

Sparse Regularization with Non-convex Regularization Terms

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Outline

- 1 Sparse Regularization
 - Quadratic Regularization
 - Regularization with Non-convex Functionals
- 2 Well-Posedness
- 3 Convergence Rates
 - Rates for Quadratic Regularization
 - Rates for Non-convex Regularization
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Setting

Let U, V be Hilbert spaces and $F: U \rightarrow V$ bounded linear.
Consider the approximative solution of the operator equation

$$F(u) = v$$

for given $v \in V$.

If the operator equation is ill-posed (e.g. if $F: U \rightarrow V$ is compact),
regularization is necessary: search for $u_\alpha \in U$ minimizing

$$\mathcal{T}(u; \alpha, v) := \|Fu - v\|^2 + \alpha \mathcal{R}(u)$$

with *regularization functional* $\mathcal{R}: U \rightarrow \mathbb{R}_{\geq 0}$ and *regularization term* $\alpha > 0$.

Quadratic Regularization

Consider

$$\mathcal{T}(u; \alpha, v) := \|Fu - v\|_V^2 + \alpha \|u\|_U^2.$$

Original setting by Tikhonov: $U = W^{k,2}(\Omega)$.

Regularization term enforces *smoothness* (differentiability) of the approximate solutions.

In some applications (signal / image processing), smoothness no realistic assumption / no important property.

Recent idea: instead of smoothness, try to enforce sparsity with respect to a given basis / frame / subset.

Sparsity

Let $(\phi_i)_{i \in I} \subset U$ be some bounded family. Find

$$u = \sum_{i \in I} u_i \phi_i \in U$$

with

$$Fu \approx v$$

such that (weak sense)

$$\#\{i \in I : |u_i| \gg 0\} \text{ is small}$$

or (strong sense)

$$\#\{i \in I : u_i \neq 0\} \text{ is finite .}$$

Sub-quadratic Regularization

Let U be a Hilbert space and $(\phi_i)_{i \in I}$ an orthonormal basis. Then

$$\|u\|_U^2 = \sum_i |u_i|^2 .$$

Idea: Obtain (weak) sparsity by replacing quadratic regularization with sub-quadratic regularization:

Consider

$$\mathcal{R}(u) := \sum_i |u_i|^p \quad \text{with } 1 \leq p < 2 .$$

Stronger penalization of small coefficients, weaker penalization of large coefficients.

Minimizer of Tikhonov functional will be in ℓ^p .

Sparsity by Differentiability

Consider $(\phi_k)_{k \in \mathbb{N}}$ Fourier-basis of $L^2(0, 2\pi)$. Then

$$\|u'\|^2 = \sum_k k^2 |u_k|^2 .$$

Reverse Hölder inequality:

$$\sum_k k^2 |u_k|^2 \geq \left(\sum_k k^{-2q} \right)^{-1/q} \left(\sum_k |u_k|^{2p} \right)^{1/p}$$

with $0 < p < 1$, $q > 0$, and $1/p - 1/q = 1$. Therefore:

$$\|u'\|^2 < +\infty \implies (u_k)_{k \in \mathbb{N}} \in \ell^{2/3+\varepsilon} .$$

But: “Scale dependent sparsity pattern.”

Non-convex Regularization

Achieve sparsity in the strong sense by choosing

$$\mathcal{R}(u) = \sum_i |u_i|^p \quad \text{with } 0 < p < 1 .$$

More general setting:

$$\mathcal{R}(u) := \sum_i w_i \phi(u_i)$$

with

$$w_i > w_{\min} \geq 0 \quad \text{and} \quad \phi: \mathbb{R} \rightarrow [0, +\infty] .$$

Conditions for this to make sense?

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Important Properties

Existence:

$\mathcal{T}(\cdot; \alpha, v)$ attains a minimizer for every $\alpha > 0$ and $v \in V$.

Stability:

If $y^{(k)} \rightarrow y$ and $u_\alpha^{(k)} \in \arg \min \mathcal{T}(\cdot; \alpha, v^{(k)})$ then

$$u_\alpha^{(k)} \rightarrow u_\alpha \in \arg \min \mathcal{T}(\cdot; \alpha, v) .$$

Convergence:

If $\|v^\delta - v^\dagger\| \leq \delta \rightarrow 0$, $\alpha \rightarrow 0$ and $\delta^2/\alpha \rightarrow 0$, then

$$\arg \min \mathcal{T}(\cdot; \alpha, v^\delta) = u_\alpha^\delta \rightarrow u^\dagger = \arg \min \{ \mathcal{R}(u) : Fu = v^\dagger \} .$$

Lower Semi-continuity

Direct method of the calculus of variations:

If \mathcal{T} is weakly lower semi-continuous and coercive, then a minimizer exists.

Recall:

$$\mathcal{R}(u) = \sum_i w_i \phi(u_i) .$$

Lemma

The following are equivalent:

- *The functional \mathcal{R} is lower semi-continuous.*
- *The functional \mathcal{R} is weakly lower semi-continuous.*
- *The function ϕ is lower semi-continuous.*

Coercivity

Recall: \mathcal{R} is coercive, if $\|u\| \rightarrow \infty$ implies $\mathcal{R}(u) \rightarrow \infty$.

Lemma

Assume that there exists $C > 0$ with

$$\phi(t) \geq \frac{Ct^2}{1+t^2}$$

and

$$\lim_{t \rightarrow \pm\infty} \phi(t) = +\infty.$$

Then \mathcal{R} is coercive.

If $\sup_j w_j < +\infty$, then also the converse holds.

If $\sup_j w_j = +\infty$, weaker growth of ϕ is possible.

Radon–Riesz Property

Under the natural assumptions introduced above, the functional \mathcal{R} satisfies the *Radon–Riesz* property:

Lemma

Let the assumptions for lower semi-continuity and coercivity be satisfied.

If $(u^{(k)})_{k \in \mathbb{N}} \subset \ell^2$ converges weakly to $u \in \ell^2$ and $\mathcal{R}(u^{(k)}) \rightarrow \mathcal{R}(u) < +\infty$, then

$$\|u^{(k)} - u\| \rightarrow 0 .$$

Important property for deducing stability and convergence in norm topology.

Well-posedness

Theorem

Assume that the following hold:

- The function ϕ is lower semi-continuous and $\phi(0) = 0$.
- $\lim_{t \rightarrow \pm\infty} \phi(t) = +\infty$.
- There exists $C > 0$ with

$$\phi(t) \geq \frac{Ct^2}{1+t^2}.$$

Then Tikhonov regularization with $\mathcal{R}(u) = \sum_i w_i \phi(u_i)$ is well-posed, stable, and convergent.

Here: stability and convergence in sub-sequential sense.

Necessary Conditions for Sparsity

Lemma

Assume that there exists $C > 0$ such that

$$\phi(t) \geq \frac{C|t|}{1 + |t|}.$$

Then every local minimizer of $\mathcal{T}(\cdot; \alpha, \nu)$ is sparse in the strong sense.

In a sense:

Sparsity of solution \iff Non-differentiability of ϕ at 0.

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Convergence Rates for Quadratic Regularization

Quantitative estimate of the quality of the regularized solutions:

Let

$$\mathcal{R}(u) = \|u\|^2 \quad \text{and} \quad u^\dagger \in \text{Ran } F^* .$$

If

$$\delta \sim \alpha, \quad \|v^\delta - v^\dagger\| \leq \delta \rightarrow 0,$$

and

$$u_\alpha^\delta \in \arg \min_u \mathcal{T}(u; \alpha, v^\delta),$$

then

$$\|u_\alpha^\delta - u^\dagger\| = O(\sqrt{\delta}) \quad \text{as } \delta \rightarrow 0 .$$

Infinite Growth at Zero

Recall: lower Dini derivatives of $\phi: \mathbb{R} \rightarrow [0, +\infty]$ defined as

$$D_+\phi(t) = \liminf_{\varepsilon \rightarrow 0^+} \frac{\phi(t + \varepsilon) - \phi(t)}{\varepsilon},$$

$$D_-\phi(t) = \liminf_{\varepsilon \rightarrow 0^-} \frac{\phi(t + \varepsilon) - \phi(t)}{\varepsilon}.$$

In particular:

$$D_{\pm}\phi(0) = \pm\infty \quad \iff \quad \phi \text{ has infinite growth near zero.}$$

Convergence Rates for Sparse Regularization

Define

$$\text{supp}(u^\dagger) := \{i \in I : u_i^\dagger \neq 0\}.$$

Theorem

Assume that the following hold:

- $D_\pm \phi(0) = \pm\infty$.
- u^\dagger is the unique \mathcal{R} -minimizing solution of $Fu = y^\dagger$.
- u^\dagger is sparse and F is injective on $\ell^2(\text{supp}(u^\dagger))$.

If $\alpha \sim \delta$ we have

$$\|u_\alpha^\delta - u^\dagger\| = O(\delta).$$

Restricted Injectivity

Uniqueness of u^\dagger necessary for obtaining any convergence rates (else: convergence to different minimizers).

In non-convex case, uniqueness of u^\dagger stronger condition than restricted injectivity:

If $\phi \in C^2(\mathbb{R} \setminus \{0\})$ and $\phi''(t) \leq 0$ for $t \neq 0$, then:

$$\text{Uniqueness of } u^\dagger \implies \text{Injectivity of } F \text{ on } \text{supp}(u^\dagger).$$

More general: same implication holds, if ϕ is locally concave on $\mathbb{R} \setminus \{0\}$.

Summary

- General setting for (componentwise) Tikhonov regularization on ℓ^2 :

$$\mathcal{R}(u) = \sum_i w_i \phi(u_i) .$$

- Necessary and sufficient conditions for well-posedness (existence, stability, convergence) only in terms of ϕ .
- Sparsity for sufficiently fast growth at zero.
- Linear convergence rates for infinite growth at zero — if minimizer is unique.