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Inverse Problems

Example sheet 3 Presentation 28 February 2018, 2-3pm, MR15 Submission 26 February 2018, 12pm, MR14

Please submit exercises 1, 2a and 4a.

Exercise 1 (Subdifferential)

Let \mathcal{U} be a Banach space and $J: \mathcal{U} \to \mathbb{R}_{\infty}$ be a functional. We define the *subdifferential* of J at any $v \in \mathcal{U}$ as

$$\partial J(v) := \left\{ p \in \mathcal{U}^* \, \middle| \, J(u) \ge J(v) + \langle p, u - v \rangle \text{ for all } u \in \mathcal{U} \right\}$$

Characterise the subdifferential for the

- a) quadratic function: $\mathcal{U} = \mathbb{R}, J(u) = \frac{1}{2}u^2$,
- b) absolute value function: $\mathcal{U} = \mathbb{R}, J(u) = |u|,$
- c) squared ℓ^2 -norm: $\mathcal{U} = \ell^2, J(u) = \frac{1}{2} ||u||_{\ell^2}^2 := \frac{1}{2} \sum_{j=1}^{\infty} |u_j|^2$,
- d) ℓ^1 -norm: $\mathcal{U} = \ell^2$,

$$J(u) = \|u\|_{\ell^1} := \begin{cases} \sum_{j=1}^{\infty} |u_j| & \text{if } u \in \ell^1 \\ \infty & \text{else} \end{cases}, \text{ and}$$

e) characteristic function of the unit ball in \mathbb{R} : $\mathcal{U} = \mathbb{R}, J(u) = \chi_C(u), C := \{u \in \mathbb{R} \mid |u| \le 1\}.$

Exercise 2 (Proximal operators)

Let \mathcal{U} be a Hilbert space and $J: \mathcal{U} \to \mathbb{R}_{\infty}$ be a l.s.c., coercive, convex and proper functional. The *proximal operator* of J at any $z \in \mathcal{U}$ and step size $\alpha \geq 0$ is defined as $\operatorname{prox}_{J}^{\alpha}: \mathcal{U} \to \mathcal{U}$ with

$$\operatorname{prox}_{J}^{\alpha}(z) := \arg\min_{u \in \mathcal{U}} \Phi_{\alpha, z}(u)$$

and $\Phi_{\alpha,z}(u) := \frac{1}{2} \|u - z\|_{\mathcal{U}}^2 + \alpha J(u)$. It can be shown that $\partial \Phi_{\alpha,z}(u) = u - z + \alpha \partial J(u)$.

- a) Compute the proximal operators for the functionals defined in Exercise 1.
- b) For a subset $C \subset \mathcal{U}$ of the Hilbert space \mathcal{U} we consider the characteristic function

$$\chi_C(u) := \begin{cases} 0 & \text{if } u \in C \\ \infty & \text{else} \end{cases}$$

- i. For which subsets C is the proximal operator of χ_C well-defined? Hint: You may use any standard results from linear / functional analysis.
- ii. Compute the proximal operators for
 - $C = [0, \infty) \subset \mathbb{R},$
 - $C = \{ u \in \mathbb{R}^n \mid ||u||_2 \le 1 \}$, and
 - $C = \{ u \in \mathbb{R}^n \mid ||u||_{\infty} \le 1 \}.$

Exercise 3 (Bregman distances)

Let $u, v \in \mathcal{U}$ and $p \in \partial J(v)$ be an element of the subdifferential. Then the *Bregman distance* of J at u, v is defined as

$$D_J^p(u,v) := J(u) - J(v) - \langle p, u - v \rangle.$$

- a) In this exercise, we will investigate the properties of the Bregman distance for convex J.
 - i. Show that Bregman distances are non-negative, i.e. for all $u, v \in \mathcal{U}, p \in \partial J(v)$ it holds

$$D_J^p(u,v) \ge 0$$
.

ii. Let J be absolutely one-homogeneous, i.e. for all $\lambda \in \mathbb{R}$, $u \in \mathcal{U}$ we have $J(\lambda u) = |\lambda|J(u)$. Show that $p \in \partial J(v)$ if and only if $J(v) = \langle p, v \rangle$ and for all $u \in \mathcal{U}$ there is $J(u) \ge \langle p, u \rangle$. Thus,

$$D_J^p(u,v) = J(u) - \langle p, u \rangle.$$

iii. Let J be absolutely one-homogeneous. Show that Bregman distances fulfill the triangle inequality in the first argument, i.e. for all $u, v, w \in \mathcal{U}$ and $p \in \partial J(w)$ there is

$$D_{J}^{p}(u+v,w) \leq D_{J}^{p}(u,w) + D_{J}^{p}(v,w)$$
.

iv. Show that Bregman distances may not be symmetric, i.e. there exists a J and $u, v \in \mathcal{U}$ with $p \in \partial J(v), q \in \partial J(u)$ so that

$$D_J^p(u,v) \neq D_J^q(v,u)$$
.

- v. Show that a vanishing Bregman distance may not imply that the two arguments are already the same, i.e. $D_J^p(u, v) = 0 \neq u = v$? What if J is strictly convex?
- b) Compute the Bregman distances for the functions and functionals defined in Exercise 1.

Exercise 4 (Variational regularisation)

We analyse some of the motivating examples for variational regularisation models which are of the form $R_{\alpha}f := \arg\min_{u \in \mathcal{U}} \Phi_{\alpha,f}(u)$ with

$$\Phi_{\alpha,f}(u) := \frac{1}{2} \|Ku - f\|_{\mathcal{V}}^2 + \alpha J(u)$$

and $J: \mathcal{U} \to \mathbb{R}_{\infty}$ being a regularization functional.

a) On ℓ^2 we can define the regularization operators

$$R^{1}_{\alpha}f := \arg\min_{u \in \mathcal{U}} \left\{ \frac{1}{2} \|Ku - f\|_{\mathcal{V}}^{2} + \alpha \|u\|_{1} \right\}$$

with $||u||_1 := \infty$ if $u \in \ell^2 \setminus \ell^1$ and

$$R_{\alpha}^{2}f := \arg\min_{u \in \mathcal{U}} \left\{ \frac{1}{2} \|Ku - f\|_{\mathcal{V}}^{2} + \frac{\alpha}{2} \|u\|_{2}^{2} \right\}$$

which promote different properties in the regularized solution. For simplicity let K = I be the identity operator. Show that

- i. $R^1_{\alpha}f$ is always sparse if $\alpha > 0$, i.e. $|\operatorname{supp}(R^1_{\alpha}f)| < \infty$.
- ii. $R_{\alpha}^2 f$ may not be sparse.

However, the price to pay is linearity. Show that

- iii. R^1_{α} is non-linear.
- iv. R_{α}^2 is linear.

Hint: You may use the results of Exercise 2.

b) For $\Omega = [-1, 1]$, we consider total variation regularization that is naturally defined on the space of functions of bounded variation BV(Ω) which provides regularity while still containing discontinuous functions. In general one can prove that

$$\mathrm{H}^{1,1}(\Omega) \subset \mathrm{BV}(\Omega) \subset \mathrm{L}^1(\Omega)$$
.

Show that these inclusions are strict. In particular, show that

- i. $BV(\Omega)$ is larger than $H^{1,1}(\Omega)$ as it contains discontinuous functions.
- ii. $BV(\Omega)$ is smaller than $L^1(\Omega)$ as it provides more regularity.

Exercise 5 (Denoising with basis representations)

In this exercise we are considering the task of denoising with the help of different basis representations. Let $f \in \mathbb{R}^n$ be a given image and $f^{\delta} \in \mathbb{R}^n$ a noisy observation of it, the task is to find f. Obviously the task is ill-posed in the sense that there is not even a deterministic model that maps f to f^{δ} which we could invert. Instead we approach this problem by assuming that f is regular and that $f^{\delta} = f + \eta$ where η is an instance of a multi-variate Gaussian distribution with zero mean and uniform standard deviation. Then this task can be modelled by minimising the cost functional

$$\Phi_{\alpha, f^{\delta}}(u) = \frac{1}{2} \|u - f^{\delta}\|_{2}^{2} + \alpha J(u) ,$$

where the first term penalises a mismatch to the data f^{δ} and the second term J is designed such that desirable solutions have a low value. It is reasonable to assume that for a regular f there exists a basis $\{b_1, \ldots, b_n\}$ of \mathbb{R}^n such that an energy

$$J(f) = \frac{1}{p} ||Bf||_p^p = \frac{1}{p} \sum_{j=1}^n |\langle f, b_j \rangle|^p \qquad p \in \{1, 2\}.$$

or

$$J(f) = ||Bf||_0 := \sum_{j=1}^n |\langle f, b_j \rangle|^0 = |\{j \in \{1, \dots, n\} | \langle f, b_j \rangle \neq 0\}|$$

of the basis representation Bf is small. Here $B: \mathbb{R}^n \to \mathbb{R}^n$ denotes the basis transformation

$$Bf = \sum_{j=1}^{n} \langle f, b_j \rangle b_j \,.$$

- a) Does $\Phi_{\alpha, f^{\delta}}$ have minimisers and are they unique?
- b) Compute explicit formulas that minimise $\Phi_{\alpha, f^{\delta}}$. Do all solutions depend on B?
- c) Consider the Fourier basis and the wavelet bases 'haar' and 'db10'. Write a function in MATLAB that computes the solution of 2.
 Hint: You can use the MATLAB functions fft2 and wavedec2 for the transformation into the Fourier and wavelet basis.
- d) Load your favourite picture (if you do not have one, take 'cameraman.tif' which is built into MATLAB) and generate several noisy data sets (e.g. with MATLAB's randn) and denoise them. Choose the regularisation parameter by
 - i. by the eye-ball-metric (select a few parameters and choose the solution you like) and
 - ii. by Morozov's discrepancy principle.