Deep learning Ex1

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Question 1

1.

$$softmax_{[i]}(z+m\cdot\mathbf{1}) = \frac{\exp(z_i+m)}{\sum_j \exp(z_j+m)} = \frac{\exp(z_i)\exp(m)}{\exp(m)\sum_j \exp(z_j)} = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$
$$= softmax_{[i]}(z)$$

2. for
$$c = 2$$
:
$$z = \begin{bmatrix} z_0 \\ z_1 \end{bmatrix}, \quad softmax_{[0]}(z) = \frac{\exp(z_0)}{\exp(z_0) + \exp(z_1)} = \frac{1}{1 + \exp(z_1 - z_0)} = \sigma(z_0 - z_1)$$
$$softmax_{[1]}(z) = \frac{\exp(z_1)}{\exp(z_0) + \exp(z_1)} = \frac{1}{1 + \exp(z_0 - z_1)} = \sigma(z_1 - z_0)$$
3.
$$f(z) = \frac{1}{\pi} \arctan(z) + \frac{1}{2}$$

Question 3

1.

$$U = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}, b_1 = -0.5, w = 1, b_2 = -0.5$$

```
For x = [0\ 0] hidden layer output is [0.\ 0.]
import numpy as np
                                                              For x = [0 \ 0] output is 0
                                                              For x = [0.1] hidden layer output is [0.0.5]
U = np.array([[1,-1],[-1,1]])
b1 = -0.5
                                                              For x = [0 1] output is 1
w = np.array([1,1]).T
                                                              For x = [1 \ 0] hidden layer output is [0.5 \ 0.]
b2 = -0.1
                                                              For x = [1 \ 0] output is 1
                                                              For x = [1 \ 1] hidden layer output is [0. \ 0.]
X = [np.array([0,0]).T, np.array([0,1]).T,
                                                              For x = [1 \ 1] output is 0
np.array([1,0]).T, np.array([1,1]).T]
for x in X:
  h = np.maximum(U.T@x + b1, np.zeros((2,)))
  print("For x = ", x, "hidden layer output is ", h)
  f = w.T@h + b2
  if(f>=0):
    print("For x = ", x, "output is 1")
  else:
    print("For x = ", x, "output is 0")
```

verified using python:

2. No, it would not be possible, replacing the max function with the identity will effectively eliminate the hidden layer:

hate the nidden tayer:

$$f(x) = w^T (U^T x + b_1) + b_2 = w^T U^T x + w^T b_1 + b_2$$

 $w' = Uw, b' = w^T b_1 + b_2$
 \downarrow
 $f(x) = w'^T x + b'$

turning f into a linear classifier, and XOR cannot be linearly classified.

3. ReLU(x) can in fact be defined as max(x,0). Maybe the question meant weather we can set $b_1 = 0$? If so yes, it is still possible:

```
import numpy as np
                                                               For x = [0 \ 0] hidden layer output is [0. \ 0.]
                                                               For x = [0 \ 0] output is 0
U = np.array([[1,-1],[-1,1]])
                                                               For x = [0 \ 1] hidden layer output is [1. \ 0.]
b1 = 0
                                                               For x = [0 1] output is 1
w = np.array([1,1]).T
                                                               For x = [1 \ 0] hidden layer output is [0. \ 1.]
b2 = -0.1
                                                               For x = [1 \ 0] output is 1
                                                               For x = [1 \ 1] hidden layer output is [0. \ 0.]
                                                               For x = [1 \ 1] output is 0
X = [np.array([0,0]).T, np.array([0,1]).T,
np.array([1,0]).T, np.array([1,1]).T]
for x in X:
  h = np.maximum(U.T@x + b1, np.zeros((2,)))
  print("For x = ", x, "hidden layer output is ", h)
  f = w.T@h + b2
  if(f>=0):
    print("For x = ", x, "output is 1")
    print("For x = ", x, "output is 0")
```

Question 3

To use backward propagation, we need to calculate the gradients:

$$L = (y - \hat{y})^{2}$$

$$\hat{y} = f(x) = w^{T}h + b_{2} = w_{1}h_{1} + w_{2}h_{2} + b_{2}$$

$$h = ReLU(U^{T}x + b_{1}) = ReLU(z) \Rightarrow h'(z) = U(z)$$

$$z = U^{T}x + b_{1} = \begin{bmatrix} U_{1,1}x_{1} + U_{2,1}x_{2} + b_{1,1} \\ U_{1,2}x_{1} + U_{2,2}x_{2} + b_{1,2} \end{bmatrix}$$

$$\frac{\partial L}{\partial w_{i}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} = -2(y - \hat{y})h_{i}$$

$$\frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b_2} = -2(y - \hat{y})$$

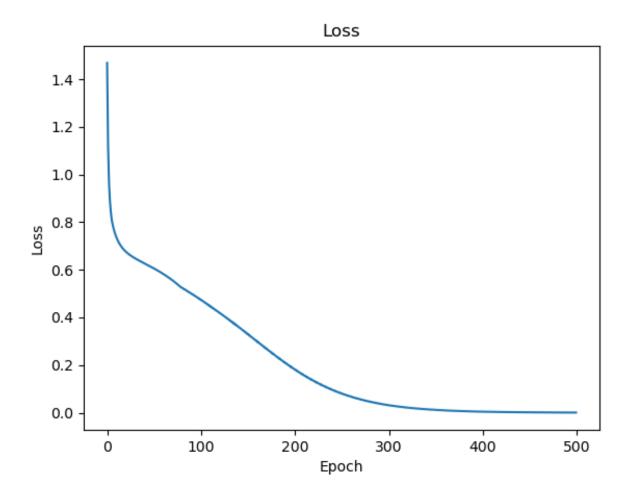
$$\frac{\partial L}{\partial U_{ij}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h_j} \frac{\partial h_j}{\partial z_j} \frac{\partial z_j}{\partial U_{ij}} = -2(y - \hat{y}) w_j \mathcal{U}(z_j) x_i$$

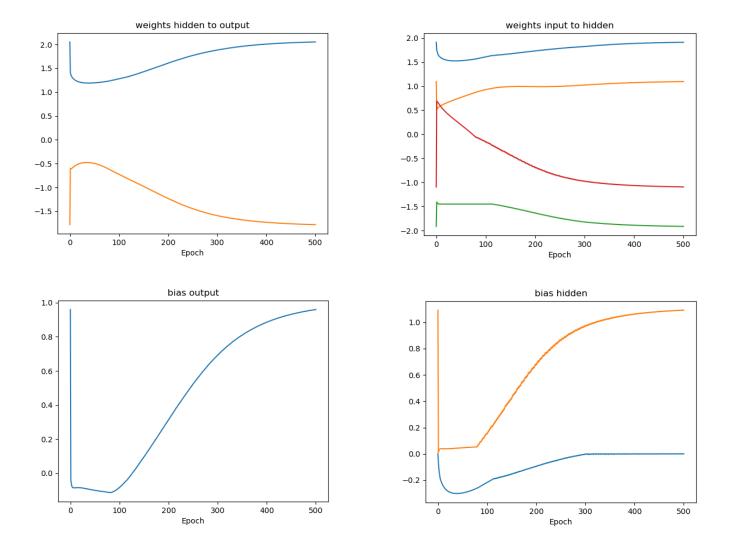
$$\frac{\partial L}{\partial b_{1,i}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial h_i} \frac{\partial h}{\partial z_i} \frac{\partial z_i}{\partial b_{1,i}} = -2(y - \hat{y}) w_i \mathcal{U}(z_i)$$

And implement in the code.

The code uses pandas for visualization, it can be easily installed via `pip install pandas` To run the code, open a terminal window, cd into the directory where you stored the script, and run it with `python3 Q3.py`, the code will generate 5 png files.

Here are the plots from my run with 500 epochs:





Challenges:

Initially I tried creating the weights and biases history by simply appending the numpy array to a list, I was surprised to see that the result was the same number. My mistake was appending the actual array which is static in memory instead of a copy of it.

Going from calculus to python code was challenging, I ended taking a matlab approach of representing everything as a matrix.