# Chapter 10 Equality constrained minimization

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#### equality constrained minimization problem

minimize 
$$f(x)$$
  
subject to  $Ax = b$ 

- f convex and twice continuously differentiable
- $ightharpoonup A \in \mathbb{R}^{p \times n}$  with  $\operatorname{\mathbf{rank}} A = p$
- ightharpoonup assume optimal value  $p^*$  is finite and attained

### optimality condition (review)

$$x^* \text{ is optimal} \qquad \Longleftrightarrow \qquad x^* \in \operatorname{dom} f, \quad Ax^* = b,$$
 there exists  $\nu^*$  such that  $\nabla f(x^*) + A^T \nu^* = 0$ 

### equality constrained quadratic minimization (with $P \in \mathbb{S}^n_+$ )

minimize 
$$(1/2)x^TPx + q^Tx + r$$
 subject to  $Ax = b$ 

optimality condition

$$\begin{bmatrix} P & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} x^* \\ \nu^* \end{bmatrix} = \begin{bmatrix} -q \\ b \end{bmatrix}$$

- coefficient matrix is called KKT matrix
- ► KKT matrix is nonsingular if and only if

$$Ax = 0, \quad x \neq 0 \qquad \Longrightarrow \qquad x^T Px > 0$$

equivalent condition for nonsingularity

$$P + A^T A \succ 0$$

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# Eliminating equality constraints

represent solutions of  $\{x \mid Ax = b\}$  as

$${x \mid Ax = b} = {Fz + \hat{x} \mid z \in \mathbb{R}^{n-p}}$$

- $\triangleright$   $\hat{x}$  is any particular solution
- ▶ range of  $F \in \mathbb{R}^{n \times (n-p)}$  is nullspace of A

#### reduced or eliminated problem

minimize 
$$f(Fz + \hat{x})$$

- unconstrained problem with variable  $z \in \mathbb{R}^{n-p}$
- ▶ from solution  $z^*$ , obtain  $x^*$  and  $\nu^*$  as

$$x^* = Fz^* + \hat{x}, \qquad \nu^* = -(AA^T)^{-1}A\nabla f(x^*)$$

### **example** optimal allocation with resource constraint

minimize 
$$f_1(x_1) + \cdots + f_n(x_n)$$
 subject to  $x_1 + \cdots + x_n = b$ 

eliminate  $x_n = b - x_1 - \cdots - x_{n-1}$ , namely, choose

$$\hat{x} = be_n, \qquad F = \begin{bmatrix} I \\ -\mathbf{1}^T \end{bmatrix} \in \mathbb{R}^{n \times (n-1)}$$

reduced problem

minimize 
$$f_1(x_1) + \cdots + f_{n-1}(x_{n-1}) + f_n(b - x_1 - \cdots - x_{n-1})$$

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### Newton step

Newton step  $\Delta x_{\rm nt}$  of f at feasible x is given by the solution v of

$$\begin{bmatrix} \nabla^2 f(x) & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} v \\ w \end{bmatrix} = \begin{bmatrix} -\nabla f(x) \\ 0 \end{bmatrix}$$

#### interpretations

 $ightharpoonup \Delta x_{
m nt}$  solves second order approximation (with variable v)

minimize 
$$\widehat{f}(x+v) = f(x) + \nabla f(x)^T v + (1/2) v^T \nabla^2 f(x) v$$
 subject to 
$$A(x+v) = b$$

 $ightharpoonup \Delta x_{
m nt}$  equations follow from linearizing optimality conditions

$$\nabla f(x+v) + A^T w \approx \nabla f(x) + \nabla^2 f(x)v + A^T w = 0, \qquad A(x+v) = b$$

### Newton decrement

$$\lambda(x) = \left(\Delta x_{\rm nt}^T \nabla^2 f(x) \Delta x_{\rm nt}\right)^{1/2} = \left(-\nabla f(x)^T \Delta x_{\rm nt}\right)^{1/2}$$

#### interpretations

lacktriangle gives an estimate of  $f(x)-p^*$  using quadratic approximation  $\widehat{f}$ 

$$f(x) - \inf_{Ay=b} \widehat{f}(y) = (1/2)\lambda(x)^2$$

directional derivative in Newton direction

$$\frac{\mathrm{d}}{\mathrm{d}t}f\left(x+t\Delta x_{\mathrm{nt}}\right)\bigg|_{t=0} = -\lambda(x)^{2}$$

• in general  $\lambda(x) \neq \left(\nabla f(x)^T \nabla^2 f(x)^{-1} \nabla f(x)\right)^{1/2}$ 

Newton's method with equality constraints

given starting point  $x \in \operatorname{\mathbf{dom}} f$  with Ax = b, tolerance  $\epsilon > 0$  repeat

- 1. Compute the Newton step and decrement  $\Delta x_{\rm nt}$ ,  $\lambda(x)$
- 2. Stopping criterion. quit if  $\lambda^2/2 \le \epsilon$
- 3. Line search. Choose step size t by backtracking line search
- 4. Update.  $x := x + t\Delta x_{\rm nt}$

- feasible descent method:  $x^{(k)}$  feasible and  $f\left(x^{(k+1)}\right) < f\left(x^{(k)}\right)$
- affine invariant

### Newton's method and elimination

#### Newton's method for reduced problem

$$\text{minimize } \tilde{f}(z) = f(Fz + \hat{x})$$

- lacksquare  $z \in \mathbb{R}^{n-p}$  are variables,  $\hat{x}$  satisfies  $A\hat{x} = b$ , range of F is the nullspace of A
- Newton's method for  $\tilde{f}$  starts at  $z^{(0)}$ , generates iterates  $z^{(k)}$

#### relation to Newton's method with equality constraints

when starting at  $x^{(0)} = Fz^{(0)} + \hat{x}$ , iterates are

$$x^{(k)} = Fz^{(k)} + \hat{x}$$

hence no separate convergence analysis is needed

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# Newton step at infeasible points

Newton step  $\Delta x_{\mathrm{nt}}$  of f at infeasible x is given by the solution of

$$\begin{bmatrix} \nabla^2 f(x) & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \Delta x_{\rm nt} \\ w \end{bmatrix} = - \begin{bmatrix} \nabla f(x) \\ Ax - b \end{bmatrix}$$

#### interpretation

 $ightharpoonup \Delta x_{
m nt}$  equations follow from linearizing optimality conditions

$$\nabla f(x+v) + A^T w \approx \nabla f(x) + \nabla^2 f(x)v + A^T w = 0, \qquad A(x+v) = b$$

#### primal-dual interpretation

ightharpoonup write optimality condition as r(y) = 0 where

$$y = (x, \nu),$$
  $r(y) = (\nabla f(x) + A^T \nu, Ax - b)$ 

linearizing r(y) = 0 gives

$$r(y + \Delta y) \approx r(y) + Dr(y)\Delta y = 0$$

which is equivalent to

$$\begin{bmatrix} \nabla^2 f(x) & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \Delta x_{\rm nt} \\ \Delta \nu_{\rm nt} \end{bmatrix} = - \begin{bmatrix} \nabla f(x) + A^T \nu \\ Ax - b \end{bmatrix}$$

same as the above equation with  $w=
u+\Delta 
u_{
m nt}$ 

given starting point  $x\in {
m dom}\, f$ ,  $\nu$ , tolerance  $\epsilon>0$ ,  $\alpha\in (0,1/2)$ ,  $\beta\in (0,1)$  repeat

- 1. Compute primal and dual Newton steps  $\Delta x_{
  m nt}$ ,  $\Delta 
  u_{
  m nt}$
- 2. Backtracking line search on  $||r||_2$ .  $t \coloneqq 1$ . while  $||r(x + t\Delta x_{\rm nt}, \nu + t\Delta \nu_{\rm nt})||_2 > (1 \alpha t)||r(x, \nu)||_2$ ,  $t \coloneqq \beta t$
- 3. Update.  $x \coloneqq x + t\Delta x_{\rm nt}, \nu \coloneqq \nu + t\Delta \nu_{\rm nt}$

**until** 
$$Ax = b \text{ and } ||r(x, \nu)||_2 \le \epsilon$$

▶ not a descent method:  $f(x^{(k+1)}) > f(x^{(k)})$  is possible

 $\frac{\mathrm{d}}{\mathrm{d}t} \|r(y + t\Delta y)\|_2 \Big|_{t=0} = -\|r(y)\|_2$ 

 $\blacktriangleright$  directional derivative of  $\|r(y)\|_2$  in direction  $\Delta y = (\Delta x_{\rm nt}, \Delta \nu_{\rm nt})$  is