

Primal-Dual Interior Point Methods

Key idea: follow central path WITHOUT solving repeated minimization problems.

Developed extensively in the late 80s + early 90s for LP, & extended to SDP and SOCP in the mid 90s.

Text continues to use the general convex programming framework, but we'll switch to addressing LP and SDP specifically - our derivation is quite different from that in the BV text.

(I) LP. $\min c^T x$
 s.t. $Ax = b$ $A \begin{matrix} n \\ m \end{matrix}$
 $x \geq 0$

Pt on central path is characterized by $\nabla B(x) = A^T v$
 where $B(x) = \underbrace{\frac{1}{\mu} c^T x}_{\text{BAR. PAR.}} - \frac{1}{\mu} \sum_{i=1}^n \log x_i$

$$\nabla B(x) = c - \mu \begin{bmatrix} 1/x_1 \\ \vdots \\ 1/x_n \end{bmatrix} \quad \text{where } \mu = \frac{1}{t} \rightarrow 0.$$

$$= c - \mu X^{-1} e \quad \text{where } X = \begin{bmatrix} x_1 & & \\ & \ddots & \\ & & x_n \end{bmatrix}, e = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

diag(x)

∴ need

~~$c - \mu X^{-1} e$~~
 $c - \mu X^{-1} e = A^T v$

A.K.A. $v(BV), \lambda(N+W)$
 A.K.A. λ, s

Recall LP dual: $\max b^T y$
 s.t. $A^T y + z = c$ $z \geq 0$
 "dual slack".

Thus $\mu X^{-1}e = z$, i.e. $\frac{\mu}{x_i} = z_i \quad i=1, \dots, n$

just a special case of what we write last week,

$$\lambda_i = -\frac{1}{tf_i(x)} \quad \left(\begin{array}{l} f_i(x) \text{ is now } -x_i \\ \lambda_i \text{ " " } z_i \\ t \text{ " " } 1/\mu \end{array} \right)$$

Thus pts on the central path are characterized by

$$\left. \begin{array}{l} A^T y + \mu X^{-1} e = c \\ Ax = b \end{array} \right\} \begin{array}{l} m+n \text{ eqns} \\ m+n \text{ vars.} \end{array}$$

Let's write

$$F(x, y) = \begin{bmatrix} A^T y + \mu X^{-1} e - c \\ Ax - b \end{bmatrix} = 0 \quad (X = \text{Diag}(x))$$

+ consider apply Newton's method for NONLINEAR EQNS to solve $F(x, y) = 0$ and ~~followed by~~ optimize.

$$F'(x_k, y_k) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = -F(x_k, y_k).$$

$$\begin{bmatrix} -\mu X_k^{-2} & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = \begin{bmatrix} c - A^T y_k - \mu X_k^{-1} e \\ b - Ax_k \end{bmatrix}$$

Looks just like Newton for minimizing $B(x)$ s.t. $Ax = b$
 -INDEED IT IS, as $\nabla^2 B(x) = \mu X^{-2} (> 0)$.

To see equivalence, ~~rather~~ change sign of 1st eqn:
 RHS is $+\nabla B(x_k) - A^T y_k$.

NO SURPRISE: we are applying Newton to $F(x, y) = 0$,
 and 1st block of F is $-\nabla B(x) + A^T y$.

Recall block Gauss: add $A \left(\frac{1}{\mu} X_k^{-2} \right) * 1^{\text{st}} \text{ eqn to } 2^{\text{nd}}$, get

$$\left[\begin{array}{c} \ominus \\ \frac{1}{\mu} A X_k^{-2} A^T \end{array} \right] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = \text{some rhs.}$$

SCHUR COMPL. MTX. $\square \setminus \square = \square$

PD3

New Idea: REWRITE THE EQNS AS

$$A^T y + z = c \quad \text{dual feas.}$$

$$Ax = b \quad \text{primal feas}$$

$$\text{diag}(x) \text{diag}(z) e = XZe = \mu e \quad \text{centrality} \xrightarrow{\mu \rightarrow 0} XZ = 0 \text{ compl.}$$

equiv, $Xz = \mu e$, i.e. $x_i z_i = \mu \quad i=1, \dots, n$.

Now

$$F(x, y, z) = \begin{bmatrix} A^T y + z - c \\ Ax - b \\ XZe - \mu e \end{bmatrix}$$

Newton: $F'(x_k, y_k, z_k) \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta z \end{bmatrix} = -F(x_k, y_k, z_k)$

$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ Z_k & 0 & X_k \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta z \end{bmatrix} = \begin{bmatrix} c - A^T y_k - z_k \\ b - Ax_k \\ \mu e - X_k Z_k e \end{bmatrix}$$

Block Gauss: subtract X_k^{-1} * 3rd row from 1st row

$$\begin{bmatrix} -X_k^{-1} Z_k & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta z \end{bmatrix} = \dots$$

Block Gauss again: ~~subtract~~ $A Z_k^{-1} X_k$ * 1st row ~~to~~ 2nd row
~~add~~



$$A D_k A^T \Delta y = \text{r.h.s.}$$

where now $D_k = Z_k^{-1} X_k$ instead of $\frac{1}{\mu} X_k$.

SAME ON CENTRAL PATH, NOT OTHERWISE.

THEN GET $\Delta x, \Delta z$ BY SUBSTITUTION.

NOTE: UNLIKE BEFORE, F is defined at the end pt of the central path, the limit as $\mu \rightarrow 0$.

Furthermore,

turns out that $F'(x^*, y^*, z^*)$ is NONSINGULAR if LP is NONDEGENERATE, i.e. has a UNIQUE sol'n (x^*, y^*, z^*) , which must be the limit of the central path as $\mu \rightarrow 0$, and ~~and~~ must satisfy strict complementarity: only one of $x_i^*, z_i^* = 0$ for each i : thus NO ROW of $[z_k^* \ 0 \ x_k^*]$ is 0.

But how do we

(a) make sure $\{x_k\}, \{z_k\}$ stay > 0

(b) let $\mu \rightarrow 0$.

simplest:

$$x_{k+1} = x_k + \alpha_k \Delta x$$

where $\alpha_k = \min(1, \tau \hat{\alpha})$

where τ is close to 1, e.g. 0.999

$$\hat{\alpha} = \max \{ \alpha : x_k + \alpha \Delta x \geq 0 \}$$

"ratio test"

$$y_{k+1} = y_k + \beta_k \Delta y$$

$$z_{k+1} = z_k + \beta_k \Delta z$$

where $\beta_k = \min(1, \tau \hat{\beta})$

$$\hat{\beta} = \max \{ \beta : z_k + \beta \Delta z \geq 0 \}$$

simplest:

$$\mu = \sigma \frac{x_k^T z_k}{n}$$

$$\sigma < 1$$

e.g. $\sigma = 1/4$.

KEY POINT:

NO INNER ITERATION!

These choices work very well in practice.

Mehrotra's predictor-corrector: greatly speeds things up.

Methods with complexity results

"short-step" method: best complexity, v. slow (in practice)

"long-step" methods: more practical
use the $N_{-\infty}(\gamma)$ region to keep $x_i z_i \geq \gamma (x^T e / n)$

CAN START INFEASIBLE - BECOME FEAS IF EVER TAKE $\alpha_k = 1, \beta_k = 1$

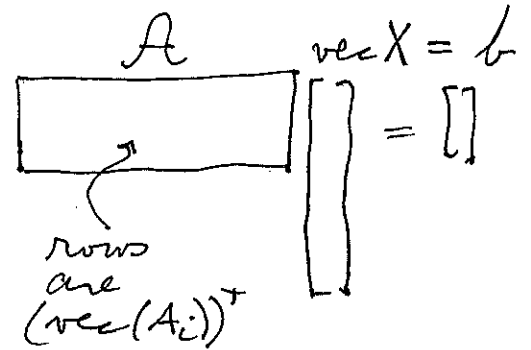
PDS

(II) SDP. $\min C \cdot X \leftarrow \text{tr} CX = \sum c_{ij} x_{ij}$

s.t. $A_i \cdot X = b_i$

$X \succeq 0$

$X \in S^n$
NO LONGER
DIAGONAL!



$B(X) = C \cdot X - \mu \log \det X$

$\nabla_X B(X) = C - \mu X^{-1}$ (like X , this is $\in S^n$)

condition for X on central path is

$C - \mu X^{-1} = \sum_{i=1}^m y_i A_i$

Recall dual: $\max b^T y$

s.t. $(\sum y_i A_i) + Z = C$

$Z \succeq 0$

thus need

$\mu X^{-1} = Z$.

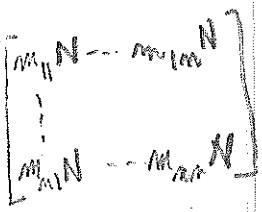
Let $F(X, y) = \begin{bmatrix} \text{vec} \left\{ \sum_{i=1}^m y_i A_i + \mu X^{-1} - C \right\} \\ A \text{vec} X - b \end{bmatrix}$

a matrix eqn and m scalar eqns
is a matrix var and m " vars.

As earlier, Newton for $F(X, y) = 0$ is equivalent to
Newton for minimizing $B(X)$ s.t. $A \text{vec} X = b$

Let $\begin{bmatrix} -\mu X_k^{-1} \otimes X_k^{-1} & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \text{vec} \Delta X \\ \Delta y \end{bmatrix} = \dots$

k is iteration
index - unlike
 i, j



PDG

$$m^2 \times n^2$$

Here the Kronecker product $X_h^{-1} \otimes X_h^{-1}$ is the rep'n of the Hessian of B on \mathbb{R}^{m^2} .

$M \otimes N$ is an $m^2 \times n^2$ matrix representing the linear op def by $K \rightarrow NKMT$

Key thing to know about Kronecker products

$$\boxed{\text{vec}(ABC) = (C^T \otimes A) \text{vec} B} \quad A, B, C \in \mathbb{R}^{m \times m}$$

omit

The Hessian of B on $\mathbb{R}^{m \times m}$ is a linear operator defined by

$$\nabla_{XX}^2 B(X)(U, V) = \text{tr} U X^{-1} V X^{-1}$$

Likewise $\text{vec}(U)^T (X^{-1} \otimes X^{-1}) \text{vec} V = \text{tr} U (X^{-1} V X^{-1})$.

PRIMAL DUAL EQNS.

$$F(X, y, Z) = 0 \begin{cases} \{A_i \cdot X = b_i\}, i=1, \dots, m & (A \text{vec} X = b) \\ \sum y_i A_i + Z = C & (A^T y + \text{vec} Z = \text{vec} C) \\ XZ = \mu I & \text{centrality} \end{cases}$$

2 matrix eqns + m scalar eqns
 Z, " vars " " " vars.

As $\mu \rightarrow 0$, centrality eq $\rightarrow XZ = 0$.

Observe: opt ends $X \succeq 0, Z \succeq 0, \text{tr} XZ = 0$ indeed $\Rightarrow XZ = 0$

transposing, $ZX = 0$ too $X = LL^T, Z = MM^T$
 $\text{tr} XZ = \text{tr}(L^T M) / (M^T L) = 0$
 Thus X, Z commute + share common 0 (i.e. set of e-vectors).
 $\Rightarrow \|L^T M\| = 0$
 $\Rightarrow XZ = 0$.

$$Q^T X Q = \text{Diag}(\xi_i)$$

$$Q^T Z Q = \text{Diag}(\omega_i)$$

satisfies $\xi_i \omega_i = 0, i=1, \dots, n$
 Eigenvalue Complementarity!

apply Newton to $F(X, y, Z) = 0$ on $\mathbb{R}^{m \times m} \times \mathbb{R}^m \times \mathbb{R}^{m \times m}$
 Linearizing $XZ = \mu I$ $(X_k + \Delta X)(Z_k + \Delta Z) = \mu I$, get
 $X_k(\Delta Z) + (\Delta X)Z_k = \mu I - X_k Z_k$

PD7

Represent this on \mathbb{R}^{n^2} by

$$(\mathbf{I} \otimes X_k) \text{vec}(\Delta Z) + (Z_k \otimes \mathbf{I}) \text{vec}(\Delta X) = \text{vec}(\mu \mathbf{I} - X_k Z_k)$$

Thus get

$$\begin{bmatrix} 0 & A^T & \mathbf{I} \\ A & 0 & 0 \\ \mathcal{E} & 0 & \mathcal{F} \end{bmatrix} \begin{bmatrix} \text{vec} \Delta X \\ \text{vec} \Delta Y \\ \text{vec} \Delta Z \end{bmatrix} = \dots$$

where $\mathcal{E} = Z_k \otimes \mathbf{I}$
 $\mathcal{F} = \mathbf{I} \otimes X_k$

$$A = \begin{bmatrix} (\text{vec} A_1)^T \\ \vdots \\ (\text{vec} A_m)^T \end{bmatrix}$$

Block Gauss gives

$$M \equiv \underbrace{A \mathcal{E}^{-1} \mathcal{F}} A \Delta y = \dots$$

$$\begin{aligned} \text{where } \mathcal{E}^{-1} \mathcal{F} &= (Z_k \otimes \mathbf{I})^{-1} (\mathbf{I} \otimes X_k) \\ &= (Z_k^{-1} \otimes \mathbf{I}) (\mathbf{I} \otimes X_k) \\ &= Z_k^{-1} \otimes X_k \end{aligned}$$

Thus we form M by $M = AB$ where the j^{th} col of B is $(Z_k^{-1} \otimes X_k) \text{vec}(A_j)$ (NOT k^{th} !)

Thus

$$M_{ij} = \text{tr} A_i X_k A_j Z_k^{-1}$$

$$= \text{vec}(X_k A_j Z_k^{-1})$$

Don't confuse iteration index k with component index j
 Unfortunately in (2.16) in paper we use k for j .

Then solve for Δy
 set $\Delta X, \Delta Z$ by substit Δy .

Problem: ΔX is generally NOT SYMMETRIC, because we applied Newton's method in \mathbb{R}^{m^2} , NOT in S^n .

Note: product of 2 symmetric matrices is generally not symmetric.

What to do?

1. "XZ" method: replace ΔX by $\frac{1}{2}(\Delta X + (\Delta X)^T)$ "H.K.M"

2. "XZ+ZX" method: "AHO"

replace 3rd eqn in $F(X, y, Z)$ by $XZ + ZX = 2\mu I$.

Apply Newton in S^n :

$$(X_k + \Delta X)(Z_k + \Delta Z) + (Z_k + \Delta Z)(X_k + \Delta X) = 2\mu I$$

linearize:

$$\underbrace{X_k(\Delta Z) + (\Delta Z)X_k}_{2 \text{ "}\Delta Z\text{" terms}} + \underbrace{(\Delta X)Z_k + Z_k(\Delta X)}_{2 \text{ "}\Delta X\text{" terms}} = 2\mu I - X_k Z_k - Z_k X_k$$

Leads to a method with very nice properties but more expensive to implement.

Alizadeh, Harberly, Overton 1998.

3. Nesterov - Todd Method.

Also has v nice properties but more expensive to implement.

So, "XZ" has become the standard.

PD9

$$\begin{aligned} X_{k+1} &= X_k + \alpha_k \Delta X, \\ y_{k+1} &= y_k + \beta_k \Delta y, \quad Z_{k+1} = Z_k + \beta_k \Delta Z \end{aligned}$$

where $\alpha_k = \min(1, \tau \hat{\alpha})$

$$\hat{\alpha} = \max \{ \alpha : X_k + \alpha (\Delta X) \succeq 0 \}$$

$$\beta_k = \min(1, \tau \hat{\beta})$$

$$\hat{\beta} = \max \{ \beta : Z_k + \beta (\Delta Z) \succeq 0 \}$$

How?

$$\text{Let } X_k = LL^T$$

$$\text{Need } I + \alpha L^{-1}(\Delta X)L^{-T} \succeq 0$$

$$1 + \alpha \lambda_{\min}(L^{-1}(\Delta X)L^{-T}) \geq 0$$

$$1 - \alpha \lambda_{\max}(-L^{-1}(\Delta X)L^{-T}) \geq 0$$

$$\alpha \lambda_{\max}(-L^{-1}(\Delta X)L^{-T}) \leq 1$$

$$\hat{\alpha} = 1 / \lambda_{\max}(-L^{-1}(\Delta X)L^{-T}).$$

(Reduce M as before).

As in XZ method, if ever take step $\alpha_k = 1$, get primal feasible, + " " " " $\beta_k = 1$, get dual feasible (+ stay feasible)

Turns out can take τ much closer to 1, e.g. 0.999 with XZ+ZX method than with XZ method.

~~On~~ ^{when started on} central path, all methods generate same next iterate (but it won't be on central path).

\uparrow
 M same for each method.