2.828246, relative error: 7.265747e-11
numerical: -8.182323 analytic: -8.156674, relative error: 1.569810e-03
numerical: -2.335393 analytic: -2.335393, relative error: 1.502873e-10
numerical: -44.801081 analytic: -44.801081, relative error: 2.270906e-12
numerical: -2.351337 analytic: -2.351337, relative error: 6.808446e-11
numerical: 16.620457 analytic: 16.620457, relative error: 2.178703e-12
numerical: 3.598892 analytic: 3.598892, relative error: 6.603295e-12
numerical: -18.592796 analytic: -18.522169, relative error: 1.902931e-03
numerical: -44.597755 analytic: -44.597755, relative error: 6.307579e-13
numerical: 6.658053 analytic: 6.658053, relative error: 3.318770e-11
numerical: -4.884960 analytic: -4.884960, relative error: 2.855840e-11
numerical: -9.074867 analytic: -9.074867, relative error: 1.628449e-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*

Your Answer :

The SVM loss function $loss = max(0, x)$ is not differentiable when x is close to 0. Let's say h = 1e-6, the numerical way to get gradient is $(f(x+h) - f(x-h))/2h$. When x = 1e-8, which is very close to 0, the analytic gradient is 1, while numeric gradient will 0.5, so the discrepency happened.

To avoid the frequency of the problem, instead of calculate gradient we can calculate its subgradient instead.

[10]:
```
# 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: 8.672692e+00 computed in 0.095704s
Vectorized loss: 8.672692e+00 computed in 0.007337s
difference: -0.000000
```

[11]:
```
# 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.
```

```python
difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('difference: %f' % difference)
```

```
Naive loss and gradient: computed in 0.097319s
Vectorized loss and gradient: computed in 0.002329s
difference: 0.000000
```

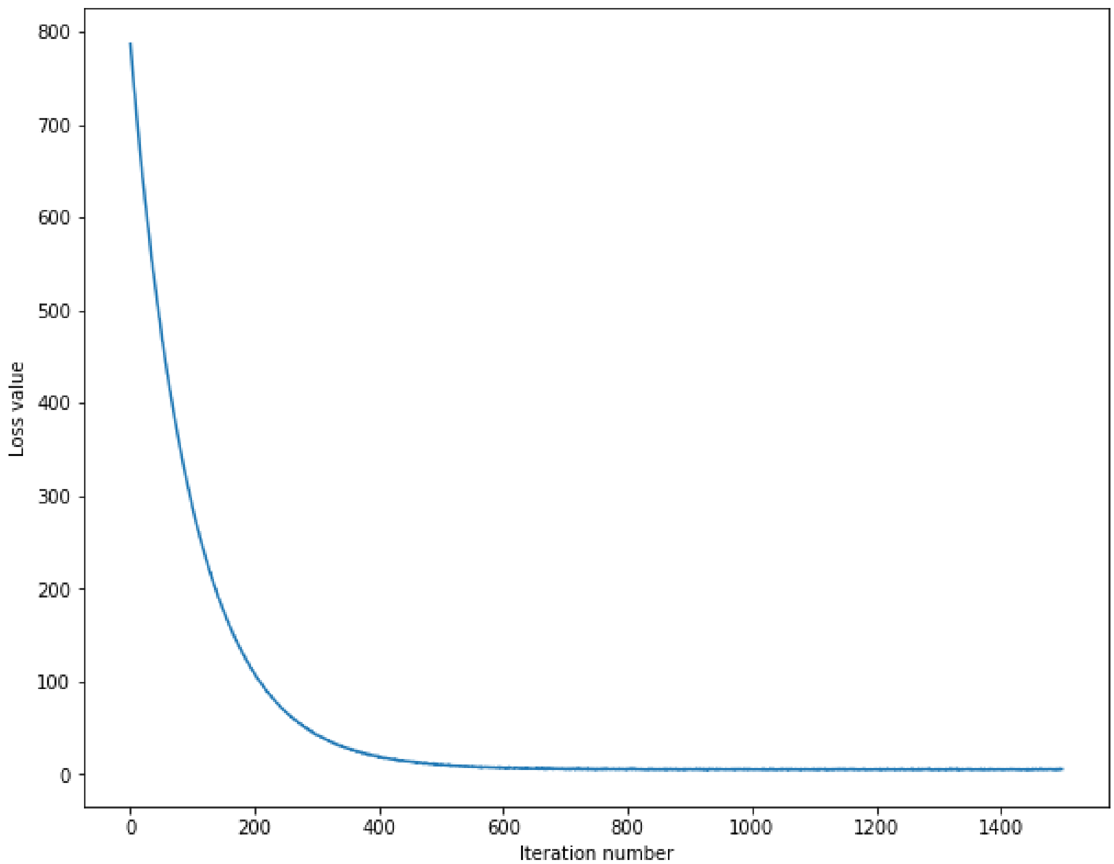
1.2.1 Stochastic Gradient Descent

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`.

[12]:
```python
# 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 786.769520
iteration 100 / 1500: loss 286.637150
iteration 200 / 1500: loss 107.885224
iteration 300 / 1500: loss 42.170219
iteration 400 / 1500: loss 18.977724
iteration 500 / 1500: loss 9.722382
iteration 600 / 1500: loss 7.254078
iteration 700 / 1500: loss 5.327599
iteration 800 / 1500: loss 5.814359
iteration 900 / 1500: loss 5.312371
iteration 1000 / 1500: loss 5.207733
iteration 1100 / 1500: loss 5.639358
iteration 1200 / 1500: loss 5.623047
iteration 1300 / 1500: loss 4.976043
iteration 1400 / 1500: loss 5.326277
That took 5.211145s
```

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



[14]:
```
# 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: 0.361776
validation accuracy: 0.364000
```

[20]:
```
# 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
```

```python
# (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]

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
for lr in learning_rates:
    for reg in regularization_strengths:
        svm = LinearSVM()
        svm.train(X_train, y_train, learning_rate=lr, reg=reg, num_iters=1500,
                  verbose=True)
        train_accuracy = np.mean(svm.predict(X_train) == y_train)
        val_accuracy = np.mean(svm.predict(X_val) == y_val)
        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)
```

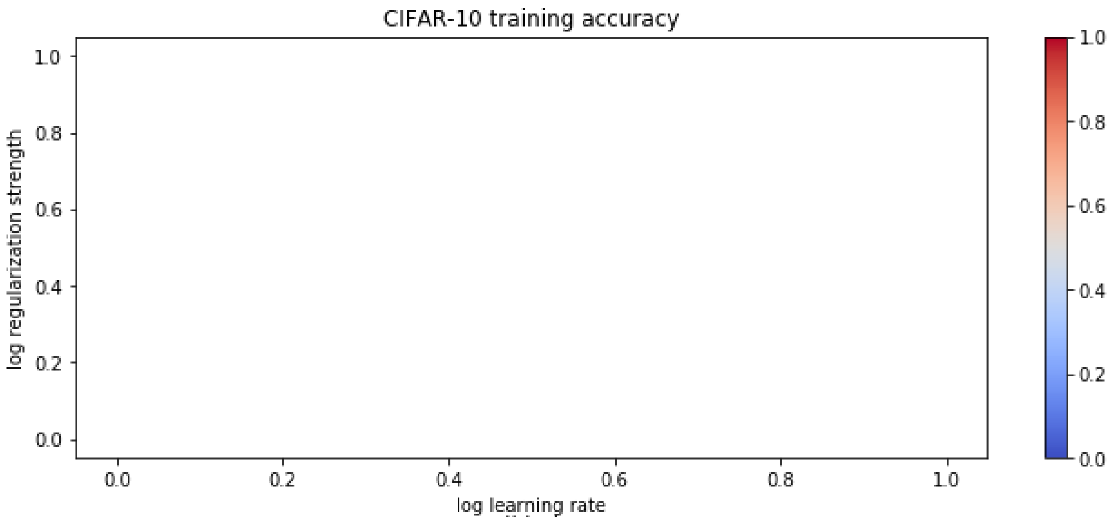
```
iteration 0 / 1500: loss 790.273576
iteration 100 / 1500: loss 286.246564
iteration 200 / 1500: loss 107.465822
iteration 300 / 1500: loss 41.676112
iteration 400 / 1500: loss 18.897850
iteration 500 / 1500: loss 9.979788
iteration 600 / 1500: loss 6.962469
iteration 700 / 1500: loss 6.002329
iteration 800 / 1500: loss 5.661723
iteration 900 / 1500: loss 5.373071
iteration 1000 / 1500: loss 5.229590
iteration 1100 / 1500: loss 5.926929
iteration 1200 / 1500: loss 4.978721
iteration 1300 / 1500: loss 5.314449
iteration 1400 / 1500: loss 5.283911
iteration 0 / 1500: loss 1549.181400
iteration 100 / 1500: loss 210.383737
iteration 200 / 1500: loss 33.357773
iteration 300 / 1500: loss 9.609001
iteration 400 / 1500: loss 6.179866
iteration 500 / 1500: loss 5.589659
iteration 600 / 1500: loss 5.376494
iteration 700 / 1500: loss 5.876961
iteration 800 / 1500: loss 5.373093
iteration 900 / 1500: loss 5.942906
iteration 1000 / 1500: loss 5.639133
iteration 1100 / 1500: loss 5.342489
iteration 1200 / 1500: loss 5.285632
iteration 1300 / 1500: loss 5.703171
iteration 1400 / 1500: loss 5.509828
iteration 0 / 1500: loss 787.046353
iteration 100 / 1500: loss 402127739640471779028271866865514446848.000000
iteration 200 / 1500: loss 66468494753200285704831773861069458569726584481775811
991243223596124864512.000000
iteration 300 / 1500: loss 10986709841768804593119878540578305632409675190149014
916220541418380452826330781914678354950540797804955041792.000000
iteration 400 / 1500: loss 18160151451512714709945182508084782577348601492788049
02830022273865297060811309198364756536598896748523004740231423272505686008825403
762752356352.000000
iteration 500 / 1500: loss 30017275917135219490394852766169600596006347129972942
10665534963048962643011494508066736634066871585013593196030338198972118843375408
82952777673095453074667926343806715017000124416.000000
iteration 600 / 1500: loss 49616153031056969785132677469174394684907006182521344
68813659353874003628359861233973945011343188494593200582974987376003923670356812
```

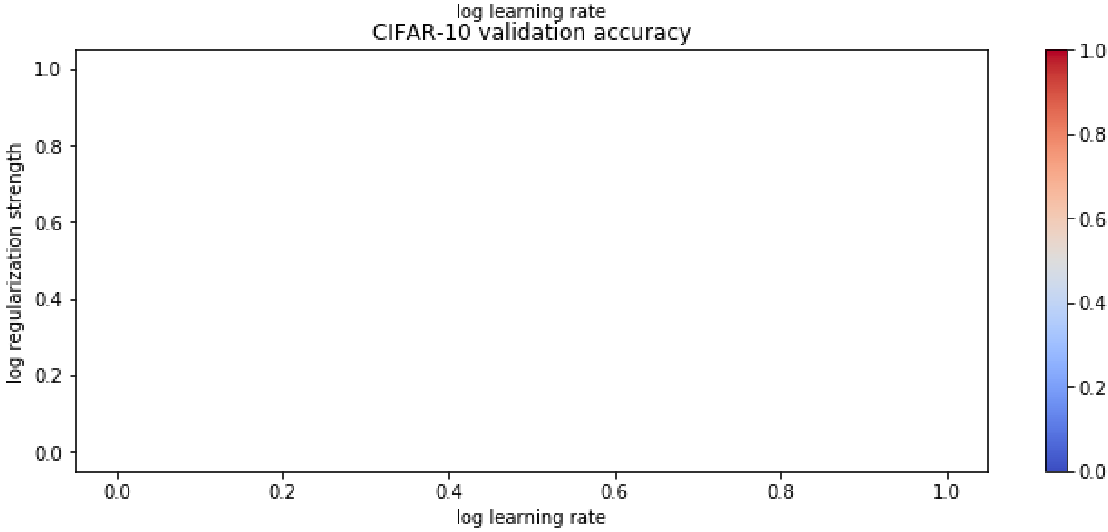
```
3723330117827641102983916174770620342768919814526928230030493421680641517809565696.000000
iteration 700 / 1500: loss 820115272417500650069804431173293394354207446259257344592075157608842754714955027155381760090705795942024389982974206492943252126509241818484761972498546183300784197053810324260782861940800854023312436747994735977805876035682128544825750311610299187 2.000000
iteration 800 / 1500: loss 135558486292040372958442982323229531565078132545758647731836656195535750582859636489946507497955265454999811158034825345134067612973291504042003317810587239685432570191433333198003404953403383721420656506956331502847648727769922020209596803114144665707703648605308447575164912507709030 4.000000
iteration 900 / 1500: loss inf
iteration 1000 / 1500: loss inf
iteration 1100 / 1500: loss inf
iteration 1200 / 1500: loss inf
iteration 1300 / 1500: loss inf
iteration 1400 / 1500: loss inf
iteration 0 / 1500: loss 1555.910196
iteration 100 / 1500: loss 4260550419129454717184700795061799705757968876796990974779753938101011512521013406587859908416580684813089012731172125409280.000000
iteration 200 / 1500: loss 1100180580038016173774119435251722883248502658755436793453368082840343603490901509266613295487966538895576225286006763654086418773647529214106626246797295657090784420857352391619914227946053023333233783569914967922283469420906155715943808892928 0.000000
iteration 300 / 1500: loss inf
iteration 400 / 1500: loss inf
iteration 500 / 1500: loss inf
iteration 600 / 1500: loss nan
iteration 700 / 1500: loss nan
iteration 800 / 1500: loss nan
iteration 900 / 1500: loss nan
iteration 1000 / 1500: loss nan
iteration 1100 / 1500: loss nan
iteration 1200 / 1500: loss nan
iteration 1300 / 1500: loss nan
iteration 1400 / 1500: loss nan
best validation accuracy achieved during cross-validation: 0.376000
```

[16]:

```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()
```



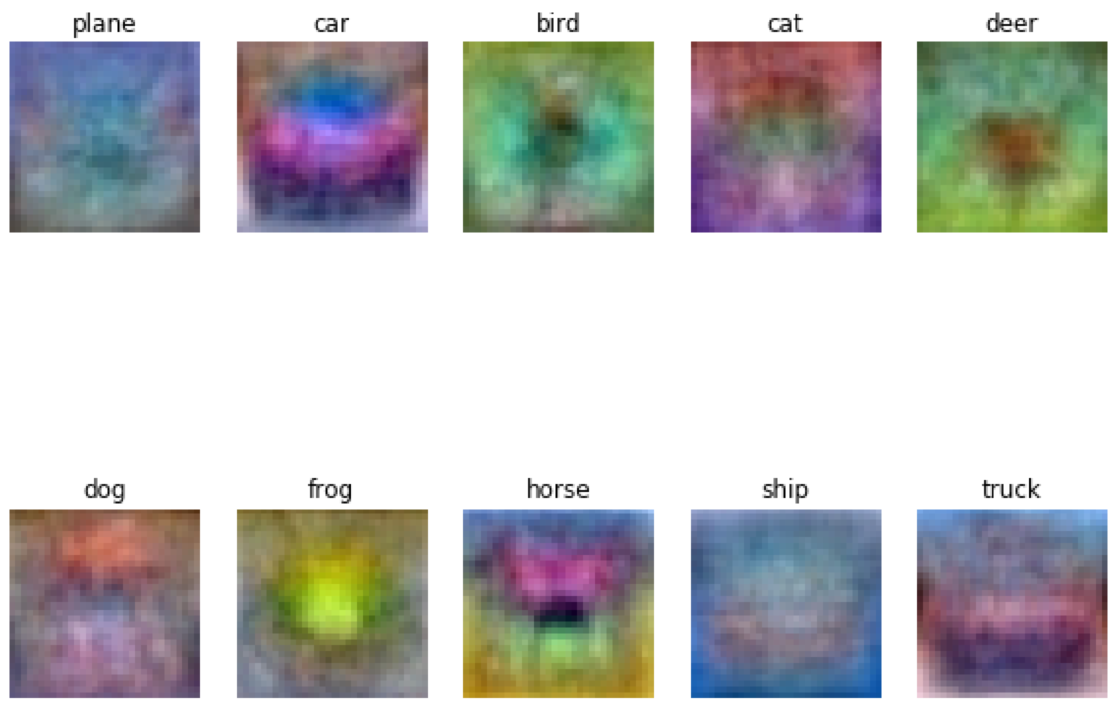


[17]:
```
# Evaluate the best svm on test set
y_test_pred = best_svm.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('linear SVM on raw pixels final test set accuracy: %f' % test_accuracy)
```

```
linear SVM on raw pixels final test set accuracy: 0.364000
```

[18]:
```
# 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)
```

```python
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.

Your Answer :

The visualized SVM weights looks like a linear combination of all images belongs to each class. It looks like this because the weight of each class can be regarded as a template of this class, then the classification is just take a test image and compare it with all templates, and choose the one with maximum similarity score. In this case the similarity score is inner product between test image and templates.

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[19]:
```
# import os

# FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
# FILES_TO_SAVE = ['cs231n/classifiers/linear_svm.py', 'cs231n/classifiers/
↪linear_classifier.py']

# for files in FILES_TO_SAVE:
#   with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])),␣
↪'w') as f:
#     f.write(''.join(open(files).readlines()))
```

softmax

April 23, 2020

[1]:
```
# from google.colab import drive
#
# drive.mount('/content/drive', force_remount=True)
#
# # enter the foldername in your Drive where you have saved the unzipped
# # 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# # folders.
# # e.g. 'cs231n/assignments/assignment1/cs231n/'
# FOLDERNAME = None
#
# assert FOLDERNAME is not None, "[!] Enter the foldername."
#
# %cd drive/My\ Drive
# %cp -r $FOLDERNAME ../../
# %cd ../../
# %cd cs231n/datasets/
# !bash get_datasets.sh
# %cd ../../
```

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

[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
```

[3]:
```
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`.

[4]:
```python
# 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: 2.408344
sanity check: 2.302585
```

Inline Question 1

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

$Your Answer:$

Because the initial weight is randomly generated, so the probability of a image belong to each class should be equal. There are 10 classes here, for each the possibility is 0.1. So the expected loss with initial weight is $-log(0.1)$

[5]:
```python
# 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: 2.652127 analytic: 2.652127, relative error: 3.787981e-08
numerical: -2.565140 analytic: -2.565140, relative error: 4.999490e-09
numerical: 2.108717 analytic: 2.108717, relative error: 1.200016e-09
numerical: 0.282413 analytic: 0.282413, relative error: 1.119501e-07
numerical: -2.608355 analytic: -2.608355, relative error: 1.109725e-08
numerical: -0.177181 analytic: -0.177181, relative error: 1.998608e-07
numerical: 2.515985 analytic: 2.515984, relative error: 2.350370e-08
```

```
numerical: 0.351726 analytic: 0.351726, relative error: 1.570948e-07
numerical: -1.460257 analytic: -1.460257, relative error: 6.923320e-08
numerical: 0.213107 analytic: 0.213107, relative error: 2.276612e-07
numerical: 3.882076 analytic: 3.882076, relative error: 4.777295e-09
numerical: 0.818587 analytic: 0.818587, relative error: 4.829094e-08
numerical: -5.875147 analytic: -5.875147, relative error: 6.959453e-09
numerical: 0.242900 analytic: 0.242900, relative error: 1.550955e-07
numerical: 2.038266 analytic: 2.038266, relative error: 3.789663e-08
numerical: -0.643731 analytic: -0.643731, relative error: 2.752044e-08
numerical: 3.087104 analytic: 3.087104, relative error: 1.718053e-08
numerical: -4.355318 analytic: -4.355318, relative error: 1.592901e-08
numerical: 1.205447 analytic: 1.205447, relative error: 6.362401e-08
numerical: 0.179128 analytic: 0.179127, relative error: 1.020302e-07
```

[6]:

```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: 2.408344e+00 computed in 0.042420s
vectorized loss: 2.408344e+00 computed in 0.004716s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[7]:

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

```python
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]

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
for lr in learning_rates:
    for reg in regularization_strengths:
        softmax = Softmax()
        softmax.train(X_train, y_train, learning_rate=lr, reg=reg,
                      verbose=True, num_iters=3000)
        train_accuracy = np.mean(softmax.predict(X_train) == y_train)
        val_accuracy = np.mean(softmax.predict(X_val) == y_val)
        results[(lr, reg)] = (train_accuracy, val_accuracy)
        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)
```

```
iteration 0 / 3000: loss 775.215336
iteration 100 / 3000: loss 284.425389
iteration 200 / 3000: loss 105.441177
iteration 300 / 3000: loss 39.912491
iteration 400 / 3000: loss 15.932751
```

```
iteration 500 / 3000: loss 7.146501
iteration 600 / 3000: loss 3.943634
iteration 700 / 3000: loss 2.742121
iteration 800 / 3000: loss 2.271104
iteration 900 / 3000: loss 2.154573
iteration 1000 / 3000: loss 2.098949
iteration 1100 / 3000: loss 2.073110
iteration 1200 / 3000: loss 2.081083
iteration 1300 / 3000: loss 2.134099
iteration 1400 / 3000: loss 2.035077
iteration 1500 / 3000: loss 2.122315
iteration 1600 / 3000: loss 2.132149
iteration 1700 / 3000: loss 2.071272
iteration 1800 / 3000: loss 2.054394
iteration 1900 / 3000: loss 2.071069
iteration 2000 / 3000: loss 2.116917
iteration 2100 / 3000: loss 2.094814
iteration 2200 / 3000: loss 2.027839
iteration 2300 / 3000: loss 2.092995
iteration 2400 / 3000: loss 2.018711
iteration 2500 / 3000: loss 2.085676
iteration 2600 / 3000: loss 2.086014
iteration 2700 / 3000: loss 2.106865
iteration 2800 / 3000: loss 2.077275
iteration 2900 / 3000: loss 2.131597
iteration 0 / 3000: loss 1542.478193
iteration 100 / 3000: loss 207.739677
iteration 200 / 3000: loss 29.559817
iteration 300 / 3000: loss 5.824649
iteration 400 / 3000: loss 2.675654
iteration 500 / 3000: loss 2.207731
iteration 600 / 3000: loss 2.138977
iteration 700 / 3000: loss 2.132184
iteration 800 / 3000: loss 2.184714
iteration 900 / 3000: loss 2.156724
iteration 1000 / 3000: loss 2.155745
iteration 1100 / 3000: loss 2.124393
iteration 1200 / 3000: loss 2.137978
iteration 1300 / 3000: loss 2.116314
iteration 1400 / 3000: loss 2.151384
iteration 1500 / 3000: loss 2.117023
iteration 1600 / 3000: loss 2.138700
iteration 1700 / 3000: loss 2.147161
iteration 1800 / 3000: loss 2.104031
iteration 1900 / 3000: loss 2.148355
iteration 2000 / 3000: loss 2.109934
iteration 2100 / 3000: loss 2.123599
iteration 2200 / 3000: loss 2.086019
```

```
iteration 2300 / 3000: loss 2.174302
iteration 2400 / 3000: loss 2.167633
iteration 2500 / 3000: loss 2.190859
iteration 2600 / 3000: loss 2.151335
iteration 2700 / 3000: loss 2.140789
iteration 2800 / 3000: loss 2.118258
iteration 2900 / 3000: loss 2.133383
iteration 0 / 3000: loss 778.703068
iteration 100 / 3000: loss 6.949183
iteration 200 / 3000: loss 2.181826
iteration 300 / 3000: loss 2.105263
iteration 400 / 3000: loss 2.075711
iteration 500 / 3000: loss 2.101473
iteration 600 / 3000: loss 2.114364
iteration 700 / 3000: loss 2.075375
iteration 800 / 3000: loss 2.029995
iteration 900 / 3000: loss 2.092774
iteration 1000 / 3000: loss 2.098348
iteration 1100 / 3000: loss 2.090716
iteration 1200 / 3000: loss 2.082147
iteration 1300 / 3000: loss 2.100524
iteration 1400 / 3000: loss 2.116520
iteration 1500 / 3000: loss 2.101326
iteration 1600 / 3000: loss 2.084627
iteration 1700 / 3000: loss 2.145161
iteration 1800 / 3000: loss 2.037428
iteration 1900 / 3000: loss 2.106044
iteration 2000 / 3000: loss 2.132573
iteration 2100 / 3000: loss 2.115919
iteration 2200 / 3000: loss 2.082979
iteration 2300 / 3000: loss 2.102768
iteration 2400 / 3000: loss 2.064252
iteration 2500 / 3000: loss 2.078615
iteration 2600 / 3000: loss 2.154617
iteration 2700 / 3000: loss 2.080576
iteration 2800 / 3000: loss 2.024483
iteration 2900 / 3000: loss 2.121982
iteration 0 / 3000: loss 1559.980832
iteration 100 / 3000: loss 2.203037
iteration 200 / 3000: loss 2.146318
iteration 300 / 3000: loss 2.164612
iteration 400 / 3000: loss 2.143634
iteration 500 / 3000: loss 2.151340
iteration 600 / 3000: loss 2.139954
iteration 700 / 3000: loss 2.150253
iteration 800 / 3000: loss 2.141797
iteration 900 / 3000: loss 2.165140
iteration 1000 / 3000: loss 2.139832
```

```
iteration 1100 / 3000: loss 2.149773
iteration 1200 / 3000: loss 2.151208
iteration 1300 / 3000: loss 2.153756
iteration 1400 / 3000: loss 2.118382
iteration 1500 / 3000: loss 2.157347
iteration 1600 / 3000: loss 2.132309
iteration 1700 / 3000: loss 2.148288
iteration 1800 / 3000: loss 2.132243
iteration 1900 / 3000: loss 2.169322
iteration 2000 / 3000: loss 2.172437
iteration 2100 / 3000: loss 2.158040
iteration 2200 / 3000: loss 2.170368
iteration 2300 / 3000: loss 2.143255
iteration 2400 / 3000: loss 2.163435
iteration 2500 / 3000: loss 2.149169
iteration 2600 / 3000: loss 2.133625
iteration 2700 / 3000: loss 2.146305
iteration 2800 / 3000: loss 2.139896
iteration 2900 / 3000: loss 2.188728
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.331653 val accuracy: 0.355000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.302510 val accuracy: 0.320000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.319184 val accuracy: 0.336000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.293816 val accuracy: 0.313000
best validation accuracy achieved during cross-validation: 0.355000
```

[8]:

```python
# 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: 0.337000
```

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.

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

True

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

For the SVM, the new datapoint would have $loss = 0$, if the score of correct class is larger than the score of rest class by a margin. For softmax, the loss is $-log(p_i)$, where p_i is the possibility of correct class. Since p_i will always be smaller than 1, $-log(p_i)$ will never be 0, so any new datapoints will add loss value to the overall loss of softmax classifier.

[9]:
```
# 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])
```

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[10]:
```
# import os
#
# FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
# FILES_TO_SAVE = ['cs231n/classifiers/softmax.py']
#
# for files in FILES_TO_SAVE:
#   with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])),
↪'w') as f:
#     f.write(''.join(open(files).readlines()))
```

two_layer_net

April 23, 2020

[1]:
```
# from google.colab import drive
#
# drive.mount('/content/drive', force_remount=True)
#
# # enter the foldername in your Drive where you have saved the unzipped
# # 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# # folders.
# # e.g. 'cs231n/assignments/assignment1/cs231n/'
# FOLDERNAME = None
#
# assert FOLDERNAME is not None, "[!] Enter the foldername."
#
# %cd drive/My\ Drive
# %cp -r $FOLDERNAME ../../
# %cd ../../
# %cd cs231n/datasets/
# !bash get_datasets.sh
# %cd ../../
```

1 Implementing a Neural Network

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

[2]:
```
# A bit of setup

import numpy as np
import matplotlib.pyplot as plt

from cs231n.classifiers.neural_net import TwoLayerNet

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

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

def rel_error(x, y):
    """ returns relative error """
    return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

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

[3]:
```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
hidden_size = 10
num_classes = 3
num_inputs = 5

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

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

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

2 Forward pass: compute scores

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

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

[4]:
```
scores = net.loss(X)
print('Your scores:')
print(scores)
print()
print('correct scores:')
correct_scores = np.asarray([
  [-0.81233741, -1.27654624, -0.70335995],
  [-0.17129677, -1.18803311, -0.47310444],
  [-0.51590475, -1.01354314, -0.8504215 ],
  [-0.15419291, -0.48629638, -0.52901952],
  [-0.00618733, -0.12435261, -0.15226949]])
print(correct_scores)
print()

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

```
Your scores:
[[-0.81233741 -1.27654624 -0.70335995]
 [-0.17129677 -1.18803311 -0.47310444]
 [-0.51590475 -1.01354314 -0.8504215 ]
 [-0.15419291 -0.48629638 -0.52901952]
 [-0.00618733 -0.12435261 -0.15226949]]

correct scores:
[[-0.81233741 -1.27654624 -0.70335995]
 [-0.17129677 -1.18803311 -0.47310444]
 [-0.51590475 -1.01354314 -0.8504215 ]
 [-0.15419291 -0.48629638 -0.52901952]
 [-0.00618733 -0.12435261 -0.15226949]]

Difference between your scores and correct scores:
3.6802720496109664e-08
```

3 Forward pass: compute loss

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

[5]:
```
loss, _ = net.loss(X, y, reg=0.05)
correct_loss = 1.30378789133

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

```
Difference between your loss and correct loss:
1.794120407794253e-13
```

4 Backward pass

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

[6]:
```
from cs231n.gradient_check import eval_numerical_gradient

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

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

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

```
W2 max relative error: 3.440708e-09
b2 max relative error: 3.865039e-11
W1 max relative error: 3.561318e-09
b1 max relative error: 2.738423e-09
```

5 Train the network

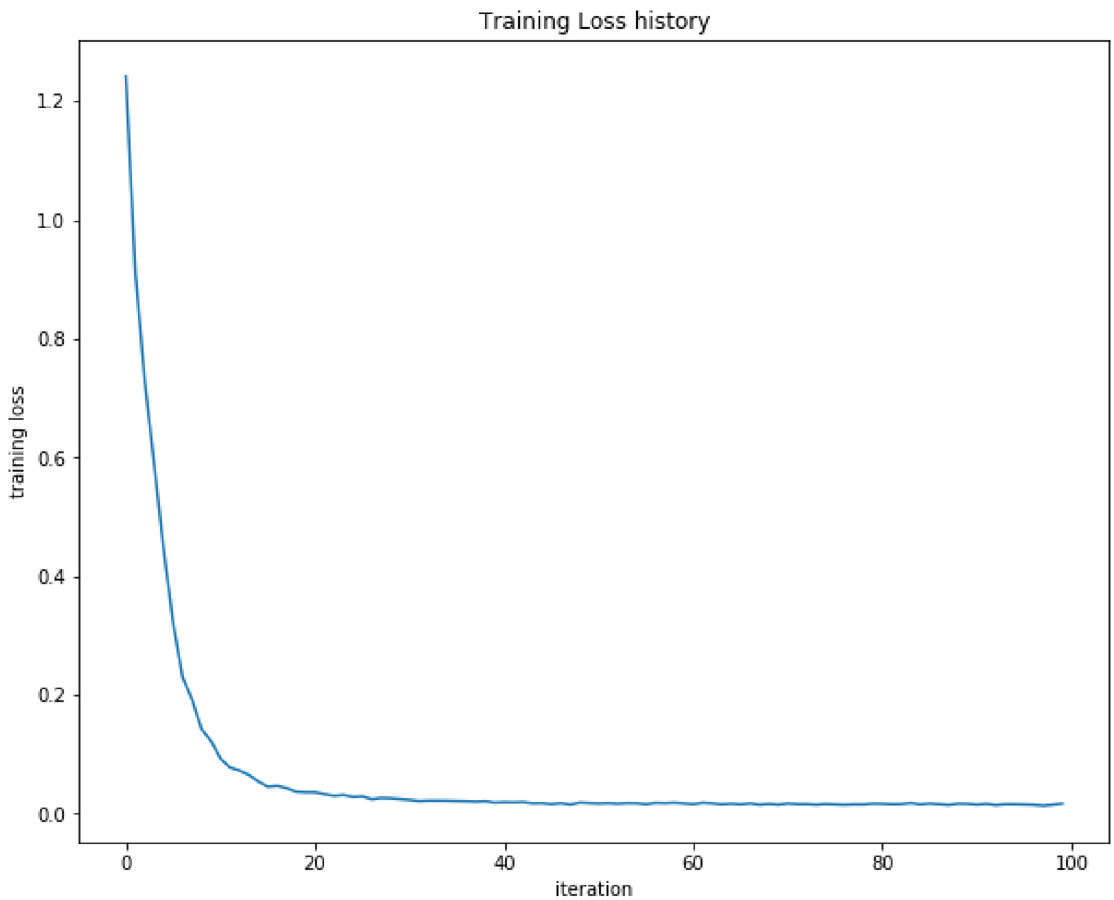
To train the network we will use stochastic gradient descent (SGD), similar to the SVM and Softmax classifiers. Look at the function `TwoLayerNet.train` and fill in the missing sections to implement the training procedure. This should be very similar to the training procedure you used for the SVM and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

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

[7]:
```
net = init_toy_model()
stats = net.train(X, y, X, y,
            learning_rate=1e-1, reg=5e-6,
```

```
            num_iters=100, verbose=False)

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

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

```
Final training loss:  0.017149607938732022
```



6 Load the data

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

[8]:
```
from cs231n.data_utils import load_CIFAR10

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

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

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

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

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

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

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

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

```
Train data shape:  (49000, 3072)
Train labels shape:  (49000,)
Validation data shape:  (1000, 3072)
Validation labels shape:  (1000,)
Test data shape:  (1000, 3072)
Test labels shape:  (1000,)
```

7 Train a network

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

[9]:
```python
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
net = TwoLayerNet(input_size, hidden_size, num_classes)

# Train the network
stats = net.train(X_train, y_train, X_val, y_val,
            num_iters=1000, batch_size=200,
            learning_rate=1e-4, learning_rate_decay=0.95,
            reg=0.25, verbose=True)

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

```
iteration 0 / 1000: loss 2.302954
iteration 100 / 1000: loss 2.302550
iteration 200 / 1000: loss 2.297648
iteration 300 / 1000: loss 2.259602
iteration 400 / 1000: loss 2.204170
iteration 500 / 1000: loss 2.118565
iteration 600 / 1000: loss 2.051535
```

```
iteration 700 / 1000: loss 1.988466
iteration 800 / 1000: loss 2.006591
iteration 900 / 1000: loss 1.951473
Validation accuracy:  0.287
```

8 Debug the training

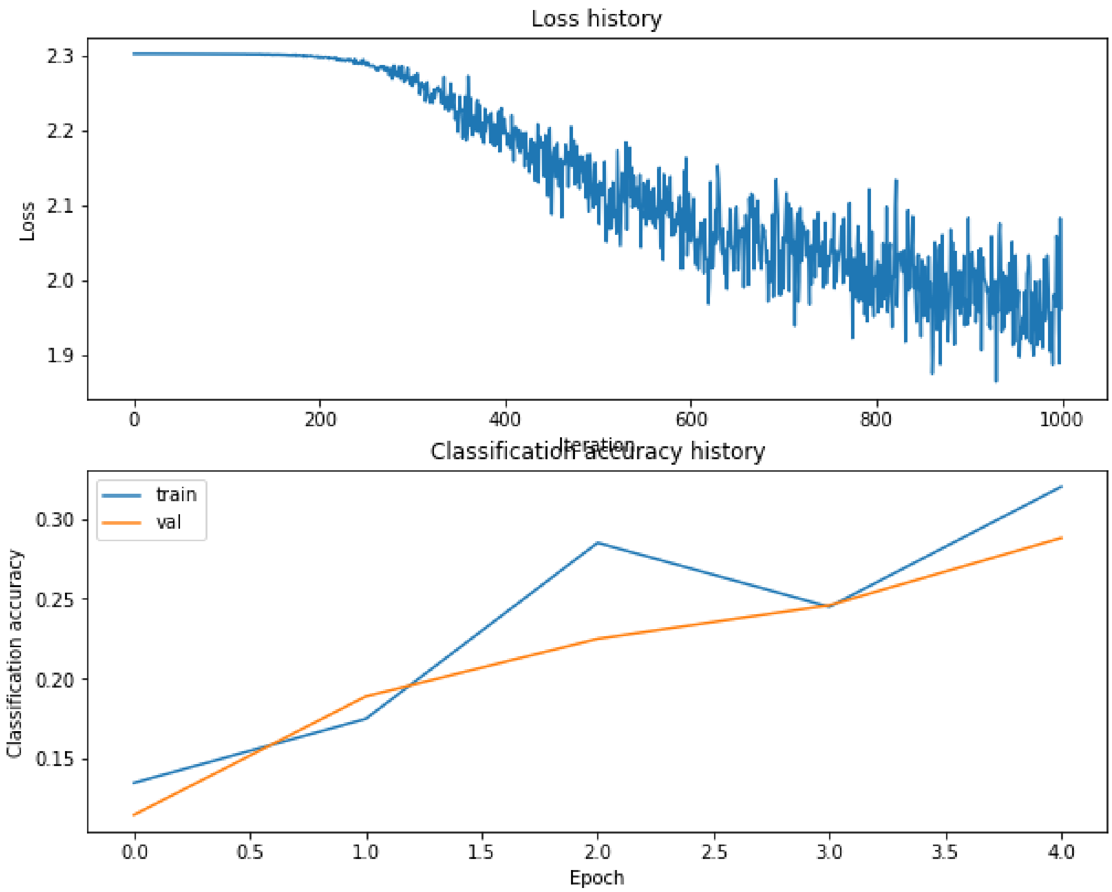
With the default parameters we provided above, you should get a validation accuracy of about 0.29 on the validation set. This isn't very good.

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

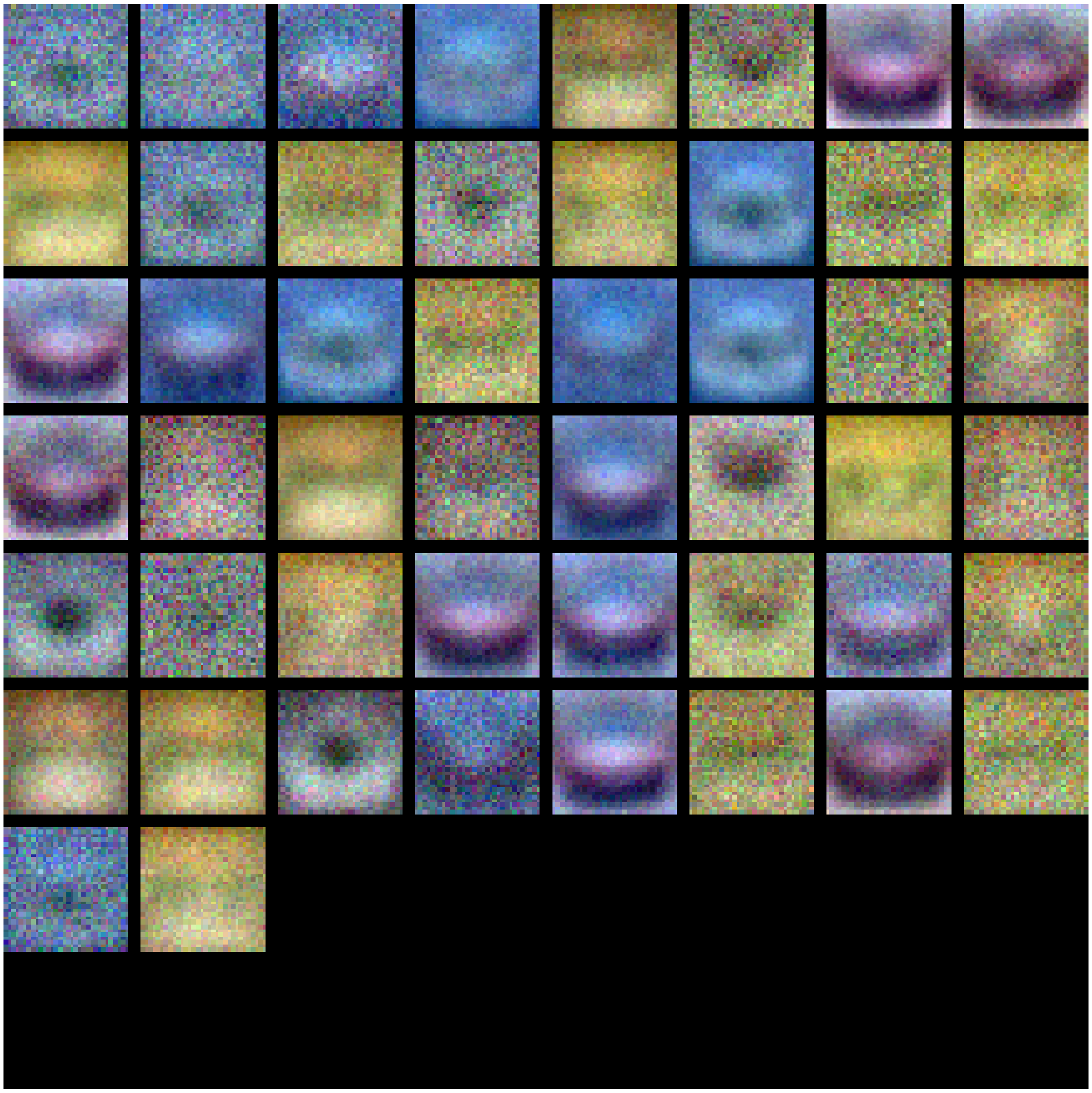
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

[10]:

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

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



[11]:
```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(net)
```



9 Tune your hyperparameters

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

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

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

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

Explain your hyperparameter tuning process below.

Your Answer : choose different parameters between learning rates, regularization strengths and hidden sizes

[12]:
```
best_net = None # store the best model into this


##################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained ␣
 ↪#
# model in best_net.                                                           ␣
 ↪#
#                                                                              ␣
 ↪#
# To help debug your network, it may help to use visualizations similar to the ␣
 ↪#
# ones we used above; these visualizations will have significant qualitative   ␣
 ↪#
# differences from the ones we saw above for the poorly tuned network.         ␣
 ↪#
#                                                                              ␣
 ↪#
# Tweaking hyperparameters by hand can be fun, but you might find it useful to ␣
 ↪#
# write code to sweep through possible combinations of hyperparameters         ␣
 ↪#
# automatically like we did on the previous exercises.                         ␣
 ↪#
##################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

best_val = -1
learning_rates = [1e-1, 1e-3, 1e-4]
regularization_strengths = [1e2, 1, 1e-1, 1e-3]
hidden_sizes = [40, 80, 120]
for lr in learning_rates:
```

```
    for reg in regularization_strengths:
        for hidden_size in hidden_sizes:
            net = TwoLayerNet(input_size, hidden_size, num_classes)
            net.train(X_train, y_train, X_val, y_val, num_iters=2000,␣
↪batch_size=200,
                      learning_rate=lr, learning_rate_decay=0.95, reg=reg,␣
↪verbose=False)
            # Predict on the training set
            train_accuracy = (net.predict(X_train) == y_train).mean()

            # Predict on the validation set
            val_accuracy = (net.predict(X_val) == y_val).mean()

            # Save best values
            if val_accuracy > best_val:
                best_val = val_accuracy
                best_net = net


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

```
/Users/chenhuang/Dropbox/Documents/Study/@Archive/Stanford University/2020Spring
/cs231n/homework/assignment1/cs231n/classifiers/neural_net.py:104:
RuntimeWarning: divide by zero encountered in log
  loss = np.sum(-np.log(probability[np.arange(num_train), y]))
/Users/chenhuang/Dropbox/Documents/Study/@Archive/Stanford University/2020Spring
/cs231n/homework/assignment1/cs231n/classifiers/neural_net.py:85:
RuntimeWarning: overflow encountered in exp
  exp_score = np.exp(score)
/Users/chenhuang/Dropbox/Documents/Study/@Archive/Stanford University/2020Spring
/cs231n/homework/assignment1/cs231n/classifiers/neural_net.py:86:
RuntimeWarning: invalid value encountered in true_divide
  probability = exp_score / np.sum(exp_score, axis=1, keepdims=True)
/Users/chenhuang/Dropbox/Documents/Study/@Archive/Stanford University/2020Spring
/cs231n/homework/assignment1/cs231n/classifiers/neural_net.py:129:
RuntimeWarning: invalid value encountered in greater
  dz1 = dh1 * np.where(z1 > 0, 1, 0)
```

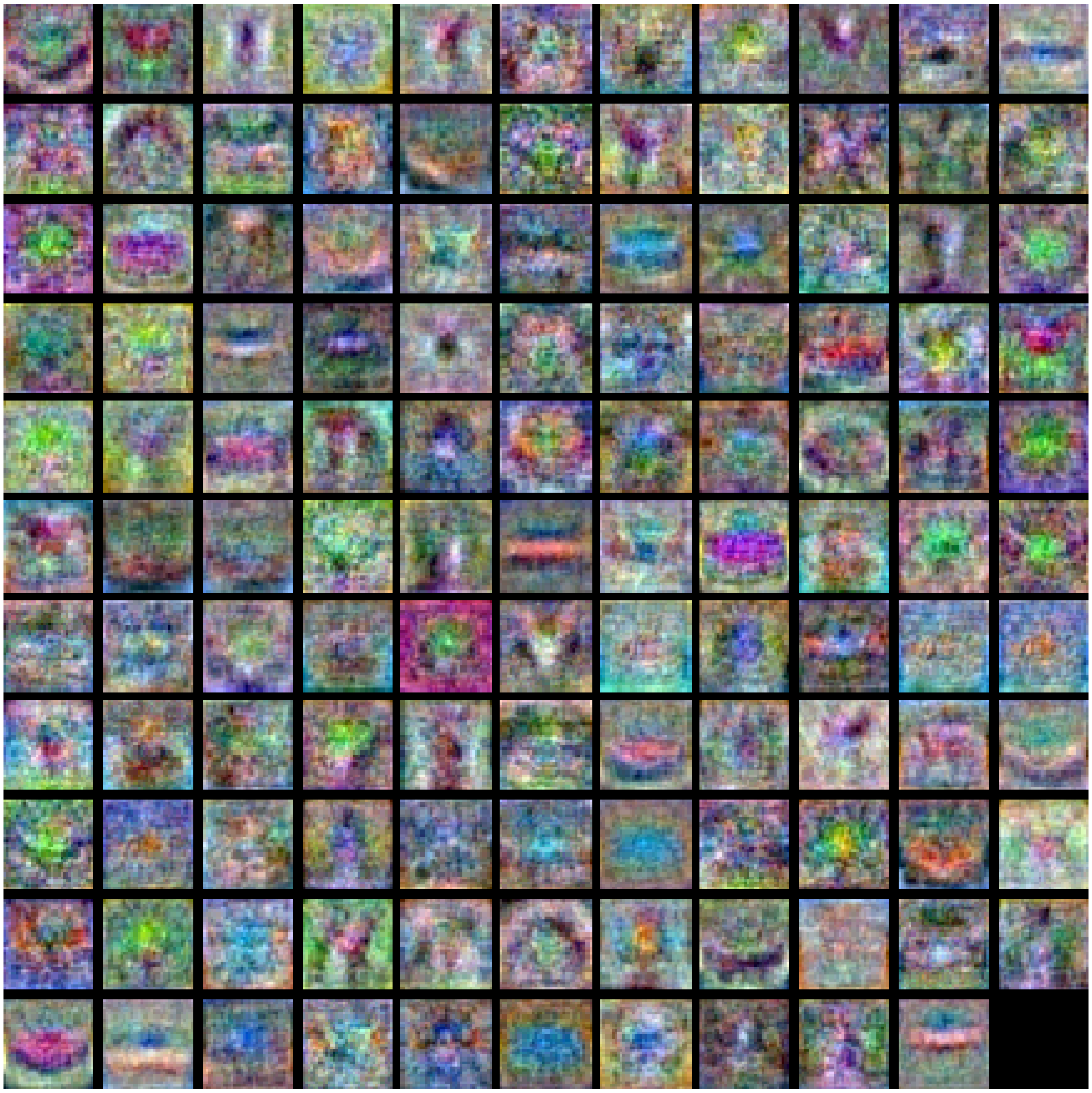
[13]:

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

```
Validation accuracy:  0.522
```

[14]:

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



10 Run on the test set

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

[15]:
```
# Print your test accuracy: this should be above 48%
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.513
```

Inline Question

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

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

$\color{blue}{\textit{Your Answer:}}$ 1, 3

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

the testing accuracy is much lower than the training accuracy, then it is the problem of overfitting, which the neural network are trained so well on training dataset, so it fail to generalized to testing dataset.

To overcome overfitting, we can either add regularization strength, or increase the dataset. Increasing the dataset means add more diversity to the training dataset, so it can make the training model more easier to generalized on unseen testing dataset.

---

11 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[16]:
```
# import os
#
# FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
# FILES_TO_SAVE = ['cs231n/classifiers/neural_net.py']
#
# for files in FILES_TO_SAVE:
#   with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])),␣
 ↪'w') as f:
#     f.write(''.join(open(files).readlines()))
```

features

April 23, 2020

[ ]:
```
# from google.colab import drive

# drive.mount('/content/drive', force_remount=True)

# # enter the foldername in your Drive where you have saved the unzipped
# # 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# # folders.
# # e.g. 'cs231n/assignments/assignment1/cs231n/'
# FOLDERNAME = None

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

# %cd drive/My\ Drive
# %cp -r $FOLDERNAME ../../
# %cd ../../
# %cd cs231n/datasets/
# !bash get_datasets.sh
# %cd ../../
```

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.

[1]:
```
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.

[2]:
```
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.

[3]:
```
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
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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.

[4]:
```python
# 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)*****

for lr in learning_rates:
    for reg in regularization_strengths:
        svm = LinearSVM()
        svm.train(X_train_feats, y_train, learning_rate=lr, reg=reg,␣
↪num_iters=2000)
        train_accuracy = np.mean(svm.predict(X_train_feats) == y_train)
        val_accuracy = np.mean(svm.predict(X_val_feats) == y_val)
        results[(lr, reg)] = (train_accuracy, val_accuracy)
        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)
```

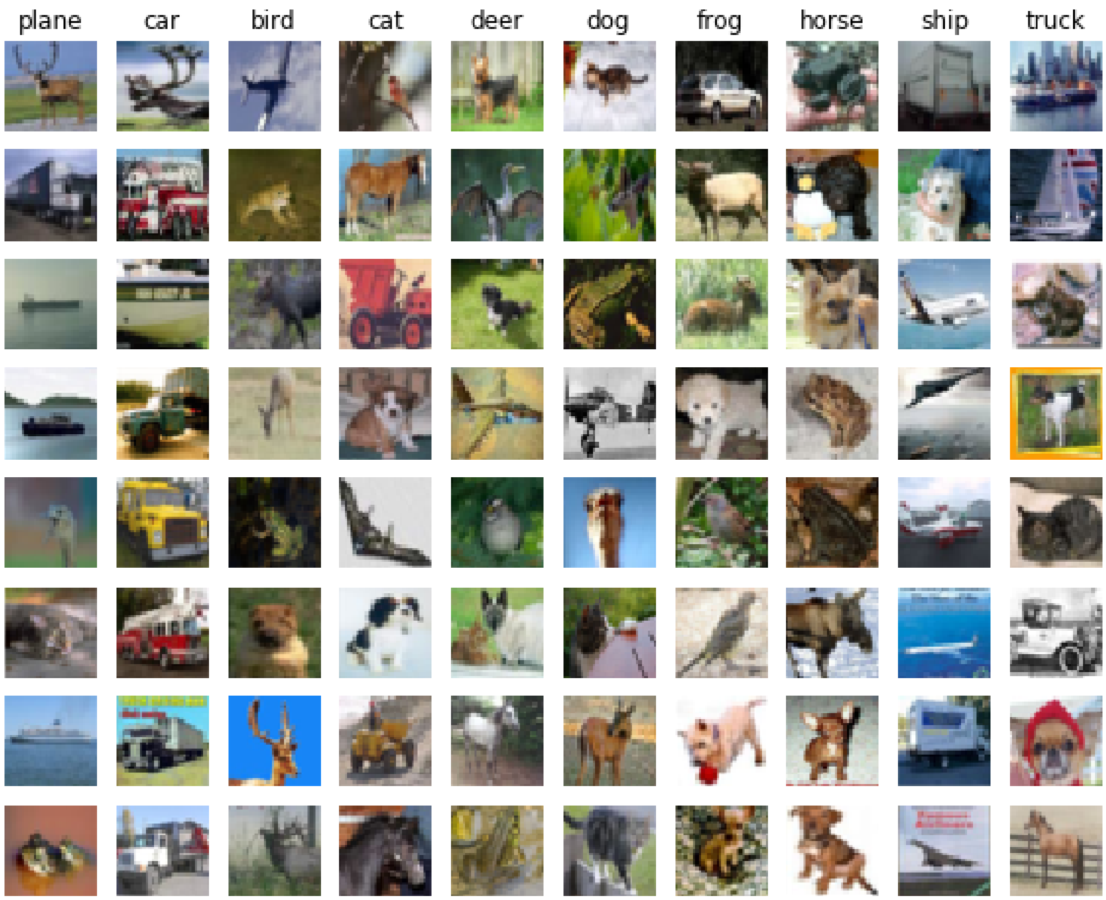
```
best validation accuracy achieved during cross-validation: 0.419000
```

[5]:
```
# 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)
```

```
0.425
```

[6]:
```
# 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?

$Your Answer:$

some cases make sense, like mistakenly take dog as cat, and car as trunk. But overall most of the cases don

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.

[7]:
```
# 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)
```

[ ]:
```
from cs231n.classifiers.neural_net import TwoLayerNet

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 = [1e-5, 1e-3, 1e-1]
regularization_strengths = [1e-1, 1e-2, 1e-3, 1e-4, 1e-5]

results = {}
best_val = -1

for lr in learning_rates:
    for reg in regularization_strengths:
        net = TwoLayerNet(input_dim, hidden_dim, num_classes)
        net.train(X_train_feats, y_train, X_val_feats, y_val, learning_rate=lr,␣
 ↪reg=reg, num_iters=2000)
        train_accuracy = np.mean(net.predict(X_train_feats) == y_train)
        val_accuracy = np.mean(net.predict(X_val_feats) == y_val)
        results[(lr, reg)] = (train_accuracy, val_accuracy)
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_net = net

# 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)

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

[14]:
```
# Run your best neural net classifier on the test set. You should be able
# to get more than 55% accuracy.

test_acc = (best_net.predict(X_test_feats) == y_test).mean()
print(test_acc)
```

```
0.532
```

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[ ]:
```
# import os

# FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
# FILES_TO_SAVE = []

# for files in FILES_TO_SAVE:
#   with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])),␣
↪'w') as f:
#     f.write(''.join(open(files).readlines()))
```