

# 9. Unconstrained minimization

- terminology and assumptions
- gradient descent method
- steepest descent method
- Newton's method
- self-concordant functions
- implementation

# Unconstrained minimization

$$\text{minimize } f(x)$$

- $f$  is convex and twice continuously differentiable; hence  $\text{dom } f$  is an open set
- we assume the optimal value  $p^\star = \inf_x f(x)$  is finite and attained

## Unconstrained minimization methods

- produce a sequence of points  $x^{(k)} \in \text{dom } f$ ,  $k = 0, 1, \dots$ , with

$$f(x^{(k)}) \rightarrow p^\star$$

- can be interpreted as iterative methods for solving optimality condition

$$\nabla f(x^\star) = 0$$

# Initial point

algorithms in this chapter require a starting point  $x^{(0)}$  that satisfies two conditions

- feasibility:  $x^{(0)} \in \text{dom } f$
- the initial sublevel set  $S$  is closed, where

$$S = \{x \mid f(x) \leq f(x^{(0)})\}$$

2nd condition is often hard to verify, except when *all* sublevel sets of  $f$  are closed

**Closed function:** a function with closed sublevel sets

- equivalent to property that the epigraph is a closed set
- convex  $f$  is closed if  $\text{dom } f = \mathbf{R}^n$
- convex  $f$  is closed if  $\text{dom } f$  is open and  $f(x) \rightarrow \infty$  as  $x \rightarrow \text{bd dom } f$

# Examples

three convex differentiable functions

$$f(x) = \log\left(\sum_{i=1}^m \exp(a_i^T x + b_i)\right), \quad \text{dom } f = \mathbf{R}^n$$

$$g(x) = -\sum_{i=1}^m \log(b_i - a_i^T x), \quad \text{dom } g = \{x \mid a_i^T x < b_i, i = 1, \dots, m\}$$

$$h(x) = x_1^2 + x_2^2, \quad \text{dom } h = \{(x_1, x_2) \mid x_1 > 1\}$$

- $f$  is closed; every  $x^{(0)} \in \mathbf{R}^n$  satisfies closed initial sublevel set condition
- $g$  is closed; every  $x^{(0)} \in \text{dom } g$  satisfies closed initial sublevel set condition
- $h$  is not closed; no  $x^{(0)}$  satisfies closed initial sublevel set condition

# Strong convexity

many convergence results in this chapter require *strong convexity*

- $f$  is strongly convex if there exists an  $m > 0$  such that

$$f(x) - \frac{m}{2} x^T x \quad \text{is a convex function}$$

- equivalent definition for differentiable function:  $\text{dom } f$  is convex and

$$f(y) \geq f(x) + \nabla f(x)^T (y - x) + \frac{m}{2} \|y - x\|_2^2 \quad \text{for all } x, y \in \text{dom } f \quad (1)$$

- equivalent definition for twice differentiable function:  $\text{dom } f$  is convex and

$$\nabla^2 f(x) \succeq mI \quad \text{for all } x \in \text{dom } f$$

# Implications of strong convexity

- sublevel sets are bounded (follows from (1))
- optimal value  $p^\star$  is finite and

$$f(x) - p^\star \leq \frac{1}{2m} \|\nabla f(x)\|_2^2 \quad \text{for all } x \in \text{dom } f \quad (2)$$

useful as stopping criterion (if you know  $m$ )

*Proof:* from (1)

$$\begin{aligned} p^\star &= \inf_y f(y) \\ &\geq \inf_{y \in \text{dom } f} (f(x) + \nabla f(x)^T (y - x) + \frac{m}{2} \|y - x\|_2^2) \\ &\geq \inf_y (f(x) + \nabla f(x)^T (y - x) + \frac{m}{2} \|y - x\|_2^2) \\ &= f(x) - \frac{1}{2m} \|\nabla f(x)\|_2^2 \end{aligned}$$

minimizer on third line is  $y = x - (1/m)\nabla f(x)$

# Descent methods

in a *descent method*, the iterates satisfy

$$f(x^{(k+1)}) < f(x^{(k)})$$

- the algorithms discussed in this chapter are of this type
- for convex  $f$ , requires that  $v = x^{(k+1)} - x^{(k)}$  is a *descent direction*, i.e.,

$$\nabla f(x^{(k)})^T v < 0 \tag{3}$$

(the *directional derivative* at  $x^{(k)}$  in the direction  $v$  is negative)

necessity of (3) can be seen from the inequality

$$f(x^{(k+1)}) \geq f(x^{(k)}) + \nabla f(x^{(k)})^T v$$

# General outline of a descent method

- different notation styles will be used for the update:

$$x^{(k+1)} = x^{(k)} + t^{(k)} \Delta x^{(k)}, \quad x^+ = x + t \Delta x, \quad x := x + t \Delta x$$

- $\Delta x$  is the *step* or *search direction*
- $t$  is the *step size* or *step length*

## Descent method

given a starting point  $x \in \text{dom } f$

repeat

1. *search direction*: determine a descent direction  $\Delta x$
2. *line search*: choose a step size  $t > 0$
3. *update*:  $x := x + t \Delta x$

until stopping criterion is satisfied

next, we discuss step 2 (line search) and then step 1 (choices for  $\Delta x$ )

# Line search types

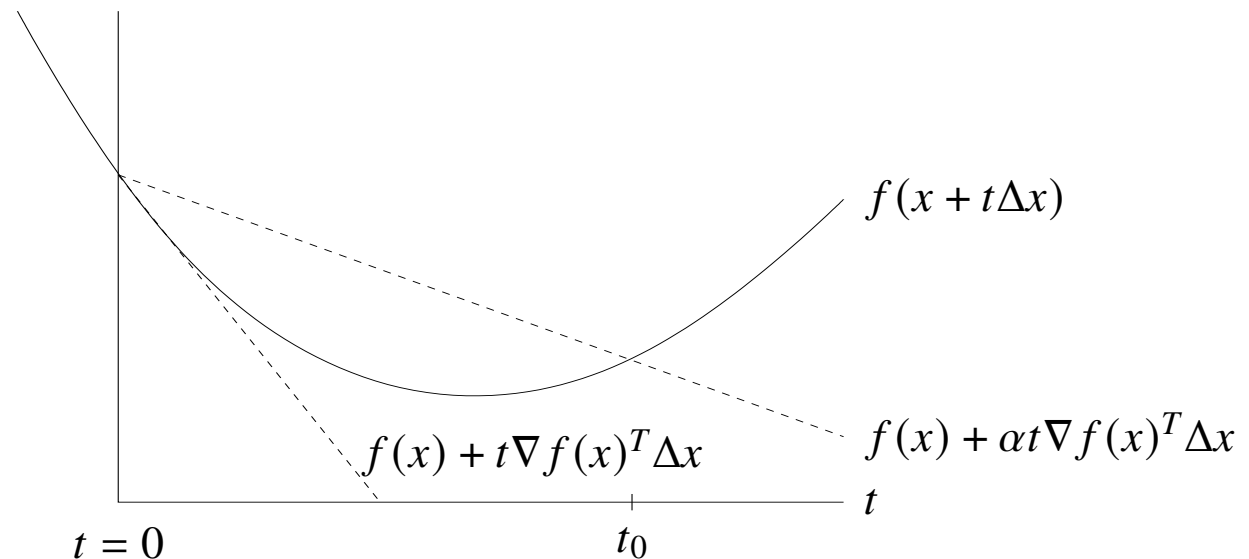
**Exact line search:**  $t = \operatorname{argmin}_{t>0} f(x + t\Delta x)$

## Backtracking line search

- starting at  $t = 1$ , repeat  $t := \beta t$  until

$$f(x + t\Delta x) < f(x) + \alpha t \nabla f(x)^T \Delta x$$

- $\alpha \in (0, 1/2)$  and  $\beta \in (0, 1)$  are algorithm parameters
- in the example of the figure, we backtrack until  $t \leq t_0$



# Gradient descent method

**Gradient descent:** the general descent method of page 9.8 with  $\Delta x = -\nabla f(x)$

given: a starting point  $x \in \text{dom } f$

repeat

1.  $\Delta x := -\nabla f(x)$

2. *line search*: choose step size  $t$  via exact or backtracking line search

3. *update*:  $x := x + t\Delta x$

until stopping criterion is satisfied

- stopping criterion usually of the form  $\|\nabla f(x)\|_2 \leq \epsilon$
- convergence result: for strongly convex  $f$ ,

$$f(x^{(k)}) - p^\star \leq c^k (f(x^{(0)}) - p^\star)$$

$c \in (0, 1)$  depends on  $m, x^{(0)}$ , line search type

- iteration is simple and inexpensive, but convergence is often very slow

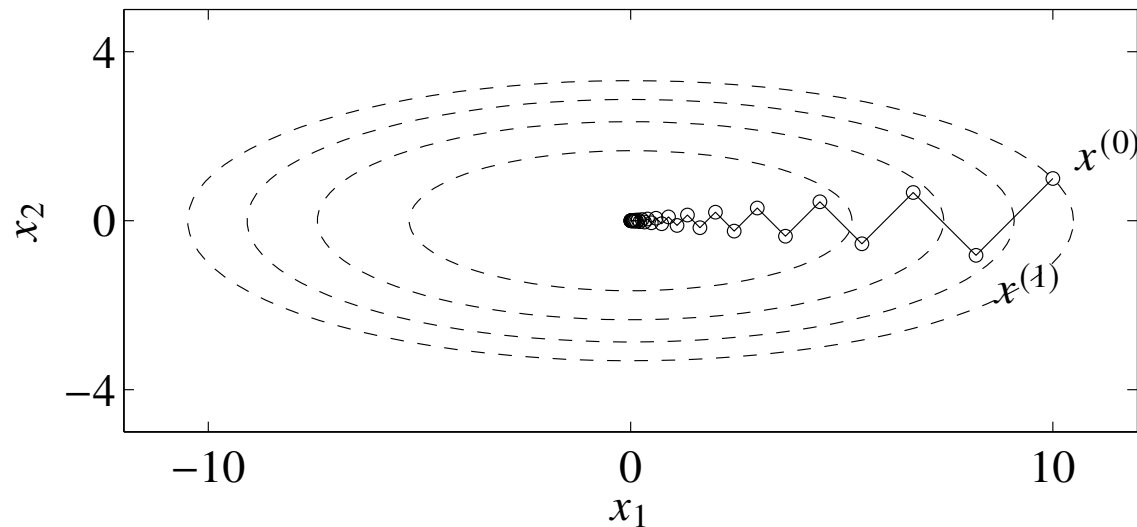
## Quadratic problem in $\mathbf{R}^2$

$$f(x) = \frac{1}{2}(x_1^2 + \gamma x_2^2) \quad (\gamma > 0)$$

with exact line search, starting at  $x^{(0)} = (\gamma, 1)$ :

$$x_1^{(k)} = \gamma \left( \frac{\gamma - 1}{\gamma + 1} \right)^k, \quad x_2^{(k)} = \left( -\frac{\gamma - 1}{\gamma + 1} \right)^k$$

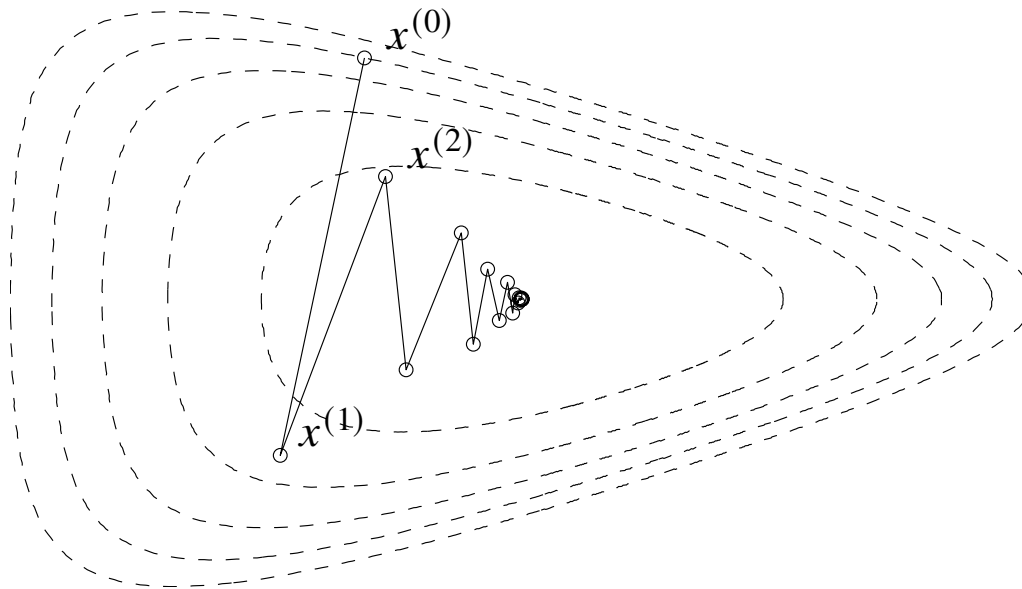
- very slow if  $\gamma \gg 1$  or  $\gamma \ll 1$
- example for  $\gamma = 10$ :



# Nonquadratic example

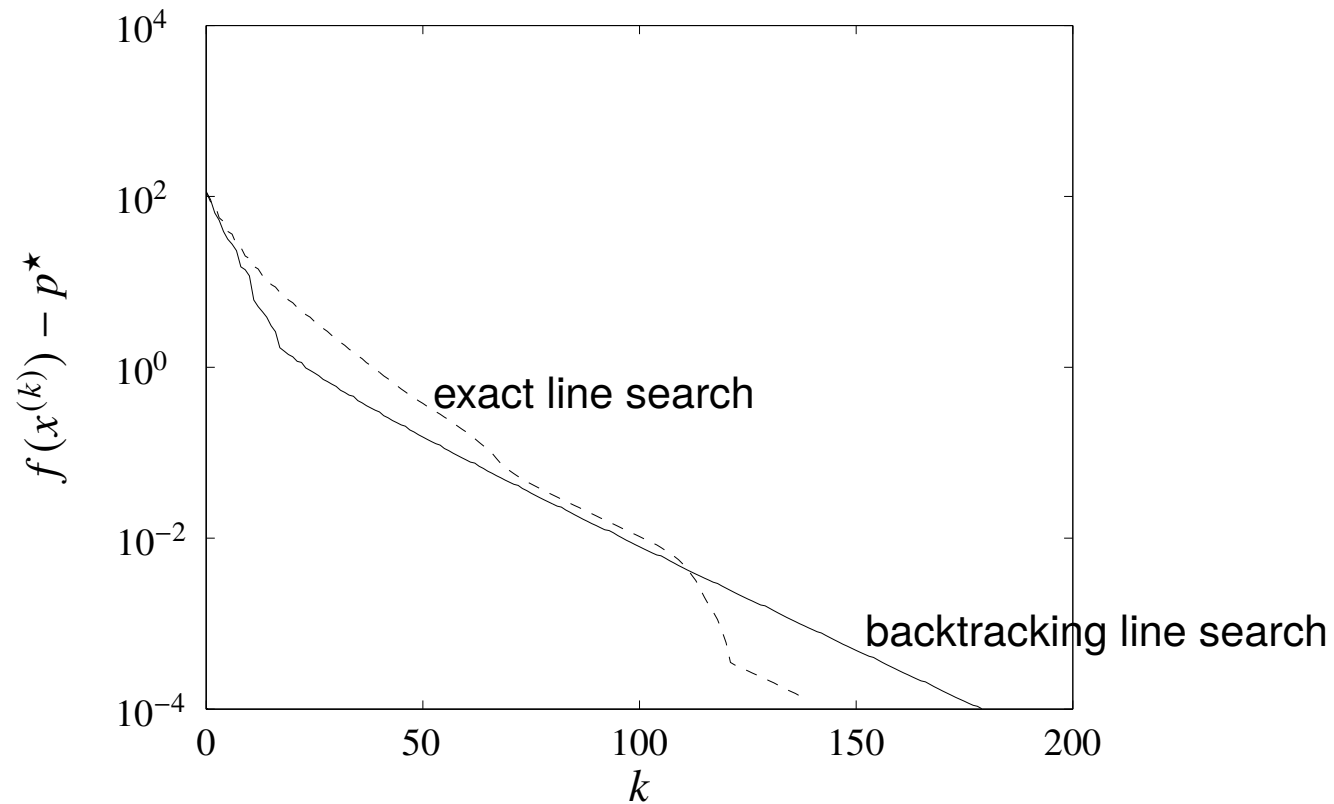
$$f(x_1, x_2) = e^{x_1+3x_2-0.1} + e^{x_1-3x_2-0.1} + e^{-x_1-0.1}$$

figure shows iterates with backtracking line search



## Example in $\mathbf{R}^{100}$

$$f(x) = c^T x - \sum_{i=1}^{500} \log(b_i - a_i^T x)$$



shows linear convergence, *i.e.*, a straight line on a semilog plot

# Steepest descent method

**Normalized steepest descent direction** (at  $x$ , for norm  $\|\cdot\|$ )

$$\Delta x_{\text{nsd}} = \operatorname{argmin} \{ \nabla f(x)^T v \mid \|v\| = 1 \}$$

- direction  $\Delta x_{\text{nsd}}$  is unit-norm step with most negative directional derivative
- directional derivative in this direction is  $\nabla f(x)^T \Delta x_{\text{nsd}} = -\|\nabla f(x)\|_*$   
(recall definition of dual norm  $\|v\|_* = \sup_{\|u\|=1} v^T u$ )

**(Unnormalized) steepest descent direction**

$$\Delta x_{\text{sd}} = \|\nabla f(x)\|_* \Delta x_{\text{nsd}}$$

multiple of  $\Delta x_{\text{nsd}}$ , scaled to make  $\nabla f(x)^T \Delta x_{\text{sd}} = -\|\nabla f(x)\|_*^2$

**Steepest descent method**

- general descent method of page 9.8 with  $\Delta x = \Delta x_{\text{sd}}$
- convergence properties are similar to gradient descent

# Steepest descent direction for quadratic norm

- for Euclidean norm ( $\|\cdot\| = \|\cdot\|_* = \|\cdot\|_2$ )

$$\Delta x_{\text{nsd}} = \frac{-\nabla f(x)}{\|\nabla f(x)\|_2}, \quad \Delta x_{\text{sd}} = -\nabla f(x)$$

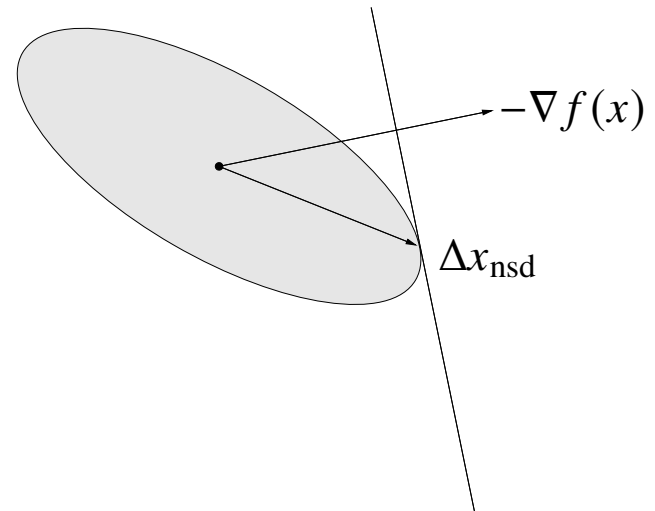
- as an extension, define quadratic norm and dual norm (for  $P \in \mathbf{S}_{++}^n$ )

$$\|x\| = (x^T P x)^{1/2} = \|P^{1/2} x\|_2, \quad \|y\|_* = (y^T P^{-1} y)^{1/2} = \|P^{-1/2} y\|_2$$

- normalized and unnormalized steepest descent directions for this norm are

$$\Delta x_{\text{nsd}} = \frac{-P^{-1} \nabla f(x)}{\|P^{-1/2} \nabla f(x)\|_2}$$

$$\Delta x_{\text{sd}} = -P^{-1} \nabla f(x)$$

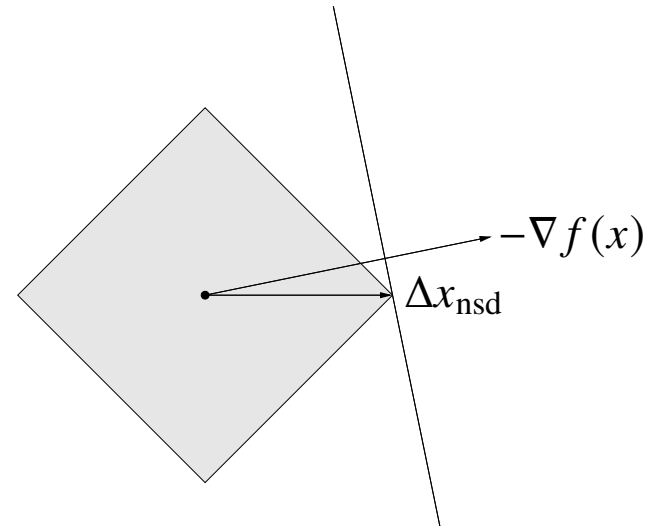


# Steepest descent direction for 1-norm

- for  $\| \cdot \| = \| \cdot \|_1$  and its dual norm  $\| \cdot \|_\infty$ , steepest descent directions are

$$\Delta x_{\text{nsd}} = \frac{-\partial f(x)/\partial x_i}{|\partial f(x)/\partial x_i|} e_i$$

$$\Delta x_{\text{sd}} = -\frac{\partial f(x)}{\partial x_i} e_i,$$

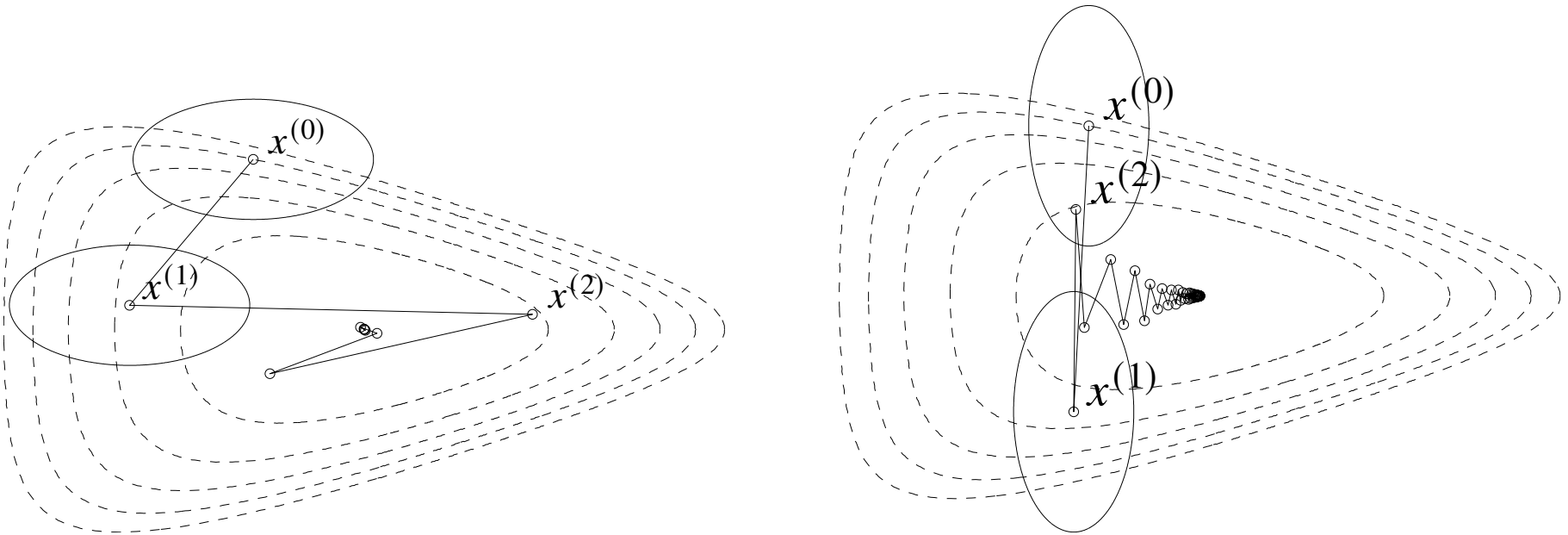


where  $i$  is an index with

$$\left| \frac{\partial f(x)}{\partial x_i} \right| = \|\nabla f(x)\|_\infty = \max_{k=1,\dots,n} \left| \frac{\partial f(x)}{\partial x_k} \right|$$

- not necessarily unique
- steepest descent method for 1-norm updates one coordinate of  $x$  at a time

# Choice of norm for steepest descent



- steepest descent with backtracking line search for two quadratic norms
- ellipses show  $\{x \mid \|x - x^{(k)}\|_P = 1\}$
- equivalent to gradient descent after change of variables  $\bar{x} = P^{1/2}x$
- figures show that choice of  $P$  has strong effect on speed of convergence

# Newton step

$$\Delta x_{\text{nt}} = -\nabla^2 f(x)^{-1} \nabla f(x)$$

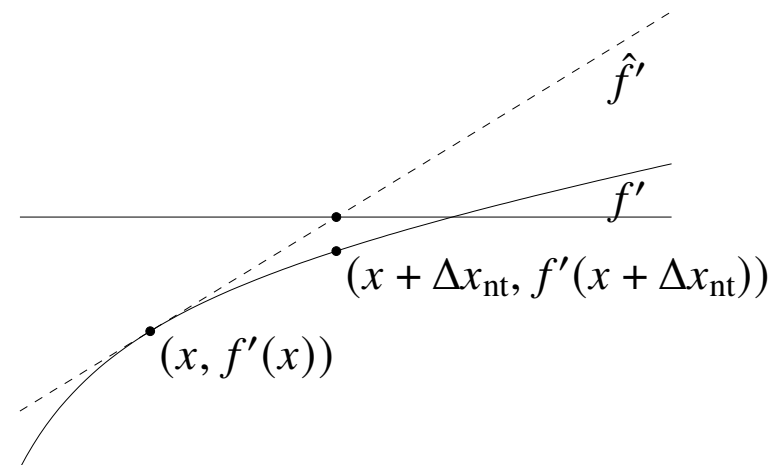
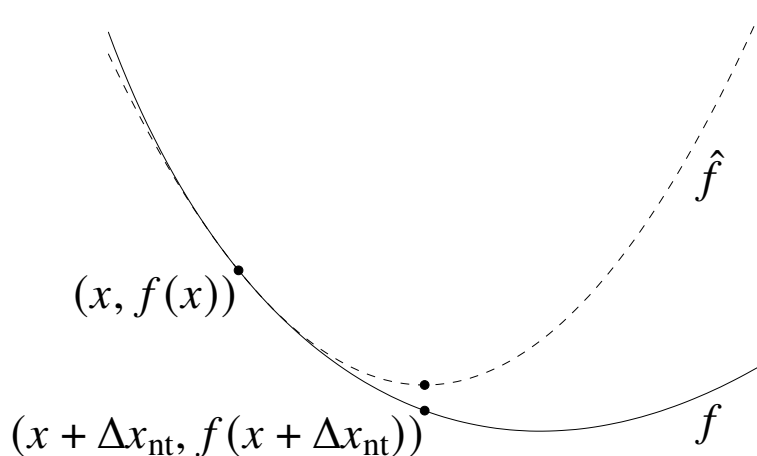
## Interpretations

- $x + \Delta x_{\text{nt}}$  minimizes second order approximation  $\hat{f}$  of  $f$  at  $x$

$$\hat{f}(x + v) = f(x) + \nabla f(x)^T v + \frac{1}{2} v^T \nabla^2 f(x) v \quad (4)$$

- $x + \Delta x_{\text{nt}}$  solves linearized optimality condition

$$\nabla f(x + v) \approx \nabla \hat{f}(x + v) = \nabla f(x) + \nabla^2 f(x) v = 0$$

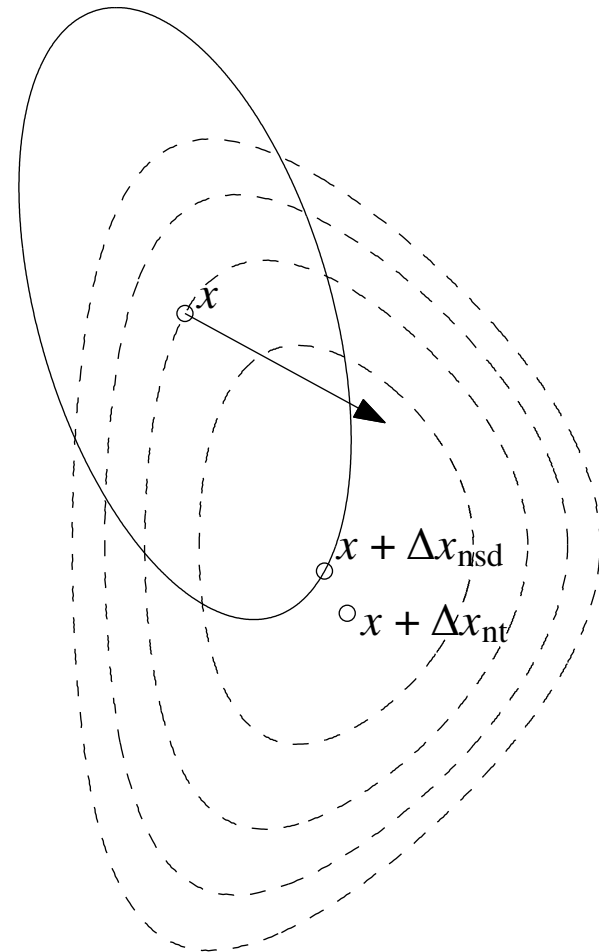


# Interpretation as steepest descent direction in local norm

$\Delta x_{nt}$  is steepest descent direction at  $x$  in local norm defined by Hessian

$$\|u\|_{\nabla^2 f(x)} = (u^T \nabla^2 f(x) u)^{1/2}$$

- dashed lines are contour lines of  $f$
- ellipse is  $\{x + v \mid v^T \nabla^2 f(x) v = 1\}$
- arrow shows  $-\nabla f(x)$



## Affine invariance of Newton step

suppose we make a change of variables  $x = Ay$ , with  $A$  nonsingular, and solve

$$\text{minimize } g(y) = f(Ay)$$

- gradient and Hessian of  $g$  are

$$\nabla g(y) = A^T \nabla f(Ay), \quad \nabla^2 g(y) = A^T \nabla^2 f(Ay) A$$

- Newton step of  $g$  at  $y$  is

$$\Delta y_{\text{nt}} = -\nabla^2 g(y)^{-1} \nabla g(y) = -A^{-1} \nabla^2 f(Ay)^{-1} \nabla^2 f(Ay)$$

- if  $y = A^{-1}x$ , then

$$\Delta y_{\text{nt}} = A^{-1} \Delta x_{\text{nt}}, \quad \text{where } \Delta x_{\text{nt}} \text{ is Newton step of } f \text{ at } x$$

Newton step is invariant under affine change of variables

# Newton decrement

$$\lambda(x) = (\nabla f(x)^T \nabla^2 f(x)^{-1} \nabla f(x))^{1/2}$$

a measure of the proximity of  $x$  to the minimizer  $x^\star$

- $\lambda(x)^2 = -\nabla f(x)^T \Delta x_{\text{nt}}$  is negative of directional derivative in Newton direction
- $\lambda(x)$  is the norm of the Newton step in the quadratic Hessian norm

$$\lambda(x) = (\Delta x_{\text{nt}}^T \nabla^2 f(x) \Delta x_{\text{nt}})^{1/2}$$

- $\lambda(x)$  gives estimate of  $f(x) - p^\star$ , estimated using quadratic approximation (4)

$$f(x) - \inf_y \hat{f}(y) = \frac{1}{2} \lambda(x)^2$$

- $\lambda(x)$  is affine invariant (unlike  $\|\nabla f(x)\|_2$ )

# Newton's method

given: a starting point  $x \in \text{dom } f$ , tolerance  $\epsilon > 0$

repeat

1. *compute Newton step and decrement*

$$\Delta x_{\text{nt}} := -\nabla^2 f(x)^{-1} \nabla f(x); \quad \lambda(x) := (\nabla f(x)^T \nabla^2 f(x)^{-1} \nabla f(x))^{1/2}$$

2. *stopping criterion*: quit if  $\lambda(x)^2/2 \leq \epsilon$

3. *line search*: choose step size  $t$  by backtracking line search

4. *update*:  $x := x + t\Delta x_{\text{nt}}$

- we use line search of page 9.9: starting at  $t = 1$ , backtrack ( $t := \beta t$ ) until

$$\begin{aligned} f(x + t\Delta x_{\text{nt}}) &< f(x) + \alpha t \nabla f(x)^T \Delta x_{\text{nt}} \\ &= f(x) - \alpha t \lambda(x)^2 \end{aligned}$$

- typical values of line search parameters are  $\alpha = 0.01$ ,  $\beta = 1/2$

# Affine invariance of Newton's method

- we already noted that Newton step and Newton decrement are affine invariant
- affine invariance of  $\lambda(x)$  makes line search, stopping criterion affine invariant
- hence, for Newton method applied to  $g(y) = f(Ay)$ , started at  $y^{(0)} = A^{-1}x^{(0)}$ ,

$$y^{(k)} = A^{-1}x^{(k)} \quad \text{for all } k$$

where  $x^{(k)}$  are iterates of Newton method applied to  $f(x)$ , started at  $x^{(0)}$

- number of iterates is independent of linear changes of coordinates

# Classical convergence analysis

## Assumptions

- $f$  strongly convex with constant  $m$
- $\nabla^2 f$  is Lipschitz continuous: there exists a constant  $L$  such that

$$\|\nabla^2 f(x) - \nabla^2 f(y)\|_2 \leq L\|x - y\|_2 \quad \text{for all } x, y \in \text{dom } f$$

constant  $L$  measures how well  $f$  is approximated by a quadratic function

**Summary:** there exist constants  $\eta \in (0, m^2/L)$  and  $\gamma > 0$  such that

- if  $\|\nabla f(x^{(k)})\|_2 \geq \eta$ , then

$$f(x^{(k+1)}) - f(x^{(k)}) \leq -\gamma$$

- if  $\|\nabla f(x^{(k)})\|_2 < \eta$ , then

$$\frac{L}{2m^2} \|\nabla f(x^{(k+1)})\|_2 \leq \left( \frac{L}{2m^2} \|\nabla f(x^{(k)})\|_2 \right)^2$$

# Classical convergence analysis

## Damped Newton phase ( $\|\nabla f(x^{(k)})\|_2 \geq \eta$ )

- most iterations require backtracking steps
- function value decreases by at least  $\gamma$
- if  $p^\star > -\infty$ , this phase ends after at most

$$\frac{f(x^{(0)}) - p^\star}{\gamma} \text{ iterations}$$

## Quadratically convergent phase ( $\|\nabla f(x^{(k)})\|_2 < \eta$ )

- all iterations use step size  $t = 1$
- gradient converges to zero quadratically: once  $\|\nabla f(x^{(j)})\|_2 < \eta$ ,

$$\frac{L}{2m^2} \|\nabla f(x^k)\|_2 \leq \left( \frac{L}{2m^2} \|\nabla f(x^j)\|_2 \right)^{2^{k-j}} \leq \left( \frac{1}{2} \right)^{2^{k-j}}, \quad k \geq j$$

- inequality (2) shows that  $(f(x^{(k)}) - p^\star) \rightarrow 0$  quadratically

# Classical convergence analysis

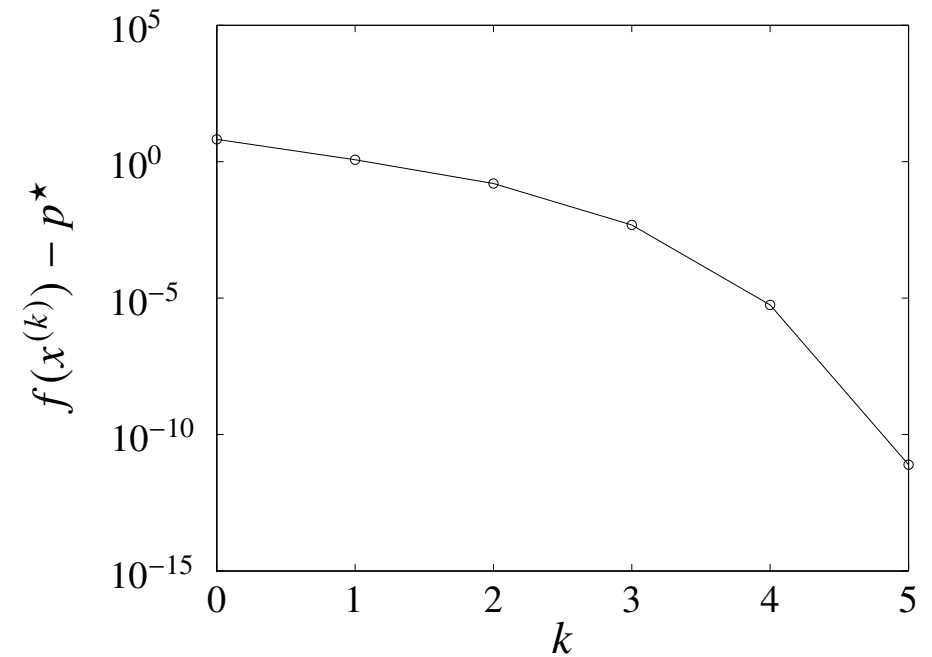
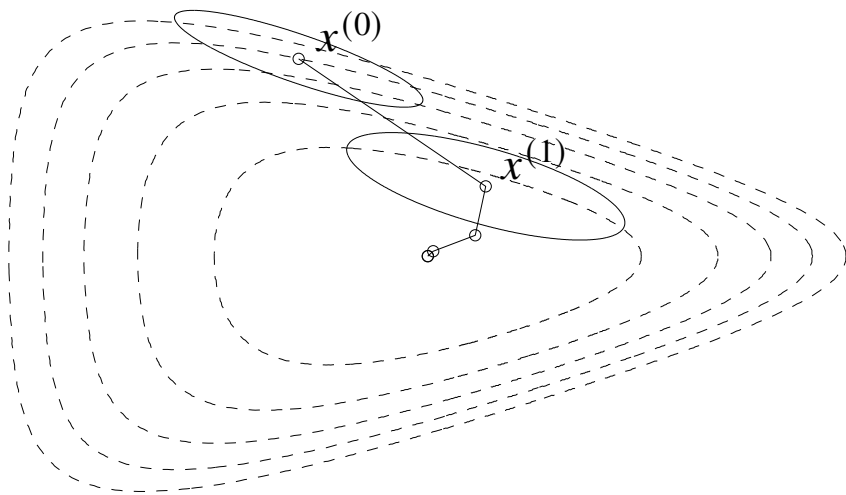
**Conclusion:** number of iterations until  $f(x^{(k)}) - p^\star \leq \epsilon$  is bounded above by

$$\frac{f(x^{(0)}) - p^\star}{\gamma} + \log_2 \log_2(\epsilon_0/\epsilon)$$

- $\gamma, \epsilon_0$  are constants that depend on  $m, L, x^{(0)}$
- 2nd term is small (of the order of 6), almost constant for practical purposes
- in practice, constants  $m, L$  (hence  $\gamma, \epsilon_0$ ) are usually unknown
- provides qualitative insight in convergence properties (two algorithm phases)

# Examples

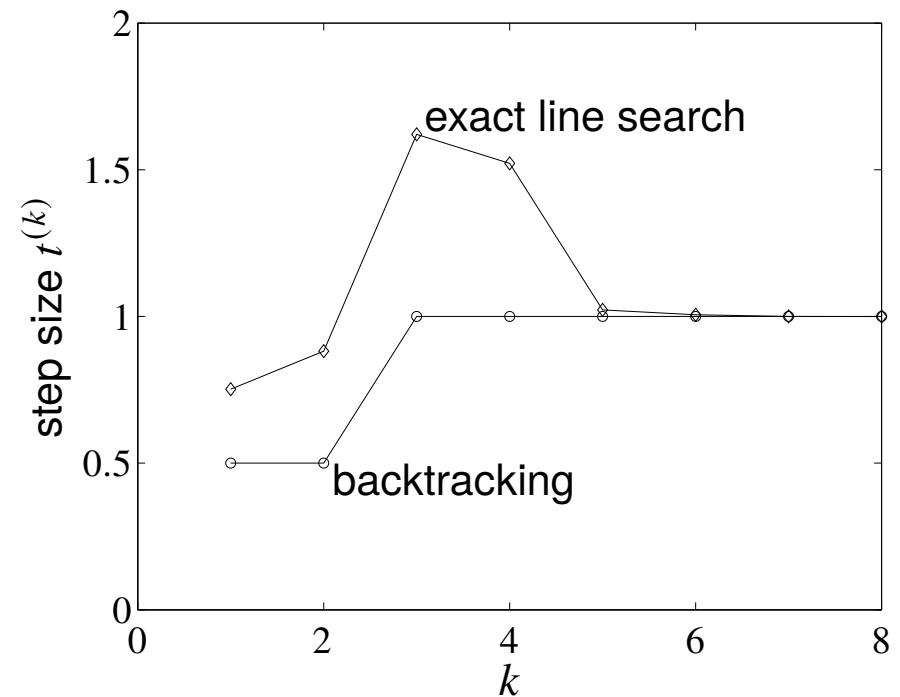
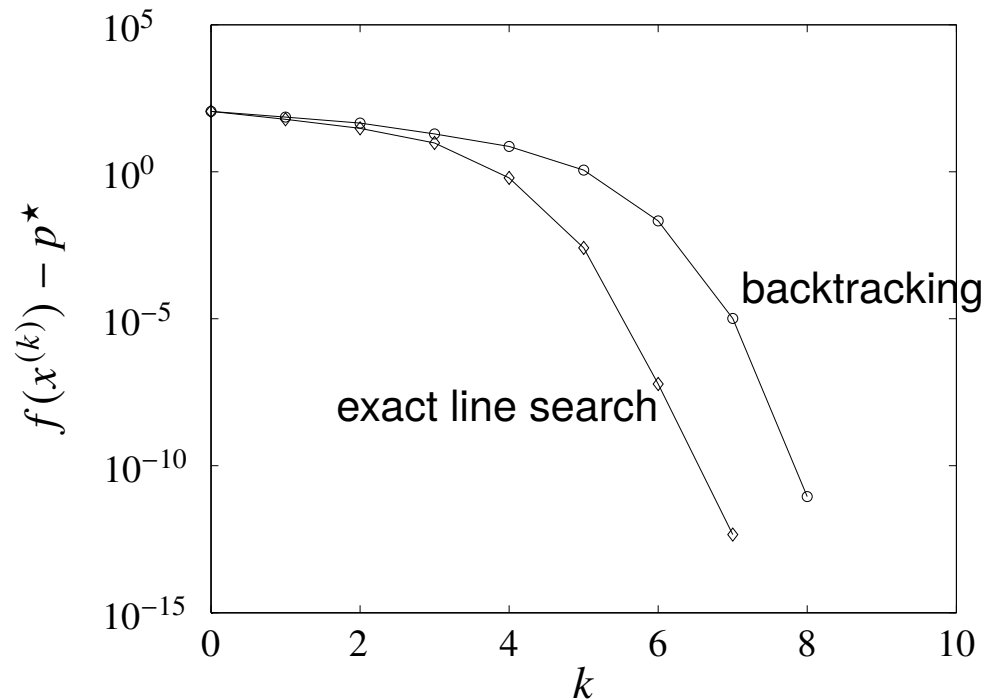
## Example in $\mathbf{R}^2$ (page 9.12)



- backtracking parameters  $\alpha = 0.1, \beta = 0.7$
- converges in only 5 steps
- quadratic local convergence

# Examples

## Example in $\mathbf{R}^{100}$ (page 9.13)

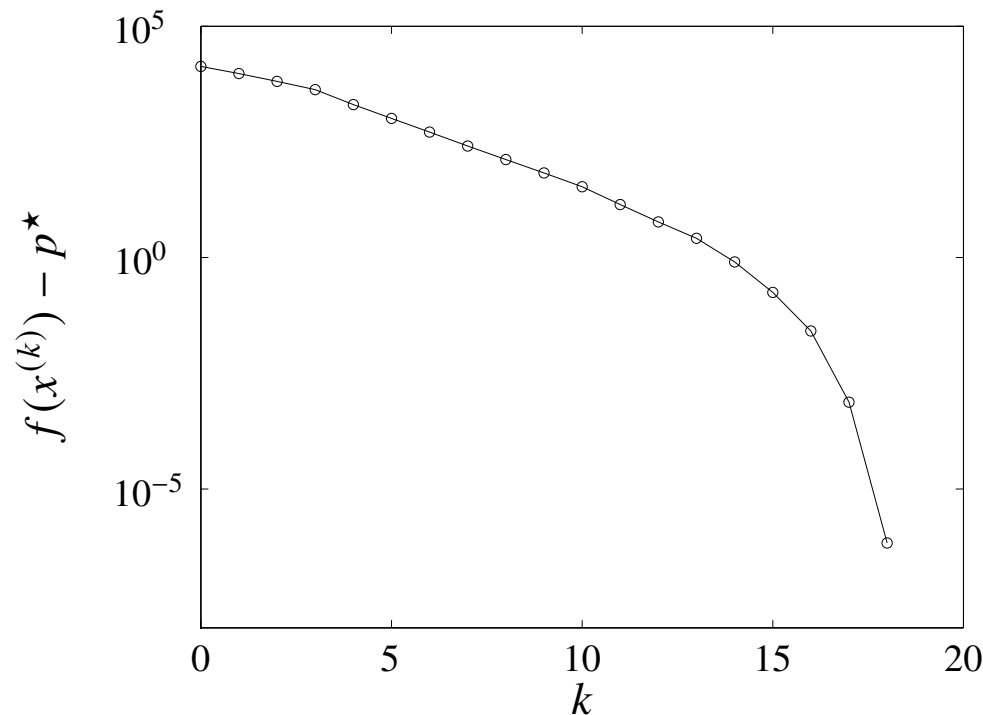


- backtracking parameters  $\alpha = 0.01, \beta = 0.5$
- backtracking line search almost as fast as exact l.s. (and much simpler)
- clearly shows two phases in algorithm

# Examples

Example in  $\mathbf{R}^{10000}$  (with sparse  $a_i$ )

$$f(x) = - \sum_{i=1}^{10000} \log(1 - x_i^2) - \sum_{i=1}^{100000} \log(b_i - a_i^T x)$$



- backtracking parameters  $\alpha = 0.01, \beta = 0.5$
- performance similar as for the small examples

# Self-concordance

## Shortcomings of classical convergence analysis

- depends on unknown constants  $(m, L)$
- bound is not affinely invariant, although Newton's method is

## Convergence analysis via self-concordance (Nesterov and Nemirovski)

- does not depend on any unknown constants
- gives affine-invariant bound
- applies to special class of convex functions (*self-concordant* functions)
- developed to analyze interior-point methods for convex optimization

# Self-concordant functions

## Definition

- a convex function  $f : \mathbf{R} \rightarrow \mathbf{R}$  is self-concordant if

$$|f'''(x)| \leq 2f''(x)^{3/2} \quad \text{for all } x \in \text{dom } f$$

- a convex function  $f : \mathbf{R}^n \rightarrow \mathbf{R}$  is self-concordant if restriction to a line

$$g(t) = f(x + tv)$$

is a self-concordant function of  $t$  for all  $x \in \text{dom } f$  and  $v$

## Affine invariance

- if  $f : \mathbf{R}^n \rightarrow \mathbf{R}$  is self-concordant, then  $\tilde{f}(y) = f(Ay)$  is self-concordant
- this is easily checked for  $f : \mathbf{R} \rightarrow \mathbf{R}$  and  $\tilde{f}(y) = f(ay)$ :

$$|\tilde{f}'''(y)| = |a|^3 |f'''(ay)| \leq 2|a|^3 f''(ay)^{3/2} = 2\tilde{f}''(y)^{3/2}$$

# Examples of self-concordant functions

- linear and quadratic functions
- negative logarithm:  $f(x) = -\log x$
- negative entropy plus negative logarithm:  $f(x) = x \log x - \log x$
- logarithmic barrier for set of linear inequalities

$$f(x) = -\sum_{i=1}^m \log(b_i - a_i^T x), \quad \text{dom } f = \{x \mid a_i^T x < b_i, i = 1, \dots, m\}$$

- log-det barrier

$$f(X) = -\log \det X, \quad \text{dom } f = \mathbf{S}_{++}^n$$

- logarithmic barrier for second order cone

$$f(x) = -\log(y^2 - x^T x), \quad \text{dom } f = \{(x, y) \mid \|x\|_2 < y\}$$

# Newton's method for self-concordant functions

Newton's method of page 9.22

**Summary:** there exist constants  $\eta \in (0, 1/4]$ ,  $\gamma > 0$  such that

- if  $\lambda(x^{(k)}) > \eta$ , then

$$f(x^{(k+1)}) - f(x^{(k)}) \leq -\gamma$$

- if  $\lambda(x^{(k)}) \leq \eta$ , then

$$2\lambda(x^{(k+1)}) \leq (2\lambda(x^{(k)}))^2$$

$\eta$  and  $\gamma$  only depend on backtracking parameters  $\alpha, \beta$

**Complexity bound:** number of iterations until  $f(x^{(k)}) - p^* \leq \epsilon$  is bounded by

$$\frac{f(x^{(0)}) - p^*}{\gamma} + \log_2 \log_2(1/\epsilon)$$

# Implementation of Newton's method

main effort in each iteration: evaluate derivatives and solve Newton system

$$H\Delta x = -g$$

where  $H = \nabla^2 f(x)$  and  $g = \nabla f(x)$

## Via Cholesky factorization

$$H = LL^T, \quad \Delta x_{\text{nt}} = -L^{-T}L^{-1}g, \quad \lambda(x) = \|L^{-1}g\|_2$$

- cost:  $(1/3)n^3$  flops for unstructured system, plus cost of evaluating derivatives
- cost  $\ll (1/3)n^3$  if  $H$  sparse or highly structured (for example, banded)

# Structured-plus-low-rank matrices

a type of structured linear equations, common in optimization:

$$(A + BC)x = b \quad \text{with } A \in \mathbf{R}^{n \times n}, B \in \mathbf{R}^{n \times p}, C \in \mathbf{R}^{p \times n} \quad (5)$$

- $A$  has some property that makes  $Ax = b$  easy to solve, for example, diagonal
- $B, C$  are dense, with  $p \ll n$
- using an auxiliary variable  $y$ , equation can be written as

$$\begin{bmatrix} A & B \\ C & -I \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} b \\ 0 \end{bmatrix} \quad (6)$$

- instead of solving (5) directly, can solve (6) by eliminating  $x$ : first solve equation

$$(I + CA^{-1}B)y = CA^{-1}b$$

to find  $y$ ; then solve  $Ax = b - By$  to find  $x$

## Matrix inversion lemma

if  $A$  and  $A + BC$  are nonsingular, then  $I + CA^{-1}B$  is nonsingular and

$$(A + BC)^{-1} = A^{-1} - A^{-1}B(I + CA^{-1}B)^{-1}CA^{-1} \quad (7)$$

- easily verified by multiplying  $A + BC$  and right-hand side of (7)
- can be derived via method on previous page:  $x = (A + BC)^{-1}b$  is equal to

$$\begin{aligned} x &= A^{-1}(b - By) \\ &= A^{-1}(b - B(I + CA^{-1}B)^{-1}CA^{-1}b) \\ &= (A^{-1} - A^{-1}B(I + CA^{-1}B)^{-1}CA^{-1})b \end{aligned} \quad (8)$$

since this is true for all  $b$ , matrix on the right-hand side of (8) is  $(A + BC)^{-1}$

- method on previous page can be viewed as evaluating  $(A + BC)^{-1}b$  via (8)

## Example

Newton method for unconstrained optimization with cost function  $f : \mathbf{R}^n \rightarrow \mathbf{R}$ ,

$$f(x) = \sum_{i=1}^n \psi_i(x_i) + \phi(Ax + b)$$

- functions  $\psi_i : \mathbf{R} \rightarrow \mathbf{R}$  and  $\phi : \mathbf{R}^p \rightarrow \mathbf{R}$  are convex
- assume  $A \in \mathbf{R}^{p \times n}$ , dense, with  $p \ll n$
- Hessian of  $f$  is diagonal plus low rank:

$$H = D + A^T G A$$

where  $D$  is diagonal with  $D_{ii} = \psi_i''(x_i)$ , and  $G = \nabla^2 \phi(Ax + b)$

## Example

compare two methods for solving Newton equation  $(D + A^T G A)\Delta x = -g$

**Method 1:** form  $D + A^T G A$ , solve via dense Cholesky

cost dominated by cost of factorization  $((1/3)n^3$  flops)

**Method 2:** follow idea on page 9.35

- compute Cholesky factorization  $G = LL^T$  and write Newton system as

$$\begin{bmatrix} D & A^T L \\ L^T A & -I \end{bmatrix} \begin{bmatrix} \Delta x \\ y \end{bmatrix} = \begin{bmatrix} -g \\ 0 \end{bmatrix}$$

- eliminate  $\Delta x$  from first equation: solve two equations

$$(I + L^T A D^{-1} A^T L)y = -L^T A D^{-1} g, \quad D\Delta x = -g - A^T L y$$

- cost is roughly  $2p^2n$  flops, dominated by computation of  $L^T A D^{-1} A^T L$

complexity of method 2 is linear in  $n$