

MATHEMATICAL TRIPOS      Part III

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Monday, 14 June, 2021    12:00 pm to 3:00 pm

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PAPER 326

INVERSE PROBLEMS

*Before you begin please read these instructions carefully*

*Candidates have THREE HOURS to complete the written examination.*

*Attempt **ALL** questions.*

*There are **FOUR** questions in total.*

*The questions carry equal weight.*

**STATIONERY REQUIREMENTS**

*Cover sheet*

*Treasury tag*

*Script paper*

*Rough paper*

**SPECIAL REQUIREMENTS**

*None*

<p><b>You may not start to read the questions printed on the subsequent pages until instructed to do so by the Invigilator.</b></p>
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## 1 Spectral Regularisation

Let  $\mathcal{X}$  and  $\mathcal{Y}$  be Hilbert spaces and  $A: \mathcal{X} \rightarrow \mathcal{Y}$  a linear bounded operator. We consider the following inverse problem

$$Au = f$$

for  $f \in \mathcal{Y}$ .

1. Give the definition of a *well-posed problem* and an *ill-posed problem* in the sense of Hadamard. Give the definitions of a *regularisation* and a *convergent regularisation*.
2. Let  $(\sigma_i, x_i, y_i)$  be the singular system of a compact operator  $A$ . Consider the following operator

$$T_n := AP_n,$$

where  $P_n$  is the projector onto the subspace spanned by the first  $n$  singular vectors  $x_i$ ,  $i = 1, \dots, n$ . Show that the Moore-Penrose inverse of  $T_n$  is given by

$$(T_n)^\dagger = A^\dagger Q_n,$$

where  $Q_n$  is the projector onto the subspace spanned by the first  $n$  singular vectors  $y_i$ ,  $i = 1, \dots, n$ , and  $A^\dagger$  is the Moore-Penrose inverse of  $A$ .

*Hint: verify the Moore-Penrose equations.*

3. The following iterative process is referred to as *Landweber iteration*

$$\begin{cases} u^{k+1} = (I - \tau A^* A)u^k + \tau A^* f, & k = 1, 2, \dots, \\ u^0 \equiv 0, \end{cases}$$

where  $f \in \mathcal{D}(A^\dagger)$  and  $\tau > 0$ .

- (a) Show that this method can be expressed as a spectral regularisation method and give the corresponding representation in terms of the singular system of  $A$ .
- (b) What is the regularisation parameter in this method?
- (c) Give sufficient conditions under which Landweber iteration defines a regularisation [proof required]. Write these conditions in terms of the norm of  $A$ .

*Hint: you can use the fact that for any  $k \in \mathbb{N}$  and any  $a > 0$*

$$\sum_{i=1}^k (1-a)^{k-i} = \frac{1}{a}(1 - (1-a)^k).$$

## 2 Variational Regularisation

1. Define *Total Variation* of a function  $u \in L^1(\Omega)$ , where  $\Omega \subset \mathbb{R}^n$  is a bounded domain. Define the spaces  $BV(\Omega)$  and  $BV_0(\Omega)$ . Write down the *Poincaré inequality* for Total Variation.
2. Let  $\mathcal{X}$  and  $\mathcal{Y}$  be Hilbert spaces,  $A: \mathcal{X} \rightarrow \mathcal{Y}$  a linear bounded operator and  $\mathcal{J}: \mathcal{X} \rightarrow \mathbb{R} \cup \{+\infty\}$  a proper convex lower semicontinuous functional. Give the definition of a  $\mathcal{J}$ -minimising solution  $u_{\mathcal{J}}^{\dagger}$  of the equation

$$Au = f$$

with  $f \in \mathcal{R}(A)$ . Formulate the *source condition* for a  $\mathcal{J}$ -minimising solution  $u_{\mathcal{J}}^{\dagger}$ . Prove that the source condition is equivalent to the following *range condition*

**Range condition.** For any fixed  $\alpha > 0$  there exists  $g \in \mathcal{Y}$  such that

$$u_{\mathcal{J}}^{\dagger} \in \arg \min_{u \in \mathcal{X}} \frac{1}{2} \|Au - g\|_{\mathcal{Y}}^2 + \alpha \mathcal{J}(u).$$

*Hint: Consider necessary and sufficient first order optimality conditions for the optimisation problem above.*

3. Let  $\mathcal{X}$  be a Hilbert space and  $\mathcal{J}: \mathcal{X} \rightarrow \mathbb{R} \cup \{+\infty\}$  a proper convex lower semicontinuous and absolutely one-homogeneous functional.
  - (a) Show that for any  $c > 0$  and any  $u \in \mathcal{X}$

$$\partial \mathcal{J}(cu) = \partial \mathcal{J}(u),$$

where  $\partial \mathcal{J}$  is the subdifferential of  $\mathcal{J}$ .

*Hint: You may use the characterisation of the subdifferential of an absolutely one-homogeneous functional from one of the example sheets.*

- (b) A function  $f \in \mathcal{X}$  is called an eigenfunction of  $\mathcal{J}$  corresponding to the eigenvalue  $\lambda \in \mathbb{R}$  if

$$\lambda f \in \partial \mathcal{J}(f).$$

Show that if  $f$  is an eigenfunction corresponding to an eigenvalue  $\lambda > 0$  then the function  $u = (1 - \lambda\alpha)f$  solves the following optimisation problem

$$\min_{u \in \mathcal{X}} \frac{1}{2} \|u - f\|^2 + \alpha \mathcal{J}(u),$$

where  $\alpha < \frac{1}{\lambda}$ .

*Hint: Consider necessary and sufficient first order optimality conditions for the optimisation problem above.*

### 3 Bayesian inverse problems and well-posedness

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. Let  $\mathcal{X}$  be a separable  $\mathbb{R}$ -Banach space and  $\mathcal{B}\mathcal{X}$  be the associated Borel- $\sigma$ -algebra. Let  $\mathbb{N} := \{1, 2, \dots\}$  denote the positive integers. Let  $(\Omega_1, \mathcal{F}_1), (\Omega_2, \mathcal{F}_2)$  be two measurable spaces and let  $g : \Omega_1 \rightarrow \Omega_2$  be a function. We denote  $g : (\Omega_1, \mathcal{F}_1) \rightarrow (\Omega_2, \mathcal{F}_2)$ , if  $g$  is measurable from  $(\Omega_1, \mathcal{F}_1)$  to  $(\Omega_2, \mathcal{F}_2)$ .

1. (a) Define a *Bayesian inverse problem* on  $(\mathcal{X}, \mathcal{B}\mathcal{X})$  with prior  $\mu_0 \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X})$  and likelihood  $L : (\mathcal{X} \times \mathcal{Y}, \mathcal{B}\mathcal{X} \otimes \mathcal{B}\mathcal{Y}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$ .  
 (b) Define the *total variation distance*  $d_{\text{TV}}$  on  $\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X})$ .  
 (c) Define the  $(\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}), d_{\text{TV}})$ -*well-posedness of a Bayesian inverse problem* and explain the role of  $d_{\text{TV}}$  in this definition.  
 (d) Give the four general assumptions on  $\mu_0$  and  $L$  under which the associated Bayesian inverse problem is  $(\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}), d_{\text{TV}})$ -well-posed (a proof is not necessary).
2. Let  $\mathcal{Y} := \mathbb{R}^k$ , where  $k \in \mathbb{N}$ . We consider the inverse problem where we aim to identify  $u \in \mathcal{X}$  from the observation  $f_n \in \mathcal{Y}$  which is defined as a sample from

$$\mathcal{A}(u) + N,$$

where  $\mathcal{A} : (\mathcal{X}, \mathcal{B}\mathcal{X}) \rightarrow (\mathcal{Y}, \mathcal{B}\mathcal{Y})$  and  $N : (\Omega, \mathcal{F}) \rightarrow (\mathcal{Y}, \mathcal{B}\mathcal{Y})$ , where  $N \sim \mu_{\text{noise}}$ . Here,  $\mu_{\text{noise}}$  is the probability measure which has the following density with respect to the Lebesgue measure  $\lambda_k$ :

$$g(y) = \exp(-2\|y\|_1) \quad (y \in \mathcal{Y}).$$

- (a) Show that for any value of the parameter  $u \in \mathcal{X}$ , the probability distribution of the observable  $\mathbb{P}(\mathcal{A}(u) + N \in \cdot)$  has a  $\lambda_k$ -density. Write down a likelihood function that is associated to the inverse problem of identifying  $u$  from the observation  $f_n$  and show that it is measurable.
- (b) Let  $\mu_0 \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X})$  be a probability measure. Find a likelihood  $L'$  that is  $\mu_0 \otimes \lambda_k$ -almost everywhere identical to the likelihood in (a) such that the Bayesian inverse problem with prior  $\mu_0$  and likelihood  $L'$  is  $(\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}, \mu_0), d_{\text{TV}})$ -well-posed.

*Hint: You may apply the conditions in part 1(d) without proof.*

**[QUESTION CONTINUES ON THE NEXT PAGE]**

3. (a) Let  $\mu, \mu' \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X})$ . Show that there is a  $\sigma$ -finite measure  $\nu$  on  $(\mathcal{X}, \mathcal{B}\mathcal{X})$ , such that  $\mu, \mu' \ll \nu$ .
- (b) Let now  $\rho$  be some  $\sigma$ -finite measure on  $(\mathcal{X}, \mathcal{B}\mathcal{X})$  and

$$\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}, \rho) := \{\mu \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}) : \mu \ll \rho\}.$$

We define the Hellinger distance between  $\mu, \mu' \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}, \rho)$  by

$$d_{\text{Hel}}(\mu, \mu') = \sqrt{\int_{\mathcal{X}} \left( \sqrt{\frac{d\mu}{d\rho}} - \sqrt{\frac{d\mu'}{d\rho}} \right)^2 d\rho}$$

Show that this function is well-defined by proving that the integral

$$\int_{\mathcal{X}} \left( \sqrt{\frac{d\mu}{d\rho}} - \sqrt{\frac{d\mu'}{d\rho}} \right)^2 d\rho$$

is finite.

- (c) Let  $\mu, \mu' \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}, \rho)$ . Show that the following inequality holds:

$$d_{\text{Hel}}(\mu, \mu')^2 \leq 2d_{\text{TV}}(\mu, \mu')$$

*Hint: You may use the formula  $d_{\text{TV}}(\mu, \mu') = \frac{1}{2} \int_{\mathcal{X}} \left| \frac{d\mu}{d\rho} - \frac{d\mu'}{d\rho} \right| d\rho$  without proving it.*

- (d) Consider a Bayesian inverse problem with prior  $\mu_0 \in \text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X})$  and likelihood  $L : (\mathcal{X} \times \mathcal{Y}, \mathcal{B}\mathcal{X} \otimes \mathcal{B}\mathcal{Y}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$  and assume that it is  $(\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}), d_{\text{TV}})$ -well-posed. Show that the Bayesian inverse problem is then also  $(\text{Prob}(\mathcal{X}, \mathcal{B}\mathcal{X}, \mu_0), d_{\text{Hel}})$ -well-posed.

#### 4 Gaussian measures

Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a probability space. Let  $\mathcal{X}$  be a separable  $\mathbb{R}$ -Banach space and  $\mathcal{B}\mathcal{X}$  be the associated Borel- $\sigma$ -algebra. Let  $\mathbb{N} := \{1, 2, \dots\}$  denote the positive integers. Let  $(\Omega_1, \mathcal{F}_1), (\Omega_2, \mathcal{F}_2)$  be two measurable spaces and let  $g : \Omega_1 \rightarrow \Omega_2$  be a function. We denote  $g : (\Omega_1, \mathcal{F}_1) \rightarrow (\Omega_2, \mathcal{F}_2)$ , if  $g$  is measurable from  $(\Omega_1, \mathcal{F}_1)$  to  $(\Omega_2, \mathcal{F}_2)$ .

*Hint: Throughout this exercise you may use the following results without proof: Let  $m_1, m_2, \sigma_1^2, \sigma_2^2, a, b \in \mathbb{R}$ , and  $\sigma_1^2, \sigma_2^2 \geq 0$ . Moreover, let  $\xi_1 : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$  and  $\xi_2 : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$  be random variables, where  $\xi_1 \sim N(m_1, \sigma_1^2), \xi_2 \sim N(m_2, \sigma_2^2)$  are independent and identically distributed. Then, (i)  $a\xi_1 + b\xi_2 \sim N(am_1 + bm_2, a^2\sigma_1^2 + b^2\sigma_2^2)$  and (ii)  $\int_{\Omega} \xi_1 d\mathbb{P} = m_1$  and  $\int_{\Omega} \xi_1^2 d\mathbb{P} = \sigma_1^2 + m_1^2$ .*

1. Give the definition of a *Gaussian measure* on  $(\mathcal{X}, \mathcal{B}\mathcal{X})$  and its *mean and covariance operator*.
2. Let  $\mathcal{X} := L^2([0, 1], \mathcal{B}[0, 1], \lambda_1)$  and  $A \in \mathcal{B}[0, 1]$ , with  $\lambda_1(A) \in (0, 1)$ . Moreover, let  $\varphi_1 := \mathbf{1}_A$ , and  $\varphi_2 := \mathbf{1}_{[0, 1] \setminus A}$ . Let  $\xi_1 : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$  and  $\xi_2 : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$  be random variables with  $\xi_1, \xi_2 \sim N(0, 1^2)$  independent and identically distributed.

- (a) Show that  $\varphi_1, \varphi_2 \in \mathcal{X}$ .
- (b) Show that the distribution of the random variable  $U : (\Omega, \mathcal{F}) \rightarrow (\mathcal{X}, \mathcal{B}\mathcal{X})$  given by

$$U := \xi_1\varphi_1 + \xi_2\varphi_2$$

is a Gaussian measure on  $(\mathcal{X}, \mathcal{B}\mathcal{X})$  and determine its mean and covariance operator.

- (c) Show that  $\varphi_1, \varphi_2$  are orthogonal eigenvectors of the covariance operator of  $U$ . Then determine the associated eigenvalues and show how they depend on the Lebesgue measure of  $A$ .
3. Let  $D := [0, 1]^n, n \in \mathbb{N}$  be a compact space and  $\mathcal{X} := L^2(D, \mathcal{B}D, \lambda_n)$ . Moreover, let  $k \in \mathbb{N}$ ,  $(\varphi_i)_{i=1}^k \in \mathcal{X}^k$  be an orthonormal family, and  $\nu_1, \dots, \nu_k > 0$ . Let  $\xi : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}^k, \mathcal{B}\mathbb{R}^k)$  be a random variable, with  $\xi_1, \dots, \xi_k \sim N(0, 1^2)$  independent and identically distributed and  $U : (\Omega, \mathcal{F}) \rightarrow (\mathcal{X}, \mathcal{B}\mathcal{X})$  be a Gaussian random field, given by  $U := \sum_{i=1}^k \sqrt{\nu_i} \xi_i \varphi_i$ . Show that the random variable  $X : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B}\mathbb{R})$ ,

$$\omega \mapsto \int_D U(\omega; x) d\lambda_n(x)$$

is distributed according to a Gaussian measure and determine its mean and variance. Finally, determine  $\int_{\Omega} \|U\|_{\mathcal{X}}^2 d\mathbb{P}$ .

**END OF PAPER**