Derivatives of Multi-variable Funtion.

$$\frac{\partial f}{\partial x_i} = \lim_{\epsilon \to 0} \frac{f(x_1, \dots, x_i + \epsilon, \dots, x_n) - f(x_1, \dots, x_n)}{\epsilon}$$

of 
$$f(x,y) = x^2 + y^2$$
  $\frac{\partial f}{\partial x} = 2x$   $\frac{\partial f}{\partial y} = 2y$ .

## · Differential

$$df = \sum_{i} \frac{\partial f}{\partial x_{i}} \cdot dx_{i}$$

Idea: linear approximation of f. 
$$\Delta z = 2x_0 \Delta x + 2y_0 \Delta y$$

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$$f_x = y$$
  $f_y = x$ 

$$f_x = y$$
  $f_y = x$   $df = y dx + x dy = 1 \cdot dx + i dy$ 

## (\*) Normal Vector of Tayant Plane.

(\*) Gradient 
$$\nabla f = \begin{pmatrix} f_x \\ f_y \end{pmatrix}$$
 for  $f = f(x,y)$ 

if  $f = f(x_1, ..., x_n)$  then  $\nabla f = \begin{pmatrix} f_{x_1}(\bar{x}) \\ \vdots \\ f_{x_n}(\bar{x}) \end{pmatrix}$ 

$$df = \sum_{i} \frac{\partial f}{\partial x_{i}} dx_{i} = \nabla f \cdot \begin{pmatrix} dx_{i} \\ \vdots \\ dx_{n} \end{pmatrix} = \nabla f \cdot d\vec{x}$$

(\*) Directional Derivative

$$\vec{u}$$
: unit vector  $\vec{u} = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}$ 

$$D_{\vec{u}}f = \lim_{\epsilon \to 0} \frac{f(x+u,\epsilon,y+u,\epsilon) - f(x,y)}{\epsilon}$$

$$= \nabla f \cdot \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \nabla f \cdot \vec{u}$$

ey 
$$\vec{u} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$
  $\nabla f \cdot \vec{u} = f_x$ 

(\*) Property of 
$$\nabla f$$
:  $\nabla f$  is the direction where  $f$  increases the fastest.

since  $\nabla f \cdot \vec{u} = ||\nabla f|| \cdot \cos \theta$  attains the maximal value when  $\cos \theta = | \iff \theta = 0$ 

eg. 
$$f = \chi^2 + y^2$$
 then at (1,1,2) what is the direction where f increases the fastest?

$$\nabla f = \begin{pmatrix} 2 \times \\ 2 y \end{pmatrix} = \begin{pmatrix} 2 \\ 2 \end{pmatrix}$$

$$-\nabla f = \begin{pmatrix} -2 \\ -2 \end{pmatrix}$$
 is the direction where f decreases

the fastest. 
$$\vec{u} \longleftrightarrow \nabla f$$

· Chain Rule 
$$f = f(x_1, \dots, x_n)$$

$$\begin{array}{c|c}
x_1 & \cdots & x_n \\
\downarrow & \downarrow & \ddots \\
\downarrow & \downarrow & \downarrow \\
t_1 & \cdots & t_j & \cdots & t_m
\end{array}$$

$$x_i = x_i(t_i, \dots, t_m)$$
 then

$$\frac{\lambda_{1} - \lambda_{1} - \lambda_{2}}{\lambda_{1} - \lambda_{1}} = \sum_{i} \frac{\partial f}{\partial \lambda_{i}} \frac{\partial \lambda_{i}}{\partial t_{i}}$$

eg 
$$f(x, y) = x^2 + y^2$$

$$\chi = \chi(t_1, t_2) = 2t_1$$

$$y = y(t_1, t_2) = t_1^2 + t_1^2$$

$$\frac{\partial f}{\partial t_i} = \frac{\partial f}{\partial x} \cdot \frac{\partial x}{\partial t_i} + \frac{\partial f}{\partial y} \cdot \frac{\partial y}{\partial t_i} = 2x \cdot 2 + 2y \cdot 2t.$$

$$\frac{\partial f}{\partial t_2} = 2y \cdot 2t_2$$

· Higher Order Derivatives.

$$\frac{\partial f_{x}(x,y)}{\partial x} = f_{xx}(x,y)$$

$$\frac{\partial f_{x}(x,y)}{\partial x} = f_{xx}(x,y) \qquad \frac{\partial f_{x}(x,y)}{\partial y} = f_{xy}(x,y)$$

Similarly for fyx, fyy, fxxy, ....

$$y. f(x,y) = x^2 + y^2$$

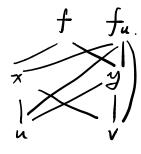
$$\chi(u,v)=u^2+v^2$$

$$f_{u} = \frac{\partial f}{\partial x} \cdot \frac{\partial y}{\partial u} + \frac{\partial f}{\partial y} \cdot \frac{\partial y}{\partial u}$$

= 
$$2x \cdot 2u + 2y \cdot 2v = f_{u}(x, y, u, v)$$

$$f_{uu} = \frac{\partial f_u}{\partial x} \cdot \frac{\partial x}{\partial u} + \frac{\partial f_u}{\partial y} \cdot \frac{\partial y}{\partial u} + \frac{\partial f_u}{\partial u}$$

$$= 4u \cdot 2u + 4v \cdot 2v + 4x$$



· Application of Derivatives

\* Local Min/Max  $f_x = f_y = 0$ 

+ alobal Min/Max ( within Region).

- $f_x = f_y = 0$
- points on the bonday
- points where fx or fy is not defined.