## 201600282 엄기산

```
from IPython.core.interactiveshell import InteractiveShell
          InteractiveShell.ast_node_interactivity = "all"
          import math
          import numpy as np
         # 1. f1 = xy
          \# df1/dx = y, df1/dy = x
          x = 4; y = -3
                                #then f become -12
          f1 = x * y
          df1dx = y
                                #then dfdx become -3
          df1dy = x
                                #then dfdy become 4
          f 1
          df 1dx
          df 1dv
Out[23]: 4
Out[23]: -3
Out[23]: -12
Out[23]: -3
Out[23]: 4
[10, [24]: ] # 2. [24]: ] # 2. [24]: ]
          \# df2/dx = 1, df2/dy = 1
          x = 4; y = -3
          f2 = x + y
                                #then f2 become 1
          df2dx = 1
                                #then df2dx become 1
          df2dy = 1
                                #then df2dy become 1
          f2
          df2dx
          df2dy
Out[24]: 4
Out[24]: -3
Out[24]: 1
Out[24]: 1
Out[24]: 1
         # 3. f3 = max(x, y)
          x = 4; y = -3
          i f(x>=y):
              f3 = x
                             #since f3 = max(x,y) f3 become 4
              df3dx = 1
              df3dy = 0
          else:
```

```
f3 = y
              df3dx = 0
              df3dy = 1
          Χ
          У
          f3
          df3dx
          df3dy
Out[25]: 4
Out[25]: -3
Out[25]: 4
Out[25]: 1
Out[25]: 0
[10.526]: #4. [4] = [4]
          x = -2; y = 5; z = -4
          # perform the forward pass
          q = x + y \# q \text{ becomes } 3
          f4 = q * z # f becomes -12
          # perform the backward pass (backpropagation) in reverse order:
          # first backprop through f = q * z
          df4dz = q \# df/dz = q, so gradient on z becomes 3
          df4dq = z \# df/dq = z, so gradient on q becomes -4
          \# now backprop through q = x + y
          df4dx = 1.0 * df4dq # dq/dx = 1. And the multiplication here is the chain rule!
          df4dy = 1.0 * df4dq # dq/dy = 1
          У
          Z
          f4
          df4dx
          df4dv
          df4dz
          df4dq
Out[26]: -2
Out[26]: 5
Out[26]: -4
Out [26]: -12
Out [26]: -4.0
Out[26]: -4.0
Out[26]: 3
Out[26]: -4
In [27]: | #5. 시그모이드 예제
          \mathbf{w} = [2, -3, -3] # assume some random weights and data
          x = [-1, -2]
          # forward pass
          dot = w[0] * x[0] + w[1] * x[1] + w[2]
          f = 1.0 / (1 + math.exp(-dot)) # sigmoid function
```

```
# backward pass through the neuron (backpropagation) ddot = (1 - f) * f # gradient on dot variable, using the sigmoid gradient derivation dx = [w[0] * ddot, w[1] * ddot] # backprop into x dw = [x[0] * ddot, x[1] * ddot, 1.0 * ddot] # backprop into w # we're done! we have the gradients on the inputs to the circuit w x dot f ddot dx dw
```

Out[27]: [2, -3, -3]

Out[27]: [-1, -2]

Out[27]: 1

Out[27]: 0.7310585786300049

Out [27]: 0.19661193324148185

Out[27]: [0.3932238664829637, -0.5898357997244456]

Out[27]: [-0.19661193324148185, -0.3932238664829637, 0.19661193324148185]

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