

## EQUALITY CONSTRAINED MINIMIZATION

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} \quad f(x) \quad \text{subject to} \quad c(x) = 0$$

where the **objective function**  $f : \mathbb{R}^n \longrightarrow \mathbb{R}$  and the **constraints**  $c : \mathbb{R}^n \longrightarrow \mathbb{R}^m$  ( $m \leq n$ )

- assume that  $f, c \in C^1$  (sometimes  $C^2$ ) and Lipschitz
- often in practice this assumption violated, but not necessary
- easily generalized to inequality constraints ... but may be better to use interior-point methods for these

## Part 5: SQP methods for equality constrained optimization

Nick Gould (RAL)

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} \quad f(x) \quad \text{subject to} \quad c(x) = 0$$

MSc course on nonlinear optimization

## OPTIMALITY AND NEWTON'S METHOD

**1st order optimality:**

$$g(x, y) \equiv g(x) - A^T(x)y = 0 \quad \text{and} \quad c(x) = 0$$

nonlinear system (linear in  $y$ )

$\implies$

use Newton's method to find a correction  $(s, w)$  to  $(x, y)$

$\implies$

$$\begin{pmatrix} H(x, y) & -A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ w \end{pmatrix} = - \begin{pmatrix} g(x, y) \\ c(x) \end{pmatrix}$$

unsymmetric:

$$\begin{pmatrix} H(x, y) & -A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ w \end{pmatrix} = - \begin{pmatrix} g(x, y) \\ c(x) \end{pmatrix}$$

or symmetric:

$$\begin{pmatrix} H(x, y) & A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ -w \end{pmatrix} = - \begin{pmatrix} g(x, y) \\ c(x) \end{pmatrix}$$

or (with  $y^+ = y + w$ ) unsymmetric:

$$\begin{pmatrix} H(x, y) & -A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ y^+ \end{pmatrix} = - \begin{pmatrix} g(x) \\ c(x) \end{pmatrix}$$

or symmetric:

$$\begin{pmatrix} H(x, y) & A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ -y^+ \end{pmatrix} = - \begin{pmatrix} g(x) \\ c(x) \end{pmatrix}$$

## DETAILS

- Often approximate with symmetric  $B \approx H(x, y) \implies$  e.g.

$$\begin{pmatrix} B & A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ -y^+ \end{pmatrix} = - \begin{pmatrix} g(x) \\ c(x) \end{pmatrix}$$

- solve system using

- unsymmetric (LU) factorization of  $\begin{pmatrix} B & -A^T(x) \\ A(x) & 0 \end{pmatrix}$

- symmetric (indefinite) factorization of  $\begin{pmatrix} B & A^T(x) \\ A(x) & 0 \end{pmatrix}$

- symmetric factorizations of  $B$  and the

Schur Complement  $A(x)B^{-1}A^T(x)$

- iterative method (GMRES(k), MINRES, CG within  $\mathcal{N}(A), \dots$ )

## SEQUENTIAL QUADRATIC PROGRAMMING - SQP

or **successive** quadratic programming

or **recursive** quadratic programming (RQP)

Given  $(x_0, y_0)$ , set  $k = 0$

Until “convergence” iterate:

Compute a suitable symmetric  $B_k$  using  $(x_k, y_k)$

Find

$$s_k = \arg \min_{s \in \mathbb{R}^n} g_k^T s + \frac{1}{2} s^T B_k s \text{ subject to } A_k s = -c_k$$

along with associated Lagrange multiplier estimates  $y_{k+1}$

Set  $x_{k+1} = x_k + s_k$  and increase  $k$  by 1

## AN ALTERNATIVE INTERPRETATION

**QP** : minimize  $g(x)^T s + \frac{1}{2} s^T B s$  subject to  $A(x)s = -c(x)$   
 $s \in \mathbb{R}^n$

- QP = **quadratic program**

- first-order model of constraints  $c(x + s)$

- second-order model of objective  $f(x + s) \dots$  but  $B$  includes curvature of constraints

solution to QP satisfies

$$\begin{pmatrix} B & A^T(x) \\ A(x) & 0 \end{pmatrix} \begin{pmatrix} s \\ -y^+ \end{pmatrix} = - \begin{pmatrix} g(x) \\ c(x) \end{pmatrix}$$

## ADVANTAGES

- simple

- fast

- quadratically convergent with  $B_k = H(x_k, y_k)$

- superlinearly convergent with good  $B_k \approx H(x_k, y_k)$

▷ don't actually need  $B_k \longrightarrow H(x_k, y_k)$

## PROBLEMS WITH PURE SQP

- how to choose  $B_k$ ?

- what if QP<sub>k</sub> is unbounded from below? and when?

- how do we globalize this iteration?

## QP SUB-PROBLEM

minimize  $g^T s + \frac{1}{2} s^T B s$  subject to  $As = -c$   
 $s \in \mathbb{R}^n$

- need constraints to be consistent
  - OK if  $A$  is full rank
- need  $B$  to be positive (semi-) definite when  $As = 0$

$\Longleftrightarrow$

$N^T B N$  positive (semi-) definite where the columns of  $N$  form a basis for  $\text{null}(A)$

$\Longleftrightarrow$

$$\begin{pmatrix} B & A^T(x) \\ A(x) & 0 \end{pmatrix}$$

(is non-singular and) has  $m - \nu$  eigenvalues

## LINESEARCH SQP METHODS

$s_k = \arg \min_{s \in \mathbb{R}^n} g_k^T s + \frac{1}{2} s^T B_k s$  subject to  $A_k s = -c_k$

Basic idea:

- Pick  $x_{k+1} = x_k + \alpha_k s_k$ , where
  - $\alpha_k$  is chosen so that

$$\Phi(x_k + \alpha_k s_k, p_k) \text{ “} < \text{” } \Phi(x_k, p_k)$$

- $\Phi(x, p)$  is a “suitable” merit function
- $p_k$  are parameters
- vital that  $s_k$  is a descent direction for  $\Phi(x, p_k)$  at  $x_k$
- normally require that  $B_k$  is positive definite

## SUITABLE MERIT FUNCTIONS. I

The **quadratic penalty function**:

$$\Phi(x, \mu) = f(x) + \frac{1}{2\mu} \|c(x)\|_2^2$$

**Theorem 5.1.** Suppose that  $B_k$  is positive definite, and that  $(s_k, y_{k+1})$  are the SQP search direction and its associated Lagrange multiplier estimates for the problem

minimize  $f(x)$  subject to  $c(x) = 0$   
 $x \in \mathbb{R}^n$

at  $x_k$ . Then if  $x_k$  is not a first-order critical point,  $s_k$  is a descent direction for the quadratic penalty function  $\Phi(x, \mu_k)$  at  $x_k$  whenever

$$\mu_k \leq \frac{\|c(x_k)\|_2}{\|y_{k+1}\|_2}$$

## PROOF OF THEOREM 5.1

SQP direction  $s_k$  and associated multiplier estimates  $y_{k+1}$  satisfy

$$B_k s_k - A_k^T y_{k+1} = -g_k \quad (1)$$

and

$$A_k s_k = -c_k. \quad (2)$$

$$(1) + (2) \implies s_k^T g_k = -s_k^T B_k s_k + s_k^T A_k^T y_{k+1} = -s_k^T B_k s_k - c_k^T y_{k+1} \quad (3)$$

$$(2) \implies \frac{1}{\mu_k} s_k^T A_k^T c_k = -\frac{\|c_k\|_2^2}{\mu_k}. \quad (4)$$

(3) + (4), the positive definiteness of  $B_k$ , the Cauchy-Schwarz inequality, the required bound on  $\mu_k$ , and  $s_k \neq 0$  if  $x_k$  is not critical  $\implies$

$$\begin{aligned} s_k^T \nabla_x \Phi(x_k) &= s_k^T \left( g_k + \frac{1}{\mu_k} A_k^T c_k \right) = -s_k^T B_k s_k - c_k^T y_{k+1} - \frac{\|c_k\|_2^2}{\mu_k} \\ &< -\|c_k\|_2 \left( \frac{\|c_k\|_2}{\mu_k} - \|y_{k+1}\|_2 \right) \leq 0 \end{aligned}$$

## NON-DIFFERENTIABLE EXACT PENALTIES

The **non-differentiable exact penalty function**:

$$\Phi(x, \rho) = f(x) + \rho \|c(x)\|$$

for any norm  $\|\cdot\|$  and scalar  $\rho > 0$ .

**Theorem 5.2.** Suppose that  $f, c \in C^2$ , and that  $x_*$  is an isolated local minimizer of  $f(x)$  subject to  $c(x) = 0$ , with corresponding Lagrange multipliers  $y_*$ . Then  $x_*$  is also an isolated local minimizer of  $\Phi(x, \rho)$  provided that

$$\rho > \|y_*\|_D,$$

where the **dual norm**

$$\|y\|_D = \sup_{x \neq 0} \frac{y^T x}{\|x\|}.$$

## SUITABLE MERIT FUNCTIONS. II

The non-differentiable exact penalty function:

$$\Phi(x, \rho) = f(x) + \rho \|c(x)\|$$

for any norm  $\|\cdot\|$  (with dual norm  $\|\cdot\|_D$ ) and scalar  $\rho > 0$ .

**Theorem 5.3.** Suppose that  $B_k$  is positive definite, and that  $(s_k, y_{k+1})$  are the SQP search direction and its associated Lagrange multiplier estimates for the problem

$$\text{minimize } f(x) \text{ subject to } c(x) = 0 \\ x \in \mathbb{R}^n$$

at  $x_k$ . Then if  $x_k$  is not a first-order critical point,  $s_k$  is a descent direction for the non-differentiable penalty function  $\Phi(x, \rho_k)$  at  $x_k$  whenever  $\rho_k \geq \|y_{k+1}\|_D$

## PROOF OF THEOREM 5.3

Taylor's theorem applied to  $f$  and  $c + (2) \implies$  (for small  $\alpha$ )

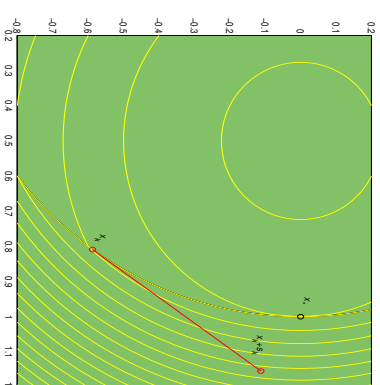
$$\begin{aligned} \Phi(x_k + \alpha s_k, \rho_k) - \Phi(x_k, \rho_k) &= \alpha s_k^T g_k + \rho_k \left( \|c_k + \alpha A_k s_k\| - \|c_k\| \right) + O(\alpha^2) \\ &= \alpha s_k^T g_k + \rho_k \left( \|(1 - \alpha) c_k\| - \|c_k\| \right) + O(\alpha^2) \\ &= \alpha \left( s_k^T g_k - \rho_k \|c_k\| \right) + O(\alpha^2) \end{aligned}$$

+ (3), the positive definiteness of  $B_k$ , the Hölder inequality, and  $s_k \neq 0$  if  $x_k$  is not critical  $\implies$

$$\begin{aligned} \Phi(x_k + \alpha s_k, \rho_k) - \Phi(x_k, \rho_k) &= -\alpha \left( s_k^T B_k s_k + c_k^T y_{k+1} + \rho_k \|c_k\| \right) + O(\alpha^2) \\ &< -\alpha \left( -\|c_k\| \|y_{k+1}\|_D + \rho_k \|c_k\| \right) + O(\alpha^2) \\ &= -\alpha \|c_k\| \left( \rho_k - \|y_{k+1}\|_D \right) + O(\alpha^2) < 0 \end{aligned}$$

because of the required bound on  $\rho_k$ , for sufficiently small  $\alpha$ . Hence sufficiently small steps along  $s_k$  from non-critical  $x_k$  reduce  $\Phi(x, \rho_k)$ .

## THE MARATOS EFFECT



$\ell_1$  non-differentiable exact penalty function ( $\rho = 1$ ):  
 $f(x) = 2(x_1^2 + x_2^2 - 1) - x_1$   
and  $c(x) = x_1^2 + x_2^2 - 1$   
solution:  $x_* = (1, 0)$ ,  $y_* = \frac{3}{2}$

**Maratos effect:** merit function may prevent acceptance of the SQP step arbitrarily close to  $x_*$   $\implies$  slow convergence

## AVOIDING THE MARATOS EFFECT

The Maratos effect occurs because the curvature of the constraints is not adequately represented by linearization in the SQP model:

$$c(x_k + s_k) = O(\|s_k\|^2)$$

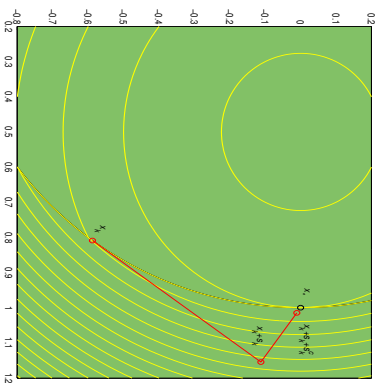
$\Rightarrow$  need to correct for this curvature

$\Rightarrow$  use a **second-order correction** from  $x_k + s_k$ :

$$c(x_k + s_k + s_k^c) = o(\|s_k\|^2)$$

also do not want to destroy potential for fast convergence  $\Rightarrow$

$$s_k^c = o(s_k)$$



$l_1$  non-differentiable exact  
penalty function ( $\rho = 1$ ):  
 $f(x) = 2(x_1^2 + x_2^2 - 1) - x_1$   
and  $c(x) = x_1^2 + x_2^2 - 1$   
solution:  $x_* = (1, 0)$ ,  $y_* = \frac{3}{2}$

- (very) fast convergence
- $x_k + s_k + s_k^c$  reduces  $\Phi \Rightarrow$  global convergence

## POPULAR 2ND-ORDER CORRECTIONS

- minimum norm solution to  $c(x_k + s_k) + A(x_k + s_k)s_k^c = 0$

$$\begin{pmatrix} I & A^T(x_k + s_k) \\ A(x_k + s_k) & 0 \end{pmatrix} \begin{pmatrix} s_k^c \\ -y_{k+1}^c \end{pmatrix} = - \begin{pmatrix} 0 \\ c(x_k + s_k) \end{pmatrix}$$

- minimum norm solution to  $c(x_k + s_k) + A(x_k)s_k^c = 0$

$$\begin{pmatrix} I & A^T(x_k) \\ A(x_k) & 0 \end{pmatrix} \begin{pmatrix} s_k^c \\ -y_{k+1}^c \end{pmatrix} = - \begin{pmatrix} 0 \\ c(x_k + s_k) \end{pmatrix}$$

- another SQP step from  $x_k + s_k$

$$\begin{pmatrix} H(x_k + s_k, y_k^+) & A^T(x_k + s_k) \\ A(x_k + s_k) & 0 \end{pmatrix} \begin{pmatrix} s_k^c \\ -y_{k+1}^c \end{pmatrix} = - \begin{pmatrix} g(x_k + s_k) \\ c(x_k + s_k) \end{pmatrix}$$

- etc., etc.

## TRUST-REGION SQP METHODS

Obvious trust-region approach:

$$s_k = \arg \min_{s \in \mathbb{R}^n} g_k^T s + \frac{1}{2} s^T B_k s \text{ subject to } A_k s = -c_k \text{ and } \|s\| \leq \Delta_k$$

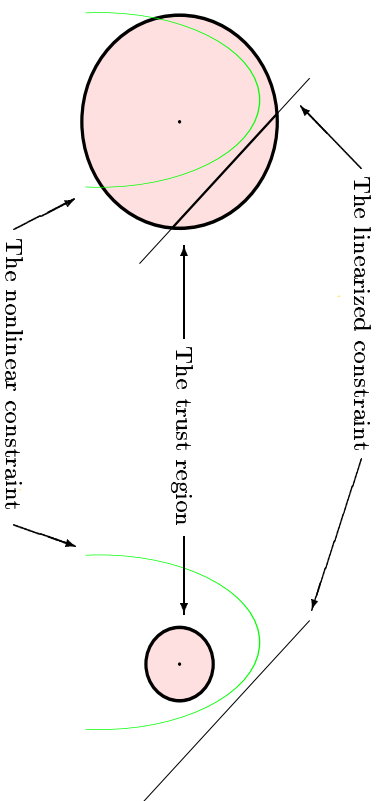
- do not require that  $B_k$  be positive definite  
 $\Rightarrow$  can use  $B_k = H(x_k, y_k)$
- if  $\Delta_k < \Delta^{\text{crit}}$  where

$$\Delta^{\text{crit}} \stackrel{\text{def}}{=} \min \|s\| \text{ subject to } A_k s = -c_k$$

$\Rightarrow$  **no solution to trust-region subproblem**

$\Rightarrow$  simple trust-region approach to SQP is flawed if  $c_k \neq 0 \Rightarrow$  need to consider alternatives

## INFEASIBILITY OF THE SQP STEP



## THE $S\ell_p$ QP METHOD

Try to minimize the  $\ell_p$  (exact) penalty function

$$\Phi(x, \rho) = f(x) + \rho \|c(x)\|_p$$

for sufficiently large  $\rho > 0$  and some  $\ell_p$  norm ( $1 \leq p \leq \infty$ ), using a trust-region approach

Suitable model problem:  $\ell_p$  QP

$$\underset{s \in \mathbb{R}^n}{\text{minimize}} \quad (f_k +) \quad g_k^T s + \frac{1}{2} s^T B_k s + \rho \|c_k + A_k s\|_p \quad \text{subject to} \quad \|s\| \leq \Delta_k$$

- model problem always consistent
- when  $\rho$  and  $\Delta_k$  are large enough, model minimizer = SQP direction
- when the norms are polyhedral (e.g.,  $\ell_1$  or  $\ell_\infty$  norms),  $\ell_p$  QP is equivalent to a quadratic program ...

## ALTERNATIVES

- the  $S\ell_p$  QP method of Fletcher
- composite step SQP methods
  - ◊ constraint relaxation (Yardi)
  - ◊ constraint reduction (Byrd–Omojokun)
  - ◊ constraint lumping (Celis–Dennis–Tapia)
- the filter-SQP approach of Fletcher and Leyffer

## THE $\ell_1$ QP SUBPROBLEM

$\ell_1$  QP model problem with an  $\ell_\infty$  trust region

$$\underset{s \in \mathbb{R}^n}{\text{minimize}} \quad g_k^T s + \frac{1}{2} s^T B_k s + \rho \|c_k + A_k s\|_1 \quad \text{subject to} \quad \|s\|_\infty \leq \Delta_k$$

But

$$c_k + A_k s = u - v, \quad \text{where} \quad (u, v) \geq 0$$

$\Rightarrow \ell_1$  QP equivalent to quadratic program (QP):

$$\begin{aligned} &\underset{s \in \mathbb{R}^n, u, v \in \mathbb{R}^m}{\text{minimize}} && g_k^T s + \frac{1}{2} s^T B_k s + \rho (e^T u + e^T v) \\ &\text{subject to} && A_k s - u + v = -c_k \\ &&& u \geq 0, \quad v \geq 0 \\ &&& \text{and} \quad -\Delta_k e \leq s \leq \Delta_k e \end{aligned}$$

- good methods for solving QP
- can exploit structure of  $u$  and  $v$  variables

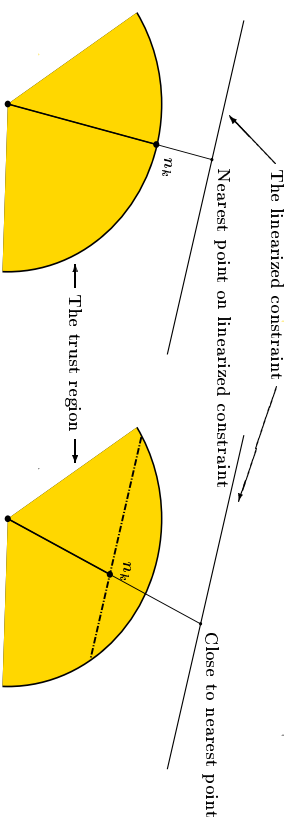
## PRACTICAL $S\ell_1QP$ METHODS

- Cauchy point requires solution to  $\ell_1LP$  model:

$$\underset{s \in \mathbb{R}^n}{\text{minimize}} \quad g_k^T s + \rho \|c_k + A_k s\|_1 \quad \text{subject to} \quad \|s\|_\infty \leq \Delta_k$$

- approximate solutions to both  $\ell_1LP$  and  $\ell_1QP$  subproblems suffice
- need to adjust  $\rho$  as method progresses
- easy to generalize to inequality constraints
- globally convergent, but needs second-order correction for fast asymptotic convergence
- if  $c(x) = 0$  are inconsistent, converges to (locally) least value of infeasibility  $\|c(x)\|$

## NORMAL AND TANGENTIAL STEPS



Points on dotted line are all potential tangential steps

## COMPOSITE-STEP METHODS

**Aim:** find **composite step**

$$s_k = n_k + t_k$$

where

the **normal step**  $n_k$  moves towards feasibility of the linearized constraints (within the trust region)

$$\|A_k n_k + c_k\| < \|c_k\|$$

(model objective may get worse)

the **tangential step**  $t_k$  reduces the model objective function (within the trust-region) without sacrificing feasibility obtained from  $n_k$

$$A_k(n_k + t_k) = A_k n_k \implies A_k t_k = 0$$

## CONSTRAINT RELAXATION — VARDI

**normal step:** relax

$$A_k s = -c_k \quad \text{and} \quad \|s\| \leq \Delta_k$$

to

$$A_k n = -\sigma_k c_k \quad \text{and} \quad \|n\| \leq \Delta_k$$

where  $\sigma_k \in [0, 1]$  is small enough so that there is a feasible  $n_k$

**tangential step:**

$$(\text{approximate}) \arg \min_{t \in \mathbb{R}^n} (g_k + B_k n_k)^T t + \frac{1}{2} t^T B_k t$$

$$\text{subject to} \quad A_k t = 0 \quad \text{and} \quad \|n_k + t\| \leq \Delta_k$$

Snags:

- choice of  $\sigma_k$
- incompatible constraints

## CONSTRAINT REDUCTION — BYRD-OMOJOKUN

**normal step:** replace

$$A_k s = -c_k \quad \text{and} \quad \|s\| \leq \Delta_k$$

by

approximately minimize  $\|A_k n + c_k\|$  subject to  $\|n\| \leq \Delta_k$

**tangential step:** as in Vardi

- use conjugate gradients to solve both subproblems  
 $\implies$  Cauchy points in both cases
- globally convergent using  $\ell_2$  merit function
- basis of successful **KNITRO** package

## FILTER METHODS — FLETCHER AND LEYFFER

Rationale:

- trust-region and linearized constraints compatible if  $c_k$  is small enough so long as  $c(x) = 0$  is compatible  
 $\implies$  if trust-region subproblem incompatible, simply move closer to constraints
- merit functions depend on arbitrary parameters  
 $\implies$  use a different mechanism to measure progress

Let  $\theta = \|c(x)\|$

A **filter** is a set of pairs  $\{(\theta_k, f_k)\}$  such that no member dominates another, i.e., it does not happen that

$$\theta_i < \theta_j \quad \text{and} \quad f_i < f_j$$

for any pair of filter points  $i \neq j$

## CONSTRAINT LUMPING — CELIS-DENNIS-TAPIA

**normal step:** replace

$$A_k s = -c_k \quad \text{and} \quad \|s\| \leq \Delta_k$$

by

$$\|A_k n + c_k\| \leq \sigma_k \quad \text{and} \quad \|n\| \leq \Delta_k$$

where  $\sigma_k \in [0, \|c_k\|]$  is large enough so that there is a feasible  $n_k$

**tangential step:**

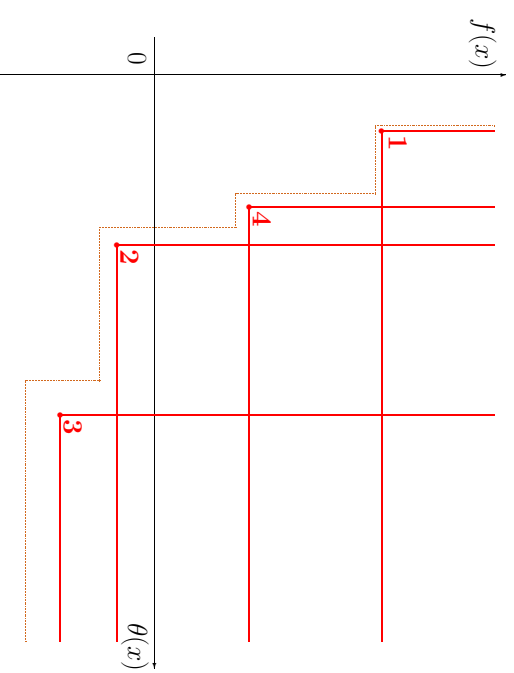
(approximate)  $\arg \min_{t \in \mathbb{R}^n} (g_k + B_k n_k)^T t + \frac{1}{2} t^T B_k t$

subject to  $\|A_k t + A_k n_k + c_k\| \leq \sigma_k$  and  $\|t + n_k\| \leq \Delta_k$

Snags:

- choice of  $\sigma_k$
- tangential subproblem is (NP?) hard

## A FILTER WITH FOUR ENTRIES





## BASIC FILTER METHOD

- if possible find

$$s_k = \arg \min_{s \in \mathbb{R}^n} g_k^T s + \frac{1}{2} s^T B_k s \text{ subject to } A_k s = -c_k \text{ and } \|s\| \leq \Delta_k$$

- otherwise, find  $s_k$ :

$$\theta(x_k + s_k) \text{ “} < \text{” } \theta_i \text{ for all } i \leq k$$

- if  $x_k + s_k$  is “acceptable” for the filter, set  $x_{k+1} = x_k + s_k$  and possibly increase  $\Delta_k$  and “prune” filter
- otherwise reduce  $\Delta_k$  and try again

In practice, far more complicated than this!