

# Chapter 1

## Convex Analysis

*Convex Optimization for Computer Vision*  
SS 2016

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Convex Analysis

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Basics

- Convex sets
- Convex functions
- Existence
- Uniqueness

Optimality conditions

- Derivative
- Subdifferential



# Convexity

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# Convex energy minimization problems

This lecture is all about

$$\hat{u} = \arg \min_{u \in C} E(u),$$

where  $C \subset \mathbb{R}^n$  convex set,  $E : C \rightarrow \mathbb{R}$  convex function.



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## 1. What is a convex set?

### Definition

A set  $C \subset \mathbb{R}^n$  is called convex, if

$$\alpha x + (1 - \alpha)y \in C, \quad \forall x, y \in C, \quad \forall \alpha \in [0, 1].$$



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→ *Draw a picture.*

→ *Online TED.*



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# Convex set - summary of online TED

Definitions and things to recall from analysis 1:

## Definitions

- A set  $C \subset \mathbb{R}^n$  is called **open** if for all  $x \in C$  there exists a  $\epsilon > 0$  such that the ball with radius  $\epsilon$  around  $x$ ,  $B(x, \epsilon)$ , is contained in  $C$ :  $B(x, \epsilon) \subset C$ .



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- A set  $C \subset \mathbb{R}^n$  is called **closed** if its complement is open.



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- A set  $C \subset \mathbb{R}^n$  is called **closed** if its complement is open.
- A set is closed if and only if it contains all its limit points.



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- A set is closed if and only if it contains all its limit points.
- The **closure** of a set  $C \subset \mathbb{R}^n$  is

$$\bar{C} = \{x \mid \text{there exists a convergent sequence } (x_n)_n \subset C \text{ such that } \lim_{n \rightarrow \infty} x_n = x\}$$



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- The **interior** of a set  $C \subset \mathbb{R}^n$  is

$$\mathring{C} = \{x \in C \mid \text{there exists } \epsilon > 0 \text{ such that } B(x, \epsilon) \subset C\}$$



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The following operations preserve the convexity of a set

- Intersection
- Vector sum
- Closure
- Interior
- Linear Transformation

The union of convex sets is not convex in general.

Polyhedral sets are always convex, cones are not necessarily convex.

# Convex energy minimization problems

Let's get back to what the lecture is all about:

$$\hat{u} = \arg \min_{u \in C} E(u),$$

where  $C \subset \mathbb{R}^n$  convex set,  $E : C \rightarrow \mathbb{R}$  convex function.



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1. What is a convex set? We know this now!
2. What is a convex function?



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**1. What is a convex set? We know this now!**

**2. What is a convex function?**

## Definition: Convex Function

We call  $E : C \rightarrow \mathbb{R}$  a convex function if  $C$  is a convex set and for all  $u, v \in C$  and all  $\theta \in [0, 1]$  it holds that

$$E(\theta u + (1 - \theta)v) \leq \theta E(u) + (1 - \theta)E(v)$$

We call  $E$  strictly convex, if the inequality is strict for all  $\theta \in ]0, 1[$ , and  $v \neq u$ .

→ *Draw a picture.*



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# Convex functions - summary of online TED

The following operations do preserve the convexity of a function

- Summation
- Linear Transformation



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The following operations do preserve the convexity of a function

- Summation
- Linear Transformation

The following operations do not preserve the convexity of a function

- Multiplication, Division, Difference
- Composition



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The following operations do preserve the convexity of a function

- Summation
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The sum of a convex function and a strictly convex function is strictly convex.



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The following operations do preserve the convexity of a function

- Summation
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The following operations do not preserve the convexity of a function

- Multiplication, Division, Difference
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The sum of a convex function and a strictly convex function is strictly convex.

Remember to check two conditions to show that a function is convex!

## Convex energy minimization problems

Let's get back to what the lecture is all about:

$$\hat{u} = \arg \min_{u \in C} E(u), \quad (1)$$

where  $C \subset \mathbb{R}^n$  convex set,  $E : C \rightarrow \mathbb{R}$  convex function.



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$$\hat{u} = \arg \min_{u \in C} E(u), \quad (1)$$

where  $C \subset \mathbb{R}^n$  convex set,  $E : C \rightarrow \mathbb{R}$  convex function.

It is sometimes convenient to “introduce” the constraint  $u \in C$  into the energy function  $E$  itself. We therefore introduce the notion of **extended real valued functions**.

$$E : \mathbb{R}^n \rightarrow \bar{\mathbb{R}} := \mathbb{R} \cup \{\infty\}.$$



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$$E : \mathbb{R}^n \rightarrow \bar{\mathbb{R}} := \mathbb{R} \cup \{\infty\}.$$

The minimization problem (1) can then be written as

$$\hat{u} = \arg \min_{u \in \mathbb{R}^n} \tilde{E}(u),$$

by defining

$$\tilde{E}(u) = \begin{cases} E(u) & \text{if } u \in C, \\ \infty & \text{else.} \end{cases}$$



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## Definition

- For  $E : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ , we call

$$\text{dom}(E) := \{u \in \mathbb{R}^n \mid E(u) < \infty\}$$

the domain of  $E$ .

- We call  $E$  proper if  $\text{dom}(E) \neq \emptyset$ .



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## Revisiting the definition of convex functions

We call  $E : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$  a convex function if

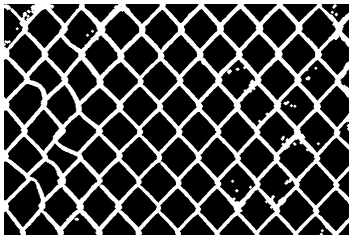
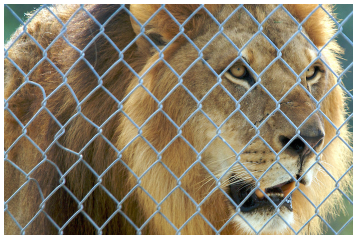
- $\text{dom}(E)$  is a convex set.
- For all  $u, v \in \text{dom}(E)$  and all  $\theta \in [0, 1]$  it holds that

$$E(\theta u + (1 - \theta)v) \leq \theta E(u) + (1 - \theta)E(v)$$

We call  $E$  strictly convex, if the inequality in 2 is strict for all  $\theta \in ]0, 1[$ , and  $v \neq u$ .

# First example of an imaging problem: Inpainting

Example: Inpainting



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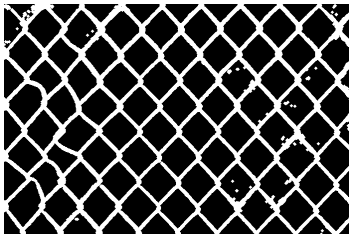
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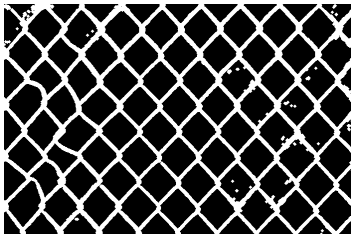
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# First example of an imaging problem: Inpainting

Example: Inpainting



$$\min_{u \in \mathbb{R}^{n \times m}} \sum_{i,j} (u_{i,j} - u_{i-1,j})^2 + (u_{i,j} - u_{i,j-1})^2 \quad \text{s.t. } u_{i,j} = f_{i,j} \quad \forall (i,j) \in I$$

with index set  $I$  of pixels to keep and suitable boundary conditions.

→ *Discuss convexity.*



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