

# CS 59300 – Algorithms for Data Science

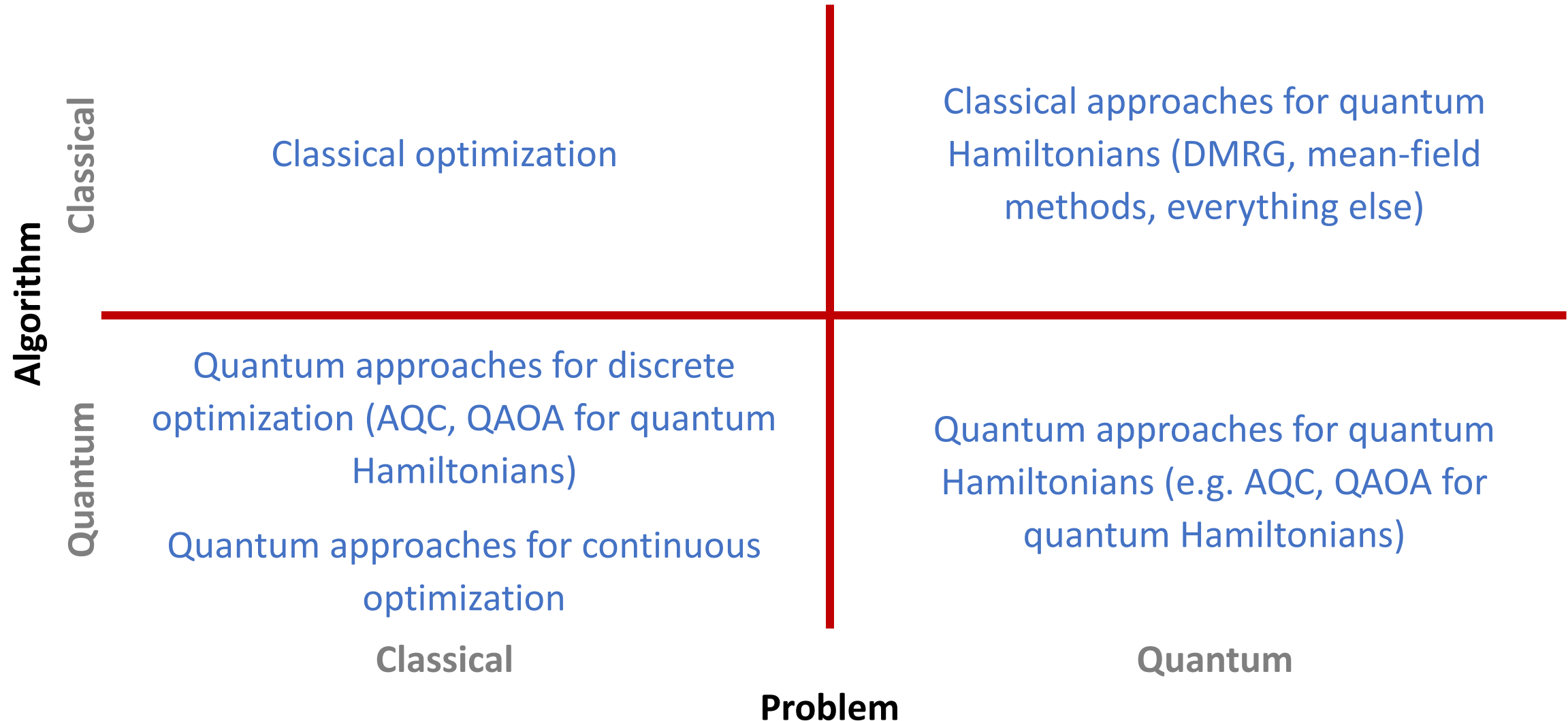
## Classical and Quantum approaches

### Lecture 10 (10/07)

### Sum-of-Squares (III)

[https://ruizhezhang.com/course\\_fall\\_2025.html](https://ruizhezhang.com/course_fall_2025.html)

# What is quantum optimization?



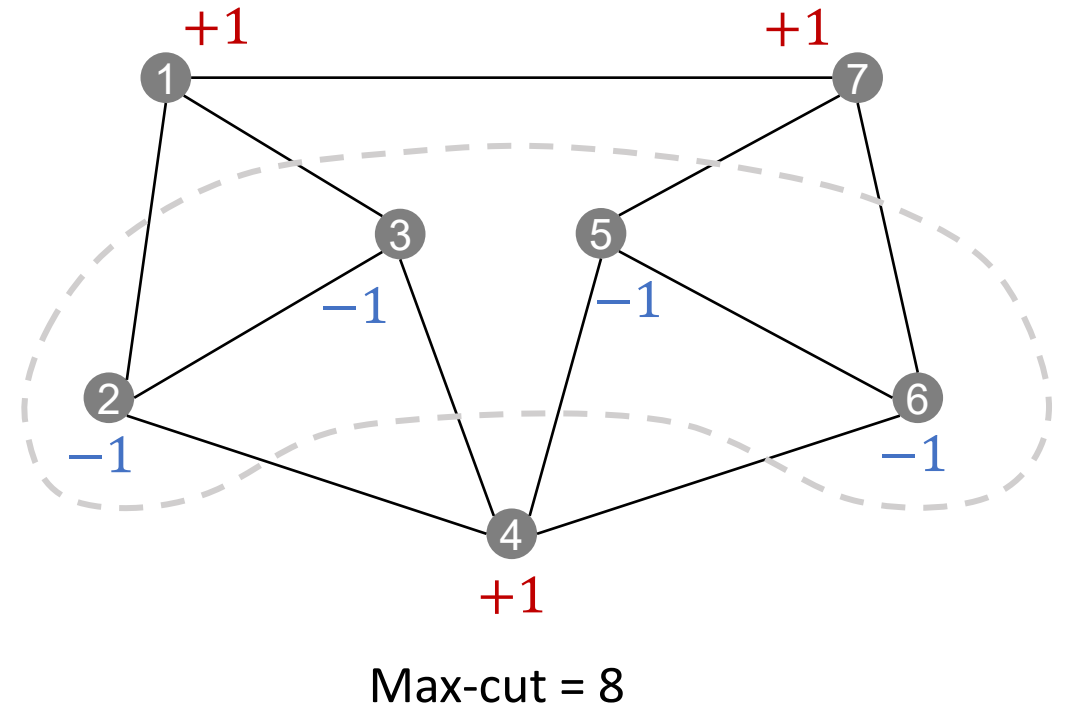
# (Classical) Max Cut

Given a graph  $G(V, E)$ , find a partition  $f: V \rightarrow \{+1, -1\}$  maximizing

$$\sum_{ij \in E} \left( \frac{1 - f(i)f(j)}{2} \right)$$

*“ $f(i) \neq f(j)$ ”*

- One of Karp's 21 **NP**-complete problems
- **0.878**-approximation by Goemans and Williamson using SDP and randomized rounding



# Interlude: Approximation algorithm

An  $\alpha$ -approximation algorithm runs in polynomial time, and for any instance  $I$ , delivers an approximate solution such that:

$$\frac{\text{Value}(\text{Approximation}_I)}{\text{Value}(\text{Optimal}_I)} \geq \alpha$$

Approximation algorithm = Relaxation + Rounding

- The approximation ratio can be lower bounded by:

$$\rho := \min_I \frac{\text{Value}(\text{Approximation}_I)}{\text{fValue}(\text{Relaxation}_I)} \leq \alpha$$

- Integrality gap (barrier of the specific relaxation proof)

$$\min_I \frac{\text{Value}(\text{Optimal}_I)}{\text{fValue}(\text{Relaxation}_I)} \geq \rho$$

# Goemans-Williamson algorithm

## Relaxation:

For each vertex  $i \in V$ , assign  $v_i \in \mathbb{R}^d$

$$\begin{aligned} \max \quad & \sum_{(i,j) \in E} (1 - \langle v_i, v_j \rangle) / 2 \\ \text{s.t.} \quad & \|v_i\| = 1 \quad \forall i \in V \end{aligned}$$



## Solving SDP:

$$\begin{aligned} \max \quad & \langle -A_G/2, X \rangle \\ \text{s.t.} \quad & X_{ii} = 1 \quad \forall i \in V \\ & X \succeq 0 \end{aligned}$$



## Gaussian rounding:

- Sample a unit vector  $g \in \mathbb{R}^d$
- $\sigma_i \leftarrow \text{sign}(\langle g, v_i \rangle) \quad \forall i \in V$



## Cholesky decomposition:

$$X = \begin{bmatrix} - & v_1^\top & - \\ - & v_2^\top & - \\ & \vdots & \\ - & v_n^\top & - \end{bmatrix} \cdot \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \cdots & v_n \\ | & | & & | \end{bmatrix}$$

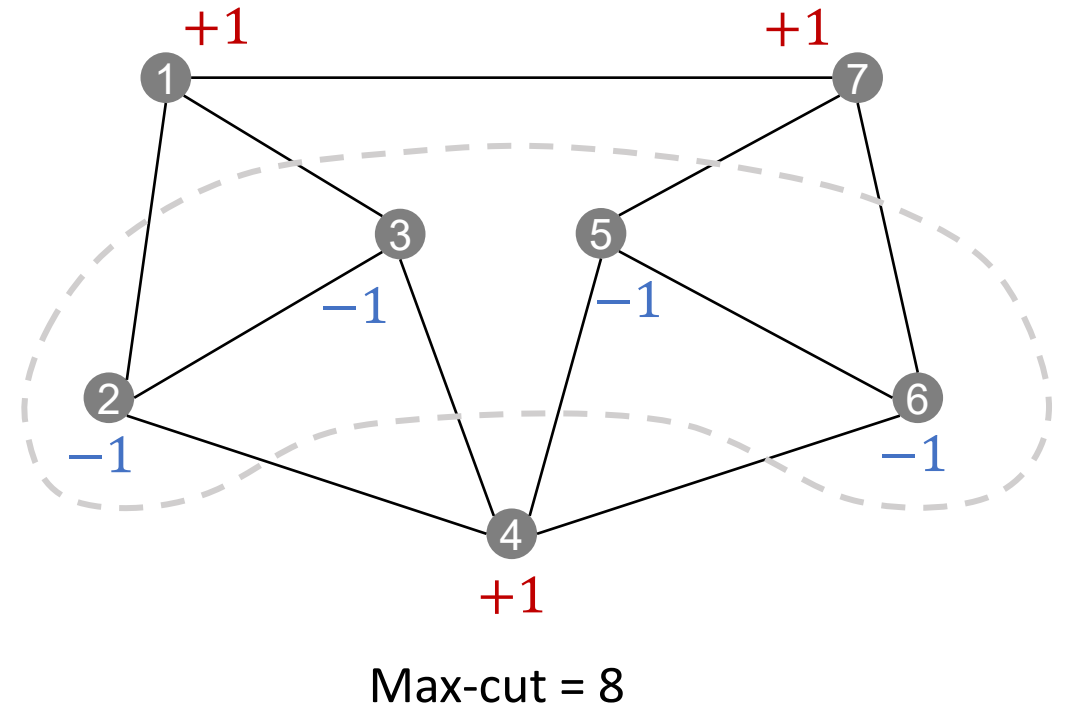
# (Classical) Max Cut

Given a graph  $G(V, E)$ , find a partition  $f: V \rightarrow \{+1, -1\}$  maximizing

$$\sum_{ij \in E} \left( \frac{1 - f(i)f(j)}{2} \right)$$

“ $f(i) \neq f(j)$ ”

- One of Karp's 21 **NP**-complete problems
- **0.878**-approximation by Goemans and Williamson using SDP and randomized rounding



What is the quantum version of Max Cut?

# Pauli matrices

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad Y = \begin{bmatrix} 0 & -\mathbf{i} \\ \mathbf{i} & 0 \end{bmatrix}, \quad Z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

- $\{I, X, Y, Z\}$  is a basis for  $2 \times 2$  Hermitian matrices
- $X^2 = Y^2 = Z^2 = I$
- Commutator and anticommutator:  $[A, B] := AB - BA$  and  $\{A, B\} := AB + BA$

$$[X, Y] = 2\mathbf{i}Z, \quad [Y, Z] = 2\mathbf{i}X, \quad [Z, X] = 2\mathbf{i}Y$$

$$\{X, Y\} = \{Y, Z\} = \{Z, X\} = 0 \quad \text{“swap flips the sign”}$$

- Each of  $X, Y, Z$  has one eigenvalue  $+1$  and one eigenvalue  $-1$   
(their eigenvectors are called  $X$ -basis,  $Y$ -basis,  $Z$ -basis)

$$\text{X-basis:} \quad |+\rangle = \frac{|0\rangle + |1\rangle}{\sqrt{2}}, \quad |-\rangle = \frac{|0\rangle - |1\rangle}{\sqrt{2}}$$



# Pauli matrices (multiple qubits)

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad Y = \begin{bmatrix} 0 & -\mathbf{i} \\ \mathbf{i} & 0 \end{bmatrix}, \quad Z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

- For an  $n$ -qubit system, we use  $\sigma_i$  for  $\sigma \in \{X, Y, Z\}$  to denote applying  $\sigma$  to the  $i$ -th qubit:

$$I \otimes \cdots \otimes I \otimes \sigma \otimes I \otimes \cdots \otimes I \in \mathbb{C}^{2^n \times 2^n}$$

## Pauli polynomial

- A monomial  $\tau = \sigma_1 \sigma_2 \cdots \sigma_n$  with  $\sigma_i \in \{I, X_i, Y_i, Z_i\}$
- $\deg(\tau) = |\{i \in [n]: \sigma_i \neq I\}|$
- $\mathcal{P}_n(k)$  is the set of monomials of degree at most  $k$
- A Pauli polynomial is a **real linear combination** of monomials; its degree is the maximal degree over its terms

Hermitian operator

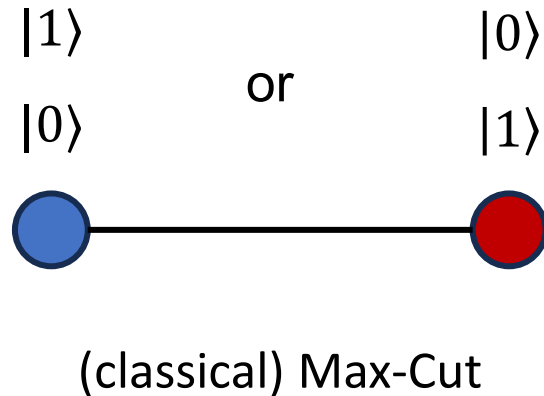


# Quantum Max-Cut (QMC)

- Let  $G = (V, E)$  be a graph
- QMC is a special case of 2-local Hamiltonian problem:

Compute  $\lambda_{\max}(H)$      $H = \sum_{ij \in E} h_{ij}$ ,    where  $h = \frac{1}{4} \cdot (I - XX - YY - ZZ)$

$$= \frac{1}{2} \cdot (|01\rangle - |10\rangle)(\langle 01| - \langle 10|)$$



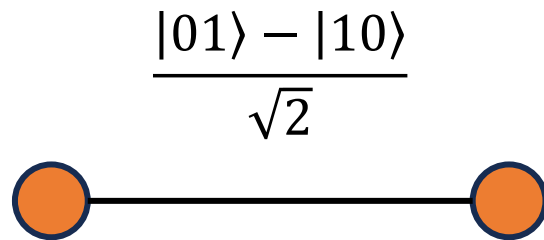
$$\begin{array}{c}
 \begin{array}{cccc}
 & 00 & 01 & 10 & 11 \\
 \begin{array}{c} 00 \\ 01 \\ 10 \\ 11 \end{array} & \left[ \begin{array}{cccc}
 0 & & & \\
 & 1 & -1 & \\
 & -1 & 1 & \\
 & & & 0
 \end{array} \right]
 \end{array}
 \end{array}$$

# Quantum Max-Cut (QMC)

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$$= \frac{1}{2} \cdot (|01\rangle - |10\rangle)(\langle 01| - \langle 10|)$$



quantum Max-Cut

“Entangled assignment” gets  
max value

	00	01	10	11
00	$\begin{bmatrix} 0 & & & \\ & 1 & -1 & \\ & -1 & 1 & \\ & & & 0 \end{bmatrix}$			
01				
10				
11				

# Quantum Max-Cut (QMC)

- Let  $G = (V, E)$  be a graph
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quantum Max-Cut

**Term 1:** does nothing

# Quantum Max-Cut (QMC)

- Let  $G = (V, E)$  be a graph
- QMC is a special case of 2-local Hamiltonian problem:

Compute  $\lambda_{\max}(H)$      $H = \sum_{ij \in E} h_{ij}$ ,    where  $h = \frac{1}{4} \cdot (I - \boxed{XX} - YY - ZZ)$

$$= \frac{1}{2} \cdot (|01\rangle - |10\rangle)(\langle 01| - \langle 10|)$$



quantum Max-Cut

**Term 1:** does nothing

**Term 2:** measure in  $X$  basis

- $-1$  if same ( $++$  or  $--$ )
- $+1$  if same ( $+-$  or  $-+$ )

# Quantum Max-Cut (QMC)

- Let  $G = (V, E)$  be a graph
- QMC is a special case of 2-local Hamiltonian problem:

Compute  $\lambda_{\max}(H)$      $H = \sum_{ij \in E} h_{ij}$ ,    where  $h = \frac{1}{4} \cdot (I - \boxed{XX} - YY - ZZ)$

$$= \frac{1}{2} \cdot (|01\rangle - |10\rangle)(\langle 01| - \langle 10|)$$



quantum Max-Cut

**Term 1:** does nothing

**Term 2:** should be different in  $X$ -basis

# Quantum Max-Cut (QMC)

- Let  $G = (V, E)$  be a graph
- QMC is a special case of 2-local Hamiltonian problem:

Compute  $\lambda_{\max}(H)$      $H = \sum_{ij \in E} h_{ij}$ ,    where  $h = \frac{1}{4} \cdot (I - XX - YY - ZZ)$

$$= \frac{1}{2} \cdot (|01\rangle - |10\rangle)(\langle 01| - \langle 10|)$$



quantum Max-Cut

**Term 1:** does nothing

**Term 2:** should be different in  $X$ -basis

**Term 3:** should be different in  $Y$ -basis

# Quantum Max-Cut (QMC)

- Let  $G = (V, E)$  be a graph
- QMC is a special case of 2-local Hamiltonian problem:

Compute  $\lambda_{\max}(H)$      $H = \sum_{ij \in E} h_{ij}$ ,    where  $h = \frac{1}{4} \cdot (I - XX - YY - ZZ)$

$$= \frac{1}{2} \cdot (|01\rangle - |10\rangle)(\langle 01| - \langle 10|)$$



quantum Max-Cut

Like (classical) Max-Cut in  $X$ ,  $Y$ ,  
and  $Z$  basis

**Term 1:** does nothing

**Term 2:** should be different in  $X$ -basis

**Term 3:** should be different in  $Y$ -basis

**Term 4:** should be different in  $Z$ -basis

# Interlude: Quantum Lasserre hierarchy (ncSoS)

- Also called **non-commutative** sum-of-squares hierarchy
- Introduced by Navascués, Pironio, and Acin (NPA hierarchy)

## Pseudo-density

- A  $k$ -positive pseudo-density  $\tilde{\rho} \in \mathbb{C}^{2^n \times 2^n}$  is a  $2^n \times 2^n$  Hermitian matrix
- $\text{tr}[\tilde{\rho}] = 1$
- $\text{tr}[\tilde{\rho} P^2] \geq 0, \forall$  Pauli polynomial  $P$  of degree  $\leq k$

We use  $\tilde{\mathcal{D}}_n(k)$  to denote the set of  $k$ -positive pseudo-density operators

- Level  $k$  of the quantum Lasserre hierarchy finds an optimal  $k$ -positive pseudo-density matrix:

$$v_k(H) := \max_{\tilde{\rho} \in \tilde{\mathcal{D}}_k(n)} \text{tr}[H\tilde{\rho}] \geq \lambda_{\max}(H)$$

- Convergence:  $v_k(H) \geq v_{k+1}(H) \geq \dots \geq v_n(H) = \lambda_{\max}(H)$

“tighter and tighter upper-bound”



# Quantum Lasserre hierarchy

- Let  $\tilde{\rho}$  be the optimal pseudo-density solution to  $\mathcal{L}_k$  (level  $k$  Quantum Lasserre)

- For each Pauli monomial  $\tau$ , define its relaxed value to be

$$\langle \tau \rangle := \text{tr}[\tilde{\rho}\tau] \quad \text{“pseudoexpectation”}$$

- For QMC,  $v_k(H)$  can be written as:

$$v_k(H) = \sum_{ij \in E} \frac{1}{4} (1 - \langle X_i X_j \rangle - \langle Y_i Y_j \rangle - \langle Z_i Z_j \rangle)$$

# Solve quantum Lasserre hierarchy

## Pseudoexpectation program

$$v_k(H) := \max \sum_{\phi \in \mathcal{P}_n(2k)} c(\phi) \langle \phi \rangle$$

*Variables:*  $\{\langle \tau \rangle : \tau \in \mathcal{P}_n(2k)\}$

*Constraints:*

- $\langle I \rangle = 1$
- $\mathcal{M}_k \in \mathbb{C}^{n^{\mathcal{O}(k)} \times n^{\mathcal{O}(k)}} : \mathcal{M}_k(\sigma, \tau) := \langle \sigma \tau \rangle$  for any  $\sigma, \tau \in \mathcal{P}_n(k)$   
 $\mathcal{M}_k \succcurlyeq 0$
- Other symmetries

## Vector program

$$v_k(H) := \max \sum_{\phi \in \mathcal{P}_n(2k)} c(\phi) \langle \phi \rangle$$

*Variables:*  $\{|\tau\rangle \in \mathbb{C}^d : \tau \in \mathcal{P}_n(k)\}$   
(any  $d \geq |\mathcal{P}_n(k)|$ )

*Constraints:*

- $\langle \tau | \tau \rangle = 1$
- $\langle \tau | \sigma \rangle = \langle \tau \sigma \rangle$

- They yield the same SDP
- Vector version is more convenient for rounding

# Parallels between MC and QMC: relaxation

## Max Cut


$$v_{MC} := \max \sum_{ij \in E} \frac{1 - \langle Z_i | Z_j \rangle}{2}$$

s. t.  $\langle Z_i | Z_i \rangle = 1 \quad \forall i \in V$   
 $|Z_i\rangle \in \mathbb{R}^d \quad \forall i \in V$

## Quantum Max Cut ( $\mathcal{L}_1$ )

$$v_{QMC} := \max \sum_{ij \in E} \frac{1 - \langle X_i | X_j \rangle - \langle Y_i | Y_j \rangle - \langle Z_i | Z_j \rangle}{4}$$

s. t.  $\langle \tau_i | \tau_i \rangle = 1 \quad \forall i \in V, \tau \in \{X, Y, Z\}$   
 $\langle \tau_i | \sigma_i \rangle = 0 \quad \forall i \in V, \tau, \sigma \in \{X, Y, Z\}, \tau \neq \sigma$   
 $|\tau_i\rangle \in \mathbb{R}^d \quad \forall i \in V, \tau \in \{X, Y, Z\}$


$$v_{SQMC} := \max \sum_{ij \in E} \frac{1 - 3\langle W_i | W_j \rangle}{4}$$

s. t.  $\langle W_i | W_j \rangle = 1 \quad \forall i \in V$   
 $|W_i\rangle \in \mathbb{R}^d \quad \forall i \in V$

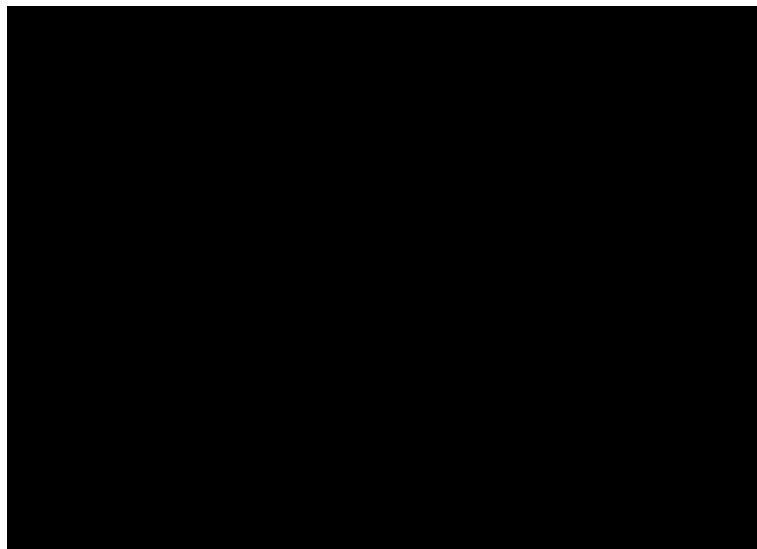
# Parallels between MC and QMC: rounding algorithms

## Max Cut

Input:  $|Z_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{sgn}(\langle Z_i | r \rangle) \in \{\pm 1\}$

## Goemans-Williamson



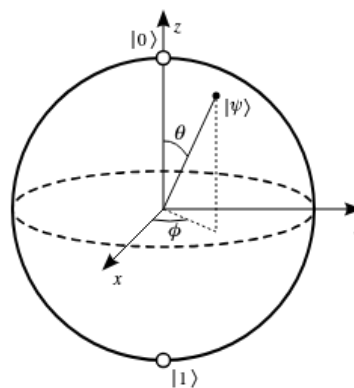
## Quantum Max Cut ( $\mathcal{L}_1$ )

Input:  $|W_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r_x\rangle, |r_y\rangle, |r_z\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle W_i | r_x \rangle, \langle W_i | r_y \rangle, \langle W_i | r_z \rangle)$

Bloch vector  $\longrightarrow \rho_i = \frac{1}{2}(I + (u_i)_1 X_i + (u_i)_2 Y_i + (u_i)_3 Z_i)$

( $\rho_i$  is a pure state)



$$\rho = \bigotimes_{i \in [n]} \rho_i$$

product state

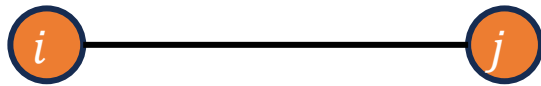
# Parallels between MC and QMC: unified analysis

## Max Cut

Input:  $|Z_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle Z_i | r \rangle) \in \{\pm 1\}$

$$\text{fval} = (1 - \langle Z_i | Z_j \rangle) / 2$$



$$\text{val} = (1 - u_i u_j) / 2$$

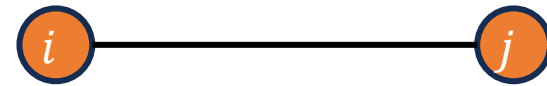
$$\mathbb{E}_r[u_i u_j] = \mathbb{E} \left[ \frac{\langle Z_i | r \rangle}{|\langle Z_i | r \rangle|} \cdot \frac{\langle Z_j | r \rangle}{|\langle Z_j | r \rangle|} \right]$$

## Quantum Max Cut ( $\mathcal{L}_1$ )

Input:  $|W_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r_x\rangle, |r_y\rangle, |r_z\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle W_i | r_x \rangle, \langle W_i | r_y \rangle, \langle W_i | r_z \rangle)$

$$\text{fval} = (1 - 3\langle W_i | W_j \rangle) / 4$$



$$\text{val} = (1 - \langle u_i, u_j \rangle) / 4$$

$$\mathbb{E}_{R=(r_x, r_y, r_z)}[\langle u_i, u_j \rangle] = \mathbb{E} \left[ \left\langle \frac{R | W_i \rangle}{\|R | W_i \rangle\|}, \frac{R | W_j \rangle}{\|R | W_j \rangle\|} \right\rangle \right]$$

# Parallels between MC and QMC: unified analysis

## Max Cut

Input:  $|Z_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle Z_i | r \rangle) \in \{\pm 1\}$

## Quantum Max Cut ( $\mathcal{L}_1$ )

Input:  $|W_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r_x\rangle, |r_y\rangle, |r_z\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle W_i | r_x \rangle, \langle W_i | r_y \rangle, \langle W_i | r_z \rangle)$

**Lemma (Briët et al. '14).** Let  $u, v$  be unit vectors in  $\mathbb{R}^d$  and let  $R \in \mathbb{R}^{k \times d}$  be a random matrix whose entries are *i.i.d.* Gaussian  $\mathcal{N}(0, 1)$ . Then,

$$\mathbb{E} \left[ \left\langle \frac{Ru}{\|Ru\|}, \frac{Rv}{\|Rv\|} \right\rangle \right] = F(k, \langle u, v \rangle)$$

Some hypergeometric function (explicitly computable)

# Parallels between MC and QMC: unified analysis

## Max Cut

Input:  $|Z_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle Z_i | r \rangle) \in \{\pm 1\}$

$$\text{fval} = (1 - \langle Z_i | Z_j \rangle) / 2$$



$$\mathbb{E}_r[\text{val}] = \frac{1 - F(1, \langle Z_i | Z_j \rangle)}{2}$$

## Quantum Max Cut ( $\mathcal{L}_1$ )

Input:  $|W_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r_x\rangle, |r_y\rangle, |r_z\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle W_i | r_x \rangle, \langle W_i | r_y \rangle, \langle W_i | r_z \rangle)$

$$\text{fval} = (1 - 3\langle W_i | W_j \rangle) / 4$$



$$\mathbb{E}_{r_x, r_y, r_z}[\text{val}] = \frac{1 - F(3, \langle W_i | W_j \rangle)}{4}$$

# Parallels between MC and QMC: unified analysis

## Max Cut

Input:  $|Z_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle Z_i | r \rangle) \in \{\pm 1\}$

$$\text{fval} = (1 - \langle Z_i | Z_j \rangle) / 2$$



$$\alpha = \frac{\mathbb{E}_r[\text{val}]}{\text{fval}} \geq \min_{t \in [-1, 1]} \frac{1 - F(1, t)}{1 - t}$$

$$\approx 0.878$$

## Quantum Max Cut ( $\mathcal{L}_1$ )

Input:  $|W_i\rangle \in \mathbb{R}^d$  for each  $i \in V$

1. Sample  $|r_x\rangle, |r_y\rangle, |r_z\rangle \sim \mathcal{N}(0, I)$
2. Output  $u_i := \text{Unit}(\langle W_i | r_x \rangle, \langle W_i | r_y \rangle, \langle W_i | r_z \rangle)$

$$\text{fval} = (1 - 3\langle W_i | W_j \rangle) / 4$$



$$\alpha = \frac{\mathbb{E}_{r_x, r_y, r_z}[\text{val}]}{\text{fval}} \geq \min_{t \in [-1, 1/3]} \frac{1 - F(3, t)}{1 - 3t}$$

$$\approx 0.498$$



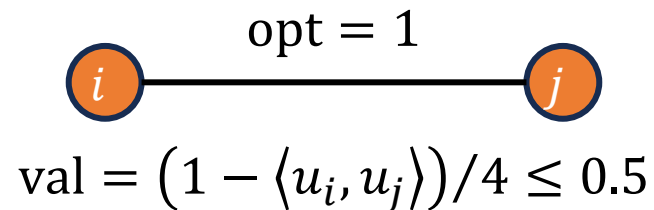
# Can we do better?

Classical max cut: No.

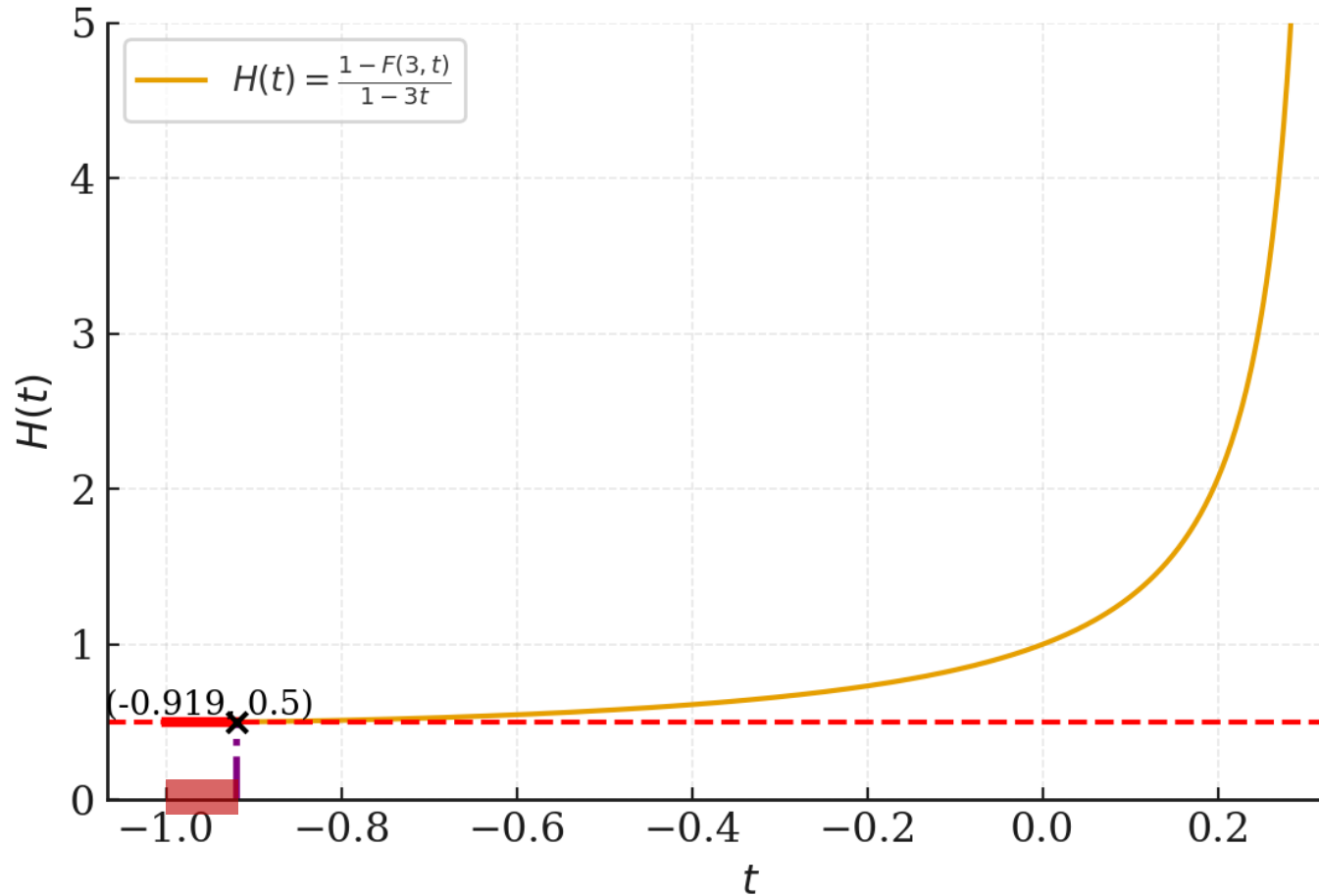
- **Khot-Kindler-Mossel-O'Donnell '07**: Assuming *Unique Game Conjecture*, it is **NP**-hard to achieve  $(0.878+\epsilon)$ -approximation for MC
- **Raghavendra '08, Raghavendra-Steurer '09**: Degree-2 SoS (level 1 SDP) is the best approximation algorithm for all constraints satisfaction problems (CSPs), assuming UGC

Quantum max cut: possible!

- If only using product state, the approximation ratio upper bound is  $0.5 > 0.498$



# Towards better approximation

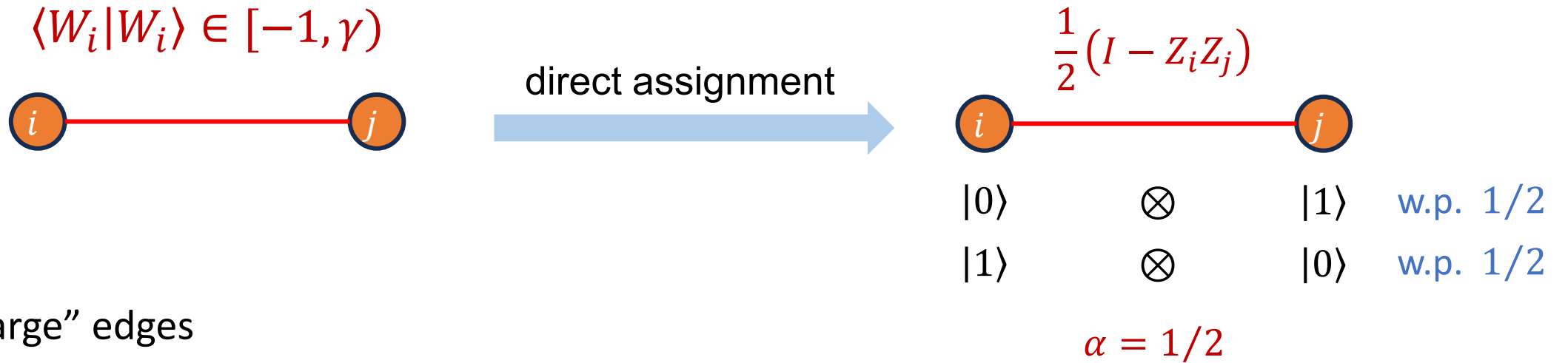


$\gamma := -0.919 \dots$  is a critical point

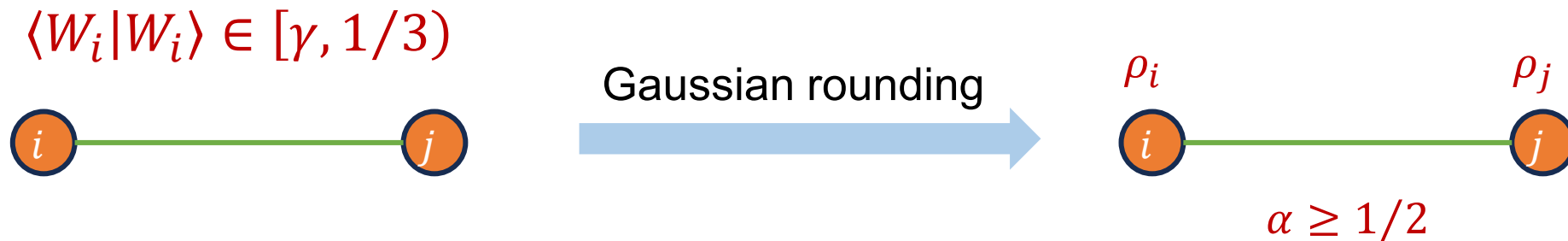
Edges with  $\langle W_i | W_i \rangle > \gamma$  have  
approximation ratio  $\geq \frac{1}{2}$

# Partial rounding

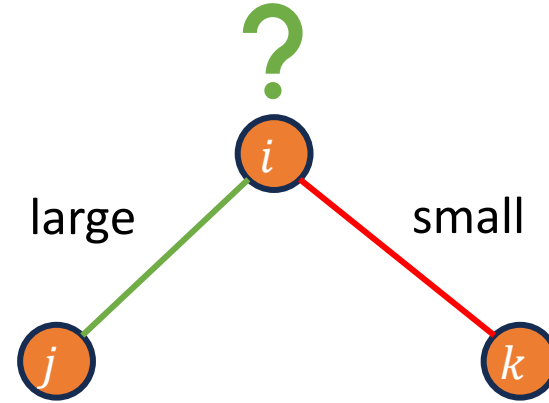
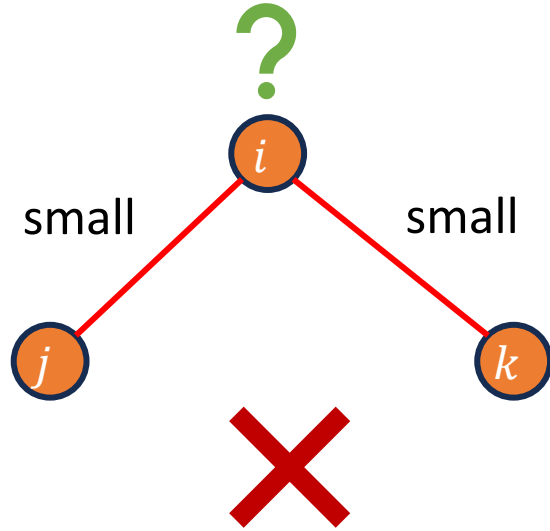
## Case 1: “small” edges



## Case 2: “large” edges

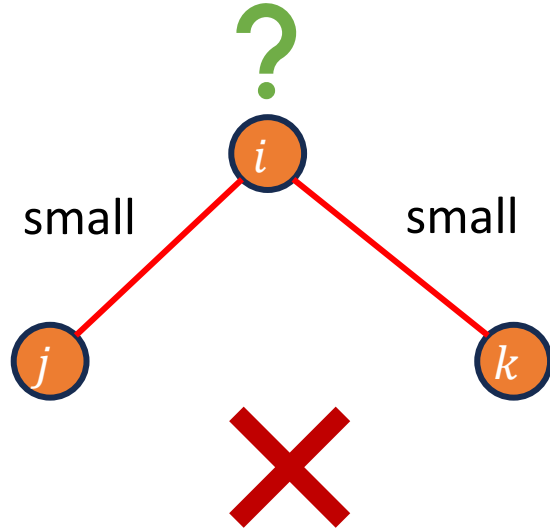


# Conflict vertices

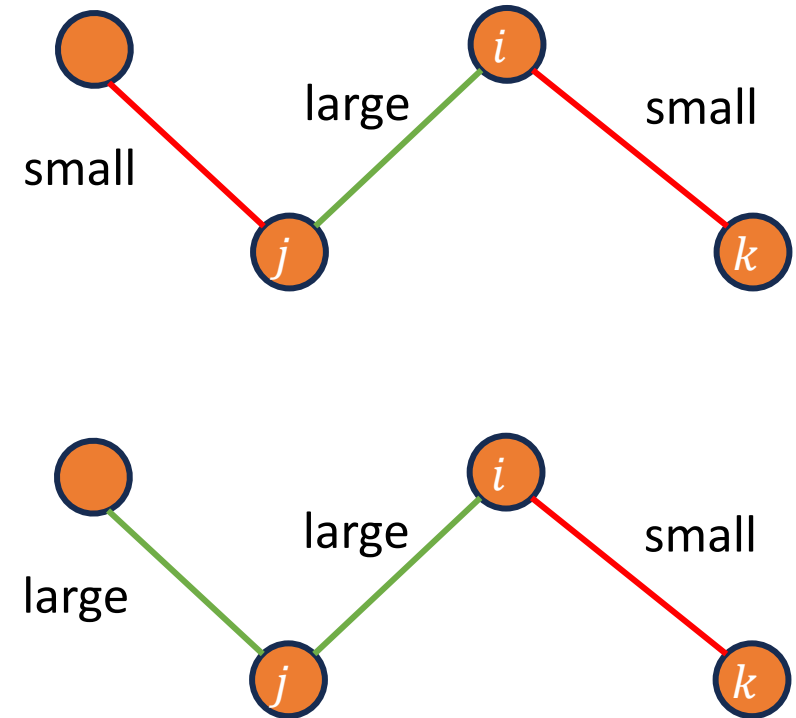


**Fact.** The small edges form a **matching** in the graph

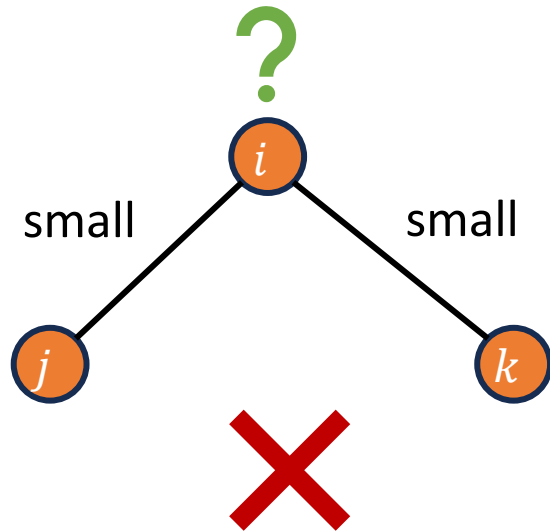
# Conflict vertices



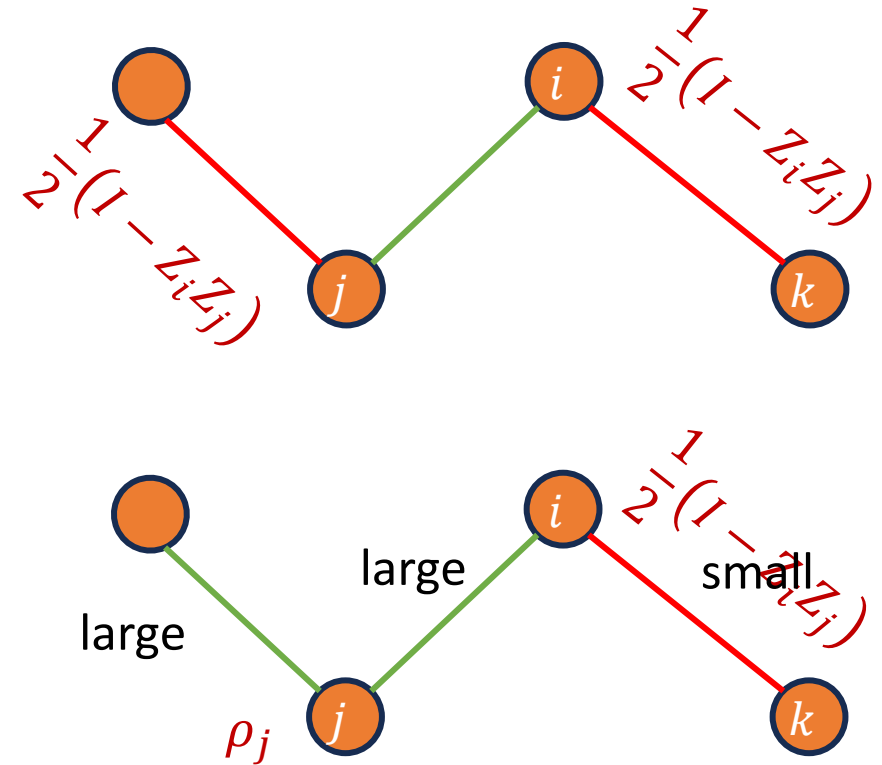
**Fact.** The small edges form a **matching** in the graph



# Conflict vertices

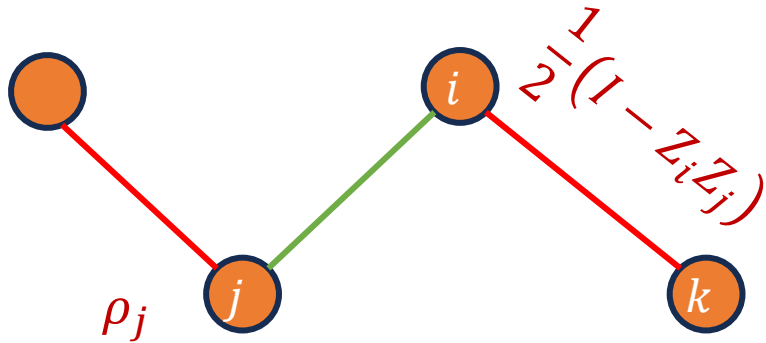
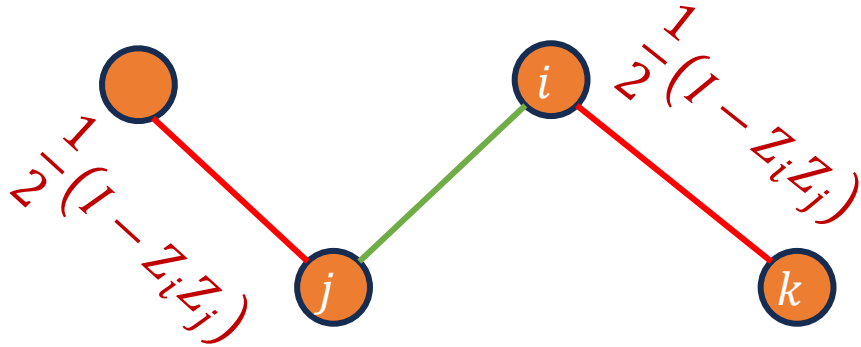


**Fact.** The small edges form a **matching** in the graph



We round a vertex only it does **not adjacent** to any small edge

# Conflict vertices



We round a large edge only if it **does not intersect** with any small edge

- Two qubits  $i$  and  $j$  are not entangled
- $\rho_i = I$  (i.e.  $|0\rangle$  w.p. 0.5 and  $|1\rangle$  w.p. 0.5)
- Then, no matter what  $\rho_j$  is,

$$\text{val} = \text{tr}[h_{ij}\rho_i \otimes \rho_j] = 1/4$$

We need to show that the SDP value  $\text{fval} < 1/2$  for this edge:

**Lemma.** If an edge  $ik$  has  $\langle W_i | W_k \rangle < \gamma$ , then any adjacent edge  $ij$  has  $\langle W_i | W_j \rangle > -1/3$

- $\text{fval} = (1 - 3\langle W_i | W_j \rangle)/4 < 1/2$
- The small edges form a matching

# Full algorithm

1. Solve the level 2 quantum Lasserre hierarchy  $\mathcal{L}_2$  for  $H$
2. Let  $S$  be the set of small edges
3. Let  $B := \{i \in V : \forall j, ij \notin S\}$
4. Gaussian rounding for  $i \in B$ , and let  $\rho_i$  be the resulting state
5. Output the state

$$\rho = \bigotimes_{ij \in L} \left( \frac{I - Z_i Z_j}{4} \right) \bigotimes_{k \in B} \rho_k \quad \text{(mixed) product state}$$

**Theorem** (Parekh-Thompson '22).

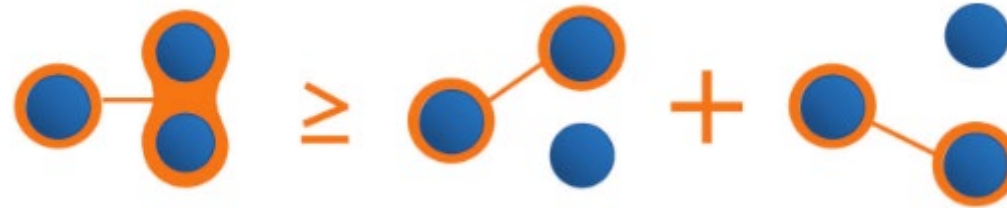
There exists an efficient classical algorithm that approximates QMC using **product states** and achieves the **optimal  $1/2$** -approximation ratio



# Proof of the key lemma

**Lemma.** If an edge  $ij$  has  $\langle W_i | W_j \rangle < \gamma$ , then any adjacent edge  $ik$  has  $\langle W_i | W_k \rangle > -1/3$

- Physical intuition: **Monogamy of entanglement**



# Proof of the key lemma

**Lemma.** If an edge  $ij$  has  $\langle W_i | W_j \rangle < \gamma$ , then any adjacent edge  $ik$  has  $\langle W_i | W_k \rangle > -1/3$

**Definition 17** (Quantum Lasserre hierarchy). We are given as input  $H = \sum_{\phi \in \mathcal{P}_n(2k)} c(\phi) \phi$ , with  $H \in \mathcal{H}_n$ . Level  $k$  of the Quantum Lasserre hierarchy, denoted  $\mathcal{L}_k$ , is defined by the following vector program:

$$v_k(H) := \max \sum_{\phi \in \mathcal{P}_n(2k)} c(\phi) \langle \phi \rangle$$

$$\text{s.t.} \quad \langle \tau | \tau \rangle = 1 \quad \forall \tau \in \mathcal{P}_n(k) \quad (19)$$

$$\langle \tau | \sigma \rangle = \langle \tau \sigma \rangle \quad \forall \tau, \sigma \in \mathcal{P}_n(k) \quad (20)$$

$$|\tau\rangle \in \mathbb{C}^d \quad \forall \tau \in \mathcal{P}_n(k),$$

for any integer  $d \geq |\mathcal{P}_n(k)|$ .

- Unitary **SWAP** operator:  $S_{ij} = (I + X_i X_j + Y_i Y_j + Z_i Z_j)/2$
- $\langle W_i | W_j \rangle = (\langle X_i X_j \rangle + \langle Y_i Y_j \rangle + \langle Z_i Z_j \rangle)/3 = (2\langle S_{ij} \rangle - 1)/3$

# Proof of the key lemma

**Lemma.** If an edge  $ij$  has  $\langle W_i | W_j \rangle < \gamma$ , then any adjacent edge  $ik$  has  $\langle W_i | W_k \rangle > -1/3$

- Unitary **SWAP** operator:  $S_{ij} = (I + X_i X_j + Y_i Y_j + Z_i Z_j)/2$
- $\langle W_i | W_j \rangle = (\langle X_i X_j \rangle + \langle Y_i Y_j \rangle + \langle Z_i Z_j \rangle)/3 = (2\langle S_{ij} \rangle - 1)/3$
- $\langle W_i | W_j \rangle < \gamma$  is equivalent to  $\langle S_{ij} \rangle < (3\gamma + 1)/2$
- $\langle W_i | W_k \rangle > -1/3$  is equivalent to  $\langle S_{ik} \rangle > 0$

If  $\langle S_{ij} \rangle < (3\gamma + 1)/2$ , then any adjacent edge  $ik$  has  $\langle S_{ik} \rangle > 0$

# Proof of the key lemma

Consider the **Gram matrix** of  $|I\rangle, |S_{12}\rangle, |S_{13}\rangle, |S_{23}\rangle$ :

$$\tilde{M}(P, Q) := \langle P|Q \rangle \quad \forall P, Q \in \{I, S_{12}, S_{13}, S_{23}\}$$

- By the **PSD** constraint in  $\mathcal{L}_2$ ,  $\tilde{M} \succcurlyeq 0$
- Define  $M := (\tilde{M} + \tilde{M}^\top)/2 \in \mathbb{R}^{4 \times 4}$ ,  $M \succcurlyeq 0$
- $M(P, P) = (\langle P^2 \rangle + \langle P^2 \rangle)/2 = \langle I \rangle = 1$
- $M(S_{ij}, I) = \langle S_{ij} \rangle$
- $M(S_{ij}, S_{ik}) = (\langle S_{ij} \rangle + \langle S_{ik} \rangle + \langle S_{jk} \rangle - \langle I \rangle)/2$

degree-4

$$M = \begin{pmatrix} 1 & p & q & r \\ p & 1 & \frac{s-1}{2} & \frac{s-1}{2} \\ q & \frac{s-1}{2} & 1 & \frac{s-1}{2} \\ r & \frac{s-1}{2} & \frac{s-1}{2} & 1 \end{pmatrix}$$

$$p = \langle S_{12} \rangle, q = \langle S_{13} \rangle, r = \langle S_{23} \rangle, \\ s = p + q + r$$

Identity for SWAP operator:

$$S_{ij}S_{ik} + S_{ik}S_{ij} = (S_{ij} + S_{ik} + S_{jk} - I)/2$$

# Proof of the key lemma

**Claim 1.**  $M \succcurlyeq 0$  is equivalent to:

$$\begin{aligned} 0 &\leq p + q + r \leq 3 \\ p^2 + q^2 + r^2 + 2(p + q + r) - 2(pq + pr + qr) &\leq 3 \end{aligned}$$

## Schur complement:

For any symmetric matrix  $M$  of the form

$$M = \begin{pmatrix} 1 & b^\top \\ b & C \end{pmatrix}$$

$M \succcurlyeq 0$  if and only if:

1.  $C \succcurlyeq 0$
2.  $(I - CC^+)b = 0$
3.  $1 - b^\top C^+ b \geq 0$

$$M = \begin{pmatrix} 1 & p & q & r \\ p & \boxed{1} & \boxed{\frac{s-1}{2}} & \boxed{\frac{s-1}{2}} \\ q & \boxed{\frac{s-1}{2}} & \boxed{1} & \boxed{\frac{s-1}{2}} \\ r & \boxed{\frac{s-1}{2}} & \boxed{\frac{s-1}{2}} & \boxed{1} \end{pmatrix}$$

# Proof of the key lemma

**Lemma.** If  $\langle S_{ij} \rangle < (3\gamma + 1)/2$ , then any adjacent edge  $ik$  has  $\langle S_{ik} \rangle > 0$

*Proof.*

- Solving the inequalities:

$$\begin{aligned} 0 &\leq p + q + r \leq 3 \\ p^2 + q^2 + r^2 + 2(p + q + r) - 2(pq + pr + qr) &\leq 3 \end{aligned}$$

- We get that if  $p \leq -\sqrt{3}/2$ , then  $q \geq 0$  (equality attained with  $p = -\sqrt{3}/2, q = 0, r = \sqrt{3}/2$ )
- Since  $(3\gamma + 1)/2 < -0.878 < -\frac{\sqrt{3}}{2} \approx -0.866$ , we are done



# Approximation algorithms for quantum max cut

Reference	Ratio	Remark
[GP19]	0.498	General graphs, outputs product state
[PT22]	1/2	General graphs, outputs product state
[HTPG24]	0.526	General graphs, uses SOC instead of SDP
[AGM20]	0.531	General graphs
[PT21]	0.533	General graphs
[Lee22]	0.562	General graphs
[LP24]	0.595	General graphs
[JKK <sup>+</sup> 24]	0.599	General graphs, improved analysis of [LP24]
Thm. 3.11	0.603	General graphs, improved analysis of [LP24]
[Kin23]	0.582	Triangle-free graphs
Thm. 4.5	0.61383	Triangle-free graphs
[Kin23]	$\frac{1}{\sqrt{2}} \approx 0.707$	Bipartite graphs
Thm. 5.6	0.8162	Bipartite graphs

(Gribling-Sinjorgo-Sotirov '25)