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شماره دانشجویی								
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صفحه 1 از 4

شماره سوال: 120

Ⓘ we know that G is k -regular graph which means $\sum_{i=1}^n A(i,j) = d(j) = k \quad \forall n$ and also $A \cdot \mathbb{1}_{n \times 1} = k \mathbb{1}_{n \times 1}$, hence $(k, \mathbb{1}_{n \times 1})$ is an eigen-pair of A . Furthermore we know that if $i \sim j$, then $A^2(i,j) = r$ (if $i \sim j$, they have r common neighbors). otherwise $(i \not\sim j)$, then $A^2(i,j) = 0$. So we can reconstruct A^2 with respect to A :

$$A^2 = \sum_{i \sim j} \gamma A + s (\mathbb{1}_{n \times n} - I - A) + kI \rightarrow \text{let } P(A) = A^2 + (s-r)A + (s-k)I = s \mathbb{1}_{n \times n}.$$

Now it's clear that the matrix $P(A) = s \mathbb{1}_{n \times n}$ is of rank 1 and the only nonzero eigenvalue is ns with eigenvector $\mathbb{1}_{n \times 1}$. So let $\{v_i\}_{i=2}^n$ form a basis perpendicular to the subspace with basis $v_1 = \mathbb{1}_{n \times 1}$. Then we know that $\forall i \geq 2: P(A)v_i = 0$ since at least one of v_i 's are not zero vector, we'd get that:

$$\begin{cases} A^2 v_i = \lambda^2 v_i \\ A v_i = \lambda v_i \end{cases} \quad (\lambda^2 + (s-r)\lambda + (s-k)) v_i = 0 \rightarrow \lambda \in \left\{ \begin{matrix} k \\ \frac{-(s-r) \pm \sqrt{(s-r)^2 + 4(k-s)}}{2} \end{matrix} \right\}$$

Since $I = D - A = kI - A \rightarrow \Delta_L = \Delta_A + k$ which suggests that

$$\Delta_L \in \left\{ 0, \frac{2k-r+s \pm \sqrt{(r-s)^2 + 4(k-s)}}{2} \right\} \quad \text{Q.E.D.}$$

Ⓚ Since $x^T \mathbb{1} = 0 \rightarrow x \perp \mathbb{1} \rightarrow x = \sum_{v_i \in V(G) \perp \mathbb{1}} \gamma_i v_i = \gamma_2 v_2 + \gamma_3 v_3 \quad (v_2 \perp v_3)$

$$\langle x, y \rangle = \gamma_2^2 - \gamma_3^2 = 1, \text{ if } y = Hx = f(L)x = \left(\sum_{i=0}^{n-1} \alpha_i L^i \right) x = \left(\sum_{i=0}^{n-1} \alpha_i L^i \right) (\gamma_2 v_2 + \gamma_3 v_3)$$

$$\rightarrow y = \sum_{i=0}^{n-1} \alpha_i (\theta_2^i v_2 + \theta_3^i v_3) = \theta_2 f(\theta_2) v_2 + \theta_3 f(\theta_3) v_3$$

$$\langle x, y \rangle = \langle \theta_2 f(\theta_2) v_2 + \theta_3 f(\theta_3) v_3, \gamma_2 v_2 + \gamma_3 v_3 \rangle = \gamma_2^2 f(\theta_2) + \gamma_3^2 f(\theta_3) = 0 \quad (\neq k)$$

$$(\star), (\star\star) \rightarrow \begin{cases} \gamma_2^2 = \frac{+f(\theta_3)}{f(\theta_2) - f(\theta_3)} \\ \gamma_3^2 = \frac{-f(\theta_2)}{f(\theta_2) - f(\theta_3)} \end{cases}$$

$$\begin{cases} y^H y = \|y\|_2^2 = f(\theta_2) f(\theta_3) \\ \|y\|_2 = \sqrt{f(\theta_2) f(\theta_3)} \end{cases}$$

$$\rightarrow \langle y, y \rangle = \theta_2^2 f(\theta_2)^2 + \gamma_3^2 f(\theta_3)^2 = \frac{-f(\theta_2) f(\theta_3)^2 + f(\theta_3) f(\theta_2)^2}{f(\theta_2) - f(\theta_3)} = f(\theta_2) f(\theta_3)$$

Q.E.D. ■

with the assumption that the vector $\frac{1}{\sqrt{n}} \mathbb{1}$ is an eigenvector of L_n .

2

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

$$y_i = \sqrt{n} \cdot y_{i-1} \otimes \delta_i$$

$$\hat{y}_i(k) = \sqrt{n} \cdot \hat{y}_{i-1}(k) \cdot \mathcal{F}\{\delta_i\}(k) = n^{1/2} \cdot \hat{y}_{i-1}(k) \cdot \bar{u}_{ik} = n^{1/2} \hat{y}_0(k) \left(\prod_{i=1}^n \bar{u}_{ik} \right)$$

$$\langle y_n, \mathbb{1} \rangle = \langle \hat{y}_n, \hat{\mathbb{1}} \rangle = \langle \hat{y}_n, U^H \mathbb{1} \rangle = \hat{y}_n(0) = n^{1/2} \hat{y}_0(0) \left(\prod_{i=1}^n \bar{u}_{i0} \right) = \hat{y}_0(0) \left(\prod_{i=1}^n \bar{u}_{i0} \right) \left(\frac{1}{\sqrt{n}} \right)$$

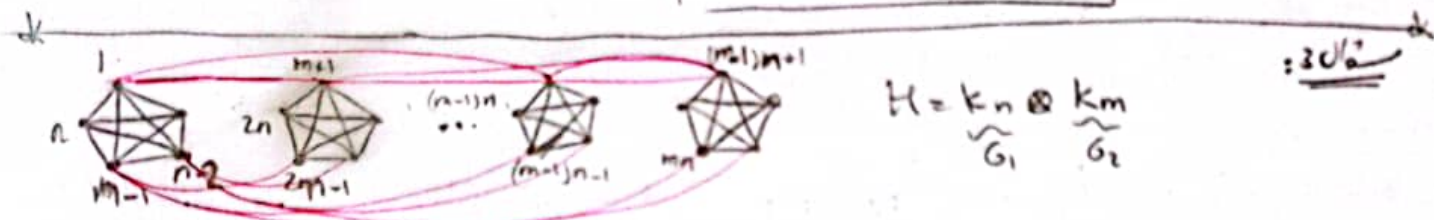
Parseval theorem

$$\langle y_0, \mathbb{1} \rangle = \langle \hat{y}_0, \hat{\mathbb{1}} \rangle = \langle \hat{y}_0, U^H \mathbb{1} \rangle = \hat{y}_0(0) \quad (*)$$

Thus $(*)$, $(**)$ will result in

$$\langle y_n, \mathbb{1}_{n \times 1} \rangle = \langle y_0, \mathbb{1}_{n \times 1} \rangle$$

Q.E.D.



shifting the signal δ_k with respect to the j -th vertex in graph H would be $y = \delta_j \otimes \delta_k$. However, since the Laplacian of graphs K_n, K_m are circulant, we know that their Basis will be the DFT matrix of sizes $n \times n, m \times m$, respectively. Furthermore, we know for graphs H, G_1, G_2 such that $H = G_1 \otimes G_2$, we have:

$L_H = L_{G_1} \otimes I_m + I_n \otimes L_{G_2}$ and also $\beta_i \gamma_j = \bar{\psi}_i \otimes \bar{\phi}_j$ will be the eigenvector of H with eigenvalue $\gamma_i + \lambda_j$. $((\gamma_i, \bar{\psi}_i) \in \text{Eigen}(G_1), (\lambda_j, \bar{\phi}_j) \in \text{Eigen}(G_2))$

Thus $U = \Psi \otimes \Phi$, where $\Psi = \text{DFT}(n), \text{DFT}(m) = \Phi$

$$\Delta_H = \left\{ 0, \frac{\#n-1}{n, n, \dots, n}, \frac{\#m-1}{m, m, \dots, m}, \frac{\#(n-1)(m-1)}{m+n, m+n, \dots, m+n} \right\}$$

$$\Delta_{G_1} = \left\{ 0, \frac{\#n-1}{n, n, \dots, n} \right\}, \Delta_{G_2} = \left\{ 0, \frac{\#m-1}{m, m, \dots, m} \right\}$$

$$\text{DFT}(U_{ik}) = \frac{1}{\sqrt{n}} e^{-j \frac{2\pi}{n} (k-1)(i-1)}$$

$$\text{DFT}(U_{jk}) = \frac{1}{\sqrt{m}} e^{-j \frac{2\pi}{m} (k-1)(j-1)}$$

Now since $\mathcal{F}\{\delta_k \otimes \delta_j\}(i) = (U^H \delta_k)(i) (U^H \delta_j)(j)$, we can say that:

$$\vec{y}_{n \times 1} = \mathcal{F}\{\delta_k \otimes \delta_j\} = \left(\underbrace{U^H \delta_k}_{u_k} \right) \otimes \left(\underbrace{U^H \delta_j}_{u_j} \right) \quad ; \quad \vec{y}_{ik} = U_{ka} = U_{ja}$$

$$u_k(a) = U_{ka} = \text{DFT}^{(n)}(k_1, a_1) \text{DFT}^{(m)}(k_2, a_2) = \frac{1}{\sqrt{mn}} \exp\left(-\frac{2\pi j}{n} k_1 a_1 - \frac{2\pi j}{m} k_2 a_2\right)$$

$$\left\{ \begin{array}{l} k_1 = \lfloor \frac{k}{n} \rfloor - 1 \quad k_2 = (k \bmod n) - 1 \\ a_1 = \lfloor \frac{a}{n} \rfloor - 1 \quad a_2 = (a \bmod n) - 1 \end{array} \right\} \rightarrow \text{change of coordinates}$$



$$\vec{\eta}(a) = U_{ka} U_{la} = u_k(a) u_l(a) = \frac{1}{mn} \exp(\theta_{ak} + \theta_{al})$$

$$\begin{aligned} \theta_{ak} + \theta_{al} &= -\frac{2\pi j}{n} a_1 k_1 - \frac{2\pi j}{m} a_2 k_2 - \frac{2\pi j}{n} a_1 l_1 - \frac{2\pi j}{m} a_2 l_2 \\ &= -\frac{2\pi j}{n} a_1 (k_1 + l_1) - \frac{2\pi j}{m} a_2 (k_2 + l_2) = \theta_{at} + 2k\pi \end{aligned}$$

therefore we can find $\forall k, l, \exists t$ such that $\theta_{ak} + \theta_{al} = \theta_{at} + 2k\pi$, we just have to put $0 \leq t_1 = k_1 + l_1 = \lfloor \frac{k}{n} \rfloor + \lfloor \frac{l}{n} \rfloor$ & $t_2 = k_2 + l_2 = (k + l \bmod n) - 2 \geq 0$.

& we can find t from $t_1, t_2 \rightarrow t = nt_1 + t_2$.

$$\text{thus we got } \forall a \in \{1, \dots, mn\}, \exists t \text{ such that } \vec{\eta}(a) = \frac{1}{mn} \exp(\theta_{ak} + \theta_{al}) = \frac{1}{mn} \exp(\theta_{at}).$$

so we can see that $\vec{\eta}$ as a vector is the t -th column of U , thus:

$$u_k \otimes u_l = (U^H \delta_k) \otimes (U^H \delta_l) = \frac{1}{\sqrt{mn}} U_t = \frac{1}{\sqrt{mn}} (U^H \delta_t).$$

$$\begin{aligned} \Rightarrow \delta_k \otimes \delta_l &= \mathcal{F}^{-1} \{ \mathcal{F} \{ \delta_k \otimes \delta_l \} \} = \mathcal{F}^{-1} \{ u_k \otimes u_l \} = \mathcal{F}^{-1} \left\{ \frac{1}{\sqrt{mn}} U^H \delta_t \right\} \\ &= \frac{U U^H}{\sqrt{mn}} \delta_t = \frac{1}{\sqrt{mn}} \delta_t \quad \text{Q.E.D.} \end{aligned}$$

$$\text{where } t = n \left(\left\lfloor \frac{k-1}{n} \right\rfloor + \left\lfloor \frac{l-1}{n} \right\rfloor \bmod n \right) + \left[(l+k-2) \bmod n \bmod mn \right]$$

$$\textcircled{1} D = \begin{bmatrix} I_{N/M} & 0_{N/M} & \dots & 0_{N/M} \end{bmatrix} \in \mathbb{C}^{N/M \times M}$$

$$(A^M)_{i,1} \in \mathbb{C}^{N/M \times N/M} \quad \text{first } \frac{N}{M} \text{ rows and cols} \quad : 40\%$$

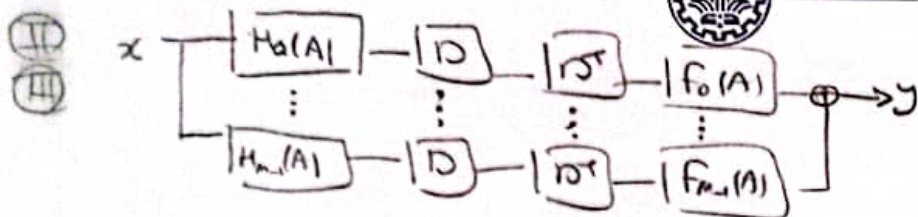
$$B^M = \begin{bmatrix} A_{1,1}^M & \Phi \\ A_{2,1}^M & A_{2,2}^M \end{bmatrix}$$

$$\bar{A} = D B^M D^T = \begin{bmatrix} I_{N/M} & \Phi \end{bmatrix} \begin{bmatrix} A_{1,1}^M & \Phi \\ A_{2,1}^M & A_{2,2}^M \end{bmatrix} \begin{bmatrix} I_{N/M} \\ \Phi \end{bmatrix} = A_{1,1}^M \quad \left. \begin{array}{l} D B^M = \bar{A} D \Rightarrow \\ D (B^M)^k = (D B^M) B^{M^{k-1}} \\ = \bar{A} D (B^M)^{k-1} \end{array} \right\}$$

$$D B^M = \begin{bmatrix} I_{N/M} & \Phi \end{bmatrix} \begin{bmatrix} A_{1,1}^M & \Phi \\ A_{2,1}^M & A_{2,2}^M \end{bmatrix} = \begin{bmatrix} A_{1,1}^M & 0 \end{bmatrix} = \bar{A} D$$

$$\text{finally } \Rightarrow D (B^M)^k = \bar{A}^k D \rightarrow D H(B^M) = D \left(\sum_{k=0}^L h_k (B^M)^k \right) = \sum_{k=0}^L h_k D (B^M)^k$$

$$= \sum_{k=0}^L h_k \bar{A}^k D = \left(\sum_{k=0}^L h_k \bar{A}^k \right) D = H(\bar{A} D) = D H(B^M) \quad \text{Q.E.D.}$$

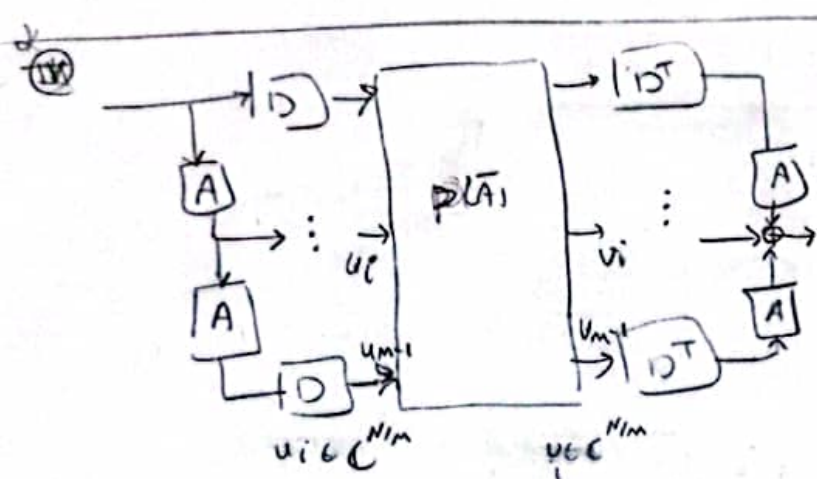


$$D^T D A^M = \begin{bmatrix} I_{N/M} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} I_{N/M} & 0 & \dots & 0 \end{bmatrix} \begin{bmatrix} A_{1,1}^M & A_{1,2}^M \\ A_{2,1}^M & A_{2,2}^M \end{bmatrix} = \begin{bmatrix} A_{1,1}^M & A_{1,2}^M \\ 0 & 0 \end{bmatrix}$$

$$A^M D^T D = \begin{bmatrix} A_{1,1}^M & A_{1,2}^M \\ A_{2,1}^M & A_{2,2}^M \end{bmatrix} \begin{bmatrix} I_{N/M} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} I_{N/M} & 0 & \dots & 0 \end{bmatrix} = \begin{bmatrix} A_{1,1}^M & 0 \\ A_{2,1}^M & 0 \end{bmatrix}$$

$$\text{So } D^T D A^M = A^M D^T D \iff A_{1,1}^M = A_{1,2}^M = 0$$

In general the described filter-bank, is not GSI and depends on whether $D^T D A^M = A^M D^T D$ is true or not, which would be true if and only if $A_{1,2}^M = A_{2,1}^M = 0$. Here we checked $SA^M = A^M$ in general form, for standard GSI we can simply use $M=1$.



$$u_i = D A^i x$$

$$u_i = \sum_{j=0}^{M-1} P_{ij}(\bar{A}) u_j$$

$$u = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{M-1} \end{bmatrix}$$

$$P(\bar{A}) u = v = \begin{bmatrix} v_0 \\ v_1 \\ \vdots \\ v_{M-1} \end{bmatrix}$$

$$P(A) = \begin{bmatrix} P_{ij}(A) \end{bmatrix} \in \mathbb{C}^{N \times N}$$

$$P_{ij}(A) \in \mathbb{C}^{N/M \times N/M}$$

$$y = \sum_{i=0}^{M-1} A^{M-i} D^T u_i = \begin{bmatrix} A^{M-1} D^T & A^{M-2} D^T & \dots & A^0 D^T \end{bmatrix} \begin{bmatrix} v_0 \\ v_1 \\ \vdots \\ v_{M-1} \end{bmatrix}$$

$$y = \begin{bmatrix} A^M & \dots & A^1 & A^0 \end{bmatrix} \text{diag}(D^T) v = \begin{bmatrix} A^{M-1} & \dots & A^1 & A^0 \end{bmatrix} \text{diag}(D)^T v$$

$$\implies y = \begin{bmatrix} A^{M-1} & \dots & A^1 & A^0 \end{bmatrix} \text{diag}(D^T) P(\bar{A}) \text{diag}(D) \begin{bmatrix} A^0 \\ A^1 \\ \vdots \\ A^{M-1} \end{bmatrix} x$$

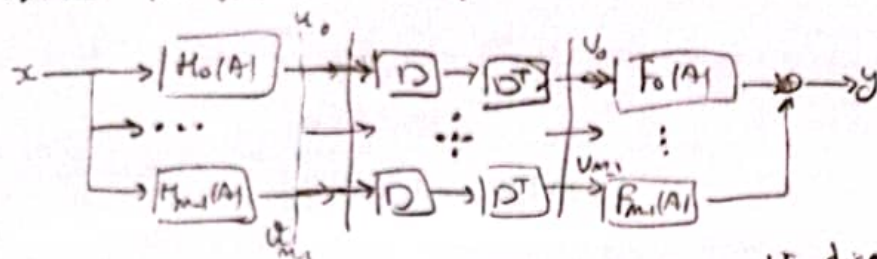
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the filter-Bank of Previous Section



$$\begin{cases} H_i(A) = \sum_{r=0}^{M-1} E_{ir}(A^M) \\ F_i(A) = \sum_{r=0}^{M-1} R_{ir}(A^M) \end{cases}$$

$$V = \text{diag}(D^T D), \quad y = [F_0(A) | F_1(A) | \dots | F_{m-1}(A)] u$$

$$u = \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{m-1} \end{bmatrix} = \begin{bmatrix} H_0(A) \\ H_1(A) \\ \vdots \\ H_{m-1}(A) \end{bmatrix} x \Rightarrow y = [F_0(A) | \dots | F_{m-1}(A)] \text{diag}(D^T D) \begin{bmatrix} H_0(A) \\ \vdots \\ H_{m-1}(A) \end{bmatrix} x$$

$$\textcircled{a} \quad F_i(A) = [A^M | \dots | A^0] \begin{bmatrix} R_{i0}(A^M) \\ \vdots \\ R_{i,M-1}(A^M) \end{bmatrix} = [A^{M-1} | \dots | A^0] R_i(A^M)$$

Likewise

$$\textcircled{b} \quad H_i(A) = [E_{i0}(A^M) | \dots | E_{i,M-1}(A^M)] \begin{bmatrix} A^0 \\ \vdots \\ A^{M-1} \end{bmatrix} = E_i(A^M) \begin{bmatrix} A^0 \\ \vdots \\ A^{M-1} \end{bmatrix}$$

$$\textcircled{c} \quad \text{Putting all together for all } i \quad \begin{bmatrix} H_0(A) \\ H_1(A) \\ \vdots \\ H_{m-1}(A) \end{bmatrix} = \underbrace{\begin{bmatrix} E_0(A^M) \\ E_1(A^M) \\ \vdots \\ E_{m-1}(A^M) \end{bmatrix}}_{E(A^M)} \begin{bmatrix} A^0 \\ A^1 \\ \vdots \\ A^{M-1} \end{bmatrix} = E(A^M) \begin{bmatrix} A^0 \\ A^1 \\ \vdots \\ A^{M-1} \end{bmatrix} ; \quad E(A^M) = \begin{bmatrix} E_{00}(A^M) & \dots & E_{0,M-1}(A^M) \\ \vdots & \ddots & \vdots \\ E_{m-1,0}(A^M) & \dots & E_{m-1,M-1}(A^M) \end{bmatrix}$$

$$\textcircled{d} \quad \text{the same here} \quad [F_0(A) | F_1(A) | \dots | F_{m-1}(A)] = [A^{M-1} | \dots | A^1 | A^0] \underbrace{[R_0(A^M) | \dots | R_{m-1}(A^M)]}_{R^T(A^M)}$$

$A = A^T \rightarrow A^M = (A^M)^T$ is the needed constraints in Noble



$$y = [A^{m-1} | \dots | A^1 | A^0] R^T(A^m) \text{diag}(D)^T \text{diag}(D) E(A^m) \begin{bmatrix} A^0 \\ A^1 \\ \vdots \\ A^{m-1} \end{bmatrix} x$$

if $A_{2,1}^m = \emptyset$ in

$$B^m = \begin{bmatrix} A_{1,1}^m & A_{1,2}^m \\ A_{2,1}^m & A_{2,2}^m \end{bmatrix} = A^m \rightarrow D H(A^m) = H(\bar{A}) D$$

$$D E_{in}(A^m) = E_{in}(\bar{A}) D \rightarrow \text{diag}(D) E(A^m) = E(\bar{A}) \text{diag}(D)$$

$$D R_{ir}(A^m) = R_{ir}(\bar{A}) D \rightarrow \text{diag}(D) R(A^m) = R(\bar{A}) \text{diag}(D)$$

$$\rightarrow R^T(A^m) \text{diag}(D^T) = \text{diag}(D)^T R^T(\bar{A})$$

$$\Rightarrow y = [A^{m-1} | \dots | A^1 | A^0] \text{diag}(D^T) \underbrace{R^T(\bar{A})}_{R^T(\bar{A})} E(\bar{A}) \text{diag}(D) \begin{bmatrix} A^0 \\ A^1 \\ \vdots \\ A^{m-1} \end{bmatrix} x$$

$$\Rightarrow \begin{cases} A = A^T, P(A) = R^T(\bar{A}) E(\bar{A}) \end{cases}$$

$$P_{ij}(A) = \sum_{r=0}^m R_{ri}(\bar{A}) E_{rj}(\bar{A})$$

Q.E.D.

$$\textcircled{I} \min_{w \in W_n} \left\{ \|Z \odot W\|_{1,1} + \gamma \sum_{i,j} w_{ij} (\log w_{ij} - 1) \right\}$$

$Z(z, w)$

$$w_{ij} = \exp\left(\frac{-z_{ij}}{\gamma}\right) = \exp\left(-\frac{\|x_i - x_j\|}{\gamma}\right)$$

$$\frac{\partial Z}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}} \left(\sum_{i,j} z_{ij} w_{ij} + \gamma \sum_{i,j} w_{ij} (\log w_{ij} - 1) \right) = z_{ij} + \gamma \log(w_{ij}) = 0$$

Q.E.D.

$$\textcircled{II} \text{ Let } w = F(Z, \alpha, \beta) \text{ be the solution to } \min_w \left\{ \|Z \odot w\|_{1,1} + \alpha \mathbb{1}^T \log(w \mathbb{1}) + \beta \|w\|_F^2 \right\}.$$

$$\text{then we can say that } \delta F(Z, \alpha, \beta) = \delta w = \arg \min_w \left\{ \gamma \sum_{i,j} w_{ij} z_{ij} - \alpha \mathbb{1}^T \log(w \mathbb{1}) + \sum_{i,j} 2\beta \gamma^2 w_{ij}^2 \right\}$$

$$= \arg \min_w \left\{ \gamma \sum_{i,j} w_{ij} z_{ij} - \alpha \mathbb{1}^T \log(w \mathbb{1}) - n\gamma\alpha + \sum_{i,j} 2\beta \gamma^2 w_{ij}^2 \right\} \quad (\text{assumption } \gamma > 0)$$

$$= \arg \min_w \left\{ \sum_{i,j} w_{ij} z_{ij} - \frac{\alpha}{\gamma} \mathbb{1}^T \log(w \mathbb{1}) + \sum_{i,j} 2\beta \gamma w_{ij}^2 \right\} = F(Z, \frac{\alpha}{\gamma}, \beta \gamma)$$

$$\text{thus: } w = F(Z, \alpha, \beta) = F(Z, \frac{\alpha}{\gamma}, \beta \gamma)$$



using the same technique we get:

$$\begin{aligned}
 \text{obj} = F(Z, \alpha, \beta) &= \arg \min_w \left\{ \|W_0 Z\|_{1,1} - \alpha \mathbb{1}^T \log(W \mathbb{1}) + \beta \|W\|_F^2 \right\} \\
 &= \alpha \arg \min_w \left\{ \alpha \sum_{ij} w_{ij} z_{ij} - \alpha \mathbb{1}^T \log(W \mathbb{1}) - \underbrace{n \alpha \log \alpha}_{\text{cte}} + \beta \sum_{ij} \alpha^2 w_{ij}^2 \right\} \quad \times 1/\alpha \\
 &= \alpha \cdot \arg \min_w \left\{ \|W_0 Z\|_{1,1} - \mathbb{1}^T \log(W \mathbb{1}) + \beta \alpha \sum_{ij} w_{ij}^2 \right\} = \alpha F(Z, 1, \beta \alpha) \\
 \text{at last} \Rightarrow & \boxed{W = F(Z, \alpha, \beta) = \gamma F(Z, \frac{\alpha}{\gamma}, \beta \gamma) = \alpha F(Z, 1, \beta \alpha)} \quad \text{Q.E.D.}
 \end{aligned}$$

III

$$J(w) = \sum_{ij} z_{ij} w_{ij} - \alpha \sum_i \log\left(\sum_j w_{ij}\right) + \beta \sum_{ij} w_{ij}^2$$

$$\rightarrow \frac{\partial J}{\partial w_{ij}} = z_{ij} - \alpha \left(\underbrace{\frac{1}{\sum_k w_{ik}}}_A + \frac{1}{\sum_k w_{kj}} \right) + 4\beta w_{ij} = 0$$

in order to get maximum w_{ij} , i, j must have

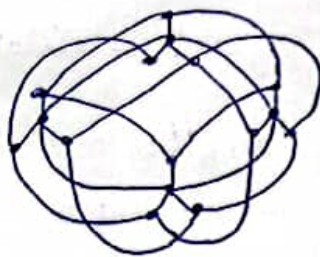
$$\text{let } A \leq \frac{2\alpha}{w_{ij}} \Rightarrow 4\beta w_{ij} = A \leq \frac{2\alpha}{w_{ij}} \rightarrow w_{ij} \leq \sqrt{\frac{\alpha}{\beta}} \quad \text{Q.E.D.}$$

*

① It was obvious that Graph J was constructed by $G \times T$.

since in graph J we put $\text{vec}(X_t)$ on graph J instead of x_i on graph G .

the mean condition does not matter since $\forall t \in \mathbb{E}[x_t] = c \mathbb{1}_N$.



$$X = \begin{bmatrix} x_1^1 & \dots & x_1^T \\ \vdots & & \vdots \\ x_N^1 & \dots & x_N^T \end{bmatrix}$$

$$\begin{aligned}
 &G \\
 &T=4 \\
 &N=4
 \end{aligned}$$

So it's the moment condition, therefore there must be a ~~vector~~ Diagonal matrix D such that $\Sigma = U \Sigma U^H$ so that Σ and $L = U \Lambda U^H$ can be commute: $\Sigma L = L \Sigma$.

Since T is a cyclic graph and has a toeplitz Laplacian matrix, the DFT(N) matrix will be its basis $\rightarrow U_T \in \text{DFT}(N)$, let $\omega_T = \frac{2\pi(T-1)}{T} = \angle(T, T)$, $\Delta_G(n, n) = \lambda_n$

II $U_S = U_G \otimes U_T$, $\Sigma = h(L_G, L_T) = U_S \underbrace{h(\Delta_G, \Omega_T)}_{\in \mathbb{R}^{N \times N}} U_S^H = \cos(\text{vec}(X))$ Q.E.D.

$H_{t_1, t_2} = \sum_{N(t_1-1); N(t_1), N(t_2-1); N(t_2)} = \sum_{\tau=1}^T U_S(t_1, \tau) \underbrace{h(\Delta_G, \Omega_T)}_{\in \mathbb{R}^{N \times N}} U_S^H(\tau, t_2)$ is block matrix

$$= \sum_{\tau=1}^T U_G U_T(t_1, \tau) h_{T\tau}(\cdot, \cdot) \overline{U_T(\tau, t_2)} U_G^H$$

$$= \frac{1}{\sqrt{T}} \frac{1}{\sqrt{T}} \sum_{\tau=1}^T e^{-j\omega_T t_2} U_G h_{T\tau}(\cdot, \cdot) U_G^H e^{j\omega_T t_1}$$

$$= \frac{1}{T} \sum_{\tau=1}^T e^{j\omega_T(t_1 - t_2)} \underbrace{U_G h_{T\tau}(\Delta_G, \Omega_T) U_G^H}_{h_{\omega_T}(L_G)} = \frac{1}{T} \sum_{\tau=1}^T e^{j\omega_T(t_1 - t_2)} h_{\omega_T}(L_G)$$

So we can see that $H_{t_1, t_2} = f(t_1 - t_2)$ and doesn't rely on t_1 and t_2 .

III (i) X is JWSS $\rightarrow E[X] = C \mathbb{1}_{N \times T}$ (a) $\Rightarrow \boxed{\text{JWSS} \subseteq \text{JWSS}}$
 $\rightarrow H_{t_1, t_2} = f(t_1 - t_2)$ (b)

X is TWSS $\rightarrow E[X] = C \mathbb{1}_{N \times T} \rightarrow$ already is true since (a) due to JWSS.
 $\rightarrow \begin{cases} H_{t_1, t_2} = f(t_1 - t_2 + \lambda) = f(t_1 - t_2) \rightarrow \text{already is true} \\ t_2 \geq 1 \\ t_1 \geq t_2 + 1 \end{cases}$ Since (b) due to JWSS

(ii) X is VWSS $\rightarrow E[X] = C \mathbb{1}_{N \times T} \rightarrow$ already being satisfied due to (a), JWSS.
 $\rightarrow \Sigma_{t_1, t_2} = \gamma_{t_1, t_2}(L_G) \Rightarrow \boxed{\text{VWSS} \subseteq \text{JWSS}}$

It follows from the definition that for a JWSS process, each block of Σ has to be a linear graph filter $\Sigma_{t_1, t_2} = \gamma_{t_1, t_2}(L_G)$. Hence the covariance matrix can be

written as:

$$\Sigma = \begin{bmatrix} \gamma_{1,1}(L_G) & \gamma_{1,2}(L_G) & \dots & \gamma_{1,T}(L_G) \\ \gamma_{2,1}(L_G) & \gamma_{2,2}(L_G) & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{T,1}(L_G) & \dots & \dots & \gamma_{T,T}(L_G) \end{bmatrix}$$

Thus if JWSS holds, automatically VWSS and TWSS will hold as well since $(\text{JWSS} \supseteq \text{TWSS})$ & $(\text{JWSS} \supseteq \text{VWSS})$. Q.E.D.

IV) JWS $\forall, \forall n, t: \lambda_n \neq 0, \omega_t \neq 0.$: 6 JWS
 By construction of the SFT basis $\hat{X}_{(0,0)}$ captures the DC offset of a signal,
 and condition $\left(\mathbb{E}[\hat{X}(n, \tau)] = 0 \text{ if } \lambda_n \neq 0, \omega_\tau \neq 0 \right)$ is equivalent to $\mathbb{E}[\hat{X}] = C \mathbb{I}_{N+T}.$
 Moreover, if the graph is connected and $\psi(u)$ holds, at least one of
 $\mathbb{E}[\hat{X}(n_1, \tau_1)]$ and $\mathbb{E}[\hat{X}(n_2, \tau_2)]$ must be zero when $n_1 \neq n_2$ or $\tau_1 \neq \tau_2$ and
 hence:

$$\mathbb{E}[\hat{X}(n_1, \tau_1) \hat{X}(n_2, \tau_2)] = \mathbb{E}[\hat{X}(n_1, \tau_1) \hat{X}(n_2, \tau_2)] - \mathbb{E}[\hat{X}(n_1, \tau_1)] \mathbb{E}[\hat{X}(n_2, \tau_2)]$$

$$= [U_J^H \Sigma U_J] (N(\tau_1-1)+n_1, N(\tau_2-1)+n_2)$$

thus, the second condition is equivalent to stating that $\Sigma = U_J D U_J^H$
 for some diagonal matrix. Now if such D exists we will have

$$\Sigma = U_J D U_J^H = U_J h(\Lambda_G, \Lambda_T) U_J^H = h(\underbrace{L_G, L_T})$$

which is the
second moment condition of JWS process. so we're done!

Q.E.D. ■