zoptional_svm

February 8, 2022

0.1 Homework 2. Optional part. SVM classifier from scratch.

This part is not required and not graded. Feel free to use it to understand SVM loss more.

0.1.1 Set COLAB to True if you work in COLAB, else, set it to False

[1]:
```python
# YOUR CODE HERE
COLAB = False
```

[2]:
```python
if COLAB:
    # 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 = None
    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
else:
    %cd cs231n/datasets/
    !bash get_datasets.sh
    %cd ../..
```

```
/home/bjeon/cs231n/datasets
/home/bjeon
```

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

[3]:
```
# 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
```

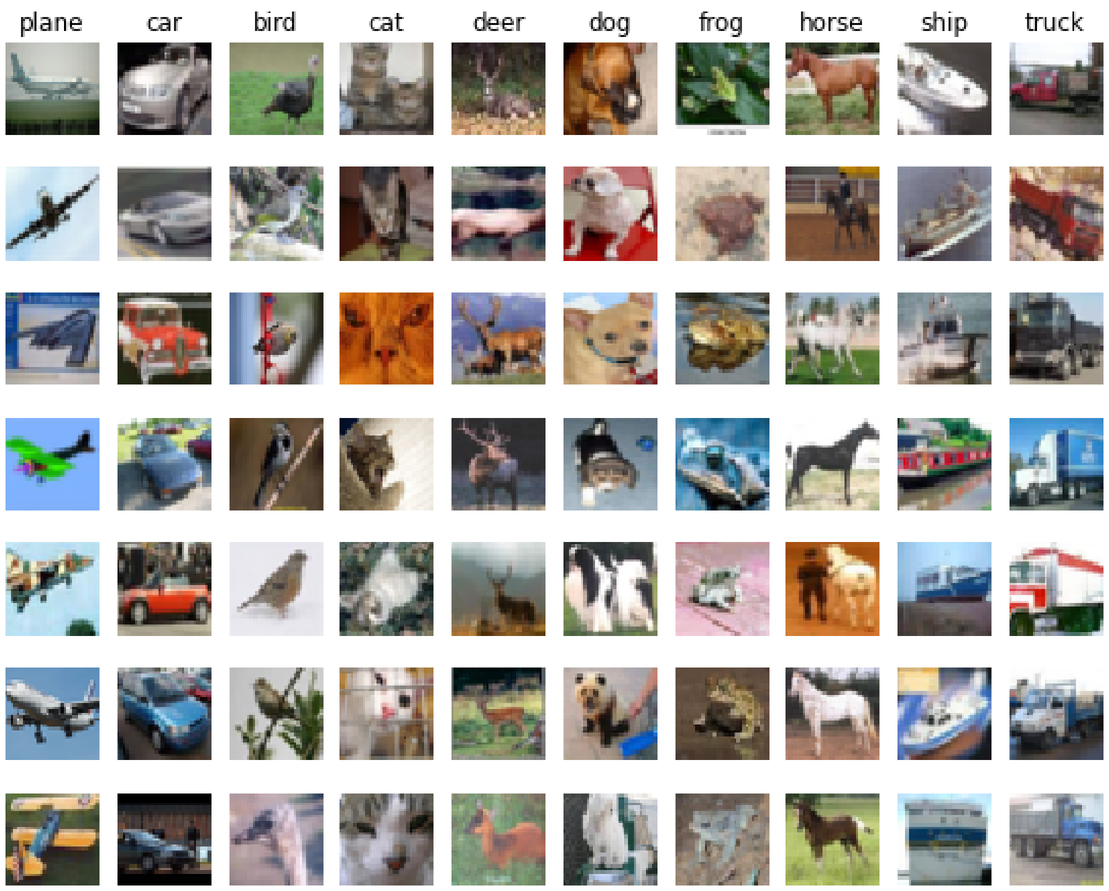
1.1 CIFAR-10 Data Loading and Preprocessing

[4]:
```
# 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,)
```

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



[6]:
```
# 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]
```

```python
# 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,)
```

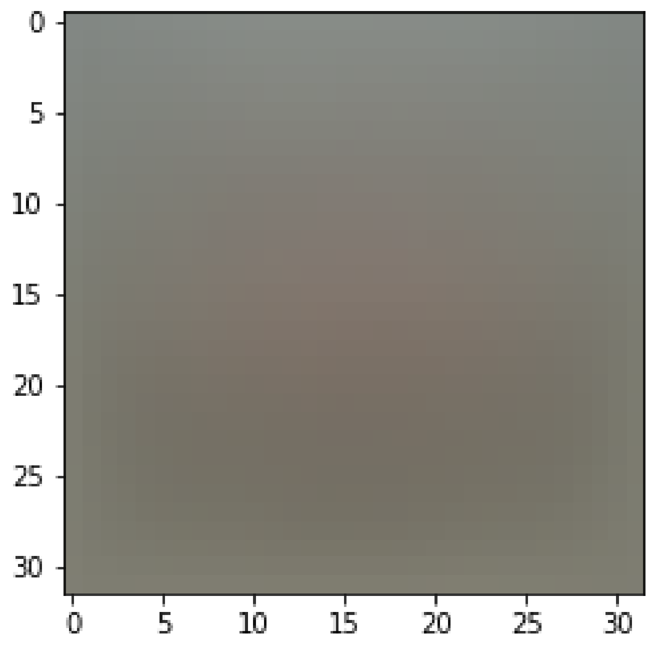
[7]:
```python
# Preprocessing: reshape the image data into rows
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_val = np.reshape(X_val, (X_val.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
X_dev = np.reshape(X_dev, (X_dev.shape[0], -1))

# 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)
```

[8]:
```python
# 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.

[9]:
```
# 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: 9.116483
```

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:

[10]:
```
# 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: 17.264902 analytic: 0.000000, relative error: 1.000000e+00
numerical: 8.985528 analytic: 0.000000, relative error: 1.000000e+00
numerical: -8.430773 analytic: 0.000000, relative error: 1.000000e+00
```

```
numerical: -19.723433 analytic: 0.000000, relative error: 1.000000e+00
numerical: 17.337564 analytic: 0.000000, relative error: 1.000000e+00
numerical: -7.119646 analytic: 0.000000, relative error: 1.000000e+00
numerical: -23.849954 analytic: 0.000000, relative error: 1.000000e+00
numerical: 14.650891 analytic: 0.000000, relative error: 1.000000e+00
numerical: -2.072571 analytic: 0.000000, relative error: 1.000000e+00
numerical: 11.747417 analytic: 0.000000, relative error: 1.000000e+00
numerical: 3.225966 analytic: -0.000576, relative error: 1.000000e+00
numerical: 7.534031 analytic: -0.005616, relative error: 1.000000e+00
numerical: -2.749990 analytic: 0.009857, relative error: 1.000000e+00
numerical: -0.495565 analytic: -0.012996, relative error: 9.488897e-01
numerical: -32.795536 analytic: -0.004251, relative error: 9.997408e-01
numerical: -8.740391 analytic: -0.005361, relative error: 9.987741e-01
numerical: -19.771417 analytic: 0.010418, relative error: 1.000000e+00
numerical: -13.391511 analytic: -0.001150, relative error: 9.998283e-01
numerical: 13.681447 analytic: 0.007501, relative error: 9.989040e-01
numerical: -13.029971 analytic: 0.005708, relative error: 1.000000e+00
```

Inline Question 1

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

$YourAnswer:$ *For weights close to zero, the discontinuity of the first derivative (at 0) of the loss function can cause inconsistency.*

[11]:
```
# 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: 9.116483e+00 computed in 0.012522s
Vectorized loss: 9.116483e+00 computed in 0.008890s
difference: 0.000000
```

[12]:
```python
# 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 0.011707s
Vectorized loss and gradient: computed in 0.003247s
difference: 2939.073620
```

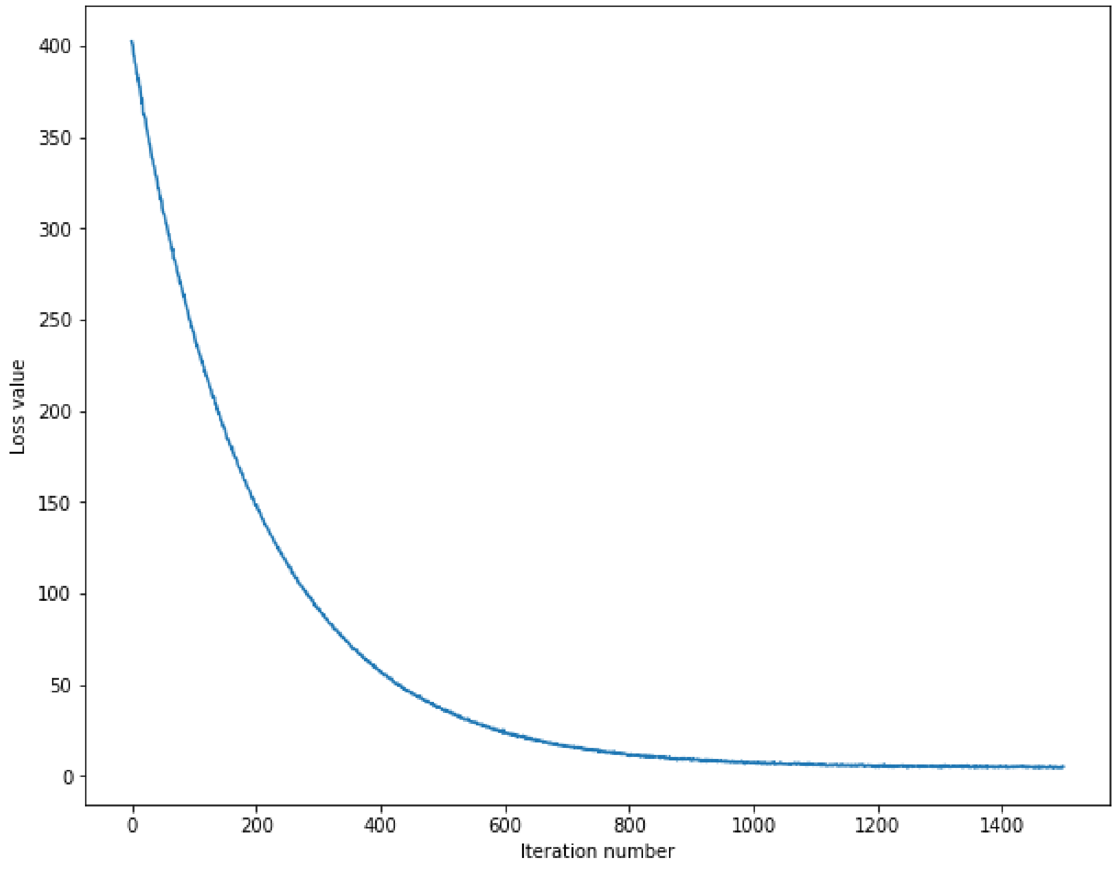
1.2.1 Stochastic Gradient Descent

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`.

[13]:
```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 402.508590
iteration 100 / 1500: loss 242.665666
iteration 200 / 1500: loss 147.977871
iteration 300 / 1500: loss 91.697847
iteration 400 / 1500: loss 57.226524
iteration 500 / 1500: loss 36.847948
iteration 600 / 1500: loss 23.818531
iteration 700 / 1500: loss 16.353357
iteration 800 / 1500: loss 11.005581
iteration 900 / 1500: loss 8.797004
iteration 1000 / 1500: loss 7.516152
iteration 1100 / 1500: loss 6.220257
iteration 1200 / 1500: loss 5.620429
iteration 1300 / 1500: loss 4.835125
iteration 1400 / 1500: loss 4.918681
That took 4.064021s
```

[14]:
```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()
```



[15]:
```python
# Write the LinearSVM.predict function and evaluate the performance on both the
# training and validation set
y_train_pred = svm.predict(X_train)
```

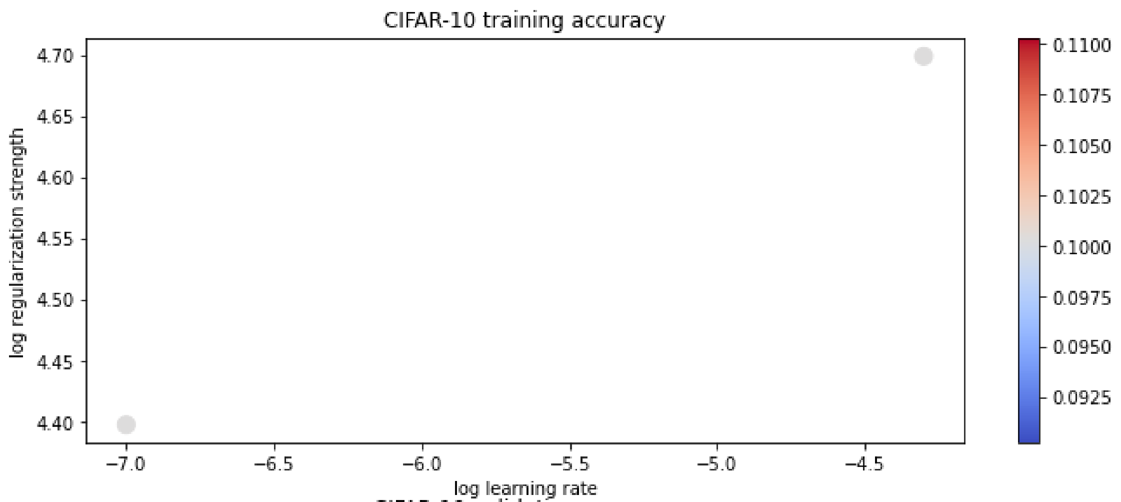
```
print('training accuracy: %f' % (np.mean(y_train == y_train_pred), ))
y_val_pred = svm.predict(X_val)
print('validation accuracy: %f' % (np.mean(y_val == y_val_pred), ))
```

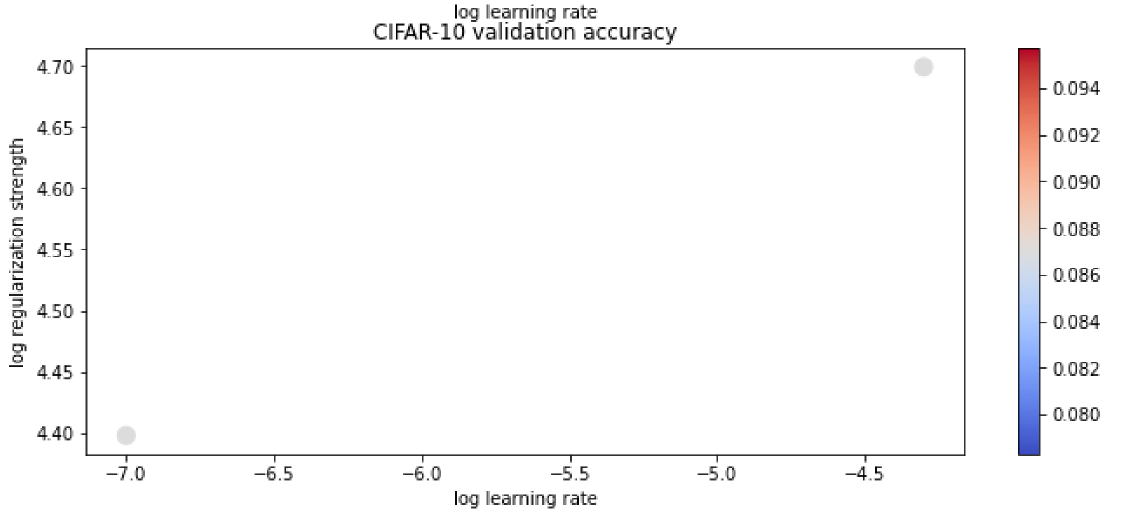
```
training accuracy: 0.100265
validation accuracy: 0.087000
```

[16]:
```
# 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)*****

for lr, reg in zip(learning_rates, regularization_strengths):
    svm = LinearSVM()
    svm.train(X_train, y_train, learning_rate=lr, reg=reg,
              num_iters=1500, batch_size=200, verbose=False)
    y_train_pred = svm.predict(X_train)
    acc_train = np.mean(y_train == y_train_pred)
    y_val_pred = svm.predict(X_val)
    acc_val = np.mean(y_val == y_val_pred)
    print('lr = %f, reg = %f, train/val accuracy: %f, %f' % (lr, reg,␣
 ↪acc_train, acc_val))

    if acc_val > best_val:
        best_val = acc_val
        best_svm = svm

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

# *****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 = 0.000000, reg = 25000.000000, train/val accuracy: 0.100265, 0.087000

/home/bjeon/cs231n/classifiers/linear_svm.py:88: RuntimeWarning: overflow
encountered in double_scalars
  loss += 0.5 * reg * np.sum(W.T.dot(W))
/home/bjeon/miniconda3/envs/nlp_class/lib/python3.7/site-
packages/numpy/core/fromnumeric.py:86: RuntimeWarning: overflow encountered in
reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
/home/bjeon/miniconda3/envs/nlp_class/lib/python3.7/site-
packages/numpy/core/fromnumeric.py:86: RuntimeWarning: invalid value encountered
in reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)

lr = 0.000050, reg = 50000.000000, train/val accuracy: 0.100265, 0.087000
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.087000
```

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



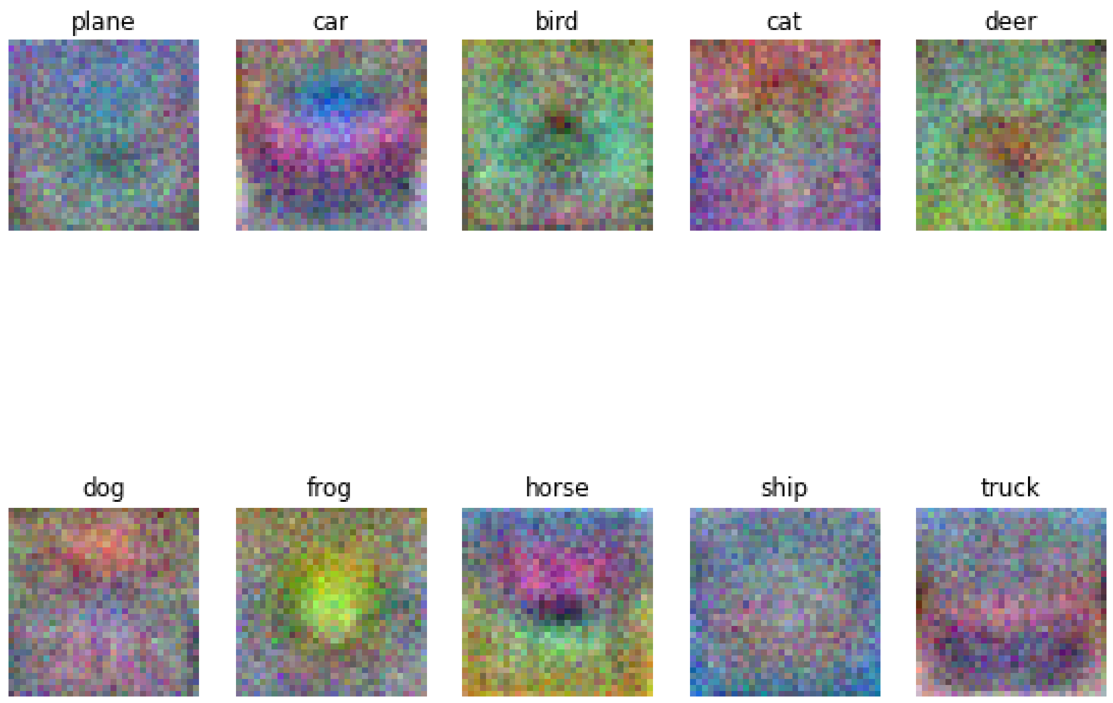


[18]:
```
# Evaluate the best svm on test set
y_test_pred = best_svm.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('linear SVM on raw pixels final test set accuracy: %f' % test_accuracy)
```

```
linear SVM on raw pixels final test set accuracy: 0.103000
```

[19]:
```
# 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']
```

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

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



Inline question 2

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

YourAnswer : SVM weights have color noises. The whole outline of SVM weights are taken, but they are not clearly. Maybe I think weights are not enough.

part1_softmax

February 8, 2022

0.1 Homework 2. Part 1. Softmax classifier (logistic regression) from scratch.

0.1.1 Set COLAB to True if you work in COLAB, else, set it to False

[1]:
```
# YOUR CODE HERE
COLAB = False
```

[2]:
```
if COLAB:
    # 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 = None
    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
else:
    %cd cs231n/datasets/
    !bash get_datasets.sh
    %cd ../..
```

```
/home/bjeon/cs231n/datasets
/home/bjeon
```

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.

In this 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

Credit: Stanford cs231n

[3]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

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

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

[4]:
```
def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000,␣
 ↪num_dev=500):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the linear classifier. These are the same steps as we used for the
    SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

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

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

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

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

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

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

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


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

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

1.1 Softmax Classifier

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

[22]:
```
# 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: 2.366561
sanity check: 2.302585
```

Inline Question 1

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

YourAnswer : Because the W is selected by random, so the probability of select the true class is 1/10.

[23]:
```
# 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)

# 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)

# 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: -0.707724 analytic: -0.707724, relative error: 3.945907e-08
numerical: 3.863193 analytic: 3.863192, relative error: 2.655904e-08
numerical: -3.779171 analytic: -3.779171, relative error: 1.467116e-08
numerical: -1.239204 analytic: -1.239204, relative error: 8.995143e-09
numerical: -0.817405 analytic: -0.817405, relative error: 9.687348e-08
numerical: 4.110435 analytic: 4.110434, relative error: 1.253577e-08
numerical: 1.240122 analytic: 1.240122, relative error: 3.015773e-08
numerical: -0.785256 analytic: -0.785256, relative error: 1.015180e-08
numerical: -4.419372 analytic: -4.419372, relative error: 9.481420e-09
numerical: 0.937309 analytic: 0.937309, relative error: 5.149608e-08
numerical: -0.769021 analytic: -0.769021, relative error: 1.880779e-08
numerical: 0.925532 analytic: 0.925532, relative error: 7.306276e-08
numerical: -4.439831 analytic: -4.439831, relative error: 1.597191e-09
numerical: -1.062949 analytic: -1.062949, relative error: 4.550210e-08
numerical: -1.199803 analytic: -1.199803, relative error: 1.964034e-08
numerical: 2.839361 analytic: 2.839361, relative error: 4.626517e-08
numerical: -0.619765 analytic: -0.619765, relative error: 4.470411e-08
numerical: 3.590058 analytic: 3.590058, relative error: 1.766597e-08
numerical: -2.821629 analytic: -2.821629, relative error: 2.660812e-09
numerical: -4.682796 analytic: -4.682796, relative error: 7.730829e-09
```

[24]:
```
# 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))

# 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: 2.366561e+00 computed in 0.078269s
vectorized loss: 2.366561e+00 computed in 0.002289s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[25]:

```
# 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
learning_rates = [1e-7, 5e-7]
regularization_strengths = [5e4, 1e8]

################################################################################
# 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.                          #
################################################################################

def compute_accuracy(y, y_pred):
    return np.mean(y == y_pred)


for lr in learning_rates:
    for reg in regularization_strengths:
        # train softmax classifier
        print("***********************************")
        print("lr: %.7f, reg: %.1f" %(lr, reg))
        model = Softmax()
        model.train(X_train, y_train, learning_rate=lr, reg=reg,␣
 ↪num_iters=1500, verbose=False)

        # compute accuracy
        train_accuracy = compute_accuracy(y_train, model.predict(X_train))
        val_accuracy = compute_accuracy(y_val, model.predict(X_val))
        print('train accuracy: %.4f' %train_accuracy)
        print('validation accuracy: %.4f' %val_accuracy)

        # store accuracy in dictionary
        results[(lr, reg)] = (train_accuracy, val_accuracy)

        # check if validation accuracy is best
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_softmax = model

# *****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)
```

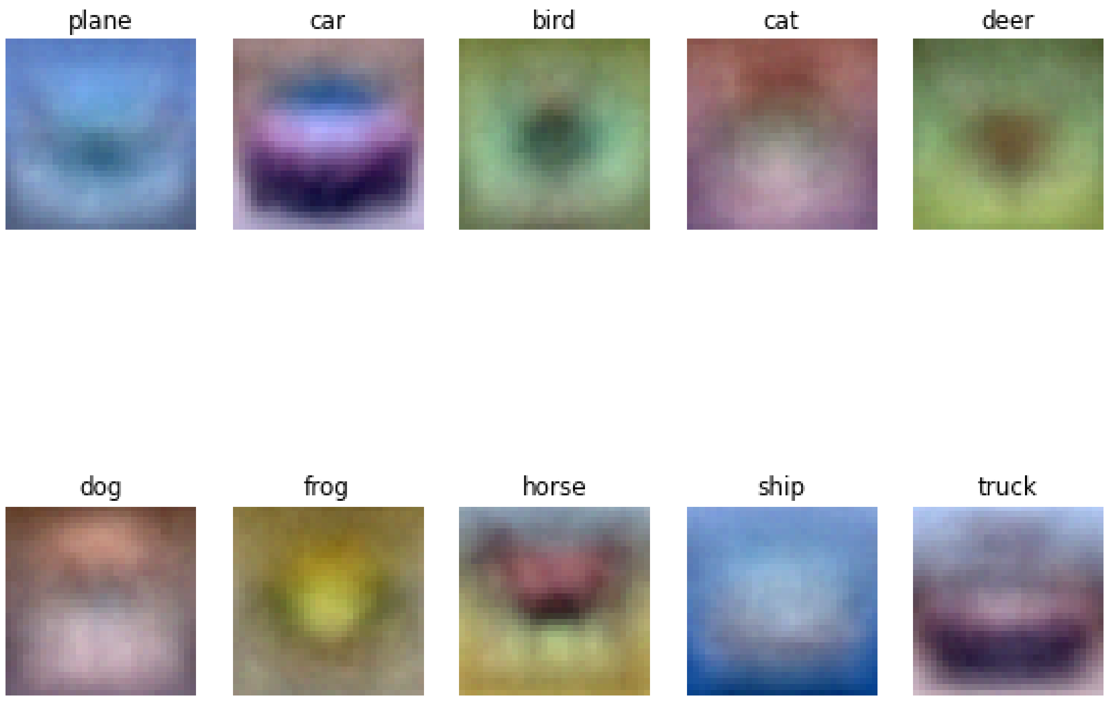
```
**********************************
lr: 0.0000001, reg: 50000.0
train accuracy: 0.1003
validation accuracy: 0.0870
**********************************
lr: 0.0000001, reg: 100000000.0
train accuracy: 0.1003
validation accuracy: 0.0870
**********************************
lr: 0.0000005, reg: 50000.0
train accuracy: 0.1003
validation accuracy: 0.0870
**********************************
lr: 0.0000005, reg: 100000000.0
train accuracy: 0.1003
validation accuracy: 0.0870
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
lr 1.000000e-07 reg 1.000000e+08 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
lr 5.000000e-07 reg 1.000000e+08 train accuracy: 0.100265 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.087000
```

[26]:
```
# 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: 0.103000
```

[27]:
```
# 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])
```



part2_two_layer_net

February 8, 2022

0.1 Homework 2. Part 2. Neural network from scratch.

0.1.1 Set COLAB to True if you work in COLAB, else, set it to False

[ ]:
```
# YOUR CODE HERE
COLAB = False
```

[ ]:
```
if COLAB:
    # 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 = None
    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
else:
    %cd cs231n/datasets/
    !bash get_datasets.sh
    %cd ../..
```

```
/home/bjeon/cs231n/datasets
/home/bjeon
```

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.

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

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

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

```
('X_train: ', (49000, 3072))
('y_train: ', (49000,))
('X_val: ', (1000, 3072))
('y_val: ', (1000,))
('X_test: ', (1000, 3072))
('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:

[ ]:
```
# 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.

[ ]:
```
# 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:

```
[ ]: # 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:

```
[ ]: 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:

The sigmoid function enters the saturation zone when the input value is too large and too small, where gradient is zero; ReLU function does not enter less than zero; Leaky ReLU does not.

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:

[ ]:
```
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:  2.2995909845854045e-11
dw error:  8.162011105764925e-11
db error:  7.826724021458994e-12
```

7 Loss layers: Softmax cross entropy loss

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

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

```
[ ]: 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: 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 softmax_loss:
loss:  2.302545844500738
dx error:  7.454884968628367e-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.

```
[ ]: 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'
```

```python
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: 1.52e-08
W2 relative error: 3.21e-10
b1 relative error: 1.02e-08
b2 relative error: 4.33e-10
Running numeric gradient check with reg =  0.7
W1 relative error: 2.53e-07
W2 relative error: 2.85e-08
b1 relative error: 1.56e-08
b2 relative error: 7.76e-10
```

9 Solver

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

[ ]:
```
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)*****

model = TwoLayerNet(hidden_dim=100, reg=0.2)
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=100)
solver.train()

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

```
(Iteration 1 / 4900) loss: 2.328988
(Epoch 0 / 10) train acc: 0.159000; val_acc: 0.135000
(Iteration 101 / 4900) loss: 1.754734
(Iteration 201 / 4900) loss: 1.774558
(Iteration 301 / 4900) loss: 1.837689
(Iteration 401 / 4900) loss: 1.743240
(Epoch 1 / 10) train acc: 0.466000; val_acc: 0.456000
(Iteration 501 / 4900) loss: 1.567255
(Iteration 601 / 4900) loss: 1.613240
```

```
(Iteration 701 / 4900) loss: 1.837204
(Iteration 801 / 4900) loss: 1.630299
(Iteration 901 / 4900) loss: 1.560961
(Epoch 2 / 10) train acc: 0.500000; val_acc: 0.474000
(Iteration 1001 / 4900) loss: 1.562475
(Iteration 1101 / 4900) loss: 1.526039
(Iteration 1201 / 4900) loss: 1.463118
(Iteration 1301 / 4900) loss: 1.669565
(Iteration 1401 / 4900) loss: 1.555207
(Epoch 3 / 10) train acc: 0.511000; val_acc: 0.484000
(Iteration 1501 / 4900) loss: 1.302166
(Iteration 1601 / 4900) loss: 1.398674
(Iteration 1701 / 4900) loss: 1.165266
(Iteration 1801 / 4900) loss: 1.453078
(Iteration 1901 / 4900) loss: 1.324924
(Epoch 4 / 10) train acc: 0.503000; val_acc: 0.487000
(Iteration 2001 / 4900) loss: 1.430162
(Iteration 2101 / 4900) loss: 1.310965
(Iteration 2201 / 4900) loss: 1.437788
(Iteration 2301 / 4900) loss: 1.509555
(Iteration 2401 / 4900) loss: 1.393299
(Epoch 5 / 10) train acc: 0.513000; val_acc: 0.481000
(Iteration 2501 / 4900) loss: 1.455275
(Iteration 2601 / 4900) loss: 1.543933
(Iteration 2701 / 4900) loss: 1.401015
(Iteration 2801 / 4900) loss: 1.250506
(Iteration 2901 / 4900) loss: 1.295311
(Epoch 6 / 10) train acc: 0.561000; val_acc: 0.485000
(Iteration 3001 / 4900) loss: 1.507553
(Iteration 3101 / 4900) loss: 1.486481
(Iteration 3201 / 4900) loss: 1.355930
(Iteration 3301 / 4900) loss: 1.322673
(Iteration 3401 / 4900) loss: 1.330320
(Epoch 7 / 10) train acc: 0.547000; val_acc: 0.505000
(Iteration 3501 / 4900) loss: 1.481103
(Iteration 3601 / 4900) loss: 1.349870
(Iteration 3701 / 4900) loss: 1.481646
(Iteration 3801 / 4900) loss: 1.268472
(Iteration 3901 / 4900) loss: 1.314758
(Epoch 8 / 10) train acc: 0.607000; val_acc: 0.519000
(Iteration 4001 / 4900) loss: 1.320503
(Iteration 4101 / 4900) loss: 1.261022
(Iteration 4201 / 4900) loss: 1.417740
(Iteration 4301 / 4900) loss: 1.254633
(Iteration 4401 / 4900) loss: 1.242097
(Epoch 9 / 10) train acc: 0.579000; val_acc: 0.502000
(Iteration 4501 / 4900) loss: 1.310867
(Iteration 4601 / 4900) loss: 1.294264
```

```
(Iteration 4701 / 4900) loss: 1.399901
(Iteration 4801 / 4900) loss: 1.261028
(Epoch 10 / 10) train acc: 0.582000; val_acc: 0.532000
```

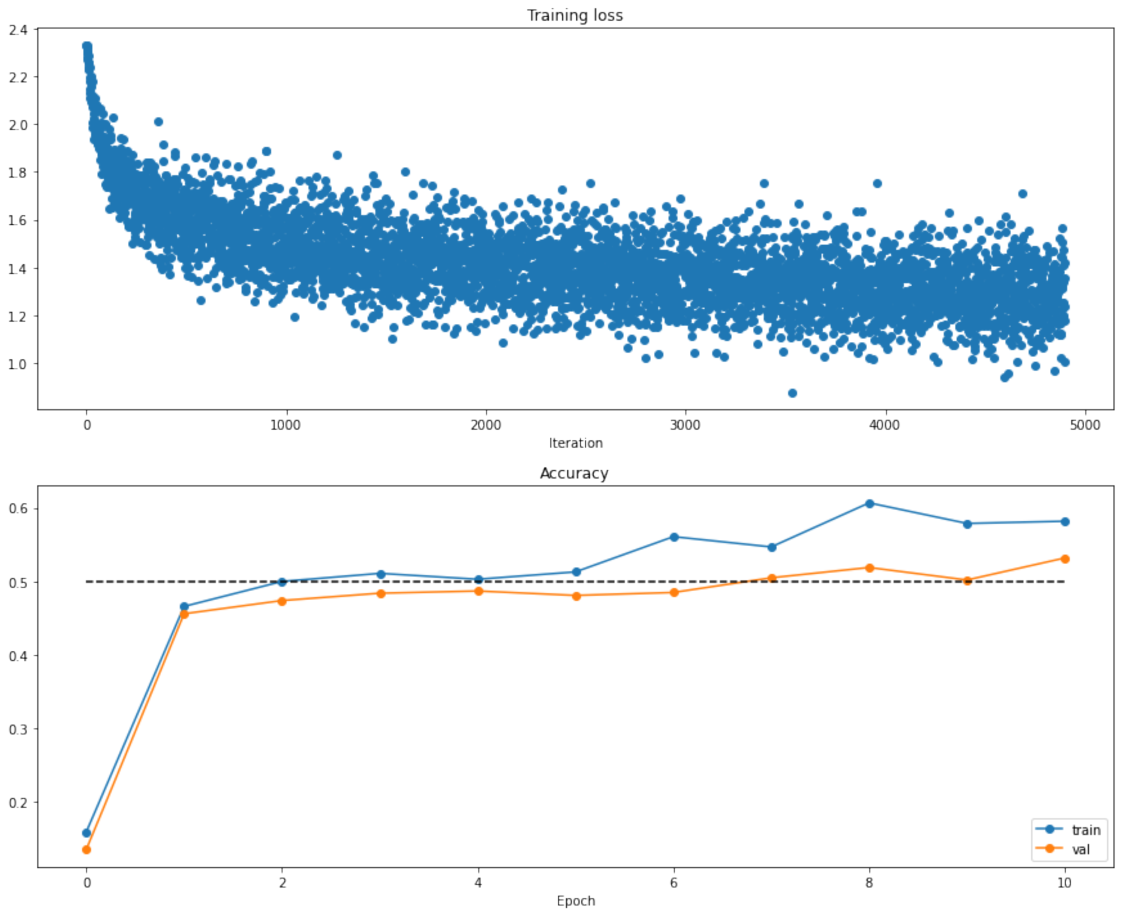
10 Debug the training

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.

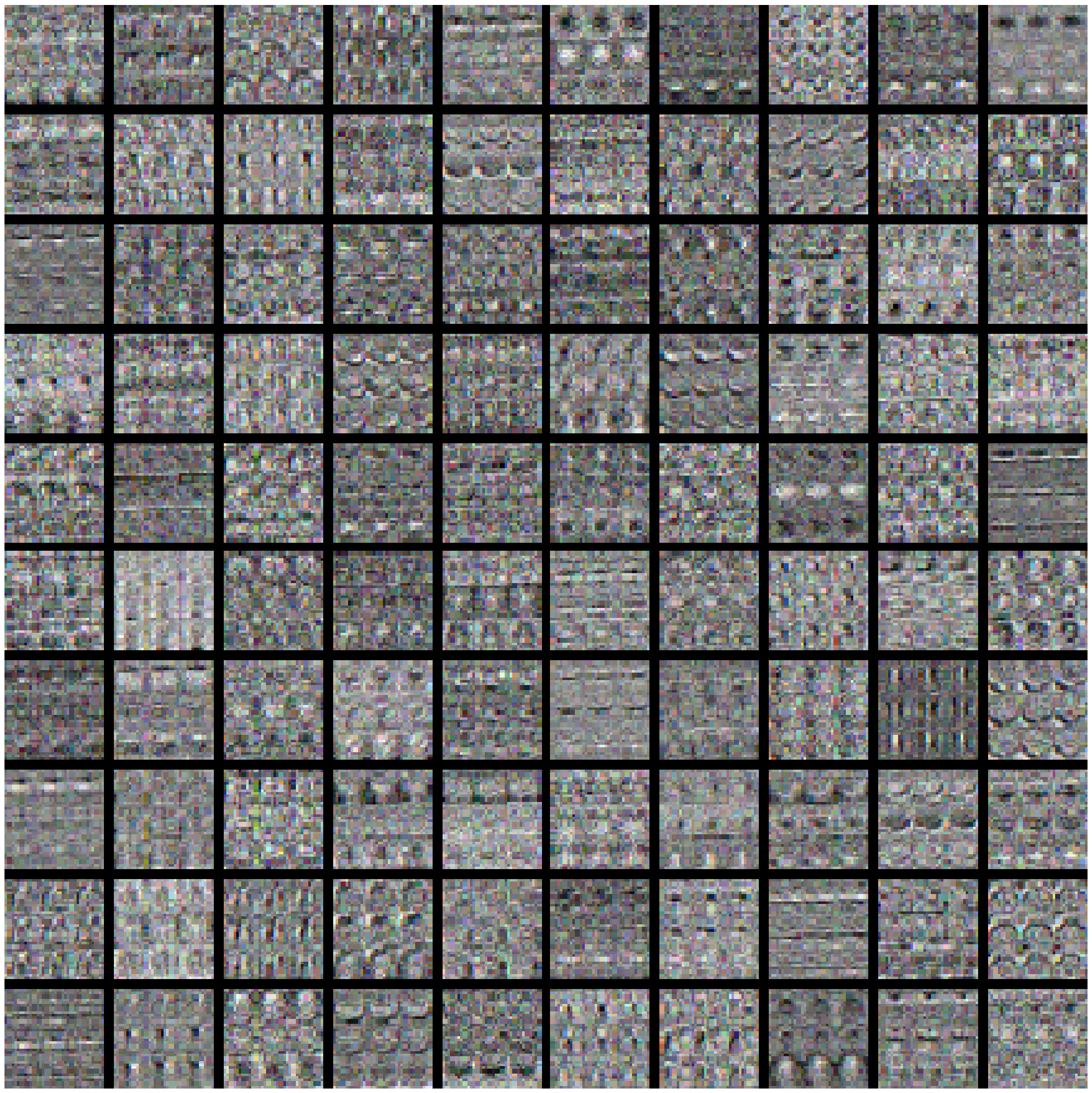
One strategy for getting insight into what's wrong is to plot the loss function and the accuracies on the training and validation sets during optimization.

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.

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



[ ]:
```
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.).

[16]:
```
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)*****

learning_rate = [1.6e-3]
regularization_strengths = [1e-2]
hidden_size = 400
results = {}
best_val = -1

for lr in learning_rate:
    for rs in regularization_strengths:
        model = TwoLayerNet(input_size, hidden_size, num_classes)
        stats = model.train(data['X_train'], data['y_train'], data['X_val'],␣
 ↪data['y_val'],
            num_iters=2000, batch_size=400,
            learning_rate=lr, learning_rate_decay=0.9,
            reg=rs, verbose=True)
        y_train_pred = model.predict(data['X_train'])
        acc_tr = np.mean(data['y_train'] == y_train_pred)
        y_val_pred = model.predict(data['X_val'])
        acc_val = np.mean(data['y_val'] == y_val_pred)

        results[(lr, rs)] = (acc_tr, acc_val)
        if acc_val > best_val:
            best_val = acc_val
            best_model = model

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)*****
################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

```
iteration 0 / 2000: loss 2.306004
iteration 100 / 2000: loss 1.727052
iteration 200 / 2000: loss 1.501074
iteration 300 / 2000: loss 1.426558
iteration 400 / 2000: loss 1.382654
iteration 500 / 2000: loss 1.333807
iteration 600 / 2000: loss 1.389497
iteration 700 / 2000: loss 1.207397
iteration 800 / 2000: loss 1.254256
iteration 900 / 2000: loss 1.193423
iteration 1000 / 2000: loss 1.183095
iteration 1100 / 2000: loss 1.150538
iteration 1200 / 2000: loss 1.149141
iteration 1300 / 2000: loss 1.124625
iteration 1400 / 2000: loss 1.226118
iteration 1500 / 2000: loss 1.018110
iteration 1600 / 2000: loss 1.095556
iteration 1700 / 2000: loss 1.106075
iteration 1800 / 2000: loss 1.008558
iteration 1900 / 2000: loss 1.036056
lr 1.600000e-03 reg 1.000000e-02 train accuracy: 0.673367 val accuracy: 0.538000
best validation accuracy achieved during cross-validation: 0.538000
```

12 Test your model!

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

[17]:
```python
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:  0.538
```

[18]:
```python
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:  0.536
```

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.

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

$\textit{Your Explanation}:$ Train on a larger dataset: Without a large training set, an increasingly large network is likely to overfit and in turn reduce accuracy on the test data.

Increase the regularization strength: Regularization in neural network is a technique used to prevent overfitting so we can improve the accuracy of neural network model when more regularization strength.