Softmax Classifier

This exercise guides you through the process of classifying images using a Softmax classifier. As part of this you will:

- · Implement a fully vectorized loss function for the Softmax classifier
- · Calculate the analytical gradient using vectorized code
- · Tune hyperparameters on a validation set
- Optimize the loss function with Stochastic Gradient Descent (SGD)
- · Visualize the learned weights

```
In [1]: # start-up code!
            import random
            import matplotlib.pyplot as plt
            import numpy as np
            %matplotlib inline
            plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
            plt.rcParams['image.interpolation'] = 'nearest'
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
In [2]: from load_cifar10_tvt import load_cifar10_train_val
            X_train, y_train, X_val, y_val, X_test, y_test = load_cifar10_train_val()
print("Train data shape: ", X_train.shape)
print("Train labels shape: ", y_train.shape)
           print("Val data shape: ", X_val.shape)
print("Val labels shape: ", Y_val.shape)
print("Test data shape: ", Y_test.shape)
print("Test labels shape: ", Y_test.shape)
            Train, validation and testing sets have been created as
            X_i and y_i where i=train,val,test
Train data shape: (3073, 49000)
            Train labels shape: (49000,)
            Val data shape: (3073, 1000)
            Val labels shape: (1000,)
Test data shape: (3073, 1000)
Test labels shape: (1000,)
```

Code for this section is to be written in cs231n/classifiers/softmax.py

```
In [3]: # Now, implement the vectorized version in softmax loss vectorized.
        from cs231n.classifiers.softmax import softmax_loss_vectorized
        # gradient check.
        from cs231n.gradient_check import grad check sparse
        W = np.random.randn(10, 3073) * 0.0001
        tic = time.time()
        loss, grad = softmax_loss_vectorized(W, X_train, y_train, 0.00001)
        toc = time.time()
        print("vectorized loss: %e computed in %fs" % (loss, toc - tic))
        # 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)))
        f = lambda w: softmax_loss_vectorized(w, X_train, y_train, 0.0)[0]
        grad_numerical = grad_check_sparse(f, W, grad, 10)
        vectorized loss: 2.344749e+00 computed in 0.257661s
        loss: 2.344749
        sanity check: 2.302585
        numerical: 1.965265 analytic: 1.965265, relative error: 4.050525e-08
        numerical: 4.230704 analytic: 4.230704, relative error: 1.309142e-08
        numerical: -0.892266 analytic: -0.892266, relative error: 5.395355e-08
        numerical: 2.159850 analytic: 2.159850, relative error: 6.890465e-09
        numerical: 0.289739 analytic: 0.289739, relative error: 1.286889e-07
        numerical: -0.882801 analytic: -0.882801, relative error: 5.561869e-08
```

Code for this section is to be written in cs231n/classifiers/linear_classifier.py

numerical: 2.027293 analytic: 2.027293, relative error: 1.478793e-08 numerical: -0.146122 analytic: -0.146122, relative error: 3.984646e-07 numerical: -0.920213 analytic: -0.920213, relative error: 4.301624e-08 numerical: -2.725859 analytic: -2.725859, relative error: 3.388619e-08

```
In [4]: # Now that efficient implementations to calculate loss function and gradient of the softmax are ready,
# use it to train the classifier on the cifar-10 data
# Complete the `train` function in cs231n/classifiers/linear_classifier.py

from cs231n.classifiers.linear_classifier import Softmax

classifier = Softmax()
loss_hist = classifier.train(
    X_train,
    y_train,
    learning_rate=le=5,
    reg=le=5,
    num_iters=100,
    batch_size=200,
    verbose=True,
)
# Plot loss vs. iterations
plt.plot(loss_hist)
plt.xlabel("Iteration number")
plt.ylabel("Toss value")
```

found batch. loss + grad computed. weights updated. iteration 0 / 100: loss 6.316712 found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed.
weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. iteration 10 / 100: loss 3.519489 found batch. loss + grad computed. weights updated. found batch. loss + grad computed.
weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. iteration 20 / 100: loss 3.028383 found batch. loss + grad computed. weights updated. iteration 30 / 100: loss 2.901936 found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch.

```
loss + grad computed.
weights updated.
found batch.
loss + grad computed.
weights updated.
iteration 40 / 100: loss 3.395893
found batch.
loss + grad computed.
weights updated.
iteration 50 / 100: loss 3.307890
found batch.
loss + grad computed.
weights updated.
iteration 60 / 100: loss 3.959330
found batch.
loss + grad computed.
weights updated.
found batch.
```

loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. iteration 70 / 100: loss 3.508856 found batch. loss + grad computed.
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weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. iteration 80 / 100: loss 3.023361 found batch. loss + grad computed. weights updated. iteration 90 / 100: loss 2.433835 found batch. loss + grad computed. weights updated. found batch. loss + grad computed. weights updated. found batch. loss + grad computed.
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```
6.5
6.0
5.5
5.0
4.5
4.5
4.0
3.5
3.0
2.5
0 20 40 60 80 100
```

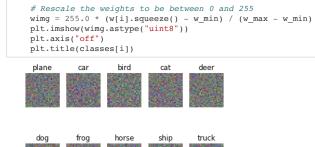
```
In [5]: # Complete the `predict` function in cs231n/classifiers/linear_classifier.ppy
# Evaluate on test set
y_test_pred = classifier.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print("softmax on raw pixels final test set accuracy: %f" % (test_accuracy,))

softmax on raw pixels final test set accuracy: 0.273000

In [6]: # Visualize the learned weights for each class
w = classifier.W[:, :-1] # strip out the bias
w = w.reshape(10, 32, 32, 3)

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)

In []: