

Wiener-Hopf kernel estimation

NEU 466M

Spring 2020

Problem setup

$$\left\{ \cdots x_{t-1}, x_t, x_{t+1} \cdots \right\} \quad \text{time-varying signal (stimulus) sampled at discrete intervals}$$
$$\left\{ \cdots y_{t-1}, y_t, y_{t+1} \cdots \right\} \quad \text{time-varying signal (response)}$$

Assume y derived from x , through convolution with **unknown** kernel h and small noise term ϵ :

$$y(n) = \sum_{m=M_1}^{M_2} x(n-m)h(m) + \epsilon(n)$$

$\{h_{M_1}, \cdots, h_{M_2}\}$ unknown kernel.
If $M_1=0$: causal.

Question

$$y(n) = \sum_{m=M_1}^{M_2} x(n-m)h(m) + \epsilon(n)$$

What is the best possible estimate of h , given x , y ?

Minimization problem

$$E = \frac{1}{2} \sum_{n=-\infty}^{\infty} \left(y_n - \sum_{m=M_1}^{M_2} x_{n-m} h_m \right)^2$$

$$\hat{h}_{M_1} \cdots \hat{h}_{M_2} = \arg \min_{h_{M_1} \cdots h_{M_2}} E$$

Find h that minimizes the squared error between measured y and values predicted from x by the model.

Minimization problem

$$E = \frac{1}{2} \sum_{n=-\infty}^{\infty} \left(y_n - \sum_{m=M_1}^{M_2} x_{n-m} h_m \right)^2$$

$$\hat{h}_{M_1} \cdots \hat{h}_{M_2} = \arg \min_{h_{M_1} \cdots h_{M_2}} E$$

Compare: (very similar) linear regression framework.

Solve: minimization problem

$$\begin{aligned} 0 &= \frac{\partial E}{\partial h_i} = - \sum_n \left(y_n - \sum_{m=M_1}^{M_2} x_{n-m} h_m \right) x_{n-i} \\ &= - \sum_n y_n x_{n-i} + \sum_m (h_m \sum_n x_{n-m} x_{n-i}) \\ &= C_i^{xy} - \sum_{m=M_1}^{M_2} h_m C_{i-m}^{xx} \end{aligned}$$

Wiener-Hopf equations

$$C_i^{xy} = \sum_{m=M_1}^{M_2} h_m C_{i-m}^{xx}$$

Diagram illustrating the Wiener-Hopf equation:

- C_i^{xy} is labeled as "cross-correlation/STA".
- h_m is labeled as "unknown kernel".
- C_{i-m}^{xx} is labeled as "input auto-correlation".

- This is the least-squares optimal solution for the unknown kernel h .
- It depends on the cross-correlation of the input and the response (STA).
- But it also depends on the auto-correlation of the input, unlike the STA.

Linear regression as special case of Wiener-Hopf

$$C_i^{xy} = \sum_{m=M_1}^{M_2} h_m C_{i-m}^{xx}$$

No time-lags in auto- and cross-correlation since x, y independent samples not time series (so $i=0$). Only one term h (the slope between x, y), no convolution, so $M_1 = M_2 = 0$

$$C^{xy} = C^{xx} h_0$$

$$h_0 = \frac{C^{xy}}{C^{xx}}$$

Optimal least-squares estimate of slope in linear regression (look back at notes)

Wiener-Hopf equations: solution?

$$C_i^{xy} = \sum_{m=M_1}^{M_2} h_m C_{i-m}^{xx}$$

(M₂-M₁+1) x 1 cross-correlation/STA (arrow pointing to C_i^{xy})

unknown kernel: (M₂-M₁+1) x 1 (arrow pointing to h_m)

input auto-correlation (arrow pointing to C_{i-m}^{xx})

$M_2 - M_1 + 1$ unknowns h_m .

$M_2 - M_1 + 1$ equations: i^{th} equation obtained by differentiating w.r.t. h_i .

Thus, generically, a solution exists.

Easy way to solve?