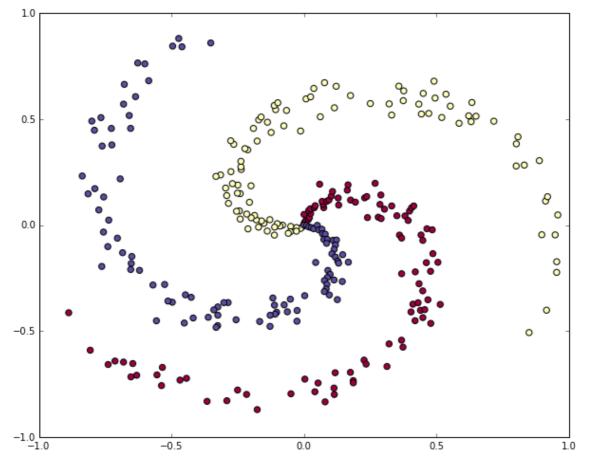
```
In [1]: # A bit of setup
    import numpy as np
    import matplotlib.pyplot as plt

%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
```

```
In [323]: np.random.seed(0)
          N = 100 \# number of points per class
          D = 2 # dimensionality
          K = 3 # number of classes
          X = np.zeros((N*K,D))
          y = np.zeros(N*K, dtype='uint8')
          for j in xrange(K):
            ix = range(N*j,N*(j+1))
            r = np.linspace(0.0,1,N) # radius
            t = np.linspace(j*4,(j+1)*4,N) + np.random.randn(N)*0.2 # theta
            X[ix] = np.c_[r*np.sin(t), r*np.cos(t)]
            y[ix] = j
          fig = plt.figure()
          plt.scatter(X[:, 0], X[:, 1], c=y, s=40, cmap=plt.cm.Spectral)
          plt.xlim([-1,1])
          plt.ylim([-1,1])
          #fig.savefig('spiral_raw.png')
```



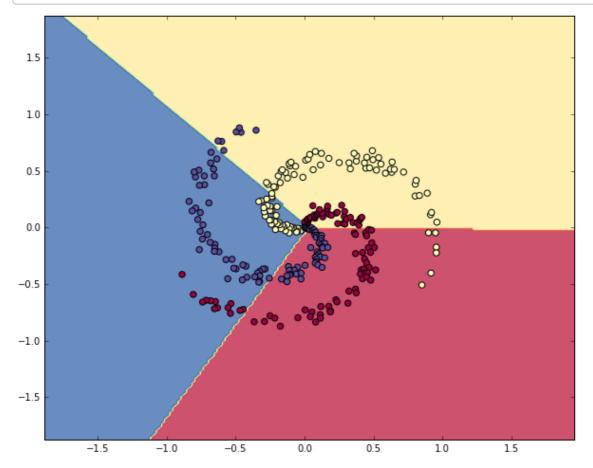
1 of 6 2020/2/21, 4:04 PM

```
Notebook
In [329]: #Train a Linear Classifier
               # initialize parameters randomly
               W = 0.01 * np.random.randn(D,K)
               b = np.zeros((1,K))
               # some hyperparameters
               step\_size = 1e-0
               reg = 1e-3 # regularization strength
               # gradient descent loop
               num examples = X.shape[0]
               for i in xrange(200):
                 # evaluate class scores, [N x K]
                 scores = np.dot(X, W) + b
                 # compute the class probabilities
                 exp_scores = np.exp(scores)
                 probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True) # [N x
               KJ
                 # compute the loss: average cross-entropy loss and regularization
                 corect_logprobs = -np.log(probs[range(num_examples),y])
                 data_loss = np.sum(corect_logprobs)/num_examples
                 reg loss = 0.5*reg*np.sum(W*W)
                 loss = data_loss + reg_loss
                 if i % 10 == 0:
                   print "iteration %d: loss %f" % (i, loss)
                 # compute the gradient on scores
                 dscores = probs
                 dscores[range(num examples),y] -= 1
                 dscores /= num_examples
                 # backpropate the gradient to the parameters (W,b)
                 dW = np.dot(X.T, dscores)
                 db = np.sum(dscores, axis=0, keepdims=True)
                 dW += reg*W # regularization gradient
                 # perform a parameter update
                 W += -step_size * dW
                 b += -step_size * db
```

```
iteration 10: loss 0.917265
iteration 20: loss 0.851503
iteration 30: loss 0.822336
iteration 40: loss 0.807586
iteration 50: loss 0.799448
iteration 60: loss 0.794681
iteration 70: loss 0.791764
iteration 80: loss 0.789920
iteration 90: loss 0.788726
iteration 100: loss 0.787938
iteration 110: loss 0.787409
iteration 120: loss 0.787049
iteration 130: loss 0.786803
iteration 140: loss 0.786633
iteration 150: loss 0.786514
iteration 160: loss 0.786431
iteration 170: loss 0.786373
iteration 180: loss 0.786331
iteration 190: loss 0.786302
```

iteration 0: loss 1.096956

training accuracy: 0.49



3 of 6 2020/2/21, 4:04 PM

```
Notebook In [332]: # initialize parameters randomly
               h = 100 # size of hidden layer
               W = 0.01 * np.random.randn(D,h)
               b = np.zeros((1,h))
               W2 = 0.01 * np.random.randn(h,K)
               b2 = np.zeros((1,K))
               # some hyperparameters
               step\_size = 1e-0
               reg = 1e-3 # regularization strength
               # gradient descent loop
               num examples = X.shape[0]
               for i in xrange(10000):
                 # evaluate class scores, [N x K]
                 hidden_layer = np.maximum(0, np.dot(X, W) + b) # note, ReLU activation
                 scores = np.dot(hidden_layer, W2) + b2
                 # compute the class probabilities
                 exp scores = np.exp(scores)
                 probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True) # [N x
               K ]
                 # compute the loss: average cross-entropy loss and regularization
                 corect_logprobs = -np.log(probs[range(num_examples),y])
                 data_loss = np.sum(corect_logprobs)/num_examples
                 reg_loss = 0.5*reg*np.sum(W*W) + 0.5*reg*np.sum(W2*W2)
                 loss = data loss + reg loss
                 if i % 1000 == 0:
                   print "iteration %d: loss %f" % (i, loss)
                 # compute the gradient on scores
                 dscores = probs
                 dscores[range(num_examples),y] -= 1
                 dscores /= num_examples
                 # backpropate the gradient to the parameters
                 # first backprop into parameters W2 and b2
                 dW2 = np.dot(hidden layer.T, dscores)
                 db2 = np.sum(dscores, axis=0, keepdims=True)
                 # next backprop into hidden layer
                 dhidden = np.dot(dscores, W2.T)
                 # backprop the ReLU non-linearity
                 dhidden[hidden_layer <= 0] = 0</pre>
                 # finally into W,b
                 dW = np.dot(X.T, dhidden)
                 db = np.sum(dhidden, axis=0, keepdims=True)
                 # add regularization gradient contribution
                 dW2 += reg * W2
                 dW += reg * W
                 # perform a parameter update
                 W += -step_size * dW
                 b += -step size * db
                 W2 += -step size * dW2
                 b2 += -step size * db2
```

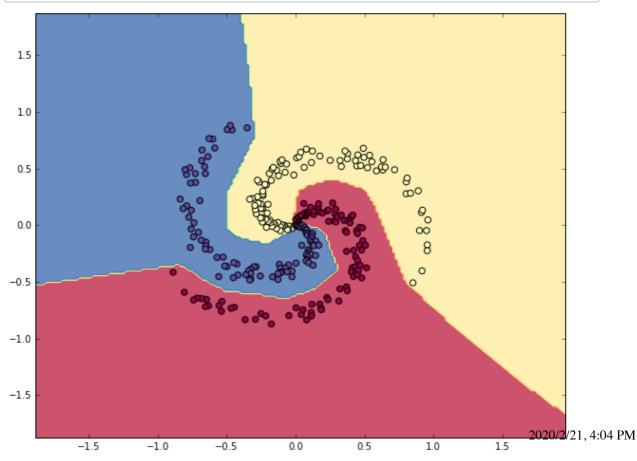
4 of 6 2020/2/21, 4:04 PM

```
iteration 0: loss 1.098744
iteration 1000: loss 0.294946
iteration 2000: loss 0.259301
iteration 3000: loss 0.248310
iteration 4000: loss 0.246170
iteration 5000: loss 0.245649
iteration 6000: loss 0.245491
iteration 7000: loss 0.245400
iteration 8000: loss 0.245335
iteration 9000: loss 0.245292
```

```
In [333]: # evaluate training set accuracy
hidden_layer = np.maximum(0, np.dot(X, W) + b)
scores = np.dot(hidden_layer, W2) + b2
predicted_class = np.argmax(scores, axis=1)
print 'training accuracy: %.2f' % (np.mean(predicted_class == y))
```

training accuracy: 0.98

```
In [336]: # plot the resulting classifier
          h = 0.02
          x_{\min}, x_{\max} = X[:, 0].min() - 1, X[:, 0].max() + 1
          y_{min}, y_{max} = X[:, 1].min() - 1, X[:, 1].max() + 1
          xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                                np.arange(y_min, y_max, h))
          Z = np.dot(np.maximum(0, np.dot(np.c [xx.ravel(), yy.ravel()], W) + b), W
          2) + b2
          Z = np.argmax(Z, axis=1)
          Z = Z.reshape(xx.shape)
          fig = plt.figure()
          plt.contourf(xx, yy, Z, cmap=plt.cm.Spectral, alpha=0.8)
          plt.scatter(X[:, 0], X[:, 1], c=y, s=40, cmap=plt.cm.Spectral)
          plt.xlim(xx.min(), xx.max())
          plt.ylim(yy.min(), yy.max())
          #fig.savefig('spiral_net.png')
```



T . 1 1		
Notebook The Class	https://cs.stanford.edu/people/karpathy/cs231nfiles/minimal	l_n
TII [] •		

6 of 6 2020/2/21, 4:04 PM