

Optimization Methods (CS1.404)

Spring 2023

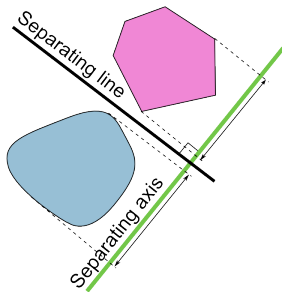
Naresh Manwani

Machine Learning Lab, IIIT-H

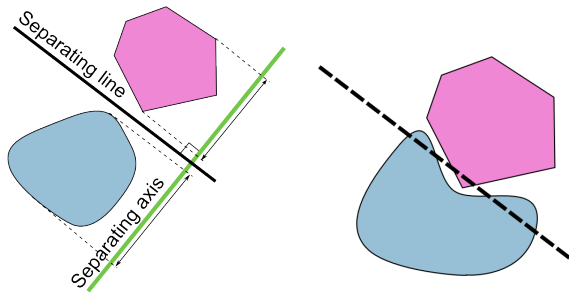
January 16th, 2023



Separating Hyperplane



Separating Hyperplane



Separating Hyperplane Theorem

Theorem

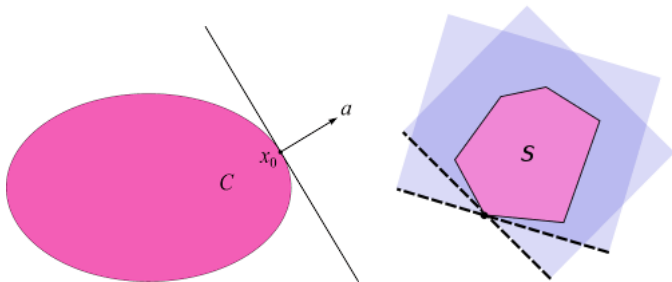
Let \mathcal{X}_1 and \mathcal{X}_2 be two disjoint, non-empty closed convex subsets of \mathbb{R}^d (one of them being bounded), then there exists a non-zero vector $\mathbf{w} \in \mathbb{R}^d$ and $b \in \mathbb{R}$ such that $\mathbf{w}^T \mathbf{x} \geq b, \forall \mathbf{x} \in \mathcal{X}_1$ and $\mathbf{w}^T \mathbf{x} \leq b, \forall \mathbf{x} \in \mathcal{X}_2$. Thus, $\mathbf{w}^T \mathbf{x} = b$ separates \mathcal{X}_1 and \mathcal{X}_2 .

- If $\mathbf{w}^T \mathbf{x} > b, \forall \mathbf{x} \in \mathcal{X}_1$ and $\mathbf{w}^T \mathbf{x} < b, \forall \mathbf{x} \in \mathcal{X}_2$, the the hyperplane $\mathbf{w}^T \mathbf{x} = b$ is said to strictly separate \mathcal{X}_1 and \mathcal{X}_2 .
- The hyperplane is said to strongly separate \mathcal{X}_1 and \mathcal{X}_2 if $\mathbf{w}^T \mathbf{x} \geq b + \epsilon, \forall \mathbf{x} \in \mathcal{X}_1$ and $\mathbf{w}^T \mathbf{x} \leq b, \forall \mathbf{x} \in \mathcal{X}_2$ for some $\epsilon > 0$. If $\mathcal{X}_1 \cap \mathcal{X}_2 = \phi$, then strong separation happens.

Supporting Hyperplane Theorem

Theorem

If C is convex, then there exists a supporting hyperplane at every boundary point of C . Let \mathbf{x}_0 be a boundary point of set C , then there exists $\mathbf{a} \neq \mathbf{0}$ such that $\{\mathbf{x} : \mathbf{a}^T \mathbf{x} = \mathbf{a}^T \mathbf{x}_0\}$ is a supporting hyperplane to C and $\mathbf{a}^T \mathbf{x} \leq \mathbf{a}^T \mathbf{x}_0, \forall \mathbf{x} \in C$.



Definition

Let $\mathcal{X} \subset \mathbb{R}^n$ be a set. The **convex hull** of \mathcal{X} is the intersection of all convex sets containing it.

Definition

Let $\mathcal{X} \subset \mathbb{R}^n$ be a set. The **convex hull** of \mathcal{X} is the intersection of all convex sets containing it.

Lemma

The convex hull of the vectors $\mathbf{x}_1, \dots, \mathbf{x}_n$ is the set of all convex combinations of these vectors.

Definition

Let $\mathcal{X} \subset \mathbb{R}^n$ be a set. The **convex hull** of \mathcal{X} is the intersection of all convex sets containing it.

Lemma

The convex hull of the vectors $\mathbf{x}_1, \dots, \mathbf{x}_n$ is the set of all convex combinations of these vectors.

- The convex hull of finite number of vectors is a convex set.

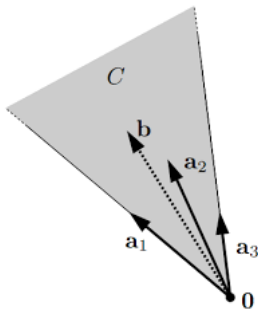
Homework: Prove this statement.

Convex Cone

Definition

Given vectors $\mathbf{a}_1, \dots, \mathbf{a}_n$, the convex cone generated by these vectors is the set of all non-negative linear combinations of \mathbf{a}_i 's. That is,

$$\text{Convex-Cone}(\mathbf{a}_1, \dots, \mathbf{a}_n) = \{t_1\mathbf{a}_1 + \dots + t_n\mathbf{a}_n \mid t_1, \dots, t_n \geq 0\}$$



Lemma

Let $A \in \mathbb{R}^{m \times n}$ and let $C = \{A\mathbf{x} \mid \mathbf{x} \geq \mathbf{0}\}$. Note that C is a closed convex cone. Then, exactly, one of the two systems has a solution:

- ① $A\mathbf{x} = \mathbf{b}$ and $\mathbf{x} \geq \mathbf{0}$
- ② $A^T \mathbf{y} \geq \mathbf{0}$ and $\mathbf{b}^T \mathbf{y} < 0$

