

图谱论讲稿 I(修改稿)

会议中未解决的问题

Q1 正则图补图的特征多项式?

A1 设 G 为度为 k 的正则图, 顶点数为 n . 由于 \overline{G} 度为 $n - k$, 故 $\lambda_1(\overline{G}) = n - k$, 相应的特征向量为 $\mathbf{1}$. 若 $\lambda_i x_i = A(G)x_i$, 则

$$(J - I - A)x_1 = \mathbf{1}\mathbf{1}^T x_i - (\lambda_i + 1)x_i = -(\lambda_i + 1)x_i.$$

$$\text{故 } P_{\overline{G}}(x) = P_G(-x - 1) \cdot \frac{(-1)^n(x - n + k + 1)}{x + k + 1}.$$

将结论用于join graph, 则

$$P_{G_1 \nabla G_2}(x) = \frac{P_{G_1}(x)P_{G_2}(x)}{(x - k_1)(x - k_2)} [(x - k_1)(x - k_2) - n_1 n_2].$$

Q2 称 G 为Cartesian product可分解的, 若且仅若存在非平凡图 G_1, G_2 使得 $G_1 \square G_2 = G$. 试寻找例子以说明Cartesian product可分解的图不一定存在唯一的最小分解.

A2 等价于说明非负整系数多项式环非UFD. 注意到

$$(x^3 + 1)(x^2 + x + 1) = (x + 1)(x^4 + x^2 + 1).$$

对图 G , 定义 $G^1 = G, G^n = G \square G^{n-1}$, 则

$$(G^3 \dot{\cup} K_1) \square (G^2 \dot{\cup} G \dot{\cup} K_1) = (G \dot{\cup} K_1) \square (G^4 \dot{\cup} G^2 \dot{\cup} K_1).$$

不妨取 $G = P_2 = Q_1$ 为1维超立方体, 下证明 $(G^3 \dot{\cup} K_1)$ 非Cartesian product可分解: 注意到 $(G^3 \dot{\cup} K_1)$ 顶点数为9且不连通, 显然无法成为两个不连通3-顶点图之Cartesian product. 同理, $(G^2 \dot{\cup} G \dot{\cup} K_1)$ 之顶点数为质数, 显然不可Cartesian product分解.

Q3 给定 $A(G)$ 与 $A(G - j)$ 的谱(邻接矩阵未知), 试计算 $A(G)$ 中特征值 λ_j 对应的特征向量 x^j 中第 k 项分量之模长, 即 x_k^j . 此处需假定 $A(G)$ 之谱无重根.

A3 注意到 $P_{G-j}(x)$ 为 $\text{adj}(xI - A)$ 的 j, j 项余子式, 设 $\mathbf{1}^j$ 为第 j 项为1而其余项为0的向量, 则

$$\begin{aligned} P_{G-j}(x) &= (\mathbf{1}^j)^T \text{adj}(xI - A) \mathbf{1}^j \\ &= P_G(x) (\mathbf{1}^j)^T (xI - A)^{-1} \mathbf{1}^j \\ &= P_G(x) (\mathbf{1}^j)^T \left(\sum_i \frac{1}{x - \lambda_i} P_i \right) \mathbf{1}^j \\ &= P_G(x) e_i^T \left(\sum_i \frac{E_i}{x - \lambda_i} \right) e_i \\ &= P_G(x) \sum_i \frac{\alpha_{ij}^2}{x - \lambda_i} \end{aligned}$$

代入 $x = \lambda_k$, 则

$$P_{G-j}(\lambda_k) = \alpha_{jk}^2 \prod_{i \neq k} (\lambda_k - \lambda_i).$$

此处

$$|x_k^j|^2 = \alpha_{jk}^2 = \frac{\prod_{i \neq k} (\lambda_k - \lambda_j)}{\prod_{\mu \in \text{Spec}(G-j)} (\lambda_k - \mu)}.$$

Angle Matrix of a Graph

α_{ij} , the angle

For any simple graph $G(V, E)$ with neither directions, multiple edges, loops $G(V, E)$, the adjacency matrix $A = A(G)$ is symmetric. In light of the *polar decomposition*, we have

$$A = Q^T \Lambda Q = \sum_{i=1}^r \lambda_i \cdot P_i = \sum_{i=1}^r \lambda_i \cdot Q^T E_i Q$$

where $\lambda_1 > \lambda_2 > \dots > \lambda_r$, $O_n(\mathbb{R}) \ni Q = (x_1, x_2, \dots, x_n)$.

- $\alpha_{ij} : \|E_i x_j\| = \sqrt{x_j^T E_i x_j}$ denotes the ij -th *angle*, that is, the i -th index of eigenvector x_j .
The *angle matrix* is given by $(\alpha_{ij})_{r \times n}$.
- $\sum_{i=1}^r \alpha_{ij}^2 = \sum_i x_j^T E_i x_j = x_j^T I x_j = 1$.
- $\sum_{j=1}^n \alpha_{ij}^2 = \sum_j x_j^T E_i x_j = \text{trace}(Q^T E_i Q) = \dim \mathcal{E}_{\lambda_i}$. Here \mathcal{E}_{λ_i} denotes the root space of λ_i .

β_i , the main angle

The *main angle* β_i is defined as $\frac{\|P_i \cdot \mathbf{1}_n\|}{\sqrt{n}}$. Hence

$$\sum_i \beta_i^2 = \frac{\mathbf{1}^T I \mathbf{1}}{n} = 1.$$

For any polynomial $P(x)$ which is well-defined on the ring R and matrix ring $\mathcal{M}(n, R)$, we notice that $P_i P_j = O$ for any $i \neq j$. Hence we deduce that

$$P(A) = \sum_i P(\lambda_i) P_i$$

with the corollary

$$\mathbf{1}^T P(A) \mathbf{1} = n \sum_i P(\lambda_i) \beta_i^2.$$

Further more, the polynomial P can be replaced by *some function* once its convergence is determined.

Operation, Modification&Compositions of Graphs

Basic Graph Operations

Simple operations:

- The *disjoint union* $G_1 \dot{\cup} G_2$.
- The *complement* \overline{G} .
- The *join* $G_1 \nabla G_2 := \overline{\overline{G_1} \dot{\cup} \overline{G_2}}$.
- The *vertex-deleted graph* $G - j$.
- The *pendant-added graph* G_j .

- The *coalescence* $G_u \cdot H_v$, or $G \cdot H$ for short, w.r.t. $u \in V(G), v \in V(H)$.
- The *bridged graph* $GuvH$.

Some special operations:

- The *corona* $G \circ H$.
- The *subdivision* graph $S(G)$.
- The *line graph* $L(G)$.

NEPS(non-complete extended p -sum) operations.

Characteristic Polynomials under the Modifications

For *disjoint union*, we have

$$P_{G_1 \dot{\cup} G_2}(x) = P_{G_1}(x)P_{G_2}(x).$$

Further more, for any finite graph set $\{G_i\}_{i=1}^m$ we have

$$P_{\dot{\cup}\{G_i\}_{i=1}^m}(x) = \prod_{i=1}^m P_{G_i}(x).$$

For *complement*, we have

$$\begin{aligned} P_{\overline{G}}(x) &= \det(xI - J + I + A) \\ &= \det((x+1)I + A) - \mathbf{1}^T \text{adj}((x+1)I + A) \mathbf{1} \\ &= (-1)^n P_G(-x-1)(1 - \mathbf{1}^T((x+1)I + A)^{-1} \mathbf{1}) \\ &= (-1)^n P_G(-x-1) \left(1 - n \sum_{i=1}^r \frac{\beta_i^2}{x+1+\lambda_i} \right) \end{aligned}$$

Lemma (UNNECESSARY). $\det(A + uv^T) = \det(A) + v^T \text{adj}(A)u$.

Proof of the lemma. Since

$$\begin{vmatrix} 1 & v^T \\ \mathbf{0} & A + uv^T \end{vmatrix} = \begin{vmatrix} 1 & v^T \\ -u & A \end{vmatrix} = \begin{vmatrix} 1 + v^T A^{-1}u & v^T \\ 0 & A \end{vmatrix}$$

Q.E.D.

For *join*, we have

$$\begin{aligned} P_{\overline{G_1 \dot{\cup} G_2}}(x) &= (-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \left(1 - (n_1 + n_2) \sum_{i=1}^s \frac{\beta_i^2}{x+1+\lambda_i} \right) \\ &= (-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \left(1 - n_1 \sum_{i=1}^s \frac{(\beta_i^{(1)})^2}{x+1+\lambda_i} - n_2 \sum_{i=1}^s \frac{(\beta_i^{(2)})^2}{x+1+\lambda_i} \right) \\ &= -(-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \\ &\quad + (-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \left(1 - n_1 \sum_{i=1}^s \frac{(\beta_i^{(1)})^2}{x+1+\lambda_i} \right) \\ &\quad + (-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \left(1 - n_2 \sum_{i=1}^s \frac{(\beta_i^{(2)})^2}{x+1+\lambda_i} \right) \\ &= (-1)^{n_2} P_{\overline{G_1}}(x) P_{G_2}(-x-1) + (-1)^{n_1} P_{\overline{G_2}}(x) P_{G_1}(-x-1) \\ &\quad - (-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \end{aligned}$$

Hence

$$\begin{aligned}
& P_{G_1 \nabla G_2}(x) + (-1)^{n_1+n_2} P_{G_1 \dot{\cup} G_2}(-x-1) \\
& = (-1)^{n_2} P_{\overline{G_1}}(x) P_{G_2}(-x-1) + (-1)^{n_1} P_{\overline{G_2}}(x) P_{G_1}(-x-1).
\end{aligned}$$

We deduce that

$$P_{G_1 \nabla G_2}(x) = P_{G_1}(x) P_{G_2}(x) \left(1 - n_1 n_2 \sum_{i=1}^{r_1} \sum_{j=1}^{r_2} \frac{(\beta_i^{(1)} \beta_j^{(2)})^2}{(x - \lambda_i^{(1)})(x - \lambda_j^{(2)})} \right).$$

Characteristic Polynomials under the Compositions

For *vertex-deleted graph* $G - j$, $P_{G-j}(x)$ is the j -th diagonal element of $\text{adj}(xI - A)$. Since

$$\text{adj}(xI - A) = P_G(x)(xI - A)^{-1} = P_G(x) \sum_{i=1}^r \frac{P_i}{x - \lambda_i}$$

we deduce that $P_{G-j}(x) = P_G(x) \sum_{i=1}^r \frac{\alpha_{ij}^2}{x - \lambda_i}$.

For the *pendant-added graph* G_j , we notice that

$$P_{G_j}(x) = x P_G(x) - P_{G-j}(x).$$

Hence $P_{G_j}(x) = P_G(x) \left(x - \sum_{i=1}^r \frac{\alpha_{ij}^2}{x - \lambda_i} \right)$.

For *coalescence* $G \cdot H$ in which $u \in G$ and $v \in H$, we have

$$\begin{aligned}
P_{G \cdot H}(x) &= \begin{vmatrix} xI - A' & -r & O \\ -r^T & x & -s^T \\ O & -s & xI - B' \end{vmatrix} \\
&= \begin{vmatrix} xI - A' & -r & O \\ -r^T & x & -s^T \\ O & \mathbf{0} & xI - B' \end{vmatrix} + \begin{vmatrix} xI - A' & \mathbf{0} & O \\ -r^T & x & -s^T \\ O & -s & xI - B' \end{vmatrix} \\
&\quad - \begin{vmatrix} xI - A' & \mathbf{0} & O \\ -r^T & x & -s^T \\ O & \mathbf{0} & xI - B' \end{vmatrix} \\
&= P_G(x) P_{H-v}(x) + P_{G-u}(x) P_H(x) - x P_{G-u}(x) P_{H-v}(x)
\end{aligned}$$

For the *bridged graph* $GuvH$, we have

$$\begin{aligned}
P_{GuvH}(x) &= P_{G_u}(x) P_{H-v}(x) + P_G(x) P_H(x) - x P_G(x) P_{H-v}(x) \\
&= P_G(x) P_H(x) - P_{G-u}(x) P_{H-v}(x)
\end{aligned}$$

For *corona graph* $G \circ H$, we have

$$\begin{aligned}
P_{G \circ H}(x) &= \det \begin{vmatrix} xI - A & -J_1 & -J_2 & \cdots & -J_n \\ -J_1^T & xI - B & & & \\ -J_2^T & & xI - B & & \\ \vdots & & & \ddots & \\ -J_n^T & & & & xI - B \end{vmatrix} \\
&= \det \begin{vmatrix} xI - A - \frac{m}{x-r}I & -J_1 & -J_2 & \cdots & -J_n \\ \mathbf{0} & xI - B & & & \\ \mathbf{0} & & xI - B & & \\ \vdots & & & \ddots & \\ \mathbf{0} & & & & xI - B \end{vmatrix} \\
&= P_G \left(x - \frac{m}{x-r} \right) (P_H(x))^n
\end{aligned}$$

where $n = |V(G)|$.

For *subdivision graph*, we can notice that $A(S(G)) = \begin{pmatrix} O & B^T \\ B & O \end{pmatrix}$. Here B denotes the *induced graph* (from edges to vertices). Hence

$$P_{S(G)}(x) = x^{|E|-|V|} Q_G(x^2)$$

where $Q_G(x)$ denotes the characteristic polynomial of *signless Laplacian* $BB^T = A + D$.

For *line graph* $L(G)$, the characteristic polynomial is given by

$$P_{L(G)}(x) = (x+2)^{|E|-|V|} (x) Q_G(x+2).$$

NEPS(non-complete extended p -sum)

The *NEPS* is a multiple operation of a set of graph via a given tuple $\mathcal{B} \subset \{0, 1\}^n \setminus \{0\}^n$, e.g. $\{G_i\}_{i=1}^n$. It outcomes $\text{NEPS}(\{G_i\}_{i=1}^n, \mathcal{B})$ satisfying:

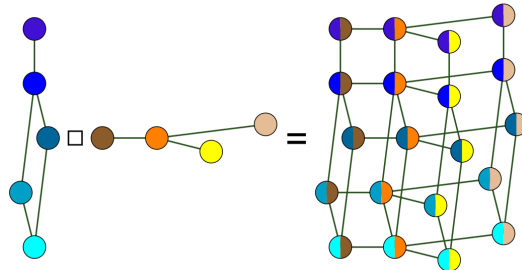
- The vertices of the the outcome is the (classical) *Cartesian product*

$$\prod_{i=1}^n V(G_i) = G_1 \times \cdots \times G_n.$$

- The vertices (x_1, \dots, x_n) and (y_1, \dots, y_n) are adjacent if and only if there exists a $\beta \in \mathcal{B}$ such that $\beta_i = 0 \Leftrightarrow x_i = y_i$ and $x_j \sim y_j \Leftrightarrow \beta_j = 1$.

As for *Cartesian product* $G \square H$, $V(G \square H) \cong V(G) \times V(H)$, $(g_i, h_i) \sim (g_j, h_j)$ if either

- $g_1 = g_2$ and $h_1 \sim h_2$ in H , w.r.t. $(0, 1) \in \mathcal{B}$.
- $h_1 = h_2$ and $g_1 \sim g_2$ in G , w.r.t. $(1, 0) \in \mathcal{B}$.

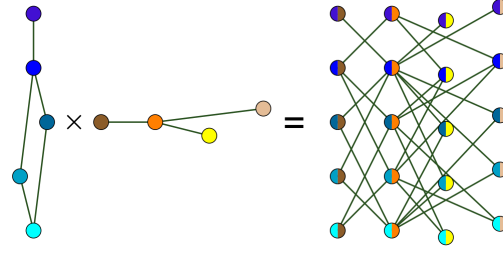


It is trivial to verify that:

- \square is commutative.
- \square is associative.

that is, the associativity and commutativity.

As for *tensor product* $G \times H$, $V(G \times H) \cong V(G) \times V(H)$, $(g_i, h_i) \sim (g_j, h_j)$ if and only if $(g_i \sim g_j) \wedge (h_i \sim h_j)$, w.r.t. $\mathcal{B} = \{(1, 1)\}$.



The strong product $G \boxtimes H$, w.r.t. $\mathcal{B} = \{0, 1\}^2 - \{0, 0\}$, etc.

The adjacency matrix (trivial proof by definition) is

$$A(\text{NEPS}(\{G_i\}_{i=1}^n; \mathcal{B})) = \sum_{\beta \in \mathcal{B}} \otimes_{i=1}^n A(G_i)^{\beta_i}.$$

Since $(A \otimes C)(B \otimes D) = (AC) \otimes (BD)$, the spectral outcome

$$\sum_{\beta \in \mathcal{B}} \left(\prod_{i=1}^n \lambda_i^{i_k \beta_i} \right)$$

where $\lambda_i^{i_k}$ is the k -th eigenvalue of G_i with corresponding eigenvalue $x_i^{i_k}$. Thus the eigen vector of $A(\text{NEPS}(\{G_i\}_{i=1}^n; \mathcal{B}))$ is

$$\sum_{\beta \in \mathcal{B}} \otimes_{i=1}^n x_i^{i_k}.$$