

Today. Convexity.

• Convex Sets

• Convex functions.

Def: Convex Combination.

$$\sum_{i=1}^n \lambda_i \vec{x}_i$$

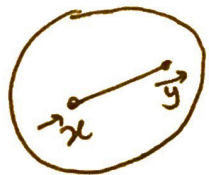
if

$$\sum_{i=1}^n \lambda_i = 1$$

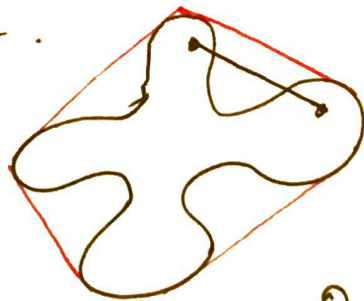
$$\lambda_i \geq 0.$$

Def: Convex set.

A set C is convex if the line joining any two points in set is contained in the set.



Convex



Not convex.

$$\vec{x}_1 \in C, \vec{x}_2 \in C.$$

$$\theta \cdot \vec{x}_1 + (1-\theta) \cdot \vec{x}_2 \in C$$

$$\theta \in [0, 1].$$

Def: Convex Hull.

e.g. $C = \{ \vec{x} \mid \vec{a}^T \vec{x} = b \}$.

$$\vec{a}^T (\vec{x} - \vec{x}_0) = 0$$

Hyperplane.

$$\vec{x}_1 \in C, \vec{x}_2 \in C.$$

Consider: $\vec{x}_3 = \theta \cdot \vec{x}_1 + (1-\theta) \cdot \vec{x}_2$

$$\begin{aligned} \vec{a}^T \vec{x}_3 &= \theta \cdot \vec{a}^T \vec{x}_1 + (1-\theta) \cdot \vec{a}^T \vec{x}_2 \\ &= \theta \cdot b + (1-\theta) \cdot b \\ &= b \end{aligned}$$

$$\Rightarrow \vec{x}_3 \in C. \quad \therefore C \text{ is convex.}$$

$$\{ \vec{x} \mid \vec{a}^T \vec{x} > b \}$$

$$\{ \vec{x} \mid \vec{a}^T \vec{x} \leq b \}$$

Half-spaces.

e.g.: $P = \{A \mid A \in \mathbb{R}^{n \times n}, A \text{ is PSD (symmetric)}\}$.

A : PSD $\Rightarrow \vec{x}^T A \vec{x} \geq 0 \quad \forall \vec{x} \in \mathbb{R}^n$.

Consider: $A_1, A_2 \in P$.

$$A_3 = \theta \cdot A_1 + (1-\theta)A_2.$$

$\theta \in [0, 1]$.

Consider: $\vec{x}^T A_3 \vec{x} = \vec{x}^T (\theta A_1 + (1-\theta)A_2) \vec{x}$
 $= \theta \vec{x}^T A_1 \vec{x} + (1-\theta) \vec{x}^T A_2 \vec{x}$.

$$\geq 0.$$

$\forall \vec{x}$

A_3 is also PSD. $A_3 \in P$.

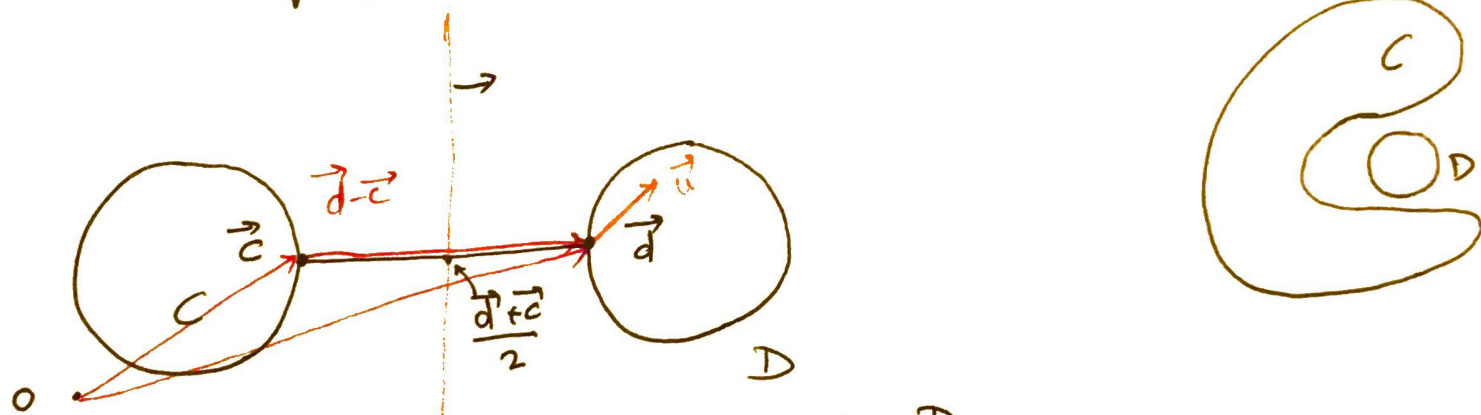


Separating Hyperplane Theorem.

Let C and D be two convex sets.

$$C \cap D = \emptyset = \phi.$$

Then, there exists a hyperplane ~~which~~ $\vec{a}^T \vec{x} = b$.
s.t. $\forall \vec{x} \in C, \quad \vec{a}^T \vec{x} \geq b$
 $\forall \vec{x} \in D, \quad \vec{a}^T \vec{x} \leq b$.



Proof: Define: "distance" between C, D .

$$\text{dist}(C, D) = \inf \{ \|\vec{c} - \vec{d}\|_2 \mid \vec{c} \in C, \vec{d} \in D \}$$

Say \vec{c}, \vec{d} the two points that are ~~close~~ closest together.

Assume. \vec{c}, \vec{d} exists.

Consider, the hyperplane with $\vec{d} - \vec{c}$ as a normal
and that passes through the midpoint of the segment joining \vec{d}, \vec{c} .

$$\text{midpoint} = \frac{\vec{d} + \vec{c}}{2}$$

$$f(\vec{x}) = \vec{a}^T (\vec{x} - \vec{x}_0)$$

$$= (\vec{d} - \vec{c})^T \left(\vec{x} - \frac{1}{2} (\vec{d} + \vec{c}) \right)$$

$$f(\vec{d}) = (\vec{d} - \vec{c})^T \left(\vec{d} - \frac{1}{2} (\vec{d} + \vec{c}) \right)$$

$$= \frac{1}{2} \|\vec{d} - \vec{c}\|_2^2$$

$$\geq 0$$

$$\vec{a}^T = (\vec{d} - \vec{c})^T$$

$$\vec{x}_0 = \frac{\vec{d} + \vec{c}}{2}$$

$$f(\vec{c}) = -\frac{1}{2} \|\vec{d} - \vec{c}\|_2^2 \leq 0.$$

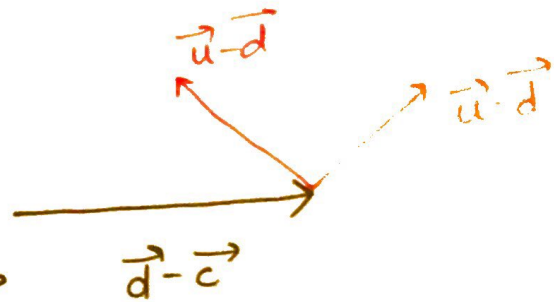
To show: $f(\vec{x}) \geq 0 \quad \forall \vec{x} \in \mathcal{D}.$

Assume, if possible $\exists \vec{u} \in \mathcal{D}$ st. $f(\vec{u}) < 0$

$$\begin{aligned}
 f(\vec{u}) &= (\vec{d} - \vec{c})^T \left(\vec{u} - \frac{1}{2}(\vec{d} + \vec{c}) \right) \\
 &= (\vec{d} - \vec{c})^T \left(\vec{u} - \vec{d} + \vec{d} - \frac{1}{2}(\vec{d} + \vec{c}) \right) \\
 &= (\vec{d} - \vec{c})^T \left((\vec{u} - \vec{d}) + \frac{1}{2}(\vec{d} - \vec{c}) \right) \\
 &= (\vec{d} - \vec{c})^T (\vec{u} - \vec{d}) + \underbrace{\frac{1}{2} \|\vec{d} - \vec{c}\|_2^2}_{\geq 0} < 0
 \end{aligned}$$

$$\begin{aligned}
 f(\vec{u}) < 0 \\
 \Rightarrow (\vec{d} - \vec{c})^T (\vec{u} - \vec{d}) < 0
 \end{aligned}$$

Intuition: I can move along the vector $\vec{u} - \vec{d}$ to get "closer" to \vec{c}



Consider: $\vec{p} = \vec{d} + t(\vec{u} - \vec{d}) = t \cdot \vec{u} + (1-t)\vec{d}$

Consider: $\|\vec{c} - \vec{p}\|_2^2 = \|\vec{c} - \vec{d} - t(\vec{u} - \vec{d})\|_2^2$

$$\|\vec{c} - \vec{p}\|_2^2 = \|\vec{c} - \vec{d} - t(\vec{u} - \vec{d})\|_2^2$$

$$= ((\vec{c} - \vec{d}) - t(\vec{u} - \vec{d}))^T ((\vec{c} - \vec{d}) - t(\vec{u} - \vec{d}))$$

$$= \|\vec{c} - \vec{d}\|_2^2 - 2 \langle \vec{c} - \vec{d}, t(\vec{u} - \vec{d}) \rangle + t^2 \|\vec{u} - \vec{d}\|_2^2 \quad t \in [0, 1]$$

WANT: $2t \langle \vec{d} - \vec{c}, \vec{u} - \vec{d} \rangle + t^2 \|\vec{u} - \vec{d}\|_2^2 < 0$

$$(*) \quad 2 \langle \vec{d} - \vec{c}, \vec{u} - \vec{d} \rangle + t \|\vec{u} - \vec{d}\|_2^2 < 0$$

Since $\langle \vec{d} - \vec{c}, \vec{u} - \vec{d} \rangle$ is negative,

if we choose t , small enough, $(*) \leq 0$.

$$\Rightarrow \|\vec{c} - \vec{p}\|_2^2 < \|\vec{c} - \vec{d}\|_2^2$$

This contradicts the minimal distance between C, D .

$\vec{p} \in D$ ~~(*)~~ \Rightarrow Our assumption was wrong
 $\Rightarrow f(\vec{x})$ is a separating hyperplane. \square

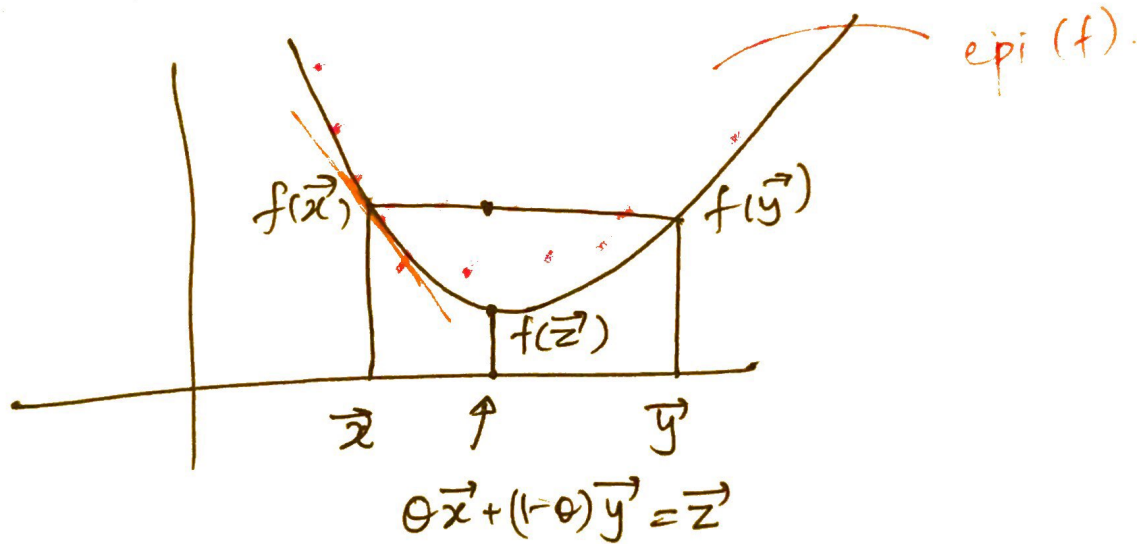
Convex functions:

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if



domain f is a convex set.

$$f(\theta \vec{x} + (1-\theta)\vec{y}) \leq \theta \cdot f(\vec{x}) + (1-\theta)f(\vec{y}) \quad \left. \vphantom{f(\theta \vec{x} + (1-\theta)\vec{y})} \right\} \text{ Jensen's Inequality}$$



• Epi graph: $\text{Epi } f = \{(x, t) \mid x \in \text{dom } f ; f(x) \leq t\}$

Prop 1: f is a convex function \Leftrightarrow $\text{Epi } f$ is a convex set.

• First-order conditions.

f : differentiable.

$$f: \mathbb{R}^n \rightarrow \mathbb{R}.$$

Then. f is convex, iff $\text{dom} f$ is convex.

and.

$$f(\vec{y}) \geq f(\vec{x}) + \underbrace{\nabla f(\vec{x})^T (\vec{y} - \vec{x})}_{\text{Taylor approximation}}.$$

$$\forall \vec{x}, \vec{y} \in \text{dom}.$$

Taylor approximation.

Implication: If $\nabla f(\vec{x}_*) = 0$

$$f(\vec{y}) \geq f(\vec{x}_*) + 0$$

$\Rightarrow f(\vec{x}_*)$ is a global minimum.

• Second-order condition

f is convex iff.

f : twice differentiable.

$\text{dom} f$ is convex.

$$\nabla^2 f(x) \succeq 0$$

Jensen in probability:

f : convex:

$$f(E[x]) \leq E[f(x)]$$