

Python Learning

5.4 : Implementation of simple layer

5.5 : Implementation of activation function layer

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Overview of this presentation

- 5.4 Implementation of simple layer
 - Multiplication layer
 - Addition layer
- 5.5 Implementation of activation function layer
 - ReLU layer
 - Sigmoid layer

Implementation of multiplication layer

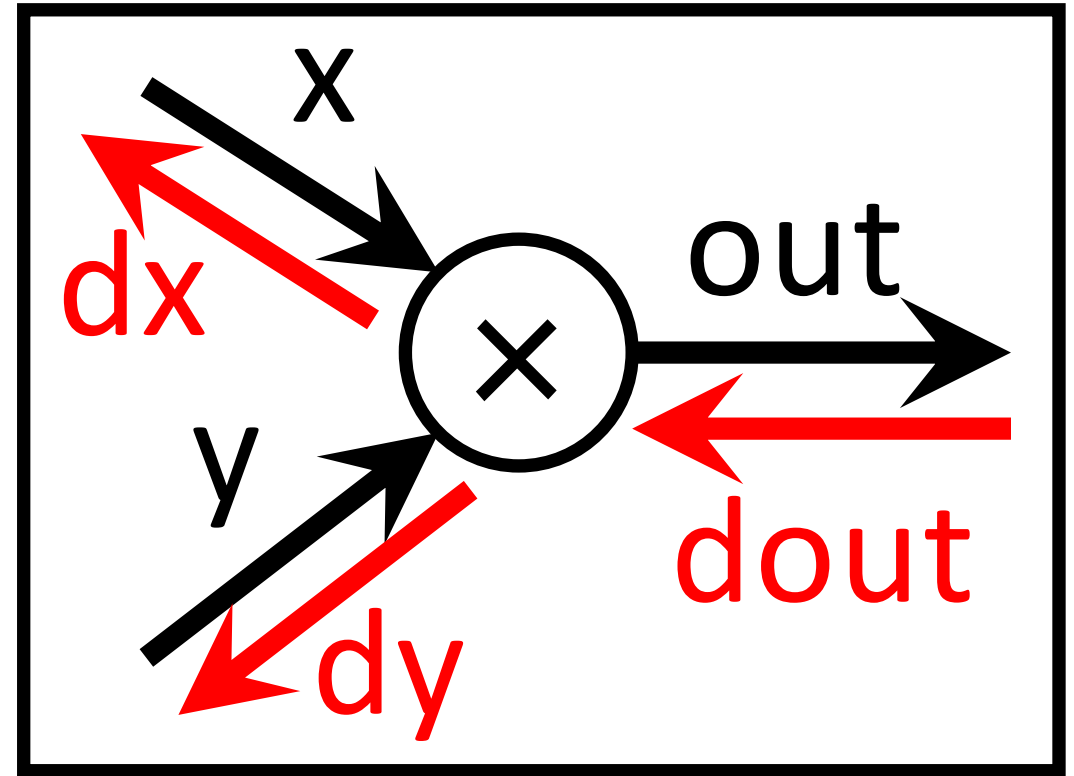
```
class MulLayer:
    def __init__(self):
        self.x = None
        self.y = None

    def forward(self, x, y):
        self.x = x
        self.y = y
        out = x * y

        return out

    def backward(self, dout):
        dx = dout * self.y
        dy = dout * self.x

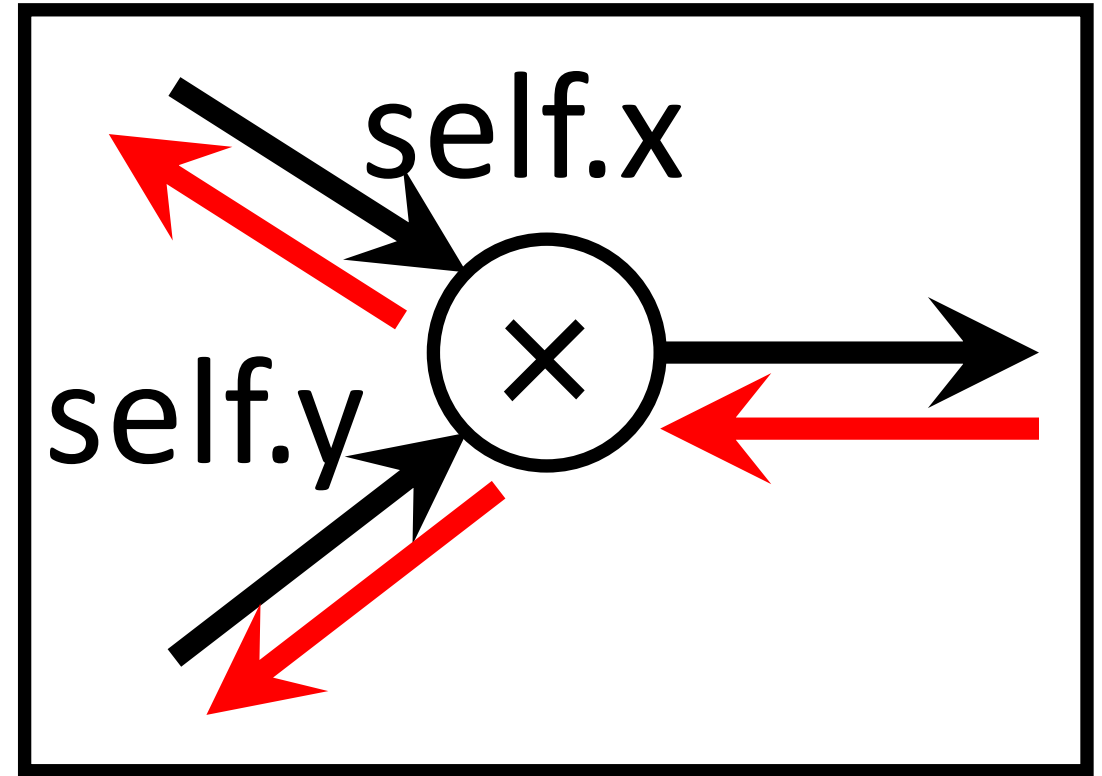
        return dx, dy
```



MulLayer

Implementation of multiplication layer

```
class MulLayer:  
    def __init__(self):  
        self.x = None  
        self.y = None  
  
    def forward(self, x, y):  
        self.x = x  
        self.y = y  
        out = x * y  
  
        return out  
  
    def backward(self, dout):  
        dx = dout * self.y  
        dy = dout * self.x  
  
        return dx, dy
```



MulLayer

Implementation of “Buy Apples”

```
apple = 100  
apple_num = 2  
tax = 1.1
```

```
mul_apple_layer = MulLayer()  
mul_tax_layer = MulLayer()
```

```
# forward
```

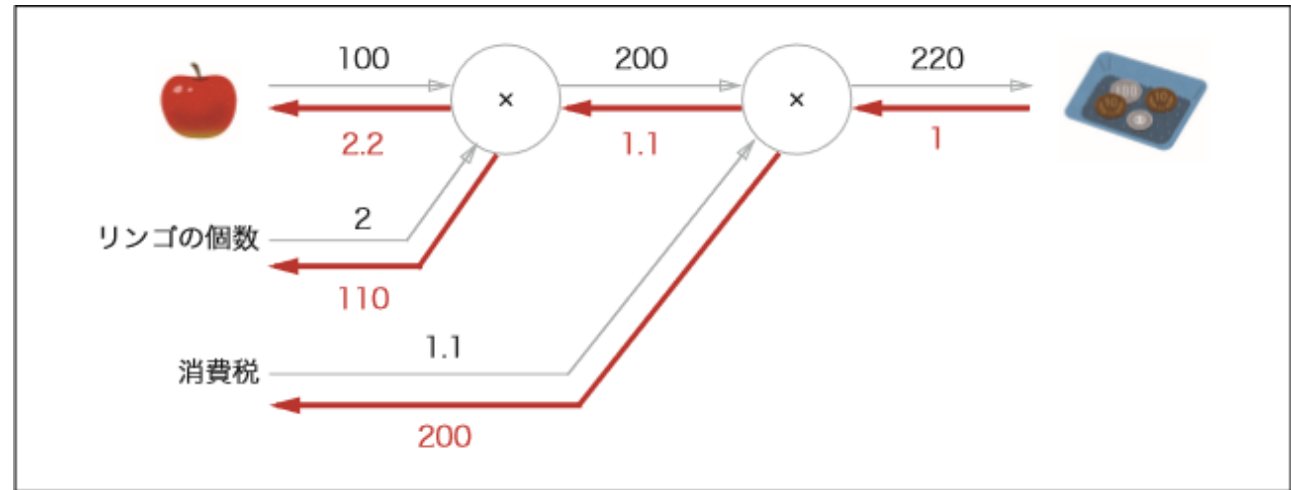
```
apple_price = mul_apple_layer.forward(apple, apple_num)  
price = mul_tax_layer.forward(apple_price, tax)
```

```
print(price) # 220
```

```
# backward
```

```
dprice = 1  
dapple_price, dtax = mul_tax_layer.backward(dprice)  
dapple, dapple_num = mul_apple_layer.backward(dapple_price)
```

```
print(dapple, dapple_num, dtax) # 2.2 110 200
```



Implementation of “Buy Apples”

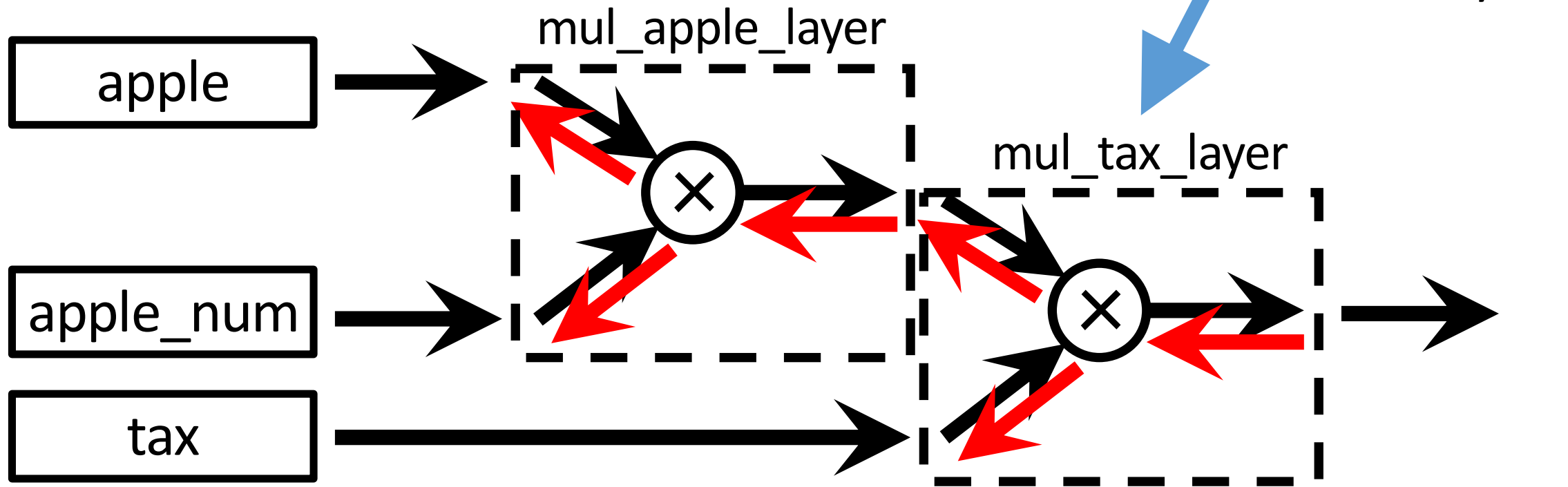
apple = 100

apple_num = 2

tax = 1.1

mul_apple_layer = MulLayer()

mul_tax_layer = MulLayer()



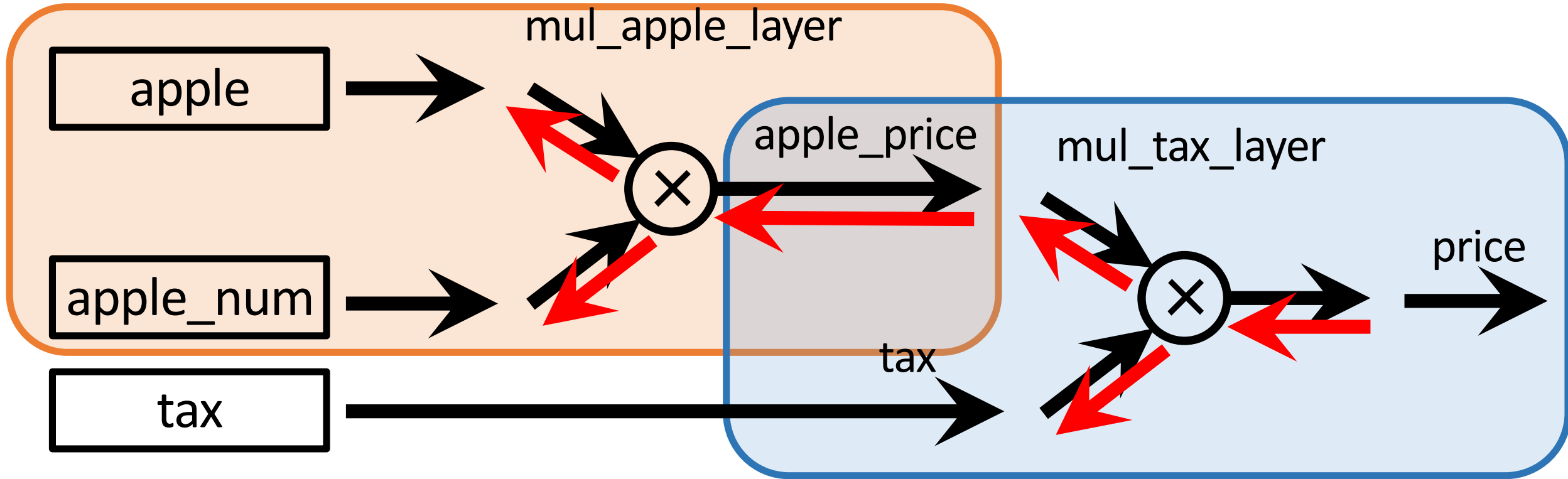
Implementation of “Buy Apples”

forward

```
apple_price = mul_apple_layer.forward(apple, apple_num)
```

```
price = mul_tax_layer.forward(apple_price, tax)
```

```
print(price) # 220
```



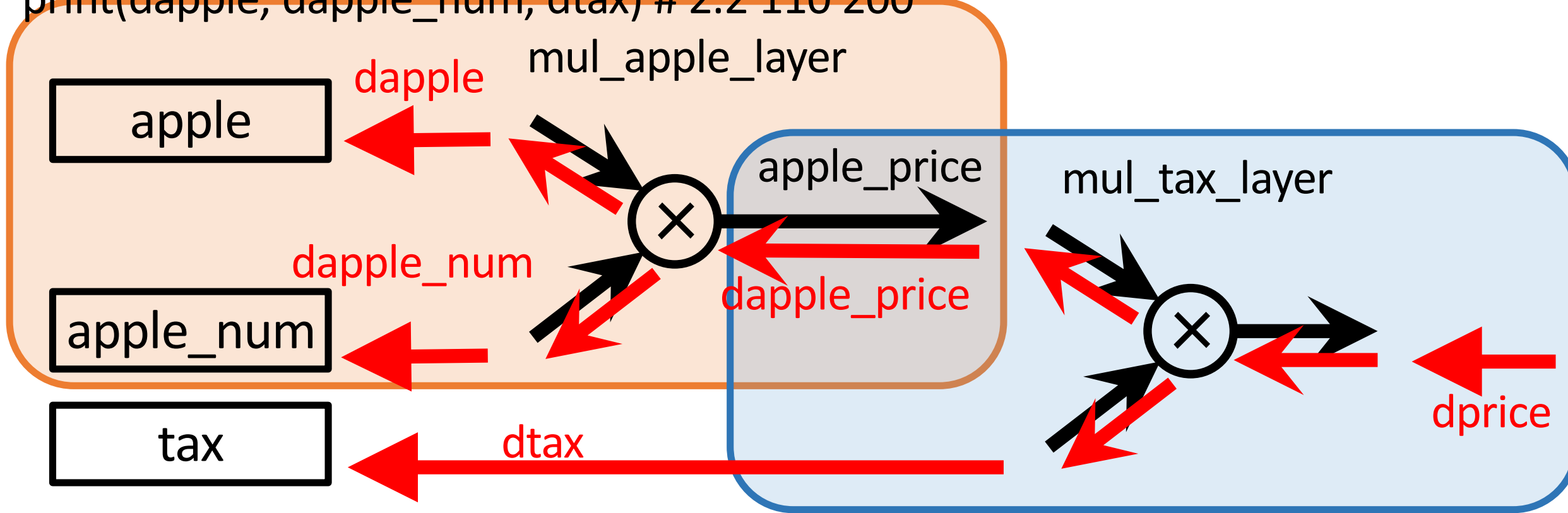
Implementation of “Buy Apples”

```
# backward  
dprice = 1
```

```
dapple_price, dtax = mul_tax_layer.backward(dprice)
```

```
dapple, dapple_num = mul_apple_layer.backward(dapple_price)
```

```
print(dapple, dapple_num, dtax) # 2.2 110 200
```



Implementation of “Buy Apples”

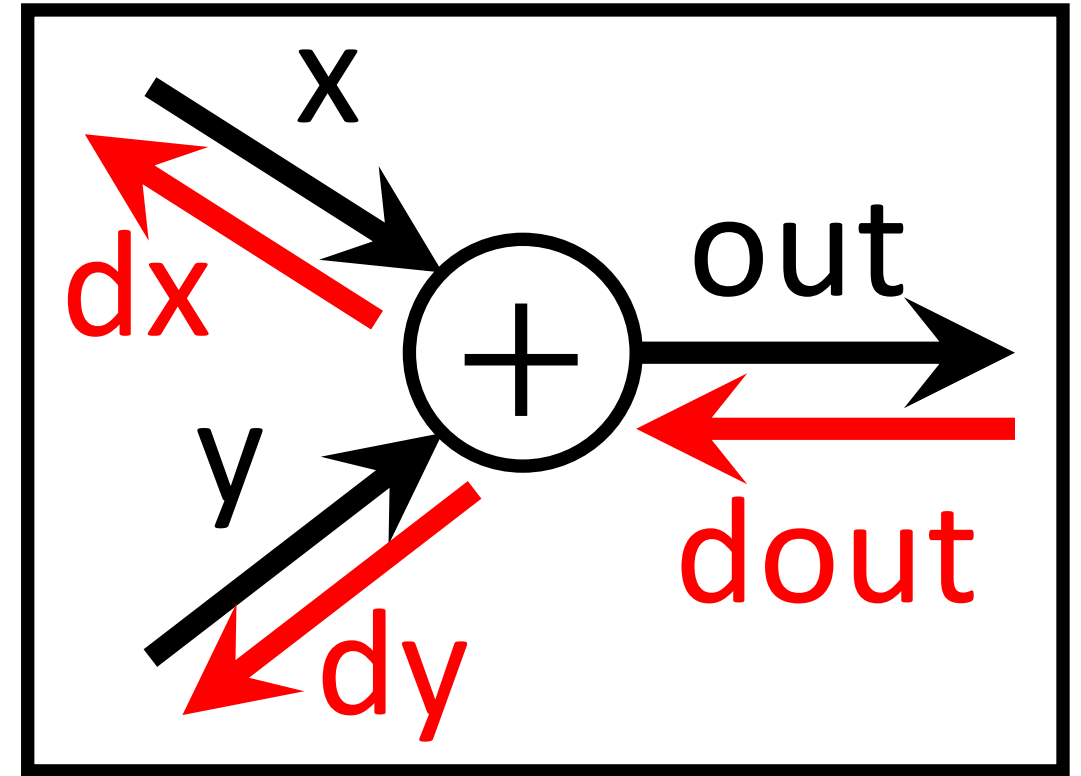
```
print(price) # 220
```

```
print(dapple, dapple_num, dtax) # 2.2 110 200
```

```
[MacBook-Pro:PythonLearning tsuda$ python3 BuyApple.py  
220.000000000000003  
2.2 110.000000000000001 200
```

Implementation of addition layer

```
class AddLayer:  
    def __init__(self):  
        pass  
  
    def forward(self, x, y):  
        out = x + y  
        return out  
  
    def backward(self, dout):  
        dx = dout * 1  
        dy = dout * 1  
        return dx, dy
```



MulLayer

Implementation of “Buy apples and oranges”

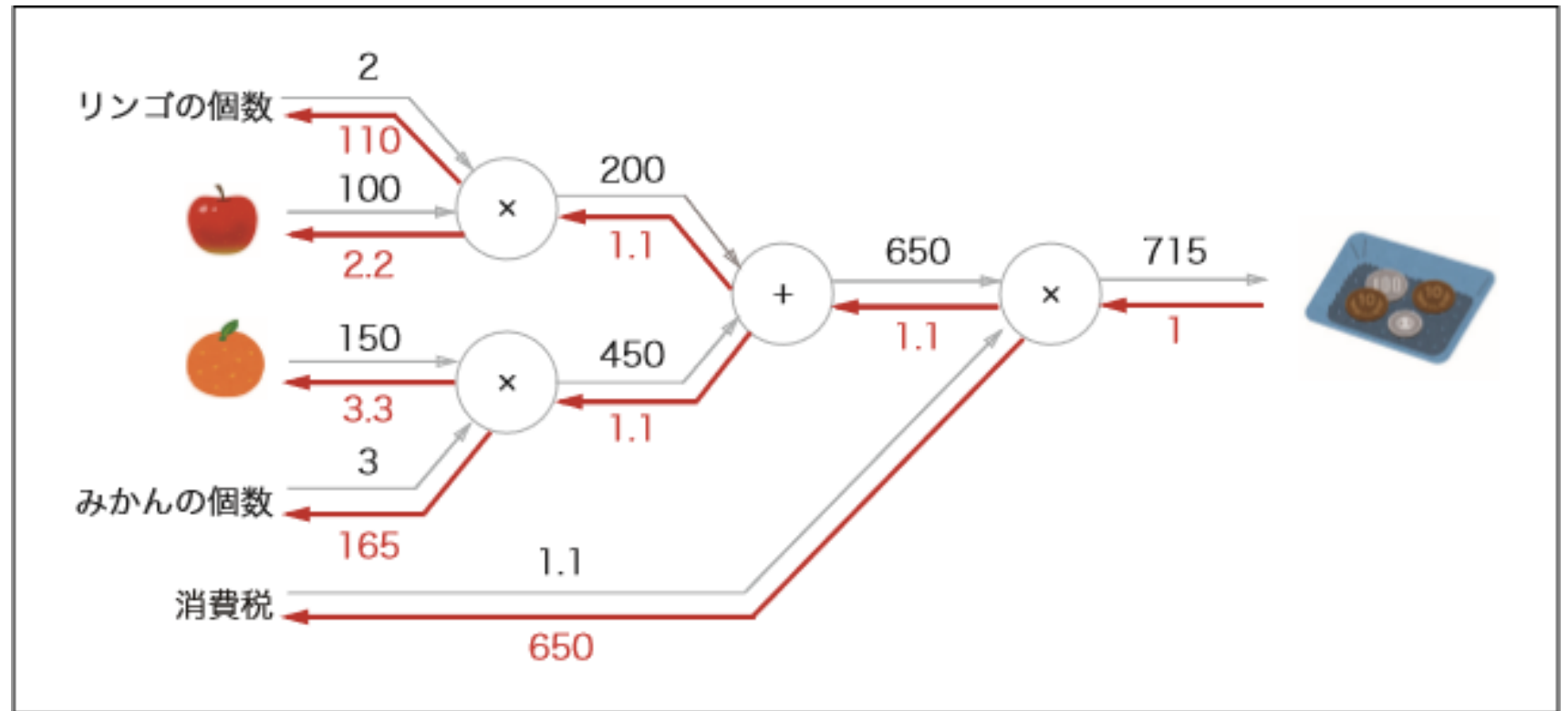
```
BuyFruits.py x
26
27 # Buy apple and orange
28 apple = 100
29 apple_num = 2
30 orange = 150
31 orange_num = 3
32 tax = 1.1
33
34 # layer
35 mul_apple_layer = MulLayer()
36 mul_orange_layer = MulLayer()
37 add_apple_orange_layer = AddLayer()
38 mul_tax_layer = MulLayer()
39
40 # forward
41 apple_price = mul_apple_layer.forward(apple, apple_num) #(1)
42 orange_price = mul_orange_layer.forward(orange, orange_num) #(2)
43 all_price = add_apple_orange_layer.forward(apple_price, orange_price) #(3)
44 price = mul_tax_layer.forward(all_price, tax) #(4)
45
46 # backward
47 dprice = 1
48 dall_price, dtax = mul_tax_layer.backward(dprice) #(4)
49 dapple_price, dorange_price = add_apple_orange_layer.backward(dall_price) #(3)
50 dorange, dorange_num = mul_orange_layer.backward(dorange_price) #(2)
51 dapple, dapple_num = mul_apple_layer.backward(dapple_price) #(1)
52
53 print(price) # 715
54 print(dapple_num, dapple, dorange, dorange_num, dtax) # 110 2.2 3.3 165 650
```

Implementation of “Buy apples and oranges”

apple = 100
apple_num = 2
orange = 150
orange_num = 3
tax = 1.1

layer

```
mul_apple_layer = MulLayer()  
mul_orange_layer = MulLayer()  
add_apple_orange_layer = AddLayer()  
mul_tax_layer = MulLayer()
```



Implementation of “Buy apples and oranges”

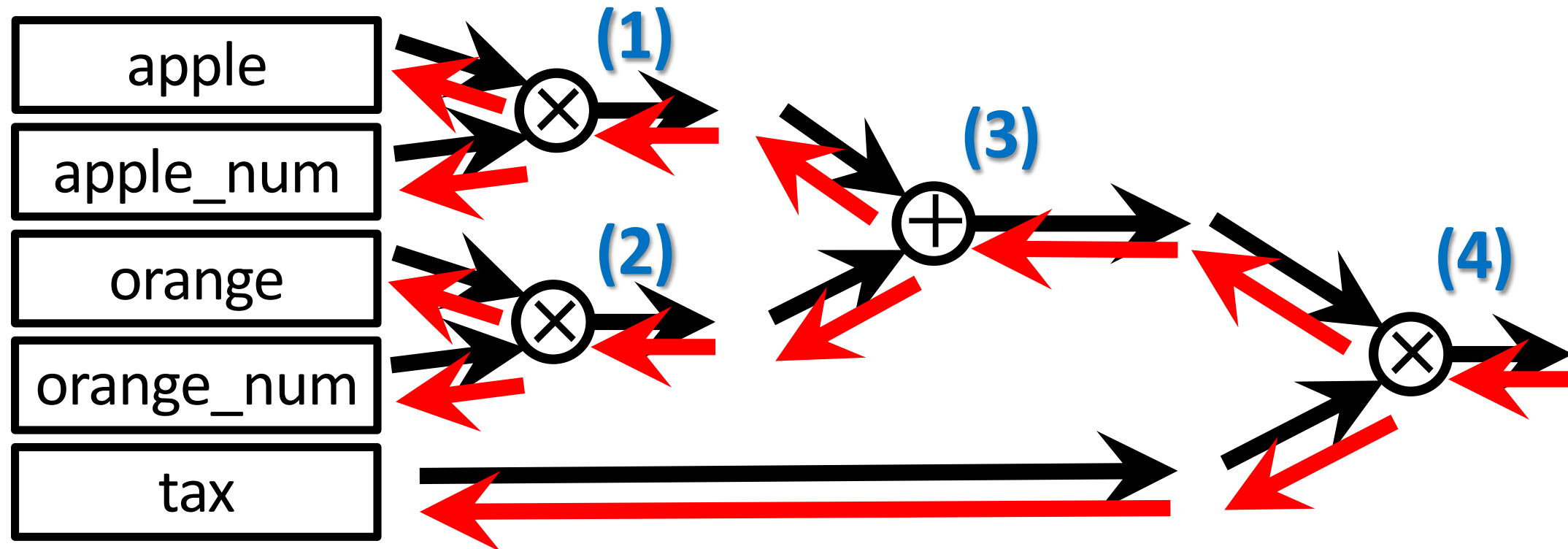
forward

apple_price = mul_apple_layer.forward(apple, apple_num) #(1)

orange_price = mul_orange_layer.forward(orange, orange_num) #(2)

all_price = add_apple_orange_layer.forward(apple_price, orange_price) #(3)

price = mul_tax_layer.forward(all_price, tax) #(4)



Implementation of “Buy apples and oranges”

```
# backward
```

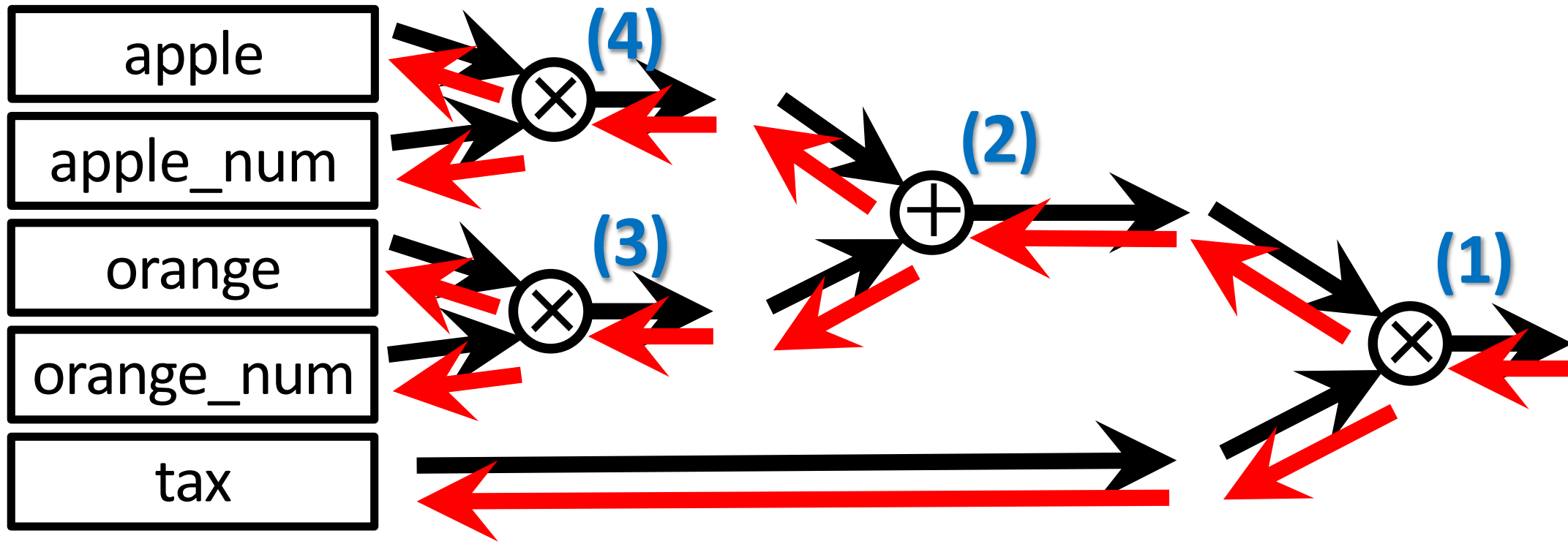
```
dprice = 1
```

```
dall_price, dtax = mul_tax_layer.backward(dprice) #(4)
```

```
dapple_price, dorange_price = add_apple_orange_layer.backward(dall_price) #(3)
```

```
dorange, dorange_num = mul_orange_layer.backward(dorange_price) #(2)
```

```
dapple, dapple_num = mul_apple_layer.backward(dapple_price) #(1)
```



Implementation of “Buy apples and oranges”

```
print(price) # 715
```

```
print(dapple_num, dapple, dorange, dorange_num, dtax) # 110 2.2 3.3 165 650
```

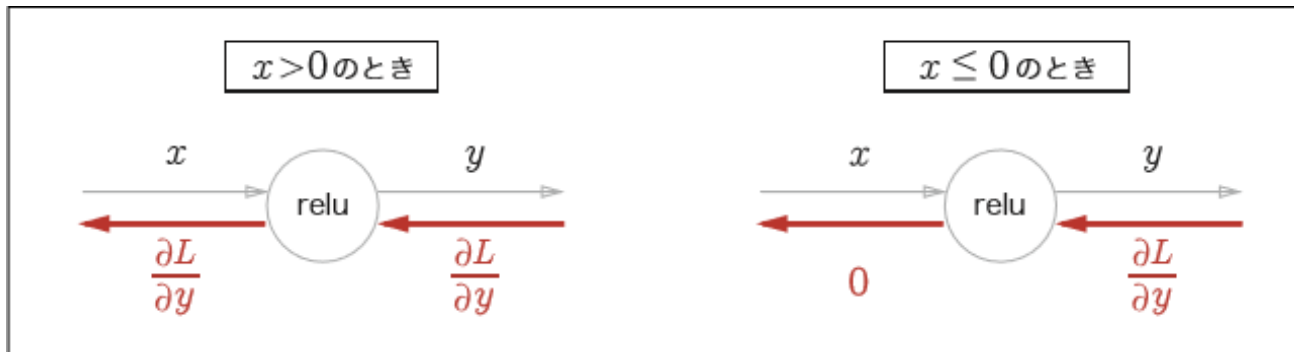
```
[MacBook-Pro:PythonLearning tsuda$ python3 BuyFruits.py  
715.000000000000001  
110.000000000000001 2.2 3.3000000000000003 165.0 650
```

Implementation of activation function layer

- Apply the idea of **computational graph** to **neural network**
- Implement layers as classes
- At first, implement activation function layer
 - ReLU layer
 - Sigmoid layer

Implementation of ReLU layer

- ReLU function :
$$y = \begin{cases} x & (x > 0) \\ 0 & (x \leq 0) \end{cases}$$
- A differential of ReLU :
$$\frac{\partial y}{\partial x} = \begin{cases} 1 & (x > 0) \\ 0 & (x \leq 0) \end{cases}$$
- ReLU behaves like as a switch.



Implementation of ReLU layer

```
class Relu:
```

```
    def __init__(self):  
        self.mask = None
```

```
    def forward(self, x):  
        self.mask = (x <= 0)  
        out = x.copy()  
        out[self.mask] = 0
```

```
        return out
```

```
    def backward(self, dout):  
        dout[self.mask] = 0  
        dx = dout
```

```
        return dx
```

About “Boolean ndarray”

```
[>>> x = np.array( [[1.0, -0.5], [-2.0, 3.0]] )
[>>> mask = (x <= 0)
[>>> print(x)
[[ 1.  -0.5]
 [-2.   3. ]]
[>>> print(mask)
[[False  True]
 [ True False]]
[>>>
[>>> print(x[mask])
[-0.5 -2. ]
[>>> print(x[mask]+1)
[ 0.5 -1. ]
[>>> x = x[mask] + 2
[>>> print(x)
[1.5 0. ]
```

References : <https://hydrocul.github.io/wiki/numpy/ndarray-ref-boolean.html>

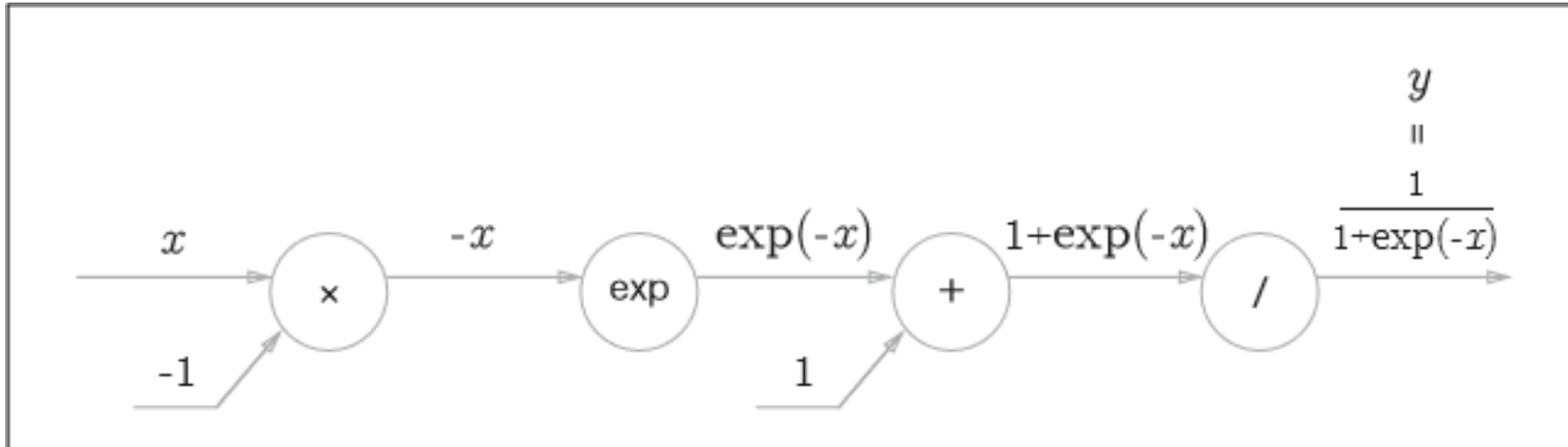
About “Boolean ndarray”

```
[>>> x = np.array( [[1.0, -0.5], [-2.0, 3.0]] )
[>>> mask = (x <= 0)
[>>> print(x)
[[ 1.  -0.5]
 [-2.   3. ]]
[>>> print(mask)
[[False  True]
 [ True False]]
[>>> x[mask] = 0
[>>> print(x)
[[1.  0.]
 [0.  3.]]
[>>> x[mask] = [10, 20]
[>>> print(x)
[[ 1. 10.]
 [20.  3.]]
```

References : <https://hydrocul.github.io/wiki/numpy/ndarray-ref-boolean.html>

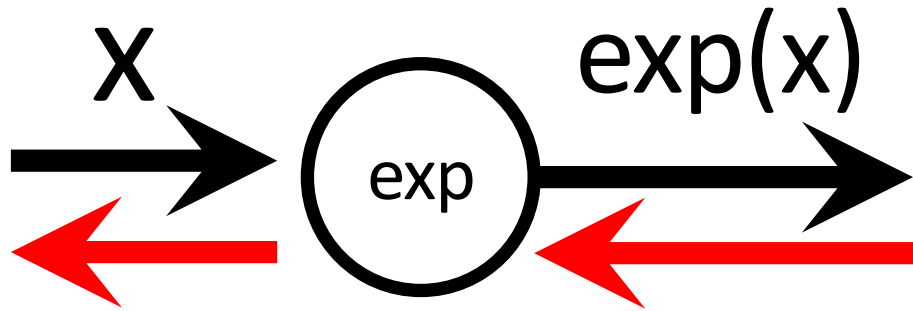
Implementation of Sigmoid layer

- Sigmoid function : $y = \frac{1}{1+\exp(-x)}$
- Computation graph of Sigmoid function

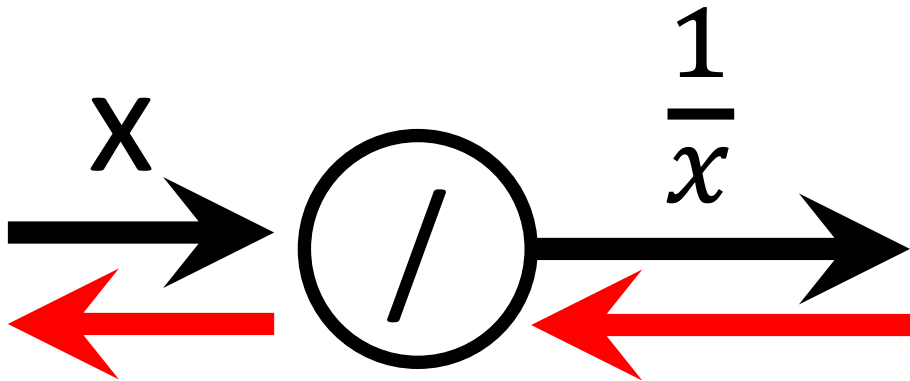


New nodes

- “exp” node



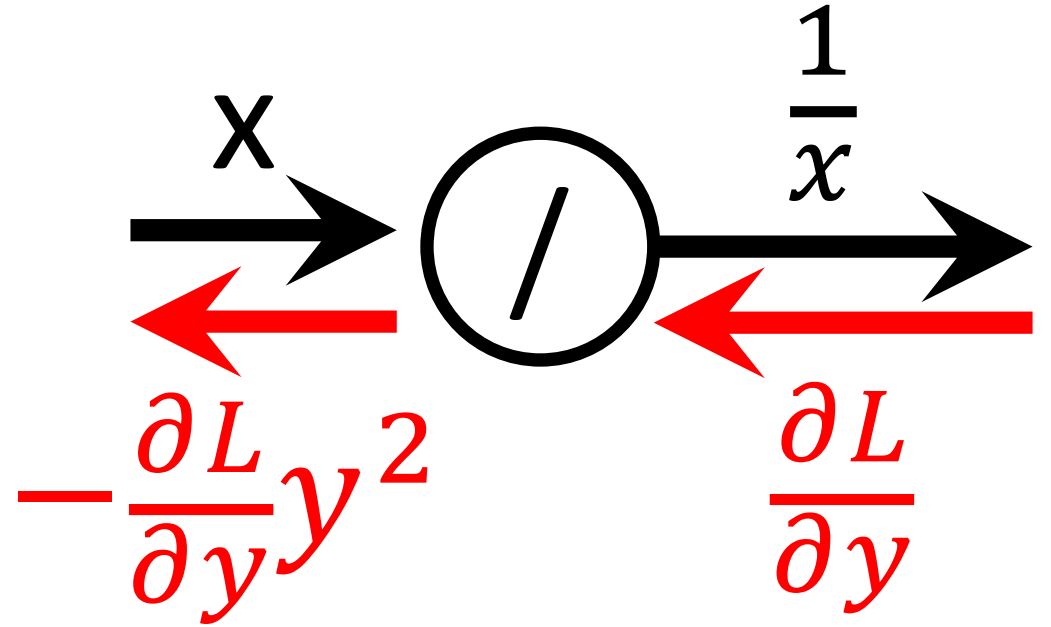
- “/” node



Backward propagation of new node

- “/” node

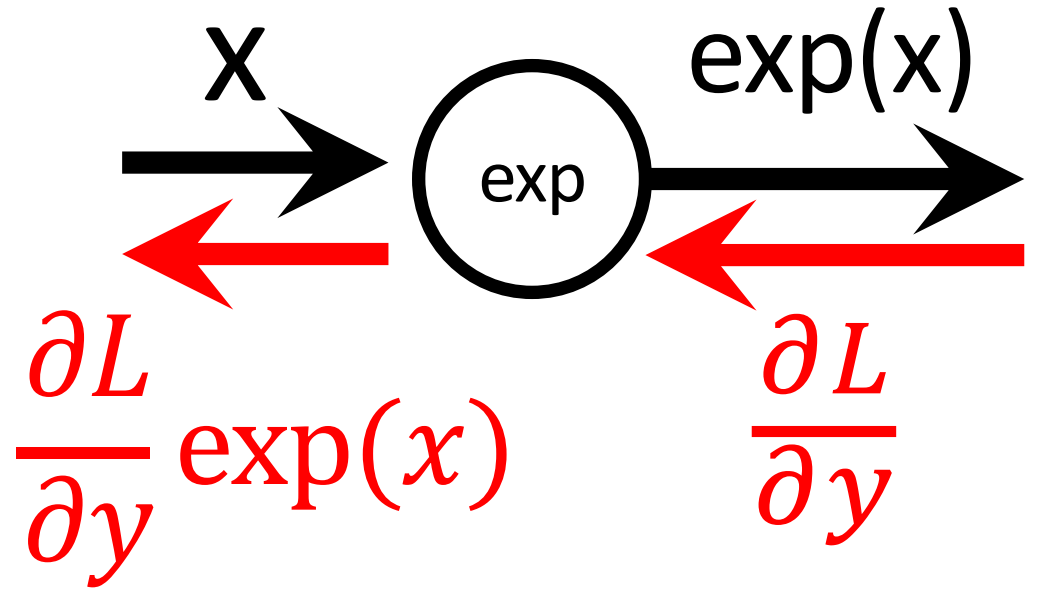
$$\begin{aligned}\frac{\partial y}{\partial x} &= \frac{\partial}{\partial x} x^{-1} \\ &= (-1)x^{-2} \\ &= -\frac{1}{x^2} = -y^2\end{aligned}$$



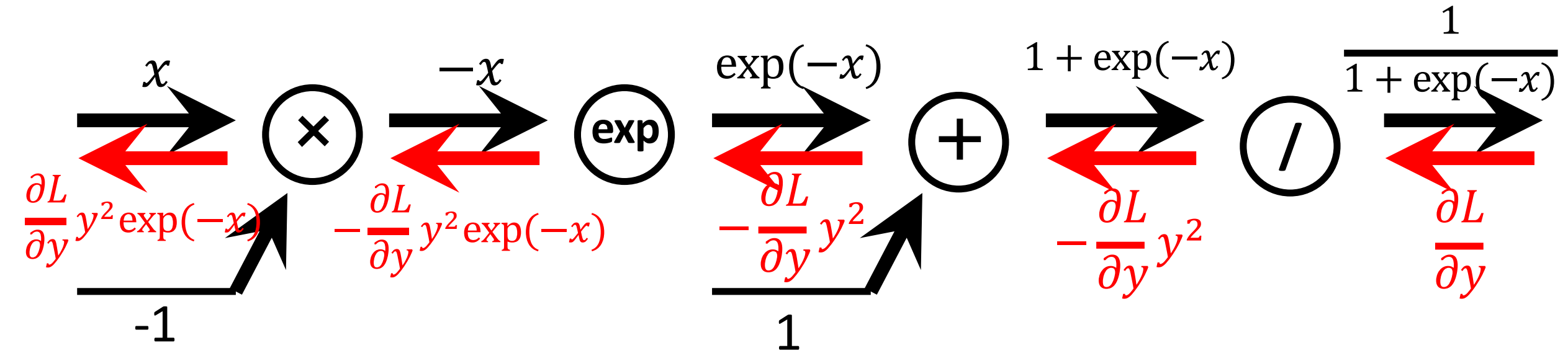
Backward propagation of new node

- “exp” node

$$\begin{aligned}\frac{\partial y}{\partial x} &= \frac{\partial}{\partial x} \exp(x) \\ &= \exp(x)\end{aligned}$$



Implementation of Sigmoid layer



Implementation of Sigmoid layer



Implementation of Sigmoid layer

- A differential of Sigmoid function

$$\begin{aligned}\frac{\partial L}{\partial y} y^2 \exp(-x) &= \frac{\partial L}{\partial y} \frac{1}{(1 + \exp(-x))^2} \exp(-x) \\ &= \frac{\partial L}{\partial y} \frac{1}{1 + \exp(-x)} \frac{\exp(-x)}{1 + \exp(-x)} = \frac{\partial L}{\partial y} y(1 - y)\end{aligned}$$

- Expressible only by output

Implementation of Sigmoid layer

```
class Sigmoid:
    def __init__(self):
        self.out = None

    def forward(self, x):
        out = 1 / (1 + np.exp(-x))
        self.out = out

        return out

    def backward(self, dout):
        dx = dout * (1.0 - self.out) * self.out

        return dx
```

