# Introduction to nonsmooth dynamical systems Lecture 1. Introduction and motivations.

Cours. "Systèmes dynamiques." ENSIMAG 2A

2021-2022

#### Contents

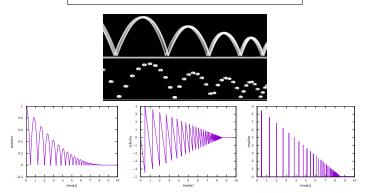
- Motivations for studying nonsmooth dynamical systems
- An archetypal example: a RLC circuit with an ideal diode
- ▶ Basics on convex and nonsmooth analysis
  - convex sets and functions
  - epigraph and indicator functions
  - subdifferential of convex functions
  - normal cone

# Outline

#### Motivations

# Nonsmooth dynamical systems

 $nonsmooth = lack\ of\ continuity/differentiability$ 



- nonsmooth solutions in time (jumps, kinks, distributions, measures)
- nonsmooth modeling and constitutive laws (set-valued mapping, inequality constraints, complementarity, impact laws)

# Application fields.





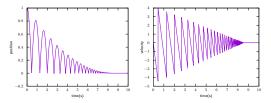


- Computational mechanics. Plasticity. Unilateral contact, Coulomb friction and impacts: multi-body systems, robotic systems, frictional contact oscillators, granular materials.
- ► Electronics. Switched electrical circuits (digital/analog converters and power electronics, diodes, transistors, switchs).
- Computer science. Hybrid and Cyber-physical systems
- ▶ Bio-mathematics. Gene regulatory networks
- ► Transportation science. Fluid transportation networks with queues.
- ► Economy and Finance. Oligopolistic market equilibrium

Nonsmooth approach is crucial for a correct modeling and a efficient simulation

# Sources of nonsmoothness

- ► Two largely different time-scales of evolution:
  - 1. a slow smooth dynamics (free flight of the bouncing ball)
  - a very fast dynamics (events, transitions, impacts) that can be modeled as a punctual event.



# Nonsmooth dynamical systems

# Difficulty

Standard tools of numerical analysis and simulation (in finite dimension) are no longer suitable due to the lack of regularity.

# Specific tools

Differential measure theory. Convex, nonsmooth and variational Analysis (Clarke, Wets & Rockafellar). Complementarity theory. Maximal monotone operators.

# Examples of nonsmooth dynamical systems

- ▶ Piecewise smooth systems
- ▶ Complementarity systems and differential variational inequality.
- Specific differential inclusions (Filippov, Moreau sweeping process, Normal cone inclusion).

# Outline

Motivations

An archetypal example: a RLC circuit with an ideal diode

Basics on convex, nonsmooth analysis and complementarity theory

# Example (The RLC circuit with a diode. A half wave rectifier) A LC oscillator supplying a load resistor through a half-wave rectifier.

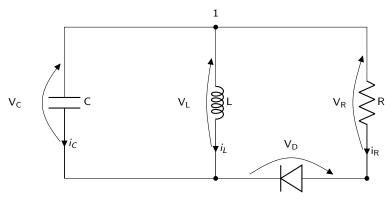
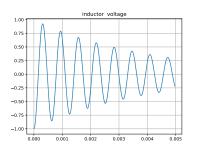
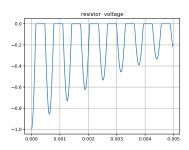
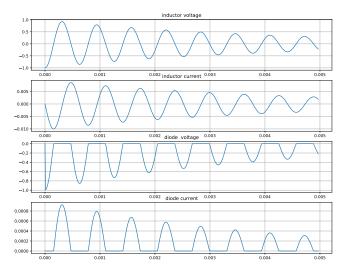


Figure: Electrical oscillator with half-wave rectifier







Kirchhoff laws :

$$v_L = v_C$$

$$v_R + v_D = v_C$$

$$i_C + i_L + i_R = 0$$

$$i_R = i_D$$

Branch constitutive equations for linear devices are :

$$i_C = C\dot{v}_C$$
  
 $v_L = L\dot{i}_L$   
 $v_R = Ri_R$ 

"branch constitutive equation" of the ideal diode ?

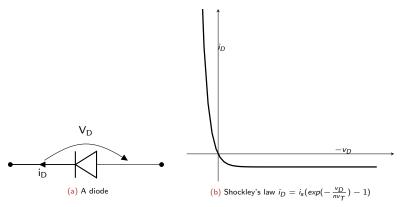
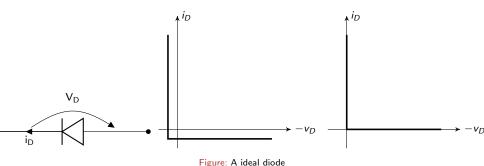


Figure: A nonlinear model of diode



## Complementarity condition:

$$i_D \geqslant 0, -v_D \geqslant 0, i_D v_D = 0 \Longleftrightarrow 0 \leqslant i_D \perp -v_D \geqslant 0$$

Kirchhoff laws :

$$v_L = v_C$$

$$v_R + v_D = v_C$$

$$i_C + i_L + i_R = 0$$

$$i_R = i_D$$

▶ Branch constitutive equations for linear devices are :

$$\begin{aligned} i_C &= C \dot{v}_C \\ v_L &= L \dot{i}_L \\ v_R &= R i_R \end{aligned}$$

"branch constitutive equation" of the ideal diode

$$0 \leqslant i_D \perp -v_D \geqslant 0$$

The following linear complementarity system is obtained :

$$\left(\begin{array}{c} \dot{v}_L \\ \dot{i}_L \end{array}\right) = \left(\begin{array}{cc} 0 & \frac{-1}{C} \\ \frac{1}{L} & 0 \end{array}\right) \cdot \left(\begin{array}{c} v_L \\ i_L \end{array}\right) + \left(\begin{array}{c} \frac{-1}{C} \\ 0 \end{array}\right) \cdot i_D$$

together with a state variable  $\boldsymbol{x}$  and one of the complementary variables  $\boldsymbol{\lambda}$  :

$$x = \begin{pmatrix} v_L \\ i_L \end{pmatrix}, \qquad \lambda = i_D, \qquad y = -v_D$$

and

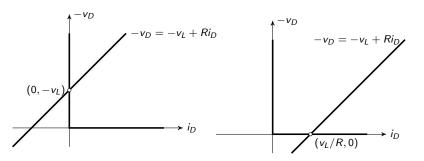
$$y = -v_D = \begin{pmatrix} -1 & 0 \end{pmatrix} x + \begin{pmatrix} R \end{pmatrix} \lambda,$$

Standard form for LCS

$$\begin{cases} \dot{x} = Ax + B\lambda \\ y = Cx + D\lambda \\ 0 \leqslant y \perp \lambda \geqslant 0 \end{cases}$$

$$\begin{cases}
y = Cx + D\lambda \\
0 \leqslant y \perp \lambda \geqslant 0
\end{cases} \Rightarrow
\begin{cases}
-v_D = -v_L + R i_D \\
0 \leqslant -v_D \perp i_D \geqslant 0
\end{cases} (1)$$

$$\begin{array}{ll}
\bullet & i_D = 0, -v_D = -v_L \geqslant 0, v_L \leqslant 0 \\
\bullet & i_D > 0, -v_D = 0, i_D = \frac{V_L}{R}, V_L > 0
\end{array} \right\} \Rightarrow i_D = \max(0, \frac{v_L}{R})$$
(2)



Example (The RLC circuit with a diode. A half wave rectifier) Note that the matrix of the LCP is D = (R) > 0 is a scalar :

$$\left\{ \begin{array}{l} y = \mathit{C} x + \mathit{D} \lambda \\ 0 \leqslant y \perp \lambda \geqslant 0 \end{array} \right. \iff \lambda = \max (0, -\mathit{D}^{-1} \mathit{C} x)$$

In the application,  $i_D = max(0, \frac{v_L}{R})$  and we get

$$\left(\begin{array}{c} \dot{v}_L \\ \dot{i}_L \end{array}\right) = \left(\begin{array}{cc} 0 & \frac{-1}{C} \\ \frac{1}{L} & 0 \end{array}\right) \cdot \left(\begin{array}{c} v_L \\ i_L \end{array}\right) + \left(\begin{array}{c} \frac{-1}{C} \\ 0 \end{array}\right) \cdot max(0, \frac{v_L}{R})$$

Since max is a Lipschitz operator, we get a standard ODE with Lipschitz r.h.s.

Basics on convex, nonsmooth analysis and complementarity theory

# Outline

Motivations

An archetypal example: a RLC circuit with an ideal diode

Basics on convex, nonsmooth analysis and complementarity theory

# Nonsmooth analysis

# Standard (smooth) analysis

# Definition (differentiability)

A function  $f: \mathbb{R}^n \to \mathbb{R}^m$  is said to be differentiable at a point  $x_0$  if there exists a linear map  $J: R^m \to R^n$  such that

$$\lim_{\|h\| \to 0} \frac{\|f(x+h) - f(x) + J(h)\|}{\|h\|} \tag{1}$$

- If a function is differentiable at  $x_0$ , then all of the partial derivatives exist at  $x_0$ , and the linear map J is given by the Jacobian matrix.
- If a function is differentiable for all  $x \in \mathbb{R}^n$  then the function is said to be  $\mathcal{C}^1$  function

# Nonsmooth analysis

If the function is not  $\mathcal{C}^1$ , how can we extend the notion of differentiability ?

# Extension of the notion of differentiability

- Convex functions and the notion of subdifferential
- Clarke nonsmooth analysis for locally Lipschitz functions
- ► Mordukhovich generalized differentiation
- **.**..

#### Convex sets

# Definition (Convex set)

A set  $C \in \mathbb{R}^n$  is said to be convex if, for all x and y in C and all  $\alpha$  in the interval (0,1), the point  $(1-\alpha)x + \alpha y$  also belongs to C:

$$\forall \alpha \in (0,1), \forall x \in C, \forall y \in C \implies (1-\alpha)x + \alpha y \in C$$
 (2)

#### Convex sets

## Definition (Convex set)

A set  $C \in \mathbb{R}^n$  is said to be convex if, for all x and y in C and all  $\alpha$  in the interval (0,1), the point  $(1-\alpha)x + \alpha y$  also belongs to C:

$$\forall \alpha \in (0,1), \forall x \in C, \forall y \in C \implies (1-\alpha)x + \alpha y \in C$$
 (2)

#### **Properties**

Closed under convex combinations (possible alternative definition) If C is a convex set in  $\mathbb{R}^n$ , then for any collection of r vectors  $u_1, \ldots u_r$  in C (r>1) and for any r numbers  $\alpha_i \geqslant 0$  such that  $\sum_{i=1}^{r} \alpha_i = 1$ , we have

$$\sum_{i}^{r} \alpha_{i} u_{i} \in C \tag{3}$$

- $ightharpoonup \mathbb{R}^n$  and  $\emptyset$  are convex
- ► Any intersection of convex sets is convex

### Extended real-valued functions

In Convex analysis, we use extended real-valued functions.

## Definition (Extended real-valued function)

An extended real-valued function is a function  $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty = (-\infty, +\infty]$ 

#### Conventions for calculus in $\mathbb{R} \cup +\infty$

Obvious rules are generally adopted in convex analysis:

addition and subtraction:

$$\begin{array}{l} \alpha+\infty=\infty+\alpha=\infty \text{ for } -\infty<\alpha\leqslant\infty\\ \alpha-\infty=-\infty+\alpha=\infty \text{ for } -\infty\leqslant\alpha<\infty\\ \text{multiplication:}\\ \alpha\infty=\infty\alpha=\infty,\quad \alpha(-\infty)=(-\infty)\alpha=-\infty \text{ for } 0<\alpha\leqslant\infty\\ \alpha\infty=\infty\alpha=\infty,\quad \alpha(-\infty)=(-\infty)\alpha=\infty \text{ for } -\infty\leqslant\alpha<0\\ 0\infty=\infty0=0=0(-\infty)=(-\infty)0,\quad -(-\infty)=\infty\\ \text{infimum and supremum:}\\ \text{inf } \emptyset=\infty, \sup \emptyset=-\infty \end{array} \tag{4}$$

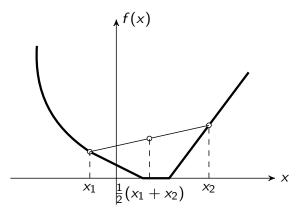
Some combinations as  $+\infty-\infty$  and  $-\infty+\infty$  are undefined and forbidden

# Convex functions

# Definition (Convex function)

A function  $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  is a convex function if it satisfies

$$f(\alpha x_1 + (1 - \alpha)x_2) \le \alpha f(x_1) + (1 - \alpha)f(x_2)$$
 for all  $x_1, x_2 \in \mathbb{R}^n, \alpha \in [0, 1]$  (5)



#### Convex functions

## Definition (Proper convex function)

A convex function  $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  is proper if  $f \not\equiv +\infty$ 

# Definition (Domain of a convex function)

Let  $f:\mathbb{R}^n o \mathbb{R} \cup +\infty$  be a convex function. Its domain D(f) is defined by

$$D(f) = \{x \mid f(x) < +\infty\} \tag{5}$$

## Theorem (Regularity)

If  $f: \mathbb{R} \to \mathbb{R} \cup +\infty$  is a convex function, then f is Lipschitz continuous on all compact interval  $I \subset D(f)$ .

If  $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  is a convex function, then f is locally Lipschitz continuous on all open set  $\Omega \subset D(f)$ .

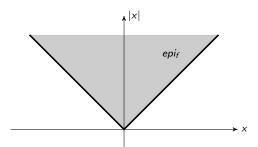
Basics on convex, nonsmooth analysis and complementarity theory

# Epigraph

# Definition (Epigraph)

 $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  a proper function (not necessarily convex)

$$epi_f = \{(y, x) \mid y \geqslant f(x)\}$$
 (6)



#### Lemma

A function is convex if and only if its epigraph is convex

Convex functions are not necessarily differentiable. We have only Lipschitz continuity property. How to extend the definition of differentiability to any convex functions?

# Definition (Subgradient of convex functions)

 $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  a convex function.

A vector  $p \in \mathbb{R}^n$  is said to be a subgradient of f at x if

$$f(y) \geqslant f(x) + p^{T}(y - x) \text{ for all } y \in \mathbb{R}^{n}$$
 (7)

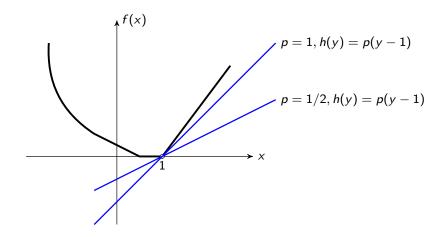
## Geometrical interpretation

▶ If f is finite in x, the graph of the affine function

$$h(y) = f(x) + p^{T}(y - x)$$
(8)

is the (non vertical) supporting hyperplane to the convex set,  $epi_f$  at (x, f(x)).

In the scalar case, p is the slope.



# Definition (Subdifferential of convex functions)

 $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  a convex function.

$$\partial f(x) = \{ p \in \mathbb{R}^n \mid f(y) \geqslant f(x) + p^T(y - x) \text{ for all } y \in \mathbb{R}^n \}$$
 (9)

## Definition (Subdifferential of convex functions)

A convex function  $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  is subdifferentiable at x is  $\partial f(x) \neq \emptyset$ 

#### Remarks

- ▶ The subdifferential is the set of subgradients. It is a closed convex set.
- ▶ The subdifferential can always be computed if the function is proper
- ▶ The subdifferential is a set that can be empty. For instance, if  $x \notin D(f)$  then  $f(x) = +\infty$  and  $\partial f(x) = \emptyset$  if the function is proper.

#### Standard cases

- ▶ If  $f : \mathbb{R} \to \mathbb{R}$  is continuously differentiable,  $\partial f(x) = f'(x)$
- ▶ If  $f: \mathbb{R}^n \to \mathbb{R}$  is continuously differentiable,  $\partial f(x) = \nabla f(x)$

Example (Absolute value function f(x) = |x|)

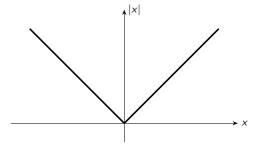


Figure: Absolute value function

Example (Absolute value function f(x) = |x|)

$$|y|-|x|\geqslant p(y-x)$$

 $x > 0, |x| = x, |y| - x \ge p(y - x)$ 

$$ightharpoonup x < 0, |x| = x, |y| + x \ge p(y - x)$$

$$y = x \qquad \Rightarrow p \in \mathbb{R}$$

$$0 \ge y \ge x, \quad -(y - x) \ge p(y - x) \Rightarrow p \ge -1$$

$$y \le x < 0, \quad -(y - x) \ge p(y - x) \Rightarrow p \le -1$$

$$y \ge 0, \quad y + x \ge p(y - x) \Rightarrow p = -1$$

$$\Rightarrow p = -1$$

$$\Rightarrow p = -1$$

$$\Rightarrow p = -1$$

$$\Rightarrow p = -1$$

$$ightharpoonup x = 0 \ |y| \geqslant py \Rightarrow p \in [-1, 1]$$

Example (Absolute value function f(x) = |x|)

$$\partial |x| = \begin{cases} -1 & \text{if } x < 0\\ 1 & \text{if } x > 0\\ [-1, 1] & \text{if } x = 0 \end{cases} = \operatorname{sgn}(x)$$
 (10)

where sgn() is the multivalued signum function

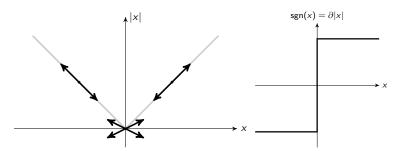


Figure: Absolute value function

## Indicator function of a convex set

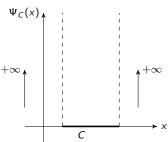
# Definition (Indicator function of a convex set)

Let  ${\it C}$  be a nonempty convex set. The indicator of a convex function  $\Psi_{\it C}(x)$  is defined by

$$\Psi_{C}(x) = \begin{cases} 0 \text{ if } x \in C \\ +\infty \text{ if } x \notin C \end{cases}$$
 (11)

#### Remark

If C is convex, the epigraph of  $\Psi_C$  is convex and  $\Psi_C$  is a convex function.



# Indicator function of a convex set – Subdifferential

# Standard examples

$$C = \mathbb{R}_+ \subset \mathbb{R}$$
.

$$\Psi_{\mathbb{R}_{+}}(x) = \begin{cases} 0 \text{ if } x \geqslant 0\\ +\infty \text{ otherwise } . \end{cases}$$
 (12)

$$ightharpoonup x > 0$$
,  $f(y) \geqslant p(y-x)$ 

$$\begin{array}{ccc}
y \geqslant 0, & 0 \geqslant p(y-x) & \Longrightarrow & p=0 \\
y < 0, & +\infty \geqslant p(y-x) & \Longrightarrow & p \in \mathbb{R}
\end{array} \right\} \implies p = 0$$
(13)

$$\triangleright$$
  $x = 0$ ,  $f(y) \geqslant py$ 

$$\begin{array}{ccc}
y \geqslant 0, & 0 \geqslant py & \Longrightarrow & p \leqslant 0 \\
y < 0, & +\infty \geqslant py & \Longrightarrow & p \in \mathbb{R}
\end{array} \right\} \Longrightarrow p \leqslant 0 \tag{14}$$

$$ightharpoonup x < 0, \quad f(y) - \infty \geqslant p(y - x)$$

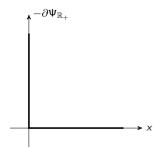
$$\begin{cases}
y \geqslant 0 & -\infty \geqslant p(y-x) & \Longrightarrow \emptyset \\
y < 0 & forbidden
\end{cases} \Longrightarrow \emptyset$$
(15)

# Indicator function of a convex set - Subdifferential

## Standard examples

$$C = \mathbb{R}_+ \subset \mathbb{R}$$
.

$$\partial \Psi_{\mathbb{R}_{+}}(x) = \begin{cases} 0 & \text{if } x > 0 \\ \mathbb{R}_{-} & \text{if } x = 0 \\ \emptyset & \text{if } x < 0 \end{cases}$$
 (12)



$$y \in -\partial \Psi_{\mathbb{R}_+}(x)$$

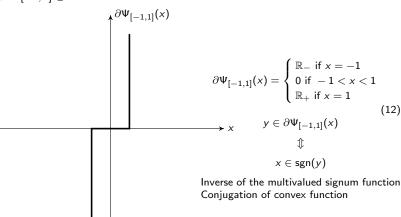
$$\updownarrow$$

$$0 \leqslant y \perp x \geqslant 0$$

# Indicator function of a convex set - Subdifferential

# Standard examples

$$C = [-1, 1] \subset \mathbb{R}$$



### Calculus of sub-differentials

- ► The domain of  $\partial$ Φ is defined by  $D(\partial$ Φ $) = \{x \mid \partial$ Φ $(x) \neq \emptyset\}$
- ▶ Sum of (proper) convex functions  $\Phi_1 + \Phi_2$  is convex. Moreover, if the relative interior  $\operatorname{ri}(D(\partial \Phi_1))$  and  $\operatorname{ri}(D(\partial \Phi_2))$  have a common point then

$$\partial(\Phi_1(x) + \Phi_2(x)) = \partial\Phi_1(x) + \partial\Phi_2(x) \tag{13}$$

Relative interior :  $\operatorname{ri}(X) = \{x \in X \mid \exists \varepsilon > 0, B_{\varepsilon} \cap \operatorname{Aff}(X) \subset X\}$  where  $\operatorname{Aff}(X)$  is the affine hull of X, the smallest affine set containing X:

$$Aff(X) = \{ \sum_{i=0}^{k} \alpha_i x_i \mid k > 0, x_i \in X, \alpha_i \in \mathbb{R}, \sum_{i=0}^{k} \alpha_i = 1 \}$$
 (14)

Ex:  $C = \{x \in \mathbb{R}^2 \mid x_1 \in [-1, 1], x_2 = 0\}$  Aff $(C) = \mathbb{R} \times \{0\}$ 

▶ Chain rule.  $\Phi: \mathbb{R}^m \to \mathbb{R}$  a proper convex function and  $E \in \mathbb{R}^{m \times n}$ . The function  $\phi(x) = \Phi(Ex)$  is a proper convex function and its subdifferential is given by

$$\partial \phi(x) = E^{\mathsf{T}} \partial \Psi_{\mathbb{R}_{+}^{m}}(Ex) \tag{15}$$

(Im(E) must contain a point of ri(D(Phi)))

### Normal cone to a convex set

### Definition (Normal cone to a convex set)

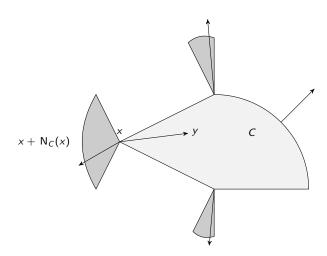
C a nonempty convex set in  $\mathbb{R}^n$  and  $x \in C$ 

$$N_C(x) = \{ s \in \mathbb{R}^n \mid s^T(y - x) \leqslant 0 \text{ for all } y \in C \}$$
 (16)

### **Properties**

- ▶ By convention,  $N_X(x) = \emptyset$  for  $x \notin C$ .
- If the boundary is smooth, the normal cone reduces automatically to the standard normal.

## Normal cone to a convex set



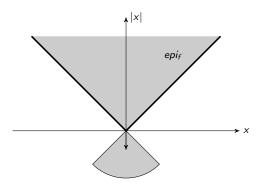
Basics on convex, nonsmooth analysis and complementarity theory

# Epigraph and normal cone

## Lemma (Epigraph and normal cone)

 $f: \mathbb{R}^n \to \mathbb{R} \cup +\infty$  a proper convex function

$$N_{epi_f}(x) = \{(\lambda y, -\lambda) \mid y \in \partial f(x) \text{ and } \lambda \geqslant 0\}$$
 (16)



### Remark

The normal cone is generated by vectors (y,-1) with  $y \in \partial f(x)$ ,  $\partial y \in \partial y \in \mathbb{R}$ 

# Indicator function of a convex set, normal cone and subdifferential

#### Lemma

C a nonempty convex set.

$$\partial \Psi_C(x) = N_C(x) \tag{17}$$

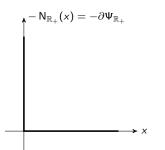
# Indicator function of a convex set, normal cone and subdifferential

### Standard examples

$$C = \mathbb{R}_+ \subset \mathbb{R}$$
.

$$N_{\mathbb{R}_{+}}(x) = \begin{cases} 0 \text{ if } x > 0\\ \mathbb{R}_{-} \text{ if } x = 0 \end{cases}$$

$$(17)$$



$$-y \in N_{\mathbb{R}_{+}}(x)$$

$$\updownarrow$$

$$-y \in \partial \Psi_{\mathbb{R}_{+}}(x)$$

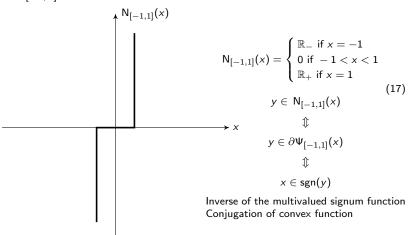
$$\updownarrow$$

 $0 \leqslant y \perp x \geqslant 0$ 

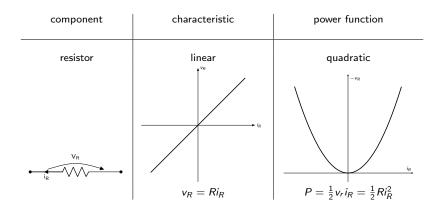
# Indicator function of a convex set, normal cone and subdifferential

# Standard examples

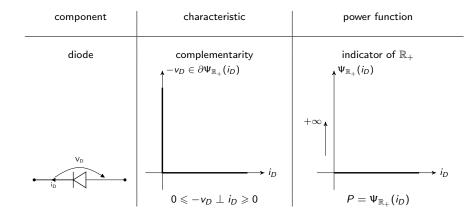
$$C = [-1, 1] \subset \mathbb{R}$$



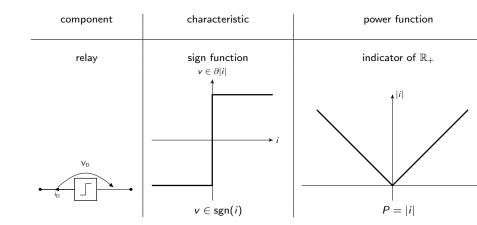
# Nonsmooth power and energy



# Nonsmooth power and energy



# Nonsmooth power and energy



# Nonsmooth power and potential energy

#### Comments

$$y = \nabla_x f(x)$$
, with  $f \in \mathcal{C}^1$  (18)

$$y = \partial f(x)$$
, with  $f$  proper convex. (19)

- Convex analysis allows one to define a constitutive law that derives from a potential energy (or a power) that might be non differentiable.
- Non differentiable points correspond to set-valued part of the constitutive law.
- The potential energy can take some infinite values that describe forbidden (or non feasible) values for the system.
- ▶ The same applies with dissipative potential or power.