Lecture 7: Active Set Method for Quadratic Programming

Sondre Pedersen

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1 Background for Active Set Method

Simplified preview:

- Make a guess of which inequality constraints are active
- Solve corresponding EQP
- Check KKT-conditions
 - If KKT OK: done
 - else: update active contraint guess and go to 2.

KKT for QP
$$\min_{x \in \mathbb{R}^n} \frac{1}{2} x^\top G x + c^\top x$$
 s.t.
$$\begin{cases} a_i^\top x = b_i, \ i \in \mathcal{E} \\ a_i^\top x \ge b_i, \ i \in \mathcal{I} \end{cases}$$

Lagrangian:

$$\mathcal{L}(x,\lambda) = \frac{1}{2} x^{\top} G x + x^{\top} x - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \lambda_i (a_i^{\top} x - b_i).$$

KKT:

$$Gx^* + c - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \lambda_i^* a_i = 0$$

$$a_i^\top x^* = b_i, \ i \in \mathcal{E}$$

$$a_i^\top x^* \ge b_i, \ i \in \mathcal{I}$$

$$\lambda_i^* \ge, \ i \in \mathcal{I}$$

$$\lambda_i^* (a_i^\top x - b_i) = 0, i \in \mathcal{I} \cup \mathcal{E}$$

To make active set method, we reformulate KKT via the active set, which was defined as:

$$\mathcal{A}(x^*) = \{ i \in \mathcal{E} \cup \mathcal{I} | a_i^\top x^* = b_i \}$$

Assume we know $\mathcal{A}(x^*)$, then KKT is

$$Gx^* + x - \sum_{\mathcal{A}(x^*)} \lambda_i^* a_i = 0$$

$$a_i^\top x^* = b_i, \ i \in \mathcal{A}(x^*)$$

$$a_i^\top x^* \ge b_i, \ i \in \mathcal{I} \backslash \mathcal{A}(x^*)$$

$$\lambda_i^* \ge 0, \ i \in \mathcal{I} \cup \mathcal{A}(x^*)$$

The lambdas that are not active equals 0.

Theorem 16.4: If x^* satisfies KKT and $G \ge 0$ then x^* is a global solution

Proof: Assume x is feasible, $x \neq x^*$. Note first: $(x - x^*)^{\top}(Gx^* + c) = (x - x^*)^{\top} \sum_{i \in \mathcal{A}(x^*)} \lambda_i^* a_i = \sum_{i \in \mathcal{E}} \lambda_i^* a_i^{\top}(x - x^*) + \sum_{i \in \mathcal{A}(x^*) \cup \mathcal{I}} \lambda_i^* a_i^{\top}(x - x^*)$

$$\begin{split} q(x) &= \frac{1}{2}(x^* + (x - x^*)^\top)G(x^* + (x - x^*)) + c^\top(x^* + (x - x^*)) \\ &= \frac{1}{2}x^{*\top}Gx^* + c^\top x^* + (x - x^*)^\top G(x - x^*) + (x - x^*)^\top Gx + c^\top(x - x^*) \\ &= q(x^*) + \frac{1}{2}(x - x^*)^\top G(x - x^*) + (x - x^*)^\top (Gx^* + c) \\ &\geq q(x^*) \quad \text{proof complete} \end{split}$$

Note: $Z^{\top}GZ > 0 \implies q(x) > q(x^*)$, that is: x^* is strict global solution.

If we know $A(x^*)$, QP can be forumalted as

$$\min_{xin\mathbb{R}^n} \frac{1}{2} x^\top G x + c^\top x \qquad \text{s-t-} \qquad a_i^\top x = b_i, \ i \in \mathcal{A}(x^\top).$$

This can then be solved by solving the KKT-system:

$$\begin{bmatrix} G & -A^{\top} \\ A & 0 \end{bmatrix} \begin{bmatrix} x^* \\ \lambda^* \end{bmatrix} = \begin{bmatrix} -c \\ b \end{bmatrix} \begin{cases} A = \begin{bmatrix} \vdots \\ a_i^{\top} \\ \vdots \end{bmatrix}, & i \in \mathcal{A}(x^*) \\ b = \begin{bmatrix} \vdots \\ b_i \\ \vdots \end{bmatrix}, & i \in \mathcal{A}(x^*) \end{cases}$$

2 One step of active set method for QP

Iteration k:

- \mathcal{W}_k : current 'guess' of $\mathcal{A}(x^*)$.
- x_k : current feasible estimate of x^* .
- g_k : $(Gx_k+c)^{\top}$

Define
$$A_x = \begin{bmatrix} \vdots \\ Q_i^\top \\ \vdots \end{bmatrix}, i \in \mathcal{W}_k, \ b_k = \begin{bmatrix} \vdots \\ b_i \\ \vdots \end{bmatrix}, i \in \mathcal{W}_k$$

Consider EQP: $x = x_k + p$:

$$\min_{p \in \mathbb{R}^n} \quad \frac{1}{2} (x_k + p)^\top G(x_k + p) + c^\top (x_k + p)$$
s.t.
$$A_k (x_k + p) = b_k$$

$$\implies \min_{p \in \mathbb{R}^4} \quad \frac{1}{2} p^\top G p + (G x_k + c)^\top p \quad \text{s.t.} \quad Ap = 0$$

- If $p_k = 0$: solve $\sum_{i \in \mathcal{W}_k} a_i \hat{\lambda_i} = g_k$ for $\hat{\lambda}$ $(A_k \hat{\lambda} = g_k)$
 - If $\hat{\lambda} \geq 0$:
 - * All KKT-conditions fulfulled
 - * x_k is our solution

– If
$$\hat{\lambda} \ngeq 0$$
:

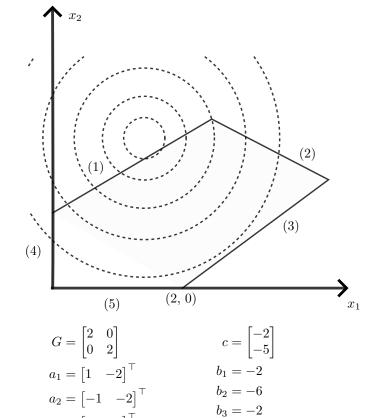
- * Pick index of one negative $\hat{\lambda_i}$
- * Remove this index from \mathcal{W}_k
- * Start over.
- If $p_k \neq 0$:
 - If $x_{k+1} = x_k + p_k$ is feasible: Set $\mathcal{W}_{k+1} = \mathcal{W}_k$, start over
 - If $x_{k+1} = x_k + p_k$ is not feasible: find blocking constraint
 - * For $i \in \{i | a_i^\top p_k < 0\}$
 - * want $a_i^{\top}(x_k + \alpha_i p_k) \ge b_i$

$$\implies \lambda_i = rac{b_i - a_i^{ op} x_k}{\alpha_i^{ op} p_k}$$

- * Set j = "i with smallest α_i "
- * $x_{k+1} = x_n + \alpha_j p_k$, $\mathcal{W}_{k+1} = \mathcal{W}_k + \{j\}$
- * start over...

This is one of the key algorithms in the course.

Example 16.4 -



$$\min_{x} q(x) = (x_1 - 1)^2 + (x_2 - 2.5)^2$$

s.t.
$$x_1 - 2x_2 + 2 \ge 0$$
 (1)

$$-x_1 - 2x_2 + 6 \ge 0 \tag{2}$$

$$-x_1 + 2x_2 + 2 \ge 0 \tag{3}$$

$$x_1 \ge 0 \qquad (4)$$

$$x_2 \ge 0 \qquad (5)$$

We have two different indices, one for iteration and one for variable. Denote iteration k like x^k .

 $b_4 = 0$

 $b_5 = 0$

$$x^{0} = \begin{bmatrix} 2 \\ 0 \end{bmatrix}, \ \mathcal{W} = \{3, 5\}, \ g_{k} = Gx^{0} + c = \begin{bmatrix} 2 \\ -5 \end{bmatrix}$$

 $a_3 = \begin{bmatrix} -1 & 2 \end{bmatrix}^\top$

 $a_4 = \begin{bmatrix} 1 & 0 \end{bmatrix}^\top$

 $a_5 = \begin{bmatrix} 0 & 1 \end{bmatrix}^{\mathsf{T}}$

EQP:

$$\begin{aligned} & \min_{p} \frac{1}{2} p^{\top} G p + g_{0}^{\top} p \\ & \text{s.t. } A_{0} p = 0 \\ & \min_{p} p_{1}^{2} + p_{2}^{2} + 2 p_{1} - 5 p_{2} \\ & \text{s.t. } -p_{1} + 2 p_{2} = 0 \\ & p_{2} = 0 \end{aligned}$$

$$\sum_{i \in \mathcal{W}_0} a_i \hat{\lambda}_i = g_0 : \begin{bmatrix} -1 \\ -2 \end{bmatrix} \hat{\lambda}_3 + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \hat{\lambda}_5 = \begin{bmatrix} 2 \\ -5 \end{bmatrix}$$

Remove {3} from \mathcal{W}_0 . Continue with next iteration. We have $x^1 = \begin{bmatrix} 2 \\ 0 \end{bmatrix}$, $\mathcal{W}_1 = \{5\}$, $g_1 = \begin{bmatrix} 2 \\ -5 \end{bmatrix}$ EQP gives $p^1 = \begin{bmatrix} -1 \\ 0 \end{bmatrix}$. $x^2 = x^1 + p^1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, which is feasible. $\mathcal{W}_2 = \mathcal{W}^1$