Quantum inspired Data @ HEP

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arXiv:2410.22417 (양자알고리즘)

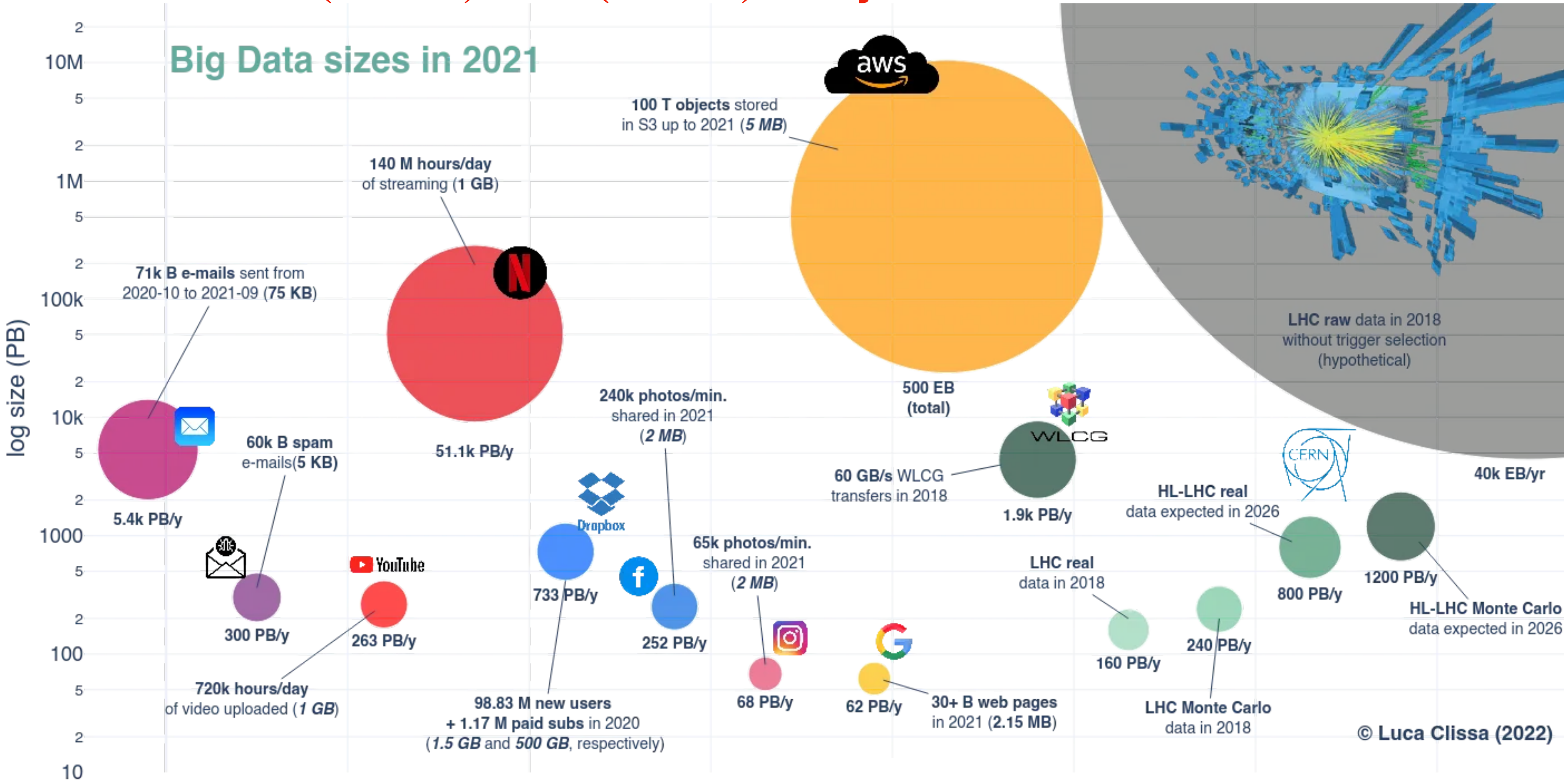
arXiv:2412.13982 (인공지능을 활용한 Monte Carlo)

2024 Meeting of the Division of Particles and Fields of the Korean Physical Society

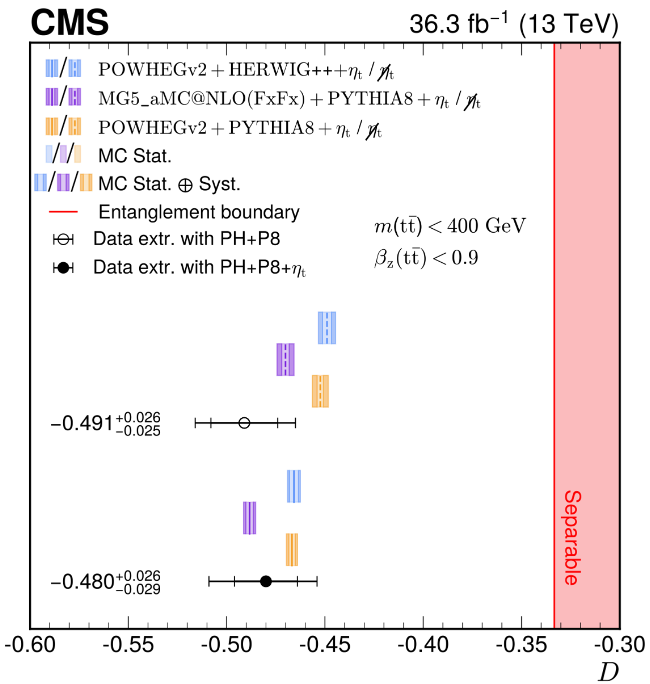
고에너지 물리학, 빅 데이터

- **Data of the (interesting) energy scale:** $\mathcal{O}(100)\,\mathrm{GeV} - \mathcal{O}(10)\,\mathrm{TeV}$

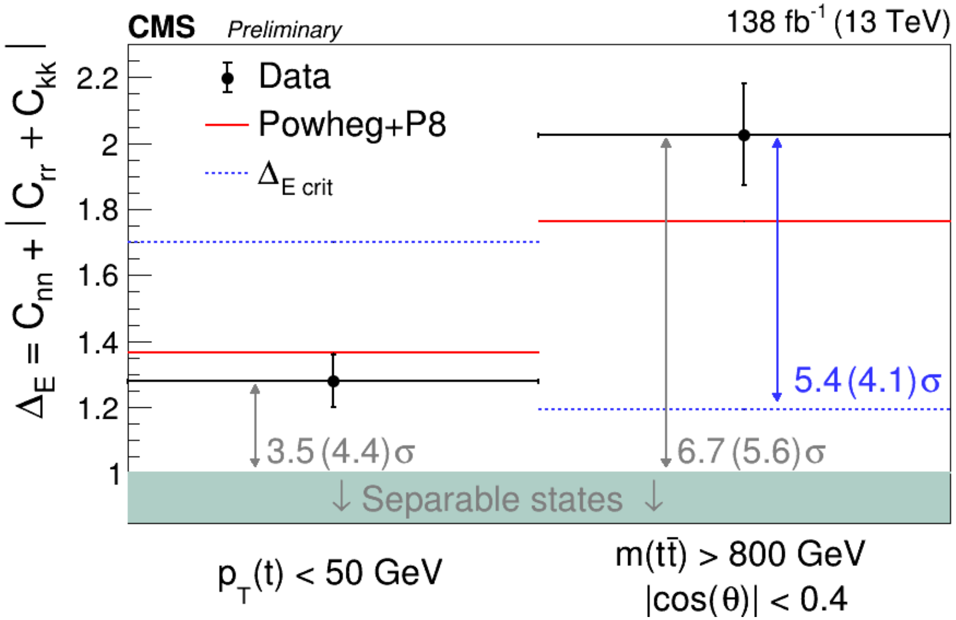
= Data from $\mathcal{O}(10^{-14}) - \mathcal{O}(10^{-10})$ sec just after the "start of our universe"



- **고에너지 물리학의 빅데이터는, 상업용 데이터와 근본적으로 다름**



CMS Physics Analysis Summary (TOP-23-001)



CMS Physics Analysis Summary (TOP-23-007)

- **Threshold** limit for $gg \to t\bar{t}$: $\rho \to |\Psi^-\rangle\langle\Psi^-|, |\Psi^-\rangle = \frac{1}{\sqrt{2}}(|\uparrow\downarrow\rangle - |\downarrow\uparrow\rangle)$

- **High Mass** limit for $gg \to t\bar{t}$: $\rho \to |\Psi^+\rangle\langle\Psi^+|, |\Psi^+\rangle = \frac{1}{\sqrt{2}}(|\uparrow\downarrow\rangle + |\downarrow\uparrow\rangle)$

2024 연구

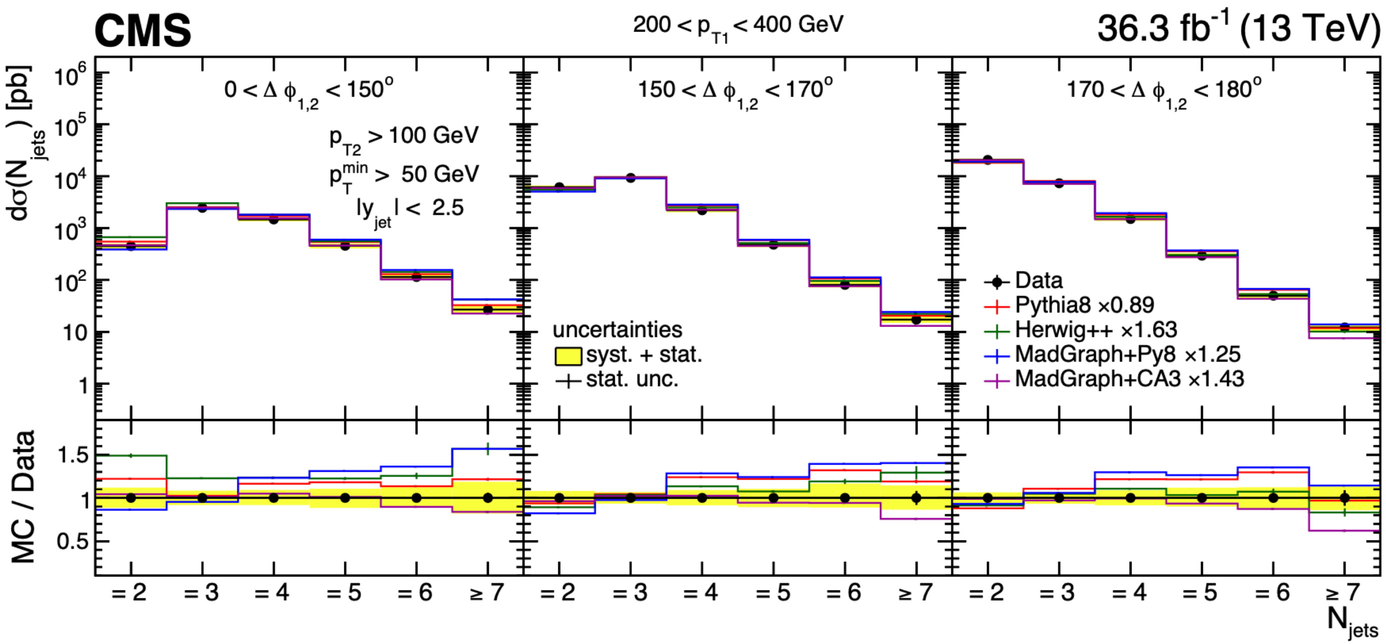
1. 미래가속기에 대한 이론적인 준비
2. 양자기반 데이터를 다루기 위한 양자알고리즘 개발
3. 미래: 양자데이터 자체를 이용할 수 있는 방법 연구

1. FCC 준비

- High multiplicity에 대한 이론적 엄밀한 예측 (Monte Carlo)
  - **Step 1: 고차원 (large n) phase-space 적분**

$$\sigma = \frac{1}{2s}\int \prod_{i=1}^{n} \frac{d^3 p_i}{(2\pi)^3 2E_i} \delta\left(k_1 + k_2 - \sum_{i=1}^{n} p_i\right) |M_{fi}|^2 \theta_{\text{cut}}(p1, \cdots, p_n)$$

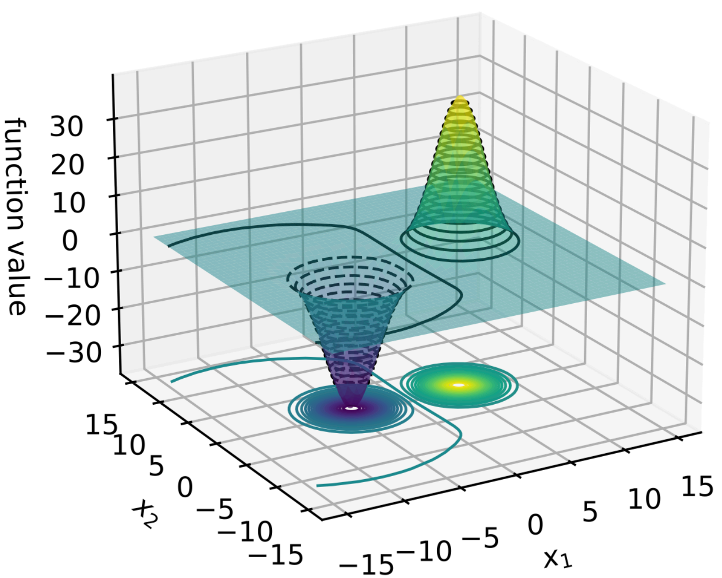
$$n \to \infty$$

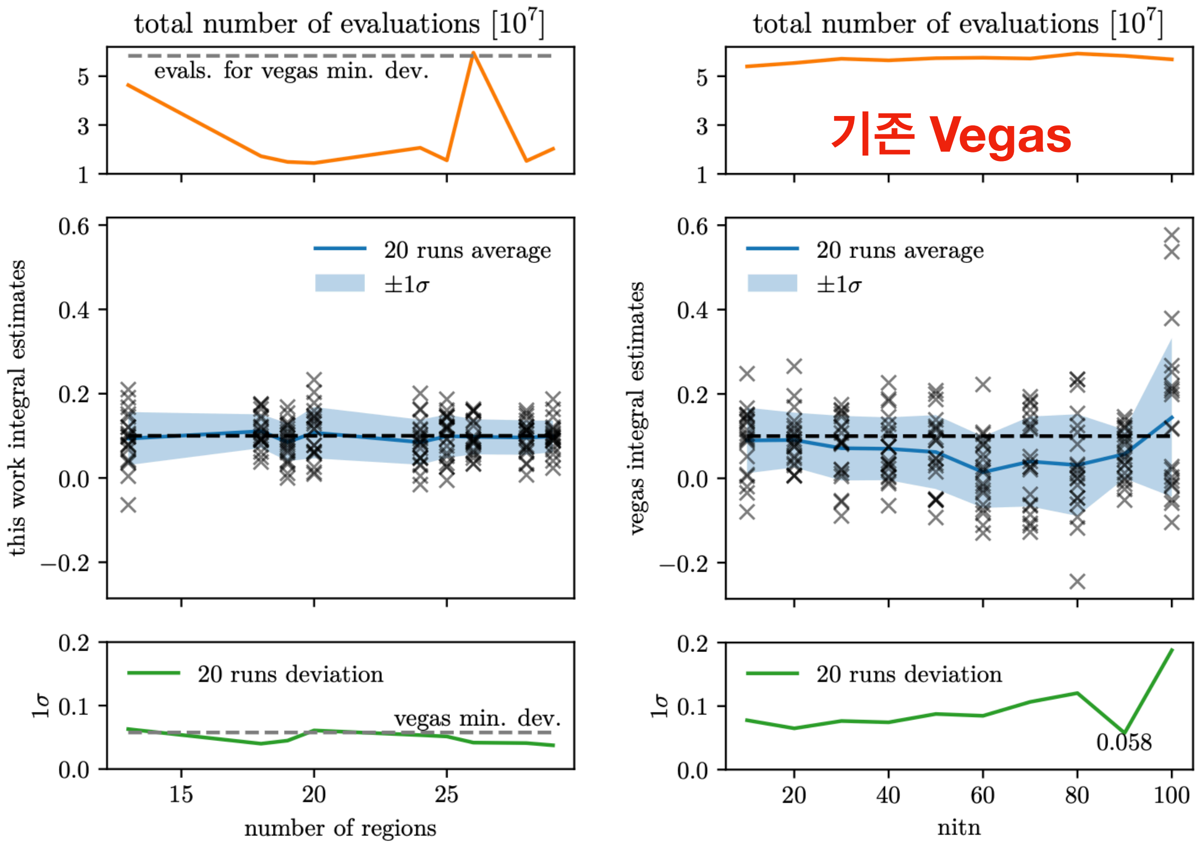


- 고차원 Monte Carlo 적분을 위한 인공지능 알고리즘 개발
  arXiv:2412.13982
  (with 고등과학원 반가영 박사, Raymundo Ramos)

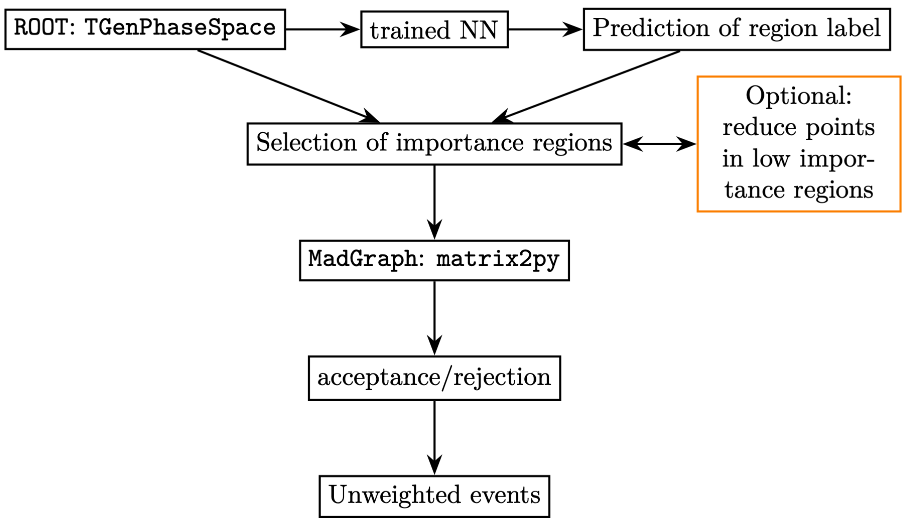
Example: $\infty - \infty = \text{finite}$ **in High Dimension phase-space**

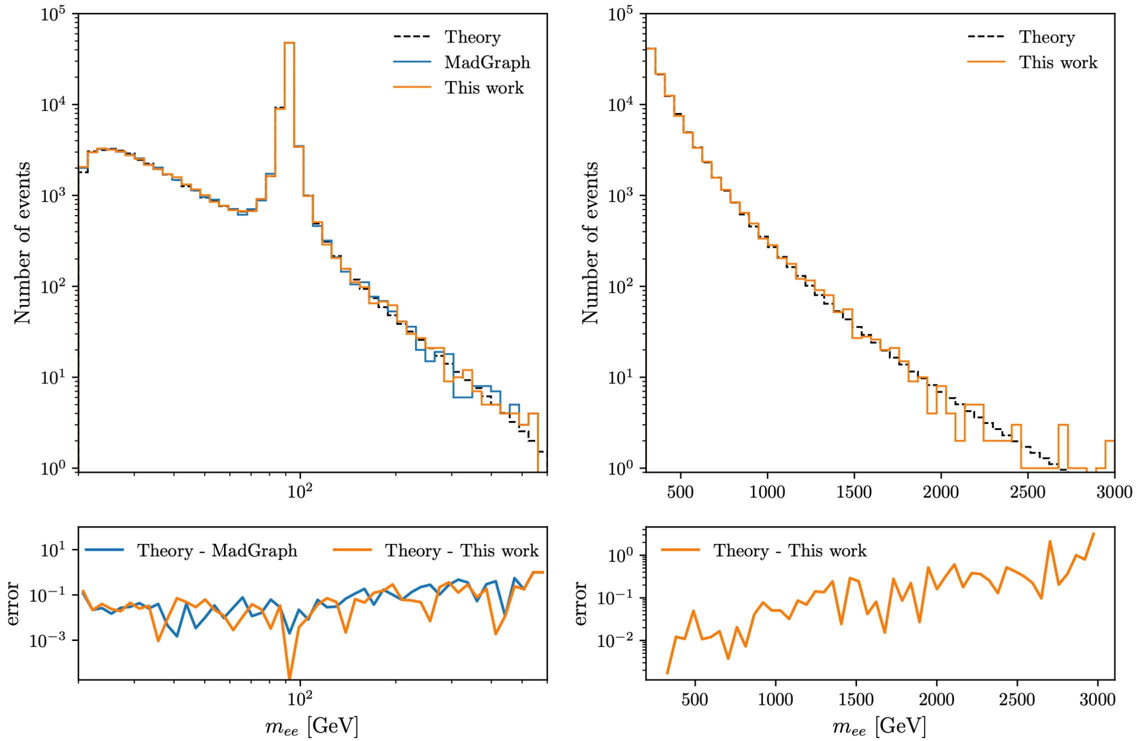
$$f_{7D}(\vec{x}) = 100 \times [G(\vec{x};\vec{\mu}_+,\sigma_+) - G(\vec{x};\vec{\mu}_-,\sigma_-)] + 0.1 \times G(\vec{x};\vec{0},\sigma_0)$$





- 이를 이용한 효율적인 샘플링을 통한 Monte Carlo 이벤트 생성

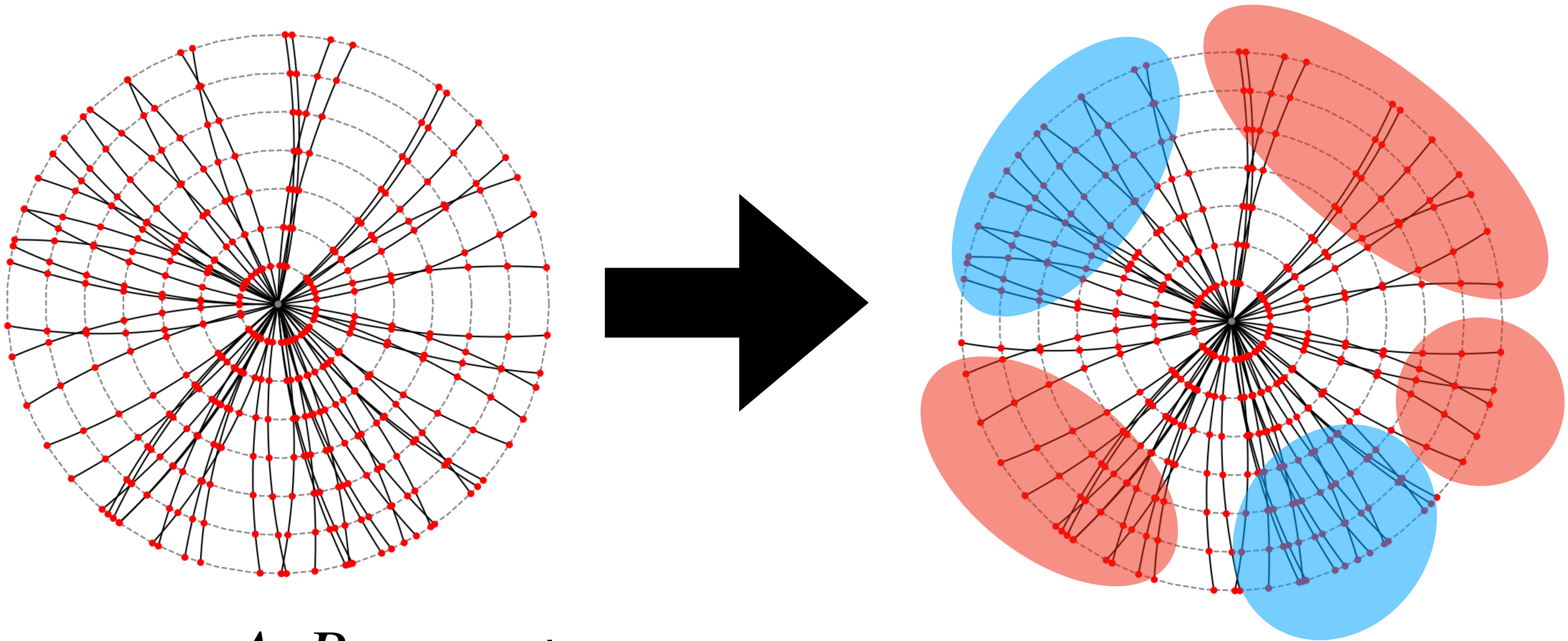




- Next step:
  - Quantum Important sampling을 이용한 새로운 방법 연구

2. 양자 알고리즘

- **High multiplicity 데이터 분석** 양자알고리즘 (clustering)
  arXiv:2410.22417 (with KC Kong's group)



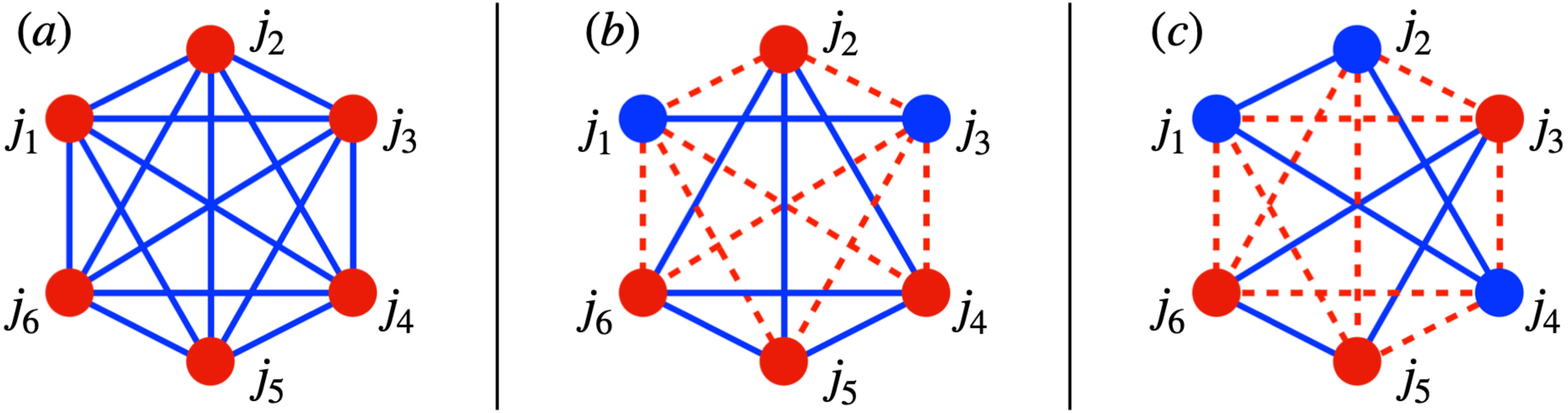
$pp \rightarrow A, B \rightarrow n_A + n_B$ **with large** n_A, n_B

- 그래프 최적화 문제

- 고에너지 물리 문제 → 그래프 최적화 문제

$$pp \to A, B \to n_A + n_B$$ **with large** n_A, n_B

- 예) $n_A + n_B = 6$ (붕괴 과정에 대한 어떠한 가정도 하지 않음)



$n_A = 6$
$n_B = 0$

$n_A = 2$
$n_B = 4$

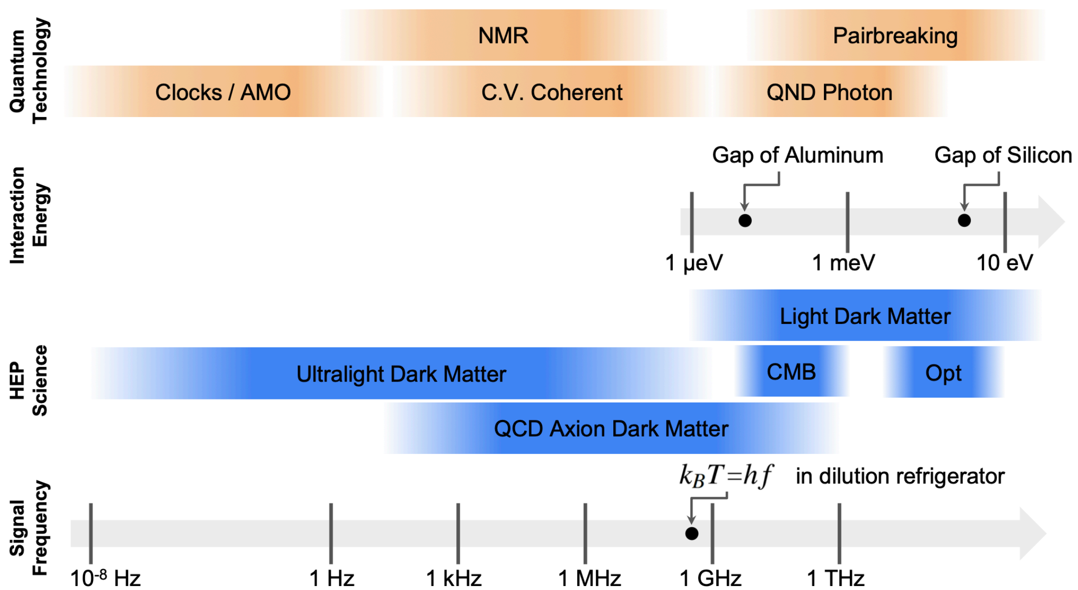
$n_A = 3$
$n_B = 3$

Methods	matching accuracy (efficiency)		n_{train}	$n_{\text{parameters}}$	depth (p)	n_{CNOT}	n_{R_Z}	n_{R_X}
	parton-level	smeared events						
Hemisphere	50%	48%	N/A					
QAOA	55%	53%	N/A	16	8	240	120	48
ma-QAOA	75%	73%		168				
FALQON	72%	69%		2	250	7,500	3,750	1,500
SPANet	91%	70%	5×10^5	10^6	N/A			
	81%	62%	2×10^4	1.9×10^3				

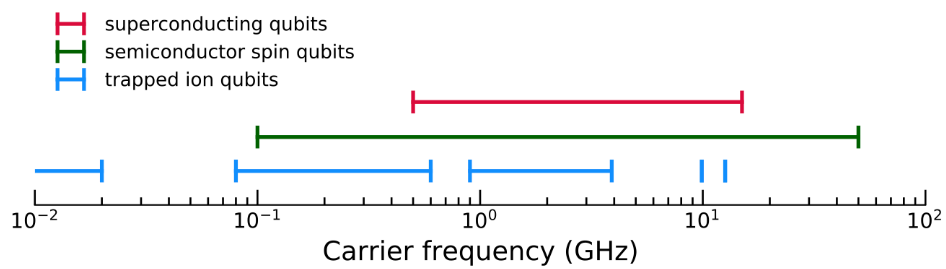
- 양자머신러닝 알고리즘 : 양자게이트 + (머신러닝) 수치적 최적화 : 양자머신러닝의 문제점
- (Pure) 양자알고리즘 : 최적화가 필요없는 iterative 양자알고리즘
- 최신 머신러닝 알고리즘 : 최신 거대언어모델(Transformer)를 활용한 인공지능 알고리즘
  - 이 머신러닝 알고리즘은 학습을 위한 빅데이터가 필요

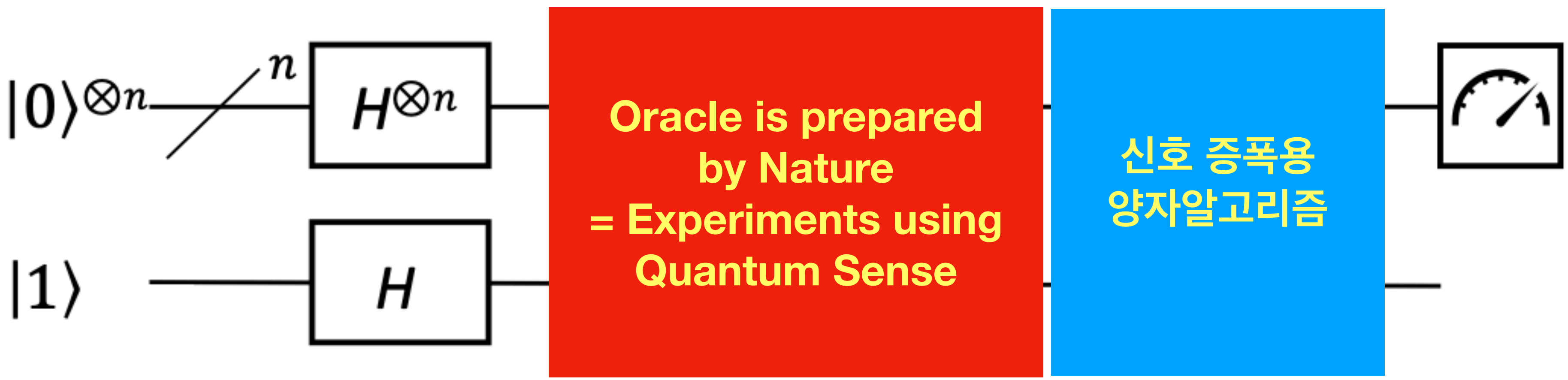
3. 미래

- 입자물리 실험(암흑물질 탐색, Axion search)에서 오는 양자데이터 활용



Qubit control Microwave frequency





workshops

1. Focused workshop on AI in High Energy Physics
   (1월 6일 - 7일, 고등과학원)

   https://indico.kias.re.kr/e/AIHEP2025

2. KCMS-Theory Joint Annual Workshop
   (1월 8일 - 11일, 하이원)

   https://indico.kias.re.kr/e/jointworkshop2025

Back-up

Utilizing Gate Quantum Circuit

- Starting from a well-known QAOA (arXiv:1411.4028) (Quantum Approximation Optimization Algorithm)

$$H(t) = (1 - a(t))\, H_M + a(t) H_P$$

- with $H_M = \sum \sigma_i^X$ and $H_P = \sum_{ij} J_{ij} \sigma_i^Z \sigma_j^Z$ for qubit i and j

- Starting from the ground state of H_M : $|\psi_0\rangle = |+\rangle$, evolve to the ground state of H_P : $|\psi\rangle = U(T,0)\,|\psi_0\rangle$

$$\begin{aligned} U(T,0) &= U(T, T-\Delta t) U(T-\Delta t, T-2\Delta t) \cdots U(\Delta t, 0) \\ &= \prod_{j=1}^{p} U(j\Delta t, (j-1)\Delta t) \end{aligned}$$

- Evolution operator $U(T{,}0)$

$$U(T,0) \approx \prod_{j=1}^{p} e^{-i\Delta t H(j\Delta t)} = \prod_{j=1}^{p} \exp\Big[-i\Delta t\big[(1-a(j\Delta t))H_M + a(j\Delta t)H_P\big]\Big]$$

- With Suzuki-Trotter decomposition, $\lim_{n\to\infty} (e^{iAt/n}e^{iBt/n})^n = e^{i(A+B)t}$

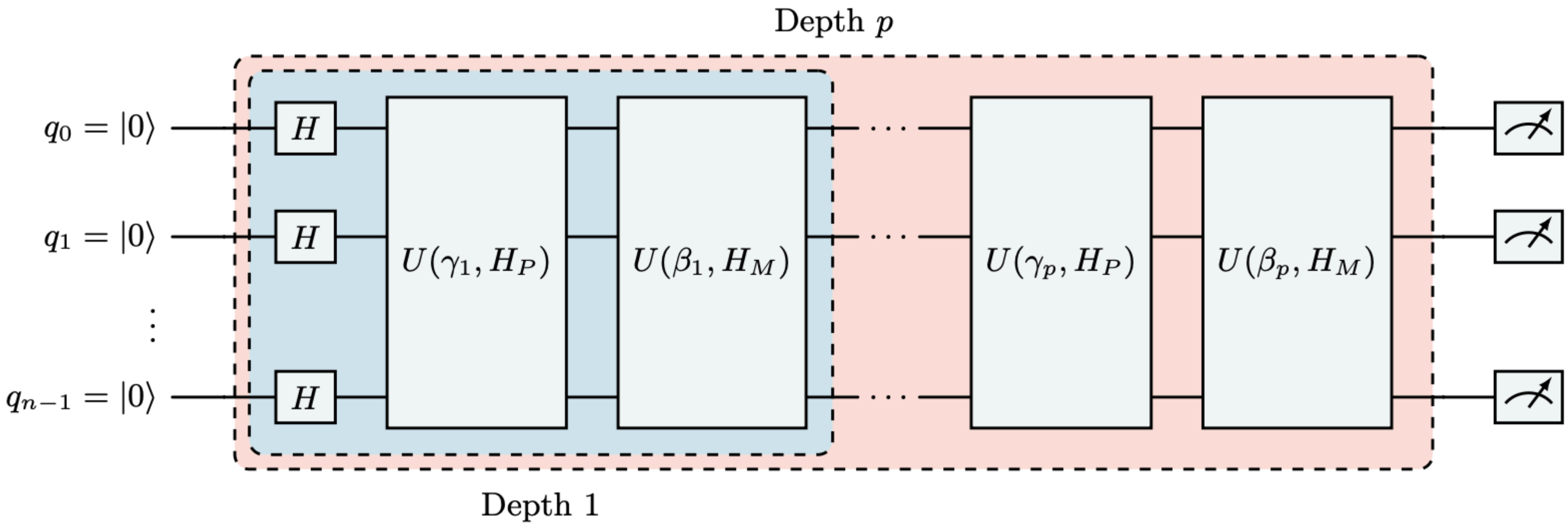
$$U(T,0) \approx \prod_{j=1}^{p} \exp\Big[-i\Delta t(1-a(j\Delta t))H_M\Big]\exp\Big[-i\Delta t a(j\Delta t)H_P\Big]$$

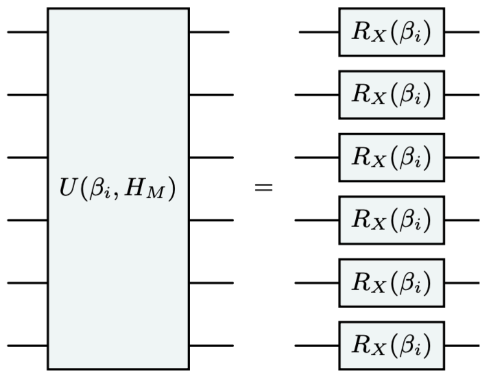
$$= \prod_{j=1}^{p} \exp\Big[-i\beta_j H_M\Big]\exp\Big[-i\gamma_j H_P\Big]$$

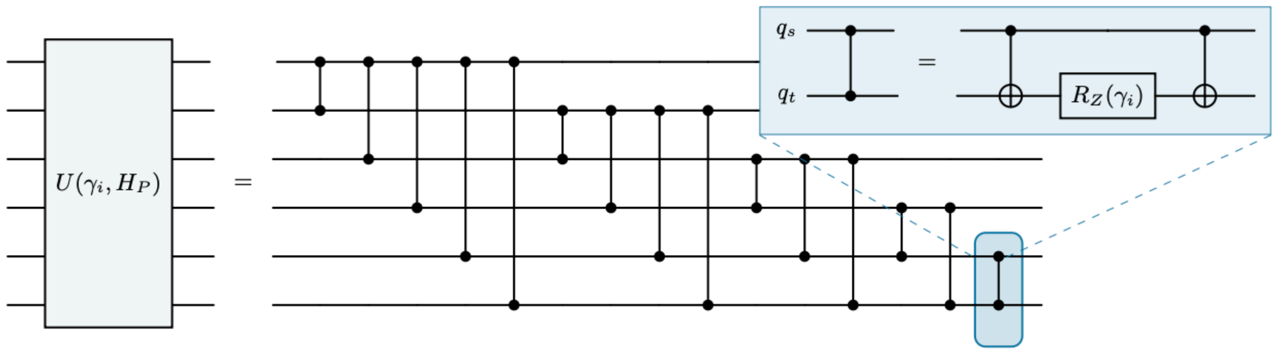
$$|\psi\rangle \equiv |\boldsymbol{\beta},\boldsymbol{\gamma}\rangle = \sum_{j=1}^{p} U(\beta_j, H_M)U(\gamma_j, H_P)\,|+\rangle^{\otimes n}$$

- Try to minimize $\langle H_P\rangle = \langle \boldsymbol{\beta},\boldsymbol{\gamma}|H_P|\boldsymbol{\beta},\boldsymbol{\gamma}\rangle = \langle\psi|H_P|\psi\rangle$

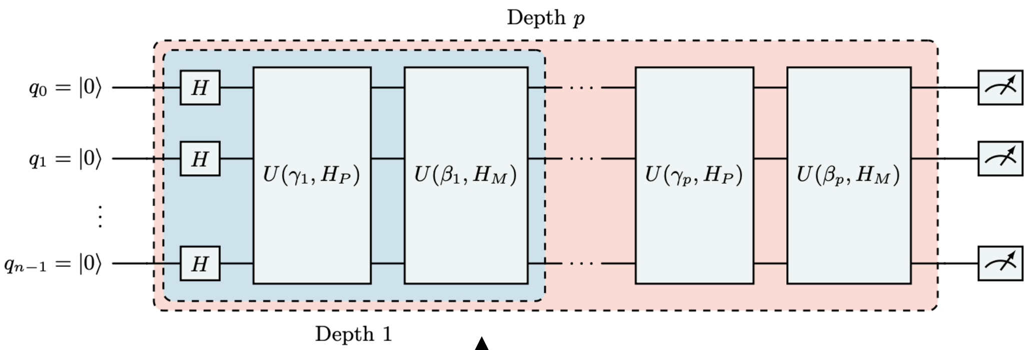
QAOA gate


Depth p
$q_0 = |0\rangle$
$q_1 = |0\rangle$
$q_{n-1} = |0\rangle$
H
$U(\gamma_1, H_P)$
$U(\beta_1, H_M)$
$U(\gamma_p, H_P)$
$U(\beta_p, H_M)$
Depth 1


$U(\beta_i, H_M)$
=
$R_X(\beta_i)$


$U(\gamma_i, H_P)$
=
q_s
q_t
=
$R_Z(\gamma_i)$

Variational Method



Measurement:

$$L(\beta, \gamma) \equiv |\langle \psi(\beta, \gamma) | H_P | \psi(\beta, \gamma) \rangle|^2$$

Using "classical optimizer"

$$(\beta, \gamma) \rightarrow (\beta^*, \gamma^*)$$

update

- Find the minimum of a given hamiltonian H.

  - The state $|\psi(\beta, \gamma)\rangle = U(\beta, \gamma)|0\rangle$

  - $L(\beta, \gamma) \equiv |\langle \psi(\beta, \gamma) | H_P | \psi(\beta, \gamma) \rangle|^2$ will have a minimum

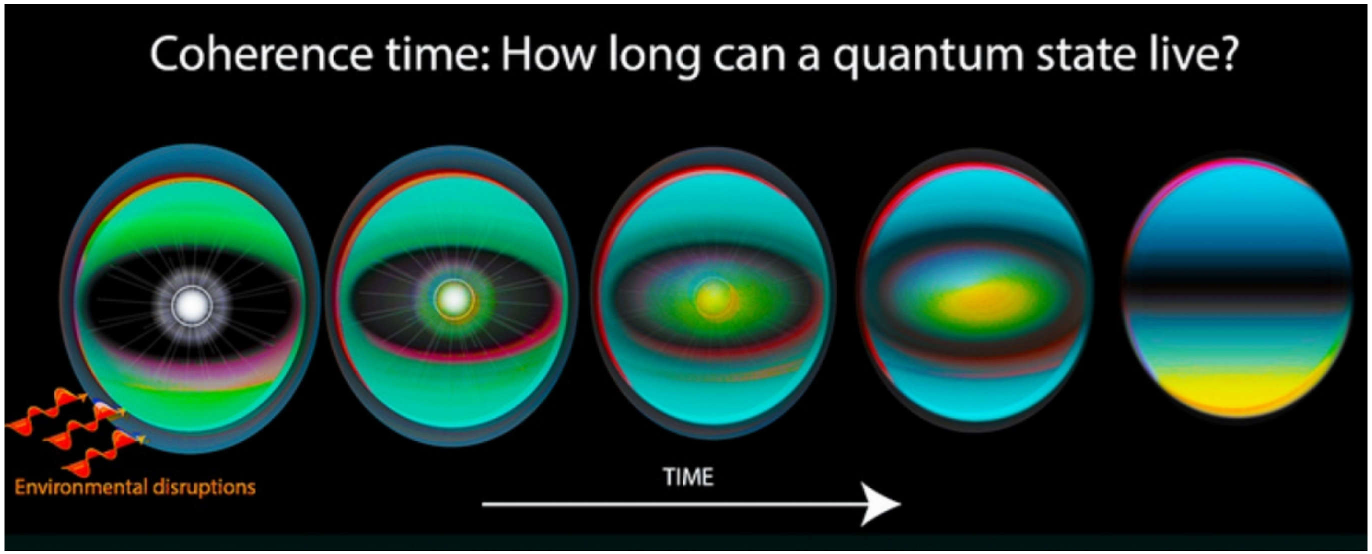
    when $|\psi(\beta^*, \gamma^*)\rangle = U(\beta^*, \gamma^*)|0\rangle \simeq |\psi_{\min}\rangle$

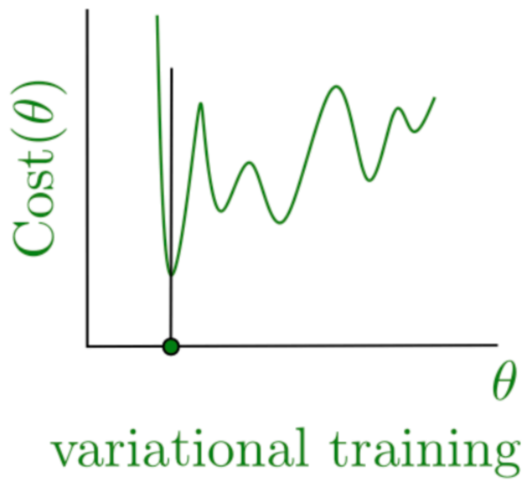
- Finding the $(\beta^*, \gamma^*) = \text{argmin}\, L(\beta, \gamma)$ with a classical optimizer method. (For example, Gradient Descent Method)

Issue of vanilla QAOA

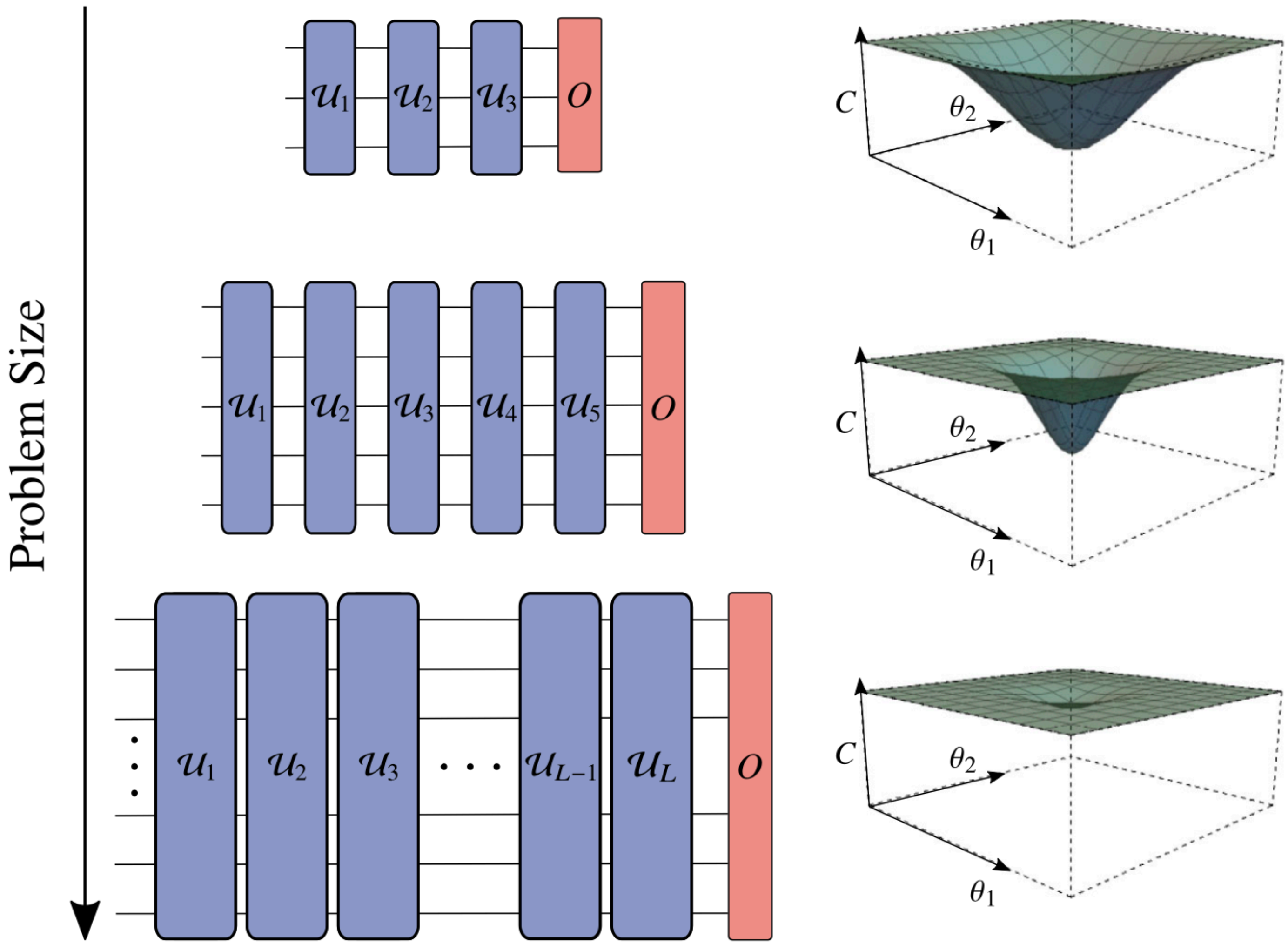
- The approximation requires the depth of circuit $p \to \infty$
  : Practical issue of QC (decoherence)

- Local minima issue / barren plateau





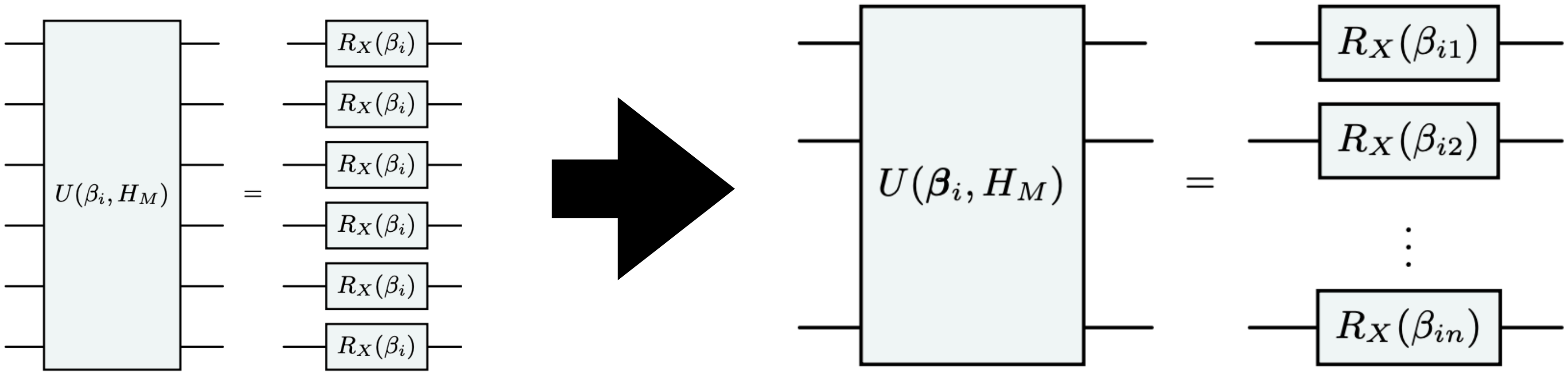
- With increasing size of a circuit, the gradient vanishes exponentially.



Nature Communications volume **12**, Article number: 6961 (2021) by Samson Wang et.al.

Variations of QAOA

- ma-QAOA: What if each qubit has it's own free parameter? (increase degree of freedom)



- XQAOA: What if there is also another Mixer Hamiltonian, H_X ?

$$|\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}\rangle = \sum_{j=1}^{p} U(\boldsymbol{\alpha}_j, H_X) U(\boldsymbol{\beta}_j, H_M) U(\boldsymbol{\gamma}_j, H_P)$$

with $$U(\boldsymbol{\alpha}_j, H_X) = \exp\left[-i \sum_{i=1}^{n} \alpha_{ji} \sigma_i^Y\right]$$

- FALQON: Purely quantum. What if we iteratively build the circuit where the next free parameter depends on an expectation value of the current circuit