softmax

September 26, 2019

1 Softmax exercise

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

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

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

[1]:
```
from __future__ import print_function
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
```

```python
    SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

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

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

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

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

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

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


# Cleaning up variables to prevent loading data multiple times (which may cause
 ↪memory issue)
try:
   del X_train, y_train
```

```
    del X_test, y_test
    print('Clear previously loaded data.')
except:
    pass

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

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

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: 2.337439
sanity check: 2.302585
```

[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: -4.201883 analytic: -4.201884, relative error: 1.062573e-08
numerical: -2.448731 analytic: -2.448731, relative error: 2.172825e-08
numerical: -1.628155 analytic: -1.628155, relative error: 1.586141e-08
numerical: -0.608704 analytic: -0.608704, relative error: 2.895591e-08
numerical: 2.007179 analytic: 2.007179, relative error: 1.433332e-08
numerical: 1.705836 analytic: 1.705836, relative error: 2.589906e-08
numerical: 0.711577 analytic: 0.711577, relative error: 3.458888e-08
numerical: 0.785290 analytic: 0.785290, relative error: 3.599886e-08
numerical: 2.725483 analytic: 2.725483, relative error: 1.524648e-08
numerical: 1.298813 analytic: 1.298813, relative error: 5.616155e-09
numerical: -1.599427 analytic: -1.599427, relative error: 3.203826e-08
numerical: -1.116127 analytic: -1.116127, relative error: 3.263291e-09
numerical: 2.377927 analytic: 2.377927, relative error: 9.583506e-09
numerical: 1.060793 analytic: 1.060793, relative error: 2.226404e-09
numerical: 0.298422 analytic: 0.298422, relative error: 6.734193e-08
numerical: 1.137911 analytic: 1.137911, relative error: 8.713932e-09
numerical: 5.203028 analytic: 5.203028, relative error: 2.043302e-08
numerical: 4.076289 analytic: 4.076289, relative error: 1.074337e-09
numerical: -0.384054 analytic: -0.384054, relative error: 6.277739e-09
numerical: 2.116082 analytic: 2.116082, relative error: 9.852325e-09
```

[6]:
```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: 2.337439e+00 computed in 0.123000s
vectorized loss: 2.337439e+00 computed in 0.006000s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[7]:
```
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of over 0.35 on the validation set.
from cs231n.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None
learning_rates = [1e-7, 5e-7]
regularization_strengths = [2.5e4, 5e4]

################################################################################
# TODO:                                                                        ␣
 ↪#
# Use the validation set to set the learning rate and regularization strength.␣
 ↪#
# This should be identical to the validation that you did for the SVM; save   ␣
 ↪#
# the best trained softmax classifer in best_softmax.                          ␣
 ↪#
################################################################################
iters = 2000
for lr in learning_rates:
    for rs in regularization_strengths:
        softmax = Softmax()
        softmax.train(X_train, y_train, learning_rate=lr, reg=rs,␣
 ↪num_iters=iters)

        y_train_pred = softmax.predict(X_train)
```

```
        acc_train = np.mean(y_train == y_train_pred)
        y_val_pred = softmax.predict(X_val)
        acc_val = np.mean(y_val == y_val_pred)

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

        if best_val < acc_val:
            best_val = acc_val
            best_softmax = softmax
################################################################################
#                              END OF YOUR CODE                                ␣
 ↪#
################################################################################

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

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

```
lr 1.000000e-07 reg 2.500000e+04 train accuracy: 0.353816 val accuracy: 0.374000
lr 1.000000e-07 reg 5.000000e+04 train accuracy: 0.328898 val accuracy: 0.343000
lr 5.000000e-07 reg 2.500000e+04 train accuracy: 0.348878 val accuracy: 0.365000
lr 5.000000e-07 reg 5.000000e+04 train accuracy: 0.330265 val accuracy: 0.343000
best validation accuracy achieved during cross-validation: 0.374000
```

[8]:
```
# 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: 0.359000
```

Inline Question - *True or False*

It's possible to add a new datapoint to a training set that would leave the SVM loss unchanged, but this is not the case with the Softmax classifier loss.

Your answer:

Your explanation:

[9]:
```
# 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])
```