# Quadratic Programming 

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## Quadratic Programming

## General Formulation

$$
\begin{equation*}
\min _{\mathbf{x} \in \mathbb{R}^{n}} \mathbf{c}^{T} \mathbf{x}+\frac{1}{2} \mathbf{x}^{T} \mathbf{H} \mathbf{x}, \text { s.t. } \mathbf{b}_{/} \leq \mathbf{A} \mathbf{x} \leq \mathbf{b}_{u} \text { and } \mathbf{I} \leq \mathbf{x} \leq \mathbf{u} \tag{1}
\end{equation*}
$$

- $\mathbf{b}_{/} \leq \mathbf{A} \mathbf{x} \leq \mathbf{b}_{u}$ are general linear constraints
- $\mathbf{I} \leq \mathbf{x} \leq \mathbf{u}$ are simple bound constraints
- problem (1) is convex QP if Hessian matrix $\mathbf{H}$ is positive definite, otherwise it is a general QP problem.
- Mathwrist takes the general form (1).
- without loss of generality, we will be looking at a convenient form,

$$
\begin{equation*}
\min _{\mathbf{x} \in \mathbb{R}^{n}} \mathbf{c}^{T} \mathbf{x}+\frac{1}{2} \mathbf{x}^{T} \mathbf{H} \mathbf{x} \text {, s.t. } \mathbf{A} \mathbf{x} \geq \mathbf{b} \tag{2}
\end{equation*}
$$

## Quadratic Programming

## Review of Active Set Method

- maintain index sets $\mathcal{W}$ and $\mathcal{N}$ for working and non-working general constraints respectively.
- seek a descent null space direction $\mathbf{p}=\mathbf{Z} \mathbf{p}_{\boldsymbol{z}}$ for some $\mathbf{p}_{z}$, where $\mathbf{Z}$ is the null space columns of the $\mathbf{Q R}$ factorization

$$
\mathbf{A}_{\mathcal{W}}^{T}=\underbrace{(\mathbf{Y} \mid \mathbf{Z})}_{\mathbf{Q}}\binom{\mathbf{R}}{0}
$$

- at a non-stationary iteration $k$, make a step move $\mathbf{x}_{k+1}=\mathbf{x}_{k}+\alpha \mathbf{p}$, where $\alpha$ is determined by the first blocking constraint $a_{i}$. $i$ is then added to working set $\mathcal{W}$.


## Quadratic Programming

## Convex QP: KKT System

We solve the following KKT system for search direction $\mathbf{p}$ and Lagrange multipliers $\lambda$,

$$
\left(\begin{array}{cc}
\mathbf{H} & \mathbf{A}_{\mathcal{W}}^{T}  \tag{3}\\
\mathbf{A}_{\mathcal{W}} &
\end{array}\right)\binom{-\mathbf{p}}{\lambda}=\binom{\mathbf{g}\left(\mathbf{x}_{k}\right)}{\mathbf{0}}
$$

The second KKT equation implies $\mathbf{p}$ is a null space direction wrt the set of working constraints.

## Quadratic Programming

## Convex QP: Null Space Direction

- write $\mathbf{p}=\mathbf{Z} \mathbf{p}_{z}$ for some $\mathbf{p}_{z}$.
- the first KKT equation in (3) is

$$
\begin{equation*}
-\mathbf{H Z} \mathbf{p}_{z}+\mathbf{A}_{\mathcal{W}}^{T} \lambda=\mathbf{g}\left(\mathbf{x}_{k}\right) \tag{4}
\end{equation*}
$$

- multiply $\mathbf{Z}^{T}$ at both sides of (4), solve $\tilde{\mathbf{H}} \mathbf{p}_{z}=-\tilde{\mathbf{g}}$ where
- $\tilde{\mathbf{H}}=\mathbf{Z}^{\top} \mathbf{H Z}$ is the reduce Hessian.
- $\tilde{\mathbf{g}}=\mathbf{Z}^{\top} \mathbf{g}\left(\mathbf{x}_{k}\right)$ is the reduced gradient.


## Quadratic Programming

## Convex QP: Performance Efficiency

- retain $\mathbf{Q R}$ factorization of $\mathbf{A}_{\mathcal{W}}^{T}$.
- retain Cholesky factorization of reduced Hessian $\tilde{\mathbf{H}}=\mathbf{L L}{ }^{T}$ to solve $\mathbf{p}_{z}$ in equation (4).
- $\mathbf{A}_{\mathcal{W}}$ and $\tilde{\mathbf{H}}$ changes whenever the working set $\mathcal{W}$ changes.
- apply economical updates on QR and Cholesky instead of refactoring the new matrix from the scratch.


## Quadratic Programming

## Convex QP: Step Update

- move along $\mathbf{p}$ at step length $\alpha \in[0,1]$
- if a blocking constraint $a_{i}$ is hit before making a unit step move $\alpha=1$,
- add constraint $i$ to $\mathcal{W}$.
- update $\mathbf{x}_{k+1}=\mathbf{x}_{k}+\alpha \mathbf{p}$ and start the $k+1$ iteration.
- otherwise, making a unit step move at $\alpha=1$ reaches the local optimal, test Lagrange multiplier conditions


## Quadratic Programming

## Convex QP: Lagrange Multipliers

- after $\mathbf{p}$ is computed, from the first KKT equation in (5) we have

$$
\mathbf{A}_{\mathcal{W}}^{T} \lambda=\mathbf{g}\left(\mathbf{x}_{k}\right)+\mathbf{H p}
$$

- multiply $\mathbf{Y}^{T}$ at both sides and solve

$$
\mathbf{R} \lambda=\mathbf{Y}^{T}\left(\mathbf{g}\left(\mathbf{x}_{k}\right)+\mathbf{H} \mathbf{p}\right)
$$

## Quadratic Programming

## Convex QP: Local Optimal

- when a local optimal is reached, the algorithm terminates if $\lambda_{i} \geq 0$ for all lower bounded constraints $i \in \mathcal{W}$.
- if lower bounded constraint $i \in \mathcal{W}$ has the most negative Lagrange multiplier, delete $i$ from $\mathcal{W}$ and add it to $\mathcal{N}$.
- such active constraint deletion operation results to a descent feasible direction in the next iteration.


## Quadratic Programming

## Handle Simple Bound Constraints

- partion variable $\mathbf{x}$ to a set of fixed variables $\mathbf{x}_{b}$ and the complement set of free variables $\mathbf{x}_{f}$.
- $\mathbf{x}_{b}$ have values fixed at one side of the bounds, effectively as active constraints $\mathbf{l x}_{b}=\mathbf{v}_{b}$ for relevant boundary value $\mathbf{v}_{b}$.
- KKT system (3) then has the following block structure,

$$
\left(\begin{array}{cccc}
\mathbf{H}_{b b} & \mathbf{H}_{b f} & \mathbf{I} & \mathbf{B}_{\mathcal{W}}^{T}  \tag{5}\\
\mathbf{H}_{f b} & \mathbf{H}_{f f} & & \mathbf{F}_{\mathcal{W}}^{T} \\
\mathbf{I} & & & \\
\mathbf{B}_{\mathcal{W}} & \mathbf{F}_{\mathcal{W}} & &
\end{array}\right)\left(\begin{array}{c}
-\mathbf{p}_{b} \\
-\mathbf{p}_{f} \\
\lambda_{b} \\
\lambda_{\mathcal{W}}
\end{array}\right)=\left(\begin{array}{c}
\mathbf{g}_{b} \\
\mathbf{g}_{f} \\
\mathbf{0} \\
\mathbf{0}
\end{array}\right)
$$

- subscript $b$ and $f$ represent the sub matrix/vector blocks that correspond to fixed and free variables respectively.
- the 3rd equation $\mathbf{l p}_{b}=\mathbf{0} \rightarrow \mathbf{p}_{b}=0$, representing $\mathbf{x}_{b}$ is fixed.
- seek a null space direction $\mathbf{p}_{f}$ wrt free variables $\mathbf{x}_{f}$.


## Quadratic Programming

## General QP: What is special at an active set iteration?

- need efficiently determine the definiteness of $\tilde{\mathbf{H}}$, along the course of active set $\mathcal{W}$ changes.
- cases to consider at iteration $k$,
- $\tilde{H}$ is indefinite, surely not optimal.
- $\tilde{\mathbf{H}}$ is positive semi-definite and $\mathbf{x}_{k}$ is not a stationary point wrt $\mathcal{W}$, not optimal either.
- $\tilde{\mathbf{H}}$ is at least positive semi-definite, $\mathbf{x}_{k}$ is a stationary point wrt $\mathcal{W}$, it is a local optimal.


## Quadratic Programming

## General QP: Local Optimal

At a local optimal point, everything stays same as the convex QP situation. The active set algorithm will

- compute Lagrange multipliers from KKT system (3).
- test Lagrange multiplier conditions, $\lambda_{\mathcal{W}} \geq 0$ for lower bounded constraints, $\leq 0$ for upper bounded ones.
- terminate if $\lambda_{\mathcal{W}}$ pass the test.
- otherwise, find the worst $i \in \mathcal{W}$ and delete $i$ from $\mathcal{W}$.


## Quadratic Programming

## General QP: Inertia Control and Extended KKT

- ensure $\tilde{\mathbf{H}}$ has at most one negative eigen value.
- at a local optimal, if deleting an active constraint $a_{*}$ will cause the new $\tilde{\mathbf{H}}$ being indefinite, mark $a_{*}$ as "pending deletion" and still keep it in an extended KKT system.

$$
\left(\begin{array}{ccc}
\mathbf{H} & \mathbf{A}_{\mathcal{W}}^{T} & a_{*}^{T} \\
\mathbf{A}_{\mathcal{W}} & & \\
a_{*} & &
\end{array}\right)
$$

- keep moving along descent feasible directions and adding blocking constraints until $\mathbf{H}$ becomes positive definite again, at that point, physically remove $a_{*}$ from the extended KKT system.


## Quadratic Programming

## General QP: p for Indefinite $\tilde{\mathbf{H}}_{f f}$

- if $\mathbf{x}_{k}$ is non-stationary wrt $\mathcal{W}, \mathbf{p}$ is a direction of negative curvature, solved from KKT

$$
\left(\begin{array}{cc}
\mathbf{H} & \mathbf{A}_{\mathcal{W}}^{T}  \tag{6}\\
\mathbf{A}_{\mathcal{W}} &
\end{array}\right)\binom{\mathbf{p}}{\nu}=\binom{\mathbf{g}\left(\mathbf{x}_{k}\right)}{\mathbf{0}}
$$

- if stationary, a negative curvature direction $\mathbf{p}$ can be found from extended KKT

$$
\left(\begin{array}{ccc}
\mathbf{H} & \mathbf{A}_{\mathcal{W}}^{T} & a_{*}^{T}  \tag{7}\\
\mathbf{A}_{\mathcal{W}} & & \\
a_{*} & &
\end{array}\right)\left(\begin{array}{c}
\mathbf{p} \\
\nu \\
\nu_{*}
\end{array}\right)=\left(\begin{array}{l}
\mathbf{0} \\
\mathbf{0} \\
1
\end{array}\right)
$$

## Quadratic Programming

## General QP: p for Semi-definite and Singular $\tilde{\mathbf{H}}$

- $\mathbf{p}$ is a direction of zero curvature solved from KKT

$$
\left(\begin{array}{cc}
\mathbf{H} & \mathbf{A}_{\mathcal{W}}^{T}  \tag{8}\\
\mathbf{A}_{\mathcal{W}} &
\end{array}\right)\binom{\mathbf{p}}{\nu}=\binom{\mathbf{0}}{\mathbf{0}}
$$

## Quadratic Programming

## Initial Working Set and Feasible Point

- find an initial feasible point same as linear programming active set method.
- inertial control requires to start with a positive definite $\tilde{\mathbf{H}}$.
- for general QP, perform a partial Cholesky [5],

$$
\mathbf{P}^{T} \tilde{\mathbf{H}} \mathbf{P}=\left(\begin{array}{ll}
\mathbf{L}_{11} & \\
\mathbf{L}_{21} & \mathbf{I}
\end{array}\right)\left(\begin{array}{ll}
\mathbf{D} & \\
& \mathbf{K}
\end{array}\right)\left(\begin{array}{cc}
\mathbf{L}_{11}^{T} & \mathbf{L}_{21}^{T} \\
& \mathbf{I}
\end{array}\right)
$$

, where permutation $\mathbf{P}$ arranges the null space as $\mathbf{Z}=\left(\mathbf{Z}_{+} \mathbf{Z}_{-}\right)$ such that $\mathbf{Z}_{+}^{T} \mathbf{H} \mathbf{Z}_{+}=\mathbf{L}_{11} \mathbf{D L} \mathbf{1}_{11}^{T}$ is positive definite.

- $\mathbf{Z}_{\text {- }}$ are treated as artificial constraints and added to the initial working set.


## Quadratic Programming

## General QP: Performance Efficiency

- same matrix factorization update technique as convex QP.
- stationary condition and definiteness of $\tilde{\mathbf{H}}$ is determined by various vector update schemes, details in [3].
- KKT solutions are economically updated as well, details in [3]


## References I

[1] Jorge Nocedal and Stephen J. Wright: Numerical Optimization, Springer, 1999
[2] Philip E. Gill, Walter Murray and Margaret H. Wright: Practical Optimization, Academic Press, 1981
[3] Philip E. Gill, Walter Murray, Michael A. Saunders and Margaret H. Wright: Inertia-Controlling Methods For General Quadratic Programming, SIAM Review, Volume 33, Number 1, 1991, pages 1-36.
[4] Philip E. Gill, Walter Murray, Michael A. Saunders and Margaret H. Wright: Procedures for Optimization Problems with a Mixture of Bounds and General Linear Constraints, ACM Transactions on Mathematical Software, Vol.10, No. 3, September 1984, Pages 282-298

## References II

[5] Anders. Forsgren, Philip E. Gill and Walter Murray: Computing Modified Newton Directions Using a Partial Cholesky Factorization, SIAM J. SCI. COMPUT. Vol. 16, No. 1, pp. 139-150

