22108125 Lab 3: Study of Activation Functions and its role.

Aim: To study the activation functions and its role

Objective:

- To understand why activation functions are necessary in neural network.
- To study commonly used activation fn: sigmoid, Tanh, ReLu, Leaky ReLu, softmax
- To compare their advantages, disadvantages and suitable application.

Pseudo code

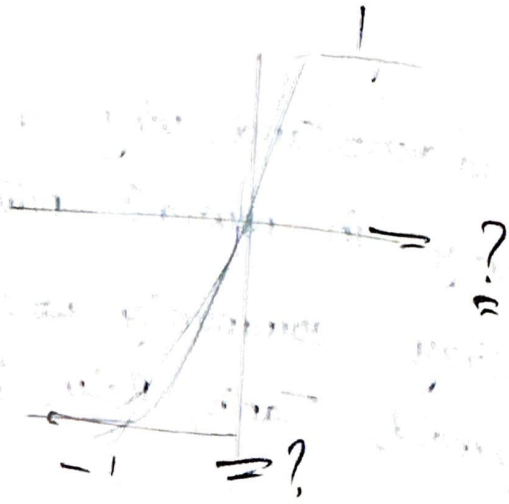
1) Import required libraries.
2) Define mathematical functions for sigmoid, tanh, relu, leaky relu, softmax.
3) Generate a range of input values (x).
4) Compute outputs of all activation functions
5) Plot Graph of each activation functions
6) Compare their behaviour and note observation.

Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

Tanh

$\tanh(x)$



ReLU

$\max(0, x)$

Leaky ReLU

Observation

Formula :

1) Sigmoid = $f(x) = \frac{1}{1+e^{-x}}$ $[0,1]$

2) Tanh : $f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$ $[-1,1]$

3) ReLU (Rectified Linear Unit)

$f(x) = \max(0,x)$

4) Leaky ReLU

$$f(x) = \begin{cases} a & x > 0 \\ ax & x \leq 0 \end{cases}$$

5) Softmax

$$f(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

Observation Table :

Activation fn	Output Range	Advantage	Use Case
1) Sigmoid	(0,1)	Smooth, probabilistic output	Binary Classification
2) Tanh	(-1,1)	Centered around 0, better than sigmoid	Hidden layer (old older networks)
3) ReLU	[0, ∞)	Fast, reduce computation Time	Hidden layer (modern CNN/ ANN)
4) Leaky ReLU	(-∞, ∞)	Fixed ReLU (dying) issues	Deep Hidden layers
5) Softmax	(0,1), sum=1	Give probability distribution	Output layer for multi-class

* ReLU and Leaky ReLU are most effective in hidden layer.
* Sigmoid and Tanh are rarely used today due to vanishing gradient
* Softmax for multiclass classification problems

Result

Studied different activation function & their roles.

Kernel Tabs Settings Help

l5.ipynb

Code

Notebook

Python 3 (ipykernel)

Modified

onths ago
nutes ago
onths ago
onths ago
onths ago
days ago
days ago
days ago
nutes ago
conds ago
days ago
days ago

```
[2]: import torch
     import torch.nn.functional as F

Input: tensor([-2., -1.,  0.,  1.,  2.])
Sigmoid: tensor([0.1192, 0.2689, 0.5000, 0.7311, 0.8808])
Tanh: tensor([-0.9640, -0.7616,  0.0000,  0.7616,  0.9640])
ReLU: tensor([0., 0., 0., 1., 2.])
Leaky ReLU: tensor([-0.2000, -0.1000,  0.0000,  1.0000,  2.0000])
Softmax: tensor([0.0117, 0.0317, 0.0861, 0.2341, 0.6364])

     x = torch.tensor([-2.0, -1.0, 0.0, 1.0, 2.0])

[6]: sigmoid = torch.sigmoid(x)
     tanh = torch.tanh(x)
     relu = F.relu(x)
     leaky_relu = F.leaky_relu(x, negative_slope=0.1)
     softmax = F.softmax(x, dim=0)  # Softmax over the tensor elements

[7]: print("Input:", x)
     print("Sigmoid:", sigmoid)
     print("Tanh:", tanh)
     print("ReLU:", relu)
     print("Leaky ReLU:", leaky_relu)
```

l5.ipynb

Code

Notebook

Python 3 (ipykernel)

```
leaky_relu = F.leaky_relu(x, negative_slope=0.1)
softmax = F.softmax(x, dim=0)  # Softmax over the tensor elements
```

[7]:
```
print("Input:", x)
print("Sigmoid:", sigmoid)
print("Tanh:", tanh)
print("ReLU:", relu)
print("Leaky ReLU:", leaky_relu)
print("Softmax:", softmax)
```

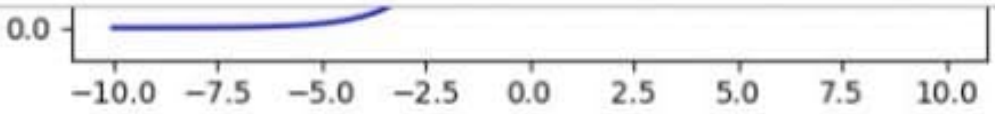
```
Input: tensor([-2., -1.,  0.,  1.,  2.])
Sigmoid: tensor([0.1192, 0.2689, 0.5000, 0.7311, 0.8808])
Tanh: tensor([-0.9640, -0.7616,  0.0000,  0.7616,  0.9640])
ReLU: tensor([0., 0., 0., 1., 2.])
Leaky ReLU: tensor([-0.2000, -0.1000,  0.0000,  1.0000,  2.0000])
Softmax: tensor([0.0117, 0.0317, 0.0861, 0.2341, 0.6364])
```

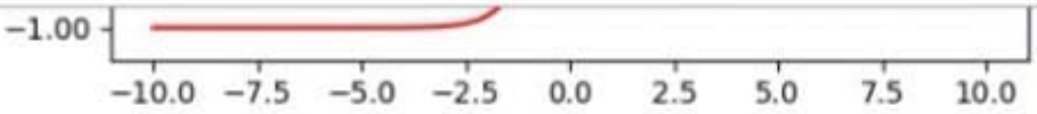
[ ]:

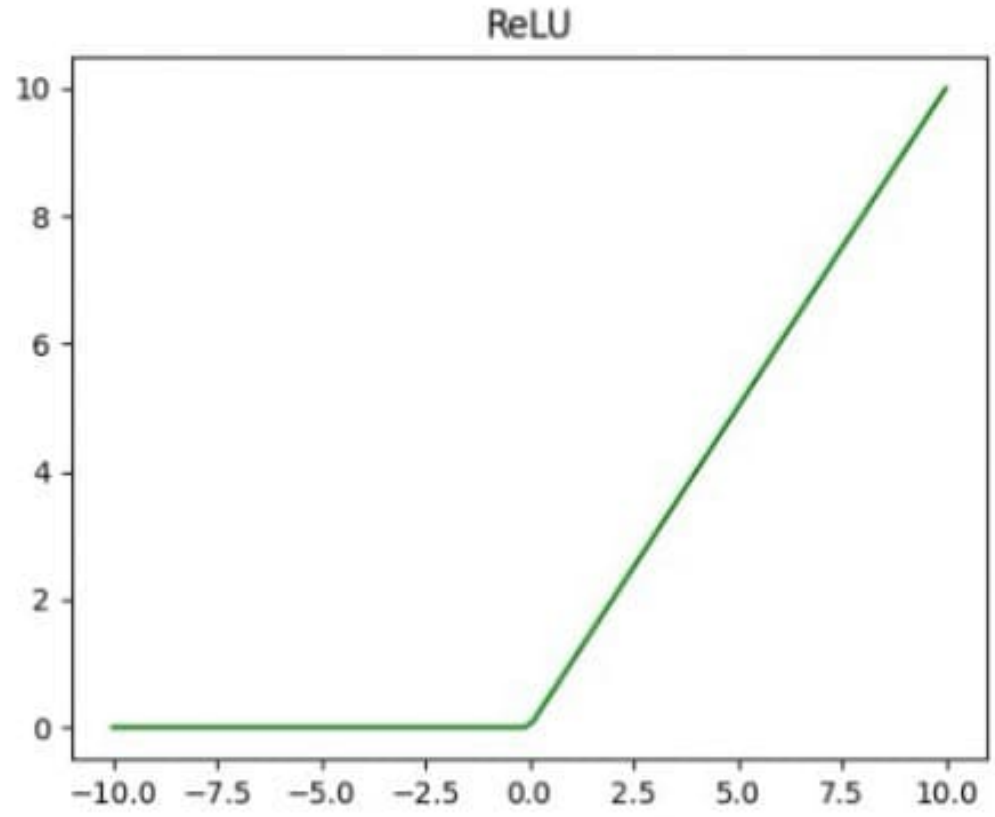
tings Help

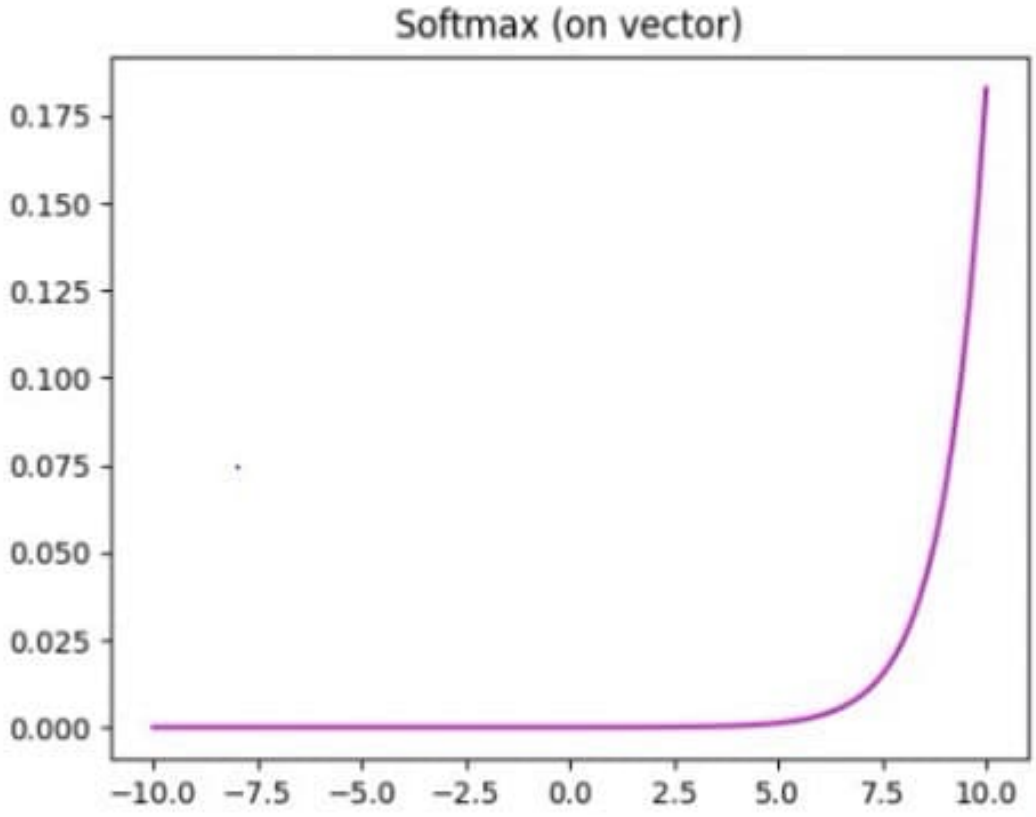
dl4.ipynb dl5.ipynb

Code Notebook Python 3 (ipykernel)









[ ]:

```
plt.title("Softmax (on vector)")

plt.tight_layout()
plt.show()
```