

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.

Wiener-Hopf equations

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

cross-correlation/STA

unknown kernel

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?

Brief algebra detour before we solve Wiener-Hopf equations

MATRIX-VECTOR ALGEBRA

Matrix-vector algebra

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix}$$

size $(n \times m)$ matrix

$$\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix}$$

size $(m \times 1)$ column vector

Notation

- Matrices: upper-case

A, B, U, W

- Vector: **bold**, (usually) lower-case

$\mathbf{x}, \mathbf{y}, \mathbf{v}, \mathbf{w}$ (handwriting: $\mathbf{x} \rightarrow \underline{x}$)

- Elements of matrix, vector: lower-case

a_{ij}, b_i, v_j, u_{kl}

- Scalar numbers: lower-case, no indices

a, b, c, γ, α

Matrix-vector algebra

$$A\mathbf{v} = \begin{matrix} \xrightarrow{(1)} \\ \xrightarrow{(2)} \end{matrix} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} a_{11}v_1 + a_{12}v_2 + \cdots + a_{1m}v_m \\ a_{21}v_1 + a_{22}v_2 + \cdots + a_{2m}v_m \\ \vdots \\ a_{n1}v_1 + a_{n2}v_2 + \cdots + a_{nm}v_m \end{bmatrix}$$

$(n \times m)$ $(m \times 1)$ $(n \times 1)$

$$(A\mathbf{v})_i = \sum_{j=1}^m a_{ij}v_j \quad i \text{ any index in } \{1, \dots, n\}$$

Matrix-matrix product

$$AB = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1l} \\ b_{21} & b_{22} & \cdots & b_{2l} \\ \cdots & \cdots & \cdots & \cdots \\ b_{m1} & b_{m2} & \cdots & b_{ml} \end{bmatrix}$$

$(n \times m)$ $(m \times l)$

$$= \begin{bmatrix} (a_{11}b_{11} + \cdots + a_{1m}b_{m1}) & \cdots & (a_{11}b_{1l} + \cdots + a_{1m}b_{ml}) \\ (a_{21}b_{11} + \cdots + a_{2m}b_{m1}) & \cdots & (a_{21}b_{1l} + \cdots + a_{2m}b_{ml}) \\ \cdots & \cdots & \cdots \\ (a_{n1}b_{11} + \cdots + a_{nm}b_{m1}) & \cdots & (a_{n1}b_{1l} + \cdots + a_{nm}b_{ml}) \end{bmatrix}$$

$(n \times l)$

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$(n \times m)$ $(m \times l)$

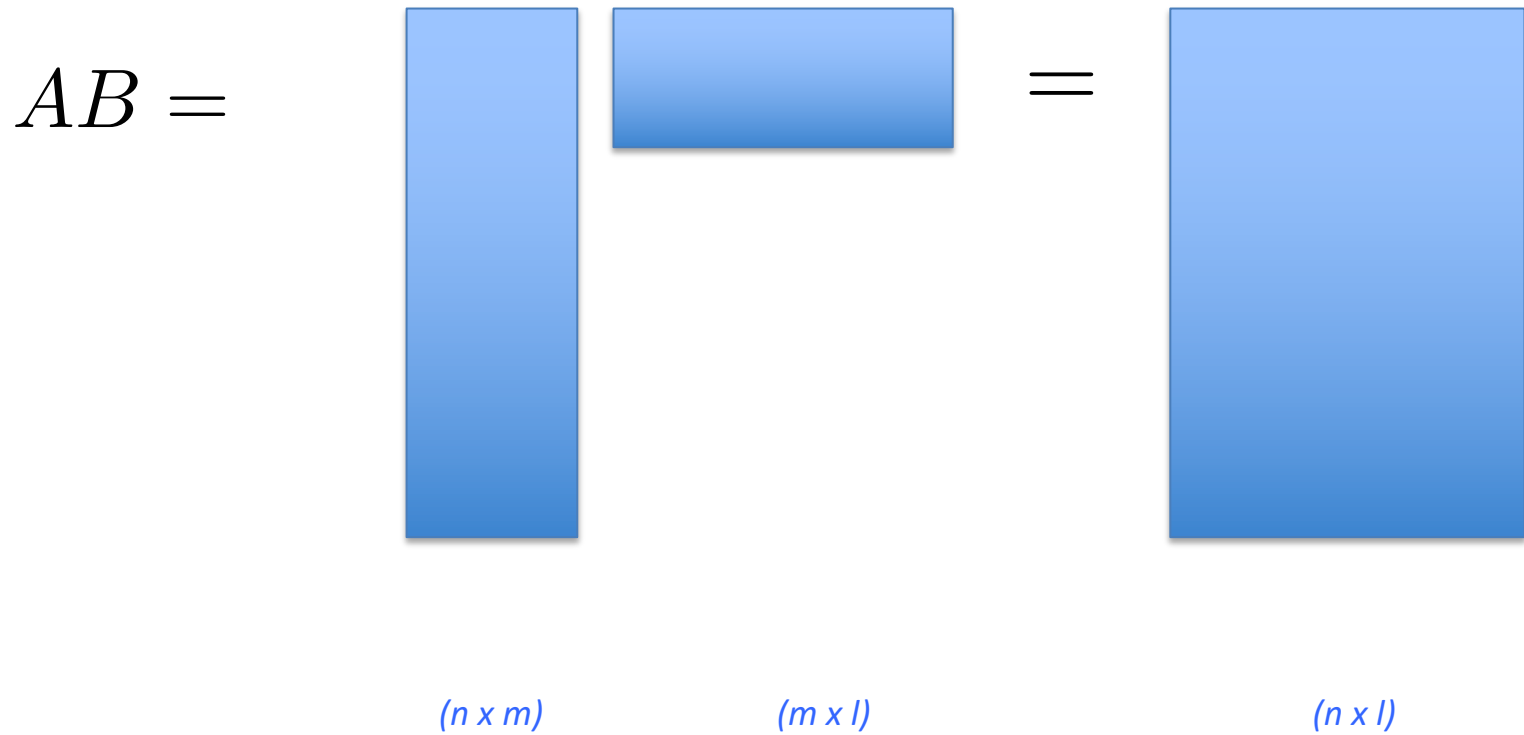
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Matrix-matrix product

$$AB = \begin{matrix} \text{[Blue rectangle]} \\ (n \times m) \end{matrix} \begin{matrix} \text{[Blue vertical bar]} \\ (m \times l) \end{matrix} = \begin{matrix} \text{[Blue vertical bar]} \\ (n \times l) \end{matrix}$$

The diagram illustrates the matrix-matrix product AB . It shows a blue rectangle representing matrix A with dimensions $(n \times m)$, followed by a blue vertical bar representing matrix B with dimensions $(m \times l)$. An equals sign follows, leading to a blue vertical bar representing the resulting product matrix AB with dimensions $(n \times l)$.

Matrix-matrix product



System of equations

n equations in m unknowns (v_1, \dots, v_m):

$$a_{11}v_1 + \cdots + a_{1m}v_m = b_1$$

$$a_{21}v_1 + \cdots + a_{2m}v_m = b_2$$

.....

$$a_{n1}v_1 + \cdots + a_{nm}v_m = b_n$$

System of equations

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.....

$$a_{n1}v_1 + \cdots + a_{nm}v_m = b_n$$

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}$$

$(n \times m)$ $(m \times 1)$ $(n \times 1)$

System of equations

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$(n \times m)$ $(m \times 1)$ $(n \times 1)$

$$\mathbf{A}\mathbf{v} = \mathbf{b}$$

System of equations: when does unique solution exist?

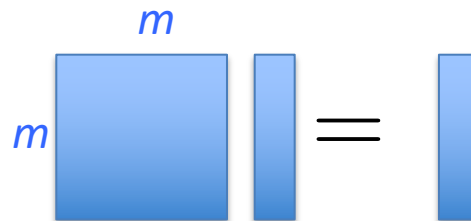
n equations in m unknowns: *generically*, a unique solution exists when same number of Constraints (n) as unknowns (m): $n=m$ or A is square

$$\begin{bmatrix} a_{11} & \cdots & a_{1m} \\ a_{21} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots \\ a_{m1} & \cdots & a_{mm} \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}$$

$(m \times m)$ $(m \times 1)$ $(n \times 1)$

$$A \mathbf{v} = \mathbf{b}$$

$(m \times m)$ $(m \times 1)$ $(m \times 1)$



System of equations: when does unique solution exist?

n equations in m unknowns: *generically*, a unique solution exists when $n=m$, or A is square

$$\underset{(n \times n)}{A} \underset{(n \times 1)}{\mathbf{v}} = \underset{(n \times 1)}{\mathbf{b}}$$

When solution exists, it is given by:

$$\underset{(n \times 1)}{\mathbf{v}} = \underset{(n \times n)}{A^{-1}} \underset{(n \times 1)}{\mathbf{b}}$$

Where A^{-1} is the inverse of the matrix A , and is defined as:

$$A^{-1}A = AA^{-1} = I \leftarrow \text{Identity matrix}$$

Identity matrix

$(n \times m)$ $(m \times m)$ $(n \times m)$

$$BI = B$$

$$IB = B$$

$(n \times n)$ $(n \times m)$ $(n \times m)$

Square matrix with 1's on the diagonal, 0's everywhere else:

$$I = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ & & \ddots & \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

Return to

SOLUTION OF WIENER-HOPF EQUATIONS

Wiener-Hopf equations: matrix form

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

define matrix C^{xx} such that $(C^{xx})_{i,m} \equiv C_{i-m}^{xx}$

size $(M_2-M_1+1) \times (M_2-M_1+1)$

vector \mathbf{C}^{xy} such that $(\mathbf{C}^{xy})_i \equiv C_i^{xy}$

size $(M_2-M_1+1) \times 1$

vector \mathbf{h} such that $(\mathbf{h})_i \equiv h_i$

size $(M_2-M_1+1) \times 1$

$$\begin{aligned} (\mathbf{C}^{xy})_i &= \sum_{m=M_1}^{M_2} (C^{xx})_{i,m} h_m \\ &= (C^{xx} \mathbf{h})_i \end{aligned}$$

$$\mathbf{C}^{xy} = C^{xx} \mathbf{h}$$

Wiener-Hopf equations in
matrix-vector form

Solution of the Wiener-Hopf equations

$$\mathbf{C}^{xy} = \mathbf{C}^{xx} \mathbf{h}$$

$(M_2 - M_1 + 1) \times (M_2 - M_1 + 1)$ inverse auto-correlation matrix

$$\mathbf{h} = (\mathbf{C}^{xx})^{-1} \mathbf{C}^{xy}$$

unknown kernel: $(M_2 - M_1 + 1) \times 1$

STA: $(M_2 - M_1 + 1) \times 1$

Matlab: `toeplitz` for autocorrelation matrix, `A\b` for $A^{-1}b$

The autocorrelation matrix

$$C^{xx} = \begin{bmatrix} C_0^{xx} & C_1^{xx} & C_2^{xx} & \dots & C_K^{xx} \\ C_1^{xx} & C_0^{xx} & C_1^{xx} & & \\ \vdots & \ddots & \ddots & \ddots & \\ C_{K-1}^{xx} & & \ddots & C_0^{xx} & C_1^{xx} \\ C_K^{xx} & C_{K-1}^{xx} & & C_1^{xx} & C_0^{xx} \end{bmatrix}$$

$K=M_2-M_1+1$
square
Toeplitz

The autocorrelation matrix

$$C^{xx} = \begin{bmatrix} C_0^{xx} & C_1^{xx} & C_2^{xx} & \dots & C_K^{xx} \\ C_1^{xx} & C_0^{xx} & C_1^{xx} & & \\ \vdots & \ddots & \ddots & \ddots & \\ C_{K-1}^{xx} & & \ddots & C_0^{xx} & C_1^{xx} \\ C_K^{xx} & C_{K-1}^{xx} & & C_1^{xx} & C_0^{xx} \end{bmatrix}$$

$K=M_2-M_1+1$
square
Toeplitz

When stimulus x is white noise then autocorrelation zero everywhere except at 0-lag.
Thus, $C_{ij}^{xx} = 0$ except along main diagonal $\rightarrow C_{ij}^{xx} = I$ (identity matrix).

Wiener-Hopf solution when stimulus is white

$$\mathbf{h} = (\mathbf{C}^{xx})^{-1} \mathbf{C}^{xy}$$

$$\mathbf{C}^{xx}, (\mathbf{C}^{xx})^{-1} = \mathbf{I} \quad \text{for white noise stimulus}$$

$$\mathbf{h} = \mathbf{C}^{xy} = \mathit{STA}$$

The Wiener-Hopf estimate of the kernel is the STA when the stimulus is uncorrelated.

Summary

- Wiener-Hopf equations give the (least-squared error) optimal estimate of an unknown kernel between input x and response y .
- Linear regression is special case of Wiener-Hopf filtering for stationary (non time-series) data.
- STA is a special case of the Wiener-Hopf kernel if the stimulus is white. Thus, STA is the best (minimum squared-error) kernel estimate for uncorrelated stimulus.
- For positively correlated stimulus, STA kernel estimate is always wider than the true kernel. Wiener-Hopf solution: normalize kernel by inverse of stimulus correlation matrix (this accounts for the stimulus-induced response correlation).