

Augmented Lagrangian Method

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General Constrained Optimization Problem

- ▶ Optimize nonlinear objective function

$$\min_{x \in \mathbb{R}^n} f(x)$$

- ▶ Subject to nonlinear constraints:

$$c(x) = 0$$

Sequential Quadratic Programming (SQP)

- ▶ **Step Generation:** Apply Newton method to solve 1st order optimality conditions:

$$\begin{aligned} \min & g(x_k)^T \Delta x + \frac{1}{2} \Delta x^T H(x_k, \lambda_k) \Delta x \\ \text{s.t.} & c(x_k) + J(x_k) \Delta x = 0 \end{aligned}$$

Sequential Quadratic Programming (SQP)

- ▶ **Step Acceptance:** Merit function balances the conflicting goals of reducing the objective function $f(x)$ and the constraint violation $\|c(x)\|$, e.g., L_1 merit function:

$$\Phi(x, \rho) = f(x) + \frac{\rho}{2} \|c(x)\|_1$$

SQP Characteristics

- ▶ Not a feasible method
- ▶ Solving QP at each iteration is expensive in large scale constrained optimization
- ▶ Dependent on rapid algorithms for solving quadratic programs
- ▶ Only guarantee to find a local solution

Penalty Methods

- ▶ Main idea: solving a constrained optimization problem by solving a sequence of unconstrained optimization problems
- ▶ Another type of merit function - **quadratic penalty**

$$P(x, \rho) = f(x) + \frac{\rho}{2} \|c(x)\|_2^2$$

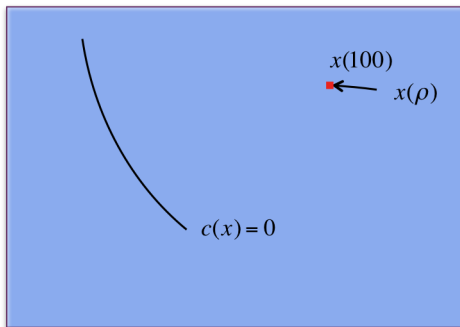
$$x(\rho) = \arg \min_{x \in \mathbb{R}^n} P(x, \rho)$$

- ▶ The solution to original optimization problem:

$$\lim_{\rho \rightarrow \infty} x(\rho) = x^*$$

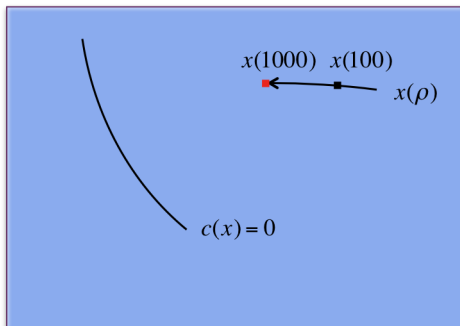
Limitations of Penalty Methods

- ▶ $\lim_{\rho \rightarrow \infty} x(\rho) = x^*$ is not computationally reasonable



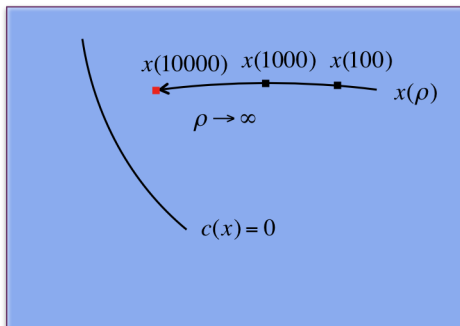
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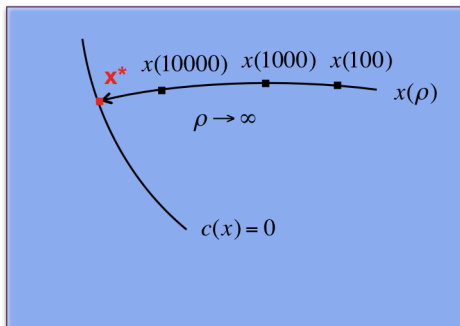
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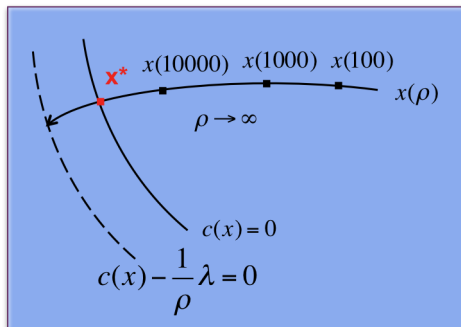
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Introducing Augmented Lagrangian Method

- ▶ $\lim_{\rho \rightarrow \infty} x(\rho) = x^*$ is not computationally reasonable



- ▶ If we relax $c(x = 0)$ by some value e.g., $\frac{1}{\rho} \lambda$ then we can achieve x^* with finite ρ

Problem Reformulation

- ▶ We reformulate the original problem **NLP**

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

- ▶ into a new problem **PNLP**:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} f(x) \\ \text{s.t. } c(x) - \frac{1}{\rho} \lambda = 0 \end{aligned}$$

Introducing Augmented Lagrangian

- ▶ Penalty Method:

$$x(\rho) = \arg \min_{x \in \mathbb{R}^n} f(x) + \frac{\rho}{2} \|c(x)\|_2^2$$

- ▶ Augmented Lagrangian:

$$\begin{aligned} x(\rho, \lambda) &= \arg \min_{x \in \mathbb{R}^n} f(x) + \frac{\rho}{2} \|c(x) - \frac{1}{\rho} \lambda\|_2^2 = \\ &= \arg \min_{x \in \mathbb{R}^n} f(x) + \frac{\rho}{2} \|c(x)\|_2^2 - c(x)^T \lambda \\ x(\rho, \lambda) &\doteq \arg \min_{x \in \mathbb{R}^n} \underbrace{f(x) - c(x)^T \lambda + \frac{\rho}{2} \|c(x)\|_2^2}_{\mathcal{L}_A(x, \rho, \lambda)} \end{aligned}$$

- ▶ optimal shift = optimal multiplier

1st Order Optimality Conditions for Original Optimization Problem

- ▶ Original problem

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

- ▶ 1st order optimality conditions for original problem
 - $c(x) = 0$
 - $\nabla f(x) - \nabla c(x)^T \lambda = 0 \Rightarrow g(x) - J(x)^T \lambda = 0$

1st Order Optimality Conditions for Modified Optimization Problem

- ▶ Modified problem

$$\min_{x \in \mathbb{R}^n} f(x)$$

$$\text{s.t. } c(x) - \frac{1}{\rho} \lambda = 0$$

$$L(x, \rho, \lambda) = f(x) - c(x)^T \lambda + \frac{\rho}{2} \|c(x)\|_2^2$$

- ▶ 1st order optimality conditions for modified problem:

$$c(x) - \frac{1}{\rho} \lambda = 0$$

$$\nabla L(x, \rho, \lambda) = \nabla f(x) - \nabla c(x)^T \lambda + \frac{\rho}{2} \nabla \|c(x)\|_2^2 =$$

$$= g(x) - J(x)^T \lambda + \rho J(x)^T c(x)$$

$$g(x) - J(x)^T (\lambda - \rho c(x)) = 0$$

Augmented Lagrangian vs. SQP

- ▶ SQP generates a step and then pairs it with a merit function
- ▶ AL similarly to penalty methods directly minimizes penalty function

Extend Augmented Lagrangian Method to Inequality Constraints

- ▶ Inequality constraints:

$$\begin{aligned} \min_{x,s \in \mathbb{R}^n} f(x) \\ \text{s.t. } c(x) \geq 0 \end{aligned}$$

- ▶ Use slack variables

$$\begin{aligned} \min_{x,s \in \mathbb{R}^n} f(x) \\ \text{s.t. } c(x) - s = 0 \\ s \geq 0 \end{aligned}$$

- ▶ solving a sequence of bounded constrained problems