

## SUMMARY

**Inverse Problems** are concerned with determining causes for a desired or an observed effect. In our context, we want to invert a linear operator from noisy observations of its image.

**Aim:** To study the consistency of the **Bayesian Approach** to Linear Inverse Problems in the small noise limit.

We start with the Laplacian-like Inverse Problem with noise and prior covariances diagonalizable in the eigenbase of the Laplacian and generalize to more general situations. We are always assuming a separable Hilbert-Space setting.

Numerical results are presented which support this theory.

## PROBLEM SET-UP - GENERAL CASE

Consider the Inverse Problem to find  $u$  from  $y$ , for

$$y = \mathcal{A}^{-\ell}u + \frac{1}{\sqrt{n}}\xi, \quad \ell > 0, \quad (IP)$$

where  $\xi \sim \mathcal{N}(0, C_1)$  and  $\mathcal{A}$  is selfadjoint.

- **Likelihood:** for fixed  $u$  the law of  $y|u$ , called the *likelihood*, is  $\mathcal{N}(\mathcal{A}^{-\ell}u, C_1)$ .

- **Prior:** we now need to choose a *prior* distribution for the unknown  $u$ , based on any prior knowledge we have about  $u$ . Let  $u \sim \mathcal{N}(0, \tau^2 C_0)$ .

- **Posterior:** in the Bayesian Approach, the solution of (IP) is the distribution of  $u|y$ , called the *posterior* distribution. Here the posterior is  $\mathcal{N}(m, C)$  where

$$m = C_0 \mathcal{A}^{-\ell} (n^{-1} \tau^{-2} C_1 + \mathcal{A}^{-\ell} C_0 \mathcal{A}^{-\ell})^{-1} y := Ly$$

and

$$C = \tau^2 C_0 - \tau^2 L \mathcal{A}^{-\ell} C_0.$$

Assume we have observations of the form

$$y_n = \mathcal{A}^{-\ell} u^\dagger + \frac{1}{\sqrt{n}} \xi \quad (DM)$$

where  $u^\dagger$  is the true solution. Then the posterior mean is

$$m_n = Ly_n. \quad (PM)$$

We examine the consistency of the posterior mean in the sense

$$\mathbb{E} \|m_n - u^\dagger\|^2 \rightarrow 0$$

as  $n \rightarrow \infty$  and for appropriate choice of  $\tau = \tau(n)$ .

## PROBLEM SET-UP - DIAGONAL CASE

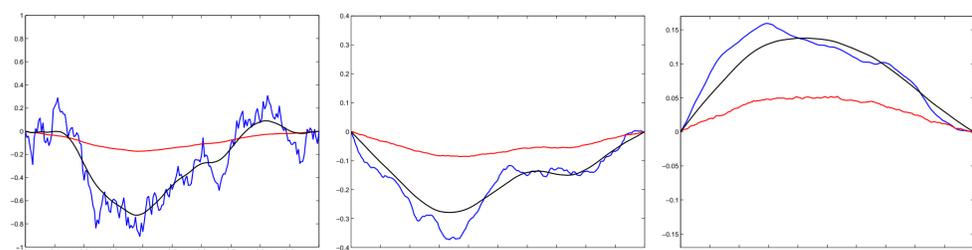
Let  $\Delta$  be the Dirichlet Laplacian in  $I = (0, 1)$  and  $\{k^2, \phi_k\}$  its orthonormal eigenbasis. Define the "Sobolev-like" spaces

$$\mathcal{H}^s = \{u : \sum_{k=1}^{\infty} k^{2s} \langle u, \phi_k \rangle^2 < \infty\}, \quad \|u\|_s^2 = \sum_{k=1}^{\infty} k^{2s} \langle u, \phi_k \rangle^2.$$

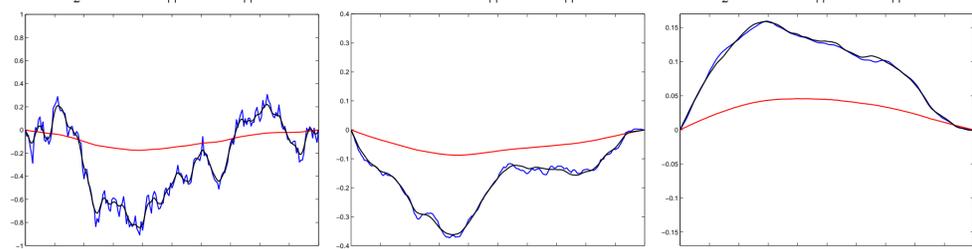
Suppose that in (IP) we have  $C_0 = (-\Delta)^{-\frac{1}{2}-\alpha}$ ,  $\mathcal{A}^{-\ell} = C_0^{\frac{2\ell}{1+2\alpha}}$  and  $C_1 = C_0^{\frac{2\beta}{1+2\alpha}}$  where  $\alpha > 0, \beta \geq 0$ , i.e.  $C_0, \mathcal{A}^{-\ell}$  and  $C_1$  are diagonalizable in the same eigenbasis.

Following the usual practice in Inverse Problems, we will assume in (DM) that we have the a-priori information on the regularity of  $u^\dagger$ , that  $u^\dagger \in \mathcal{H}^\gamma$ ,  $\gamma \geq 0$ .

## NUMERICAL SIMULATION - DIAGONAL CASE



(a)  $\gamma = \frac{1}{2}, n = 10^4, \|m_n - u^\dagger\| \approx 0.29$  (b)  $\gamma = 1, n = 10^4, \|m_n - u^\dagger\| \approx 0.097$  (c)  $\gamma = \frac{3}{2}, n = 10^4, \|m_n - u^\dagger\| \approx 0.046$



(d)  $\gamma = \frac{1}{2}, n = 10^6, \|m_n - u^\dagger\| \approx 0.11$  (e)  $\gamma = 1, n = 10^6, \|m_n - u^\dagger\| \approx 0.022$  (f)  $\gamma = \frac{3}{2}, n = 10^6, \|m_n - u^\dagger\| \approx 0.0073$

**Figure:** Realizations of the true solution (blue), the posterior mean (black) and the observation (red) for  $\alpha = \frac{1}{4}, \beta = \frac{1}{2}, \ell = \frac{1}{2}$ , for three values of  $\gamma$  and for  $n = 10^4$  (1st line) and  $n = 10^6$  (2nd line).

**Observation:** We have a better reconstruction when the truth is more regular.

## POSTERIOR CONSISTENCY - DIAGONAL CASE

Define  $\Delta = \frac{1}{4} + \frac{\alpha}{2} + \ell - \frac{\beta}{2}$ , and assume that  $\Delta > 0$  (the prior is indeed regularizing).

We study optimal rates of convergence for the different values of  $\gamma$ :

- **Theorem:** If the truth is smooth enough, in particular if  $\gamma \geq 0$

i) If the noise and the true solution are not too smooth,  $\beta - 2\ell \leq \frac{1}{2}$  and  $\gamma < 4\Delta$ , for

$$\tau_n = n^{\frac{\alpha-\gamma}{4\Delta+2\gamma-2\alpha+\varepsilon}},$$

we have

$$\mathbb{E} \|m_n - u^\dagger\|^2 \asymp n^{\frac{-\gamma}{2\Delta+\gamma-\alpha+\varepsilon}}.$$

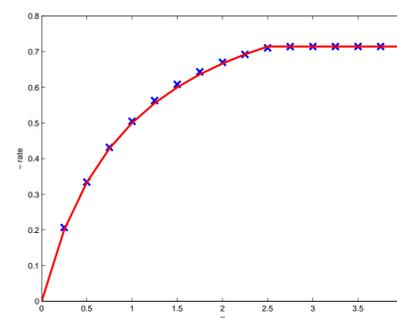
If the true solution is too smooth,  $\gamma \geq 4\Delta$ , then the rate does not improve as  $\gamma$  increases, i.e. the rate saturates at

$$n^{\frac{-4\Delta}{6\Delta-\alpha+\varepsilon}}.$$

ii) If the noise is too smooth,  $\beta - 2\ell > \frac{1}{2}$ , then the resulting rate is arbitrarily close to  $n^{-1}$ .

**Observation:** in (i) for  $\alpha > \gamma$  the prior distribution becomes uniform as  $n \rightarrow \infty$ ,  $\alpha < \gamma$  it contracts to a Dirac,  $\alpha = \gamma$  it stays fixed. In the last case the prior regularity matches the regularity of the true solution so rescaling is redundant.

## SIMULATED RATES OF CONVERGENCE



**Figure:** Rates of convergence of  $\mathbb{E} \|m_n - u^\dagger\|^2$  plotted against  $\gamma$ . In red we have the rates predicted by the theory and in blue we have estimated rates using the average of 160 realizations.

**Observation:** The estimated rates saturate at  $\gamma = 2.5$  as predicted by the theory.

## POSTERIOR CONSISTENCY - NON-DIAGONAL CASE

- **Theorem:** Under weaker, non-diagonal assumptions on the equivalence of  $C_0$  to  $\mathcal{A}^{-\ell}$  and  $C_1$ , using PDE methods and interpolation inequalities we have that for  $\theta \in [0, 1]$

$$\mathbb{E} \left\| C_0^{\frac{2\ell-\beta-2\theta\Delta}{1+2\alpha}} (m_n - u^\dagger) \right\|^2 \leq c \mathbb{E}(\kappa^2) n^{\frac{\theta_2+\theta-2}{\theta_1-\theta_2+2}},$$

where

$$\kappa = \max \left\{ \left\| C_0^{\frac{2\theta_1\Delta-\beta}{1+2\alpha}} \xi \right\|, \left\| C_0^{\frac{2(\theta_2-1)\Delta}{1+2\alpha}} \frac{1}{2} u^\dagger \right\| \right\}$$

and where  $\theta_1, \theta_2$  are chosen so that  $\mathbb{E}(\kappa^2) < \infty$ .

In the diagonal case the assumptions are trivially satisfied, so we can examine if the general theory agrees with the rates obtained in the diagonal case.

- For  $\beta - 2\ell \leq 0$ , we can choose  $\theta = \frac{2\ell-\beta}{2\Delta}$  in the general method to get the rate for  $\mathbb{E} \|m_n - u^\dagger\|^2$ . Compared to the diagonal case, we require higher regularity of the true solution in order to have convergence ( $\gamma \geq \frac{1}{2} + \alpha$ ) and the rate saturates earlier ( $\gamma = \frac{1}{2} + \alpha + 2\Delta$ ). For  $\gamma \in [\frac{1}{2} + \alpha, \frac{1}{2} + \alpha + 2\Delta]$  the rate agrees with the diagonal case.

The discrepancies can be explained by the fact that in the general method, the choice of  $\theta_1, \theta_2$  which determines both the minimum requirement on the regularity of  $u^\dagger$  and the saturation point, is independent of the choice of  $\theta$ . This means that on the one hand to get convergence of  $\mathbb{E} \|m_n - u^\dagger\|^2$  we require conditions which secure the convergence of stronger norms of the error and on the other hand the saturation rate for  $\mathbb{E} \|m_n - u^\dagger\|^2$  is the same as the saturation rates for weaker norms of the error.

- For  $\beta - 2\ell > 0$ , the general method provides rates only for stronger norms of the error, hence it secures the convergence of  $\mathbb{E} \|m_n - u^\dagger\|^2$  but at suboptimal rates.

## REFERENCES

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