

Math for AI

(Linear Algebra and Differential Calculus)

Vector and Matrix :

to process various input and output at once

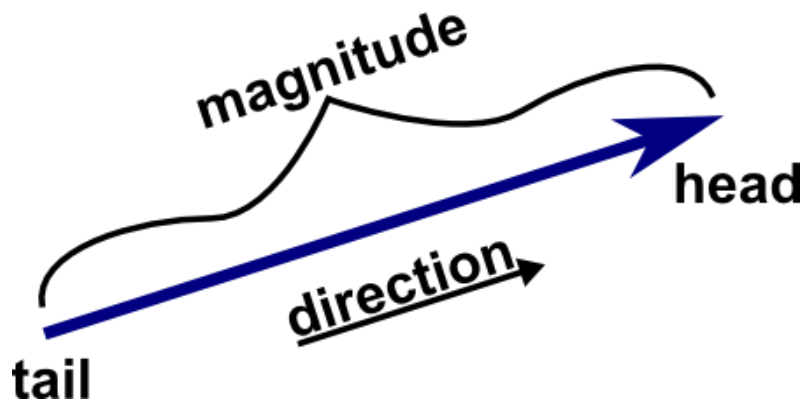
3.1 Vector

❖ 1. Scalar, Vector, Matrix, Tensor

- **Scalar** : Any real number, or any quantity that can be measured using a single real number.

ex) length, width, temperature

- **Vector** : A vector is an object that has both a magnitude and a direction.



ex) 2D coordinate plane : $\vec{a} = [2,1]$, $\vec{b} = [1,2]$

3.1 Vector



❖ 1. Scala, Vector, Matrix, Tensor

- **Vector** : column vector, row vector
 - **column vector** : n by 1 matrix consisting of a single column of n elements

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n = \mathbb{R}^{n \times 1}$$

- **row vector** : 1 by n matrix consisting of a single row of n elements

$$\mathbf{x}^T = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}^T = [x_1 \quad x_2 \quad \cdots \quad x_n] \in \mathbb{R}^{1 \times n}$$

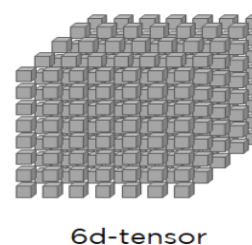
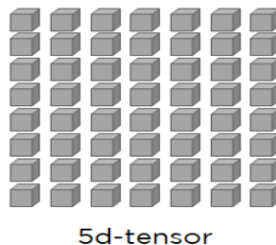
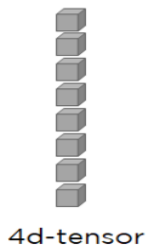
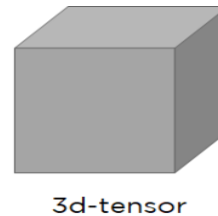
3.1 Vector

❖ 1. Scala, Vector, Matrix, Tensor

- **Matrix** : a rectangular array of numbers, symbols, or expression, arranged in rows and columns.

$$A = \begin{bmatrix} 1 & 6 \\ 3 & 4 \\ 5 & 2 \end{bmatrix}$$

- **Tensor** : a type of data structure used in linear algebra. you can calculate arithmetic operations with tensors. → **multidimensional data array**



<https://rekt77.tistory.com/102>
<https://machinelearningmastery.com/introduction-to-tensors-for-machine-learning/>

3.1 Vector



❖ 1. Scala, Vector, Matrix, Tensor

Rank	Math entity	Python example
0	Scalar (magnitude only)	<code>s = 483</code>
1	Vector (magnitude and direction)	<code>v = [1.1, 2.2, 3.3]</code>
2	Matrix (table of numbers)	<code>m = [[1, 2, 3], [4, 5, 6], [7, 8, 9]]</code>
3	3-Tensor (cube of numbers)	<code>t = [[[2], [4], [6]], [[8], [10], [12]], [[14], [16], [18]]]</code>
n	n-Tensor (you get the idea)	<code>....</code>

3.1 Vector

❖ 2. Addition, Subtraction, Magnitude of Vector

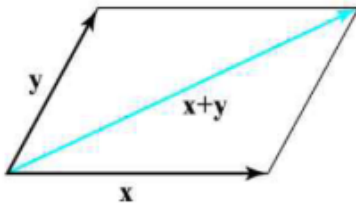
- **Addition and Subtraction of Vector:** element-wise addition of vector and element-wise subtraction of vector

$C = A + B$: Element-wise **addition**, i.e., $C_{ij} = A_{ij} + B_{ij}$

- A, B, C should have the same size, i.e., $A, B, C \in \mathbb{R}^{m \times n}$

ex) $\vec{a} = [3, 2], \vec{b} = [1, 4]$

$$\vec{a} + \vec{b} = [3+1, 2+4] = [4, 6], \vec{a} - \vec{b} = [3-1, 2-4] = [2, -2]$$

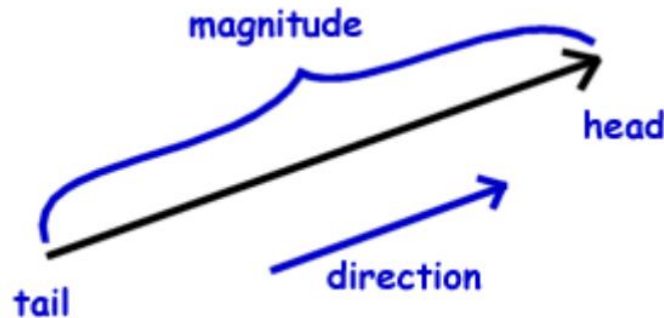


addition of vector ($\vec{x} + \vec{y}$) is called **parallelogram rule** ←
 \vec{x}, \vec{y} form the sides of a parallelogram and $\vec{x} + \vec{y}$ is one of the diagonals

3.1 Vector

❖ 2. Addition, Subtraction, Magnitude of Vector

- **Magnitude (or Length or Norm) of Vector** : magnitude of a vector is represented by the length of the arrow



- **Norm** : compute the length of the vector **a**

$$\|\mathbf{a}\| = \sqrt{a_1^2 + a_2^2 + a_3^2}$$

- ex) when \vec{a} is $[3,2]$, $\|\vec{a}\| = \sqrt{3^2 + 2^2} = \sqrt{13}$

3.1 Vector



❖ 3. Dot Product of Vectors

- **Dot product of two vector \vec{a} and \vec{b} :** The dot product can be defined **algebraically or geometrically**. These two definitions is equal.
Dot product is denoted by ' \cdot '
- **Algebraic definition :**
The dot product of two vectors $a = [a_1, a_2, \dots, a_n]$ and $b = [b_1, b_2, \dots, b_n]$ is defined as $\vec{a} \cdot \vec{b} = a_1b_1 + a_2b_2 + \dots + a_nb_n$.

ex) when \vec{a} is (1,3,-2) and \vec{b} is (4,2,1),

$$(1,3,-2) \cdot (4,2,1) = 1*4 + 3*2 + (-2)*1 = 8$$

3.1 Vector

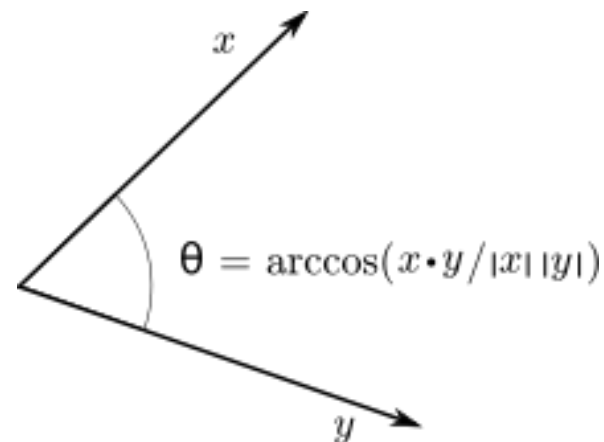
❖ 3. Dot Product of Vectors

▪ Geometric definition :

based on the notions of magnitude ($\|\vec{a}\|$) and angle($\cos\theta$)

$$\mathbf{a} \cdot \mathbf{b} = \begin{cases} \|\mathbf{a}\| \|\mathbf{b}\| \cos \angle(\mathbf{a}, \mathbf{b}) & \mathbf{a} \neq \mathbf{0} \wedge \mathbf{b} \neq \mathbf{0} \\ 0 & \mathbf{a} = \mathbf{0} \vee \mathbf{b} = \mathbf{0} \end{cases}$$

- $\|\vec{a}\|$: the magnitude of a vector \vec{a} .
- $\|\vec{b}\|$: the magnitude of a vector \vec{b} .
- $\cos\theta$: the angle of \vec{a} and \vec{b}

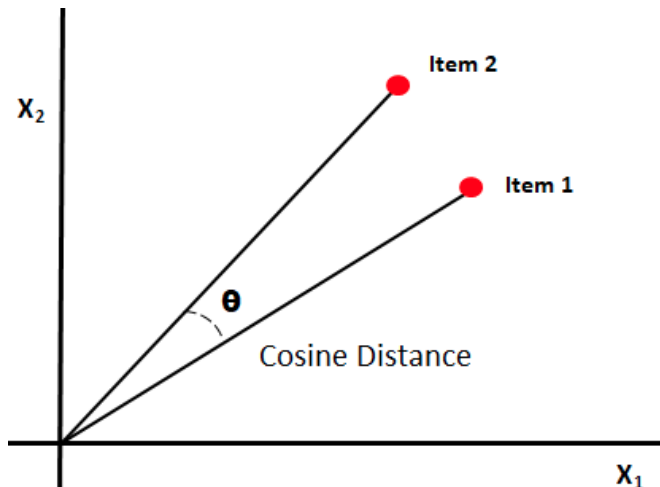


3.1 Vector

❖ 4. Cosine Similarity

- **Cosine Similarity** : measure of similarity between two non-zero vectors by measuring the cosine of the angle between them.

$$\mathbf{A} \cdot \mathbf{B} = \|\mathbf{A}\| \|\mathbf{B}\| \cos \theta \quad \rightarrow \quad \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

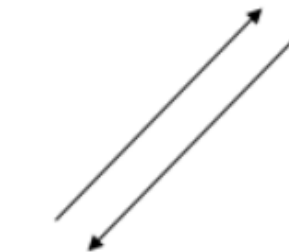
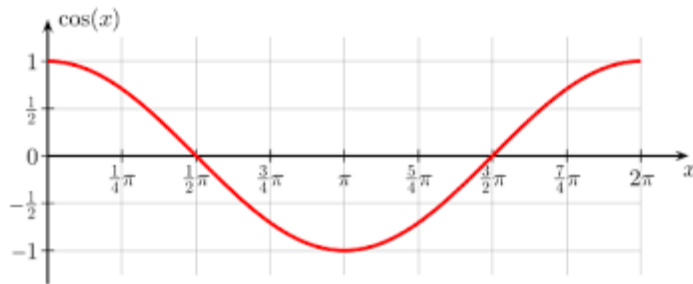


3.1 Vector

❖ 4. Cosine Similarity

▪ Cosine similarity's properties:

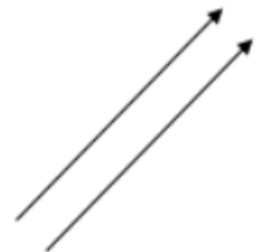
- measure of similarity between two vectors that measures the cosine of the angle between them.
- cosine similarity is neatly bounded in $[0, 1]$
- **cosine similarity of -1** : two vectors diametrically opposed
- **cosine similarity of 0** : two vectors oriented at 90° relative to each other
- **cosine similarity of 1** : two vectors with the same orientation



Cosine similarity :
-1



Cosine similarity :
0



Cosine similarity :
1

3.2 Matrix

❖ 1. Matrix Addition and Product

▪ Matrix addition:

$C = A + B$: Element-wise **addition**, i.e., $C_{ij} = A_{ij} + B_{ij}$

- A, B, C should have the same size, i.e., $A, B, C \in \mathbb{R}^{m \times n}$

예) If we have

$$\mathbf{A} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} \quad \text{and} \quad \mathbf{B} = \begin{bmatrix} 7 & 10 \\ 8 & 11 \\ 9 & 12 \end{bmatrix}$$

then we can calculate $\mathbf{C} = \mathbf{A} + \mathbf{B}$ by

$$\mathbf{C} = \mathbf{A} + \mathbf{B} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix} + \begin{bmatrix} 7 & 10 \\ 8 & 11 \\ 9 & 12 \end{bmatrix} = \begin{bmatrix} 8 & 12 \\ 11 & 15 \\ 14 & 18 \end{bmatrix}$$

3.2 Matrix

❖ 1. Matrix Addition and Product

- **Matrix product** : If A is an $m \times n$ matrix and B is an $n \times p$ matrix, the matrix product $C = AB$ is defined to be the $m \times p$ matrix

$$c_{ij} = a_{i1}b_{1j} + a_{i2}b_{2j} + \cdots + a_{in}b_{nj} = \sum_{k=1}^n a_{ik}b_{kj},$$

$$C = \begin{pmatrix} a_{11}b_{11} + \cdots + a_{1n}b_{n1} & a_{11}b_{12} + \cdots + a_{1n}b_{n2} & \cdots & a_{11}b_{1p} + \cdots + a_{1n}b_{np} \\ a_{21}b_{11} + \cdots + a_{2n}b_{n1} & a_{21}b_{12} + \cdots + a_{2n}b_{n2} & \cdots & a_{21}b_{1p} + \cdots + a_{2n}b_{np} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1}b_{11} + \cdots + a_{mn}b_{n1} & a_{m1}b_{12} + \cdots + a_{mn}b_{n2} & \cdots & a_{m1}b_{1p} + \cdots + a_{mn}b_{np} \end{pmatrix}$$

ex)

If we have $A = \begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix}$ and $B = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix}$

then $AB = \begin{bmatrix} 1 & 4 & 7 \\ 2 & 5 & 8 \\ 3 & 6 & 9 \end{bmatrix} \times \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \\ c_{31} & c_{32} \end{bmatrix} = \begin{bmatrix} 30 & 66 \\ 36 & 81 \\ 42 & 96 \end{bmatrix}$

3.2 Matrix



❖ 2. Transpose of Matrix and Invertible Matrix

- **Transpose of matrix** : operator which flips a matrix over its diagonal → switches the row and column indices of the matrix

ex) $A = \begin{bmatrix} 1 & 6 \\ 3 & 4 \\ 5 & 2 \end{bmatrix} \quad A^T = \begin{bmatrix} 1 & 3 & 5 \\ 6 & 4 & 2 \end{bmatrix}$

- If A is equal to A^T , A is called a **symmetric matrix**

3.2 Matrix



❖ 2. Transpose of Matrix and Invertible Matrix

- **Invertible matrix** : n-by-n square matrix A , if there exists an n-by-n square matrix B such that $AB = BA = I_n$.
The matrix B is called the inverse of A

Example :

$M = \begin{bmatrix} 4 & 3 \\ 3 & 2 \end{bmatrix}$ and it's inverse is $M^{-1} = \begin{bmatrix} -2 & 3 \\ 3 & -4 \end{bmatrix}$ since

$$MM^{-1} = \begin{bmatrix} 4 & 3 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} -2 & 3 \\ 3 & -4 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$

$$M^{-1}M = \begin{bmatrix} -2 & 3 \\ 3 & -4 \end{bmatrix} \begin{bmatrix} 4 & 3 \\ 3 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

Therefore, $\begin{bmatrix} 4 & 3 \\ 3 & 2 \end{bmatrix}$ and $\begin{bmatrix} -2 & 3 \\ 3 & -4 \end{bmatrix}$ are inverses of each other

3.2 Matrix



❖ 3. Transformation Matrix

- **linear transformation** : mapping $V \rightarrow W$ between two modules (for example, two vector spaces)

linear transformation maps linear subspaces onto linear subspaces

- **Invertible matrix** : linear transformations can be represented by matrices.

If T is a linear transformation mapping \mathbb{R}^n to \mathbb{R}^m and \vec{x} is a column vector with n entries, then

$$T(\vec{x}) = A\vec{x}$$

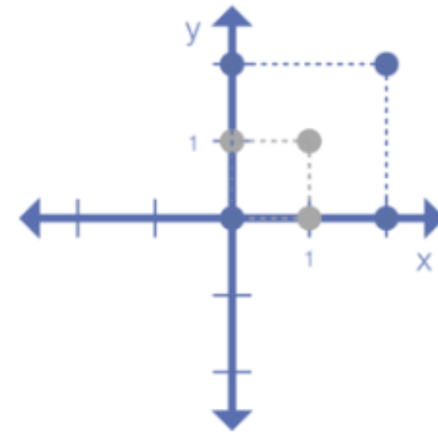
for some $m \times n$ matrix A , called **the transformation of T**

3.2 Matrix

❖ 3. Transformation Matrix

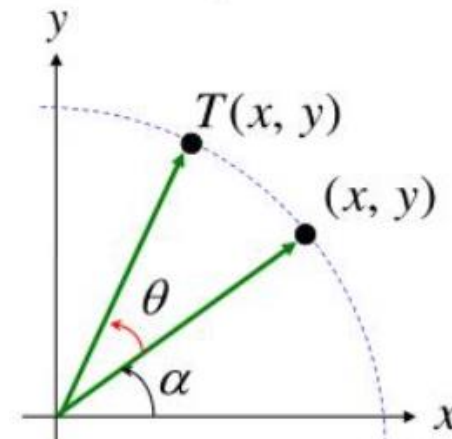
- Example 1: Transformation matrix for scale

$$\begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 2x \\ 2y \end{bmatrix}$$



- Example 2: Transformation matrix for rotation by an angle θ clockwise about the origin the functional form

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

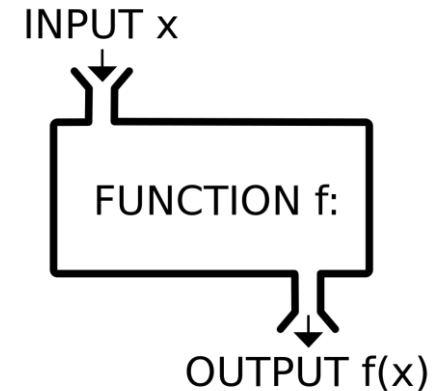
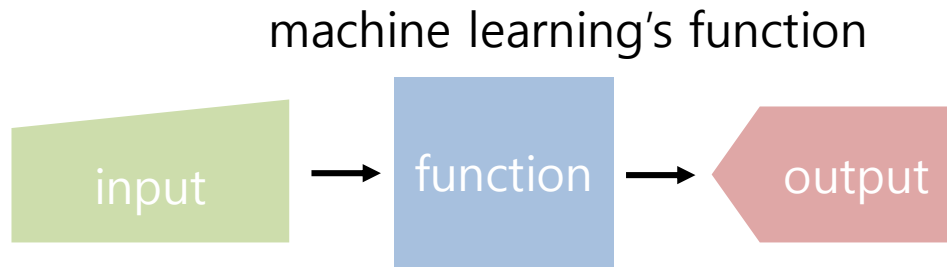


Function and Differential Calculus:

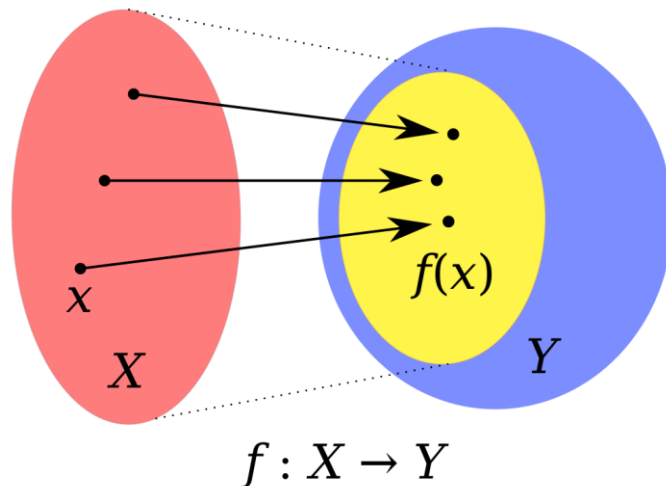
How to converge for the optimization

1. Function and Loss Function

❖ 1. Function



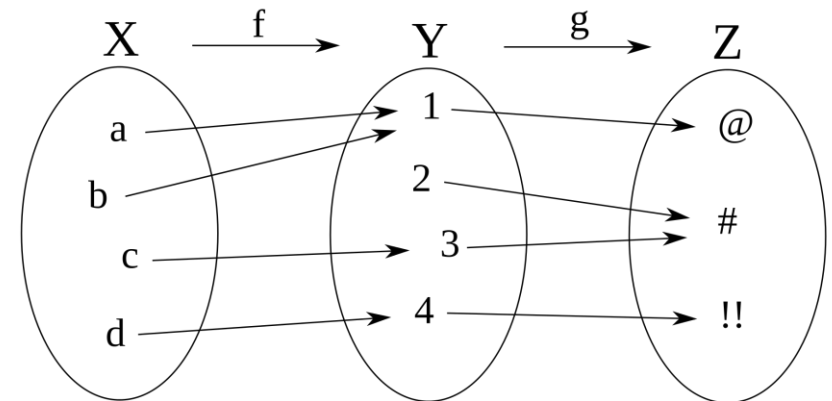
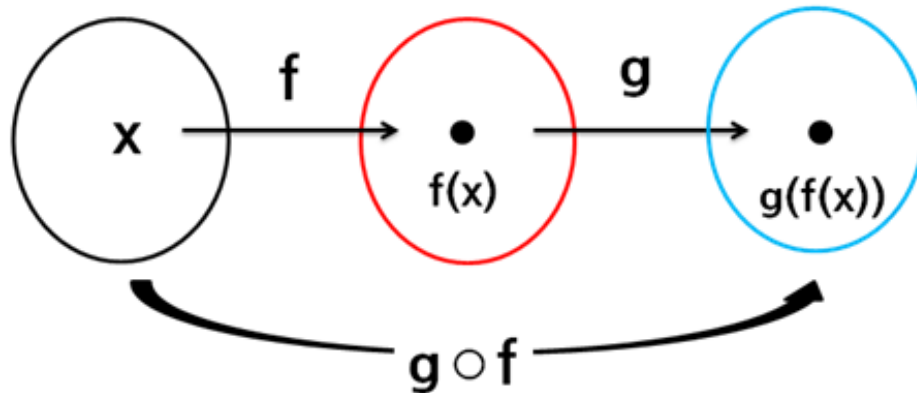
- **Function's definition** : a relation between sets that associates to every element of the first set exactly one element of the second set.



1. Function and Loss Function

❖ 2. Composition of Function

- **Definition of Composite Function** : operation that takes two functions f and g and produces a new function h such that $h(x) = g(f(x))$



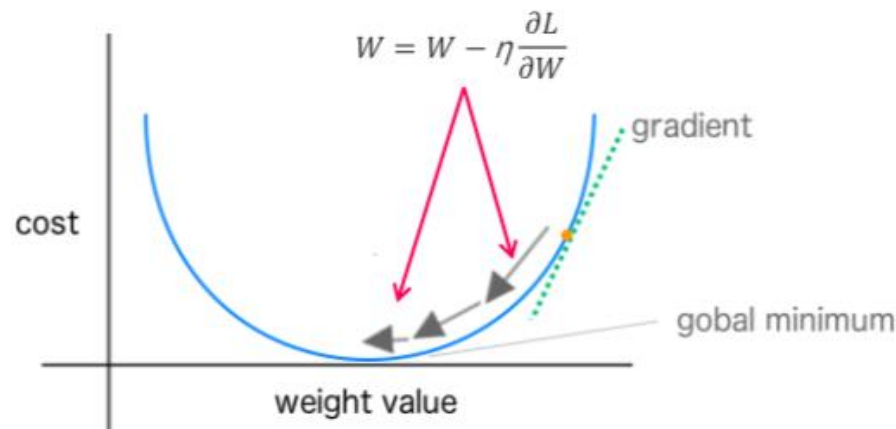
$g \circ f$, the **composition** of f and g .
For example, $(g \circ f)(c) = \#$.

- **Properties of Function composition** :
 - $f \circ (g \circ h) = (f \circ g) \circ h$
 - $g \circ f \neq f \circ g$

1. Function and Loss Function

❖ 3. Loss Function

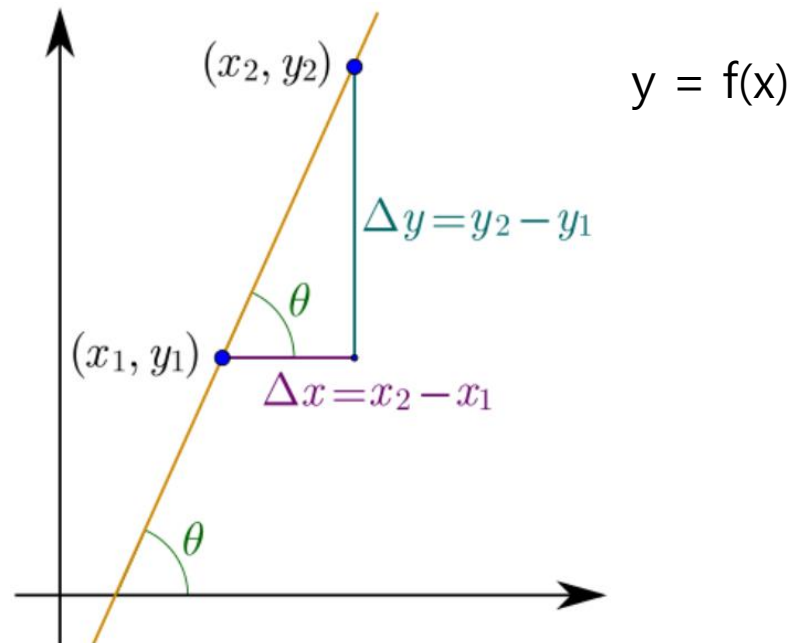
- **loss function** : a function that maps an event or values of one or more variables onto a real number intuitively representing some "cost" associated with the event.
- **optimization problem** → seeking to minimize a loss function.
- **loss functions and optimization**
 - step 1: loss function's setting.
 - step 2: loss function's partial differential calculation
 - step 3: find global minimum of the loss function using gradient descent



2. Derivative, Chain Rule

❖ 1. Derivative

- The **derivative** of a function of a real variable measures **the sensitivity to change (gradient)** of the function value (output value) with respect to a change in its argument (input value)



- $$\text{gradient} = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

2. Derivative, Chain Rule



➤ Derivatives

$$1. \frac{d}{dx}(c) = 0$$

$$2. \frac{d}{dx}[cf(x)] = cf'(x)$$

$$3. \frac{d}{dx}[f(x)+g(x)] = f'(x)+g'(x)$$

$$4. \frac{d}{dx}[f(x)-g(x)] = f'(x)-g'(x)$$

$$5. \frac{d}{dx}[f(x)g(x)] = f(x)g'(x)+g(x)f'(x)$$

$$6. \frac{d}{dx}\left[\frac{f(x)}{g(x)}\right] = \frac{g(x)f'(x)-f(x)g'(x)}{[g(x)]^2}$$

$$7. \frac{d}{dx}f(g(x)) = f'(g(x))g'(x)$$

$$8. \frac{d}{dx}(x^n) = nx^{n-1}$$

2. Derivative, Chain Rule



❖ 2. Chain Rule

- **Definition** : formula to compute the derivative of a composite function.

Suppose $F(x) = f(g(x))$,

$$F'(x) = f'(g(x))g'(x) \text{ <-Lagrange's notation}$$

$$\frac{dy}{dx} = \frac{dy}{du} \cdot \frac{du}{dx} \text{ <- Leibniz's notation}$$

2. Derivative, Chain Rule



❖ 2. Chain Rule

- example : $f = (g(x))^2$, $g = (2x^2 + 3x + 1)$

solution :

$$\frac{df}{dg} = \frac{d}{dg} (g(x))^2 = 2g(x)$$

$$\frac{dg}{dx} = \frac{d}{dx} (2x^2 + 3x + 1) = 4x + 3$$

$$\frac{df}{dx} = \frac{df}{dg} \cdot \frac{dg}{dx} = 2(2x^2 + 3x + 1)(4x + 3)$$

2. Derivative, Chain Rule



❖ 2. Chain Rule

- example : $f = (g(h))^2$, $g = (h(x))^2$, $h = (2x + 1)$

solution :

$$\frac{df}{dg} = \frac{d}{dg} (g(h))^2 = 2g(h)$$

$$\frac{dg}{dh} = \frac{d}{dh} (h(x))^2 = 2h(x)$$

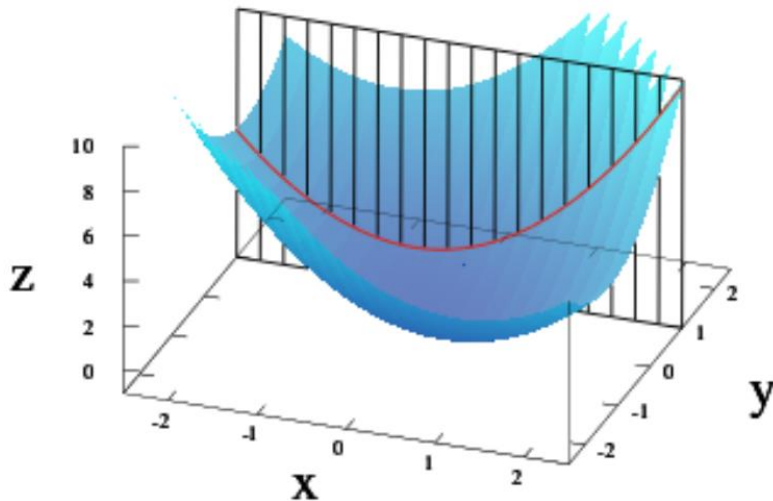
$$\frac{dh}{dx} = \frac{d}{dx} (2x + 1) = 2$$

$$\begin{aligned} \frac{df}{dx} &= \frac{df}{dg} \cdot \frac{dg}{dh} \cdot \frac{dh}{dx} = 2(2x + 1)^2 * 2(2x + 1) * 2 \\ &= 8(2x + 1)^3 \end{aligned}$$

2. Derivative, Chain Rule

❖ 3. Partial Derivative

- Functions used in machine learning → have multi-variable
- derivative of function having multi-variable → Partial Derivative

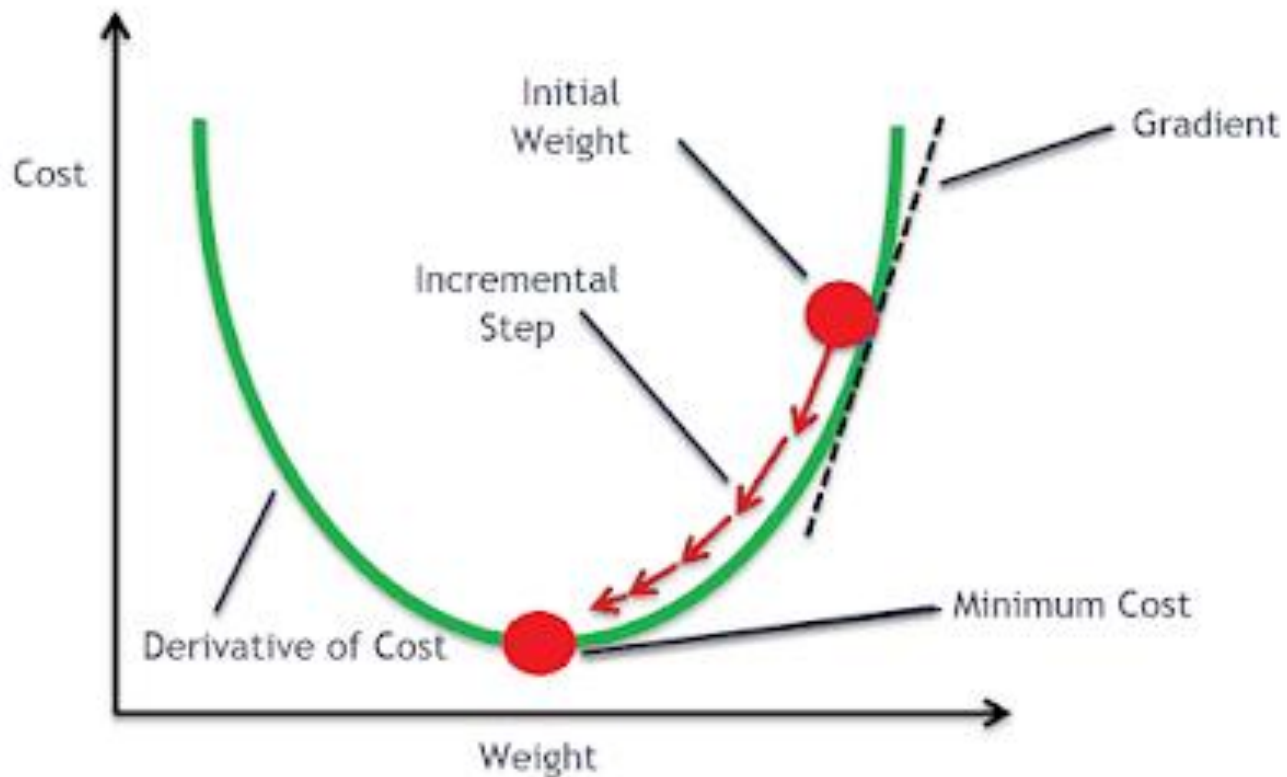


예) $f(x, y) = x^2 + 3xy + 2y^2$

$$\frac{\partial f}{\partial x} = 2x + 3y, \quad \frac{\partial f}{\partial y} = 3x + 4y$$

3. Gradient Descent

❖ 1. Gradient Descent of single variable



3. Gradient Descent

❖ 2. Gradient Descent of multi-variable

Gradient Descent

$f(x) = \text{nonlinear function of } x$

