

# pytorch\_NN\_single\_layer

September 14, 2023

## 1 Single-Layer feedforward network

We code a very simple 1-layer network to learn a step function

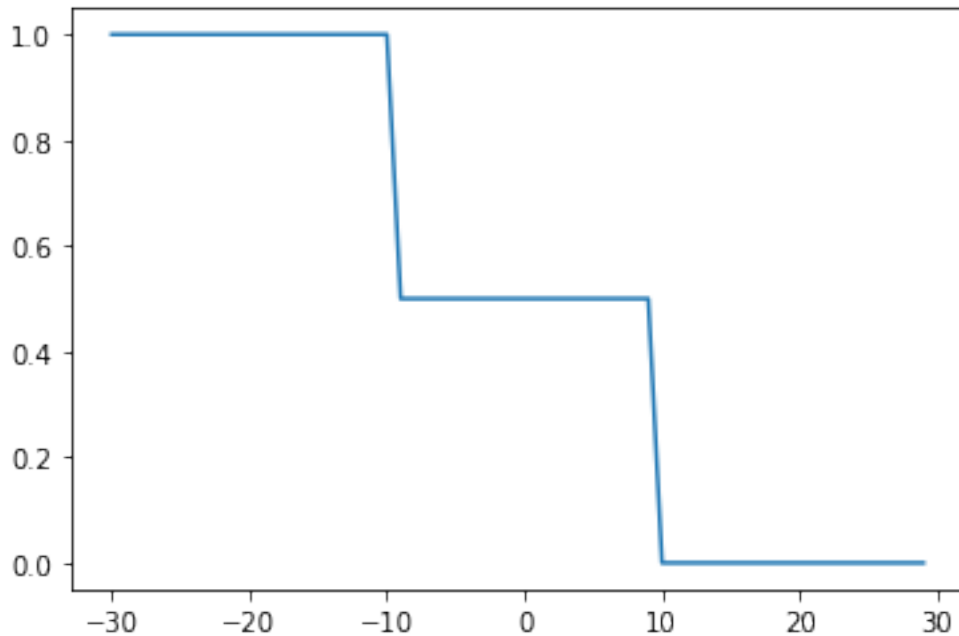
$$f(x) = \begin{cases} 1, & -30 \leq x < -10, \\ 0.5, & -10 \leq x < 10, \\ 0, & 10 \leq x \leq 30. \end{cases}$$

This kind of function is often encountered in (partial) differential equations, where it represents some medium property that varies abruptly over a spatial, or temporal variable.

In a previous example, we learned a sine function from noisy measurements. Here we do not add any noise.

```
[1]: import torch
import matplotlib.pyplot as plt

# generate (synthetic) data
X = torch.arange(-30, 30, 1).view(-1, 1).type(torch.FloatTensor)
Y = torch.zeros(X.shape[0])
Y[(X[:, 0] <= -10)] = 1.0
Y[(X[:, 0] > -10) & (X[:, 0] < 10)] = 0.5
Y[(X[:, 0] > 10)] = 0
# plot f(x)
plt.plot(X, Y)
plt.show()
```



## 1.1 Build the network

This neural network features - an input layer, - a hidden layer with two neurons, - and an output layer.

After each layer, a sigmoid activation function is applied.

```
[2]: # Define the class for single layer NN
class one_layer_net(torch.nn.Module):
    # Constructor
    def __init__(self, input_size, hidden_neurons, output_size):
        super(one_layer_net, self).__init__()
        # hidden layer
        self.linear_one = torch.nn.Linear(input_size, hidden_neurons)
        self.linear_two = torch.nn.Linear(hidden_neurons, output_size)
        # defining layers as attributes
        self.layer_in = None
        self.act = None
        self.layer_out = None
    # prediction function
    def forward(self, x):
        self.layer_in = self.linear_one(x)
        self.act = torch.sigmoid(self.layer_in)
        self.layer_out = self.linear_two(self.act)
        y_pred = torch.sigmoid(self.linear_two(self.act))
        return y_pred
```

Instantiate the model class to create a model object

```
[3]: # create the model
model = one_layer_net(1, 2, 1) # 2 represents two neurons in one hidden layer
```

Instantiate the loss class, and the optimizer class

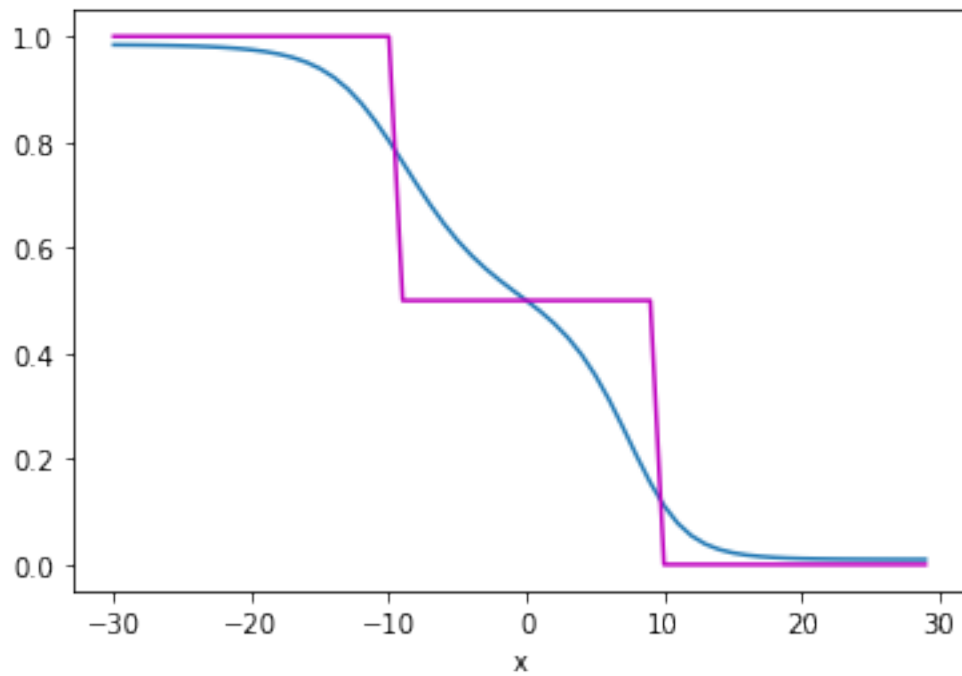
- loss = cross-entropy
- optimizer = standard SGD

```
[4]: def criterion(y_pred, y):
      out = -1 * torch.mean(y * torch.log(y_pred) + (1 - y) * torch.log(1 -
      ↪y_pred))
      return out
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
```

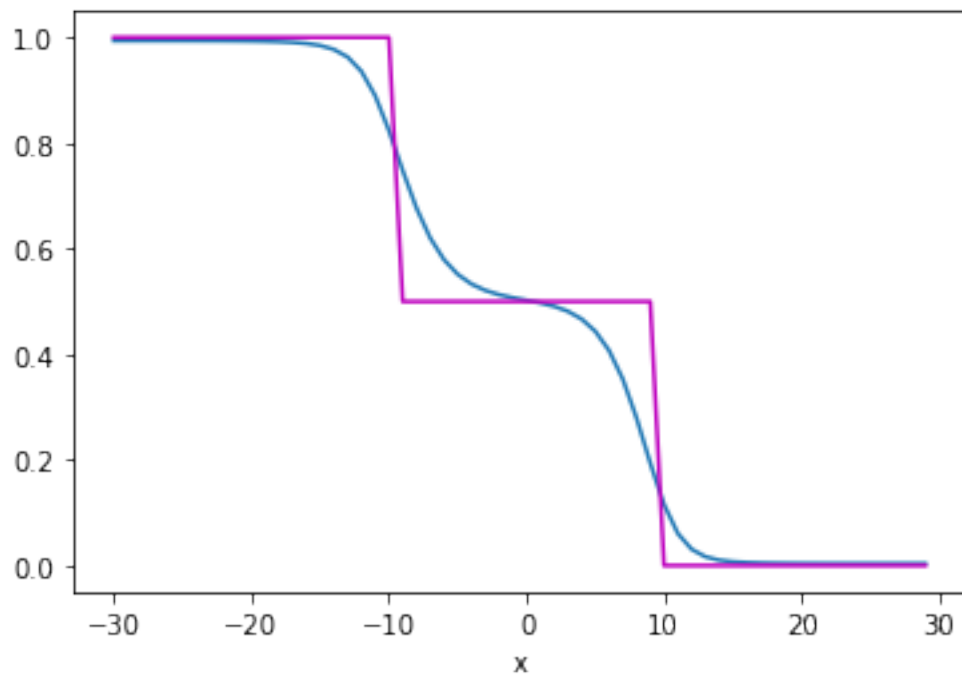
Train the model, looping over epochs, compute loss, and plot result every 1000 iterations.

```
[5]: # Define the training loop
epochs=5000
cost = []
total=0
for epoch in range(epochs):
    total=0
    epoch = epoch + 1
    for x, y in zip(X, Y):
        yhat = model(x)
        loss = criterion(yhat, y)
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
        # get total loss
        total+=loss.item()
    cost.append(total)
    if epoch % 1000 == 0:
        print(str(epoch)+ " " + "epochs done!") # visualize results after every
        ↪1000 epochs
        # plot the result of function approximator
        plt.plot(X.numpy(), model(X).detach().numpy())
        plt.plot(X.numpy(), Y.numpy(), 'm')
        plt.xlabel('x')
        plt.show()
```

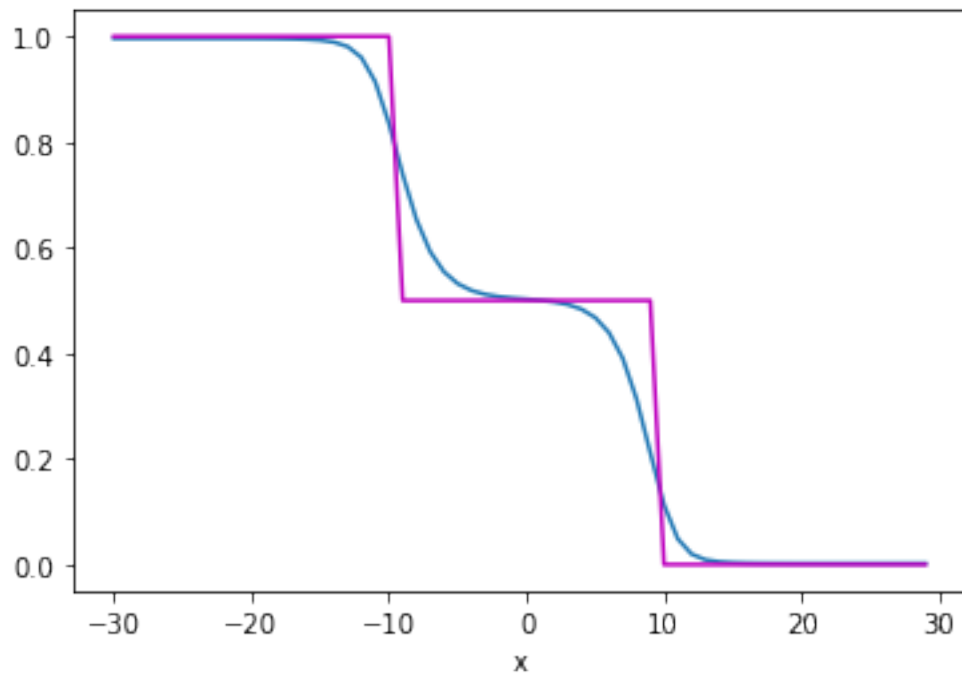
1000 epochs done!



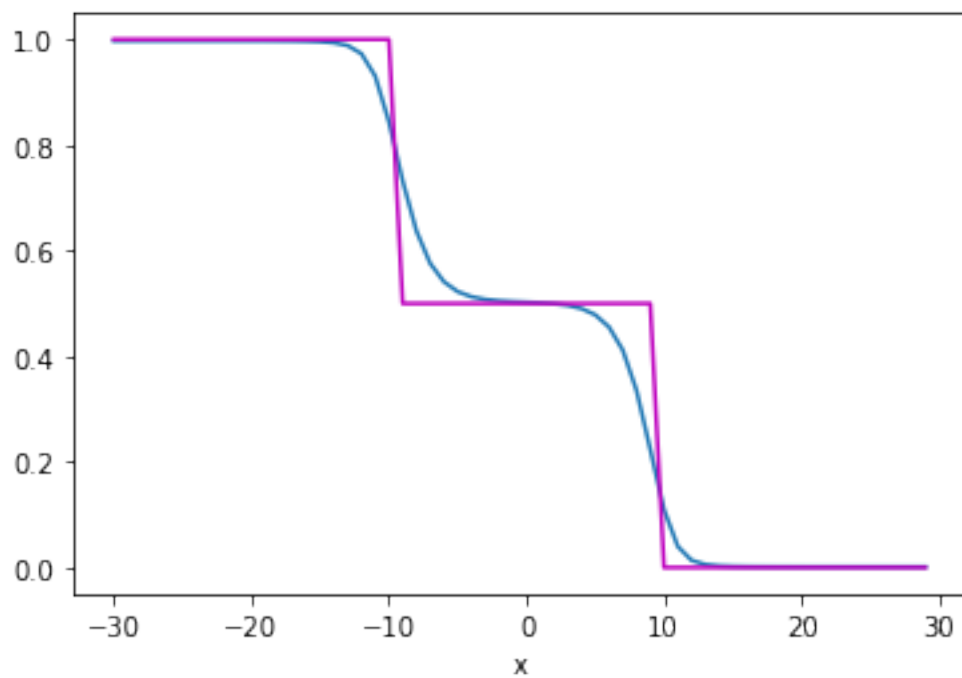
2000 epochs done!



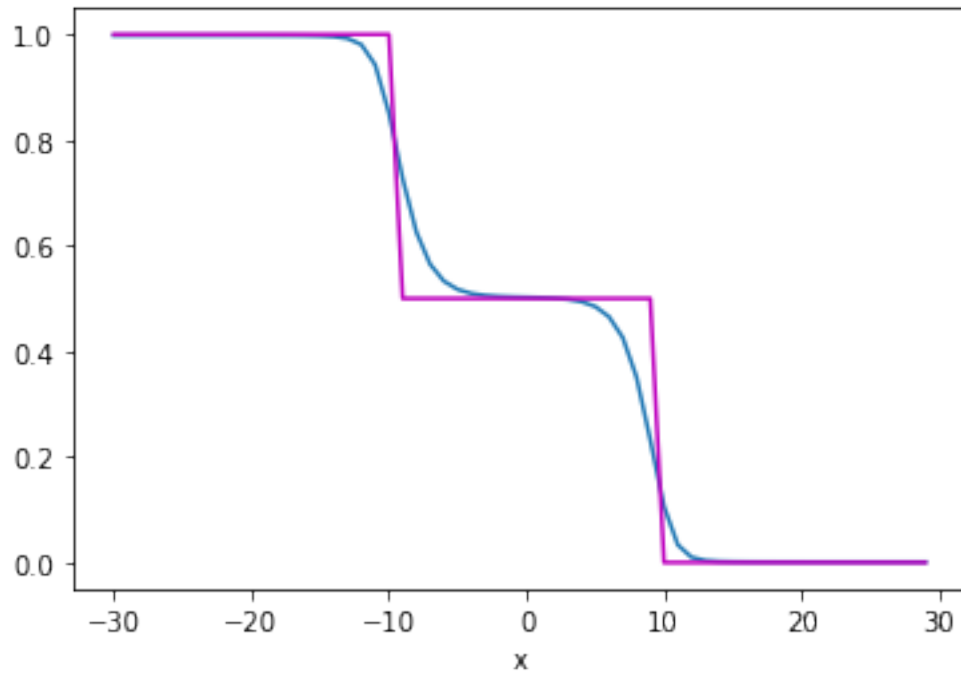
3000 epochs done!



4000 epochs done!

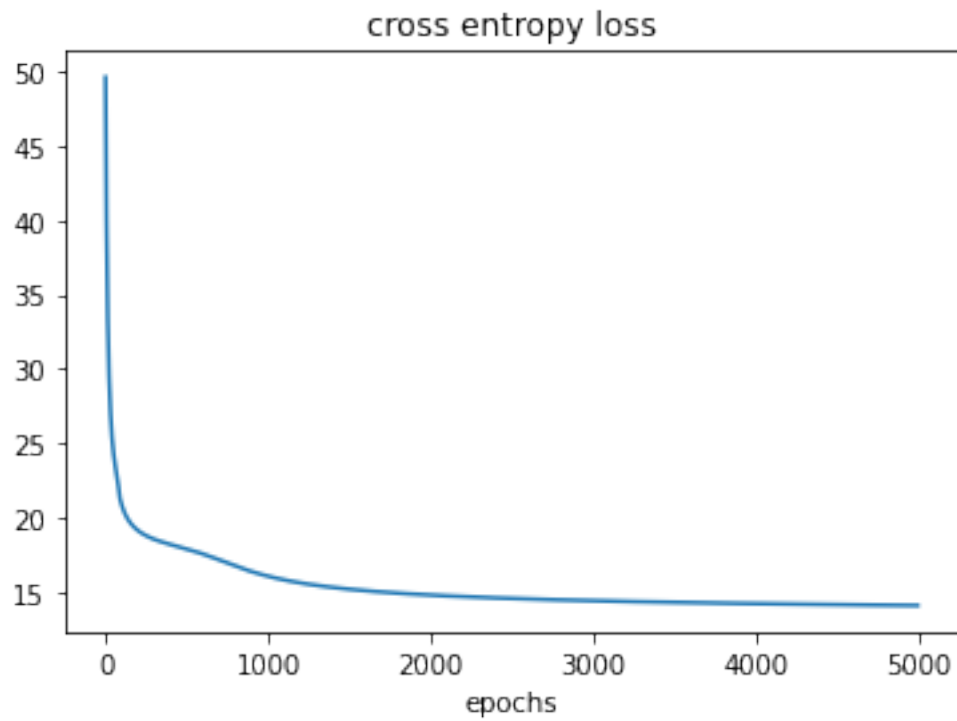


5000 epochs done!



Finally, plot the loss function over the iterations/epochs

```
[6]: # plot the cost
plt.plot(cost)
plt.xlabel('epochs')
plt.title('cross entropy loss')
plt.show()
```



## 1.2 Things to try as exercises

1. Change the activation function.
2. Use MSE, or MAE loss.
3. Change the network architecture - use more neurons, more layers (overfitting...).
4. Modify the optimisation parameters (lr), or the optimization method.

[ ]: