# Computational Graph and Linear Regression (Draft)

**Quang-Vinh Dinh Ph.D. in Computer Science** 

# Outline

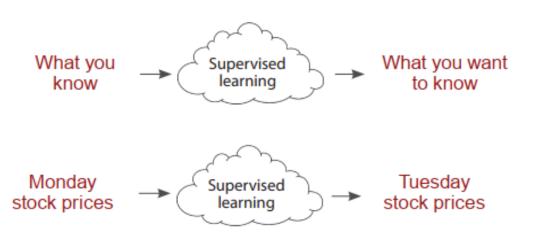
- > Machine Learning
- > Derivative/Gradient
- > Linear Regression
- > Computational Graph
- > Summary

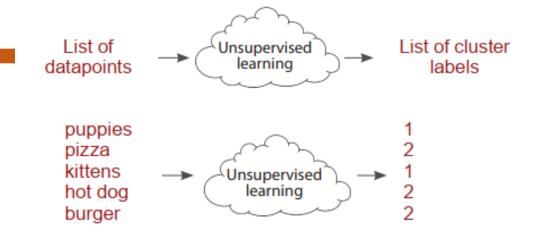
### **Definition**

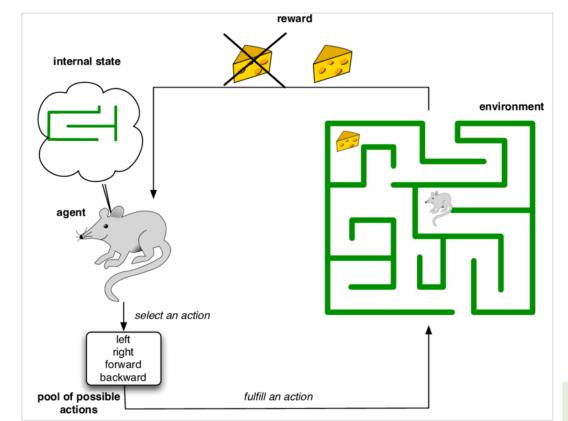
### What is machine learning?

A field of study that gives computers the ability to learn without being explicitly programmed.

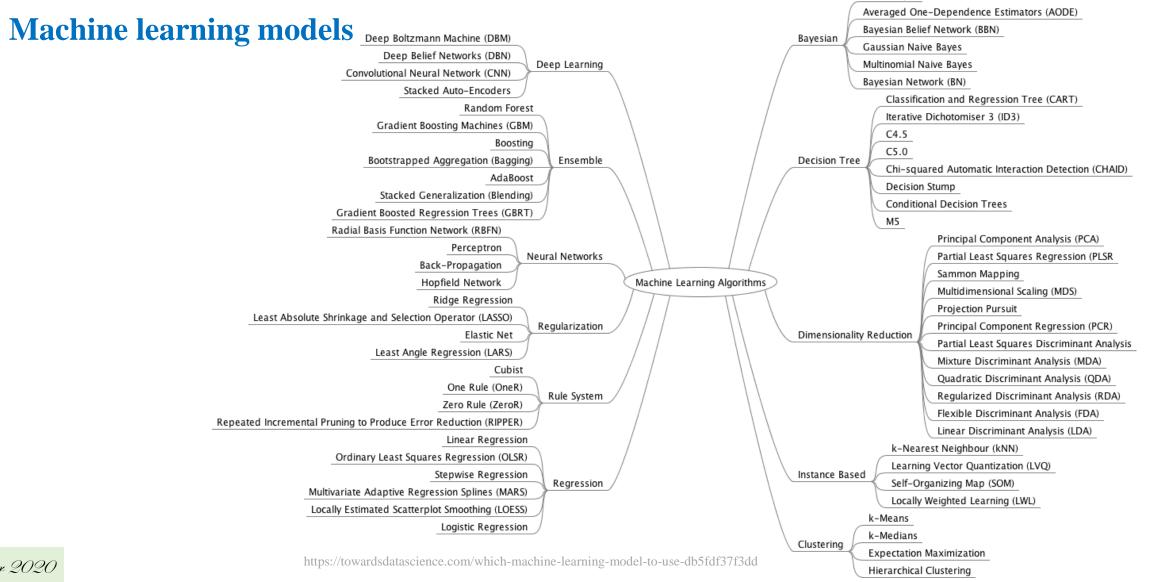
-Attributed to Arthur Samuel







Naive Bayes



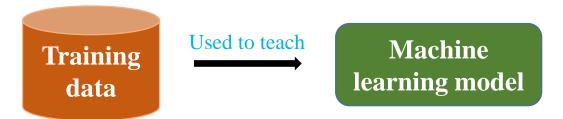
### **Supervised learning**

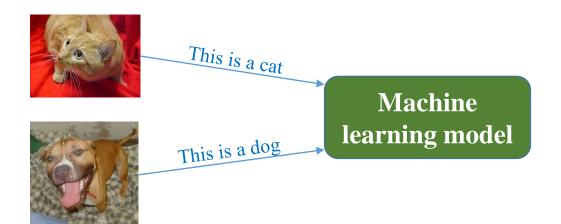
Input and output data is provided

- Training data
- Cats
- Dogs



### **Supervised learning**





From Cat-Dog dataset



**Testing data (≠ training data)** 



**Training phase** 

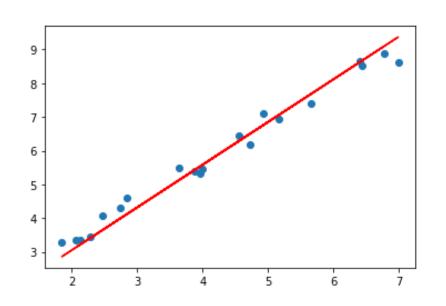
**Testing phase** 

- **Supervised learning** 
  - **Regression** (prediction)

Linear regression models ← Linear equations

Linear equation =  $w_1x_1 + w_2x_2 + \cdots + w_nx_n + b$ 

where w is a weight vector and x is feature vector



### **Supervised learning**

**\*** Linear Regression: Data processing

Feature	Label				
area	price				
6.7	9.1				
4.6	5.9				
3.5	4.6				
5.5	6.7				

House price data

Model: 
$$y = w_1x_1 + b$$
  
price =  $a * area + b$ 

	Label			
TV	<b>+ Radio</b>	Newspaper	Sales	
230.1	37.8	69.2	22.1	
44.5	39.3	45.1	10.4	
17.2	45.9	69.3	12	
151.5	41.3	58.5	16.5	
180.8	10.8	58.4	17.9	

Advertising data

Model: 
$$y = w_1x_1 + w_2x_2 + w_3x_3 + b$$
  
Sale =  $w_1 * TV + w_2 * Radio + w_3 * Newspaper + b$ 

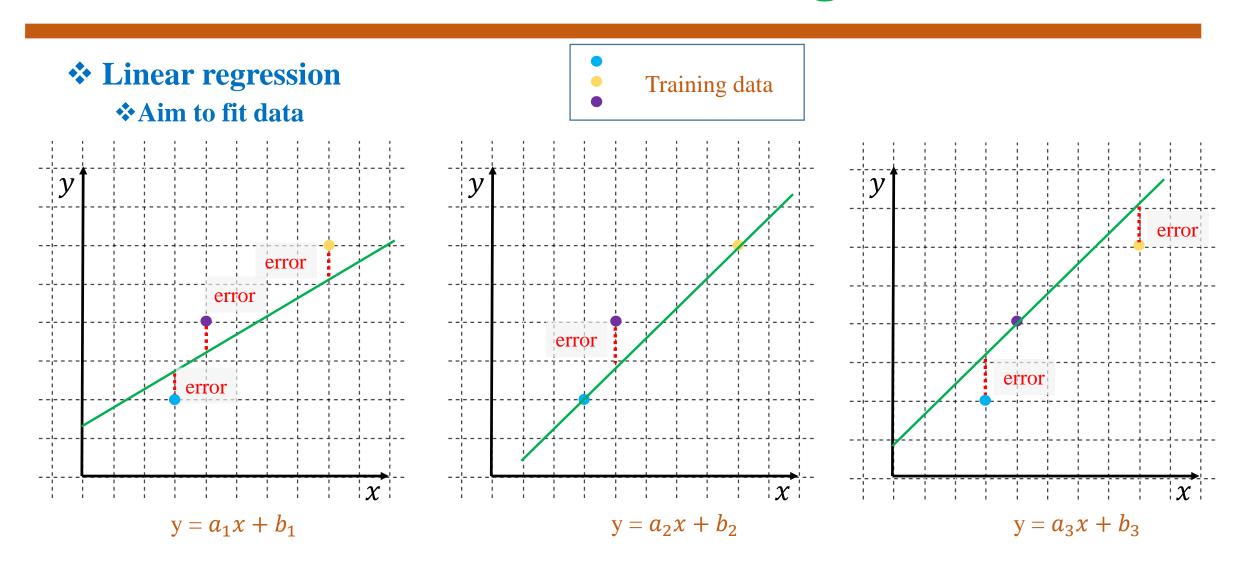
- **Supervised learning** 
  - **\*** Linear Regression: Data processing

Features	Label

Boston House Price Data

crim \$	zn ÷	indus \$	chas \$	nox \$	rm 💠	age \$	dis	≑ rad ≎	tax \$	ptratio \$	black \$	Istat \$	medv \$
0.00632	18	2.31	0	0.538	6.575	65.2	4.09	1	296	15.3	396.9	4.98	24
0.02731	0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.9	9.14	21.6
0.03237	0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
0.06905	0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.9	5.33	36.2
0.08829	12.5	7.87	0	0.524	6.012	66.6	5.5605	5 5	311	15.2	395.6	12.43	22.9

$$medv = w_1 * x_1 + \dots + w_{13} * x_{13} + b$$



Find w and b that have the smallest error.

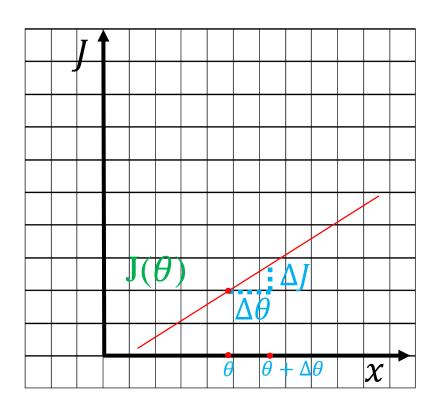
How?

# Outline

- > Machine Learning
- > Derivative/Gradient
- > Linear Regression
- > Computational Graph
- > Summary

### Derivative/Gradient

### **A** cue to optimize a function



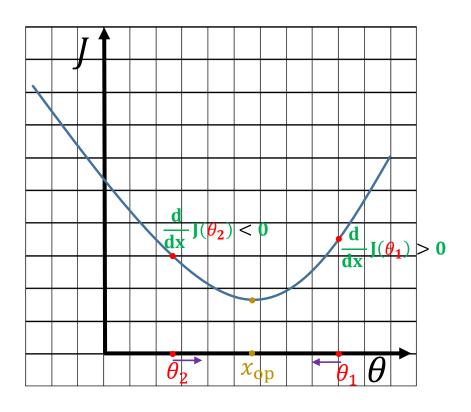
Đạo hàm = 
$$\frac{Thay \, \text{đổi theo } J}{Thay \, \text{đổi theo } \theta} = \frac{\Delta J}{\Delta \theta}$$

$$\frac{d}{d\theta}J(\theta) = \lim_{\Delta\theta \to 0} \frac{J(\theta + \Delta\theta) - J(\theta)}{\Delta\theta}$$

 $\Delta\theta$  cần tiến về 0 để đường tiếp tuyến tiến về hàm  $J(\theta)$  trong vùng lân cận tại  $\theta$ 

### Derivative/Gradient

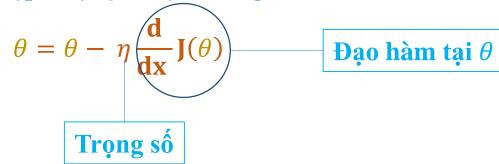
### **A** cue to optimize a function



Quan sát:  $\theta_{op}$  ở vị trí ngược hướng đạo hàm tại  $\theta_1$  và  $\theta_2$ 

Cách xử lý việc di chuyển ngược hướng đạo hàm cho  $\theta_1$  và  $\theta_2$  (để tìm  $\theta_{op}$ ) khác nhau hình thành các thuật toán tối ưu hóa khác nhau

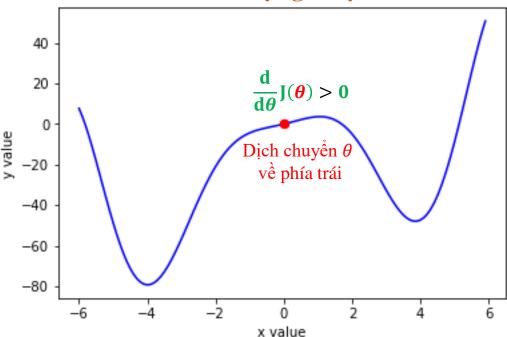
Cách cập nhật giá trị x đơn giản

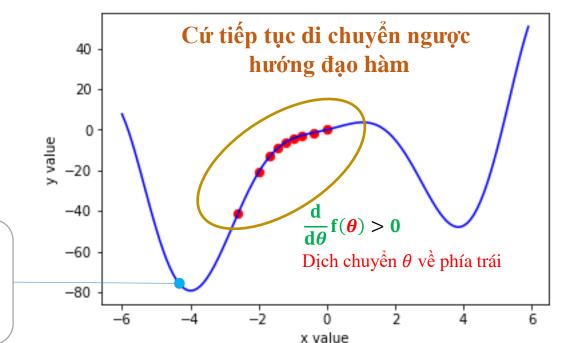


### Derivative/Gradient

### **A** cue to optimize a function







Di chuyển  $\theta$  ngược hướng đạo hàm

 $\frac{\mathrm{d}}{\mathrm{d}\theta}\mathrm{f}(\theta) > 0$ 

Dịch chuyển  $\theta$  về phía trái

x value

 $\frac{\mathrm{d}}{\mathrm{d}\theta}\mathrm{f}(\theta) > 0$ 

Dịch chuyển  $\theta$ 

về phía trái

40

20

0

-20

-40

-60

-80

y value

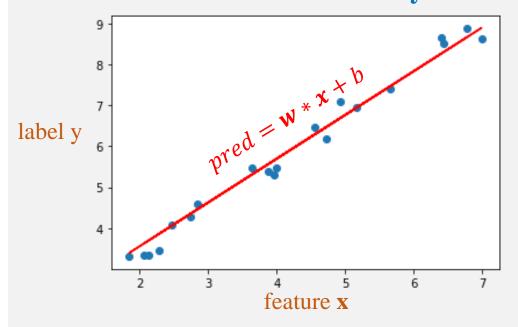
 $\frac{\mathrm{d}}{\mathrm{d}\theta}\mathrm{f}(\theta)<0$ 

Dịch chuyển *θ* về phía phải

# Outline

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# Model the relationship between feature x and label y



Using a linear equation to fit data
Samples (x, y) are given in advance

### **Linear equation**

$$o = w_1 x_1 + w_2 x_2 + \dots + w_n x_n + b$$

where o is a predicted value,  $w_1, w_2, ..., w_n$  and b are parameters and  $\mathbf{x} = [x_1 \ x_2 \ ... \ x_n]^T$  is feature vector.

### **Error** (loss) computation

**Idea:** compare predicted values **o** and label values **y** Squared loss

$$L(\mathbf{w}, \mathbf{b}) = (o - y)^2$$

### **Linear equation**

$$o = w_1 x_1 + w_2 x_2 + \dots + w_n x_n + b$$

where o is a predicted value,  $w_1, w_2, ..., w_n$  and b are parameters and  $\mathbf{x} = [x_1 \ x_2 \ ... \ x_n]^T$  is feature vector.

### **Error** (loss) computation

**Idea:** compare predicted values **o** and label values **y** Squared loss

$$L(\mathbf{w}, \mathbf{b}) = (o - y)^2$$

### How to find optimal w and b?

Use gradient descent to minimize the loss function

Tính đạo hàm

$$\frac{\partial L}{\partial w_j} = \frac{\partial L}{\partial o} \frac{\partial o}{\partial w_j} = 2x_j(o - y)$$

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial o} \frac{\partial o}{\partial b} = 2(o - y)$$

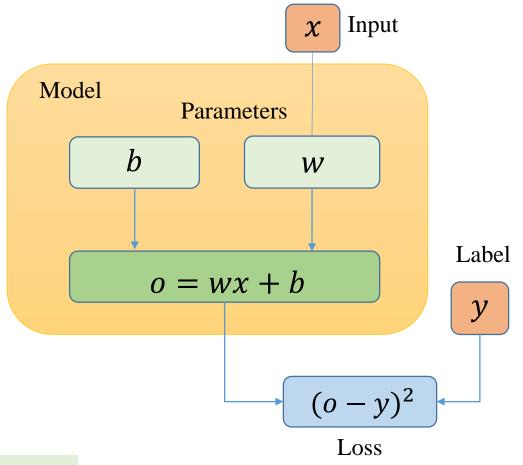
Cập nhật tham số

$$w_{j} = w_{j} - \eta L'_{w_{j}}$$

$$b = b - \eta L'_{b}$$

$$\eta \text{ is learning rate}$$

### **Diagram**



#### **Cheat sheet**

#### Tính output o

$$o = wx + b$$

#### Tính Loss

$$L = (o - y)^2$$

#### Tính đạo hàm

$$L'_{w_j} = 2x_j(o - y)$$
  $w_j = w_j - \eta L'_{w_j}$ 

$$L_b' = 2(o - y) \qquad b = b - \eta L_b'$$

### Cập nhật tham số

$$w_j = w_j - \eta L'_{w_j}$$

$$b = b - \eta L_b'$$

#### **Cheat sheet**

Tính output o

Tính Loss

$$o = wx + b \qquad \qquad L = (o - y)^2$$

Tính đao hàm

Cập nhật tham số

$$L'_{w_j} = 2x_j(o - y)$$
  $w_j = w_j - \eta L'_{w_j}$   
 $L'_b = 2(o - y)$   $b = b - \eta L'_b$ 

$$L_h' = 2(o - y)$$

$$w_j = w_j - \eta L'_{w_j}$$

$$b = b - \eta L_b'$$

```
# forward
    def predict(x,w,b):
        return x*w + b
    # compute gradient
    def gradient(z,y,x):
        dw = 2*x*(z-y)
        db = 2*(z-y)
        return (dw, db)
10
11
    # update weights
    def update_weight(w,b,n,dw,db):
        w_new = w - n*dw
14
        b new = b - n*db
15
16
17
        return (w_new, b_new)
```

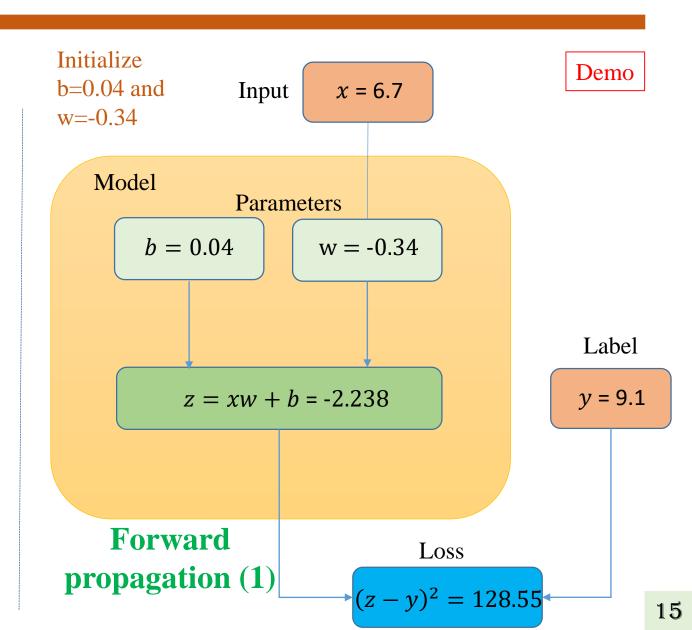
# Al Insight Course Linear Regression

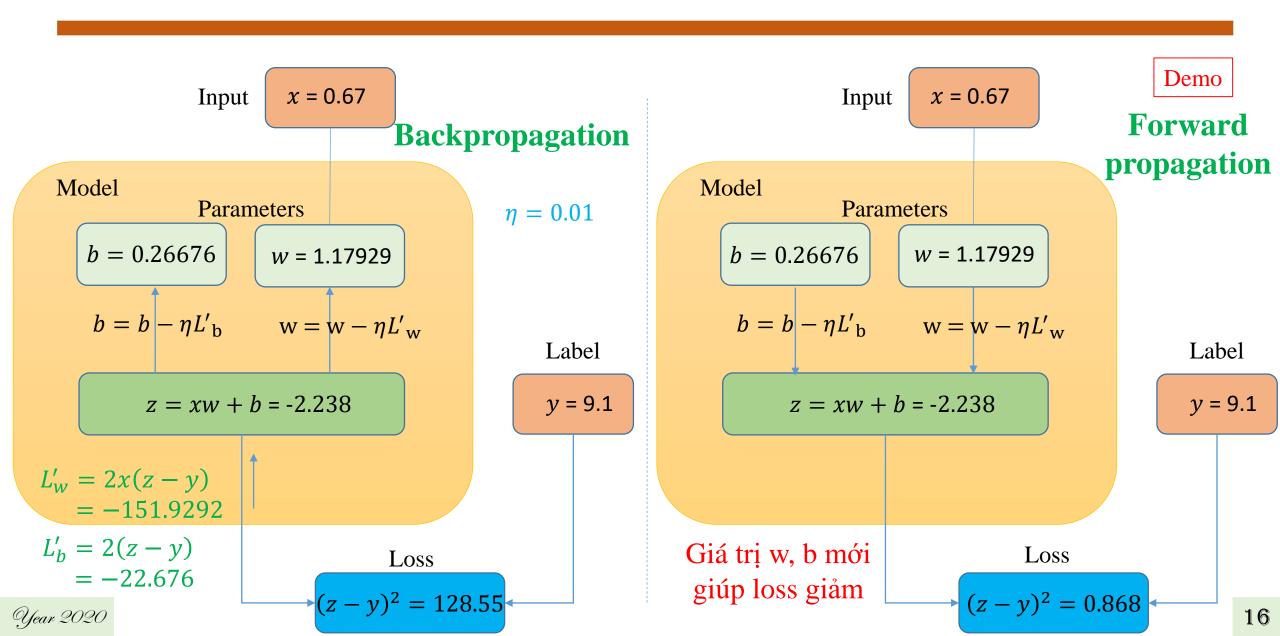
```
# forward
    def predict(x,w,b):
        return x*w + b
 4
    # compute gradient
    def gradient(z,y,x):
        dw = 2*x*(z-y)
        db = 2*(z-y)
 8
10
        return (dw, db)
11
    # update weights
    def update_weight(w,b,n,dw,db):
        w new = w - n*dw
14
15
        b new = b - n*db
16
17
        return (w_new, b_new)
```

```
19 # test with a sample
20
   x = 6.7
   v = 9.1
22
23
   # init weight
    b = 0.04
   W = -0.34
   n = 0.01
26
27
28
   # predict z
    z = predict(x, w, b)
    print('z: ', z)
31
   # compute loss
    loss = (z-y)*(z-y)
    print('Loss: ', loss)
35
   # compute gradient
    (dw, db) = gradient(z,y,x)
38
    print('dw: ', dw)
    print('db: ', db)
40
41
    # update weights
    (w_new, b_new) = update_weight(w,b,n,dw,db)
    print('w_new: ', w_new)
    print('b_new: ', b_new)
```

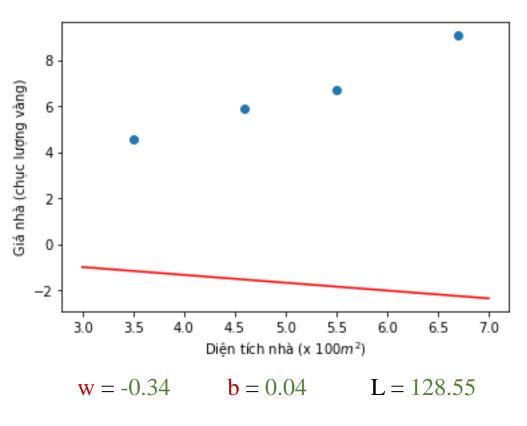


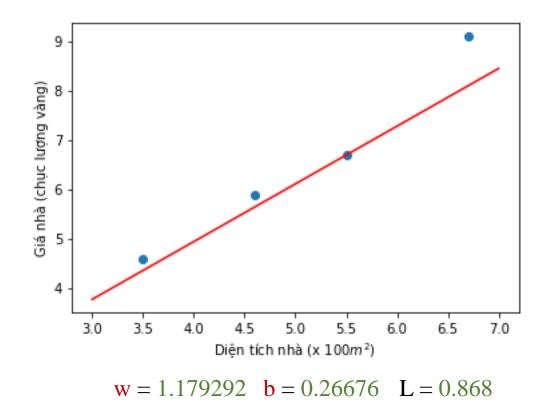






### Model prediction before and after the first update





**Before updating** 

After updating

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
$$L'_b = 2(o - y)$$

5) Cập nhật tham số

$$w = w - \eta L'_{w}$$

$$b = b - \eta L'_{b}$$

$$\eta \text{ is learning rate}$$

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o-y)$$

5) Cập nhật tham số

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta L_{\boldsymbol{\theta}}'$$

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
$$L'_b = 2(o - y)$$

5) Cập nhật tham số

$$w = w - \eta L'_{w}$$

$$b = b - \eta L'_{b}$$

$$\eta \text{ is learning rate}$$

```
# forward
    def predict(x,w,b):
        return x*w + b
    # compute gradient
    def gradient(z,y,x):
        dw = 2*x*(z-y)
        db = 2*(z-y)
        return (dw, db)
10
11
    # update weights
    def update_weight(w,b,n,dw,db):
13
        w new = w - n*dw
14
15
        b new = b - n*db
16
        return (w_new, b_new)
17
```

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

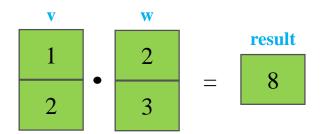
$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o-\boldsymbol{y})$$

5) Cập nhật tham số

$$\theta = \theta - \eta L_{\theta}'$$



```
# aivietnam.ai
import numpy as np

v = np.array([1, 2])
w = np.array([2, 3])

# Tinh inner product giữa v và w
print('method 1 \n', v.dot(w))
print('method 2 \n', np.dot(v, w))
```

```
method 1
8
method 2
8
```

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

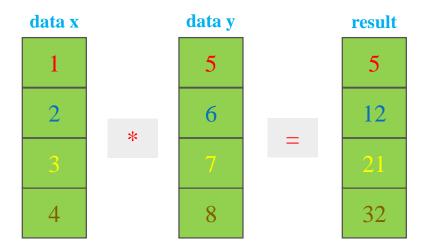
$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o - y)$$

5) Cập nhật tham số

$$\theta = \theta - \eta L_{\theta}'$$



```
# aivietnam.ai
import numpy as np

x = np.array([1,2,3,4])
y = np.array([5,6,7,8])

print('data x \n', x)
print('data y \n', y)

# Tich các phần tử tương ứng giữa x và y
print('method 1 \n', x*y)
print('method 2 \n', np.multiply(x, y))
```

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o-\boldsymbol{y})$$

5) Cập nhật tham số

$$\theta = \theta - \eta L_{\theta}'$$

```
import numpy as np
    # forward
    def predict(x,theta):
        return x.dot(theta)
    # compute gradient
    def gradient(z,y,x):
        dtheta = 2*x*(z-y)
10
11
        return dtheta
12
    # update weights
14
    def update_weight(theta,n,dtheta):
15
        dtheta_new = theta - n*dtheta
16
17
        return dtheta_new
18
```

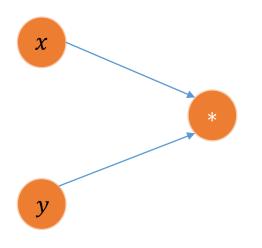
```
import numpy as np
   # forward
    def predict(x,theta):
        return x.dot(theta)
 5
 6
   # compute gradient
    def gradient(z,y,x):
        dtheta = 2*x*(z-y)
10
        return dtheta
11
12
13
   # update weights
    def update_weight(theta,n,dtheta):
15
        dtheta new = theta - n*dtheta
16
17
        return dtheta new
18
```

```
# test with a sample
   x = np.array([6.7, 1])
   y = np.array([9.1])
22
   # init weight
   n = 0.01
   # thetas = [w, b]
   theta = np.array([-0.34, 0.04])
27
28
29
   # predict z
    z = predict(x, theta)
    print('Input data: ', x)
    print('Theta: ', theta)
33
    print('z: ', z)
34
   # compute loss
35
   loss = (z-y)*(z-y)
    print('Loss: ', loss)
37
38
   # compute gradient
    dtheta = gradient(z,y,x)
    print('dtheta: ', dtheta)
42
43
    # update weights
    theta_new = update_weight(theta,n,dtheta)
    print('theta_new: ', theta_new)
```

# Outline

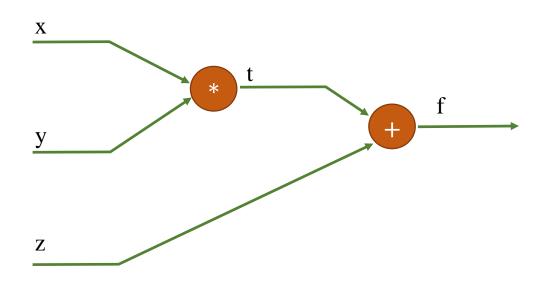
- > Machine Learning
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- **A** directed graph
- Nodes represent variables or operations



- **Construct computational graph for** f(x, y, z) = x \* y + z
- ightharpoonup Rewrite f(x, y, z) as

$$f(t,z) = t + z$$
 where  $t = x * y$ 

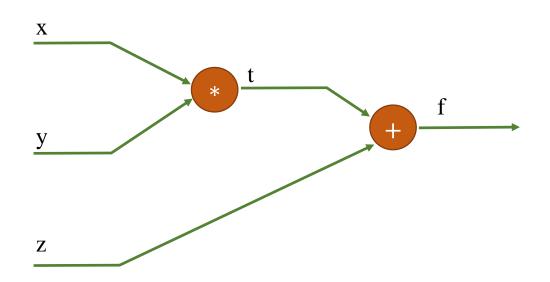


### **Construct computational graph for**

$$f(x, y, z) = x * y + z$$

### ightharpoonup Rewrite f(x, y, z) as

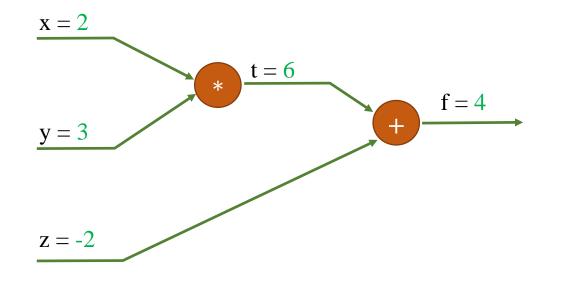
$$f(t,z) = t + z$$
 where  $t = x * y$ 



$$\frac{\partial t}{\partial x} = y \qquad \qquad \frac{\partial f}{\partial z} = 1 \qquad \qquad \frac{\partial f}{\partial x} = y$$

$$\frac{\partial t}{\partial y} = x \qquad \qquad \frac{\partial f}{\partial t} = 1 \qquad \qquad \frac{\partial f}{\partial y} = x$$

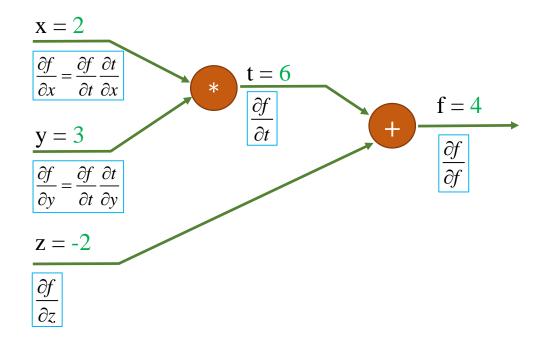
**Compute** f(x, y, z) **vói** x = 2, y = 3 **và** z = -2.



$$\frac{\partial t}{\partial x} = y \qquad \qquad \frac{\partial f}{\partial z} = 1 \qquad \qquad \frac{\partial f}{\partial x} = y$$

$$\frac{\partial t}{\partial y} = x \qquad \qquad \frac{\partial f}{\partial t} = 1 \qquad \qquad \frac{\partial f}{\partial y} = x$$

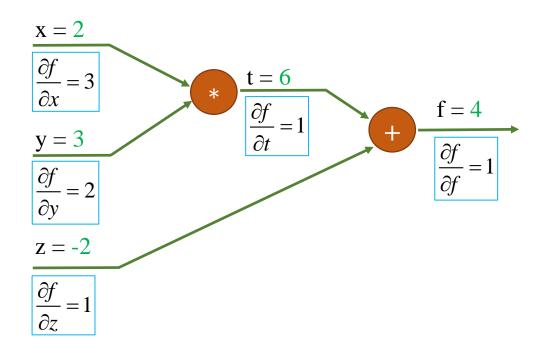
**Compute** f(x, y, z) **vói** x = 2, y = 3 **và** z = -2.



$$\frac{\partial t}{\partial x} = y \qquad \qquad \frac{\partial f}{\partial z} = 1 \qquad \qquad \frac{\partial f}{\partial x} = y$$

$$\frac{\partial t}{\partial y} = x \qquad \qquad \frac{\partial f}{\partial t} = 1 \qquad \qquad \frac{\partial f}{\partial y} = x$$

**Compute** f(x, y, z) **vói** x = 2, y = 3 **và** z = -2.



$$\frac{\partial t}{\partial x} = y \qquad \qquad \frac{\partial f}{\partial z} = 1 \qquad \qquad \frac{\partial f}{\partial x} = z$$

$$\frac{\partial t}{\partial y} = x \qquad \qquad \frac{\partial f}{\partial t} = 1 \qquad \qquad \frac{\partial f}{\partial y} = z$$

# Outline

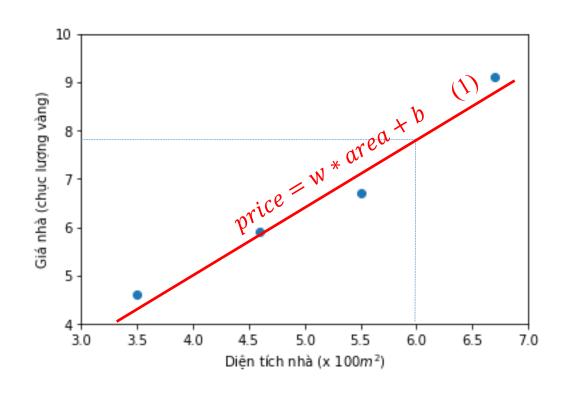
- > Machine Learning
- > Derivative/Gradient
- > Linear Regression
- > Computational Graph
  - > 1-sample training
- > Summary

#### **\*** House price predictions

**\clubsuit** How much for a 600- $m^2$  house?

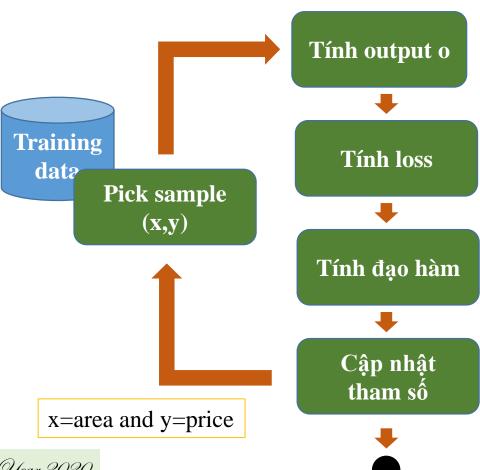
area	price
6.7	9.1
4.6	5.9
3.5	4.6
5.5	6.7

Given sample data



#### How to compute (1) using computational graph

- **\*** House price prediction
  - **\*** One-sample training



- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

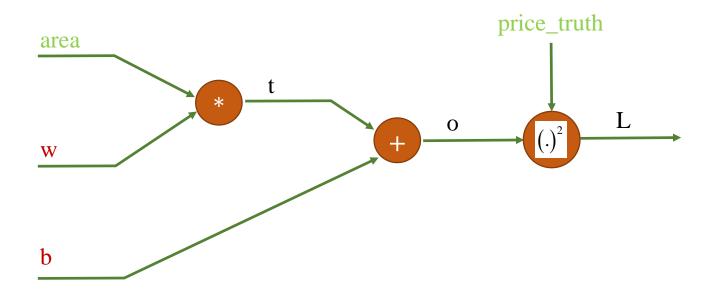
4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
  
$$L'_h = 2(o - y)$$

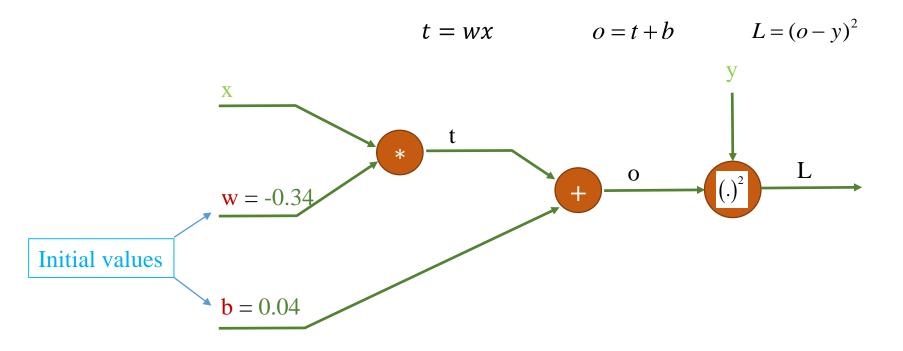
$$w = w - \eta L'_{w}$$
 $b = b - \eta L'_{h}$ 
Learning rate  $\eta$ 

- **\*** House price prediction
  - **\*** One-sample training

$$price = w * area + b$$
  
 $t = w * area$ 



- **\*** House price prediction
  - **\*** One-sample training



 area
 price

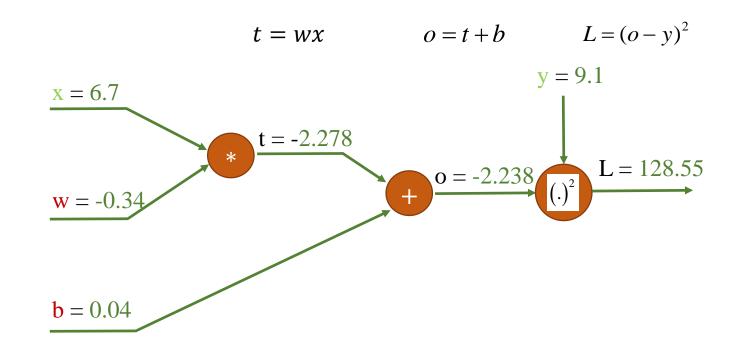
 6.7
 9.1

 4.6
 5.9

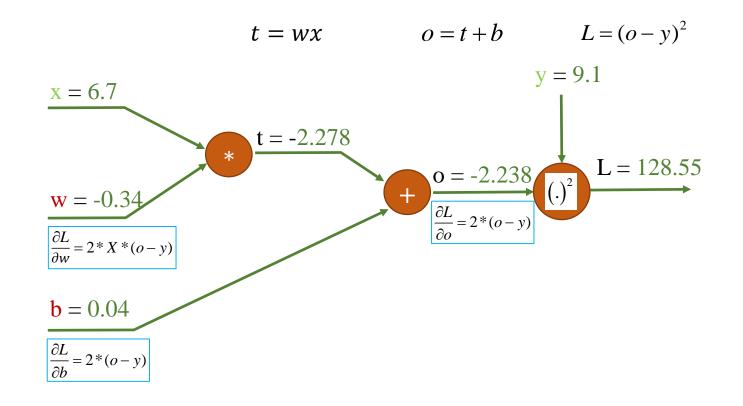
 3.5
 4.6

 5.5
 6.7

- **\*** House price prediction
  - **\*** One-sample training



- **\*** House price prediction
  - **\*** One-sample training

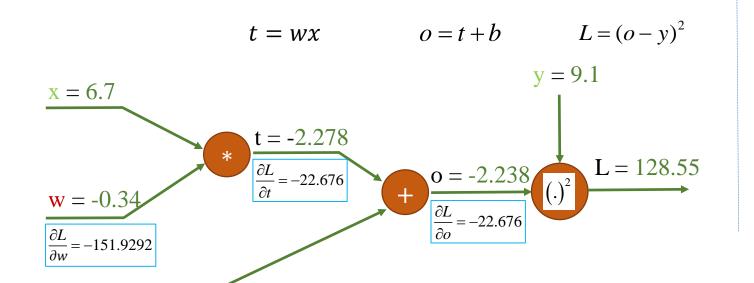


#### **\*** House price prediction

b = 0.04

 $\frac{\partial L}{\partial b} = -22.676$ 

**❖** One-sample training



#### Cách cập nhật a và b

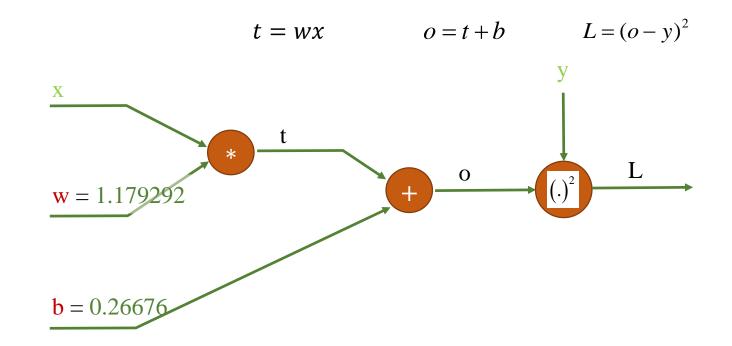
$$w = w - \eta * \frac{\partial L}{\partial w}$$
$$b = b - \eta * \frac{\partial L}{\partial b}$$

Learning rate  $\eta = 0.01$ 

$$w = -0.34 - (0.01 * (-151.9)) = 1.179$$

$$b = 0.04 - (0.01 * (-22.67)) = 0.266$$

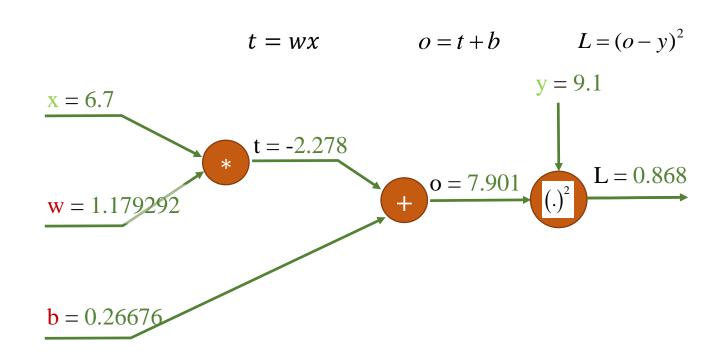
- **\*** House price prediction
  - **\*** One-sample training



Feature	Label
area	price
6.7	9.1
4.6	5.9
3.5	4.6
5.5	6.7

#### **\*** House price prediction

**\*** One-sample training

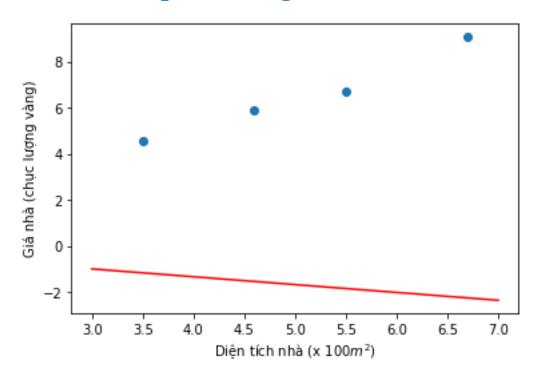


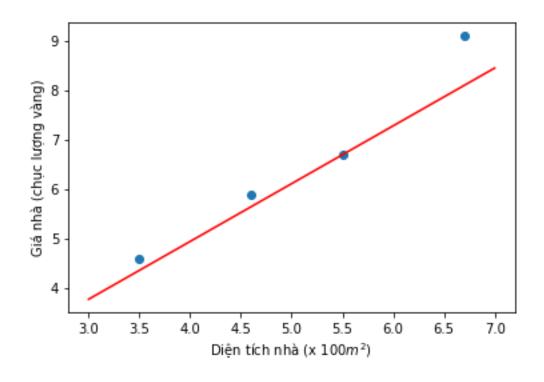
previous L = 128.55

Updated a and b values help to reduce the L value

#### **\*** House price prediction

#### **\*** One-sample training





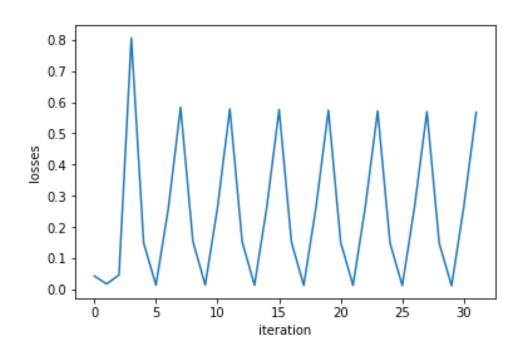
w = -0.34

b = 0.04

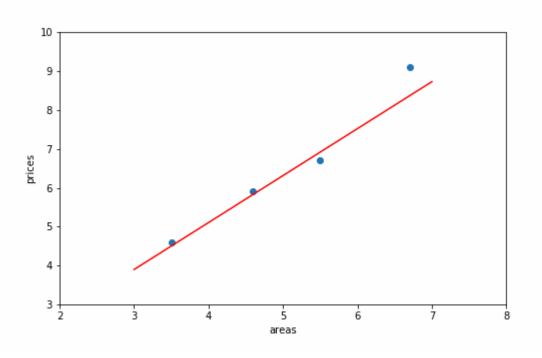
L = 128.55

 $\mathbf{w} = 1.179292$   $\mathbf{b} = 0.26676$   $\mathbf{L} = 0.868$ 

- **\*** House price prediction
  - **\*** One-sample training



**Losses for 30 iterations** 



**Model updating for different iterations** 

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
$$L'_b = 2(o - y)$$

5) Cập nhật tham số

$$w = w - \eta L'_{w}$$

$$b = b - \eta L'_{b}$$

$$\eta \text{ is learning rate}$$

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

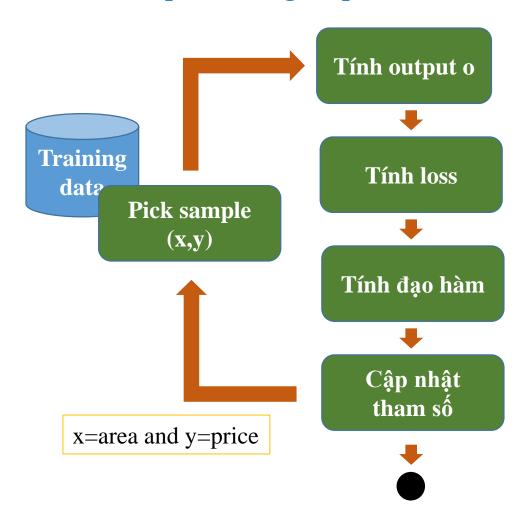
$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o - \boldsymbol{y})$$

5) Cập nhật tham số

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta L_{\boldsymbol{\theta}}'$$

 $\eta$  is learning rate

- **\*** House price prediction
  - **\*** One-sample training: implementation



```
# Naive implementaion
   # Load data
   from numpy import genfromtxt
    import matplotlib.pyplot as plt
    data = genfromtxt('data.csv', delimiter=',')
   areas = list(data[:,0])
   prices = list(data[:,1])
   data_size = len(areas)
11
   print('areas: ', areas)
   print('prices: ', prices)
   print('data_size: ', data_size)
15
   plt.scatter(areas, prices)
   plt.xlabel('Diện tích nhà (x 100$m^2$)')
   plt.ylabel('Giá nhà (chục lượng vàng)')
19 plt.xlim(3,7)
   plt.ylim(4,10)
   plt.show()
```

#### **\*** House price prediction

- **One-sample training: implementation** 
  - 1) Pick a sample (x, y) from training data
  - 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
  
$$L'_b = 2(o - y)$$

```
\eta is learning rate w = w - \eta L_w' b = b - \eta L_b'
```

```
# forward
   def predict(x,w,b):
        return x*w + b
   # compute gradient
    def gradient(z,y,x):
        dw = 2*x*(z-y)
        db = 2*(z-y)
        return (dw, db)
10
11
12
    # update weights
    def update_weight(w,b,n,dw,db):
13
        w_new = w - n*dw
14
15
        b new = b - n*db
16
        return (w_new, b_new)
17
```

#### **\*** House price prediction

- **One-sample training: implementation** 
  - 1) Pick a sample (x, y) from training data
  - 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
  
$$L'_b = 2(o - y)$$

$$\eta$$
 is learning rate  $w = w - \eta L_w'$   $b = b - \eta L_b'$ 

```
1 # init weights
    b = 0.04
   W = -0.34
    n = 0.01
    # how Long
    epoch_max = 10
 8
    for epoch in range(epoch_max):
        for i in range(data size):
10
            # get a sample
11
12
            # predict z
13
14
15
            # compute loss
16
            # compute gradient
17
18
            # update weights
19
20
```

#### **\*** House price prediction

- **\*** One-sample training: implementation
  - 1) Pick a sample (x, y) from training data
  - 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

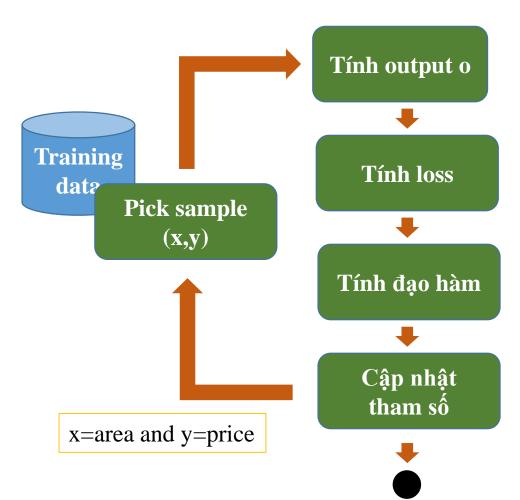
4) Tính đao hàm

$$L'_w = 2x(o - y)$$
  
$$L'_b = 2(o - y)$$

$$\eta$$
 is learning rate  $w = w - \eta L_w'$ 
 $b = b - \eta L_h'$ 

```
1 # init weights
    w = -0.34
    n = 0.01
    # how Long
    epoch_max = 10
    for epoch in range(epoch_max):
        for i in range(data_size):
10
            # get a sample
11
12
            x = areas[i]
            y = prices[i]
13
            print('sample: ', x, y)
14
15
            # predict z
16
            z = predict(x, w, b)
17
            print('z: ', z)
18
19
            # compute Loss
20
            loss = (z-y)*(z-y)
21
            print('Loss: ', loss)
22
23
            # compute gradient
24
25
            (dw, db) = gradient(z,y,x)
26
            print('dw: ', dw)
27
            print('db: ', db)
28
            # update weights
29
            (w, b) = update_weight(w,b,n,dw,db)
30
31
            print('w_new: ', w)
32
            print('b_new: ', b)
33
            print('\n\n')
```

- **\*** House price prediction
  - **\*** One-sample training: implementation



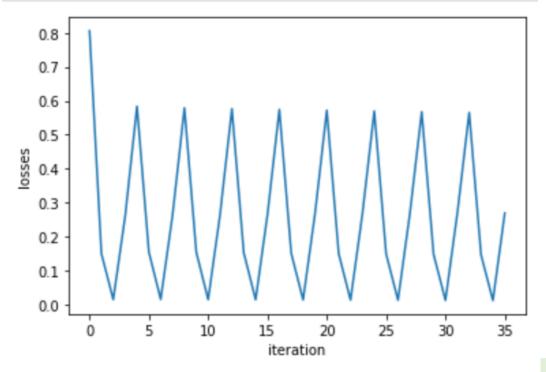
```
import matplotlib.pyplot as plt

plt.plot(losses)

plt.xlabel('iteration')

plt.ylabel('losses')

plt.show()
```

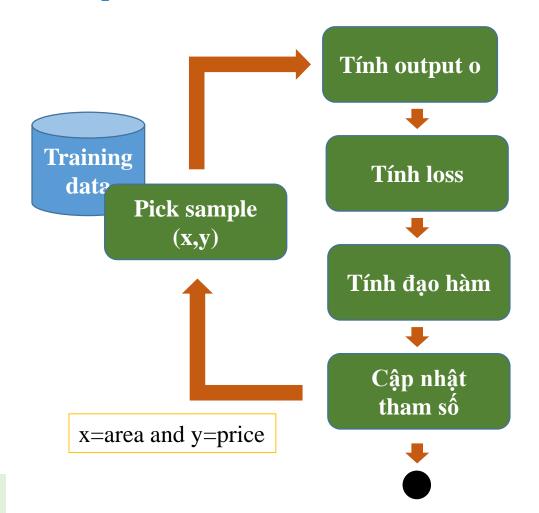


### **Linear Regression**

#### **\*** House price prediction

#### Demo

- **\*** House price prediction
  - **\*** Implementation: Vectorization



```
# Implementation - vectorization
   # Load data
    import numpy as np
   from numpy import genfromtxt
    import matplotlib.pyplot as plt
   data = genfromtxt('data.csv', delimiter=',')
   areas = data[:,0]
   prices = data[:,1]
   data_size = areas.size
12
   print(type(areas))
   print('areas: ', areas)
   print('prices: ', prices)
   print('data_size: ', data_size)
17
   plt.scatter(areas, prices)
   plt.xlabel('Diện tích nhà (x 100$m^2$)')
   plt.ylabel('Giá nhà (chục lượng vàng)')
   plt.xlim(3,7)
   plt.ylim(4,10)
   plt.show()
```

#### **\*** House price prediction

- **\*** Implementation: Vectorization
- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o-y)$$

5) Cập nhật tham số

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta L_{\boldsymbol{\theta}}'$$

 $\eta$  is learning rate

```
# forward
   def predict(x,theta):
        return x.dot(theta)
   # compute gradient
   def gradient(z,y,x):
        dtheta = 2*x*(z-y)
        return dtheta
10
   # update weights
   def update_weight(theta,n,dtheta):
13
        dtheta new = theta - n*dtheta
14
15
        return dtheta new
```

- **\*** House price prediction
  - **\*** Implementation: Vectorization
  - 1) Pick a sample (x, y) from training data
  - 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o-y)$$

$$\theta = \theta - \eta L'_{\theta}$$
 $\eta$  is learning rate

```
1  # vector [x, b]
2  data = np.c_[areas, np.ones((data_size, 1))]
3  print(data)
4  
5  # init weight
6  n = 0.01
7  theta = np.array([-0.34, 0.04]) #[w, b]
8  print('theta', theta)
```

#### **\*** House price prediction

- **\*** Implementation: Vectorization
- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đao hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o-y)$$

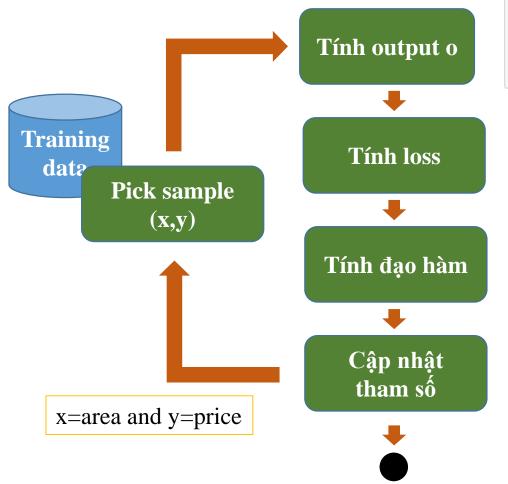
5) Cập nhật tham số

$$\theta = \theta - \eta L'_{\theta}$$

 $\eta$  is learning rate

```
# how Long
   epoch_max = 10
   for epoch in range(epoch_max):
        for i in range(data size):
            # get a sample
            x = data[i]
            y = prices[i:i+1]
            print('sample: ', x, y)
10
            # predict z
11
            z = predict(x, theta)
12
            print('Input data: ', x)
13
            print('Theta: ', theta)
14
            print('z: ', z)
15
16
            # compute Loss
17
            loss = (z-y)*(z-y)
18
19
            print('Loss: ', loss)
20
            # compute gradient
21
            dtheta = gradient(z,y,x)
22
            print('dtheta: ', dtheta)
23
24
25
            # update weights
26
            theta = update_weight(theta,n,dtheta)
27
            print('dtheta new: ', theta)
            print('\n\n')
28
```

- **\*** House price prediction
  - **\*** Implementation: Vectorization



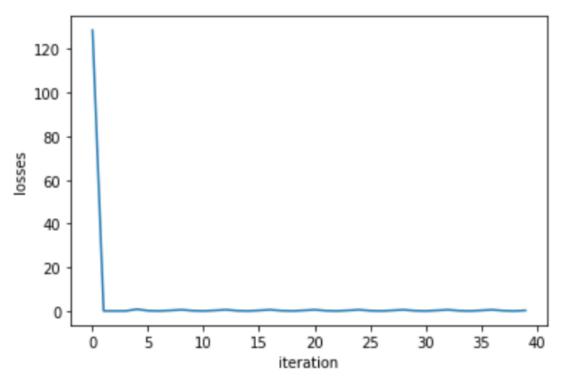
```
import matplotlib.pyplot as plt

plt.plot(losses)

plt.xlabel('iteration')

plt.ylabel('losses')

plt.show()
```



### **Linear Regression**

#### **\*** House price prediction

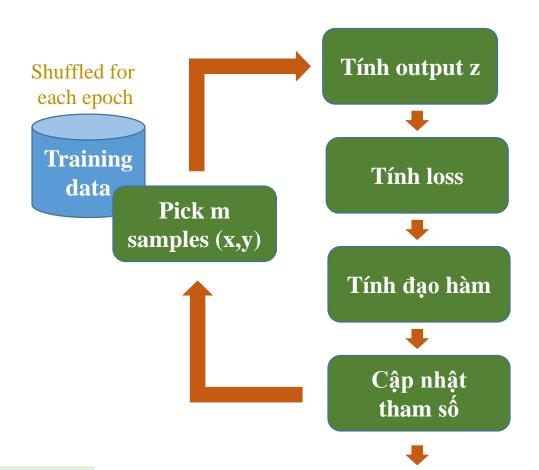
#### Demo

Year 2020

# Outline

- > Machine Learning
- > Derivative/Gradient
- > Linear Regression
- > Computational Graph
  - > 1-sample training
  - m-sample training
- > Summary

- **\*** House price prediction
  - **❖** m-sample training (1<m<N)



- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 2) Tính output o<sub>i</sub>

$$o^{(i)} = wx^{(i)} + b \qquad \text{for } 0 \le i < m$$

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

4) Tính đạo hàm

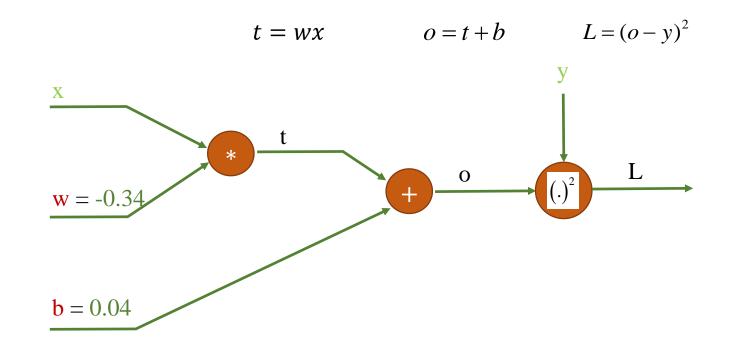
$$L_w^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
  

$$L_h^{\prime(i)} = 2(o^{(i)} - y^{(i)}) \text{ for } 0 \le i < m$$

$$w = w - \eta \frac{\sum_{i} L_{w}^{\prime(i)}}{m}$$

$$b = b - \eta \frac{\sum_{i} L_{b}^{\prime(i)}}{m}$$
Learning rate  $\eta$ 

- **\*** House price prediction
  - **❖** m-sample training (1<m<N)



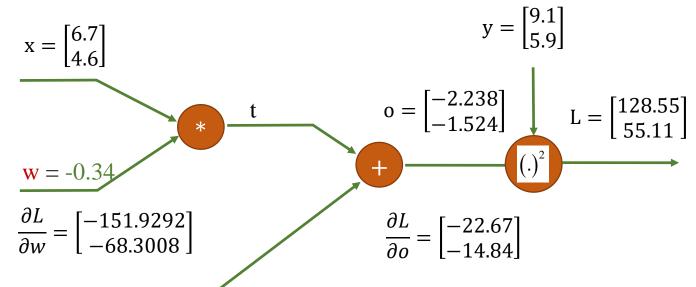
#### **\*** House price prediction

**❖** m-sample training (1<m<N)

$$m = 2$$

$$\frac{sum(\frac{\partial L}{\partial w})}{m} = -110.115 \qquad \frac{\partial L}{\partial w} = \begin{bmatrix} -151.9292\\ -68.3008 \end{bmatrix}$$

$$\frac{sum(\frac{\partial L}{\partial b})}{m} = -18.762$$



$$\frac{\partial L}{\partial h} = \begin{bmatrix} -22.676 \\ -14.848 \end{bmatrix}$$

$$t = wx$$

$$o = t + b$$

$$o = t + b L = (o - y)^2$$

#### **\*** House price prediction

\* m-sample training (1<m<N)

#### Cách cập nhật a và b

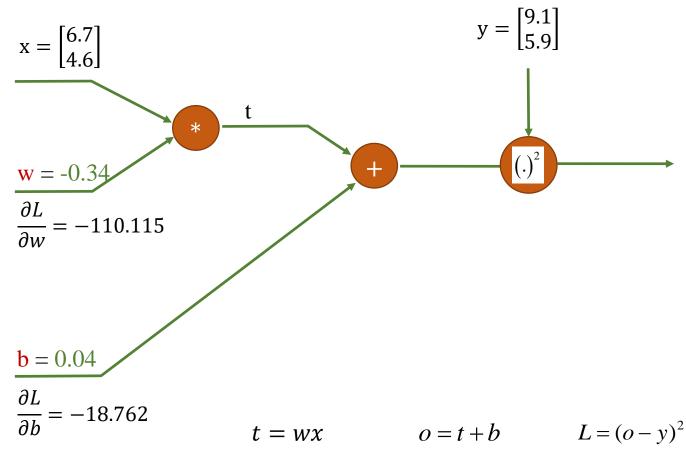
$$w = w - \eta * \frac{\partial L}{\partial w}$$

$$b = b - \eta * \frac{\partial L}{\partial b}$$

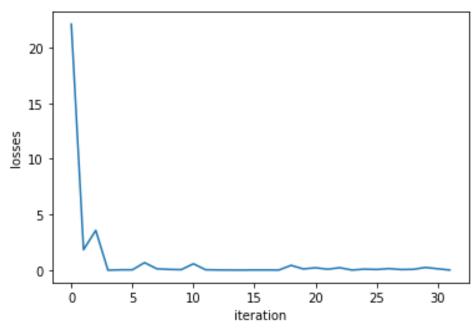
Learning rate  $\eta = 0.01$ 

$$w = -0.34 - (0.01 * (-110.115)) = 0.761$$

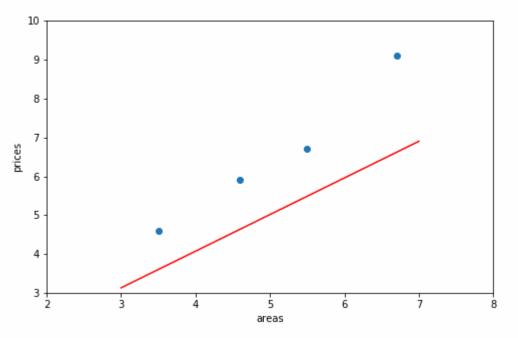
$$b = 0.04 - (0.01 * (-18.762)) = 0.227$$



- **\*** House price prediction
  - **❖** m-sample training (1<m<N)



**Losses for 30 iterations** 



**Model updating for different iterations** 

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = wx^{(i)} + b \qquad \text{for } 0 \le i < m$$

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đao hàm

$$L_w^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
  

$$L_h^{\prime(i)} = 2(o^{(i)} - y^{(i)}) \text{ for } 0 \le i < m$$

2) Cập nhật tham số 
$$w = w - \eta \frac{\sum_{i} L'_{w}^{(i)}}{m}$$
 
$$b = b - \eta \frac{\sum_{i} L'_{b}^{(i)}}{m}$$
  $\eta$  is learning rate

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)} \qquad \text{for } 0 \le i < m$$

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đao hàm

$$L_{\theta}^{'(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < m$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{m}$$
  $\eta$  is learning rate

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < m$ 

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < m$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{m}$$
  $\eta$  is learning rate

```
# Load data
   import numpy as np
   from numpy import genfromtxt
   import matplotlib.pyplot as plt
   data = genfromtxt('data.csv', delimiter=',')
   areas = data[:,0]
   prices = data[:,1]
   data size = areas.size
11
   print(type(areas))
   print('areas: ', areas)
   print('prices: ', prices)
   print('data size: ', data size)
16
   plt.scatter(areas, prices)
   plt.xlabel('areas')
19 plt.ylabel('prices')
20 plt.xlim(3,7)
21 plt.ylim(4,10)
   plt.show()
```

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < m$ 

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < m$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{m}$$
  $\eta$  is learning rate

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < m$ 

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < m$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{m}$$
  $\eta$  is learning rate

```
16 for epoch in range(epoch max):
        sum of losses = 0
18
        gradients = np.zeros((2,))
19
20
        for j in range(0, m, m):
21
            for index in range(j, j+m):
22
                xi = data[index]
23
                yi = prices[index]
24
                print('\ndata: ', xi, yi)
25
26
                # predict z/o
27
                oi = xi.dot(theta)
28
                print('z: ', oi)
29
30
                # compute loss
                li = (oi - vi)*(oi - vi)
31
32
                print('loss: ', index, li)
33
34
                # compute gradient
35
                g li = 2*(oi - yi)
36
                print('g li: ', g li)
37
                gradient i = xi*g li
                print('gradient i: ', index, gradient i)
38
39
                gradients = gradients + gradient i
40
                sum of losses = sum of losses + li
41
42
            sum_of_losses = sum_of_losses/2
43
            gradients
                          = gradients/2
44
            print('\ngradients: ', gradients)
45
46
47
            theta = theta - eta*gradients
            print('new params: ', theta)
48
```

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < m$ 

1.2) Tính loss

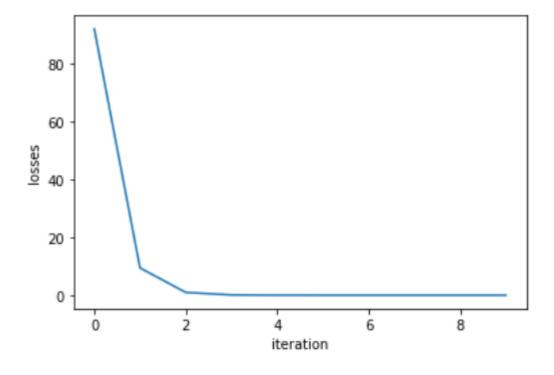
$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đao hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < m$ 

$$oldsymbol{ heta} = oldsymbol{ heta} - \eta \frac{\sum_i L_{oldsymbol{ heta}}^{\prime(i)}}{m}$$
  $\eta$  is learning r

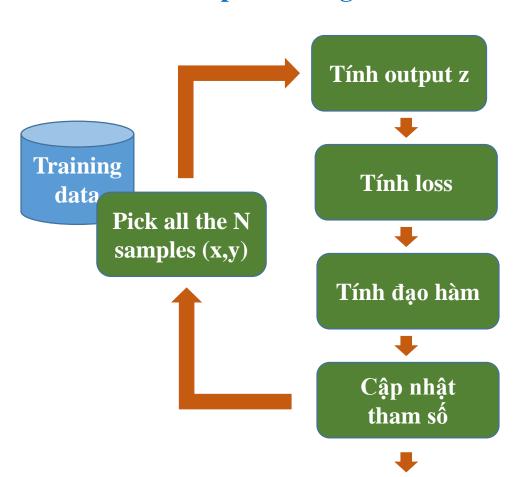
```
import matplotlib.pyplot as plt
plt.plot(losses)
plt.xlabel('iteration')
plt.ylabel('losses')
plt.show()
```



## Outline

- > Machine Learning
- > Derivative/Gradient
- > Linear Regression
- > Computational Graph
  - > 1-sample training
  - m-sample training
  - > N-sample training
- Summary

- **\*** House price prediction
  - **❖** N-sample training



- 1) Pick all the N samples  $(x^{(i)}, y^{(i)})$  from training data
- 2) Tính output o<sub>i</sub>

$$o^{(i)} = wx^{(i)} + b \qquad \text{for } 0 \le i < N$$

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đạo hàm

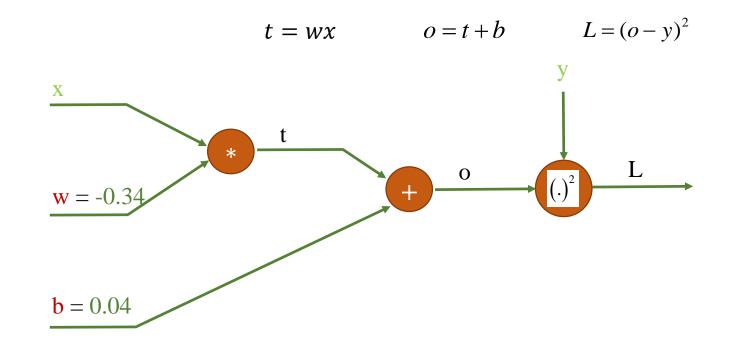
$$L_w^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
  

$$L_h^{\prime(i)} = 2(o^{(i)} - y^{(i)}) \text{ for } 0 \le i < N$$

$$w = w - \eta \frac{\sum_{i} L_{w}^{\prime(i)}}{N}$$

$$b = b - \eta \frac{\sum_{i} L_{b}^{\prime(i)}}{N}$$
Learning rate  $\eta$ 

- **\*** House price prediction
  - **\*** N-sample training

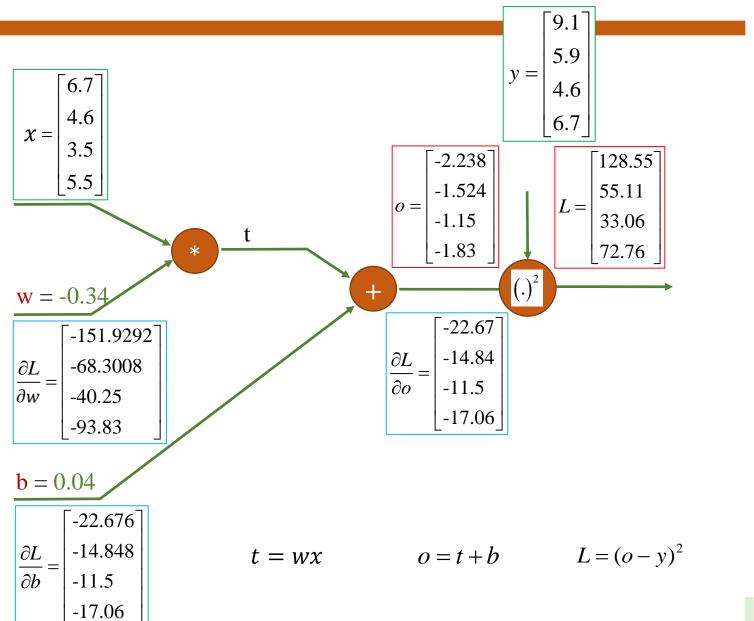


**\*** House price prediction

**❖** N-sample training

$$\frac{sum(\frac{\partial L}{\partial w})}{4} = -88.5775$$

$$\frac{sum(\frac{\partial L}{\partial b})}{4} = -16.521$$



### **\*** House price prediction

**❖** N-sample training

### Cách cập nhật a và b

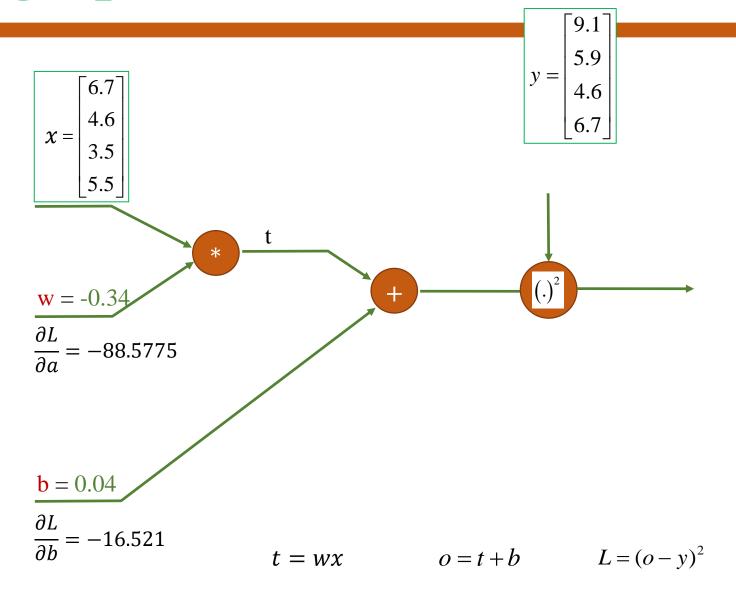
$$w = w - \eta * \frac{\partial L}{\partial w}$$

$$b = b - \eta * \frac{\partial L}{\partial b}$$

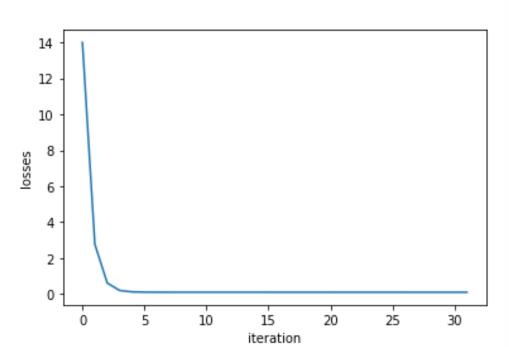
Learning rate  $\eta = 0.01$ 

$$w = -0.34 - (0.01 * (-88.5775)) = 0.54$$

$$b = 0.04 - (0.01 * (-16.521)) = 0.205$$



- **\*** House price prediction
  - **\*** N-sample training



10 9 - 8 - 7 - 5 - 4 - 5 - 6 - 7 - 8 areas

**Losses for 30 iterations** 

**Model updating for different iterations** 

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

$$o^{(i)} = wx^{(i)} + b \qquad \text{for } 0 \le i < N$$

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đao hàm

$$L_w^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
  

$$L_h^{\prime(i)} = 2(o^{(i)} - y^{(i)}) \text{ for } 0 \le i < N$$

5) Cập nhật tham số 
$$w = w - \eta \frac{\sum_{i} L'_{w}^{(i)}}{N}$$
 
$$b = b - \eta \frac{\sum_{i} L'_{b}^{(i)}}{N}$$
  $\eta$  is learning rate

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)} \qquad \text{for } 0 \le i < N$$

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đao hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < N$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < N$ 

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < N$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

```
# Load data
   import numpy as np
   from numpy import genfromtxt
   import matplotlib.pyplot as plt
   data = genfromtxt('data.csv', delimiter=',')
   areas = data[:,0]
   prices = data[:,1]
   data size = areas.size
11
   print(type(areas))
   print('areas: ', areas)
   print('prices: ', prices)
   print('data size: ', data size)
16
   plt.scatter(areas, prices)
   plt.xlabel('areas')
19 plt.ylabel('prices')
20 plt.xlim(3,7)
21 plt.ylim(4,10)
   plt.show()
```

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < N$ 

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < N$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

```
1  # vector [x, b]
2  data = np.c_[areas, np.ones((data_size, 1))]
3  print(data)
4  
5  n_epochs = 1
6  eta = 0.01
7  
8  theta = np.array([[-0.34],[0.04]])
9  print('theta', theta)
```

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < N$ 

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < N$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

```
11 for epoch in range(n epochs):
12
        sum of losses = 0
        gradients = np.zeros((2,1))
13
14
        for index in range(data size):
15
16
            xi = data[index:index+1]
17
            yi = prices[index:index+1]
18
            print('\ndata: ', xi, yi)
19
20
            oi = xi.dot(theta)
            li = (oi - yi)*(oi - yi)
21
            g li = 2*(oi - yi)
22
23
            print('z: ', oi)
24
            print('loss: ', index, li)
25
            print('gradient loss: ', index, g li)
26
27
28
            cg = xi.T.dot(g li)
            print('variable gradient: ', index, cg)
29
30
            gradients = gradients + cg
31
            sum of losses = sum of losses + li
32
33
        sum of losses = sum of losses/data size
34
35
        print('\nsum of losses: ', sum of losses)
36
37
        gradients = gradients/data size
        print('\ngradients: ', gradients)
38
39
40
        theta = theta - eta*gradients
        print('new params: ', theta)
41
```

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)}$$

for  $0 \le i < N$ 

3) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

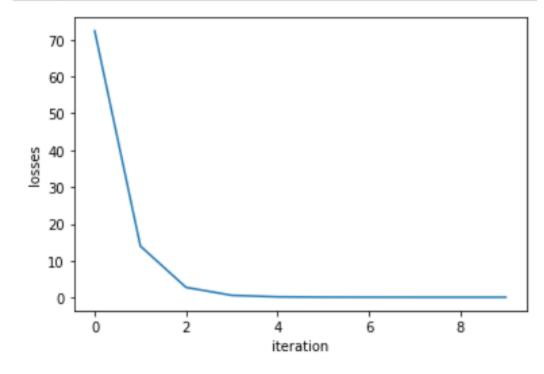
4) Tính đạo hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < N$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

```
import matplotlib.pyplot as plt

plt.plot(losses)
plt.xlabel('iteration')
plt.ylabel('losses')
plt.show()
```



### **Linear Regression**

	4				
Λ	4	an	+0	0	30
$\overline{}$	$\mathbf{u}$		Па	$\mathbf{y}_{t}$	
_	~			_	$\sim$

Disadvantages

1 sample

Simple to understand and implement Faster learning on some problems Noisy update is beneficial sometime Computationally expensive
Noisy gradient signal
Convergence problem

m sample

A balance between the robustness of 1-sample and the efficiency of N-sample

N sample

Computationally efficient
More stable error gradient

parallel processing

Premature convergence Memory problem Training speed is slower

# Outline

- > Machine Learning
- > Derivative/Gradient
- > Linear Regression
- > Computational Graph
- > Summary

### **Linear Regression**

### Generalized formula

Feature

House price data

price
9.1
5.9
4.6
6.7

Lahel

### Model

$$price = w * area + b$$
$$y = wx + b$$

### Model (vectorization)

$$y = \boldsymbol{\theta}^T \boldsymbol{x}$$
 where  $\boldsymbol{\theta}^T = [b \ w]^T$ 

$$\boldsymbol{x} = [x_0 \ area]^T$$

$$x_0 = 1$$

### **Features**

### Label

TV	<b>Radio</b>	Newspaper	<b>\$ Sales</b>
230.1	37.8	69.2	22.1
44.5	39.3	45.1	10.4
17.2	45.9	69.3	12
151.5	41.3	58.5	16.5
180.8	10.8	58.4	17.9

Advertising data

### Model

Sale = 
$$w_1 * TV + w_2 * Radio + w_3 * Newspaper + b$$
  
 $y = w_1x_1 + w_2x_2 + w_3x_3 + b$ 

### Model (vectorization)

$$y = \boldsymbol{\theta}^T \boldsymbol{x}$$
 where  $\boldsymbol{\theta}^T = [b \ w_1 \ w_2 \ w_3]^T$   $\boldsymbol{x} = [x_0 \ TV \ Radio \ Newspaper]^T$   $x_0 = 1$ 

### **Linear Regression**

### **&** Generalized formula

Features	Label
1 catales	Label

Boston House Price Data

crim \$	zn ÷	indus \$	chas \$	nox ÷	rm 💠	age \$	dis	≑ rad ≑	tax \$	ptratio \$	black \$	lstat <b>≑</b>	medv \$
0.00632	18	2.31	0	0.538	6.575	65.2	4.09	1	296	15.3	396.9	4.98	24
0.02731	0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.9	9.14	21.6
0.03237	0	2.18	0	0.458	6.998	45.8	6.0622	2 3	222	18.7	394.63	2.94	33.4
0.06905	0	2.18	0	0.458	7.147	54.2	6.0622	2 3	222	18.7	396.9	5.33	36.2
0.08829	12.5	7.87	0	0.524	6.012	66.6	5.5605	5 5	311	15.2	395.6	12.43	22.9

#### Model

$$medv = w_1 * x_1 + \dots + w_{13} * x_{13} + b$$

Model (vectorization)

$$y = \boldsymbol{\theta}^T \boldsymbol{x}$$
 where  $\boldsymbol{\theta}^T = [b \quad w_1 \quad \dots \quad w_{13}]^T$   
 $\boldsymbol{x} = [x_0 \quad x_1 \quad \dots \quad x_{13}]^T$   
 $x_0 = 1$ 

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = wx + b$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L'_w = 2x(o - y)$$
$$L'_b = 2(o - y)$$

5) Cập nhật tham số

$$w = w - \eta L'_{w}$$

$$b = b - \eta L'_{b}$$

$$\eta \text{ is learning rate}$$

- 1) Pick a sample (x, y) from training data
- 2) Tính output o

$$o = \boldsymbol{\theta}^T \boldsymbol{x}$$

3) Tính loss

$$L = (o - y)^2$$

4) Tính đạo hàm

$$L_{\boldsymbol{\theta}}' = 2\boldsymbol{x}(o - \boldsymbol{y})$$

5) Cập nhật tham số

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta L_{\boldsymbol{\theta}}'$$

 $\eta$  is learning rate

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = wx^{(i)} + b \qquad \text{for } 0 \le i < m$$

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đao hàm

$$L_w^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
  

$$L_h^{\prime(i)} = 2(o^{(i)} - y^{(i)}) \text{ for } 0 \le i < m$$

2) Cập nhật tham số 
$$w = w - \eta \frac{\sum_{i} L'_{w}^{(i)}}{m}$$
 
$$b = b - \eta \frac{\sum_{i} L'_{b}^{(i)}}{m}$$
  $\eta$  is learning rate

- 1) Pick m samples  $(x^{(i)}, y^{(i)})$  from training data
- 1.1) Tính output  $o^{(i)}$

$$o^{(i)} = \boldsymbol{\theta}^T \boldsymbol{x}^{(i)} \qquad \text{for } 0 \le i < m$$

1.2) Tính loss

$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < m$ 

1.3) Tính đao hàm

$$L_{\theta}^{'(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < m$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{m}$$
  $\eta$  is learning rate

- 1) Pick all the N samples from training data
- 2) Tính output  $o^{(i)}$

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 for  $0 \le i < N$ 

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$$L_h^{\prime(i)} = 2(o^{(i)} - y^{(i)}) \text{ for } 0 \le i < N$$

5) Cập nhật tham số
$$w = w - \eta \frac{\sum_{i} L'_{w}^{(i)}}{N}$$

$$\sum_{i} L'_{v}^{(i)}$$

$$b = b - \eta \frac{\sum_{i} L_{b}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

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for  $0 \le i < N$ 

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$$L^{(i)} = (o^{(i)} - y^{(i)})^2$$
 for  $0 \le i < N$ 

4) Tính đao hàm

$$L_{\theta}^{\prime(i)} = 2x(o^{(i)} - y^{(i)})$$
 for  $0 \le i < N$ 

$$\boldsymbol{\theta} = \boldsymbol{\theta} - \eta \frac{\sum_{i} L_{\boldsymbol{\theta}}^{\prime(i)}}{N}$$
  $\eta$  is learning rate

