Colab: https://colab.research.google.com/drive/1sXSvXiSBK67Sfm8SwXzDkYXyY1HnZ_jh?usp=sharing

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

!gdown 1dLOPwh01o3k8p_hK633ixhD1ehz6nNWk
df = pd.read_csv("/content/spiral.csv")
df.head()
```

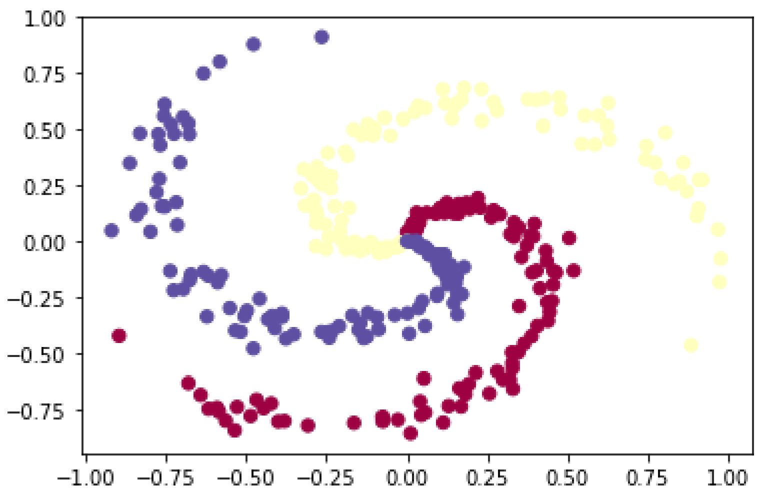
```
Downloading...
From: https://drive.google.com/uc?id=1dLOPwh01o3k8p_hK633ixhD1ehz6nNWk
To: /content/spiral.csv
100% 12.9k/12.9k [00:00<00:00, 15.0MB/s]
```

	x1	x2	y
0	0.000000	0.000000	0
1	-0.000650	0.010080	0
2	0.009809	0.017661	0
3	0.007487	0.029364	0
4	-0.000027	0.040404	0

```
df.shape
```

Saving...

```
plt.scatter(df["x1"], df["x2"], c=df["y"], s=40, cmap=plt.cm.Spectral)
plt.show()
```




```
X = df.iloc[:, :-1].to_numpy()
y = df.iloc[:, -1].to_numpy()
```

```
d = 2
n = 3
m = X.shape[0]
h = 100
W1 = 0.01 * np.random.randn(d, h)
b1 = np.zeros((1, h))
W2 = 0.01 * np.random.randn(h, n)
b2 = np.zeros((1, n))
```

Forward Propogation

```
Z1 = np.dot(X, W1) + b1
A1 = np.maximun(Z1, 0)
Z2 = np.dot(A1, W2) + b2
Z2_exp = np.exp(Z2)
A2 = Z2_exp / np.sum(Z2_exp, axis=1, keepdims=True)
probs = A2
```

Backward Propogation

```
dZ2 = probs
dZ2[range(m), y] -= 1
dW2 = np.dot(A1.T, dZ2)/m
db2 = np.sum(dZ2, axis=0, keepdims=True)/m
```



```
dZ1[Z1 <= 0] = 0
dW1 = np.dot(X.T, dZ1)/m
db1 = np.sum(dZ1, axis=0, keepdims=True)/m
```

Update Weights and biases

```
lr = 1e-0
W1 += -lr * dW1
b1 += -lr * db1
W2 += -lr * dW2
b2 += -lr * db2
```

Complete Code

```
# initialize parameters randomly
d = 2
h = 100 # size of hidden layer
n = 3
```

```
W1 = 0.01 * np.random.randn(d,h)
b1 = np.zeros((1,h))
W2 = 0.01 * np.random.randn(h,n)
b2 = np.zeros((1,n))

# some hyperparameters
lr = 1e-0
reg = 1e-3 # regularization strength
num_examples = X.shape[0]

for i in range(10000):

    # forward prop
    Z1 = np.dot(X, W1) + b1
    A1 = np.maximum(0, Z1)
    Z2 = np.dot(A1, W2) + b2
    Z2 = np.exp(Z2)
    A2 = Z2 / np.sum(Z2, axis=1, keepdims=True)
    probs = A2

    # calc. loss
    correct_logprobs = -np.log(probs[range(num_examples),y])
    data_loss = np.sum(correct_logprobs)/num_examples
    reg_loss = 0.5*reg*np.sum(W1*W1) + 0.5*reg*np.sum(W2*W2) # regularization
    loss = data_loss + reg_loss # adding reg. to loss
    if i % 1000 == 0:
        print("iteration %d: loss %f" % (i, loss))

    # backprop
    # compute the gradient on scores
    [illegible] 1
    dZ2 /= num_examples

    # first backprop into parameters W2 and b2
    dW2 = np.dot(A1.T, dZ2)
    db2 = np.sum(dZ2, axis=0, keepdims=True)
    # next backprop into hidden layer, A1
    dA1 = np.dot(dZ2, W2.T)
    # backprop the ReLU non-linearity
    dA1[Z1 <= 0] = 0
    # finally into W,b
    dZ1 = dA1
    dW1 = np.dot(X.T, dZ1)
    db1 = np.sum(dZ1, axis=0, keepdims=True)

    # add regularization gradient contribution
    dW2 += reg * W2
    dW1 += reg * W1

    # perform a parameter update
    W1 += -lr * dW1
    b1 += -lr * db1
    W2 += -lr * dW2
    b2 += -lr * db2
```

```
iteration 0: loss 1.098773
iteration 1000: loss 0.325943
iteration 2000: loss 0.264767
iteration 3000: loss 0.262636
iteration 4000: loss 0.259373
iteration 5000: loss 0.252881
iteration 6000: loss 0.260316
iteration 7000: loss 0.252657
iteration 8000: loss 0.251868
iteration 9000: loss 0.252115
```

```
class NN:

    def __init__(self, n_features, n_hidden, n_classes):
        self.d = n_features
        self.h = n_hidden
        self.n = n_classes
        self.W1 = 0.01 * np.random.randn(self.d, self.h)
        self.b1 = np.zeros((1,self.h))
        self.W2 = 0.01 * np.random.randn(self.h,self.n)
        self.b2 = np.zeros((1,self.n))

    def fwd_prop(self, X):
        Z1 = np.dot(X, self.W1) + self.b1
        A1 = np.maximum(0, Z1)
        Z2 = np.dot(A1, self.W2) + self.b2
        Z2 = np.exp(Z2)
        A2 = Z2 / np.sum(Z2, axis=1, keepdims=True)
        return A1, A2
```



```
        correct_logprobs = -np.log(probs[range(num_examples),y])
        loss = np.sum(correct_logprobs)/num_examples
        return loss

    def back_prop(self, X, A1, A2, y):
        # compute the gradient on scores
        num_examples = y.shape[0]
        dZ2 = A2
        dZ2[range(num_examples),y] -= 1
        dZ2 /= num_examples
        # first backprop into parameters W2 and b2
        dW2 = np.dot(A1.T, dZ2)
        db2 = np.sum(dZ2, axis=0, keepdims=True)
        # next backprop into hidden layer, A1
        dA1 = np.dot(dZ2, self.W2.T)
        # backprop the ReLU non-linearity
        dA1[A1 <= 0] = 0
        # finally into W,b
        dZ1 = dA1
        dW1 = np.dot(X.T, dZ1)
        db1 = np.sum(dZ1, axis=0, keepdims=True)
        return dW1, db1, dW2, db2
```

```
    def fit(self, X, lr, reg, max_iters):
        num_examples = X.shape[0]
        for i in range(max_iters):
            #foward prop
            A1, A2 = self.fwd_prop(X)
            # calculate loss
            data_loss = self.cce_loss(y, A2)
            reg_loss = 0.5*reg*np.sum(self.W1*self.W1) + 0.5*reg*np.sum(self.W2*sel
            loss = data_loss + reg_loss

            if i % 1000 == 0:
                print("iteration %d: loss %f" % (i, loss))

            dW1, db1, dW2, db2  = self.back_prop(X, A1, A2, y)

            # add regularization gradient contribution
            dW2 += reg * self.W2
            dW1 += reg * self.W1

            # perform a parameter update
            self.W1 += -lr * dW1
            self.b1 += -lr * db1
            self.W2 += -lr * dW2
            self.b2 += -lr * db2

    def predict(self, X):
        A1 = np.maximum(0, np.dot(X, self.W1) + self.b1) # ReLU(Z1) = ReLU(W1T. X +
        Z2 = np.dot(A1, self.W2) + self.b2 # Z2 = W2T.A1 + b2 => 3 probab
        y_hat = np.argmax(Z2, axis=1) # taking index of max probab
```



```
nn_model = NN(n_features=2, n_hidden=100, n_classes=3)
nn_model.fit(X, lr=1, reg=1e-3, max_iters=10000)
print('training accuracy: %.2f' % (np.mean(nn_model.predict(X) == y)))
```

```
iteration 0: loss 1.098823
iteration 1000: loss 0.319607
iteration 2000: loss 0.252365
iteration 3000: loss 0.249224
iteration 4000: loss 0.248282
iteration 5000: loss 0.247995
iteration 6000: loss 0.247727
iteration 7000: loss 0.247629
iteration 8000: loss 0.247557
iteration 9000: loss 0.247491
training accuracy: 0.99
```

```
from matplotlib import pyplot as plt

# create a 2D grid
step = 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, step), np.arange(y_min, y_max, step))
```

```
# predict for all the points in the grid

y_hat = nn_model.predict(np.c_[xx.ravel(), yy.ravel()])
y_hat = y_hat.reshape(xx.shape)

# plot
fig = plt.figure()
plt.contourf(xx, yy, y_hat, 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())
plt.show()
```