Lecture #2: LLSE — geometric interpretation

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1 Geometric Interpretation

Recall from Lecture #1, the llse. of x, \hat{x} is given by

$$\hat{x} = \Sigma_{xy} \Sigma_{yy}^{-1} y = K_o y$$

Interpretation:

$$K_o = \Sigma_{xy} \Sigma_{yy}^{-1} \Leftrightarrow K_o \mathsf{E}[yy^*] = \mathsf{E}[xy^*] \Leftrightarrow \mathsf{E}[(x - K_o y)y^*] = 0$$

Thus, if the random variables are viewed as vectors, with the inner product defined as $\langle x, y \rangle = \mathsf{E}[xy^*]$, then $\mathsf{E}[(x - K_o y)y^*]$ has the geometric interpretation

$$\langle x - K_o y, y \rangle = 0 \leftrightarrow x - K_o y \perp y,$$

that is, the estimation error is orthogonal to observations!

Two questions related to the geometric interpretation:

Hilbert space, i.e., a complete normed linear vector space.

- 2. Is $\langle x, y \rangle = \mathsf{E}[xy^*]$ a proper inner product?
 - Linearity: $\langle \alpha x + \beta y, z \rangle = \alpha \langle x, z \rangle + \beta \langle y, z \rangle$

$$\mathsf{E}[(\alpha x + \beta y)z^*] = \alpha \mathsf{E}[xz^*] + \beta \mathsf{E}[yz^*] \quad Check!$$

• Symmetry: $\langle x, y \rangle = \langle y, x \rangle^*$

$$\mathsf{E}[xy^*] = \mathsf{E}[(yx^*)^*] = \mathsf{E}[yx^*]^* \quad Check!$$

• Non-degeneracy: $\langle x, x \rangle \succeq 0$, *i.e.*, positive semi-definite, and $\langle x, x \rangle = 0$ if and only if x = 0. $E[xx^*] = \Sigma_{xx}$: *Covariance matrices are per definition always positive (semi-)definite.*

^{1.} Which vector space?

1.1 Geometric Derivation of LLSE

Find a vector \hat{x} in the linear space spanned by $\{y_1, \ldots, y_N\}$ such that $||x - \hat{x}||$ is minimized.



2 Winer filtering (WF)

Given the observations $\{y_i\}_{i=-\infty}^k$, find the llse. of x_{k+n} .

Assumptions: x_k and y_k are scalar processes, that are jointly stationary with exponentially bounded (cross-)covariance, *i.e.*, $|r_{xx}(k)| < K\alpha^{|k|} \forall k, K > 0, 0 < \alpha < 1$, then a spectrum exists.

That is, find

$$\hat{x}_{k+n} = \sum_{i=0}^{\infty} h_{k,i} y_{k-i},$$

where $h_{k,i}$ is possibly time varying filter coefficients subjects to $\mathsf{E}[(x_{k+n} - \hat{x}_{k+n})^2]$ is minimized.

$$\dots, y_{k-2}, y_{k-1}, \underbrace{\underbrace{y_k}_{n<0} \qquad \underbrace{filtering}_{n<0} \qquad prediction}_{n>0}$$

Orthogonality properties gives, for all $j \le k$:

$$\begin{aligned} x_{k+n} - \hat{x}_{k+n} \perp y_i, \\ \langle x_{k+n} - \sum_{i=0}^{\infty} h_{k,i} y_{k-i}, y_j \rangle &= 0, \\ \mathsf{E}[x_{k+n} y_j^*] &= \sum_{i=0}^{\infty} h_{k,i} \mathsf{E}[y_{k-i} y_j^*], \\ r_{xy}(k+n-j) &= \sum_{j=0}^{\infty} h_{k,i} r_{yy}(k-i-j) \end{aligned}$$

Make a change variable, $k - j \rightarrow \ell$, gives

$$r_{xy}(\ell+n) = \sum_{i=0}^{\infty} h_{\ell+j,i} r_{yy}(\ell-i), \quad \forall \ell \ge 0.$$

Note, neither $r_{xy}(\ell + n)$ nor $r_{yy}(\ell - i)$ depend on *j*; hence, $h_{\ell+j,i} = h_i$, *i.e.*, the filter coefficients are time invariant.

Wiener-Hopf equation:

$$r_{xy}(\ell+n) = \sum_{i=a}^{b} h_i r_{yy}(\ell-i), \quad \forall \ell \ge 0.$$

- If: $\sum_{-\infty}^{\infty}$: Non-causual *Wiener filter* (WF, *z*-transform), easy to solve.
 - \sum_{a}^{b} : FIR (*finite impulse response*) WF (linear system equation), easy to solve.
 - \sum_{0}^{∞} : Casual WF.
 - $\sum_{-\infty}^{-1}$: Anti-casual WF.

2.1 Spectral Factorization

The spectrum of a signal y_k

$$\Phi_{yy}(\omega) = \tilde{\Phi}_{yy}(z) \Big|_{z=e^{i\omega}}$$
$$\tilde{\Phi}_{yy}(z) = \mathscr{Z}\{\underbrace{r_{yy}(k)}_{\text{acf}}\} = \sum_{k=\infty}^{\infty} r_{yy}(k) z^{-k}$$

Note, $r_{yy}(k) = r_{yy}(-k) \Rightarrow \tilde{\Phi}_{yy}(z) = \tilde{\Phi}_{yy}(z^{-1})$ which implies that $\tilde{\Phi}_{yy}(z)$ has symmetry with respect to mirroring in the unit circle. Hence, if $z = r_i$ has a pole (zero) in the unit circle, then $z = r_i^{-1}$ is also a pole (zero).

If $\tilde{\Phi}_{yy}(z)$ has no poles of zeroes on the unit circle, *i.e.*, $0 < \Phi_{yy}(\omega) < \infty \forall \omega$, then

$$\tilde{\Phi}_{yy}(z) = \underbrace{\sigma_e \frac{\prod_{i=1}^{m} (z-r_i)}{\prod_{j=1}^{b} (z-p_j)}}_{=T(z), \text{ stable, causal}} \cdot \underbrace{\sigma_e \frac{\prod_{i=1}^{m} (z^{-1}-r_i^*)}{\prod_{j=1}^{b} (z^{-1}-p_j^*)}}_{=T^*(z^{-*}), \text{ stable, anti-causual}} ,$$

assuming $|r_i|\langle 1, |p_i|\langle 1, \text{and } \sigma_e^2\rangle 0$.



2.2 Additive Decomposition

Let the sequence $\{f_k\}$ have a \mathscr{Z} -transform that exist in an annulus containing the unit circle. Then

$$F(z) = \sum_{k=-\infty}^{\infty} f_k z^{-k} = \sum_{\substack{k=0\\[F(z)]_+ \text{ casual part}}}^{\infty} f_k z^{-k} + \sum_{\substack{k=-\infty\\[F(z)]_- \text{ strictly anti-causal part}}}^{-1} f_k z^{-k}$$

2.3 Solving the Wiener-Hopf equation

Original problem:

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$$\xrightarrow{y_k} H^c_{\hat{x}y}(z) \xrightarrow{\hat{x}_{k+n}}$$

New problem:

$$\xrightarrow{y_k} 1/T(z) \xrightarrow{e_k} H^c_{\hat{x}e}(z) \xrightarrow{\hat{x}_{k+n}}$$

$$r_{xy}(\ell+n) = \sum_{i=0}^{\infty} h_i r_{yy}(\ell-i), \quad \forall \ell \ge 0$$

$$\begin{aligned} r_{xe}(\ell+n) &= \sum_{i=0}^{\infty} \bar{h}_i r_{ee}(\ell-i) = \sum_{i=0}^{\infty} \bar{h}_i \delta(\ell-i), \quad \forall \ell \ge 0 \\ &\implies \bar{h}_i = \begin{cases} r_{xe}(i+n), & i \ge 0 \\ 0, & i < 0 \end{cases} \\ &\implies H_{\hat{x}e}^c(z) = \left[\Phi_{xe}(z) z^n \right]_+ \end{aligned}$$

Putting it all together

$$w_{k} = \begin{pmatrix} e_{k} \\ x_{k} \end{pmatrix} \longrightarrow \tilde{\Phi}_{ww} = \begin{pmatrix} \tilde{\Phi}_{ee} & \tilde{\Phi}_{ex} \\ \tilde{\Phi}_{xe} & \tilde{\Phi}_{xx} \end{pmatrix}$$
$$u_{k} = \begin{pmatrix} y_{k} \\ x_{k} \end{pmatrix} \longrightarrow \tilde{\Phi}_{uu} = \begin{pmatrix} \tilde{\Phi}_{yy} & \tilde{\Phi}_{yx} \\ \tilde{\Phi}_{xy} & \tilde{\Phi}_{xx} \end{pmatrix}$$

Super formula:

$$\begin{array}{c}
u_k \\ \hline G(z) \\
\end{array} & G(z) \\
\end{array} & \tilde{\Phi}_{ww} = G(z) \tilde{\Phi}_{ww} G^*(z^{-*}) \\
\end{array}$$

$$\begin{array}{c}
\tilde{\Phi}_{xe} = \tilde{\Phi}_{xy} / T^*(z^{-*}) \\
\end{array}$$

$$\implies H^c_{\hat{x}e}(z) = \left[\frac{z^n \tilde{\Phi}_{xy}(z)}{T^*(z^{-*})}\right]_+ \qquad \implies \quad H^c_{\hat{x}y}(z) = \frac{1}{T(z)} \cdot \left[\frac{z^n \tilde{\Phi}_{xy}(z)}{T^*(z^{-*})}\right]_+$$

Note: A factor z^{-n} is in some books added to $H_{\hat{x}y}^c(z)$. Without this factor (as given above) $\hat{x}_{k+n|k} = H_{\hat{x}y}^c(\Delta)y_k$ and with the factor $\hat{x}_{k+n|k} = \Delta^{-n}H_{\hat{x}y}^c(\Delta)y_{k+n}$. Be sure to know which convention you are adhering to, and both works just fine.