

Optimization for image processing

I Generalities

II Differentiable problems

- without constraints
- with general constraints
- constraints equality
inequality

III Nonsmooth optimization

1.1. Optimization problems

Find $\hat{u} \in V$ such that

normed vect. space

$$\hat{u} \in U \text{ and } F(\hat{u}) = \inf_{u \in V} F(u)$$

\uparrow
subset of V

$$U = \{ u \in \mathbb{R}^n : g_i(u) = 0 \quad 1 \leq i \leq n \}$$

... $h_i(u) \leq 0$...

$\mathcal{O}(U)$ neigh. of U

minimum of F $F(\hat{u})$

minimizer of F is \hat{u}

Standard form

$$F(u) = \frac{1}{2} \langle B u, u \rangle - \langle c, u \rangle$$

\uparrow
matrix $n \times n$

2. Best Image restoration via the minimization of an energy

- Observation model $v = Au + n$
 \uparrow data $\quad \quad \quad \uparrow$ noise

A - blur, degradation...
 (integral operator...)

After sampling A matrix $M \times N$

Solution: $A^{-1}v$ cannot work

e.g. $A = I$. $v = u + n$.

if we do $A^{-1}v$ we get the noisy data.

Objective function \uparrow param. > 0 regularization

$$F(u) = \Psi(u, v) + \beta \Phi(u)$$

\uparrow data fidelity term $\quad \quad \quad \uparrow$ e.g. $\Phi(u) = \sum_i \varphi(|D_i u|)$

$$(A \hat{u} \approx v)$$

$$\varphi(t) = \sqrt{t^2 + \alpha}, |t|, \dots$$

discrete approx of the grad. of the image.

$\Psi(u, v) = \|Au - v\|^2$. the most classical.

Quadratic regularization

$$\Phi(u) = \|D_i u\|^2$$

Constraints $U = \{u \in V : Au = v\}$
 $\{u \in V : \|Au - v\|^2 - \epsilon^2 \leq 0\}$

$\hat{u} \in \bigcap_{i \geq 1} U_i$ U_i - properties required by \hat{u} .

1.3. Analysis of the solution.

a) Existence, unicity

Def. F is coercive if $\lim_{\|u\| \rightarrow \infty} F(u) \rightarrow \infty$

Thm. V normed vector space, finite dim.

$U \subset V$ non empty closed

$F : V \rightarrow \mathbb{R}$ continuous.

If U is not bounded we suppose that F is coercive.

$\Rightarrow \exists \hat{u} \in U$ such that $F(\hat{u}) = \inf F(u)$

Proof. U bounded $\Rightarrow U$ is compact } \Rightarrow
 F continuous

\Rightarrow Thm. Weierstrass - existence of \hat{u} .

$u_0 \in U$

F coercive $\Rightarrow \exists r > 0$ such that

$\|u\| > r \Rightarrow F(u_0) < F(u)$

$\Rightarrow \hat{u}$ satisfies

$$F(\hat{u}) = \inf \{ F(u) : u \in \overline{B(u_0, r) \cap U} \}$$

\nearrow compact
closed ball, radius r .

The result can be extended to general Hilbert spaces. (separable)

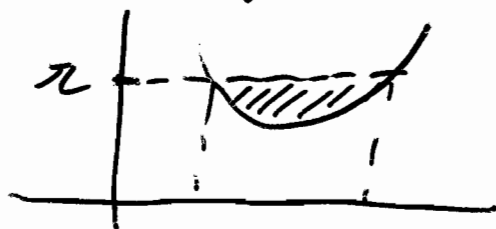
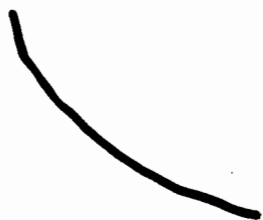
Alternative proof with minimizing sequence
 $u_k \in U$

$$\lim_{k \rightarrow \infty} F(u_k) = \inf F(u)$$

Feasible optim. pb. if F, U convex

Def. $F: U \rightarrow \mathbb{R}$ convex if $\forall u, v \in U$
 $\forall \theta \in (0, 1) \quad F(\theta u + (1-\theta)v) \leq$
 $\theta F(u) + (1-\theta)F(v)$

F can be convex without being concave



Def. Epigraph

$\text{epi } F = \{ (u, z) \in V \times \mathbb{R} : F(u) \leq z \}$

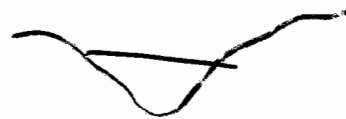
F convex \iff $\text{epi } F$ convex

F lower semi-continuous \iff $\text{epi } F$ closed
in $V \times \mathbb{R}$,

sublevel sets

$(u, z) \in \text{epi } F \iff u \in S_z, \{v : F(v) \leq z\}$

F convex $\implies S_z$ convex



Ex. $F: U \rightarrow \mathbb{R}$ convex, continuous

If F has a local minimum at $\hat{u} \in U$

$\implies \hat{u}$ is a global min. / U

$$\hat{U} = \{ \bar{u} \in U : F(\bar{u}) = \inf_{u \in U} F(u) \}$$

is closed and convex.

F strictly convex $\Rightarrow F$ has at most one minimum and it is strict.

$$\exists r > 0 \text{ such that } F(\bar{u}) \leq F(u) \quad \forall u \in \overline{B(\bar{u}, r)} \cap U$$

By the def. of local min.

$u \in U \setminus B(\bar{u}, r)$ arbitrary.

$$\theta = \frac{r}{\|u - \bar{u}\|} \Rightarrow \theta \in (0, 1)$$

$$u_\theta = (1 - \theta)\bar{u} + \theta u \Rightarrow u_\theta \in \overline{B(\bar{u}, r)} \cap U$$

because $u_\theta - \bar{u} = \theta(u - \bar{u}) = r \frac{u - \bar{u}}{\|u - \bar{u}\|}$

$$F(\bar{u}) \leq F(u_\theta) = F((1 - \theta)\bar{u} + \theta u)$$

$$\leq (1 - \theta)F(\bar{u}) + \theta F(u)$$

$\underbrace{F(\bar{u}) - \theta F(\bar{u})}$

$$\theta F(\bar{u}) \leq \theta F(u) \Rightarrow \bar{u} \text{ global min.}$$

$$\hat{U} = U \cap \{ u \in V : F(u) \leq F(\bar{u}) \}$$

convex since closed since F continuous

(b) Characterize the solution

\hat{u} - implicitly defined in general.

1.4. Algorithms to approximate \hat{u}

(a) Iterative schemes

$(u_k)_{k \geq 1}$ starting from u_0 and
converging to \hat{u}

$$u_k = G(u_{k-1})$$

↑ iterative scheme $V \rightarrow V$

G often use $\nabla F, F(u_k), g(u_k), \dots$

\hat{u} is a fixed point for G iff

$$\boxed{G(\hat{u}) = \hat{u}}$$

Def. G is a contraction if $\exists \gamma \in (0, 1)$
such that

$$d(G(u_1), G(u_2)) \leq \gamma d(u_1, u_2)$$

↑ distance (e.g. $\|u_1 - u_2\|$)

$\Rightarrow G$ is Lip. \Rightarrow uniformly continuous.

Re Fixed point theorem: (V complete)

G is contraction $\Rightarrow G$ has a fixed point \hat{u}

Proof. Unicity

Suppose 2 fixed points \hat{u}_1 and \hat{u}_2 .

$$\begin{aligned} 0 < \underline{d(\hat{u}_1, \hat{u}_2)} &= d(G\hat{u}_1, G\hat{u}_2) \leq \\ &\leq \gamma d(\hat{u}_1, \hat{u}_2) < \underline{d(\hat{u}_1, \hat{u}_2)} \\ \Rightarrow \hat{u}_1 &= \hat{u}_2. \end{aligned}$$

Existence

$u_0 \in V$ arbitrary

$$u_1 = G(u_0), \dots, u_k = G(u_{k-1}) \dots$$

we will show that (u_k) is a Cauchy sequence.

$$d(u_2, u_1) \leq \gamma d(u_1, u_0)$$

$$d(u_3, u_2) \leq \gamma d(u_2, u_1) \leq \gamma^2 d(u_1, u_0)$$

...

$$d(u_{k+1}, u_k) \leq \gamma^k d(u_1, u_0)$$

$$\underline{d(u_{k+l}, u_k)} \stackrel{\Delta \text{ inequality}}{\leq} d(u_{k+l}, u_{k+l-1}) + \dots$$

$$+ d(u_{k+1}, u_k)$$

$$\leq \gamma^k (\gamma^{l-1} + \dots + \gamma^0) d(u_1, u_0)$$

$$\leq \frac{\gamma^k}{1-\gamma} d(u_1, u_0) \xrightarrow{k \rightarrow \infty} 0$$

since (u_k) is Cauchy.

V complete $\Rightarrow \exists \hat{u} \in V \quad u_k \rightarrow \hat{u}$

G continuous $\Rightarrow G(u_k) \rightarrow G(\hat{u})$

$$0 = \lim (u_{k+1} - G(u_k)) = \hat{u} - G(\hat{u}).$$

$\rightarrow 0$

(b) Convergence speed.

- Q convergence factor (quotient)

$$Q((u_k)_k) = \limsup_{k \rightarrow \infty} \frac{\|u_{k+1} - \hat{u}\|}{\|u_k - \hat{u}\|}$$

the worst case $\underline{Q}(G, \hat{u}) = \sup_{\text{all seq.}} Q((u_k)_k)$

compare G_1 and G_2 converging to \hat{u}

speed is Q superlinear $\underline{Q} = 0$

linear \underline{Q} finite

sublinear $\underline{Q} = \infty$

- R convergence factor (root)

$$R((u_k)_{k \geq 1}) = \limsup_{k \rightarrow \infty} \|u_k - \hat{u}\|^{1/k}$$

R indep. of the norm.

the worst case $\underline{R}(G, \hat{u}) = \sup R((u_k)_{k \geq 1})$

R - superlinear $\underline{R} = 0$

linear $0 < \underline{R} < 1$

sublinear $\underline{R} = 1$

the Ostrowski theorem

$G: \mathbb{R}^n \rightarrow \mathbb{R}^n$ differentiable at \bar{u}
and $G(\bar{u}) = \bar{u}$ (fixed point)

$\max_{1 \leq i \leq n} |\lambda_i| < 1$ where λ_i is an
eigenvalue of $\nabla DG(\bar{u})$

$\Rightarrow O(\bar{u})$ neighborhood such that
 $\forall u_0 \in O(\bar{u}), u_k \rightarrow \bar{u}$.

The linear convergence thm.

Under the same conditions

$$\max_{1 \leq i \leq n} |\lambda_i| = R(G, \bar{u})$$

to analyze the conv. speed we should
check the eigenvalues of ∇DG .

II Differentiable optim. problems.

1. Preliminaries.

$f: V \rightarrow Y$ is differentiable at $u \in V$ if
 $\exists Df(u)$ linear continuous app. from V
to Y such that

$$f(u+v) = f(u) + Df(u)v + \|v\| \cdot \varepsilon(v)$$

$$\varepsilon(v) \xrightarrow{\|v\| \rightarrow 0} 0$$

the u_0 of the definition

$$F(\bar{u}) \geq F(u + \theta(u_0 - u)) - \theta \langle \nabla F(u + \theta(u_0 - u)), u_0 - u \rangle + (1 - \theta)$$

$$F(\bar{u}_0) \geq F(u + \theta(u_0 - u)) + (1 - \theta) \langle \nabla F(u + \theta(u_0 - u)), u_0 - u \rangle \times \theta \quad / \times$$

$$(1 - \theta) F(u) + \theta F(u_0) \geq F(\theta u_0 + (1 - \theta)u) \quad \left(\begin{array}{l} \text{the def of} \\ \text{convexity} \end{array} \right)$$

strict convexity!

$$\Rightarrow) F(u_0 + \theta(u - u_0)) - F(u_0) < \theta(F(u) - F(u_0))$$

$\forall \theta$ the non strict ineq. holds true.

$$\langle \nabla F(u_0), \theta(u - u_0) \rangle \leq F(u_0 + \theta(u - u_0)) - F(u_0)$$

$$\leq \theta(F(u) - F(u_0)).$$

\Leftarrow change $\cdot >$.

identification $Df(u)$ and $\nabla f(u)$

$$\langle \nabla f(u), v \rangle = Df(u) v.$$

Property. V -n.v.s. U convex
 F differentiable in $\mathcal{O}(U)$

a) F convex $\Leftrightarrow F(u) \geq F(u_0) + \langle \nabla F(u_0), u - u_0 \rangle$

b) ... strictly ... $\Leftrightarrow \dots > \dots \quad \forall u, u_0 \in U, u \neq u_0$

Proof. F convex \Rightarrow take $u, u_0 \in U, \theta \in (0, 1)$

$$(\theta u + (1-\theta) u_0) \leq \theta F(u) + (1-\theta) F(u_0)$$

$\in U$ since U convex

$$(\theta u + (1-\theta) u_0) - F(u_0) \leq \theta (F(u) - F(u_0))$$

lim for $\theta \rightarrow 0$

$$\lim_{\theta \rightarrow 0} \frac{F(u_0 + \theta(u - u_0)) - F(u_0)}{\theta} \leq F(u) - F(u_0)$$

$$= \langle \nabla F(u_0), u - u_0 \rangle$$

$$\Rightarrow F(u) \geq F(u_0) + \langle \nabla F(u_0), u - u_0 \rangle$$

F 2 times differentiable in $\mathcal{O}(U)$

c) F convex $U \Leftrightarrow \nabla^2 F(u_0)(u - u_0, u - u_0) \geq 0$

$\forall u_0, u \in U$ ($\nabla^2 F$ is semi-positive definite)

d) if strict incr. $u \neq u_0 \Rightarrow F$ strictly convex

Def. F is elliptic if : $F \in C^2$ and $\exists \mu > 0$
 such that $\langle \nabla F(u) - \nabla F(u_0), u - u_0 \rangle \geq \mu \|u - u_0\|^2$
 $\forall u, u_0$

$$F(u) = \frac{1}{2} \langle Bu, u \rangle - \langle c, u \rangle$$

\uparrow elliptic if $B = B^*$ (symmetric) and
 $\lambda_i(B) > 0 \quad \forall i$
 \rightarrow eigenvalues

topology. $\overset{\text{suppose}}{F}$ differentiable \forall

F elliptic $\Rightarrow F$ strictly convex and coercive

$$F(u) - F(u_0) \geq \langle \nabla F(u_0), u - u_0 \rangle + \frac{\mu}{2} \|u - u_0\|^2$$

$\forall u, u_0 \in V$



Let F be 2 times differentiable

$$F \text{ elliptic} \Leftrightarrow \langle \nabla^2 F(u_0) u, u \rangle \geq \mu \|u\|^2$$

$\forall u \in V$

2. Problems without constraints

- stopping rules $\|\nabla F(u_n)\| \approx 0$
- descent direction $-d \in V$ at u_k
 $\langle \nabla F(u_k), d \rangle > 0$
- line search - finding ρ_k such that
 $F(u_k + \rho_k d_k) = \inf_0 F(u_k + \rho d_k)$