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(http://cocl.us/pytorch_link_top)

COGNITIVE CLASS

Simple One Hidden Layer Neural Network

Table of Contents

In this lab, you will use a single-layer neural network to classify non linearly seprable data in 1-Ddatabase.

Estimated Time Needed: **25 min**

Preparation

We'll need the following libraries

In [1]:

```
# Import the libraries we need for this lab

import torch
import torch.nn as nn
from torch import sigmoid
import matplotlib.pylab as plt
import numpy as np
torch.manual_seed(0)
```

Out[1]:

```
<torch._C.Generator at 0x7f1682cfc3b0>
```

Used for plotting the model

In [2]:

```
# The function for plotting the model

def PlotStuff(X, Y, model, epoch, leg=True):

    plt.plot(X.numpy(), model(X).detach().numpy(), label=('epoch ' + str(epoch)))
    plt.plot(X.numpy(), Y.numpy(), 'r')
    plt.xlabel('x')
    if leg == True:
        plt.legend()
    else:
        pass
```

Neural Network Module and Training Function

Define the activations and the output of the first linear layer as an attribute. Note that this is not good practice.

In [3]:

```
# Define the class Net

class Net(nn.Module):

    # Constructor
    def __init__(self, D_in, H, D_out):
        super(Net, self).__init__()
        # hidden layer
        self.linear1 = nn.Linear(D_in, H)
        self.linear2 = nn.Linear(H, D_out)
        # Define the first linear layer as an attribute, this is not good practice
        self.a1 = None
        self.l1 = None
        self.l2=None

    # Prediction
    def forward(self, x):
        self.l1 = self.linear1(x)
        self.a1 = sigmoid(self.l1)
        self.l2=self.linear2(self.a1)
        yhat = sigmoid(self.linear2(self.a1))
        return yhat
```

Define the training function:

In [4]:

```
# Define the training function

def train(Y, X, model, optimizer, criterion, epochs=1000):
    cost = []
    total=0
    for epoch in range(epochs):
        total=0
        for y, x in zip(Y, X):
            yhat = model(x)
            loss = criterion(yhat, y)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
            #cumulative loss
            total+=loss.item()
        cost.append(total)
        if epoch % 300 == 0:
            PlotStuff(X, Y, model, epoch, leg=True)
            plt.show()
            model(X)
            plt.scatter(model.a1.detach().numpy()[:, 0], model.a1.detach().numpy()
[:, 1], c=Y.numpy().reshape(-1))
            plt.title('activations')
            plt.show()
    return cost
```

Make Some Data

In [5]:

```
# Make some data

X = torch.arange(-20, 20, 1).view(-1, 1).type(torch.FloatTensor)
Y = torch.zeros(X.shape[0])
Y[(X[:, 0] > -4) & (X[:, 0] < 4)] = 1.0
```

Define the Neural Network, Criterion Function, Optimizer and Train the Model

Create the Cross-Entropy loss function:

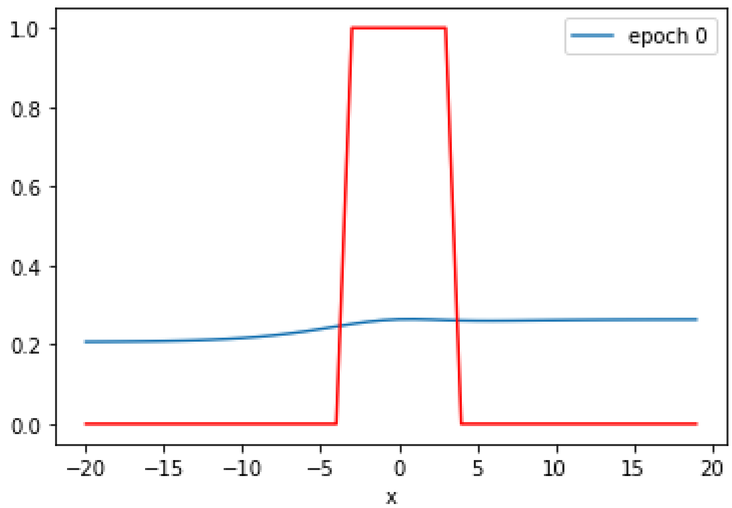
In [6]:

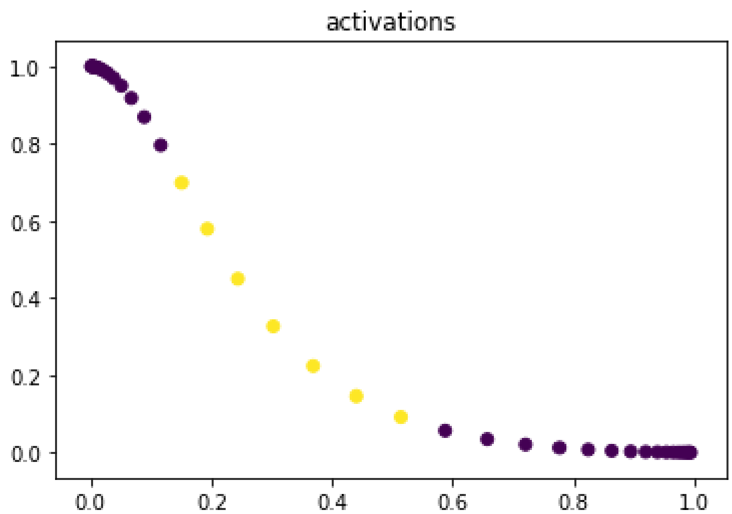
```
# The loss function

def criterion_cross(outputs, labels):
    out = -1 * torch.mean(labels * torch.log(outputs) + (1 - labels) * torch.log(1
- outputs))
    return out
```

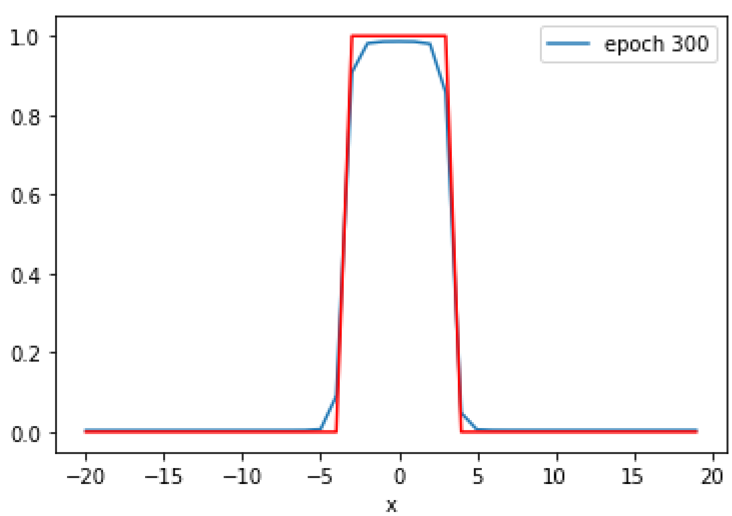
Define the Neural Network, Optimizer, and Train the Model:

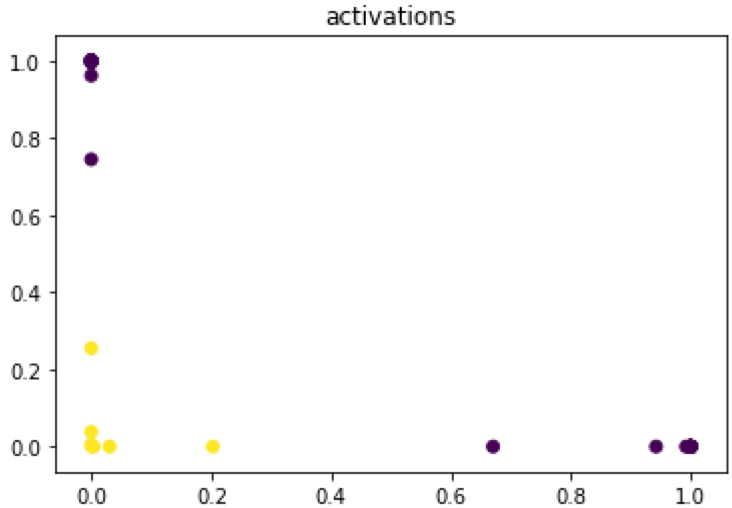
In [7]:

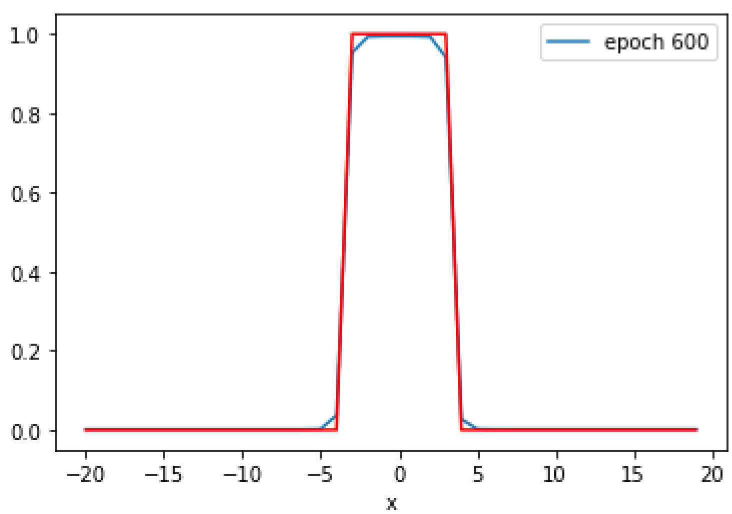
```
# Train the model
# size of input
D_in = 1
# size of hidden layer
H = 2
# number of outputs
D_out = 1
# learning rate
learning_rate = 0.1
# create the model
model = Net(D_in, H, D_out)
#optimizer
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
#train the model usein
cost_cross = train(Y, X, model, optimizer, criterion_cross, epochs=1000)
#plot the loss
plt.plot(cost_cross)
plt.xlabel('epoch')
plt.title('cross entropy loss')
```

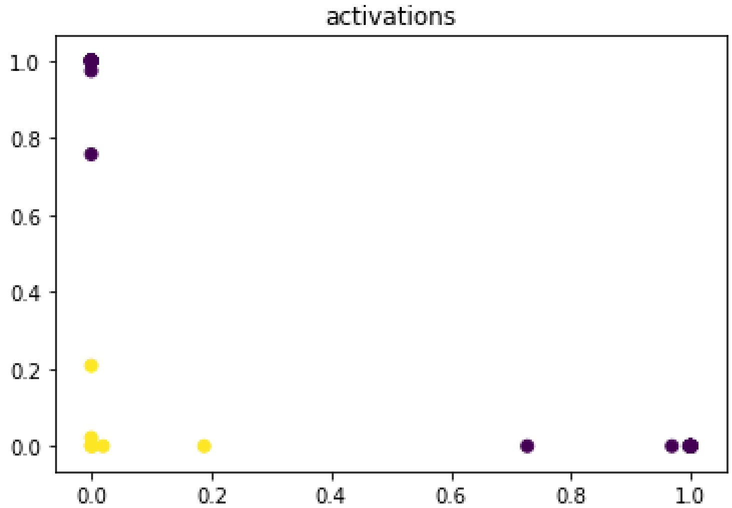

epoch 0
1.0
0.8
0.6
0.4
0.2
0.0
−20 −15 −10 −5 0 5 10 15 20
x

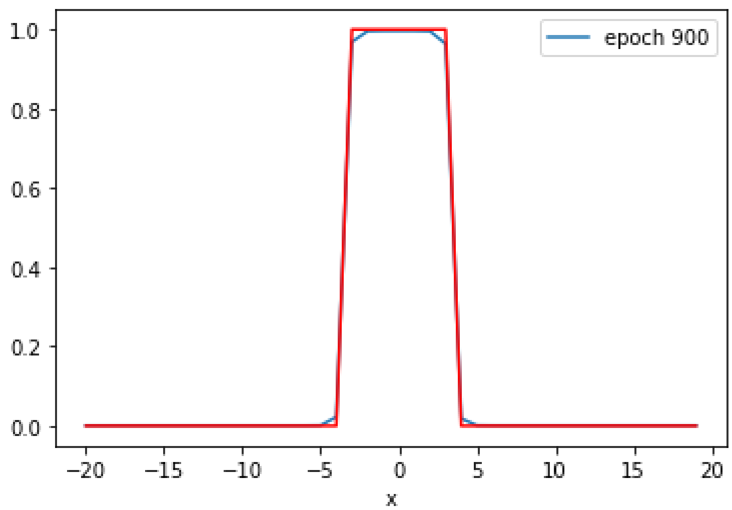

activations
1.0
0.8
0.6
0.4
0.2
0.0
0.0 0.2 0.4 0.6 0.8 1.0

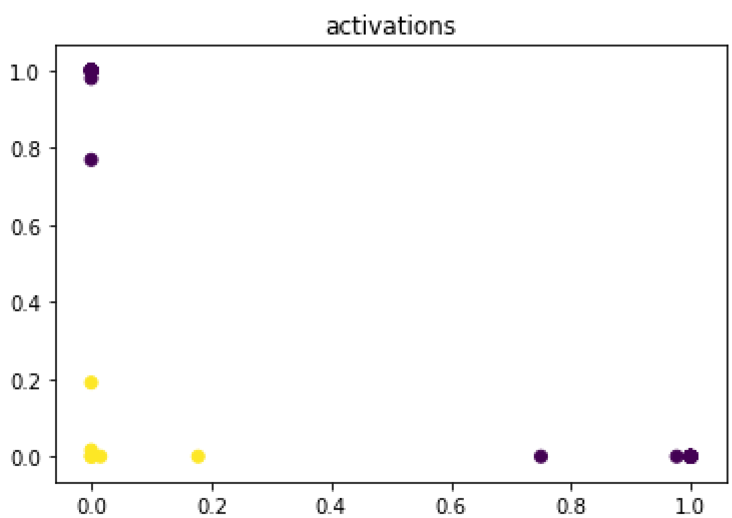

epoch 300
1.0
0.8
0.6
0.4
0.2
0.0
−20 −15 −10 −5 0 5 10 15 20
x


activations
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


epoch 600
1.0
0.8
0.6
0.4
0.2
0.0
−20
−15
−10
−5
0
5
10
15
20
x

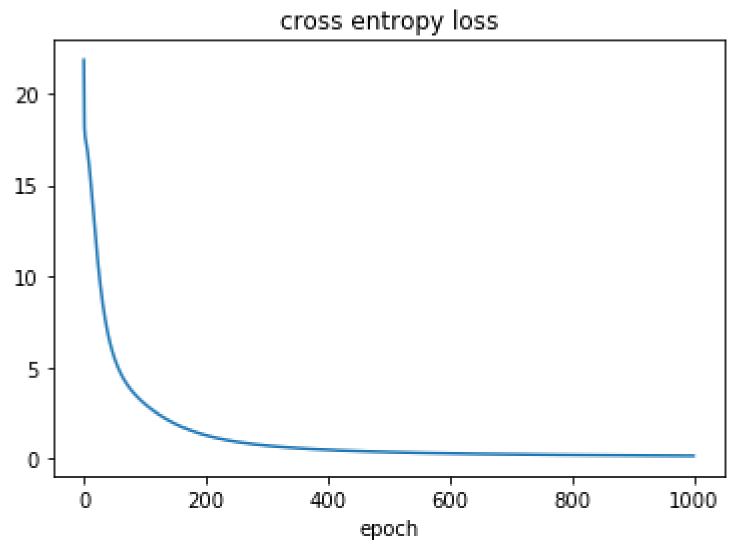






Out[7]:

```
Text(0.5, 1.0, 'cross entropy loss')
```



By examining the output of the activation, you see by the 600th epoch that the data has been mapped to a linearly separable space.

we can make a prediction for a arbitrary one tensors

In [8]:

```
x=torch.tensor([0.0])
yhat=model(x)
yhat
```

Out[8]:

```
tensor([0.9969], grad_fn=<SigmoidBackward>)
```

we can make a prediction for some arbitrary one tensors

In [9]:

```
X_=torch.tensor([[0.0],[2.0],[3.0]])
Yhat=model(X_)
Yhat
```

Out[9]:

```
tensor([[0.9969],
        [0.9963],
        [0.9680]], grad_fn=<SigmoidBackward>)
```

we can threshold the predication

In [10]:

```
Yhat=Yhat>0.5
Yhat
```

Out[10]:

```
tensor([[True],
        [True],
        [True]])
```

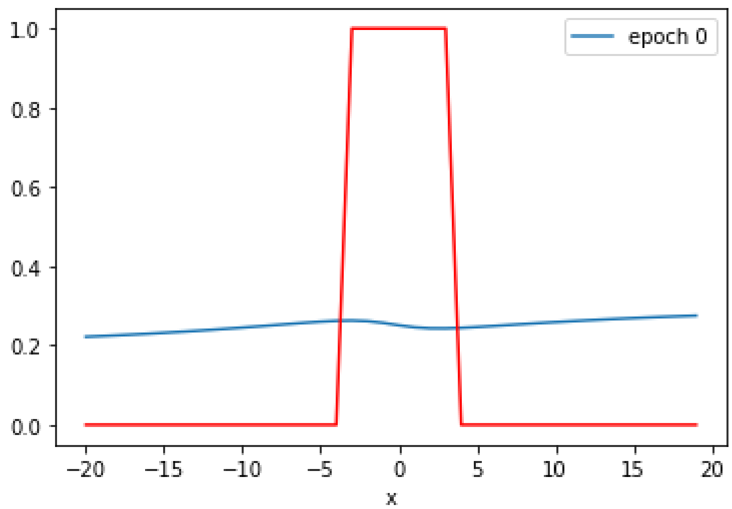
Practice

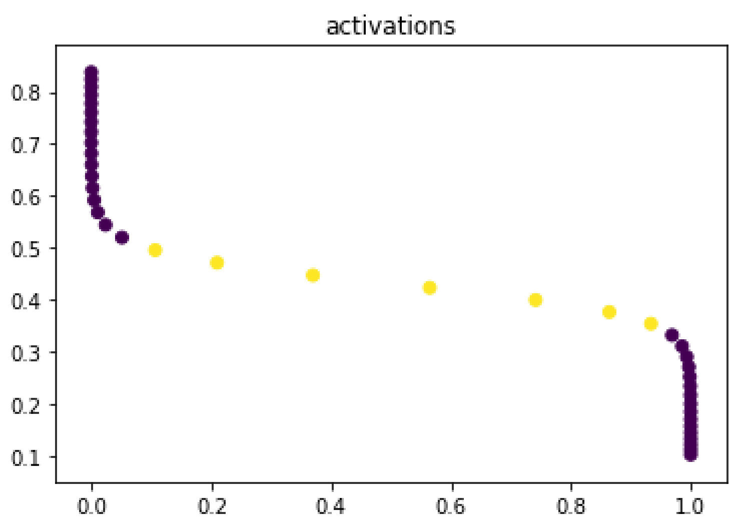
Repeat the previous steps above by using the MSE cost or total loss:

In [ ]:

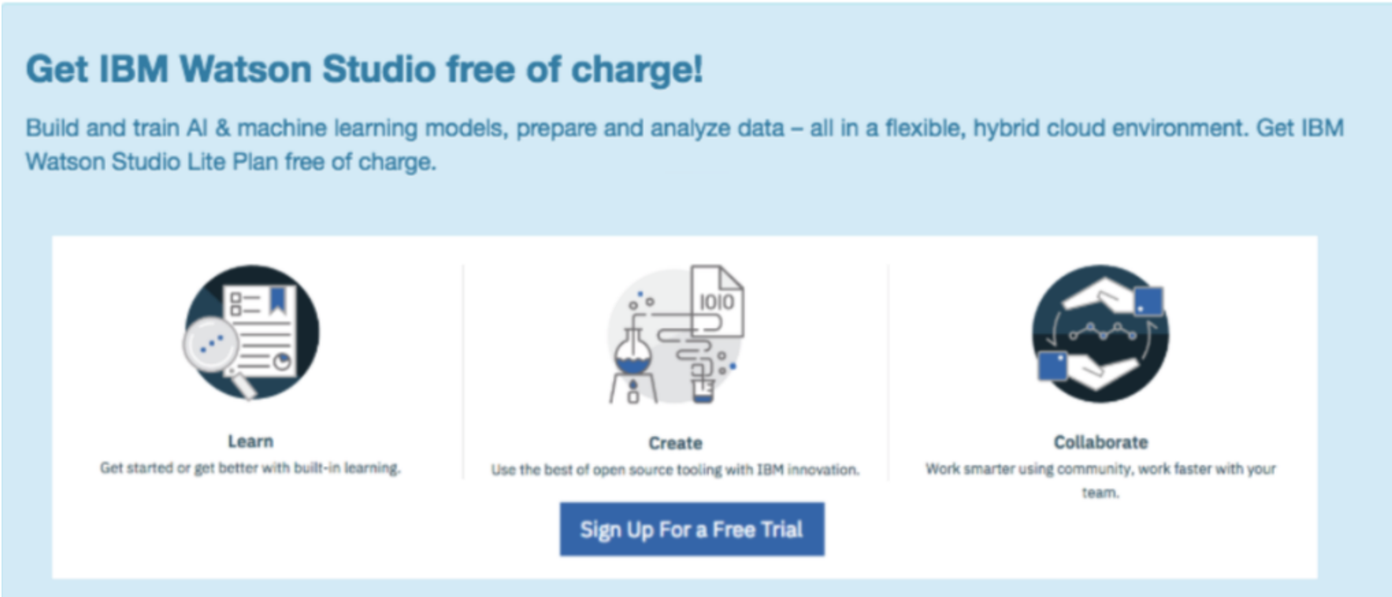
```
# Practice: Train the model with MSE Loss Function

learning_rate = 0.1
criterion_mse = nn.MSELoss()
model = Net(D_in, H, D_out)
optimizer = torch.optim.SGD(model.parameters(), lr = learning_rate)
cost_mse = train(Y, X, model, optimizer, criterion_mse, epochs = 1000)
plt.plot(cost_mse)
plt.xlabel('epoch')
plt.title('MSE loss')
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/torch/n
n/modules/loss.py:431: UserWarning: Using a target size (torch.Size
([])) that is different to the input size (torch.Size([1])). This will
likely lead to incorrect results due to broadcasting. Please ensure the
y have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
```





Double-click **here** for the solution.



(http://cocl.us/pytorch_link_bottom)

About the Authors:

Joseph Santarcangelo (https://www.linkedin.com/in/joseph-s-50398b136/) has a PhD in Electrical Engineering, his research focused on using machine learning, signal processing, and computer vision to determine how videos impact human cognition. Joseph has been working for IBM since he completed his PhD.

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