

# Primal-dual interior point method (Mortingley & Boyd)

~~Wolfe~~

minimize  $\frac{1}{2} x^T Q x + q^T x$   $Q \in S^n, q \in \mathbb{R}^n$

subject to  $Gx \leq h, Ax = b$   $G \in \mathbb{R}^{p \times n}, h \in \mathbb{R}^p, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$

$Gx \leq h$   
 $Gx - h \leq 0$

Introduce slack variables

minimize  $\frac{1}{2} x^T Q x + q^T x$

subject to  $Gx + s = h, Ax = b, s \geq 0$

symmetrizing matrix:  
 $M = \frac{M + M^T}{2} + \frac{M - M^T}{2}$   
symmetric part

KKT conditions

$z$ : inequality dual

$y$ : equality dual

For  $\min f(x)$

$h_i(x) \leq 0$

$l_i(x) = 0$

$Gx + s = h, Ax = b, s \geq 0$  primal feasibility

$z \geq 0, (z \in \mathbb{R}^p)$  dual feasibility

$Qx + q + G^T z + A^T y = 0$  stationarity

$z_i s_i = 0, i = 1, \dots, p$  complementary slackness

$\nabla f_0(x) + G^T z + A^T y$   
 $\sum z_i \partial h_i(x) + \sum y_i \partial l_i$

Initialization

Solve for optimality conditions of both primal and dual problems of related problem

Analytically

$$\begin{bmatrix} Q & G^T & A^T \\ G & -I & 0 \\ A & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ z \\ y \end{bmatrix} = \begin{bmatrix} -q \\ h \\ b \end{bmatrix}$$

TODO work this out

$h(x) = Gx - h \leq 0$

$\partial h(x) = G$

$l(x) = Ax - b = 0$

$\partial l = A$

Gives starting point  $(x^{(0)}, s^{(0)}, z^{(0)}, y^{(0)})$

Main iteration

1. Evaluate stopping criteria (residuals, duality gap)

2. Compute affine scaling directions

$\Delta x^{\text{aff}}, \Delta s^{\text{aff}}, \Delta z^{\text{aff}}, \Delta y^{\text{aff}}$

3. Compute ~~centering~~ centering-plus-corrector directions

$\Delta x^{\text{cc}}, \Delta s^{\text{cc}}, \Delta z^{\text{cc}}, \Delta y^{\text{cc}}$

4. Update primal and dual variables

booth use this

$$\begin{bmatrix} n & 0 & 0 & 0 \\ n & 0 & z & s & 0 \\ n & G & I & 0 & 0 \\ n & A & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta s \\ \Delta z \\ \Delta y \end{bmatrix} = \begin{bmatrix} \Delta x \\ \Delta s \\ \Delta z \\ \Delta y \end{bmatrix}$$

want efficient way to do  $l = K^{-1}r$

$Kl = r$

symmetrize this

Lots of structure (see 5.3) for explanation symmetric gives conditions

Two more tricks:

- Dynamic regularization to avoid divide-by-zero errors
- Choosing permutation  $P$  that leads to sparse  $L$

$K$  depends on  $z$  and  $s$

$PKP^T = LDL^T$

permutation matrix diagonal unit lower-triangular

Amos, Kottler use LU factorization. Does not matter for us

We can even just do  $\text{inv}(K)$  at first

Regularize  $K$  to ensure factorization always exists, numerically stable.

$\tilde{K} = K + \begin{bmatrix} \epsilon I & 0 \\ 0 & -\epsilon I \end{bmatrix}$

$\tilde{r} = \tilde{K}^{-1}r = P^T L^{-T} D^{-1} L^{-1} P r$

solutions to perturbed system can also just use this

Iterative refinement to move towards  $Kl = r$

$Z = \text{diag}(z), S = \text{diag}(s)$

OptNet

minimize  $\frac{1}{2} \mathbf{z}^T \mathbf{Q} \mathbf{z} + \mathbf{q}^T \mathbf{z}$   
 subject to  $\mathbf{A} \mathbf{z} = \mathbf{b}, \mathbf{G} \mathbf{z} \leq \mathbf{h}$

Lagrangian

$$L(\mathbf{z}, \mathbf{v}, \lambda) = \frac{1}{2} \mathbf{z}^T \mathbf{Q} \mathbf{z} + \mathbf{q}^T \mathbf{z} + \mathbf{v}^T (\mathbf{A} \mathbf{z} - \mathbf{b}) + \lambda^T (\mathbf{G} \mathbf{z} - \mathbf{h})$$

• KKT conditions

$$\mathbf{Q} \mathbf{z}^* + \mathbf{q} + \mathbf{A}^T \mathbf{v}^* + \mathbf{G}^T \lambda^* = \mathbf{0} \quad (\text{stationarity})$$

$$\mathbf{A} \mathbf{z}^* - \mathbf{b} = \mathbf{0} \quad (\text{primal feasibility})$$

$$\mathbf{D}(\lambda^*)(\mathbf{G} \mathbf{z}^* - \mathbf{h}) = \mathbf{0} \quad (\text{complementary slackness})$$

$$\lambda^* \geq \mathbf{0} \quad (\text{dual feasibility})$$

Derivatives

they ignore this

$$d\mathbf{Q} \mathbf{z}^* + \mathbf{Q} d\mathbf{z} + d\mathbf{q} + d\mathbf{A}^T \mathbf{v}^* + \mathbf{A}^T d\mathbf{v} + d\mathbf{G}^T \lambda^* + \mathbf{G}^T d\lambda = \mathbf{0}$$

$$d\mathbf{A} \mathbf{z}^* + \mathbf{A} d\mathbf{z} - d\mathbf{b} = \mathbf{0}$$

$$\mathbf{D}(\mathbf{G} \mathbf{z}^* - \mathbf{h}) d\lambda + \mathbf{D}(\lambda^*)(d\mathbf{G} \mathbf{z}^* + \mathbf{G} d\mathbf{z} - d\mathbf{h}) = \mathbf{0}$$

seems like rules for matrix differentials are pretty much same as scalars

matrix form

$$\begin{bmatrix} \mathbf{Q} & \mathbf{G}^T & \mathbf{A}^T \\ \mathbf{D}(\lambda^*) \mathbf{G} & \mathbf{D}(\mathbf{G} \mathbf{z}^* - \mathbf{h}) & \mathbf{0} \\ \mathbf{A} & \mathbf{0} & \mathbf{0} \end{bmatrix} \begin{bmatrix} d\mathbf{z} \\ d\lambda \\ d\mathbf{v} \end{bmatrix} = \begin{bmatrix} -d\mathbf{Q} \mathbf{z}^* - d\mathbf{q} - d\mathbf{G}^T \lambda^* - d\mathbf{A}^T \mathbf{v}^* \\ -\mathbf{D}(\lambda^*) d\mathbf{G} \mathbf{z}^* + \mathbf{D}(\lambda^*) d\mathbf{h} \\ -d\mathbf{A} \mathbf{z}^* + d\mathbf{b} \end{bmatrix}$$

call this  $\mathbf{H}$

$$\begin{bmatrix} d\mathbf{z} \\ d\lambda \\ d\mathbf{v} \end{bmatrix} = \mathbf{H}^{-1} \begin{bmatrix} \left( \frac{dL}{d\mathbf{z}^*} \right)^T \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix}$$

This gives us gradients

This comes from chain rule  $\frac{\partial L}{\partial \mathbf{z}^*} \frac{\partial \mathbf{z}^*}{\partial \mathbf{b}}$

Not fast way  $\rightarrow$  Found by setting  $d\mathbf{b} = \mathbf{I}$  and setting all other differential forms in right side to zero, then solving equation.

If we want  $\frac{d\mathbf{z}^*}{d\mathbf{h}}$ :

$$\begin{bmatrix} d\mathbf{z} \\ d\lambda \\ d\mathbf{v} \end{bmatrix} = \mathbf{H}^{-1} \begin{bmatrix} \mathbf{0} \\ \mathbf{D}(\lambda^*) d\mathbf{h} \\ \mathbf{0} \end{bmatrix} \quad d\mathbf{h} = \mathbf{I}$$