# Functional Optimization for Machine Learning: Exercises 

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June 6, 2024

## 1 Representer Theorems

### 1.1 Inverse problems with Tikhonov regularization

Let $\mathcal{H}$ be a Hilbert space with inner product $\langle\cdot, \cdot\rangle_{\mathcal{H}}$. We recall that the Riesz map $\mathrm{R}: \mathcal{H} \rightarrow \mathcal{H}^{\prime}$ is the unitary transform that maps $\mathcal{H}$ into its dual $\mathcal{H}^{\prime}$ equipped with the inner product $\langle\cdot, \cdot\rangle_{\mathcal{H}^{\prime}}$. In effect, each point $f \in \mathcal{H}$ is mapped into its (unique) Hilbert conjugate $f^{*}=\mathrm{R}\{f\} \in \mathcal{H}^{\prime}$. The unitary nature of R is expressed by the characteristic identity

$$
\begin{equation*}
\forall f, g \in \mathcal{H}: \quad\langle f, g\rangle_{\mathcal{H}}=\left\langle f, g^{*}\right\rangle=\left\langle f^{*}, g^{*}\right\rangle_{\mathcal{H}^{\prime}} \tag{1}
\end{equation*}
$$

where $f^{*}=\mathrm{R}\{f\}, g^{*}=\mathrm{R}\{g\} \in \mathcal{H}^{\prime}$. Moreover, $\mathrm{R}^{*}=\mathrm{R}^{-1}: \mathcal{H}^{\prime} \rightarrow \mathcal{H}$ so that the adjoint operator $\mathrm{R}^{*}$ is the Riesz map from $\mathcal{H}^{\prime} \rightarrow \mathcal{H}^{\prime \prime}=\mathcal{H}$, due to the reflexivity of Hilbert spaces. This invertibility property is summarized by $f^{* *}=f$ for all $f \in \mathcal{H}$.

The goal here is to invoke the general representer theorem in order to solve the generic linear inverse problem

$$
\begin{equation*}
f_{0}=\arg \min _{f \in \mathcal{H}}\left(\sum_{m=1}^{M}\left|y_{m}-\left\langle\nu_{m}, f\right\rangle\right|^{2}+\lambda\|f\|_{\mathcal{H}}^{2}\right) \tag{2}
\end{equation*}
$$

where $\lambda \in \mathbb{R}^{+}$is an adjustable regularization parameter. The only hypothesis is that the linear measurement functionals are well defined over $\mathcal{H}$-that is, $\nu_{1}, \ldots, \nu_{M} \in \mathcal{H}^{\prime}=\mathcal{X}$-and linearly independent.

Specifically, we want you address the following points:

1. Show that the solution is unique and can be written as $f_{0}=\sum_{m=1}^{M} a_{m} \varphi_{m}$ where the $\varphi_{m}$ are suitable basis functions.
2. Recast the problem as a finite dimensional optimization.

[^0]3. Solve 2. explicitly by showing that the optimal expansion coefficients in 1 . can be evaluated as $\mathbf{a}=\left(\mathbf{H}+\lambda \mathbf{I}_{M}\right)^{-1} \mathbf{y}$ for some suitable "system" matrix $\mathbf{H} \in \mathbb{R}^{M \times M}$.

### 1.2 Application of Banach conjugates

The signal space of our interest is $\mathcal{X}^{\prime}=\left(\mathbb{R}^{N},\|\cdot\|_{\ell_{p}}\right)$ with $p \geq 1$ whose predual is $\mathcal{X}=\left(\mathbb{R}^{N},\|\cdot\|_{\ell_{q}}\right)$ with $\frac{1}{p}+\frac{1}{q}=1$. These spaces are strictly convex for $p \in(1, \infty)$.

### 1.2.1 Exercise on Compressed Sensing

Our goal is to recover an unknown signal $\mathbf{s}=\left(s_{n}\right) \in \mathbb{R}^{N}$ from a set of corrupted linear measurements $y_{m}=\mathbf{h}_{m}^{\top} \mathbf{s}+\epsilon_{m}, m=1, \ldots, M$ where $\epsilon_{m}$ represents some measurement noise. To favour sparse solutions, we formulate the problem as

$$
\begin{equation*}
\mathbf{s}=\arg \min _{\mathbf{x} \in \mathbb{R}^{N}}\|\mathbf{y}-\mathbf{H} \mathbf{x}\|^{2}+\lambda\|\mathbf{x}\|^{p} \tag{3}
\end{equation*}
$$

with $p$ close to one. Here, $\mathbf{y} \in \mathbb{R}^{M}$ is the data vector, $\mathbf{H}=\left[\mathbf{h}_{1} \mathbf{h}_{2} \cdots \mathbf{h}_{M}\right]^{\top} \in$ $\mathbb{R}^{M \times N}$ is the system matrix, and $\lambda \in \mathbb{R}^{+}$is an adjustable regularization parameter.

1. Prove the Hölder inequality 7 for $p=1$.
2. Prove that the duality map $\mathrm{J}_{\ell_{q}}:\left(\mathbb{R}^{N},\|\cdot\|_{\ell_{q}}\right) \rightarrow\left(\mathbb{R}^{N},\|\cdot\|_{\ell_{p}}\right)$ is given by

$$
\begin{equation*}
\mathrm{J}_{\ell_{q}}(\mathbf{y})=\mathbf{y}^{*} \quad \text { with } \quad\left[\mathbf{y}^{*}\right]_{n}=\frac{\left|y_{n}\right|^{q-1}}{\|\mathbf{y}\|_{\ell_{q}}^{q-2}} \operatorname{sign}\left(y_{n}\right) \tag{4}
\end{equation*}
$$

3. Use the general representer theorem to give the parametric form of the solution for $p>1$.

### 1.2.2 Theoretical background

Let $\left(\mathcal{X}, \mathcal{X}^{\prime}\right)$ be a dual pair of Banach spaces. Formally, an element of the dual space, $g \in \mathcal{X}^{\prime}$, is a continuous linear functional on $\mathcal{X}$ whose action $g: \mathcal{X} \rightarrow \mathbb{R}$ results in the linear mapping $f \mapsto\langle g, f\rangle_{\mathcal{X}^{\prime} \times \mathcal{X}}=\langle g, f\rangle$ (for short) with the induced (operator-) norm of this functional being

$$
\begin{equation*}
\|g\|_{\mathcal{X}^{\prime}}=\sup _{f \in \mathcal{X} \backslash\{0\}} \frac{\langle g, f\rangle}{\|f\|_{\mathcal{X}}} \tag{5}
\end{equation*}
$$

This association also goes the other way around in that, by fixing $f \in \mathcal{X}$, one can specify a linear functional on $\mathcal{X}^{\prime}$ via the rule $f: g \mapsto\langle g, f\rangle$. This is to say that there is a natural pairing between $\mathcal{X}$ and $\mathcal{X}^{\prime}$ encoded in the bilinear $\operatorname{map}\langle\cdot, \cdot\rangle: \mathcal{X}^{\prime} \times \mathcal{X} \rightarrow \mathbb{R}$ (duality pairing) whose continuity (in both variables) is ruled by the duality bound

$$
\begin{equation*}
\forall(f, g) \in \mathcal{X} \times \mathcal{X}^{\prime}: \quad|\langle g, f\rangle| \leq\|g\|_{\mathcal{X}^{\prime}}\|f\|_{\mathcal{X}} \tag{6}
\end{equation*}
$$

This bound is tight because of (5). In fact, we like to view (6) as the Banach counterpart of the Cauchy-Schwartz inequality.

As prototypical example, we now consider the finite-dimensional Banach space $\mathcal{X}=\left(\mathbb{R}^{N},\|\cdot\|_{\ell_{p}}\right)$ with $p \geq 1$ and

$$
\forall \mathbf{x}=\left(x_{n}\right) \in \mathbb{R}^{N}: \quad\|\mathbf{x}\|_{\ell_{p}}= \begin{cases}p \in[1, \infty) & \left(\sum_{n=1}^{N}\left|x_{n}\right|^{p}\right)^{1 / p}  \tag{7}\\ p=\infty & \sup _{n \in\{1, \ldots, N\}}\left|x_{n}\right|\end{cases}
$$

The dual space is $\mathcal{X}^{\prime}=\left(\mathbb{R}^{N},\|\cdot\|_{\ell_{q}}\right)$ with $\frac{1}{p}+\frac{1}{q}=1$, which is the same set $\mathbb{R}^{N}$, but equipped with a different norm. The duality pairing between those two topological vector spaces is ruled by the Hölder inequality

$$
\begin{equation*}
\forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^{N}: \quad|\langle\mathbf{x}, \mathbf{y}\rangle| \leq\|\mathbf{x}\|_{\ell_{p}}\|\mathbf{y}\|_{\ell_{q}} \tag{8}
\end{equation*}
$$

Definition 1. Let $\left(\mathcal{X}, \mathcal{X}^{\prime}\right)$ be a dual pair of Banach spaces. Then, the elements $f^{*} \in \mathcal{X}^{\prime}$ and $f \in \mathcal{X}$ form a conjugate pair if

- $\left\|f^{*}\right\|_{\mathcal{X}^{\prime}}=\|f\|_{\mathcal{X}}$ (norm preservation), and
- $\left\langle f^{*}, f\right\rangle_{\mathcal{X}^{\prime} \times \mathcal{X}}=\left\|f^{*}\right\|_{\mathcal{X}^{\prime}}\|f\|_{\mathcal{X}} \quad$ (sharp duality bound).

For any given $f \in \mathcal{X}$, the set of admissible conjugates defines the duality mapping

$$
J(f)=\left\{f^{*} \in \mathcal{X}^{\prime}:\left\|f^{*}\right\|_{\mathcal{X}^{\prime}}=\|f\|_{\mathcal{X}} \text { and }\left\langle f^{*}, f\right\rangle_{\mathcal{X}^{\prime} \times \mathcal{X}}=\left\|f^{*}\right\|_{\mathcal{X}^{\prime}}\|f\|_{\mathcal{X}}\right\}
$$

which is a non-empty subset of $\mathcal{X}^{\prime}$. Whenever the duality mapping is singlevalued (for instance, when $\mathcal{X}^{\prime}$ is strictly convex), one also defines the duality operator $\mathrm{J}_{\mathcal{X}}: \mathcal{X} \rightarrow \mathcal{X}^{\prime}$, which is such that $f^{*}=\mathrm{J}_{\mathcal{X}}(f)$.

## 2 Deep splines with stability control

### 2.1 Simple convolution layer

We shall investigate the stability properties of the convolution operator $\mathrm{T}_{h}$ : $\ell_{2}(\mathbb{Z}) \rightarrow \ell_{2}(\mathbb{Z})$, which is such that $\mathrm{T}_{h}\{x\}[n]=(h * x)[n]=\sum_{k \in \mathbb{Z}} h[k] x[n-k]$. The Lipschitz constant of $\mathrm{T}_{h}$ is the operator norm

$$
\begin{equation*}
\operatorname{Lip}\left(\mathrm{T}_{h}\right)=\left\|\mathrm{T}_{h}\right\|=\sup _{x \in \ell_{2}(\mathbb{Z}) \backslash\{0\}} \frac{\|h * x\|_{\ell_{2}}}{\|x\|_{\ell_{2}}} \tag{9}
\end{equation*}
$$

This convolution operator can also be characterized by its frequency response $\hat{h}(\omega)=\mathcal{F}_{\mathrm{d}}\{h\}=\sum_{k \in \mathbb{Z}} h[k] \mathrm{e}^{-\mathrm{j} \omega k}$ where the operator $\mathcal{F}_{\mathrm{d}}: \ell_{2}(\mathbb{Z}) \rightarrow L_{2}([-\pi, \pi])$ is the discrete Fourier transform. The latter is an isometry, as expressed Parseval's formula:

$$
\begin{equation*}
\forall x \in \ell_{2}(\mathbb{Z}): \quad\|x\|_{\ell_{2}}^{2}=\sum_{k \in \mathbb{Z}}|x[k]|^{2}=\int_{-\pi}^{+\pi}|\hat{x}(\omega)|^{2} \frac{\mathrm{~d} \omega}{2 \pi}=\|\hat{x}\|_{L_{2}([-\pi, \pi])}^{2} \tag{10}
\end{equation*}
$$

1. Use the discrete Fourier transform and Parseval's formula to get an estimate of $\operatorname{Lip}\left(\mathrm{T}_{h}\right)$.
2. Show that $\operatorname{Lip}\left(\mathrm{T}_{h}\right)=\left\|\mathrm{T}_{h}\right\| \leq \sum_{k \in \mathbb{Z}}|h[k]|=\|h\|_{\ell_{1}(\mathbb{Z})}$, the advantage of the latter being that it is very easy to calculate.
3. Can you ensure that the bound in Item 1 is tight? Are there scenarios where the simpler bound in Item 2 is tight as well?

### 2.2 Pointwise nonlinearities

Let us consider the following functions, which are shown in Fig. 1.

$$
\begin{align*}
\operatorname{tri}(x) & = \begin{cases}0, & x \leq-1 \\
1+x, & x \in[-1,0) \\
1-x, & x \in[0,1) \\
0, & x \geq 1\end{cases}  \tag{11}\\
f(x) & =\frac{1}{2}+x-\operatorname{ReLU}(x-1)  \tag{12}\\
g(x) & = \begin{cases}0, & x \leq 0 \\
x, & x \in[0,1) \\
1-\frac{1}{2}(x-1), & x \in[1,3) \\
0, & x \geq 3\end{cases} \tag{13}
\end{align*}
$$

where $\operatorname{ReLU}(x)=(x)_{+}=\max (x, 0)$.

1. Compute $f^{\prime}, \operatorname{Lip}(f), f^{\prime \prime}, \mathrm{TV}^{(2)}(f)=\left\|\mathrm{D}^{2} f\right\|_{\mathcal{M}}$.

Hint: Use the property that $\left\|\delta\left(\cdot-x_{0}\right)\right\|_{\mathcal{M}}=1$ for any $x_{0} \in \mathbb{R}$.


Figure 1: Continuous piece-wise linear (CPWL) functions/activations.
2. Compute $g^{\prime}, \operatorname{Lip}(g), \operatorname{TV}^{(2)}(g)=\left\|\mathrm{D}^{2} g\right\|_{\mathcal{M}}$.
3. Express $f$ as $f(x)=b_{0}+b_{1} x+a|x-1|$ with suitable values of $b_{0}, b_{1}, a \in \mathbb{R}$,.
4. Can you express $f$ as $f(x)=\sum_{k \in \mathbb{Z}} c[k] \operatorname{tri}(x-k)$ ? If yes, give the explicit value of the B -spline coefficients $c[k]$.
5. Express $g$ as $g(x)=\sum_{k} a_{k} \operatorname{ReLU}\left(x-x_{k}\right)$ with suitable values of $\left(a_{k}, x_{k}\right)$ and show that $\mathrm{TV}^{(2)}(g)=\sum_{k}\left|a_{k}\right|$.
6. Let $\sigma(x)=\sum_{k \in \mathbb{Z}} c[k] \operatorname{tri}(x-k)$. Give the explicit expression of $\operatorname{Lip}(\sigma)$ and $\mathrm{TV}^{(2)}(\sigma)$ in terms of the B-spline coefficients $c[k]$.
Hint: Express $\sigma^{\prime}(x)$ in terms of rectangular basis functions.


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