Assignment- 0

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Inference from Task-1

- Changing the hidden_size parameter changes the number of neurons in the hidden layer.
- Initially as we increase the parameter from 1 the loss value reduces till the parameter's value is 5. After that value loss increases.
- Hidden _Size parameter needs to be tuned to an optimum value.
- One important thing to note is that each time the value of hidden_size is changed and the model is run, the values of the initialization matrix changes as it is just a random matrix. Hence, we must take this into account while examining the effect of hidden_size.
- The optimum value for hidden_size is either 4 or 5.

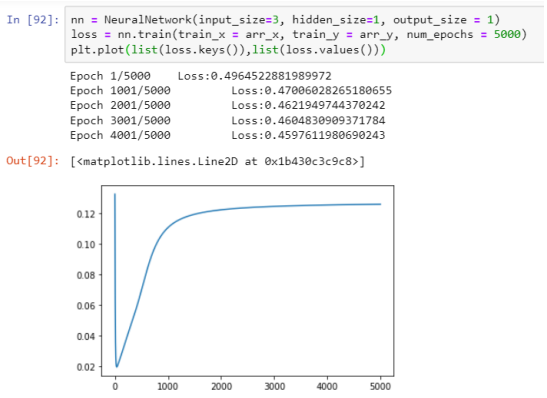


Fig 1: Hidden_size=1

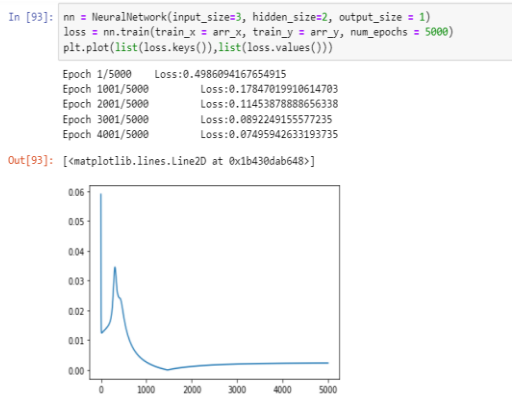


Fig 2: Hidden_size=2

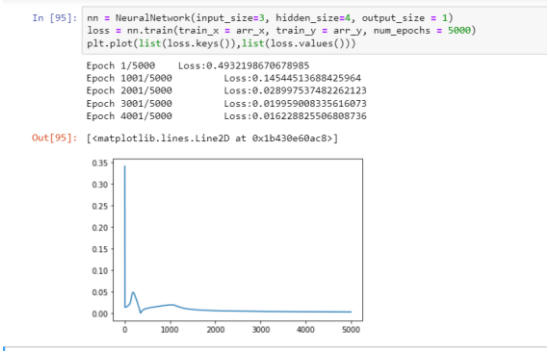


Fig 3: Hidden_size=4

Loss= 0.0162

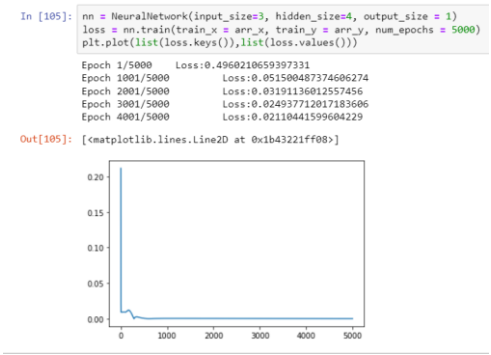


Fig 4: Hidden_size=4

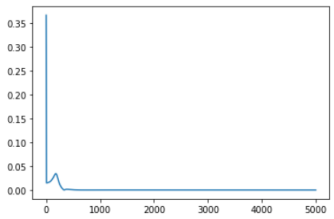
Loss=0.0211

Fig 5: Hidden_Size=5 , Loss= 0.019

```
In [106]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 5000)
          plt.plot(list(loss.keys()),list(loss.values()))

          Epoch 1/5000    Loss:0.4933089778924767
          Epoch 1001/5000         Loss:0.049300335075250445
          Epoch 2001/5000         Loss:0.0295859842310969
          Epoch 3001/5000         Loss:0.022915125704319278
          Epoch 4001/5000         Loss:0.019308434547043295

Out[106]: [<matplotlib.lines.Line2D at 0x1b4322bcec8>]
```



Here the lower value of loss can be for hidden_size=4 or hidden_size=5 depending on the result chosen.

- The number of iterations or the value of epochs determine the degree of reduction in loss. Greater the number of epochs, lower the loss. However, the loss saturates after a while and so we can stop after a certain number of iterations

```
In [109]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 50)
          plt.plot(list(loss.keys()),list(loss.values()))

          Epoch 1/50      Loss:0.4960840459072607
          Epoch 11/50     Loss:0.49966152462567875
          Epoch 21/50     Loss:0.4978741608789447
          Epoch 31/50     Loss:0.49582605557909804
          Epoch 41/50     Loss:0.4932650931014508

Out[109]: [<matplotlib.lines.Line2D at 0x1b432383548>]
```

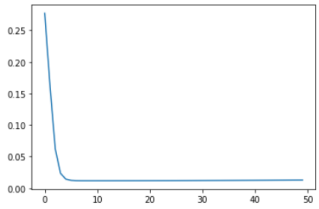


Fig 6: Epochs=50

```
In [110]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 100)
          plt.plot(list(loss.keys()),list(loss.values()))

          Epoch 1/100     Loss:0.4935213018124511
          Epoch 11/100    Loss:0.4963531778209105
          Epoch 21/100    Loss:0.4941940214090601
          Epoch 31/100    Loss:0.4910269939229647
          Epoch 41/100    Loss:0.48669178968919585
          Epoch 51/100    Loss:0.4813292517915235
          Epoch 61/100    Loss:0.4754590992200652
          Epoch 71/100    Loss:0.46973775797589085
          Epoch 81/100    Loss:0.46458617075598735
          Epoch 91/100    Loss:0.4600751014394102

Out[110]: [<matplotlib.lines.Line2D at 0x1b4323e6bc8>]
```

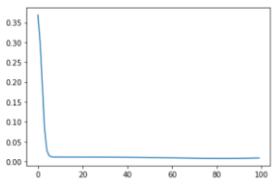


Fig 7: Epochs=100

```
In [113]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 200)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 1/200     Loss:0.4970217734938003
Epoch 41/200    Loss:0.4989401197611313
Epoch 81/200    Loss:0.493274261858911
Epoch 121/200   Loss:0.4772341055551839
Epoch 161/200   Loss:0.4424135959898072

Out[113]: [<matplotlib.lines.Line2D at 0x1b43245d908>]
```

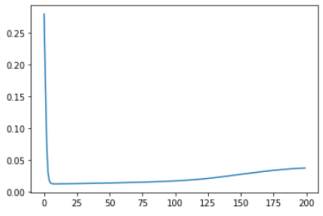


Fig 8: Epochs=200

```
In [114]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 500)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 1/500     Loss:0.493042600949165
Epoch 41/500    Loss:0.4945648011241535
Epoch 81/500    Loss:0.47668218234734955
Epoch 121/500   Loss:0.4443981790062082
Epoch 161/500   Loss:0.40919686071083466
Epoch 201/500   Loss:0.3712453113588813
Epoch 241/500   Loss:0.3339745100011404
Epoch 281/500   Loss:0.295897379164942
Epoch 321/500   Loss:0.2506836570675408
Epoch 361/500   Loss:0.20348976267966493
Epoch 401/500   Loss:0.16606685779898375
Epoch 441/500   Loss:0.13958896728614
Epoch 481/500   Loss:0.12095071430532489

Out[114]: [<matplotlib.lines.Line2D at 0x1b4324c4cc8>]
```

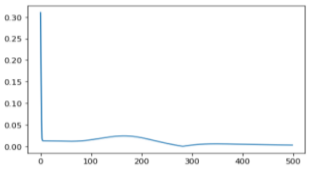


Fig 9: Epochs=500

```
In [122]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 1000)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 981/1000  Loss:0.04968281713727806
Epoch 991/1000  Loss:0.04920023810970686

Out[122]: [<matplotlib.lines.Line2D at 0x1b43364f588>]
```

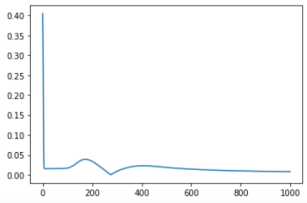


Fig 9: Epochs=1000

```
In [123]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 5000)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 4981/5000         Loss:0.01731814483133378
Epoch 4991/5000         Loss:0.01729840308992108

Out[123]: [<matplotlib.lines.Line2D at 0x1b4336f4a08>]
```

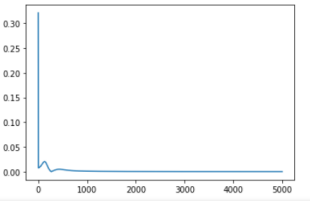


Fig 10: Epochs=5000

```
In [124]: nn = NeuralNetwork(input_size=3, hidden_size=5, output_size = 1)
          loss = nn.train(train_x = arr_x, train_y = arr_y, num_epochs = 50000)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 49981/50000       Loss:0.004663463539066184
Epoch 49991/50000       Loss:0.004662979281721811

Out[124]: [<matplotlib.lines.Line2D at 0x1b4336ac648>]
```

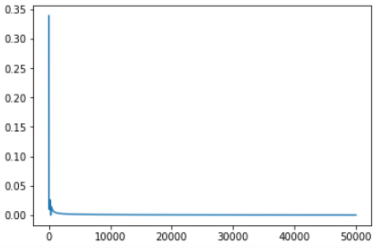


Fig 11: Epochs=50000

Inference from Task 2

- The activation functions for the hidden layer was changed.
- For each application a different activation function may give a better result.
- Hence we need to figure out the best activation function by trial and error.
- Sigmoid function has lower loss compared with tanh and relu for this model.

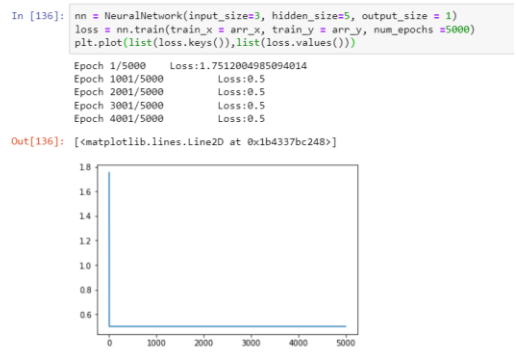


Fig 12: Relu function

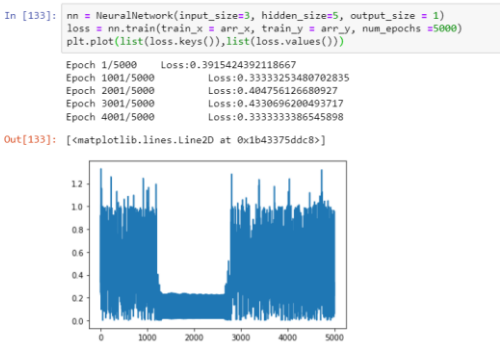


Fig 13 : Tanh function

Inference from Task 3

- The given task was to use the model for different data.

1. F = !((A.B)+C) + D

a	b	c	d	X
0	0	0	0	1
0	0	0	1	1
0	0	1	0	0
0	0	1	1	1
0	1	0	0	1
0	1	0	1	1
0	1	1	0	0
0	1	1	1	1
1	0	0	0	1
1	0	0	1	1
1	0	1	0	0
1	0	1	1	1
1	1	0	0	0
1	1	0	1	1
1	1	1	0	0
1	1	1	1	1

2. F = !(A.B) xor !(C.D)

0	0	0	0	0
0	0	0	1	0
0	0	1	0	0
0	0	1	1	1
0	1	0	0	0
0	1	0	1	0
0	1	1	0	0
0	1	1	1	1
1	0	0	0	0
1	0	0	1	0
1	0	1	0	0
1	0	1	1	1
1	1	0	0	1
1	1	0	1	1
1	1	1	0	1
1	1	1	1	0

- Using sigmoid function as the activation function for hidden layer, these are the results:

```
In [184]: nn_task3 = NeuralNetwork(input_size=4, hidden_size =4, output_size = 1)
          loss = nn_task3.train(train_x = arr_x, train_y = arr_y, num_epochs = 5000)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 1/5000    Loss:0.3965907433362492
Epoch 1001/5000         Loss:0.023018609722171682
Epoch 2001/5000         Loss:0.012058524455694861
Epoch 3001/5000         Loss:0.008392591510443583
Epoch 4001/5000         Loss:0.006560794148877O7

Out[184]: [<matplotlib.lines.Line2D at 0x1b436a6cd48>]
```

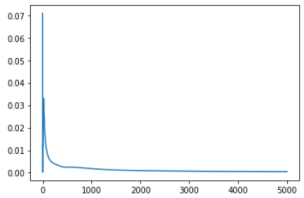


Fig 14:

The result after plugging in the training data for equation 1

```
In [194]: nn_task3 = NeuralNetwork(input_size=4, hidden_size =4, output_size = 1)
          loss = nn_task3.train(train_x = arr_x, train_y = arr_y, num_epochs = 5000)
          plt.plot(list(loss.keys()),list(loss.values()))

Epoch 1/5000    Loss:0.5756476448078502
Epoch 1001/5000         Loss:0.025120811506066994
Epoch 2001/5000         Loss:0.01294121699716637
Epoch 3001/5000         Loss:0.009604983442384734
Epoch 4001/5000         Loss:0.007952166215020408

Out[194]: [<matplotlib.lines.Line2D at 0x1b437cb4388>]
```

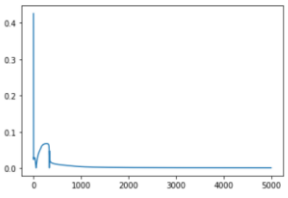


Fig 15:

The result after plugging in the training data for equation 2

- Hidden size was optimum at 3 and 4 for equation one's model. Hidden size was optimum at 4 and 5 for equation two's model. Greater the number of epochs, lower the loss but again we can reduce the number of epochs by observing when the loss saturates.