

# Mathematics of Image and Data Analysis

## Math 5467

### Lecture 13: TV Denoising

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## Last time

- Tikhonov regularized denoising

## Today

- Total Variation (TV) regularized denoising

# 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

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

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

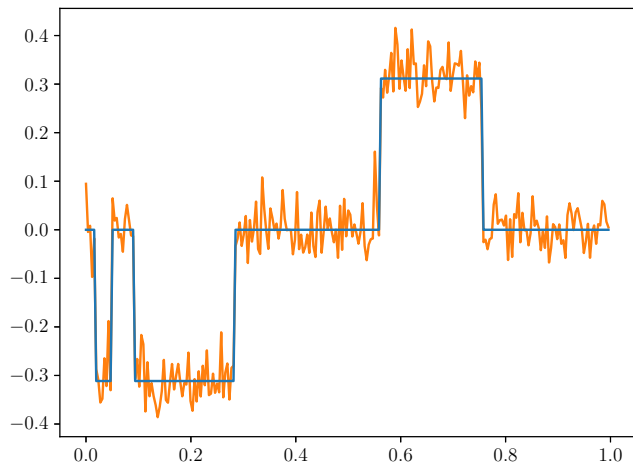
$$(2) \quad \min_{u \in L^2(\mathbb{Z}_n)} E(u) = \|u - f\|^2 + \lambda \|\nabla^- u\|^2.$$

**Theorem 1.** *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 (2). Furthermore, the minimizer  $u$  is also characterized as the unique solution of the Euler-Lagrange equation*

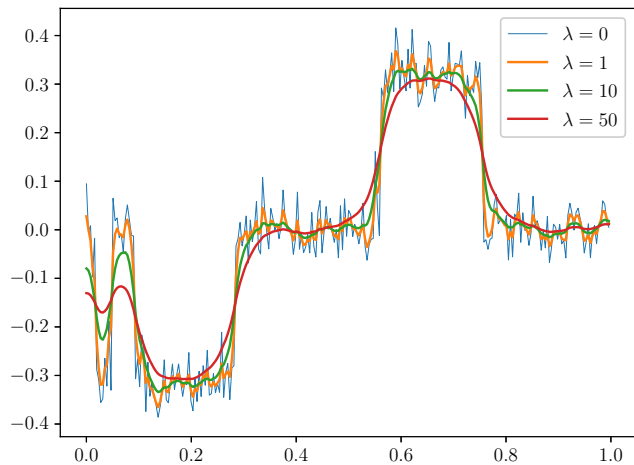
$$(3) \quad u - \lambda \Delta u = f.$$

$$\nabla E = 0$$

# Tikhonov regularization



(a) Noisy signal



(b) Tikhonov denoising

# Total Variation Regularization

Total Variation (TV) regularization replaces the squared difference by the absolute differences in the regularizer.

$$(4) \quad E(u) = \frac{1}{2} \sum_{k=0}^{n-1} |u(k) - f(k)|^2 + \lambda \sum_{k=0}^{n-1} |u(k) - u(k-1)|.$$

Total variation of  $u$ .

- TV regularization is better at preserving edges (sharp changes) in the signal.
- The analysis is more involved, since the denoising equation is *nonlinear*.

# Variational Regularized Denoising

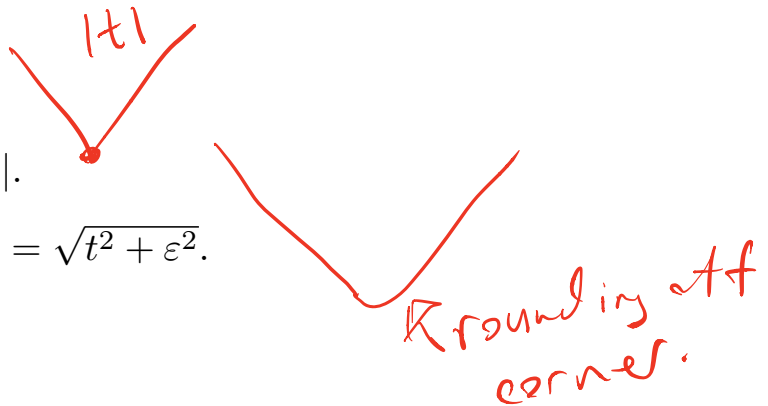
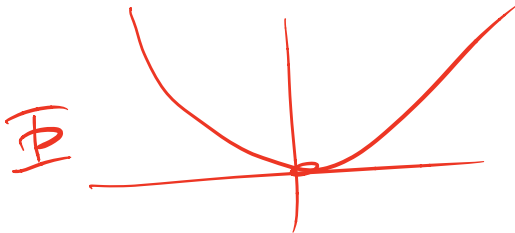
$$\|x\|_2 = \sum_{k=0}^{n-1} |x(k)|$$

We will proceed in generality, studying regularizers of the form

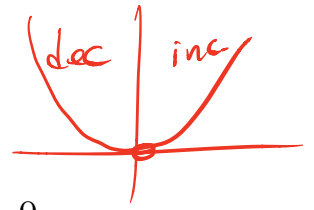
$$(5) \quad \sum_{k=0}^{n-1} \Phi(u(k) - u(k-1)) = \sum_{k=0}^{n-1} \Phi(\nabla^- u(k)) = \|\Phi(\nabla^- u)\|_1,$$

where  $\Phi : \mathbb{R} \rightarrow \mathbb{R}$  is a twice continuously differentiable, convex, and even function satisfying  $\Phi(0) = 0$ .

- Tikhonov is  $\Phi(t) = t^2$
- Total Variation (TV) is  $\Phi(t) = |t|$ .
- We will approximate TV by  $\Phi(t) = \sqrt{t^2 + \varepsilon^2}$ .



# Convexity



We say  $\Phi$  convex if  $\Phi'' \geq 0$ . We also assumed  $\Phi$  is even and  $\Phi(0) = 0$ .

The following properties hold:

$$\Phi'(0) = \lim_{h \rightarrow 0} \frac{\Phi(h) - \Phi(-h)}{2h} = 0$$

(i)  $\Phi'$  is increasing. ✓

(ii) Since  $\Phi$  is even and  $\Phi(0) = 0$  we have  $\Phi'(0) = 0$ .

(iii)  $\Phi'(t) \leq 0$  for  $t < 0$  and  $\Phi'(t) \geq 0$  for  $t > 0$ .  $\Rightarrow \Phi \geq 0$

(iv) For any  $t, s \in \mathbb{R}$  we have

$$(\Phi'(t) - \Phi'(s))(t - s) \geq 0. \quad (\text{monotonicity})$$

Proof (iv): If  $t \geq s$  then  $\Phi'(t) - \Phi'(s) \geq 0$  and  $t - s \geq 0$

If  $t \leq s$  then  $\Phi'(t) - \Phi'(s) \leq 0$  and  $t - s \leq 0$






# Total Variation Denoising

The Total Variation (TV) regularized denoising function is

$$(6) \quad E_{\Phi}(u) = \frac{1}{2} \|u - f\|^2 + \lambda \|\Phi(\nabla^{-} u)\|_1.$$

The denoised signal  $u$  is found by minimizing  $E_{\Phi}$ .

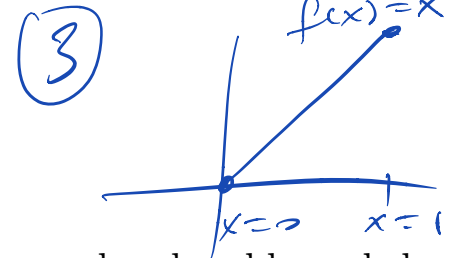
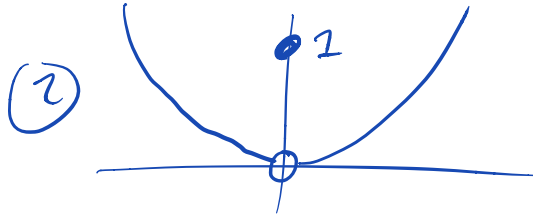
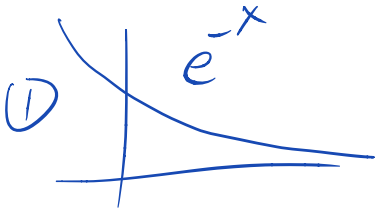
**Note:** We will work with real-value signals in this lecture, for simplicity. We denote by  $L^2(\mathbb{Z}_n; \mathbb{R})$  the subspace of  $L^2(\mathbb{Z}_n)$  consisting of  $f : \mathbb{Z}_n \rightarrow \mathbb{R}$ .



# Existence of a minimizer

**Lemma 2.** For any  $f \in L^2(\mathbb{Z}_n; \mathbb{R})$  and  $\lambda \geq 0$ , there exists  $u \in L^2(\mathbb{Z}_n; \mathbb{R})$  minimizing  $E_\Phi$ , i.e.,  $E_\Phi(u) \leq E_\Phi(w)$  for all  $w \in L^2(\mathbb{Z}_n; \mathbb{R})$ . Furthermore,  $u$  satisfies

$$(7) \quad \min_{\mathbb{Z}_n} f \leq u \leq \max_{\mathbb{Z}_n} f.$$



The proof is based on a simple fact: A continuous function on a closed and bounded subset of  $\mathbb{R}^n$  attains its minimum value.

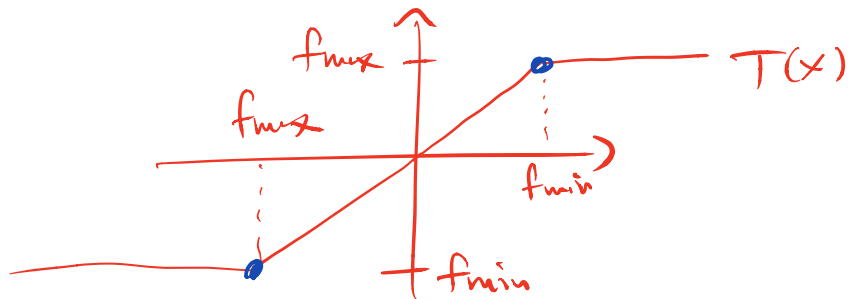
- $f(x) = e^{-x}$  does not have a minimum value on  $\mathbb{R}$  (unbounded set).
- $f(x) = x^2$  for  $x \neq 0$  and  $f(0) = 1$  does not have a minimum value (discontinuous function).
- $f(x) = x$  does not have a minimum value on  $(0, 1)$  (open set).

Proof: Define

$$T(x) = \begin{cases} f_{\min}, & \text{if } x < f_{\min} \\ x, & \text{if } f_{\min} \leq x \leq f_{\max} \\ f_{\max}, & \text{if } x > f_{\max} \end{cases}$$

$$f_{\min} = \min_{\mathbb{R}^n} f$$

$$f_{\max} = \max_{\mathbb{R}^n} f$$



Claim:

$$|T(x) - T(y)| \leq |x - y|$$

Assume  $x \geq y$  and compute

$$T(x) - T(y) = \int_y^x T'(t) dt \leq \int_y^x \left( \max_{\mathbb{R}} T' \right) dt$$

$$= (\max_{\mathbb{R}} T') \int_y^x 1 dt$$

$$= \underbrace{(\max_{\mathbb{R}} T')}_{=1} |x-y| \quad \checkmark$$

Let  $u \in L^2(\mathbb{R}_n; \mathbb{R})$  and define  $w(k) = T(u(k))$

Claim:  $E_{\Phi}(w) \leq E_{\Phi}(u)$ .

$$E_{\Phi}(w) = \frac{1}{2} \sum_{k=0}^{n-1} |w(k) - f(k)|^2 + \lambda \sum_{k=0}^{n-1} |w(k) - w(k-1)|^2$$

$$|w(k) - f(k)|^2 = |T(u(k)) - T(f(k))|^2 \leq |u(k) - f(k)|^2$$

Works for  
TV

$$T(f) = f.$$

Lipschitzness  
of  $T$

$$|w(k) - w(k-1)| = |T(w(k)) - T(w(k-1))|$$

(\*)

$T$   
Lipschitz

$$\rightarrow \leq |w(k) - w(k-1)| \quad \checkmark$$

This means we can minimize  $E_{\mathbb{F}}$  over  
the closed and bounded set

$$M = \left\{ u \in L^2(\mathbb{Z}_n; \mathbb{R}) : f_{\min} \leq u(k) \leq f_{\max} \right. \\ \left. \text{for all } k \right\}.$$

$$\hat{\cong} [f_{\min}, f_{\max}]^n \subseteq \mathbb{R}^n.$$

So  $\exists$  minimizer  $u \in M$  of  $E_{\Phi}$ , minimal over  $M$ , so

$$E_{\Phi}(u) \leq E_{\Phi}(w) \quad \forall w \in M.$$

If  $v \in L^2(\mathbb{Z}^n; \mathbb{R})$ , then

$$E_{\Phi}(u) \leq E_{\Phi}(T(v)) \leq E_{\Phi}(v).$$



(\*) For general  $\Phi$ : (Recall  $w(k) = T(u(k))$ )

$$\Phi(\nabla^- w(k)) = \Phi(w(k) - w(k-1))$$

$$\Phi \text{ even} = \Phi(|w(k) - w(k-1)|)$$

$$\Phi(t) \text{ is increasing for } t > 0 \leq \Phi(|w(k) - w(k-1)|)$$

$$= \Phi(w(k) - w(k-1)) = \Phi(\nabla^- u(k)).$$





# Euler-Lagrange equation

**Lemma 3.** Let  $f \in L^2(\mathbb{Z}_n; \mathbb{R})$  and  $\lambda \geq 0$ . Then the minimizer  $u \in L^2(\mathbb{Z}_n; \mathbb{R})$  of  $E_\Phi$  is unique and is characterized as the unique solution of the Euler-Lagrange equation

$$(8) \quad u - \lambda \nabla^+ \Phi'(\nabla^- u) = f.$$

Tikhonov:  $u - \lambda \Delta u = f$

$$(\Phi(t) = \frac{1}{2} t^2)$$

$$\Phi'(t) = t$$

Recall

**Proposition 4.** For all  $u, v \in L^2(\mathbb{Z}_n)$  the following hold.

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

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

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

Proof: let  $u$  be a minimizer of  $E_{\mathbb{F}}$ .

Let  $v \in L^2(\mathbb{Z}_n; \mathbb{R})$  and set

$$e(t) = E_{\mathbb{F}}(u + tv).$$

Since  $e(0) = E_{\mathbb{F}}(u) \leq E_{\mathbb{F}}(u + tv) = e(t)$

$e$  has a minimizer at  $t=0$ . Hence

$$0 = e'(0) = \left. \frac{d}{dt} \right|_{t=0} E_{\mathbb{F}}(u + tv).$$

$$e(t) = E_{\mathbb{F}}(u + tv)$$

$$\begin{aligned}
 &= \frac{1}{2} \|u + tv - f\|^2 + \lambda \sum_{k=0}^{n-1} \Phi(\nabla^{-}u(k) + t \nabla^{-}v(k)) \\
 &= \frac{1}{2} \left( \|u - f\|^2 + 2t \langle u - f, v \rangle + t^2 \|v\|^2 \right)
 \end{aligned}$$

$$\begin{aligned}
 e'(t) &= \langle u - f, v \rangle + \cancel{t \|v\|^2} \rightarrow 0 \text{ when } t=0. \\
 &\quad + \lambda \sum_{k=0}^{n-1} \Phi'(\nabla^{-}u(k) + t \nabla^{-}v(k)) \nabla^{-}v(k)
 \end{aligned}$$

$$\begin{aligned}
 0 = e'(0) &= \langle u - f, v \rangle + \lambda \langle \Phi'(\nabla^{-}u), \nabla^{-}v \rangle \\
 &= \langle u - f, v \rangle - \lambda \langle \nabla^{+} \Phi'(\nabla^{-}u), v \rangle
 \end{aligned}$$

Gateaux Derivative =  $\langle u - \lambda \nabla^T \Phi'(\nabla^- u) - f, v \rangle$ .

$$\frac{d}{dt} \Big|_{t=0} E_{\Phi}(u+tv) = \langle u - \lambda \nabla^T \Phi'(\nabla^- u) - f, v \rangle = 0$$

↑ Directional Derivative

$\nabla E_{\Phi}(u)$  = Gradient of E.

Since this holds for all  $v$ , choose

$$v = \nabla E_{\Phi}(u) \quad \text{to get} \quad \|\nabla E_{\Phi}(u)\|^2 = 0$$

$$\text{or} \quad \nabla E_{\Phi}(u) = 0.$$

Aside = If  $f: \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $\frac{d}{dt} \Big|_{t=0} f(x+tv) = \nabla f(x) \cdot v$

We now show that solutions of

$$\textcircled{1} \quad u - \lambda \nabla^+ \Phi'(\nabla^- u) = f$$

are unique. Let  $v$  be another solution

$$\textcircled{2} \quad v - \lambda \nabla^+ \Phi'(\nabla^- v) = f$$

Diff of  $\textcircled{1} - \textcircled{2}$

$$u - v - \lambda \nabla^+ (\Phi'(\nabla^- u) - \Phi'(\nabla^- v)) = 0$$

Take inner product with  $u-v$  on both sides:

$$\langle u-v - \lambda \nabla^T (\Phi'(\bar{v}u) - \Phi'(\bar{v}v)), u-v \rangle = 0$$

$$\|u-v\|^2 - \lambda \langle \nabla^T (\Phi'(\bar{v}u) - \Phi'(\bar{v}v)), u-v \rangle = 0$$

*prop.*  $\nabla^T$

$$\|u-v\|^2 + \lambda \langle \Phi'(\bar{v}u) - \Phi'(\bar{v}v), \bar{v}u - \bar{v}v \rangle = 0$$

$$(\Phi'(t) - \Phi'(s))(t-s) \geq 0$$

due to convexity of  $\Phi$

$\Rightarrow$  both terms above are  $\geq 0$

and they sum to zero, so

both vanish  $\Rightarrow u = v$ .







# The gradient of $E_{\Phi}$

The gradient of  $E_{\Phi}$  can be interpreted as

$$\nabla E_{\Phi}(u) = u - \lambda \nabla^+ \Phi'(\nabla^- u) - f.$$

Definition of  $\nabla E_{\Phi}$  is

$$\frac{d}{dt} \Big|_{t=0} E_{\Phi}(u + tv) = \langle \nabla E_{\Phi}(u), v \rangle.$$

If  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  then 

$$x, v \in \mathbb{R}^n \quad \frac{d}{dt} \Big|_{t=0} f(x + tv) = \nabla f(x) \cdot v = \langle \nabla f, v \rangle.$$



# Gradient Descent

We can minimize  $E_{\Phi}$  by gradient descent

$$(GD) \quad u_{j+1} = u_j - dt \nabla E_{\Phi}(u_j) = u_j - dt (u_j - \lambda \nabla^+ \Phi'(\nabla^- u_j) - f)$$

$C \lambda \Delta u$  Linear approx.

Time step restriction: For stability and convergence of the gradient descent iteration, we have a time step restriction

$$dt \leq \frac{2}{1 + 4C_{\Phi}\lambda},$$

where  $C_{\Phi} = \max_{t \in \mathbb{R}} \Phi''(t)$ . This follows from a Von Nuemann analysis using the DFT.

## Von Neumann Analysis:

① Linearize the GD equation.

$$\Phi'(t) - \Phi'(s) = \int_s^t \Phi''(\tau) d\tau$$

$$\approx \Phi''(t) \cdot (t-s)$$

Set  $C_{\Phi} = \max_{t \in \mathbb{R}} \Phi''(t)$

and replace

$$\begin{aligned}
 \nabla^+ \Phi'(\nabla^- u(k)) &= \Phi'(\nabla^- u(k+1)) - \Phi'(\nabla^- u(k)) \\
 &\approx C_{\Phi} (\nabla^- u(k+1) - \nabla^- u(k)) \\
 &= C_{\Phi} \nabla^+ \nabla^- u(k) = C_{\Phi} \Delta u
 \end{aligned}$$

Linearized eq =

$$u_{j+1} = u_j - \Delta t (u_j - \lambda C_{\Phi} \Delta u_j - f).$$

Take DFT on both sides

$$Du_{j+1} = (1 - dt) Du_j + \lambda c_{\Phi} dt D(\Delta u_j) + \cancel{dt Df}$$

assume  $D$

$$D(\Delta u_j)(k) = 2(\cos(2\pi k/a) - 1) Du_j(k).$$

$$Du_{j+1} = \left(1 - dt + \underbrace{2\lambda c_{\Phi} dt}_{\lambda_k} (\cos(2\pi k/a) - 1)\right) Du_j$$

$\uparrow$   
 $\frac{k}{a} = \text{frequency}$

$$Du_{j+1}(k) = \lambda_k Du_j(k)$$

induction

$$Du_j(k) = \lambda_k^j Du_0(k).$$

For the scheme to be stable need

$$\forall k; \quad -1 \leq \lambda_k \leq 1$$

$$1 \geq \lambda_k = 1 - dt + 2\lambda C_{\Phi} dt \underbrace{(\cos(2\pi k/n) - 1)}_{\leq 0} \geq 1 - dt - 4\lambda C_{\Phi} dt$$

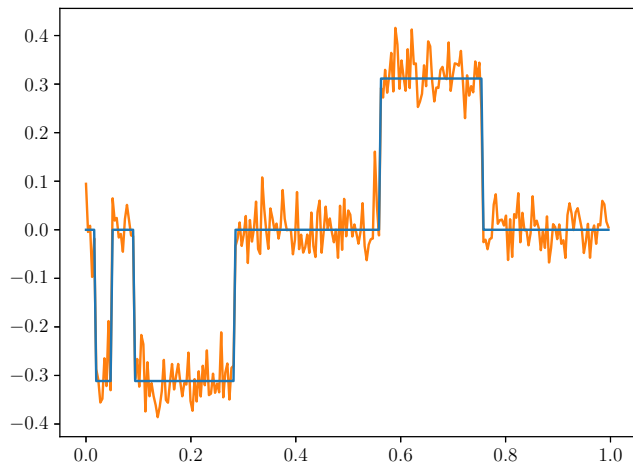
want  $\geq -1$

$$1 - dt(1 + 4\lambda C_{\Phi}) \geq -1$$

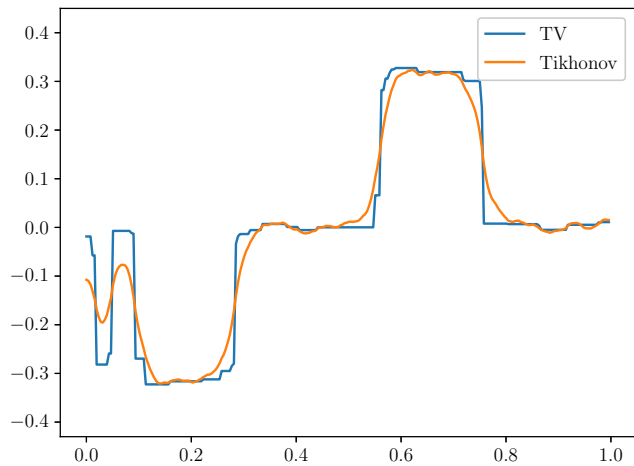
$\Leftrightarrow$

$$dt \leq \frac{2}{1 + 4\lambda C_{\Phi}}$$

# Total Variation Denoising



(c) Noisy signal



(d) Denoised



# Convergence of Gradient Descent

**Theorem 5.** Let  $f \in L^2(\mathbb{Z}_n; \mathbb{R})$  and  $\lambda \geq 0$ . Let  $u_j$  be the iterations of the gradient descent scheme for minimizing  $E_\Phi$  and let  $u$  be the solution of (8) (the minimizer of  $E_\Phi$ ). Assume that the time step  $dt$  satisfies

$$(9) \quad dt < \frac{2}{1 + 16C_\Phi^2 \lambda^2}.$$

Then  $u_j$  converges to  $u$  as  $j \rightarrow \infty$ , and the difference  $u_j - u$  satisfies

$$(10) \quad \|u_{j+1} - u\|^2 \leq \mu \|u_j - u\|^2$$

where

$$(11) \quad \mu := (1 - dt)^2 + 16C_\Phi^2 dt^2 \lambda^2 < 1.$$

Linear convergence rate  $\mu$ .

$$(8) \quad u - \lambda \nabla^+ \Phi'(\nabla u) = f$$

Proof: Write GD as

$$\textcircled{1} \quad u_{j+1} = (1-dt)u_j + dt\lambda\nabla^+\Phi'(\bar{\nabla}u_j) + dtf$$

and write (8) as

$$\textcircled{2} \quad u = (1-dt)u + dt\lambda\nabla^+\Phi'(\bar{\nabla}u) + dtf$$

Write  $e_j = u_j - u$ . Subtract  $\textcircled{2}$  from  $\textcircled{1}$ :

$$e_{j+1} = (1-dt)e_j + dt\lambda\nabla^+(\Phi'(\bar{\nabla}u_j) - \Phi'(\bar{\nabla}u)).$$

Take  $\|\cdot\|^2$  on both sides

$$\|f+g\|^2 = \|f\|^2 + \|g\|^2 + 2\langle f, g \rangle$$

$$\|e_{j+1}\|^2 = \|(1-\Delta t)e_j + \Delta t\lambda \nabla^+(\Phi'(\nabla^-u_j) - \Phi'(\nabla^-u))\|^2$$

$$= (1-\Delta t)^2 \|e_j\|^2 + \Delta t^2 \lambda^2 \|\nabla^+(\Phi'(\nabla^-u_j) - \Phi'(\nabla^-u))\|^2$$

$$+ 2\Delta t(1-\Delta t)\lambda \langle \nabla^+(\Phi'(\nabla^-u_j) - \Phi'(\nabla^-u)), e_j \rangle.$$

$$\langle \nabla^+ f, g \rangle = -\langle f, \nabla^- g \rangle$$

A

$$A = -\langle \Phi'(\nabla^-u_j) - \Phi'(\nabla^-u), \nabla^-e_j \rangle. \quad e_j = u_j - u$$

$$= -\langle \Phi'(\nabla^-u_j) - \Phi'(\nabla^-u), \nabla^-u_j - \nabla^-u \rangle$$

$$\leq 0 \quad \text{by monotonicity property (iv).}$$

If  $\Delta t \leq 1$ , drop 3<sup>rd</sup> term (since  $\leq 0$ )

to get

$$\|e_{j+1}\|^2 \leq (1-\Delta t)^2 \|e_j\|^2 + \Delta t^2 \lambda^2 \left\| \nabla^T (\mathbb{E}'(\nabla \bar{u}_j) - \mathbb{E}'(\nabla \bar{u})) \right\|^2$$

Aside:  $\|\nabla^T f\|^2 = \sum_{k=0}^{n-1} |f(k) - f(k-1)|^2$

$$= \sum_{k=0}^{n-1} (f(k)^2 + f(k-1)^2 - 2f(k)f(k-1))$$
$$= 2\|f\|^2 - 2 \sum_{k=0}^{n-1} f(k)f(k-1).$$

Claim:  $2ab \leq a^2 + b^2$  for any  $a, b \in \mathbb{R}$ .

True since  $(a-b)^2 = a^2 + b^2 - 2ab \geq 0$ .

$$\Rightarrow -2f(k)f(k-1) \leq f(k)^2 + f(k-1)^2$$

by taking  $a = -f(k)$ ,  $b = f(k-1)$ .

$$\Rightarrow \begin{cases} \|\mathcal{D}^+ f\|^2 \leq 4 \|f\|^2 \\ \|\mathcal{D}^- f\|^2 \leq 4 \|f\|^2 \end{cases}$$

Bound on  
operator  
norm of  
 $\mathcal{D}^+$

Hence

$$\begin{aligned} \|\mathcal{D}^+(\Phi'(\mathcal{D}^- u_j) - \Phi'(\mathcal{D}^- u))\|^2 &\leq 4 \|\Phi'(\mathcal{D}^- u_j) - \Phi'(\mathcal{D}^- u)\|^2 \\ &\leq 4 C_{\Phi}^2 \|\mathcal{D}^- u_j - \mathcal{D}^- u\|^2 \quad (*) \end{aligned}$$

Since  
 $t > s$

$$\Phi'(t) - \Phi'(s) = \int_s^t \Phi''(\tau) d\tau \leq C_{\Phi} (t-s)$$

$$(*) = 4 C_{\mathbb{F}}^2 \|\nabla e_j\|^2 \leq 16 C_{\mathbb{F}}^2 \|e_j\|^2 \quad \left\{ \begin{array}{l} \uparrow \\ C_{\mathbb{F}} = \max \mathbb{F}'' \end{array} \right.$$

Hence

$$\|e_{j+1}\|^2 \leq \underbrace{\left[ (1-dt)^2 + 16dt^2 \lambda^2 C_{\mathbb{F}}^2 \right]}_{=\mu} \|e_j\|^2$$

$$= \mu.$$

$$e_j = u_j - u.$$

It  $\mu < 1$  then GD converge at rate  $\mu$ , and  $dt \leq \dots$  follows from this  $\square$

Note:

(TV)

$$\Phi(t) = |t|, \quad C_{\Phi} = \infty$$

✓

$$(TV_{\varepsilon}) \quad \Phi_{\varepsilon}(t) = \sqrt{t^2 + \varepsilon^2}$$

✓

$$\Phi_{\varepsilon}'(t) = \frac{t}{\sqrt{t^2 + \varepsilon^2}}$$

$$\Phi_{\varepsilon}''(t) = \frac{\sqrt{t^2 + \varepsilon^2} - t \frac{t}{\sqrt{t^2 + \varepsilon^2}}}{t^2 + \varepsilon^2}$$

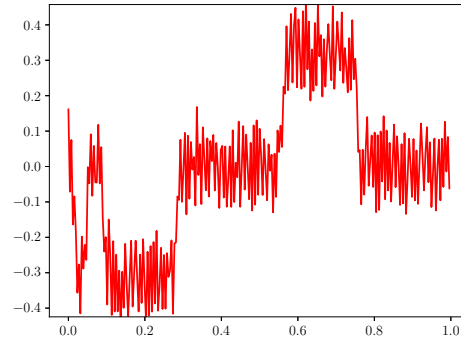
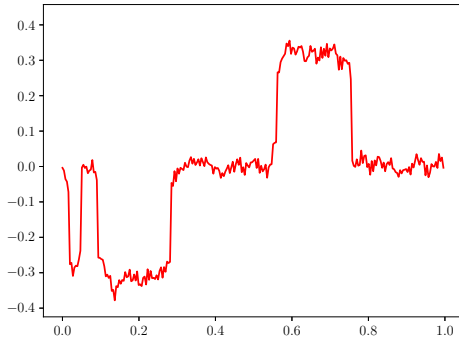
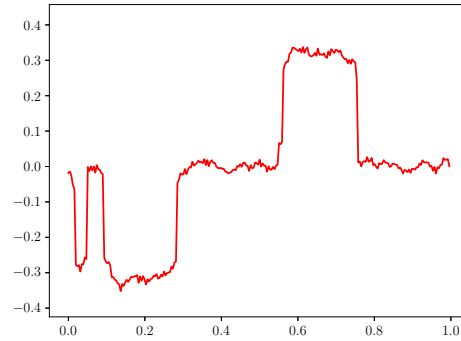
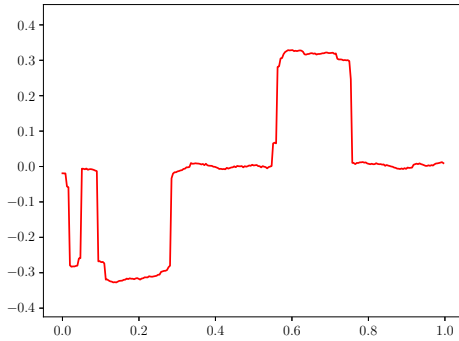
$$= \frac{\varepsilon^2}{(t^2 + \varepsilon^2)^{3/2}} \leq \frac{\varepsilon^2}{\varepsilon^3} = \frac{1}{\varepsilon} = C_{\Phi}$$





# Nonlinear stability at larger time steps

We set  $\varepsilon = 10^{-10}$  and the CFL condition is  $dt \sim 5 \times 10^{-10}$ .  
Figures are  $dt = 0.01, 0.05, 0.1, 0.5$ .



# Local nonlinear stability

A heuristic local version of the Von Neumann analysis for  $\varepsilon$ -regularized TV shows that the scheme is stable wherever the gradient of  $u$  satisfies

$$|\nabla^- u|^3 \geq \frac{4\lambda\varepsilon^2 dt}{2 - dt}.$$

Thus, oscillations cannot grow infinitely large, since the scheme is stable for larger gradients.

$$(CFL) \quad dt \leq \frac{2}{1 + 4C_{\Phi}\lambda}$$

Von Neumann  
analysis.

$$\text{Instead of } C_{\Phi} = \max \Phi''$$

$$\nabla^+ \Phi'(\nabla^- u) = \Phi'(\nabla^- u_{k+1}) - \Phi'(\nabla^- u_k)$$

$$\begin{aligned}
&\approx \Phi''(\bar{v}^u(k)) (\bar{v}^u(k+1) - \bar{v}^u(k)) \\
&= \Phi''(\bar{v}^u) \nabla^+ \bar{v}^u \\
&= \Phi''(\bar{v}^u) \Delta u.
\end{aligned}$$

leave as  $\Phi''$ :

$$\Delta t \leq \frac{2}{1 + 4\Phi''(\bar{v}^u)\lambda}$$

Flip around

$$\Phi''(\bar{v}^u) \leq \frac{1}{4\lambda} \left( \frac{2}{\Delta t} - 1 \right)$$

$$\Phi(t) = \sqrt{t^2 + \Sigma^2}$$

Check  $\Phi''(t) = \frac{\Sigma^2}{(t^2 + \Sigma^2)^{3/2}} \leq \frac{\Sigma^2}{t^3}$

(\*) holds if  $\frac{\Sigma^2}{|v|^{-3}} \leq \frac{1}{4\lambda} \left( \frac{2}{dt} - 1 \right)$

Rearrange  $|v|^{-3} \geq \frac{4\lambda \Sigma^2 dt}{2 - dt}$







Total Variation denoising ([.ipynb](#))