

## 10 Karmarkars Algorithm

- ▶ inequalities  $Ax \leq b$ ;  $m \times n$  matrix  $A$  with rows  $a_i^T$
- ▶  $P = \{x \mid Ax \leq b\}$ ;  $P^\circ := \{x \mid Ax < b\}$
- ▶ interior point algorithm:  $x \in P^\circ$  throughout the algorithm
- ▶ for  $x \in P^\circ$  define

$$s_i(x) := b_i - a_i^T x$$

as the **slack** of the  $i$ -th constraint

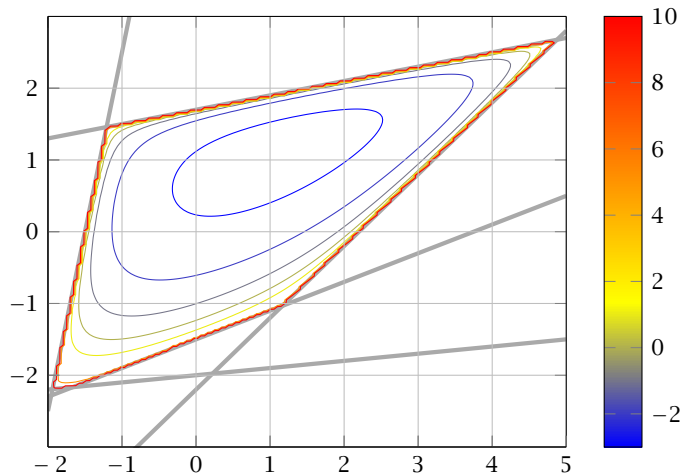
**logarithmic barrier function:**

$$\phi(x) = - \sum_{i=1}^m \ln(s_i(x))$$

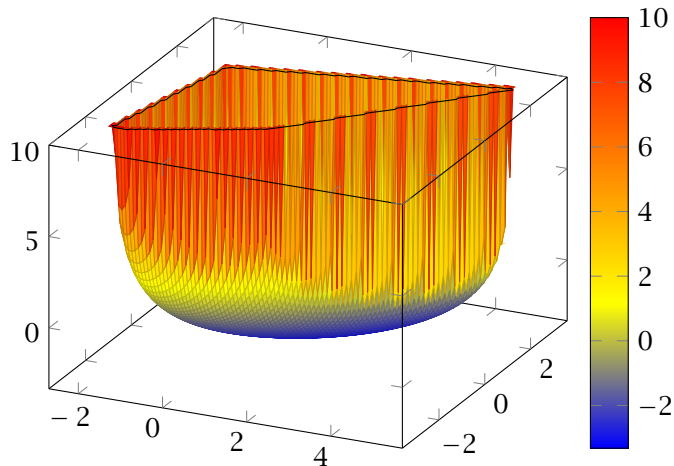
**Penalty** for point  $x$ ; points close to the boundary have a very large penalty.

Throughout this section  $a_i$  denotes the  $i$ -th row as a column vector.

# Penalty Function



# Penalty Function



# Gradient and Hessian

**Taylor approximation:**

$$\phi(x + \epsilon) \approx \phi(x) + \nabla \phi(x)^T \epsilon + \frac{1}{2} \epsilon^T \nabla^2 \phi(x) \epsilon$$

**Gradient:**

$$\nabla \phi(x) = \sum_{i=1}^m \frac{1}{s_i(x)} \cdot a_i = A^T d_x$$

where  $d_x^T = (1/s_1(x), \dots, 1/s_m(x))$ . ( $d_x$  vector of **inverse slacks**)

**Hessian:**

$$H_x := \nabla^2 \phi(x) = \sum_{i=1}^m \frac{1}{s_i(x)^2} a_i a_i^T = A^T D_x^2 A$$

with  $D_x = \text{diag}(d_x)$ .

## Proof for Gradient

$$\begin{aligned}\frac{\partial \phi(x)}{\partial x_i} &= \frac{\partial}{\partial x_i} \left( - \sum_r \ln(s_r(x)) \right) \\ &= - \sum_r \frac{\partial}{\partial x_i} \left( \ln(s_r(x)) \right) = - \sum_r \frac{1}{s_r(x)} \frac{\partial}{\partial x_i} \left( s_r(x) \right) \\ &= - \sum_r \frac{1}{s_r(x)} \frac{\partial}{\partial x_i} \left( b_r - a_r^T x \right) = \sum_r \frac{1}{s_r(x)} \frac{\partial}{\partial x_i} \left( a_r^T x \right) \\ &= \sum_r \frac{1}{s_r(x)} A_{ri}\end{aligned}$$

The  $i$ -th entry of the gradient vector is  $\sum_r 1/s_r(x) \cdot A_{ri}$ . This gives that the gradient is

$$\nabla \phi(x) = \sum_r 1/s_r(x) a_r = A^T d_x$$

## Proof for Hessian

$$\begin{aligned}\frac{\partial}{\partial x_j} \left( \sum_r \frac{1}{s_r(x)} A_{ri} \right) &= \sum_r A_{ri} \left( -\frac{1}{s_r(x)^2} \right) \cdot \frac{\partial}{\partial x_j} (s_r(x)) \\ &= \sum_r A_{ri} \frac{1}{s_r(x)^2} A_{rj}\end{aligned}$$

Note that  $\sum_r A_{ri} A_{rj} = (A^T A)_{ij}$ . Adding the additional factors  $1/s_r(x)^2$  can be done with a diagonal matrix.

Hence the Hessian is

$$H_x = A^T D^2 A$$

# Properties of the Hessian

$H_x$  is positive semi-definite for  $x \in P^\circ$

$$u^T H_x u = u^T A^T D_x^2 A u = \|D_x A u\|_2^2 \geq 0$$

This gives that  $\phi(x)$  is convex.

If  $\text{rank}(A) = n$ ,  $H_x$  is positive definite for  $x \in P^\circ$

$$u^T H_x u = \|D_x A u\|_2^2 > 0 \text{ for } u \neq 0$$

This gives that  $\phi(x)$  is **strictly** convex.

$\|u\|_{H_x} := \sqrt{u^T H_x u}$  is a (semi-)norm; the unit ball w.r.t. this norm is an ellipsoid.

## Dikin Ellipsoid

$$E_x = \{y \mid (y - x)^T H_x (y - x) \leq 1\} = \{y \mid \|y - x\|_{H_x} \leq 1\}$$

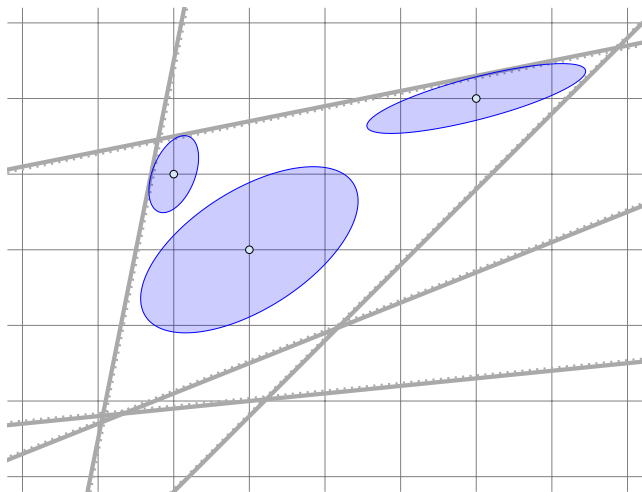
**Points in  $E_x$  are feasible!!!**

$$\begin{aligned}(y - x)^T H_x (y - x) &= (y - x)^T A^T D_x^2 A (y - x) \\ &= \sum_{i=1}^m \frac{(a_i^T (y - x))^2}{s_i(x)^2} \\ &= \sum_{i=1}^m \frac{(\text{change of distance to } i\text{-th constraint going from } x \text{ to } y)^2}{(\text{distance of } x \text{ to } i\text{-th constraint})^2} \\ &\leq 1\end{aligned}$$

In order to become infeasible when going from  $x$  to  $y$  one of the terms in the sum would need to be larger than 1.



# Dikin Ellipsoids



$$x_{\text{ac}} := \arg \min_{x \in P^\circ} \phi(x)$$

- ▶  $x_{\text{ac}}$  is solution to

$$\nabla \phi(x) = \sum_{i=1}^m \frac{1}{s_i(x)} a_i = 0$$

- ▶ depends on the **description** of the polytope
- ▶  $x_{\text{ac}}$  exists and is unique iff  $P^\circ$  is nonempty and bounded

# Central Path

In the following we assume that the LP and its dual are **strictly feasible** and that  $\text{rank}(A) = n$ .

## Central Path:

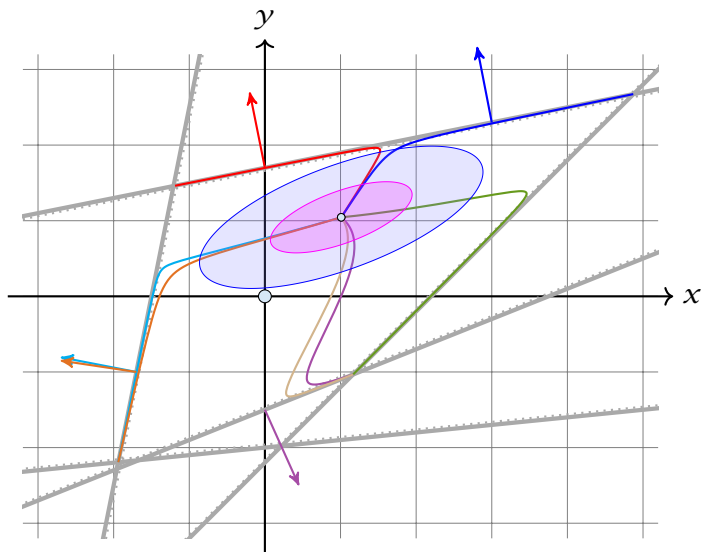
Set of points  $\{x^*(t) \mid t > 0\}$  with

$$x^*(t) = \operatorname{argmin}_x \{tc^T x + \phi(x)\}$$

- ▶  $t = 0$ : analytic center
- ▶  $t = \infty$ : optimum solution

$x^*(t)$  exists and is unique for all  $t \geq 0$ .

# Different Central Paths



# Central Path

## Intuitive Idea:

Find point on central path for large value of  $t$ . Should be close to optimum solution.

## Questions:

- ▶ Is this really true? How large a  $t$  do we need?
- ▶ How do we find corresponding point  $x^*(t)$  on central path?

# The Dual

primal-dual pair:

$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & Ax \leq b \end{array}$$

$$\begin{array}{ll} \max & -b^T z \\ \text{s.t.} & A^T z + c = 0 \\ & z \geq 0 \end{array}$$

## Assumptions

- ▶ primal and dual problems are strictly feasible;
- ▶  $\text{rank}(A) = n$ .

Note that the right LP in standard form is equal to  $\max\{-b^T y \mid -A^T y = c, y \geq 0\}$ . The dual of this is  $\min\{c^T x \mid -Ax \geq -b\}$  (variables  $x$  are unrestricted).

# Force Field Interpretation

Point  $x^*(t)$  on central path is solution to  $tc + \nabla\phi(x) = 0$

- ▶ We can view each constraint as generating a repelling force. The combination of these forces is represented by  $\nabla\phi(x)$ .
- ▶ In addition there is a force  $tc$  pulling us towards the optimum solution.

The “gravitational force” actually pulls us in direction  $-\nabla\Phi(x)$ . We are minimizing, hence, optimizing in direction  $-c$ .

## How large should $t$ be?

Point  $x^*(t)$  on central path is solution to  $tc + \nabla\phi(x) = 0$ .

This means

$$tc + \sum_{i=1}^m \frac{1}{s_i(x^*(t))} a_i = 0$$

or

$$c + \sum_{i=1}^m z_i^*(t) a_i = 0 \quad \text{with} \quad z_i^*(t) = \frac{1}{ts_i(x^*(t))}$$

- ▶  $z^*(t)$  is strictly dual feasible: ( $A^T z^* + c = 0$ ;  $z^* > 0$ )
- ▶ duality gap between  $x := x^*(t)$  and  $z := z^*(t)$  is

$$c^T x + b^T z = (b - Ax)^T z = \frac{m}{t}$$

- ▶ if gap is less than  $1/2^{\Omega(L)}$  we can snap to optimum point



# How to find $x^*(t)$

## First idea:

- ▶ start somewhere in the polytope
- ▶ use iterative method (**Newtons method**) to minimize  $f_t(x) := tc^T x + \phi(x)$

# Newton Method

Quadratic approximation of  $f_t$

$$f_t(\mathbf{x} + \epsilon) \approx f_t(\mathbf{x}) + \nabla f_t(\mathbf{x})^T \epsilon + \frac{1}{2} \epsilon^T H_{f_t}(\mathbf{x}) \epsilon$$

Suppose this were exact:

$$f_t(\mathbf{x} + \epsilon) = f_t(\mathbf{x}) + \nabla f_t(\mathbf{x})^T \epsilon + \frac{1}{2} \epsilon^T H_{f_t}(\mathbf{x}) \epsilon$$

Then gradient is given by:

$$\nabla f_t(\mathbf{x} + \epsilon) = \nabla f_t(\mathbf{x}) + H_{f_t}(\mathbf{x}) \cdot \epsilon$$

Note that for the one-dimensional case  $g(\epsilon) = f(x) + f'(x)\epsilon + \frac{1}{2}f''(x)\epsilon^2$ , then  $g'(\epsilon) = f'(x) + f''(x)\epsilon$ .

# Newton Method

Observe that  $H_{f_t}(x) = H(x)$ , where  $H(x)$  is the Hessian for the function  $\phi(x)$  (adding a linear term like  $tc^T x$  does not affect the Hessian).

Also  $\nabla f_t(x) = tc + \nabla \phi(x)$ .

We want to move to a point where this gradient is  $0$ :

**Newton Step** at  $x \in P^\circ$

$$\begin{aligned}\Delta x_{nt} &= -H_{f_t}^{-1}(x) \nabla f_t(x) \\ &= -H_{f_t}^{-1}(x) (tc + \nabla \phi(x)) \\ &= -(A^T D_x^2 A)^{-1} (tc + A^T d_x)\end{aligned}$$

**Newton Iteration:**

$$x := x + \Delta x_{nt}$$

# Measuring Progress of Newton Step

**Newton decrement:**

$$\begin{aligned}\lambda_t(\mathbf{x}) &= \|D_{\mathbf{x}}A\Delta\mathbf{x}_{nt}\| \\ &= \|\Delta\mathbf{x}_{nt}\|_{H_{\mathbf{x}}}\end{aligned}$$

Square of Newton decrement is linear estimate of reduction if we do a Newton step:

$$-\lambda_t(\mathbf{x})^2 = \nabla f_t(\mathbf{x})^T \Delta\mathbf{x}_{nt}$$

- ▶  $\lambda_t(\mathbf{x}) = 0$  iff  $\mathbf{x} = \mathbf{x}^*(t)$
- ▶  $\lambda_t(\mathbf{x})$  is measure of proximity of  $\mathbf{x}$  to  $\mathbf{x}^*(t)$

Recall that  $\Delta\mathbf{x}_{nt}$  fulfills  $-H(\mathbf{x})\Delta\mathbf{x}_{nt} = \nabla f_t(\mathbf{x})$ .

# Convergence of Newtons Method

## Theorem 55

If  $\lambda_t(x) < 1$  then

- ▶  $x_+ := x + \Delta x_{nt} \in P^\circ$  (new point feasible)
- ▶  $\lambda_t(x_+) \leq \lambda_t(x)^2$

This means we have **quadratic convergence**. Very fast.

# Convergence of Newtons Method

**feasibility:**

- ▶  $\lambda_t(\mathbf{x}) = \|\Delta\mathbf{x}_{nt}\|_{H_x} < 1$ ; hence  $\mathbf{x}_+$  lies in the **Dikin ellipsoid** around  $\mathbf{x}$ .

# Convergence of Newtons Method

**bound on  $\lambda_t(\mathbf{x}^+)$ :**

we use  $D := D_x = \text{diag}(d_x)$  and  $D_+ := D_{x^+} = \text{diag}(d_{x^+})$

$$\begin{aligned}\lambda_t(\mathbf{x}^+)^2 &= \|D_+ A \Delta \mathbf{x}_{\text{nt}}^+\|^2 \\ &\leq \|D_+ A \Delta \mathbf{x}_{\text{nt}}^+\|^2 + \|D_+ A \Delta \mathbf{x}_{\text{nt}}^+ + (I - D_+^{-1} D) D A \Delta \mathbf{x}_{\text{nt}}\|^2 \\ &= \|(I - D_+^{-1} D) D A \Delta \mathbf{x}_{\text{nt}}\|^2\end{aligned}$$

To see the last equality we use Pythagoras

$$\|a\|^2 + \|a + b\|^2 = \|b\|^2$$

if  $a^T(a + b) = 0$ .

## Convergence of Newtons Method

$$\begin{aligned}DA\Delta x_{nt} &= DA(x^+ - x) \\ &= D(b - Ax - (b - Ax^+)) \\ &= D(D^{-1}\vec{1} - D_+^{-1}\vec{1}) \\ &= (I - D_+^{-1}D)\vec{1}\end{aligned}$$

$$a^T(a + b)$$

$$\begin{aligned}&= \Delta x_{nt}^{+T} A^T D_+ \left( D_+ A \Delta x_{nt}^+ + (I - D_+^{-1} D) D A \Delta x_{nt} \right) \\ &= \Delta x_{nt}^{+T} \left( A^T D_+^2 A \Delta x_{nt}^+ - A^T D^2 A \Delta x_{nt} + A^T D_+ D A \Delta x_{nt} \right) \\ &= \Delta x_{nt}^{+T} \left( H_+ \Delta x_{nt}^+ - H \Delta x_{nt} + A^T D_+ \vec{1} - A^T D \vec{1} \right) \\ &= \Delta x_{nt}^{+T} \left( -\nabla f_t(x^+) + \nabla f_t(x) + \nabla \phi(x^+) - \nabla \phi(x) \right) \\ &= 0\end{aligned}$$



# Convergence of Newtons Method

**bound on  $\lambda_t(\mathbf{x}^+)$ :**

we use  $D := D_x = \text{diag}(d_x)$  and  $D_+ := D_{x^+} = \text{diag}(d_{x^+})$

$$\begin{aligned}\lambda_t(\mathbf{x}^+)^2 &= \|D_+ A \Delta \mathbf{x}_{\text{nt}}^+\|^2 \\ &\leq \|D_+ A \Delta \mathbf{x}_{\text{nt}}^+\|^2 + \|D_+ A \Delta \mathbf{x}_{\text{nt}}^+ + (I - D_+^{-1} D) D A \Delta \mathbf{x}_{\text{nt}}\|^2 \\ &= \|(I - D_+^{-1} D) D A \Delta \mathbf{x}_{\text{nt}}\|^2 \\ &= \|(I - D_+^{-1} D)^2 \vec{1}\|^2 \\ &\leq \|(I - D_+^{-1} D) \vec{1}\|^4 \\ &= \|D A \Delta \mathbf{x}_{\text{nt}}\|^4 \\ &= \lambda_t(\mathbf{x})^4\end{aligned}$$

The second inequality follows from  $\sum_i y_i^4 \leq (\sum_i y_i^2)^2$

If  $\lambda_t(x)$  is large we do not have a guarantee.

**Try to avoid this case!!!**

# Path-following Methods

Try to slowly travel along the central path.

## Algorithm 1 PathFollowing

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- 1: start at analytic center
- 2: **while** solution not good enough **do**
- 3:     make step to improve objective function
- 4:     recenter to return to central path

# Short Step Barrier Method

## simplifying assumptions:

- ▶ a first central point  $x^*(t_0)$  is given
- ▶  $x^*(t)$  is computed exactly in each iteration

$\epsilon$  is approximation we are aiming for

start at  $t = t_0$ , repeat until  $m/t \leq \epsilon$

- ▶ compute  $x^*(\mu t)$  using Newton starting from  $x^*(t)$
- ▶  $t := \mu t$

where  $\mu = 1 + 1/(2\sqrt{m})$

## Short Step Barrier Method

gradient of  $f_{t+}$  at  $(x = x^*(t))$

$$\begin{aligned}\nabla f_{t+}(x) &= \nabla f_t(x) + (\mu - 1)tc \\ &= -(\mu - 1)A^T D_x \vec{1}\end{aligned}$$

This holds because  $0 = \nabla f_t(x) = tc + A^T D_x \vec{1}$ .

The Newton decrement is

$$\begin{aligned}\lambda_{t+}(x)^2 &= \nabla f_{t+}(x)^T H^{-1} \nabla f_{t+}(x) \\ &= (\mu - 1)^2 \vec{1}^T B (B^T B)^{-1} B^T \vec{1} \quad B = D_x^T A \\ &\leq (\mu - 1)^2 m \\ &= 1/4\end{aligned}$$

This means we are in the range of quadratic convergence!!!

# Number of Iterations

the number of Newton iterations per outer iteration is very small; in practise only 1 or 2

## Number of outer iterations:

We need  $t_k = \mu^k t_0 \geq m/\epsilon$ . This holds when

$$k \geq \frac{\log(m/(\epsilon t_0))}{\log(\mu)}$$

We get a bound of

$$\mathcal{O}\left(\sqrt{m} \log \frac{m}{\epsilon t_0}\right)$$

We show how to get a starting point with  $t_0 = 1/2^L$ . Together with  $\epsilon \approx 2^{-L}$  we get  $\mathcal{O}(L\sqrt{m})$  iterations.

**Explanation for previous slide**  
 $P = B(B^T B)^{-1} B^T$  is a symmetric real-valued matrix; it has  $n$  linearly independent Eigenvectors. Since it is a **projection matrix** ( $P^2 = P$ ) it can only have Eigenvalues 0 and 1 (because the Eigenvalues of  $P^2$  are  $\lambda_i^2$ , where  $\lambda_i$  is Eigenvalue of  $P$ ). The expression

$$\max_v \frac{v^T P v}{v^T v}$$

gives the largest Eigenvalue for  $P$ . Hence,  $\vec{1}^T P \vec{1} \leq \vec{1}^T \vec{1} = m$

# Damped Newton Method

We assume that the polytope (not just the LP) is bounded. Then  $Av \leq 0$  is not possible.

For  $x \in P^\circ$  and direction  $v \neq 0$  define

$$\sigma_x(v) := \max_i \frac{a_i^T v}{s_i(x)}$$

$a_i^T v$  is the change on the left hand side of the  $i$ -th constraint when moving in direction of  $v$ .

If  $\sigma_x(v) > 1$  then for one coordinate this change is larger than the slack in the constraint at position  $x$ .

By downscaling  $v$  we can ensure to stay in the polytope.

**Observation:**

$$x + \alpha v \in P \quad \text{for } \alpha \in \{0, 1/\sigma_x(v)\}$$

## Damped Newton Method

Suppose that we move from  $x$  to  $x + \alpha v$ . The linear estimate says that  $f_t(x)$  should change by  $\nabla f_t(x)^T \alpha v$ .

The following argument shows that  $f_t$  is well behaved. For small  $\alpha$  the reduction of  $f_t(x)$  is close to linear estimate.

$$f_t(x + \alpha v) - f_t(x) = t c^T \alpha v + \phi(x + \alpha v) - \phi(x)$$

$$\begin{aligned}\phi(x + \alpha v) - \phi(x) &= - \sum_i \log(s_i(x + \alpha v)) + \sum_i \log(s_i(x)) \\ &= - \sum_i \log(s_i(x + \alpha v)/s_i(x)) \\ &= - \sum_i \log(1 - a_i^T \alpha v / s_i(x))\end{aligned}$$

$$s_i(x + \alpha v) = b_i - a_i^T x - a_i^T \alpha v = s_i(x) - a_i^T \alpha v$$



# Damped Newton Method

$$\begin{aligned}\nabla f_t(x)^T \alpha v &= (tc^T + \sum_i a_i^T / s_i(x)) \alpha v \\ &= tc^T \alpha v + \sum_i \alpha w_i\end{aligned}$$

Define  $w_i = a_i^T v / s_i(x)$  and  $\sigma = \max_i w_i$ . Then

Note that  $\|w\| = \|v\|_{H_x}$ .

$$\begin{aligned}f_t(x + \alpha v) - f_t(x) - \nabla f_t(x)^T \alpha v &= - \sum_i (\alpha w_i + \log(1 - \alpha w_i)) \\ &\leq - \sum_{w_i > 0} (\alpha w_i + \log(1 - \alpha w_i)) + \sum_{w_i \leq 0} \frac{\alpha^2 w_i^2}{2} \\ &\leq - \sum_{w_i > 0} \frac{w_i^2}{\sigma^2} (\alpha \sigma + \log(1 - \alpha \sigma)) + \frac{(\alpha \sigma)^2}{2} \sum_{w_i \leq 0} \frac{w_i^2}{\sigma^2}\end{aligned}$$

For  $|x| < 1, x \leq 0$ :

$$x + \log(1 - x) = -\frac{x^2}{2} - \frac{x^3}{3} - \frac{x^4}{4} - \dots \geq -\frac{x^2}{2} = -\frac{y^2}{2} \frac{x^2}{y^2}$$

For  $|x| < 1, 0 < x \leq y$ :

$$\begin{aligned}x + \log(1 - x) &= -\frac{x^2}{2} - \frac{x^3}{3} - \frac{x^4}{4} - \dots = \frac{x^2}{y^2} \left( -\frac{y^2}{2} - \frac{y^2 x}{3} - \frac{y^2 x^2}{4} - \dots \right) \\ &\geq \frac{x^2}{y^2} \left( -\frac{y^2}{2} - \frac{y^3}{3} - \frac{y^4}{4} - \dots \right) = \frac{x^2}{y^2} (y + \log(1 - y))\end{aligned}$$

# Damped Newton Method

$$\text{For } x \geq 0 \quad \frac{x^2}{2} \leq \frac{x^2}{2} + \frac{x^3}{3} + \frac{x^4}{4} + \dots = -(x + \log(1-x))$$

$$\begin{aligned} &\leq -\sum_i \frac{w_i^2}{\sigma^2} (\alpha\sigma + \log(1-\alpha\sigma)) \\ &= -\frac{1}{\sigma^2} \|v\|_{H_x}^2 (\alpha\sigma + \log(1-\alpha\sigma)) \end{aligned}$$

## Damped Newton Iteration:

In a damped Newton step we choose

$$x_+ = x + \frac{1}{1 + \sigma_x(\Delta x_{nt})} \Delta x_{nt}$$

This means that in the above expressions we choose  $\alpha = \frac{1}{1+\sigma}$  and  $v = \Delta x_{nt}$ . Note that it wouldn't make sense to choose  $\alpha$  larger than 1 as this would mean that our real target  $(x + \Delta x_{nt})$  is inside the polytope but we overshoot and go further than this target.

## Damped Newton Method

### Theorem:

In a damped Newton step the cost decreases by at least

$$\lambda_t(x) - \log(1 + \lambda_t(x))$$

**Proof:** The decrease in cost is

$$-\alpha \nabla f_t(x)^T v + \frac{1}{\sigma^2} \|v\|_{H_x}^2 (\alpha\sigma + \log(1 - \alpha\sigma))$$

Choosing  $\alpha = \frac{1}{1+\sigma}$  and  $v = \Delta x_{nt}$  gives

$$\begin{aligned} \frac{1}{1+\sigma} \lambda_t(x)^2 + \frac{\lambda_t(x)^2}{\sigma^2} \left( \frac{\sigma}{1+\sigma} + \log\left(1 - \frac{\sigma}{1+\sigma}\right) \right) \\ = \frac{\lambda_t(x)^2}{\sigma^2} (\sigma - \log(1 + \sigma)) \end{aligned}$$

With  $v = \Delta x_{nt}$  we have  $\|w\|_2 = \|v\|_{H_x} = \lambda_t(x)$ ; further recall that  $\sigma = \|w\|_\infty$ ; hence  $\sigma \leq \lambda_t(x)$ .

# Damped Newton Method

The first inequality follows since the function  $\frac{1}{x^2}(x - \log(1+x))$  is monotonically decreasing.

$$\begin{aligned} &\geq \lambda_t(x) - \log(1 + \lambda_t(x)) \\ &\geq 0.09 \end{aligned}$$

for  $\lambda_t(x) \geq 0.5$

## Centering Algorithm:

Input: precision  $\delta$ ; starting point  $x$

1. compute  $\Delta x_{nt}$  and  $\lambda_t(x)$
2. if  $\lambda_t(x) \leq \delta$  return  $x$
3. set  $x := x + \alpha \Delta x_{nt}$  with

$$\alpha = \begin{cases} \frac{1}{1 + \sigma_x(\Delta x_{nt})} & \lambda_t \geq 1/2 \\ 1 & \text{otw.} \end{cases}$$

# Centering

## Lemma 56

The centering algorithm starting at  $x_0$  reaches a point with  $\lambda_t(x) \leq \delta$  after

$$\frac{f_t(x_0) - \min_y f_t(y)}{0.09} + \mathcal{O}(\log \log(1/\delta))$$

iterations.

This can be very, very slow...

# How to get close to analytic center?

Let  $P = \{Ax \leq b\}$  be our (**feasible**) polyhedron, and  $x_0$  a feasible point.

We change  $b \rightarrow b + \frac{1}{\lambda} \cdot \vec{1}$ , where  $L = \langle A \rangle + \langle b \rangle + \langle c \rangle$  (**encoding length**) and  $\lambda = 2^{2L}$ . Recall that a basis is feasible in the old LP iff it is feasible in the new LP.

**Lemma** [without proof]

The inverse of a matrix  $M$  can be represented with rational numbers that have denominators  $z_{ij} = \det(M)$ .

For two basis solutions  $x_B, x_{\bar{B}}$ , the cost-difference  $c^T x_B - c^T x_{\bar{B}}$  can be represented by a rational number that has denominator  $z = \det(A_B) \cdot \det(A_{\bar{B}})$ .

This means that in the perturbed LP it is sufficient to decrease the duality gap to  $1/2^{4L}$  (i.e.,  $t \approx 2^{4L}$ ). This means the previous analysis essentially also works for the perturbed LP.

For a point  $x$  from the polytope (not necessarily BFS) the objective value  $\bar{c}^T x$  is at most  $n2^M 2^L$ , where  $M \leq L$  is the encoding length of the largest entry in  $\bar{c}$ .

## How to get close to analytic center?

Start at  $x_0$ .

Choose  $\hat{c} := -\nabla\phi(x)$ .

Note that an entry in  $\hat{c}$  fulfills  $|\hat{c}_i| \leq 2^{2L}$ . This holds since the slack in every constraint at  $x_0$  is at least  $\lambda = 1/2^{2L}$ , and the gradient is the vector of inverse slacks.

$x_0 = x^*(1)$  is point on central path for  $\hat{c}$  and  $t = 1$ .

You can travel the central path in both directions. Go towards  $0$  until  $t \approx 1/2^{\Omega(L)}$ . This requires  $O(\sqrt{m}L)$  outer iterations.

Let  $x_{\hat{c}}$  denote this point.

Let  $x_c$  denote the point that minimizes

$$t \cdot c^T x + \phi(x)$$

(i.e., same value for  $t$  but different  $c$ , hence, different central path).



## How to get close to analytic center?

Clearly,

$$t \cdot \hat{c}^T x_{\hat{c}} + \phi(x_{\hat{c}}) \leq t \cdot \hat{c}^T x_c + \phi(x_c)$$

The difference between  $f_t(x_{\hat{c}})$  and  $f_t(x_c)$  is

$$\begin{aligned} t c^T x_{\hat{c}} + \phi(x_{\hat{c}}) - t c^T x_c - \phi(x_c) \\ \leq t(c^T x_{\hat{c}} + \hat{c}^T x_c - \hat{c}^T x_{\hat{c}} - c^T x_c) \\ \leq 4tn2^{3L} \end{aligned}$$

For  $t = 1/2^{\Omega(L)}$  the last term becomes constant. Hence, using damped Newton we can move from  $x_{\hat{c}}$  to  $x_c$  quickly.

In total for this analysis we require  $\mathcal{O}(\sqrt{m}L)$  outer iterations for the whole algorithm.

One iteration can be implemented in  $\tilde{\mathcal{O}}(m^3)$  time.