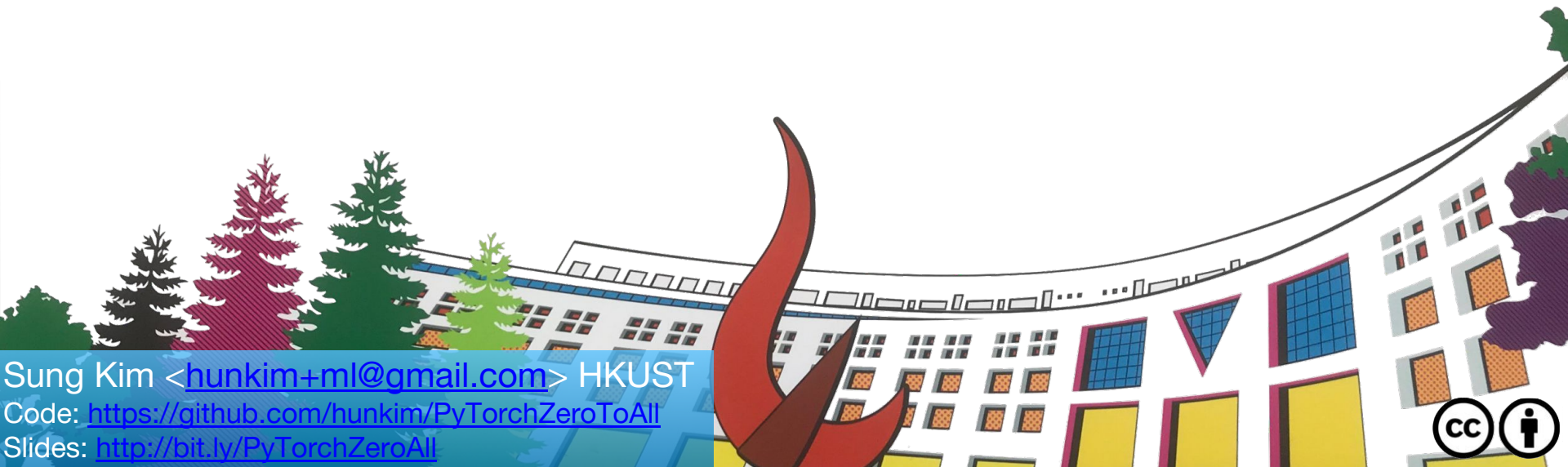


ML/DL for Everyone with PYTORCH

Lecture 4: Back-propagation



Sung Kim <hunkim+ml@gmail.com> HKUST

Code: <https://github.com/hunkim/PyTorchZeroToAll>

Slides: <http://bit.ly/PyTorchZeroAll>



Call for Comments

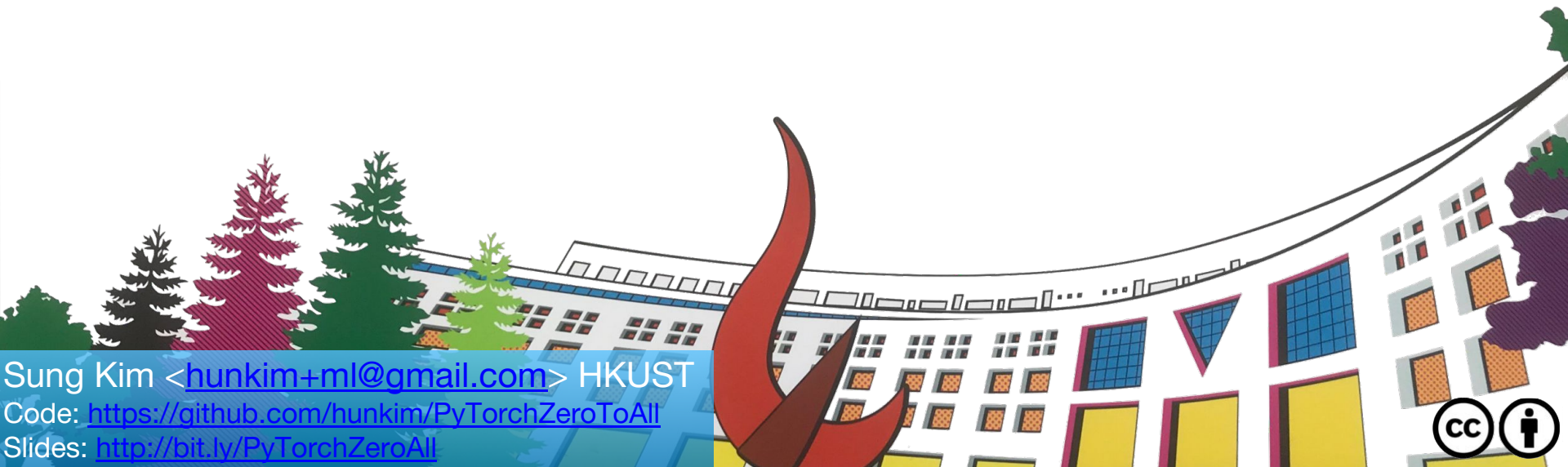
Please feel free to add comments directly on these slides.

Other slides: <http://bit.ly/PyTorchZeroAll>



ML/DL for Everyone with PYTORCH

Lecture 4: Back-propagation



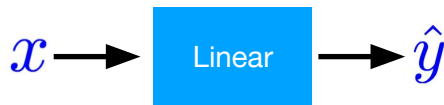
Sung Kim <hunkim+ml@gmail.com> HKUST

Code: <https://github.com/hunkim/PyTorchZeroToAll>

Slides: <http://bit.ly/PyTorchZeroAll>



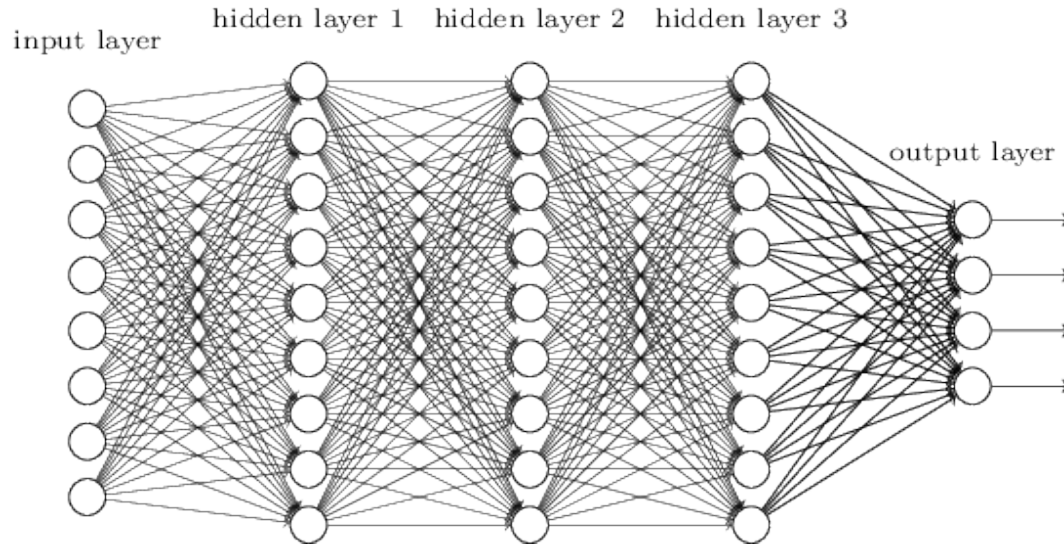
Computing gradient in simple network



Gradient of **loss**
with respect to **w** $\frac{\partial \text{loss}}{\partial w} = ?$

```
# compute gradient
def gradient(x, y): # d_loss/d_w
    return 2 * x * (x * w - y)
```

Complicated network?



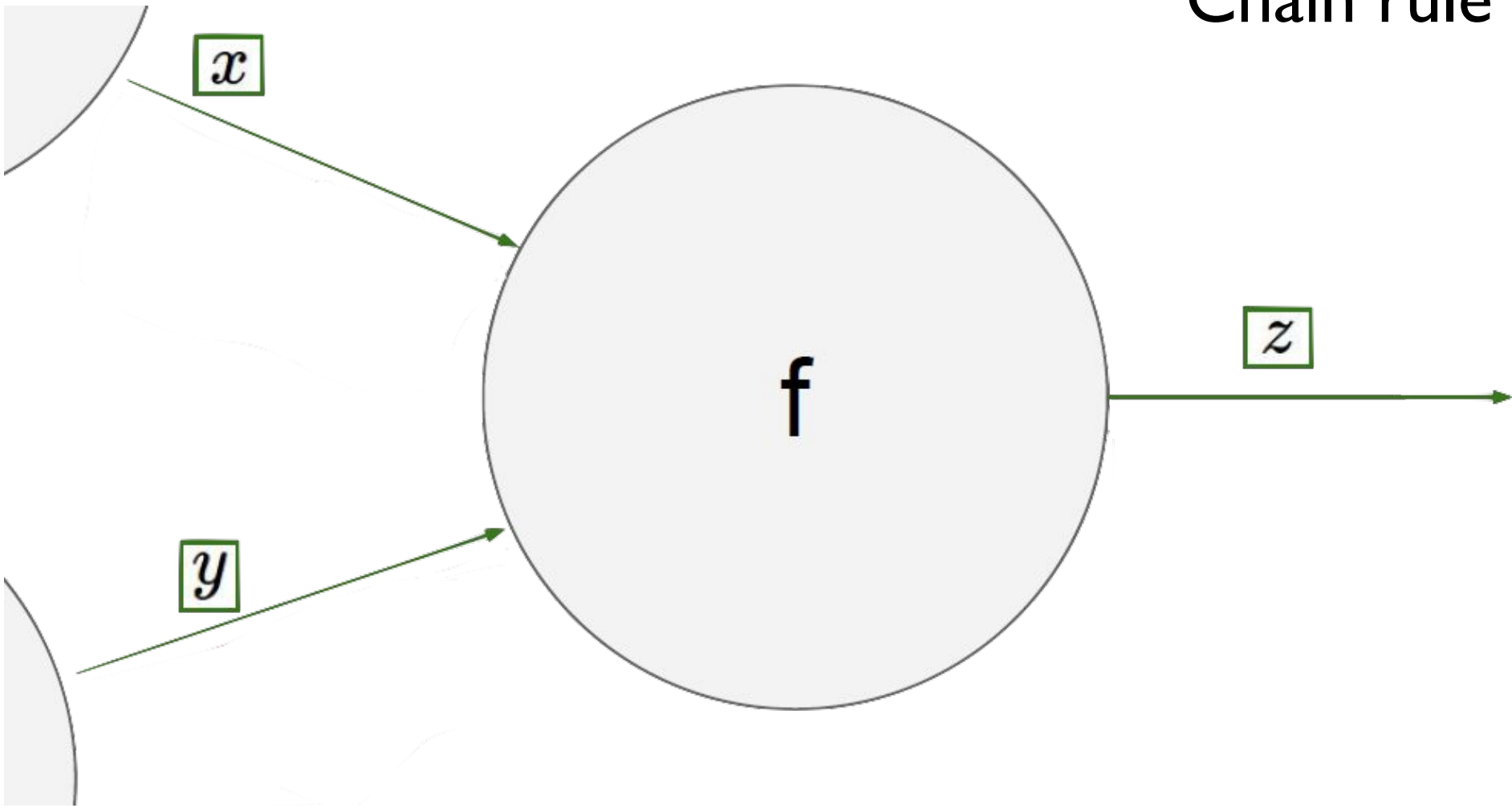
Gradient of **loss**
with respect to **w**

$$\frac{\partial \text{loss}}{\partial w} = ?$$

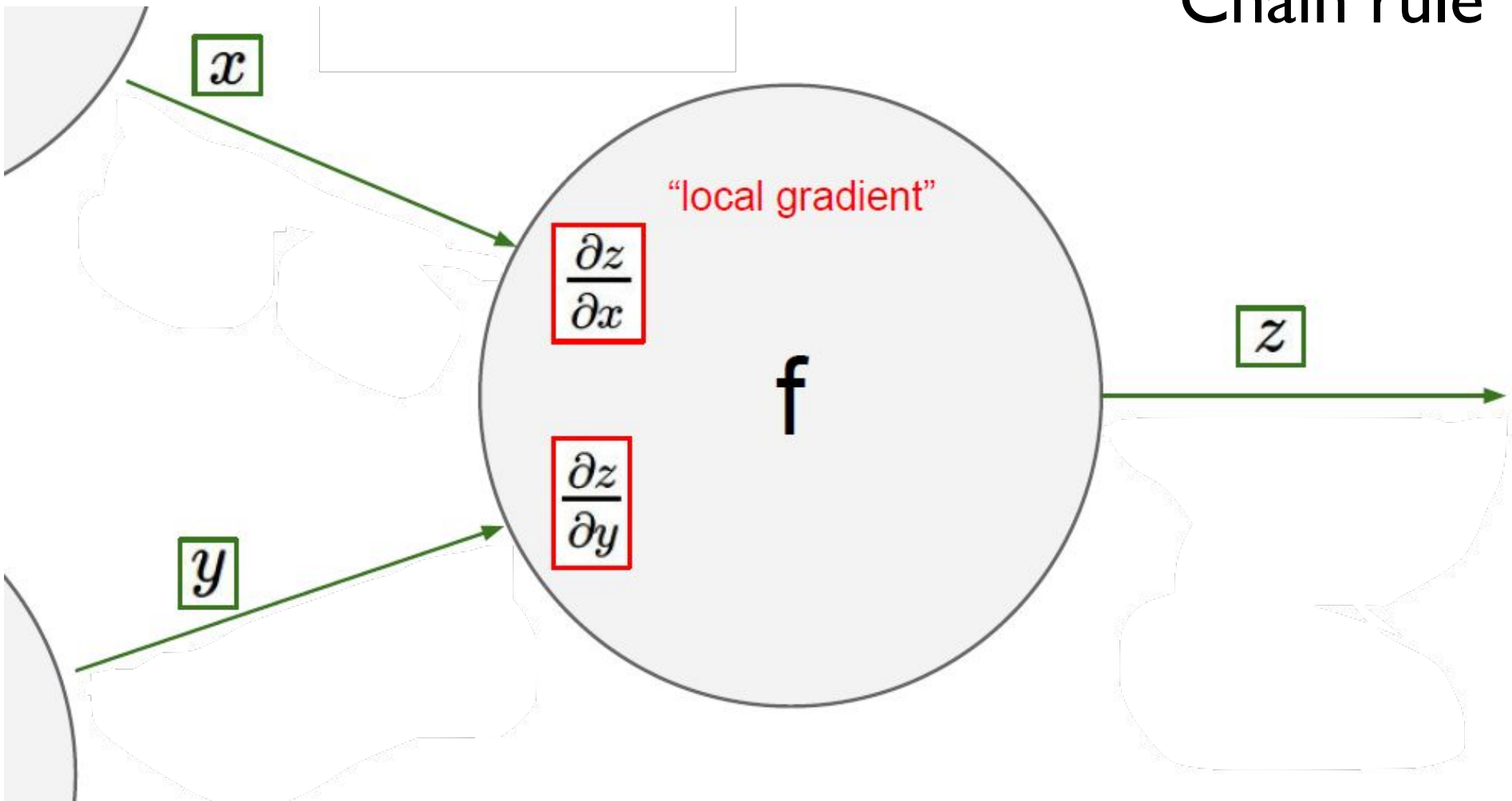
Better way? Computational graph + chain rule



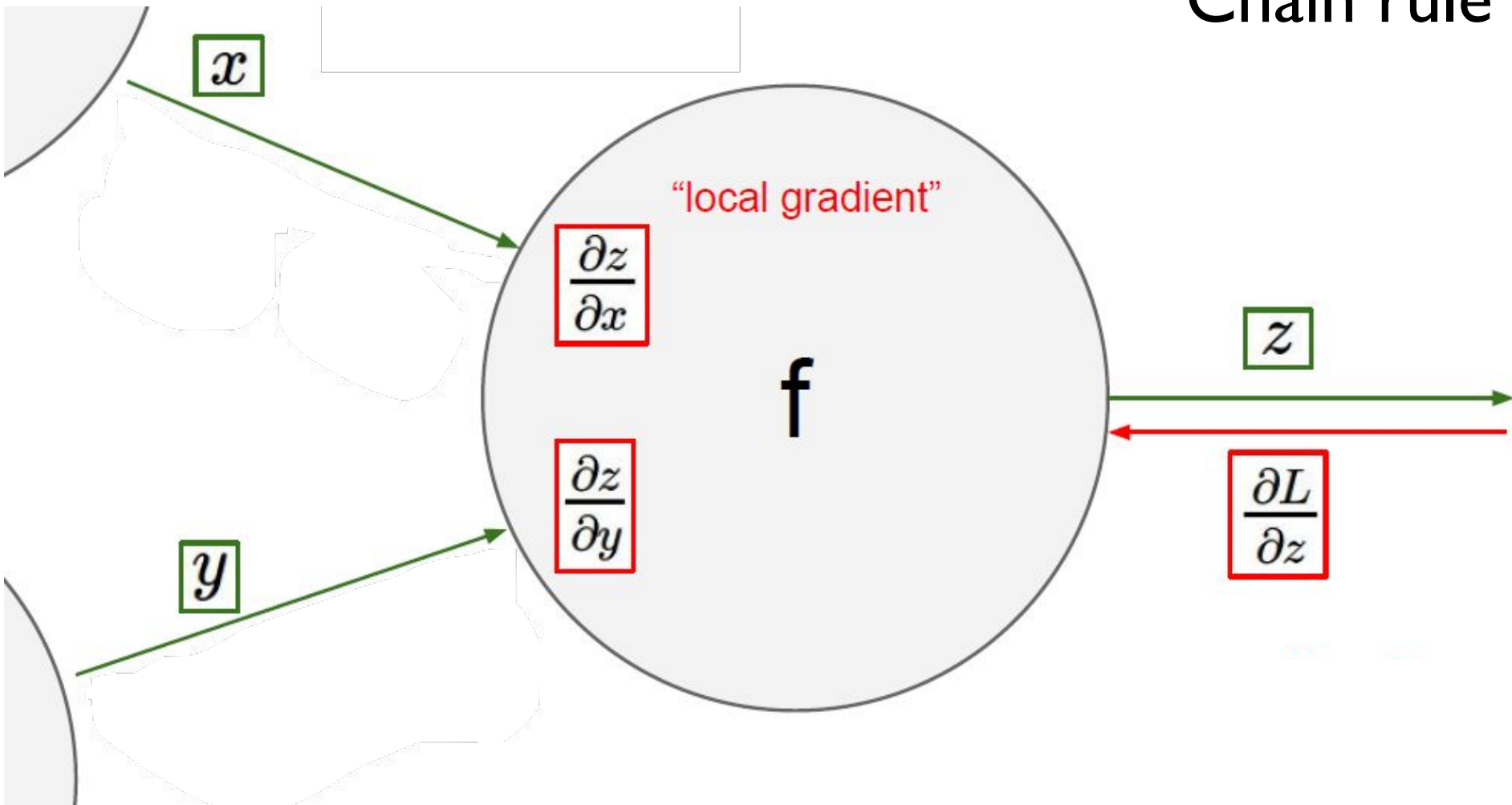
Chain rule



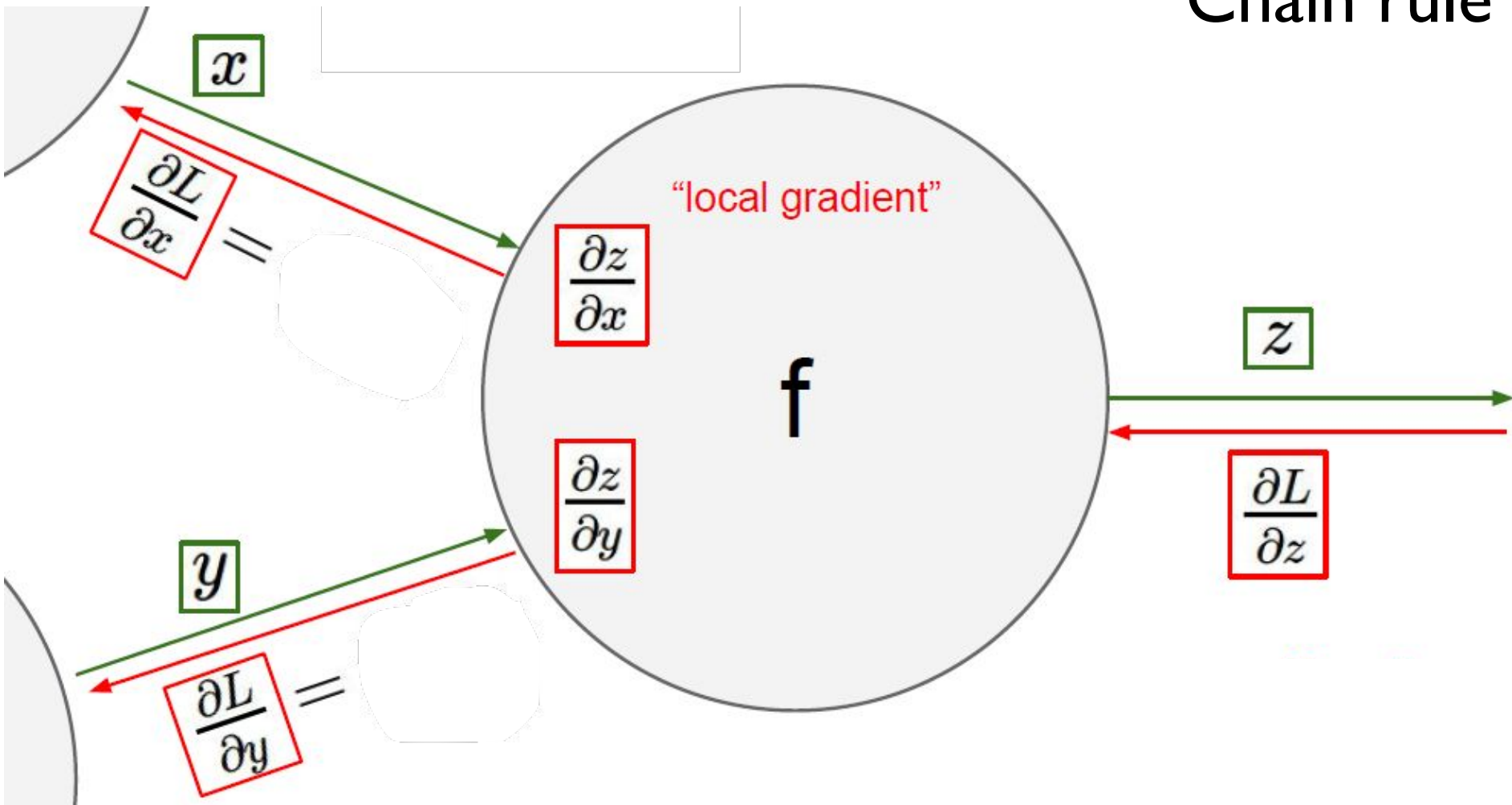
Chain rule



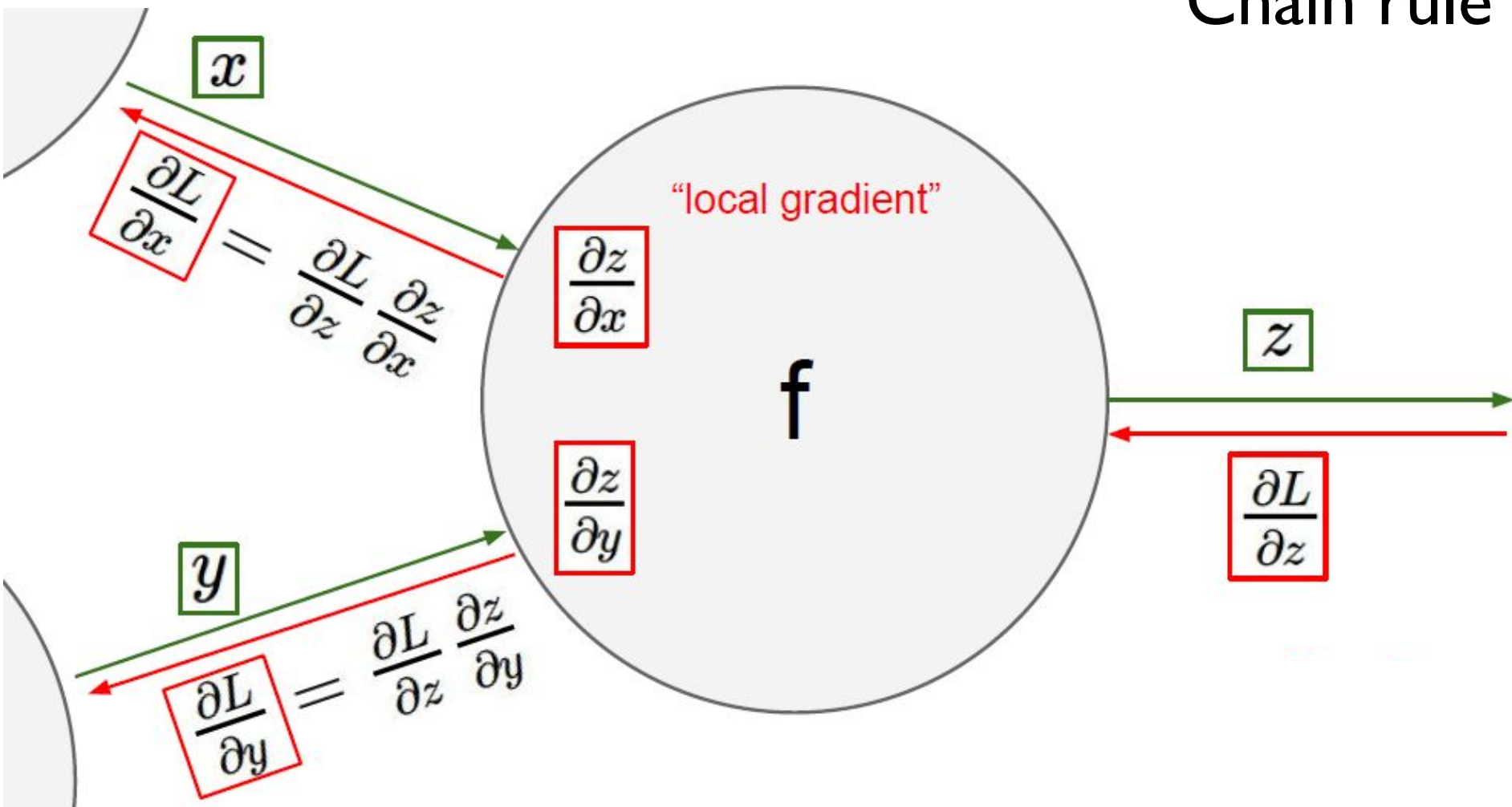
Chain rule

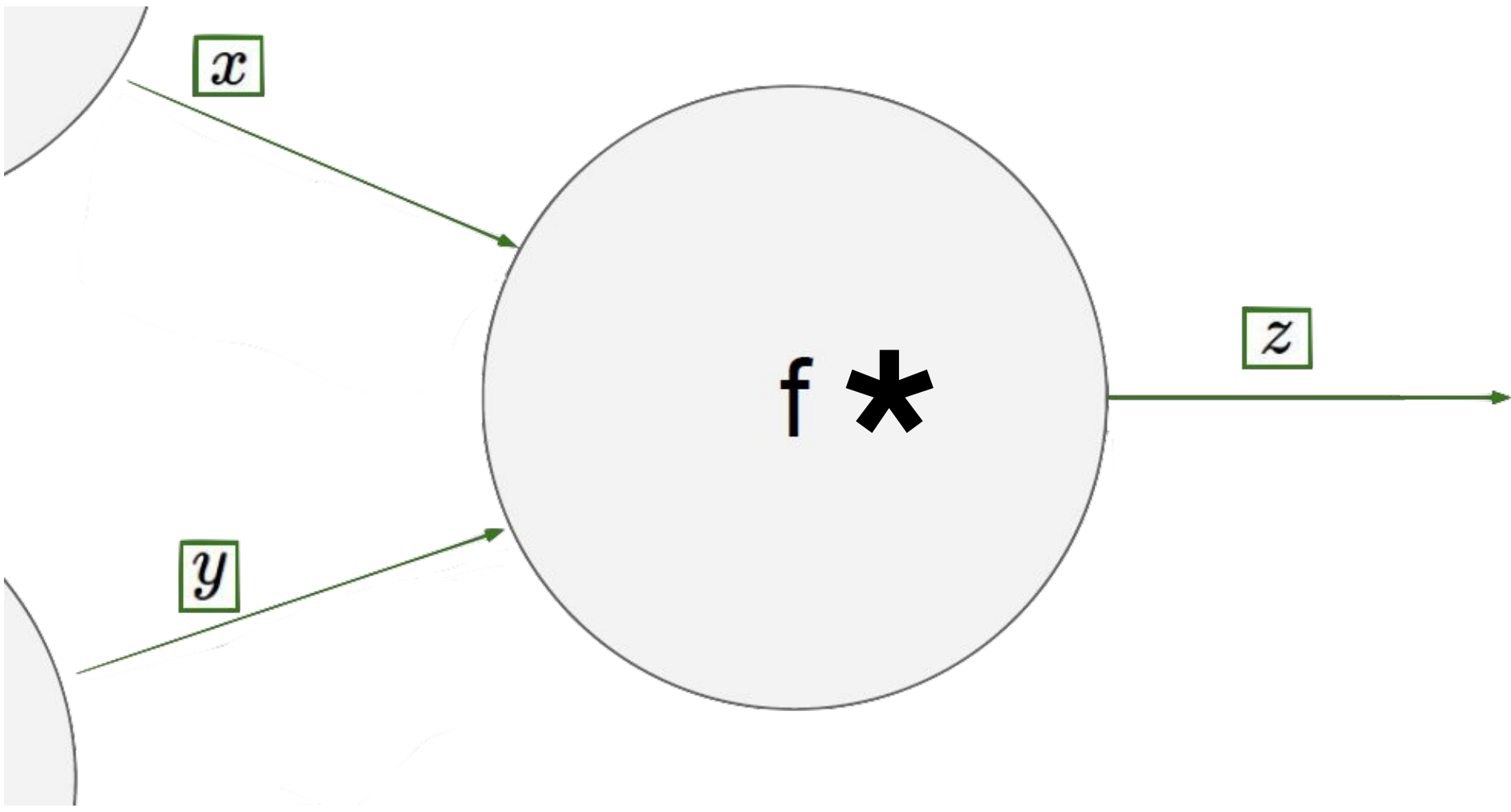


Chain rule



Chain rule





1

Forward pass $x = 2, y = 3$

x



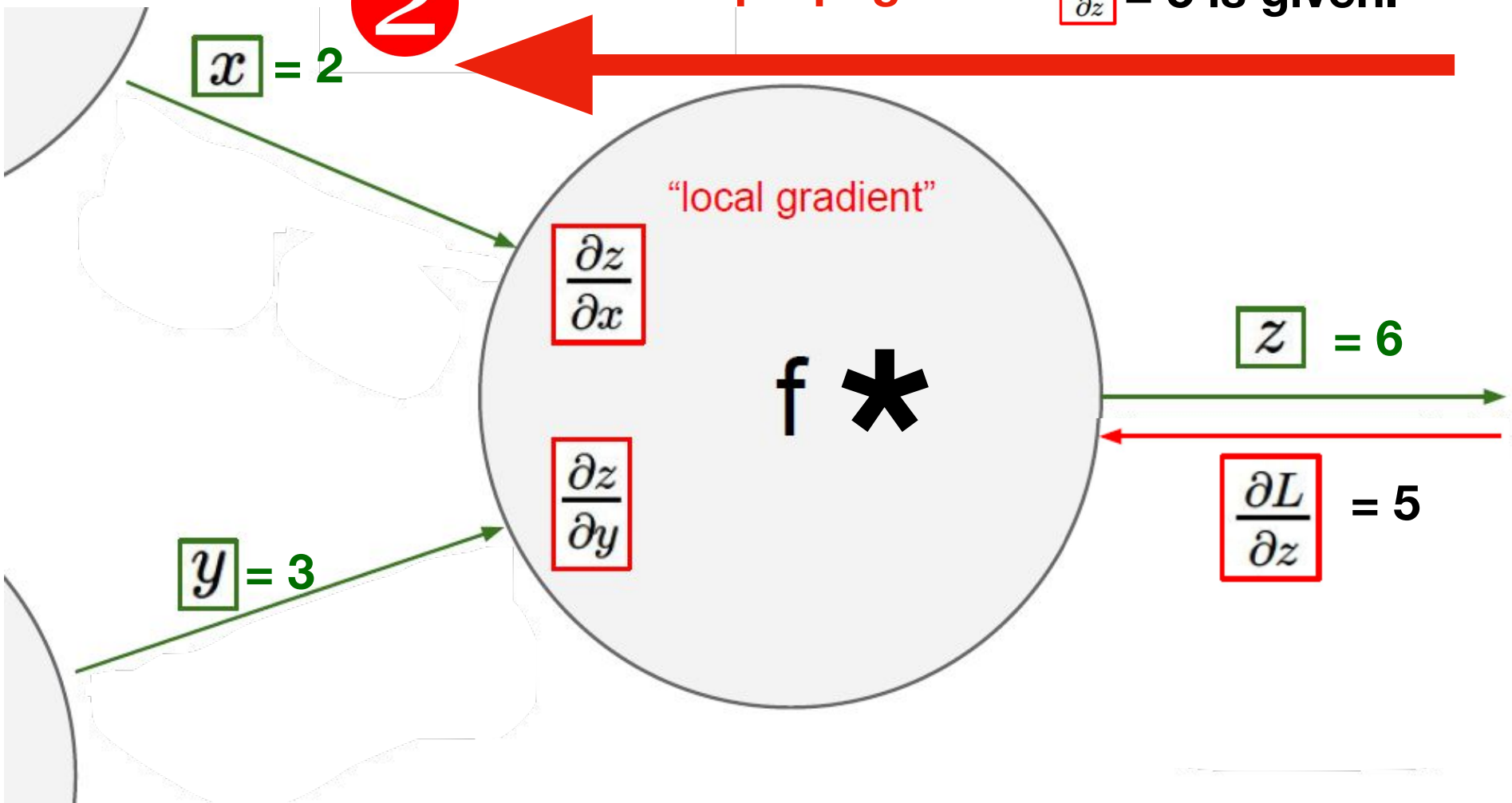
$f *$

y

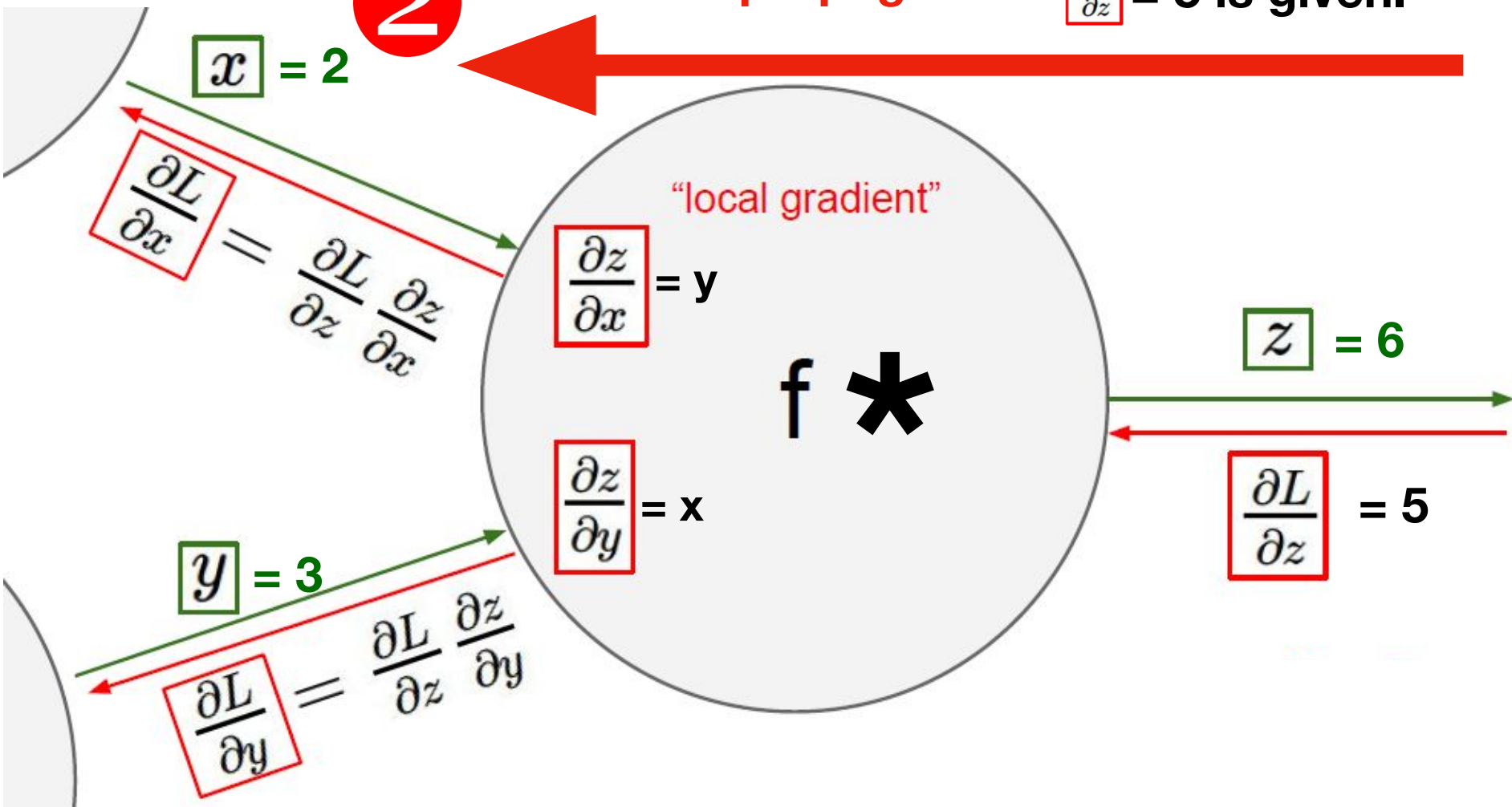
z



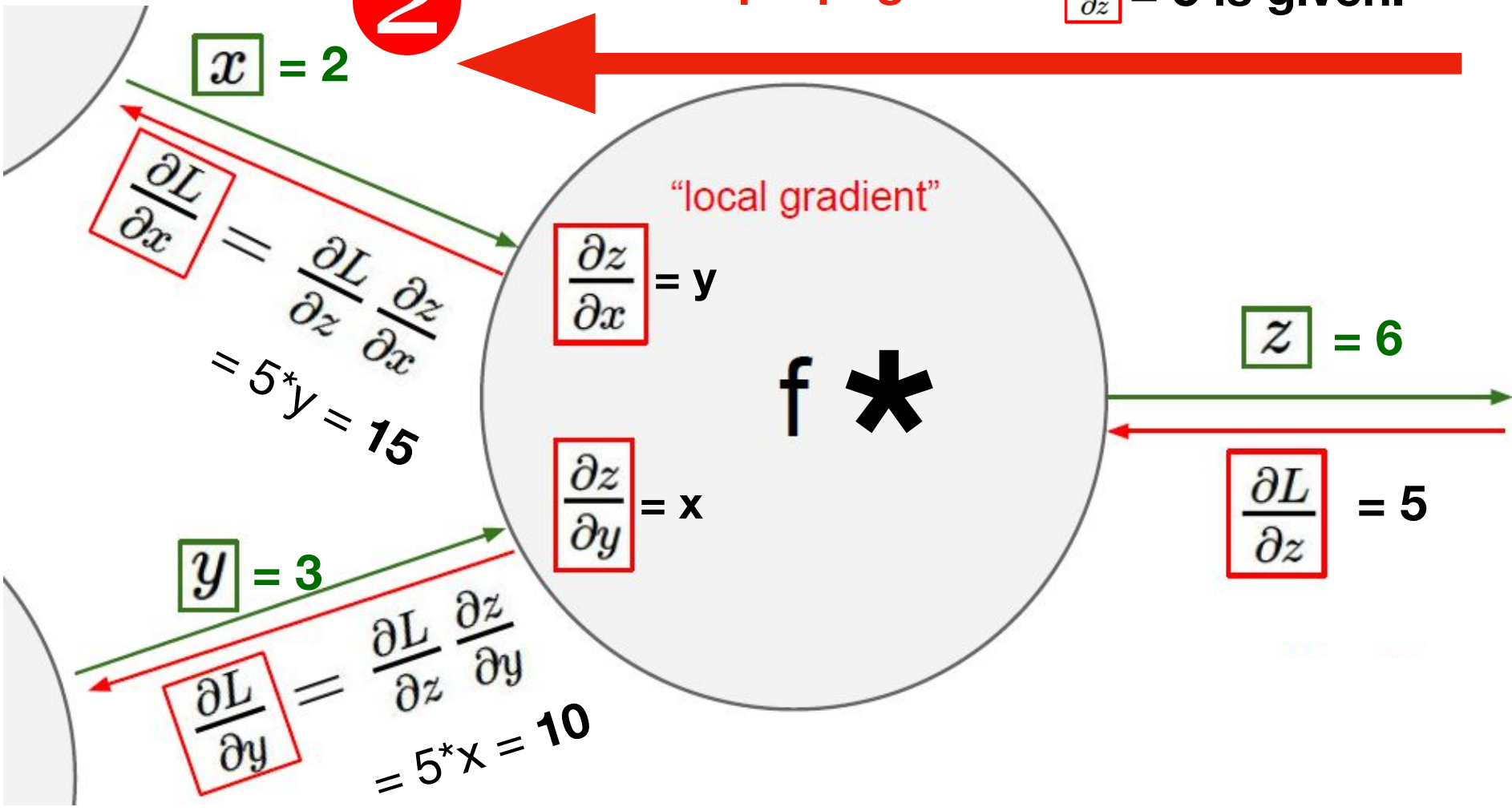
2 Backward propagation $\frac{\partial L}{\partial z} = 5$ is given.



2 Backward propagation $\frac{\partial L}{\partial z} = 5$ is given.



2 Backward propagation $\frac{\partial L}{\partial z} = 5$ is given.

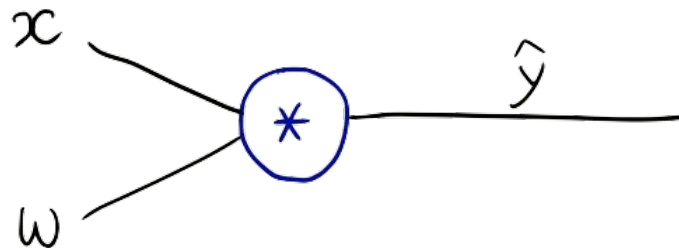


Computational graph

$$\hat{y} = x * w$$

Computational graph

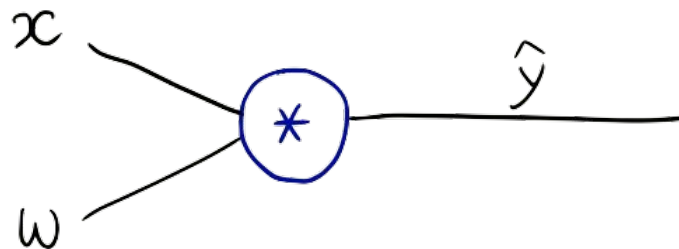
$$\hat{y} = x * w$$



Computational graph

$$\hat{y} = x * w$$

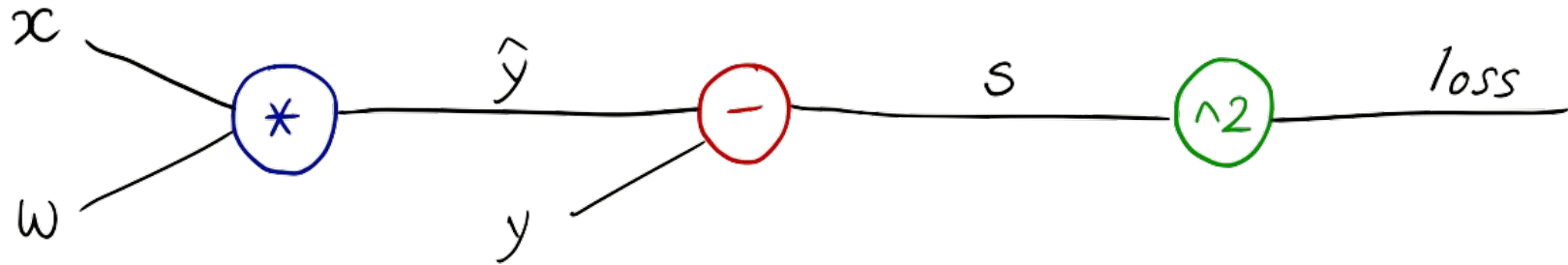
$$loss = (\hat{y} - y)^2 = (x * w - y)^2$$



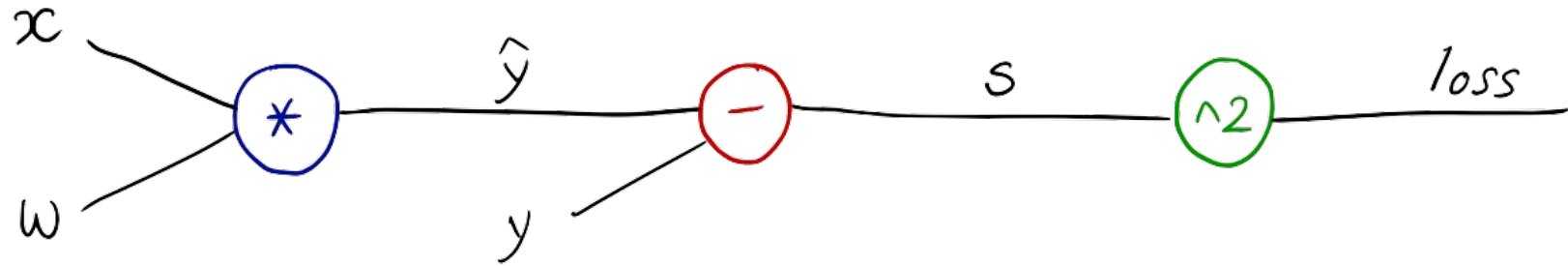
Computational graph

$$\hat{y} = x * w$$

$$loss = (\hat{y} - y)^2 = (x * w - y)^2$$

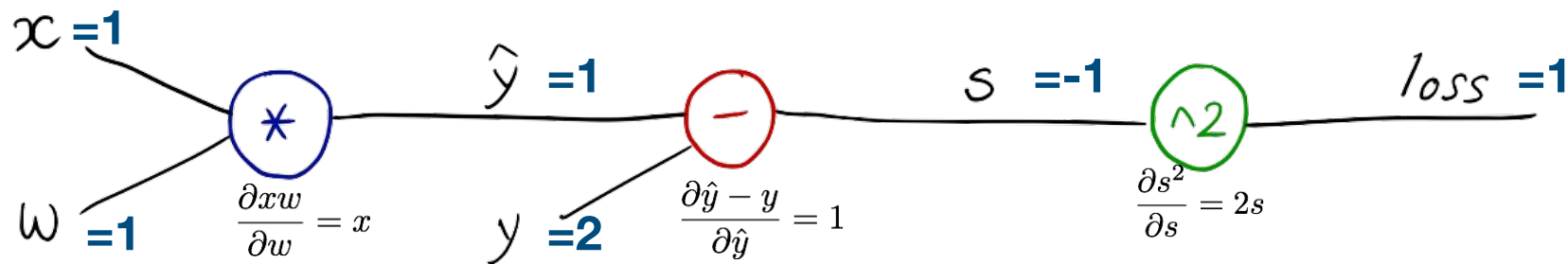


1 Forward pass $x=1, y=2$ where $w=1$



2

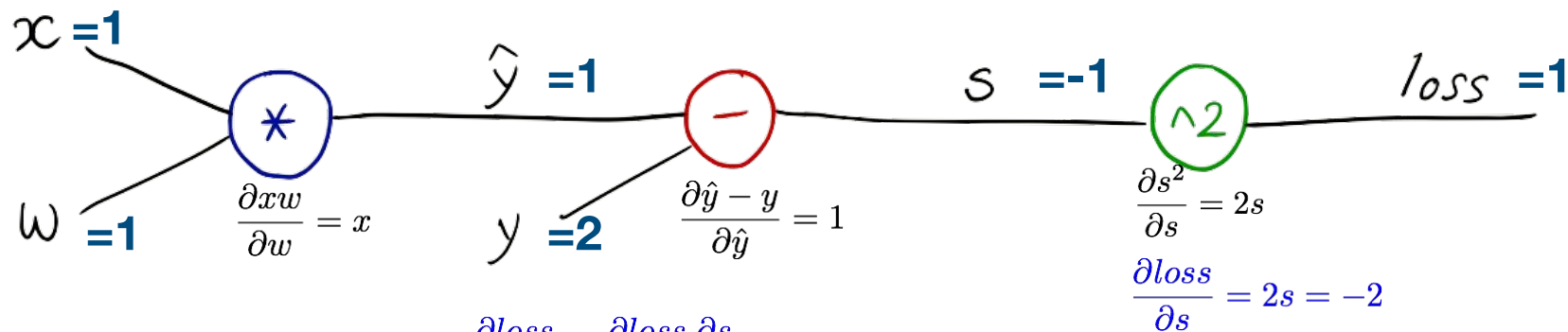
Backward propagation



$$\frac{\partial loss}{\partial w} =$$

2

Backward propagation

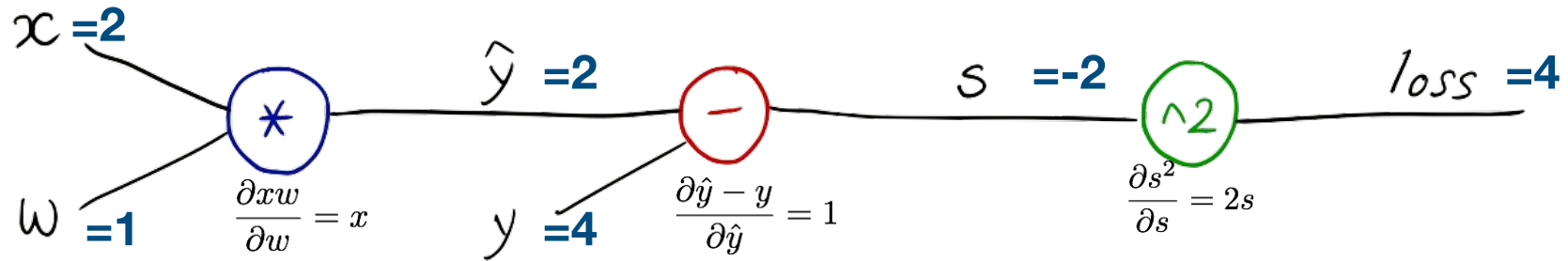


$$\frac{\partial loss}{\partial \hat{y}} = \frac{\partial loss}{\partial s} \frac{\partial s}{\partial \hat{y}} = -2 * 1 = -2$$

$$\frac{\partial loss}{\partial w} = \frac{\partial loss}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w} = -2 * x = -2 * 1 = -2$$

```
grad: 1.0 2.0 -2.0
grad: 2.0 4.0 -7.84
grad: 3.0 6.0 -16.2288
progress: 0 4.919240100095999
```

Exercise 4-1: $x = 2, y=4, w=1$

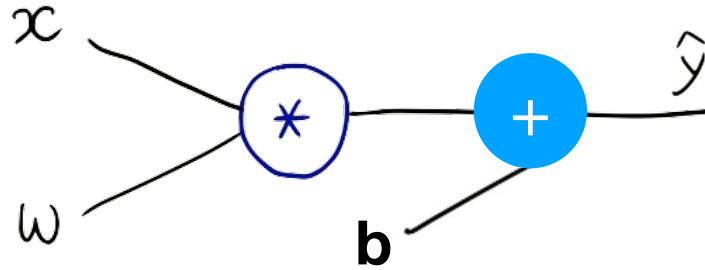


$$\frac{\partial loss}{\partial w} =$$

Exercise 4-2: $x = 1, y=2, w=1, b=2$

$$\hat{y} = x * w + b$$

$$loss = (\hat{y} - y)^2$$



Data and Variable



```
import torch
from torch.autograd import Variable
```

```
x_data = [1.0, 2.0, 3.0]
y_data = [2.0, 4.0, 6.0]
```

```
w = Variable(torch.Tensor([1.0]), requires_grad=True) # Any random value
```

Data and Variable



A graph is created on the fly

```
from torch.autograd import Variable

x = Variable(torch.randn(1, 10))
prev_h = Variable(torch.randn(1, 20))
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))
```

W_h

h

W_x

x

Model and Loss



```
import torch
from torch.autograd import Variable

x_data = [1.0, 2.0, 3.0]
y_data = [2.0, 4.0, 6.0]

w = Variable(torch.Tensor([1.0]), requires_grad=True) # Any random value

# our model forward pass
def forward(x):
    return x * w

# Loss function
def loss(x, y):
    y_pred = forward(x)
    return (y_pred - y) * (y_pred - y)

# Before training
print("predict (before training)", 4, forward(4).data[0])
```

Training: forward, backward, and update weight

Training Loop

```
for epoch in range(10):  
    for x_val, y_val in zip(x_data, y_data):  
        l = loss(x_val, y_val)  
        l.backward()  
        print("\tgrad: ", x_val, y_val, w.grad.data[0])  
        w.data = w.data - 0.01 * w.grad.data  
  
        # Manually zero the gradients after updating weights  
        w.grad.data.zero_()  
  
    print("progress:", epoch, l.data[0])
```

After training

```
print("predict (after training)", 4, forward(4).data[0])
```

Output

```
# Training Loop
for epoch in range(10):
    for x_val, y_val in zip(x_data, y_data):
        l = loss(x_val, y_val)
        l.backward()
        print("\tgrad: ", x_val, y_val, w.grad.data[0])
        w.data = w.data - 0.01 * w.grad.data

        # Manually zero the gradients after updating weights
        w.grad.data.zero_()

    print("progress:", epoch, l.data[0])

# After training
print("predict (after training)", 4, forward(4).data[0])
```

```
predict (before training) 4 4.0
grad: 1.0 2.0 -2.0
grad: 2.0 4.0 -7.840000152587891
grad: 3.0 6.0 -16.228801727294922
progress: 0 7.315943717956543
grad: 1.0 2.0 -1.478623867034912
grad: 2.0 4.0 -5.796205520629883
grad: 3.0 6.0 -11.998146057128906
progress: 1 3.9987640380859375
grad: 1.0 2.0 -1.0931644439697266
grad: 2.0 4.0 -4.285204887390137
grad: 3.0 6.0 -8.870372772216797
progress: 2 2.1856532096862793
grad: 1.0 2.0 -0.8081896305084229
grad: 2.0 4.0 -3.1681032180786133
grad: 3.0 6.0 -6.557973861694336
progress: 3 1.1946394443511963
grad: 1.0 2.0 -0.5975041389465332
grad: 2.0 4.0 -2.3422164916992188
grad: 3.0 6.0 -4.848389625549316
progress: 4 0.6529689431190491
grad: 1.0 2.0 -0.4417421817779541
grad: 2.0 4.0 -1.7316293716430664
grad: 3.0 6.0 -3.58447265625
progress: 5 0.35690122842788696
grad: 1.0 2.0 -0.3265852928161621
grad: 2.0 4.0 -1.2802143096923828
grad: 3.0 6.0 -2.650045394897461
progress: 6 0.195076122879982
grad: 1.0 2.0 -0.24144840240478516
grad: 2.0 4.0 -0.9464778900146484
grad: 3.0 6.0 -1.9592113494873047
progress: 7 0.10662525147199631
grad: 1.0 2.0 -0.17850565910339355
grad: 2.0 4.0 -0.699742317199707
grad: 3.0 6.0 -1.4484672546386719
```

```

predict (before training) 4 4.0
grad: 1.0 2.0 -2.0
grad: 2.0 4.0 -7.84
grad: 3.0 6.0 -16.2288
progress: 0 4.919240100095999
grad: 1.0 2.0 -1.478624
grad: 2.0 4.0 -5.796206079999999
grad: 3.0 6.0 -11.998146585599997
progress: 1 2.688769240265834
grad: 1.0 2.0 -1.093164466688
grad: 2.0 4.0 -4.285204709416961
grad: 3.0 6.0 -8.87037374849311
progress: 2 1.4696334962911515
grad: 1.0 2.0 -0.8081896081960389
grad: 2.0 4.0 -3.1681032641284723
grad: 3.0 6.0 -6.557973756745939
progress: 3 0.8032755585999681
grad: 1.0 2.0 -0.59750427561463
grad: 2.0 4.0 -2.3422167604093502
grad: 3.0 6.0 -4.848388694047353
progress: 4 0.43905614881022015
grad: 1.0 2.0 -0.44174208101320334
grad: 2.0 4.0 -1.7316289575717576
grad: 3.0 6.0 -3.584471942173538
progress: 5 0.2399802903801062
grad: 1.0 2.0 -0.3265852213980338
grad: 2.0 4.0 -1.2802140678802925
grad: 3.0 6.0 -2.650043120512205
progress: 6 0.1311689630744999
grad: 1.0 2.0 -0.241448373202223
grad: 2.0 4.0 -0.946477622952715
grad: 3.0 6.0 -1.9592086795121197
progress: 7 0.07169462478267678
grad: 1.0 2.0 -0.17850567968888198
grad: 2.0 4.0 -0.6997422643804168
grad: 3.0 6.0 -1.4484664872674653
progress: 8 0.03918700813247573
grad: 1.0 2.0 -0.13197139106214673
grad: 2.0 4.0 -0.5173278529636143
grad: 3.0 6.0 -1.0708686556346834
progress: 9 0.021418922423117836
predict (after training) 4 7.804863933862125

```

Output

(from numeric gradient computation)



```

# Before training
print("predict (before training)", 4, forward(4))

# Training loop
for epoch in range(10):
    for x, y in zip(x_data, y_data):
        grad = gradient(x, y)
        w = w - 0.01 * grad
        print("\tgrad: ", x, y, grad)
        l = loss(x, y)

    print("progress:", epoch, l)

# After training
print("predict (after training)", 4, forward(4))

```

Output

(from numeric gradient computation)

```
predict (before training) 4 4.0
grad: 1.0 2.0 -2.0
grad: 2.0 4.0 -7.84
grad: 3.0 6.0 -16.2288
progress: 0 4.919240100095999
grad: 1.0 2.0 -1.478624
grad: 2.0 4.0 -5.796206079999999
grad: 3.0 6.0 -11.998146585599997
progress: 1 2.688769240265834
grad: 1.0 2.0 -1.093164466688
grad: 2.0 4.0 -4.285204709416961
grad: 3.0 6.0 -8.87037374849311
progress: 2 1.4696334962911515
grad: 1.0 2.0 -0.8081896081960389
grad: 2.0 4.0 -3.1681032641284723
grad: 3.0 6.0 -6.557973756745939
progress: 3 0.8032755585999681
grad: 1.0 2.0 -0.59750427561463
grad: 2.0 4.0 -2.3422167604093502
grad: 3.0 6.0 -4.848388694047353
progress: 4 0.43905614881022015
grad: 1.0 2.0 -0.44174208101320334
grad: 2.0 4.0 -1.7316289575717576
grad: 3.0 6.0 -3.584471942173538
progress: 5 0.2399802903801062
grad: 1.0 2.0 -0.3265852213980338
grad: 2.0 4.0 -1.2802140678802925
grad: 3.0 6.0 -2.650043120512205
progress: 6 0.1311689630744999
grad: 1.0 2.0 -0.241448373202223
grad: 2.0 4.0 -0.946477622952715
grad: 3.0 6.0 -1.9592086795121197
progress: 7 0.07169462478267678
grad: 1.0 2.0 -0.17850567968888198
grad: 2.0 4.0 -0.6997422643804168
```

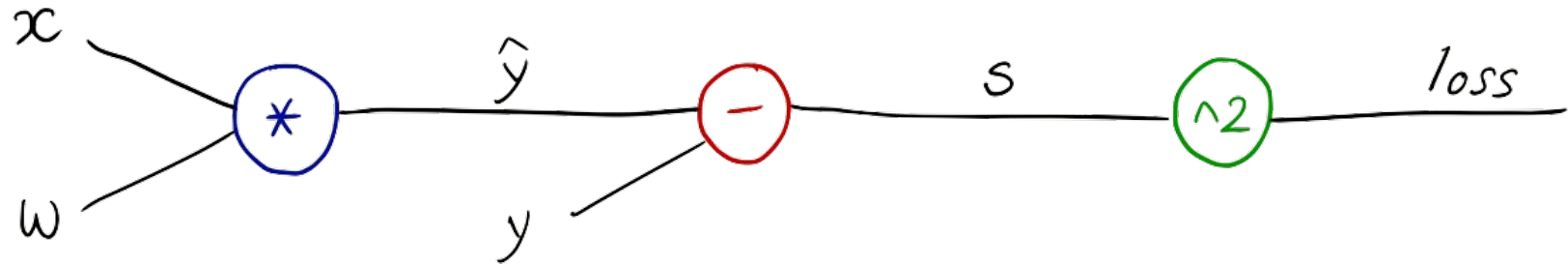
Output

(computational graph)

```
predict (before training) 4 4.0
grad: 1.0 2.0 -2.0
grad: 2.0 4.0 -7.84
grad: 3.0 6.0 -16.2288
progress: 0 4.919240100095999
grad: 1.0 2.0 -1.478624
grad: 2.0 4.0 -5.796206079999999
grad: 3.0 6.0 -11.998146585599997
progress: 1 2.688769240265834
grad: 1.0 2.0 -1.093164466688
grad: 2.0 4.0 -4.285204709416961
grad: 3.0 6.0 -8.87037374849311
progress: 2 1.4696334962911515
grad: 1.0 2.0 -0.8081896081960389
grad: 2.0 4.0 -3.1681032641284723
grad: 3.0 6.0 -6.557973756745939
progress: 3 0.8032755585999681
grad: 1.0 2.0 -0.59750427561463
grad: 2.0 4.0 -2.3422167604093502
grad: 3.0 6.0 -4.848388694047353
progress: 4 0.43905614881022015
grad: 1.0 2.0 -0.44174208101320334
grad: 2.0 4.0 -1.7316289575717576
grad: 3.0 6.0 -3.584471942173538
progress: 5 0.2399802903801062
grad: 1.0 2.0 -0.3265852213980338
grad: 2.0 4.0 -1.2802140678802925
grad: 3.0 6.0 -2.650043120512205
progress: 6 0.1311689630744999
grad: 1.0 2.0 -0.241448373202223
grad: 2.0 4.0 -0.946477622952715
grad: 3.0 6.0 -1.9592086795121197
progress: 7 0.07169462478267678
grad: 1.0 2.0 -0.17850567968888198
grad: 2.0 4.0 -0.6997422643804168
```



PyTorch forward/backward

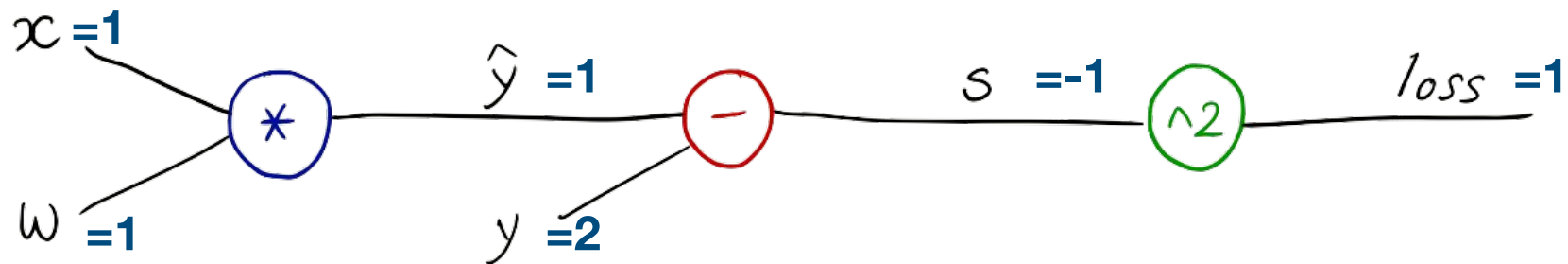


Forward pass

Any random value

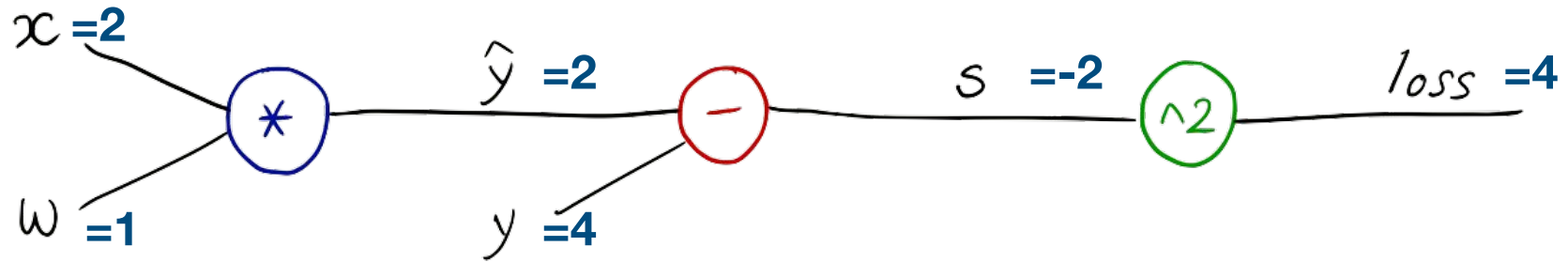
```
w = Variable(torch.Tensor([1.0]), requires_grad=True)
```

```
l = loss(x=1, y=1)
```



$$\frac{\partial loss}{\partial w} =$$

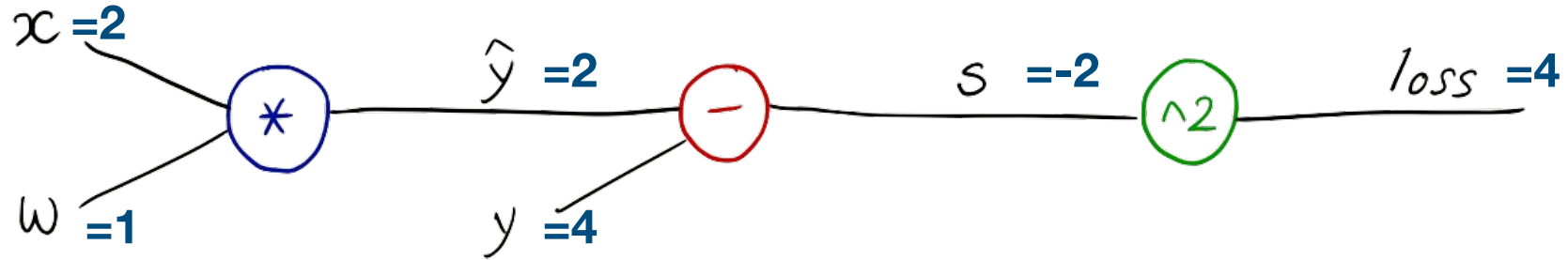
Back propagation: l.backward()



$$\frac{\partial loss}{\partial w} = w.grad$$

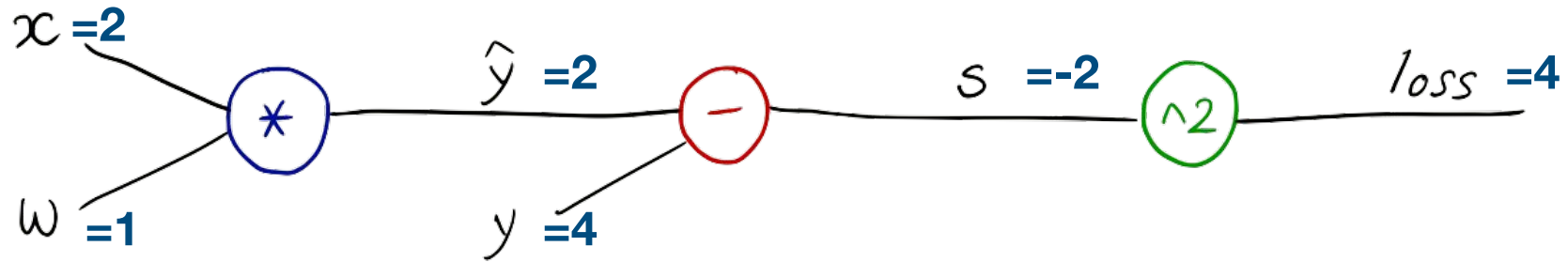
Weight update (step)

$$w.data = w.data - 0.01 * w.grad.data$$



$$\frac{\partial loss}{\partial w} = w.grad$$

Exercise 4-3: implement computational graph and backprop using NumPy



$$\frac{\partial loss}{\partial w} =$$

Exercise 4-4: Compute gradients using computational graph (manually)

$$\hat{y} = x^2 w_2 + x w_1 + b$$

$$loss = (\hat{y} - y)^2$$

$$\frac{\partial loss}{\partial w_1} = ?$$

$$\frac{\partial loss}{\partial w_2} = ?$$

Exercise 4-5: compute gradients using PyTorch

$$\hat{y} = x^2 w_2 + x w_1 + b$$
$$loss = (\hat{y} - y)^2$$

$$\frac{\partial loss}{\partial w_1} = ?$$

$$\frac{\partial loss}{\partial w_2} = ?$$



Lecture 5: Linear regression in the PyTorch way