

# Combinatorial Geometry & Topology arising in Game Theory and Optimization

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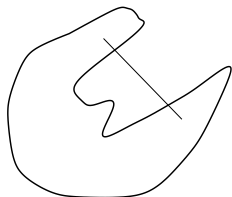
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# LAST EPISODE...

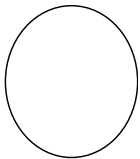
We discuss the content of the course...

## Convex Sets

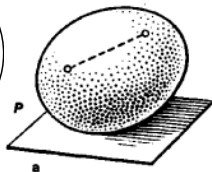
A set is **CONVEX** if it contains any line segment joining two of its points:



NOT CONVEX



CONVEX



a



b

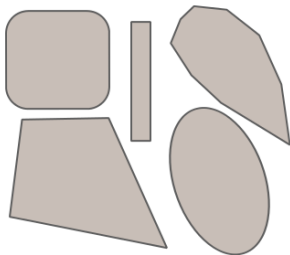
The **line segment** between  $x$  and  $y$  is given by

$$[x, y] := \{\alpha x + (1 - \alpha)y : 0 \leq \alpha \leq 1\}$$

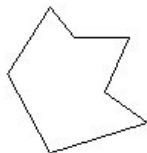
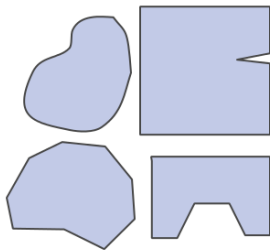
**EXERCISE** Prove or disprove: the image of a convex set under a linear transformation is again a convex set.

# Examples

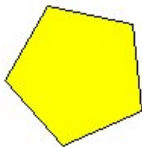
Convex Solids



Non-convex solids



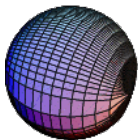
A Non-Convex Polygon



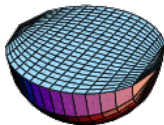
A convex Polygon

TEST: Which of the following are convex sets?

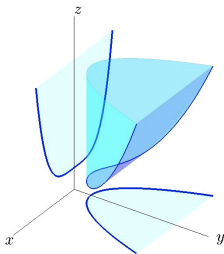
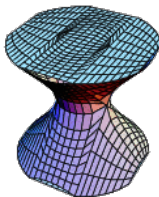
$$x^2 + y^2 + z^2 < 1$$



$$x^2 + y^2 + z^2 < 1 \wedge z < 0$$



$$x^2 + y^2 - z^2 < 1$$



$$x^4 - (z - 1) \leq 0 \quad \text{and} \quad x^2 - (y - 1) \leq 0 \quad \text{and} \quad z \geq 0$$

**Proposition:** The intersection of convex sets is always convex.

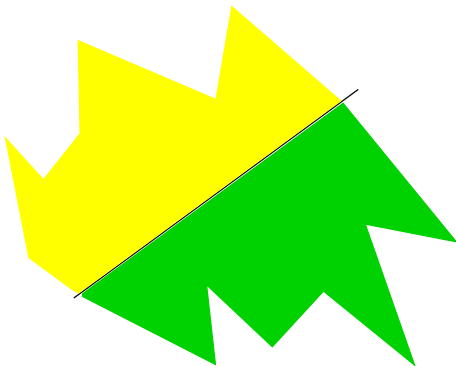
# HYPERPLANES

- ▶ A linear functional  $f : \mathbf{R}^d \rightarrow \mathbf{R}$  is given by a vector  $c \in \mathbf{R}^d, c \neq 0$ .
- ▶ For a number  $\alpha \in \mathbf{R}$  we say that  $H_\alpha = \{x \in \mathbf{R}^d : f(x) = \alpha\}$  is an *affine hyperplane* or **hyperplane** for short.
- ▶ The intersection of finitely many hyperplanes is an **affine space**.
- ▶ The **affine hull** of a set  $A$  is the smallest affine space containing  $A$ .
- ▶ Affine spaces are important examples of convex sets in particular because they allow us to speak about dimension:
- ▶ The **dimension of an affine set** is the largest number of **affinely independent points** in the set minus one.
- ▶ The **dimension of a convex set** in  $\mathbf{R}^d$  is the dimension of its affine hull.

## HALF-SPACES

A hyperplane divides  $\mathbf{R}^d$  into two **halfspaces**

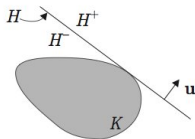
$H_{\alpha}^{+} = \{x \in \mathbf{R}^d : f(x) \geq \alpha\}$  and  $H_{\alpha}^{-} = \{x \in \mathbf{R}^d : f(x) \leq \alpha\}$ .



Half-spaces are convex sets each denoted formally by a **linear inequality**:

$$a_1x_1 + a_2x_2 + \cdots + a_dx_d \leq b$$

- ▶ For a convex set  $S$  in  $\mathbf{R}^d$ . A linear inequality  $f(x) \leq \alpha$  is said to be **valid** on  $S$  if every point in  $S$  satisfies it.
- ▶ A set  $F \subset S$  is a **face** of  $S$  if there exists a linear inequality  $f(x) \leq \alpha$  which is valid on  $P$  and such that  $F = \{x \in P : f(x) = \alpha\}$ .
- ▶ The hyperplane defined by  $f$  is a **supporting hyperplane** of  $F$ . It defines a **supporting half-space**

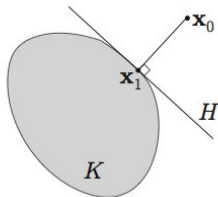


$K$  has a supporting hyperplane orthogonal to  $\mathbf{u}$ .

- ▶ A face of dimension 0 is called a **vertex**. A face of dimension 1 is called an **edge**, and a face of dimension  $\dim(P) - 1$  is called a **facet**.



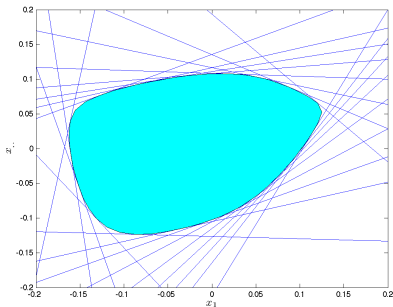
- ▶ Let  $K$  be a closed and bounded convex set in  $\mathbf{R}^d$ . Let  $x_0 \notin K$ . Then,
  - ▶ There is a unique nearest point  $x_1$  of  $K$  to  $x_0$ .
  - ▶ The hyperplane  $H$  through  $x_1$  orthogonal to  $x_1 - x_0$  is a supporting hyperplane of  $K$ .



- ▶ A hyperplane  $H$  *red* separates sets  $X$  and  $Y$  if and only if  $X$  and  $Y$  lie in different closed halfspaces of  $H$ . If  $X$  and  $Y$  lie in different open halfspaces, we say that  $H$  *strictly separates*  $X$  and  $Y$ .

## CONVEX BODIES ARE INTERSECTION OF HALF-SPACES!!!

**Theorem** A convex body  $K$  is the intersection of its closed supporting half-spaces.



**Theorem** convex bodies are the sets of solutions of **systems of LINEAR inequalities**.

**WARNING:** It may require **infinitely many hyperplanes**

# POLYHEDRA: THE INTERSECTION OF FINITELY MANY HALF-SPACES



# Examples

- ▶ **d-dimensional unit cube**

$$C_d = \{x \in \mathbf{R}^d : 0 \leq x_i \leq 1, i = 1..n\}$$

- ▶ **the  $(d - 1)$ -dimensional standard simplex**

$$\Delta_{n-1} = \{x \in \mathbf{R}^d : \sum_i^d x_i = 1, x_i \geq 0\}.$$

- ▶ **the  $d$ -dimensional cross-polytope**

$$O_n = \{x \in \mathbf{R}^d : \sum_i^d |x_i| \leq 1\}.$$

- ▶ **a simplotope** is the Cartesian product of several simplices

$$\Delta_{m_1} \times \Delta_{m_2} \times \cdots \times \Delta_{m_r}.$$

# SOLVABILITY OF SYSTEMS OF LINEAR INEQUALITIES

Find a vector  $(x_1, x_2, \dots, x_d)$ , satisfying:

$$a_{1,1}x_1 + a_{1,2}x_2 + \dots + a_{1,d}x_d \leq b_1$$

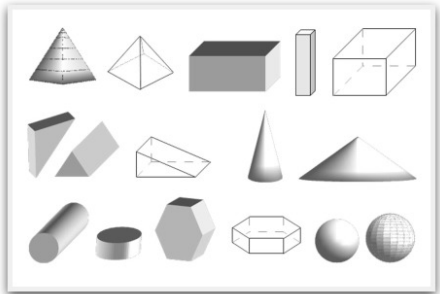
$$a_{2,1}x_1 + a_{2,2}x_2 + \dots + a_{2,d}x_d \leq b_2$$

$$\vdots$$

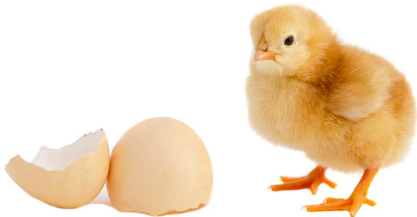
$$a_{k,1}x_1 + a_{k,2}x_2 + \dots + a_{k,d}x_d \leq b_k$$

This is the **Linear feasibility problem**

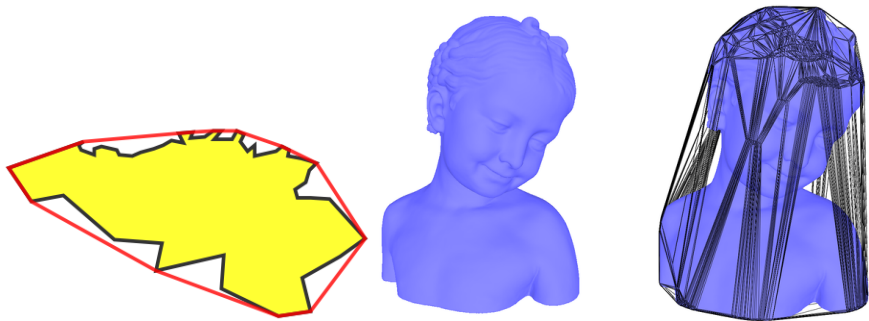
# Convex Sets are EVERYWHERE!



and ALTHOUGH not all sets in nature are convex!



## Convex Sets APPROXIMATE ALL SHAPES!



Let  $A \subset \mathbf{R}^d$ . The **convex hull** of  $A$ , denoted by  $\text{conv}(A)$ , is the intersection of all the convex sets containing  $A$ . The smallest convex set that contains  $A$ .

A **polytope** is the convex hull of a finite set of points in  $\mathbf{R}^d$ . It is the smallest convex set containing the points.



# linear convex and conic combinations

- ▶ **Definition:** Given finitely many points  $A := \{x_1, x_2, \dots, x_n\}$  we say the linear combination  $\sum \gamma_i x_i$  is
  - ▶ a **conic combination** is one with all  $\gamma_i$  non-negative.
  - ▶ an **affine combination** if  $\sum \gamma_i = 1$ .
  - ▶ a **convex combination** if it is affine and  $\gamma_i \geq 0$  for all  $i$ .
- ▶ **Lemma: (EXERCISE)** For a set of points  $A$  in  $\mathbf{R}^d$  we have that  $\text{conv}(A)$  equals all finite convex combinations of  $A$ :

$$\text{conv}(A) = \left\{ \sum_{x_i \in A} \gamma_i x_i : \gamma_i \geq 0 \text{ and } \gamma_1 + \dots + \gamma_k = 1 \right\}$$

- ▶ **Definition** A set of points  $x_1, \dots, x_n$  is **affinely dependent** if there is a linear combination  $\sum a_i x_i = 0$  with  $\sum a_i = 0$ . Otherwise we say they are **affinely independent**.
- ▶ **Lemma:** A set of  $d + 2$  or more points in  $\mathbf{R}^d$  is affinely dependent.
- ▶ **Lemma:** A set  $B \in \mathbf{R}^d$  is **affinely independent**  $\iff$  every point has a unique representation as an affine combination of points in  $B$ .
- ▶ A  $k$ -dimensional **simplex** is the convex hull of  $k + 1$  affinely independent points.

# Weyl-Minkowski: How to represent the points of a polyhedron?

- ▶ There are **TWO ways** to represent a convex set: As the intersection of half-spaces OR as the convex/conic hull of extreme points.
- ▶ For polyhedra, even better!! Either as a finite system of inequalities or with finitely many generators.



# Weyl-Minkowski Theorem

- ▶ **Theorem:** ([Weyl-Minkowski's Theorem](#)): For a polyhedral subset  $P$  of  $\mathbf{R}^d$  the following statements are equivalent:
  - ▶  $P$  is an **H-polyhedron**, i.e.,  $P$  is given by a system of linear inequalities  $P = \{x : Ax \geq b\}$ .
  - ▶  $P$  is a **V-polyhedron**, i.e., For finitely many vectors  $v_1, \dots, v_n$  and  $r_1, \dots, r_s$  we can write

$$P = \text{conv}(v_1, v_2, \dots, v_n) + \text{cone}(r_1, r_2, \dots, r_s)$$

- ▶  $R + S$  denotes the **Minkowski sum** of two sets,  
 $R + S = \{r + s : r \in R, s \in S\}$ .
- ▶ There are algorithms for the conversion between the H-polyhedron and V-polyhedron.
- ▶ **NOTE:** Any cone can be decomposed into a **pointed cone** plus a **linear space**.