

# Minimizers, intro to convexity

Tuesday, January 19, 2021 5:26 PM

First, go over discussion questions from last time

## Solutions

Generic problem:  $\min_{x \in C} f(x), \quad C \subseteq \mathbb{R}^n$

- A **feasible point**  $x$  means  $x \in C$
  - A **solution or minimizer or global minimizer**  $x^*$  means
    - 1)  $x^* \in C$
    - 2)  $\forall y \in C, f(x^*) \leq f(y)$  (NOT  $f(x^*) < f(y)$ )
- i.e.,  $x^* \in \operatorname{arg\,min}_{x \in C} f(x)$
- This is what we usually really want



Solutions may not exist ... even for convex problems

$$\underline{\text{Ex}} \quad \min_{x \in \mathbb{R}} x$$

$$\underline{\text{Ex}} \quad \min_{x \in (0,1)} x^2$$

} abuse of notation. it's more proper to write  $\inf_{x \in (0,1)} x^2$  but optimizers are too lazy



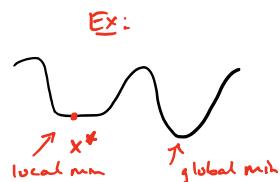
Solutions need not be unique ... even for convex problems

$$\underline{\text{Ex}} \quad \min_{x \in \mathbb{R}} f(x) \quad \text{where} \quad f(x) = 0 \quad \forall x$$

- $x^*$  is a **local minimizer** if  $x^*$  is feasible and  $\exists \varepsilon > 0$  s.t.

$$f(x^*) \leq f(y) \quad \forall y \in C \cap B_\varepsilon(x^*) := \{y : \|y - x^*\| < \varepsilon\}$$

open ball of radius  $\varepsilon$



- $x^*$  is a **strict local minimizer** if  $x^*$  is feasible and  $\exists \varepsilon > 0$  s.t.

$$f(x^*) < f(y) \quad \forall y \in B_\varepsilon(x^*) \cap C$$



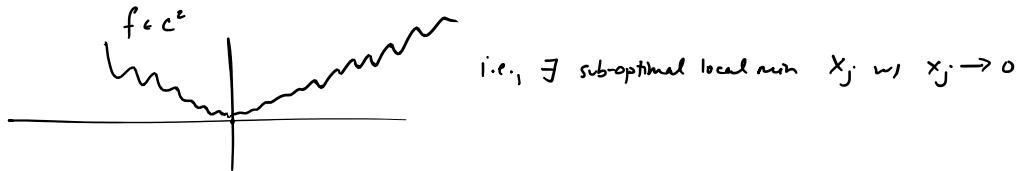
- $x^*$  is an **isolated (and strict) local min**

if a local min, and no other local min are nearby

} FAIRLY ESOTERIC

$$\underline{\text{Ex}} \quad f(x) = \begin{cases} x^4 \cos(\frac{1}{x}) + 2x^4 & x \neq 0 \\ 0 & x = 0 \end{cases}$$

$x = 0$  is a strict but not isolated local min



Btw, notation

$f \in C^3$  means  $f, f', f'', f'''$  all exist and are continuous

or  $f \in C^3(\mathbb{R}^n)$  means  $f, \nabla f, \nabla^2 f, \nabla^3 f$  all exist and are continuous

### Connections w/ Calc. I

$$\min_{x \in [a,b]} f(x)$$

The procedure: 1) find all points  $x_i$  such that  $f'(x_i) = 0$   
 "critical numbers" or where  $f$  is discontinuous or  
 not differentiable

- 2) throw in  $\{a, b\}$  boundary  
 3) minimize  $\{a, b, x_i\}$

in textbook exercises,  $\{x_i\}$  was always finite

Ex:  
 Minimize  $\{3, -2, 5, 17, -31, 21\}$   
 It's easy: it's  $-31$

- A critical or stationary point of  $f(x)$  is a point where  $\nabla f(x) = 0$

... but this isn't enough usually.

- 1) it doesn't take into account constraints.

If  $x \in \partial C$  then don't expect  $\nabla f(x) = 0$  here

$$\text{boundary}_c = \bar{C} \setminus \text{int}(c), \quad \text{int}(c) = \text{largest open set in } C \\ \bar{C} = \text{closure}(c) = \text{smallest closed set containing } c \\ = \{x \in C : \exists \varepsilon > 0 \quad B_\varepsilon(x) \subseteq C\}$$

- 2) we can't just check boundary separately

in  $\mathbb{R}$ , if  $C = [0, 1]$ ,  $\partial C = \{0, 1\}$ , so  $|\partial C| = 2$

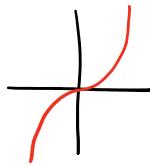
in  $\mathbb{R}^2$ , if  $C = [0, 1]^2$ ,  $\partial C = \boxed{\phantom{0}}$  so  $|\partial C| = \infty$

- 3) often there are an  $\infty$  # (or at least a large #) of critical points, so can't check all

- If  $x^*$  is a local or global minimizer and  $C = \mathbb{R}^n$  (i.e., unconstrained) then  $x^*$  is a critical point  $\xrightarrow{\text{"necessary"}}$  minimizer  $\Rightarrow$  crit. pt. HW exrc.

but if  $x^*$  is a critical point, it need not be a local or global minimizer (so not sufficient) in which case we often call it a saddle point

Ex:  $f(x) = x^3$



$x^* = 0$  is a saddle point

( $f'(0) = 3x^2|_{x=0} = 0$  so it's a crit. pt., but not a local min.)

19<sup>th</sup> century analysis theorem

Sometimes called "Weierstrass thm":

if  $f$  is continuous and  $C$  is compact then

$f$  achieves its infimum over  $C$ , i.e.,  $\inf_{x \in C} f(x) = \min_{x \in C} f(x)$

(our first existence of minimizers result)

proof

**Q1**

on your own, using these ingredients:

1) in  $\mathbb{R}^n$ , compact  $\Leftrightarrow$  sequentially compact (i.e., every sequence in  $C$  has a convergent subseq. whose limit is in  $C$ )

2) in  $\mathbb{R}^n$  w/ usual topology (i.e., induced by a norm),

a function  $f$  is cts  $\Leftrightarrow$  sequentially cts (i.e.,  $x_n \rightarrow x$

shorthand for continuous

$\Rightarrow f(x_n) \rightarrow f(x)$

One way to prove it:

first, note the set  $f(C) := \{f(x), x \in C\}$  is bounded (compact in fact)  
since if not bounded, pick  $(\alpha_k) \subseteq f(C)$  s.t.  $|\alpha_k| \geq k$   
but then  $\exists x_k$  s.t.  $\alpha_k = f(x_k)$ , and  $\exists$  convergent subseq.  $x_{k_j} \rightarrow x \in C$   
so  $f$  cts  $\Rightarrow \lim_{j \rightarrow \infty} \underbrace{f(x_{k_j})}_{\text{R limit}} = f(x)$   
 $= \lim \alpha_k$   $\leftarrow$  unbounded

Convergent sequences  
are bdd.  
Contradiction

So this guarantees  $\inf_{x \in C} f(x) =: f^*$  is finite.

So second step, by "infimum", pick  $\alpha_k \in f(C)$  s.t.  $\alpha_k \rightarrow f^*$   
again,  $\exists x_k$  s.t.  $\alpha_k = f(x_k)$ , again pick convergent subseq.  $x_{k_j}$ ,  
again use continuity of  $f$ .  $\square$

So... it's nice when our constraints  $C$  are compact

It turns out that's often too much to ask for, but at the  
very least, we like our constraint sets to be closed

$$\text{Ex: } \min \|x\|^2 \quad (1) \quad \min \|x\|^2 \quad (2)$$

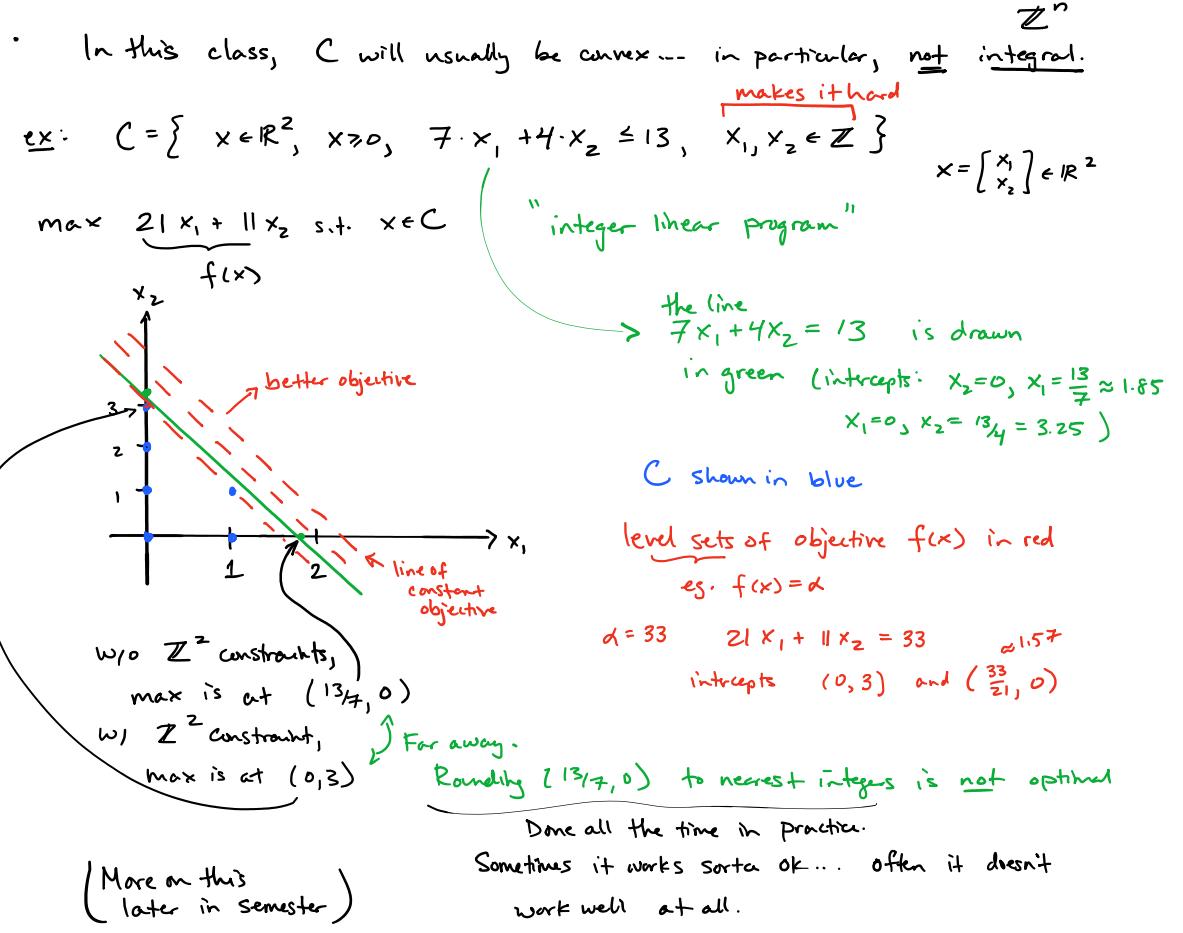
$$\text{s.t. } \|Ax - b\| < \varepsilon \quad \text{s.t. } \|Ax - b\| \leq \varepsilon$$

very similar, but (1) probably doesn't  
have a solution, whereas (2) does.

Other high-level properties of the feasible set  $C$ :

- If  $C = \emptyset$ , the problem is "infeasible".

Not always obvious to spot, ex:  $C = \{x : Ax \leq b\}$   
may or may not be empty.

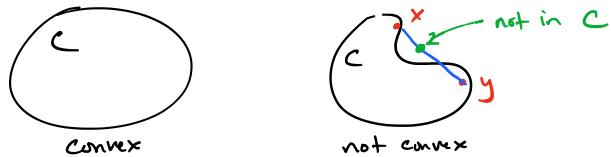


## Convexity

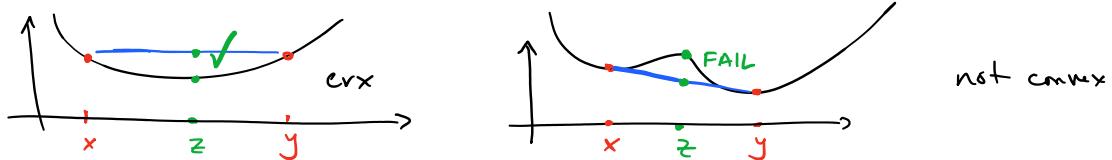
from now on, this is always implicitly assumed in this class

Def. A set  $C$  inside any vector space is **convex** if  $\forall x, y \in C$  and  $\forall t \in [0, 1]$ ,  
then  $t \cdot x + (1-t)y \in C$

i.e.,

$$\overline{xy} = \{t \cdot x + (1-t)y : t \in [0, 1]\}$$


Def A function  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  is **convex** if  $\forall x, y \in \mathbb{R}^n, \forall t \in [0, 1]$   
then  $f(t \cdot x + (1-t)y) \leq t \cdot f(x) + (1-t)f(y)$

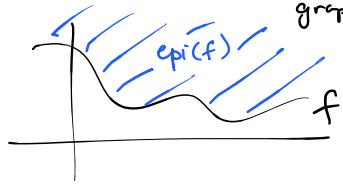


or, since mathematicians don't like to write/talk more than necessary,

a function  $f$  is **convex** iff the set "epi( $f$ )" is **convex**

where

$$\text{epi}(f) = \text{epigraph}(f) = \{(x, s) : x \in \mathbb{R}^n, s \in \mathbb{R}, s \geq f(x)\}$$



$$\text{graph}(f) = \{(x, s) : \dots, s = f(x)\}$$

Why do we like convexity?

Basic thm #1: If  $f$  is convex and  $C$  is convex, then any local minimizer of  $\min_{x \in C} f(x)$  is in fact global. (Also,  $X := \arg\min_{x \in C} f(x)$ , the set of global sol'n, is convex, and in particular, connected)

proof

Q2

on your own (scroll down for answer)

Proof: let  $x$  be a local sol'n. For contradiction, assume it's not global, so  $\exists y \in C$  s.t.  $f(y) < f(x)$ .

Since  $x \in C$  is a local sol'n,  $\exists \varepsilon \in \mathbb{R}_+$  s.t.  $f(x) \leq f(z) \forall z \in B_\varepsilon(x) \cap C$

Pick  $t \in [0, 1]$  sufficiently close to 1 to guarantee

$z = t x + (1-t)y$  is within  $\varepsilon$  of  $x$

Since  $C$  is convex,  $z \in C$ , thus by

we know  $f(x) \leq f(z)$ . (\*)

But by convexity of  $f$ ,

$$f(z) = f(tx + (1-t)y)$$

$$\leq t \cdot f(x) + (1-t)f(y)$$

$$< t \cdot f(x) + (1-t)f(x) \quad \text{since } (1-t) \geq 0 \text{ and } f(y) < f(x)$$

$$= f(x)$$

so  $f(z) < f(x)$  which contradicts (\*).