

Handout 17

Recall: Chain Rule for $y=f(x)$, $x=g(t)$: $\frac{dy}{dt} = \frac{dy}{dx} \frac{dx}{dt}$

Theorem: Chain Rule for $z=f(x,y)$, $x(t)=g(t)$, $y(t)=h(t)$: $\frac{dz}{dt} = \frac{\partial f}{\partial x} \frac{dx}{dt} + \frac{\partial f}{\partial y} \frac{dy}{dt}$

Theorem: Chain Rule for $z=f(x,y)$, $x(t)=g(s,t)$, $y(t)=h(s,t)$:

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

Theorem: Implicit differentiation

1) Given equation $F(x, y(x)) = 0$, one differentiates both sides with respect to x to get $F_y \frac{dy}{dx} + F_x \frac{\partial x}{\partial x} = 0$ then solve it for $\frac{dy}{dx} = -\frac{F_x}{F_y}$

2) Similarly, given $F(x, y, z(x, y)) = 0$:

a. Differentiating with respect to x gives $F_x \frac{\partial x}{\partial x} + F_y \frac{\partial y}{\partial x} + F_z \frac{\partial z}{\partial x} = 0 \Rightarrow z_x = -\frac{F_x}{F_z}$

b. Differentiating with respect to y gives $F_x \frac{\partial x}{\partial y} + F_y \frac{\partial y}{\partial y} + F_z \frac{\partial z}{\partial y} = 0 \Rightarrow z_y = -\frac{F_y}{F_z}$

Definition: The (Directional) Derivative of a function $f(x, y)$ in a direction of a unit vector $\vec{u} = \langle a, b \rangle$ is given by $D_{\vec{u}}f(x_0, y_0) = \lim_{h \rightarrow 0} \frac{f(x_0 + ah, y_0 + bh) - f(x_0, y_0)}{h}$ if the limit exists.

Theorem: $D_{\vec{u}}f(x_0, y_0) = f_x(x_0, y_0)a + f_y(x_0, y_0)b$

Definition: Gradient vector of a function of 2 variables is defined as

$$\vec{\nabla}f(x, y) = \langle f_x(x, y), f_y(x, y) \rangle = \frac{\partial f}{\partial x} \mathbf{i} + \frac{\partial f}{\partial y} \mathbf{j}$$

Similarly $\vec{\nabla}f(x, y, z) = \langle f_x(x, y, z), f_y(x, y, z), f_z(x, y, z) \rangle = \frac{\partial f}{\partial x} \mathbf{i} + \frac{\partial f}{\partial y} \mathbf{j} + \frac{\partial f}{\partial z} \mathbf{k}$

And $\vec{\nabla}f(x_1, \dots, x_n) = \langle f_1(x_1, \dots, x_n), \dots, f_n(x_1, \dots, x_n) \rangle$

Definition: Another definition of directional derivative:

$$D_{\langle a, b \rangle} f(x, y) = \vec{\nabla}f(x, y) \cdot \langle a, b \rangle$$

$$D_{\langle a, b, c \rangle} f(x, y, z) = \vec{\nabla}f(x, y, z) \cdot \langle a, b, c \rangle$$

$$D_{\langle y_1, \dots, y_n \rangle} f(x_1, \dots, x_n) = \vec{\nabla}f(x_1, \dots, x_n) \cdot \langle y_1, \dots, y_n \rangle$$

Definition: Yet another way to define directional derivative: let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a real valued function with a vector space domain \mathbb{R}^n , i.e. $f(\vec{x}) \in \mathbb{R}$. Thus, the directional derivative is given by $D_{\vec{u}}f(\vec{x}) = \lim_{h \rightarrow 0} \frac{f(\vec{x} + h\vec{u}) - f(\vec{x})}{h}$

Theorem: The maximum of a directional derivative at given point occurs when the vector \vec{u} has the same direction as the gradient vector.