



# Hybrid Quantum and Classic Computing to Solve Optimization and Machine Learning Problems for Future Networking

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Thanks to Prof. Lei Fan, Wenlu Xuan, Zhongqi Zhao, Mingze Li, and NSF



# Outline

- Motivation and Quantum Computing Basics
- Quantum Annealing
  - Adiabatic Quantum Computing
  - Quadratic Unconstrained Binary Optimization (QUBO)
- Hybrid Quantum Benders' Decomposition
  - Benders Decomposition Basics
  - Quantum and Classical Computing Bender Decomposition
- Applications
  - Federated Learning in Mobile Edge Computing
  - Feature Selection for Machine Learning
  - Cable-Routing Problem in Solar Power Plants
- Conclusions

# Quantum Computing

Started in the 1980s

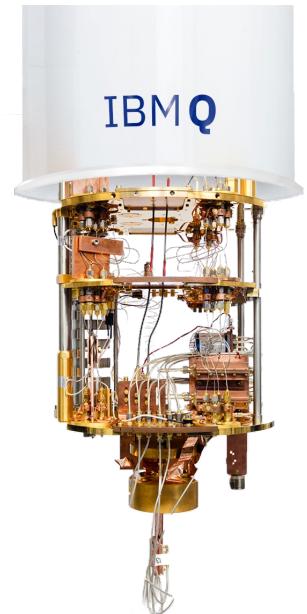


*Maybe we need to use quantum mechanics in our computers.*



Many years later ...

Quantum Computer

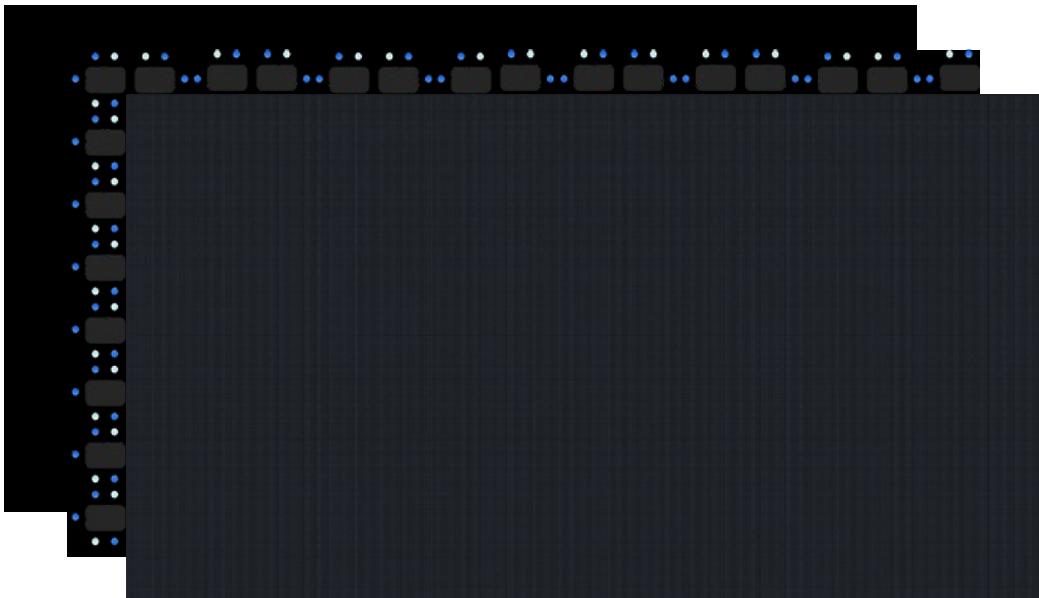


...

Feynman

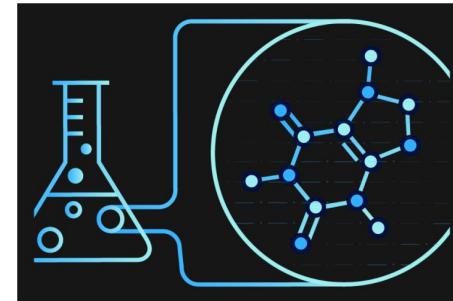
# Quantum Computing

What is wrong in classic computing?

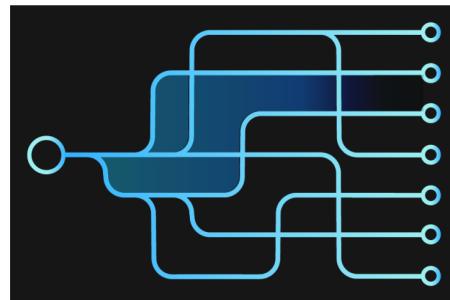


Total number of combinations  
exponentially grows

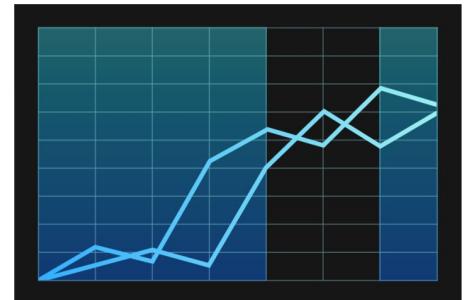
Many Practical NP hard Problems



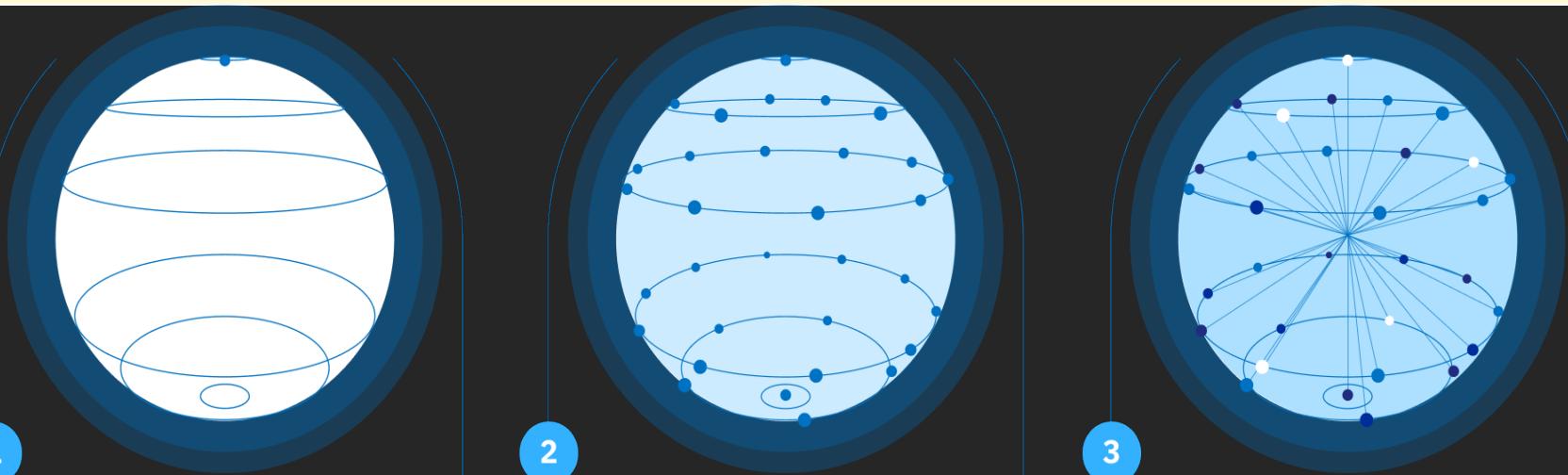
Life science



Manufacturing  
& Logistics



Financial Services



1

Activate the spread

2

Encode the problem

3

Unleash the power

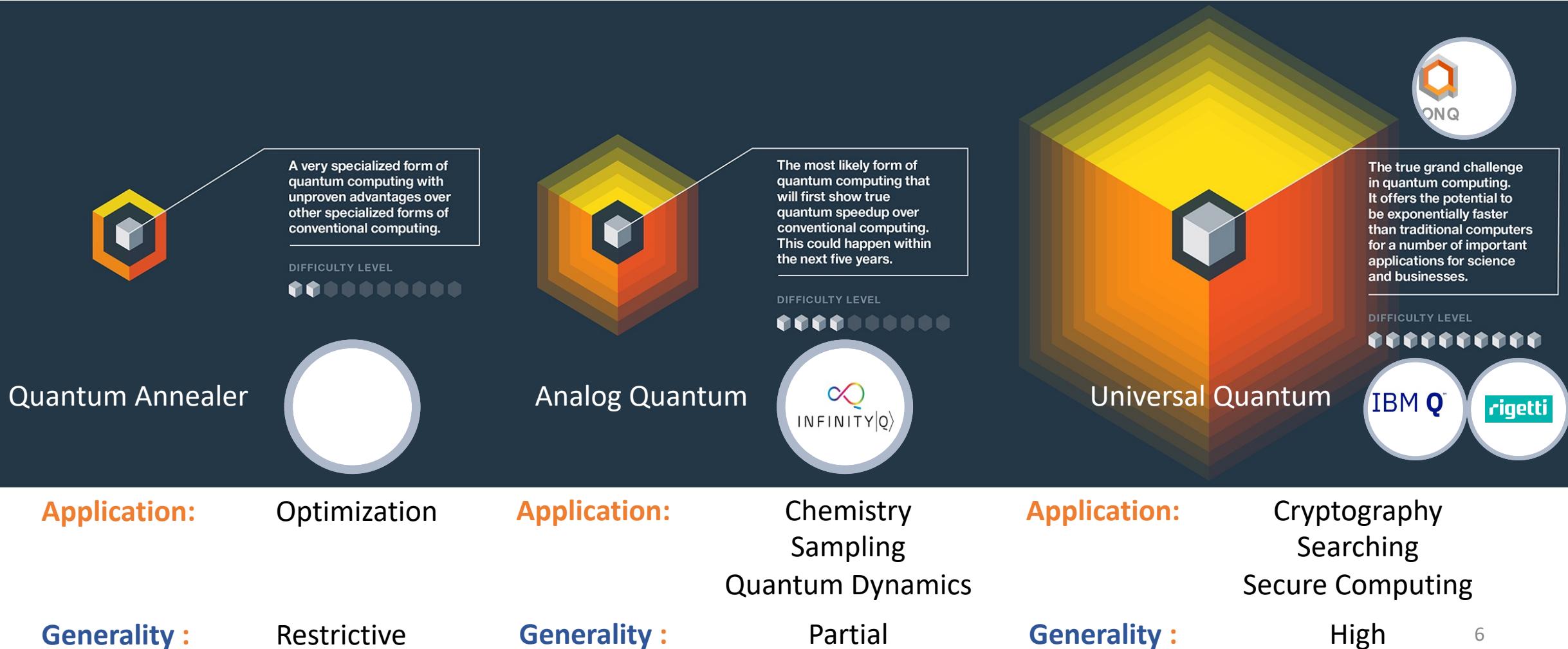
Quantum computers  
Can

create vast multidimensional spaces  
to deal with large problems,

and translate them back into  
what we can use,

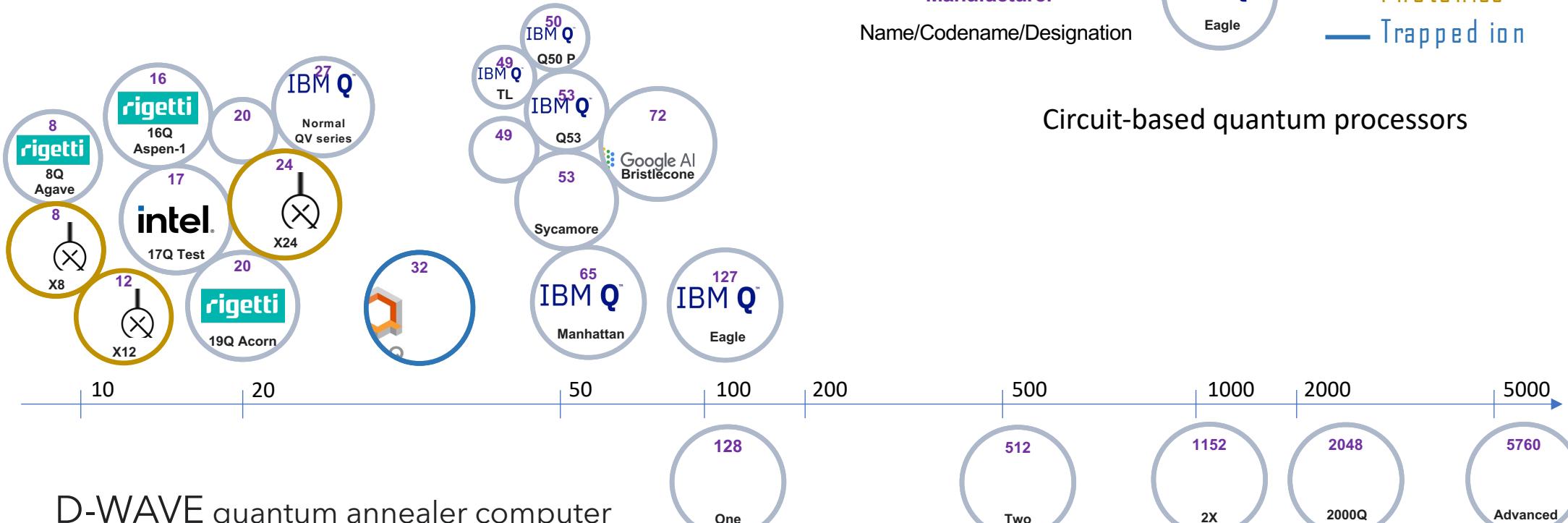
while  
classical computers  
may have  
**difficulties**  
to do the same.

## Known Types of Quantum Computing and Their Applications and Generality.



# Quantum Processors

## Rank of quantum processors



D-WAVE quantum annealer computer fits our problem setting the most.

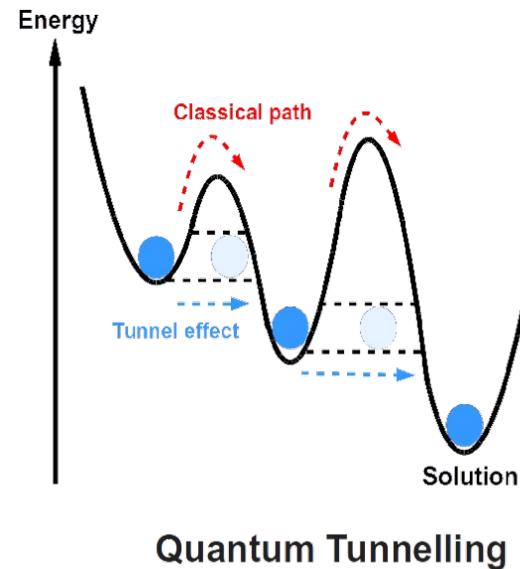
Annealing quantum processors

# Quantum Computing

## Quantum Computer

- Gate Model
- Analog Quantum Model
- **Quantum Annealing**

## Why Quantum Annealing?





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# Quantum Annealing

## Annealing a Metal

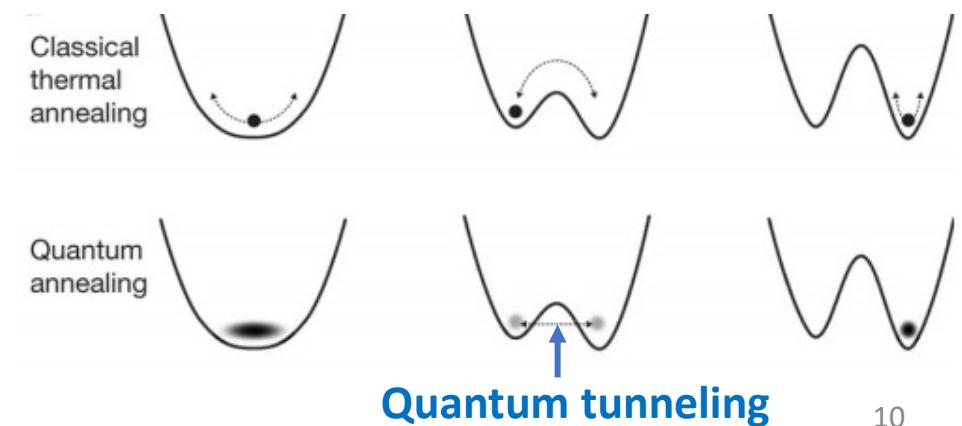
- Heat the metal to a temperature;
- Lower the temperature;

## Simulated Annealing

- Heuristic algorithm;
- Random search method;
- **The temperature variable;**

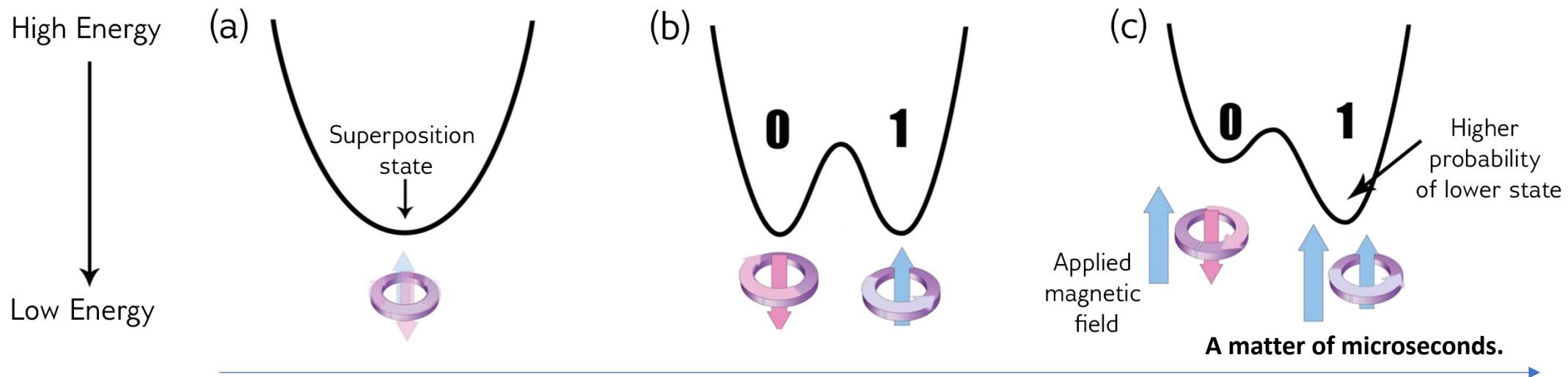
## Quantum Annealing

- **Enables jumping from one classical state to another**
  - Decreases likelihood of getting stuck in a local minimum
- **Width of energy barrier is important, but height is not**



# Quantum Annealing

## Energy diagram in Quantum Annealing



- Initial Qubits
- Superposition at  $|0\rangle$ s and  $|1\rangle$ s.
- Not yet coupled.

- Qubits are entangled.
- At state of many possible answers.
- Couplers & biases applied

- Inputs' energy are set.
- Lowest energy is at or closes to the optima.
- Energy  $\square$  possibility

- Superposition

- A quantum bit  $|\phi\rangle = \alpha|0\rangle + \beta|1\rangle$
- $||\alpha||^2$ : the probability in state  $|0\rangle$
- $||\beta||^2$ : the probability in state  $|1\rangle$
- $||\alpha||^2 + ||\beta||^2 = 1$

A general  $n$ -qubit system:

•

$$|\Phi\rangle = \sum_{i=0}^{N-1} \alpha_i |i\rangle = \begin{pmatrix} \alpha_0 \\ \alpha_1 \\ \vdots \\ \alpha_{N-2} \\ \alpha_{N-1} \end{pmatrix}, N = 2^n.$$

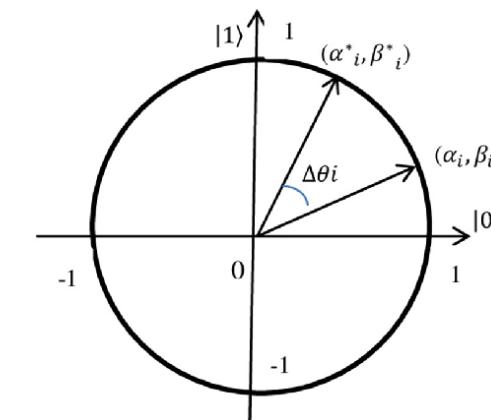
- Tensor Product

$|i\rangle$  is the  $i^{th}$  computational basis of the space, and  $\alpha_i$  is the amplitude of the  $i^{th}$  computational basis.

$|\psi\rangle \otimes |\phi\rangle$  represents the overall state of two quantum bits.

$$|\psi\rangle \otimes |\phi\rangle = \alpha_{00}|00\rangle + \alpha_{01}|01\rangle + \alpha_{10}|10\rangle + \alpha_{11}|11\rangle,$$

$$||\alpha_{00}||^2 + ||\alpha_{01}||^2 + ||\alpha_{10}||^2 + ||\alpha_{11}||^2 = 1.$$



# Schrödinger Equation

Before studying quantum



after studying quantum



- Evolution from  $t = 0$  to  $t = T$
- $i\frac{\partial|\psi(t)\rangle}{\partial t} = H(t)|\psi(t)\rangle$
- $|\psi(t)\rangle$  : The actual state of the system
- $H(t)$  : a time-dependent Hamiltonian (i.e., Kinetic Energy + Potential Energy)
- $H(t)|\phi_j(t)\rangle = E_j(t)|\phi_j(t)\rangle$
- $|\phi_j(t)\rangle$  : the  $j$ -th instantaneous eigenstate
- $E_j(t)$  : the  $j$ -th instantaneous eigenvalue



## Overview

- A computing approach utilizing the quantum mechanics (e.g., superposition, entanglement).
- Prepare the system in an initial state and transform it to the final state.
- Has the potential to speed up the computing process.
- Polynomial equivalent to circuit model
- Applications: PageRank algorithm, Quadratic Unconstrained Binary Optimization, Machine Learning.

## Algorithm

- 1: Encoding the solution
  - 1) Encoding target solution in final state  $|\phi_j(T)\rangle, j = 0$ .
  - 2) Encoding target function in the final eigenvalue  $E_j(T)$ .
  - 3) Find the Hamiltonian  $H(T) = H_{fin}$  based the encoding rules.
- 2: Prepare the initial Hamiltonian  $H(0) = H_{ini}$  and its eigenstates  $|\phi_j(0)\rangle, j = 0$ .
- 3: Prepare the time dependent Hamiltonian  $H(t) = (1 - f(t))H_{ini} + f(t)H_{fin}$ ,  
 $f(0) = 0, f(1) = 1, 0 \leq f(t) \leq 1$ , for  $t \in [0, T]$ . function  $f(t)$  is at least twice differentiable.
- 4: Evolve the system from  $t = 0$  to  $t = T$ , then observe the final state to obtain the solution.

**Core idea:** Encoding the objective function as the eigenvalue of the final ground state of Schrodinger equation, based on Adiabatic Quantum Computing Model

## Ising Model

$$H(s) = \sum_i h_i s_i + \sum_i \sum_{i < j} J_{i,j} s_i s_j$$

↑  
Spins interact with applied field

←  
Neighboring spins interact with each other

## QUBO (Quadratic Unconstrained Binary Optimization)

$$f(x) = \sum_i Q_{i,i} x_i + \sum_i \sum_{i < j} Q_{i,j} x_i x_j$$

$Q$  : upper-diagonal matrix

These important optimization problems can be transformed into QUBO model:

- Knapsack Problems
- Assignment Problems
- Task Allocation Problems
- Capital Budgeting Problems
- ... (NP-hard problem)

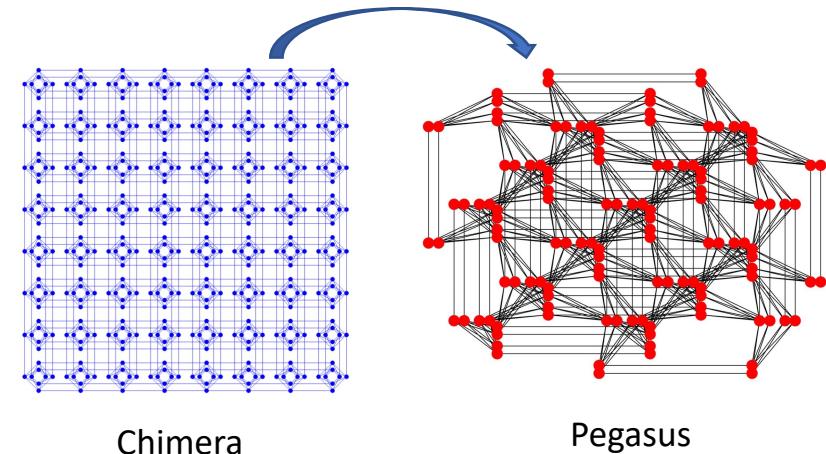


**Quantum Computing:  
provide an alternative  
method to solve some  
NP-hard problems**

# Dwave Hamiltonian

- Problem of Hamiltonian:

$$H_{ising} = \underbrace{-\frac{A(s)}{2} \left( \sum_i \hat{\sigma}_x^{(i)} \right)}_{\text{Initial Hamiltonian}} + \underbrace{\frac{B(s)}{2} \left( \sum_i h_i \hat{\sigma}_z^{(i)} + \sum_{i>j} J_{i,j} \hat{\sigma}_z^{(i)} \hat{\sigma}_z^{(j)} \right)}_{\text{Final Hamiltonian}}$$



- Goal (what the hardware does)

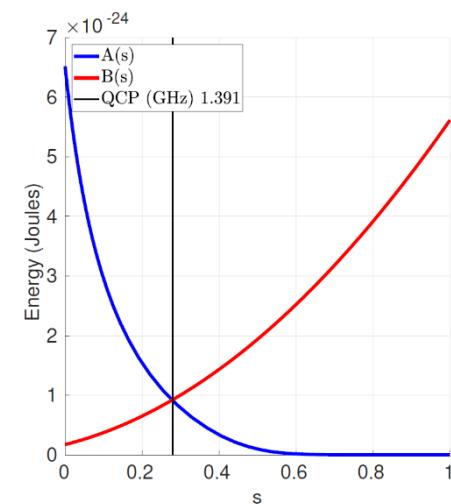
- Minimize  $\sigma_i \in \{-1, +1\}$  subject to provided  $J_{i,j} \in R$  and  $h_i \in R$  coefficients
- In other words, a quantum optimization program is merely a list of  $J_{i,j}$  and  $h_i$

- Classical

- Much easier to reason than a quantum Hamiltonian
- Quantum effects are used internally to work towards the goal

- Sparsely connected

- Possible to map fully connected problems onto the D-Wave's Chimera graph





# Dwave Hamiltonian

- Considering only the external field:

$$\mathcal{H}_P = \sum_{i=0}^{N-2} \sum_{j=i+1}^{N-1} J_{i,j} \sigma_i^z \sigma_j^z + \sum_{i=0}^{N-1} h_i \sigma_i^z$$

- We arbitrarily call  $\sigma^z = +1$  “TRUE” and  $\sigma^z = -1$  “FALSE”
- Here are the optimal values of  $\sigma^z$  for different values of  $h$

Negative  
(say,  $h_i = -5$ )

$\sigma_i^z$	$h_i \sigma_i^z$
-1	+5
+1	-5

Zero

$\sigma_i^z$	$h_i \sigma_i^z$
-1	0
+1	0

Positive  
(say,  $h_i = +5$ )

$\sigma_i^z$	$h_i \sigma_i^z$
-1	-5
+1	+5

- Observations

- A negative  $h_i$  means, “I want  $\sigma^z$  to be TRUE”
- A zero  $h_i$  means, “I don’t care if  $\sigma^z$  is TRUE or FALSE”
- A positive  $h_i$  means, “I want  $\sigma^z$  to be FALSE”

# Dwave Hamiltonian

- Consider only the coupler strengths:

$$\mathcal{H}_P = \sum_{i=0}^{N-2} \sum_{j=i+1}^{N-1} J_{i,j} \sigma_i^z \sigma_j^z + \sum_{i=0}^{N-1} h_i \sigma_i^z$$

- Here are the optimal values of  $\sigma_i^z$  and  $\sigma_j^z$  for different values of  $J_{i,j}$ :

Negative ( $J_{i,j} = -5$ )

$\sigma_i^z$	$\sigma_j^z$	$J_{i,j} \sigma_i^z \sigma_j^z$
-1	-1	-5
-1	+1	+5
+1	-1	+5
+1	+1	-5

Zero

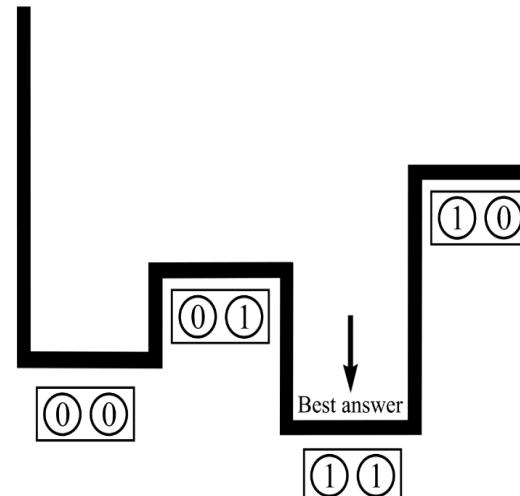
$\sigma_i^z$	$\sigma_j^z$	$J_{i,j} \sigma_i^z \sigma_j^z$
-1	-1	0
-1	+1	0
+1	-1	0
+1	+1	0

Positive ( $J_{i,j} = +5$ )

$\sigma_i^z$	$\sigma_j^z$	$J_{i,j} \sigma_i^z \sigma_j^z$
-1	-1	+5
-1	+1	-5
+1	-1	-5
+1	+1	+5

- Observations

- A negative  $J_{i,j}$  means, “I want  $\sigma_i^z$  and  $\sigma_j^z$  to be equal”
- A zero  $J_{i,j}$  means, “I don’t care how  $\sigma_i^z$  and  $\sigma_j^z$  are related”
- A positive  $J_{i,j}$  means, “I want  $\sigma_i^z$  and  $\sigma_j^z$  to be different”





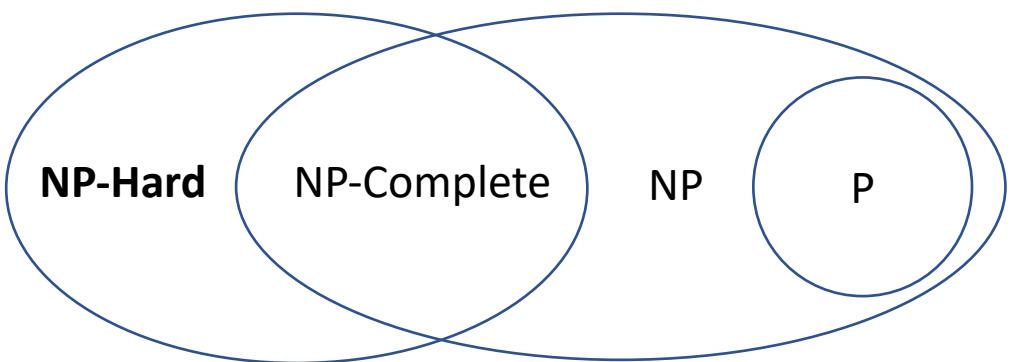
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## Mixed-integer Linear Programming is of:

$$\begin{aligned} \max_{\mathbf{x}, \mathbf{y}} \quad & \mathbf{c}^T \mathbf{x} + \mathbf{h}^T \mathbf{y} \\ \text{s.t.} \quad & \mathbf{Ax} + \mathbf{Gy} \leq \mathbf{b} \\ & \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n \\ & \mathbf{y} \in \mathbb{R}^p \end{aligned}$$

- Mixed-Integer linear Programming (MILP) is **NP-Hard**.
- It can't be solved in polynomial time unless P=NP.



Problem type	Example Problem
NP-Hard	Matrix Permanent Turing Halting Problem <b>MILP</b>
NP-Complete	Steiner Tree Graph 3-coloring Maximum Clique
NP	Factoring Graph Isomorphism
P	Linear Programming Graph Connectivity

# Benders' Decomposition



## Consider a Mixed-integer Linear Programming

$$\begin{aligned} \max_{\mathbf{x}, \mathbf{y}} \quad & \mathbf{c}^T \mathbf{x} + \mathbf{h}^T \mathbf{y} \\ \text{s.t.} \quad & \mathbf{A}\mathbf{x} + \mathbf{G}\mathbf{y} \leq \mathbf{b} \\ & \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n \\ & \mathbf{y} \in \mathbb{R}_+^p \end{aligned}$$

$\xrightarrow{z_{LP} \text{ Replacement}}$

$$\begin{aligned} \max_{\mathbf{x}} \quad & \mathbf{c}^T \mathbf{x} + z_{LP}(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n \end{aligned}$$

We denote the value of the best choice for  $\mathbf{y}$  by  $z_{LP}(\mathbf{x})$

$$\begin{aligned} z_{LP}(\mathbf{x}) = \max_{\mathbf{y}} \quad & \mathbf{h}^T \mathbf{y} \\ \text{s.t.} \quad & \mathbf{G}\mathbf{y} \leq \mathbf{b} - \mathbf{A}\mathbf{x} \\ & \mathbf{y} \in \mathbb{R}_+^p \end{aligned}$$

$\xrightarrow{\text{LP Duality}}$

$$\begin{aligned} z_{LP}(\mathbf{x}) = \min_{\mathbf{u}} \quad & (\mathbf{b} - \mathbf{A}\mathbf{x})^T \mathbf{u} \\ \text{s.t.} \quad & \mathbf{G}^T \mathbf{u} \geq \mathbf{h} \\ & \mathbf{u} \in \mathbb{R}_+^m \end{aligned}$$

Feasible Region Q

# Benders' Decomposition



Continue:

$$\begin{aligned}
z_{LP}(\mathbf{x}) &= \min \quad (\mathbf{b} - \mathbf{Ax})^\top \mathbf{u} \\
\max_{\mathbf{x}} \quad &\mathbf{c}^\top \mathbf{x} + z_{LP}(\mathbf{x}) \\
&\text{s.t.} \quad \mathbf{G}^\top \mathbf{u} \geq \mathbf{h} \\
\text{s.t.} \quad &(\mathbf{b} - \mathbf{Ax})^\top u^k \geq z_{LP}(\mathbf{x}) \quad \text{for } k \in K \\
&(\mathbf{b} - \mathbf{Ax})^\top r^j \geq 0 \quad \text{for } j \in J \\
&z_{LP}(\mathbf{x}) \in \mathbb{R}, \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n
\end{aligned}$$

The feasible region Q does not depend on x.

$$\begin{aligned}
\max_{\mathbf{x}} \quad &\mathbf{c}^\top \mathbf{x} + z_{LP}(\mathbf{x}) \\
\text{s.t.} \quad &\mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n
\end{aligned}$$

The feasible region Q does not exist  
extreme points:  $u^k, k \in K$   
extreme rays:  $r^j, j \in J$

→

The original problem is not feasible

→  $z_{LP}$  bounded

s.t.  $(\mathbf{b} - \mathbf{Ax})^\top u^k \geq z_{LP}(\mathbf{x})$

→  $z_{LP} = -\infty$

$(\mathbf{b} - \mathbf{Ax})^\top r^j \geq 0$

$z_{LP}(\mathbf{x}) \in \mathbb{R}$

# Benders' Decomposition



Continue:

$$\max_{\mathbf{x}} \quad \mathbf{c}^T \mathbf{x} + z_{LP}(\mathbf{x})$$

$$\text{s.t. } (\mathbf{b} - \mathbf{Ax})^T u^k \geq z_{LP}(\mathbf{x}) \quad \text{for } k \in K$$

$$(\mathbf{b} - \mathbf{Ax})^T r^j \geq 0 \quad \text{for } j \in J$$

$$z_{LP}(\mathbf{x}) \in \mathbb{R}, \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n$$

$$z_{LP}(\mathbf{x}) = \min_{\mathbf{u}} \quad (\mathbf{b} - \mathbf{Ax})^T \mathbf{u}$$

$$\begin{aligned} \text{s.t. } & \mathbf{G}^T \mathbf{u} \geq \mathbf{h} \\ & \mathbf{u} \in \mathbb{R}_+^m \end{aligned}$$

Feasible Region Q

Replace  $z_{LP}(\mathbf{x})$  with symbol  $t$

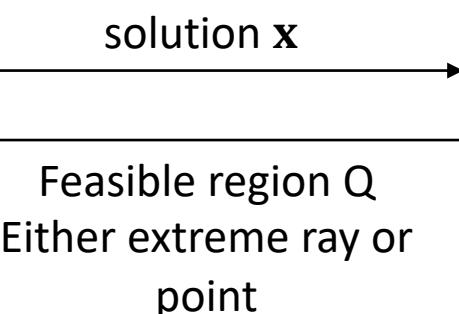
$$\max_{\mathbf{x}, t} \quad \mathbf{c}^T \mathbf{x} + t$$

$$\text{s.t. } (\mathbf{b} - \mathbf{Ax})^T u^k \geq t \quad \text{for } k \in K$$

$$(\mathbf{b} - \mathbf{Ax})^T r^j \geq 0 \quad \text{for } j \in J$$

$$t \in \mathbb{R}, \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n$$

Master Problem

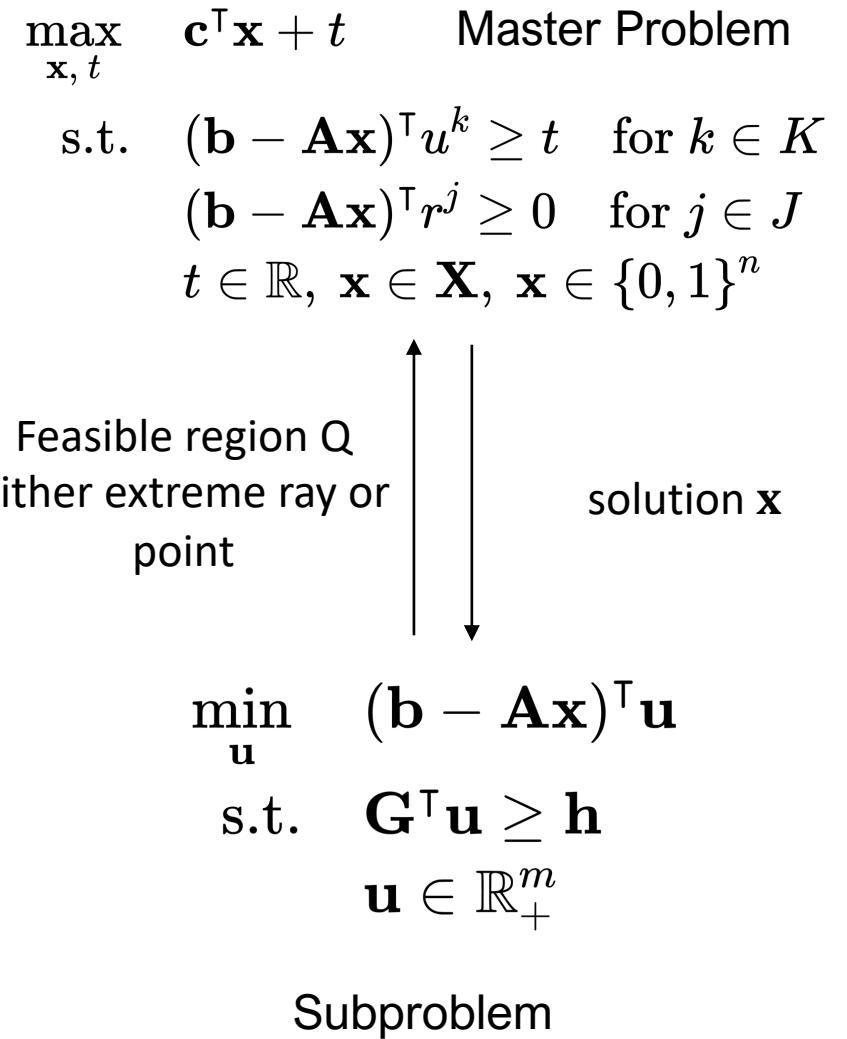


$$\begin{aligned} \min_{\mathbf{u}} \quad & (\mathbf{b} - \mathbf{Ax})^T \mathbf{u} \\ \text{s.t. } & \mathbf{G}^T \mathbf{u} \geq \mathbf{h} \\ & \mathbf{u} \in \mathbb{R}_+^m \end{aligned}$$

Subproblem

## Algorithm:

- 1) Determine (possibly empty) initial sets  $\hat{K}$  of extreme points and  $\hat{J}$  of extreme rays of Q.
- 2) Solve problem (6), the relaxation of the Benders reformulation.  
Obtain solution  $\bar{x}$  and corresponding  $\bar{t}$ .
- 3) Determine  $z_{LP}(\bar{x})$  by solving the dual (3) of the subproblem.
- 4) If  $\bar{z}_{LP} = -\infty$ , an extreme ray of Q has been found. Add the extreme ray to  $\hat{J}$  and return to Step 2. (Feasibility Cuts).
- 5) If  $z_{LP}(\bar{x}) < \bar{t}$  and finite, Add the extreme point of Q to  $\hat{K}$  and return to Step 2. (Optimality Cuts)
- 6) If  $z_{LP}(\bar{x}) = \bar{t}$  then  $\bar{x}$  solves the original mixed integer program (1), with optimal y equal to the solution to the primal subproblem (2) with  $x = \bar{x}$ .



# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming



Classical Benders' Decomposition (CBD)

$$\begin{aligned} \max_{\mathbf{x}, t} \quad & \mathbf{c}^T \mathbf{x} + t \\ \text{s.t.} \quad & (\mathbf{b} - \mathbf{Ax})^T u^k \geq t \quad \text{for } k \in K \\ & (\mathbf{b} - \mathbf{Ax})^T r^j \geq 0 \quad \text{for } j \in J \\ & t \in \mathbb{R}, \mathbf{x} \in \mathbf{X}, \mathbf{x} \in \{0, 1\}^n \end{aligned}$$

Master Problem

solution  $\mathbf{x}$   
Feasible region Q  
Either an extreme ray  
or a point

$$\begin{aligned} \min_{\mathbf{u}} \quad & (\mathbf{b} - \mathbf{Ax})^T \mathbf{u} \\ \text{s.t.} \quad & \mathbf{G}^T \mathbf{u} \geq \mathbf{h} \\ & \mathbf{u} \in \mathbb{R}_+^m \end{aligned}$$

Subproblem

QUBO (Quadratic Unconstrained Binary Optimization)

$$\mathbf{Q}_{\text{obj}} = \sum_i x_i \mathbf{Q}_{i,i} x_i + \sum_i \sum_{i < j} \mathbf{Q}_{i,j} x_i x_j$$

$\mathbf{Q}_{\text{Obj}}$ : Upper triangular matrix

$x_i$  : Binary variable

**Master problem** of the **CBD** is  
one step away from  
pure **ILP** (Integer-linear programming).

The **last barrier** is the scalar  $t$ .

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming



## Classical Benders' Decomposition Master Problem

$$\begin{aligned} \max_{\mathbf{x}, t} \quad & \mathbf{c}^T \mathbf{x} + t \\ \text{s.t.} \quad & (\mathbf{b} - \mathbf{Ax})^T u^k \geq t \quad \text{for } k \in K \\ & (\mathbf{b} - \mathbf{Ax})^T r^j \geq 0 \quad \text{for } j \in J \\ & t \in \mathbb{R}, \mathbf{x} \in \mathbf{X} \end{aligned}$$

In order to reformulate the master problem into the QUBO formulation,

We use a **binary** vector  $\mathbf{w}$  with length of  $M = \bar{m}_+ + \underline{m} + \bar{m}_- + 1$  bits to replace the continuous variable  $t$ .

$$\begin{aligned} t &= \sum_{i=-\underline{m}}^{\bar{m}_+} 2^i w_{i+\underline{m}} - \sum_{j=0}^{\bar{m}_-} 2^j w_{j+(1+\underline{m}+\bar{m}_+)} & \bar{m}_+ &: \# \text{ of bits of } \mathbb{N} \text{ part.} \\ &= \bar{t}(\mathbf{w}) & \underline{m} &: \# \text{ of bits of the decimal part.} \\ & & \bar{m}_- + 1 &: \# \text{ of bits of } \mathbb{Z}_- \text{ part.} \end{aligned}$$

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming

Classical Benders' Decomposition Master Problem

$$\begin{aligned} \max_{\mathbf{x}, t} \quad & \mathbf{c}^T \mathbf{x} + t \\ \text{s.t.} \quad & (\mathbf{b} - \mathbf{A}\mathbf{x})^T u^k \geq t \quad \text{for } k \in K \\ & (\mathbf{b} - \mathbf{A}\mathbf{x})^T r^j \geq 0 \quad \text{for } j \in J \\ & t \in \mathbb{R}, \mathbf{x} \in \mathbf{X} \end{aligned}$$

$\xrightarrow{\text{t reformulation}}$

Alternative Benders' Decomposition Subproblem

$$\begin{aligned} \max_{\mathbf{x}, \mathbf{w}} \quad & c^T \mathbf{x} + \sum_{i=-m}^{\bar{m}_+} 2^i w_{i+m} - \sum_{j=0}^{\bar{m}_-} 2^j w_{j+(1+m+\bar{m}_+)} \\ \text{s.t.} \quad & (b - A\mathbf{x})^T u^k \geq \bar{t}(\mathbf{w}), \quad \text{for } k \in \hat{K}, \\ & (b - A\mathbf{x})^T r^j \geq 0, \quad \text{for } j \in \hat{J}, \\ & \mathbf{x} \in X, \quad \mathbf{x} \in \{0, 1\}^n, \\ & \mathbf{w} \in W, \quad \mathbf{w} \in \{0, 1\}^M. \end{aligned}$$

MILP

Pure ILP

QUBO can be applied now.

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming

UNIVERSITY of  
**HOUSTON**

CULLEN COLLEGE of ENGINEERING  
Electrical & Computer Engineering



## Algorithm Overview: Benders' Decomposition Master Problem

$$\max_{\mathbf{x}, \mathbf{w}} \quad c^\top \mathbf{x} + \sum_{i=-\underline{m}}^{\bar{m}_+} 2^i w_{i+\underline{m}} - \sum_{j=0}^{\bar{m}_-} 2^j w_{j+(1+\underline{m}+\bar{m}_+)}$$

$$\begin{aligned} \text{s.t. } & (b - A\mathbf{x})^\top u^k \geq \bar{t}(\mathbf{w}), \quad \text{for } k \in \hat{K}, \\ & (b - A\mathbf{x})^\top r^j \geq 0, \quad \text{for } j \in \hat{J}, \\ & \mathbf{x} \in X, \quad \mathbf{x} \in \{0, 1\}^n, \\ & \mathbf{w} \in W, \quad \mathbf{w} \in \{0, 1\}^M. \end{aligned}$$

TABLE I  
TABLE OF COMMON CONSTRAINT-PENALTY PAIRS

Constraint	Equivalent Penalty
$x_1 + x_2 = 1$	$P(x_1 + x_2 - 1)^2$
$x_1 + x_2 \geq 1$	$P(1 - x_1 - x_2 + x_1 x_2)^2$
$x_1 + x_2 \leq 1$	$P(x_1 x_2)$
$x_1 + x_2 + x_3 \leq 1$	$P(x_1 x_2 + x_1 x_3 + x_2 x_3)$

1) Objective Function:

$$c^\top \mathbf{x} + \sum_{i=-\underline{m}}^{\bar{m}_+} 2^i w_{i+\underline{m}} - \sum_{j=0}^{\bar{m}_-} 2^j w_{j+(1+\underline{m}+\bar{m}_+)} \Rightarrow \mathbf{Q}_{obj} = \mathbf{x}^\top \text{diag}(c)\mathbf{x} + \sum_{i=-\underline{m}}^{\bar{m}_+} w_{i+\underline{m}} 2^i w_{i+\underline{m}} - \sum_{j=0}^{\bar{m}_-} w_{j+(1+\underline{m}+\bar{m}_+)} 2^j w_{j+(1+\underline{m}+\bar{m}_+)}.$$

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming



## Hybrid Quantum Benders' Decomposition

### Master Problem

$$\max_{\mathbf{x}, \mathbf{w}} \quad c^\top \mathbf{x} + \sum_{i=-\underline{m}}^{\bar{m}_+} 2^i w_{i+\underline{m}} - \sum_{j=0}^{\bar{m}_-} 2^j w_{j+(1+\underline{m}+\bar{m}_+)}$$

$$\text{s.t. } (b - A\mathbf{x})^\top u^k \geq \bar{t}(\mathbf{w}), \quad \text{for } k \in \hat{K},$$

$$(b - A\mathbf{x})^\top r^j \geq 0, \quad \text{for } j \in \hat{J},$$

$$\mathbf{x} \in X, \quad \mathbf{x} \in \{0, 1\}^n,$$

$$\mathbf{w} \in W, \quad \mathbf{w} \in \{0, 1\}^M.$$

2) Optimality Cuts :

$$\bar{t}(\mathbf{w}) + (u^k)^\top A\mathbf{x} \leq b^\top u^k, \quad \text{for } k \in \hat{K}.$$

$$\Rightarrow P_k \left( \bar{t}(\mathbf{w}) + (u^k)^\top A\mathbf{x} + \sum_{l=-\underline{m}}^{\bar{l}^K} 2^l s_{kl}^K - b^\top u^k \right)^2,$$

$$\text{where } \bar{l}^K = \left\lceil \log_2 \left( b^\top u^k - \min_{\mathbf{w}, \mathbf{x}} (\bar{t}(\mathbf{w}) + (u^k)^\top A\mathbf{x}) \right) \right\rceil$$

3) Feasibility Cuts :

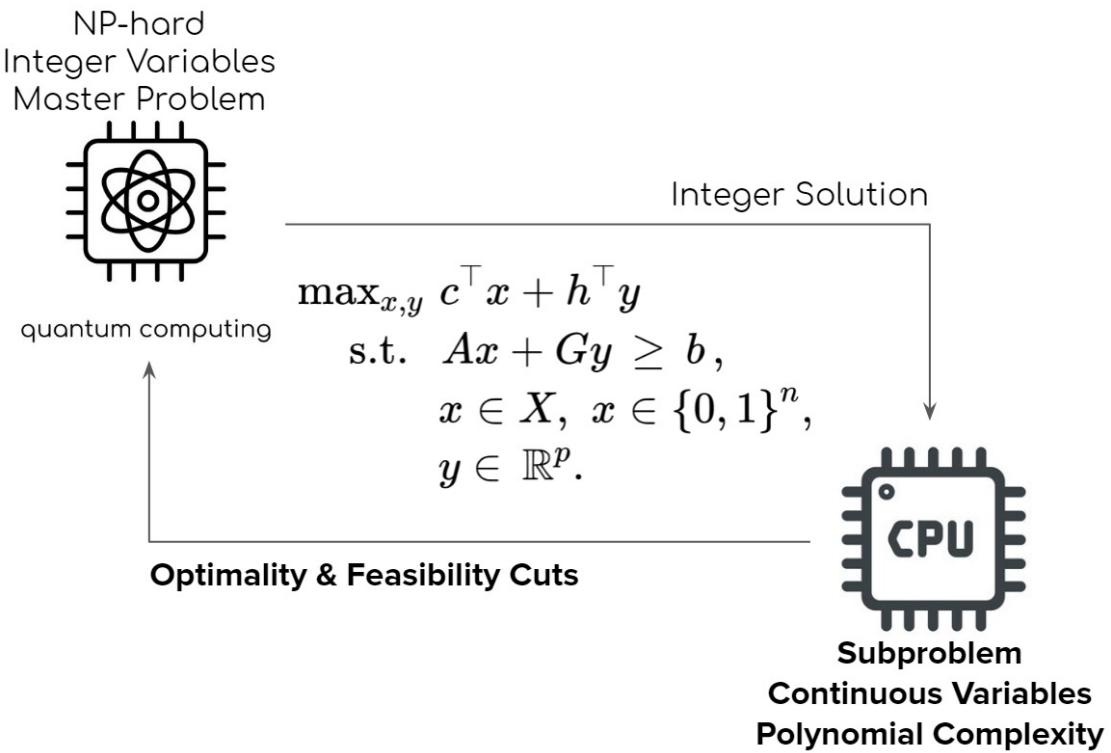
$$(r^j)^\top A\mathbf{x} \leq b^\top r^j, \quad \text{for } j \in \hat{J}.$$

$$\Rightarrow P_j \left( (r^j)^\top A\mathbf{x} + \sum_{l=0}^{\bar{l}^J} 2^l s_{kl}^J - b^\top r^j \right)^2,$$

$$\text{where } \bar{l}^J = \left\lceil \log_2 \left( b^\top r^j - \min_{\mathbf{x}} ((r^j)^\top A\mathbf{x}) \right) \right\rceil$$

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming

## Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming



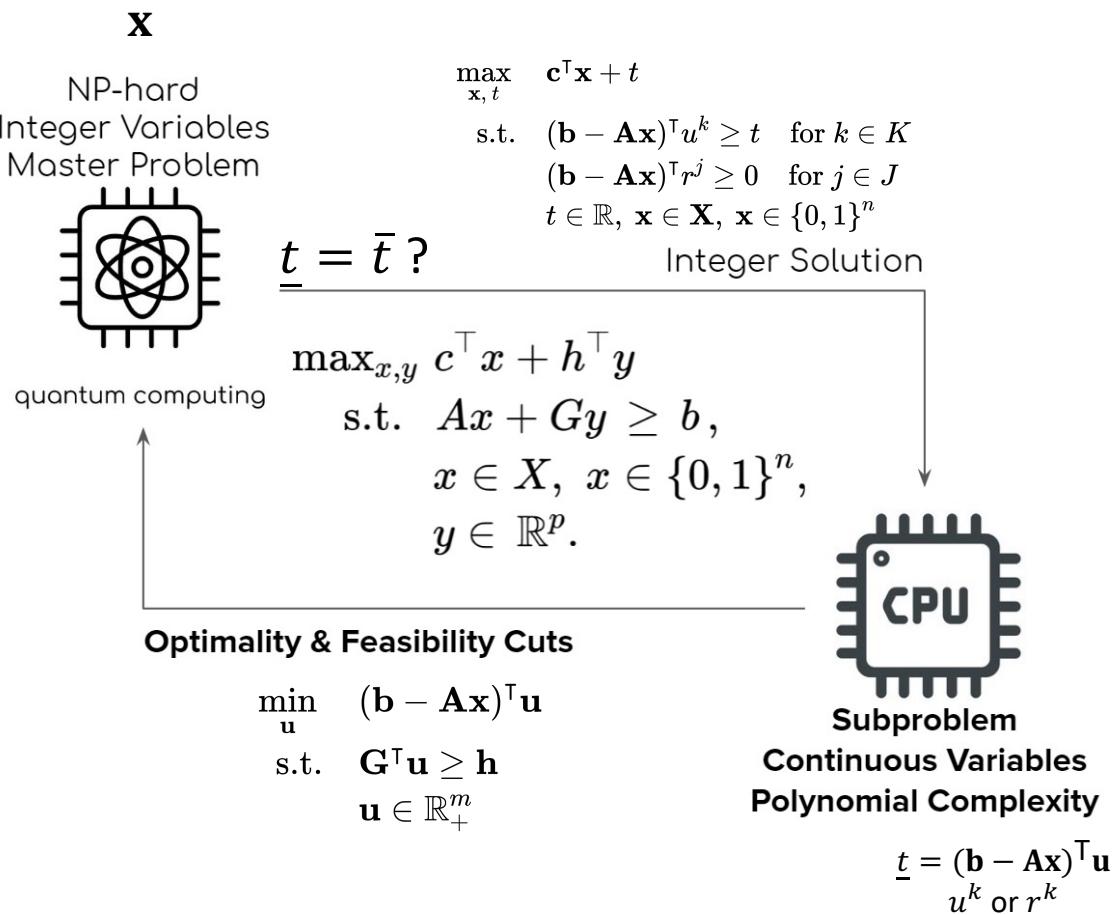
$$\mathbf{x}' = \{\mathbf{w}, \mathbf{x}_j\mathbf{s}\}$$

$$f(\mathbf{x}') = \mathbf{x}'^\top \mathbf{Q}_{\text{QUBO}} \mathbf{x}'$$

$$\begin{aligned} \mathbf{Q}_{\text{QUBO}} = & \mathbf{x}^\top \text{diag}(c) \mathbf{x} \\ & + \sum_{i=-m}^{\bar{m}_+} w_{i+m} 2^i w_{i+m} - \sum_{j=0}^{\bar{m}_-} w_{j+(1+m+\bar{m}_+)} 2^j w_{j+(1+m+\bar{m}_+)} \\ & + \sum_{k \in K} P_k \left( \bar{t}(\mathbf{w}) + (u^k)^\top A \mathbf{x} + \sum_{l=-m}^{\bar{l}^K} 2^l s_{kl}^K - b^\top u^k \right)^2 \\ & + \sum_{j \in J} P_j \left( (r^j)^\top A \mathbf{x} + \sum_{l=0}^{\bar{l}^J} 2^l s_{kl}^J - b^\top r^j \right)^2 \end{aligned}$$

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming

## Hybrid Quantum Benders' Decomposition Algorithm



**Algorithm 1** Hybrid Quantum-Classical Benders' Decomposition Algorithm

**Require:** Initial sets  $\hat{K}$  of extreme points and  $\hat{J}$  of extreme rays of  $Q$   
 $\bar{t} \leftarrow +\infty$   
 $\underline{t} \leftarrow -\infty$   
**while**  $|\bar{t} - \underline{t}| \geq \epsilon$  **do**  
     $\mathbf{P} \leftarrow$  Appropriate penalties numbers or arrays  
     $\mathbf{Q} \leftarrow$  Reformulate both objective and constraints in (2) and construct the QUBO formulation by using corresponding rules  
         $\mathbf{x}' \leftarrow$  Solve problem (6) by quantum computer.  
         $\bar{t} \leftarrow$  Extract  $\mathbf{w}$  and replace the  $\bar{t}$  with  $\bar{t}(\mathbf{w})$  (8)  
         $z_{LP}(\mathbf{x}) \leftarrow$  Solve the problem (3)  
         $\underline{t} \leftarrow z_{LP}(\mathbf{x})$   
        **if**  $z_{LP}(\mathbf{x}) = -\infty$  **then**  
            An extreme ray  $j$  of  $Q$  has been found.  
             $\hat{J} = \hat{J} \cup \{j\}$   
        **else if**  $z_{LP}(\mathbf{x}) < \bar{t}$  **and**  $\bar{t} \neq +\infty$  **then**  
            An extreme point  $k$  of  $Q$  has been found.  
             $\hat{K} = \hat{K} \cup \{k\}$   
        **end if**  
**end while**  
**return**  $\bar{t}, \mathbf{x}$

# Hybrid Quantum Benders' Decomposition for Mixed-integer Linear Programming

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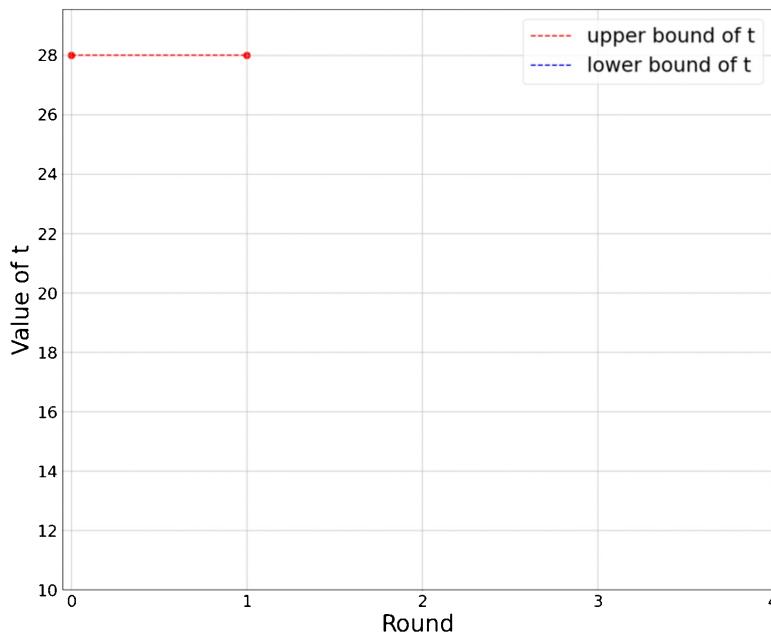
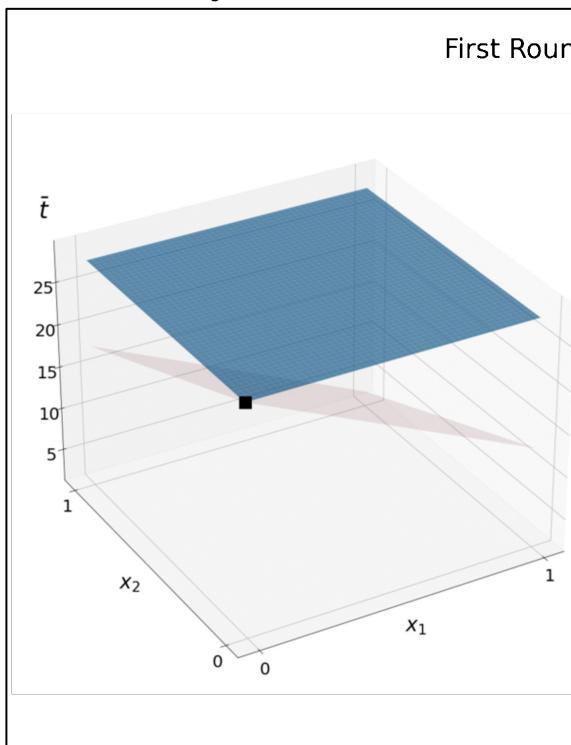
**HOUSTON**CULLEN COLLEGE of ENGINEERING  
Electrical & Computer Engineering

## Hybrid Quantum Benders' Decomposition Algorithm

$$A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ -1 & -1 \\ -1 & 0 \\ -1 & 0 \\ 0 & -1 \\ 0 & -1 \end{bmatrix}, G = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, b = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ -1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

$$h^T = [8 \quad 9 \quad 5 \quad 6], \quad c^T = [-15 \quad -10].$$

D-Wave hybrid solver: use classical computation to assist quantum annealing.



Zhongqi Zhao, Lei Fan, and Zhu Han, ``Hybrid Quantum Benders' Decomposition For Mixed-integer Linear Programming," IEEE Wireless Communications and Networking Conference (WCNC), Austin, TX, April 2022.

Lei Fan and Zhu Han, ``Hybrid Quantum-Classical Computing for Future Network Optimization," IEEE Network, special issue on Quantum Communications and Networking.

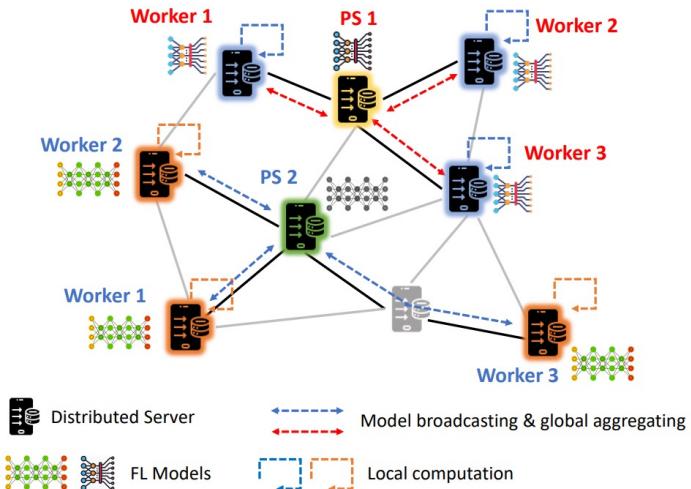


# Outline

- Motivation and Quantum Computing Basics
- Quantum Annealing
  - Adiabatic Quantum Computing
  - Quadratic Unconstrained Binary Optimization (QUBO)
- Hybrid Quantum Benders' Decomposition
  - Benders Decomposition Basics
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- Applications
  - Federated Learning in Mobile Edge Computing
  - Feature Selection for Machine Learning
  - Cable-Routing Problem in Solar Power Plants
- Conclusions

# Federated Learning in Mobile Edge Computing

- Federated Edge Learning (FEL)
  - multiple FL models trained **simultaneously** (**resource competition, performance degradation**), scheduling problem is **NP-hard**
- Quantum Computing (QC)
  - has the **parallel computing** capability
  - a powerful tool for **optimization**
- Existing Optimization in Quantum Computing
  - result in **longer computational times** with no guarantee of feasibility<sup>[1]</sup>
  - focus on **theoretical analysis, mathematical optimization**<sup>[2]</sup>



Computation Model



[1] A. Ajagekar, et al., "Quantum computing based hybrid solution strategies for large-scale discrete-continuous optimization problems", Computers & Chemical Engineering, 2020.

[2] Z. Zhao, et al., "Hybrid quantum Benders' decomposition for mixed-integer linear programming", IEEE WCNC, 2022.

# Problem Formulation

- Participant selection and learning scheduling of multi-model FEL

$$\min_{x,y,\rho} \quad \sum_{j=1}^W (C_j^{trans} + C_j^{local} + C_j^{global} + C_j^{rent}) \quad (5)$$

Storage, CPU constraints

$$\text{s.t. } x_{i,j}\mu_j\kappa_j \leq c_i, \quad x_{i,j}\chi_j \leq f_i, \quad \forall i, j, \quad (6)$$

$$y_{i,j}\mu_j \leq c_i, \quad y_{i,j}\chi_j \leq f_i, \quad \forall i, j, \quad (7)$$

$$\sum_{i=1}^N x_{i,j} = 1, \quad \sum_{i=1}^N y_{i,j} = \kappa_j, \quad \text{One PS, } \kappa_j \text{ FL workers} \quad \forall j, \quad (8)$$

$$\sum_{j=1}^W (x_{i,j} + y_{i,j}) \leq 1, \quad \text{One edge server can at most work as one of three roles} \quad \forall i, \quad (9)$$

$$i \in (1, \dots, N), j \in (1, \dots, W), \quad (10)$$

$$x_{i,j}, y_{i,j} \in \{0, 1\}, \varrho_j \in [0.01, 0.99]. \quad (11)$$

Participant Selection and learning schedule decision

- Transmission Cost Communication cost based on shortest path

$$C_j^{trans} = 2 \cdot \vartheta_j \sum_{k=1}^N \sum_{i=1}^N x_{k,j} \cdot y_{i,j} \cdot \boxed{\rho_j(v_i, v_k)}.$$

- Local Update Cost CPU cycles to process the sample data

$$C_j^{local} = \vartheta_j \cdot \varphi_j \cdot \sum_{i=1}^N y_{i,j} \cdot \boxed{\frac{\psi(D_{j,i})}{f_i}}.$$

- Global Aggregation Cost

$$C_j^{global} = \vartheta_j \cdot \sum_{i=1}^N x_{i,j} \cdot \boxed{\frac{\psi(\mu_j)}{f_i}}.$$

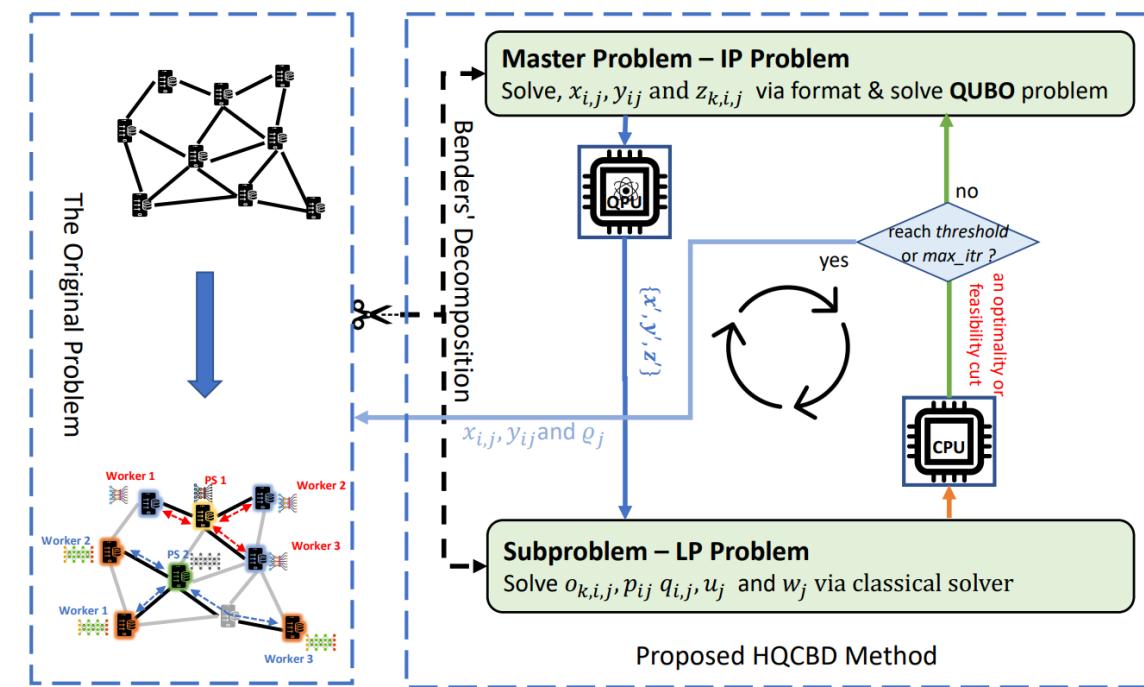
- Participant Cost The unit price for a CPU unit

$$C_j^{rent} = \sum_{i=1}^N (x_{i,j} + y_{i,j}) \cdot \boxed{p_j} \cdot f_i.$$

# Challenges

## ➤ Challenges

1. *How to convert our original MINLP problem into an ILP problem that can be recognized by the quantum computer?*
2. *How to further convert the reformulated ILP problem into a QUBO model as the input to the quantum annealer computer?*



# HQCBD Algorithm

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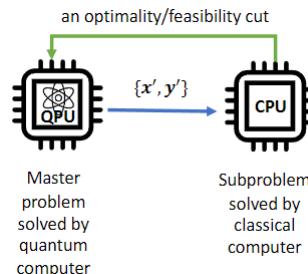
**Algorithm 1** Hybrid Quantum-Classical Benders' Decomposition (HQCBD) Method
 

---

**Input:** Distributed network with  $N$  servers  $V$ ,  $W$  FL models  $M$ , Coefficient of the objective function and constraints in master problem and subproblem

**Output:** PS selection  $x'$ , worker selection  $y'$ , and local convergence rate  $\varrho'$

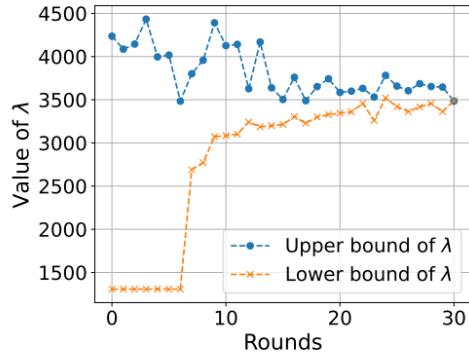
- 1: Initialize upper/lower bound of  $\lambda$ ,  $\bar{\lambda} = +\infty$ ,  $\underline{\lambda} = -\infty$
  - 2: Initialize threshold  $\epsilon = 0.001$ ,  $max\_itr = 100$ ,  $itr = 1$
  - 3: **while**  $|\bar{\lambda} - \underline{\lambda}| > \epsilon$  and  $itr < max\_itr$  **do**
  - 4:   **P**  $\leftarrow$  Appropriate penalty numbers or arrays
  - 5:   **Q**  $\leftarrow$  Reformulate both objective and constraints in (33) and construct QUBO formulation as (47)
  - 6:    $x', y', z' \leftarrow$  Solve problem (47) by quantum computer
  - 7:    $\lambda \leftarrow$  Extract  $w$  and replace  $\underline{\lambda}$  with  $\hat{\lambda}(w)$  as (46)
  - 8:    $SUP(x, y, z) \leftarrow$  Solve problem (30) with fixed  $x', y', z'$
  - 9:   Extract  $\varrho'$  from  $SUP(x, y, z)$
  - 10:    $\bar{\lambda} \leftarrow SUP(x, y, z)$
  - 11:   Add a new benders' cut to the master problem as (44)
  - 12:    $itr += 1$
  - 13: **end while**
  - 14: **return**  $x', y', \varrho'$
- 



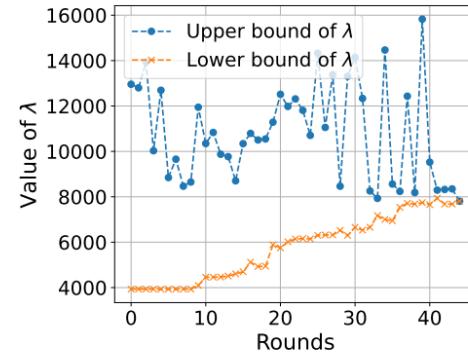
➤ **Workflow**

1. *Initialize parameters (Lines 1 and 2)*
2. *Generate appropriate penalty numbers or arrays (Line 4)*
3. *Solve the master problem with a quantum annealer (Lines 5-7)*
4. *Solve the subproblem with a classical CPU computer (Lines 8-10)*
5. *Add the Benders' cut to the master problem and continue the next iteration (Lines 11 and 12)*

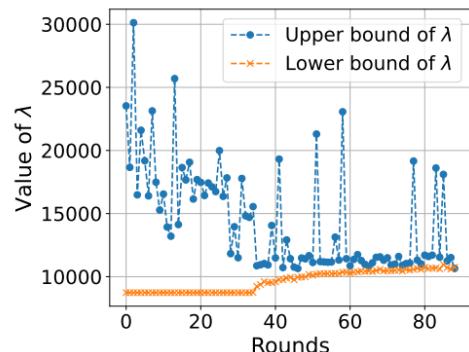
# Experiments



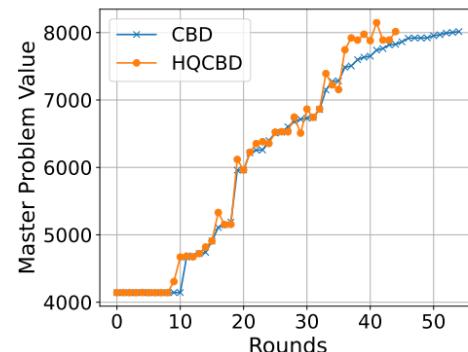
(a) Case 1



(b) Case 2



(c) Case 3



(d) Master problem value

The upper bound and lower bound finally converge.

## ➤ Baselines

- **Classical Benders' Decomposition (CBD):** solve the master problem and subproblem by using classical solver in CPU computer.

TABLE I: Iteration of CBD and HQCBD over three different cases. Here, the set up column shows {# of servers, # of models, # of workers per model} used in each case.

Case #	Set up	# of Variables	Itr. of CBD	Itr. of HQCBD
1	{7, 1, 3}	63	32	31
2	{7, 2, 2}	126	55	45
3	{9, 2, 3}	198	91	89

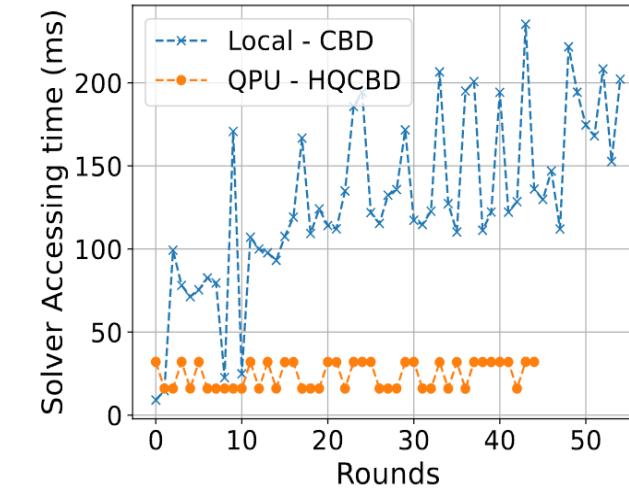
HQCB takes few iterations to converge.

# Experiments

TABLE II: Solver accessing time (*ms*) of CBD and HQCBD.

Case #	CBD		HQCBD	
	Max./Min.	Mean/Std.	Max/Min.	Mean/Std.
1	190.47/6.71	117.14/50.12	32.10/15.93	31.49/2.79
2	235.29/9.11	129.56/50.04	32.11/15.92	24.10/7.98
3	395.48/14.45	120.25/63.19	32.11/16.00	25.53/7.85

*the maximal, average accessing time and the standard deviation value of CBD is significantly higher than HQCBD.*



**Solver accessing time (SAT):** the real accessing time of QPU solver and local solver without considering other overheads.

*CBD in each round/iteration varies significantly, HQCBD in each round keeps stable and is even smaller than that of CBD*



# Outline

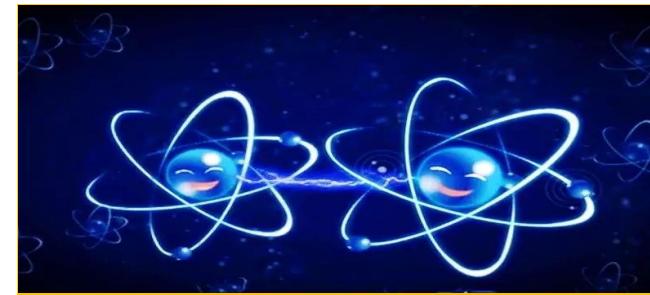
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# Quantum Machine learning



**Machine Learning**

Classical learning techniques  
facing complex tasks



**Quantum Computing**

Quadratic speed-up



**QML**

- Quantum Machine Learning
- Machine learning and *fast*
- Not only fast

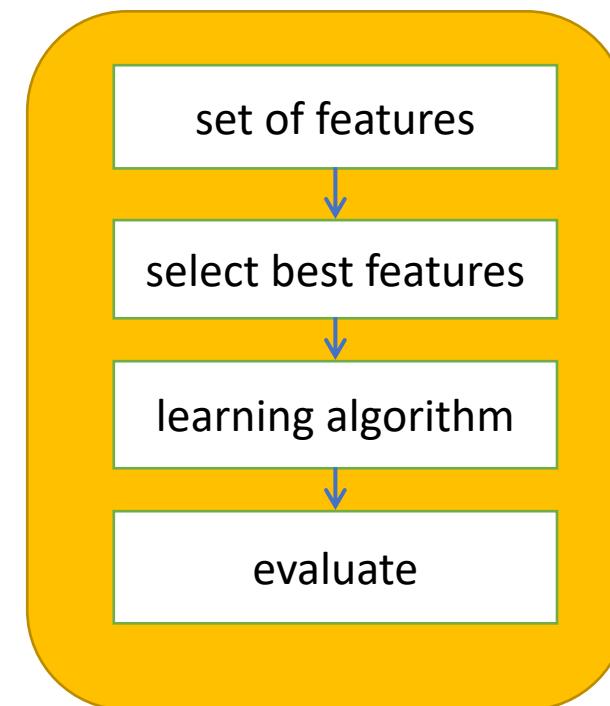
# Feature Selection

Need for feature selection

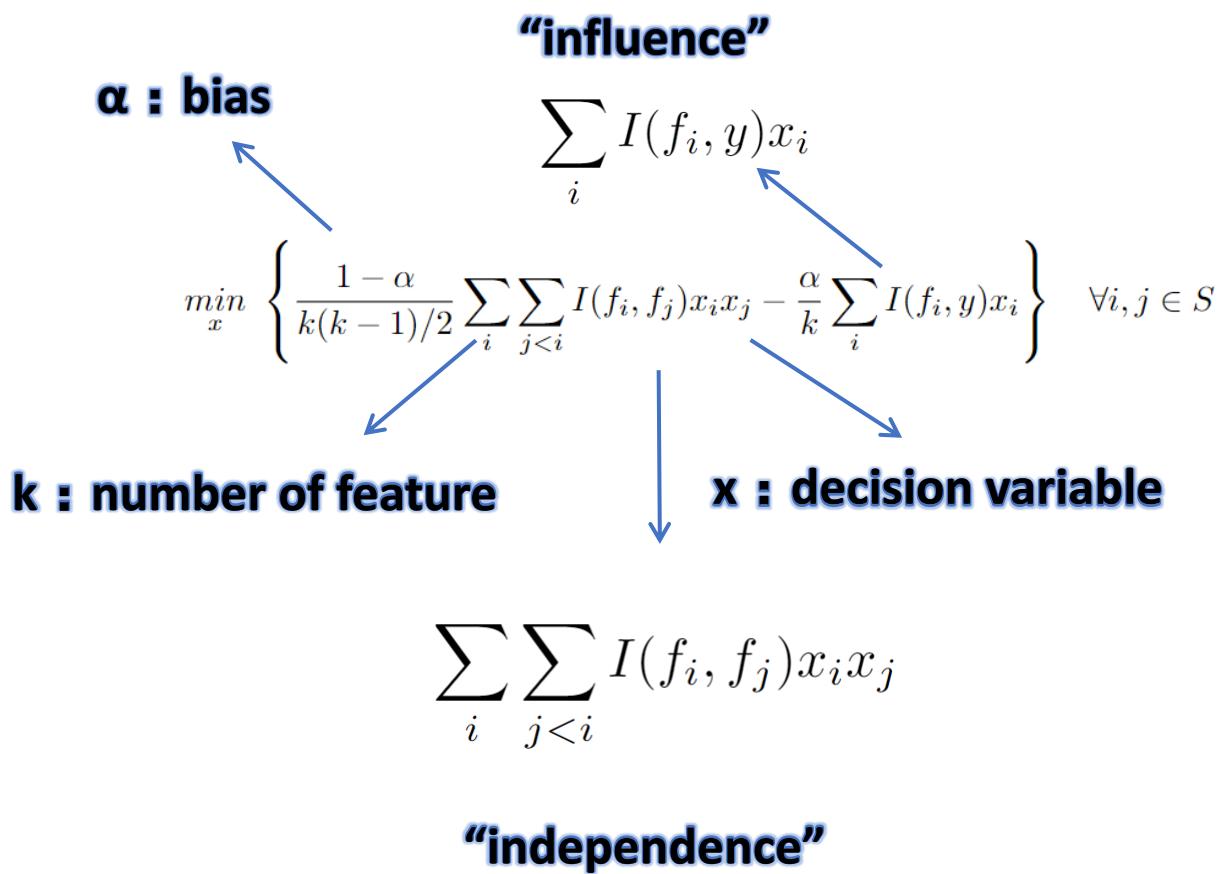
With feature selection, we can optimize our model in some way

- Huge data to train
- Relevant feature
- Irrelevant feature
- Redundant feature

- Prevent overfitting
- Improve accuracy
- Reduce training time



**Objective function: maximize relevant feature  
while minimizing redundant feature**



## Many Constraints

$$\sum x_i = K_j \quad \forall i \in S_j \quad j \in 1, \dots, z$$

<b>Basic</b>	1	duration	Content	10	Hot
	2	protocol_type		11	num_failed_logins
	3	service		12	logged_in
	4	Flag		13	num_compromised
	5	src_bytes		14	root_shell
	6	dst_bytes		15	su_attempted
	7	Land		16	num_root
	8	wrong_fragment		17	num_file_creations
	9	urgent		18	num_shells
				19	num_access_files
				20	num_outbound_cmds
				21	is_host_login
<b>Content</b>	22	is_guest_login	Traffic	32	dst_host_count
	23	count		33	dst_host_srv_count
	24	srv_count		34	dst_host_same_src_rate
	25	serror_rate		35	dst_host_diff_src_rate
	26	srv_serror_rate		36	dst_host_same_src_port_rate
	27	rerror_rate		37	dst_host_srv_diff_host_rate
	28	srv_rerror_rate		38	dst_host_serror_rate
	29	same_src_rate		39	dst_host_srv_serror_rate
	30	diff_src_rate		40	dst_host_rerror_rate
	31	srv_diff_host_rate		41	dst_host_srv_rerror_rate
				42	Class

*Set K is decided by a wrapper method*

# Constraints

$$\sum_{i \in C_g} x_i \leq 1, \quad \forall C_g \in \mathbf{C};$$

Some are conflict



*Feature in  $C_g$  may have the same information, and are selected at most once*



Some rely on others

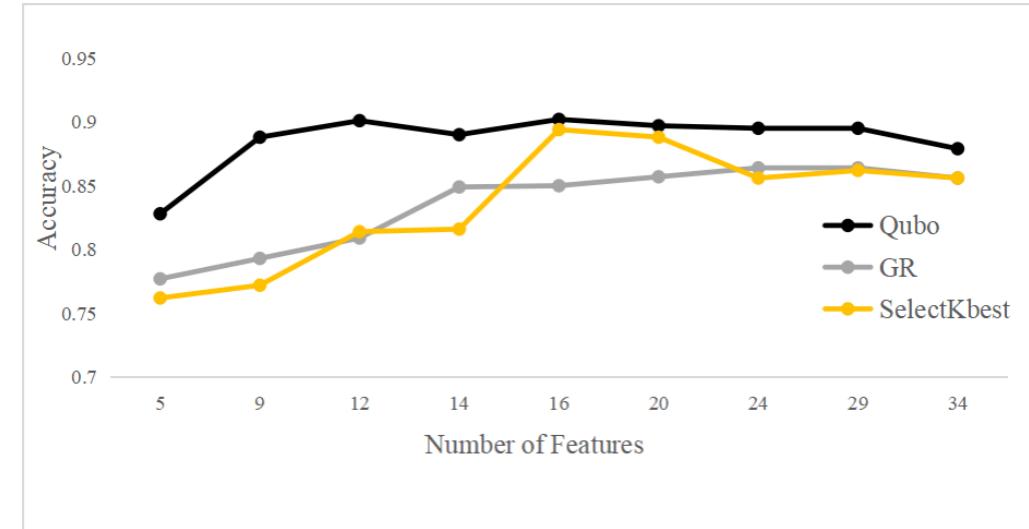
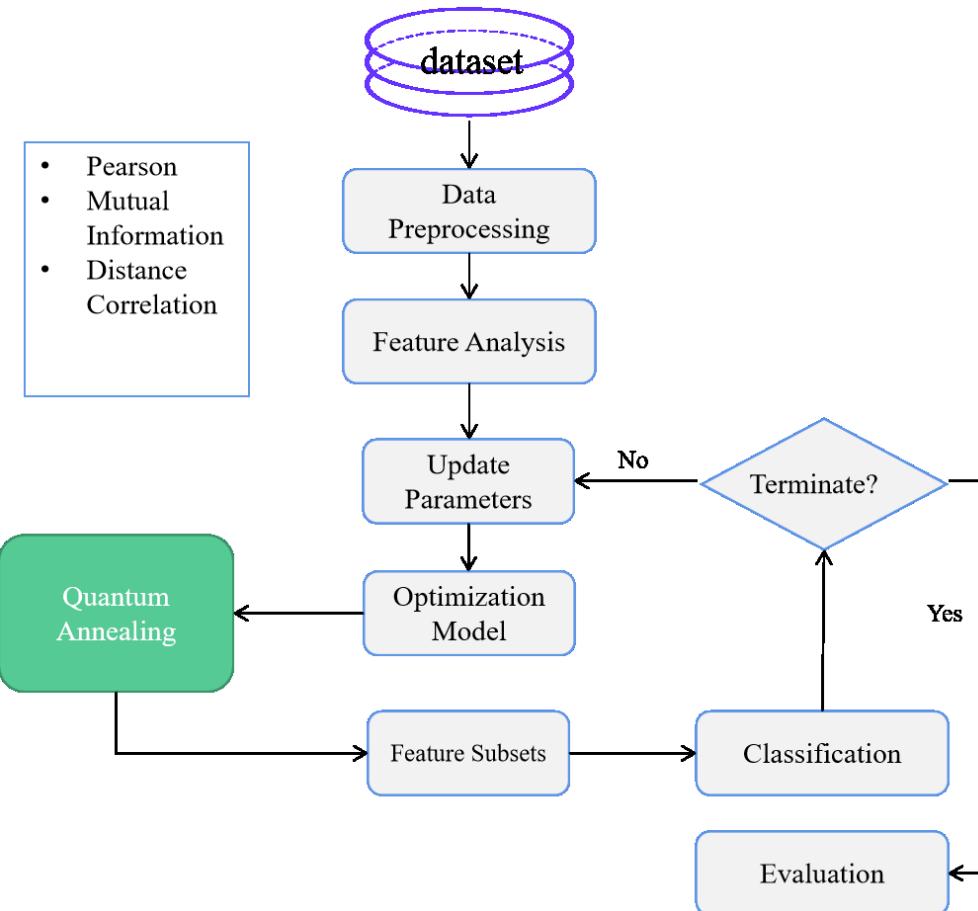
$$x_i - x_j \leq 0 \quad \forall (i, j) \in \mathbb{E}$$

$$\sum x_i = T \quad \forall i \in \mathbb{D}$$

Some are essential and have priority



# Algorithm & Experiments



Accuracy of feature selection methods, including Qubo, GR<sup>[1]</sup>

- QUBO get best performance when k = 12
- QUBO's performance is better than other feature selection methods



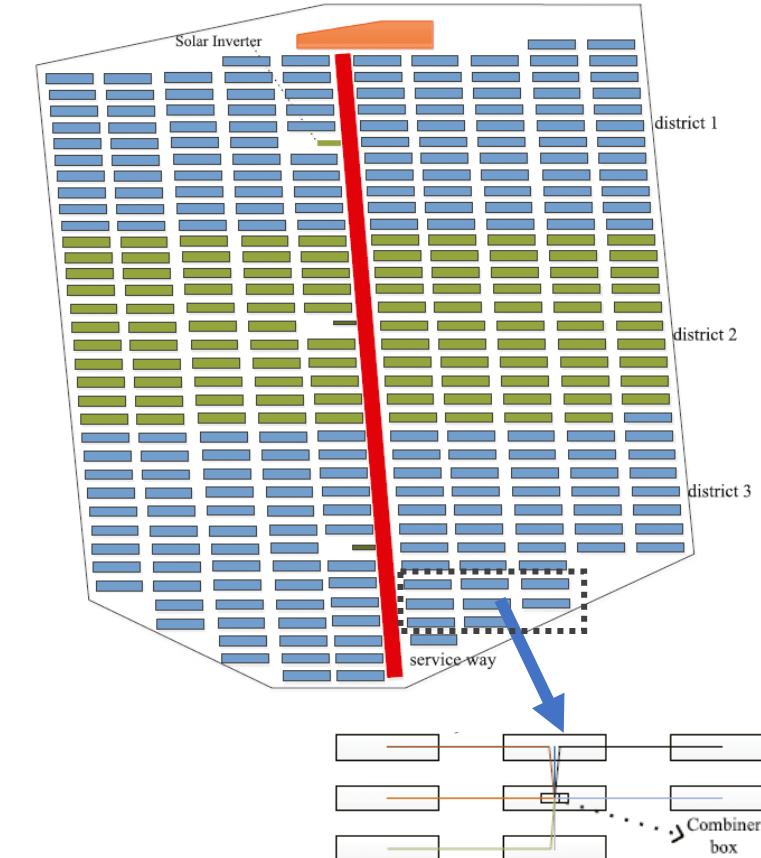
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# Cable-Routing Problem (CRP) in Solar Power Plants

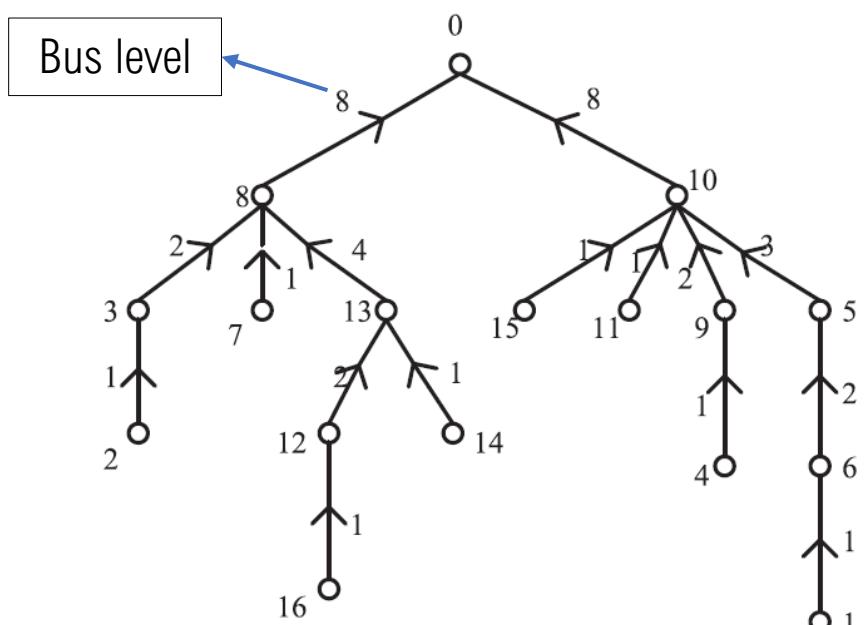
## Quantum Computing for Cable-Routing Problem in Solar Power Plants

Exploring the edge of quantum annealing in the networking problem



Fast arrangement with minimum building cost is one objective of the solar power plant design.

## Quantum Computing for Cable-Routing Problem in Solar Power Plants



Pure integer Programming problem

$$\begin{aligned}
 \min_{\mathbf{x}} \quad & \sum_{e \in E} c_e \sum_{d=1}^Q x_{e,d} + p \sum_{e \in E'} \sum_{d=1}^Q (d-1)c_e x_{e,d}, \\
 \text{s.t.} \quad & \sum_{e \in \delta^+(i)} \sum_{d=1}^Q x_{e,d} = 1, \quad \forall i \in V', \quad \text{Electricity unity leaving} \\
 & \sum_{e \in \delta^+(i)} \sum_{d=1}^Q dx_{e,d} - \sum_{e' \in \delta^-(i)} \sum_{d=1}^Q dx_{e',d} = 1, \quad \forall i \in V', \quad \text{Electricity I/O unity difference} \\
 & m_t^l \leq \sum_{e \in E \setminus E'} x_{e,t} \leq m_t^u, \quad \forall t \in T, \quad \text{Bus level requirements} \\
 & x_{e,t} = 0, \quad \forall e \in E \setminus E', \forall t \notin T, \quad \text{Special requirements} \\
 & x_{e,t} \in \{0, 1\}, \quad \forall e \in E, t \in \{1, 2, \dots, Q\}.
 \end{aligned}$$

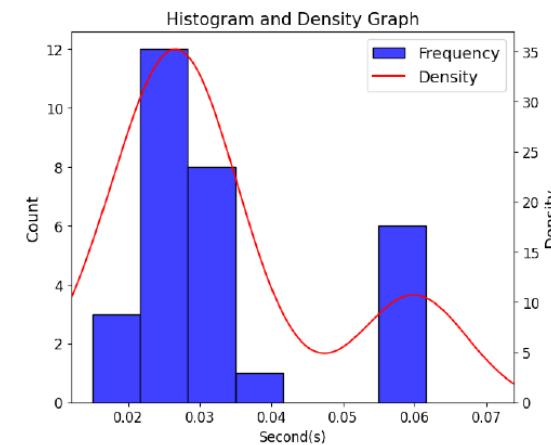
# Experiments

Histogram and Density Graph of Gurobi & D-Wave's Quantum computer in 2 Cases with 30 Attempts

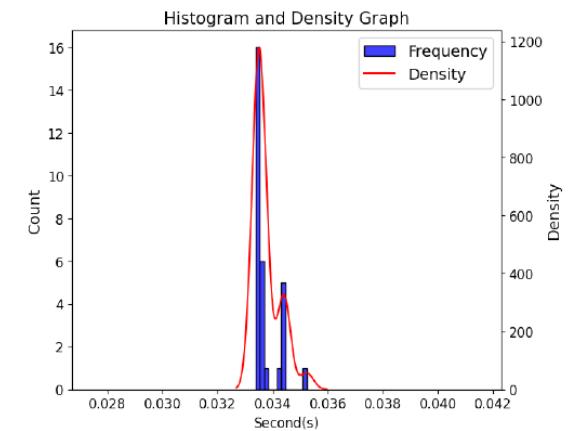
TABLE II: Standard Deviation Comparison

Model \ Detail	Standard Deviation Unit: $10^{-3}$			
	1st Try	2nd Try	3rd Try	Average
W3H3 Gurobi	19.7234	19.3967	19.589	19.5697
W3H3 Quantum	0.4234	0.566	0.2919	0.4271
W3H4 Gurobi	14.0653	14.3928	14.5188	14.3256
W3H4 Quantum*	0.3945	0.5358	0.6339	0.5214

\* It excludes 3 failure attempt samples out of 30 samples.



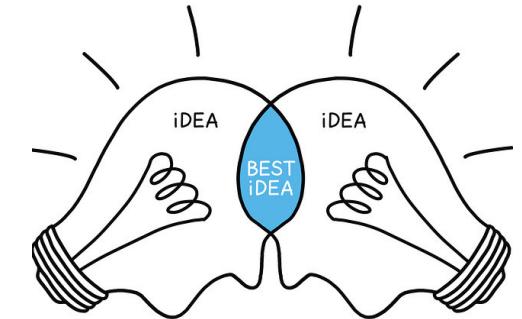
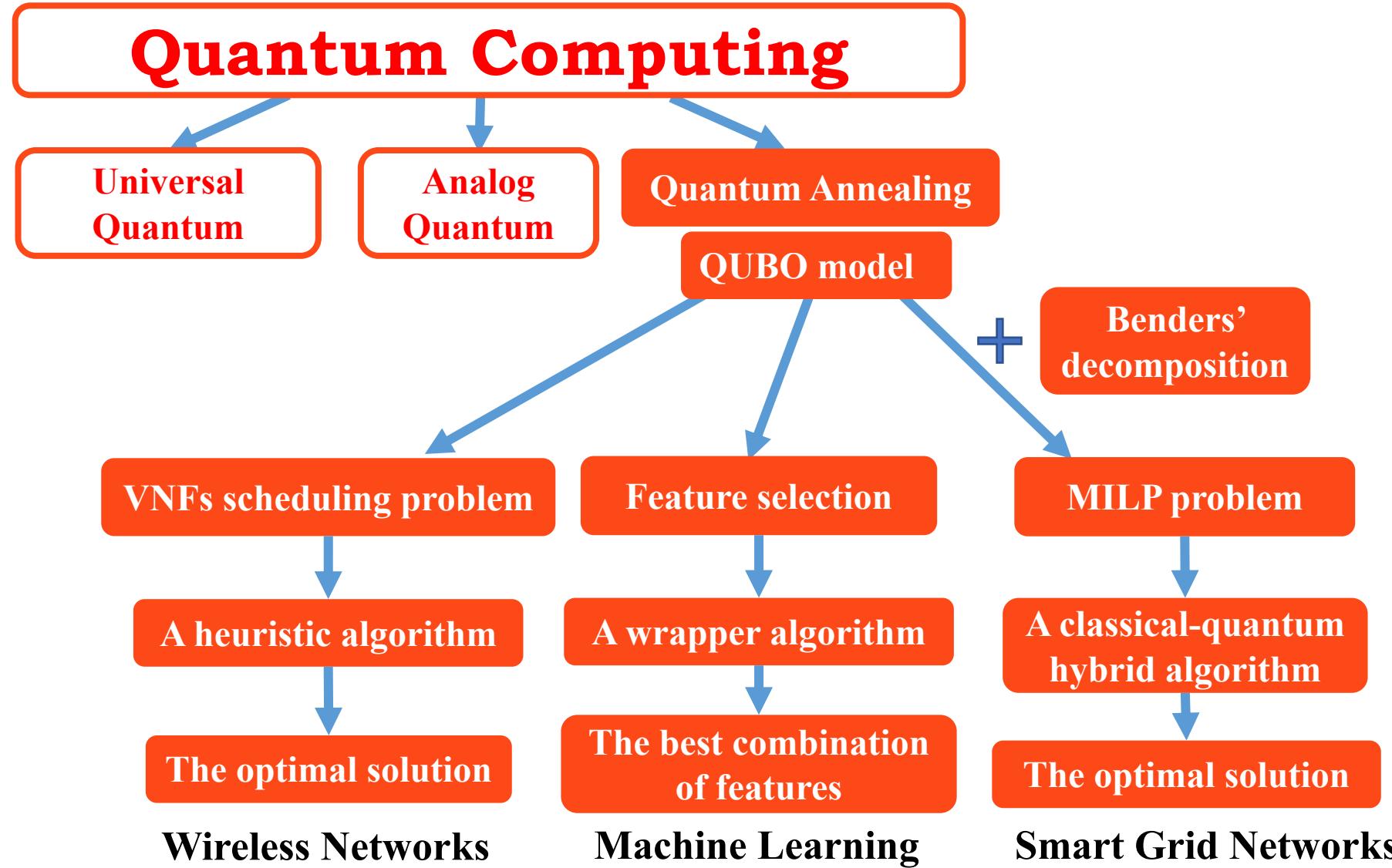
(a) Gurobi  $3 \times 3$



(b) D-Wave  $3 \times 3$

The quantum computing approach **outperforms** the classical computing approach in terms of *solution quality*, *average running time*, and *robustness*.

# Conclusion



Collaboration

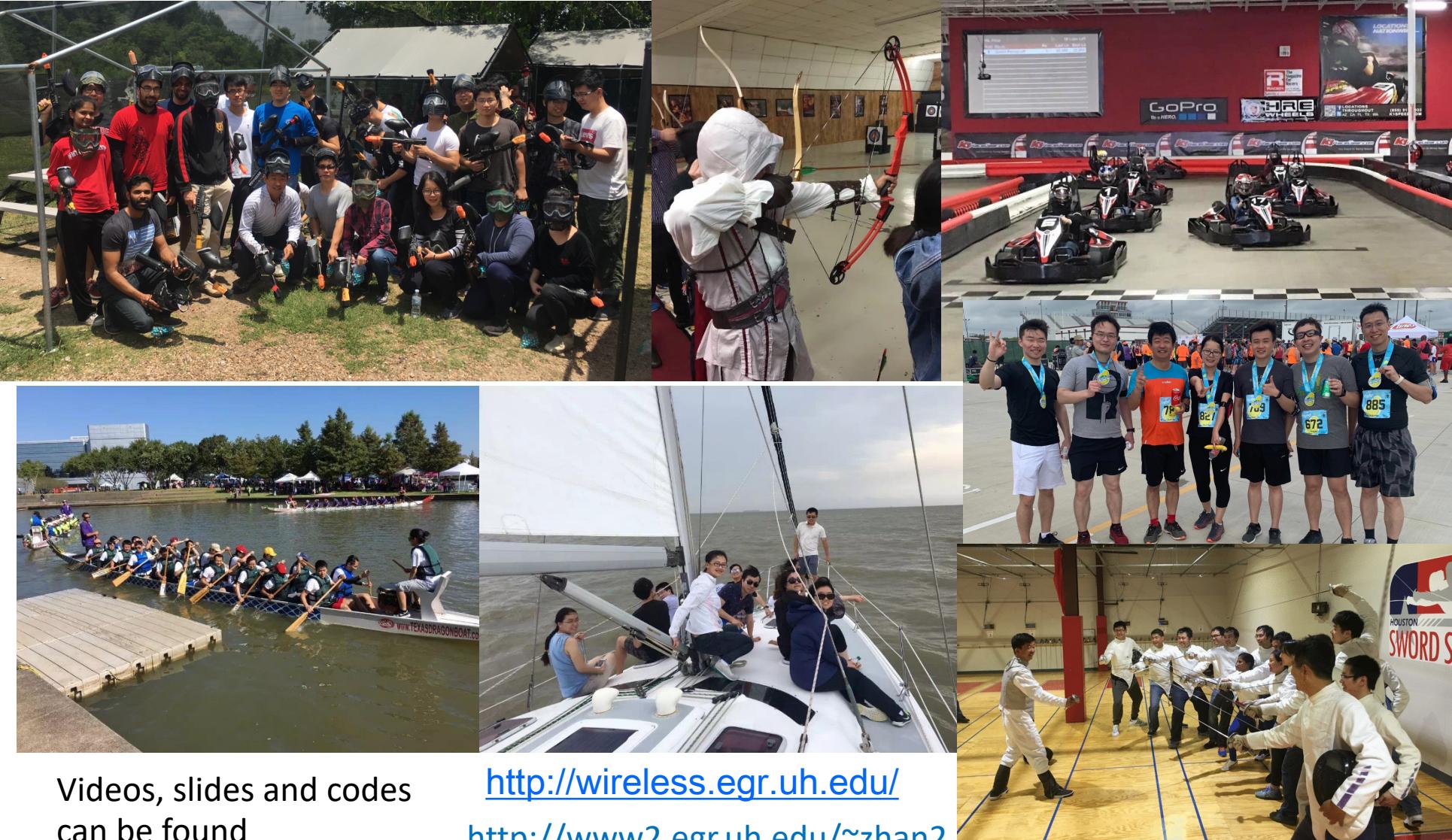


More Applications ...

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