knn

October 7, 2021

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

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

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME+'/cs231n'))

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

```
Mounted at /content/drive
/content/drive/My Drive/assignment1
```

1 k-Nearest Neighbor (kNN) exercise

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

The kNN classifier consists of two stages:

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

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

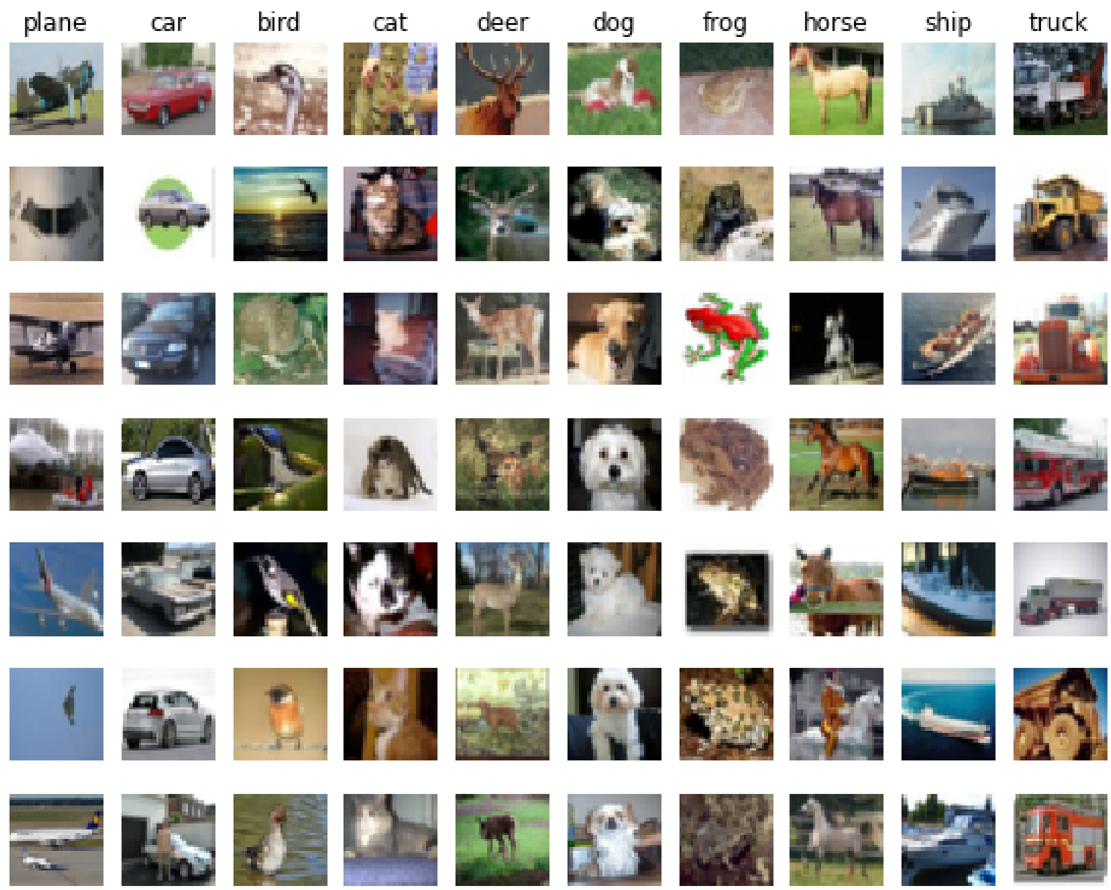
[ ]:
```
# Run some setup code for this notebook.

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
```

[ ]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

# Cleaning up variables to prevent loading data multiple times (which may cause␣
↪memory issue)
try:

   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

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

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

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

[ ]:

```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes):
    idxs = np.flatnonzero(y_train == y)
    idxs = np.random.choice(idxs, samples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls)
plt.show()
```



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

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

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

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

[ ]:
```python
from 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.

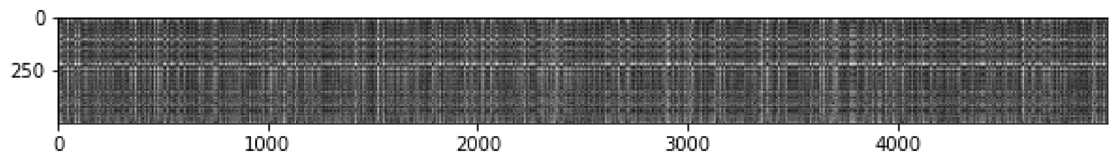
Note: For the three distance computations that we require you to implement in this notebook, you may not use the np.linalg.norm() function that numpy provides.

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.

[ ]:
```python
# 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)
```

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



Inline Question 1

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

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

Your Answer : fill this in.

1.The data with bright rows indicates it's very different from most training data.

2.Outliers, training data points isn't similar with others points.

[ ]:
```python
# 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`:

[ ]:
```python
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 143 / 500 correct => accuracy: 0.286000
```

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

Inline Question 2

svm

October 7, 2021

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

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

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

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

```
Mounted at /content/drive
/content/drive/My Drive/assignment1/cs231n/datasets
bash: get_datasets.sh: No such file or directory
/content/drive/My Drive/assignment1
```

1 Multiclass Support Vector Machine exercise

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

In this exercise you will:

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

- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

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

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

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

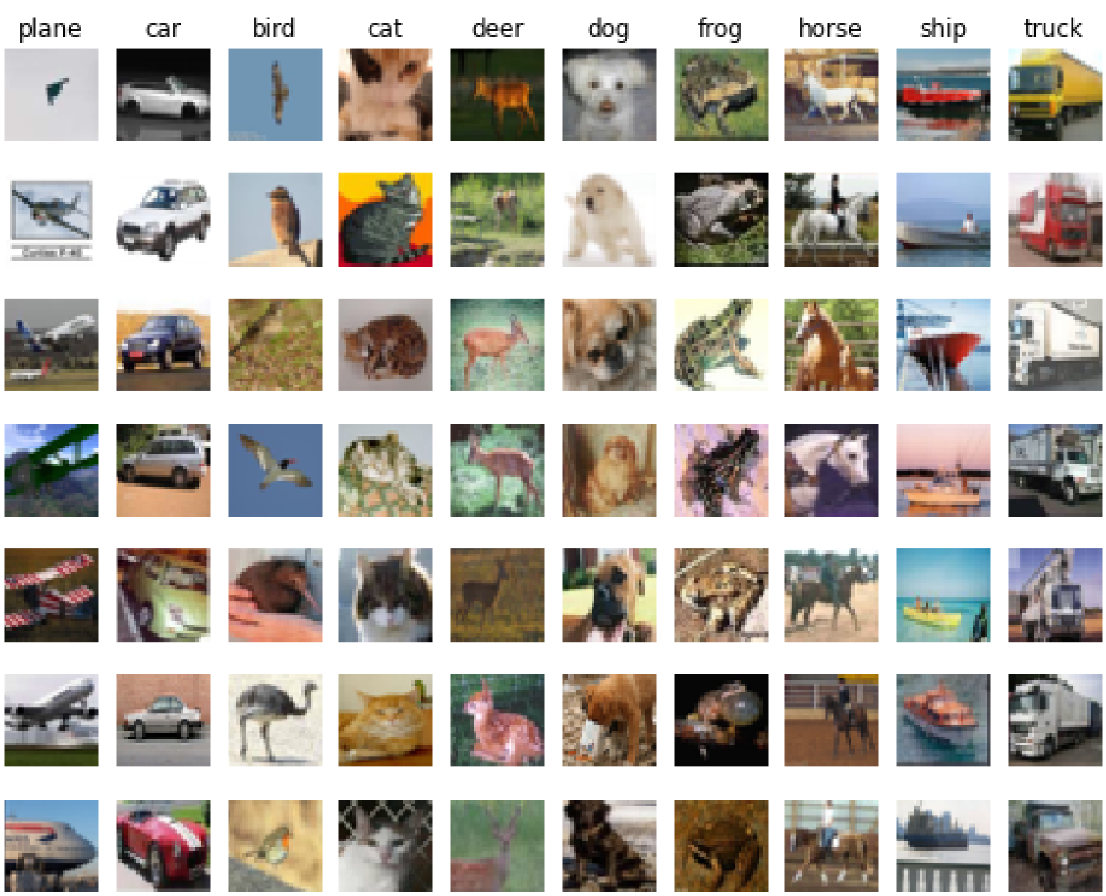
1.1 CIFAR-10 Data Loading and Preprocessing

[ ]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

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

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

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

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

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

[ ]:
```python
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes):
    idxs = np.flatnonzero(y_train == y)
    idxs = np.random.choice(idxs, samples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls)
plt.show()
```



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

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

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

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

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

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

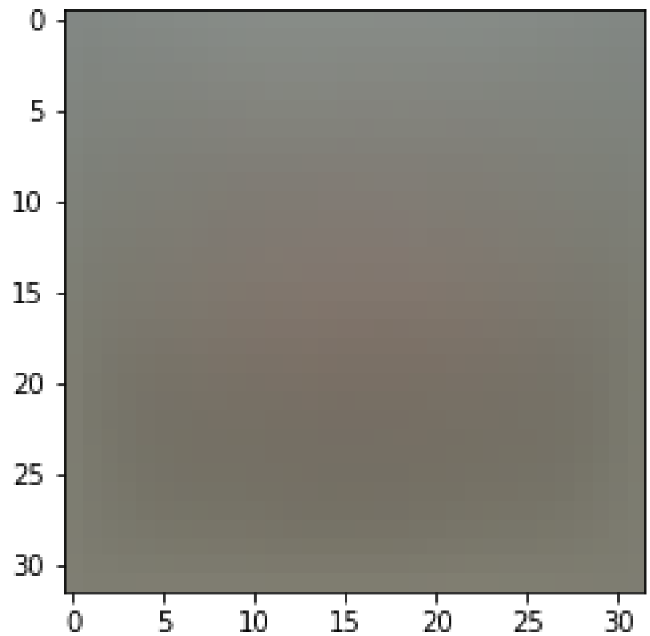
```
Train data shape:  (49000, 32, 32, 3)
Train labels shape:  (49000,)
Validation data shape:  (1000, 32, 32, 3)
Validation labels shape:  (1000,)
Test data shape:  (1000, 32, 32, 3)
Test labels shape:  (1000,)
```

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

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

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

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

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

# third: append the bias dimension of ones (i.e. bias trick) so that our SVM
# only has to worry about optimizing a single weight matrix W.
X_train = np.hstack([X_train, np.ones((X_train.shape[0], 1))])
X_val = np.hstack([X_val, np.ones((X_val.shape[0], 1))])
X_test = np.hstack([X_test, np.ones((X_test.shape[0], 1))])
X_dev = np.hstack([X_dev, np.ones((X_dev.shape[0], 1))])

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

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




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

1.2 SVM Classifier

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

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

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

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

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

```
loss: 9.733352
```

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:

[ ]:

```python
# 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: 0.413349 analytic: 0.413349, relative error: 1.359035e-09
numerical: -4.506885 analytic: -4.506885, relative error: 9.103242e-11
numerical: 23.430165 analytic: 23.430165, relative error: 4.239421e-12
numerical: 11.363743 analytic: 11.363743, relative error: 1.132961e-11
numerical: -1.342352 analytic: -1.342352, relative error: 1.839704e-10
numerical: -4.304874 analytic: -4.326714, relative error: 2.530240e-03
numerical: 1.530464 analytic: 1.530464, relative error: 1.197905e-10
numerical: 4.369300 analytic: 4.308413, relative error: 7.016462e-03
numerical: -20.779456 analytic: -20.779456, relative error: 1.709297e-12
numerical: -8.040400 analytic: -8.040400, relative error: 4.374260e-11
numerical: 4.555261 analytic: 4.532835, relative error: 2.467690e-03
numerical: -5.979447 analytic: -5.979447, relative error: 1.204631e-10
numerical: 9.535522 analytic: 9.535522, relative error: 4.749655e-11
numerical: -14.030845 analytic: -14.030845, relative error: 2.573625e-11
numerical: -0.581273 analytic: -0.581273, relative error: 9.247285e-11
numerical: -4.780782 analytic: -4.768758, relative error: 1.259076e-03
numerical: -7.268697 analytic: -7.224199, relative error: 3.070322e-03
numerical: -10.248922 analytic: -10.248922, relative error: 1.144761e-11
numerical: 6.080962 analytic: 6.080962, relative error: 4.533236e-11
numerical: -3.035271 analytic: -3.035271, relative error: 1.149442e-10
```

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 :
In zero loss function is not differentiable so the numerical will fail to check

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

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

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

```
Naive loss: 9.733352e+00 computed in 0.189222s
Vectorized loss: 9.733352e+00 computed in 0.014897s
difference: 0.000000
```

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

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

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

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

```
Naive loss and gradient: computed in 0.162701s
Vectorized loss and gradient: computed in 0.012885s
difference: 0.000000
```

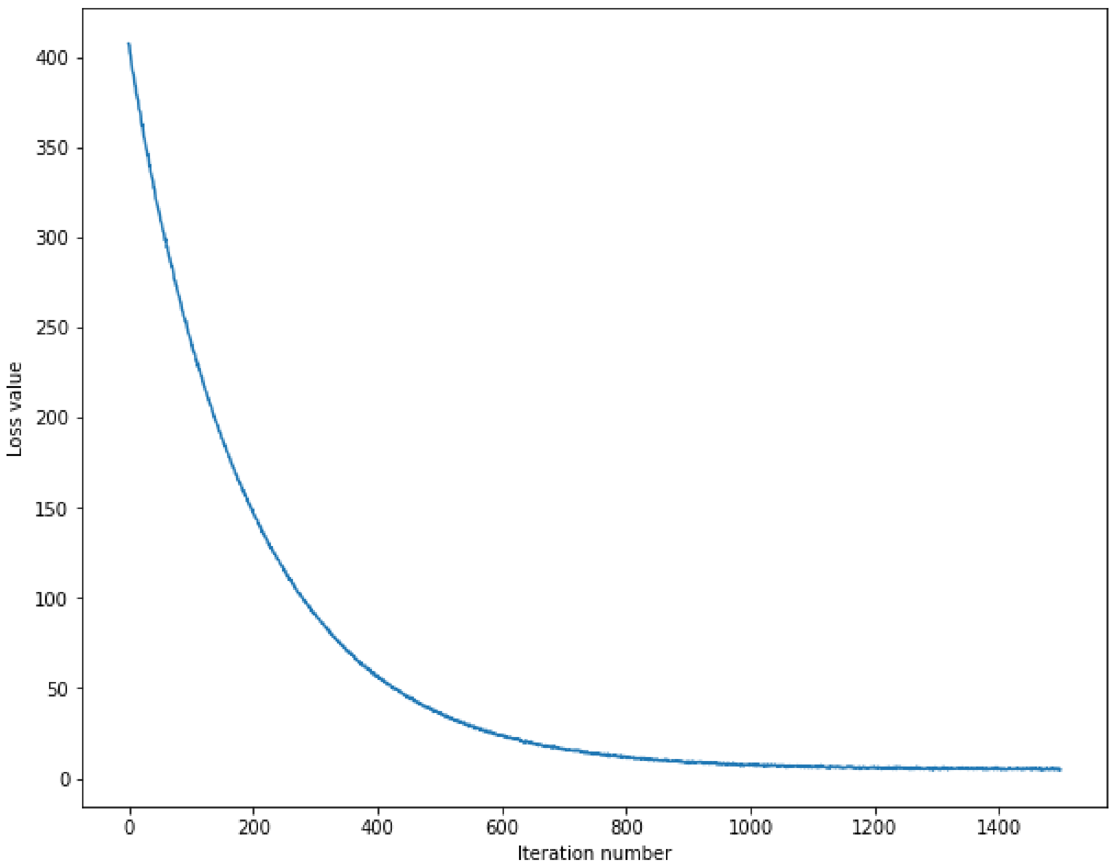
1.2.1 Stochastic Gradient Descent

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

[ ]:
```
# In the file linear_classifier.py, implement SGD in the function
# LinearClassifier.train() and then run it with the code below.
from cs231n.classifiers import LinearSVM
svm = LinearSVM()
tic = time.time()
loss_hist = svm.train(X_train, y_train, learning_rate=1e-7, reg=2.
 ↪5e4,num_iters=1500, verbose=True)
toc = time.time()
print('That took %fs' % (toc - tic))
```

```
iteration 0 / 1500: loss 407.297226
iteration 100 / 1500: loss 242.854618
iteration 200 / 1500: loss 147.046868
iteration 300 / 1500: loss 91.289261
iteration 400 / 1500: loss 56.975304
iteration 500 / 1500: loss 36.637068
iteration 600 / 1500: loss 23.941623
iteration 700 / 1500: loss 16.352463
iteration 800 / 1500: loss 11.639019
iteration 900 / 1500: loss 9.561283
iteration 1000 / 1500: loss 7.959696
iteration 1100 / 1500: loss 6.299710
iteration 1200 / 1500: loss 6.586489
iteration 1300 / 1500: loss 5.561079
iteration 1400 / 1500: loss 5.610549
That took 12.824589s
```

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



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

```
training accuracy: 0.381959
validation accuracy: 0.382000
```

[ ]:
```
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of about 0.39 on the validation set.

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

# results is dictionary mapping tuples of the form
# (learning_rate, regularization_strength) to tuples of the form
```

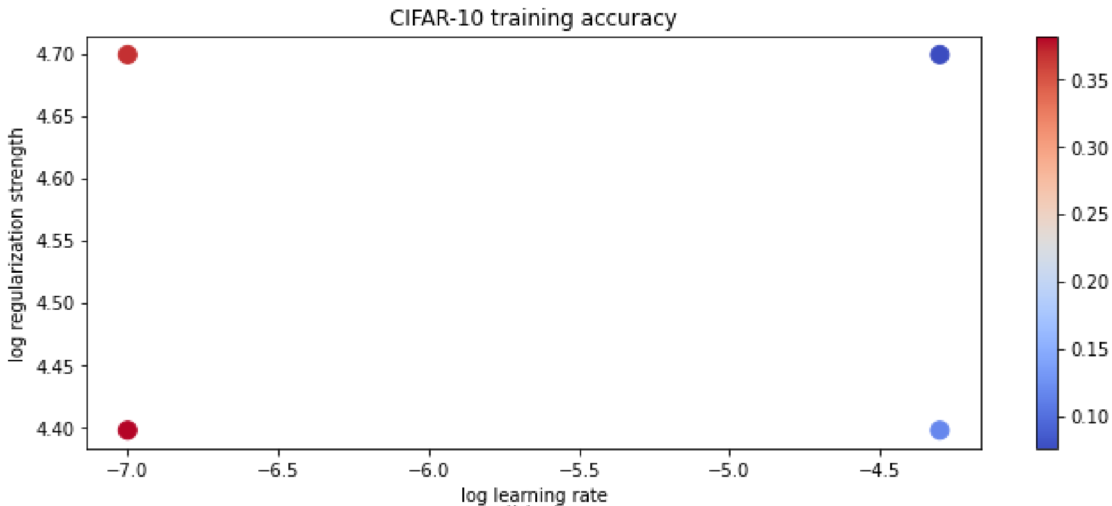
```
# (training_accuracy, validation_accuracy). The accuracy is simply the fraction
# of data points that are correctly classified.
results = {}
best_val = -1   # The highest validation accuracy that we have seen so far.
best_svm = None # The LinearSVM object that achieved the highest validation␣
 ↪rate.

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

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

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
# import SVM
iters = 1500
svm = LinearSVM()
# record the best model
for lr in learning_rates:
    for rs in regularization_strengths:
```

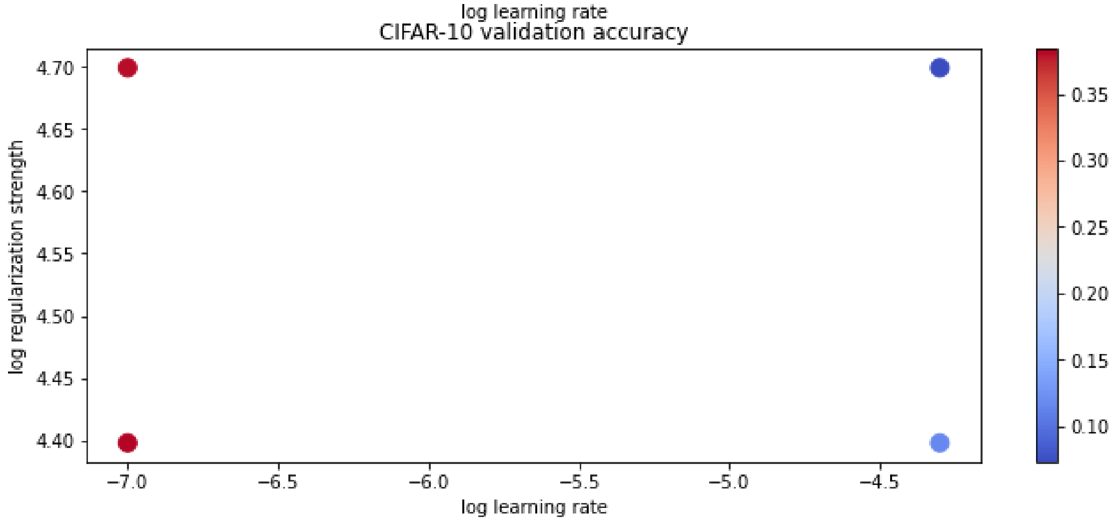
```
        svm.train(X_train, y_train, learning_rate=lr, reg=rs, num_iters=iters)
        y_train_pred = svm.predict(X_train)
        accu_train = np.mean(y_train == y_train_pred)
        y_val_pred = svm.predict(X_val)
        accu_val = np.mean(y_val == y_val_pred)
        results[(lr, rs)] = (accu_train, accu_val)
        # update the best
        if best_val < accu_val:
            best_val = accu_val
            best_svm = svm
# pass

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

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

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

```
/content/drive/My Drive/assignment1/cs231n/classifiers/linear_svm.py:97:
RuntimeWarning: overflow encountered in double_scalars
  loss += 0.5 * reg * np.sum(W * W)
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:87:
RuntimeWarning: overflow encountered in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
/content/drive/My Drive/assignment1/cs231n/classifiers/linear_svm.py:97:
RuntimeWarning: overflow encountered in multiply
  loss += 0.5 * reg * np.sum(W * W)

lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.382449 val accuracy: 0.384000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.368286 val accuracy: 0.381000
lr 5.000000e-05 reg 2.500000e+04 train accuracy: 0.117694 val accuracy: 0.117000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.075265 val accuracy: 0.073000
best validation accuracy achieved during cross-validation: 0.384000
```

[ ]:
```
# 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]
```

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

# plot validation accuracy
colors = [results[x][1] for x in results] # default size of markers is 20
plt.subplot(2, 1, 2)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 validation accuracy')
plt.show()
```





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

```
linear SVM on raw pixels final test set accuracy: 0.070000
```

[ ]:
```
# Visualize the learned weights for each class.
# Depending on your choice of learning rate and regularization strength, these␣
↪may
# or may not be nice to look at.
w = best_svm.W[:-1,:] # strip out the bias
w = w.reshape(32, 32, 3, 10)
w_min, w_max = np.min(w), np.max(w)
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
```

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

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

Inline question 2

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

Your Answer : It's the image of sum of the class

softmax

October 7, 2021

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

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

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

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

```
Mounted at /content/drive
/content/drive/My Drive/assignment1/cs231n/datasets
bash: get_datasets.sh: No such file or directory
/content/drive/My Drive/assignment1
```

1 Softmax exercise

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

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

- implement a fully-vectorized **loss function** for the Softmax classifier
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** with numerical gradient

- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

[ ]:
```
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
```

[ ]:
```
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`.

[ ]:
```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: 2.341930
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 W is selected by random, so the probability of select the true class is 1/10. That is, 0.1.

[ ]:
```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: 0.851795 analytic: 0.851795, relative error: 2.123176e-08
numerical: 0.802420 analytic: 0.802420, relative error: 5.968778e-08
numerical: 1.552947 analytic: 1.552947, relative error: 7.038761e-09
```

```
numerical: 1.211799 analytic: 1.211799, relative error: 1.706134e-08
numerical: 1.461709 analytic: 1.461709, relative error: 1.295048e-08
numerical: -0.132414 analytic: -0.132414, relative error: 1.828766e-08
numerical: 3.556647 analytic: 3.556647, relative error: 1.421155e-08
numerical: 0.020592 analytic: 0.020592, relative error: 3.237701e-07
numerical: 1.676295 analytic: 1.676295, relative error: 8.325853e-09
numerical: -1.080429 analytic: -1.080429, relative error: 4.031607e-09
numerical: -3.264548 analytic: -3.264548, relative error: 3.732279e-09
numerical: 3.369769 analytic: 3.369769, relative error: 5.805068e-09
numerical: 0.402632 analytic: 0.402632, relative error: 9.268360e-08
numerical: -3.409001 analytic: -3.409001, relative error: 2.525785e-08
numerical: 1.185210 analytic: 1.185210, relative error: 5.864038e-08
numerical: 0.039545 analytic: 0.039545, relative error: 9.134075e-07
numerical: 0.446004 analytic: 0.446004, relative error: 5.909431e-08
numerical: 0.031756 analytic: 0.031756, relative error: 1.187718e-06
numerical: 2.165285 analytic: 2.165285, relative error: 2.744449e-10
numerical: -4.298654 analytic: -4.298654, relative error: 1.095917e-09
```

[ ]:

```
# 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: 2.341930e+00 computed in 0.105435s
vectorized loss: 2.322124e+00 computed in 0.014968s
Loss difference: 0.019806
Gradient difference: 0.000000
```

[ ]:

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

from cs231n.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None

################################################################################
# TODO:                                                                        ␣
↪#
# Use the validation set to set the learning rate and regularization strength.␣
↪#
# This should be identical to the validation that you did for the SVM; save   ␣
↪#
# the best trained softmax classifer in best_softmax.                          ␣
↪#
################################################################################
# Provided as a reference. You may or may not want to change these␣
↪hyperparameters
learning_rates = [1e-7, 5e-7]
regularization_strengths = [2.5e4, 5e4]

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
from cs231n.classifiers import LinearSVM
iters = 1500
svm = LinearSVM()
# try out the best model
for lr in learning_rates:
    for rs in regularization_strengths:
        # add reguliztion in model and calculate the score
        svm.train(X_train, y_train, learning_rate=lr, reg=rs, num_iters=iters)
        y_train_pred = svm.predict(X_train)
        accu_train = np.mean(y_train == y_train_pred)
        y_val_pred = svm.predict(X_val)
        accu_val = np.mean(y_val == y_val_pred)
        results[(lr, rs)] = (accu_train, accu_val)
        # record the best model
        if best_val < accu_val:
            best_val = accu_val
            best_softmax = 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)
```

```
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.380694 val accuracy: 0.377000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.369306 val accuracy: 0.368000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.350735 val accuracy: 0.350000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.315878 val accuracy: 0.353000
best validation accuracy achieved during cross-validation: 0.377000
```

[ ]:
```
# 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: 0.327000
```

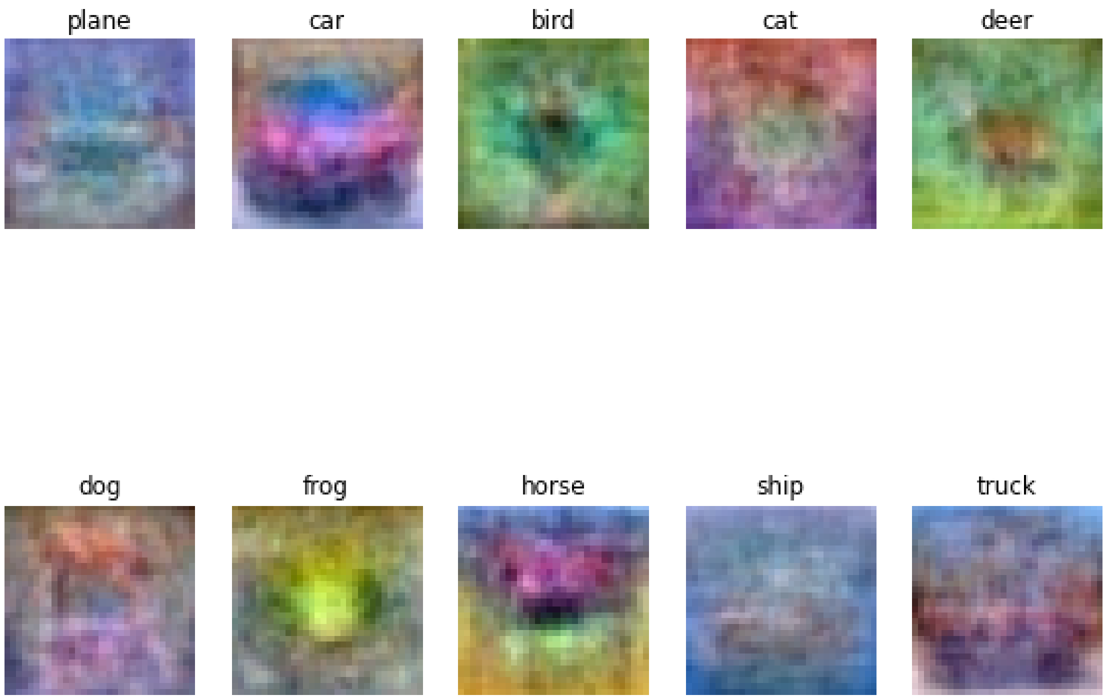
Inline Question 2 - *True or False*

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.

Your Answer : True

Your Explanation : In the SVM if the new data point has a score that is out of the margin range from the correct class score the loss wouldn't change but in the Softmax loss if the score of the new added datapoint be close to +infinity it will adversely affect the loss, but definitely the loss of Softmax will change.

[ ]:
```
# Visualize the learned weights for each class
w = best_softmax.W[:-1,:] # strip out the bias
w = w.reshape(32, 32, 3, 10)

w_min, w_max = np.min(w), np.max(w)

classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
for i in range(10):
    plt.subplot(2, 5, i + 1)

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


plane
car
bird
cat
deer
dog
frog
horse
ship
truck

two_layer_net

October 7, 2021

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

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

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

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

```
Mounted at /content/drive
/content/drive/My Drive/assignment1/cs231n/datasets
bash: get_datasets.sh: No such file or directory
/content/drive/My Drive/assignment1
```

1 Fully-Connected Neural Nets

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

```
def layer_forward(x, w):
  """ Receive inputs x and weights w """
  # Do some computations ...
```

```
    z = # ... some intermediate value
    # Do some more computations ...
    out = # the output

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

    return out, cache
```

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

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

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

    return dx, dw
```

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

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

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

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

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

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

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

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

2 Affine layer: forward

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

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

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

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

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

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

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

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

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

3 Affine layer: backward

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

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

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

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

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

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

4 ReLU activation: forward

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

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

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

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

# Compare your output with ours. The error should be on the order of e-8
```

```
print('Testing relu_forward function:')
print('difference: ', rel_error(out, correct_out))
```

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

5 ReLU activation: backward

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

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

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

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

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

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

5.1 Inline Question 1:

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

5.2 Answer:

[FILL THIS IN] Sigmoid,Relu.When the input is approaching negative infinity.

6 "Sandwich" layers

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

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

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

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

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

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

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

7 Loss layers: Softmax and SVM

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

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

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

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

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

```
print('dx error: ', rel_error(dx_num, dx))

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

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

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

Testing softmax_loss:
loss:  2.3025458445007376
dx error:  8.234144091578429e-09
```

8 Two-layer network

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

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

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

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

print('Testing test-time forward pass ... ')
model.params['W1'] = np.linspace(-0.7, 0.3, num=D*H).reshape(D, H)
model.params['b1'] = np.linspace(-0.1, 0.9, num=H)
```

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

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

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

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

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

```
Testing initialization ...
Testing test-time forward pass ...
Testing training loss (no regularization)
Running numeric gradient check with reg =  0.0
W1 relative error: 1.83e-08
W2 relative error: 3.20e-10
b1 relative error: 9.83e-09
b2 relative error: 4.33e-10
Running numeric gradient check with reg =  0.7
W1 relative error: 2.53e-07
W2 relative error: 7.98e-08
```

```
b1 relative error: 1.56e-08
b2 relative error: 9.09e-10
```

9 Solver

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

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

##############################################################################
# TODO: Use a Solver instance to train a TwoLayerNet that achieves about 36% #
# accuracy on the validation set.                                            #
##############################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
# ('X_train: ', (49000, 3, 32, 32))
# ('y_train: ', (49000,))
# ('X_val: ', (1000, 3, 32, 32))
# ('y_val: ', (1000,))
# ('X_test: ', (1000, 3, 32, 32))
# ('y_test: ', (1000,))
# pass
# training model
solver=Solver(model, data,
        update_rule='sgd',
        optim_config={
        'learning_rate': 1e-3,
        },
        lr_decay=0.95,
        num_epochs=10, batch_size=100,
        print_every=1000
      )
solver.train()
print('best accu',solver.best_val_acc)
# Predict on the validation set
val_acc=solver.check_accuracy(data['X_val'],data['y_val'])
print('Validation accuracy: ', val_acc)

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

```
(Iteration 1 / 4900) loss: 2.300089
(Epoch 0 / 10) train acc: 0.171000; val_acc: 0.170000
(Epoch 1 / 10) train acc: 0.399000; val_acc: 0.428000
(Epoch 2 / 10) train acc: 0.463000; val_acc: 0.443000
(Iteration 1001 / 4900) loss: 1.340071
(Epoch 3 / 10) train acc: 0.477000; val_acc: 0.430000
(Epoch 4 / 10) train acc: 0.497000; val_acc: 0.467000
(Iteration 2001 / 4900) loss: 1.422221
(Epoch 5 / 10) train acc: 0.508000; val_acc: 0.483000
(Epoch 6 / 10) train acc: 0.533000; val_acc: 0.492000
(Iteration 3001 / 4900) loss: 1.264002
(Epoch 7 / 10) train acc: 0.545000; val_acc: 0.489000
(Epoch 8 / 10) train acc: 0.546000; val_acc: 0.474000
(Iteration 4001 / 4900) loss: 1.187435
(Epoch 9 / 10) train acc: 0.586000; val_acc: 0.486000
(Epoch 10 / 10) train acc: 0.545000; val_acc: 0.483000
best accu 0.492
Validation accuracy:  0.492
```

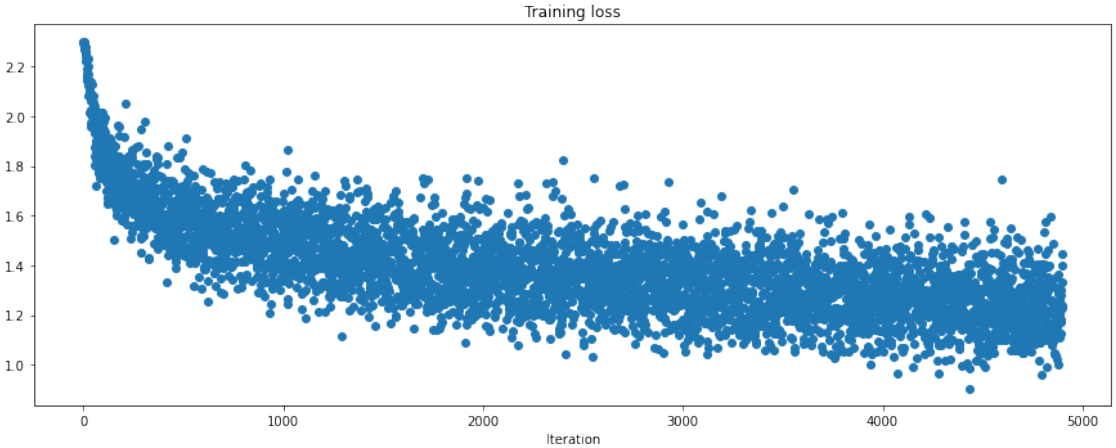
10 Debug the training

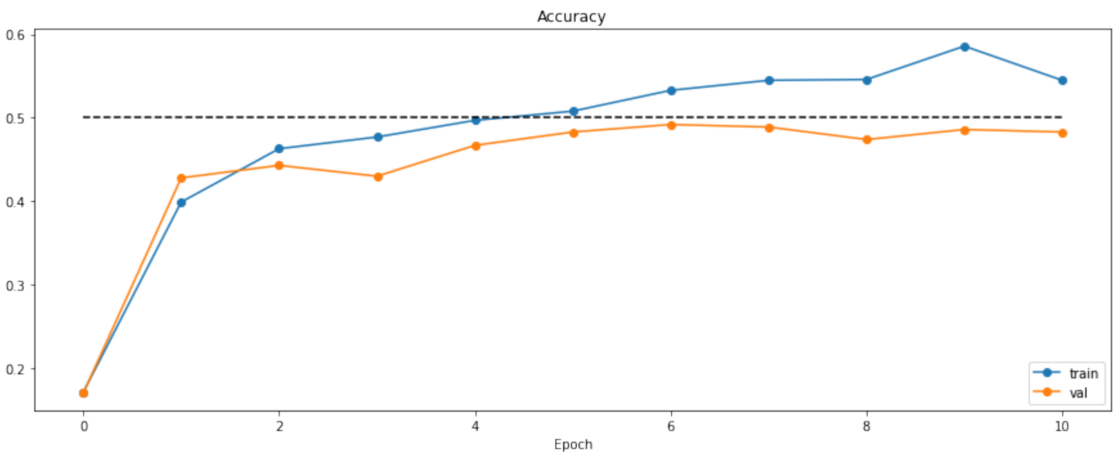
With the default parameters we provided above, you should get a validation accuracy of about 0.36 on the validation set. This isn't very good.

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

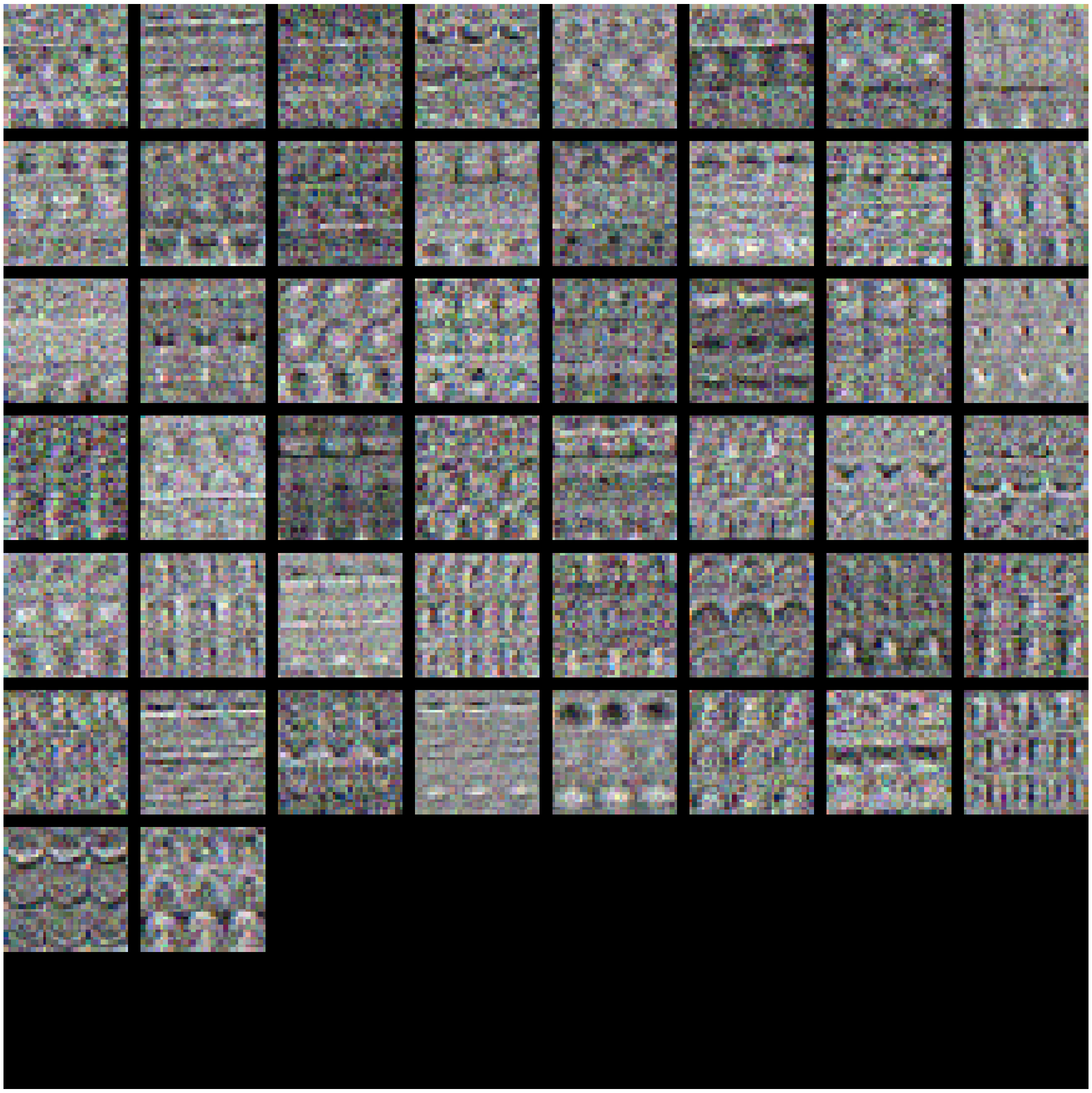
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

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

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

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





[13]:
```
from cs231n.vis_utils import visualize_grid

# Visualize the weights of the network

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

show_net_weights(model)
```



11 Tune your hyperparameters

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

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

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

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

[15]:
```
best_model = None



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

# hyper parameters choice
learning_rates=[1e-3,1e-4]
regs=[0, 0.02, 0.05]
hidden_choice = [0,25,50]
input_size = 32 * 32 * 3
num_classes = 10
best_val=0
epoches=[10,15,20]
# hidden layer size, learning rate, numer of training epochs, and␣
↪regularization
```

```
for lr in learning_rates:
  for reg in regs:
    for hidden_size in hidden_choice:
      for e in epoches:
        # fit two layers net
        model = TwoLayerNet(  input_dim=input_size,hidden_dim=hidden_size, ␣
↪num_classes=num_classes,reg=reg)
        # Train the network
        solver=Solver(model, data,
            update_rule='sgd',
            optim_config={
            'learning_rate': lr,
            },
            lr_decay=0.95,
            num_epochs=e, batch_size=100,
            print_every=1000,
            verbose=False
          )
        solver.train()

        # Predict on the validation set
        val_accuracy=solver.check_accuracy(data['X_val'],data['y_val'])




        # Predict on the training set
        train_accuracy =solver.check_accuracy(data['X_train'],data['y_train'])
        # val_accuracy=solver.check_accuracy(data['X_val'],data['y_val'])

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

        # Save best values
        if solver.best_val_acc>best_val:
            best_model = model
            best_val=solver.best_val_acc
        # Print results
        print('lr %e reg %e hid %d epoches %d train accuracy: %f val accuracy:␣
↪%f' % (
                        lr, reg, hidden_size,e, train_accuracy, val_accuracy))
print('best validation accuracy achieved: %f' % best_val)
# pass

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

```
#                              END OF YOUR CODE                              ␣
↪#
##############################################################################
```

```
lr 1.000000e-03 reg 0.000000e+00 hid 0 epoches 10 train accuracy: 0.099755 val
accuracy: 0.112000
lr 1.000000e-03 reg 0.000000e+00 hid 0 epoches 15 train accuracy: 0.100041 val
accuracy: 0.098000
lr 1.000000e-03 reg 0.000000e+00 hid 0 epoches 20 train accuracy: 0.099735 val
accuracy: 0.113000
lr 1.000000e-03 reg 0.000000e+00 hid 25 epoches 10 train accuracy: 0.510367 val
accuracy: 0.483000
lr 1.000000e-03 reg 0.000000e+00 hid 25 epoches 15 train accuracy: 0.521755 val
accuracy: 0.471000
lr 1.000000e-03 reg 0.000000e+00 hid 25 epoches 20 train accuracy: 0.528776 val
accuracy: 0.490000
lr 1.000000e-03 reg 0.000000e+00 hid 50 epoches 10 train accuracy: 0.512592 val
accuracy: 0.503000
lr 1.000000e-03 reg 0.000000e+00 hid 50 epoches 15 train accuracy: 0.567694 val
accuracy: 0.512000
lr 1.000000e-03 reg 0.000000e+00 hid 50 epoches 20 train accuracy: 0.579449 val
accuracy: 0.498000
lr 1.000000e-03 reg 2.000000e-02 hid 0 epoches 10 train accuracy: 0.099755 val
accuracy: 0.112000
lr 1.000000e-03 reg 2.000000e-02 hid 0 epoches 15 train accuracy: 0.099612 val
accuracy: 0.119000
lr 1.000000e-03 reg 2.000000e-02 hid 0 epoches 20 train accuracy: 0.099612 val
accuracy: 0.119000
lr 1.000000e-03 reg 2.000000e-02 hid 25 epoches 10 train accuracy: 0.507245 val
accuracy: 0.489000
lr 1.000000e-03 reg 2.000000e-02 hid 25 epoches 15 train accuracy: 0.536633 val
accuracy: 0.494000
lr 1.000000e-03 reg 2.000000e-02 hid 25 epoches 20 train accuracy: 0.543694 val
accuracy: 0.486000
lr 1.000000e-03 reg 2.000000e-02 hid 50 epoches 10 train accuracy: 0.571163 val
accuracy: 0.499000
lr 1.000000e-03 reg 2.000000e-02 hid 50 epoches 15 train accuracy: 0.595224 val
accuracy: 0.518000
lr 1.000000e-03 reg 2.000000e-02 hid 50 epoches 20 train accuracy: 0.611653 val
accuracy: 0.524000
lr 1.000000e-03 reg 5.000000e-02 hid 0 epoches 10 train accuracy: 0.099959 val
accuracy: 0.102000
lr 1.000000e-03 reg 5.000000e-02 hid 0 epoches 15 train accuracy: 0.099612 val
accuracy: 0.119000
lr 1.000000e-03 reg 5.000000e-02 hid 0 epoches 20 train accuracy: 0.099755 val
accuracy: 0.112000
lr 1.000000e-03 reg 5.000000e-02 hid 25 epoches 10 train accuracy: 0.478429 val
```

```
accuracy: 0.480000
lr 1.000000e-03 reg 5.000000e-02 hid 25 epoches 15 train accuracy: 0.523041 val
accuracy: 0.496000
lr 1.000000e-03 reg 5.000000e-02 hid 25 epoches 20 train accuracy: 0.530061 val
accuracy: 0.497000
lr 1.000000e-03 reg 5.000000e-02 hid 50 epoches 10 train accuracy: 0.542041 val
accuracy: 0.520000
lr 1.000000e-03 reg 5.000000e-02 hid 50 epoches 15 train accuracy: 0.592429 val
accuracy: 0.509000
lr 1.000000e-03 reg 5.000000e-02 hid 50 epoches 20 train accuracy: 0.586571 val
accuracy: 0.524000
lr 1.000000e-04 reg 0.000000e+00 hid 0 epoches 10 train accuracy: 0.099612 val
accuracy: 0.119000
lr 1.000000e-04 reg 0.000000e+00 hid 0 epoches 15 train accuracy: 0.099735 val
accuracy: 0.113000
lr 1.000000e-04 reg 0.000000e+00 hid 0 epoches 20 train accuracy: 0.099898 val
accuracy: 0.105000
lr 1.000000e-04 reg 0.000000e+00 hid 25 epoches 10 train accuracy: 0.445347 val
accuracy: 0.443000
lr 1.000000e-04 reg 0.000000e+00 hid 25 epoches 15 train accuracy: 0.465980 val
accuracy: 0.473000
lr 1.000000e-04 reg 0.000000e+00 hid 25 epoches 20 train accuracy: 0.462735 val
accuracy: 0.451000
lr 1.000000e-04 reg 0.000000e+00 hid 50 epoches 10 train accuracy: 0.458918 val
accuracy: 0.465000
lr 1.000000e-04 reg 0.000000e+00 hid 50 epoches 15 train accuracy: 0.487714 val
accuracy: 0.474000
lr 1.000000e-04 reg 0.000000e+00 hid 50 epoches 20 train accuracy: 0.496408 val
accuracy: 0.485000
lr 1.000000e-04 reg 2.000000e-02 hid 0 epoches 10 train accuracy: 0.099735 val
accuracy: 0.113000
lr 1.000000e-04 reg 2.000000e-02 hid 0 epoches 15 train accuracy: 0.099755 val
accuracy: 0.112000
lr 1.000000e-04 reg 2.000000e-02 hid 0 epoches 20 train accuracy: 0.099735 val
accuracy: 0.113000
lr 1.000000e-04 reg 2.000000e-02 hid 25 epoches 10 train accuracy: 0.441510 val
accuracy: 0.466000
lr 1.000000e-04 reg 2.000000e-02 hid 25 epoches 15 train accuracy: 0.465102 val
accuracy: 0.454000
lr 1.000000e-04 reg 2.000000e-02 hid 25 epoches 20 train accuracy: 0.481429 val
accuracy: 0.492000
lr 1.000000e-04 reg 2.000000e-02 hid 50 epoches 10 train accuracy: 0.465061 val
accuracy: 0.465000
lr 1.000000e-04 reg 2.000000e-02 hid 50 epoches 15 train accuracy: 0.479224 val
accuracy: 0.482000
lr 1.000000e-04 reg 2.000000e-02 hid 50 epoches 20 train accuracy: 0.508041 val
accuracy: 0.492000
lr 1.000000e-04 reg 5.000000e-02 hid 0 epoches 10 train accuracy: 0.099755 val
```

```
accuracy: 0.112000
lr 1.000000e-04 reg 5.000000e-02 hid 0 epoches 15 train accuracy: 0.099735 val
accuracy: 0.113000
lr 1.000000e-04 reg 5.000000e-02 hid 0 epoches 20 train accuracy: 0.099898 val
accuracy: 0.105000
lr 1.000000e-04 reg 5.000000e-02 hid 25 epoches 10 train accuracy: 0.449551 val
accuracy: 0.461000
lr 1.000000e-04 reg 5.000000e-02 hid 25 epoches 15 train accuracy: 0.470796 val
accuracy: 0.469000
lr 1.000000e-04 reg 5.000000e-02 hid 25 epoches 20 train accuracy: 0.473122 val
accuracy: 0.454000
lr 1.000000e-04 reg 5.000000e-02 hid 50 epoches 10 train accuracy: 0.452490 val
accuracy: 0.455000
lr 1.000000e-04 reg 5.000000e-02 hid 50 epoches 15 train accuracy: 0.485122 val
accuracy: 0.469000
lr 1.000000e-04 reg 5.000000e-02 hid 50 epoches 20 train accuracy: 0.499429 val
accuracy: 0.484000
best validation accuracy achieved: 0.524000
```

12 Test your model!

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

[16]:
```
y_val_pred = np.argmax(best_model.loss(data['X_val']), axis=1)
print('Validation set accuracy: ', (y_val_pred == data['y_val']).mean())
```

```
Validation set accuracy:  0.524
```

[17]:
```
y_test_pred = np.argmax(best_model.loss(data['X_test']), axis=1)
print('Test set accuracy: ', (y_test_pred == data['y_test']).mean())
```

```
Test set accuracy:  0.507
```

12.1 Inline Question 2:

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

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

$Your Answer:$1,3
$Your Explanation:$
This senerio happens when the model over fits the training data.

1.Adding more dataset will result in generalize better model.
3.Increasing regularization strength will decrease the complexity of the model.

[ ]:

```

```

features

October 7, 2021

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

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

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

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

```
Mounted at /content/drive
/content/drive/My Drive/assignment1/cs231n/datasets
bash: get_datasets.sh: No such file or directory
/content/drive/My Drive/assignment1
```

1 Image features exercise

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

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

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

[2]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt


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

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

1.1 Load data

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

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

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

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

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

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

```
    y_test = y_test[mask]

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

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

1.2 Extract Features

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

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

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

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

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

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

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

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

```
Done extracting features for 1000 / 49000 images
```

```
Done extracting features for 2000 / 49000 images
Done extracting features for 3000 / 49000 images
Done extracting features for 4000 / 49000 images
Done extracting features for 5000 / 49000 images
Done extracting features for 6000 / 49000 images
Done extracting features for 7000 / 49000 images
Done extracting features for 8000 / 49000 images
Done extracting features for 9000 / 49000 images
Done extracting features for 10000 / 49000 images
Done extracting features for 11000 / 49000 images
Done extracting features for 12000 / 49000 images
Done extracting features for 13000 / 49000 images
Done extracting features for 14000 / 49000 images
Done extracting features for 15000 / 49000 images
Done extracting features for 16000 / 49000 images
Done extracting features for 17000 / 49000 images
Done extracting features for 18000 / 49000 images
Done extracting features for 19000 / 49000 images
Done extracting features for 20000 / 49000 images
Done extracting features for 21000 / 49000 images
Done extracting features for 22000 / 49000 images
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Done extracting features for 43000 / 49000 images
Done extracting features for 44000 / 49000 images
Done extracting features for 45000 / 49000 images
Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
Done extracting features for 49000 / 49000 images
```

1.3 Train SVM on features

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

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

from cs231n.classifiers.linear_classifier import LinearSVM

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

results = {}
best_val = -1
best_svm = None

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

# pass
# funcation for accuracy
def compute_accuracy(y, y_pred):
    return np.mean(y == y_pred)
# tune parameters
for lr in learning_rates:
  for reg in regularization_strengths:
    # train SVM
    svm=LinearSVM()
    svm.train(X_train_feats, y_train,learning_rate=lr,reg=reg,num_iters=10000,␣
↪verbose=False)
    # train, val accuracy
    train_accuracy = compute_accuracy(y_train, svm.predict(X_train_feats))
    val_accuracy = compute_accuracy(y_val, svm.predict(X_val_feats))
    print( 'train accuracy: %.4f' %train_accuracy)
```

```
    print( 'validation accuracy: %.4f' %val_accuracy)
    results[(lr, reg)] = (train_accuracy, val_accuracy)
    # compare 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: %f' % best_val)
```

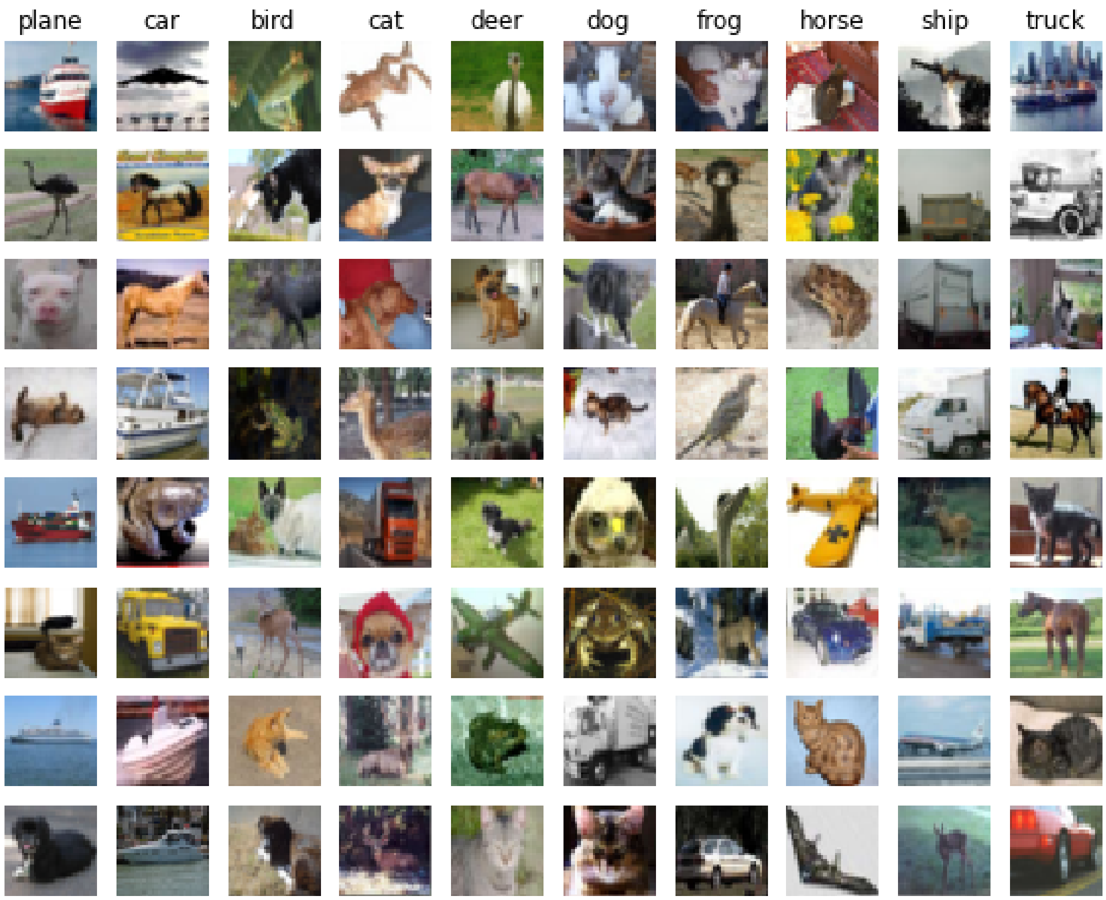
```
train accuracy: 0.1121
validation accuracy: 0.1220
train accuracy: 0.1055
validation accuracy: 0.1050
train accuracy: 0.4138
validation accuracy: 0.4240
train accuracy: 0.3218
validation accuracy: 0.3220
train accuracy: 0.4167
validation accuracy: 0.4180
train accuracy: 0.4167
validation accuracy: 0.4320
train accuracy: 0.4155
validation accuracy: 0.4120
train accuracy: 0.4161
validation accuracy: 0.4180
train accuracy: 0.3463
validation accuracy: 0.3440
lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.112122 val accuracy: 0.122000
lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.105490 val accuracy: 0.105000
lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.413816 val accuracy: 0.424000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.321796 val accuracy: 0.322000
lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.416673 val accuracy: 0.418000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.416673 val accuracy: 0.432000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.415469 val accuracy: 0.412000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.416061 val accuracy: 0.418000
lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.346286 val accuracy: 0.344000
best validation accuracy achieved: 0.432000
```

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

```
0.416
```

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

examples_per_class = 8
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
for cls, cls_name in enumerate(classes):
    idxs = np.where((y_test != cls) & (y_test_pred == cls))[0]
    idxs = np.random.choice(idxs, examples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt.subplot(examples_per_class, len(classes), i * len(classes) + cls +␣
↪1)
        plt.imshow(X_test[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls_name)
plt.show()
```



1.3.1 Inline question 1:

Describe the misclassification results that you see. Do they make sense?
Your Answer : No,so the SVM isn't the best choice

1.4 Neural Network on image features

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

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

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

```
X_test_feats = X_test_feats[:, :-1]

print(X_train_feats.shape)
```

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

[11]:
```
from cs231n.classifiers.fc_net import TwoLayerNet
from cs231n.solver import Solver

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

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

################################################################################
# TODO: Train a two-layer neural network on image features. You may want to   ␣
↪#
# cross-validate various parameters as in previous sections. Store your best   ␣
↪#
# model in the best_net variable.                                              ␣
↪#
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
best_val=-1
# learning_rates =1.0
# hyper parameters choice
learning_rates=[1.0,1e-3,1e-4,1e-5]
# regs=[0, 0.02, 0.05]
# hidden_choice = [0,25,50]
input_size = 32 * 32 * 3
num_classes = 10
best_val=0
epoches=[10,15,20]
data={'X_train':X_train_feats,'y_train':y_train,'X_val':X_val_feats,'y_val':
↪y_val,'X_test':X_test_feats,'y_test':y_test}
# regularization_strengths = [1e-3, 3e-3]
for lr in learning_rates:
  # for reg in regs:
      for e in epoches:
        solver=Solver(net, data,
                update_rule='sgd',
                optim_config={
                'learning_rate': lr,
                },
```

```
                lr_decay=0.95,
                num_epochs=e, batch_size=100,
                print_every=1000,
                verbose= False
              )
        solver.train()
        # Predict on the validation set
        val_accuracy=solver.check_accuracy(data['X_val'],data['y_val'])
        # Predict on the training set
        train_accuracy =solver.check_accuracy(data['X_train'],data['y_train'])
        # val_accuracy=solver.check_accuracy(data['X_val'],data['y_val'])

        # Save best values
        if solver.best_val_acc>best_val:
            best_net = net
            best_val=solver.best_val_acc
        # Print results
        print('lr %e   epoches %d train accuracy: %f val accuracy: %f' % (
                    lr,e, train_accuracy, val_accuracy))
print('best validation accuracy achieved: %f' % best_val)
# pass

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

```
lr 1.000000e+00   epoches 10 train accuracy: 0.605082 val accuracy: 0.562000
lr 1.000000e+00   epoches 15 train accuracy: 0.893653 val accuracy: 0.568000
lr 1.000000e+00   epoches 20 train accuracy: 0.881000 val accuracy: 0.557000
lr 1.000000e-03   epoches 10 train accuracy: 0.889490 val accuracy: 0.564000
lr 1.000000e-03   epoches 15 train accuracy: 0.903449 val accuracy: 0.565000
lr 1.000000e-03   epoches 20 train accuracy: 0.915163 val accuracy: 0.567000
lr 1.000000e-04   epoches 10 train accuracy: 0.915163 val accuracy: 0.567000
lr 1.000000e-04   epoches 15 train accuracy: 0.915163 val accuracy: 0.567000
lr 1.000000e-04   epoches 20 train accuracy: 0.915163 val accuracy: 0.567000
lr 1.000000e-05   epoches 10 train accuracy: 0.915163 val accuracy: 0.567000
lr 1.000000e-05   epoches 15 train accuracy: 0.915163 val accuracy: 0.567000
lr 1.000000e-05   epoches 20 train accuracy: 0.915163 val accuracy: 0.567000
best validation accuracy achieved: 0.568000
```

[12]:
```
# Run your best neural net classifier on the test set. You should be able
# to get more than 55% accuracy.

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

```
0.554
```