knn

April 30, 2023

1 k-Nearest Neighbor (kNN) exercise

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

The kNN classifier consists of two stages:

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

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

[1]:
```
from google.colab import drive
drive.mount('/content/drive' , force_remount=True)


#enter your foldername assignments/assignement1
FOLDERNAME = 'CV7062610/assignments/assignment1/'

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

import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

#this will download the CIFAR-10 dataset to your drive
#if it isnt already there

%cd drive/My\ Drive/$FOLDERNAME/CV7062610/datasets/
!bash get_datasets.sh
%cd /content
```

```
Mounted at /content/drive
/content/drive/My Drive/CV7062610/assignments/assignment1/CV7062610/datasets
--2023-04-09 15:23:29--  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  40.2MB/s    in 4.1s

2023-04-09 15:23:34 (40.0 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
```

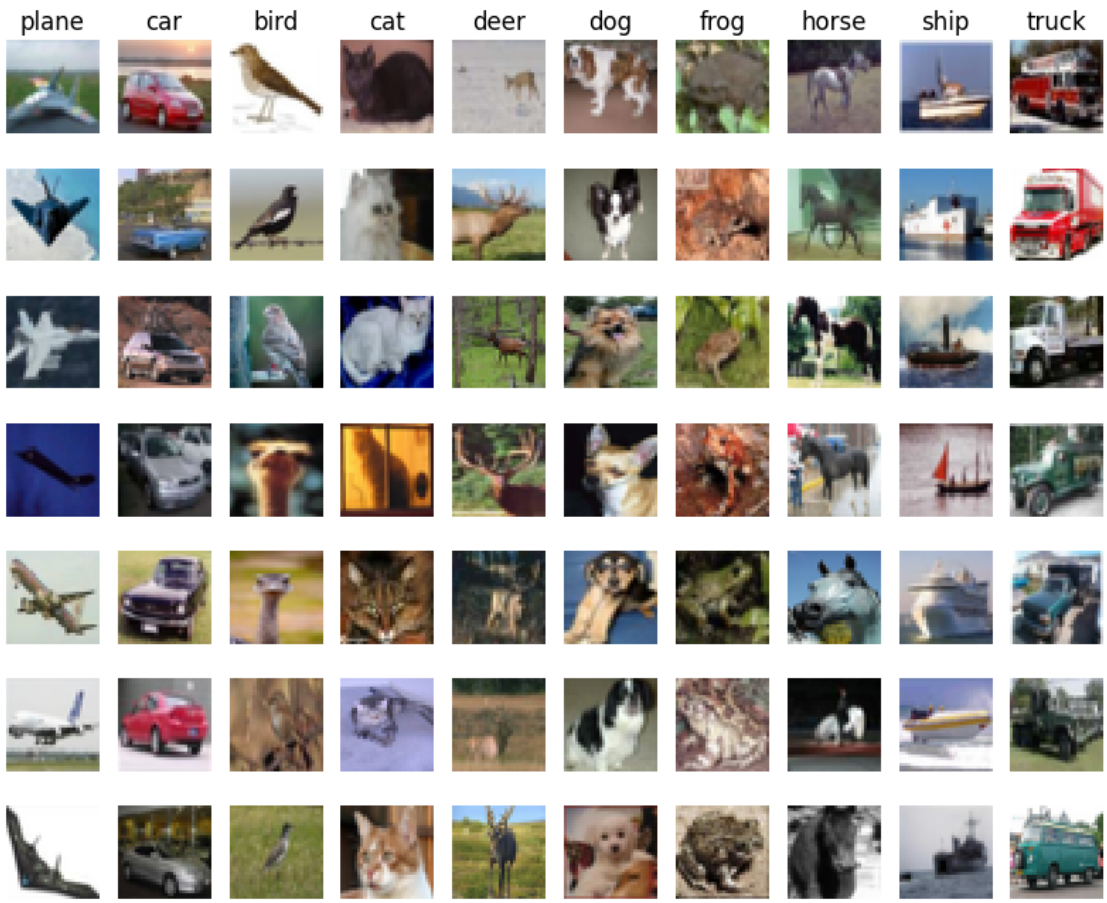
[ ]:
```
# Run some setup code for this notebook.

import random
import numpy as np
from CV7062610.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 = '/content/drive/MyDrive/' + FOLDERNAME + '/CV7062610/datasets/
↪cifar-10-batches-py'
```

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

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

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

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

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



[ ]:
```
# 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
# The -1 in the second dimension tells NumPy to calculate the number
# of columns automatically so that the total number of elements in the
# resulting matrix is the same as in the original matrix.
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 CV7062610.classifiers import KNearestNeighbor

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

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

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

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

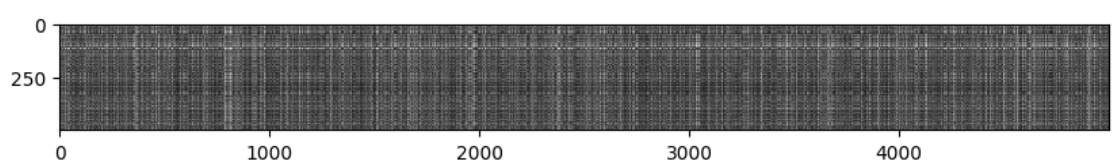
Note: For the three distance computations that we require you to implement in this notebook, you may not use the np.linalg.norm() function that numpy provides.

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

[ ]:
```
# Open CV7062610/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()
```



** *italicized text*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?

YourAnswer : fill this in.

There are 500 test examples, each represented test represents a row, and 5,000 training examples represented as columns in the plot above. Each cell in that matrix store the Euclidean distance between a single test example to the corresponding train example. As the test dot is more distant from the corresponding train dot, the cell gets a brighter representation in the plot. Therefore, if some row appears distinctly brighter, it means that the test example is very distant from all/most of the train ones. It can also happen if the test examples come from a different distribution. Moreover, it can also indicate that the features used to represent the data are not well-suited for the task. Therefore, indicate that the metric formed from them is not appropriate.

About the columns, as I explained, the columns can provide information about how well the training examples match the test examples in terms of their features and overall distribution.

[ ]:
```
# 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`.

Inline Question 2

We can also use other distance metrics such as L1 distance. For pixel values $p_{ij}^{(k)}$ at location (i, j) of some image I_k,

the mean μ across all pixels over all images is

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

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

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

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

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

YourAnswer : 1, 2, 3

YourExplanation :

In both cases 1,2, subtracting the mean or the per-pixel mean ij from the data will shift the pixel values for all images by the same amount, But the relative differences between the pixel values would remain the same. Therefore, the performance of NN classifier will not change.

mathematical explaintion:

$$L1_{case1} = \frac{1}{n} \sum_{k=1}^{n} ||(x_{test} - \mu) - (x_{train}^{(k)} - \mu)||_1$$

$$L1_{case2} = \frac{1}{nhw} \sum_{k=1}^{n} \sum_{i=1}^{h} \sum_{j=1}^{w} ||(p_{ij} - \mu_{ij}) - (p_{ij}^{(k)} - \mu_{ij})||_1$$

As we can see, the mean reduces and we are left with the same L1 calculation as before. Therefore, the performence of the NN classifier should remain the same.

In case 3, subtracting the mean and dividing it by the standard deviation will normalize the pixel values across all images. However, it will not change the relative differences between the pixel values. Hence, the L1 distance between two images will remain the same.

In case 4, subtracting the pixel-wise mean ij and dividing by the pixel-wise standard deviation ij is a common normalization technique called "pixel-wise normalization". This technique is used to normalize each pixel value in an image independently based on its mean and standard deviation across all images. However, in our case, it will change L1 distance between images. As I explained above subtracting only the pixel-wise mean will not change the distance between the pixel values, but it is also divided by ij. Therefore, pixel-wise normalization will change the L1 distance between images, and it will affect the performance of the NN classifier that uses L1 distance.

in case 5, Rotating the coordinate axes of the data can change the relative position of data points in the feature space. Therefore, it can affect the L1 distance between images.

Example: let's consider two images I1 and I2 with corresponding pixel values p1 and p2 at location (i,j). The L1 distance between these two images is given by:

L1_distance = |p1(i,j) - p2(i,j)|

Now, let's assume that we rotate the coordinate axes of the data by 45 degrees. This rotation will change the orientation of the axes, so that the vertical and horizontal pixel values are no longer aligned with the coordinate axes. Instead, the new axes will be at 45 degrees to the original axes.

As a result, the pixel values for each image will change. Specifically, the pixel values for each location (i,j) will now be a linear combination of the original pixel values, since they will be projected onto the new axes. Therefore, the L1 distance between the rotated images I1' and I2' will be different from the original L1 distance between the images I1 and I2. Hence, it will affect the performance of a NN classifier that uses L1 distance.

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

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

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

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

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

```
No loop difference was: 0.000000
```

```
Good! The distance matrices are the same
```

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

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

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

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

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

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

```
Two loop version took 41.259520 seconds
One loop version took 37.129691 seconds
No loop version took 0.563105 seconds
```

1.0.1 Cross-validation

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

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

X_train_folds = []
y_train_folds = []
################################################################################
# TODO:                                                                        #
# Split up the training data into folds. After splitting, X_train_folds and    #
# y_train_folds should each be lists of length num_folds, where                #
```

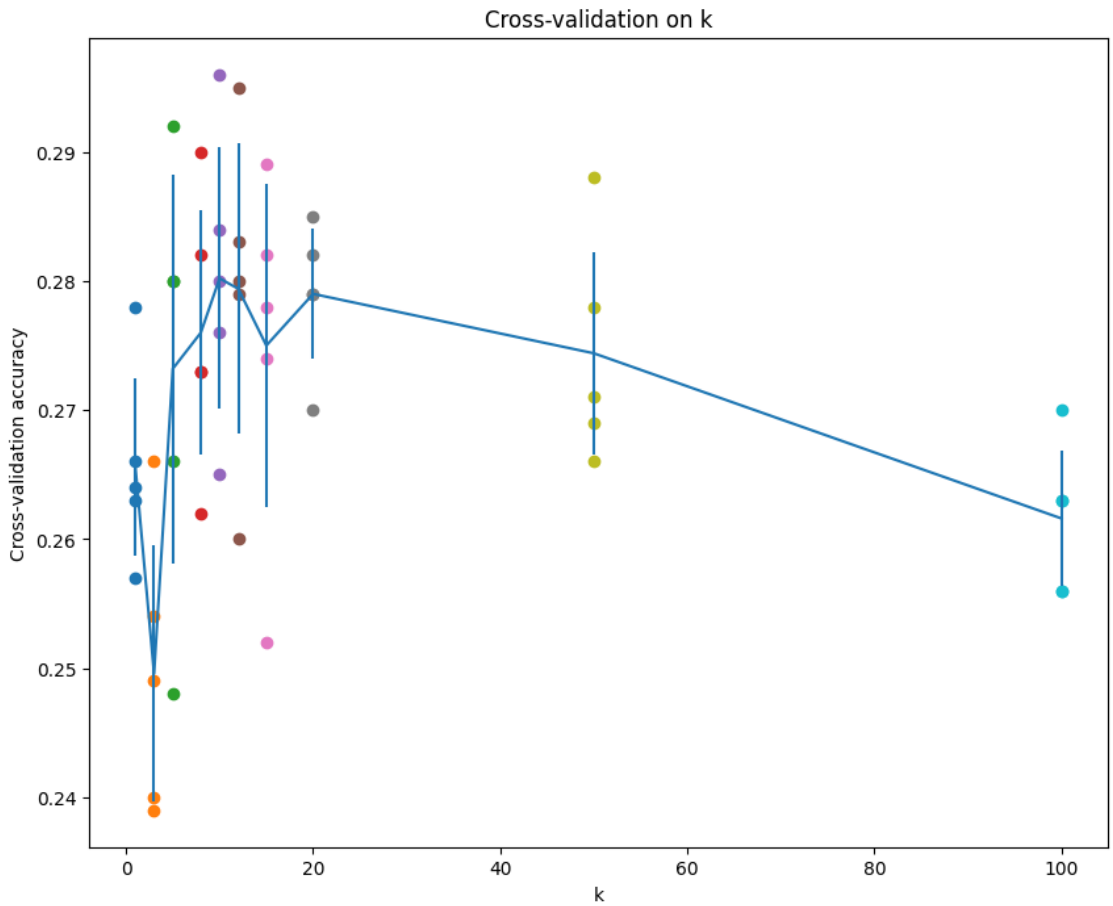
```
# y_train_folds[i] is the label vector for the points in X_train_folds[i].     #
# Hint: Look up the numpy array_split function.                                #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

X_train_folds = np.array_split(X_train, num_folds)
y_train_folds = np.array_split(y_train, num_folds)

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

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


################################################################################
# TODO:                                                                        #
# Perform k-fold cross validation to find the best value of k. For each        #
# possible value of k, run the k-nearest-neighbor algorithm num_folds times,   #
# where in each case you use all but one of the folds as training data and the #
# last fold as a validation set. Store the accuracies for all fold and all     #
# values of k in the k_to_accuracies dictionary.                               #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

for k in k_choices:
    k_to_accuracies[k] = []
    for fold_idx in range(num_folds):
        # Split the data into training and validation sets
        X_train = np.concatenate([X_train_folds[i] for i in range(num_folds) if␣
 ↪i != fold_idx])
        y_train = np.concatenate([y_train_folds[i] for i in range(num_folds) if␣
 ↪i != fold_idx])
        X_val = X_train_folds[fold_idx]
        y_val = y_train_folds[fold_idx]

        # Train a k-NN classifier on the training data
        classifier.train(X_train, y_train)

        # Predict labels for the validation set
        y_pred = classifier.predict(X_val, k=k)

        # Compute the accuracy of the classifier on the validation set
        num_correct = np.sum(y_pred == y_val)
        accuracy = float(num_correct) / y_val.shape[0]
```

```python
        k_to_accuracies[k].append(accuracy)

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

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

```
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 = 12

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 142 / 500 correct => accuracy: 0.284000
```

Inline Question 3

Which of the following statements about k-Nearest Neighbor (k-NN) are true in a classification setting, and for all k? Select all that apply. 1. The decision boundary of the k-NN classifier is

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

YourAnswer : 2, 4

YourExplanation :

1. The decision boundary of the k-NN classifier is not necessarily linear. It depends on the distribution of the data.
2. The training error of a 1-NN will always be 0, since the closest point to a training example is itself. Therefore, it will always be lower.
3. The test error may be higher than that of a 5-NN, since a 1-NN is more susceptible to noise in the data.
4. The time needed to classify a test example with the k-NN classifier grows with the size of the training set, since the algorithm needs to compute distances to all training examples.

[ ]:

```
```

softmax

April 30, 2023

1 Softmax exercise

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

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

- implement a fully-vectorized **loss function** for the Softmax classifier
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** with numerical gradient
- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

[1]:
```
from google.colab import drive
drive.mount('/content/drive' , force_remount=True)


#enter your foldername assignments/assignement1
FOLDERNAME = 'CV7062610/assignments/assignment1/'

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

import sys
sys.path.append('/content/drive/MyDrive/{}'.format(FOLDERNAME))

#this will download the CIFAR-10 dataset to your drive
#if it isnt already there

%cd drive/My\ Drive/$FOLDERNAME/CV7062610/datasets/
!bash get_datasets.sh
%cd /content
```

```
Mounted at /content/drive
/content/drive/My Drive/CV7062610/assignments/assignment1/CV7062610/datasets
--2023-04-26 10:15:46--  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  16.1MB/s    in 11s

2023-04-26 10:15:58 (14.3 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
```

[ ]:
```
import random
import numpy as np
from CV7062610.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
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

2 New Section

[ ]:
```
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 = '/content/drive/MyDrive/' + FOLDERNAME + '/CV7062610/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,)
```

2.1 Softmax Classifier

Your code for this section will all be written inside `CV7062610/classifiers/softmax.py`.

[ ]:
```
# First implement the naive softmax loss function with nested loops.
# Open the file CV7062610/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from CV7062610.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: 2.324480
sanity check: 2.302585
```

Inline Question 1

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

Your Answer :

We have 10 classes, so a random guess for the correct class would be correct with probability 1/10. Since we are using the cross-entropy loss, which is equivalent to the negative log likelihood, we expect the loss for a random guess to be close to -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 CV7062610.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: -3.683274 analytic: -3.683274, relative error: 1.713556e-08
numerical: 1.453356 analytic: 1.453356, relative error: 7.558492e-08
numerical: 0.329022 analytic: 0.329022, relative error: 1.108124e-07
numerical: 4.909565 analytic: 4.909565, relative error: 1.688719e-08
numerical: -0.032706 analytic: -0.032706, relative error: 8.757724e-07
numerical: 1.694612 analytic: 1.694612, relative error: 3.747667e-08
numerical: -3.237550 analytic: -3.237550, relative error: 1.122994e-09
numerical: 1.490228 analytic: 1.490228, relative error: 2.026406e-08
numerical: -1.213774 analytic: -1.213774, relative error: 5.734681e-08
numerical: -0.666416 analytic: -0.666416, relative error: 6.682627e-08
numerical: -2.534233 analytic: -2.534233, relative error: 3.130104e-09
numerical: -1.019083 analytic: -1.019083, relative error: 5.915665e-08
numerical: -0.002750 analytic: -0.002750, relative error: 3.134136e-06
numerical: -1.165249 analytic: -1.165249, relative error: 2.089053e-08
numerical: 2.116484 analytic: 2.116484, relative error: 2.864828e-08
numerical: -1.813540 analytic: -1.813540, relative error: 3.132238e-08
numerical: 0.063807 analytic: 0.063807, relative error: 7.310007e-07
numerical: -0.792398 analytic: -0.792398, relative error: 2.480717e-08
numerical: -0.335738 analytic: -0.335739, relative error: 8.327640e-08
numerical: -0.553695 analytic: -0.553695, relative error: 1.325868e-08
```

[ ]:
```
# 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 CV7062610.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: 2.324480e+00 computed in 0.107084s
vectorized loss: 2.324480e+00 computed in 0.015082s
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 CV7062610.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None

################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# save the best trained softmax classifer in best_softmax.                     #
################################################################################

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

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


# Loop over all hyperparameter combinations
for lr in learning_rates:
    for reg in regularization_strengths:
        # Train a Softmax classifier with the current hyperparameters
        softmax_model  = Softmax()
        softmax_model.train(X_train, y_train, learning_rate=lr, reg=reg,␣
 ↪num_iters=1500)

        # Evaluate the classifier on the training and validation sets
        train_accuracy = np.mean(softmax_model.predict(X_train) == y_train)
        val_accuracy = np.mean(softmax_model.predict(X_val) == y_val)

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

        # Update the best validation accuracy and best classifier
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_softmax = 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 1.000000e-07 reg 2.500000e+04 train accuracy: 0.351449 val accuracy: 0.363000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.330000 val accuracy: 0.345000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.351776 val accuracy: 0.371000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.321816 val accuracy: 0.340000
best validation accuracy achieved during cross-validation: 0.371000
```

[ ]:
```
# 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: 0.351000
```

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

[ ]:
```

```

two_layer_net

April 30, 2023

1 Implementing a Neural Network

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

[3]:
```
# A bit of setup

import numpy as np
import matplotlib.pyplot as plt

from CV7062610.classifiers.neural_net import TwoLayerNet

# configures Jupyter Notebook to display Matplotlib plots inline within the␣
↪notebook.
%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

#  takes two NumPy arrays x and y as input and returns the maximum absolute␣
↪difference
# between them, divided by the maximum absolute value of either array.
# This measures the relative error between x and y, which is useful for␣
↪comparing
# floating point numbers that may not be exactly equal due to rounding errors.
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))))
```

[2]:
```
from google.colab import drive
drive.mount('/content/drive' , force_remount=True)
#enter your foldername assignments/assignement1
```

```
FOLDERNAME = 'CV7062610/assignments/assignment1/'

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

import sys
sys.path.append('/content/drive/MyDrive/{}'.format(FOLDERNAME))
```

```
Mounted at /content/drive
```

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

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

3 Forward pass: compute scores

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

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

[5]:
```
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
```

4 Forward pass: compute loss

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

[6]:
```
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:
1.7985612998927536e-13
```

5 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:

[7]:
```
from CV7062610.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: 4.447646e-11
W1 max relative error: 3.561318e-09
b1 max relative error: 2.738421e-09
```

6 Train the network

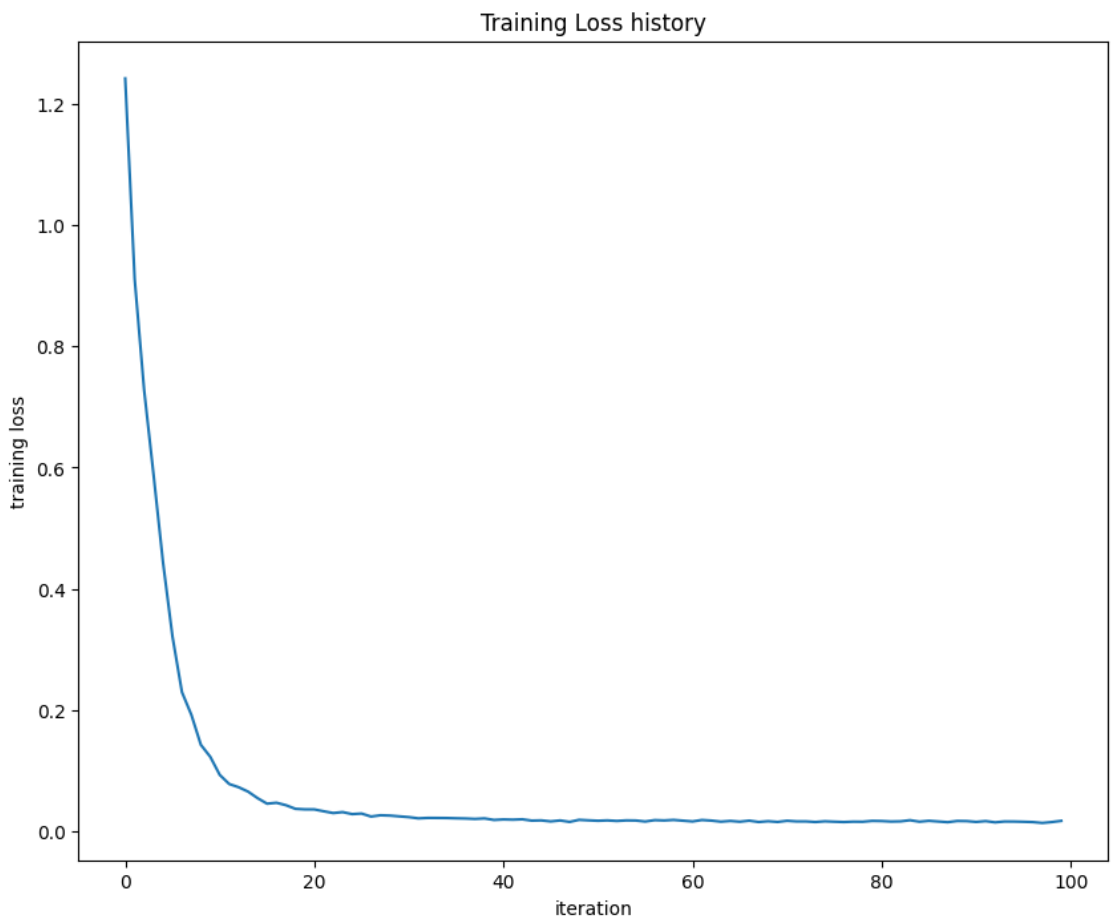
To train the network we will use stochastic gradient descent (SGD), similar to the SVM and Softmax classifiers. Look at the function `TwoLayerNet.train` and fill in the missing sections to implement the training procedure. This should be very similar to the training procedure you used for the SVM and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

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

[8]:
```
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:  0.017149607938732048
```



7 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.

[9]:
```
from CV7062610.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 = '/content/drive/MyDrive/CV7062610/assignments/assignment1/
↪CV7062610/datasets/cifar-10-batches-py'

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

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

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

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

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

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


# 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,)
```

8 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.

[10]:
```
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
```

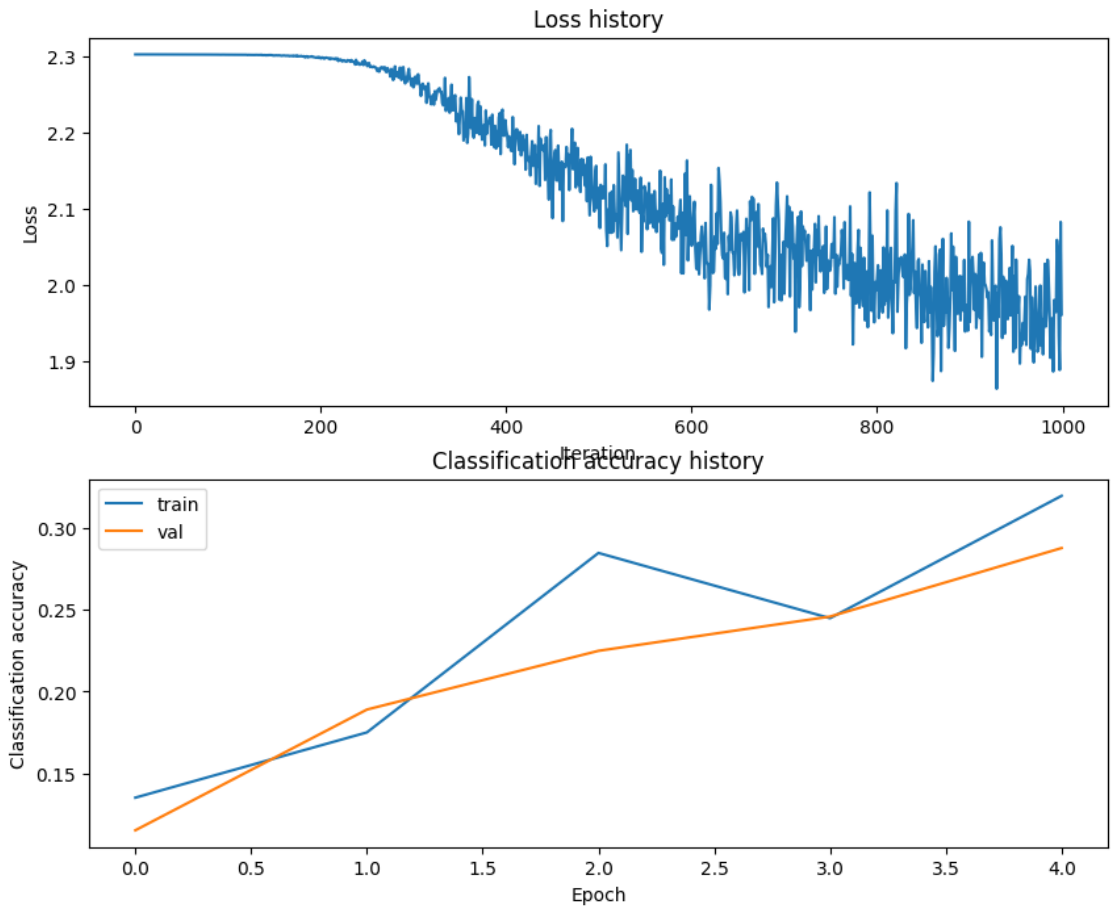
9 Debug the training

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.

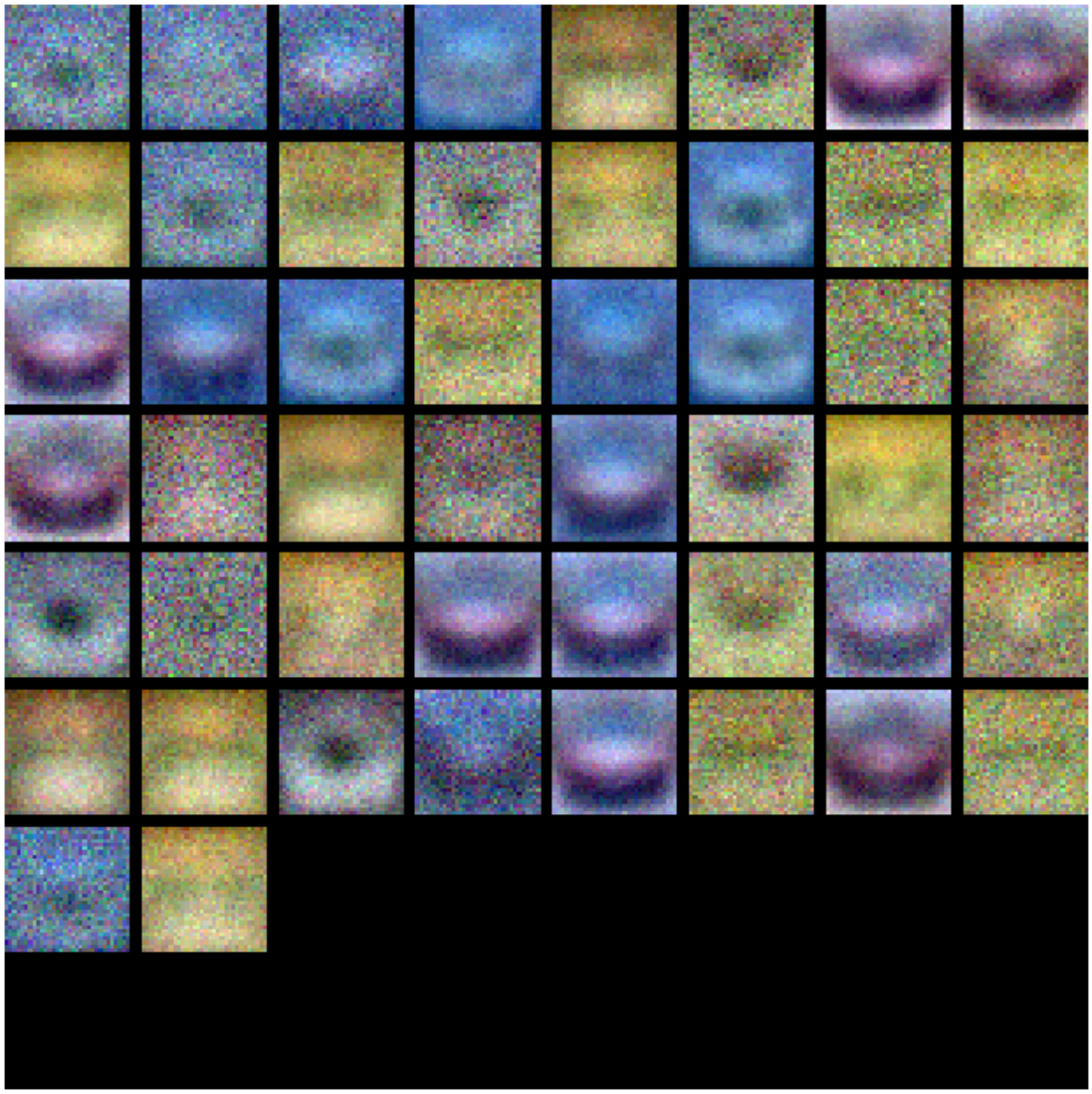
One strategy for getting insight into what's wrong is to plot the loss function and the accuracies on the training and validation sets during optimization.

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.

[11]:
```
# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

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



[12]:
```
from CV7062610.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)
```



10 Tune your hyperparameters

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

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

tuning the learning rate decay, but you should be able to get good performance using the default value.

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

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

Explain your hyperparameter tuning process below.

$Your Answer:$

Learning rate:

Controls how fast the weights of the neural network are updated during training. If the learning rate is too high, the updates can be too large, causing the network to overshoot the optimal weights and potentially diverge. On the other hand, if the learning rate is too low, the network may converge very slowly or not at all. I chose a range of learning rates that are relatively small to avoid overshooting the optimal weights, but not too small to ensure that the network converges in a reasonable amount of time.

Regularization strength:

Regularization is a technique used to prevent overfitting by adding a penalty term to the loss function. The penalty term discourages the weights from taking on large values, which can lead to overfitting. I chose to test three different regularization strengths. These values are relatively small and should be effective at preventing overfitting without overly constraining the weights.

Hidden layer size:

Determines the number of neurons in the layer, which in turn controls the complexity of the model. Too few neurons can lead to underfitting, while too many neurons can lead to overfitting. I chose to test three different hidden layer sizes. These values are relatively large and should provide enough capacity for the network to learn complex representations of the data without overfitting

Number of epochs:

Determines how many times the training data is passed through the network during training. Too few epochs can lead to underfitting, while too many epochs can lead to overfitting. I chose to test three different numbers. These values are relatively large and should provide enough time for the network to converge to a good solution without overfitting the training data.

[13]:
```
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   #
```

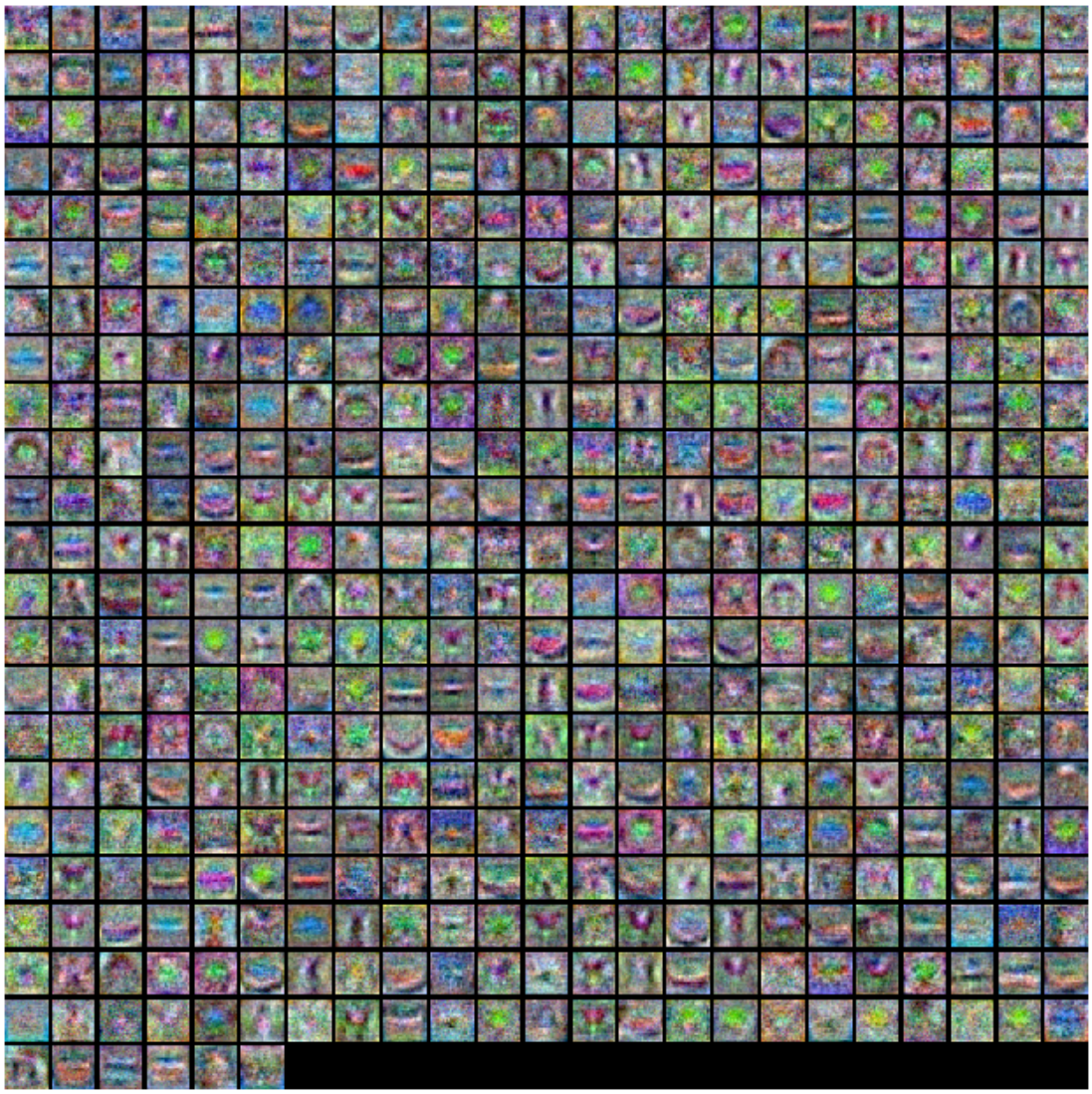
```python
# differences from the ones we saw above for the poorly tuned network.         #
#                                                                               #
# Tweaking hyperparameters by hand can be fun, but you might find it useful to #
# write code to sweep through possible combinations of hyperparameters        #
# automatically like we did on the previous exercises.                          #
#################################################################################

best_val_acc = -1

learning_rates = [0.0005, 0.001, 0.002]
regularization_strengths = [0.001, 0.005, 0.01]
hidden_sizes = [128, 256, 512]
num_epochs = [500, 1000, 1500]

for lr in learning_rates:
    for reg in regularization_strengths:
        for hidden_size in hidden_sizes:
            for epochs in num_epochs:
                net = TwoLayerNet(input_size, hidden_size, num_classes)
                stats = net.train(X_train, y_train, X_val, y_val,
                                  num_iters=epochs,
                                  batch_size=200,
                                  learning_rate=lr,
                                  learning_rate_decay=0.95,
                                  reg=reg)
                val_acc = (net.predict(X_val) == y_val).mean()
                if val_acc > best_val_acc:
                    best_val_acc = val_acc
                    best_net = net
                    print(f"lr {lr:.6f} reg {reg:.6f} hidden_size {hidden_size:
 ↪d} "
                          f"epochs {epochs:d} val accuracy: {val_acc:.6f}")
print(f"Best validation accuracy achieved during cross-validation:␣
 ↪{best_val_acc:.6f}")
```

```
lr 0.000500 reg 0.001000 hidden_size 128 epochs 500 val accuracy: 0.416000
lr 0.000500 reg 0.001000 hidden_size 128 epochs 1000 val accuracy: 0.454000
lr 0.000500 reg 0.001000 hidden_size 128 epochs 1500 val accuracy: 0.463000
lr 0.000500 reg 0.001000 hidden_size 256 epochs 1000 val accuracy: 0.464000
lr 0.000500 reg 0.001000 hidden_size 256 epochs 1500 val accuracy: 0.466000
lr 0.000500 reg 0.001000 hidden_size 512 epochs 1000 val accuracy: 0.479000
lr 0.000500 reg 0.005000 hidden_size 512 epochs 1500 val accuracy: 0.480000
lr 0.000500 reg 0.010000 hidden_size 256 epochs 1500 val accuracy: 0.489000
lr 0.001000 reg 0.001000 hidden_size 128 epochs 1500 val accuracy: 0.509000
lr 0.001000 reg 0.001000 hidden_size 512 epochs 1500 val accuracy: 0.520000
Best validation accuracy achieved during cross-validation: 0.520000
```

[14]:
```
# Print your validation accuracy: this should be above 48%
val_acc = (best_net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

```
Validation accuracy:  0.52
```

[15]:
```
# Visualize the weights of the best network
show_net_weights(best_net)
```



11 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%.

[16]:
```
# Print your test accuracy: this should be above 48%
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.514
```

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.

YourAnswer : 1, 3

YourExplanation :

One reason for the gap is overfitting. Overfitting occurs when a model learns to fit the training data too closely, including the noise and random variations in the data, instead of learning the underlying patterns that generalize to new data.

Train on a larger dataset:

If we will train on a larger dataset, we can reduce the chance of overfitting as the model is exposed to a more diverse set of examples, making it more likely to learn generalizable patterns.

Add more hidden units:

Adding more hidden units can increase the capacity of the model to fit the training data more closely, which may lead to overfitting and a larger gap between training and testing accuracy. However, there are cases where adding more hidden units can improve the performance of the model on the test set, especially if the model is underfitting the training data.

Increase the regularization strength:

Regularization techniques can be used to prevent overfitting by adding a penalty term to the loss function. This penalty term encourages the model to learn simpler patterns that generalize better to new data. By increasing the strength of the regularization, we can further encourage the model to learn those simpler patterns that are less likely to overfit to the training data.

[ ]:
```

```