

# The Prove of a Class of Variational Inequalities

Xiangrui Meng, Wenya Gu

College of Binjiang, Nanjing University of Information Science & Technology, Nanjing Jiangsu 210044, China

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**Abstract.** If  $f(x)$  is a differentiable convex function and its Hessian matrix is positive semi-definite, we can prove the inequality  $(x - x^*)^T \nabla f(x) \geq -\frac{1}{2}(x - x^*)^T (\nabla^2 f(x) - \nabla^2 f(x^*))$ .

Meet the above inequality from the general convex function of the convergence card sequence of functions on the measurable set.

**Keyword.** Convex function, positive semidefinite, cauchy sequences, convergence

## 1. Introduction

Let  $f(x)$  be a differentiable convex function, and  $\nabla f(x)$  be the gradient of the function.  $x^*$  is the only optimal value point, which makes  $\nabla f(x^*) = 0$ . Then to any  $x$  and  $x^*$ , if  $H$  is positive semi-definite,

$$(x - x^*)^T \nabla f(x) \geq -\frac{1}{2}(x - x^*)^T (\nabla^2 f(x) - \nabla^2 f(x^*)) \quad (1)$$

(see [11],[12],[13],[14],[15],[16],[17]), but if  $f(x)$  only be a differentiable convex function we can get weaker inequality(see [18],[19]), can we get the inequality to any convex function?

## 2. Some properties

**Conclusion 1:** Let  $H$  be positive semi-definite. Then we have

$$a^T H b \geq -\frac{1}{2}(a - b)^T H (a - b)$$

**Proof:**  $(a - b)^T H (a - b)$   
 $= (a - b, H(a - b))$   
 $= (a, Ha) - (b, Ha) - (a, Hb) + (b, Hb)$   
 since  $H$  is positive semi-definite and  $(a, Hb) = (b, Ha)$ ,

we have  $(a, Hb) \geq -\frac{1}{2}(a - b, H(a - b))$ .

**Conclusion 2:** assume that  $f(x)$  is differentiable on  $R^n$ , then  $f(x)$  convex if and only if

$$f(y) - f(x) \geq \nabla f(x)^T (y - x).$$

**Proof:** if  $f(x)$  is convex, then

$$f((1 - \theta)x + \theta y) \leq (1 - \theta)f(x) + \theta f(y), \quad \theta \in [0, 1], x, y \in R^n$$

So we have  $f(y) - f(x) \geq \frac{f(x + \theta(y - x)) - f(x)}{\theta}$

letting  $\theta \rightarrow 0_+$ , we get  $f(y) - f(x) \geq (y - x)^T \nabla f(x)$ .

Conversely if  $f(x) = \frac{1}{2}x^T Hx + c^T x, H^T = H$  and  $H$  is semi-definite, the conclusion is obviously.

**Theorem 1.** Let  $f(x) = \frac{1}{2}x^T Hx + c^T x, H^T = H$  and  $H$  be positive semi-definite, Then we have

$$(x - x^*)^T \nabla f(x) \geq -\frac{1}{2}(x - x^*)^T (\nabla f(x) - \nabla f(x^*)) \tag{2}$$

**Proof:** note that in this case  $\nabla f(x) = Hx + c$  and thus the equivalent of (2) is

$$(x - x^*)^T (Hx + c) \geq -\frac{1}{2}(x - x^*)^T H(x - x^*) \tag{3}$$

By using  $Hx^* + c = 0$ , we have  $(x - x^*)^T \{(Hx + c) - H(x - x^*)\} = 0$  and consequently  $(x - x^*)^T (Hx + c) = (x - x^*)^T H(x - x^*)$

Since  $H$  is positive semi-definite, we can get the conclusion.

For a general convex function, weaker than (1) the conclusion is clearly established.

**Theorem 2.** Let  $f(x) : R^n \rightarrow R$  be convex and differentiable. Then we have

$$(x - x^*)^T \nabla f(x) \geq -(x - x^*)^T (\nabla f(x) - \nabla f(x^*)). \text{ (see [15],[16])} \tag{4}$$

**Proof:** since  $f(x)$  is convex and differentiable, we have

$$f(x^*) \geq f(x) + (x^* - x)^T \nabla f(x). \tag{5}$$

Since  $x^*$  is the minimum point,  $f(\tilde{x}) \geq f(x^*)$ . Therefore, it follows from (5) that

$$(x - x^*)^T \nabla f(x) \geq f(x) - f(\tilde{x}) \tag{6}$$

Since  $f$  is convex,  $f(x) - f(\tilde{x}) \geq \nabla f(\tilde{x})^T (x - \tilde{x})$  Using (5) (6) we have:

$$(x - \tilde{x})^T \nabla f(x) \geq (x - \tilde{x})^T \nabla f(\tilde{x}) \tag{7}$$

Adding  $(\tilde{x} - x^*)^T \nabla f(x)$  to the both sides of (7), we get

$$(\tilde{x} - x^*)^T \nabla f(x) \geq (x - \tilde{x})^T (\nabla f(\tilde{x}) - \nabla f(x)).$$

For general convex function, can conclude that (1).

### 3. The main result

**Conclusion 3:**  $L^p(\mu)$  is a complete metric space, that is to say any cauchy sequence of the  $L^p(\mu)$  converges to an element of the  $L^p(\mu)$ .

**Theorem 3:** If  $1 \leq p \leq \infty$ , and if  $\{f_n\}$  is a Cauchy sequence in  $L^p(\mu)$ , with limit  $f$ , then  $\{f_n\}$  has a subsequence which converges pointwise almost everywhere to  $f(x)$ .

According to Theorem 3 (see [20]), for a differentiable convex function  $f(x)$ ,  $x \in R^n$ , can always find a Cauchy sequence  $\{f_n\}$  of  $L^p(\mu)$ . By the conclusion of Theorem 3 shows that a subsequence  $\{f_{n_i}\}$  can always be found in the above Cauchy sequence, which converge to  $f(x)$ .  $f_{n_i}$  is a differentiable convex function and meets  $f_{n_i}(x) = \frac{1}{2}x^T H_{n_i} x + c^T x, H_{n_i} = H_{n_i}^T$ , among which,  $H_{n_i}$  is positive semi-definite.

### 4. References

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