

Faux-determinism

Shalev Ben-David

University of Waterloo
Institute for Quantum computing

M. H. Ebtelahaj

University of Waterloo
Institute for Quantum computing

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Overview

- ❖ Define faux deterministic algorithms in decision tree model which
- ❖ roughly characterizes “computationally indistinguishable” from deterministic

Introduction Some preliminary definitions

Motivation Search problems and why randomness could be different for them

Definition Defining faux deterministic model

Construction Building the construction for FIND1 problem

Introduction

Some preliminary definitions

Decision tree model

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Goal: compute $f: \{0,1\}^* \rightarrow \{0,1,\perp\}$

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Decision tree T :

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Decision tree T :

* Given an input string $x \in \{0,1\}^n$ to f

$x =$

1	0	1	...	x_i	...	0	0	1
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Decision tree model

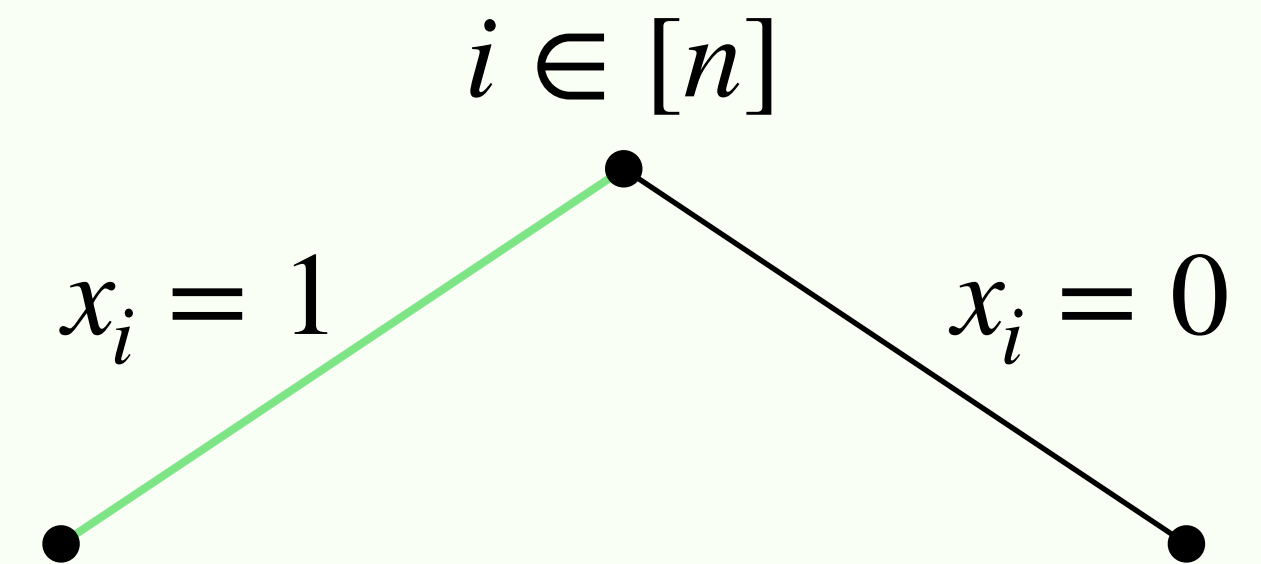
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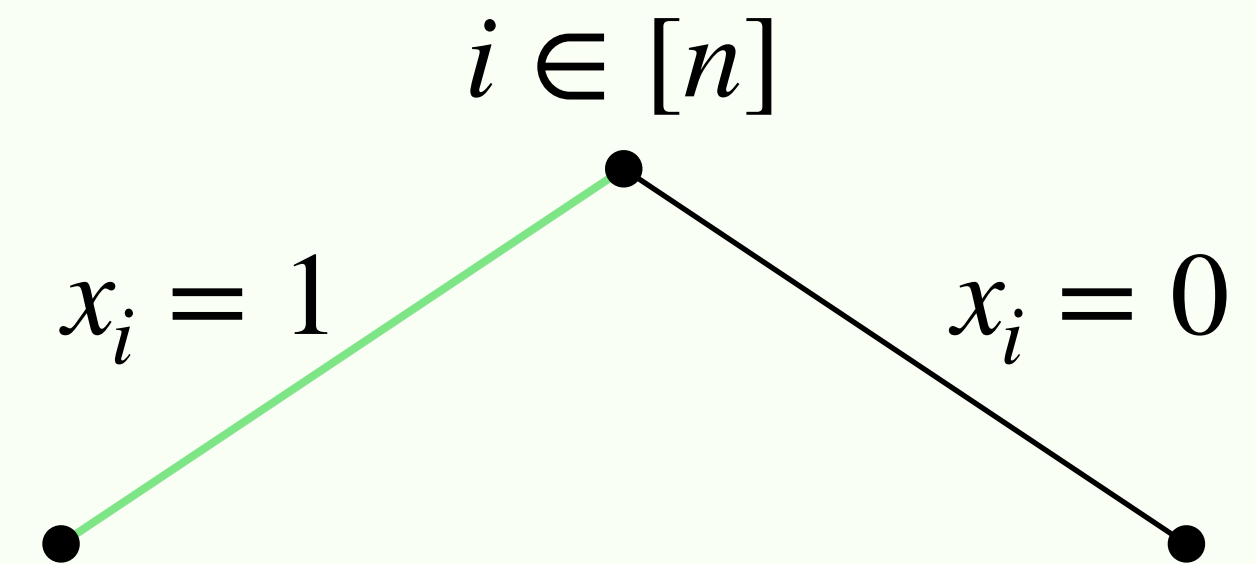
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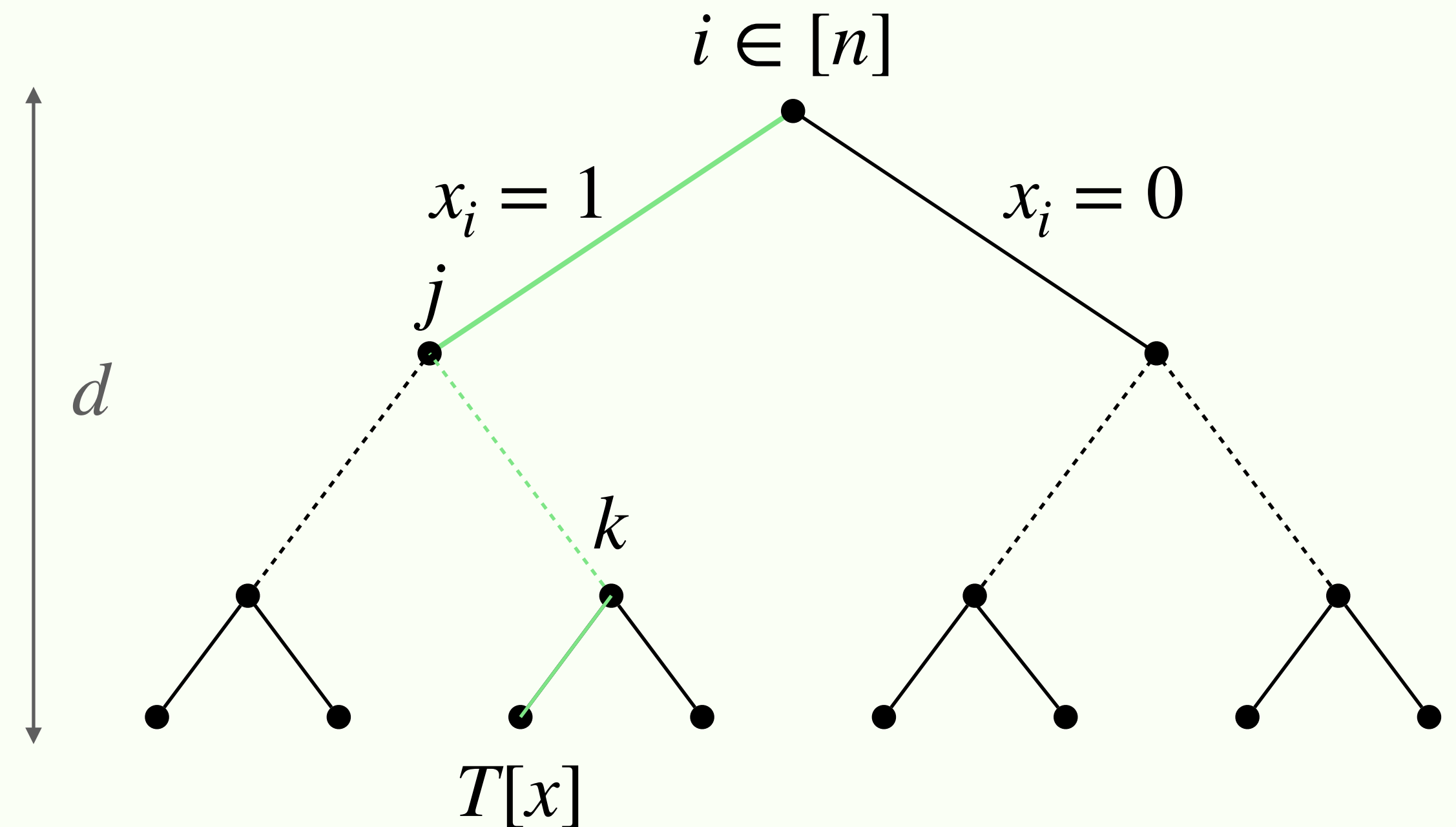
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- * output $T[x] = f(x)$

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Randomized decision tree

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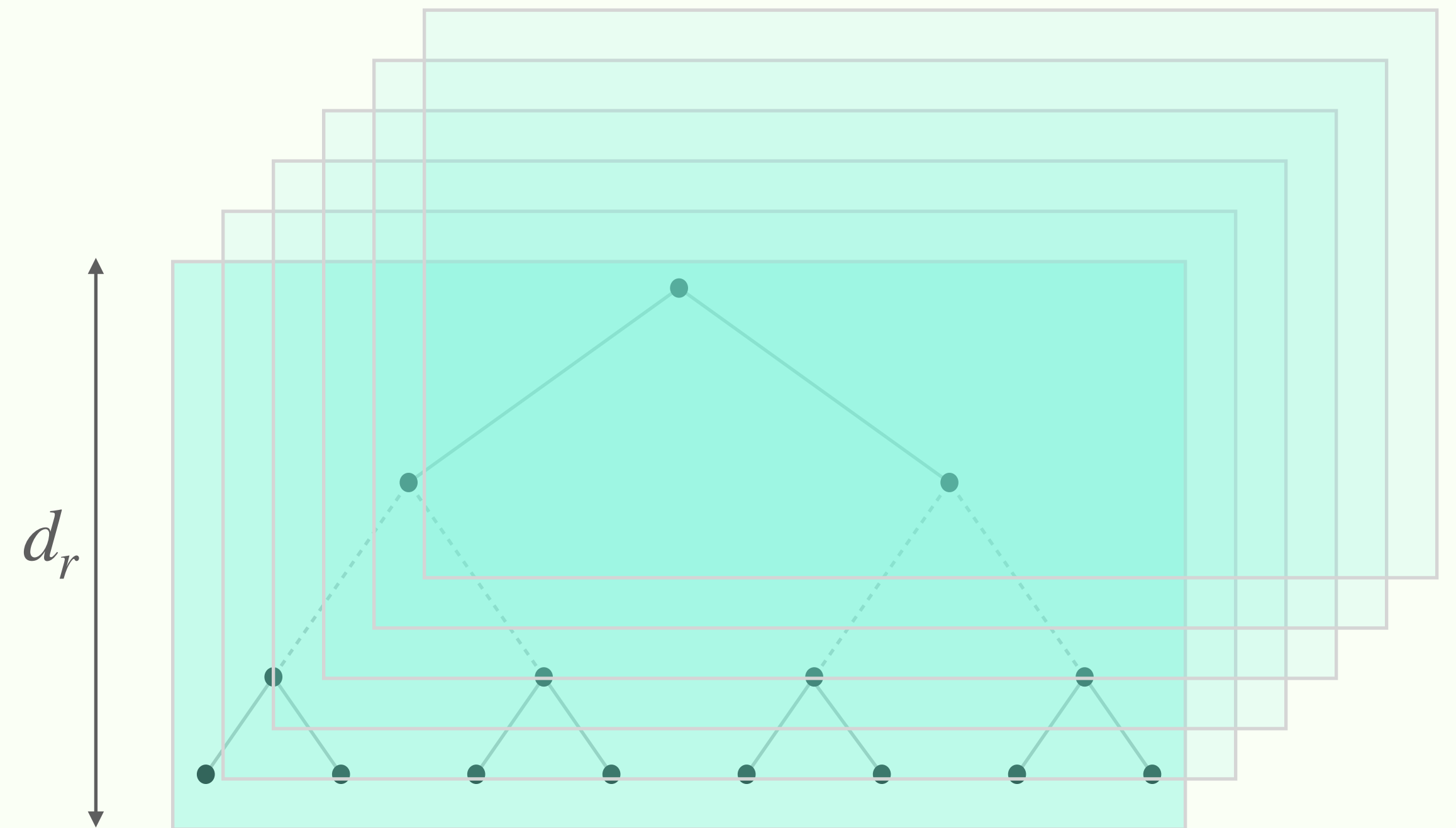
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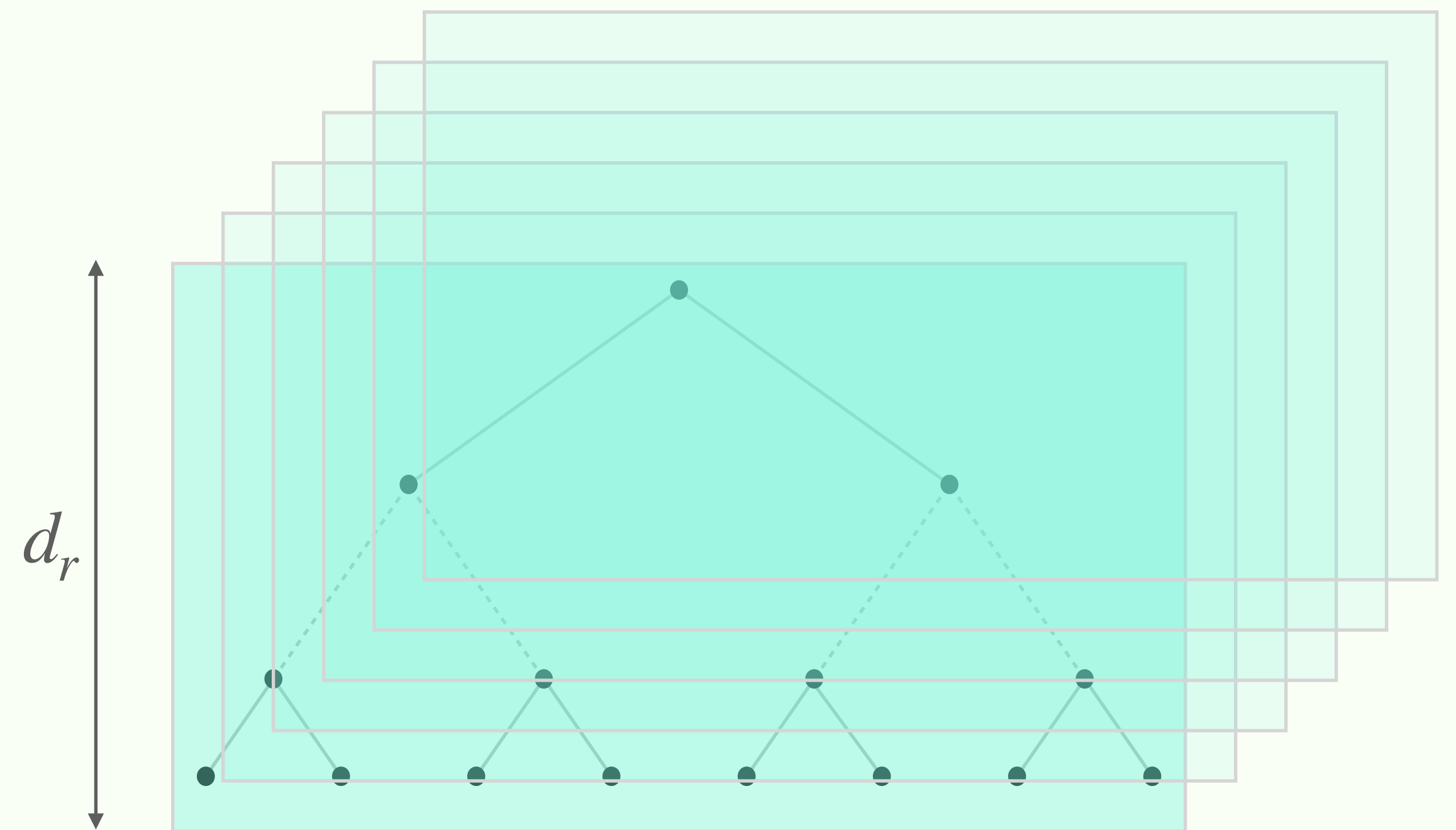
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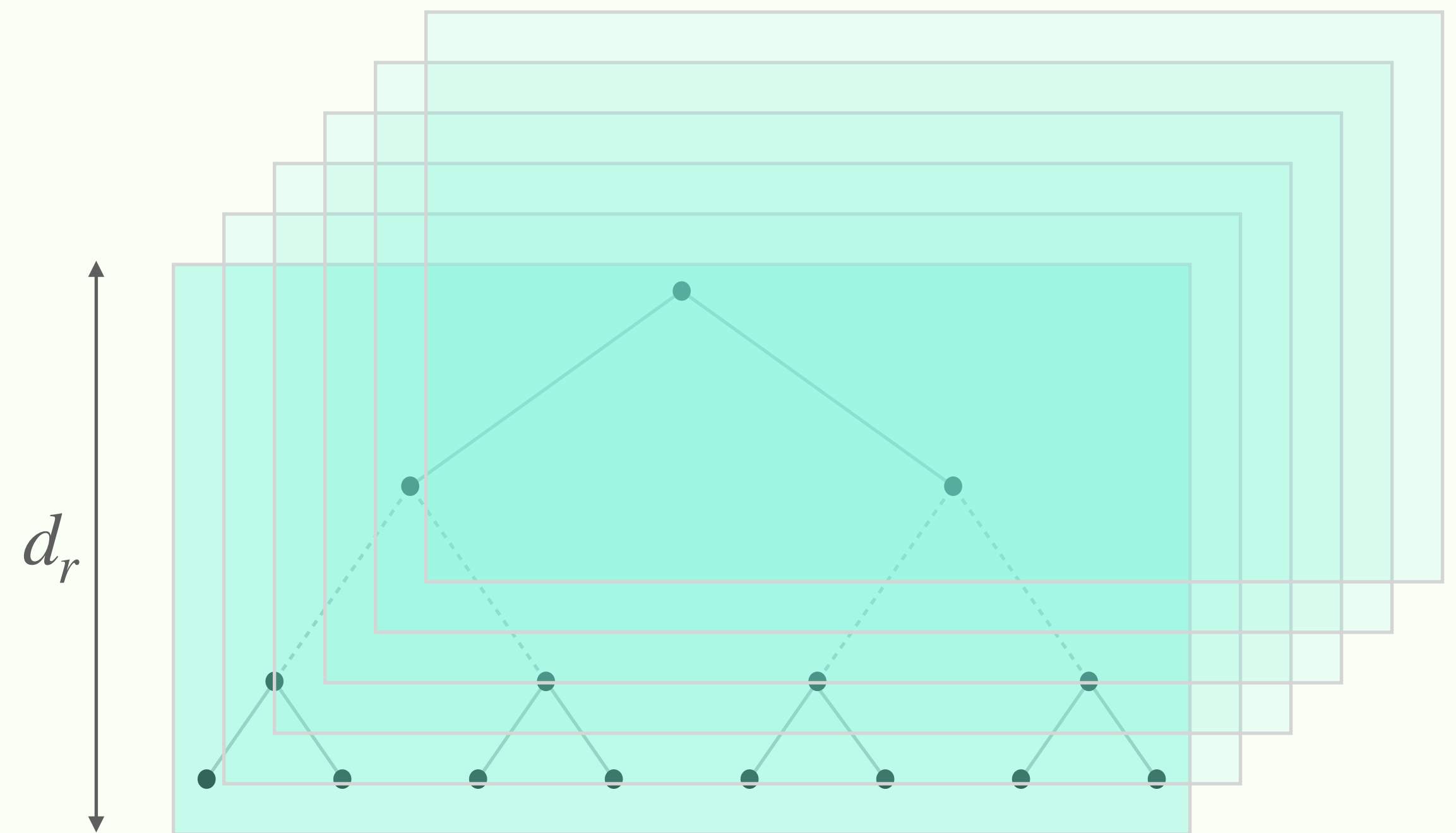
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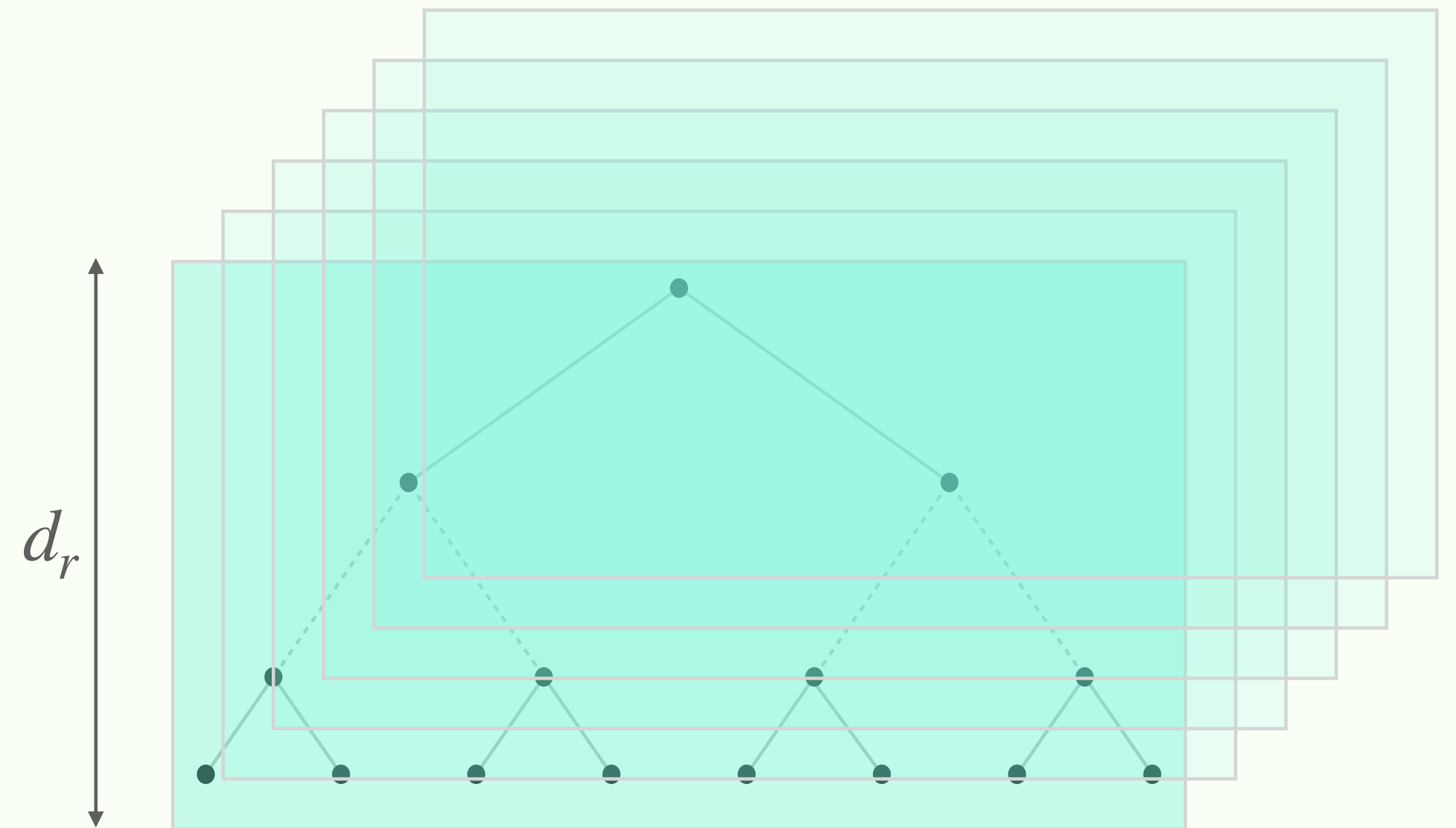
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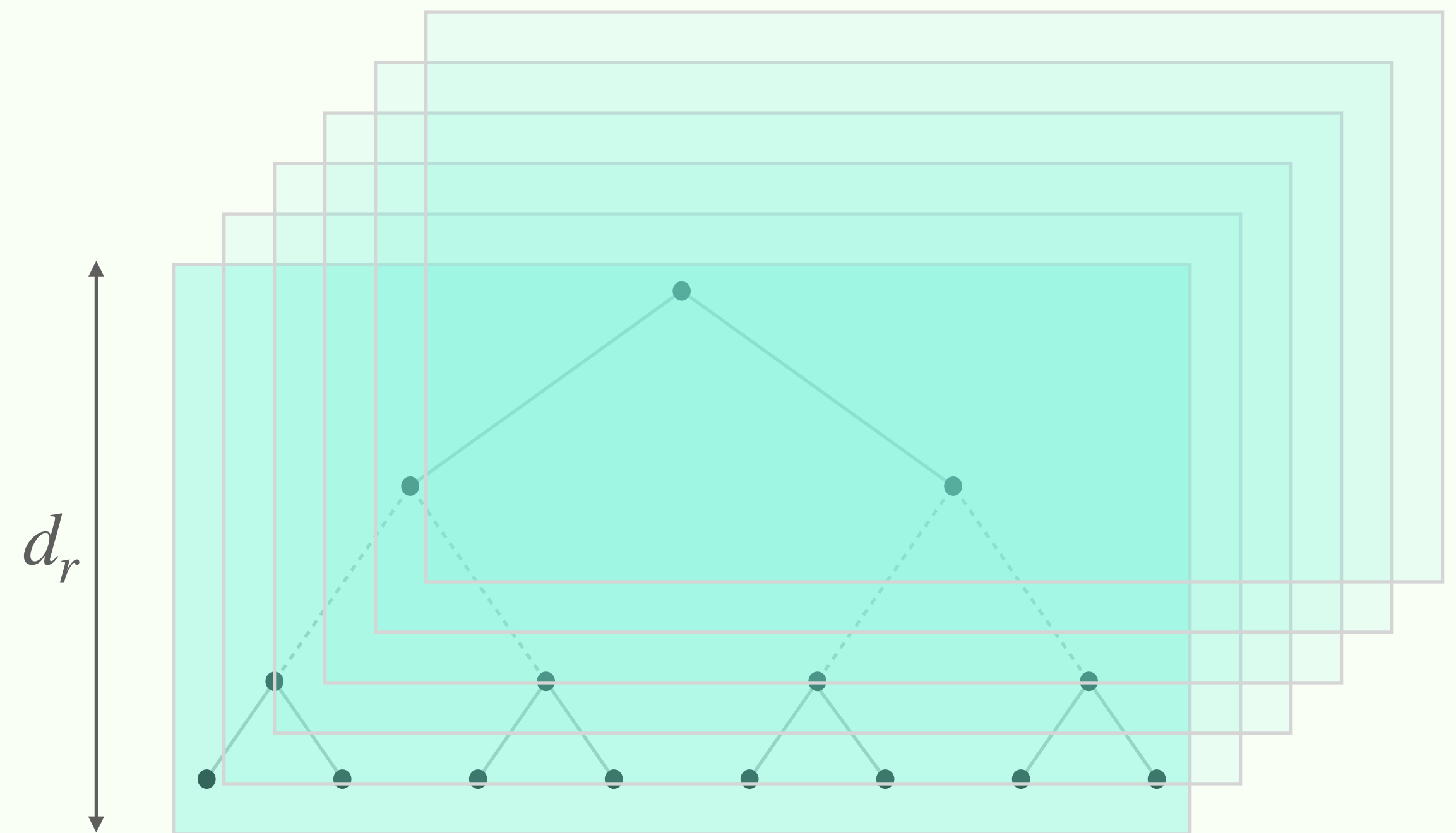
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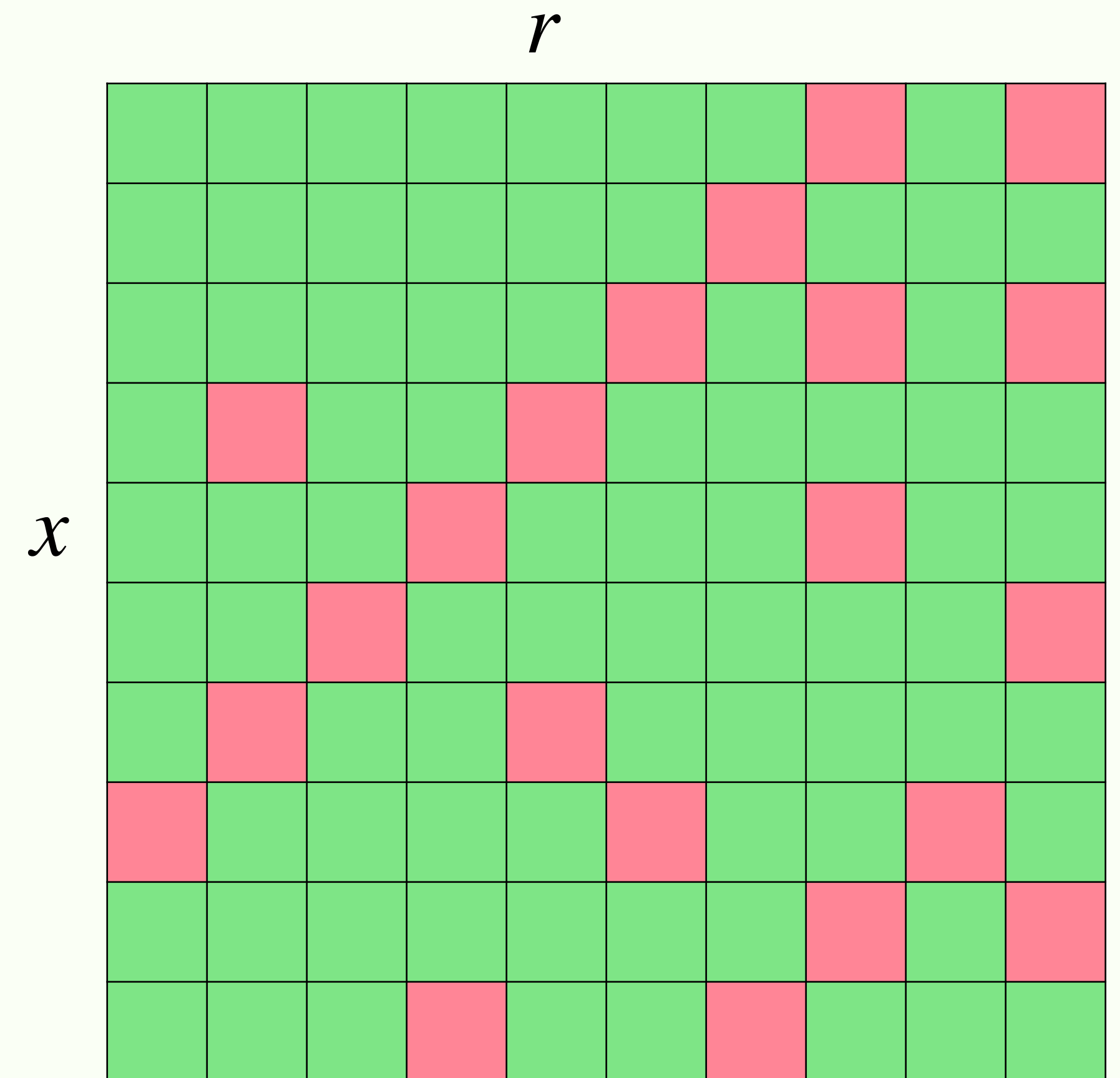
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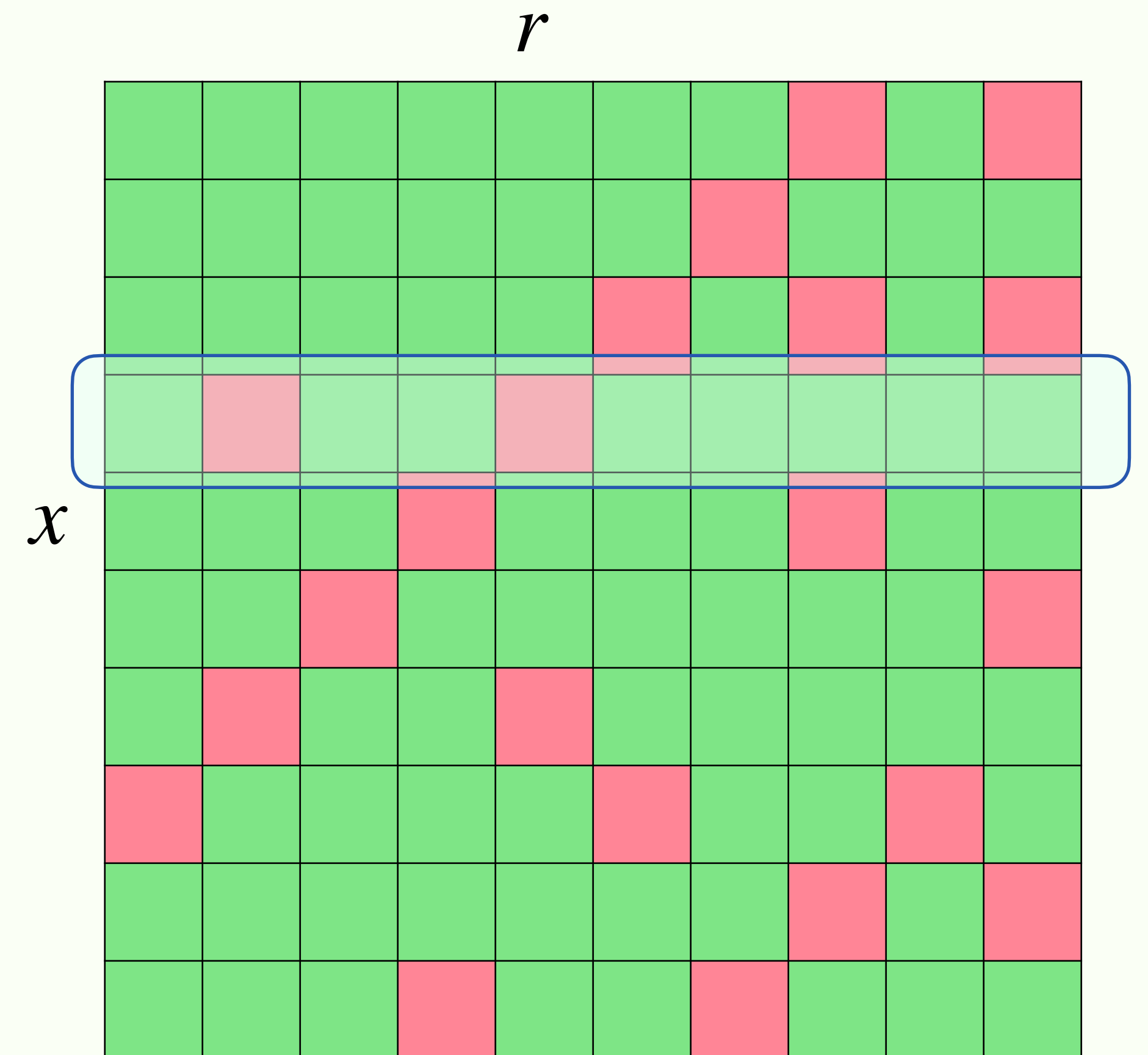


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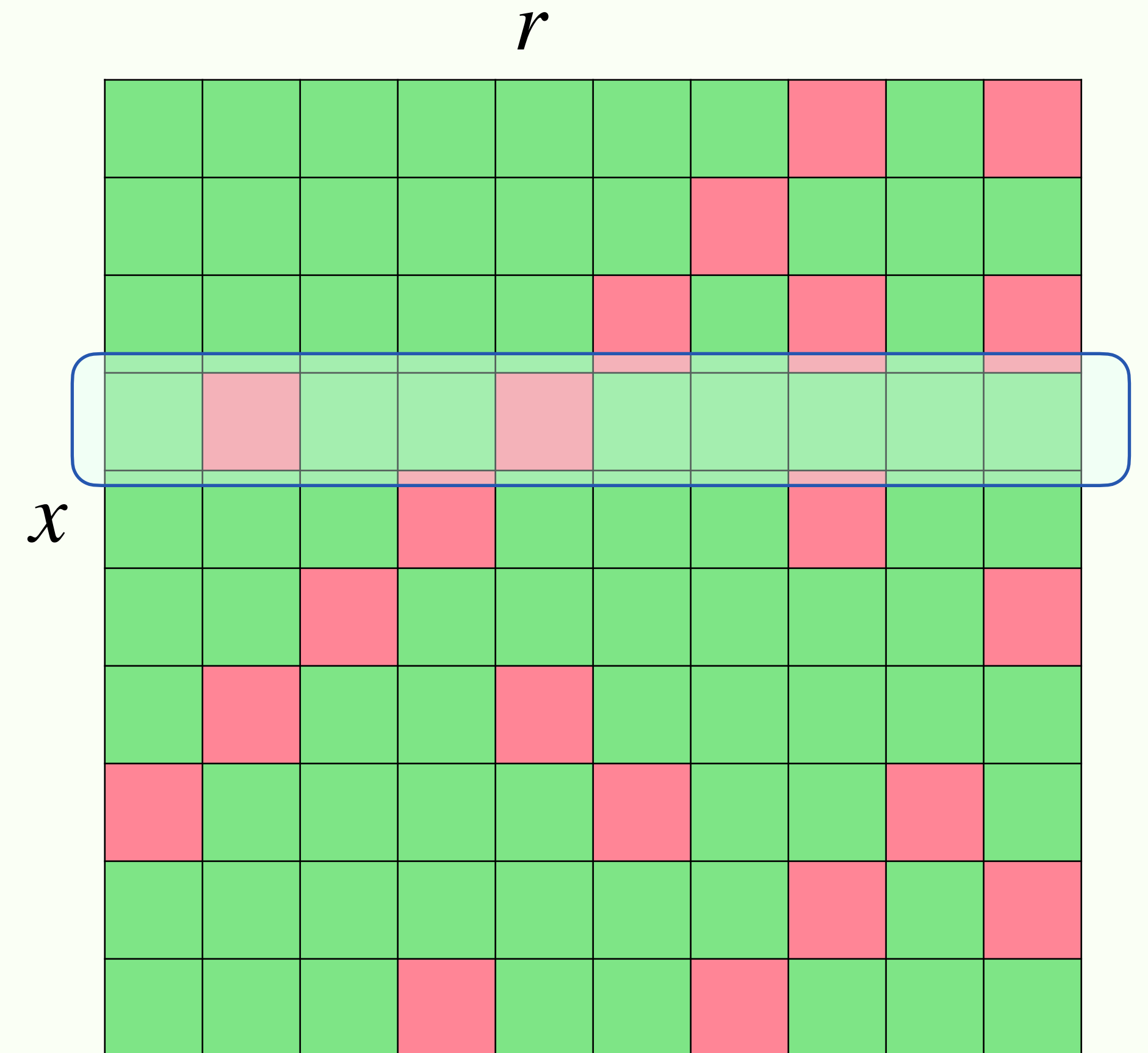


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-
- ❖ Error amplification to $\epsilon = 1/\text{quasipoly}(n)$

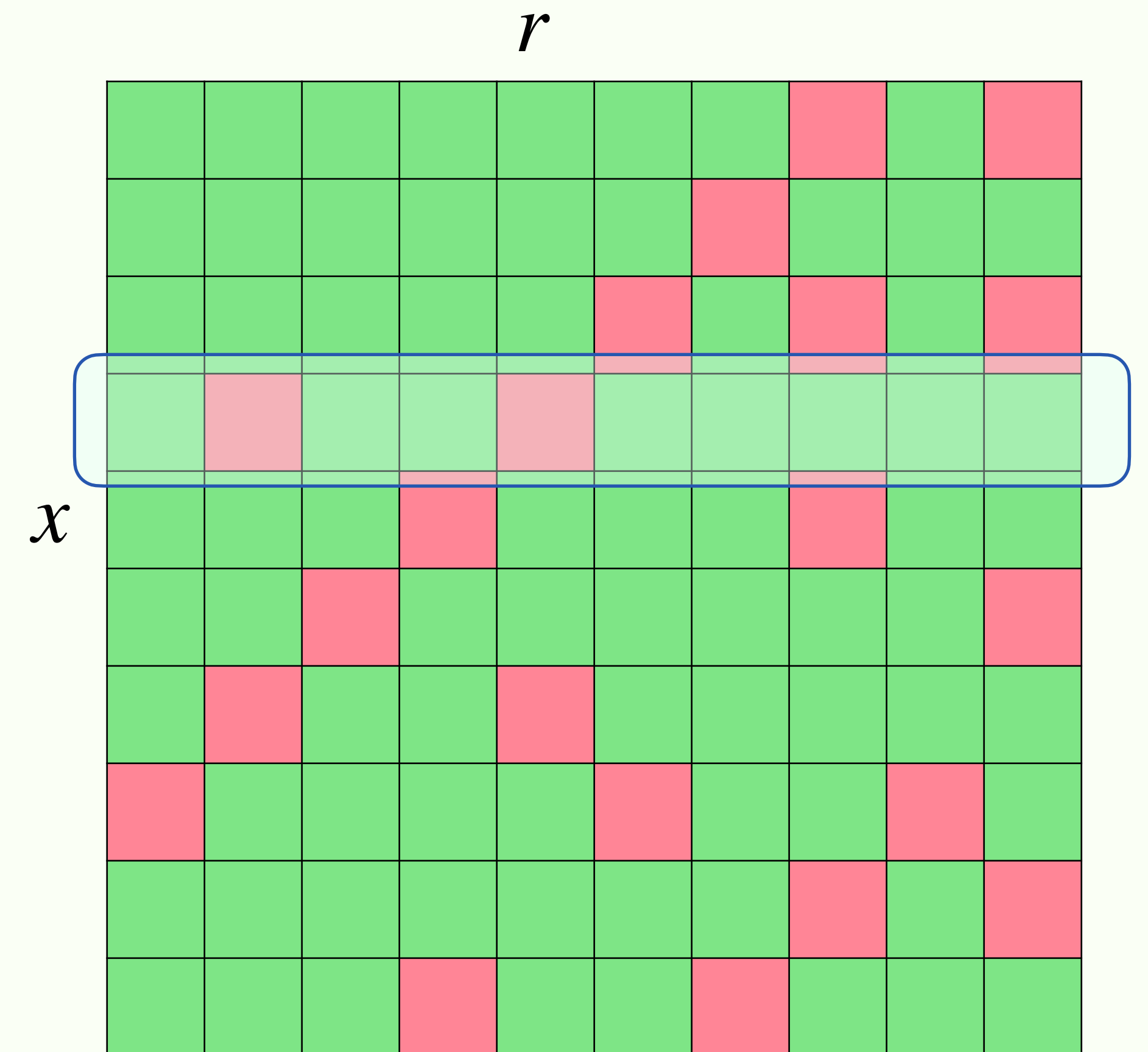


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- ❖ Error amplification to $\epsilon = 1/\text{quasipoly}(n)$
 - ❖ indistinguishable from deterministic algorithm



Computational distinguishability from deterministic algorithms

Computational distinguishability from deterministic algorithms

Algorithm

$$\mathcal{T} = \{T_r\}$$



r

x

1	1	1	1	1	0	1	0	1	
0	0	1	0	0	0	0	0	0	1

Computational distinguishability from deterministic algorithms



Adversary

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Computational distinguishability from deterministic algorithms



Adversary

Algorithm
 $\mathcal{T} = \{T_r\}$



Goal: distinguish $\mathcal{T}$ from a deterministic algorithm

r

x

1	1	1	1	1	0	1	0	1	
0	0	1	0	0	0	0	0	0	1

Computational distinguishability from deterministic algorithms



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x

r

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0	0	1	0	0	0	0	0	0	1

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Budget: $\text{polylog}(2^n) = \text{poly}(n)$ many queries

x

r

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What is $f(x_1)$?

r

1	1	1	1	1	0	1	0	1	
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x

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What is $f(x_2)$?

r

1	1	1	1	1	0	1	0	1	
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x

Computational distinguishability from deterministic algorithms



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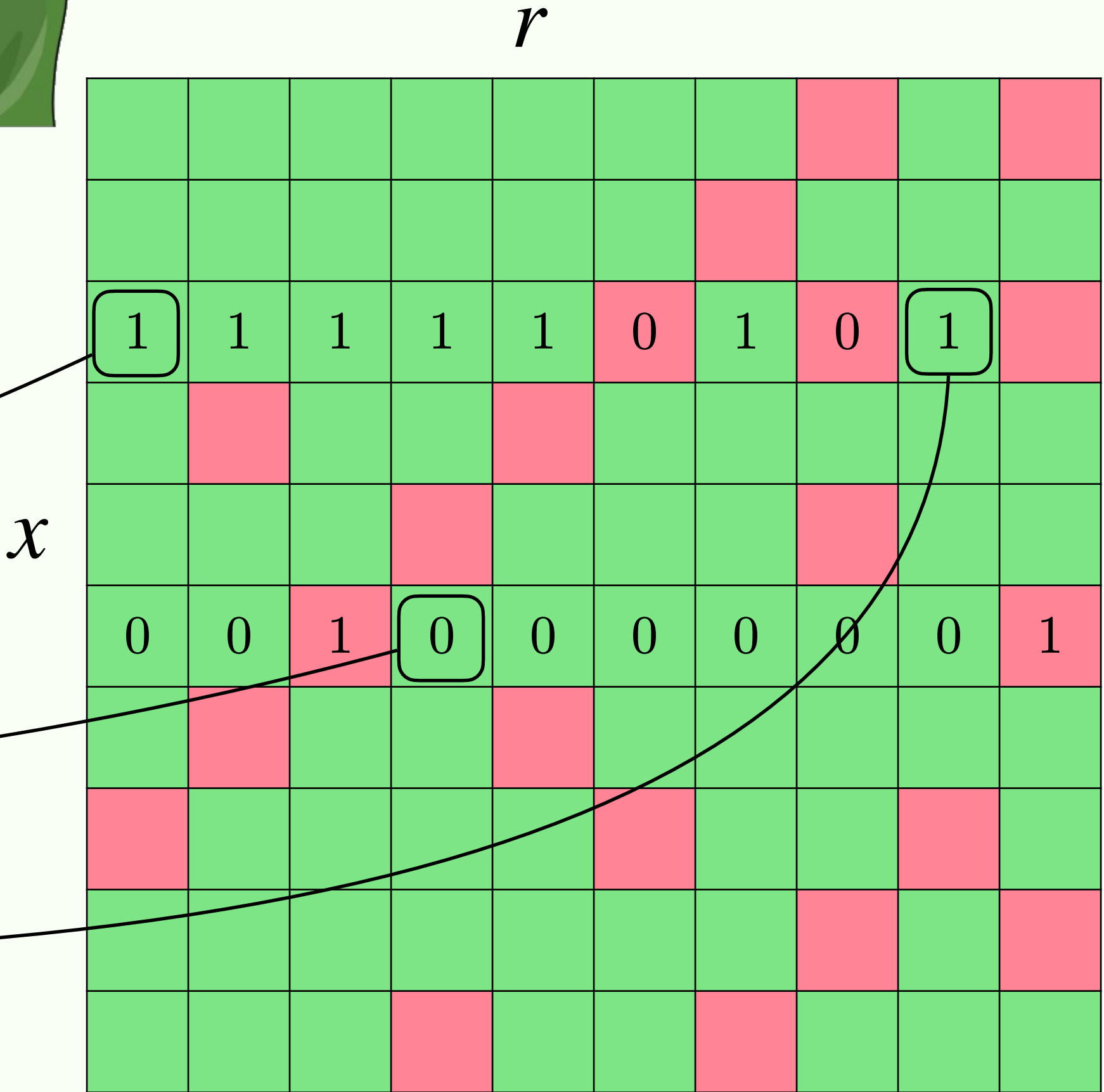


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What is $f(x_1)$?

Success: $\text{poly}(n) \times \frac{1}{\text{quasipoly}(n)} \ll 1$

r

1	1	1	1	1	0	1	0	1	
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x

Motivation

Search problems and why randomness could be different for them

Algorithms for search problems

Algorithms for search problems

Goal: compute **search** problem $S \subset \{0,1\}^* \times \Gamma$ $(y \in S(x) \iff (x, y) \in S)$

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Randomized tree $\mathcal{T} = \{T_r : r \sim R\}$:

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- * $\text{FBPP}^{\text{dt}} = \{S : \exists \text{ efficient } \mathcal{T} \text{ computing } S\}$

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r

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- * ~~Error amplification~~

$$(y \in S(x)) \iff (x, y) \in S$$

r

x

							X		
						X			
					X				X
	X			X					
			X				X		
		X							
				X					
X					X				
							X		X
						X			

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$$(y \in S(x) \iff (x, y) \in S)$$

r

x

							X		
						X			
					X				X
	X			X					
			X				X		
		X							
				X					
X					X				
							X		X
						X			

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$$(y \in S(x) \iff (x, y) \in S)$$

r

x

							X		
						X			
					X				X
	X			X					
			X				X		
		X							
				X					
X					X				
							X		X
						X			

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$$(y \in S(x) \iff (x, y) \in S)$$

r

x

							X		
						X			
					X				X
	X			X					
			X				X		
		X							
				X					
X					X				
							X		X
						X			

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r

x

							X		
						X			
					X				X
	X			X					
			X				X		
		X							
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X					X				
							X		X
						X			

Problem: not necessarily consistent answers
(different outputs for the same input)

Algorithms for search problems

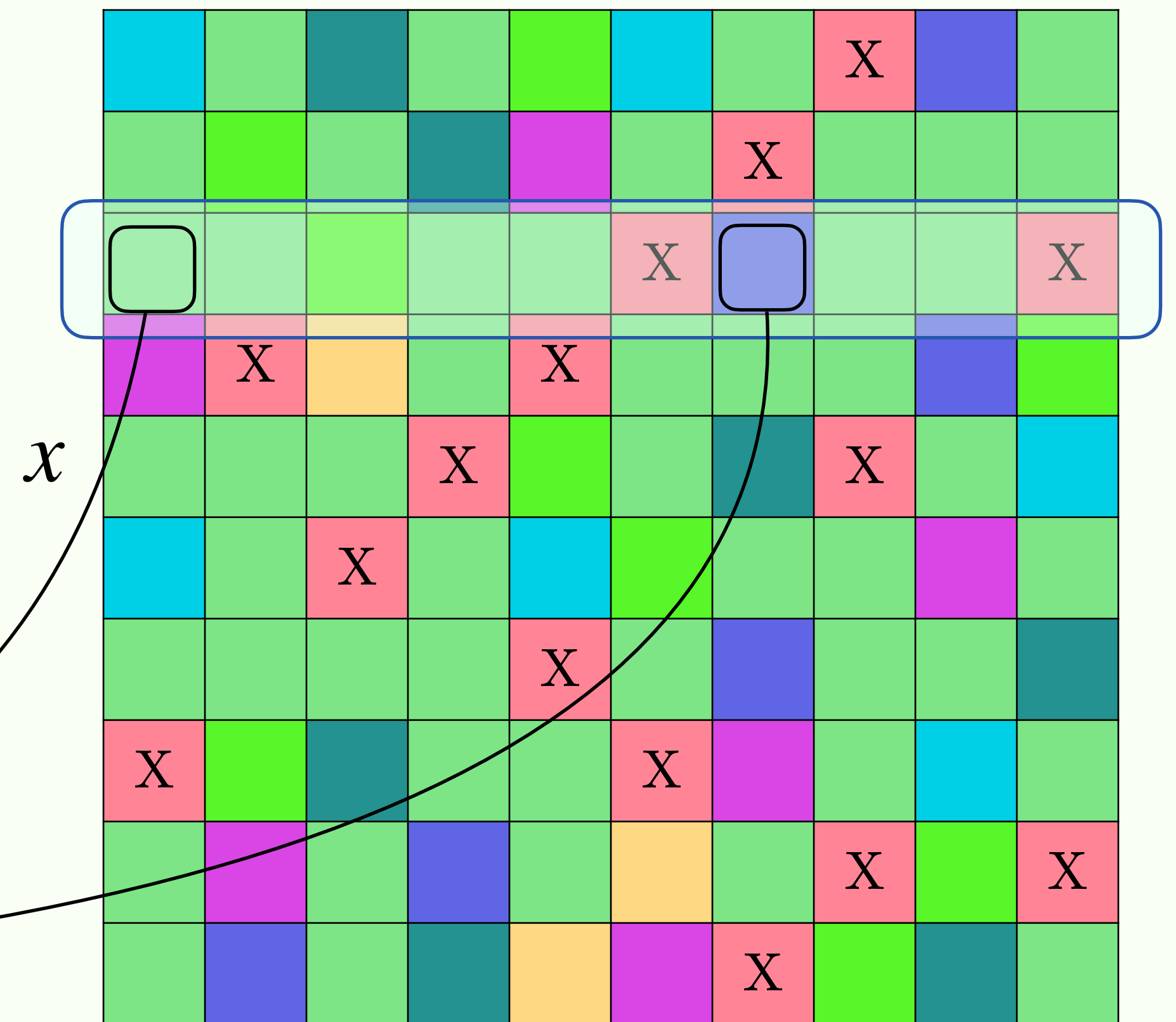
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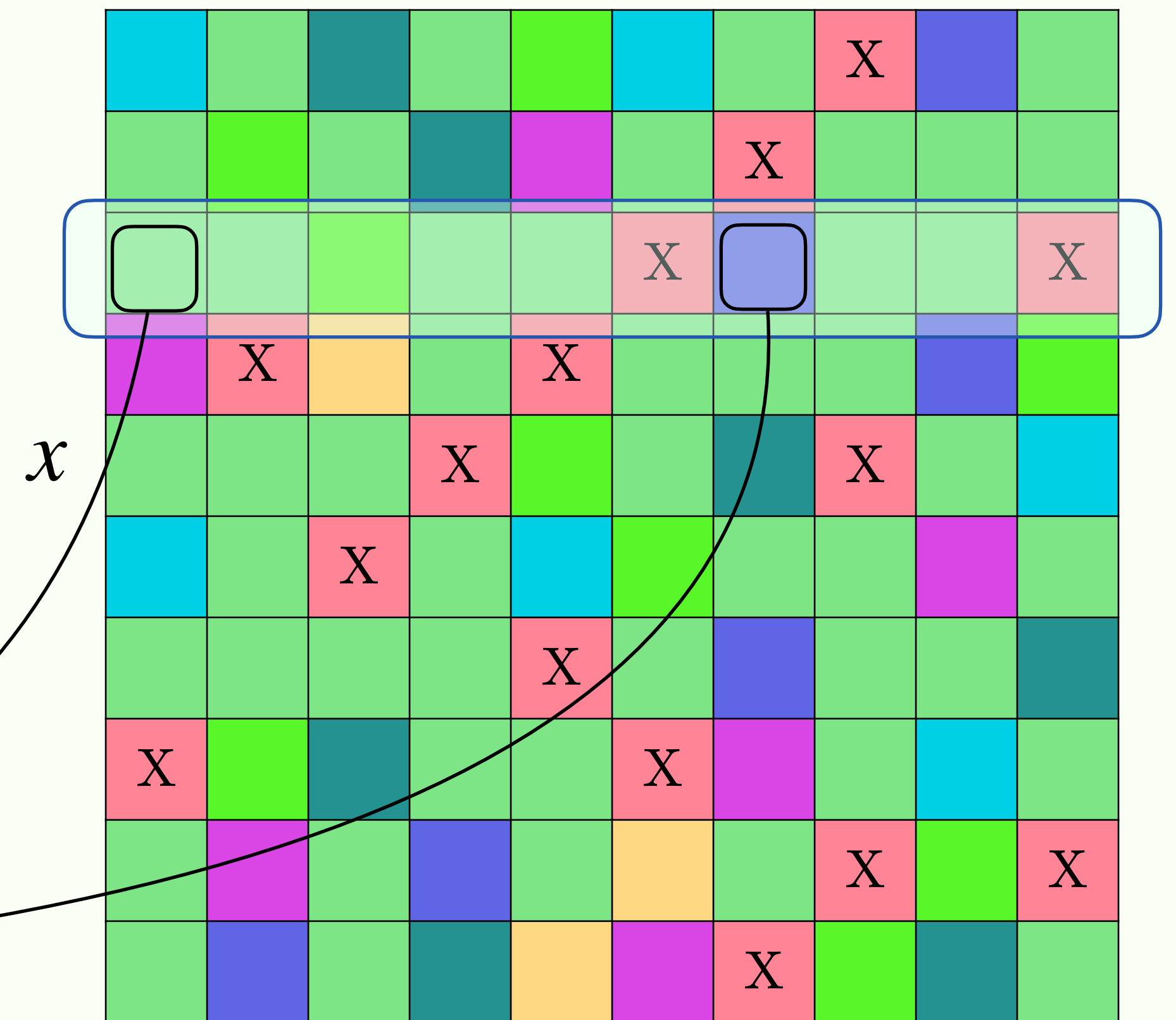
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Pseudo-deterministic algorithm?

Pseudo-deterministic algorithms for search problems [GG11]

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Pseudo-deterministic algorithm:

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Pseudo-deterministic algorithm:

✦ $\mathcal{T} = \{T_r : r \sim R\}$

✦ input $x \in \{0,1\}^n$, seed r , output $T_r[x]$

Pseudo-deterministic algorithms for search problems [GG11]

❖ **Goal:** compute **search** problem $S \subset \{0,1\}^* \times \Gamma$

Pseudo-deterministic algorithm:

- ❖ $\mathcal{T} = \{T_r : r \sim R\}$
- ❖ input $x \in \{0,1\}^n$, seed r , output $T_r[x]$
- ❖ Correctness: there exists a canonical $y_x \in S(x)$ such that $\Pr_r[T_r[x] = y_x] \geq 2/3$

Pseudo-deterministic algorithms for search problems [GG11]

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r

x

							X		
						X			
					X				X
	X			X					
			X				X		
		X							
				X					
X					X				
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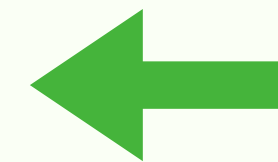
r

x

							X		
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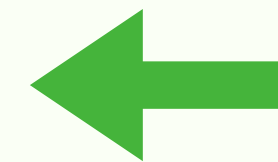
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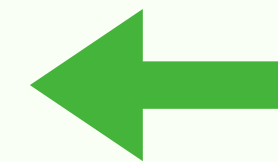
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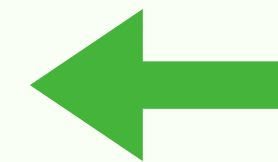
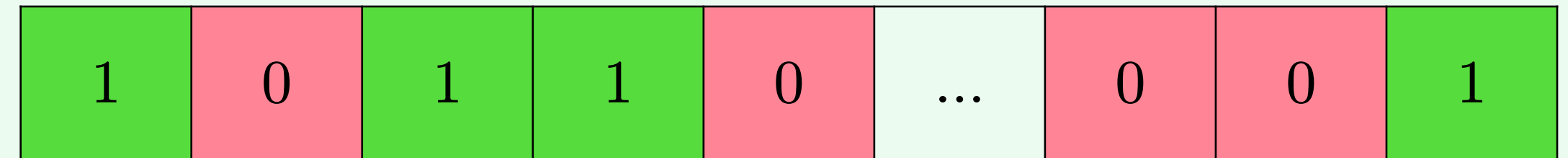


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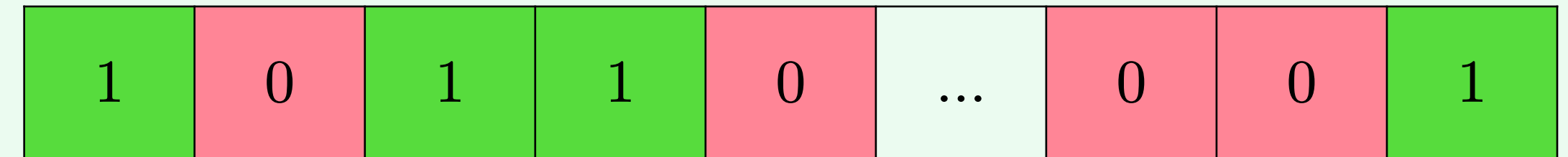


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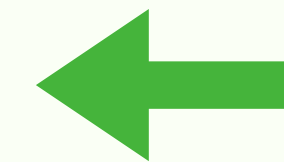
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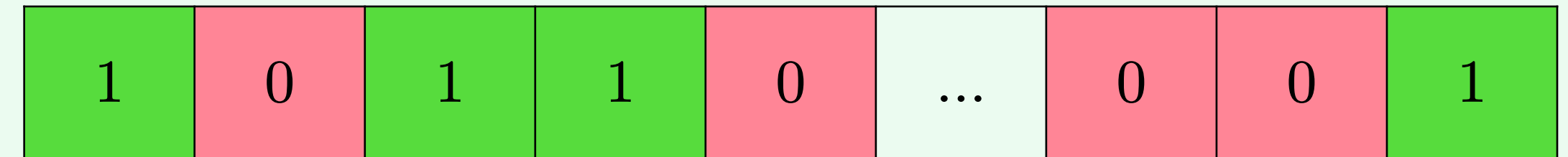


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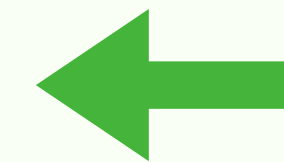
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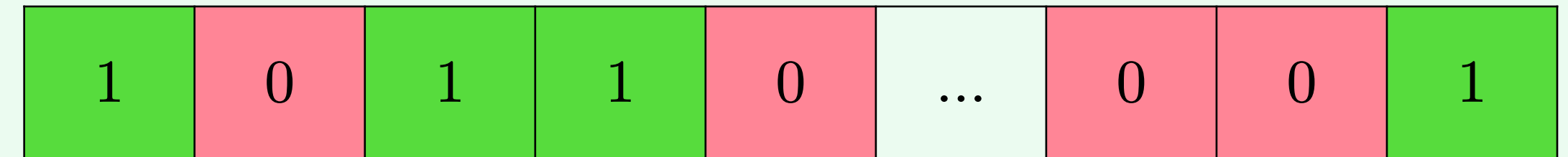


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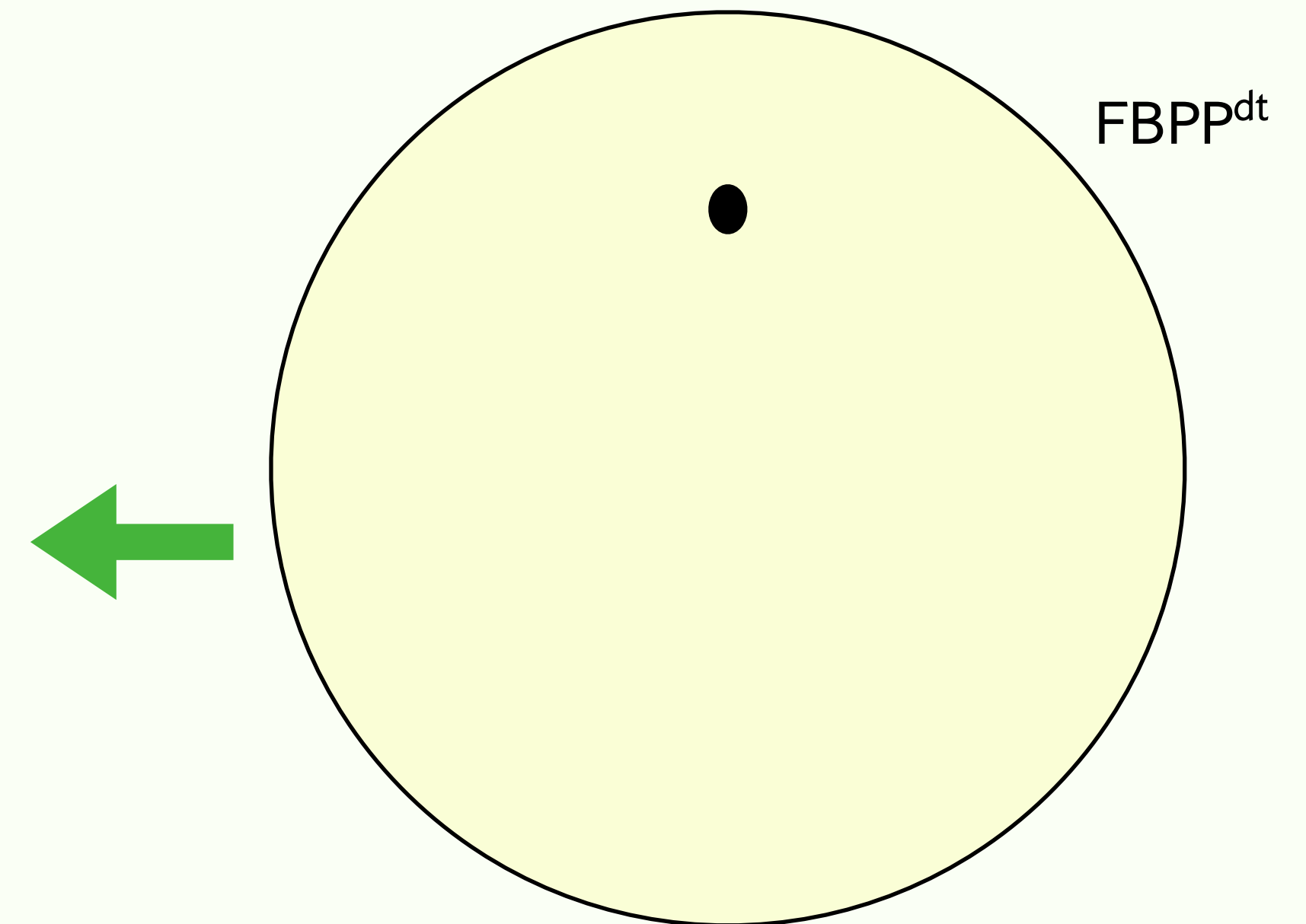
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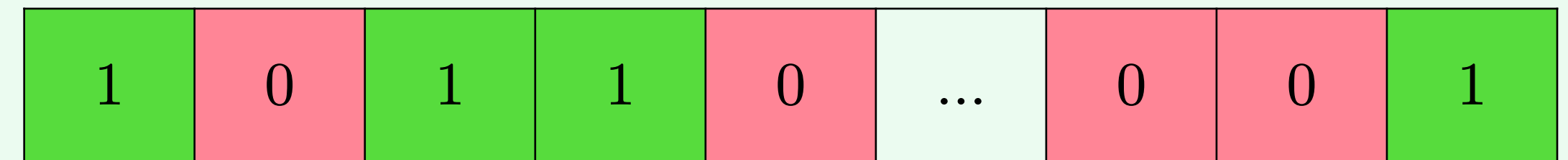


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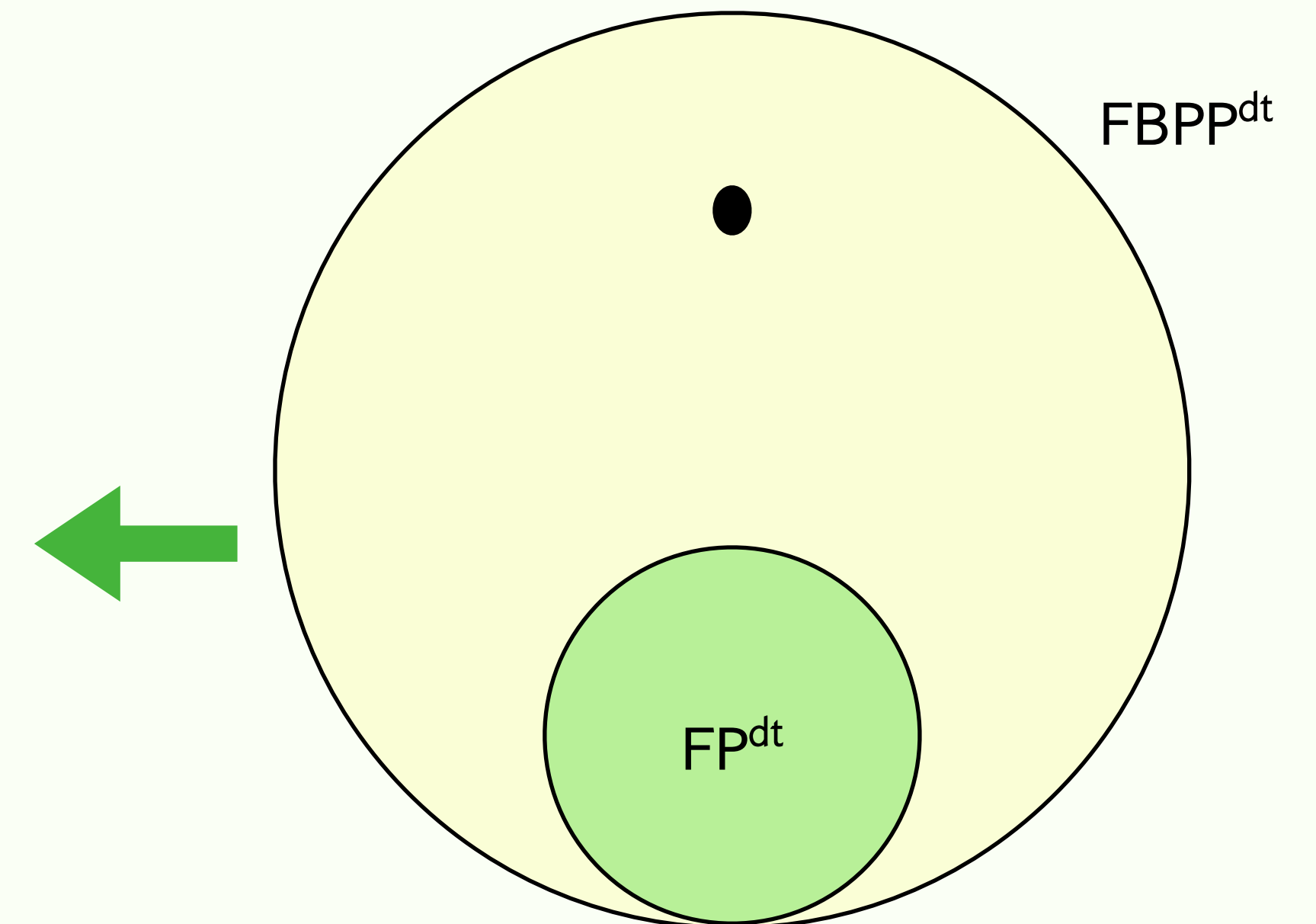
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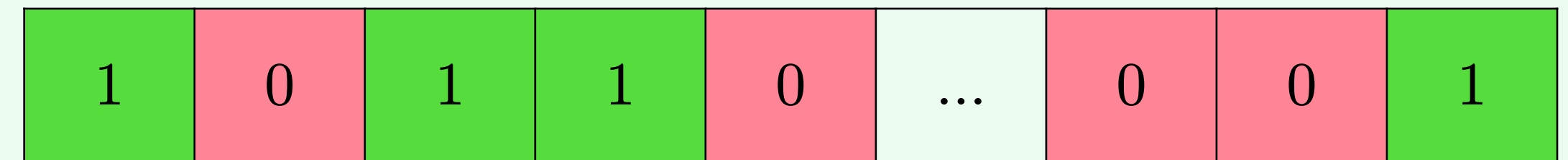


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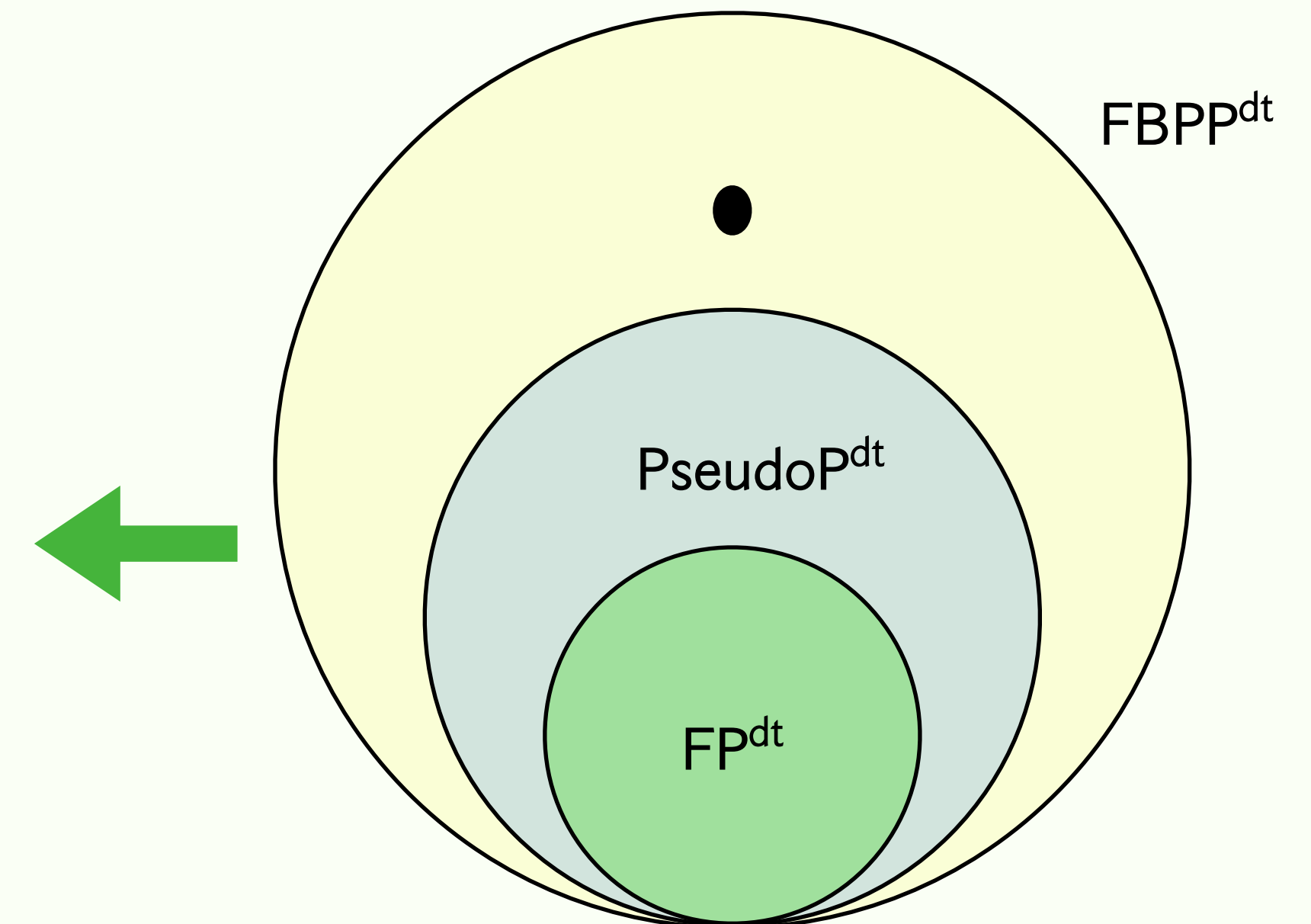
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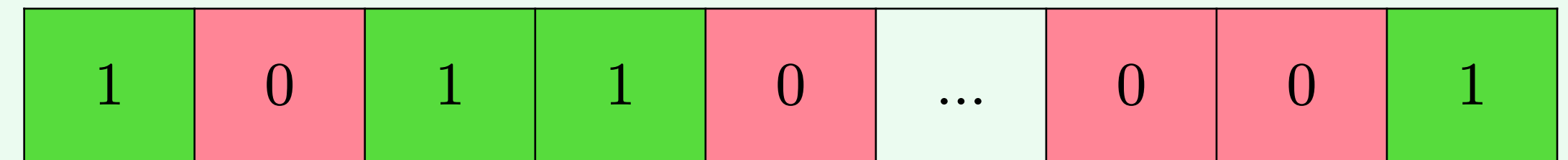


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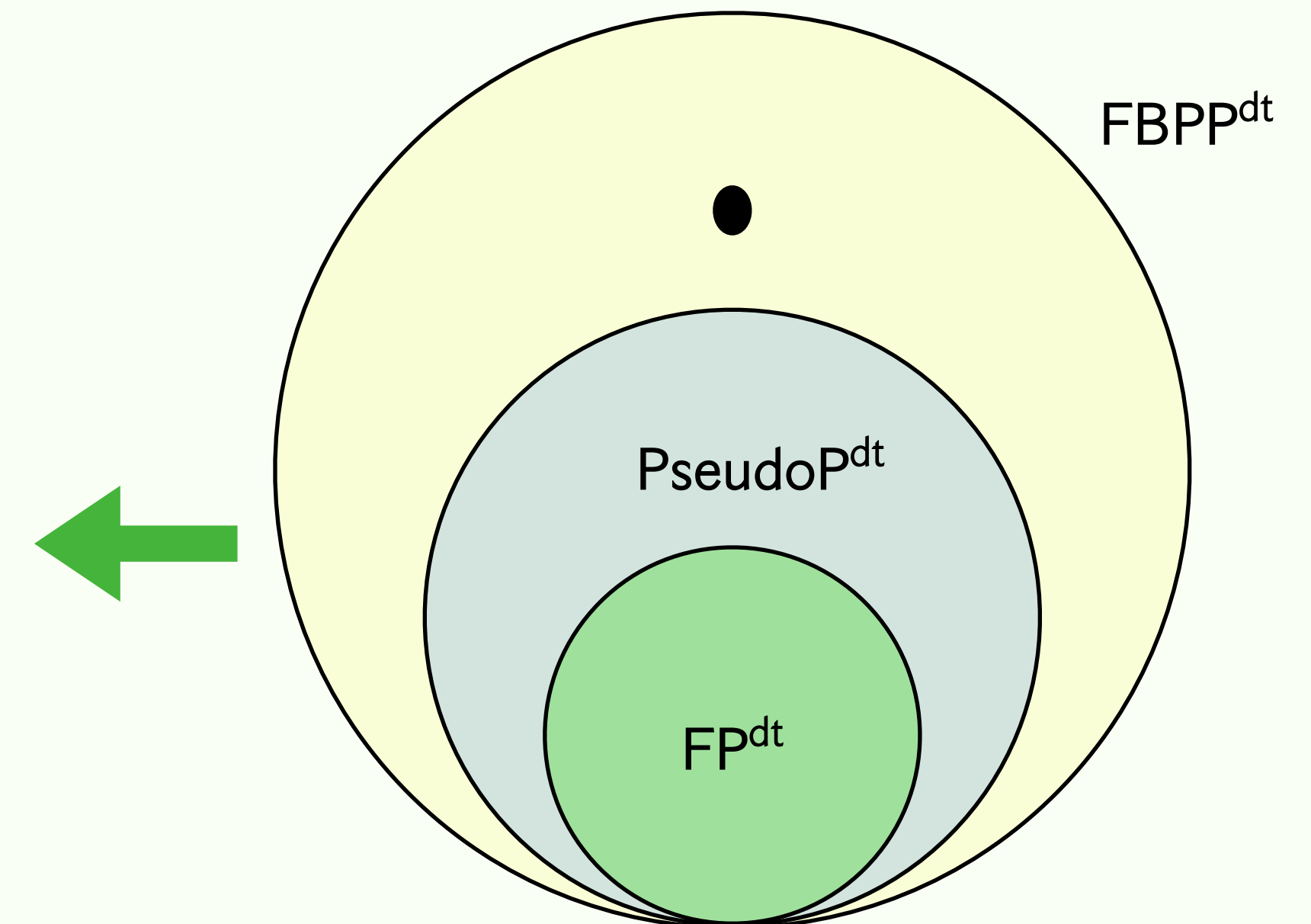
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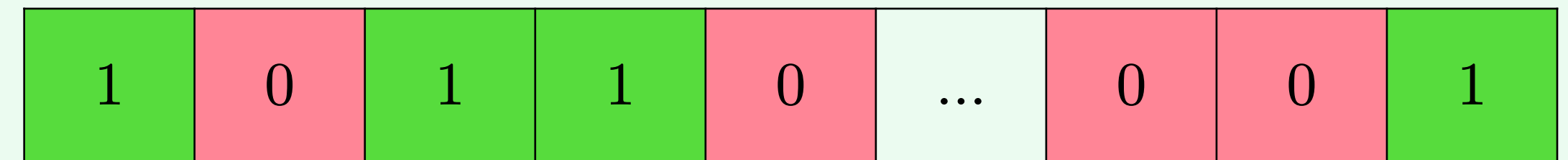


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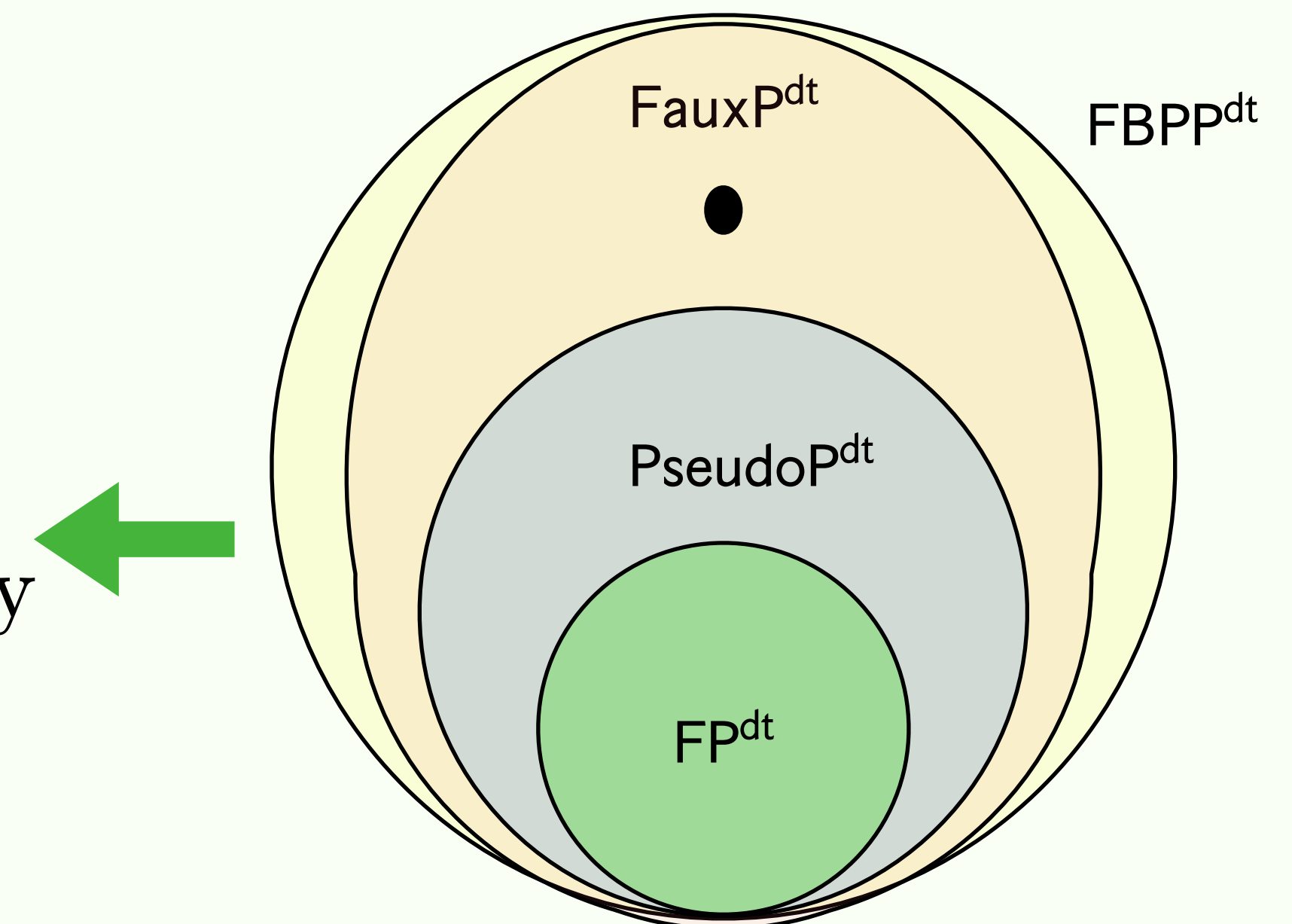
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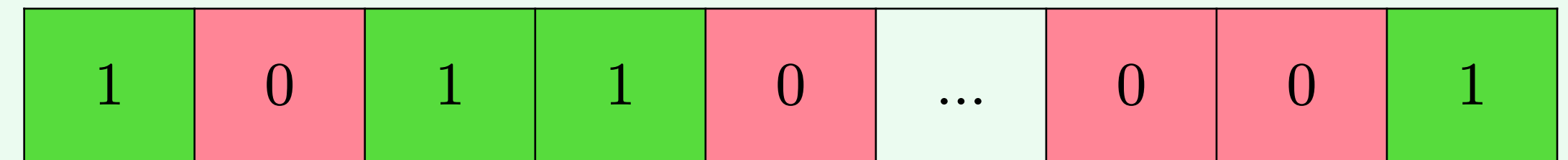


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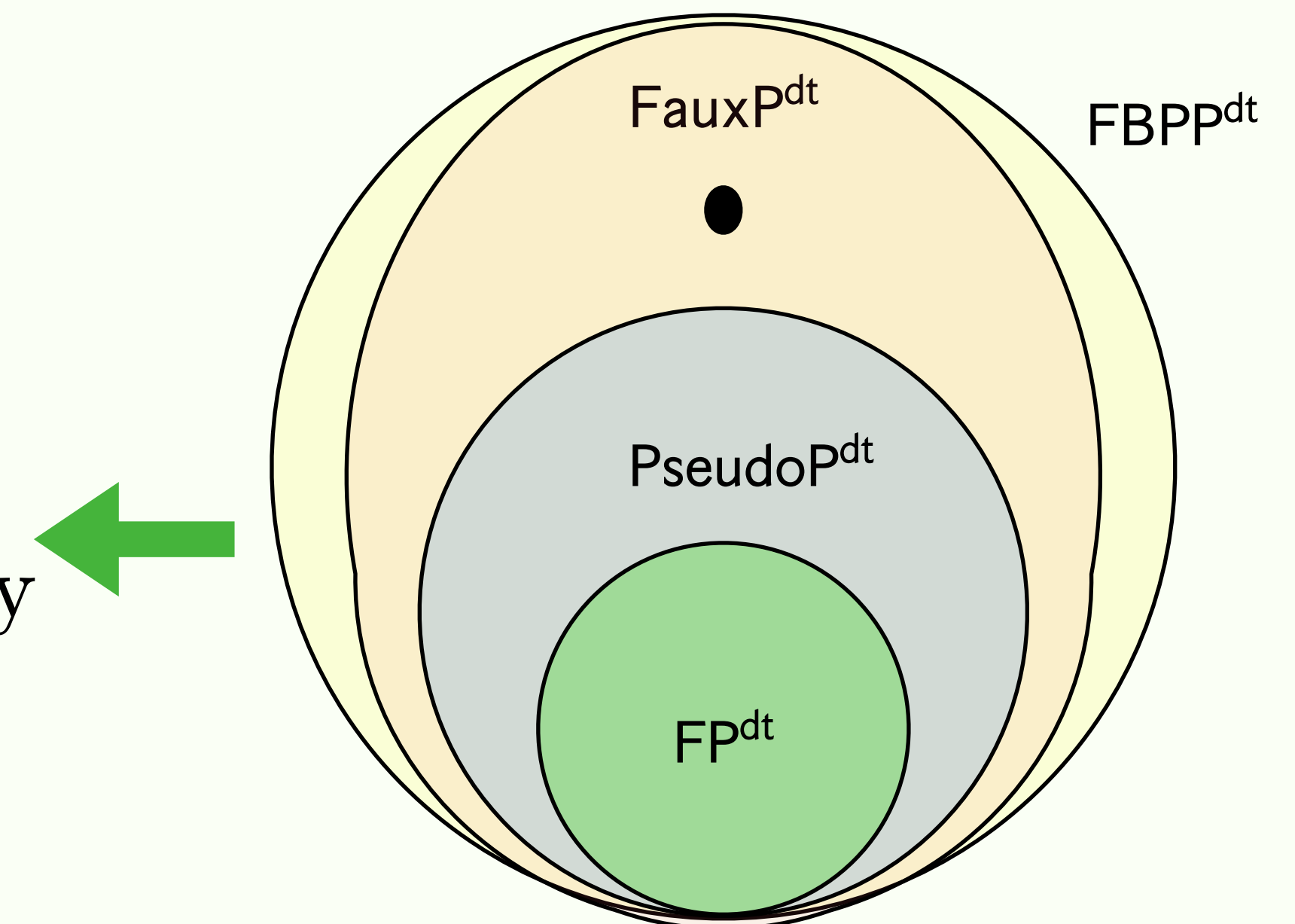
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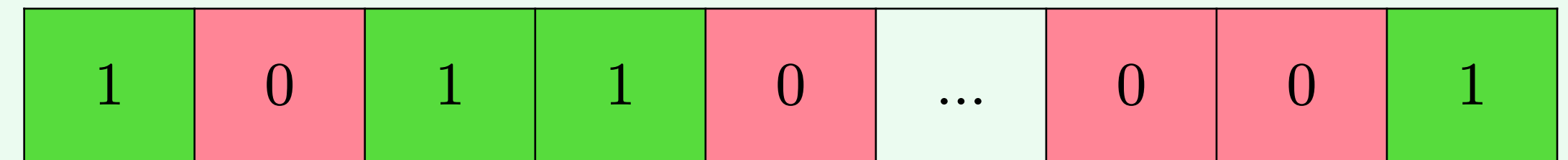


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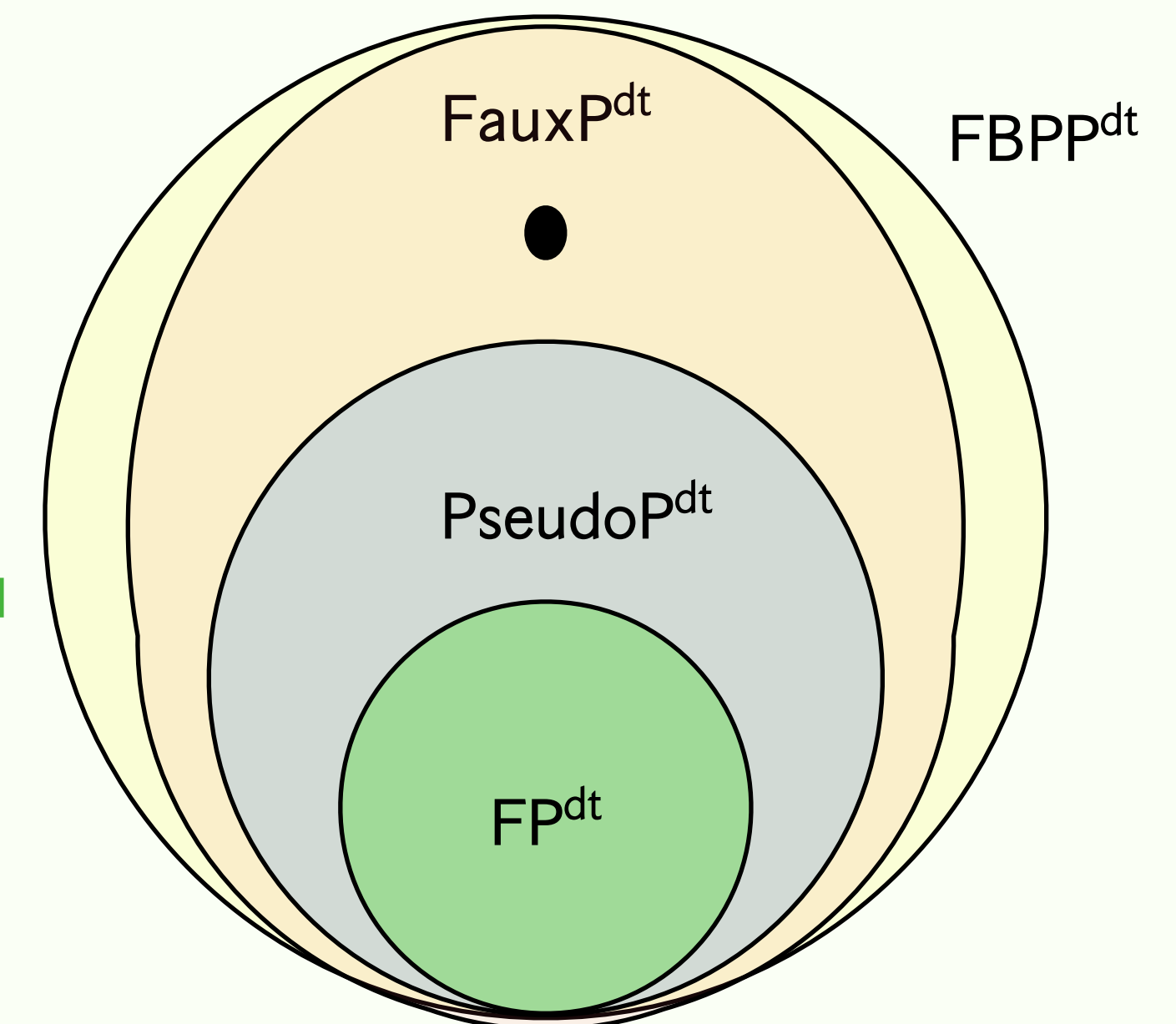
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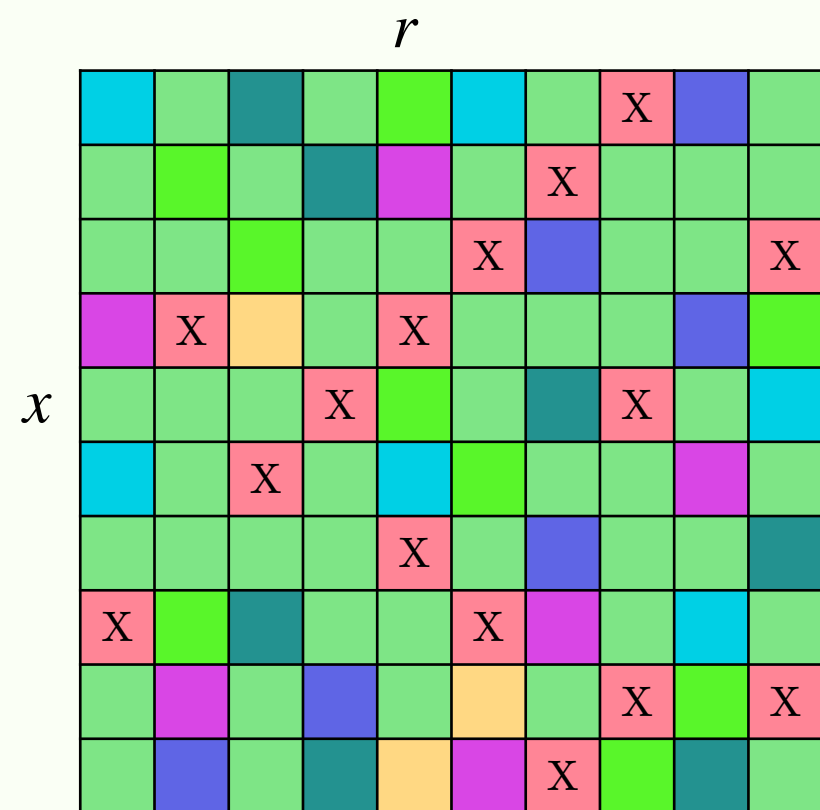
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Defining faux deterministic algorithms

Faux-deterministic algorithms for search problems

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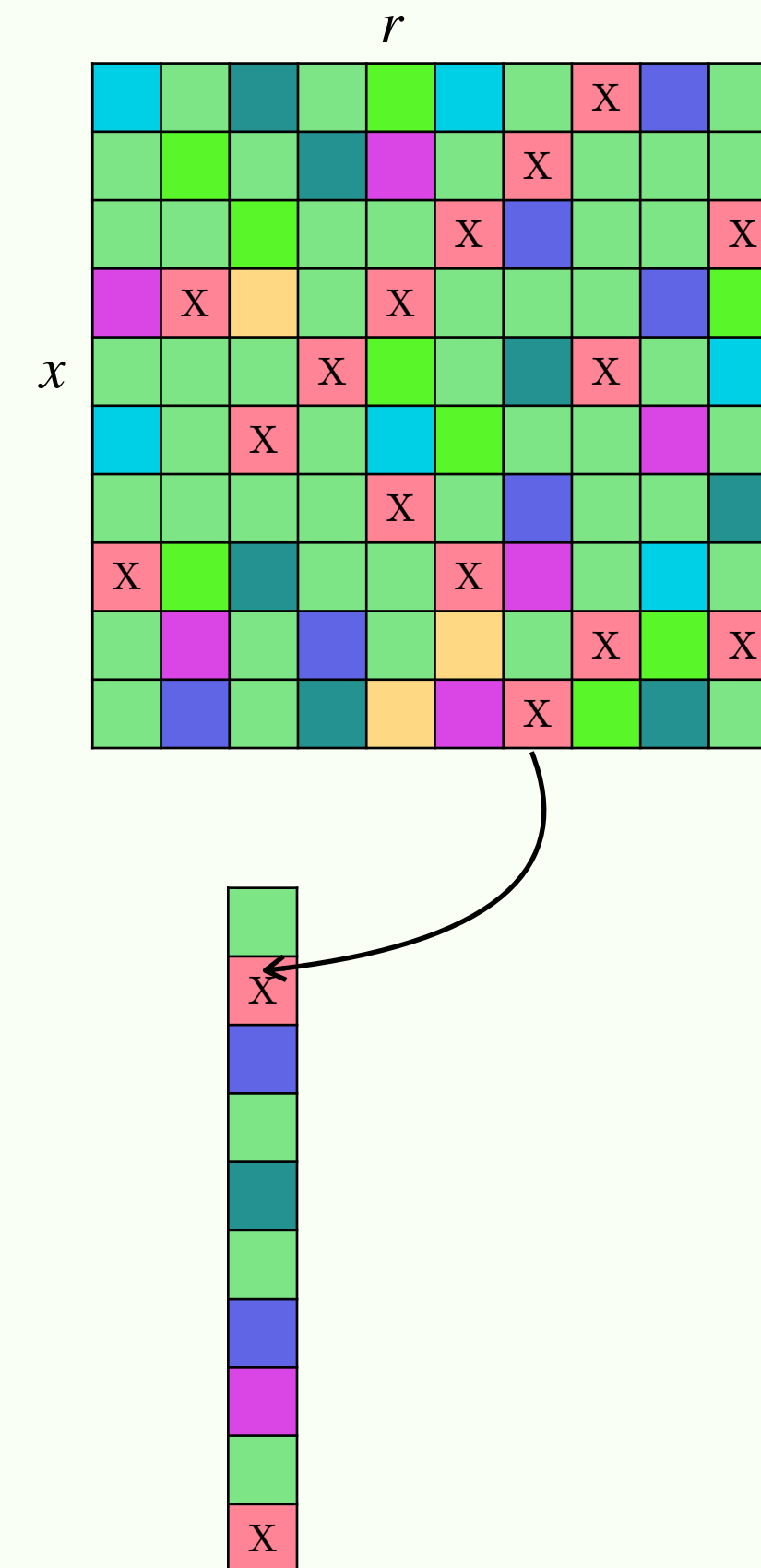
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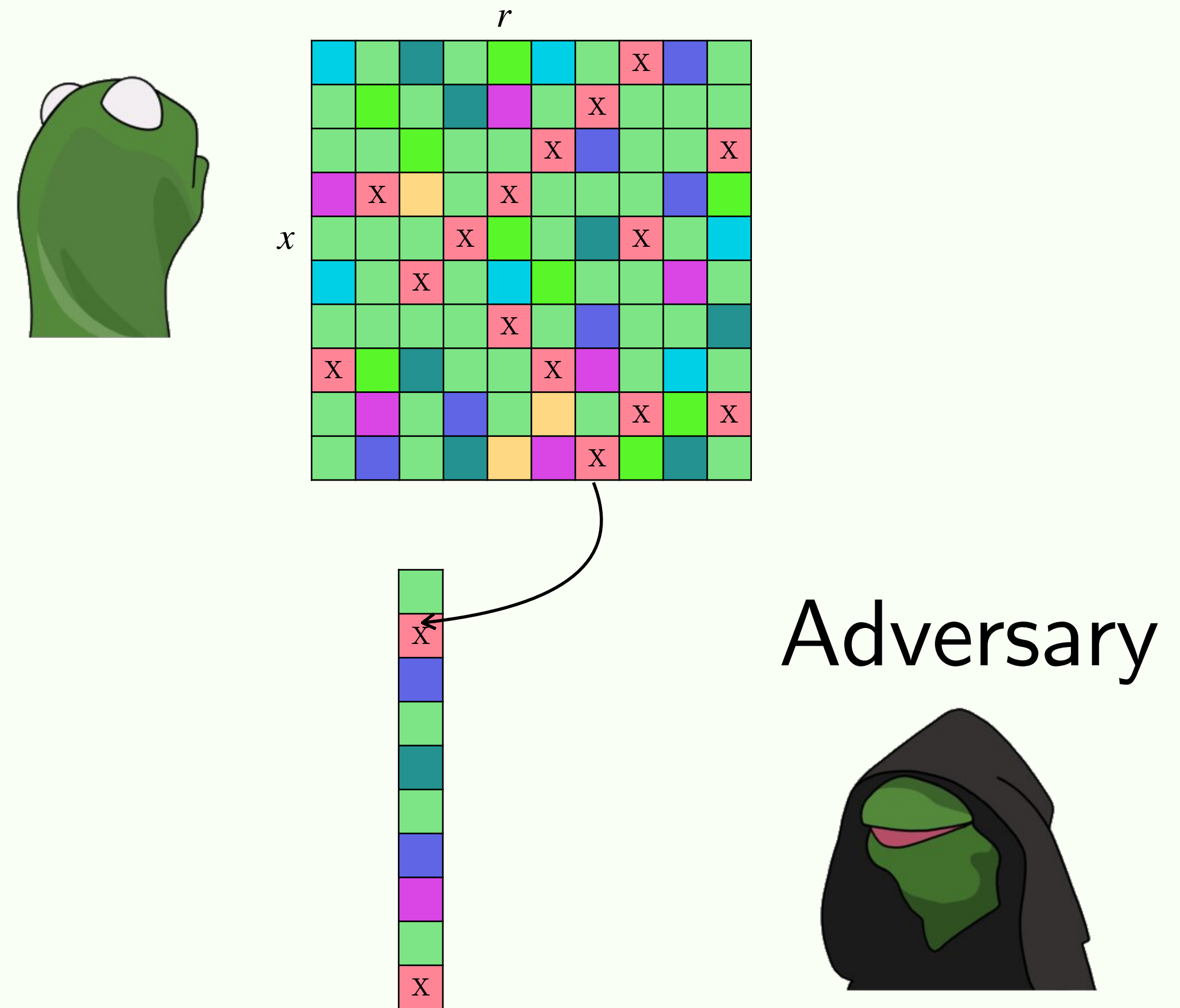
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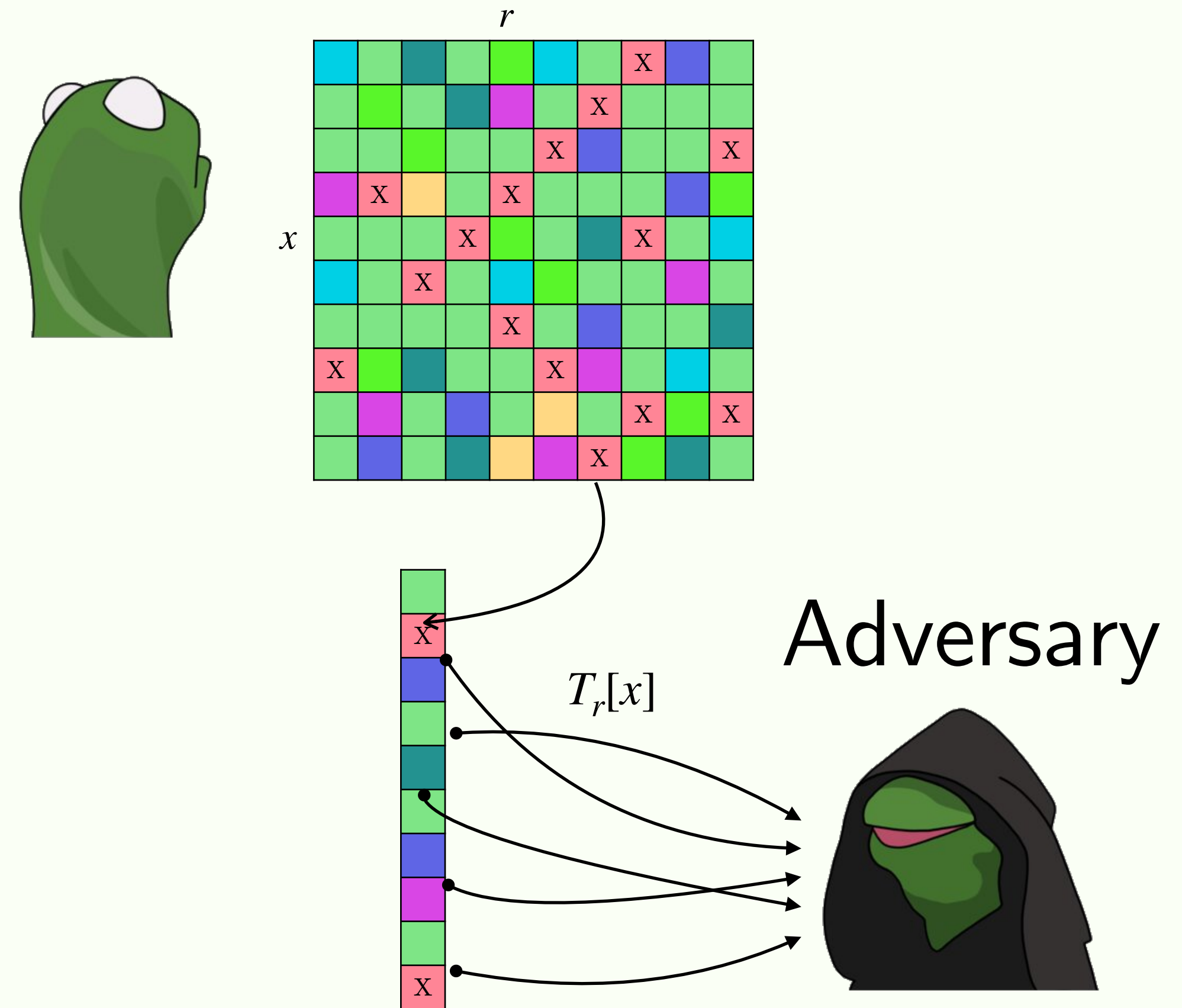
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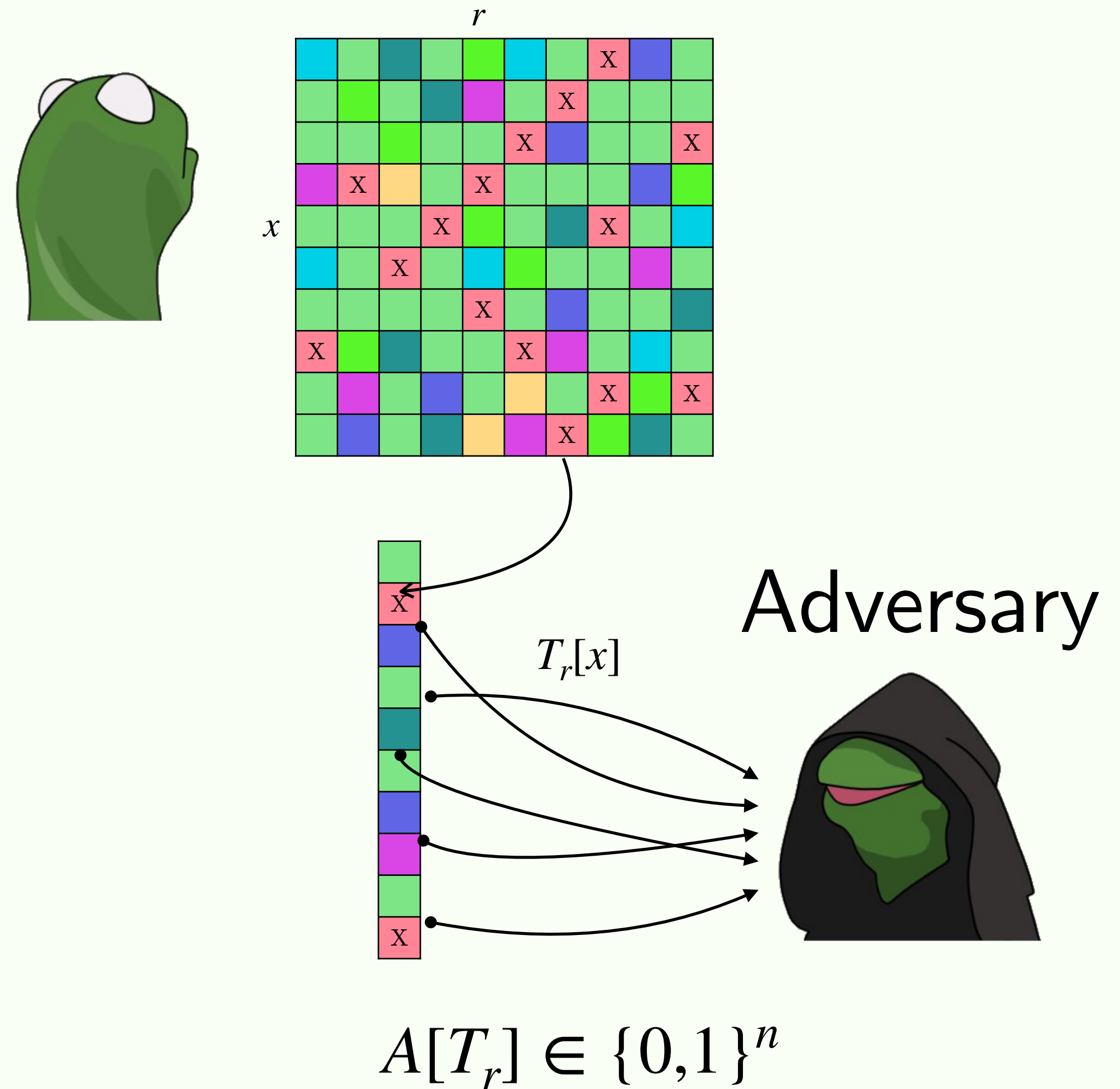
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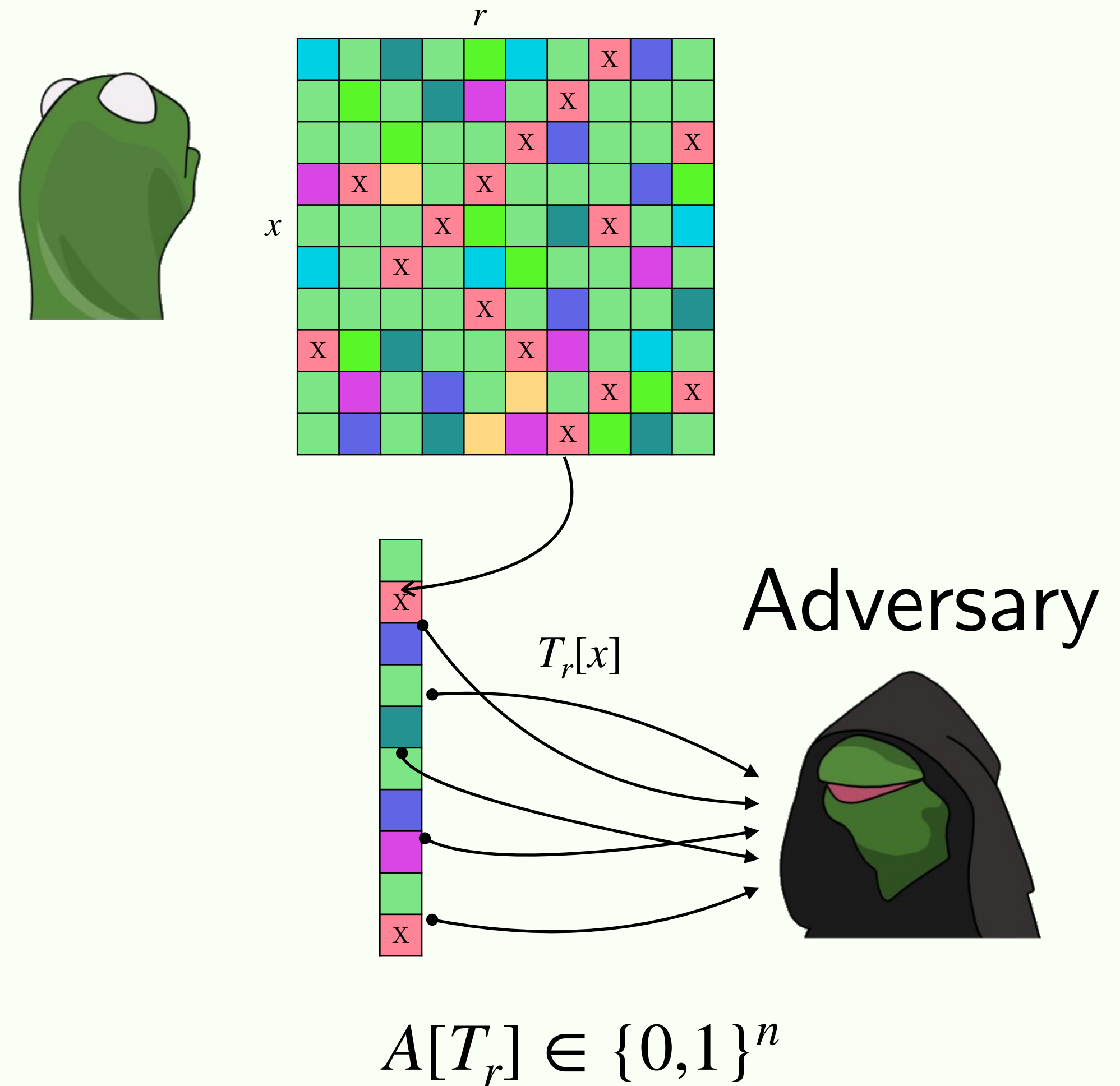
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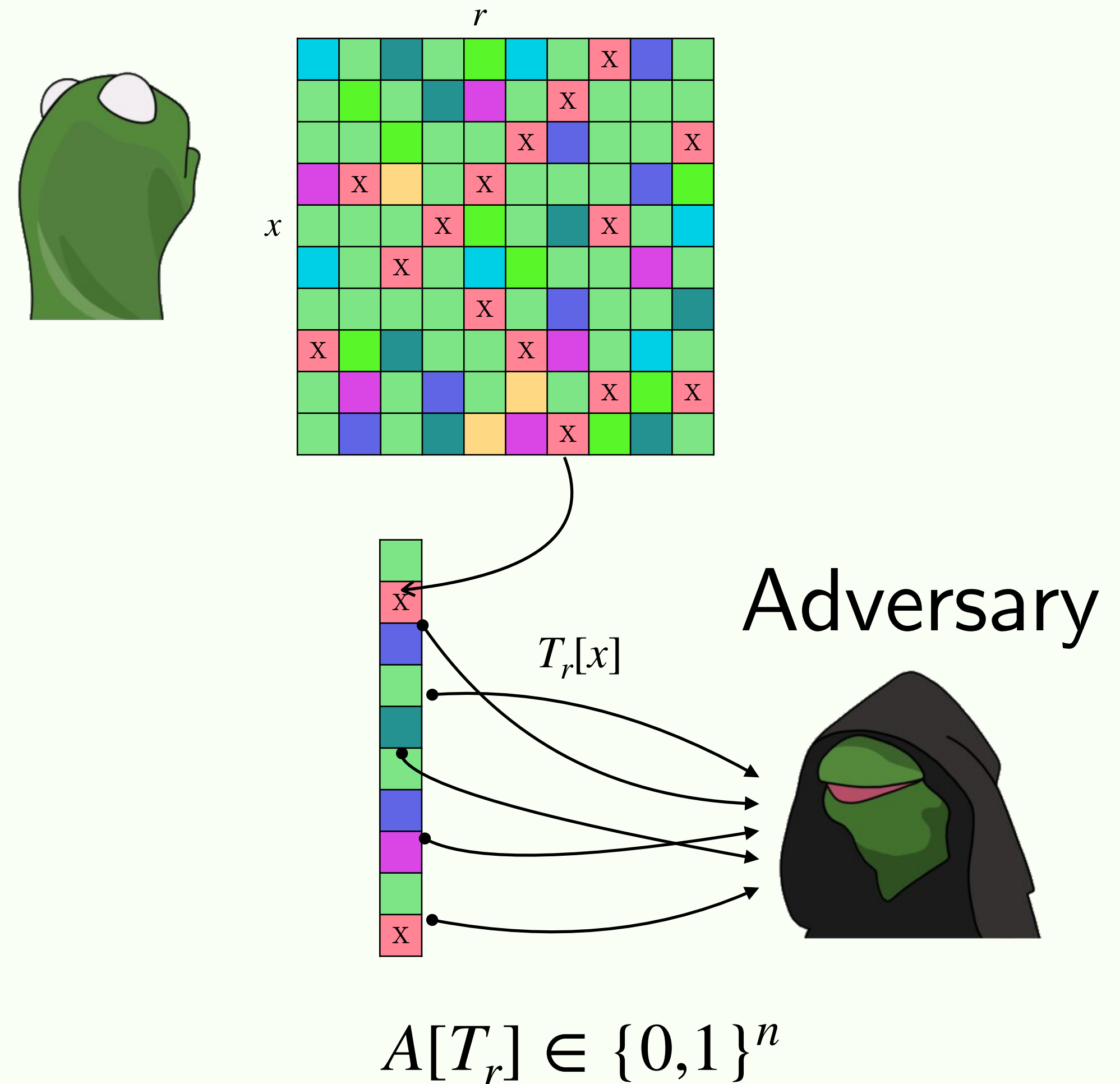
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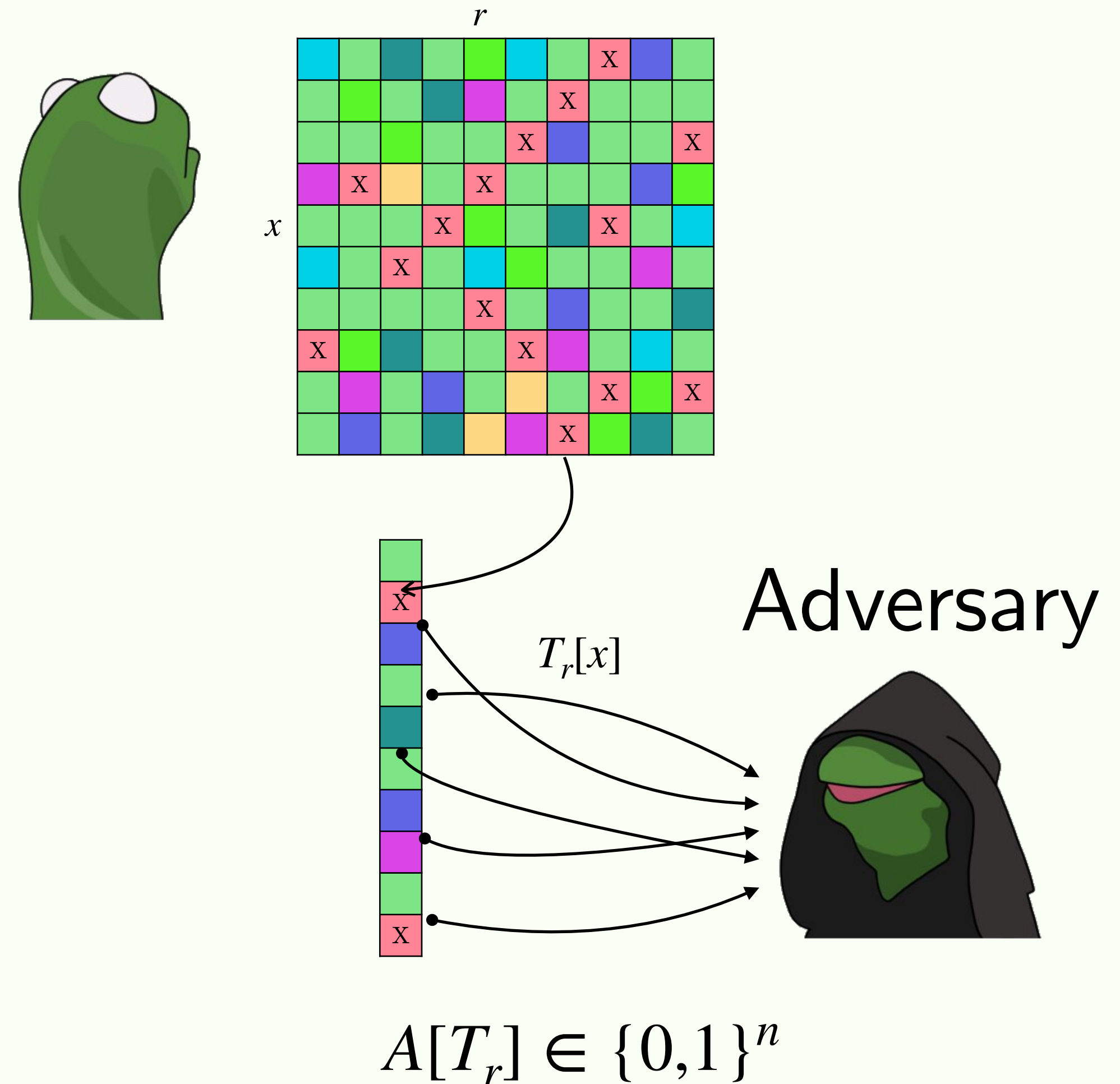


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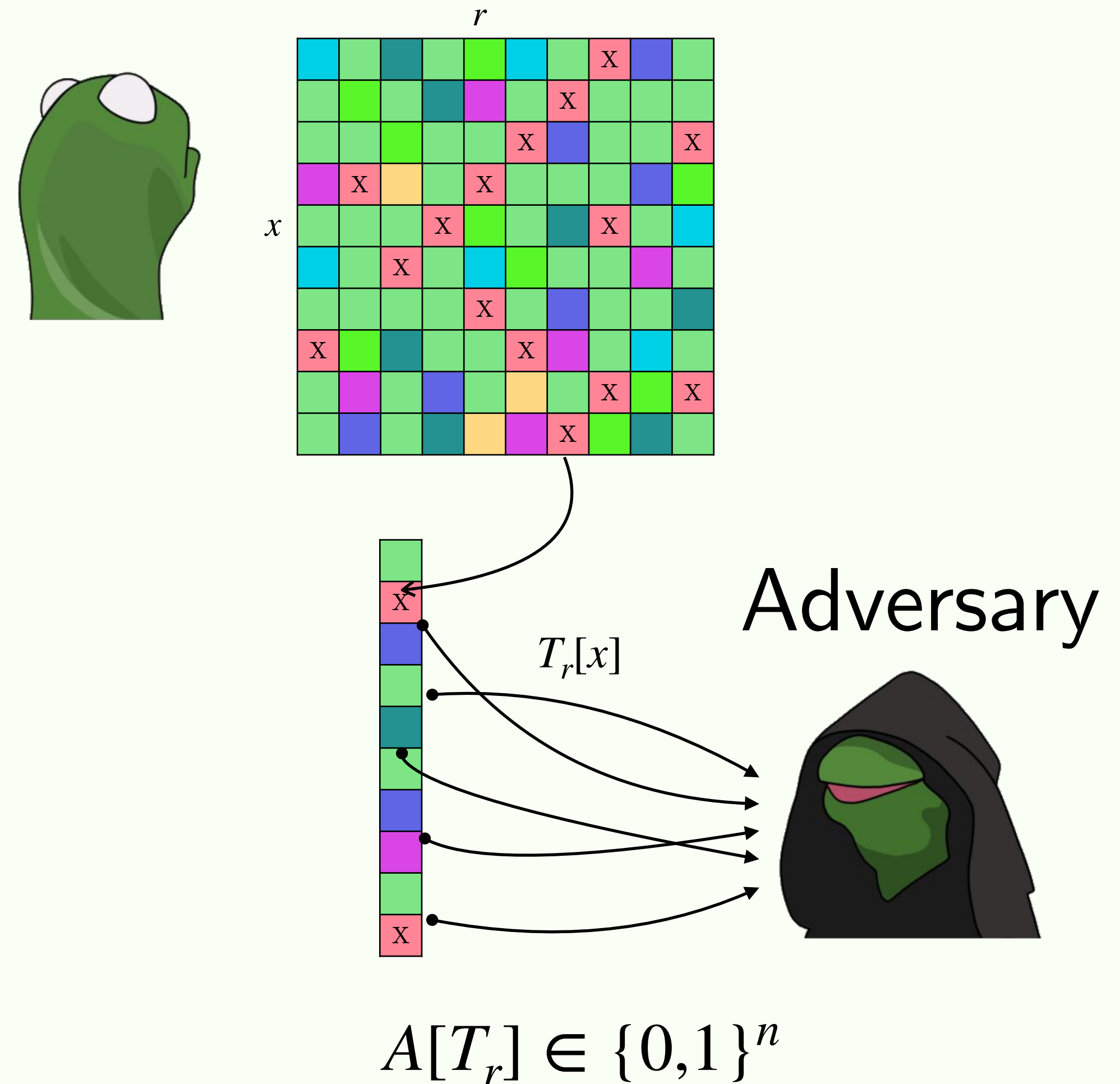
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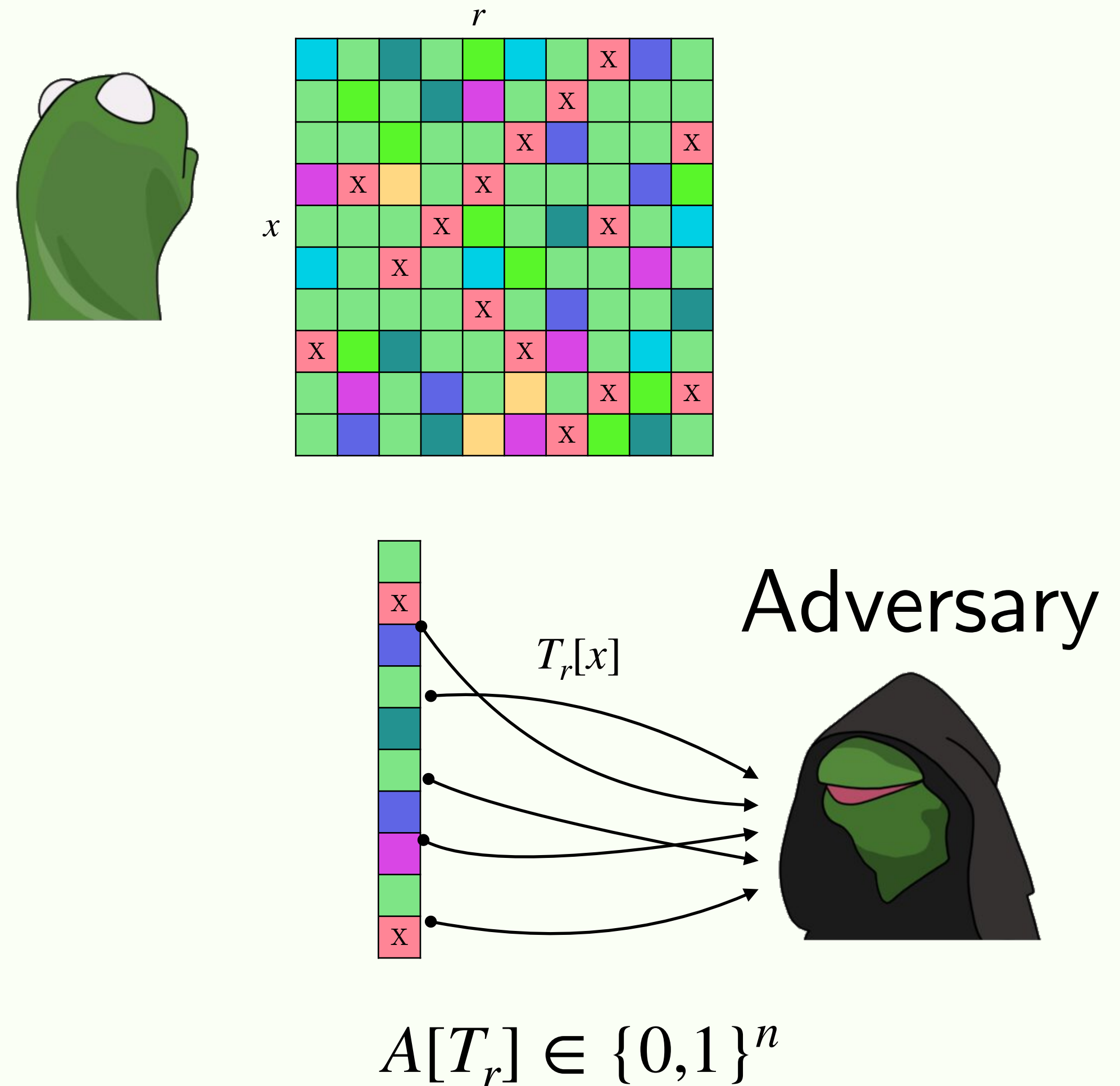
Remark: “set it and forget it” paradigm: the given tree is a fixed deterministic tree



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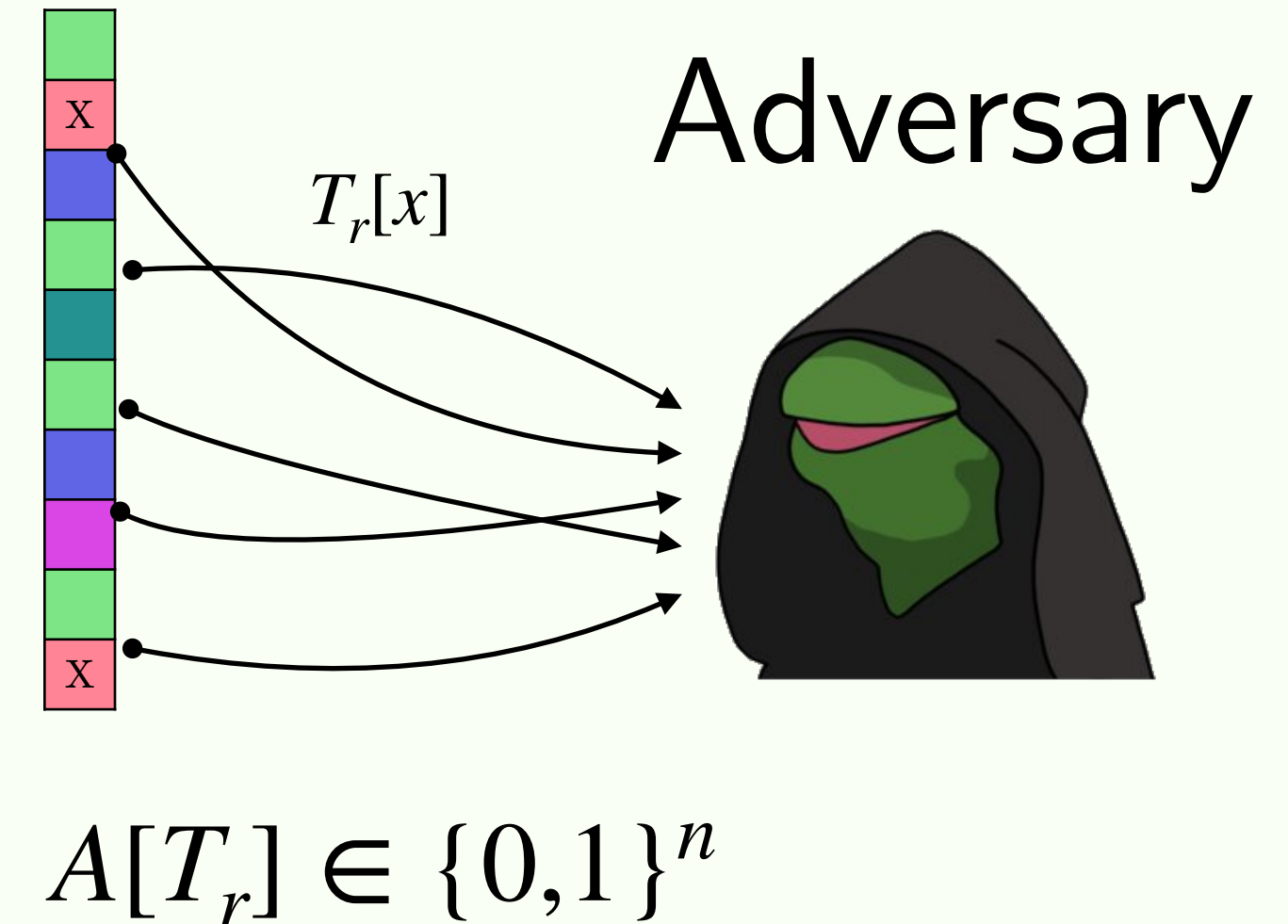
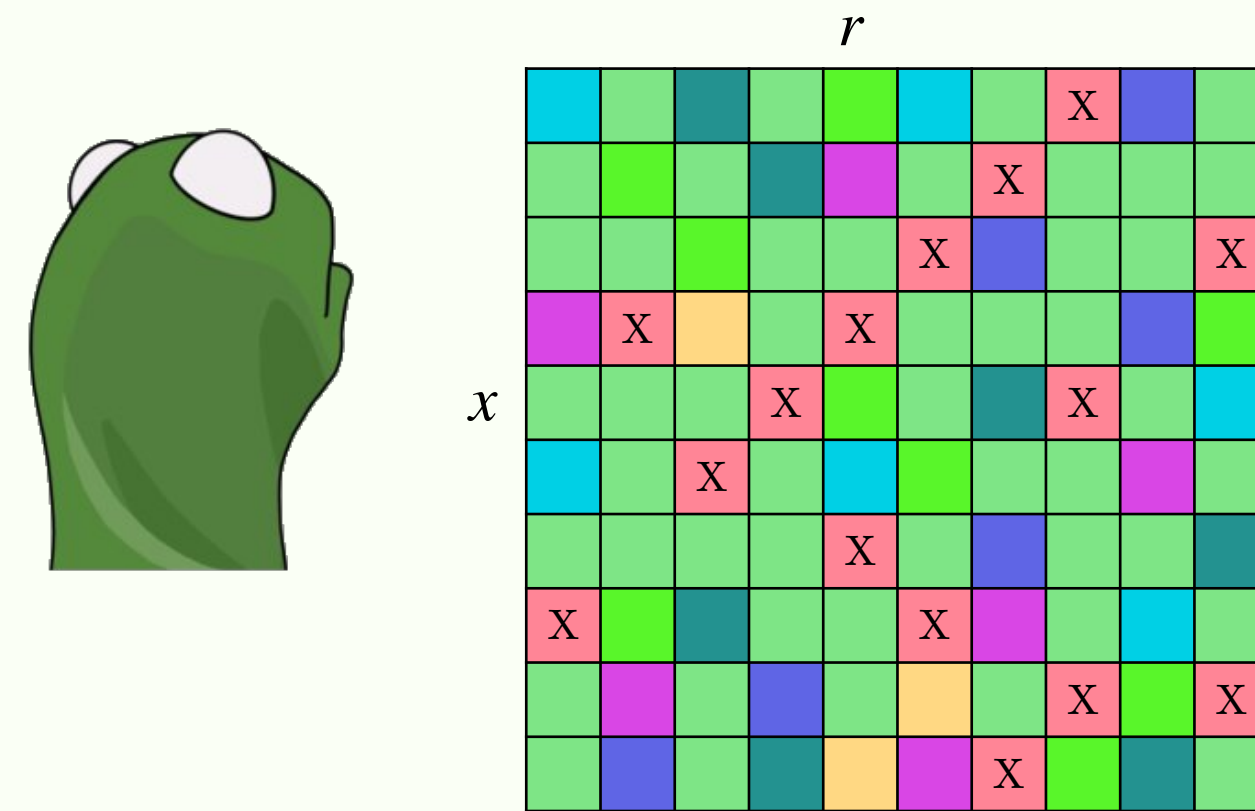


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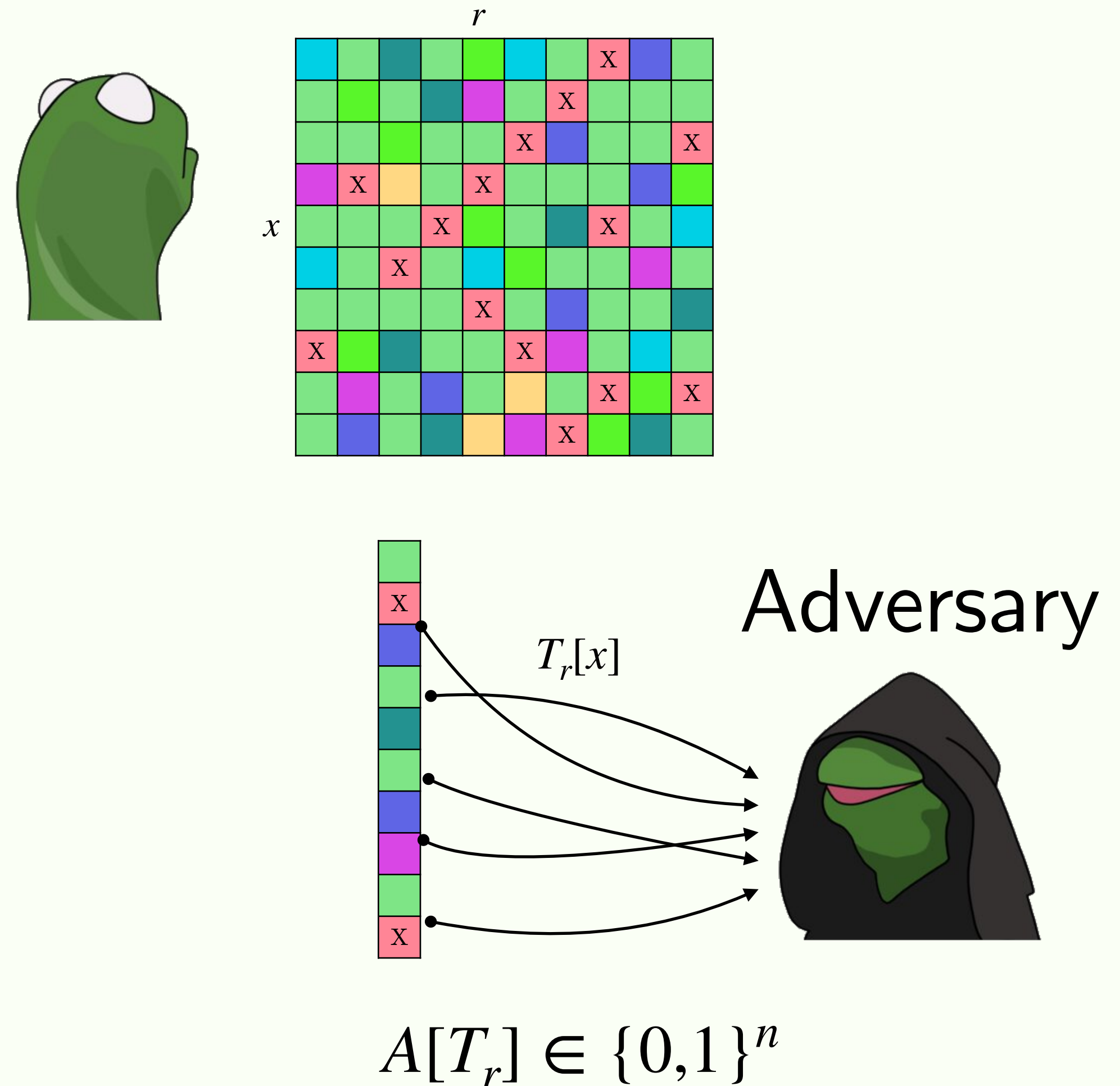
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Theorem (faux derandomization).

$\text{FIND1} \in \text{FauxP}^{\text{dt}}$, and by completeness of FIND1 ,
 $\text{FBPP}^{\text{dt}} \cap \text{FNP}^{\text{dt}} \subset \text{FauxP}^{\text{dt}}$



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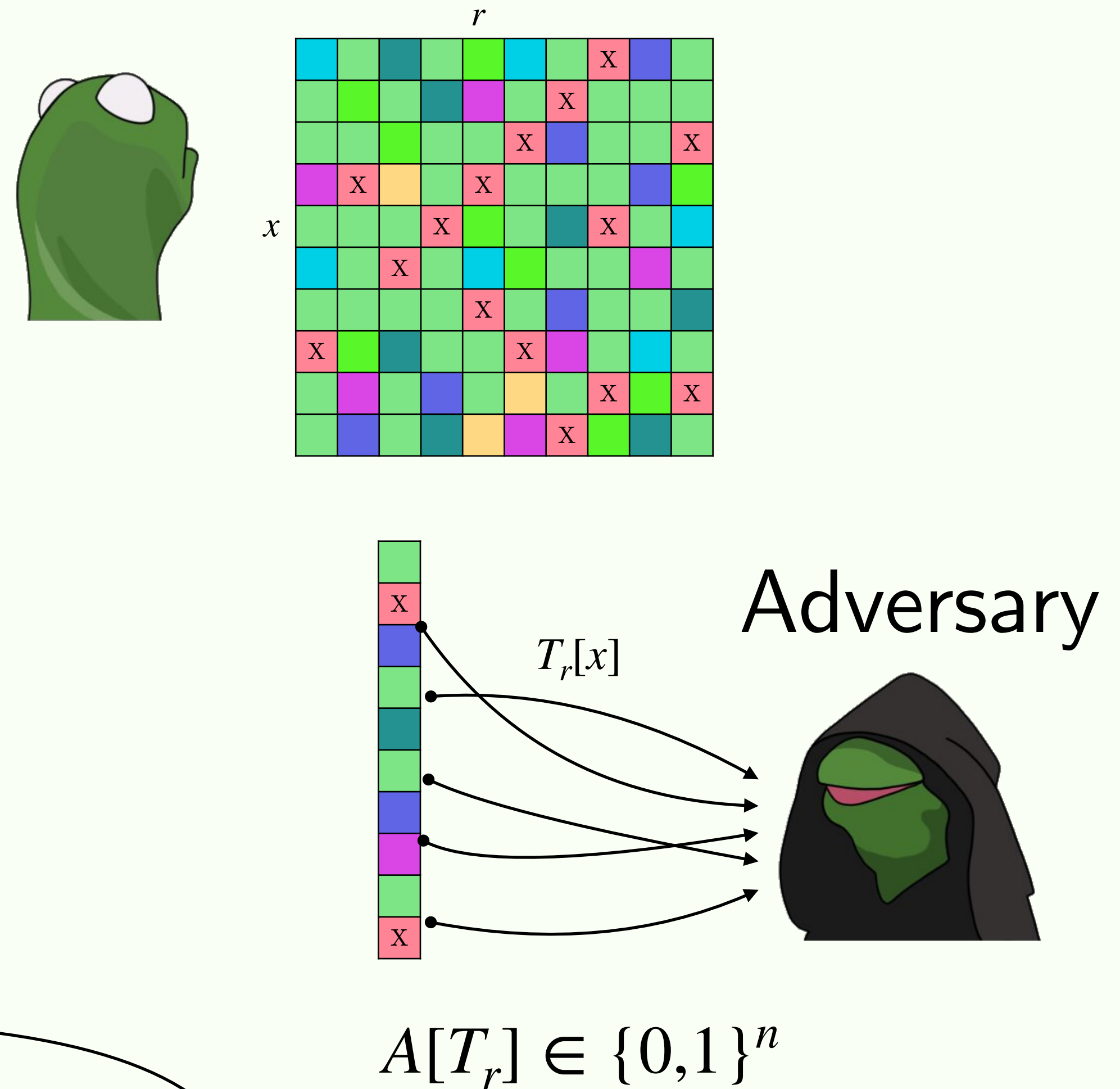
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Lemma. $\text{FP}^{\text{dt}} \subsetneq \text{PseudoP}^{\text{dt}} \subsetneq \text{FauxP}^{\text{dt}} \subsetneq \text{FBPP}^{\text{dt}}$

Theorem (faux derandomization).

$\text{FIND1} \in \text{FauxP}^{\text{dt}}$, and by completeness of FIND1,
 $\text{FBPP}^{\text{dt}} \cap \text{FNP}^{\text{dt}} \subset \text{FauxP}^{\text{dt}}$



Faux-deterministic algorithms for search problems

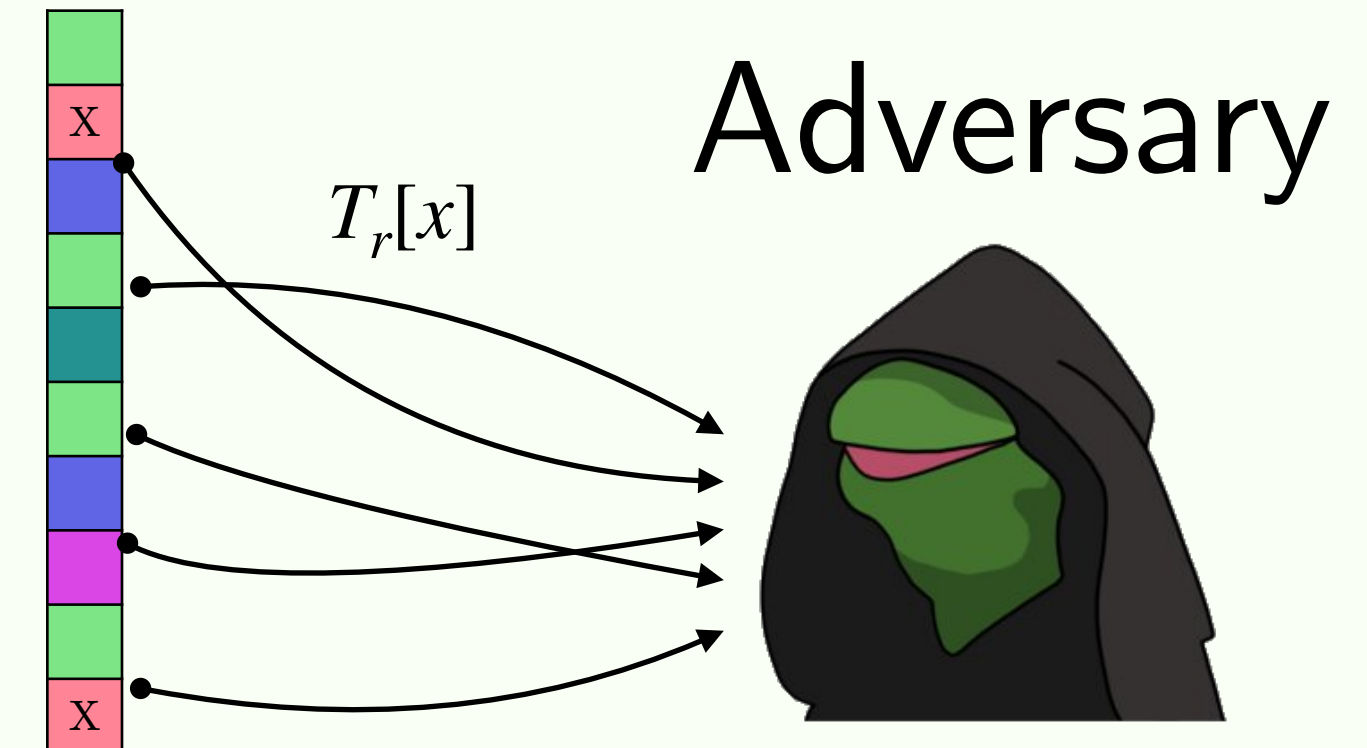
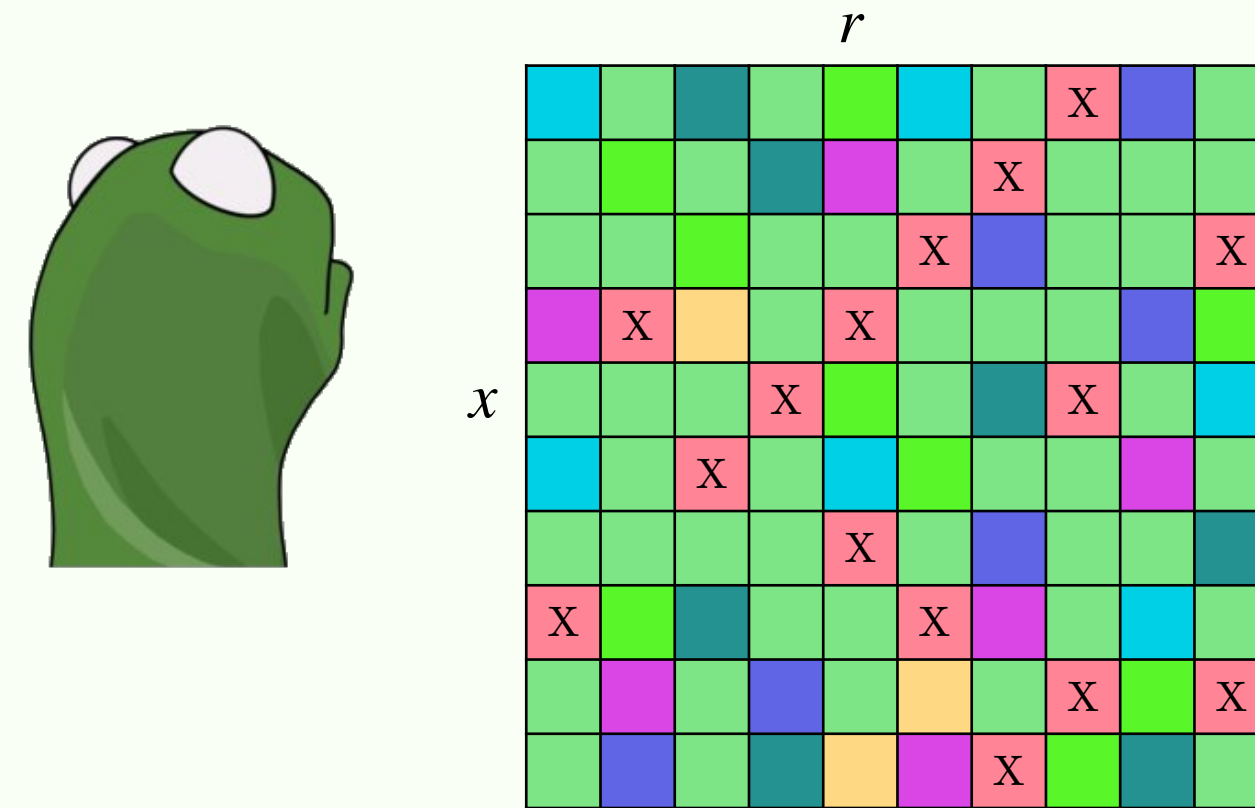
Faux-deterministic tree $\mathcal{T} = \{T_r : r \sim R\}$:

- ❖ Sample a random seed $r \sim \text{Unif}$ and **fix it**
- ❖ Give truth table of $T_r \in \Gamma^{\{0,1\}^n}$ to any adversary A
- ❖ A makes $\text{poly}(n)$ queries to the truth table of $T_r \in \Gamma^{\{0,1\}^n}$
- ❖ Succeeds to find a “bad” input $T_r[x] \notin S(x)$ with negligible probability
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$A[T_r] \in \{0,1\}^n$

See the construction

Faux-deterministic Construction for FIND1

Failure + Failure = Success ?

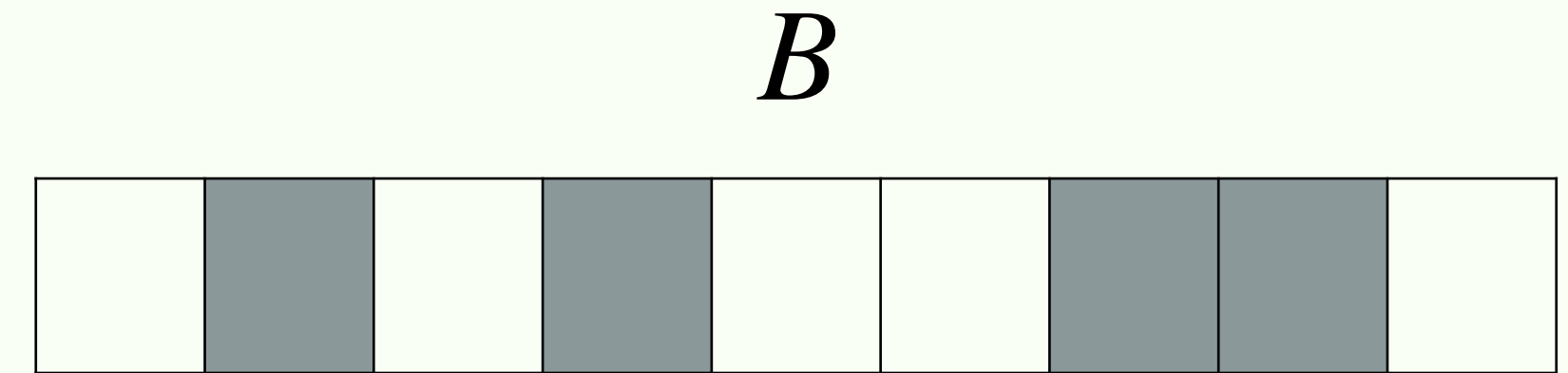
Faux-deterministic construction for FIND1

Attempt 1: non-adaptive approach

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*Choose a random block $B \subset [n]$ of width
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Faux-deterministic construction for FIND1

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- Given x , query $\{x_i : i \in B\}$



B

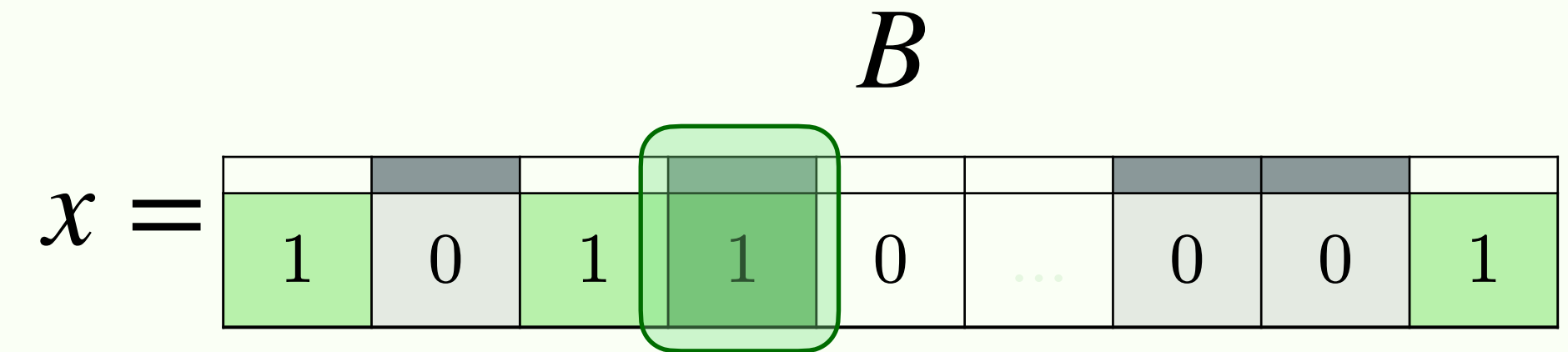
$x =$

1	0	1	1	0	...	0	0	1

Faux-deterministic construction for FIND1

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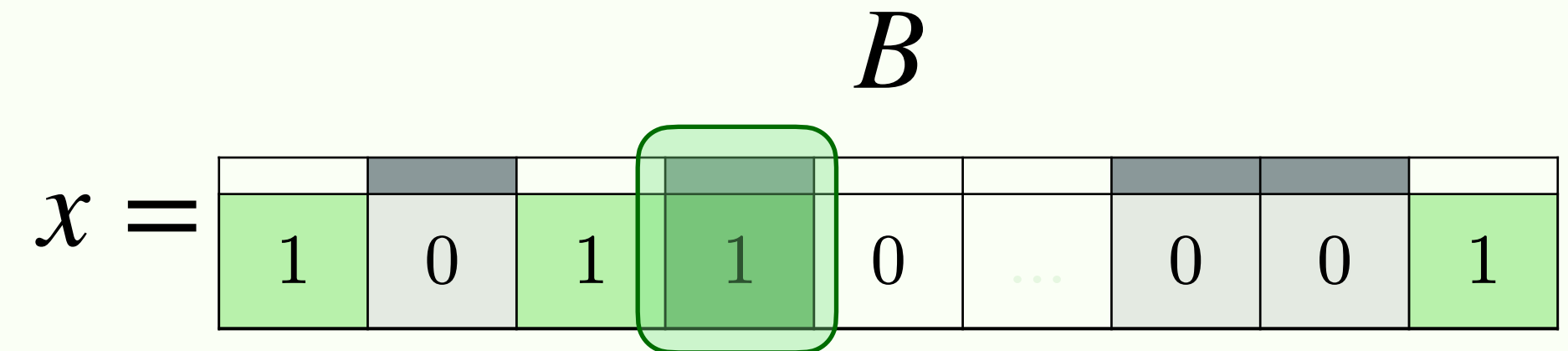
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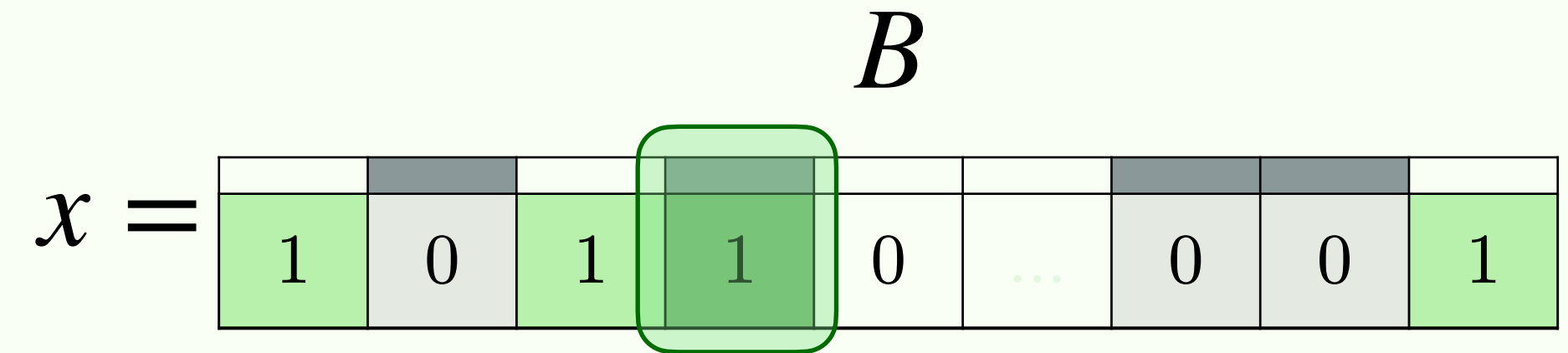
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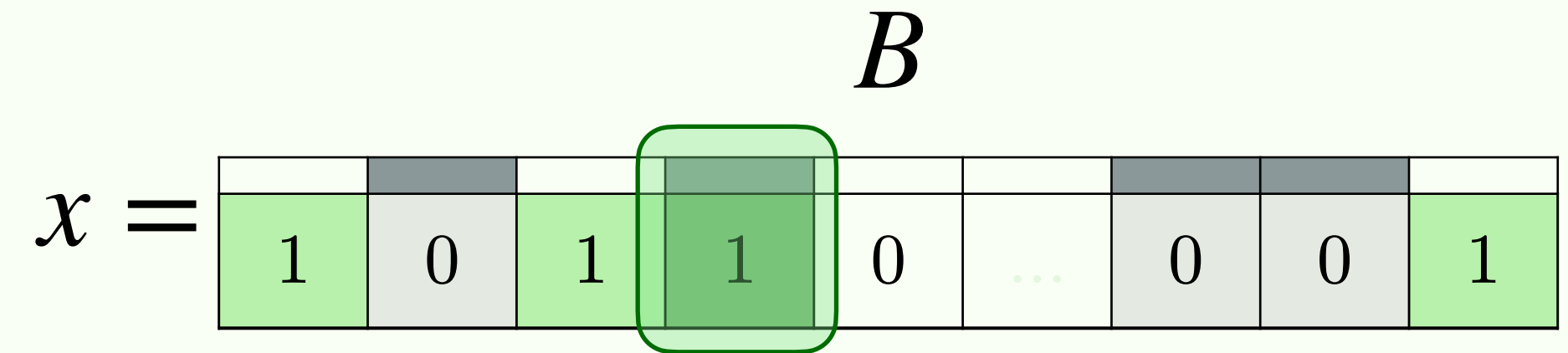
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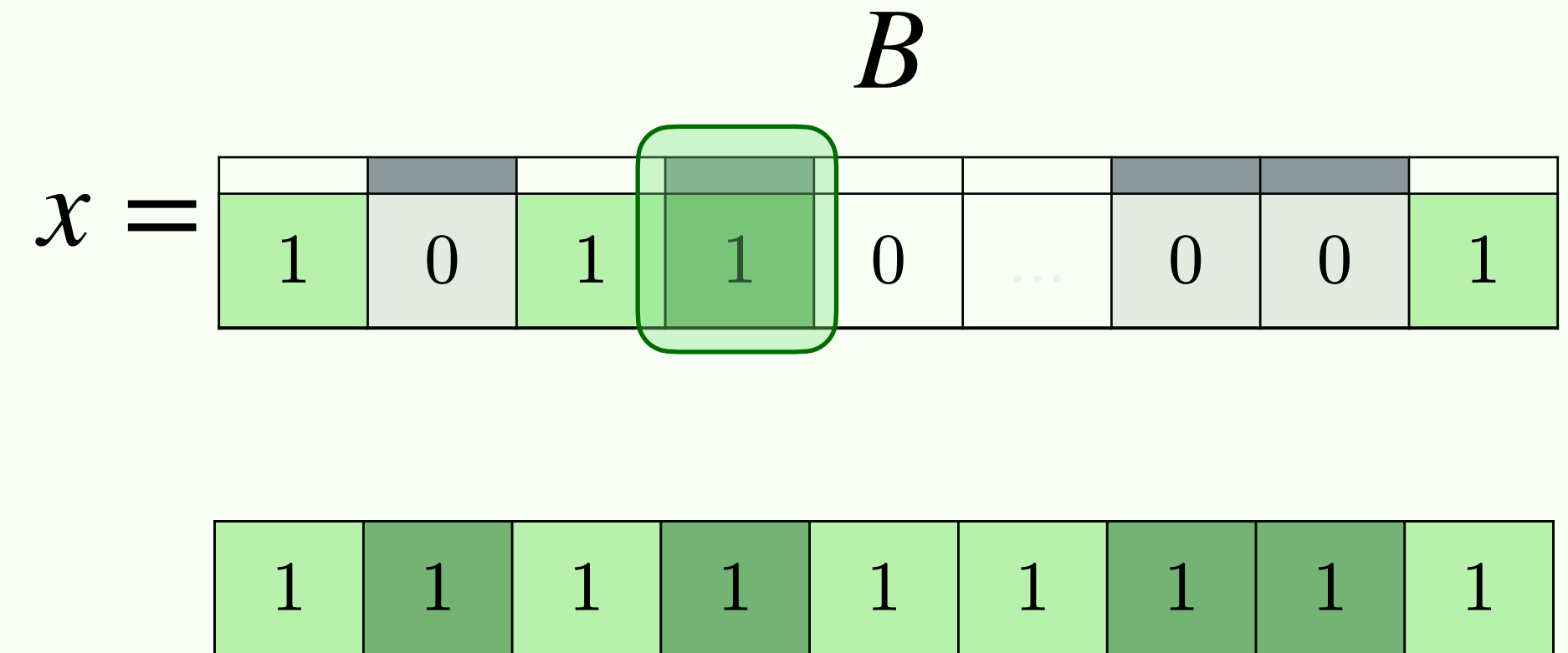
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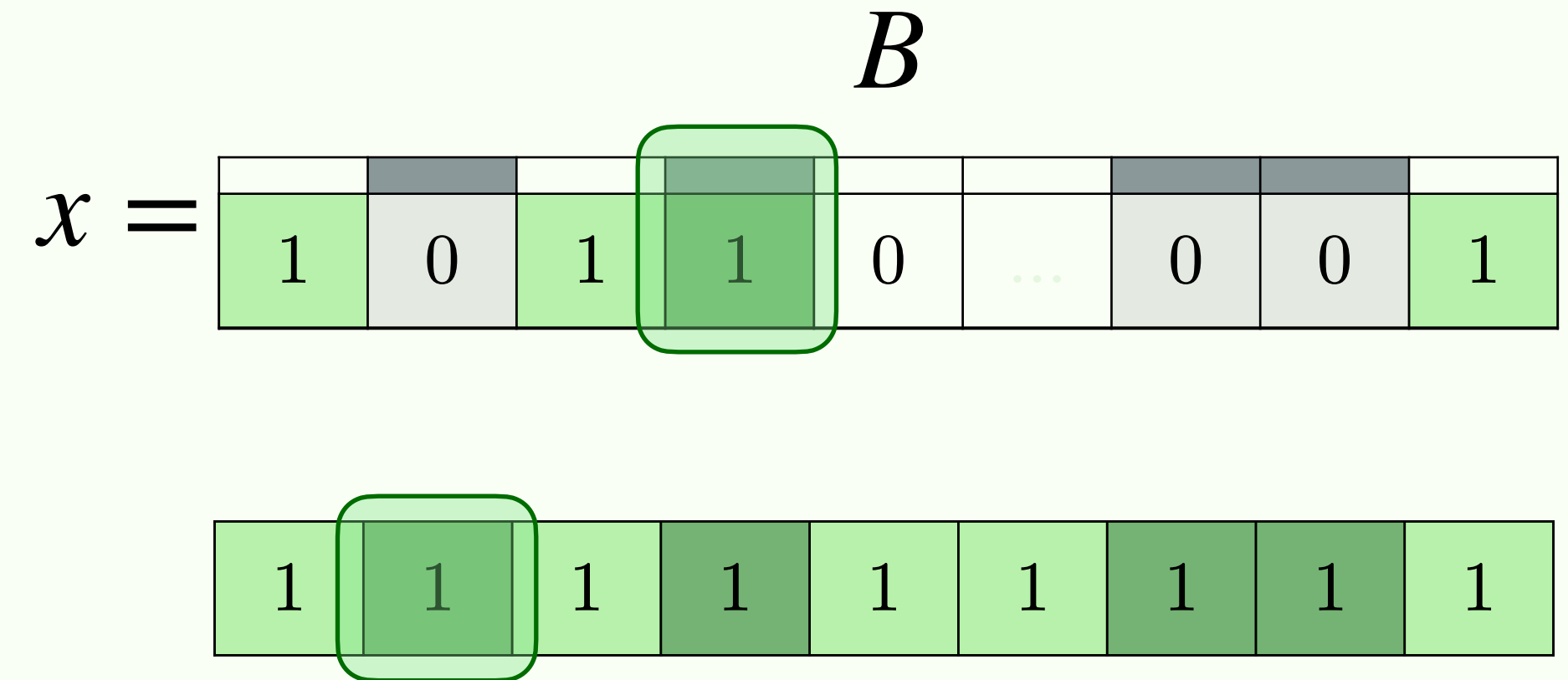
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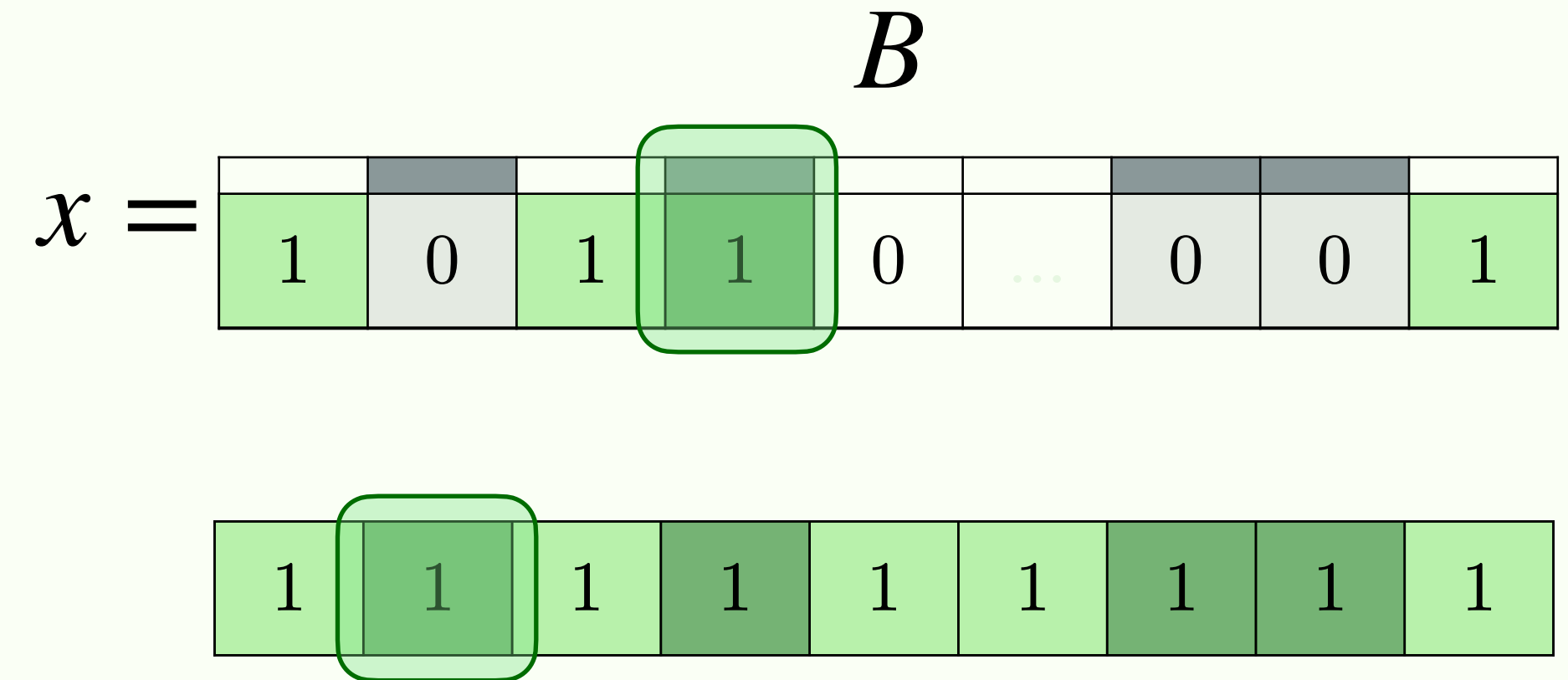
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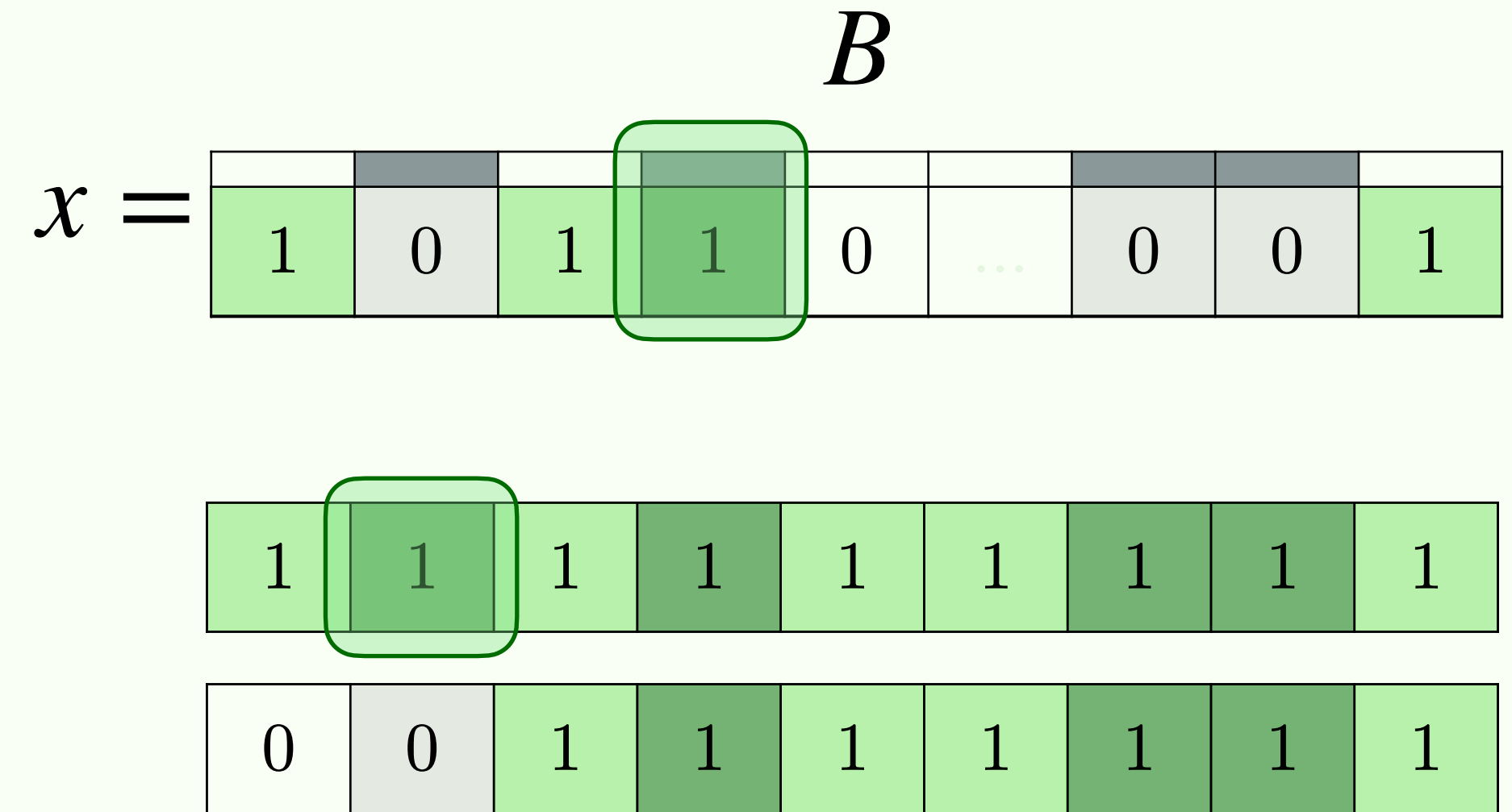
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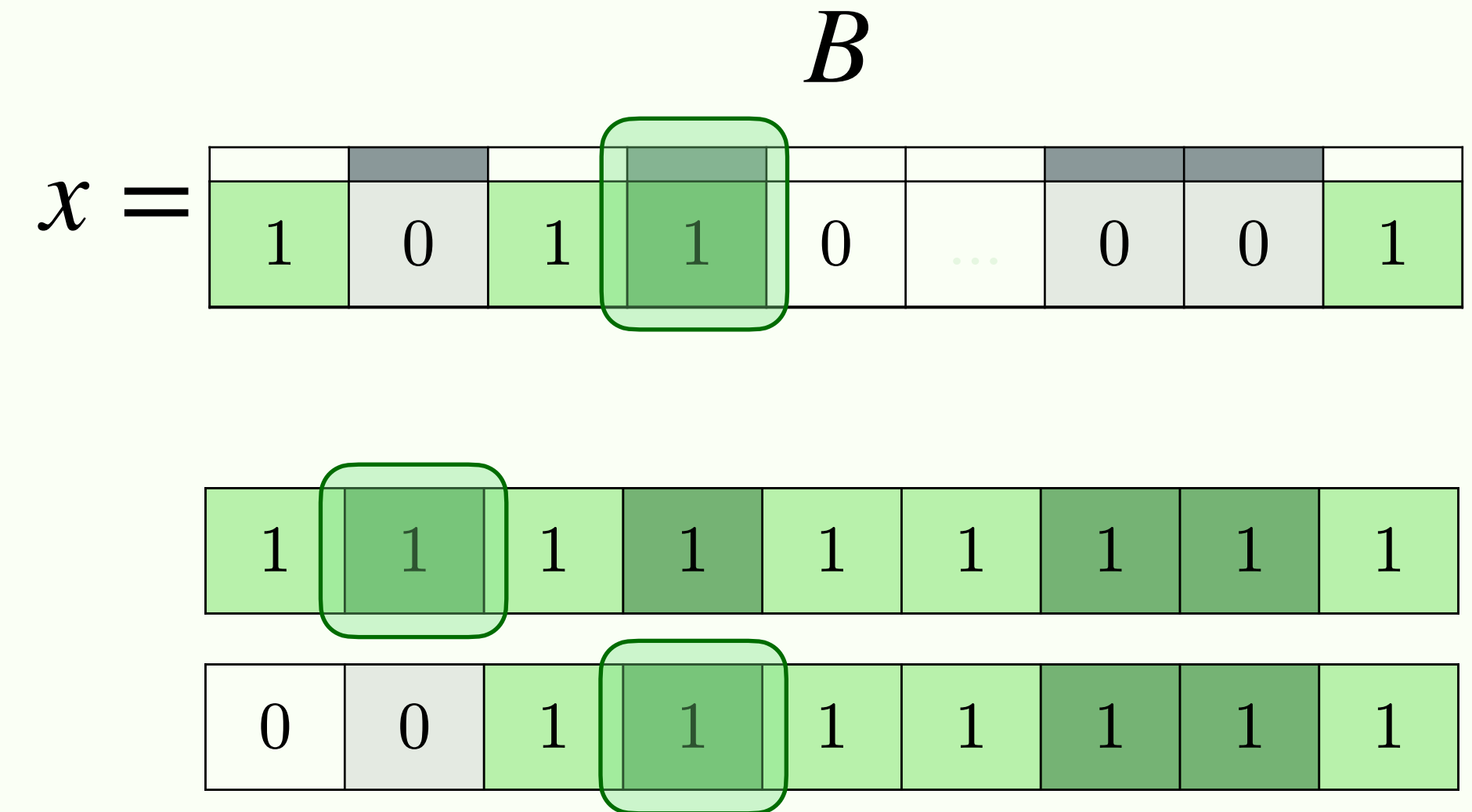
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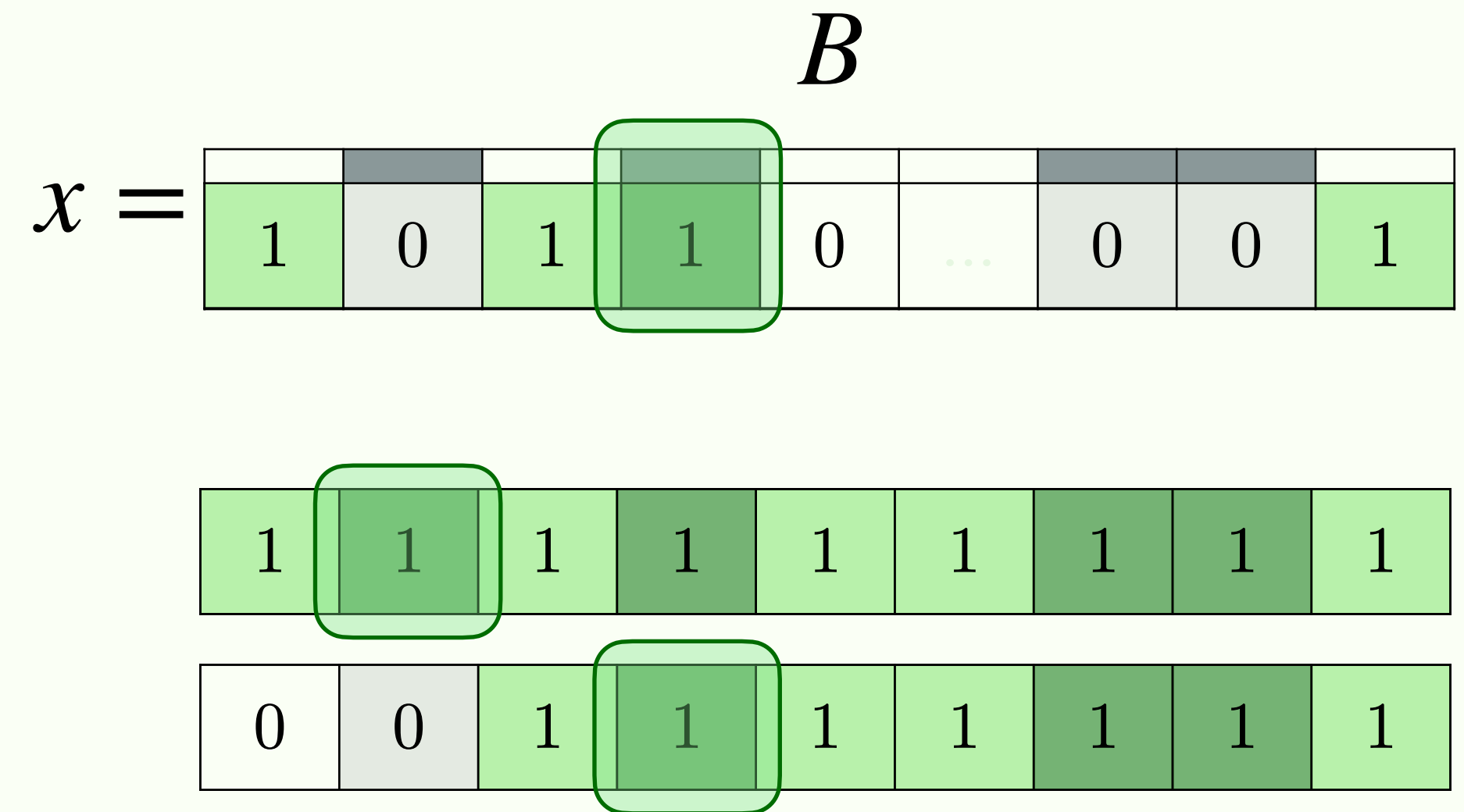


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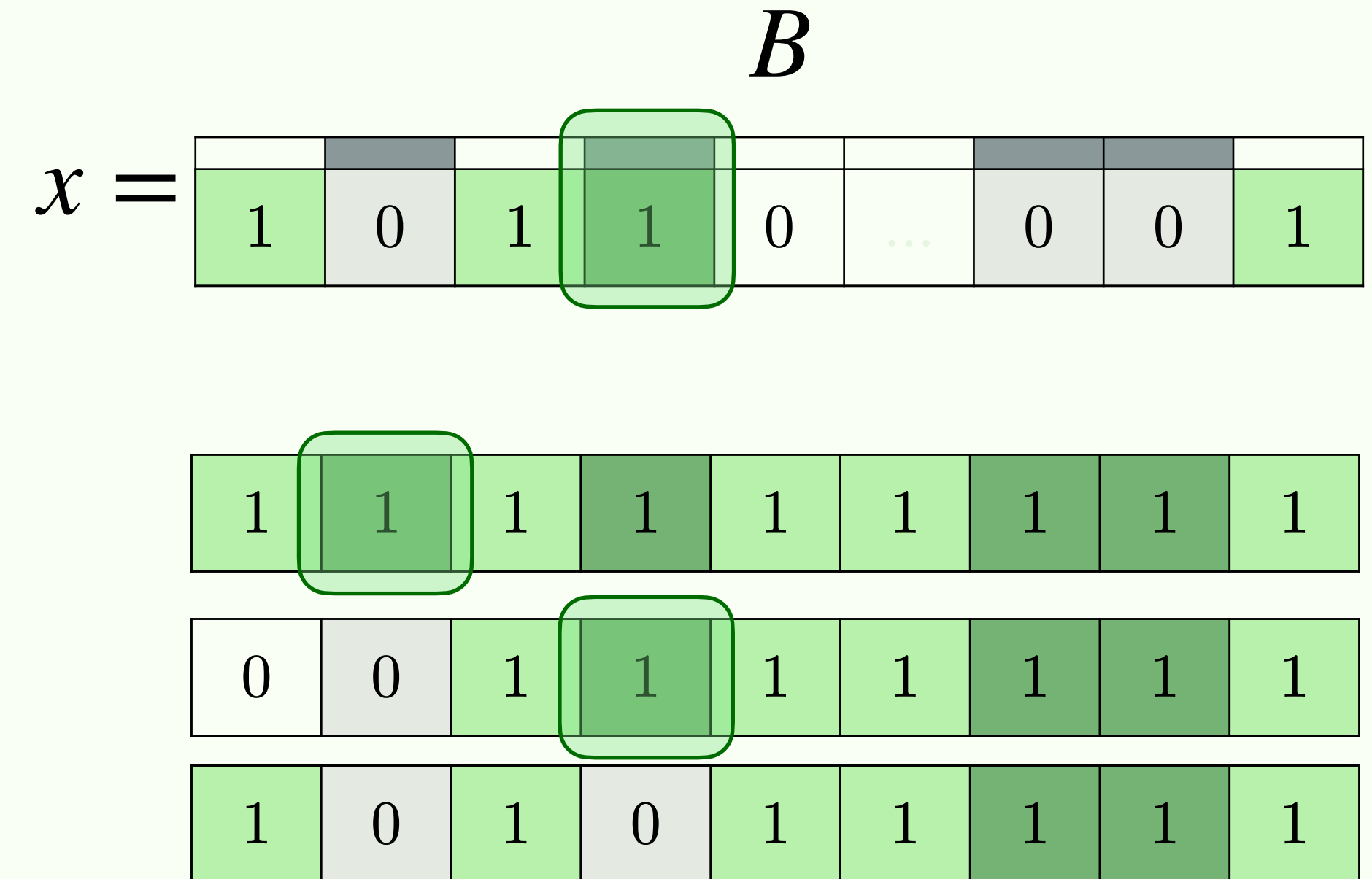


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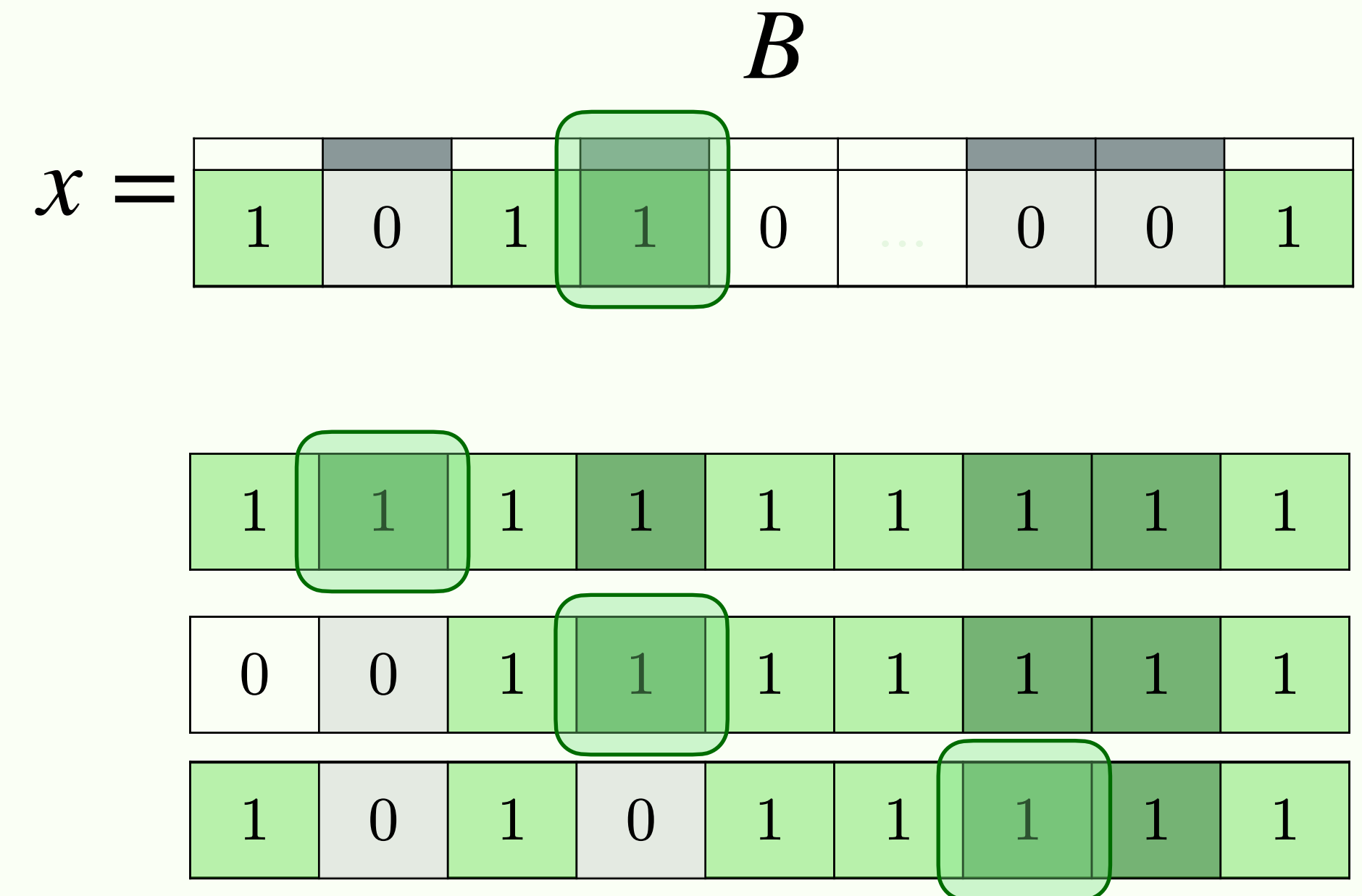


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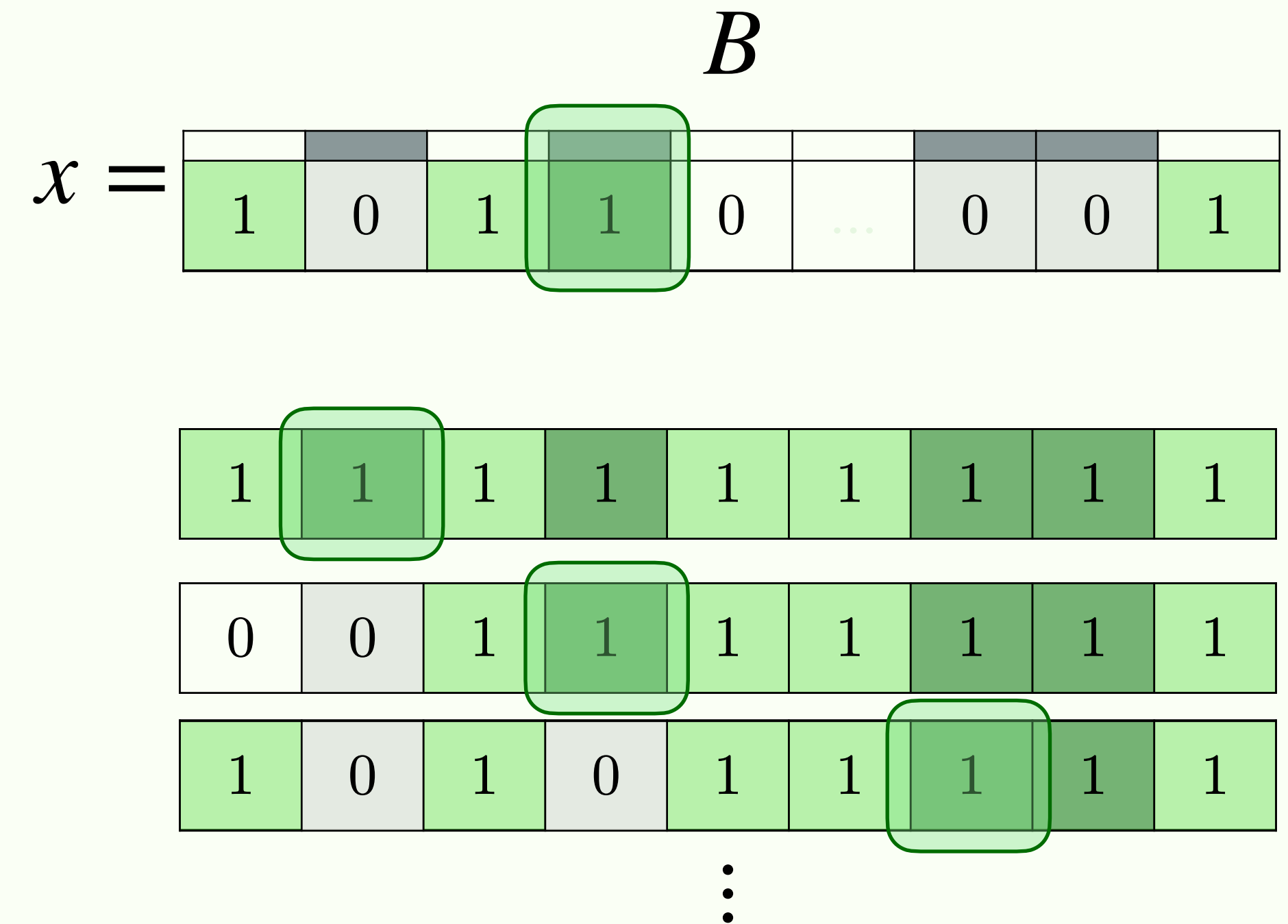


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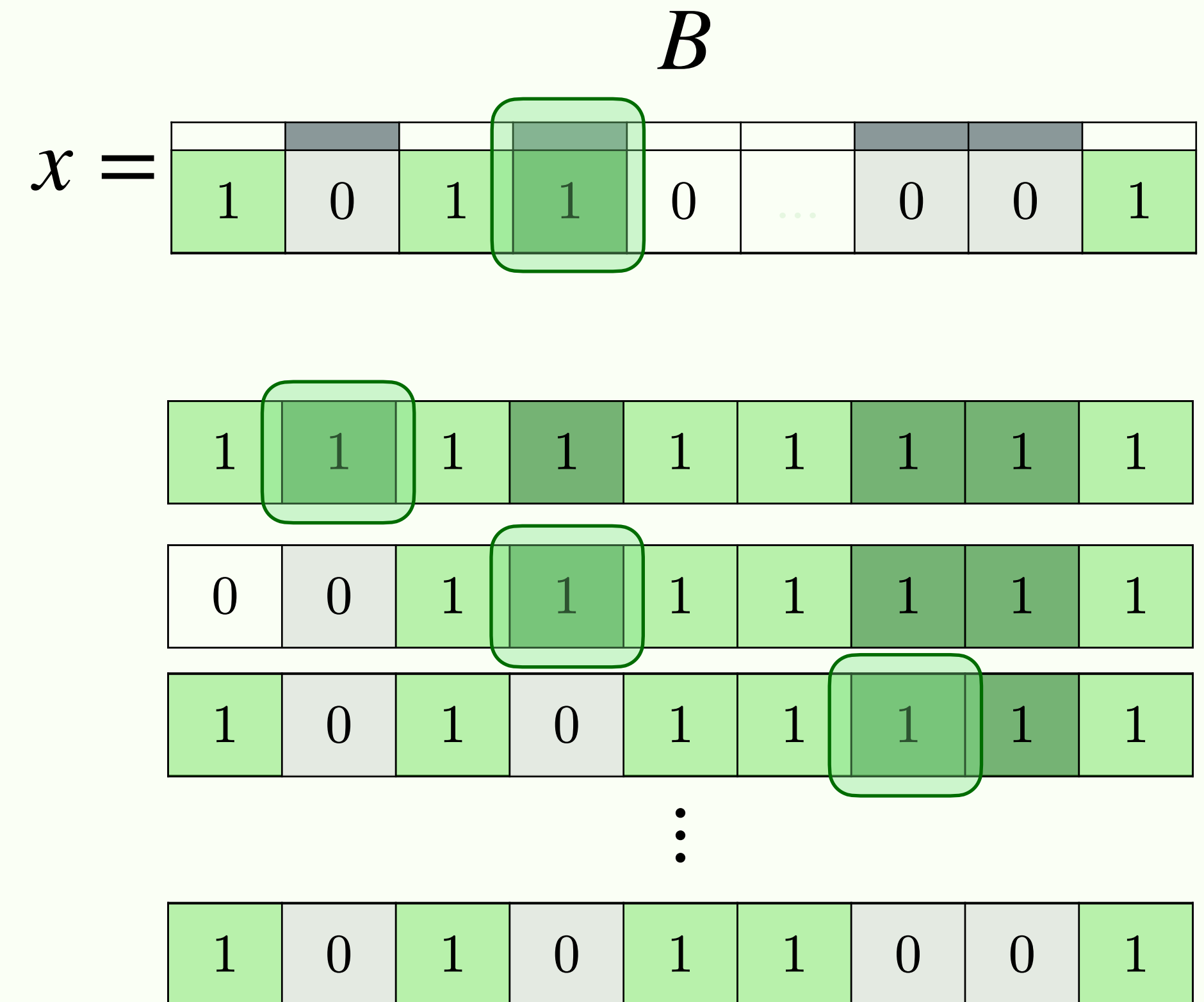


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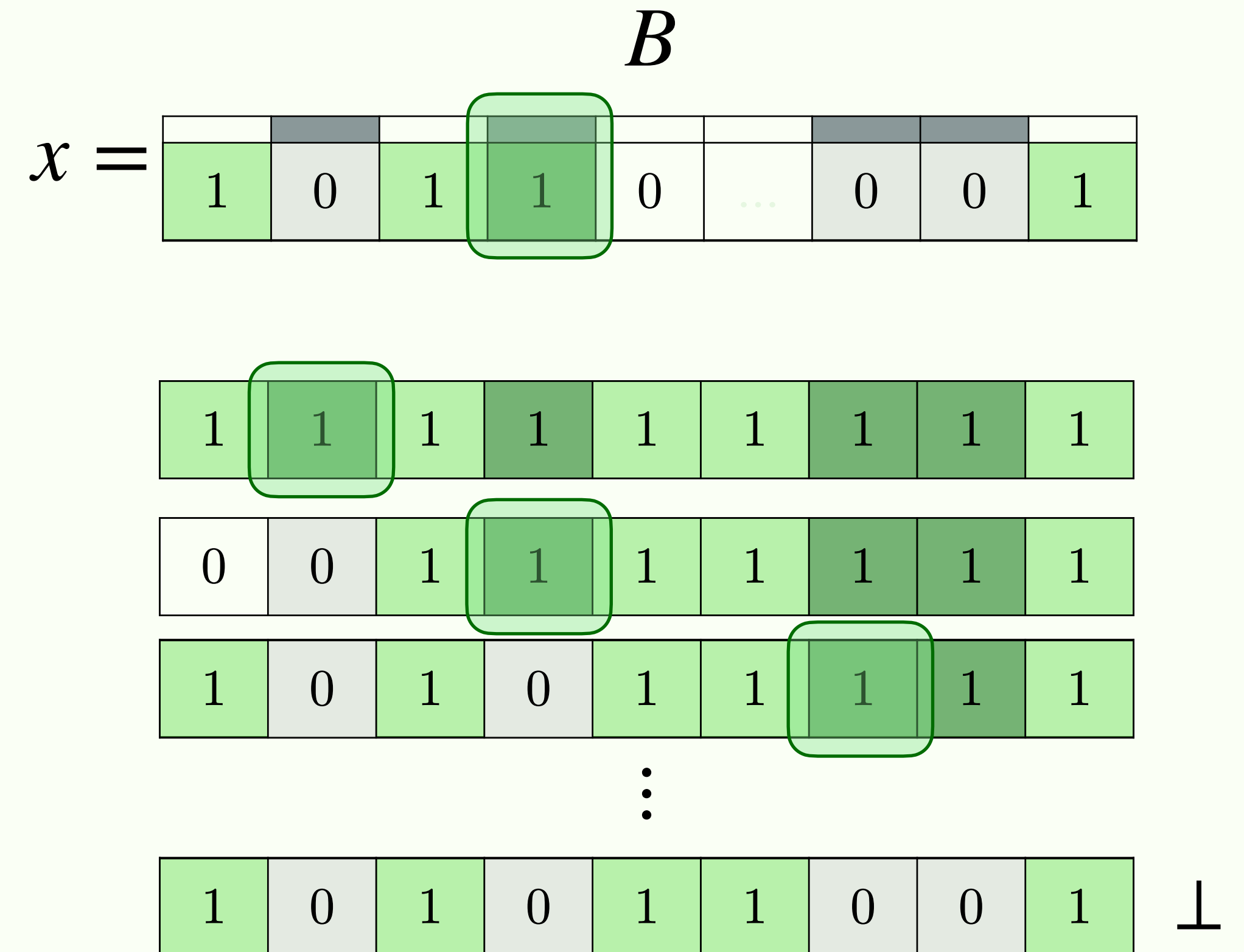
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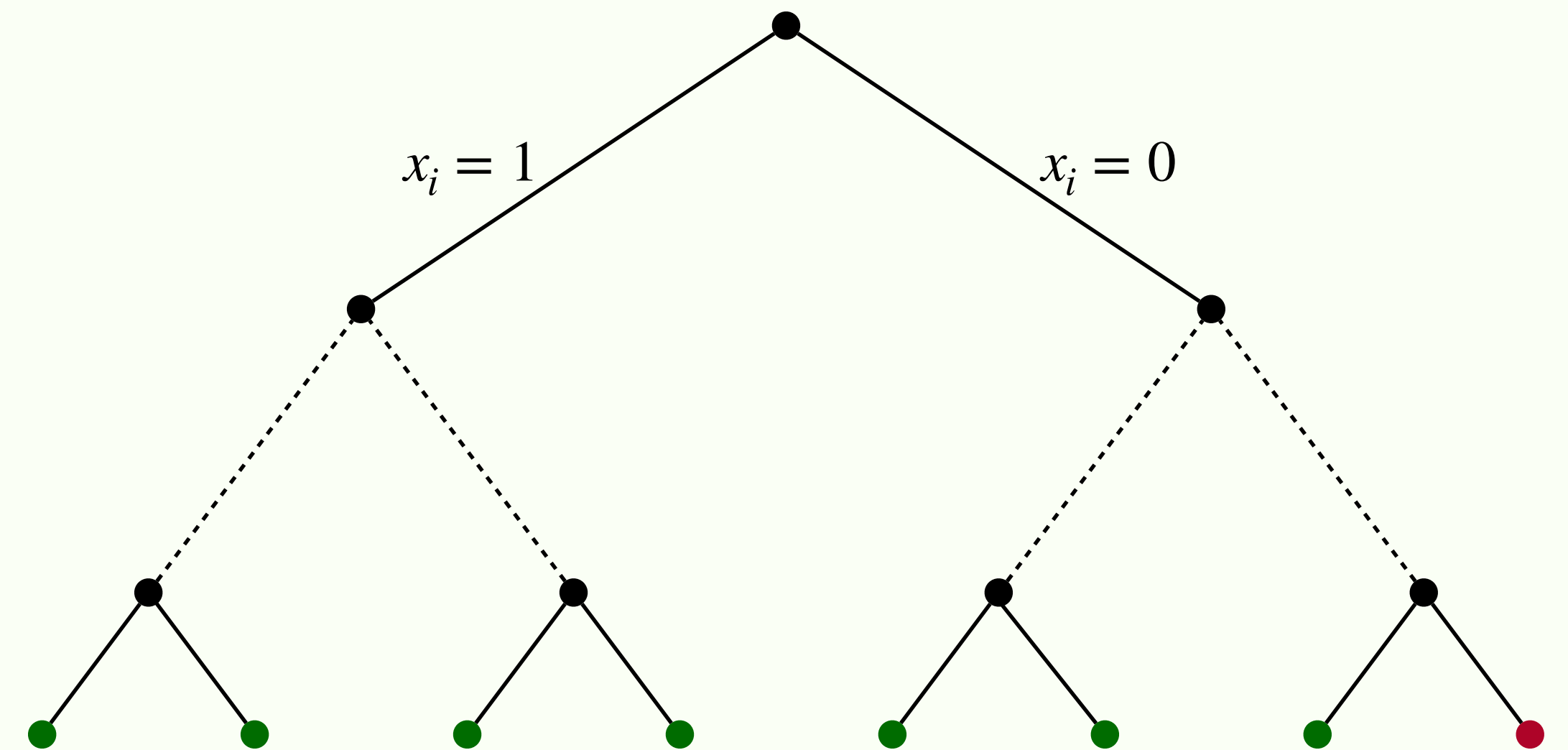
Attempt 2: adaptive approach



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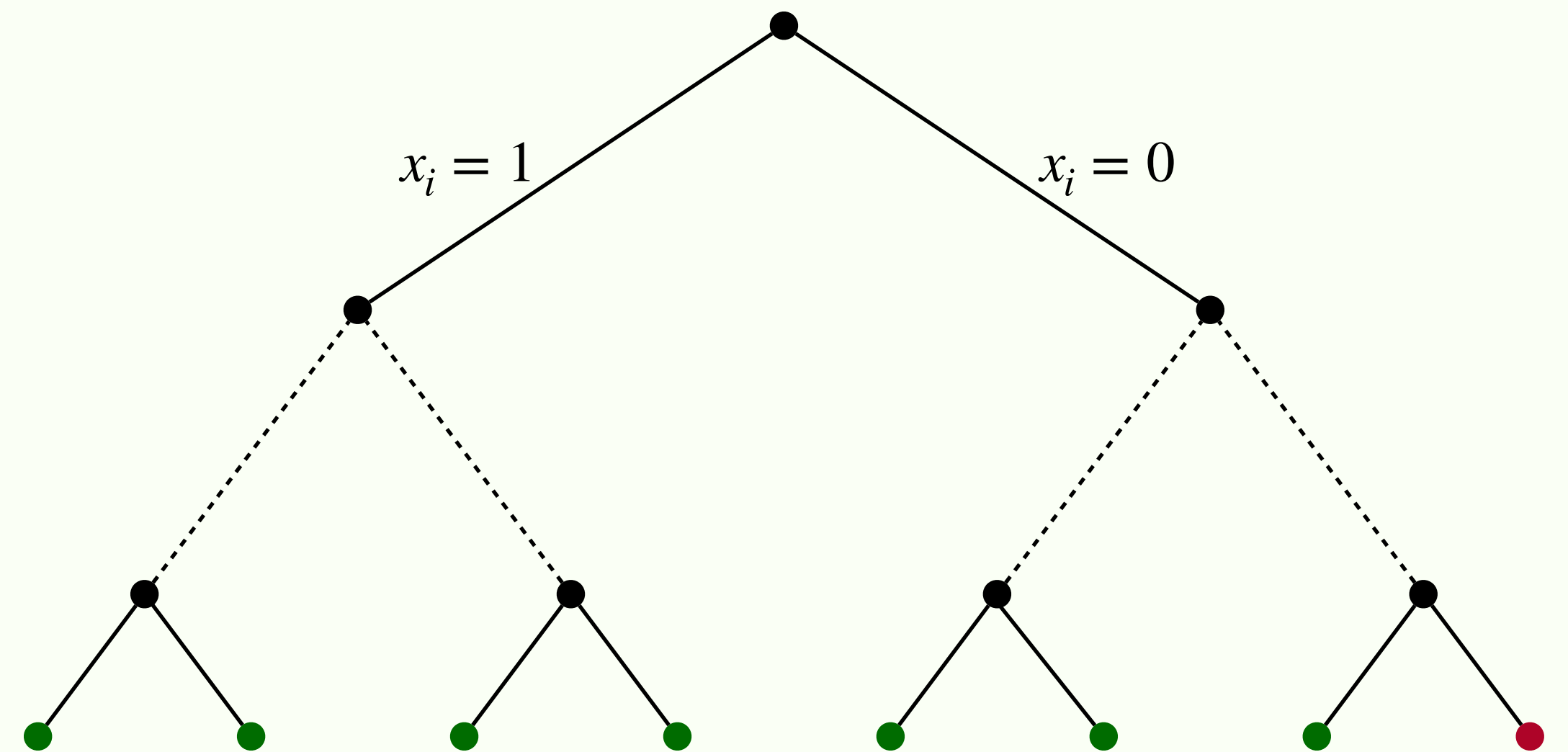
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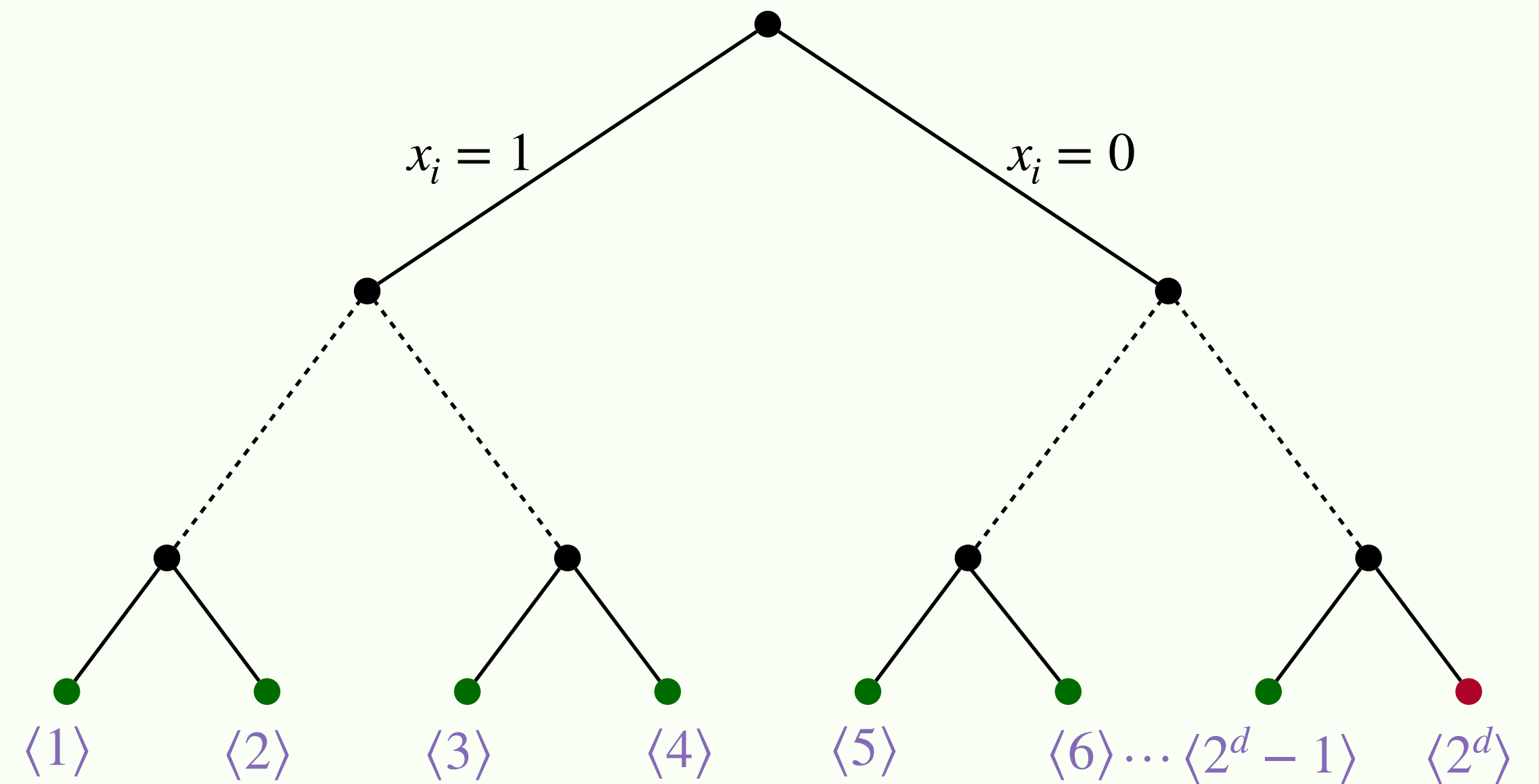
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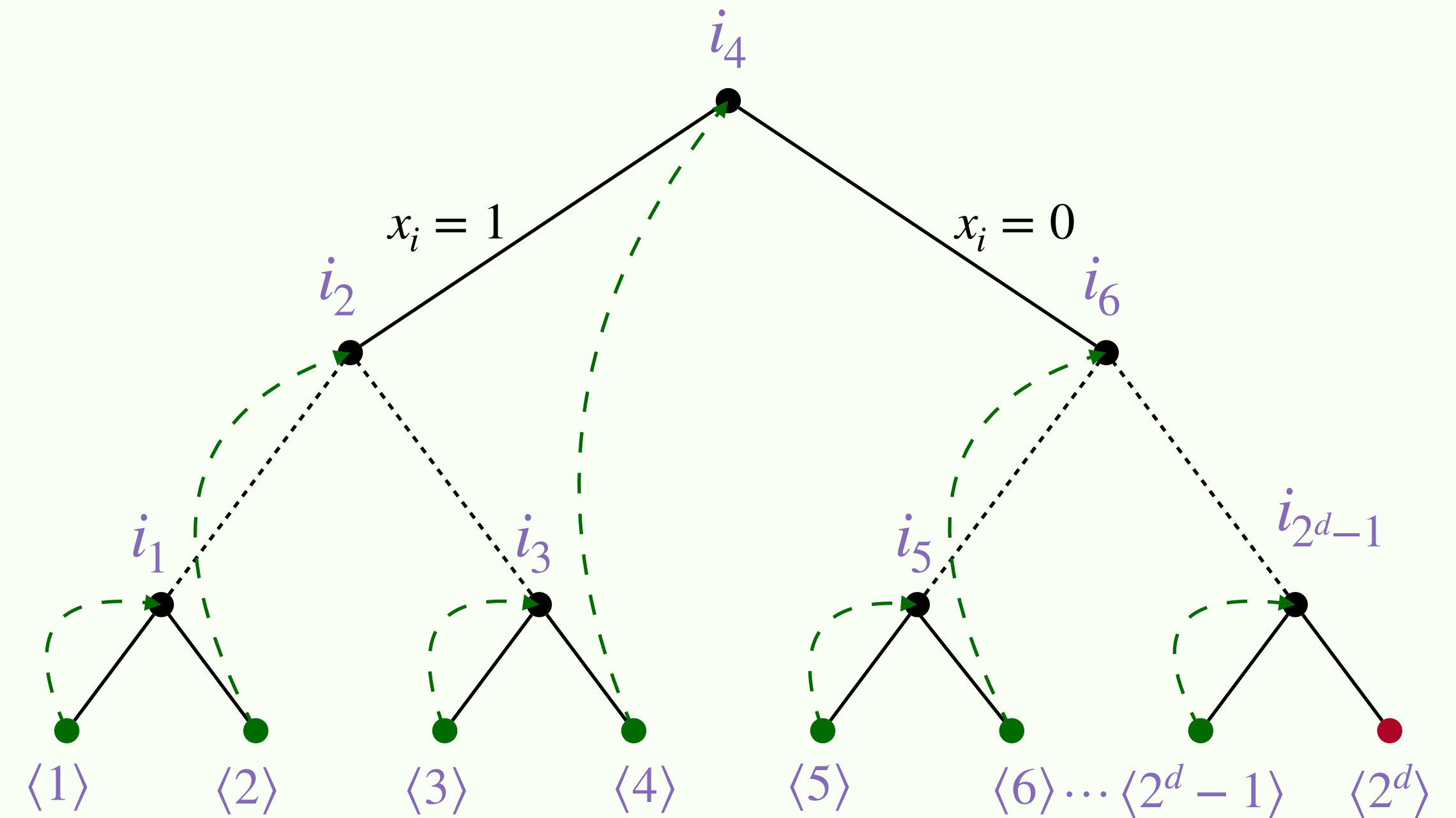
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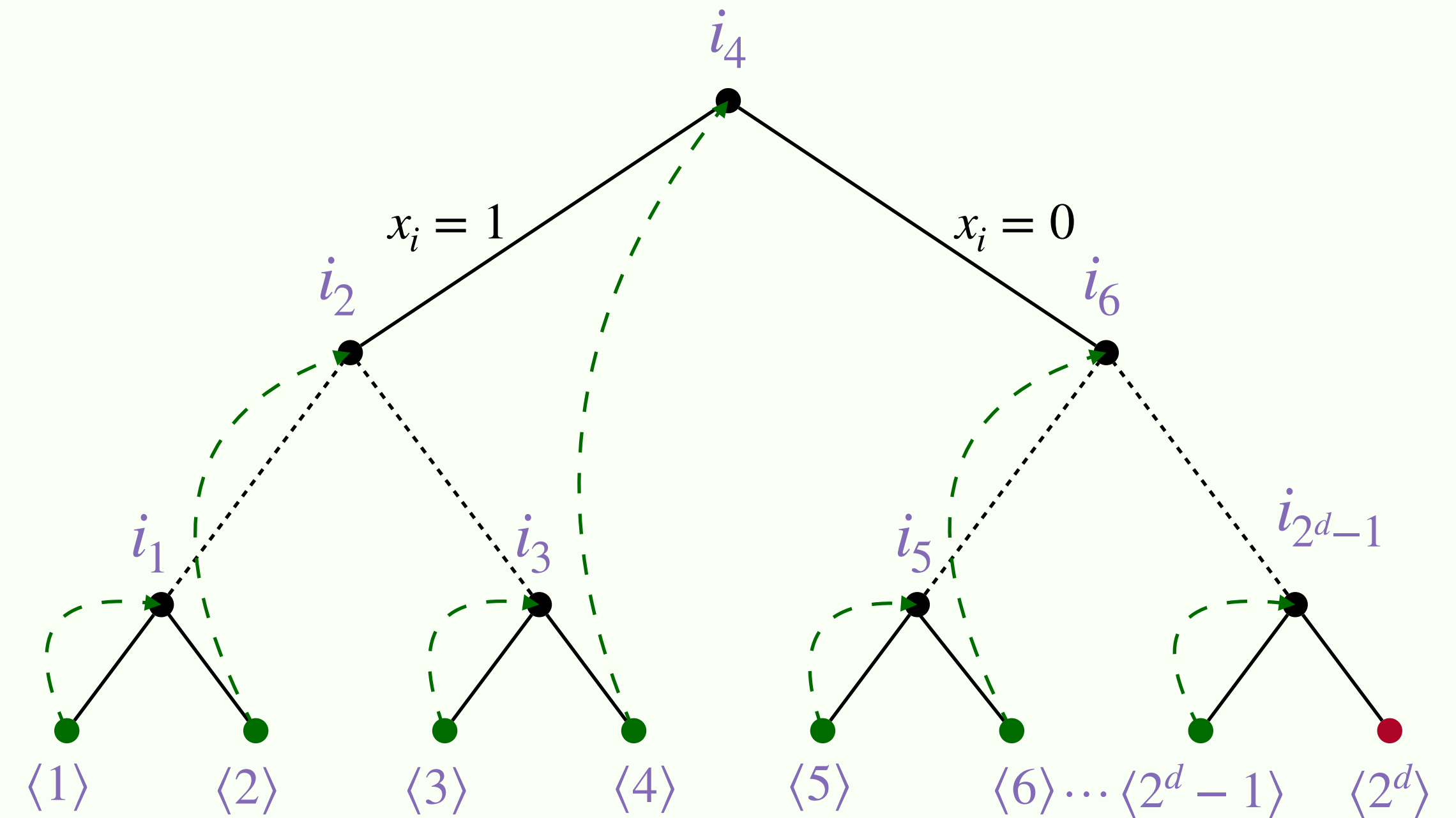
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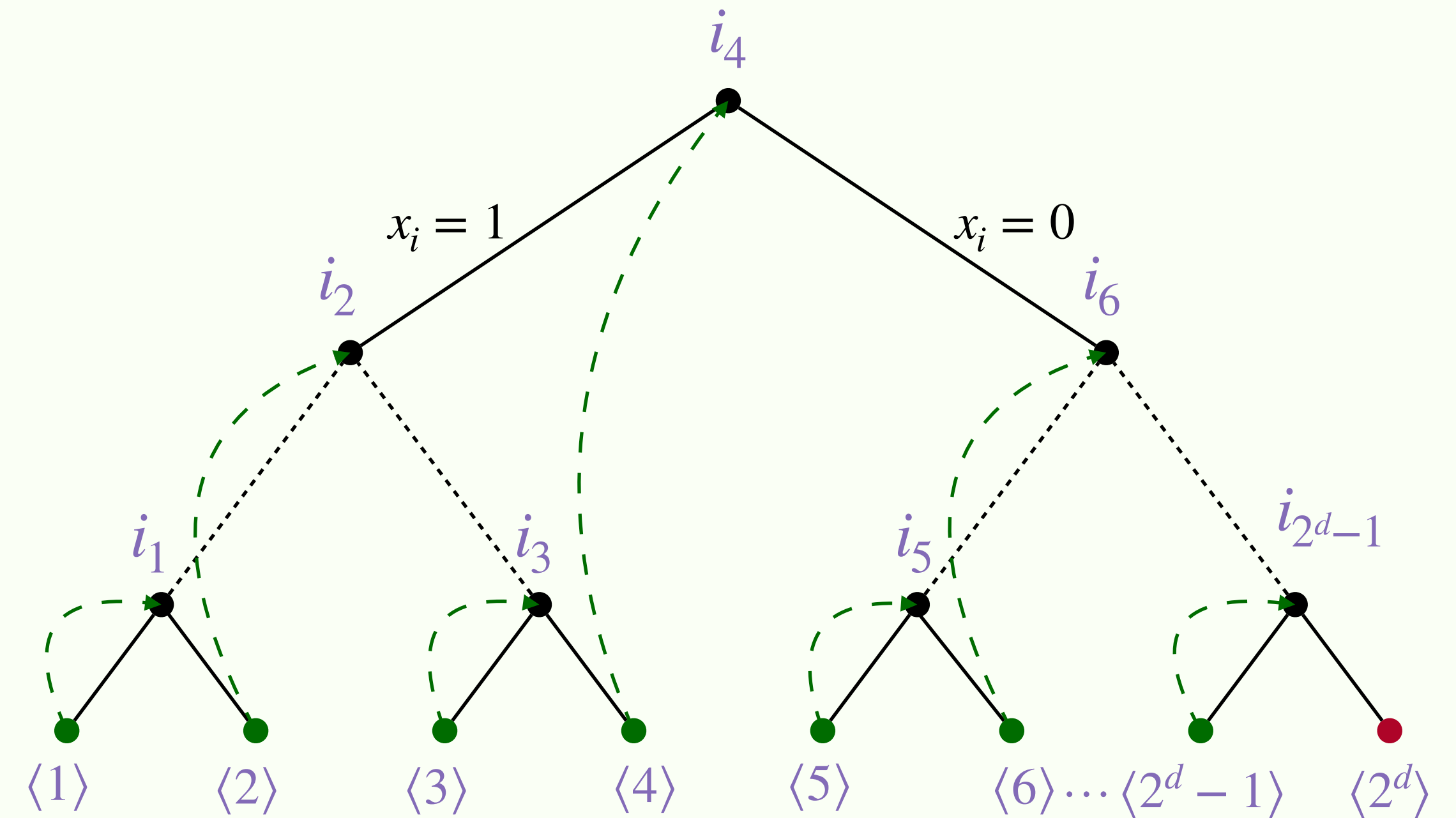
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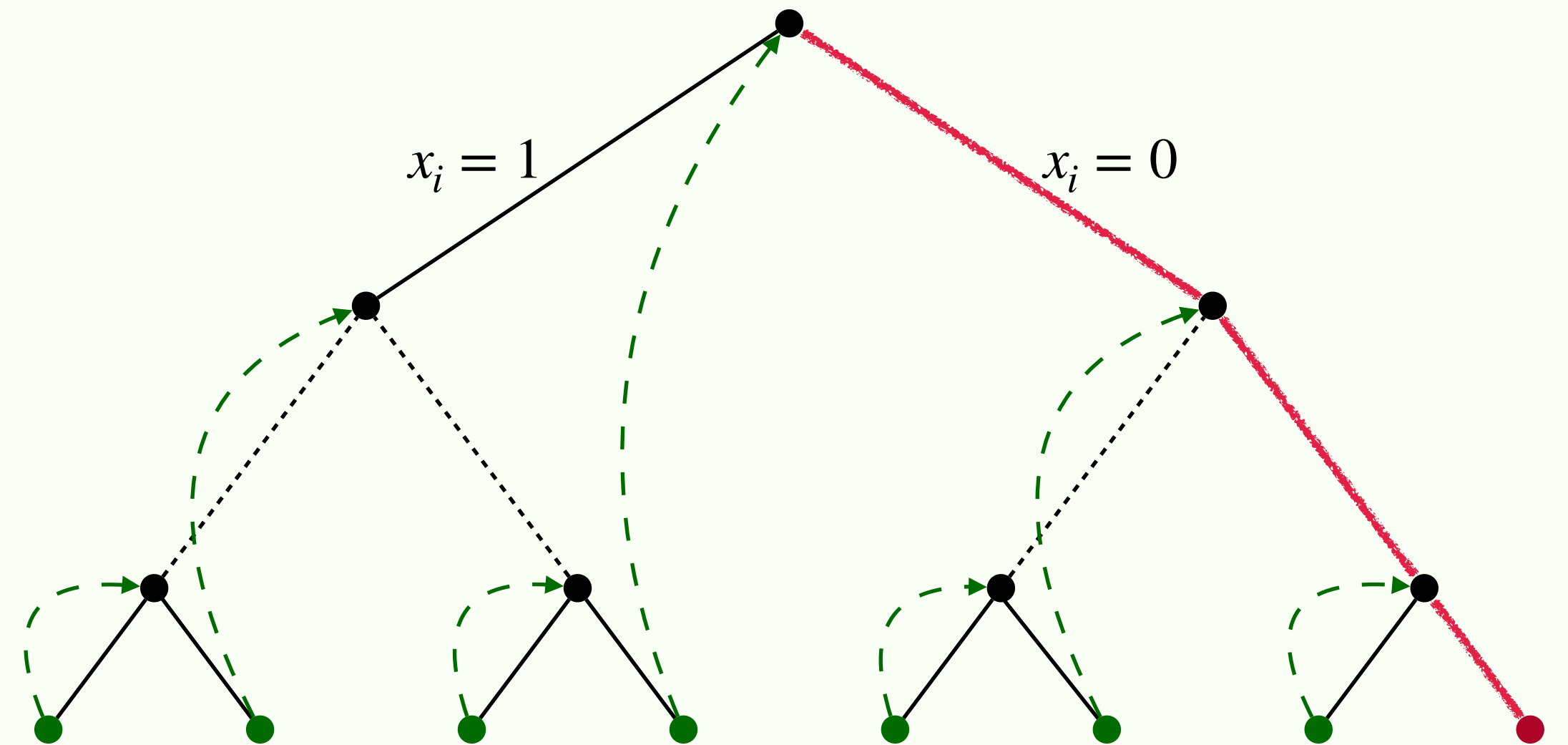
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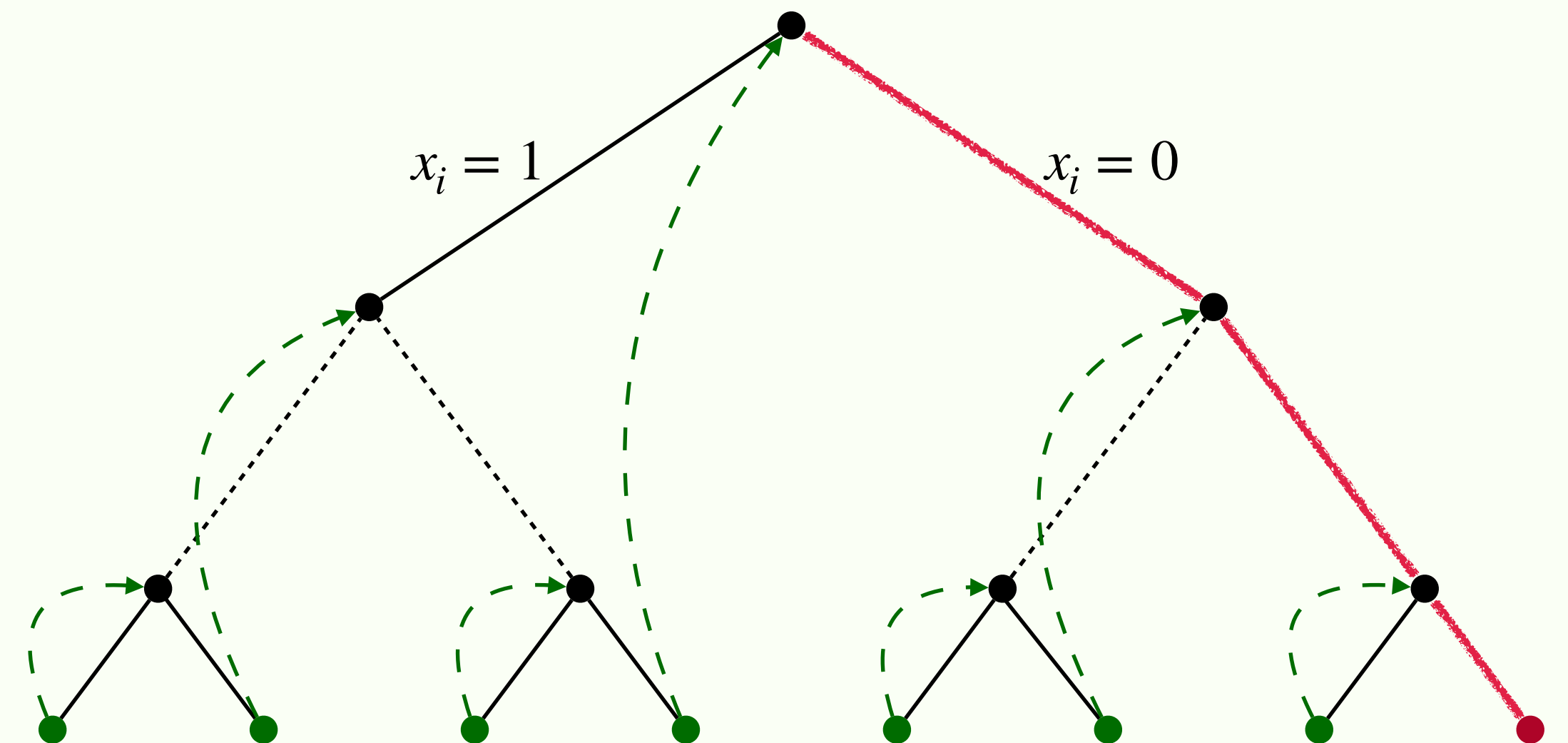
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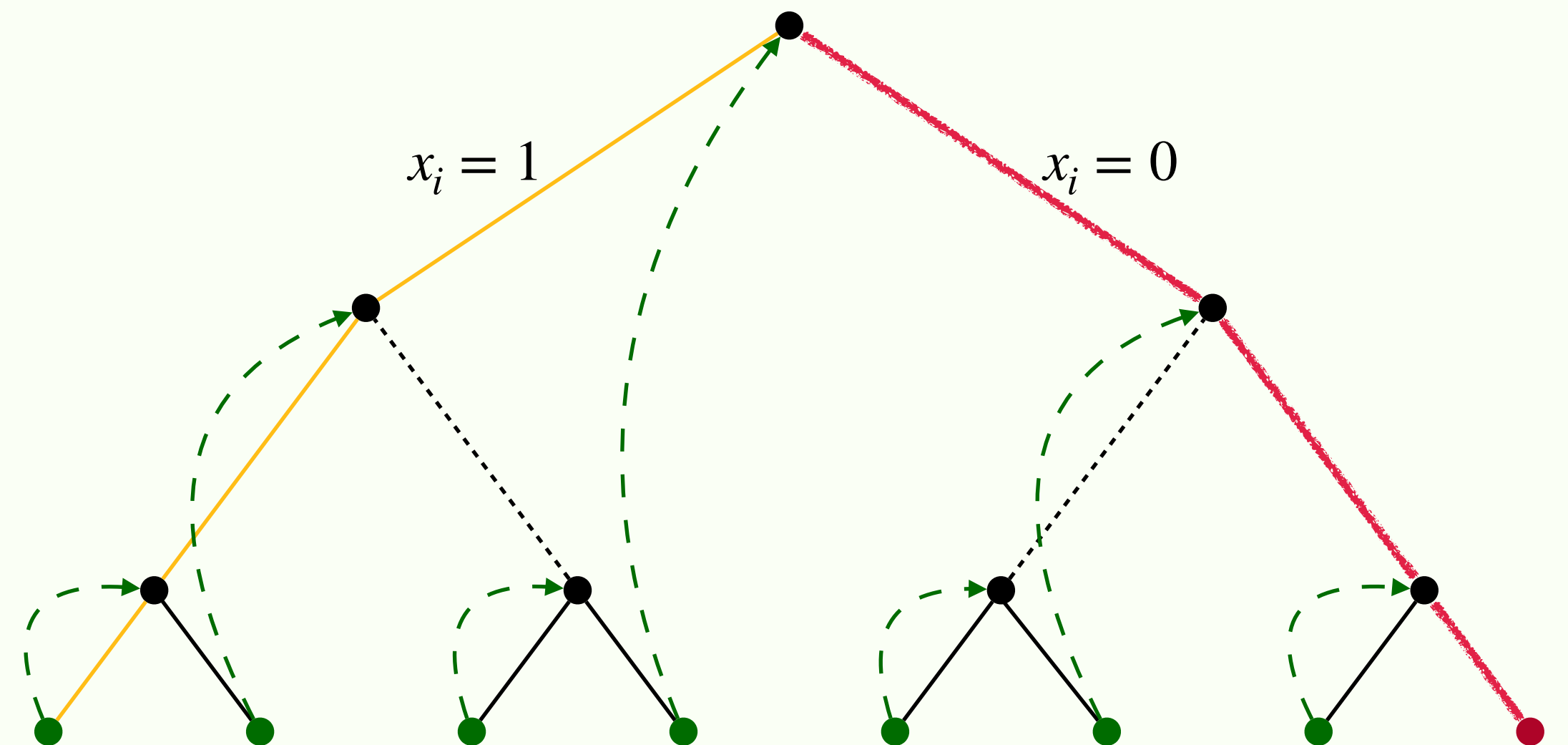
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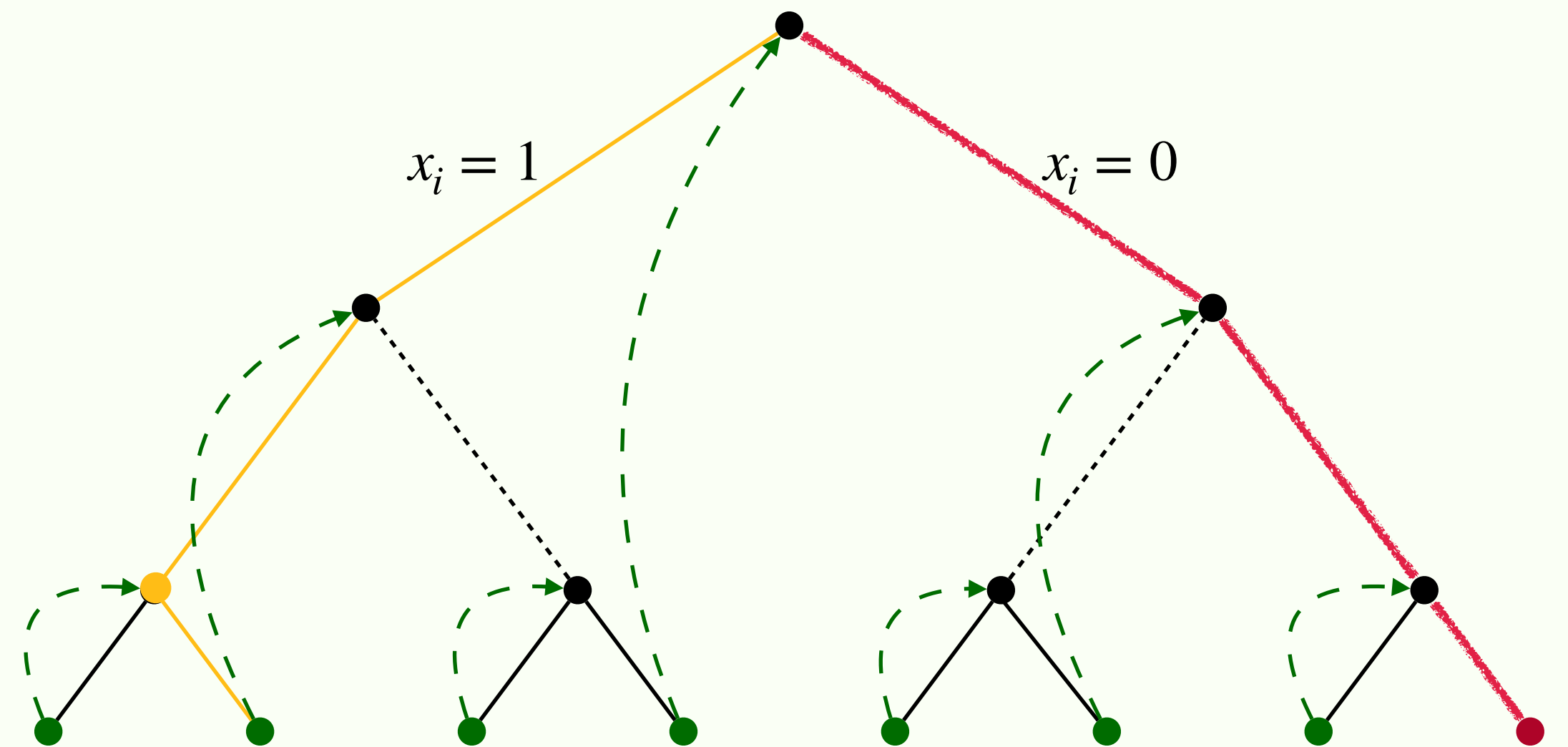
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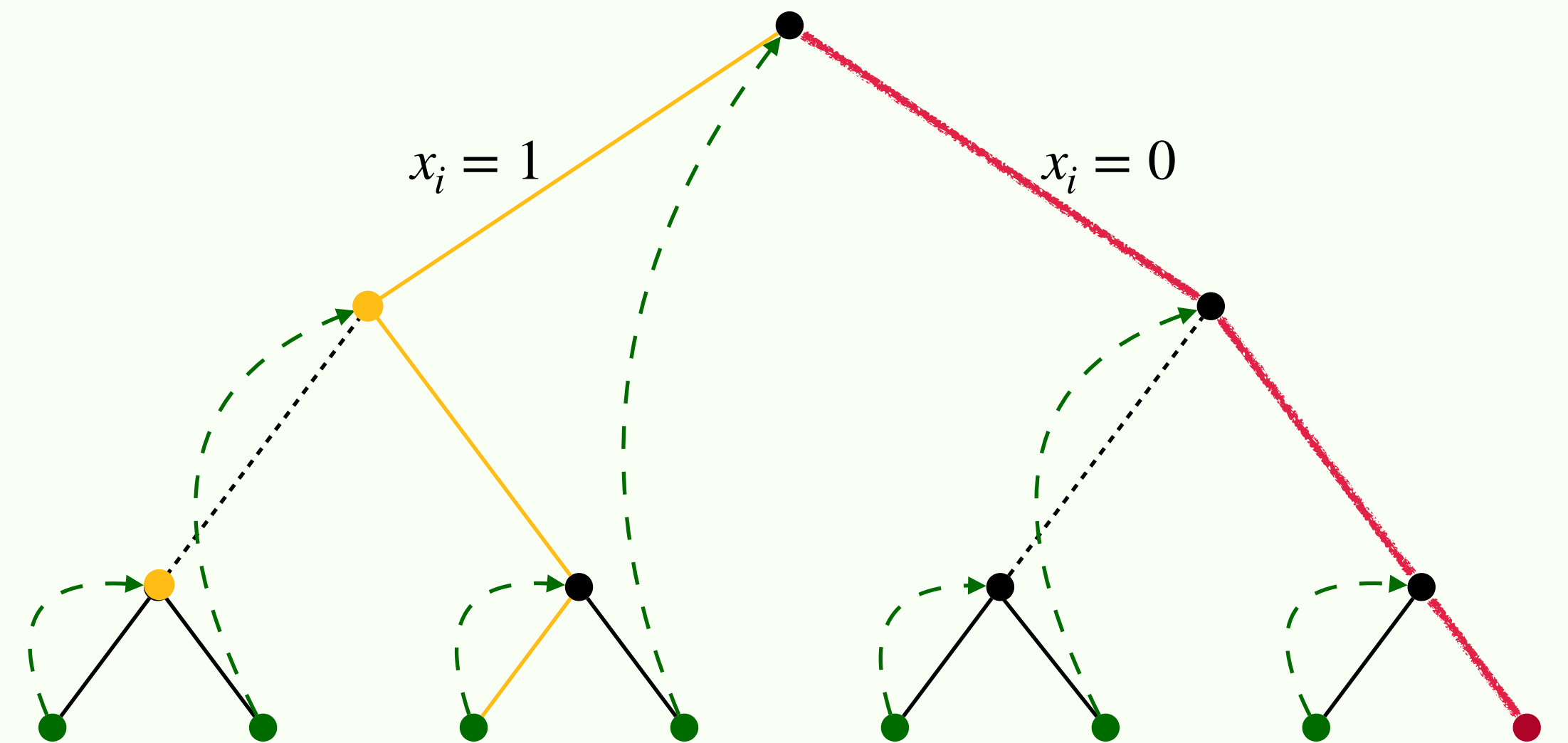
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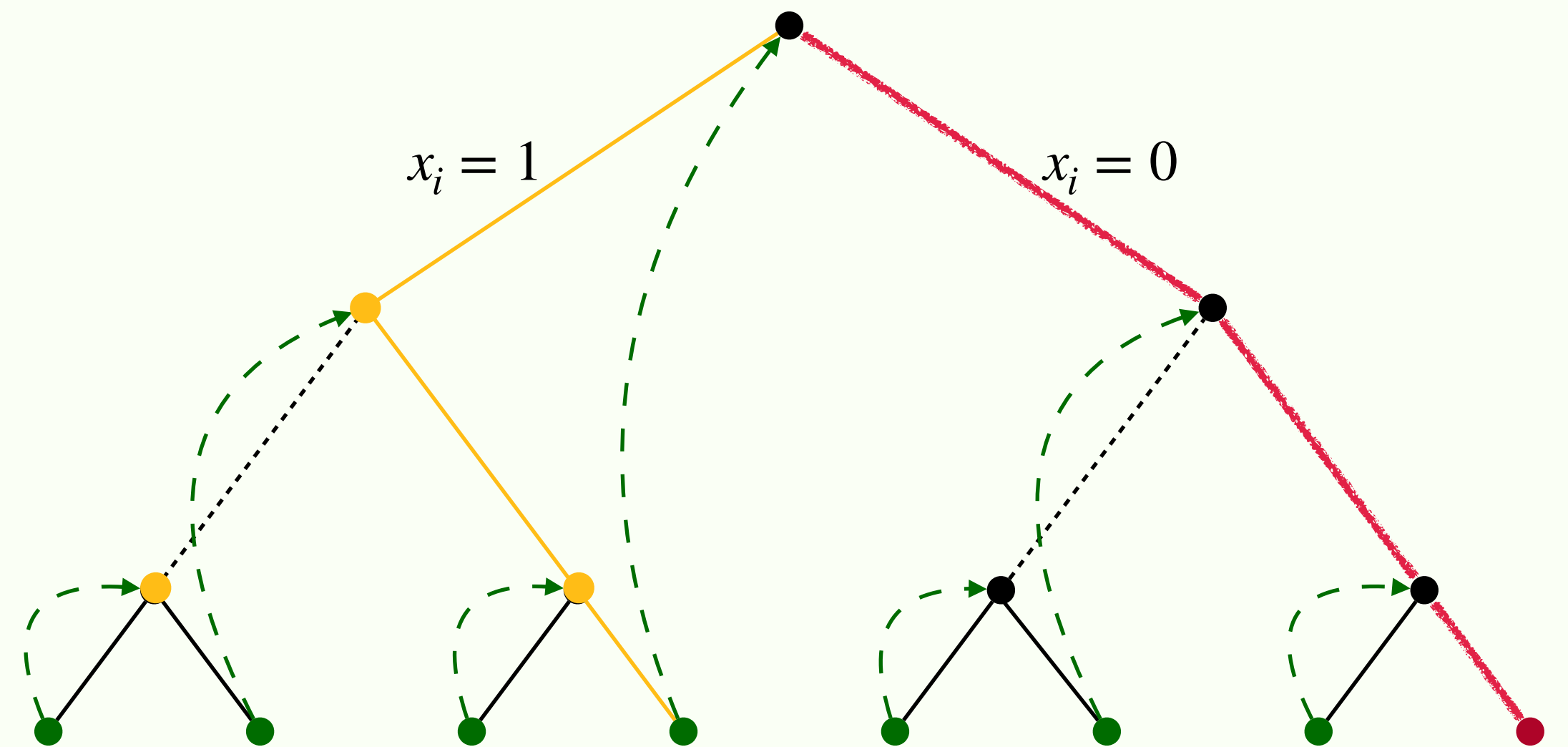
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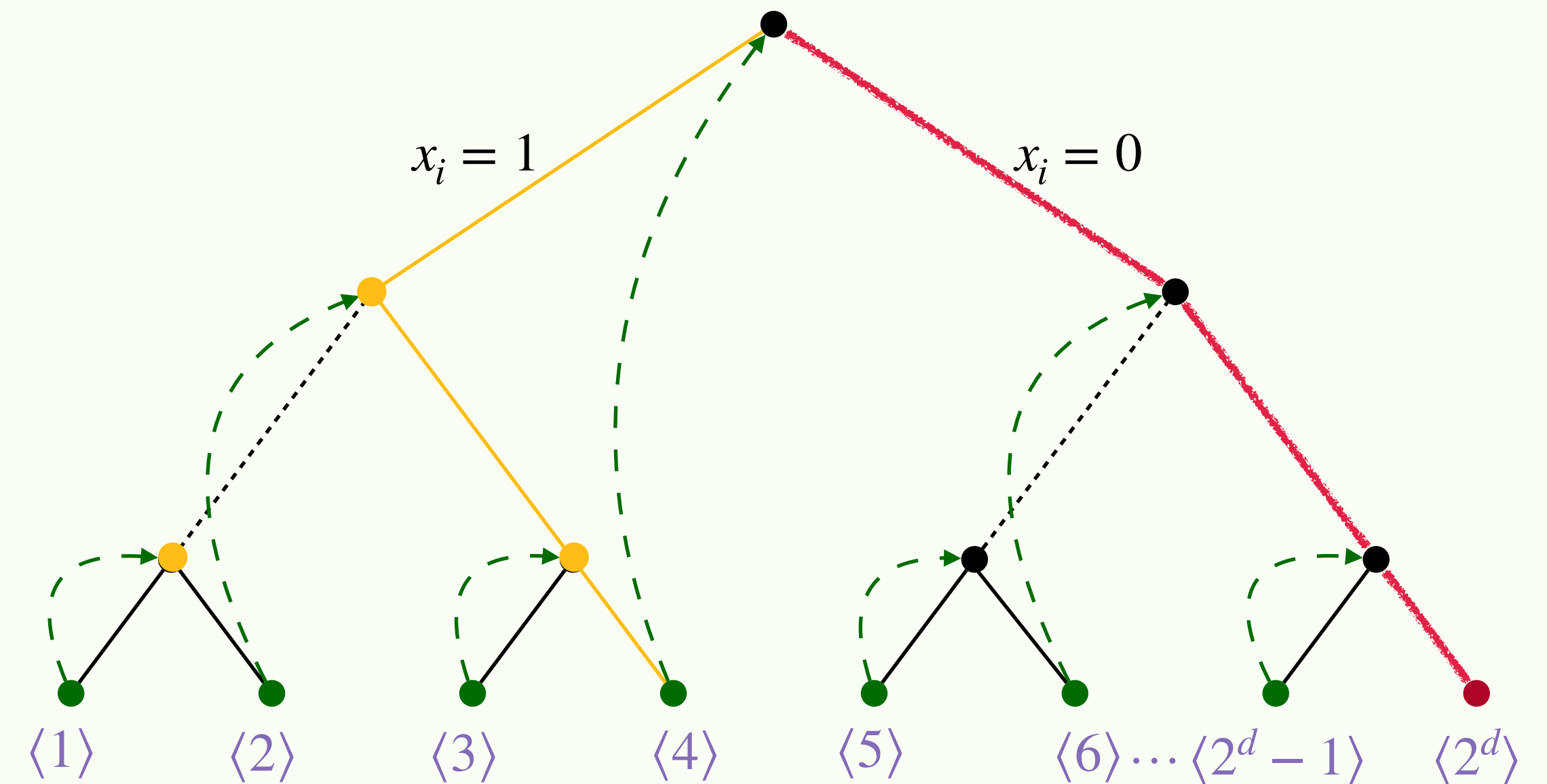
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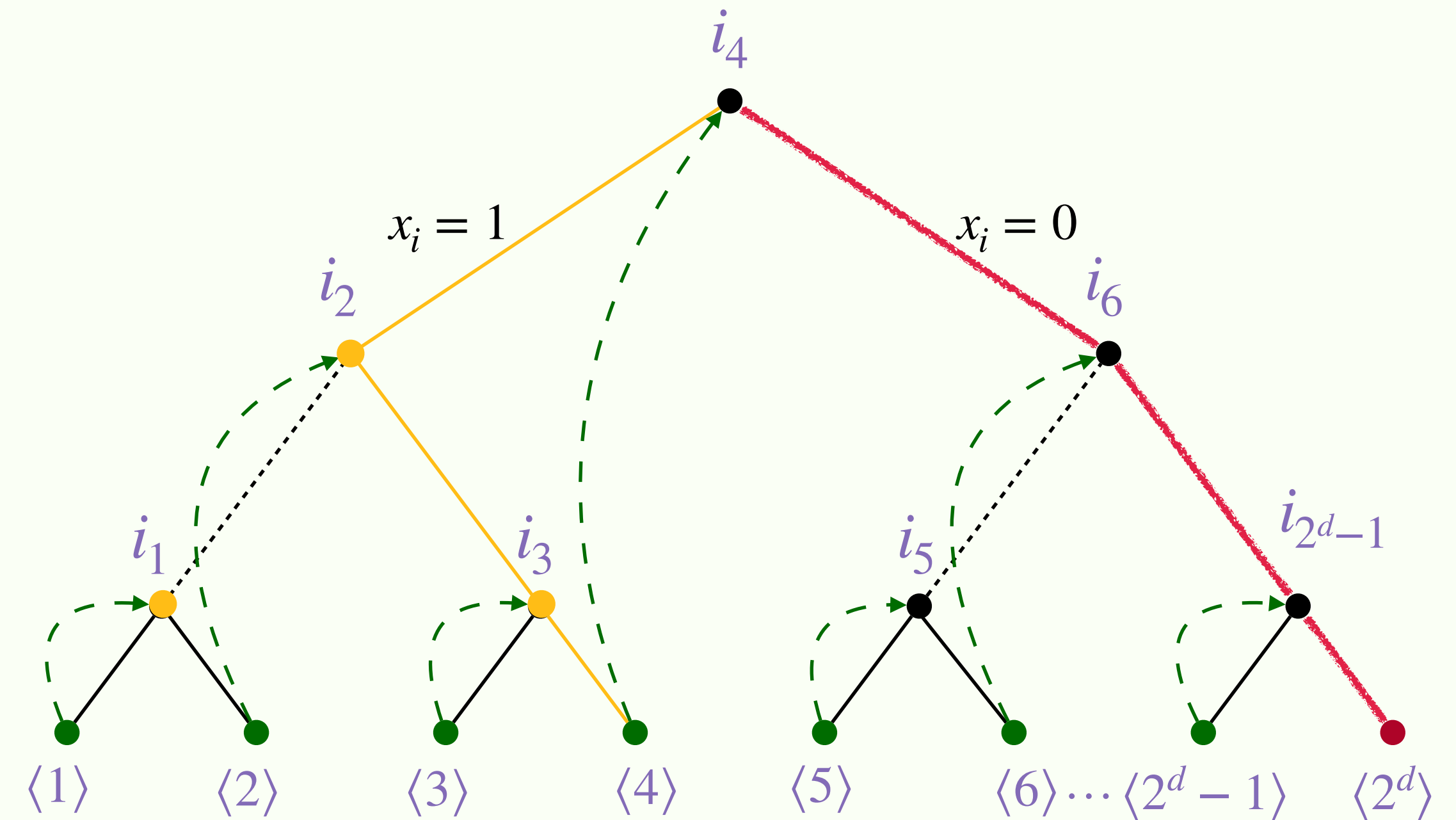
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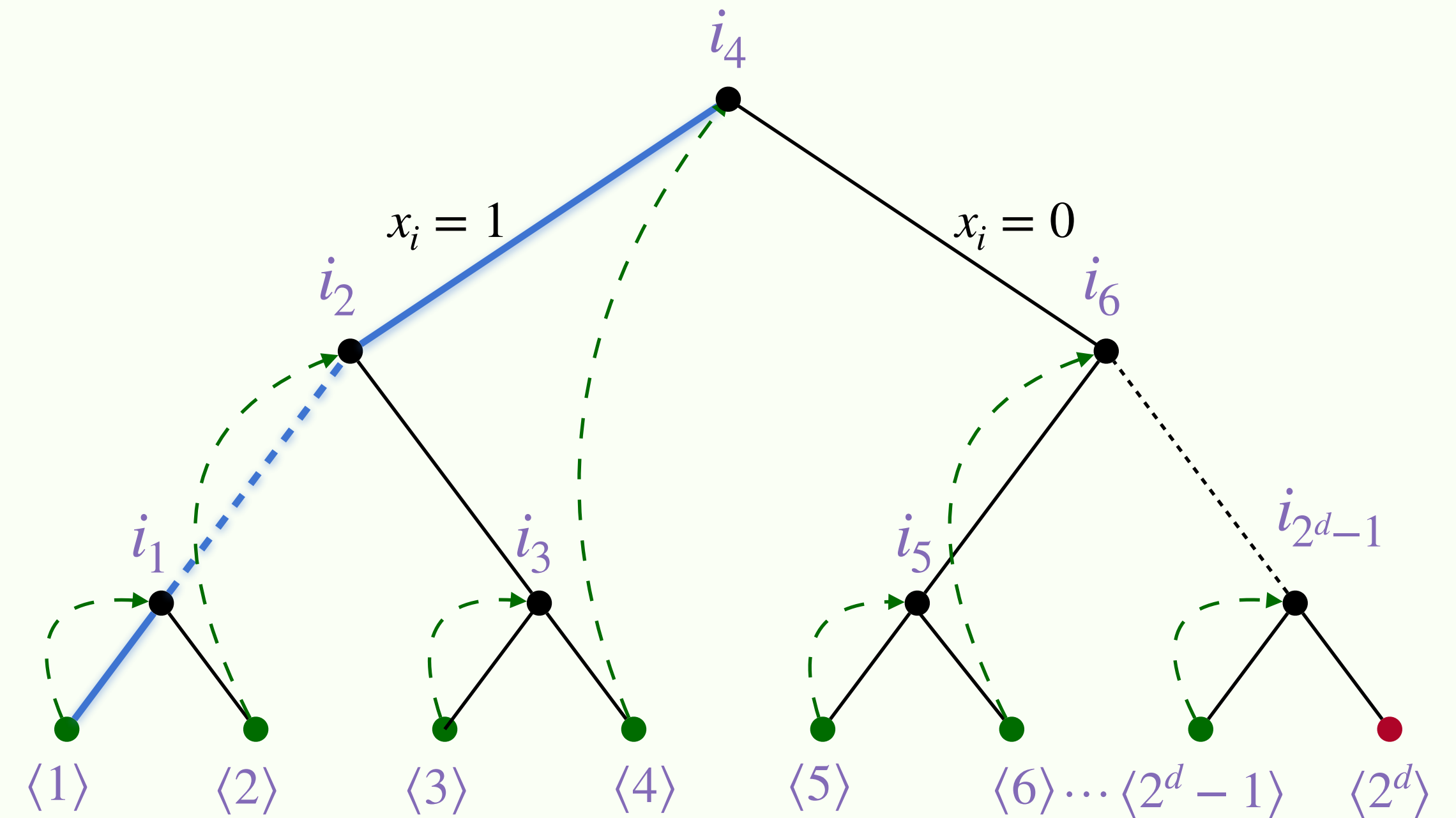
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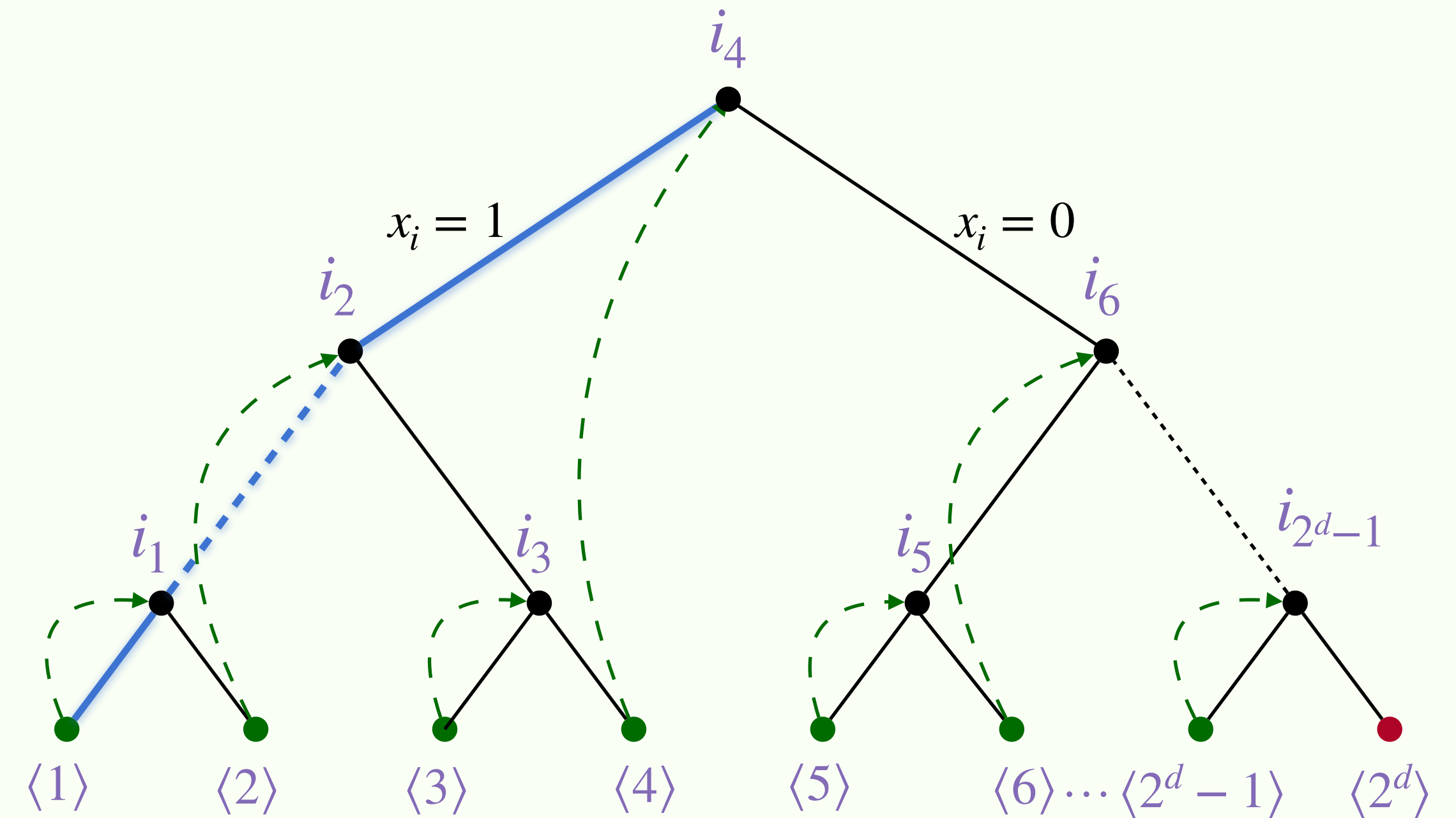
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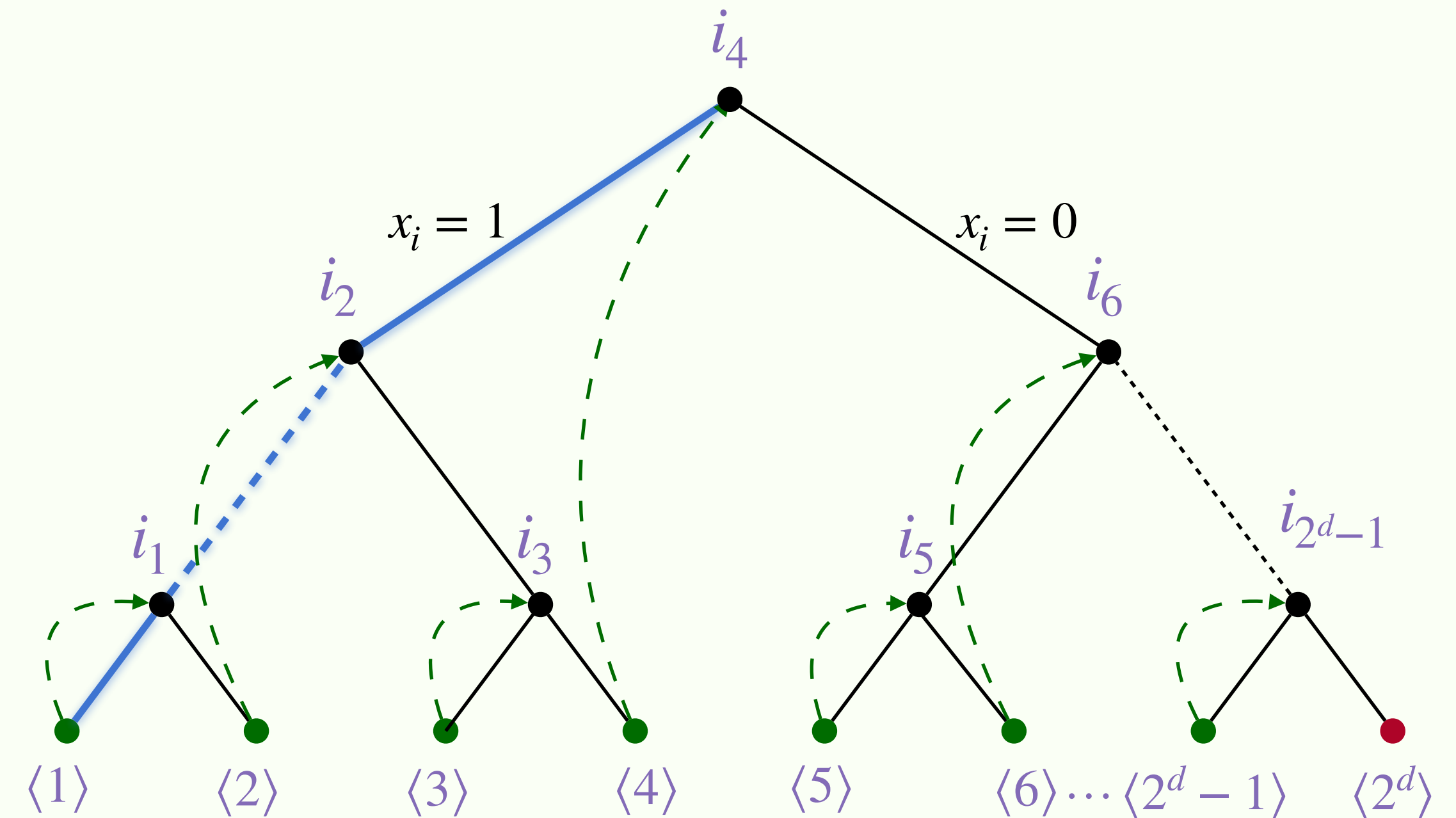
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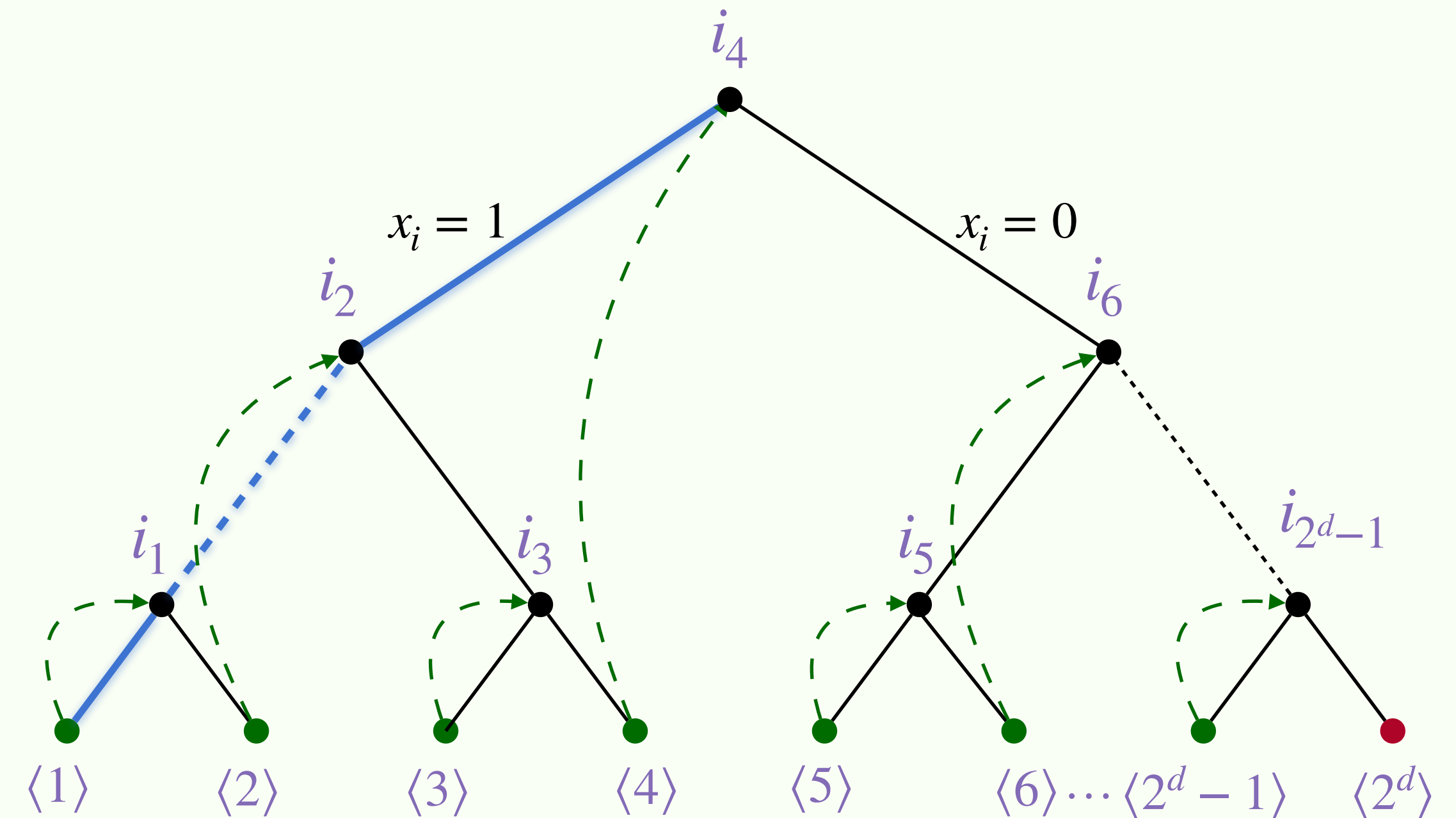
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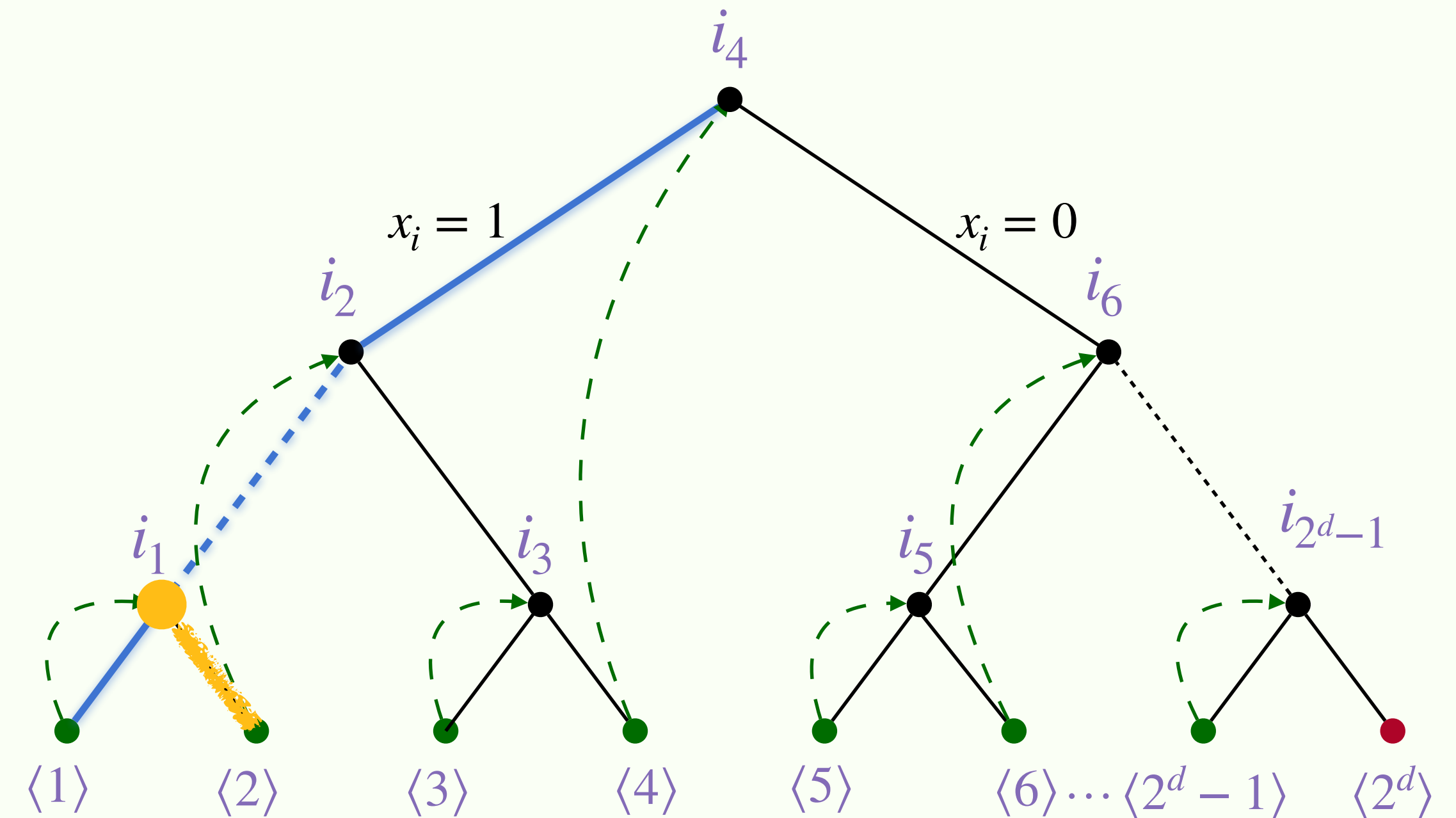
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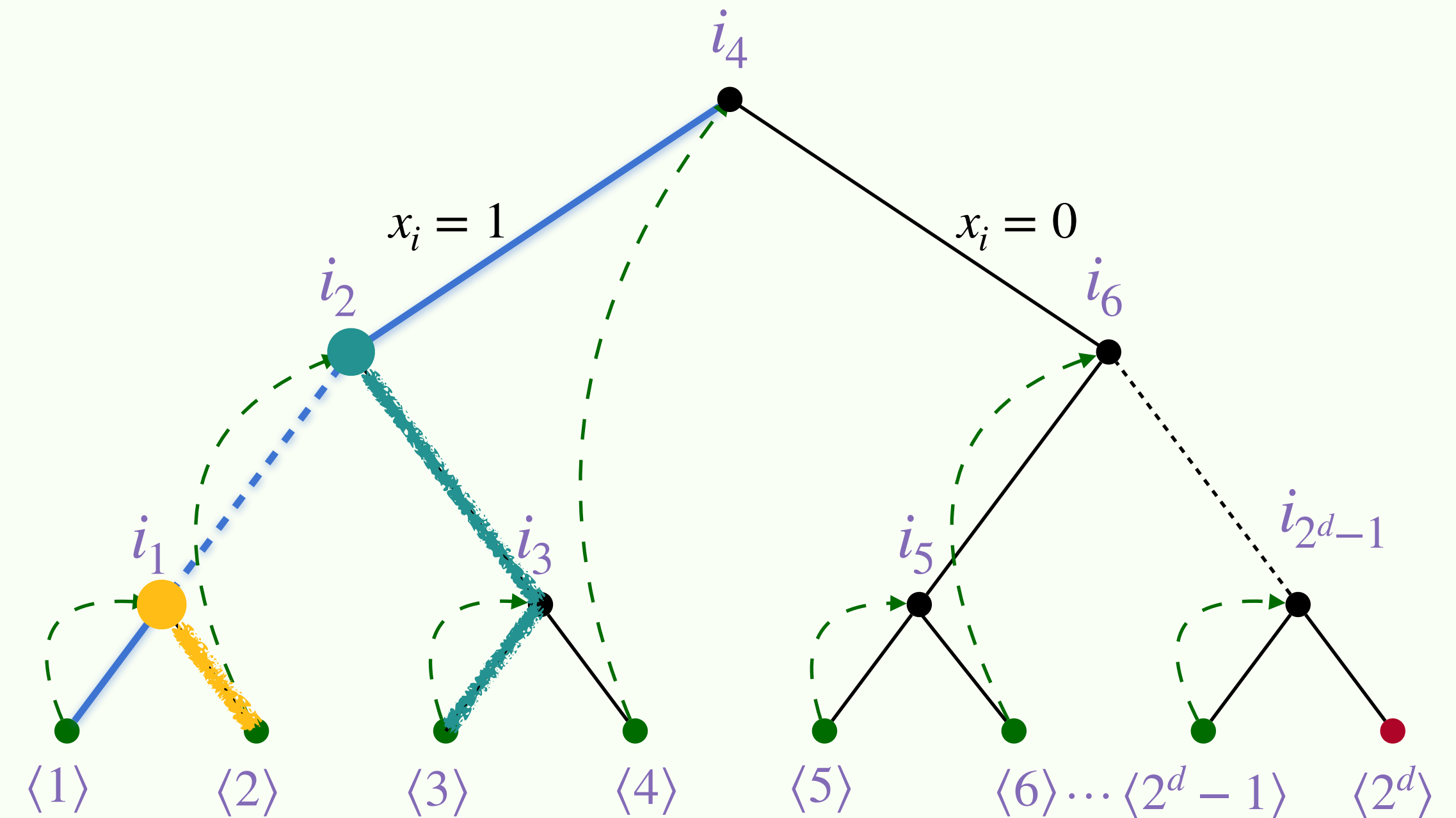
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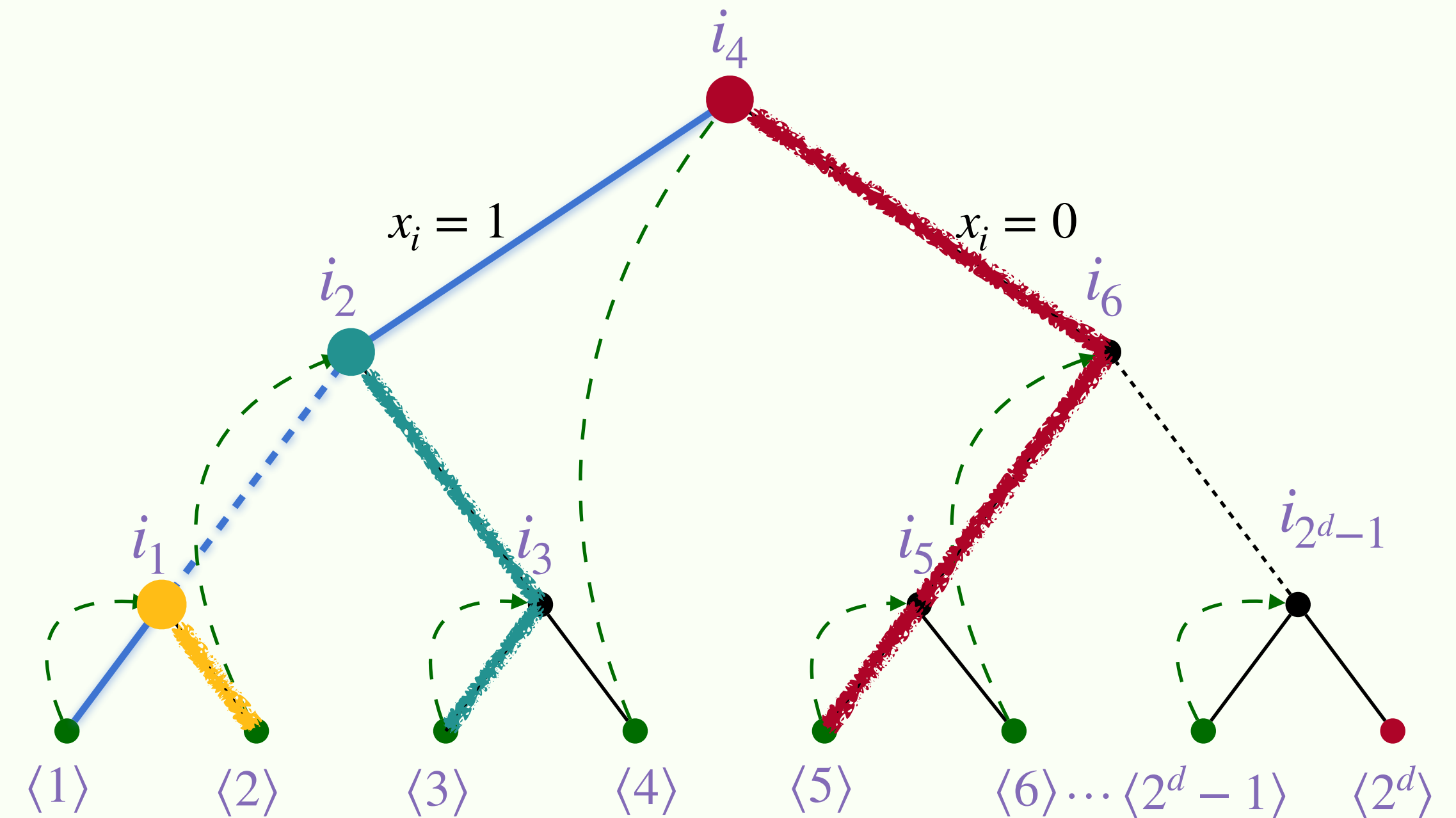
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The successful design: a mixed approach

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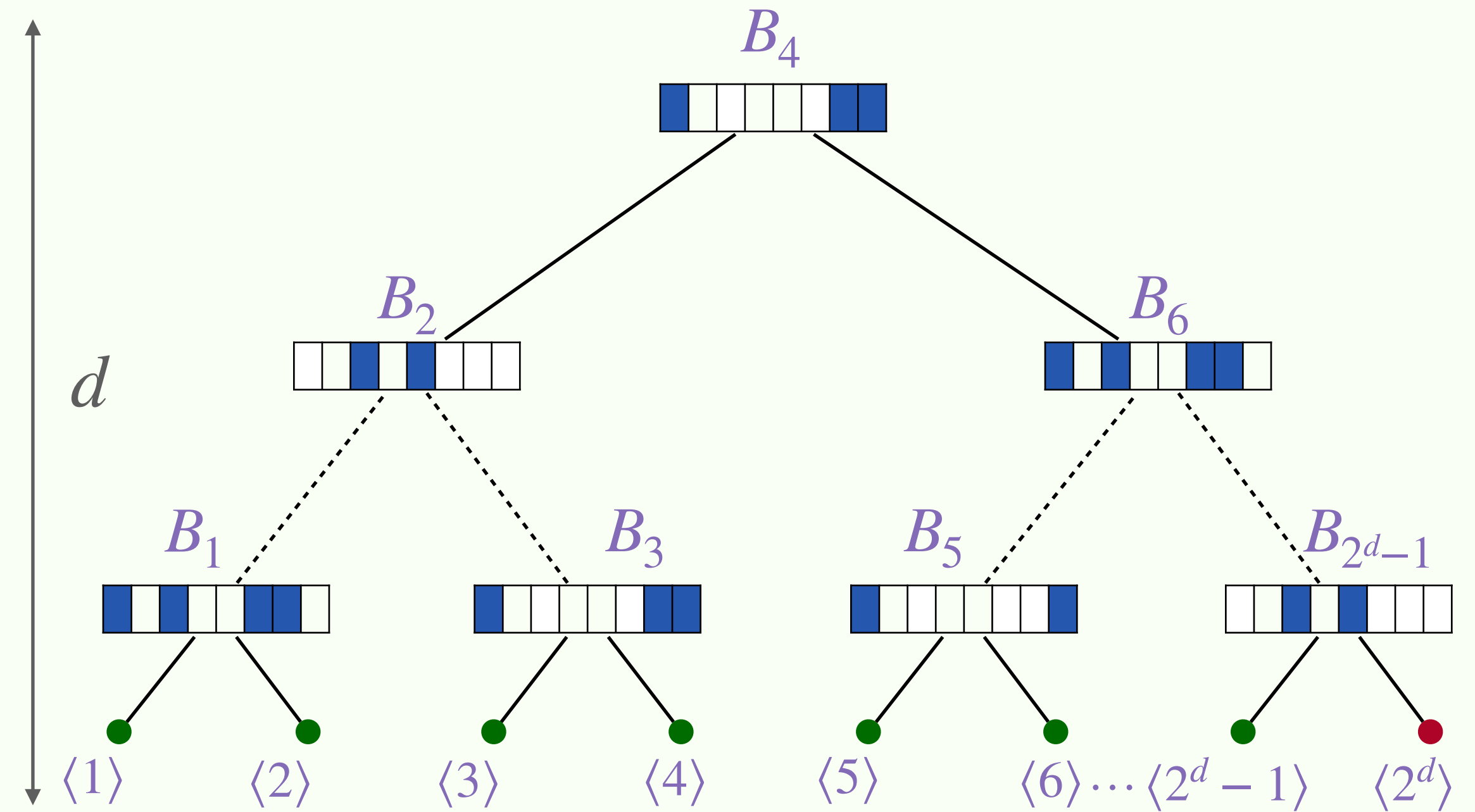
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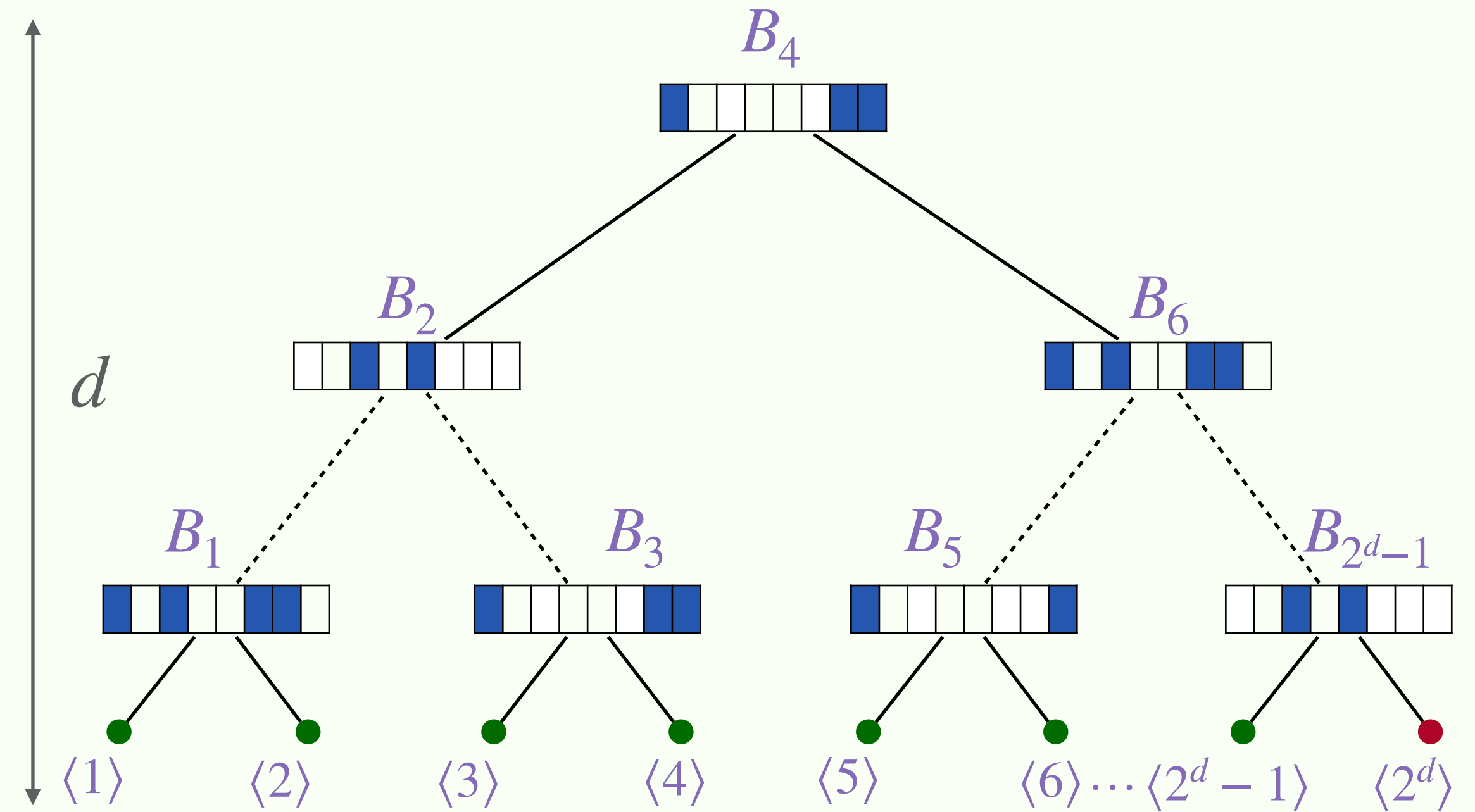


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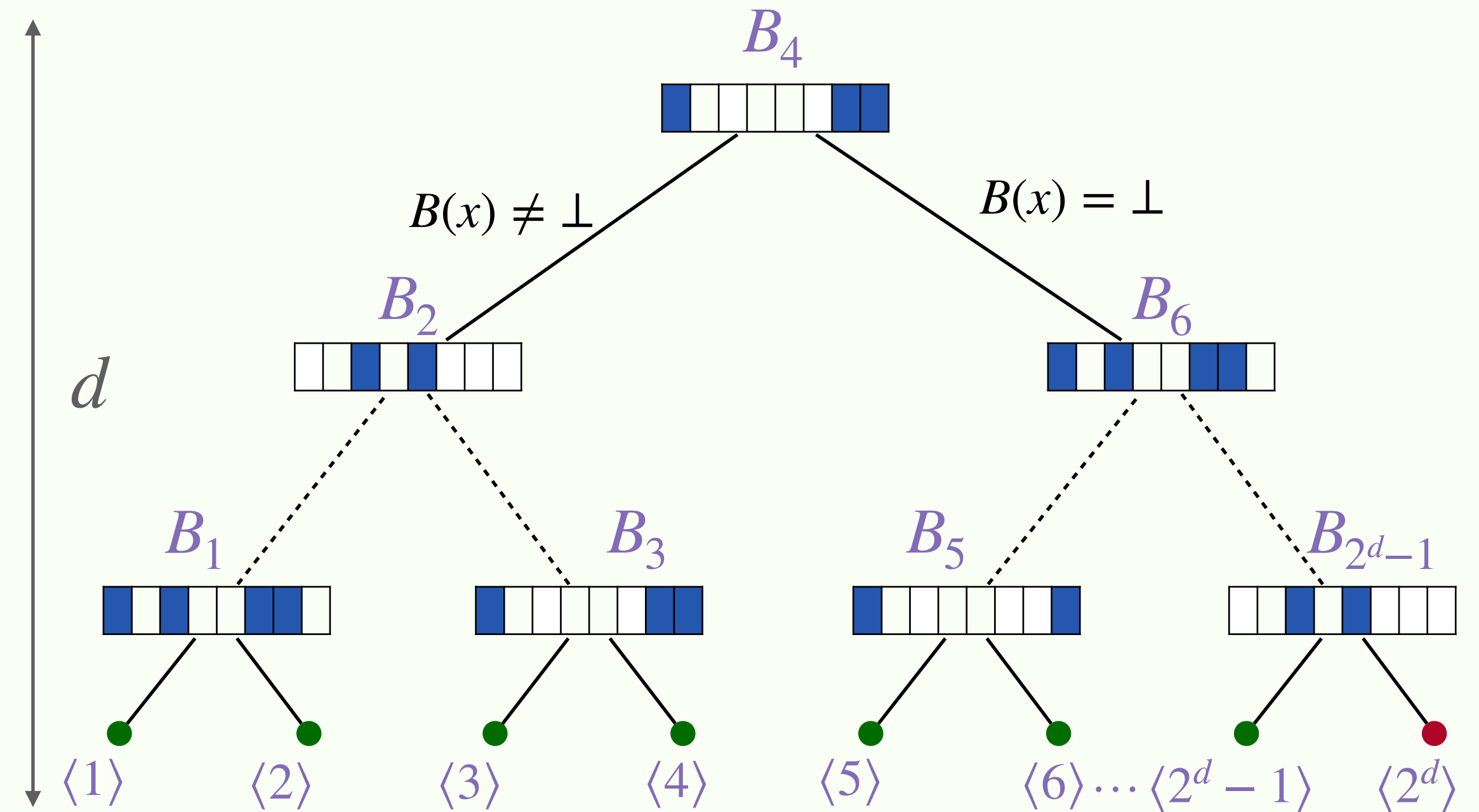


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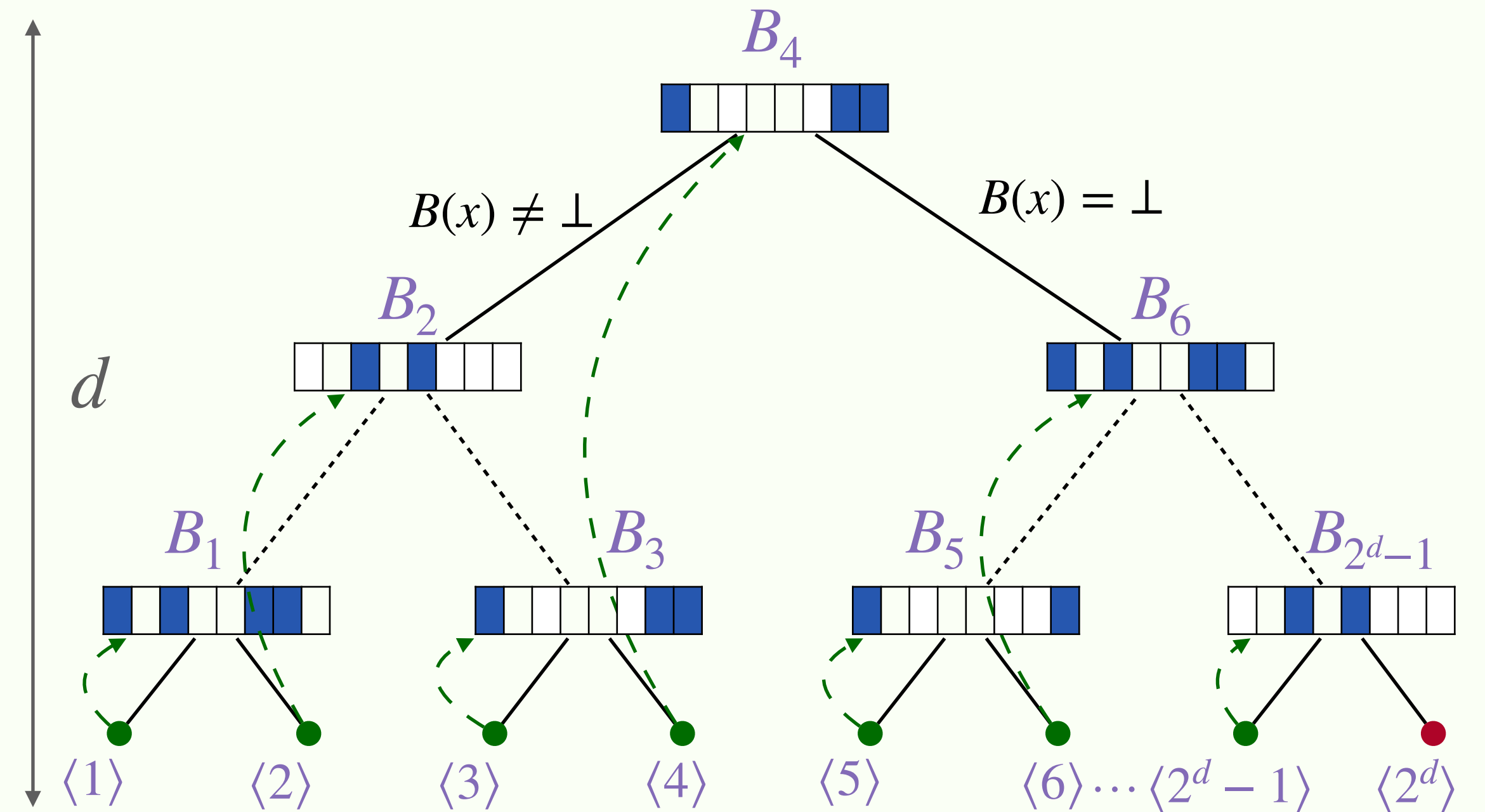


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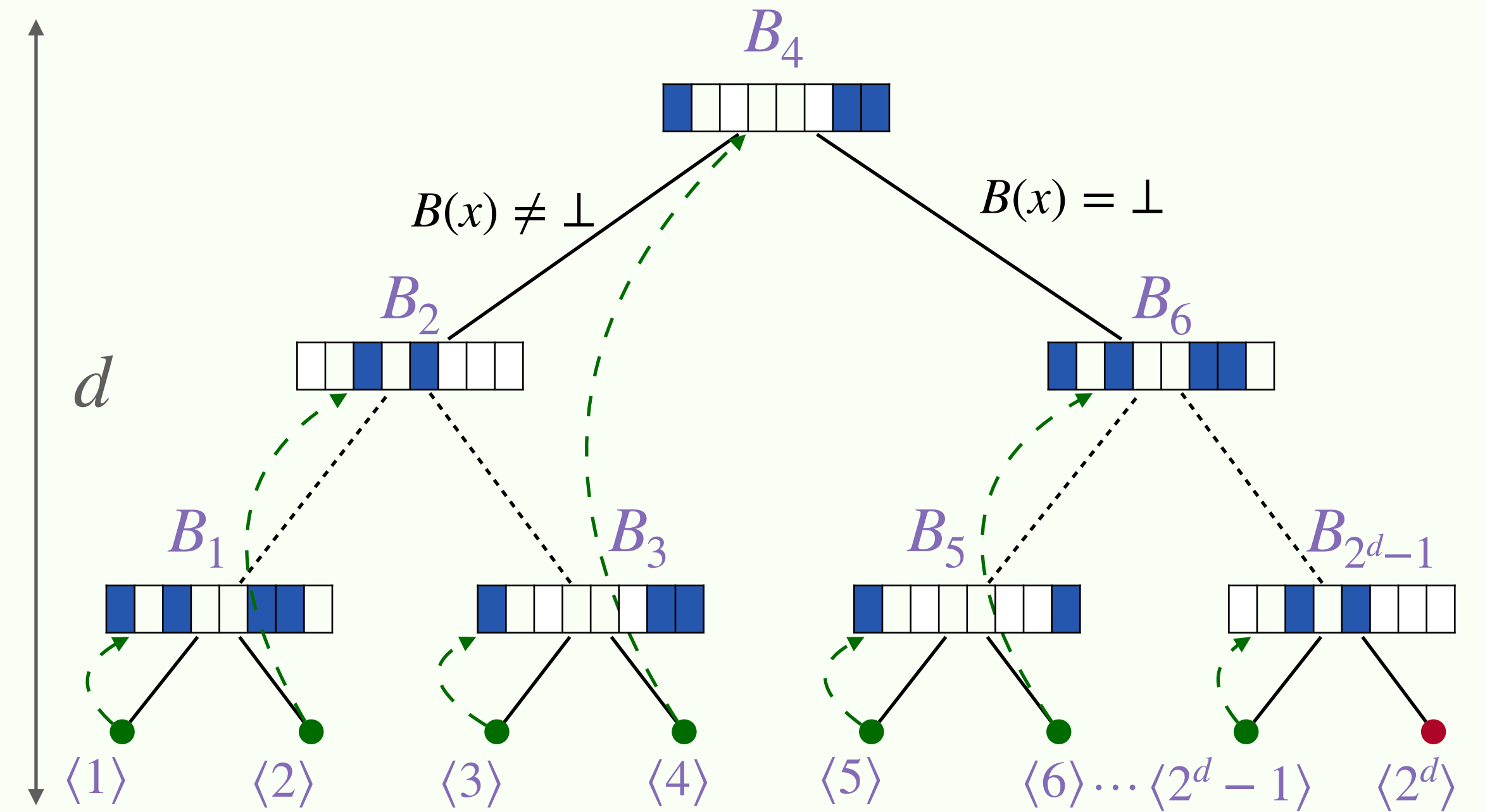


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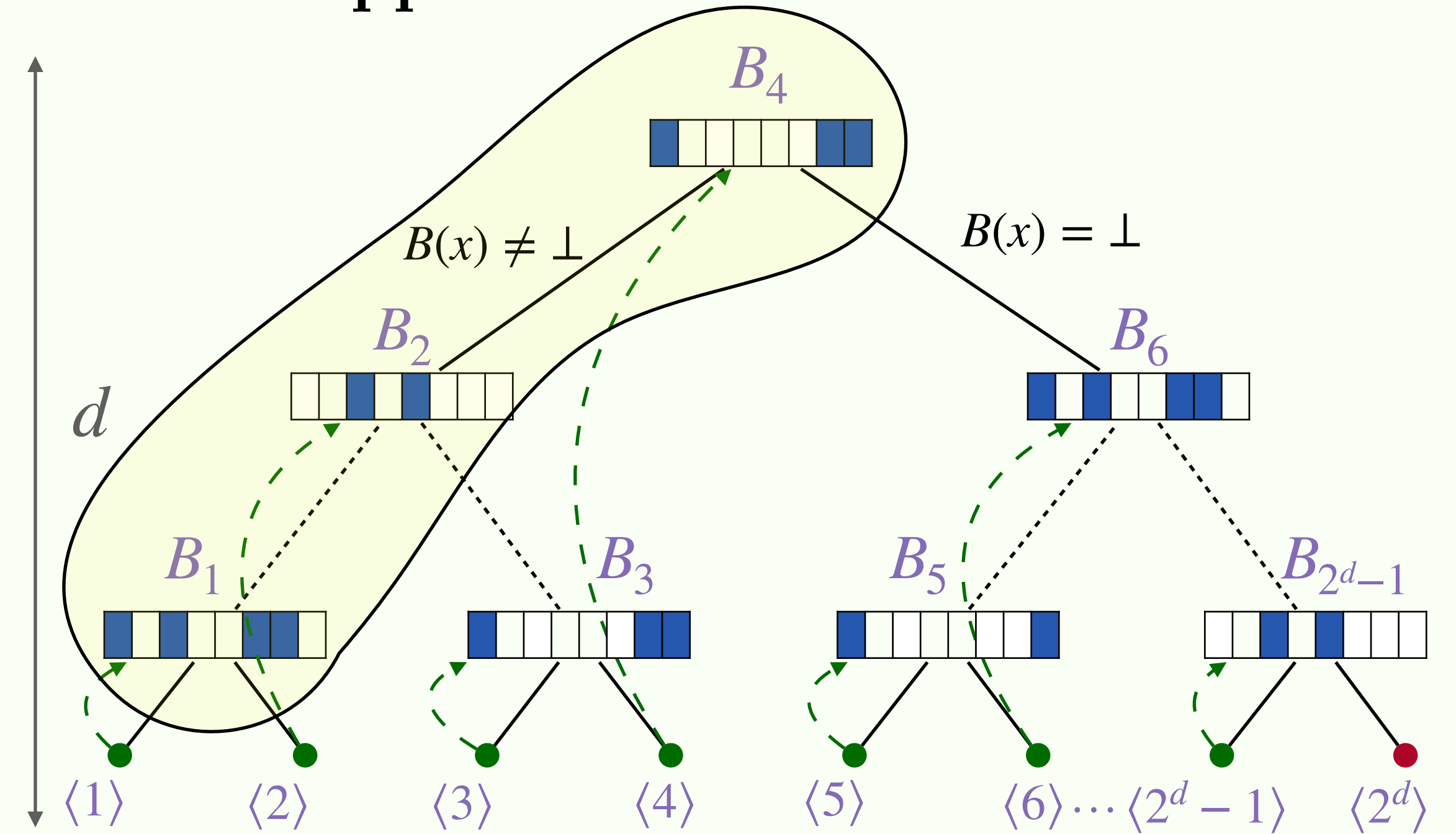
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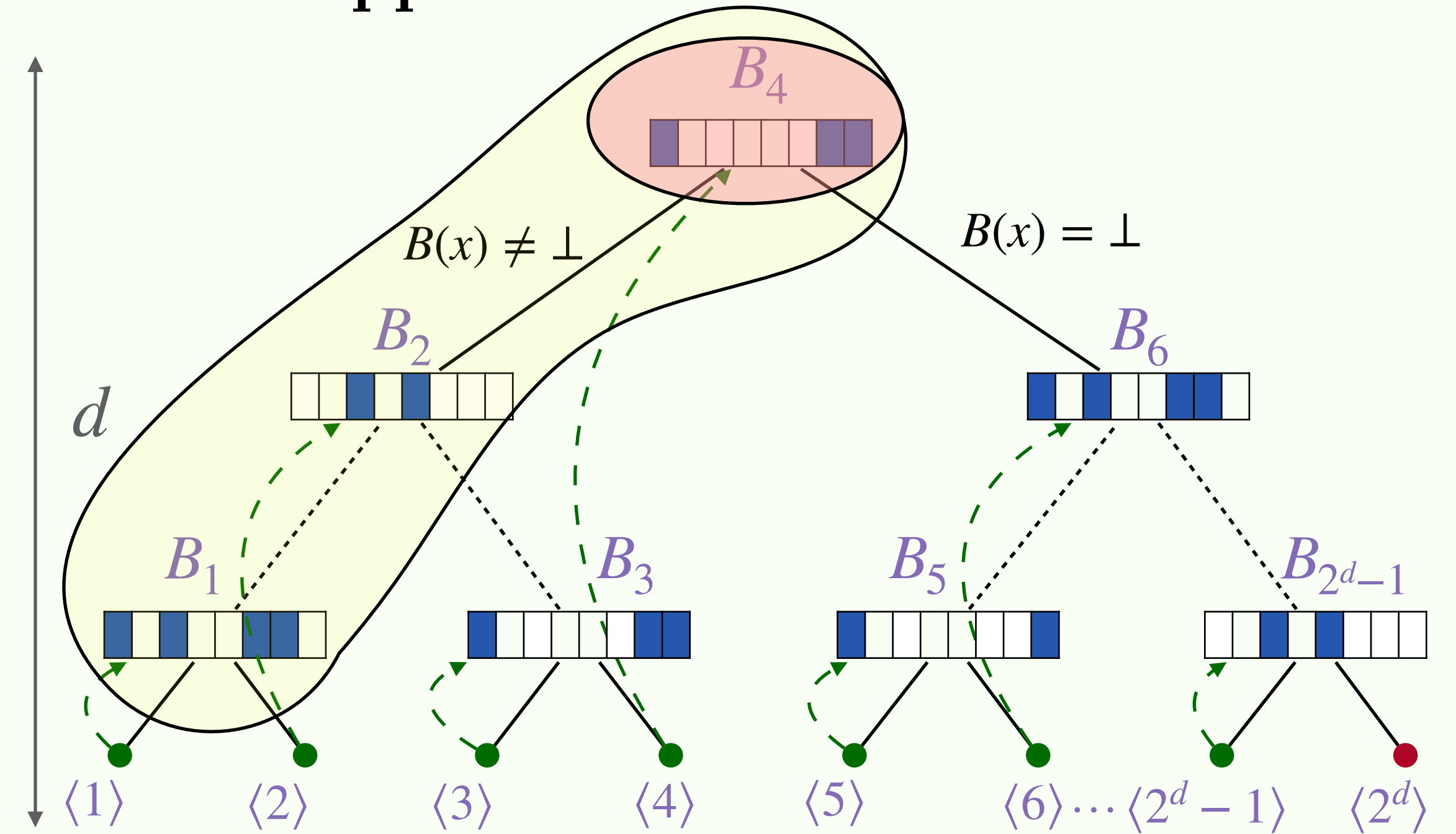
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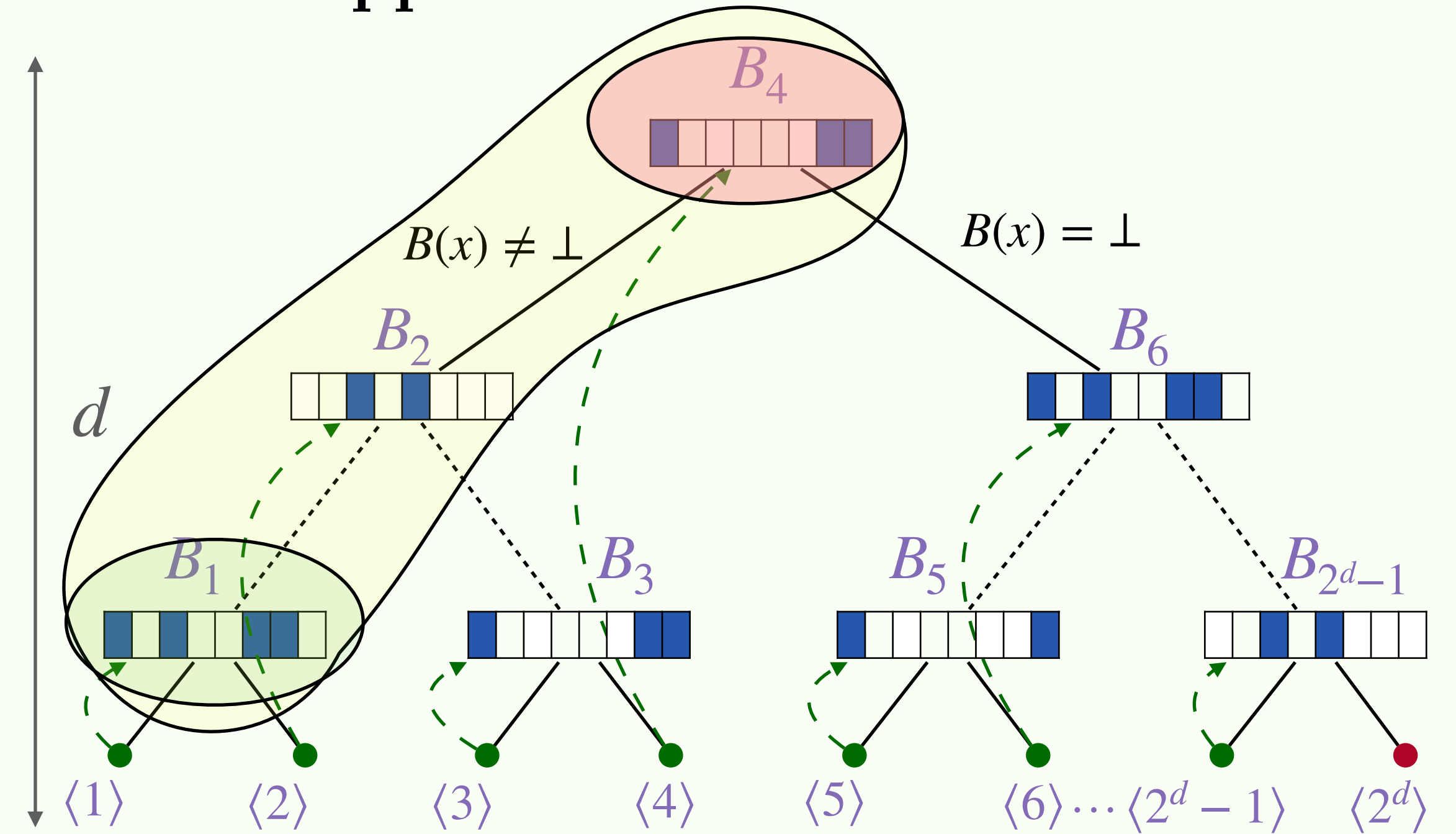
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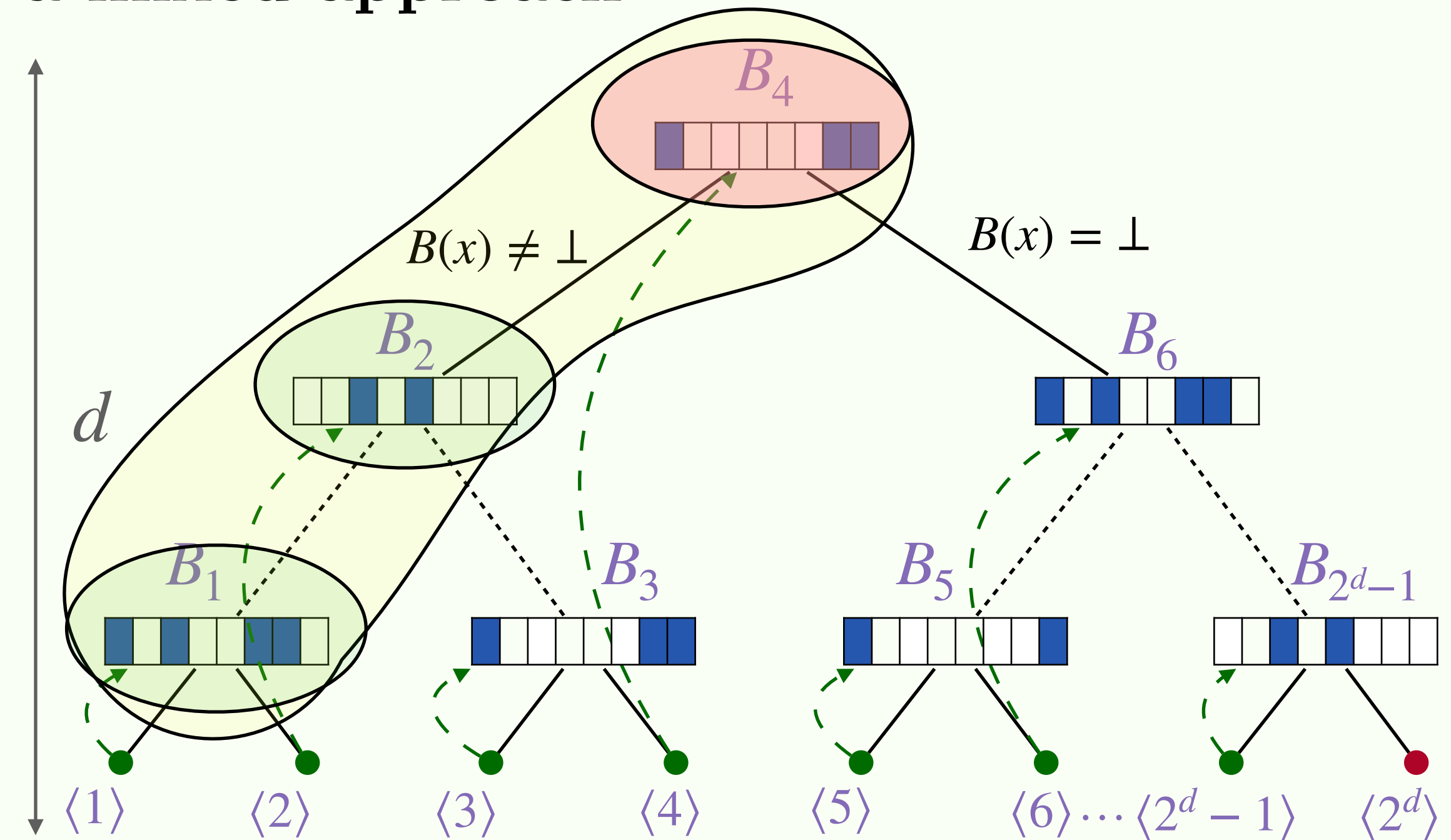
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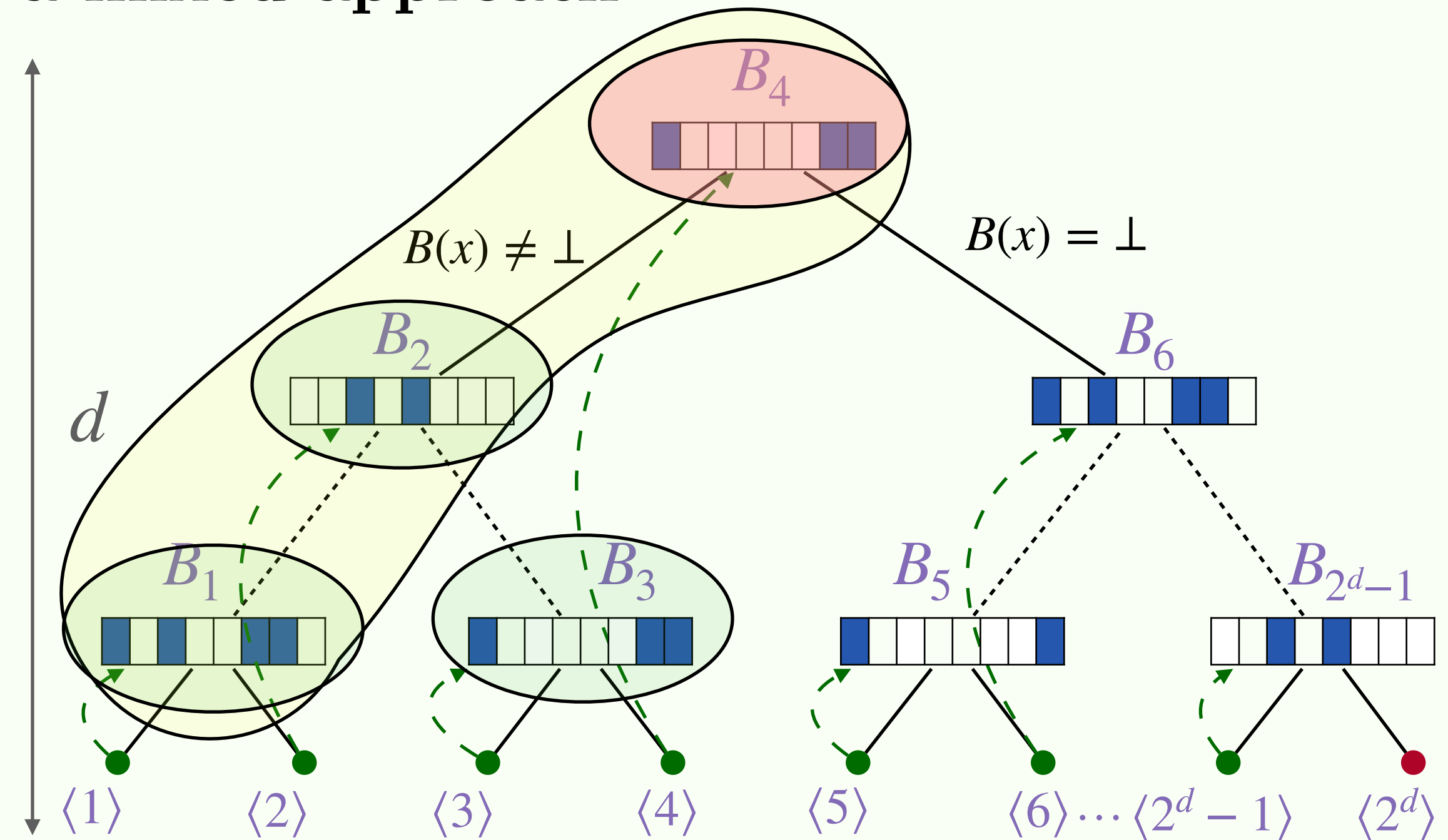
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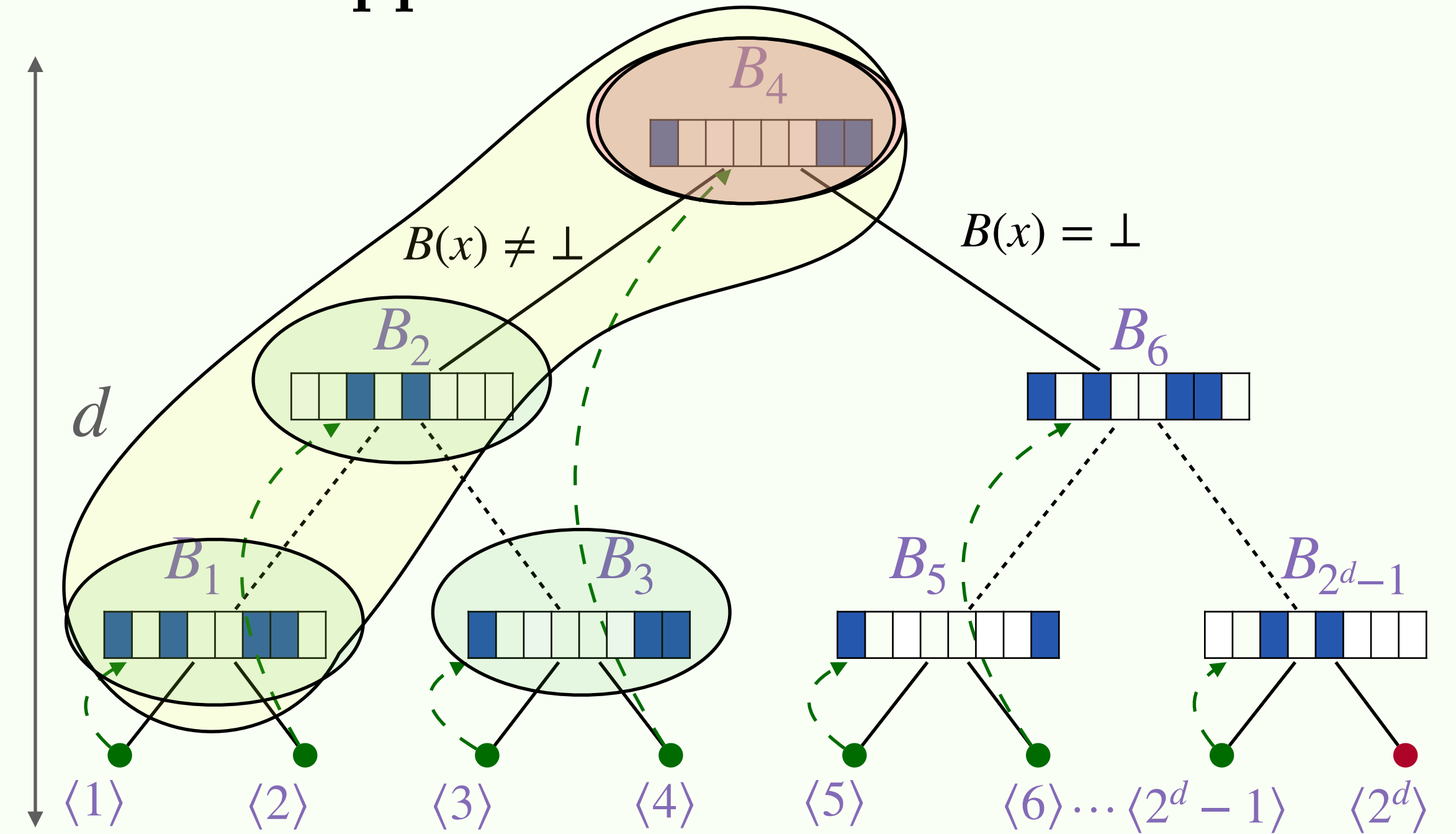
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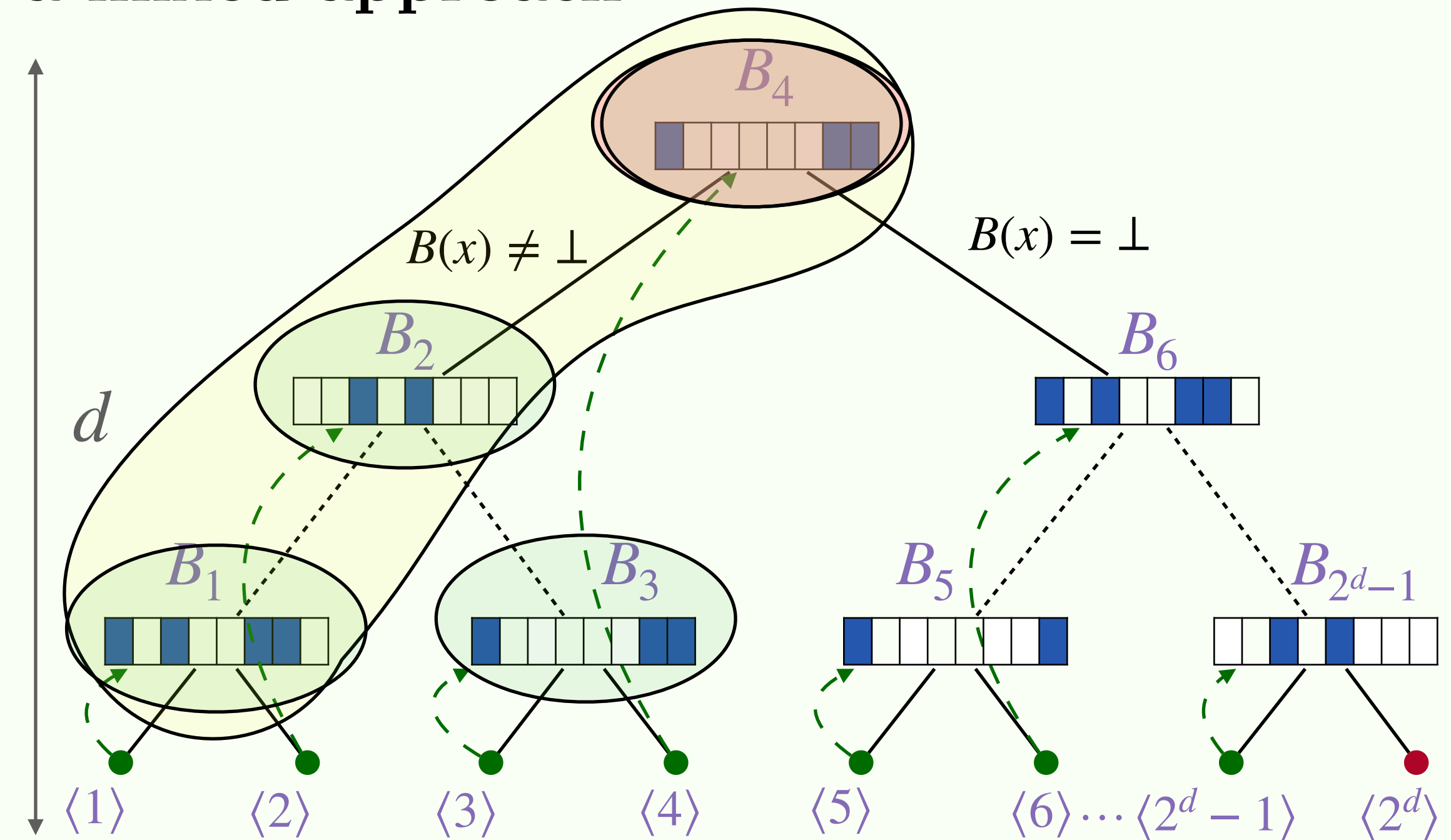
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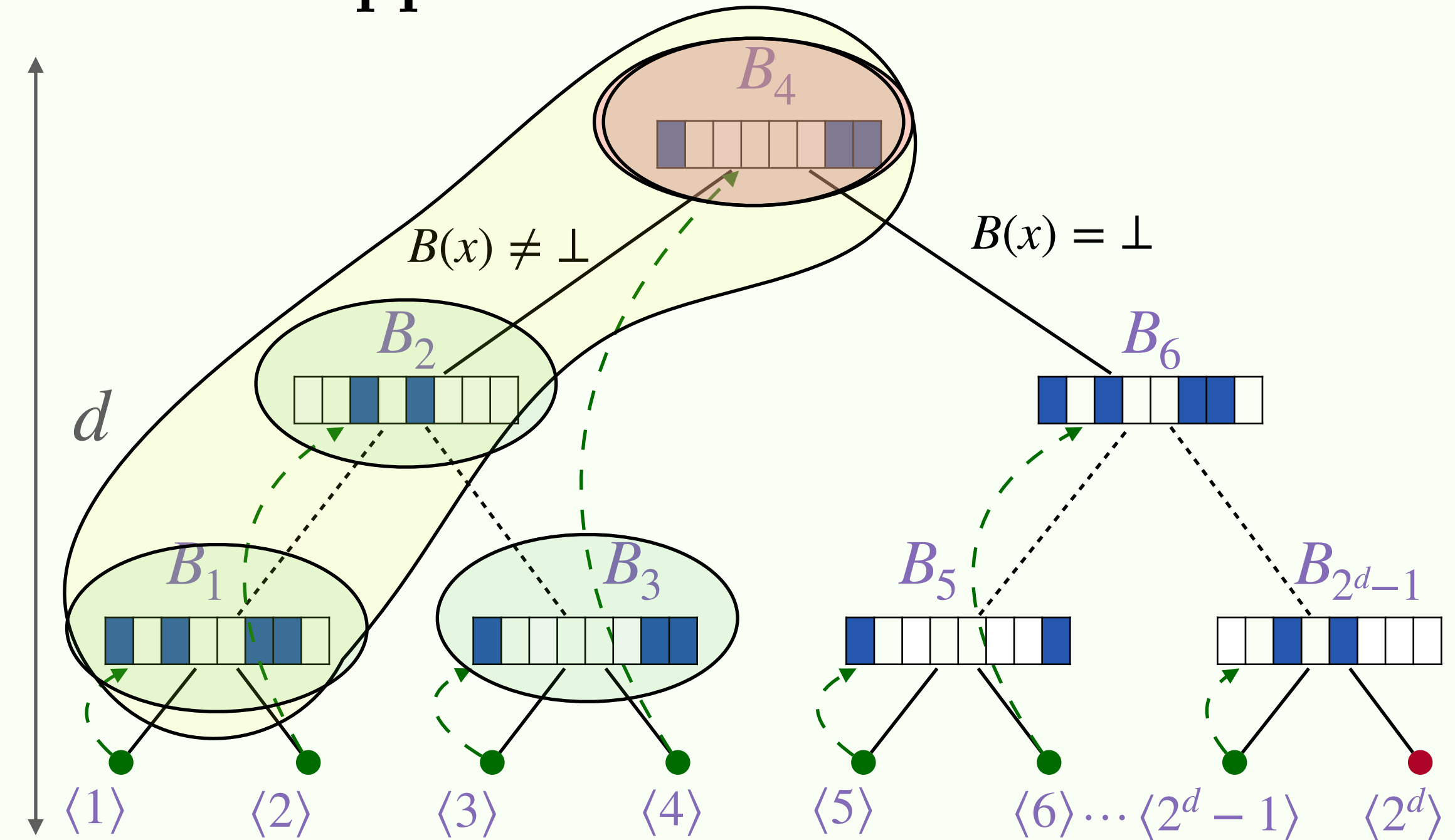
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Lemma. A similar bound of $2^{\Omega(\sqrt{q})}$ many queries can be proven against quantum adversaries.

Conclusion

In summary:

- Faux determinism: fix the randomness once; failures may exist, but bounded-query adversaries cannot find them.
- Faux derandomization: every efficiently verifiable randomized search problem has an efficient faux-deterministic algorithm
- Pseudo-deterministic lower bounds need to be non-constructive in a sense

Some future directions?

- Closing the gap $\sqrt{n} \lesssim D^{\text{pseudo}}(\text{FIND1}) \lesssim n$
- Constructing a faux-deterministic algorithm resisting $2^{\Omega(q)}$ many queries?
- In which models does faux determinists algorithms make sense
- Relation to other complexity measures?

Thank you!

References.

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Electronic Colloquium on Computational Complexity, Report TR11-136, 2011.
- [GIPS21] Shafi Goldwasser, Russell Impagliazzo, Toniann Pitassi, and Rahul Santhanam.
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Proceedings of the 36th Computational Complexity Conference (CCC 2021), LIPIcs 200, Article 36, 2021.

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