## 1 21st of September 2018 — A. Frangioni

## 1.1 Mathematical background for optimization problems

**Definition 1.1** (Minimum problem). Let X be a set, called **feasible region** and let  $f: X \to \mathbb{R}$  be any function, called **objective function** we call **problem** the following

$$(P) f_* = \min\{f(x) : x \in X\}$$

**Definition 1.2** (Feasible solution). Let  $x \in F$  be a solution of the minumim problem in which the domain is a superset of  $X \subset F$ . We say that x is a **feasible solution** if  $x \in X$ . On the other hand, x is **unfeasible** if  $x \in F \setminus X$ .

**Definition 1.3** (Optimal solution). Under the same hypothesis of the above definition, we define  $x_*$  such that  $f(x_*) = f_*$  an **optimal solution**, where  $f_* \leq f(x) \, \forall x \in X, \, \forall v > f_* \, \exists \, x \in X \, s.t. \, f(x) < v$ .

It is possible to find problems where there is no optimal solution at all.

**Example 1.1.** There are two cases in which it is not possible to find an optimal solution:

- 1. The domain is empty, which may be not trivial to prove, since it is an NP-hard problem sometimes;
- 2. We want to find the minimum of the objective function but it is unbounded below  $(\forall M \exists x_M \in X \text{ s.t. } f(x_M) \leq M)$ . On the other hand, we need to maximize the function, but it is unbounded above.

We can now rewrite the problem of solving an optimization problem as:

- 1. Finding  $x_*$  and proving it is optimal
- 2. Or proving  $X = \emptyset$
- 3. Or constructively prove  $\forall M \exists x_M \in X \text{ s.t. } f(x_M) \leq M$ .

Most of the times we consider optimal a solution which is close to the true optimal value, modulo some error.

**Definition 1.4** (Absolute error). We call **absolute error** the gap between the real value and the one we obtained. Formally,

$$f(\bar{x}) - f_* \le \varepsilon$$

**Definition 1.5** (Relative error). We define as **relative error** the absolute error, normalized by the true value of the function

$$(f(\bar{x}) - f_*)/|f_*| \le \varepsilon$$

Let us consider an iterative algorithm that moves towards the optimum. It may happen that the function decreases and decreases along a certain direction but its non-continuity leads to the impossibility of reaching the optimum. As an example, let us take the following

$$f(x) = \begin{cases} x & \text{if } x > 0\\ 1 & \text{if } x = 0 \end{cases}$$

**Definition 1.6** (Totally ordered set). We say that set X is **totally ordered** if  $\forall x, y \in X$ , either  $f(x) \leq f(y)$  or  $f(y) \leq f(x)$ .

**Definition 1.7** (Infima and suprema). Given a totally ordered set R and one of its subsets  $(say S \subseteq R)$ 

s is the **infimum** of  $S \Leftrightarrow \underline{s} = \inf S \quad \Leftrightarrow \quad \underline{s} \leq s \ \forall s \in S \ \land \ \forall t > \underline{s} \ \exists \ s \in S \ s.t. \ s \leq t$ 

 $s \ \textit{is the \bf supremum} \ \textit{of} \ S \Leftrightarrow \bar{s} = \sup S \quad \Leftrightarrow \quad \bar{s} \geq s \ \forall s \in S \ \land \ \forall t < \bar{s} \ \exists \ s \in S \ \textit{s.t.} \ s \geq t$ 

What happens if we have more than one objective function? We are provided with two tools in order to reduce them into one:

SCALARIZATION: using a linear combination of the two functions:  $f(x) = \alpha f_1(x) + \beta f_2(x)$ ;

BUDGETING:  $f(x) = f_1(x)$ ,  $X := X \cup \{f_2(x) \le b\}$ , which intuitively corresponds to taking into account only one objective function, provided that the values of the othr functions are not too high.

**Definition 1.8** (Extended real). In the case of unbounded functions the value of infima or suprema are  $\infty$ , and we call **extended reals**  $\overline{\mathbb{R}} = -\infty \cup \mathbb{R} \cup +\infty$ .

We are interested in studying sequences, because iterative methods start from a certain point and move towards the optimal, hopefully.

**Definition 1.9** (Limit). Given a sequence  $\{x_i\}$  the **limit** for  $i \to \infty$  is defined as

$$\lim_{i \to \infty} v_i = v \iff \forall \varepsilon > 0 \; \exists \; h \; s.t. \; |v_i - v| \le \varepsilon \; \forall i \ge h$$

It may happen that a sequence has or does not have a limit. For example  $\{\frac{1}{n}\}$  has limit 0 for  $n \to +\infty$ , while  $\{(-1)^n\}$  does not.

Fact 1.1. Let us be given a monotone sequence, then the sequence does have a limit.

Notice that given a sequence either it is monotone or it can be "split" into two monotone sequences (for example  $\{(-1)^n\}$  can be transformed into  $\{(-1)^{2n}\}$  and  $\{(-1)^{2n+1}\}$  and these two sequences are both monotone).

Definition 1.10 (Euclidean vector space). We call Euclidean space

$$\mathbb{R}^n := \left\{ \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} : x_i \in \mathbb{R}, i = 1, \dots, n \right\}$$

Equivalently, we can characterize the Euclinean space as Cartesian product of  $\mathbb{R}$  n times:  $\mathbb{R}^n = \mathbb{R} \times \mathbb{R} \times \dots \mathbb{R}$ .

The main operations on elements of the Euclidean space (vectors) are:

SUM: 
$$x + y := \begin{pmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{pmatrix}$$

SCALAR MULTIPLICATION: 
$$\alpha x = \begin{pmatrix} \alpha x_1 \\ \alpha x_2 \\ \vdots \\ \alpha x_n \end{pmatrix}$$

In order to be able to compute limits in a vector space we need to use norms (see ??).

Fact 1.2. The norms on a vector space have the following properties:

- 1.  $||x|| \ge 0$  and  $\forall x \in \mathbb{R}^n$ ,  $||x|| = 0 \iff x = 0$ ;
- 2.  $\|\alpha x\| = |\alpha| \|x\|, \ \forall x \in \mathbb{R}^n, \ \alpha \in \mathbb{R};$
- 3.  $||x+y|| \le ||x|| + ||y||$ ,  $\forall x, y \in \mathbb{R}^n$  (triangle inequality).

**Definition 1.11** (Ball). We term **ball** centered in  $\bar{x}$  and having  $\varepsilon$  as radius as the set of points that are close enough to  $x \in \mathbb{R}^n$ :  $B(\bar{x}, \varepsilon) = \{x \in \mathbb{R}^n : ||x - \bar{x}|| \le \varepsilon\}.$ 

In Figure 1.1 we may observe the different shapes of the same ball varying the value of p in the p-norm.

**Definition 1.12** (Scalar product). Let  $x, y \in \mathbb{R}^n$  we define the **scalar product** between these two vectors

$$\langle x, y \rangle := y^T x = \sum_{i=1}^n x_i y_i = x_1 y_1 + \dots + x_n y_n$$

Fact 1.3. A scalar product has the following properties:

1. 
$$\langle x, y \rangle = \langle y, x \rangle \quad \forall x, y \in \mathbb{R}^n \ (symmetry)$$

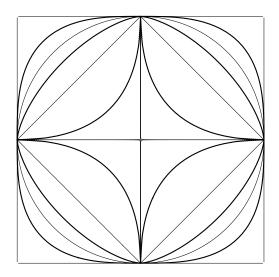


FIGURE 1.1: The shapes of balls centered in the origin of radius 1 varying the value of p.

$$2. < x, x \ge 0, \ \forall x \in \mathbb{R}^n, < x, x \ge 0 \iff x = 0;$$

$$\beta$$
.  $\langle \alpha x, y \rangle = \alpha \langle x, y \rangle, \ \forall x \in \mathbb{R}^n, \alpha \in \mathbb{R};$ 

4. 
$$\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle, \ \forall x, y, z \in \mathbb{R}^n$$
.

Fact 1.4 (Cauchy-Schwartz inequality). Let  $x, y \in \mathbb{R}^n$ . The following holds:

$$|\langle x, y \rangle|^2 \le \langle x, x \rangle < y, y \rangle \equiv |\langle x, y \rangle| \le ||x|| \, ||y||, \, \forall x, y \in \mathbb{R}^n$$

An important characterization of the scalar product is the one that uses angles:

 $< x,y> = \|x\| \, \|y\| \cos \theta$ :  $x\perp y \iff < x,y> = 0$  and  $< x,y> > 0 \iff$  "x and y point in the same direction"

We have now all the tools to define the notion of limit of a sequence in  $\mathbb{R}^n$ .

**Definition 1.13** (Limit of a sequence in the Euclidean space). Let  $\{x_i\} \subset \mathbb{R}^n$  be a sequence in  $\mathbb{R}^n$ . The **limit** of  $\{x_i\}$  for  $i \to +\infty$  is the following:

$$\lim_{i \to \infty} x_i = x \equiv \{x_i\} \to x$$

$$\updownarrow$$

$$\forall \varepsilon > 0 \; \exists h \; s.t. \; d(x_i, x) \le \varepsilon \; \forall i \ge h$$

$$\updownarrow$$

$$\forall \varepsilon > 0 \; \exists h \; s.t. \; x_i \in \mathcal{B}(x, \varepsilon) \; \forall i \ge h$$

$$\updownarrow$$

$$\lim_{i \to \infty} d(x_i, x) = 0$$