

# INTERIOR POINT METHODS - part 1

14/12/2020

## PRIMAL-DUAL AFFINE SCALING POTENTIAL REDUCTION ALGORITHM

### PRELIMINARIES

Given: integer matrix  $A^{m \times n} \in \mathbb{Z}$ , integer vectors  $b \in \mathbb{Z}^m, c \in \mathbb{Z}^n$

Goal: to find an optimal solution  $\min c^T x$  (P)

s.t.  $Ax = b$

$x \geq 0$

let  $P = \{x \in \mathbb{R}^n \mid Ax = b, x \geq 0\}$

(D)  $\max y^T b$

$A^T y + s = c$

$s \geq 0$

$s \dots$  slack variables

$L = \langle A/b \rangle$  input size

Assume, wlog:  $\text{rank}(A) = m$  (Then  $AA^T$  is regular)

$\Rightarrow$  for a feasible  $(y, s)$  of (D),  $y$  is uniquely given by  $s$

Duality gap:

$c^T x - y^T b = \underbrace{y^T A}_{\text{cancel}} x + s^T x - \underbrace{y^T A}_{\text{cancel}} x = s^T x$

Theorem 1: Under the above assumptions, let  $u$  and  $v$  be vertices of  $P$ . If  $c^T u \neq c^T v$ , then

$|c^T u - c^T v| > 2^{-2L}$

Proof: by the same arguments as in the proof of the last lemma in the first lecture on ellipsoid alg.

we know:  $u_i = \frac{\det \dots}{\det \dots}$

$\det \dots$  submatrix of  $\begin{pmatrix} A \\ I \end{pmatrix}$

$v_i = \frac{\det \dots}{\det \dots}$  also a submatrix of  $\begin{pmatrix} A \\ I \end{pmatrix}$

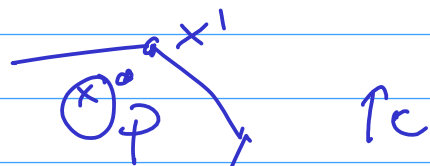
we also know:

$|\det B| < 2^L$  for any square submatrix of  $A$

$\Rightarrow |c^T u - c^T v| = \left| \frac{q \cdot c^T u}{2} - \frac{p \cdot c^T v}{p} \right| =$   
 $= \left| \frac{q \cdot p (c^T u - c^T v)}{2 \cdot p} \right| \geq \frac{1}{q \cdot 2} \geq \frac{1}{2^{2L}}$

\* see the last page of lecture notes for this lecture

Corollary: If  $x^T s \leq 2^{-2L}$ , for feasible solutions  $x$  of (P) and  $s$  of (D), then any vector  $x'$  s.t.  $c^T x' \leq c^T x$  is an optimal solution.



## POTENTIAL FUNCTION

Def:  $G(x, s) = (n + \sqrt{n}) \ln x^T s - \sum_{i=1}^n \ln(x_i s_i)$

Fact 1: for  $x > 0, s > 0$   
for any  $t_j \geq 0, j=1, \dots, n$ :

geometric and arithmetic means

$$\left( \prod_{j=1}^n t_j \right)^{1/n} \leq \frac{1}{n} \sum_{j=1}^n t_j \quad (*)$$

Fact 2: for  $x, a$  s.t.  $|x| \leq a < 1$ :

$$-x - \frac{x^2}{2(1-a)} \leq \ln(1-x) \leq -x$$

Lemma: If  $G(x, s) \leq -2\sqrt{n}L$ , then  $x^T s < e^{-2L}$ .

Proof: for  $j=1, \dots, n$ , let  $t_j = x_j s_j$

Consider  $\ln$  of (\*):

$$\frac{1}{n} \ln \prod_{j=1}^n x_j s_j \leq \ln \left( \frac{1}{n} x^T s \right)$$

$$\frac{1}{n} \sum_{j=1}^n \ln x_j s_j \leq \ln x^T s - \ln n \quad (**)$$

Thus:

our assumption

definition of G

scale by n

$$-2\sqrt{n}L \geq G(x, s) = (n + \sqrt{n}) \ln x^T s - \sum_{j=1}^n \ln x_j s_j$$

$$\geq \sqrt{n} \ln x^T s + n \ln n \geq \sqrt{n} \ln x^T s$$

$$\Rightarrow e^{-2L} \geq e^{\ln x^T s} = x^T s$$

Assume that an optimal solution exists

### Algorithm - sketch

1. Find a strictly feasible solution  $x_0 > 0, s_0 > 0$  s.t.  
 $G(x_0, s_0) = O(\sqrt{n}L)$ ;  $k=0$

2. While  $x_k^T s_k \geq e^{-2k}$ ,  
 Find strictly feasible solutions  $x_{k+1} > 0, s_{k+1} > 0$   
 s.t.  $G(x_k, s_k) - G(x_{k+1}, s_{k+1}) > \epsilon$   
 $k=k+1$

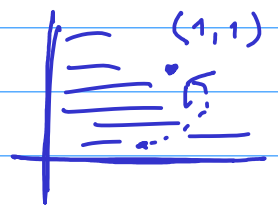
3. "Jump" from  $x_k$  to an optimal solution.

### SCALING

Assume we have a strictly feasible  $\bar{x} = (\bar{x}_1, \dots, \bar{x}_n) > 0$   
 and a strictly feasible  $\bar{s} = (\bar{s}_1, \dots, \bar{s}_n) > 0$ .

We want a mapping:  $\bar{x} \rightarrow (1, 1, \dots, 1)$

$$\text{Let } \bar{X} = \begin{pmatrix} \bar{x}_1 & \bar{x}_2 & & 0 \\ & & \ddots & \\ 0 & & & \bar{x}_n \end{pmatrix} \quad \bar{X}^{-1} \bar{X} = I$$



Then  $\bar{X}^{-1} \bar{x} = (1, 1, \dots, 1)$  ... i.e., the desired mapping  
 in general:  $x' = \bar{X}^{-1} x$        $x = \bar{X} x'$

rewrite (P) in terms of transformed variables:

$$\begin{aligned} \min \quad & c^T \bar{X} x' \\ & A \bar{X} x' = b \\ & x' \geq 0 \end{aligned}$$

$$\begin{aligned} \text{Let } \quad & \bar{c}^T = c^T \bar{X} \\ & \bar{A} = A \bar{X} \end{aligned}$$

$$\begin{aligned} (P') \quad & \min \bar{c}^T x' \\ & \rightarrow \bar{A} x' = b \\ & x' \geq 0 \end{aligned}$$

$x$  is feasible for (P)  
 $\Leftrightarrow x' = \bar{X}^{-1} x$  is feasible for (P')

$$\begin{aligned} \text{Dual (D')} \quad & \max b^T y \\ \rightarrow & (\bar{A} \bar{X})^T y + s' = \bar{c}^T \bar{X} \quad \rightsquigarrow s' = \bar{X} s \\ & s' \geq 0 \end{aligned}$$

Recall  $G(x, s) = (n + \sqrt{n}) \ln x^T s - \sum_{j=1}^n \ln x_j s_j$

$$s' = \begin{pmatrix} s_1 \bar{x}_1 \\ s_2 \bar{x}_2 \\ \vdots \\ s_n \bar{x}_n \end{pmatrix}$$

$x^T s = x^T \underbrace{\bar{X}^T \bar{X}^{-1}}_I \cdot s' = x^T \cdot s'$

i.e. the duality gap remains the same.

**HOW TO DO THE ITERATIVE STEP = e**

given a pair of feasible solutions  $(1, 1, \dots, 1)$  -- of (P)   
 gradient of the potential function  $s'$  ...  $f'(1)$

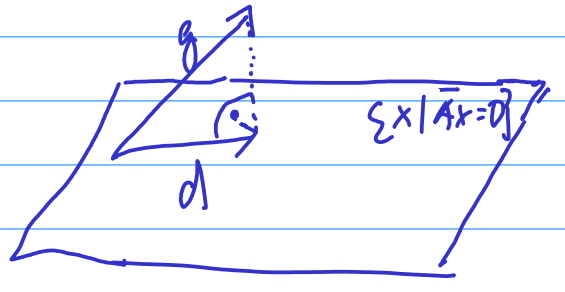
let  $g = \nabla_x G(x, s) \Big|_{(e, s')}$   $= \frac{n + \sqrt{n}}{e^T s'} \cdot s' - e$

(partial derivatives  $\frac{\partial}{\partial x_i} G(x, s) \Big|_{(e, s')} = \left[ \frac{(n + \sqrt{n})}{x^T s} \cdot s_i - \frac{s_i}{x_i s_i} \right]_{(e, s')} = \frac{n + \sqrt{n}}{e^T s} s_i - 1$ )

First idea: change  $e$  in the direction  $-g$ .

Note: by doing so, we might violate the constraints  $Ax = b$

let  $d$  be the projection of  $g$  to the  $\{x \mid \bar{A}x = 0\}$



Second idea: change  $e$  in the direction  $-d$

(i.e.,  $e \rightsquigarrow e + \alpha \cdot (-d)$ , for some  $\alpha > 0$ )

**Lemma:**  $d = (I - \bar{A}^T (\bar{A} \bar{A}^T)^{-1} \bar{A}) \cdot g$

An addendum for the proof of Thm 1:

**Theorem:** let  $F$  be a minimal nonempty face of  $P = \{x \mid Cx \leq d\}$ .   
 then  $F = \{x \mid C'x = d'\}$  for some subsystem  $C'x \leq d'$  of  $Cx \leq d$ .

Note: a minimal nonempty face of  $P = \{x \mid Ax = b, x \geq 0\}$  is a vertex.

Thus, for every vertex  $v$  of  $P$  there is a system of linear equations - derived from  $Ax = b, x \geq 0$ , s.t.  $v$  is the unique solution.   
 $\Rightarrow v$  can be expressed by Cramer's rule.