

Coursework 2

8 December 2023

1 Problem Sheet 7 Problem 3

Step 1: T is well-defined.

Let $f \in L^2(0, 1)$, then

$$\begin{aligned}\|Tf\|_{L^2(0,1)}^2 &= \int_0^1 \left| \int_0^1 e^{-st} f(t) dt \right|^2 ds \\ &\stackrel{\text{T.I}}{\leq} \int_0^1 \left(\int_0^1 |e^{-st}| |f(t)| dt \right)^2 ds \\ &\stackrel{\text{Hölder's}}{\leq} \int_0^1 \left(\left(\int_0^1 e^{-2st} dt \right)^{\frac{1}{2}} \|f\|_{L^2(0,1)} \right)^2 ds \\ &= \|f\|_{L^2(0,1)}^2 \int_0^1 \int_0^1 e^{-2st} dt ds \\ &= \|f\|_{L^2(0,1)}^2 \int_0^1 \frac{1 - e^{-2s}}{2s} ds \\ &\stackrel{(1)}{\leq} \|f\|_{L^2(0,1)}^2 \\ &< \infty\end{aligned}$$

where (1) follows as $\frac{1-e^{-2s}}{2s} \leq 1$ for $s \in (0, 1)$. Therefore, $Tf \in L^2(0, 1)$ and so the map $T : L^2(0, 1) \rightarrow L^2(0, 1)$ is well-defined.

Step 2: $T \in \mathcal{L}(L^2(0, 1), L^2(0, 1))$.

Note that for $f_1, f_2 \in L^2(0, 1)$ and $\lambda \in \mathbb{R}$ we have that

$$\begin{aligned}T(f_1 + \lambda f_2)(s) &= \int_0^1 e^{-st} (f_1 + \lambda f_2)(t) dt \\ &= \int_0^1 e^{-st} f_1(t) dt + \lambda \int_0^1 e^{-st} f_2(t) dt \\ &= Tf_1(s) + \lambda Tf_2(s).\end{aligned}$$

Therefore, T is a linear map. Recall from Step 1 that

$$\|Tf\|_{L^2(0,1)} \leq \|f\|_{L^2(0,1)}$$

and so

$$\|T\|_{L^2(0,1) \rightarrow L^2(0,1)} = \sup_{0 \neq f \in L^2(0,1)} \frac{\|Tf\|_{L^2(0,1)}}{\|f\|_{L^2(0,1)}} \leq 1.$$

Hence, T is a bounded linear map which implies that $T \in \mathcal{L}(L^2(0, 1), L^2(0, 1))$.

Step 3: $T \in \mathcal{K}(L^2(0, 1), L^2(0, 1))$.

For $f \in L^2(0, 1)$ such that $\|f\|_{L^2(0,1)} \leq 1$ let $x, y \in (0, 1)$. Then observe that

$$\begin{aligned}
|Tf(x) - Tf(y)| &= \left| \int_0^1 (e^{-xt} - e^{-yt}) f(t) dt \right| \\
&\stackrel{\text{T.I}}{\leq} \int_0^1 |e^{-xt} - e^{-yt}| |f(t)| dt \\
&\stackrel{\text{Hölder's}}{\leq} \left(\int_0^1 |e^{-xt} - e^{-yt}|^2 dt \right)^{\frac{1}{2}} \|f\|_{L^2(0,1)} \\
&\leq \left(\int_0^1 |e^{-xt} - e^{-yt}|^2 dt \right)^{\frac{1}{2}}.
\end{aligned}$$

Using the the mean value theorem we note that for $t \in (0, 1)$ we have that

$$\begin{aligned}
|e^{-xt} - e^{-yt}| &\leq |x - y| \sup_{z \in (0,1)} \left| \frac{d}{dt} e^{-zt} \right| \\
&= |x - y| \sup_{z \in (0,1)} |-te^{-zt}| \\
&\leq |x - y|.
\end{aligned}$$

It follows that

$$|Tf(x) - Tf(y)| \leq |x - y| \quad (1)$$

which implies that $T \left(\bar{B}^{L^2(0,1)} \right) \subseteq \mathcal{C}^0(0, 1)$. Hence, for a sequence $(f_n)_{n \in \mathbb{N}} \subseteq \bar{B}^{L^2(0,1)}$ we have that $(Tf_n)_{n \in \mathbb{N}} \subseteq \mathcal{C}^0(0, 1)$. As

$$Tf_n(0) = \int_0^1 f_n(t) dt \leq \int_0^1 |f_n(t)| dt \leq \|1\|_{L^2(0,1)} \|f_n\|_{L^2(0,1)} \leq 1$$

for any $n \in \mathbb{N}$, it follows by using (1) that

$$|Tf_n(x)| \leq |Tf_n(x) - Tf_n(0)| + |Tf_n(0)| \leq |x| + 1 \leq 2$$

for all $n \in \mathbb{N}$ and $x \in (0, 1)$. Which implies that $(Tf_n)_{n \in \mathbb{N}}$ is bounded. Moreover, for any $\epsilon > 0$, let $\delta = \epsilon$ so that for any $x, y \in (0, 1)$ such that $|x - y| < \delta$ we have

$$|Tf_n(x) - Tf_n(y)| \stackrel{(1)}{\leq} |x - y| < \delta = \epsilon$$

for all $n \in \mathbb{N}$. This implies that the sequence $(Tf_n)_{n \in \mathbb{N}} \subseteq \mathcal{C}^0(0, 1)$ is also equicontinuous. Therefore, it admits a convergent by the Arzela-Ascoli theorem and so $T \left(\bar{B}^{L^2(0,1)} \right)$ is pre-compact. Hence, the operator T is compact.

Problem Sheet 8 Problem 4

(i)

Let $(u_n) \subseteq F$ be a sequence that converges to u in H . Then for fixed v_i it follows that

$$\begin{aligned}
|(u, v_i) - (u_n, v_i)| &= |(u - u_n, v_i)| \\
&\stackrel{\text{C.S}}{\leq} \|u - u_n\| \|v_i\|.
\end{aligned}$$

The right-hand side tends to 0 as $n \rightarrow \infty$ as $\|u - u_n\| \rightarrow 0$ by assumption and $\|v_i\|$ is a finite constant. Therefore, $0 = (u_n, v_i) \rightarrow (u, v_i)$ and so $(u, v_i) = 0$. Hence, $u \in F$ meaning F is closed.

(ii)

Expanding out the equation $M\Lambda = V$ we see that

$$\begin{pmatrix} \lambda_1(v_1, v_1) + \cdots + \lambda_n(v_1, v_n) \\ \vdots \\ \lambda_1(v_n, v_1) + \cdots + \lambda_n(v_n, v_n) \end{pmatrix} = \begin{pmatrix} (u, v_1) \\ \vdots \\ (u, v_n) \end{pmatrix}.$$

Using the properties of the inner product this is equivalent to

$$\begin{pmatrix} (v_1, \sum_{k=1}^n \lambda_k v_k) \\ \vdots \\ (v_n, \sum_{k=1}^n \lambda_k v_k) \end{pmatrix} = \begin{pmatrix} (v_1, u) \\ \vdots \\ (v_n, u) \end{pmatrix}.$$

In other words, we want to find $\lambda_1, \dots, \lambda_n \in \mathbb{R}$ such that

$$\left(v_i, \sum_{k=1}^n \lambda_k v_k \right) = (v_i, u)$$

for all $i \in \{1, \dots, n\}$. Which is equivalent to finding a $\tilde{u} \in \text{span}(v_1, \dots, v_n) =: M$ such that $(v, \tilde{u}) = (v, u)$ for all $v \in M$. In particular, $(u - \tilde{u}, v) = 0$ for all $v \in M$.

Claim 1. Let H be a real Hilbert space. For a linearly independent set of vectors $\{v_1, \dots, v_n\} \subseteq H$ the set $M := \text{span}(v_1, \dots, v_n) \subset H$ is a closed and convex linear subspace.

Proof. It is clear that M is a linear subspace, from which the convexity of M easily follows. Suppose that we have a sequence $(m_k)_{k \in \mathbb{N}} \subseteq M$ that is convergent in H to m . Note that due to the linear independence of $\{v_1, \dots, v_n\}$ we have a bijection from M to \mathbb{R}^n given by $m_k = \sum_{i=1}^n x_i^{(k)} v_i \mapsto (x_1^{(k)}, \dots, x_n^{(k)})$. Since norms in finite dimensions are equivalent, it follows that the sequences $(x_i^{(k)})$ are Cauchy for each $i \in \{1, \dots, n\}$ in \mathbb{R} as $(m_k)_{k \in \mathbb{N}}$ is Cauchy in M . Therefore, as \mathbb{R} is complete it follows that each sequence $(x_i^{(k)})_{k \in \mathbb{N}}$ converges to some $x_i \in \mathbb{R}$. Hence, $(m_k)_{k \in \mathbb{N}}$ converges to $m := \sum_{i=1}^n x_i v_i \in M$. Therefore, M is closed. \square

Claim 2. Let H be a Hilbert space. Let $K \subset H$ be a closed and convex linear subspace. Then for $f \in H$, its projection onto K , as given by the Hilbert Projection theorem, is characterised by the unique vector $u \in K$ such that

$$(f - u, v) = 0 \tag{2}$$

for all $v \in K$.

Proof. Recall, that the original characterisation of the projection of f onto K is the unique vector $u \in K$ such that

$$\|f - u\| = \min_{v \in K} \|f - v\|. \tag{3}$$

Suppose that $u \in K$ satisfies (2). Then for $v \in K$ as $u - v \in K$ we that $(f - u, u - v) = 0$ by (2). Hence,

$$\begin{aligned} \|f - v\|^2 &= \|f - u + u - v\|^2 \\ &= \|f - u\|^2 + 2(f - u, u - v) + \|u - v\|^2 \\ &= \|f - u\|^2 + \|u - v\|^2. \end{aligned}$$

In particular, this implies that $\|f - v\|^2 \geq \|f - u\|^2$ for all $v \in K$. Conversely, suppose that (3) is satisfied for u . Then for $v \in K$ and $t \in \mathbb{R}$, as K is a linear subspace, we have that $u + tv \in K$ and so $\|f - u\|^2 \leq \|f - (u + tv)\|^2$. Therefore,

$$0 \leq \|f - (u + tv)\|^2 - \|f - u\|^2 = 2t(u - f, v) + t^2\|v\|^2 =: g(t).$$

If $(u - f, v) \neq 0$, then as $g(t)$ is minimised by $t = -\frac{(u-f, v)}{\|v\|^2}$ we get a minimum of

$$g\left(-\frac{(u-f, v)}{\|v\|^2}\right) = -2\frac{(u-f, v)^2}{\|v\|^2} + \frac{(f-u, v)^2}{\|v\|^2} = -\frac{(u-f, v)^2}{\|v\|^2} < 0.$$

This is a contradiction and so it must be the case that $(f - u, v) = 0$. \square

Using Claim 1 we can apply Claim 2 to deduce that \tilde{u} is the unique projection of u onto M , which we denote $P_M u \in M$. As the set $\{v_1, \dots, v_n\}$ is linearly independent we can write

$$P_M u = \lambda_1 v_1 + \dots + \lambda_n v_n$$

for unique $\lambda_1, \dots, \lambda_n \in \mathbb{R}^n$. Hence, there is a unique solution for $\Lambda \in \mathbb{R}^n$ satisfying $M\Lambda = V$.

(iii)

Note that if $u \in F$, it is clear that for any $m = \sum_{i=1}^n \mu_i v_i \in M$ we have

$$\left(u, \sum_{i=1}^n \mu_i v_i\right) = \sum_{i=1}^n \mu_i (u, v_i) = 0.$$

Thus $u \in M^\perp$ and $F \subseteq M^\perp$. On the other hand, let $\tilde{m} \in M^\perp$. Then as $v_i \in M$ for all $i \in \{1, \dots, n\}$, it follows that $(\tilde{m}, v_i) = 0$ for all $i \in \{1, \dots, n\}$. Hence, $\tilde{m} \in F$ and so $F = M^\perp$. As M is closed, it follows by using Problem Sheet 8 Problem 2(iii) that $F^\perp = (M^\perp)^\perp = M$. Hence using by part (ii) we get that $P^\perp u = P_M u = \sum_{i=1}^n \lambda_i v_i$. Now let $\tilde{u} = u - P^\perp u$. We are now going to show that $Pu = \tilde{u}$. As $v_i \in M = F^\perp$ we can use the characterisation of $P^\perp u$ given in Claim 2 to deduce that

$$0 = (u - P^\perp u, v_i) = (\tilde{u}, v_i).$$

Which implies that $\tilde{u} \in F$. Moreover, for $v \in F$ we have

$$(u - \tilde{u}, v) = (u - (u - P^\perp u), v) = (P^\perp u, v) \stackrel{(1)}{=} 0,$$

where (1) follows from the fact that $P^\perp u \in F^\perp$. Hence, as F is a closed and convex linear subspace we can use Claim 2 to deduce that $Pu = \tilde{u} = u - P^\perp u$.

Problem Sheet 9 Problem 5

Step 1: Show that S is closed.

Let $(f_n)_{n \in \mathbb{N}} \subset S$ be a sequence converging to $f \in H$. Let $f \mathbf{1}_E$ be non-zero on a set $F \subset E$. Note that as $F \subset E$ it must be the case that each f_n is almost everywhere zero in F , hence,

$$\begin{aligned} \|f - f_n\|_{L^2(\mathbb{R}^d)}^2 &= \int_{\mathbb{R}^d} (f - f_n)^2 \\ &= \int_F (f - f_n)^2 + \int_{\mathbb{R}^d \setminus F} (f - f_n)^2 \\ &\geq \int_F f^2. \end{aligned}$$

If F has non-zero measure then $\int_F f^2 = c > 0$ as $f^2 > 0$ on F . This then implies that $\|f - f_n\|_{L^2(\mathbb{R}^2)} \geq c$ for all $n \in \mathbb{N}$, which contradicts the assumption that $\|f - f_n\|_{L^2(\mathbb{R}^d)} \rightarrow 0$ as $n \rightarrow \infty$. Therefore, F has zero measure meaning f is zero almost everywhere in E as we know f is zero on $E \setminus F$. Hence, $f \in S$ meaning S is closed.

Step 2: Show that S is linear, and in particular convex.

Let $f, g \in S$ and $0 \neq \lambda \in \mathbb{R}$. Then by construction $f \mathbf{1}_E$ and $g \mathbf{1}_E$ are non-zero on zero-measures sets $F_1, F_2 \subset E$ respectively. Suppose that $(f + \lambda g) \mathbf{1}_E$ is non-zero on the set $F \subset E$. It is clear that if $(f + \lambda g) \mathbf{1}_E \neq 0$ then

either $f\mathbf{1}_E \neq 0$ or $g\mathbf{1}_E \neq 0$. Hence $F \subset F_1 \cup F_2$ which implies that F also has zero-measure as $F_1 \cup F_2$ has zero measure. Therefore, $f + \lambda g \in S$ and the set S is linear, which in particular means it is convex.

Step 3: For $f \in L^2(\mathbb{R}^d)$, find its projection, Pf , onto S .

For $f \in L^2(\mathbb{R}^d)$ let

$$(Pf)(x) = \begin{cases} f(x) & x \in \mathbb{R}^d \setminus E \\ 0 & x \in E. \end{cases}$$

Clearly, $(Pf) \in S$. Moreover, for $g \in S$ we have that

$$\begin{aligned} (f - Pf, g) &= \int_{\mathbb{R}^d} (f - Pf) \cdot g \\ &= \int_E (f - Pf) \cdot g + \int_{\mathbb{R}^d \setminus E} (f - Pf) \cdot g \\ &= \int_E f \cdot g \\ &\leq \int_E |f| |g| \\ &\stackrel{\text{H\"older's}}{\leq} \|f\|_{L^2(E)} \|g\|_{L^2(E)} \\ &= 0. \end{aligned}$$

Therefore, $(f - Pf, g) \leq 0$ for all $g \in S$, hence as we know S is a linear subspace from Step 2 it is clear that $(f - Pf, g - Pf) \leq 0$ for all $g \in S$. Thus, Pf is the projection of f onto S .

Step 4: For $f \in L^2(\mathbb{R}^d)$ find its projection, $P^\perp f$, onto S^\perp .

As S is closed we can use Problem Sheet 8 Problem 3 part (iii) to conclude that

$$P^\perp f = f - Pf = \begin{cases} 0 & x \in \mathbb{R}^d \setminus E \\ f(x) & x \in E. \end{cases}$$