

Recent Advances in Nonlinear Optimization

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New Applications, New Algorithms, New Software

The general nonlinear programming formulation covers many interesting applications

Why discuss algorithms?

$$\begin{array}{ll} \min_x & f(x) \\ \text{s.t.} & h_i(x) = 0, i \in E \\ & g_i(x) \geq 0, i \in I \end{array}$$

Active research area; significant algorithmic advances

New applications

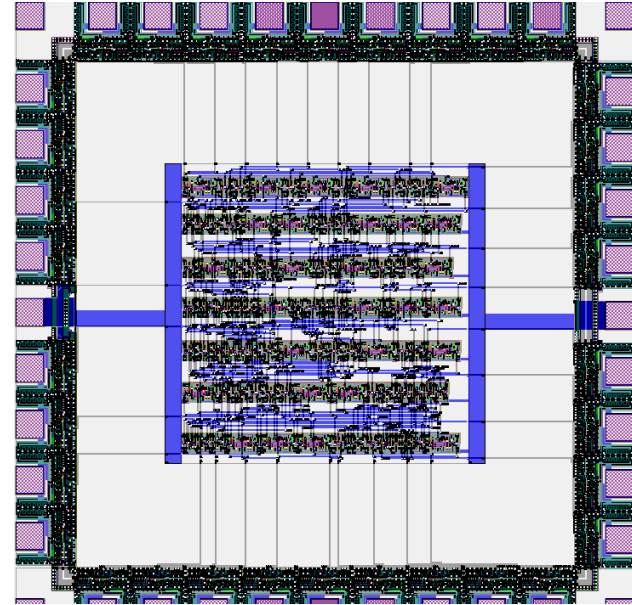
Solve larger problems, more difficult (degenerate), noisy

Interior-point, Active-set: dominate; Penalty approaches

Outline

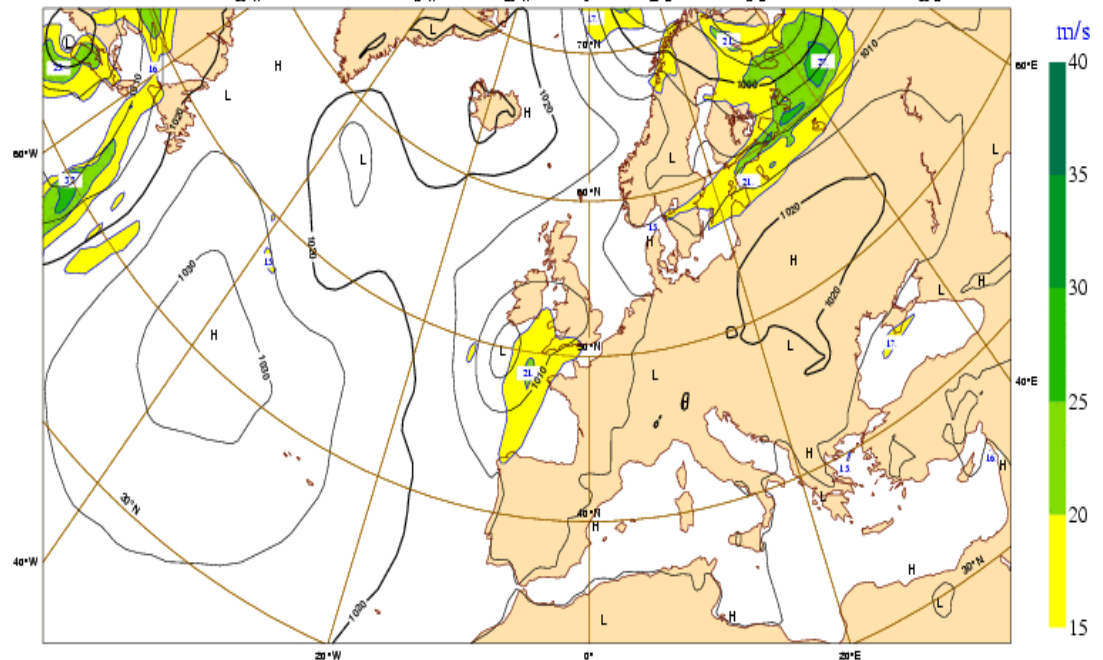
- Applications
- Software (KNITRO)
- New Optimization Methods
- Mathematical Foundations

Problem 1: Circuit simulation. Given a design of a computer chip (integrated circuit) find a way to resize elements to achieve optimal performance (power consumption)
Hundreds of thousands of elements. **INTEL**



Problem 2: Guess initial conditions of the atmosphere at 1 million locations so that predicted fluid flow matches observations during a 12-hour period. **ECMWF**

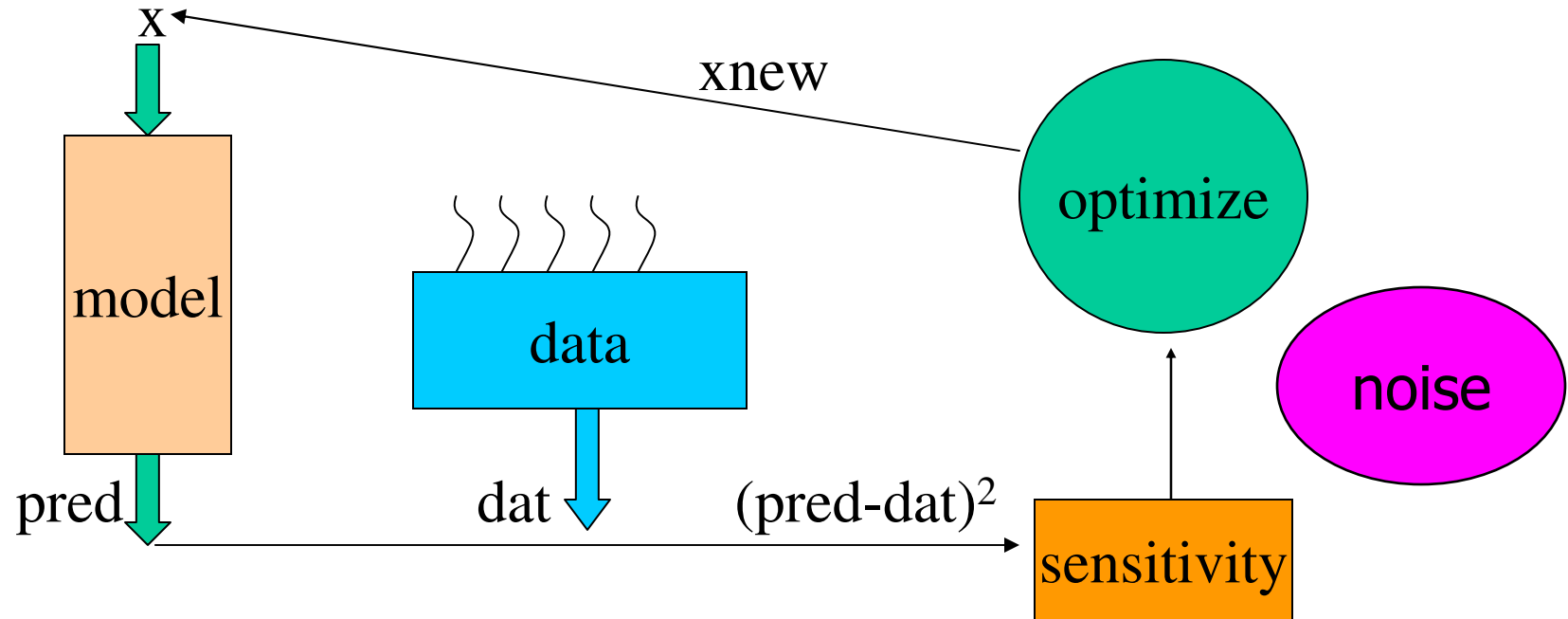
Monday 23 May 2005 12UTC ©ECMWF Forecast t+096 VT: Friday 27 May 2005 12UTC
Surface: Mean sea level pressure / 850-hPa wind speed



2 Cases: prototypical of many present/future applications

Mathematical model (circuit simulation)

Control it to produce the desired results



Cannot afford many attempts (20)

Lower resolution models

Some current research areas

- Larger and larger problems
- Noisy functions
- Integer/continuous variables
- Games (Nash, Stackelberg,...)
- Real time (warm starts)
- **Degenerate problems** (deficient geometry)

General NLP techniques preferred over specialized algorithms

Challenging geometry of feasible region

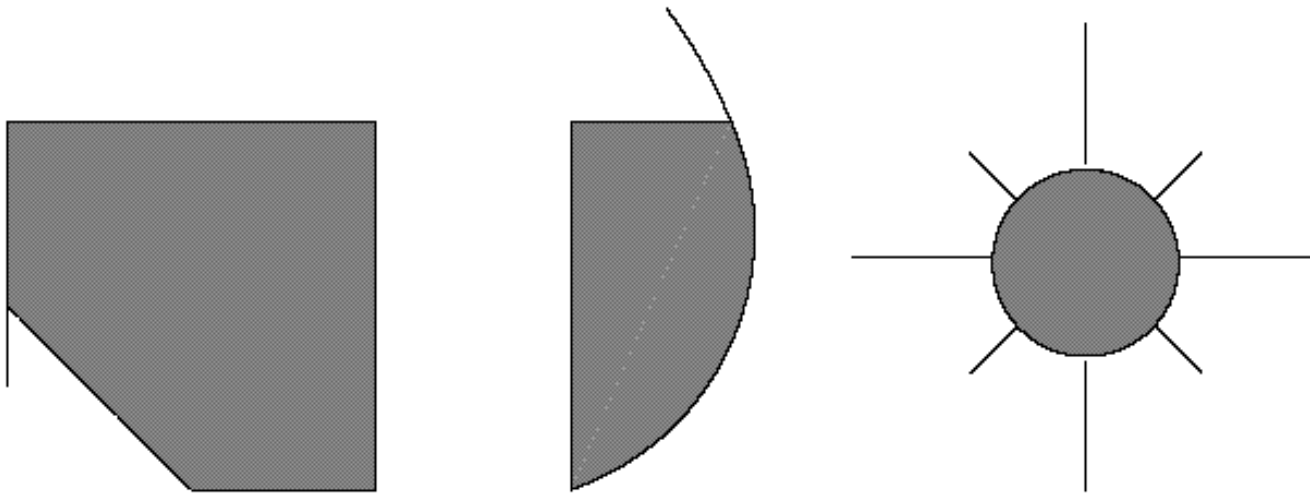


Figure 9.1: Feasible regions for switch-off problems.

Mathematical Difficulties

Many new areas of application are modeled as:

$$\min \quad f(x)$$

$$\text{s.t.} \quad g(x) \geq 0$$

$$h(x) = 0$$

$$\left. \begin{array}{l} x_1 x_2 = 0 \\ x_1, x_2 \geq 0 \end{array} \right\} \longrightarrow \text{these constraints cause} \\ \text{regularity to be lost}$$

where does
this occur?
Optimality!

$$g(x)\lambda = 0$$

$$g(x) \geq 0, \quad \lambda \geq 0$$

Moral Hazard



Principal

Principal: Determines compensation scheme;
can only observe outcome (not action)

c_1, c_2, \dots, c_N

β

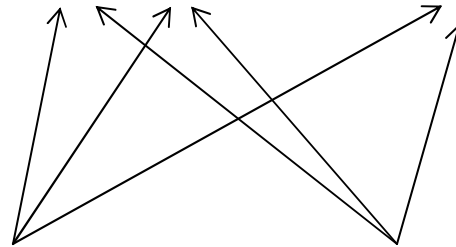
Compensation



q_1, q_2, \dots, q_N

β

Outcome



Action \rightarrow

a_1, \dots, a_M

Agent: Chooses action a_j ; outcome q_i occurs
With probability $p(q_i | a_j)$



Agent

Moral Hazard (cont...)

$$\text{Maximize}_{c,a} \quad W(c,a) = \sum_{i=1}^N p(q_i | a) w(q_i - c_i)$$

$$\text{Subject to} \quad U(c,a) = \sum_{i=1}^N p(q_i | a) u(c_i, a) \geq U_0$$

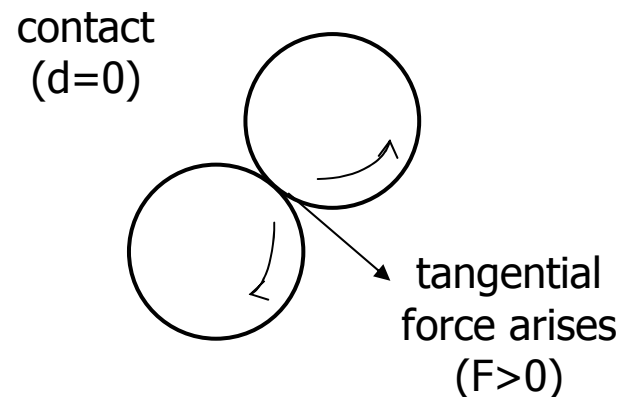
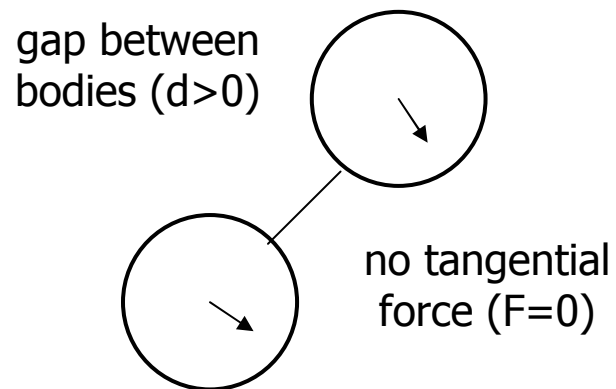
$$a \in \arg \max \{ U(c,a) : a \in \{a_1, \dots, a_M\} \}$$

$$c = (c_1, \dots, c_N) \in \mathfrak{R}_+^N$$

If a **mixed strategy** profile $(\delta_1, \dots, \delta_M)$ is introduced for the **agent's action choice** (a_1, \dots, a_M) , this can be **reformulated as an MPEC** by substituting the lower level problem by its optimality conditions (Judd-Su)

Frictional contact

- Tangential force only exists when bodies are in contact



Optimal control (trajectory) of robots with contact

Theoretical/Algorithmic Limits

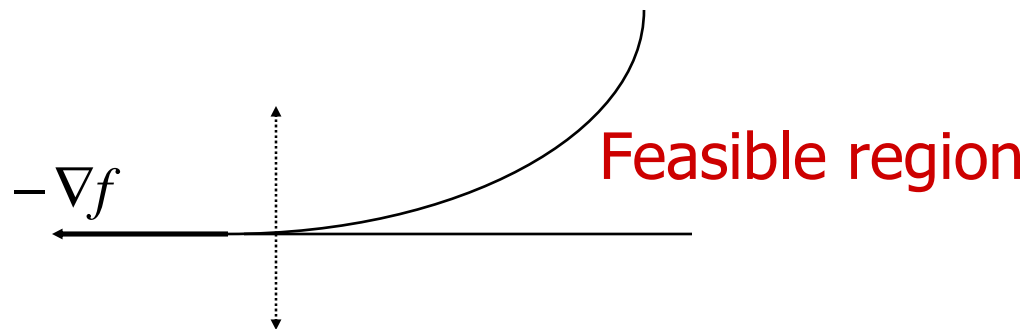
$$\min f(x)$$

$$s.t \quad g(x) \geq 0$$

$$\nabla f(x) - \nabla g(x)\lambda = 0$$

$$g(x) \geq 0 \quad \lambda g(x) = 0$$

$$\lambda \geq 0$$



- Algorithms based on KKT conditions
- What to do? Perturbation

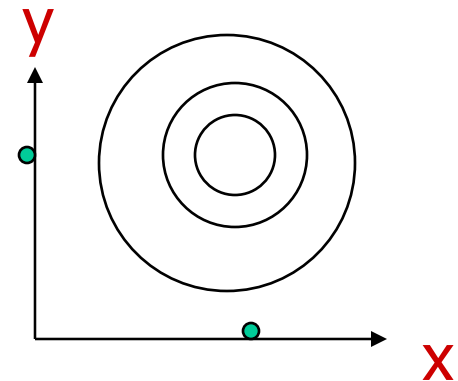
Equilibrium (Complementarity) Constraints

$$\begin{aligned} \min \quad & (x - 1)^2 + (y - 1)^2 \\ & x \geq 0, \quad y \geq 0 \\ & xy = 0 \end{aligned}$$

(disjunction)

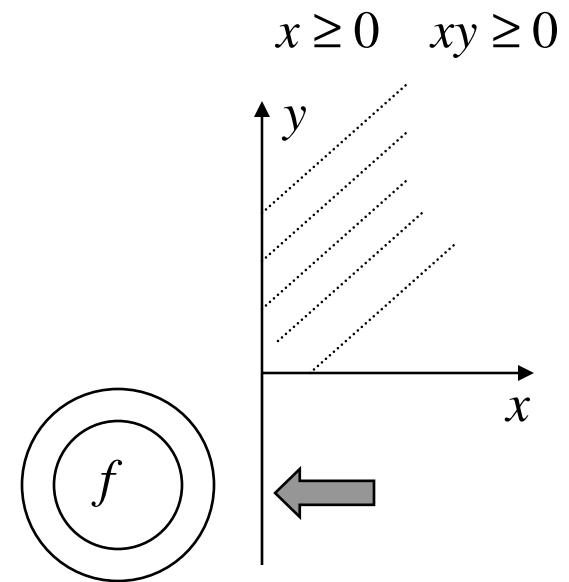
Deficient geometry:

Minimal conditions for
KKT conditions not satisfied



$$\begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix} \begin{pmatrix} y \\ x \end{pmatrix}$$

- Moral Hazard (Judd-Lin)
- Switch-off constraints
- Interior-point methods fail
 - Intrinsic difficulty
- Active-set methods may or may not work



One Solution: L1-Penalty

L1-penalty relaxation of optimization problem with equilibrium constraints

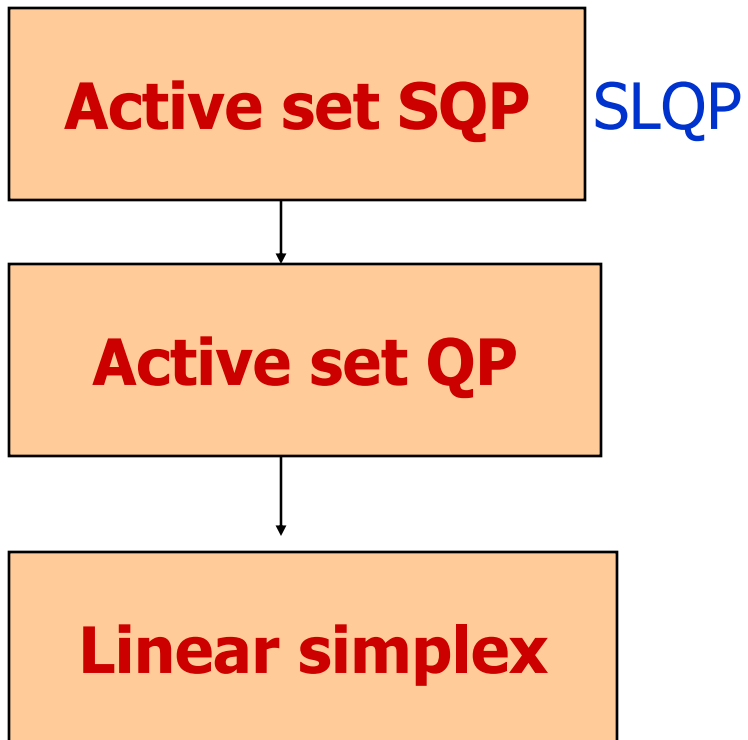
$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & g(x) \geq 0 \\ & h(x) = 0 \\ & x_1 x_2 = 0 \\ & x_1, x_2 \geq 0 \end{array} \quad \longrightarrow \quad \begin{array}{ll} \min & f(x) + \pi x_1^T x_2 \\ \text{s.t.} & g(x) \geq 0 \\ & h(x) = 0 \\ & x_1 \geq 0, x_2 \geq 0 \end{array}$$

Penalty problem always regular
General technique?

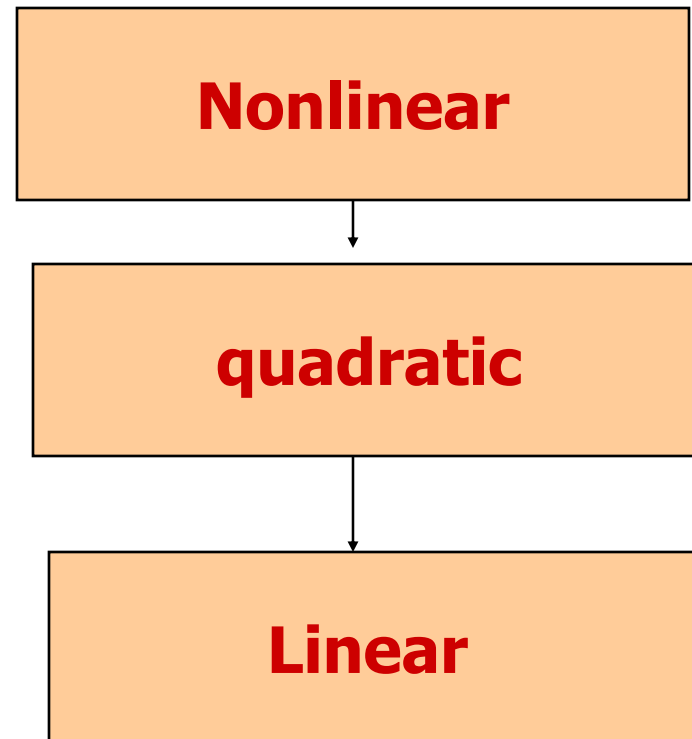
Algorithms and Software

50 years of algorithmic work

Active set



Interior (barrier)



KNITRO 5.0

Byrd, Waltz, N.
2006

An integrated
package

Interior

Active-Set

SLQP

Iterative

Direct

Iterative

crossover

Projected CG

Augmented Sys

LP-Projected CG

Downward compatibility, Integration

- Applicable and robust for:
 - Unconstrained
 - Bound constrained
 - Equality constrained
 - Nonlinear systems of equations
 - Nonlinear least squares
 - Quadratic programming
 - Linear programming (in progress)
- Multiple derivative options
 - No derivatives
 - First derivatives only
 - First and second (others)

New:
penalty formulation
for degenerate
constraints

Penalty Methods

- History
- Recent advances

Cutting-edge??

Gould, Orban, Toint 03

Fletcher and Chin 03

Chen and Goldfarb 04

Benson, Vanderbei, Shanno 04

Leyffer, Lopez, N. 04

Anitescu, 2000, 2004

Scholtes 2001

Hu and Ralph, 2002

Benson, Shanno 2005

One Solution: L1-Penalty

L1-penalty relaxation of optimization problem with equilibrium constraints

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & g(x) \geq 0 \\ & h(x) = 0 \\ & x_1 x_2 = 0 \\ & x_1, x_2 \geq 0 \end{array} \quad \longrightarrow \quad \begin{array}{ll} \min & f(x) + \pi x_1^T x_2 \\ \text{s.t.} & g(x) \geq 0 \\ & h(x) = 0 \\ & x_1 \geq 0, x_2 \geq 0 \end{array}$$

Penalty problem always regular
General technique?

Theoretical Results

Algorithms

Solns of penalty problem \rightarrow problem solutions Various stationarity concepts

Scholtes, Ralph, Animescu, Pang, Luo

Active set methods

Fletcher-Leyffer, Scholtes, Ralph- Zhu, Animescu

Relaxation (non-penalty):

Friedlander-DeMiguel-Scholtes

Interior-Point methods

Biegler-Ragunathan, Leyffer-Lopez-N, Vanderbei-Shanno

Classical Unconstrained Formulation

Courant 50s, Fiacco-McCormick 60s

$$\min_x f(x)$$

$$\text{s.t. } h_i(x) = 0,$$

$$g_i(x) \geq 0,$$

$$\min_x \varphi_\nu(x) = f(x) + \nu \|h(x)\|_2^2 + \nu \|g(x)^-\|_2^2$$

$$g(x)^- = \max\{0, -g(x)\}$$

Weaknesses:

- Complicating constraints;
- Infinite family of problems, $\nu \rightarrow \infty$
- Ill-conditioning: delicate solution. Need scale invariant method, warm start

Not competitive!

Nonsmooth penalty, L-1

$$\varphi_{\nu}(x) = f(x) + \nu \|h(x)\|_1 + \nu \|g(x)^-\|_1$$

- One minimization for fixed ν
- Critical points of ϕ are KKT points or infeasible stationary points
- *Almost* parameter free
- Non-smooth, difficult minimization
 - Bundle methods, special techniques?
- Choice of penalty parameter?

Breakthrough: (Fletcher, 1980s)

As in unconstrained minimization:

Create a **model** of penalty function

Compute steps d by minimizing the model

$$q(d) = \nabla f^T d + \frac{1}{2} d^T W d + \nu \|h + \nabla h^T d\|_1 + \nu \| [g + \nabla g^T d]^+ \|_1$$

Non-smooth, but can be reformulated as smooth problem

Note: linear/quadratic -- not quadratic/quadratic

$$q(d) = \nabla f^T d + d^T W d + \nu \|h + \nabla h^T d\|_1 + \nu \| [g + \nabla g^T d]^+ \|_1$$

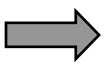
Remove non-smoothness: **Linear/quadratic** model

Quadratic program


$$\begin{array}{ll} \min & \nabla f^T d + d^T W d + \nu(u + w + t) \\ \text{s.t.} & h + \nabla h^T d = u - w \\ & g + \nabla g^T d \geq -t, \quad u, w, t \geq 0 \\ & \|d\| \leq \Delta \quad (\text{possibly}) \end{array}$$

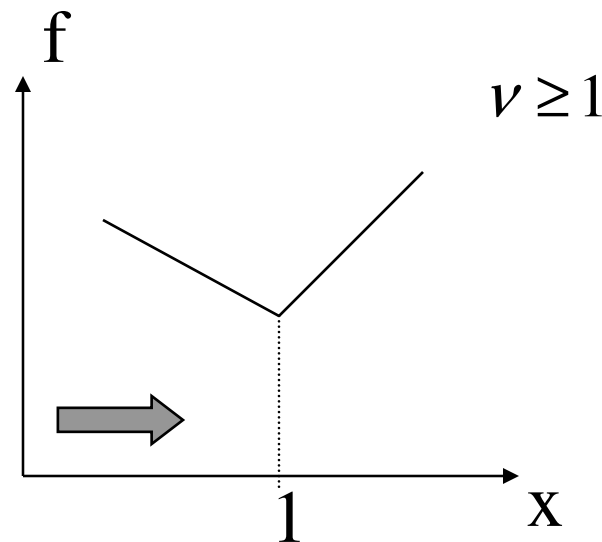
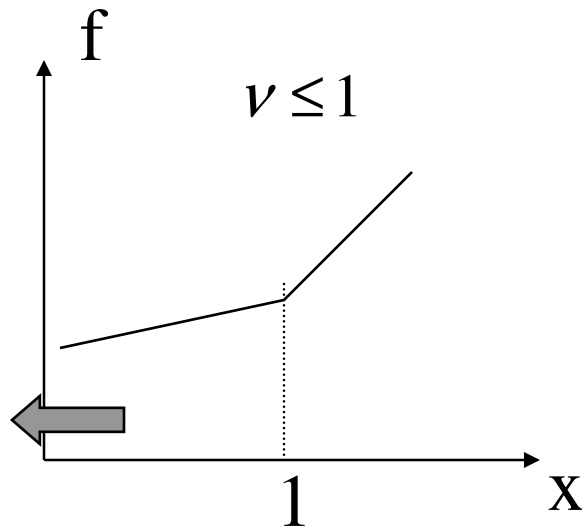
Similar to SQP \Rightarrow SL₁QP *Fletcher*

How is the penalty parameter chosen?

Choose ν_0 and starting point x_0^s
For $k=0,1,\dots$
 Solve penalty problem (linearly cons)
 If $\|\text{feasibility}\| < 10^{-6}$  Stop
 Else
 Choose new penalty $\nu_{k+1} > \nu_k$
 Choose new starting point x_{k+1}^s
End

ADLITTLE LP: Fletcher 1992

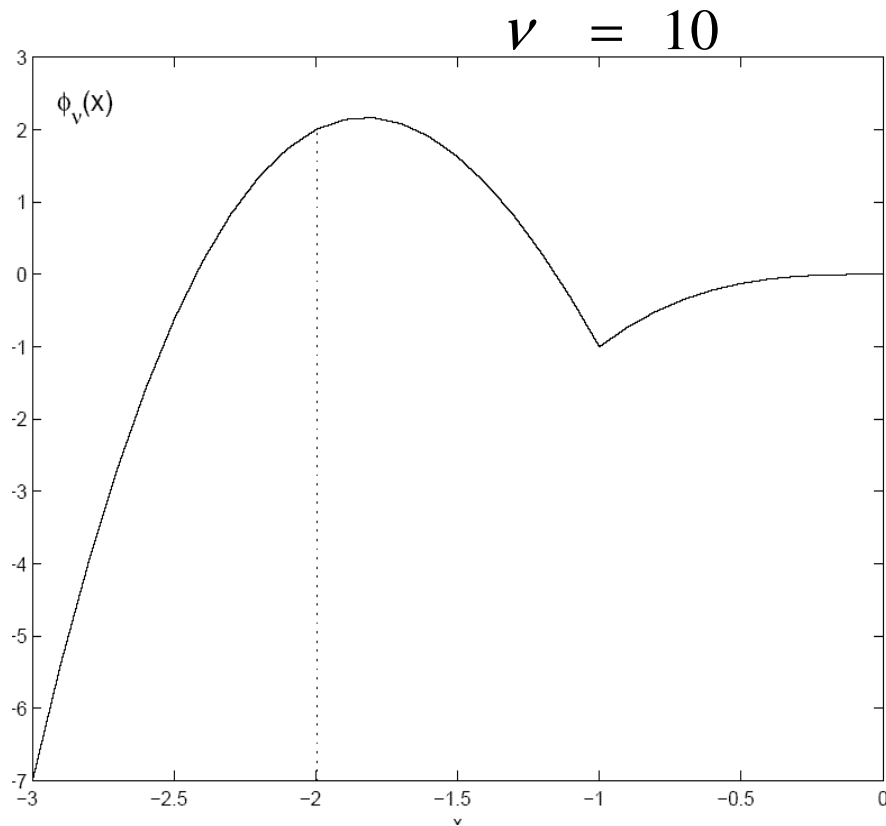
- Want ν small to avoid ill-conditioning
- It must be greater than unknown threshold (10^5)
- Hope: if ν is less than threshold, penalty problem infeasible; alerted to increase it
- If ν is about below $10^5/3$:
 - Penalty problem is unbounded
 - Inefficiencies
- Abandon penalty functions  filters



$$\boxed{\min x \quad \text{s.t.} \quad x \geq 1} \Rightarrow \min x + v \max(0, 1-x)$$

Can you trust your surrogate....? Consider $x=1/2$

*Only if the improvement in feasibility (to first order) is comparable to the **best** possible improvement*



$$\min x^3 \quad x \geq -1$$

$x^* = -1$ is a local minimizer of ϕ
if $\nu > 3$.

But ϕ is unbounded as
 $x \rightarrow -\infty$

For any value of ν there is
A starting point x_0 s.t. there is no
Decreasing path from x_0
To x^*

This example shows that it is not possible to prescribe in advance a value of ν that is adequate to every iteration

- Unconstrained minimization: we control Newton step so that it decreases the objective to first order (descent direction)

$$(\nabla^2 f) p = -\nabla f \quad \text{pos. def. or trust region}$$

- Similar goal is desirable with respect to the constraints, for constrained optimization...
- Generalize concept to feasibility:
 - Not immediate, requires **computation!**
 - Implementation in each context
 - It is not a switch but an **integral** part of the iteration

A Dynamic Strategy For Selecting the Penalty Parameter

Context: Successive Quadratic Programming
Method (Also: Knitro/Active)

$$\begin{array}{ll}
 \text{QP} & \min \quad \nabla f^T d + \frac{1}{2} d^T W d \\
 & \text{s.t.} \quad \left. \begin{array}{l} h + \nabla h^T d = 0 \\ g + \nabla g^T d \geq 0 \end{array} \right\} \Rightarrow \text{Incompatible?} \\
 & \quad \quad \quad \|d\|_\infty \leq \Delta
 \end{array}$$

Relaxation of quadratic program

$$\begin{array}{ll}
 \text{QP}' & \min \nabla f^T d + \nu(u + w + t) \\
 & \text{s.t.} \quad h + \nabla h^T d = u - w \quad \text{Always feasible} \\
 & \quad \quad g + \nabla g^T d \geq -t, \quad u, w, t \geq 0 \\
 & \quad \quad \|d\|_\infty \leq \Delta
 \end{array}$$

Motivation for new strategy

$$\begin{aligned}
 & \min \nabla f^T d + \frac{1}{2} d^T W d + \nu(u + w + t) \\
 \text{s.t.} \quad & h + \nabla h^T d = u - w \\
 & g + \nabla g^T d \geq -t, \quad u, w, t \geq 0 \\
 & \|d\|_\infty \leq \Delta
 \end{aligned}$$

Idea: if u, w, t
 can be zero, do so.
 Choose ν accordingly

$$\begin{aligned}
 & \min (u + w + t) \\
 \text{s.t.} \quad & h + \nabla h^T d = u - w \\
 & g + \nabla g^T d \geq -t, \\
 & u, w, t \geq 0 \\
 & \|d\|_\infty \leq \Delta
 \end{aligned}$$

Otherwise solve
 Feasibility problem
 With $\nu = \infty$
 A linear program

Adaptive Strategy :

ν : given

Compute $d(\nu)$

If $u=v=t=0$

accept ν

Else

$\nu = \infty$ compute d^∞

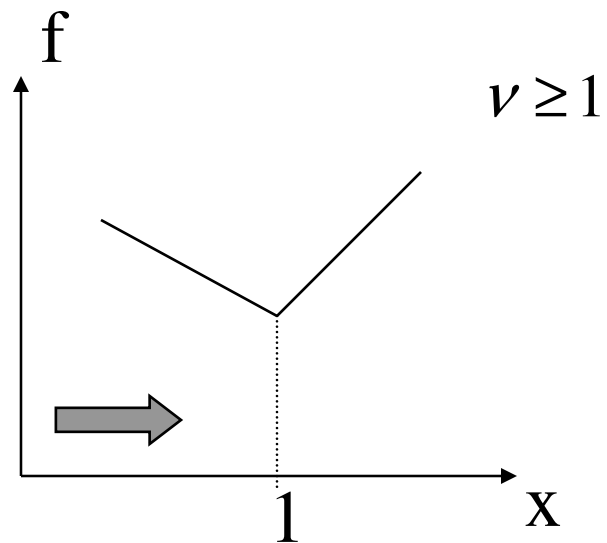
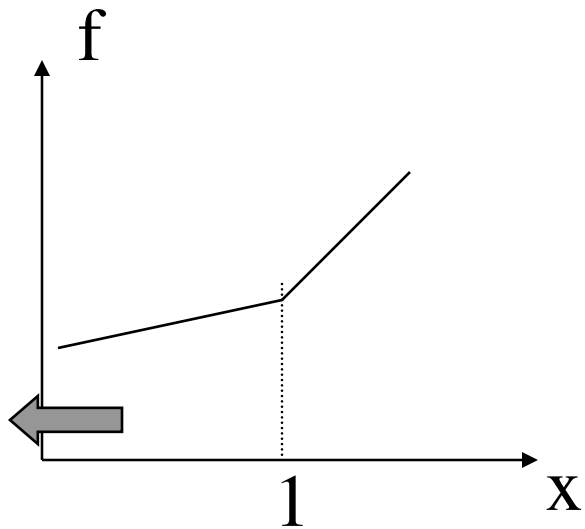
$$m_\infty \equiv \|h + \nabla h^T d^\infty\| + \|[g + \nabla g^T d^\infty]^-\|$$

End

Choose ν so that

$$m(0) - m(d^\nu) \geq 0.1 [m(0) - m_\infty]$$

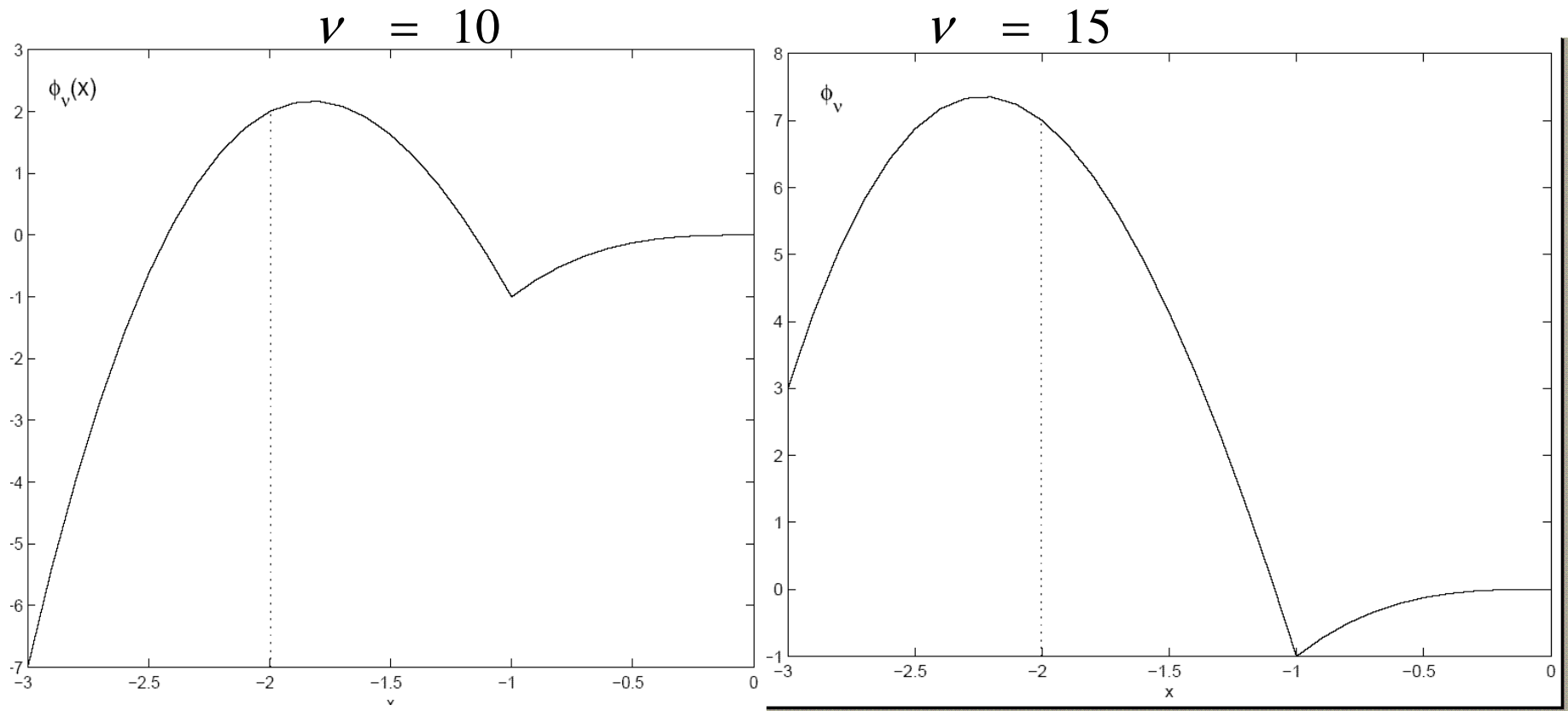
$$\begin{aligned} \min \quad & \nabla f^T d + \frac{1}{2} d^T W d + \nu(u + v + t) \\ \text{s.t.} \quad & h + \nabla h^T d = u - v \\ & g + \nabla g^T d \geq -t, \\ & u, v, t \geq 0 \\ & \|d\|_\infty \leq \Delta \end{aligned}$$



$$\min x \quad \text{s.t.} \quad x \geq 1$$

$$m_{\infty} \equiv \|h + \nabla h^T d^{\infty}\| + \|[g + \nabla g^T d^{\infty}]^{-}\|$$

$$\|d^{\infty}\| \leq \Delta$$



$$\min x^3 \quad x \geq -1$$

Our criterion: choose
 $\nu > 15$

We have expanded
 The basin of attraction

Optimality + Feasibility

Improvement in feasibility is not enough. Let

$$l(d) = \nabla f^T d + \nu \|h + \nabla h^T d\|_1 + \nu \| [g + \nabla g^T d]^-\|_1$$

After penalty parameter has been chosen, increase it if necessary s.t.

$$l(0) - l(d^\nu) \geq 0.1\nu [m(0) - m_\infty] \quad \text{Promote acceptance of step}$$

In trust region notation:

$$pred(d) \geq 0.1\nu [cred(d)]$$

Knitro-Interior
Dennis, Vicente,
Heinkenschloss,
etc

Adopted in [KNITRO/ACTIVE](#)

ADLITTLE LP: Revisited Fletcher 1992

- Running **knitro/active**:
 - For small trust region radius:
 - Solves in 7 iterations,
 - Penalty from 10 to 10^5 in first 4 iters
 - If trust region includes feasible points, correct adjustment after **one** LP

Crucial questions:

- Does it actually work in practice?
 - Yes, extensive testing **Waltz**
- Possibly solving several subproblems/iteration?
 - Negligible cost
- Can one prove global and local results?
 - Global convergence (Byrd, Gould, Nocedal, Waltz, 2004),
 - active set identification, to be done

The End