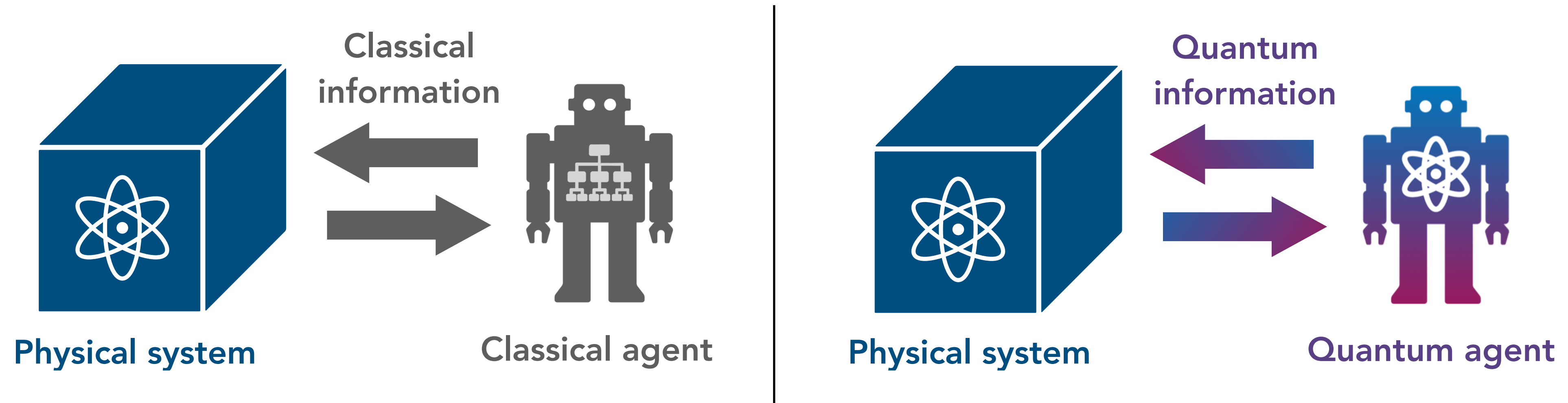


Ph 220: Lecture 20

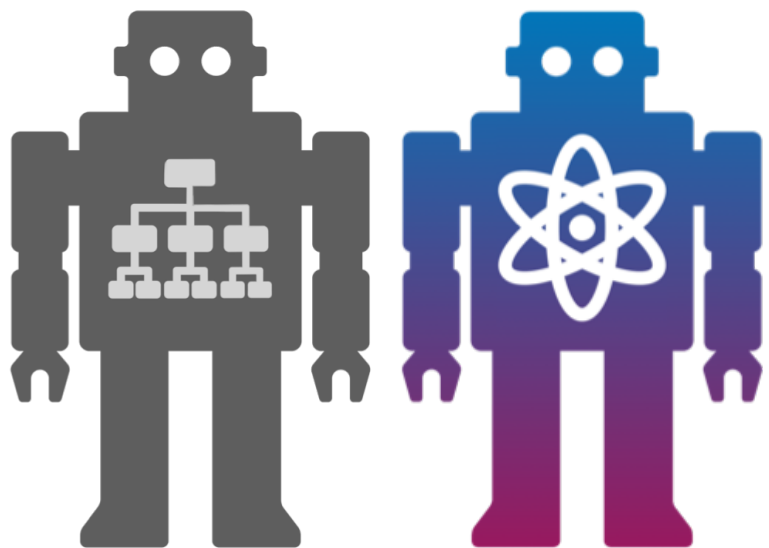
Next Steps for Quantum x AI

Classical vs Quantum AI

- What are the **advantages** of quantum AI agents over classical AI?
- Could quantum technology fundamentally alter our ability to **learn** about the world?



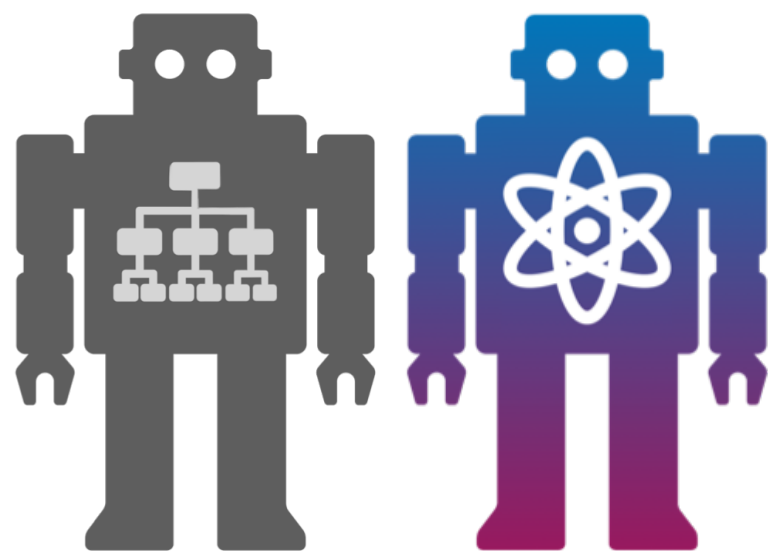
Exponential quantum advantage



Exponential quantum advantage

Predicting many incompatible observables

To predict all Pauli observables $\{I, X, Y, Z\}^{\otimes n}$,
classical agent needs $\Omega(2^n)$ experiments,
quantum agent only needs $\mathcal{O}(n)$ experiments.



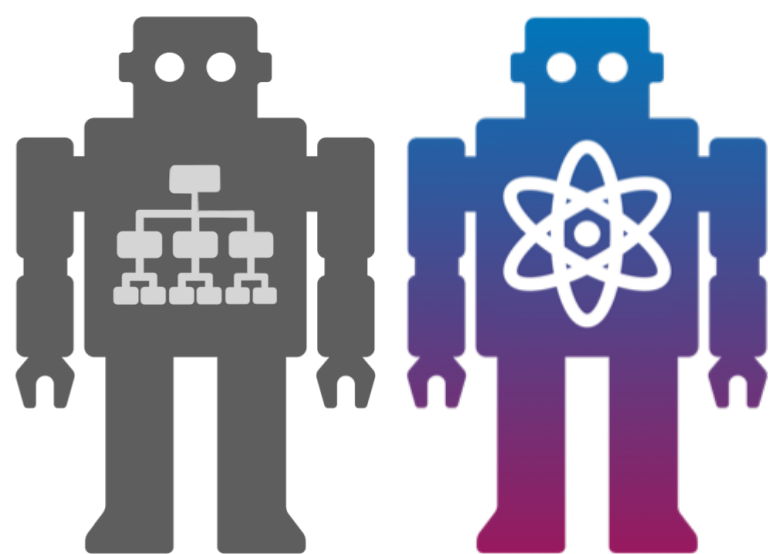
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Performing quantum PCA

To estimate property of principal component,
classical agent needs exponential time,
quantum agent needs polynomial time.



Exponential quantum advantage

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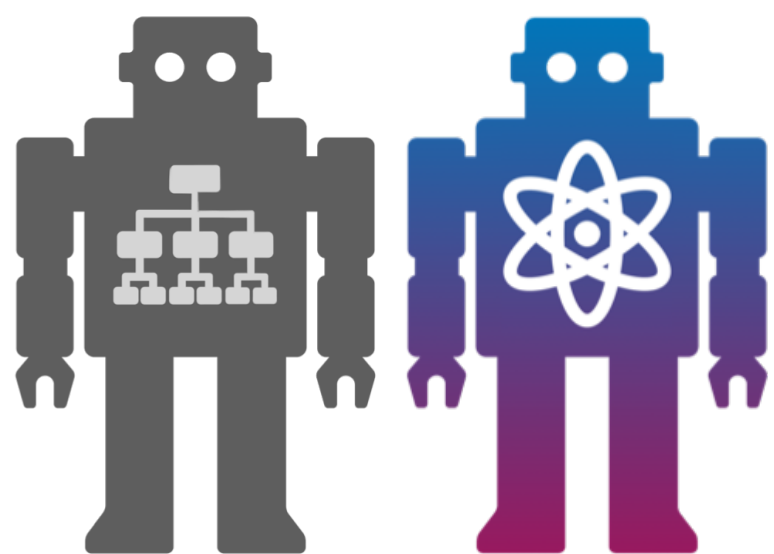
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Uncovering symmetry in dynamics

Classifying dynamics with or without time-reversal
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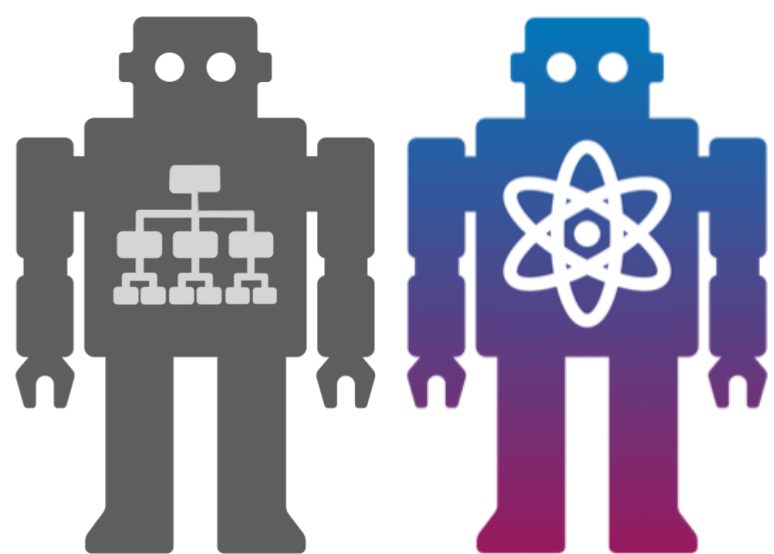
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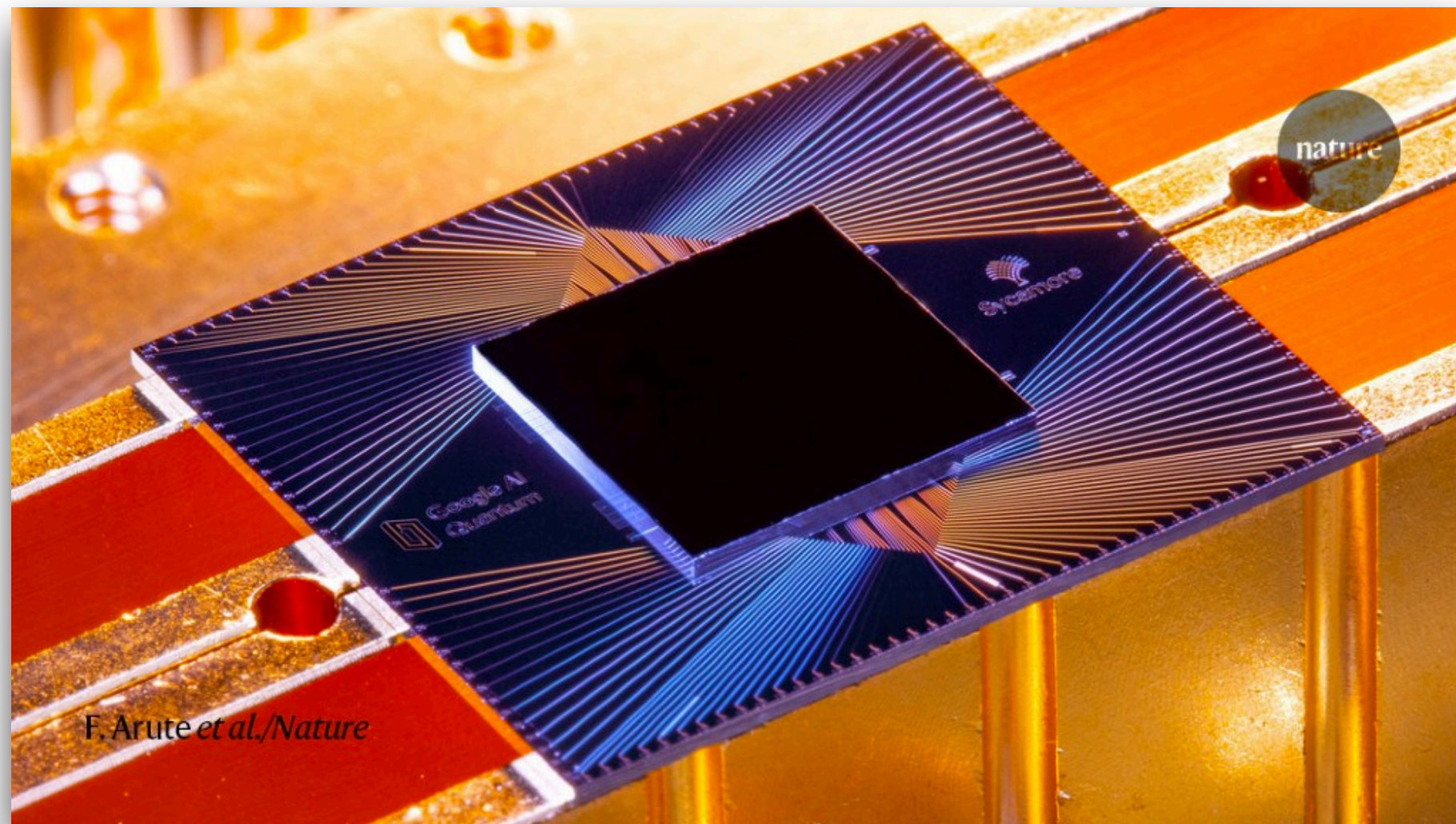
Learning physical dynamics

To learn a polynomial-time quantum process,
a classical agent requires **exponential experiments**,
a quantum agent only needs **polynomial experiments**.

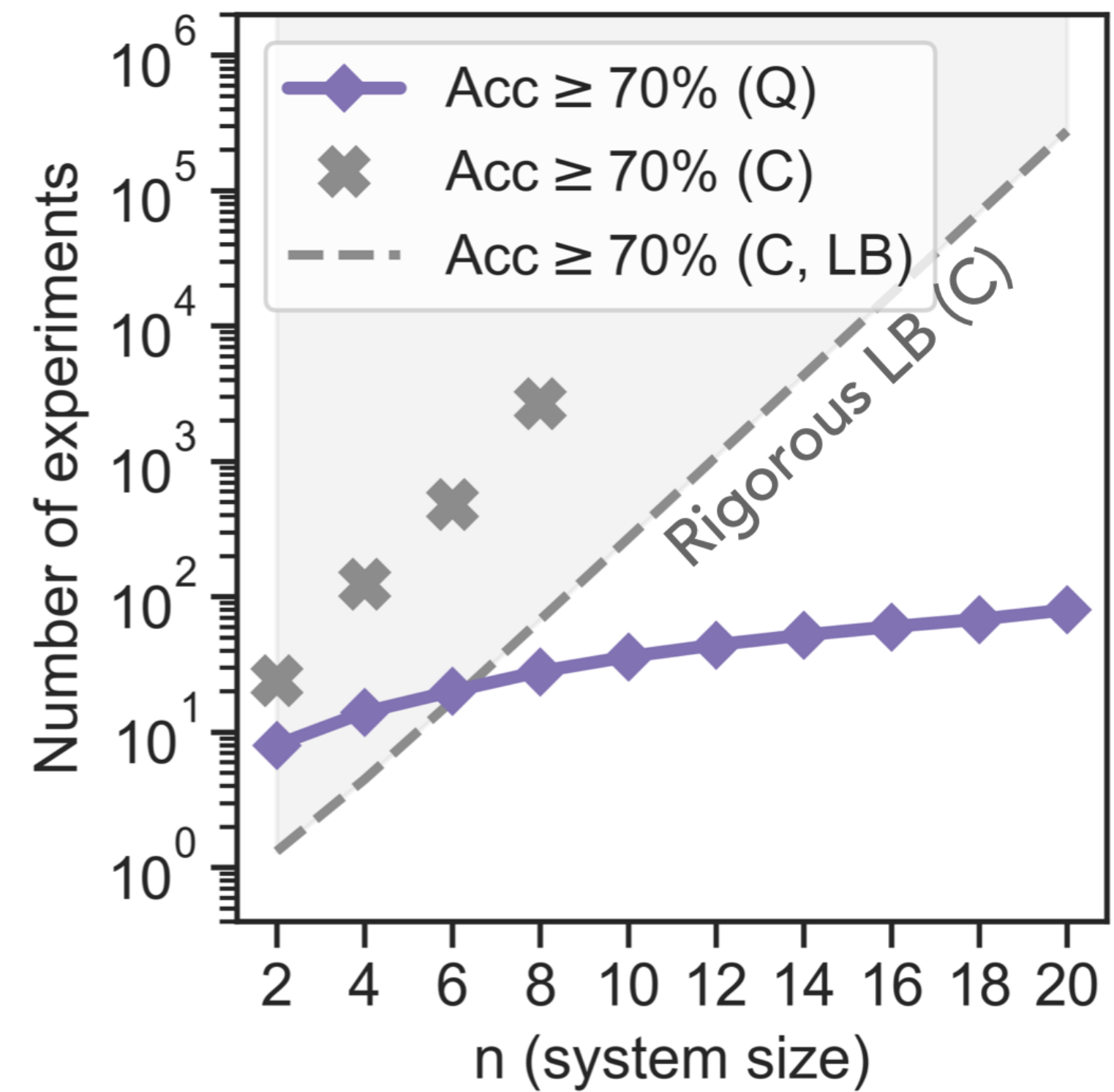


Demonstration on Sycamore: Quantum advantage in learning states

Utilizing a total of 40 qubits

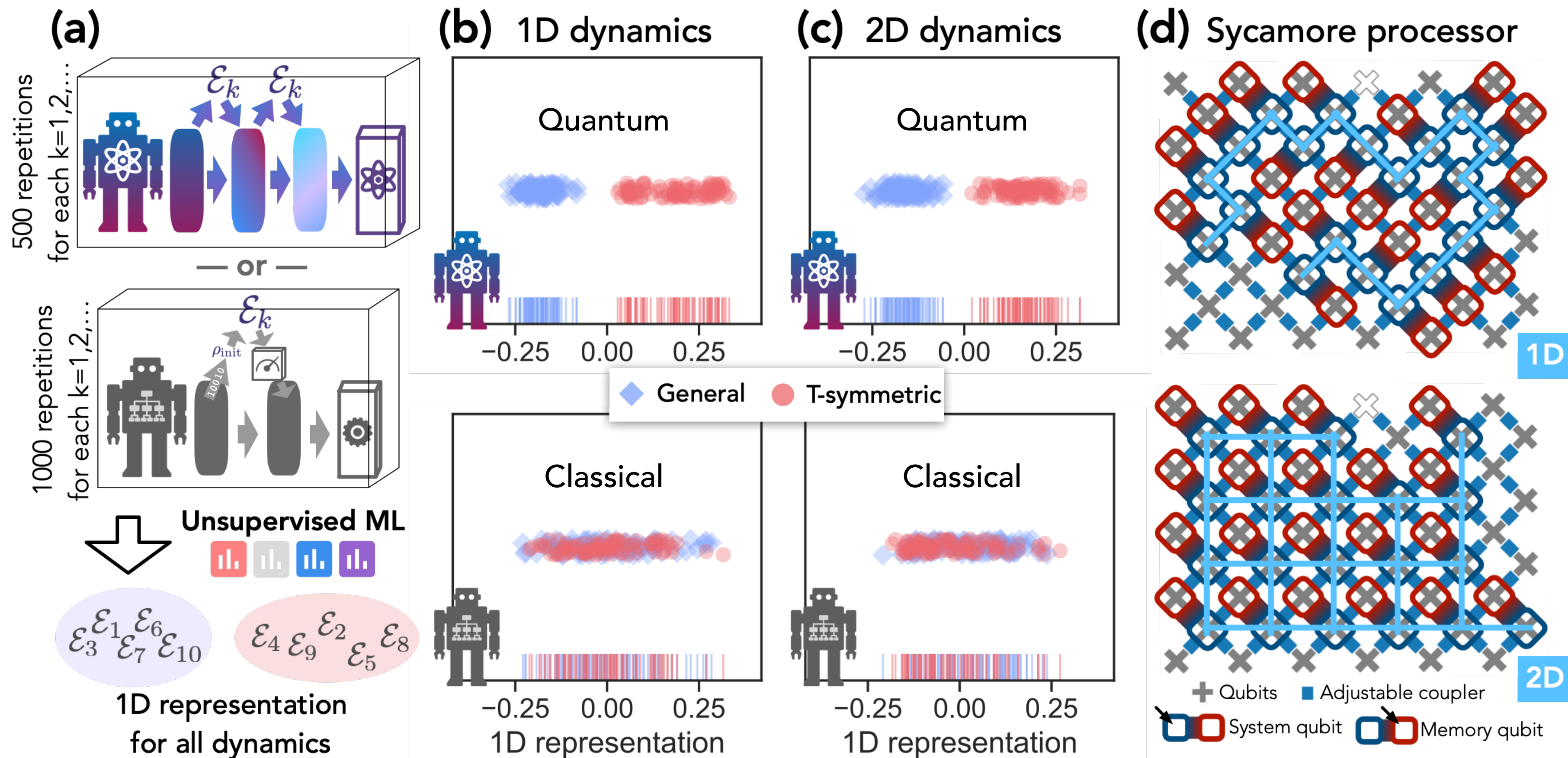


Sycamore Processor



Demonstration on Sycamore:

Quantum advantage in learning dynamics



What we learned so far

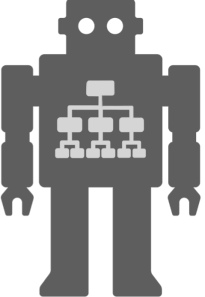
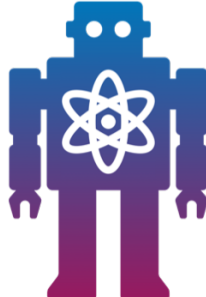
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♣ How to efficiently learn in the quantum universe?

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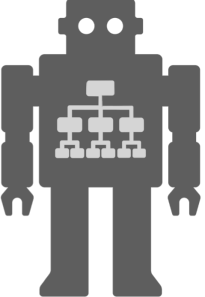
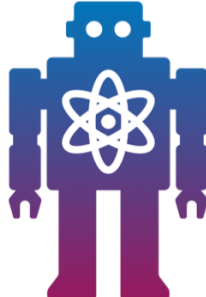
We have seen how to learn fields, **states**, **unitaries**, **Hamiltonians**, **devices**

( via randomized measurement,  via gentle entangled measurement)

What we learned so far

♣ How to efficiently learn in the quantum universe?

We have seen how to learn fields, **states**, **unitaries**, **Hamiltonians**, **devices**

( via randomized measurement,  via gentle entangled measurement)

Mathematical tools: concentration inequality, Weingarten calculus, gentle measurements, matrix analysis.

What we learned so far

♣ What physical phenomena can quantum machines learn?

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Evolution time, causal structure, entanglement, topological order, noise
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What we learned so far

♣ What physical phenomena can quantum machines learn?

Evolution time, causal structure, entanglement, topological order, noise in state/measurement are **quantumly hard** to feel/see/measure/learn.

Mathematical tools: cryptography, purification, pseudorandom states and unitaries, representation theory.

What we learned so far

♣ When can quantum machines learn/predict better than classical?

What we learned so far

♣ When can quantum machines learn/predict better than classical?

QNNs can learn to generate classically hard distributions.

Quantum AI can learn exponentially faster than classical AI in quantum tasks.

What we learned so far

♣ When can quantum machines learn/predict better than classical?

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Mathematical tools: teleportation/MBQC, quantum complexity theory, learning tree, uncertainty principle.

Where do we go from here?

Where do we go from here?

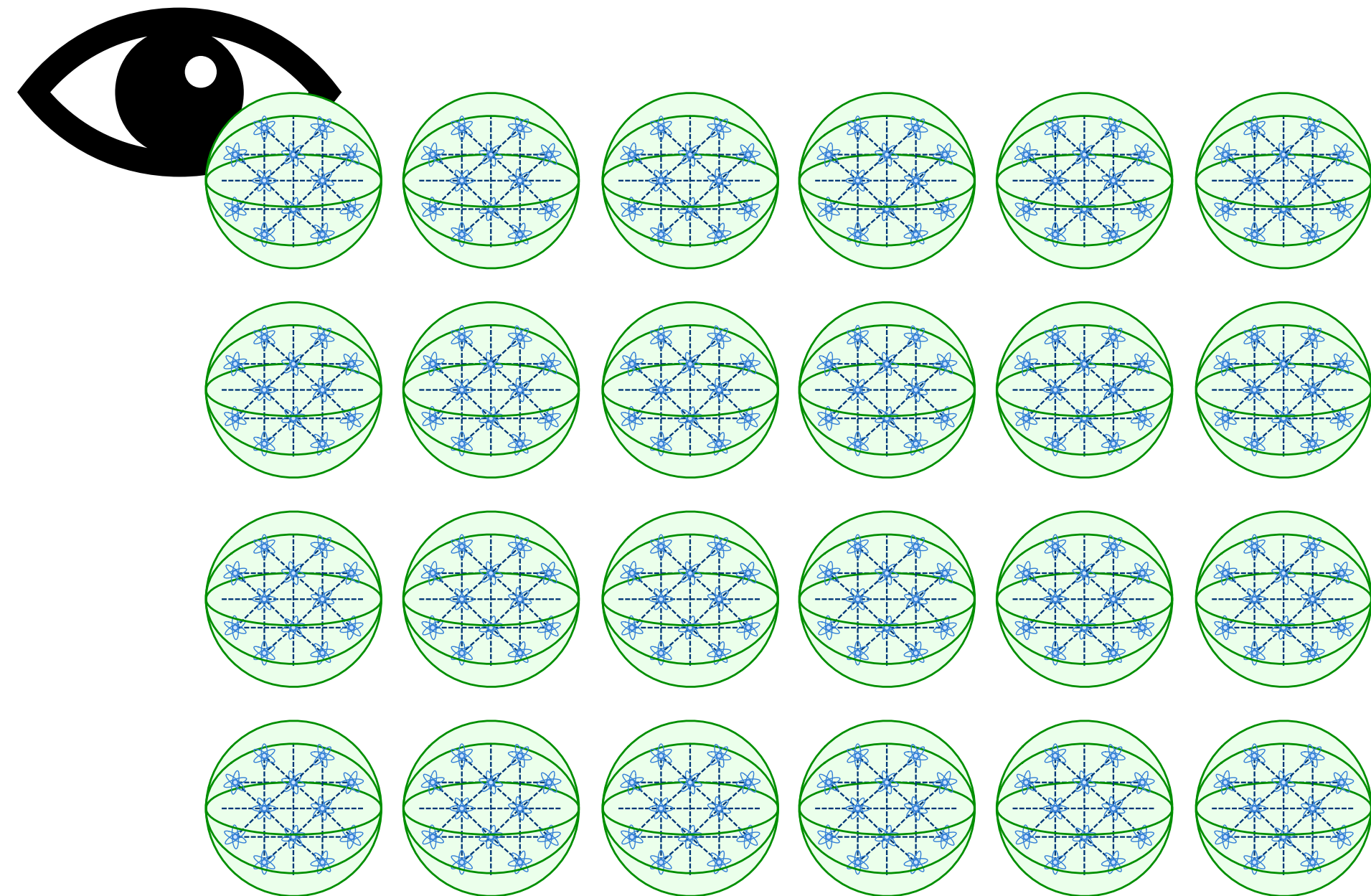
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How to **accelerate/automate** quantum technology with AI?

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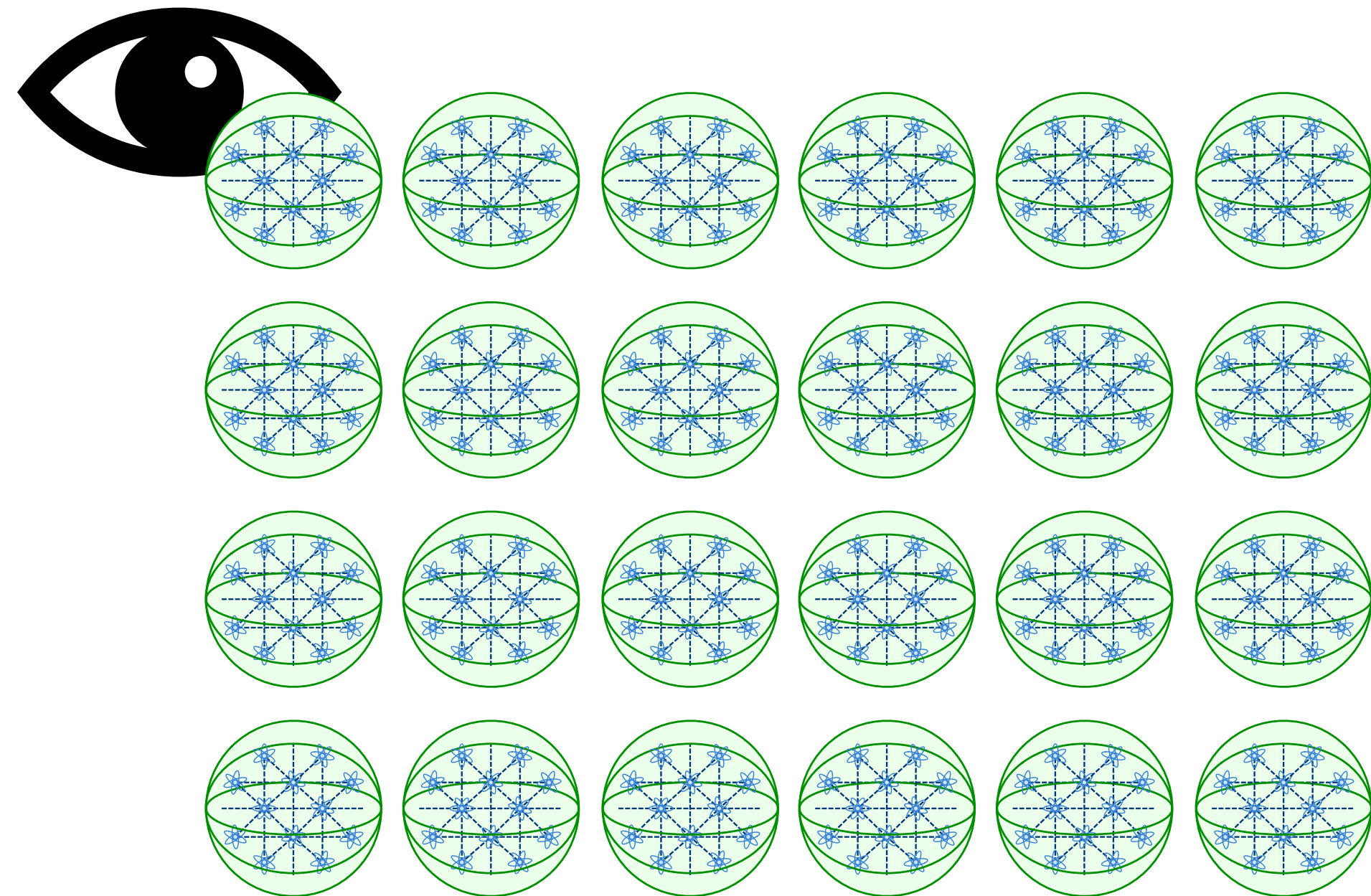
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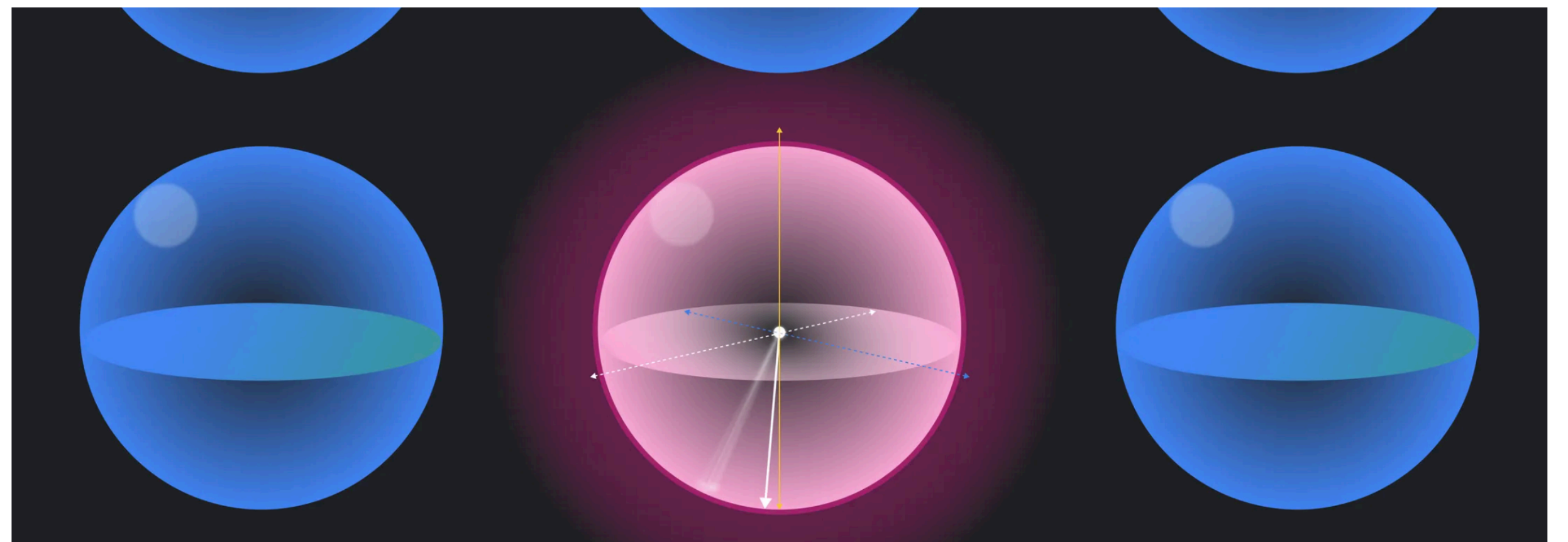


AlphaQubit tackles one of quantum computing's biggest challenges



Google DeepMind and Quantum AI teams

 Share



Where do we go from here?

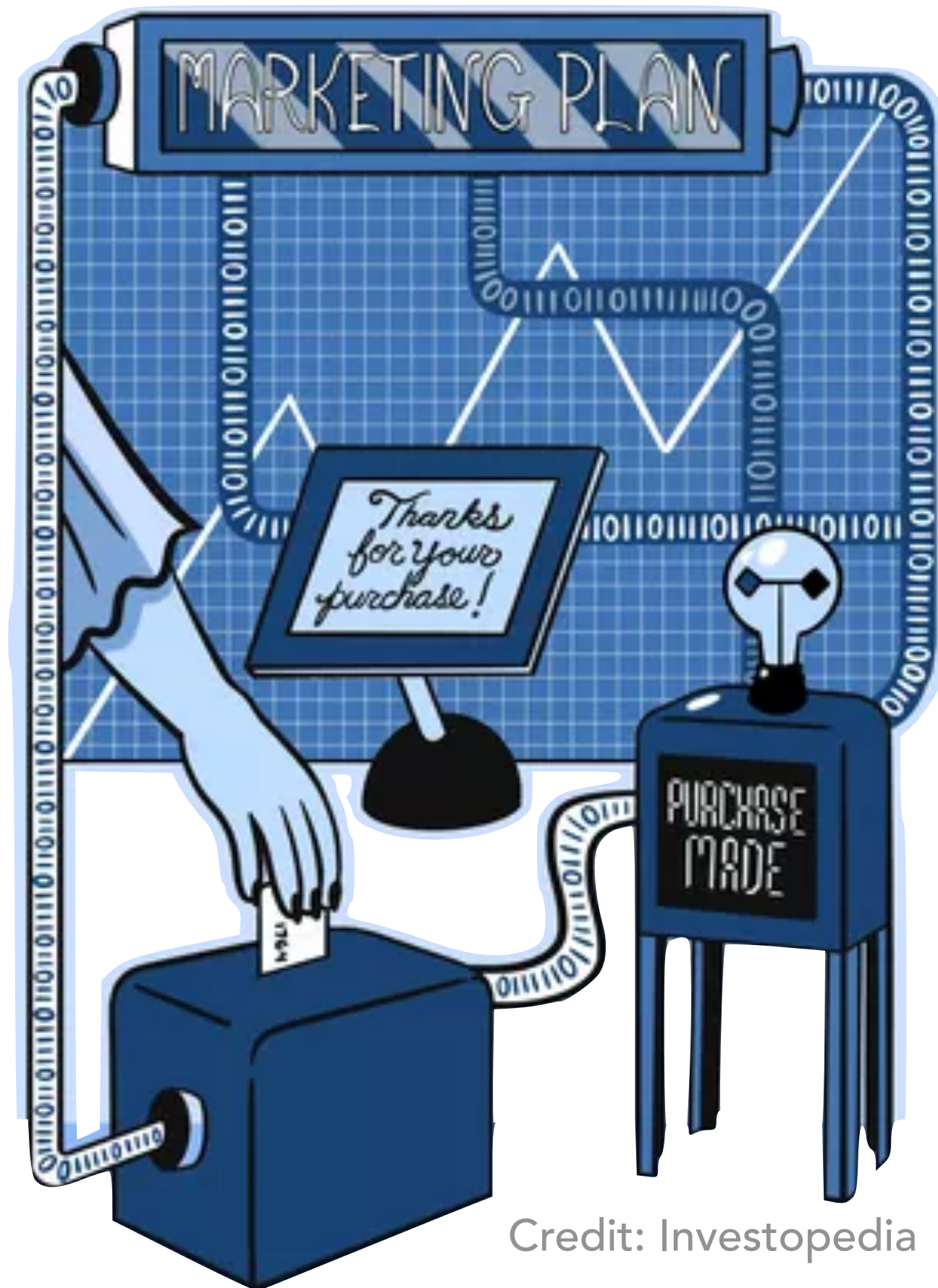
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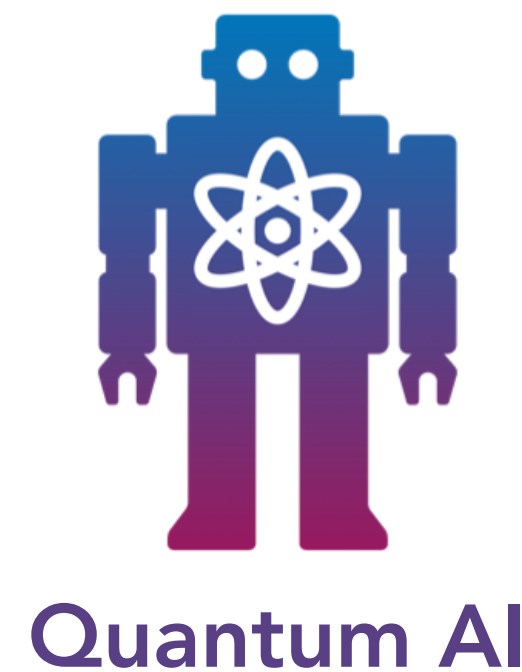
♣ Quantum Advantage for Classical AI:

Can quantum machines achieve **significant advantage** in learning problems arising from **classical ML/AI**?

Quantum Advantage for Analyzing Classical Data



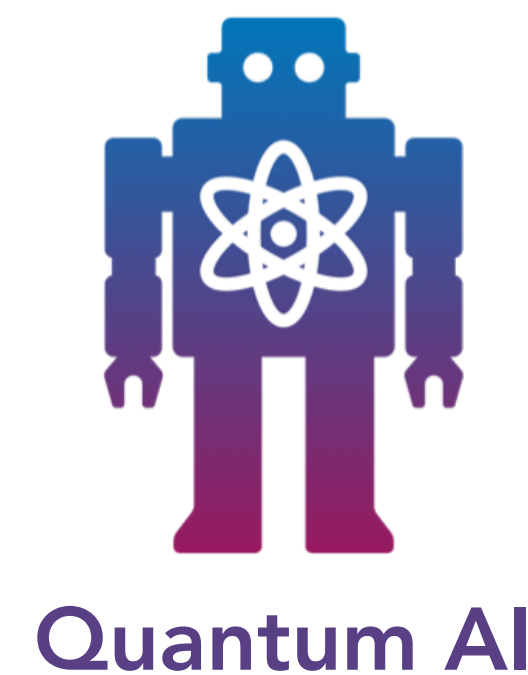
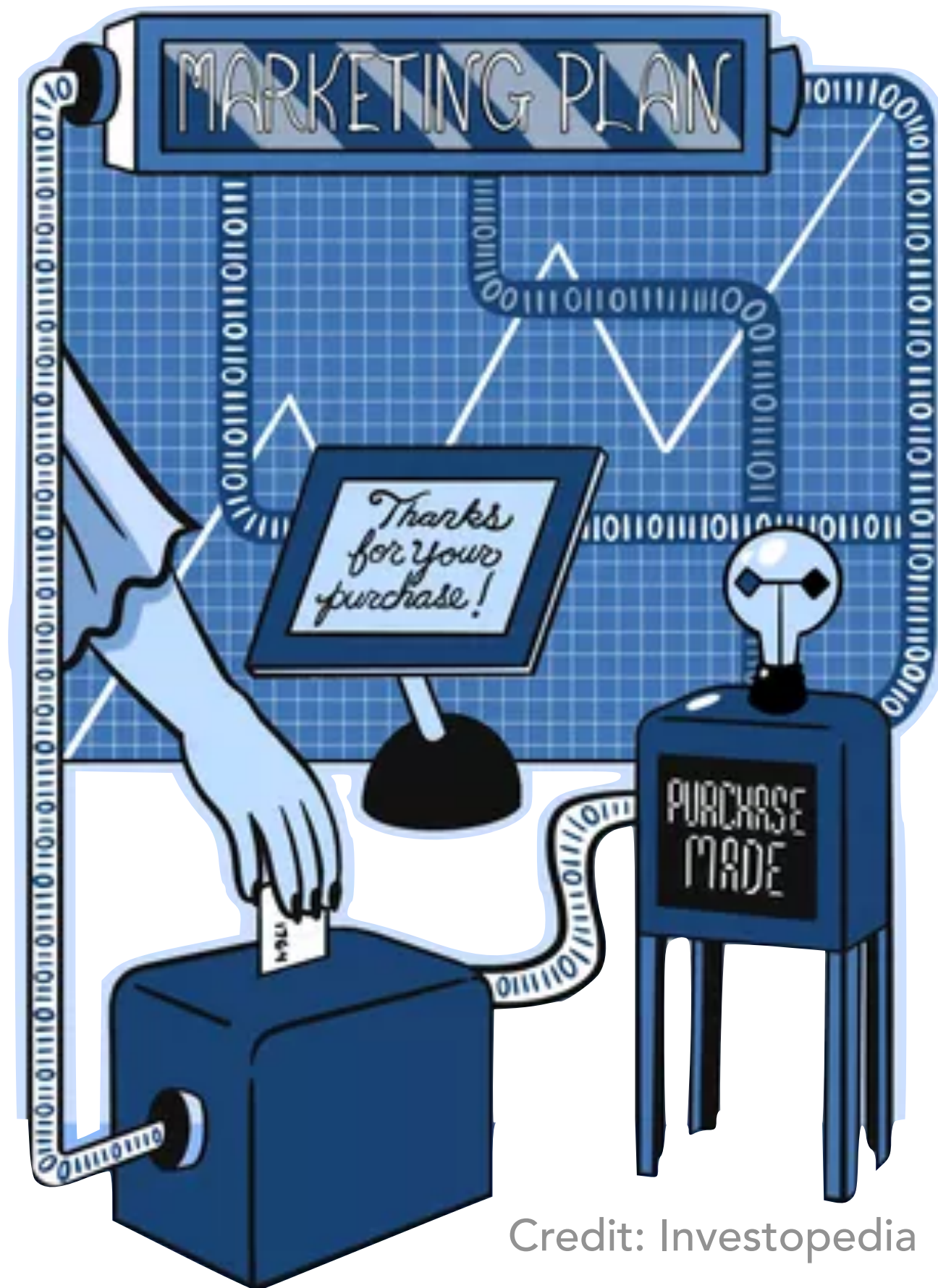
Credit: Investopedia



Question:

Can quantum AI offer useful advantage in analyzing large amount of **classical data**?

Quantum Advantage for Analyzing Classical Data

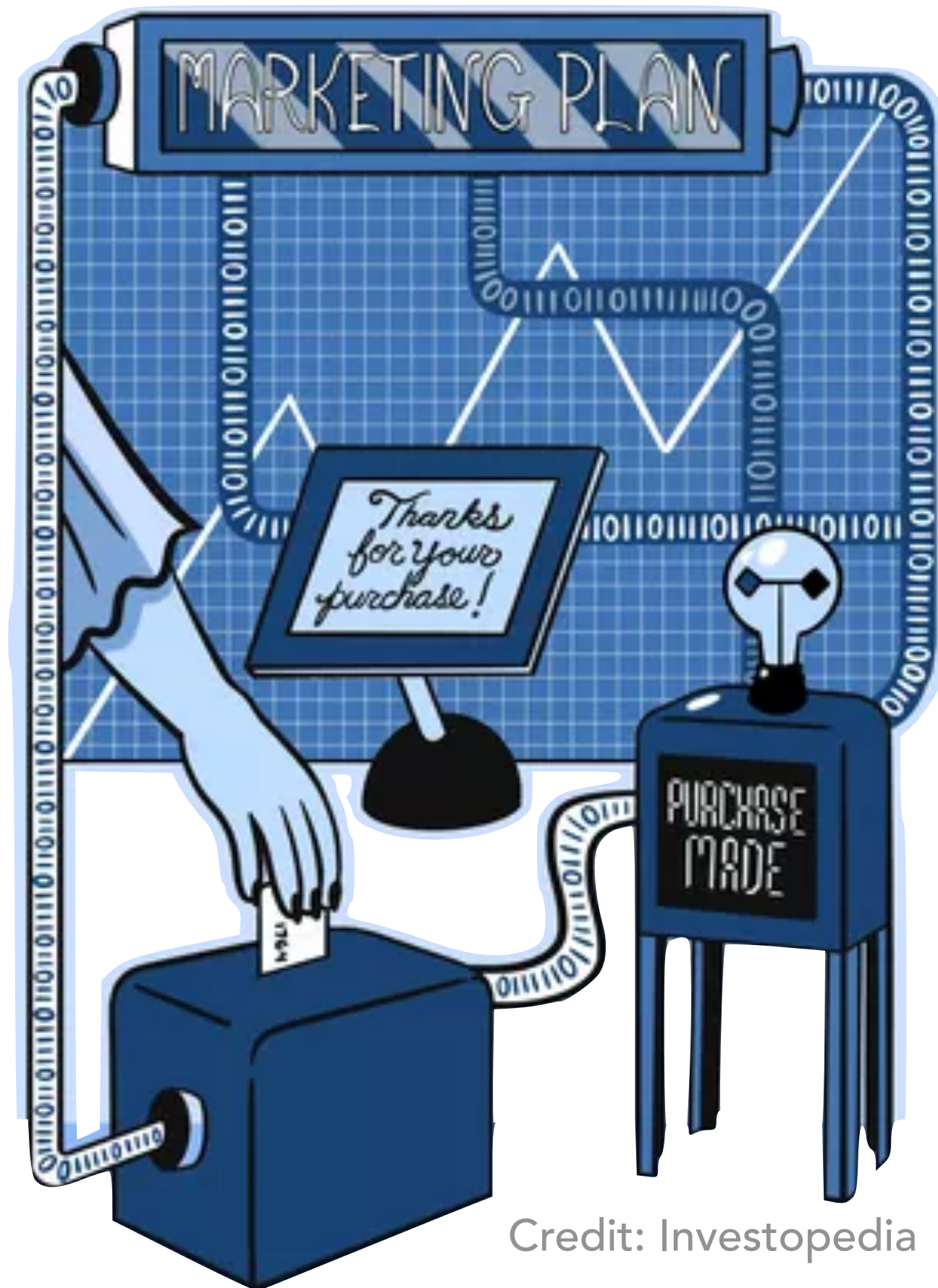


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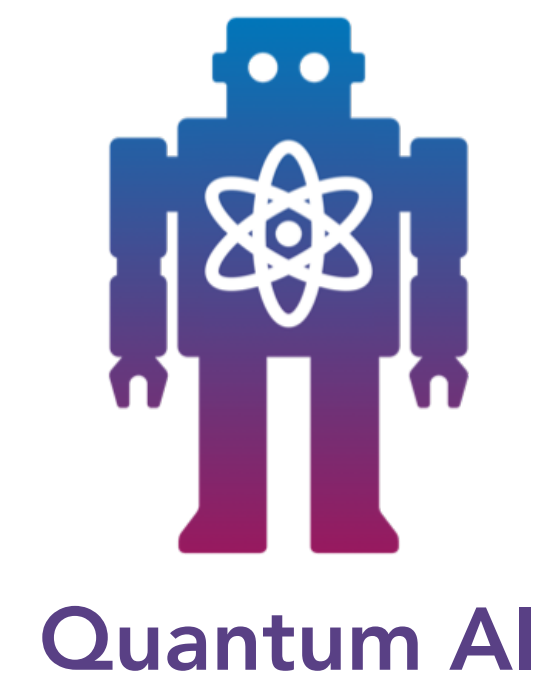
Can quantum AI offer useful advantage in analyzing large amount of **classical data**?

Existing QML algorithms
does not seem useful.

Quantum Advantage for Analyzing Classical Data



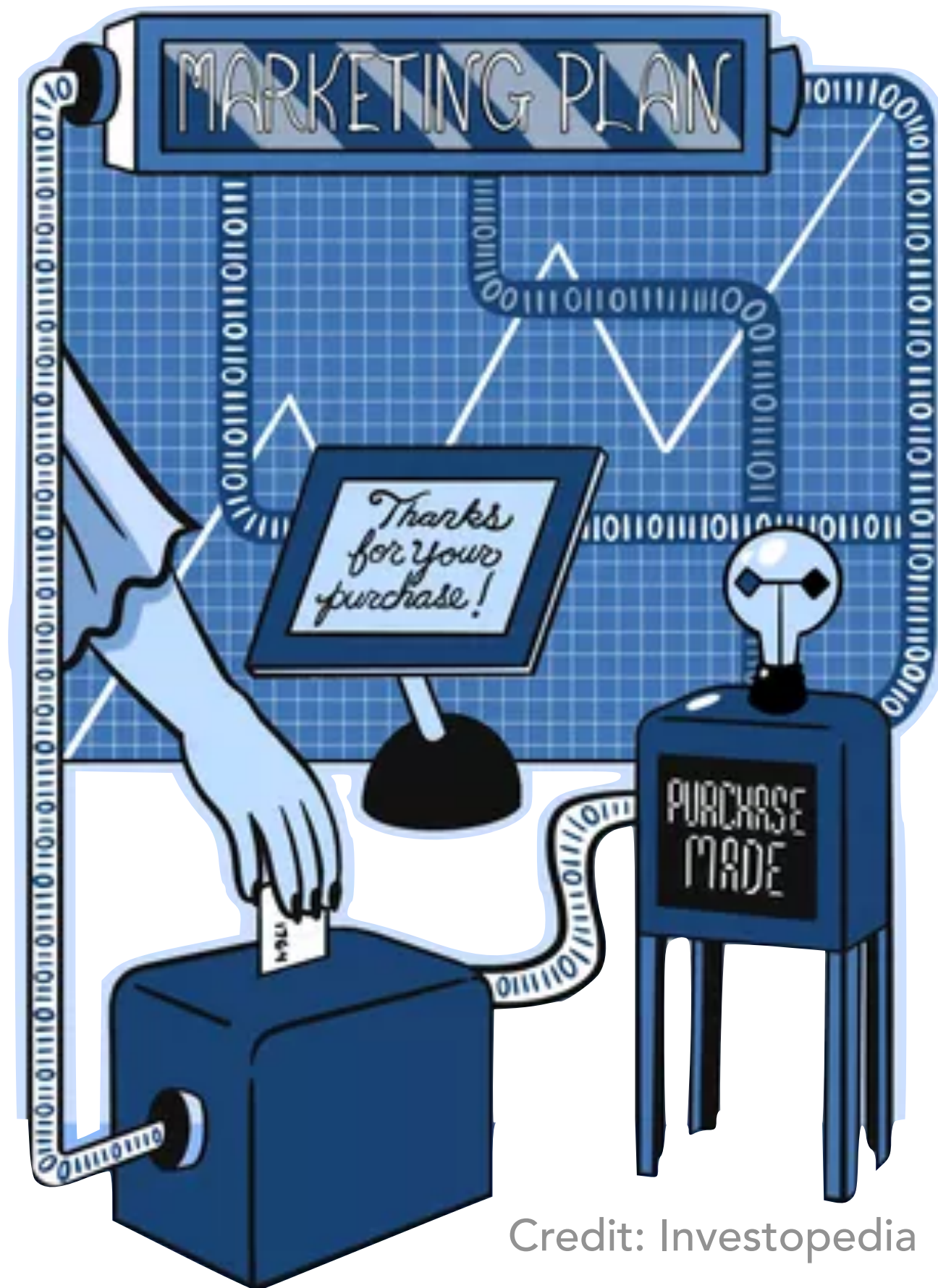
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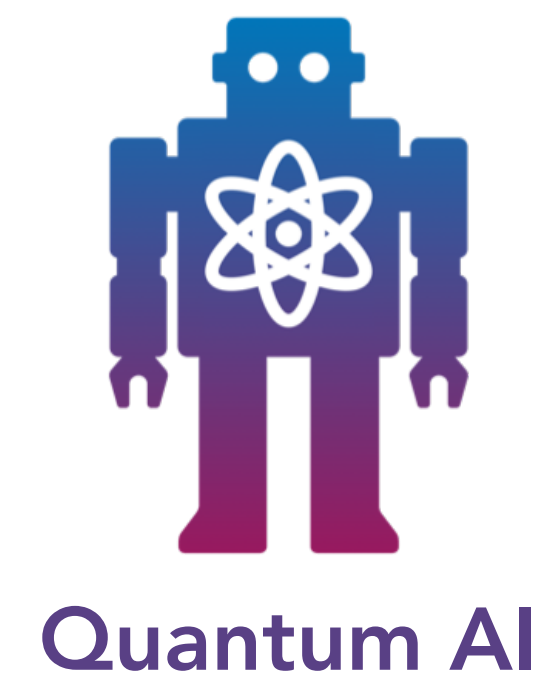
Data loading problem
(data loading \gg computation)



Quantum Advantage for Analyzing Classical Data



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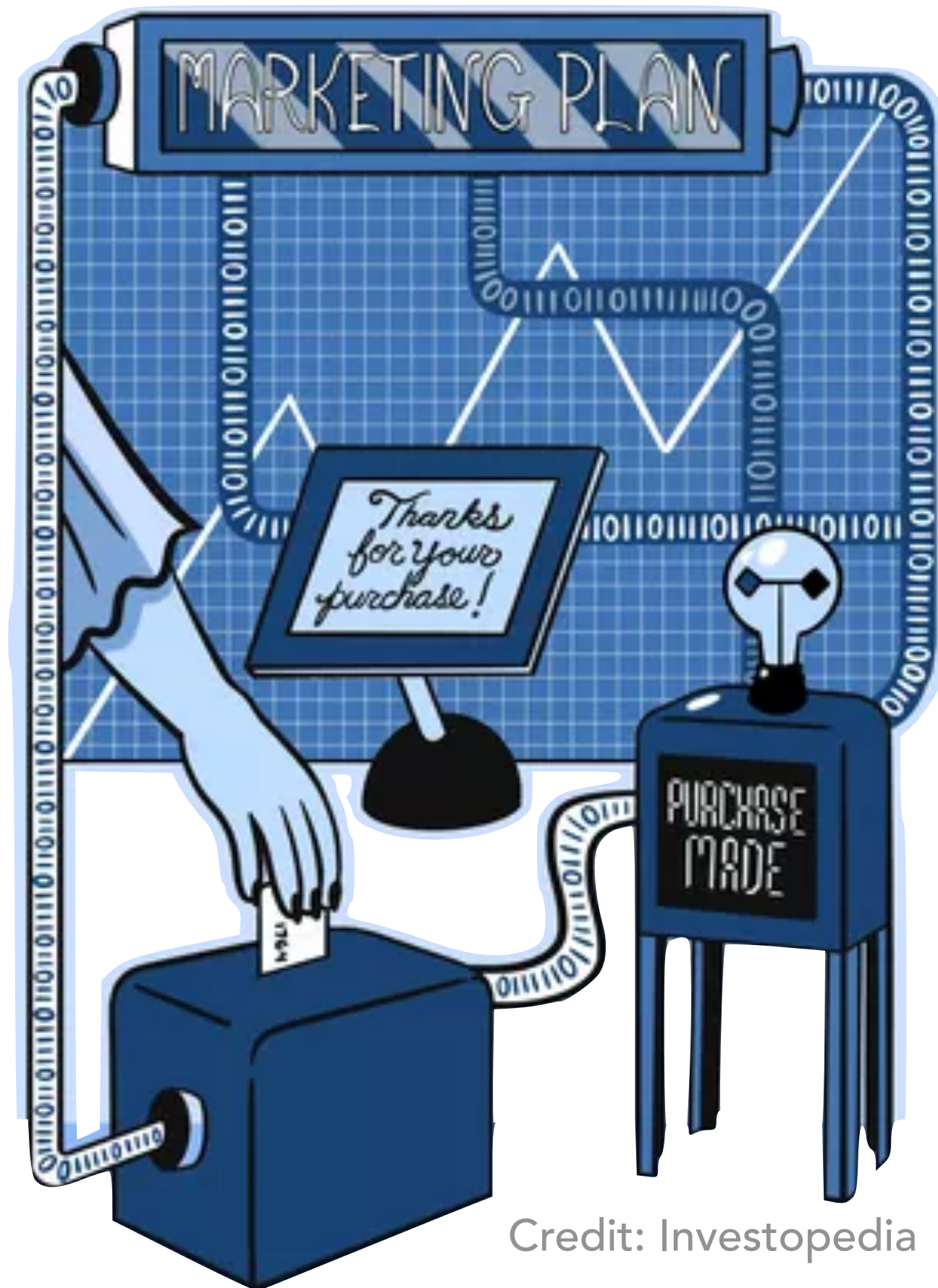


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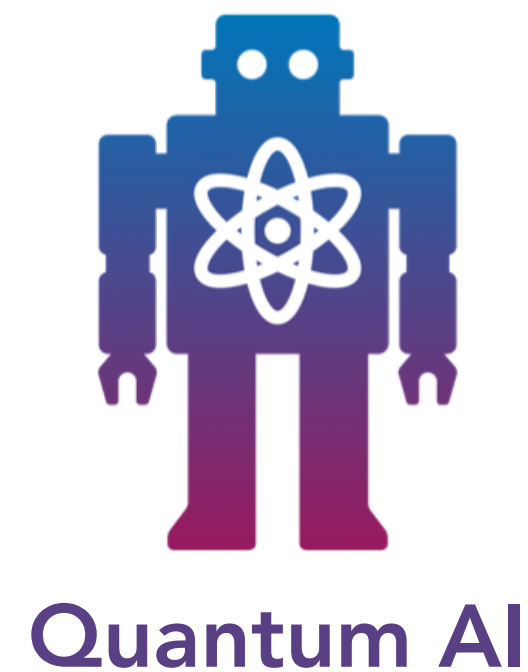
Exponentially large QRAM



Quantum Advantage for Analyzing Classical Data



Credit: Investopedia

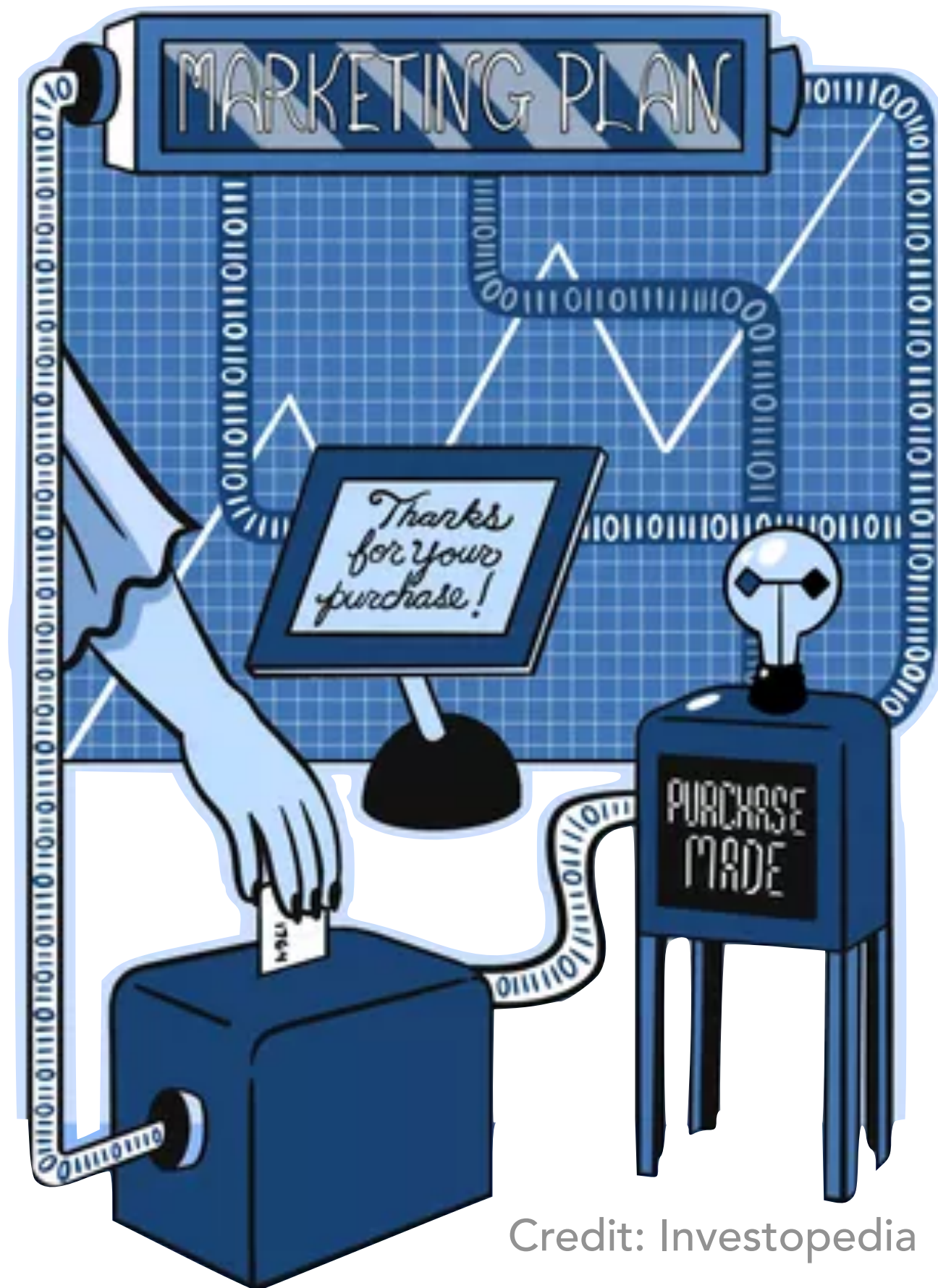


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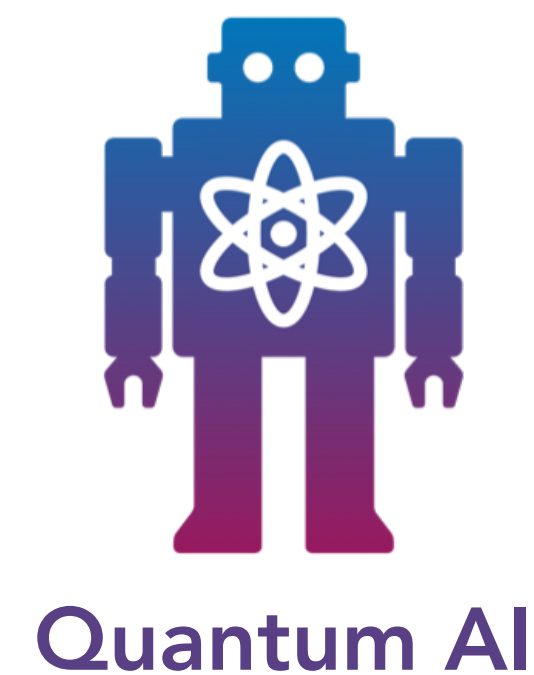
Exponentially large QRAM

Only polynomial speedup
(dequantization)

Quantum Advantage for Analyzing Classical Data



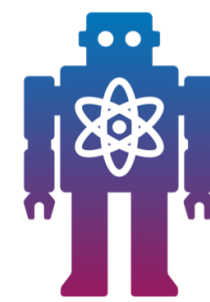
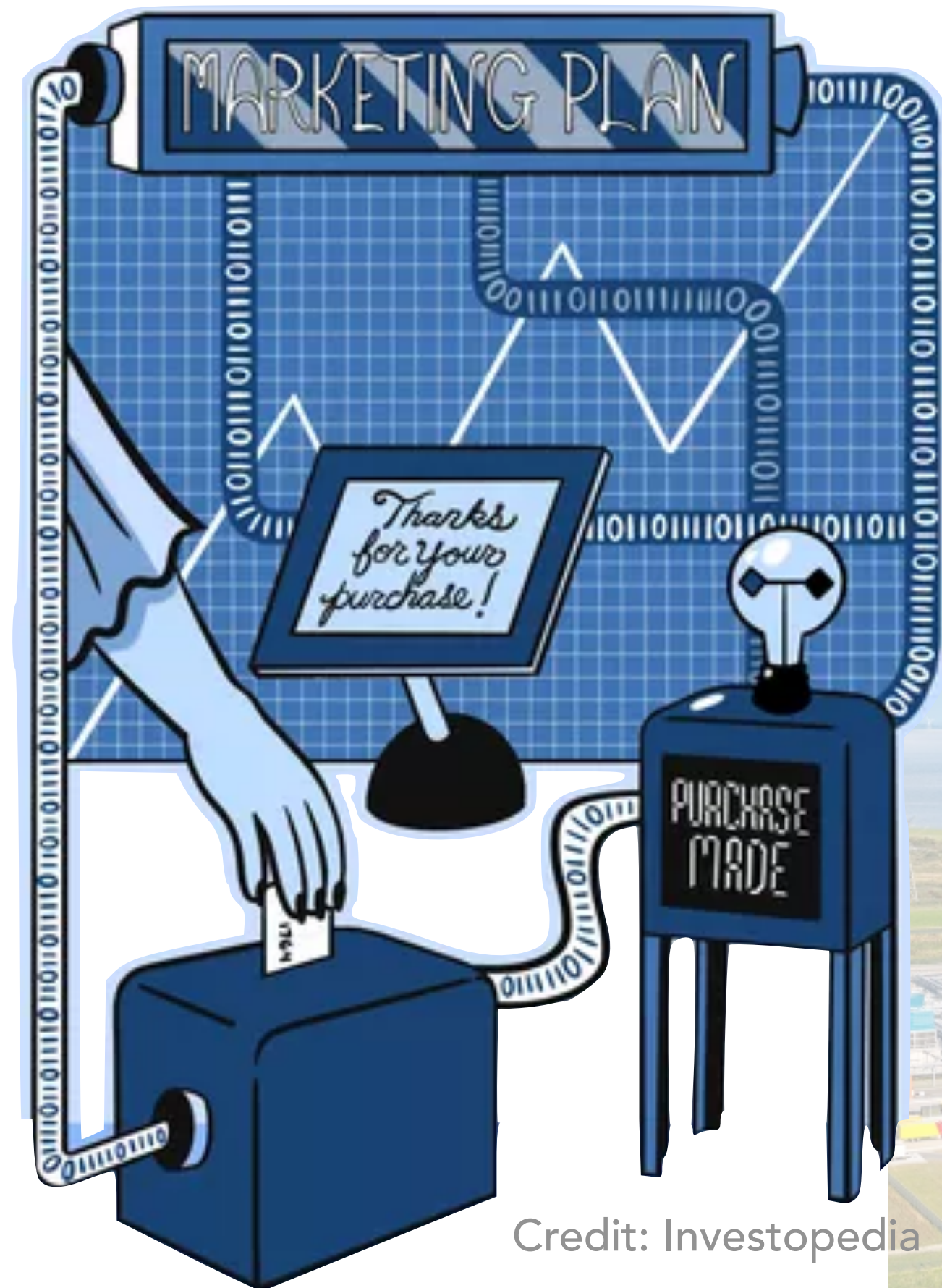
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Question:

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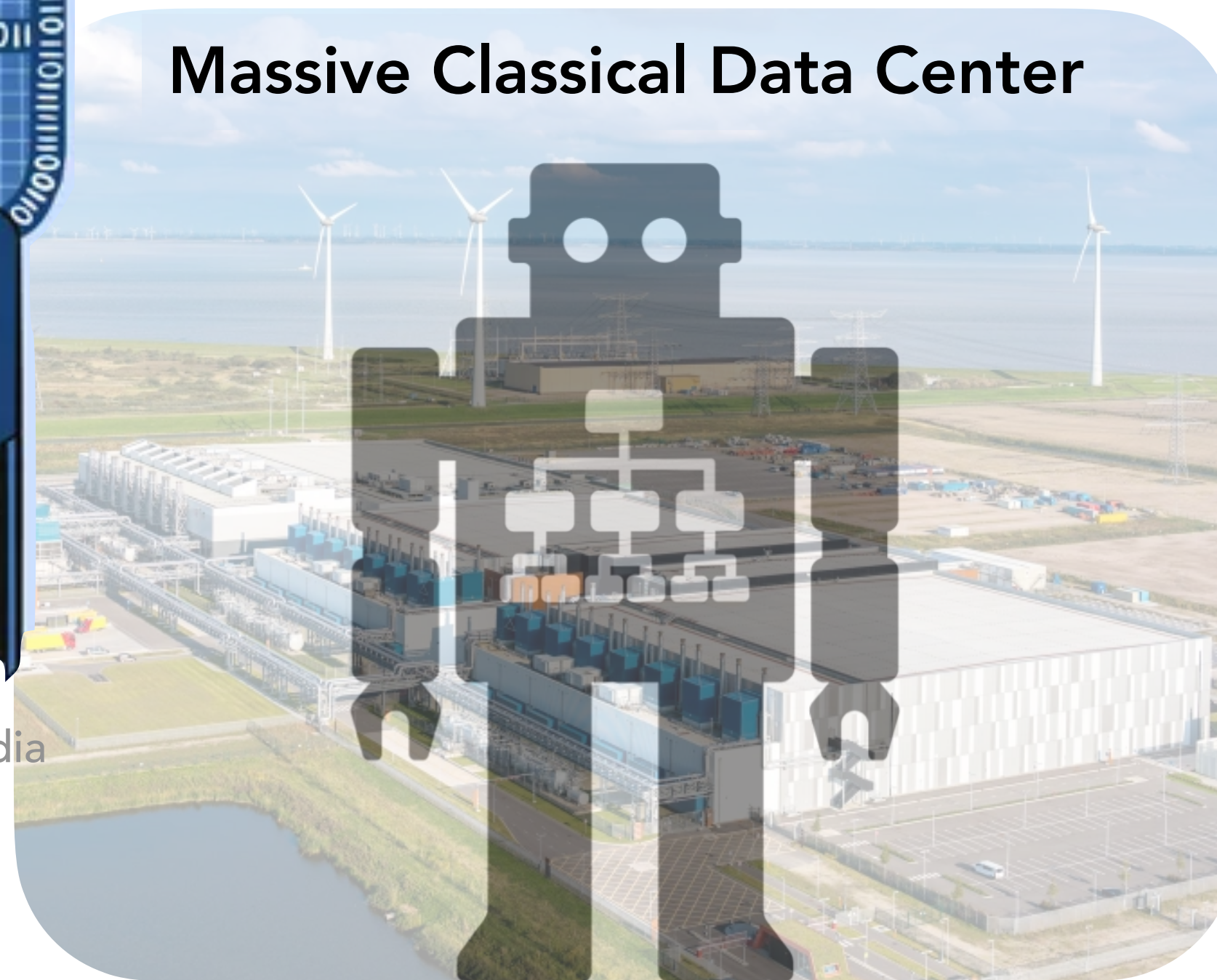
Quantum Advantage for Analyzing Classical Data



Tiny Quantum AI running on
100 logical qubit chip

v.s.

Massive Classical Data Center



Question:

Can QML running on
small quantum chips
outperform
exponentially larger
classical machines?

Quantum Advantage for Analyzing Classical Data

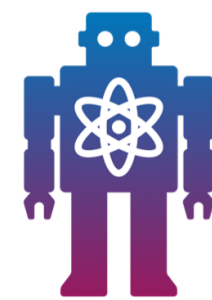


User data, internet data,
sensor data, financial data,
consumer data, market data, ...

Classical
Data
Samples

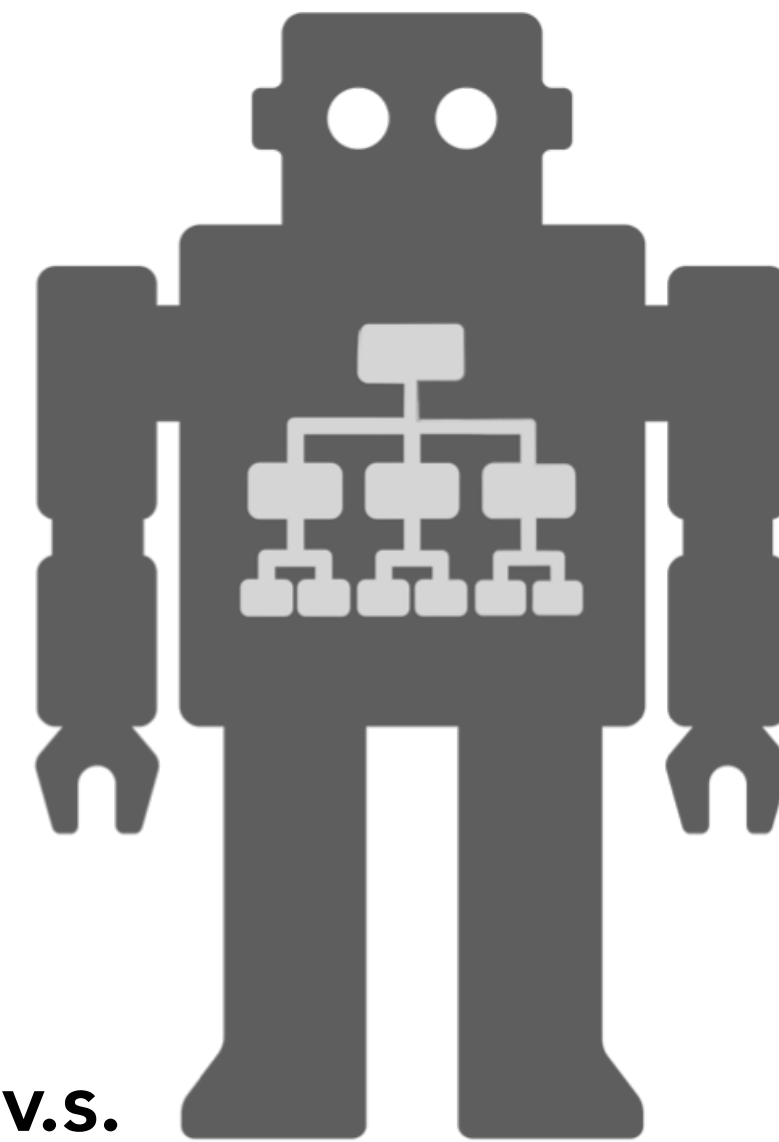


$$z \sim \mathcal{D}$$



Tiny
Quantum AI

v.s.



Massive
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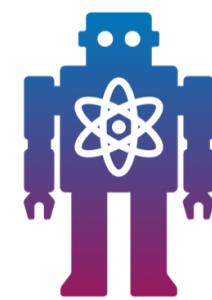
High-level algorithmic idea:



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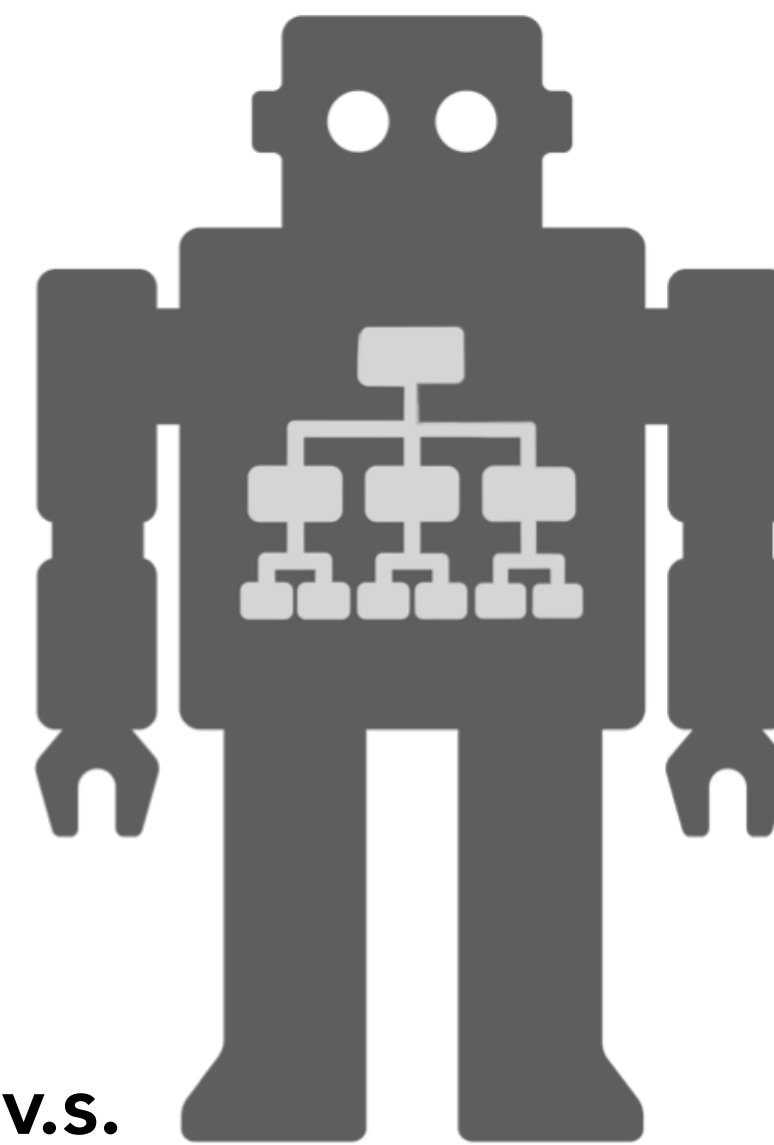


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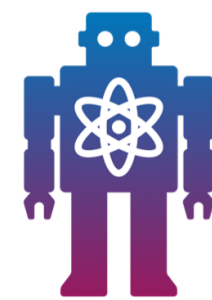


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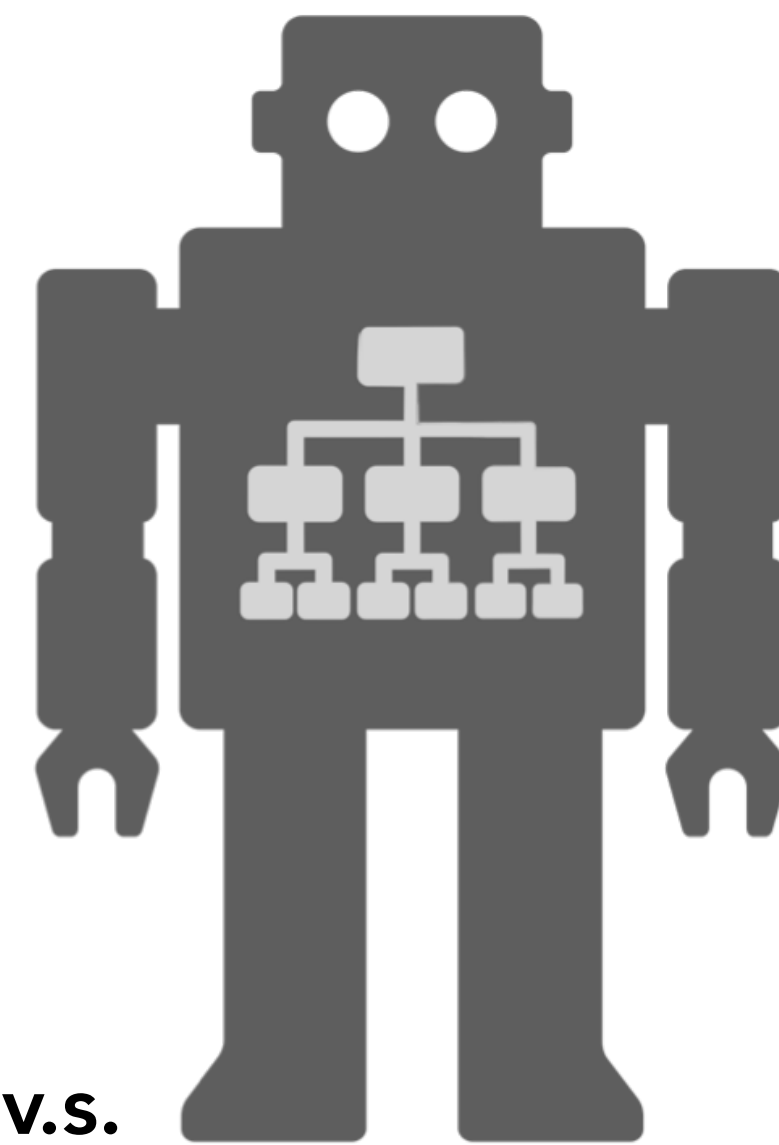


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Tiny
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Classical AI

High-level algorithmic idea:

(1) Get data sample $z \sim \mathcal{D}$

Quantum Advantage for Analyzing Classical Data

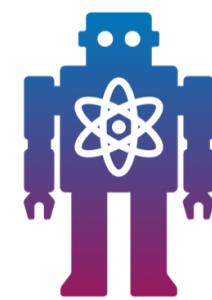


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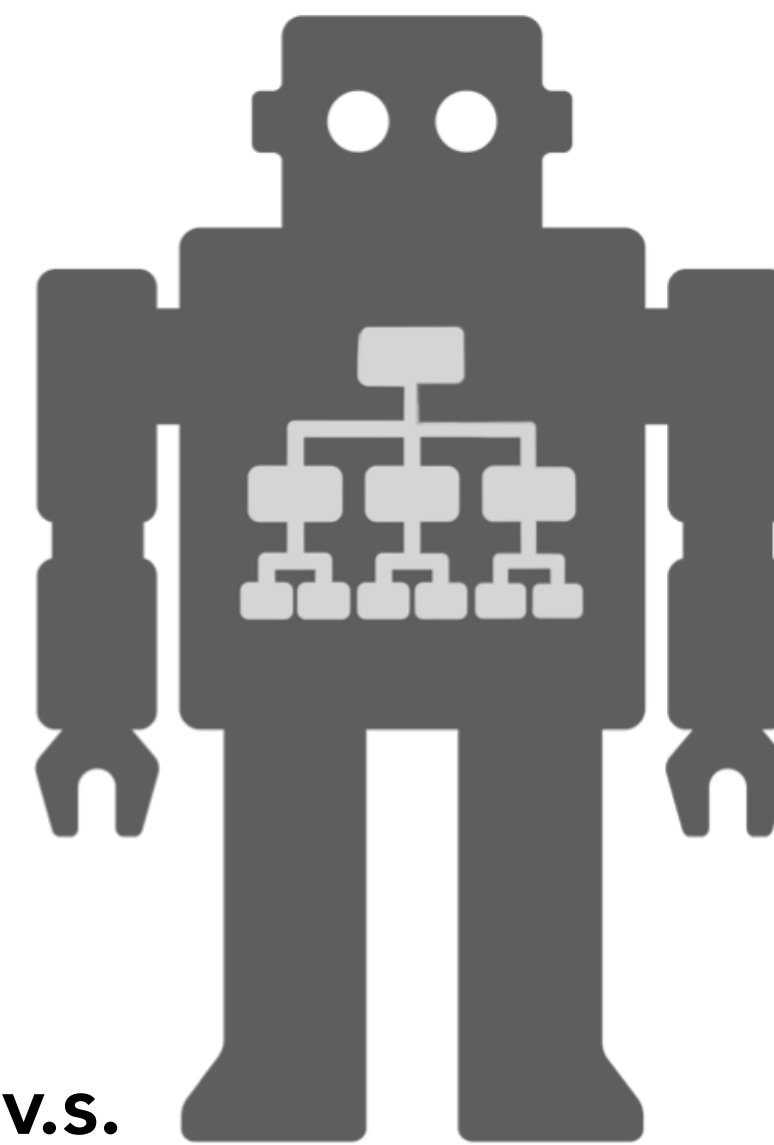


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Tiny
Quantum AI

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Massive
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High-level algorithmic idea:

- (1) Get data sample $z \sim \mathcal{D}$
- (2) Create Hamiltonian term h_z

Quantum Advantage for Analyzing Classical Data

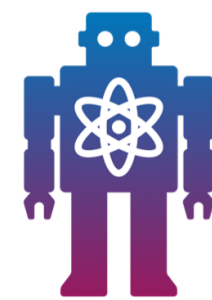


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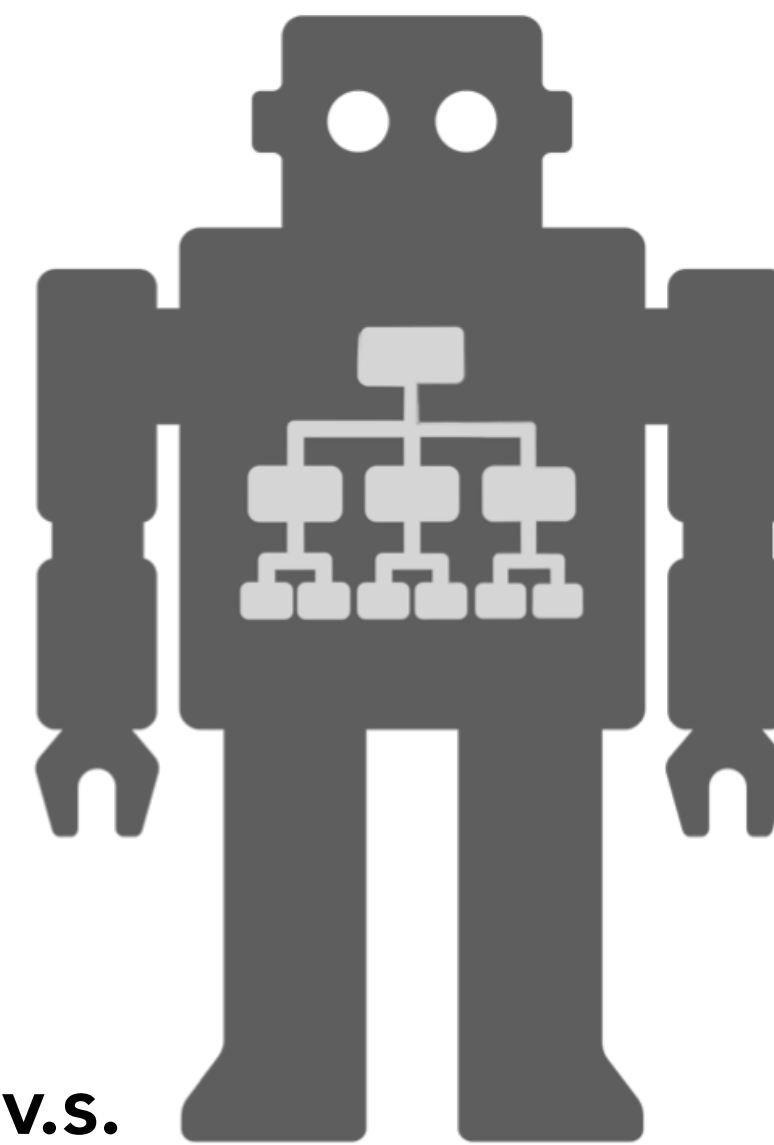


$z \sim \mathcal{D}$



Tiny
Quantum AI

v.s.



Massive
Classical AI

High-level algorithmic idea:

- (1) Get data sample $z \sim \mathcal{D}$
- (2) Create Hamiltonian term h_z
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Quantum Advantage for Analyzing Classical Data

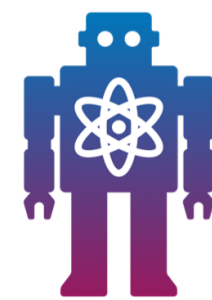


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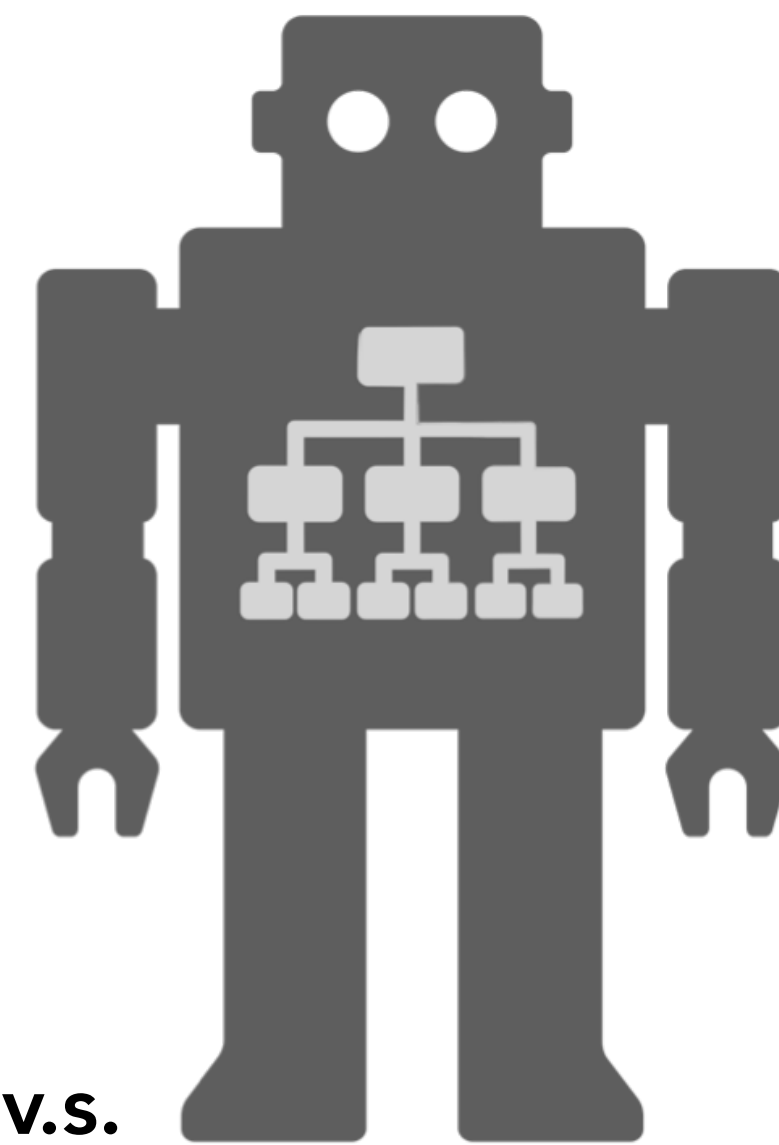


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Quantum Advantage for Analyzing Classical Data

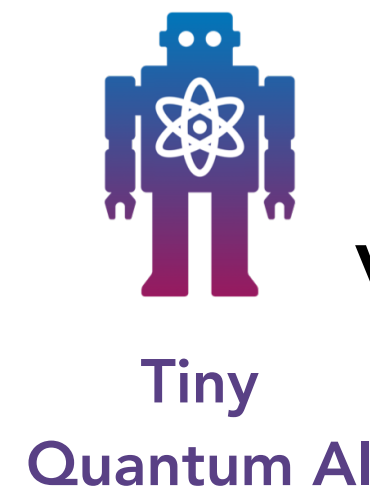


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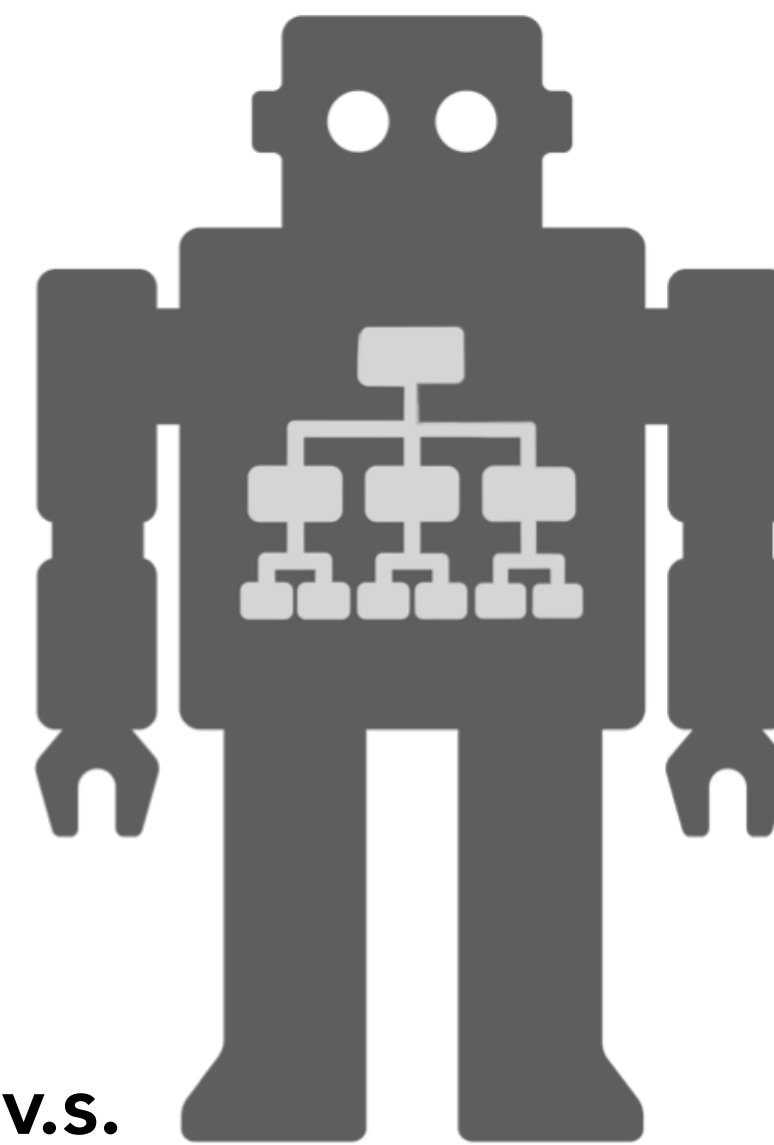


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- (4) Repeat

After seeing some samples,
the random unitary converges to
 $e^{-it \cdot \mathbb{E}_{z \sim \mathcal{D}}[h_z]}$ for a tunable t .

Quantum Advantage for Analyzing Classical Data

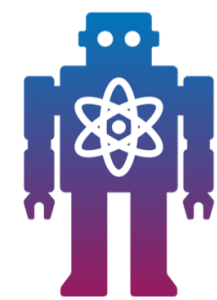


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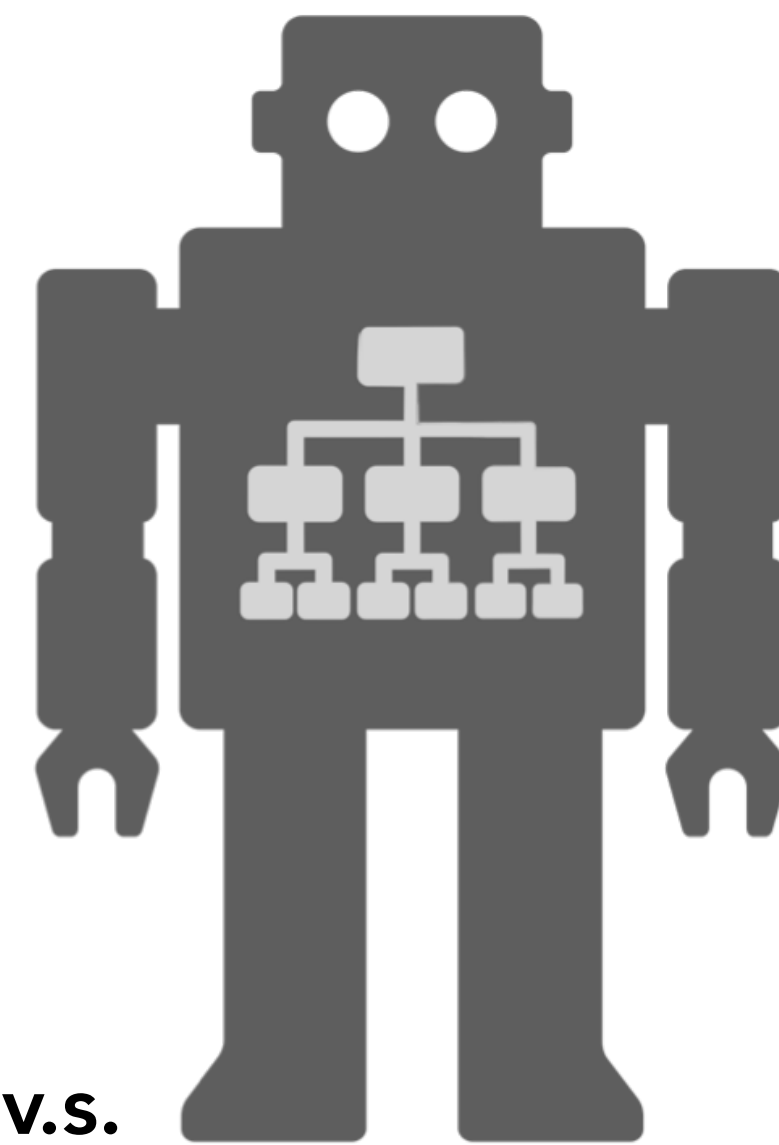


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Tiny
Quantum AI

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Massive
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Central Idea:

Replace **QRAM** with
a **quantum oracle**
sketched from
classical data samples.

Quantum Advantage for Analyzing Classical Data

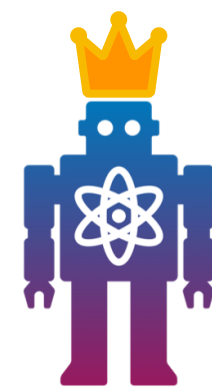


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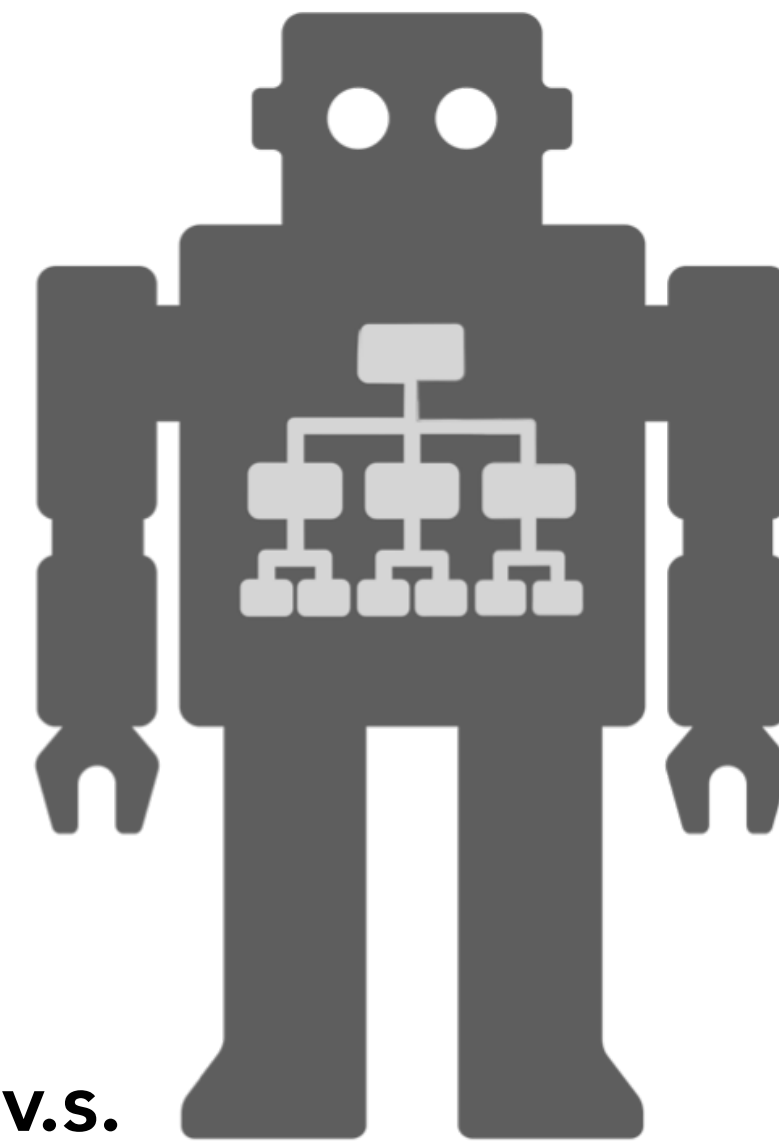


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Tiny
Quantum AI

v.s.



Massive
Classical AI

Claim:

With $\mathcal{O}(N)$ samples,
poly(log N)-qubit machine
can solve SVM, PCA, ...
better than any classical
machines with $\mathcal{O}(N^{0.99})$ **bits.**

Where do we go from here?

♣ AI for Quantum Technology:

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What are the **fundamental limit** in **space**, **time**, and **energy** governing **any** physical system that can learn?

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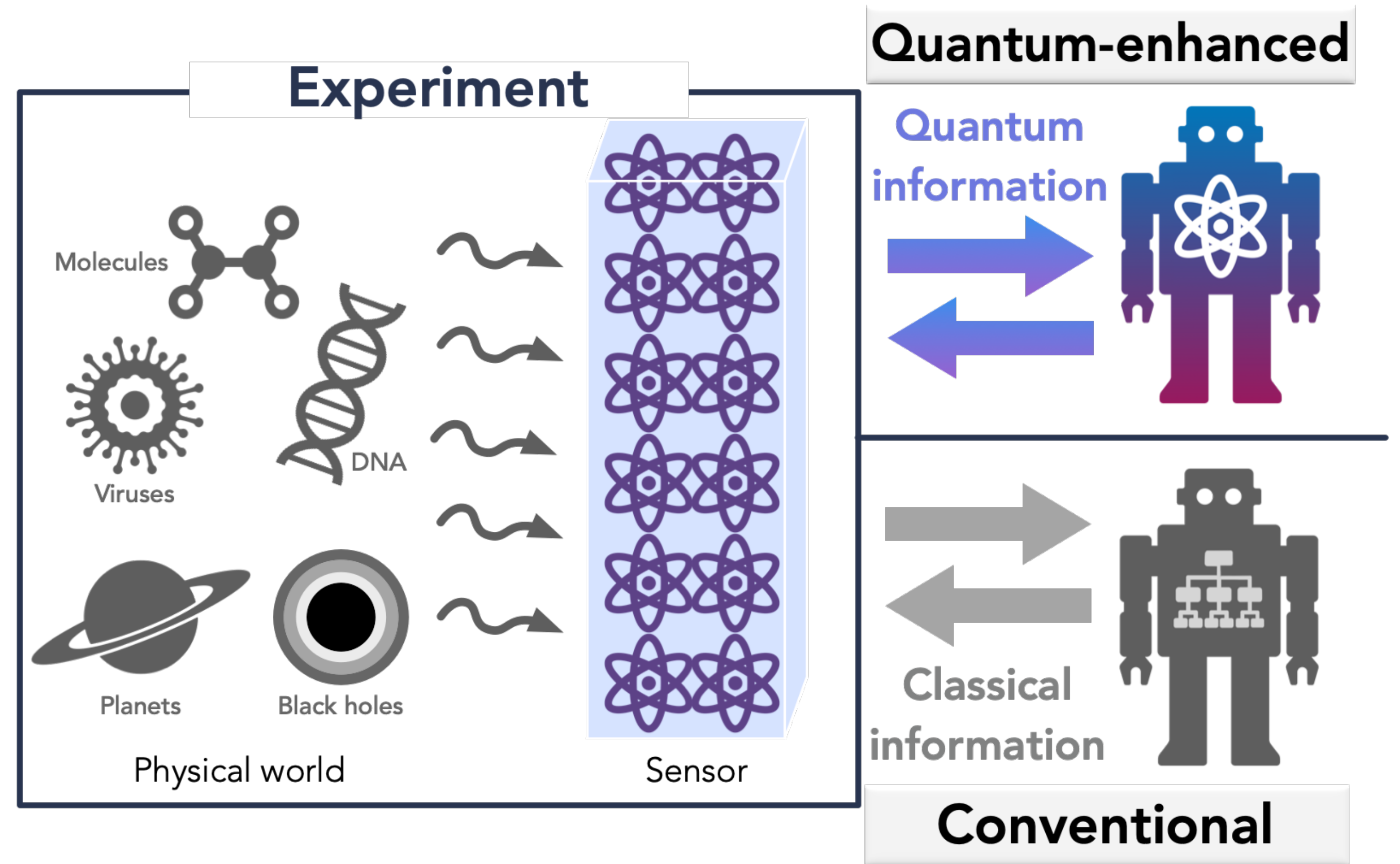
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♣ Quantum AI Discovery:

How can quantum machines learn to **discover new physics**?

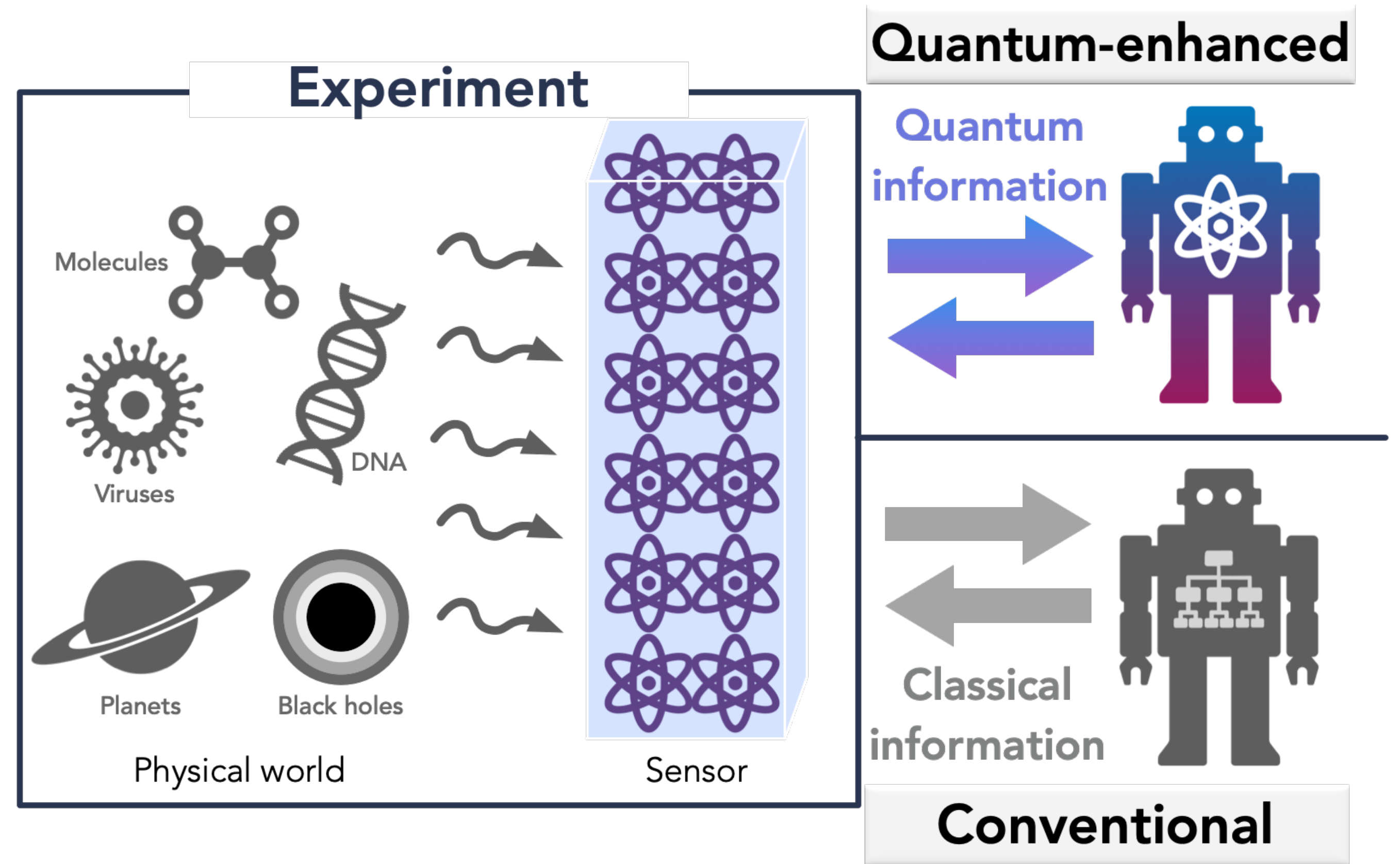
Sensing Classical Fields

- **Sensing classical fields** has wide-ranging applications.



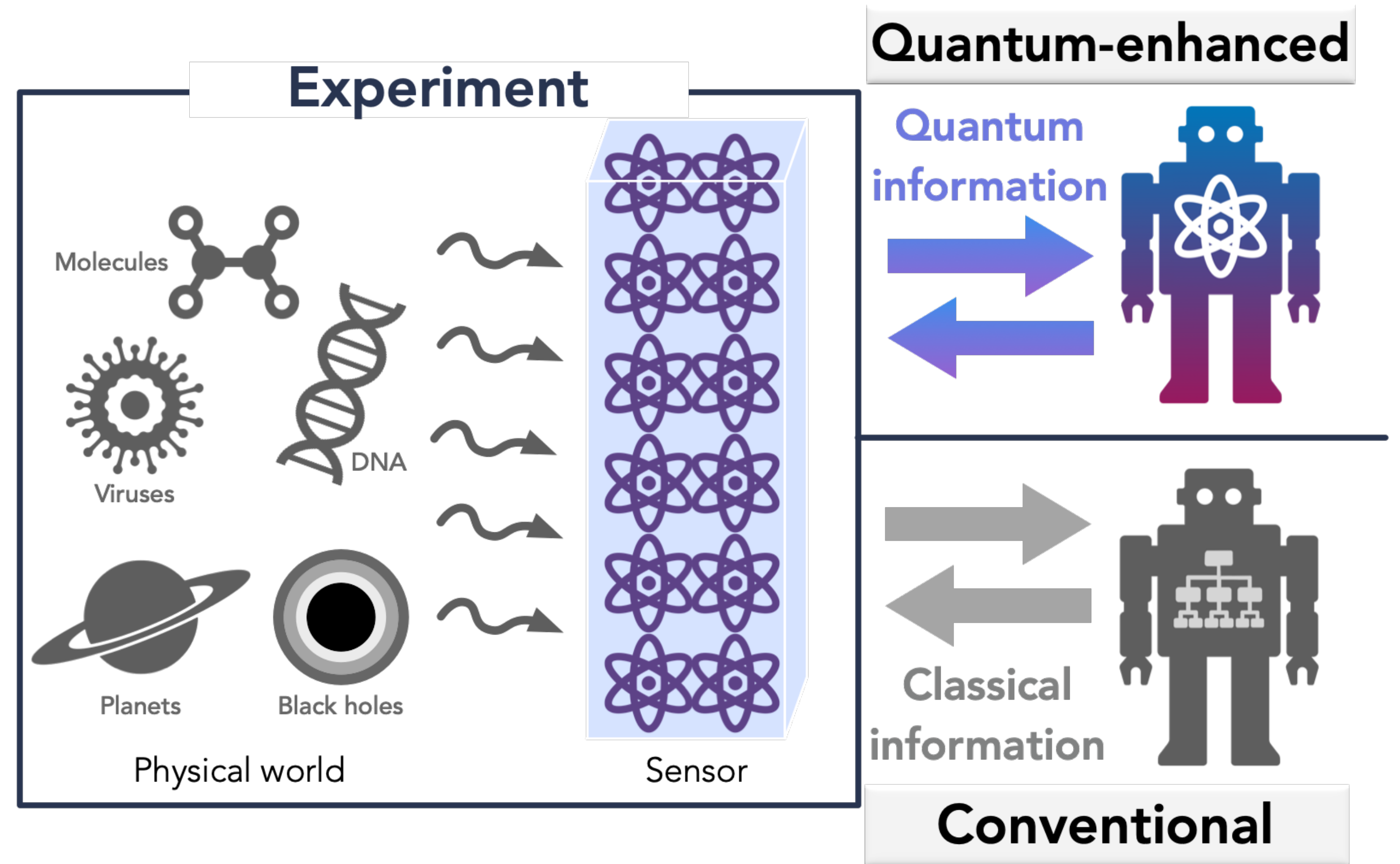
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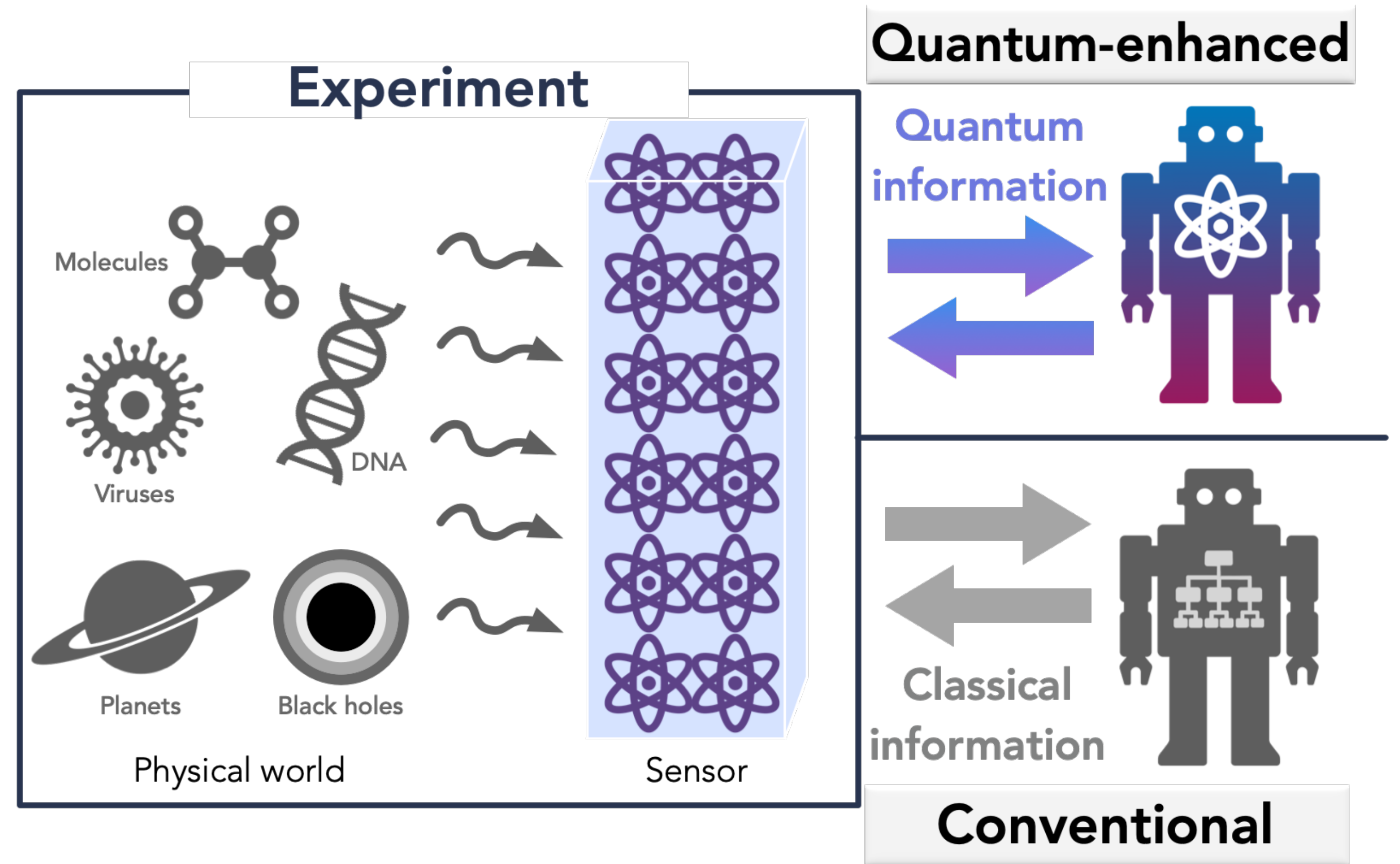
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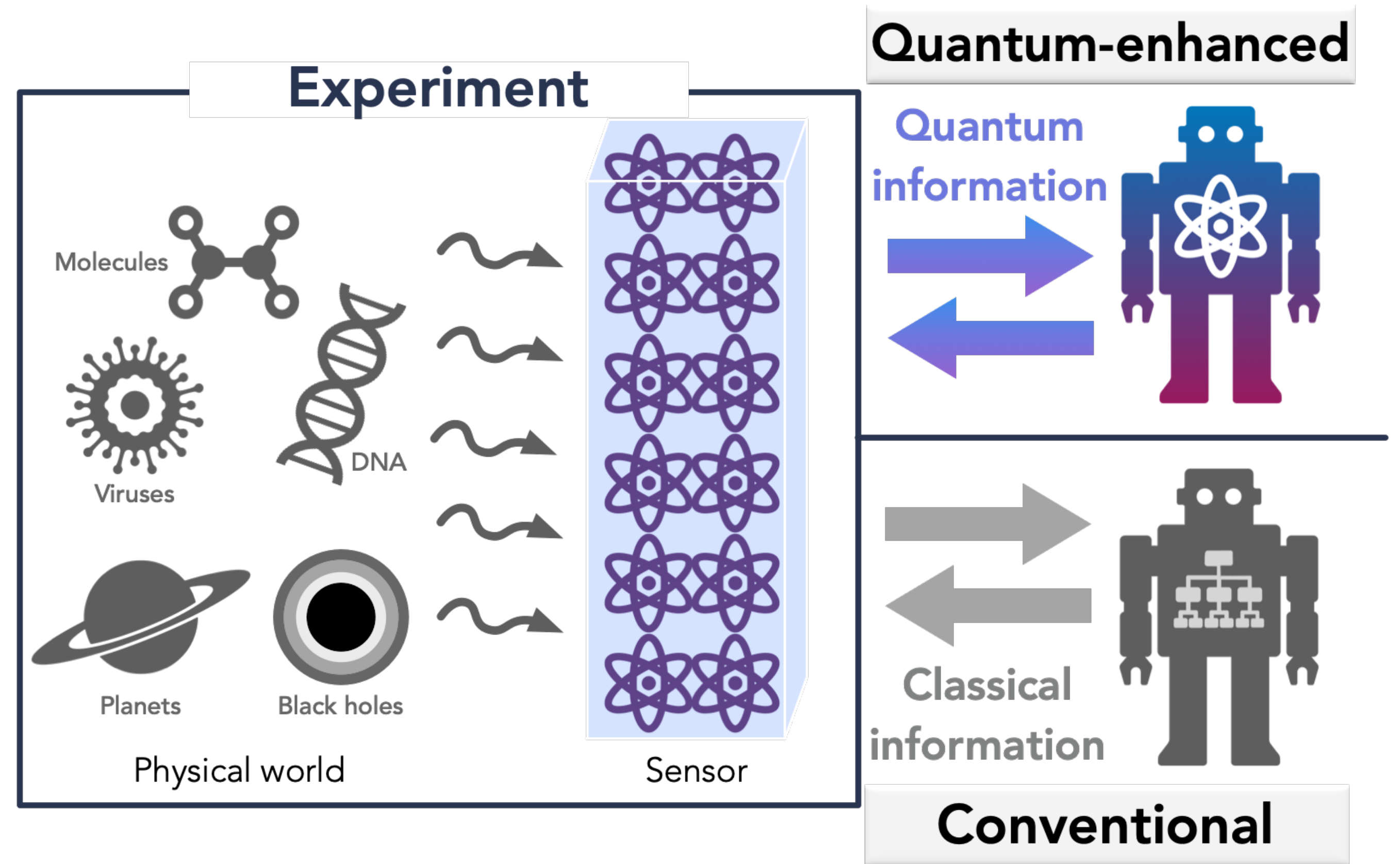
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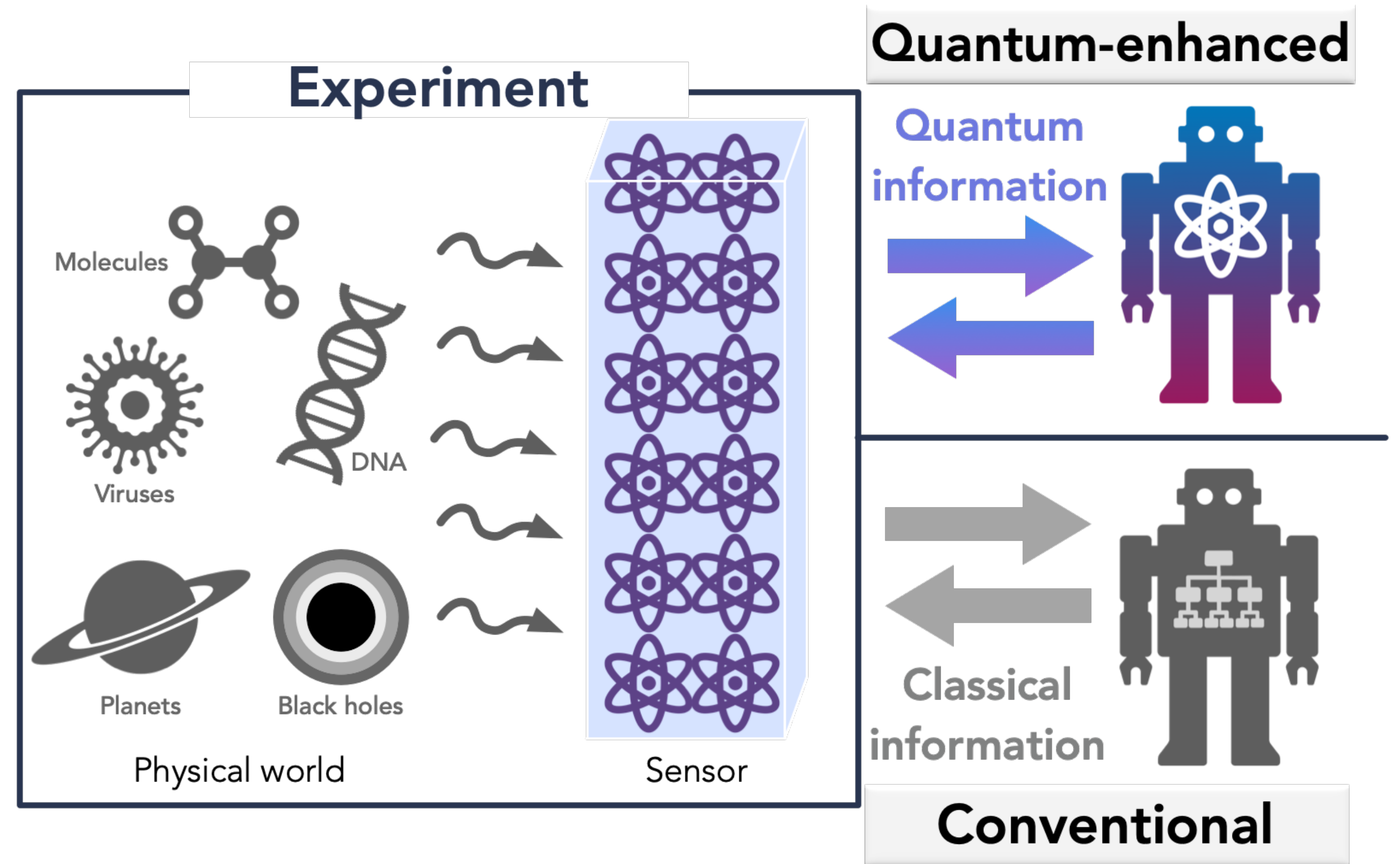
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 - Detecting **dark matter**, ...



Sensing Classical Fields

- Simplest task (from Lec. 1):

$$B(t) = B \text{ vs } B(t) = 0$$

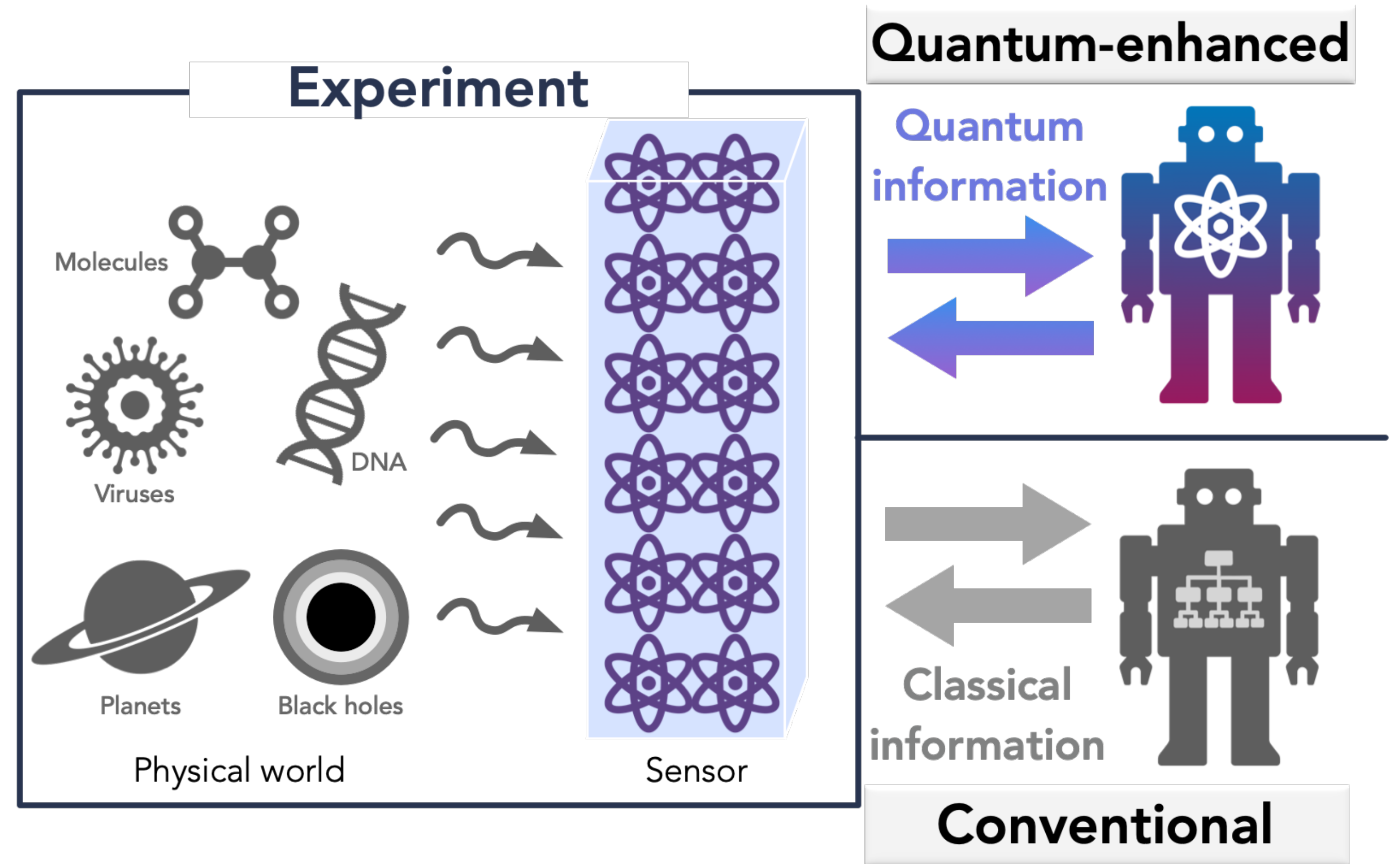


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- Sensing spin is affected by the Hamiltonian $H(t) = B(t) \cdot Z$

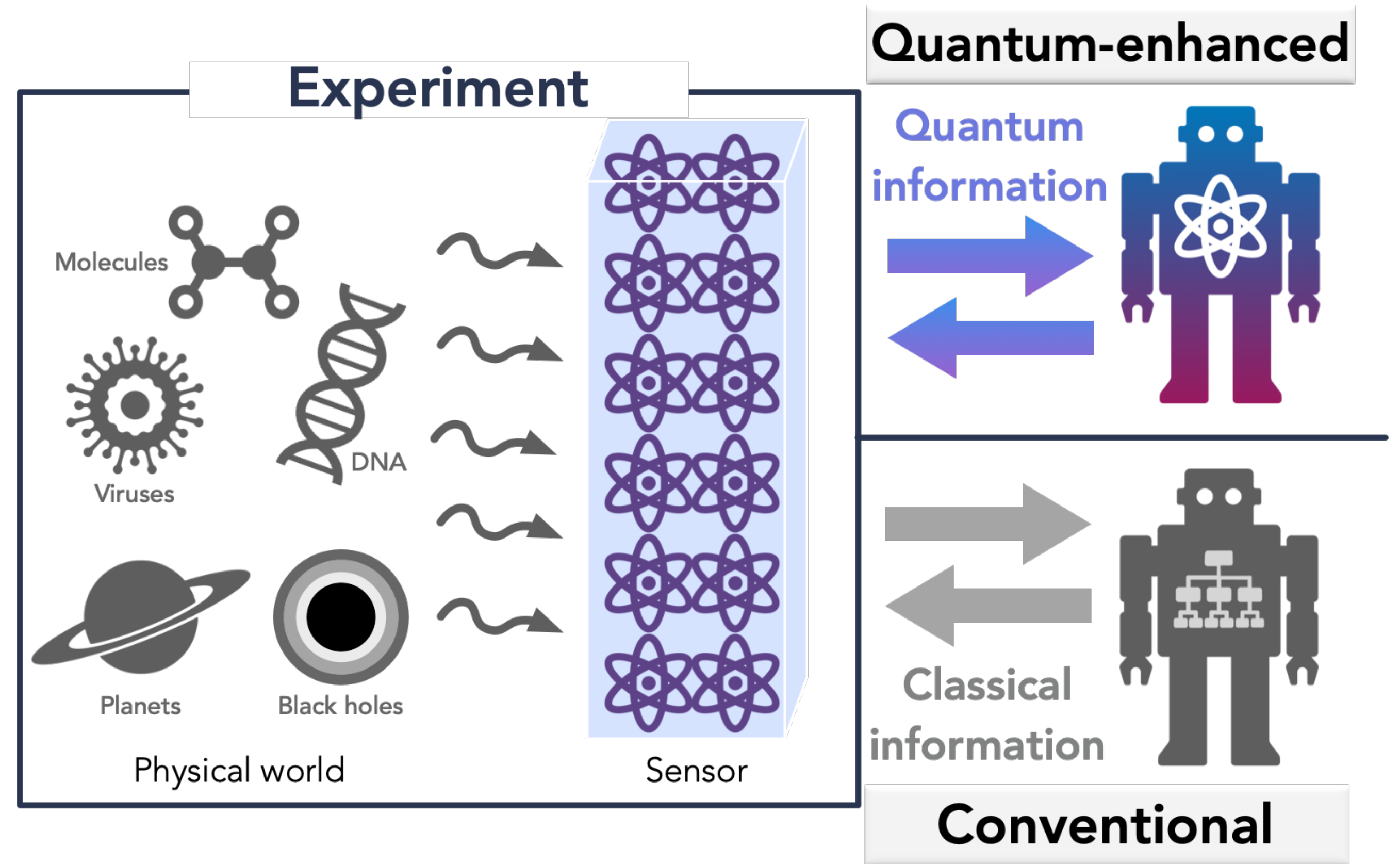


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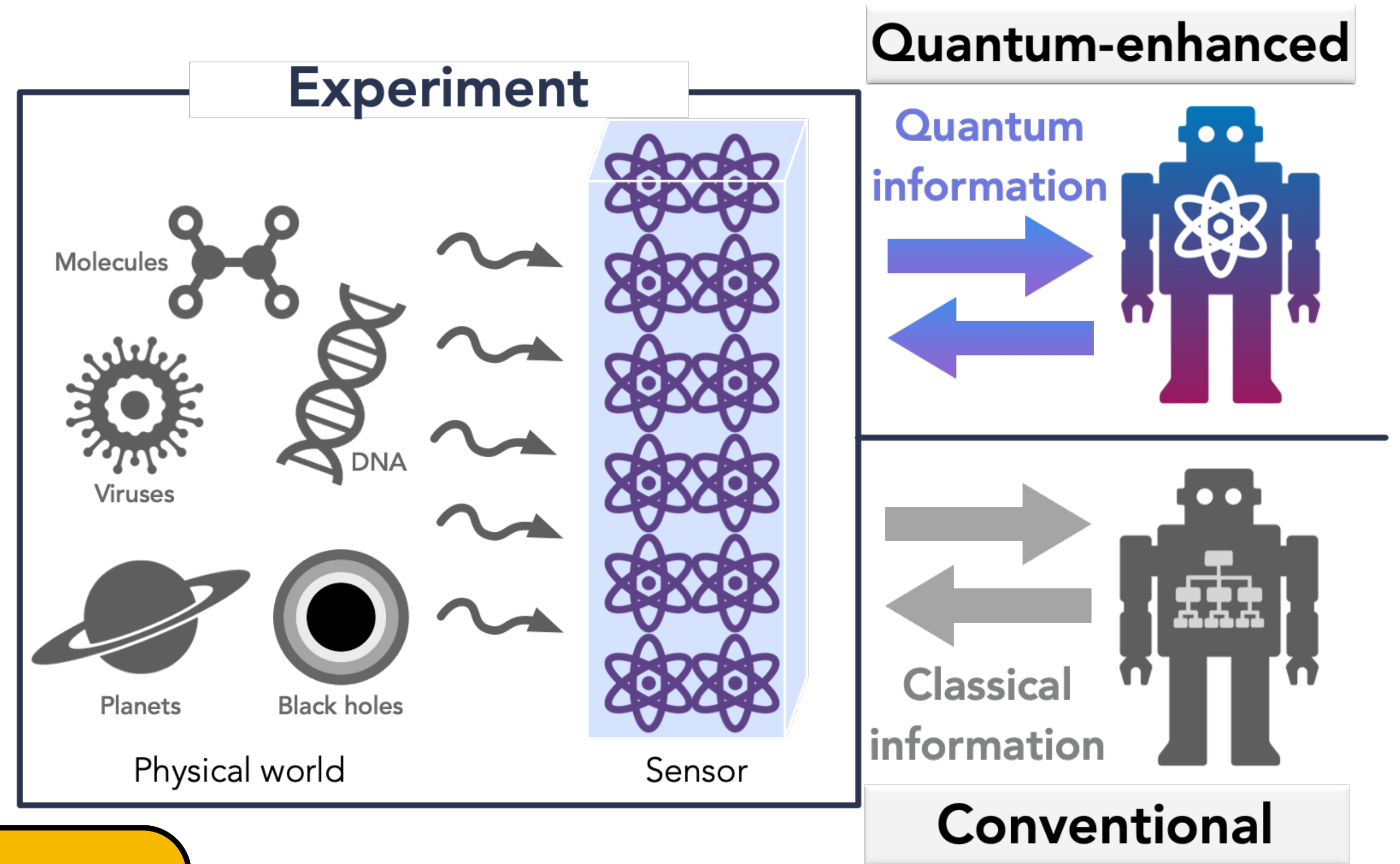
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- Optimal time: $\Theta(1/B)$

This optimality has spawned the field of **quantum sensing**



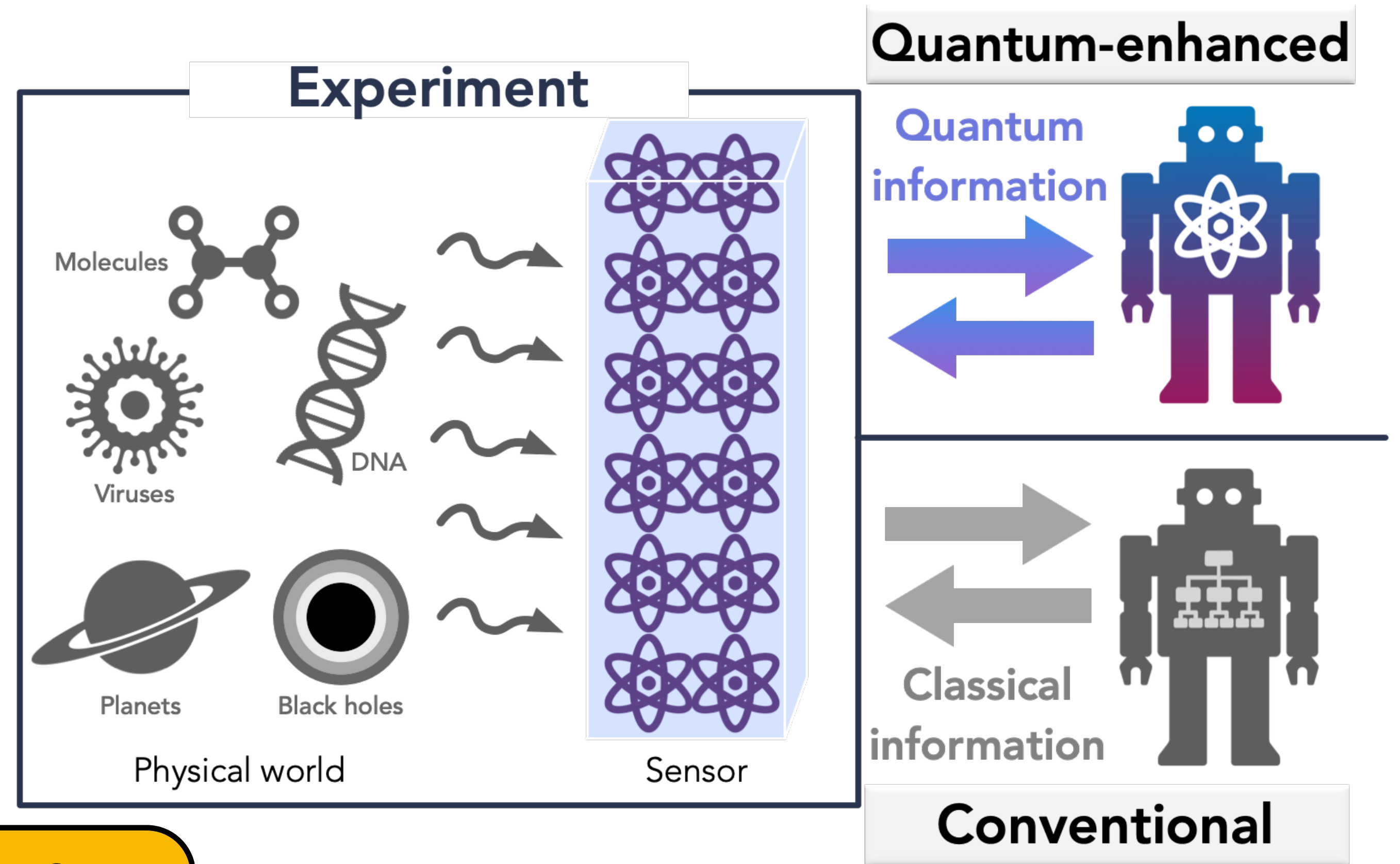
Sensing Classical Fields

- Simplest task (from Lec. 1):

$$B(t) = B \text{ vs } B(t) = 0$$

- Sensing spin is affected by the Hamiltonian $H(t) = B(t) \cdot Z$
- Optimal time: $\Theta(1/B)$

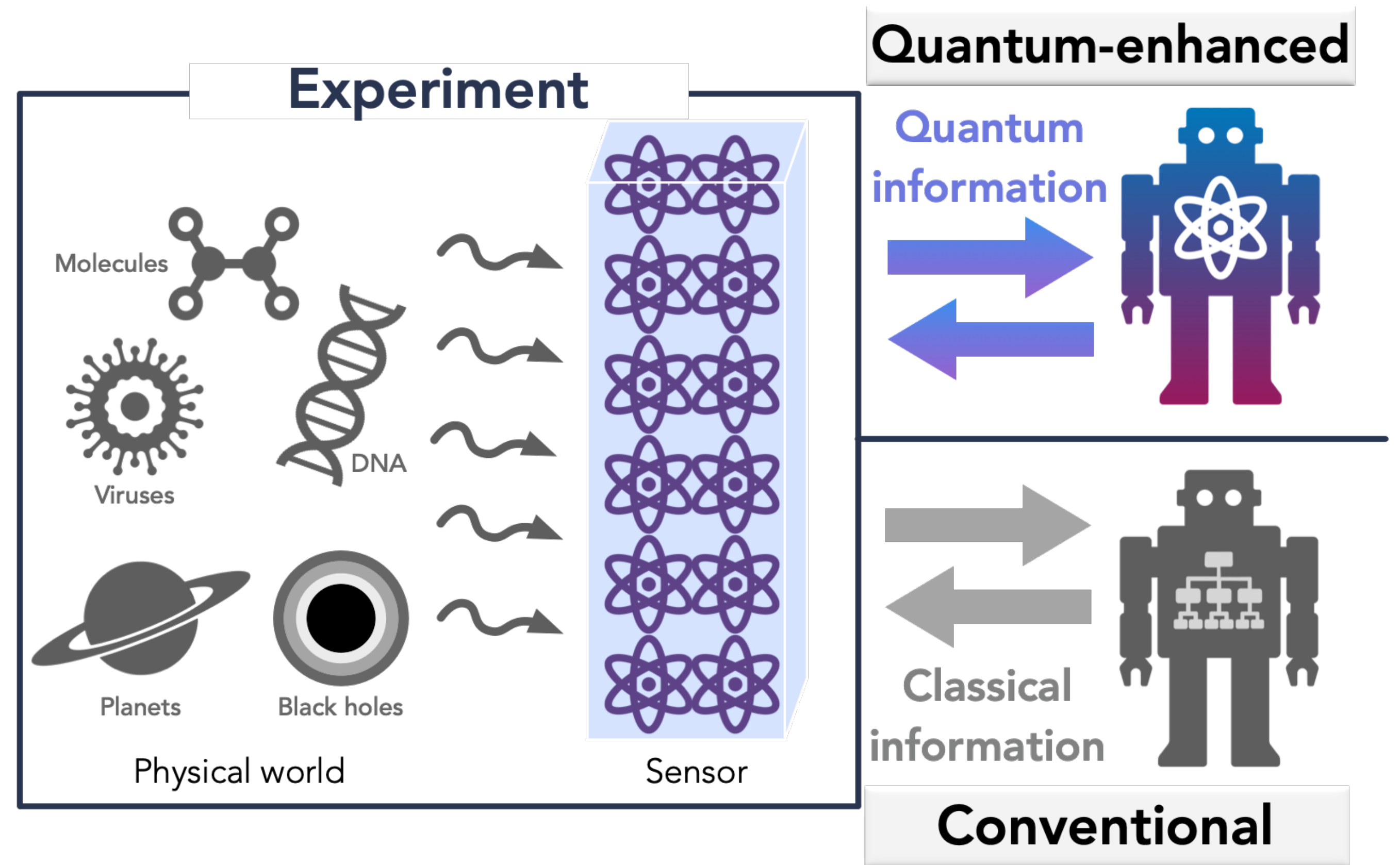
But **no need** for quantum AI & the speedup is just quadratic.



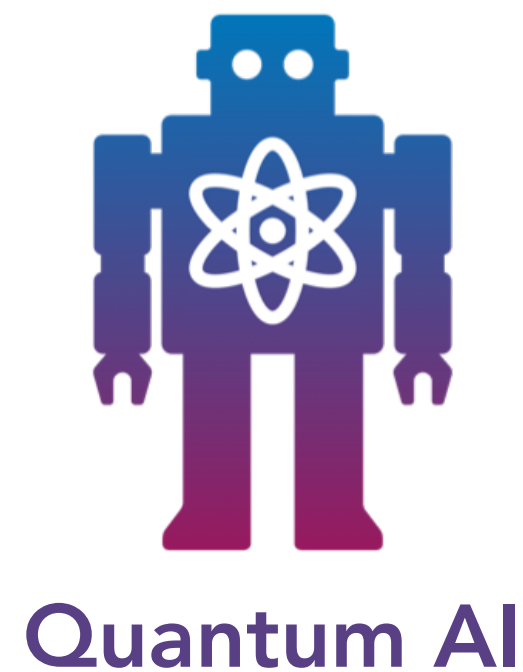
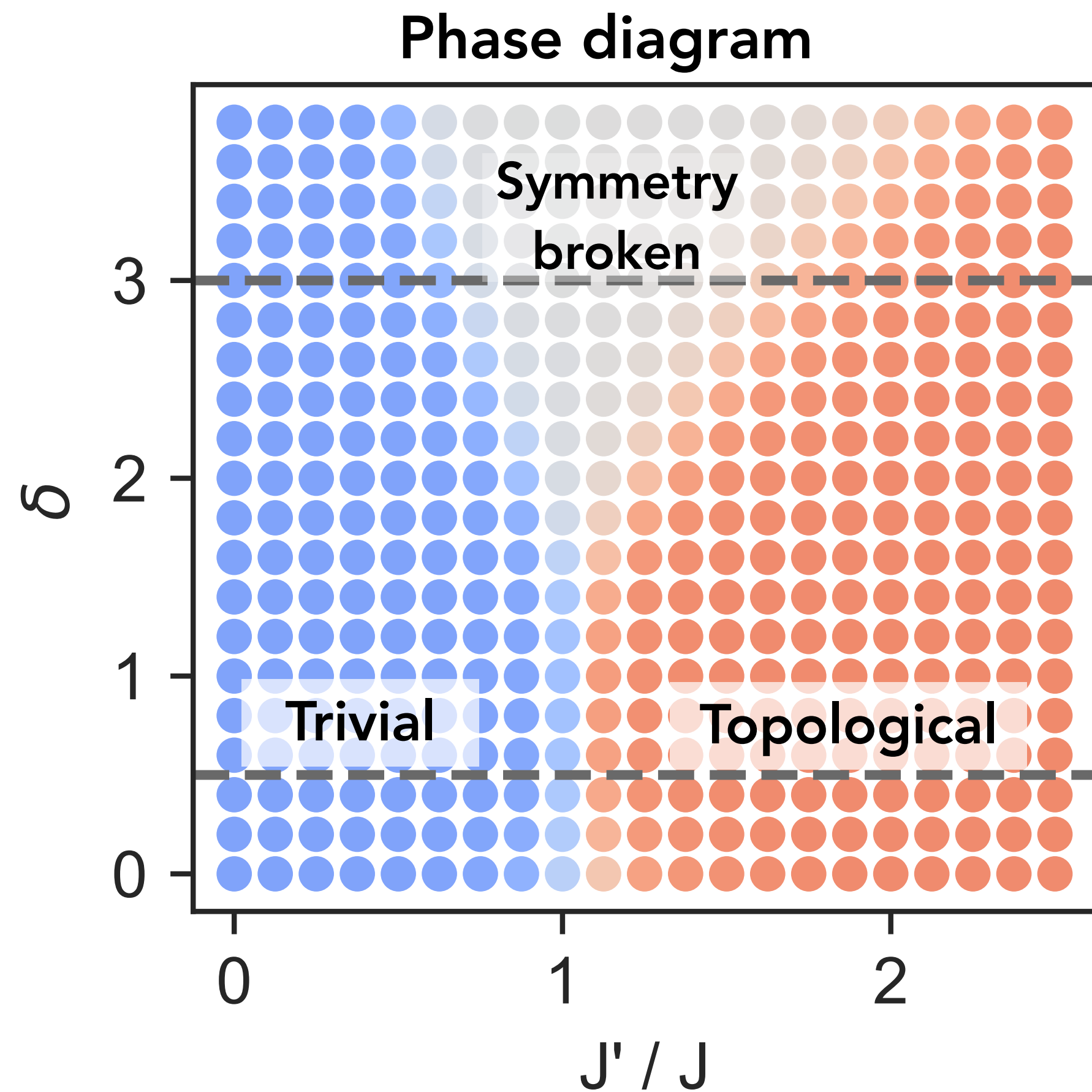
Sensing Classical Fields

Question:

Can quantum AI offer
superpolynomial
quantum advantage
in sensing classical fields?



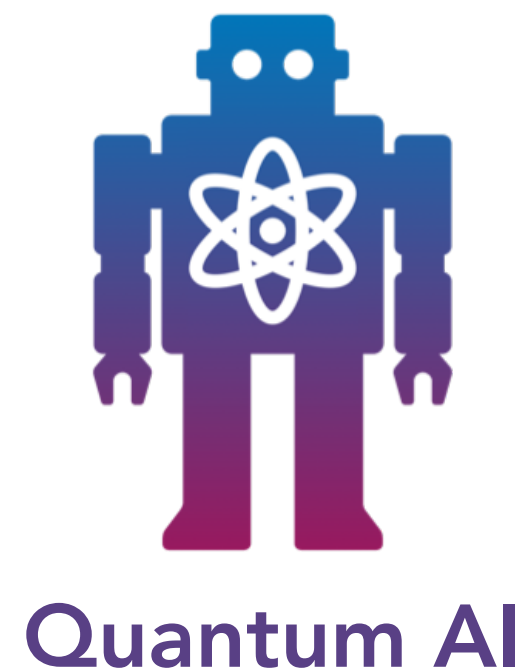
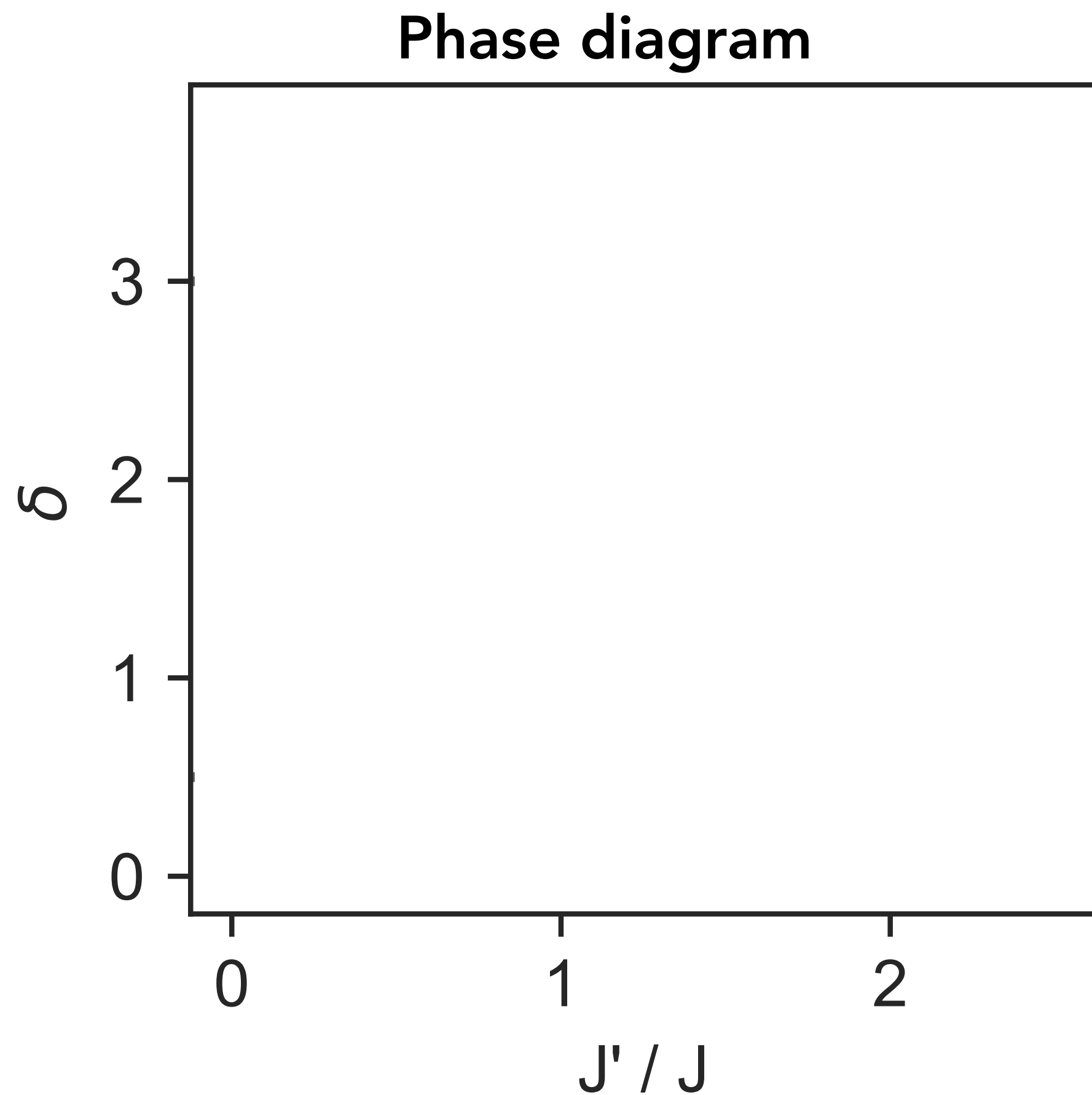
Discovering New Phases of Matter



Question:

How can quantum AI
discover phases of
matter on its own?

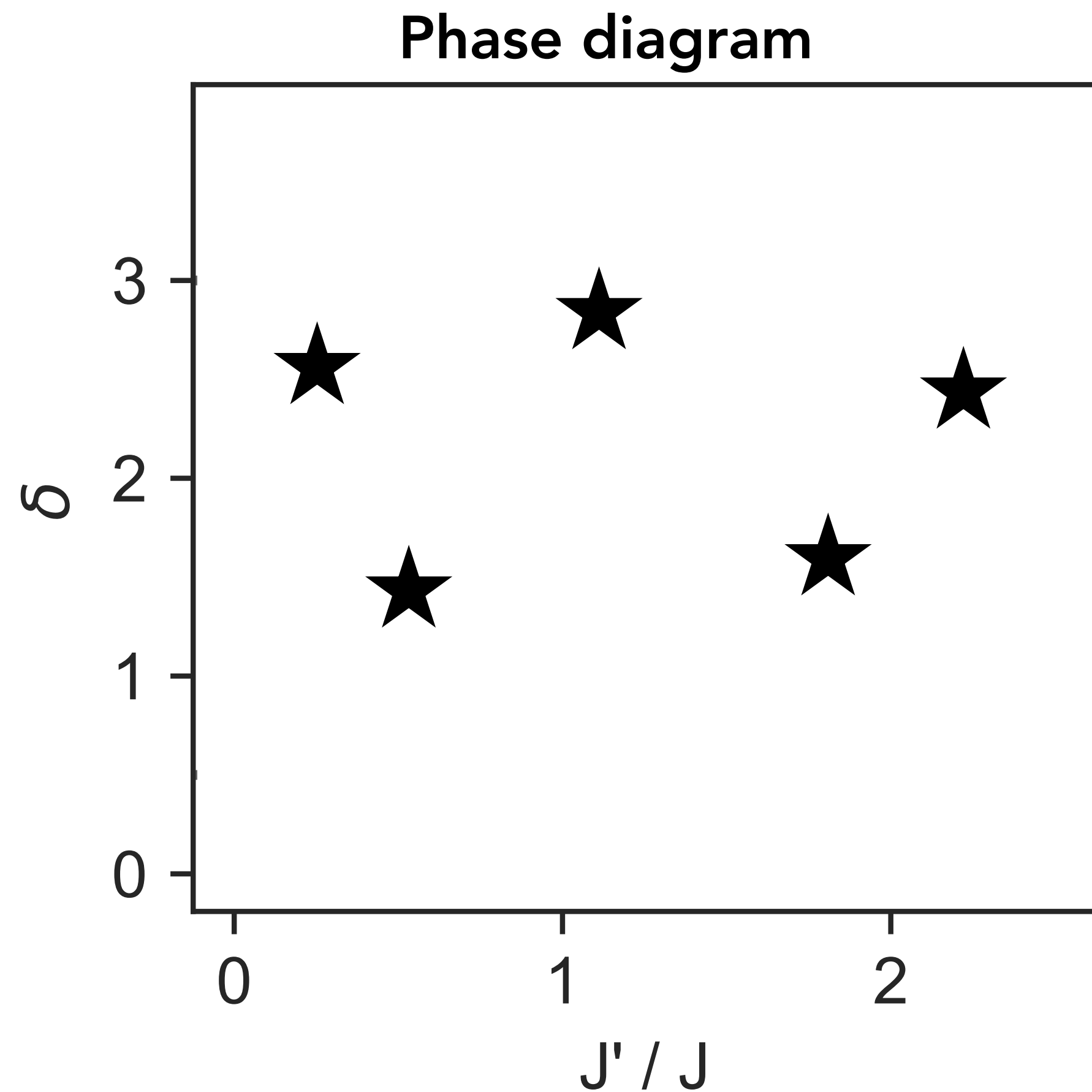
Discovering New Phases of Matter



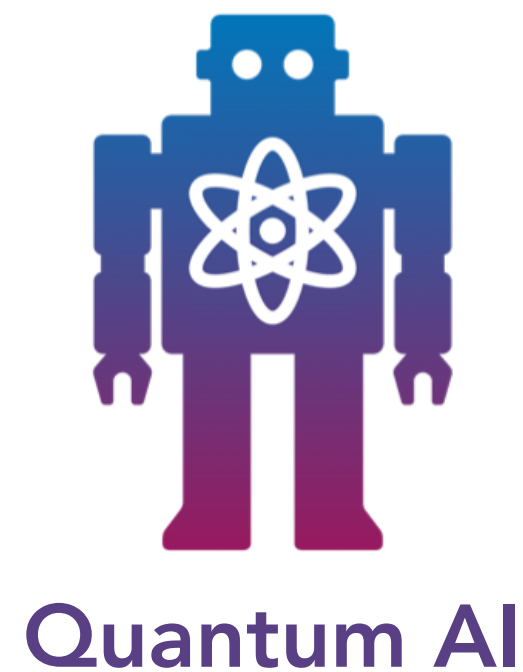
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Discovering New Phases of Matter



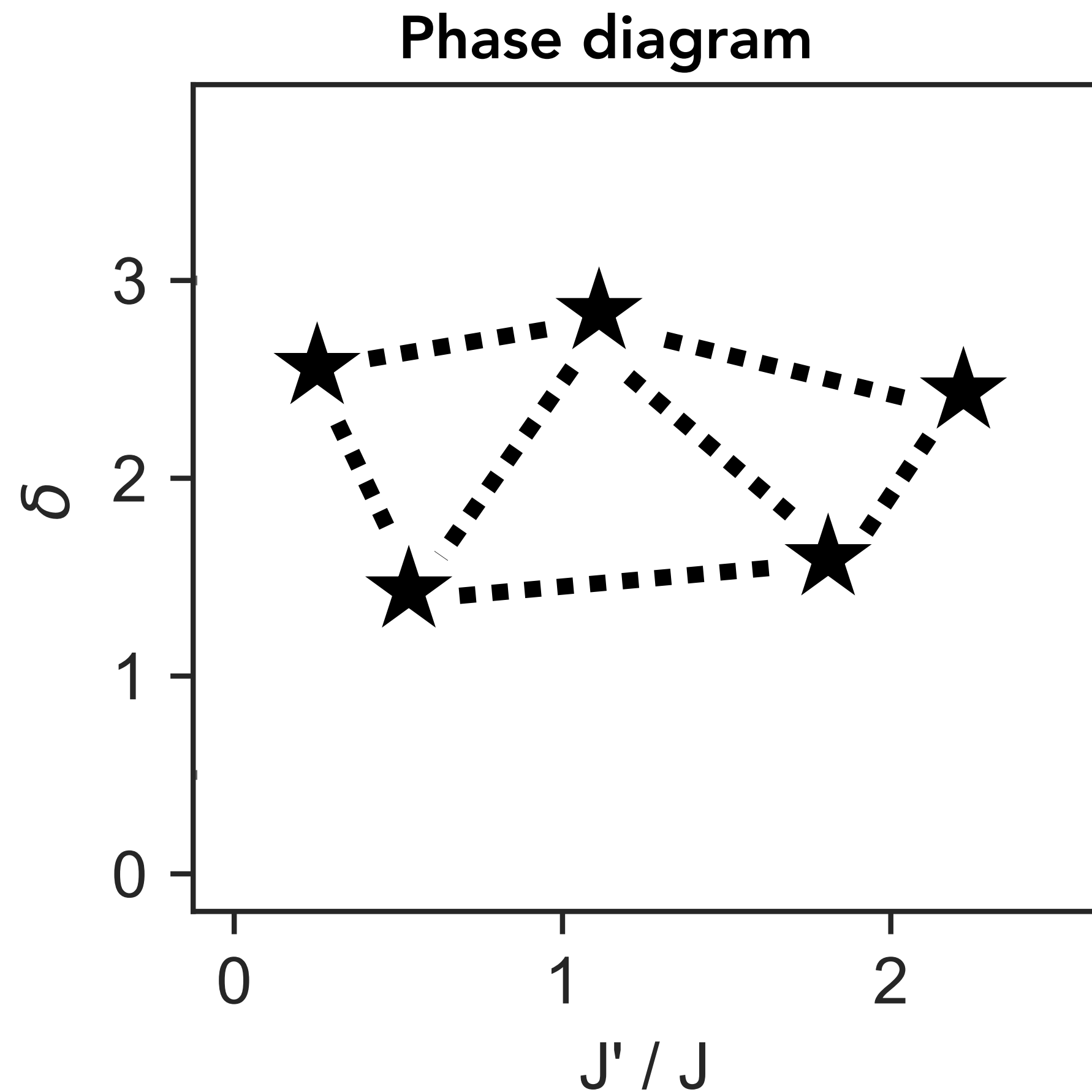
★ : ground states we found on QC



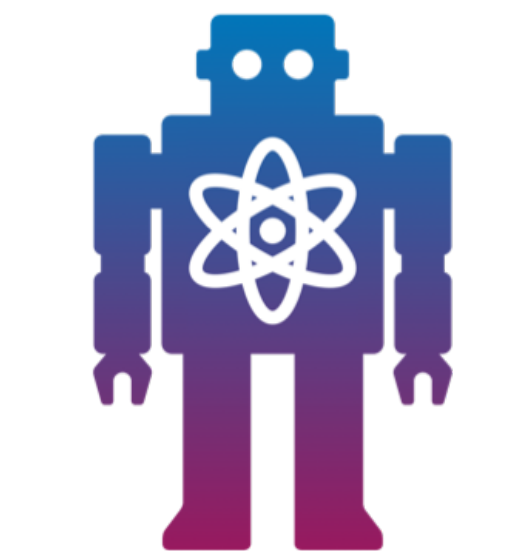
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Discovering New Phases of Matter



★ : ground states we found on QC

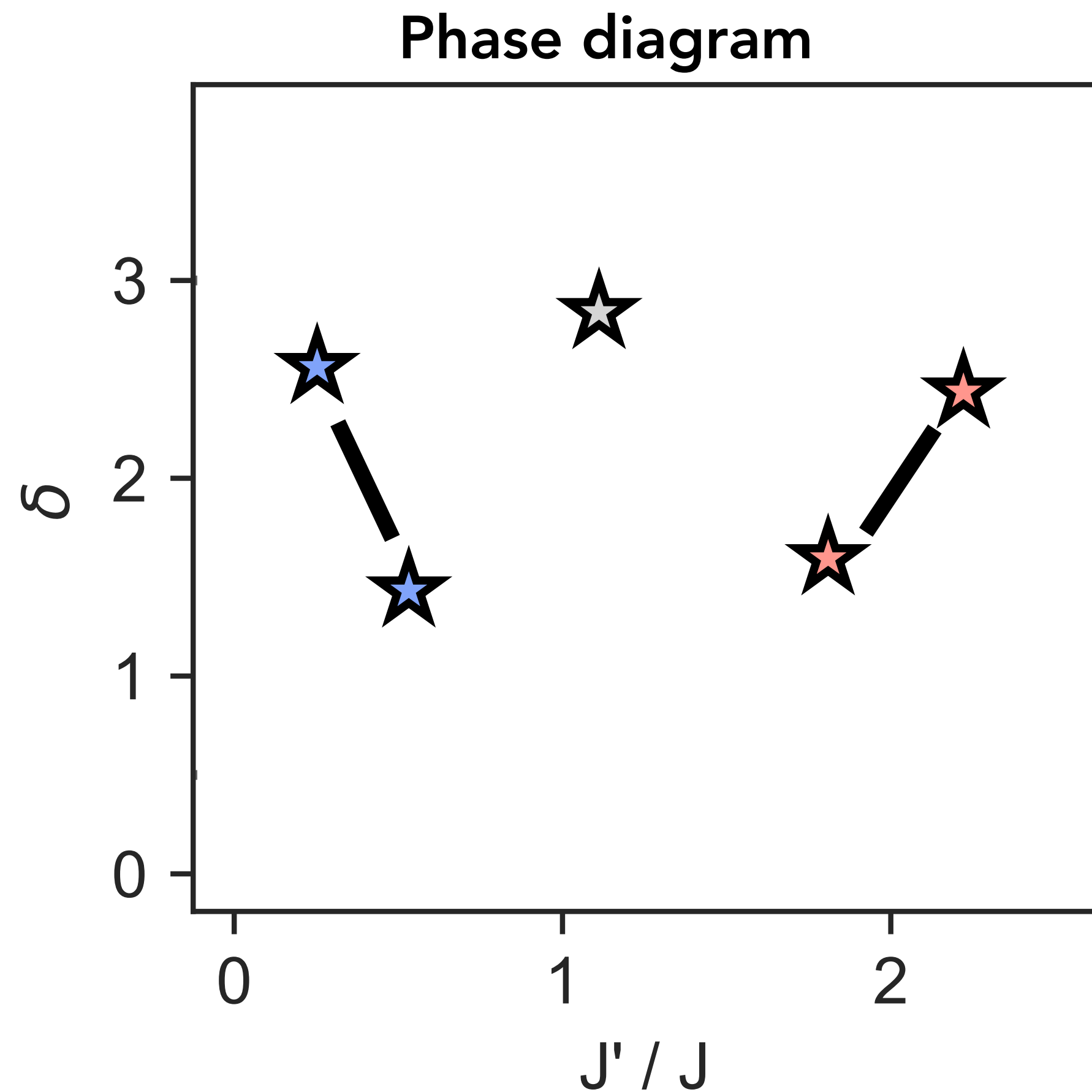


Quantum AI

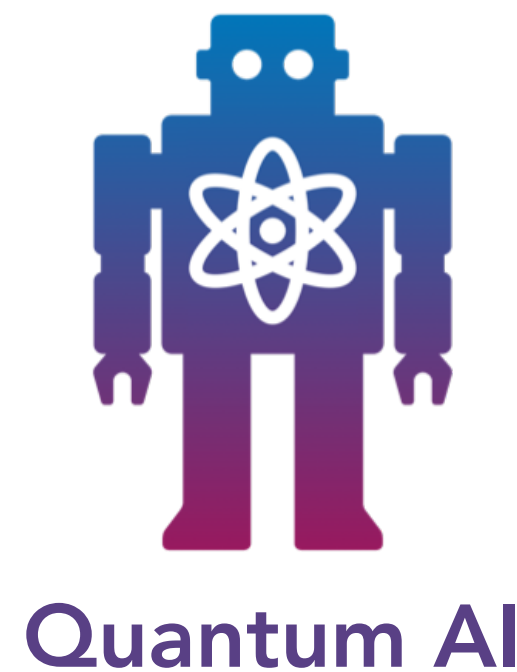
Question:

Can quantum AI tell if **two states** are in the same phase or not?

Discovering New Phases of Matter



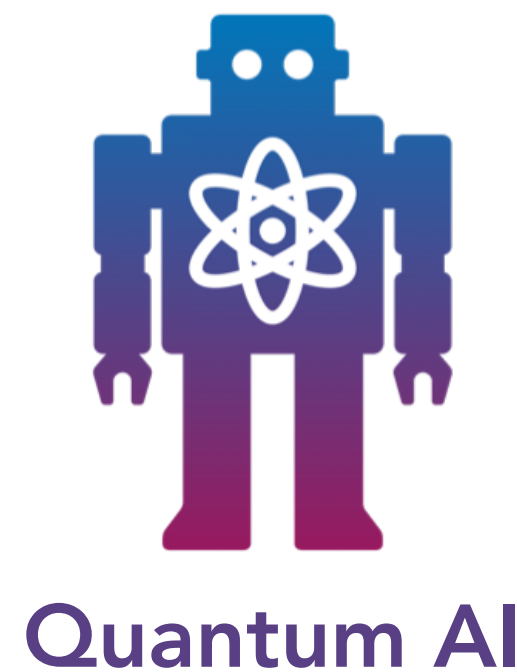
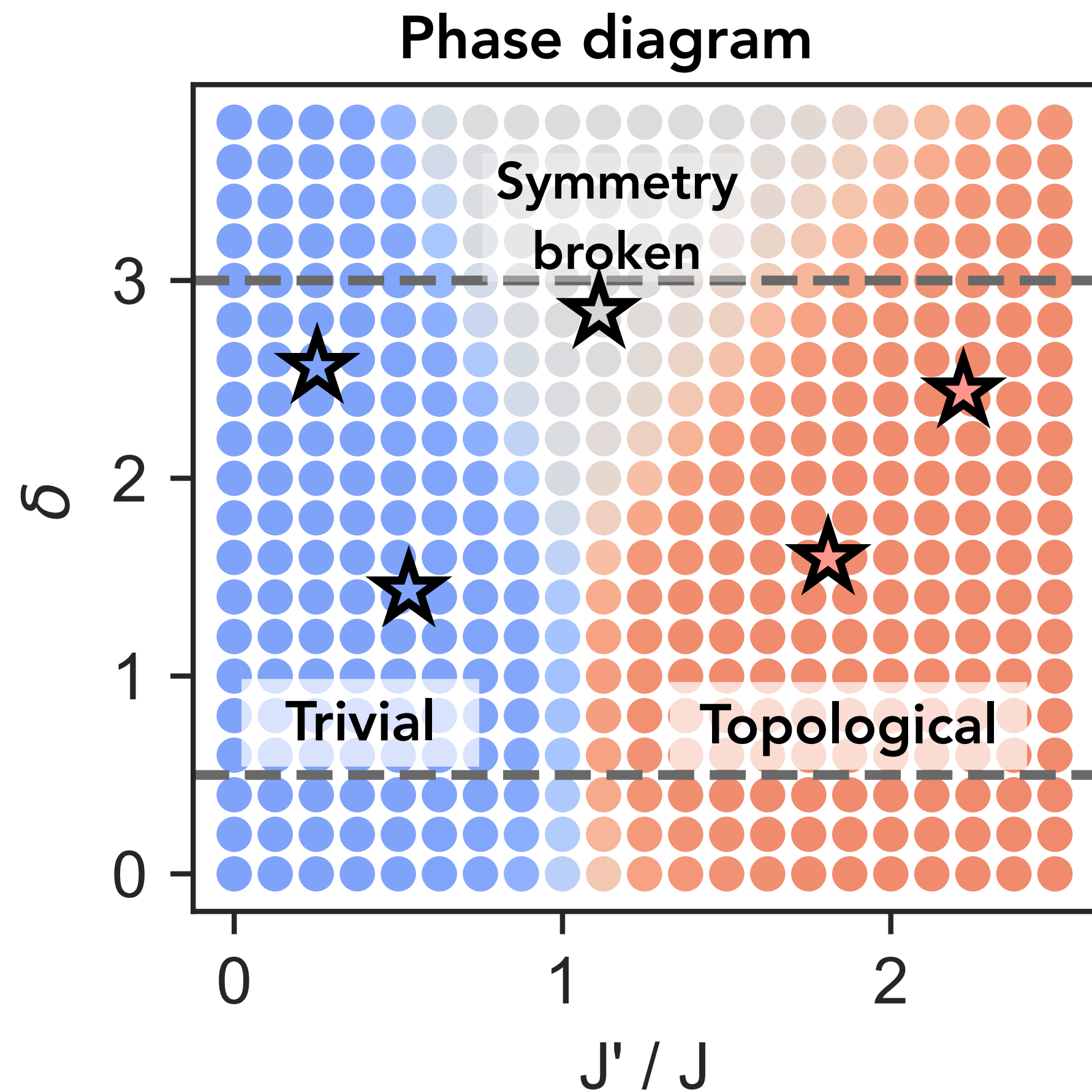
★ : ground states we found on QC



Question:

Can quantum AI tell if **two states** are in the same phase or not?

Discovering New Phases of Matter



If yes, quantum AI can **discover new phases** by mapping out the entire phase diagram.

Long-term ambitions

1. Develop our understanding of learning to accelerate/automate science.
2. Build a **quantum machine** capable of learning and discovering new facets of our universe beyond humans and classical machines.



AI imagination of itself learning and discovering new facets of our quantum universe