

descent algorithms

topic: (deterministic) gradient descent algorithms for unconstrained optimization

refs:

**OPTIMAL CONTROL
AND ESTIMATION**

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section 3.6

Nonlinear Programming

SECOND EDITION

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chapter 1

• we've seen why derivatives can be useful to characterize (local) optima in

(NLP) $\min_{u \in \mathbb{R}^m} C(u)$ \leftarrow assume C is "smooth", i.e. continuously differentiable as many times as needed

• suppose we start with a "guess" $u \in \mathbb{R}^m$ and find $\underbrace{D_C(u)}_{\text{"gradient" of } C} \neq 0$

\rightarrow how should we modify our guess to get closer to a (local) min?

– regarding "D_C(u)" as a function $D_C(u): \mathbb{R}^m \rightarrow \mathbb{R}$
 $: v \mapsto \langle D_C(u), v \rangle$

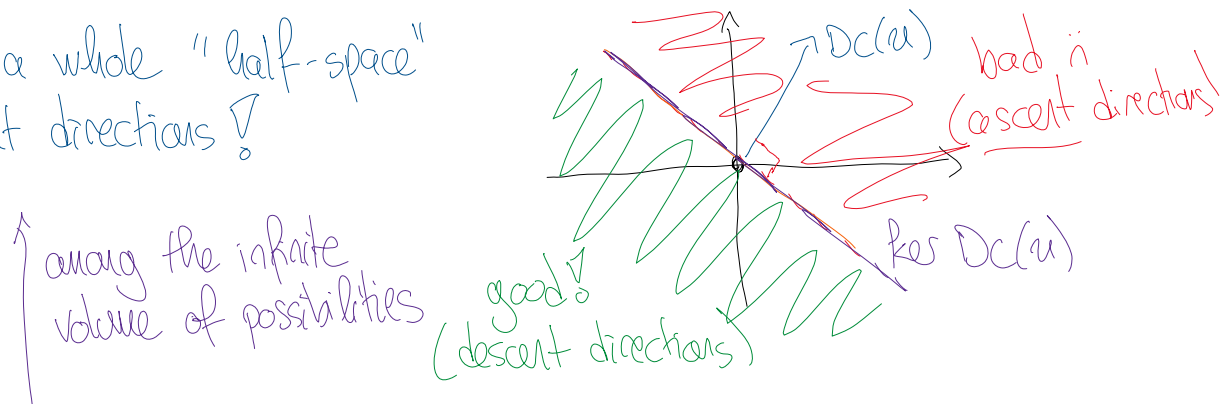
we see that the gradient defines a function that tells us, for any given direction $v \in \mathbb{R}^m$, how quickly c changes in the v direction:

$$c(u + \gamma \cdot v) \simeq c(u) + \gamma \cdot \langle Dc(u), v \rangle$$

* any $v \in \mathbb{R}^m$ s.t. $\langle Dc(u), v \rangle < 0$ is a valid descent direction

e.g. $v = -Dc(u) \Rightarrow \langle Dc(u), -Dc(u) \rangle = -\|Dc(u)\|^2 < 0$

but there's a whole "half-space" of descent directions!



• to select a descent direction, we can formulate another optimization problem

→ solve $\min_{v \in \mathbb{R}^m} \langle Dc(u), v \rangle \leftarrow$ find the steepest / most rapid descent direction
s.t. $\|v\|_2 \leq \|Dc(u)\|_2$

– recalling that $\langle x, y \rangle = \|x\|_2 \|y\|_2 \cos \theta$,

θ = angle between x & y

\Rightarrow solution is $v^* = -Dc(u)^T \in \mathbb{R}^m$

algorithm (gradient descent): (*) $u^+ = u - \gamma \cdot Dc(u)^T$, step size $\gamma > 0$

* note that (*) defines a difference equation (DE)

→ observe/show that local minima of (NLP) are equilibria of (DE)

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* let's use stability analysis of (DE) to find largest choice for $\gamma > 0$

→ linearize (DE) about a local min of (NLP)

- differentiating (*) wrt u : $D_u[u - \gamma \cdot Dc(u)^T] = \underbrace{I - \gamma \cdot D^2c(u)}_{A(\gamma)}$
evaluating at u^* yields $(u - u^*)^+ \simeq A(\gamma) \cdot (u - u^*)$, $A(\gamma) =$

* need $|\lambda| < 1$ for all $\lambda \in \text{spec } A(\gamma) = \text{spec } I - \gamma \cdot D^2c(u)$

• spectral mapping theorem says that:

if $\sigma \in D^2c(u)$ then $\lambda = 1 - \gamma \cdot \sigma \in \text{spec } I - \gamma \cdot D^2c(u)$

→ so we need $-1 < 1 - \gamma \cdot \sigma < +1 \Leftrightarrow 0 < \gamma < \frac{2}{\sigma}$, all $\sigma \in \text{spec } D^2c(u)$

CHALLENGE

* → solve $\min_{v \in \mathbb{R}^m} \langle Dc(u), v \rangle$

s.t. $\|v\|_{D^2c(u)} \leq \|Dc(u)\|_{D^2c(u)}$

where $\|v\|_S := \sqrt{\frac{1}{2} v^T S v}$