

Student task: Interpolation with Neural Networks

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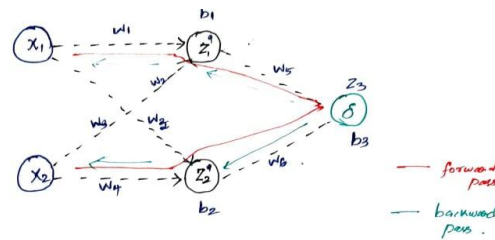
28.09.2022

Solutions

1. Theoretical Questions

1. How is the forward pass of a neural network defined?

- In forward pass, values of the output layers are calculated using the input data by traversing through all the neurons from first to the last layer.
- Weighted inputs (z) and respective outputs (a) of the hidden layers will be calculated from input data (x) and weights (w)
- Then, output node (y) will be calculated
- The final step in the forward pass is to compute the loss function (δ), loss function is calculated from the output values.
- After doing forward pass, back propagation will be carried out to update the weights.



$x_1, x_2 \rightarrow$ Input nodes.

$w_1, w_2, \dots, w_6 \rightarrow$ weights of the intermediate layers.

$b_1, \dots, b_3 \rightarrow$ bias function.

$\delta \rightarrow$ output node value error.

$a_1, a_2 \rightarrow$ Output value of intermediate nodes.

$y \rightarrow$ Output node value.

Example problem,

$x_1 = 0.35, x_2 = 0.9, w_1 = 0.1, w_2 = 0.8, w_3 = 0.4, w_4 = 0.6,$

$w_5 = 0.3, w_6 = 0.9, t = 0.5, b = 0, \text{ sigmoidal function } (\sigma)$

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} w_1 & w_2 & b_1 \\ w_3 & w_4 & b_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 0.1 & 0.8 & 0 \\ 0.4 & 0.6 & 0 \end{bmatrix} \begin{bmatrix} 0.35 \\ 0.9 \\ 1 \end{bmatrix}$$

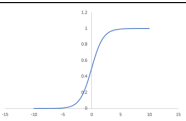
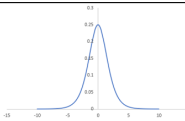
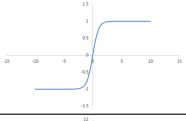
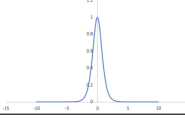
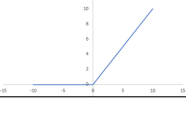
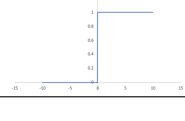
$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 0.76 \\ 0.68 \end{bmatrix} \Rightarrow \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \sigma(z_1) \\ \sigma(z_2) \end{bmatrix} = \begin{bmatrix} 0.68 \\ 0.66 \end{bmatrix}$$

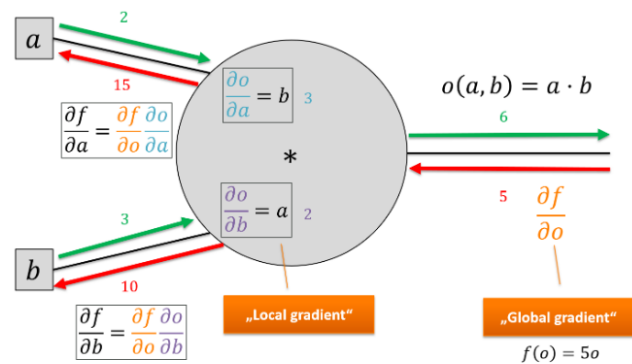
$$\text{In } y: \boxed{z_3 = 0.8}, \boxed{a_y = 0.69}$$

$$\text{Loss function } \frac{1}{2} \cdot (a - t)^2 \text{ or } (1 - a)^2 \Rightarrow \boxed{\delta = 0.04}$$

2. Let u be a fully connected neural network consisting of 4 layers with ReLU activation function approximating the sine function $\sin(x)$. Is it possible to compute the second order derivative with respect to x of the network by auto differentiation and obtain the correct derivative, i.e., the approximation of $-\sin(x)$. If not, why?

- No, it is not possible to compute the second order derivative for $\sin(x)$ function by auto-differentiation using 4 layers with the ReLU activation function.
- Sigmoid function has a similar shape to sin function, so it will work out. But ReLU is a linear function, so it requires a bigger network for approximation of sin function.

Activation function	$f(x)$	$f(x)$	$\frac{df(x)}{dx}$
sigmoid	$\frac{1}{1 + e^{-x}}$		
tanh	$\tanh(x)$		
ReLU	$\max(0, x)$		



- The periodic nature of sinusoidal activation functions can give rise to a 'rippling' cost function with bad local minima, which may make training difficult
- The problem may not be so bad when the data is dominated by low-frequency components.

3. Let x be a tensor with shape $(12, 3, 128, 128)$. What is the output shape of the tensor x if I perform a calculation with 2D convolution layers with 32 3×3 filters, a stride of 2 and zero padding?

Solution:

3)

Given:

$$\rightarrow \text{Input tensor} = [N, H, W, C] = [12, 3, 128, 128]$$

$$N - \text{Batch size} = 12$$

$$H - \text{Height} = 3$$

$$W - \text{Width} = 128$$

$$C - \text{No. of channels} = 128$$

$$\rightarrow \text{Filter Kernel} = [K_H, K_W, K_C] = [3, 3, 32]$$

$$K_H - \text{Kernel height} = 3$$

$$K_W - \text{Kernel width} = 3$$

$$K_C - \text{Kernel channels} = 32$$

$$\rightarrow \text{Stride} = [S_H, S_W] = [2, 2]$$

$$S_H - \text{Stride height} = 2$$

$$S_W - \text{Stride width} = 2$$

$$\rightarrow \text{Padding} = [P] = 0$$

$$\text{Output size: } [N_1, H_1, W_1, C_1]$$

$$\rightarrow \text{o/p height, } H_1 = \frac{H - K_H + P + 1}{S}$$

$$H_1 = \frac{3 - 3 + 0 + 1}{2} = 1$$

$$W_1 = \frac{128 - 3 + 0 + 1}{2} = 63$$

$$N_1 = \text{Batch size} = N = 12$$

$$C_1 = \text{Kernel channels} = 32$$

$$\text{o/p size} = [N_1, H_1, W_1, C_1] = [12, 1, 63, 32]$$

$$\left| \frac{n - f + 2p}{s} + 1 \right|$$

n - input size

f - filter size

p - padding

s - stride

- The output shape of the tensor is **[12, 1, 63, 32]**
- If we take $N=12$, $C=3$, $H=128$, $W=128$, then output tensor size = **[12, 32, 63, 63]**

2. Programming Task

Build a neural network that fixed the measured data y at given sampling points X . Use a supervised learning technique in order to train the neural network. Finally, visualize the given data and the trained function by the neural network.

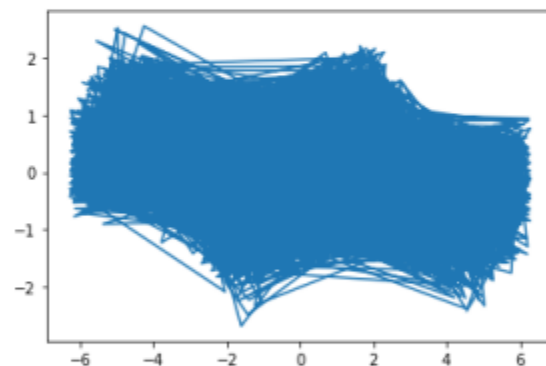
```
In [16]: import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
```

```
In [17]: data1 = np.load('C:\\Users\\RAJIAS\\Desktop\\HZDR\\Student_Task\\x.npy')
data2 = np.load('C:\\Users\\RAJIAS\\Desktop\\HZDR\\Student_Task\\y.npy')

print(data1[0:5000])
print(data2[0:5000])
print(len(data1))
print(len(data2))

plt.plot(data1, data2)
plt.show()
```

```
[-0.02693753  0.1913795 -2.91954442 ... -4.58140501  5.36439399
-6.16835198]
[ 0.00358727 -0.22992998 -0.12298599 ...  1.01926216 -0.98550066
-0.03792922]
5000
5000
```



```
In [18]: x = pd.DataFrame(data1)
y = pd.DataFrame(data2)
```

```
In [19]: from sklearn.model_selection import train_test_split
```

```
In [20]: X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)
```

```
-----
ValueError                                Traceback (most recent call last)
Input In [20], in <cell line: 1>()
----> 1 X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, r
andom_state=42)

ValueError: too many values to unpack (expected 3)
```