

Mathematics of Image and Data Analysis

Math 5467

Lecture 12: Signal Denoising

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Last time

- Parseval and Convolution

Today

- Signal Denoising with Tikhonov regularization

Recall

Definition 1. The *Discrete Fourier Transform (DFT)* is the mapping $\mathcal{D} : L^2(\mathbb{Z}_n) \rightarrow L^2(\mathbb{Z}_n)$ defined by

$$\mathcal{D}f(\ell) = \sum_{k=0}^{n-1} f(k)\omega^{-k\ell} = \sum_{k=0}^{n-1} f(k)e^{-2\pi i k\ell/n},$$

where $\omega = e^{2\pi i/n}$ and $\mathbb{Z}_n = \{0, 1, \dots, n-1\}$ is the cyclic group $\mathbb{Z}_n = \mathbb{Z}/n$.

Definition 2 (Inverse Discrete Fourier Transform). The *Inverse Discrete Fourier Transform (IDFT)* is the mapping $\mathcal{D}^{-1} : L^2(\mathbb{Z}_n) \rightarrow L^2(\mathbb{Z}_n)$ defined by

$$\mathcal{D}^{-1}f(\ell) = \frac{1}{n} \sum_{k=0}^{n-1} f(k)\omega^{k\ell} = \frac{1}{n} \sum_{k=0}^{n-1} f(k)e^{2\pi i k\ell/n}.$$

Lemma 3 (Convolution and the DFT). For $f, g \in L^2(\mathbb{Z}_n)$ we have

(1)
$$\mathcal{D}(f * g) = \mathcal{D}f \cdot \mathcal{D}g. \quad \underbrace{(f * g)(k)} = \sum_{j=0}^{n-1} f(j)g(k-j)$$

Exercise on discrete derivatives

Exercise 4. Discrete derivatives (difference quotients) can be interpreted as convolutions. Complete the following exercises.

(i) For $f \in L^2(\mathbb{Z}_n)$ define the backward difference

$$\nabla^- f(k) = f(k) - f(k-1).$$

Find $g \in L^2(\mathbb{Z}_n)$ so that $\nabla^- f = g * f$ and use this with Lemma 3 to show that $\mathcal{D}(\nabla^- f)(k) = (1 - \omega^{-k})\mathcal{D}f(k)$, where $\omega = e^{2\pi i/n}$.

(ii) For $f \in L^2(\mathbb{Z}_n)$ define the forward difference

$$\nabla^+ f(k) = f(k+1) - f(k).$$

Find $g \in L^2(\mathbb{Z}_n)$ so that $\nabla^+ f = g * f$ and use this with Lemma 3 to show that $\mathcal{D}(\nabla^+ f)(k) = (\omega^k - 1)\mathcal{D}f(k)$.

(iii) For $f \in L^2(\mathbb{Z}_n)$ define the centered difference by

$$\nabla f(k) = \frac{1}{2}(\nabla^- f(k) + \nabla^+ f(k)) = \frac{1}{2}(f(k+1) - f(k-1)).$$

Use parts (i) and (ii) to show that

$$\mathcal{D}(\nabla f)(k) = \frac{1}{2}(\omega^k - \omega^{-k})\mathcal{D}f(k) = i \sin(2\pi k/n)\mathcal{D}f(k).$$

(iv) For $f \in L^2(\mathbb{Z}_n)$, define the discrete Laplacian as

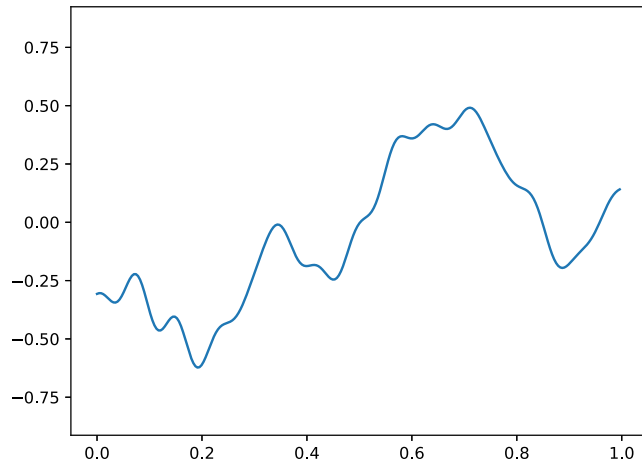
$$\Delta f(k) = \nabla^+ \nabla^- f(k) = f(k+1) - 2f(k) + f(k-1).$$

Use parts (i) and (ii) to show that

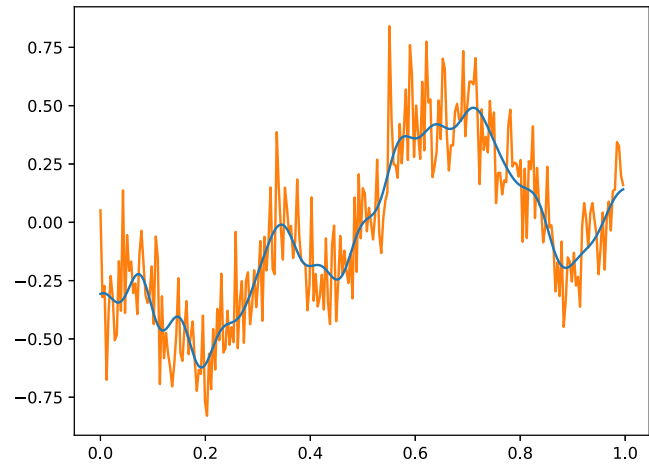
$$\mathcal{D}(\Delta f)(k) = (\omega^k + \omega^{-k} - 2)\mathcal{D}f(k) = 2(\cos(2\pi k/n) - 1)\mathcal{D}f(k). \quad \triangle$$

$$\nabla^+ f - \nabla^- f$$

Signal denoising



(a) Clean signal



(b) Noisy signal

Figure 1: Example of a clean signal, and a noisy version, corrupted with additive Gaussian noise. The clean signal is superimposed over the noisy one in (b) for reference.

Sources of noise

A brief (and not exhaustive) list of sources of signal noise.

- Signal acquisition (microphone diaphragm, camera sensor).
- Thermal noise in electronic circuitry.
- Noise from signal compression artifacts.
- Corruption of wireless signals.

Tikhonov regularization

Let $f \in L^2(\mathbb{Z}_n)$ be the noisy signal. Tikhonov regularized denoising minimizes the energy $E : L^2(\mathbb{Z}_n) \rightarrow L^2(\mathbb{Z}_n)$ defined by

$$(2) \quad E(u) = \underbrace{\sum_{k=0}^{n-1} |u(k) - f(k)|^2}_{\text{Data Fidelity}} + \lambda \underbrace{\sum_{k=0}^{n-1} |u(k) - u(k-1)|^2}_{\text{Regularizer}},$$

(Handwritten red annotations: $\nabla u(k)$ above the second sum, and a red bracket above it)

where $\lambda \geq 0$ is a parameter.

Main ideas:

- Data fidelity keeps the denoised signal close to the noisy signal f .
- Regularizer removes the noise.

Tikhonov regularization

We recall the backward difference $\nabla^- : L^2(\mathbb{Z}_n) \rightarrow L^2(\mathbb{Z}_n)$ is defined by

$$\nabla^- u(k) = u(k) - u(k-1),$$

while the forward difference is $\nabla^+ u(k) = u(k+1) - u(k)$. The discrete Laplacian is

$$\Delta u = \nabla^+ \nabla^- u = \nabla^- \nabla^+ u.$$

In terms of this notation, the Tikhonov regularized denoising problem is

$$(3) \quad \min_{u \in L^2(\mathbb{Z}_n)} E(u) = \|u - f\|^2 + \lambda \|\nabla^- u\|^2.$$

fidelity regularizer

Theorem 5. Let $\lambda \geq 0$ and $f \in L^2(\mathbb{Z}_n)$. Then there exists a unique solution $u \in L^2(\mathbb{Z}_n)$ of the optimization problem (3). Furthermore, the minimizer u is also characterized as the unique solution of the Euler-Lagrange equation

$$(4) \quad \nabla E = 0 \quad \longleftrightarrow \quad \underline{u - \lambda \Delta u = f.} \quad \text{on } \mathbb{Z}_n.$$

Properties of discrete derivatives

Before proving the theorem, we need to establish some basic properties of discrete derivatives. These are the discrete analogs of integration by parts formulas.

Proposition 6. For all $u, v \in L^2(\mathbb{Z}_n)$ the following hold.

(i) $\langle \nabla^- u, v \rangle = -\langle u, \nabla^+ v \rangle$

(ii) $\langle \nabla^+ u, v \rangle = -\langle u, \nabla^- v \rangle$

(iii) $\langle \Delta u, v \rangle = \langle u, \Delta v \rangle$

$$\int_0^1 u'v \, dx = uv \Big|_0^1 - \int_0^1 uv' \, dx$$

on periodic domain

$$u(0) = u(1)$$

$$v(0) = v(1).$$

Remark 7. We can take $u = v$ to obtain

$$\|\nabla^+ u\|^2 = \|\nabla^- u\|^2 = -\langle \Delta u, u \rangle.$$

$$\|\nabla^- u\|^2 = \langle \nabla^- u, \nabla^- u \rangle = -\langle \nabla^+ \nabla^- u, u \rangle$$

\uparrow Regularizer (ii)

(i) Proof $\langle \nabla^- u, v \rangle = \sum_{k=0}^{n-1} \underbrace{(u(k) - u(k-1)) \overline{v(k)}}_{\nabla^- u(k)}$

$$\Rightarrow \sum_{k=0}^{n-1} u(k) \overline{v(k)} - \sum_{k=0}^{n-1} u(k-1) \overline{v(k)}.$$

$j = k-1$

$$= \sum_{k=0}^{n-1} u(k) \overline{v(k)} - \sum_{j=-1}^{n-2} u(j) \overline{v(j+1)}$$

$$\boxed{-1 \equiv n-1 \pmod{n}}$$

$$= \sum_{k=0}^{n-1} u(k) \overline{v(k)} - \sum_{j=0}^{n-1} u(j) \overline{v(j+1)}$$

$$= \sum_{k=0}^{n-1} u(k) \overbrace{(v(k) - v(k+1))}^{-\Delta^+ v(k)}$$

$$= -\langle u, \Delta^+ v \rangle. \quad \square$$

(ii) Similar proof, or by (i).

$$(iii) \quad \langle \Delta u, v \rangle = \langle \Delta^+ \Delta^- u, v \rangle$$

$$(ii) = -\langle \Delta^- u, \Delta^- v \rangle$$

$$(i) = \langle u, \Delta^+ \Delta^- v \rangle = \langle u, \Delta v \rangle. \quad \square$$

Proof of Theorem: First show that

$$(*) \quad u - \lambda \Delta u = f$$

has a unique solution u for each $\lambda \geq 0$, $f \in L^2(\mathbb{R}^n)$

Uniqueness: Let u, v be solutions of $(*)$. Set $w = u - v$.

Note

$$w - \lambda \Delta w = 0$$

Take inner product on both sides with w :

$$\langle w - \lambda \Delta w, w \rangle = 0$$

$$\|w\|^2 - \lambda \langle \Delta w, w \rangle = 0$$

$$\|w\|^2 + \lambda \|\nabla w\|^2 = 0 \implies w = 0$$

$\implies u = v$. Existence of a solution follows

by Rank-Nullity Theorem.

Now, we show that the unique solution u of $(\#)$ minimizes $E(u) = \|u - f\|^2 + \lambda \|\nabla u\|^2$.

Let $w \in L^2(\mathbb{R}^n)$. Want to show $E(u) \leq E(w)$.

Set $v = w - u$ and for $t \in \mathbb{R}$, set

$$e(t) = E(u + tv).$$

Then

$$E(w) - E(u) = e(1) - e(0) = \int_0^1 e'(t) dt$$

for $t \geq 0$

We claim $e'(t) \geq 0$ and so $E(u) - E(u) \geq 0$.

Aside: $\|g+h\|^2 = \|g\|^2 + 2\operatorname{Re}\langle g, h \rangle + \|h\|^2$

EX \rightarrow

$$\begin{aligned} e(t) &= \|u + tv - f\|^2 + \lambda \|\nabla^- u + t\nabla^- v\|^2 \\ &= \|u - f\|^2 + 2t\operatorname{Re}\langle u - f, v \rangle + t^2\|v\|^2 \\ &\quad + \lambda\|\nabla^- u\|^2 + 2\lambda t\operatorname{Re}\langle \nabla^- u, \nabla^- v \rangle + \lambda t^2\|\nabla^- v\|^2 \end{aligned}$$

$$\langle \nabla^- u, \nabla^- v \rangle = -\langle \nabla^+ \nabla^- u, v \rangle = -\langle \Delta u, v \rangle$$

$$\begin{aligned} e(t) &= E(u) + 2t\operatorname{Re}\langle u - f - \lambda \Delta u, v \rangle \\ &\quad + t^2(\|v\|^2 + \lambda\|\nabla^- v\|^2). \end{aligned}$$

$$(**) e'(t) = 2 \operatorname{Re} \langle u - \lambda \Delta u - f, v \rangle$$

Since u solves (*) $+ 2t (\|v\|^2 + \lambda \|\nabla v\|^2)$

$$= 2t (\|v\|^2 + \lambda \|\nabla v\|^2) \geq 0 \text{ for } t \geq 0. \quad \checkmark$$

$\Rightarrow u$ minimizes E . To show that minimizer is unique, let u be any minimizer. Let $v \in L^2(\mathbb{R}^n)$ and $e(t) = E(u + tv)$. Note $e'(0) = 0$, since $e(0) = E(u) \leq E(u + tv) = e(t)$.

By (**), $0 = e'(0) = 2 \operatorname{Re} \langle u - \lambda \Delta u - f, v \rangle$

Take $v = u - \lambda \Delta u - f$ to get $\|u - \lambda \Delta u - f\|^2 = 0$.

$\Rightarrow u - \lambda \Delta u = f \Rightarrow$ minimizers are unique \square

Maximum principle

Proposition 8 (Maximum Principle). *Let $\lambda \geq 0$ and let $f \in L^2(\mathbb{Z}_n)$ be real-valued. Let $u \in L^2(\mathbb{Z}_n)$ be the denoised signal, i.e., the solution of*

$$u - \lambda \Delta u = f,$$

which is also real-valued. Then we have

$$(5) \quad \min_{\mathbb{Z}_n} f \leq u \leq \max_{\mathbb{Z}_n} f.$$

How to solve the Euler-Lagrange equation?

We can use the DFT (and FFT) to solve the Tikhonov regularized denoising equation

$$u - \lambda \Delta u = f.$$

Indeed, the solution is given by

$$(6) \quad u = \mathcal{D}^{-1}(G_\lambda \cdot \mathcal{D}f).$$

where

$$G_\lambda(k) = \frac{1}{1 + 2\lambda - 2\lambda \cos(2\pi k/n)}.$$

Take DFT on both sides of $u - \lambda \Delta u = f$

$$\mathcal{D}u - \lambda \mathcal{D}(\Delta u) = \mathcal{D}f$$

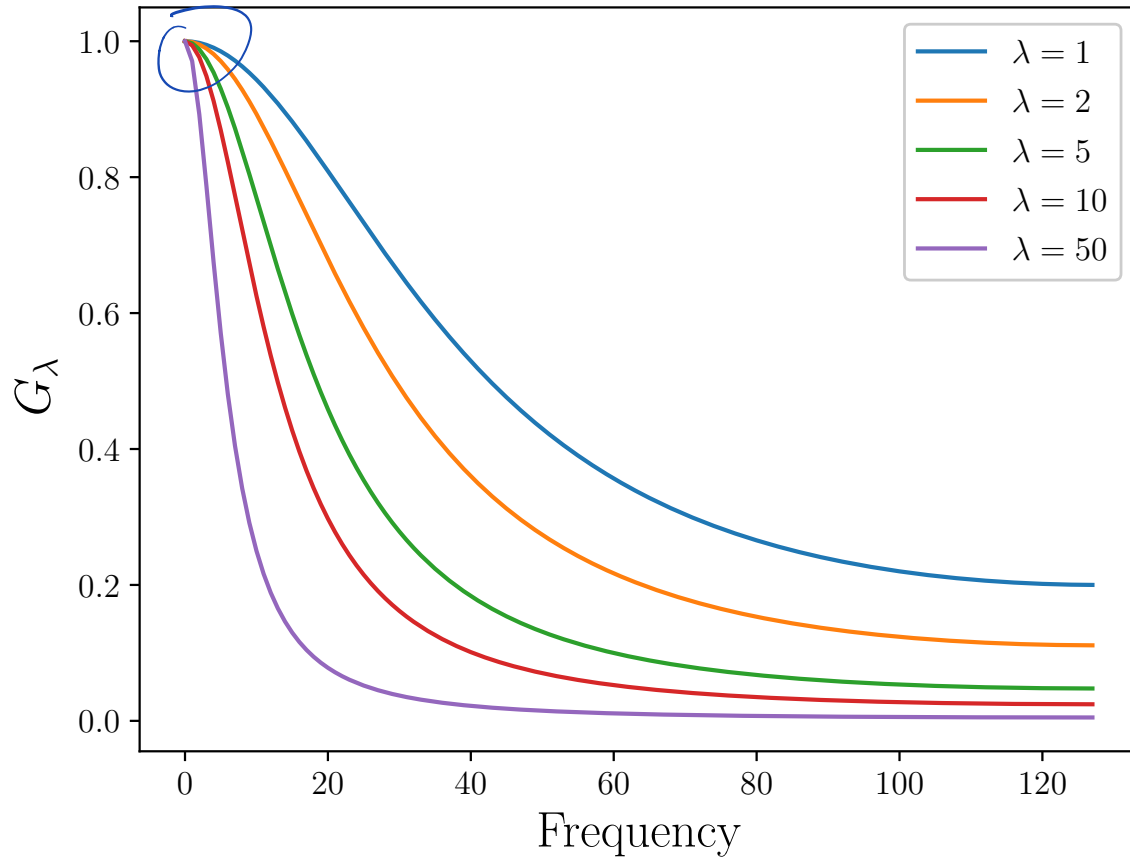
$$\mathcal{D}u(k) - \lambda 2(\cos(2\pi k/n) - 1)\mathcal{D}u(k) = \mathcal{D}f(k)$$

$$Du(k) (1 - 2\lambda (\cos(2\pi k/n) - 1)) = Df(k)$$

$$Du(k) = G_\lambda(k) \underline{\underline{Df(k)}}$$

$$u = D^{-1}(G_\lambda \cdot Df).$$

The low-pass filter G_λ



The filtering perspective

$$\mathcal{D}(f * g) = \mathcal{D}f \cdot \mathcal{D}g.$$

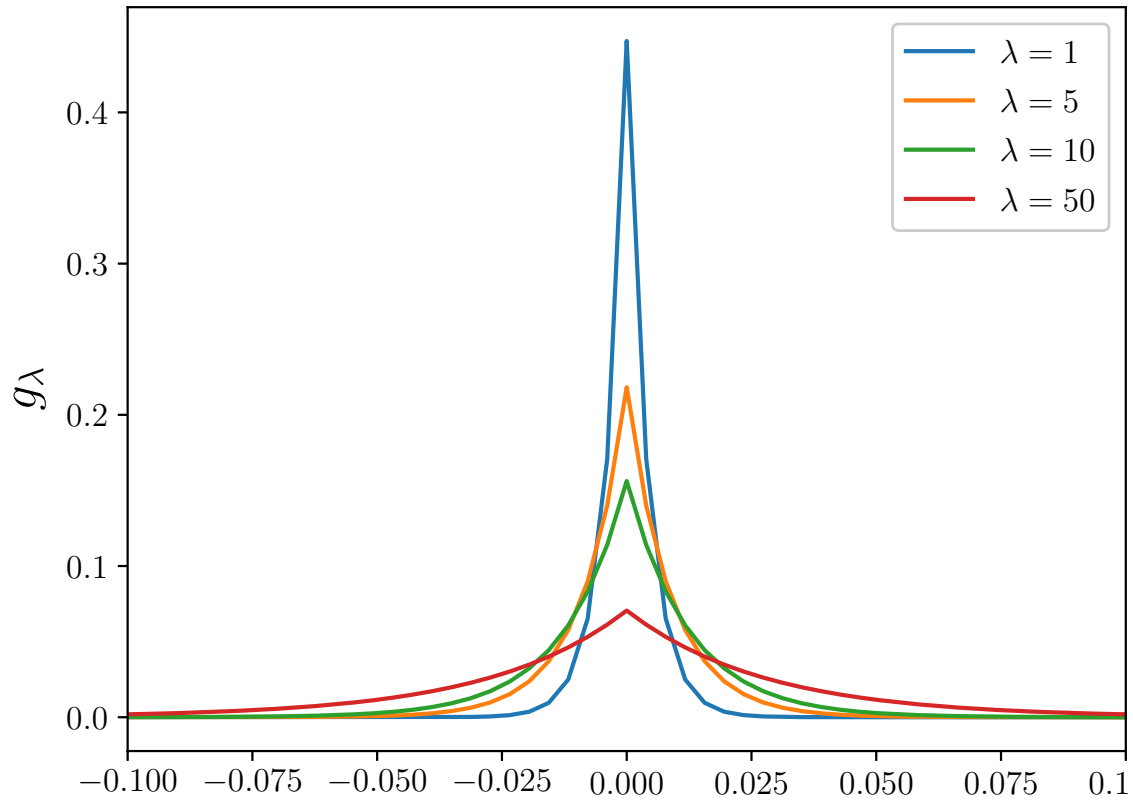
Defining $g_\lambda = \mathcal{D}^{-1}G_\lambda$ we have

$$u = \mathcal{D}^{-1}(\mathcal{D}g_\lambda \cdot \mathcal{D}f) = g_\lambda * f.$$

The function g_λ is often called a *kernel*. The convolution to compute $u(k)$ should be thought of as a weighted average, weighted by g_λ , of the values of f nearby k . Indeed, we have

$$u(k) = (g_\lambda * f)(k) = \sum_{j=0}^{n-1} g_\lambda(j) f(k-j).$$

The convolutional kernel g_λ (fundamental solution)



Tikhonov denoising ([.ipynb](#))