

GSP - HW4

$\vec{h}_i = V_i^H \vec{x}_i$

$\vec{x}_0 = V_i \vec{h}_i, \vec{h}_i \sim N(0, \Lambda_i^{-1}) \rightarrow E[\vec{h}_i \vec{h}_i^H] = \Lambda_i^{-1}, \sum_{i \neq j} [h_i h_j] = 0$

$\vec{x} = \sum_{i=1}^n x_i, n \sim N(0, \sigma^2 I)$

GSP 4 سہ ماہی
40001204 سہ ماہی

10/5

MAP estimation: $\max_{\vec{h}_{1:k}} P[\vec{h}_{1:k} | \vec{x}] = \max_{\vec{h}_{1:k}} \frac{P(\vec{x} | \vec{h}_{1:k}) P(\vec{h}_{1:k})}{\int_{\mathcal{H}^k} P(\vec{x} | \vec{h}_{1:k}) P(\vec{h}_{1:k}) d\vec{h}_{1:k}}$

$= \max P(\vec{x} | \vec{h}_{1:k}) P(\vec{h}_{1:k})$ (i.e.)

(i) $P(\vec{h}_{1:k}) = \prod_{i=1}^k P(h_i) = \prod_{i=1}^k \frac{1}{(2\pi)^{N/2} |\Lambda_i|^{1/2}} \exp\left(-\frac{1}{2} h_i^T \Lambda_i h_i\right)$

constant important

(ii) $P(\vec{x} | \vec{h}_{1:k}) = P(\vec{x} | \vec{x}_{1:k}) = \frac{1}{(2\pi\sigma^2)^{N/2}} \exp\left[-\frac{(\vec{x} - \sum V_i \vec{h}_i)^T (n - \sum V_i^H \vec{h}_i)}{2\sigma^2}\right]$

constant important

(i.e.), (i), (ii) $\rightarrow \arg \max_{\vec{h}_{1:k}} P(\vec{h}_{1:k} | \vec{x}) = \arg \min_{\vec{x}} \left[\frac{1}{2\sigma^2} \|\vec{x} - \sum_{i=1}^k x_i\|^2 + \sum_{i=1}^k x_i^H \Lambda_i x_i \right]$

$= \arg \min_{x_{1:k}} \left\{ \|\vec{x} - \sum_{i=1}^k x_i\|^2 + \sigma^2 \sum_{i=1}^k x_i^H \Lambda_i x_i \right\}$ Q.E.D.

I $\vec{x}_i \in \{0, 1\}^N$ $(\vec{x}_i)_k \sim \text{Ber}(p)$ $w_{ij} = \begin{cases} 0 & i=j \\ 1 & i \neq j \end{cases}$ 20/6

$\vec{y} \sim N(0, \sigma^2 I)$ $w = W^T, w_{ii} = 0$

$1 + \sum_{k=1}^M ((\vec{x}_k)_i - (\vec{x}_k)_j)^2$

$\Rightarrow \vec{y}^H \vec{z} = \sum_{i,k} w_{ik} |\vec{y}_i - \vec{y}_k|^2 = \frac{1}{2} \sum_{i,k} w_{ik} |\vec{y}_i - \vec{y}_k|^2$

$\Rightarrow E[\vec{y}^H \vec{z} | \mathcal{Z}] = E[\vec{y}^H \vec{z} | w_{11}, \dots, w_{MM}] = \frac{1}{2} \sum_{i,k} w_{ik} E[|\vec{y}_i - \vec{y}_k|^2]$

$\forall i,k: E[|\vec{y}_i - \vec{y}_k|^2] = E[\vec{y}_i^2] + E[\vec{y}_k^2] - 2E[\vec{y}_i \vec{y}_k] = 2\sigma^2$

which suggest $E[\vec{y}^H \vec{z} | \mathcal{Z}] = \frac{2\sigma^2}{2} \sum_{i,k} E[w_{ij}]$

so now we'd go to get the distribution of w_{ij} and $|\vec{x}_k(i) - \vec{x}_k(j)|^2 = S_{ij}$

$X_k(i) \sim \bar{p}, p \Rightarrow S_{ij} \sim \text{Ber}(2p\bar{p}) \Rightarrow \sum_{k=1}^M |\vec{x}_k(i) - \vec{x}_k(j)|^2 \sim \text{Bin}(M, \bar{p})$

$\bar{p} = 0$ $p = 1$

$X_k(i)$	\bar{p}	p
$X_k(j)$	0	1
	1	0

where $\bar{p} = 2p(1-p) = 2p\bar{p}$

10/10 $\bar{p} = 1-p$

so we calculate $E[W_{ij}]$ for all i, j :

$$\tilde{q} = 1 - \tilde{p} = 1 - 2p(1-p)$$

$$E[W_{ij}] = E_{Z \sim \text{Bin}(M, \tilde{p})} \left[\frac{1}{1+Z} \right] = \sum_{k=0}^M \binom{M}{k} \tilde{p}^k \tilde{q}^{M-k} \frac{1}{1+k} = f(\tilde{p}, \tilde{q}) \quad (*)$$

$$\rightarrow \frac{\partial f}{\partial \tilde{p}} = \sum_{k=0}^{M-1} \frac{k}{1+k} \binom{M}{k} \tilde{p}^{k-1} \tilde{q}^{M-k} \Rightarrow (*), (*) \text{ can lead to: } \underline{2(1) \text{ result}}$$

$$\frac{\partial f}{\partial \tilde{p}} \cdot \tilde{p} + f(\tilde{p}, \tilde{q}) = \sum_{k=0}^M \frac{1}{1+k} \binom{M}{k} \tilde{p}^k \tilde{q}^{M-k} = \sum_{k=0}^M \binom{M}{k} \tilde{p}^k \tilde{q}^k = (\tilde{p} + \tilde{q})^M = 1$$

$$\frac{\partial f}{\partial \tilde{p}} \cdot \tilde{p} + f = \frac{\partial}{\partial \tilde{p}} (\tilde{p} \cdot f(\tilde{p}, \tilde{q})) \xrightarrow{\text{integration}} \tilde{p} \cdot f(\tilde{p}, \tilde{q}) = \frac{1}{M+1} \tilde{q}^{M+1} + h(\tilde{q}) \quad (**)$$

a function of \tilde{q} .

Now let $\tilde{p}=0$ in $f(\tilde{p}, \tilde{q})|_{\tilde{p}=0} = \tilde{q}^M \Rightarrow \tilde{p} \cdot f(\tilde{p}, \tilde{q})|_{\tilde{p}=0} = 0 \Rightarrow$ which suggests

$$h(\tilde{q}) = -\frac{1}{M+1} \tilde{q}^{M+1} + f(\tilde{p}, \tilde{q}) \quad (***) \Rightarrow$$

$$\xrightarrow{(**), (***)} f(\tilde{p}, \tilde{q}) = \frac{(\tilde{p} + \tilde{q})^{M+1} - \tilde{q}^{M+1}}{(M+1)\tilde{p}} = \frac{1 - \tilde{q}^{M+1}}{(M+1)\tilde{p}} = \frac{1 - [2p(1-p)]^{M+1}}{2(M+1)p(1-p)} \quad (****)$$

So now from (****) and before, we can deduce that

$$E[Y^M Z_0] = N\sigma^2 E[W_{ij}] = N\sigma^2 \cdot \frac{1 - \tilde{q}^{M+1}}{(M+1)\tilde{p}} = N\sigma^2 \cdot \frac{1 - [2p(1-p)]^{M+1}}{(M+1)2p(1-p)}$$

II From the first hw, we know that $\sum_{\substack{S \subseteq [k] \\ |S|=k}} \sum_{i \in S} \lambda_i = \sum_{\substack{S \subseteq [k] \\ |S|=k}} \det(A(S, S))$

$$\Rightarrow \sum_{i+j} \lambda_i \lambda_j = \sum_{\substack{S \subseteq [N] \\ |S|=2}} \det(W(S, S)) \rightarrow \left\{ \begin{array}{l} \text{because } \sum_{i+j} \lambda_i \lambda_j \text{ is the 2nd coeff} \\ \text{in } P(\lambda) \text{ of } W \text{ matrix.} \end{array} \right.$$

$$\text{However, } W(S, S) = \begin{bmatrix} w_{ii} & w_{ij} \\ w_{ji} & w_{jj} \end{bmatrix} = -w_{ij}^2$$

$$\Rightarrow E\left[\sum_{i+j} \lambda_i \lambda_j\right] = E\left[-\sum_{i+j} w_{ij}^2\right] = -\binom{N}{2} E[w_{ij}^2]$$

Now writing $E\left[\frac{1}{1+s^2}\right]$ is very hard differential equation. Thus in order to get $\frac{1}{1+s^2}$, we may use its Taylor series and hence (we only use the second moment):

$$\Rightarrow E\left[\frac{1}{1+s^2}\right] = \text{Var}\left(\frac{1}{1+s}\right) + \left(E\left[\frac{1}{1+s}\right]\right)^2 \rightarrow \text{thus next page}$$

(I)

$$P_{t+1}(x=k) = \sum_l P_t(x=l) P(l \rightarrow k) = \frac{1}{2} P_t(x=k) + \frac{1}{2} \sum_{l=1}^n \frac{W_{kl}}{d(l)} P_t(x=l)$$

equations above describe the markov chain process of the problem.

$$\Rightarrow P_{t+1}(x=k) = \frac{1}{2} P_t(x=k) + \frac{1}{2} \sum_l (D^{-1}W)_{kl} P_t(x=l) \rightarrow \vec{P}_{t+1} = \frac{1}{2} (I + D^{-1}W^T) \vec{P}_t$$

$$\Rightarrow \vec{P}_{t+1} = \tilde{W} \vec{P}_t, \text{ where } \tilde{W} = \frac{1}{2} (I + D^{-1}W^T) = \frac{1}{2} D^{-1/2} (I + A) D^{-1/2}, \text{ where } A = D^{-1/2} W D^{-1/2}.$$

Now if we suppose that $\omega_1 \geq \dots \geq \omega_n$ are the eigenvalues associated with eigenvectors

$$\psi_1, \dots, \psi_n; \text{ then } \tilde{W} \psi_i = \omega_i \psi_i = \frac{1}{2} D^{-1/2} (I + A) D^{-1/2} \psi_i = \omega_i \psi_i \Rightarrow (I + A) (D^{-1/2} \psi_i) = 2 \omega_i (D^{-1/2} \psi_i)$$

$$\Rightarrow \text{which suggests } A(D^{-1/2} \psi_i) = \underbrace{(2\omega_i - 1)}_{\lambda_i} \underbrace{(D^{-1/2} \psi_i)}_{\phi_i} \Rightarrow \begin{cases} \forall i \rightarrow 2\omega_i - 1 \in \Lambda_A, \omega_i \in \Lambda_W \\ \phi_i = D^{-1/2} \psi_i \end{cases}$$

from Perron-Frobenius, we know that:

$$\forall i, \mu_1(i) > 0; \mu_1 \geq -\mu_n, \mu_1 > \mu_2 \text{ if } M_{ij} \geq 0$$

$$A \phi_i = \mu_i \phi_i \xrightarrow[A = D^{-1/2} W D^{-1/2}]{\vec{x} = \sqrt{D}} x = [\sqrt{d_1}, \dots, \sqrt{d_n}]^T \Rightarrow A \vec{x} = D^{-1/2} W D^{-1/2} \vec{x} = \vec{x}$$

$$\text{thus } \vec{x} \text{ is an eigenvector of } A \text{ with } \mu = 1. \rightarrow \forall i: x(i) > 0 \rightarrow \begin{cases} x = u_1 = \phi_1 \\ 1 = \mu_1 = 2\omega_1 - 1 \\ \omega_1 = 1 \end{cases}$$

$$\vec{v}_1 = D^{-1/2} \vec{\psi}_1 \Rightarrow \vec{\psi}_1 = D^{1/2} \phi_1 = D^{1/2} [\sqrt{d_1}, \dots, \sqrt{d_n}]^T = (d_{11}, \dots, d_{nn})^T$$

$$\mu_1 = 1 \xrightarrow[\text{Perron}]{\text{Frobenius}} \begin{cases} \mu_2 = 2\omega_2 - 1 \geq 2\omega_2 - 1 \\ \mu_2 < \mu_1 = 1 \end{cases} \quad \boxed{\forall i: \omega_i \leq 1} \quad (d)$$

$$\begin{cases} \mu_n \geq -\mu_1 = -1 \rightarrow 2\omega_i - 1 \geq -1 \rightarrow \boxed{\omega_i \geq 0} \quad \forall i \quad (d+1) \end{cases}$$

$$\text{Now, we can add these two } (d), (d+1) \text{ and get: } \begin{cases} \omega_1 = 1; \vec{d} = W \vec{1}_{n \times 1} \\ \vec{\phi}_1 = \vec{d} = [d_{11}, \dots, d_{nn}] \\ 0 \leq \omega_i < 1, i \neq 1 \end{cases}$$

$$\text{III } \vec{P}_{t+1} = \tilde{W} \vec{P}_t, 0 \leq \omega_i \leq 1, \tilde{W} = \frac{1}{4} W^T W \Rightarrow \lim_{t \rightarrow \infty} \tilde{W}^t = \frac{1}{4} \lim_{t \rightarrow \infty} W^T W^t = \frac{1}{4} \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} W^T$$

Since \tilde{W} has only one eigenvalue & the rest are of less size than 1.

$$\exists \vec{\pi}: \pi = \lim_{t \rightarrow \infty} P_t = \left(\lim_{t \rightarrow \infty} \tilde{W}^t \right) \vec{P}_0 \Rightarrow \tilde{W} \vec{\pi} = \vec{\pi} \Rightarrow \vec{\pi} = \phi_1 = \vec{d}$$

(due to $t \rightarrow \infty$)

and if we normalize $\vec{r} \rightarrow$ we get $\vec{r} = \frac{[d(1), \dots, d(n)]^T}{\sum_{i=1}^n d_i}$: 30/10/19

$\Rightarrow \boxed{\vec{r} = \frac{\vec{d}}{\|\vec{d}\|_1}}$ No matter where we start, ($P_0 = \delta_a$), we will (end up at) converge to the vector \vec{r} in probability.

IV $\vec{P}_t = \tilde{W}^t P_0 = \tilde{W}^t \delta_a = D^{1/2} \left(\frac{I+A}{2} \right)^t D^{-1/2} \delta_a \Rightarrow D^{-1/2} \vec{P}_t = \left(\frac{I+A}{2} \right)^t (D^{-1/2} \delta_a)$

$D^{-1/2} \vec{r} = \lim_{t \rightarrow \infty} \left(\frac{I+A}{2} \right)^t (D^{-1/2} \delta_a) \Rightarrow D^{-1/2} (\vec{P}_t - \vec{r}) = \left[\left(\frac{I+A}{2} \right)^t - \lim_{t \rightarrow \infty} \left(\frac{I+A}{2} \right)^t \right] (D^{-1/2} \delta_a)$

$\Rightarrow = \sigma_{\max} \left\{ B^t - \lim_{t \rightarrow \infty} B^t \right\} = \lambda_{\max} \{ \dots \}$

$\Rightarrow \lambda_i \left(\left(\frac{I+A}{2} \right)^t - \lim_{t \rightarrow \infty} \left(\frac{I+A}{2} \right)^t \right) = \begin{cases} 0 & i=0 \\ \omega_i^t & \text{o.w.} \end{cases} \Rightarrow \lambda_{\max} = \omega_2^t$

$\|D^{-1/2} (\vec{P}_t - \vec{r})\|_2 = \|C \dots\|_2 \leq \|C\|_2 \cdot \|D^{-1/2} \delta_a\|_2 = \omega_2^t \|D^{-1/2} \delta_a\|_2$

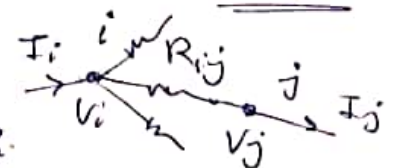
$\|D^{-1/2} \delta_a\|_2 = \frac{1}{\sqrt{d(a)}} \Rightarrow \|D^{-1/2} v\|_2 \geq \|(D^{-1/2} v)_{(b)}\|_2 = \frac{1}{\sqrt{d(b)}} |v(b)|$

Thus $\|D^{-1/2} (\vec{P}_t - \vec{r})\|_2 \leq \frac{1}{\sqrt{d(a)}} \omega_2^t \xrightarrow{a,b} \boxed{P_i^{(b)} - \pi(b) \leq \sqrt{\frac{d(b)}{d(a)}} \omega_2^t}$ Q.E.D.

I $w_{ij} = \frac{1}{R_{ij}}$: 40/10/19

if $I_i = I_j = I \Rightarrow v_i - v_j = R_{eff}(i,j) I$

Let $I_i = \sum_{j=1}^n \frac{v_i - v_j}{R_{ij}} = \sum_{j=1}^n (v_i - v_j) w_{ij}$ } $\vec{I} = \mathcal{L} \vec{V}$
 $\vec{V} = \mathcal{L}^+ \vec{I}$



Let $\vec{I} = \vec{\delta}_u - \vec{\delta}_v \xrightarrow{u,v} \vec{V}(u) - \vec{V}(v) = R_{eff}(u,v) = (\delta_u - \delta_v)^T \vec{V}$

Since $\mathcal{L} \vec{V} = \vec{I} = \vec{\delta}_u - \vec{\delta}_v \Rightarrow \vec{V} = \mathcal{L}^+ (\vec{\delta}_u - \vec{\delta}_v) \rightarrow \boxed{R_{eff}(u,v) = (\delta_u - \delta_v)^T \mathcal{L}^+ (\delta_u - \delta_v)}$ Q.E.D.

So we have a subset $B \subseteq V$ of arbitrary voltages. (II) : 401.3, 3.3.3

Let $LV = I \xrightarrow{a_u} (LV)_{(u)} = I_{(u)} = 0 = d(u) \vec{V}_{(u)} - (WV)_{(u)} = d(u) \vec{V}_{(u)} - \sum_{s=1}^n w_{su} \vec{V}_{(s)}$
 \rightarrow Thus, we can deduce that $\vec{V}_{(u)} = \frac{1}{d(u)} \sum_{s \sim u} w_{su} \vec{V}_{(s)}$ Q.E.D. \square

Let $f(v) = v^T L v = \sum_{i,j} w_{ij} \|\vec{v}_i - \vec{v}_j\|^2 \rightarrow \nabla f(v) \big|_{V_B} = 0$

$\rightarrow \sum_{s \sim u} 2 w_{us} (\vec{V}_{(u)} - \vec{V}_{(s)}) = 0 \rightarrow \vec{V}_{(u)} \sum w_{su} = \sum w_{su} \vec{V}_{(s)}$ the same equation as before

$\begin{cases} \nabla f(\vec{V}^T L \vec{V}) = 0 \\ \vec{V} \in V/B \end{cases}$

*
 (III) we need to find L_B : $V_{(B)}^T L_B \vec{V}_B = \vec{V}^T L \vec{V}$

$\forall u \in V/B \rightarrow (L\vec{V})_{(u)} = 0$ (harmonic)

$\vec{V}^T L \vec{V} = \sum_u \vec{V}_{(u)} (L\vec{V})_{(u)} = \sum_{u \in B} \vec{V}_{(u)} (L\vec{V})_{(u)} + \sum_{u \in V/B} \vec{V}_{(u)} (L\vec{V})_{(u)} = \sum_{u \in B} \sum_s \vec{V}_{(u)} L_{us} \vec{V}_{(s)}$

consider only remaining node $k \rightarrow B = V/\{k\}$

$\rightarrow \vec{V}^T L \vec{V} = \sum_{u \in V} \sum_s \vec{V}_{(u)} L_{us} \vec{V}_{(s)} = \sum_{u \in V} \sum_{s \neq k} \vec{V}_{(u)} \left[L_{us} \vec{V}_{(s)} + \sum_{s \neq k} L_{us} \vec{V}_{(s)} \right]$

$(L\vec{V})_{(k)} = 0 \rightarrow \vec{V}_{(k)} = \frac{1}{d(k)} \sum_{s \in V} w_{sk} \vec{V}_{(s)}$

$\Rightarrow \vec{V}^T L \vec{V} = \sum_{u \in V} \sum_{s \neq k} \vec{V}_{(u)} \left(L_{us} + \frac{L_{uk} w_{sk}}{d(k)} \right) \vec{V}_{(s)} = \sum_{u,s \in B} \vec{V}_{(u)} \left(L_{us} + \frac{w_{sk}}{d(k)} L_{uk} \right) \vec{V}_{(s)}$

$= V_{(B)}^T L' \vec{V}_B \rightarrow$ if L' here is valid, then we have an algorithm to remove nodes.

$\sum_{j=1}^n \sum_{i \neq k} L'_{ij} = L_{ii} + \sum_{i \neq k} \left(L_{ij} + \frac{L_{kj}}{d(k)} w_{ik} \right) = L_{ii} + \sum_{i \neq k} L_{ij} + L_{kj} \sum_{i \neq k} \frac{w_{ik}}{d(k)} = 0$

thus, since the sum of a row of L' is zero $L' \vec{1} = \vec{0}$, thus, L' is a valid Laplacian. So inductively we can remove nodes and we can get $L^{(2)}$ from $L^{(1)} = L'$ and so on and so forth.

\Rightarrow So as we said, we can find L_B such that: $\vec{V}^T L \vec{V} = V_{(B)}^T L_B \vec{V}_B$ Q.E.D. \square

$$f(L^{n \times n}, k) = L^{(n-1) \times (n-1)}$$

node to remove

node removal algorithm

$$\begin{cases} L'_{su} = L_{su} + \frac{w_{sk}}{d(k)} L_{ku} \\ s, u \in V \end{cases}$$

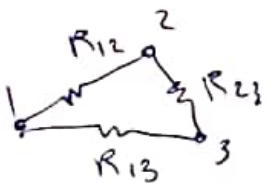
$$(L_B)_{(s,u)} = L_{(s,u)} + \sum_{k \in V/B} \frac{w_{sk}}{d(k)} L_{(k,u)} \quad \text{for removal of } V/B.$$

IV if we can prove the triangle inequality for three nodes, then we can show that $d = \frac{1}{R_{ij}}$ is a metric.

for two nodes:

$$i \xrightarrow{R} j \quad L = \begin{bmatrix} 1/R & -1/R \\ -1/R & 1/R \end{bmatrix} \Rightarrow L^+ = \begin{bmatrix} R & -R \\ -R & R \end{bmatrix} \frac{1}{4}$$

$$\Rightarrow \text{Req}(1,2) = \frac{1}{4} (1 \ -1) \begin{bmatrix} R & -R \\ -R & R \end{bmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix} = R \quad \checkmark$$



$$\begin{cases} R_{eq}^1 = R_1 \parallel (R_2 + R_3) \\ R_{eq}^2 = R_2 \parallel (R_1 + R_3) \\ R_{eq}^3 = R_3 \parallel (R_1 + R_2) \end{cases}$$

$$R_{eq}^1 + R_{eq}^2 = \frac{R_3(R_1 + R_2)}{R_1 + R_2 + R_3} + \frac{2R_1R_2}{R_1 + R_2 + R_3}$$

$\Rightarrow R_{eq}^1 + R_{eq}^2 \geq R_{eq}^3$ which proves that $\frac{1}{R}$ is a valid metric. Q.E.D.

① $C_\psi = \int_0^\infty \frac{\hat{\psi}(w)}{w} dw$, let $x, \psi \in L^2(\mathbb{R})$, $0 < C_\psi < \infty$

5012

$$W_f(a, b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \overline{\psi\left(\frac{t-b}{a}\right)} dt = \int_{-\infty}^{\infty} \hat{x}(w) \frac{1}{\sqrt{a}} \cdot a \overline{\hat{\psi}(aw)} e^{-j2\pi bw} dw$$

$$= \sqrt{a} \int_{-\infty}^{\infty} \hat{x}(w) e^{j2\pi bw} \overline{\hat{\psi}(aw)} dw$$

$$\Rightarrow \frac{1}{C_\psi} \int_0^\infty W_f(a, t) \frac{da}{a^{3/2}} = \frac{1}{C_\psi} \int_0^\infty \frac{\sqrt{a}}{a^{3/2}} \int_{-\infty}^{\infty} \hat{x}(w) e^{j2\pi bw} \overline{\hat{\psi}(aw)} dw da \Big|_{b=t}$$

$$= \frac{1}{C_\psi} \int_{-\infty}^{\infty} \hat{x}(w) e^{j2\pi bw} \underbrace{\int_0^\infty \frac{\overline{\hat{\psi}(aw)}}{a} da}_{C_\psi} dw \Big|_{b=t} = \frac{C_\psi}{C_\psi} \int_{-\infty}^{\infty} \hat{x}(w) e^{j2\pi bw} dw \Big|_{b=t} = x(b) = x(t)$$

Q.E.D.

② By definition of wavelet transform.

$$\begin{cases} W_f(a, b) = \int_{-\infty}^{\infty} f(t) \overline{\psi_{ab}(t)} dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(w) \sqrt{|a|} \overline{\hat{\psi}(aw)} e^{j2\pi bw} dw \\ W_g(a, b) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{g}(w) \sqrt{|a|} \hat{\psi}(aw) e^{-j2\pi bw} dw \end{cases}$$

Therefore

$$\Rightarrow \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a, b) \overline{W_g(a, b)} \frac{da db}{a^2} = \frac{1}{4\pi^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{da db}{a^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |a| \hat{f}(w) \overline{\hat{g}(w)} \overline{\hat{\psi}(aw)} \hat{\psi}(aw) e^{j2\pi b(\varepsilon - w)} d\varepsilon dw$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{da}{|a|} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \hat{f}(\varepsilon) \overline{\hat{g}(w)} \overline{\hat{\psi}(a\varepsilon)} \hat{\psi}(aw) \left(\frac{1}{2\pi} \int_{-\infty}^{\infty} e^{j2\pi b(\varepsilon - w)} db \right) d\varepsilon dw$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{da}{|a|} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \hat{f}(\varepsilon) \overline{\hat{g}(w)} \overline{\hat{\psi}(a\varepsilon)} \hat{\psi}(aw) \delta(\varepsilon - w) d\varepsilon dw$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{da}{|a|} \int_{-\infty}^{\infty} \hat{f}(w) \overline{\hat{g}(w)} |\hat{\psi}(aw)|^2 dw$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(w) \overline{\hat{g}(w)} dw \cdot \underbrace{\int_{-\infty}^{\infty} \frac{|\hat{\psi}(aw)|^2}{|a|} da}_{C_\psi} = C_\psi \int_{-\infty}^{\infty} f(t) \overline{g(t)} dt$$

note that $\int_{-\infty}^{\infty} \hat{f}(t) \overline{\hat{g}(t)} dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(w) \overline{\hat{g}(w)} dw$

$$\Rightarrow \langle f, g \rangle = \int_{-\infty}^{\infty} f(t) \overline{g(t)} dt = \frac{1}{C_\psi} \int_0^\infty \int_{-\infty}^{\infty} W_f(u, s) \overline{W_g(u, s)} \frac{du ds}{s^2}$$

$u=b$
 $s=a$

Q.E.D.

$$\begin{aligned}
 C_4 \langle f, f \rangle &= C_4 \cdot \int_{-\infty}^{\infty} dt \int_{-\infty}^{\infty} \overline{f(t)} f(t) dt = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a, b) \overline{W_f(a, b)} \frac{da db}{b^2} \\
 &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a, b) \int_{-\infty}^{\infty} \overline{f(t)} \varphi_{a, b}(t) dt \frac{da db}{a^2} \\
 &= \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a, b) \varphi_{a, b}(t) \frac{da db}{a^2} \right) \overline{f(t)} dt = \left\langle f(t), \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a, b) \frac{da db}{a^2} \varphi_{a, b}(t) \right\rangle
 \end{aligned}$$

$$\Rightarrow \begin{cases} C_4 \cdot f(t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a, b) \varphi_{a, b}(t) \frac{da db}{a^2} \\ \|f\|^2 = \frac{1}{C_4} \int_{-\infty}^{\infty} |W_f(a, b)|^2 \frac{da db}{a^2} \end{cases} \quad \text{Q.E.D.}$$

since $s < d(i, j) \rightarrow W^s(i, j) = 0 \rightarrow L^s(i, j) = \begin{cases} d(i) & i=j \\ -w(i, j) & i \neq j \end{cases} \quad \text{Q.E.D.}$

(I) $\Rightarrow L^s(i, j) = \sum_{l_1} \sum_{l_2} \dots \sum_{l_{s-1}} \sum_{l_s} \epsilon_{l_1, l_2} \dots \epsilon_{l_{s-1}, l_s} = (-1)^{d(i, j)} W^s(i, j) = 0 \quad \forall s < d(i, j)$

$l_1 \neq l_2 \neq \dots \neq l_{s-1}$

$\forall i \in \{1, \dots, n\}$

$$\|\psi_{s, n}(i) - \tilde{\psi}_{s, n}(i)\| = \left| \sqrt{s} \cdot \begin{bmatrix} g(s\lambda_1) - \tilde{g}(s\lambda_1) & 0 \\ 0 & \tilde{g}(s\lambda_n) - g(s\lambda_n) \end{bmatrix} \delta_n \right| \leq \sqrt{s} \cdot M(s) \|\delta_n\| = \sqrt{s} M(s)$$

$\leq M(s) I$ Q.E.D.

$$\Rightarrow \|\psi_{s, n} - \tilde{\psi}_{s, n}\| = \sqrt{\sum_{i=1}^n |\psi_{s, n}(i) - \tilde{\psi}_{s, n}(i)|^2} \leq \sqrt{N \cdot s M(s)^2} = \sqrt{N s} M(s)$$

(III) $M(s) = \sup_{\lambda \in [c, d]} |g(s\lambda) - \tilde{g}(s\lambda)|$

$$\begin{cases} g^{(k)}(c) = C, g^{(r)}(c) = 0 \quad \forall r < k \\ |g^{(k+1)}(\lambda)| \leq B \quad \forall \lambda \in [c, d] \\ \tilde{g}(\lambda) = \frac{C(t\lambda)^k}{k!} = \frac{g^{(k)}(c)(t\lambda)^k}{k!} \end{cases}$$

$$g(\lambda) = \frac{\lambda^k g^{(k)}(c)}{k!} + \frac{\lambda^{k+1} g^{(k+1)}(c)}{(k+1)!} + o(\lambda^{k+2})$$

Q.E.D.

$$\sup_{\lambda} |g(\lambda) - \tilde{g}(\lambda)| = \left| \frac{(t\lambda)^{k+1}}{(k+1)!} g^{(k+1)}(c) + o(t^{k+2}) \right| \leq \sup_{\lambda \in [c, d]} \left\{ \frac{B(t\lambda)^{k+1}}{(k+1)!} \right\} = \frac{B(t\lambda)^{k+1}}{(k+1)!}$$