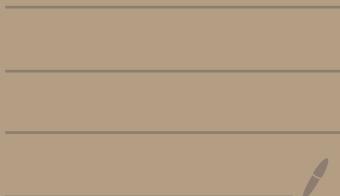


A math 515 Jan 13

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- \* More concepts: closed, proper, level bounded
- \* strong convexity
- \* measuring rates.



Last time: characterized behavior  
 of continuously differentiable  
 convex fns.

Cor 2.19 For  $f \in C^1$  and convex, TFAE:

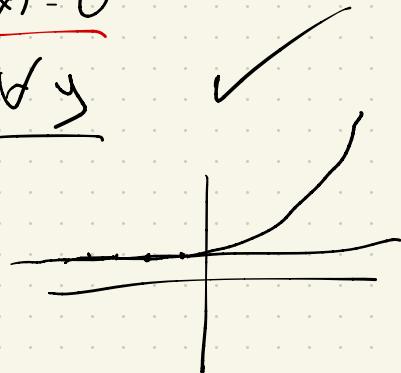
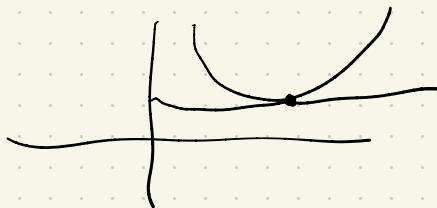
- ①  $x$  is a global minimizer for  $f$
- ②  $x$  is a local minimizer for  $f$
- ③  $x$  is a stationary pt ( $\nabla f(x) = 0$ )

Pf:  $1 \Rightarrow 2$  trivial,  $2 \Rightarrow 3$  we did earlier

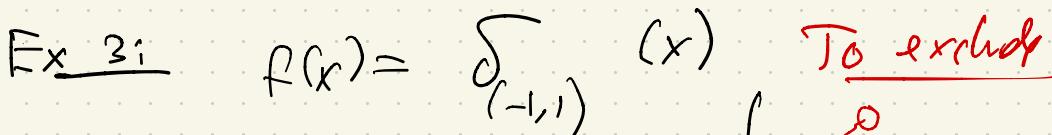
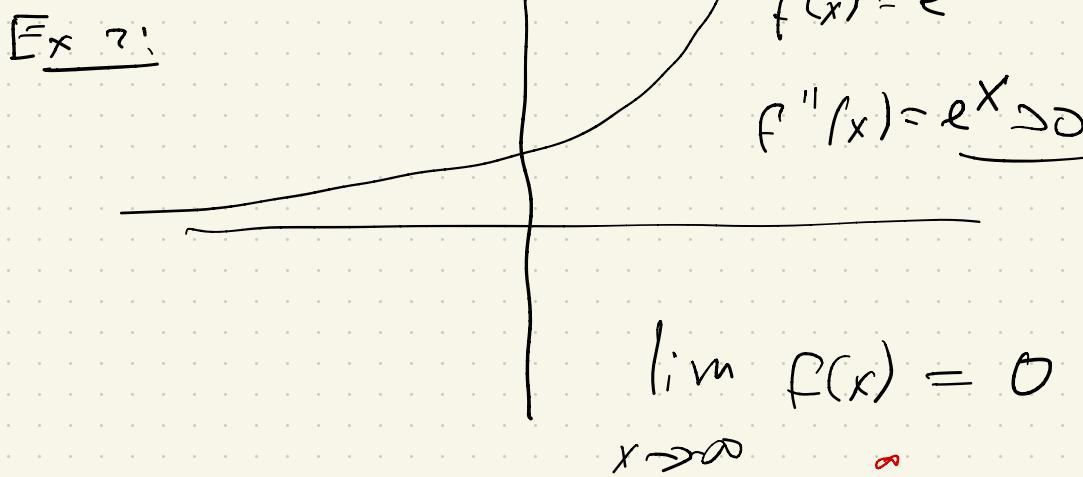
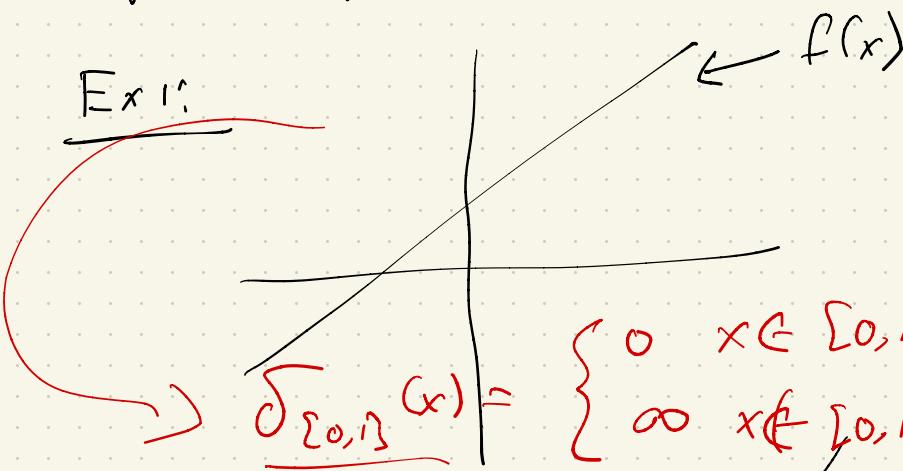
$$3 \Rightarrow 1: f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle \quad \forall x, y$$

$$\text{At } x, \nabla f(x) = 0$$

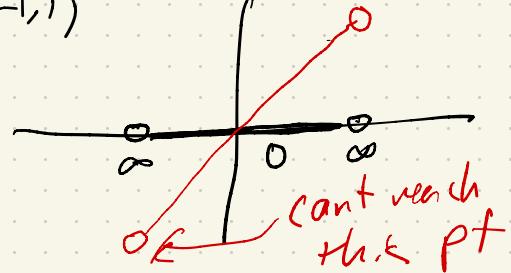
$$f(y) \geq f(x) \quad \underline{\forall y} \quad \checkmark$$



Even for convex funcs, a minimizer need not exist.



$$g(x) = x + \delta_{(-1, 1)}$$



Read p. 5-11 of 'variational analysis'!

Def: let  $\bar{\mathbb{R}} = \mathbb{R} \cup \{-\infty, \infty\}$

Def: For a  $f: \mathbb{R}^n \rightarrow \bar{\mathbb{R}}$ , we call

dom f =  $\{x: \mathbb{R}^n : f(x) < \infty\}$ .

→ 'effective domain'

$f(x) = \delta_{[0, 1]}(x)$ , then  $\text{dom } f = [0, 1]$

$\inf f = \inf_{x \in \mathbb{R}^n} f(x) = \inf_{x \in \text{dom } f} f(x)$

= smallest value f can take.

$\arg \min f = \{x : f(x) = \inf f\}$

could be empty.

Ex:  $f(x) = e^x$ ,  $\text{dom } f = \mathbb{R}$

$\inf f = 0$

$\arg \min f = \{x\}$

\*  $\arg \min$  = set of global minimizers.

\* Lets exclude some funcs.

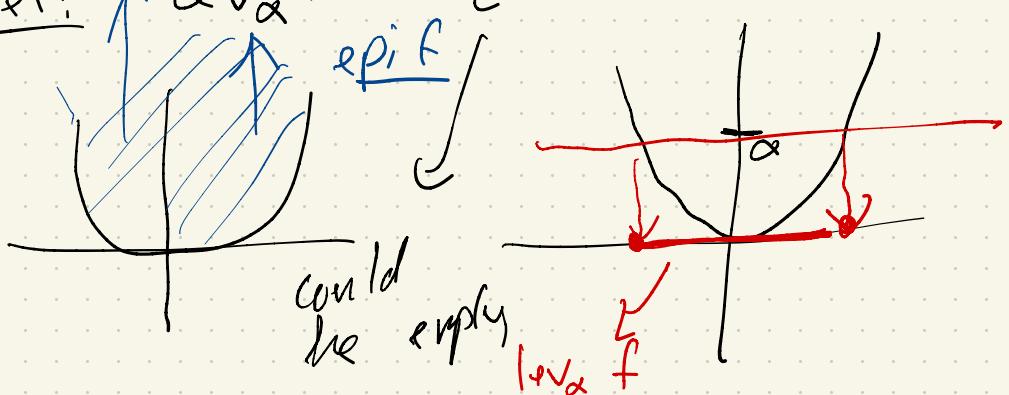
- $f = \infty$ , not useful
- $f(x) = -\infty$ , not useful

Def:  $f$  is a proper function if  $f(x) < \infty$  for at least one  $x$ , and  $f(x)$  never equals  $-\infty$  for any  $x$ .

\* All functions we work with are proper.

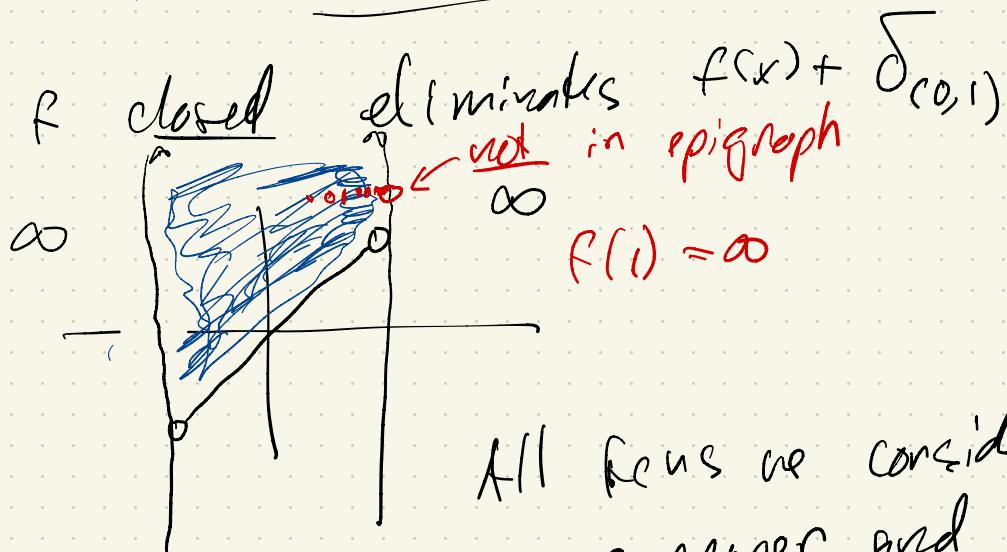
Def:  $\text{epi } f = \{ [x] : f(x) \leq \alpha \}$

Def:  $\text{lev}_\alpha f = \{ x : f(x) \leq \alpha \}$



Now, we require epif (equivalently, all  $\text{lev}_\alpha f$ ) to be closed.

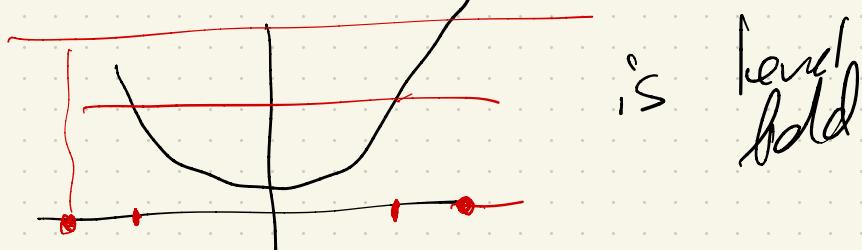
Def:  $f$  is a closed function if epif (equivalently, all  $\text{lev}_\alpha f$ ) are closed sets.



All focus we consider  
are proper and

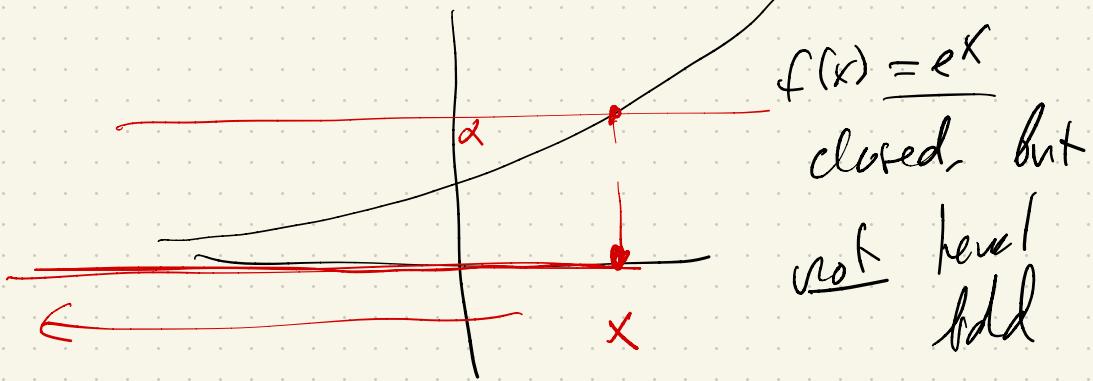
closed.

Def:  $f: \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$  is level bounded  
if all  $\text{lev}_\alpha f$  are bounded  
(possibly empty)



ex: show  $f(x) = \frac{1}{2} x^2$  has level sets is level bdd

$$\text{or } \frac{1}{2} \|x\|^2$$



Thm: Rock-Wets, 1.9

Suppose  $F: \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$  is closed, proper, and level bounded. Then  $\inf f$  is finite, and  $\arg\min f$  is nonempty and compact (closed & bounded).

$f(x) = e^x$ , what are  $\text{lev}_\alpha f(x)$ ?

$$\text{lev}_\alpha f = \{x : f(x) \leq \alpha\}$$

Given  $\alpha$ , easily find  $x$ ,  $f(x) = \alpha$ :

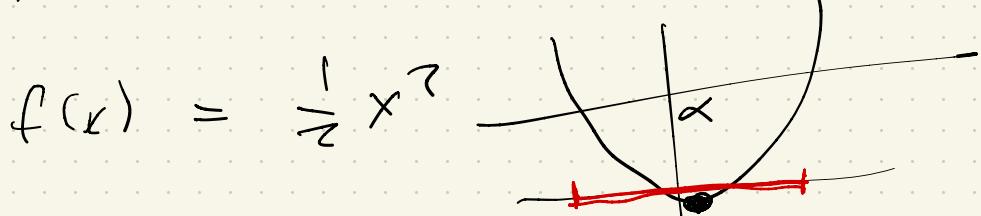
$$\alpha = e^x, \text{ so } x = \ln(\alpha)$$

$$\text{So } \text{lev}_\alpha e^x = \underline{(-\infty, \ln \alpha]}$$

$\xrightarrow{\text{closed set}}$

All closed,  $e^x$  closed fn.

But  $\text{lev}_\alpha e^x$  not bounded.



$$\alpha = \frac{1}{2} x^2, x = \pm \sqrt{2\alpha}$$

If  $\alpha \geq 0$ , then  $\text{lev}_\alpha (\frac{1}{2} x^2) = [-\sqrt{2\alpha}, \sqrt{2\alpha}]$

$\alpha < 0$ ,  $\text{lev}_\alpha(\frac{1}{2} x^2) = \emptyset$

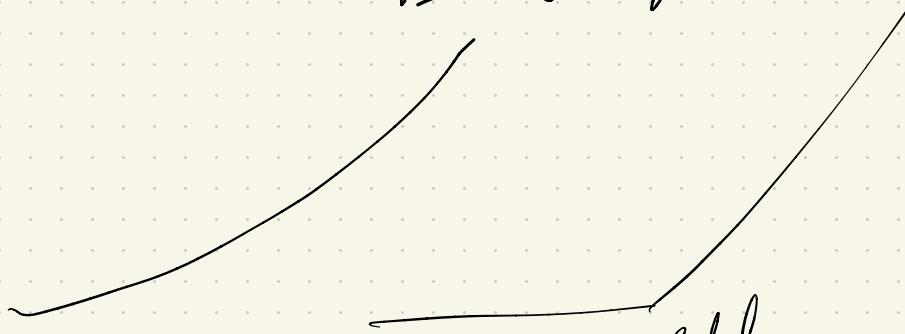
Upshot: the more assumptions we make, the nicer the behavior we can expect.

Consider closed, proper, level bdd, then they have minimizers.

+  $c_1^1$  minimizers identified by  
 $\nabla f(x) = 0$

+ convex :  $\nabla f(x) = 0 \Rightarrow$  global minimizer

+ .. get global minimizer  
is unique



Convex, but not level bdd.

\* Very useful concept: convex funcs that are bounded below by gradients.

Def. a function  $f: \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $C^1$  is called  $\alpha$ -strongly convex if

$$f(y) \geq f(x) + \langle \nabla f(x), y-x \rangle + \frac{\alpha}{2} \|y-x\|^2$$

convex grad. ineq.      quadratic

Ex:  $f(x) = \frac{1}{2} \|x\|^2$  is 1-strongly conv

$f(x) = g(x) + \frac{\alpha}{2} \|x\|^2$  g convex,  
is  $\alpha$ -strongly convex

Ex: Show  $f \in C^1$  is  $\alpha$ -strongly conv  
 $\Leftrightarrow f(x) - \frac{\alpha}{2} \|x\|^2$  is CUX

Thm 2.23: For  $f \in C^1$ , TFAE:

- ①  $f$  is  $\alpha$ -strongly cvx
- ②  $\langle \nabla f(y) - \nabla f(x), y-x \rangle \geq \alpha \|y-x\|^2$
- ③ If  $f$  twice cont. diffble, then  
 $\nabla^2 f \succeq \alpha I$   
 $\hookrightarrow \nabla^2 f - \alpha I \text{ PSD}$   
 $\hookrightarrow \lambda(\nabla^2 f) \geq \alpha$

Ex: Show that every  $\alpha$ -strongly cvx function is level bounded.

∴ every  $\alpha$ -strongly cvx fn  
has a minimizer.

Ex: Show that an  $\alpha$ -strongly cvx function must have a unique minimizer.

Next time: consider  $\min_x f(x)$ ,  
 $f$  is  $C^1$

Algo:  $\underline{x^{k+1} = x^k - \gamma \nabla f(x^k)}$

If all we know about  $f$  is flat  
— it is  $C^1$ , all we can look at

is  $\|\nabla f(x^k)\|$  → If are we close  
to a stationary pt? ↗

If in addition,  $f$  is convex and  
level bounded, minimizers exist  
and  $f^* = \inf f$  is finite.

Can now look at  $\underline{f(x^k) - f^*}$   
how big is this?

Finally, if  $f$  is  $\alpha$ -strongly convex,  
then a unique minimizer exists,  
call it  $x^*$ , and can directly  
look at  $\|x^K - x^*\|$

Three measures:  $\|\nabla f(x^K)\|$

for three cases,

$$\begin{aligned} f(x^K) - f^* &\leftarrow \\ \underline{\|x^K - x^*\|} \end{aligned}$$

Any of these measures will  
give us some sequence indexed  
by  $K$ , the iteration counter

$$(x^{K+1} = x^K - \gamma \nabla f(x^K))$$

$$\begin{cases} a_K = \|\nabla f(x^K)\| \\ a_K = f(x^K) - f^* \\ a_K = \|x^K - x^*\| \end{cases}$$

hopefully  $\downarrow 0$

Now fast?

How do we measure speed at which some sequence  $a_k \downarrow 0$ ?

①  $a_k \downarrow 0$  at a sublinear rate

if can find constants  $c > 0, \beta > 0$

where  $\underline{a_k} \leq \frac{c}{k^\beta}$

usually, we see  $\beta = \frac{1}{2}, 1, \text{ or } 2$

$$a_k \leq \frac{c}{\sqrt{k}}$$

(slowest)

$$a_k \leq \frac{c}{k^2}$$

(fastest)

Usually, you terminate algorithm  
at a target  $\varepsilon$  for  $a_k$

Q: After what  $K$  will  $a_k \leq \varepsilon$ ?

$a_k \leq \varepsilon$ , want  $\min K$  so  $\varepsilon = \frac{c}{k^\beta}$

$$k^\beta = \frac{c}{\varepsilon}$$

$$K \geq \left(\frac{\varepsilon}{c}\right)^{\frac{1}{\beta}}$$

$c, \beta$   
both matter

$$C=1, \varepsilon = 1e^{-6} \quad \frac{C}{\varepsilon} = 10^6$$

$$g = \frac{1}{2}, K \geq (10^6)^2 = 10^{12}$$

$$g = 2, K \geq (10^6)^{1/2} = \underline{10^3}$$

(2)  $a_n \downarrow 0$  at a linear (or geom)  
rate if  $\underbrace{a_K \leq C(1-g)^K}_{g \in (0,1)}$

Ex: Follow book with index p 28  
to check why \* implies

That given  $\varepsilon$ ,  $a_K \leq \varepsilon$   
after  $K \geq \frac{1}{g} \ln \left( \frac{C}{\varepsilon} \right)$

(3)  $a_n \downarrow 0$  at a quadratic rate if

$$\begin{aligned} a_{n+1} &\leq C \cdot a_n^2 \\ &\leq \frac{1}{C} \left( C a_0 \right)^{2^{n+1}} \end{aligned} \quad (\text{algebra})$$

