Exponential Quantum Advantage in Processing Massive Classical Data

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arXiv:2604.07639

with Alexander Zlokapa, Hartmut Neven, Ryan Babbush, John Preskill, Jarrod McClean, Hsin-Yuan Huang

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Will QC impact our daily life? How?

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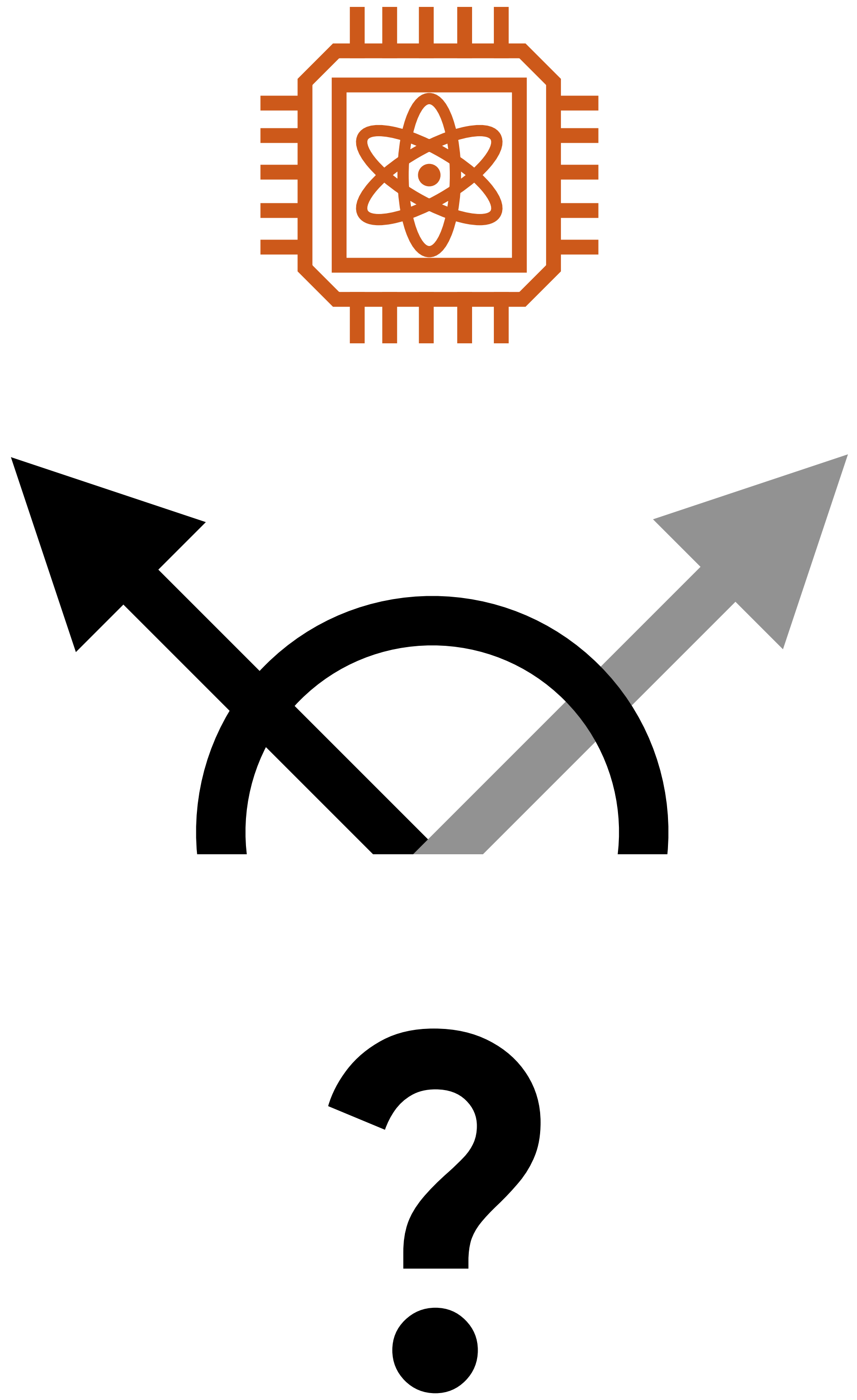
Utility of QC

Specialized devices
for niche tasks

General utility
with wide impact



Utility of QC

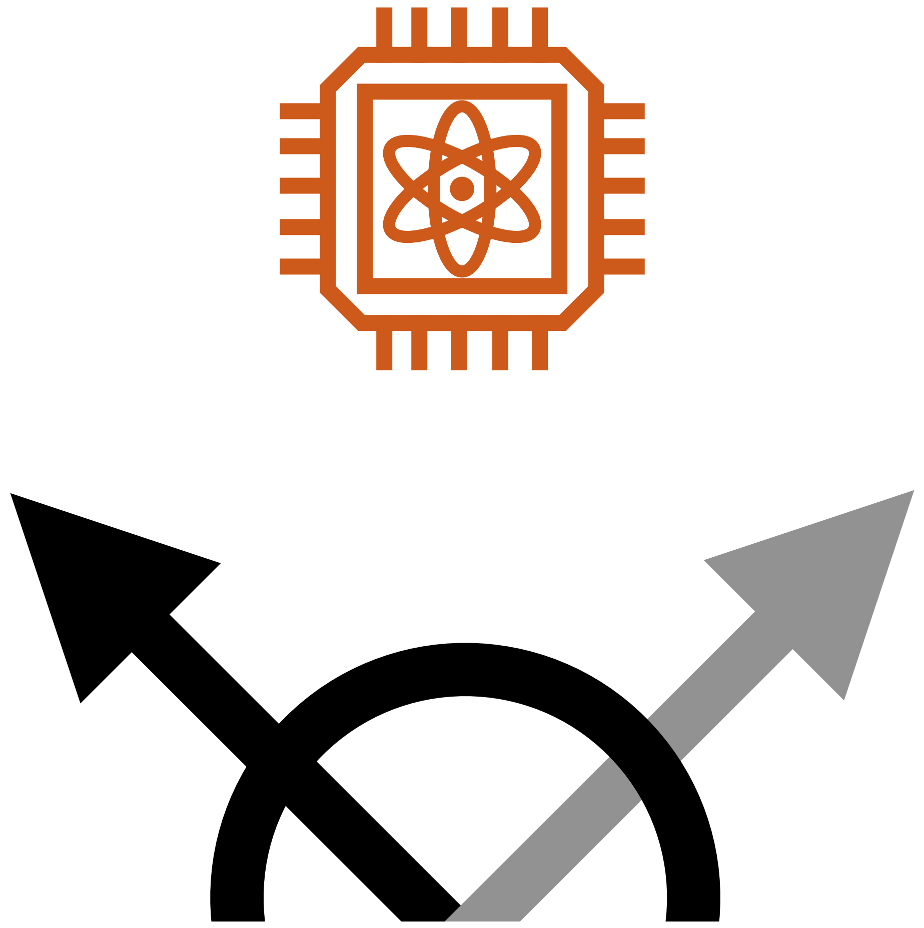
Specialized devices for niche tasks

Cryptanalysis

Shor’94

Quantum Simulation

Feynman’82, Lloyd’96



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General utility with wide impact

?

Utility of QC

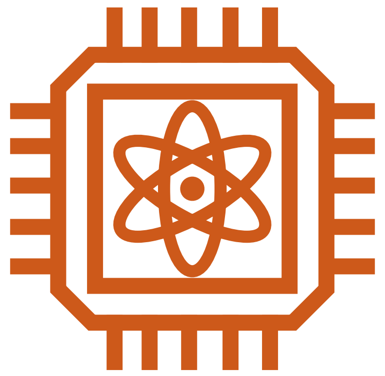
Specialized devices for niche tasks

Special structures exploitable by QC but classically hard

e.g., inherently quantum

Quantum Chemistry

Condensed Matter Physics



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General utility with wide impact

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Utility of QC

Specialized devices for niche tasks

Special structures exploitable by QC but classically hard

e.g., inherently quantum

Quantum Chemistry

Condensed Matter Physics

General utility with wide impact

AI

Healthcare

Finance

Unstructured massive classical data

Media

?

Science

Engineering

Life in a classical world

Life in a classical world

Reviews

"One of the best movies."

"Fantastic production."

"Story makes no sense."

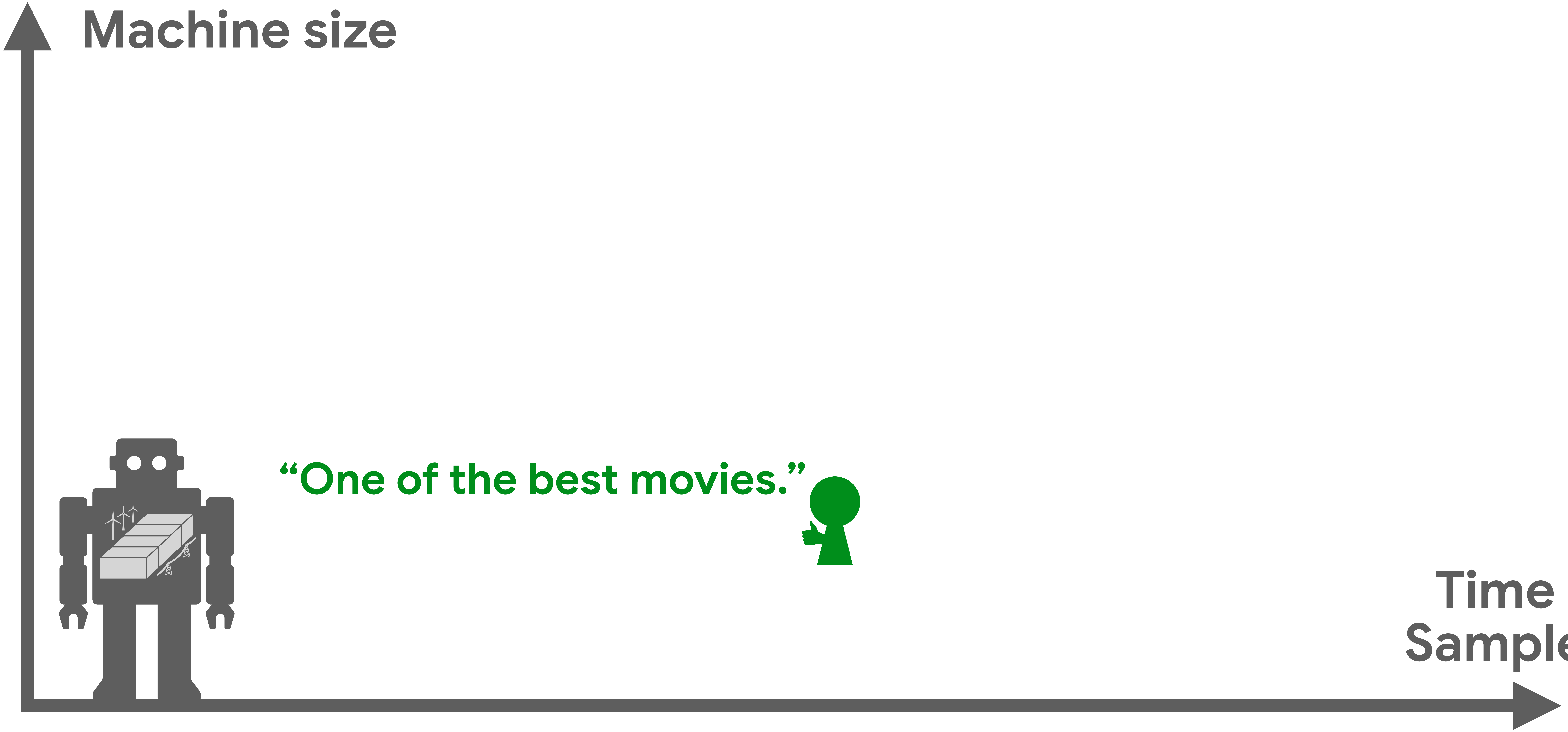
Life in a classical world

Reviews	Classical Data
"One of the best movies."	$\vec{x}_1$
"Fantastic production."	$\vec{x}_2$
"Story makes no sense."	$\vec{x}_3$

Life in a classical world

Reviews	Classical Data	
"One of the best movies."	$\vec{x}_1$	👍
"Fantastic production."	$\vec{x}_2$	👍
"Story makes no sense."	$\vec{x}_3$	👎
Task: sentiment analysis	$\vec{x}$	👍/👎

Classical ML



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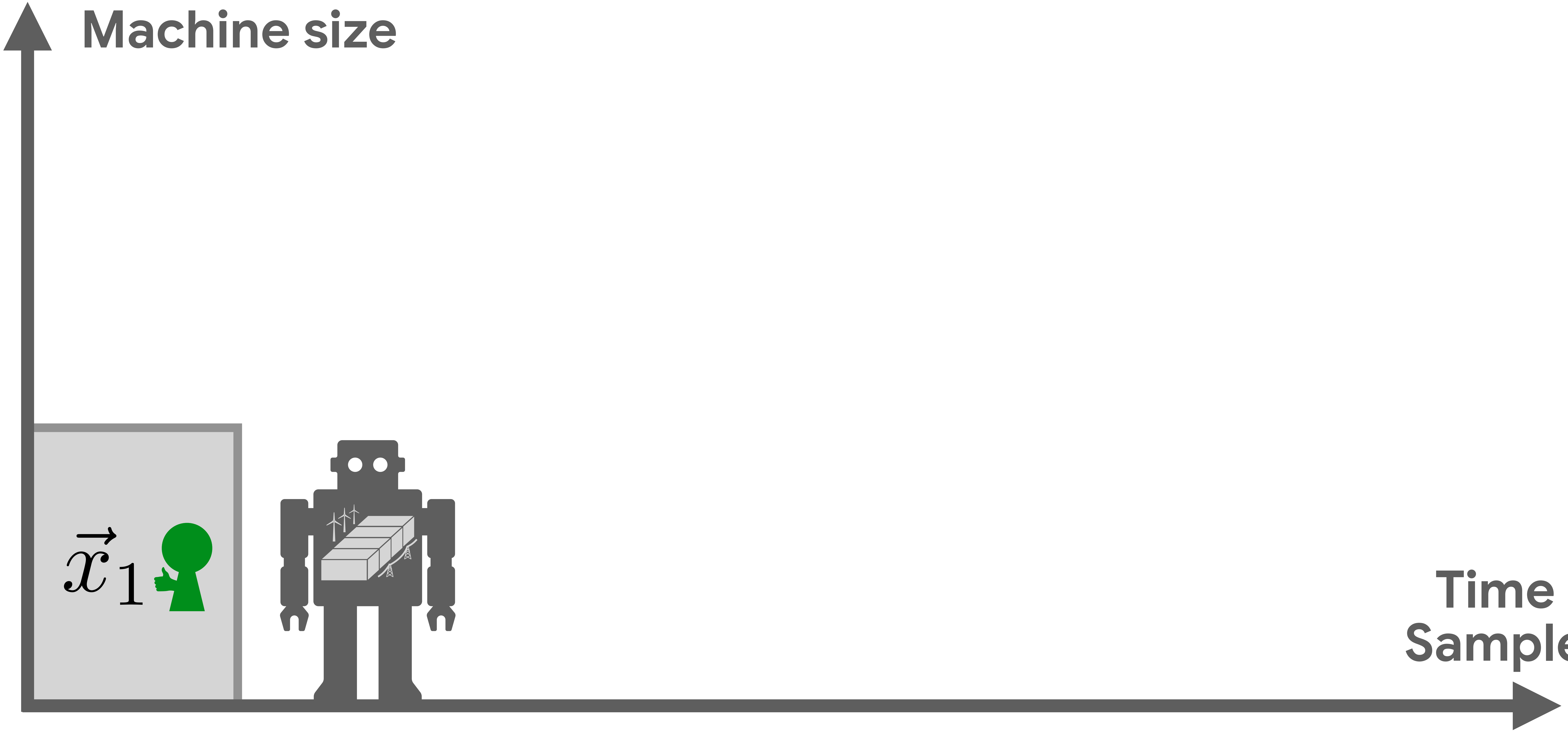

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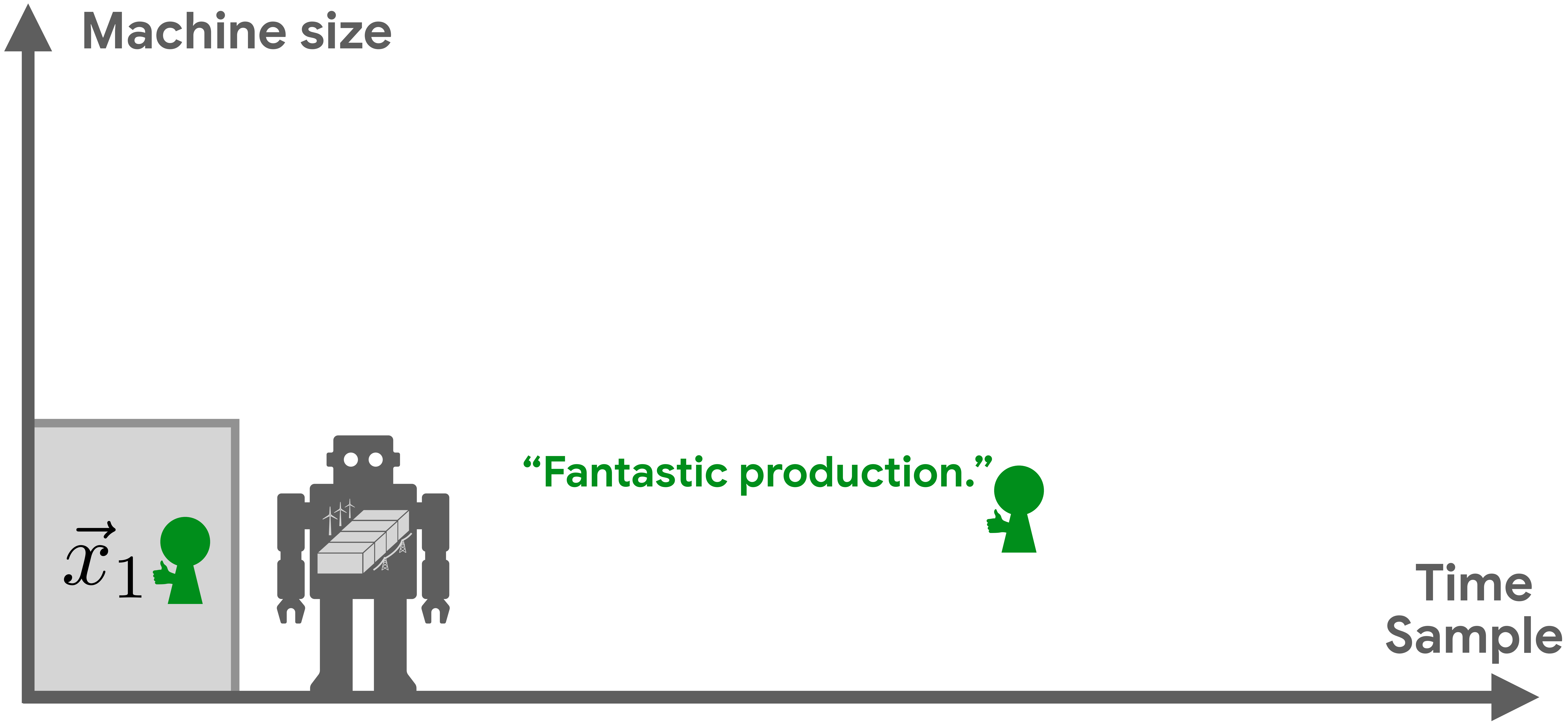

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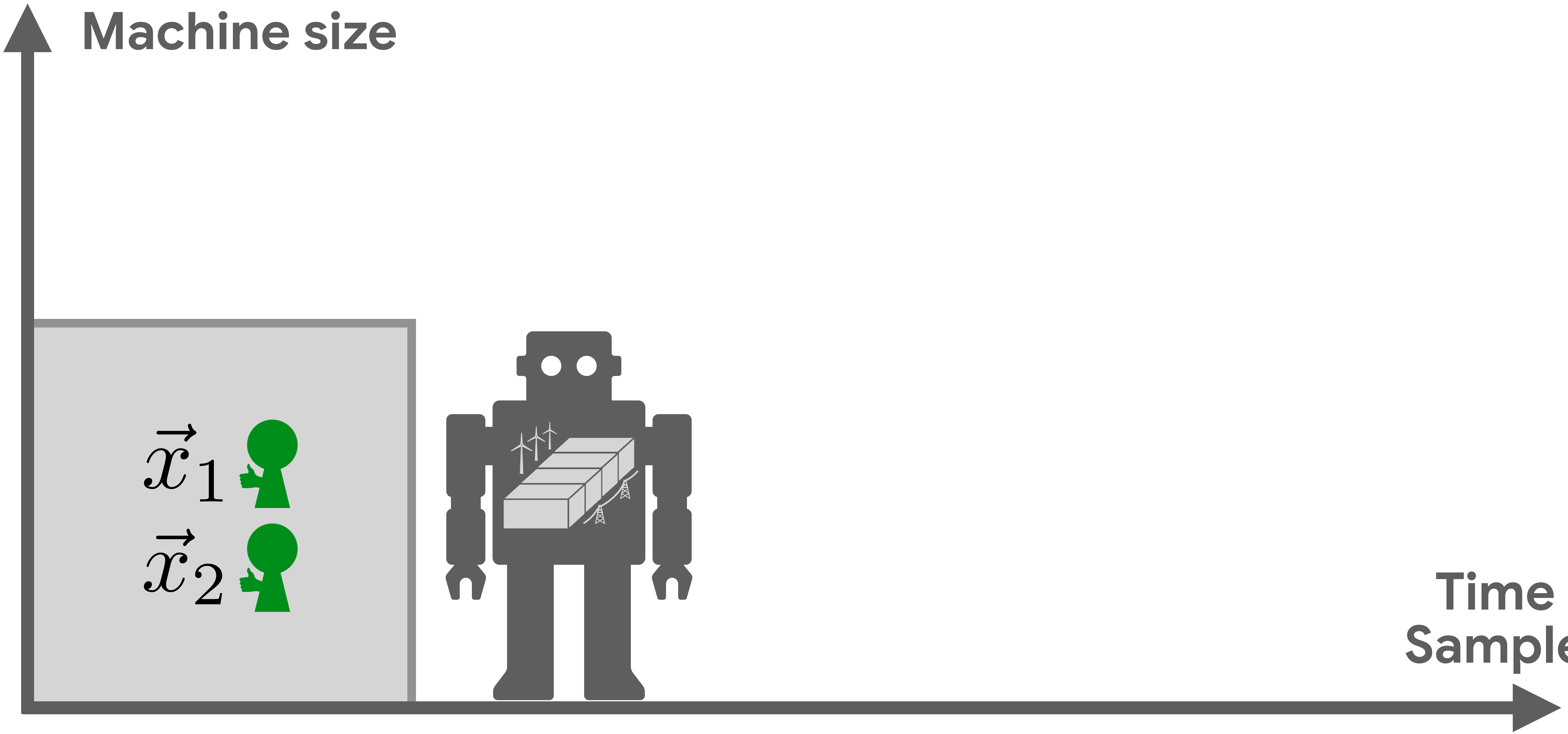

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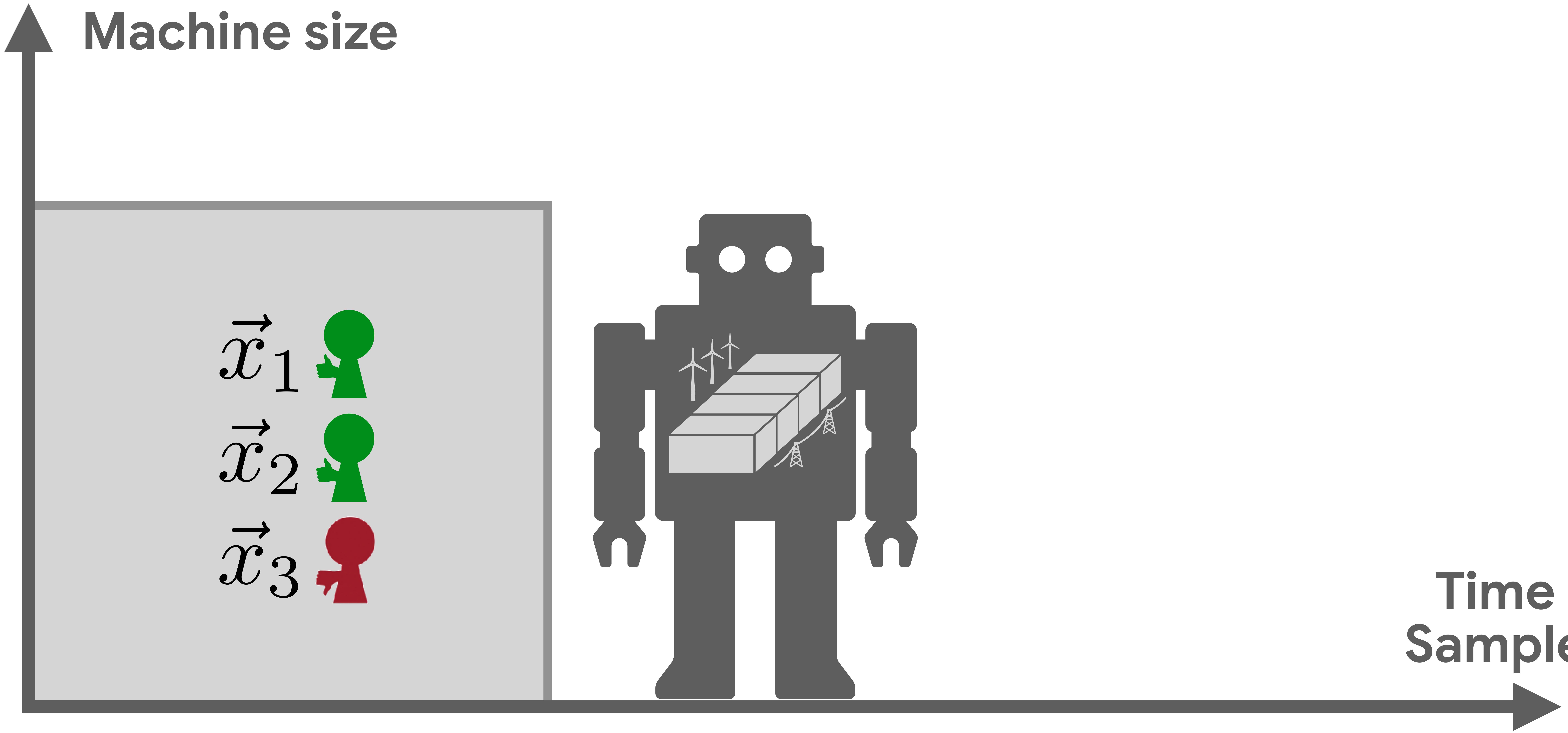

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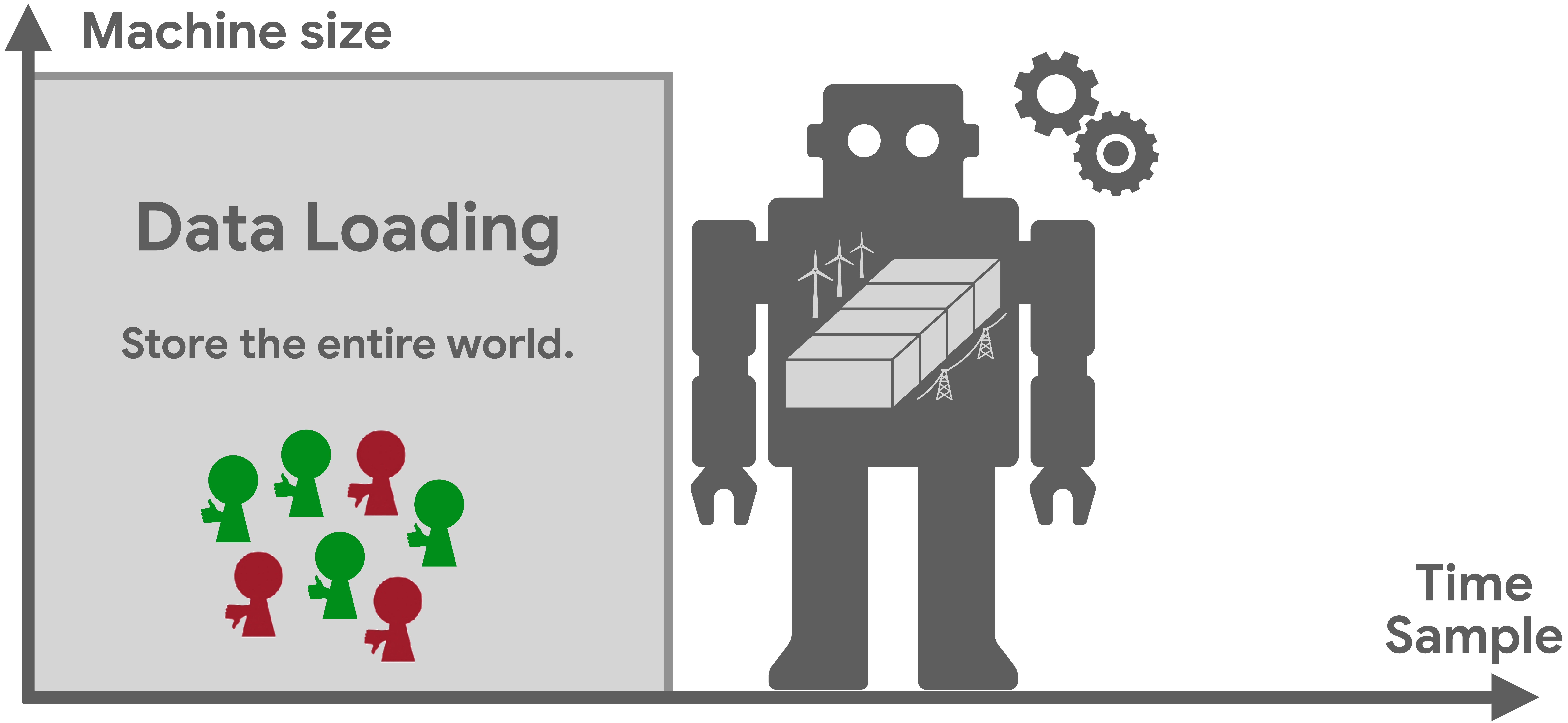

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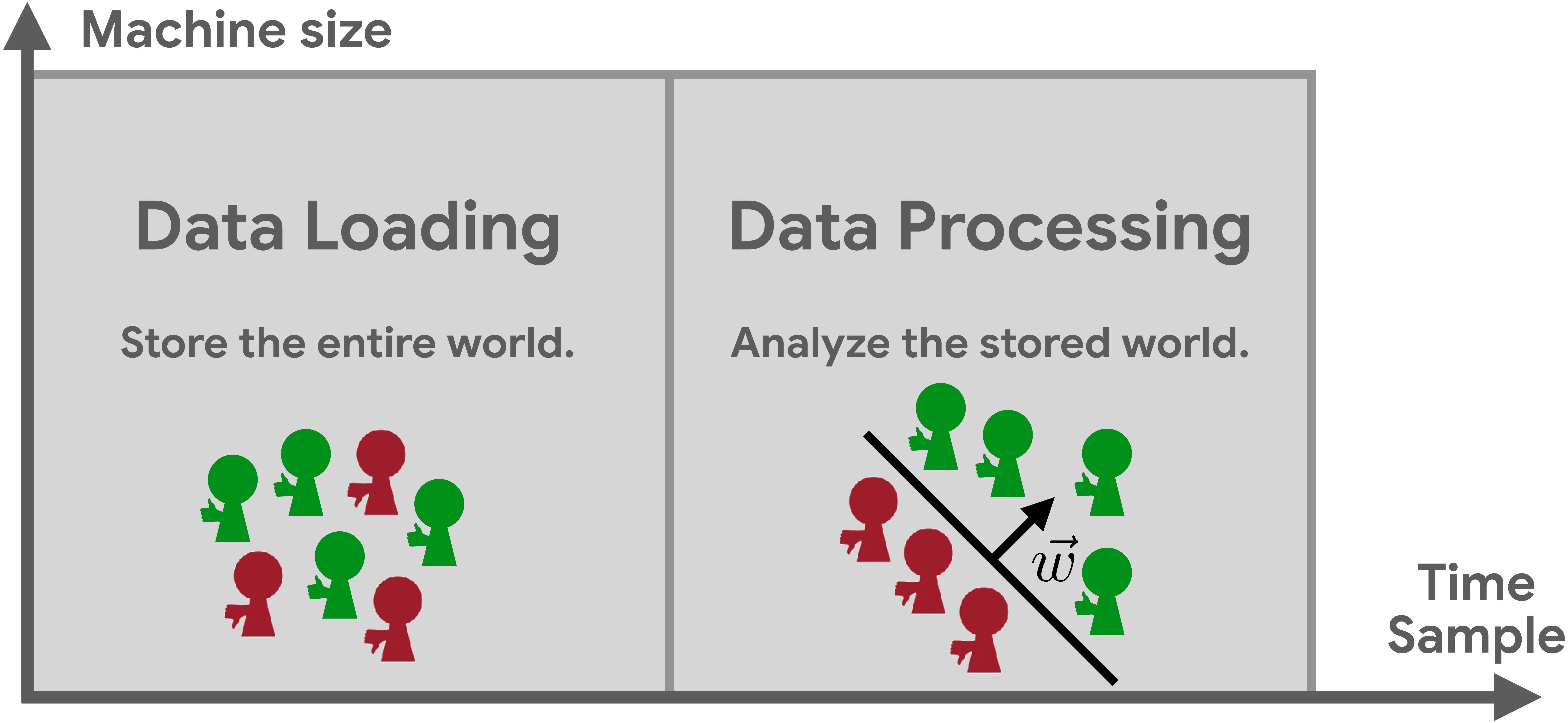
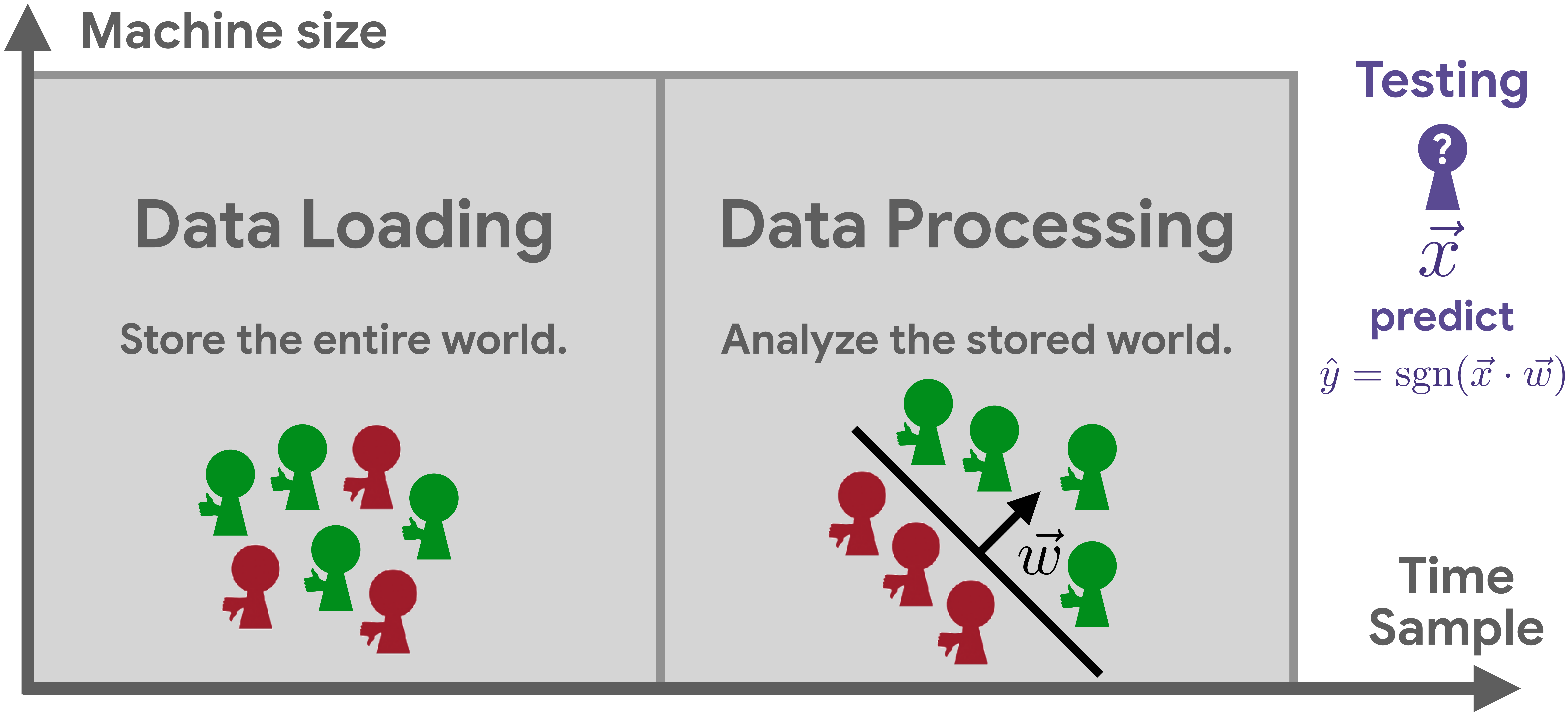


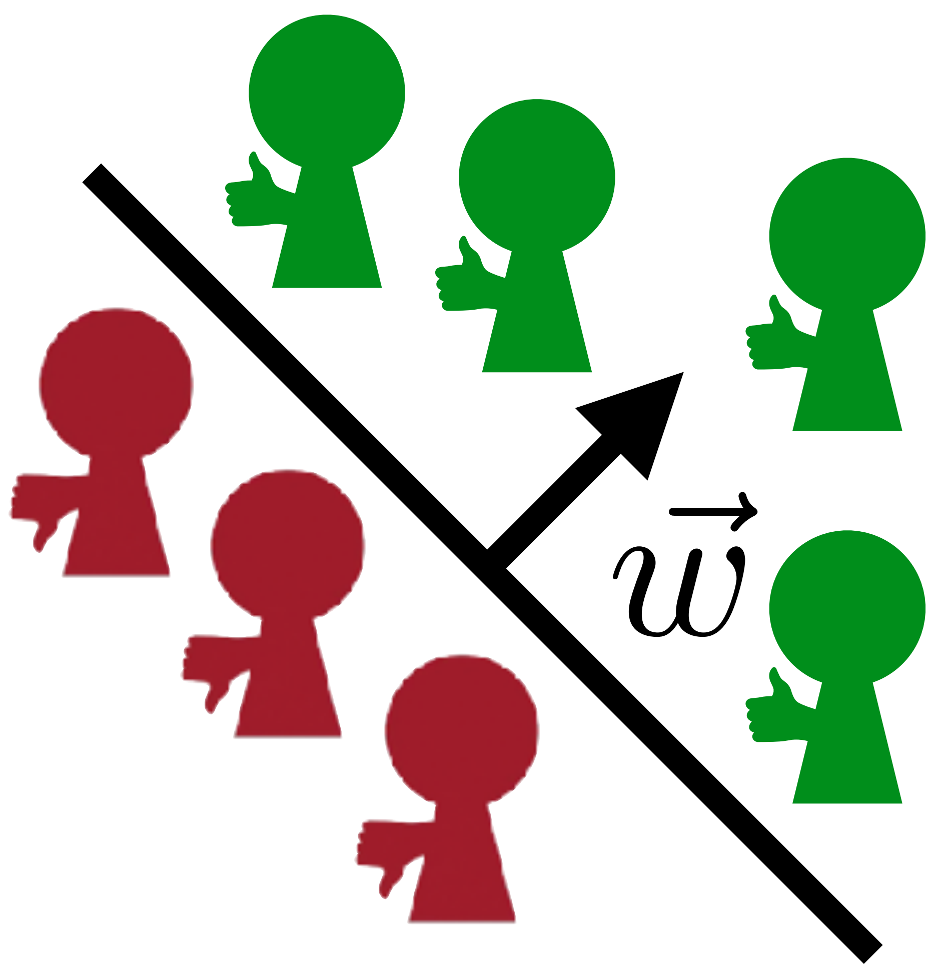
Classical ML

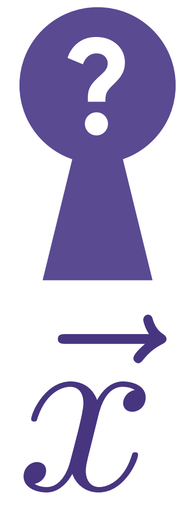


Main Results

Classification: given data $(i, \vec{x}_i, y_i)$ randomly sampled from N examples, each with a D-dim sparse feature vector and a label, train a regularized D-dim classifier $\vec{w}$ such that we can predict the label of any classifiable sparse test vectors.

margin not too small





predict

$$\hat{y} = \mathrm{sgn}(\vec{x} \cdot \vec{w})$$

Main Results

Classification: given data $(i, \vec{x}_i, y_i)$ randomly sampled from N examples, each with a D-dim sparse feature vector and a label, train a regularized D-dim classifier $\vec{w}$ such that we can predict the label of any classifiable sparse test vectors.

margin not too small

Theorem 1 (Classification)

With $\tilde{O}(N)$ samples, a quantum machine of $\mathrm{poly}(\log D)$ size can solve classification, whereas any classical machine of $O(D^{0.99})$ size cannot.

Main Results

Classification: often the training examples change over time, but the underlying classification rule remains the same.

Example: large particle colliders

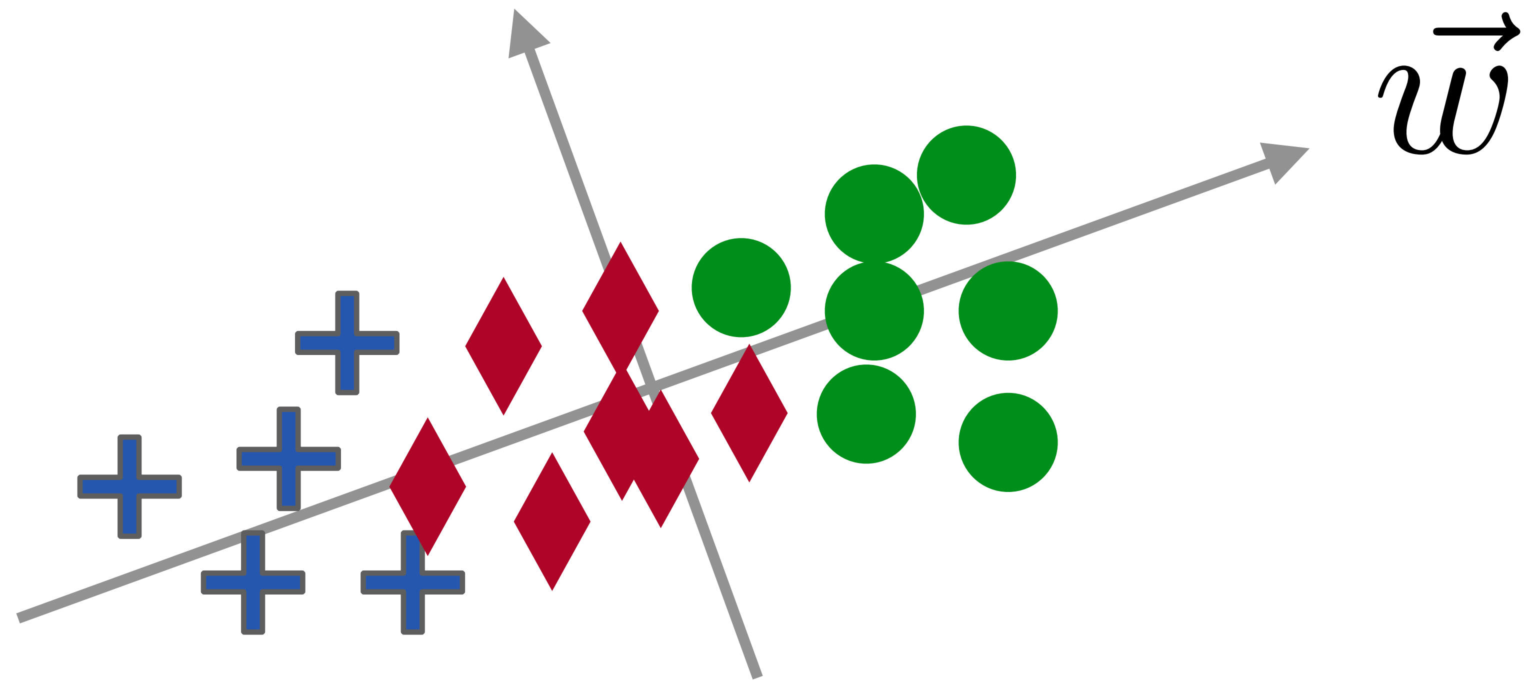
Theorem 2 (Dynamic Classification)

A quantum machine of $\mathrm{poly}(\log D)$ size can solve classification using only $\tilde{O}(N)$ samples, whereas any classical machine of $O(D^{0.99})$ size requires at least $\mathrm{superpoly}(N)$ samples.

Main Results

Dimension reduction: given data $(i, \vec{x}_i)$ sampled from N examples, each with a D-dim sparse feature vector, learn an identifiable D-dim principal component $\vec{w}$ such that we can predict the 1D representation of any new sparse test vectors.

eigenvalue gapped, non-negligible overlap with a prominent feature



unsupervised

Main Results

Dimension reduction: given data $(i, \vec{x}_i)$ sampled from N examples, each with a D-dim sparse feature vector, learn an identifiable D-dim principal component $\vec{w}$ such that we can predict the 1D representation of any new sparse test vectors.

eigenvalue gapped, non-negligible overlap with a prominent feature

Theorem 3 (Dim Reduction)

With $\tilde{O}(N)$ samples, a quantum machine of $\mathrm{poly}(\log D)$ size can solve dim. reduct., whereas any classical machine of $O(D^{0.99})$ size cannot.

Main Results

Dimension reduction: given data $(i, \vec{x}_i)$ sampled from N examples, each with a D-dim sparse feature vector, learn an identifiable D-dim principal component $\vec{w}$ such that we can predict the 1D representation of any new sparse test vectors.

eigenvalue gapped, non-negligible overlap with a prominent feature

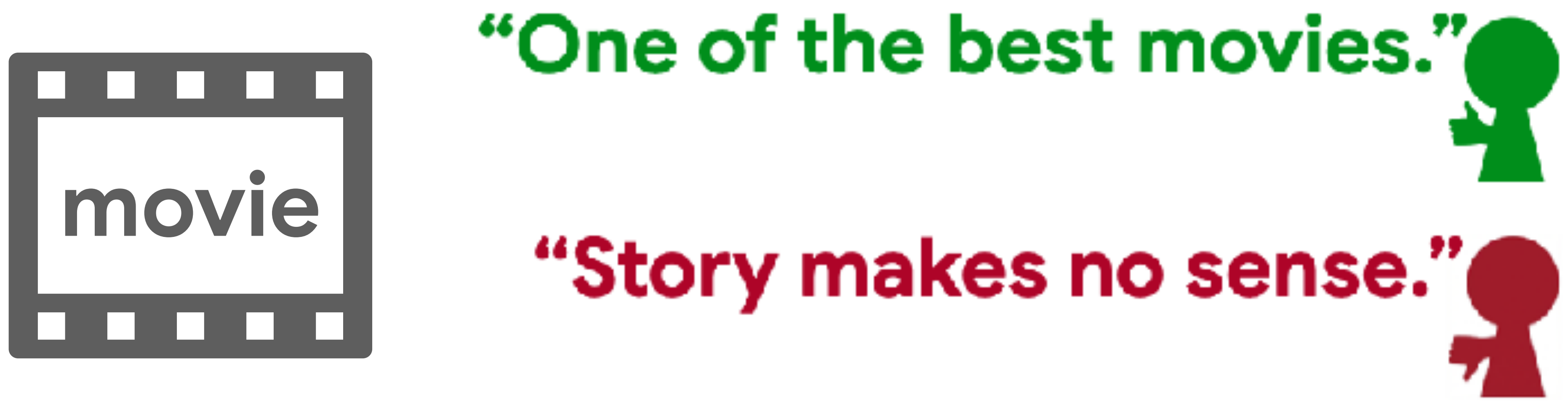
Theorem 4 (Dynamic Dim Reduction)

A quantum machine of $\mathrm{poly}(\log D)$ size can solve dim. reduct. using only $\tilde{O}(N)$ samples, whereas any classical machine of $O(D^{0.99})$ size requires at least $\mathrm{superpoly}(N)$ samples.

Theory in Practice

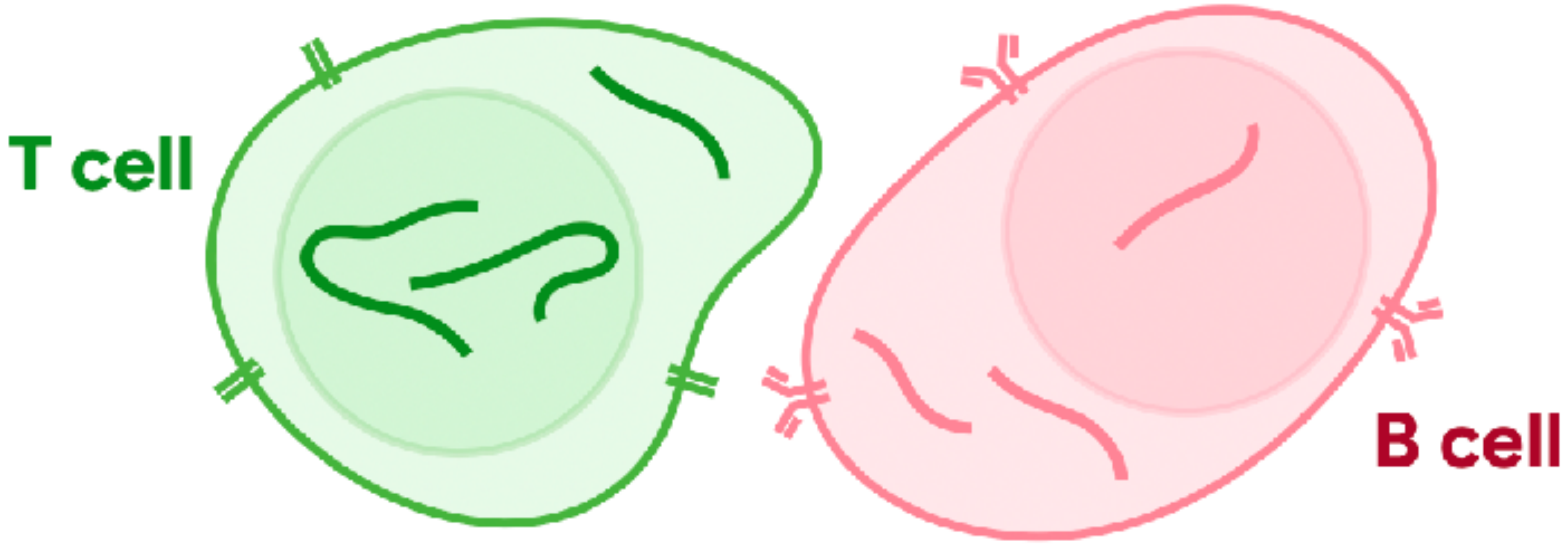
IMDb

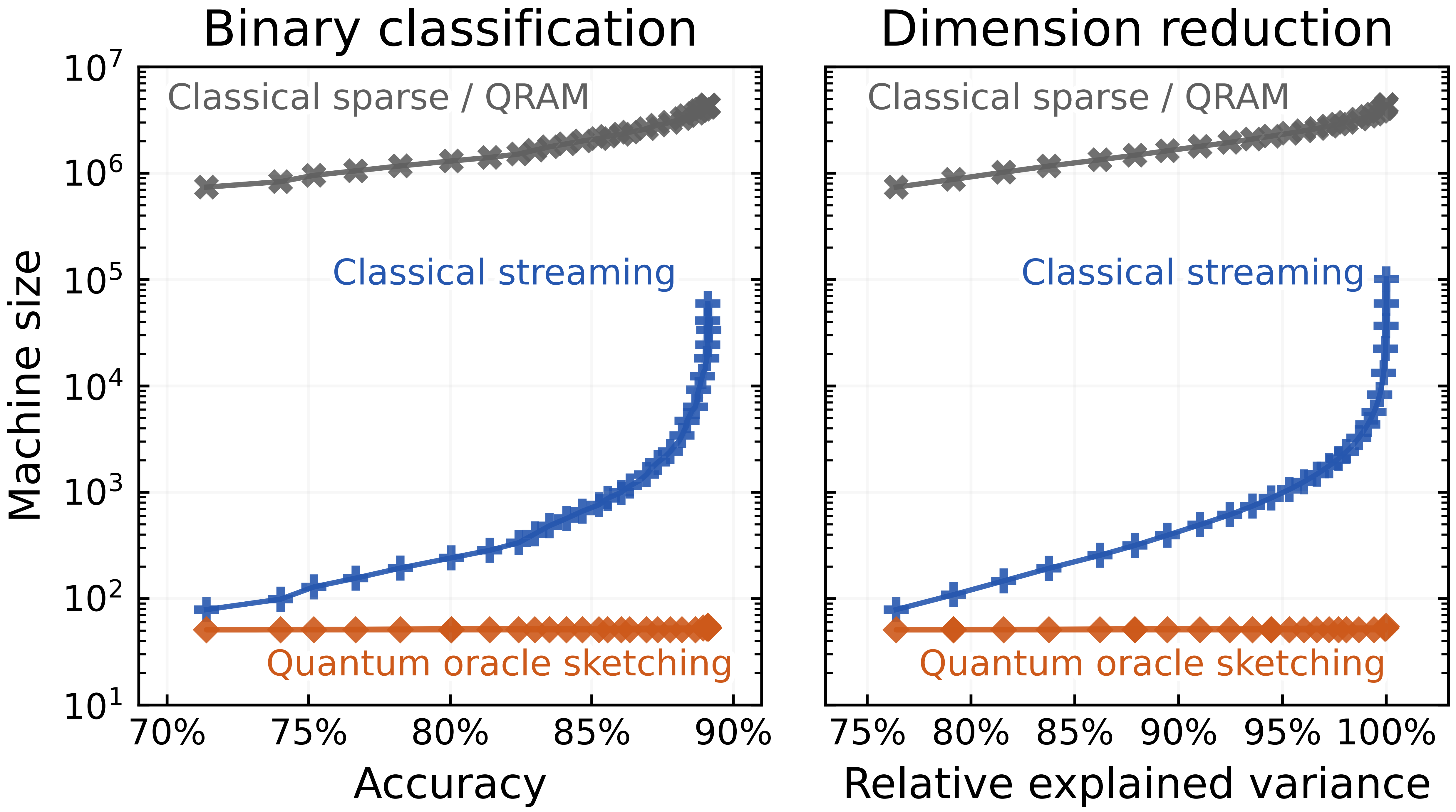
Movie review sentiment analysis

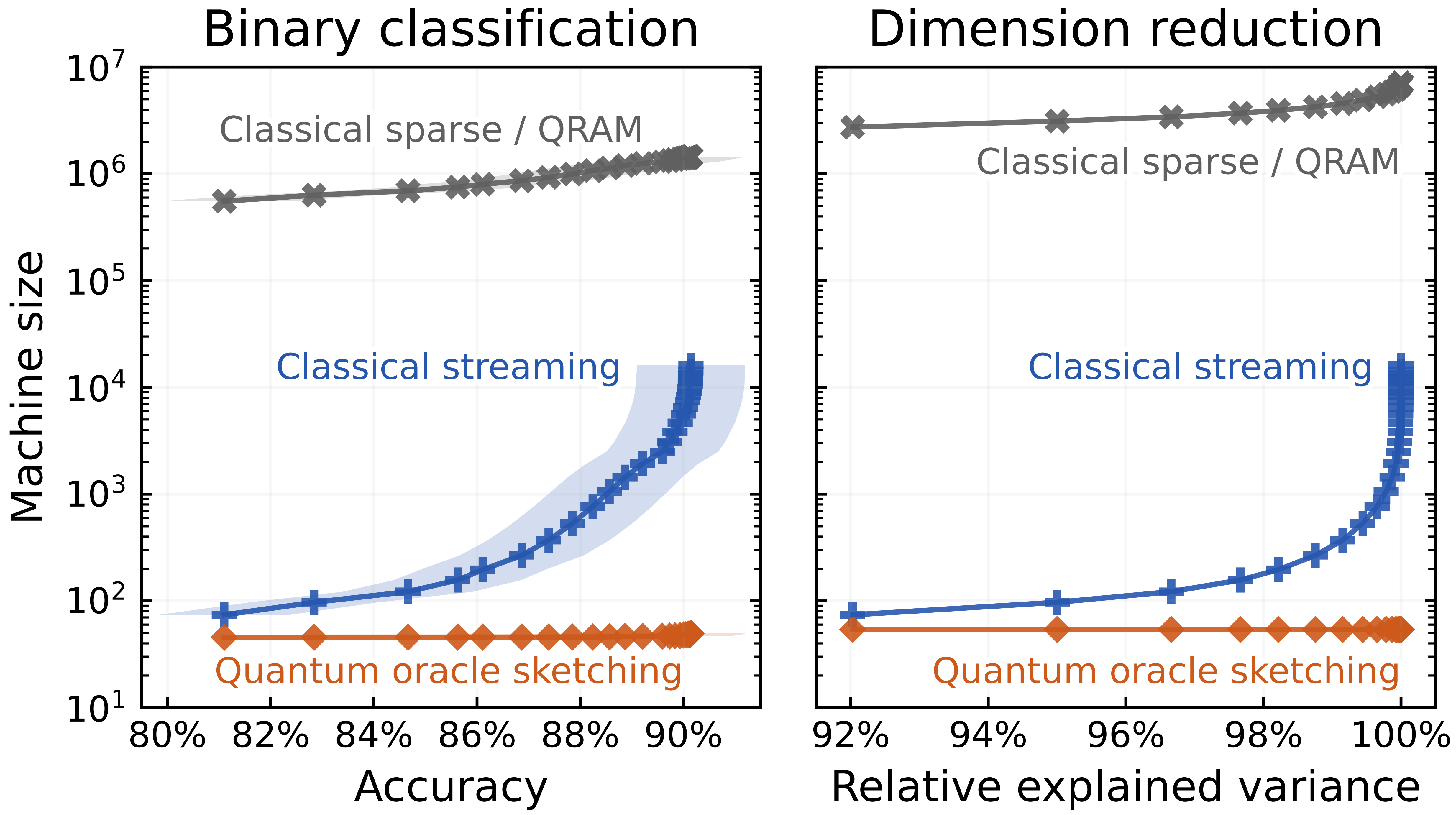


PBMC68k

Single cell RNA sequencing







Theory in Practice

20Newsgroup

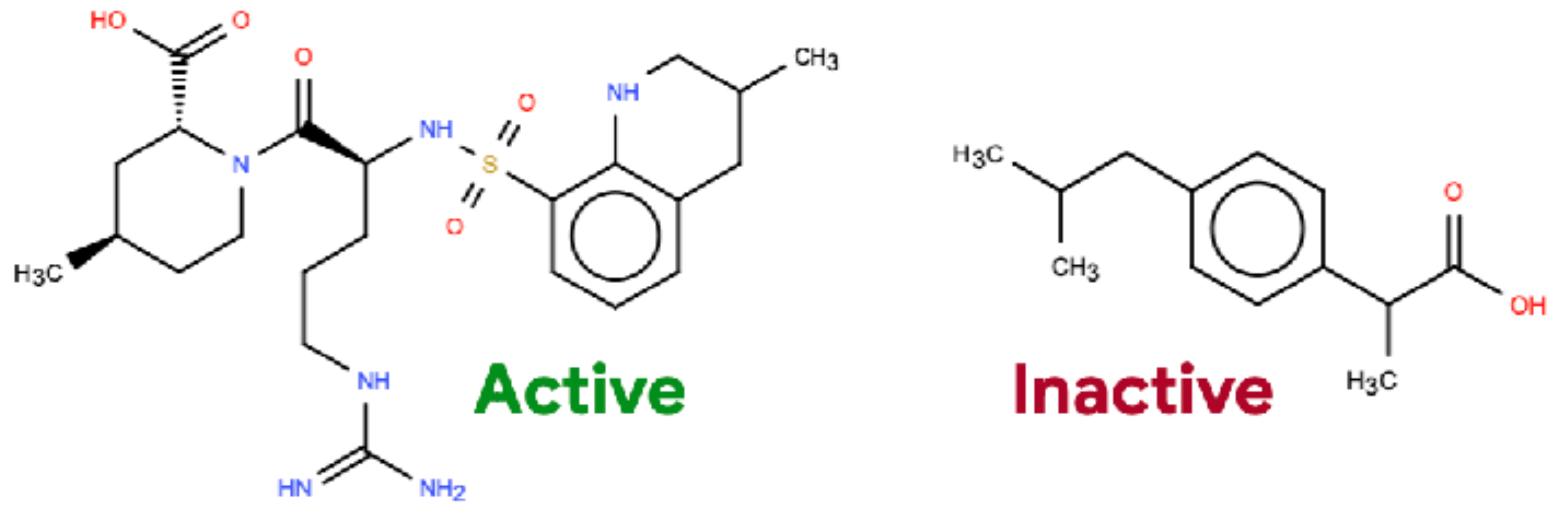
Social media topic analysis

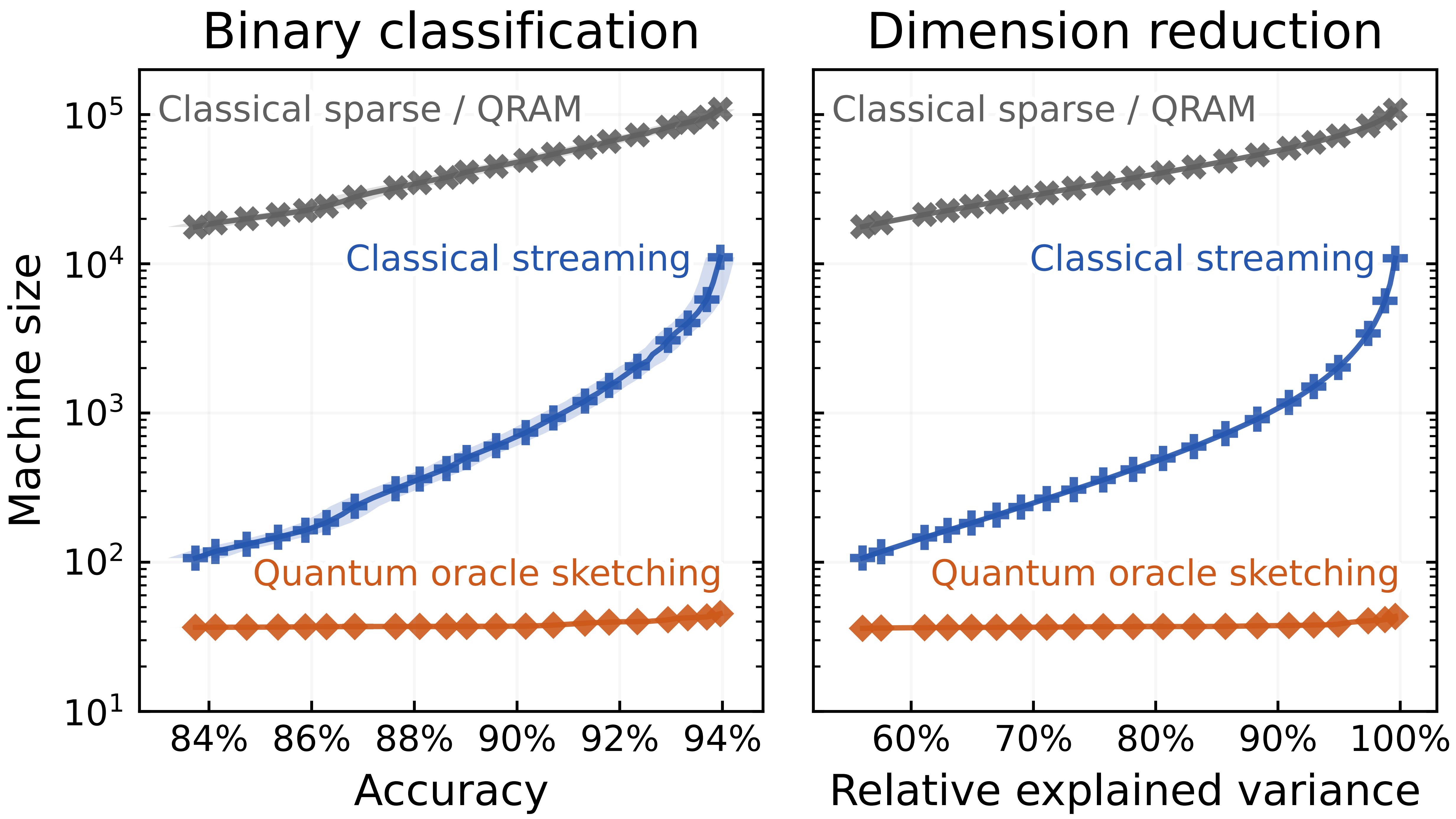

Good offer at our local dealership.

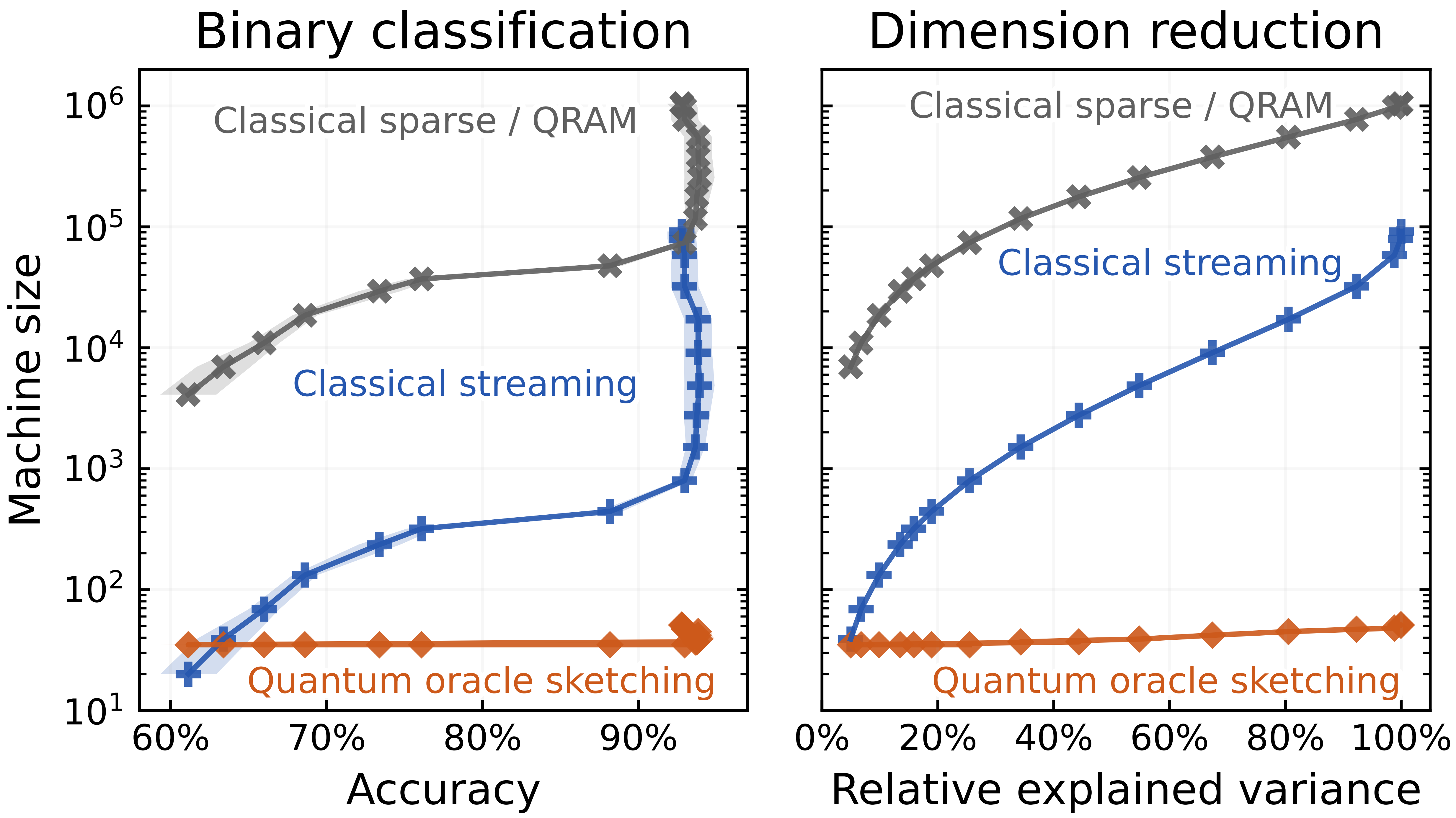

Any opinions on this new medication?

Thrombin

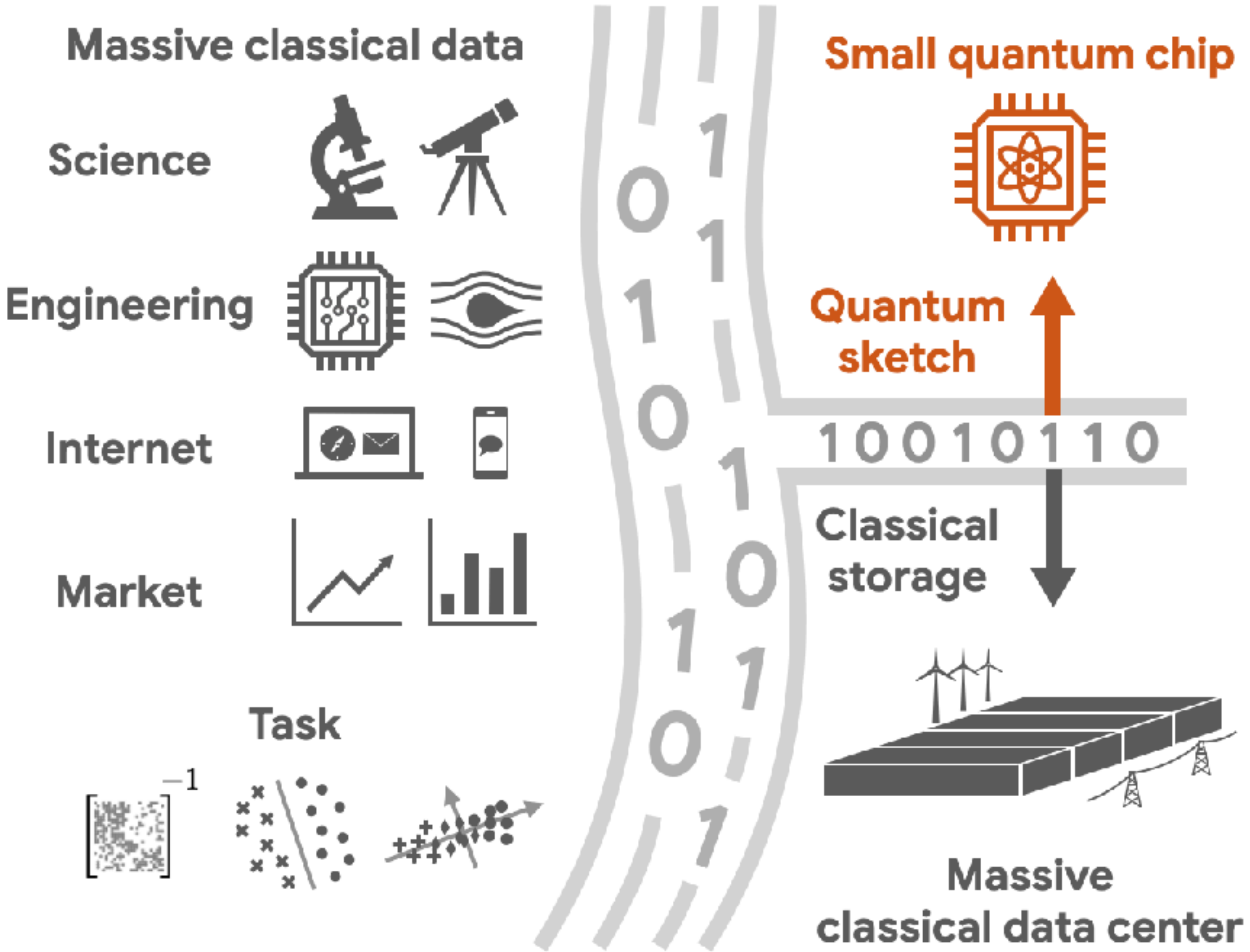
Pharmaceutical drug discovery





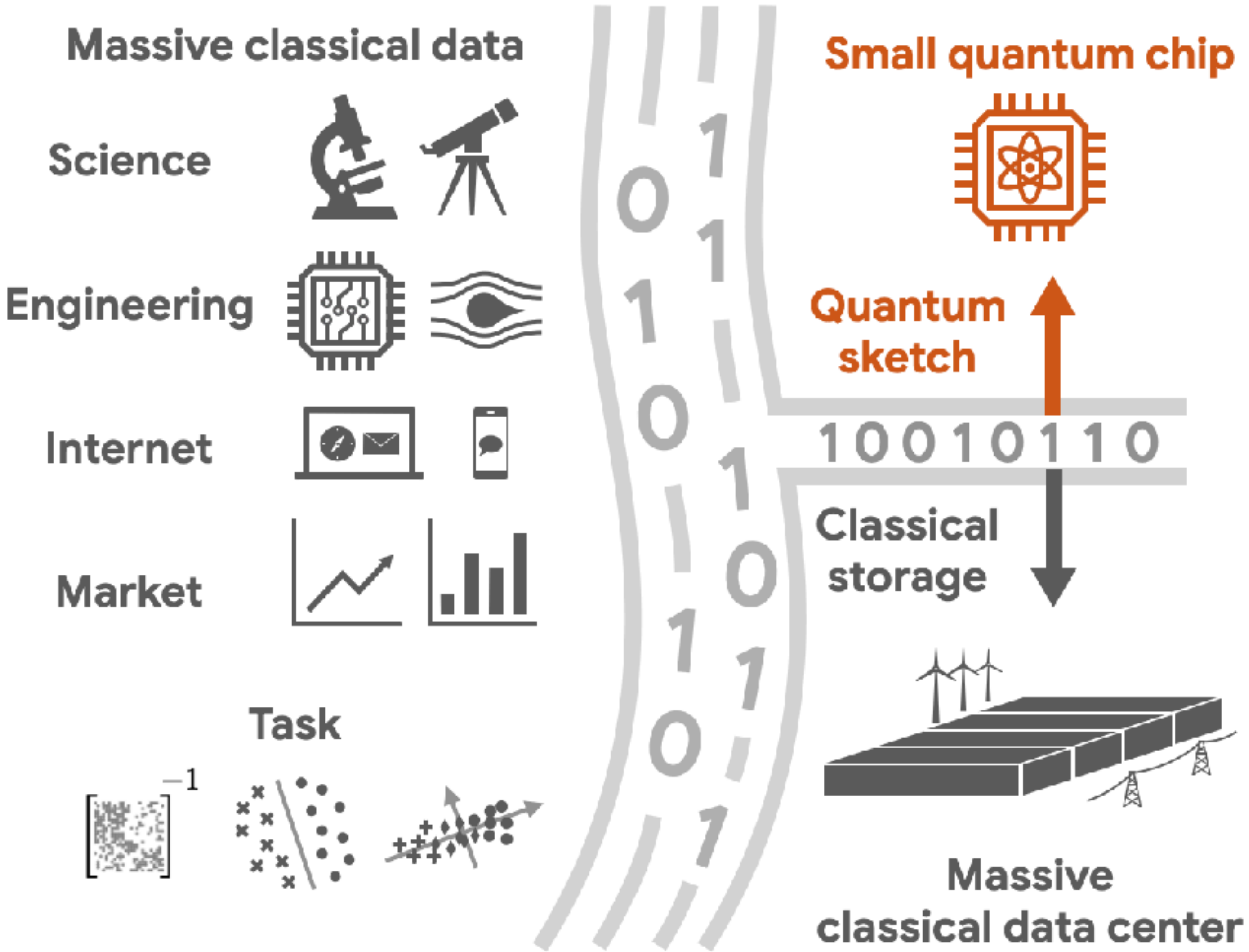


Main Results



Machine learning is a broad domain of **exponential quantum advantage.**

Main Results



Machine learning

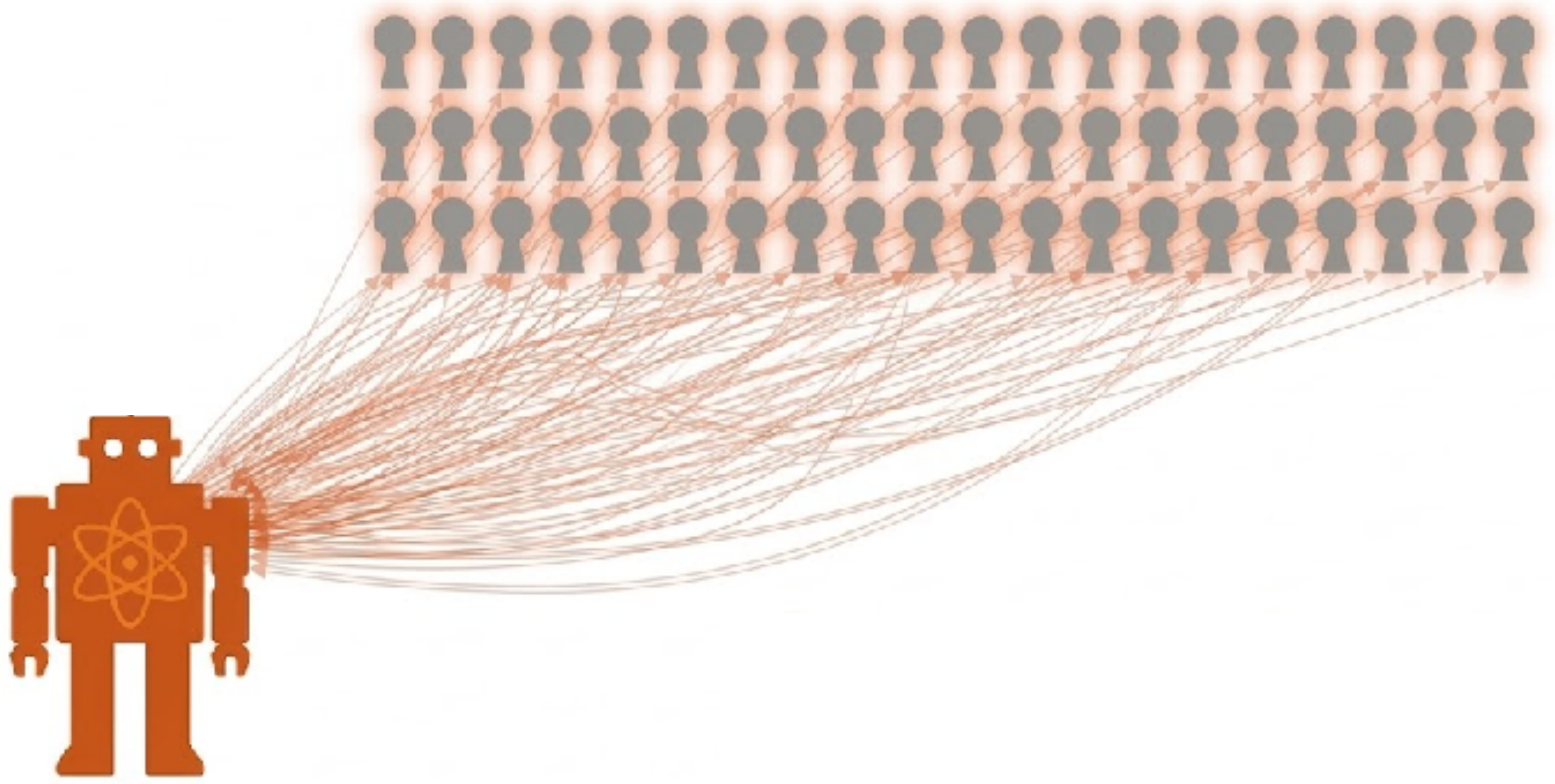
is a broad domain of

exponential quantum advantage.

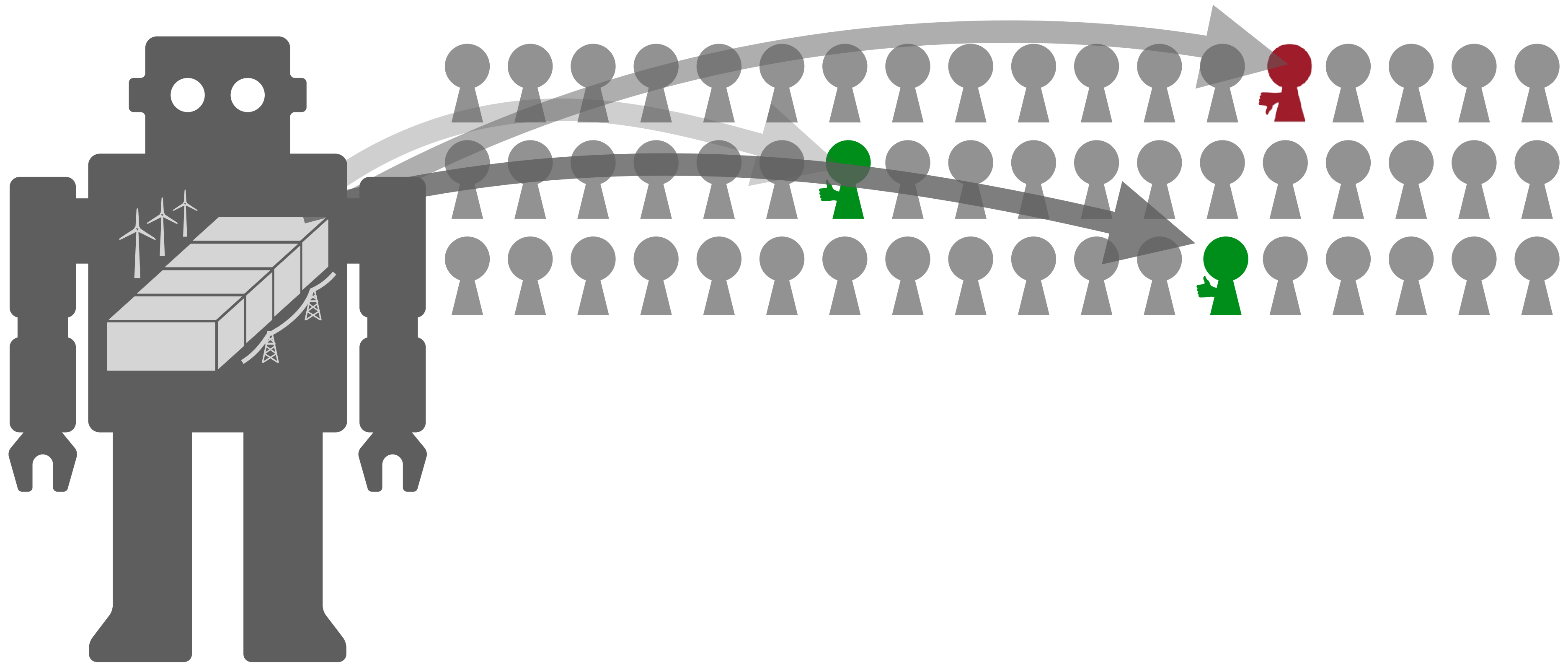
persist even if BPP=BQP, P=NP, granted infinite time

Origin of Advantage

Quantum Algorithm

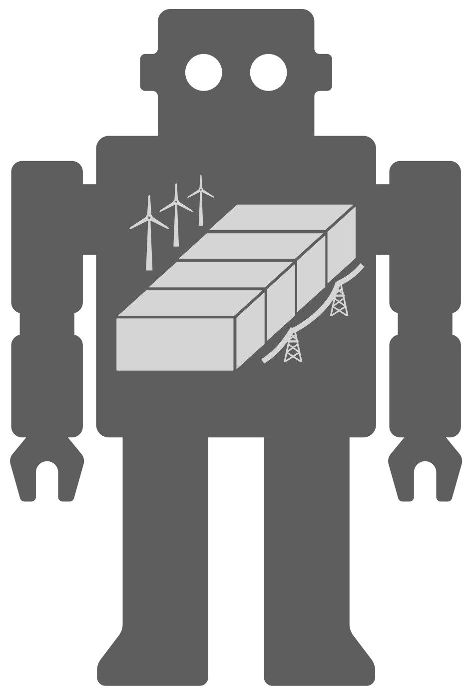


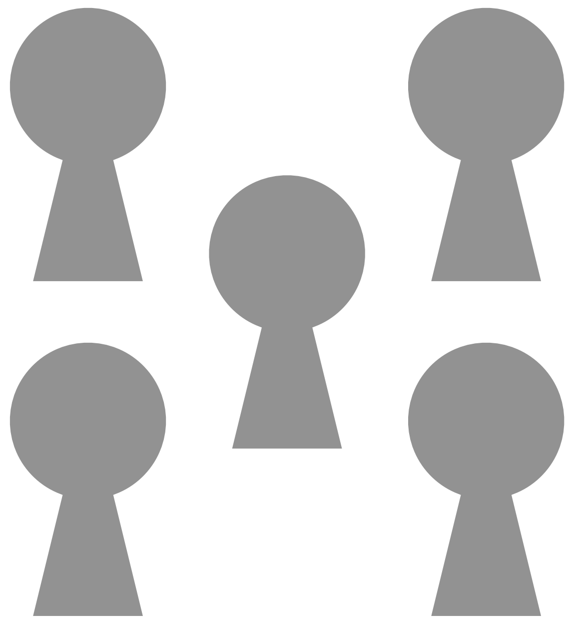
Classical Hardness



Quantum advantage?

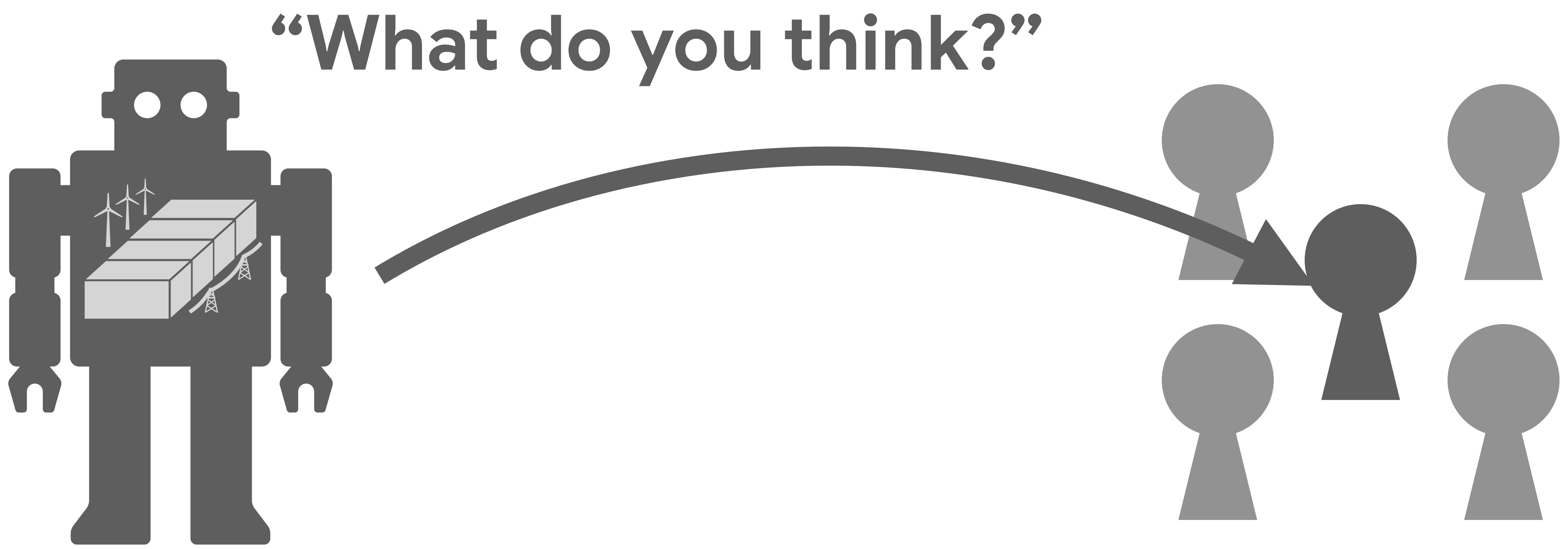
Classical ML





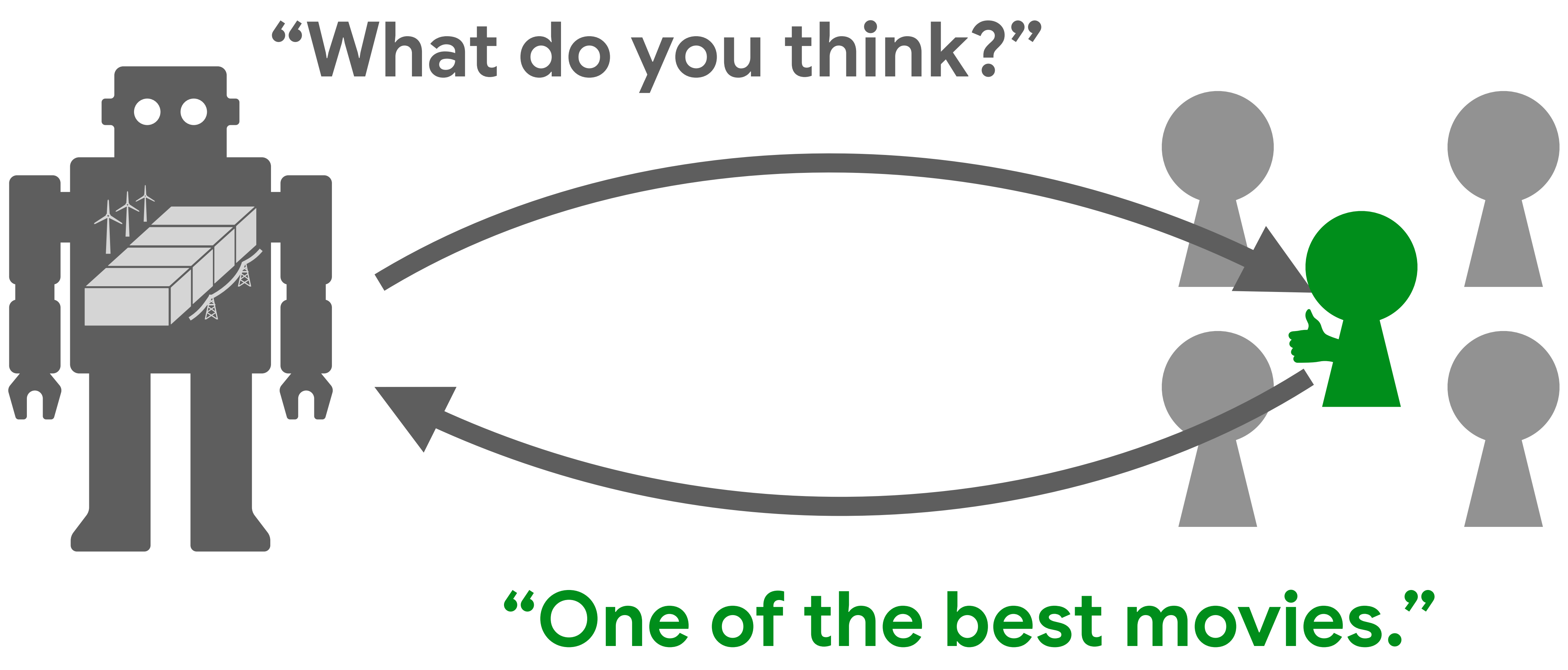
Quantum advantage?

Classical ML



Quantum advantage?

Classical ML



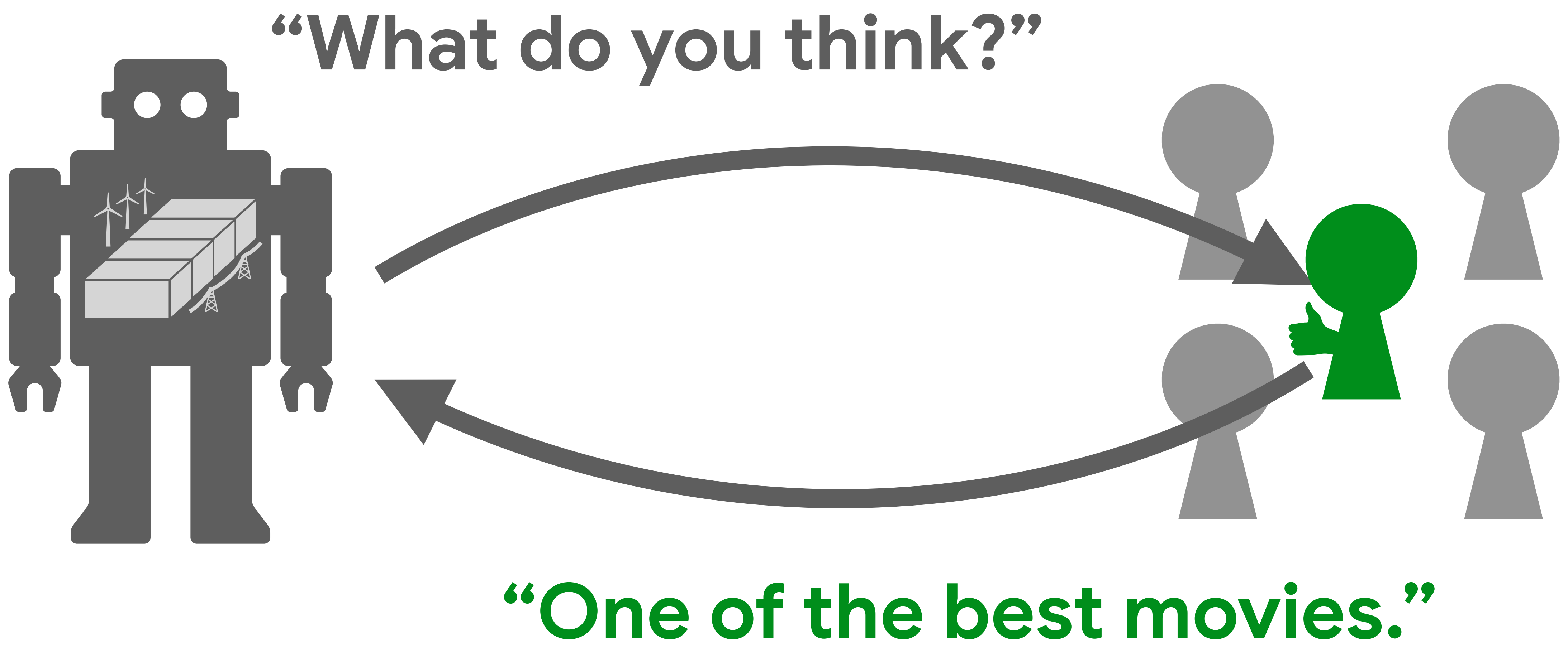
Quantum advantage?

Classical ML

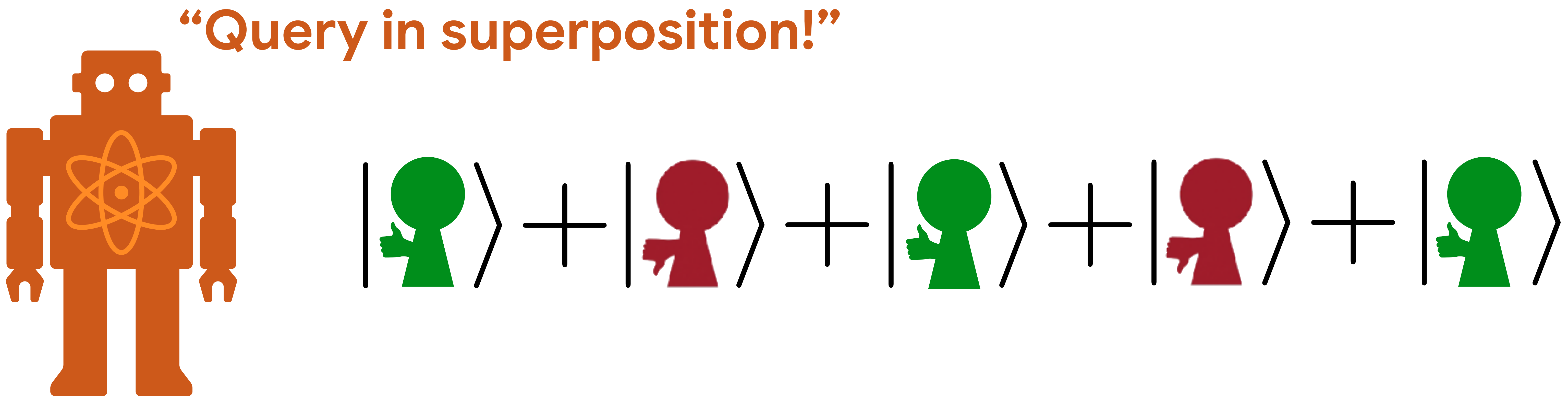
Quantum ML

Quantum advantage?

Classical ML



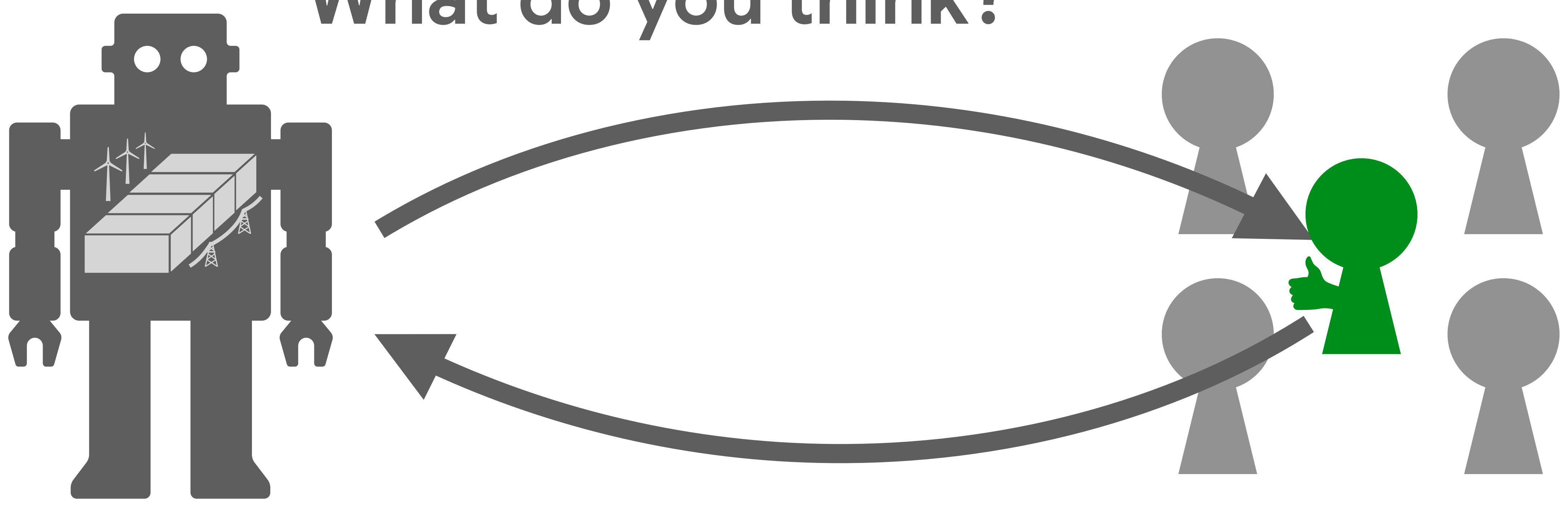
Quantum ML



Quantum advantage?

Classical ML

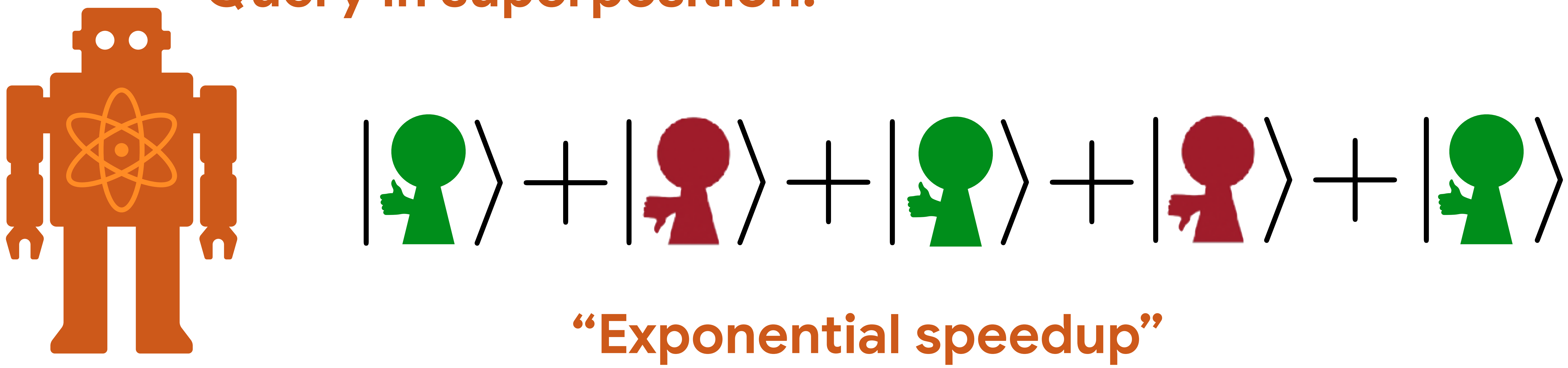
“What do you think?”



“One of the best movies.”

Quantum ML

“Query in superposition!”

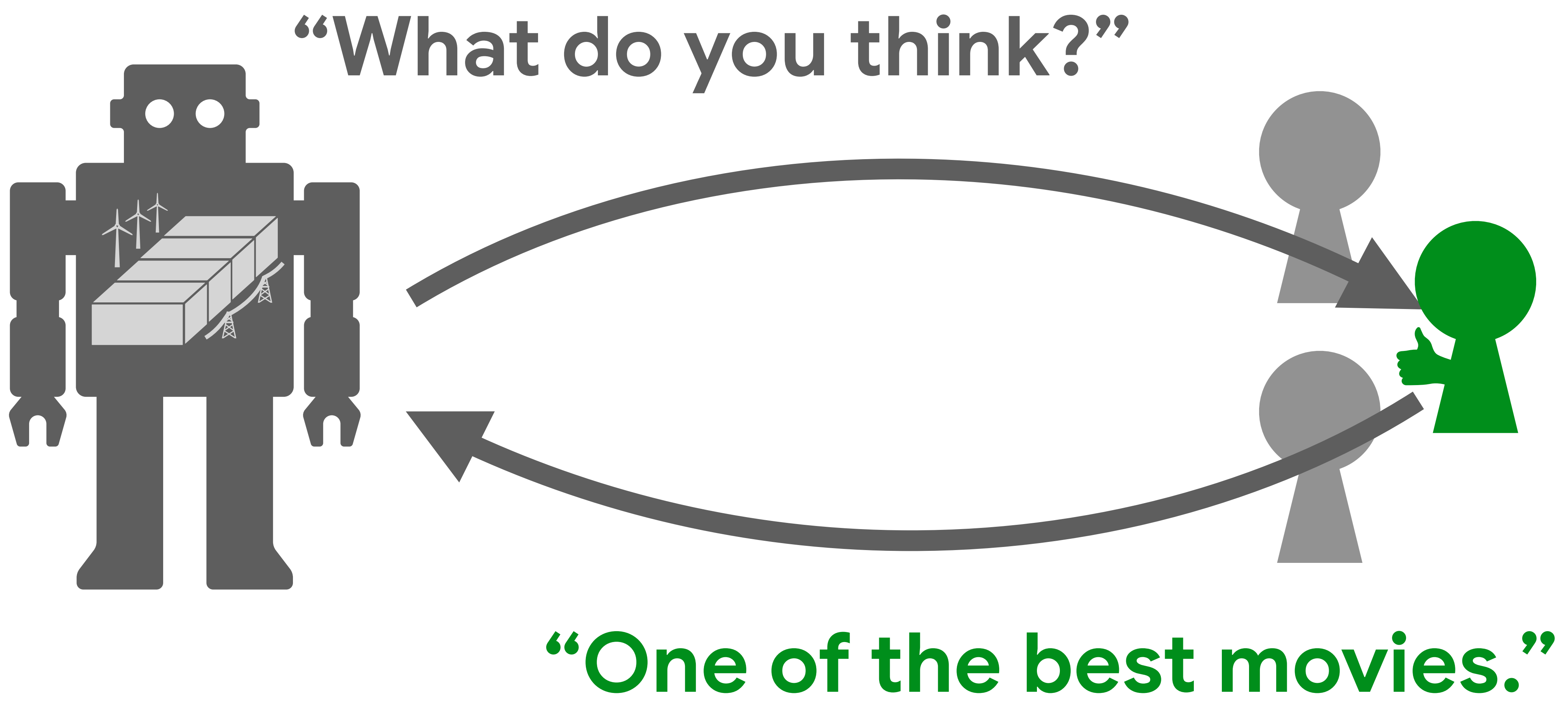


“Exponential speedup”

[quantum oracle query algorithm]

Quantum advantage?

Classical ML

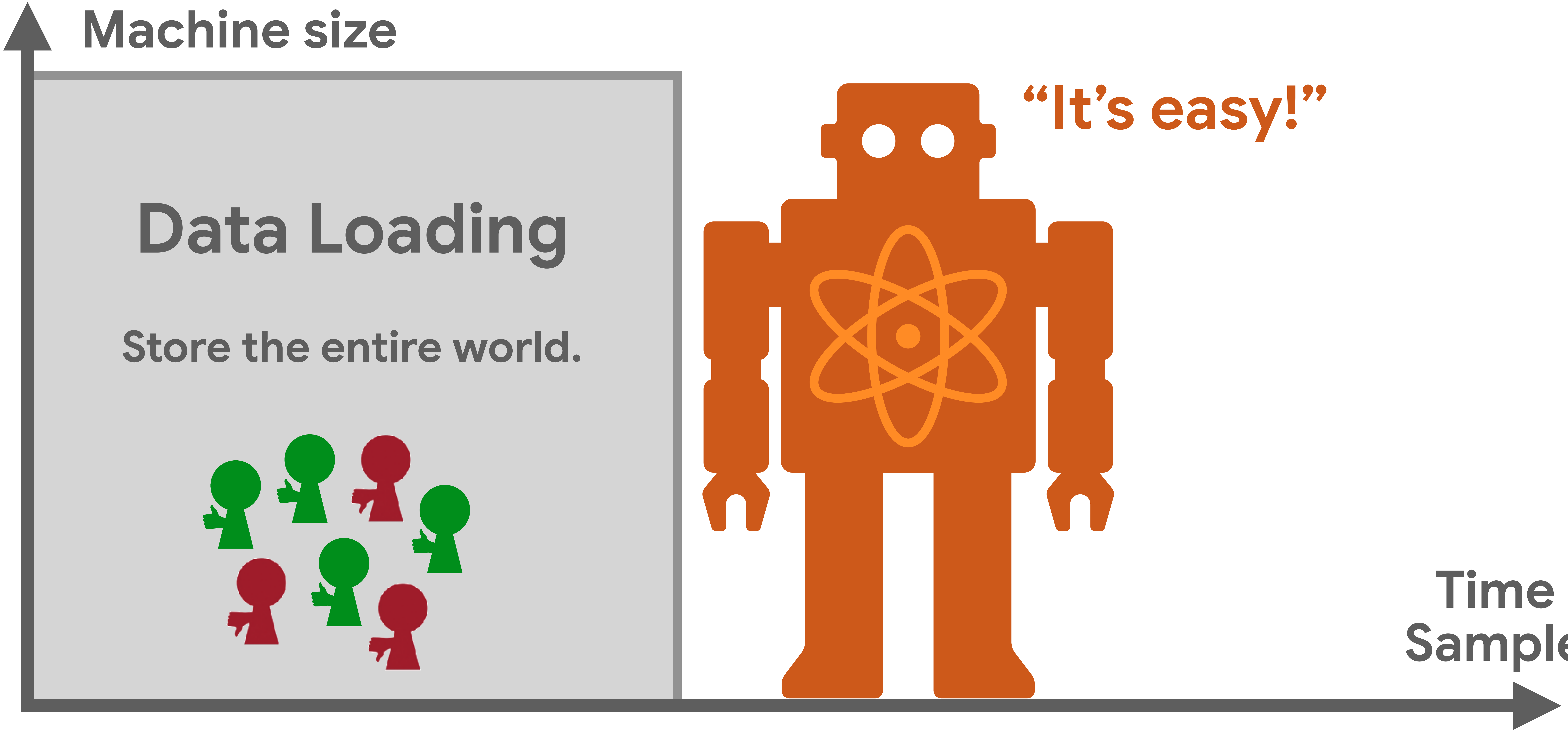


Quantum ML

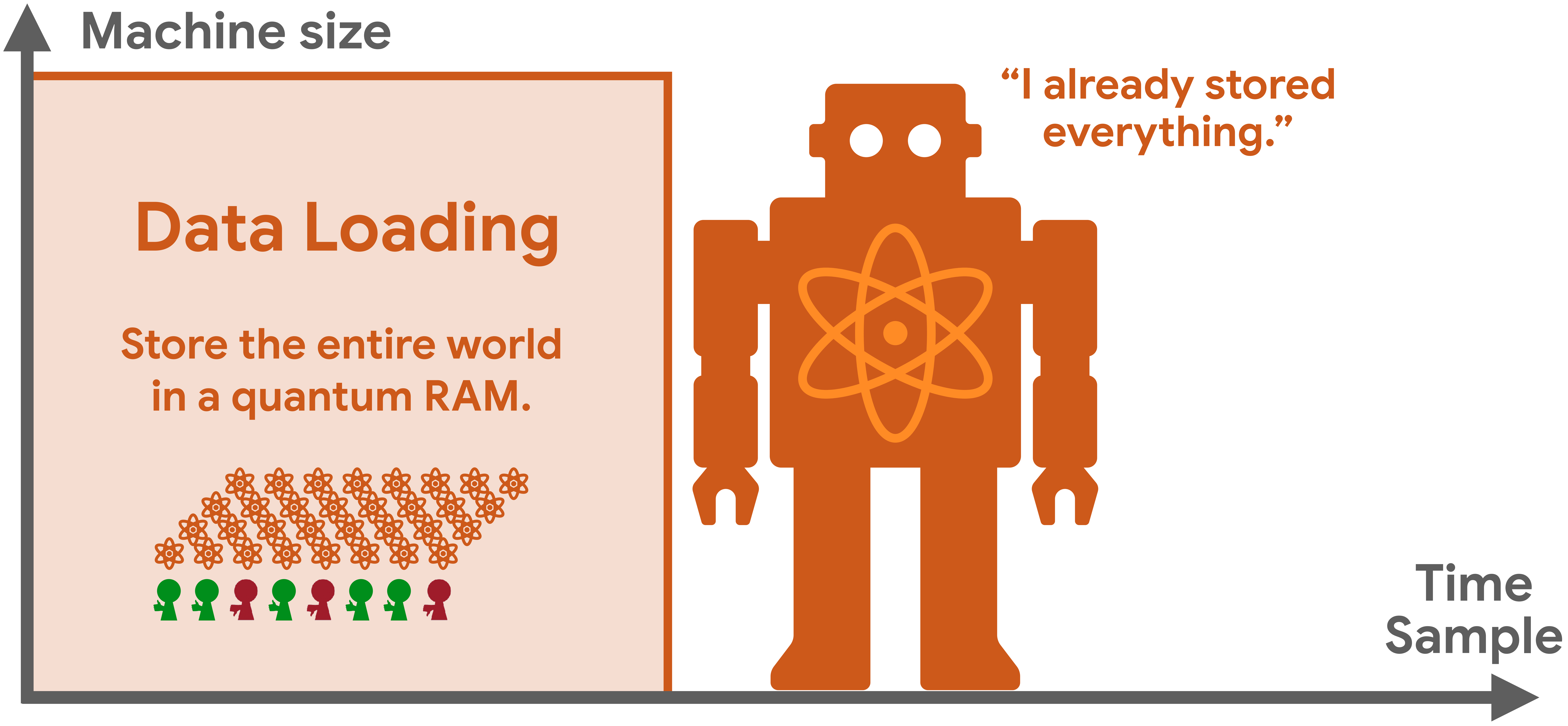
Challenge

Can we access a classical world in quantum superposition?

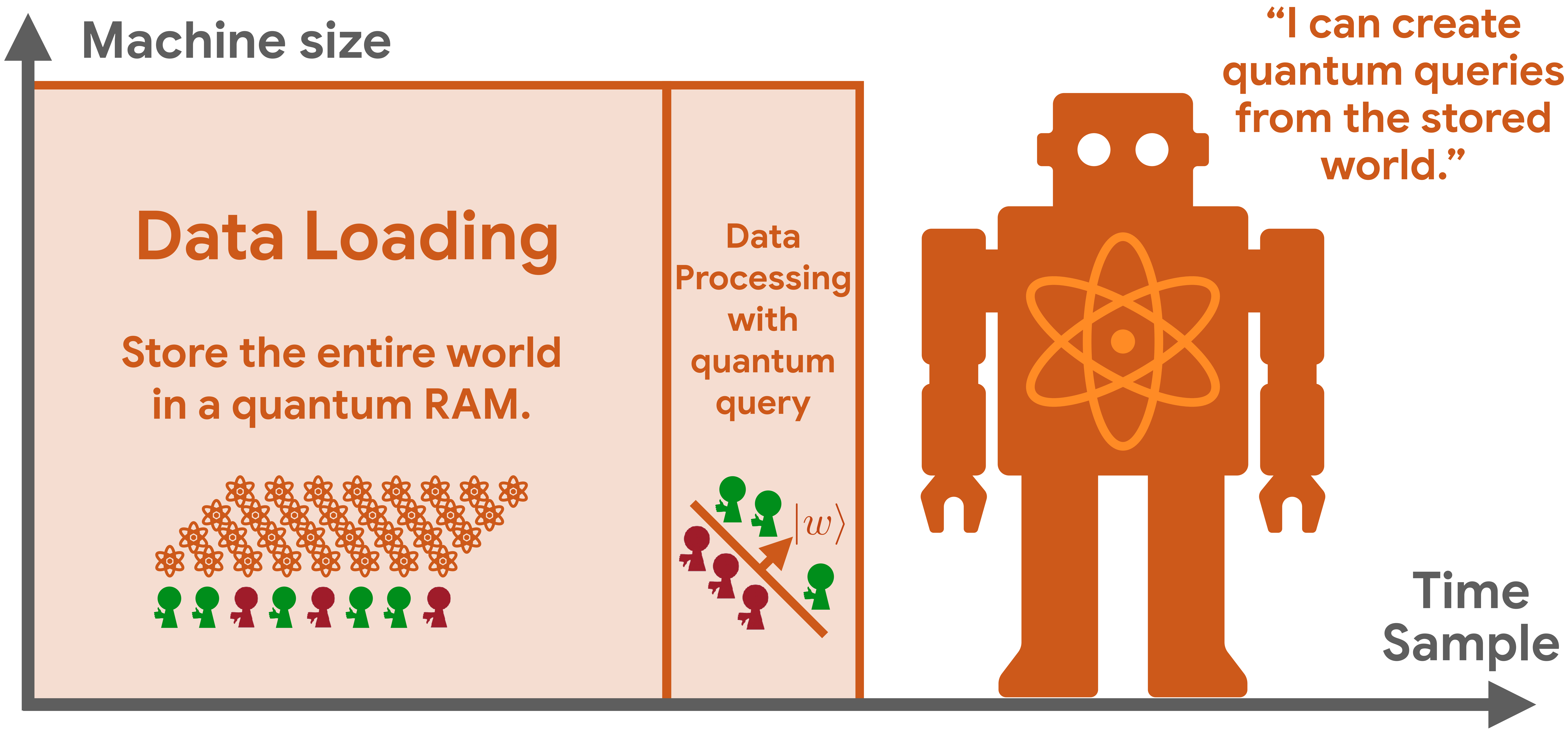
Attempt: QRAM



Attempt: QRAM



Attempt: QRAM



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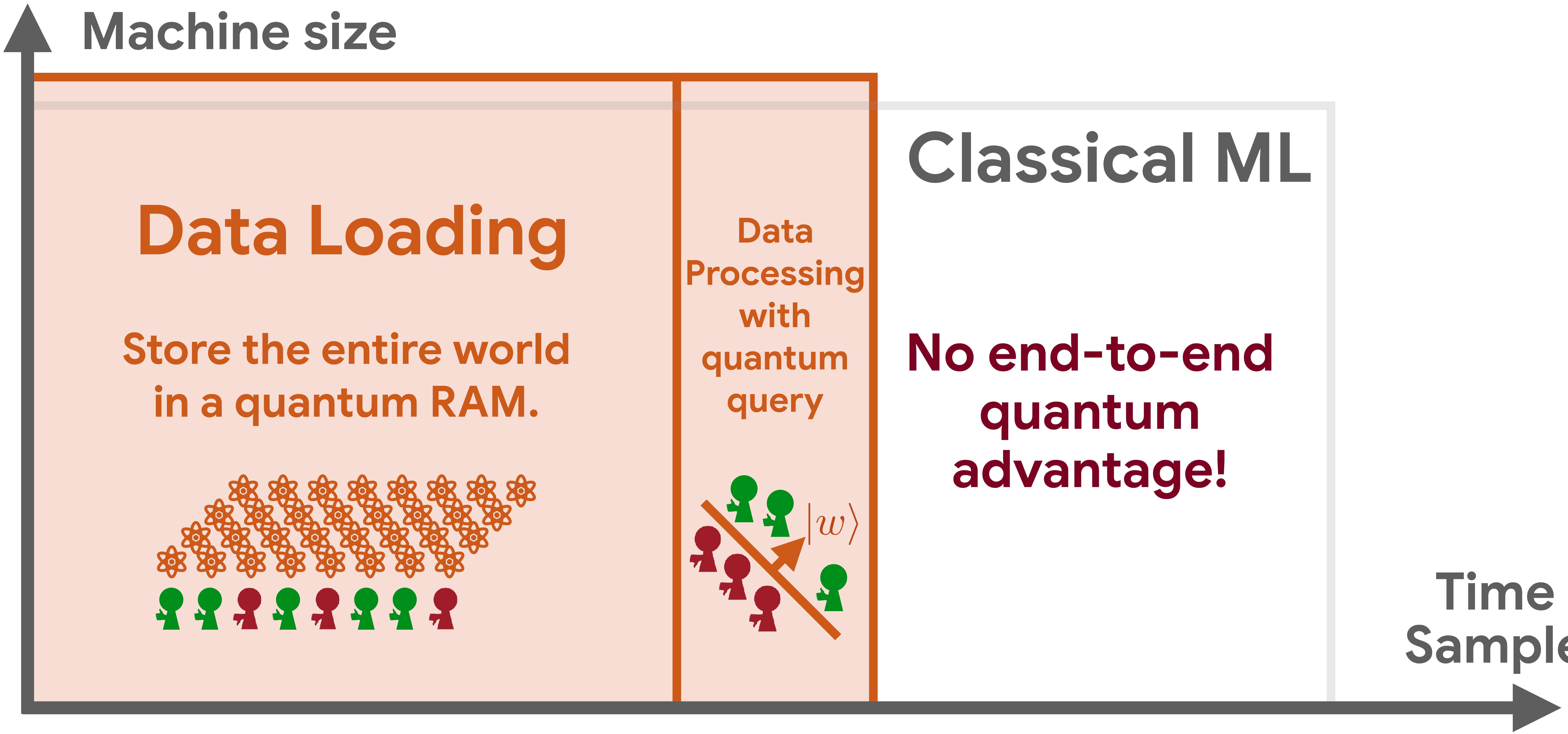


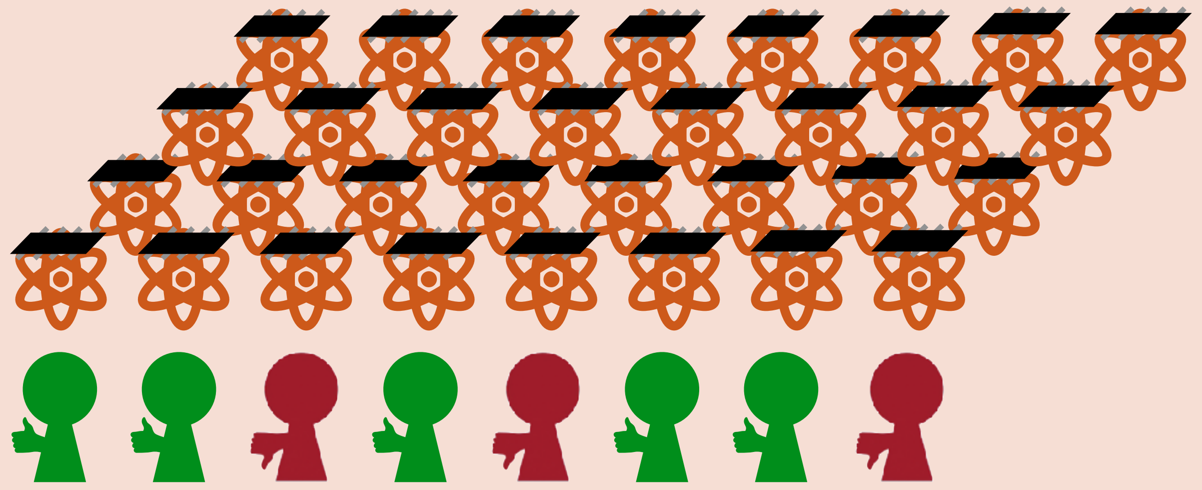
Attempt: QRAM

Machine size

Classical ML

Maintaining a coherent copy of the entire world.

Data loading + QEC.



Time

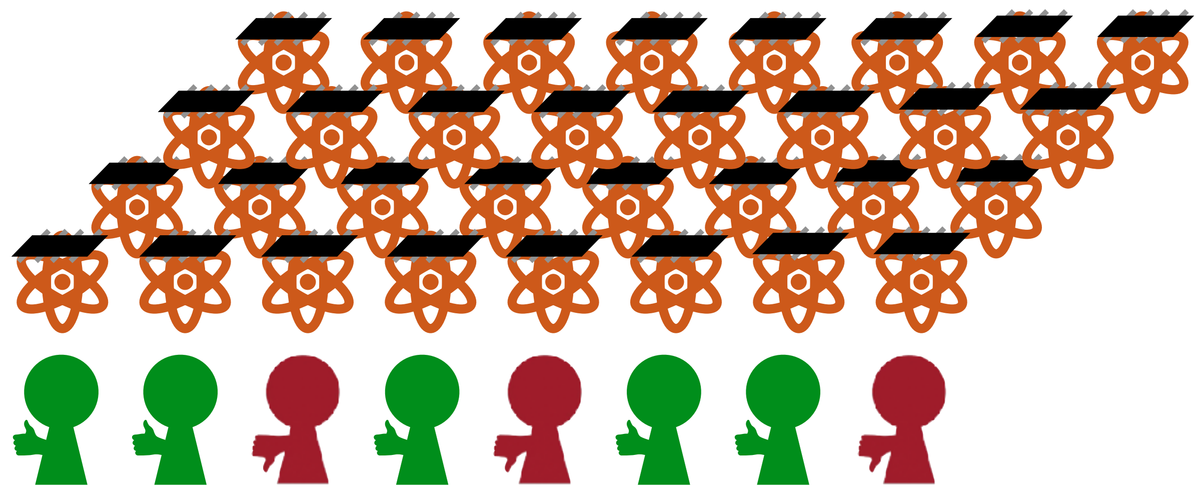
Sample

Attempt: QRAM

Challenge

Can we access a classical world in quantum superposition?

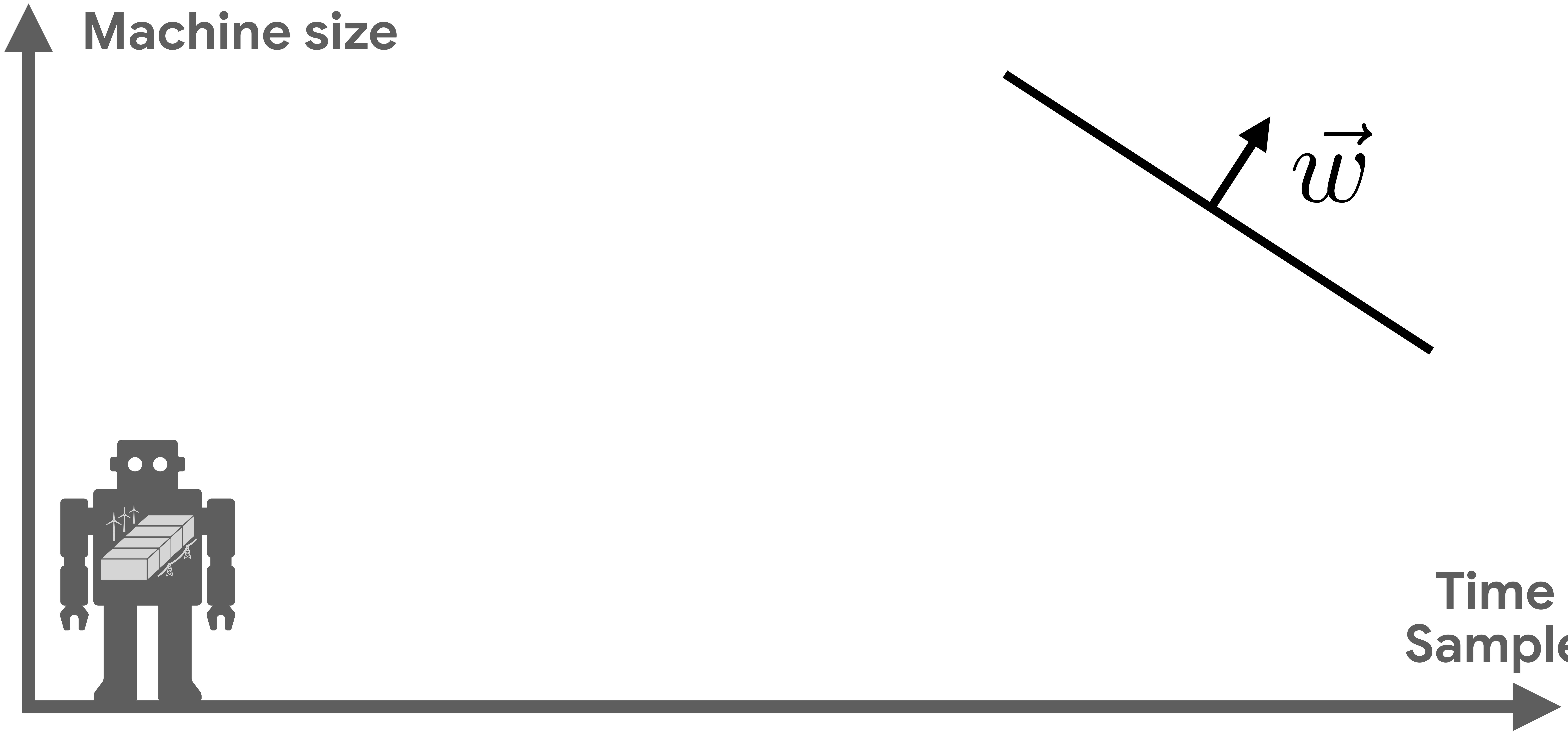
(without storing the entire world)



Challenge

How to do ML without storing the entire dataset?

Train a model on the fly



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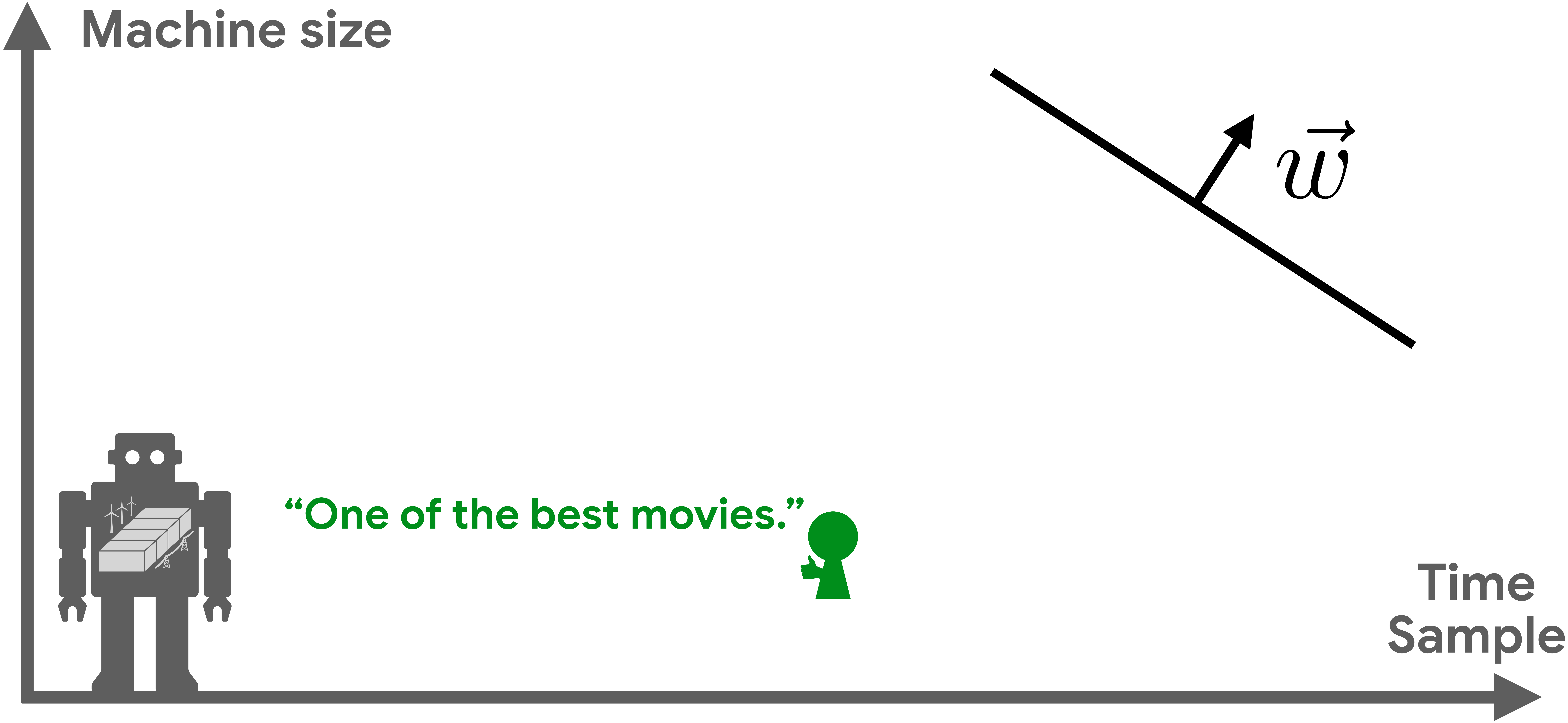

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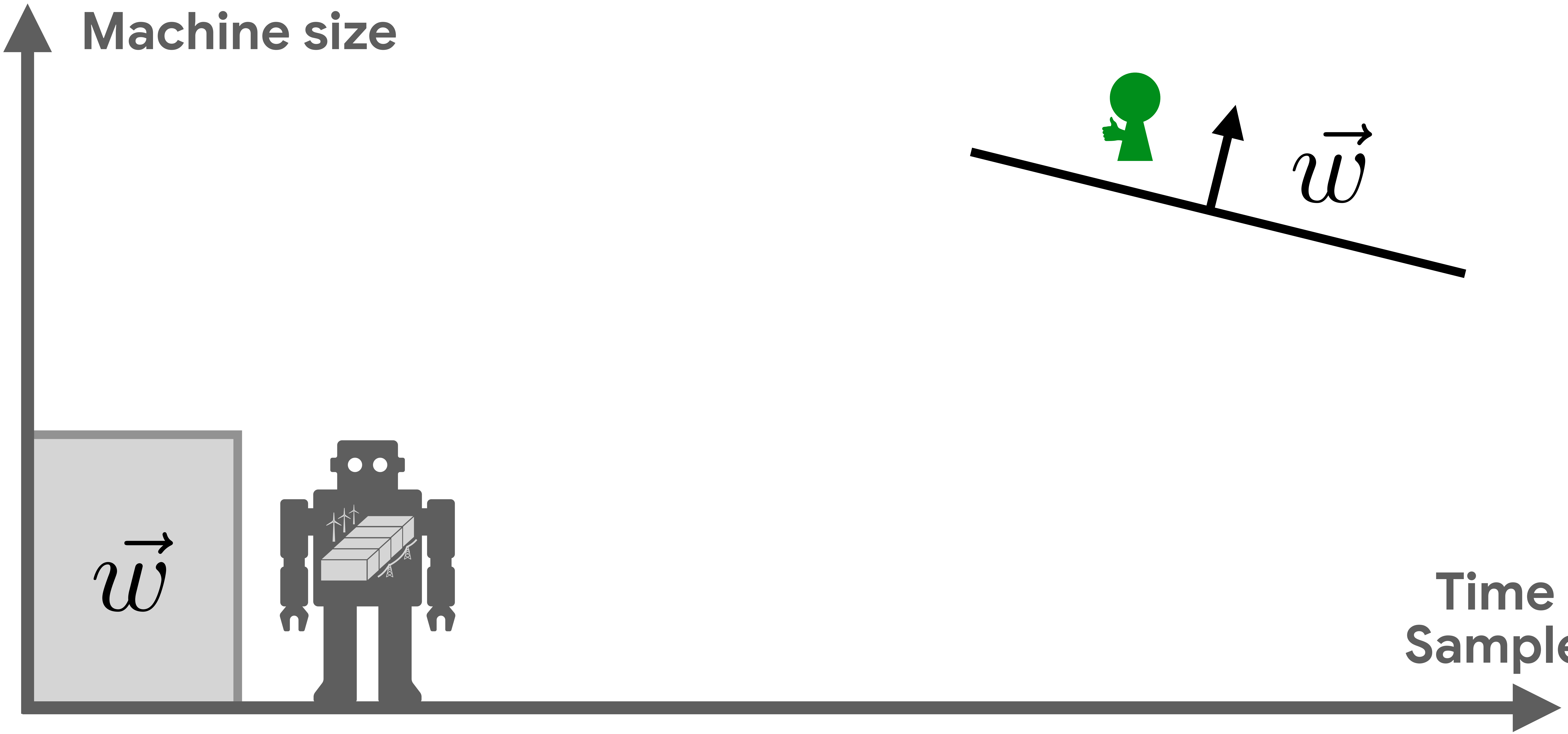

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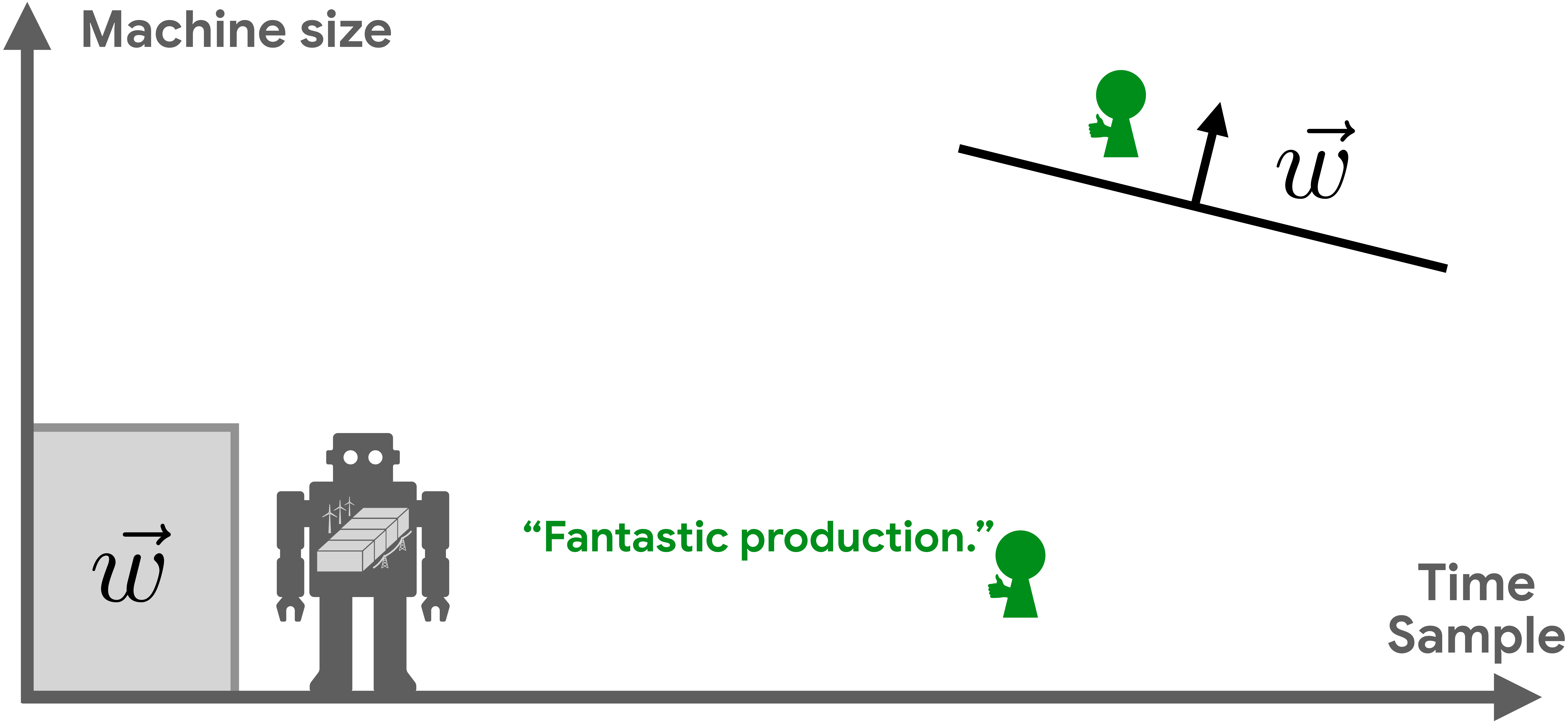

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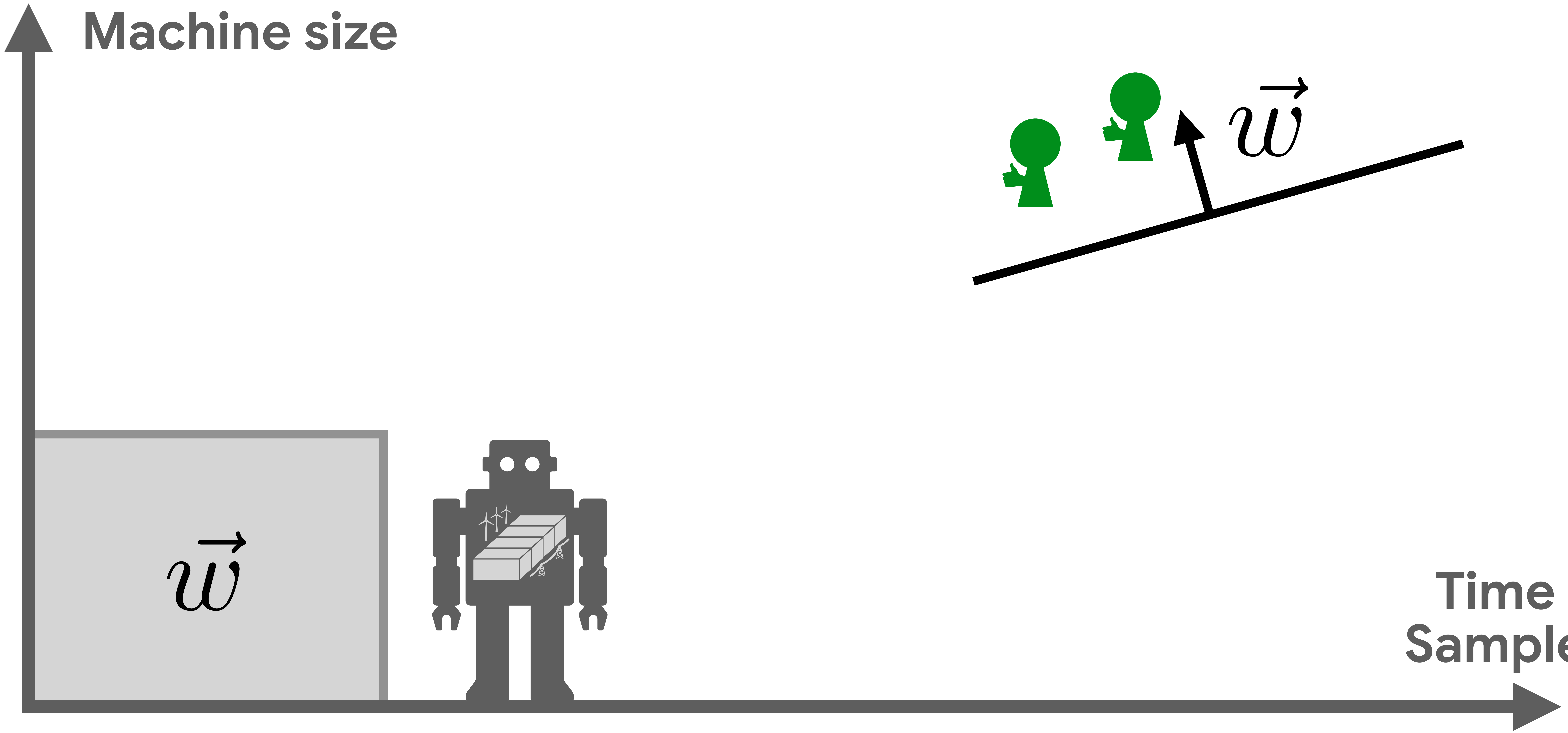

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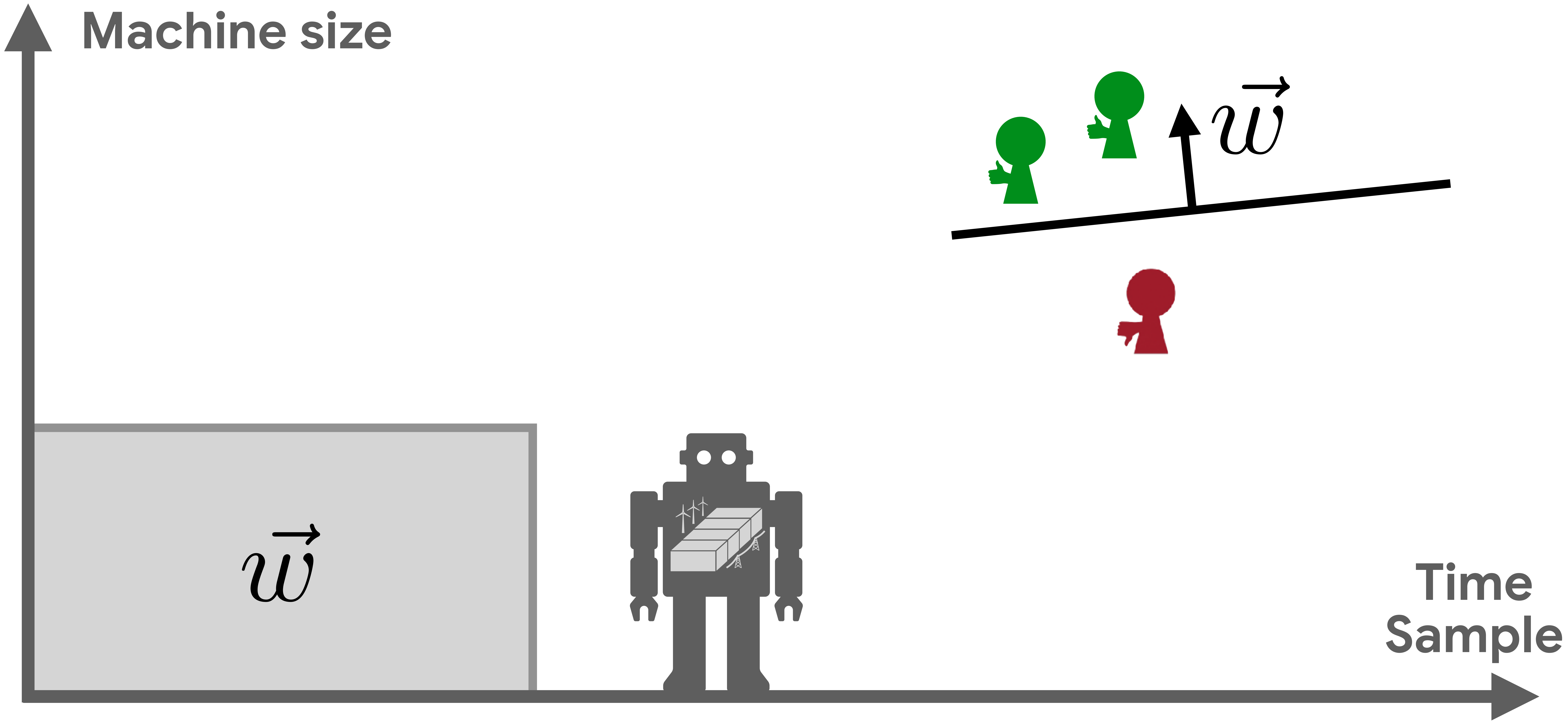

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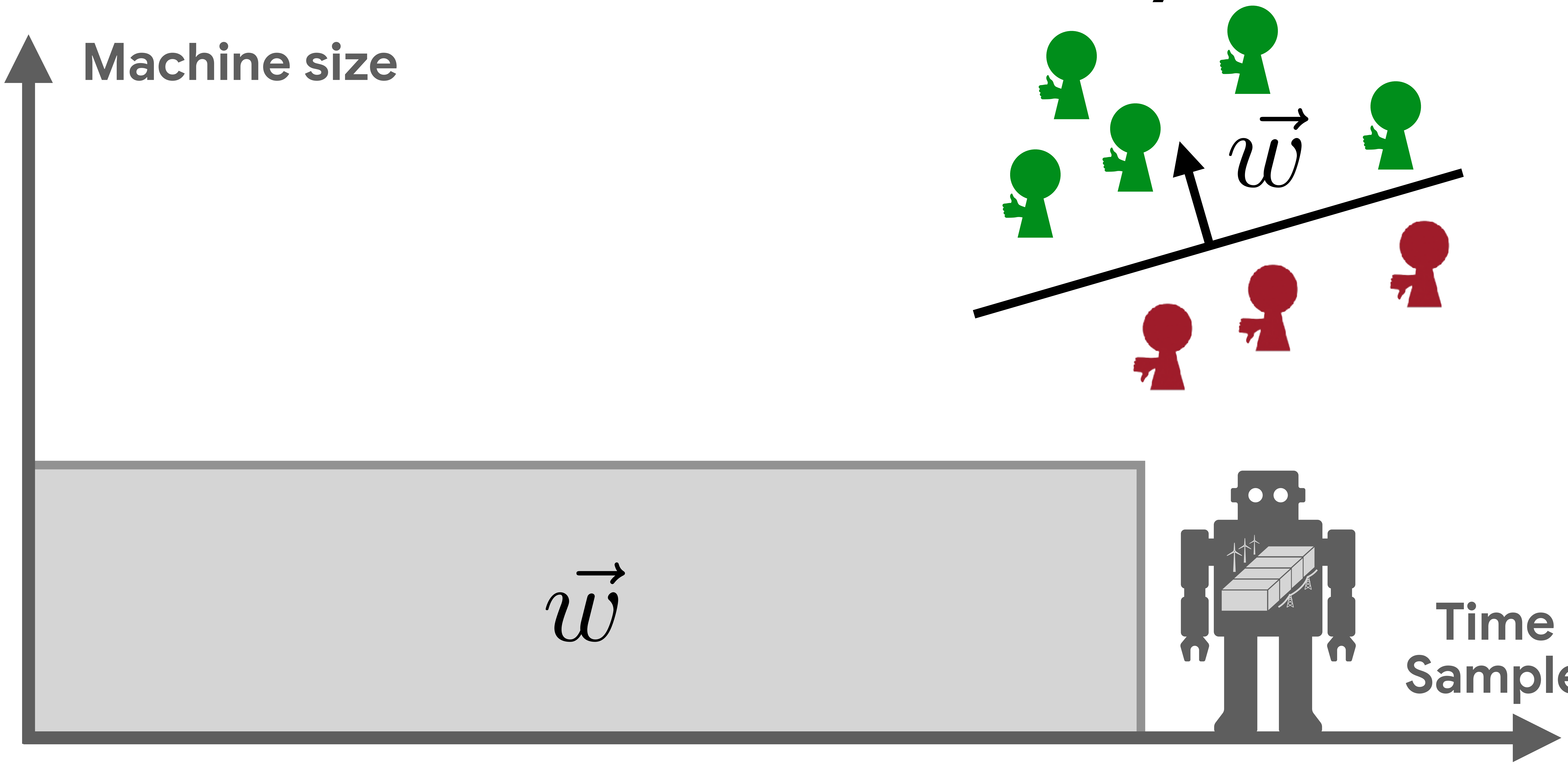

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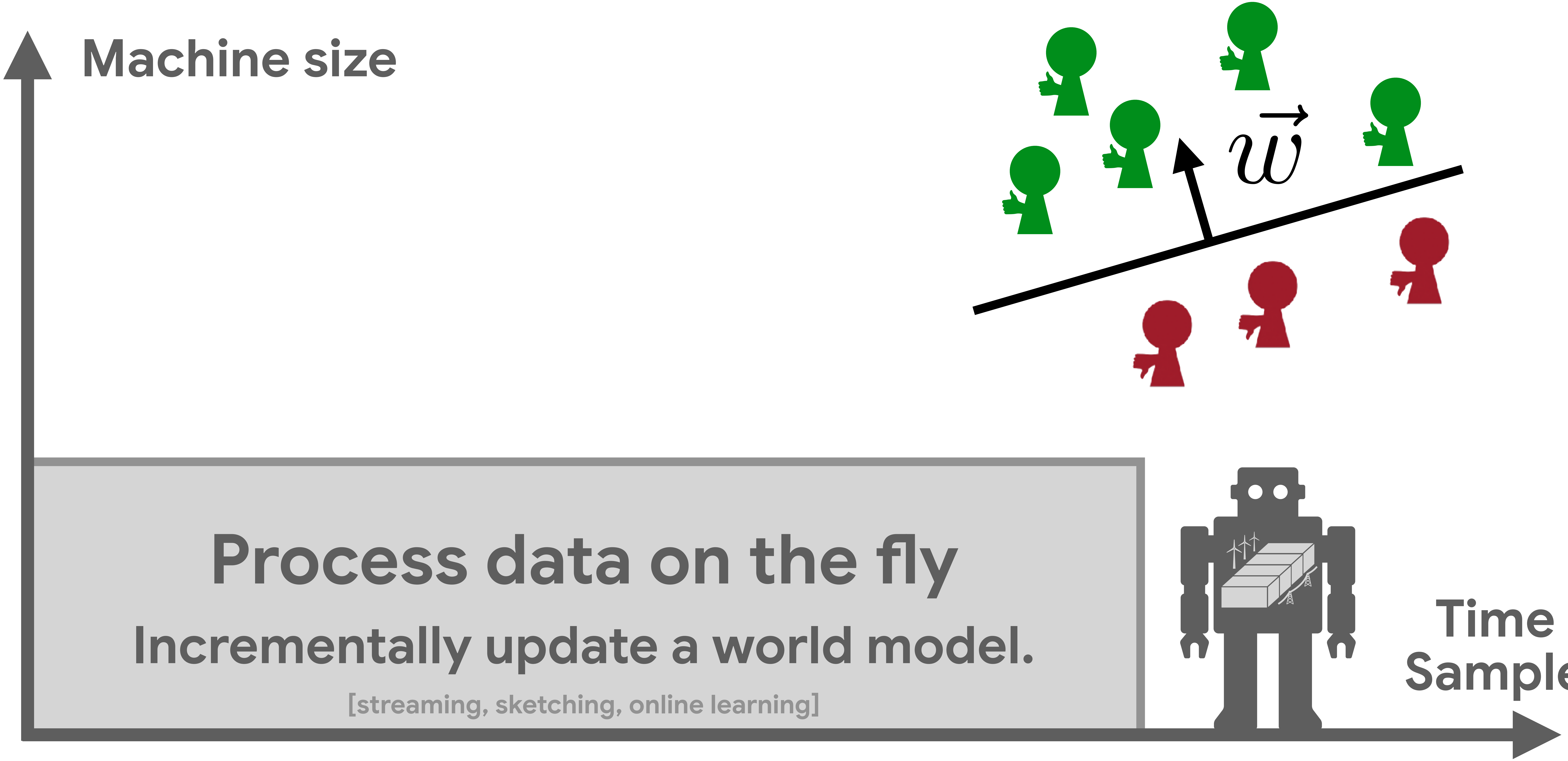
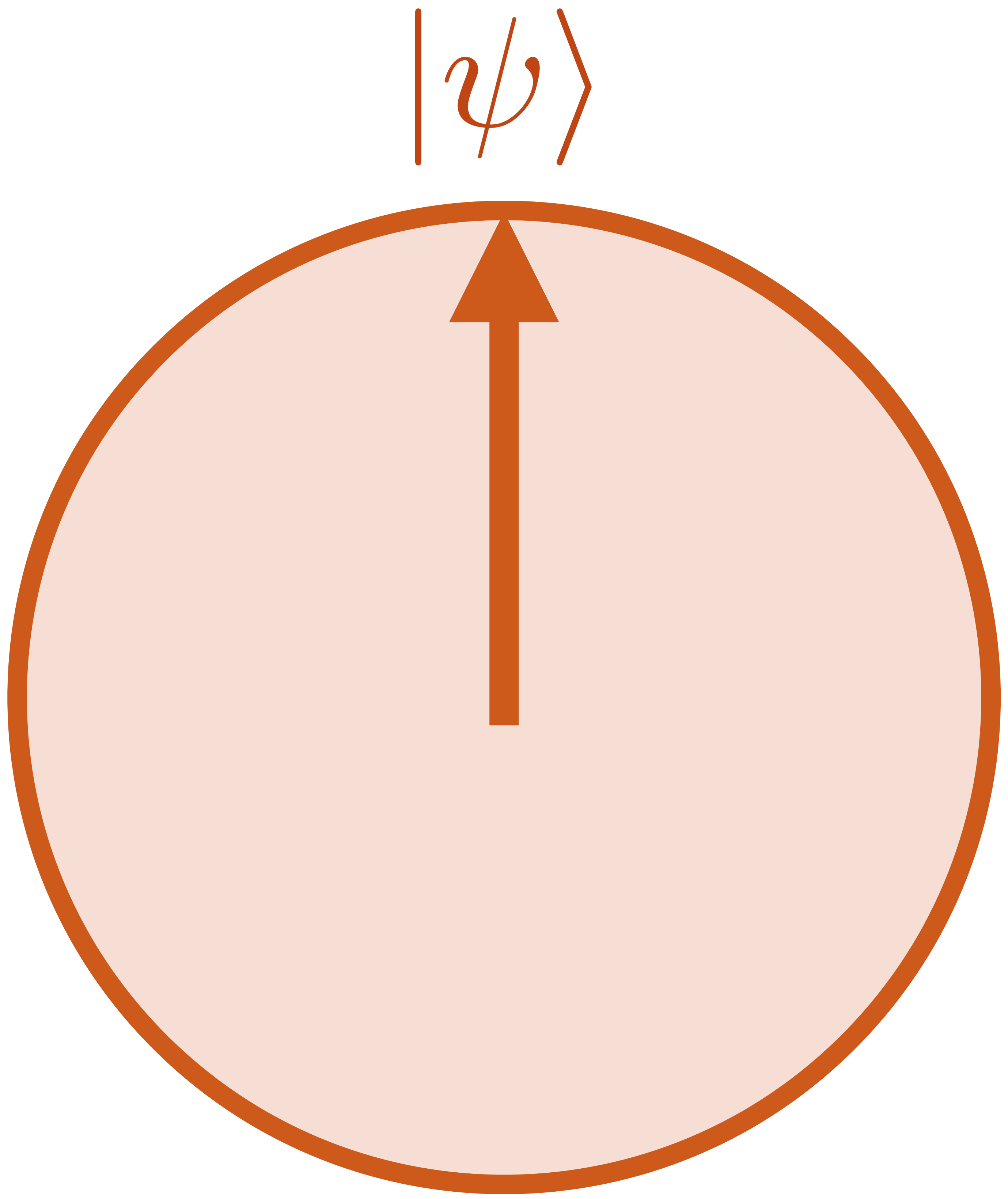
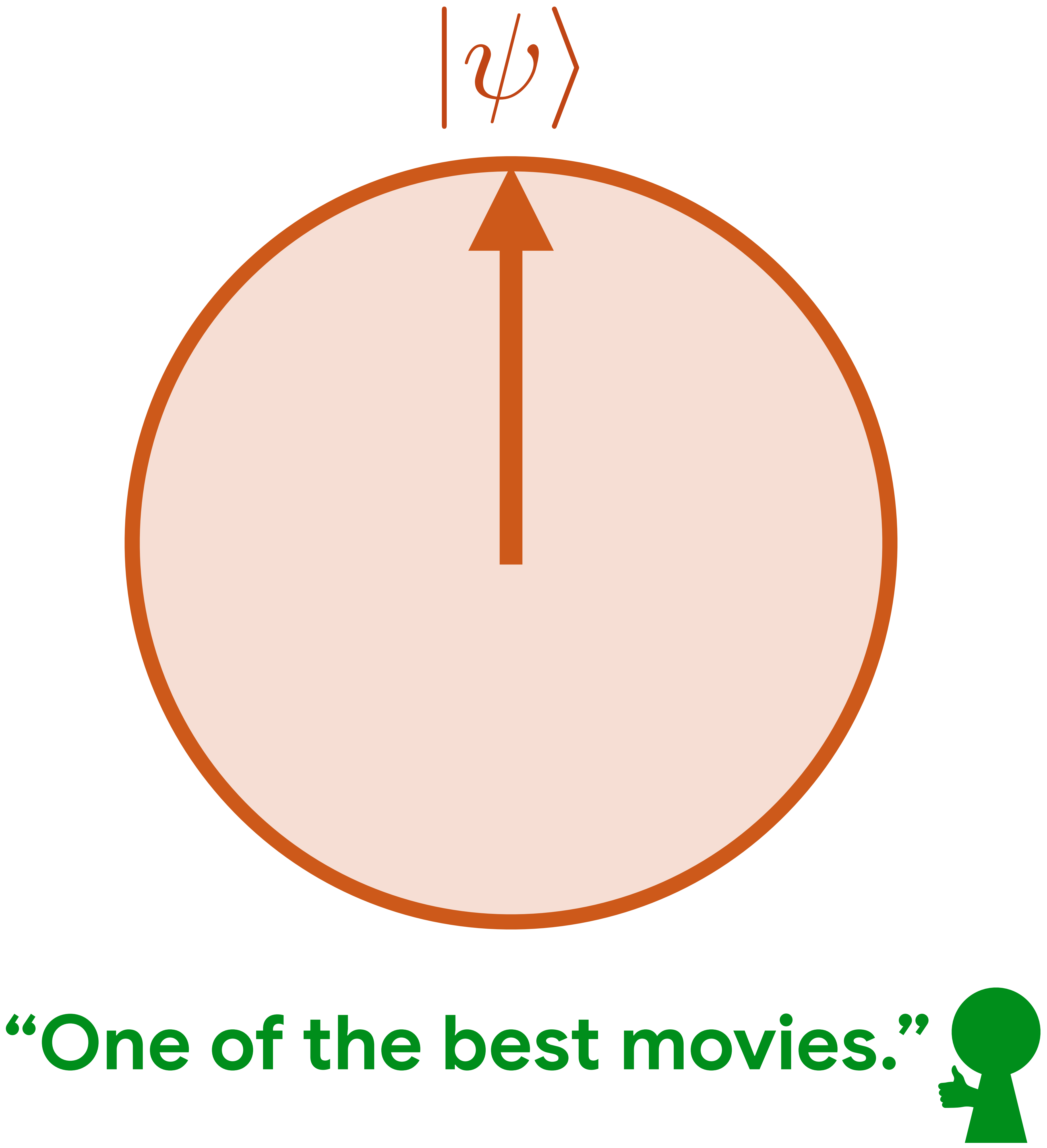


Quantum oracle sketching



Maintain a quantum model

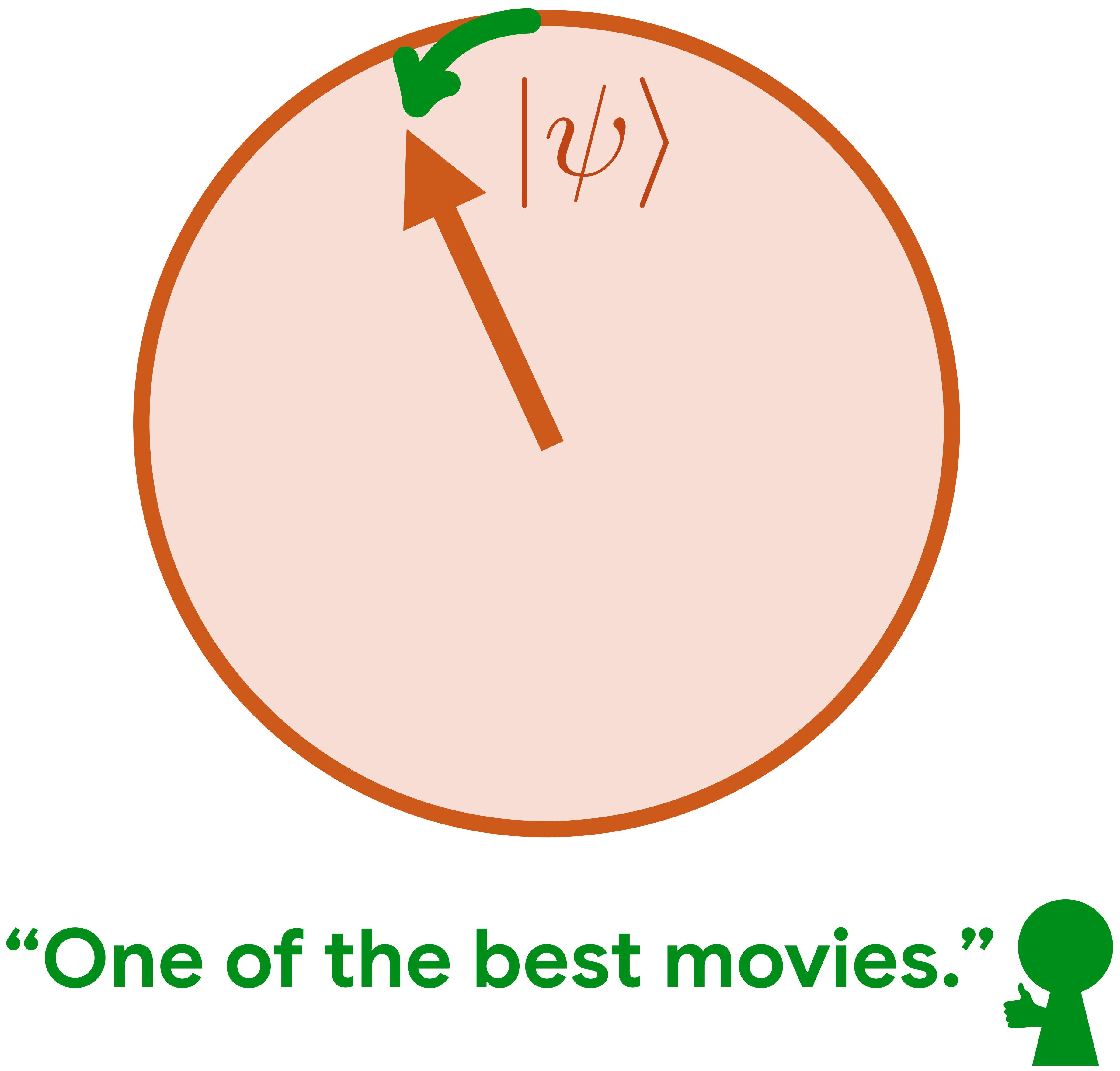
Quantum oracle sketching



Maintain a quantum model

For each data sample z

Quantum oracle sketching

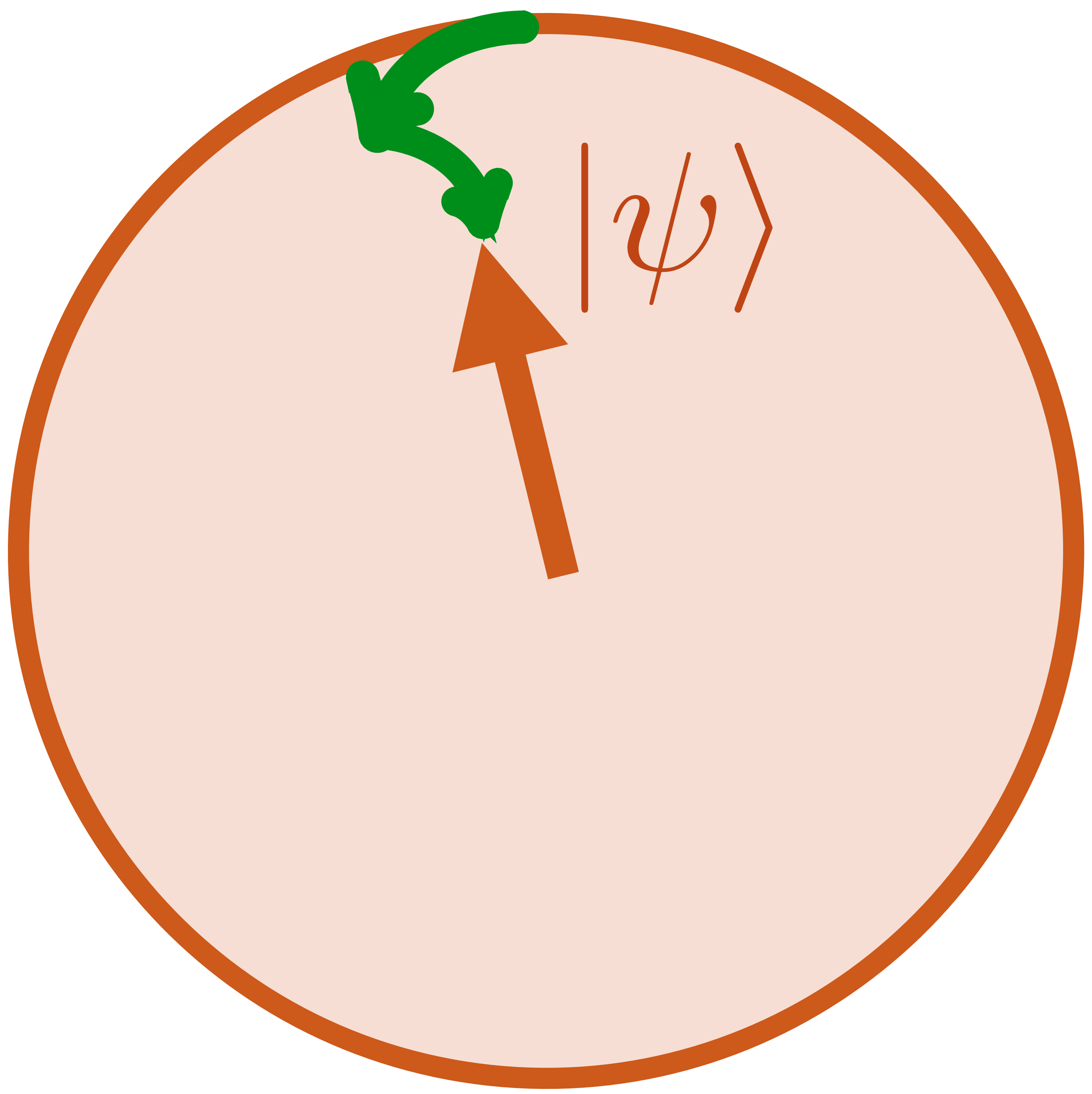


Maintain a quantum model

For each data sample z

apply a small quantum rotation V_z

Quantum oracle sketching



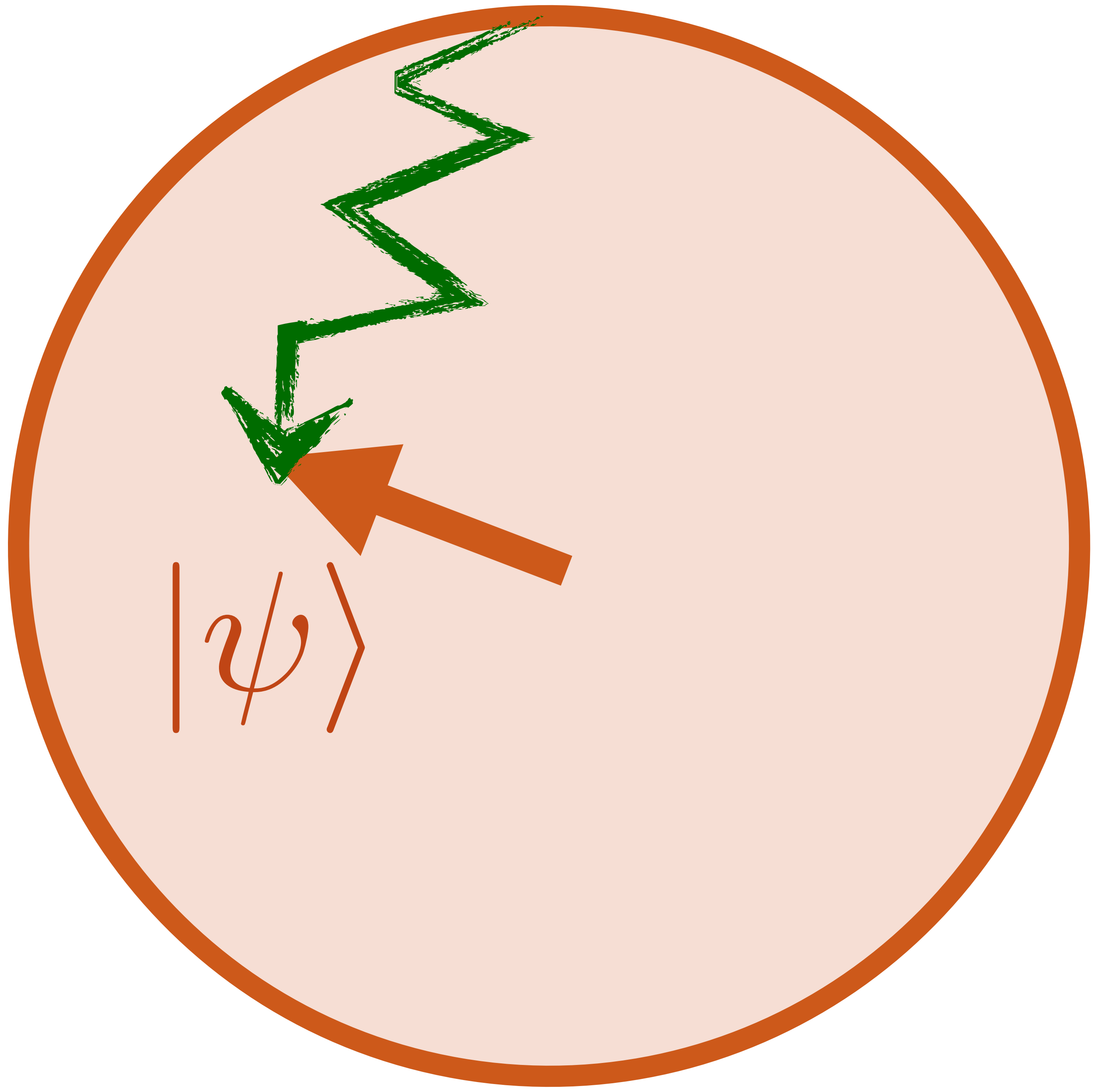
Maintain a quantum model

For each data sample z

apply a small quantum rotation V_z

Repeat for M samples

Quantum oracle sketching



a random gate sequence

$$V_{z_M} \cdots V_{z_1}$$

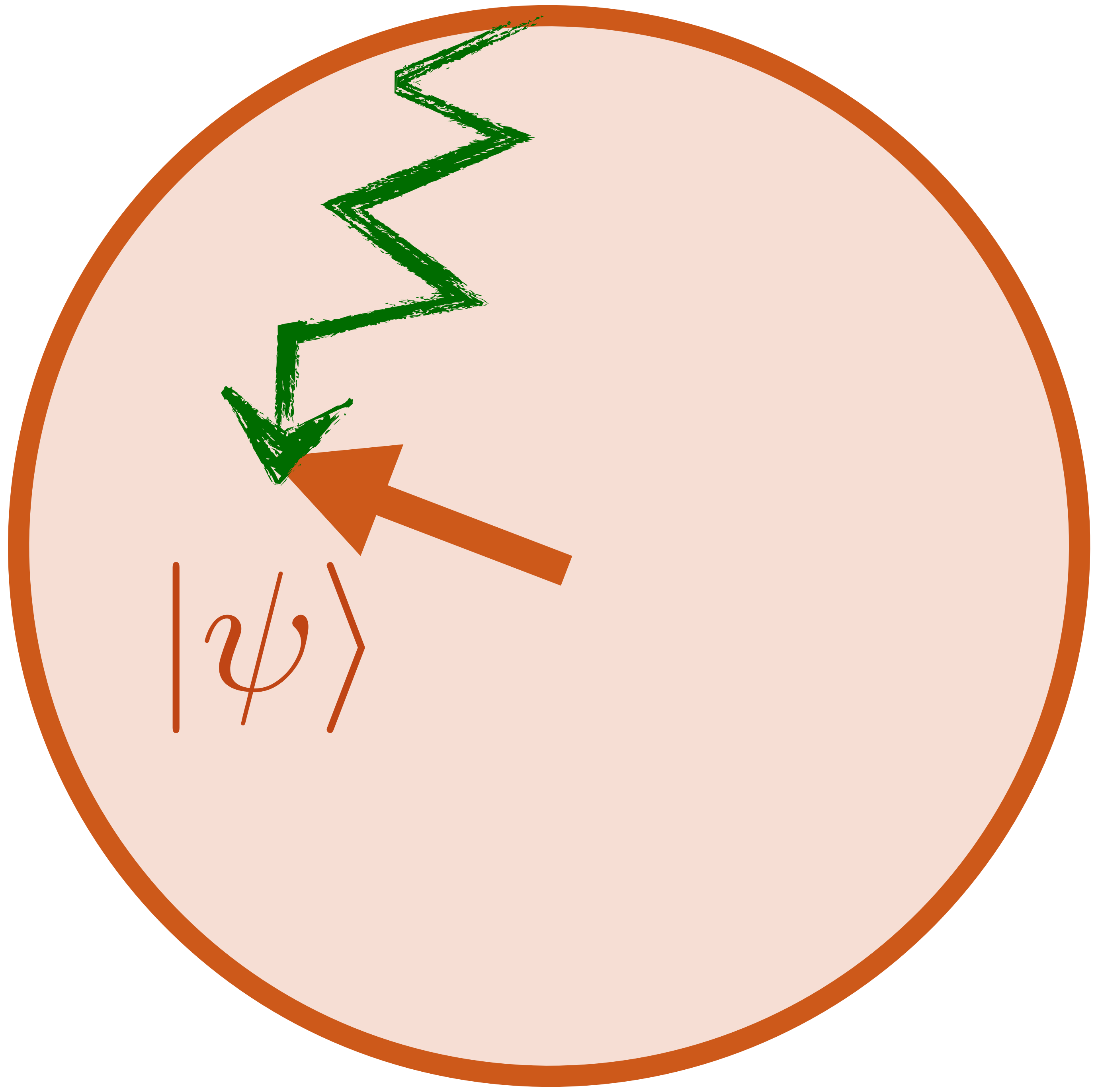
Maintain a quantum model

For each data sample z

- apply a small quantum rotation V_z

Repeat for M samples

Quantum oracle sketching



a random gate sequence

$$V_{z_M} \cdots V_{z_1}$$

Maintain a quantum model

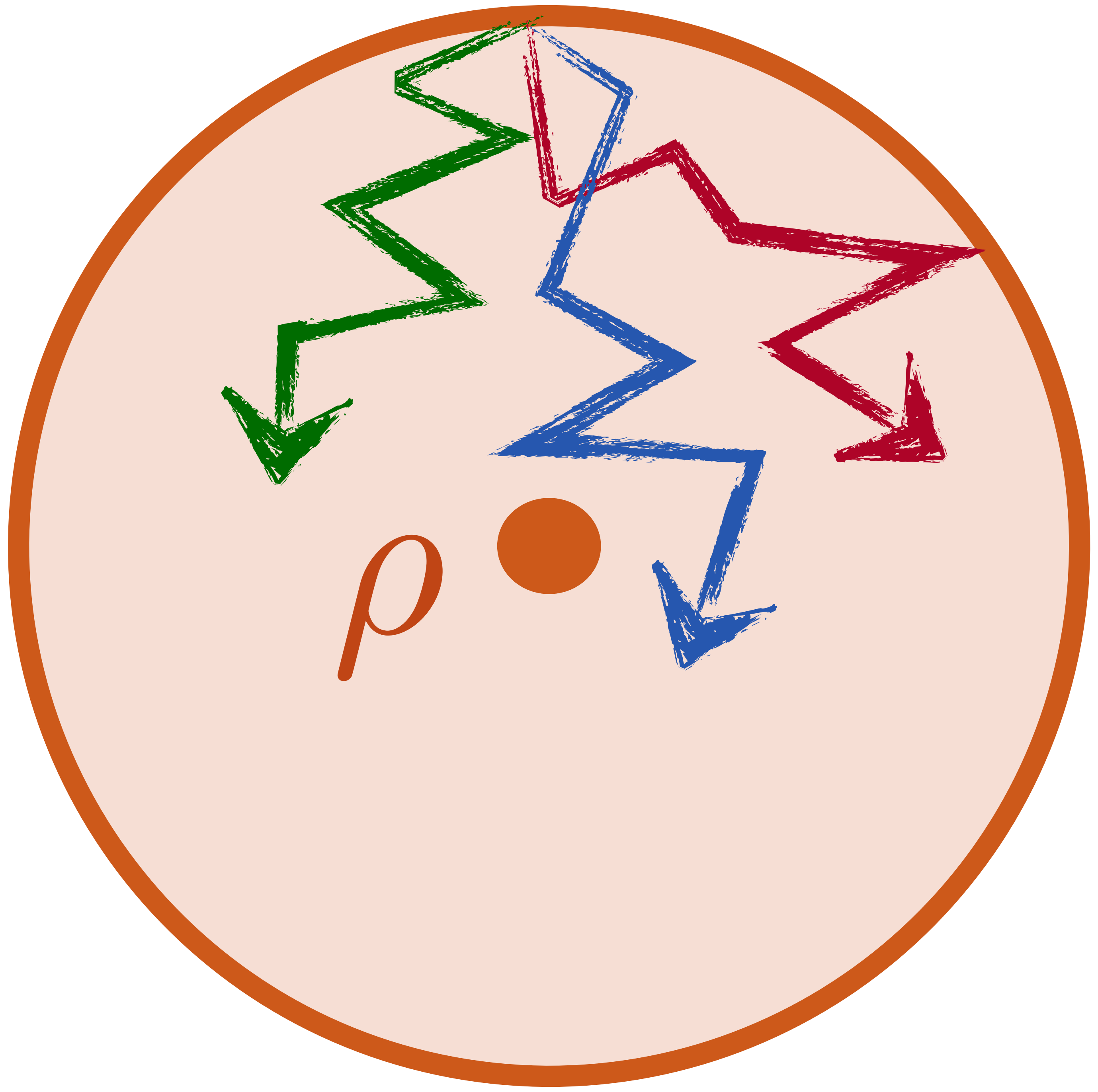
For each data sample z

apply a small quantum rotation V_z

Repeat for M samples

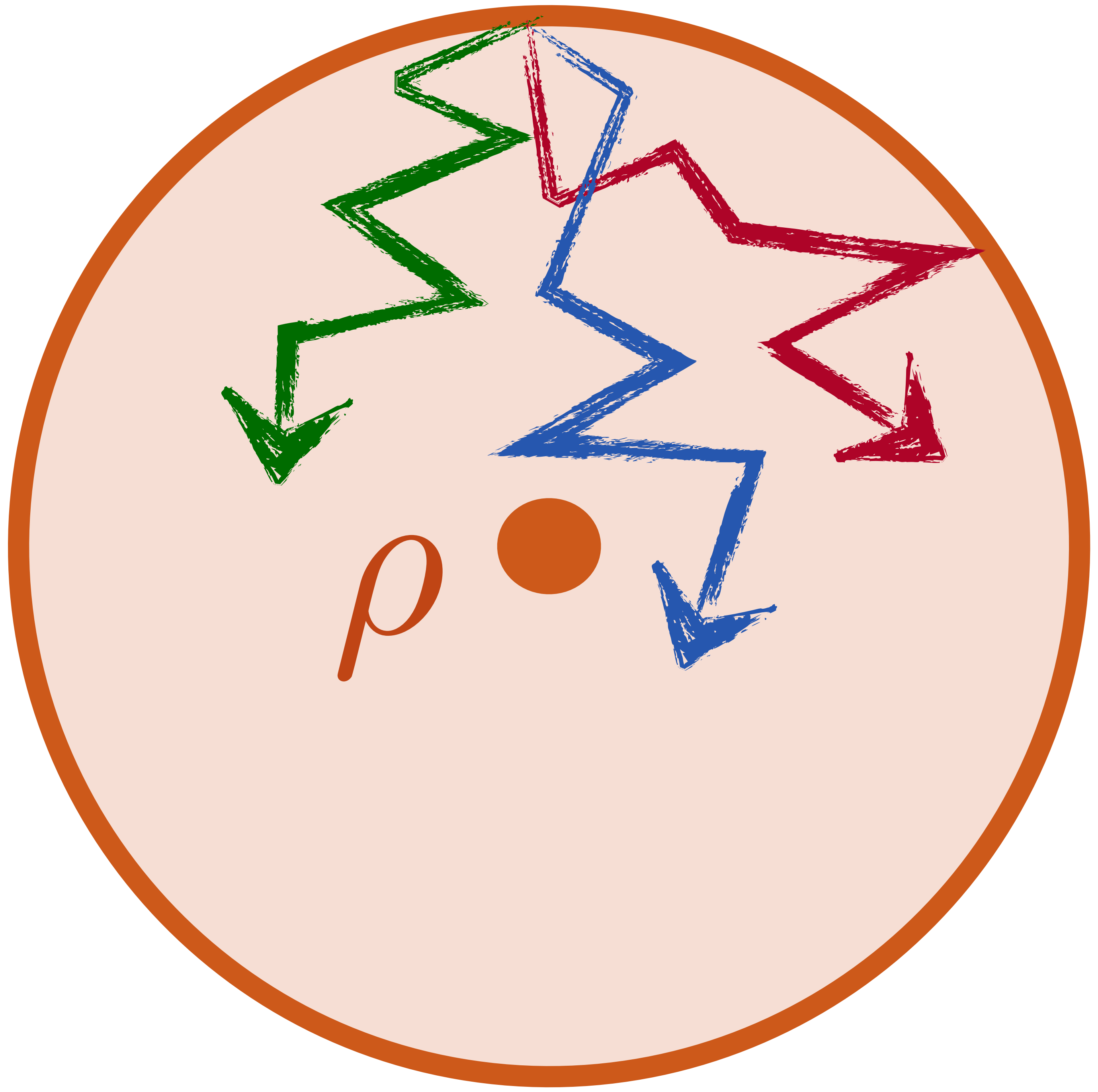
≈ a quantum oracle query

Quantum oracle sketching



Data randomness leads to decoherence for generic rotations $V_{z_M} \cdots V_{z_1}$

Quantum oracle sketching

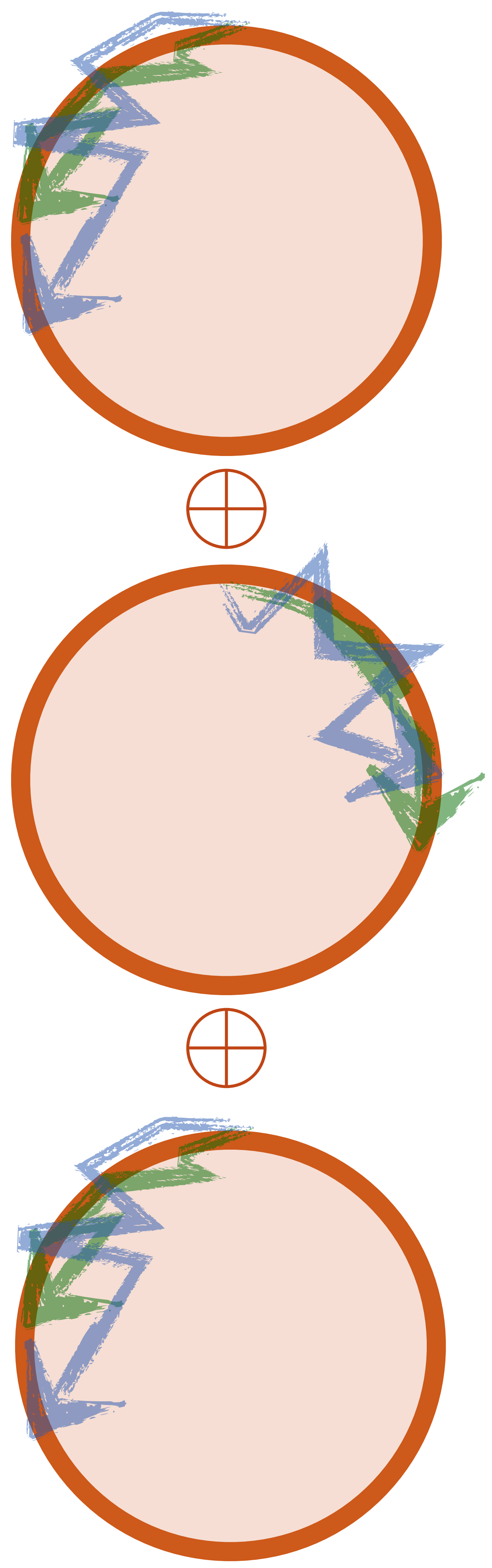


Data randomness leads to decoherence for generic rotations $V_{z_M} \cdots V_{z_1}$

❌ **no quantum advantage**

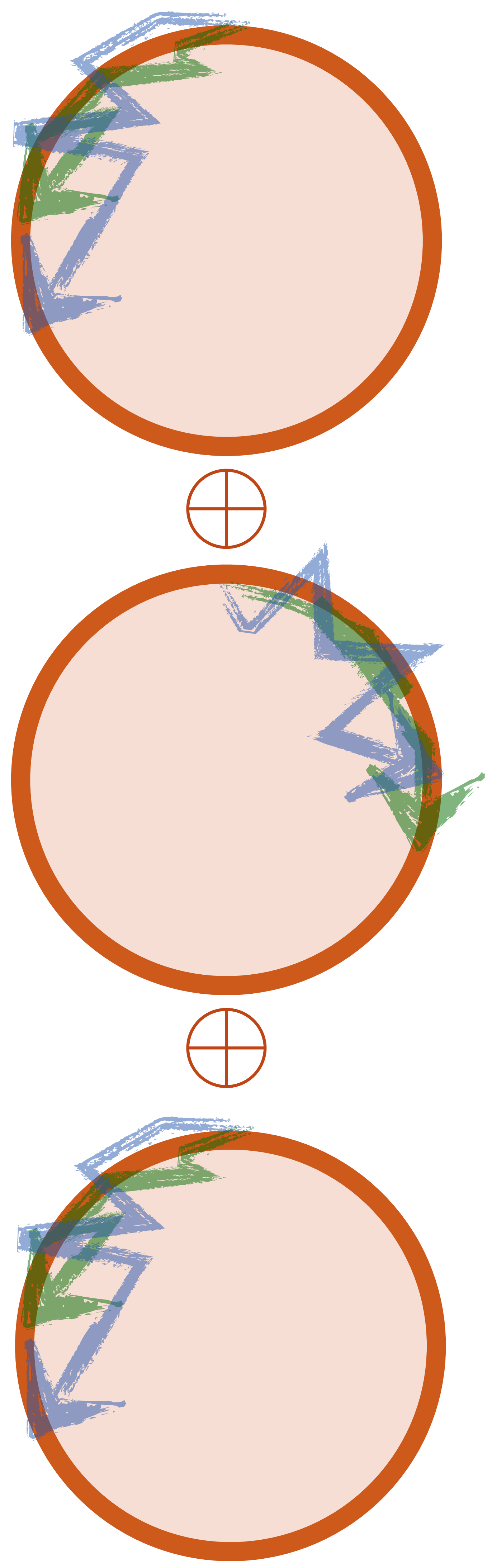
[randomized Hamiltonian simulation; qDrift]

Quantum oracle sketching



Carefully design the rotations
to be nearly orthogonal
to avoid decoherence.

Quantum oracle sketching



Carefully design the rotations to be nearly orthogonal to avoid decoherence.

Theorem (Quantum Oracle Sketch)

With $\Theta(NQ^2)$ samples, we can emulate Q quantum queries to an oracle of N items with no memory overhead.

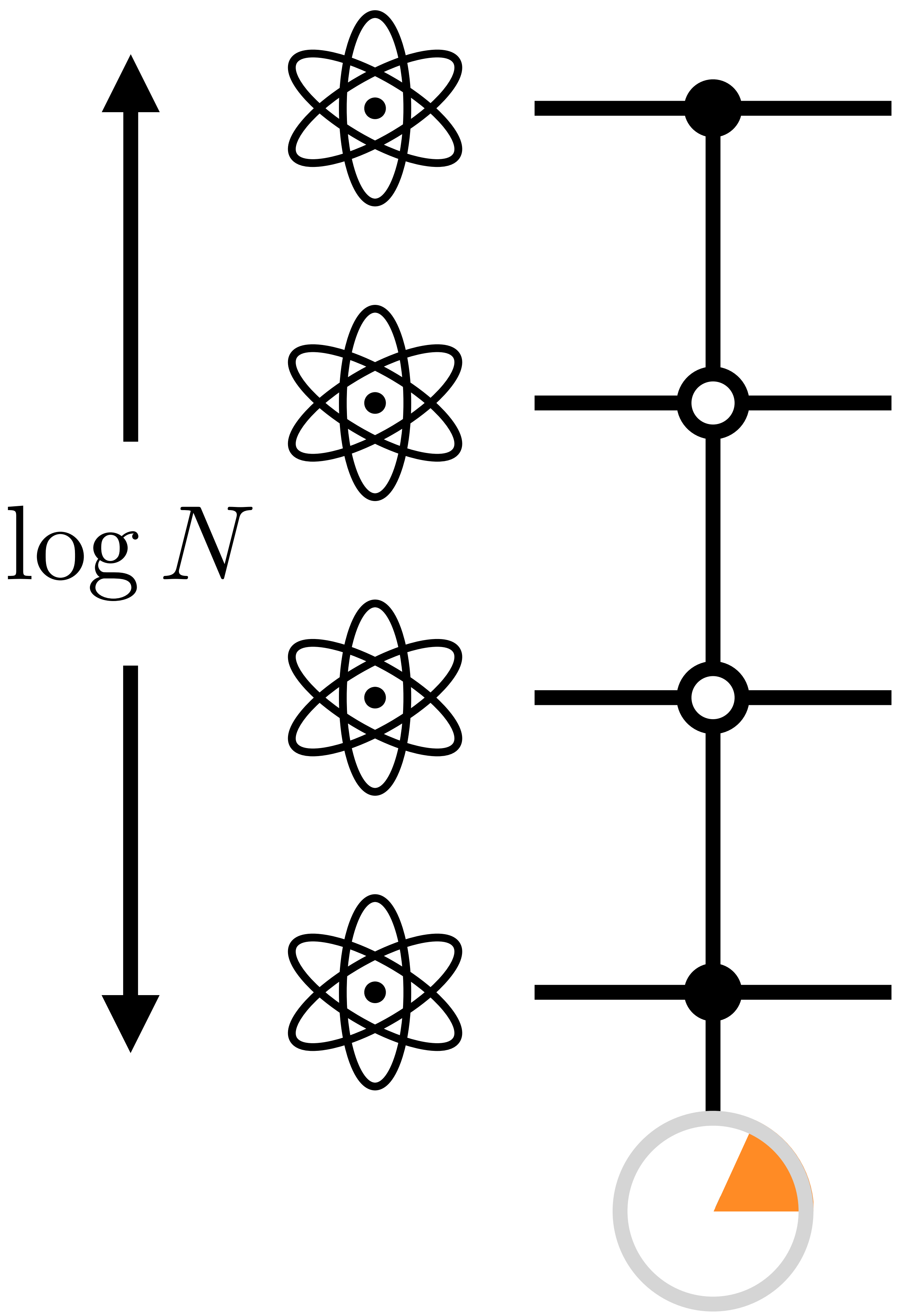
Toy example

Example

Goal: estimate property of $f : [N] \rightarrow \{0, 1\}$, given $\{x_i, f(x_i)\}_{i=1}^M, p(x) = 1/N$

Toy example

Example Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$



$x_i = 1001$

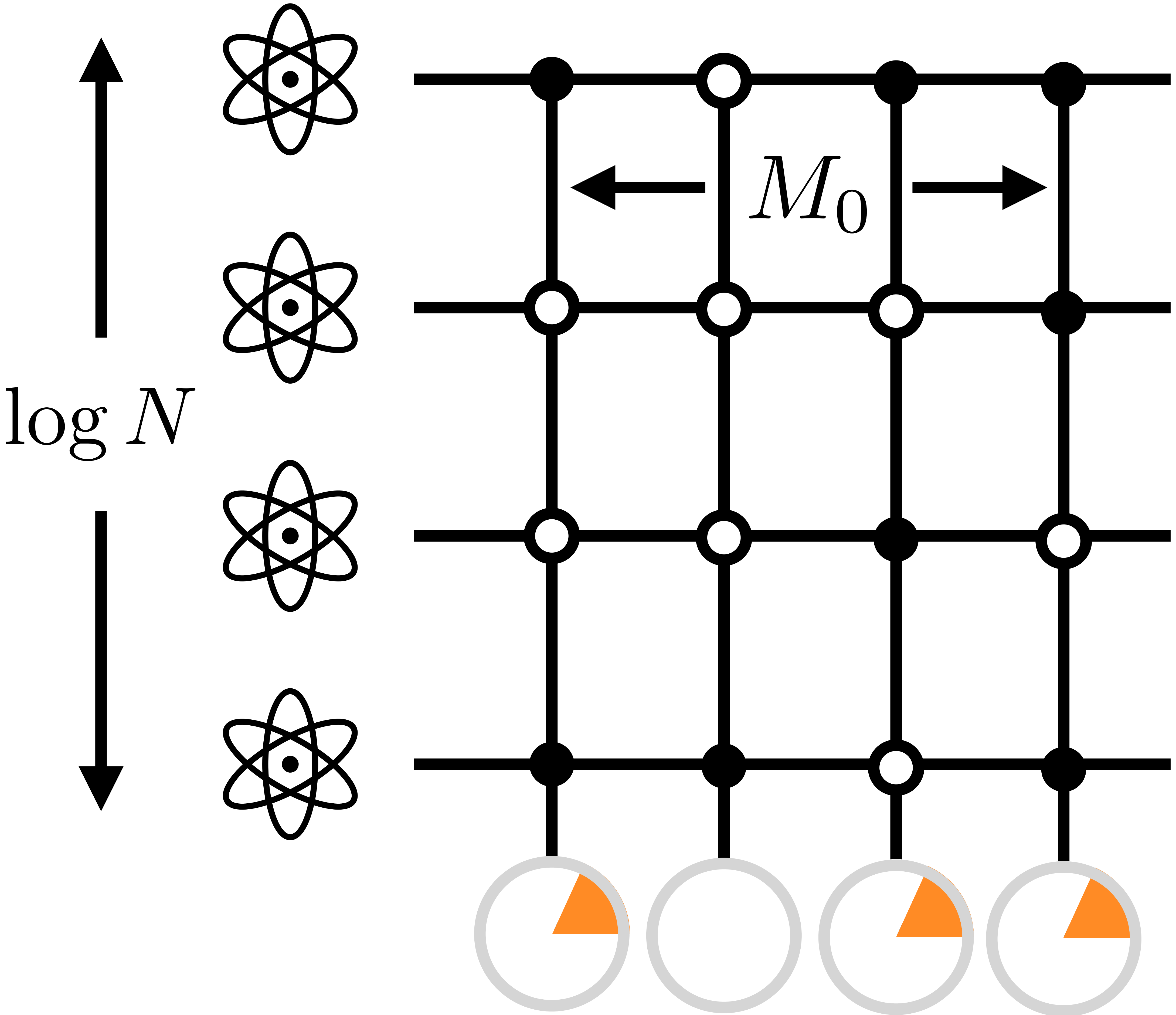
$f(x_i) = 1$

multi-controlled phase gate

$$V_i = \exp\left(i \frac{t}{M_0} f(x_i) |x_i\rangle\langle x_i|\right)$$

Toy example

Example Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$



$$V_i = \exp\left(i \frac{t}{M_0} f(x_i) |x_i\rangle\langle x_i|\right)$$

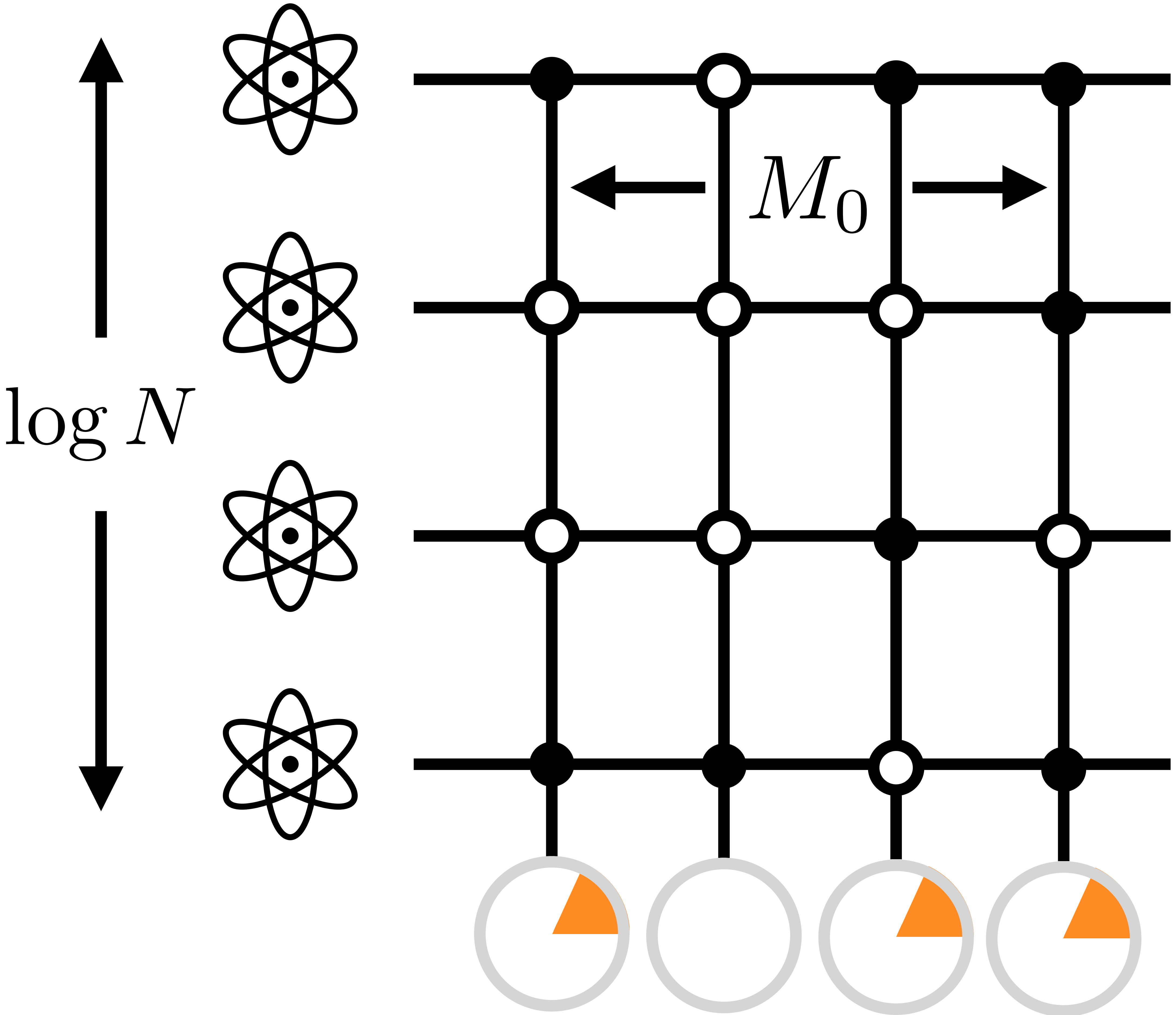
$$V_{M_0} \cdots V_1$$

$$= \exp\left(it \sum_x m_x f(x) |x\rangle\langle x|\right)$$

frequency of $x_i = x$

Toy example

Example Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$



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$$V_{M_0} \cdots V_1$$

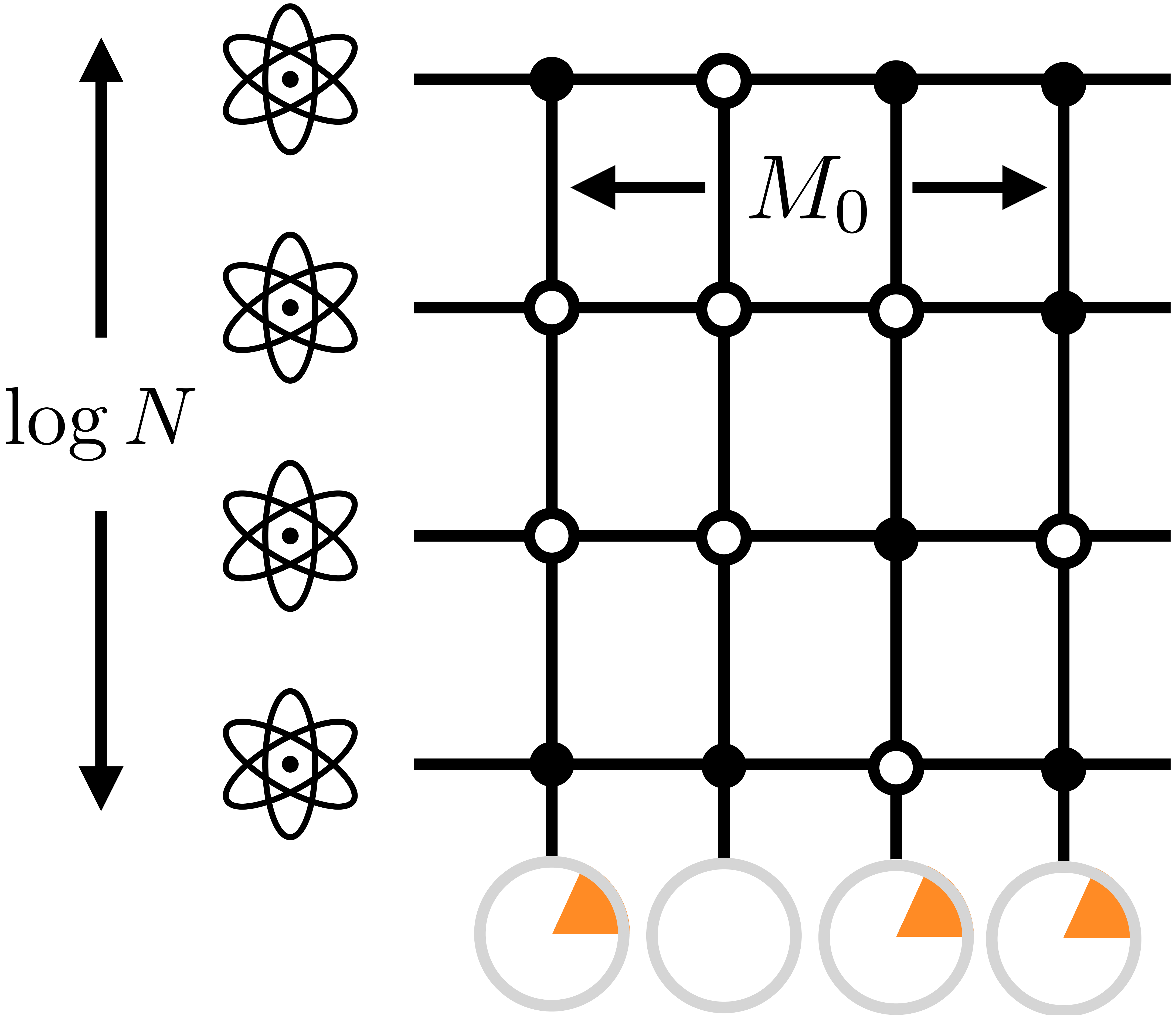
$$= \exp\left(it \sum_x m_x f(x) |x\rangle\langle x|\right)$$

$\approx p(x) = 1/N$

frequency of $x_i = x$

Toy example

Example Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$



$$V_i = \exp\left(i \frac{t}{M_0} f(x_i) |x_i\rangle\langle x_i|\right)$$

$$V_{M_0} \cdots V_1$$

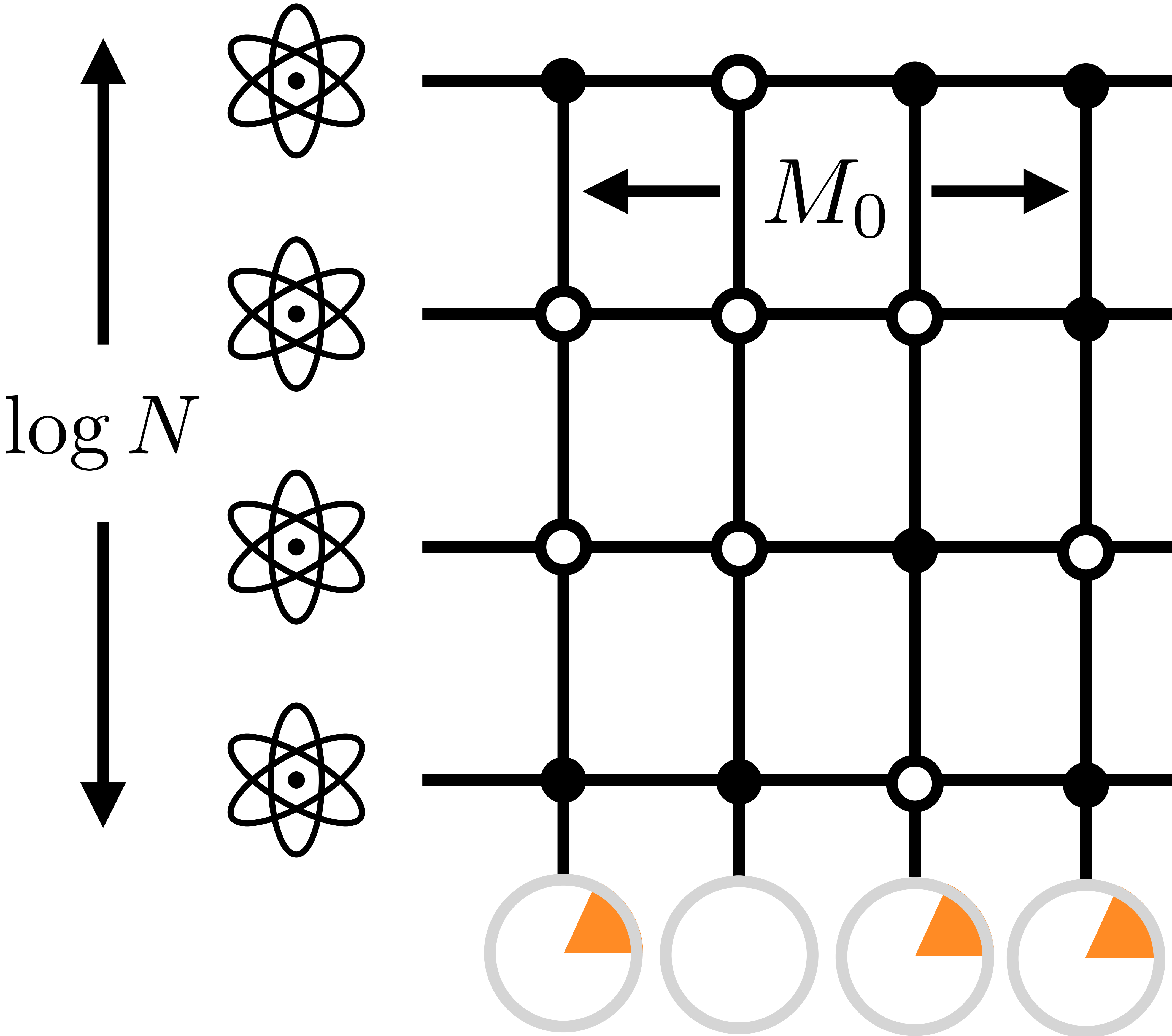
$$= \exp\left(it \sum_x m_x f(x) |x\rangle\langle x|\right)$$

$t = \pi N$ $\quad m_x \approx p(x) = 1/N$

$$\approx \sum_x \exp(i\pi f(x)) |x\rangle\langle x|$$

Toy example

Example Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$

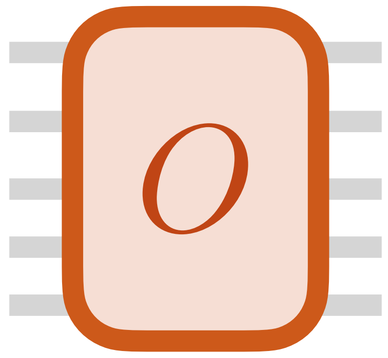


$$V_i = \exp\left(i \frac{t}{M_0} f(x_i) |x_i\rangle\langle x_i|\right)$$

$$V_{M_0} \cdots V_1$$

$$\approx_{\epsilon} \sum_x (-1)^{f(x)} |x\rangle\langle x|$$

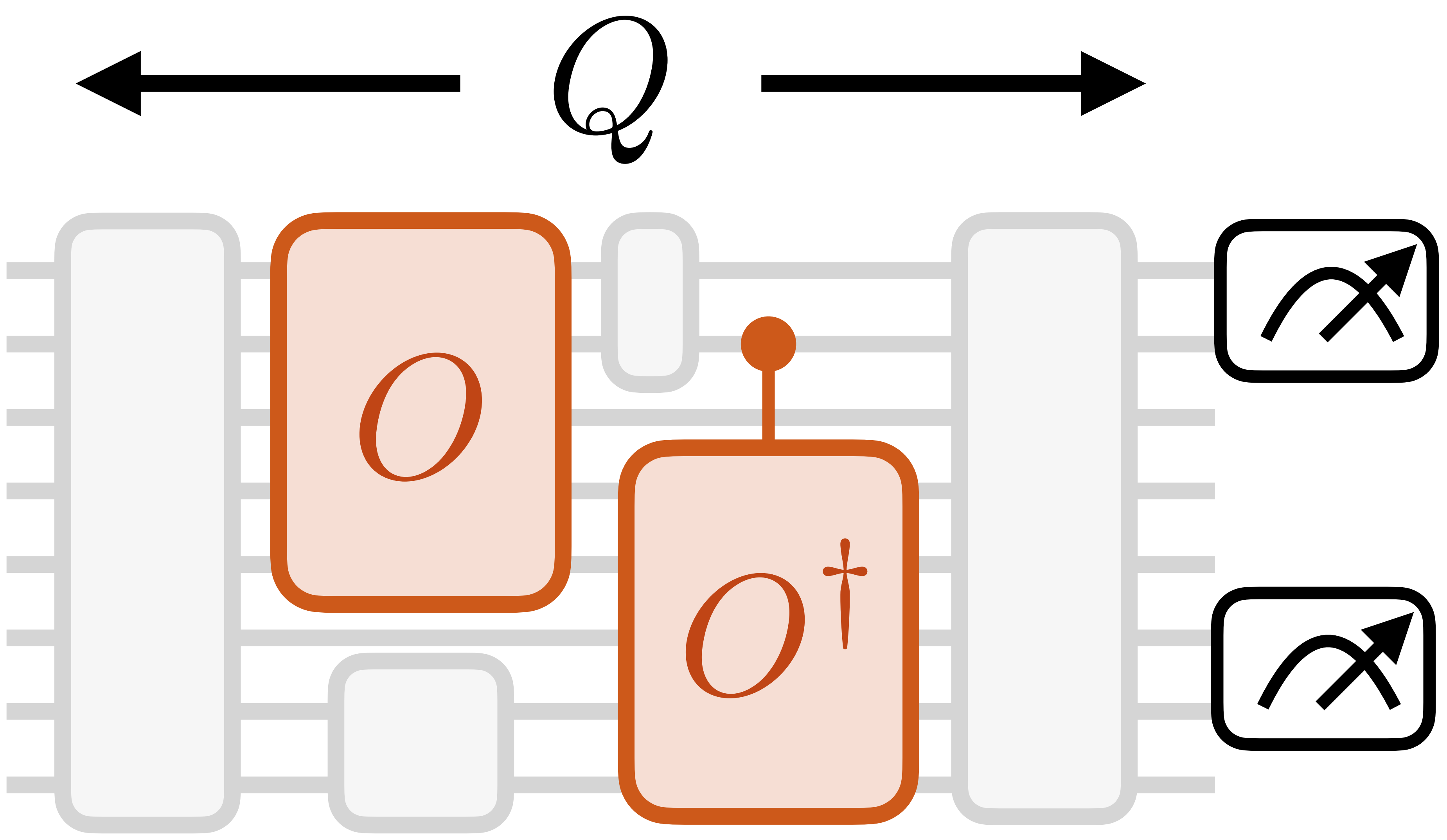
phase oracle



Theorem $M_0 = \Theta(N/\epsilon)$

Toy example

Example Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$



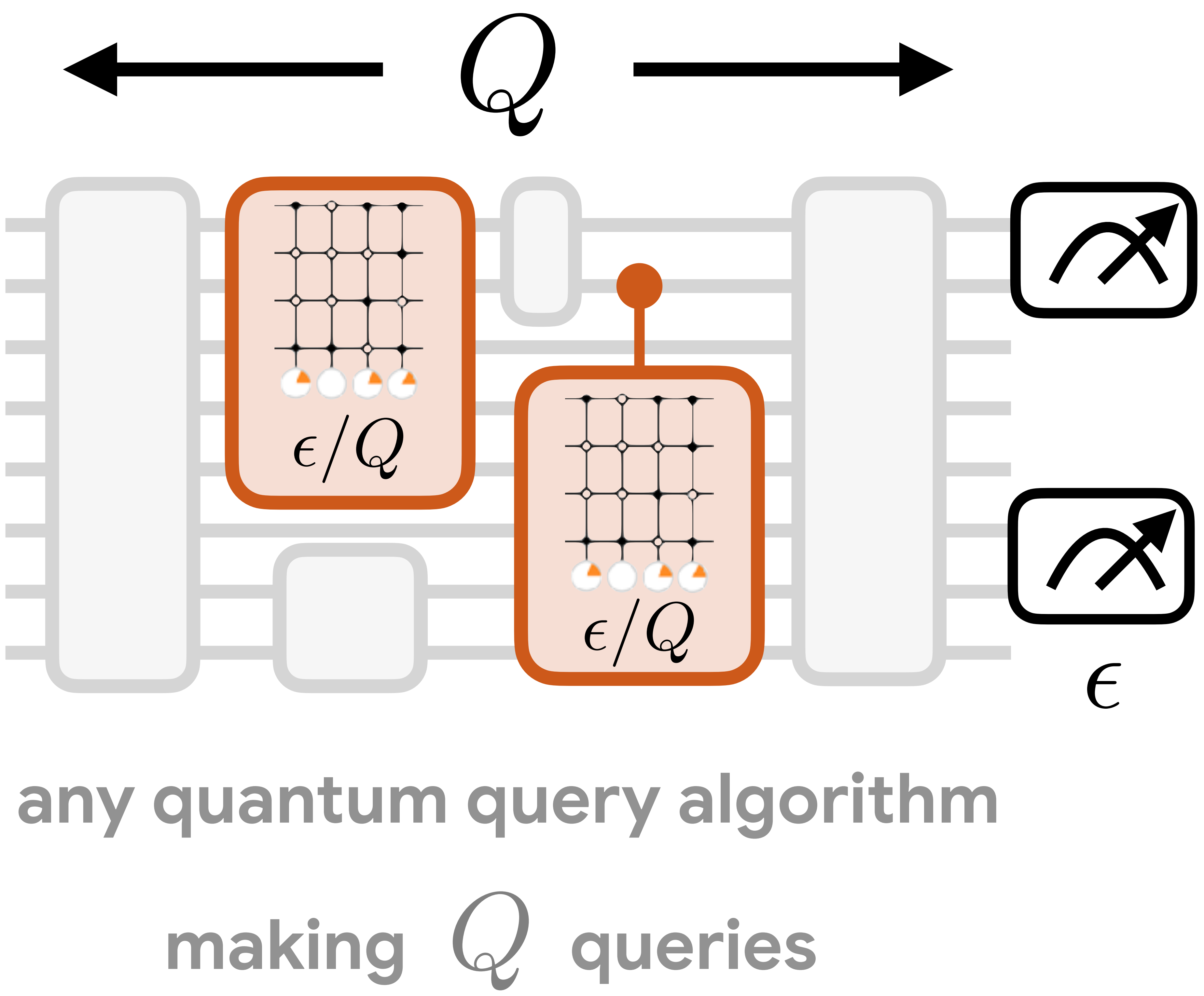
any quantum query algorithm

making Q queries

Toy example

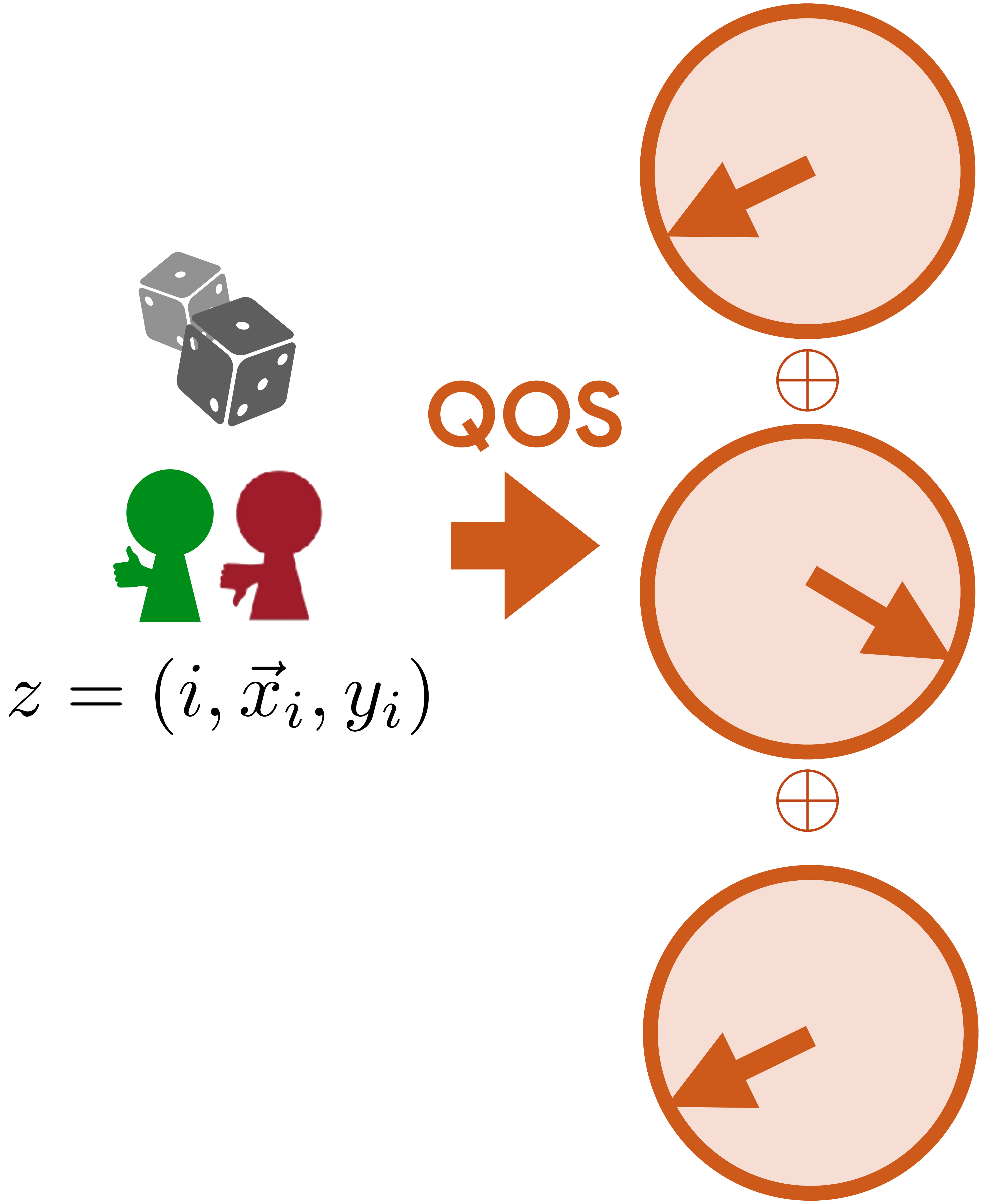
Example

Goal: estimate property of $f : [N] \to \{0,1\}$, given $\{x_i, f(x_i)\}_{i=1}^{M}, p(x) = 1/N$



$$M = Q \cdot \underbrace{O\left(\frac{N}{\epsilon/Q}\right)}_{M_0} = O\left(\frac{NQ^2}{\epsilon}\right)$$

Quantum oracle sketching



Quadratic slowdown in Q is the fundamental price to pay.

incoherent sampling of data, amp^2=prob, HL^2=SQL

Theorem (Quantum Oracle Sketch)

With $\Theta(NQ^2)$ samples, we can emulate Q quantum queries to an oracle of N items with no memory overhead.

Quantum oracle sketching

$z = (x, f(x))$

$|x\rangle \to (-1)^{f(x)}|x\rangle$

phase oracle

$|x\rangle|y\rangle \to |x\rangle|y \oplus f(x)\rangle$

XOR oracle

A

$z = (i, j, A_{ij})$

QOS

$U = \begin{pmatrix} A & \star \\ \star & \star \end{pmatrix}$

block encoding

$\vec{v}$

$z = (k, v_k)$

$|0\rangle \to |v\rangle$

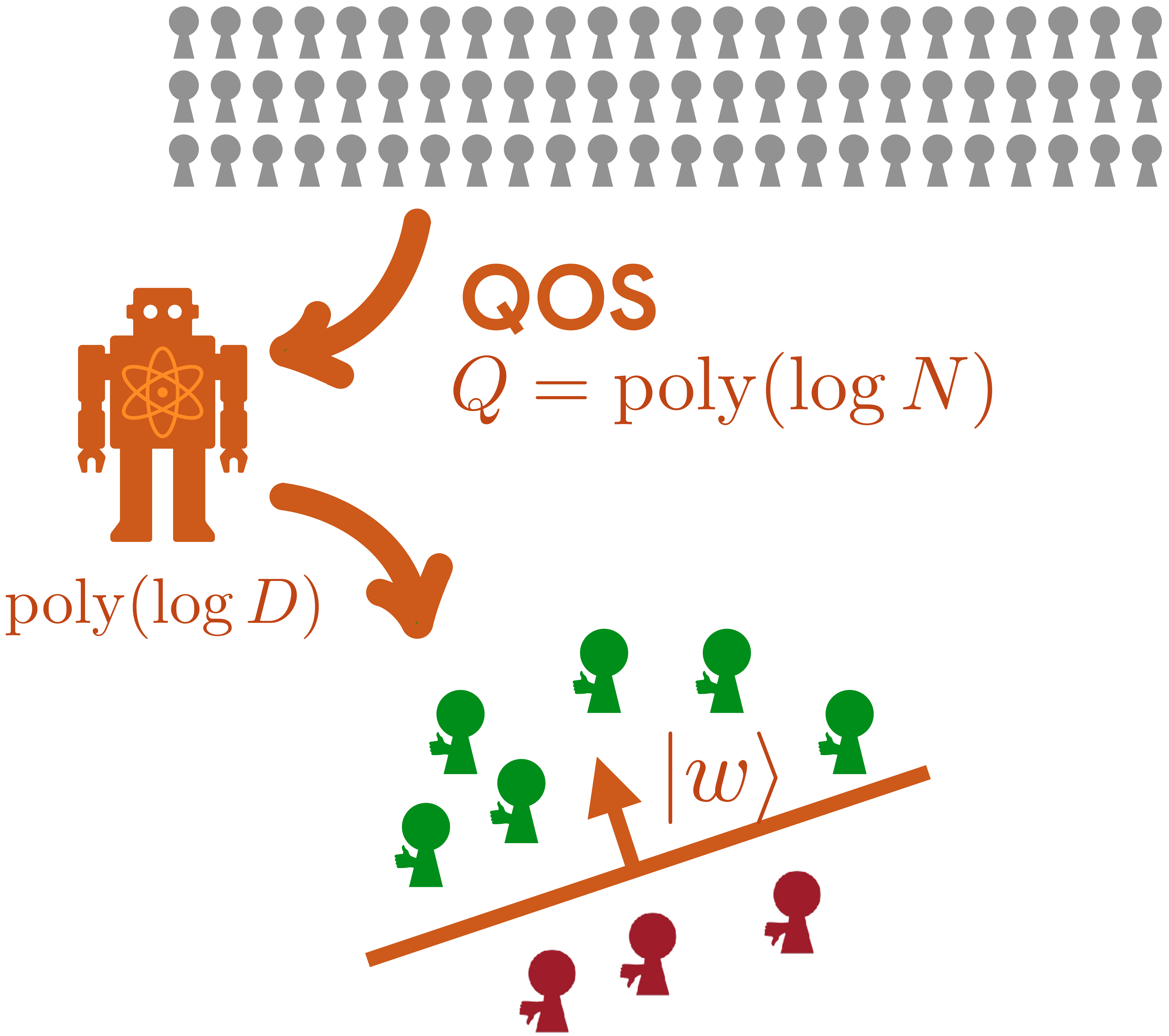
state preparation unitary

Robust to noise and correlation in data; support flexible data structures.

Theorem (Quantum Oracle Sketch)

With $\Theta(NQ^2)$ samples, we can emulate Q quantum queries to an oracle of N items with no memory overhead.

Quantum oracle sketching



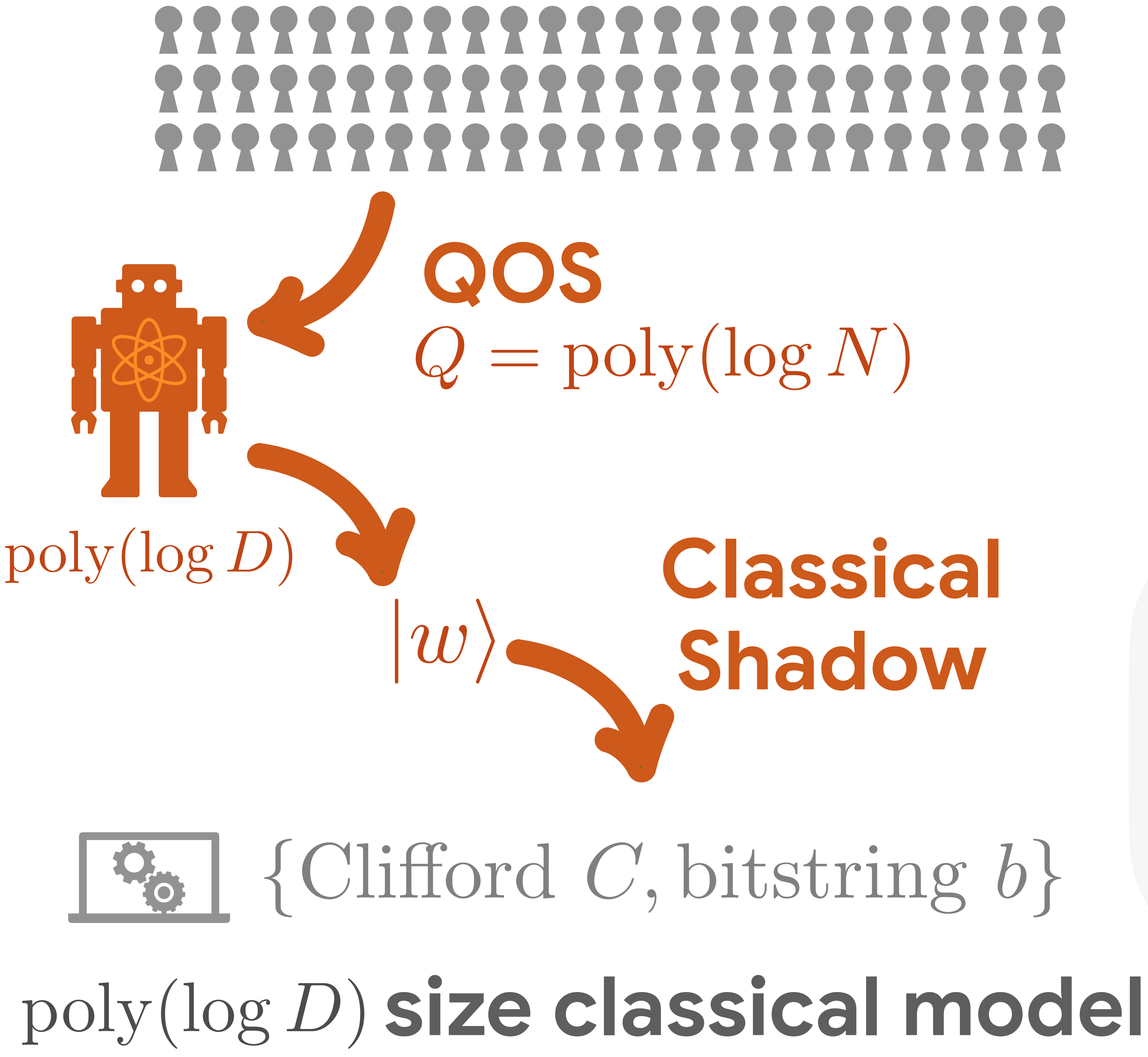
ML tasks can be solved with $\mathrm{poly}(\log D)$ size and $Q = \mathrm{poly}(\log N)$ queries.

SVM: linear system
PCA: ground state prep

Theorem (Quantum Oracle Sketch)

With $\tilde{\Theta}(N)$ samples, a quantum machine of $\mathrm{poly}(\log D)$ size can solve the ML tasks.

Quantum oracle sketching



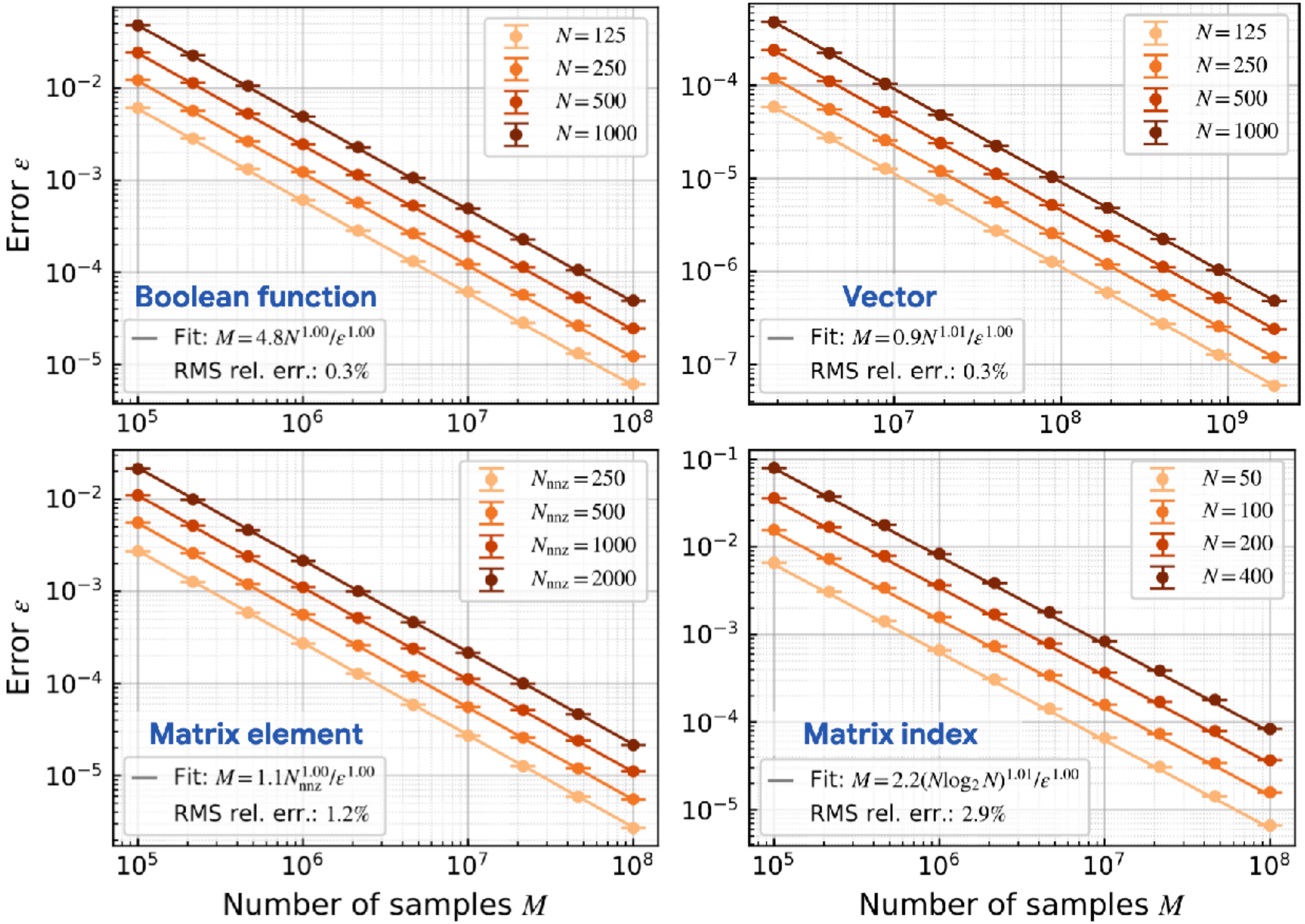
Interferometric classical shadow:

exponentially compact classical model possible only via quantum technology.

Theorem (Quantum Oracle Sketch)

With $\tilde{\Theta}(N)$ samples, a quantum machine of $\text{poly}(\log D)$ size can solve the ML tasks.

Quantum oracle sketching

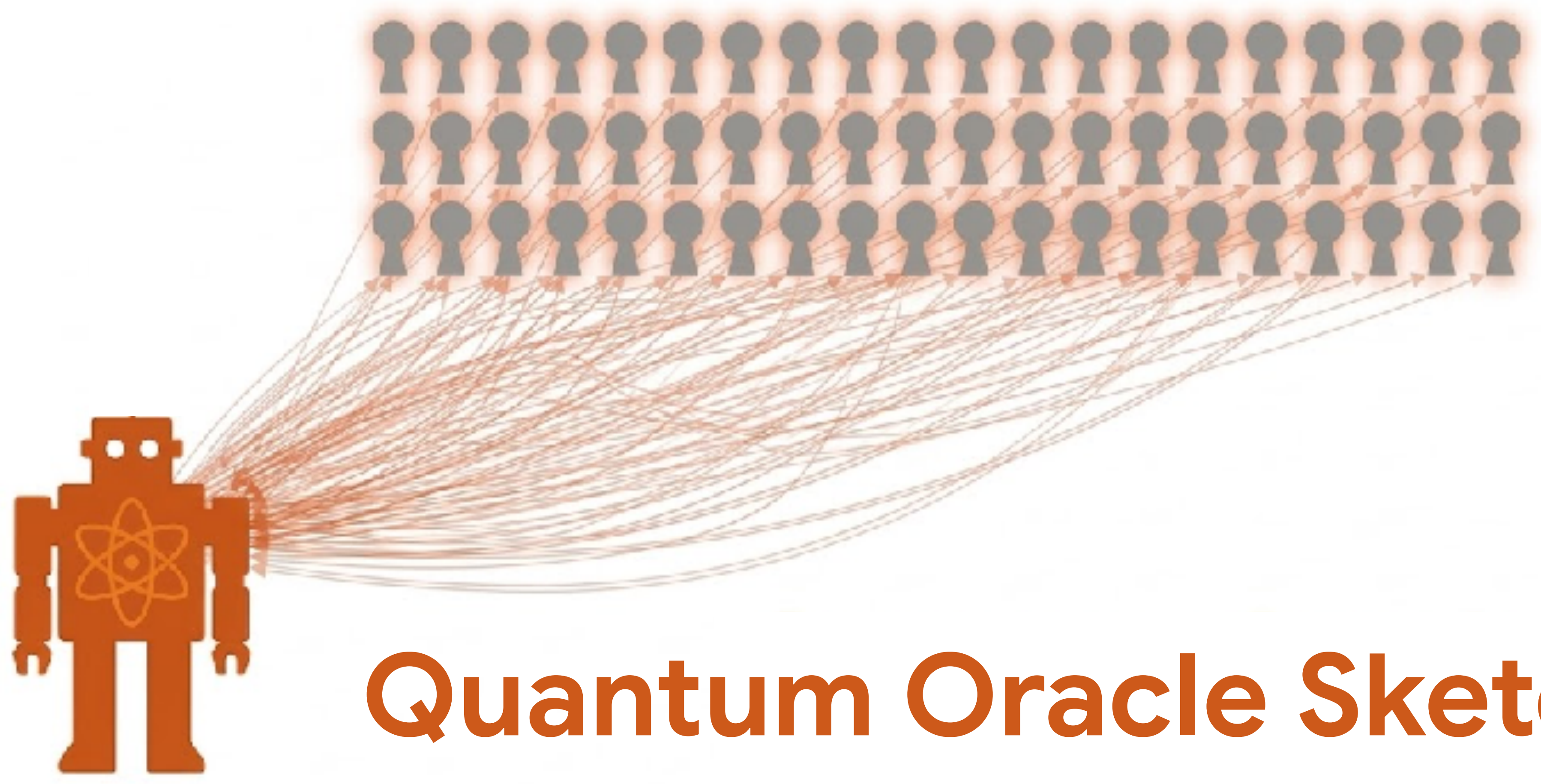


GitHub

haimengzhao/quantum-oracle-sketching

JAX-powered, support GPU/TPU, auto-differentiation

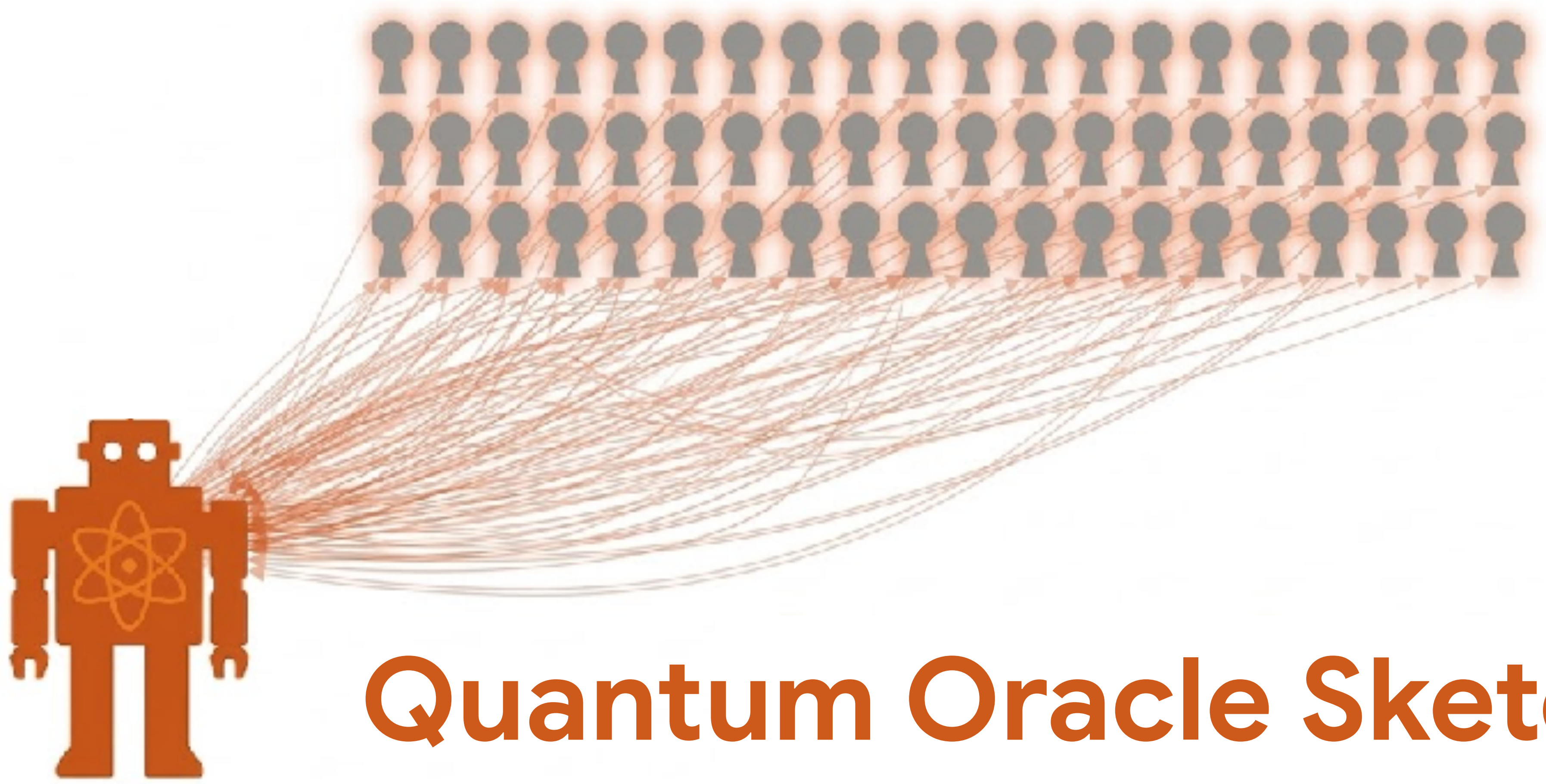
Quantum Algorithm



Quantum Oracle Sketching

query the classical world in quantum superposition

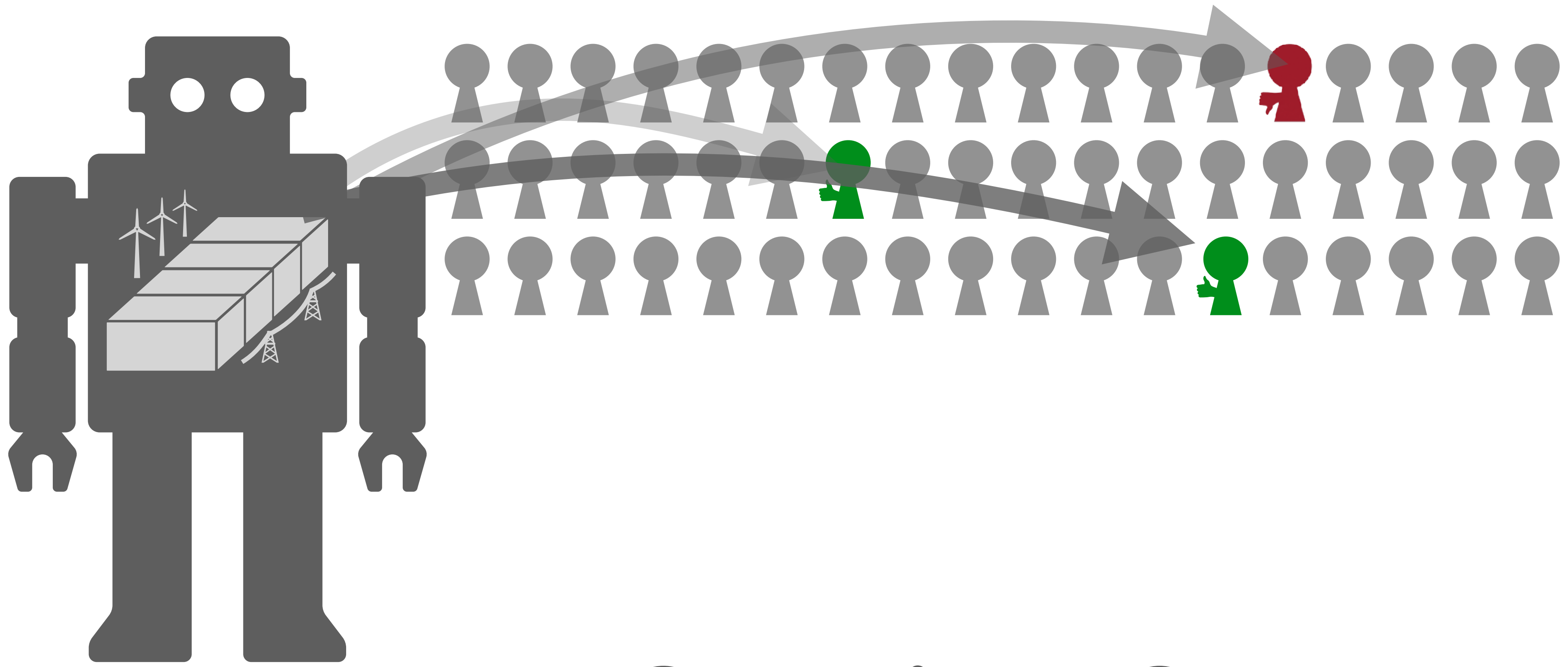
Quantum Algorithm



Quantum Oracle Sketching

query the classical world in quantum superposition

Classical Hardness



Classical Query

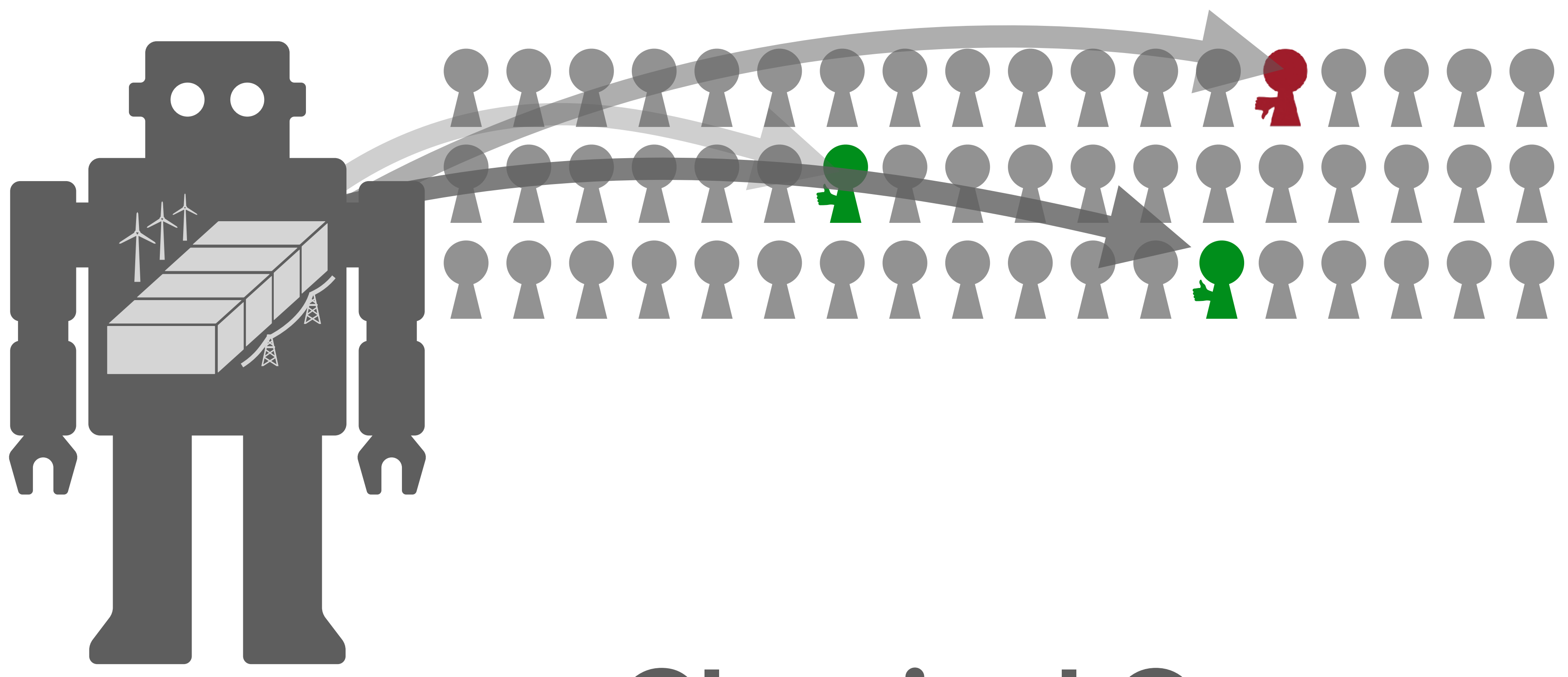
separation in query ability
→ memory advantage

Classical Hardness

1. Connect query separation to memory advantage

2. Insufficient memory must be compensated by more samples

3. Embed into ML tasks



Classical Query

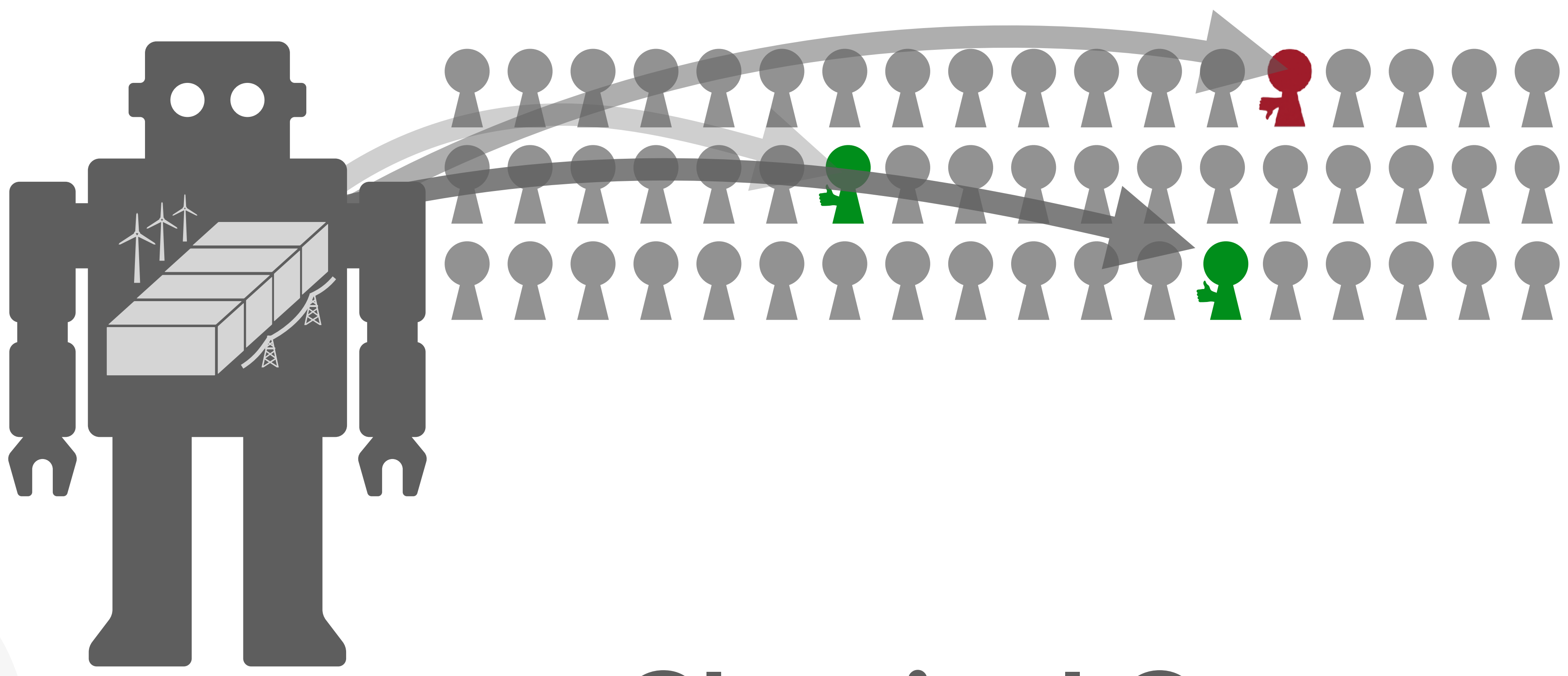
Classical Hardness

1. Connect query separation to memory advantage

Theorem (Classical Hardness)

For any query problem requiring Q quantum queries or Q_C classical queries, to solve an associated learning task with $\Theta(NQ^2)$ samples, any classical machine must have size

$$S \geq \Omega(Q_C/Q^2)$$



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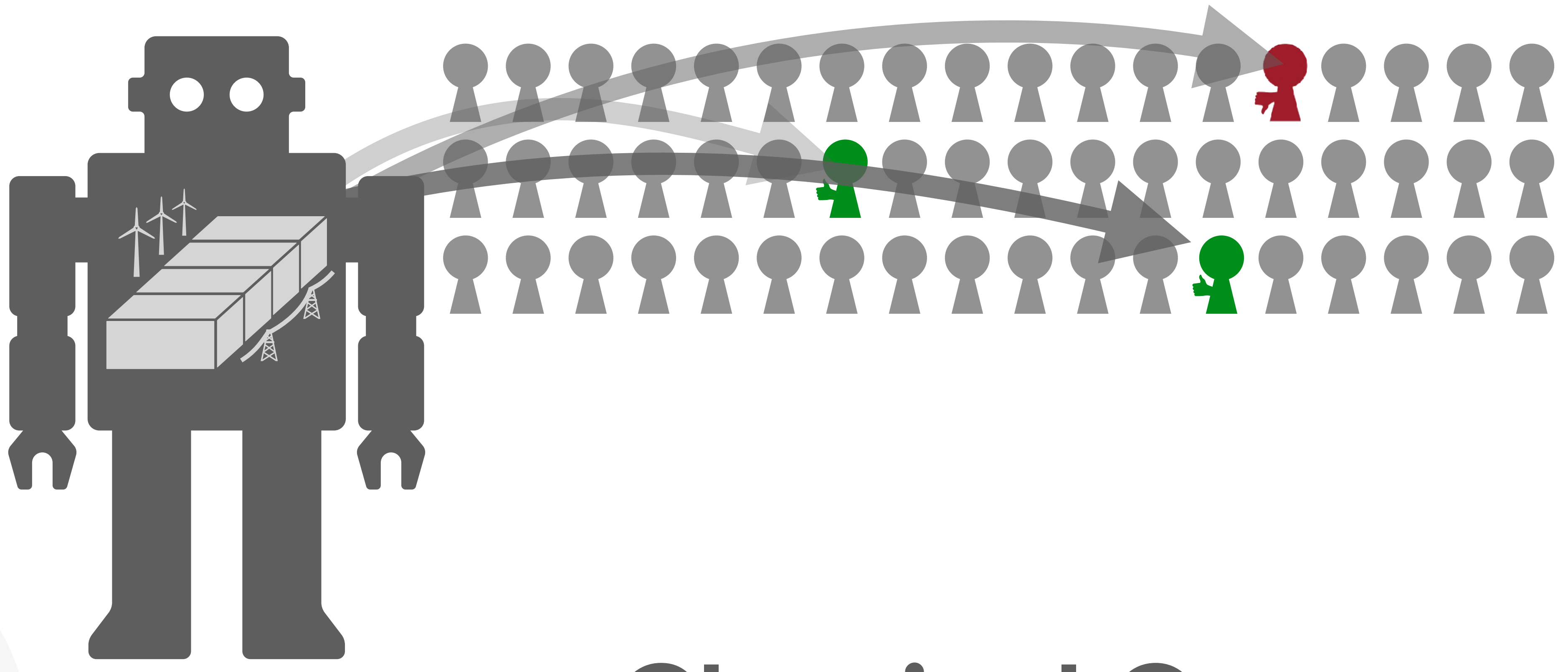

Any super-quadratic query separation,

$$Q = O(N^{0.49}), Q_C = \Theta(N)$$
$$\Longrightarrow \quad S \geq \Omega(N^{0.02})$$

Classical Hardness

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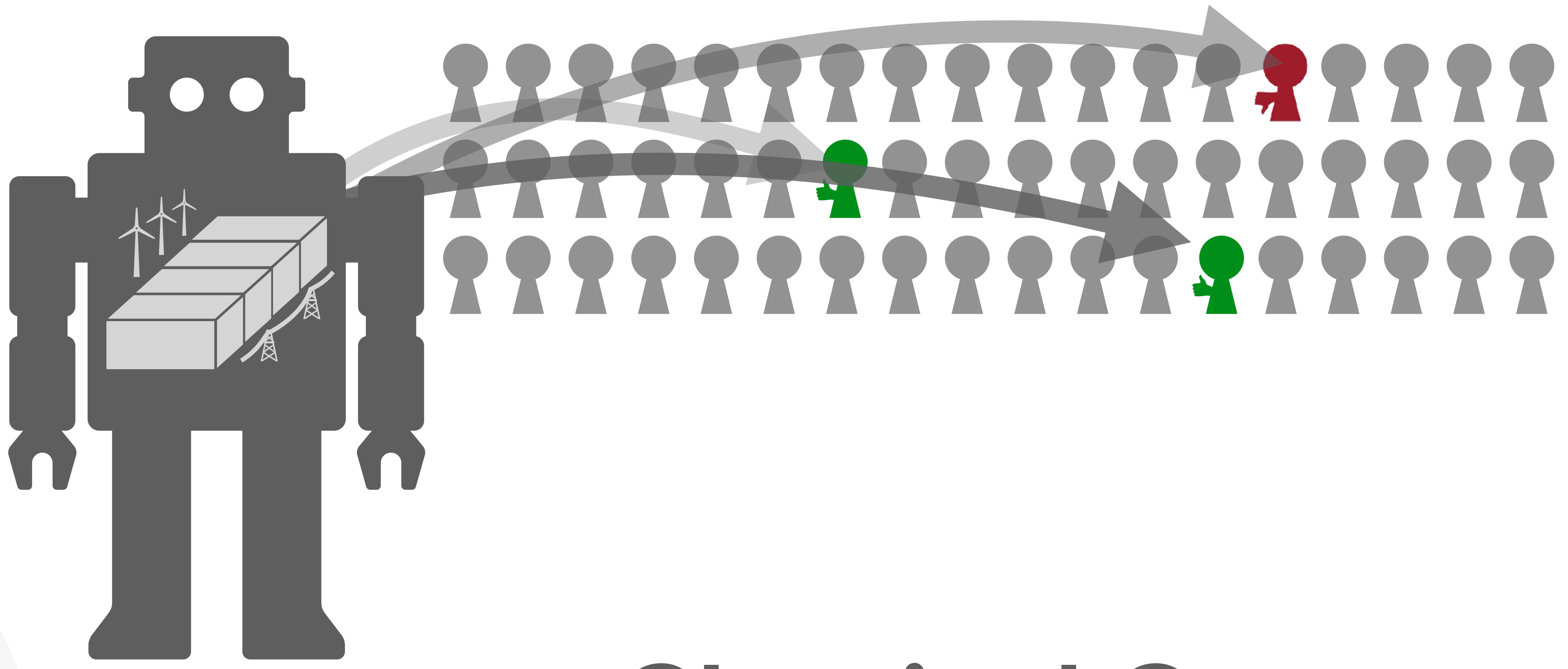

Classical Query

For ML tasks,

$$Q = \text{poly}(\log N), Q_C = \Theta(N^{0.99})$$
$$\implies S \geq \Omega(N^{0.99})$$

Classical Hardness

1. Connect query separation to memory advantage

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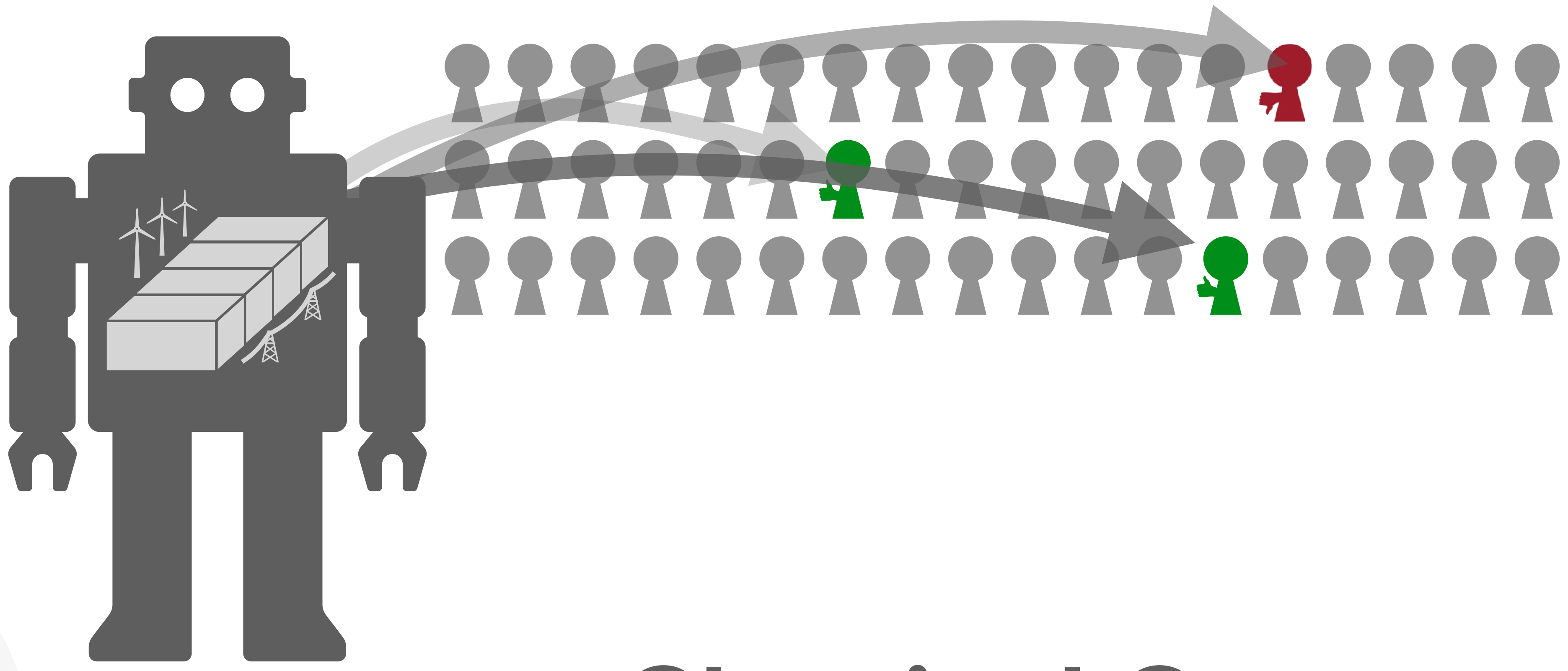


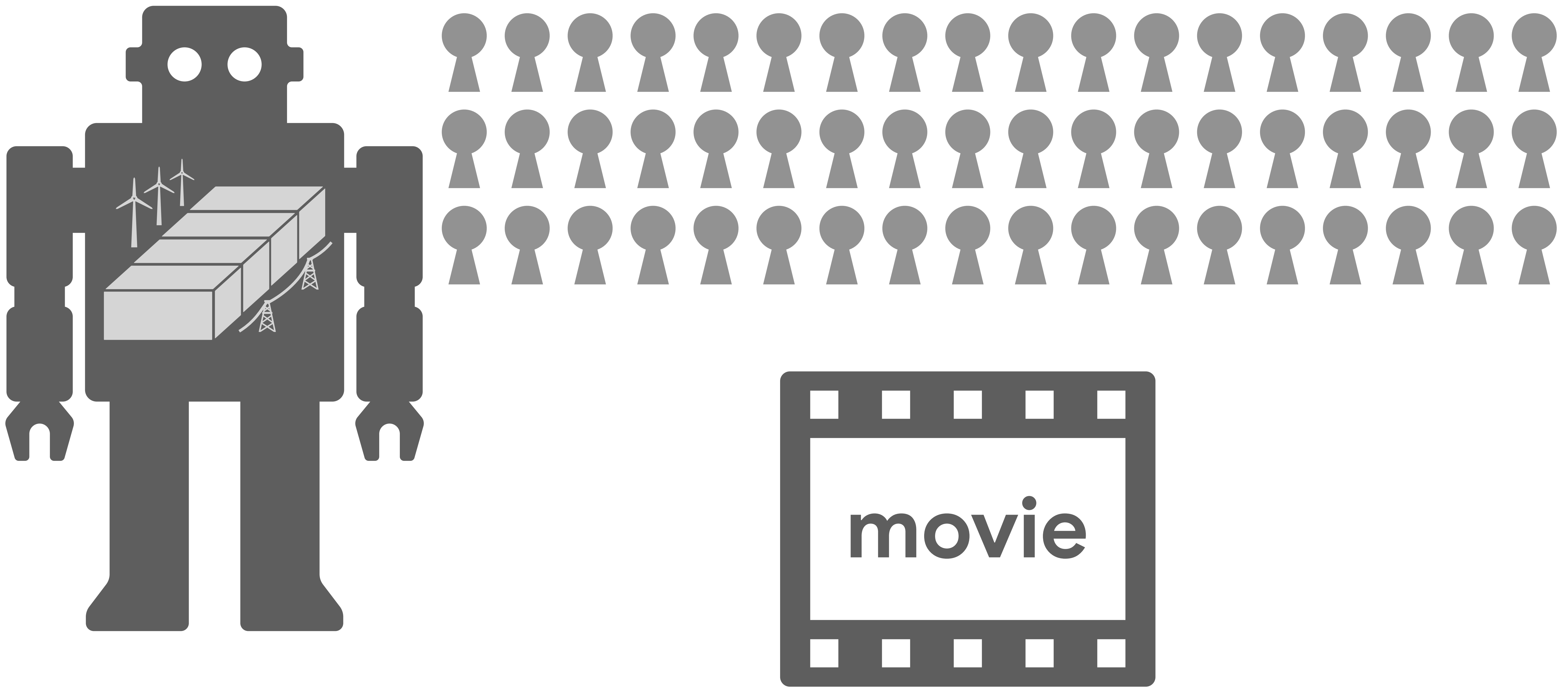
Classical Query

Sample-space lower bound

$$MS \geq \Omega(NQ_C)$$

#sample $M = \Theta(NQ^2)$ from QOS

Query Problem

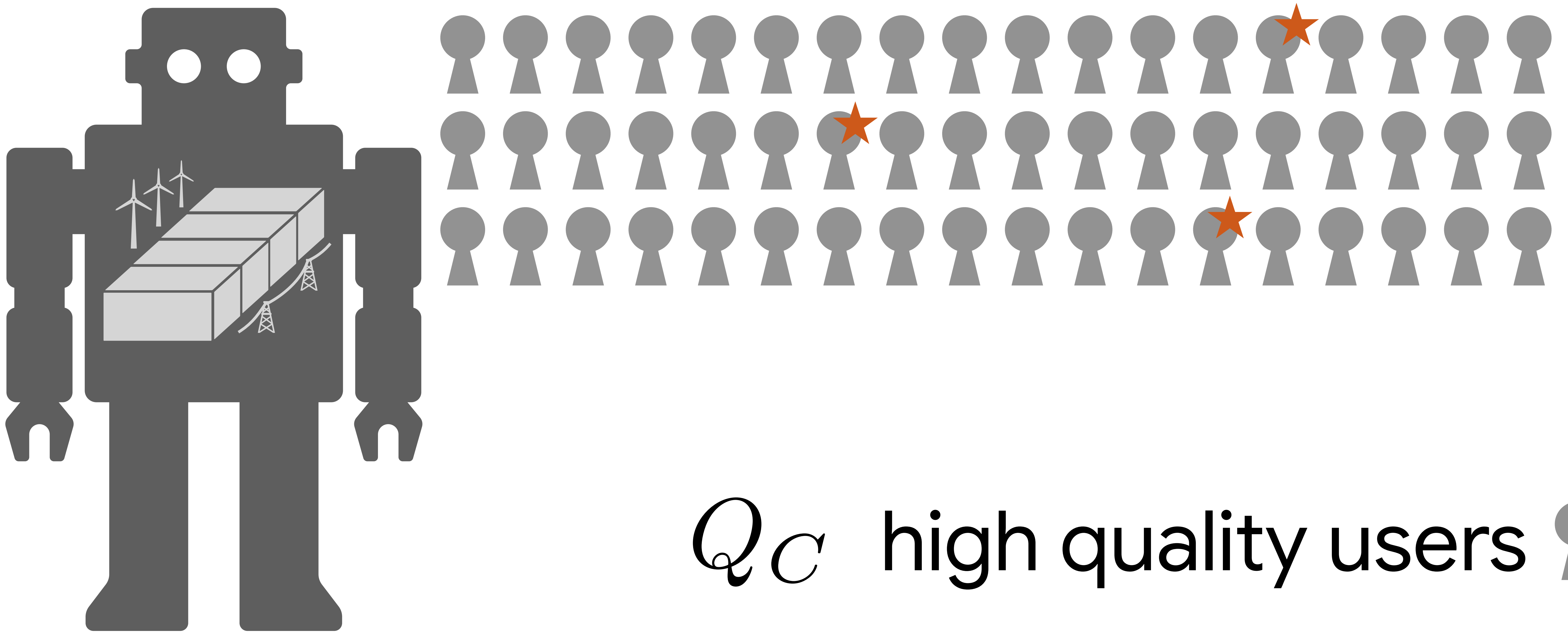


N users

Goal

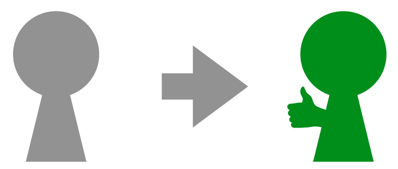
rate the movie

Query Problem



N users

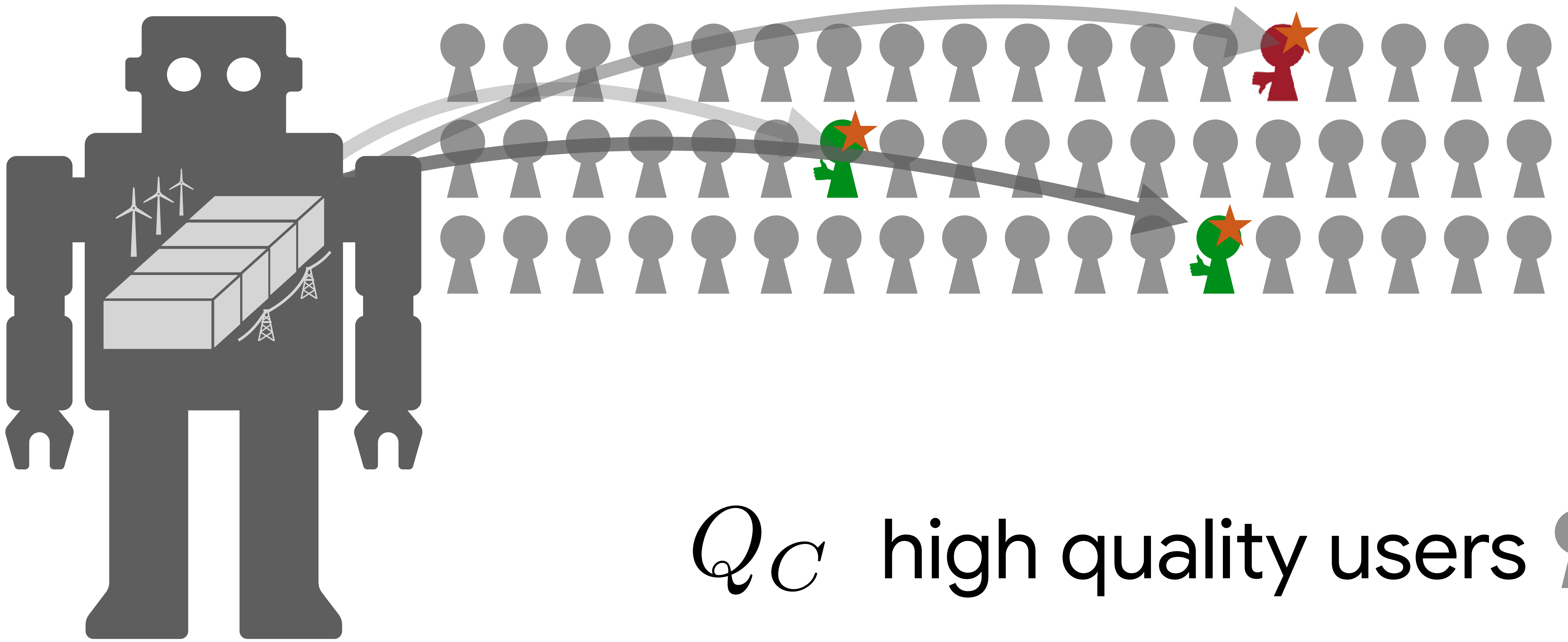
[oracle]



$x \to f(x)$

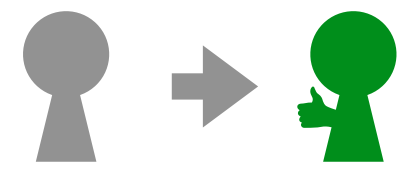
Q_C high quality users

Query Problem



N users

[oracle]



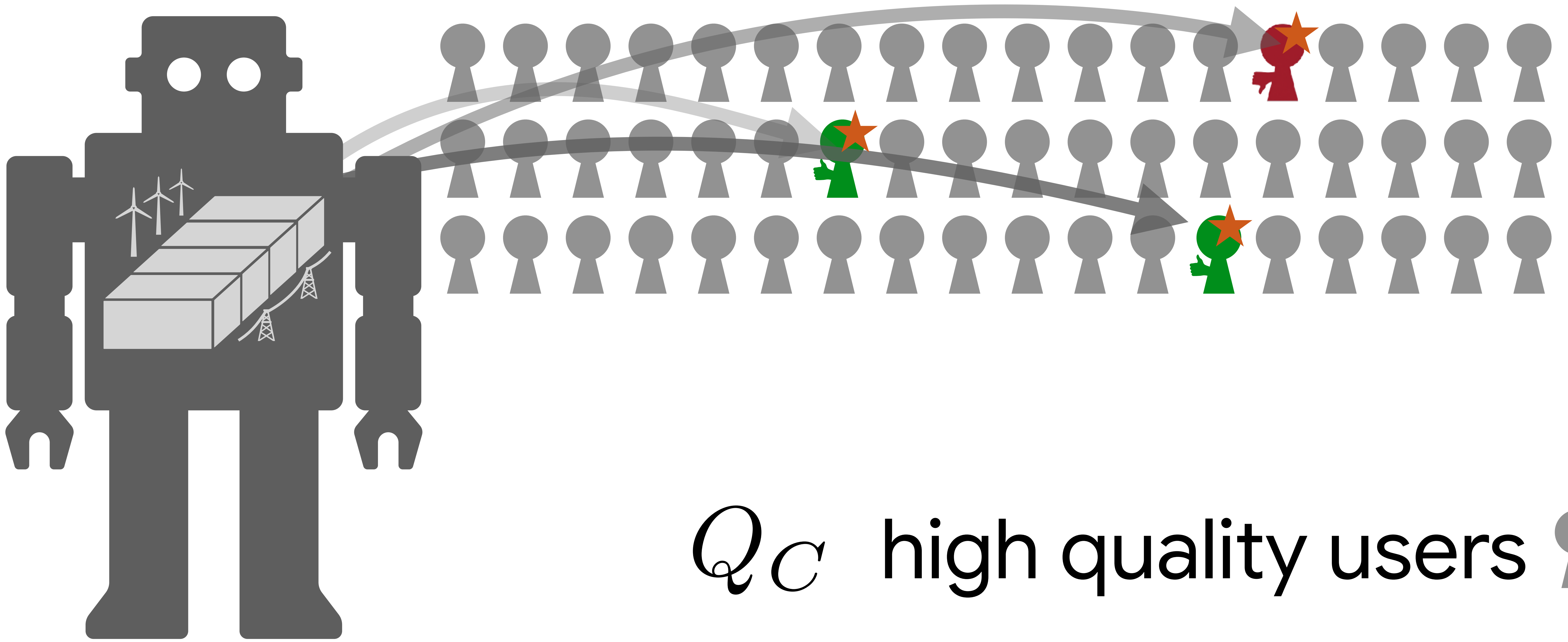
$x \to f(x)$

Q_C high quality users

querying them suffices to determine the goal

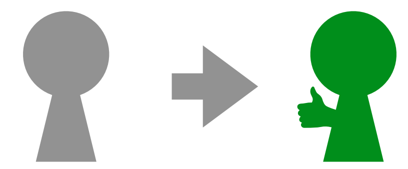
[classical query complexity]

Query Problem



N users

[oracle]

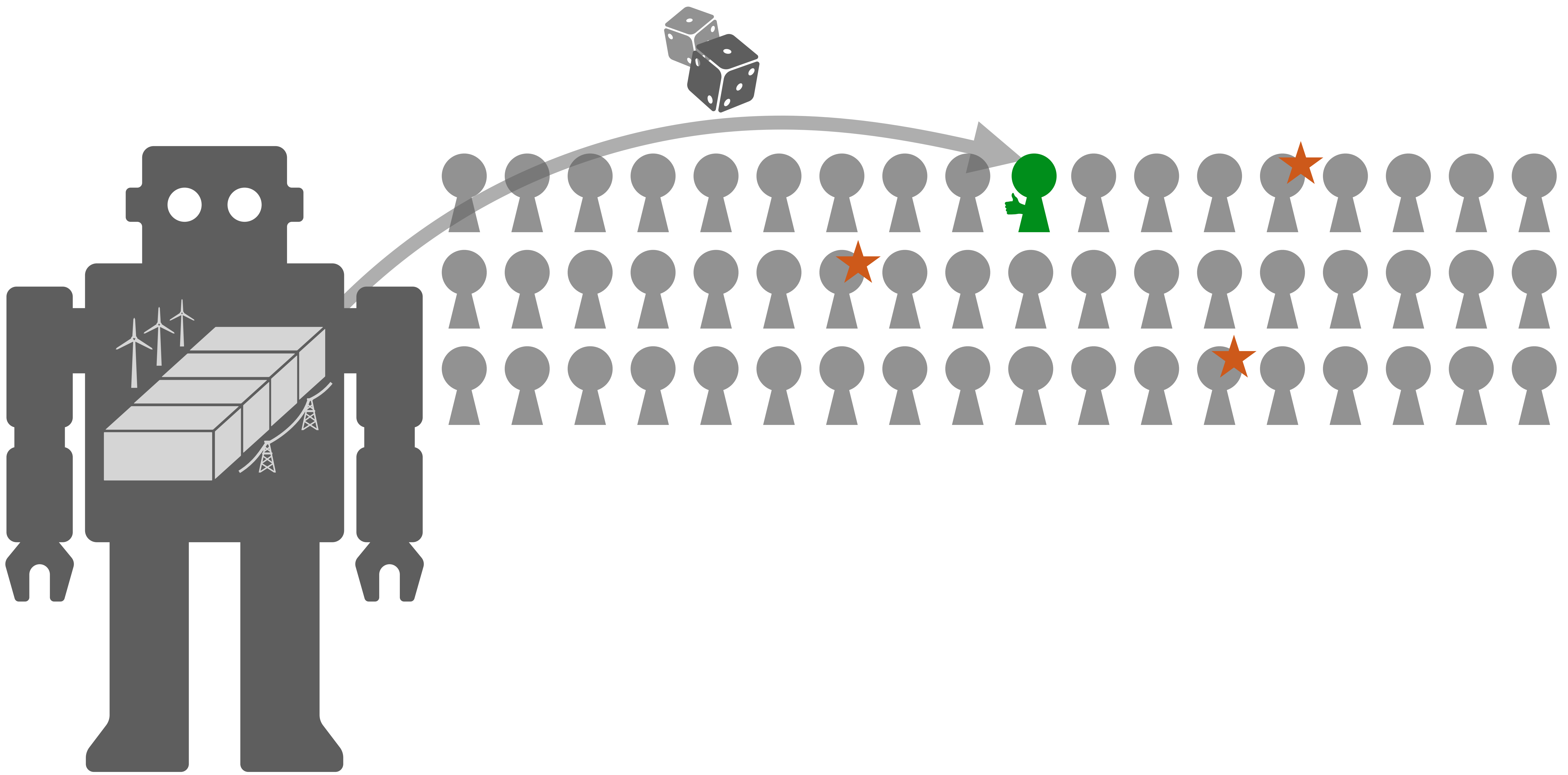


$x \to f(x)$

Q_C high quality users 

amount of info needed to estimate some property of the oracle [classical query complexity]

Oracle Property Estimation



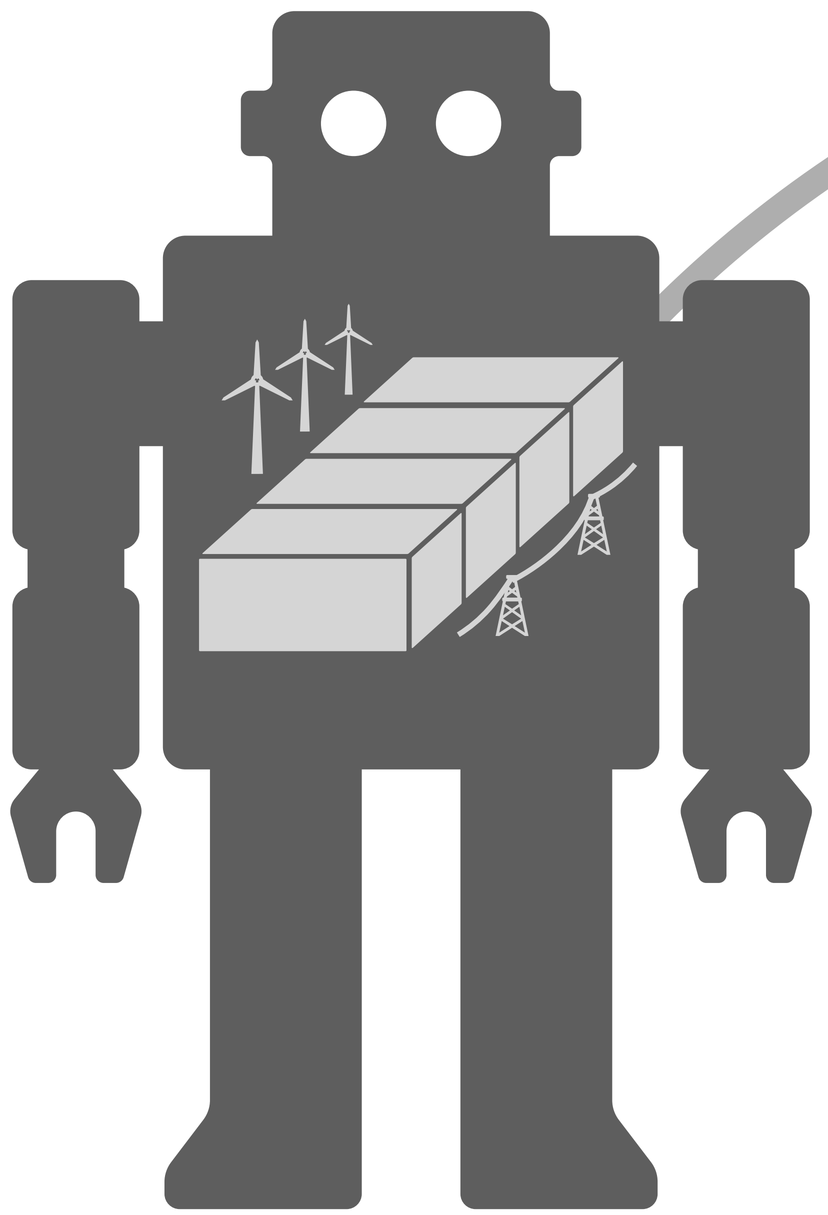
random data
from N users

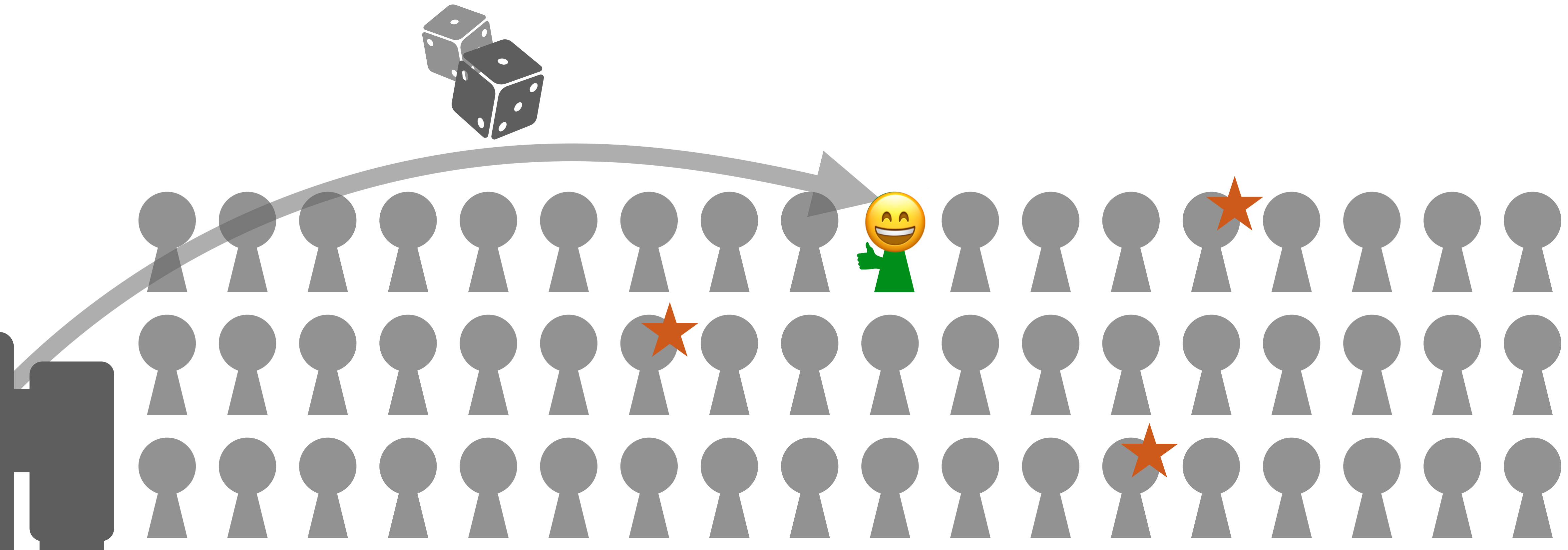
$z = (x, f(x))$

Q_C

info needed to estimate
oracle property

Noisy Oracle Property Estimation (NOPE)





noisy data
from N users

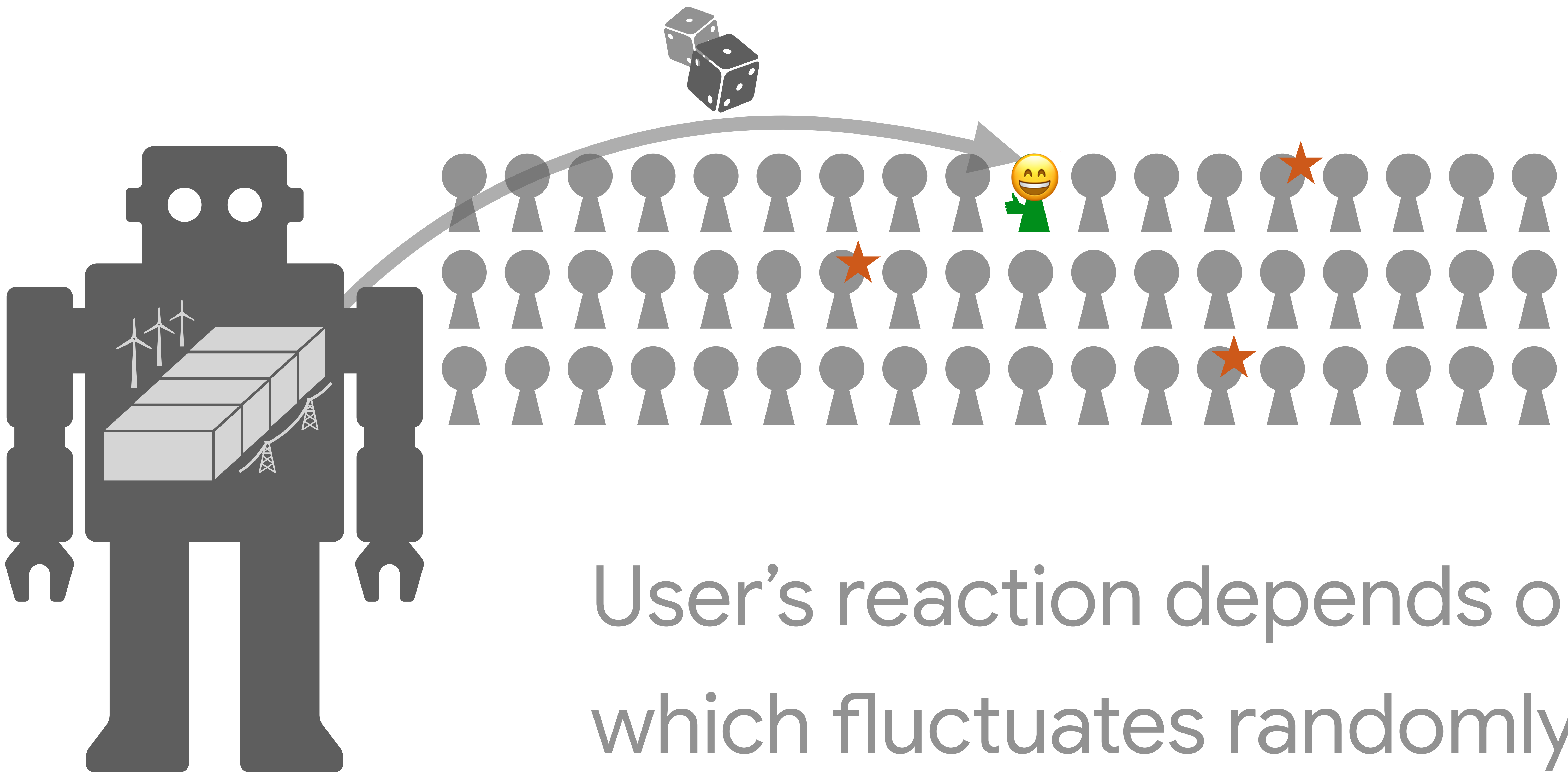
$z = (x, f_\alpha(x), \alpha)$

User's reaction depends on their mood,
which fluctuates randomly over time.

Q_C

info needed to estimate
oracle property

Noisy Oracle Property Estimation (NOPE)



noisy data

from N users

$z = (x, f_\alpha(x), \alpha)$

User's reaction depends on their mood, which fluctuates randomly over time.

Need to gather both for accurate feedback.

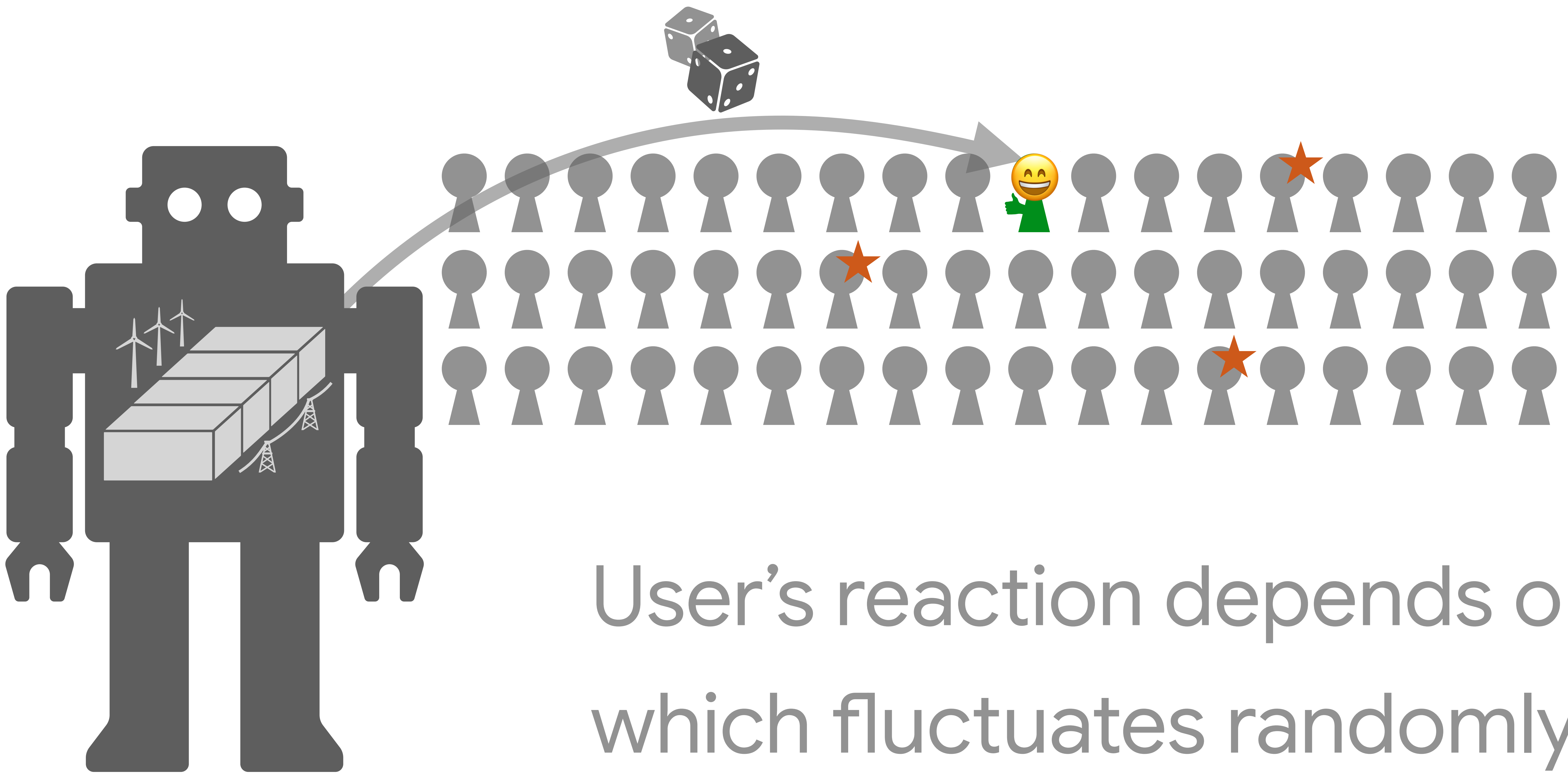
$f_1(x), f_2(x) \rightarrow f(x)$

via low-discrepancy encoding

Q_C

info needed to estimate oracle property

Noisy Oracle Property Estimation (NOPE)



noisy data

from N users

$z = (x, f_\alpha(x), \alpha)$

User's reaction depends on their mood,

which fluctuates randomly over time.

Q_C

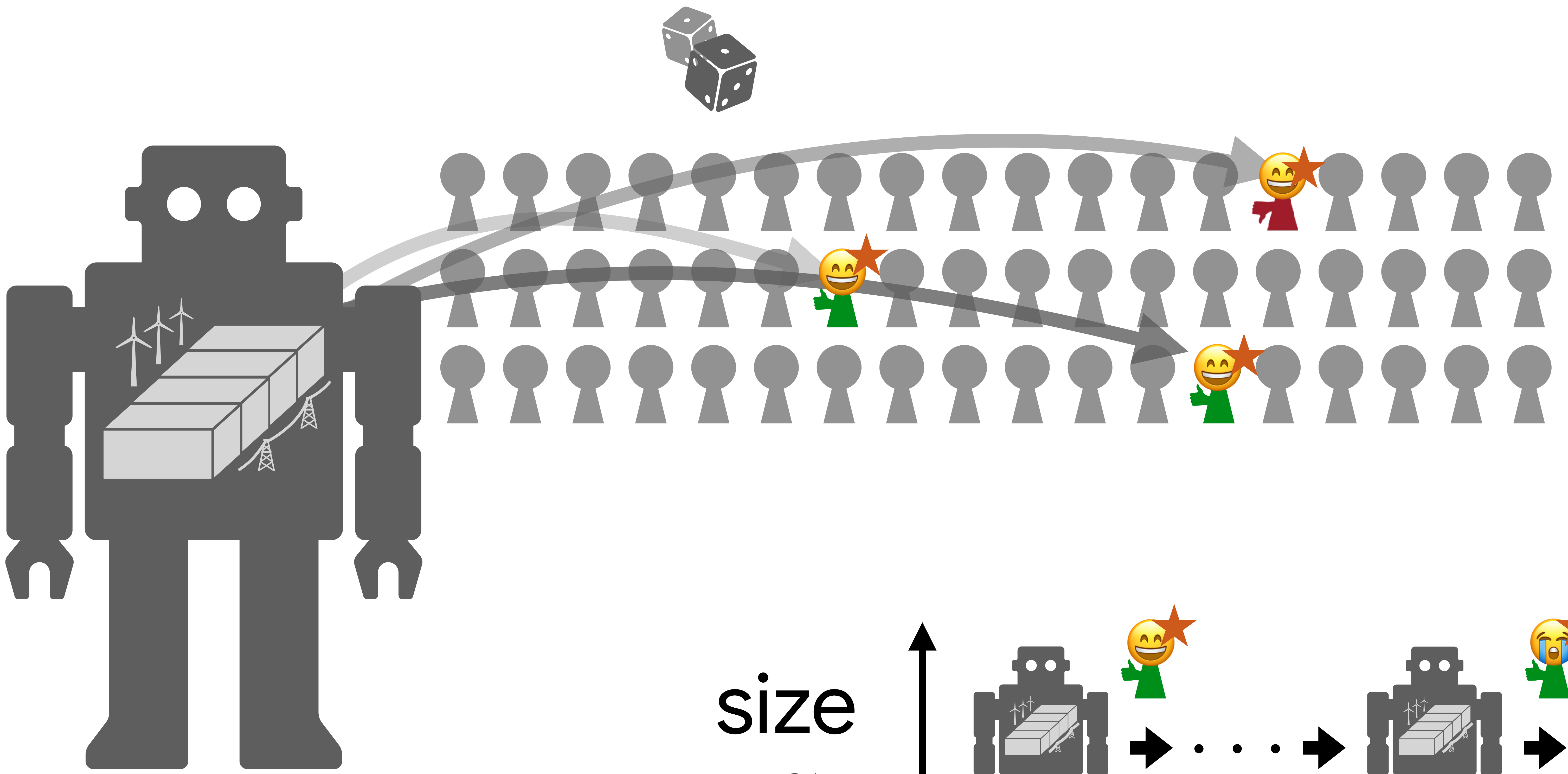
info needed to estimate oracle property

Need to gather both for accurate feedback.

$f_1(x), f_2(x) \rightarrow f(x)$

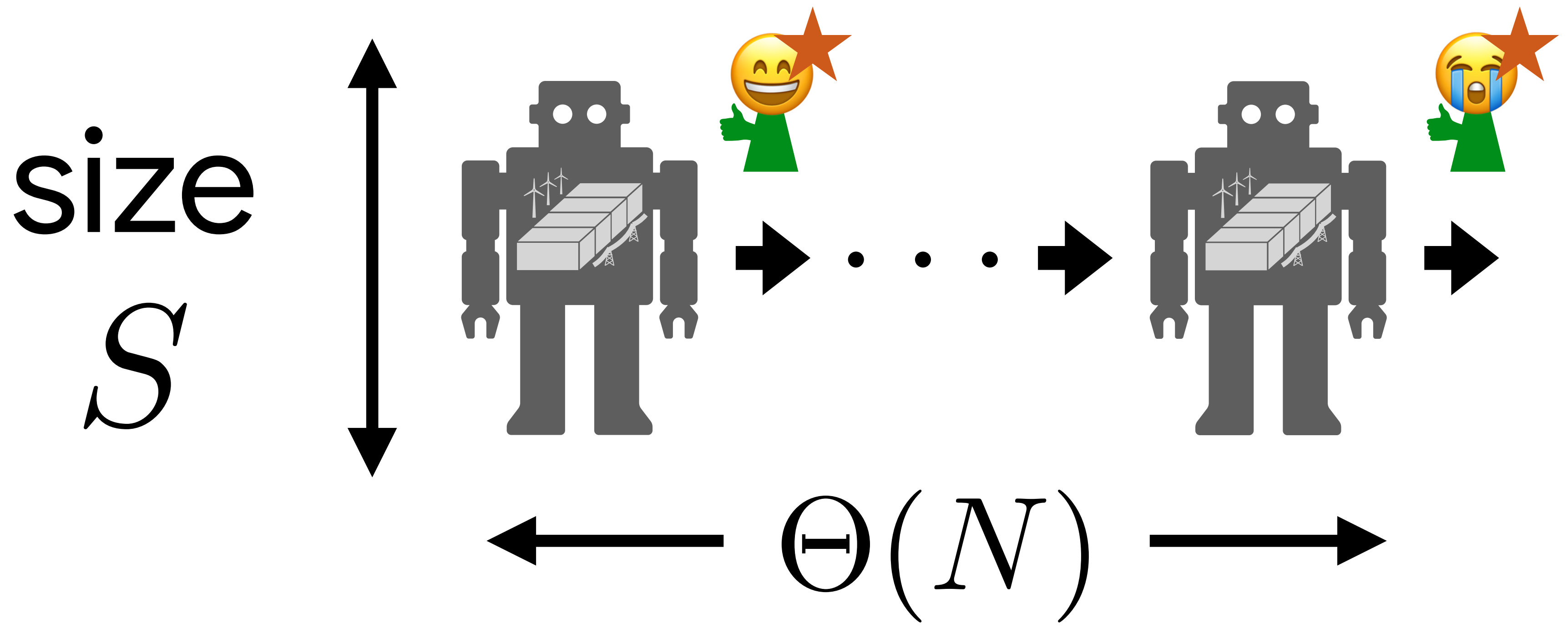
That takes $\Theta(N)$ time/samples. $p(x) = 1/N$

Noisy Oracle Property Estimation (NOPE)



noisy data
from N users

$z = (x, f_\alpha(x), \alpha)$



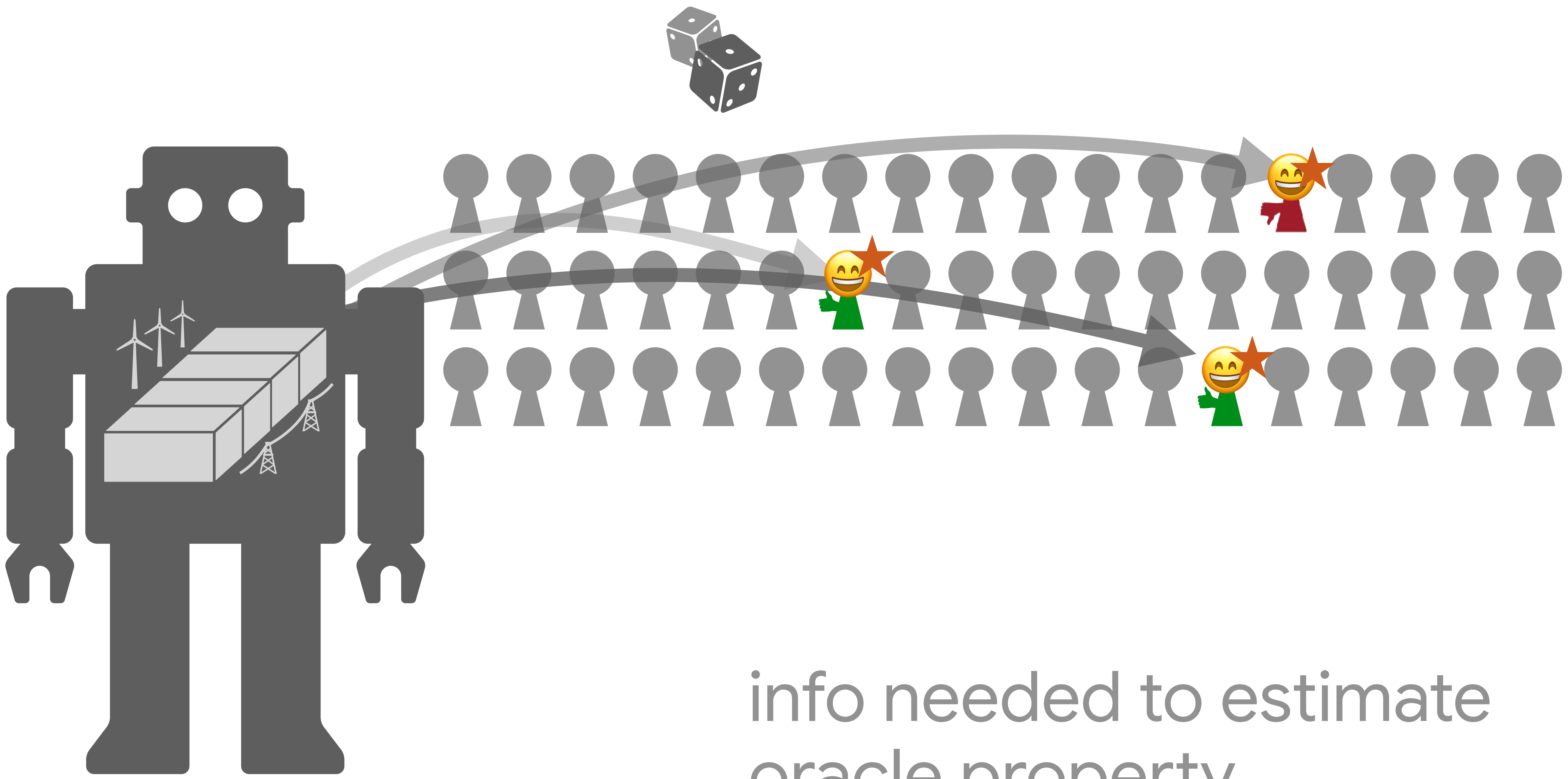
info $\leq O\left(\frac{M}{N}\right) \cdot S$

rounds

Q_C

info needed to estimate
oracle property

Noisy Oracle Property Estimation (NOPE)



noisy data

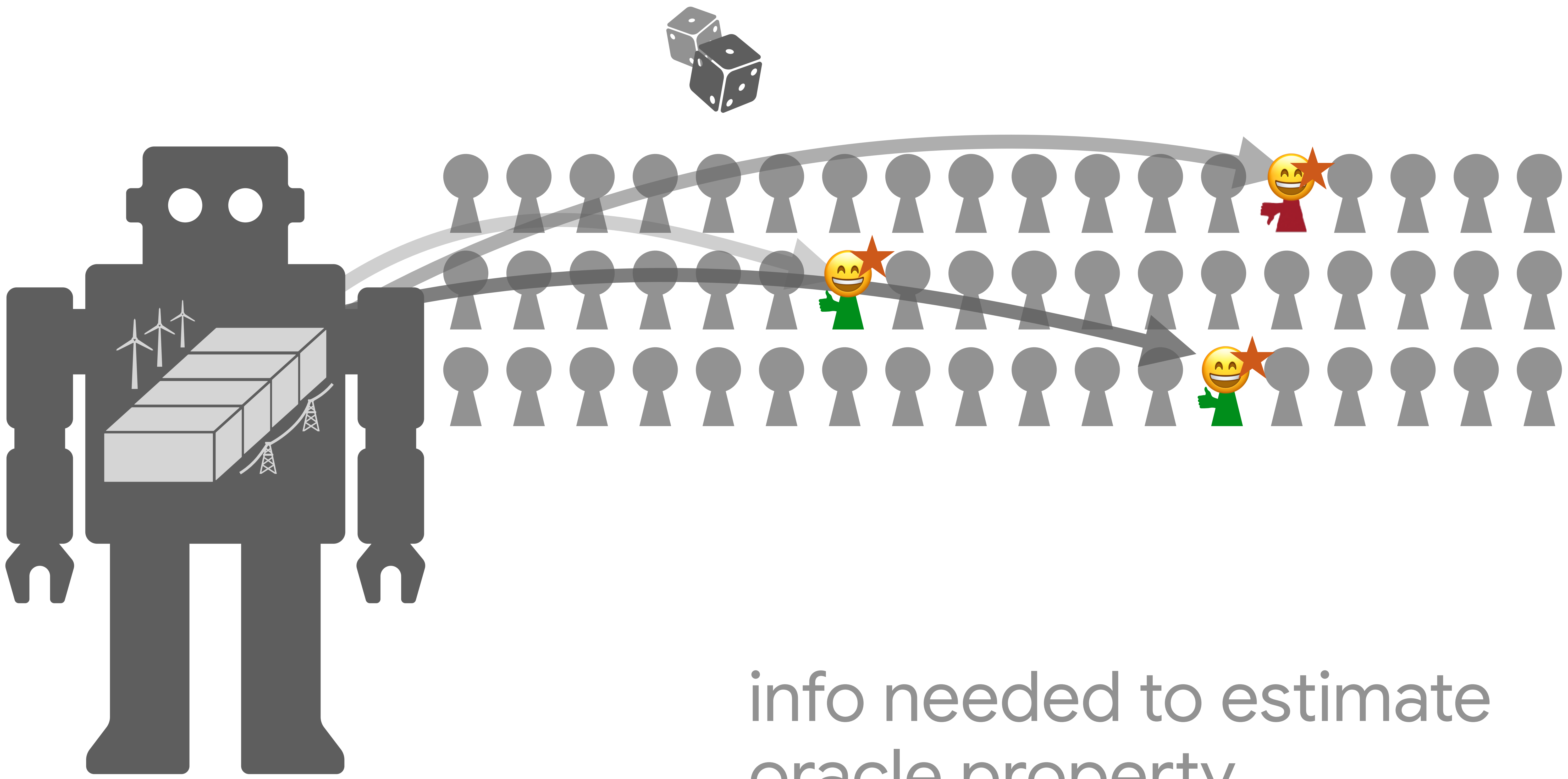
from N users

$z = (x, f_\alpha(x), \alpha)$

info needed to estimate oracle property

$$Q_C \leq \text{info} \leq O\left(\frac{M}{N}\right) \cdot S$$

Noisy Oracle Property Estimation (NOPE)



noisy data
from N users

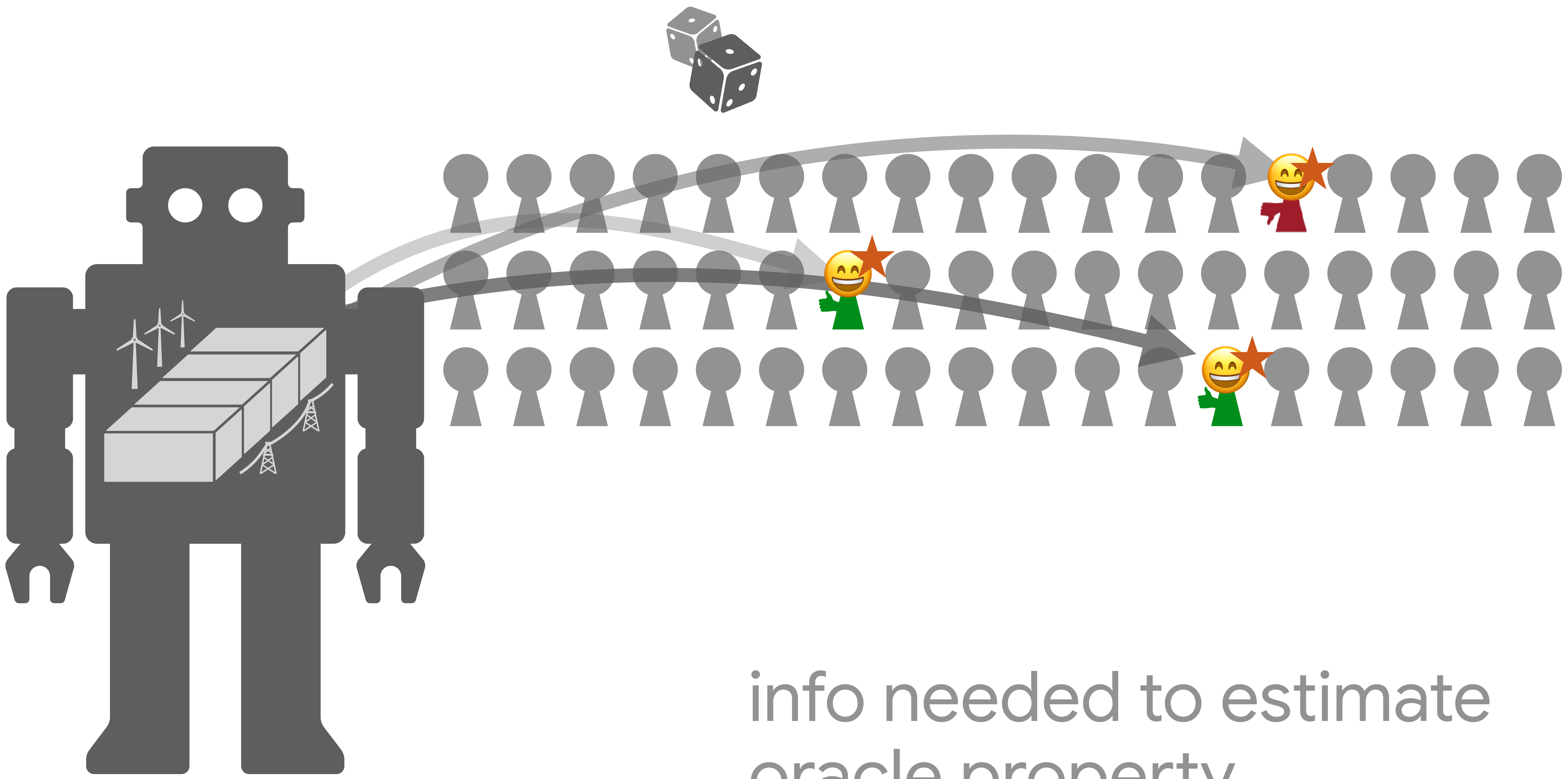
$z = (x, f_\alpha(x), \alpha)$

info needed to estimate
oracle property

$$Q_C \leq \text{info} \leq O\left(\frac{M}{N}\right) \cdot S$$

Sample-space lower bound $MS \geq \Omega(NQ_C)$

Noisy Oracle Property Estimation (NOPE)



noisy data
from N users

$z = (x, f_\alpha(x), \alpha)$

info needed to estimate oracle property

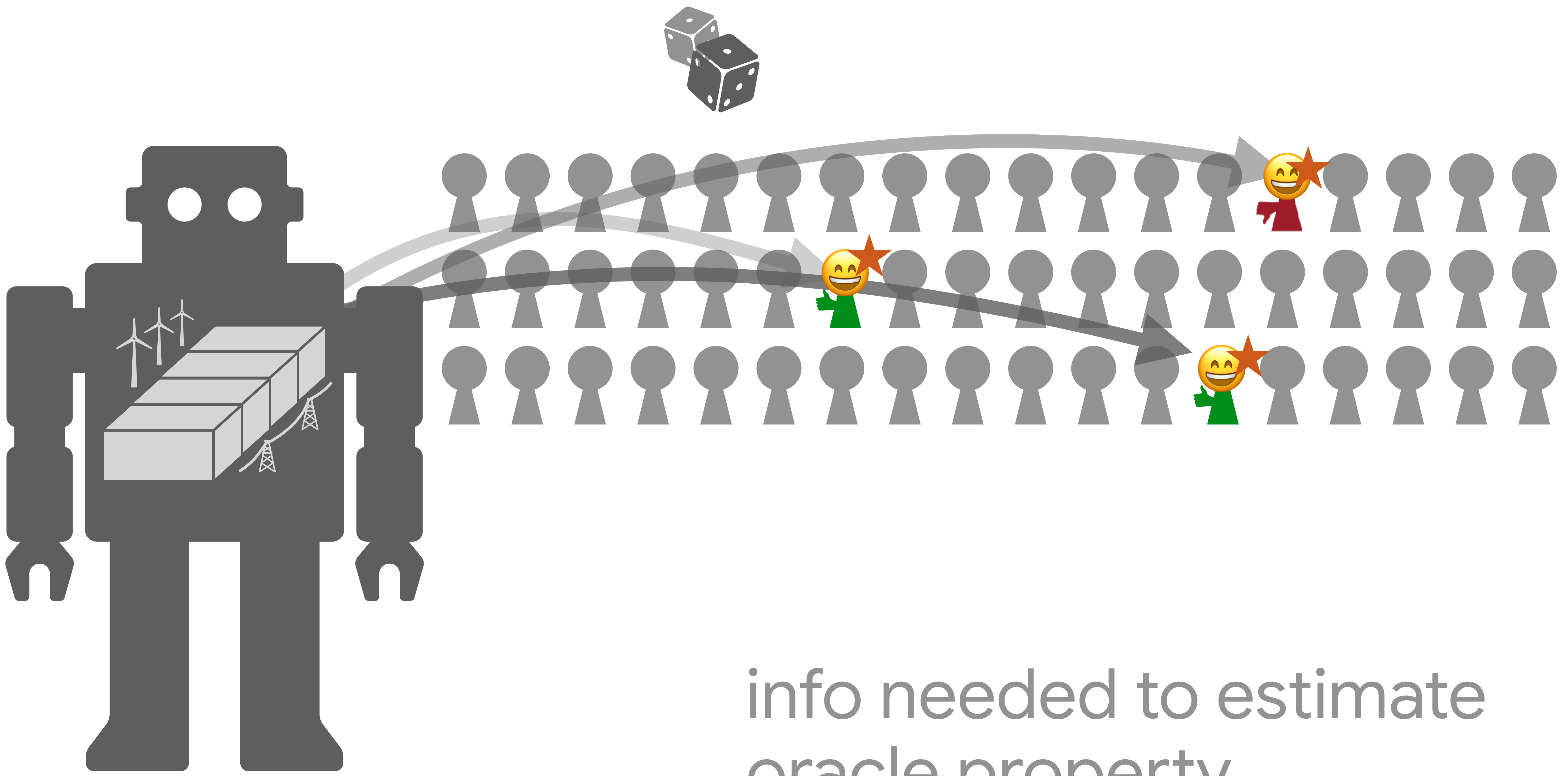
$$Q_C \leq \text{info} \leq O\left(\frac{M}{N}\right) \cdot S$$

Theorem (Classical Hardness) $S \geq \Omega(Q_C/Q^2)$

$$MS \geq \Omega(NQ_C)$$

#sample $M = \Theta(NQ^2)$ from QOS

Noisy Oracle Property Estimation (NOPE)



noisy data
from N users

$z = (x, f_\alpha(x), \alpha)$

info needed to estimate
oracle property

$$Q_C \leq \text{info} \leq O\left(\frac{M}{N}\right) \cdot S$$

Theorem (Classical Hardness) $S \geq \Omega(N^{1-\zeta})$

NOPE of Forrelation

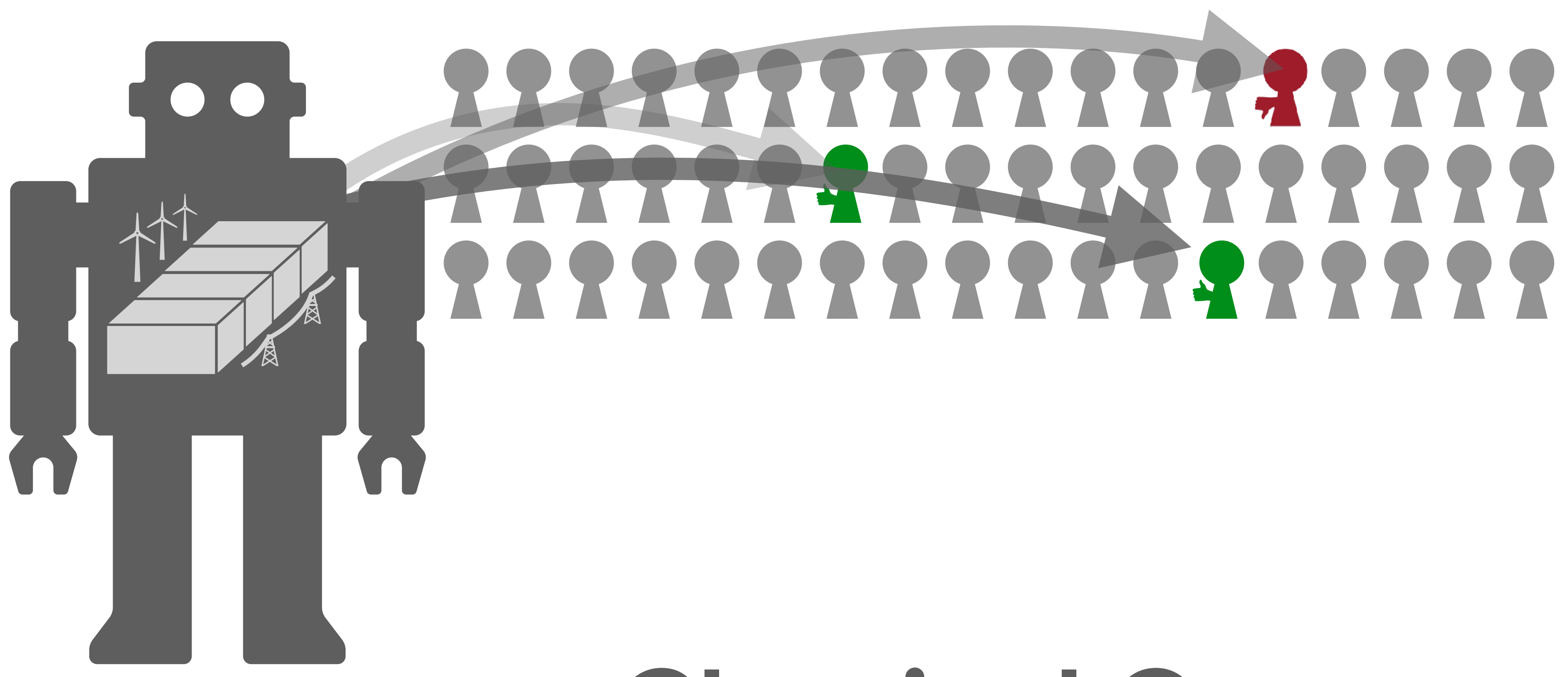
$Q_C = \Omega(N^{1-\zeta}), Q = O(1)$

Classical Hardness

1. Connect query separation to memory advantage

$$S \geq \Omega(N^{0.99})$$

2. Insufficient memory must be compensated by more samples



Classical Query

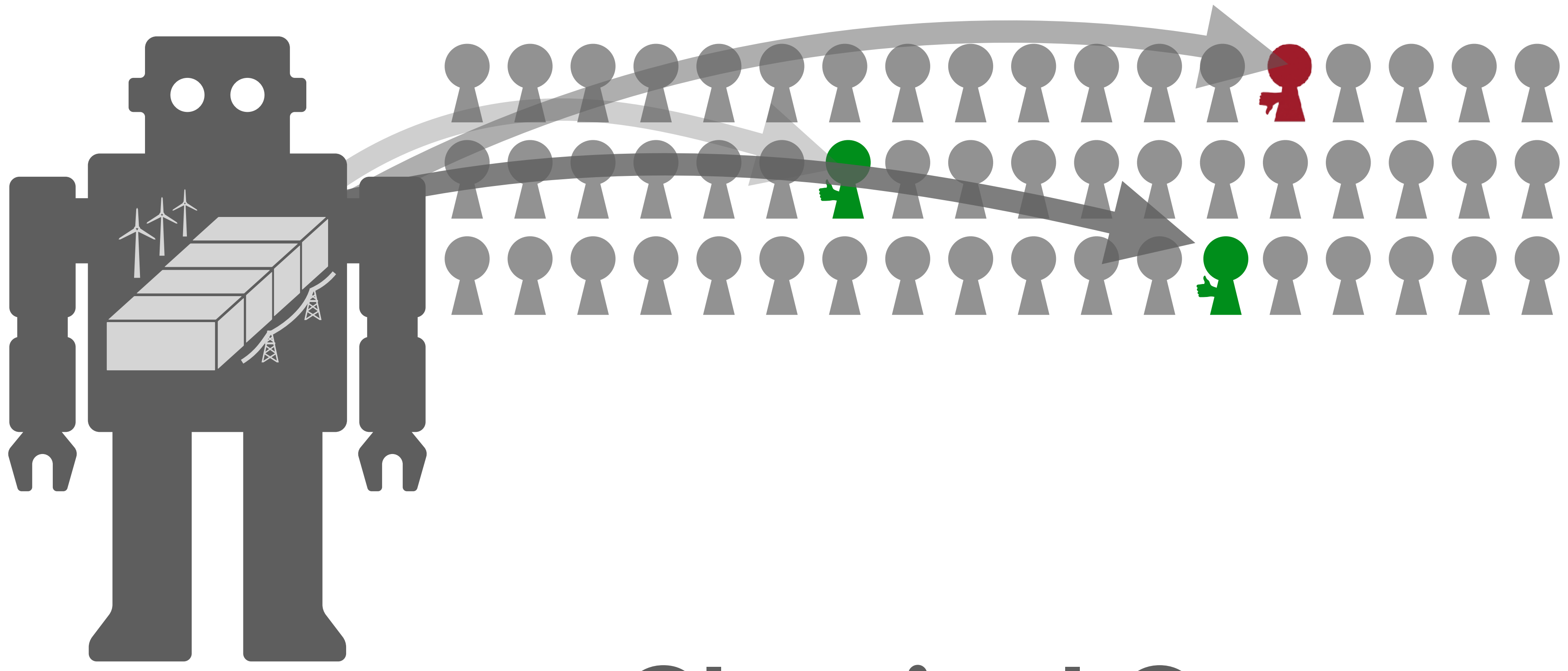
Classical Hardness

1. Connect query separation to memory advantage

$$S \geq \Omega(N^{0.99})$$

2. Insufficient memory must be compensated by more samples

NOPE: if $S \leq O(N^{0.99})$, then progress ≤ 0.1

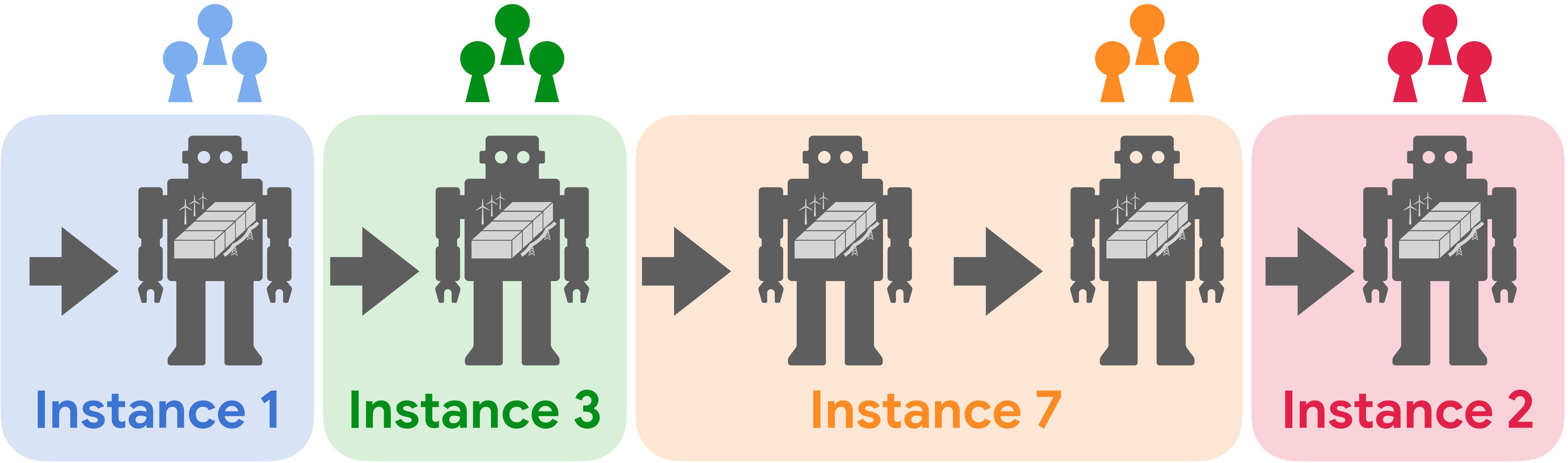


Classical Query

Classical Hardness

1. Connect query separation to memory advantage

$$S \geq \Omega(N^{0.99})$$



2. Insufficient memory must be compensated by more samples

simultaneously solve
indep. instances of NOPE (the XOR)

NOPE: if $S \leq O(N^{0.99})$, then progress ≤ 0.1

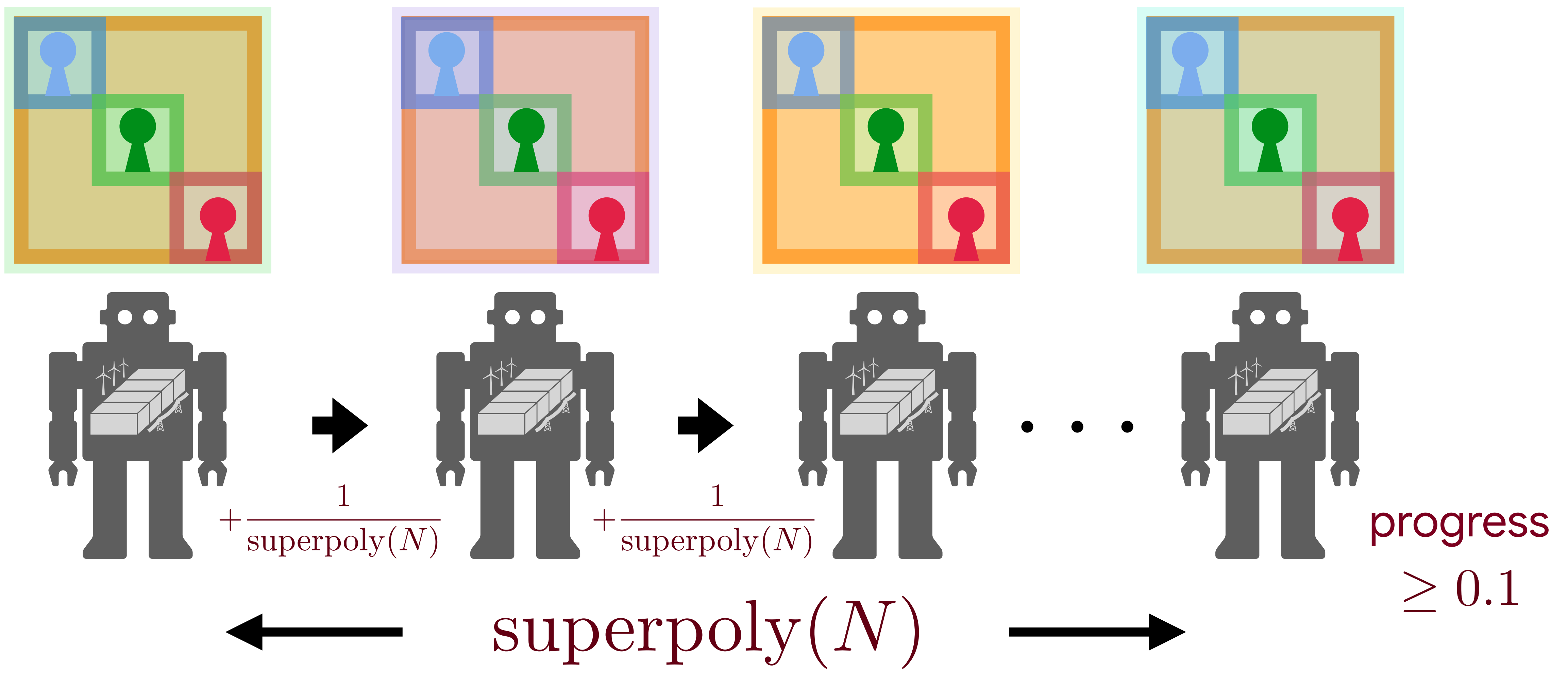
XOR NOPE: if $S \leq O(N^{0.99})$, then progress $\leq (0.1)^{\text{poly}(\log N)} = 1/\text{superpoly}(N)$

Classical Hardness

1. Connect query separation to memory advantage

$$S \geq \Omega(N^{0.99})$$

2. Insufficient memory must be compensated by more samples



NOPE: if $S \leq O(N^{0.99})$, then progress ≤ 0.1

XOR NOPE: if $S \leq O(N^{0.99})$, then progress $\leq (0.1)^{\mathrm{poly}(\log N)} = 1/\mathrm{superpoly}(N)$

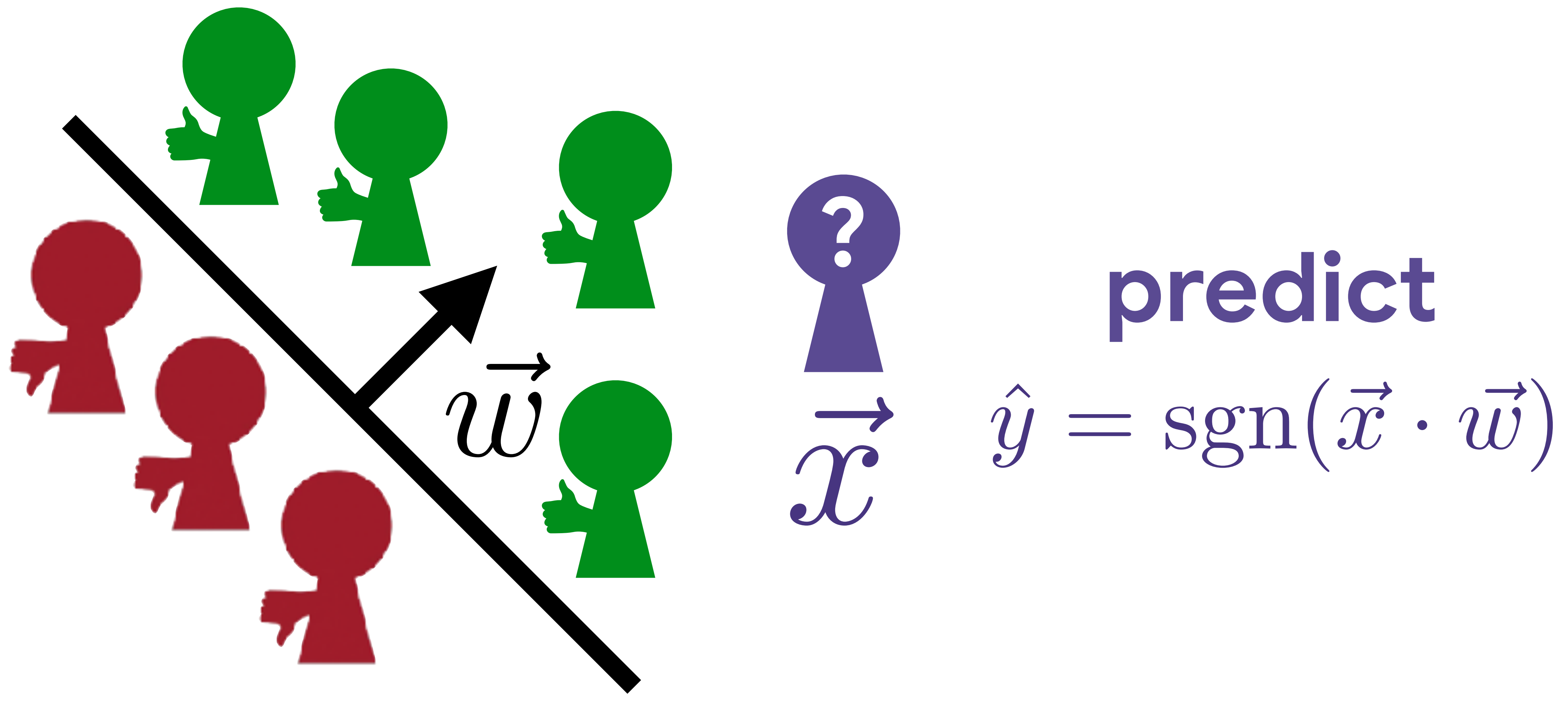
dynamic NOPE: if $S \leq O(N^{0.99})$, then requires $\mathrm{superpoly}(N)$ samples

Classical Hardness

1. Connect query separation to memory advantage

2. Insufficient memory must be compensated by more samples

3. Embed into ML tasks



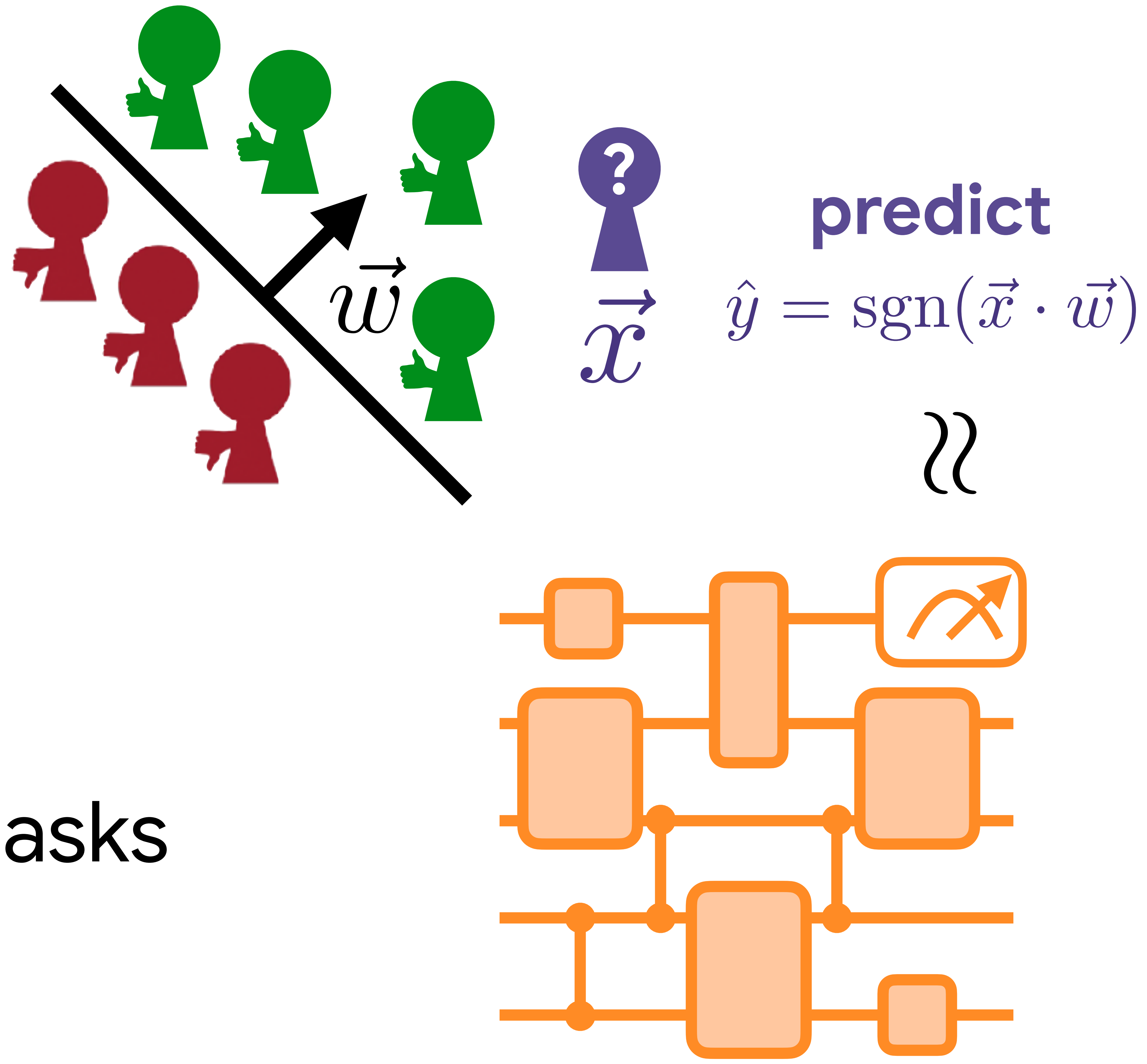
Classical Hardness

1. Connect query separation to memory advantage

2. Insufficient memory must be compensated by more samples

3. Embed into ML tasks

   a. prove BQP hardness of ML tasks



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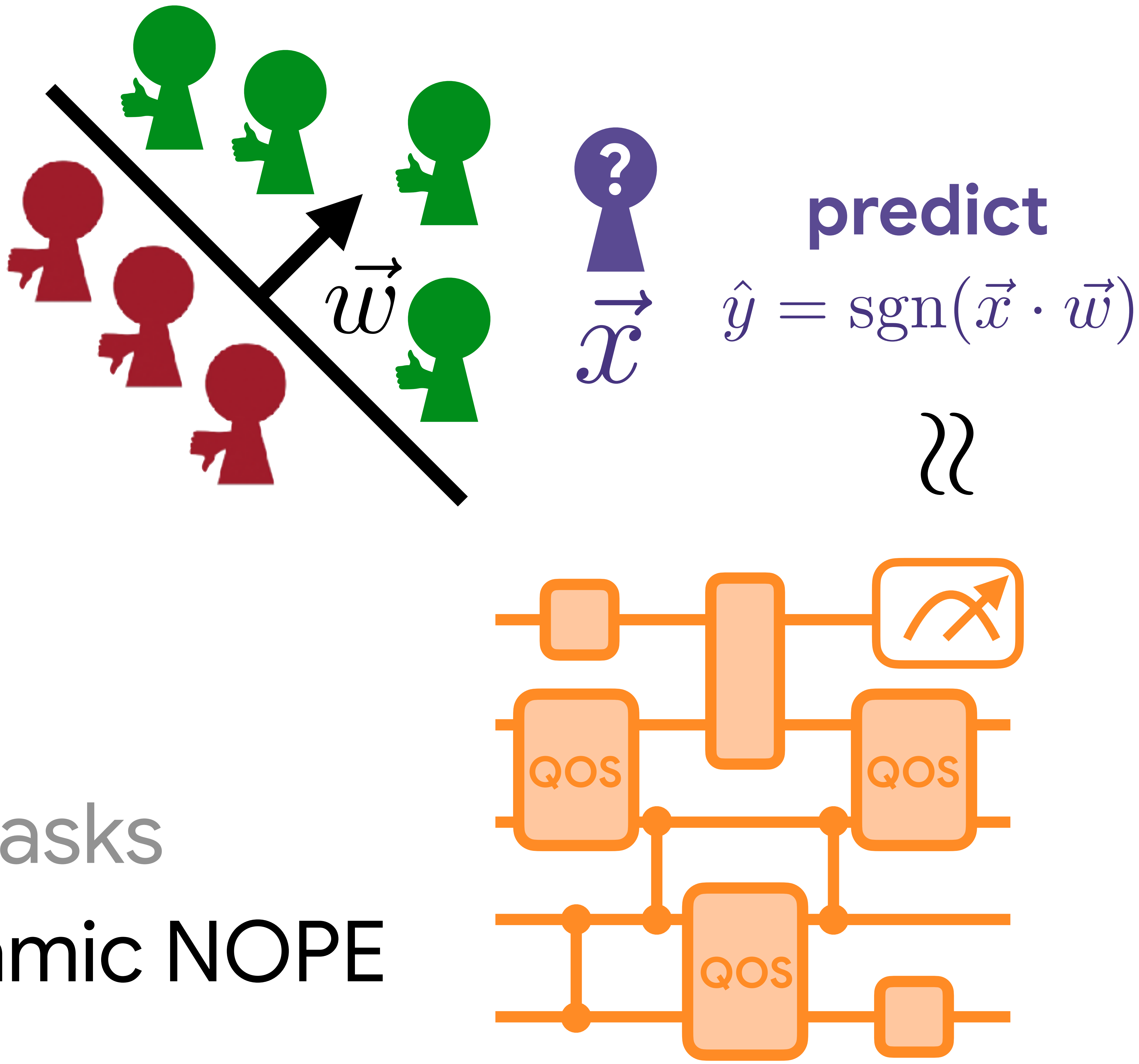
b. embed QOS circuit for dynamic NOPE



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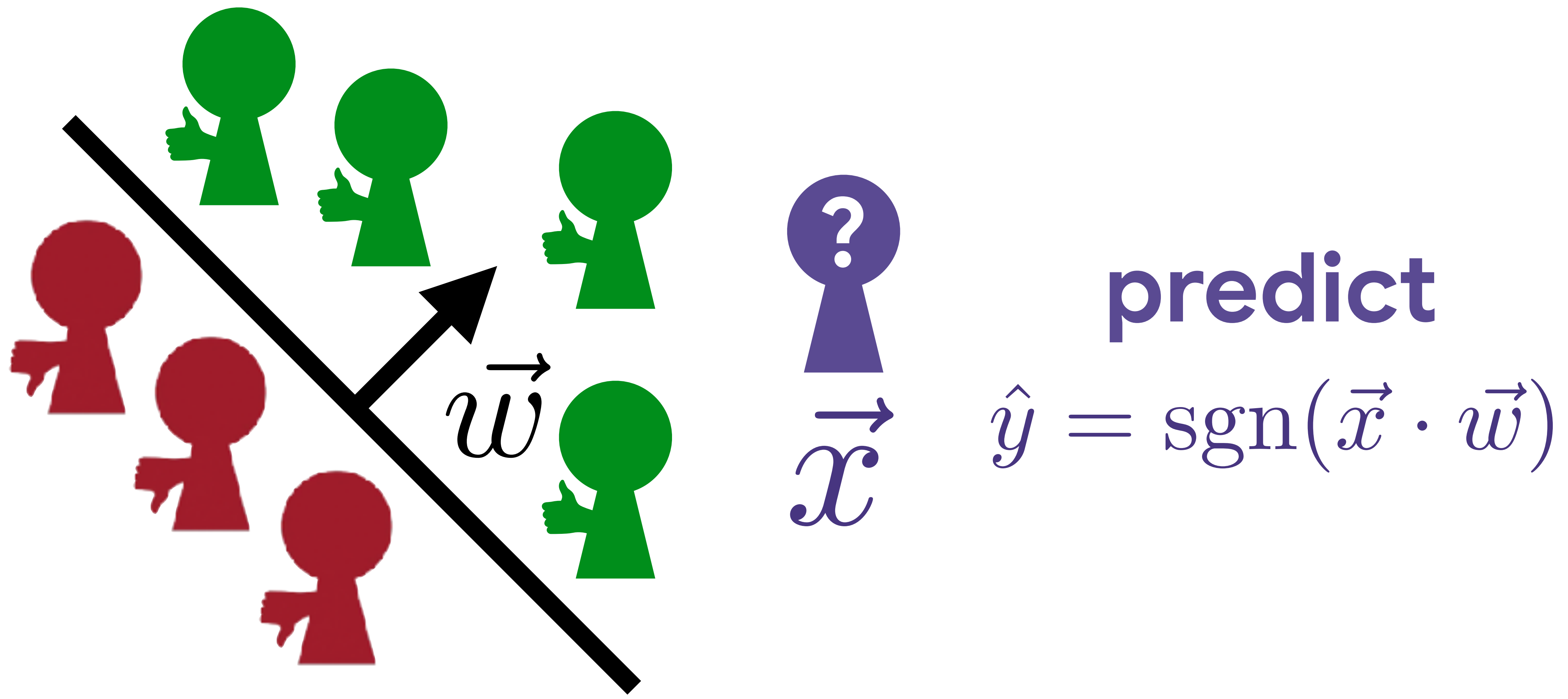
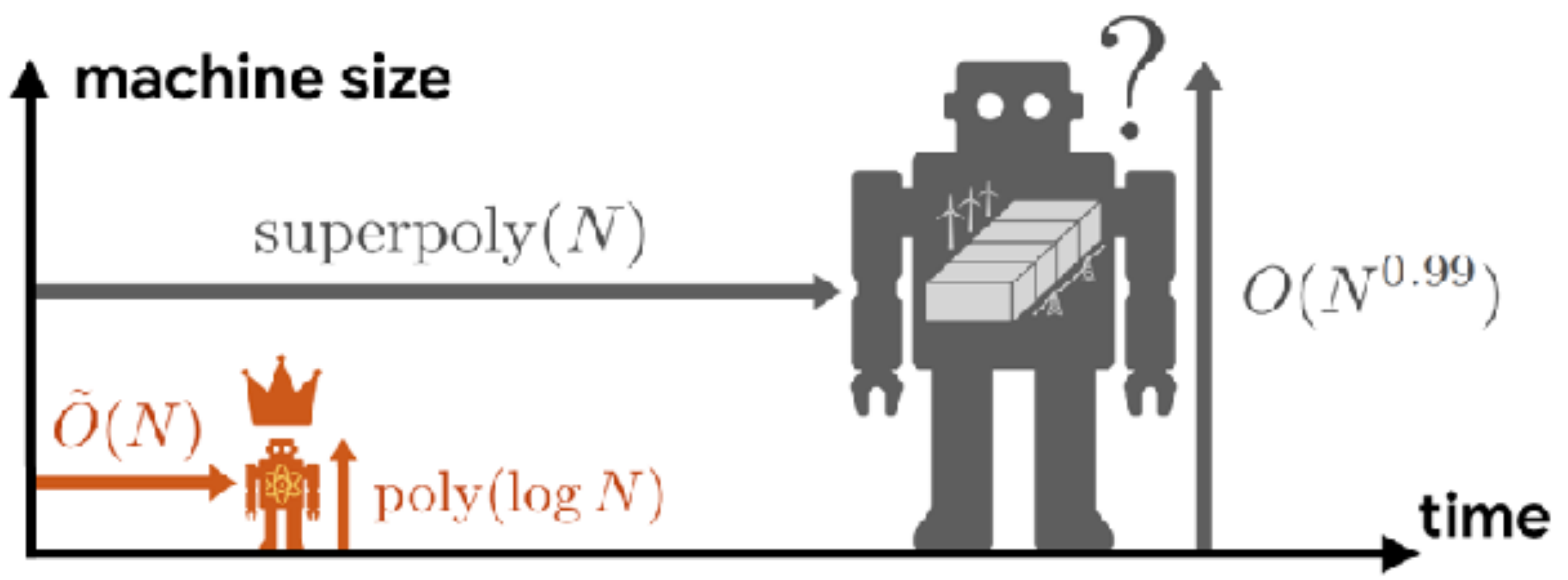


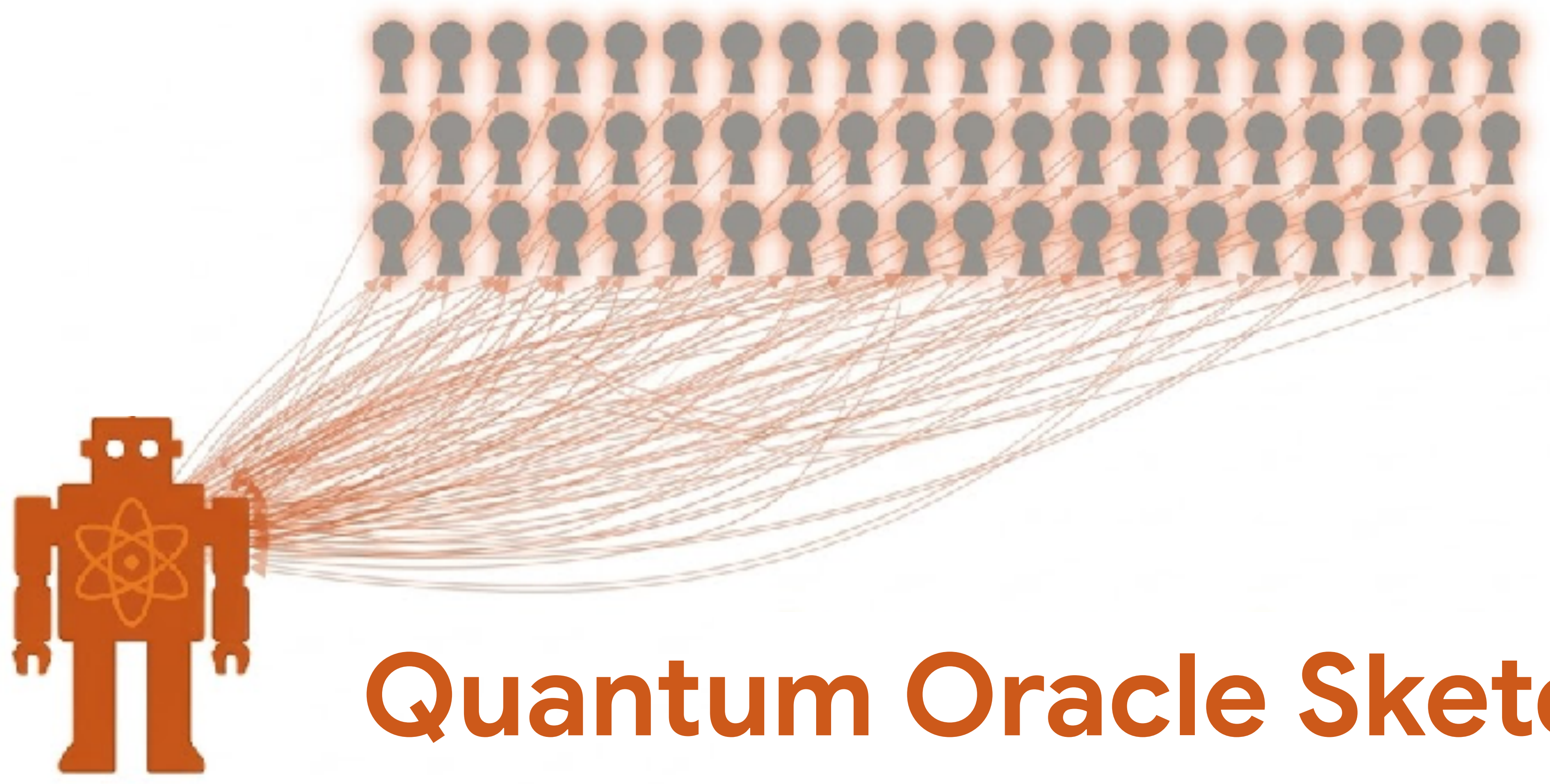


a. prove BQP hardness of ML tasks

b. embed QOS circuit for dynamic NOPE

$\longrightarrow$ dynamic ML is classically hard

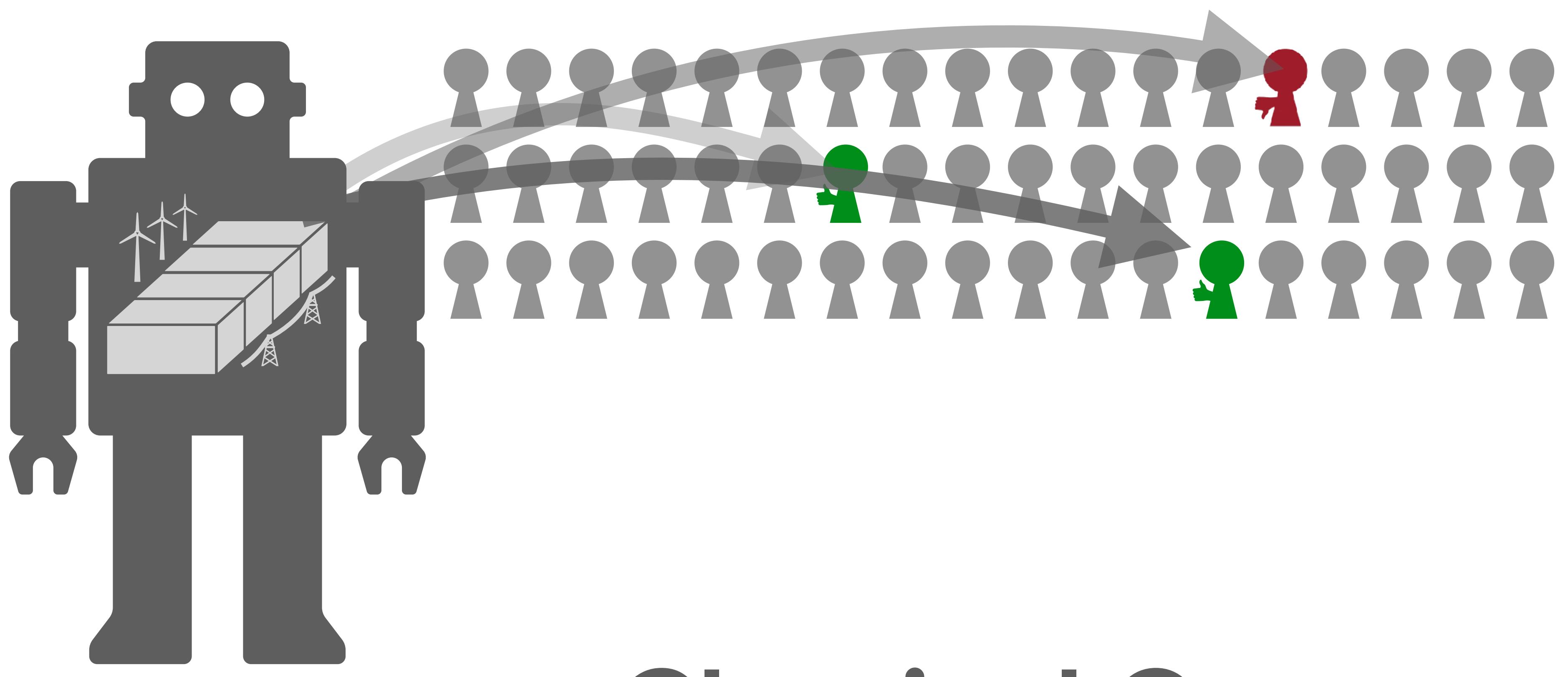
Quantum Algorithm



Quantum Oracle Sketching

query the classical world in quantum superposition

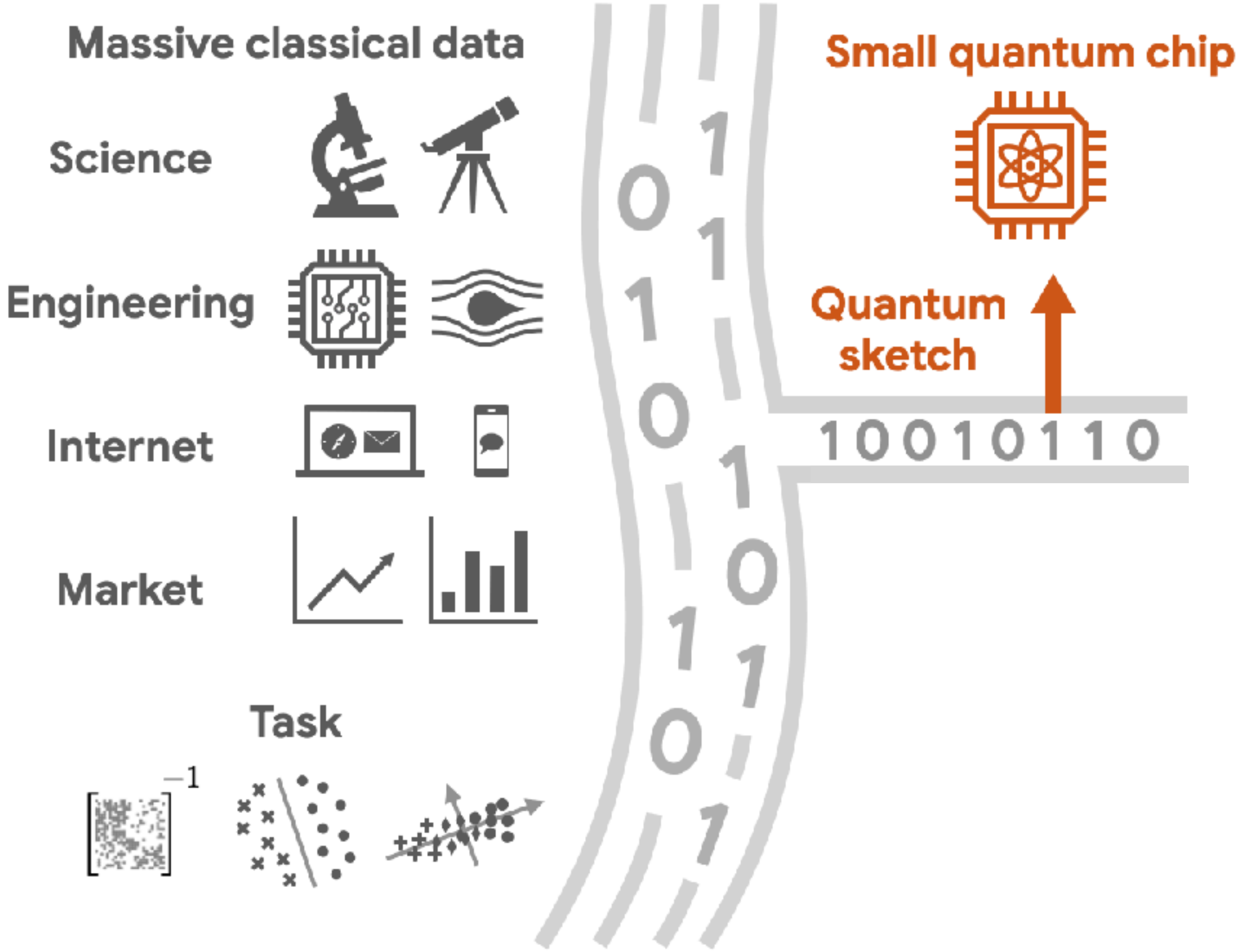
Classical Hardness



Classical Query

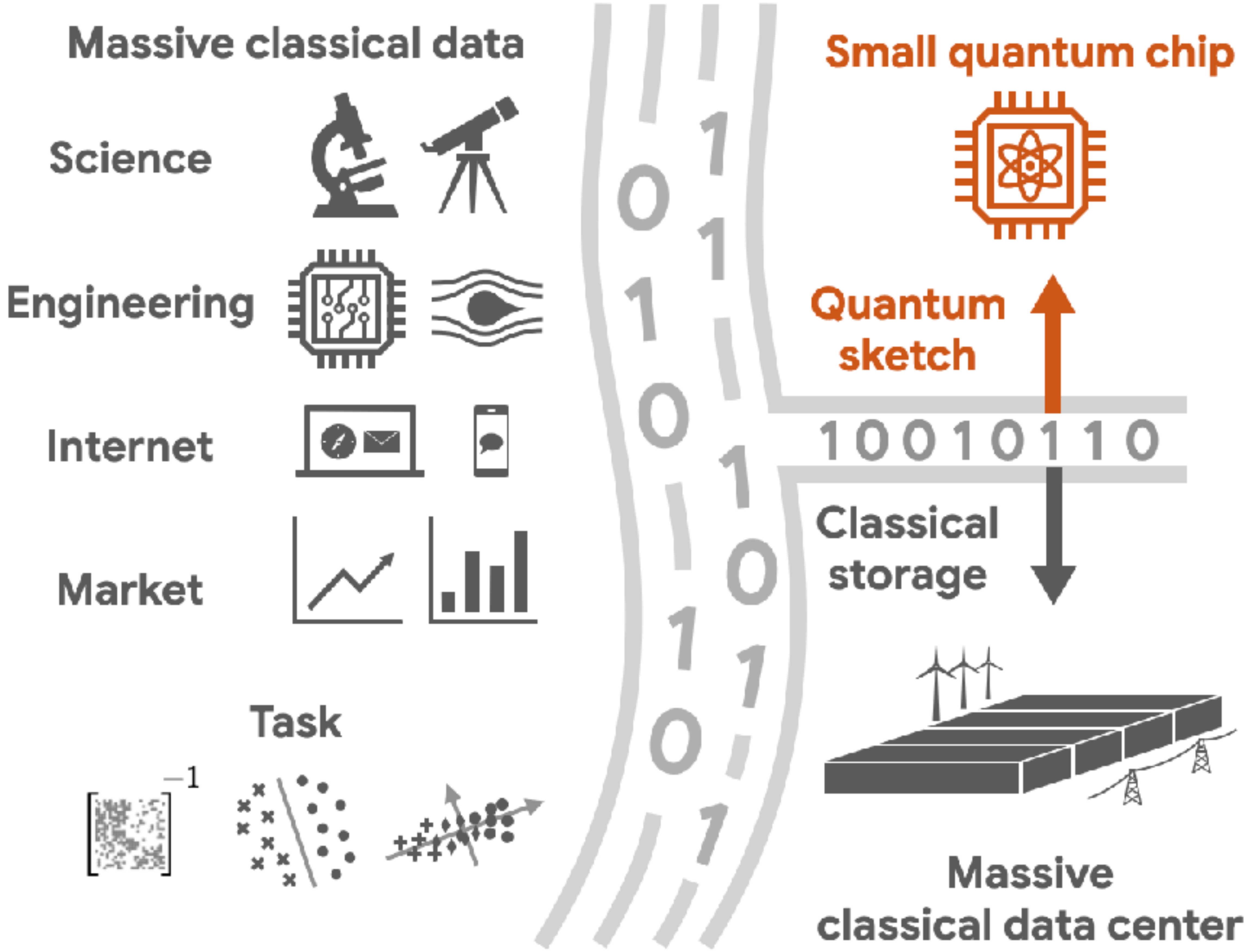
separation in query ability → memory advantage

Conclusions



We prove that
small quantum machines
can process
massive classical data
and solve large-scale
machine learning problems.

Conclusions



We prove that

any classical machine

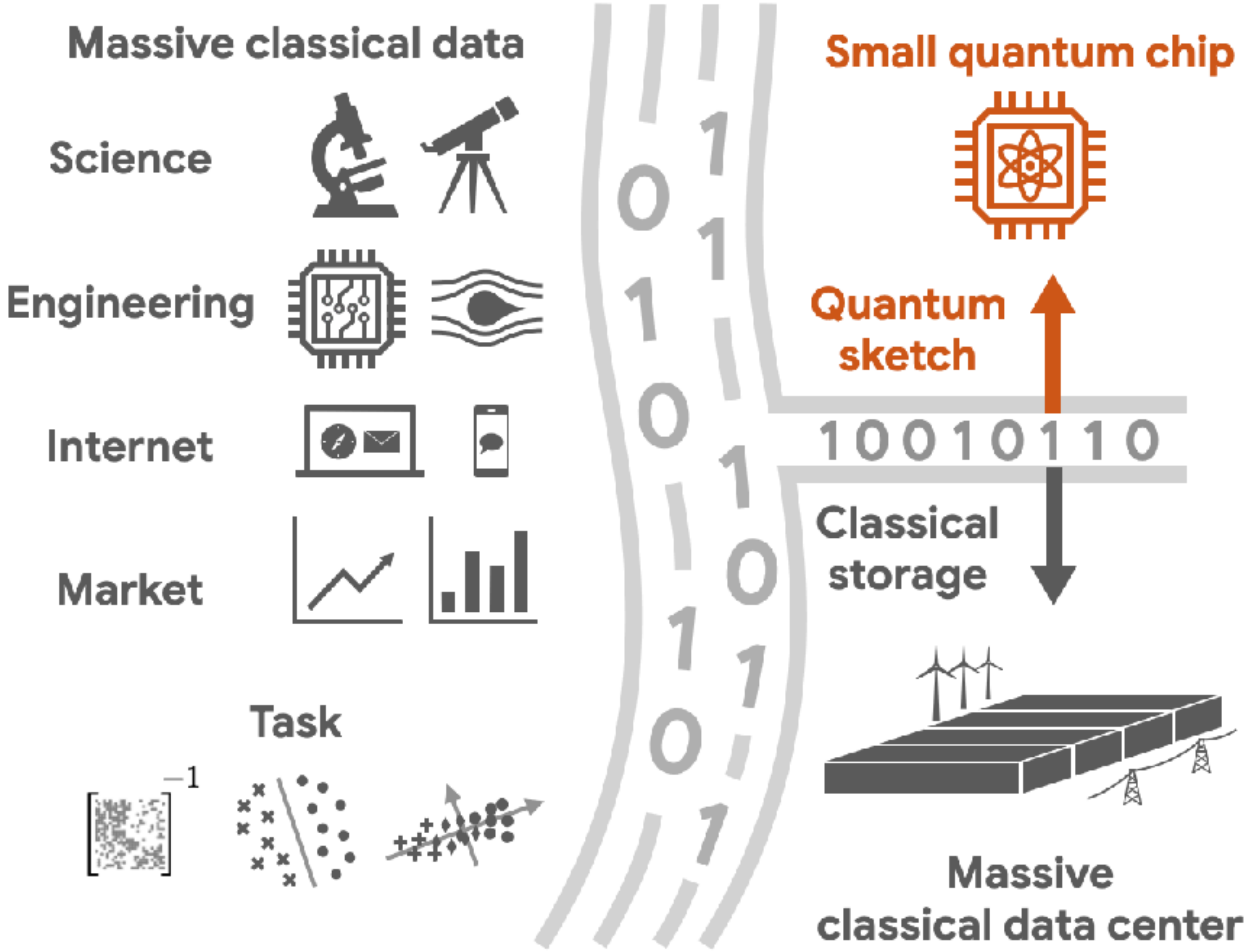
with the same performance

needs exponentially larger size

or superpolynomially

more samples.

Conclusions



Our results open the possibility for quantum computers to be broadly useful in our daily life.

Conclusions

This exponential quantum advantage relies solely on the correctness of quantum mechanics, persisting even if P=NP, BPP=BQP, etc.

Given sufficient time

$\gg$

small quantum chip

massive classical data center

Conclusions

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Given sufficient time

$\gg$

hundreds of logical qubits

universe-scale classical computer

Conclusions

Machine learning offers a fundamental test of quantum mechanics at the complexity frontier.

Given sufficient time

≫

hundreds of logical qubits

universe-scale classical computer