



NTNU

Norwegian University of
Science and Technology

TTK4135 – Lecture 18

Sequential Quadratic Programming (SQP)

Lecturer: Lars Imsland

Outline

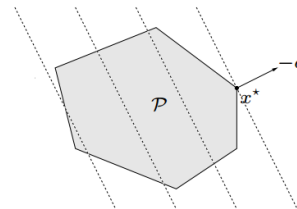
- Recap: Newton's method for solving nonlinear equations
- Recap: Equality-constrained QPs
- SQP for *equality-constrained* nonlinear programming problems
 - Next time: SQP for general

Reference: N&W Ch.18-18.1

Types of Constrained Optimization Problems

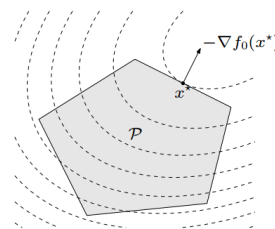
- Linear programming
 - Convex problem
 - Feasible set polyhedron

$$\begin{array}{ll} \min & c^\top x \\ \text{subject to} & Ax \leq b \\ & Cx = d \end{array}$$



- Quadratic programming
 - Convex problem if $P \geq 0$
 - Feasible set polyhedron

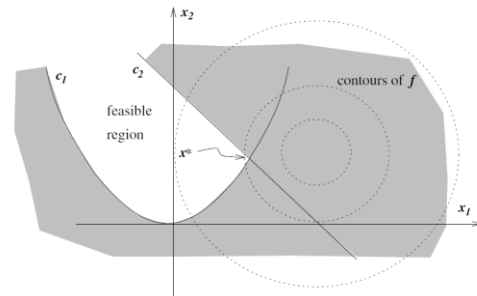
$$\begin{array}{ll} \min & \frac{1}{2}x^\top Px + q^\top x \\ \text{subject to} & Ax \leq b \\ & Cx = d \end{array}$$



- Nonlinear programming
 - In general non-convex!

$$\begin{array}{ll} \min & f(x) \\ \text{subject to} & g(x) = 0 \\ & h(x) \geq 0 \end{array}$$

$$\begin{array}{ll} \min_{x \in \mathbb{R}^n} & f(x) \\ \text{subject to} & c_i(x) = 0, \quad i \in \mathcal{E}, \\ & c_i(x) \geq 0, \quad i \in \mathcal{I}. \end{array}$$

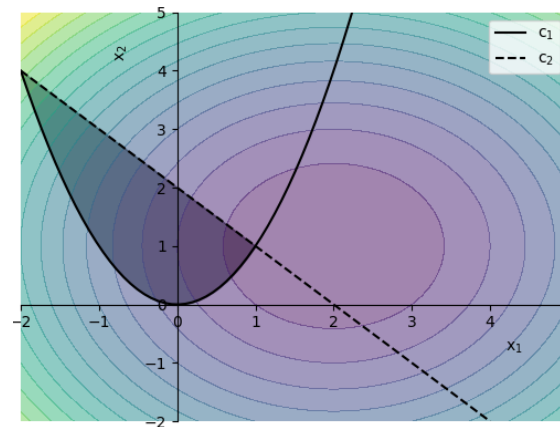
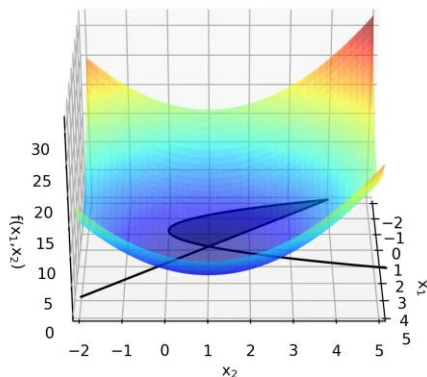


General Optimization Problem

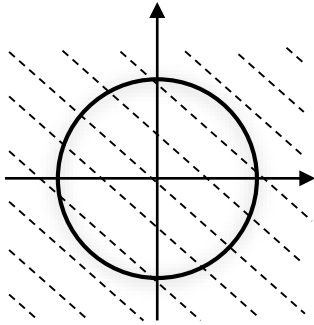
$$\min_{x \in \mathbb{R}^n} f(x) \quad \text{subject to} \quad \begin{aligned} c_i(x) &= 0, & i \in \mathcal{E}, \\ c_i(x) &\geq 0, & i \in \mathcal{I}. \end{aligned}$$

- Example:

$$\min (x_1 - 2)^2 + (x_2 - 1)^2 \quad \text{subject to} \quad \begin{aligned} x_1^2 - x_2 &\leq 0, \\ x_1 + x_2 &\leq 2. \end{aligned}$$



Today: Only equality constraints



The Lagrangian

For constrained optimization problems, introduce modification of objective function:

$$\mathcal{L}(x, \lambda) = f(x) - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \lambda_i c_i(x)$$

- Multipliers for *equality* constraints may have both signs in a solution
- Multipliers for *inequality* constraints cannot be negative (cf. shadow prices)
- For (inequality) constraints that are *inactive*, multipliers are zero

KKT conditions (Theorem 12.1)

$$\mathcal{L}(x, \lambda) = f(x) - \sum_{i \in \mathcal{E} \cup \mathcal{I}} \lambda_i c_i(x)$$

KKT conditions (First-order necessary conditions): If x^* is a local solution and LICQ holds, then there exist λ^* such that

$$\nabla_x \mathcal{L}(x^*, \lambda^*) = 0,$$

(stationarity)

$$c_i(x^*) = 0, \quad \forall i \in \mathcal{E},$$

$$c_i(x^*) \geq 0, \quad \forall i \in \mathcal{I},$$

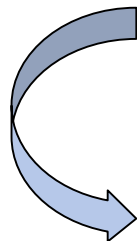
$$\lambda_i^* \geq 0, \quad \forall i \in \mathcal{I},$$

$$\lambda_i^* c_i(x^*) = 0, \quad \forall i \in \mathcal{E} \cup \mathcal{I}.$$

} (primal feasibility)

(dual feasibility)

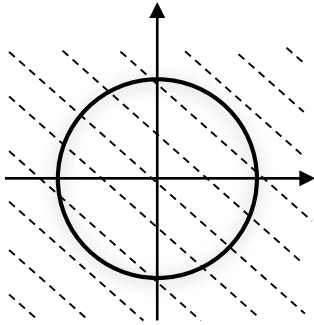
(complementarity condition/
complementary slackness)



Either $\lambda_i^* = 0$ or $c_i(x^*) = 0$

Example KKT system

$$\min_{x \in \mathbb{R}^2} -x_1 - x_2 \quad \text{s.t.} \quad x_1^2 + x_2^2 - 1 = 0$$



Today: Equality-constrained NLP

Newton's method for solving nonlinear equations (Ch. 11)

- Solve equation system $r(x) = 0$, $r(x) : \mathbb{R}^n \rightarrow \mathbb{R}^n$
- Assume Jacobian $J(x) \in \mathbb{R}^{n \times n}$ exists and is continuous
- Taylor: $r(x + p) = r(x) + J(x)p + O(\|p\|^2)$

$$J(x) = \begin{pmatrix} \frac{\partial r_1}{\partial x_1} & \frac{\partial r_1}{\partial x_2} & \cdots \\ \frac{\partial r_2}{\partial x_1} & \frac{\partial r_2}{\partial x_2} & \cdots \\ \vdots & \vdots & \ddots \end{pmatrix}$$

Algorithm 11.1 (Newton's Method for Nonlinear Equations).

Choose x_0 ;

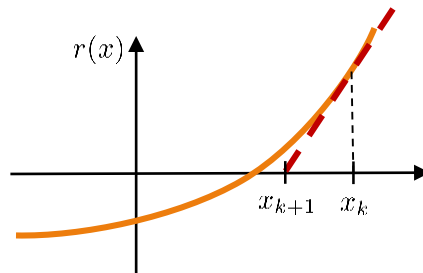
for $k = 0, 1, 2, \dots$

 Calculate a solution p_k to the Newton equations

$$J(x_k)p_k = -r(x_k);$$

$$x_{k+1} \leftarrow x_k + p_k;$$

end (for)



- Convergence rate (Thm 11.2): **Quadratic convergence** if $J(x)$ is invertible
(quadratic convergence is very good, but only holds close to the solution)
- If we set $r(x) = \nabla f(x)$, then this method corresponds to Newton's method for minimizing $f(x)$

$$p_k = -J(x_k)^{-1}r(x_k) \quad \longleftrightarrow \quad p_k = -(\nabla^2 f(x_k))^{-1} \nabla f(x_k)$$

Newton's method to solve $F(\mathbf{x}, \lambda) = \mathbf{0}$

$$F(x, \lambda) = \begin{pmatrix} \nabla f(x) - A^\top(x)\lambda \\ c(x) \end{pmatrix}$$

Equality-constrained QP (EQP)

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & \frac{1}{2} x^\top G x + c^\top x \\ \text{subject to} \quad & A x = b, \quad A \in \mathbb{R}^{m \times n} \end{aligned}$$

Basic assumption:
A full row rank

- KKT-conditions (KKT system, KKT matrix):

$$\begin{pmatrix} G & -A^\top \\ A & 0 \end{pmatrix} \begin{pmatrix} x^* \\ \lambda^* \end{pmatrix} = \begin{pmatrix} -c \\ b \end{pmatrix} \quad \text{or, if we let } x^* = x + p, \quad \begin{pmatrix} G & A^\top \\ A & 0 \end{pmatrix} \begin{pmatrix} -p \\ \lambda^* \end{pmatrix} = \begin{pmatrix} c + Gx \\ Ax - b \end{pmatrix}$$

- Solvable when $Z^\top G Z > 0$ (columns of Z basis for nullspace of A)
- That is: QP with only equality constraints is solved by solving a set of linear equations (*linear system*)

Alternative “derivation” of KKT-system

$$\min_{x \in \mathbb{R}^n} f(x) \quad \text{s.t.} \quad c(x) = 0$$

Local SQP-algorithm for solving equality-constrained NLPs

$$\begin{array}{ll} \min & f(x) \\ \text{subject to} & c(x) = 0 \end{array}$$

Algorithm 18.1 (Local SQP Algorithm for solving (18.1)).

Choose an initial pair (x_0, λ_0) ; set $k \leftarrow 0$;

repeat until a convergence test is satisfied

 Evaluate $f_k, \nabla f_k, \nabla_{xx}^2 \mathcal{L}_k, c_k$, and A_k ;

 Solve (18.7) to obtain p_k and l_k ;

 Set $x_{k+1} \leftarrow x_k + p_k$ and $\lambda_{k+1} \leftarrow l_k$;

end (repeat)

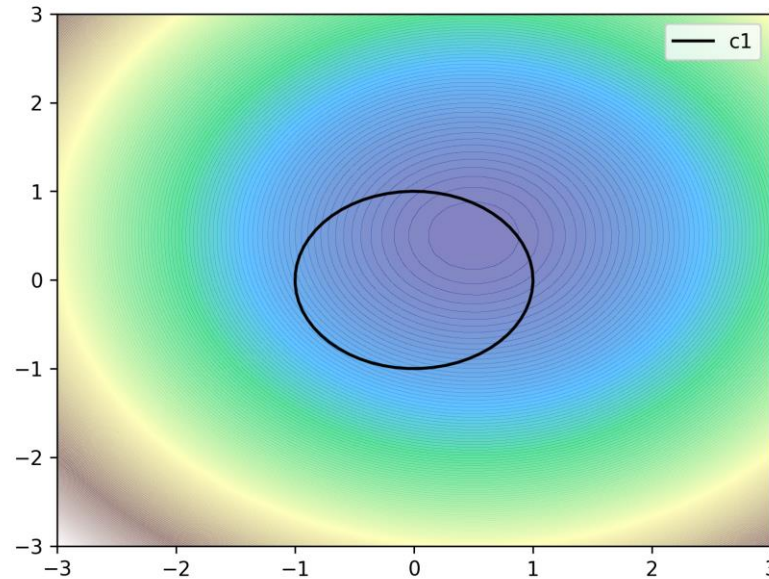
EQP:

$$\begin{array}{ll} \min_p & f_k + \nabla f_k^T p + \frac{1}{2} p^T \nabla_{xx}^2 \mathcal{L}_k p \\ \text{subject to} & A_k p + c_k = 0. \end{array}$$

Local SQP

$$f(x) = (x_1 - 0.5)^2 + (x_2 - 0.5)^2$$

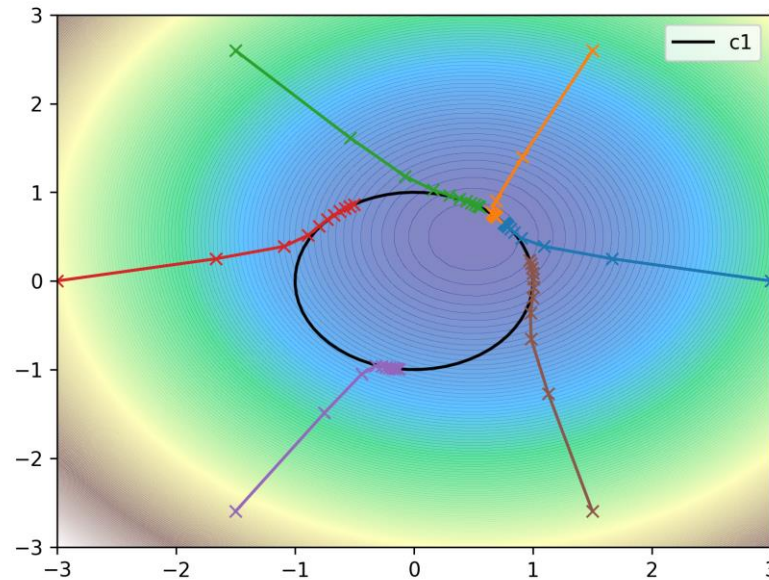
$$c_1(x) = x_1^2 + x_2^2 - 1 = 0$$



Local SQP

$$f(x) = (x_1 - 0.5)^2 + (x_2 - 0.5)^2$$

$$c_1(x) = x_1^2 + x_2^2 - 1 = 0$$



$$\begin{aligned} \min_p \quad & f_k + \nabla f_k^T p + \frac{1}{2} p^T \nabla_{xx}^2 \mathcal{L}_k p \\ \text{subject to} \quad & A_k p + c_k = 0. \end{aligned}$$