# On linear-algebraic notions of expansion

Speaker: Chuanqi Zhang Joint work with Yinan Li, Youming Qiao, Avi Wigderson, and Yuval Wigderson

> Centre for Quantum Software and Information University of Technology Sydney

45th Australasian Combinatorics Conference, December 2023



### Outline

- Introduction about graph-theoretic expansion and a classical result.
- Introduction about linear-algebraic expansion and some previous results.
- An overview of our main results.
  - ① Dimension expansion  $\Rightarrow$  Quantum expansion.
  - 2 Quantum expansion  $\Rightarrow$  Dimension expansion.
  - 3 Linear-algebraic expansion properly generalizes graph-theoretic expansion



### Outline

- Introduction about graph-theoretic expansion and a classical result.
- $\bullet$  Introduction about linear-algebraic expansion and some previous results.
- An overview of our main results.
  - ① Dimension expansion  $\Rightarrow$  Quantum expansion.
  - 2 Quantum expansion  $\Rightarrow$  Dimension expansion.
  - Linear-algebraic expansion properly generalizes graph-theoretic expansion.

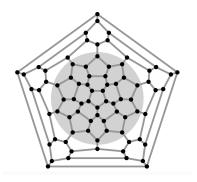
### Outline

- Introduction about graph-theoretic expansion and a classical result.
- $\bullet$  Introduction about linear-algebraic expansion and some previous results.
- An overview of our main results.
  - Dimension expansion 

    Quantum expansion.
  - 2 Quantum expansion  $\Rightarrow$  Dimension expansion.
  - ${\color{red} {\bf 0}} \ \, {\rm Linear-algebraic} \ \, {\rm expansion} \ \, {\rm properly} \ \, {\rm generalizes} \ \, {\rm graph-theoretic} \ \, {\rm expansion}.$

### What are expanders?

 $\bullet\,$  Expanders are graphs that are simultaneously sparse and highly connected.

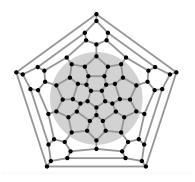


• Expanders are graphs for which a random walk converges to its limiting distribution as rapidly as possible.



# What are expanders?

• Expanders are graphs that are simultaneously sparse and highly connected.



• Expanders are graphs for which a random walk converges to its limiting distribution as rapidly as possible.



- Let G = ([n], E) be a d-regular graph.
- The spectral expansion of *G*:

 $\lambda(G) :=$  the second-largest absolute value over all eigenvalues of A, where A is the adjacency matrix of G.

- The largest absolute value over all eigenvalues of A is 1!
- The larger the spectral gap  $1 \lambda(G)$  is, the better the expansion is.



- Let G = ([n], E) be a d-regular graph.
- The **spectral expansion** of *G*:
  - $\lambda(G) :=$  the second-largest absolute value over all eigenvalues of A, where A is the adjacency matrix of G.
- The largest absolute value over all eigenvalues of A is 1!
- The larger the spectral gap  $1 \lambda(G)$  is, the better the expansion is.



- Let G = ([n], E) be a d-regular graph.
- The **spectral expansion** of *G*:
  - $\lambda(G) :=$  the second-largest absolute value over all eigenvalues of A, where A is the adjacency matrix of G.
- The largest absolute value over all eigenvalues of A is 1!
- The larger the spectral gap  $1 \lambda(G)$  is, the better the expansion is.



- Let G = ([n], E) be a d-regular graph.
- The spectral expansion of G:

 $\lambda(G) :=$  the second-largest absolute value over all eigenvalues of A, where A is the adjacency matrix of G.

- $\bullet$  The largest absolute value over all eigenvalues of A is 1!
- The larger the spectral gap  $1 \lambda(G)$  is, the better the expansion is.

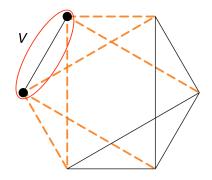


- Let G = ([n], E) be a d-regular graph.
- The spectral expansion of G:

 $\lambda(G) :=$  the second-largest absolute value over all eigenvalues of A, where A is the adjacency matrix of G.

- The largest absolute value over all eigenvalues of A is 1!
- The larger the spectral gap  $1 \lambda(G)$  is, the better the expansion is.

# Examples of graph expansion



Edge expansion for vertex subset  $V = \frac{6}{2} = 3$ 

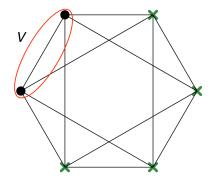
- Let G = ([n], E) be a d-regular graph.
- The edge expansion of G:

$$h(G) := \min_{\substack{V \subseteq [n]\\1 \le |V| \le \frac{n}{2}}} \frac{|\partial(V)|}{|V|},$$

where 
$$\partial(V) := \{\{i, j\} \in E : i \in V, j \in [n] \setminus V\}.$$



# Examples of graph expansion



Vertex expansion for vertex subset  $V = \frac{4}{2} = 2$ 

- Let G = ([n], E) be a d-regular graph.
- The vertex expansion of G:

$$\mu(G) := \min_{\substack{V \subseteq [n]\\1 \le |V| \le \frac{n}{2}}} \frac{|\partial_{\text{out}}(V)|}{|V|},$$

where  $\partial_{\text{out}}(V) := \{j \in [n] \setminus V : \exists i \in V, \text{ s.t. } \{i, j\} \in E\}.$ 



### A classical result of their relationship

#### Recall that

- $\lambda$ : spectral expansion
- $\bullet$  h: edge expansion
- $\mu$ : vertex expansion

For any d-regular graph G, the three notions of expansion are all equivalent, in the sense that

- $\frac{\mu(G)}{d} \le h(G) \le \mu(G)$  (By definition);
- $\frac{1-\lambda(G)}{2} \le h(G) \le \sqrt{2(1-\lambda(G))}$  (discrete Cheeger's inequality)

[Dodziuk'84, Alon-Milman'85, Alon'86]



### A classical result of their relationship

#### Recall that

- $\lambda$ : spectral expansion
- $\bullet$  h: edge expansion
- $\mu$ : vertex expansion

For any d-regular graph G, the three notions of expansion are all equivalent, in the sense that

- $\frac{\mu(G)}{d} \le h(G) \le \mu(G)$  (By definition);
- $\frac{1-\lambda(\mathit{G})}{2} \leq h(\mathit{G}) \leq \sqrt{2(1-\lambda(\mathit{G}))}$  (discrete Cheeger's inequality)

[Dodziuk'84, Alon-Milman'85, Alon'86]



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- **B** is a doubly stochastic matrix tuple if  $\sum_{i=1}^d B_i B_i^* = \sum_{i=1}^d B_i^* B_i = dI_n$ .
- The associated quantum operator is the linear map  $\Phi_{\mathbf{B}}: \mathrm{M}(n,\mathbb{C}) \to \mathrm{M}(n,\mathbb{C})$  defined by

$$\Phi_{\mathbf{B}}(X) := \frac{1}{d} \sum_{i=1}^{d} B_i X B_i^*.$$



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- **B** is a doubly stochastic matrix tuple if  $\sum_{i=1}^d B_i B_i^* = \sum_{i=1}^d B_i^* B_i = dI_n$ .
- The associated quantum operator is the linear map  $\Phi_{\mathbf{B}}: \mathrm{M}(n,\mathbb{C}) \to \mathrm{M}(n,\mathbb{C})$  defined by

$$\Phi_{\mathbf{B}}(X) := \frac{1}{d} \sum_{i=1}^{d} B_i X B_i^*.$$



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- **B** is a doubly stochastic matrix tuple if  $\sum_{i=1}^d B_i B_i^* = \sum_{i=1}^d B_i^* B_i = dI_n$ .
- The associated quantum operator is the linear map  $\Phi_{\mathbf{B}}: \mathrm{M}(n,\mathbb{C}) \to \mathrm{M}(n,\mathbb{C})$  defined by

$$\Phi_{\mathbf{B}}(X) := \frac{1}{d} \sum_{i=1}^{d} B_i X B_i^*.$$

- The quantum expansion of  $\Phi_{\mathbf{B}}$  [Ben–Aroya-Ta–shma'07, Hastings'07]:
  - $\lambda(\mathbf{B}) :=$  the second-largest absolute value over all eigenvalues of  $\Phi_{\mathbf{B}}$ .
- The quantum edge expansion of  $\Phi_B$  [Hastings'07]:

$$h_Q(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\langle I_n - P_V, \Phi_{\mathbf{B}}(P_V) \rangle}{\dim(V)},$$

where  $P_V$  is the orthogonal projection to the subspace  $V \leq \mathbb{C}^n$ .



- $\bullet$  The quantum expansion of  $\Phi_{\textbf{B}}$  [Ben–Aroya-Ta–shma'07, Hastings'07]:
  - $\lambda(B):=$  the second-largest absolute value over all eigenvalues of  $\Phi_B.$
- The quantum edge expansion of  $\Phi_{\mathbf{B}}$  [Hastings'07]:

$$h_Q(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\langle I_n - P_V, \Phi_{\mathbf{B}}(P_V) \rangle}{\dim(V)},$$

where  $P_V$  is the orthogonal projection to the subspace  $V \leq \mathbb{C}^n$ .

#### edge expansion

$$\min_{\substack{V\subseteq [n]\\1\leq |V|\leq \frac{n}{2}}}\frac{|\partial(V)|}{|V|} \quad ===\Rightarrow \quad \min_{\substack{V\leq \mathbb{C}^n\\1\leq \dim(V)\leq \frac{n}{2}}}\frac{\langle I_n-P_V,\Phi_{\mathbf{B}}(P_V)\rangle}{\dim(V)}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
- Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_B(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_{\mathbf{B}}(P_V) \rangle$  counts the edges between a set and its complement.



### edge expansion

$$\min_{\substack{V\subseteq [n]\\1\leq |V|\leq \frac{n}{2}}}\frac{|\partial(V)|}{|V|} \quad ===\Rightarrow \quad \min_{\substack{V\leq \mathbb{C}^n\\1\leq \dim(V)\leq \frac{n}{2}}}\frac{\langle I_n-P_V,\Phi_{\mathbf{B}}(P_V)\rangle}{\dim(V)}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
- Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_B(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_{\mathbf{B}}(P_V) \rangle$  counts the edges between a set and its complement.



#### edge expansion

$$\min_{\substack{V\subseteq [n]\\1\leq |V|\leq \frac{n}{2}}}\frac{|\partial(\mathit{V})|}{|\mathit{V}|} \quad ===\Rightarrow \quad \min_{\substack{V\leq \mathbb{C}^n\\1\leq \dim(\mathit{V})\leq \frac{n}{2}}}\frac{\langle \mathit{I}_n-\mathit{P}_\mathit{V},\Phi_{\mathbf{B}}(\mathit{P}_\mathit{V})\rangle}{\dim(\mathit{V})}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
- Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_B(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_{\mathbf{B}}(P_V) \rangle$  counts the edges between a set and its complement.



### edge expansion

$$\min_{\substack{V\subseteq [n]\\1\leq |V|\leq \frac{n}{2}}}\frac{|\partial(V)|}{|V|} ===\Rightarrow \min_{\substack{V\subseteq \mathbb{C}^n\\1\leq \dim(V)\leq \frac{n}{2}}}\frac{\langle I_n-P_V,\Phi_{\mathbf{B}}(P_V)\rangle}{\dim(V)}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
  - $\bullet$  A d-regular graph can be decomposed as a union of d permutations.
- $\bullet$  Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_B(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_B(P_V) \rangle$  counts the edges between a set and its complement.



#### edge expansion

$$\min_{\substack{V \subseteq [n]\\1 \le |V| \le \frac{n}{2}}} \frac{|\partial(V)|}{|V|} \quad == = \Rightarrow \quad \min_{\substack{V \le \mathbb{C}^n\\1 \le \dim(V) \le \frac{n}{2}}} \frac{\langle I_n - P_V, \Phi_{\mathbf{B}}(P_V) \rangle}{\dim(V)}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
- $\bullet$  Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_B(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_{\mathbf{B}}(P_V) \rangle$  counts the edges between a set and its complement.



#### edge expansion

$$\min_{\substack{V \subseteq [n]\\1 \le |V| \le \frac{n}{2}}} \frac{|\partial(V)|}{|V|} \quad == = \Rightarrow \quad \min_{\substack{V \le \mathbb{C}^n\\1 \le \dim(V) \le \frac{n}{2}}} \frac{\langle I_n - P_V, \Phi_{\mathbf{B}}(P_V) \rangle}{\dim(V)}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
- $\bullet$  Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_{\mathbf{B}}(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_{\mathbf{B}}(P_V) \rangle$  counts the edges between a set and its complement.



#### edge expansion

$$\min_{\substack{V \subseteq [n]\\1 \le |V| \le \frac{n}{2}}} \frac{|\partial(V)|}{|V|} \quad == = \Rightarrow \quad \min_{\substack{V \le \mathbb{C}^n\\1 \le \dim(V) \le \frac{n}{2}}} \frac{\langle I_n - P_V, \Phi_{\mathbf{B}}(P_V) \rangle}{\dim(V)}$$

- $\Phi_{\mathbf{B}}$  is an analogue of the normalized adjacency matrix A of a graph G.
- Consider that all the  $B_i$ 's are permutation matrices.
- Consider that V is a coordinate subspace. (So  $P_V$  is diagonal of 0 and 1!)
- Then  $I_n P_V$  can be treated as an indicator vector x, and  $\Phi_{\mathbf{B}}(P_V) = Ax$ .
- So  $\langle I_n P_V, \Phi_{\mathbf{B}}(P_V) \rangle$  counts the edges between a set and its complement.



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- The dimension expansion of **B** [Barak-Impagliazzo-Shipilka-Wigderson'04]

$$\mu(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(\mathit{V} + \mathbf{B}(\mathit{V})) - \dim(\mathit{V})}{\dim(\mathit{V})},$$

where  $\mathbf{B}(V) := \langle \bigcup_{i \in [d]} \{B_i v : v \in V\} \rangle$ .

• Given the vertex expansion  $\mu(G)$  and treat G as a tuple of permutations  $(P_1, \ldots, P_d)$  acting on [n]:

$$\forall V \subseteq [n], \left| V \cup \bigcup_{i=1}^{d} P_i(V) \right| \ge (1 + \mu(G)) |V|$$

• Change the permutation action and underlying object to be more general.



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- The dimension expansion of **B** [Barak-Impagliazzo-Shipilka-Wigderson'04]

$$\mu(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(\mathit{V} + \mathbf{B}(\mathit{V})) - \dim(\mathit{V})}{\dim(\mathit{V})},$$

where  $\mathbf{B}(V) := \langle \bigcup_{i \in [d]} \{ B_i v : v \in V \} \rangle$ .

• Given the vertex expansion  $\mu(G)$  and treat G as a tuple of permutations  $(P_1, \ldots, P_d)$  acting on [n]:

$$\forall V \subseteq [n], \left| V \cup \bigcup_{i=1}^{d} P_i(V) \right| \ge (1 + \mu(G))|V|$$

• Change the permutation action and underlying object to be more general.



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- $\bullet$  The dimension expansion of B [Barak-Impagliazzo-Shipilka-Wigderson'04]

$$\mu(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(V + \mathbf{B}(V)) - \dim(V)}{\dim(V)},$$

where  $\mathbf{B}(V) := \langle \bigcup_{i \in [d]} \{ B_i v : v \in V \} \rangle$ .

• Given the vertex expansion  $\mu(G)$  and treat G as a tuple of permutations  $(P_1, \ldots, P_d)$  acting on [n]:

$$\forall V \subseteq [n], \left| V \cup \bigcup_{i=1}^{d} P_i(V) \right| \ge (1 + \mu(G))|V|$$

• Change the permutation action and underlying object to be more general.

- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- The **dimension edge expansion** of **B** (proposed by us!):

$$h_D(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T^*_{V^\perp} B_i T_V)}{\dim(V)},$$

where  $V^{\perp}$  means the orthogonal complement of V, and the columns of  $T_V$  form an orthonormal basis of V.

• Let dim(V) = r and  $U = \begin{bmatrix} T_V & T_{V^{\perp}} \end{bmatrix}$  be an  $n \times n$  unitary matrix.

$$U^*B_iU = \begin{bmatrix} * & * \\ T^*_{V^{\perp}}B_iT_V & * \end{bmatrix},$$

where  $T_{V^{\perp}}^* B_i T_V \in \mathcal{M}((n-r) \times r, \mathbb{C})$ 



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- The **dimension edge expansion** of **B** (proposed by us!):

$$h_D(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(\boldsymbol{T}^*_{V^\perp} \boldsymbol{B}_i \boldsymbol{T}_V)}{\dim(V)},$$

where  $V^{\perp}$  means the orthogonal complement of V, and the columns of  $T_V$  form an orthonormal basis of V.

• Let dim(V) = r and  $U = \begin{bmatrix} T_V & T_{V^{\perp}} \end{bmatrix}$  be an  $n \times n$  unitary matrix.

$$U^*B_iU = \begin{bmatrix} * & * \\ T^*_{V^{\perp}}B_iT_V & * \end{bmatrix},$$

where  $T_{V^{\perp}}^* B_i T_V \in \mathcal{M}((n-r) \times r, \mathbb{C}).$ 



- Given a matrix tuple  $\mathbf{B} = (B_1, \dots, B_d) \in \mathrm{M}(n, \mathbb{C})^d$ .
- The **dimension edge expansion** of **B** (proposed by us!):

$$h_D(\mathbf{B}) := \min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T_{V^{\perp}}^* B_i T_V)}{\dim(V)},$$

where  $V^{\perp}$  means the orthogonal complement of V, and the columns of  $T_V$  form an orthonormal basis of V.

• Let dim(V) = r and  $U = \begin{bmatrix} T_V & T_{V^{\perp}} \end{bmatrix}$  be an  $n \times n$  unitary matrix.

$$U^*B_iU = \begin{bmatrix} * & * \\ T^*_{V^{\perp}}B_iT_V & * \end{bmatrix},$$

where  $T_{V^{\perp}}^* B_i T_V \in \mathrm{M}((n-r) \times r, \mathbb{C}).$ 



```
vertex expansion ===\Rightarrow dimension expansion
edge expansion ===\Rightarrow dimension edge expansion
```

- If we restrict
  - the matrix tuple consisting of permutation matrices only and;
  - the minimum to coordinate subspaces only,

one can precisely recover the definition of corresponding graph expansion



```
vertex expansion ===\Rightarrow dimension expansion

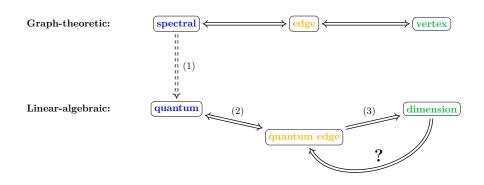
edge expansion ===\Rightarrow dimension edge expansion
```

- If we restrict
  - the matrix tuple consisting of permutation matrices only and;
  - the minimum to coordinate subspaces only,

one can precisely recover the definition of corresponding graph expansion.

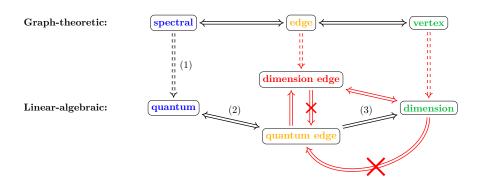


### Overview of previous results



- (1): [Bannink-Briët-Labib-Maassen'20]
- (2): [Hastings'07]
- (3): [Lubotzky-Zelmanov'08]

### Overview of our main results



- (1): [Bannink-Briët-Labib-Maassen'20]
- (2): [Hastings'07]
- (3): [Lubotzky-Zelmanov'08]

- Dimension expansion  $\neq$  Quantum expansion.
- For any matrix tuple  $\mathbf{B}_n = (B_1, \dots, B_d)$  consisting of unitary matrices,  $\mathbf{B}_n^s = (B_1^s, \dots, B_d^s)$  satisfies that

$$\mu(\mathbf{B}_n^s) \ge \frac{\mu(\mathbf{B}_n)}{d}$$
 and  $\lim_{n \to \infty} \lambda(\mathbf{B}_n^s) = 1$ 

for some sufficiently small power s > 0

• This proof requires some advanced techniques, such as a number of compactness arguments.



- Dimension expansion  $\neq$  Quantum expansion.
- For any matrix tuple  $\mathbf{B}_n = (B_1, \dots, B_d)$  consisting of unitary matrices,  $\mathbf{B}_n^s = (B_1^s, \dots, B_d^s)$  satisfies that

$$\mu(\mathbf{B}_n^s) \ge \frac{\mu(\mathbf{B}_n)}{d}$$
 and  $\lim_{n \to \infty} \lambda(\mathbf{B}_n^s) = 1$ 

for some sufficiently small power s > 0.

• This proof requires some advanced techniques, such as a number of compactness arguments.



- Dimension expansion  $\Rightarrow$  Quantum expansion.
- For any matrix tuple  $\mathbf{B}_n = (B_1, \dots, B_d)$  consisting of unitary matrices,  $\mathbf{B}_n^s = (B_1^s, \dots, B_d^s)$  satisfies that

$$\mu(\mathbf{B}_n^s) \ge \frac{\mu(\mathbf{B}_n)}{d}$$
 and  $\lim_{n \to \infty} \lambda(\mathbf{B}_n^s) = 1$ 

for some sufficiently small power s > 0.

• This proof requires some advanced techniques, such as a number of compactness arguments.



- Quantum expansion  $\Rightarrow$  Dimension expansion.
- For any doubly stochastic matrix tuple B,

$$\frac{1 - \lambda(\mathbf{B})}{2d} \le \frac{h_Q(\mathbf{B})}{d} \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

- It follows that if there is a spectral gap  $1 \lambda(\mathbf{B}) > 0$ , then  $\mu(\mathbf{B}) > 0$ .
- $\bullet$  In case B consists of unitary matrices only, we can make a stronger bound,

$$\frac{1 - \lambda(\mathbf{B})}{2} \le h_Q(\mathbf{B}) \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

$$\frac{1 - \lambda(\mathbf{B})}{6} \le \mu(\mathbf{B}).$$

- Quantum expansion  $\Rightarrow$  Dimension expansion.
- For any doubly stochastic matrix tuple B,

$$\frac{1-\lambda(\mathbf{B})}{2d} \le \frac{h_Q(\mathbf{B})}{d} \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

- It follows that if there is a spectral gap  $1 \lambda(\mathbf{B}) > 0$ , then  $\mu(\mathbf{B}) > 0$ .
- In case B consists of unitary matrices only, we can make a stronger bound

$$\frac{1 - \lambda(\mathbf{B})}{2} \le h_Q(\mathbf{B}) \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

$$\frac{1 - \lambda(\mathbf{B})}{6} \le \mu(\mathbf{B}).$$



- Quantum expansion  $\Rightarrow$  Dimension expansion.
- For any doubly stochastic matrix tuple B,

$$\frac{1 - \lambda(\mathbf{B})}{2d} \le \frac{h_Q(\mathbf{B})}{d} \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

- It follows that if there is a spectral gap  $1 \lambda(\mathbf{B}) > 0$ , then  $\mu(\mathbf{B}) > 0$ .
- In case B consists of unitary matrices only, we can make a stronger bound

$$\frac{1 - \lambda(\mathbf{B})}{2} \le h_Q(\mathbf{B}) \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

$$\frac{1 - \lambda(\mathbf{B})}{6} \le \mu(\mathbf{B}).$$

- Quantum expansion  $\Rightarrow$  Dimension expansion.
- For any doubly stochastic matrix tuple B,

$$\frac{1 - \lambda(\mathbf{B})}{2d} \le \frac{h_Q(\mathbf{B})}{d} \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

- It follows that if there is a spectral gap  $1 \lambda(\mathbf{B}) > 0$ , then  $\mu(\mathbf{B}) > 0$ .
- $\bullet$  In case B consists of unitary matrices only, we can make a stronger bound,

$$\frac{1 - \lambda(\mathbf{B})}{2} \le h_Q(\mathbf{B}) \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

$$\frac{1 - \lambda(\mathbf{B})}{6} \le \mu(\mathbf{B}).$$

- Quantum expansion  $\Rightarrow$  Dimension expansion.
- For any doubly stochastic matrix tuple B,

$$\frac{1 - \lambda(\mathbf{B})}{2d} \le \frac{h_Q(\mathbf{B})}{d} \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

- It follows that if there is a spectral gap  $1 \lambda(\mathbf{B}) > 0$ , then  $\mu(\mathbf{B}) > 0$ .
- In case B consists of unitary matrices only, we can make a stronger bound,

$$\frac{1 - \lambda(\mathbf{B})}{2} \le h_Q(\mathbf{B}) \le h_D(\mathbf{B}) \le \mu(\mathbf{B}).$$

$$\frac{1 - \lambda(\mathbf{B})}{6} \le \mu(\mathbf{B}).$$

• The graphical matrix tuple associated to a d-regular graph G = ([n], E) is defined as

$$\mathbf{B}_G := (\sqrt{n} \cdot \mathbf{E}_{i,j} : \{i, j\} \in E),$$

where  $E_{i,j}$  is the elementary matrix with a 1 in position (i,j) and zeros in all other entries.

• For example, when n = 3,

$$\mathbf{E}_{2,3} := \left[ \begin{array}{ccc} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{array} \right].$$



• The graphical matrix tuple associated to a d-regular graph G = ([n], E) is defined as

$$\mathbf{B}_G := (\sqrt{n} \cdot \mathbf{E}_{i,j} : \{i, j\} \in E),$$

where  $E_{i,j}$  is the elementary matrix with a 1 in position (i,j) and zeros in all other entries.

• For example, when n = 3,

$$E_{2,3} := \left[ \begin{array}{ccc} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{array} \right].$$



• The graphical matrix tuple associated to a d-regular graph G = ([n], E) is defined as

$$\mathbf{B}_G := (\sqrt{n} \cdot \mathbf{E}_{i,j} : \{i, j\} \in E),$$

where  $E_{i,j}$  is the elementary matrix with a 1 in position (i,j) and zeros in all other entries.

 $\bullet$  [Bannink-Briët-Labib-Maassen'20] proved that for any d-regular graph G,

$$\lambda(\mathbf{B}_G) = \lambda(G).$$

• We showed some analogous results that

$$h_Q(\mathbf{B}_G) \not\equiv h(G)$$
  
 $h_D(\mathbf{B}_G) = h(G)$   
 $\mu(\mathbf{B}_G) = \mu(G)$ 



• The graphical matrix tuple associated to a d-regular graph G = ([n], E) is defined as

$$\mathbf{B}_G := (\sqrt{n} \cdot \mathbf{E}_{i,j} : \{i, j\} \in E),$$

where  $E_{i,j}$  is the elementary matrix with a 1 in position (i,j) and zeros in all other entries.

 $\bullet$  [Bannink-Briët-Labib-Maassen'20] proved that for any d-regular graph G,

$$\lambda(\mathbf{B}_G) = \lambda(G).$$

• We showed some analogous results that

$$h_Q(\mathbf{B}_G) \not\equiv h(G);$$
  
 $h_D(\mathbf{B}_G) = h(G);$   
 $\mu(\mathbf{B}_G) = \mu(G).$ 

• The graphical matrix tuple associated to a d-regular graph G = ([n], E) is defined as

$$\mathbf{B}_G := (\sqrt{n} \cdot \mathbf{E}_{i,j} : \{i, j\} \in E),$$

where  $E_{i,j}$  is the elementary matrix with a 1 in position (i,j) and zeros in all other entries.

 $\bullet$  [Bannink-Briët-Labib-Maassen'20] proved that for any d-regular graph G,

$$\lambda(\mathbf{B}_G) = \lambda(G).$$

• We showed some analogous results that

$$h_Q(\mathbf{B}_G) \not\equiv h(G);$$
  
 $h_D(\mathbf{B}_G) = h(G);$   
 $\mu(\mathbf{B}_G) = \mu(G).$ 

### dimension expansion

### dimension edge expansion

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(V + \mathbf{B}(V)) - \dim(V)}{\dim(V)}$$

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T_{V^\perp}^t B_i T_V)}{\dim(V)}$$

$$B_{i}(V) = \begin{bmatrix} * & * & * \\ * & * & * \\ b_{31} & b_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} * & * \\ * & * \\ b_{31} & b_{32} \end{bmatrix}$$

$$T_{V^{\perp}}^{t}B_{i}T_{V} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^{t} \cdot \begin{bmatrix} * & * & * \\ * & * & * \\ b_{31} & b_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} b_{31} & b_{32} \end{bmatrix}$$

$$\dim(V + B_i(V)) - \dim(V) = \operatorname{rank}(T_{V^{\perp}}^t B_i T_V)$$



#### dimension expansion

### dimension edge expansion

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 < \dim(V) < \frac{n}{2}}} \frac{\dim(V + \mathbf{B}(V)) - \dim(V)}{\dim(V)}$$

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T_{V^\perp}^t B_i T_V)}{\dim(V)}$$

$$B_i(V) = \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} * & * \\ * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$T_{V^{\perp}}^{t}B_{i}T_{V} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^{t} \cdot \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$\dim(V + B_i(V)) - \dim(V) = \operatorname{rank}(T_{V^{\perp}}^t B_i T_V)$$



#### dimension expansion

### dimension edge expansion

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(V + \mathbf{B}(V)) - \dim(V)}{\dim(V)}$$

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T_{V^\perp}^t B_i T_V)}{\dim(V)}$$

$$B_i(V) = \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} * & * \\ * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$T_{V^{\perp}}^{t}B_{i}T_{V} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^{t} \cdot \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$\dim(V + B_i(V)) - \dim(V) = \operatorname{rank}(T_{V^{\perp}}^t B_i T_V)$$



### dimension expansion

### dimension edge expansion

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(V + \mathbf{B}(V)) - \dim(V)}{\dim(V)}$$

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T_{V^\perp}^t B_i T_V)}{\dim(V)}$$

$$B_i(V) = \left[ \begin{array}{ccc} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{array} \right] \cdot \left[ \begin{array}{ccc} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{array} \right] = \left[ \begin{array}{ccc} * & * \\ * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{array} \right]$$

$$T_{V^{\perp}}^{t}B_{i}T_{V} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^{t} \cdot \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$\dim(V + B_i(V)) - \dim(V) = \operatorname{rank}(T_{V^{\perp}}^t B_i T_V)$$



#### dimension expansion

### dimension edge expansion

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\dim(V + \mathbf{B}(V)) - \dim(V)}{\dim(V)}$$

$$\min_{\substack{V \leq \mathbb{C}^n \\ 1 \leq \dim(V) \leq \frac{n}{2}}} \frac{\sum_{i=1}^d \operatorname{rank}(T_{V^\perp}^t B_i T_V)}{\dim(V)}$$

$$B_i(V) = \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} * & * \\ * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$T_{V^{\perp}}^{t}B_{i}T_{V} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}^{t} \cdot \begin{bmatrix} * & * & * \\ * & * & * \\ \boldsymbol{b}_{31} & \boldsymbol{b}_{32} & * \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \boldsymbol{b}_{31} & \boldsymbol{b}_{32} \end{bmatrix}$$

$$\dim(V + B_i(V)) - \dim(V) = \operatorname{rank}(T_{V^{\perp}}^t B_i T_V)$$

