

Quantum Time-Space Tradeoff for Finding Multiple Collision Pairs

Yassine Hamoudi, Frédéric Magniez

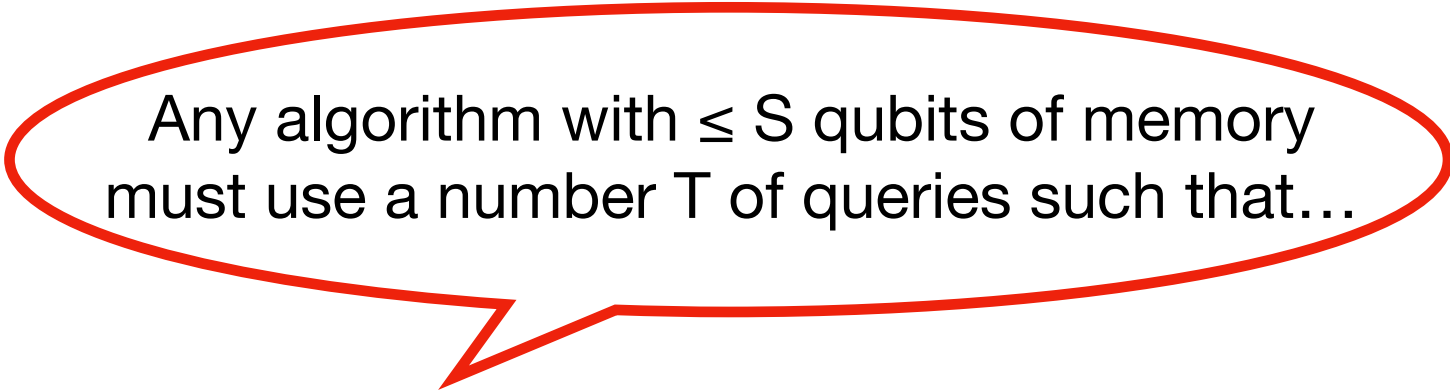
IRIF, Université de Paris

TQC 2021

arXiv: [2002.08944](https://arxiv.org/abs/2002.08944)

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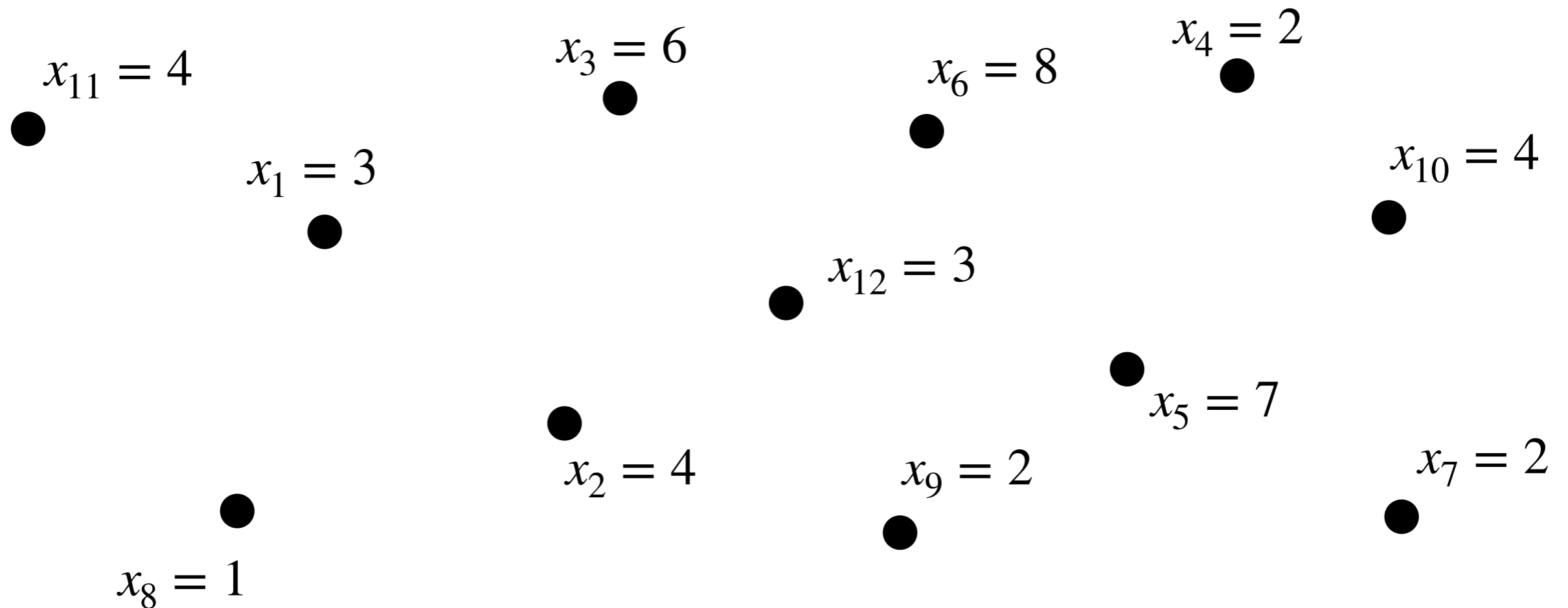
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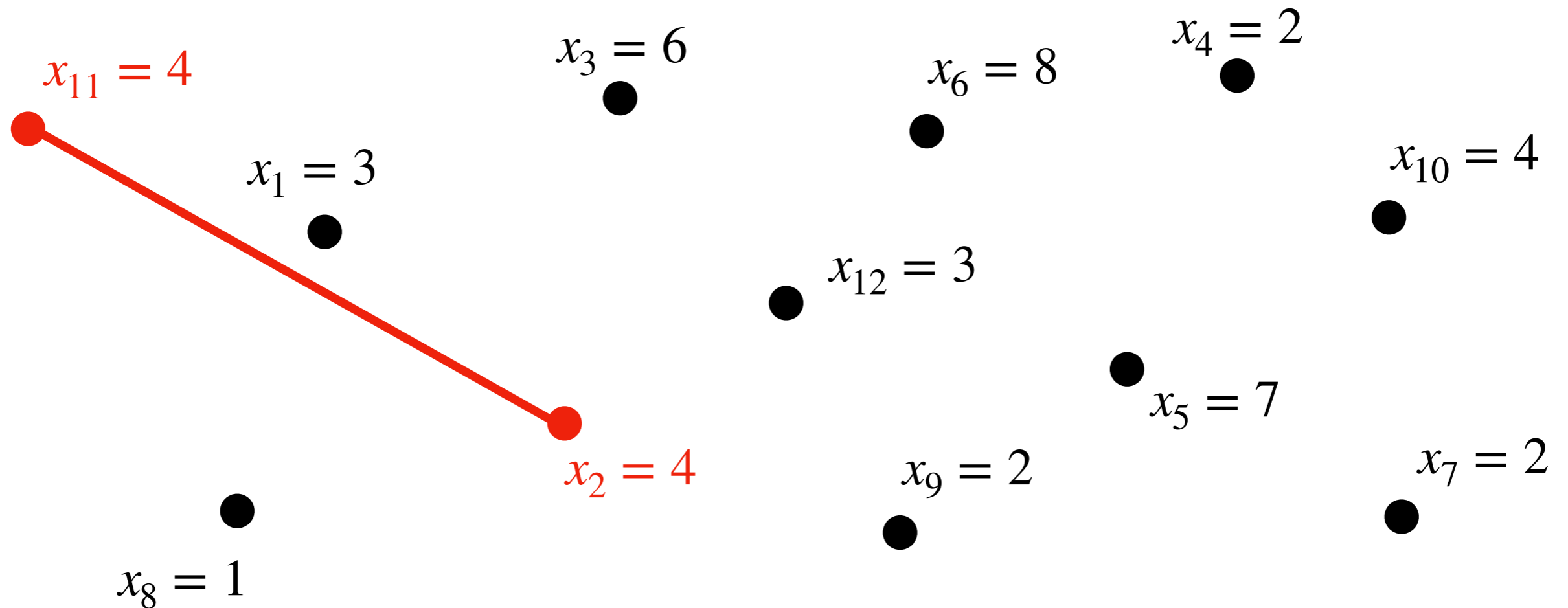
Our contribution: a new tradeoff for the **Collision Pairs Finding** problem.

1

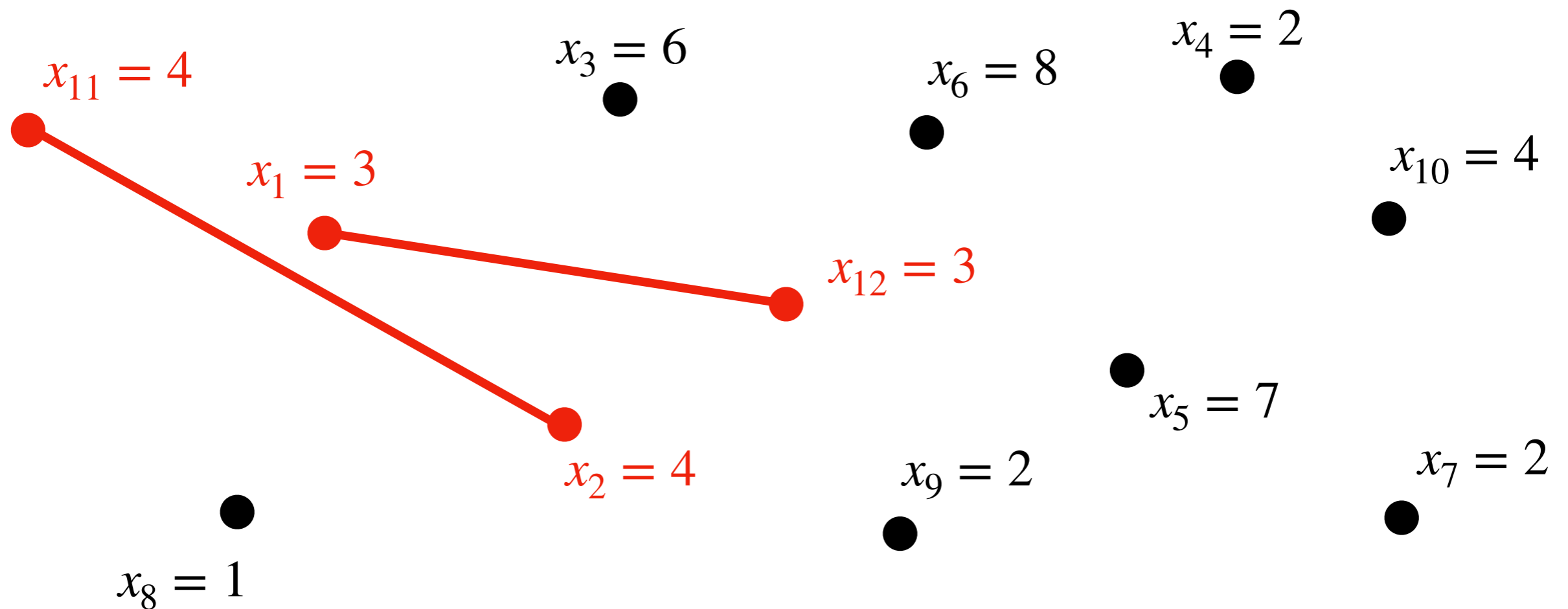
The Collision Pairs Finding Problem



Collision pair: $x_i = x_j$



Collision pair: $x_i = x_j$



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K-Collision Pairs

Find K collision pairs in a **random** input $x_1, \dots, x_N \sim [N]$.

K-Collision Pairs

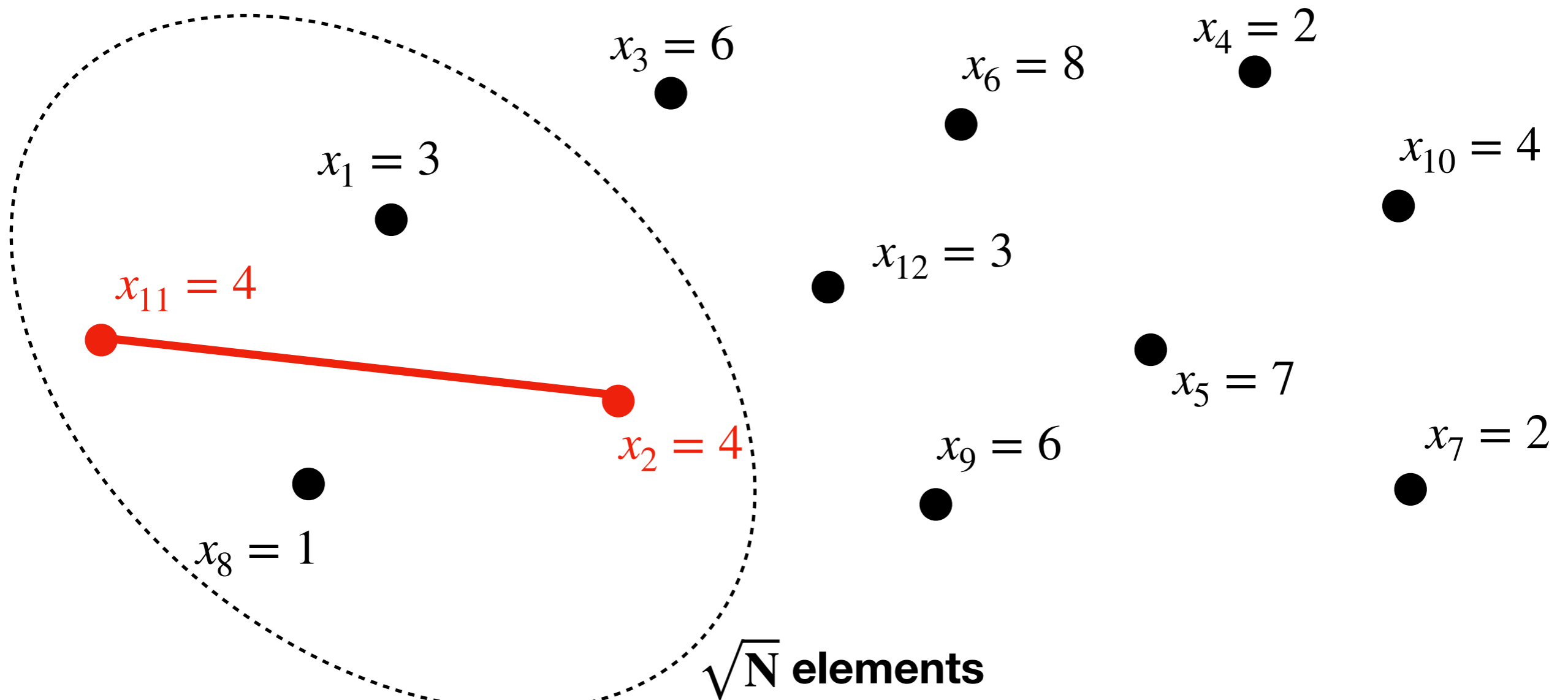
Find K collision pairs in a **random** input $x_1, \dots, x_N \sim [N]$.

→ A random input contains $\sim \Theta(N)$ collision pairs with high probability.

K-Collision Pairs

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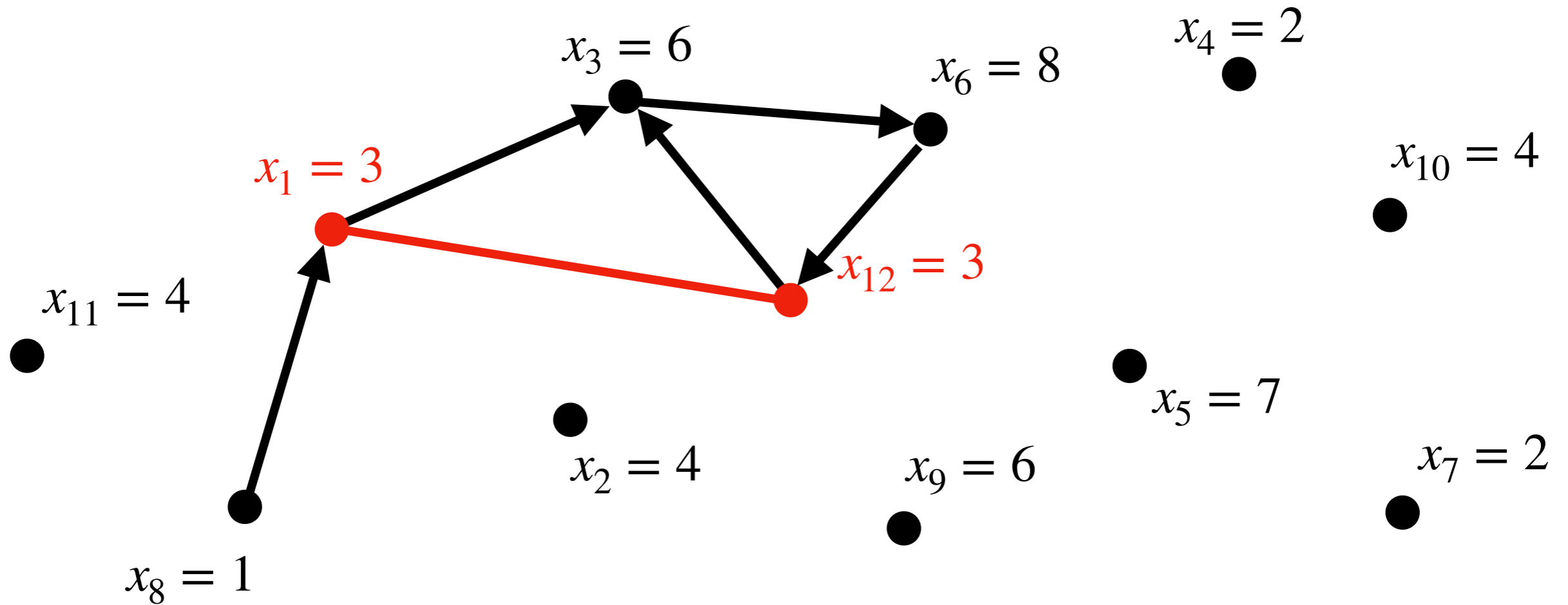
- **A random input contains $\sim \Theta(N)$ collision pairs with high probability.**
- **Finding collisions is an important problem in cryptanalysis:**
 - preimage attacks on hash functions
 - meet-in-the-middle attacks ← **requires to find many collisions**
 - computing discrete logarithms
 - ...



Birthday attack

$$T = O(\sqrt{N})$$

$$S = O(\sqrt{N})$$



Birthday attack

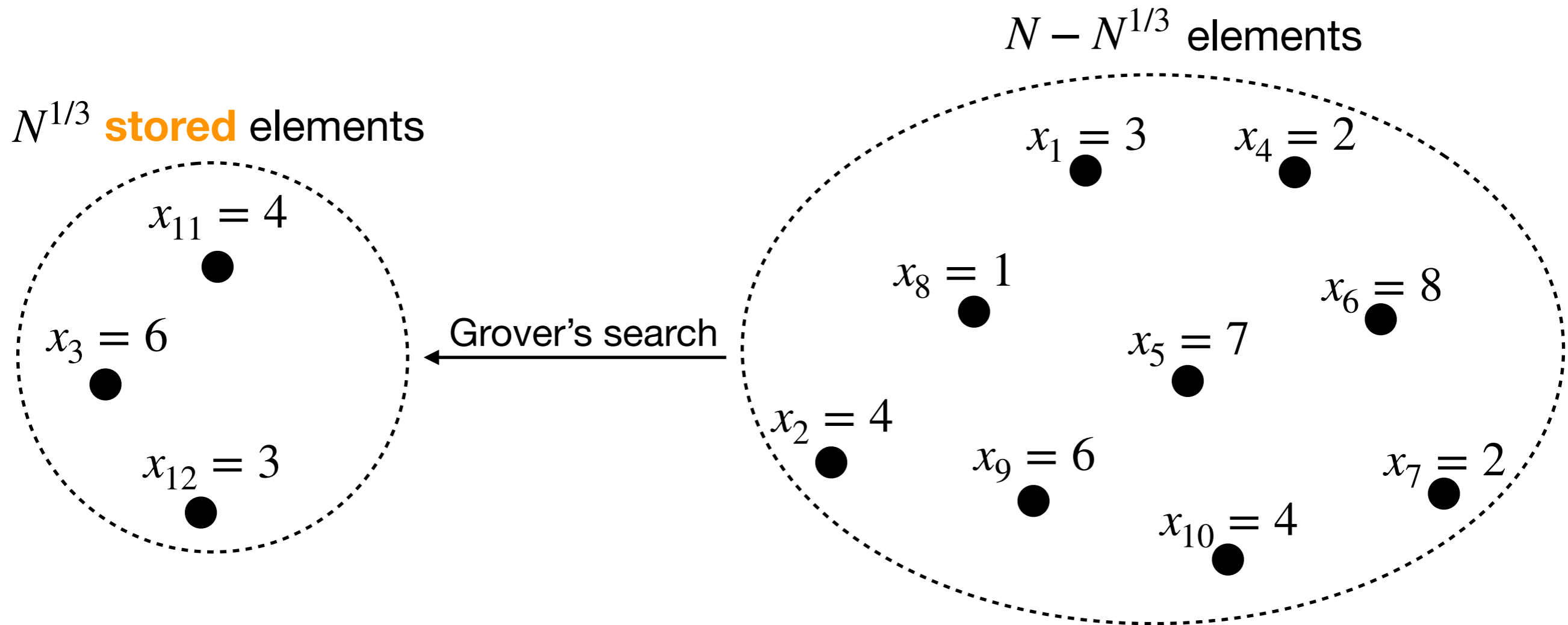
$$T = O(\sqrt{N})$$

$$S = O(\sqrt{N})$$

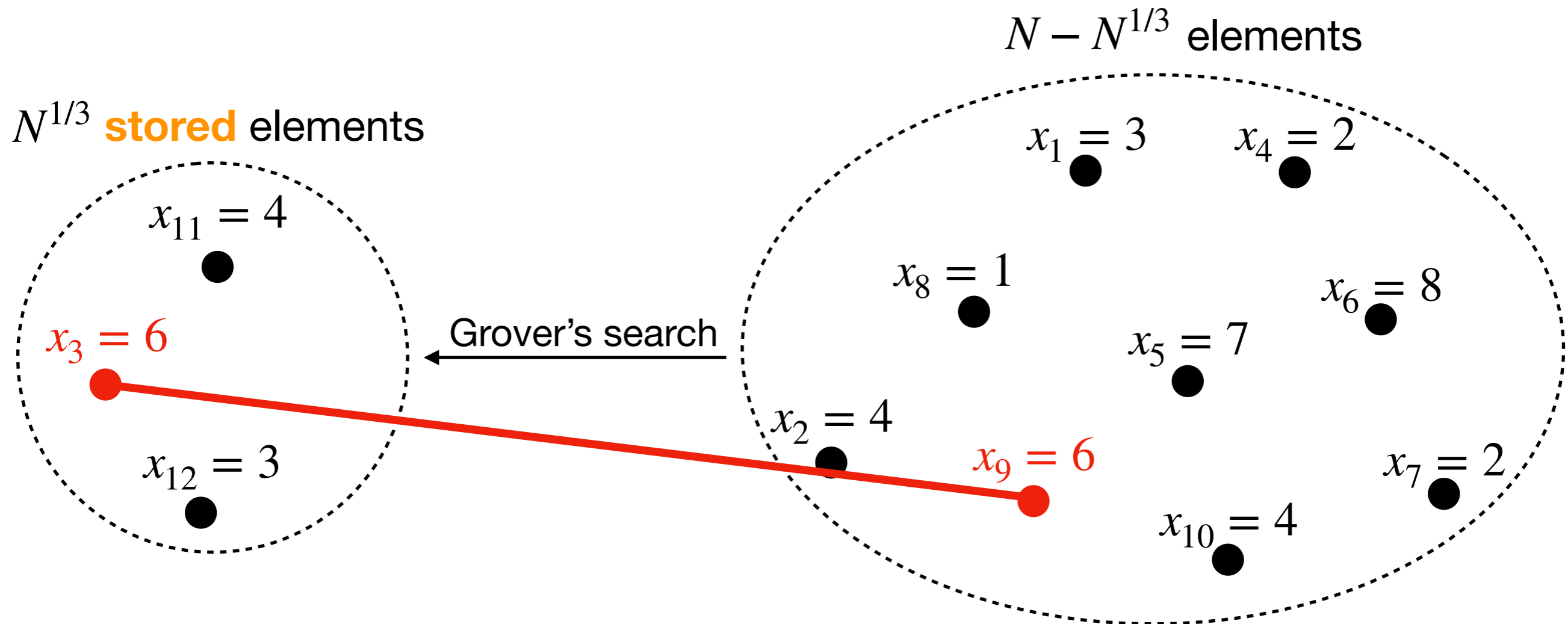
Birthday attack + Floyd's cycle finding

$$T = O(\sqrt{N})$$

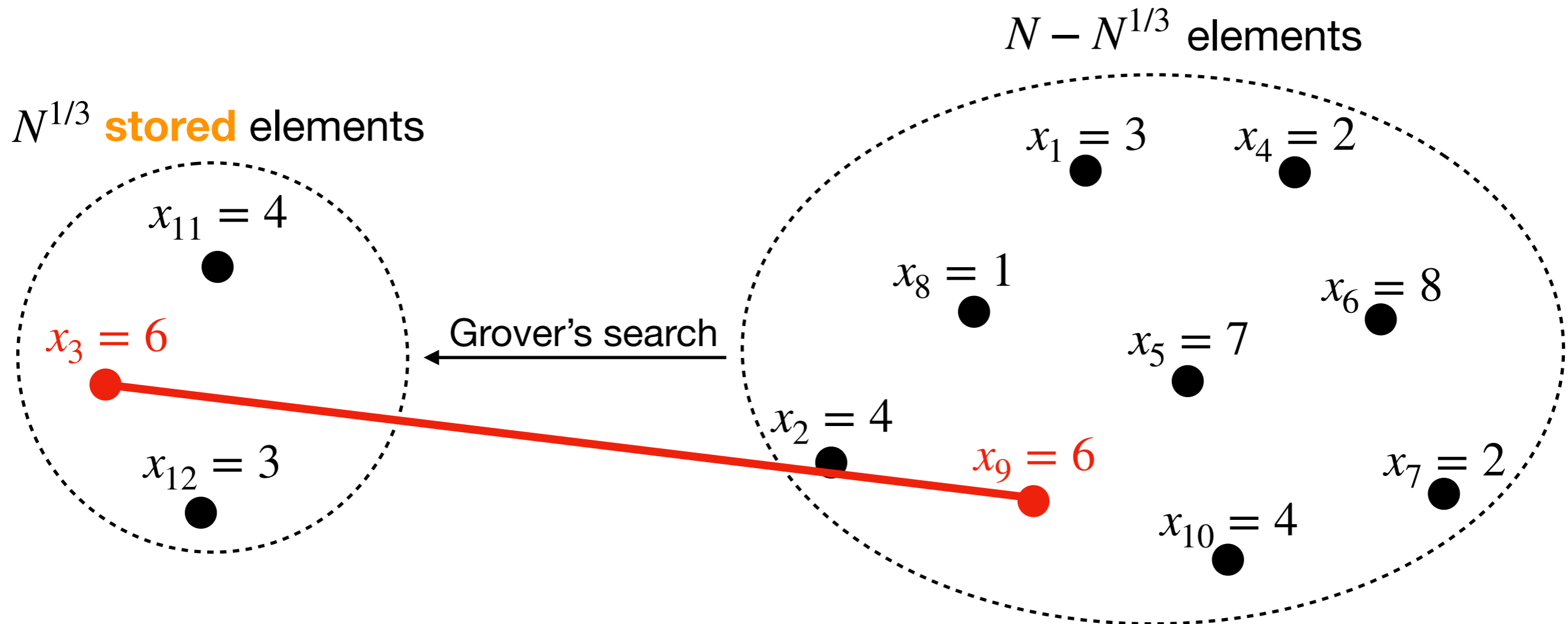
$$S = O(\log N)$$



Quantum BHT algorithm



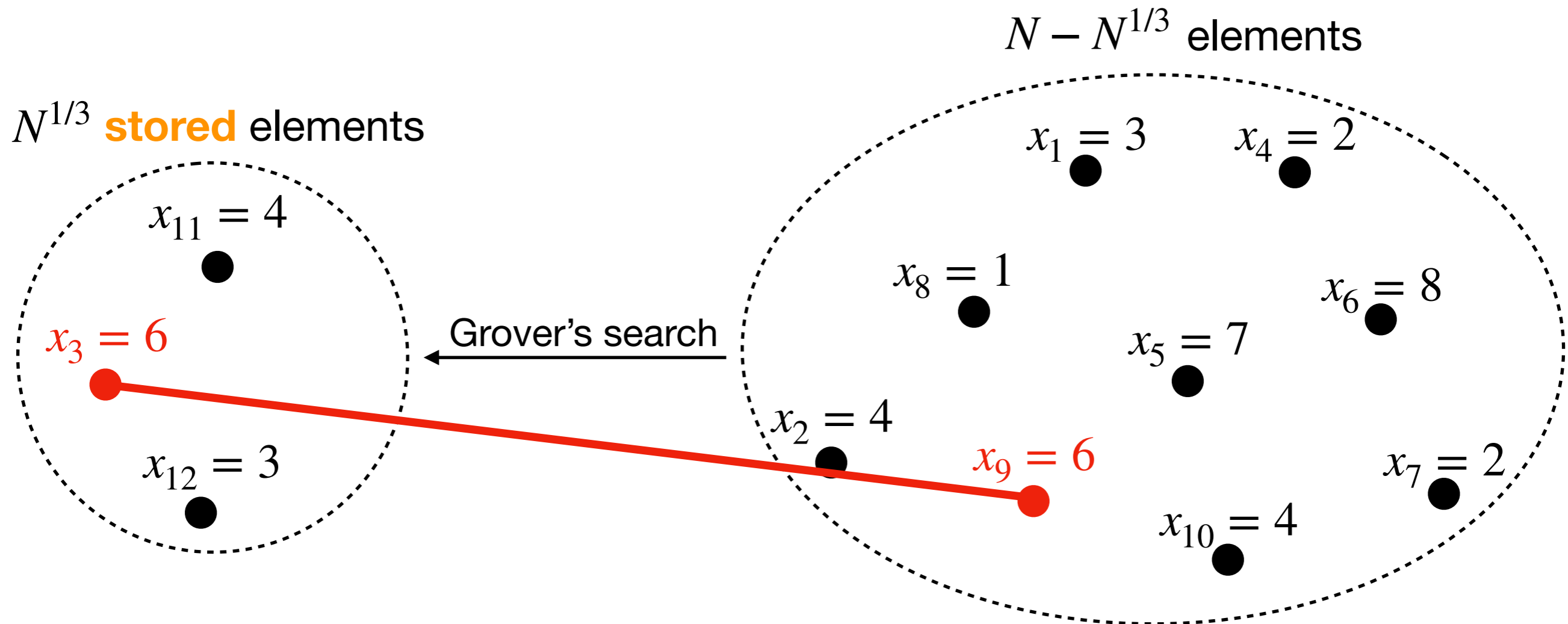
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Quantum BHT algorithm

$$T = O(N^{1/3})$$

$$S = O(N^{1/3})$$



Quantum BHT algorithm

$$T = O(N^{1/3})$$

$$S = O(N^{1/3})$$

Open problem:

Is there a quantum algorithm with $T \leq o(\sqrt{N})$ and $S = O(\log N)$?

Classical Tradeoff

Upper bound

$$T^2S \leq \tilde{O}(K^2N)$$

when

$$\tilde{\Omega}(\log N) \leq S \leq \tilde{O}(K)$$

Parallel Collision Search
[van Oorschot and Wiener'99]

	Classical Tradeoff	Quantum Tradeoff
Upper bound	$T^2S \leq \tilde{O}(K^2N)$ when $\tilde{\Omega}(\log N) \leq S \leq \tilde{O}(K)$ Parallel Collision Search [van Oorschot and Wiener'99]	$T^2S \leq \tilde{O}(K^2N)$ when $\tilde{\Omega}(\log N) \leq S \leq \tilde{O}(K^{2/3}N^{1/3})$ Adaptation of the BHT algorithm

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Upper bound	$T^2S \leq \tilde{O}(K^2N)$ when $\tilde{\Omega}(\log N) \leq S \leq \tilde{O}(K)$ Parallel Collision Search [van Oorschot and Wiener'99] → $T = \tilde{O}(K^{1/2}N^{1/2})$ at best	$T^2S \leq \tilde{O}(K^2N)$ when $\tilde{\Omega}(\log N) \leq S \leq \tilde{O}(K^{2/3}N^{1/3})$ Adaptation of the BHT algorithm → $T = \tilde{O}(K^{2/3}N^{1/3})$ at best

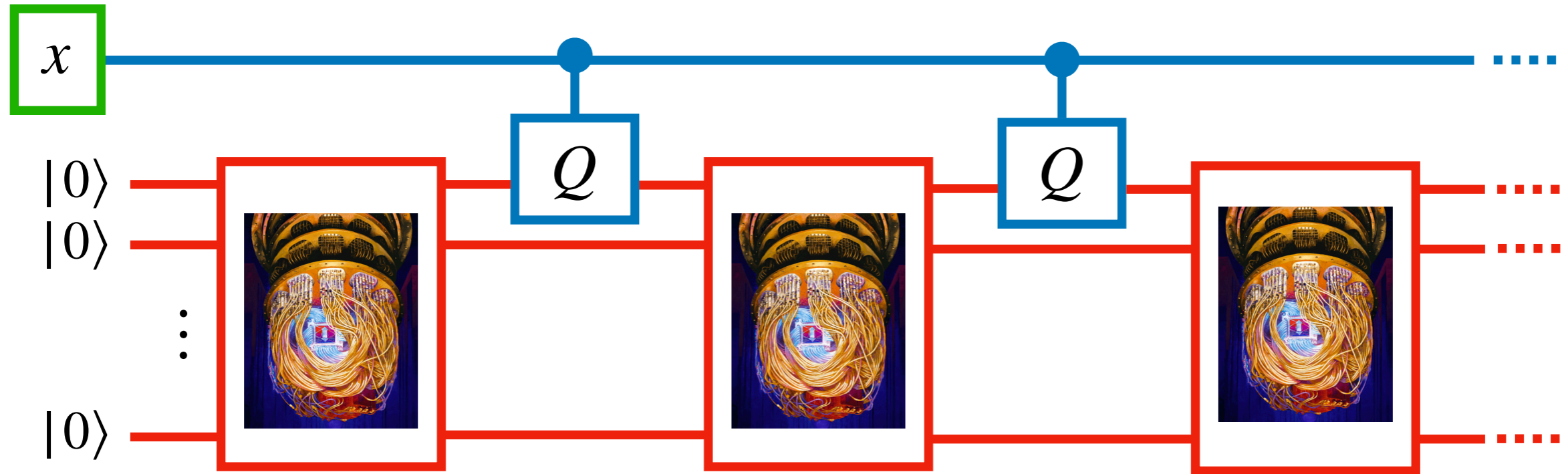
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Lower bound	$T^2S \geq \tilde{\Omega}(K^2N)$ [Chakrabarti,Chen'17] [Dinur'20]	

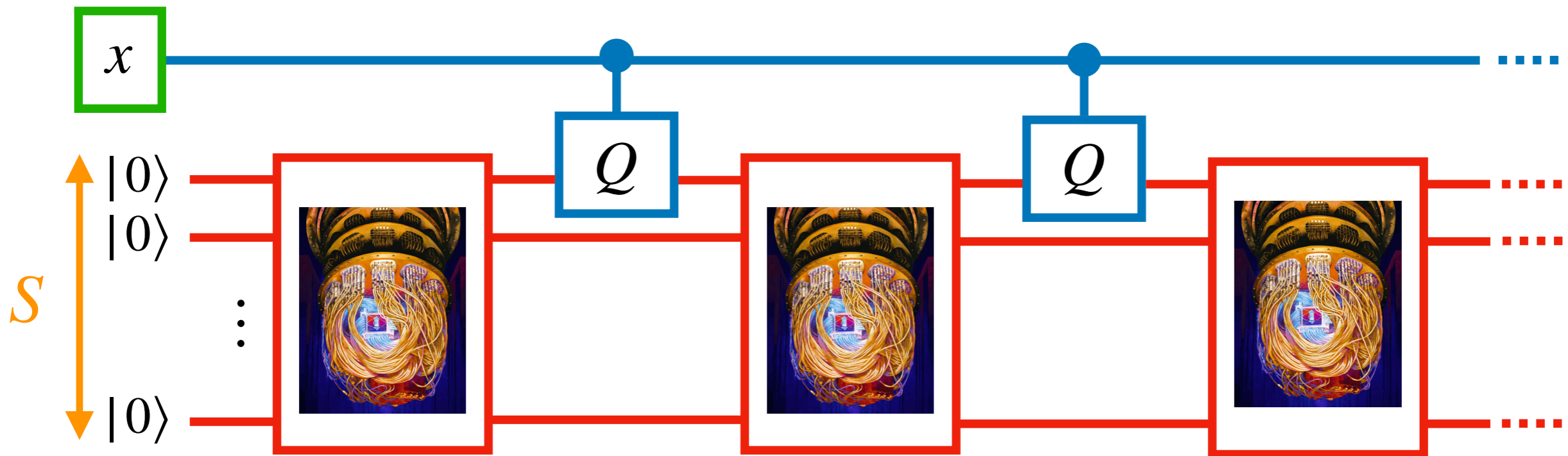
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Lower bound	<p>$T^2S \geq \tilde{\Omega}(K^2N)$</p> <p>[Chakrabarti,Chen'17] [Dinur'20]</p>	<p>$T^3S \geq \Omega(K^3N)$</p> <p>Our result</p>

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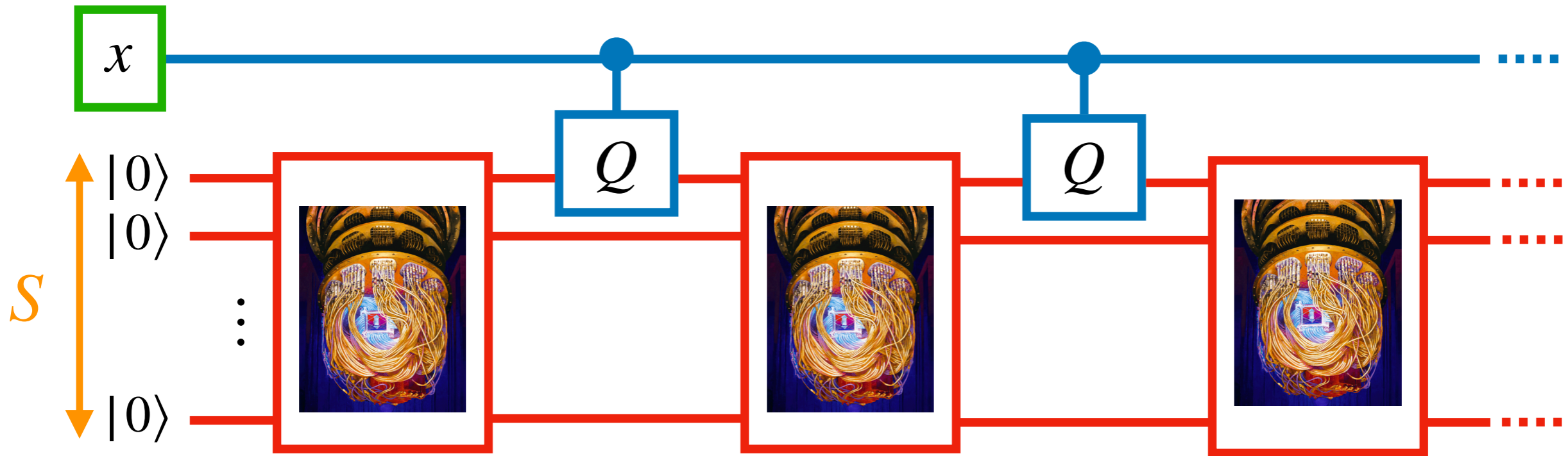
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Lower Bound Method



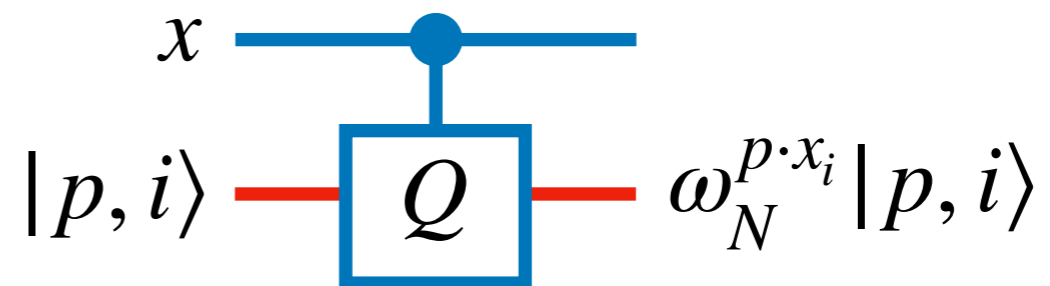


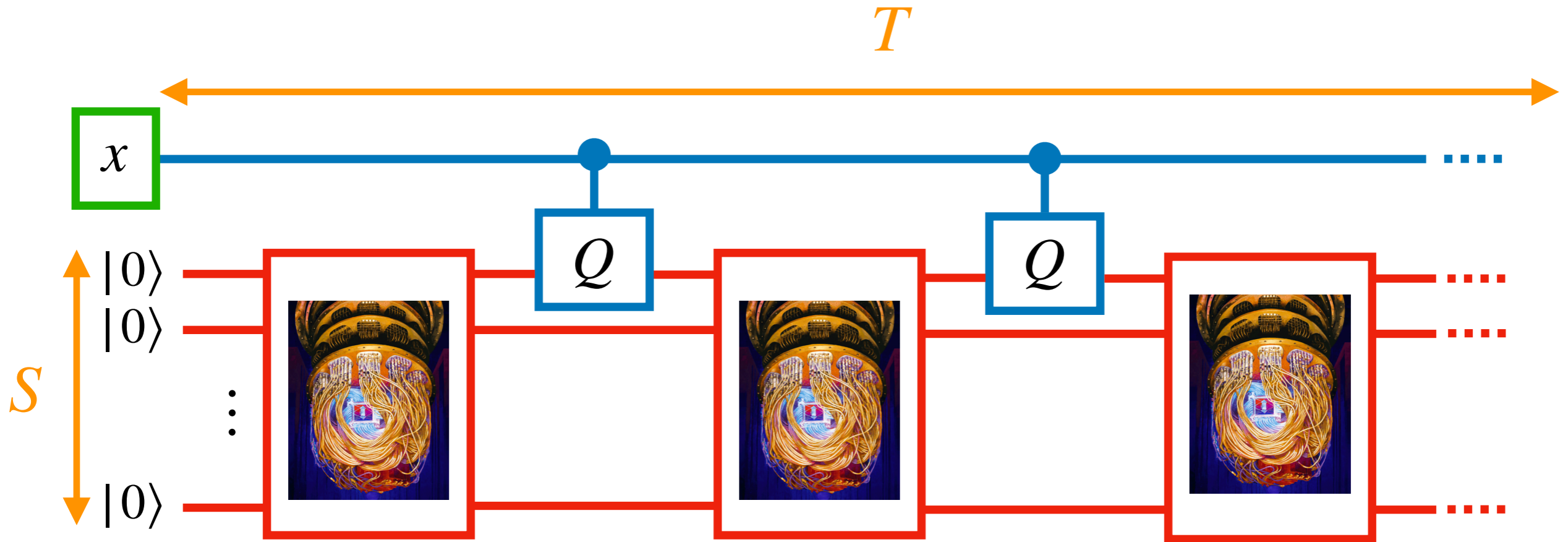
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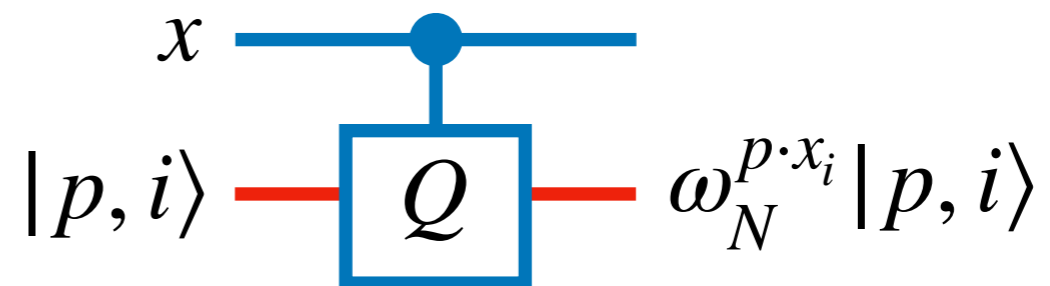
- The quantum “Query Operator” Q is:
(when $x_i \in [N]$)



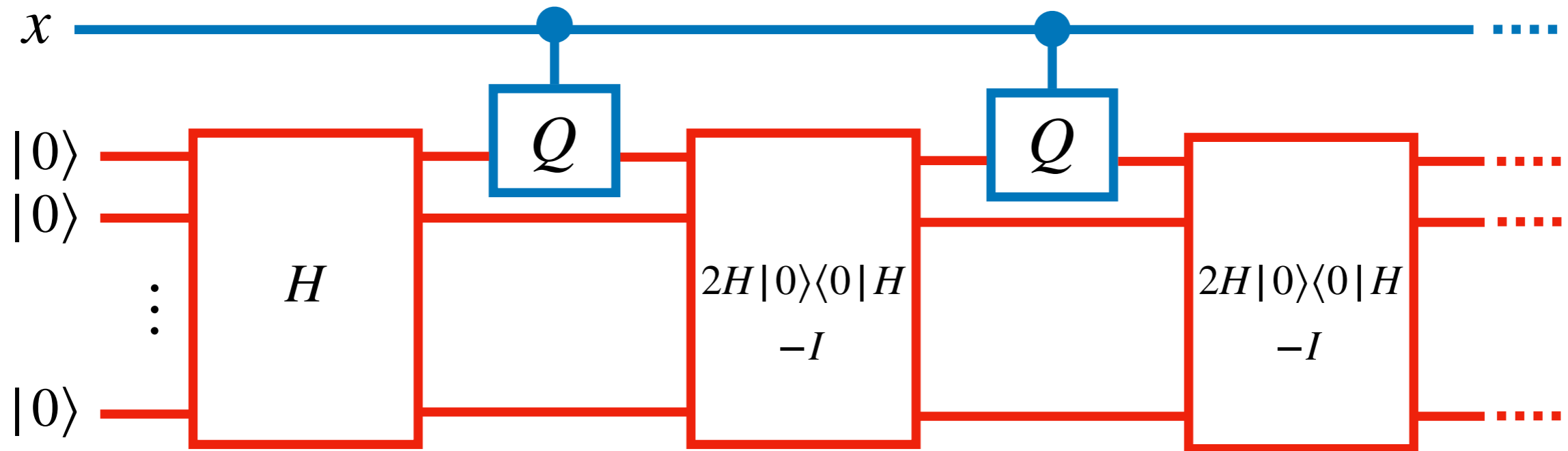


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- The computation alternates between **T quantum queries** and **T quantum operations** on the memory.



Example: Grover's Search

$$\begin{cases} T = O(\sqrt{N}) \\ S = O(\log N) \end{cases}$$

- A method to deduce Time-Space lower bounds from **Time lower bounds**.
- Introduced by [Borodin et al.'81], and by [Klauck'03] for the quantum version.
- Applicable when the problem has a large **output of size K** (\neq decision problem).

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Time lower bound

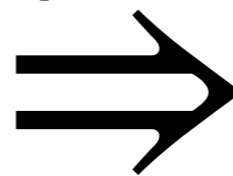
For all K , it is impossible to compute
 K parts of the output with success
probability $\geq 2^{-o(K)}$ in time $\tau(K)$.

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$K \geq S$

Time-Space lower bound

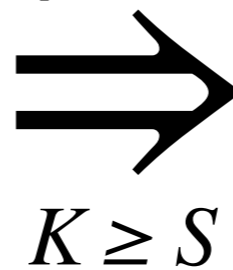
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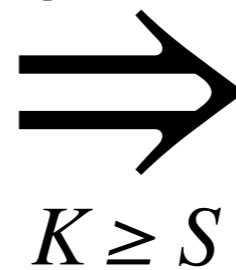
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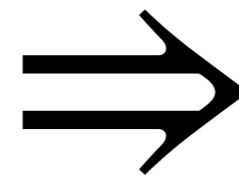
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$$T \geq \Omega\left(KN^{1/3}/S^{1/3}\right)$$

It is impossible to find **K collisions**
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in time $\tau(K) = O(K^{2/3}N^{1/3})$.

- + We don't care about space anymore.
- We must deal with the exponentially small success probability regime.

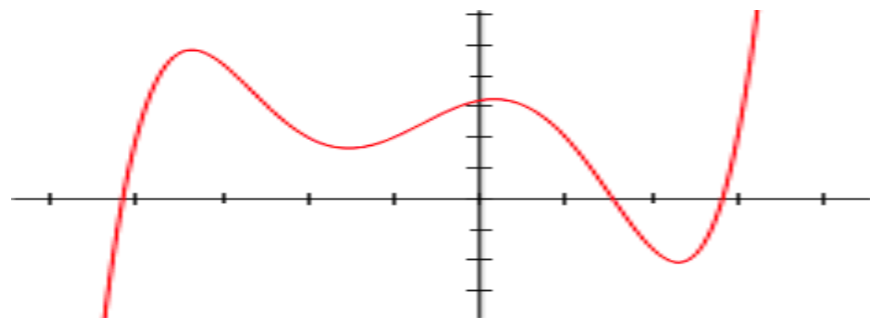
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Two main methods for proving such lower bounds:

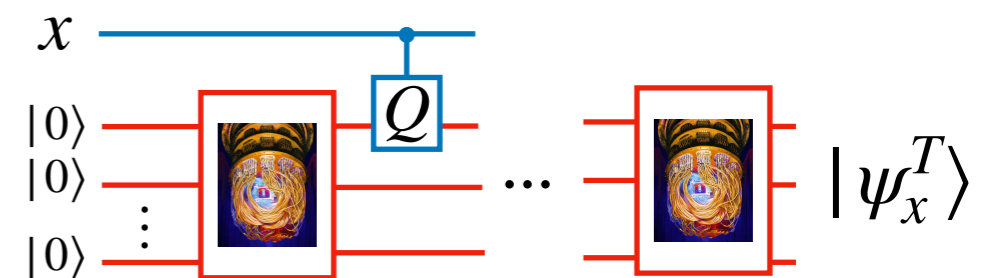
Polynomial Method

The acceptance probability of a T-query algorithm is a polynomial in x of degree at most 2T.



Adversary Method

Bound the progress $W^t = \sum_{x,y} w_{x,y} \langle \psi_x^t | \psi_y^t \rangle$.



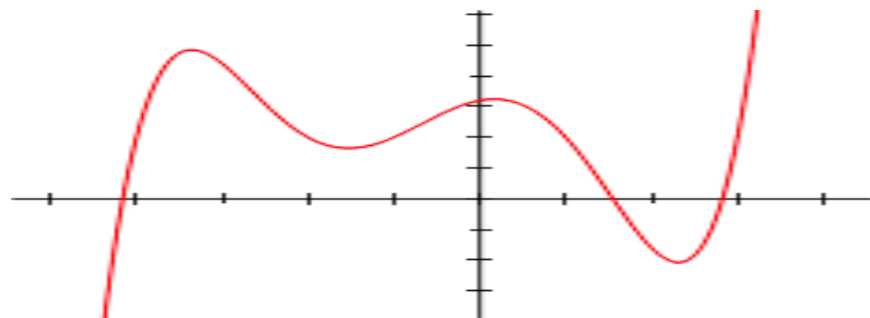
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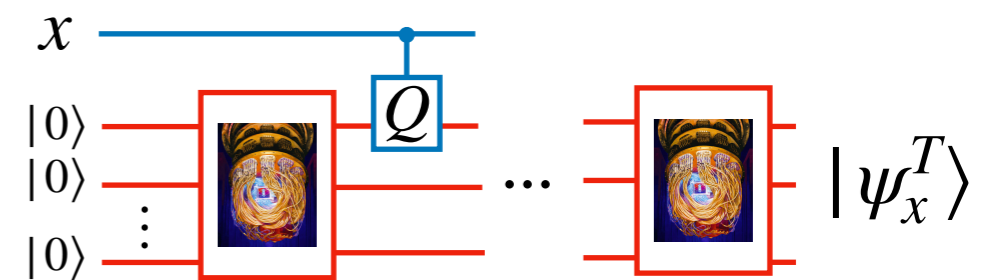
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Our approach: a refined version of Zhandry's **recording technique**

Input: $x = (x_1, \dots, x_N)$ where $x_i = y \in [N]$ with probability $1/N$.

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Strategy: sample each entry only when it is queried, and record its value.

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Algorithm



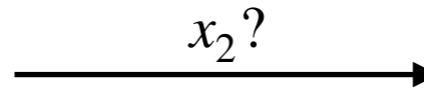
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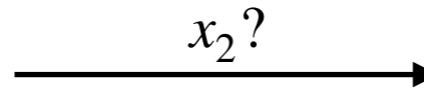
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Strategy: sample each entry only when it is queried, and record its value.

Algorithm



Input

$$x = (\perp, \perp, \perp, \perp)$$

$$x = (\perp, 4, \perp, \perp)$$

Input: $x = (x_1, \dots, x_N)$ where $x_i = y \in [N]$ with probability $1/N$.

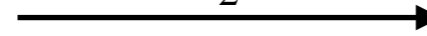
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Algorithm



Input

$$x = (\perp, \perp, \perp, \perp)$$

 $x_2?$  $x_2 = 4$ 

$$x = (\perp, 4, \perp, \perp)$$

Input: $x = (x_1, \dots, x_N)$ where $x_i = y \in [N]$ with probability $1/N$.

Strategy: sample each entry only when it is queried, and record its value.

Algorithm



Input

$$x = (\perp, \perp, \perp, \perp)$$

$$\xrightarrow{x_2?}$$

$$\xleftarrow{x_2 = 4}$$

$$\xrightarrow{x_1?}$$

$$x = (\perp, 4, \perp, \perp)$$

Input: $x = (x_1, \dots, x_N)$ where $x_i = y \in [N]$ with probability $1/N$.

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Input

$$x = (\perp, \perp, \perp, \perp)$$

$$\xrightarrow{x_2?}$$

$$x = (\perp, 4, \perp, \perp)$$

$$\xleftarrow{x_2 = 4}$$

$$\xrightarrow{x_1?}$$

$$x = (7, 4, \perp, \perp)$$

Input: $x = (x_1, \dots, x_N)$ where $x_i = y \in [N]$ with probability $1/N$.

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Algorithm



Input

$$x = (\perp, \perp, \perp, \perp)$$

$$\xrightarrow{x_2?}$$

$$\xleftarrow{x_2 = 4}$$

$$x = (\perp, 4, \perp, \perp)$$

$$\xrightarrow{x_1?}$$

$$\xleftarrow{x_1 = 7}$$

$$x = (7, 4, \perp, \perp)$$

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Input

$$x = (\perp, \perp, \perp, \perp)$$

$$\xrightarrow{x_2?}$$

$$x = (\perp, 4, \perp, \perp)$$

$$\xleftarrow{x_2 = 4}$$

$$\xrightarrow{x_1?}$$

$$x = (7, 4, \perp, \perp)$$

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Algorithm



Input

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$$\xrightarrow{x_2?}$$

$$\xleftarrow{x_2 = 4}$$

$$x = (\perp, 4, \perp, \perp)$$

$$\xrightarrow{x_1?}$$

$$\xleftarrow{x_1 = 7}$$

$$x = (7, 4, \perp, \perp)$$

$$\xrightarrow{x_2?}$$

$$\xleftarrow{x_2 = 4}$$

$$x = (7, 4, \perp, \perp)$$

$$\xrightarrow{x_4?}$$

$$\xleftarrow{x_4 = 4}$$

$$x = (7, 4, \perp, 4)$$

⋮

Input: $x = (x_1, \dots, x_N)$ where $x_i = y \in [N]$ with probability $1/N$.

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Algorithm



Input

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$$\xrightarrow{x_2?}$$

$$\xleftarrow{x_2 = 4}$$

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$$\xleftarrow{x_4 = 4}$$

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⋮

Progress measure: probability to have recorded at least k collisions after t queries

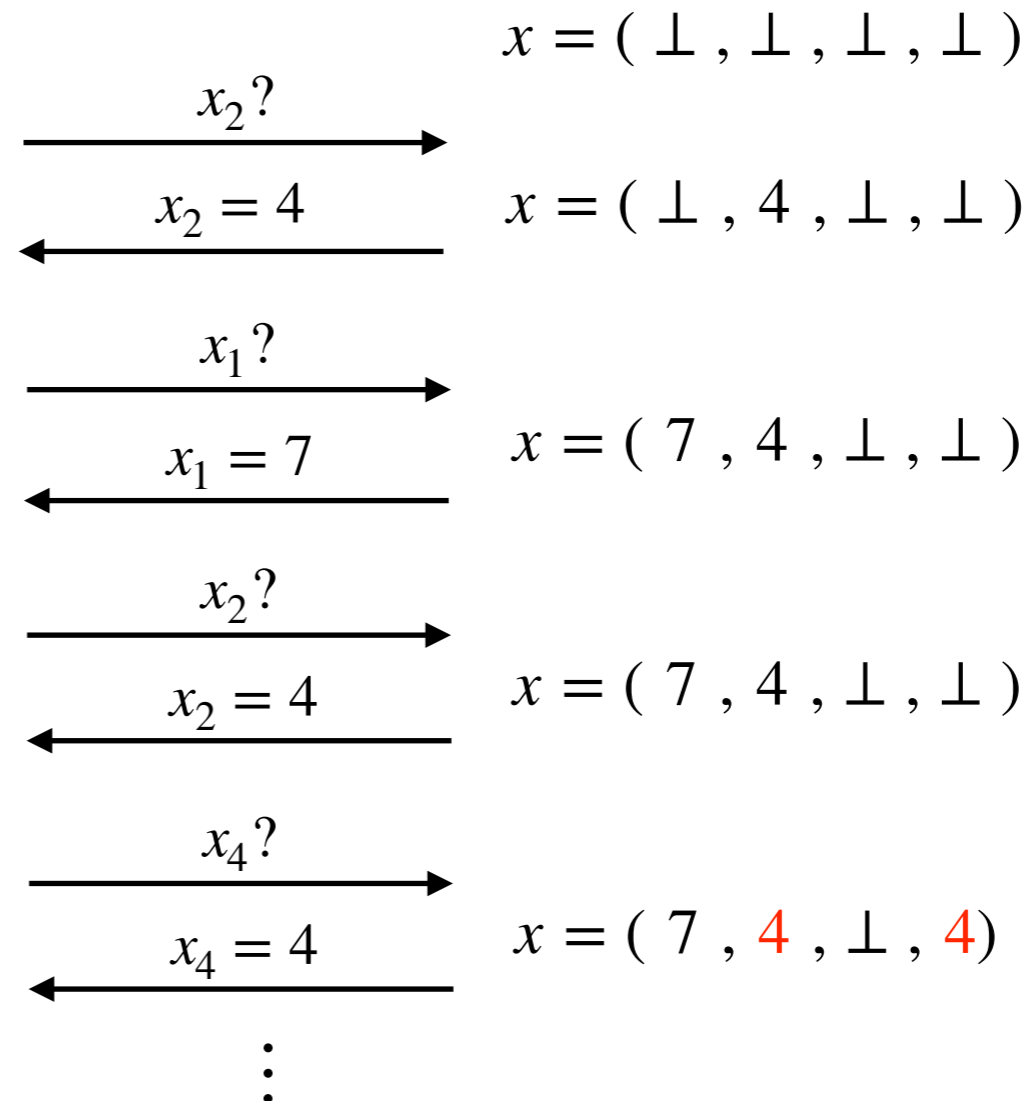
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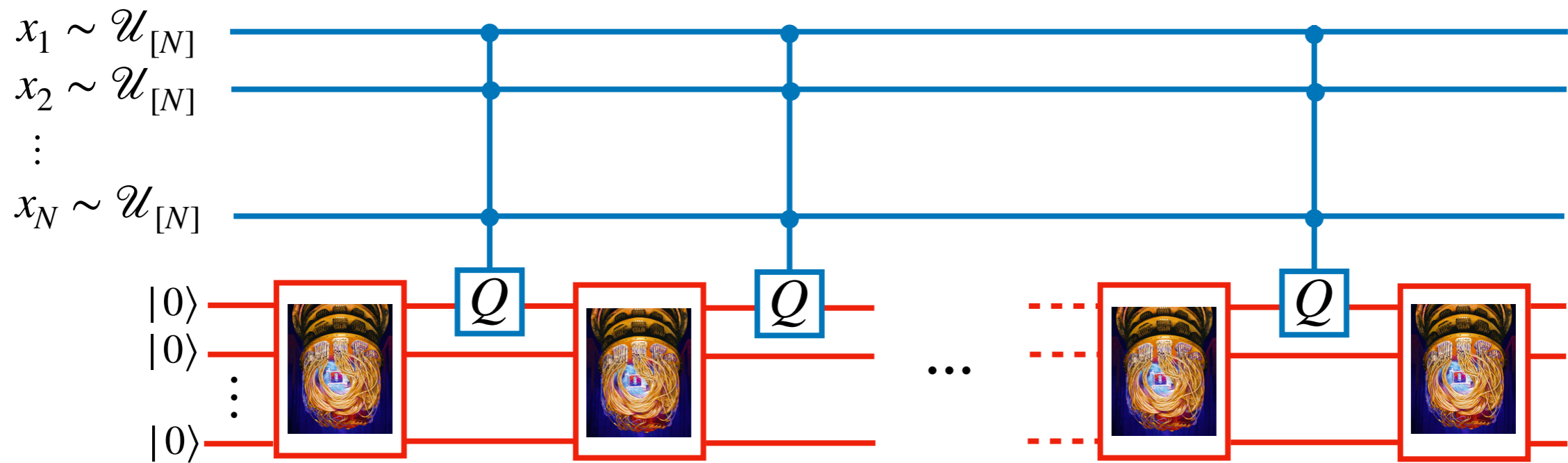


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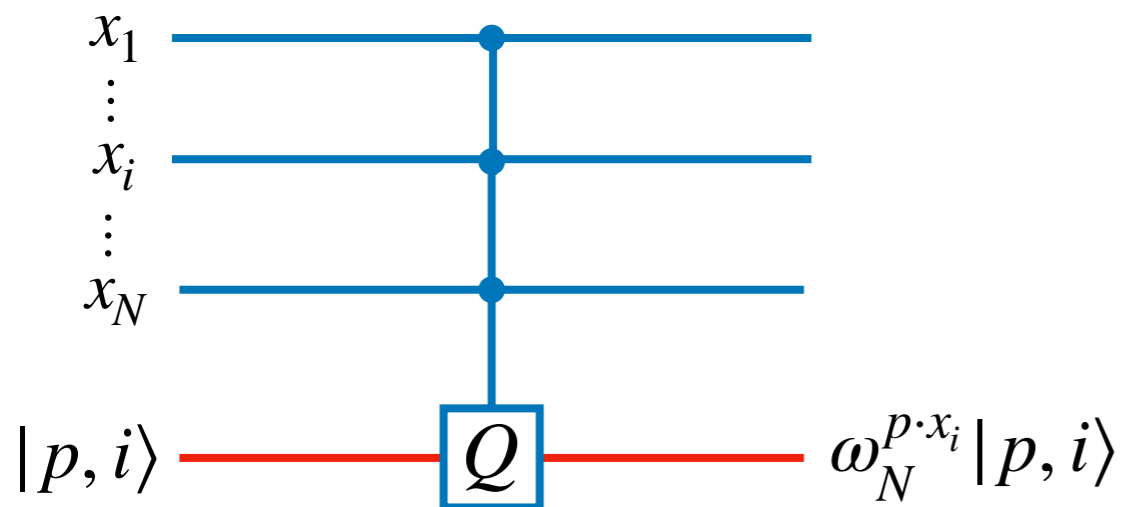


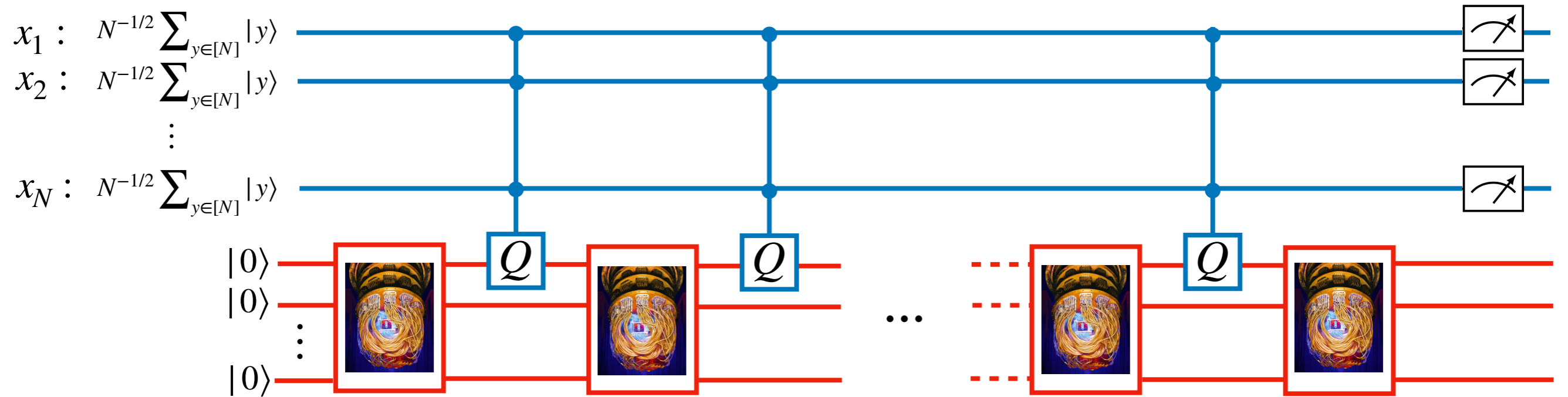
Progress measure: probability to have recorded at least k collisions after t queries

→ the algorithm must force the recording of many collisions to succeed with high probability

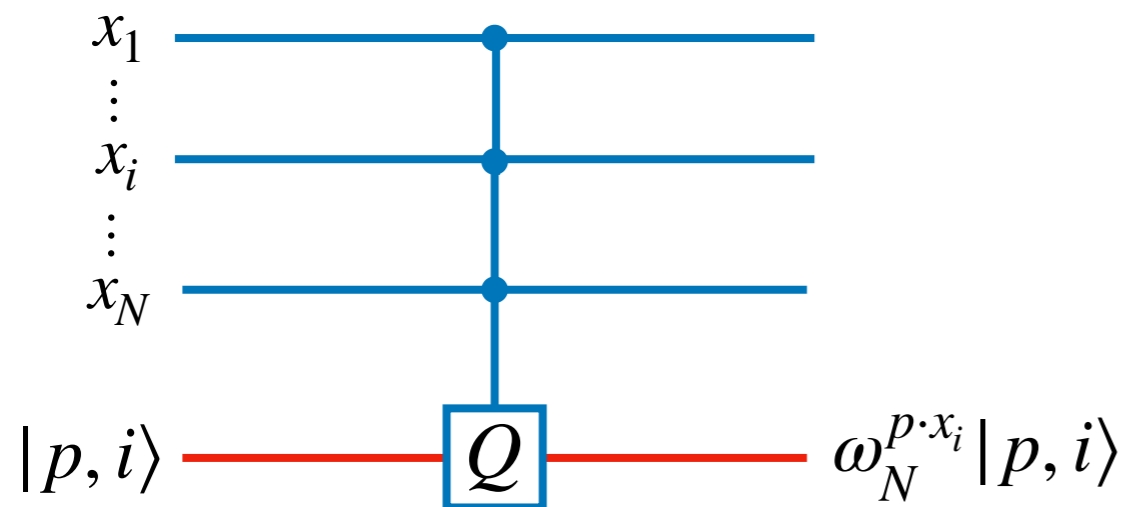


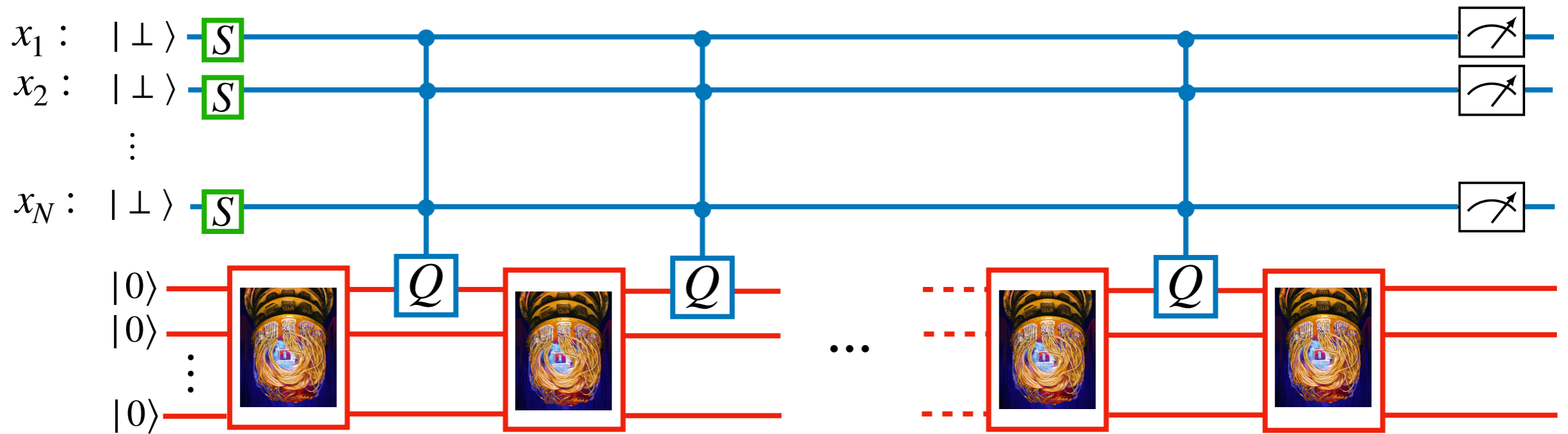
Query Operator





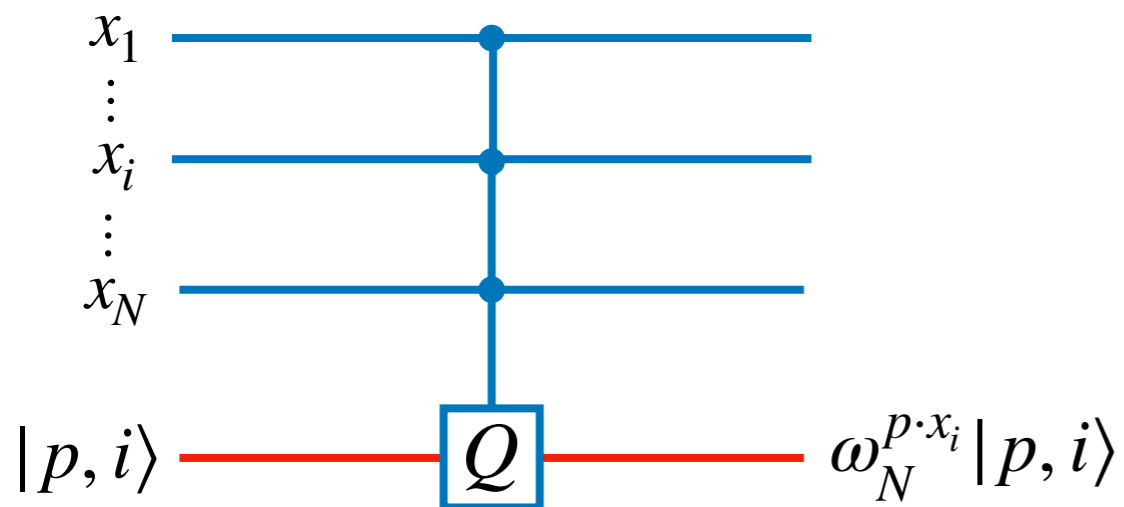
Query Operator

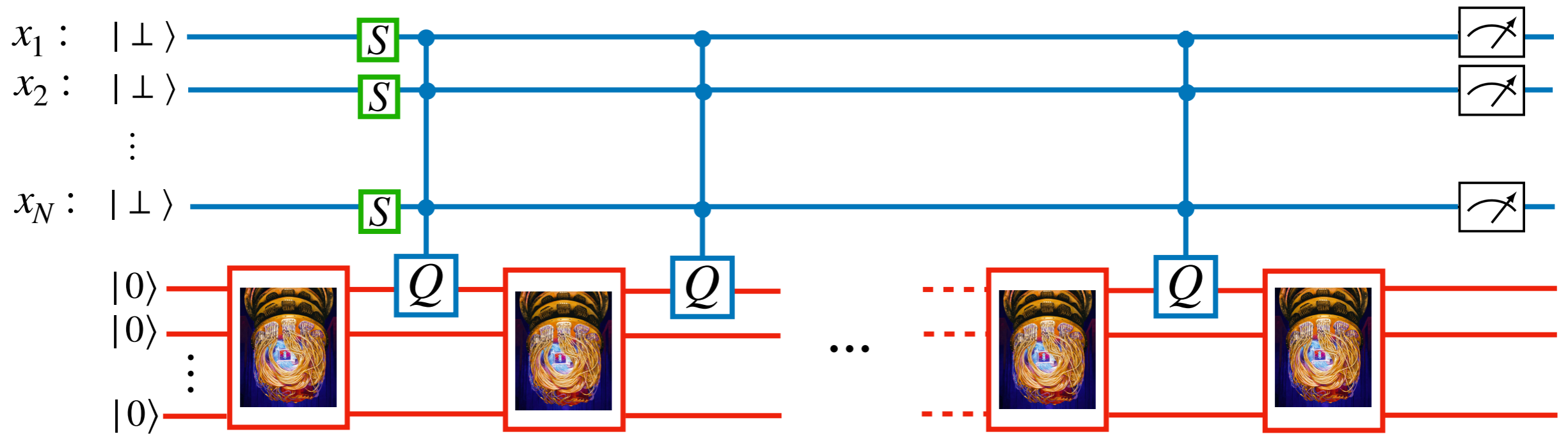




$$|\perp\rangle \text{---} \boxed{S} \text{---} N^{-1/2} \sum_{y \in [N]} |y\rangle$$

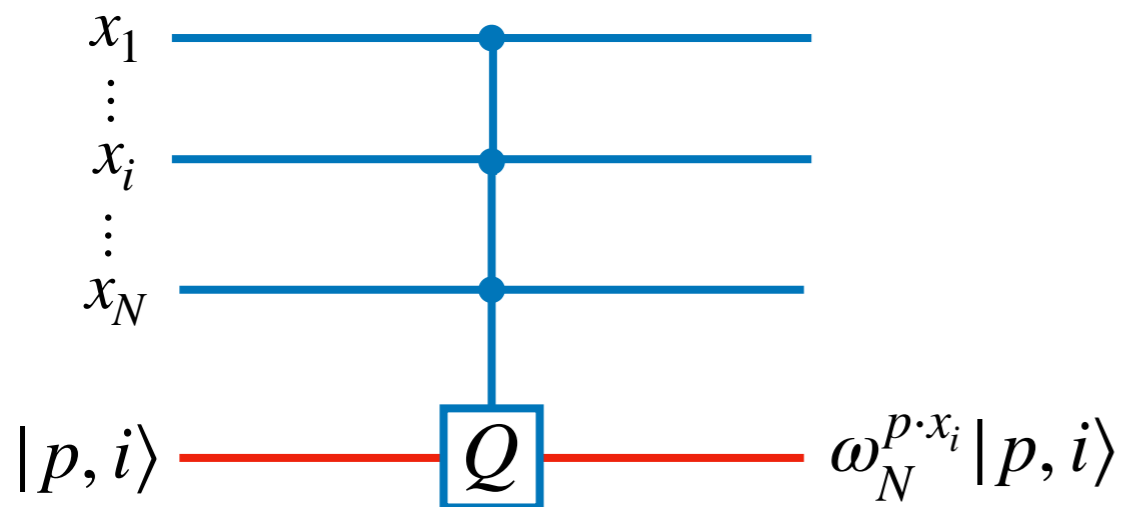
Query Operator

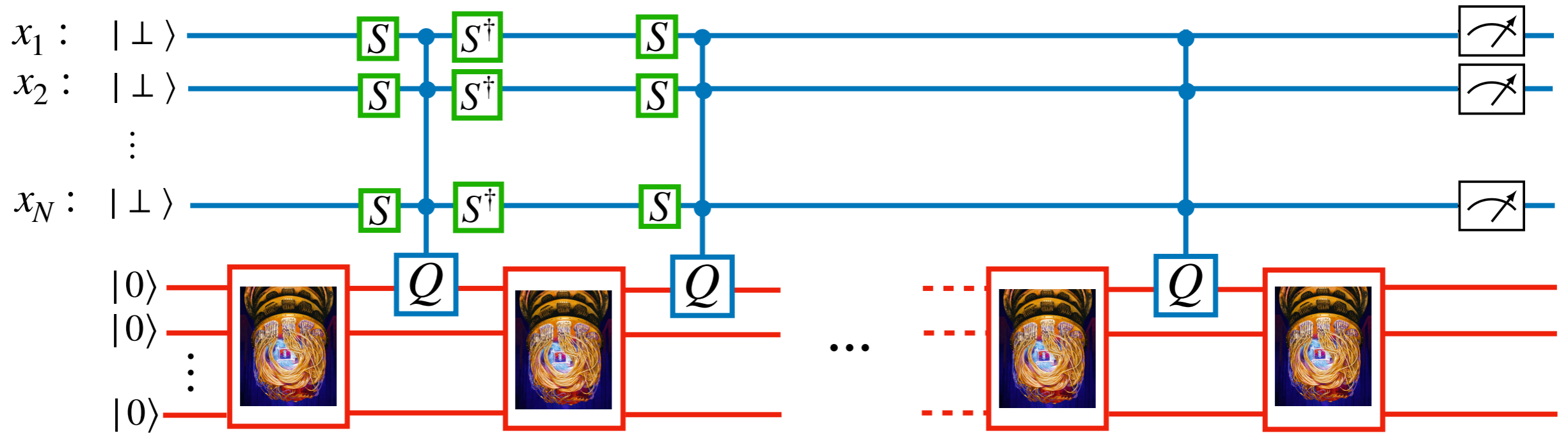




$$|\perp\rangle \xrightarrow{S} N^{-1/2} \sum_{y \in [N]} |y\rangle$$

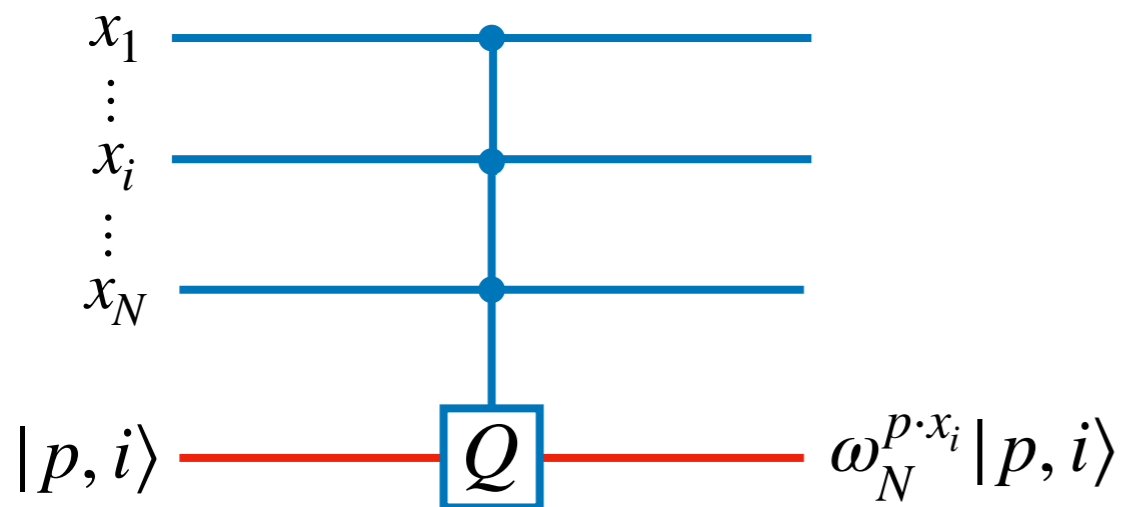
Query Operator

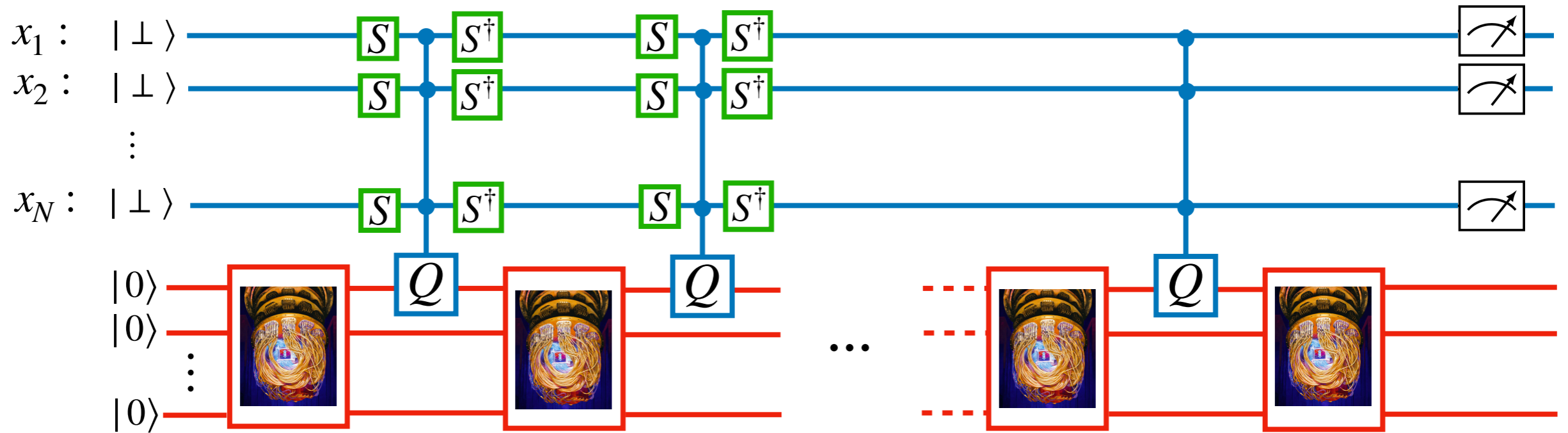




$$|\perp\rangle \xrightarrow{S} N^{-1/2} \sum_{y \in [N]} |y\rangle$$

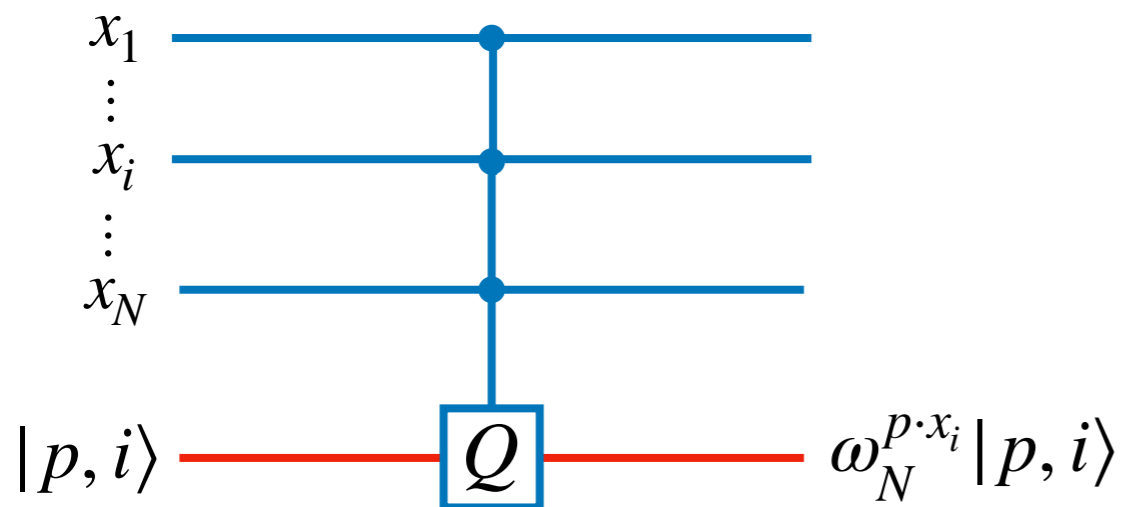
Query Operator

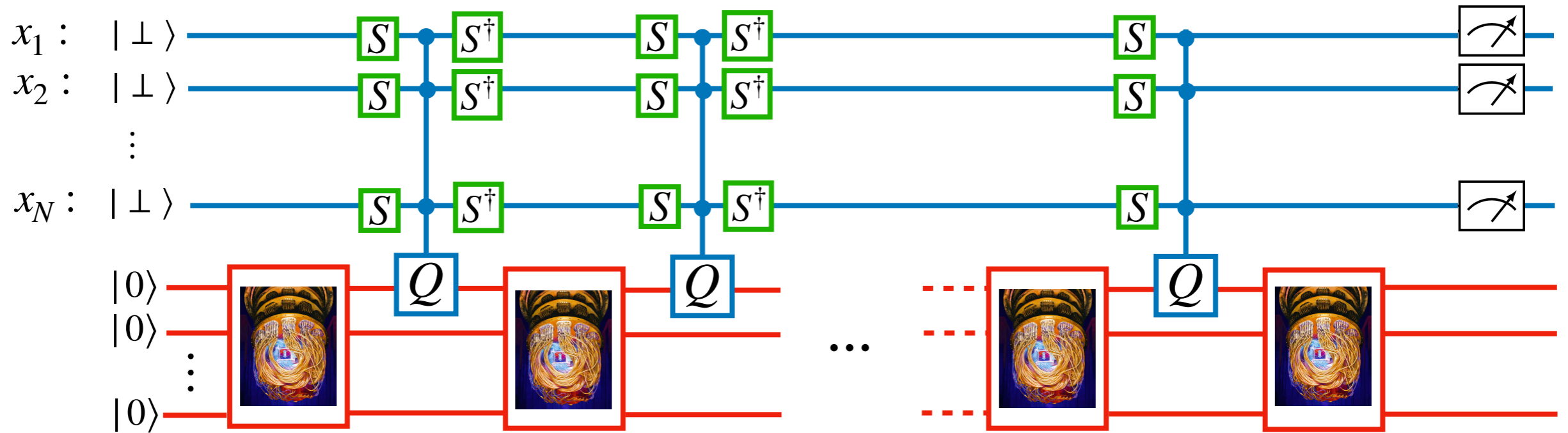




$$|\perp\rangle \xrightarrow{S} N^{-1/2} \sum_{y \in [N]} |y\rangle$$

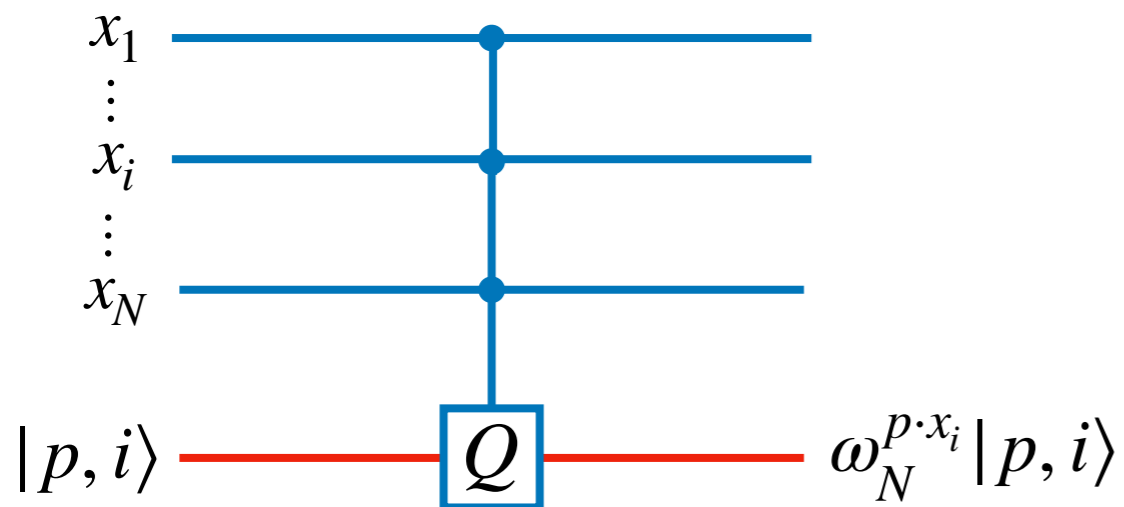
Query Operator

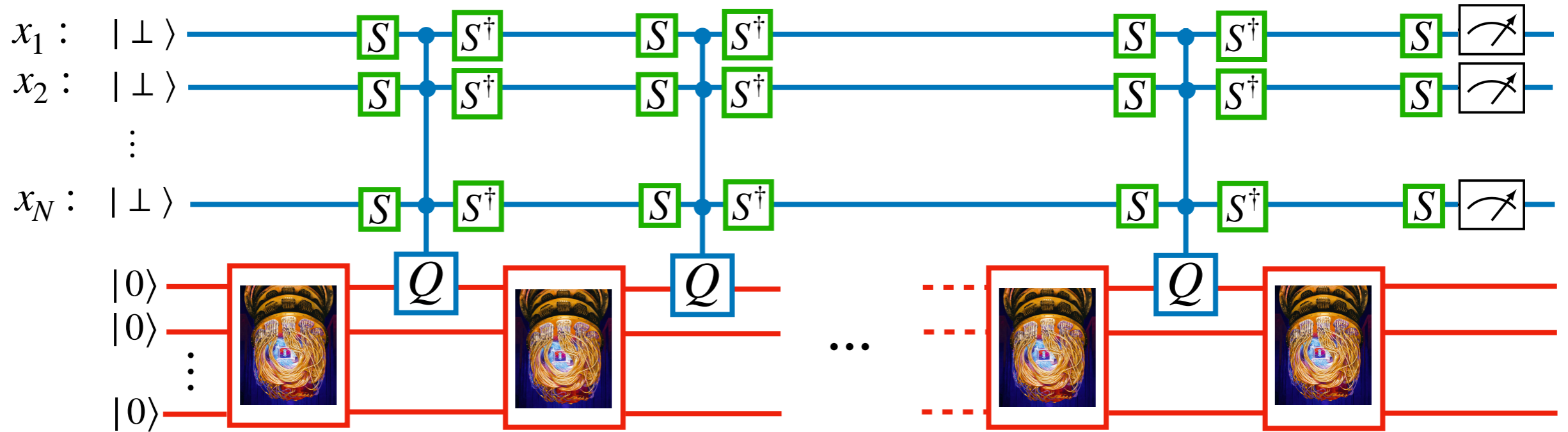




$$|\perp\rangle \xrightarrow{S} N^{-1/2} \sum_{y \in [N]} |y\rangle$$

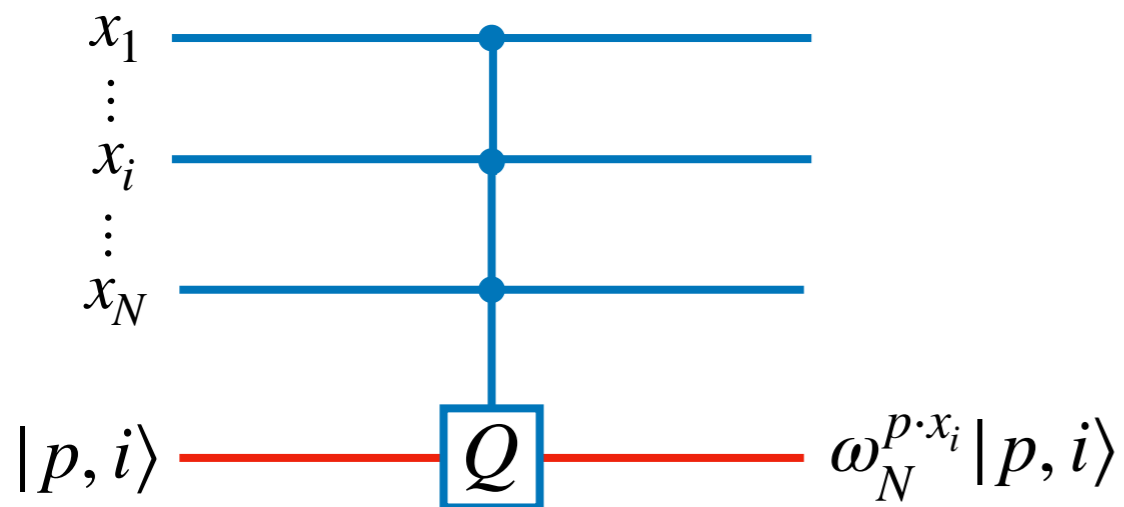
Query Operator

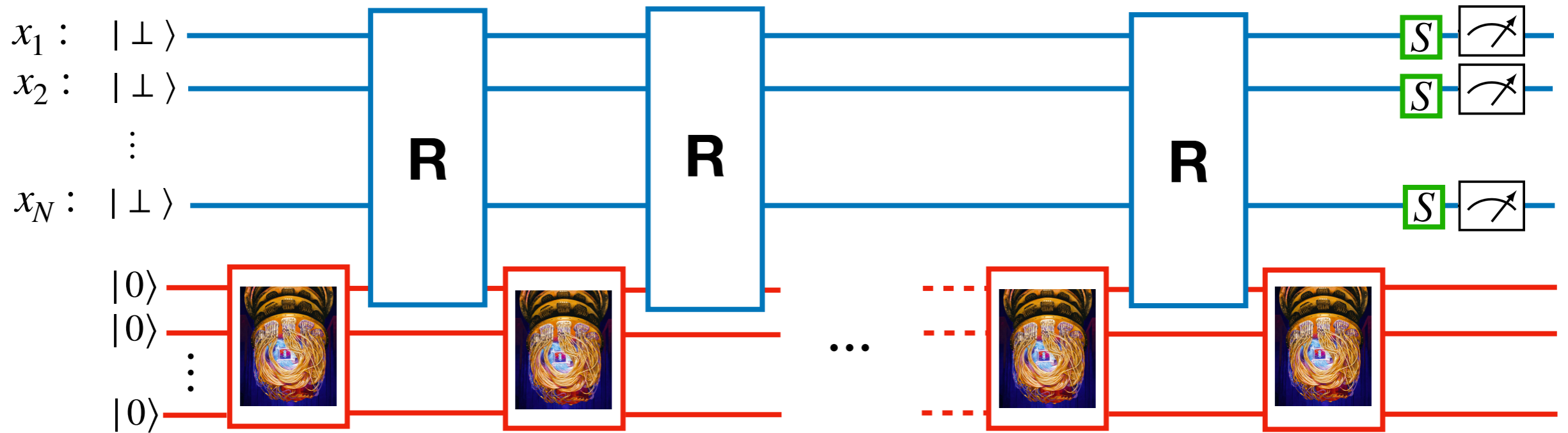




$$|\perp\rangle \xrightarrow{S} N^{-1/2} \sum_{y \in [N]} |y\rangle$$

Query Operator

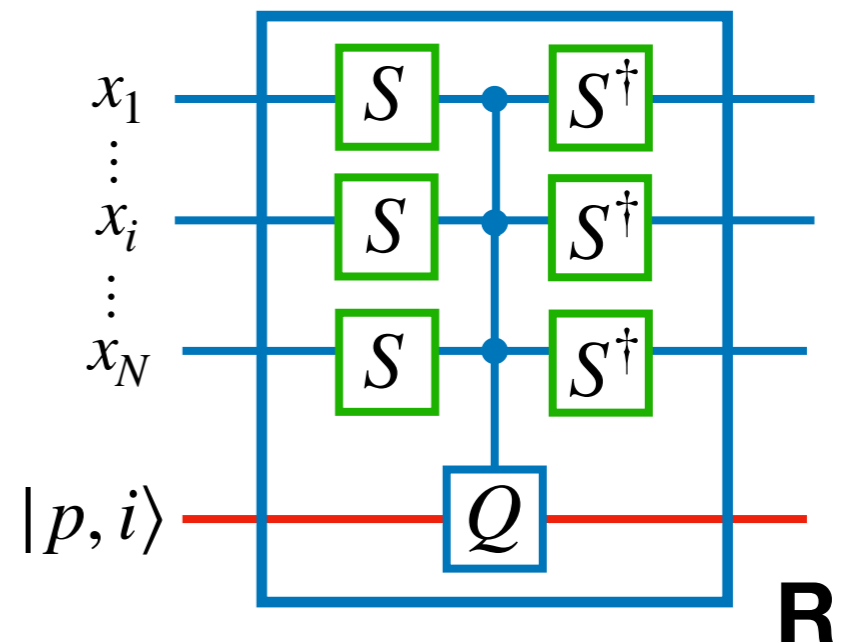
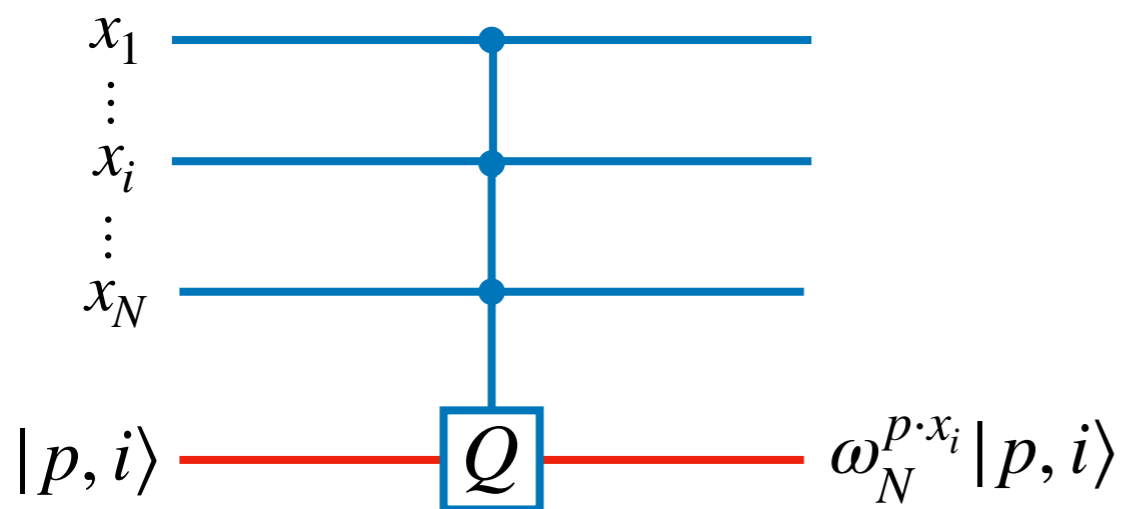


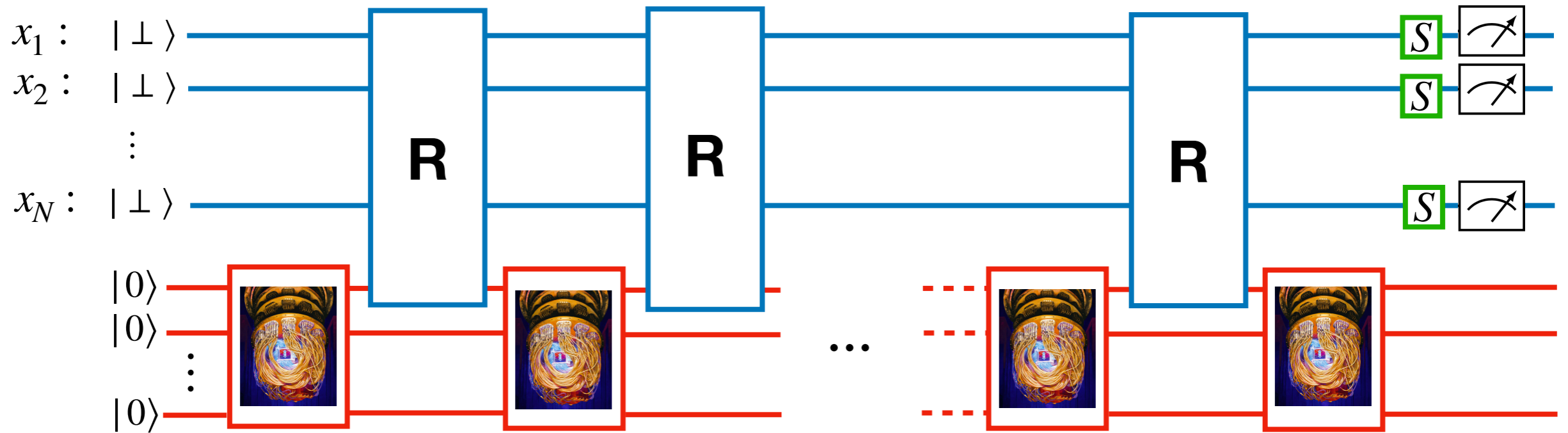


$$|\perp\rangle \text{ --- } S \text{ --- } N^{-1/2} \sum_{y \in [N]} |y\rangle$$

Query Operator

Recording Query Operator



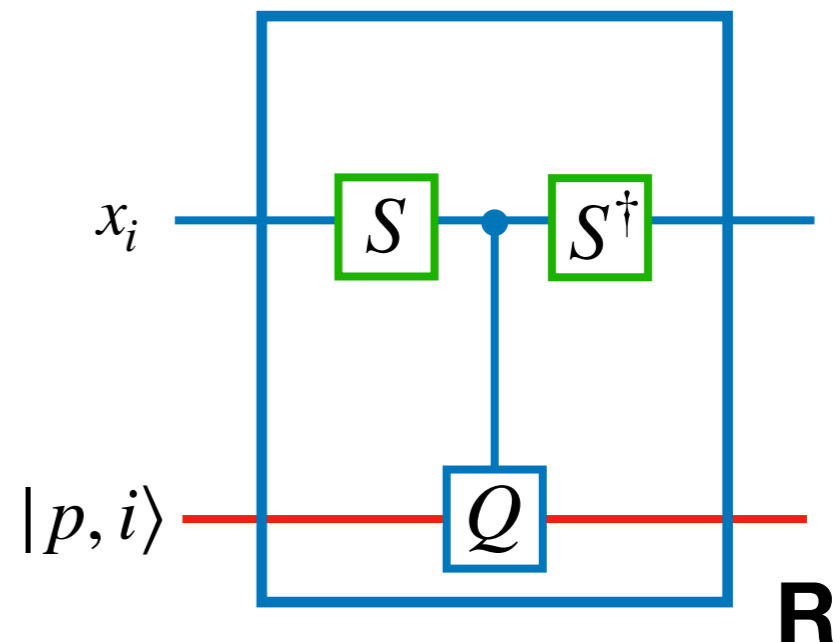
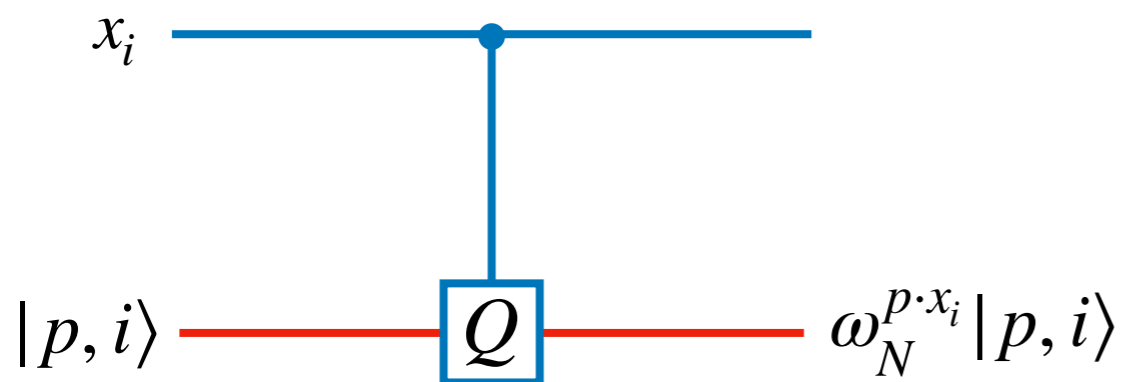


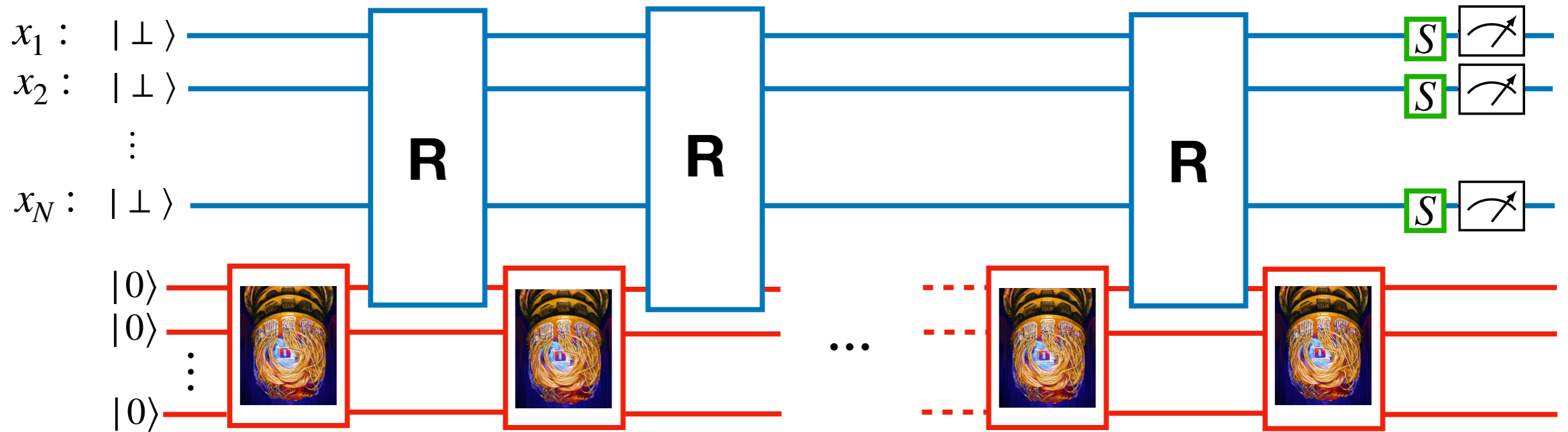
$$|\perp\rangle \text{ --- } \boxed{S} \text{ --- } N^{-1/2} \sum_{y \in [N]} |y\rangle$$

Query Operator

Recording Query Operator

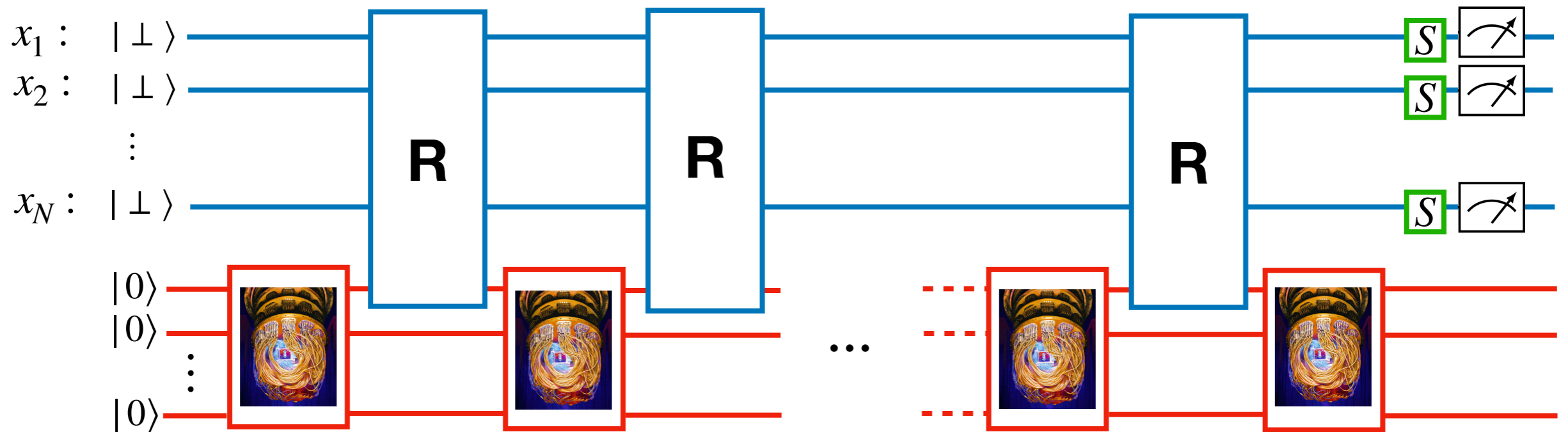
✓ If x_j is not queried it stays unchanged.





Recording Query Operator

$$\begin{array}{l}
 x_i : |\perp\rangle \\
 |p, i\rangle
 \end{array}
 \begin{array}{c}
 \boxed{\text{R}} \\
 \hline
 \end{array}
 \begin{array}{l}
 N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \\
 |p, i\rangle
 \end{array}$$



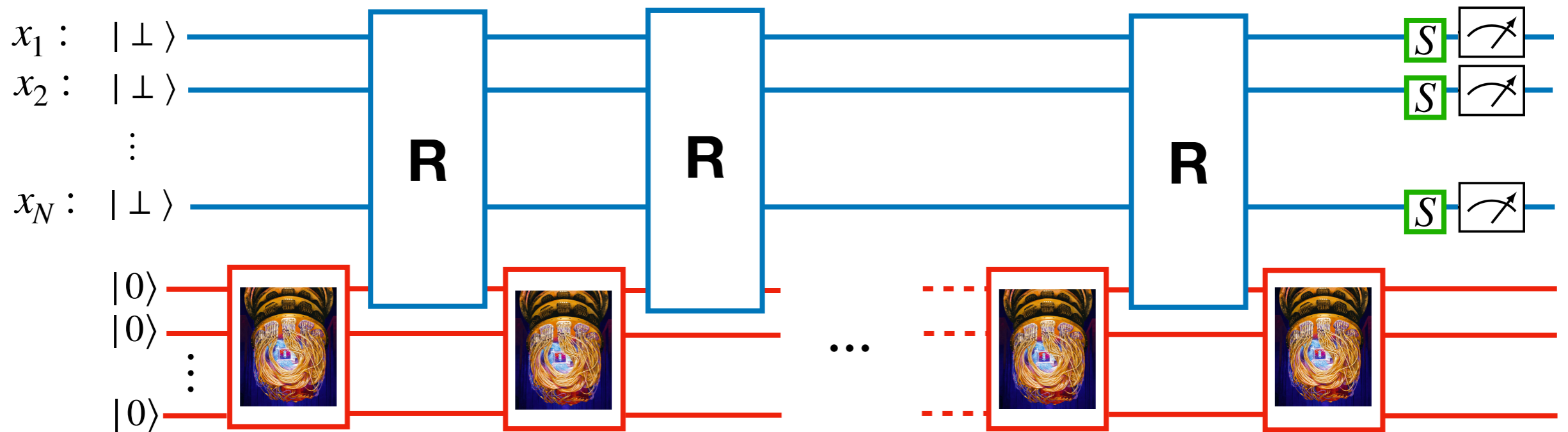
Recording Query Operator

$$x_i : |\perp\rangle \text{ --- } \boxed{R} \text{ --- } N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle$$

$$|p, i\rangle \text{ --- } \boxed{R} \text{ --- } |p, i\rangle$$

$$x_i : |y\rangle \text{ --- } \boxed{R} \text{ --- } \approx \omega_N^{p \cdot y} |y\rangle$$

$$|p, i\rangle \text{ --- } \boxed{R} \text{ --- } |p, i\rangle$$

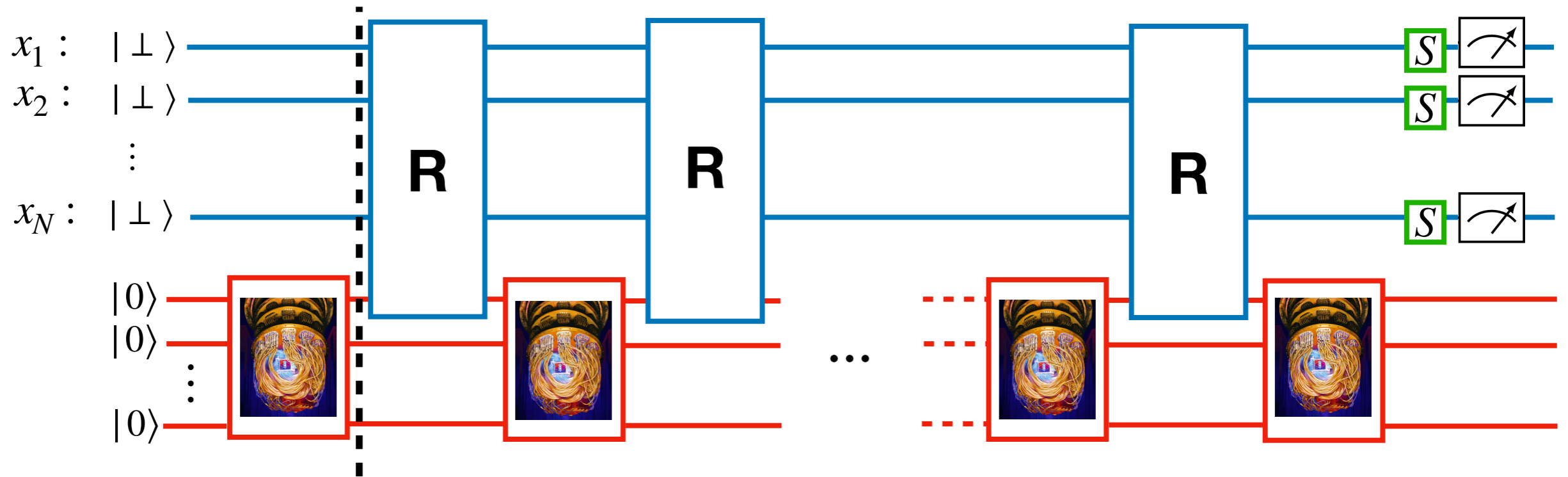


Recording Query Operator

$$x_i : |\perp\rangle \quad |p, i\rangle \quad \text{---} \quad \boxed{R} \quad \text{---} \quad N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \quad |p, i\rangle$$

$$x_i : |y\rangle \quad |p, i\rangle \quad \text{---} \quad \boxed{R} \quad \text{---} \quad \approx \omega_N^{p \cdot y} |y\rangle \quad |p, i\rangle$$

$\Delta(t, k)$ = **amplitude** of the basis states containing $\geq k$ (disjoint) collisions after t queries.



$$\Delta(0,0) = 1$$

$$\Delta(0,k) = 0 \text{ for } k > 0$$

Recording Query Operator

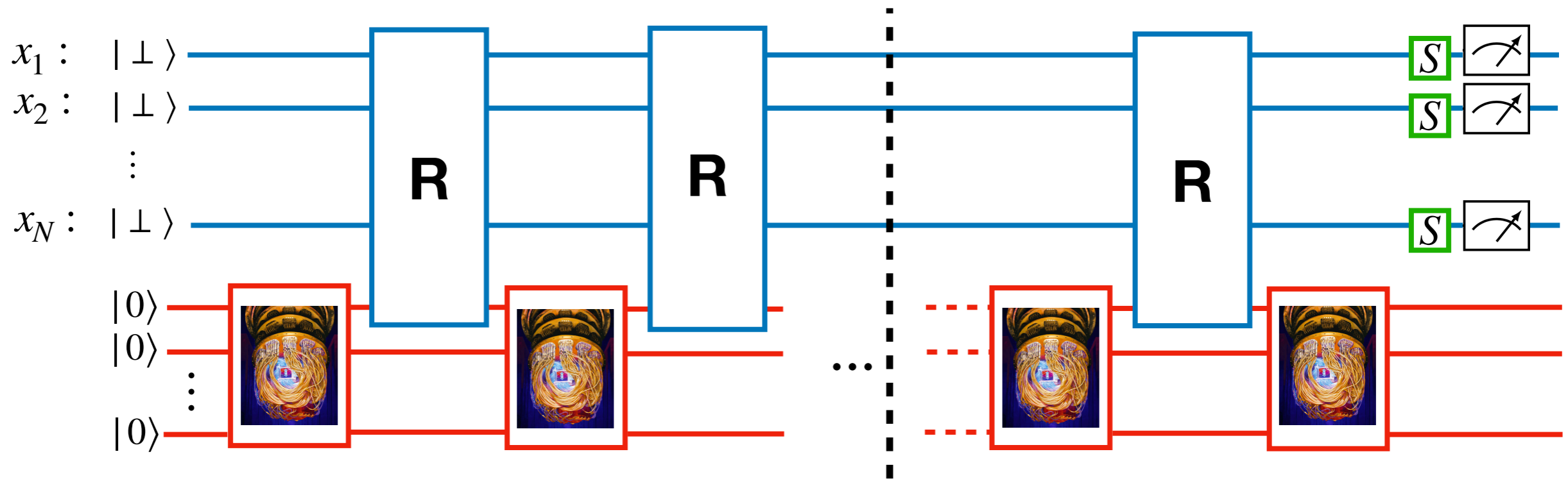
$$x_i : |\perp\rangle \text{ --- } \boxed{\text{R}} \text{ --- } N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle$$

$$|p, i\rangle \text{ --- } \boxed{\text{R}} \text{ --- } |p, i\rangle$$

$$x_i : |y\rangle \text{ --- } \boxed{\text{R}} \text{ --- } \approx \omega_N^{p \cdot y} |y\rangle$$

$$|p, i\rangle \text{ --- } \boxed{\text{R}} \text{ --- } |p, i\rangle$$

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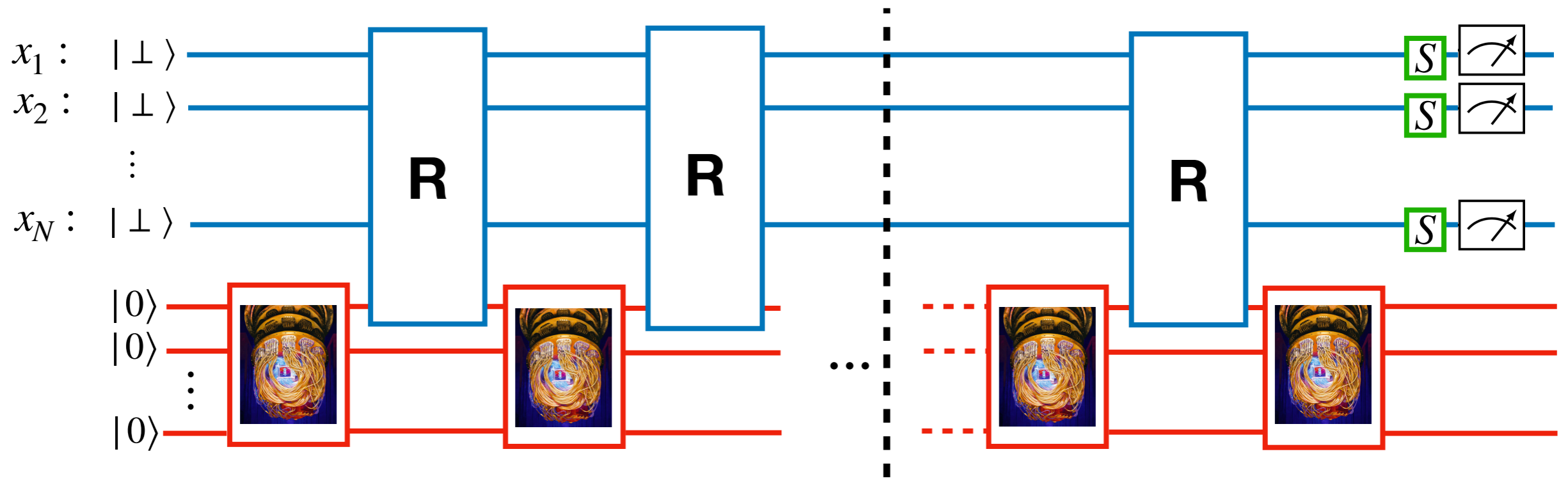
$$\Delta(t+1, k+1) \leq \Delta(t, k+1) + \Delta(t, k) \cdot O\left(\sqrt{\frac{t}{N}}\right)$$

Recording Query Operator

$$x_i : |\perp\rangle \quad |p, i\rangle \quad \text{---} \quad \boxed{\text{R}} \quad \text{---} \quad N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \quad |p, i\rangle$$

$$x_i : |y\rangle \quad |p, i\rangle \quad \text{---} \quad \boxed{\text{R}} \quad \text{---} \quad \approx \omega_N^{p \cdot y} |y\rangle \quad |p, i\rangle$$

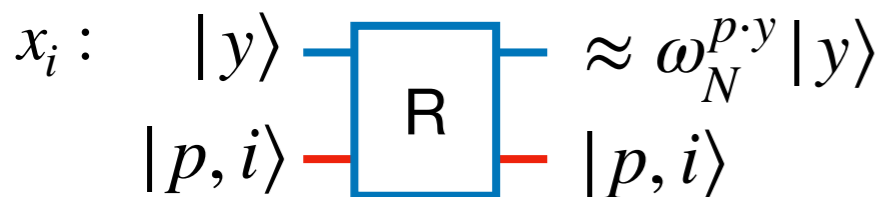
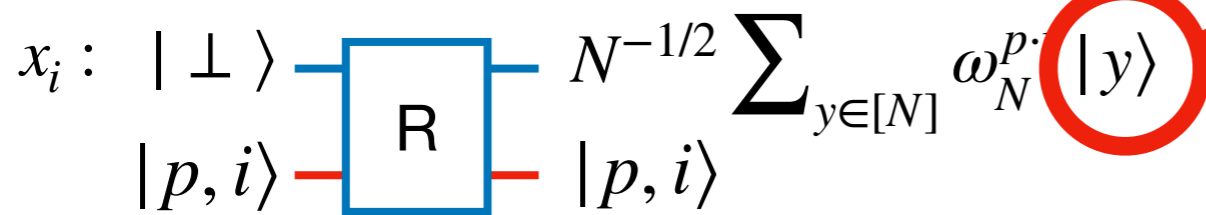
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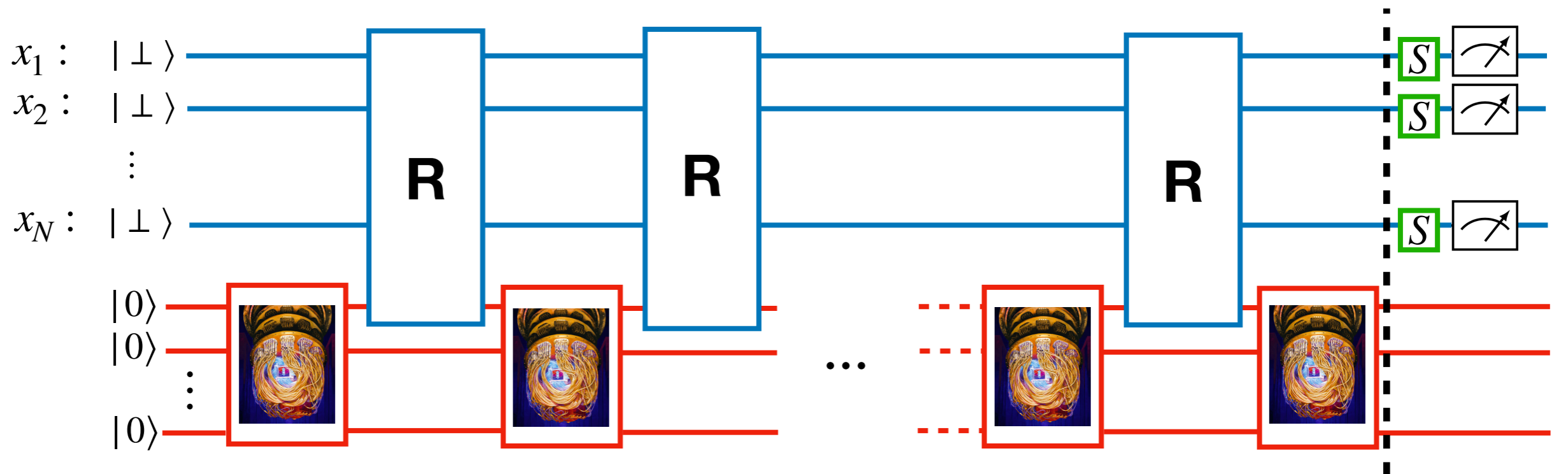
$$\Delta(t + 1, k + 1) \leq \Delta(t, k + 1)$$

$$+ \Delta(t, k) \cdot o\left(\sqrt{\frac{t}{N}}\right)$$

Recording Query Operator



$\Delta(t, k)$ = **amplitude** of the basis states containing $\geq k$ (disjoint) collisions after t queries.



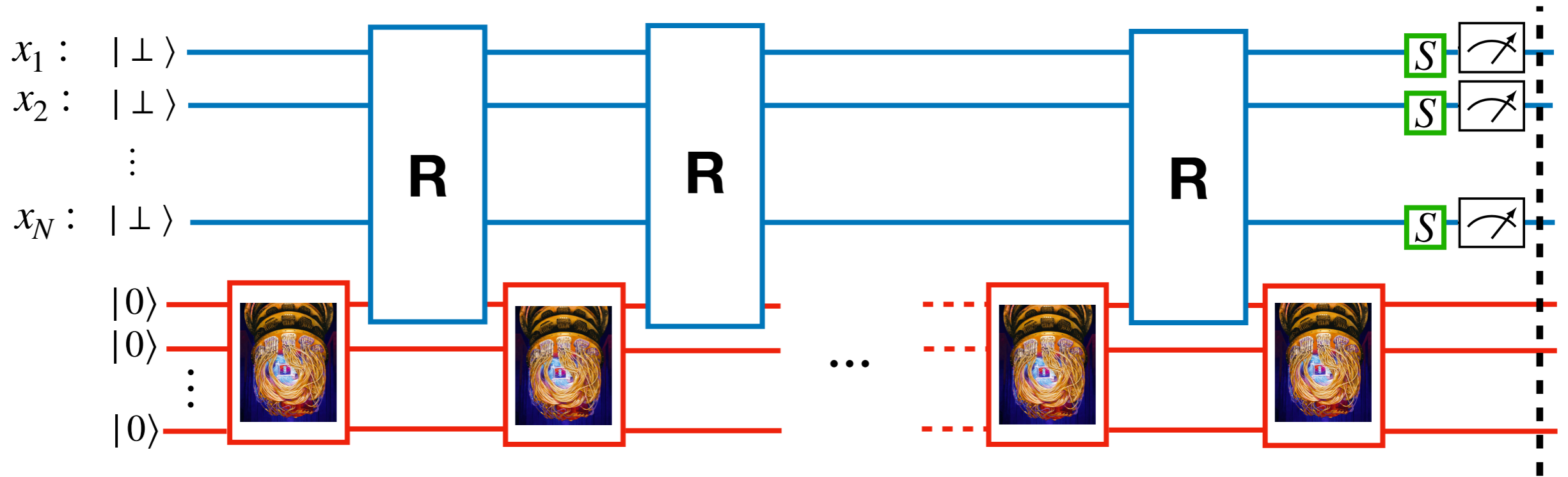
$$\Delta(K^{2/3}N^{1/3}, K/2) \leq 2^{-K}$$

Recording Query Operator

$$x_i : \begin{array}{l} |\perp\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

$$x_i : \begin{array}{l} |y\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \approx \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

$\Delta(t, k)$ = **amplitude** of the basis states containing $\geq k$ (disjoint) collisions after t queries.



Success

\leq

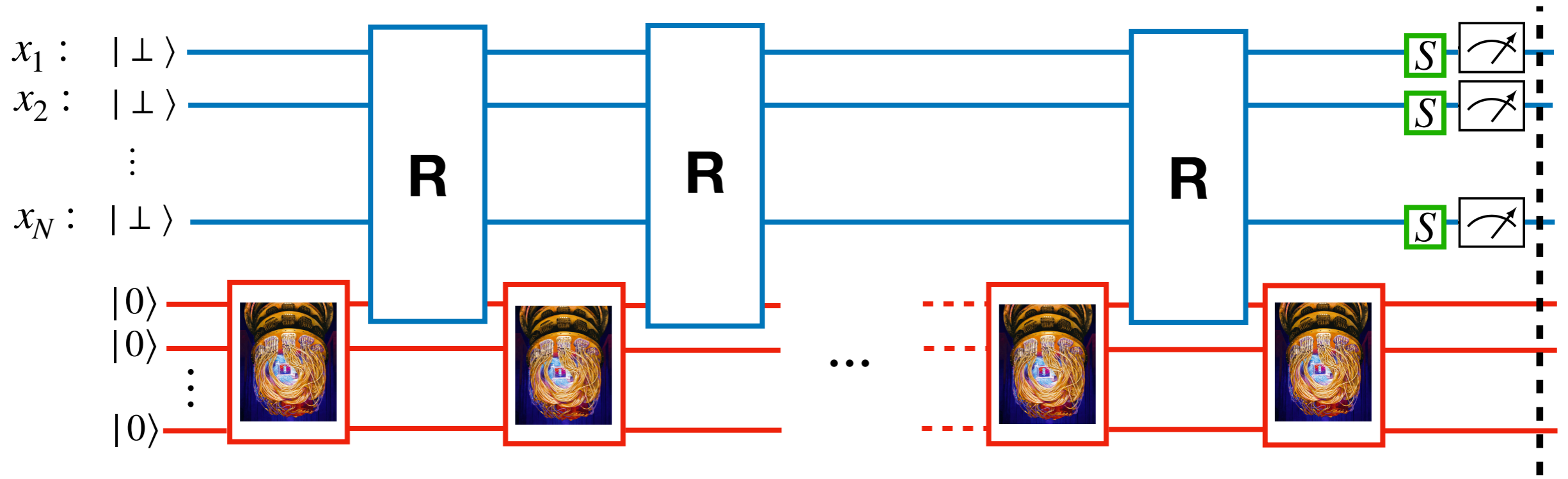
$$\Delta(K^{2/3} N^{1/3}, K/2) + O(K/N)^{K/2}$$

Recording Query Operator

$$x_i : \begin{array}{l} |\perp\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

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$\Delta(t, k)$ = **amplitude** of the basis states containing $\geq k$ (disjoint) collisions after t queries.



Success

≤

$$\Delta(K^{2/3} N^{1/3}, K/2)$$

$$= O(K/N)^{K/2}$$

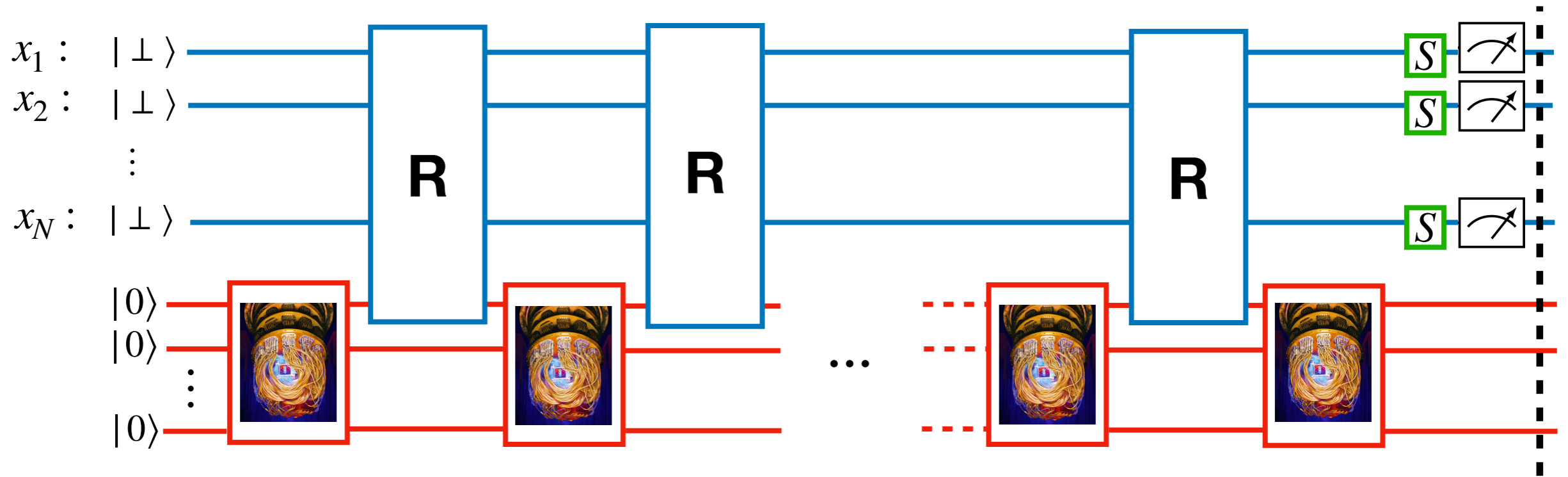
Recording Query Operator

$$x_i : \begin{array}{l} |\perp\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{l} N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

≈ guess K/2 unrecorded collisions

$$x_i : \begin{array}{l} |y\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{l} \approx \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

$\Delta(t, k)$ = **amplitude** of the basis states containing $\geq k$ (disjoint) collisions after t queries.



Success

$$\leq \Delta(K^{2/3}N^{1/3}, K/2) + O(K/N)^{K/2} \leq 2^{-\Omega(K)}$$

Recording Query Operator

$$x_i : \begin{array}{l} |\perp\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} N^{-1/2} \sum_{y \in [N]} \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

$$x_i : \begin{array}{l} |y\rangle \\ |p, i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \approx \omega_N^{p \cdot y} |y\rangle \\ |p, i\rangle \end{array}$$

$\Delta(t, k)$ = **amplitude** of the basis states containing $\geq k$ (disjoint) collisions after t queries.

Conclusion

- Generalization to any **product** distribution

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→ **K-Search**: find K ones in x where $x_i = 1$ with probability K/N

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$$\begin{array}{c} |\perp\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \approx \begin{array}{c} |\perp\rangle \\ |i\rangle \end{array} - \sqrt{K/N} \textcircled{|1\rangle}$$

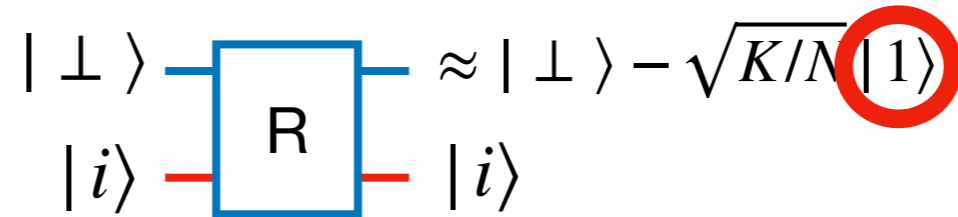
Record a new 1

$$\begin{array}{c} |0\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \approx \begin{array}{c} |0\rangle \\ |i\rangle \end{array} + \sqrt{K/N} \textcircled{|1\rangle}$$

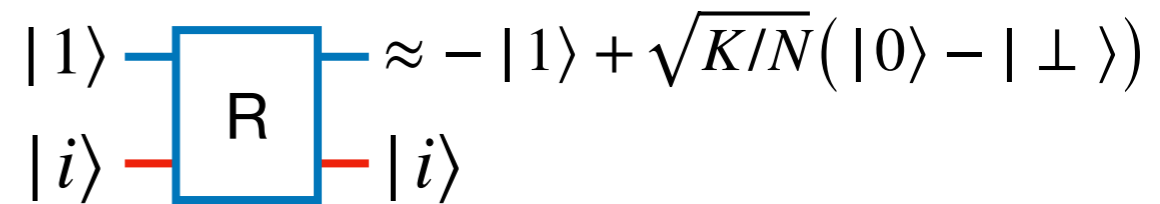
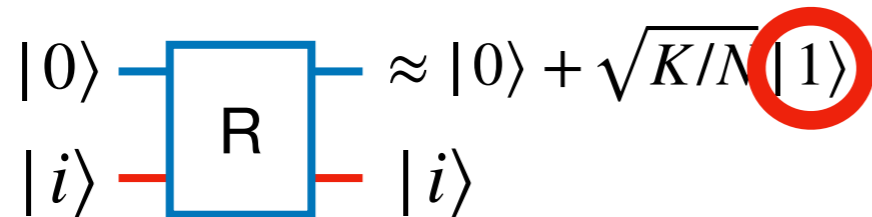
$$\begin{array}{c} |1\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \approx \begin{array}{c} -|1\rangle \\ |i\rangle \end{array} + \sqrt{K/N} (|0\rangle - |\perp\rangle)$$

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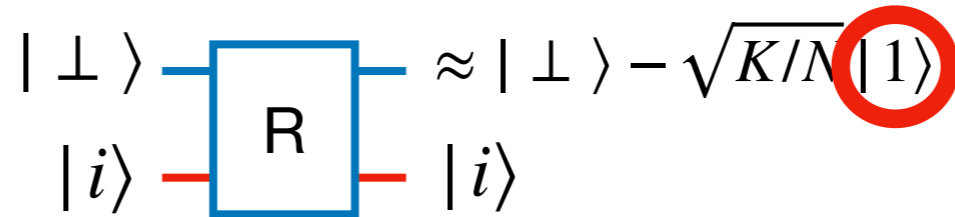
Record a new 1



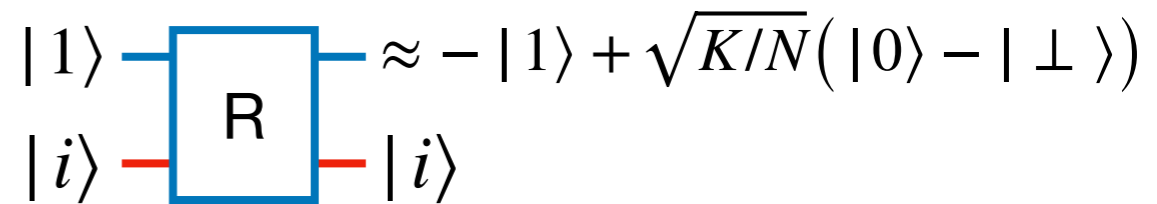
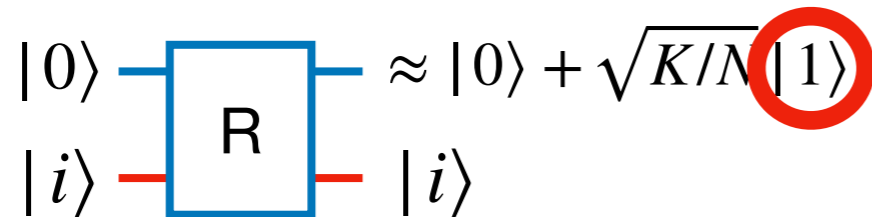
Solving the K-Search problem with success probability at least $2^{-O(K)}$ requires time $T \geq \Omega(\sqrt{NK})$.

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Record a new 1



Solving the K-Search problem with success probability at least $2^{-O(K)}$ requires time $T \geq \Omega(\sqrt{NK})$.

- + **Simpler** proof than previous work [Klauck et al.'07, Ambainis'10, ...]
- + Implies several quantum time-space tradeoffs (e.g. for **Sorting**).

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$$\begin{array}{c} |\perp\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \approx |\perp\rangle - \sqrt{K/N} |1\rangle \\ |i\rangle \end{array}$$

Record a new 1

$$\begin{array}{c} |0\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \approx |0\rangle + \sqrt{K/N} |1\rangle \\ |i\rangle \end{array}$$

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Record a new 1

$$\begin{array}{c} |0\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \approx |0\rangle + \sqrt{K/N} |1\rangle \\ |i\rangle \end{array}$$

$$\begin{array}{c} |1\rangle \\ |i\rangle \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \boxed{\text{R}} \\ \boxed{\text{R}} \end{array} \begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \begin{array}{c} \approx -|1\rangle + \sqrt{K/N} (|0\rangle - |\perp\rangle) \\ |i\rangle \end{array}$$

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- Conjecture: $T^2S \geq \Omega(K^2N)$ for finding K collisions.