

## 12. Interior-point methods

- inequality constrained minimization
- logarithmic barrier function and central path
- barrier method
- feasibility and phase I methods
- complexity analysis via self-concordance
- generalized inequalities

# Inequality constrained minimization

$$\begin{array}{ll} \text{minimize} & f_0(x) \\ \text{subject to} & f_i(x) \leq 0, \quad i = 1, \dots, m \\ & Ax = b \end{array} \quad (1)$$

- $f_i$  convex, twice continuously differentiable
- $A \in \mathbf{R}^{p \times n}$  with  $\text{rank } A = p$
- we assume  $p^*$  is finite and attained
- we assume problem is strictly feasible: there exists  $\tilde{x}$  with

$$\tilde{x} \in \text{dom } f_0, \quad f_i(\tilde{x}) < 0, \quad i = 1, \dots, m, \quad A\tilde{x} = b$$

hence, strong duality holds and dual optimum is attained

# Examples

- LP, QP, QCQP, GP
- entropy maximization with linear inequality constraints

$$\begin{array}{ll}\text{minimize} & \sum_{i=1}^n x_i \log x_i \\ \text{subject to} & Fx \preceq g \\ & Ax = b\end{array}$$

with  $\text{dom } f_0 = \mathbf{R}_{++}^n$

- differentiability may require reformulating the problem, *e.g.*, piecewise-linear minimization or  $\ell_\infty$ -norm approximation via LP
- SDPs and SOCPs are better handled as problems with generalized inequalities (see later)

# Logarithmic barrier

reformulation of (1) via indicator function:

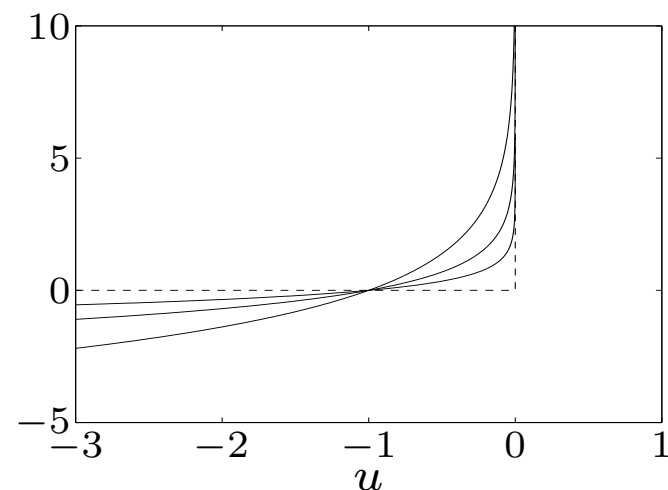
$$\begin{array}{ll} \text{minimize} & f_0(x) + \sum_{i=1}^m I_-(f_i(x)) \\ \text{subject to} & Ax = b \end{array}$$

where  $I_-(u) = 0$  if  $u \leq 0$ ,  $I_-(u) = \infty$  otherwise (indicator function of  $\mathbf{R}_-$ )

approximation via logarithmic barrier

$$\begin{array}{ll} \text{minimize} & f_0(x) - (1/t) \sum_{i=1}^m \log(-f_i(x)) \\ \text{subject to} & Ax = b \end{array}$$

- an equality constrained problem
- for  $t > 0$ ,  $-(1/t) \log(-u)$  is a smooth approximation of  $I_-$
- approximation improves as  $t \rightarrow \infty$



## logarithmic barrier function

$$\phi(x) = -\sum_{i=1}^m \log(-f_i(x)), \quad \mathbf{dom} \phi = \{x \mid f_1(x) < 0, \dots, f_m(x) < 0\}$$

- convex (follows from composition rules)
- twice continuously differentiable, with derivatives

$$\nabla \phi(x) = \sum_{i=1}^m \frac{1}{-f_i(x)} \nabla f_i(x)$$

$$\nabla^2 \phi(x) = \sum_{i=1}^m \frac{1}{f_i(x)^2} \nabla f_i(x) \nabla f_i(x)^T + \sum_{i=1}^m \frac{1}{-f_i(x)} \nabla^2 f_i(x)$$

# Central path

- for  $t > 0$ , define  $x^*(t)$  as the solution of

$$\begin{array}{ll}\text{minimize} & t f_0(x) + \phi(x) \\ \text{subject to} & Ax = b\end{array}$$

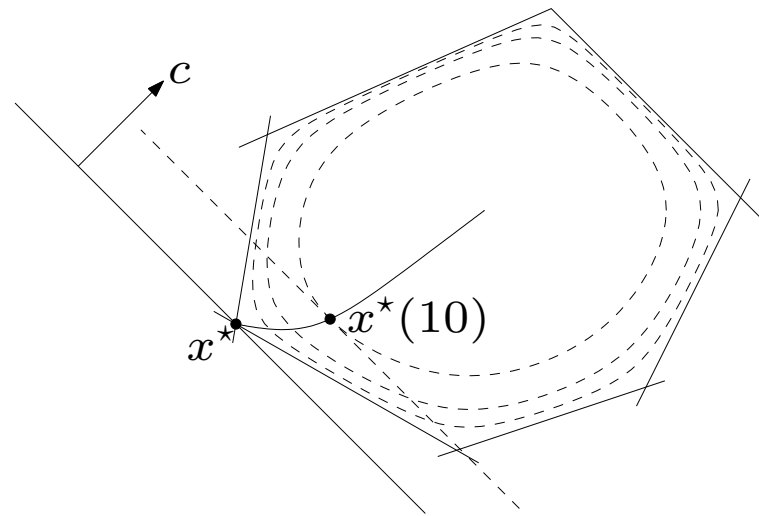
(for now, assume  $x^*(t)$  exists and is unique for each  $t > 0$ )

- central path is  $\{x^*(t) \mid t > 0\}$

**example:** central path for an LP

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & a_i^T x \leq b_i, \quad i = 1, \dots, 6\end{array}$$

hyperplane  $c^T x = c^T x^*(t)$  is tangent to level curve of  $\phi$  through  $x^*(t)$



## Dual points on central path

$x = x^*(t)$  if there exists a  $w$  such that

$$t \nabla f_0(x) + \sum_{i=1}^m \frac{1}{-f_i(x)} \nabla f_i(x) + A^T w = 0, \quad Ax = b$$

- therefore,  $x^*(t)$  minimizes the Lagrangian

$$L(x, \lambda^*(t), \nu^*(t)) = f_0(x) + \sum_{i=1}^m \lambda_i^*(t) f_i(x) + \nu^*(t)^T (Ax - b)$$

where we define  $\lambda_i^*(t) = 1/(-t f_i(x^*(t)))$  and  $\nu^*(t) = w/t$

- this confirms the intuitive idea that  $f_0(x^*(t)) \rightarrow p^*$  if  $t \rightarrow \infty$ :

$$\begin{aligned} p^* &\geq g(\lambda^*(t), \nu^*(t)) \\ &= L(x^*(t), \lambda^*(t), \nu^*(t)) \\ &= f_0(x^*(t)) - m/t \end{aligned}$$

## Interpretation via KKT conditions

$x = x^*(t)$ ,  $\lambda = \lambda^*(t)$ ,  $\nu = \nu^*(t)$  satisfy

1. primal constraints:  $f_i(x) \leq 0$ ,  $i = 1, \dots, m$ ,  $Ax = b$
2. dual constraints:  $\lambda \succeq 0$
3. approximate complementary slackness:  $-\lambda_i f_i(x) = 1/t$ ,  $i = 1, \dots, m$
4. gradient of Lagrangian with respect to  $x$  vanishes:

$$\nabla f_0(x) + \sum_{i=1}^m \lambda_i \nabla f_i(x) + A^T \nu = 0$$

difference with KKT is that condition 3 replaces  $\lambda_i f_i(x) = 0$



# Force field interpretation

**centering problem** (for problem with no equality constraints)

$$\text{minimize } tf_0(x) - \sum_{i=1}^m \log(-f_i(x))$$

## force field interpretation

- $tf_0(x)$  is potential of force field  $F_0(x) = -t\nabla f_0(x)$
- $-\log(-f_i(x))$  is potential of force field  $F_i(x) = (1/f_i(x))\nabla f_i(x)$

the forces balance at  $x^*(t)$ :

$$F_0(x^*(t)) + \sum_{i=1}^m F_i(x^*(t)) = 0$$

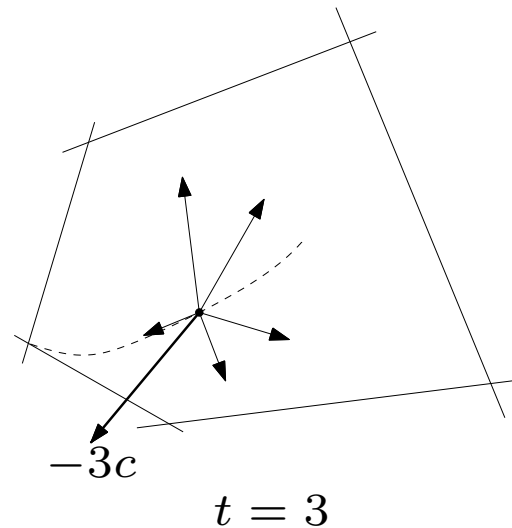
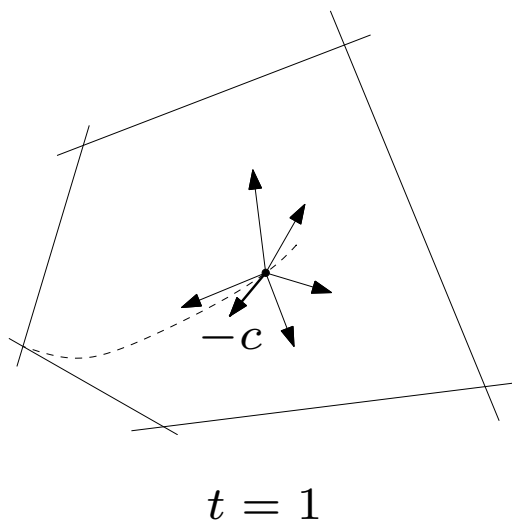
## example

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & a_i^T x \leq b_i, \quad i = 1, \dots, m\end{array}$$

- objective force field is constant:  $F_0(x) = -tc$
- constraint force field decays as inverse distance to constraint hyperplane:

$$F_i(x) = \frac{-a_i}{b_i - a_i^T x}, \quad \|F_i(x)\|_2 = \frac{1}{\mathbf{dist}(x, \mathcal{H}_i)}$$

where  $\mathcal{H}_i = \{x \mid a_i^T x = b_i\}$



# Barrier method

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**given** strictly feasible  $x$ ,  $t := t^{(0)} > 0$ ,  $\mu > 1$ , tolerance  $\epsilon > 0$ .

**repeat**

1. *Centering step.* Compute  $x^*(t)$  by minimizing  $tf_0 + \phi$ , subject to  $Ax = b$ .
  2. *Update.*  $x := x^*(t)$ .
  3. *Stopping criterion.* **quit** if  $m/t < \epsilon$ .
  4. *Increase  $t$ .*  $t := \mu t$ .
- 

- terminates with  $f_0(x) - p^* \leq \epsilon$  (stopping criterion follows from  $f_0(x^*(t)) - p^* \leq m/t$ )
- centering usually done using Newton's method, starting at current  $x$
- choice of  $\mu$  involves a trade-off: large  $\mu$  means fewer outer iterations, more inner (Newton) iterations; typical values:  $\mu = 10\text{--}20$
- several heuristics for choice of  $t^{(0)}$

# Convergence analysis

**number of outer (centering) iterations:** exactly

$$\left\lceil \frac{\log(m/(\epsilon t^{(0)}))}{\log \mu} \right\rceil$$

plus the initial centering step (to compute  $x^*(t^{(0)})$ )

**centering problem**

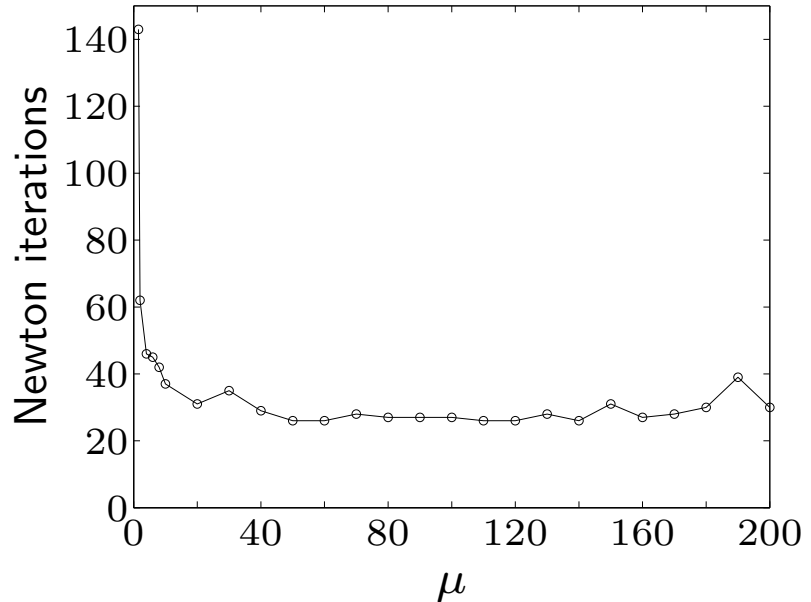
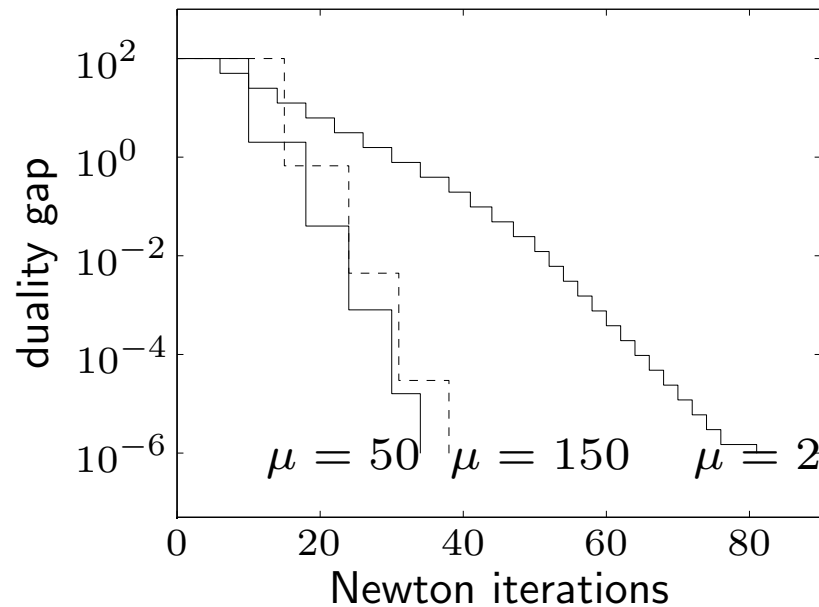
$$\text{minimize } tf_0(x) + \phi(x)$$

see convergence analysis of Newton's method

- $tf_0 + \phi$  must have closed sublevel sets for  $t \geq t^{(0)}$
- classical analysis requires strong convexity, Lipschitz condition
- analysis via self-concordance requires self-concordance of  $tf_0 + \phi$

# Examples

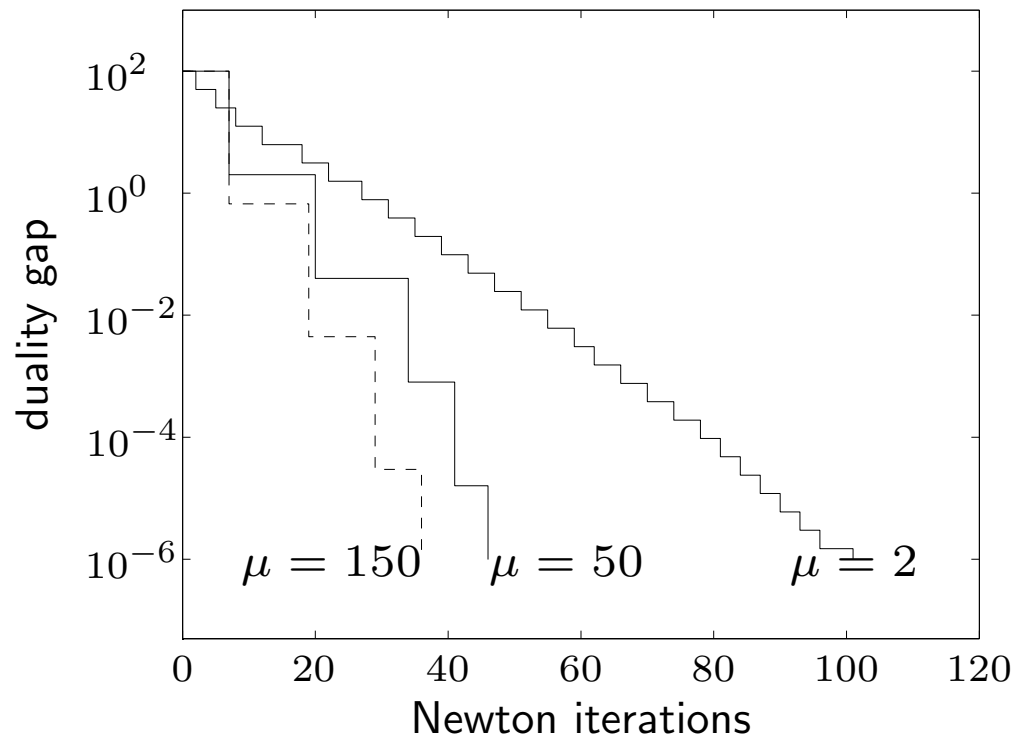
**inequality form LP** ( $m = 100$  inequalities,  $n = 50$  variables)



- starts with  $x$  on central path ( $t^{(0)} = 1$ , duality gap 100)
- terminates when  $t = 10^8$  (gap  $10^{-6}$ )
- centering uses Newton's method with backtracking
- total number of Newton iterations not very sensitive for  $\mu \geq 10$

**geometric program** ( $m = 100$  inequalities and  $n = 50$  variables)

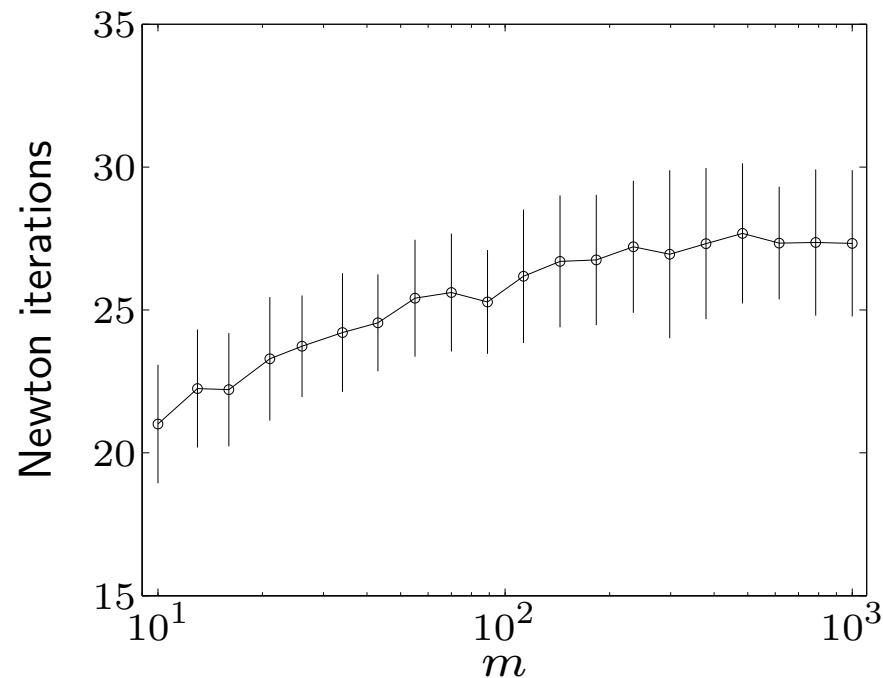
$$\begin{array}{ll} \text{minimize} & \log \left( \sum_{k=1}^5 \exp(a_{0k}^T x + b_{0k}) \right) \\ \text{subject to} & \log \left( \sum_{k=1}^5 \exp(a_{ik}^T x + b_{ik}) \right) \leq 0, \quad i = 1, \dots, m \end{array}$$



family of standard LPs ( $A \in \mathbf{R}^{m \times 2m}$ )

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax = b, \quad x \succeq 0 \end{array}$$

$m = 10, \dots, 1000$ ; for each  $m$ , solve 100 randomly generated instances



number of iterations grows very slowly as  $m$  ranges over a 100 : 1 ratio

# Feasibility and phase I methods

**feasibility problem:** find  $x$  such that

$$f_i(x) \leq 0, \quad i = 1, \dots, m, \quad Ax = b \quad (2)$$

**phase I:** computes strictly feasible starting point for barrier method

**basic phase I method**

$$\begin{array}{ll} \text{minimize (over } x, s) & s \\ \text{subject to} & f_i(x) \leq s, \quad i = 1, \dots, m \\ & Ax = b \end{array} \quad (3)$$

- if  $x, s$  feasible, with  $s < 0$ , then  $x$  is strictly feasible for (2)
- if optimal value  $\bar{p}^*$  of (3) is positive, then problem (2) is infeasible
- if  $\bar{p}^* = 0$  and attained, then problem (2) is feasible (but not strictly);  
if  $\bar{p}^* = 0$  and not attained, then problem (2) is infeasible

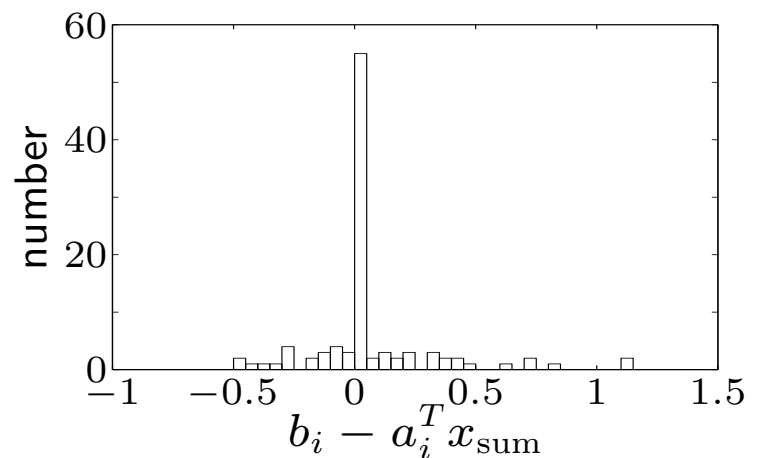
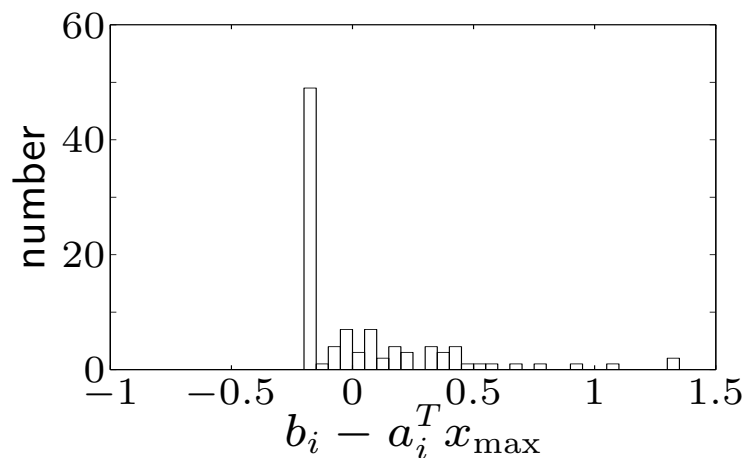


## sum of infeasibilities phase I method

$$\begin{array}{ll}\text{minimize} & \mathbf{1}^T s \\ \text{subject to} & s \succeq 0, \quad f_i(x) \leq s_i, \quad i = 1, \dots, m \\ & Ax = b\end{array}$$

for infeasible problems, produces a solution that satisfies many more inequalities than basic phase I method

**example** (infeasible set of 100 linear inequalities in 50 variables)

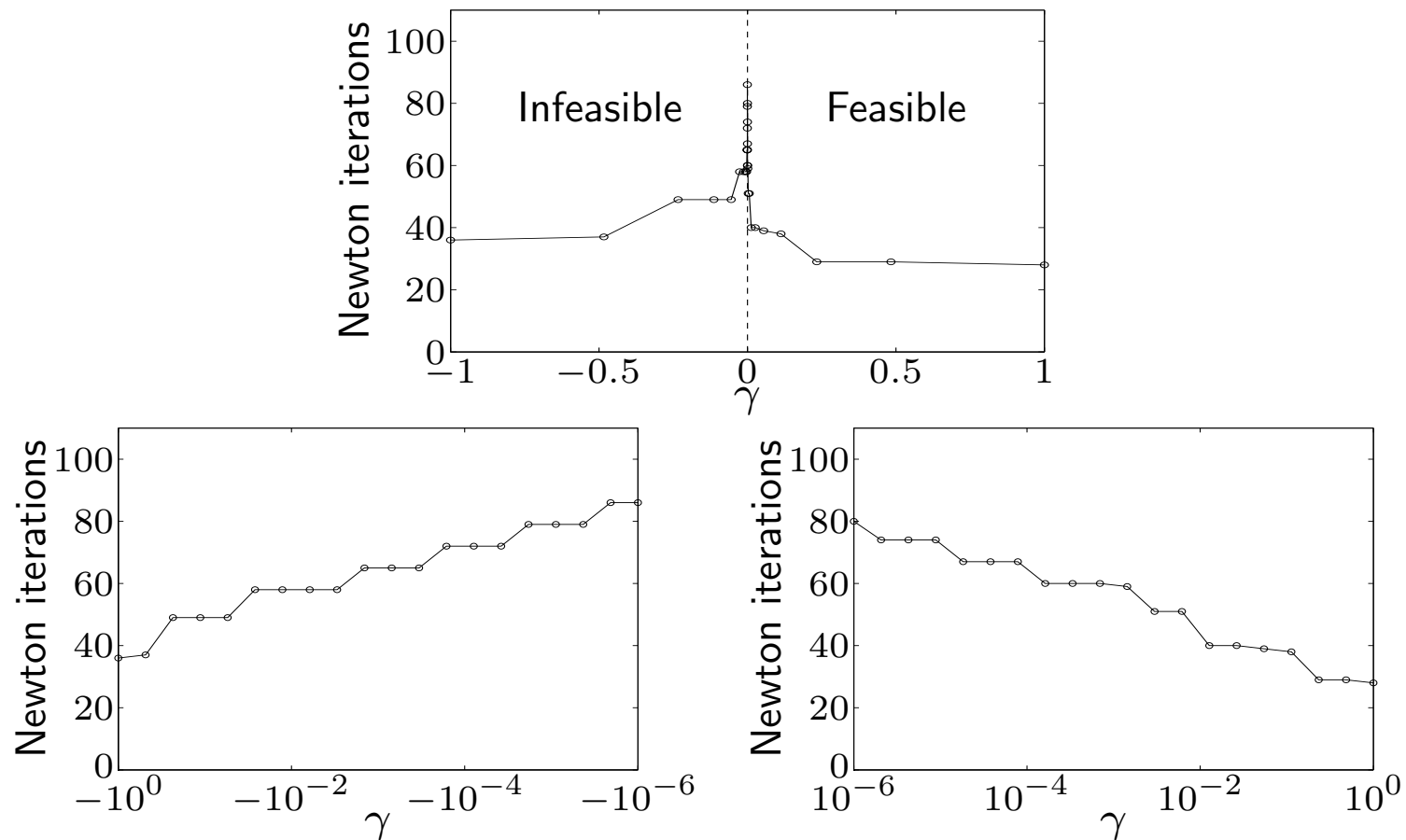


left: basic phase I solution; satisfies 39 inequalities

right: sum of infeasibilities phase I solution; satisfies 79 solutions

**example:** family of linear inequalities  $Ax \preceq b + \gamma \Delta b$

- data chosen to be strictly feasible for  $\gamma > 0$ , infeasible for  $\gamma \leq 0$
- use basic phase I, terminate when  $s < 0$  or dual objective is positive



number of iterations roughly proportional to  $\log(1/|\gamma|)$

# Complexity analysis via self-concordance

same assumptions as on page 1–2, plus:

- sublevel sets (of  $f_0$ , on the feasible set) are bounded
- $tf_0 + \phi$  is self-concordant with closed sublevel sets

second condition

- holds for LP, QP, QCQP
- may require reformulating the problem, *e.g.*,

$$\begin{array}{ll} \text{minimize} & \sum_{i=1}^n x_i \log x_i \\ \text{subject to} & Fx \preceq g \end{array} \quad \longrightarrow \quad \begin{array}{ll} \text{minimize} & \sum_{i=1}^n x_i \log x_i \\ \text{subject to} & Fx \preceq g, \quad x \succeq 0 \end{array}$$

- needed for complexity analysis; barrier method works even when self-concordance assumption does not apply

## Newton iterations per centering step: from self-concordance theory

$$\# \text{Newton iterations} \leq \frac{\mu t f_0(x) + \phi(x) - \mu t f_0(x^+) - \phi(x^+)}{\gamma} + c$$

- bound on effort of computing  $x^+ = x^*(\mu t)$  starting at  $x = x^*(t)$
- $\gamma, c$  are constants (depend only on Newton algorithm parameters)
- from duality (with  $\lambda = \lambda^*(t), \nu = \nu^*(t)$ ):

$$\begin{aligned} & \mu t f_0(x) + \phi(x) - \mu t f_0(x^+) - \phi(x^+) \\ &= \mu t f_0(x) - \mu t f_0(x^+) + \sum_{i=1}^m \log(-\mu t \lambda_i f_i(x^+)) - m \log \mu \\ &\leq \mu t f_0(x) - \mu t f_0(x^+) - \mu t \sum_{i=1}^m \lambda_i f_i(x^+) - m - m \log \mu \\ &\leq \mu t f_0(x) - \mu t g(\lambda, \nu) - m - m \log \mu \\ &= m(\mu - 1 - \log \mu) \end{aligned}$$

**total number of Newton iterations** (excluding first centering step)

$$\# \text{Newton iterations} \leq N = \left\lceil \frac{\log(m/(t^{(0)}\epsilon))}{\log \mu} \right\rceil \left( \frac{m(\mu - 1 - \log \mu)}{\gamma} + c \right)$$

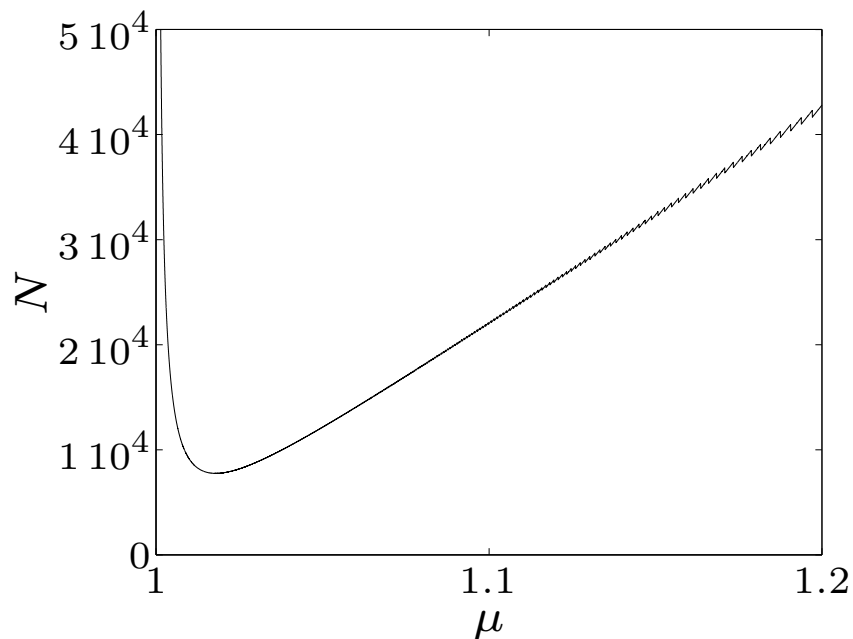


figure shows  $N$  for typical values of  $\gamma, c$ ,

$$m = 100, \quad \frac{m}{t^{(0)}\epsilon} = 10^5$$

- confirms trade-off in choice of  $\mu$
- in practice, #iterations is in the tens; not very sensitive for  $\mu \geq 10$

## polynomial-time complexity of barrier method

- for  $\mu = 1 + 1/\sqrt{m}$ :

$$N = O\left(\sqrt{m} \log\left(\frac{m/t^{(0)}}{\epsilon}\right)\right)$$

- number of Newton iterations for fixed gap reduction is  $O(\sqrt{m})$
- multiply with cost of one Newton iteration (a polynomial function of problem dimensions), to get bound on number of flops

this choice of  $\mu$  optimizes worst-case complexity; in practice we choose  $\mu$  fixed ( $\mu = 10, \dots, 20$ )

# Generalized inequalities

$$\begin{array}{ll}\text{minimize} & f_0(x) \\ \text{subject to} & f_i(x) \preceq_{K_i} 0, \quad i = 1, \dots, m \\ & Ax = b\end{array}$$

- $f_0$  convex,  $f_i : \mathbf{R}^n \rightarrow \mathbf{R}^{k_i}$ ,  $i = 1, \dots, m$ , convex with respect to proper cones  $K_i \in \mathbf{R}^{k_i}$
- $f_i$  twice continuously differentiable
- $A \in \mathbf{R}^{p \times n}$  with  $\text{rank } A = p$
- we assume  $p^*$  is finite and attained
- we assume problem is strictly feasible; hence strong duality holds and dual optimum is attained

examples of greatest interest: SOCP, SDP

## Generalized logarithm for proper cone

$\psi : \mathbf{R}^q \rightarrow \mathbf{R}$  is generalized logarithm for proper cone  $K \subseteq \mathbf{R}^q$  if:

- $\text{dom } \psi = \text{int } K$  and  $\nabla^2 \psi(y) \prec 0$  for  $y \succ_K 0$
- $\psi(sy) = \psi(y) + \theta \log s$  for  $y \succ_K 0$ ,  $s > 0$  ( $\theta$  is the degree of  $\psi$ )

### examples

- nonnegative orthant  $K = \mathbf{R}_+^n$ :  $\psi(y) = \sum_{i=1}^n \log y_i$ , with degree  $\theta = n$
- positive semidefinite cone  $K = \mathbf{S}_+^n$ :

$$\psi(Y) = \log \det Y \quad (\theta = n)$$

- second-order cone  $K = \{y \in \mathbf{R}^{n+1} \mid (y_1^2 + \cdots + y_n^2)^{1/2} \leq y_{n+1}\}$ :

$$\psi(y) = \log(y_{n+1}^2 - y_1^2 - \cdots - y_n^2) \quad (\theta = 2)$$



**properties** (without proof): for  $y \succ_K 0$ ,

$$\nabla\psi(y) \succeq_{K^*} 0, \quad y^T \nabla\psi(y) = \theta$$

- nonnegative orthant  $\mathbf{R}_+^n$ :  $\psi(y) = \sum_{i=1}^n \log y_i$

$$\nabla\psi(y) = (1/y_1, \dots, 1/y_n), \quad y^T \nabla\psi(y) = n$$

- positive semidefinite cone  $\mathbf{S}_+^n$ :  $\psi(Y) = \log \det Y$

$$\nabla\psi(Y) = Y^{-1}, \quad \text{tr}(Y \nabla\psi(Y)) = n$$

- second-order cone  $K = \{y \in \mathbf{R}^{n+1} \mid (y_1^2 + \dots + y_n^2)^{1/2} \leq y_{n+1}\}$ :

$$\psi(y) = \frac{2}{y_{n+1}^2 - y_1^2 - \dots - y_n^2} \begin{bmatrix} -y_1 \\ \vdots \\ -y_n \\ y_{n+1} \end{bmatrix}, \quad y^T \nabla\psi(y) = 2$$

# Logarithmic barrier and central path

**logarithmic barrier** for  $f_1(x) \preceq_{K_1} 0, \dots, f_m(x) \preceq_{K_m} 0$ :

$$\phi(x) = - \sum_{i=1}^m \psi_i(-f_i(x)), \quad \text{dom } \phi = \{x \mid f_i(x) \prec_{K_i} 0, \ i = 1, \dots, m\}$$

- $\psi_i$  is generalized logarithm for  $K_i$ , with degree  $\theta_i$
- $\phi$  is convex, twice continuously differentiable

**central path:**  $\{x^*(t) \mid t > 0\}$  where  $x^*(t)$  solves

$$\begin{array}{ll} \text{minimize} & t f_0(x) + \phi(x) \\ \text{subject to} & Ax = b \end{array}$$

## Dual points on central path

$x = x^*(t)$  if there exists  $w \in \mathbf{R}^p$ ,

$$t \nabla f_0(x) + \sum_{i=1}^m Df_i(x)^T \nabla \psi_i(-f_i(x)) + A^T w = 0$$

$(Df_i(x) \in \mathbf{R}^{k_i \times n}$  is derivative matrix of  $f_i$ )

- therefore,  $x^*(t)$  minimizes Lagrangian  $L(x, \lambda^*(t), \nu^*(t))$ , where

$$\lambda_i^*(t) = \frac{1}{t} \nabla \psi_i(-f_i(x^*(t))), \quad \nu^*(t) = \frac{w}{t}$$

- from properties of  $\psi_i$ :  $\lambda_i^*(t) \succ_{K_i^*} 0$ , with duality gap

$$f_0(x^*(t)) - g(\lambda^*(t), \nu^*(t)) = (1/t) \sum_{i=1}^m \theta_i$$

**example: semidefinite programming** (with  $F_i \in \mathbf{S}^p$ )

$$\begin{array}{ll}\text{minimize} & c^T x \\ \text{subject to} & F(x) = \sum_{i=1}^n x_i F_i + G \preceq 0\end{array}$$

- logarithmic barrier:  $\phi(x) = \log \det(-F(x)^{-1})$
- central path:  $x^*(t)$  minimizes  $tc^T x - \log \det(-F(x))$ ; hence

$$tc_i - \text{tr}(F_i F(x^*(t))^{-1}) = 0, \quad i = 1, \dots, n$$

- dual point on central path:  $Z^*(t) = -(1/t)F(x^*(t))^{-1}$  is feasible for

$$\begin{array}{ll}\text{maximize} & \text{tr}(GZ) \\ \text{subject to} & \text{tr}(F_i Z) + c_i = 0, \quad i = 1, \dots, n \\ & Z \succeq 0\end{array}$$

- duality gap on central path:  $c^T x^*(t) - \text{tr}(GZ^*(t)) = p/t$

# Barrier method

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**given** strictly feasible  $x$ ,  $t := t^{(0)} > 0$ ,  $\mu > 1$ , tolerance  $\epsilon > 0$ .

**repeat**

1. *Centering step.* Compute  $x^*(t)$  by minimizing  $tf_0 + \phi$ , subject to  $Ax = b$ .
  2. *Update.*  $x := x^*(t)$ .
  3. *Stopping criterion.* **quit** if  $(\sum_i \theta_i)/t < \epsilon$ .
  4. *Increase  $t$ .*  $t := \mu t$ .
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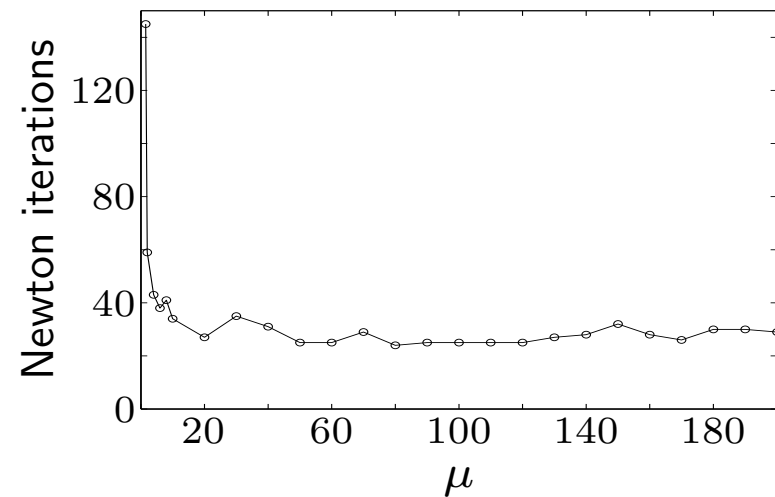
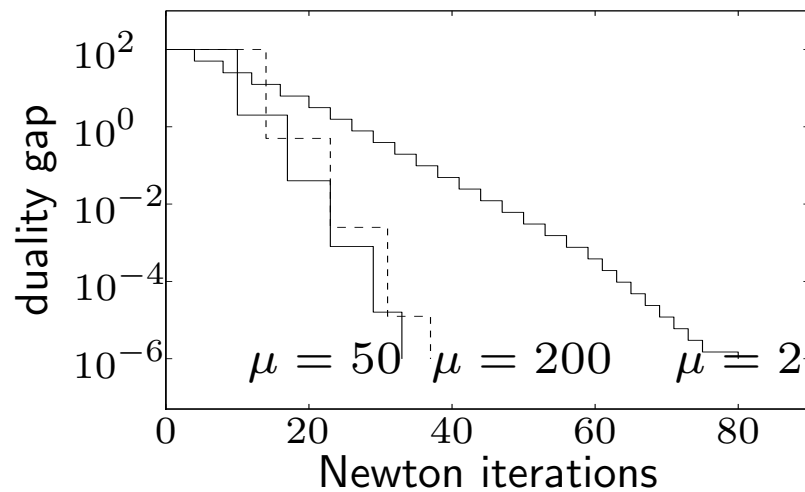
- only difference is duality gap  $m/t$  on central path is replaced by  $\sum_i \theta_i/t$
- number of outer iterations:

$$\left\lceil \frac{\log((\sum_i \theta_i)/(\epsilon t^{(0)}))}{\log \mu} \right\rceil$$

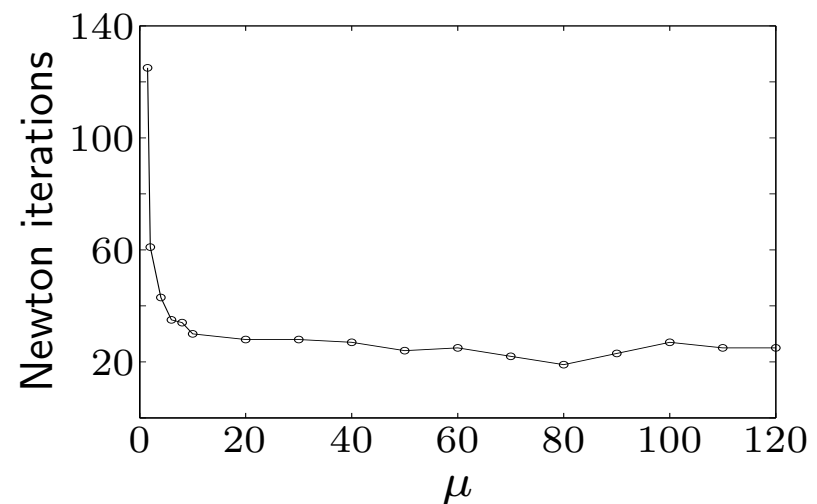
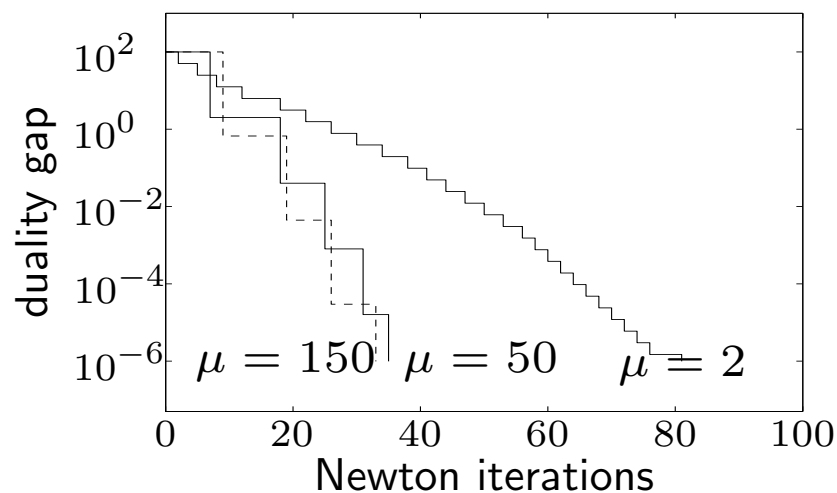
- complexity analysis via self-concordance applies to SDP, SOCP

# Examples

**second-order cone program** (50 variables, 50 SOC constraints in  $\mathbf{R}^6$ )



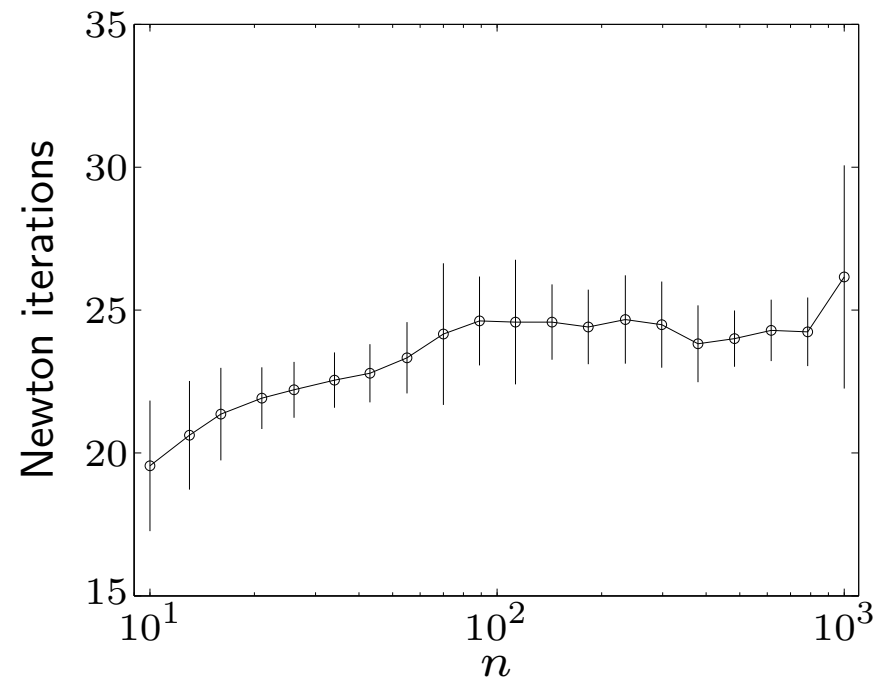
**semidefinite program** (100 variables, LMI constraint in  $\mathbf{S}^{100}$ )



family of SDPs ( $A \in \mathbf{S}^n$ ,  $x \in \mathbf{R}^n$ )

$$\begin{array}{ll}\text{minimize} & \mathbf{1}^T x \\ \text{subject to} & A + \mathbf{diag}(x) \succeq 0\end{array}$$

$n = 10, \dots, 1000$ , for each  $n$  solve 100 randomly generated instances



# Primal-dual interior-point methods

more efficient than barrier method when high accuracy is needed

- update primal and dual variables at each iteration; no distinction between inner and outer iterations
- often exhibit superlinear asymptotic convergence
- search directions can be interpreted as Newton directions for modified KKT conditions
- can start at infeasible points
- cost per iteration same as barrier method