

Lecture 3 : Optimization Terminology

goals:

- introduce ^{basic} terminology for optimization problems

Mathematical Optimization Problem

minimize $f(x)$

subject to $x \in \mathcal{X}$

- $x \in \mathbb{R}^n$: ^(decision) optimization variables
- $f : \mathbb{R}^n \rightarrow \mathbb{R}$: objective/cost function
- $\mathcal{X} \subseteq \mathbb{R}^n$: feasible / constraint set

$$\mathcal{X} = \{x \in \mathbb{R}^n \mid g_i(x) \leq 0, i=1, \dots, m, h_i(x) = 0, i=1, \dots, p\}$$

$g_i(x)$: inequality constraint functions

$h_i(x)$: equality constraint functions

- aka a nonlinear program

- Note: all other parameters used to specify objective and constraint functions are referred to as problem data

$$\begin{array}{ll} \underline{\underline{\text{Ex}}} & \min \quad c^T x \\ & \text{subject to } Ax \leq b \end{array}$$

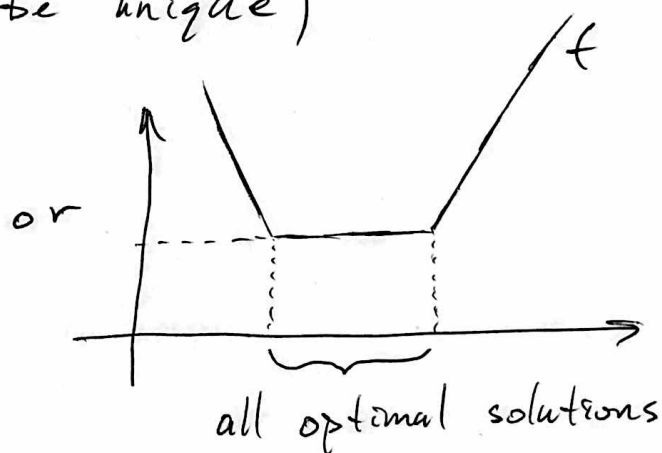
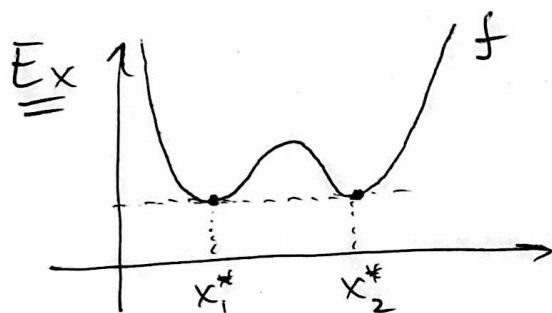
$$\text{Variable: } x \in \mathbb{R}^n$$

$$\text{problem data: } A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m, \quad c \in \mathbb{R}^n$$

- Note: any maximization problem can be written this way by changing the sign of the objective
- an optimal solution x^* has the smallest value of f among all vectors satisfying the constraints

$$x^* \in \mathcal{X} \text{ satisfies } f(x^*) \leq f(x) \quad \forall x \in \mathcal{X}$$

- there may be more than one optimal solution (i.e. it might not be unique)



the set of all optimal solutions is written

$$\operatorname{argmin}_{x \in \mathcal{X}} f(x) = \left\{ x \in \mathcal{X} \mid f(x) = \min_{x \in \mathcal{X}} f(x) \right\}$$

and we can write $x^* \in \operatorname{argmin}_{x \in \mathcal{X}} f(x)$

- the optimal value is $f^* = \min_{x \in \mathcal{X}} f(x)$

- It's also possible an optimal solution does not exist

① If X is empty ($X = \emptyset$)

the problem is called infeasible

- In this case, we set $f^* = +\infty$
- This means the constraints are inconsistent, i.e. there's no point that satisfies all of them

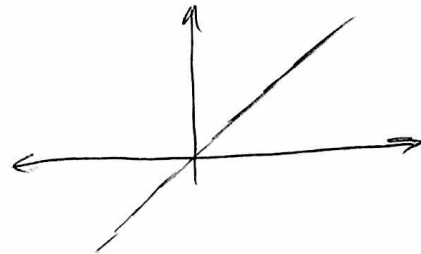
$$\begin{aligned} \text{Ex} \quad & \min_{x \in \mathbb{R}} \quad x^2 \\ & \text{subject to} \quad x \leq -1 \\ & \quad \quad \quad x \geq 1 \end{aligned}$$

- In control design, this means the design specifications are too strict

② If $f(x)$ can be made arbitrarily negative without violating any constraints, the problem is unbounded (below)

- In this case, we set $f^* = -\infty$

$$\begin{aligned} \text{Ex} \quad & \min_{x \in \mathbb{R}} \quad x \\ & \text{subject to} \quad x \leq 0 \end{aligned}$$



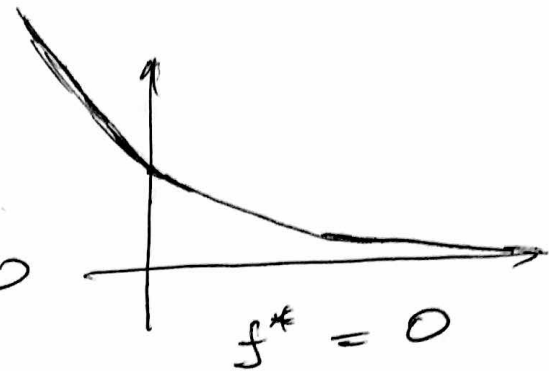
- Usually means the problem is ill-posed as an engineering design problem

③ $f(x)$ might be bounded below, but there exists no point that achieves the bound

• Here we set $f^* = \inf_{x \in X} f(x)$
greatest lower bound

• The optimal value exists but an optimal solution does not

Ex $\inf_{x \in \mathbb{R}} e^{-x}$
subject to $x \geq 0$



• Two cases where x^* guaranteed to exist

① If f is continuous and X is nonempty and compact (i.e., closed and bounded)

• Weierstrass Extreme Value Theorem (1830)

② If f is continuous and radially unbounded

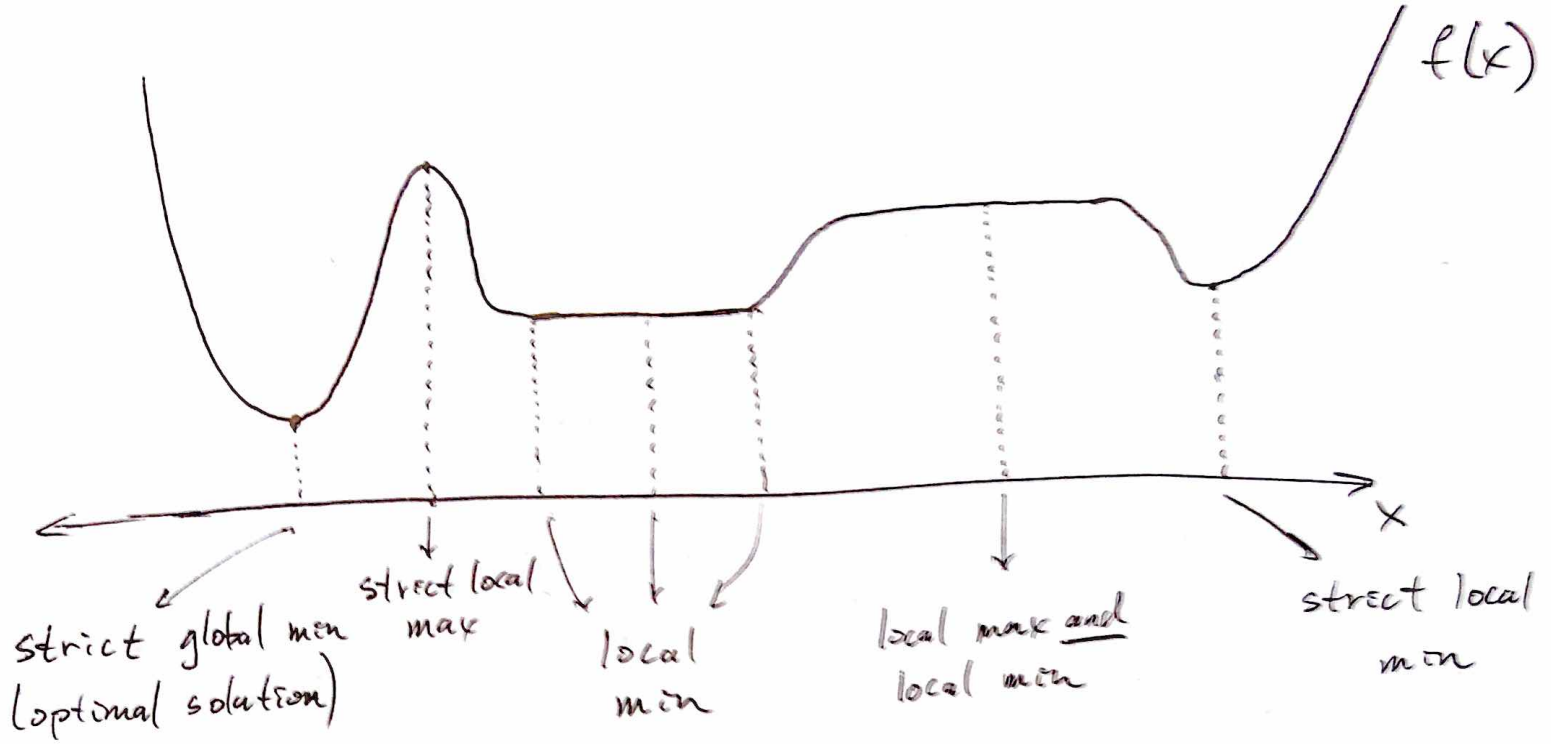
i.e. $\lim_{\|x\| \rightarrow \infty} f(x) = \infty$

- Feasible point : A vector $x \in X$ satisfying the inequality and equality constraints
- Strictly feasible point : A vector $x \in X$ satisfying the inequality constraints strictly: $g_i(x) < 0 \quad i=1, \dots, m$
- If $X = \mathbb{R}^n$ (i.e. there are no constraints) then the problem is called unconstrained

Let $\bar{x} \in X$ and $B(\bar{x}, \varepsilon) = \{x \mid \|x - \bar{x}\| \leq \varepsilon\}$

The point \bar{x} is called a

- local minimum if $\bar{x} \in X$ and $\exists \varepsilon > 0$ such that $f(\bar{x}) \leq f(x) \quad \forall x \in B(\bar{x}, \varepsilon) \cap X$
- strict local minimum if $\bar{x} \in X$ and $\exists \varepsilon > 0$ s.t. $f(\bar{x}) < f(x) \quad \forall x \in B(\bar{x}, \varepsilon) \cap X, x \neq \bar{x}$
- global minimum if $\bar{x} \in X$ and $f(\bar{x}) \leq f(x) \quad \forall x \in X$
- strict global minimum if $\bar{x} \in X$ and $f(\bar{x}) < f(x) \quad \forall x \in X, x \neq \bar{x}$
- saddle point if it's a ^{strict} local minimum restricted along at least one direction and a strict local maximum along at least one other direction



Some Common Optimization Problems

• Linear Program (LP)

- linear cost and constraint functions
- feasible set is a polyhedron (more later)

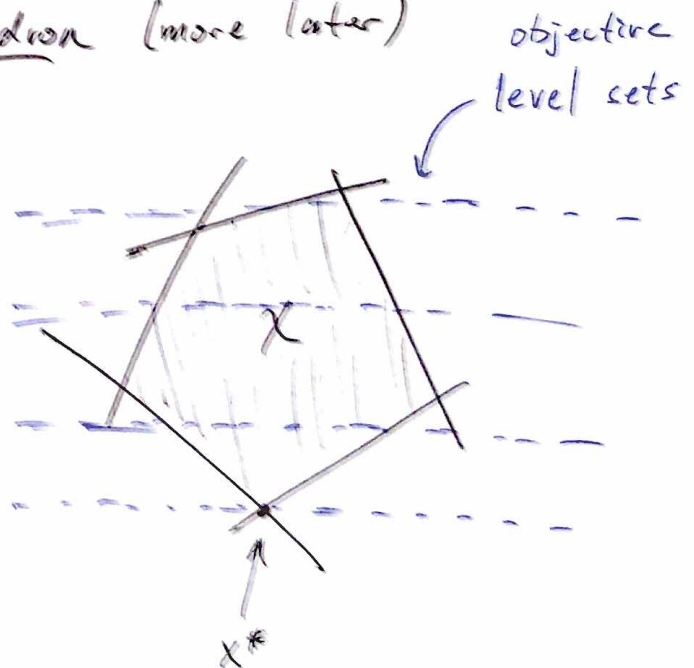
minimize

$$c^T x$$

subject to

$$Gx \leq h$$

$$Ax = b$$



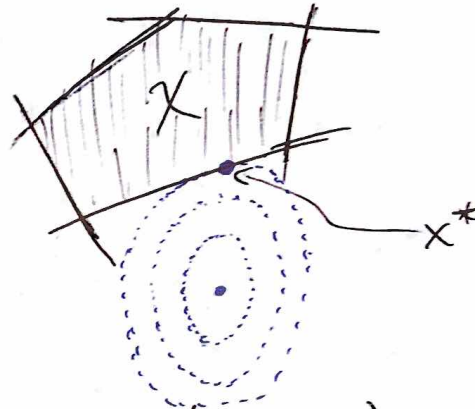
- Quadratic Program (QP)

- quadratic cost, linear constraints
- feasible set is a polyhedron
- convex if $P \succeq 0$, nonconvex otherwise (more later)

$$\text{minimize } x^T P x + q^T x$$

$$\text{subject to } Gx \leq h$$

$$Ax = b$$



- Mixed Integer Linear Program (MILP)

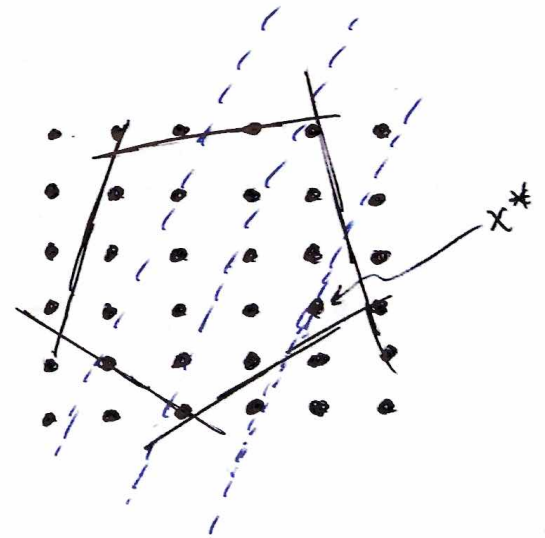
- LP with binary or integer constraints
- nonconvex (more later)

$$\text{minimize } c^T x$$

$$\text{subject to } Gx \leq h$$

$$Ax = b$$

$$x \in \{0, 1\}^n \text{ or } x \in \mathbb{Z}^n$$



- Others: second-order cone program, semidefinite program, sum of squares program, geometric program, robust or stochastic program, etc.

Optimization Algorithms & Software

- Huge range of algorithms for many types of problems (both convex + nonconvex)
 - Check out Nocedal + Wright book to get an idea of breadth
 - gradient descent + many variations, Newton methods + many variations, line search + trust region methods, simplex, active set, interior point, augmented Lagrangian, projected + proximal, etc. etc.
 - A highly active research area
- Huge range of software implementations, both proprietary + open source
 - Matlab (linprog/quadprog), CPLEX (IBM), Gurobi, GLPK, XPRESS, ODDP, FORCES, SDPT3, Sedumi, Mosek, IPOPT, ELOD, etc. etc.
 - No standard solver interface
 - Modelling tools/parsers allow easy switching b/t solvers
 - GAMS, AMPL, CVX, YALMIP, CVXpy, CVX.jl, etc.
 - slower than direct solvers, but great for rapid prototyping in research