

# Intro to LO, Lecture 4

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## Refresh: Concepts from metric spaces

All of the definitions below work for general topological spaces, but we are only interested in the Euclidean space  $\mathbb{R}^n$ .

**D(Open set):** A set  $S \subseteq \mathbb{R}^n$  is called open if for each point  $p \in S$ , there exists a radius  $r$  such that all points from a ball  $B(p, r)$  are present in  $S$ .

**D(Closed set):** A set  $S$  is closed if its complement  $(\mathbb{R}^n \setminus S)$  is open.

**D(Bounded set):** A set  $S$  is bounded if  $S$  fits into a ball of some finite diameter  $d$ .

**D(Compact set):** A set  $S$  is compact if it is closed and bounded.

**T:** Consider a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ . If  $S$  is a compact set and  $f$  is continuous on  $S$ , then there exists points in  $S$  where  $f$  attains its infimum and supremum value over  $S$ .

## Refresh: Convexity

**D:** A set  $K \subseteq \mathbb{R}^d$  is a *convex set*, if  $\forall x, y \in K, \forall t \in [0, 1] : tx + (1-t)y \in K$ . In other words, if you take two points inside the convex set  $K$ , the entire line segment between those two points must belong to  $K$ .

**D:** A vector  $x$  is a *convex combination* of a set of vectors  $a_1, a_2, \dots, a_n$  if  $x = \sum_{i=1}^n \alpha_i a_i$ , where  $\alpha_i$  are real numbers satisfying  $\sum_{i=1}^n \alpha_i = 1$  and also  $\forall i : \alpha_i \in [0, 1]$ .

A set of vectors/points  $V \subseteq \mathbb{R}^d$  is in a *convex position*, if it holds that no vector  $v \in V$  is a convex combination of the rest.

**O:** Let  $Y$  be the set of convex combinations of points from  $X$ . Then every convex combination of points of  $Y$  is a convex combination of points of  $X$ .

**O:** If all points  $x \in X$  satisfy the inequality  $a^T x \leq b$ , then any convex combination of points from  $X$  satisfies this inequality.

**D:** As with linearity and affinity, for convexity we also define a span/hull:

If we have a set of vectors  $V \subseteq \mathbb{R}^d$ , its *convex hull* is a set of all vectors  $C$ , which are convex combinations of any finite subset of the vectors in  $V$ .

Here, we really need to consider any finite subset of  $V$ , because convex sets in general do not have a finite basis.

**T:** The convex hull of  $X$ ,  $\text{conv}(X)$ , is equal to the set of all convex combinations

$$Y = \left\{ \alpha_0 a_0 + \dots + \alpha_k a_k \mid k \in \mathbb{N}, a_i \in X, \alpha_i \geq 0, \sum_{i=0}^k \alpha_i = 1 \right\}.$$

**T(Caratheodory):** Let  $X \subseteq \mathbb{R}^n, \dim(X) = d$ . Then,

$$\text{conv}(X) = \left\{ \alpha_0 a_0 + \dots + \alpha_d a_d \mid a_i \in X, \alpha_i \geq 0, \sum_{i=0}^d \alpha_i = 1 \right\}.$$

**D:** A *hyperplane* is any affine space in  $\mathbb{R}^d$  of dimension  $d - 1$ . Thus, on a 2D plane, any line is a hyperplane. In the 3D space, any plane is a hyperplane, and so on.

A hyperplane splits the space  $\mathbb{R}^d$  into two *halfspaces*. We count the hyperplane itself as a part of both halfspaces.

**D:** A *convex polyhedron* (sometimes also called *H-polytope*) is any object in  $\mathbb{R}^d$  that is an intersection of finitely many halfspaces. Alternatively, we can say that a convex polytope is any set of points of the form  $\{x \mid Ax \leq b\}$  for some real matrix  $A$  and some real vector  $b$ .

## Two observations from high school

**O:** Consider the angle  $\phi$  at  $b$  for the triangle  $abc$ . Then,  $(b - a)^T(c - b) = \|b - a\| \cdot \|c - b\| \cdot \cos \phi$ . Since the two norms are always non-negative, the sign of the scalar product depends only on  $\cos \phi$ .

**O:** Consider a triangle  $abc$  and again  $\phi$  angle at  $b$ . Then:

- If the angle is a right angle, then  $b$  is the closest point to  $c$  on the entire line generated by  $ab$ .
- If the angle is acute (less than  $\pi/2$ ), then there is some point other than  $a$  and  $b$  that is closest to  $c$  on the line segment  $ab$ .
- If the angle is obtuse, then the point closest to  $c$  on the line segment  $ab$  is  $b$  (and the closest point on the line  $ab$  is outside the line segment  $ab$ ).

## Separation theorem

**T(Separation theorem):** Let  $C, D \subseteq \mathbb{R}^n$  be nonempty, closed, convex and disjoint. and let  $C$  be bounded. Then there is a hyperplane  $\{x \mid a^T x = b\}$ , which strongly separates  $C$  and  $D$ , i.e., one that  $C \subseteq \{x \mid a^T x < b\}$  and  $D \subseteq \{x \mid a^T x > b\}$ .

### Proof steps.

1. If both  $C \times D$  are bounded, they are also compact and so is the product  $C \times D \subseteq \mathbb{R}^{2n}$ , and since the Euclidean norm is continuous, we can find minimizers  $c \in C$  and  $d \in D$ .
2. If  $D$  is unbounded, we restrict ourselves to a set  $D' \subseteq D$  that is bounded as follows: Let the max distance in  $C$  be  $\alpha$ . We sample one  $c' \in C$  and  $d' \in D$  and let their distance be  $\beta$ . Now, restrict  $D$  to  $D' = D \cap B(c', \alpha + \beta)$ . A simple observation shows that all points in  $D$  that have a chance to be closer than  $\beta$  to  $C$  live in  $D'$ .
3. Find the closest points in  $C$  and  $D$ , call them  $c, d$ , respectively. Let  $a = c - d$  be the direction between them. The separating hyperplane will be orthogonal to  $c - d$  and will touch the point  $(c + d)/2$ .
4.  $a^T d - a^T c = \|a\|^2 > 0$ .
5. If the difference of two numbers is a non-negative real, then their average is strictly between them, in other words: if  $b = a^T(c + d)/2$ , then  $a^T c < b < a^T d$ .
6. Finally, we observe that for all other points  $c'' \in C$  holds that  $a^T c'' < a^T c$ . We observe this geometrically, using our observations from high school.

## Vertices and basic feasible solutions

**D(Polyhedron):** A set of points is called a *polyhedron* (or an *H-polytope*) if it is the intersection of finitely many halfspaces.

**D(Polytope):** A set of points is called a *polytope* (or a *V-polytope*) if it is a convex hull of a finite number of points.

**D(Vertex):** Let  $P$  be a convex set. A point  $z \in P$  is a *vertex* if  $z$  cannot be written as a convex combination of any other two points in  $P$ .

**D(Basic feasible solution):** Let  $P = \{x \mid Ax \leq b\}$  be a polyhedron and let  $z \in P$ . Then  $A_z$  is the submatrix of  $A$  consisting of those rows  $a_i$  of  $A$  for which  $a_i z = b_i$ . We say a point  $z \in P$  is an *basic feasible solution* if  $\text{rank}(A_z) = n$ .

**T:** Let  $P = \{x \mid Ax \leq b\}$  be a polyhedron in  $\mathbb{R}^n$  and let  $z \in P$ . Then  $z$  is a vertex of  $P$  if and only if  $z$  is a basic feasible solution.

**P:**  $\Rightarrow$ :  $A_z$  not full rank  $\rightarrow$  find  $c : A_z c = 0$ .  $z$  is then a conv. combination of  $z + \delta c, z - \delta c$  for some  $\delta > 0$ .

We can find this  $\delta$  since every equation outside  $A_z$  held with a strict inequality, so even though  $c$  might be the direction where the inequality breaks eventually, it will hold at least for some small  $\delta$ .

$\Leftarrow$ : If  $z$  not a vertex  $\leftarrow$  find two elements which combine to it;  $A_v(x - y) = 0$ .

## A polyhedron is a convex hull of its vertices

**T:** Let  $P$  be a bounded polyhedron, with vertices  $x_1, \dots, x_t$ . Then  $P = \text{conv.hull} \{x_1, \dots, x_t\}$ .

**P:** Clearly

$$\text{conv.hull} \{x_1, \dots, x_t\} \subseteq P$$

since  $x_1, \dots, x_t$  belong to  $P$  and since  $P$  is convex. The reverse inclusion amounts to:

$$\text{if } z \in P \text{ then } z \in \text{conv.hull} \{x_1, \dots, x_t\}.$$

We prove it by induction on  $n - \text{rank}(A_z)$ . Informally, we take a point  $z \in P$  and we find two points in  $P$  of higher rank of  $A_z$  which have  $z$  within their line segment. To find these, we take  $z$  and move in opposite directions until we reach the boundary of  $P$ , since the boundary points will satisfy more equalities than  $z$ .

Formally, we find the respective increases

$$\begin{aligned} \mu_0 &:= \max\{\mu \mid z + \mu c \in P\}, \\ \nu_0 &:= \max\{\nu \mid z - \nu c \in P\}. \end{aligned}$$

And define  $x := z + \mu_0 c$  and  $y := z - \nu_0 c$  to be the two boundary points.

For the computation, we need to observe a “form of duality”: For the  $\mu_0$  defined above, we have

$$\mu_0 = \min \left\{ \frac{b_i - a_i z}{a_i c} \mid a_i \text{ is a row of } A; a_i c > 0 \right\}.$$

**C:** Every bounded polyhedron is a polytope.

**T(Without proof):** Every polytope is a bounded polyhedron.

## Exercises

**Exercise one.** Find all the vertices of the following polytope:  $P = \{(x, y, z) \mid x + y \leq 2, y + z \leq 4, x + z \leq 3, -2x - y \leq 3, -y - 2z \leq 3, -2x - z \leq 2\}$ .

**Exercise two.** Prove the following statements that give insight into where optimal solutions lie for a linear program. We have already mentioned some of them at the lecture.

1. If the polyhedron of feasible solutions of a linear program is *bounded*, and it has at least one feasible solution, it has an optimal solution.
2. If a linear program has an optimal solution, it also has one on the boundary of the polyhedron.
3. If a bounded linear program has an optimal solution, it also has one in a *vertex* of the polyhedron. (Induction might be useful for this one.)

**Exercise three.** Check if the point  $v = (1, 1, 1, 1)$  is a vertex of a polytope  $P$  defined as the following set of inequalities:

$$\begin{pmatrix} -1 & -6 & 1 & 3 \\ -1 & -2 & 7 & 1 \\ 0 & 3 & -10 & -1 \\ -6 & -11 & -2 & -12 \\ 1 & 6 & -1 & -3 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} \leq \begin{pmatrix} -3 \\ 5 \\ -8 \\ -7 \\ 4 \end{pmatrix}$$

The next two exercises introduce a bit more naming for the boundary objects of polyhedra, which we call *faces*.

**D:** Let  $P$  be some convex polyhedron in  $\mathbb{R}^d$ . We say that a hyperplane  $H$  is a *supporting hyperplane* if it touches the polyhedron, but does not cut it.

In other words, if the hyperplane  $H$  is defined as  $\{x \in \mathbb{R}^d \mid c^T x = t\}$ , then we say  $H$  is supporting if and only if it holds that (i)  $P \cap H$  is nonempty; and (ii)  $\forall y \in P : \{c^T y \leq t\}$  or it holds that  $\forall y \in P : \{c^T y \geq t\}$ .

**D:** A *face*  $F$  of a polytope  $P$  is any set of the form  $F = P \cap H$  for any supporting hyperplane  $H$ .

**D:** A *vertex* of a polytope  $P$  is a face of dimension 0 (a single point). An *edge* is any face of dimension 1 (a line segment, half-line or a line). On the other side of the spectrum, a *facet* of  $P$  is a face of dimension  $d - 1$ .

**Exercise four.** We need to establish the equivalence of the vertex definition above with the one from the lecture. In other words, prove that for any point  $v$  in a bounded convex polyhedron  $P$ :

The point  $v$  is a basic feasible solution if and only if there exists a supporting hyperplane  $H$  such that  $P \cap H = \{v\}$ .

**Exercise five.** Prove that any bounded convex polyhedron of dimension  $d$  in  $\mathbb{R}^d$  has at least  $d + 1$  vertices and at least  $d + 1$  facets.

The next two exercises deal with *convex cones*. Citing from Schrijver's lecture notes:

Convex cones are special cases of convex sets. A subset  $C$  of  $\mathbb{R}^n$  is called a *convex cone* if for any  $x, y \in C$  and any  $\lambda, \mu \geq 0$  one has  $\lambda x + \mu y \in C$ .

For any  $X \subseteq \mathbb{R}^n$ ,  $\text{cone}(X)$  is the smallest cone containing  $X$ . One easily checks:

$$\text{cone}(X) = \{\lambda_1 x_1 + \cdots + \lambda_t x_t \mid x_1, \dots, x_t \in X; \lambda_1, \dots, \lambda_t \geq 0\}$$

**Exercise six.** Let  $C \subseteq \mathbb{R}^n$ . Then  $C$  is a closed convex cone if and only if  $C = \bigcap \mathcal{F}$  for some collection  $\mathcal{F}$  of linear halfspaces. (Notice the halfspaces are linear, i.e., going through 0.)

**Exercise seven.** For any subset  $X$  of  $\mathbb{R}^n$ , define

$$X^* := \left\{ y \in \mathbb{R}^n \mid x^T y \leq 1 \text{ for each } x \in X \right\}$$

1. Show that for each convex cone  $C$ ,  $C^*$  is a closed convex cone.
2. Show that for each closed convex cone  $C$ ,  $(C^*)^* = C$ .