# Part II

# constrained optimization problems

#### constrained optimization problems

constrained optimization algorithms

interior-point method

## nonlinear constrained optimization problem

Using a term like nonlinear science is like referring to the bulk of zoology as the study of non-elephant animals.

Stanislaw Ulam

### constrained optimization problem: definitions

$$\min_{x \in X} f(x) \quad \text{subject to} \quad \begin{cases} c_{\alpha}(x) = 0, \text{ if } \alpha \in \mathcal{E} \\ c_{\beta}(x) \ge 0, \text{ if } \beta \in \mathcal{I}. \end{cases}$$

- A *feasible set* is a set  $\Omega \subset X$  such that if  $x \in \Omega$ , then  $c_{\alpha}(x) = 0$  and  $c_{\beta}(x) \ge 0$  for  $\alpha \in \mathcal{E}, \ \beta \in \mathcal{I}$ .
- For x ∈ Ω an *active set* is a subset A<sub>x</sub> ⊂ E ∪ I such that
   E ⊂ A<sub>x</sub> and c<sub>β</sub>(x) = 0 for all β ∈ A<sub>x</sub>.
- For x ∈ Ω, we say that the *linear independence constraint* qualification (LICQ) holds at x if ∂<sub>a</sub>c<sub>α</sub>(x) are linearly independent for α ∈ A<sub>x</sub>.
- The Lagrangian function is

$$\mathcal{L}(x,\lambda) = f(x) - \sum_{\alpha \in \mathcal{E} \cup \mathcal{I}} \lambda^{\alpha} c_{\alpha}.$$

### constrained optimization problem: KKT conditions

lf

- 1.  $x^*$  is a local minimizer, and
- 2. the LICQ holds at  $x^*$ ,

then there exists  $\lambda_*^{\alpha}$  such that

$$egin{aligned} &\partial_a \mathcal{L}(x^*,\lambda_*)=0,\ &c_{oldsymbol{lpha}}(x^*)=0,\quad orall lpha\in\mathcal{E},\ &c_{oldsymbol{eta}}(x^*)\geq 0,\quad oralleta\in\mathcal{I},\ &\lambda_*^{oldsymbol{eta}}\geq 0,\quad oralleta\in\mathcal{I},\ &\lambda_*^{oldsymbol{lpha}}c_{oldsymbol{lpha}}(x^*)=0,\quad orall lpha\in\mathcal{E}\cup\mathcal{I}. \end{aligned}$$

(Karush-Kuhn-Tucker conditions)

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# merit function: $l_1$ penalty function

The  $l_1$  penalty function is given by

$$\phi_1(x;\mu) = f(x) + \mu \sum_{\alpha \in \mathcal{E}} |c_\alpha(x)| + \mu \sum_{\beta \in \mathcal{I}} \max(0, -c_\beta(x)).$$

An *exact metric function* is a metric function  $\phi(x; \mu)$  if there exists  $\mu^*$  such that for any  $\mu > \mu^*$ , a local minimizer of the constrained optimization problem is a local minimizer of  $\phi(x; \mu)$ .

### filter

#### The infeasibility is given by

$$h(x) = \sum_{lpha \in \mathcal{E}} |c_{lpha}(x)| + \sum_{eta \in \mathcal{I}} \max(0, -c_{eta}(x)).$$

Given a sequence of  $\langle x_l : l = 1, 2, ..., k - 1 \rangle$  an iterate  $x_k$  is *acceptable* if  $f(x_k) < f(x_l)$  or  $h(x_k) < h(x_l)$  for l = 1, 2, ..., k - 1.

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## slack variables

Instead of

$$\min_{x \in X} f(x) \quad \text{subject to} \quad \begin{cases} c_{\alpha}(x) = 0, \text{ if } \alpha \in \mathcal{E} \\ c_{\beta}(x) \ge 0, \text{ if } \beta \in \mathcal{I}. \end{cases}$$

we can formulate the problem as

$$\min_{x \in X, s \in Y} f(x) \quad \text{subject to} \quad \begin{cases} c_{\alpha}(x) = 0, \text{ if } \alpha \in \mathcal{E} \\ c_{\beta}(x) - s_{\beta} = 0, \text{ if } \beta \in \mathcal{I} \\ s_{\beta} \ge 0. \end{cases}$$

# **KKT** conditions

$$egin{aligned} \partial_a f(x) &- \sum_{lpha \in \mathcal{E} \cup \mathcal{I}} \lambda^lpha \partial_a c_lpha(x) = 0, \ &\sum_{eta \in \mathcal{I}} s_eta \lambda^eta = 0, \ &c_lpha(x) = 0, \; lpha \in \mathcal{E}, \ &c_eta(x) = 0, \; lpha \in \mathcal{E}, \ &c_eta(x) - s = 0, \; eta \in \mathcal{I}, \ &s_eta \geq 0, \; \lambda_eta \geq 0, \; eta \in \mathcal{I}. \end{aligned}$$

### combinatorial complexity

$$\sum_{oldsymbol{eta}\in\mathcal{I}}s_{oldsymbol{eta}}\lambda^{oldsymbol{eta}}=0 \leftrightarrow \lambda^{oldsymbol{eta}}=0 ext{ if }oldsymbol{eta}
otin \mathcal{A}_{x^*}$$

leads to  $2^{||\mathcal{I}||}$  choices.

# barrier method and perutrbed KKT conditions

By introducing a barrier term

$$\min_{x,s} \left( f(x) - \mu \sum_{\beta \in \mathcal{I}} \log s_{\beta} \right)$$

we have no combinatorial complexity.

Under some technical conditions there exists  $(x(\mu), s(\mu), \lambda(\mu))$  in an open set of a solution converging to the solution.

# perutrbed KKT conditions

$$egin{aligned} \partial_a f(x) &- \sum_{lpha \in \mathcal{E} \cup \mathcal{I}} \lambda^lpha \partial_a c_lpha(x) = 0, \ &\sum_{eta \in \mathcal{I}} (s_eta \lambda^eta - \mu) = 0, \ &c_lpha(x) = 0, \; lpha \in \mathcal{E}, \ &c_eta(x) - s = 0, \; eta \in \mathcal{I}, \ &s_eta \geq 0, \; \lambda_eta \geq 0, \; eta \in \mathcal{I}. \end{aligned}$$

## interior-point method: primal-dual system

Search for a Newton direction by solving

$$egin{aligned} & \left( egin{aligned} \partial^2_{ab}\mathcal{L} & 0 & -\partial_a c_{m lpha}(x) & -\partial_a c_{m eta}(x) \ 0 & \lambda^{m eta} & 0 & s_{m eta} \ \partial_a c_{m lpha}(x) & 0 & 0 & 0 \ \partial_a c_{m eta}(x) & -1 & 0 & 0 \ \end{array} 
ight) egin{aligned} & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \delta \lambda^{m lpha} \ \delta \lambda^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \delta \lambda^{m lpha} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ \end{pmatrix} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ & \left( egin{aligned} \delta x^a \ \delta s^{m eta} \ & \left( egin{aligned} \delta x^a \ & \left( egin{aligned}$$

# interior-point method: interior-point algorithm

#### Algorithm 1: interior-point algorithm

```
Data: x_0, s_0 > 0, \mu_0 > 0, \nu > 0, \tau > 0, r \in (0, 1), \sigma \in (0, 1).
Data: \phi(x, s; \mu, \nu) = f(x) - \mu \log s + \nu \|c_{\alpha}(x)\| + \nu \|c_{\beta}(x)\|
compute \lambda_0 from KKT conditions;
while \phi(x,s;\mu,\nu) < \tau do
       while ||KKT||_{\mu_k} < \mu_k do
              solve the primal-dual system for (\delta x, \delta s, \delta \lambda);
              \alpha_s \leftarrow \max \{ \alpha \in (0,1] : s + \alpha \delta s > (1-r)s \};
             \alpha_z \leftarrow \max\left\{ \pmb{lpha} \in (0,1] : s + \pmb{lpha} \delta \lambda^{\pmb{eta}} \geq (1-r) \lambda^{\pmb{eta}} 
ight\};
              x_{k+1} \leftarrow x_k + \alpha_s \delta x;
             \lambda_{k+1}^{\alpha} \leftarrow \lambda_k^{\alpha} + \alpha_z \delta \lambda^{\alpha};
             s_{k+1} \leftarrow s_k + \alpha_s \delta s;
             \lambda_{k+1}^{\beta} \leftarrow \lambda_{k}^{\beta} + \alpha_{z} \delta \lambda^{\beta};
       end
       \mu_k \leftarrow m \in (0, \sigma \mu_k)
end
```