

# Variational Inequalities with Monotonicity

## Consequences for Optimization

Jarle Sogn

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Institute of Computational Mathematics

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# Topic of this talk

Definitions and Preliminaries

Variational Inequalities with Monotonicity

Consequences for Optimization

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Variational Inequalities with Monotonicity

- Convexity of solution

- Existence without monotonicity and boundedness (improving a 2A.1)

- Existence for monotone V.I.

- V.I. with strong monotonicity (property of the solutions)

Consequences for Optimization

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## Definitions and Preliminaries

## Variational Inequalities with Monotonicity

- Convexity of solution

- Existence without monotonicity and boundedness (improving a 2A.1)

- Existence for monotone V.I.

- V.I. with strong monotonicity (property of the solutions)

## Consequences for Optimization

- 2nd-Order optimality on polyhedral convex set

- Parametrized minimization problem

- Tilted minimization problem

- Minimization problem with system of constraints (not convex)

# Normal Cone and Variational inequality

Let  $C \subset \mathbb{R}^n$  be convex,  $x \in C$ .

## Definition (Normal Cone)

$$N_C(x) = \{v \mid \langle v, x' - x \rangle \leq 0, \quad \forall x' \in C\} \text{ (closed and convex)}$$

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## Definition (Variational inequality)

$$\begin{aligned} f(x) + N_C(x) \ni 0 \\ \Leftrightarrow \\ -f(x) \in N_C(x) \\ \Leftrightarrow \\ \langle f(x), x' - x \rangle \geq 0, \quad \forall x' \in C \end{aligned}$$

# Monotonicity, strong monotonicity and solution mapping

Let  $C \subset \mathbb{R}^n$  be convex,  $x \in C$  and let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ .

**Definition (Monotone and strongly monotone functions)**

$f$  is said to be monotone on  $C$  if

$$\langle f(x') - f(x), x' - x \rangle \geq 0, \quad \forall x, x' \in C.$$

$f$  is said to be strongly monotone on  $C$  with constant  $\mu > 0$  if

$$\langle f(x') - f(x), x' - x \rangle \geq \mu |x - x'|^2, \quad \forall x, x' \in C.$$

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## Definition (Solution mapping)

The mapping to the perturbation scheme  $f(x) - p$  (where  $p$  is a parameter vector  $p \in \mathbb{R}^n$ ) is

$$S(p) = \{x \mid p - f(x) \in N_C\} = (f + N_C)^{-1}(p).$$



## 2F.1: Solution Convexity for Monotone Variational Inequalities

### Theorem

Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be monotone in a nonempty closed convex set  $C$ . The solution mapping  $S$  is closed and convex valued. In particular, the set of solutions (if any) to the variational inequality is **closed** and **convex**.

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### Proof.

Since  $S(p) = (f_p + N_C)^{-1}(0)$  for  $f_p(x) = f(x) - p$  (which is monotone and continuous like  $f$ ), it is sufficient to deal with  $S(0)$ . The closedness of  $S(0)$  is already shown in **Theorem 2A.1** by W. Stockinger for non-monotone functions (I will state it later). It remains to show convexity on the black board. □

## 2F.2: Solution Existence for Variational Inequalities without boundedness

This is an extension of **Theorem 2A.1** from W. Stockinger presentation:

### Theorem

*Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be continuous in a nonempty closed convex set  $C$ . Suppose there exist a  $\hat{x} \in C$  and  $\rho > 0$  such that*

*there is no  $x \in C$  with  $|x - \hat{x}| \geq \rho$  and  $\langle f(x), x - \hat{x} \rangle \leq 0$ .*

*Then the variational inequality has a solution and every solution satisfies  $|x - \hat{x}| < \rho$ .*

## Proof of Theorem 2F.2

We need the following ingredients which was shown in W. Stockinger presentation:

### Theorem (Solutions to Variational Inequalities)

*Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be continuous in a nonempty closed convex set  $C$ . The set of solutions to the variational equation is always closed. It is sure to be nonempty when  $C$  is bounded.*

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### Remark

*If  $C = C_1 \cap C_2$  for closed, convex sets  $C_1$  and  $C_2$  in  $\mathbb{R}^n$ , then the formula*

$$N_C(x) = N_{C_1}(x) + N_{C_2}(x) = \{v_1 + v_2 \mid v_1 \in N_{C_1}(x), v_2 \in N_{C_2}(x)\},$$

*holds for every  $x \in C$  such that there is no  $v \neq 0$  with  $v \in N_{C_1}(x)$  and  $-v \in N_{C_2}(x)$ .*

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Proof on blackboard!

## 2F.3: Uniform Local Existence

## Corollary

Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be continuous in a nonempty closed convex set  $C$ . Suppose there exist a  $\hat{x} \in C$ ,  $\rho > 0$  and  $\eta > 0$  such that

there is no  $x \in C$  with  $|x - \hat{x}| \geq \rho$  and  $\langle f(x), x - \hat{x} \rangle / |x - \hat{x}| \leq \eta$ .

Then the solution mapping  $S$  has the property that

$$\emptyset \neq S(v) \subset \{x \in C \mid |x - \hat{x}| < \rho\} \text{ when } |v| \leq \eta.$$

## Proof of Corollary 2F.3

Proof.

We show that stronger condition hold for Theorem 2F.2 with  $f_v(x) = f(x) - v, \forall |v| < \eta$ . Assume that there exists a  $x$  s. t.  $|x - \hat{x}| \geq \rho$ , then from the assumption in the Corollary  $\langle f(x), x - \hat{x} \rangle > \eta|x - \hat{x}|$ .

We need to show  $\langle f(x) - v, x - \hat{x} \rangle > 0$ .

$$\begin{aligned} \langle f(x) - v, x - \hat{x} \rangle / |x - \hat{x}| &> \eta - \langle v, x - \hat{x} \rangle / |x - \hat{x}| \\ &> \eta - |v||x - \hat{x}| / |x - \hat{x}| \\ &= \eta - |v| > 0, \quad \forall x \in C, \end{aligned}$$

$$\text{i.e. } \langle f(x) - v, x - \hat{x} \rangle > (\eta - |v|)\rho > 0.$$

The assumption in the Theorem is assured from the stronger assumption in the Corollary. □



## 2F.4: Solution Existence for Monotone Variational Inequalities

### Theorem

Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be continuous and monotone in a nonempty closed convex set  $C$ . Let  $\hat{x} \in C$  and let  $W$  consist of the vectors  $w$  with  $|w| = 1$  such that  $\hat{x} + \tau w \in C$ , for all  $\tau \in (0, \infty)$ , if any.

- (a) If  $\lim_{\tau \rightarrow \infty} \langle f(\hat{x} + \tau w), w \rangle > 0$  for all  $w \in W$ , then the solution mapping  $S$  is nonempty-valued on a neighborhood of 0.
- (b) If  $\lim_{\tau \rightarrow \infty} \langle f(\hat{x} + \tau w), w \rangle = \infty$  for all  $w \in W$ , then the solution mapping  $S$  is nonempty-valued on all of  $\mathbb{R}^n$ .

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### Theorem

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### Proof.

The idea of the proof for (a) is to show that limit criteria i (a), which we call  $A$ , ensures the assumption in corollary 2F.3, which we call  $B$ . This is shown by showing that  $A \rightarrow B$ . □

## 2F.6: Variational Inequalities with Strong Monotonicity

### Theorem

*Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  be continuous and strongly monotone with constant  $\mu > 0$  in a nonempty closed convex set  $C$ . Then the solution mapping  $S$  is single-valued on all of  $\mathbb{R}^n$  and moreover Lipschitz continuous with constant  $\mu^{-1}$ .*

### Proof.

Proof on the blackboard! □

# Preliminaries

We look at the variational inequality

$$\nabla g(x) + N_C(x) \ni 0,$$

where  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  is a continuously differentiable function over a nonempty, closed, convex set  $C \subset \mathbb{R}^n$ .

Or equivalently

$$\langle \nabla g(x), w \rangle \geq 0 \quad \forall w \in T_C(x),$$

where  $T_C(x)$  is the tangent cone.

We recall the critical cone from Peter's presentation:

$$K_C(x, -\nabla g(x)) = \{w \in T_C(x) \mid \langle \nabla g(x), w \rangle = 0\},$$

## 2G.1: Second-Order Optimality on a Polyhedral Convex Set

## Theorem

Let  $C$  be a polyhedral convex set in  $\mathbb{R}^n$  and let  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  be twice continuously differentiable on  $C$ . Let  $\bar{x} \in C$  and  $\bar{v} = -\nabla g(\bar{x})$ .

- (a) (necessary condition) If  $g$  has a local minimum with respect to  $C$  at  $\bar{x}$ , then  $\bar{x}$  satisfies the variational inequality and has  $\langle w, \nabla^2 g(\bar{x}) w \rangle \geq 0$  for all  $w \in K_C(\bar{x}, \bar{v})$ .
- (b) (sufficient condition) If  $\bar{x}$  satisfy the variational inequality and has  $\langle w, \nabla^2 g(\bar{x}) w \rangle > 0$  for all nonzero  $w \in K_C(\bar{x}, \bar{v})$ , then  $g$  has a local minimum relative to  $C$  at  $\bar{x}$ , indeed a strong local minimum in the sense of there being an  $\epsilon > 0$  such that

$$g(x) \geq g(\bar{x}) + \epsilon |x - \bar{x}|^2 \quad \forall x \in C \text{ near } \bar{x}.$$

# Proof of Theorem 2G.1

Proof.

We will prove the necessary condition on the blackboard!



# Proof of Theorem 2G.1

## Proof.

We will prove the necessary condition on the blackboard!

For the sufficient condition (b) the 1D case is inadequate, since we need a neighborhood of  $\bar{x}$  relative to  $C$ .

To show (b) one use the 2nd-order Taylor expansion of  $g$  at  $\bar{x}$ . Furthermore one use the tangent cone property is 2E.3, which requires  $C$  is *polyhedral*.



# Stationary Points

## Definition

An  $x$  satisfying the variational inequality, will be called a stationary point of  $g$  with respect to minimizing over  $C$ , regardless of whether or not it furnishes a local or global minimum.



## Stationary point mapping for perturbations

We now look at the parametrized problem on the form

$$\text{minimize } g(p, x) \text{ over all } x \in C,$$

where  $g : \mathbb{R}^d \times \mathbb{R}^n \rightarrow \mathbb{R}$  is twice continuously differentiable w.r.t.  $x$ , and  $C$  is a nonempty, closed, convex subset of  $\mathbb{R}^n$ .

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The variational inequality

$$\nabla_x g(p, x) + N_C(x) \ni 0,$$

provides for each  $p$  a first-order condition which  $x$  must satisfy if it furnishes a local minimum. It describes the stationary points.

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### Definition

The stationary point mapping,  $S : \mathbb{R}^d \rightrightarrows \mathbb{R}^n$ , is defined by

$$S(p) = \{x \mid \nabla_x g(p, x) + N_C(x) \ni 0\}$$

# Stationary point mapping for tilt perturbations

We also look at the auxiliary problem with parameter  $v \in \mathbb{R}^n$ , in which  $g(\bar{p}, \cdot)$  is replaced with it's 2nd-order expansion at  $\bar{x}$ :

minimize  $\bar{g}(w) - \langle v, w \rangle$  over all  $w \in W$ , where

$$\bar{g}(w) = g(\bar{p}, \bar{x}) + \langle \nabla_x g(\bar{p}, \bar{x}), w \rangle + \frac{1}{2} \langle w, \nabla_{xx}^2 g(\bar{p}, \bar{x}) w \rangle,$$

$$W = \{w \mid \bar{x} + w \in C\} = C - \bar{x}.$$

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The variational inequality

$$\begin{aligned} \nabla_x g(\bar{p}, \bar{x}) + \nabla_{xx}^2 g(\bar{p}, \bar{x}) w - v + N_W(w) \ni 0, \\ \text{where } N_W(w) = N_C(\bar{x} + w) \end{aligned}$$

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The stationary point mapping,  $\bar{S} : \mathbb{R}^n \rightrightarrows \mathbb{R}^n$ , is defined by

$$\bar{S}(v) = \{w \mid \nabla_x g(\bar{p}, \bar{x}) + \nabla_{xx}^2 g(\bar{p}, \bar{x}) w + N_W(w) \ni v\}.$$

## 2G.2: Parametric Minimization Over a Convex Set

## Theorem (part 1)

Using the notation from the two previous slides, with  $\bar{x} \in S(\bar{p})$ , that

- (a)  $\nabla_{x^p} g$  is strictly differentiable at  $(\bar{p}, \bar{x})$ .
- (b)  $\bar{S}$  has a Lipschitz continuous single-valued localization  $\bar{s}$  around 0 for 0.

Then  $S$  has a Lipschitz continuous single-valued localization  $s$  around  $\bar{p}$  for  $\bar{x}$  with

$$\text{lip}(s; \bar{p}) \leq \text{lip}(\bar{s}; 0) |\nabla_{x^p}^2 g(\bar{p}, \bar{x})|$$

and  $s$  has a first-order approximation  $\eta$  at  $\bar{p}$  given by

$$\eta(p) = \bar{x} + \bar{s}(-\nabla_{x^p}^2 g(\bar{p}, \bar{x})(p - \bar{p})).$$

(b) is necessary for  $S$  to have a Lipschitz continuous single-valued localization around  $\bar{p}$  for  $\bar{x}$  when the  $n \times d$  matrix  $\nabla_{x^p}^2 g(\bar{p}, \bar{x})$  has rank  $n$ .

## 2G.2: Parametric Minimization Over a Convex Set

## Theorem (part 2)

If additionally assuming that  $C$  is a polyhedral, condition (b) is equivalent to the condition that, for the critical cone  $K = K_C(\bar{x}, -\nabla_x g(\bar{p}, \bar{x}))$ , the mapping

$$v \mapsto \bar{S}_0(v) = \{w \mid \nabla_{xx}^2 g(\bar{p}, \bar{x}) w + N_K(w) \ni v\}$$

is everywhere single-valued.

Moreover, a sufficient condition for this can be expressed in terms of the critical subspaces  $K_C^+(\bar{x}, \bar{v}) = K_C(\bar{x}, \bar{v}) - K_C(\bar{x}, \bar{v})$  and  $K_C^-(\bar{x}, \bar{v}) = K_C(\bar{x}, \bar{v}) \cap [-K_C(\bar{x}, \bar{v})]$  for  $v = -\nabla_x g(\bar{p}, \bar{x})$ :

$$\langle w, \nabla_{xx}^2 g(\bar{p}, \bar{x}) w \rangle > 0,$$

for every nonzero  $w \in K_C^+(\bar{x}, \bar{v})$  with  $\nabla_{xx}^2 g(\bar{p}, \bar{x}) w \perp K_C^-(\bar{x}, \bar{v})$ .



# Proof of Theorem 2G.2 (part 1)

We recall Theorem 2E.1 from Peter's presentation:

## Theorem (2E.1)

For a variational inequality and its solution mapping, let  $\bar{p}$  and  $\bar{x}$  be such that  $\bar{x} \in S(\bar{p})$ . Assume that

- (a)  $f$  is strictly differentiable at  $(\bar{p}, \bar{x})$ ;
- (b) the inverse  $G^{-1}$  of the mapping

$$G(x) = f(\bar{p}, \bar{x}) + \nabla_x f(\bar{p}, \bar{x})(x - \bar{x}) + N_C(x), \quad \text{with } G(\bar{x}) \ni 0,$$

has a Lipschitz continuous single-valued localization  $\sigma$  around 0 for  $\bar{x}$ .

Then  $S$  has a Lipschitz continuous single-valued localization  $s$  around  $\bar{p}$  for  $\bar{x}$  with

$$\text{lip}(s; \bar{p}) \leq \text{lip}(\sigma; 0) \cdot |\nabla_p f(\bar{p}, \bar{x})|,$$

and this localization  $s$  has a first-order approximation  $\eta$  at  $\bar{p}$  given by

$$\eta(p) = \sigma(-\nabla_p f(\bar{p}, \bar{x})(p - \bar{p})).$$

# Proof of Theorem 2G.2 (part 2 )

Theorem (2E.1 (cont'd))

Moreover, under the ample parametrization condition

$$\text{rank } \nabla_p f(\bar{p}, \bar{x}) = n,$$

the existence of a Lipschitz continuous single-valued localization  $s$  of  $S$  around  $\bar{p}$  for  $\bar{p}$  not only follows from, but also necessitates the existence of a localization  $\sigma$  of  $G^{-1}$  having the properties described.

Proof.

We apply this Theorem with  $f(x, p) = \nabla_x g(p, x)$  □

## 2G.3 Stability of a Local Minimum on Polyhedral Convex Set

### Theorem

*In the setting of the parametrized minimization problem (not the auxiliary tilted problem) and its stationary point mapping  $S$  we assume that  $C$  is polyhedral and that  $\nabla_x g(p, x)$  is strictly differentiable with respect to  $(p, x)$  at  $(\bar{p}, \bar{x})$ , where  $\bar{x} \in S(\bar{p})$ . W.r.t. the critical subspace  $K_C^+(\bar{x}, \bar{v})$  for  $\bar{v} = -\nabla_x g(\bar{p}, \bar{x})$ , assume that*

$$\langle w, \nabla_{xx}^2 g(\bar{p}, \bar{x}) w \rangle > 0, \text{ for every nonzero } w \in K_C^+(\bar{x}, \bar{v}).$$

*Then  $S$  has a localization  $s$  with the properties from Theorem 2G.2 and also with the property that for every  $p$  in some neighborhood of  $\bar{p}$ , the point  $x = s(p)$  furnishes a strong local minimum. Moreover the assumption is necessary for the existence of a localization  $s$  with all these properties, when the  $n \times d$  matrix  $\nabla_{xp}^2 g(\bar{p}, \bar{x})$  has rank  $n$ .*

## 2G.4: Tilted Minimization of Strongly Convex Functions

## Proposition

Let  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  be continuously differentiable on an open set  $O$  and let  $g$  be strongly convex with constant  $\mu > 0$  on  $C \subset O$ , where  $C$  is a nonempty, closed, convex set. Then for every  $v \in \mathbb{R}^n$  the problem

$$\text{minimize } g(x) - \langle v, x \rangle \text{ over } x \in C$$

has a unique solution  $s(v)$ , and the solution mapping  $s$  is a Lipschitz continuous function on  $\mathbb{R}^n$  with constant  $\mu^{-1}$ .

# Proof of Proposition 2G.4

We need the **Theorem 2A.7** which was shown in W. Stockinger presentation:

## Theorem (Basic Variational Inequality for Minimization)

*Let  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  be differentiable on an open convex set  $O$  and let  $C$  is a nonempty, closed, convex subset of  $O$ . In minimizing  $g$  over  $C$ , the variation inequality*

$$\nabla g(x) + N_C(x) \ni 0,$$

*is necessary for  $x$  to furnish a local minimum. It is both necessary and sufficient for a global minimum if  $g$  is convex.*

And we need the lemma:

## Lemma (shown in exercise 2A.6 (a))

*Let  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  be continuously differentiable on an open set  $O$  and let  $g$  be strongly convex with constant  $\mu > 0$  on  $C \subset O$ , then the function  $f(x) = \nabla g(x)$  strongly monotone on  $C$  with constant  $\mu$ . This is an if and only if condition.*

# Minimization with system of constraints

The set  $C$  is now not necessary convex!

We look at the nonlinear programming problem:

$$\text{minimize } g_0(x) \text{ over all } x \text{ satisfying } g_i(x) \begin{cases} \leq 0 & \text{for } i \in [1, s], \\ = 0 & \text{for } i \in [s + 1, m]. \end{cases}$$

We assume that the functions  $g_0, g_1, \dots, g_m$  are twice continuously differentiable on  $\mathbb{R}^n$ .

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We look at the nonlinear programming problem:

$$\text{minimize } g_0(x) \text{ over all } x \text{ satisfying } g_i(x) \begin{cases} \leq 0 & \text{for } i \in [1, s], \\ = 0 & \text{for } i \in [s+1, m]. \end{cases}$$

We assume that the functions  $g_0, g_1, \dots, g_m$  are twice continuously differentiable on  $\mathbb{R}^n$ . From **Theorem 2A.9** we know that there exists a multiplier vector  $y = (y_1, \dots, y_m)$  relative to  $x$ , fulfilling the Karush-Kuhn-Tucker (KKT) conditions:

$$y \in \mathbb{R}_+^s \times \mathbb{R}^{m-s}, g_i(x) \begin{cases} \leq 0 & \text{for } i \in [1, s], \text{ with } y_i = 0, \\ = 0 & \text{for all other } i \in [1, m], \end{cases}$$

$$\nabla g_0(x) + y_1 \nabla g_1(x) + \dots + y_m \nabla g_m(x) = 0.$$

# Lagrangian function

We want to take a second-order approach to local sufficiency, hence we rewrite the problem in terms of the Lagrangian.

From **Theorem 2A.10** we know that the KKT formulation on the previous slide can be identified in terms of the Lagrangian function

$$L(x, y) = g_0(x) + y_1 g_1(x) + \dots + y_m g_m(x)$$

with the V.I. for a continuously differentiable function  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}^n \times \mathbb{R}^m$  and a polyhedral convex cone  $E \subset \mathbb{R}^n \times \mathbb{R}^m$ ,

$$f(x, y) + N_E(x, y) \ni (0, 0),$$

where

$$\begin{cases} f(x, y) &= (\nabla_x L(x, y) - \nabla_y L(x, y))^T, \\ E &= \mathbb{R}^n \times [\mathbb{R}_+^s \times \mathbb{R}^{m-s}]. \end{cases}$$



## 2G.6: Second-Order Optimality in Nonlinear Programming

## Theorem

Let  $\bar{x}$  be a point satisfying the constraints,  $g_i(\bar{x})$ . Let  $I(\bar{x})$  be the set of indices  $i$  of the active constraints at  $\bar{x}$ , and assume that the gradients  $\nabla g_i(\bar{x})$  for  $i \in I(\bar{x})$  are linear independent. Let  $K$  consists of the vector  $w \in \mathbb{R}^n$  satisfying

$$\langle \nabla g_i(\bar{x}), w \rangle \begin{cases} \leq 0 & \text{for } i \in I(\bar{x}) \text{ with } i \leq s, \\ = 0 & \text{for all other } i \in I(\bar{x}) \text{ and also for } i = 0. \end{cases}$$

- (a) (Necessary Condition) If  $\bar{x}$  furnishes a local minimum in the minimization problem, then a multiplier vector  $\bar{y}$  exist such that  $(\bar{x}, \bar{y})$  satisfies the V.I and also has

$$\langle w, \nabla_{xx}^2 L(\bar{x}, \bar{y}) w \rangle \geq 0 \quad \forall w \in K.$$

- (b) (Sufficient Condition) If a multiplier vector  $\bar{y}$  exists such that  $(\bar{x}, \bar{y})$  satisfies the KKT conditions, or equivalently the V.I. and if the inequality in part (a) hold strictly when  $w \neq 0$ , then  $\bar{x}$  furnishes a local minimum in the minimization problem. It is a strong local minimum in the sense that  $\exists \epsilon > 0$  such that

$$g_0(x) \geq g_0(\bar{x}) + \epsilon |x - \bar{x}|^2$$

# Summary of this talk

## Definitions and Preliminaries

## Variational Inequalities with Monotonicity

- Convexity of solution

- Existence without monotonicity and boundedness (improving a 2A.1)

- Existence for monotone V.I.

- V.I. with strong monotonicity (property of the solutions)

## Consequences for Optimization

- 2nd-Order optimality on polyhedral convex set

- Parametrized minimization problem

- Tilted minimization problem

- Minimization problem with system of constraints (not convex)

Thank you for attention!