

# ECEn 671: Mathematics of Signals and Systems

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# Section 1

## Dual Approximation

# Dual Approximation

This section develops an approach that allows approximation in infinite dimensional spaces with finite constraints.

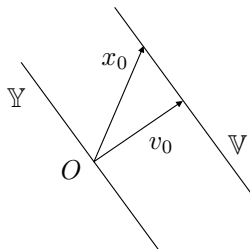
For matrices, we will solve the problem

$$\begin{array}{ll} \min & \|x\| \\ \text{s.t.} & Ax = b \end{array}$$

# Dual Approximation, cont.

## Definition (Affine Space)

Let  $\mathbb{Y}$  be a subspace of  $\mathbb{S}$  and let  $x_0 \in \mathbb{S}$ . The set  $\mathbb{V} = x_0 + \mathbb{Y}$  is called a linear variety or an affine space.



The projection theorem says that there exists a  $v_0 \in \mathbb{V}$  such that  $v_0 = \arg \min_{v \in \mathbb{V}} \|v\|$  such that  $v_0 \perp \mathbb{Y}$ .

## Dual Approximation, cont.

Let  $M = \text{span}\{y_1, \dots, y_m\}$  then  $\dim(M) < \infty$ .

If  $\dim(\mathbb{S}) = \infty$  then  $\dim(M^\perp) = \infty$  where  $M^\perp$  is the set of all  $x \in \mathbb{S}$  such that

$$\langle x, y_1 \rangle = 0$$

$$\vdots$$

$$\langle x, y_m \rangle = 0$$

## Dual Approximation, cont.

Now suppose that there are  $m$  inner product constraints:

$$\langle x, y_1 \rangle = a_1$$

$$\vdots$$

$$\langle x, y_m \rangle = a_m$$

If  $\exists x_0$  that satisfies the constraints then so does  $x_0 + v$  where  $v \in M^\perp$  since

$$\begin{aligned}\langle x_0 + v, y_j \rangle &= \langle x_0, y_j \rangle + \langle v, y_j \rangle \\ &= \langle x_0, y_j \rangle \\ &= a_j\end{aligned}$$

Therefore all solutions are in the (infinite dimensional) affine space

$$v = x_0 + M^\perp$$

## Dual Approximation, cont.

### Theorem (Moon Theorem 3.4)

*Let  $\{y_1, \dots, y_m\}$  be linearly independent in a Hilbert space  $\mathbb{S}$ , and let  $M = \text{span}\{y_1, \dots, y_m\}$ . The solution of the problem*

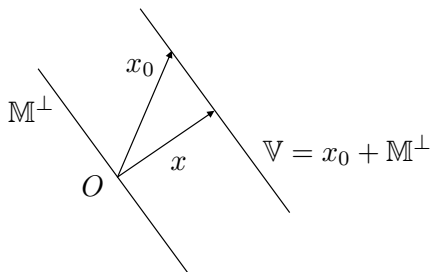
$$\begin{aligned} \min_{x \in \mathbb{S}} \quad & \|x\|^2 \\ \text{s.t.} \quad & \langle x, y_1 \rangle = \alpha_1, \\ & \vdots, \\ & \langle x, y_m \rangle = \alpha_m \end{aligned}$$

*is an element of  $M$ , i.e.,  $\hat{x} = \arg \min_{x \in \mathbb{S}} \|x\|^2 = \sum_{i=1}^m c_i y_i$ , where  $\mathbf{c}$  satisfies  $R\mathbf{c} = \alpha$ , where  $R$  is the Gramian and*

$$\alpha = (\alpha_1, \dots, \alpha_m)^\top.$$

## Proof:

From the previous discussion, the solution lies in the affine space  $\mathbb{V} = x_0 + M^\perp$  for some  $x_0 \in \mathbb{S}$ .



The minimum norm solution is orthogonal to  $M^\perp$  i.e.

$$\hat{x} \perp M^\perp \Rightarrow \hat{x} \in M^{\perp\perp} = M$$

So  $\hat{x}$  is of the form  $\hat{x} = \sum_{j=1}^m c_j y_j$



## Proof, cont.

Now projecting  $x$  onto  $M$  gives

$$\begin{aligned}\langle \hat{x}, y_1 \rangle &= \left\langle \sum c_j y_j, y_1 \right\rangle &= \sum c_j \langle y_j, y_1 \rangle &= \alpha_1 \\ \vdots &= \vdots &= \vdots &= \vdots \\ \langle \hat{x}, y_m \rangle &= \left\langle \sum c_j y_j, y_m \right\rangle &= \sum c_j \langle y_j, y_m \rangle &= \alpha_m\end{aligned}$$

rewriting in matrix notation gives

$$R\mathbf{c} = \boldsymbol{\alpha}$$

## Dual Approximation, Example

Given the differential equation

$$\ddot{y} + 6\dot{y} + 8y = 4\dot{u} + 10u, \quad y(0) = \dot{y}(0) = 0$$

Solve the following optimal control problem:

$$\begin{aligned} \min_{u \in L_2} \quad & \|u\|^2 \\ \text{s.t.} \quad & y(1) = 1, \\ & \int_0^1 y(t) dt = 0 \end{aligned}$$

## Dual Approximation, Example, cont.

The corresponding transfer function is

$$\begin{aligned}H(s) &= \frac{4s + 10}{s^2 + 6s + 8} = \frac{1}{s + 2} + \frac{3}{s + 4} \\ \Rightarrow h(t) &= e^{-2t} + 3e^{-4t} \\ \Rightarrow y(t) &= \int_0^t \left[ e^{-2(t-\tau)} + 3e^{-4(t-\tau)} \right] u(\tau) d\tau\end{aligned}$$

Define the following inner product

$$\langle f(t), g(t) \rangle = \int_0^1 f(\tau) g(\tau) d\tau$$

then  $y(1) = 1$  can be written as

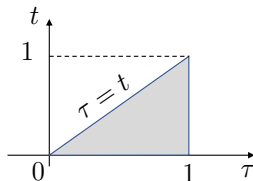
$$\int_0^1 \left[ e^{-2(1-\tau)} + 3e^{-4(1-\tau)} \right] u(\tau) d\tau = \langle u, y_1 \rangle = 1$$

where  $y_1(t) = e^{-1(1-t)} + 3e^{-4(1-t)}$

## Dual Approximation, Example, cont.

The second constraint is of the form

$$\int_0^1 y(t) dt = \int_{t=0}^{t=1} \int_{\tau=0}^{\tau=t} h(t-\tau) u(\tau) d\tau dt = 0$$



Changing order of integration gives

$$= \int_{\tau=0}^1 \left[ \int_{t=\tau}^1 h(t-\tau) dt \right] u(\tau) d\tau.$$

## Dual Approximation, Example, cont.

Letting  $\sigma = t - \tau \Rightarrow t = \sigma + \tau \Rightarrow dt = d\sigma$  gives

$$\begin{aligned} &= \int_{\tau=0}^1 \left[ \int_{\sigma=0}^{\sigma=1-\tau} h(\sigma) d\sigma \right] u(\tau) d\tau \\ &= \int_{\tau=0}^1 \left( \frac{5}{4} - \frac{3}{4} e^{-4(1-\tau)} - \frac{1}{2} e^{-2(1-\tau)} \right) u(\tau) d\tau \\ &= \langle u, y_2 \rangle = 0 \end{aligned}$$

where

$$y_2(t) = \frac{5}{4} - \frac{3}{4} e^{-4(1-\tau)} - \frac{1}{2} e^{-2(1-\tau)}$$

so we have that

$$\langle u, y_1 \rangle = 1$$

$$\langle u, y_2 \rangle = 0$$

and we want to minimize  $\|u\|_{L_2[0,1]}^2$

## Dual Approximation, Example, cont.

Let  $M = \text{span}\{y_1, y_2\}$ .

By Theorem 3.4

$$u \in M \Rightarrow u(t) = c_1 y_1(t) + c_2 y_2(t)$$

where

$$\begin{pmatrix} \langle y_1, y_1 \rangle & \langle y_2, y_1 \rangle \\ \langle y_1, y_2 \rangle & \langle y_2, y_2 \rangle \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$