

Optimization

– Introduction –

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(several slides in this part traced back Tutorial ICASSP 2014 written in collaboration with **Jean-Christophe Pesquet** from Centre de Vision Numérique, CentraleSupélec, University Paris-Saclay, Inria, France.)

Optimization ?

We think that convex optimization is an important enough topic that everyone who uses computational mathematics should know at least a little bit about it. In our opinion, convex optimization is a natural next topic after advanced linear algebra and linear programming.

(Stephen Boyd and Lieven Vandenbergh)



Optimization ?

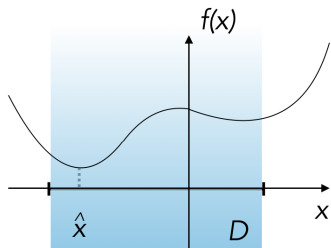
Whatever people do, at some point they get a craving to organize things in a best possible way. This intention, converted in a mathematical form, turns out to be an optimization problem of certain type.

(Yurii Nesterov)



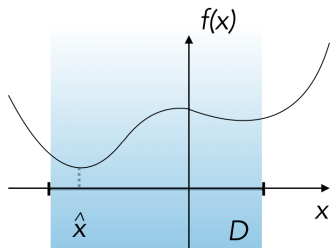
Optimization: Minimization problems

- **Minimization problems** involve :
 - a cost function $f: \mathbb{R}^N \rightarrow \mathbb{R}$;
 - a subset D of \mathbb{R}^N .



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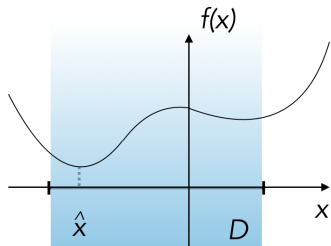
Find $\hat{x} \in D$ such that $(\forall x \in D) f(\hat{x}) \leq f(x)$

\Leftrightarrow Find $\hat{x} \in D$ such that $f(\hat{x}) = \inf_{x \in D} f(x)$

\Leftrightarrow Find $\hat{x} \in \underset{x \in D}{\text{Argmin}} f(x)$.

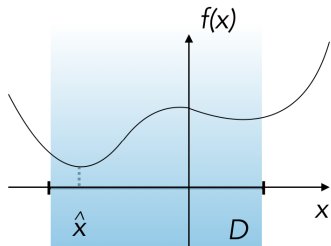
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Find $\hat{x} \in D$ such that $(\forall x \in D) f(\hat{x}) \geq f(x)$

\Leftrightarrow Find $\hat{x} \in D$ such that $(\forall x \in D) -f(\hat{x}) \leq -f(x)$

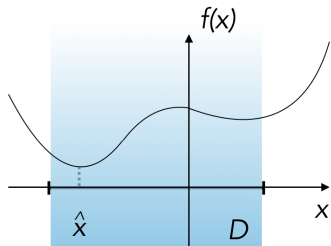
\Leftrightarrow Find $\hat{x} \in \underset{x \in D}{\text{Argmin}} (-f(x))$.

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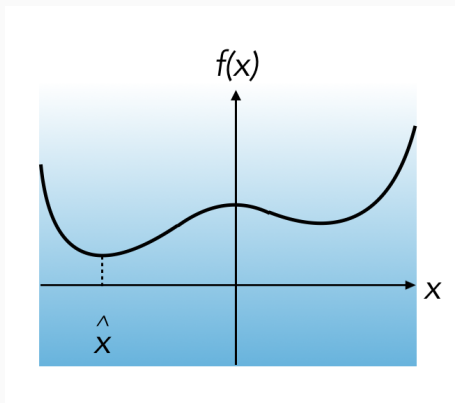
Without loss of generality, we
can focus on
minimization problems

$$\text{Find } \hat{x} \in \underset{x \in D}{\text{Argmin}} f(x).$$



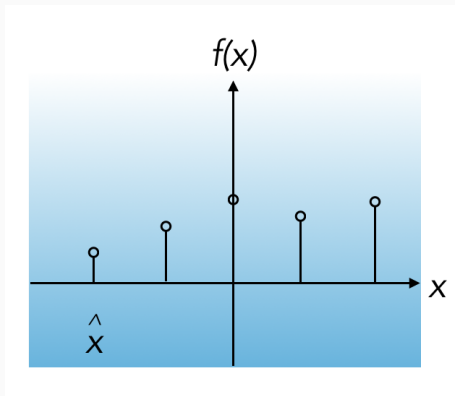
Various types of minimization problems

- Find $\hat{x} \in \underset{x \in D}{\text{Argmin}} f(x)$ with $D = \mathbb{R}^N$: **unconstrained problem**



Various types of minimization problems

- Find $\hat{x} \in \underset{x \in D}{\text{Argmin}} f(x)$ with D **countable**: **discrete optimization**



Various types of minimization problems

- Find $\hat{x} \in \underset{x \in D}{\text{Argmin}} f(x)$ with D being equality or inequality constraints

- Example: Optimization problem with P equality constraints

$$D = \{x \in \mathbb{R}^N \mid (\forall i \in \{1, \dots, P\}) \quad g_i(x) = 0\}$$

where $g_i: \mathbb{R}^N \rightarrow \mathbb{R}$.

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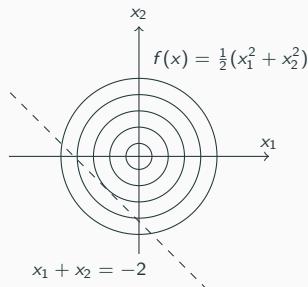
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- Particular case: linear (or affine) constraints

$$\begin{aligned} g_i(x) &= \langle a_i \mid x \rangle + b_i \\ &= \sum_{n=1}^N a_{i,n} x_n + b_i \end{aligned}$$

where $a_i \in \mathbb{R}^N$ and $b_i \in \mathbb{R}$.



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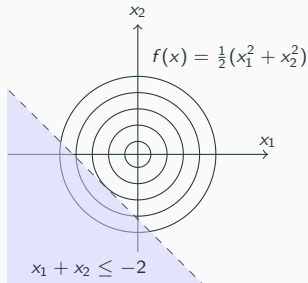
$$D = \{x \in \mathbb{R}^N \mid (\forall i \in \{1, \dots, P\}) \quad g_i(x) \leq 0\}$$

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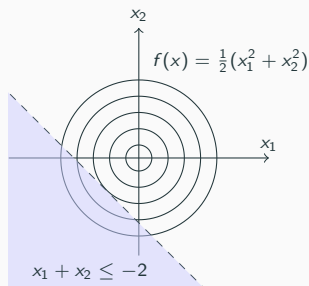


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→ **Continuous optimization**

Constrained and unconstrained minimization problems

- Reformulation using **indicator function**

$$\text{Find } \hat{x} \in \underset{x \in D}{\text{Argmin}} f(x) \quad \Leftrightarrow \quad \text{Find } \hat{x} \in \underset{x \in \mathbb{R}^N}{\text{Argmin}} f(x) + \iota_D(x)$$

where

$$(\forall x \in \mathbb{R}^N) \quad \iota_D(x) = \begin{cases} 0 & \text{if } x \in D \\ +\infty & \text{otherwise.} \end{cases}$$

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- or equivalently

$$\text{Find } \hat{x} \in \underset{x \in \mathbb{R}^N}{\text{Argmin}} \tilde{f}(x)$$

where

$$(\forall x \in \mathbb{R}^N) \quad \tilde{f}(x) = \begin{cases} f(x) & \text{if } x \in D \\ +\infty & \text{otherwise.} \end{cases}$$

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Allowing non finite valued functions leads to a **unifying view of constrained and unconstrained minimization problems.**

Main questions to be addressed

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2. Characterization of solutions: **necessary/sufficient conditions** for \hat{x} to be a solution.
3. Designing an **algorithm** to approximate a solution in the frequent case when no closed form solution is available, i.e. building a sequence $(x_n)_{n \in \mathbb{N}}$ of \mathbb{R}^N such that

$$\lim_{n \rightarrow +\infty} x_n = \hat{x}.$$

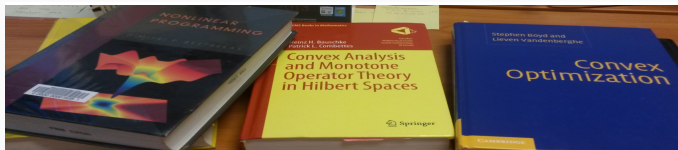
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4. Evaluation of the performance of the optimization algorithm:
 - **Convergence rate** or at least convergence of the iterates
Example: If there exists $\rho \in]0, 1[$ and $n^* \in \mathbb{N}$ such that $(\forall n \geq n^*)$
 $\|x_{n+1} - \hat{x}\| \leq \rho \|x_n - \hat{x}\|$, then *(Q-)linear* convergence rate.
 - **Robustness** to numerical errors
 - Amenability to **parallel/distributed implementations**.

Reference books



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