

Example: Regularization by truncated SVD

$$\text{Motivated by: } T^*g = \sum_{j: \sigma_j \neq 0} \sigma_j^{-1} (g, g_j) f_j$$

$$\rightarrow R_\alpha g := \sum_{j: \sigma_j^2 > \alpha} \sigma_j^{-1} (g, g_j) f_j, \alpha > 0$$

$$\text{Recall: } g_j = \frac{1}{\sigma_j} T f_j$$

$$(g, g_j)_Y = (g, \frac{1}{\sigma_j} T f_j)_Y = (\frac{1}{\sigma_j} T^* g, f_j)_X$$

Related filter

$$R_\alpha g = \sum_{j: \sigma_j^2 > \alpha} \frac{1}{\sigma_j^2} (T^* g, f_j) f_j$$

$$q_\alpha(\lambda) = \frac{1}{\lambda} \chi_{[\alpha, \infty)}(\lambda)$$

$$r_\alpha(\lambda) = 1 - \lambda q_\alpha(\lambda) = \chi_{[0, \alpha]}(\lambda)$$

(F<sub>1</sub>) - (F<sub>2</sub>) - (F<sub>3</sub>) with  $c_r = 1, c_q = 1$

$T \in K(X, Y)$  with singular system  $\{\sigma_j, f_j, g_j\}$

Reconstruction operator induced by filter fact  $q_2: \mathbb{R}^+ \rightarrow \mathbb{R}$

$$\begin{aligned} R_2 g &:= q_2(T^* T) T^* g \\ &= \sum_{j=1}^{\infty} q_2(\sigma_j^2) (T^* g, f_j) f_j \end{aligned}$$

Approximation error:

$$f - R_2 T f = f - q_2(T^* T) T^* T f = r_2(T^* T) f$$

$$\text{with } r_2(\lambda) = 1 - \lambda q_2(\lambda)$$

$$\begin{aligned} \text{residual: } T R_2 g^\delta - g^\delta &= \sum_k \sigma_k (R_2 g^\delta, f_k)_X g_k - (g^\delta, g_k)_Y g_k \\ &= \sum_k \sigma_k q_2(\sigma_k^2) (T^* g^\delta, f_k)_X g_k - (g^\delta, g_k)_Y g_k \end{aligned}$$

$$\begin{aligned} &= \sum_k \underbrace{(\sigma_k^2 q_2(\sigma_k^2) - 1)}_{= r_2(\sigma_k^2)} (g^\delta, g_k)_Y g_k \quad [\sigma_k^2 \text{ EV of } TT^*] \\ &= -r_2(TT^*) g^\delta \end{aligned}$$

$\boxed{TT^*}$  its because  $g_k$  are eigenfcts

Filter properties: (F1)  $\lim_{\lambda \rightarrow 0} q_\alpha(\lambda) = \frac{1}{\lambda}$  for  $\lambda > 0$

$$\text{(equivalent to } \lim_{\lambda \rightarrow 0} r_\alpha = \begin{cases} 1 & \lambda = 0 \\ 0 & \lambda > 0 \end{cases}$$

$$(F2) |r_\alpha(\lambda)| \leq C_r$$

$$(F3) \sqrt{\lambda} |q_\alpha(\lambda)| \leq C_q / \sqrt{\lambda}$$

$$\text{Tikhonov: } q_\alpha(\lambda) = \frac{1}{\lambda + \alpha}$$

$$\text{Landweber: } q_\alpha(\lambda) = \frac{1}{\lambda} (1 - (1-\lambda)^{\alpha}), \alpha = \frac{1}{2}$$

$$\text{truncated SVD: } q_\alpha(\lambda) = \frac{1}{\lambda} \chi_{[\alpha^2, \infty)}(\lambda)$$

Lemma 1.3.5.B  $\{q_\alpha\}_{\alpha \in \mathbb{R}}$  filter, Def. 1.3.5.A

$$\Rightarrow (i) \lim_{\lambda \rightarrow 0} R_\alpha g = T^+ g \quad \forall g \in D(T^*)$$

$$(ii) \|R_\alpha\| \leq C_q / \sqrt{\alpha}$$

Proof: (i)  $g \in D(T^+), f^+ := T^+ g \in N(T)^+$

$$r_0(T^*T)f = \sum_{j, \sigma_j \neq 0} (f, f_j)_X f_j = P_{N(T)} f$$

$$\Rightarrow r_0(T^*T)f^+ = 0 \quad \underbrace{Tf^+ = T T^+ g = P_{\overline{R(T)}} g}_{= 0}$$

$$T^+ g - R_\alpha g = f^+ - R_\alpha g = f^+ - R_\alpha T f^+ + R_\alpha P_{R(T)} g$$

$$= r_\alpha(T^*T)f^+ \quad \underbrace{= 0, \text{ because}}_{R_\alpha g = \sum_j q_\alpha(\sigma_j^{-2}) (g, T f_j)_X f_j}$$

$$\begin{aligned} \| (r_\alpha(T^*T) - r_0(T^*T))f^+ \|_X^2 &= \sum_j |r_\alpha(\sigma_j^{-2}) - r_0(\sigma_j^{-2})|^2 |(f^+, f_j)_X|^2 \\ &= \sum_{j, \sigma_j > 0} |r_\alpha(\sigma_j^{-2})|^2 |(f^+, f_j)_X|^2 \quad \underbrace{= 0, \text{ if}}_{\sigma_j \neq 0} \quad \underbrace{= 0, \text{ if}}_{\sigma_j = 0} \end{aligned}$$

$$\text{Fix } \varepsilon > 0: \exists \bar{\delta}_\varepsilon \in \mathbb{N}: \sum_{j > \bar{\delta}_\varepsilon} C_r^2 |(f^+, f_j)_X|^2 < \frac{\varepsilon}{2}$$

$$\lim_{\alpha \rightarrow 0^+} r_\alpha(\sigma_j^{-2}) = 0: \exists \alpha_\varepsilon: |r_\alpha(\sigma_j)| < \varepsilon/2 \quad \forall j = 1, \dots, \bar{\delta}_\varepsilon$$

$$\leq \sum_{j < \bar{\delta}_\varepsilon} (\varepsilon/2) |(f^+, f_j)_X|^2 + \varepsilon/2 \leq \varepsilon \|f^+\|_X^2 \quad (\text{and } \varepsilon \text{ arbitrary small})$$

$$(ii) \text{ General: } \|F(T)\| \leq \sup_{\lambda \in \sigma(T)} |F(\lambda)|$$

$$\|R_\alpha\|^2 = \|R_\alpha^* R_\alpha\| = \|q_\alpha(T^*T) T^* T q_\alpha(T^*T)\|$$

$$\leq \sup_{0 \leq \lambda \leq \|T\|^2} q_\alpha^2(\lambda) \lambda \stackrel{F_3}{\leq} \frac{C_q^2}{\alpha}$$

□

$$g \in \mathcal{D}(T^+), \|g - g^\delta\|_Y \leq \delta$$

(PCR1) (PCR2)

$$\|T^+g - R_\alpha g^\delta\|_X \leq \underbrace{\|T^+g - R_\alpha g\|_X}_{\rightarrow 0 \text{ as } \alpha \rightarrow 0} + \underbrace{\|R_\alpha(g - g^\delta)\|_X}_{\leq (\epsilon_0/\sqrt{\alpha}) \delta}$$

Thm 1.3.5.c:  $\{R_\alpha\}_{\alpha \in \mathbb{R}}$  induced by a filter  $\{q_\alpha\}_{\alpha \in \mathbb{R}}$   
 If  $\bar{\alpha}: \mathbb{R}_0^+ \times Y \rightarrow \mathbb{R}$ ,  $\bar{\alpha} = \bar{\alpha}(\delta, g^\delta)$  is a parameter choice rule with

$$\begin{aligned} \text{(PCR1)} \quad & \sup \left\{ \bar{\alpha}(\delta, g^\delta) : g^\delta \in Y, \|g - g^\delta\|_Y \leq \delta \right\} \rightarrow 0 \\ \text{(PCR2)} \quad & \sup \left\{ \frac{\delta}{\sqrt{\bar{\alpha}(\delta, g^\delta)}} : " " " \right\} \rightarrow 0 \end{aligned} \quad \text{as } \delta \rightarrow 0$$

for all  $g \in \mathcal{D}(T^+)$ . Then  $(R_\alpha, \bar{\alpha})_{\alpha \in \mathbb{R}}$  is a deterministic regularization method (Def 1.3.3.A).

### 1.3.5.2 Spectral source condition (a priori knowledge)

Hölder/Sobolev source condition:

$$f^+ \in X_2 := \left\{ f \in X : \sum_{j=1}^{\infty} \sigma_j^{-2} |(f, f_j)|^2 < \infty \right\}, \quad j \geq 0$$

$\nearrow$  exact solution

(a priori knowledge  
 defined through operator  
 in practice very difficult to check)

Relationship with Sobolev spaces:

$$L^2_{\text{per}}([0, 2\pi]) =: X$$

$$f_j(j) = \frac{1}{2\pi} e^{ijx} \quad : \text{ONB of } X$$

$$H^m([0, 2\pi]) = \left\{ f : \sum_{j \in \mathbb{Z}} (1+j)^{-2m} |(f, f_j)|^2 < \infty \right\}$$

$$\text{Notation: } \|f\|_2^2 := \sum_{j=1}^{\infty} \sigma_j^{-2} |(f, f_j)|^2$$

$$\text{Example: } (ff)(x) = \int_0^x f(t) dt \quad : 0 \leq x \leq 1, \quad X = L^2(0, 1)$$

→ singular system:  $\left\{ \frac{1}{\pi(j-\pi/2)}, \sqrt{2} \cos((j-\pi/2)\pi x), \sqrt{2} \sin((j-\pi/2)\pi x) \right\}$

Known:  $\left( \int_0^1 \varphi(x) \cos((j-\pi/2)\pi x) dx \right)_{j \in \mathbb{N}}$  is square summable  
 and  $\varphi \in L^2(0, 1)$

$$\Rightarrow X_1 = \{f \in L^2(0, 1), f' \in L^2(0, 1), f(0) = 0\} \subset H^1(0, 1)$$

$$X_2 = \{f \in L^2(0, 1), f' \in L^2(0, 1), f'' \in L^2(0, 1), f(0) = f'(0) = 0\} \subset H^2(0, 1)$$

### 1.3.5.3 Optimality

Def 1.3.5.E worst case error

$$\text{wce}(\delta, K, R) := \sup_{\substack{\text{noise} \\ \text{level}}} \left\{ \|f^+ - Rg^\delta\|_X : g^\delta \in K, f \in K, \|Tf - g^\delta\|_Y \leq \delta \right\}$$

reconstruction operator  $R: Y \rightarrow X$  continuous,  $R(0) = 0$

$\propto$  reflects a priori knowledge

best worst case error

$$\text{wce}(\delta, K) := \inf_R \text{wce}(\delta, K, R) \quad (\text{inf. over any reconstruction operator})$$

$$\text{Now: } K = K_{\nu, g} := \{f \in X_Y : \|f\|_Y \leq g\}$$

$\{R_\alpha\}_{\alpha \in \mathcal{A}}$  induced by filter  $\{q_\alpha\}_{\alpha \in \mathcal{A}}$ ,  $R_\alpha \in \mathcal{L}(X, Y)$

$$\|f^+ - R_\alpha g^\delta\| \leq \|f^+ - R_\alpha T f^+\|_X + \underbrace{\|R_\alpha(T f^+ - g^\delta)\|_X}_{\text{Lemma 1.3.5.B} \leq (\gamma/\tau_\alpha) \delta}$$

$$\|f^+ - R_\alpha T f^+\|^2 = \sum_{j, \sigma_j > 0} |\tau_\alpha(\sigma_j)|^2 |(f^+, f_j)|^2 \leq \sup_{f^+ \in K_{\nu, g}} \sum_{j, \sigma_j > 0} \tau_j^{-2} |\tau_\alpha(\sigma_j)|^2 \underbrace{\sum_{j, \sigma_j > 0} \sigma_j^{-2} |(f^+, f_j)|_X^2}_{= \|f^+\|_Y^2}$$

We'll see:

Needed: Qualification condition

$$\exists C_\nu > 0 : \sup_{0 \leq \lambda \leq \|T\|^2} \lambda^{1/2} |\tau_\alpha(\lambda)| \leq C_\nu \sqrt{\alpha} \quad \forall \alpha \in \mathcal{A} \quad (1.3.5.F)$$

$$\rightarrow \|f^+ - R_\alpha T f^+\|_X^2 \leq C_\nu^2 \alpha g^2$$

Inverse Problems

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A priori knowledge  $f^+ \in K_{\nu, g} := \{f \in X : \|f\|_Y \leq g\}$ , where

$$\|f\|_Y^2 = \sum_j \sigma_j^{-2} |(f, f_j)_X|^2$$

Using  $f^+ \in K_{\nu, g}$ :

$$\begin{aligned} \|f^+ - R_\alpha T f^+\|_X^2 &= \sum_j \sigma_j^{-2} |\tau_\alpha(\sigma_j)|^2 \sigma_j^{-2} |(f^+, f_j)_X|^2 \\ &\leq \max_{0 \leq \lambda \leq \|T\|^2} \lambda^{1/2} |\tau_\alpha(\lambda)|^2 \|f^+\|_Y^2 \end{aligned}$$

Assumption 1.3.5.F: (Qualification assumption)

$$\exists C_\nu > 0 : \lambda^{1/2} |\tau_\alpha(\lambda)| \leq C_\nu \lambda^{1/2} \quad \forall \lambda$$

If this holds for all  $\nu \in [0, \nu_0]$ , we say that the filter has qualification  $\nu_0$ .

With Q.A. 1.3.5.F:

$$\|f^+ - R_\alpha T f^+\|_X \leq C_v \alpha^{1/2} \delta^{1/2}$$

Lemma 1.3.5.B

$$\text{Data noise error: } \|R_\alpha T f^+ - R_\alpha g^\delta\| \leq \|R_\alpha\| \|T f^+ - g^\delta\| \leq \frac{C_q}{\sqrt{\alpha}} \delta$$

Total reconstruction error:

$$\|f^+ - R_\alpha g^\delta\|_X \leq \underbrace{C_v \alpha^{1/2} \delta^{1/2}}_{\text{minimize this w.r.t. } \alpha} + C_q \alpha^{-1/2} \delta$$

minimize this w.r.t.  $\alpha$

$$\left. \begin{array}{l} \psi(t) = A t^{1/2} + B t^{-1/2} \\ \psi'(t) = \frac{1}{2} A t^{1/2-1} + \frac{B}{2} t^{-3/2} = 0 \\ \alpha = 0 + \frac{1}{2} t^{1/2+1/2} = \frac{B}{2A} \end{array} \right\} \alpha_{\text{opt}} = \left( \frac{C_q \delta}{\sqrt{C_v \delta}} \right)^{2/v+1}$$

$$\begin{aligned} \|f^+ - R_{\alpha_{\text{opt}}} g^\delta\|_X &\leq C_v \left( \frac{C_q \delta}{\sqrt{C_v \delta}} \right)^{v/v+1} \delta + C_q \left( \frac{C_q \delta}{\sqrt{C_v \delta}} \right)^{-1/v+1} \delta^{1/v+1} \\ &\leq \underbrace{C_v^{1/v+1} C_q^{1/v+1} \left( \frac{1}{v^{v/v+1}} + v^{1/v+1} \right)}_{\text{constant}} \delta^{1/v+1} \delta^{1/v+1} \delta^{1/v+1} \end{aligned}$$

↑  
rate of avg.  
of reconstruction  
error

Thm 1.3.5.G: Assume  $f \in K_{v, \delta}$  and  $\{q_\alpha\}_{\alpha \in \mathbb{R}}$  a filter with qualification v.o.v. Then, for

$$\alpha \approx \left( \frac{\delta}{\delta} \right)^{2/v+1} =: \alpha_{\text{opt}} \quad (\star)$$

$$\text{wce}(\delta, K_{v, \delta}, R_{\alpha_{\text{opt}}}) \leq C(v) \delta^{v/v+1} \delta^{1/v+1}$$

with  $C(v) > 0$  independent of  $\delta, \delta$

(\*)  $\hat{\alpha}$  = a priori parameter choice rule

Recall Thm 1.3.5.C:  $\Rightarrow (R_{\alpha}, \alpha = \alpha_{\text{opt}}(\delta))$  is a deterministic regularization method

$$\text{wce}(\delta, K_{v, \delta}) = \inf_{R_\alpha} \sup \left\{ \|f^+ - R_\alpha g^\delta\|_X : f^+ \in K_{v, \delta}, \|T f^+\|_Y \leq \delta \right\}$$

$$\sup_{\substack{f^+ \\ \|f^+\|_X = 1}} \left\{ \|f^+\|_X : f^+ \in K_{v, \delta}, \|T f^+\|_Y \leq \delta \right\} =: w(\delta, K_{v, \delta})$$

(so as with  $K_{v, \delta}$  replaced with  $B_1(0)$  in X)

$$\text{Thm 1.3 S.11} \quad \omega(\delta, K_{\nu, \beta}) \leq \delta^{\frac{\nu}{\nu+1}} s^{\frac{\nu}{\nu+1}}$$

and the rate w.r.t.  $\delta \rightarrow 0$  is sharp

$$\text{Proof: } \|f^+\|_x^2 = \sum_j |(f, f_j)_x|^2$$

$$\text{Hölder ineq } \sum_{j=1}^{\infty} x_j y_j \leq (\sum_j x_j^p)^{1/p} (\sum_j y_j^q)^{1/q}, \quad \begin{cases} 1 \leq p, q < \infty \\ \frac{1}{p} + \frac{1}{q} = 1 \end{cases}$$

$$\text{with } q = \nu + 1, \quad p = \frac{\nu+1}{\nu}$$

$$\begin{aligned} \|f^+\|_x^2 &= \sum_j \underbrace{\sigma_j^{2/p} |(f^+, f_j)_x|^2}_{x_j}^{2/p} \underbrace{\sigma_j^{-2/q} |(f^+, f_j)_x|^2}_{y_j}^{2/q} \\ &\leq (\sum_j \sigma_j^2 |(f, f_j)_x|^2)^{1/p} \cdot (\sum_j \sigma_j^{-2q/p} |(f, f_j)_x|^2)^{1/q} \end{aligned}$$

$$[Tf^+ = \sum_j \sigma_j (f^+, f_j)_x f_j] \quad [q/p = \nu]$$

$$\leq \underbrace{\|Tf^+\|_Y^p}_{\leq \delta} \cdot \underbrace{\|f^+\|_Y^q}_{\leq s} \leq (\delta^{\frac{\nu}{\nu+1}})^2 (s^{\frac{\nu}{\nu+1}})^2$$

"Sharpness"  
(incomplete)  $\delta_k := s \sigma_k^{\nu+1} \xrightarrow{k \rightarrow \infty} 0$

$$f_k^+ = s \sigma_k^\nu f_k \quad \|f_k^+\|_\nu = s$$

$$Tf_k^+ = s \sigma_k^{\nu+1} g_k \quad \|Tf_k^+\|_Y = s \sigma_k^{\nu+1} = \delta_k$$

$$\omega(\delta_k, K_{\nu, \beta}) \geq \|f_k^+\|_x = s \tau_k^\nu = s (\delta_k/s)^{\frac{\nu}{\nu+1}} = \delta_k^{\frac{\nu}{\nu+1}} s^{\frac{1}{\nu+1}}$$

□

⇒ Using thm 1.3.5.c:

$$\delta^{\frac{\nu}{\nu+1}} s^{\frac{1}{\nu+1}} = \text{wce}(\delta, K_{\nu, \beta}) \leq \text{wce}(\delta, K_{\nu, \beta}, R_{\text{opt}}) \leq C \delta^{\frac{\nu}{\nu+1}} s^{\frac{\nu}{\nu+1}}$$

### Qualifications

Tikhonov:  $r_\alpha(\lambda) = \frac{\alpha}{\lambda + \alpha}$   
 $\lambda^{\nu/2} \frac{\alpha}{\lambda + \alpha} \leq C_\nu \alpha^{\nu/2}$

$$g = \frac{1}{2} = j^{\nu/2} \frac{1}{j+1} \leq C_\nu \quad \forall j$$

$$\Leftrightarrow \nu = 2$$

$$\Rightarrow \text{qualification } \nu_0 = 2$$

Landweber:  $r_\lambda(\lambda) = (\lambda - \lambda)^j, \quad \lambda = \frac{j}{j}, \quad j \in \mathbb{N}$   
 $\lambda^{\nu/2} (\lambda - \lambda)^j \leq C_\nu \left(\frac{j}{j}\right)^{\nu/2} \frac{1}{j}$   
 $(j\lambda)^{\nu/2} (\lambda - \frac{j\lambda}{j})^j \leq C_\nu$   
 $\frac{\Gamma(e^{\delta} - 1 + \delta)}{e^{-\delta/j} - (1 - \frac{\delta}{j})^j} \leq C_\nu \left(\frac{j\lambda}{j}\right)^{\nu/2} e^{-\delta/j}$  bold  $\delta \rightarrow \infty$   
qualification  $\nu_0 = \infty$