

Summary from Saturday Reading Group on Optimization
January 2007

1 Summary of Necessary/Sufficient Conditions

1.1 Lagrange Multiplier Theorem: Necessary Conditions

Nonlinear Program:

$$\min_{x \in F} f(x) \text{ s.t. } h_i(x) = 0, i = 1, \dots, m$$

Assume that the constraint gradients are $\nabla h_1(x^*), \nabla h_2(x^*), \dots, \nabla h_m(x^*)$ are linearly **independent**. If x^* is a local minimum of f subject to $h(x) = 0$, then there exists a **unique** vector $\lambda^* = (\lambda_1^*, \lambda_2^*, \dots, \lambda_m^*)$, called Lagrange multiplier vector such that

$$\nabla f(x^*) + \sum_{i=1}^m \lambda_i^* \nabla h_i(x^*) = 0.$$

In addition, if f and h are twice continuously differentiable, we have

$$y^T (\nabla^2 f(x^*) + \sum_{i=1}^m \lambda_i^* \nabla^2 h_i(x^*)) y \geq 0 \forall y \in V(x^*),$$

where

$$V(x^*) = \{y | \nabla h_i(x^{*T})y = 0, i = 1, \dots, m\}$$

From now on, the following function is defined as $L(x, \lambda)$, the Lagrangian function:

$$L(x, \lambda) = f(x^*) + \sum_{i=1}^m \lambda_i^* h_i(x^*)$$

1.2 Lagrange Multiplier Theorem: Second-order Sufficient Condition

Nonlinear Program:

$$\min_{x \in F} f(x) \text{ s.t. } h_i(x) = 0, i = 1, \dots, m$$

Assume that f and h are twice continuously differentiable, and let $x^* \in \mathcal{R}^n$ and $\lambda^* \in \mathcal{R}^m$ satisfy

$$\begin{aligned}\nabla_x L(x^*, \lambda^*) &= 0, \\ \nabla_\lambda L(x^*, \lambda^*) &, \\ y^T \nabla_{xx} L(x^*, \lambda^*) y &> 0, \\ \forall y \neq 0 \text{ with } \nabla h(x^*)^T y &= 0.\end{aligned}$$

Then x^* is a strict local minimum of f subject to $h(x) = 0$. In fact, there exists scalars $\gamma > 0$ and $\epsilon > 0$ such that

$$f(x) \geq f(x^*) + \frac{\gamma}{2} \|x - x^*\|^2, \forall x \text{ with } h(x) = 0 \text{ and } \|x - x^*\| < \epsilon.$$

References

- [1] D.P.Bertsekas, *Nonlinear Programming*, second edition, Athena Scientific(2004).
- [2] Reading Group on Optimization <http://individual.utoronto.ca/quanyan/>.

Updated 29 January 2007.