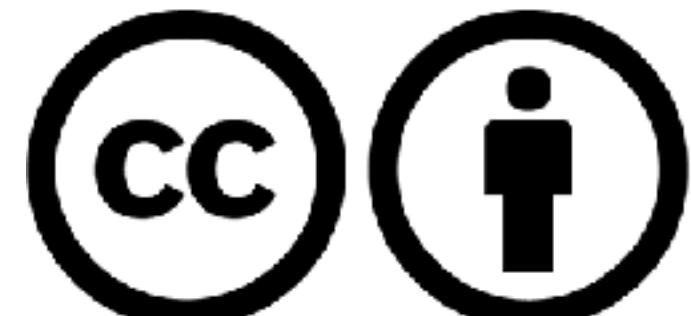


# ML/DL for Everyone with PYTORCH

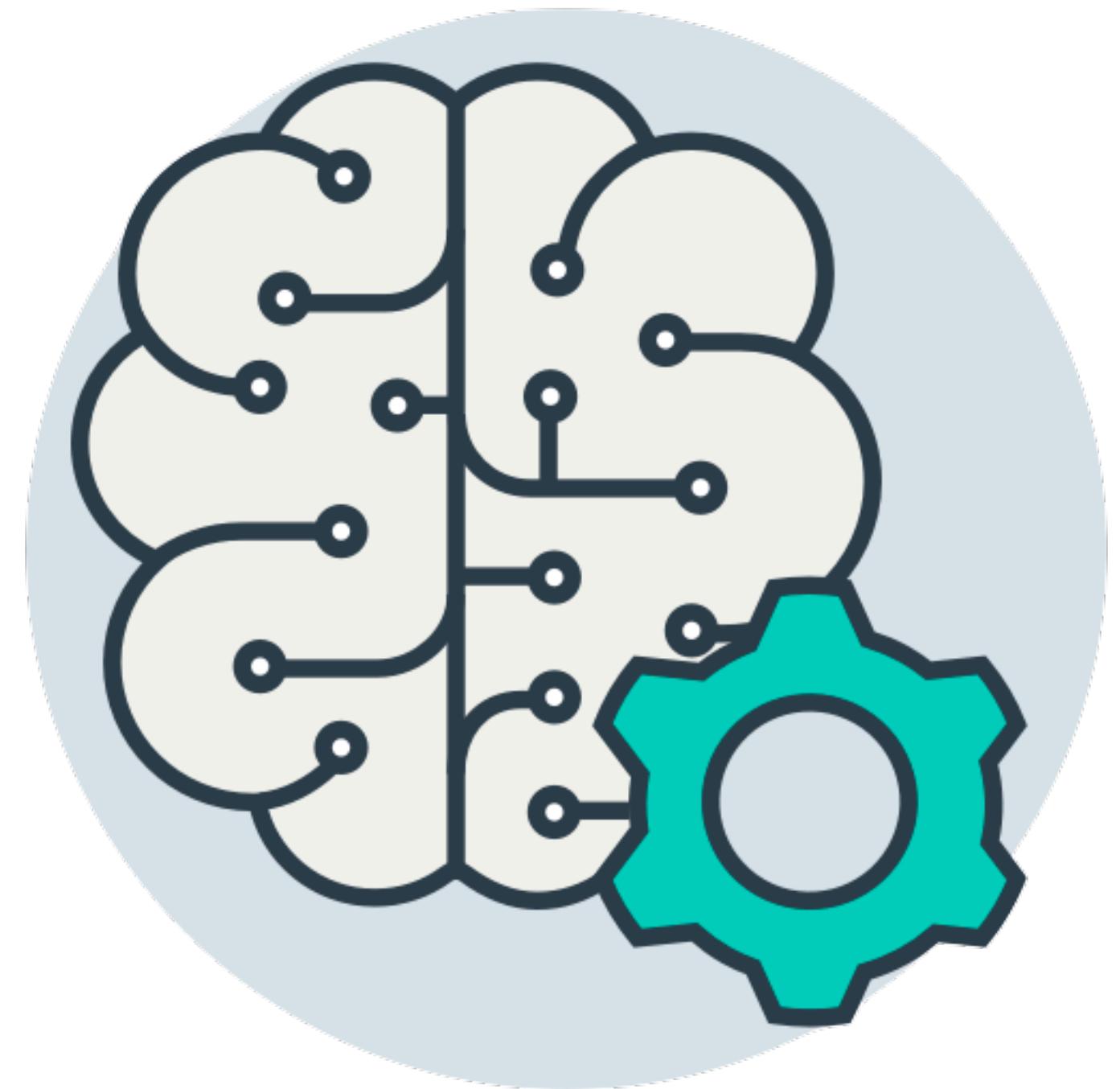


Call for Comments

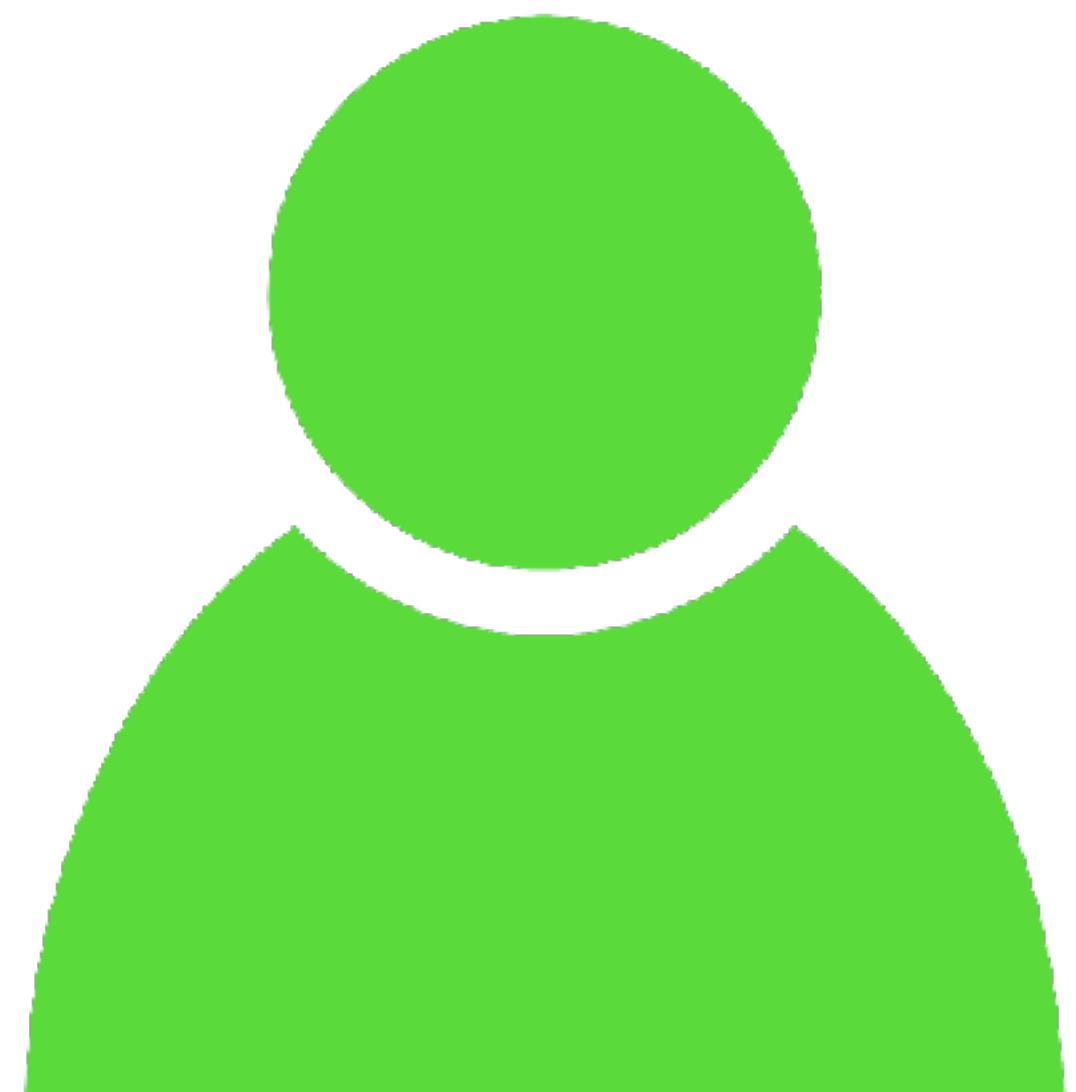
Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# What is ML?

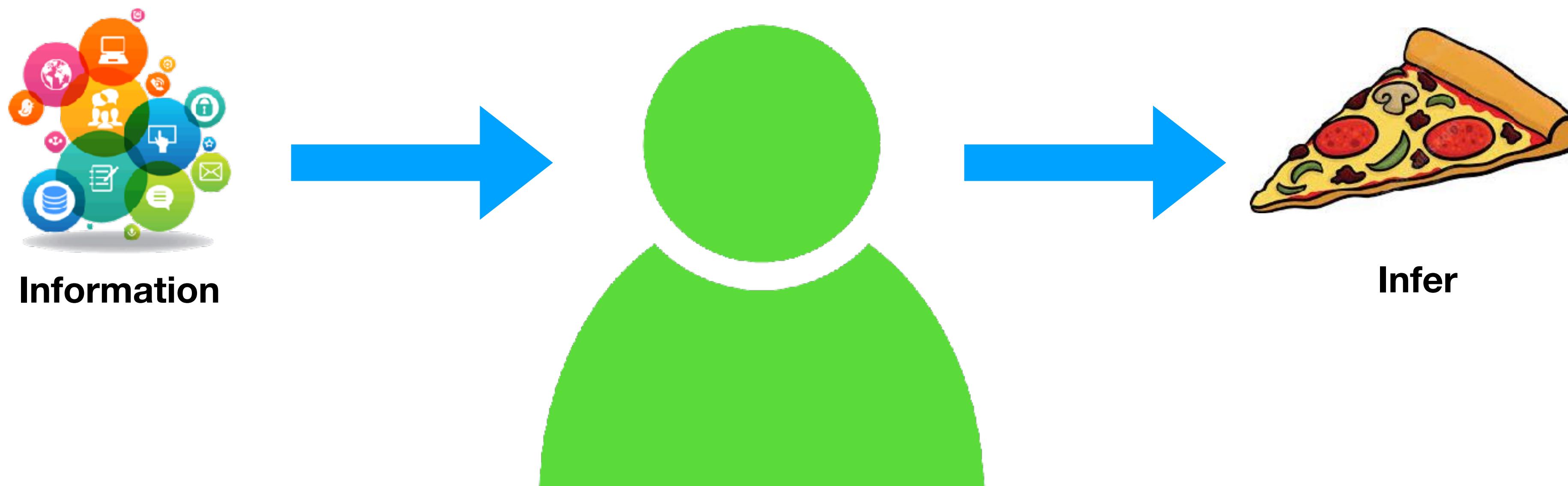


# What is Human Intelligence?



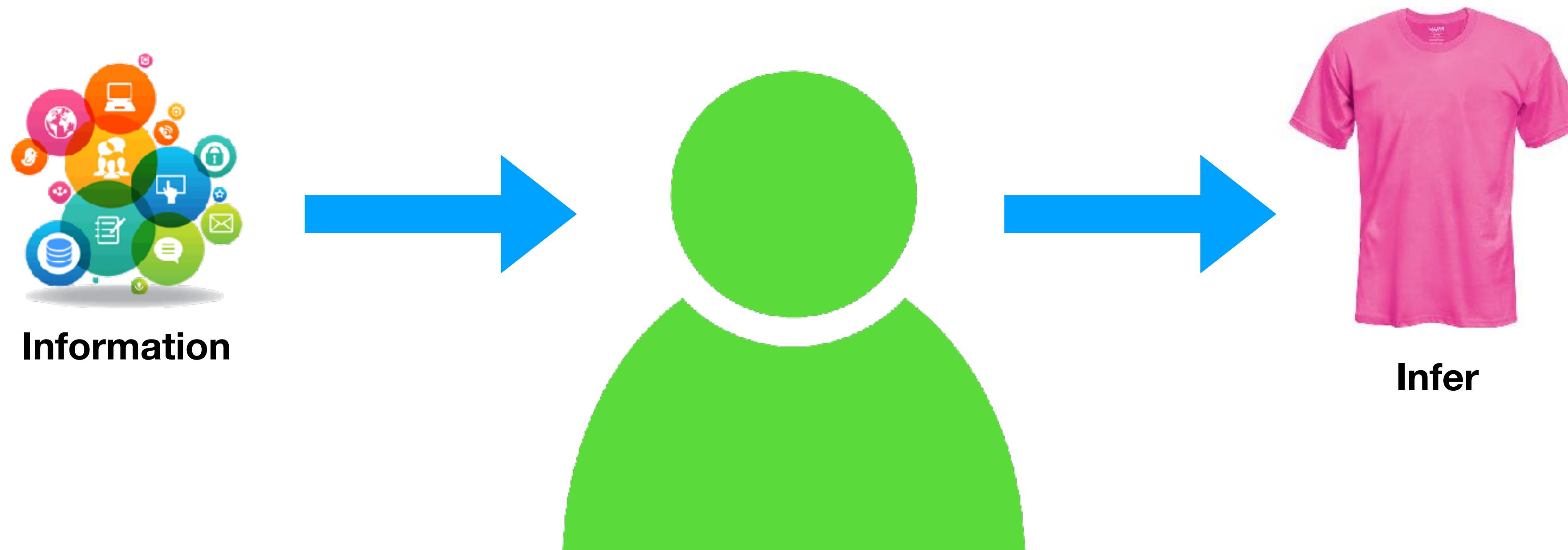
# What is Human Intelligence?

## *What to eat for lunch?*



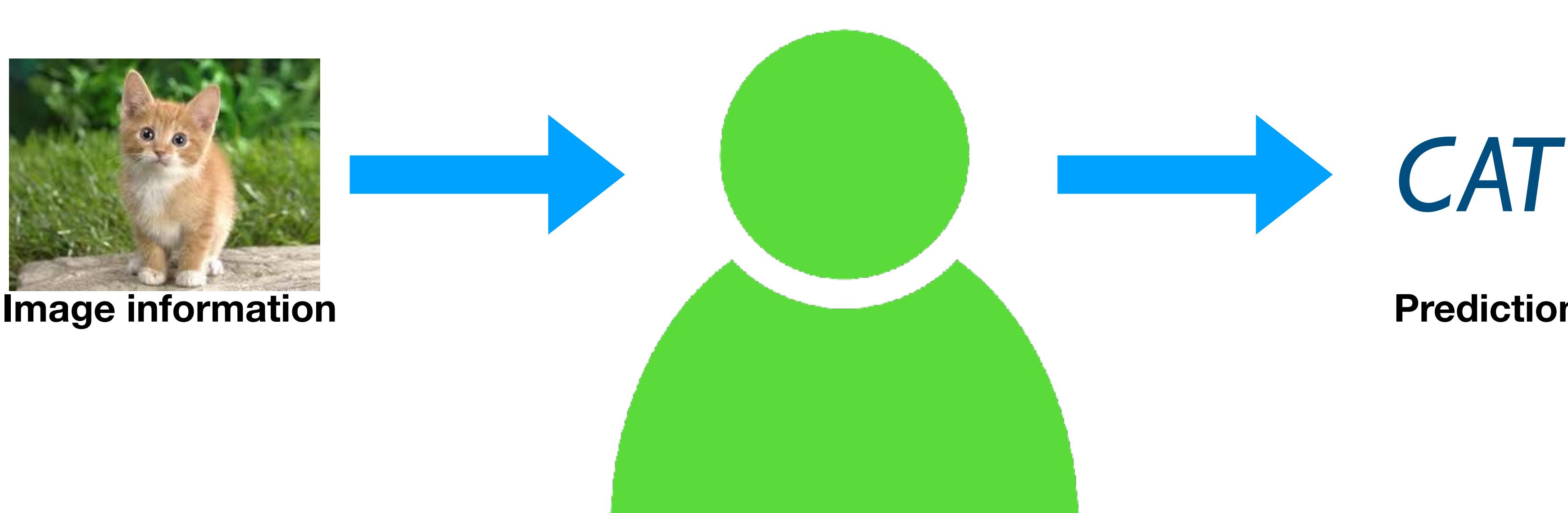
# What is Human Intelligence?

## *What to dress?*



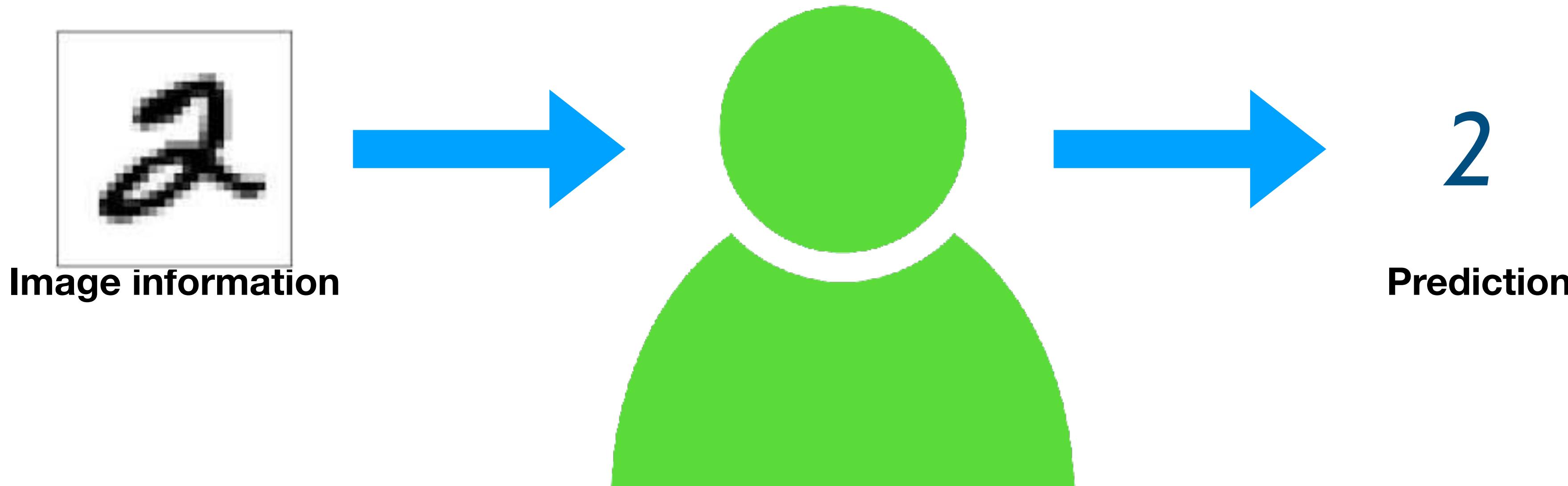
# What is Human Intelligence?

*What is this picture?*



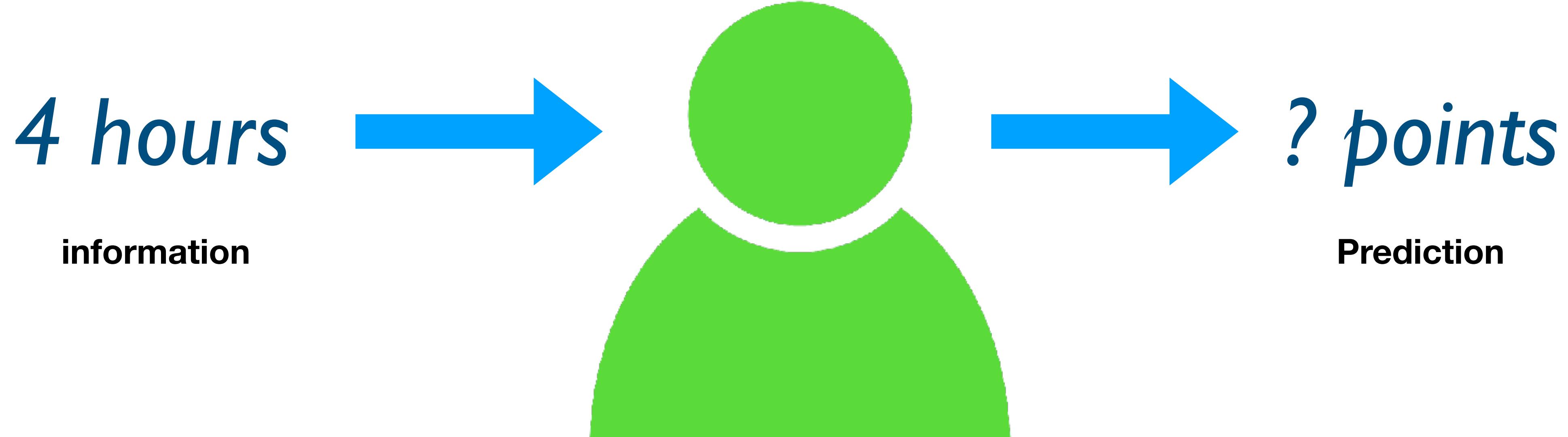
# What is Human Intelligence?

## *What is this number?*



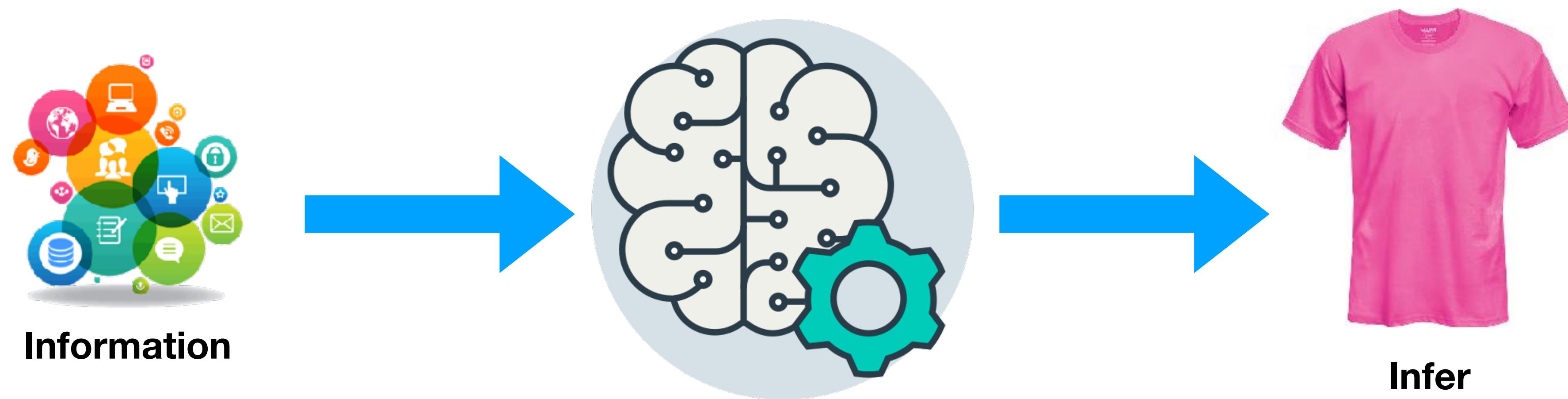
# What is Human Intelligence?

*What would be the grade if I study 4 hours?*



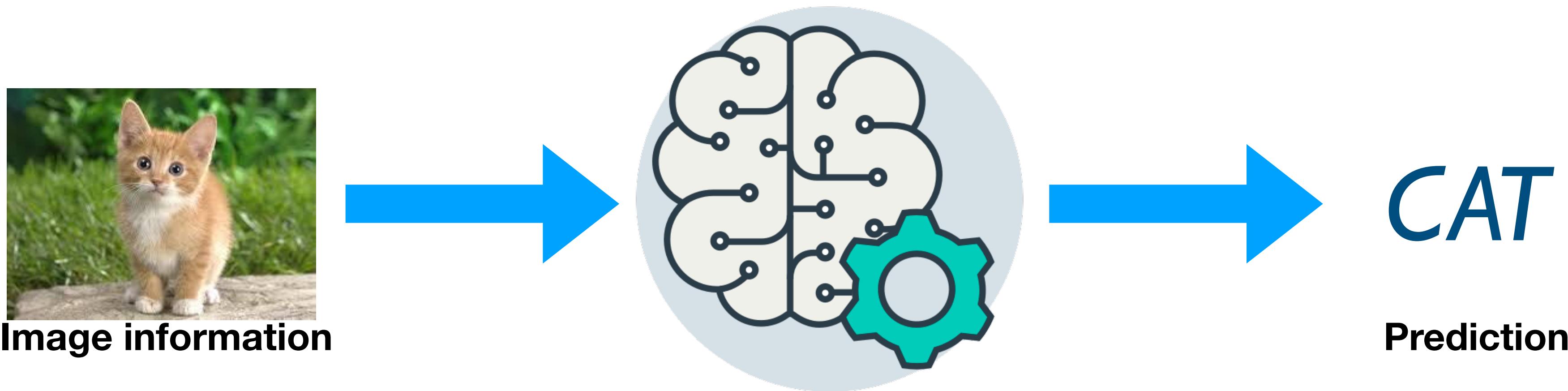
# Machine Learning

## *What to dress?*



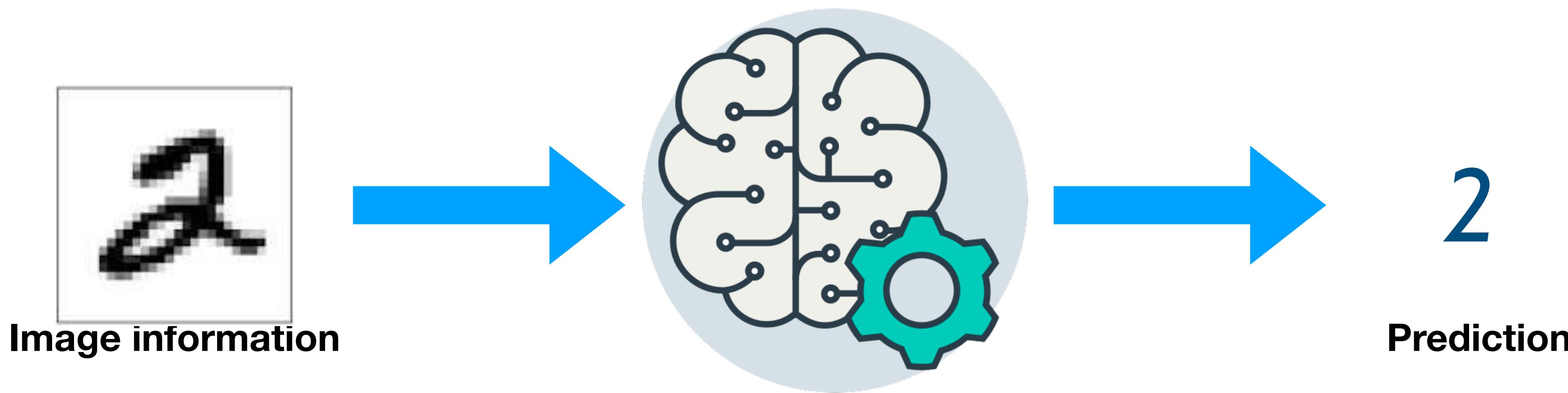
# Machine Learning

*What is this picture?*



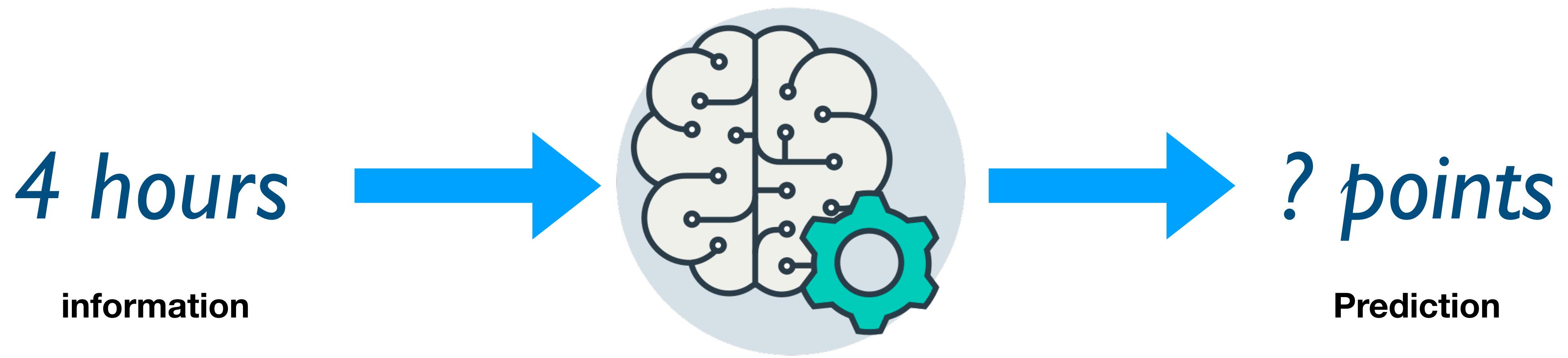
# Machine Learning

## *What is this number?*



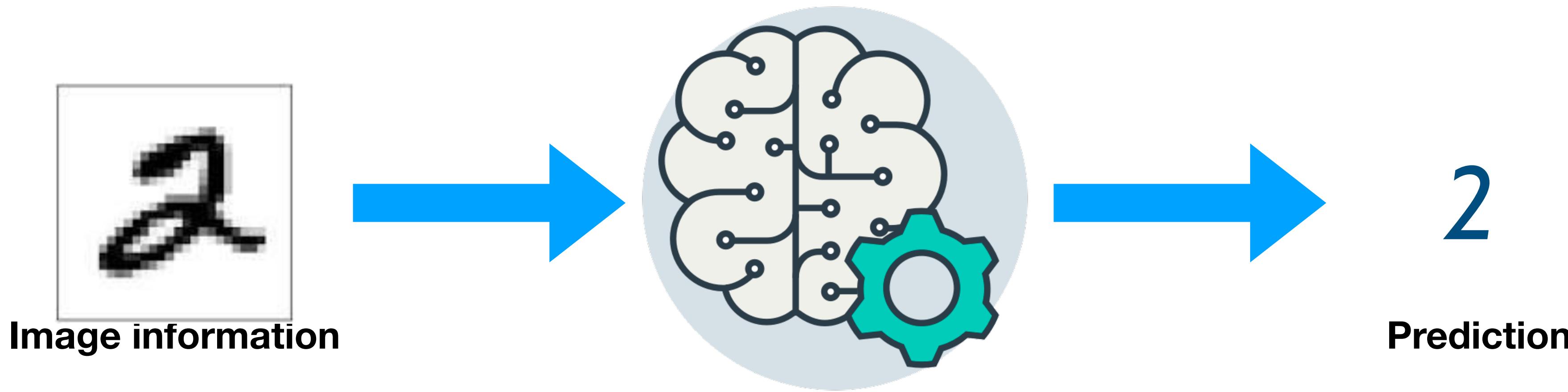
# Machine Learning

*What would be the grade if I study 4 hours?*



# Machine Learning

*Machine need lots of training*



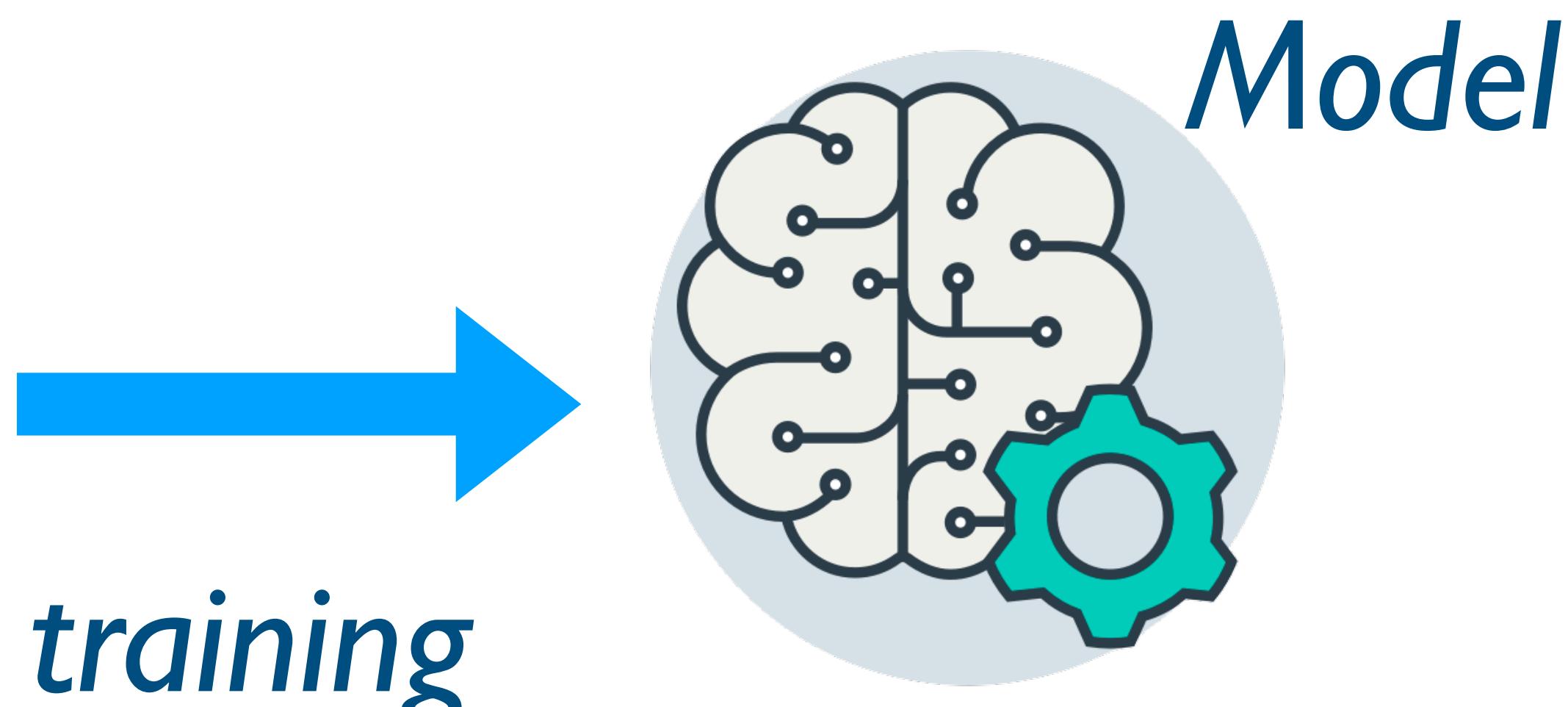
# Machine Learning

*Machine need lots of training*

label = 5	5	label = 0	0	label = 4	4	label = 1	1	label = 9	9
label = 2	2	label = 1	1	label = 3	3	label = 1	1	label = 4	4
label = 3	3	label = 5	5	label = 3	3	label = 6	6	label = 1	1
label = 7	7	label = 2	2	label = 8	8	label = 6	6	label = 9	9

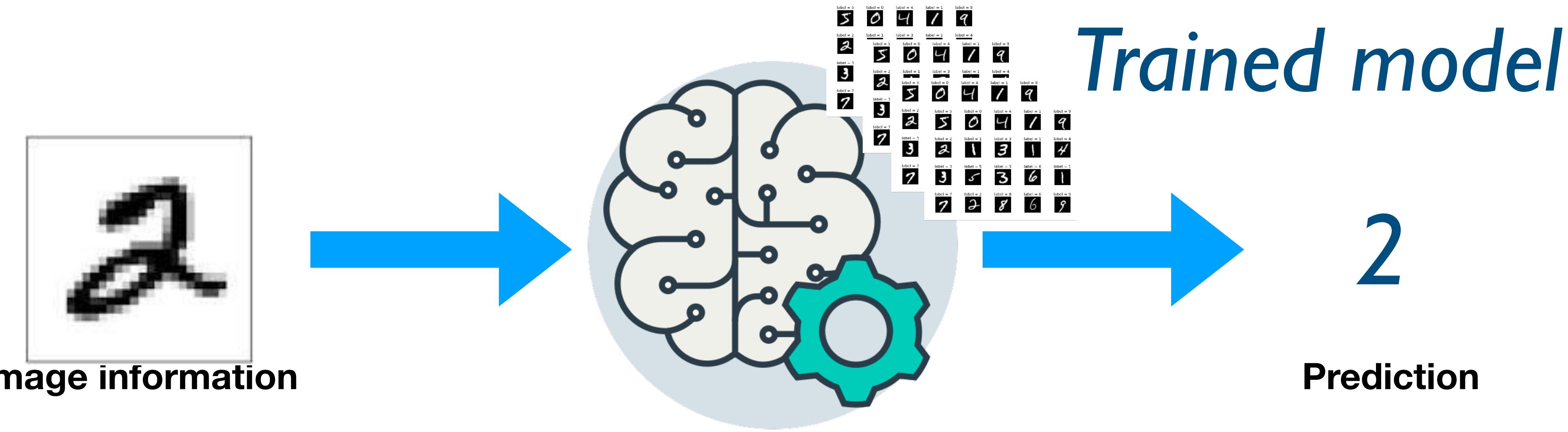
---

*Labeled dataset*



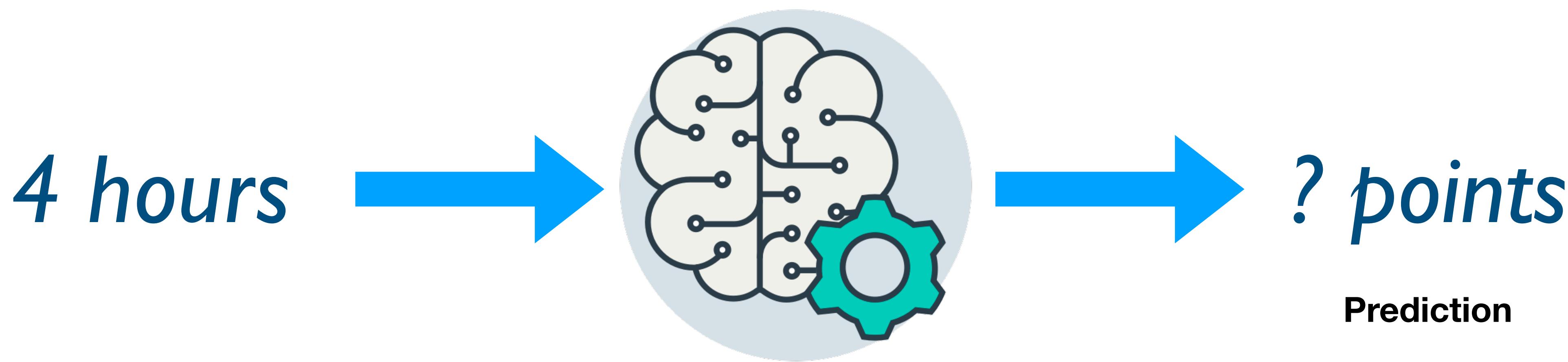
# Machine Learning

*Predict (test) with trained model*



# Machine Learning

*What would be the grade if I study 4 hours?*



Hours (x)	Points (y)
1	2
2	4
3	6
4	?

**Training dataset**

**Test dataset**

# Install PYTORCH



## Get Started.

Select your preferences, then run the PyTorch install command.

Please ensure that you are on the latest pip and numpy packages.  
Anaconda is our recommended package manager

OS	Linux	OSX
Package Manager	conda	pip
Python	2.7	3.5
CUDA	7.5	8.0

### Run this command:

```
pip3 install http://download.pytorch.org/whl/torch-0.2.0.post3-cp36-cp36m-macosx_10_7_x86_64.whl  
pip3 install torchvision  
# OSX Binaries dont support CUDA, install from source if CUDA is needed
```

**WHAT**  
**NEXT!**



## Lecture 2: Linear Model

# ML/DL for Everyone with PYTORCH

## Lecture 2: Linear Model



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# Machine Learning

*What would be the grade if I study 4 hours?*



Hours (x)	Points (y)
1	2
2	4
3	6
4	?

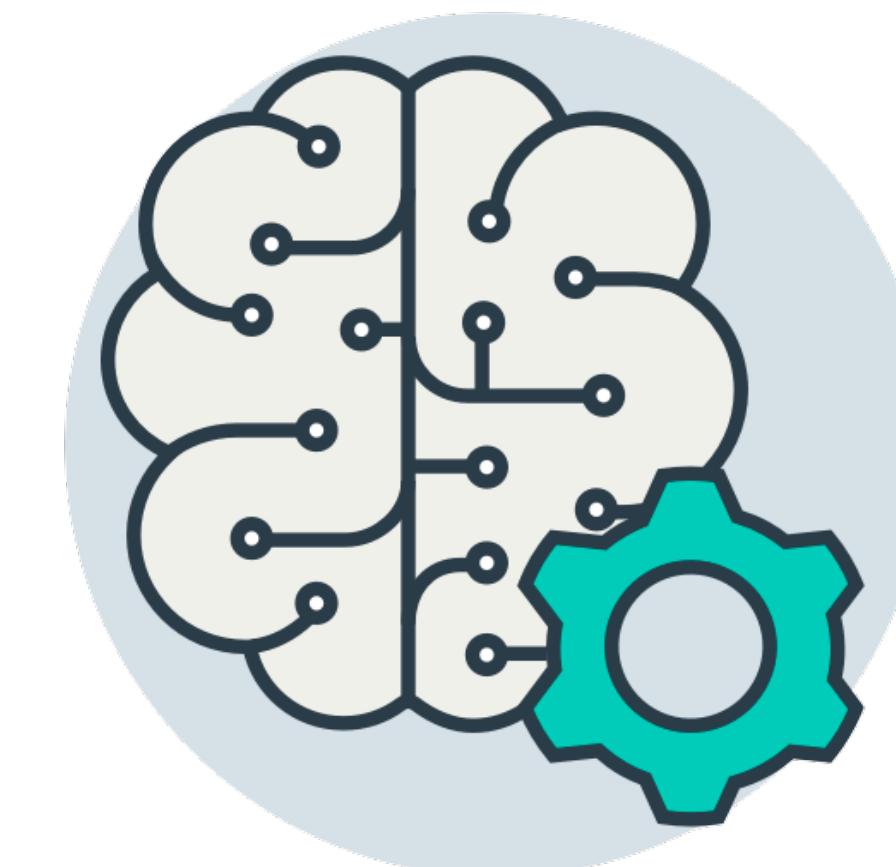
**Training dataset**

**Test dataset**

# Model design

*What would be the best model for the data? Linear?*

Hours (x)	Points (y)
1	2
2	4
3	6
4	?



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

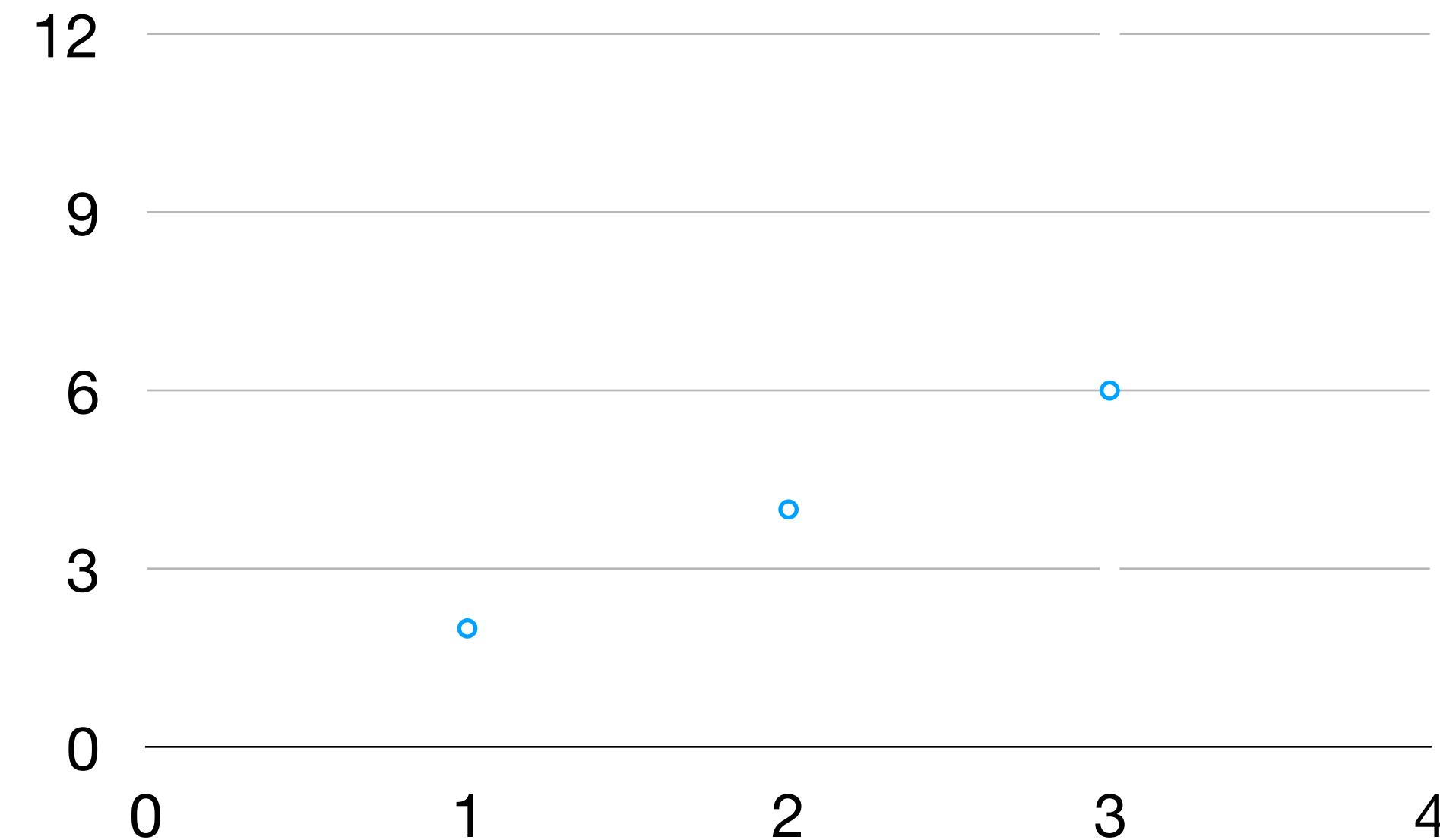
$x \longrightarrow$  Linear  $\longrightarrow \hat{y}$

A diagram showing a linear model architecture. An input variable  $x$  enters a blue rectangular block labeled "Linear". The output of this block is  $\hat{y}$ . Above the diagram, the equation  $\hat{y} = x * w + b$  is written in blue.

# Linear Regression

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

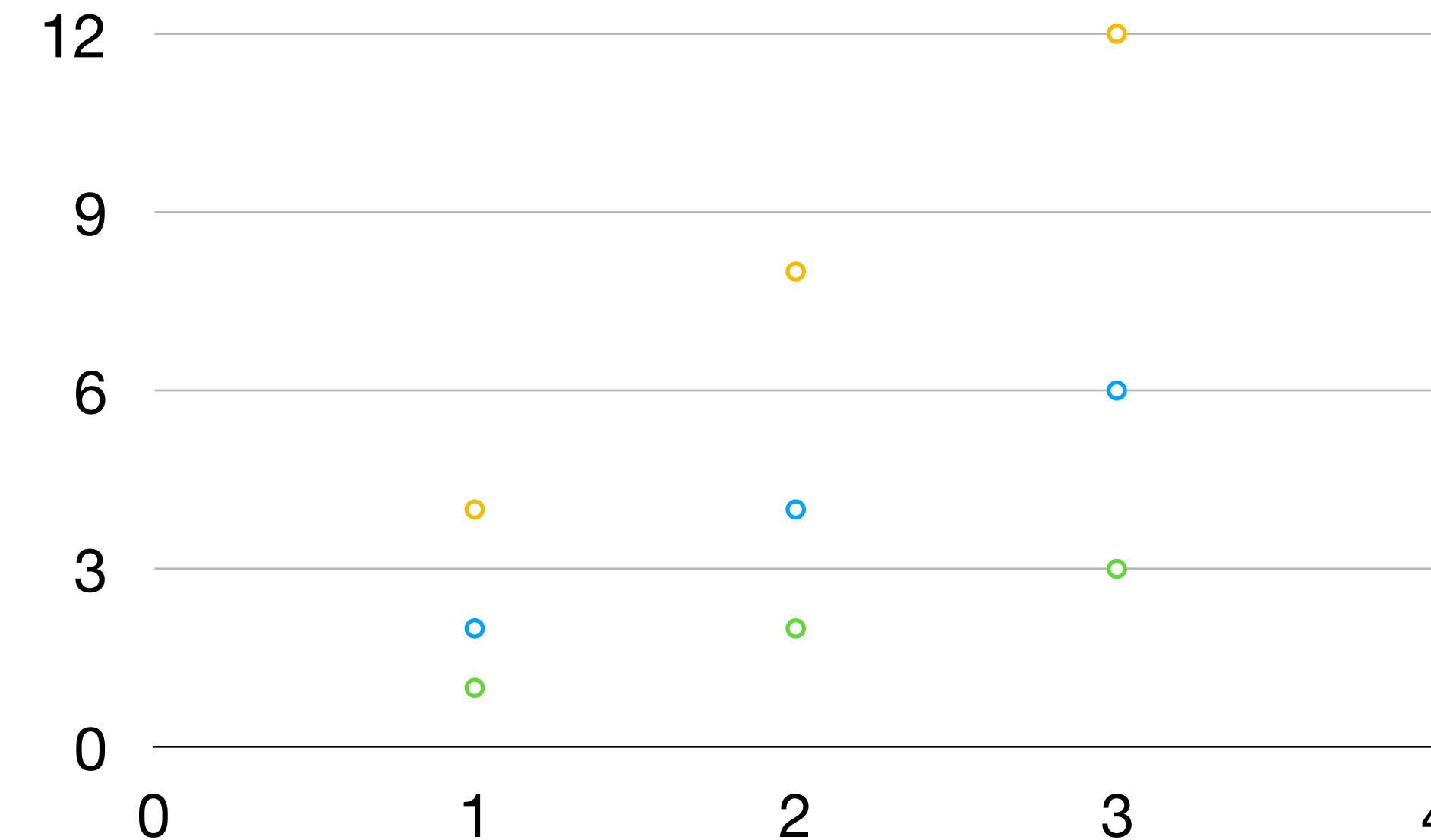
Hours (x)	Points (y)
1	2
2	4
3	6



# Linear Regression error?

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

Hours (x)	Points (y)
1	2
2	4
3	6



# Training Loss (error)

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

Hours, x	Points, y	Prediction, $y^{\wedge}(w=3)$	Loss (w=3)
1	2	3	1
2	4	6	4
3	6	9	9
			mean=14/3

# Training Loss (error)

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

Hours, x	Points, y	Prediction, $y^w(w=4)$	Loss ( $w=4$ )
1	2	4	4
2	4	8	16
3	6	12	36
			mean=56/3

# Training Loss (error)

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

Hours, x	Points, y	Prediction, $y^{\wedge}(w=0)$	Loss (w=0)
1	2	0	4
2	4	0	16
3	6	0	36
			mean=56/3

# Training Loss (error)

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

Hours, x	Points, y	Prediction, $y^{\wedge}(w=1)$	Loss (w=1)
1	2	1	1
2	4	2	4
3	6	3	9
			mean=14/3

# Training Loss (error)

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

Hours, x	Points, y	Prediction, $y^{\wedge}(w=2)$	Loss (w=2)
1	2	0	0
2	4	0	0
3	6	0	0
			mean=0

# Training Loss (error)

$$loss = (\hat{y} - y)^2 = (x * w - y)^2 \quad loss = \frac{1}{N} \sum_{n=1}^N (\hat{y}_n - y_n)^2$$

**MSE, mean square error**

Hours, x	Loss (w=0)	Loss (w=1)	Loss (w=2)	Loss (w=3)	Loss (w=4)
1	4	1	0	1	4
2	16	4	0	4	16
3	36	9	0	9	36
	MSE=56/3=18.7	MSE=14/3=4.7	MSE=0	MSE=14/3=4.7	MSE=56/3=18.7

# Loss graph

$$loss = \frac{1}{N} \sum_{n=1}^N (\hat{y}_n - y_n)^2$$

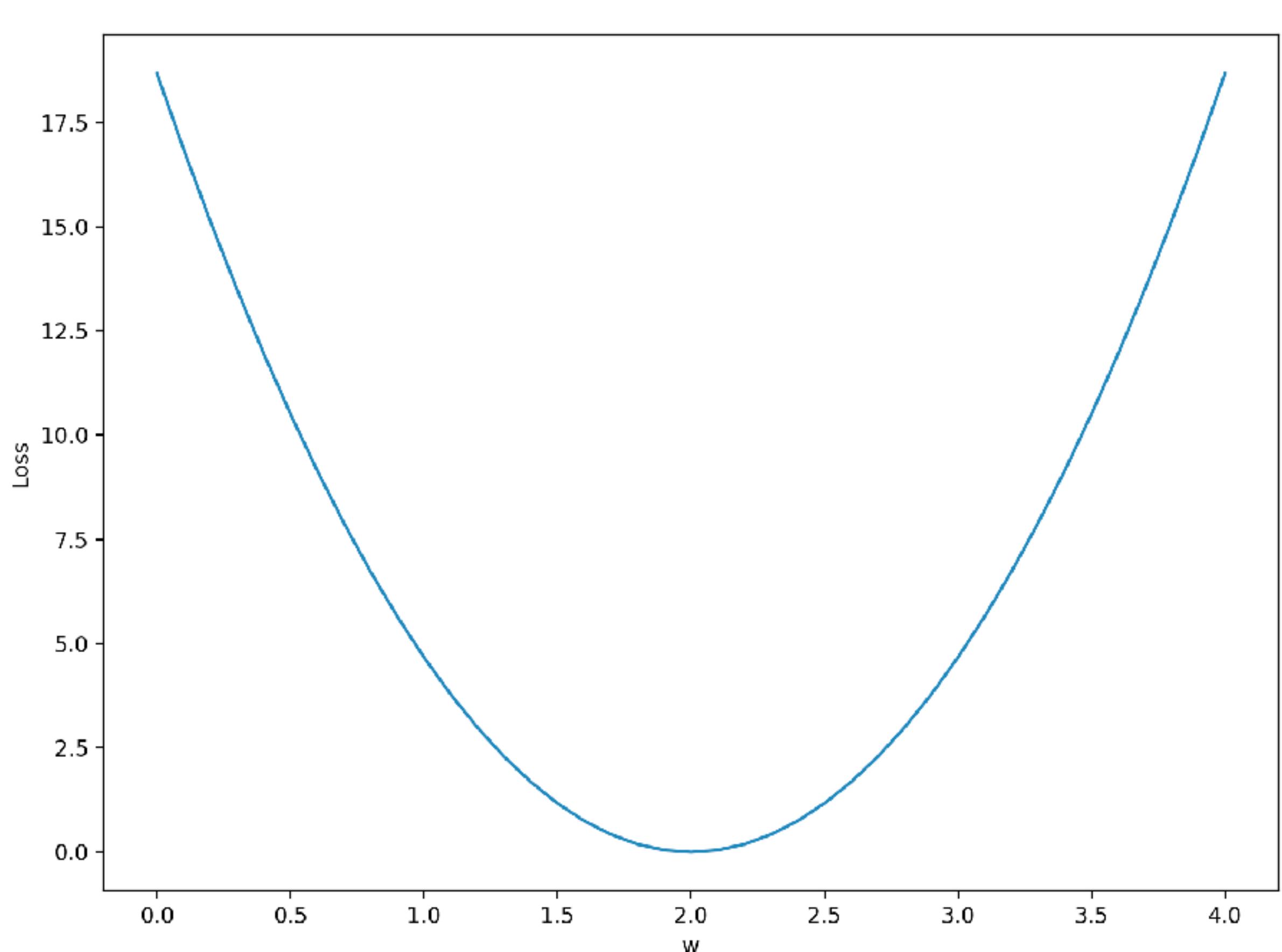
Loss (w=0)	Loss (w=1)	Loss (w=2)	Loss (w=3)	Loss (w=4)
mean=56/3=18.7	mean=14/3=4.7	mean=0	mean=14/3=4.7	mean=56/3=18.7



# Loss graph

$$loss = \frac{1}{N} \sum_{n=1}^N (\hat{y}_n - y_n)^2$$

Loss (w=0)	Loss (w=1)	Loss (w=2)	Loss (w=3)	Loss (w=4)
mean=56/3=18.7	mean=14/3=4.7	mean=0	mean=14/3=4.7	mean=56/3=18.7



# Model & Loss



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

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

```
# 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)
```



# Compute loss for w

```
for w in np.arange(0.0, 4.1, 0.1):
    print("w=", w)
    l_sum = 0
    for x_val, y_val in zip(x_data, y_data):
        y_pred = forward(x_val)
        l = loss(x_val, y_val)
        l_sum += l
        print("\t", x_val, y_val, y_pred, l)
    print("NSE=", l_sum/3)
```

```
w= 0.0
    1.0 2.0 0.0 4.0
    2.0 4.0 0.0 16.0
    3.0 6.0 0.0 36.0
NSE= 18.6666666667
w= 0.1
    1.0 2.0 0.1 3.61
    2.0 4.0 0.2 14.44
    3.0 6.0 0.3 32.49
NSE= 16.8466666667
w= 0.2
    1.0 2.0 0.2 3.24
    2.0 4.0 0.4 12.96
    3.0 6.0 0.6 29.16
NSE= 15.12
w= 0.3
    1.0 2.0 0.3 2.89
    2.0 4.0 0.6 11.56
    3.0 6.0 0.9 26.01
NSE= 13.4866666667
w= 0.4
    1.0 2.0 0.4 2.56
    2.0 4.0 0.8 10.24
    3.0 6.0 1.2 23.04
NSE= 11.9466666667
w= 0.5
    1.0 2.0 0.5 2.25
    2.0 4.0 1.0 9.0
    3.0 6.0 1.5 20.25
NSE= 10.5
```

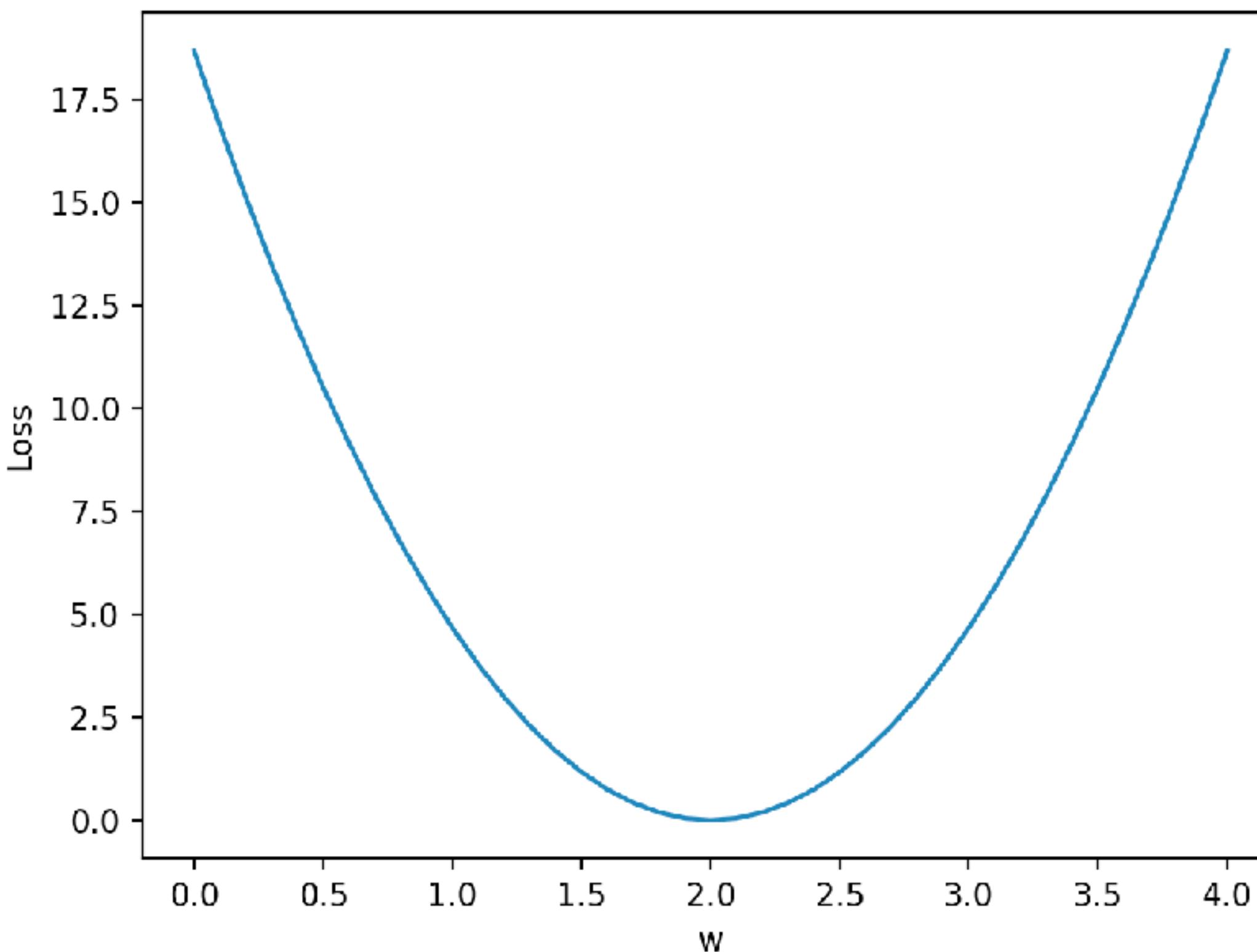


# Plot graph

```
w_list = []
mse_list = []

for w in np.arange(0.0, 4.1, 0.1):
    print("w=", w)
    l_sum = 0
    for x_val, y_val in zip(x_data, y_data):
        y_pred = forward(x_val)
        l = loss(x_val, y_val)
        l_sum += l
        print("\t", x_val, y_val, y_pred, l)
    print("NSE=", l_sum/3)
    w_list.append(w)
    mse_list.append(l_sum/3)

plt.plot(w_list, mse_list)
plt.ylabel('Loss')
plt.xlabel('w')
plt.show()
```



```

import numpy as np
import matplotlib.pyplot as plt

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

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

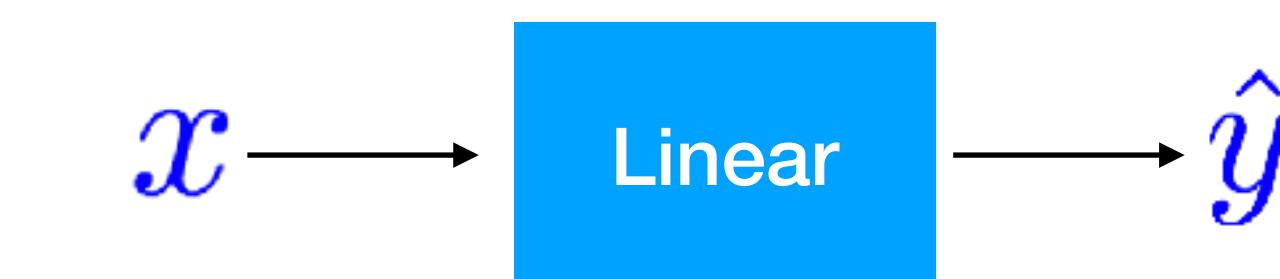
# Loss function
def loss(x, y):
    y_pred = forward(x)
    return (y_pred-y)*(y_pred-y)

w_list = []
mse_list = []

for w in np.arange(0.0, 4.1, 0.1):
    print("w=", w)
    l_sum = 0
    for x_val, y_val in zip(x_data, y_data):
        y_pred = forward(x_val)
        l = loss(x_val, y_val)
        l_sum += l
        print("\t", x_val, y_val, y_pred, l)
    print("NSE=", l_sum/3)
    w_list.append(w)
    mse_list.append(l_sum/3)

plt.plot(w_list, mse_list)
plt.ylabel('Loss')
plt.xlabel('w')
plt.show()

```





**WHAT**  
**NEXT!**

A woman with dark hair tied back in a ponytail, wearing a dark blue blazer over a light blue shirt, is shown in profile facing right. She has her right hand raised to her ear, fingers forming a funnel shape to listen more closely. In the upper right corner of the image, there is a graphic element consisting of the words "WHAT" in orange and "NEXT!" in blue, followed by a gray outline of a lit lightbulb.

## Lecture 3: Gradient Descent

# ML/DL for Everyone with PYTORCH

## Lecture 3: Gradient Descent



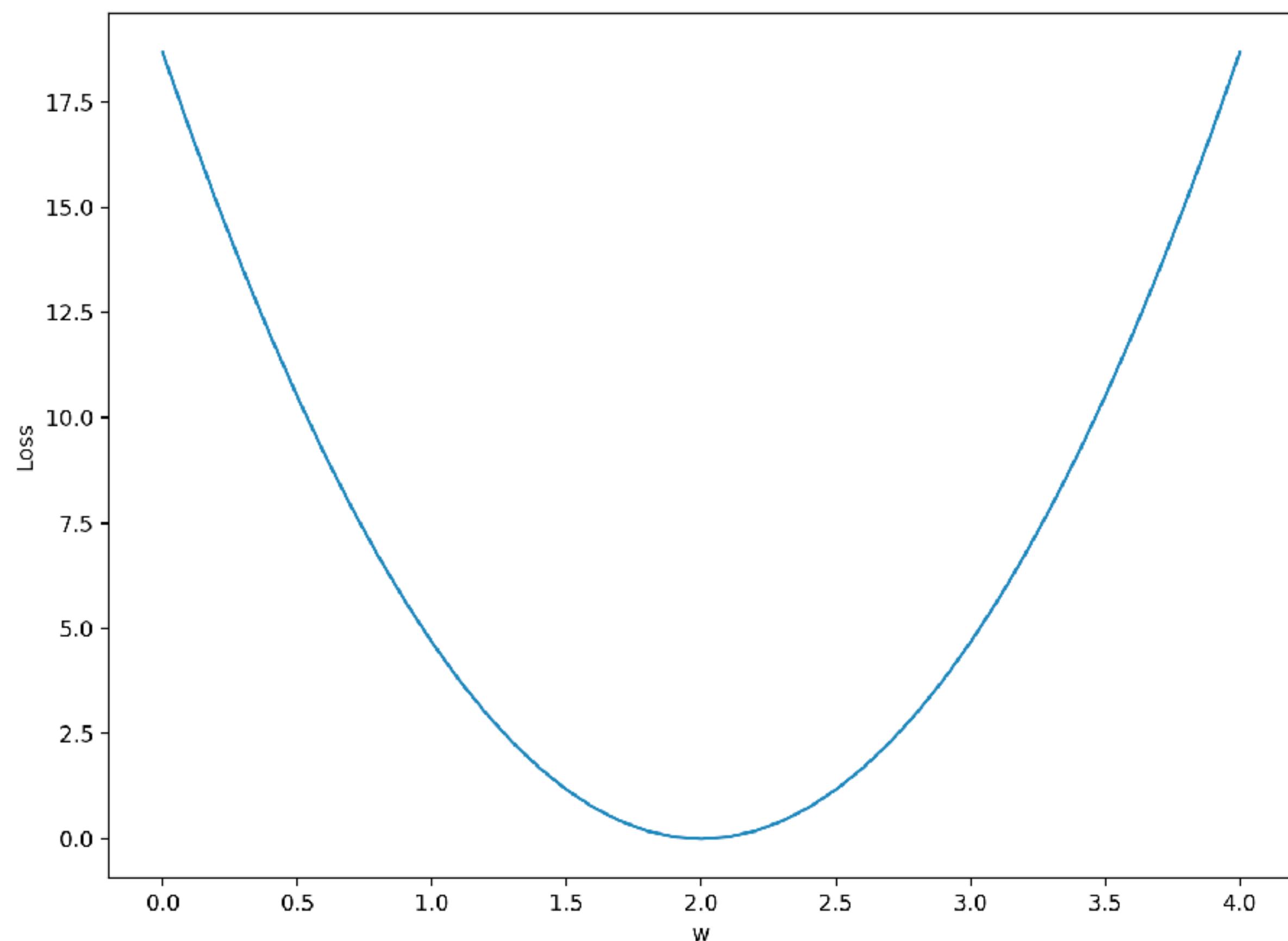
Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# Loss graph

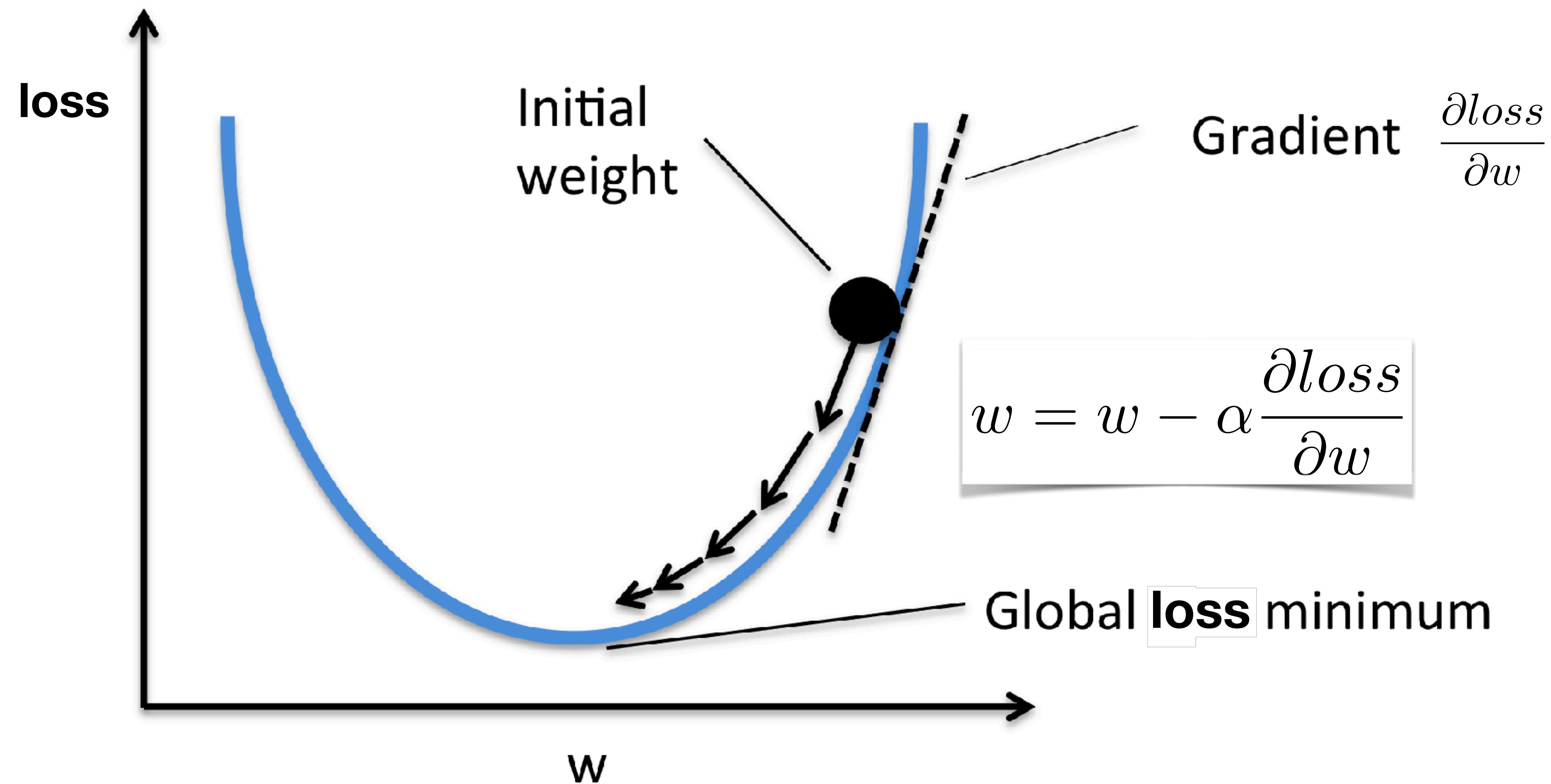
Loss (w=0)	Loss (w=1)	Loss (w=2)	Loss (w=3)	Loss (w=4)
mean=56/3=18.7	mean=14/3=4.7	mean=0	mean=14/3=4.7	mean=56/3=18.7



$$loss(w) = \frac{1}{N} \sum_{n=1}^N (\hat{y}_n - y_n)^2$$

$$\arg \min_w loss(w)$$

# Gradient descent algorithm



# Derivative

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

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

# Derivative

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

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

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

# Derivative

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

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

YOUR INPUT:  
 $f(w) =$

$(xw - y)^2$

**Simplify** **Roots/zeros**

FIRST DERIVATIVE:  
 $\frac{d}{dw}[f(w)] = f'(w) =$

The steps of calculation are displayed.  
Move the mouse over a derivative  $\frac{d}{dw}[\dots]$  or tap it in order to show its calculation.

$$\begin{aligned} & \frac{d}{dw} [(xw - y)^2] \\ &= 2(xw - y) \cdot \frac{d}{dw}[xw - y] \\ &= 2 \left( x \cdot \frac{d}{dw}[w] + \frac{d}{dw}[-y] \right) (xw - y) \\ &= 2(1x + 0)(xw - y) \\ &= 2x(xw - y) \end{aligned}$$



# Data, Model, Loss, and Gradient

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

w = 1.0 # 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)

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

# Training: updating weight



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

w = 1.0 # 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)

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

```
# 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))
```

```
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 gradient numeric 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))
```



**WHAT**  
**NEXT?**

A woman with dark hair tied back in a ponytail, wearing a dark blue blazer over a light blue shirt, is shown in profile facing right. She has her right hand raised to her ear, as if listening intently or trying to hear something. In the upper right corner of the image, there is a graphic element consisting of the words "WHAT" in orange and "NEXT?" in blue, followed by a simple line drawing of a lit lightbulb.

## Lecture 4: Back-propagation

# ML/DL for Everyone with PYTORCH

## Lecture 4: Back-propagation



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



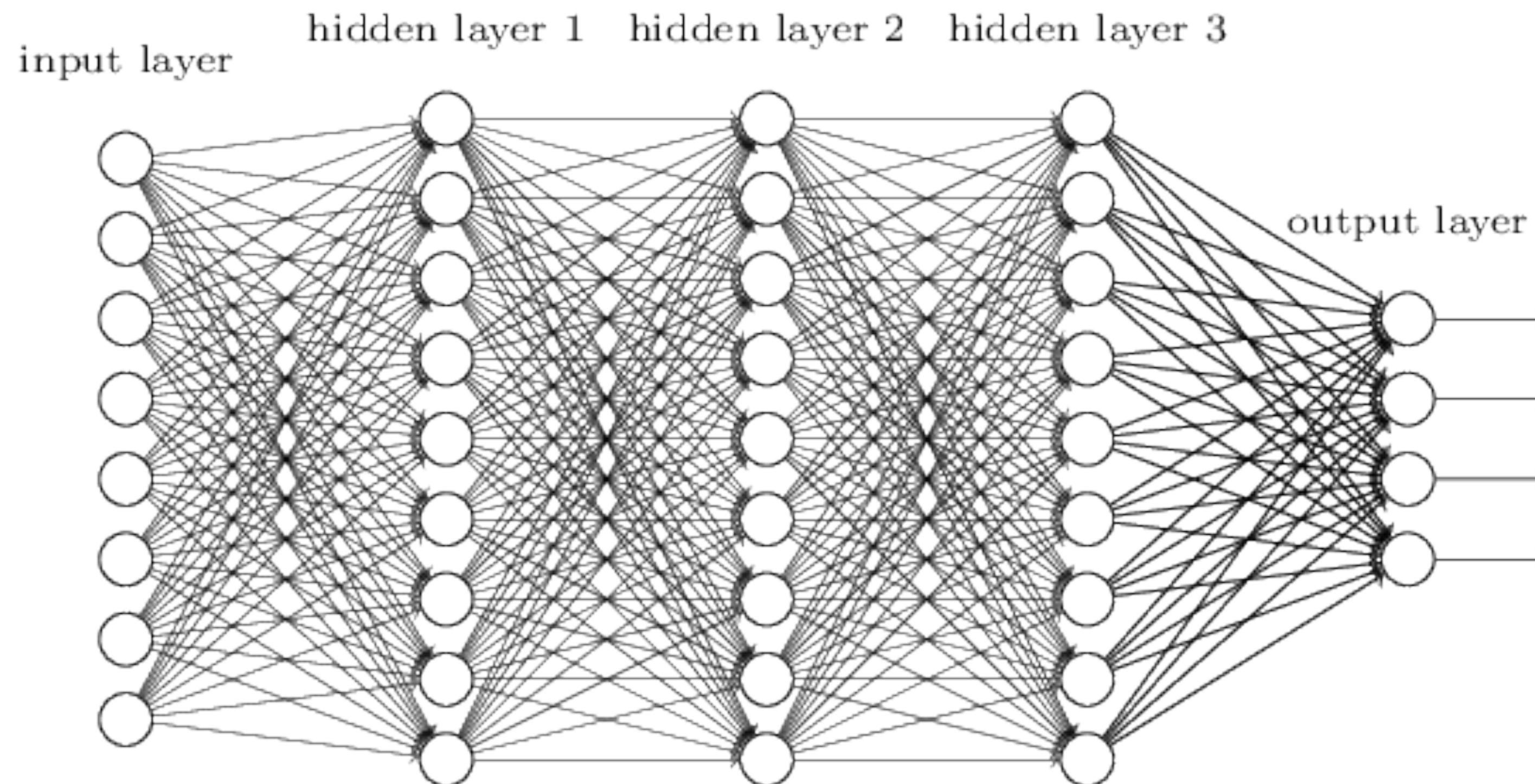
# Computing gradient in simple network



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

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

# Complicated network?

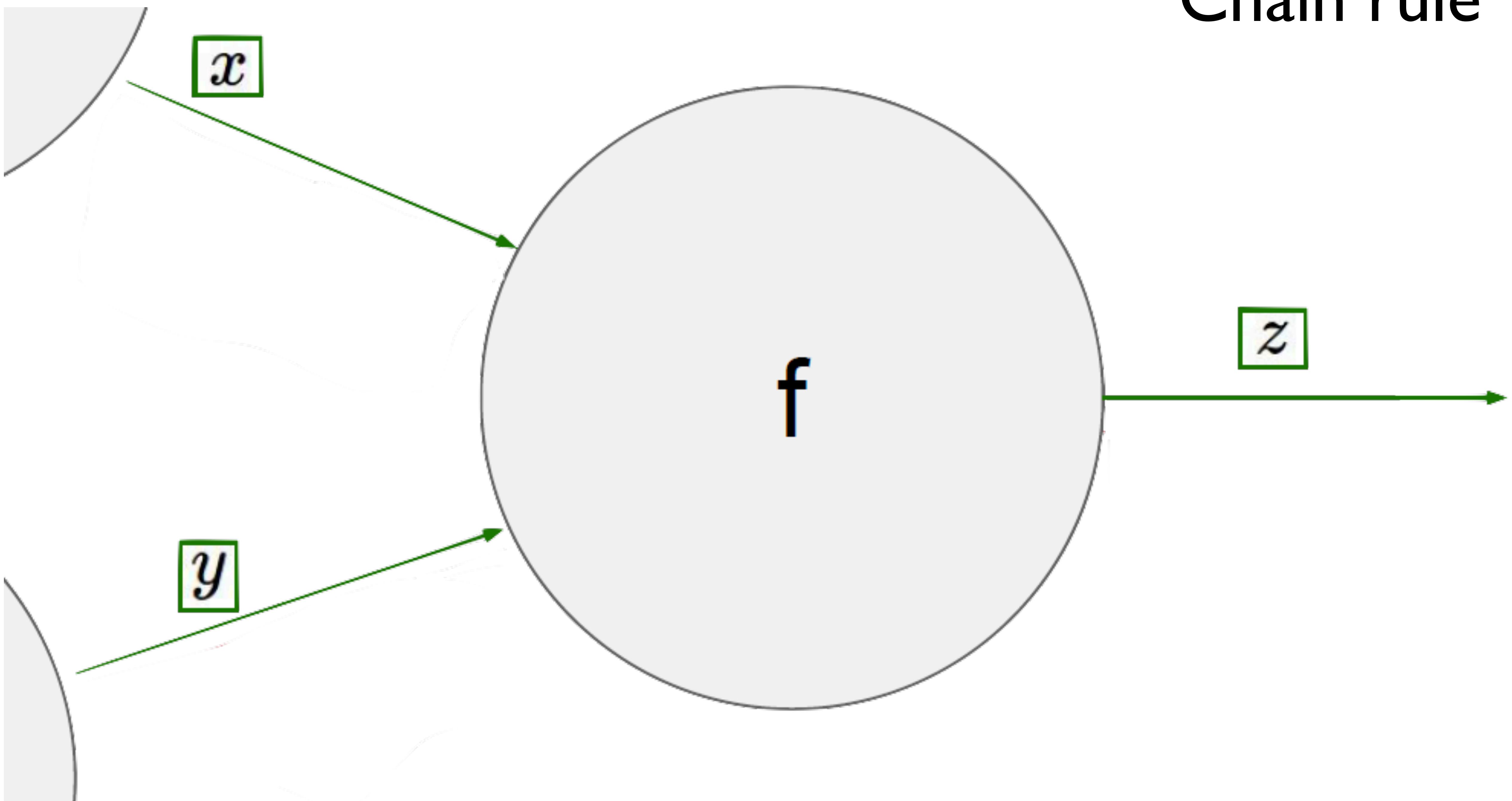


$$\frac{\partial \text{loss}}{\partial w} = ?$$

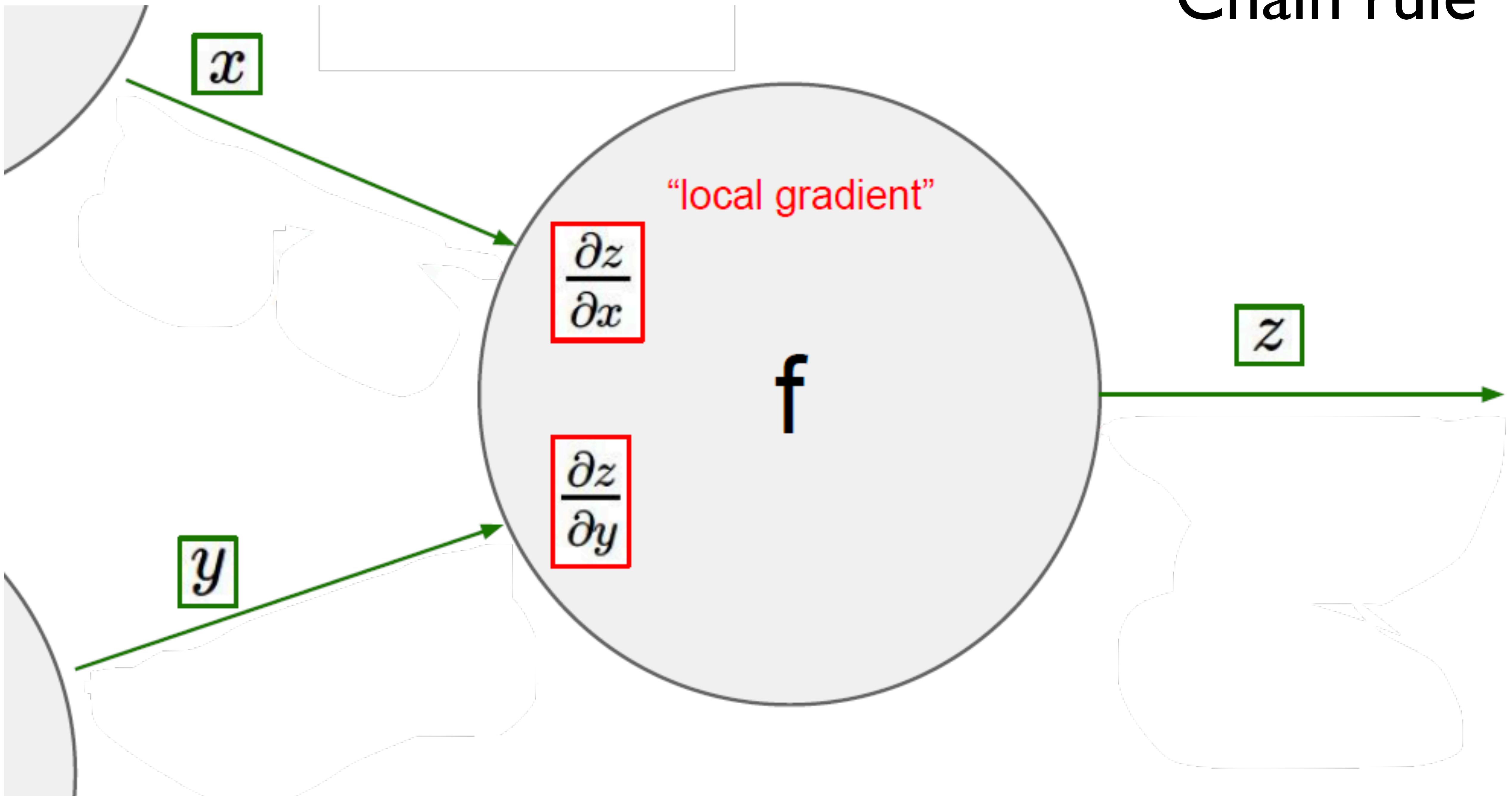
# Better way? Computational graph + chain rule



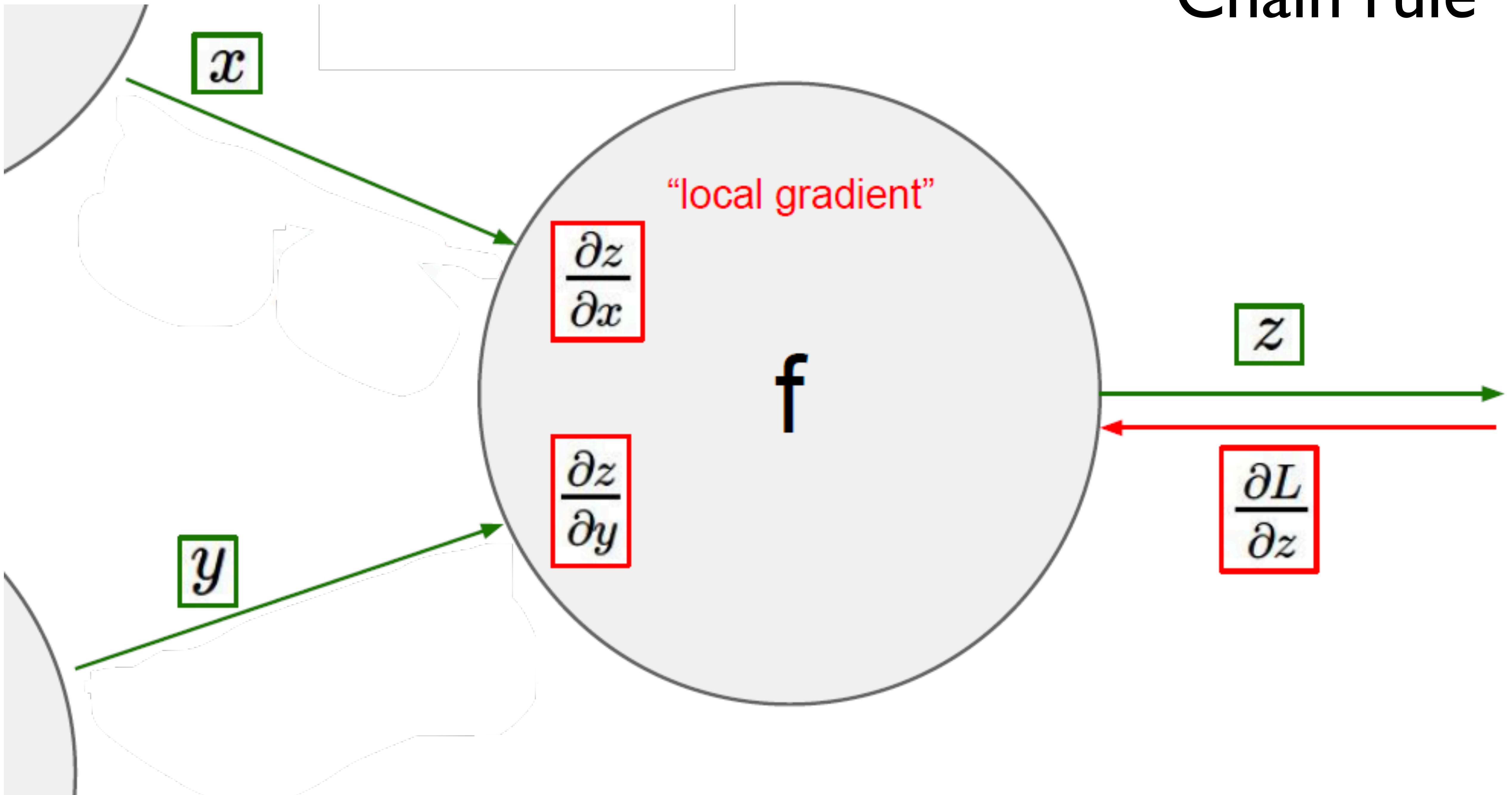
# Chain rule



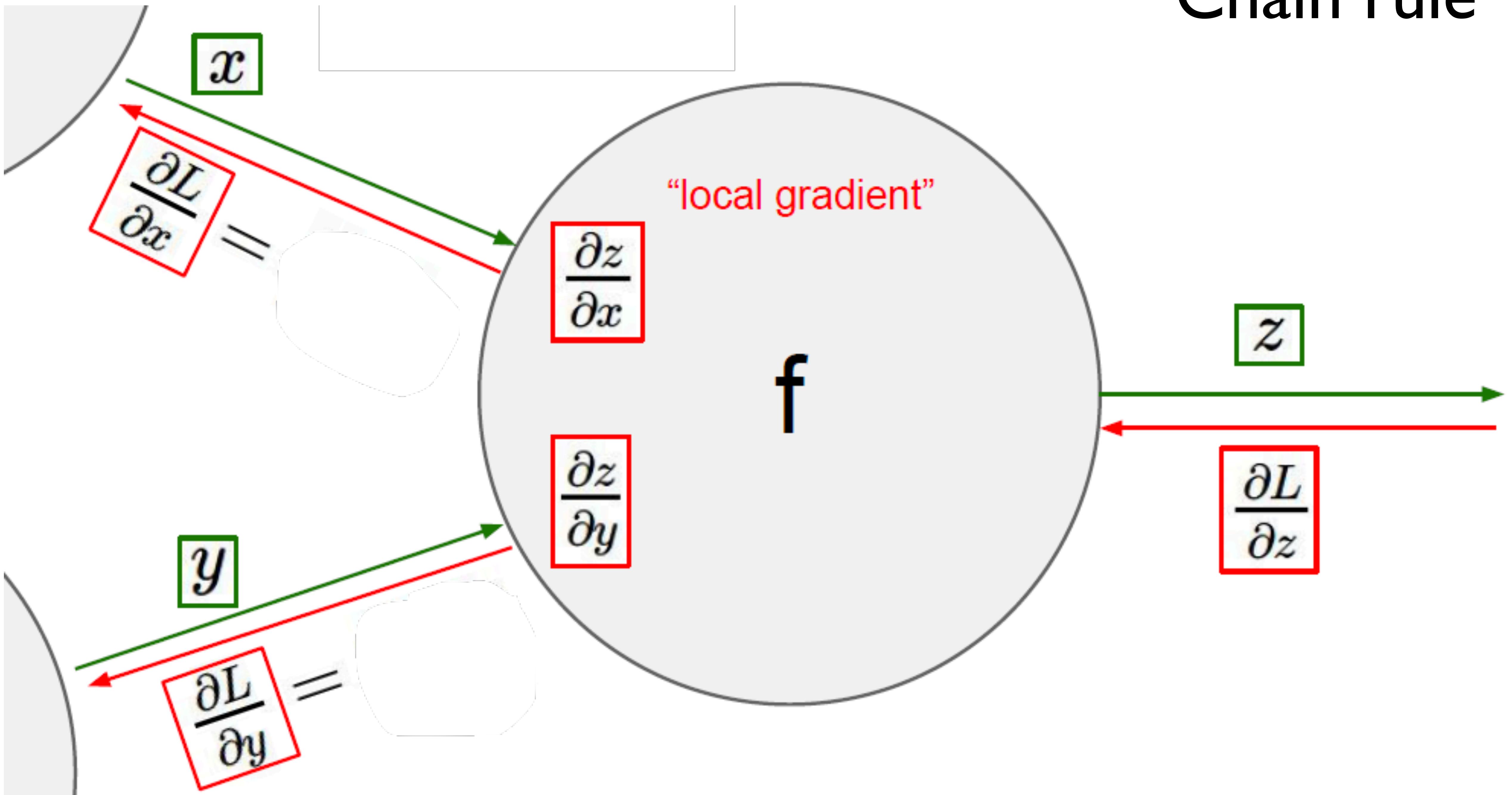
# Chain rule



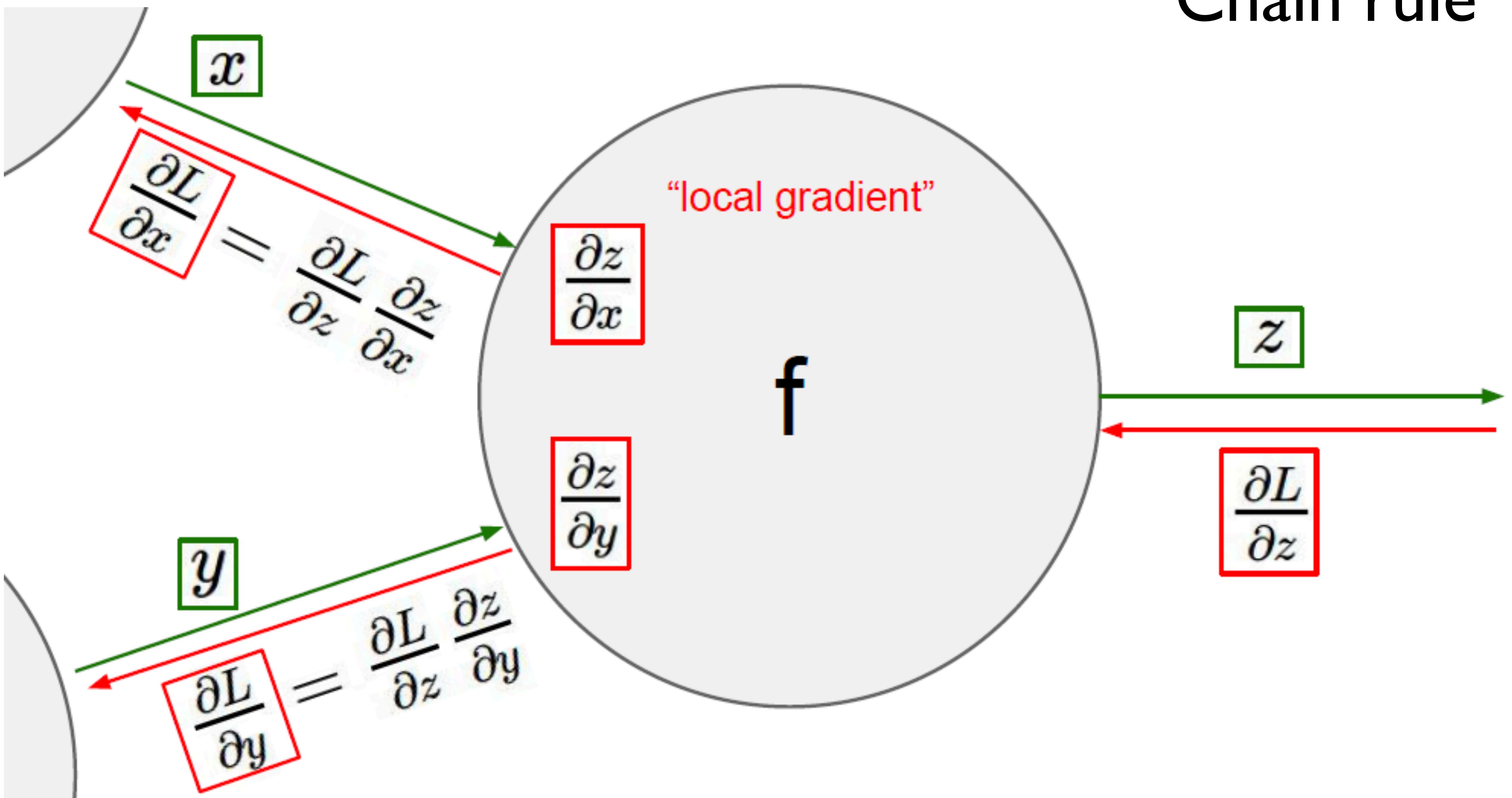
# Chain rule



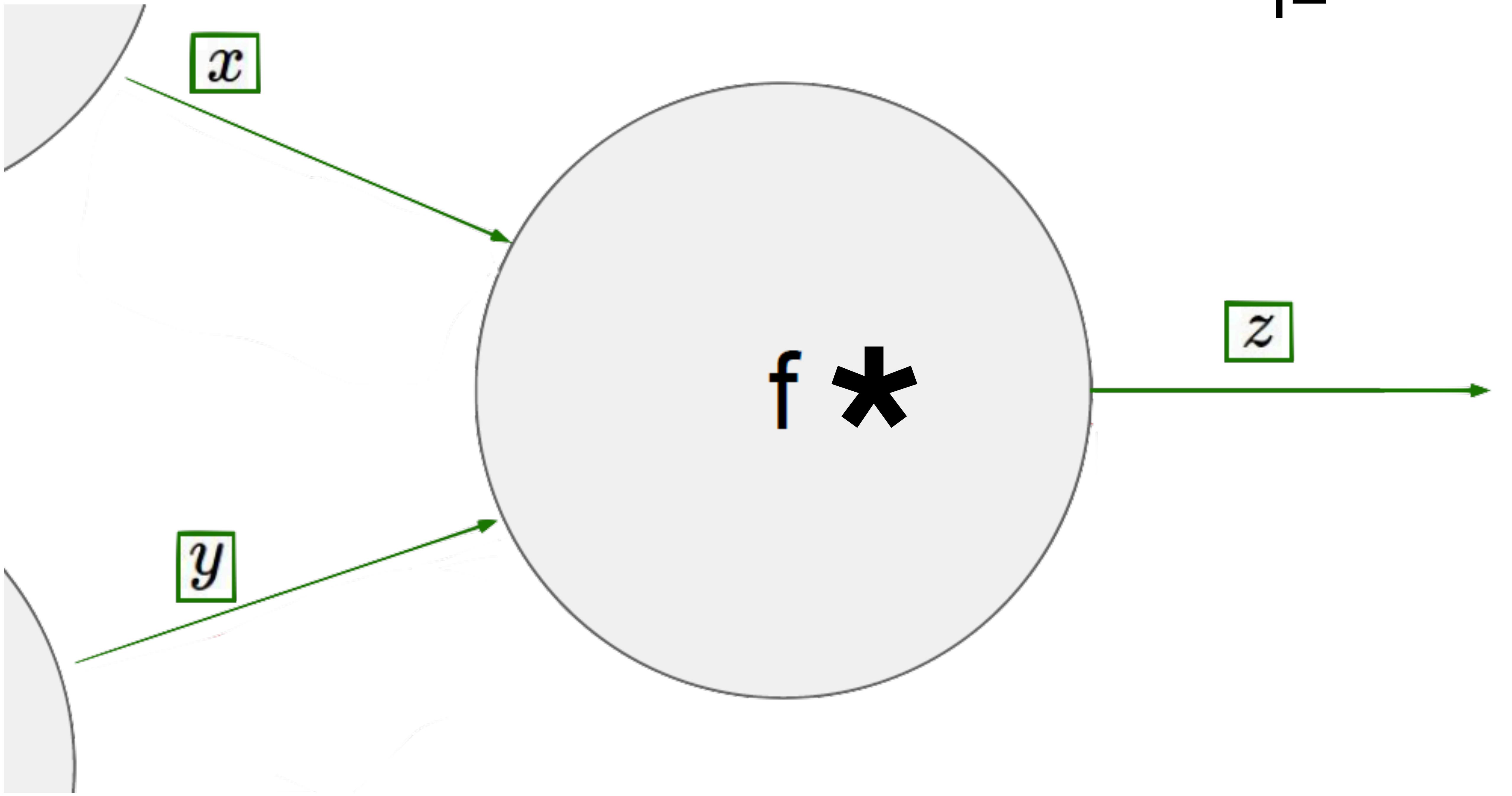
# Chain rule



# Chain rule



$f = *$



$f = *$

Forward pass  $x=2, y = 3$

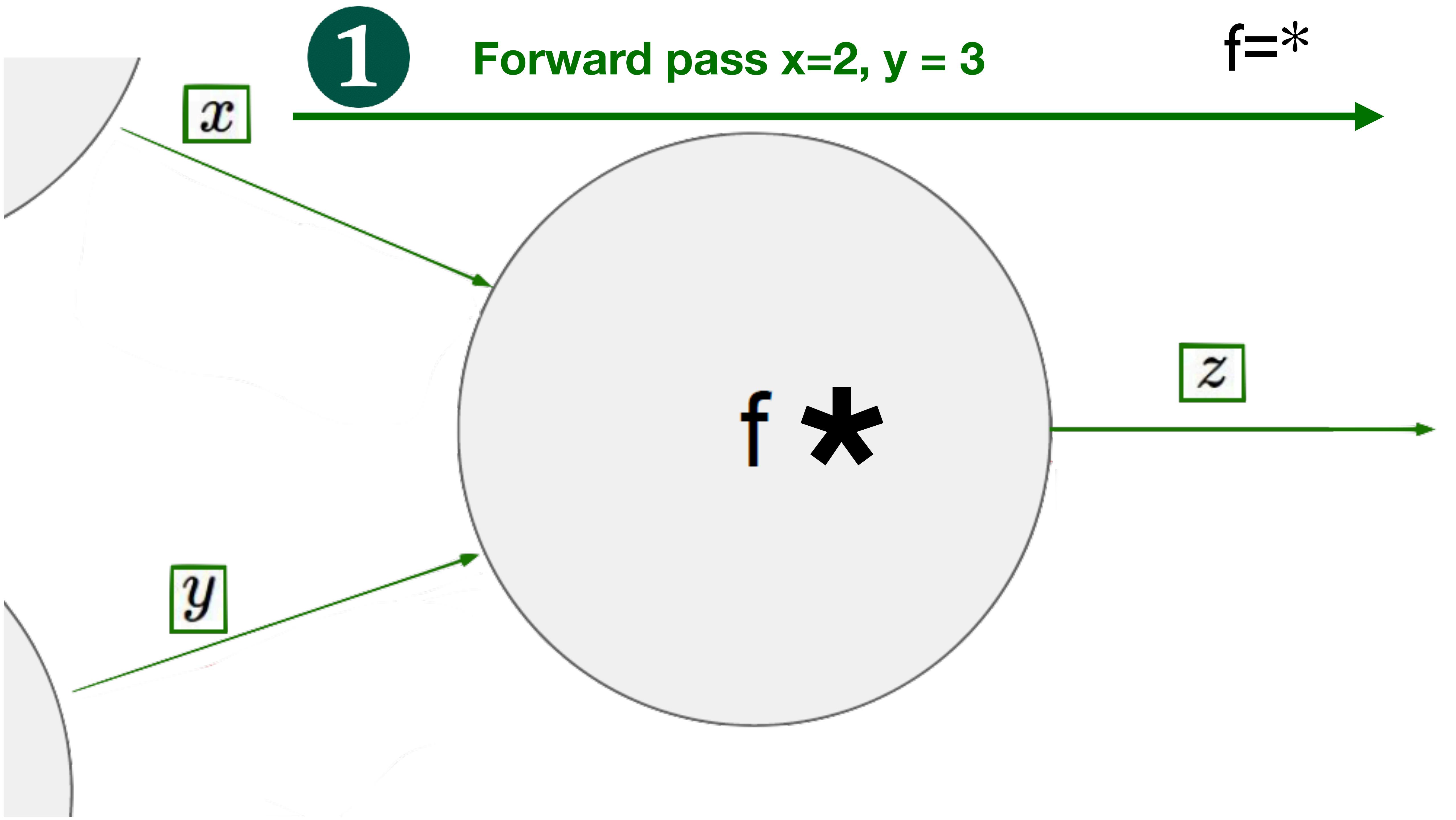
1

$x$

$y$

$f *$

$z$



**Backward propagation**

$$\frac{\partial L}{\partial z}$$

$=5$  is given.

$$x = 2$$

2

$$\frac{\partial z}{\partial x}$$

"local gradient"

$f \star$

$$\frac{\partial z}{\partial y}$$

$$y = 3$$

$$z = 6$$

$$\frac{\partial L}{\partial z} = 5$$

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

2

$$x = 2$$

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x}$$

"local gradient"

$$\frac{\partial z}{\partial x} = y$$

**f \***

$$z = 6$$

$$\frac{\partial L}{\partial z} = 5$$

$$y = 3$$

$$\frac{\partial z}{\partial y} = x$$

$$\frac{\partial L}{\partial y} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial y}$$

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

2

$$x = 2$$

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x} = 5 * y = 15$$

$$y = 3$$

$$\frac{\partial L}{\partial y} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial y} = 5 * x = 10$$

"local gradient"

$$\frac{\partial z}{\partial x} = y$$

$$\frac{\partial z}{\partial y} = x$$

**f \***

$$z = 6$$

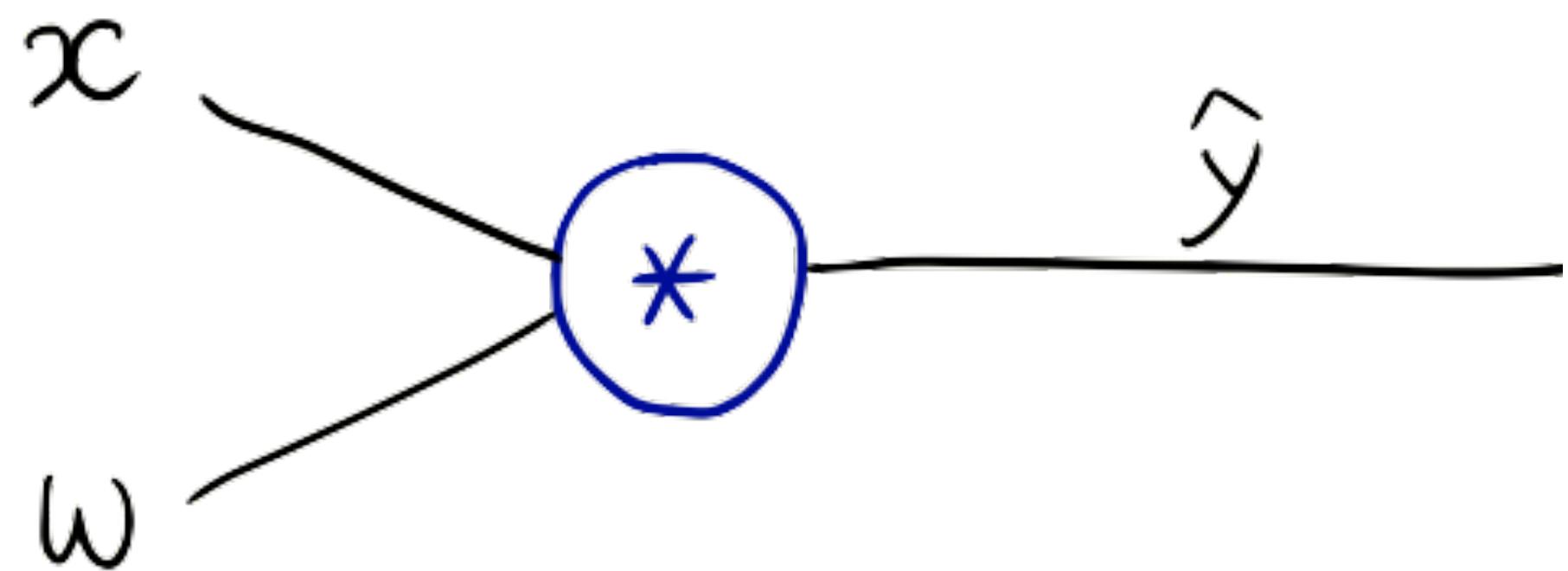
$$\frac{\partial L}{\partial z} = 5$$

# Computational graph

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

# Computational graph

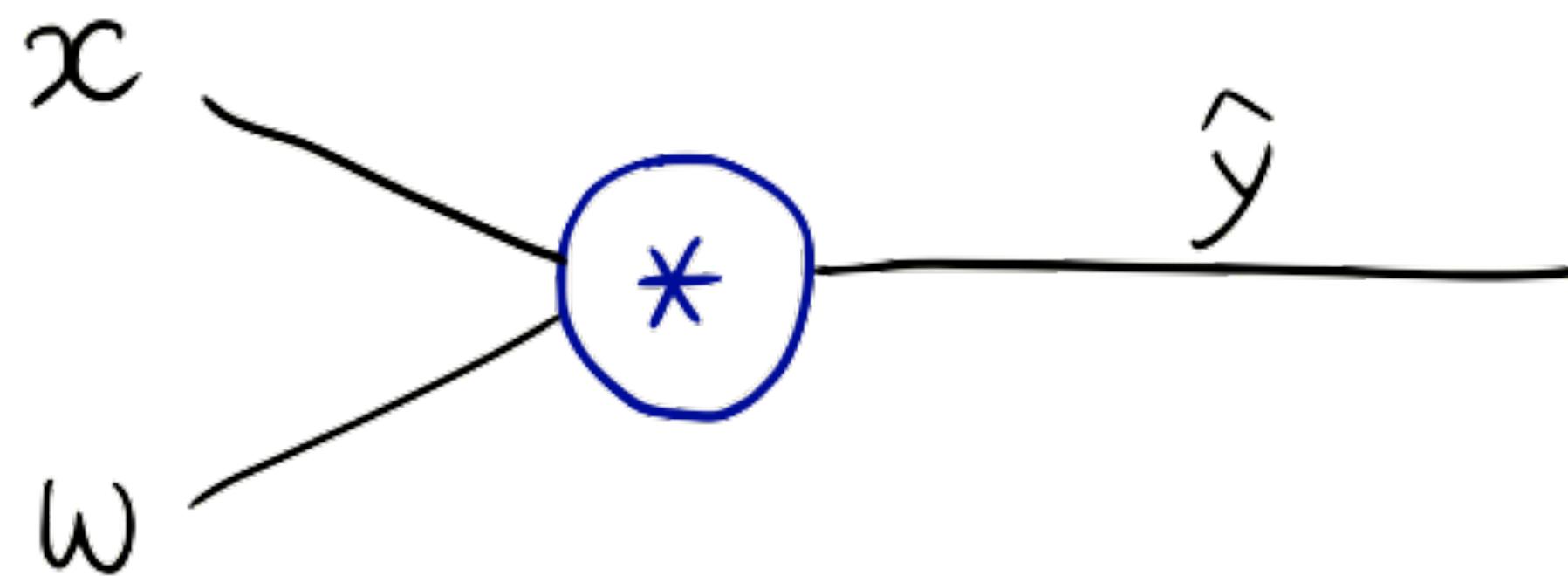
$$\hat{y} = x * w$$



# Computational graph

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

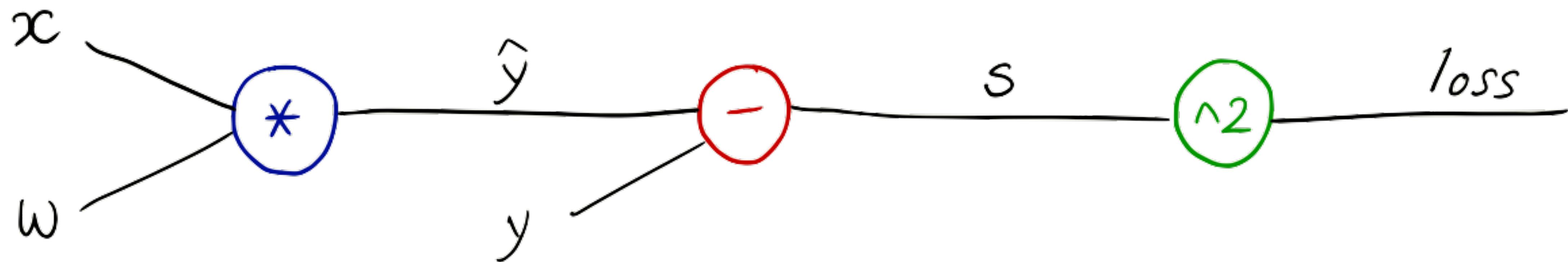
$$loss = (\hat{y} - y)^2 = (x * w - y)^2$$



# Computational graph

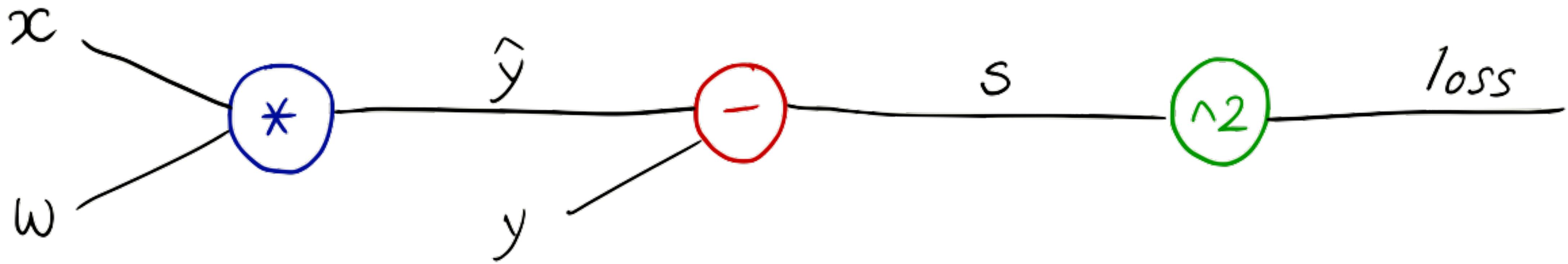
$$\hat{y} = x * w$$

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



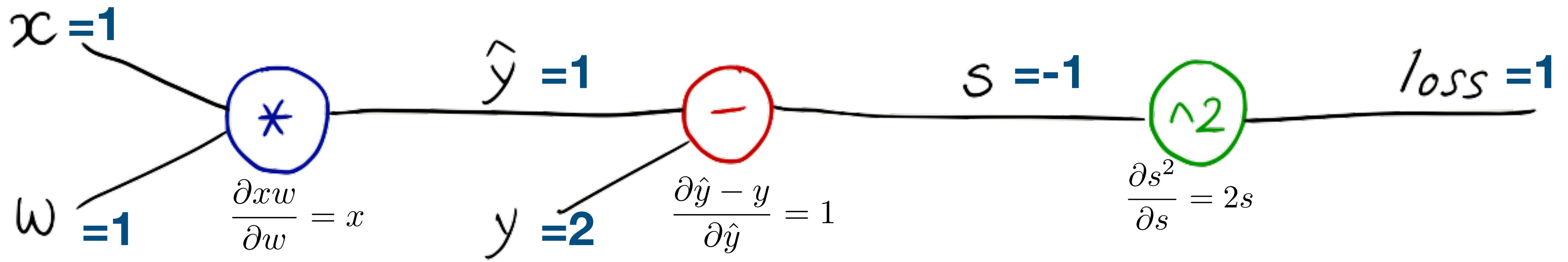
**1**

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



# 2

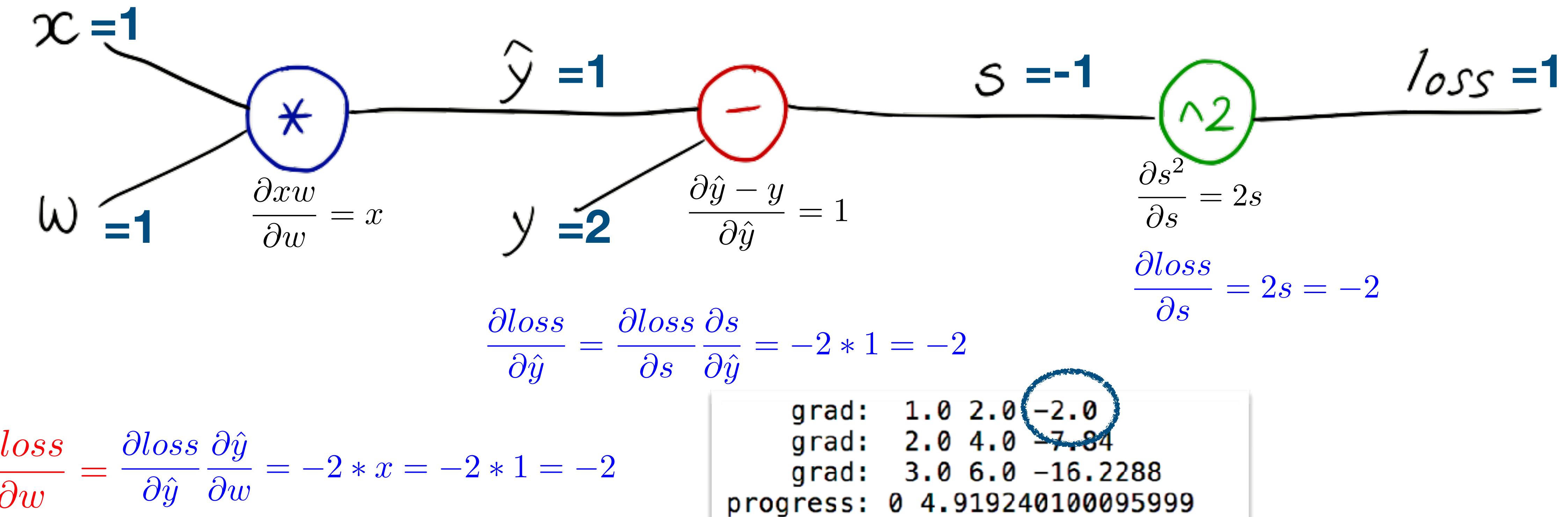
## Backward propagation



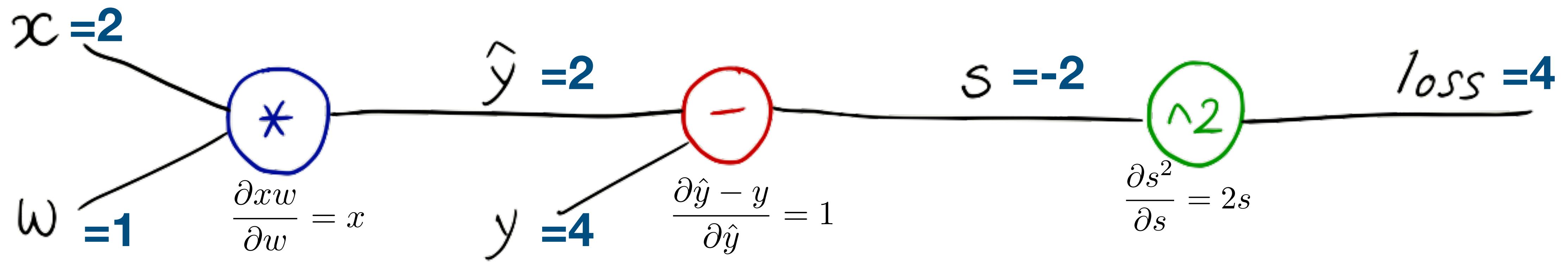
$$\frac{\partial loss}{\partial w} =$$

# 2

## Backward propagation



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

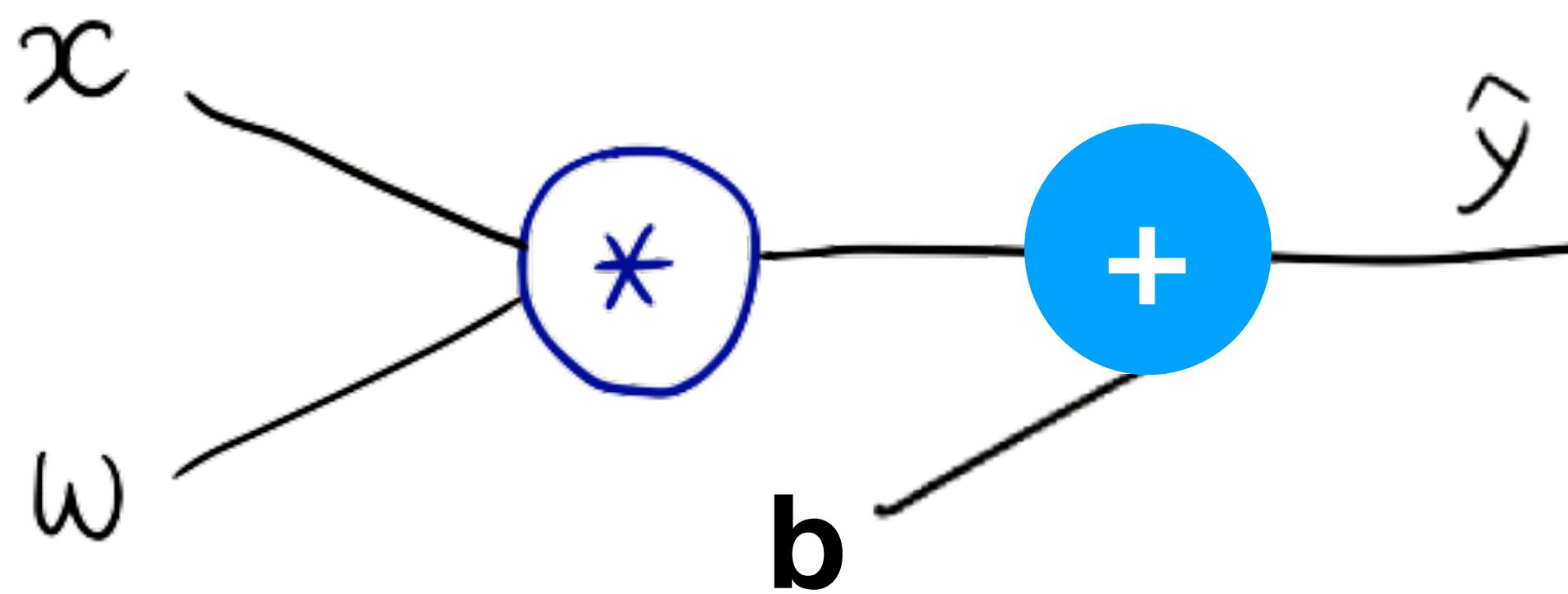


$$\frac{\partial loss}{\partial w} =$$

Exercise 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 import nn
from torch.autograd import Variable

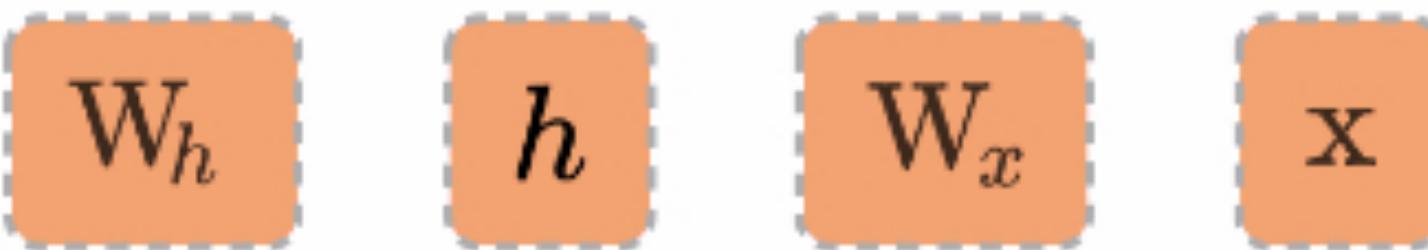
x_data = [1.0, 2.0, 3.0]
y_data = [2.0, 4.0, 6.0]

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))
```

# Model and Loss



```
import torch
from torch import nn
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)
```

# Training: forward, backward, and update weight

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

        # Manually zero the gradients after running the backward pass and update w
        w.grad.data.zero_()

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

# Output

```
# Training loop
for epoch in range(10):
    for x, y in zip(x_data, y_data):
        l = loss(x, y)
        l.backward() # Click here to see the code
        print("\tgrad: ", x, y, w.grad.data[0])
        w.data = w.data - 0.01 * w.grad.data

    # Manually zero the gradients after running the backward pass and update w
    w.grad.data.zero_()

print("progress:", epoch, l.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
```

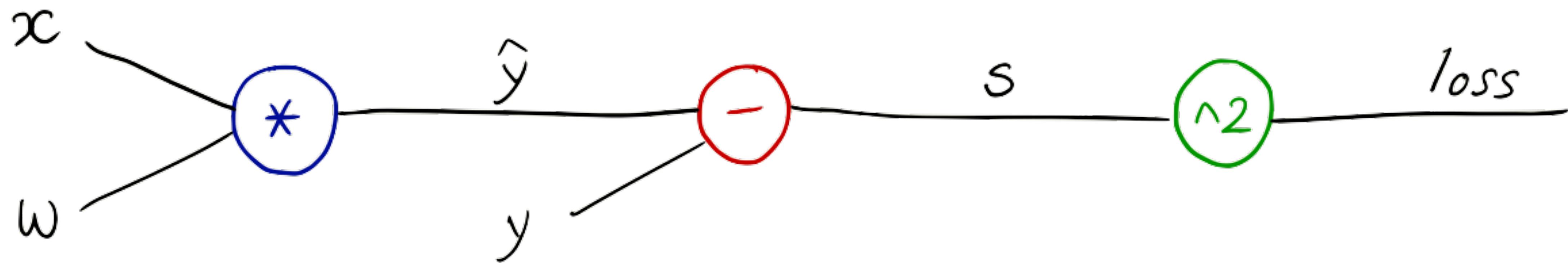
# Output

(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
```

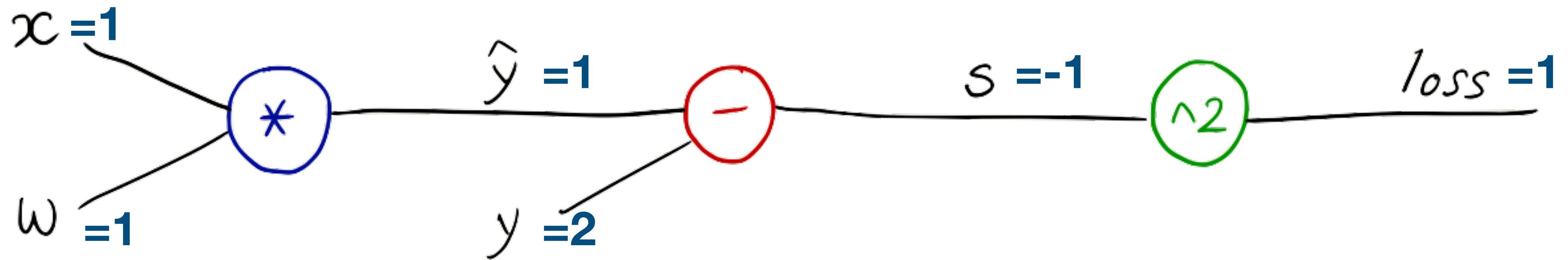


# PyTorch forward/backward



# Forward pass

```
w = Variable(torch.Tensor([1.0]), requires_grad=True) # Any random value  
l = loss(x=1, y=1)
```

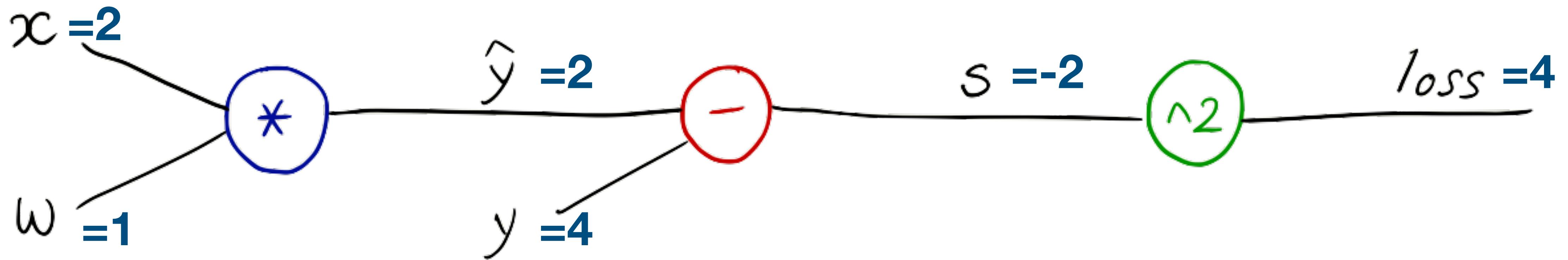


$$\frac{\partial loss}{\partial w} =$$

# Back propagation

```
l.backward()
```

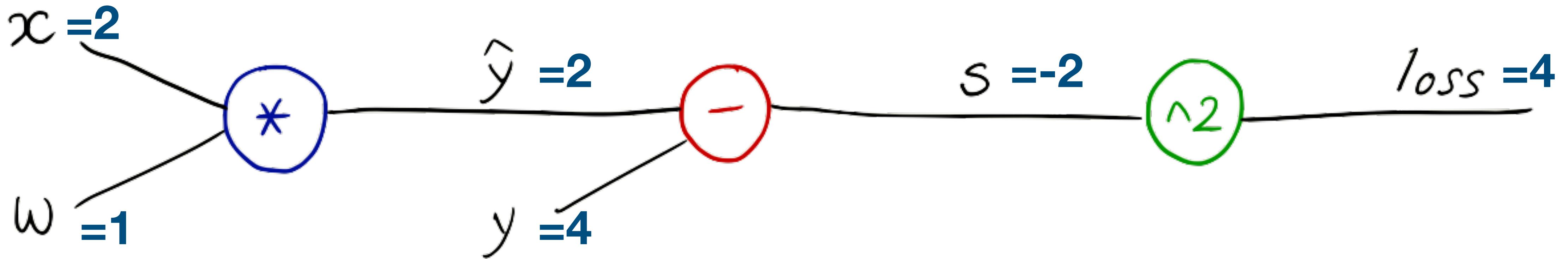
```
# Manually zero the gradients after running the backward pass and update w  
w.grad.data.zero_()
```



$$\frac{\partial loss}{\partial w} = w \cdot \text{grad}$$

# Weight update (step)

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



$$\frac{\partial loss}{\partial w} = w \cdot \text{grad}$$



# Lecture 5:

## Linear regression in the PyTorch way

# ML/DL for Everyone with PYTORCH

## Lecture 5: Linear regression in PyTorch way



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# Data definition (3x1)



```
import torch
from torch.autograd import Variable

x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0]]))
y_data = Variable(torch.Tensor([[2.0], [4.0], [6.0]]))
```

# Model class in PyTorch way



```
import torch
from torch.autograd import Variable

x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0]]))
y_data = Variable(torch.Tensor([[2.0], [4.0], [6.0]]))

class Model(torch.nn.Module):
    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.linear = torch.nn.Linear(1, 1) # One in and one out

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        y_pred = self.linear(x)
        return y_pred

# our model
model = Model()
```

# Construct loss and optimizer



```
# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
```

# Training: forward, loss, backward, step



```
# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

# Testing Model



```
# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward() # This line is highlighted in yellow
    optimizer.step()

# After training
hour_var = Variable(torch.Tensor([[4.0]]))
print("predict (after training)", 4, model.forward(hour_var).data[0][0])
```

# Output



```
# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

# After training
hour_var = Variable(torch.Tensor([[4.0]]))
print("predict (after training)", 4, model.forward(hour_var).data[0][0])
```

```
470 1.52139027704834e-05
471 1.4996051504567731e-05
472 1.4781335266889073e-05
473 1.4567947800969705e-05
474 1.4360077329911292e-05
475 1.4153701158647891e-05
476 1.3949686035630293e-05
477 1.3749523532169405e-05
478 1.3551662959798705e-05
479 1.3357152056414634e-05
480 1.3165942618797999e-05
481 1.2975904610357247e-05
482 1.2790364962711465e-05
483 1.2605956726474687e-05
484 1.2424526175891515e-05
485 1.2245835932844784e-05
486 1.2070459888491314e-05
487 1.1897350304934662e-05
488 1.1724299838533625e-05
489 1.155646714323666e-05
490 1.1392002306820359e-05
491 1.1226966307731345e-05
492 1.1066998922615312e-05
493 1.090722162189195e-05
494 1.0750130059022922e-05
495 1.0595314961392432e-05
496 1.0444626241223887e-05
497 1.029352642945014e-05
498 1.0146304703084752e-05
499 9.999960639106575e-06
predict (after training) 4 7.996364593505859
```

```

import torch
from torch.autograd import Variable

x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0]]))
y_data = Variable(torch.Tensor([[2.0], [4.0], [6.0]]))

class Model(torch.nn.Module):
    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.linear = torch.nn.Linear(1, 1) # One in and one out

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        y_pred = self.linear(x)
        return y_pred

# our model
model = Model()

# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

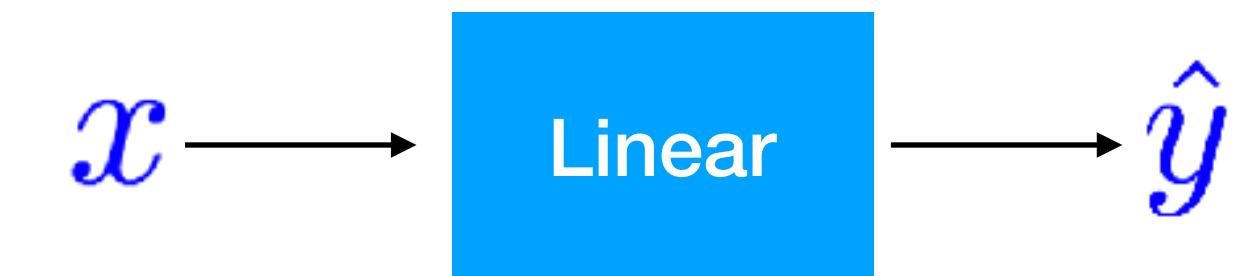
    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

# After training
hour_var = Variable(torch.Tensor([[4.0]]))
print("predict (after training)", 4, model.forward(hour_var).data[0][0])

```

1

## Design your model using class



2

## Construct loss and optimizer (select from PyTorch API)

3

## Training cycle (forward, backward, update)

# Training CIFAR10 Classifier

```
# 1. Define a Neural Network
# ~~~~~
# Copy the neural network from the Neural Networks section before and modify it to
# take 3-channel images (instead of 1-channel images as it was defined).

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

net = Net()

# 2. Define a Loss function and optimizer
# ~~~~~
# Let's use a Classification Cross-Entropy loss and SGD with momentum
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)

# 3. Train the network
# ~~~~~
#
# This is when things start to get interesting.
# We simply have to loop over our data iterator, and feed the inputs to the
# network and optimize
for epoch in range(2): # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs
        inputs, labels = data

        # wrap them in Variable
        inputs, labels = Variable(inputs), Variable(labels)

        # zero the parameter gradients
        optimizer.zero_grad()

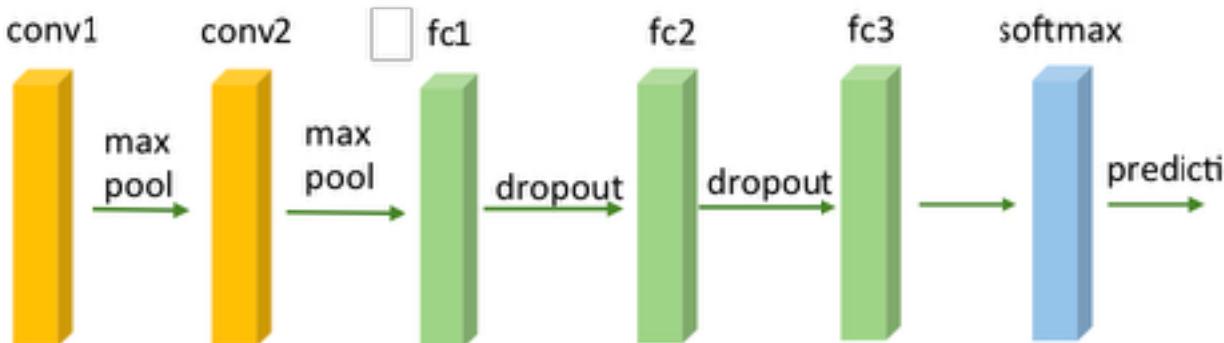
        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.data[0]
        if i % 2000 == 1999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

print('Finished Training')
```

1

## Design your model using class



airplane  
automobile  
bird  
cat  
deer  
dog  
frog  
horse  
ship  
truck



2

## Construct loss and optimizer (select from PyTorch API)

3

## Training cycle (forward, backward, update)

# Building fun models

- Neure Net components
  - CNN
  - RNN
  - Activations
- Losses
- Optimizers

## ⊖ Convolution Layers

Conv1d

Conv2d

Conv3d

ConvTranspose1d

ConvTranspose2d

ConvTranspose3d

## ⊖ Recurrent layers

RNN

LSTM

GRU

RNNCell

LSTMCell

GRUCell

# torch.nn

- ⊕ Containers
- ⊕ Convolution Layers
- ⊕ Pooling Layers
- ⊕ Padding Layers
- ⊕ Non-linear Activations
- ⊕ Normalization layers
- ⊕ Recurrent layers
- ⊕ Linear layers
- ⊕ Dropout layers
- ⊕ Sparse layers
- ⊕ Distance functions
- ⊕ Loss functions
- ⊕ Vision layers

## ⊖ Non-linear Activations

ReLU

ReLU6

ELU

SELU

PReLU

LeakyReLU

Threshold

Hardtanh

Sigmoid

Tanh

LogSigmoid

Softplus

Softshrink

Softsign

Tanhshrink

Softmin

Softmax

Softmax2d

LogSoftmax

## ⊖ Loss functions

L1Loss

MSELoss

CrossEntropyLoss

NLLLoss

PoissonNLLLoss

NLLLoss2d

KLDivLoss

BCELoss

BCEWithLogitsLoss

MarginRankingLoss

HingeEmbeddingLoss

MultiLabelMarginLoss

SmoothL1Loss

SoftMarginLoss

MultiLabelSoftMarginLoss

CosineEmbeddingLoss

MultiMarginLoss

TripletMarginLoss

# Loss functions

Table 1: List of losses analysed in this paper.  $\mathbf{y}$  is true label as one-hot encoding,  $\hat{\mathbf{y}}$  is true label as  $+1/-1$  encoding,  $\mathbf{o}$  is the output of the last layer of the network,  $\cdot^{(j)}$  denotes  $j$ th dimension of a given vector, and  $\sigma(\cdot)$  denotes probability estimate.

symbol	name	equation
$\mathcal{L}_1$	$L_1$ loss	$\ \mathbf{y} - \mathbf{o}\ _1$
$\mathcal{L}_2$	$L_2$ loss	$\ \mathbf{y} - \mathbf{o}\ _2^2$
$\mathcal{L}_1 \circ \sigma$	expectation loss	$\ \mathbf{y} - \sigma(\mathbf{o})\ _1$
$\mathcal{L}_2 \circ \sigma$	regularised expectation loss <sup>1</sup>	$\ \mathbf{y} - \sigma(\mathbf{o})\ _2^2$
$\mathcal{L}_\infty \circ \sigma$	Chebyshev loss	$\max_j  \sigma(\mathbf{o})^{(j)} - \mathbf{y}^{(j)} $
hinge	hinge [13] (margin) loss	$\sum_j \max(0, \frac{1}{2} - \hat{\mathbf{y}}^{(j)} \mathbf{o}^{(j)})$
hinge <sup>2</sup>	squared hinge (margin) loss	$\sum_j \max(0, \frac{1}{2} - \hat{\mathbf{y}}^{(j)} \mathbf{o}^{(j)})^2$
hinge <sup>3</sup>	cubed hinge (margin) loss	$\sum_j \max(0, \frac{1}{2} - \hat{\mathbf{y}}^{(j)} \mathbf{o}^{(j)})^3$
log	log (cross entropy) loss	$-\sum_j \mathbf{y}^{(j)} \log \sigma(\mathbf{o})^{(j)}$
log <sup>2</sup>	squared log loss	$-\sum_j [\mathbf{y}^{(j)} \log \sigma(\mathbf{o})^{(j)}]^2$
tan	Tanimoto loss	$-\sum_j \sigma(\mathbf{o})^{(j)} \mathbf{y}^{(j)} \over \ \sigma(\mathbf{o})\ _2^2 + \ \mathbf{y}\ _2^2 - \sum_j \sigma(\mathbf{o})^{(j)} \mathbf{y}^{(j)}$
D <sub>CS</sub>	Cauchy-Schwarz Divergence [3]	$-\log \frac{\sum_j \sigma(\mathbf{o})^{(j)} \mathbf{y}^{(j)}}{\ \sigma(\mathbf{o})\ _2 \ \mathbf{y}\ _2}$

<https://arxiv.org/pdf/1702.05659.pdf>

# torch.optim

- **class**torch.optim.Adadelta
- **class**torch.optim.Adagrad
- **class**torch.optim.Adam
- **class**torch.optim.Adamax
- **class**torch.optim.ASGD
- **class**torch.optim.RMSprop
- **class**torch.optim.Rprop
- **class**torch.optim.SGD

# Three simple steps



**Design your model using class**



**Construct loss and optimizer  
(select from PyTorch API)**



**Training cycle  
(forward, backward, update)**



**WHAT**  
**NEXT!**

A woman with dark hair tied back in a ponytail, wearing a dark blue blazer over a light blue shirt, is shown in profile facing right. She has her right hand raised to her ear, fingers forming a funnel shape to listen more closely. In the upper right corner of the image, there is a graphic element consisting of the words "WHAT NEXT!" in large, bold, sans-serif font. The word "WHAT" is orange and "NEXT!" is blue. A simple gray outline of a lit lightbulb is positioned to the right of the exclamation mark.

## Lecture 6:

# Logistic regression

# ML/DL for Everyone with PYTORCH

## Lecture 6: Logistic Regression



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>

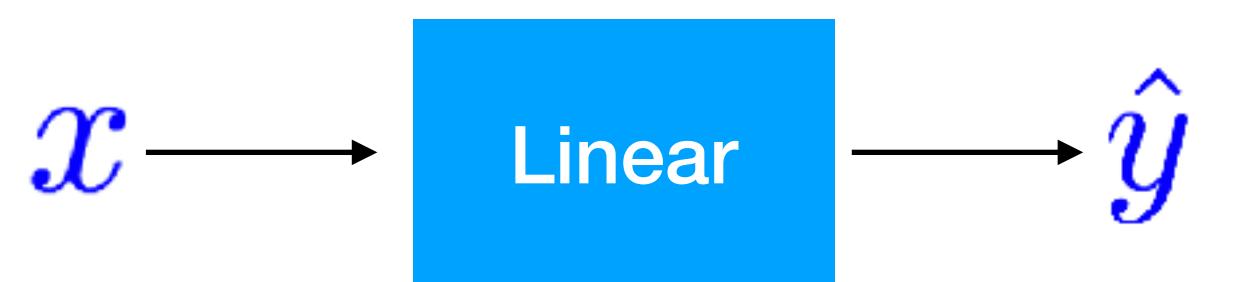


# Binary prediction (0 or 1) is very useful!

- Spent n hours for study, **pass or fail?**
- GPA and GRE scores for the HKUST PHD program, **admit or not?**
- Soccer game against Japan, **win or lose?**
- She/he looks good, **propose or not?**
- ...

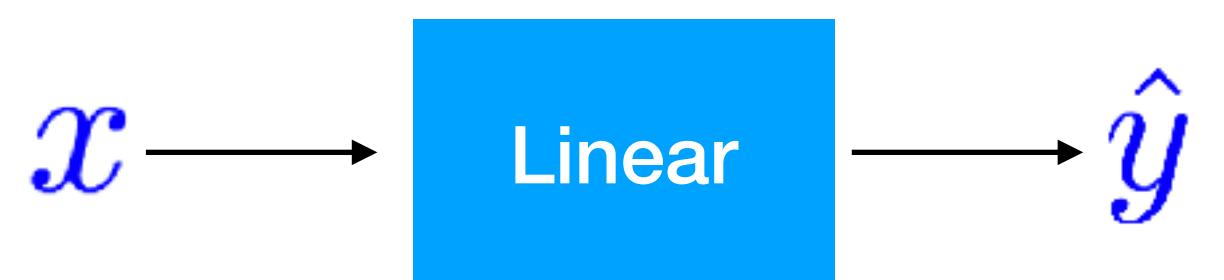


# Linear model



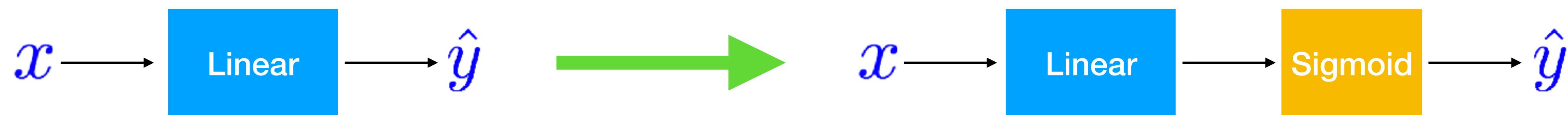
Hours (x)	Points
1	2
2	4
3	6
4	?

# Logistic regression: pass/fail (0 or 1)



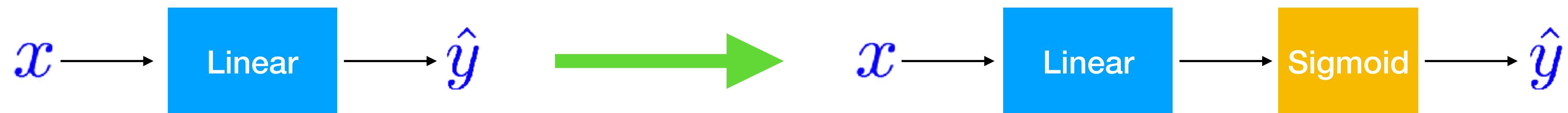
Hours (x)	Points	fail/pass
1	2	0
2	4	0
3	6	1
4	?	?

# Logistic regression: pass/fail (0 or 1)

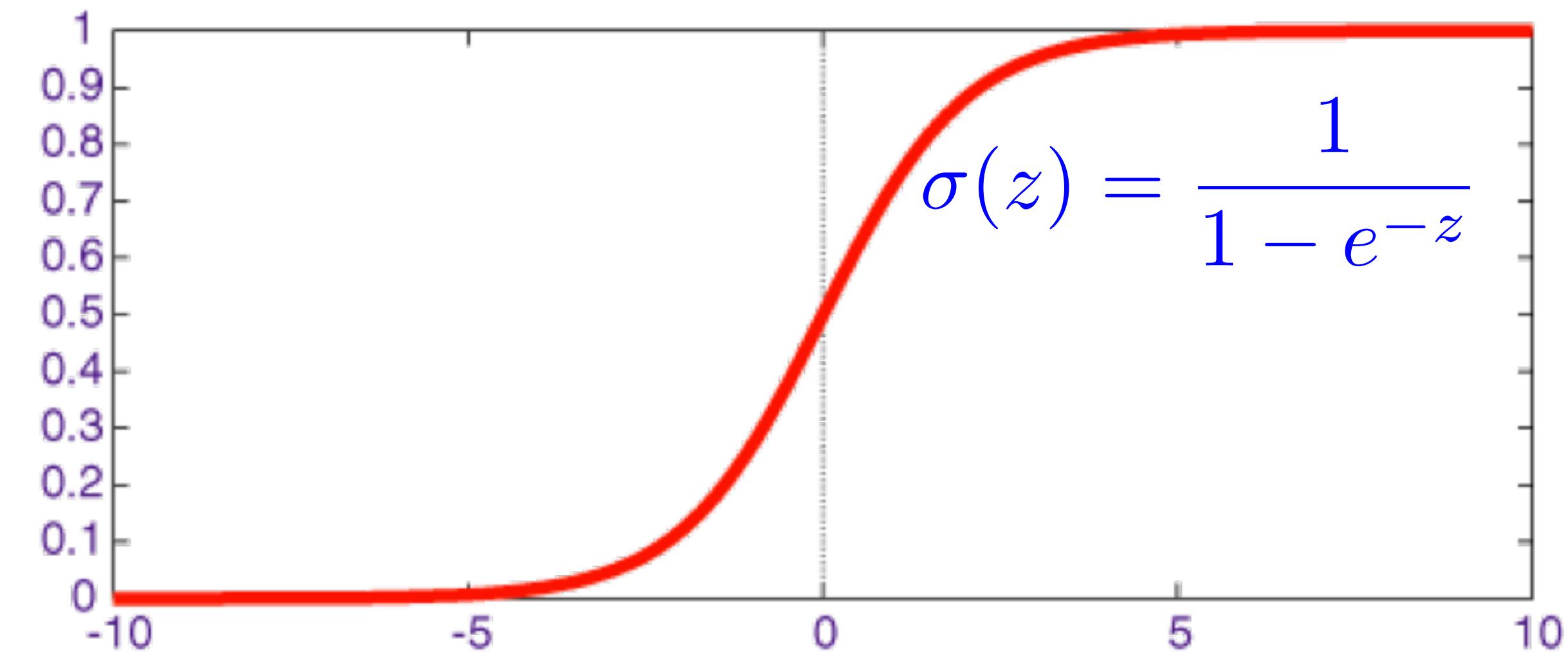


Hours (x)	Points	fail/pass
1	2	0
2	4	0
3	6	1
4	?	?

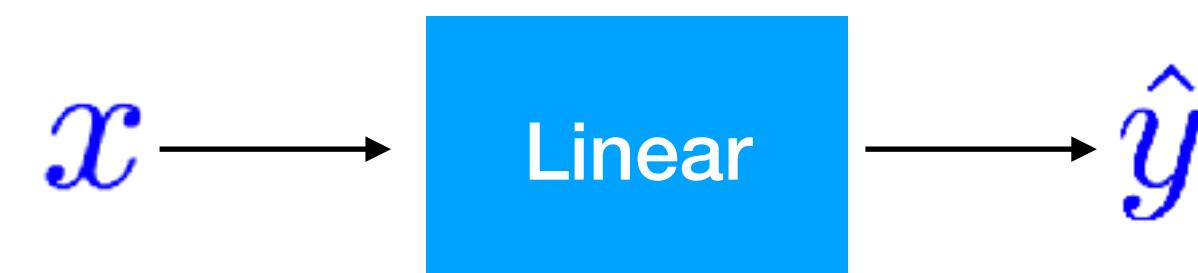
# Meet sigmoid



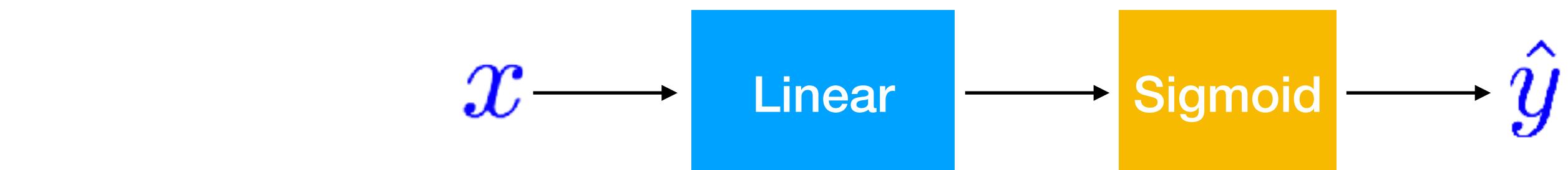
Hours (x)	Points	fail/pass
1	2	0
2	4	0
3	6	1
4	?	?



# Meet sigmoid

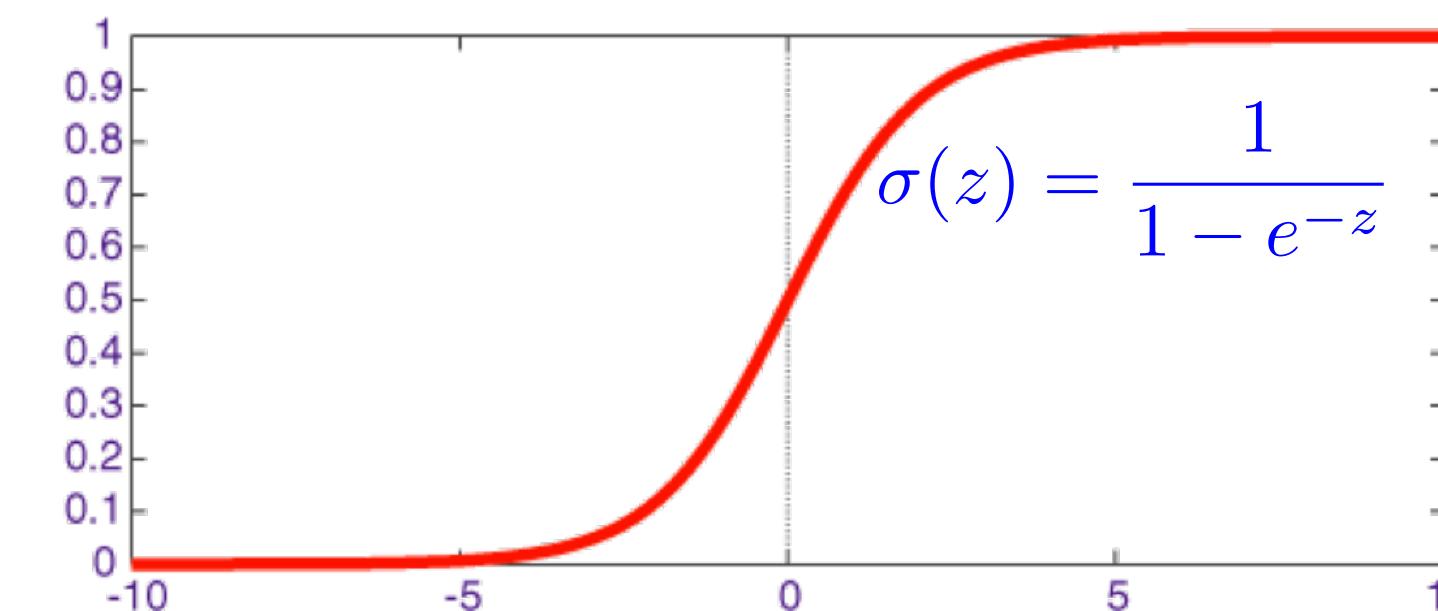


$$\hat{y} = x * w + b$$

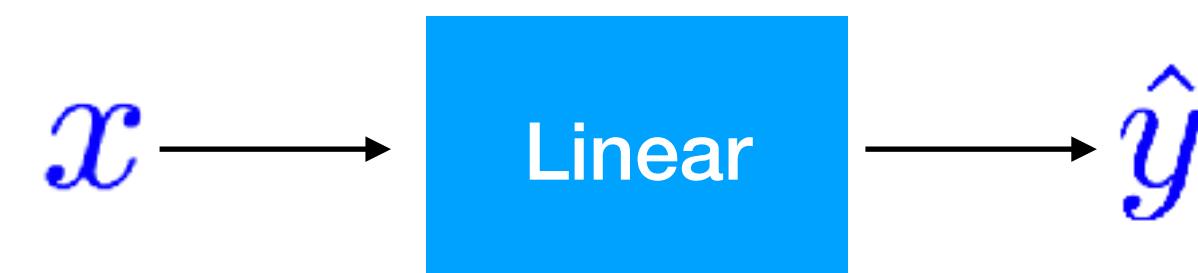


$$\sigma(z) = \frac{1}{1 - e^{-z}}$$
$$\hat{y} = \sigma(x * w + b)$$

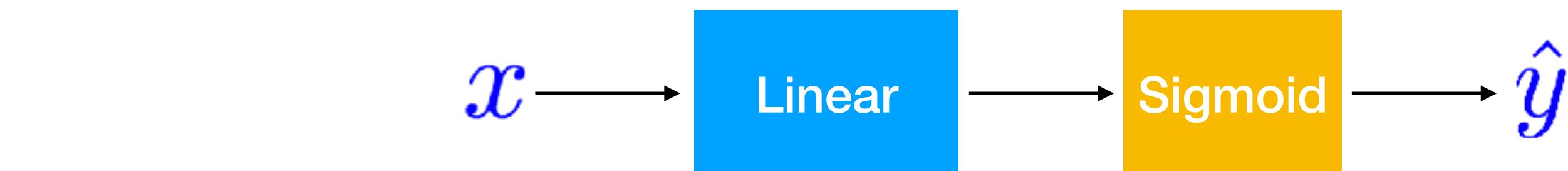
Hours (x)	Points	fail/pass
1	2	0
2	4	0
3	6	1
4	?	?



# Meet Cross Entropy Loss



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



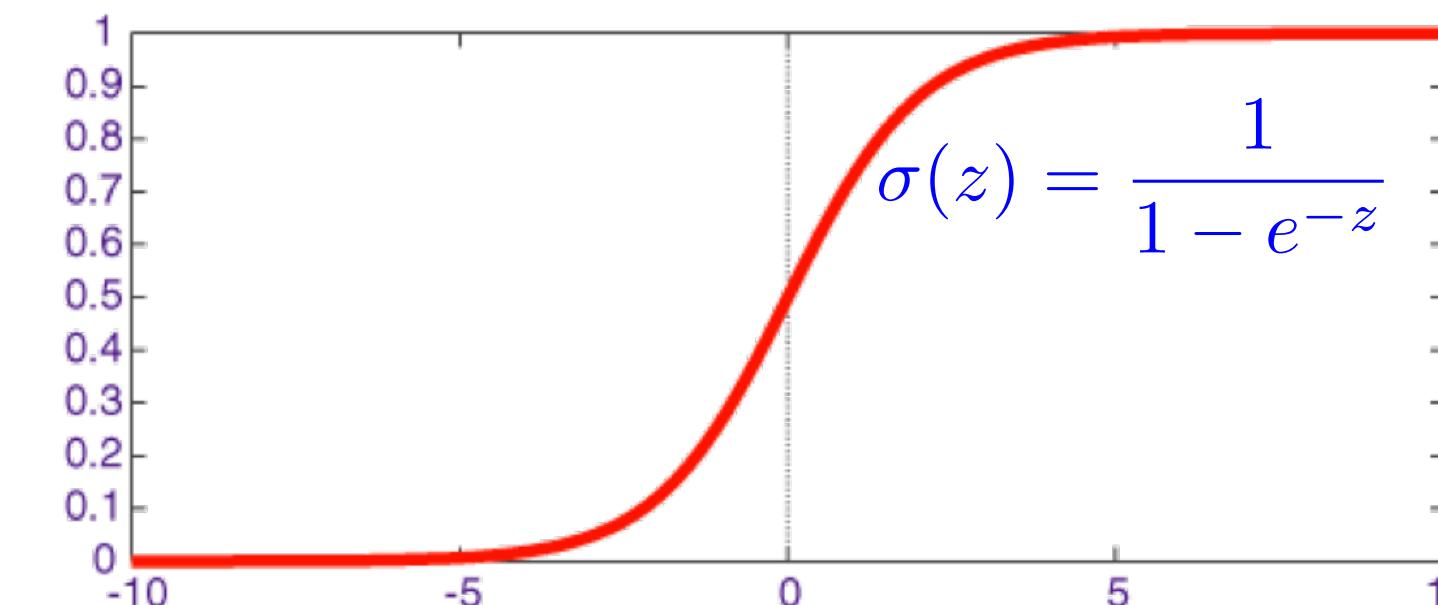
$\sigma(z) = \frac{1}{1 - e^{-z}}$

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

$$loss = \frac{1}{N} \sum_{n=1}^N (\hat{y}_n - y_n)^2$$

$$loss = -\frac{1}{N} \sum_{n=1}^N y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n)$$

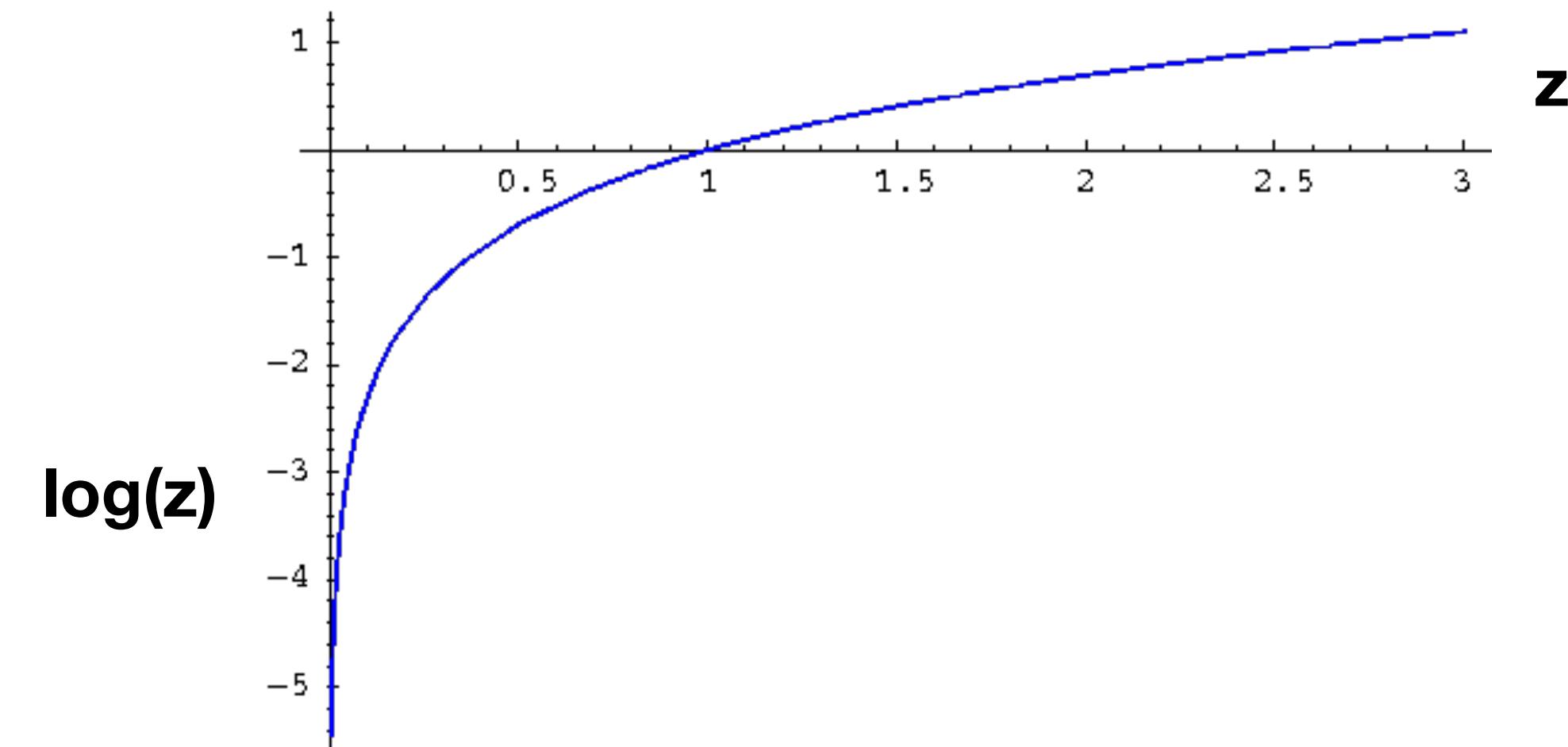
Hours (x)	Points	fail/pass
1	2	0
2	4	0
3	6	1
4	?	?



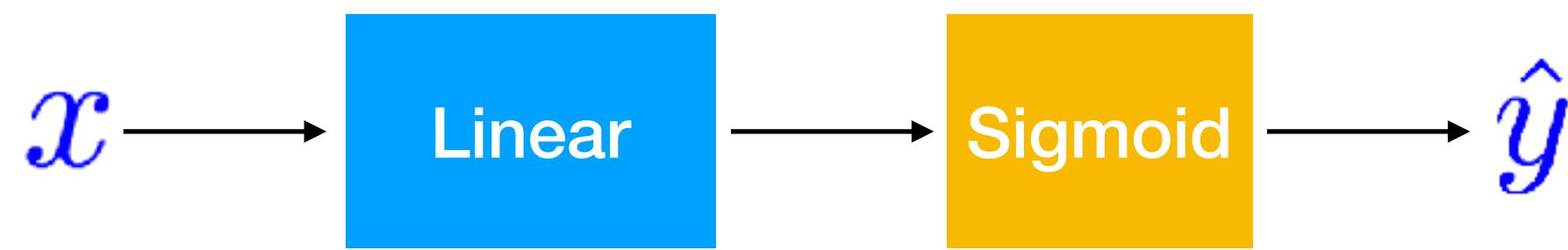
# (Binary) Cross Entropy Loss

$$loss = -\frac{1}{N} \sum_{n=1}^N y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n)$$

y	y_pred	loss
0	0.2	
0	0.8	
1	0.1	
1	0.9	



# Logistic regression



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

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



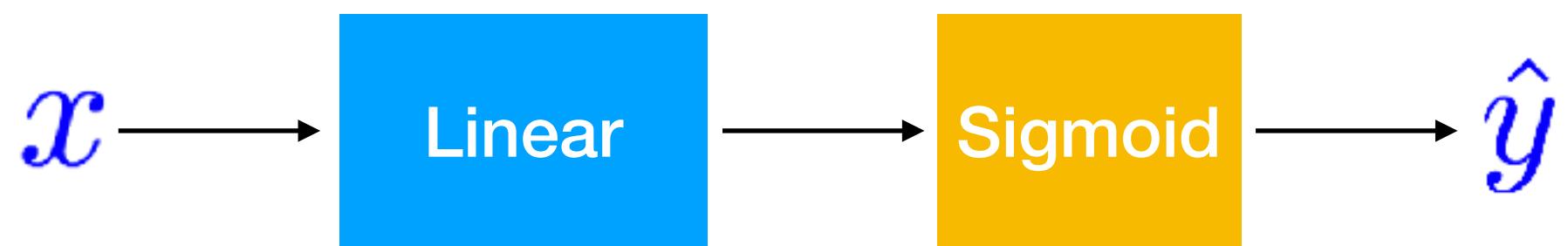
`class torch.nn.Sigmoid` [\[source\]](#)

Applies the element-wise function  $f(x) = 1/(1 + \exp(-x))$

```
class Model(torch.nn.Module):
    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.linear = torch.nn.Linear(1, 1) # One in and one out
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        y_pred = self.sigmoid(self.linear(x))
        return y_pred
```

# Logistic regression



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

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



[class torch.nn.Sigmoid](#) [source]

Applies the element-wise function  $f(x) = 1/(1 + \exp(-x))$

`class Model(torch.nn.Module):`

`def __init__(self):`

*In the constructor we instantiate two nn.Linear module*  
“““

`super(Model, self).__init__()`

`self.linear = torch.nn.Linear(1, 1) # One in and one out`

`self.sigmoid = torch.nn.Sigmoid()`

`def forward(self, x):`

*In the forward function we accept a Variable of input data and we must return a Variable of output data. We can use Modules defined in the constructor as well as arbitrary operators on Variables.*  
“““

`y_pred = self.sigmoid(self.linear(x))`  
`return y_pred`

$$loss = -\frac{1}{N} \sum_{n=1}^N y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n)$$



[class torch.nn.BCELoss\(weight=None, size\\_average=True\)](#) [source]

Creates a criterion that measures the Binary Cross Entropy between the target and the output:

$$loss(o, t) = -1/n \sum_i (t[i] * \log(o[i]) + (1 - t[i]) * \log(1 - o[i]))$$

`criterion = torch.nn.BCELoss(size_average=True)`

```

x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0], [4.0]]))
y_data = Variable(torch.Tensor([[0.], [0.], [1.], [1.]]))

class Model(torch.nn.Module):

    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.linear = torch.nn.Linear(1, 1) # One in and one out
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        y_pred = self.sigmoid(self.linear(x))
        return y_pred

# our model
model = Model()

# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.BCELoss(size_average=True)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

# After training
hour_var = Variable(torch.Tensor([[0.5]]))
print("predict (after training)", 0.5, model.forward(hour_var).data[0][0])
hour_var = Variable(torch.Tensor([[7.0]]))
print("predict (after training)", 7.0, model.forward(hour_var).data[0][0])

```

# Logistic regression



```
x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0], [4.0]]))  
y_data = Variable(torch.Tensor([[0.], [0.], [1.], [1.]]))
```

```
class Model(torch.nn.Module):
```

```
def __init__(self):  
    """  
In the constructor we instantiate two nn.Linear module  
    """  
    super(Model, self).__init__()  
    self.linear = torch.nn.Linear(1, 1) # One input, one output  
    self.sigmoid = torch.nn.Sigmoid()
```

```
def forward(self, x):
```

*In the forward function we accept a Variable of input a Variable of output data. We can use Modules defined well as arbitrary operators on Variables.*

```
y_pred = self.sigmoid(self.linear(x))  
return y_pred
```

```
# our model  
model = Model()
```

```
# Construct our loss function and an Optimizer. The call to
# in the SGD constructor will contain the learnable parameters
# nn.Linear modules which are members of the model.
criterion = torch.nn.BCELoss(size_average=True)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
```

```
# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)
```

```
# Compute and print loss
loss = criterion(y_pred, y_data)
print(epoch, loss.data[0])
```

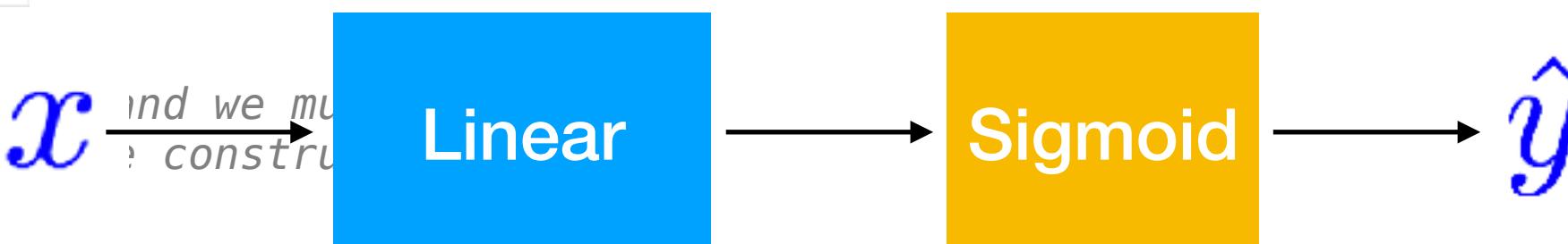
```
# Zero gradients, perform a backward pass, and update the weights.  
optimizer.zero_grad()  
loss.backward()  
optimizer.step()
```

```
# After training
hour_var = Variable(torch.Tensor([[0.5]]))
print("predict (after training)", 0.5, model.forward(hour_var).data[0][0])
hour_var = Variable(torch.Tensor([[7.0]]))
print("predict (after training)", 7.0, model.forward(hour_var).data[0][0])
```

# Logistic regression



# Design your model using class



## 2 Construct loss and optimizer (select from PyTorch API)

# 3 Training cycle (forward, backward, update)

```

x_data = Variable(torch.Tensor([[1.0], [2.0], [3.0], [4.0]]))
y_data = Variable(torch.Tensor([[0.], [0.], [1.], [1.]]))

class Model(torch.nn.Module):

    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.linear = torch.nn.Linear(1, 1) # One in and one out
        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        y_pred = self.sigmoid(self.linear(x))
        return y_pred

# our model
model = Model()

# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.BCELoss(size_average=True)
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Training loop
for epoch in range(500):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

# After training
hour_var = Variable(torch.Tensor([[0.5]]))
print("predict (after training)", 0.5, model.forward(hour_var).data[0][0])
hour_var = Variable(torch.Tensor([[7.0]]))
print("predict (after training)", 7.0, model.forward(hour_var).data[0][0])

```

# Logistic regression



```

0 1.6369143724441528
1 1.6119738817214966
2 1.5872894525527954
3 1.5628681182861328
4 1.5387169122695923
5 1.514843225479126
6 1.4912540912628174
7 1.467956781387329
8 1.4449583292007446
9 1.4222657680511475
10 1.3998862504959106
...
...
484 0.5245369672775269
485 0.5243527293205261
486 0.5241686701774597
487 0.5239847302436829
488 0.5238009095191956
489 0.5236172080039978
490 0.5234336256980896
491 0.523250162601471
492 0.5230668187141418
493 0.5228836536407471
494 0.5227005481719971
495 0.5225176215171814
496 0.5223348140716553
497 0.5221521258354187
498 0.5219695568084717
499 0.5217871069908142
predict (after training) 0.5 0.3970
predict (after training) 7.0 0.9398

```

Process finished with exit code 0

**WHAT**  
**NEXT!**



## Lecture 7: Wide and Deep

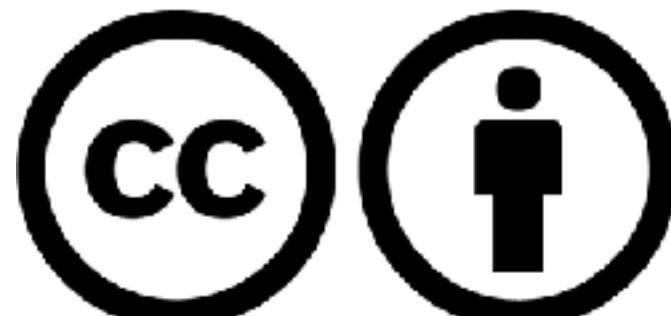
# ML/DL for Everyone with PYTORCH

## Lecture 7: Wide & Deep



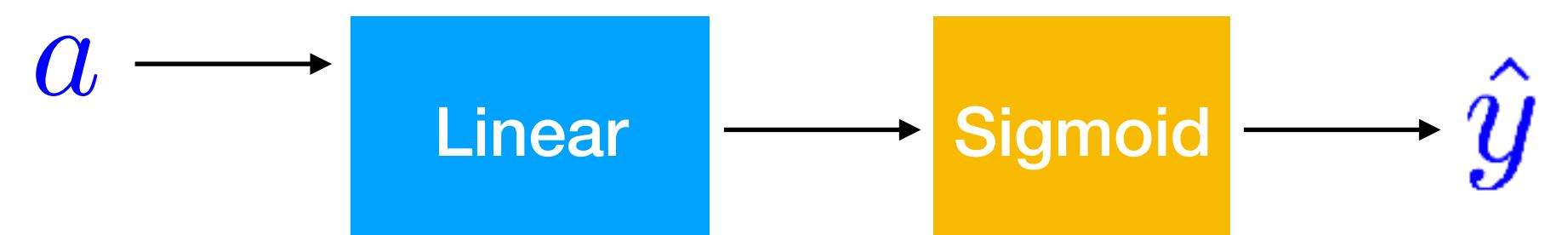
Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# HKUST PHD Program Application

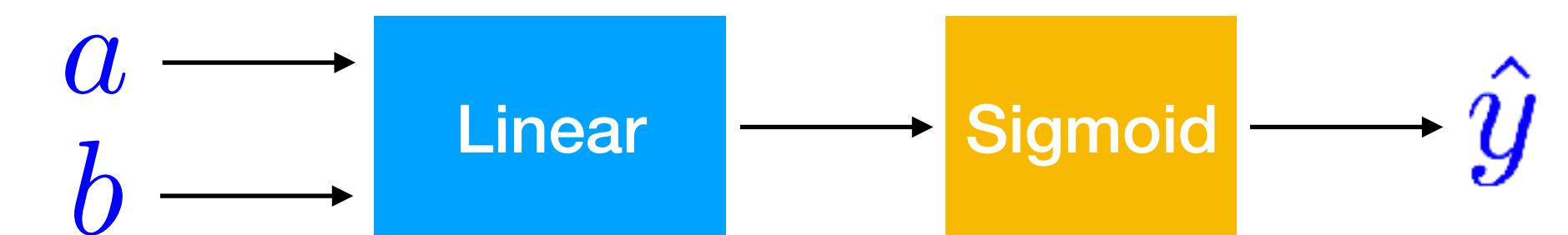
GPA (a)	Admission?
2.1	0
4.2	1
3.1	0
3.3	1



```
x_data = [[2.1],    y_data = [[0.0],
           [4.2],             [1.0],
           [3.1],             [0.0],
           [3.3]]            [1.0]]
```

# GPA enough? How about experience and others?

GPA (a)	Experience (b)	Admission?
2.1	0.1	0
4.2	0.8	1
3.1	0.9	0
3.3	0.2	1

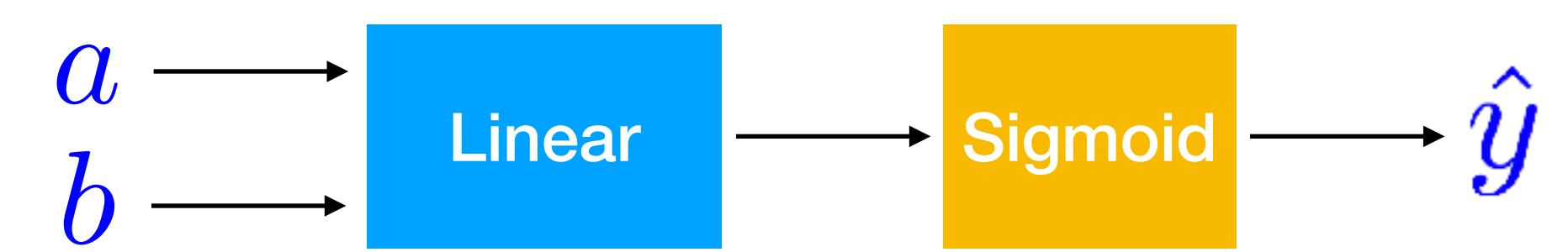


```
x_data = [[2.1, 0.1], [4.2, 0.8], [3.1, 0.9], [3.3, 0.2]]  
y_data = [[0.0], [1.0], [0.0], [1.0]]
```

# Matrix Multiplication

```
x_data = [[2.1, 0.1],  
          [4.2, 0.8],  
          [3.1, 0.9],  
          [3.3, 0.2]]
```

```
y_data = [[0.0],  
          [1.0],  
          [0.0],  
          [1.0]]
```



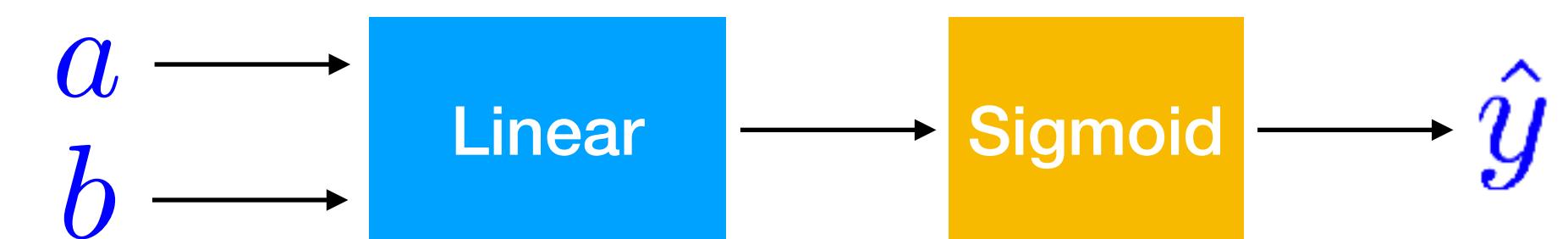
$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$

# Matrix Multiplication

```
x_data = [[2.1, 0.1],  
          [4.2, 0.8],  
          [3.1, 0.9],  
          [3.3, 0.2]]
```

```
y_data = [[0.0],  
          [1.0],  
          [0.0],  
          [1.0]]
```

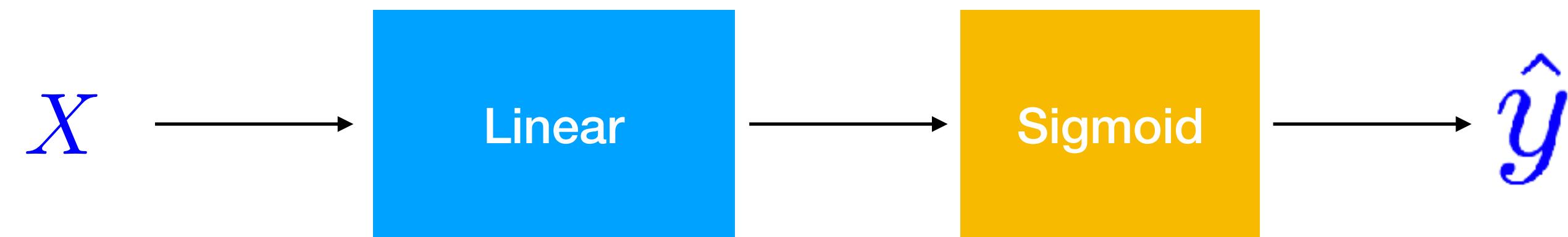
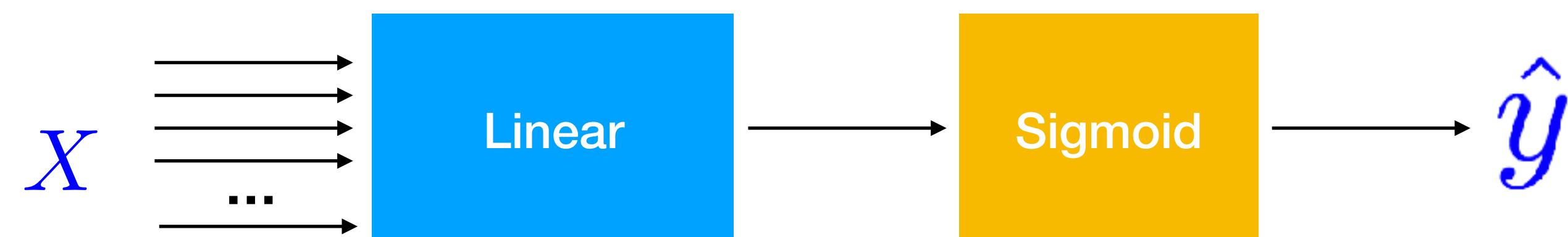
$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$



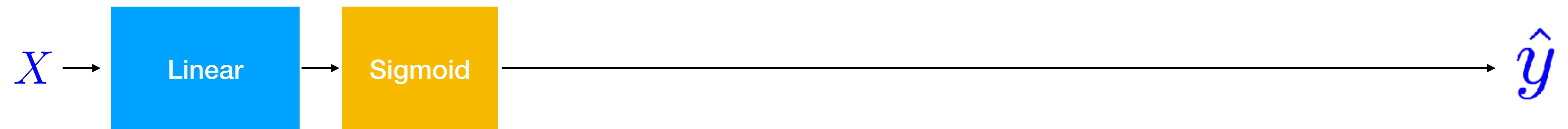
$$XW = \hat{Y}$$

```
linear = torch.nn.Linear(2, 1)  
y_pred = linear(x_data)
```

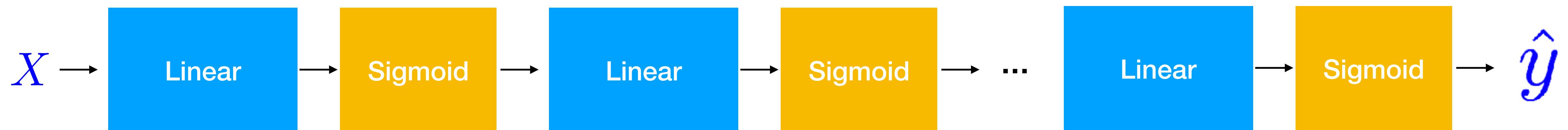
# Go Wide!



# Go Deep!



# Go Deep!

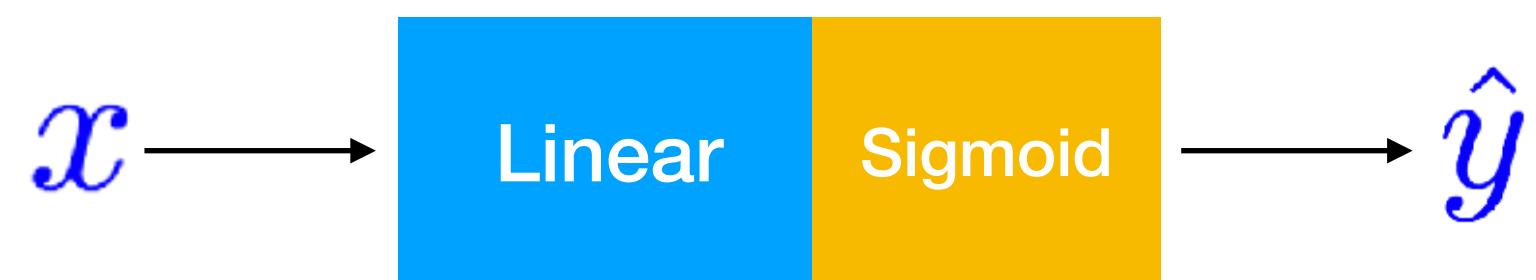


```
sigmoid = torch.nn.Sigmoid()

l1 = torch.nn.Linear(2, 2)
l2 = torch.nn.Linear(2, 2)
l3 = torch.nn.Linear(2, 1)

out1    = sigmoid(l1(x_data))
out2    = sigmoid(l2(out1))
y_pred = sigmoid(l3(out2))
```

# Sigmoid Activation Functions



## Non-linear Activations

ReLU  
ReLU6  
ELU  
SELU  
PReLU  
LeakyReLU  
Threshold  
Hardtanh  
Sigmoid  
Tanh  
LogSigmoid  
Softplus  
Softshrink  
Softsign  
Tanhshrink  
Softmin  
Softmax  
Softmax2d  
LogSoftmax

# Activation Functions



Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = \max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^z)$	Multi-layer Neural Networks	

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(<http://sebastianraschka.com>)



# Classifying Diabetes



-0.411765	0.165829	0.213115	0	0	-0.23696	-0.894962	-0.7	1
-0.647059	-0.21608	-0.180328	-0.353535	-0.791962	-0.0760059	-0.854825	-0.833333	0
0.176471	0.155779	0	0	0	0.052161	-0.952178	-0.733333	1
-0.764706	0.979899	0.147541	-0.0909091	0.283688	-0.0909091	-0.931682	0.0666667	0
-0.0588235	0.256281	0.57377	0	0	0	-0.868488	0.1	0
-0.529412	0.105528	0.508197	0	0	0.120715	-0.903501	-0.7	1
0.176471	0.688442	0.213115	0	0	0.132638	-0.608027	-0.566667	0
0.176471	0.396985	0.311475	0	0	-0.19225	0.163962	0.2	1

```
xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)

x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
y_data = Variable(torch.from_numpy(xy[:, [-1]]))

print(x_data.data.shape) # torch.Size([759, 8])
print(y_data.data.shape) # torch.Size([759, 1])
```

# Wide & Deep



```
class Model(torch.nn.Module):

    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """

        super(Model, self).__init__()
        self.l1 = torch.nn.Linear(8, 6)
        self.l2 = torch.nn.Linear(6, 4)
        self.l3 = torch.nn.Linear(4, 1)

        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """

        out1 = self.sigmoid(self.l1(x))
        out2 = self.sigmoid(self.l2(out1))
        y_pred = self.sigmoid(self.l3(out2))
        return y_pred
```

```

xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
y_data = Variable(torch.from_numpy(xy[:, [-1]]))

class Model(torch.nn.Module):

    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.l1 = torch.nn.Linear(8, 6)
        self.l2 = torch.nn.Linear(6, 4)
        self.l3 = torch.nn.Linear(4, 1)

        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        out1 = self.sigmoid(self.l1(x))
        out2 = self.sigmoid(self.l2(out1))
        y_pred = self.sigmoid(self.l3(out2))
        return y_pred

# our model
model = Model()

# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters of the two
# nn.Linear modules which are members of the model.
criterion = torch.nn.BCELoss(size_average=True)
optimizer = torch.optim.SGD(model.parameters(), lr=0.1)

# Training loop
for epoch in range(100):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

```

# Classifying Diabetes



1

## Design your model using class

2

## Construct loss and optimizer (select from PyTorch API)

3

## Training cycle (forward, backward, update)



**WHAT**  
**NEXT?**

A woman with dark hair tied back in a ponytail, wearing a dark blazer over a light blue shirt, is shown from the side and slightly from behind. She has her right hand raised to her ear, fingers forming a funnel shape to listen more closely. Her gaze is directed upwards and to the right. In the upper right corner of the slide, there is a graphic of a lit lightbulb with a grey outline and a yellow glow.

## Lecture 8: DataLoader

# ML/DL for Everyone with PYTORCH

## Lecture 8: DataLoader



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# Manual data feed



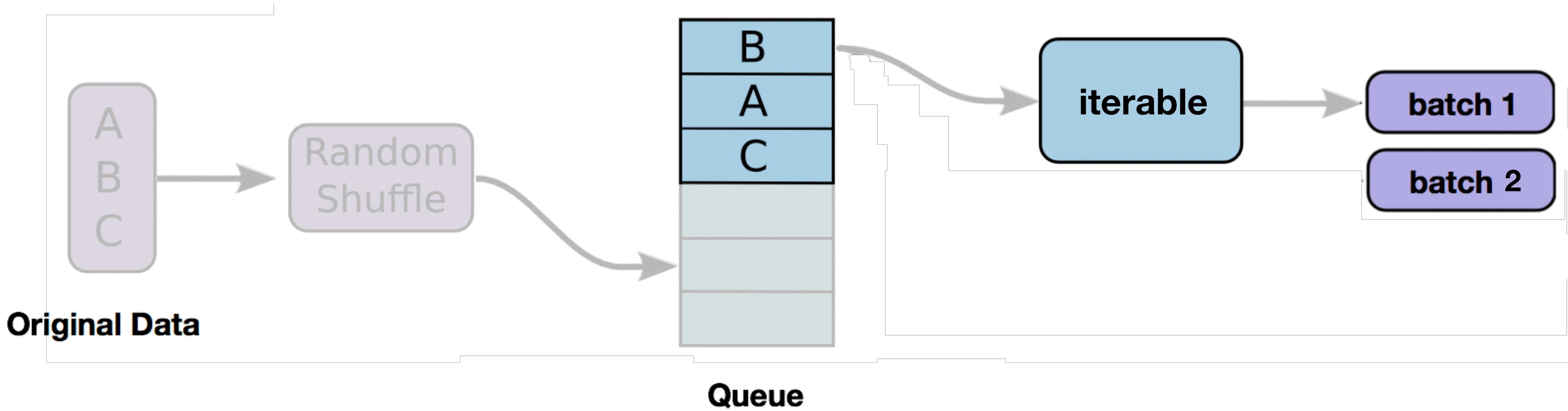
```
xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
y_data = Variable(torch.from_numpy(xy[:, [-1]]))

...
# Training loop
for epoch in range(100):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

# DataLoader



```
for i, data in enumerate(train_loader, 0):
    # get the inputs
    inputs, labels = data

    # wrap them in Variable
    inputs, labels = Variable(inputs), Variable(labels)

    # Run your training process
    print(epoch, i, "inputs", inputs.data, "labels", labels.data)
```

# Custom DataLoader

```
class DiabetesDataset(Dataset):
    """ Diabetes dataset."""

    # Initialize your data, download, etc.
    def __init__(self):

        ① download, read data, etc.

    def __getitem__(self, index):
        return

    def __len__(self):
        return

dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                         batch_size=32,
                         shuffle=True,
                         num_workers=2)
```

② return one item on the index

③ return the data length

# Custom DataLoader

```
class DiabetesDataset(Dataset):
    """ Diabetes dataset."""

    # Initialize your data, download, etc.
    def __init__(self):
        xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
        self.len = xy.shape[0]
        self.x_data = torch.from_numpy(xy[:, 0:-1])
        self.y_data = torch.from_numpy(xy[:, [-1]])

    def __getitem__(self, index):
        return self.x_data[index], self.y_data[index]

    def __len__(self):
        return self.len

dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                         batch_size=32,
                         shuffle=True,
                         num_workers=2)
```



# Classifying Diabetes

```
# References
# https://github.com/yunjey/pytorch-tutorial/blob/master/tutorials/01-basics/pytorch_basics/main.py
# http://pytorch.org/tutorials/beginner/data_loading_tutorial.html#dataset-class

import torch
import numpy as np
from torch.autograd import Variable
from torch.utils.data import Dataset, DataLoader

class DiabetesDataset(Dataset):
    """ Diabetes dataset. """

    # Initialize your data, download, etc.
    def __init__(self):
        xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
        self.len = xy.shape[0]
        self.x_data = torch.from_numpy(xy[:, 0:-1])
        self.y_data = torch.from_numpy(xy[:, [-1]])

    def __getitem__(self, index):
        return self.x_data[index], self.y_data[index]

    def __len__(self):
        return self.len

dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                         batch_size=32,
                         shuffle=True,
                         num_workers=2)
```

```
class Model(torch.nn.Module):

    def __init__(self):
        """
        In the constructor we instantiate two nn.Linear module
        """
        super(Model, self).__init__()
        self.l1 = torch.nn.Linear(8, 6)
        self.l2 = torch.nn.Linear(6, 4)
        self.l3 = torch.nn.Linear(4, 1)

        self.sigmoid = torch.nn.Sigmoid()

    def forward(self, x):
        """
        In the forward function we accept a Variable of input data and we must return
        a Variable of output data. We can use Modules defined in the constructor as
        well as arbitrary operators on Variables.
        """
        out1 = self.sigmoid(self.l1(x))
        out2 = self.sigmoid(self.l2(out1))
        y_pred = self.sigmoid(self.l3(out2))
        return y_pred

    # our model
    model = Model()

    # Construct our loss function and an Optimizer. The call to model.parameters()
    # in the SGD constructor will contain the learnable parameters of the two
    # nn.Linear modules which are members of the model.
    criterion = torch.nn.BCELoss(size_average=True)
    optimizer = torch.optim.SGD(model.parameters(), lr=0.1)

    # Training loop
    for epoch in range(2):
        for i, data in enumerate(train_loader, 0):
            # get the inputs
            inputs, labels = data

            # wrap them in Variable
            inputs, labels = Variable(inputs), Variable(labels)

            # Forward pass: Compute predicted y by passing x to the model
            y_pred = model(inputs)

            # Compute and print loss
            loss = criterion(y_pred, labels)
            print(epoch, i, loss.data[0])

            # Zero gradients, perform a backward pass, and update the weights.
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
```

# The following dataset loaders are available

- MNIST and FashionMNIST
- COCO (Captioning and Detection)
- LSUN Classification
- ImageFolder
- Imagenet-12
- CIFAR10 and CIFAR100
- STL10
- SVHN
- PhotoTour

# MNIST dataset loading

```
# MNIST Dataset
train_dataset = datasets.MNIST(root='./data/',
                                train=True,
                                transform=transforms.ToTensor(),
                                download=True)

test_dataset = datasets.MNIST(root='./data/',
                               train=False,
                               transform=transforms.ToTensor())

# Data Loader (Input Pipeline)
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                            batch_size=batch_size,
                                            shuffle=True)

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                           batch_size=batch_size,
                                           shuffle=False)

for batch_idx, (data, target) in enumerate(train_loader):
    data, target = Variable(data), Variable(target)
    ...
```



# More dataset loaders are available

- MNIST and FashionMNIST
- COCO (Captioning and Detection)
- LSUN Classification
- ImageFolder
- Imagenet-12
- CIFAR10 and CIFAR100
- STL10
- SVHN
- PhotoTour



**WHAT**  
**NEXT?**

A woman with dark hair tied back in a ponytail, wearing a dark blue blazer over a light blue shirt, is shown in profile facing right. She has her right hand raised to her ear, as if listening intently or trying to hear something. In the upper right corner of the image, there is a graphic element consisting of the words "WHAT" in orange and "NEXT?" in blue, followed by a gray outline of a lit lightbulb.

# Lecture 9:

# Softmax Classifier

# ML/DL for Everyone with PYTORCH

## Lecture 9: Softmax Classifier



Call for Comments

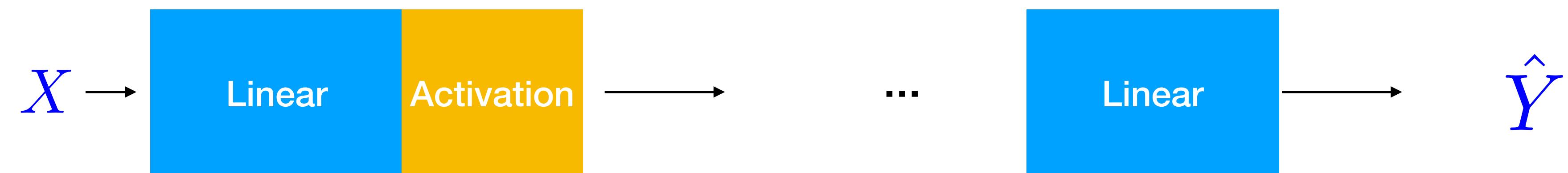
Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



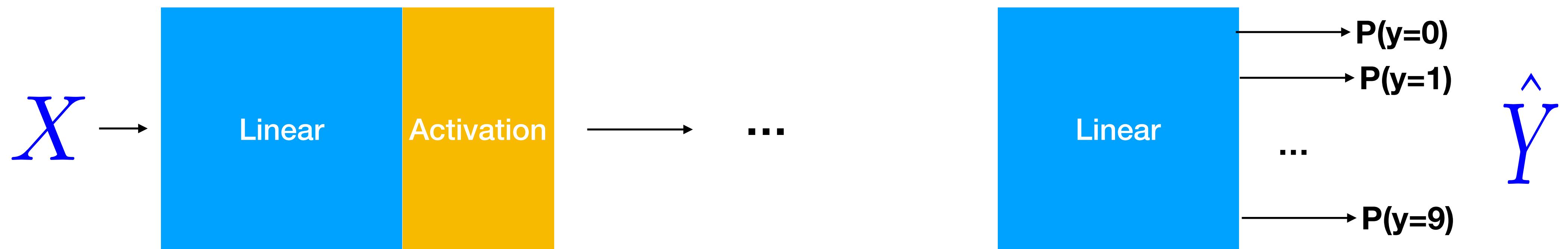
# MNIST: 10 labels



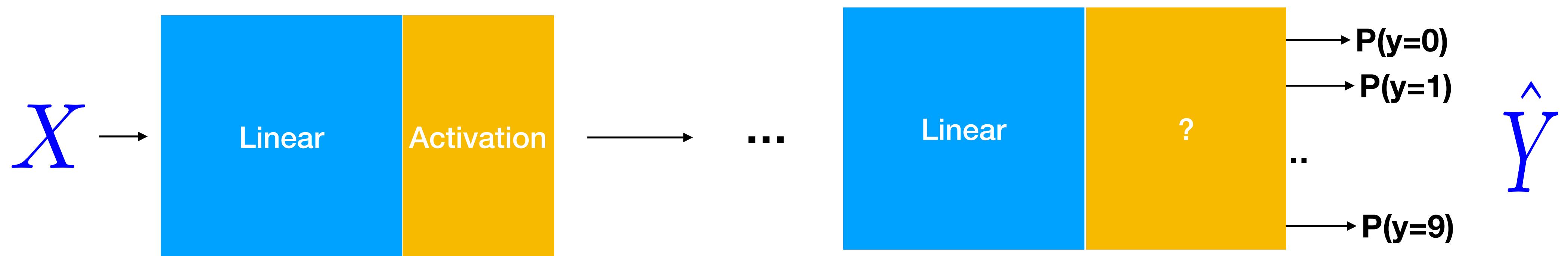
# 10 labels: 10 outputs



# 10 labels: 10 outputs

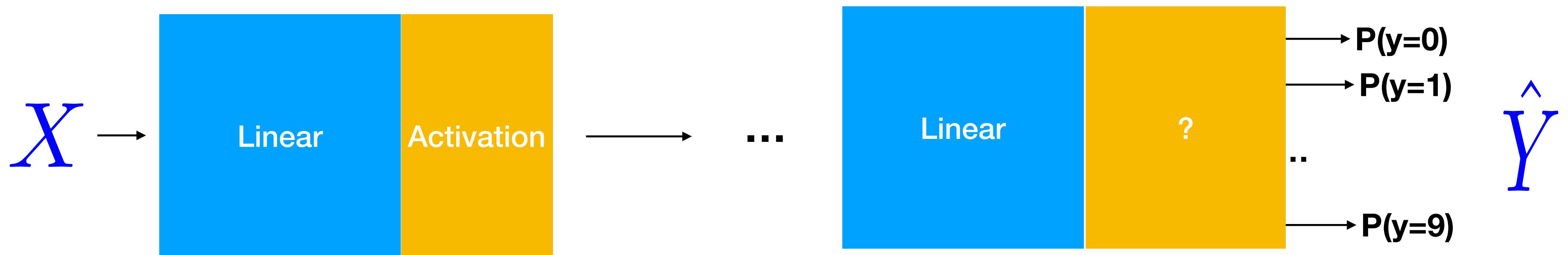


# 10 outputs



$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$

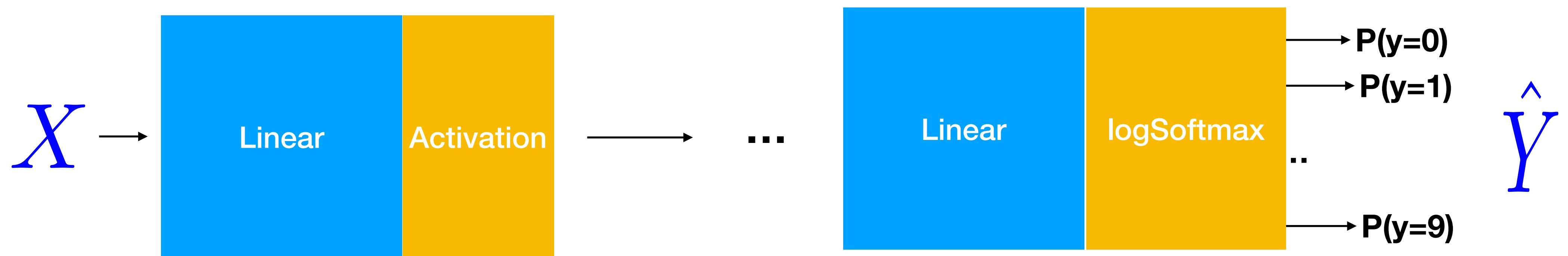
# 10 outputs



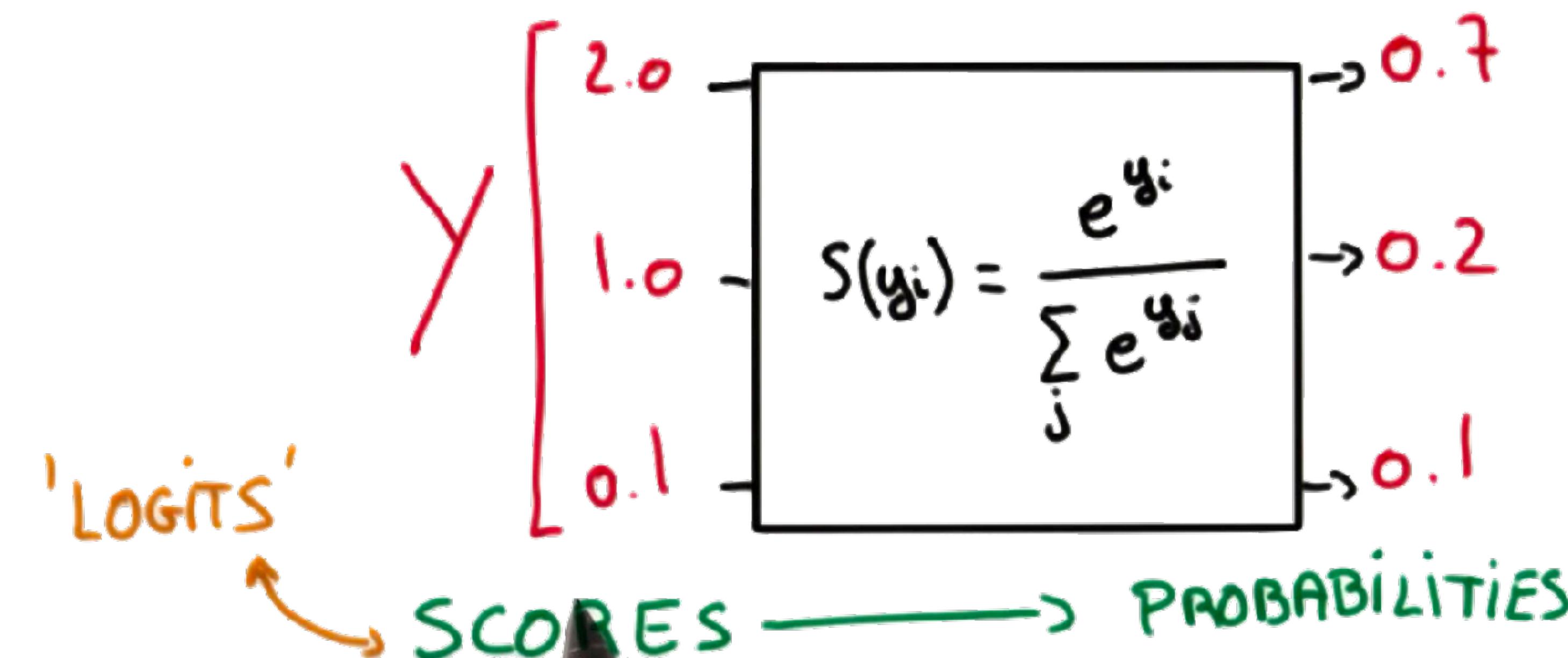
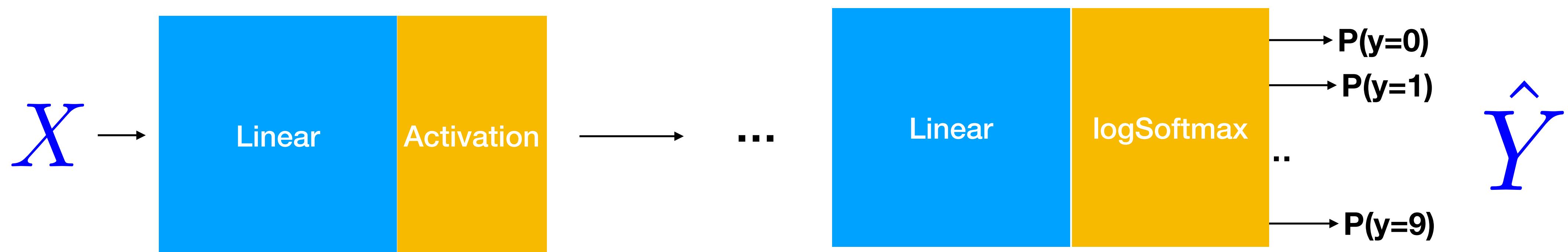
$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}}_{w \in \mathbb{R}^{2 \times 1}} = \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$

$$\underbrace{\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \dots & \dots \\ a_n & b_n \end{bmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{bmatrix} ? \end{bmatrix}}_{w \in \mathbb{R}^{N \times ?}} = y \in \mathbb{R}^{N \times 10}$$

# (log)Softmax



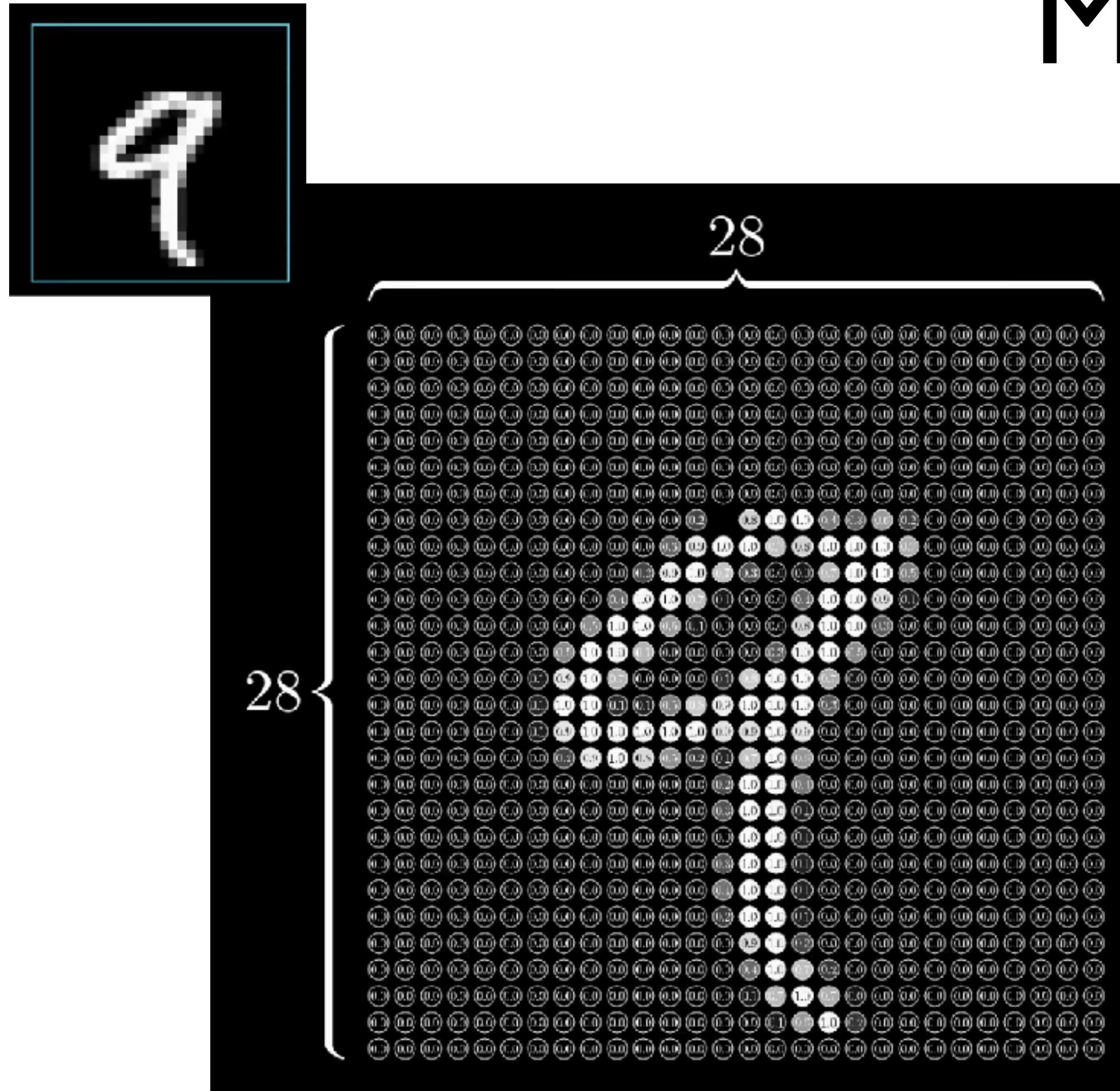
# Softmax



# LogSoftmax with NLLLoss

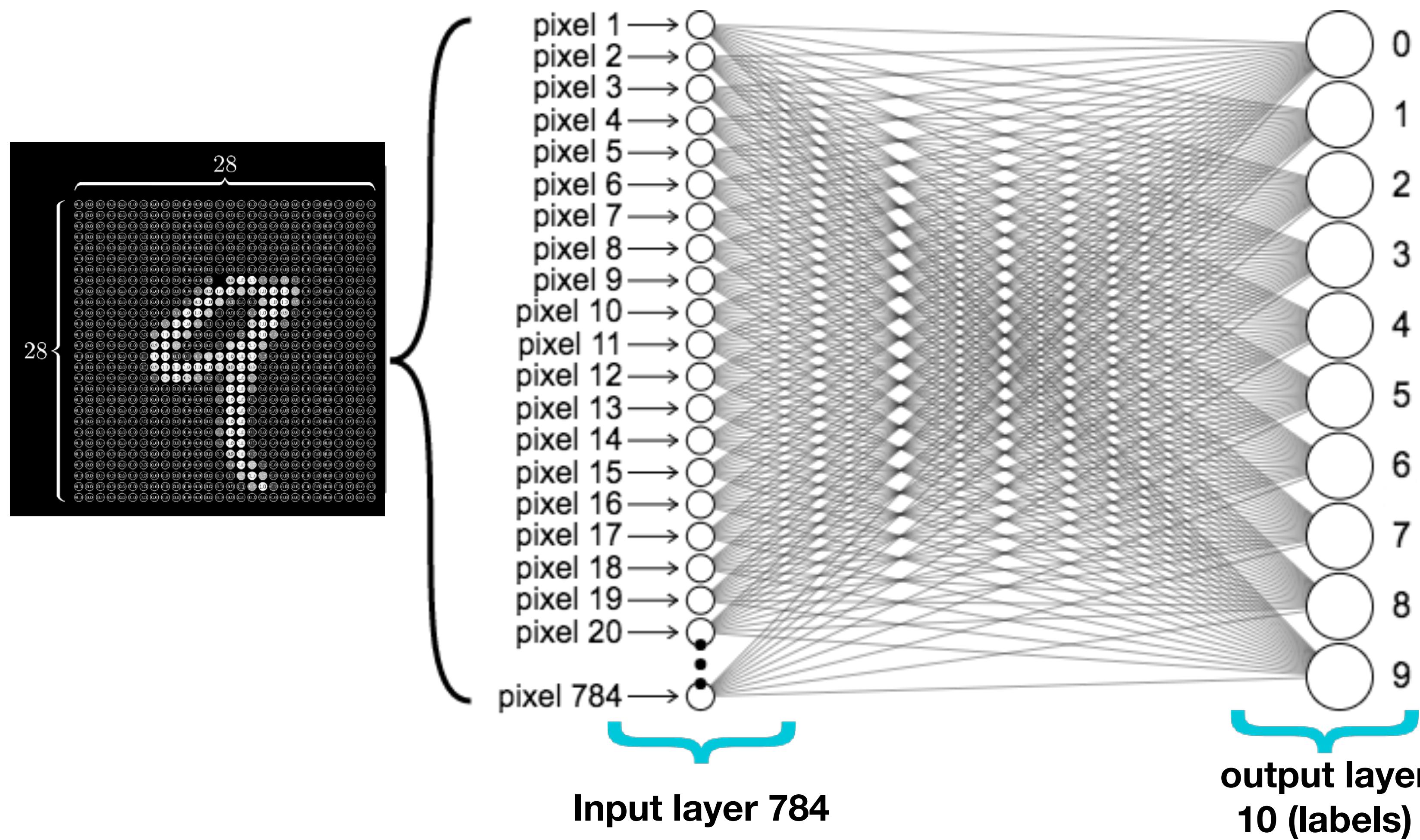
```
>>> m = nn.LogSoftmax()  
>>> loss = nn.NLLLoss()  
>>> # input is of size nBatch x nClasses = 3 x 5  
>>> input = autograd.Variable(torch.randn(3, 5), requires_grad=True)  
>>> # each element in target has to have 0 <= value < nclasses  
>>> target = autograd.Variable(torch.LongTensor([1, 0, 4]))  
>>> output = loss(m(input), target)  
>>> output.backward()
```

# MNIST input

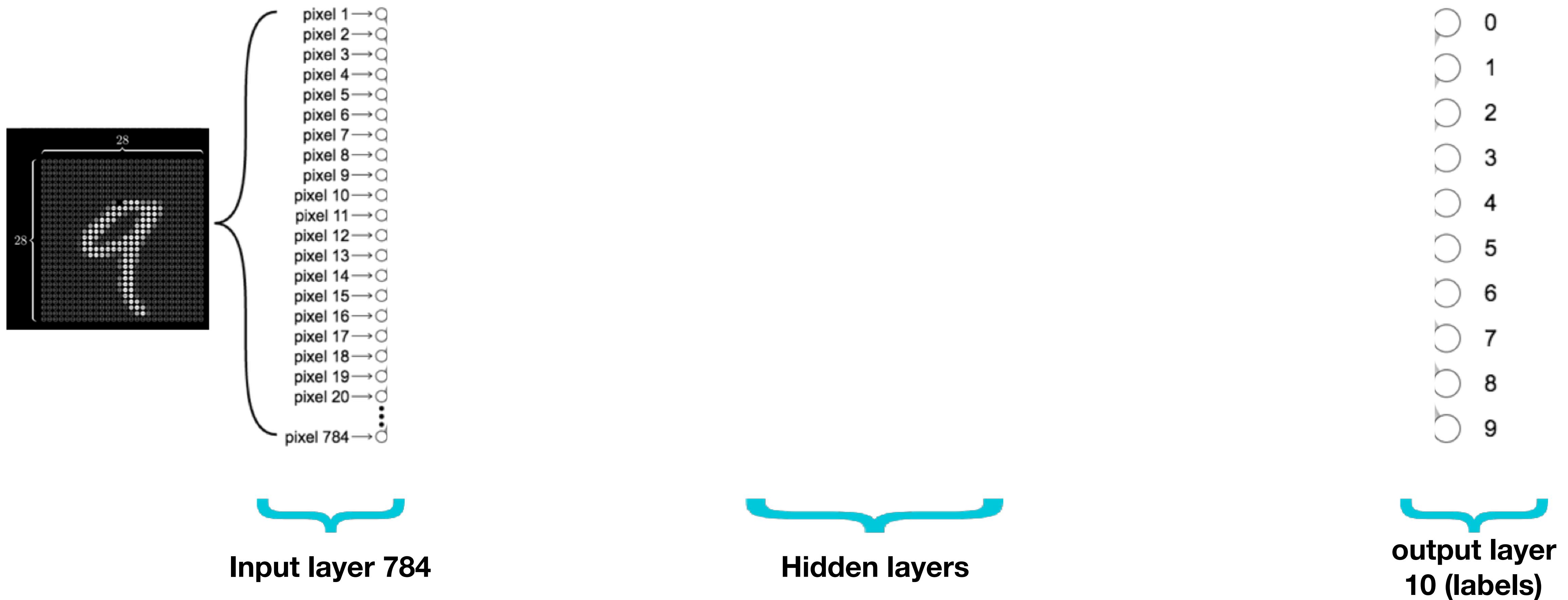


**28x28 pixels = 748**

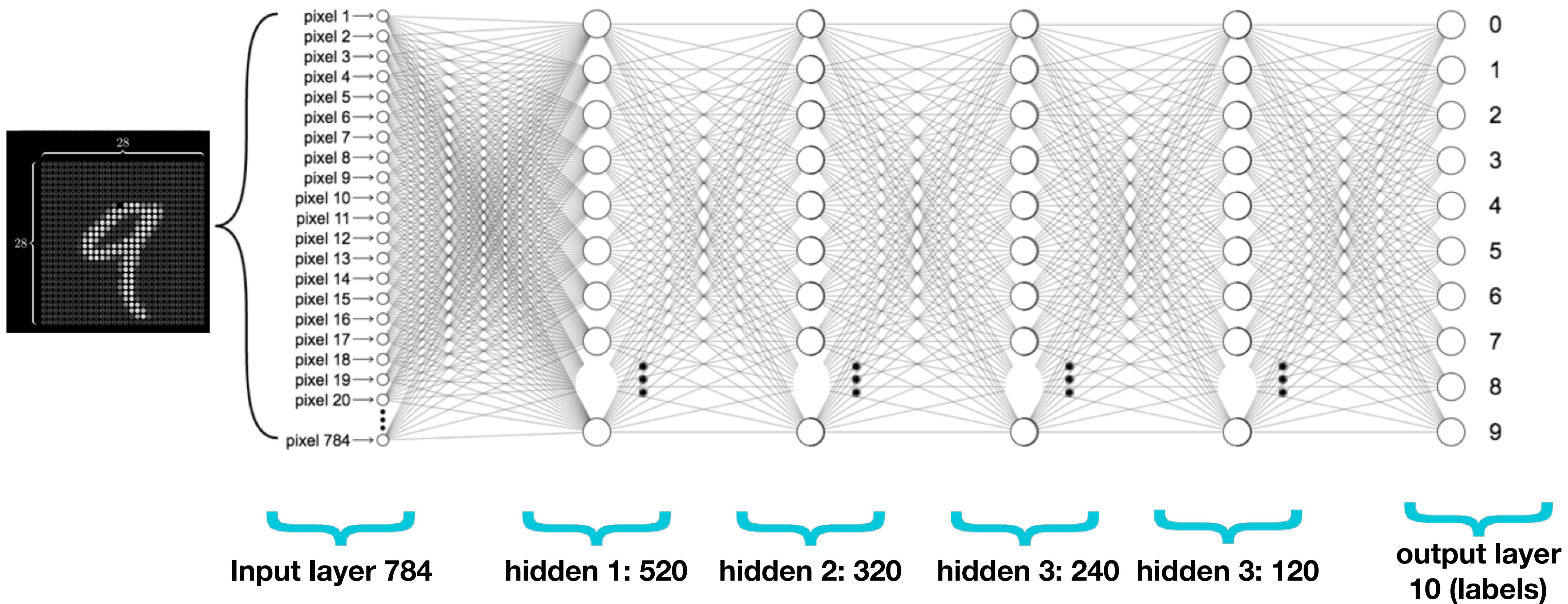
# MNIST Network



# MNIST Network

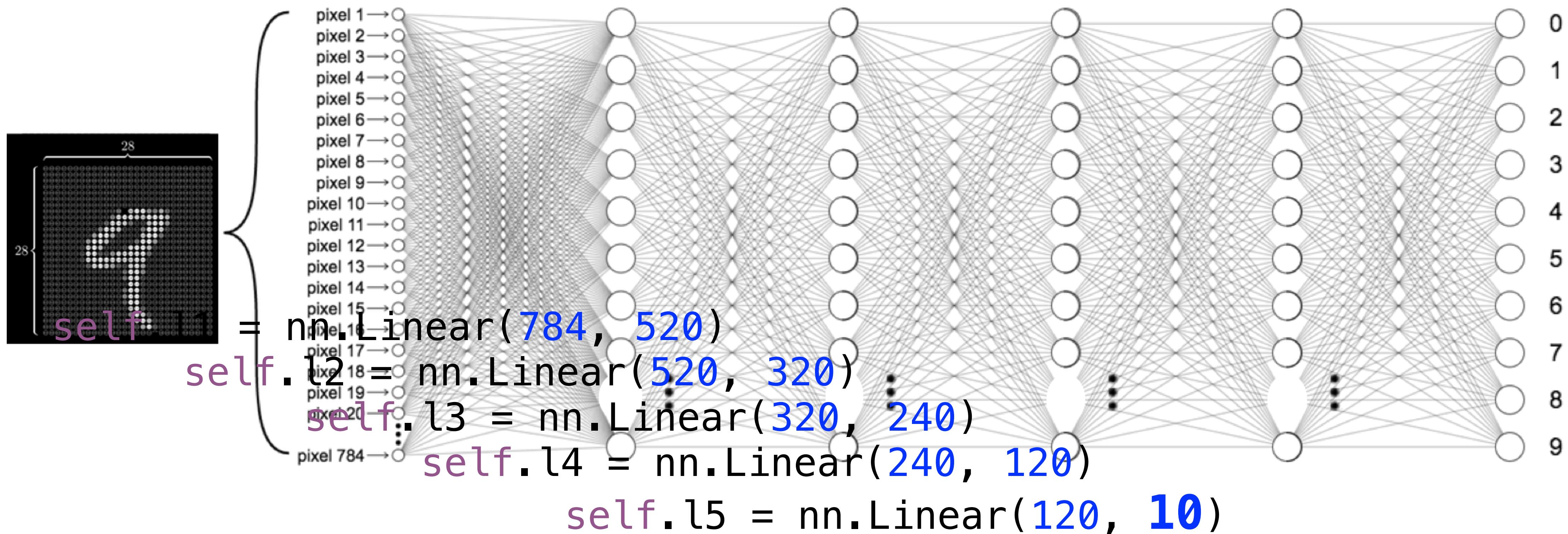


# MNIST Network





# MNIST Network



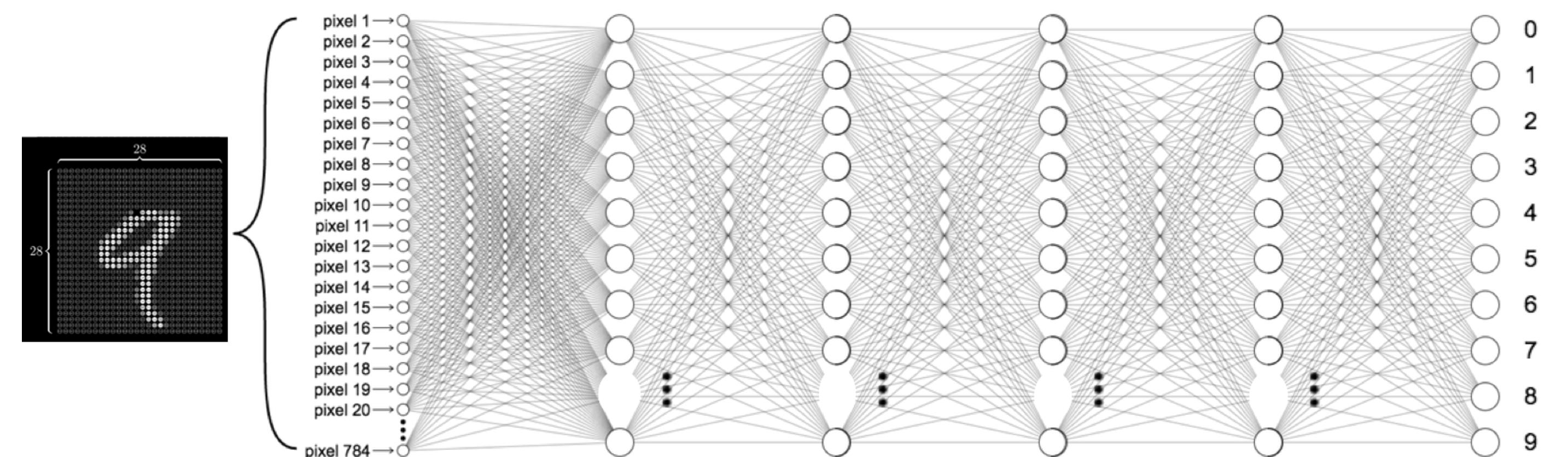
# Softmax & NLL loss



```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        self.l1 = nn.Linear(784, 520)
        self.l2 = nn.Linear(520, 320)
        self.l3 = nn.Linear(320, 240)
        self.l4 = nn.Linear(240, 120)
        self.l5 = nn.Linear(120, 10)

    def forward(self, x):
        # Flatten the data (n, 1, 28, 28) -> (n, 784)
        x = x.view(-1, 784)
        x = F.relu(self.l1(x))
        x = F.relu(self.l2(x))
        x = F.relu(self.l3(x))
        x = F.relu(self.l4(x))
        x = F.relu(self.l5(x))
        return F.log_softmax(x)
```



# Softmax & NLL loss



```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        self.l1 = nn.Linear(784, 520)
        self.l2 = nn.Linear(520, 320)
        self.l3 = nn.Linear(320, 240)
        self.l4 = nn.Linear(240, 120)
        self.l5 = nn.Linear(120, 10)

    def forward(self, x):
        # Flatten the data (n, 1, 28, 28) -> (n, 784)
        x = x.view(-1, 784)
        x = F.relu(self.l1(x))
        x = F.relu(self.l2(x))
        x = F.relu(self.l3(x))
        x = F.relu(self.l4(x))
        x = F.relu(self.l5(x))
        return F.log_softmax(x)
```

```
for batch_idx, (data, target) in enumerate(train_loader):
    data, target = Variable(data), Variable(target)
    optimizer.zero_grad()
    output = model(data)
    loss = F.nll_loss(output, target)
    loss.backward()
    optimizer.step()
```

```

# Training settings
batch_size = 64

train_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=True, download=True, transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))]))
),
batch_size=batch_size, shuffle=True)
test_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=False, transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))]))
),
batch_size=batch_size, shuffle=True)

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.l1 = nn.Linear(784, 520)
        self.l2 = nn.Linear(520, 320)
        self.l3 = nn.Linear(320, 240)
        self.l4 = nn.Linear(240, 120)
        self.l5 = nn.Linear(120, 10)

    def forward(self, x):
        x = x.view(-1, 784) # Flatten the data (n, 1, 28, 28)-> (n, 784)
        x = F.relu(self.l1(x))
        x = F.relu(self.l2(x))
        x = F.relu(self.l3(x))
        x = F.relu(self.l4(x))
        x = F.relu(self.l5(x))
        return F.log_softmax(x)

model = Net()
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.5)

def train(epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = Variable(data), Variable(target)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % 10 == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.data[0]))

```

# MNIST Softmax



```

# Training settings
batch_size = 64

train_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=True, download=True, transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))]))
),
batch_size=batch_size, shuffle=True)
test_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=False, transform=transforms.Compose([
        transforms.ToTensor(),
        transforms.Normalize((0.1307,), (0.3081,))]))
),
batch_size=batch_size, shuffle=True)

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.l1 = nn.Linear(784, 520)
        self.l2 = nn.Linear(520, 320)
        self.l3 = nn.Linear(320, 240)
        self.l4 = nn.Linear(240, 120)
        self.l5 = nn.Linear(120, 10)

    def forward(self, x):
        x = x.view(-1, 784) # Flatten the data (n, 1, 28, 28)-> (n, 784)
        x = F.relu(self.l1(x))
        x = F.relu(self.l2(x))
        x = F.relu(self.l3(x))
        x = F.relu(self.l4(x))
        x = F.relu(self.l5(x))
        return F.log_softmax(x)

model = Net()
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.5)

def train(epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = Variable(data), Variable(target)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % 10 == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.data[0]))

```



# Accuracy?





```
train_loader = torch.utils.data.DataLoader(  
    datasets.MNIST('../data', train=True, download=True, transform=transforms.Compose([  
        transforms.ToTensor(),  
        transforms.Normalize((0.1307,), (0.3081,))  
    ]),  
    batch_size=batch_size, shuffle=True)  
test_loader = torch.utils.data.DataLoader(  
    datasets.MNIST('../data', train=False, transform=transforms.Compose([  
        transforms.ToTensor(),  
        transforms.Normalize((0.1307,), (0.3081,))  
    ]),  
    batch_size=batch_size, shuffle=True)
```

```
def train(epoch):
```

```
    ...
```

```
def test():  
    model.eval()  
    test_loss = 0  
    correct = 0  
    for data, target in test_loader:  
        data, target = Variable(data, volatile=True), Variable(target)  
        output = model(data)  
        # sum up batch loss  
        test_loss += F.nll_loss(output, target, size_average=False).data[0]  
        # get the index of the max log-probability  
        pred = output.data.max(1, keepdim=True)[1]  
        correct += pred.eq(target.data.view_as(pred)).cpu().sum()  
  
    test_loss /= len(test_loader.dataset)  
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(  
        test_loss, correct, len(test_loader.dataset),  
        100. * correct / len(test_loader.dataset)))
```

```

def train(epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = Variable(data), Variable(target)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % 10 == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.data[0]))
    def test():
        model.eval()
        test_loss = 0
        correct = 0
        for data, target in test_loader:
            data, target = Variable(data, volatile=True), Variable(target)
            output = model(data)
            # sum up batch loss
            test_loss += F.nll_loss(output, target, size_average=False).data[0]
            # get the index of the max log-probability
            pred = output.data.max(1, keepdim=True)[1]
            correct += pred.eq(target.data.view_as(pred)).cpu().sum()

        test_loss /= len(test_loader.dataset)
        print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{}
              ({:.0f}%)\n'.
              format(test_loss, correct, len(test_loader.dataset),
              100. * correct / len(test_loader.dataset)))
    for epoch in range(1, 10):
        train(epoch)
        test()

```

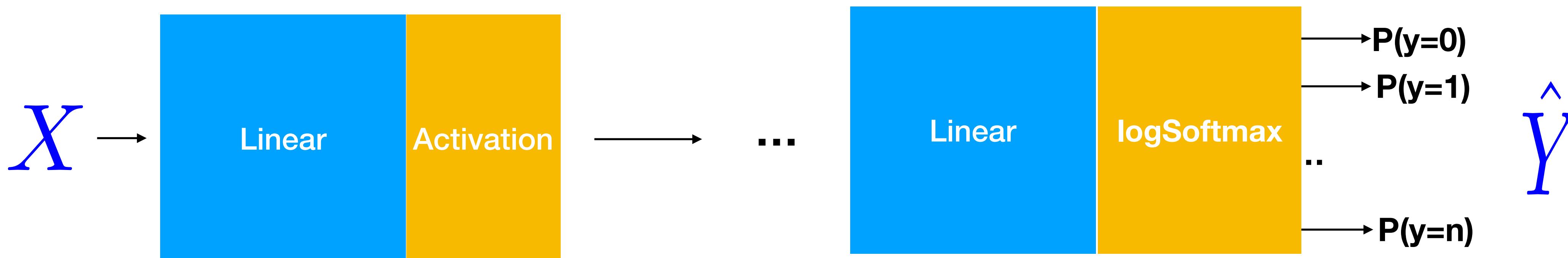


# Accuracy?

Train Epoch: 9 [46720/60000 (78%)]	Loss: 0.790513
Train Epoch: 9 [47360/60000 (79%)]	Loss: 0.335216
Train Epoch: 9 [48000/60000 (80%)]	Loss: 0.675538
Train Epoch: 9 [48640/60000 (81%)]	Loss: 0.359488
Train Epoch: 9 [49280/60000 (82%)]	Loss: 0.276906
Train Epoch: 9 [49920/60000 (83%)]	Loss: 0.412109
Train Epoch: 9 [50560/60000 (84%)]	Loss: 0.556780
Train Epoch: 9 [51200/60000 (85%)]	Loss: 0.332712
Train Epoch: 9 [51840/60000 (86%)]	Loss: 0.514475
Train Epoch: 9 [52480/60000 (87%)]	Loss: 0.515686
Train Epoch: 9 [53120/60000 (88%)]	Loss: 0.462904
Train Epoch: 9 [53760/60000 (90%)]	Loss: 0.571690
Train Epoch: 9 [54400/60000 (91%)]	Loss: 0.446774
Train Epoch: 9 [55040/60000 (92%)]	Loss: 0.441682
Train Epoch: 9 [55680/60000 (93%)]	Loss: 0.438245
Train Epoch: 9 [56320/60000 (94%)]	Loss: 0.470004
Train Epoch: 9 [56960/60000 (95%)]	Loss: 0.474394
Train Epoch: 9 [57600/60000 (96%)]	Loss: 0.527718
Train Epoch: 9 [58240/60000 (97%)]	Loss: 0.614899
Train Epoch: 9 [58880/60000 (98%)]	Loss: 0.512663
Train Epoch: 9 [59520/60000 (99%)]	Loss: 0.474054

Test set: Average loss: 0.5403, Accuracy: 7820/10000 (78%)

# Multiple label prediction? No problem! Use logSoftmax + NLLLoss



With NLLLoss

**WHAT**  
**NEXT**?



## Lecture 9: CNN

# ML/DL for Everyone with PYTORCH

## Lecture 10: CNN



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# ML/DL for Everyone with PYTORCH

## Lecture 11: RNN



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>



# ML/DL for Everyone with PYTORCH

## Lecture 12: NSML



Call for Comments

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>





Many more  
fun networks



- [Language Model \(RNN-LM\)](#)
- [Generative Adversarial Network](#)
- [Image Captioning \(CNN-RNN\)](#)
- [Deep Convolutional GAN \(DCGAN\)](#)
- [Variational Auto-Encoder](#)
- [Neural Style Transfer](#)
- ...

# Upcoming topics (TBA)

- [Wasserstein GAN](#)
  - [OptNet: Differentiable Optimization as a Layer in Neural Networks](#)
  - [Paying More Attention to Attention: Improving the Performance of Convolutional Neural Networks via Attention Transfer](#)
  - [Wide ResNet model in PyTorch](#)
  - [Task-based End-to-end Model Learning](#)
  - [An End-to-End Trainable Neural Network for Image-based Sequence Recognition and Its Application to Scene Text Recognition](#)
  - [Scaling the Scattering Transform: Deep Hybrid Networks](#)
  - [Adversarial Generator-Encoder Network](#)
  - [Conditional Similarity Networks](#)
  - [Multi-style Generative Network for Real-time Transfer](#)
  - [Image-to-Image Translation with Conditional Adversarial Networks](#)
  - [Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks](#)
  - [Inferring and Executing Programs for Visual Reasoning](#)
  - [On the Effects of Batch and Weight Normalization in Generative Adversarial Networks](#)
  - [Train longer, generalize better: closing the generalization gap in large batch training of neural networks](#)
  - [Neural Message Passing for Quantum Chemistry](#)
  - [DiracNets: Training Very Deep Neural Networks Without Skip-Connections](#)
  - [Deal or No Deal? End-to-End Learning for Negotiation Dialogues](#)
- ...
- ...
- ...

# References

- <http://pytorch.org/>
- <https://github.com/pytorch/examples>
- <https://github.com/ritchieng/the-incredible-pytorch>
- <https://github.com/yunjey/pytorch-tutorial>
- <https://github.com/znxlwm/pytorch-generative-model-collections>
- <https://www.facebook.com/groups/TensorFlowKR/> (in Korean)
- <https://www.facebook.com/groups/PyTorchKR/> (in Korean)

# ML/DL for Everyone with PYTORCH

TBA

Sung Kim <[hunkim+ml@gmail.com](mailto:hunkim+ml@gmail.com)> HKUST  
Code: <https://github.com/hunkim/PyTorchZeroToAll>

