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.

```
### IF YOU ARE USING COLAB, UNCOMMENT AND RUN THIS BLOCK FIRST ###

# # Mount google drive to allow access to your files
from google.colab import drive
drive.mount('/content/drive')
drive_folder = '/content/drive/MyDrive'
# # Ajust this line to be the assignment1 folder in your google drive
notebook_folder = drive_folder + '/cs682/assignment1'
%cd {notebook_folder}
```

```
Mounted at /content/drive
/content/drive/MyDrive/cs682/assignment1
```

```
from google.colab import drive
drive.mount('/content/drive')
```

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

```
%cd ./cs682/datasets
!bash get_datasets.sh
%cd ../../
```

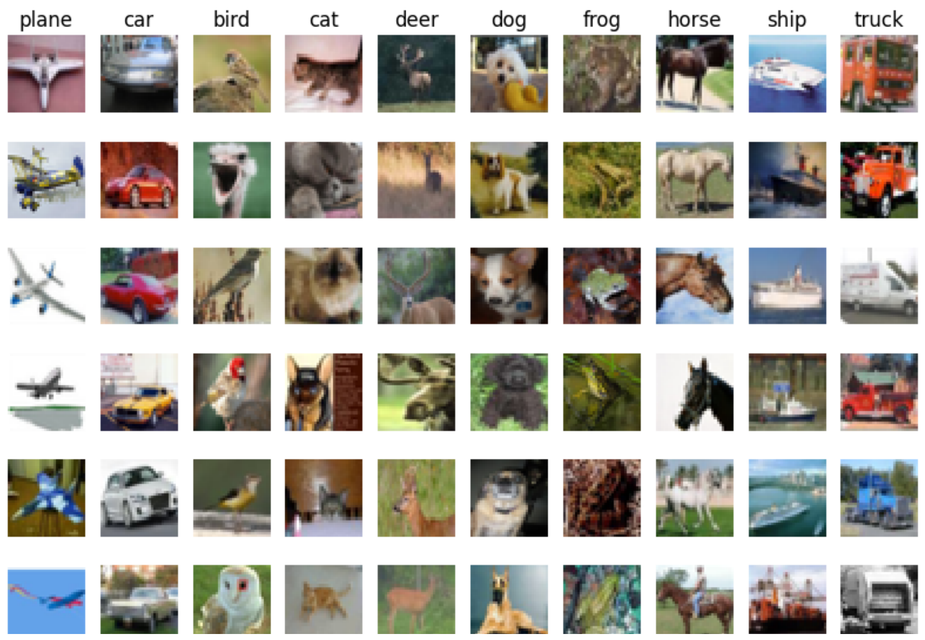
```
/content/drive/My Drive/cs682/assignment1/cs682/datasets
--2023-09-26 18:39:55--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 170498071 (163M) [application/x-gzip]
Saving to: 'cifar-10-python.tar.gz'

cifar-10-python.tar 100%[===================>] 162.60M  56.3MB/s    in 2.9s

2023-09-26 18:39:58 (56.3 MB/s) - 'cifar-10-python.tar.gz' saved [170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content/drive/My Drive/cs682/assignment1
```

```
# Run some setup code for this notebook.
from __future__ import print_function
```

```
import random
import numpy as np
from cs682.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 = 'cs682/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

# Don't forget to run get_datasets.sh, or this will throw an error
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()
```



```
# 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)
```

```
from cs682.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

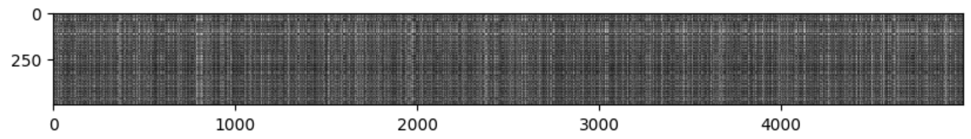
Lets begin with computing the distance matrix between all training and test examples. For example, if there are **Ntr** training examples and **Nte** test examples, this stage should result in a **Nte x Ntr** matrix where each element (i,j) is the distance between the i-th test and j-th train example.

First, open `cs682/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.

```
# Open cs682/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)
```

```
# 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:

Bright rows mean test data are quite different from training data points

Bright columns mean train data are quite different from test data points.

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

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

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

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

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

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

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

* **italicized text*Inline Question 2** We can also other distance metrics such as L1 distance. The performance of a Nearest Neighbor classifier that uses L1 distance will not change if (Select all that apply.):

1. The data is preprocessed by subtracting the mean.
2. The data is preprocessed by subtracting the mean and dividing by the standard deviation.
3. The coordinate axes for the data are rotated.
4. None of the above. (Mean and standard deviation in (1) and (2) are vectors and can be different across dimensions)

Your Answer: (1) (2)

Your explanation: let assume that m is the mean of the data and x1 and x2 is data that we are calculating L1. Then original L1 is ||x1-x2|| and applying 1 then we got ||x1-m - (x2-m)|| = ||x1-x2|| so 1 does not change l1 distance

for 2. let assume that m is the mean of the data and ||x1-x2|| < ||x1-x3|| σ = std then ||(x1-m)/σ - (x2-m)/σ|| = 1/σ||x1-x2|| < 1/σ||x1-x3|| = ||(x1-m)/σ - (x3-m)/σ|| so the KNN classifer remain the same.

3 is not true. since if matrix roate its values, it changes the value of the matrix unless it is symetric. so 3 is wrong.

```
# Now lets speed up distance matrix computation by using partial vectorization
# with one loop. Implement the function compute_distances_one_loop and run the
# code below:
dists_one = classifier.compute_distances_one_loop(X_test)

# To ensure that our vectorized implementation is correct, we make sure that it
# agrees with the naive implementation. There are many ways to decide whether
# two matrices are similar; one of the simplest is the Frobenius norm. In case
# you haven't seen it before, the Frobenius norm of two matrices is the square
# root of the squared sum of differences of all elements; in other words, reshape
# the matrices into vectors and compute the Euclidean distance between them.
difference = np.linalg.norm(dists - dists_one, ord='fro')
print('Difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
Difference was: 0.000000
Good! The distance matrices are the same
```

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

# check that the distance matrix agrees with the one we computed before:
difference = np.linalg.norm(dists - dists_two, ord='fro')
print('Difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
Difference was: 0.000000
Good! The distance matrices are the same
```

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

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

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

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

# you should see significantly faster performance with the fully vectorized implementation
```

```
Two loop version took 34.245053 seconds
One loop version took 32.322875 seconds
No loop version took 0.517862 seconds
```

Cross-validation

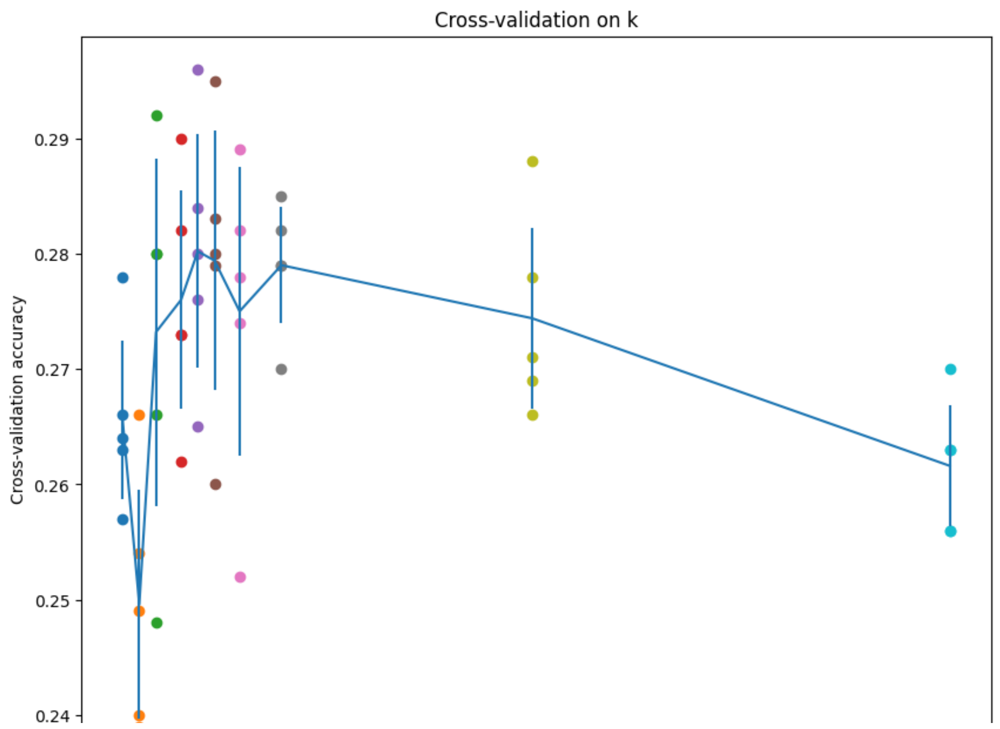
We have implemented the k-Nearest Neighbor classifier but we set the value k = 5 arbitrarily. We will now determine the best value of this hyperparameter with cross-validation.

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

X_train_folds = []
y_train_folds = []
################################################################################
# TODO:                                                                        #
# Split up the training data into folds. After splitting, X_train_folds and    #
# y_train_folds should each be lists of length num_folds, where                #
# y_train_folds[i] is the label vector for the points in X_train_folds[i].     #
# Hint: Look up the numpy array_split function.                                #
################################################################################
# Your code
X_train_folds = np.array_split(X_train,num_folds)
y_train_folds = np.array_split(y_train,num_folds)
################################################################################
#                                 END OF YOUR CODE                             #
################################################################################

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


################################################################################
# TODO:                                                                        #
# Perform k-fold cross validation to find the best value of k. For each        #
# possible value of k, run the k-nearest-neighbor algorithm num_folds times,   #
# where in each case you use all but one of the folds as training data and the #
# last fold as a validation set. Store the accuracies for all fold and all     #
# values of k in the k_to_accuracies dictionary.                               #
################################################################################
# Your code
for k in k_choices:
    k_to_accuracies[k] = []

    for n in range(num_folds):
      X_train_temp = np.concatenate([fold for i, fold in enumerate(X_train_folds) if i!=n])
      y_train_temp = np.concatenate([fold for i, fold in enumerate(y_train_folds) if i!=n])
```

```
            X_valid_temp = X_train_folds[n]
            y_valid_temp = y_train_folds[n]
            classifier = KNearestNeighbor()
            classifier.train(X_train_temp, y_train_temp)
            y_valid_pred = classifier.predict(X_valid_temp, k=k)
            num_correct = np.sum(y_valid_pred == y_valid_temp)
            accuracy = float(num_correct) / len(y_valid_temp)
            k_to_accuracies[k].append(accuracy)


    ################################################################################
    #                                 END OF YOUR CODE                             #
    ################################################################################

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

```
     k = 1, accuracy = 0.263000
     k = 1, accuracy = 0.257000
     k = 1, accuracy = 0.264000
     k = 1, accuracy = 0.278000
     k = 1, accuracy = 0.266000
     k = 3, accuracy = 0.239000
     k = 3, accuracy = 0.249000
     k = 3, accuracy = 0.240000
     k = 3, accuracy = 0.266000
     k = 3, accuracy = 0.254000
     k = 5, accuracy = 0.248000
     k = 5, accuracy = 0.266000
     k = 5, accuracy = 0.280000
     k = 5, accuracy = 0.292000
     k = 5, accuracy = 0.280000
     k = 8, accuracy = 0.262000
     k = 8, accuracy = 0.282000
     k = 8, accuracy = 0.273000
     k = 8, accuracy = 0.290000
     k = 8, accuracy = 0.273000
     k = 10, accuracy = 0.265000
     k = 10, accuracy = 0.296000
     k = 10, accuracy = 0.276000
     k = 10, accuracy = 0.284000
     k = 10, accuracy = 0.280000
     k = 12, accuracy = 0.260000
     k = 12, accuracy = 0.295000
     k = 12, accuracy = 0.279000
     k = 12, accuracy = 0.283000
     k = 12, accuracy = 0.280000
     k = 15, accuracy = 0.252000
     k = 15, accuracy = 0.289000
     k = 15, accuracy = 0.278000
     k = 15, accuracy = 0.282000
     k = 15, accuracy = 0.274000
     k = 20, accuracy = 0.270000
     k = 20, accuracy = 0.279000
     k = 20, accuracy = 0.279000
     k = 20, accuracy = 0.282000
     k = 20, accuracy = 0.285000
     k = 50, accuracy = 0.271000
     k = 50, accuracy = 0.288000
     k = 50, accuracy = 0.278000
     k = 50, accuracy = 0.269000
     k = 50, accuracy = 0.266000
     k = 100, accuracy = 0.256000
     k = 100, accuracy = 0.270000
     k = 100, accuracy = 0.263000
     k = 100, accuracy = 0.256000
     k = 100, accuracy = 0.263000
```

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

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



```
# Based on the cross-validation results above, choose the best value for k,
# retrain the classifier using all the training data, and test it on the test
# data. You should be able to get above 28% accuracy on the test data.
best_k = 10

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

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

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

Inline Question 3 Which of the following statements about k-Nearest Neighbor (k-NN) are true in a classification setting, and for all k? Select all that apply.

1. The training error of a 1-NN will always be better than or equal to that of 5-NN.
2. The test error of a 1-NN will always be better than that of a 5-NN.
3. The decision boundary of the k-NN classifier is linear.
4. The time needed to classify a test example with the k-NN classifier grows with the size of the training set.
5. None of the above.

Your Answer: 1,4 *Your explanation*:

1. it is true since 1-NN always select the datapoint by itself so error will be 0 however 5-NN doesnt. 5-NN error is always greater and equal to zero.
2. since nearest neighbor algorithn choose K neighbors. once we added new data set. It always have to figure out the k neareast neighbor again.

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

```
### IF YOU ARE USING COLAB, UNCOMMENT AND RUN THIS BLOCK FIRST ###

# # Mount google drive to allow access to your files
from google.colab import drive
drive.mount('/content/drive')
drive_folder = '/content/drive/MyDrive'
# # Ajust this line to be the assignment1 folder in your google drive
notebook_folder = drive_folder + '/cs682/assignment1'
%cd {notebook_folder}
```

```
     Mounted at /content/drive
     /content/drive/MyDrive/cs682/assignment1
```

```
# Run some setup code for this notebook.
from __future__ import print_function
import random
import numpy as np
from cs682.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
```

CIFAR-10 Data Loading and Preprocessing

```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs682/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
# Don't forget to run get_datasets.sh, or this will throw an error
X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

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

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

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

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

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

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

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

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

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

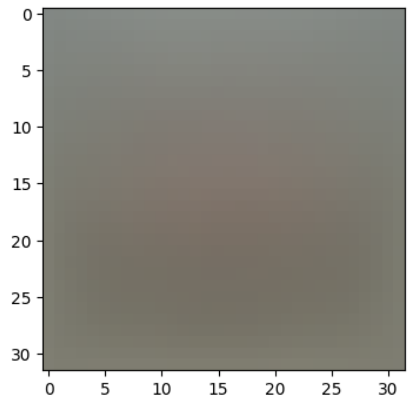
```
     Train data shape:  (49000, 32, 32, 3)
     Train labels shape:  (49000,)
     Validation data shape:  (1000, 32, 32, 3)
     Validation labels shape:  (1000,)
     Test data shape:  (1000, 32, 32, 3)
     Test labels shape:  (1000,)
```

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

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

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

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

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



```
# 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)
```

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

SVM Classifier

Your code for this section will all be written inside **cs682/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 cs682.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: 9.399920
```

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

To check that you have correctly implemented the gradient correctly, you can numerically estimate the gradient of the loss function and compare the numeric estimate to the gradient that you computed. We have provided code that does this for you:

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

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

# Numerically compute the gradient along several randomly chosen dimensions, and
# compare them with your analytically computed gradient. The numbers should match
# almost exactly along all dimensions.
from cs682.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: -7.132601 analytic: -7.132601, relative error: 2.879693e-11
    numerical: 1.945729 analytic: 1.945729, relative error: 1.941997e-10
    numerical: 8.758779 analytic: 8.758779, relative error: 1.334796e-11
    numerical: -21.229362 analytic: -21.231676, relative error: 5.449763e-05
    numerical: -14.088113 analytic: -14.088113, relative error: 2.529536e-12
    numerical: 7.651698 analytic: 7.651698, relative error: 1.533248e-12
    numerical: 25.295160 analytic: 25.295160, relative error: 8.972670e-13
    numerical: -19.073382 analytic: -19.073382, relative error: 2.170711e-11
    numerical: -49.365760 analytic: -49.275838, relative error: 9.115994e-04
    numerical: 0.425246 analytic: 0.338884, relative error: 1.130209e-01
    numerical: -11.644618 analytic: -11.644618, relative error: 3.507234e-11
    numerical: 22.055593 analytic: 22.055593, relative error: 1.846137e-12
    numerical: 15.775383 analytic: 15.775383, relative error: 5.934014e-12
    numerical: 3.757270 analytic: 3.796990, relative error: 5.258081e-03
    numerical: -1.171535 analytic: -1.171535, relative error: 1.491270e-10
    numerical: -10.223747 analytic: -10.142139, relative error: 4.007125e-03
    numerical: -5.138486 analytic: -5.138486, relative error: 1.249304e-11
    numerical: 7.375587 analytic: 7.431731, relative error: 3.791651e-03
    numerical: 1.921736 analytic: 1.921736, relative error: 1.818631e-10
    numerical: -14.495987 analytic: -14.503802, relative error: 2.694673e-04
```

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: *fill this in.* SVM loss function is max(0,s_j−s_yi+Δ) this is bascially means diference between correct and incorrect data plus delta. it causes error where hinge part of the loss function. For example max(0,x) where x=0 there analtic and numeric graident wouldnt match. Changing the margin would affect the frequency of this happening. when marigin is getting larger, frequency of gradient check fail will decrease which reduce discrepancy.

```
# 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 cs682.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: 9.399920e+00 computed in 0.103359s
Vectorized loss: 9.399920e+00 computed in 0.011461s
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 0.091001s
Vectorized loss and gradient: computed in 0.008231s
difference: 0.000000
```

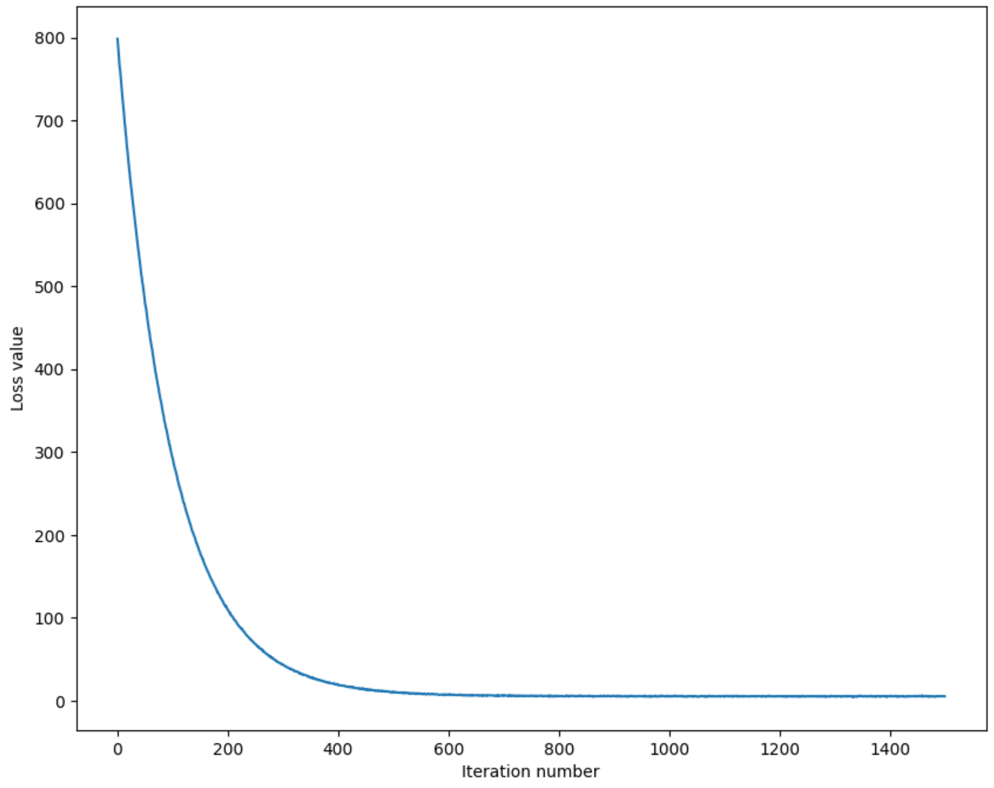
Stochastic Gradient Descent

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.

```
# In the file linear_classifier.py, implement SGD in the function
# LinearClassifier.train() and then run it with the code below.
from cs682.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 798.351674
iteration 100 / 1500: loss 292.596793
iteration 200 / 1500: loss 109.073391
iteration 300 / 1500: loss 43.701618
iteration 400 / 1500: loss 18.759894
iteration 500 / 1500: loss 10.652336
iteration 600 / 1500: loss 7.184517
iteration 700 / 1500: loss 6.428428
iteration 800 / 1500: loss 5.451237
iteration 900 / 1500: loss 5.353593
iteration 1000 / 1500: loss 4.946337
iteration 1100 / 1500: loss 4.662017
iteration 1200 / 1500: loss 5.565786
iteration 1300 / 1500: loss 5.628495
iteration 1400 / 1500: loss 5.119428
That took 5.806482s
```

```
# 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()
```



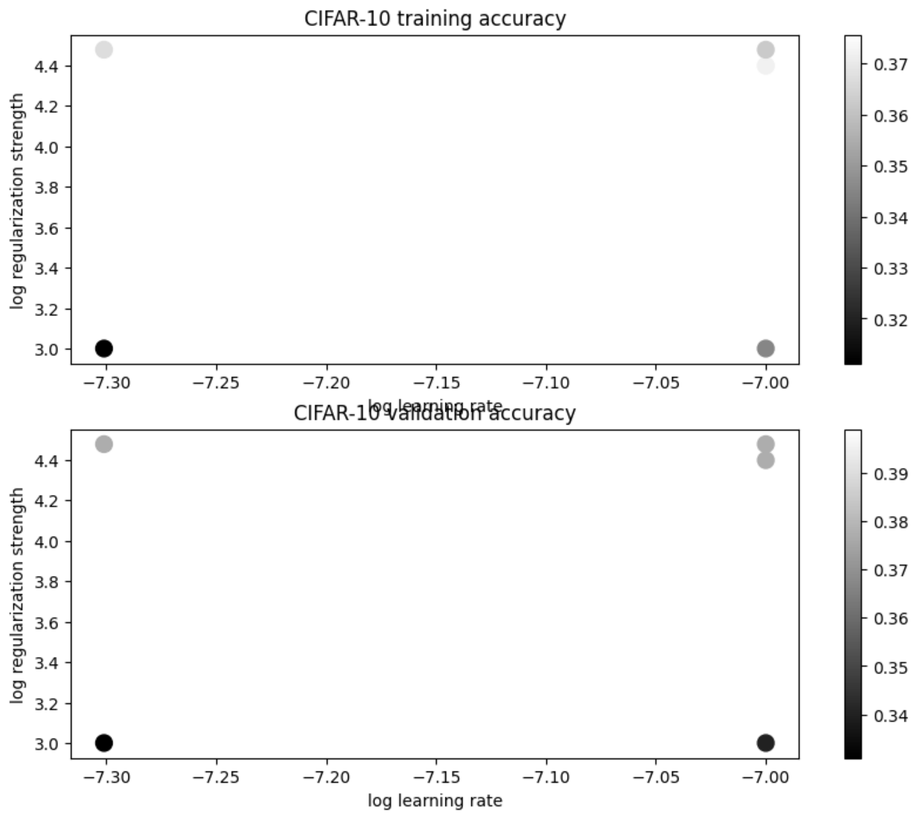
```
# Write the LinearSVM.predict function and evaluate the performance on both the
# training and validation set
y_train_pred = svm.predict(X_train)
print('training accuracy: %f' % (np.mean(y_train == y_train_pred), ))
y_val_pred = svm.predict(X_val)
print('validation accuracy: %f' % (np.mean(y_val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

```
training accuracy: 0.375837
validation accuracy: 0.391000
```

```
# 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 0.4 on the validation set.
learning_rates = [5e-8,1e-7]
regularization_strengths = [2.5e4,3e4,1e3]

# 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.                                      #
################################################################################
# Your code
for lr in learning_rates:
    for rg in regularization_strengths:
        svm = LinearSVM()
        loss_hist = svm.train(X_train, y_train, learning_rate=lr, reg=rg ,num_iters=2500, verbose=False)

        y_train_pred = svm.predict(X_train)
        training_accuracy = np.mean(y_train == y_train_pred)

        y_val_pred = svm.predict(X_val)
        val_accuracy = np.mean(y_val == y_val_pred)

        results[(lr, rg)] = (training_accuracy, val_accuracy)

        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm
################################################################################
#                              END OF YOUR CODE                                #
################################################################################

# 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 5.000000e-08 reg 1.000000e+03 train accuracy: 0.311204 val accuracy: 0.331000
lr 5.000000e-08 reg 2.500000e+04 train accuracy: 0.375633 val accuracy: 0.399000
lr 5.000000e-08 reg 3.000000e+04 train accuracy: 0.366939 val accuracy: 0.377000
lr 1.000000e-07 reg 1.000000e+03 train accuracy: 0.345041 val accuracy: 0.340000
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.372000 val accuracy: 0.377000
lr 1.000000e-07 reg 3.000000e+04 train accuracy: 0.362184 val accuracy: 0.377000
best validation accuracy achieved during cross-validation: 0.399000
```

```
# Visualize the cross-validation results
import math
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.scatter(x_scatter, y_scatter, marker_size, c=colors)
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)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 validation accuracy')
plt.show()
```

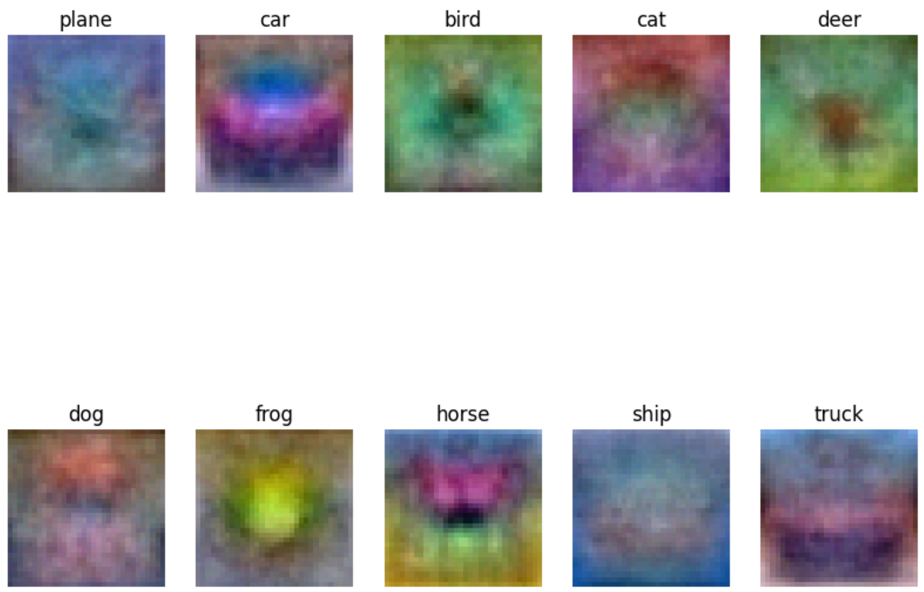


```
# Evaluate the best svm on test set
y_test_pred = best_svm.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
```

```
print('linear SVM on raw pixels final test set accuracy: %f' % test_accuracy)
```

```
    linear SVM on raw pixels final test set accuracy: 0.379000
```

```
# 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: *fill this in* The image of each calsses are blury but barely able to identify its shape. since we are using the dot product(weight and data) to get scores. it shows the average of weight in each class images. plus ship and plane images are usally located in sea or air so it looks bluish images.

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

```
### IF YOU ARE USING COLAB, UNCOMMENT AND RUN THIS BLOCK FIRST ###

# # Mount google drive to allow access to your files
from google.colab import drive
drive.mount('/content/drive')
drive_folder = '/content/drive/MyDrive'
# # Ajust this line to be the assignment1 folder in your google drive
notebook_folder = drive_folder + '/cs682/assignment1'
%cd {notebook_folder}
```

```
     Mounted at /content/drive
     /content/drive/MyDrive/cs682/assignment1
```

```
from __future__ import print_function
import random
import numpy as np
from cs682.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 = 'cs682/datasets/cifar-10-batches-py'
    # Don't forget to run get_datasets.sh, or this will throw an error
    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


# 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

# 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,)
```

Softmax Classifier

Your code for this section will all be written inside **cs682/classifiers/softmax.py**.

```
# First implement the naive softmax loss function with nested loops.
# Open the file cs682/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from cs682.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: 2.380390
    sanity check: 2.302585
```

Inline Question 1:

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

Your answer: *Fill this in* we are randomly choosing the weight. and there are 10 classes. Thus 1/10 = 0.1. Then softmax is negative log of correct class so it should be -log(0.1)

```
# 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 cs682.gradient_check import grad_check_sparse
f = lambda w: softmax_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad, 10)

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

```
    numerical: 2.113222 analytic: 2.113222, relative error: 1.965548e-09
    numerical: 2.866574 analytic: 2.866574, relative error: 1.952073e-08
    numerical: 1.052833 analytic: 1.052833, relative error: 5.314986e-08
    numerical: -0.576809 analytic: -0.576809, relative error: 5.022772e-08
    numerical: -1.807631 analytic: -1.807631, relative error: 1.735709e-09
    numerical: 0.288020 analytic: 0.288020, relative error: 1.140964e-07
    numerical: -0.974598 analytic: -0.974599, relative error: 1.554736e-08
    numerical: -0.161012 analytic: -0.161012, relative error: 1.248374e-07
    numerical: 2.052838 analytic: 2.052838, relative error: 1.488718e-08
    numerical: 2.326535 analytic: 2.326535, relative error: 2.110845e-08
    numerical: -0.296948 analytic: -0.296948, relative error: 4.416220e-08
    numerical: -1.694056 analytic: -1.694056, relative error: 1.310197e-08
    numerical: -5.947198 analytic: -5.947198, relative error: 1.517616e-08
    numerical: 0.849790 analytic: 0.849790, relative error: 3.380211e-08
    numerical: -2.060484 analytic: -2.060484, relative error: 1.095442e-08
    numerical: 0.739698 analytic: 0.739698, relative error: 5.031210e-08
    numerical: 2.716700 analytic: 2.716700, relative error: 7.766654e-10
    numerical: 2.183422 analytic: 2.183422, relative error: 1.990771e-08
    numerical: -0.040212 analytic: -0.040212, relative error: 7.675146e-07
    numerical: 3.482904 analytic: 3.482904, relative error: 5.006637e-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 cs682.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: 2.428586e+00 computed in 0.315838s
vectorized loss: 2.428586e+00 computed in 0.011940s
Loss difference: 0.000000
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 cs682.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None
learning_rates = [1e-7, 5e-7]
regularization_strengths = [2.5e4, 5e4]

################################################################################
# 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.                          #
################################################################################
for lr in learning_rates:
    for rg in regularization_strengths:
        softmax = Softmax()
        loss_hist = softmax.train(X_train, y_train, learning_rate=lr, reg=rg,num_iters=2500, verbose=True)

        y_train_pred = softmax.predict(X_train)
        training_accuracy = np.mean(y_train == y_train_pred)

        y_val_pred = softmax.predict(X_val)
        val_accuracy = np.mean(y_val == y_val_pred)

        results[(lr, rg)] = (training_accuracy, val_accuracy)

        if val_accuracy > best_val:
            best_val = val_accuracy
            best_softmax  = softmax
################################################################################
#                              END OF YOUR CODE                                #
################################################################################

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

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

```
iteration 2000 / 2500: loss 2.123497
iteration 2100 / 2500: loss 2.059888
iteration 2200 / 2500: loss 2.106812
iteration 2300 / 2500: loss 2.118368
iteration 2400 / 2500: loss 2.076774
iteration 0 / 2500: loss 1525.595081
iteration 100 / 2500: loss 2.219132
iteration 200 / 2500: loss 2.191588
iteration 300 / 2500: loss 2.196552
iteration 400 / 2500: loss 2.113817
iteration 500 / 2500: loss 2.142515
iteration 600 / 2500: loss 2.154691
iteration 700 / 2500: loss 2.217821
iteration 800 / 2500: loss 2.118040
iteration 900 / 2500: loss 2.174904
iteration 1000 / 2500: loss 2.130939
iteration 1100 / 2500: loss 2.141013
iteration 1200 / 2500: loss 2.151378
iteration 1300 / 2500: loss 2.116897
iteration 1400 / 2500: loss 2.160720
iteration 1500 / 2500: loss 2.154827
iteration 1600 / 2500: loss 2.163227
iteration 1700 / 2500: loss 2.122324
iteration 1800 / 2500: loss 2.103601
iteration 1900 / 2500: loss 2.119792
iteration 2000 / 2500: loss 2.133706
iteration 2100 / 2500: loss 2.203348
iteration 2200 / 2500: loss 2.116891
iteration 2300 / 2500: loss 2.151702
iteration 2400 / 2500: loss 2.095236
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.333143 val accuracy: 0.348000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.301510 val accuracy: 0.315000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.323694 val accuracy: 0.339000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.304918 val accuracy: 0.322000
best validation accuracy achieved during cross-validation: 0.348000
```

```
# 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: 0.346000
```

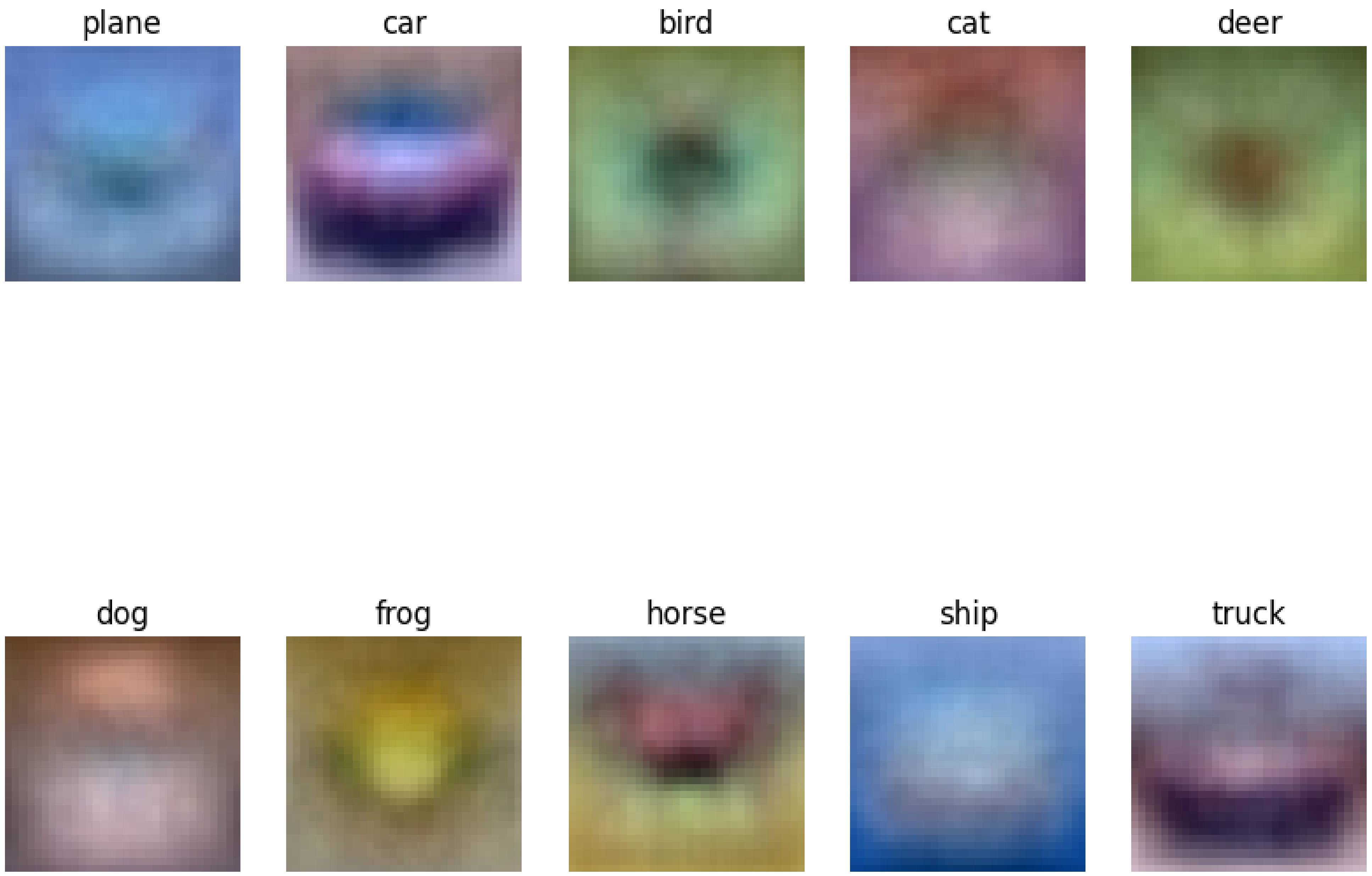
Inline Question - *True or False*

It's 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: for SVM loss if max(0,x) = 0 it would not change the svm loss. However, in softmax claisffeir, it uses exponetial function. So it would not reach to 0. Thus Softmax classifier loss will always 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])
```



Implementing a Neural Network

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

```
### IF YOU ARE USING COLAB, UNCOMMENT AND RUN THIS BLOCK FIRST ###

# # Mount google drive to allow access to your files
from google.colab import drive
drive.mount('/content/drive')
drive_folder = '/content/drive/MyDrive'
# # Ajust this line to be the assignment1 folder in your google drive
notebook_folder = drive_folder + '/cs682/assignment1'
%cd {notebook_folder}
```

```
Mounted at /content/drive
/content/drive/MyDrive/cs682/assignment1
```

```
# A bit of setup

from __future__ import print_function
import numpy as np
import matplotlib.pyplot as plt

from cs682.classifiers.neural_net import TwoLayerNet


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

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

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

We will use the class `TwoLayerNet` in the file `cs682/classifiers/neural_net.py` to represent instances of our network. The network parameters are stored in the instance variable `self.params` where keys are string parameter names and values are numpy arrays. Below, we initialize toy data and a toy model that we will use to develop your implementation.

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

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

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

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

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

Forward pass: compute scores

Open the file `cs682/classifiers/neural_net.py` and look at the method `TwoLayerNet.loss`. This function is very similar to the loss functions you have written for the SVM and Softmax exercises: It takes the data and weights and computes the class scores, the loss, and the gradients on the parameters.

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

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

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

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

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

Difference between your scores and correct scores:
3.6802720745909845e-08
```

Forward pass: compute loss

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

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

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

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

Backward pass

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

```
from cs682.gradient_check import eval_numerical_gradient

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

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

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

```
W2 max relative error: 3.440708e-09
b2 max relative error: 1.276038e-10
W1 max relative error: 3.669858e-09
b1 max relative error: 2.738422e-09
```

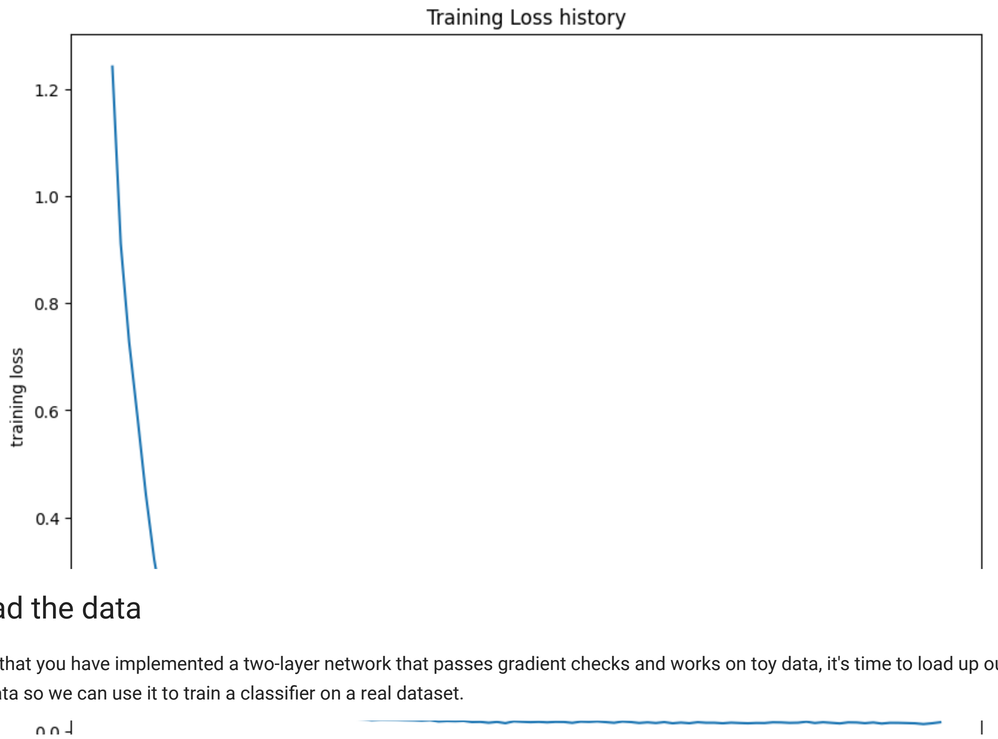
Train the network

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

Once you have implemented the method, run the code below to train a two-layer network on toy data. You should achieve a training loss less than 0.2.

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

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

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

```
Final training loss:  0.01714960793873202
```



Load the data

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

```
from cs682.data_utils import load_CIFAR10

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier. These are the same steps as
    we used for the SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs682/datasets/cifar-10-batches-py'

    # Don't forget to run get_datasets.sh, or this will throw an error
    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

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

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis=0)
    X_train -= mean_image
    X_val -= mean_image
    X_test -= mean_image
    # Reshape data to rows
    X_train = X_train.reshape(num_training, -1)
    X_val = X_val.reshape(num_validation, -1)
    X_test = X_test.reshape(num_test, -1)

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


# 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

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

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

Train a network

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

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

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

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

```
iteration 0 / 1000: loss 2.302954
iteration 100 / 1000: loss 2.302550
iteration 200 / 1000: loss 2.297648
iteration 300 / 1000: loss 2.259602
iteration 400 / 1000: loss 2.204170
iteration 500 / 1000: loss 2.118565
iteration 600 / 1000: loss 2.051535
iteration 700 / 1000: loss 1.988466
iteration 800 / 1000: loss 2.006591
iteration 900 / 1000: loss 1.951473
Validation accuracy:  0.287
```

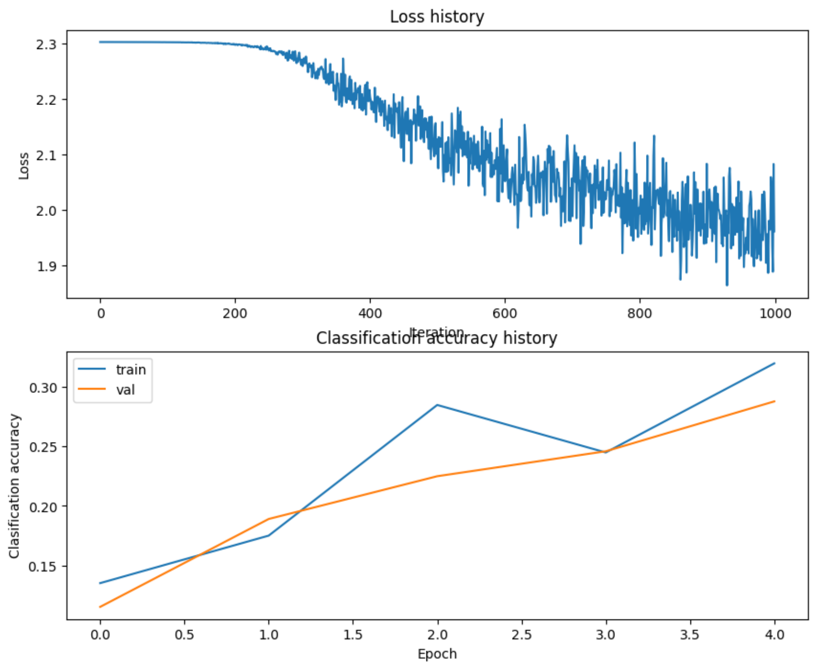
Debug the training

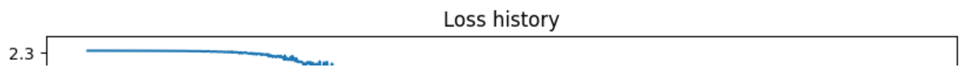
With the default parameters we provided above, you should get a validation accuracy of about 0.29 on the validation set. This isn't very good.

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

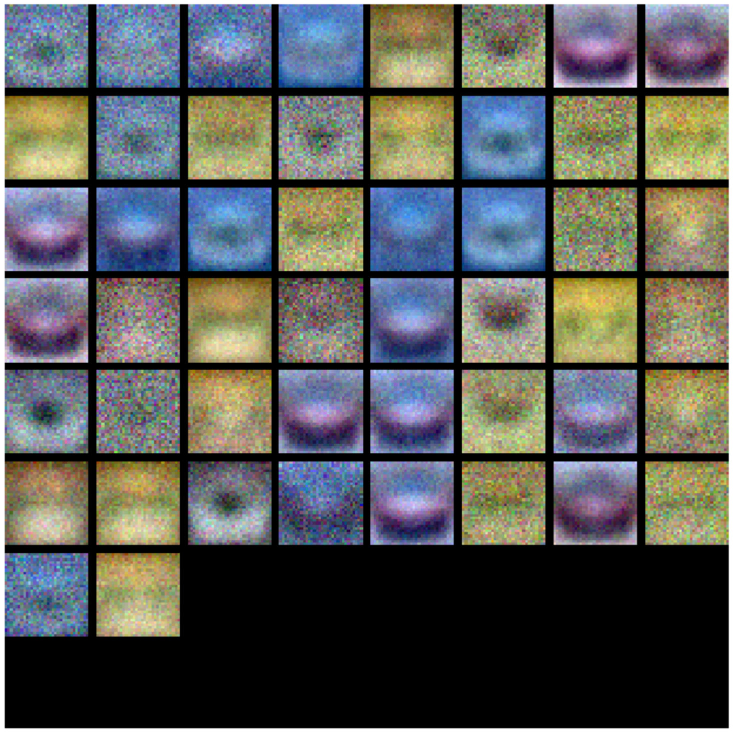
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

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

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





```
from cs682.vis_utils import visualize_grid

# Visualize the weights of the network

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

show_net_weights(net)
```



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.

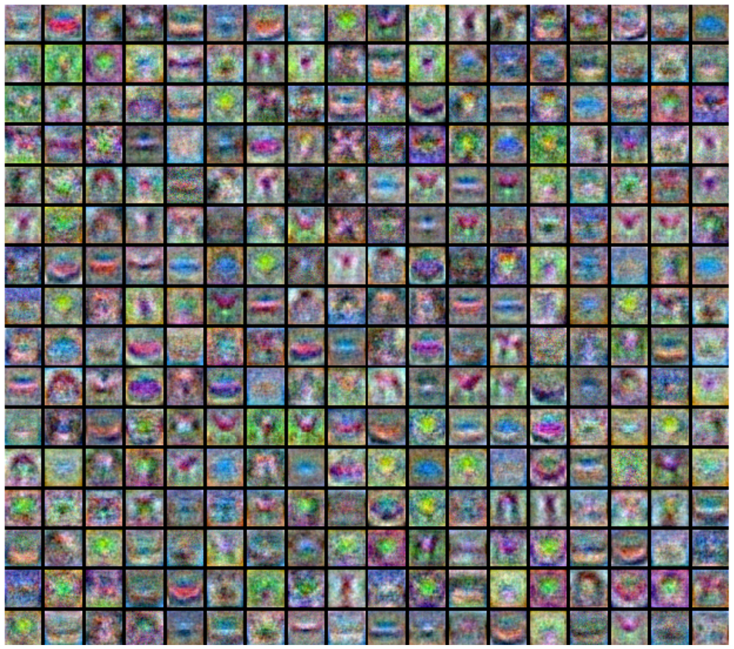
Approximate results. You should be aim to achieve a classification accuracy of greater than 48% on the validation set. Our best network gets over 52% on the validation set.

Experiment: You goal in this exercise is to get as good of a result on CIFAR-10 as you can, 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.).

```
best_net = None # store the best model into this

#################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained  #
# model in best_net.                                                            #
#                                                                               #
# To help debug your network, it may help to use visualizations similar to the  #
# ones we used above; these visualizations will have significant qualitative    #
# differences from the ones we saw above for the poorly tuned network.          #
#                                                                               #
# Tweaking hyperparameters by hand can be fun, but you might find it useful to  #
# write code to sweep through possible combinations of hyperparameters          #
# automatically like we did on the previous exercises.                          #
#################################################################################
# Your code
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
best_val = -1
learning_rates = [1e-5,1e-4,1e-3]
regularization_strengths = [0.001,0.025,0.05]
for hidden_size in [300]:
  for lr in learning_rates:
      for rg in regularization_strengths:
          net = TwoLayerNet(input_size, hidden_size, num_classes)

          stats = net.train(X_train, y_train, X_val, y_val,
                      num_iters=1000, batch_size=200,
                      learning_rate=lr, learning_rate_decay=0.95,
                      reg=rg, verbose=True)
          val_accuracy = (net.predict(X_val) == y_val).mean()
          print(val_accuracy,hidden_size,lr,rg)
          if val_accuracy > best_val:
              best_val = val_accuracy
              best_net  = net
#################################################################################
#                               END OF YOUR CODE                                #
#################################################################################
```

```
iteration 0 / 1000: loss 2.303095
iteration 100 / 1000: loss 1.896063
iteration 200 / 1000: loss 1.873373
iteration 300 / 1000: loss 1.613674
iteration 400 / 1000: loss 1.497376
iteration 500 / 1000: loss 1.545066
iteration 600 / 1000: loss 1.451363
iteration 700 / 1000: loss 1.423852
iteration 800 / 1000: loss 1.480607
iteration 900 / 1000: loss 1.565491
0.481 300 0.001 0.05
```

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



Run on the test set

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

```
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
    Test accuracy:  0.492
```

```
!bash collectSubmission.sh
```

```
adding: cs682/ (stored 0%)
adding: cs682/gradient_check.py (deflated 66%)
adding: cs682/__init__.py (stored 0%)
adding: cs682/features.py (deflated 60%)
adding: cs682/data_utils.py (deflated 67%)
adding: cs682/vis_utils.py (deflated 61%)
adding: cs682/classifiers/ (stored 0%)
adding: cs682/classifiers/__init__.py (deflated 38%)
adding: cs682/classifiers/linear_classifier.py (deflated 72%)
adding: cs682/classifiers/softmax.py (deflated 72%)
adding: cs682/classifiers/neural_net.py (deflated 72%)
adding: cs682/classifiers/k_nearest_neighbor.py (deflated 79%)
adding: cs682/classifiers/linear_svm.py (deflated 72%)
adding: knn.ipynb (deflated 28%)
adding: svm.ipynb (deflated 29%)
adding: softmax.ipynb (deflated 43%)
adding: features.ipynb (deflated 29%)
adding: two_layer_net.ipynb (deflated 25%)
adding: Untitled0.ipynb (deflated 37%)
```

Inline Question

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

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

Your answer: 1,3 *Your explanation:* training largerset make neural network classifier more general. plus it prevents overfiiting. while increasing the regularization strength, it will penalize the large value of weight so it prevents overffitting.

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.

```
### IF YOU ARE USING COLAB, UNCOMMENT AND RUN THIS BLOCK FIRST ###

# # Mount google drive to allow access to your files
from google.colab import drive
drive.mount('/content/drive')
drive_folder = '/content/drive/MyDrive'
# # Ajust this line to be the assignment1 folder in your google drive
notebook_folder = drive_folder + '/cs682/assignment1'
%cd {notebook_folder}
```

```
    Mounted at /content/drive
    /content/drive/MyDrive/cs682/assignment1
```

```
from __future__ import print_function
import random
import numpy as np
from cs682.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
```

Load data

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

```
from cs682.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 = 'cs682/datasets/cifar-10-batches-py'

    # Don't forget to run get_datasets.sh, or this will throw an error
    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

# 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_val, y_val, X_test, y_test = get_CIFAR10_data()
```

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 interests.

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.

```
from cs682.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 40000 / 49000 images
Done extracting features for 41000 / 49000 images
Done extracting features for 42000 / 49000 images
Done extracting features for 43000 / 49000 images
Done extracting features for 44000 / 49000 images
Done extracting features for 45000 / 49000 images
Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
```

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.

```
# Use the validation set to tune the learning rate and regularization strength

from cs682.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.       #
```

```
################################################################################
################################################################################


for lr in learning_rates:
    for rg in regularization_strengths:
        svm = LinearSVM()
        loss_hist = svm.train(X_train_feats, y_train, learning_rate=lr, reg=rg,num_iters=2500, verbose=True)
        y_train_pred = svm.predict(X_train_feats)
        training_accuracy = np.mean(y_train == y_train_pred)

        y_val_pred = svm.predict(X_val_feats)
        val_accuracy = np.mean(y_val == y_val_pred)

        results[(lr, rg)] = (training_accuracy, val_accuracy)

        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm
#                              END OF YOUR CODE
                       #


################################################################################

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

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

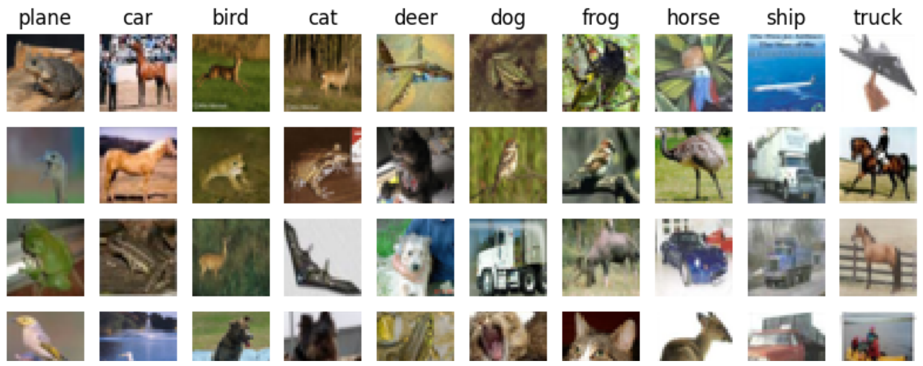
```
    iteration 1300 / 2500: loss 9.000001
    iteration 1400 / 2500: loss 8.999999
    iteration 1500 / 2500: loss 9.000001
    iteration 1600 / 2500: loss 9.000000
    iteration 1700 / 2500: loss 9.000000
    iteration 1800 / 2500: loss 8.999999
    iteration 1900 / 2500: loss 8.999999
    iteration 2000 / 2500: loss 9.000001
    iteration 2100 / 2500: loss 9.000000
    iteration 2200 / 2500: loss 9.000001
    iteration 2300 / 2500: loss 9.000000
    iteration 2400 / 2500: loss 9.000001
    lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.099306 val accuracy: 0.089000
    lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.109571 val accuracy: 0.112000
    lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.415061 val accuracy: 0.417000
    lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.118633 val accuracy: 0.132000
    lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.411878 val accuracy: 0.417000
    lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.412388 val accuracy: 0.410000
    lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.411102 val accuracy: 0.410000
    lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.407592 val accuracy: 0.402000
    lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.317163 val accuracy: 0.330000
    best validation accuracy achieved during cross-validation: 0.417000
```

```
# Evaluate your trained SVM on the test set
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print(test_accuracy)
```

```
    0.412
```

```
# 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()
```



Inline question 1:

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

most of the images does not match with classes. This make sense since result is based on the weights.

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.

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

print(X_train_feats.shape)
```

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

```
from cs682.classifiers.neural_net import TwoLayerNet

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

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

################################################################################
# TODO: Train a two-layer neural network on image features. You may want to    #
# cross-validate various parameters as in previous sections. Store your best   #
# model in the best_net variable.                                              #
################################################################################
# Your code

input_size = X_train_feats.shape[1]
```

```
num_classes = 10
best_val = -1
learning_rates = [0.1,0.2,0.3]
regularization_strengths =[1e-5,2e-5,3e-5]
for hidden_size in [600]:
  for lr in learning_rates:
      for rg in regularization_strengths:
          net = TwoLayerNet(input_size, hidden_size, num_classes)
          stats = net.train(X_train_feats, y_train, X_val_feats, y_val,num_iters=1000, batch_size=200,learning_rate=lr, learning_rate_decay=0.95,reg=rg, verbose=True)
          val_accuracy = (net.predict(X_val_feats) == y_val).mean()
          print(val_accuracy,hidden_size,lr,rg)
          if val_accuracy > best_val:
              best_val = val_accuracy
              best_net  = net
################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

```
iteration 800 / 1000: loss 1.242217
iteration 900 / 1000: loss 1.339241
0.537 600 0.2 1e-05
iteration 0 / 1000: loss 2.302585
iteration 100 / 1000: loss 2.150662
iteration 200 / 1000: loss 1.562770
iteration 300 / 1000: loss 1.434962
iteration 400 / 1000: loss 1.297404
iteration 500 / 1000: loss 1.379612
iteration 600 / 1000: loss 1.258820
iteration 700 / 1000: loss 1.360886
```

```
    iteration 500 / 1000: loss 1.336110
    iteration 600 / 1000: loss 1.182101
    iteration 700 / 1000: loss 1.112011
    iteration 800 / 1000: loss 1.295048
    iteration 900 / 1000: loss 1.297772
    0.556 600 0.3 3e-05
```

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

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

```
    0.56
```