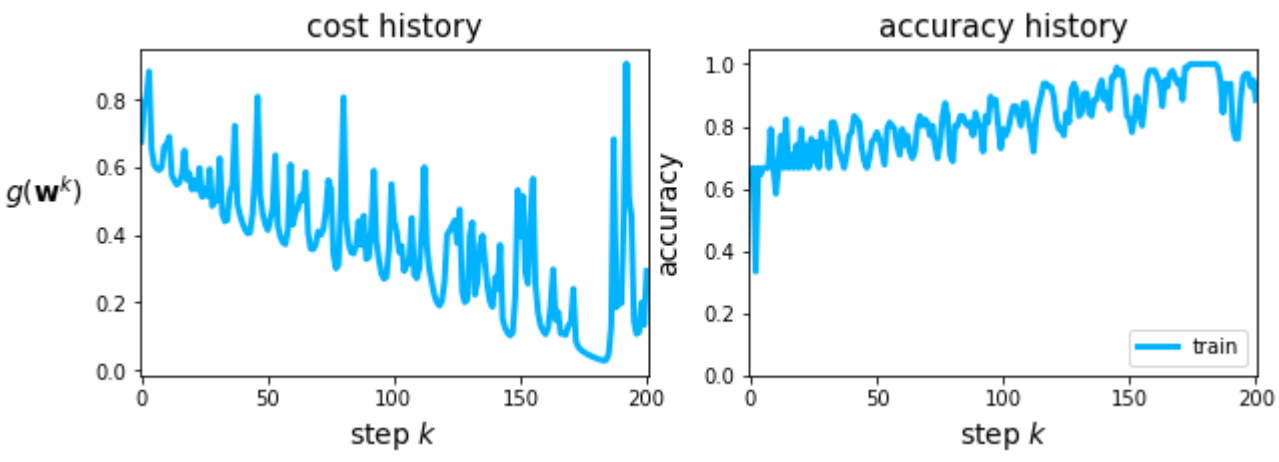
435 HW2 Xiaowei Yuan

13.1

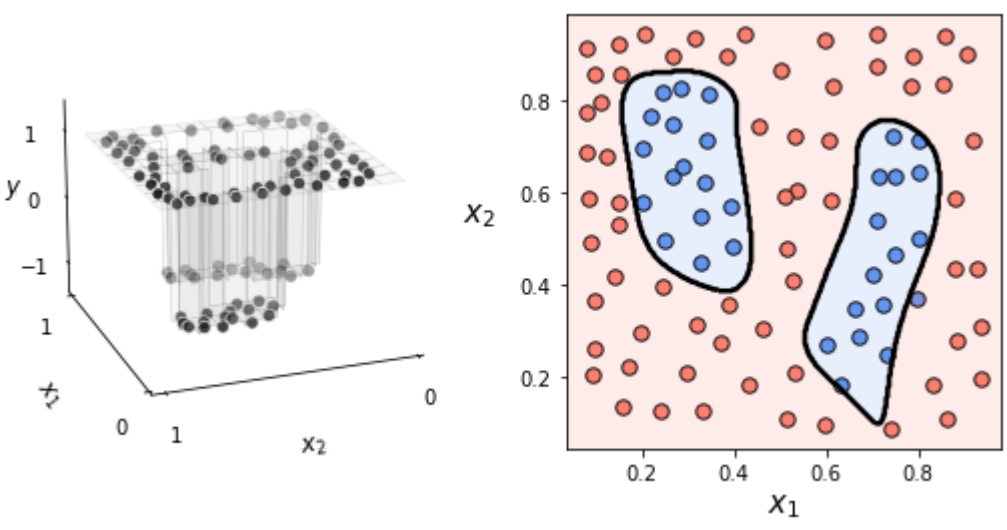
In [3]:
```
from autograd import grad
from autograd import numpy as np
from mlrefined_libraries import math_optimization_library as optlib
import matplotlib.pyplot as plt
from mlrefined_libraries import multilayer_perceptron_library as multi
```

In [15]:
```
import sys
sys.path.append('../')
datapath = 'mlrefined_datasets/nonlinear_superlearn_datasets/'

example = multi.nonlinear_classification_visualizer.Visualizer(datapath + '2_eggs.csv')
x = example.x.T
y = example.y[np.newaxis,:]

layer_sizes = [2,10,10,10,1]

case1 = multi.basic_lib.super_setup.Setup(x,y)

case1.preprocessing_steps(normalizer = 'standard')

case1.make_train_val_split(train_portion = 1)

case1.choose_cost(name = 'softmax')

layer_sizes = [10,10,10,10]

case1.choose_features(feature_name = 'multilayer_softmax',layer_sizes = layer_sizes,activation = 'tanh',scale =

case1.fit(max_its = 200,alpha_choice = 10**(0),verbose = False)

case1.show_histories()

accuracy_hist = np.argmax(case1.train_accuracy_histories[0])
```



Verify my result .

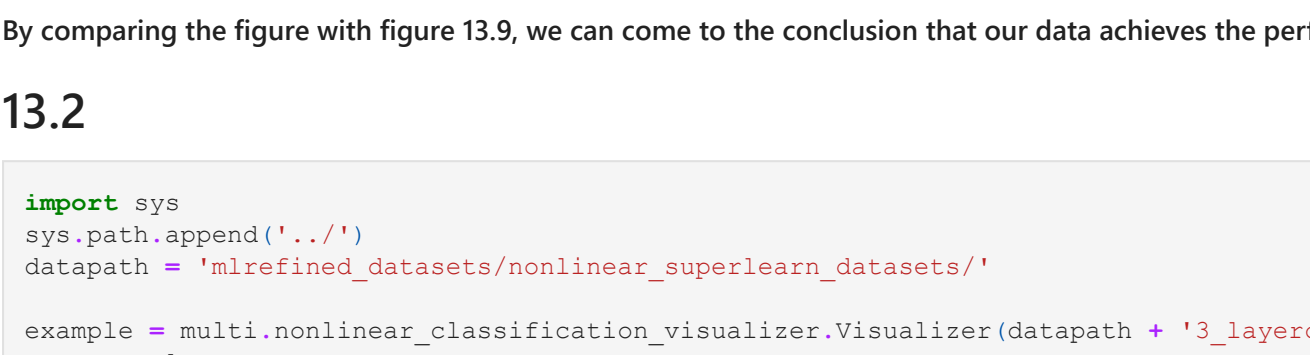
In [13]:
```
example.static_N2_simple(case1.weight_histories[0][accuracy_hist],case1,view = [20,160])
```



By comparing the figure with figure 13.9, we can come to the conclusion that our data achieves the perfect classification.

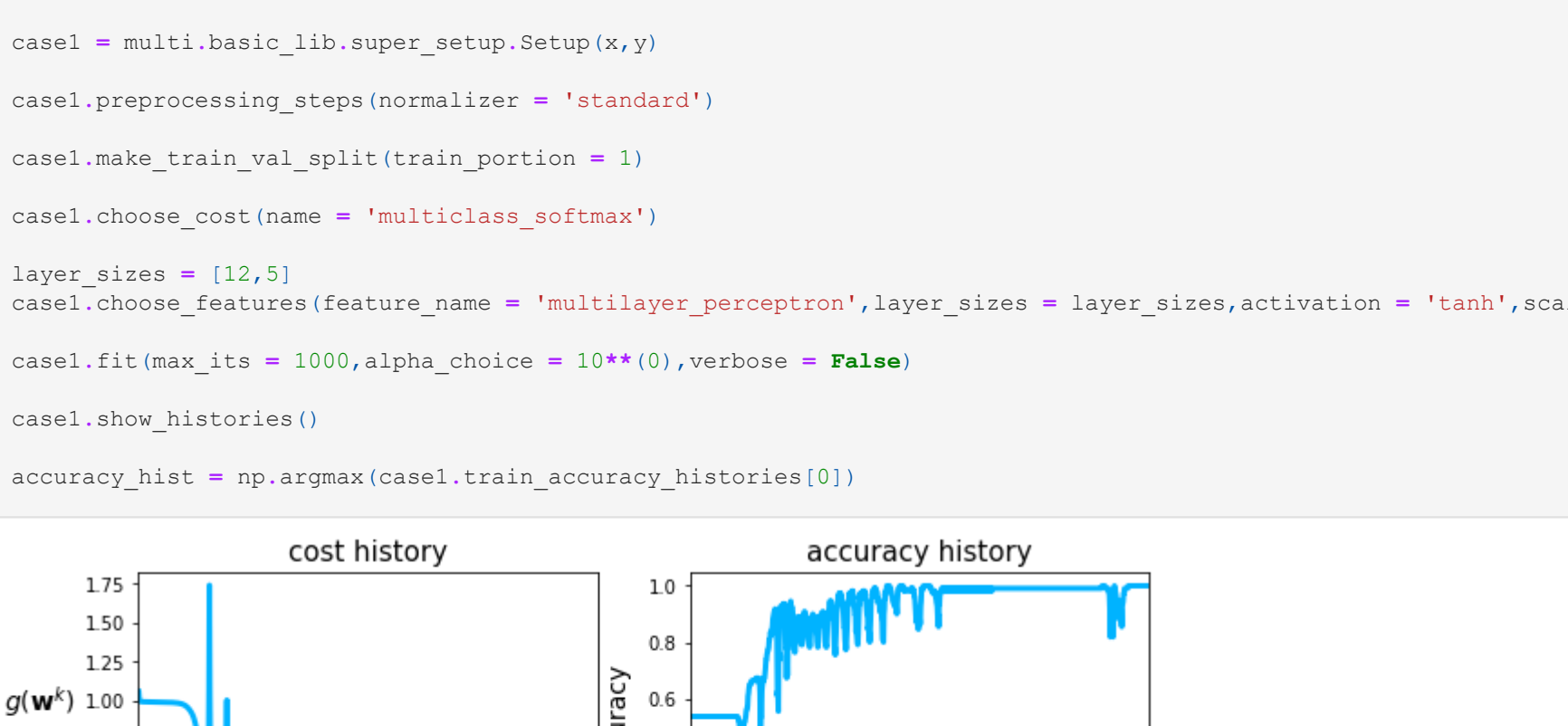
13.2

In [37]:
```
import sys
sys.path.append('../')
datapath = 'mlrefined_datasets/nonlinear_superlearn_datasets/'

example = multi.nonlinear_classification_visualizer.Visualizer(datapath + '3_layercake_data.csv')
x = example.x.T
y = example.y[np.newaxis,:]

w = [2,12,5,3]

case1 = multi.basic_lib.super_setup.Setup(x,y)

case1.preprocessing_steps(normalizer = 'standard')

case1.make_train_val_split(train_portion = 1)

case1.choose_cost(name = 'multiclass_softmax')

layer_sizes = [12,5]
case1.choose_features(feature_name = 'multilayer_perceptron',layer_sizes = layer_sizes,activation = 'tanh',scal

case1.fit(max_its = 1000,alpha_choice = 10**(0),verbose = False)

case1.show_histories()

accuracy_hist = np.argmax(case1.train_accuracy_histories[0])
```



Verify my result .

In [38]:
```
example.multiclass_plot(case1,case1.weight_histories[0][accuracy_hist])
```



By comparing the figure with figure 13.9, we can come to the conclusion that our data achieves the perfect classification.

13.3

(a) Find the total number Q of tunable parameters in a general L-hidden-layer neural network

Solution: Let's say the L*hidden layer* $i = 0, 1, 2, 3....n-1, n$. *There are $U{j}$* units. We've come to the equation :

$$Q_i = \sum_{i=0}^{L} (U_{i+1})\,(1 + U_i)$$

(b) Based on your answer in part (a), explain how the input dimension N and number of data points P each contributes to Q. How is this different from what you saw with kernel methods in the previous chapter

Solution: The part in the parentheses is the same as (a) and is a constant number if N is fixed. Given $U_0 = N$.

$$Q = \left(\sum_{i=1}^{L} (U_{i+1})\,(1 + U_i)\right) + N * U_1 + U_1$$

And we can find there is no relation with Q_i and P .

As for the difference in kernel methods, we do not use the kernel methods in the expression.