

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import copy

In [12]:

hexa = pd.read_csv('FeedForward_Data_hexa.csv', names=['dim1','dim2','label'])

In [13]:

def plot_data(X, y, filename):
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Spectral, s = 1)
    plt.savefig(filename)
    plt.close()

def plot_decision_boundary(clf, X, y, filename):
    # Set min and max values and add padding as required
    x_min, x_max = -1.0, 1.0
    y_min, y_max = -1.0, 1.0
    h = 0.01

    # Generate a grid of points with distance h between them
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    # Predict the function value for the whole grid
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z_out = clf(torch.tensor(np.c_[xx.ravel(), yy.ravel()], dtype = torch.float))
    Z = X_out.data.max(1)[1]
    # Z.shape
    Z = Z.reshape(xx.shape)
    # Plot the contour and training examples
    plt.contourf(xx, yy, Z, cmap=plt.cm.Spectral)
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Spectral, s = 1)
    plt.savefig(filename)
    plt.close()

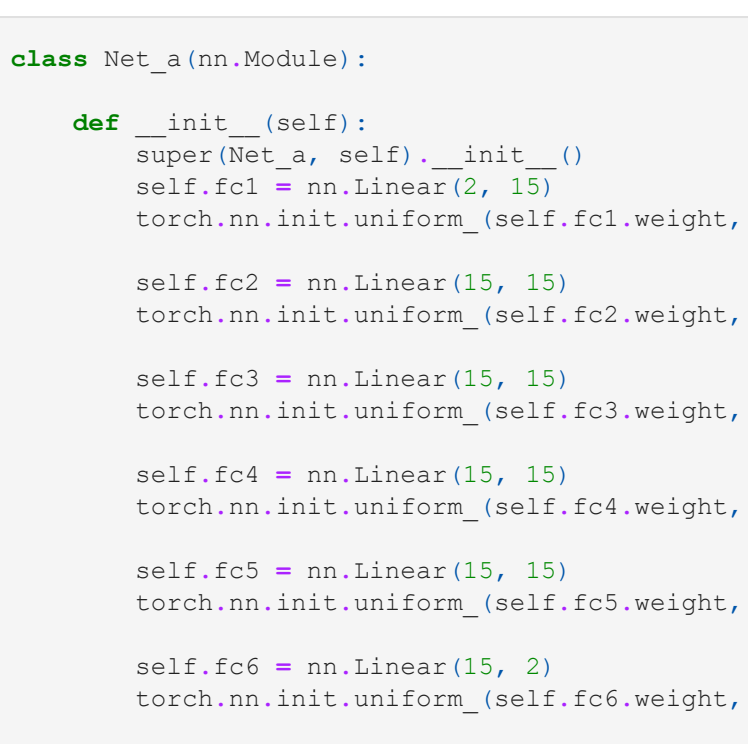
In [15]:

X_hexa = hexa.values[:, 0:2] # Take only the first two features.
X_hexa = torch.tensor(X_hexa, dtype = torch.float)
y_hexa = hexa.values[:, 2]
y_hexa = torch.tensor(y_hexa, dtype = torch.long)

In [16]:

plt.scatter(X_hexa[:, 0], X_hexa[:, 1], c=y_hexa, cmap=plt.cm.Spectral, s = 50)

Out[16]:
<matplotlib.collections.PathCollection at 0x2534b8f050>



In [17]:

class Net_a(nn.Module):

    def __init__(self):
        super(Net_a, self).__init__()
        self.fc1 = nn.Linear(2, 15)
        torch.nn.init.uniform_(self.fc1.weight, a=-2, b=2)

        self.fc2 = nn.Linear(15, 15)
        torch.nn.init.uniform_(self.fc2.weight, a=-2, b=2)

        self.fc3 = nn.Linear(15, 15)
        torch.nn.init.uniform_(self.fc3.weight, a=-2, b=2)

        self.fc4 = nn.Linear(15, 15)
        torch.nn.init.uniform_(self.fc4.weight, a=-2, b=2)

        self.fc5 = nn.Linear(15, 15)
        torch.nn.init.uniform_(self.fc5.weight, a=-2, b=2)

        self.fc6 = nn.Linear(15, 2)
        torch.nn.init.uniform_(self.fc6.weight, a=-2, b=2)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        x = F.relu(self.fc4(x))
        x = F.relu(self.fc5(x))
        x = self.fc6(x)
        return F.log_softmax(x)
        #return F.softmax(x)

In [18]:

previous_loss = 1

### train
net_a = Net_a()

# create a stochastic gradient descent optimizer
learning_rate = .02
optimizer = torch.optim.SGD(net_a.parameters(), lr=learning_rate, momentum=0.9)

# create a loss function
# criterion = nn.CrossEntropyLoss()
criterion = nn.NLLLoss()

# Stopping conditions
stopping_crit = np.power(1/10,6)
nepochs = 20000

data, target = X_hexa, y_hexa
for epoch in range(nepochs):

    optimizer.zero_grad()
    # forward propagate
    net_out = net_a(data)
    # compute loss
    loss = criterion(net_out, target)

    # backpropagate
    loss.backward()
    # update parameters
    optimizer.step()
    # print out report

    if epoch % 100 == 0:
        print('Epoch ', epoch, 'Loss ', loss.item())
        net_out = net_a(data)
        pred = net_out.data.max(1)[1] # get the index of the max log-probability
        correctidx = pred.eq(target.data)
        ncorrect = correctidx.sum()
        accuracy = ncorrect.item()/len(data)
        print('Training accuracy is ', accuracy)
        if accuracy >= 0.97:
            break

    if abs(previous_loss - loss.item()) < stopping_crit:
        break

    previous_loss = copy.copy(loss.item())

### compute accuracy on training data
net_out = net_a(data)
pred = net_out.data.max(1)[1] # get the index of the max log-probability
correctidx = pred.eq(target.data)
ncorrect = correctidx.sum()
accuracy = ncorrect.item()/len(data)
print('Training accuracy is ', accuracy)

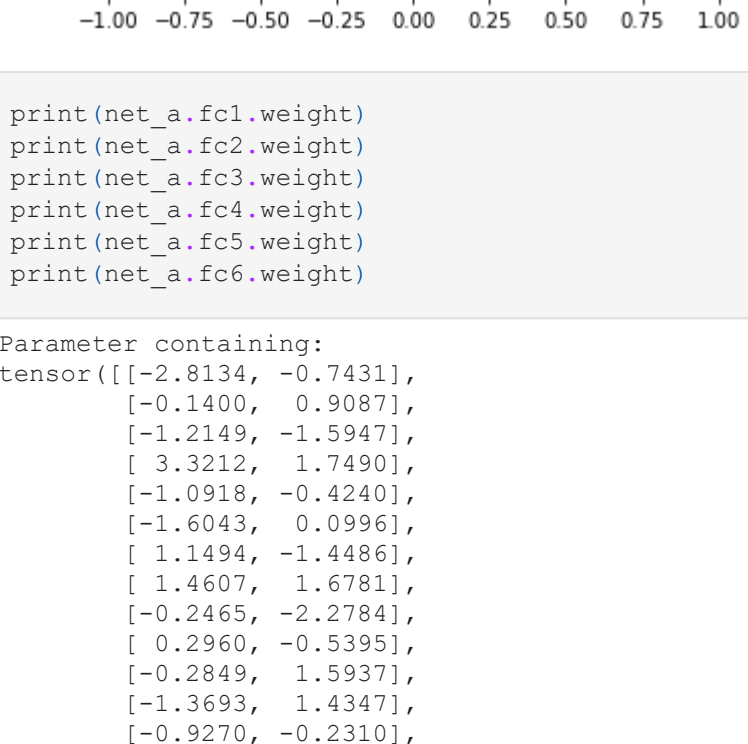
<ipython-input-17-732e73e9d00f>:31: UserWarning: Implicit dimension choice for log_softmax has been deprecated.
Change the call to log_softmax to dim=X as an argument.
    return F.log_softmax(x)

Epoch 0 Loss 20.884859085083008
Training accuracy is 0.9405799278846154
Epoch 100 Loss 0.1759939044713974
Training accuracy is 0.9405799278846154
Epoch 200 Loss 0.16694723069667816
Training accuracy is 0.9405799278846154
Epoch 300 Loss 0.154664339549225
Training accuracy is 0.9405799278846154
Epoch 400 Loss 0.1535159796476364
Training accuracy is 0.9405799278846154
Epoch 500 Loss 0.1627575308084488
Training accuracy is 0.9405799278846154
Epoch 600 Loss 0.15054650604724884
Training accuracy is 0.9405799278846154
Epoch 700 Loss 0.1530572744002838
Training accuracy is 0.9405799278846154
Epoch 800 Loss 0.1507023274898529
Training accuracy is 0.9405799278846154
Epoch 900 Loss 0.14822515845298767
Training accuracy is 0.9405799278846154
Epoch 1000 Loss 0.14909633994102478
Training accuracy is 0.9405799278846154
Epoch 1100 Loss 0.15268570184707642
Training accuracy is 0.9405799278846154
Epoch 1200 Loss 0.15150310099124908
Training accuracy is 0.9405799278846154
Epoch 1300 Loss 0.1510932594537735
Training accuracy is 0.9405799278846154
Epoch 1400 Loss 0.1531142294406891
Training accuracy is 0.9405799278846154
Epoch 1500 Loss 0.15063579380512238
Training accuracy is 0.9405799278846154
Epoch 1600 Loss 0.153206929564476
Training accuracy is 0.9405799278846154
Epoch 1700 Loss 0.14856640994548798
Training accuracy is 0.9405799278846154
Epoch 1800 Loss 0.155164228896103
Training accuracy is 0.9405799278846154
Epoch 1900 Loss 0.14954222738742828
Training accuracy is 0.9405799278846154
Epoch 2000 Loss 0.1498364359140396
Training accuracy is 0.9405799278846154
Epoch 2100 Loss 0.1518077552318573
Training accuracy is 0.9405799278846154
Epoch 2200 Loss 0.147964969273819
Training accuracy is 0.9405799278846154
Epoch 2300 Loss 0.14816322922706604
Training accuracy is 0.9405799278846154
Epoch 2400 Loss 0.1470182090997696
Training accuracy is 0.9405799278846154
Epoch 2500 Loss 0.14880245923995972
Training accuracy is 0.9405799278846154
Epoch 2600 Loss 0.14857104420661926
Training accuracy is 0.9405799278846154
Epoch 2700 Loss 0.1542617231607437
Training accuracy is 0.9405799278846154
Epoch 2800 Loss 0.16089704632759094
Training accuracy is 0.9405799278846154
Epoch 2900 Loss 0.15431243181228638
Training accuracy is 0.9405799278846154
Epoch 3000 Loss 0.15187621116638184
Training accuracy is 0.9405799278846154
Epoch 3100 Loss 0.14810438454151154
Training accuracy is 0.9405799278846154
Epoch 3200 Loss 0.14676420390605927
Training accuracy is 0.9405799278846154
Epoch 3300 Loss 0.14788338541984558
Training accuracy is 0.9405799278846154
Epoch 3400 Loss 0.14830511808395386
Training accuracy is 0.9405799278846154
Epoch 3500 Loss 0.1500018835067749
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Epoch 3800 Loss 0.1500265747308731
Training accuracy is 0.9405799278846154
Epoch 3900 Loss 0.1456853449344635
Training accuracy is 0.9405799278846154
Epoch 4000 Loss 0.14666929841041565
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Epoch 4100 Loss 0.1459705976319733
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Epoch 4200 Loss 0.15132766962051392
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Epoch 4300 Loss 0.1524515002965927
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Epoch 4400 Loss 0.14893785119056702
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Epoch 4500 Loss 0.1492107281684875
Training accuracy is 0.9405799278846154
Epoch 4600 Loss 0.1480204164981842
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Epoch 4700 Loss 0.145859494805336
Training accuracy is 0.9405799278846154
Epoch 4800 Loss 0.15279439091682434
Training accuracy is 0.9405799278846154
Epoch 4900 Loss 0.147756889462471
Training accuracy is 0.9405799278846154
Epoch 5000 Loss 0.14989760518074036
Training accuracy is 0.9405799278846154
Epoch 5100 Loss 0.14922019839286804
Training accuracy is 0.9405799278846154
Epoch 5200 Loss 0.14940524101257324
Training accuracy is 0.9405799278846154
Epoch 5300 Loss 0.1530437022447586
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Training accuracy is 0.9405799278846154
Epoch 5500 Loss 0.14702707529067993
Training accuracy is 0.9405799278846154
Epoch 5600 Loss 0.1491458630199432
Training accuracy is 0.9405799278846154
Epoch 5700 Loss 0.14579521119594574
Training accuracy is 0.9405799278846154
Epoch 5800 Loss 0.14842286705970764
Training accuracy is 0.9405799278846154
Epoch 5900 Loss 0.149422019839286804
Training accuracy is 0.9405799278846154

In [23]:

plt.scatter(X_hexa[:, 0], X_hexa[:, 1], c=correctidx, cmap=plt.cm.Spectral, s = 50)

Out[23]:
<matplotlib.collections.PathCollection at 0x2534b9afa00>



In [24]:

print(net_a.fc1.weight)
print(net_a.fc2.weight)
print(net_a.fc3.weight)
print(net_a.fc4.weight)
print(net_a.fc5.weight)
print(net_a.fc6.weight)

Parameter containing:
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        requires_grad=True)

Parameter containing:
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        requires_grad=True)

Parameter containing:
tensor([[-1.6859e+00, -3.8833e-01, 8.5158e-01, -1.0717e+00, -1.0578e+00,
        -1.1713e+00, -1.6433e-01, 1.3075e-01, -1.3831e+00, -2.0808e-01,
        -1.5632e-01, 0.0687e-01, -7.1675e-01, 6.2656e-01, -1.7944e+00],
        [-1.9314e+00, -1.0708e+00, -9.4300e-01, -3.6506e-01, -1.1020e+00,
        2.6703e-01, -1.2882e-01, -5.8048e-01, -1.6931e+00, 7.2824e-01,
        -1.8108e+00, 6.2375e-01, -1.2342e+00, -1.7003e+00, -1.5935e+00],
        [-1.4719e+00, -1.2602e+00, 1.0172e+00, 1.5335e+00, -7.7794e-01,
        5.3700e-01, 1.9255e+00, -1.9520e+00, -6.4925e-03, 1.8729e+00,
        7.9381e-01, 3.9132e-02, 1.6312e+00, -8.7431e-01, -1.6671e+00],
        [-1.1489e+00, 1.6405e-01, 4.4053e+00, -9.5674e-01, 4.3114e+00, 5.5713e-01,
        -2.8262e-01, -7.2732e-02, 4.9800e-01, 1.3750e+00, 2.7308e+00,
        6.2998e-01, -4.6607e-02, 1.4049e+00, -2.3078e+00, -9.0890e-01],
        [ 4.8536e-01, 1.0649e+00, 6.0672e-01, -8.3123e-01, 1.8866e+00,
        -3.0274e-01, -1.0483e+00, -1.4318e+00, 1.6252e+00, 5.9879e-01,
        -1.9415e+00, 2.0483e-01, 1.6392e+00, 4.9444e-01, 1.1035e+00],
        [ 1.8116e+00, 7.8504e-01, 2.5192e-01, 1.6866e+00, 1.0775e+00,
        1.1351e+00, -1.8433e-01, 9.5674e-01, 4.3114e+00, 5.5713e-01,
        1.5788e+00, -3.8501e-01, -8.6151e-02, -1.4738e+00, 1.9773e+00],
        [-9.4988e-01, 5.0892e-01, 1.1964e+00, 1.1964e+00, -5.1099e-01,
        -1.9825e+00, -1.9824e+00, -4.1693e-01, 7.9547e-01, -1.2495e+00,
        -9.2755e-01, 9.6521e-02, 5.4154e-01, 5.1194e-01, -7.2844e-01],
        [-2.6910e-01, 7.6905e-01, 1.7674e-01, 1.6091e+00, 2.9285e-01,
        3.5022e-01, -1.3494e+00, -1.8660e+00, 3.4500e-01, -1.2140e+00,
        7.1069e-01, -1.3457e+00, 1.1026e+00, 5.2942e-01, 1.7005e+00],
        [-2.3942e-01, 1.6405e-01, 4.4053e+00, -9.5674e-01, 4.3114e+00, 5.5713e-01,
        -5.1677e-01, -6.6720e+00, -1.2070e+00, -1.3714e+00, -2.1280e+00,
        -1.7735e+00, -1.8075e+00, -1.8781e+00, -5.1069e+00, 1.0671e-01],
        [ 1.1796e+00, 1.7455e+00, 1.5204e+00, -6.5927e-01, 1.5148e+00,
        -9.0277e-01, -6.5567e-01, -1.3977e+00, -3.
```