Modern Optimization Techniques

4. Inequality Constrained Optimization / 4.2. Barrier and Penalty Methods

Lars Schmidt-Thieme

Information Systems and Machine Learning Lab (ISMLL)
Institute of Computer Science
University of Hildesheim, Germany

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Outline

Outline

Inequality Constrained Minimization (ICM) Problems

A problem of the form:

$$
\begin{aligned}
\arg\min_{x \in \mathbb{R}^N} \quad & f(\mathbf{x}) \\
\text{subject to} \quad & g_p(\mathbf{x}) = 0, \quad p = 1, \ldots, P \\
& h_q(\mathbf{x}) \leq 0, \quad q = 1, \ldots, Q
\end{aligned}
$$

where:

- $f : \mathbb{R}^N \to \mathbb{R}$ **convex** and **twice differentiable**
- $g_1, \ldots, g_P : \mathbb{R}^N \to \mathbb{R}$ **convex** and **twice differentiable**
- $h_1, \ldots, h_Q : \mathbb{R}^N \to \mathbb{R}$ **convex** and **twice differentiable**
- A feasible optimal $\mathbf{x}^*$ exists, $p^* := f(\mathbf{x}^*)$

Inequality Constrained Minimization (ICM) Problems / Affine Constraints

$$\begin{aligned} \arg\min_{x \in \mathbb{R}^N} \quad & f(\mathbf{x}) \\ \text{subject to} \quad & A\mathbf{x} - a = 0 \\ & B\mathbf{x} - b \leq 0 \end{aligned}$$

where:

- $f : \mathbb{R}^N \rightarrow \mathbb{R}$ **convex** and **twice differentiable**
- $A \in \mathbb{R}^{P \times N}, a \in \mathbb{R}^P$: P affine equality constraints
- $B \in \mathbb{R}^{Q \times N}, b \in \mathbb{R}^Q$: Q affine inequality constraints
- A feasible optimal $\mathbf{x}^*$ exists, $p^* := f(\mathbf{x}^*)$

Barrier and Penalty Methods

- Barrier and Penalty methods reduce the problem to a
  - **sequence** of optimization problems
  - with a more complex objective function,
  - but with simpler constraints

- Applies a suitable optimization method to each of the problems
  - often Newton

Advantages:

1. Does not suffer from combinatorical complexity for many constraints (as primal methods / active set methods do)
2. Generally applicable, as they do not rely on special problem structure.

Outline

Idea

- search only in the interior of the feasible area S
  - ensure that an optimization algorithm stays within the interior by adding a barrier function B to the objective
    - the barrier B grows unbounded when approaching the border of the feasible area.
  - aka as interior point methods

- iteratively reduce the weight c of the barrier.
  - iterates $x^{(k)}$ converge to the optimum x^*, possibly on the border of the feasible area.

- only applicable if the interior of the feasible area is not empty, esp. there are no equality constraints.

Idea

For $f : S \to \mathbb{R}$ and $S \subseteq \mathbb{R}^N$:

$$x = \arg\min_{x \in S} f(\mathbf{x}) \quad \Longleftrightarrow \quad x = \lim x^{(k)}, \quad c^{(k)} \to 0$$

$$x^{(k)} := \arg\min_{x \in S^\circ} \tilde{f}_{c^{(k)}}(\mathbf{x})$$

$$\tilde{f}_c(x) := f(\mathbf{x}) + cB(\mathbf{x})$$

with a barrier function

$$B : S^\circ \to \mathbb{R}$$
$$(i) B \text{ continuous}$$
$$(ii) B(x) \geq 0$$
$$(iii) B(x) \to \infty \text{ for } x \to \partial(S^\circ)$$

Log Barrier Function

For an feasible area S defined by inequality constraints $h : \mathbb{R}^N \to \mathbb{R}^Q$:

$$S := \{x \in \mathbb{R}^N \mid h(x) \leq 0\}$$

log barrier function:

$$B(x) := -\sum_{q=1}^{Q} \log(-h_q(x))$$

convex and twice differentiable:

$$\nabla B(x) = -\sum_{q=1}^{Q} \frac{1}{h_q(x)} \nabla h_q(x)$$

$$\nabla^2 B(x) = \sum_{q=1}^{Q} \frac{1}{(h_q(x))^2} \nabla h_q(x)(\nabla h_q(x))^T - \frac{1}{h_q(x)} \nabla^2 h_q(x)$$

Inverse Barrier Function

For an feasible area S defined by inequality constraints $h : \mathbb{R}^N \rightarrow \mathbb{R}^Q$:

$$S := \{x \in \mathbb{R}^N \mid h(x) \leq 0\}$$

inverse barrier function:

$$B(x) := -\sum_{q=1}^{Q} \frac{1}{h_q(x)}$$

convex and twice differentiable:

$$\nabla B(x) = \sum_{q=1}^{Q} \frac{1}{(h_q(x))^2} \nabla h_q(x)$$

$$\nabla^2 B(x) = \sum_{q=1}^{Q} \frac{-2}{(h_q(x))^3} \nabla h_q(x) (\nabla h_q(x))^T + \frac{1}{(h_q(x))^2} \nabla^2 h_q(x)$$

Barrier Methods / Generic Algorithm

min-barrier$(f, B, x^{(0)}, c, \epsilon, K)$:
  for $k := 1, \dots, K$:
    $x^{(k)} := \min(f + c^{(k)} B, x^{(k-1)})$
    if $||x^{(k)} - x^{(k-1)}|| < \epsilon$:
      return $x^{(k)}$
  return "not converged"

where

- $f : \mathbb{R}^N \to \mathbb{R}$ objective function
- $B : \mathbb{R}^N \to \mathbb{R}$ barrier function (encoding inequality constraints)
- $x^{(0)} \in \mathbb{R}^N$ strictly feasible starting point, i.e., $B(x^{(0)}) < \infty$
- $c \in (\mathbb{R}^+)^*$: barrier weights, $c^{(k)} \to 0$
- min: unconstrained minimization method

Barrier Methods / Log Barrier Algorithm

min-barrier-log$(f, h, x^{(0)}, c, \epsilon, K)$:
  for $k := 1, \ldots, K$:
    $x^{(k)} := \min(f - c^{(k)} \sum_{q=1}^{Q} \log(-h_q), x^{(k-1)})$
    if $||x^{(k)} - x^{(k-1)}|| < \epsilon$:
      return $x^{(k)}$
  return "not converged"

where

- $f : \mathbb{R}^N \to \mathbb{R}$ objective function
- $h : \mathbb{R}^N \to \mathbb{R}^Q$ inequality constraints
- $x^{(0)} \in \mathbb{R}^N$ strictly feasible starting point, i.e., $h(x^{(0)}) < 0$
- $c \in (\mathbb{R}^+)^*$: barrier weights, $c^{(k)} \to 0$
- min: unconstrained minimization method

Remarks

- The inner minimization step is called centering step.
- It is usually accomplished using Newton's method.
- See for a better stopping criterion in section 4.

Equality Constraints

- equality constraints can be passed through to the inner problem:

$$
\begin{aligned}
x = \arg\min_{x \in \mathbb{R}^N} \; & f(x) \\
\text{s.t. } & g(x) = 0 \\
& h(x) \leq 0
\end{aligned}
\qquad \Longleftrightarrow \qquad
\begin{aligned}
x &= \lim x^{(k)}, \quad c^{(k)} \rightarrow 0 \\
x^{(k)} &:= \arg\min_{x \in S^\circ} \; \tilde{f}_{c^{(k)}}(x) \\
& \text{s.t. } g(x) = 0 \\
\tilde{f}_c(x) &:= f(x) + cB(x) \\
S^\circ &:= \{x \in \mathbb{R}^N \mid h(x) < 0\}
\end{aligned}
$$

with B a barrier function for inequality constraints h.

- the inner minimization method then has to be able to cope with equality constraints.

Outline

Idea

- search unconstrained in all of $\mathbb{R}^N$.
  - penalize infeasible points
    by adding a penalty function P to the objective
    - the penalty P is zero for feasible points, non-zero for infeasible points.

- iteratively increase the weight c of the penalty.
  - iterates $x^{(k)}$ converge to the optimum x^*,
    possibly on the border of the feasible area.

- applicable to both, equality and inequality constraints,
  but usually there are no inequality constraints.

Idea

For $f : S \to \mathbb{R}$ and $S \subseteq \mathbb{R}^N$:

$$x = \arg\min_{x \in S} \; f(\mathbf{x}) \qquad \Longleftrightarrow \qquad x = \lim x^{(k)}, \quad c^{(k)} \to \infty$$

$$x^{(k)} := \arg\min_{x \in \mathbb{R}^N} \; \tilde{f}_{c^{(k)}}(\mathbf{x})$$

$$\tilde{f}_c(x) := f(\mathbf{x}) + cP(\mathbf{x})$$

with a penalty function

$$\begin{aligned} P :& \mathbb{R}^N \to \mathbb{R} \\ (i)&P \text{ continuous} \\ (ii)&P(x) \geq 0 \\ (iii)&P(x) = 0 \Leftrightarrow x \in S \end{aligned}$$

Quadratic Penalty Function

For an feasible area S defined by equality constraints $g : \mathbb{R}^N \rightarrow \mathbb{R}^P$:

$$S := \{x \in \mathbb{R}^N \mid g(x) = 0\}$$

quadratic penalty function:

$$P(x) := \sum_{p=1}^{P} (g_p(x))^2$$

convex and twice differentiable:

$$\nabla P(x) = 2 \sum_{p=1}^{P} g_p(x) \nabla g_p(x)$$

$$\nabla^2 P(x) = 2 \sum_{p=1}^{P} \nabla g_p(x) (\nabla g_p(x))^T + g_p(x) \nabla^2 g_p(x)$$

Penalty Methods / Generic Algorithm

min-penalty$(f, P, x^{(0)}, c, \epsilon, K)$:
  for $k := 1, \ldots, K$:
    $x^{(k)} := \min(f + c^{(k)} P, x^{(k-1)})$
    if $||x^{(k)} - x^{(k-1)}|| < \epsilon$:
      return $x^{(k)}$
  return "not converged"

where

- $f : \mathbb{R}^N \rightarrow \mathbb{R}$ objective function
- $P : \mathbb{R}^N \rightarrow \mathbb{R}$ penalty function (encoding equality constraints)
- $x^{(0)} \in \mathbb{R}^N$ starting point (possibly infeasible)
- $c \in (\mathbb{R}^+)^*$: penalty weights, $c^{(k)} \rightarrow \infty$
- min: unconstrained minimization method

Penalty Methods / Quadratic Penalty Algorithm

min-penalty-quad$(f, g, x^{(0)}, c, \epsilon, K)$:
  for $k := 1, \ldots, K$:
    $x^{(k)} := \min(f + c^{(k)} \sum_{p=1}^{P} (g_p(x))^2, x^{(k-1)})$
    if $||x^{(k)} - x^{(k-1)}|| < \epsilon$:
      return $x^{(k)}$
  return "not converged"

where

- $f : \mathbb{R}^N \rightarrow \mathbb{R}$ objective function
- $g : \mathbb{R}^N \rightarrow \mathbb{R}^P$ equality constraints
- $x^{(0)} \in \mathbb{R}^N$ starting point (possibly infeasible)
- $c \in (\mathbb{R}^+)^*$: penalty weights, $c^{(k)} \rightarrow \infty$
- min: unconstrained minimization method

Inequality Constraints

- inequality constraints $h(x) \leq 0$ can be represented as (additional) equality constraints:

$$h(x) \leq 0 \quad \iff \quad h_q^+(x) := \max\{0, h_q(x)\} = 0, \quad q = 1, \ldots, Q$$

- the quadratic barrier function for h^+ is differentiable with a continuous gradient:

$$B(x) := \sum_{q=1}^{Q} (h_q^+(x))^2$$

$$\nabla B(x) = \sum_{q=1}^{Q} 2h_q^+(x) \begin{cases} \nabla h_q(x), & \text{if } h_q(x) \geq 0 \\ 0, & \text{else} \end{cases} = 2h_q^+(x) \nabla h_q(x)$$

- but the second derivative usually is not continuous on the border (where $h_q(x) = 0$).

Outline

Sequential Subproblems

Analysis for

- general inequality constraints $h(\mathbf{x}) \leq 0$
- affine equality constraints $A\mathbf{x} - \mathbf{a} = 0$

$$
\begin{aligned}
(v1) \qquad & \text{minimize } f(\mathbf{x}) \\
& \text{s.t. } h_q(\mathbf{x}) \leq 0, \quad q = 1, \ldots, Q \\
& \qquad A\mathbf{x} - \mathbf{a} = 0 \\
(v2) \qquad & \text{minimize } f(\mathbf{x}) + cB(\mathbf{x}), \quad c \to 0 \\
& \text{s.t. } A\mathbf{x} - \mathbf{a} = 0 \\
(v3) \qquad & \text{minimize } tf(\mathbf{x}) + B(\mathbf{x}), \quad t \to \infty \\
& \text{s.t. } A\mathbf{x} - \mathbf{a} = 0
\end{aligned}
$$

Central Path

Given our ICM problem

$$\begin{aligned} \text{minimize} \quad & tf(\mathbf{x}) + B(\mathbf{x}) \\ \text{subject to} \quad & A\mathbf{x} - \mathbf{a} = 0 \end{aligned}$$

let $\mathbf{x}^*(t)$ be its the solution for a given $t > 0$

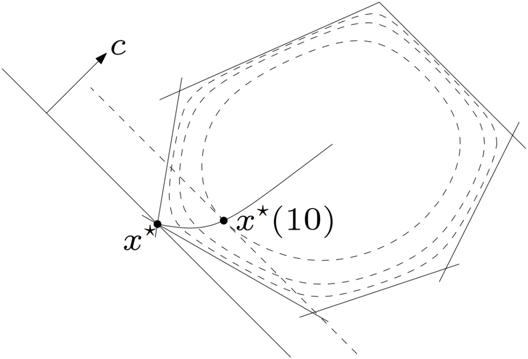
Definition
The **Central Path** associated with an ICM problem is the set of points $\mathbf{x}^*(t)$, $t > 0$, which are called **central points**

Central Path - Example

Central Path for a Linear Program

$$\begin{array}{ll} \text{minimize}_{\mathbf{x}} & \mathbf{c}^T\mathbf{x} \\ \text{subject to} & \mathbf{a}_i^T\mathbf{x} \leq b_i, \\ & i = 1, \ldots, 6 \end{array}$$

$\mathbf{c}^T\mathbf{x} = \mathbf{c}^T x^*(t)$ is tangent to the level curve of B through $\mathbf{x}^*(t)$



(From Stephen Boyd's Lecture Notes)

Central Path

Given our ICM problem

$$\begin{array}{rl} \text{minimize} & tf(\mathbf{x}) + B(\mathbf{x}) \\ \text{subject to} & A\mathbf{x} - \mathbf{a} = 0 \end{array}$$

A point $\mathbf{x}^*(t)$ on the central path is strictly feasible, i.e., satisfies

$$A\mathbf{x}^*(t) = \mathbf{a}, \qquad h_q(\mathbf{x}^*(t)) < 0, \quad q = 1, \ldots, Q$$

and there exists a $\hat{\nu} \in \mathbb{R}^P$ such that the following holds:

$$\begin{aligned} 0 &= t\nabla f(\mathbf{x}^*(t)) + \nabla B(\mathbf{x}^*(t)) + A^T\hat{\nu} \\ &= t\nabla f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \frac{1}{-h_q(\mathbf{x}^*(t))} \nabla h_q(\mathbf{x}^*(t)) + A^T\hat{\nu} \end{aligned}$$

Dual Points from Central Path

$$0 = t\nabla f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \frac{1}{-h_q(\mathbf{x}^*(t))} \nabla h_q(\mathbf{x}^*(t)) + A^T \hat{\nu}$$

$$= \nabla f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \frac{1}{-th_q(\mathbf{x}^*(t))} \nabla h_q(\mathbf{x}^*(t)) + \frac{1}{t} A^T \hat{\nu}$$

If we define:

$$\lambda_q(t) := -\frac{1}{th_q(\mathbf{x}^*(t))},\ q = 1, \ldots, Q,\ \nu^*(t) = \frac{\hat{\nu}}{t}$$

We can rewrite:

$$\nabla f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \lambda_q(t) \nabla h_q(\mathbf{x}^*(t)) + A^T \nu^*(t) = 0$$

Minimizing the Lagrangian

From the last slide:

$$\nabla f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \lambda_q(t) \nabla h_q(\mathbf{x}^*(t)) + A^T \nu^*(t) = 0$$

we can see that this is the first order condition for the lagrangian:

$$L(\mathbf{x}, \lambda, \nu) = f(\mathbf{x}) + \sum_{q=1}^{Q} \lambda_q h_q(\mathbf{x}) + \nu^T (A\mathbf{x} - \mathbf{a})$$

- $\mathbf{x}^*(t)$ minimizes the lagrangian for $\lambda = \lambda^*(t)$ and $\nu = \nu^*(t)$
- Thus $\lambda^*(t), \nu^*(t)$ is a dual feasible pair.

The dual function

The dual function $g(\lambda^*(t), \nu^*(t))$ is finite and

$$g(\lambda^*(t), \nu^*(t)) = f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \lambda_q(t) h_q(\mathbf{x}^*(t)) + \nu^*(t)^T (A\mathbf{x}^*(t) - a)$$

$$= f(\mathbf{x}^*(t)) + \sum_{q=1}^{Q} \overbrace{-\frac{1}{t h_q(\mathbf{x}^*(t))}}^{\lambda_q(t)} h_q(\mathbf{x}^*(t)) + \nu^*(t)^T \overbrace{(A\mathbf{x}^*(t) - a)}^{A\mathbf{x}^*(t) = a}$$

$$= f(\mathbf{x}^*(t)) - \frac{Q}{t}$$

As an important consequence of this we have that:

$$f(\mathbf{x}^*(t)) - p^* \leq Q/t$$

which confirms that $\mathbf{x}^*(t)$ converges to an optimal point as $t \to \infty$

Centrality Conditions and the KKT Conditions

In order for a point $\mathbf{x}$ to be a central point, i.e. $\mathbf{x} = \mathbf{x}^*(t)$, there must exist λ, ν such that:

$$A\mathbf{x} = \mathbf{a}, \quad h_q(\mathbf{x}) \leq 0, \quad q = 1, \ldots, Q$$

$$\lambda \geq 0$$

$$\nabla f(\mathbf{x}) + \sum_{q=1}^{Q} \lambda_q \nabla h_q(\mathbf{x}) + A^T \nu = 0$$

$$-\lambda_q h_q(\mathbf{x}) = \frac{1}{t}, \quad q = 1, \ldots, Q$$

- Thus, $\mathbf{x}^*(t)$ almost fulfills the KKT conditions.
  - complementary condition $-\lambda_q h_q(\mathbf{x}) = 0$ only holds approximately $(= 1/t)$

Stopping Criterion

- as stopping criterion, simply

$$\frac{Q}{t} \leq \epsilon, \quad t \to \infty$$

  or equivalently

$$Qc \leq \epsilon, \quad c \to 0$$

  can be used.
- Why solving sequential problems? Why not just solve a single problem with a sufficiently small c? E.g.,

$$c := \frac{\epsilon}{Q}$$

  - It does not work well for large scale problems.
  - It does not work well for small accuracy ϵ.
  - It needs a "good" starting point.
- Trade-off about the schedule of c:
  - the smaller c, the fewer centering steps, but the more Newton steps / centering step
  - can be adaptively controlled.

Outline

Convergence Analysis

Assume that $tf + B$ can be minimized by Newton's method for $t = t^{(0)}, \mu t^{(0)}, \mu^2 t^{(0)}, \ldots$, the t in the k-th outer step is

$$t^{(k)} = \mu^k t^{(0)}$$

From this, it follows that, in the k-th outer step, the duality gap is

$$\frac{Q}{\mu^k t^{(0)}}$$

Convergence Analysis

Then the number of outer iterations k^* needed to achieve accuracy ϵ is

$$\begin{aligned}
\epsilon &= \frac{Q}{\mu^{k^*} t^{(0)}} \\
\mu^{k^*} &= \frac{Q}{\epsilon t^{(0)}} \\
\log(\mu^{k^*}) &= \log(\frac{Q}{\epsilon t^{(0)}}) \\
k^* \log(\mu) &= \log(\frac{Q}{\epsilon t^{(0)}}) \\
k^* &= \frac{\log(\frac{Q}{\epsilon t^{(0)}})}{\log(\mu)}
\end{aligned}$$

Convergence Analysis

The **number of outer iterations** is exactly:

$$\left\lceil \frac{\log\left(\frac{Q}{\epsilon t^{(0)}}\right)}{\log \mu} \right\rceil$$

plus the initial step to compute $\mathbf{x}^*(t^{(0)})$

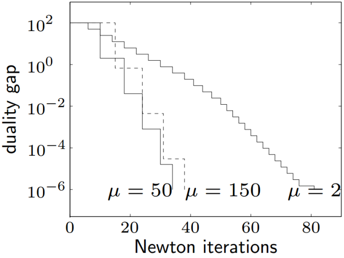
The **inner problem**

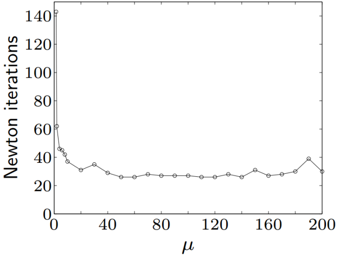
$$\text{minimize} \quad tf(\mathbf{x}) + B(\mathbf{x})$$

is solved by Newton's method (see convergence analysis for it)

Examples

Inequality form Linear Program ($m = 100$ inequalities, $n = 50$ variables)





(From Stephen Boyd's Lecture Notes)

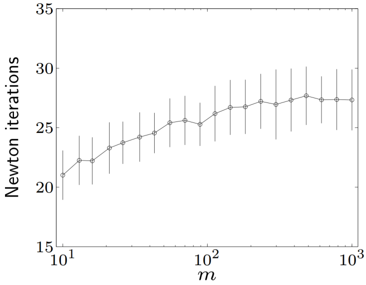
- starts with $\mathbf{x}$ on central path ($t^{(0)} = 1$, duality gap 100)
- terminates when $t = 10^8$ (gap 10^{-6})
- centering uses Newton's method with backtracking
- total number of Newton iterations not very sensitive for $\mu \geq 10$

Examples

Family of Linear Programs ($A \in \mathbb{R}^{m \times 2m}$)

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & A^T x \leq b, \quad x \succeq 0 \end{array}$$

$m = 10, \ldots, 1000$; for each m solve 100 randomly generated instances



Outline

Feasibility and Phase I Method

- The barrier method requires a strictly feasible starting point $\mathbf{x}^{(0)}$.
- Phase I denotes the computation of such a point (or the constraints are found to be infeasible).
- The barrier method algorithm then starts from $\mathbf{x}^{(0)}$ (called phase II stage).

Basic Phase I Method

Find strictly feasible $\mathbf{x}$ for constraints

$$h_q(\mathbf{x}) \leq 0, \quad q = 1, \ldots, Q, \quad A\mathbf{x} - \mathbf{a} = 0 \tag{1}$$

Phase I method for target variables $\mathbf{x} \in \mathbb{R}^N$ and $s \in \mathbb{R}$:

$$\begin{aligned} \text{minimize} \quad & s \\ \text{subject to} \quad & h_q(\mathbf{x}) \leq s, \quad q = 1, \ldots, Q \\ & A\mathbf{x} - \mathbf{a} = 0 \end{aligned} \tag{2}$$

- for (2), a strictly feasible starting point is easy to compute:
  - compute $x^{(0)}$ with $Ax^{(0)} - a = 0$
  - $s^{(0)} := \max_{q=1,\ldots,Q} h_q(x^{(0)}) + \epsilon, \quad \epsilon > 0$
- if $\mathbf{x}, s$ is feasible, with $s < 0$, then $\mathbf{x}$ is strictly feasible for (1)
- if the optimal value s^* of (2) is positive, then problem (1) is infeasible
- if $s^* = 0$ and attained, then problem (1) is feasible (but not strictly)
- if $s^* = 0$ and not attained, then problem (1) is infeasible

Sum of Infeasibilities Phase I Method

For target variables $\mathbf{x} \in \mathbb{R}^N$ and $\mathbf{s} \in \mathbb{R}^Q$:

$$\begin{aligned} \text{minimize} \quad & \mathbf{1}^T \mathbf{s} \\ \text{subject to} \quad & \mathbf{s} \geq 0 \\ & h_q(\mathbf{x}) \leq s_q, \quad q = 1, \ldots, Q \\ & A\mathbf{x} - \mathbf{a} = 0 \end{aligned}$$

Further Readings

- Barrier methods:
  - [Boyd and Vandenberghe, 2004, ch. 11]
  - [Griva et al., 2009, ch. 16]
  - [Luenberger and Ye, 2008, ch. 13]
  - [Nocedal and Wright, 2006, ch. 19.6]

- Penalty methods:
  - [Griva et al., 2009, ch. 16]
  - [Luenberger and Ye, 2008, ch. 13]
  - [Nocedal and Wright, 2006, ch. 17.1–2]

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