

## 2. Basic Mathematical Analysis and Differential Calculus

### 2.1 Supremum & Infimum vs Maximum & Minimum

This week starts with some Analysis and Differential Calculus knowledge required to go through Optimization.

Not a lot of knowledge of mathematical analysis and differential calculus is needed.

Later actually, a concept of *Lipschitz Continuous*, *Smoothness* are needed later in Algorithms, but too far ahead.

✓ Bounded Above

Let a set  $A \subset \mathbb{R}$  be bounded above if  $\exists b \in \mathbb{R}$  such that  $\forall a \in A, a \leq b$ .

$b$  is called an *upper bound* of  $A$ .

✓ Least Upper Bound = Supremum

Let  $s \in \mathbb{R}$  be the supremum of  $A \subset \mathbb{R}$  if

- 1)  $s$  is an upper bound of  $A$
- 2) If  $u$  is any upper bound of  $A$ ,  $s \leq u$ .

✓ Maximum

A real number  $m$  is a maximum of a set  $A$  if

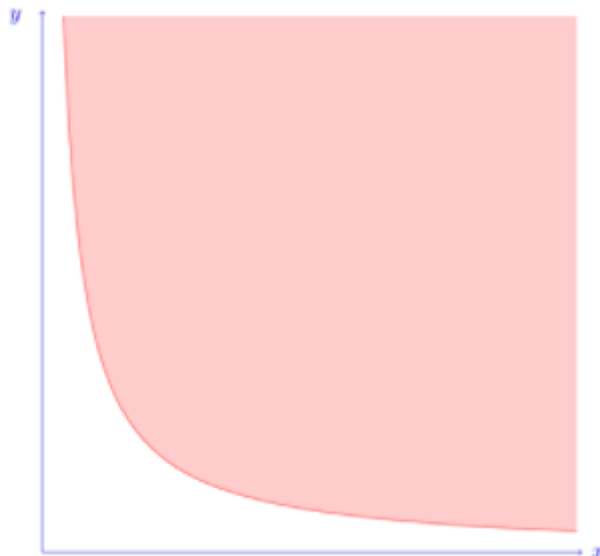
- 1)  $m$  is an upper bound of  $A$
- 2)  $m \in A$

- Why important in This course?

Ex)  $\min_{x,y \in \mathbb{R}} x \text{ s.t.}$

$$\begin{pmatrix} x & 1 \\ 1 & y \end{pmatrix} \succeq 0$$

Thus, use *inf* instead of *min*!



## 2.2 Basic Topology

### ✓ Metric Space

A function  $d : X \times X \rightarrow \mathbb{R}$  is a metric on the set  $X$  if for all  $x, y, z \in X$ ,

1) For  $x \neq y$ ,  $d(x, y) > 0$  and  $d(x, x) = 0$  : Non-negativity

"distance between distinct points is positive"

2)  $d(x, y) = d(y, x)$  : Symmetry

"direction doesn't matter"

3)  $d(x, z) \leq d(x, y) + d(y, z)$  : Triangle Inequality

"Adding a midpoint increases the distance"

Then, call  $(X, d)$  a *metric space*.

### ✓ Epsilon Ball

Let  $(M, d)$  be a metric space.

The epsilon-ball centered at  $a \in M$  " $B_\epsilon(a)$ " is set of points distance less than  $\epsilon$  from  $a$  where  $\epsilon > 0$ .

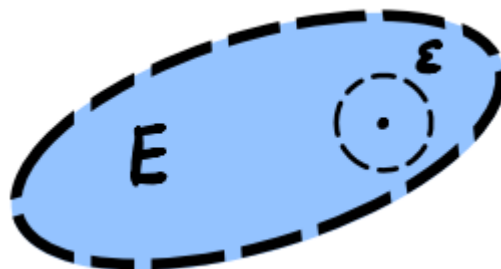
$$B_\epsilon(a) = \{x | d(x, a) < \epsilon\}.$$

Without any mention about the metric, think of "d" as the familiar  $l_2$  norm. In  $\mathbb{R}$ , it is simply  $|x - a|$ .

### ✓ Open Set

$O$  is an Open set if  $\forall o \in O, \exists \epsilon > 0$  s.t.  $B_\epsilon(o) \subseteq O$

ex) Open, bounded set in  $\mathbb{R}$  works like  $(a, b)$ .



Take any element  $x$  in  $(a, b)$ . Then, I can "choose"  $\epsilon$  as  $\frac{\min(x-a, b-x)}{2}$  using the density of  $\mathbb{R}$ .

### ✓ Limit Point

A point  $x$  is a limit point of a set  $F$  if every epsilon ball about  $x$  intersects  $F$  at some point other than  $x$ .

ex)  $F = [a, b)$  then the set of limit points of  $F$  is  $[a, b]$ .

✓ Closed

$F$  is closed if it contains all of its limit points.

ex) Closed, bounded set in  $\mathbb{R}$  works like  $[a, b]$ .

\* Practice \*

$\phi$  is *Open and Closed*.  $\mathbb{R}$  is open and closed.

$[a, b)$  is neither open nor closed.

✓ Closure

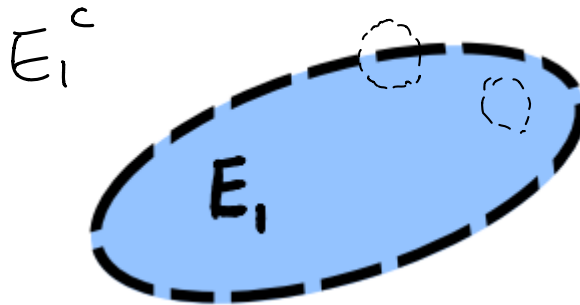
Let  $E$  be a proper, nonempty subset of  $\mathbb{R}$  and  $L$  be the set of all limit points of  $E$ . The closure of  $E$ ,

$$\bar{E} = E \cup L.$$

ex)  $E = [a, b)$  then  $\bar{E} = [a, b]$

✓ Boundary

Let  $E$  be a proper, nonempty subset of  $\mathbb{R}$ .  $\partial(E)$ , the boundary of  $E$  is set of points "a" where  $\forall B_\epsilon(a)$  contains points in  $E$  and  $E^c$ .



✓ Interior

The interior of a set  $E$ ,  $E^o := \{x \in E | \exists B_\epsilon(x) \subseteq E\}$

- Why important in This course?

The concept of *Relative Interior* is used in *Slater's condition*, a theory to satisfy  $d^* = p^*$ , the strong duality.

## 2.3 Differential Calculus

✓ Differentiation in 1 dimensional space

$f$  is differentiable at  $a \in \mathbb{R}$  if  $f$  is defined on some open set  $U$  containing  $a$  and  $\frac{d}{dx} f(x)|_{x=a} = f'(a) = \lim_{h \rightarrow 0} \frac{f(a+h) - f(a)}{h}$

$\frac{f(a+h) - f(a)}{h}$  is called *average rate of change* and  $f'(a)$  is called *instantaneous rate of change*.

✓ Gradient of Multivariable functions

The gradient of a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  at a point  $x$  where  $f$  is differentiable is defined as a column vector containing **first order partial derivative** of  $f$  w.r.t.  $x_1, x_2, \dots, x_n$ .

$$\nabla f(x) = \left[ \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right]^T$$

ex)  $h(x) = 2x_1 + 3x_2 + x_3$  then  $\nabla f(x) = [2, 3, 1]^T$

✓ Hessian of Multivariable functions

$$(H_{f(x)})_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j}. \text{ Note that } (H_{f(x)}) \in \mathbb{R}^{n \times n} \text{ and symmetric!}$$

ex)  $f(x) = 4x_1^2 + 5x_1x_2 + x_2^2$  then find the Hessian of  $f$

✓ Jacobian of *vector valued* functions

$f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ . a Jacobian of  $f$  is a matrix collecting all the first order derivatives. Jacobian of  $f(x) = [f_1(x) \dots f_m(x)]^T$

$$(J_{f(x)})_{ij} = \frac{\partial f_i}{\partial x_j}$$

ex)  $f(x) = \begin{pmatrix} 3x_1x_2 + 2x_1 \\ 4x_2 \\ 8x_1^2 \end{pmatrix}$ . Find the Jacobian of  $f$ .

✓ Taylor Series Expansion of  $f : \mathbb{R} \rightarrow \mathbb{R}$ .

Let  $f \in C^\infty(a, b)$  and  $x_0 \in (a, b)$ . The Taylor series of  $f$  centered at  $x_0$  :

$$T(x) = \sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!} (x - x_0)^n$$

ex)  $e^x = \sum_{n=0}^{\infty} \frac{x^n}{n!}, x \in \mathbb{R}$

✓ Second Order Approximation of  $R^n \rightarrow R$  at  $x$ .

$$f(y) = f(x) + \nabla f(x)^T (y - x) + \underbrace{(y - x)^T H_{f(x)} (y - x)}_{\frac{1}{2}}$$

## Vector Derivative Practice)

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_2^2 \quad \text{s.t.} \quad Gx = h, \quad A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m, \quad G \in \mathbb{R}^{p \times n}, \quad h \in \mathbb{R}^p, \quad \text{rank}(A) = n$$

" p equality constraints "

$$\begin{aligned} \mathcal{L}(x, r) &= \|Ax - b\|_2^2 + r^T (Gx - h) \\ &= (Ax - b)^T (Ax - b) + r^T (Gx - h) \\ &= (x^T A^T - b^T) (Ax - b) + r^T (Gx - h) \\ &= x^T A^T A x + (r^T G - 2b^T A) x - r^T h + b^T b \\ &= x^T A^T A x + (G^T r - 2A^T b)^T x - r^T h + b^T b \end{aligned}$$

Using convexity of the Lagrangian w.r.t.  $x$ ,

$$\nabla_x \mathcal{L}(x, r) = 2A^T A x + (G^T r - 2A^T b) x \stackrel{!}{=} 0$$

⋮

$$x^* = (A^T A)^{-1} \left( A^T b + G^T (G(A^T A)^{-1} G^T)^{-1} (h - G(A^T A)^{-1} A^T b) \right).$$