## Lecture 4: 2.3 Differentiation.

Given  $f: \mathbf{R}^3 \to \mathbf{R}$  The **partial derivative** of f with respect x is defined by

$$f_x(x,y,z) = \frac{\partial f}{\partial x}(x,y,z) = \lim_{h \to 0} \frac{f(x+h,y,z) - f(x,y,z)}{h}$$

if it exist. The partial derivatives  $\partial f/\partial y$  and  $\partial f/\partial z$  are defined similarly and the extension to functions of n variables is analogous.

What is the meaning of the derivative of a function y = f(x) of one variable? It is the slope of the tangent line  $y = f(x_0) + f'(x_0)(x - x_0)$  and the tangent line is that it is the linear function that best approximates f(x) when x is close to  $x_0$ .

The linear approximation of f(x, y) at  $(x_0, y_0)$  is

$$\ell_{x_0,y_0}(x,y) = f(x_0,y_0) + f_x(x_0,y_0)(x-x_0) + f_y(x_0,y_0)(y-y_0)$$

A function f(x, y) is called **differentiable** at  $(x_0, y_0)$  if the partial derivatives exist and if

$$\lim_{(x,y)\to(x_0,y_0)}\frac{f(x,y)-\ell_{(x_0,y_0)}(x,y)}{\|(x,y)-(x_0,y_0)\|}=0$$

The definition of differentiability is motivated by the idea that the **tangent plane** to the surface z = f(x, y) at  $(x_0, y_0)$ , i.e. the plane

$$z = \ell_{x_0, y_0}(x, y)$$

should give a good approximation to the function f close to  $(x_0, y_0)$ . If  $\mathbf{F} : \mathbf{R}^3 \to \mathbf{R}^3$  is given by  $\mathbf{F}(\mathbf{x}) = (f_1(x_1, x_2, x_3), f_2(x_1, x_2, x_3), f_3(x_1, x_2, x_3))$ then the **derivative matrix** of partial derivatives is defined by

$$\mathbf{DF} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathbf{F}}{\partial x_1} & \frac{\partial \mathbf{F}}{\partial x_2} & \frac{\partial \mathbf{F}}{\partial x_3} \end{bmatrix}$$

Here the second expression mean that the we think of  $\mathbf{F} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix}$  as a column

vector and  $\frac{\partial \mathbf{F}}{\partial x_1}$  as the derivative of the column vector. Similarly we define the  $m \times n$  matrix  $\mathbf{DF}$  for a function  $\mathbf{F} : \mathbf{R}^n \to \mathbf{R}^n$ .

A special case is the **gradient** of a function  $f : \mathbf{R}^n \to \mathbf{R}$  given by

grad 
$$f = \nabla f = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_n} \end{bmatrix}$$

A function  $\mathbf{F}: \mathbf{R}^n \to \mathbf{R}^m$  is called differentiable at **a** if

$$\lim_{\mathbf{x}\to\mathbf{a}}\frac{\|\mathbf{F}(\mathbf{x})-\mathbf{F}(\mathbf{a})-\mathbf{DF}(\mathbf{a})(\mathbf{x}-\mathbf{a})\|}{\|\mathbf{x}-\mathbf{a}\|}=0$$

Here  $\mathbf{DF}(\mathbf{a})(\mathbf{x} - \mathbf{a})$  is matrix multiplication of the  $m \times n$  matrix or column vector  $\mathbf{DF}(\mathbf{a})$  by the  $n \times 1$  matrix  $\mathbf{x} - \mathbf{a}$ . If  $f : \mathbf{R}^2 \to \mathbf{R}$  then

$$\mathbf{D}f(\mathbf{a})(\mathbf{x}-\mathbf{a}) = \begin{bmatrix} \frac{\partial f}{\partial x_1}(\mathbf{a}) & \frac{\partial f}{\partial x_2}(\mathbf{a}) \end{bmatrix} \begin{bmatrix} x_1 - a_1 \\ x_2 - a_2 \end{bmatrix} = \frac{\partial f}{\partial x_1}(\mathbf{a})(x_1 - a_1) + \frac{\partial f}{\partial x_2}(\mathbf{a})(x_2 - a_2)$$

If  $\mathbf{F}: \mathbf{R}^n \to \mathbf{R}^m$  then

$$\mathbf{DF}(\mathbf{a})(\mathbf{x}-\mathbf{a}) = \begin{bmatrix} \frac{\partial \mathbf{F}}{\partial x_1}(\mathbf{a}) & \dots & \frac{\partial \mathbf{F}}{\partial x_n}(\mathbf{a}) \end{bmatrix} \begin{bmatrix} x_1 - a_1 \\ \dots \\ x_n - a_n \end{bmatrix}$$
$$= \frac{\partial \mathbf{F}}{\partial x_1}(\mathbf{a})(x_1 - a_1) + \dots + \frac{\partial \mathbf{F}}{\partial x_n}(\mathbf{a})(x_n - a_n) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} \\ \vdots \\ \frac{\partial f_m}{\partial x_1} \end{bmatrix} (x_1 - a_1) + \dots + \begin{bmatrix} \frac{\partial f_1}{\partial x_n} \\ \vdots \\ \frac{\partial f_m}{\partial x_n} \end{bmatrix} (x_n - a_n)$$

We can think of the derivative of  $\mathbf{F}$  at the point  $\mathbf{a} \in \mathbf{R}^n$  as the linear map  $\mathbf{DF}$ :  $\mathbf{R}^n \to \mathbf{R}^m$ , mapping the vector  $\mathbf{h} = (h_1, ..., h_n)$  to the vector

$$\mathbf{DF}(\mathbf{a})\mathbf{h} = \lim_{t \to 0} \frac{\mathbf{F}(\mathbf{a} + t\mathbf{h}) - \mathbf{F}(\mathbf{a})}{t} = \frac{\partial \mathbf{F}}{\partial x_1}(\mathbf{a})h_1 + \dots + \frac{\partial \mathbf{F}}{\partial x_n}(\mathbf{a})h_n,$$

## 2.4 Paths and curves.

A **path** or a curve in  $\mathbf{R}^3$  is a map  $\mathbf{c} : I \to \mathbf{R}^3$  of an interval I = [a, b] to  $\mathbf{R}^3$ , i.e. for each  $t \in I \mathbf{c}(t)$  is a vector  $\mathbf{c} = x(t)\mathbf{i} + y(t)\mathbf{j} + z(t)\mathbf{k}$ .

The **velocity** of a path is defined to be

$$\mathbf{c}'(t) = \lim_{h \to 0} \frac{\mathbf{c}(t+h) - \mathbf{c}(t)}{h} = \mathbf{x}'(t)\mathbf{i} + \mathbf{y}'(t)\mathbf{j} + \mathbf{z}'(t)\mathbf{k}$$

The **tangent line** to the curve at  $t_0$  is given by

$$\ell(t) = \mathbf{c}(t_0) + \mathbf{c}'(t_0)(t - t_0)$$

**Ex** Let  $\mathbf{c}(t) = (\cos t, \sin t, t)$ . Find the equation of the tangent line at  $t = \pi/2$ . **Sol** We have  $\mathbf{c}'(t) = (-\sin t, \cos t, 1)$ . The equation of the tangent line is

$$\ell(t) = \mathbf{c}(\pi/2) + \mathbf{c}'(\pi/2)(t - \pi/2) = (0, 1, \pi/2) + (1, 0, 1)(t - \pi/2)$$

or  $x = -(t - \pi/2)$ , y = 1 and  $z = \pi/2 + (t - \pi/2)$ .

## 2.5 The Chain Rule.

The Chain rule in one variable: suppose that y = g(x), and z = f(y), i.e. z = h(x), where  $h(x) = f(g(x)) = f \circ g(x)$  then

$$\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx} \qquad \Leftrightarrow \qquad h'(x) = f'(y)\,g'(x)$$

The intuitive way to understand this is through the linear approximation:

 $\triangle z = f(y + \triangle y) - f(y) \sim f'(y) \triangle y$ 

which is the same as saying that f is differentiable. Similarly

$$\triangle y = g(x + \triangle x) - g(x) \sim g'(x) \triangle x$$

and if we combine the two we get

$$\triangle z \sim f'(y) g'(x) \triangle x$$

Since this is also equal to

$$\Delta z = h(x + \Delta x) - h(x) \sim h'(x) \Delta x$$

the chain rule in one variable follows.

The Chain rule in several variables: Suppose that  $g : \mathbf{R}^n \to \mathbf{R}^m$ ,  $f : \mathbf{R}^m \to \mathbf{R}^p$ and let  $h = f \circ g : \mathbf{R}^n \to \mathbf{R}^p$  (i.e. h(x) = f(g(x))). Then

$$Dh(x_0) = Df(y_0) Dg(x_0),$$
 where  $y_0 = g(x_0)$ 

and the right hand side is the  $p \times n$  matrix formed by the matrix product of the  $p \times m$  matrix  $Df(y_0)$  by the  $m \times n$  matrix  $Dg(x_0)$ .

The intuitive argument above actually generalizes to several variables just by replacing f' by Df etc. since differentiability of functions in several variables says

$$g(x + \Delta x) - g(x) \sim Dg(x) \Delta x.$$