

Séminaire de Calcul Scientifique du CERMICS



**Value Function in deterministic optimal control :  
sensitivity relations of first and second order**

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# Value Function in deterministic optimal control: sensitivity relations of first and second order

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# Outline of the talk

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  - Value Function
  - Characteristics of HJB
  - Semiconcave and Semiconvex Functions
  - Maximum Principle
- 2 **Sensitivity Relations**
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  - Second Order Sensitivity Relations
  - Propagation of Twice Fréchet Differentiability
- 3 **Local  $C^2$ –Regularity of the Value Function**
- 4 **State Constrained Systems**



# Mayer's Optimal Control Problem

Let  $T > 0$ . Consider the minimization problem

$$V(t_0, x_0) := \inf \left\{ \phi(x(T)) : x(\cdot) \in S_{[t_0, T]}(x_0) \right\} \quad \mathcal{P}(t_0, x_0)$$

where  $t_0 \in [0, T]$ ,  $\phi : \mathbb{R}^n \rightarrow \mathbb{R}$  and  $S_{[t_0, T]}(x_0)$  is the set of all absolutely continuous solutions of the **control system**

$$\begin{cases} \dot{x} = f(x, u(t)), & u(t) \in U \quad \text{a.e. in } [t_0, T] \\ x(t_0) = x_0 \end{cases}$$

where  $f : \mathbb{R}^n \times U \rightarrow \mathbb{R}^n$  is continuous and  $U$  is a complete separable metric space.  $V$  is called the **value function**.

Standard Hypothesis:  $\phi$  is locally Lipschitz and

$$\begin{cases} (i) & f(x, U) \text{ is compact for each } x \in \mathbb{R}^n \\ (ii) & f(\cdot, u) \text{ is locally Lipschitz uniformly in } u \in U \\ (iii) & \exists \gamma > 0 \text{ so that } \max\{|f(x, u)| : u \in U\} \leq \gamma(1 + |x|) \quad \forall x \in \mathbb{R}^n \end{cases}$$



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# Dynamic Programming

Value function is **nondecreasing** along trajectories of control system and is constant along optimal trajectories (**for the Mayer problem !**)

A trajectory-control pair  $(\bar{x}, \bar{u}) : [t_0, T] \rightarrow \mathbb{R}^n \times U$  is **optimal** iff

$$V(t, \bar{x}(t)) = \phi(\bar{x}(T)) \quad \forall t \in [t_0, T]$$

Let  $K := \text{epi}(V) = \{(t, x, z) : z \geq V(t, x)\} \subset [0, T] \times \mathbb{R}^n \times \mathbb{R}$ .

If  $f(x, U)$  is also **convex**  $\forall x \in \mathbb{R}^n$ , then  $K$  is **viable** for the system

$$\begin{cases} \dot{t}(s) &= 1 \\ \dot{x}(s) &\in f(x(s), U) \quad \text{a.e.} \\ \dot{z}(s) &= 0 \end{cases}$$

in the sense that for **any initial condition**  $(t_0, x_0, z_0) \in K$ , there exists a solution of the above system starting at  $(t_0, x_0, z_0)$  and satisfying  $(t(s), x(s), z(s)) \in K$  for all  $s \in [0, T - t_0]$ .



# Optimal Trajectories and Optimal Synthesis

A trajectory  $\bar{x} : [t_0, T] \rightarrow \mathbb{R}^n \times U$  is **optimal** for the problem  $\mathcal{P}(t_0, x_0)$  iff  $s \mapsto (t_0 + s, \bar{x}(t_0 + s), V(t_0, x_0))$  is a solution of

$$\left\{ \begin{array}{ll} \dot{t}(s) = 1 & t(0) = t_0 \\ \dot{x}(s) \in f(x(s), U) & \text{a.e. } x(0) = x_0 \\ \dot{z}(s) = 0 & z(0) = V(t_0, x_0) \\ (t(s), x(s), z(s)) \in K & \forall s \in [0, T - t_0] \end{array} \right.$$

Let  $T_K(t, x, V(t, x))$  denote the **contingent cone** to  $K$  at  $(t, x, V(t, x))$ . The **optimal synthesis** is given by

$$U(t, x) = \{u \in U : (1, f(x, u), 0) \in T_K(t, x, V(t, x))\}$$

A trajectory  $\bar{x} : [t_0, T] \rightarrow \mathbb{R}^n$  is **optimal** for the problem  $\mathcal{P}(t_0, x_0)$  **if and only if** it is a solution to

$$\dot{x}(s) \in f(x(s), U(s, x(s))) \quad x(t_0) = x_0$$



# Viability Kernel

If  $W : [0, T] \times \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $W(T, \cdot) = \phi(\cdot)$  and  $\text{epi}(W)$  is viable for the system

$$\begin{cases} \dot{t}(s) &= 1 \\ \dot{x}(s) &\in f(x(s), U) \quad \text{a.e.} \\ \dot{z}(s) &= 0 \end{cases}$$

then  $W \geq V$ .

Consider **any** lower semicontinuous  $W : [0, T] \times \mathbb{R}^n \rightarrow \mathbb{R}$  satisfying  $W \leq V$  and  $W(T, \cdot) = \phi(\cdot)$ . Let  $K$  be the **largest** closed subset of  $\text{epi}(W)$  such that for any initial condition  $(t_0, x_0, z_0) \in K$  there exists a **viable in  $K$**  solution of

$$\begin{cases} \dot{t}(s) &= 1 & t(0) &= t_0 \\ \dot{x}(s) &\in f(x(s), U) \quad \text{a.e.} & x(0) &= x_0 \\ \dot{z}(s) &= 0 & z(0) &= V(t_0, x_0) \end{cases}$$

then  $K = \text{epi}(V)$ .





# Generalized Differentials

Let  $\Omega \subset \mathbb{R}^n$  be open and  $g : \Omega \rightarrow \mathbb{R}$ . For any  $x \in \Omega$ , the sets

$$\partial^- g(x) = \left\{ p \in \mathbb{R}^n : \liminf_{y \rightarrow x} \frac{g(y) - g(x) - \langle p, y - x \rangle}{|y - x|} \geq 0 \right\}$$

$$\partial^+ g(x) = \left\{ p \in \mathbb{R}^n : \limsup_{y \rightarrow x} \frac{g(y) - g(x) - \langle p, y - x \rangle}{|y - x|} \leq 0 \right\}$$

are the **(Fréchet) subdifferential** and **superdifferential** of  $g$  at  $x$ , respectively. Denote by  $\partial g$  the (Clarke) generalized gradient of  $g$ .

$p \in \mathbb{R}^n$  is a **proximal subgradient** of  $g$  at  $x \in \Omega$  if  $\exists c, \rho \geq 0$

$$g(y) - g(x) - \langle p, y - x \rangle \geq -c|y - x|^2 \quad \forall y \in B(x, \rho).$$

The set of all proximal subgradients of  $g$  at  $x$  is denoted by  $\partial^{-,pr} g(x)$ .



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# HJB and Characteristics

Define the **Hamiltonian**  $H : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$  by

$$H(x, p) = \sup_{u \in U} \langle f(x, u), p \rangle \quad \forall (x, p) \in \mathbb{R}^n \times \mathbb{R}^n$$

$V$  is the unique solution, in a suitable sense, of the Hamilton-Jacobi equation

$$\begin{cases} -v_t(t, x) + H(x, -v_x(t, x)) = 0 & \text{in } [0, T] \times \mathbb{R}^n \\ v(T, x) = \phi(x) & x \in \mathbb{R}^n \end{cases}$$

**Characteristic system :**  $p(t) = -v_x(t, x(t))$

$$\begin{cases} \dot{x}(t) = \nabla_p H(x(t), p(t)) & x(T) = x_T \\ -\dot{p}(t) = \nabla_x H(x(t), p(t)) & -p(T) = \nabla \phi(x_T) \end{cases}$$

where  $\nabla_x H$  is the gradient of  $H(\cdot, p)$ , similarly for  $\nabla_p H$  whenever  $p(\cdot) \neq 0$



# HJB and Characteristics

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**Characteristic system :**  $p(t) \neq -v_x(t, x(t))$ , in general,

$$\begin{cases} \dot{x}(t) \in \partial_p^- H(x(t), p(t)) & x(T) = x_T \\ -\dot{p}(t) \in \partial_x^- H(x(t), p(t)) & -p(T) \in \partial \phi(x_T) \end{cases}$$

where  $\partial_x^- H$  is the subdifferential of  $H(\cdot, p)$ , similarly for  $\partial_p^- H$



# Maximum Principle

The **maximum principle** states that if  $(\bar{x}, \bar{u})$  is optimal, then the solution  $p$  of the **adjoint system**

$$\begin{cases} -\dot{p}(t) = p(t)f_x(\bar{x}(t), \bar{u}(t)) & \text{a.e.} \\ -p(T) = \nabla\phi(\bar{x}(T)) \end{cases}$$

satisfies the **maximality** condition :

$$\langle p(t), f(\bar{x}(t), \bar{u}(t)) \rangle = \max_{u \in U} \langle p(t), f(\bar{x}(t), u) \rangle$$

(Pontryagin and al., 1956)

If  $H$  is differentiable at  $(\bar{x}(t), p(t))$ , then

$$\begin{aligned} \nabla_x H(\bar{x}(t), p(t)) &= p(t)f_x(\bar{x}(t), \bar{u}(t)), \\ \nabla_p H(\bar{x}(t), p(t)) &= f(\bar{x}(t), \bar{u}(t)) \end{aligned}$$



# Sensitivity Relations for Smooth Control Systems

Let  $\bar{x}(\cdot)$  be an optimal solution for  $\mathcal{P}(t_0, x_0)$ .

If  $f$  and  $\phi$  are sufficiently **smooth** and  $V$  is differentiable, then the adjoint state  $p(\cdot)$  (of the **maximum principle**) satisfies the **partial** sensitivity relation

$$-p(t) = V_x(t, \bar{x}(t)) \quad \forall t \in [t_0, T]$$

and the **full** sensitivity relation

$$(H(\bar{x}(t), p(t)), -p(t)) = \nabla V(t, \bar{x}(t)) \quad \forall t \in [t_0, T]$$

The maximum principle + the last relation imply **a necessary and sufficient condition for optimality**.



# Sensitivity Relations for Smooth Control Systems

Let  $\bar{x}(\cdot)$  be an optimal solution for  $\mathcal{P}(t_0, x_0)$ .

In general,  $V$  is merely locally **Lipschitz**. By **Clarke, Vinter 1987** there **exists** an adjoint state  $p(\cdot)$  (co-state from the maximum principle) satisfying

$$-p(t) \in \partial_x V(t, \bar{x}(t)) \quad \text{a.e. in } [t_0, T]$$

and by **Vinter 1988** there exists an adjoint state  $q(\cdot)$  satisfying

$$(H(\bar{x}(t), q(t)), -q(t)) \in \partial V(t, \bar{x}(t)) \text{ for all } t \in (t_0, T)$$

This relations **do not imply** sufficient conditions for optimality. They also hold true in the state constrained case.



# Sensitivity Relations for Smooth Control Systems

Let  $\bar{x}(\cdot)$  be an optimal solution for  $\mathcal{P}(t_0, x_0)$ .

If  $f(\cdot, u)$  and  $\phi$  are **differentiable**, then the adjoint state  $p(\cdot)$  satisfies

$$-p(t) \in \partial_x^+ V(t, \bar{x}(t)) \quad \forall t \in [t_0, T]$$

and

$$(H(\bar{x}(t), p(t)), -p(t)) \in \partial^+ V(t, \bar{x}(t)) \quad \text{a.e. in } [t_0, T]$$

Subbotina 1989, Cannarsa and HF 1990.

This leads to **necessary and sufficient conditions** for optimality.





# Semiconcave and Semiconvex Functions

Let  $\Omega \subset \mathbb{R}^n$ ,  $c \geq 0$ ,  $g : \Omega \rightarrow \mathbb{R}$  is  $c$ -**semiconcave** if

$$g(\lambda x + (1 - \lambda)y) \geq \lambda g(x) + (1 - \lambda)g(y) - \lambda(1 - \lambda)c|x - y|^2$$

for all  $x, y \in \Omega$  such that  $[x, y] \subset \Omega$  and  $\lambda \in [0, 1]$ .

$g$  is called  $c$ -**semiconvex** on  $\Omega$  if  $-g$  is  $c$ -semiconcave on  $\Omega$ .

**Any locally  $C^{1,1}$  function is locally semiconvex.**

If  $f$  is sufficiently smooth in  $x$  and  $\phi$  is  $C^2$ , then the **value function** is **locally semiconcave**.

Hence it has directional derivatives and if the subdifferential of  $V$  is nonempty at some  $(t, x)$ , then  $V$  is differentiable at this point.  $V$  is then the unique locally Lipschitz solution of HJB equation in the **classical sense**.



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# Maximum Principle

## Theorem

Assume  $\forall r > 0 \exists c \geq 0$  such that  $\forall p \in S^{n-1}$ ,  $x \mapsto H(\cdot, p)$  is  $c$ -semiconvex on  $B(0, r)$ .

If  $\bar{x}(\cdot)$  is optimal for  $\mathcal{P}(t_0, x_0)$ , then there **exists** an arc  $p : [t_0, T] \rightarrow \mathbb{R}^n$  which, together with  $\bar{x}(\cdot)$ , satisfies

$$\begin{cases} \dot{x}(s) \in \partial_p^- H(x(s), p(s)), \\ -\dot{p}(s) \in \partial_x^- H(x(s), p(s)), \end{cases} \quad \text{for a.e. } s \in [t_0, T]$$

and  $-p(T) \in \partial\phi(x(T))$ .



# Sufficient Conditions for Optimality

## Theorem

Let  $x(\cdot) \in S_{[t_0, T]}(x_0)$ . If, for almost every  $t \in [t_0, T]$ ,  $\exists p(t) \in \mathbb{R}^n$

$$\langle p(t), \dot{x}(t) \rangle = H(x(t), p(t))$$

$$(H(x(t), p(t)), -p(t)) \in \partial^+ V(t, x(t))$$

then  $x$  is optimal for  $\mathcal{P}(t_0, x_0)$ .

**Regularity Assumptions:**  $\forall r > 0, \exists c \geq 0, \forall p \in S^{n-1}$

- $$\left\{ \begin{array}{l} (i) x \mapsto H(x, p) \text{ is } c\text{-semiconvex on } B(0, r) \\ (ii) \nabla_p H(x, p) \text{ exists and is } c\text{-Lipschitz continuous in } x \text{ on } B(0, r) \end{array} \right.$$

If  $\phi$  is locally semiconcave, then  $V$  is also locally semiconcave

Cannarsa and Wolenski, 2011



# Sensitivity Relations Involving Superdifferentials

## Theorem

Let  $\bar{x}(\cdot)$  be optimal for  $\mathcal{P}(t_0, x_0)$  and consider *any* arc  $\bar{p}(\cdot)$  such that  $(\bar{x}, \bar{p})$  solves the system

$$\begin{cases} -\dot{p}(t) \in \partial_x^- H(x(t), p(t)) \\ \dot{x}(t) \in \partial_p^- H(x(t), p(t)) \end{cases} \quad -p(T) \in \partial^+ \phi(\bar{x}(T))$$

Then  $\bar{p}(\cdot)$  satisfies the full sensitivity relation

$$(H(\bar{x}(t), \bar{p}(t)), -\bar{p}(t)) \in \partial^+ V(t, \bar{x}(t)) \text{ for all } t \in (t_0, T)$$

and the partial sensitivity relation

$$-\bar{p}(t) \in \partial_x^+ V(t, \bar{x}(t)) \text{ for all } t \in [t_0, T]$$



# Sensitivity Relations Involving Subdifferentials

## Theorem

Assume  $\partial_x^- V(t_0, x_0) \neq \emptyset$ . Let  $\bar{x}(\cdot)$  be optimal for  $\mathcal{P}(t_0, x_0)$  and consider *any* arc  $\bar{p}(\cdot)$  such that  $(\bar{x}, \bar{p})$  solves the system

$$\begin{cases} \dot{x}(s) \in \partial_p^- H(x(s), p(s)), & x(t_0) = x_0 \\ -\dot{p}(s) \in \partial_x^- H(x(s), p(s)), & -p(t_0) \in \partial_x^- V(t_0, x_0) \end{cases}$$

Then  $-\bar{p}(t) \in \partial_x^- V(t, \bar{x}(t))$  for all  $t \in [t_0, T]$ .

Furthermore, if  $\partial^+ \phi(\bar{x}(T)) \neq \emptyset$ , then for all  $t \in [t_0, T]$ ,  $V(t, \cdot)$  is differentiable at  $\bar{x}(t)$  and  $\nabla_x V(t, \bar{x}(t)) = -\bar{p}(t)$ .

If  $\phi$  is also locally semiconcave, then  $V(\cdot, \cdot)$  is differentiable at  $(t, \bar{x}(t))$  and  $\nabla V(t, \bar{x}(t)) = (H(\bar{x}(t), \bar{p}(t)), -\bar{p}(t)) \forall t \in [t_0, T]$ .



## Second Order Superjets and Subjets

$S(n)$  is the set of **symmetric**  $n \times n$  matrices.

Let  $g : \mathbb{R}^n \rightarrow [-\infty, +\infty]$  and  $x \in \text{dom}(g)$ .

$(q, Q) \in \mathbb{R}^n \times S(n)$  is a **superjet** of  $g$  at  $x$  if  $\exists \delta > 0, \forall y \in B(x, \delta)$

$$g(y) \leq g(x) + \langle q, y - x \rangle + \frac{1}{2} \langle Q(y - x), y - x \rangle + o(|y - x|^2)$$

The set of all the superjets of  $g$  at  $x$  is denoted by  $J^{2,+}g(x)$ .

$(q, Q) \in \mathbb{R}^n \times S(n)$  is a **subjet** of  $g$  at  $x$  if  $\exists \delta > 0, \forall y \in B(x, \delta)$

$$g(y) \geq g(x) + \langle q, y - x \rangle + \frac{1}{2} \langle Q(y - x), y - x \rangle + o(|y - x|^2).$$

The set of all the subjets of  $g$  at  $x$  is denoted by  $J^{2,-}g(x)$ .



# Properties of Superjets

## Proposition

Let  $g : \mathbb{R}^n \rightarrow [-\infty, +\infty]$  be an extended real-valued function and let  $x \in \text{dom}(g)$ . Then the following properties hold:

- (i)  $J^{2,+}g(x)$  is a convex subset of  $\mathbb{R}^n \times S(n)$ ,
- (ii) for any  $q \in \mathbb{R}^n$ , the set  $\{Q \in S(n) : (q, Q) \in J^{2,+}g(x)\}$  is a closed convex subset of  $S(n)$ ,
- (iii) if  $g' \leq g$  and  $g(\hat{x}) = g'(\hat{x})$  for some  $\hat{x} \in \mathbb{R}^n$ , then  $J^{2,+}g(\hat{x}) \subset J^{2,+}g'(\hat{x})$ .
- (iv) if  $(q, Q) \in J^{2,+}g(x)$ , then  $(q, Q') \in J^{2,+}g(x)$  for all  $Q' \in S(n)$  such that  $Q' \geq Q$ . Thus, the set  $J^{2,+}g(x)$  is either empty or unbounded.





# Matrix Riccati Equation

Assume  $H \in C^2(\mathbb{R}^n \times (\mathbb{R}^n \setminus \{0\}))$  and  $\partial^+ \phi(z) \neq \emptyset$  for all  $z \in \mathbb{R}^n$ .

Let  $\bar{x}$  be an optimal solution of  $\mathcal{P}(t_0, x_0)$  and consider a dual arc  $\bar{p}$  satisfying  $0 \neq \bar{p}(T) \in -\partial^+ \phi(\bar{x}(T))$ .

From now on set  $H_{px}[t] := \nabla_{px}^2 H(\bar{x}(t), \bar{p}(t))$ , and let  $H_{xp}[t], H_{pp}[t], H_{xx}[t]$  be defined analogously.

**Riccati Equation** :  $R(T) = -\nabla^2 \phi(\bar{x}(T))$

$$\dot{R}(t) + H_{px}[t]R(t) + R(t)H_{xp}[t] + R(t)H_{pp}[t]R(t) + H_{xx}[t] = 0$$

If  $V(t, \cdot)$  is  $C^2$  in a neighborhood of  $\bar{x}(t)$  for all  $t \in [t_0, T]$ , then

$$(\nabla_x V(t, \bar{x}(t)), \nabla_{xx}^2 V(t, \bar{x}(t))) = (-\bar{p}(t), -R(t))$$

This is a **second order sensitivity relation**.



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# Matrix Riccati Equation

Assume  $H \in C^2(\mathbb{R}^n \times (\mathbb{R}^n \setminus \{0\}))$  and  $\partial^+ \phi(z) \neq \emptyset$  for all  $z \in \mathbb{R}^n$ .

Let  $\bar{x}$  be an optimal solution of  $\mathcal{P}(t_0, x_0)$  and consider a dual arc  $\bar{p}$  satisfying  $0 \neq \bar{p}(T) \in -\partial^+ \phi(\bar{x}(T))$ .

From now on set  $H_{px}[t] := \nabla_{px}^2 H(\bar{x}(t), \bar{p}(t))$ , and let  $H_{xp}[t], H_{pp}[t], H_{xx}[t]$  be defined analogously.

**Riccati Equation** :  $R(T) = -\nabla^2 \phi(\bar{x}(T))$

$$\dot{R}(t) + H_{px}[t]R(t) + R(t)H_{xp}[t] + R(t)H_{pp}[t]R(t) + H_{xx}[t] = 0$$

If  $V(t, \cdot)$  is  $C^2$  in a neighborhood of  $\bar{x}(t)$  for all  $t \in [t_0, T]$ , then

$$(\nabla_x V(t, \bar{x}(t)), \nabla_{xx}^2 V(t, \bar{x}(t))) = (-\bar{p}(t), -R(t))$$

This is a **second order sensitivity relation**.



# Sensitivity Relations Involving Superjets

## Theorem

Let  $(q, Q) \in J^{2,+} \phi(\bar{x}(T))$ ,  $q \neq 0$  and  $\bar{p}(\cdot)$  be the dual arc such that  $\bar{p}(T) = -q$ . Consider the solution  $R(\cdot)$  of

$$\begin{cases} \dot{R}(t) + H_{px}[t]R(t) + R(t)H_{xp}[t] + R(t)H_{pp}[t]R(t) + H_{xx}[t] = 0 \\ R(T) = -Q, \end{cases}$$

defined on  $[a, T]$  for some  $a \in [t_0, T)$ . Then

$$(-\bar{p}(t), -R(t)) \in J_x^{2,+} V(t, \bar{x}(t)) \quad \text{for all } t \in [a, T].$$

Proof is an adaptation of the one in Caroff and HF, TAMS 1996



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Proof is an adaptation of the one in [Caroff and HF, TAMS 1996](#)



# Sensitivity Relations Involving Subjets

## Theorem

Let  $H \in C_{loc}^{2,1}(\mathbb{R}^n \times (\mathbb{R}^n \setminus \{0\}))$  and for some  $R_0 \in S(n)$

$$(-\bar{p}(t_0), -R_0) \in J_x^{2,-} V(t_0, x_0).$$

If the solution  $R(\cdot)$  of the Riccati equation

$$\begin{cases} \dot{R}(t) + H_{px}[t]R(t) + R(t)H_{xp}[t] + R(t)H_{pp}[t]R(t) + H_{xx}[t] = 0 \\ R(t_0) = R_0 \end{cases}$$

is well defined on  $[t_0, a]$  for some  $a \in (t_0, T]$ , then

$$(-\bar{p}(t), -R(t)) \in J_x^{2,-} V(t, \bar{x}(t)) \quad \text{for all } t \in [t_0, a].$$



# Forward Propagation of Twice Differentiability

## Theorem

If  $V(t_0, \cdot)$  is twice differentiable at  $x_0$  and the solution  $R(\cdot)$  of

$$\begin{cases} \dot{R}(t) + H_{px}[t]R(t) + R(t)H_{xp}[t] + R(t)H_{pp}[t]R(t) + H_{xx}[t] = 0 \\ R(t_0) = -\nabla_{xx} V(t_0, x_0) \end{cases}$$

is well defined on  $[t_0, a]$ , then  $V(t, \cdot)$  is twice differentiable at  $\bar{x}(t)$  for any  $t \in [t_0, a]$  and  $R(t) = -\nabla_{xx} V(t, \bar{x}(t))$ .

If  $\phi$  is locally semiconcave, then the interval  $[t_0, a]$  can be taken equal to  $[t_0, T]$ .

A similar result holds true also **backward in time**.



# Avoiding Conjugate Times

Assume  $\phi \in C^2(\mathbb{R}^n)$  and consider the Riccati equation

$$\begin{cases} \dot{R} + H_{px}[t]R + RH_{xp}[t] + RH_{pp}[t]R + H_{xx}[t] = 0, \\ R(T) = -\nabla^2\phi(\bar{x}(T)). \end{cases}$$

If for some  $t_c \in [t_0, T]$ ,  $R(\cdot)$  is well defined on  $(t_c, T]$  and  $\lim_{t \searrow t_c} \|R(t)\| = +\infty$ , then  $t_c$  is the **conjugate time** for  $\bar{x}(T)$ .

## Theorem

Let  $\bar{x}$  be optimal for  $\mathcal{P}(t_0, x_0)$  with  $\nabla\phi(\bar{x}(T)) \neq 0$ . If  $\partial_{x'}^{\cdot, pr} V(t_0, x_0) \neq \emptyset$ , then  $R(\cdot)$  is well defined on  $[t_0, T]$  and  $V(t, \cdot)$  is of class  $C^2$  in a neighborhood of  $\bar{x}(t)$  for all  $t \in [t_0, T]$ .

$\partial_{x'}^{\cdot, pr} V(t, x) \neq \emptyset$  on a dense subset of  $x \in \mathbb{R}^n$ .





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# Mayer's Problem under State Constraints

Consider the minimization problem

$$V(t_0, x_0) := \min \left\{ \phi(x(T)) : x(\cdot) \in S_{[t_0, T]}(x_0), x([t_0, T]) \subset K \right\}$$

where  $K \subset \mathbb{R}^n$  is nonempty and closed.

**Inward Pointing Condition (IPC):**

$$\text{co } f(y, U) \cap \text{int } C_K(y) \neq \emptyset \quad \forall y \in \partial K$$

where  $C_K(y)$  denotes the Clarke tangent cone to  $K$  at  $y$ .

If  $\phi$  is locally Lipschitz, then  $V$  is locally Lipschitz on  $[0, T] \times K$ .



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If  $\phi$  is locally Lipschitz, then  $V$  is locally **Lipschitz** on  $[0, T] \times K$ .



# Generalized Gradients on Closed Sets

Define partial generalized gradient of  $V$

$$\partial_x V(t, y) := \text{co Limsup}_{y' \rightarrow \text{Int}K \ y} \{ \nabla_x V(t, y') \}$$

and generalized gradient of  $V$

$$\partial V(t, y) := \text{co Limsup}_{(t', y') \rightarrow [0, T] \times \text{Int}K \ (t, y)} \{ \nabla V(t', y') \}$$

In the next result  $N_K(y)$  denotes Clarke's normal cone to  $K$  at  $y$  and  $\hat{V} : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$  is given by

$$\hat{V}(y) = \begin{cases} -V(t_0, y) & \text{if } y \in K \\ +\infty & \text{otherwise.} \end{cases}$$



# Necessary Optimality Conditions

## Theorem (Bettoli, Frankowska, Vinter, AMO 2015)

Let  $\bar{x}(\cdot)$  be optimal for the initial condition  $(t_0, x_0)$ .

Then there **exist** an arc  $p(\cdot)$ , a finite positive Borel measure  $\mu(\cdot)$  on  $[t_0, T]$  and a Borel measurable selection  $\nu(t) \in N_K(\bar{x}(t)) \cap B$   $\mu$ -a.e. in  $[t_0, T]$  such that for  **$q(s) := p(s) + \int_{[t_0, s]} \nu(\tau) d\mu(\tau)$**

$$(-\dot{p}(t), \dot{\bar{x}}(t)) \in \partial H(\bar{x}(t), q(t)) \quad \text{a.e. in } [t_0, T]$$

$-q(T) \in \partial \phi(\bar{x}(T))$ ,  $p(t_0) \in \partial \hat{V}(\bar{x}(t_0))$  and the following sensitivity relations hold true for a.e.  $t \in [t_0, T]$ :

$$-q(t) \in \partial_x V(t, \bar{x}(t))$$

$$(H(\bar{x}(t), q(t)), -q(t)) \in \partial V(t, \bar{x}(t))$$

