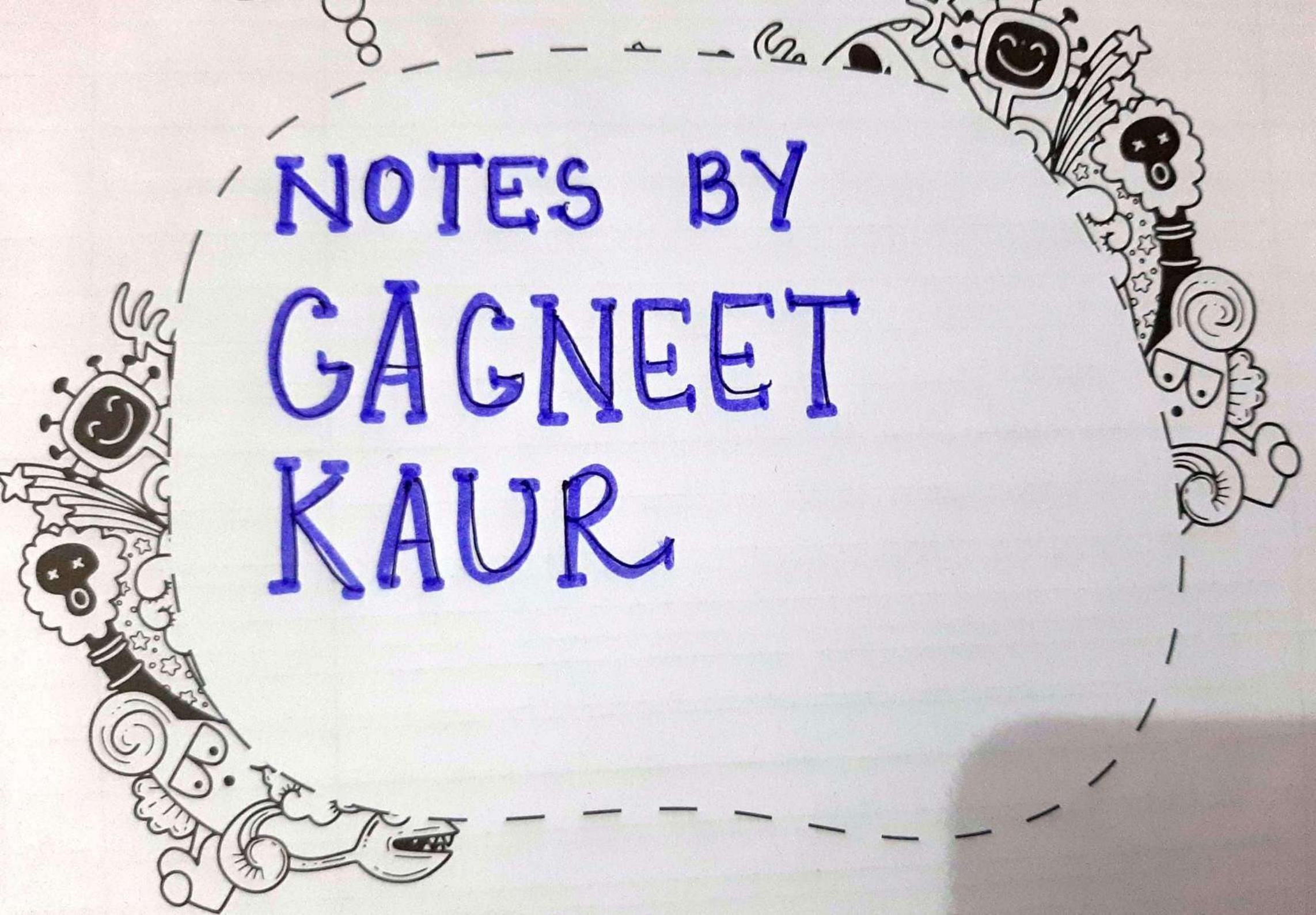


NOTES BY GAGNEET KAUR



WEEK - 2

UNIVARIATE CALCULUS

CONTINUITY

* A function $f(x)$ is continuous at a point x_0 if for any sequence of x_i converging to x_0 , $f(x_i)$ converges to $f(x_0)$.

A function $f(x)$ is continuous at $x=a$ if

$$f(a) = \lim_{x \rightarrow a^+} f(x) = \lim_{x \rightarrow a^-} f(x)$$

* A function is continuous in \mathbb{R} if it is continuous at all points in \mathbb{R} .

DIFFERENTIABILITY — means that the derivative of the function exists.

A function $f(x)$ is differentiable at $x=a$ if:

$$f'(a) = \lim_{x \rightarrow a^-} \frac{f(x) - f(a)}{x - a} = \lim_{x \rightarrow a^+} \frac{f(x) - f(a)}{x - a}$$

What is derivative? \rightarrow Rate of change of function

NOTE : If a function is differentiable, it is continuous
BUT if a function is continuous, it may or may not be differentiable.

LINEAR APPROXIMATION

The linear approximation $L(x)$ of a function $f(x)$ at a point a is given by:

$$L(x) = f(a) + f'(a)(x-a)$$

This is the equation of a tangent line:

$$y - y_1 = m(x - x_1)$$

$$y = y_1 + m(x - x_1)$$

If $x_1 = a$, $y_1 = f(a)$ and $m = f'(a)$, we get,

$$y = f(a) + f'(a)(x-a)$$

The plot of linear approximation of a function f at a point v is TANGENT to f at the point $(v, f(v))$

HIGHER ORDER APPROXIMATIONS

QUADRATIC APPROXIMATION :

$$L(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2}(x-a)^2$$

HIGHER ORDER APPROXIMATIONS :

$$L(x) = f(a) + \frac{f^{(1)}(a)}{1!}(x-a) + \frac{f^{(2)}(a)}{2!}(x-a)^2 + \frac{f^{(3)}(a)}{3!}(x-a)^3 + \dots$$

- Higher order approximations are BETTER and more ACCURATE than linear approximations.

CRITICAL POINT

A critical point of a continuous function f is a point at which the derivative is 0 or undefined.

Critical points are the points on the graph where the function's rate of change is altered — either a change from increasing to decreasing or vice versa.

Critical points are useful for determining EXTREMA (minima or maxima) and solving optimization problems.

- # To find the ^{value of} critical point of a differentiable f^n , f , put $f'(x) = 0$.

SECOND DERIVATIVE TEST

- If $f''(x) = 0$, point is saddle
- If $f''(x) < 0$, point is maximum
- If $f''(x) > 0$, point is minimum.

DERIVATIVE

For a function $f(x)$ its derivative function $f'(x)$ or $\frac{d}{dx} f(x)$ is,

$$f'(x) = \frac{d}{dx} f(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$$

PRODUCT RULE : $(fg)'(a) = f'(a) \cdot g(a) + g'(a) \cdot f(a)$

CHAIN RULE : $(f(g))'(x) = f'(g(x)) \cdot g'(x)$

- * Two important limits : (i) $\lim_{x \rightarrow 0} \frac{\sin x}{x} = 1$
- (ii), $\lim_{x \rightarrow 0} \frac{1 - \cos(x)}{x} = 0$

Linear Algebra

- What is a vector space?

A vector space V over \mathbb{R} is a set along with two functions:

- Vector Addition : $V + V \rightarrow V$
- Scalar Multiplication : $\mathbb{R} \cdot V \rightarrow V$

- What are the conditions of a set of vectors W to become a subspace of vector space V , i.e., $W \subseteq V$?

$$(1) 0 \in W$$

$$(2) \text{ If } v_1, v_2 \in W, \text{ then } v_1 + v_2 \in W$$

$$(3) \text{ If } v \in W \text{ and } c \in \mathbb{R}, \text{ then } cv \in W$$

- How Representation of a line through a point $u \in \mathbb{R}^d$ along the vector $v \in \mathbb{R}^d$ is given (-)

$$\{x \in \mathbb{R}^d : x = u + \alpha v \quad \# \alpha \in \mathbb{R}\}$$

- Representation of a line through ^{two} points u & $u' \in \mathbb{R}^d$:

$$\{x \in \mathbb{R}^d : x = u + \alpha(u' - u) \quad \# \alpha \in \mathbb{R}\}$$

- Representation of a hyperplane normal to the vector $w \in \mathbb{R}^d$ with value $b \in \mathbb{R}$ is :

$$\{x \in \mathbb{R}^d : w^T x = b\}$$

- When are two vectors x & y perpendicular to each other?

When their dot product is zero, i.e., $x \cdot y = 0$ or $x^T y = 0$

Multivariate Calculus

- * Multivariate functions are $f : \mathbb{R}^d \rightarrow \mathbb{R}$

Partial Derivatives

Suppose, we have a function $f(x, y)$ which depends on two variables x and y , where x and y are independent of each other. Then we say that the function f partially depends on x and y .

Now, if we calculate the derivative of f , then that derivative is known as the partial derivative of f .

- HOW TO COMPUTE A PARTIAL DERIVATIVE :

If we differentiate the function f wrt x , then take y as constant & if we differentiate f wrt y , then take x as constant.

Consider this function : $f(x, y) = x^2 y^3$

$$\frac{\partial f}{\partial x} = 2xy^3 \quad (\text{wrt } x) \rightarrow \text{taking } y \text{ constant}$$

$$\frac{\partial f}{\partial y} = 3y^2x^2 \quad (\text{wrt } y) \rightarrow \text{taking } x \text{ constant}$$

Gradient

The gradient of a multivariable function $f(x, y, \dots)$, denoted ∇f , is the collection of all its partial derivatives into a vector.

$$\nabla f = \left[\frac{\partial f}{\partial x} \quad \frac{\partial f}{\partial y} \quad \dots \right]^T$$

→ If you imagine standing at a point (x_0, y_0, \dots) in the input space of f , the vector $\nabla f(x_0, y_0, \dots)$ tells you which direction you should travel to increase the value of f most rapidly, which means

The gradient of a function points in the direction of STEEPEST ASCENT.

→ Gradient of a function at a point is PERPENDICULAR to the contour through the point.

Linear Approximation of Functions involving Multivariables

The linear approximation of a function f of two variables x and y in the neighbourhood of (a, b) is :

$$L(x, y) = f(a, b) + \frac{\partial f(a, b)}{\partial x}(x-a) + \frac{\partial f(a, b)}{\partial y}(y-b)$$

OR

$$f(y_1, y_2) \approx f(v_1, v_2) + \nabla f(v)^T (y - v)$$

Directional Derivatives

NOTATION : $D_{\vec{u}} [f](v)$ → directional derivative of f at the point v , along \vec{u} .

- $f_x(x, y) = \frac{\partial f}{\partial x}(x, y)$ → Rate of change of f as we vary x (keeping y fixed)
- $f_y(x, y) = \frac{\partial f}{\partial y}(x, y)$ → Rate of change of f as we vary y (keeping x fixed)
- $D_{\vec{u}}[f](x, y)$ → Rate of change of f if we allow both x and y to change simultaneously (in some direction \vec{u})

$$D_{\vec{u}} f(x, y) = \nabla f \cdot \vec{u} = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right] \cdot [u_1, u_2]$$

$$\Rightarrow D_{\vec{u}} f(x, y) = u_1 \frac{\partial f}{\partial x} + u_2 \frac{\partial f}{\partial y}$$

gradient

$$D_{\vec{u}} f(x, y) = \nabla f \cdot \vec{u}$$

unit vector

Directional derivative can be considered to be a weighted

sum of partial derivatives.

HOW TO COMPUTE : (EXAMPLE)

- What is the directional derivative of $f(x,y) = x^2 - xy$ at the point $(2, -3)$ along the vector $[3, 4]$?

$$D_{\vec{u}} f(x,y) = \nabla f \cdot \vec{u}$$

Let's calculate the gradient : $\nabla f = \begin{bmatrix} 2x-y \\ x-y \end{bmatrix}$ at $(2, -3)$

$$\therefore \nabla f \text{ at } (2, -3) = \begin{bmatrix} 2(2) - (-3) \\ -2 \end{bmatrix} = \begin{bmatrix} 7 \\ -2 \end{bmatrix}$$

Now, the unit vector of $[3, 4]$:

$$\vec{u} = \left[\frac{3}{\sqrt{3^2+4^2}}, \frac{4}{\sqrt{3^2+4^2}} \right] = \left[\frac{3}{5}, \frac{4}{5} \right]$$

$$\text{Thus, } D_{\vec{u}} f(x,y) = \nabla f \cdot \vec{u} = \begin{bmatrix} 7 \\ -2 \end{bmatrix} \begin{bmatrix} 3/5 & 4/5 \end{bmatrix}$$

$$= \frac{21}{5} - \frac{8}{5}$$

$$= \frac{13}{5} \quad \text{Ans.} \quad \text{or} \quad 2.6 \quad \text{Ans.}$$

Direction of steepest Ascent

The direction of steepest ascent is used to find a direction u , that maximises the rate of change of f as you move from v along u .

$$u = \frac{\nabla f}{\|\nabla f\|}$$

Direction of steepest Descent

To find a direction u , that minimizes the rate of change of f .

$$u = -\frac{\nabla f}{\|\nabla f\|}$$

Cauchy - Schwarz Inequality

$$-\|a\| \cdot \|b\| \leq a^T b \leq \|a\| \cdot \|b\|$$

Where $a, b \in \mathbb{R}^d$.

Important Formulae from Week 2

→ Linear Approximation for Univariable

$$L(x) = f(a) + f'(a)(x-a)$$

→ Linear Approximation for Multivariables

$$L(\mathbf{x}, \mathbf{y}) = \mathbf{f}(\mathbf{v}) + \nabla \mathbf{f}(\mathbf{v})^T (\mathbf{y} - \mathbf{v})$$

→ Gradient : collections of partial derivatives as vector

$$\nabla \mathbf{f} = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \frac{\partial f}{\partial x_2} & \dots & \end{bmatrix}^T$$

→ Directional Derivative → Steepest Ascent

$$D = \nabla \mathbf{f} \cdot \vec{u}$$

$$u = \frac{\nabla \mathbf{f}}{\|\nabla \mathbf{f}\|}$$

→ Cauchy-Schwarz Inequality

$$-\|\mathbf{a}\| \cdot \|\mathbf{b}\| \leq \mathbf{a}^T \mathbf{b} \leq \|\mathbf{a}\| \cdot \|\mathbf{b}\|$$