

Exercises: Constrained Optimization

Exercise 1 (Penalization). We consider the following problem

$$(P) \quad \begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x) \\ \text{s.t.} \quad & Ax = b, \quad x \leq 0 \end{aligned}$$

with value v and the following penalized versions

$$(P_t^{in}) \quad \begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x) - t \sum_{i=1}^n \ln(-x_i) \\ \text{s.t.} \quad & Ax = b, \quad x < 0 \end{aligned}$$

and

$$(P_t^{out}) \quad \begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x) + t \sum_{i=1}^n (x_i)^+ \\ \text{s.t.} \quad & Ax = b \end{aligned}$$

with associated value v_t^{in} and v_t^{out} , and an optimal solution x_t^{in} and x_t^{out} .

1. Intuitively, assuming that f is "well behaved", for t going to which value does (P_t^{in}) tend to the original problem (P) ? In which sense?
2. What can you say about x_t^{in} ?
3. Can you compare v_t^{in} and v ?
4. Same questions for (P_t^{out}) .

Exercise 2 (Decomposition by prices). We consider the following energy problem:

- you are an energy producer with N production units
- you have to satisfy a given demand planning for the next 24h (i.e. the total output at time t should be equal to d_t)

- the time step is the hour, and each unit have a production cost for each planning given as a convex quadratic function of the planning
 - For each unit i , the production planning $u^i = (u_t^i)_{t \in [24]}$ has to satisfy polyhedral constraints $u^i \in U^i$.
1. Model this problem as an optimization problem. In which class does it belongs ? How many variables ?
 2. Apply Uzawa's algorithm to this problem. Why could this be an interesting idea ?
 3. Give an economic interpretation to this method.
 4. What would happen if each unit had production constraints ?

Exercise 3 (Kelley's convergence). We are going to prove that, if $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is convex, and X a non-empty polytope (bounded polyhedron) then Kelley's cutting plane algorithm is converging. Consider $x_1 \in X$. We consider a sequence of points $(x^{(k)})_{k \in \mathbb{N}}$ such that $x^{(k+1)}$ is an optimal solution to

$$(\mathcal{P}^{(k)}) \quad \begin{aligned} \underline{v}^{(k+1)} = \min_{x \in X} z \\ \text{s.t.} \quad f(x^{(\kappa)}) + \langle g^{(\kappa)}, x - x^{(\kappa)} \rangle \leq z \quad \forall \kappa \in [k] \end{aligned}$$

where $g^{(k)} \in \partial f(x^{(k)})$.

Denote $v = \min_{x \in X} f(x)$.

1. Show that v exists and is finite, and that there exists a sequence $x^{(k)}$.
2. Show that there exists L such that, for all k_1 and k_2 , we have $\|f(x^{(k_1)}) - f(x^{(k_2)})\| \leq L \|x^{(k_1)} - x^{(k_2)}\|$, and $\|g^{(k)}\| \leq L$.

3. Let $K_\varepsilon = \{k \in \mathbb{N} \mid f(x^{(k)}) > v + \varepsilon\}$ be the set of index such that $x^{(k)}$ is not an ε -optimal solution. Show that $f(x_k) \rightarrow v$ if and only if K_ε is finite for all $\varepsilon > 0$

4. Consider $k_1, k_2 \in K_\varepsilon$, such that $k_2 > k_1$.
Show that

$$f(x^{(k_1)}) + \langle g^{(k_1)}, x^{(k_2)} - x^{(k_1)} \rangle \leq \underline{v}^{(k_2)} \leq v$$

5. Show that $\varepsilon + f(x^{(k_1)}) + \langle g^{(k_1)}, x^{(k_2)} - x^{(k_1)} \rangle < f(x^{(k_2)})$

6. Show that $\varepsilon < 2L\|x^{(k_2)} - x^{(k_1)}\|$.

7. Prove that $f(x^{(k)}) \rightarrow v$.

8. (Optional - hard) Find a complexity bound for the method (that is a number of iteration N_ε after which you are sure to have obtained a ε -optimal solution).