svm

December 13, 2024

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

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

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

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

```
Mounted at /content/drive
/content/drive/My Drive/cs231n/cs231n/assignment1/cs231n/datasets
/content/drive/My Drive/cs231n/cs231n/assignment1
```

1 Multiclass Support Vector Machine exercise

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

In this exercise you will:

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

[ ]:
```python
# 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
```

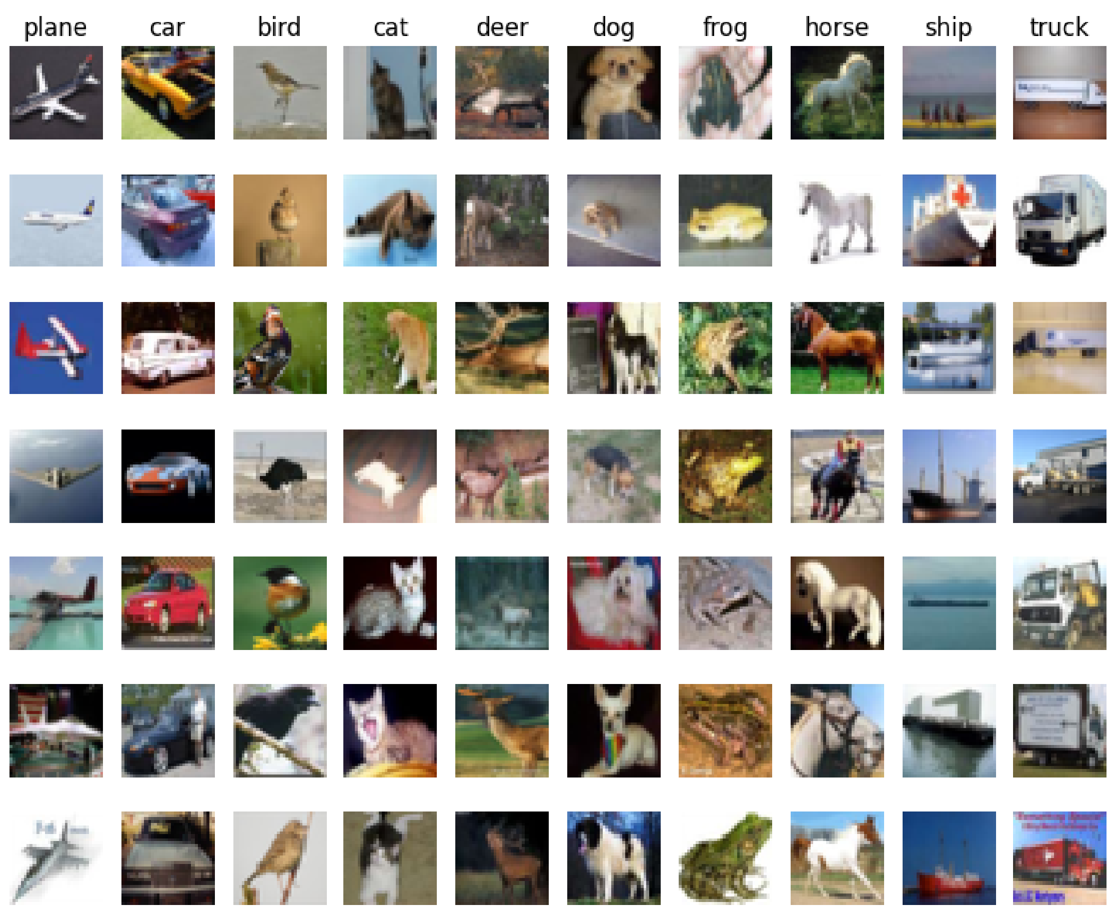
1.1 CIFAR-10 Data Loading and Preprocessing

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

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

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

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

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

[ ]:

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



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

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

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

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

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

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

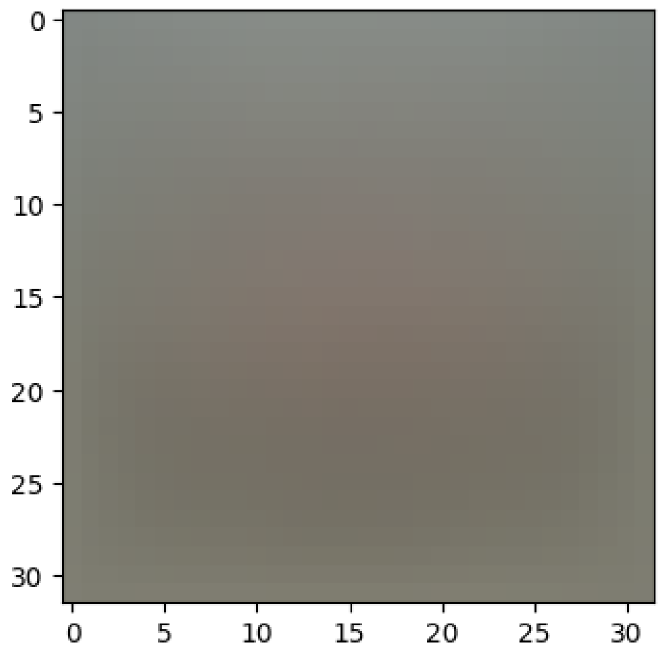
```
Train data shape:  (49000, 32, 32, 3)
Train labels shape:  (49000,)
Validation data shape:  (1000, 32, 32, 3)
Validation labels shape:  (1000,)
Test data shape:  (1000, 32, 32, 3)
Test labels shape:  (1000,)
```

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

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

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

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

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

# third: append the bias dimension of ones M(i.e. bias trick) so that our SV
# 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.

[ ]:
```python
# 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: 9.096371
```

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

[ ]:

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

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

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

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

```
numerical: 7.884859 analytic: 7.884859, relative error: 6.214882e-12
numerical: -10.235888 analytic: -10.235888, relative error: 2.335338e-11
numerical: -0.349773 analytic: -0.349773, relative error: 2.381001e-10
numerical: 9.529524 analytic: 9.529524, relative error: 2.285146e-11
numerical: 4.913359 analytic: 4.913359, relative error: 1.063102e-10
numerical: 17.000501 analytic: 17.002344, relative error: 5.421529e-05
numerical: -2.677886 analytic: -2.677886, relative error: 1.366558e-10
numerical: 10.846584 analytic: 10.846584, relative error: 1.476773e-11
numerical: -1.980903 analytic: -1.980903, relative error: 1.059119e-10
numerical: -16.229809 analytic: -16.229809, relative error: 1.357347e-11
numerical: 22.918648 analytic: 22.918648, relative error: 1.676788e-11
numerical: 12.133210 analytic: 12.133210, relative error: 2.138392e-11
numerical: -37.934926 analytic: -37.934926, relative error: 1.112081e-11
numerical: 1.727508 analytic: 1.727508, relative error: 4.223899e-11
numerical: 9.568185 analytic: 9.568185, relative error: 1.718585e-11
numerical: 3.187269 analytic: 3.187269, relative error: 2.289340e-11
numerical: -25.050671 analytic: -25.050671, relative error: 9.035990e-12
numerical: 10.159447 analytic: 10.159447, relative error: 1.384314e-11
numerical: 13.850607 analytic: 13.850607, relative error: 2.962218e-12
numerical: 5.569647 analytic: 5.569647, relative error: 2.292610e-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*

$Your Answer:$ gradient check gradient Numerical , . , . , Loss

$s_j - s_{y_i} - margin = 0$ Analytic . $$$$ Margin
$s_j - s_{y_i} - margin$ . .

[ ]:
```
# 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: 9.096371e+00 computed in 0.302793s
Vectorized loss: 9.096371e+00 computed in 0.026670s
difference: -0.000000
```

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

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

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

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

```
Naive loss and gradient: computed in 0.296514s
Vectorized loss and gradient: computed in 0.019137s
```

```
difference: 0.000000
```

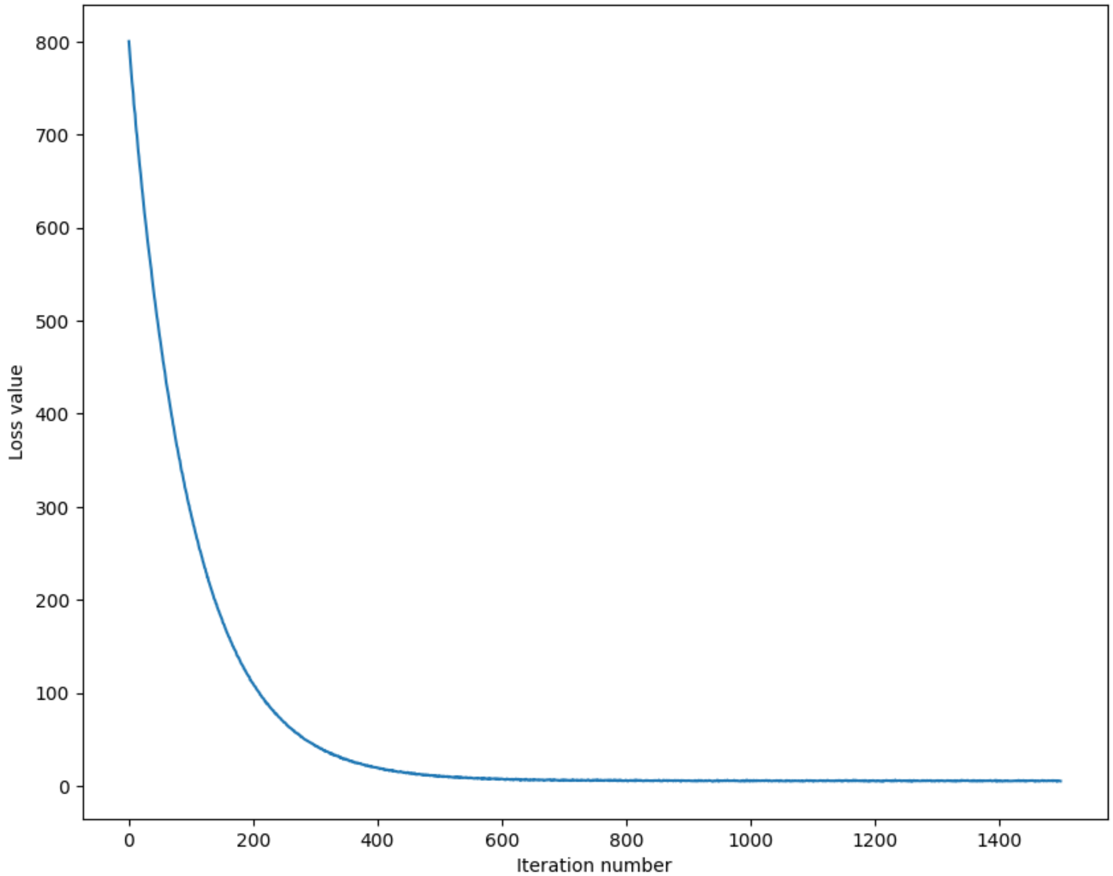
1.2.1 Stochastic Gradient Descent

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

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

```
iteration 0 / 1500: loss 800.206127
iteration 100 / 1500: loss 291.681479
iteration 200 / 1500: loss 109.490633
iteration 300 / 1500: loss 43.378999
iteration 400 / 1500: loss 19.232261
iteration 500 / 1500: loss 10.125137
iteration 600 / 1500: loss 7.274764
iteration 700 / 1500: loss 5.435390
iteration 800 / 1500: loss 5.915100
iteration 900 / 1500: loss 5.643761
iteration 1000 / 1500: loss 5.833713
iteration 1100 / 1500: loss 5.383642
iteration 1200 / 1500: loss 5.012039
iteration 1300 / 1500: loss 5.391125
iteration 1400 / 1500: loss 5.143230
That took 8.224440s
```

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



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

```
training accuracy: 0.369531
validation accuracy: 0.375000
```

[ ]:
```
# 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 (> 0.385) 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
```

```python
# (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 = np.linspace(1e-7, 5e-7, 10)
regularization_strengths = np.linspace(2.5e4, 5e4, 10)

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

for lr in learning_rates:
  for rs in regularization_strengths:
    svm = LinearSVM()
    svm.train(X_train, y_train, learning_rate=lr, reg=rs, num_iters=1500,␣
 ↪verbose=False)
    y_train_pred = svm.predict(X_train)
    y_val_pred = svm.predict(X_val)

    train_acc = np.mean(y_train == y_train_pred)
    val_acc = np.mean(y_val == y_val_pred)

    results[(lr, rs)] = (train_acc, val_acc)

    if val_acc > best_val:
      best_val = val_acc
      best_svm = svm
```

```python
# *****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)
```

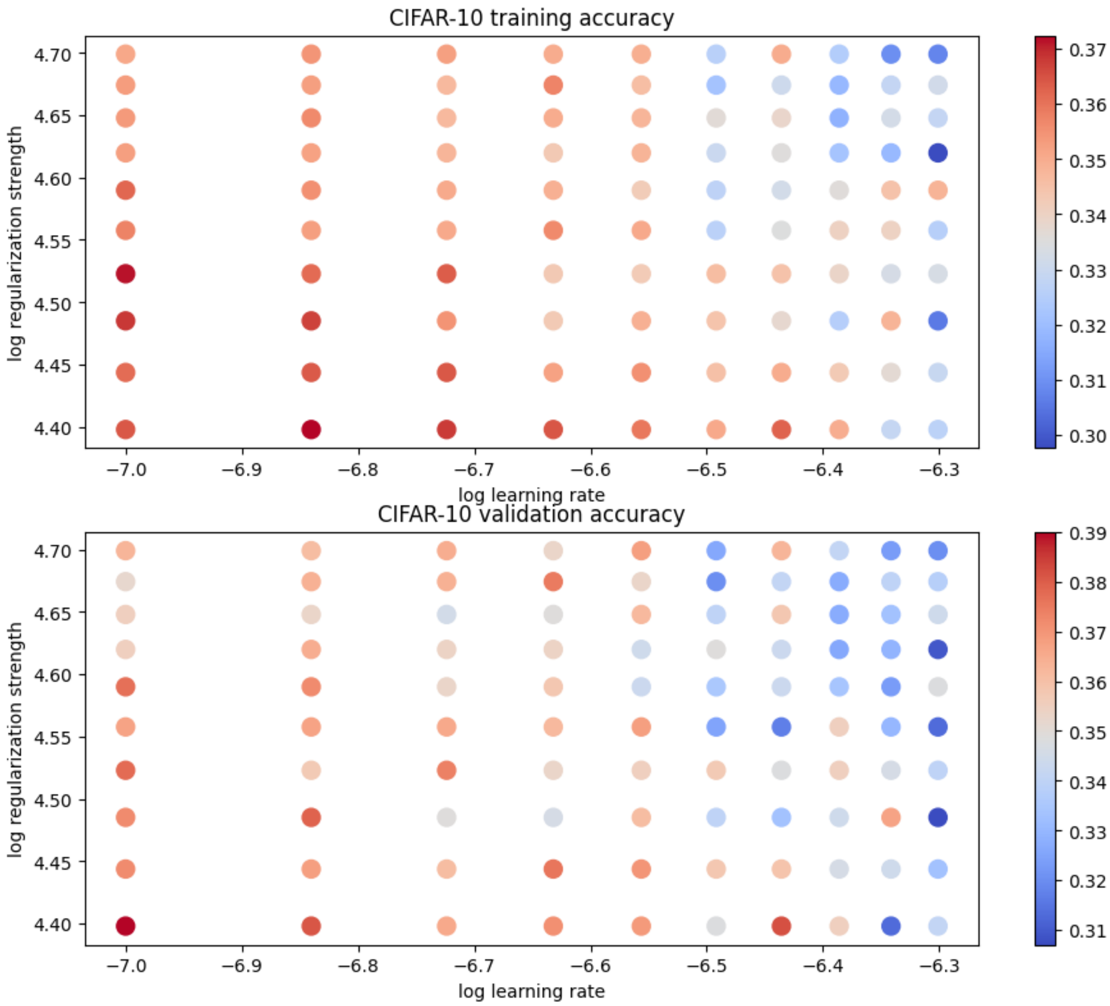
```
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.364102 val accuracy: 0.390000
lr 1.000000e-07 reg 2.777778e+04 train accuracy: 0.361163 val accuracy: 0.372000
lr 1.000000e-07 reg 3.055556e+04 train accuracy: 0.368245 val accuracy: 0.372000
lr 1.000000e-07 reg 3.333333e+04 train accuracy: 0.371245 val accuracy: 0.378000
lr 1.000000e-07 reg 3.611111e+04 train accuracy: 0.357714 val accuracy: 0.367000
lr 1.000000e-07 reg 3.888889e+04 train accuracy: 0.361898 val accuracy: 0.377000
lr 1.000000e-07 reg 4.166667e+04 train accuracy: 0.352755 val accuracy: 0.355000
lr 1.000000e-07 reg 4.444444e+04 train accuracy: 0.353633 val accuracy: 0.355000
lr 1.000000e-07 reg 4.722222e+04 train accuracy: 0.352959 val accuracy: 0.352000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.350837 val accuracy: 0.363000
lr 1.444444e-07 reg 2.500000e+04 train accuracy: 0.372408 val accuracy: 0.381000
lr 1.444444e-07 reg 2.777778e+04 train accuracy: 0.363796 val accuracy: 0.368000
lr 1.444444e-07 reg 3.055556e+04 train accuracy: 0.367020 val accuracy: 0.379000
lr 1.444444e-07 reg 3.333333e+04 train accuracy: 0.361490 val accuracy: 0.357000
lr 1.444444e-07 reg 3.611111e+04 train accuracy: 0.352653 val accuracy: 0.367000
lr 1.444444e-07 reg 3.888889e+04 train accuracy: 0.355408 val accuracy: 0.372000
lr 1.444444e-07 reg 4.166667e+04 train accuracy: 0.352000 val accuracy: 0.365000
lr 1.444444e-07 reg 4.444444e+04 train accuracy: 0.356408 val accuracy: 0.353000
lr 1.444444e-07 reg 4.722222e+04 train accuracy: 0.352796 val accuracy: 0.364000
lr 1.444444e-07 reg 5.000000e+04 train accuracy: 0.354286 val accuracy: 0.361000
lr 1.888889e-07 reg 2.500000e+04 train accuracy: 0.367918 val accuracy: 0.366000
lr 1.888889e-07 reg 2.777778e+04 train accuracy: 0.364122 val accuracy: 0.361000
lr 1.888889e-07 reg 3.055556e+04 train accuracy: 0.354735 val accuracy: 0.349000
lr 1.888889e-07 reg 3.333333e+04 train accuracy: 0.363510 val accuracy: 0.374000
lr 1.888889e-07 reg 3.611111e+04 train accuracy: 0.350490 val accuracy: 0.366000
lr 1.888889e-07 reg 3.888889e+04 train accuracy: 0.350449 val accuracy: 0.353000
lr 1.888889e-07 reg 4.166667e+04 train accuracy: 0.347857 val accuracy: 0.354000
lr 1.888889e-07 reg 4.444444e+04 train accuracy: 0.347000 val accuracy: 0.345000
lr 1.888889e-07 reg 4.722222e+04 train accuracy: 0.347041 val accuracy: 0.364000
lr 1.888889e-07 reg 5.000000e+04 train accuracy: 0.352347 val accuracy: 0.365000
lr 2.333333e-07 reg 2.500000e+04 train accuracy: 0.364286 val accuracy: 0.371000
lr 2.333333e-07 reg 2.777778e+04 train accuracy: 0.352102 val accuracy: 0.376000
lr 2.333333e-07 reg 3.055556e+04 train accuracy: 0.342837 val accuracy: 0.346000
lr 2.333333e-07 reg 3.333333e+04 train accuracy: 0.342939 val accuracy: 0.353000
lr 2.333333e-07 reg 3.611111e+04 train accuracy: 0.356347 val accuracy: 0.362000
lr 2.333333e-07 reg 3.888889e+04 train accuracy: 0.349286 val accuracy: 0.358000
```

```
lr 2.333333e-07 reg 4.166667e+04 train accuracy: 0.343082 val accuracy: 0.354000
lr 2.333333e-07 reg 4.444444e+04 train accuracy: 0.350000 val accuracy: 0.349000
lr 2.333333e-07 reg 4.722222e+04 train accuracy: 0.357327 val accuracy: 0.375000
lr 2.333333e-07 reg 5.000000e+04 train accuracy: 0.350061 val accuracy: 0.353000
lr 2.777778e-07 reg 2.500000e+04 train accuracy: 0.359265 val accuracy: 0.369000
lr 2.777778e-07 reg 2.777778e+04 train accuracy: 0.355286 val accuracy: 0.370000
lr 2.777778e-07 reg 3.055556e+04 train accuracy: 0.349184 val accuracy: 0.361000
lr 2.777778e-07 reg 3.333333e+04 train accuracy: 0.342571 val accuracy: 0.355000
lr 2.777778e-07 reg 3.611111e+04 train accuracy: 0.350776 val accuracy: 0.368000
lr 2.777778e-07 reg 3.888889e+04 train accuracy: 0.342143 val accuracy: 0.343000
lr 2.777778e-07 reg 4.166667e+04 train accuracy: 0.348327 val accuracy: 0.344000
lr 2.777778e-07 reg 4.444444e+04 train accuracy: 0.347878 val accuracy: 0.362000
lr 2.777778e-07 reg 4.722222e+04 train accuracy: 0.345980 val accuracy: 0.353000
lr 2.777778e-07 reg 5.000000e+04 train accuracy: 0.349592 val accuracy: 0.368000
lr 3.222222e-07 reg 2.500000e+04 train accuracy: 0.350592 val accuracy: 0.348000
lr 3.222222e-07 reg 2.777778e+04 train accuracy: 0.345490 val accuracy: 0.358000
lr 3.222222e-07 reg 3.055556e+04 train accuracy: 0.344490 val accuracy: 0.340000
lr 3.222222e-07 reg 3.333333e+04 train accuracy: 0.346306 val accuracy: 0.357000
lr 3.222222e-07 reg 3.611111e+04 train accuracy: 0.326408 val accuracy: 0.325000
lr 3.222222e-07 reg 3.888889e+04 train accuracy: 0.326857 val accuracy: 0.335000
lr 3.222222e-07 reg 4.166667e+04 train accuracy: 0.329837 val accuracy: 0.349000
lr 3.222222e-07 reg 4.444444e+04 train accuracy: 0.336347 val accuracy: 0.340000
lr 3.222222e-07 reg 4.722222e+04 train accuracy: 0.321306 val accuracy: 0.320000
lr 3.222222e-07 reg 5.000000e+04 train accuracy: 0.325694 val accuracy: 0.326000
lr 3.666667e-07 reg 2.500000e+04 train accuracy: 0.362531 val accuracy: 0.382000
lr 3.666667e-07 reg 2.777778e+04 train accuracy: 0.349918 val accuracy: 0.359000
lr 3.666667e-07 reg 3.055556e+04 train accuracy: 0.337816 val accuracy: 0.333000
lr 3.666667e-07 reg 3.333333e+04 train accuracy: 0.344837 val accuracy: 0.348000
lr 3.666667e-07 reg 3.611111e+04 train accuracy: 0.334816 val accuracy: 0.317000
lr 3.666667e-07 reg 3.888889e+04 train accuracy: 0.331816 val accuracy: 0.343000
lr 3.666667e-07 reg 4.166667e+04 train accuracy: 0.335367 val accuracy: 0.343000
lr 3.666667e-07 reg 4.444444e+04 train accuracy: 0.338531 val accuracy: 0.358000
lr 3.666667e-07 reg 4.722222e+04 train accuracy: 0.330633 val accuracy: 0.341000
lr 3.666667e-07 reg 5.000000e+04 train accuracy: 0.349959 val accuracy: 0.363000
lr 4.111111e-07 reg 2.500000e+04 train accuracy: 0.349612 val accuracy: 0.355000
lr 4.111111e-07 reg 2.777778e+04 train accuracy: 0.342714 val accuracy: 0.346000
lr 4.111111e-07 reg 3.055556e+04 train accuracy: 0.325184 val accuracy: 0.344000
lr 4.111111e-07 reg 3.333333e+04 train accuracy: 0.339367 val accuracy: 0.355000
lr 4.111111e-07 reg 3.611111e+04 train accuracy: 0.340286 val accuracy: 0.355000
lr 4.111111e-07 reg 3.888889e+04 train accuracy: 0.335714 val accuracy: 0.334000
lr 4.111111e-07 reg 4.166667e+04 train accuracy: 0.321755 val accuracy: 0.326000
lr 4.111111e-07 reg 4.444444e+04 train accuracy: 0.317041 val accuracy: 0.327000
lr 4.111111e-07 reg 4.722222e+04 train accuracy: 0.318408 val accuracy: 0.327000
lr 4.111111e-07 reg 5.000000e+04 train accuracy: 0.324592 val accuracy: 0.341000
lr 4.555556e-07 reg 2.500000e+04 train accuracy: 0.328592 val accuracy: 0.313000
lr 4.555556e-07 reg 2.777778e+04 train accuracy: 0.337020 val accuracy: 0.344000
lr 4.555556e-07 reg 3.055556e+04 train accuracy: 0.348408 val accuracy: 0.367000
lr 4.555556e-07 reg 3.333333e+04 train accuracy: 0.332776 val accuracy: 0.346000
```

```
lr 4.555556e-07 reg 3.611111e+04 train accuracy: 0.340224 val accuracy: 0.330000
lr 4.555556e-07 reg 3.888889e+04 train accuracy: 0.344837 val accuracy: 0.323000
lr 4.555556e-07 reg 4.166667e+04 train accuracy: 0.318633 val accuracy: 0.329000
lr 4.555556e-07 reg 4.444444e+04 train accuracy: 0.332286 val accuracy: 0.333000
lr 4.555556e-07 reg 4.722222e+04 train accuracy: 0.328469 val accuracy: 0.340000
lr 4.555556e-07 reg 5.000000e+04 train accuracy: 0.309367 val accuracy: 0.323000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.326653 val accuracy: 0.341000
lr 5.000000e-07 reg 2.777778e+04 train accuracy: 0.329265 val accuracy: 0.333000
lr 5.000000e-07 reg 3.055556e+04 train accuracy: 0.305694 val accuracy: 0.307000
lr 5.000000e-07 reg 3.333333e+04 train accuracy: 0.333224 val accuracy: 0.340000
lr 5.000000e-07 reg 3.611111e+04 train accuracy: 0.325388 val accuracy: 0.313000
lr 5.000000e-07 reg 3.888889e+04 train accuracy: 0.348245 val accuracy: 0.348000
lr 5.000000e-07 reg 4.166667e+04 train accuracy: 0.297571 val accuracy: 0.309000
lr 5.000000e-07 reg 4.444444e+04 train accuracy: 0.328531 val accuracy: 0.344000
lr 5.000000e-07 reg 4.722222e+04 train accuracy: 0.331551 val accuracy: 0.338000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.307612 val accuracy: 0.320000
best validation accuracy achieved during cross-validation: 0.390000
```

[ ]:

```python
# 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()
```



[ ]:
```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: 0.364000
```

[ ]:
```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']
```

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

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

Inline question 2

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

Your Answer : *W* *Class* . *(32x32x3)* *W(32x32x10)* *10* *Class score* . *Class Score* *W* , *W* *Class* *(feature)* .