AI and Deep Learning

Linear Regression & Back-propagation

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Agenda

- Neuron and Regression
- Loss/Error/Cost Function
- Learning and Updating Weights
- Gradient/Slope
- Computation Graph
- Forward Propagation
- Backpropagation


NAT GEO
WILD

“

After spending most of the ocean life, salmons go back home(river) where they were born.

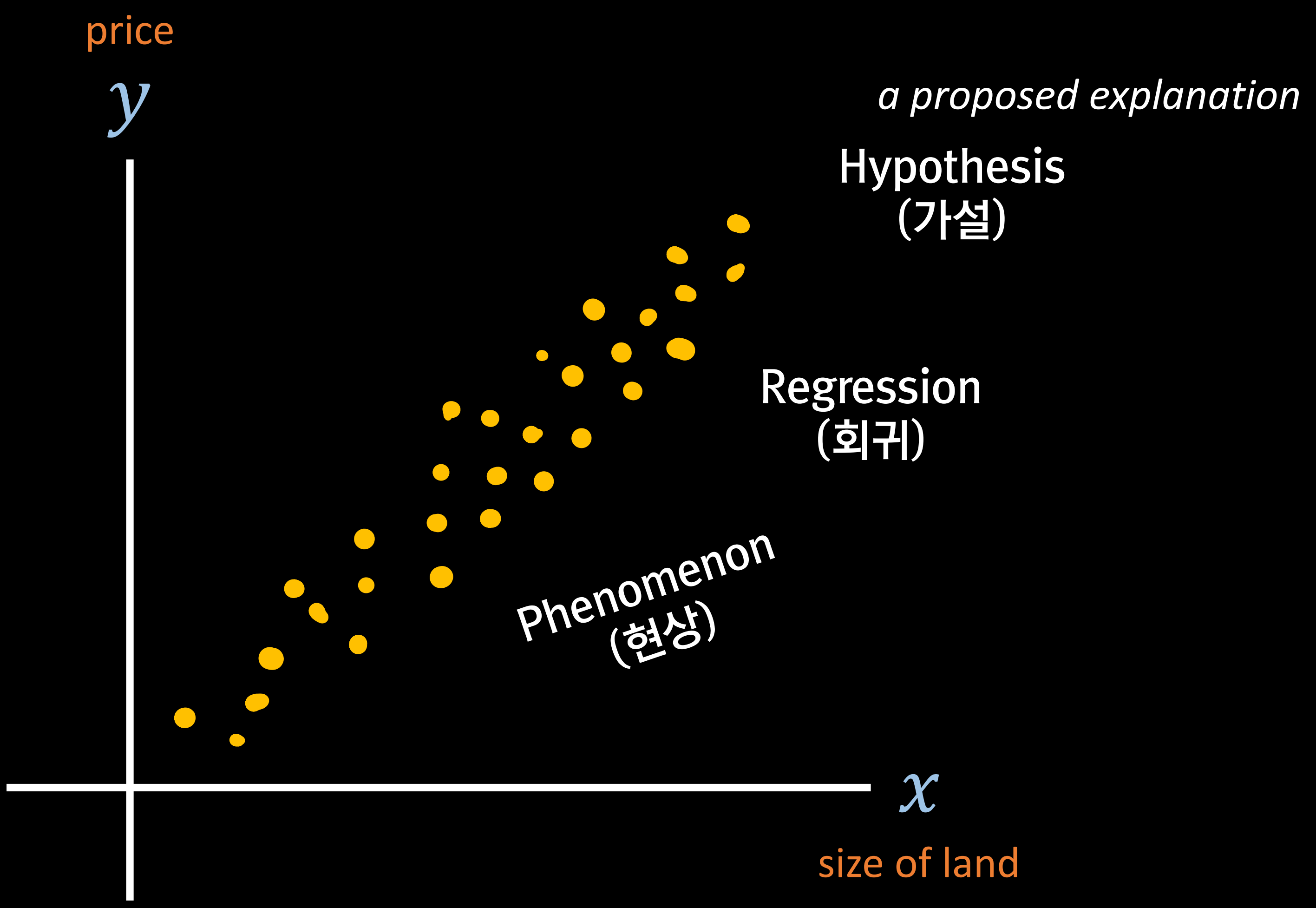
Regression (회귀)

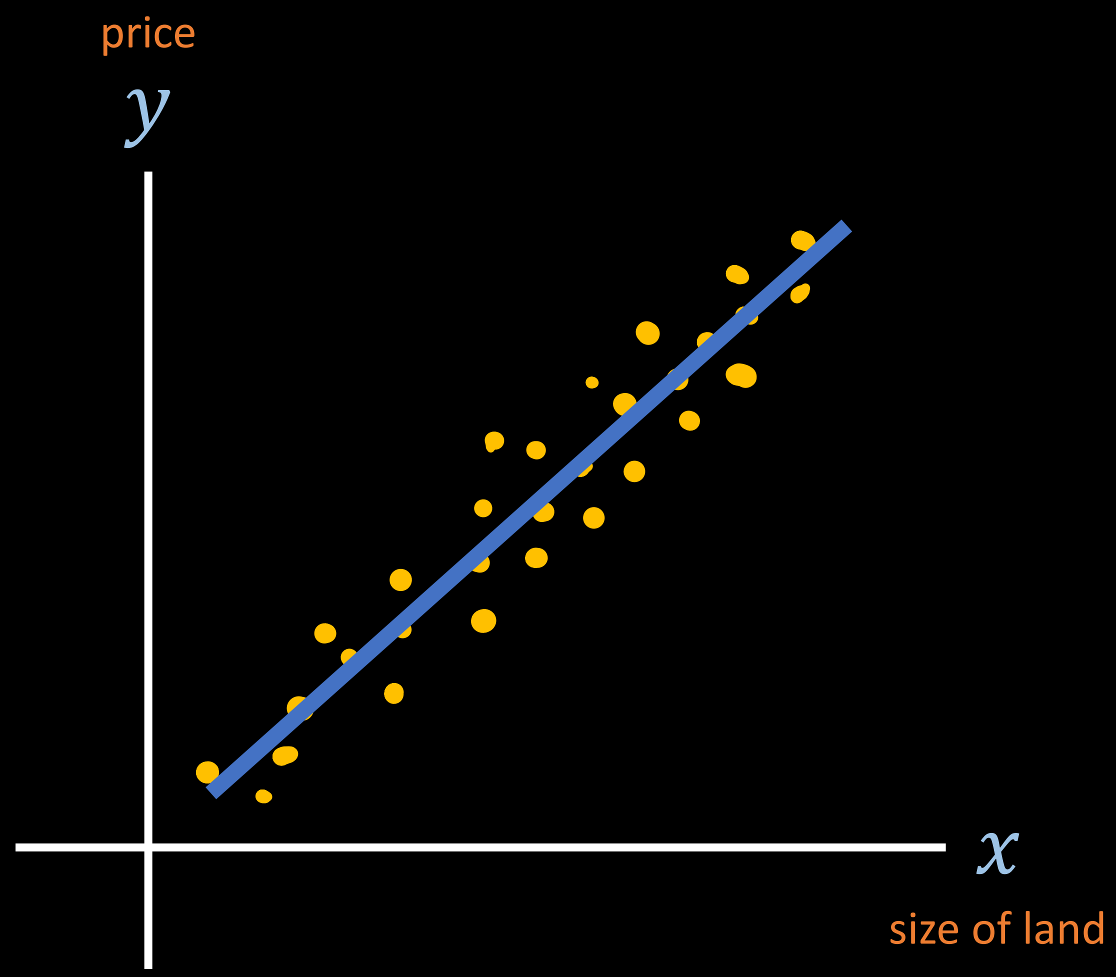
- Going back again.
- To describe a natural phenomena
- A term frequently used in anthropology(인류학) to present a natural tendency

What is ‘a proposed explanation for a phenomenon’?

Regression (회귀)

- Something (statistical measure) to determine the relationship between one dependent variable (usually denoted by Y, 종속변수)and a series of other independent variables X 독립변수 .


price
y
a proposed explanation
Hypothesis
(가설)
Regression
(회귀)
Phenomenon
(현상)
x
size of land


price
y
x
size of land

An example of Regression

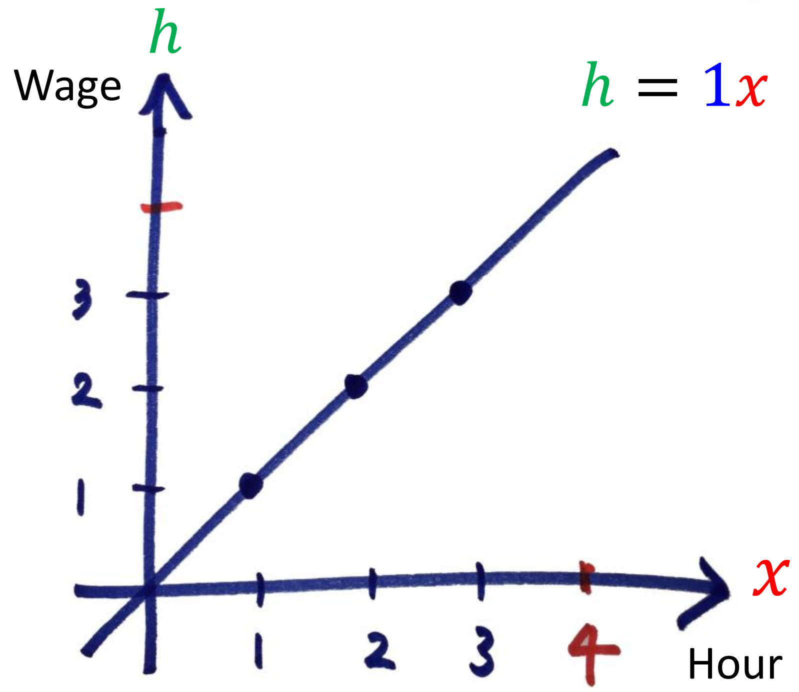
Lab
Linear Regression

using desmos

www.desmos.com

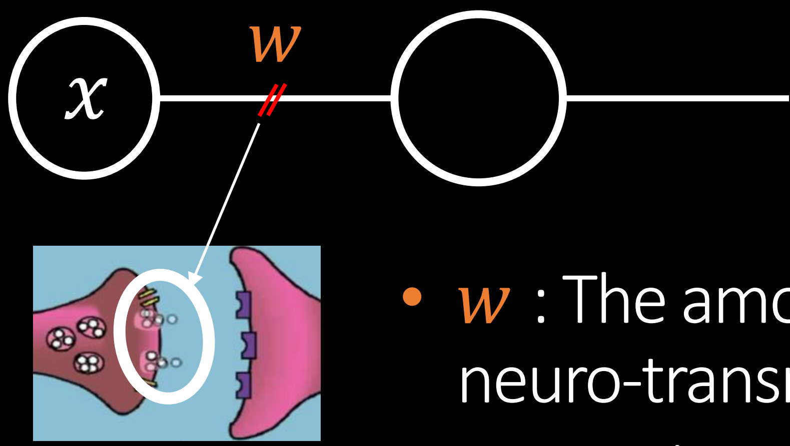
1. Draw a point(data) (1, 1)
2. Add (2, 2), (-1, -1), (-2, -2)
3. $h = x$
4. $h = 2x$
5. $h = wx$ (**rotation**)
6. Move all of the points by adding 1 to y
7. $h = wx + 1$ (**shifting**)
8. $h = wx + b$ (**rotation** and **shifting**)

www.desmos.com



$$h = wx$$

Neuron and regression



$h = wx$

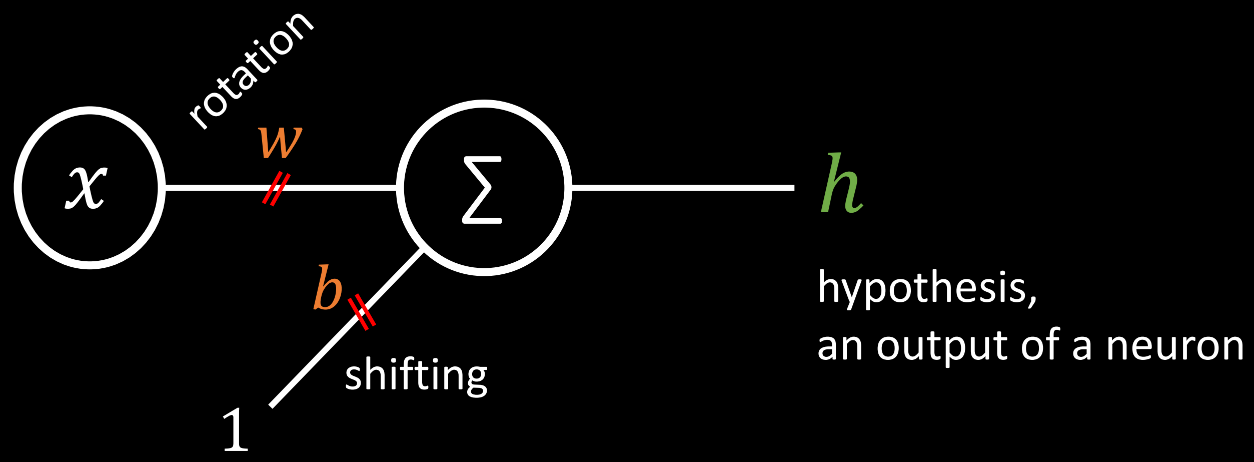
- w : The amount of neuro-transmitter
- if large / if small / if not exists (**rotation**)
- A neuron represents a simple linear regression

Hypothesis

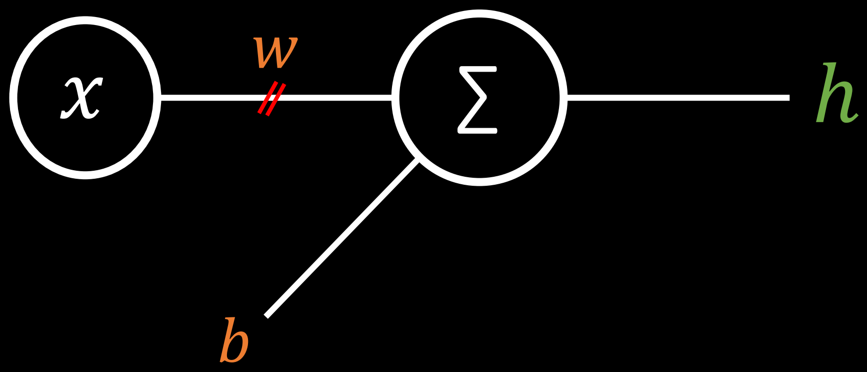
$$h = wx$$
$$h = wx + b$$

- An answer by a neuron
- $h$ypothesis : a proposed explanation for a phenomenon (regression).
- Not proved yet, but it can represents the regression correctly after updating w.
- b? for better linear regression

The role of w and b



$$h = wx + b$$



x
w
Σ
h
b

Linear Regression

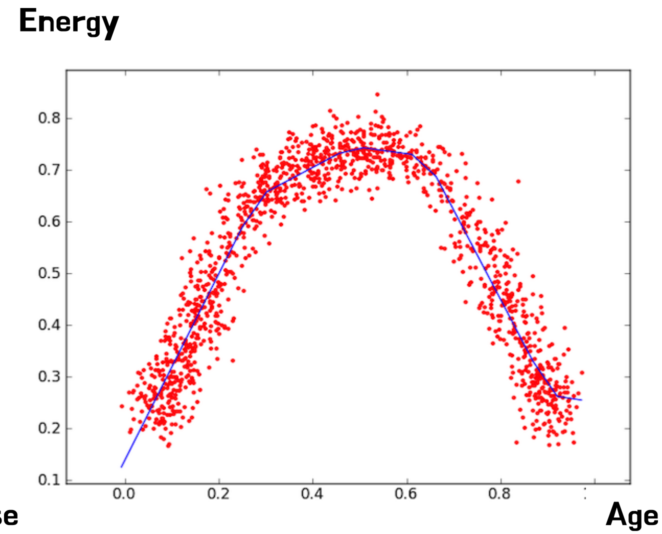
A regression expressed by linear combination of coefficients

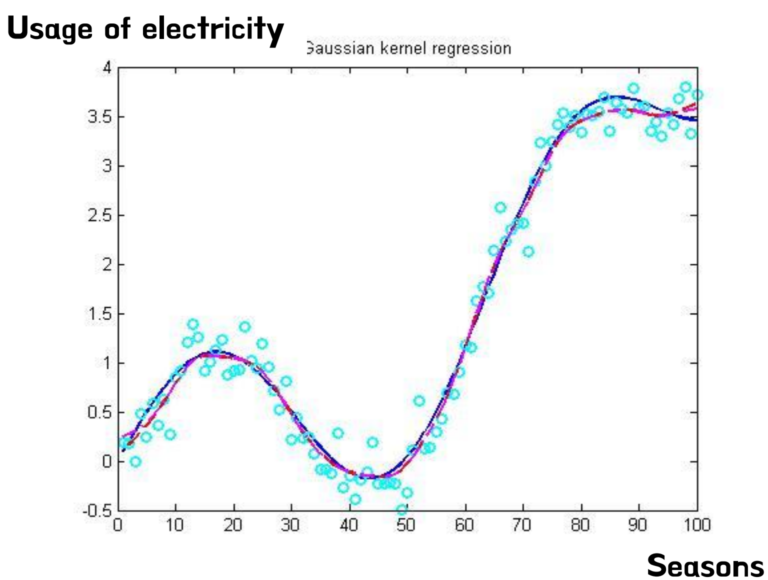
$$h = wx + b$$

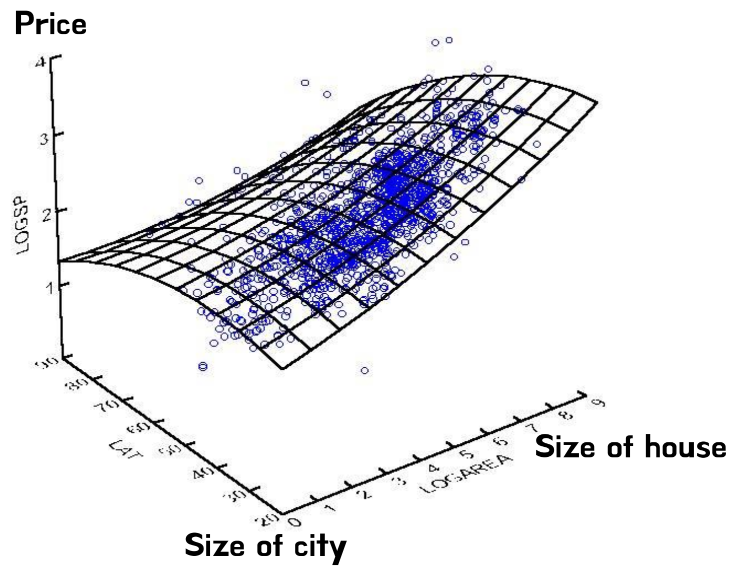
linear?
non-linear?

$$h = \frac{b}{w}x$$

Examples of Linear Regression







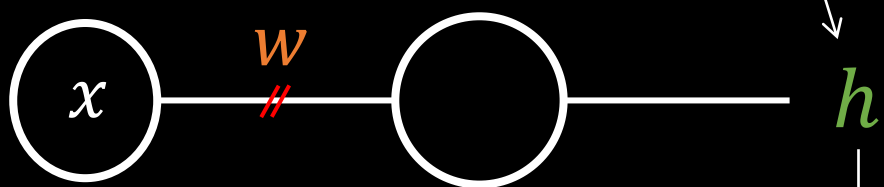
How to learn (update w, b)

- Scolding or blaming the neuron if its answer is wrong.
- The neuron gets stress and automatically updates w and b to answer well next time so that the error(difference, stress) decreases.
- How can we measure the error?

Error function

loss function
difference function
stress function

answer by a neuron



ground truth

$$E = |w \cdot x - y|$$

Why absolute?

ex) age difference

Error function

The error is the difference between a neuron's answer and it's ground truth.

$$E = |hypothesis - y|$$

$$E = |w \cdot x - y|$$

a.csv

‘1 hour, then 1 USD’ $\longrightarrow$

x_i	y_i
1	1

data, experience

$$E = |w \cdot 1 - 1|$$

Supervised Learning

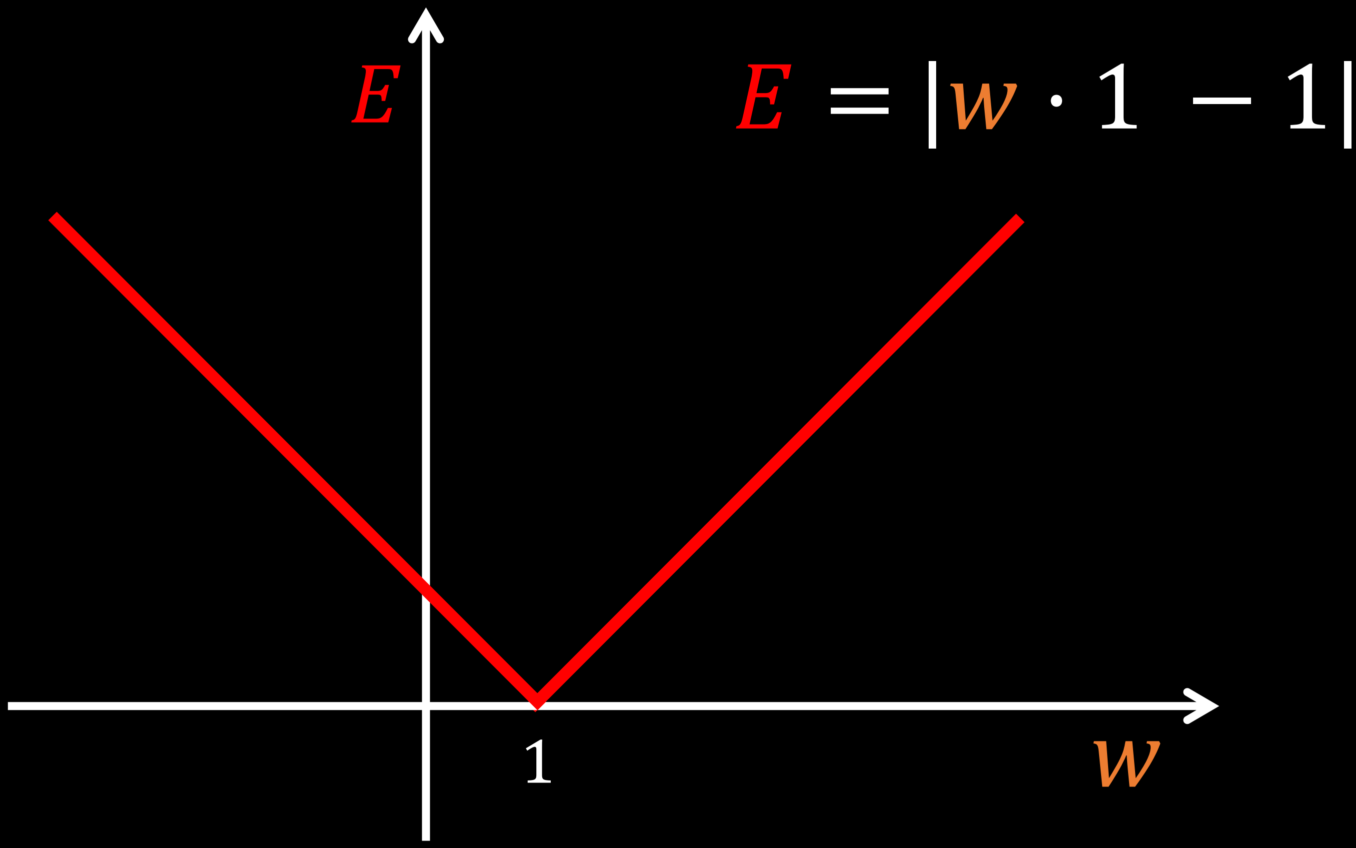
지도학습

www.desmos.com

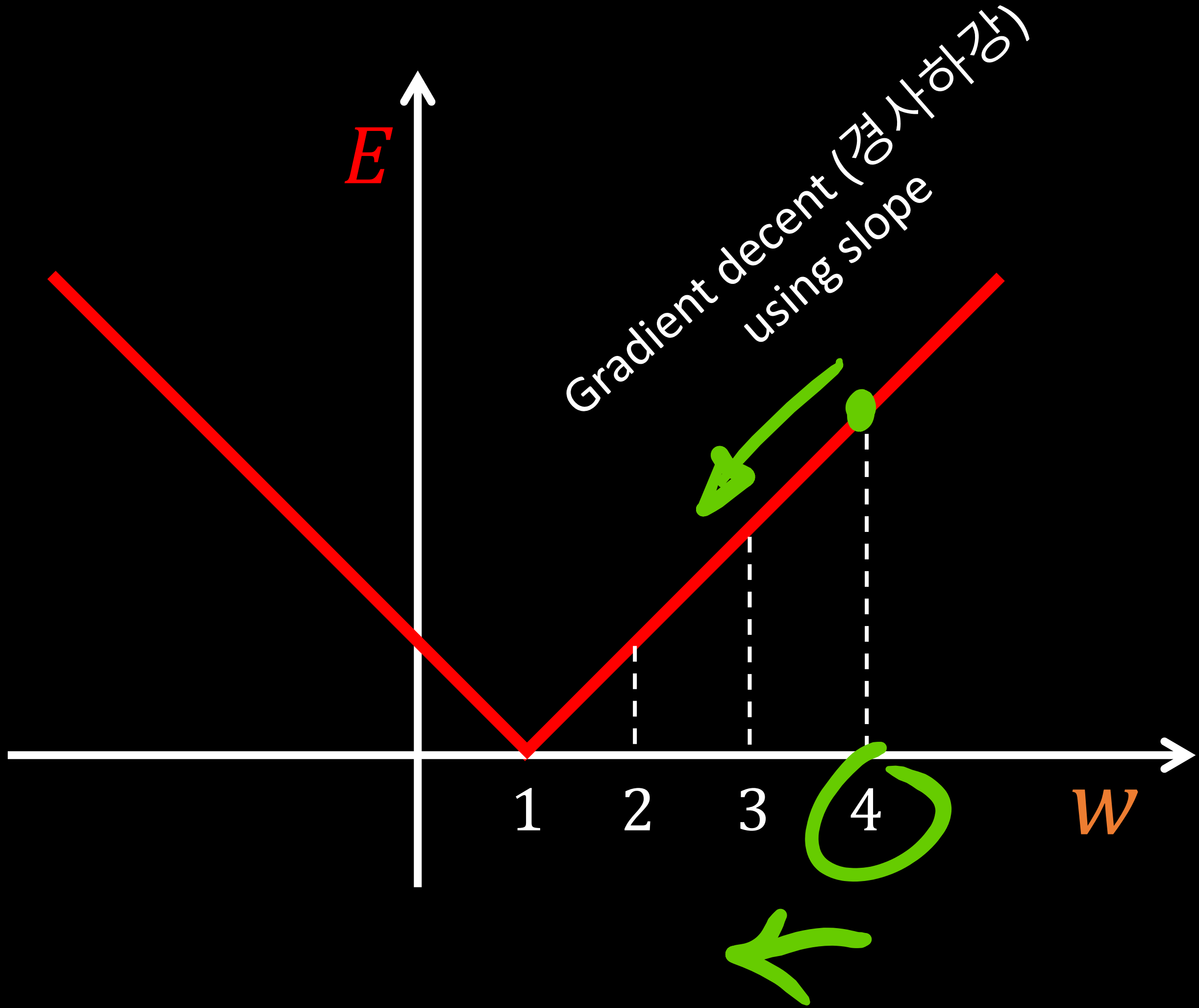
1. Plot $(1,1)$
2. $h = w \cdot x$
3. $E = w \cdot 1 - 1$
4. $E = |w \cdot 1 - 1|$
5. (w, E)

desmos

Error Function of w



How to update w

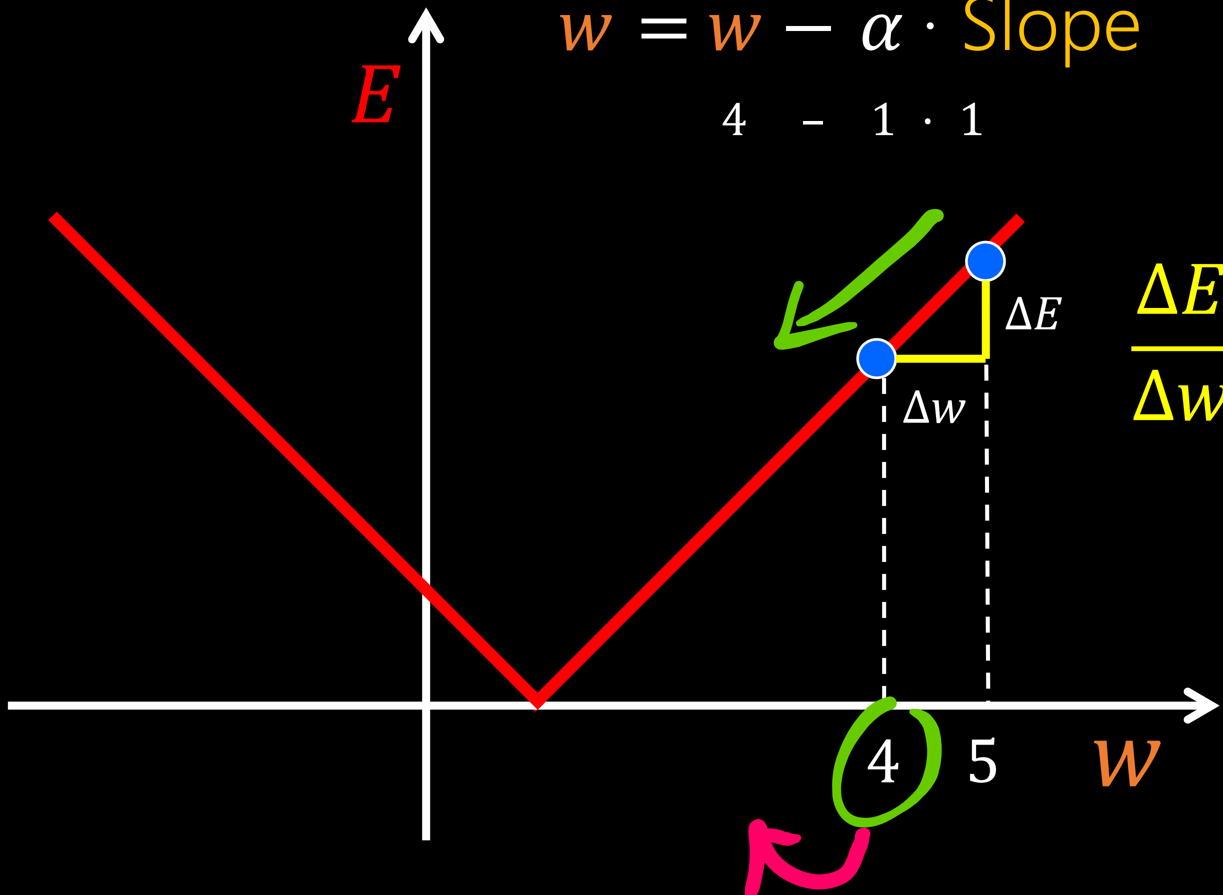


How to update w

learning rate (ex, 1)

$$w = w - \alpha \cdot \text{Slope}$$

$$4 \quad - \quad 1 \cdot 1$$



$$\frac{\Delta E}{\Delta w} = \frac{+1}{+1}$$

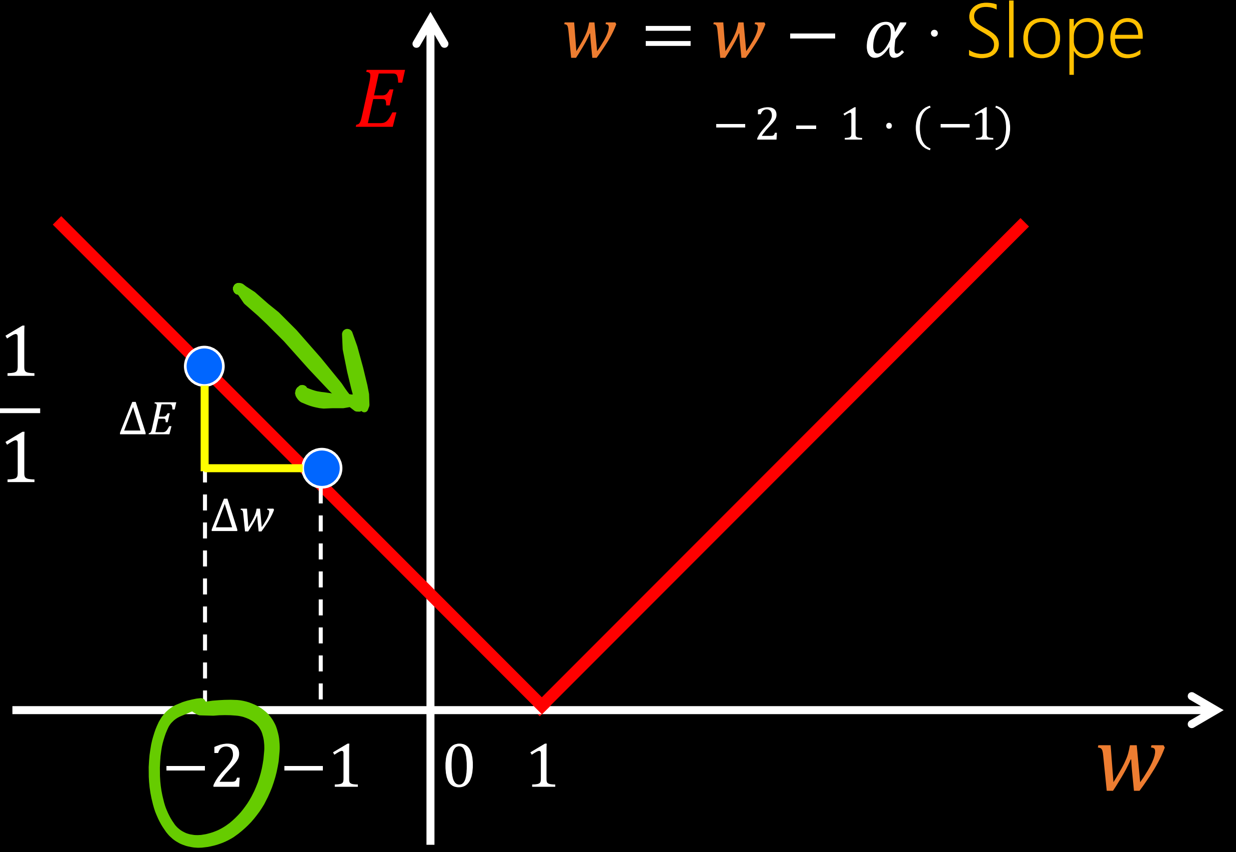
How to update w

learning rate (ex, 1)

$$w = w - \alpha \cdot \text{Slope}$$

$$-2 - 1 \cdot (-1)$$

$$\frac{\Delta E}{\Delta w} = \frac{-1}{+1}$$



$$w = 4, \alpha = 1, Slope = 1$$

$$w = w - \alpha \cdot \text{Slope}$$

$4 - 1 \cdot 1 \longrightarrow 3$ Error E = 2

$3 - 1 \cdot 1 \longrightarrow 2$ Error E = 1

$2 - 1 \cdot 1 \longrightarrow 1$ Error E = 0

$$w = -2, \alpha = 1, Slope = -1$$

$w = w - \alpha \cdot$ Slope

$-2 - 1 \cdot (-1) \longrightarrow -1$ Error $E = 2$

$-1 - 1 \cdot (-1) \longrightarrow 0$ Error $E = 1$

$0 - 1 \cdot (-1) \longrightarrow 1$ Error $E = \underline{0}$

$$w = -2, \alpha = 2, Slope = -1$$

$w = w - \alpha \cdot$ Slope

$-2 - 2 \cdot (-1) \longrightarrow 0$ Error $E = 1$

$0 - 2 \cdot (-1) \longrightarrow 2$ Error $E = 1$

$2 - 2 \cdot (1) \longrightarrow 0$ Error $E = 1$

$0 - 2 \cdot (-1) \longrightarrow 2$ Error $E = 1$

$2 - 2 \cdot (1) \longrightarrow 0$ Error $E = 1$

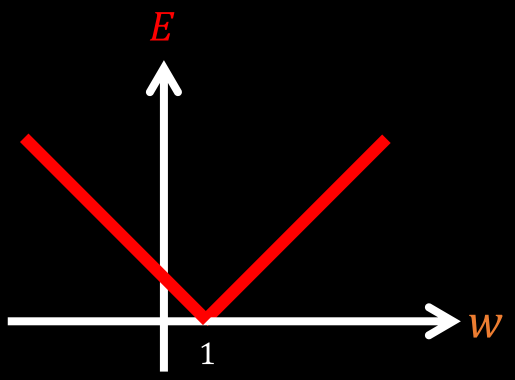
$$E = |w \cdot x - y|$$

Absolute Error

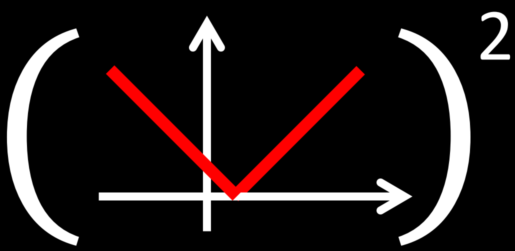
L1 Loss function

Issues in the absolute error

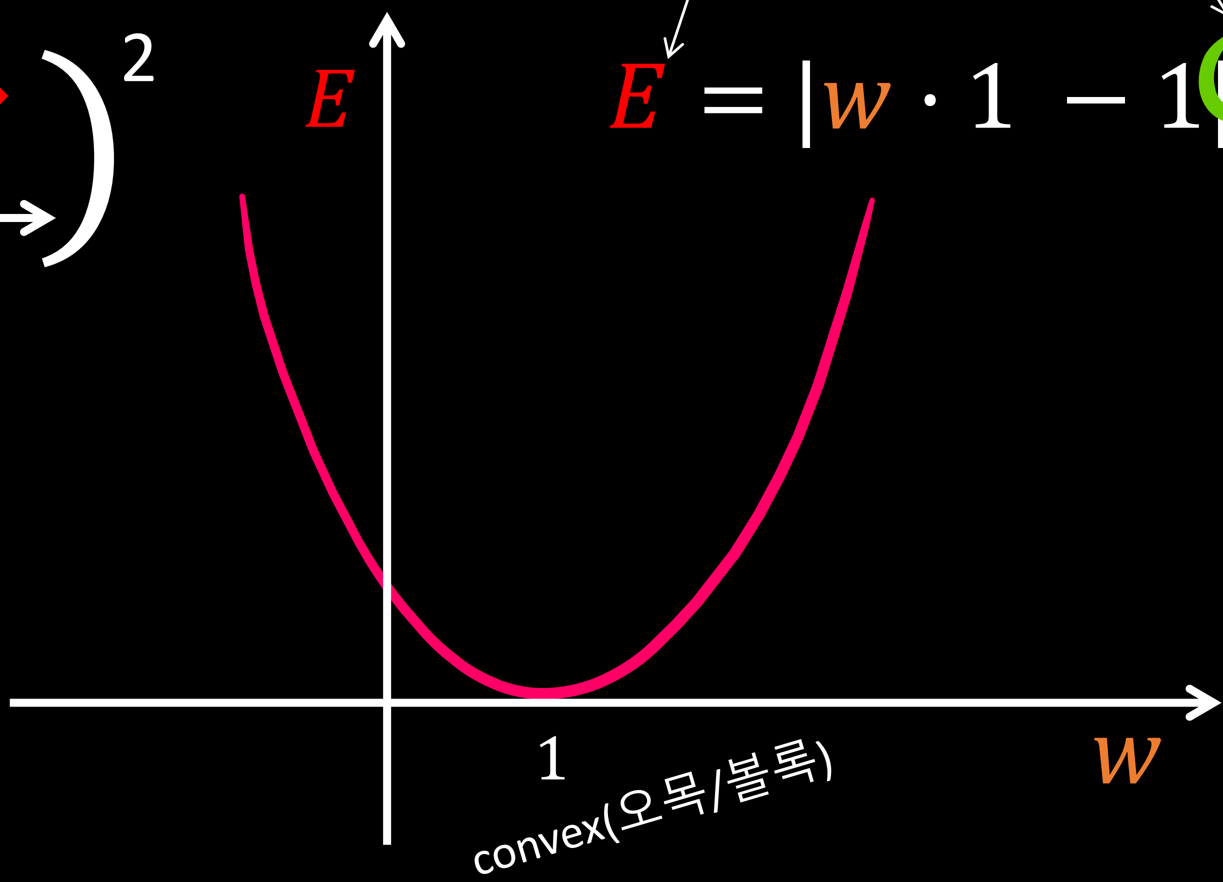
- Always the slope is 1 or -1 regardless of the value of w
- Therefore, the same speed in movement
- No guarantee for convergence of the value of w which gives 0 or almost 0 in the error.



Squared Error



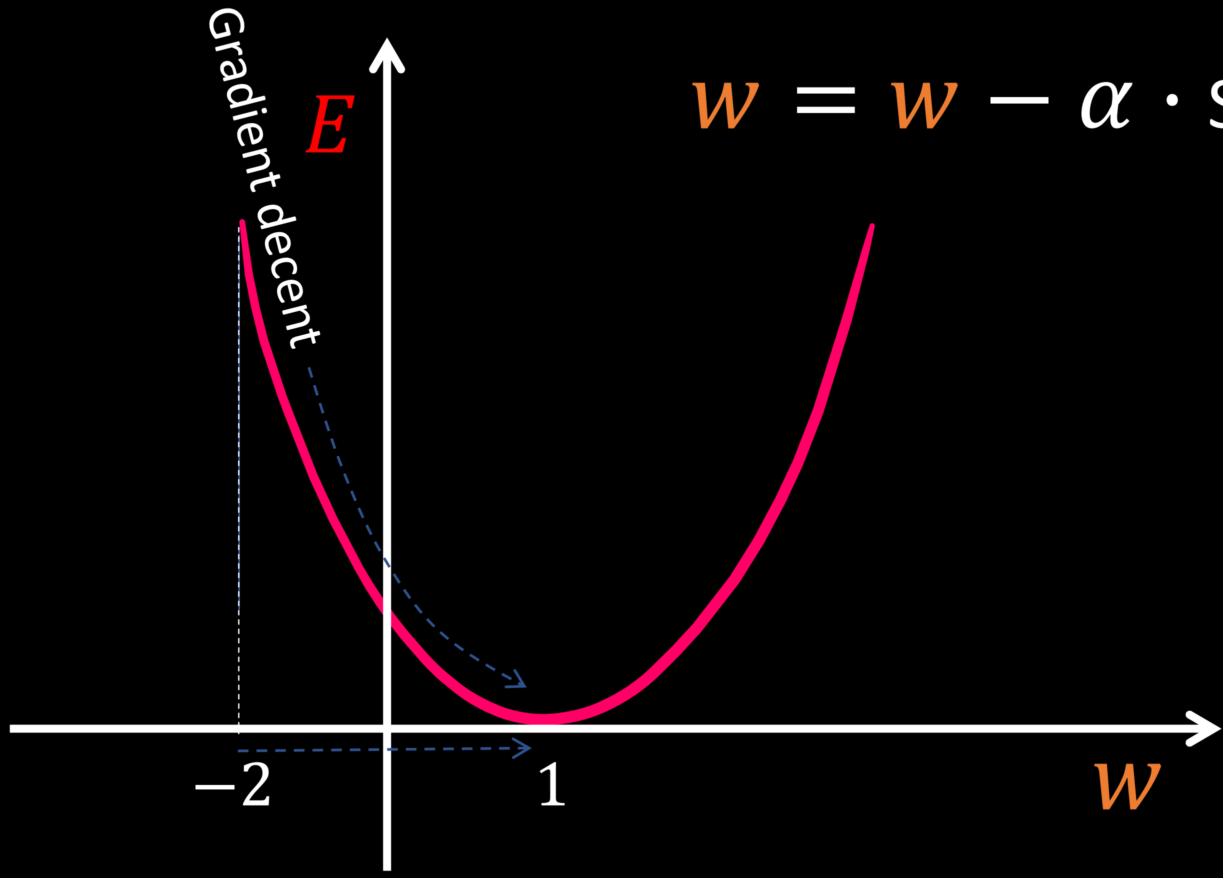
$$\underbrace{E}_{\text{error}} = |w \cdot 1 - 1|^{\overbrace{2}^{\text{square (제곱)}}}$$



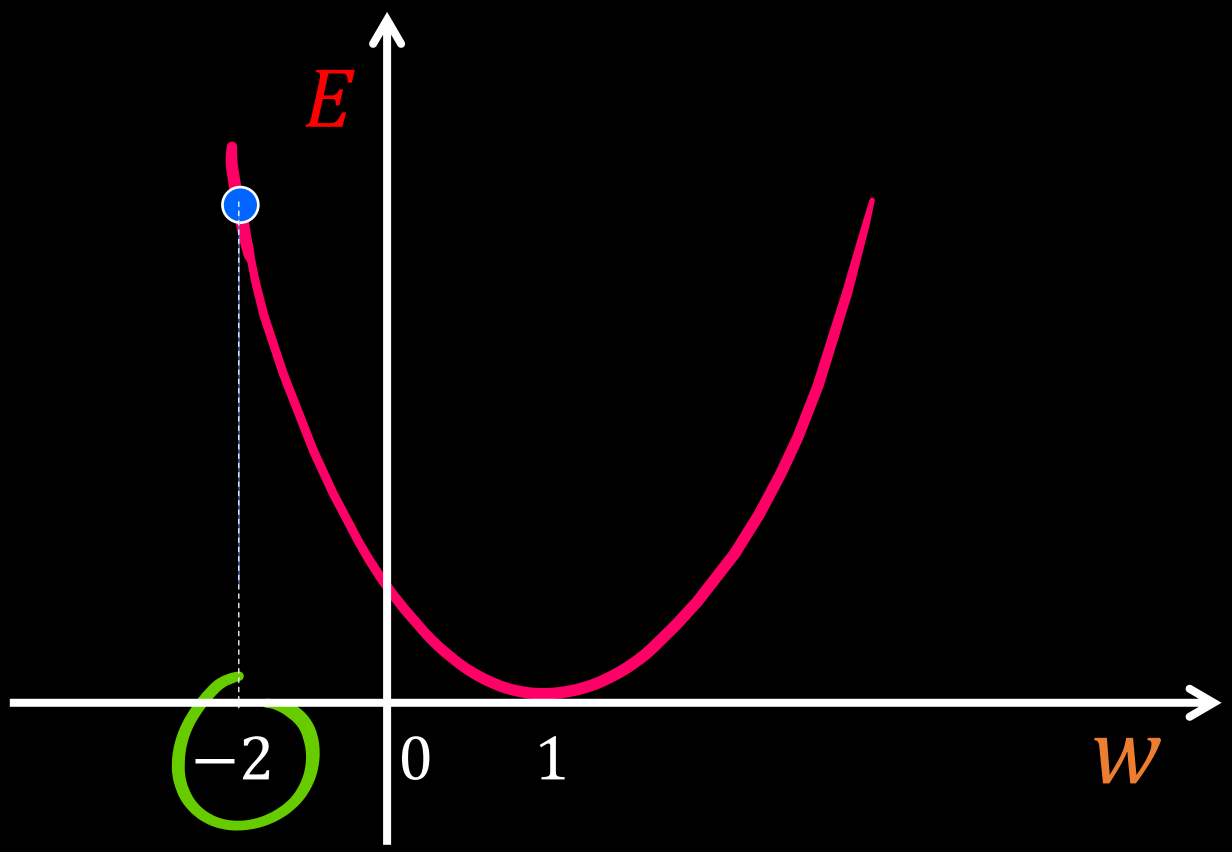
How to update w

$$\frac{\Delta E}{\Delta w}$$

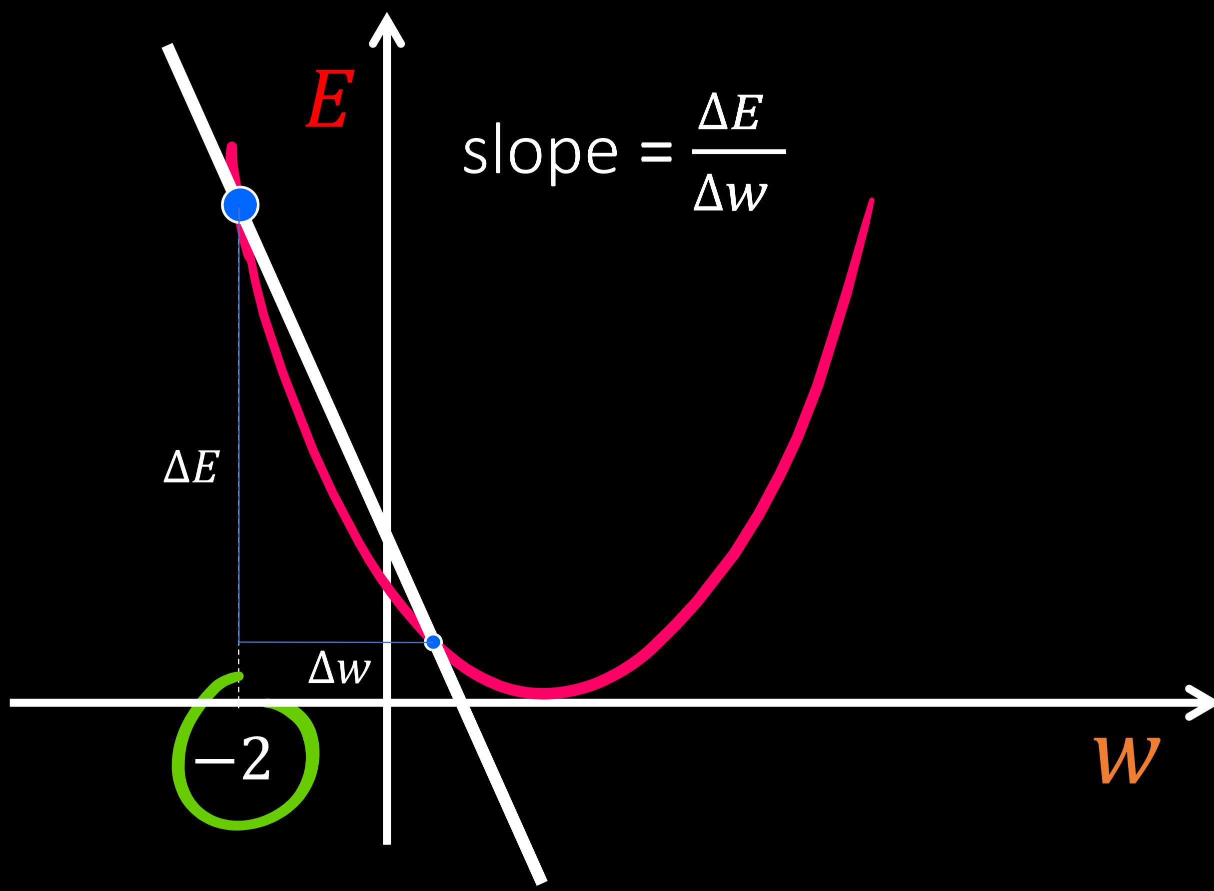
$$w = w - \alpha \cdot \text{Slope}$$



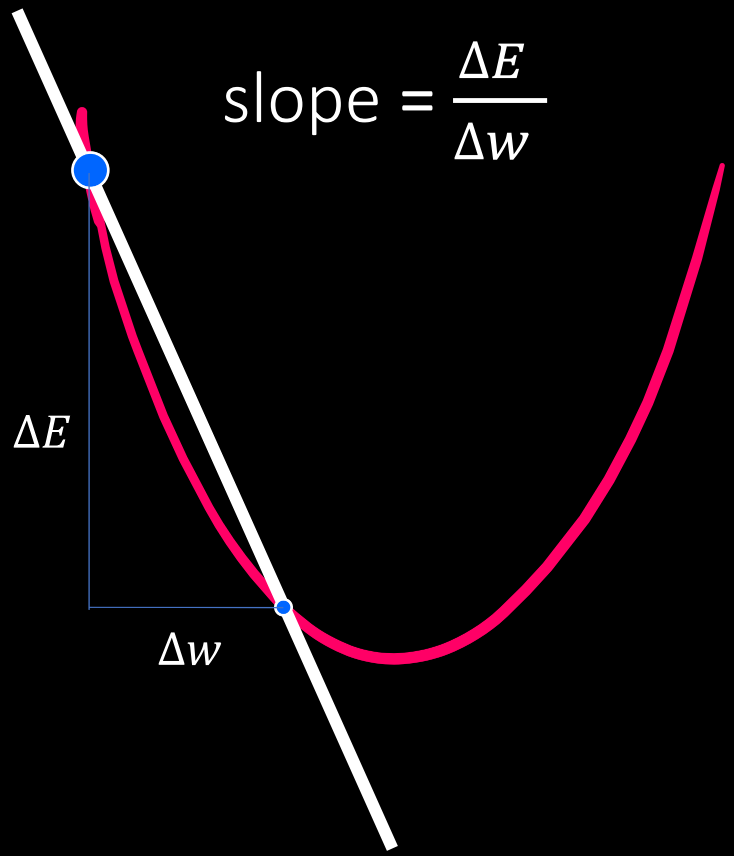
How to update w



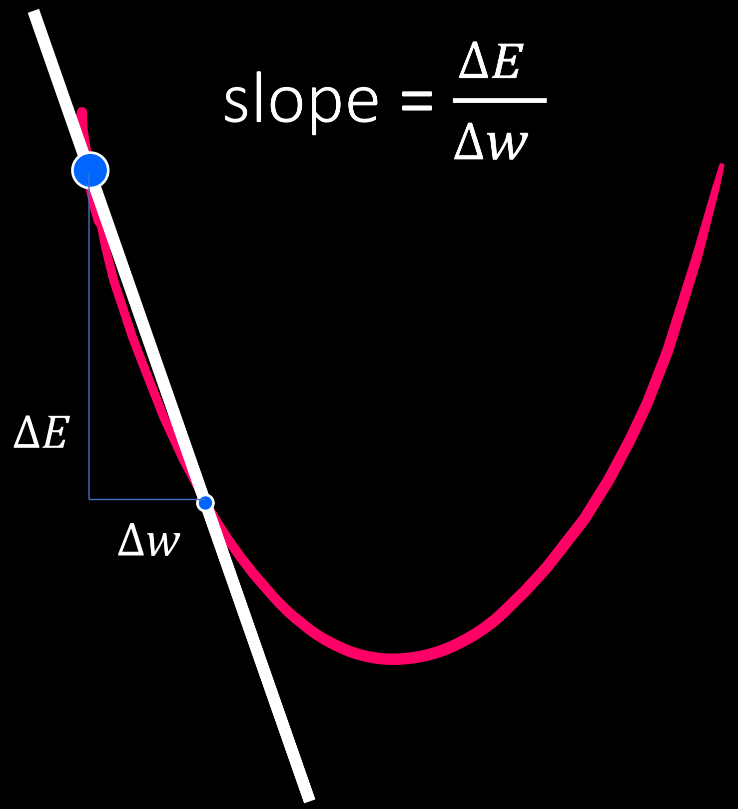
How to update w



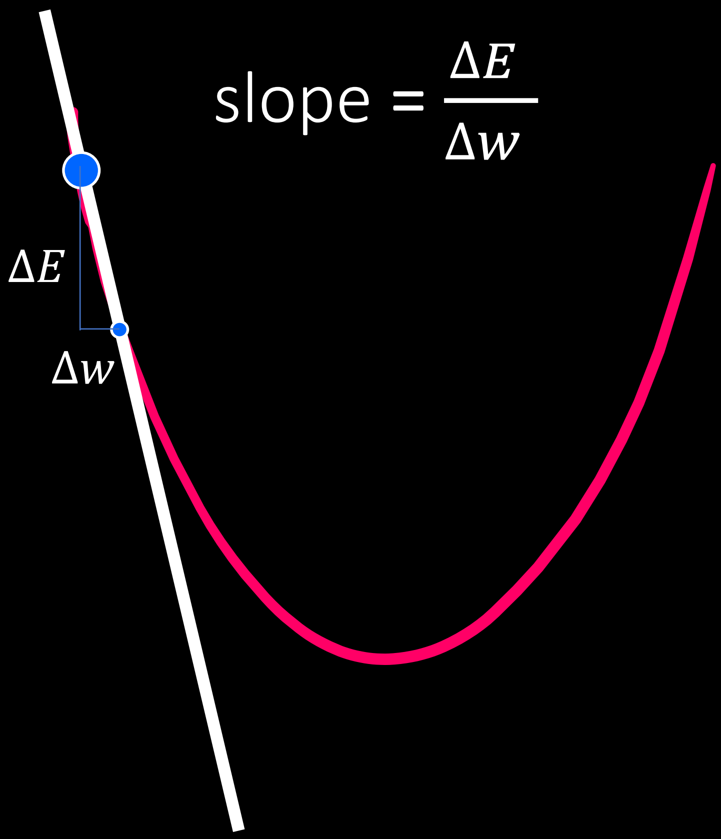
How to update w



How to update w

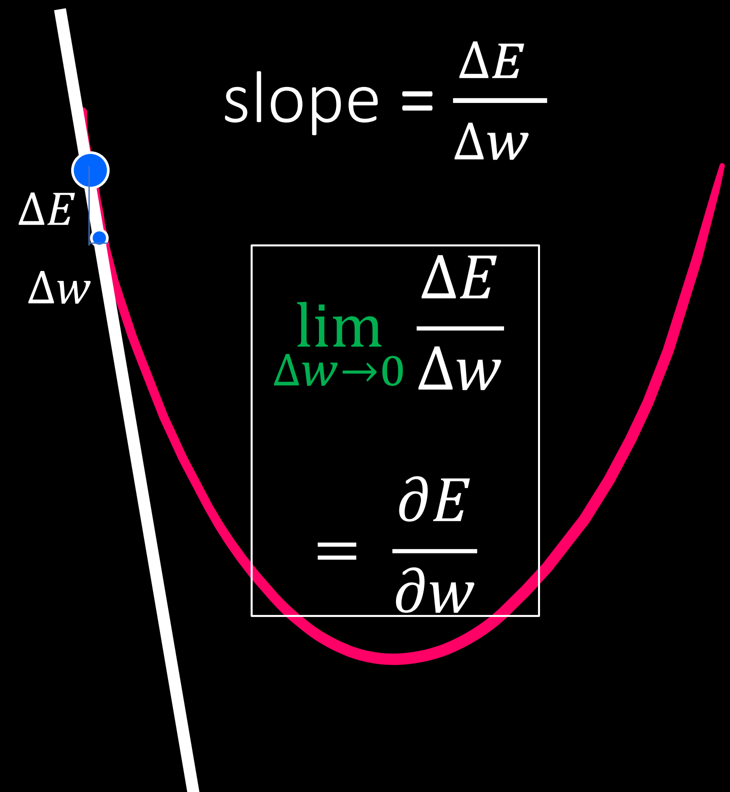


How to update w



How to update w

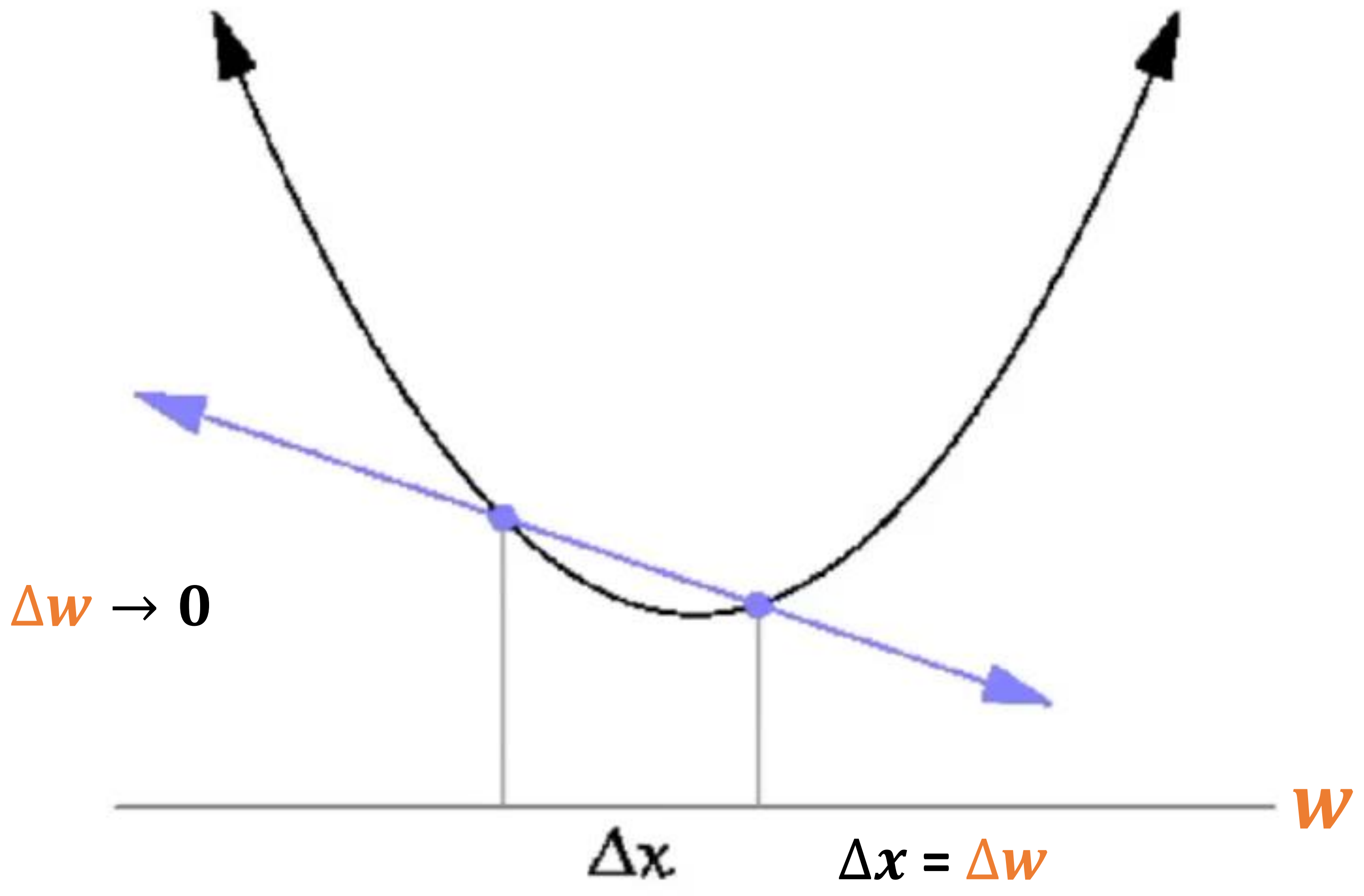
접선·Tangent line



$$\text{slope} = \frac{\Delta E}{\Delta w}$$

$$\boxed{\lim_{\Delta w \to 0} \frac{\Delta E}{\Delta w} = \frac{\partial E}{\partial w}}$$

How to update w

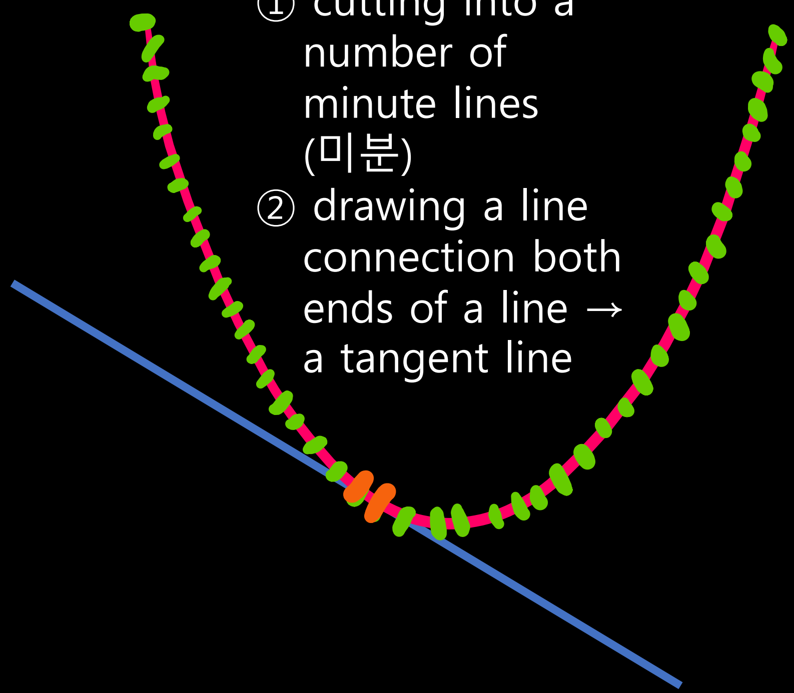


How to update w

Numerical differentiation

① cutting into a number of minute lines (미분)

② drawing a line connection both ends of a line → a tangent line



$$\lim_{\Delta w \to 0} \frac{\Delta E}{\Delta w}$$

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

= 미분 (잘게 나누다.)

How to update w

$$w = w - \alpha * \text{Slope}$$

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

$\alpha =$ learning rate (ex, 0.1)

$$E = |w \cdot 1 - 1|^2$$

Squared Error

L2 Loss function

Advantages

- Fast movement from both sides and fine(slow) tuning at the valley(center) area
- Different slope/gradient according to the value of w
- Steep slope means that the error is big and w is far from the optimal value.
- We can get the slope(gradient) at any place(differentiable).

In case of L1 Loss

- Always the same slope in the error graph regardless of the value of w
- Therefore, the same speed in the movement
- Not sure to get the w value which gives 0 error or almost 0
- No way to guess the current value of w
- Not differentiable when w is 1

Multiple Data

a.csv

x_i	y_i
1	1
2	2
3	3

data, experience

For 3 instances of data

$$E = \frac{1}{3}\sum_{i=1}^{3}(wx_i - y_i)^2$$

desmos

Add (2, 2), (3, 3)

$$E = \frac{1}{3}\sum_{i=1}^{3}(wx_i - y_i)^2$$

Draw (w, E)

$$E = \frac{1}{3}\big((w \cdot 1 - 1) + (w \cdot 2 - 2) + (w \cdot 3 - 3)\big)$$

Multiple Data

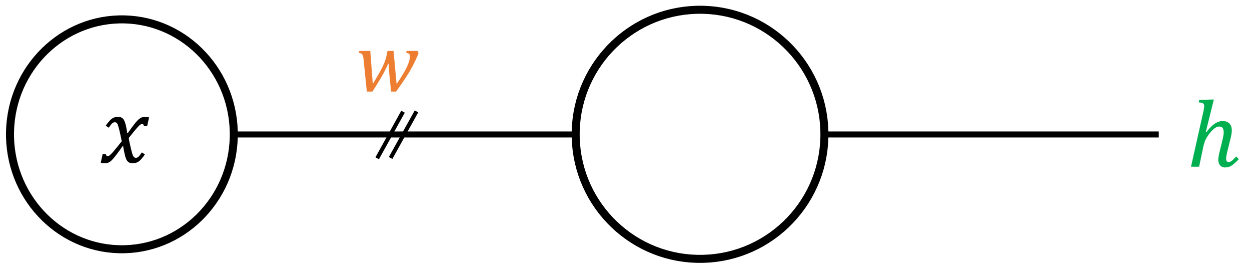
In case of m instances,

$\boxed{\text{Mean Square Error}}$

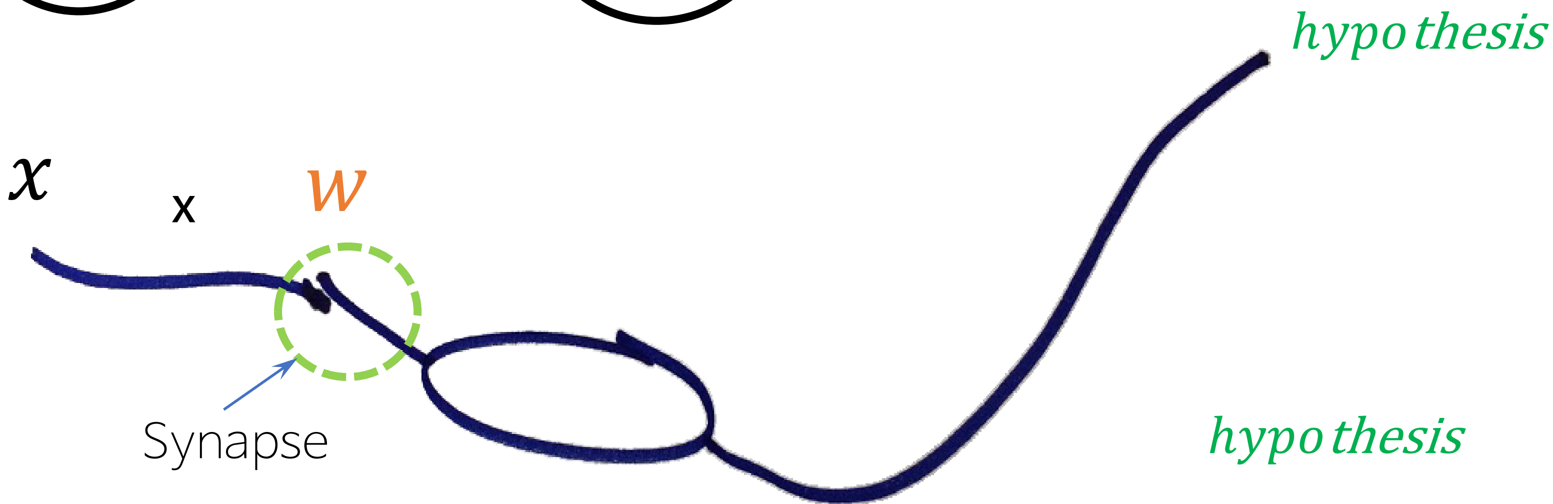
An answer by a neuron

$$E = \frac{1}{m}\sum_{i=1}^{m}(wx_i - y_i)^2$$

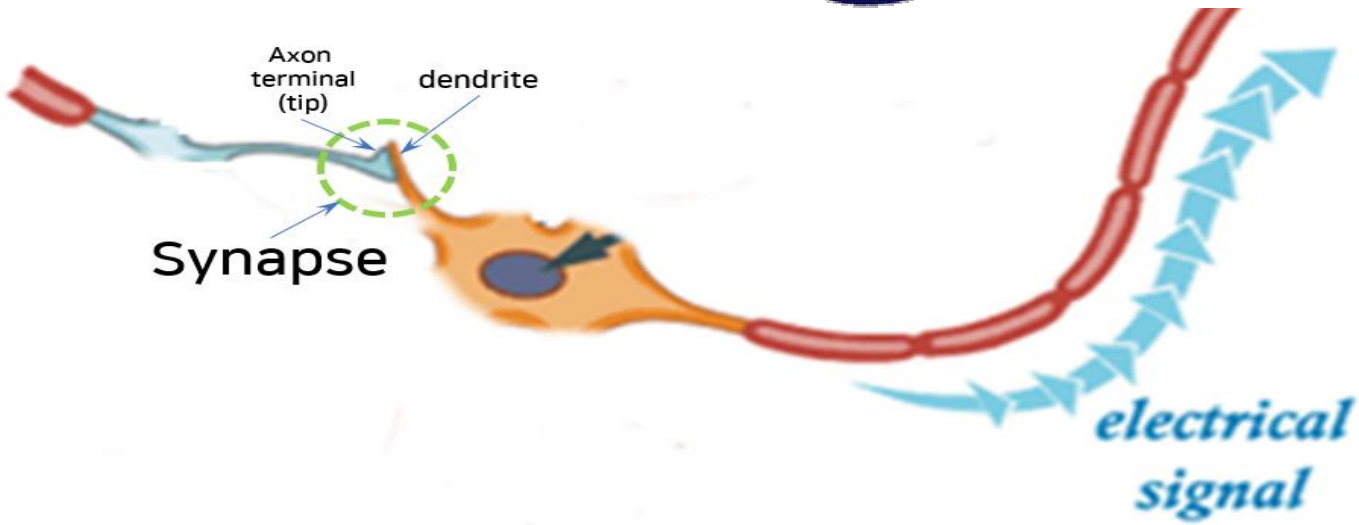
Ground truth



x
w
h



hypothesis
x
x
w
Synapse
hypothesis



Axon terminal (tip)
dendrite
Synapse
electrical signal

The meaning of slope

Steep slope $\frac{\Delta E}{\Delta w}$ $\frac{8}{1}$

The error E will change drastically when we change w.

Gentle slope $\frac{\Delta E}{\Delta w}$ $\frac{1}{10}$

The error E changes just a little bit when we change w.

$$\lim_{\Delta w \to 0} \frac{\Delta E}{\Delta w} \rightarrow \frac{\partial E}{\partial w}$$

Therefore,

Slope/Gradient

means the influence of w change on error E.

따라서 경사/기울기는
w 의 변화가 오류(E)에 얼마나 영향을
미치는지 의미 (미치는 영향력)

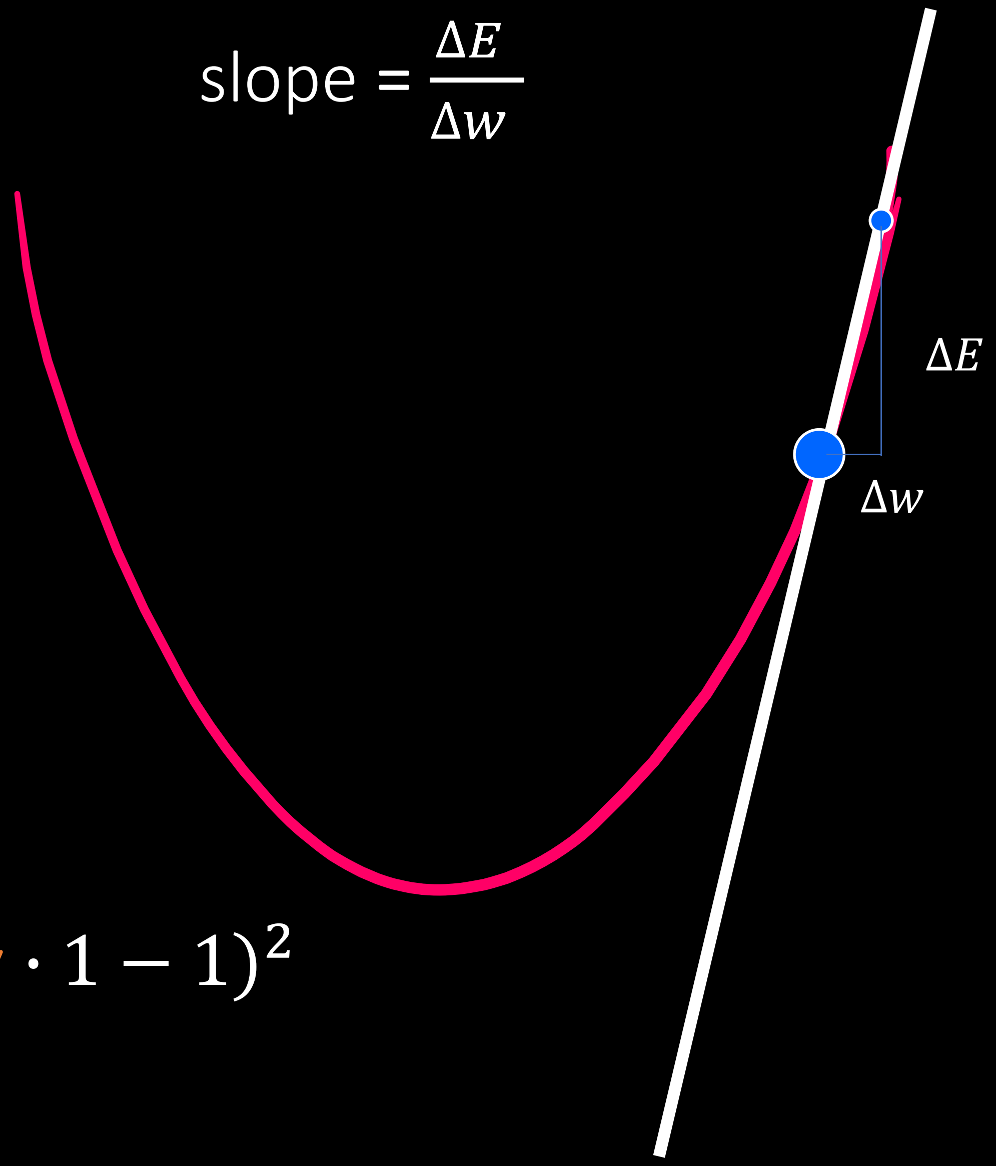
얼굴에 기미

(Q) Compute the influence

$$E = (wx - y)^2$$

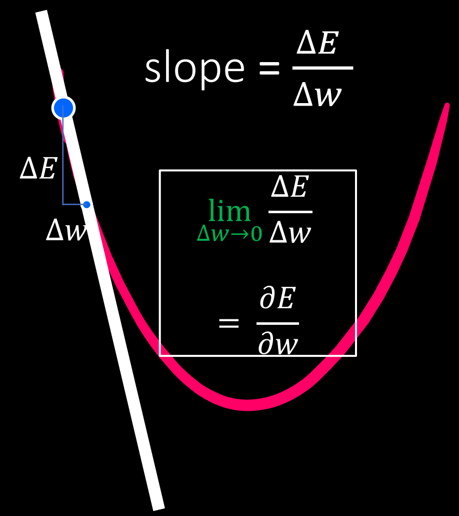
Let's assume that data (x, y) is $(1, 1)$, then compute the influence of w change on E when the current w is equal to 3.

$$\text{slope} = \frac{\Delta E}{\Delta w}$$



$$E = (w \cdot 1 - 1)^2$$

Method1 numerical gradient



$$E = (w \cdot 1 - 1)^2$$

w: 3 -> E: 4

w: 3.00001 -> E: 4.00004

Δw=0.00001

ΔE=0.00004

$$\frac{\Delta E}{\Delta w} = \frac{0.00004}{0.00001} = 4$$

Slope =

Influence of w change = 4

Method2 derivative, differential equation

$$E = (w \cdot 1 - 1)^2$$

$$\lim_{\Delta w \to 0} \frac{\Delta E}{\Delta w} = \frac{\partial E}{\partial w} = \frac{\partial}{\partial w}(w \cdot 1 - 1)^2$$

$$= 2(w \cdot 1 - 1)$$

Therefore, when $w = 3$,
the gradient is $2(3 - 1) = 4$

How to update w (Learning)

1. Initialize w with a random value $(ex, 3)$

Loop

2. Get the influence(slope) of w change on E
3. Update w using below eq:

Parameter Tuning

$$w = w - \alpha * slope$$

4. Go to step 2

TensorFlow

- Machine learning framework by Google
- Tuning parameters including w automatically instead of us
- Define w inside of TensorFlow to be tuned (managed) by it
- Hypothesis and cost_function(E)

Linear Regression using TF

hypo=$w * x$

3

w = tf.Variable(tf.random_normal([1]))

h 4

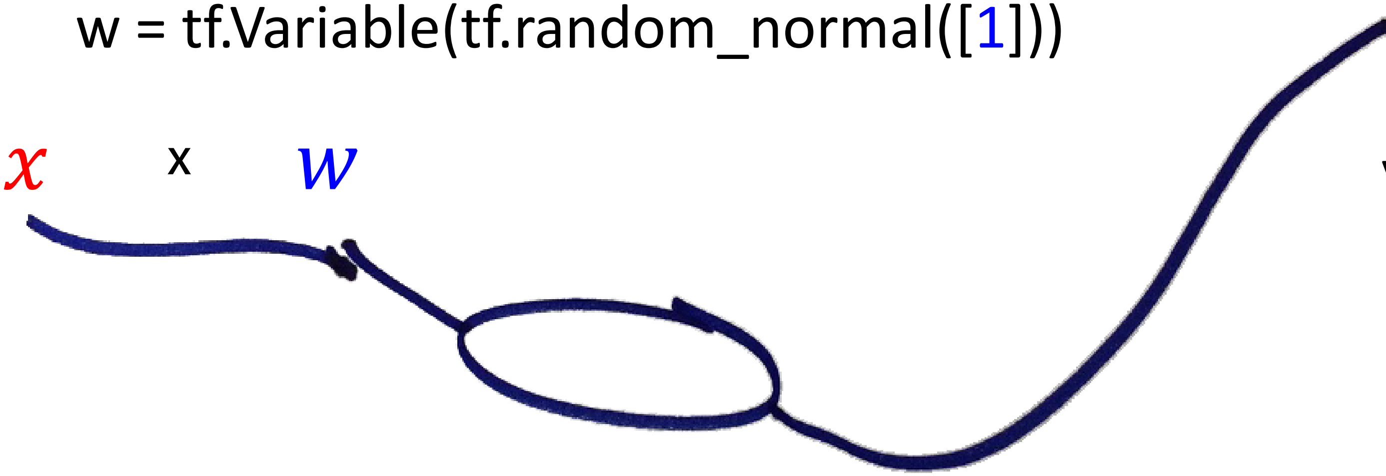
x x w

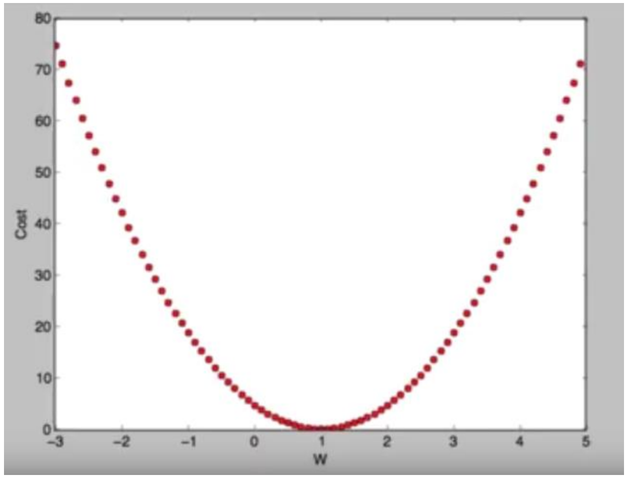
y = [1]

1

2

x = [1]





cost_function = (hypo – y) ** 2

5

$$E = (\text{hypo} - y)^2$$

Download myml.git

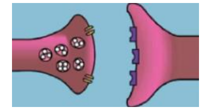
https://github.com/yungbyun/myml.git

1) Run DOS prompt
2) git clone https://github.com/yungbyun/myml.git
3) Open using PyCharm (File | Open...)

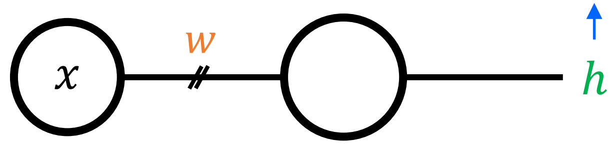
Lab 01.py

Finding w in linear regression

```python
import tensorflow as tf
```



$$E = |w \cdot x - y| ** 2$$




```python
#----- training data
x_data = [1]
y_data = [1]
```

```python
#----- a neuron / neural network
w = tf.Variable(tf.random_normal([1]))
hypo = w * x_data
```

train operation to update w to minimize error(E)

```python
#----- learning
cost = (hypo - y_data) ** 2

train = tf.train.GradientDescentOptimizer(learning_rate=0.01).minimize(cost)

sess = tf.Session()
sess.run(tf.global_variables_initializer())

for i in range(1001):
    sess.run(train) #1-run, 1-update of w -> 1001 updates

    if i % 100 == 0:
        print('w:', sess.run(w), 'cost:', sess.run(cost))
```

```python
#----- testing(prediction)
x_data = [2]
print(sess.run(x_data * w))
```

[code] www.kaggle.com/yungbyun/a-simple-neuron/

```
import tensorflow as tf
```

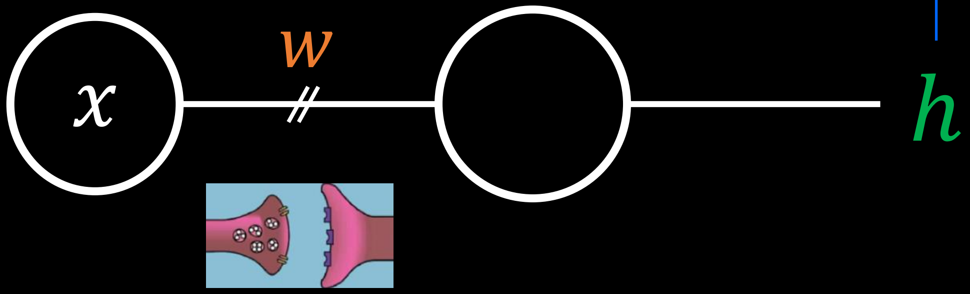
```
import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
```

```
sess.run(train)
```

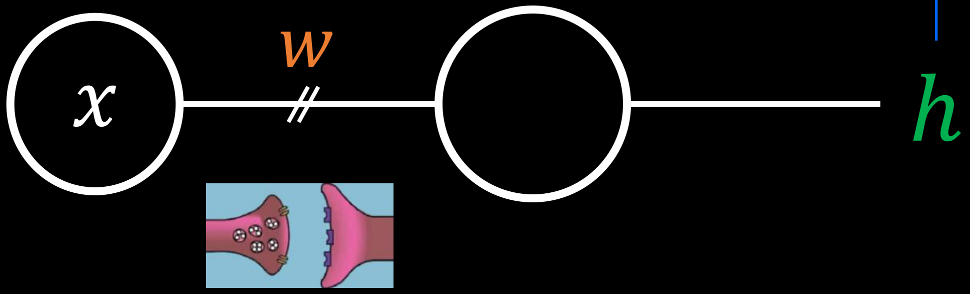
How to update w in TensorFlow

Error Computation Graph

$$E = (h - y)^2$$



$$E = (wx - y)^2$$



Loss/error function (L2)

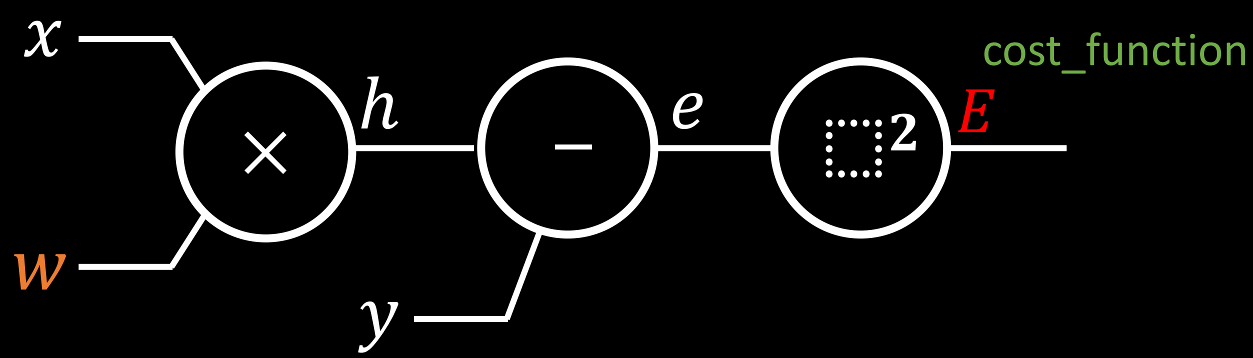
$$E = (wx - y)^2$$

- The part representing a neuron
- Where is a synapse?
- Which one is an input data?
- The output of a neuron
- **Find hypothesis**
- Find a correct answer or ground truth.
- Imagine E having multiple inputs.

Computation Graph

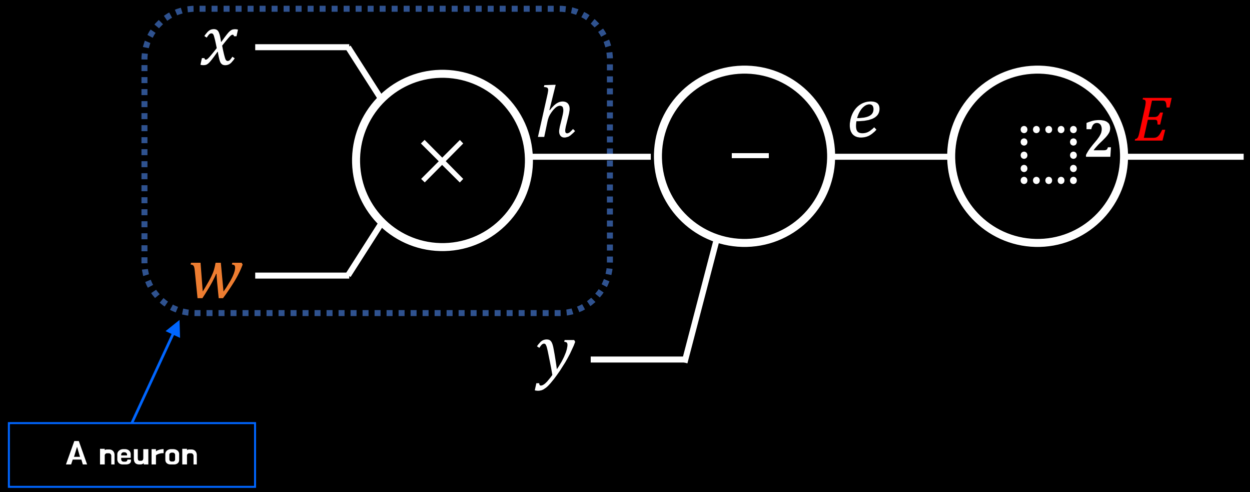
$$E = (w \cdot x - y)^2$$

```
hypo = w * x
cost_function(E) = (hypo - y) ** 2)
```



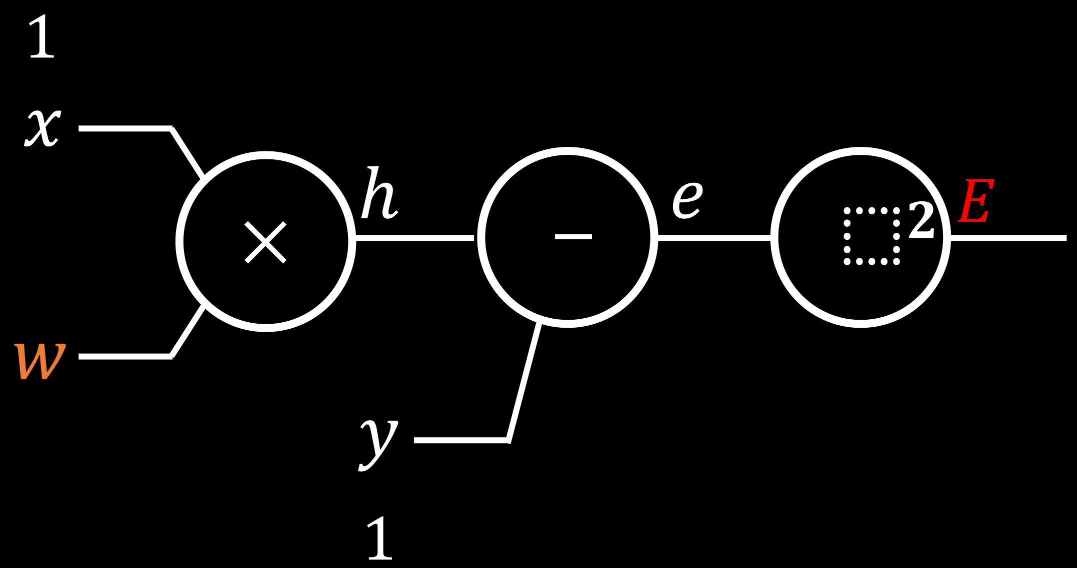
Computation Graph

$$E = (w \cdot x - y)^2$$



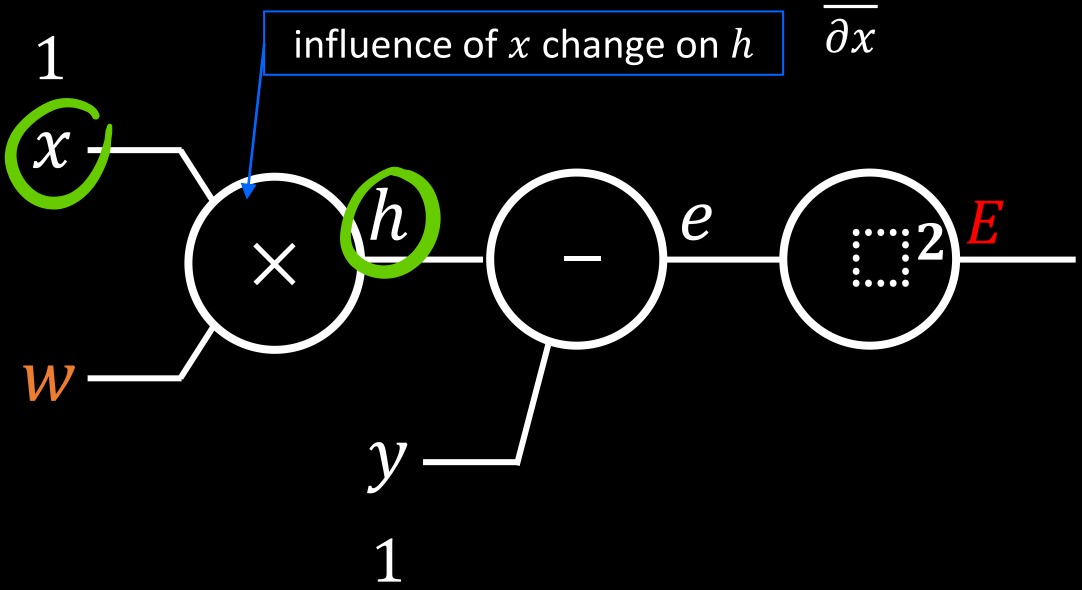
Computation Graph

Data (x, y) −> $(1, 1)$

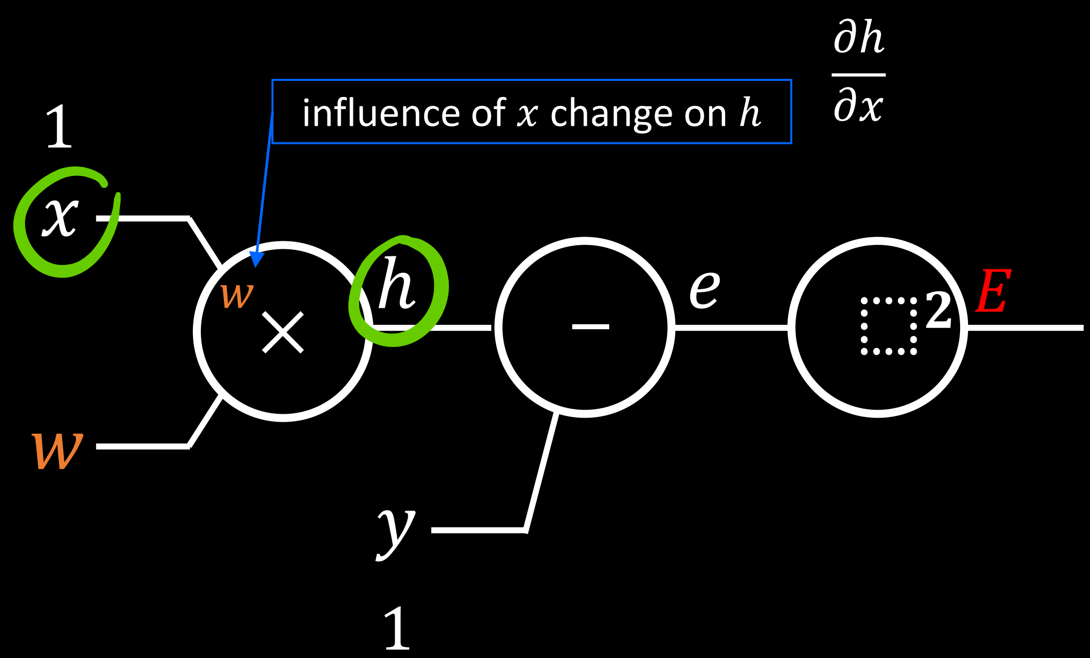


Computation Graph

$$\frac{\partial h}{\partial x}$$

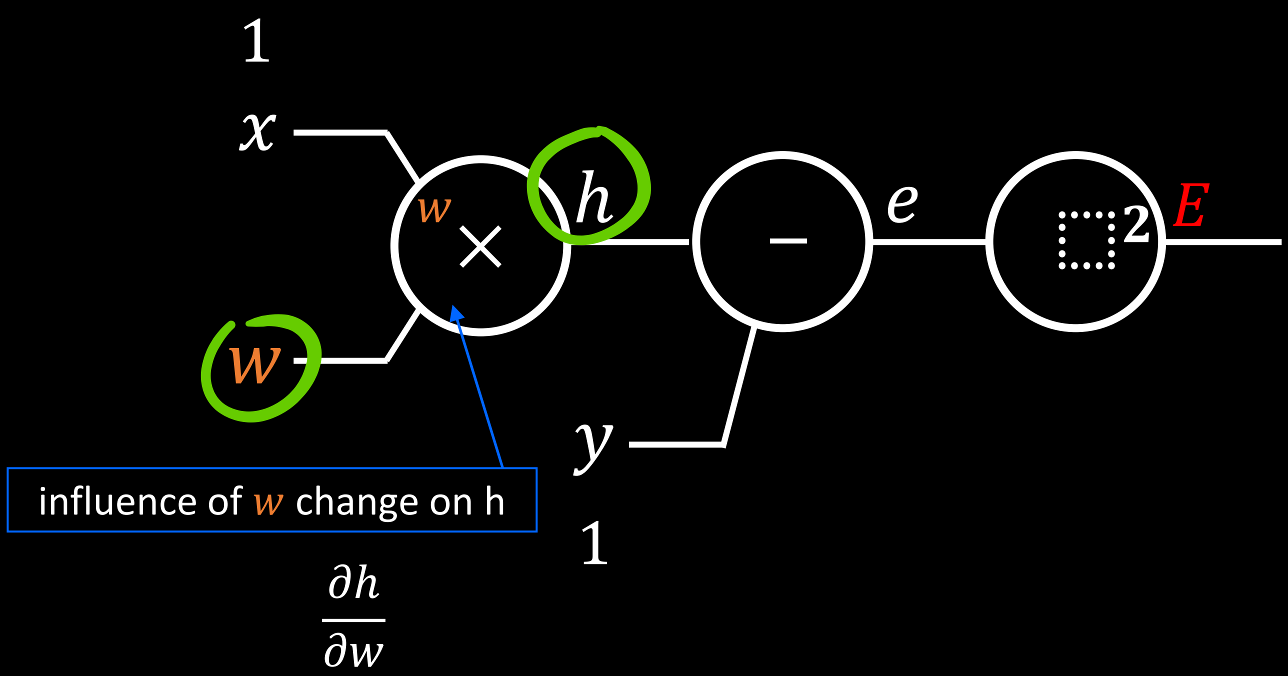


Computation Graph

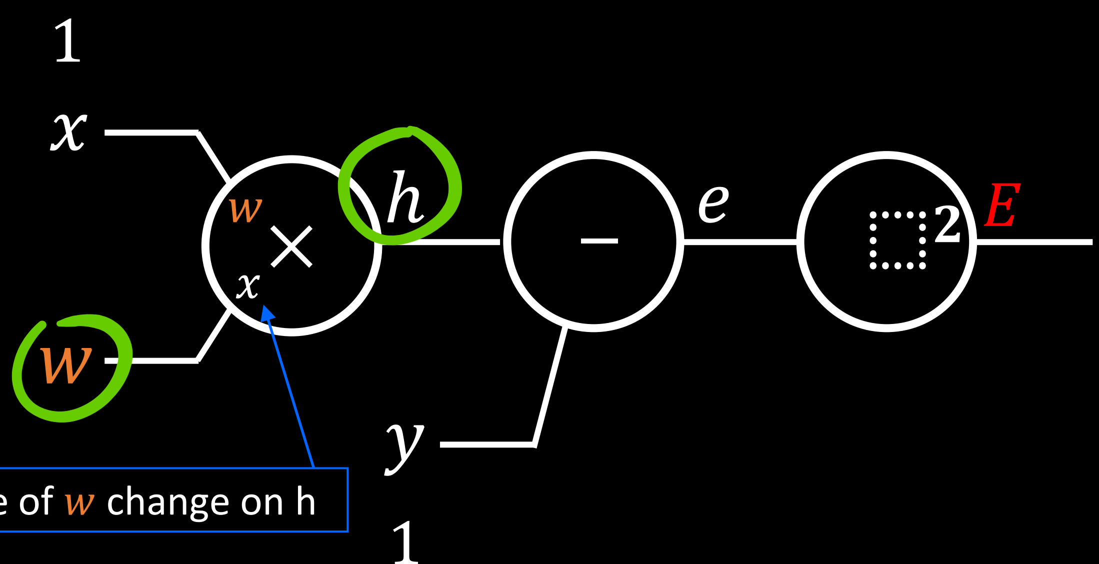


Local gradient

Computation Graph

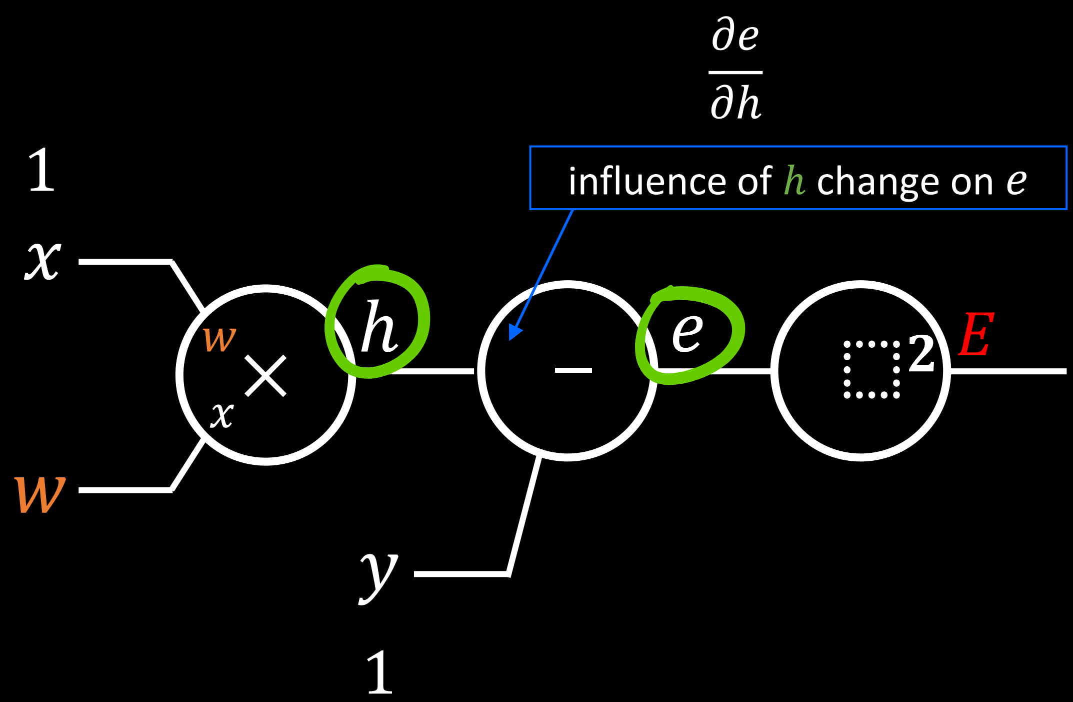


Computation Graph

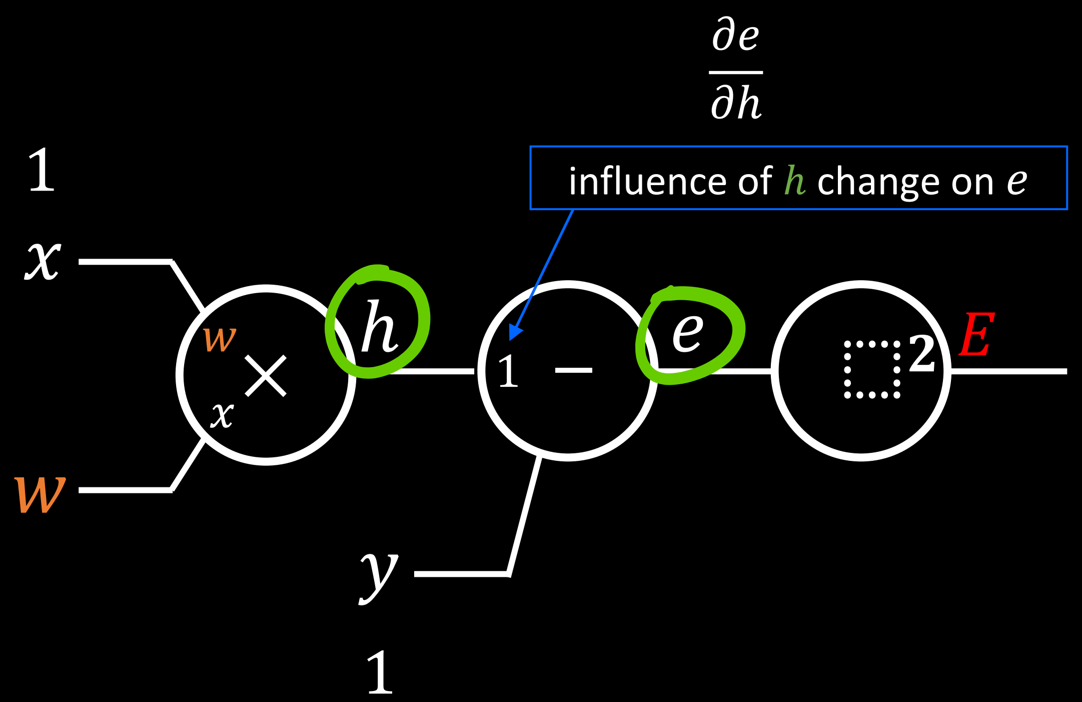


$$\frac{\partial h}{\partial w}$$

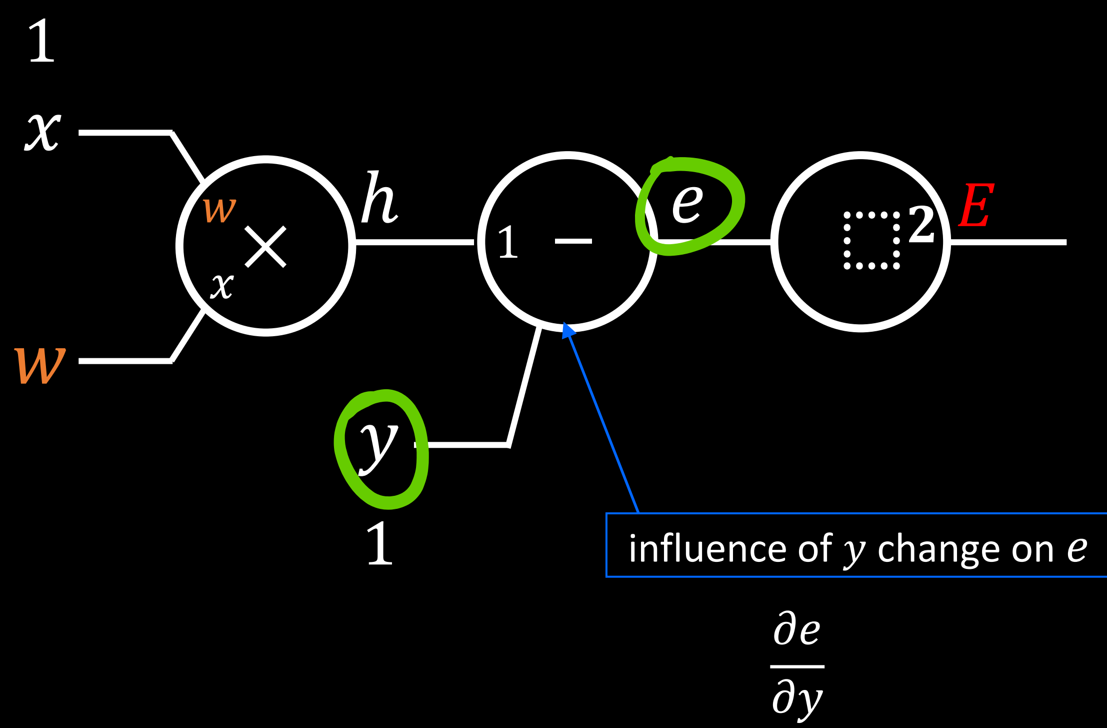
Computation Graph



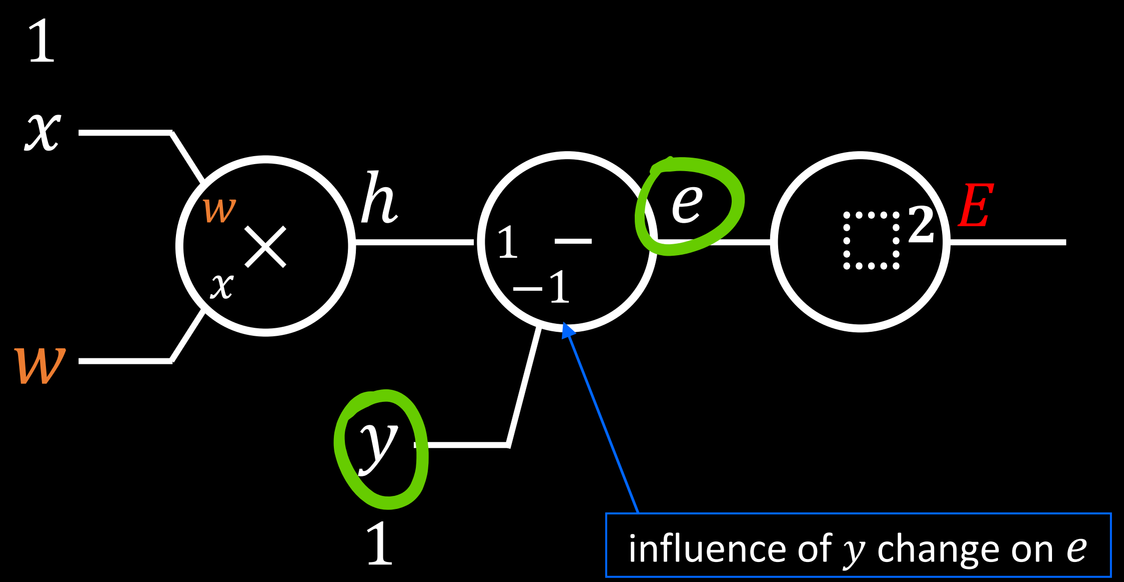
Computation Graph



Computation Graph

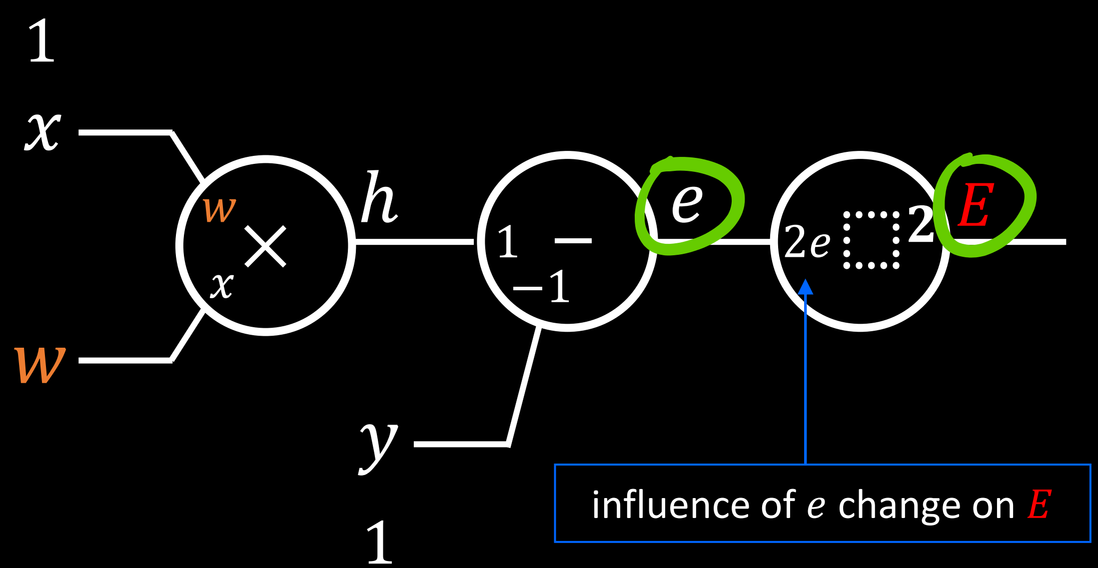


Computation Graph



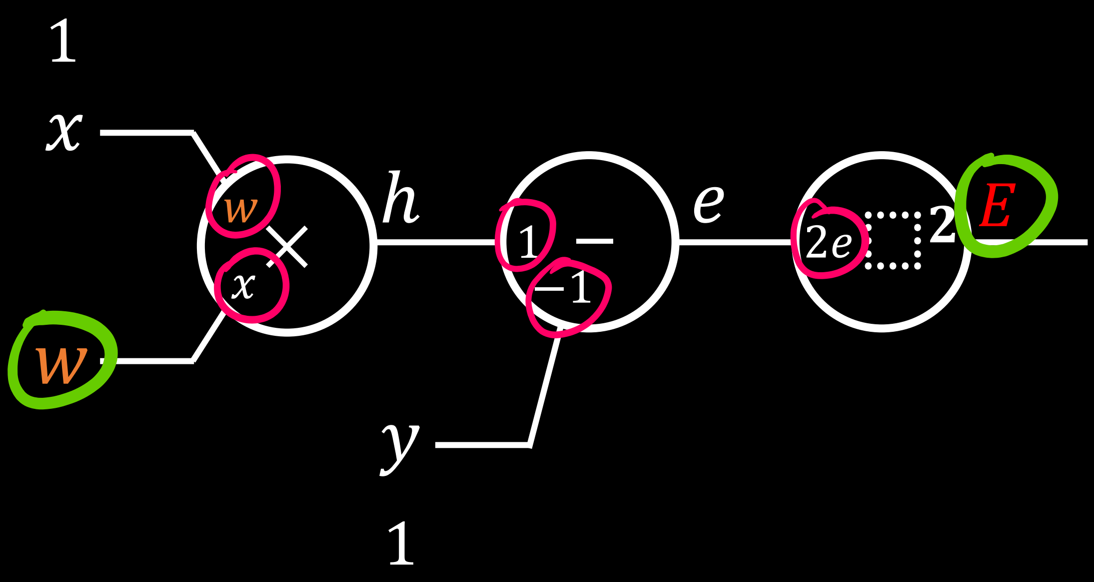
$$\frac{\partial e}{\partial y}$$

Computation Graph



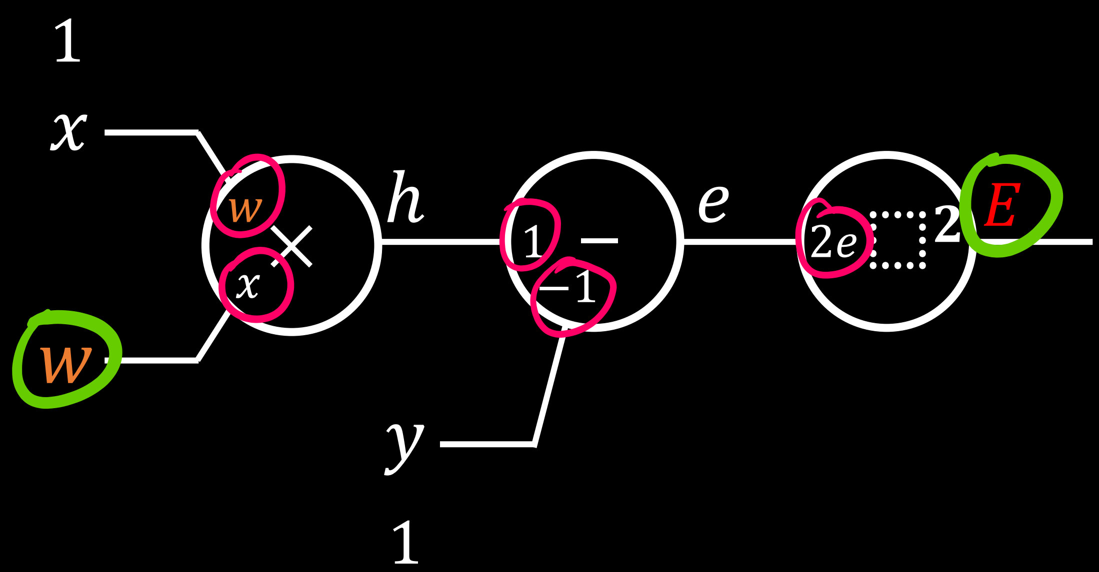
$$\frac{\partial E}{\partial e}$$

5 Local Gradients in the gates

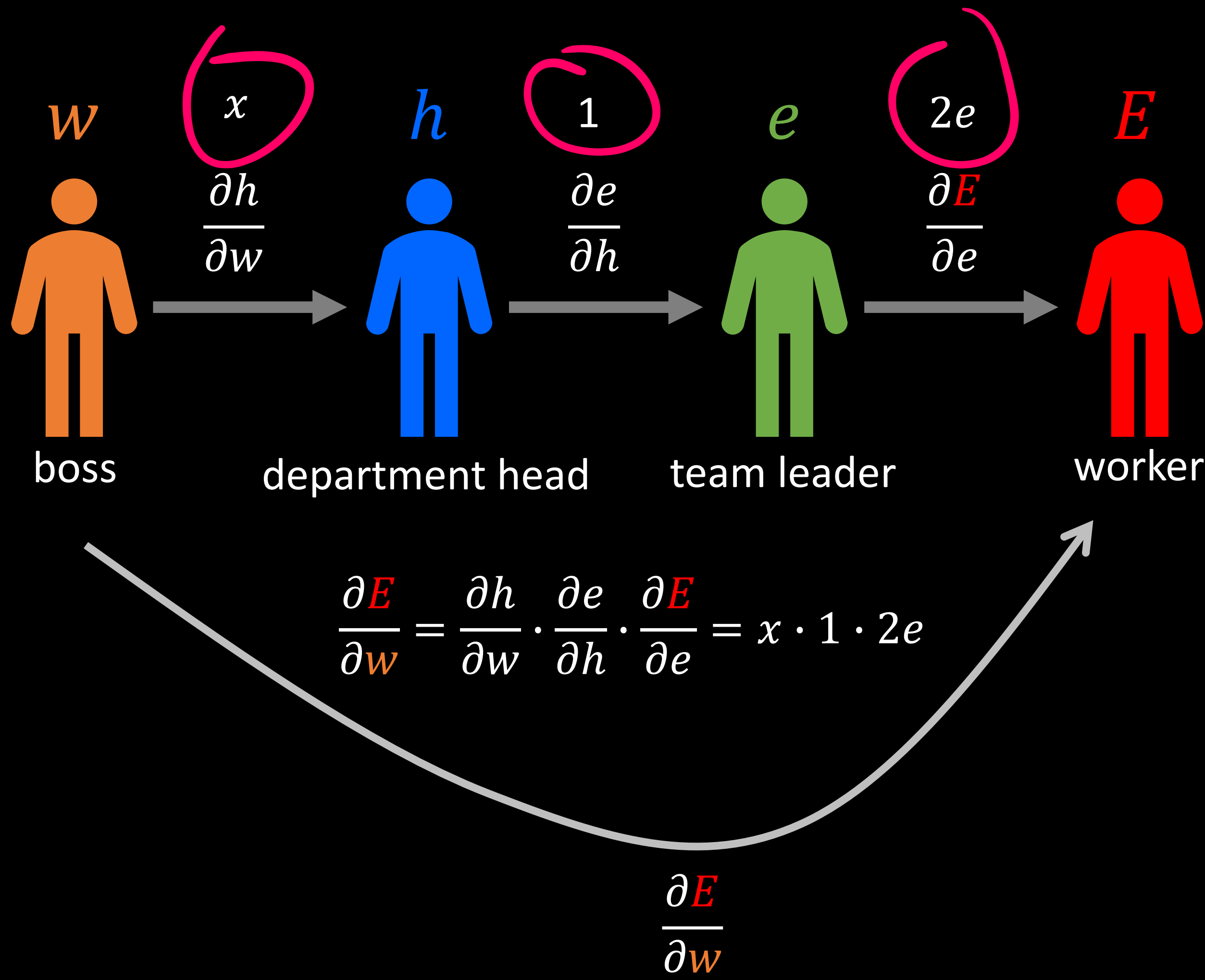


How can we get the influence of w change on E?

5 Local Gradients in gates



Influence between persons



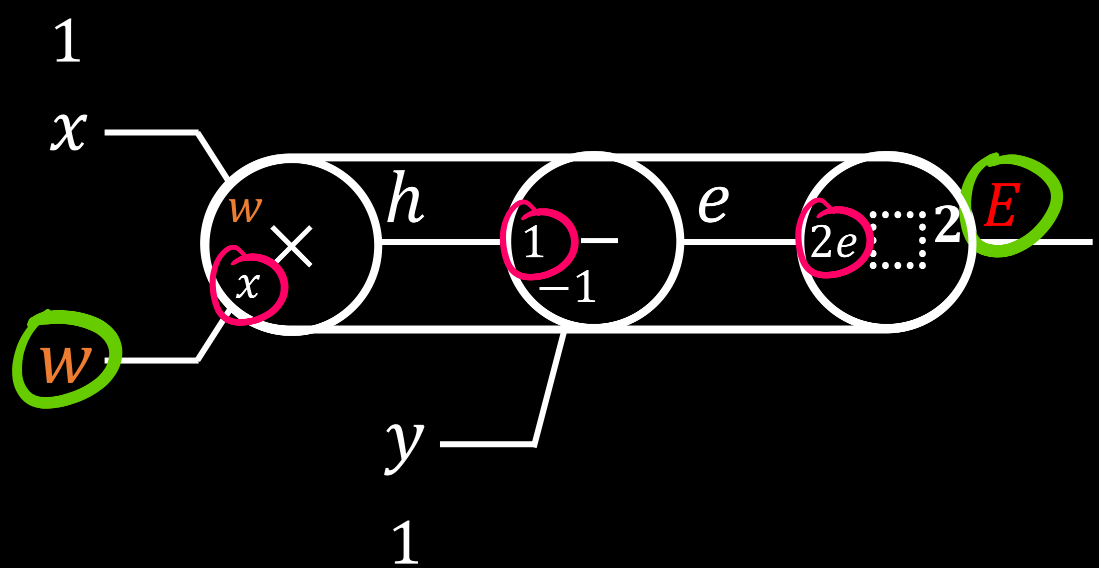
$$\frac{\partial E}{\partial w} = \frac{\partial h}{\partial w} \cdot \frac{\partial e}{\partial h} \cdot \frac{\partial E}{\partial e} = x \cdot 1 \cdot 2e$$

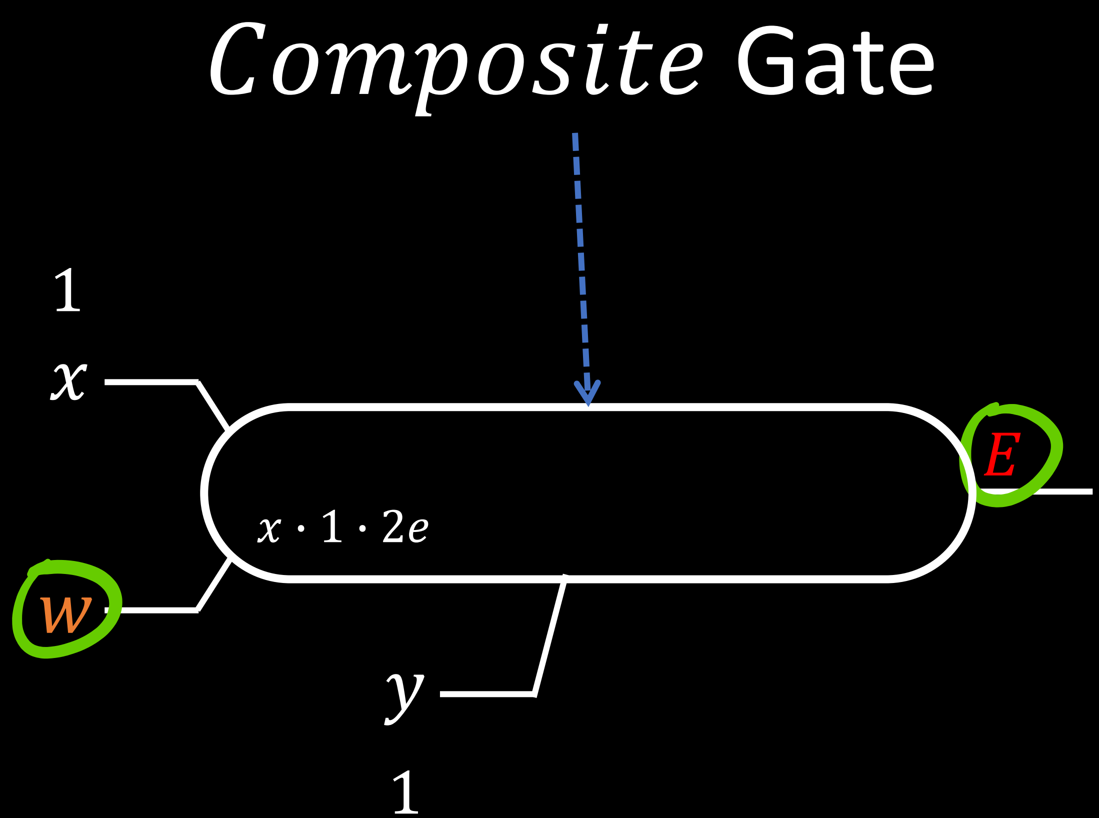
The influence of w change on E

$$\frac{\partial E}{\partial w} = \frac{\partial h}{\partial w} \times \frac{\partial e}{\partial h} \times \frac{\partial E}{\partial e}$$

Chain rule!

Merging the Gates

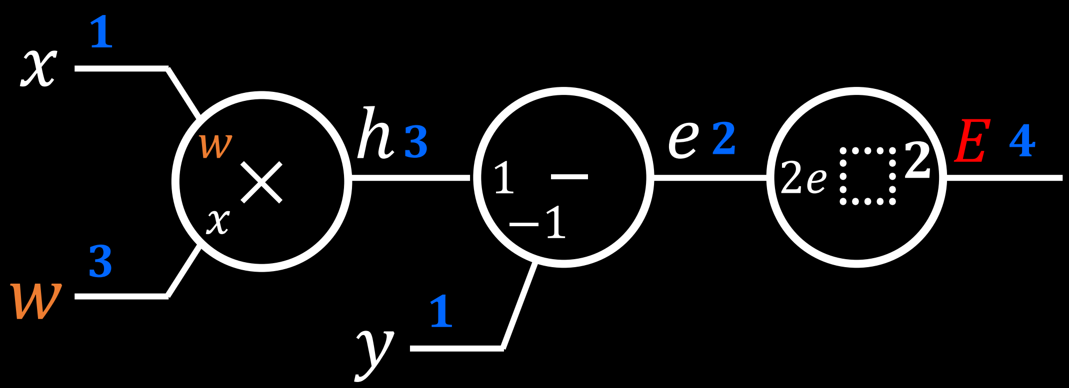




$Composite$ Gate
1
x
$x \cdot 1 \cdot 2e$
E
w
y
1

Forward propagation

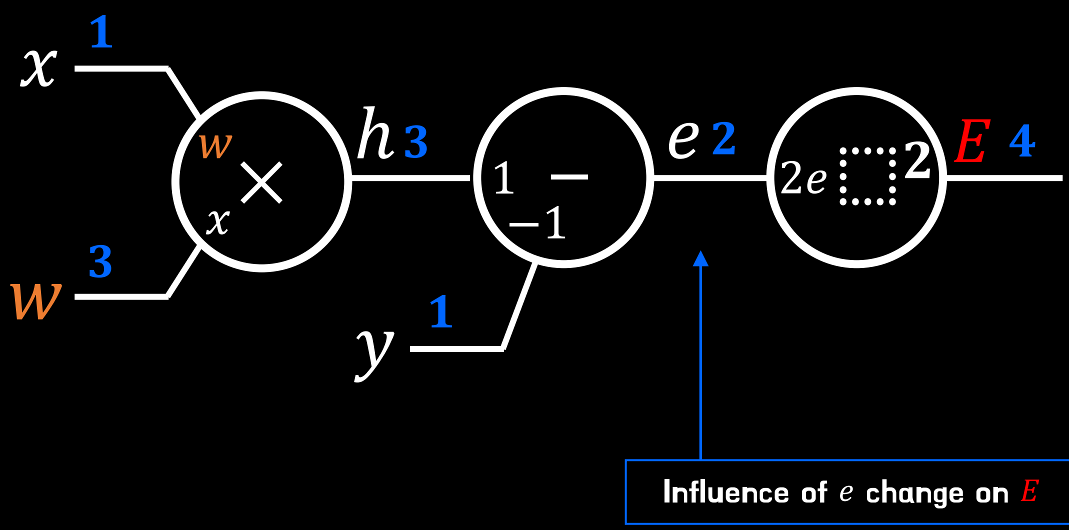
Let $(x, y) = (1, 1)$ and $w = 3$, then compute E.



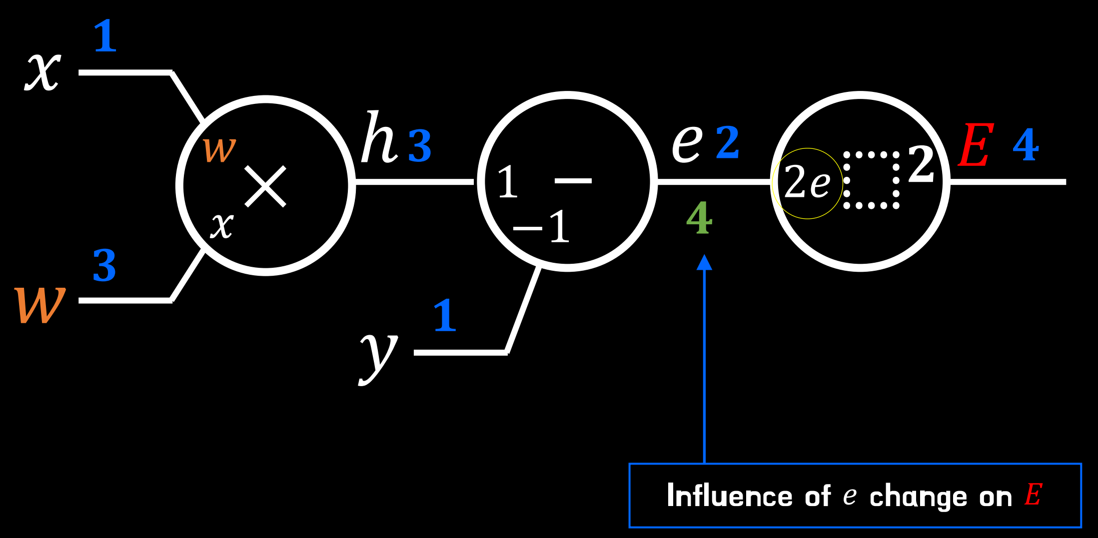
Error is big (4) ,
so let's update w

using back-propagation.

Back-propagation

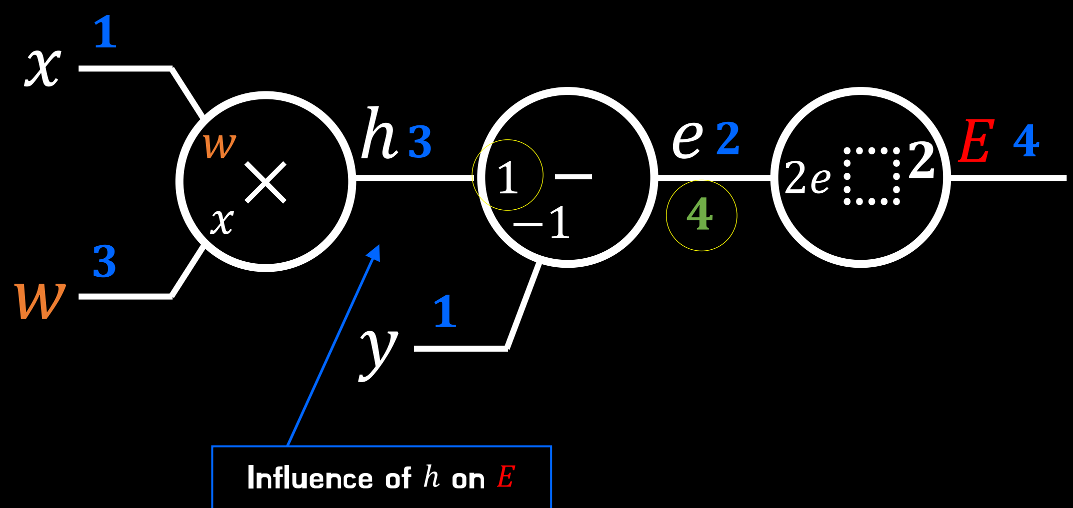


Back-propagation



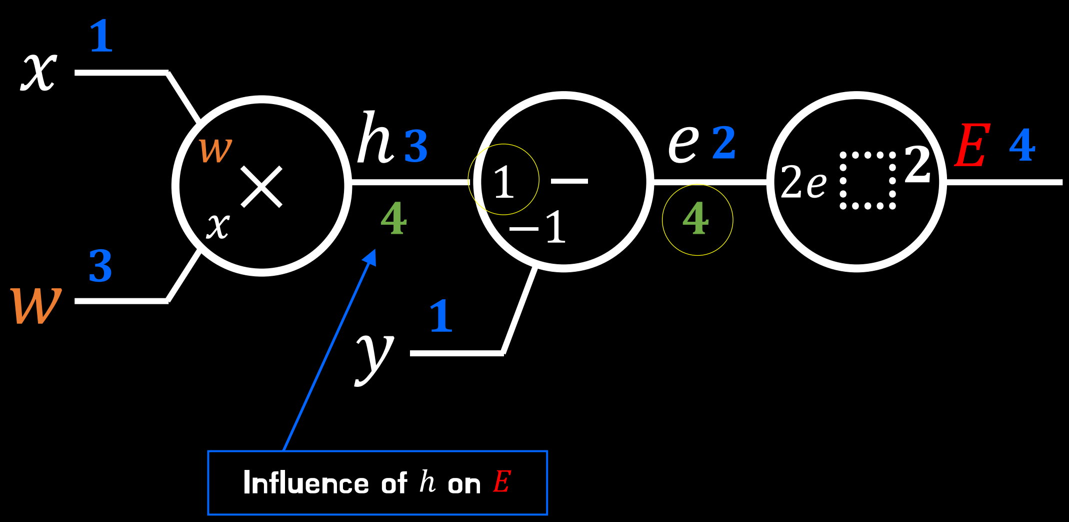
$$\frac{\partial E}{\partial e} = 2e$$

Back-propagation

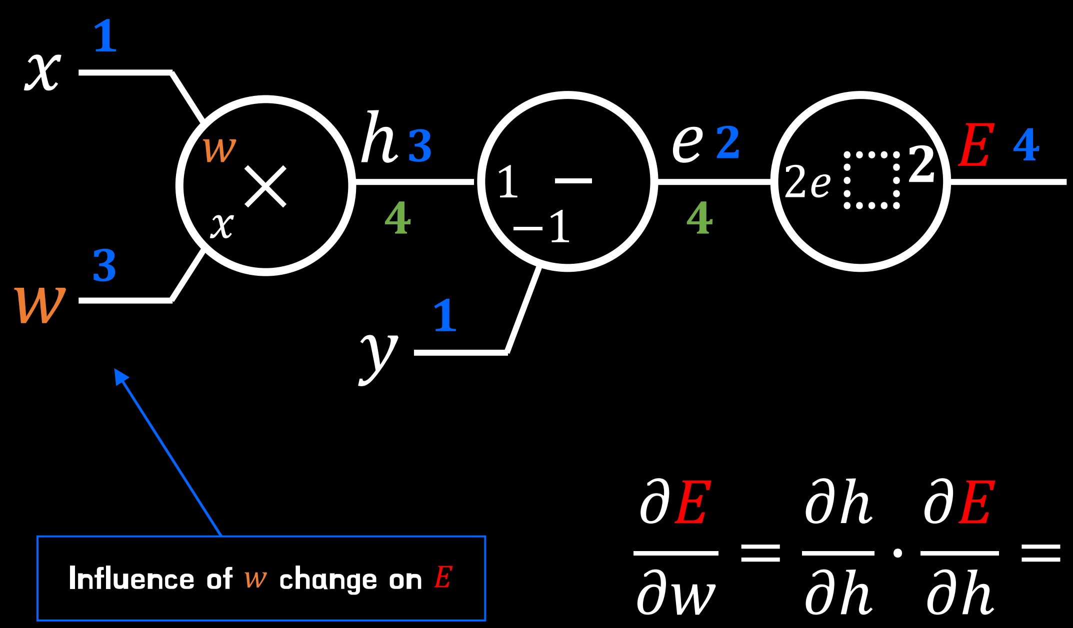


$$\frac{\partial E}{\partial h} = \frac{\partial e}{\partial h} \cdot \frac{\partial E}{\partial e} = 1 \cdot 4$$

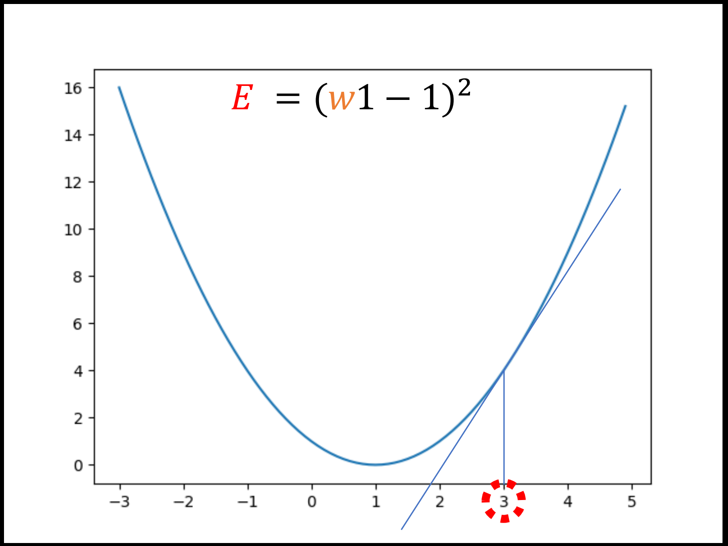
Back-propagation

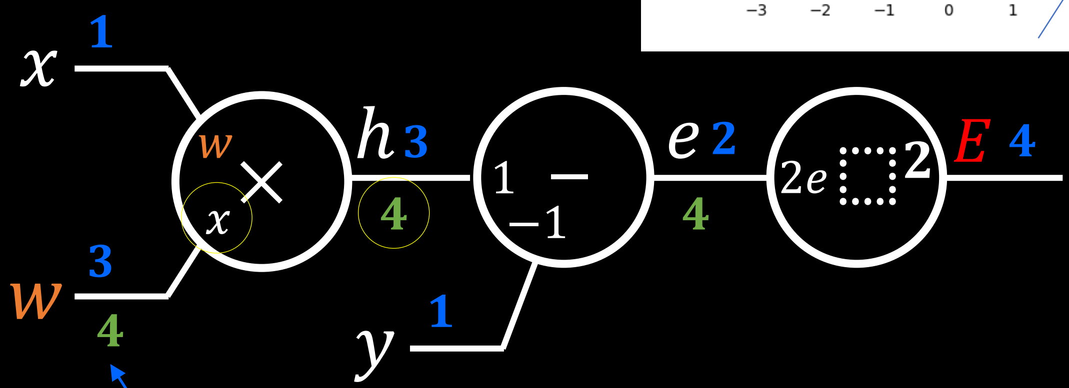


Back-propagation



$$\frac{\partial E}{\partial w} = \frac{\partial h}{\partial h} \cdot \frac{\partial E}{\partial h} = 1 \cdot 4$$





Influence of change w on E
when w = 3 is 4

$$\frac{\partial E}{\partial w}$$

Back-propagation, the process to apply chain rules

$$\frac{\partial E}{\partial w}$$

$$\frac{\partial E}{\partial w}$$

$$w = 3 - 0.1 * 4$$

$$w = 2.6 \ \textit{(updated!)}$$

Tuned parameter after 1 step learning

After enough number of steps (epochs), the parameter w will be optimized properly.

Backpropagation

by Paul Webros (1974, 1982) and

Geoffrey Hinton (1986)

Prof. Univ. of Toronto,
Google Brain
Yann LeCun (his post doc)

```python
import tensorflow as tf

#----- training data
x_data = [1]
y_data = [1]

#----- a neuron / neural network
w = tf.Variable(tf.random.normal([1]))
hypo = w * x_data

#----- learning
cost = (hypo - y_data) ** 2

train = tf.train.GradientDescentOptimizer(learning_rate=0.01).minimize(cost)

sess = tf.Session()
sess.run(tf.global_variables_initializer())

for i in range(1001):
    sess.run(train) # 1-run, 1-update of w -> 1001 updates

    if i % 100 == 0:
        print('w:', sess.run(w), 'cost:', sess.run(cost))

#----- testing(prediction)
x_data = [2]
print(sess.run(x_data * w))
```

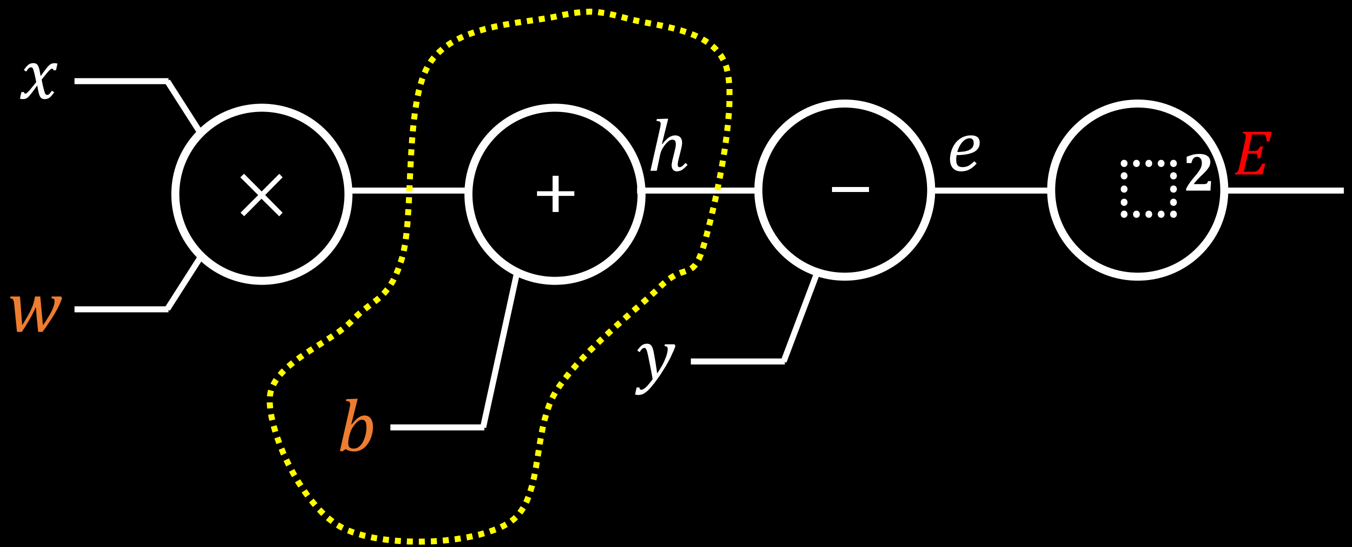
train operation to update w to minimize cost(error)

[code] www.kaggle.com/yungbyun/a-simple-neuron/

Extension of the Graph

- adding bias b (one more plus gate)

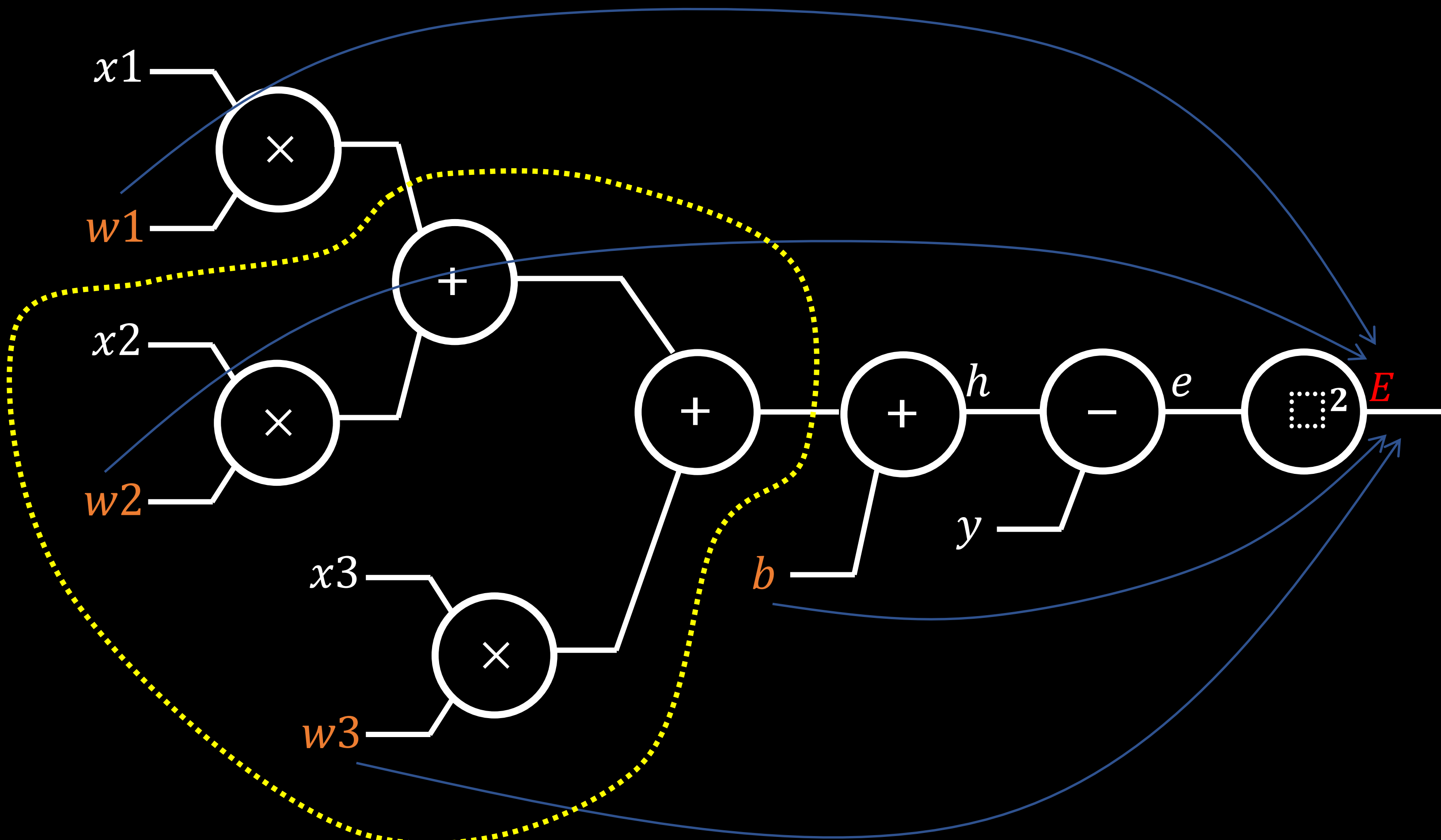
$$E = ((wx \boxed{+\, b}) - y)^2$$

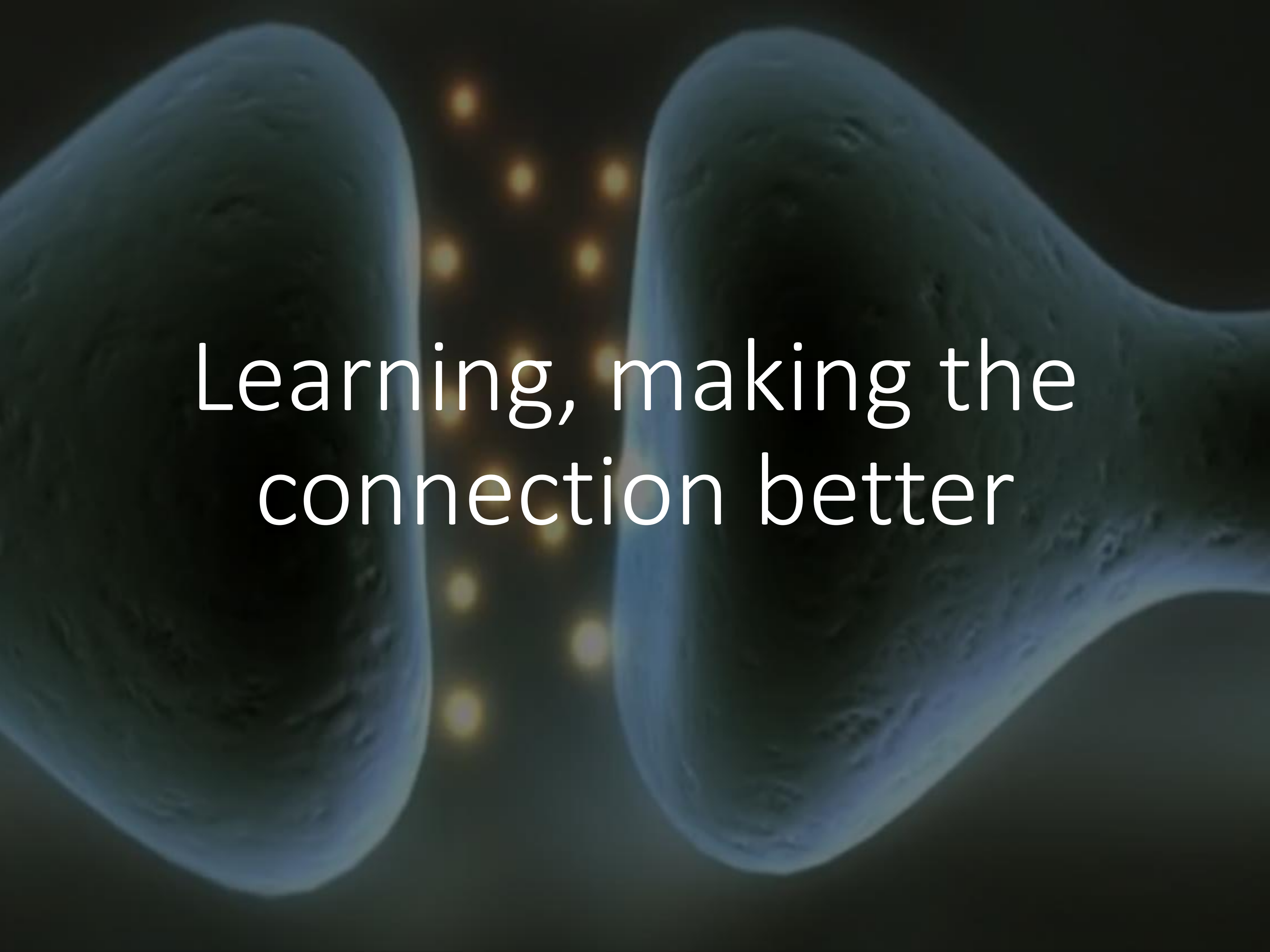


Extension of the Graph

- a neuron with 3 inputs (2 more + gate)

$$E = ((w1x1 \boxed{+ w2x2 + w3x3} + b) - y)^2$$

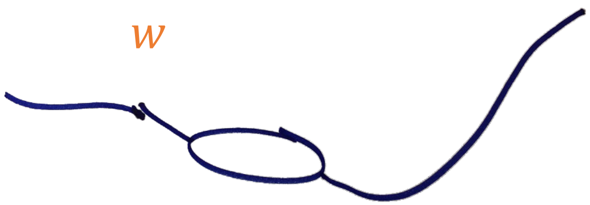


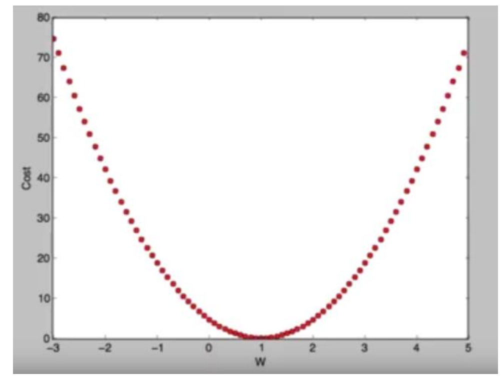


Learning, making the connection better

Cost(Error) graph

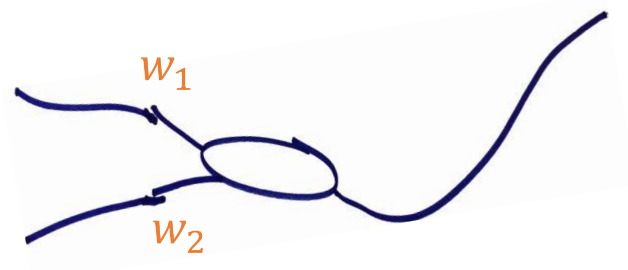
$E = (w \cdot 1 - 1)^2$

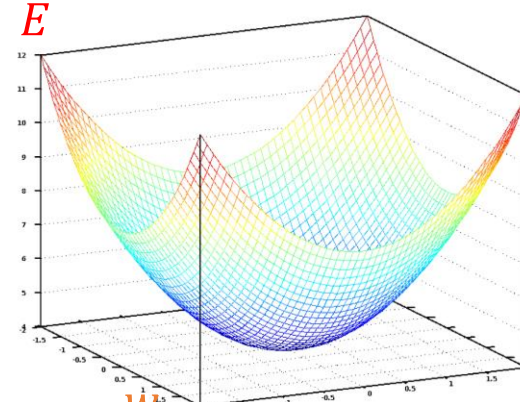




convex function

$E = (\boldsymbol{w_1} \cdot 1 + \boldsymbol{w_2} \cdot 1 - 1)^2$





convex function

Lab 02.with_bias.py

Parameter tuning including bias

Lab 03.py

Using multiple data

Lab 04.py

Training a neuron having multiple inputs