# Selection of Functions for Different Targets

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## Reference

#### **Read Chapter 1 for preparation**

#### **Calculus Volume 1**

#### SENIOR CONTRIBUTING AUTHORS

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Link to download the book https://www.dropbox.com/s/9njmu8wg0 9anex1/CalculusVolume1-OP.pdf?dl=0



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# Outline

- > Exponential Functions
- > Logarithms
- > Logarithm Applications
- Designing Functions for Evaluation
- > Functions for Imbalanced Signals

#### **Definition**

"Exponential functions model a relationship in which a constant change in the independent variable gives the same proportional change in the dependent variable."

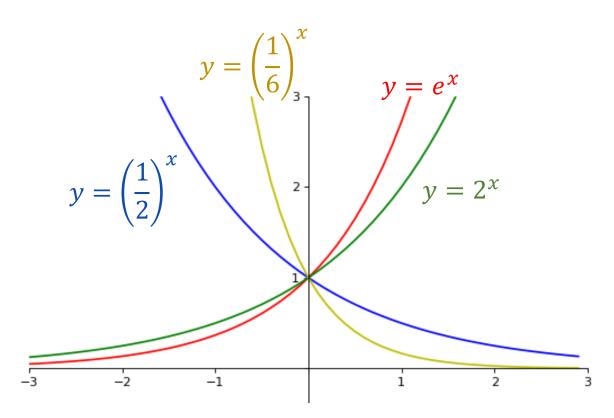
https://en.wikipedia.org/wiki/Exponential\_function

$$n \in \mathbb{N}$$

$$a^n = a * a * \cdots * a$$

$$n \text{ times}$$

An exponential function can describe growth or decay



#### **&** Laws of Exponent

For any constant a > 0, b > 0, and for all x and y

$$a^x a^y = a^{x+y}$$

$$(ab)^x = a^x b^x$$

$$(a^x)^y = a^{xy}$$

$$\frac{a^x}{a^y} = a^{x-y}$$

$$a^{x}a^{y} = (a * \cdots * a) * (a * \cdots * a)$$

$$x \text{ times} \qquad y \text{ times}$$

$$= (a * \cdots * a) * (a * \cdots * a)$$

$$x+y \text{ times}$$

$$= a^{x+y}$$

$$a^{x}b^{x} = (a * \cdots * a) * (b * \cdots * b)$$

x times

$$= (ab) * \cdots * (ab)$$

x times

$$= (ab)^{x}$$

#### **\*** Laws of Exponent

For any constant a > 0, b > 0, and for all x and y

$$a^x a^y = a^{x+y}$$

$$(ab)^{x} = a^{x}b^{x}$$

$$(a^x)^y = a^{xy}$$

$$\frac{a^x}{a^y} = a^{x-y}$$

$$(a^{x})^{y} = [(a * \cdots * a)] \times \text{times}$$

$$\vdots$$

$$(a^{x})^{y} = [(a * \cdots * a)] \times \text{times}$$

$$\vdots$$

$$= a^{xy}$$

$$\frac{a^x}{a^y} = \begin{bmatrix} a * \cdots * a \\ a * \cdots * a \end{bmatrix}$$
 x times y times

#### **&** Laws of Exponent

For any constant a > 0, b > 0, and for all x and y;  $p, q \in \mathbb{Z}, q \neq 0$ 

$$a = a^{q/q} = (a^{1/q})^q$$
$$\Rightarrow a^{1/q} = \sqrt[q]{a}$$

$$a^{\frac{p}{q}} = a^{\frac{1}{q}*p} = \left(a^{1/q}\right)^p$$
$$= (a^p)^{1/q} = \sqrt[q]{a^p}$$

$$a^{p/q} = \sqrt[q]{a^p}$$

$$\frac{a^x}{b^x} = \left(\frac{a}{b}\right)^x$$

$$a^{-x} = \frac{1}{a^x}$$

$$a^0 = 1$$

$$\frac{a^{x}}{b^{x}} = \boxed{\begin{array}{c} a * \cdots * a \\ b * \cdots * b \end{array}} \xrightarrow{\text{x times}} \rightarrow \frac{a^{x}}{b^{x}} = \left(\frac{a}{b}\right)^{x}$$

$$a^{-x} = a^{-x} \frac{a^{x}}{a^{x}} = \frac{a^{x-x}}{a^{x}} = \frac{1}{a^{x}}$$

$$a^{0} = a^{x-x} = a^{x} a^{-x} = \frac{a^{x}}{a^{x}} = 1$$

### **Example**

Initial population  $P_0$ 

Growth at an annual rate of 6%

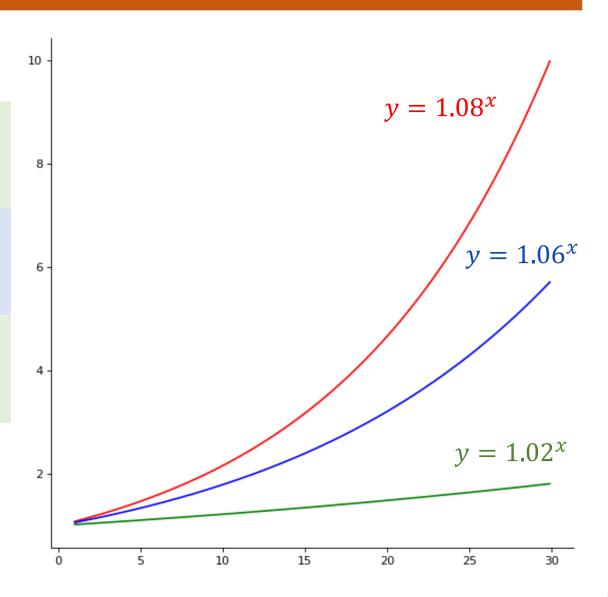
Population after 1 year is

$$P_1 = P_0 + 0.06P_0 = P_0(1 + 0.06) = P_0(1.06)$$

Population after 2 year is

$$P_2 = P_1 + 0.06P_1 = P_1(1.06) = P_0(1.06)^2$$

This example is from the reference book



#### **Example**

This example is from the reference book

Suppose a particular population of bacteria is known to double in size every 4 hours. If a culture starts with 1000 bacteria, then

The number of bacteria after 4 hours = ?

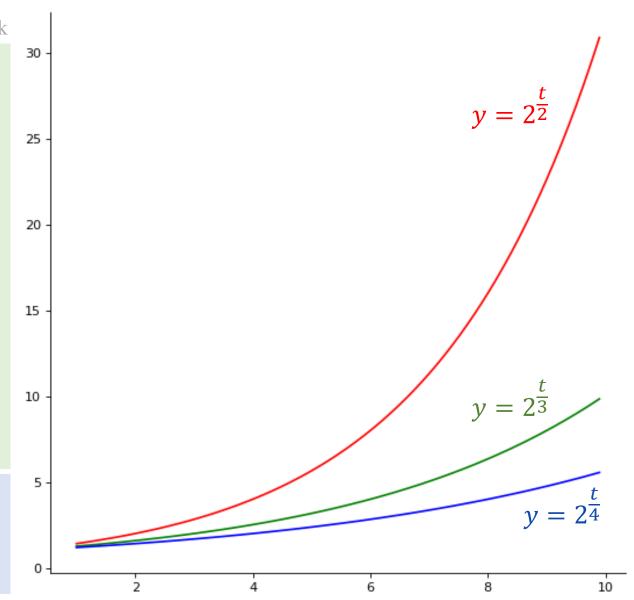
The number of bacteria after 8 hours = ?

The number of bacteria after 1 hours = ?

The number of bacteria after 6 hours = ?

The number of bacteria after 6 hours is

$$N = 1000 \times 2^{\frac{6}{4}} = 2828$$



#### **Example**

Suppose a person invests P dollars in a savings account with an annual interest rate r, compounded annually. The amount of money after 1 year is

$$A_1 = A + rA = A(1+r)$$

The amount of money after 2 years is

$$A_2 = A_1 + rA_1 = A(1+r) + rA(1+r) = A(1+r)^2$$

More generally, the amount after t years is

$$A_t = A(1+r)^t$$

If the money is compounded 2 times per year, the amount of money after half a year is

$$A_{1/2} = A + \frac{r}{2}A = A\left(1 + \frac{r}{2}\right)$$

The amount of money after 1 year is

$$A_1 = A\left(1 + \frac{r}{2}\right) + \frac{r}{2}A\left(1 + \frac{r}{2}\right) = A\left(1 + \frac{r}{2}\right)^2$$

After t years, the amount of money in the account is

$$A_t = A\left(1 + \frac{r}{2}\right)^{2t}$$

### **Example**

This example is from the reference book

After t years, the amount of money in the account is

$$A_t = A\left(1 + \frac{r}{2}\right)^{2t}$$

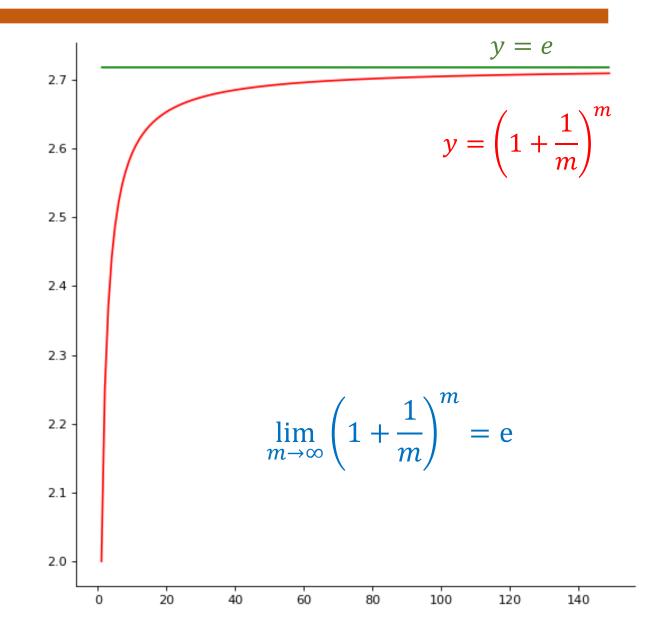
More generally, if the money is compounded n times per year, the amount of money in the account after t years is given by the function

$$A_t = A \left( 1 + \frac{r}{n} \right)^{nt}$$

set 
$$m = \frac{n}{r}$$

$$A_t = A \left( 1 + \frac{1}{m} \right)^{mrt}$$

$$A_t = Ae^{rt}$$



### **Example**

This example is from the reference book

After t years, the amount of money in the account is

$$A_t = A \left( 1 + \frac{r}{2} \right)^{2t}$$

More generally, if the money is compounded n times per year, the amount of money in the account after t years is given by the function

$$A_t = A \left( 1 + \frac{r}{n} \right)^{nt}$$

$$set m = \frac{n}{r}$$

$$A_t = A \left( 1 + \frac{1}{m} \right)^{mrt}$$

$$A_t = Ae^{rt}$$

Suppose \$5000 is invested in an account at an annual interest rate of r = 6%, compounded continuously.

After 30 years

$$A_t = Ae^{rt}$$

$$= 5000e^{0.06*30}$$

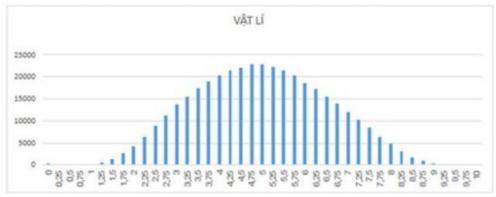
$$\approx 30248$$

#### **Example**

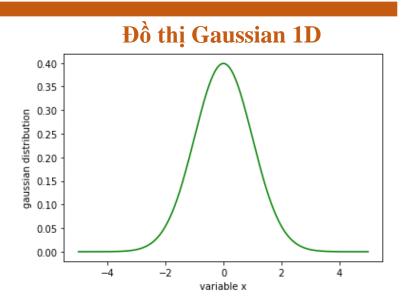
$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} -\infty < x < \infty$$

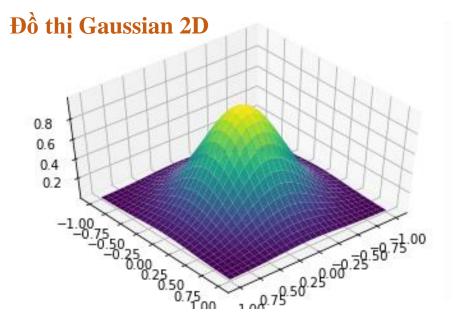
$$\mu: \text{mean}$$

$$\sigma^2: \text{variance}$$









## Bilateral filter

$$k(x) = \int_{W} c(\xi, x) s(f(\xi), f(x)) d\xi$$

where W is the filter window. The are the weight functions, essential tions of the form:

$$c(\xi, x) = e^{-\frac{1}{2}(\frac{|\xi - x|}{\sigma_d})^2},$$

$$s(f(\xi), f(x)) = e^{-\frac{1}{2}(\frac{|f(\xi) - f(x)|}{\sigma_r})^2},$$

where f(x) is an intensity value  $\sigma_d$  are the scale parameters of th components, respectively.

from my paper



Ảnh gốc bị nhiễu

Smoothing với trọng số Gausian

Smoothing với trọng số Gausian+color

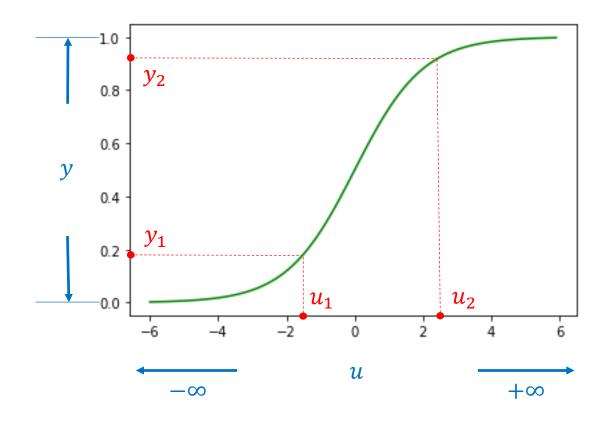
# **Sigmoid Function**

#### Sigmoid function

$$y = \sigma(u) = \frac{1}{1 + e^{-u}}$$
$$u \in (-\infty + \infty)$$
$$y \in (0 \ 1)$$

#### **Property**

$$\forall u_1 u_2 \in [a \ b] \text{ và } u_1 \leq u_2$$
  
 $\rightarrow \sigma(u_1) \leq \sigma(u_1)$ 

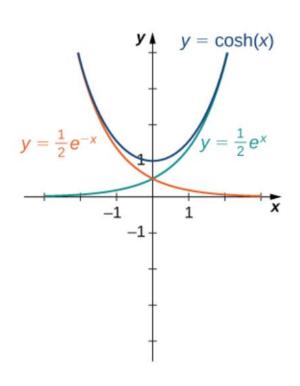


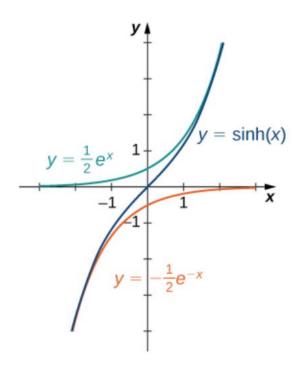
# **Hyperbolic Functions**

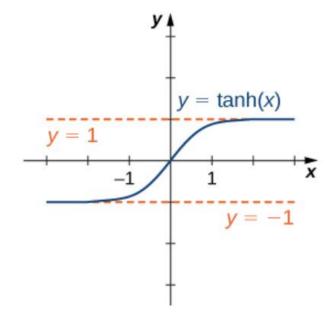
#### **Definition**

Defined in terms of certain combinations of  $e^x$  and  $e^{-x}$ 

Three figures are from the reference book







Hyperbolic cosine

$$cosh(x) = \frac{e^x + e^{-x}}{2}$$

Hyperbolic sine

$$sinh(x) = \frac{e^x - e^{-x}}{2}$$

Hyperbolic tangent

$$tanh(x) = \frac{sinh(x)}{cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

# **Implementation** (straightforward)

## **Softmax function**

Chuyển các giá trị của một vector thành các giá trị xác suất

# Formula $f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$ $0 \le f(x_i) \le 1$ $\sum_i f(x_i) = 1$

Input

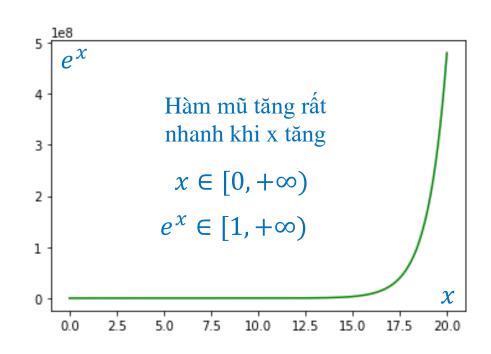
$$x_1 = 1.0$$
 $x_2 = 2.0$ 
 $x_3 = 3.0$ 

Probability

 $f(x_1) = 0.09$ 
 $f(x_2) = 0.24$ 
 $f(x_3) = 0.67$ 

Giá trị nan vì  $e^x$  vượt giới hạn lưu trữ của biến

```
def naive_softmax(data):
       exp data = [math.exp(x) for x in data]
       sum_exp_data = sum(exp_data)
6
       result = [x/sum_exp_data for x in exp_data]
       return result
   data1 = [1.0, 2.0, 3.0]
   print(naive softmax(data1))
[0.09003057317038046, 0.24472847105479767, 0.6652409557748219]
```



# **Implementation** (straightforward)

## **Softmax function**

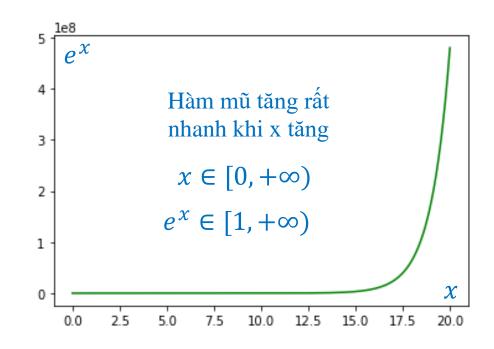
Chuyển các giá trị của một vector thành các giá trị xác suất

# Formula $f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}$ $0 \le f(x_i) \le 1$ $\sum_i f(x_i) = 1$



Giá trị nan vì  $e^x$  vượt giới hạn lưu trữ của biến

```
3 def naive_softmax(data):
       exp_data = [math.exp(x) for x in data]
       sum_exp_data = sum(exp_data)
       result = [x/sum_exp_data for x in exp_data]
       return result
   data2 = [1000.0, 1001.0, 1002.0]
   print(naive_softmax(data2))
OverflowError
                                  Traceback (most recent call last)
Cell In [8], line 2
```



## **Softmax function (stable)**

```
Formula
m = \max(x)
f(x_i) = \frac{e^{(x_i - m)}}{\sum_j e^{(x_j - m)}}
```

```
X X-m

Probability
x_{1} = 1.0 	 x_{1} = -2.0
x_{2} = 2.0 	 x_{2} = -1.0
x_{3} = 3.0 	 x_{3} = 0

Probability
f(x_{1}) = 0.09
f(x_{1}) = 0.09
f(x_{2}) = 0.24
f(x_{3}) = 0.67
f(x_{3}) = 0.67
```

```
1 import math
   def robust softmax(data):
4
       max value = max(data)
5
       data = [x-max_value for x in data]
 6
        exp_data = [math.exp(x) for x in data]
        sum_exp_data = sum(exp_data)
 8
 9
        result = [x/sum_exp_data for x in exp_data]
10
11
        return result
```

```
data1 = [1.0, 2.0, 3.0]
  print(robust_softmax(data1))
  # [0.0900305, 0.2447284, 0.6652409]
1 data2 = [1000.0, 1001.0, 1002.0]
  print(robust_softmax(data2))
3 # [0.0900305, 0.2447284, 0.6652409]
  data3 = [1.0, 1001.0, 1002.0]
  print(robust_softmax(data3))
  # [0.0, 0.26894142, 0.73105857]
```

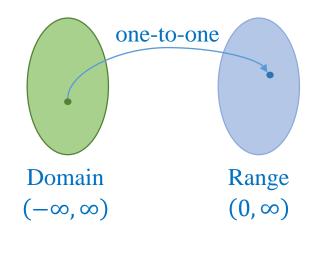
# Outline

- > Exponential Functions
- > Logarithms
- > Logarithm Applications
- Designing Functions for Evaluation
- > Functions for Imbalanced Signals

#### **Definition**



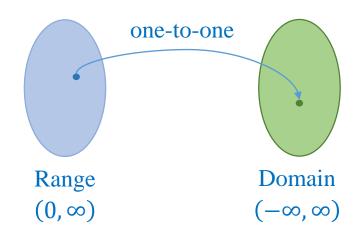
$$f(x) = a^x$$



For any constant a > 0,  $a \ne 1$ 

The logarithmic function with base b is

$$log_{\mathbf{a}}(x) = y \iff \mathbf{a}^y = x$$



#### **Properties of Logarithms**

If a, b, c > 0,  $a \ne 1$ , and r is any real number

$$log_{\mathbf{a}}(\mathbf{a}^{x}) = x$$

$$a^{\log_a(x)} = x$$

$$log_{\mathbf{a}}(bc) = log_{\mathbf{a}}(b) + log_{\mathbf{a}}(c)$$

$$\log_{\mathbf{a}} \left( \frac{b}{c} \right) = \log_{\mathbf{a}}(b) - \log_{\mathbf{a}}(c)$$

$$log_{\mathbf{a}}(b^r) = rlog_{\mathbf{a}}(b)$$

Using definition

prove 
$$log_a(bc) = log_a(b) + log_a(c)$$
  
set  $m = log_a(b) \Rightarrow a^m = b$  (1)  
set  $n = log_a(c) \Rightarrow a^n = c$  (2)  
(1) \* (2)  $\Rightarrow bc = a^n a^m = a^{n+m}$   
 $\Leftrightarrow log_a(bc) = log_a(a^{n+m})$   
 $\Leftrightarrow log_a(bc) = n + m$   
 $\Leftrightarrow log_a(bc) = log_a(b) + log_a(c)$ 

#### **Properties of Logarithms**

If a, b, c > 0,  $a \ne 1$ , and r is any real number

$$log_a(a^x) = x$$

$$a^{log_a(x)} = x$$

$$log_{\mathbf{a}}(bc) = log_{\mathbf{a}}(b) + log_{\mathbf{a}}(c)$$

$$\log_{\mathbf{a}} \left( \frac{b}{c} \right) = \log_{\mathbf{a}}(b) - \log_{\mathbf{a}}(c)$$

$$log_{\mathbf{a}}(b^r) = rlog_{\mathbf{a}}(b)$$

prove  $log_a(b^r) = rlog_a(b)$ 

set 
$$m = log_a(b) \Rightarrow a^m = b$$
 (1)

raise (1) to the r power

$$b^r = (\mathbf{a}^m)^r = \mathbf{a}^{mr} \ (2)$$

Perform logarithms with base a to (2)

$$log_{\mathbf{a}}(b^r) = log_{\mathbf{a}}(\mathbf{a}^{mr})$$

$$\Rightarrow log_{\mathbf{a}}(b^r) = mr$$

$$\Rightarrow log_{\mathbf{a}}(b^r) = rlog_{\mathbf{a}}(b)$$

#### **Natural logarithm**

### ln(x) mean $log_e(x)$

$$ln(e) = log_e(e) = 1$$

$$ln(e^5) = log_e(e^5) = 5$$

$$ln(1) = log_e(1) = 0$$

#### **Change base**

Let 
$$a, b > 0$$
, and  $a \ne 1$ ,  $b \ne 1$ 

$$log_a(x) = \frac{log_b(x)}{log_b(a)}$$

for any real number x > 0

## Logarithm

#### Logarithm trả lời câu hỏi:

Nhân bao nhiều lần cho một số để bằng một số khác

**Ví dụ:** Nhân bao nhiều lần cho số 2 để được 8 **Trả lời:**  $2x2x2 = 8 \rightarrow$  nhân 3 lần số 2 để được 8

$$2 \times 2 \times 2 = 8$$

$$\Rightarrow \log_2(8) = 3$$
base

Ví dụ: Nhân bao nhiêu lần số 2 để được 16

**Trả lời:**  $2x2x2x2 = 16 \rightarrow \text{nhân 4 lần số 2 để được 8}$ 

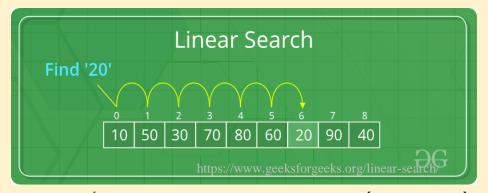
https://www.mathsisfun.com/algebra/logarithms.html



## Logarithm trong Big O

Big O: Tính độ phức tạp của thuật toán khi problem size tăng lên

Với linear search như hình bên dưới



trường hợp tệ nhất là khi tìm '40'. Lúc này, tất cả N phần tử đều phải được duyệt trước khi tìm ra '40'

→ độ phức tạp của linear search là O(N): trong trương hợp tệ nhất cần N bước để tìm ra một phần tử.

Binary search (như hình bên trái) chia đôi problem size ở mỗi bước. Do đó, trường hợp tệ nhất (như tìm key=9), chúng ta cần 3 bước với problem size N=8.

→ độ phức tạp của binary search là O(log(N)): trong trương hợp tệ nhất cần log(N) bước để tìm ra một phần tử.

Trong Computer Science, nếu không được nhắc đến, giá trị base mặc định của log là 2.

## Logarithm

#### Công thức phổ biến

$$\log_a a = 1$$
$$\log_a xy = \log_a x + \log_a y$$

Hàm log là hàm đơn điệu (~thứ tự không thay đổi)

$$\forall x_1 x_2 \in [a \ b] \text{ và } x_1 \le x_2$$
$$\to \log(x_1) \le \log(x_1)$$

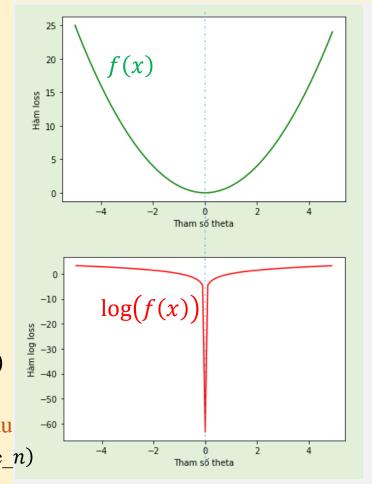
Tìm bộ tham số **0** cho một model sao cho model mô tả được dữ liệu training

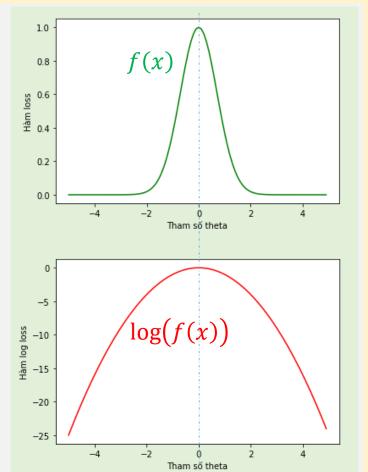
$$\underset{\theta}{\operatorname{argmax}} f(\theta) = \operatorname{argmax} P_{\theta}(\operatorname{training data})$$

Với data sample được thu nhập độc lập với nhau

$$\underset{\theta}{\operatorname{argmax}} f(\theta) = \underset{\theta}{\operatorname{argmax}} P_{\theta}(\operatorname{sample\_1}) * \dots * P_{\theta}(\operatorname{sample\_n})$$

## **Úng dụng trong Machine Learning**





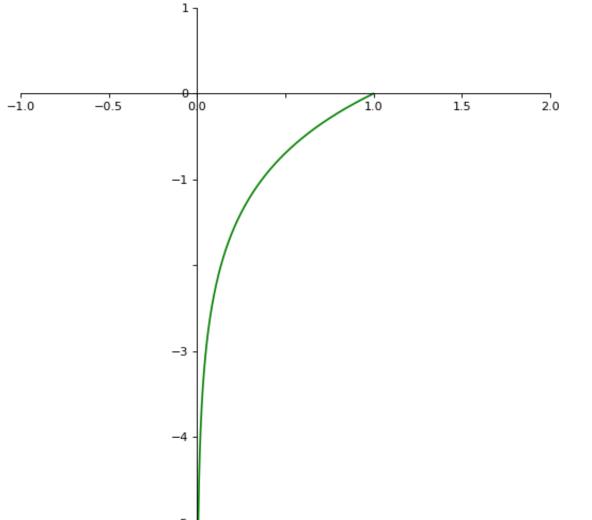
Ví trí cực đại của hàm  $f(\theta)$  và  $\log f(\theta)$  không thay đổi

#### Dùng hàm log

$$\underset{\theta}{\operatorname{argmax}} \log f(\theta) = \underset{\theta}{\operatorname{argmax}} [\log P_{\theta}(\operatorname{sample}_{-1}) + \dots + \log P_{\theta}(\operatorname{sample}_{-n})]$$

# **Logarithm and Small Numbers**

#### **Relative order of numbers is preserved**



```
v1 = 0.0004
   v2 = 0.0003
   v = v1*v2
   m1 = 0.001
   m2 = 0.0007
   m = m1*m2
 8
   print(v)
10 print(m)
```

```
1.2e-07
7e-07
```

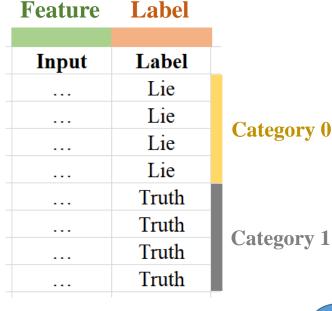
```
import math
 3 \text{ v1} = 0.0004
 4 \quad v2 = 0.0003
   v = math.log(v1) + math.log(v2)
 7 m1 = 0.001
   m2 = 0.0007
    m = math.log(m1) + math.log(m2)
10
    print(v)
    print(m)
```

```
-15.935774094164366
-14.172185501903005
```

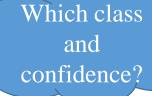
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- > Logarithms
- > Logarithm Applications
- Designing Functions for Evaluation
- > Functions for Imbalanced Signals

#### **❖** Lie/Truth classification







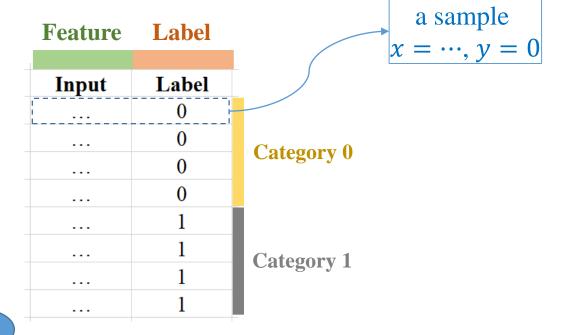


input n

input 2

input 1





evaluate

output 1: 
$$\hat{y} = 0$$
 (80%)

output 2: 
$$\hat{y} = 1 (65\%)$$

• • •

output n: 
$$\hat{y} = 0$$
 (70%)

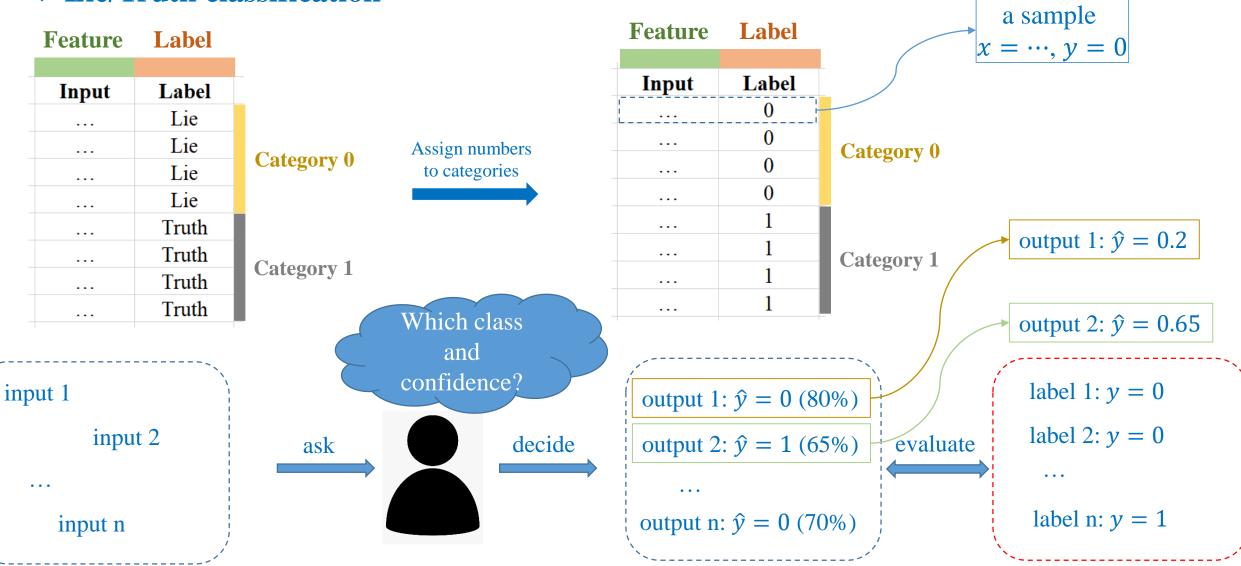
label 1: 
$$y = 0$$

label 2: 
$$y = 0$$

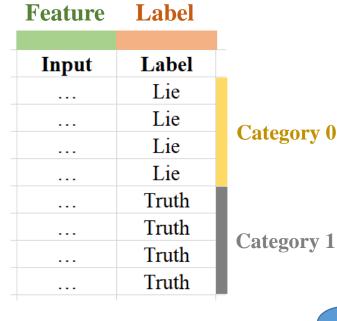
• • •

label n: 
$$y = 1$$

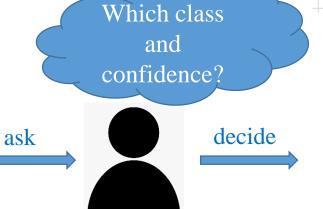
# **❖** Lie/Truth classification



#### Lie/Truth classification







Feature	Label
1 catale	Label

Input	Label
	0
	0
	0
	0
	1
	1
	1
	1
	1 1 1



Category 0

**Category 1** 

evaluate

How to measure his/her performance (accuracy)?

output 1: 
$$\hat{y} = 0.2$$

output 2: 
$$\hat{y} = 0.65$$

• • •

output n: 
$$\hat{y} = 0.3$$

label 1: y = 0

label 2: y = 0

. . .

label n: y = 1

•••

input 1

input n

input 2

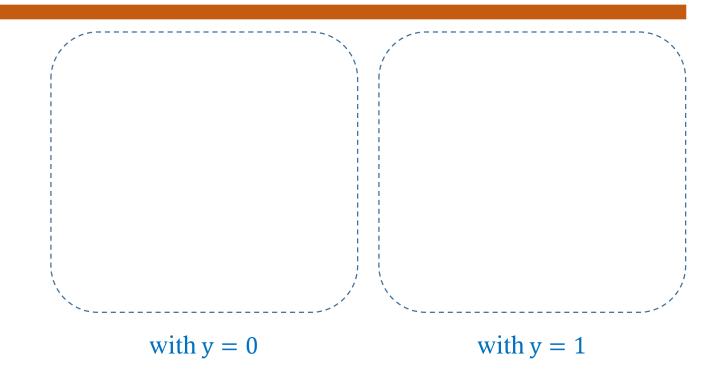
#### Lie/Truth classification

<b>Feature</b>	Output	Label

Input	Output	Label
	0.3	0
	0.8	0
	0.7	0
	0.4	0
	0.6	1
	0.8	1
	0.9	1
	0.2	1

Category 0

**Category 1** 



$$f(\hat{y}, y) = 1$$
 either  $(y = 0 \text{ and } \hat{y} \le 0.5)$   
or  $(y = 1 \text{ and } \hat{y} > 0.5)$   
 $f(\hat{y}, y) = 0$  otherwise

$$\Rightarrow$$
 accuracy  $=\frac{5}{8}$ 

weakness?

#### Lie/Truth classification

Feature Output Label
----------------------

Input	Output	Label	
	0.3	0	
	0.8	0	
	0.7	0	C
	0.4	0	
	0.6	1	
	0.8	1	C
	0.9	1	
	0.2	1	

Category 0

Category 1

Input	Output	Label
	0.1	0
	0.9	0
	0.9	0
	0.2	0
	0.9	1
	0.8	1
	0.9	1
	0.1	1

$$f(\hat{y}, y) = 1$$
 either  $(y = 0 \text{ and } \hat{y} \le 0.5)$ 

or 
$$(y = 1 \text{ and } \hat{y} > 0.5)$$

$$f(\hat{y}, y) = 0$$
 otherwise

$$\Rightarrow$$
 accuracy  $=\frac{5}{8}$ 

weakness?

Category 0

**Category 1** 



#### Lie/Truth classification

<b>Feature</b>	<b>Output</b>	Label
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Output	Label	
0.3	0	
0.8	0	
0.7	0	•
0.4	0	
0.6	1	
0.8	1	
0.9	1	
0.2	1	
	Output 0.3 0.8 0.7 0.4 0.6 0.8 0.9	Output     Label       0.3     0       0.8     0       0.7     0       0.4     0       0.6     1       0.8     1       0.9     1

Category 0

Category 1

if 
$$y = 0$$
  

$$f(\hat{y}, y) = 1 \quad \text{if } \hat{y} \le 0.5$$
if  $y = 1$   

$$f(\hat{y}, y) = 1 \quad \text{if } \hat{y} > 0.5$$
otherwise  

$$f(\hat{y}, y) = 0$$

	<b>Feature</b>	Output	Label
--	----------------	--------	-------

Input	Output	Label
	0.1	0
	0.9	0
	0.9	0
	0.2	0
	0.9	1
	0.8	1
	0.9	1
	0.1	1

**Category 0** 

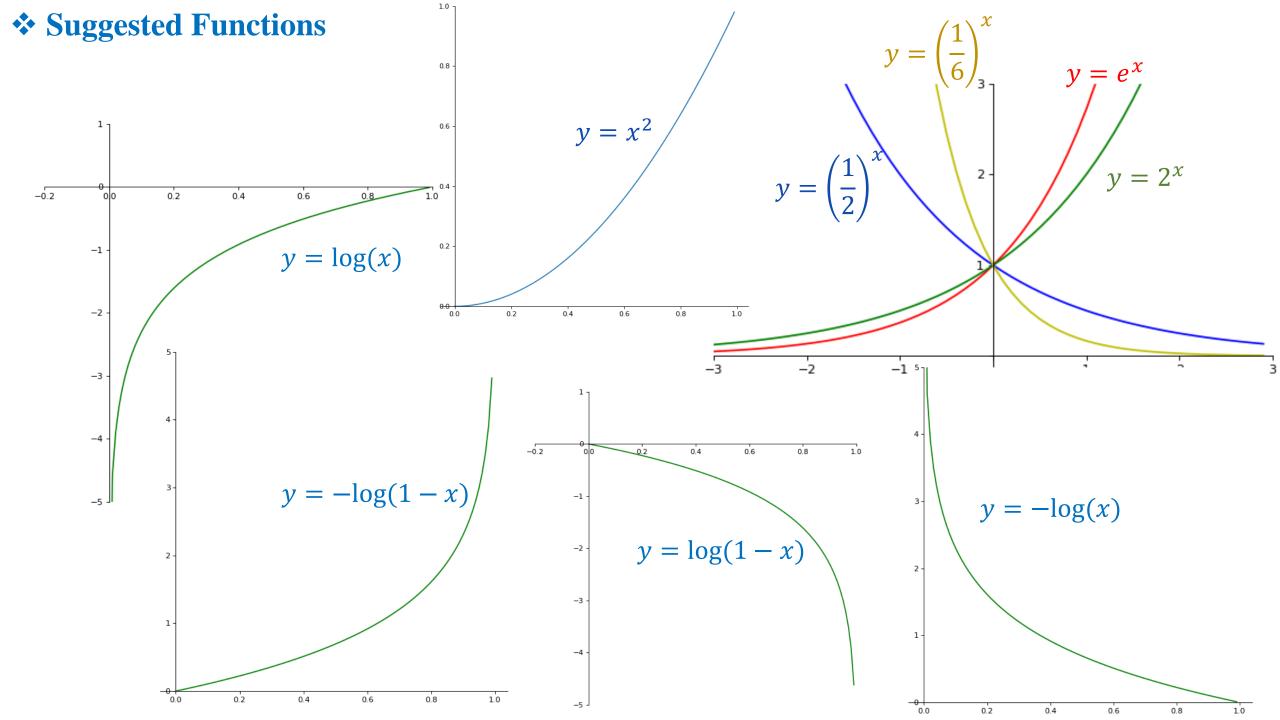
**Category 1** 

$$\Rightarrow$$
 accuracy  $=\frac{5}{8}$ 

weakness?



Wrong classification is a serious problem!!!



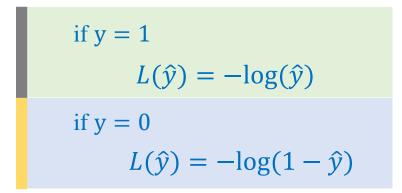
#### **❖** Lie/Truth classification

Feature	Output	Label
	O GEOP GEO	

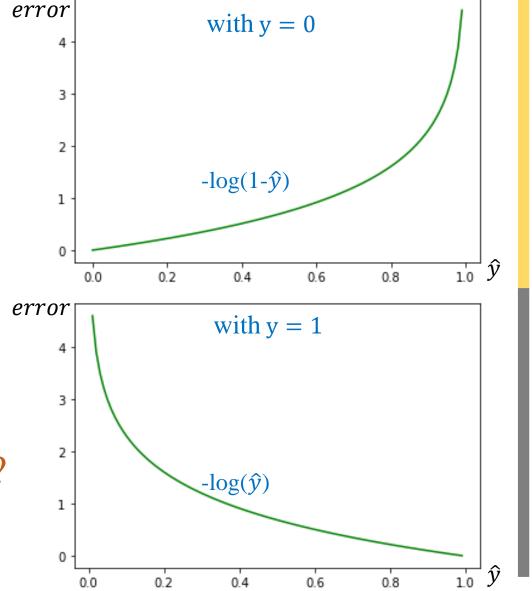
Input	Output	Label
	0.3	0
	0.8	0
	0.7	0
	0.4	0
	0.6	1
	0.8	1
	0.9	1
	0.2	1

Category 0

**Category 1** 



How to remove if?



### Lie/Truth classification

### Feature Output Label

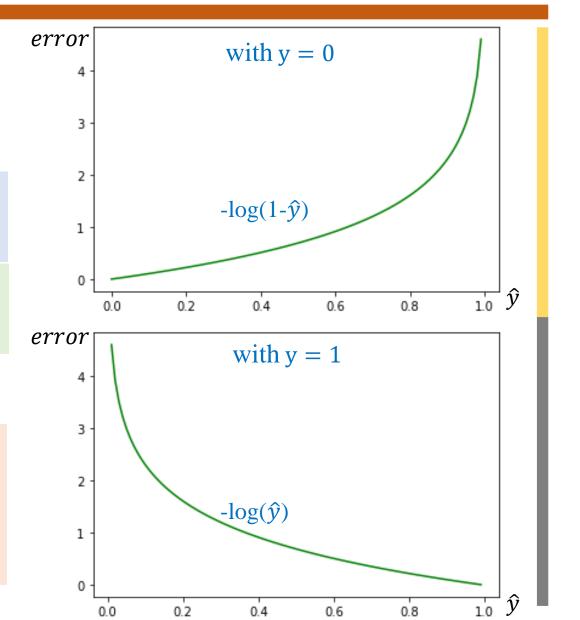
Input	Output	Label
	0.3	0
	0.8	0
	0.7	0
	0.4	0
	0.6	1
	0.8	1
	0.9	1
	0.2	1

if 
$$y = 0$$
  

$$L(\hat{y}) = -\log(1 - \hat{y})$$
if  $y = 1$   

$$L(\hat{y}) = -\log(\hat{y})$$

$$L(y, \hat{y}) = -y\log\hat{y} - (1 - y)\log(1 - \hat{y})$$



### Lie/Truth classification

#### **Output** Label **Feature**

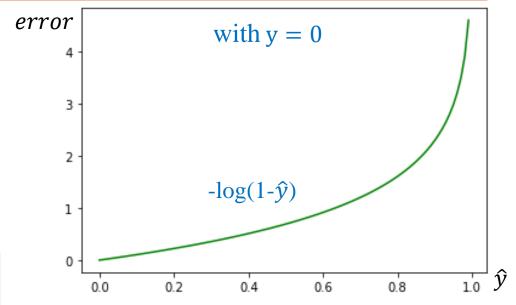
Input	Output	Label	Loss
	0.3	0	0.356
	0.8	0	1.609
	0.7	0	1.203
	0.4	0	0.511
•••	0.6	1	0.511
•••	0.8	1	0.223
•••	0.9	1	0.105
•••	0.2	1	1.609

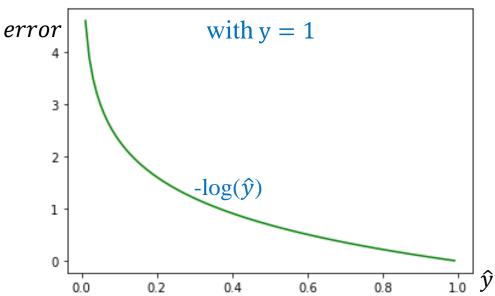
if 
$$y = 0$$
  

$$L(\hat{y}) = -\log(1 - \hat{y})$$
if  $y = 1$   

$$L(\hat{y}) = -\log(\hat{y})$$

$$L(y, \hat{y}) = -y\log\hat{y} - (1 - y)\log(1 - \hat{y})$$





### Lie/Truth classification

#### Feature Output Label

Input	Output	Label
	0.2	0
	0.8	0
	0.3	0
	0.1	0
	0.8	1
	0.8	1
	0.9	1
	0.9	1
	+	_

### After a period of time

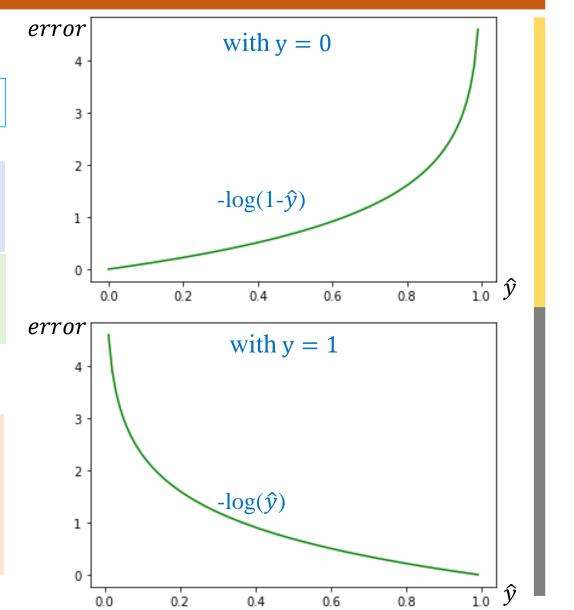
if 
$$y = 0$$
  

$$L(\hat{y}) = -\log(1 - \hat{y})$$

if 
$$y = 1$$

$$L(\hat{y}) = -\log(\hat{y})$$

$$L(y, \hat{y}) = -y\log\hat{y} - (1 - y)\log(1 - \hat{y})$$



### Lie/Truth classification

#### Feature Output Label

Input	Output	Label
	0.2	0
	0.7	0
	0.7	1
	0.8	1
	0.8	1
	0.8	1
	0.9	1
	0.9	1
	0.8	1
	0.7	1

### A special context

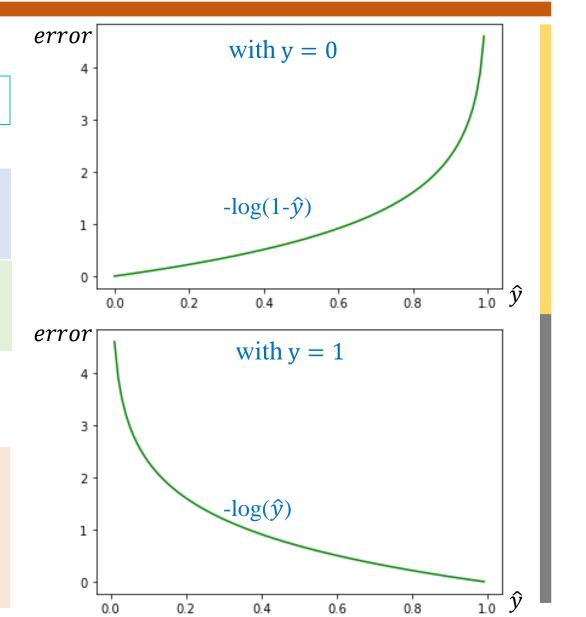
if 
$$y = 0$$
  

$$L(\hat{y}) = -\log(1 - \hat{y})$$

if 
$$y = 1$$

$$L(\hat{y}) = -\log(\hat{y})$$

$$L(y, \hat{y}) = -y\log\hat{y} - (1 - y)\log(1 - \hat{y})$$



#### Lie/Truth classification

#### Feature Output Label

Input	Output Label		Loss
	0.7	0	1.204
	0.8	1	0.223
	0.7	1	0.356
	0.8	1	0.223
	0.8	1	0.223
	0.8	1	0.223
	0.9	1	0.105
•••	0.9	1	0.105
	0.8	1	0.223
•••	0.7	1	0.356

#### a more severe context!

$$loss_{y=0} = 1.204$$

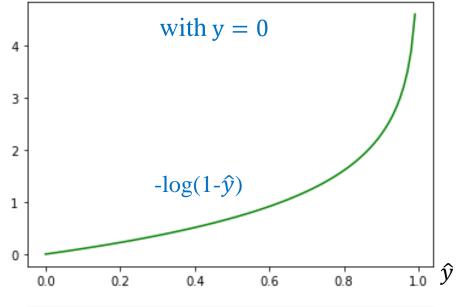
$$loss_{v=1} = 2.039$$

if 
$$y = 0$$

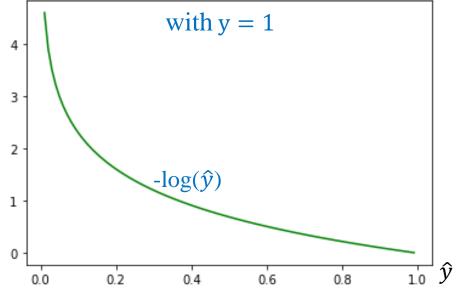
$$L(\hat{y}) = -\log(1 - \hat{y})$$

if 
$$y = 1$$

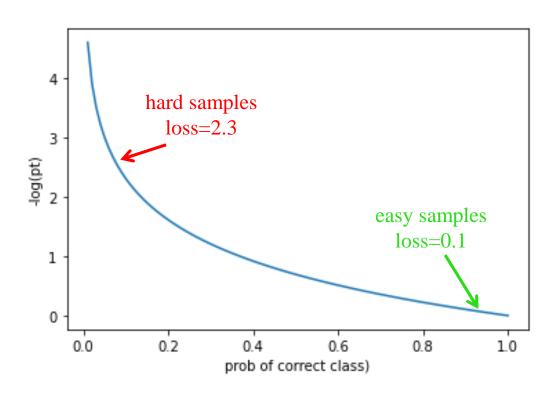
$$L(\hat{y}) = -\log(\hat{y})$$



$$L(y, \hat{y}) = -y\log\hat{y} - (1-y)\log(1-\hat{y})$$



#### **❖** Imbalance data



#### **Imbalance Case:**

- 100000 easy samples vs 100 hard samples

Easy samples loss = 100000\*0.1 = 10000

Hard samples loss = 100\*2.3 = 230

Loss = Easy samples loss + Hard samples loss

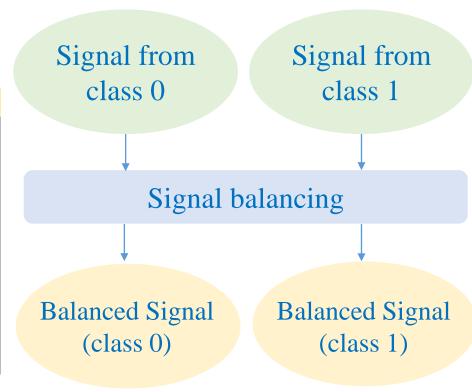
Easy samples loss: Hard samples loss =  $10000:230 \approx 43$ 

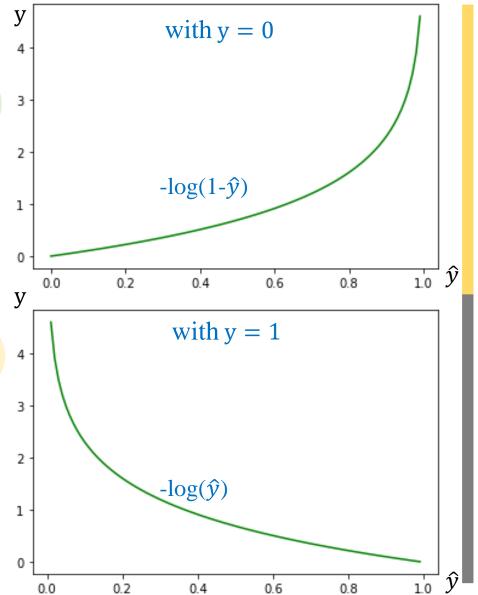
BCE không tốt cho trường hợp data bị imbalance nặng

### How to solve it!!!

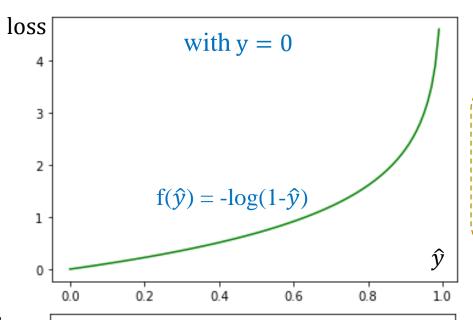
### Lie/Truth classification

Feature	Output	Label
Input	Output	Label
	0.7	0
	0.8	1
	0.7	1
	0.8	1
	0.8	1
	0.8	1
	0.9	1
	0.9	1
	0.8	1
	0.7	1



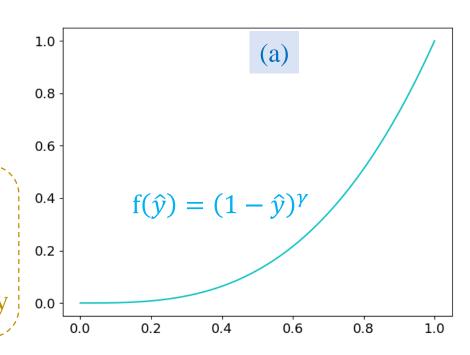


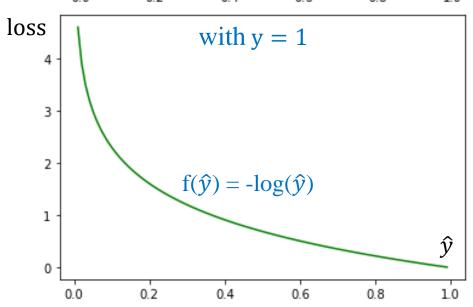
$$L(y, \hat{y}) = -y\log\hat{y} - (1 - y)\log(1 - \hat{y})$$



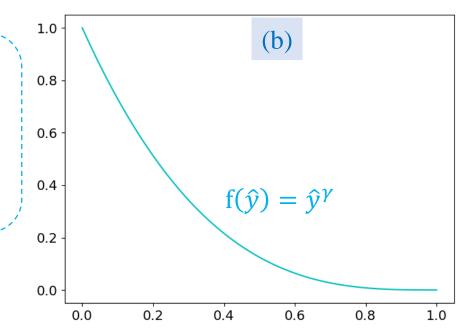
Given  $0 \le k \le 1$ 

if  $f(\hat{y}) * k$ where k approaches 1  $\rightarrow f(\hat{y}) * k \text{ reduces slightly}$ 





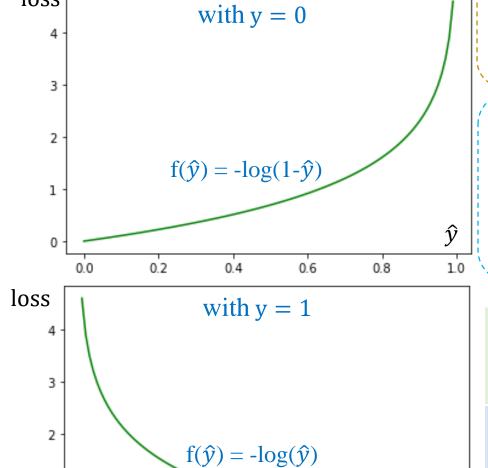
if  $f(\hat{y}) * k$ where k approaches 0  $\rightarrow f(\hat{y}) * k$  reduces significantly



loss

0.0

0.2



0.6

0.4

0.8

Given  $0 \le k \le 1$ 

if 
$$f(\hat{y}) * k$$

where k approaches 1

 $\rightarrow$  f( $\hat{y}$ ) \* k reduces slightly

$$\int if f(\hat{y}) * k$$

ŷ

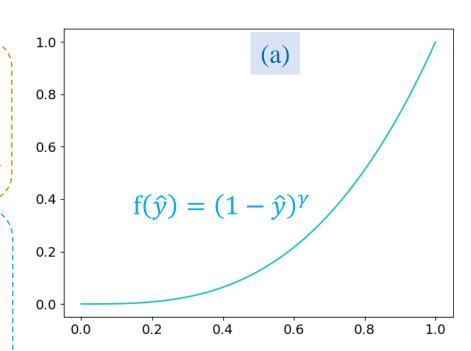
1.0

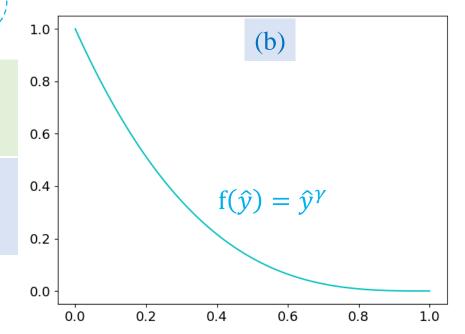
where k approaches 0

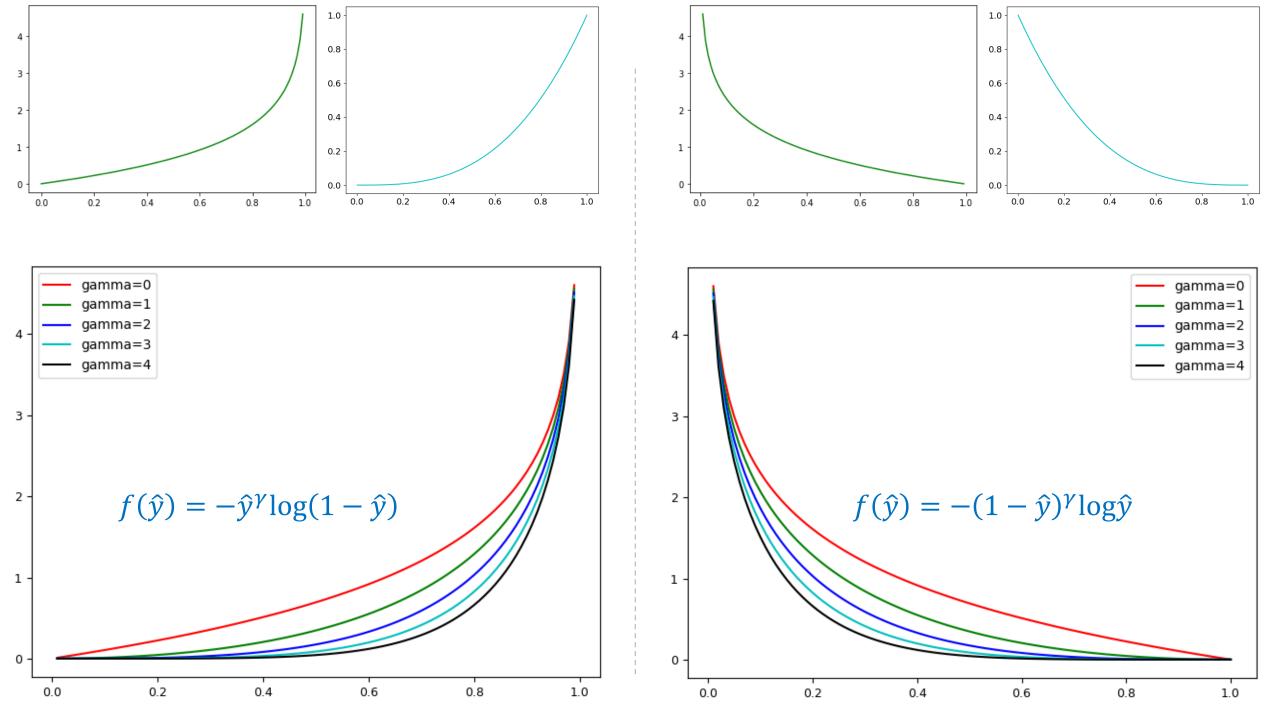
$$\rightarrow$$
 f( $\hat{y}$ ) \* k reduces significantly

Reducing slightly for the correct part

Reducing significantly for the incorrect part







## **Applying to our Problem**

$$L(y, \hat{y}, \gamma) = -y(1-\hat{y})^{\gamma}\log\hat{y} - (1-y)\hat{y}^{\gamma}\log(1-\hat{y})$$

Input	Output	Label	Gamma=0	Gamma=1	Gamma=2	Gamma=3	Gamma=4
	0.7	0	1.204	0.842	0.589	0.412	0.289
	0.8	1	0.223	0.044	0.008	0.001	0.0003
	0.7	1	0.356	0.107	0.032	0.009	0.002
	0.8	1	0.223	0.044	0.008	0.001	0.0003
	0.8	1	0.223	0.044	0.008	0.001	0.0003
	0.8	1	0.223	0.044	0.008	0.001	0.0003
	0.9	1	0.105	0.011	0.001	0.0001	0.00001
	0.9	1	0.105	0.011	0.001	0.0001	0.00001
	0.8	1	0.223	0.044	0.008	0.001	0.0003
	0.7	1	0.356	0.107	0.032	0.009	0.002

 $loss_{y=1}$ : 2.039

0.458

0.111

0.028

0.007

