

## Lecture 25

### Last time

- ▷ Ekeland's variational principle
- ▷ Inverse Problems.

### Today

- ▷ Sufficient conditions for metric regularity.
- ▷ Algorithmic implications.

### Sufficient conditions for metric regularity

Lemma (Ioffe '79) Suppose  $\Phi$  is given by

$$\Phi(x) = \begin{cases} F(x) & x \in S \\ \emptyset & \text{otherwise} \end{cases}$$

where  $F$  is continuous and  $S \subseteq E$  is a closed set. Suppose that  $\Phi$  is not metrically regular at  $\bar{x} \in S$ . Then, there is an arbitrarily small  $\delta > 0$ , a  $y$  close to  $\bar{y} = F(\bar{x})$  and  $x$  close to  $\bar{x}$  minimizing

$$\|F(\cdot) - y\| + \delta \|\cdot - x\| \text{ over } S,$$

but  $F(x) \neq y$ .

Proof: Since metric regularity doesn't hold,  $\exists (x_n)_{n \in \mathbb{N}} \subseteq S$  and  $(y_n)_{n \in \mathbb{N}} \subseteq Y$  s.t.

$x_n \rightarrow \bar{x}$ ,  $y_n \rightarrow \bar{y}$  and

$$(B) \text{dist}(x_n, S \cap F^{-1}(y_n)) = \text{dist}(x_n, \phi^{-1}(y_n)) \\ \geq n \|F(x_n) - y_n\|.$$

Next, we apply Ekeland's principle to  $f_n(\cdot) = \|F(\cdot) - y_n\| + z_S(\cdot)$ .

We take  $\varepsilon_n = \|F(x_n) - y_n\|$  and  $\delta_n = \max\{\sqrt{\varepsilon_n}, \frac{1}{n}\}$ .  
Therefore  $\exists \bar{x}_n \in S$  that minimizes

$$f_n(\cdot) + \delta_n \|\cdot - x_n\|$$

that is, it minimizes

$$\|F(\cdot) - y_n\| + \delta_n \|\cdot - \bar{x}_n\| \text{ over } S.$$

By construction  $\delta_n \rightarrow 0$  as  $n \rightarrow \infty$ .  
Moreover,

$$\|\bar{x}_n - x_n\| \leq \varepsilon_n / \delta_n$$

Further, we claim  $F(\bar{x}_n) \neq y_n$ . Otherwise we would have  $\bar{x}_n \in S \cap F^{-1}(y_n)$ , and (B) would give

$$\|\bar{x}_n - x_n\| \geq n \varepsilon_n \geq \frac{\varepsilon_n}{\delta_n},$$

which yields a contradiction.  $\square$

Next we will use this lemma to construct conditions under which metric regularity holds.

**Theorem (Identifying metric regularity):**

Suppose that  $F: E \rightarrow \mathbb{R}$  is Lipschitz,  $S \subseteq E$  and

$$\Phi(x) = \begin{cases} d(F(x)) & \text{if } x \in S, \\ \phi & \text{otherwise.} \end{cases}$$

Then,  $\Phi$  is metrically regular at  $\bar{x}$  provided that the following implication holds

$$0 \in \partial\langle w, F(\cdot)\rangle(\bar{x}) + \partial z_S(\bar{x}) \Rightarrow w = 0. \quad \dashv$$

## Intuition

This condition replaces the one we used for the Inverse Function Theorem. Indeed if  $F$  is smooth, this reduces to  $\ker \nabla F(\bar{x}) = \{0\}$ .

Proof: Assume searching contradiction that metric regularity fails. Then, there exist sequences  $x_n \rightarrow \bar{x}$ ,  $y_n \rightarrow \bar{y}$

$= F(\bar{x})$ ,  $\delta_n \rightarrow 0$  such that  $x_n$  minimizes  
 $\|F(\cdot) - y_n\| + \delta_n \|\cdot - x_n\| + z_S(\cdot)$ , which  
implies thanks to the sum rule that

$$\begin{aligned} & \partial \|F(\cdot) - y_n\|(x_n) + \delta_n B_n + \partial z_S(x_n) \\ &= \partial \langle w_n, F(\cdot) \rangle(x_n) + \delta_n B_n + \partial z_S(x_n) \end{aligned}$$

where  $w_n = (F(x_n) - y_n) / \|F(x_n) - y_n\|$  and the  
second line follows from the next lemma.

**Lemma:** Suppose  $f(x) = h \circ F(x)$  with  
 $F$  Lipschitz at  $\bar{x}$  and  $h$  smooth around  
 $F(\bar{x})$ . Then

$$\partial(h \circ F)(\bar{x}) = \partial(\langle \nabla h(F(\bar{x})), F(\cdot) \rangle)(\bar{x})$$

**Proof of the Lemma:** By assumption near  $\bar{x}$   
 $h \circ F(x) = h(F(\bar{x})) + \langle \nabla h(F(\bar{x})), F(x) - F(\bar{x}) \rangle$   
 $+ o(\|F(x) - F(\bar{x})\|)$   
 $\stackrel{F \text{ Lipschitz}}{=} h(F(\bar{x})) + \langle \nabla h(F(\bar{x})), F(x) - f(\bar{x}) \rangle$   
 $+ o(\|x - \bar{x}\|).$

Thus, the two functions are equal up  
to constant terms and  $o(\|x - \bar{x}\|)$ . A  
simple computation yields they have  
the same subdifferentials.  $\square$

WLOG, we can assume  $w_n \rightarrow w$  and so

$$0 \in \partial \langle w, F(\cdot) \rangle(x_n) + \partial \langle w_n - w, F(\cdot) \rangle(x_n) \\ + \delta_n \beta + \partial r_S(x_n).$$

Note that  $\langle w_n - w, F(\cdot) \rangle$  is an  $L_n$ -Lipschitz function with  $L_n \rightarrow 0$  as  $n \rightarrow \infty$ , and further  $\delta_n \rightarrow 0$ . Then, there exist sequences

$$u_n \in \partial \langle w, F(\cdot) \rangle(x_n) \text{ and } v_n \in \partial r_S(x_n)$$

with  $u_n + v_n \rightarrow 0$ . Once more, we can assume that both sequences converge. Therefore,  $u_n \rightarrow u \in \partial \langle w, F(\cdot) \rangle(\bar{x})$  and  $v_n \rightarrow v \in \partial r_S(\bar{x})$  (why? Use that  $r_S$  is closed). Therefore, we established  $0 \in \partial \langle w, F(\cdot) \rangle(\bar{x}) + \partial r_S(\bar{x})$  and  $w \neq 0$ , which is a contradiction.

□

## Algorithmic consequences.

The presence of regularity often leads to faster convergence (akin to strong convexity).

**Theorem:** Suppose that we are interested in finding a solution to  $0 \in \Phi(x)$  with  $\Phi: E \rightrightarrows E$ . Further assume

$$(B) \quad \text{dist}(x, \Phi^{-1}(0)) \leq \kappa \text{dist}(\Phi(x), 0)$$

for all  $x \in E$ , and we have an algorithm that generates a sequence via

$$x_{t+1} \leftarrow \alpha(x_t) \quad \begin{matrix} \downarrow \\ \alpha: E \rightarrow E \end{matrix}$$

and guarantees

$$(J) \quad \text{dist}(\Phi(x_t), 0) \leq \mu \frac{\text{dist}(x_0, \Phi^{-1}(0))}{\sqrt{t}}.$$

Then, we have

$$\text{dist}(x_t, \Phi^{-1}(0)) \leq \frac{\mu}{\kappa} e^{-\frac{1}{2} \left( \frac{t-1-\rho}{\rho} \right)} \text{dist}(x_0, \Phi^{-1}(0)),$$

with  $\rho = e\sqrt{\mu/\kappa}$ .

→

### Remarks

- ▷ Condition (B) is known as metric subregularity (note that we only vary  $x$  and not  $y$ ).
- ▷ The convergence rate (J) is satisfied by several algorithms (GD,

PPM, PDHG, ADMM\*).

- ▷ this result boost sublinear convergence of  $\text{dist}(\Phi(x_t), 0)$  to linear convergence of  $\text{dist}(x_t, \Phi^{-1}(0))$ .

## Recap

We covered a number of topics

- ▷ Convex Analysis
- ▷ Duality
- ▷ Classical algorithms for LP
  - ↳ Simplex
  - ↳ Interior Point Methods
- ▷ First order Methods
  - ↳ KM iteration
  - ↳ Examples: PPM, QR, ADMM, PDHG.
- ▷ Intro to variational analysis.

Optimization is a very broad field, there are several topics we didn't mention. But hopefully you now have the tools to explore them on your own :)