

# Quantum walks for constraint combinatorial optimisation

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# Combinatorial optimisation

(Backpack Problem, Drug Discovery, Traffic Design, Investment Portfolio,  
Graph Partition, Subset Sum, Lattice Paths, Travelling Salesman Problem, etc)

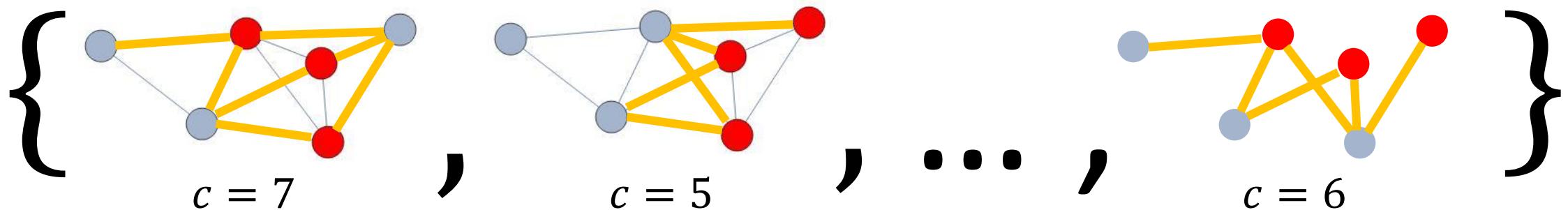
40/100 items  $\rightarrow 10^{28}$

5 pairs  $\rightarrow 10^{100}$

50 atoms  $\rightarrow 10^{48}$

500 stocks  $\rightarrow 10^{150}$

## Graph Partition



$\min c(x)$  over all possible solutions  $x$  : 500 nodes  $\rightarrow 10^{150} \xrightarrow{\log} 345$  qubits

# Quantum Annealing

- Quantum adiabatic theorem

$$i \frac{d}{dt} |\psi(t)\rangle = \hat{H}(t) |\psi(t)\rangle$$

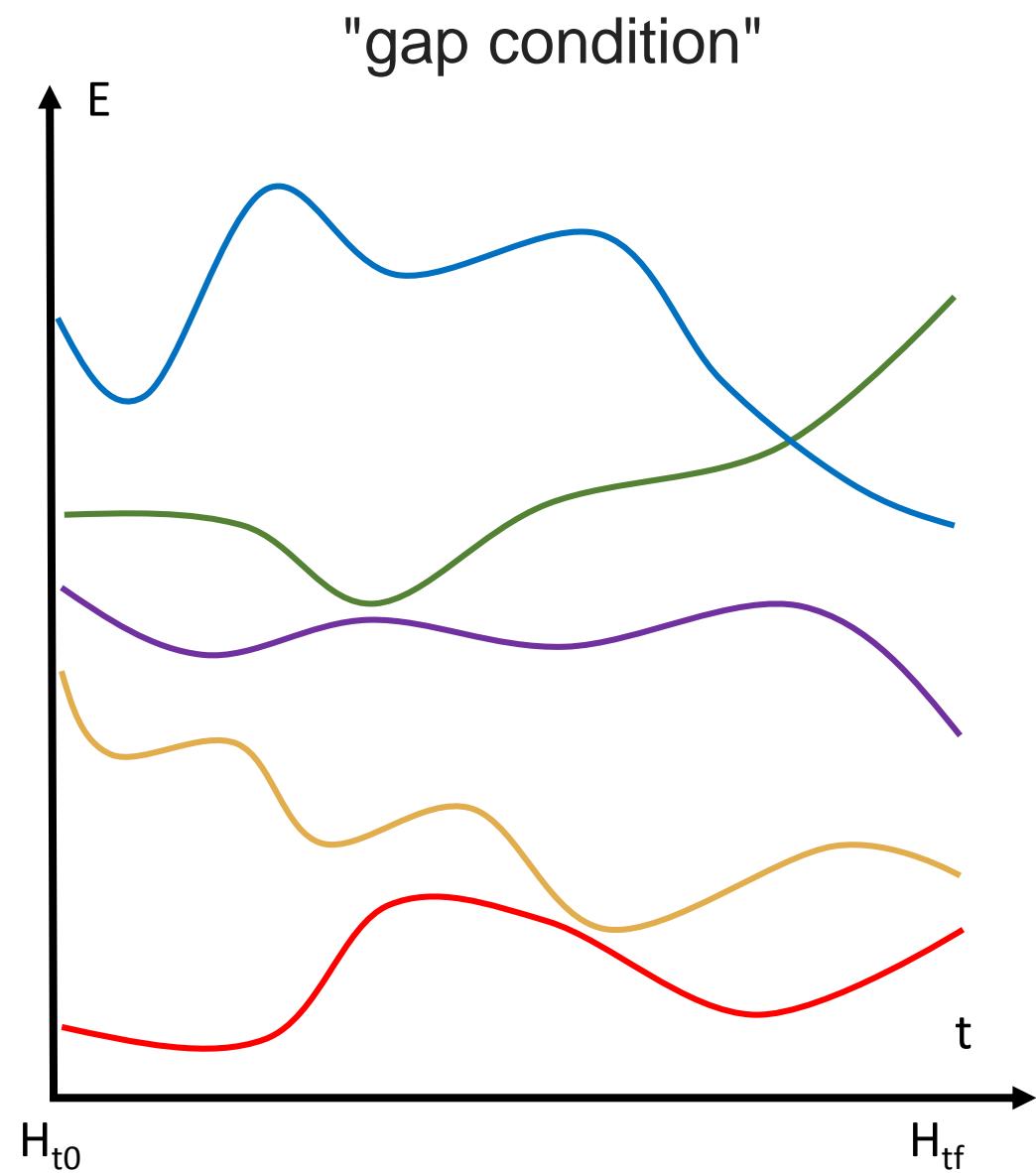
$|s\rangle$ : min/max energy state of  $\hat{H}(t_0) = \hat{B}$  :  
(known eigenvalues & eigenstates)

↓ adiabatic

$$\boxed{\hat{H}(t) = \left(1 - \frac{t}{T}\right) \hat{B} + \frac{t}{T} \hat{Q}}$$
$$t = [0, T]$$

$|\psi\rangle$ : min/max energy state of  $\hat{H}(t_f) = \hat{Q}$  :  
(encodes combinatorial optimisation solution)

Quantum Adiabatic Evolution Algorithm, Farhi et al 2001

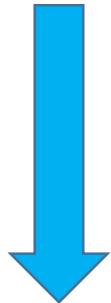


# Quantum Annealing

- Quantum adiabatic theorem

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adiabatic

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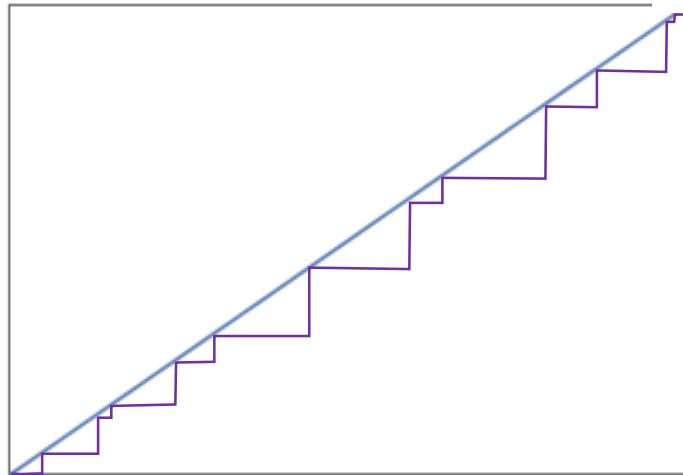
$|\psi\rangle$ : min/max energy state of  $\hat{H}(t_f) = \hat{Q}$  :  
(encodes combinatorial optimisation solution)

Quantum Adiabatic Evolution Algorithm, Farhi et al 2001

Quantum Approximate Optimisation Algorithm, Farhi et al 2016

Quantum-walk-assisted optimisation algorithm, Marsh & Wang 2019

# QAOA



$$\hat{H}_\alpha = \left(1 - \frac{\alpha}{p}\right) \hat{B} + \frac{\alpha}{p} \hat{Q}$$
$$\alpha = 0, 1, \dots (p-1)$$

$$\hat{U}_\alpha = e^{-i \Delta t \hat{H}_\alpha}$$
$$\approx e^{-i \beta \hat{B}} e^{-i \gamma \hat{Q}}$$
$$\hat{U}_B(\beta) \quad \hat{U}_Q(\gamma)$$

$$|\vec{\beta}, \vec{\gamma}\rangle \approx \hat{U}_p$$
$$= \hat{U}_B(\beta_p) \hat{U}_Q(\gamma_p) \dots \hat{U}_B(\beta_1) \hat{U}_Q(\gamma_1) |s\rangle$$

The **state evolution** using  $p$  timesteps

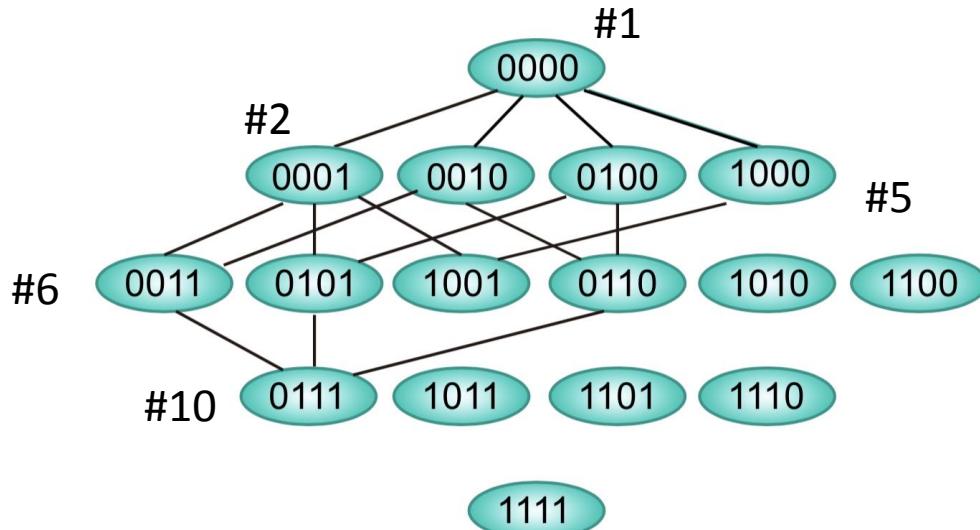
Vary  $\{\vec{\beta}, \vec{\gamma}\}$  to minimise  $\langle \vec{\beta}, \vec{\gamma} | \hat{Q} | \vec{\beta}, \vec{\gamma} \rangle$

# QWOA

$$|\vec{t}, \vec{\gamma}\rangle = \hat{U}_W(t_p) \hat{U}_Q(\gamma_p) \dots \hat{U}_W(t_1) \hat{U}_Q(\gamma_1) |s\rangle$$

**QWOA**

$$|\vec{t}, \vec{\gamma}\rangle = \hat{U}_W(t_p) \hat{U}_Q(\gamma_p) \dots \hat{U}_w(t_1) \hat{U}_Q(\gamma_1) |s\rangle$$

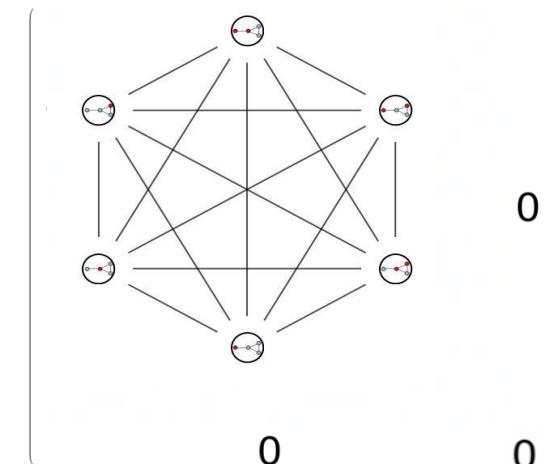


$$U_v |\#(x)\rangle |z\rangle = |\#(x)\rangle |z \oplus x\rangle$$

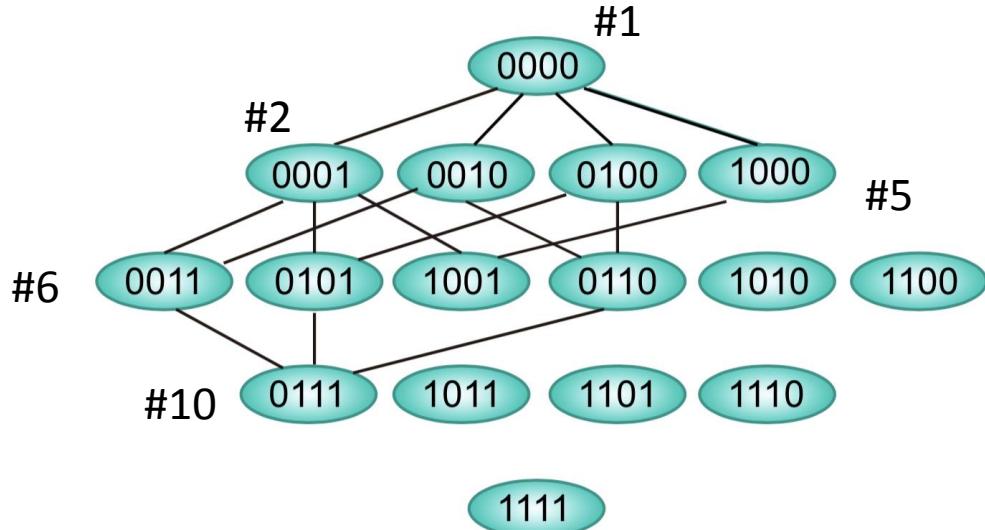
$$U_u |x\rangle |z\rangle = |x\rangle |z \oplus \#(x)\rangle$$

without sequence algorithm

with sequence algorithm



**QWOA**  $|\vec{t}, \vec{\gamma}\rangle = \hat{U}_W(t_p) \hat{U}_Q(\gamma_p) \dots \hat{U}_w(t_1) \hat{U}_Q(\gamma_1) |s\rangle$

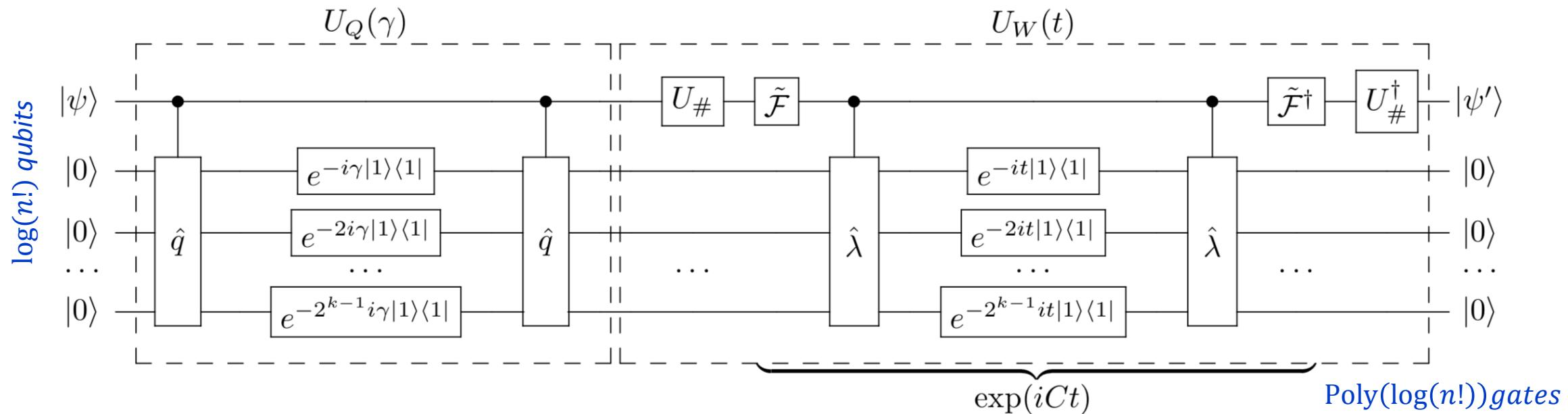


$$\begin{array}{c} |x\rangle \\ |0\rangle \end{array} \xrightarrow{\quad U_u \quad} \xrightarrow{\quad *} \xrightarrow{\quad U_v \quad} \begin{array}{c} |\#(x)\rangle \\ |0\rangle \end{array}$$

$$U_v |\#(x)\rangle |z\rangle = |\#(x)\rangle |z \oplus x\rangle$$

$$U_u |x\rangle |z\rangle = |x\rangle |z \oplus \#(x)\rangle$$

- **Highly efficient Circuit**



$$|\vec{t}, \vec{\gamma}\rangle = \hat{U}_W(t_p) \hat{U}_Q(\gamma_p) \dots \hat{U}_W(t_1) \hat{U}_Q(\gamma_1) |s\rangle$$

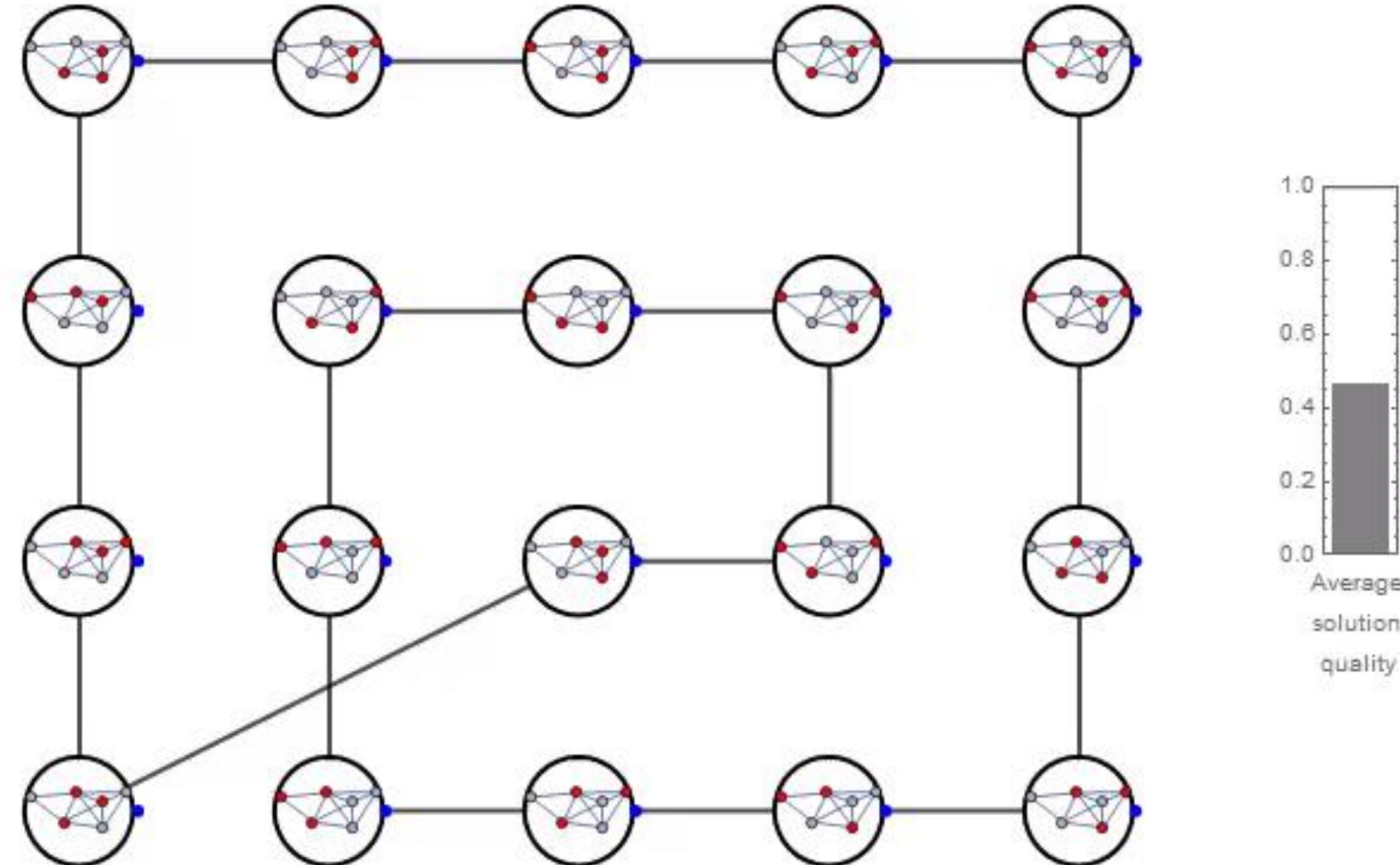
Q(0.)

## QWAO procedure

1. Start with equal superposition
2. Repeat:
  - *change phase*
  - *quantum walk*
3. Measure

500 nodes  $\rightarrow 10^{150}$

$\log$   $\rightarrow 345$  qubits

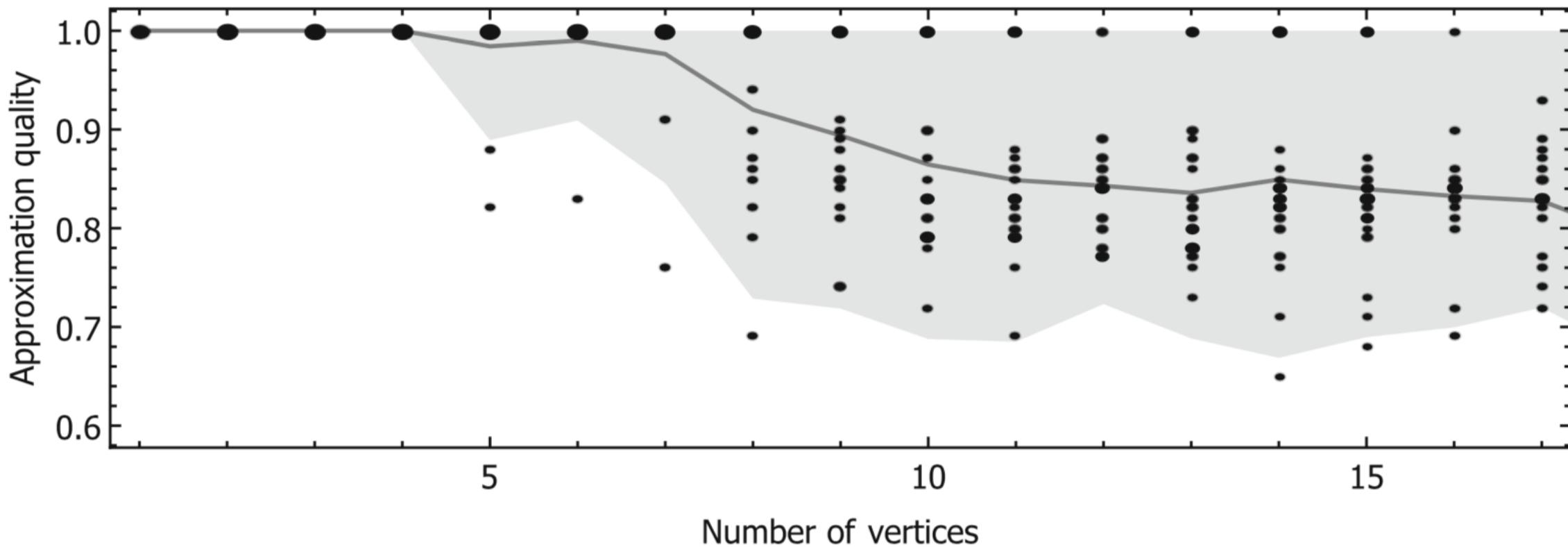


# Conclusion

- *Highly efficient* quantum walk over exponentially large set of combinatorial objects with *adaptable connectivity*;
- Substantially reduced search space using *sequence function*;
- Quantum circuit design independent of *variational parameters*;
- Applications over a wide range of NP-hard problems.

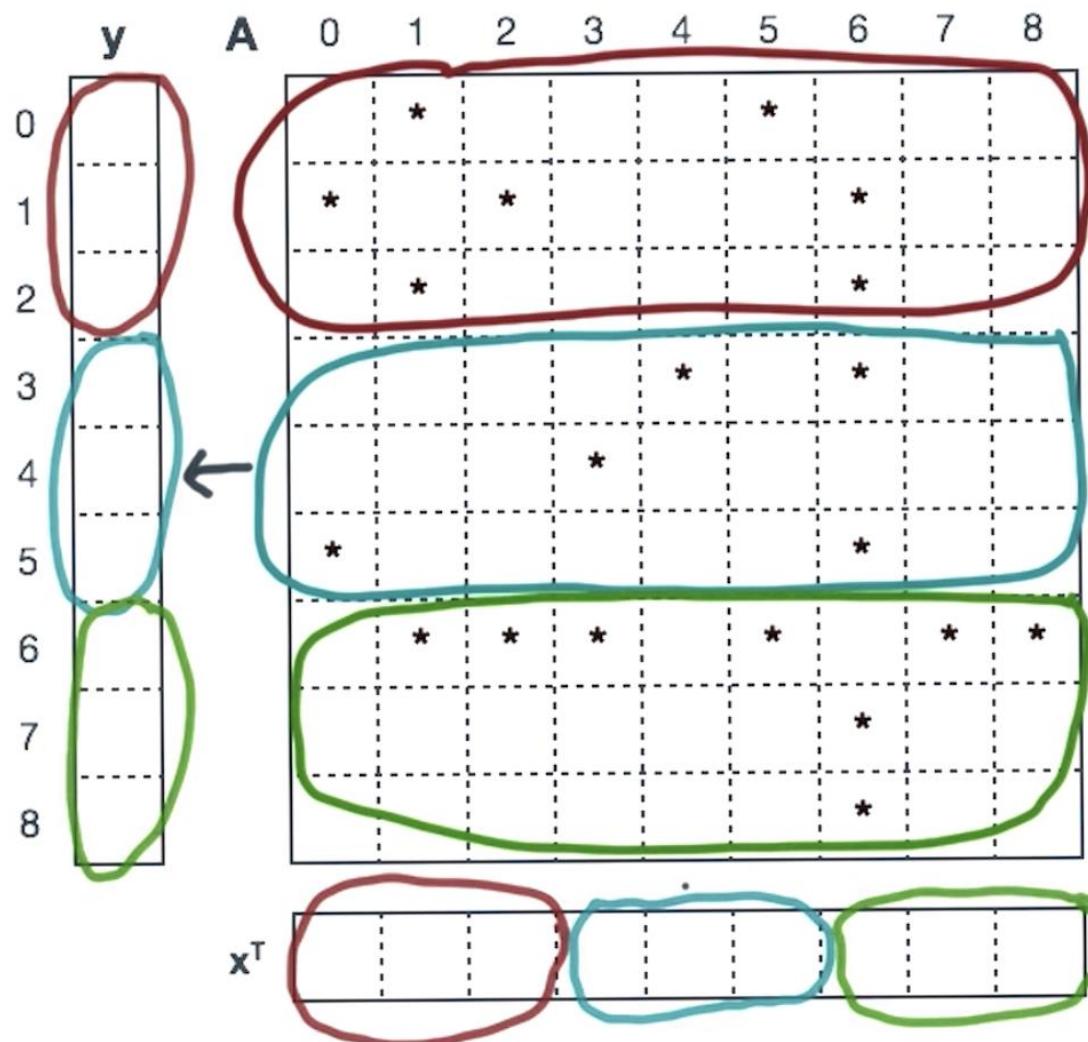


# Preliminary results



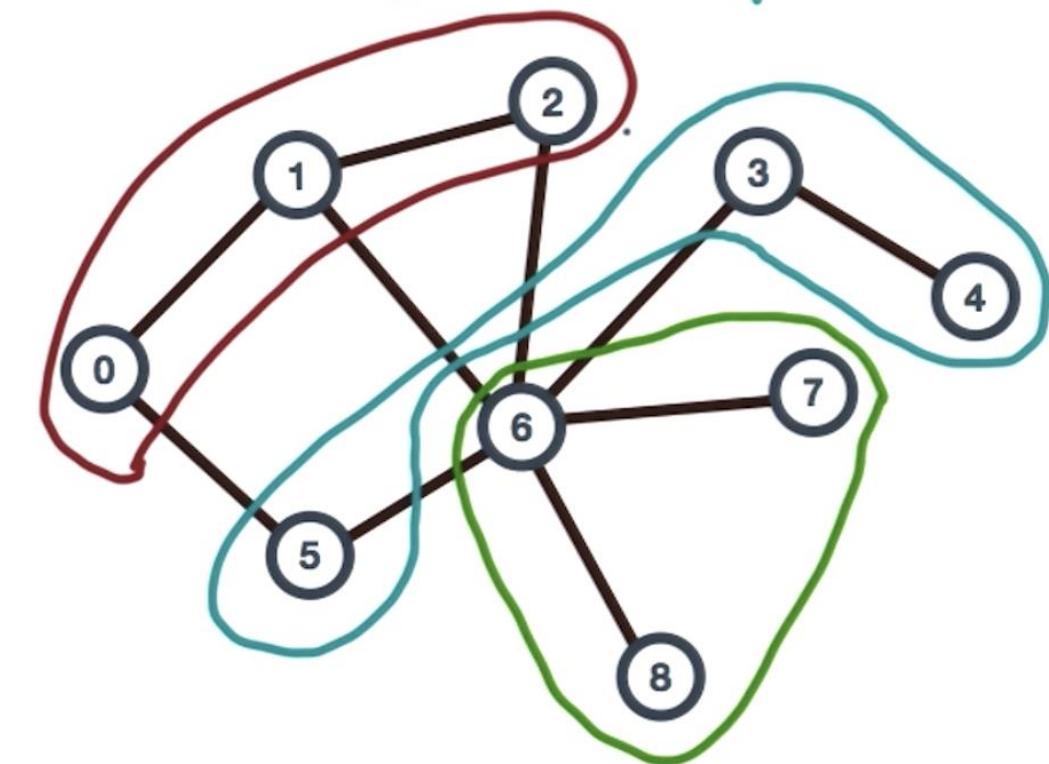
# eg: distributed computing

## The Graph Partitioning Problem



$$y \leftarrow A \cdot x$$

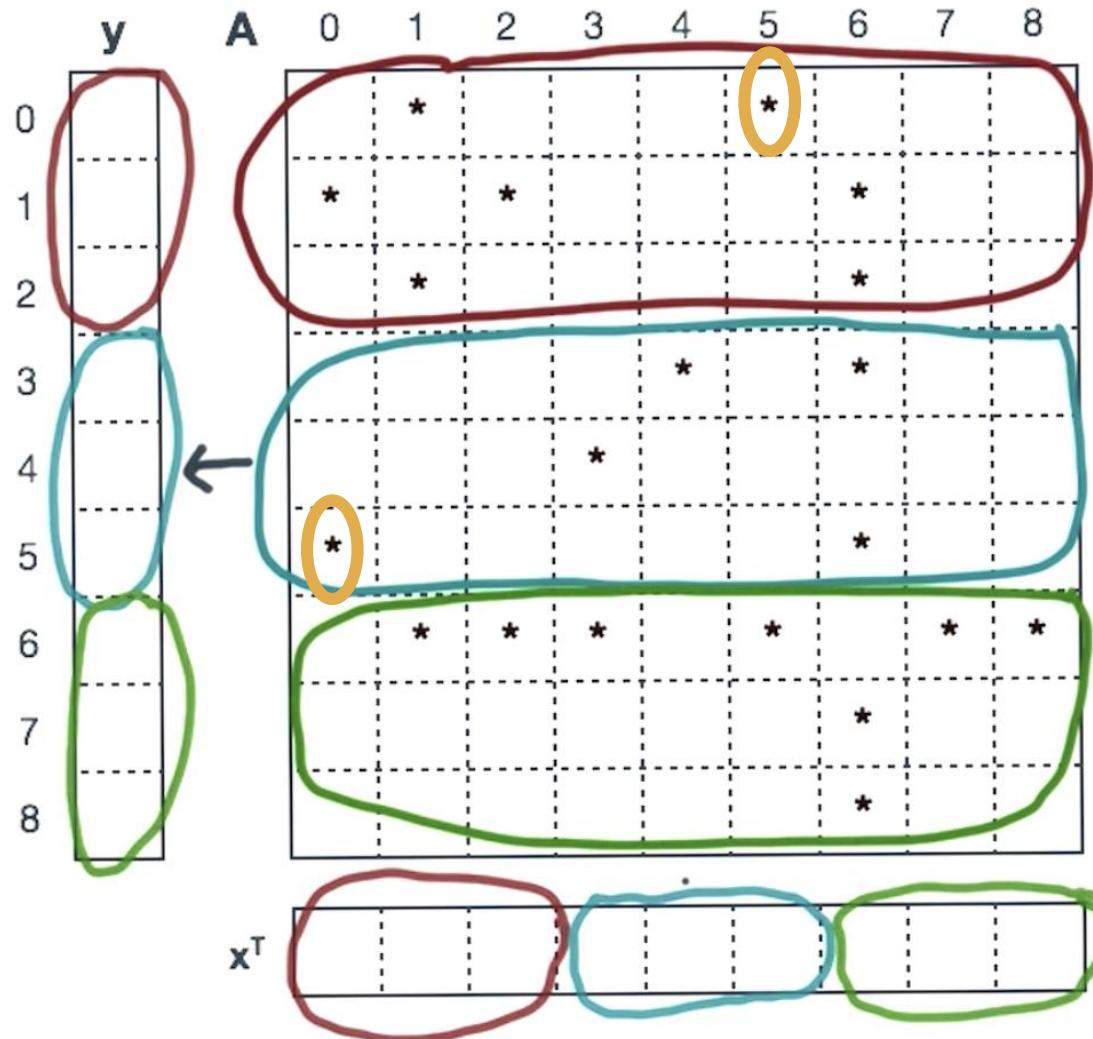
Graph (vertex) partition



Goal 1: Balance work! ( $\frac{\text{nnz}}{\text{proc}}$  equal)

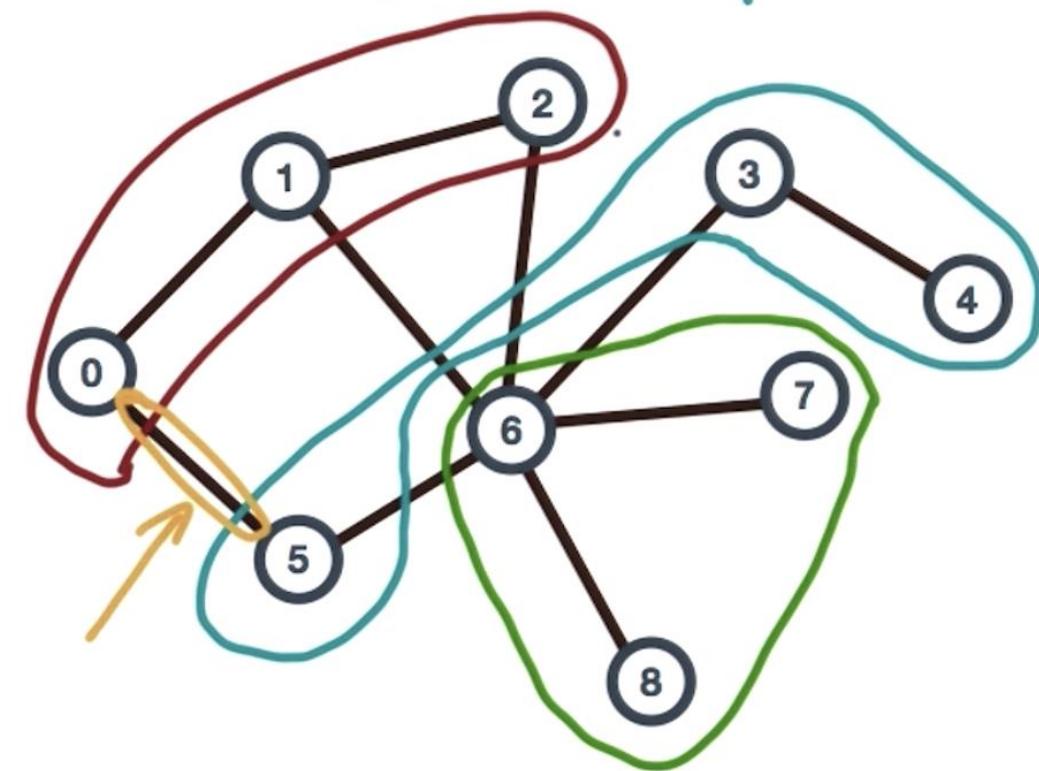
# eg: distributed computing

## The Graph Partitioning Problem



$$y \leftarrow A \cdot x$$

Graph (vertex) partition



Goal 2: Minimize edge cuts!