CS280 Fall 2022 Assignment 1
Part A

Basics & MLP

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1. *Gradient descent for fitting GMM* (10 points).

Consider the Gaussian mixture model

$$p(\mathbf{x}|\theta) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

where $\pi_j \geq 0, \sum_{j=1}^{K} \pi_j = 1$. (Assume $\mathbf{x}, \boldsymbol{\mu}_k \in \mathbb{R}^d, \boldsymbol{\Sigma}_k \in \mathbb{R}^{d\times d}$)

Define the log likelihood as

$$l(\theta) = \sum_{n=1}^{N} \log p(\mathbf{x}_n|\theta)$$

Denote the posterior responsibility that cluster k has for datapoint n as follows:

$$r_{nk} := p(z_n = k|\mathbf{x}_n, \theta) = \frac{\pi_k \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{k'} \pi_{k'} \mathcal{N}(\mathbf{x}_n|\boldsymbol{\mu}_{k'}, \boldsymbol{\Sigma}_{k'})}$$

(a) Show that the gradient of the log-likelihood wrt $\boldsymbol{\mu}_k$ is

$$\frac{d}{d\boldsymbol{\mu}_k} l(\theta) = \sum_n r_{nk} \boldsymbol{\Sigma}_k^{-1}(\mathbf{x}_n - \boldsymbol{\mu}_k)$$

Proof. By the *chain rule*, we have

$$\begin{aligned}
\frac{\partial l(\theta)}{\partial \boldsymbol{\mu}_k} &= \sum_{n=1}^{N} \frac{1}{p(\boldsymbol{x}_n|\theta)} \frac{\partial p(\boldsymbol{x}_n|\theta)}{\partial \boldsymbol{\mu}_k} \\
&= \sum_{n=1}^{N} \frac{1}{p(\boldsymbol{x}_n|\theta)} \frac{\partial \pi_k \mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\partial \boldsymbol{\mu}_k} \\
&= \sum_{n=1}^{N} \frac{\pi_k \mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{p(\boldsymbol{x}_n|\theta)} \frac{\partial(-\frac{1}{2}(\boldsymbol{x}_n - \boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}_n - \boldsymbol{\mu}_k))}{\partial \boldsymbol{\mu}_k} \\
&= \sum_{n=1}^{N} r_{nk} \boldsymbol{\Sigma}^{-1}(\boldsymbol{x}_n - \boldsymbol{\mu}_k)
\end{aligned}$$

■

(b) Derive the gradient of the log-likelihood wrt π_k without considering any constraint on π_k. (bonus 2 points: with constraint $\sum_k \pi_k = 1$.)

Proof. For the case without any constriant on π_k, by the *chain rule*, we have:

$$\begin{aligned}
\frac{\partial l(\theta)}{\partial \pi_k} &= \sum_{n=1}^{N} \frac{1}{p(\boldsymbol{x}_n|\theta)} \frac{\partial p(\boldsymbol{x}_n|\theta)}{\partial \pi_k} \\
&= \sum_{n=1}^{N} \frac{1}{p(\boldsymbol{x}_n|\theta)} \mathcal{N}(\boldsymbol{x}_n|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \\
&= \sum_{n=1}^{N} \frac{r_{nk}}{\pi_k}
\end{aligned}$$

■

2. *Sotfmax & Computation Graph* (10 points).

Recall that the softmax function takes in a vector $(z_1, \dots, z_D)$ and returns a vector $(y_1, \dots, y_D)$. We can express it in the following form:

$$r = \sum_j e^{z_j} \qquad y = \frac{e^{z_j}}{r}$$

(a) Consider $D = 2$, i.e. just two inputs and outputs to the softmax. Draw the computation graph relating z_1, z_2, r, y_1, and y_2.

Solution:

$$\begin{tikzcd}
z_1 \arrow[rr] \arrow[dr] & & y_1 \\
& r \arrow[ur] \arrow[dr] & \\
z_2 \arrow[rr] \arrow[ur] & & y_2
\end{tikzcd}$$

(b) Determine the backprop updates for computing the $\bar{z}_j$ when given the $\bar{y}_i$. You need to justify your answer. (You may give your answer either for $D = 2$ or for the more general case.)

Solution:

By the *chain rule* and the forward precess, we have the backprop updates as follows:

$$\bar{r} = \sum_{i=1}^{D} \bar{y}_i \frac{\partial y_i}{\partial r} = -\sum_{i=1}^{D} \bar{y}_i \frac{e^{z_i}}{r^2}$$

$$\bar{z}_i = \bar{y}_i \frac{\partial y_i}{\partial z_i} + \bar{r} \frac{\partial r}{\partial z_i} = \bar{y}_i \frac{e^{z_i}}{r} + \bar{r} e^{z_i}$$

(c) Write a function to implement the vector-Jacobian product (VJP) for the softmax function based on your answer from part (b). For efficiency, it should operate on a mini-batch. The inputs are:

- a matrix $\boldsymbol{Z}$ of size $N \times D$ giving a batch of input vectors. N is the batch size and D is the number of dimensions. Each row gives one input vector $z = (z_1, \dots, z_D)$.
- A matrix $\mathbf{Y_{bar}}$ giving the output error signals. It is also $N \times D$

The output should be the error signal $\mathbf{Z_{bar}}$. Do not use a for loop.

Solution:

```python
def VJP(Z, Y_bar):
    exp_Z = np.exp(Z)
    R = np.sum(exp_Z, axis=1)
    R_bar = -np.sum(Y_bar * exp_Z / (R ** 2)[:, None], axis=1)
    Z_bar = Y_bar * exp_Z / R[:, None] + R_bar[:, None] * exp_Z
    return Z_bar
```

perceptron

February 24, 2023

0.1 Perceptron Learning Algorithm

The perceptron is a simple supervised machine learning algorithm and one of the earliest neural network architectures. It was introduced by Rosenblatt in the late 1950s. A perceptron represents a binary linear classifier that maps a set of training examples (of d dimensional input vectors) onto binary output values using a $d-1$ dimensional hyperplane. But Today, we will implement **Multi-Classes Perceptron Learning Algorithm Given:** * dataset $\{(x^i, y^i)\}$, $i \in (1, M)$ * x^i is d dimension vector, $x^i = (x_1^i, \dots x_d^i)$ * y^i is multi-class target varible $y^i \in \{0, 1, 2\}$

A perceptron is trained using gradient descent. The training algorithm has different steps. In the beginning (step 0) the model parameters are initialized. The other steps (see below) are repeated for a specified number of training iterations or until the parameters have converged.

Step0: Initial the weight vector and bias with zeros
Step1: Compute the linear combination of the input features and weight. $y_{pred}^i = \arg\max_k W_k * x^i + b$
Step2: Compute the gradients for parameters W_k, b. **Derive the parameter update equation Here (5 points)**

TODO: Derive you answer hear ###################################

$$\Delta W_k = \begin{cases} 0, & k = y_{pred}^i = y^i \\ x^i, & k = y_{pred}^i \neq y^i \end{cases} \text{ and } W_k^{new} = W_k^{old} - \eta \Delta W_k$$

$$\Delta b = \begin{cases} 0, & k = y_{pred}^i = y^i \\ 1, & k = y_{pred}^i \neq y^i \end{cases} \text{ and } b^{new} = b^{old} - \eta \Delta b$$

[106]:
```
from sklearn import datasets
import numpy as np
# from sklearn.cross_validation import train_test_split
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import random

np.random.seed(0)
random.seed(0)
```

[107]:
```
iris = datasets.load_iris()
X = iris.data
print(type(X))
```

```
y = iris.target
y = np.array(y)
print('X_Shape:', X.shape)
print('y_Shape:', y.shape)
print('Label Space:', np.unique(y))
```

```
<class 'numpy.ndarray'>
X_Shape: (150, 4)
y_Shape: (150,)
Label Space: [0 1 2]
```

[108]:
```
## split the training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=0)
print('X_train_Shape:', X_train.shape)
print('X_test_Shape:', X_test.shape)
print('y_train_Shape:', y_train.shape)
print('y_test_Shape:', y_train.shape)

print(type(y_train))
```

```
X_train_Shape: (105, 4)
X_test_Shape: (45, 4)
y_train_Shape: (105,)
y_test_Shape: (105,)
<class 'numpy.ndarray'>
```

[109]:
```
class MultiClsPLA(object):

    ## We recommend to absorb the bias into weight.  W = [w, b]

    def __init__(self, X_train, y_train, X_test, y_test, lr, num_epoch,␣
↪weight_dimension, num_cls):
        super(MultiClsPLA, self).__init__()
        self.X_train = X_train  # N x (D + 1)
        self.y_train = y_train  # N x 1
        self.X_test = X_test
        self.y_test = y_test
        self.weight = self.initial_weight(weight_dimension, num_cls)  # C x (D␣
↪+ 1)
        self.sample_mean = np.mean(self.X_train, 0)
        self.sample_std = np.std(self.X_train, 0)
        self.num_epoch = num_epoch
        self.lr = lr
        self.total_acc_train = []
        self.total_acc_tst = []
    def initial_weight(self, weight_dimension, num_cls):
        weight = None
        #########################################
        ##  ToDO: Initialize the weight with   ##
        ##  small std and zero mean gaussian   ##
        #########################################
        weight = np.random.normal(0, 0.01, (num_cls, weight_dimension))

        return weight

    def data_preprocessing(self, data):
        #####################################
        ##  ToDO: Normalize the data       ##
        #####################################
        norm_data = (data - self.sample_mean) / self.sample_std
        return norm_data

    def train_step(self, X_train, y_train, shuffle_idx):
        np.random.shuffle(shuffle_idx)
        X_train: np.ndarray = X_train[shuffle_idx]
        y_train: np.ndarray = y_train[shuffle_idx]
        train_acc = None
        ##############################################
        ## TODO: to implement the training process  ##
        ## and update the weights                   ##
        ##############################################
        y_pred = np.argmax(X_train @ self.weight.T, axis=0)

        train_acc = np.sum(y_pred == y_train) / y_train.size()
        self.total_acc_train.append(train_acc)
        diff_one_hot = np.eye(X_train.shape[0], self.weight.shape[0])[y !=␣
↪y_pred]  # N x C
        self.weight -= self.lr * diff_one_hot.T @ X_train

        return train_acc

    def test_step(self, X_test, y_test):
        X_test = self.data_preprocessing(data=X_test)
        num_sample = X_test.shape[0]
        test_acc = None

        #########################################
        ##  ToDO: Evaluate the test set and    ##
        ##  return the test acc                ##
        #########################################

        y_pred = np.argmax(X_test @ self.weight.T, axis=0)
        test_acc = np.sum(y_pred == y_test) / y_test.size()
        self.total_acc_tst.append(test_acc)

        return test_acc

    def train(self):
        self.X_train = self.data_preprocessing(data=self.X_train)
        num_sample = self.X_train.shape[0]

        ######################################################
        ### TODO: In order to absorb the bias into weights ###
        ###  we need to modify the input data.            ###
        ###  So You need to transform the input data       ###
        ######################################################

        self.X_train = np.insert(self.X_train, self.X_train.shape[1], 1)
        self.X_test = np.insert(self.X_test, self.X_test.shape[1], 1)

        shuffle_index = np.array(range(0, num_sample))
        for epoch in range(self.num_epoch):
            training_acc = self.train_step(X_train=self.X_train, y_train=self.
↪y_train, shuffle_idx=shuffle_index)
            tst_acc = self.test_step(X_test=self.X_test, y_test=self.y_test)
            self.total_acc_train.append(training_acc)
            self.total_acc_tst.append(tst_acc)
            print('epoch:', epoch, 'traing_acc:%.3f' % training_acc, 'tst_acc:%.
↪3f' % tst_acc)

    def vis_acc_curve(self):
        train_acc = np.array(self.total_acc_train)
        tst_acc = np.array(self.total_acc_tst)
        plt.plot(train_acc)
        plt.plot(tst_acc)
        plt.legend(['train_acc', 'tst_acc'])
        plt.show()
```

[110]:
```
np.random.seed(0)
random.seed(0)
#######################################################
### TODO:
### 1. You need to import the model and pass some parameters.
### 2. Then training the model with some epoches.
### 3. Visualize the training acc and test acc verus epoches
perceptronModel = MultiClsPLA(X_train, y_train, X_test, y_test, lr=1e-3,␣
↪num_epoch=1000,
                              weight_dimension=X_train.shape[1] + 1, num_cls=3)
perceptronModel.train()
```

```
fig = plt.figure()
plt.plot(perceptronModel.total_acc_train)
plt.plot(perceptronModel.total_acc_tst)
```

```
epoch: 0 traing_acc:0.029 tst_acc:0.022
epoch: 1 traing_acc:0.029 tst_acc:0.022
epoch: 2 traing_acc:0.029 tst_acc:0.022
epoch: 3 traing_acc:0.029 tst_acc:0.022
epoch: 4 traing_acc:0.029 tst_acc:0.022
epoch: 5 traing_acc:0.029 tst_acc:0.022
epoch: 6 traing_acc:0.029 tst_acc:0.022
epoch: 7 traing_acc:0.029 tst_acc:0.022
epoch: 8 traing_acc:0.029 tst_acc:0.022
epoch: 9 traing_acc:0.029 tst_acc:0.022
epoch: 10 traing_acc:0.029 tst_acc:0.022
epoch: 11 traing_acc:0.029 tst_acc:0.044
epoch: 12 traing_acc:0.038 tst_acc:0.044
epoch: 13 traing_acc:0.038 tst_acc:0.044
epoch: 14 traing_acc:0.038 tst_acc:0.044
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epoch: 19 traing_acc:0.038 tst_acc:0.044
epoch: 20 traing_acc:0.038 tst_acc:0.044
epoch: 21 traing_acc:0.048 tst_acc:0.044
epoch: 22 traing_acc:0.048 tst_acc:0.044
epoch: 23 traing_acc:0.048 tst_acc:0.067
epoch: 24 traing_acc:0.048 tst_acc:0.067
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epoch: 27 traing_acc:0.048 tst_acc:0.067
epoch: 28 traing_acc:0.067 tst_acc:0.067
epoch: 29 traing_acc:0.076 tst_acc:0.089
epoch: 30 traing_acc:0.076 tst_acc:0.089
epoch: 31 traing_acc:0.076 tst_acc:0.089
epoch: 32 traing_acc:0.076 tst_acc:0.089
epoch: 33 traing_acc:0.105 tst_acc:0.133
epoch: 34 traing_acc:0.152 tst_acc:0.244
epoch: 35 traing_acc:0.229 tst_acc:0.333
epoch: 36 traing_acc:0.381 tst_acc:0.378
epoch: 37 traing_acc:0.410 tst_acc:0.400
epoch: 38 traing_acc:0.495 tst_acc:0.467
epoch: 39 traing_acc:0.524 tst_acc:0.489
epoch: 40 traing_acc:0.562 tst_acc:0.489
epoch: 41 traing_acc:0.590 tst_acc:0.511
```

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epoch: 42 traing_acc:0.610 tst_acc:0.533
epoch: 43 traing_acc:0.619 tst_acc:0.533
epoch: 44 traing_acc:0.638 tst_acc:0.533
epoch: 45 traing_acc:0.648 tst_acc:0.533
epoch: 46 traing_acc:0.629 tst_acc:0.533
epoch: 47 traing_acc:0.648 tst_acc:0.533
epoch: 48 traing_acc:0.667 tst_acc:0.556
epoch: 49 traing_acc:0.667 tst_acc:0.556
epoch: 50 traing_acc:0.667 tst_acc:0.578
epoch: 51 traing_acc:0.676 tst_acc:0.600
epoch: 52 traing_acc:0.676 tst_acc:0.622
epoch: 53 traing_acc:0.686 tst_acc:0.622
epoch: 54 traing_acc:0.705 tst_acc:0.622
epoch: 55 traing_acc:0.695 tst_acc:0.622
epoch: 56 traing_acc:0.705 tst_acc:0.622
epoch: 57 traing_acc:0.695 tst_acc:0.622
epoch: 58 traing_acc:0.705 tst_acc:0.622
epoch: 59 traing_acc:0.714 tst_acc:0.644
epoch: 60 traing_acc:0.686 tst_acc:0.644
epoch: 61 traing_acc:0.714 tst_acc:0.644
epoch: 62 traing_acc:0.695 tst_acc:0.644
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epoch: 84 traing_acc:0.695 tst_acc:0.644
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epoch: 87 traing_acc:0.686 tst_acc:0.644
epoch: 88 traing_acc:0.695 tst_acc:0.644
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epoch: 118 traing_acc:0.724 tst_acc:0.644
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epoch: 137 traing_acc:0.724 tst_acc:0.644
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epoch: 138 traing_acc:0.714 tst_acc:0.667
epoch: 139 traing_acc:0.724 tst_acc:0.667
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epoch: 143 traing_acc:0.724 tst_acc:0.689
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epoch: 148 traing_acc:0.724 tst_acc:0.689
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epoch: 150 traing_acc:0.743 tst_acc:0.667
epoch: 151 traing_acc:0.724 tst_acc:0.689
epoch: 152 traing_acc:0.733 tst_acc:0.667
epoch: 153 traing_acc:0.752 tst_acc:0.689
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epoch: 155 traing_acc:0.752 tst_acc:0.689
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epoch: 157 traing_acc:0.762 tst_acc:0.689
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epoch: 166 traing_acc:0.762 tst_acc:0.689
epoch: 167 traing_acc:0.781 tst_acc:0.689
epoch: 168 traing_acc:0.781 tst_acc:0.689
epoch: 169 traing_acc:0.800 tst_acc:0.689
epoch: 170 traing_acc:0.790 tst_acc:0.711
epoch: 171 traing_acc:0.800 tst_acc:0.689
epoch: 172 traing_acc:0.781 tst_acc:0.711
epoch: 173 traing_acc:0.810 tst_acc:0.689
epoch: 174 traing_acc:0.790 tst_acc:0.711
epoch: 175 traing_acc:0.819 tst_acc:0.711
epoch: 176 traing_acc:0.800 tst_acc:0.733
epoch: 177 traing_acc:0.829 tst_acc:0.711
epoch: 178 traing_acc:0.810 tst_acc:0.733
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[110]: <matplotlib.legend.Legend at 0x12c6f0dc0>
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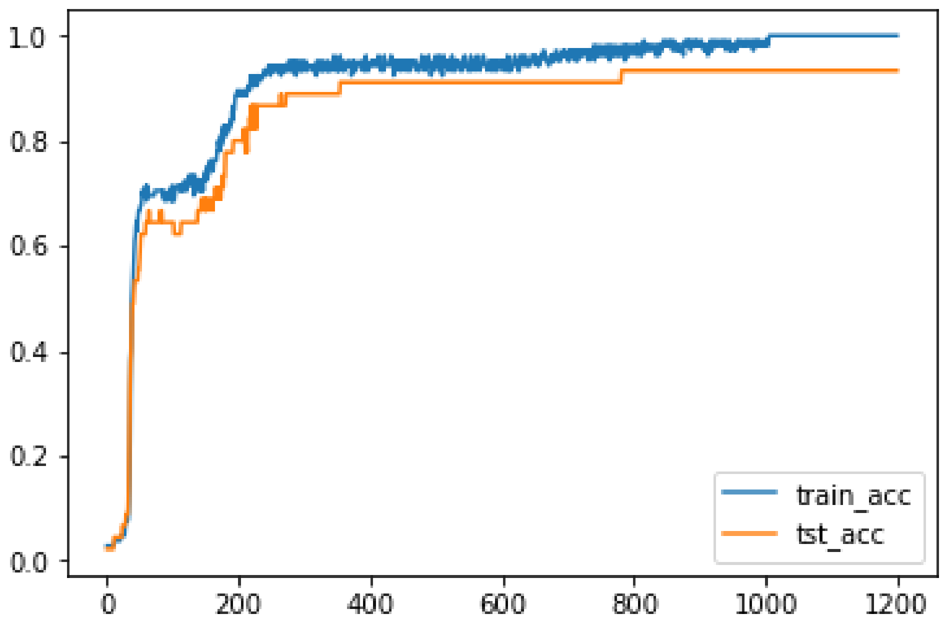

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[110]:
```

knn

February 24, 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.

[30]:
```
# Run some setup code for this notebook.

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

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

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

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

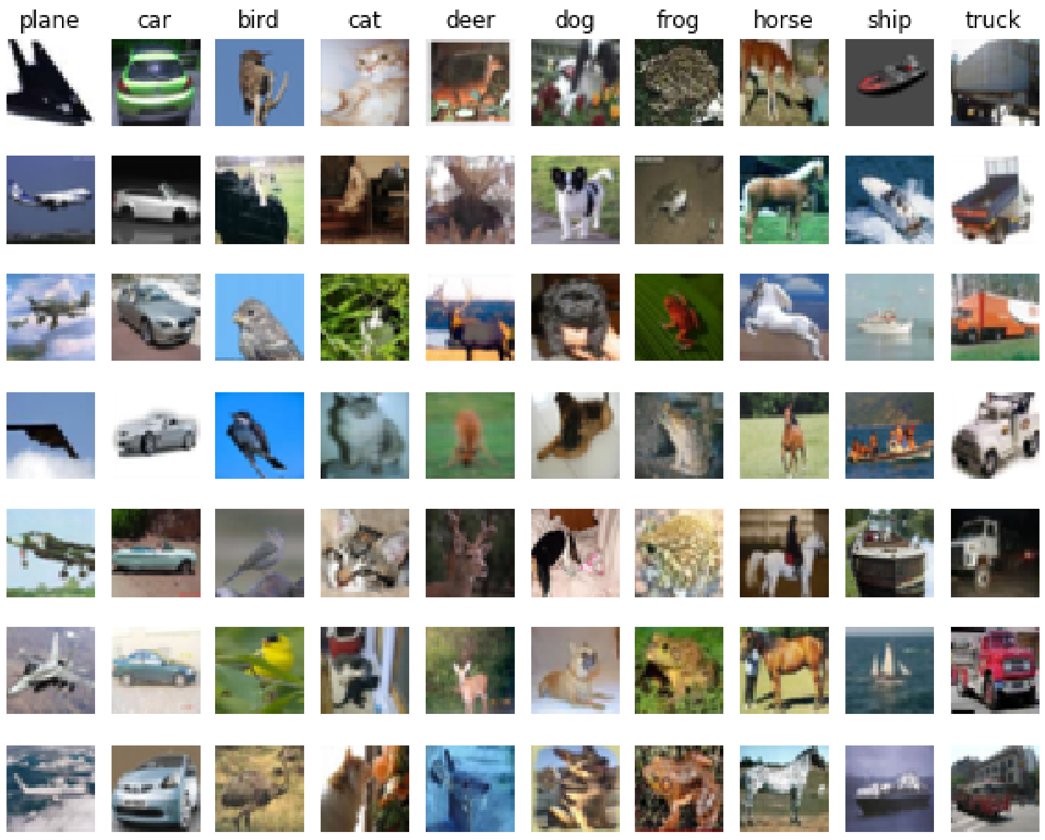
[31]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'
# Cleaning up variables to prevent loading data multiple times (which may cause␣
 ↪memory issue)
try:
   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

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

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

```
Clear previously loaded data.
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

[32]:
```
# 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()
```



[33]:
```
# 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)
```

[34]:
```python
from cs231n.classifiers import KNearestNeighbor

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

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

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

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

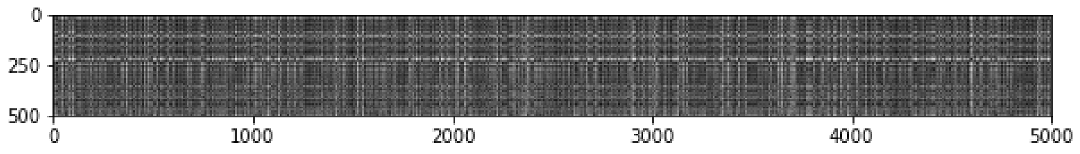
Note: For the three distance computations that we require you to implement in this notebook, you may not use the np.linalg.norm() function that numpy provides.

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

[35]:
```python
# Open cs231n/classifiers/k_nearest_neighbor.py and implement
# compute_distances_two_loops.

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

```
(500, 5000)
```

[36]:
```python
# We can visualize the distance matrix: each row is a single test example and
# its distances to training examples
plt.imshow(dists, interpolation='none')
plt.show()
```



Inline Question 1

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

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

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

If a row (say the corresponding test data r) is distinctly brighter than others, then it means the corresponding distances from r to all training points are all distinctly larger than other test points.

If a column (say the corresponding training data c) is distinctly brighter than others, then it means the corresponding distances from all test data to c are distinctly larger than other training points.

[37]:
```python
# Now implement the function predict_labels and run the code below:
# We use k = 1 (which is Nearest Neighbor).
y_test_pred = classifier.predict_labels(dists, k=1)

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

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

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

[38]:
```python
y_test_pred = classifier.predict_labels(dists, k=5)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 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.

$Your Answer:$

I choose 1, 2, 3, 5

$Your Explanation:$

The L1 distance is defined as follows:

$$d(I_p, I_q) = \sum_{i=1}^{h}\sum_{j=1}^{w} ||p_{i,j}^p - p_{i,j}^q||_1$$

Then define $d_i(\cdot,\cdot)$ as the new distance metric for the $i-th$ preprocessing step.

For $d_1(\cdot,\cdot)$, we have

$$d_1(I_p, I_q) = \sum_{i=1}^{h}\sum_{j=1}^{w} ||p_{i,j}^p - \mu - p_{i,j}^q + \mu||_1 = d(I_p, I_q)$$

For $d_2(\cdot,\cdot)$, we have

$$d_2(I_p, I_q) = \sum_{i=1}^{h}\sum_{j=1}^{w} ||p_{i,j}^p - \mu_{i,j} - p_{i,j}^q + \mu_{i,j}||_1 = d(I_p, I_q)$$

For $d_3(\cdot,\cdot)$, we have

$$d_3(I_p, I_q) = \sum_{i=1}^{h}\sum_{j=1}^{w} ||\frac{p_{i,j}^p - \mu}{\sigma} - \frac{p_{i,j}^q - \mu}{\sigma}||_1 = \frac{d(I_p, I_q)}{\sigma} \propto d(I_p, I_q)$$

For $d_4(\cdot,\cdot)$, we have

$$d_4(I_p, I_q) = \sum_{i=1}^{h}\sum_{j=1}^{w} ||\frac{p_{i,j}^p - \mu_{i,j}}{\sigma_{i,j}} - \frac{p_{i,j}^q - \mu_{i,j}}{\sigma_{i,j}}||_1 = \sum_{i=1}^{h}\sum_{j=1}^{w} ||\frac{p_{i,j}^p - p_{i,j}^q}{\sigma_{i,j}}||_1$$

For $d_5(\cdot,\cdot)$, we have

$$d_5(I_p, I_q) = \sum_{i=1}^{w}\sum_{j=1}^{h} ||p_{i,j}^p - p_{i,j}^q||_1 = d(I_p, I_q)$$

[39]:
```
# 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
```

[40]:
```
# 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
```

[41]:
```
# 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 12.713599 seconds
One loop version took 14.369608 seconds
No loop version took 0.144269 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.

[42]:
```
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 = {}
```

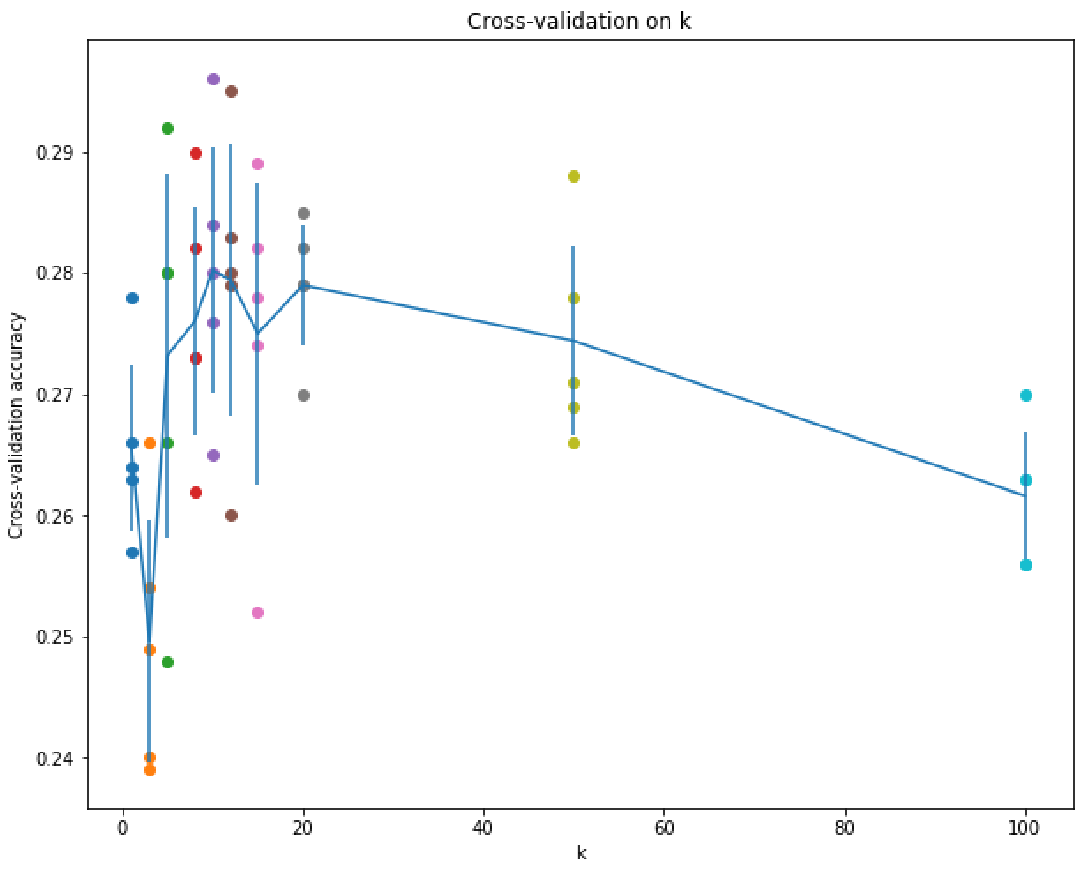
```
################################################################################
# TODO:                                                                        #
# Perform k-fold cross validation to find the best value of k. For each        #
# possible value of k, run the k-nearest-neighbor algorithm 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 i in range(num_folds):
        X_train_fold = np.concatenate(X_train_folds[:i] + X_train_folds[i+1:])
        y_train_fold = np.concatenate(y_train_folds[:i] + y_train_folds[i+1:])
        X_val_fold = X_train_folds[i]
        y_val_fold = y_train_folds[i]
        classifier.train(X_train_fold, y_train_fold)
        y_pred = classifier.predict(X_val_fold, k=k)
        k_to_accuracies[k].append(np.sum(y_pred == y_val_fold) / y_val_fold.
 ↪size)

# *****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
```

[43]:

```python
# 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()
```



[44]:
```
# 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 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.

$Your Answer:$

I choose 2, 4.

$Your Explanation:$

1. False. The decision boundary of the k-NN classifier is non-linear since the unit "sphere" under L2 norm is a unit circle in 2D and a unit sphere in 3D which is not linear.
2. True. The training error of a 1-NN is always 0 since the nearest neighbor of a point is itself.
3. False. The test error does not increase with k just like show in the picture above.
4. True. The process of classifying a test sample is to traverse through all the training data, which is an $O(n)$ operation.

```
[44]:
```

svm

February 25, 2023

1 Multiclass Support Vector Machine exercise

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

In this exercise you will:

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

[2]:
```
# Run some setup code for this notebook.
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

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

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

1.1 CIFAR-10 Data Loading and Preprocessing

[3]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

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

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

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

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

[4]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes):
    idxs = np.flatnonzero(y_train == y)
    idxs = np.random.choice(idxs, samples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls)
plt.show()
```

[5]:
```
# Split the data into train, val, and test sets. In addition we will
# create a small development set as a subset of the training data;
# we can use this for development so our code runs faster.
num_training = 49000
num_validation = 1000
num_test = 1000
num_dev = 500

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

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

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

```
y_dev = y_train[mask]

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

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

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

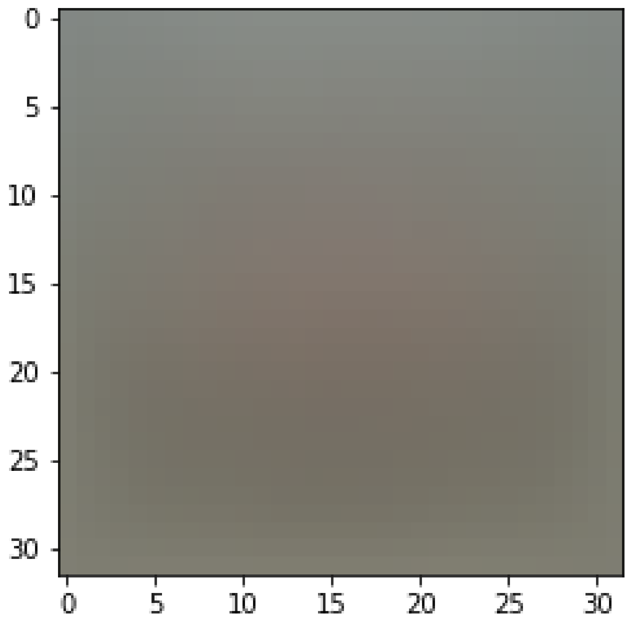
[6]:
```
# Preprocessing: reshape the image data into rows
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_val = np.reshape(X_val, (X_val.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
X_dev = np.reshape(X_dev, (X_dev.shape[0], -1))

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

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

[7]:
```
# Preprocessing: subtract the mean image
# first: compute the image mean based on the training data
mean_image = np.mean(X_train, axis=0)
print(mean_image[:10]) # print a few of the elements
plt.figure(figsize=(4,4))
plt.imshow(mean_image.reshape((32,32,3)).astype('uint8')) # visualize the mean␣
 ↪image
plt.show()
```

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

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

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

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



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

1.2 SVM Classifier

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

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

[8]:
```
# Evaluate the naive implementation of the loss we provided for you:
from cs231n.classifiers.linear_svm import svm_loss_naive
import time

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

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

```
loss: 9.318401
```

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

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

[9]:
```
# Once you've implemented the gradient, recompute it with the code below
# and gradient check it with the function we provided for you

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

# Numerically compute the gradient along several randomly chosen dimensions, and
# compare them with your analytically computed gradient. The numbers should␣
 ↪match
# almost exactly along all dimensions.
from cs231n.gradient_check import grad_check_sparse
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad)

# do the gradient check once again with regularization turned on
# you didn't forget the regularization gradient did you?
loss, grad = svm_loss_naive(W, X_dev, y_dev, 5e1)
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 5e1)[0]
grad_numerical = grad_check_sparse(f, W, grad)
```

```
numerical: 4.066394 analytic: 4.129151, relative error: 7.657412e-03
numerical: -5.600240 analytic: -5.600240, relative error: 7.350527e-11
numerical: 4.651978 analytic: 4.651978, relative error: 8.995426e-13
numerical: -22.334557 analytic: -22.334557, relative error: 1.318483e-11
numerical: -3.009755 analytic: -3.009755, relative error: 1.557965e-10
numerical: -11.344121 analytic: -11.344121, relative error: 4.304613e-13
numerical: 3.158882 analytic: 3.204693, relative error: 7.198895e-03
numerical: -18.502906 analytic: -18.382096, relative error: 3.275296e-03
numerical: -6.049070 analytic: -6.049070, relative error: 7.427929e-12
```

```
numerical: 30.572300 analytic: 30.572300, relative error: 7.611381e-12
numerical: -6.443605 analytic: -6.548512, relative error: 8.074646e-03
numerical: -3.362234 analytic: -3.294436, relative error: 1.018498e-02
numerical: -1.974795 analytic: -1.974795, relative error: 2.956606e-10
numerical: -42.768838 analytic: -42.768838, relative error: 2.457229e-12
numerical: 2.931244 analytic: 2.931244, relative error: 4.977740e-11
numerical: 1.526142 analytic: 1.601676, relative error: 2.414897e-02
numerical: -2.584603 analytic: -2.584603, relative error: 9.321052e-11
numerical: -12.417974 analytic: -12.417974, relative error: 2.307688e-11
numerical: -22.304136 analytic: -22.232664, relative error: 1.604777e-03
numerical: 25.988804 analytic: 25.988804, relative error: 1.067483e-11
```

Inline Question 1

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

$Your Answer:$

To begin with, the loss function is not totally differentiable at 0. Since the numerical result is get from approximation, the approximation will fail in the position that the loss function is not differentiable.

Given that the error is caused by approximation, it is not a concern.

A simple example in 1-D: consider ReLU function, $f(x) = max(0, x)$, if we approximate the gradient at $x = -0.02$ and take the interval length $h = 0.02$, then the approximated gradient is

$$f'(x) = \frac{f(0.01) - f(-0.03)}{2 \times 0.02} = \frac{1}{4} \neq 0$$

but the true gradient is 0.

The way to reduce the effect is to reduce the interval length h.

[10]:
```
# Next implement the function svm_loss_vectorized; for now only compute the␣
↪loss;
# we will implement the gradient in a moment.
tic = time.time()
loss_naive, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss: %e computed in %fs' % (loss_naive, toc - tic))

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

# The losses should match but your vectorized implementation should be much␣
↪faster.
```

```
print('difference: %f' % (loss_naive - loss_vectorized))
```

```
Naive loss: 9.318401e+00 computed in 0.045376s
Vectorized loss: 9.318401e+00 computed in 0.008753s
difference: -0.000000
```

[11]:
```
# Complete the implementation of svm_loss_vectorized, and compute the gradient
# of the loss function in a vectorized way.

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

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

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

```
Naive loss and gradient: computed in 0.075716s
Vectorized loss and gradient: computed in 0.009150s
difference: 0.000000
```

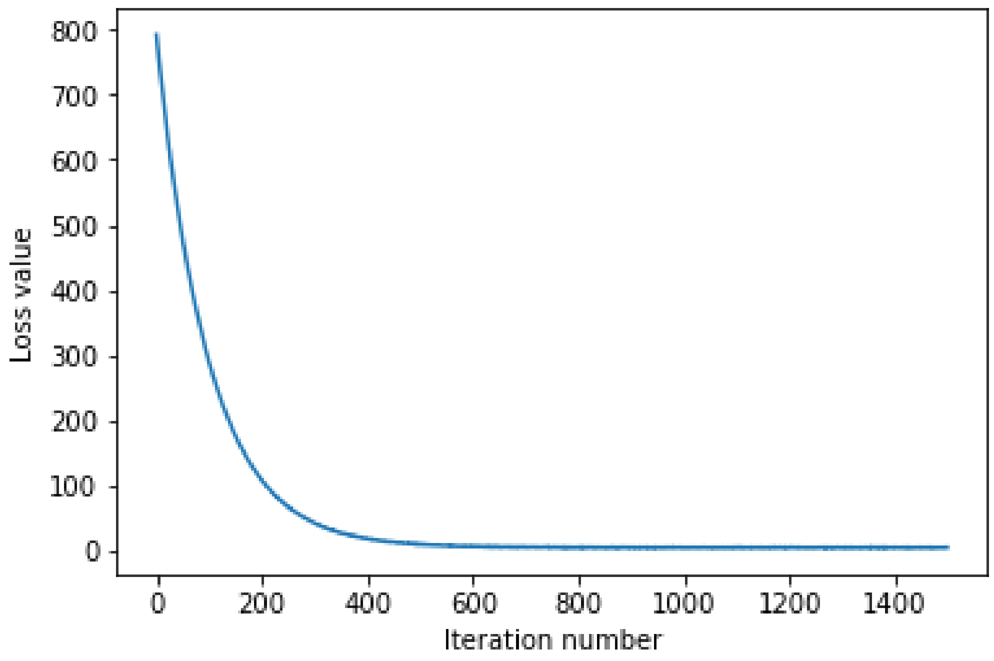
1.2.1 Stochastic Gradient Descent

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

[12]:
```
# In the file linear_classifier.py, implement SGD in the function
# LinearClassifier.train() and then run it with the code below.
from cs231n.classifiers import LinearSVM
svm = LinearSVM()
tic = time.time()
loss_hist = svm.train(X_train, y_train, learning_rate=1e-7, reg=2.5e4,
                      num_iters=1500, verbose=True)
toc = time.time()
print('That took %fs' % (toc - tic))
```

```
iteration 0 / 1500: loss 791.981194
iteration 100 / 1500: loss 289.379744
iteration 200 / 1500: loss 108.449161
iteration 300 / 1500: loss 42.430152
iteration 400 / 1500: loss 18.899496
iteration 500 / 1500: loss 10.146439
iteration 600 / 1500: loss 7.472539
iteration 700 / 1500: loss 5.959729
iteration 800 / 1500: loss 5.459304
iteration 900 / 1500: loss 5.492587
iteration 1000 / 1500: loss 5.032883
iteration 1100 / 1500: loss 5.570110
iteration 1200 / 1500: loss 5.641019
iteration 1300 / 1500: loss 5.025879
iteration 1400 / 1500: loss 5.251474
That took 7.209703s
```

[13]:
```
# A useful debugging strategy is to plot the loss as a function of
# iteration number:
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
plt.show()
```



[14]:
```python
# Write the LinearSVM.predict function and evaluate the performance on both the
# training and validation set
y_train_pred = svm.predict(X_train)
print('training accuracy: %f' % (np.mean(y_train == y_train_pred), ))
y_val_pred = svm.predict(X_val)
print('validation accuracy: %f' % (np.mean(y_val == y_val_pred), ))
```

```
training accuracy: 0.369653
validation accuracy: 0.386000
```

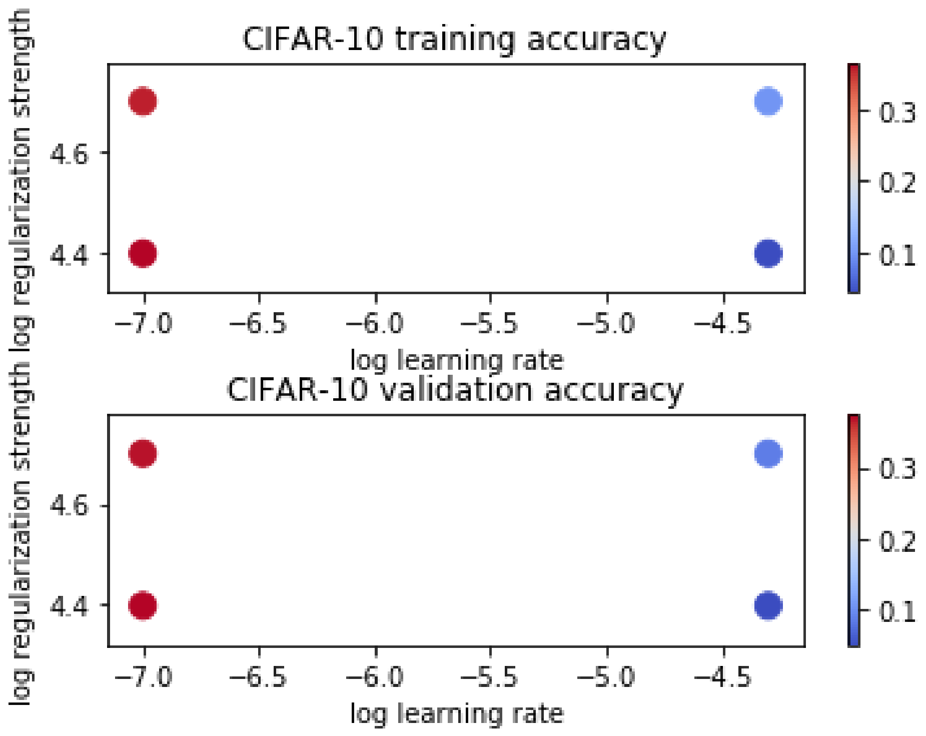
[15]:
```python
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of about 0.39 on the validation set.

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

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

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

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

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

for lr in learning_rates:
    for r in regularization_strengths:
        svm = LinearSVM()
        svm.train(X_train, y_train, learning_rate=lr, reg=r, num_iters=1500)
        y_train_pred = svm.predict(X_train)
        y_val_pred = svm.predict(X_val)
        train_accuracy = np.mean(y_train_pred == y_train)
        val_accuracy = np.mean(y_val_pred == y_val)
        results[(lr, r)] = (train_accuracy, val_accuracy)
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

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

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

```
/Users/caleblee/Desktop/CS280/CS280-Spring23-Assignment1/Homework1_partB/cs231n/
classifiers/linear_svm.py:88: RuntimeWarning: overflow encountered in scalar
multiply
  loss += reg * np.sum(W * W)
/Users/caleblee/Library/Python/3.9/lib/python/site-
packages/numpy/core/fromnumeric.py:86: RuntimeWarning: overflow encountered in
reduce
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
/Users/caleblee/Desktop/CS280/CS280-Spring23-Assignment1/Homework1_partB/cs231n/
classifiers/linear_svm.py:88: RuntimeWarning: overflow encountered in multiply
  loss += reg * np.sum(W * W)
/Users/caleblee/Desktop/CS280/CS280-Spring23-Assignment1/Homework1_partB/cs231n/
classifiers/linear_svm.py:106: RuntimeWarning: overflow encountered in multiply
  dW += reg * 2 * W
/Users/caleblee/Desktop/CS280/CS280-Spring23-Assignment1/Homework1_partB/cs231n/
classifiers/linear_svm.py:83: RuntimeWarning: invalid value encountered in
matmul
  loss = X @ W
/Users/caleblee/Desktop/CS280/CS280-Spring23-Assignment1/Homework1_partB/cs231n/
classifiers/linear_classifier.py:77: RuntimeWarning: invalid value encountered
in subtract
  self.W -= learning_rate * grad
```

```
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.366571 val accuracy: 0.375000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.358327 val accuracy: 0.371000
lr 5.000000e-05 reg 2.500000e+04 train accuracy: 0.043796 val accuracy: 0.049000
lr 5.000000e-05 reg 5.000000e+04 train accuracy: 0.100265 val accuracy: 0.087000
best validation accuracy achieved during cross-validation: 0.375000
```

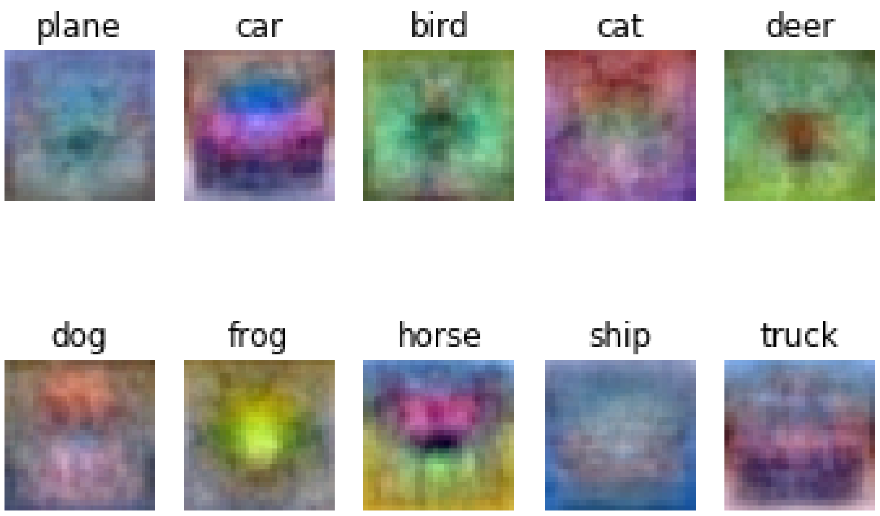
[16]:
```
# Visualize the cross-validation results
import math
import pdb

# pdb.set_trace()

x_scatter = [math.log10(x[0]) for x in results]
y_scatter = [math.log10(x[1]) for x in results]

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

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



[17]:
```python
# 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: 0.369000
```

[18]:
```python
# 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.

$Your Answer:$

Those pictures look like the "average" pictures of each class. This is because the angle between w_k and x_i affects the value of $w_k^T x_i$. Thus, the smaller the angle is, the more similar w_k is to x_i and the higher the probability that x_i si classified into class k.

[18]:
```

```

softmax

February 24, 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]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

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

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

[2]:
```
def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000,␣
 ↪num_dev=500):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the linear classifier. These are the same steps as we used for the
    SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

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

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

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

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

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

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

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

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

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

1.1 Softmax Classifier

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

[3]:
```
# First implement the naive softmax loss function with nested loops.
# Open the file cs231n/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from cs231n.classifiers.softmax import softmax_loss_naive
import time

# Generate a random softmax weight matrix and use it to compute the loss.
W = np.random.randn(3073, 10) * 0.0001
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 0.0)

# As a rough sanity check, our loss should be something close to -log(0.1).
print('loss: %f' % loss)
print('sanity check: %f' % (-np.log(0.1)))
```

```
loss: 2.370673
sanity check: 2.302585
```

Inline Question 1

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

$YourAnswer:$

Since the weight W is randomly initialized, then the probability p_i should be close to 1/{number of class}=0.1 for each class i. Thus, the value of loss function can be approximated as follows:

$$L = \frac{1}{n}\sum_{i=1}^{n} -\log p_i = -\log(\prod_{i=1}^{n} p_i)^{\frac{1}{n}} \approx -\log((0.1)^n)^{(1/n)} = -log 0.1$$

[4]:
```python
# Complete the implementation of softmax_loss_naive and implement a (naive)
# version of the gradient that uses nested loops.
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 0.0)

# As we did for the SVM, use numeric gradient checking as a debugging tool.
# The numeric gradient should be close to the analytic gradient.
from cs231n.gradient_check import grad_check_sparse
f = lambda w: softmax_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad, 10)

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

```
numerical: 1.052860 analytic: 1.052860, relative error: 2.201441e-08
numerical: -1.549930 analytic: -1.549930, relative error: 1.647477e-08
numerical: 0.119256 analytic: 0.119256, relative error: 3.456103e-07
numerical: -0.219556 analytic: -0.219556, relative error: 8.991791e-08
numerical: 0.083568 analytic: 0.083568, relative error: 5.460927e-07
numerical: 1.443529 analytic: 1.443529, relative error: 8.874940e-09
numerical: 0.796921 analytic: 0.796921, relative error: 4.137497e-08
numerical: -4.262104 analytic: -4.262104, relative error: 4.176475e-09
numerical: -1.373423 analytic: -1.373423, relative error: 8.834602e-10
numerical: 0.489926 analytic: 0.489926, relative error: 2.588278e-09
numerical: 1.725037 analytic: 1.725037, relative error: 1.961117e-08
numerical: -0.927769 analytic: -0.927769, relative error: 1.667269e-08
numerical: -0.186378 analytic: -0.186378, relative error: 1.390873e-07
numerical: 1.496357 analytic: 1.496357, relative error: 5.722065e-08
numerical: 0.658420 analytic: 0.658420, relative error: 6.588213e-08
numerical: 0.621139 analytic: 0.621139, relative error: 7.778886e-08
numerical: 1.582019 analytic: 1.582019, relative error: 4.703156e-08
numerical: -0.340721 analytic: -0.340721, relative error: 1.002202e-07
numerical: 0.169129 analytic: 0.169129, relative error: 5.742597e-08
numerical: -0.260551 analytic: -0.260551, relative error: 2.454967e-07
```

[5]:
```python
# Now that we have a naive implementation of the softmax loss function and its␣
↪gradient,
# implement a vectorized version in softmax_loss_vectorized.
# The two versions should compute the same results, but the vectorized version␣
↪should be
# much faster.
tic = time.time()
loss_naive, grad_naive = softmax_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('naive loss: %e computed in %fs' % (loss_naive, toc - tic))

from cs231n.classifiers.softmax import softmax_loss_vectorized
tic = time.time()
loss_vectorized, grad_vectorized = softmax_loss_vectorized(W, X_dev, y_dev, 0.
↪000005)
toc = time.time()
print('vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic))

# As we did for the SVM, we use the Frobenius norm to compare the two versions
# of the gradient.
grad_difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('Loss difference: %f' % np.abs(loss_naive - loss_vectorized))
print('Gradient difference: %f' % grad_difference)
```

```
naive loss: 2.370673e+00 computed in 0.037366s
vectorized loss: 2.370673e+00 computed in 0.005350s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[6]:
```
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of over 0.35 on the validation set.

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

################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# This should be identical to the validation that you did for the SVM; save    #
# the best trained softmax classifer in best_softmax.                          #
################################################################################

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

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

for lr in learning_rates:
    for r in regularization_strengths:
        softmax = Softmax()
        loss_hist = softmax.train(X_train, y_train, learning_rate=lr, reg=r,
                      num_iters=1500, verbose=False)
        y_train_pred = softmax.predict(X_train)
        y_val_pred = softmax.predict(X_val)
        train_accuracy = np.mean(y_train == y_train_pred)
        val_accuracy = np.mean(y_val == y_val_pred)
        results[(lr, r)] = (train_accuracy, val_accuracy)
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_softmax = softmax

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

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

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

```
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.328388 val accuracy: 0.340000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.303184 val accuracy: 0.318000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.326327 val accuracy: 0.331000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.298510 val accuracy: 0.311000
best validation accuracy achieved during cross-validation: 0.340000
```

[7]:
```
# 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: 0.344000
```

Inline Question 2 - *True or False*

Suppose the overall training loss is defined as the sum of the per-datapoint loss over all training examples. It is possible to add a new datapoint to a training set that would leave the SVM loss unchanged, but this is not the case with the Softmax classifier loss.

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

Yes, it’s possible.

YourExplanation :

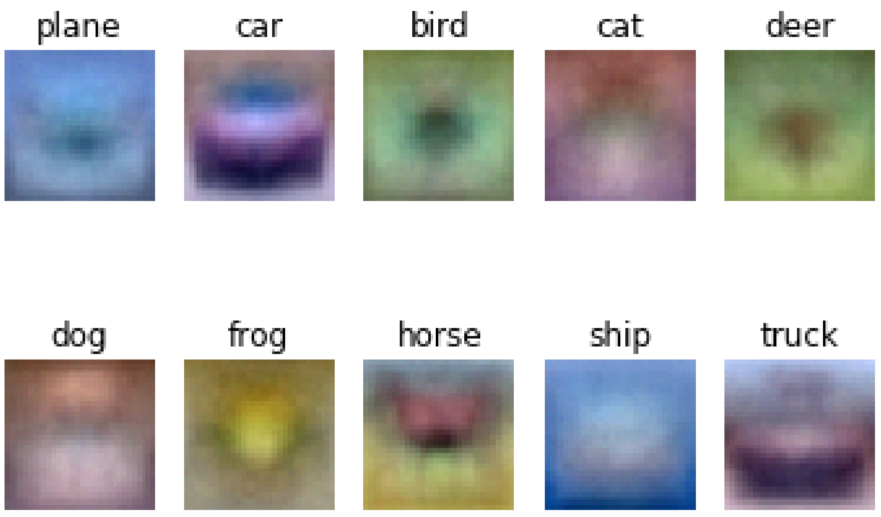
Given that the loss function of SVM is as follows:

$$L = \frac{1}{n}\sum_{i=1}^{n}\sum_{j\neq y_i} max(0, 1-(w_j - w_{y_i})x_i)$$

if the new added point x_i has the property that $(w_j - w_{y_i})x_i < 1$ for all j then the loss value will not change

However, for softmax, the loss function takes every training points into consideration. Thus, the value will change if we adda new point x_i into training set.

[8]:
```
# 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])
```



[8]:

```
```

two_layer_net

February 24, 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.

[16]:
```
# A bit of setup

import numpy as np
import matplotlib.pyplot as plt

from cs231n.classifiers.neural_net import TwoLayerNet

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

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

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

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

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.

[17]:
```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
```

```
hidden_size = 10
num_classes = 3
num_inputs = 5

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

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

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

2 Forward pass: compute scores

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

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

[18]:
```
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
```

3 Forward pass: compute loss

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

[23]:
```
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
```

4 Backward pass

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

[24]:
```
from cs231n.gradient_check import eval_numerical_gradient

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

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

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

```
W2 max relative error: 3.440708e-09
b2 max relative error: 4.447656e-11
W1 max relative error: 3.561318e-09
b1 max relative error: 2.738421e-09
```

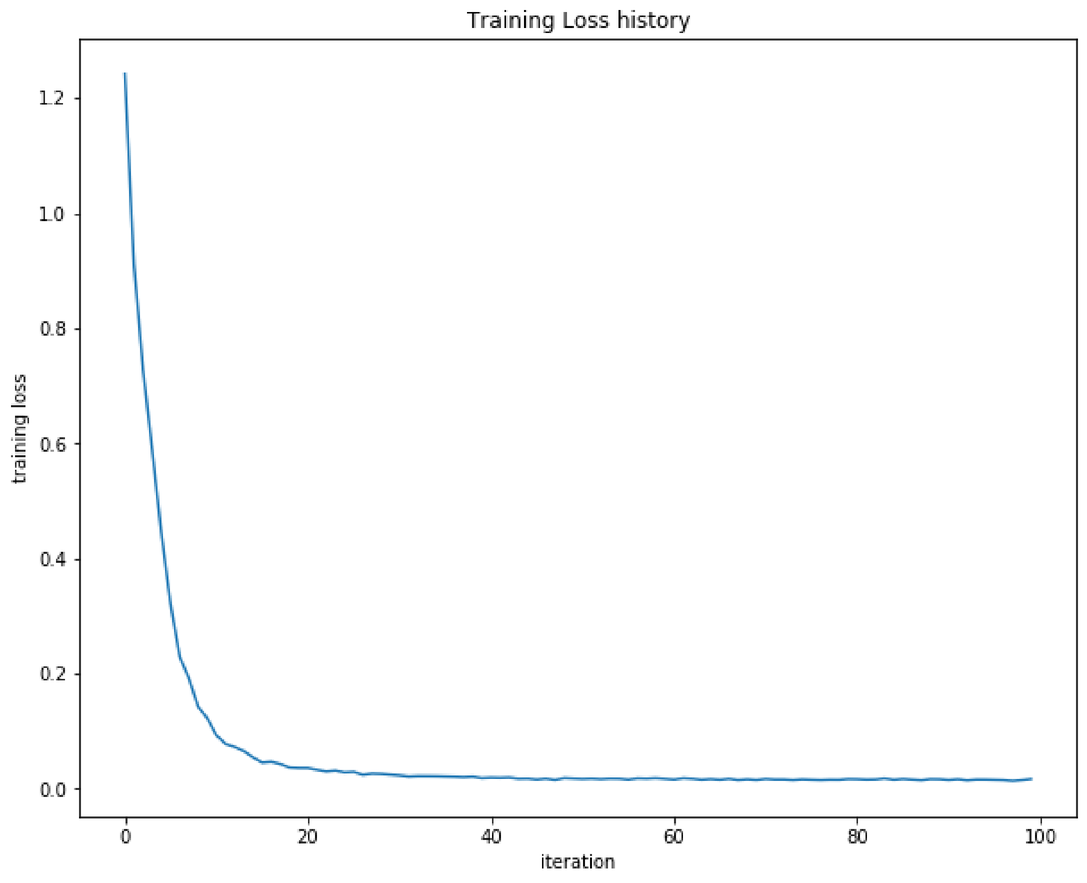
5 Train the network

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

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

[25]:
```
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
```



6 Load the data

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

[26]:
```
from cs231n.data_utils import load_CIFAR10

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier. These are the same steps as
    we used for the SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'
    # Cleaning up variables to prevent loading data multiple times (which may␣
 ↪cause memory issue)
    try:
       del X_train, y_train
       del X_test, y_test
       print('Clear previously loaded data.')
    except:
       pass

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

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

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

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

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


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

```
Train data shape:  (49000, 3072)
Train labels shape:  (49000,)
```

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

7 Train a network

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

[27]:
```python
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
net = TwoLayerNet(input_size, hidden_size, num_classes)

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

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

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

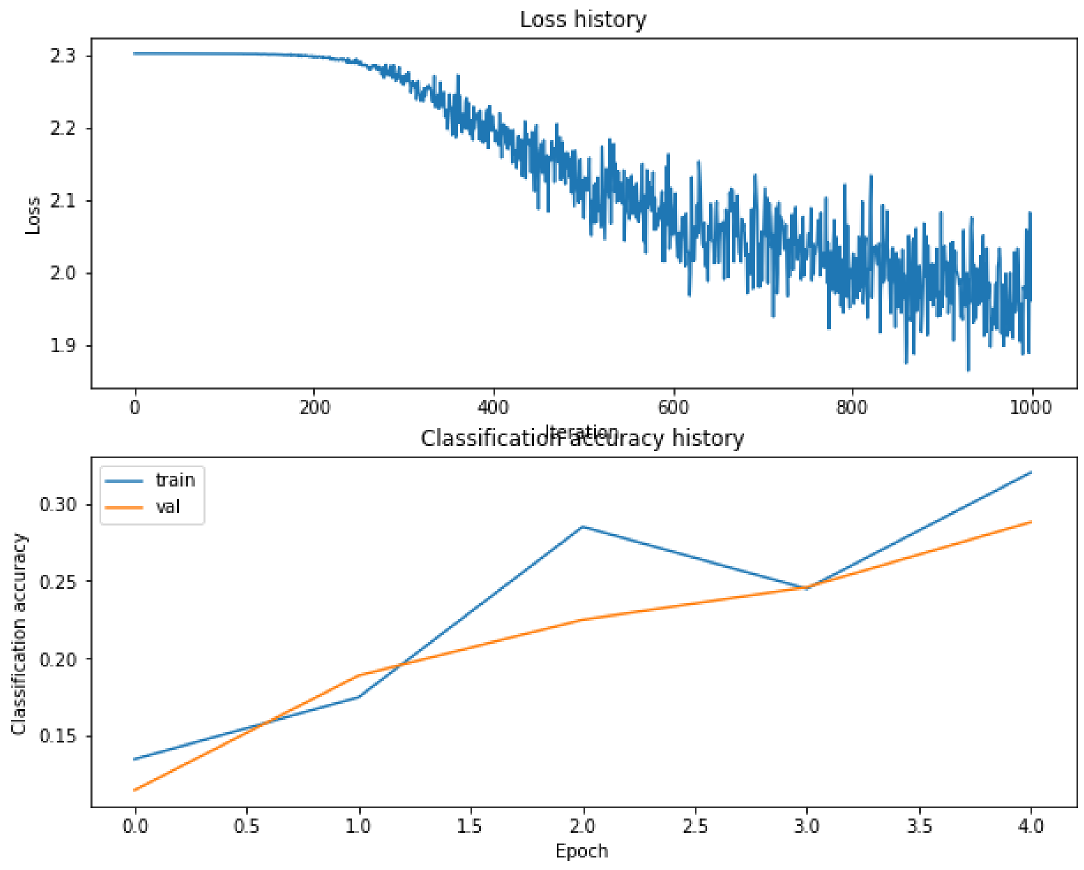
8 Debug the training

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

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

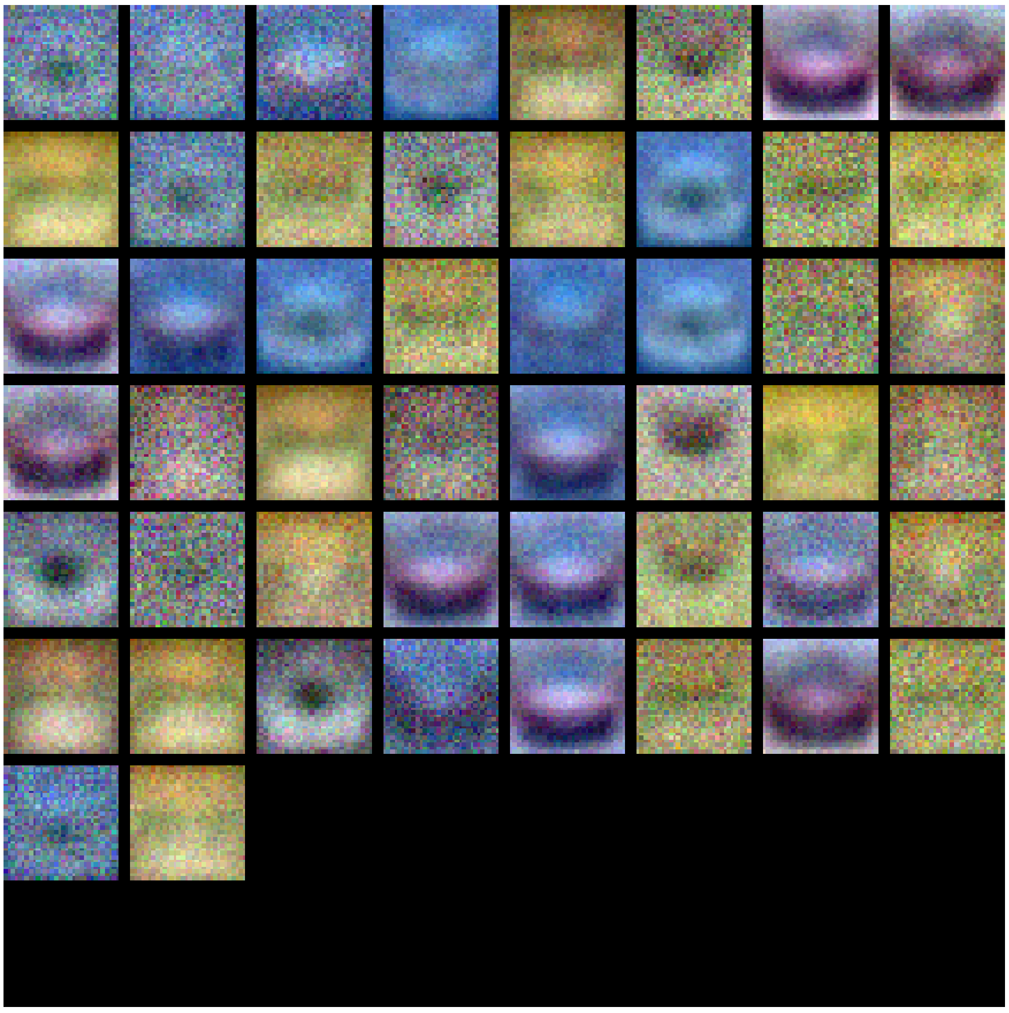
Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

[28]:
```
# 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()
```



[29]:

```python
from cs231n.vis_utils import visualize_grid

# Visualize the weights of the network

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

show_net_weights(net)
```



9 Tune your hyperparameters

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

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

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

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

Explain your hyperparameter tuning process below.

$Your Answer :$

I experimented with different hyperparameters combinations, in detail, I choose two different learning_rates: 5e-4 and 1e-3 and two different batch_size: 200 and 400.

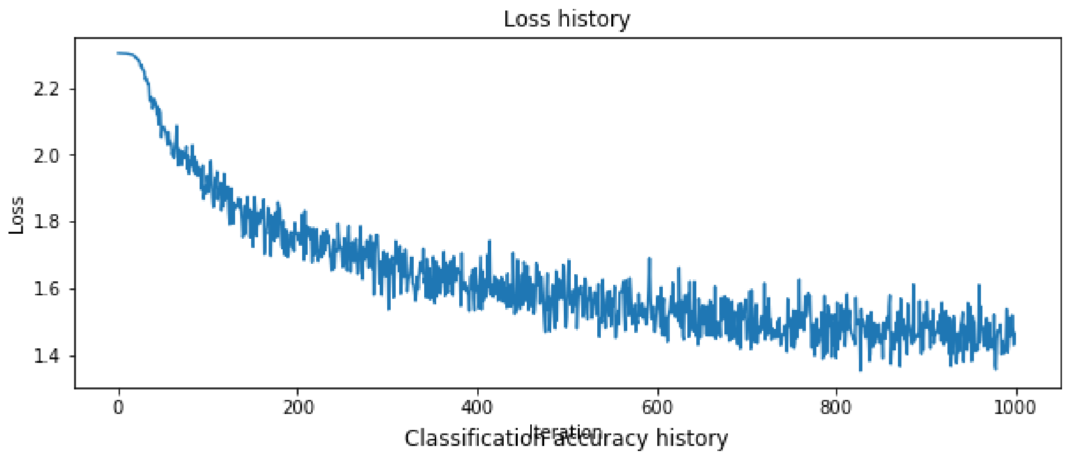
The reason why I choose to tune learning_rate is that learning rate is the plot above shows that the loss fluctuated heavily during the training process, then we can increase the learning rate to by increasing 5e-4 each time. As for batch_size, increase batch size will help the model to get more accurate gradient during training, so we compare the result of original(200) parameter and new (400) parameter.

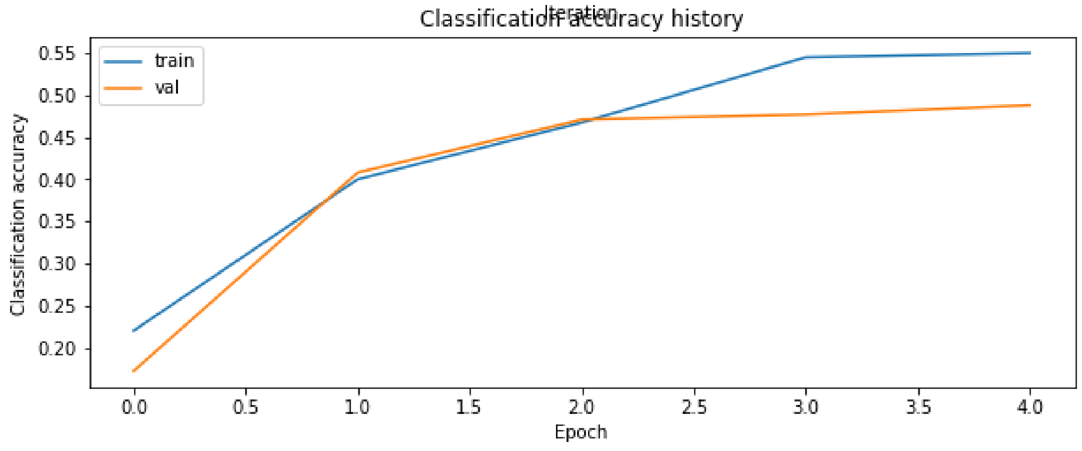
I traversed through all possible combinations of hyperparameters and save the model with the highest validation accuracy as the best model.

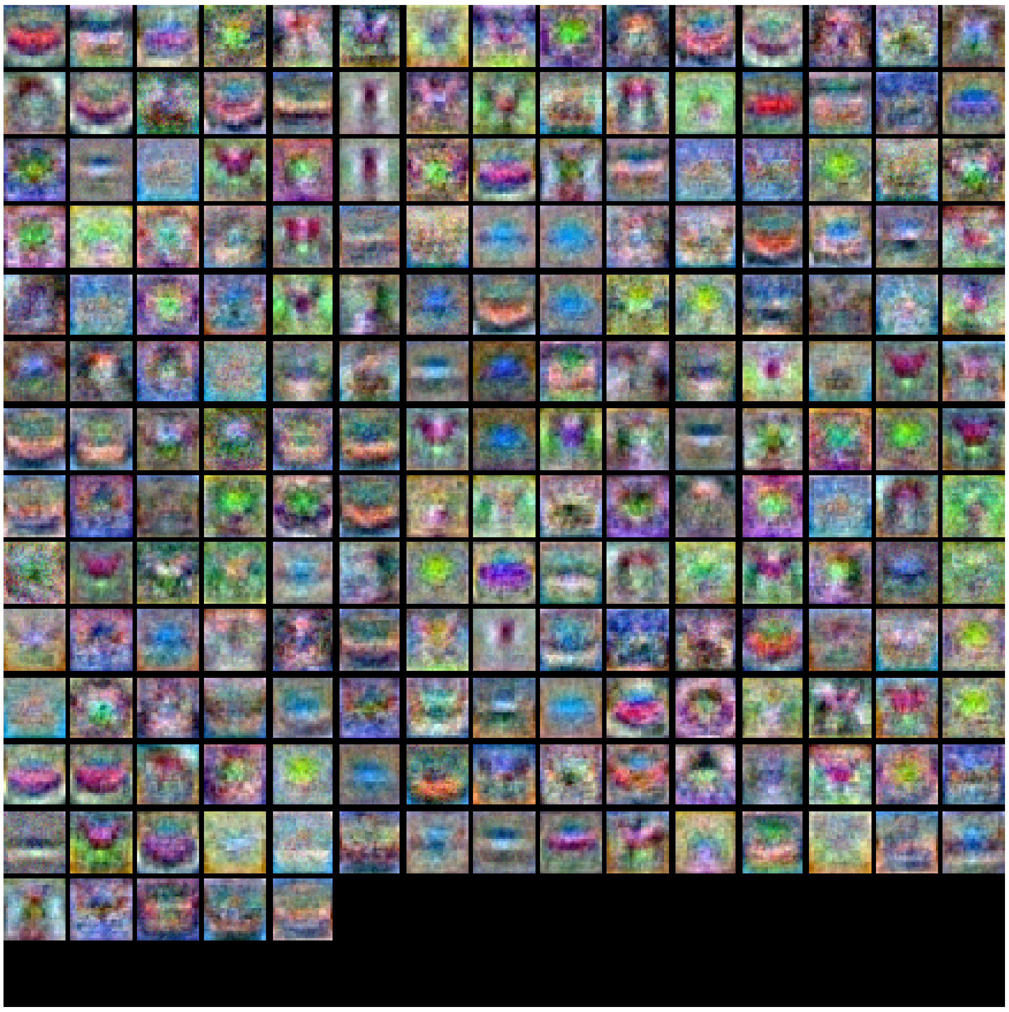
[42]:
```
best_net = None # store the best model into this

#################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained ␣
 ↪#
# model in best_net.                                                             ␣
 ↪#
#                                                                                ␣
 ↪#
# To help debug your network, it may help to use visualizations similar to the ␣
 ↪#
```

```
# ones we used above; these visualizations will have significant qualitative  ␣
↪#
# differences from the ones we saw above for the poorly tuned network.         ␣
↪#
#                                                                              ␣
↪#
# Tweaking hyperparameters by hand can be fun, but you might find it useful to ␣
↪#
# write code to sweep through possible combinations of hyperparameters         ␣
↪#
# automatically like we did on the previous exercises.                         ␣
↪#
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
learning_rates = [5e-4, 1e-3]
batch_size = [200, 400]
results = {}
best_val = -1
best_stats = None

for lr in learning_rates:
    for b in batch_size:
        net = TwoLayerNet(input_size, 200, num_classes)
        stats = net.train(X_train, y_train, X_val, y_val,
                    num_iters=1000, batch_size=b,
                    learning_rate=lr, learning_rate_decay=0.95,
                    reg=0.25, verbose=False)
        train_acc = (net.predict(X_train) == y_train).mean()
        val_acc = (net.predict(X_val) == y_val).mean()
        results[(lr, b)] = (train_acc, val_acc)
        if val_acc > best_val:
            best_val = val_acc
            best_net = net
            best_stats = stats
        print(f"lr={lr}, batch_size={b}, train_acc={train_acc},␣
↪val_acc={val_acc}")

plt.subplot(2, 1, 1)
plt.plot(best_stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

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

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

```
lr=0.0005, batch_size=200, train_acc=0.4638775510204082, val_acc=0.449
lr=0.0005, batch_size=400, train_acc=0.4653673469387755, val_acc=0.468
lr=0.001, batch_size=200, train_acc=0.5078571428571429, val_acc=0.481
lr=0.001, batch_size=400, train_acc=0.5173673469387755, val_acc=0.497
```



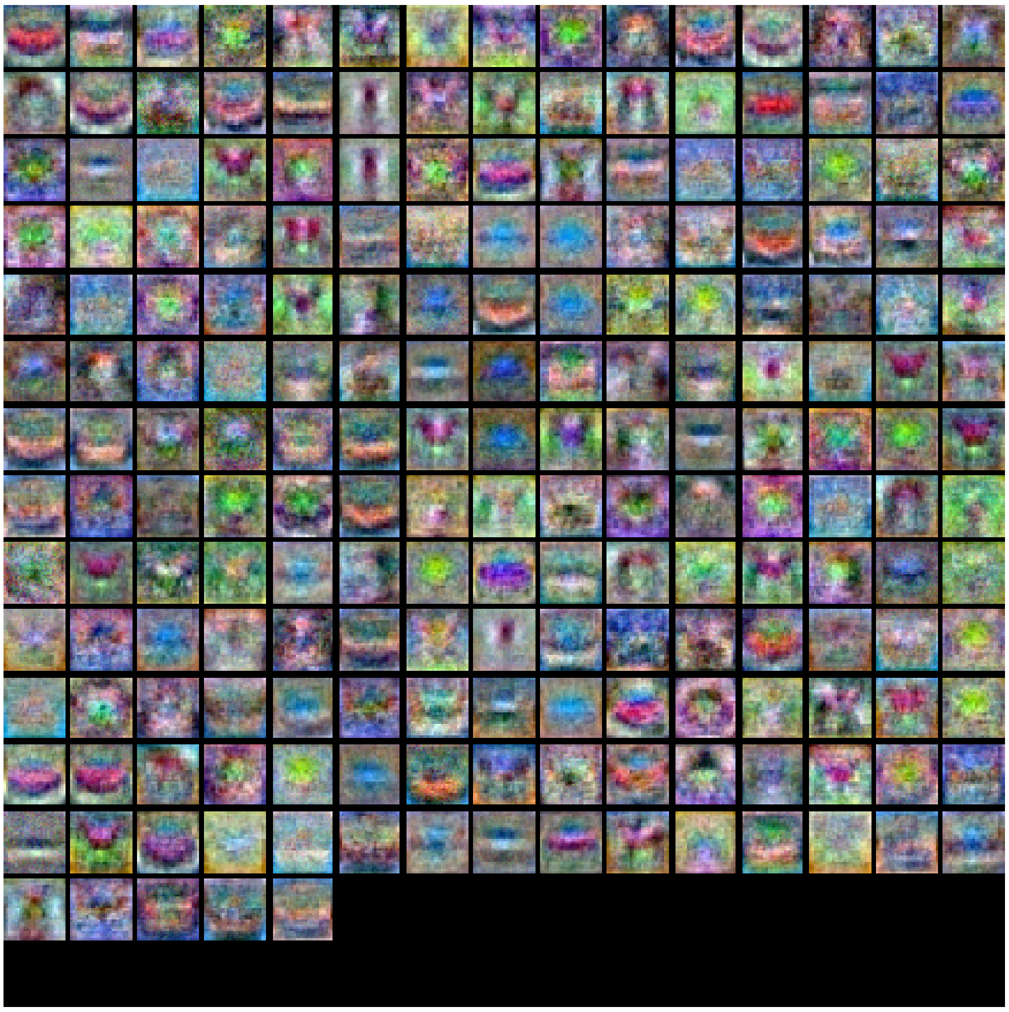




```
[43]: # Print your validation accuracy: this should be above 48%
      val_acc = (best_net.predict(X_val) == y_val).mean()
      print('Validation accuracy: ', val_acc)
```

```
Validation accuracy:  0.497
```

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



10 Run on the test set

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

[45]:
```python
# 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:  0.502
```

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.

$YourAnswer:$

I choose 1, 2, 3.

$YourExplanation:$

Actually this problem is equivalent to how to avoid overfitting because overfitting means the model nearly remembered the whole training set. For 1, the more data the model meet, the less likely that it remember all of them. For 2, the more hidden units the model has, the harder for training and the model is less likely to remember all the dataset. For 3, regularization constrains the L2 norm of weights won't be extremely large which means the model won't approximation the implicit function in an extremely complex way.

```
[ ]:
```

features

February 24, 2023

1 Image features exercise

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

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

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

[1]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt


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

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

1.1 Load data

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

[2]:
```
from cs231n.features import color_histogram_hsv, hog_feature

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'
    # Cleaning up variables to prevent loading data multiple times (which may␣
↪cause memory issue)
    try:
       del X_train, y_train
       del X_test, y_test
       print('Clear previously loaded data.')
    except:
       pass

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

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

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

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

1.2 Extract Features

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

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

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

[3]:
```
from cs231n.features import *

num_color_bins = 10 # Number of bins in the color histogram
feature_fns = [hog_feature, lambda img: color_histogram_hsv(img,␣
↪nbin=num_color_bins)]
```

```
X_train_feats = extract_features(X_train, feature_fns, verbose=True)
X_val_feats = extract_features(X_val, feature_fns)
X_test_feats = extract_features(X_test, feature_fns)

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

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

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

```
Done extracting features for 1000 / 49000 images
Done extracting features for 2000 / 49000 images
Done extracting features for 3000 / 49000 images
Done extracting features for 4000 / 49000 images
Done extracting features for 5000 / 49000 images
Done extracting features for 6000 / 49000 images
Done extracting features for 7000 / 49000 images
Done extracting features for 8000 / 49000 images
Done extracting features for 9000 / 49000 images
Done extracting features for 10000 / 49000 images
Done extracting features for 11000 / 49000 images
Done extracting features for 12000 / 49000 images
Done extracting features for 13000 / 49000 images
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
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Done extracting features for 40000 / 49000 images
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Done extracting features for 44000 / 49000 images
Done extracting features for 45000 / 49000 images
Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
Done extracting features for 49000 / 49000 images
```

1.3 Train SVM on features

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

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

from cs231n.classifiers.linear_classifier import LinearSVM

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

results = {}
best_val = -1
best_svm = None

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

for lr in learning_rates:
    for r in regularization_strengths:
        svm = LinearSVM()
        svm.train(X_train_feats, y_train, learning_rate=1e-7, reg=2.5e4,␣
 ↪num_iters=1500)
        y_train_pred = svm.predict(X_train_feats)
        y_val_pred = svm.predict(X_val_feats)
        train_accuracy = np.mean(y_train_pred == y_train)
        val_accuracy = np.mean(y_val_pred == y_val)
        results[(lr, r)] = (train_accuracy, val_accuracy)
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm

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

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

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

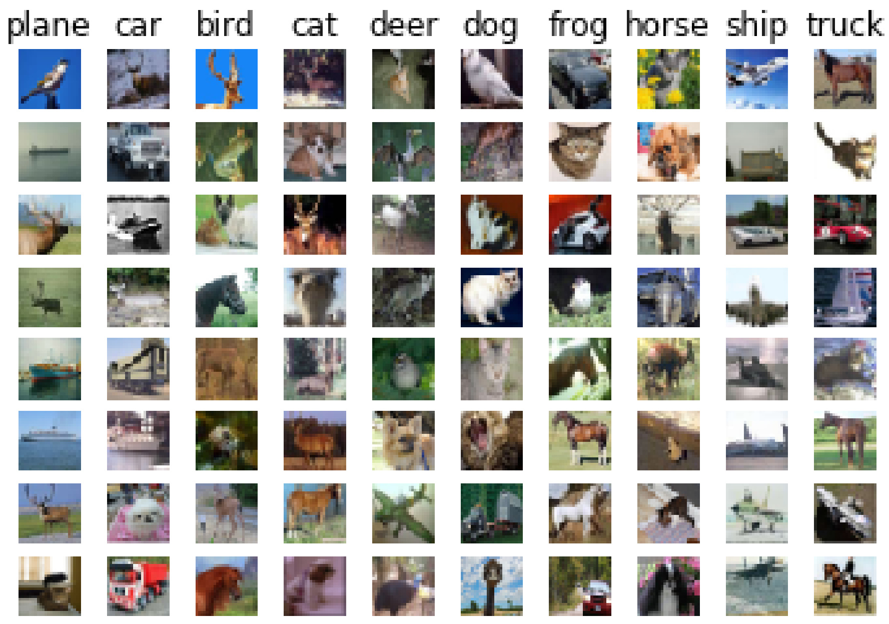
```
lr 1.000000e-09 reg 5.000000e+04 train accuracy: 0.412286 val accuracy: 0.419000
lr 1.000000e-09 reg 5.000000e+05 train accuracy: 0.411429 val accuracy: 0.416000
lr 1.000000e-09 reg 5.000000e+06 train accuracy: 0.414633 val accuracy: 0.423000
lr 1.000000e-08 reg 5.000000e+04 train accuracy: 0.418000 val accuracy: 0.424000
lr 1.000000e-08 reg 5.000000e+05 train accuracy: 0.415939 val accuracy: 0.420000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.416163 val accuracy: 0.419000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.412673 val accuracy: 0.409000
lr 1.000000e-07 reg 5.000000e+05 train accuracy: 0.411714 val accuracy: 0.413000
lr 1.000000e-07 reg 5.000000e+06 train accuracy: 0.411959 val accuracy: 0.409000
best validation accuracy achieved during cross-validation: 0.424000
```

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

```
0.423
```

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

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



1.3.1 Inline question 1:

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

Your Answer :

The misclassified images show features of both their corresponding labels and the labels they are classified into. For example, in the first column, most of the images have the streamline shape which is also an important feature of plane. Moreover, the color of images in "dog" column all have grey style, which is also the color of some typical dogs (e.g. husky and alaskan dog). In conclusion, it's reasonable for the model to misclassify.

1.4 Neural Network on image features

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

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

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

print(X_train_feats.shape)
```

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

[14]:
```
from cs231n.classifiers.neural_net import TwoLayerNet

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

best_net = None

################################################################################
# TODO: Train a two-layer neural network on image features. You may want to    #
# cross-validate various parameters as in previous sections. Store your best   #
# model in the best_net variable.                                              #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

learning_rates = [0.5, 1]
batch_size = [200, 400]

best_val = -1
```

```
for lr in learning_rates:
    for b in batch_size:
        net = TwoLayerNet(input_dim, hidden_dim, num_classes)
        net.train(X_train_feats, y_train, X_val_feats, y_val, learning_rate=lr,␣
 ↪learning_rate_decay=0.95, reg=2.5e-3, num_iters=1500, batch_size=b)
        y_train_pred = net.predict(X_train_feats)
        y_val_pred = net.predict(X_val_feats)
        train_accuracy = np.mean(y_train_pred == y_train)
        val_accuracy = np.mean(y_val_pred == y_val)
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_net = net
        print(f"lr={lr}, batch_size={b}, train_acc={train_accuracy},␣
 ↪val_acc={val_accuracy}")
# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

```
lr=0.5, batch_size=200, train_acc=0.6035918367346939, val_acc=0.573
lr=0.5, batch_size=400, train_acc=0.6208775510204082, val_acc=0.588
lr=1, batch_size=200, train_acc=0.5911224489795919, val_acc=0.565
lr=1, batch_size=400, train_acc=0.5933265306122449, val_acc=0.536
```

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

```
0.567
```

[ ]:
```

```