Program Synthesis-based Program Optimization

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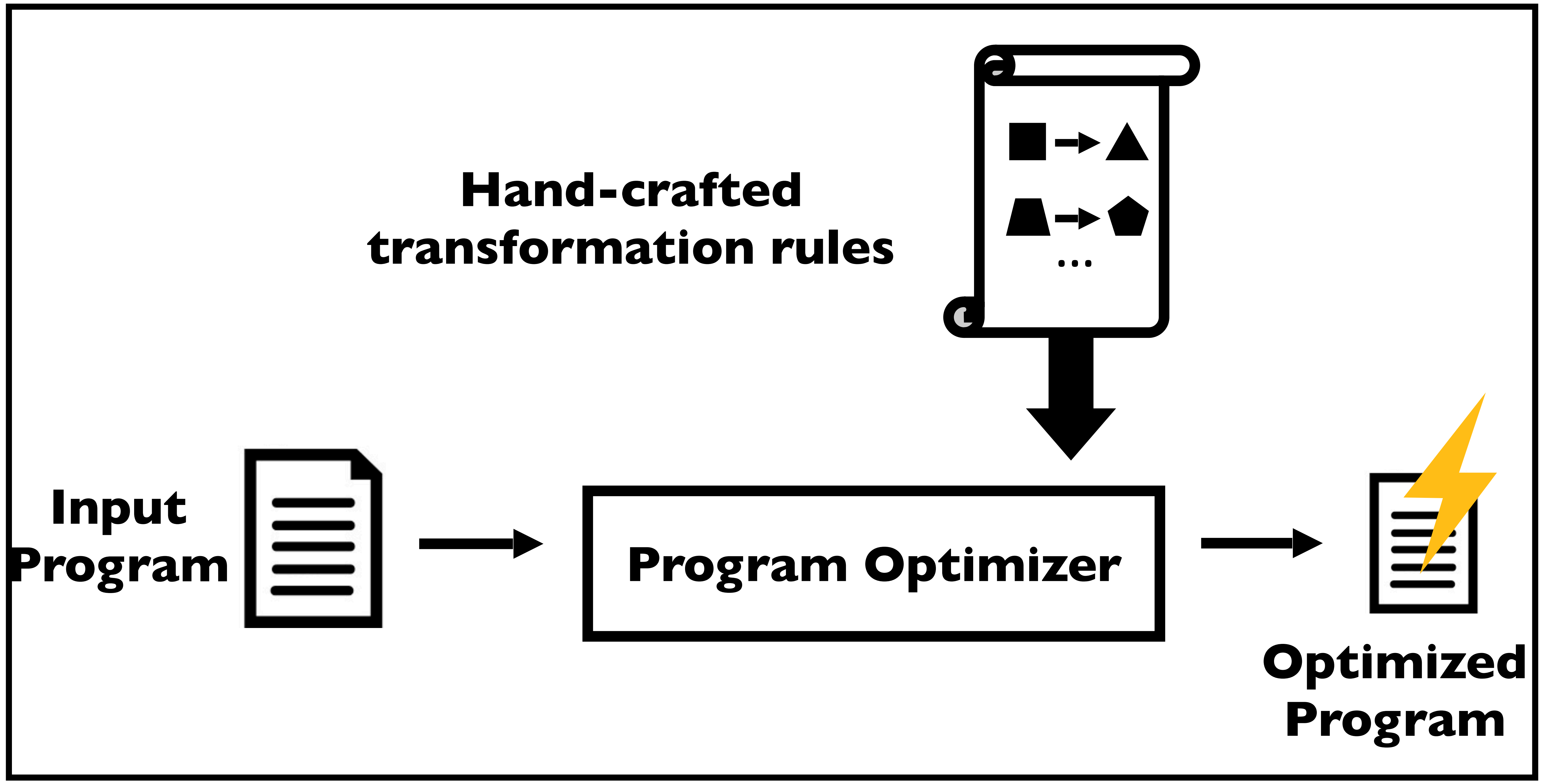
HANYANG UNIVERSITY

Who am I

- Associate Professor at Hanyang Univ. ERICA (2024.9 ~)
- Assistant Professor at Hanyang Univ. ERICA (2018.9 ~ 2024.8)
- Research Interests: program analysis, program synthesis
- Vita
  - 2012 UC Berkeley visiting researcher
  - 2016 Ph.D, Seoul National University (Advisor: Kwangkeun Yi)
  - 2016-2017 Postdoctoral fellow, Georgia Tech (Mayur Naik)
  - 2017-2018 Postdoctoral fellow, University of Pennsylvania (Mayur Naik)

Motivation

- Program optimization
  - Transforming into a better (e.g., cost) program
  - Applying transformation rules (e.g., $x + 0 \rightarrow x$)



- Rules in prior methods
  - Hand-crafted by domain experts
  - Limited search space
- Application order in prior methods
  - Heuristics by domain experts
  - May miss the optimal solutions

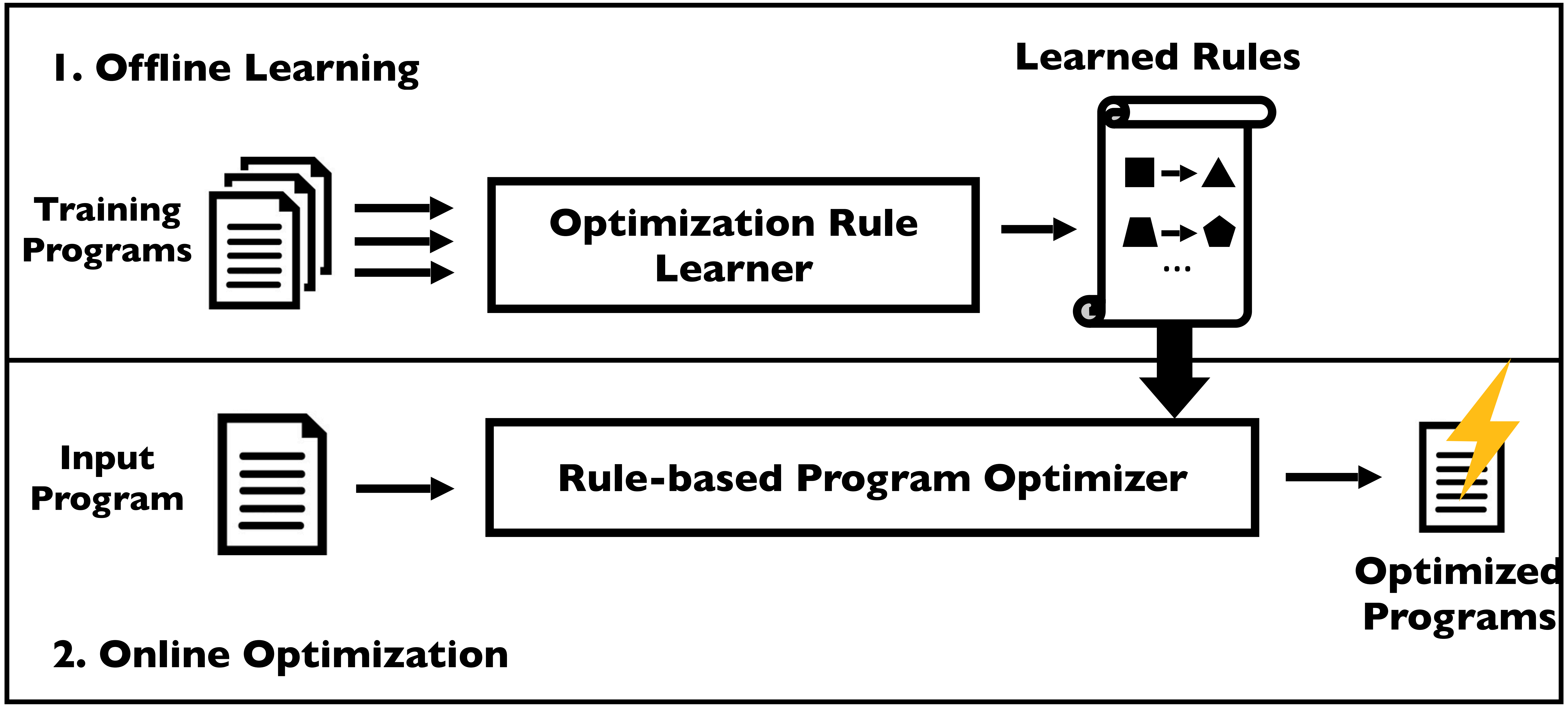
Our Solution

Discovering new rules (by *Program synthesis*) + Systematically applying the rules (by *Term rewriting*) + Finding optimal solutions by exhaustive search (by *Equality saturation*)

When rule discovery is time consuming

: Offline learning +

Online optimization

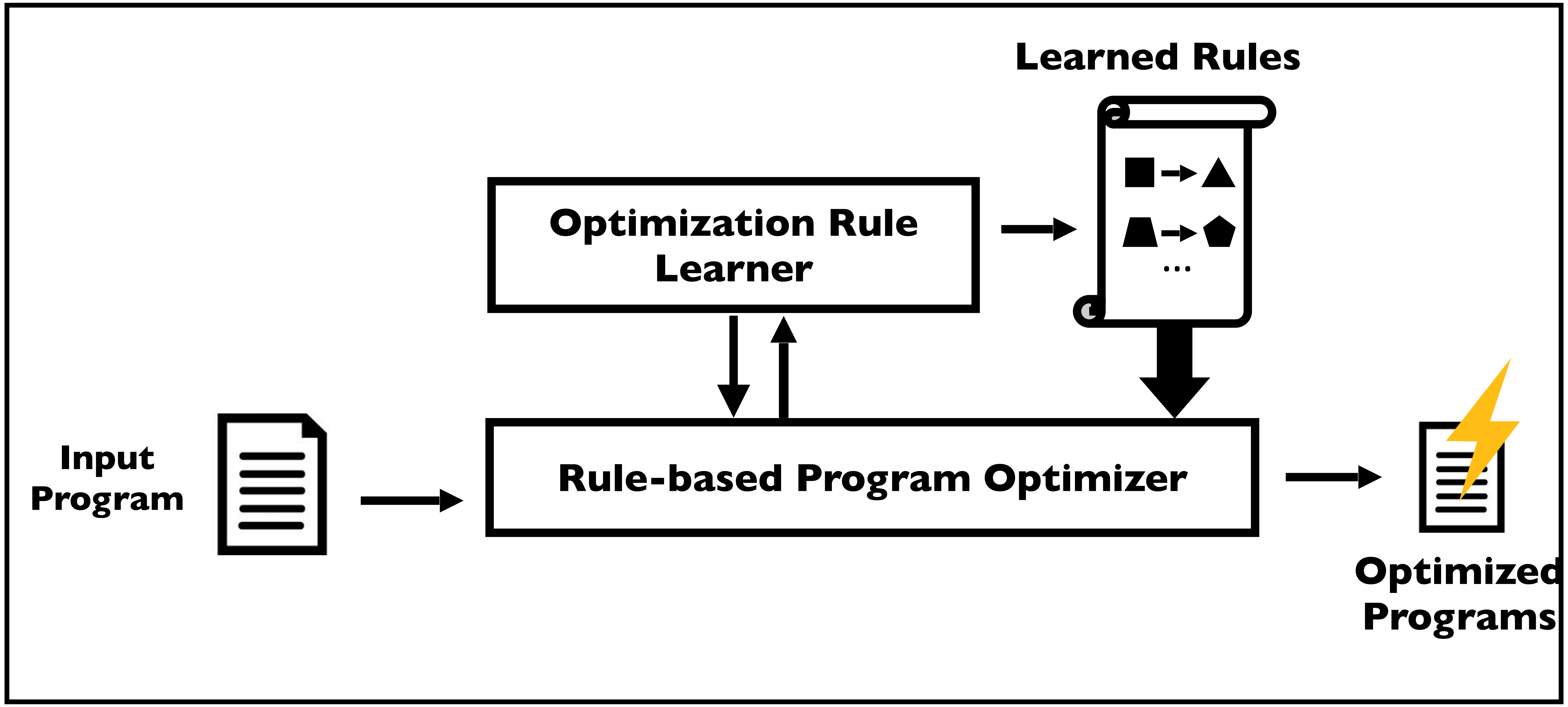


Our Solution

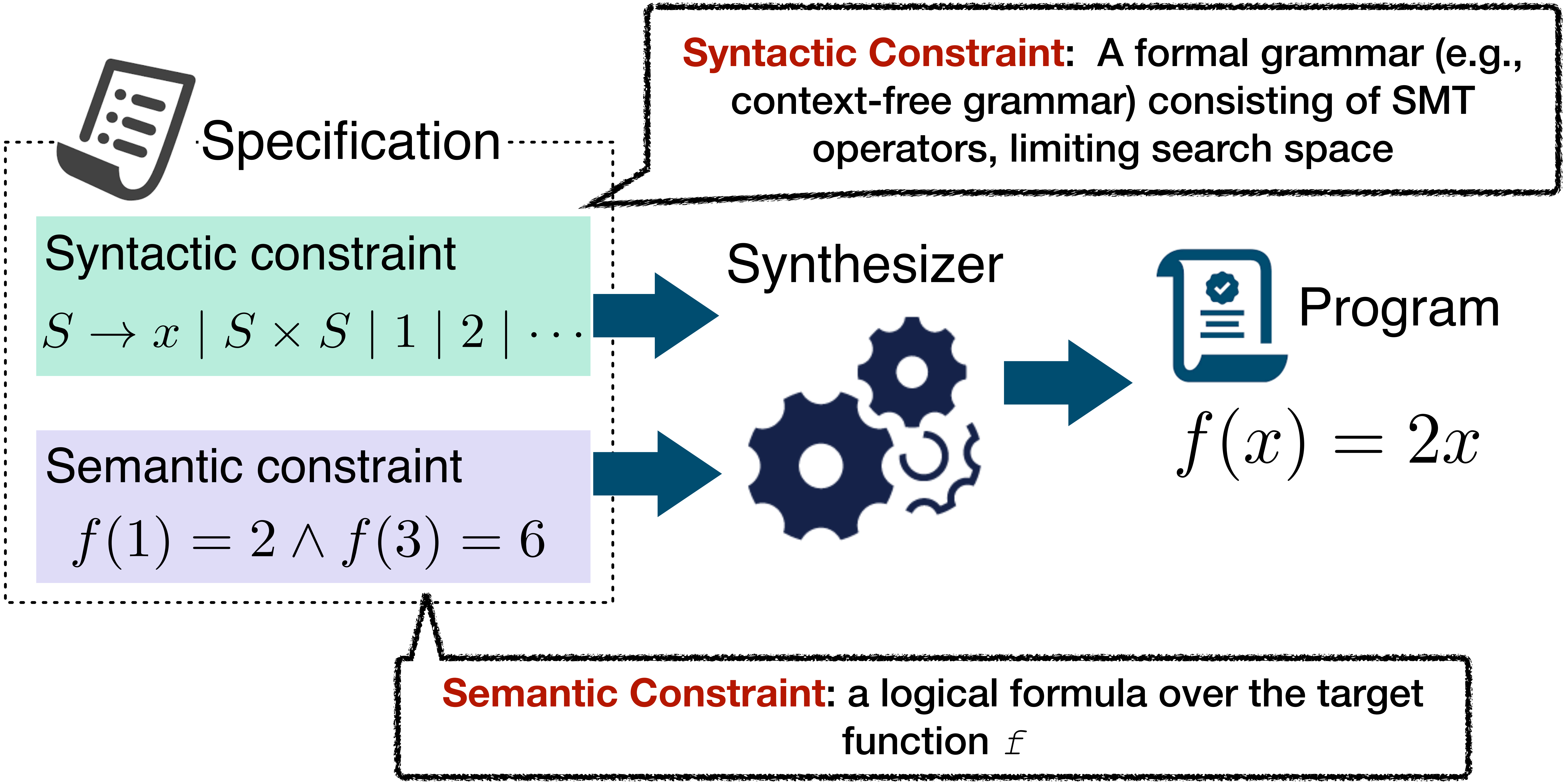
Discovering new rules (by *Program synthesis*) + Systematically applying the rules (by *Term rewriting*) + Finding optimal solutions by exhaustive search (by *Equality saturation*)

When rule discovery is cheap

: Online learning + optimization

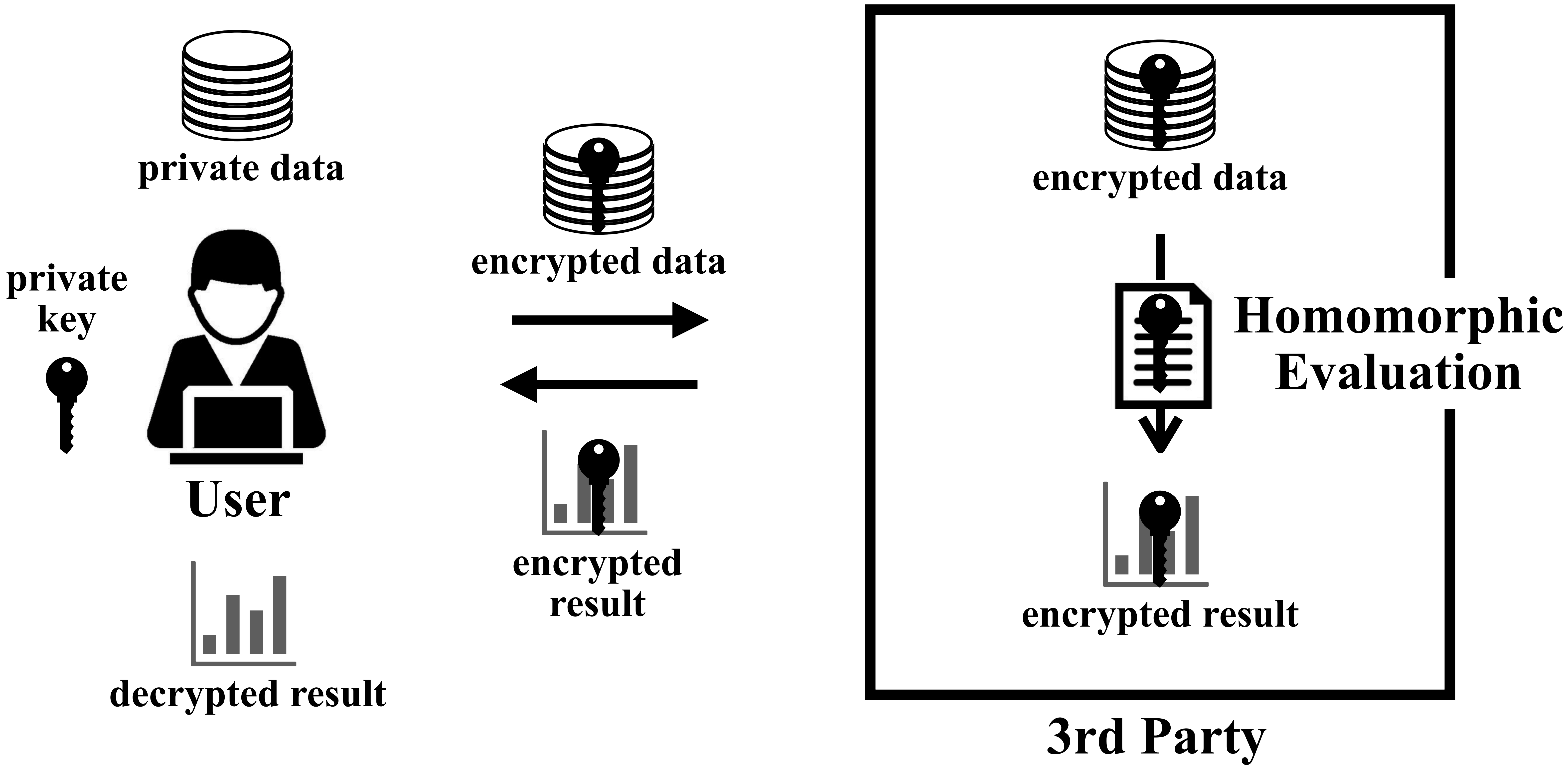


Enabled by *Program Synthesis*



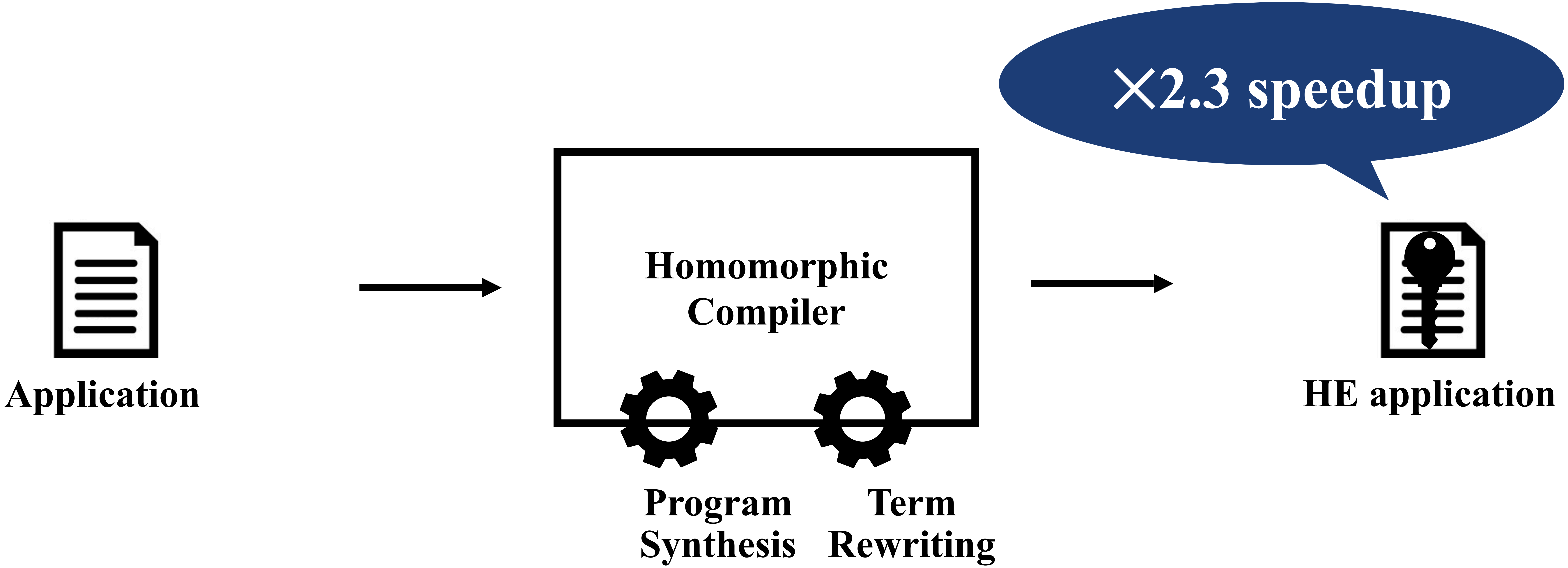
Case 1: Homomorphic Encryption (HE) (1/2)

- Allows computation on encrypted data
- Enables the outsourcing of private data storage/processing



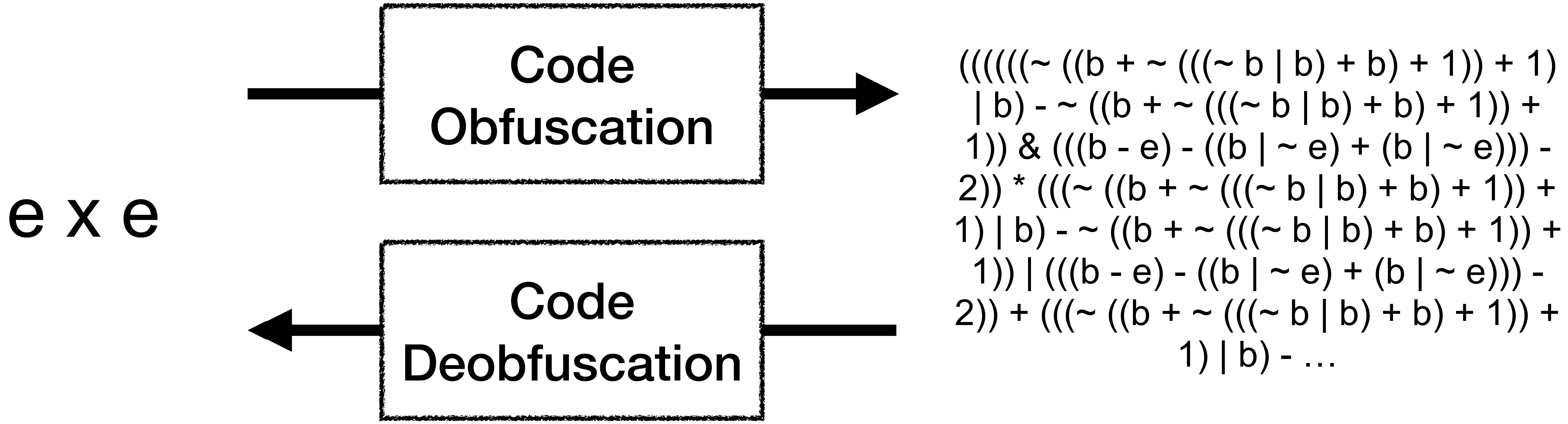
Case 1: Homomorphic Encryption (HE) (1/2)

- HE Compilers generate HE applications automatically
- Better optimization effect than the SOTA with hand-crafted rules



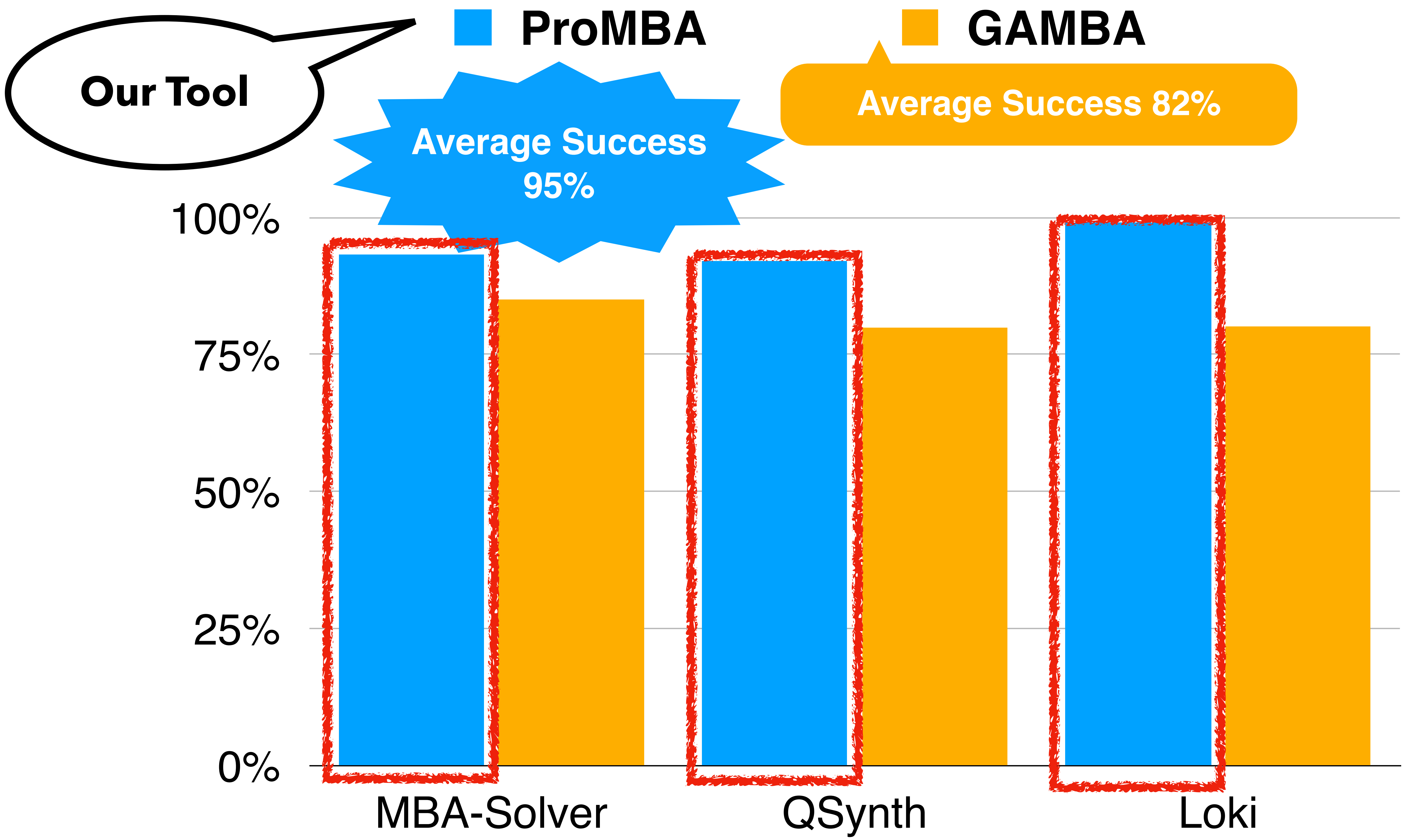
Case 2: Simplifying Obfuscated Code (1/2)

- Obfuscation: transforming programs into complex ones
  - Evasion of malware detection 👿 Copyright protection 😇
- De-obfuscation: simplifying obfuscated programs



Case 2: Simplifying Obfuscated Code (2/2)

- Success : generating simpler or as simple as original code
- Higher success rate than the SOTA based on handcrafted rules



Papers

- Case 1 : Optimizing compiler for homomorphic encryption
  - Dongkwon Lee, Woosuk Lee, Hakjoo Oh and Kwangkeun Yi, *Optimizing Homomorphic Evaluation Circuits by Program Synthesis and Time-Bounded Exhaustive Search,* **ACM TOPLAS 2023**
  - Dongkwon Lee, Woosuk Lee, Hakjoo Oh and Kwangkeun Yi, *Optimizing Homomorphic Evaluation Circuits by Program Synthesis and Term Rewriting,* **ACM PLDI 2020**
- Case 2: Deobfuscation of bit-manipulating code
  - Jaehyung Lee and Woosuk Lee, *Simplifying Mixed Boolean-Arithmetic Obfuscation by Program Synthesis and Term Rewriting,* **ACM CCS 2023**
  - Jaehyung Lee, Seoksu Lee, Eunsun Cho and Woosuk Lee, *Simplifying Mixed Boolean-Arithmetic Obfuscation by Program Synthesis and Equality Saturation,* **IEEE TDSC (Submitted)**
- Core technology: high-performance program synthesis
  - Yongho Yoon, Woosuk Lee, and Kwangkeun Yi, Inductive Program Synthesis via Iterative Forward-Backward Abstract Interpretation. **ACM PLDI 2023**

Contents

- **Case 1 : Optimizing compiler for homomorphic encryption**
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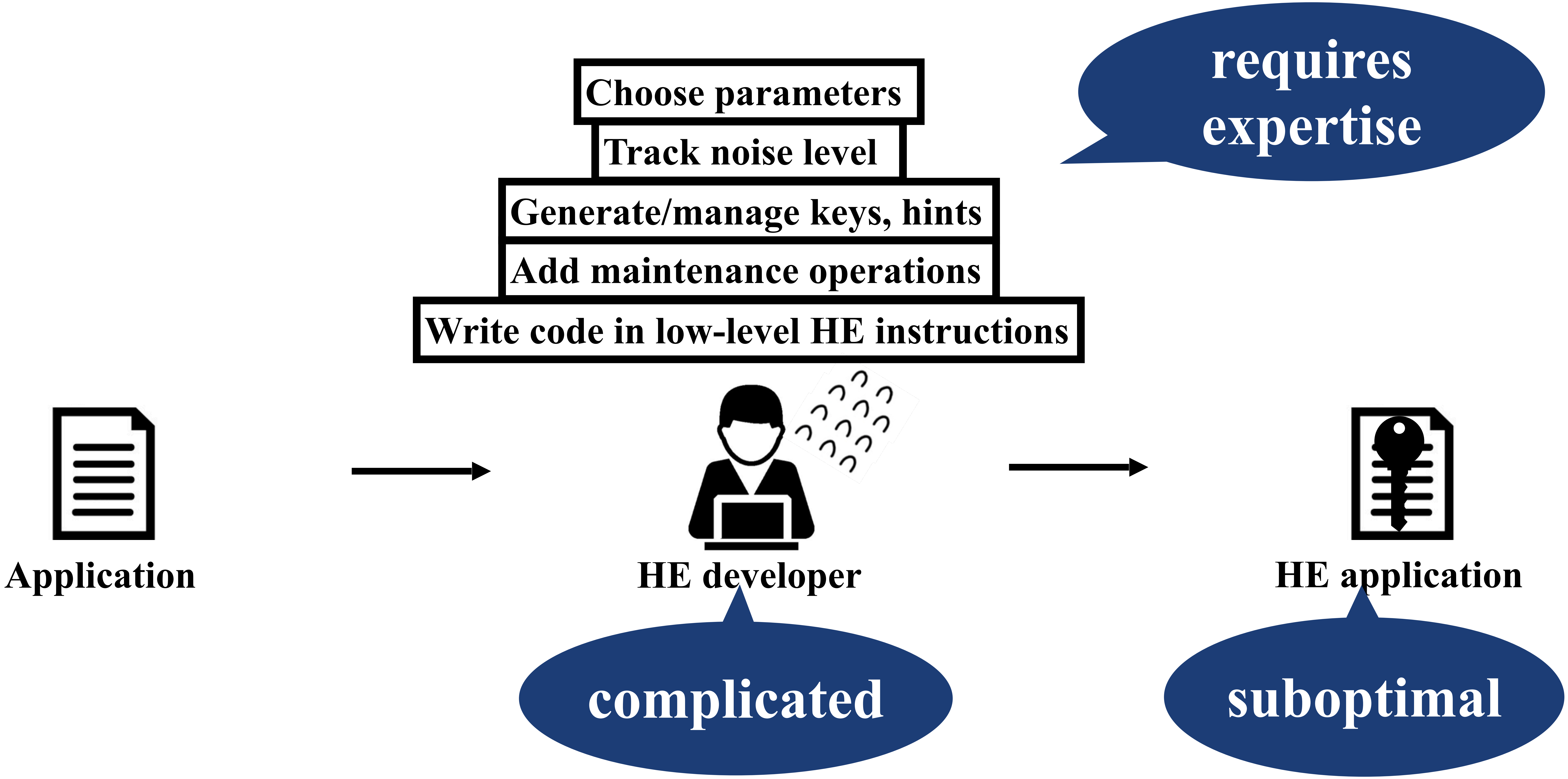
- Case 2: Deobfuscation of bit-manipulating code
- Lessons from the two cases
- Core technology: high-performance program synthesis

Homomorphic Encrytion (1/2)

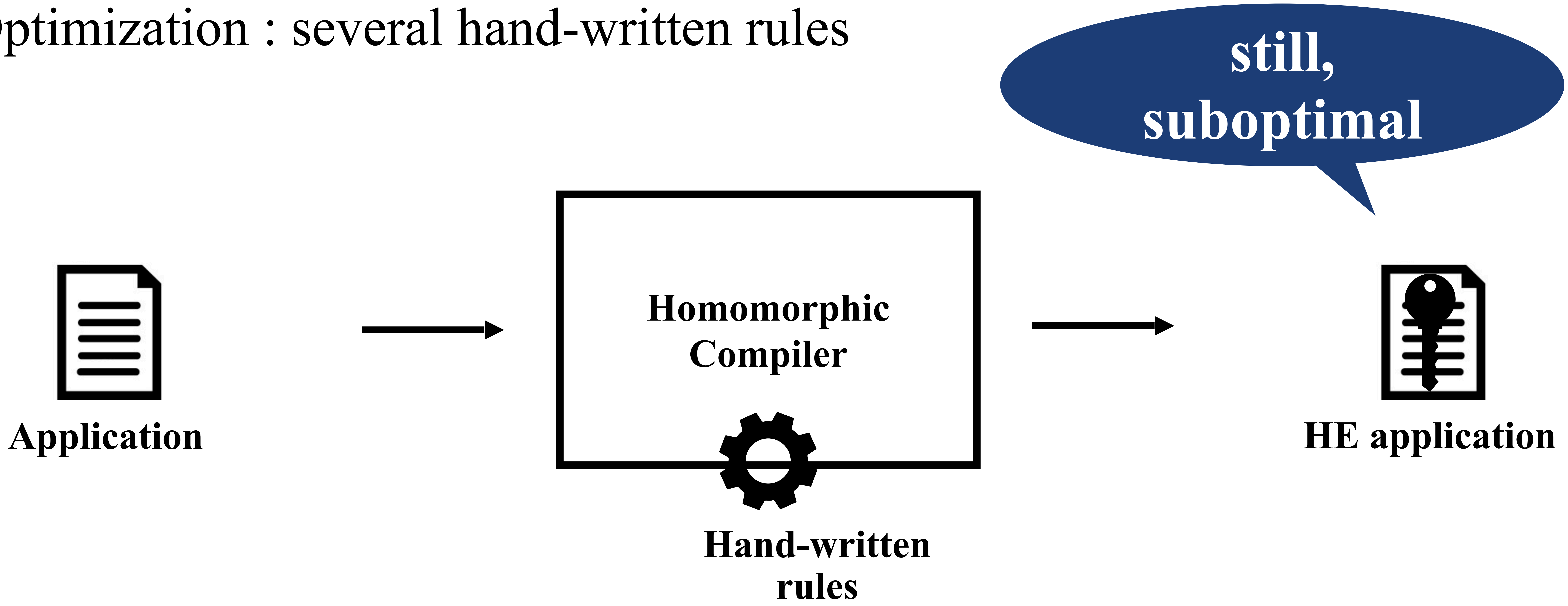
Building HE applications



Homomorphic Encrytion (2/2)

Existing Homomorphic Compiler

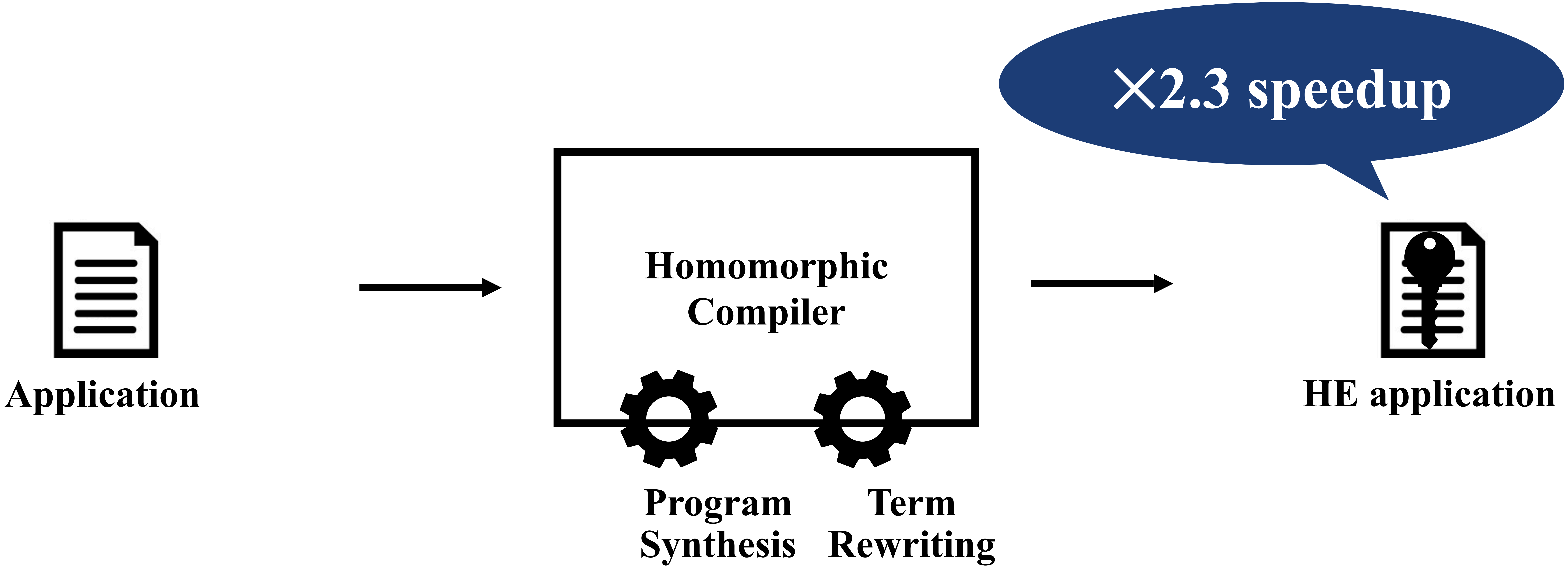
- Generates HE applications automatically
- Optimization : several hand-written rules



Our Contribution

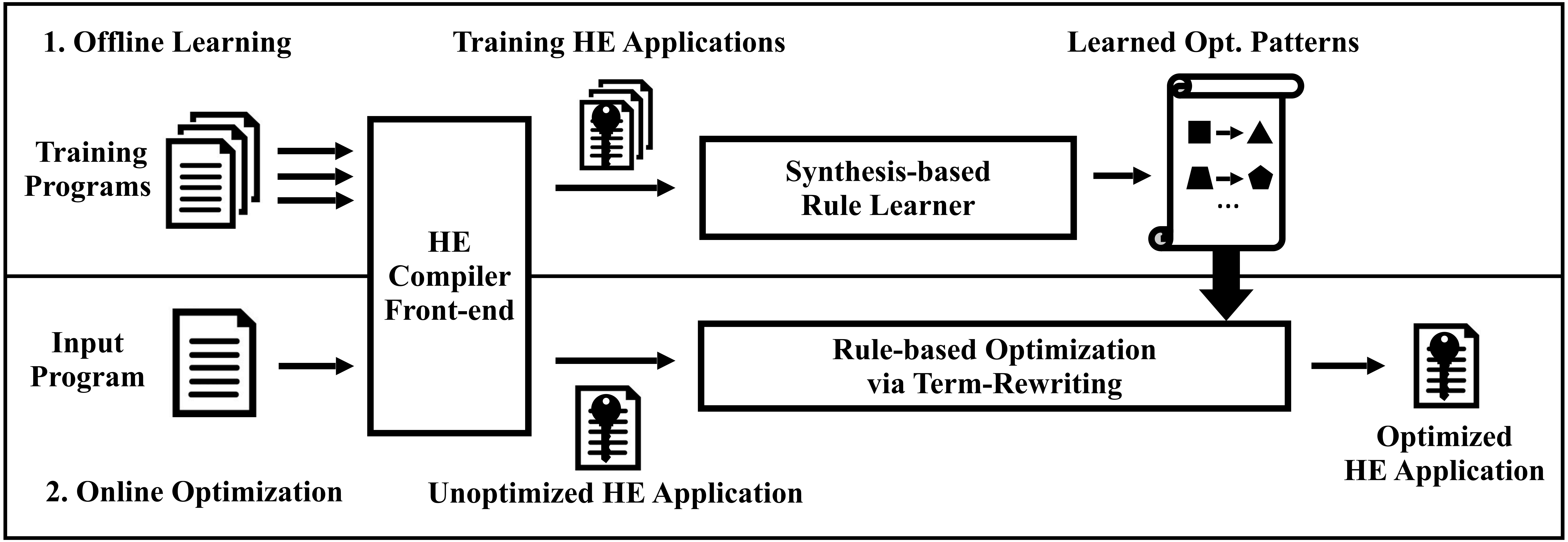
Automatic, Aggressive HE optimization Framework

- Generates HE applications automatically
- Optimization : machine-found rules by program synthesis + applying by term rewriting



Lobster

- Offline Learning via Program Synthesis + Online Optimization via Term Rewriting



Simple HE Scheme

- Based on approximate common divisor problem
- p : integer as a secret key
- q : random integer
- $r(\ll |p|)$: random noise for security

$$Enc_p(\mu \in \{0,1\}) = pq + 2r + \mu$$
$$Dec_p(c) = (c \bmod p) \bmod 2$$
$$Dec_p(Enc_p(\mu)) = Dec_p(pq + 2r + \mu) = \mu$$

- For ciphertexts $\underline{\mu_i} \leftarrow Enc_p(\mu_i)$, the following holds

$$Dec_p(\underline{\mu_1} + \underline{\mu_2}) = \mu_1 + \mu_2$$
$$Dec_p(\underline{\mu_1} \times \underline{\mu_2}) = \mu_1 \times \mu_2$$

- The scheme can evaluate all boolean circuits as $+$ and $\times$ in $\mathbb{Z}_2 = \{0,1\}$ are equal to XOR and AND

Performance Hurdle : Growing Noise

- Noise increases during homomorphic operations.
- For $\underline{\mu_i} = pq_i + 2r_i + \mu_i$

$$\underline{\mu_1} + \underline{\mu_2} = p(q_1 + q_2) + \boxed{2(r_1 + r_2) + (\mu_1 + \mu_2)} \text{ double increase}$$

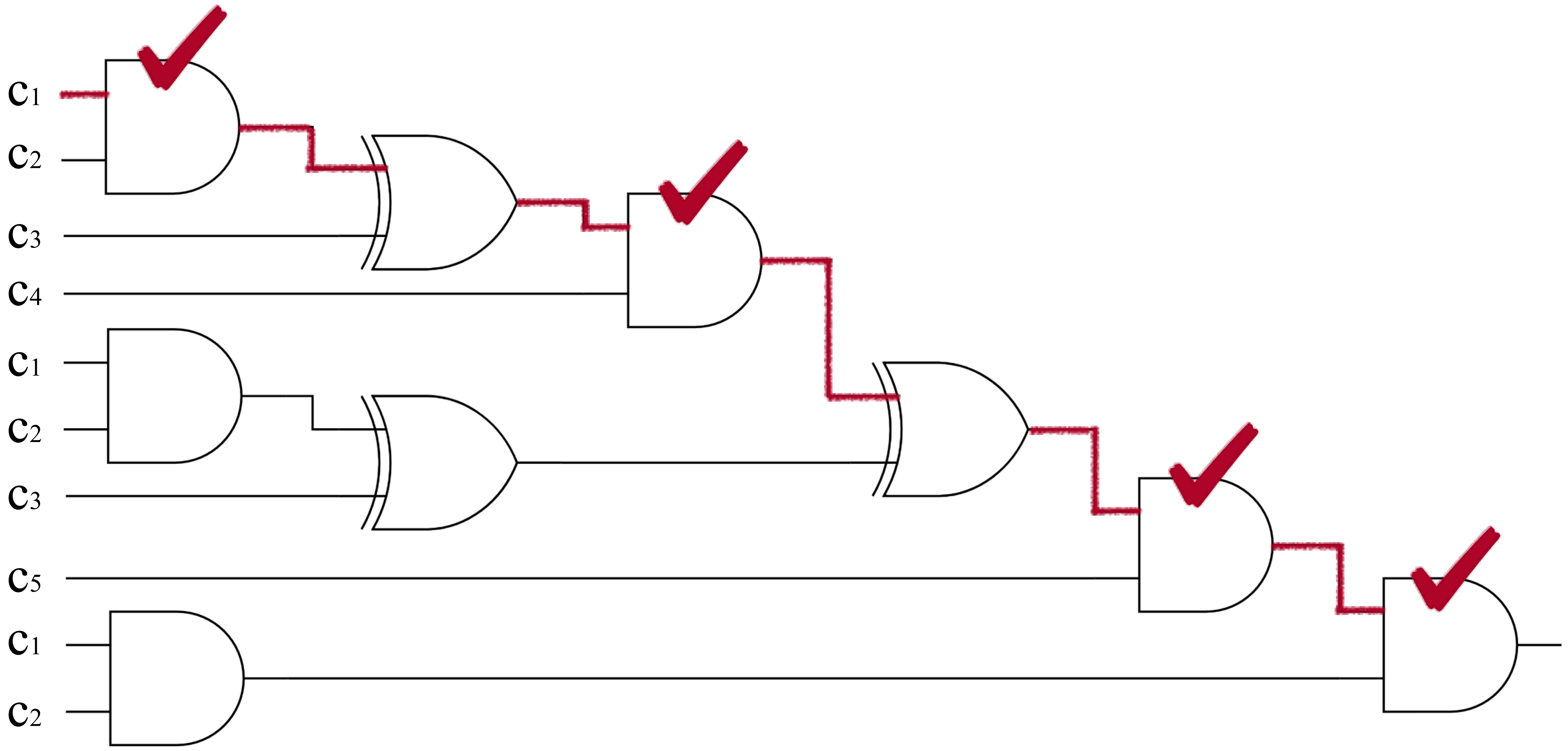
$$\underline{\mu_1} \times \underline{\mu_2} = p(pq_1q_2 + \cdots) + \boxed{2(2r_1r_2 + r_1\mu_2 + r_2\mu_1) + (\mu_1 \times \mu_2)} \text{ quadratic increase}$$

noise

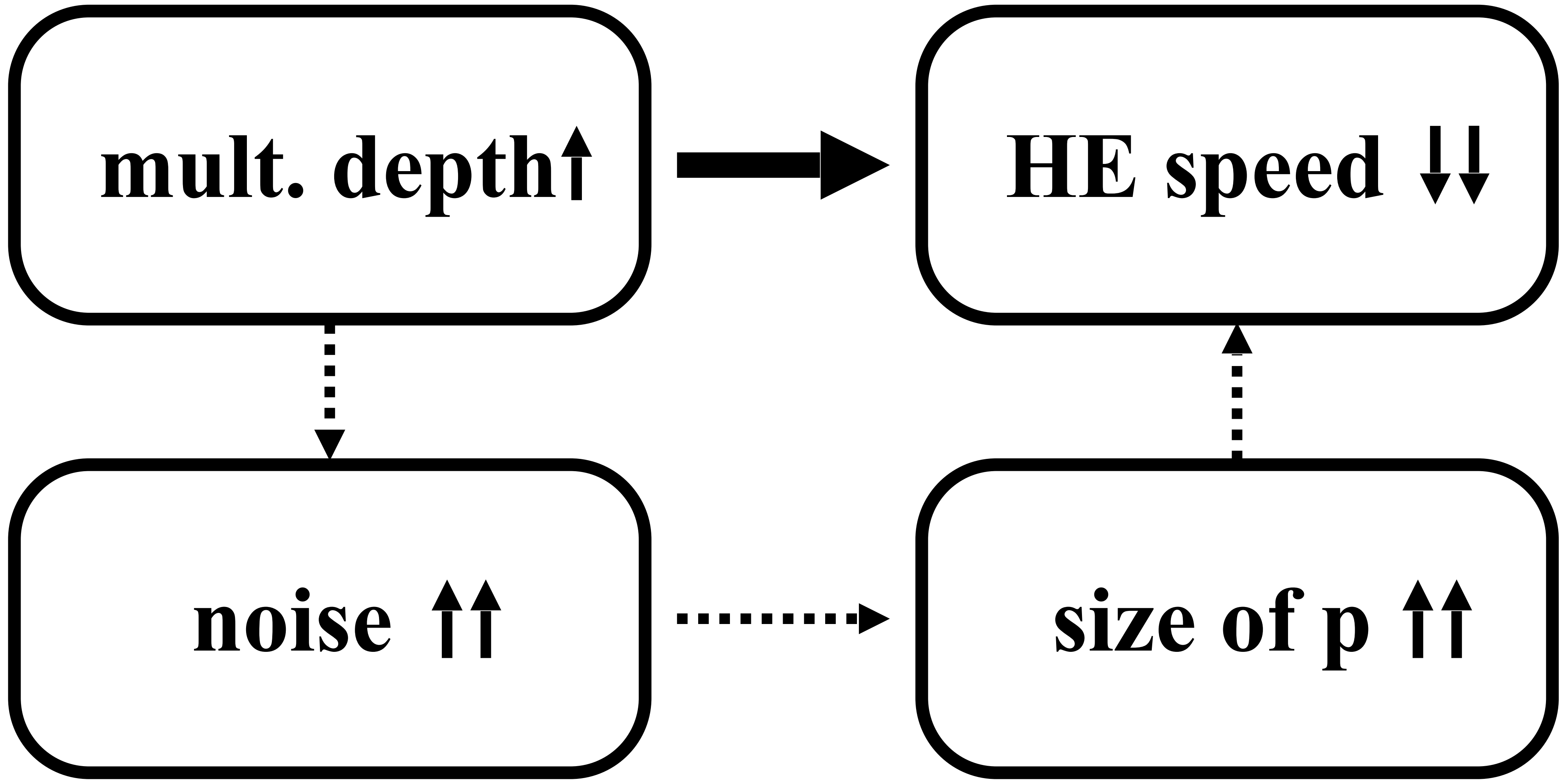
- **if (noise $> p$) then incorrect results**

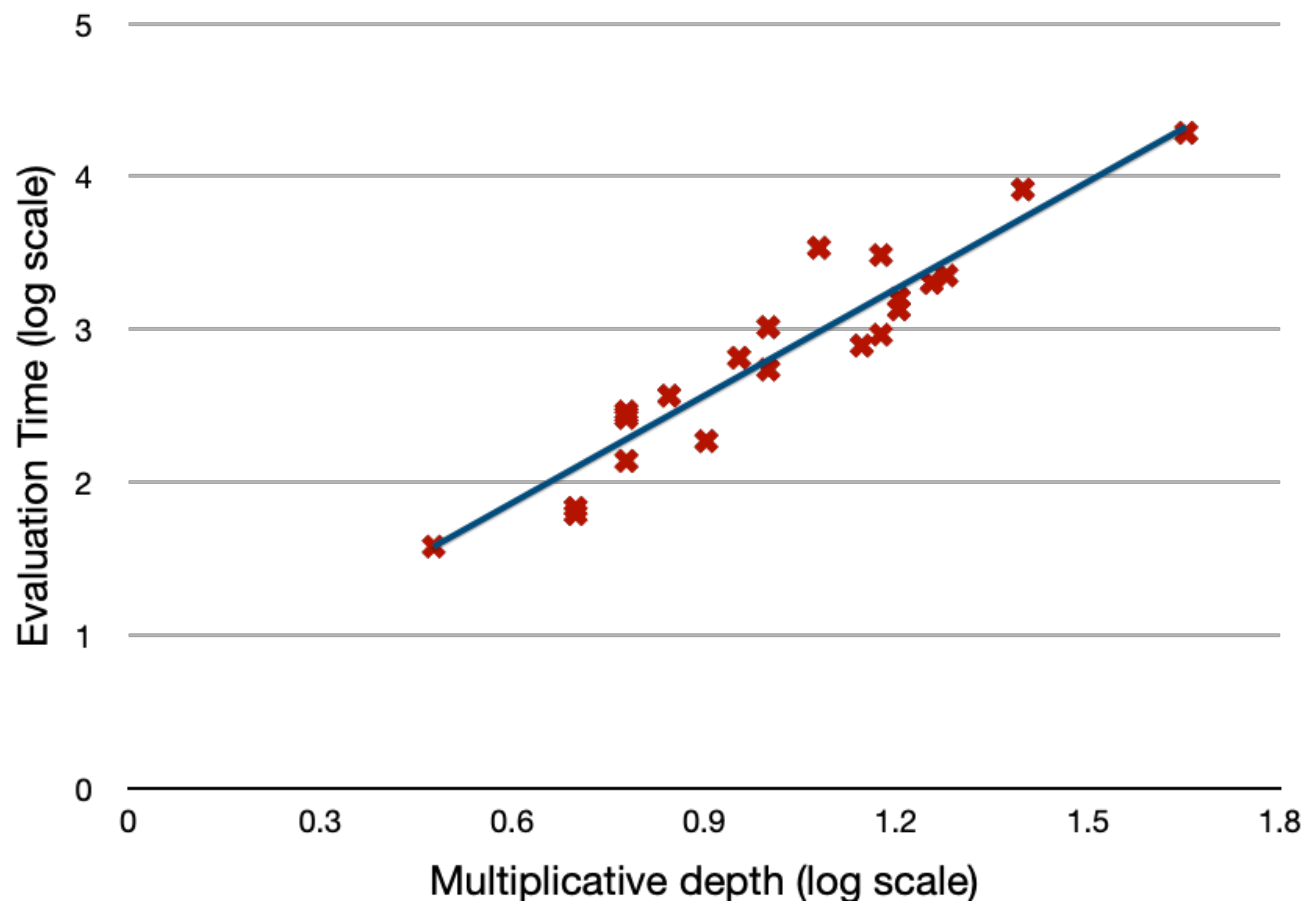
Multiplicative Depth : a Decisive Performance Factor

The maximum number of sequential multiplications from input to output



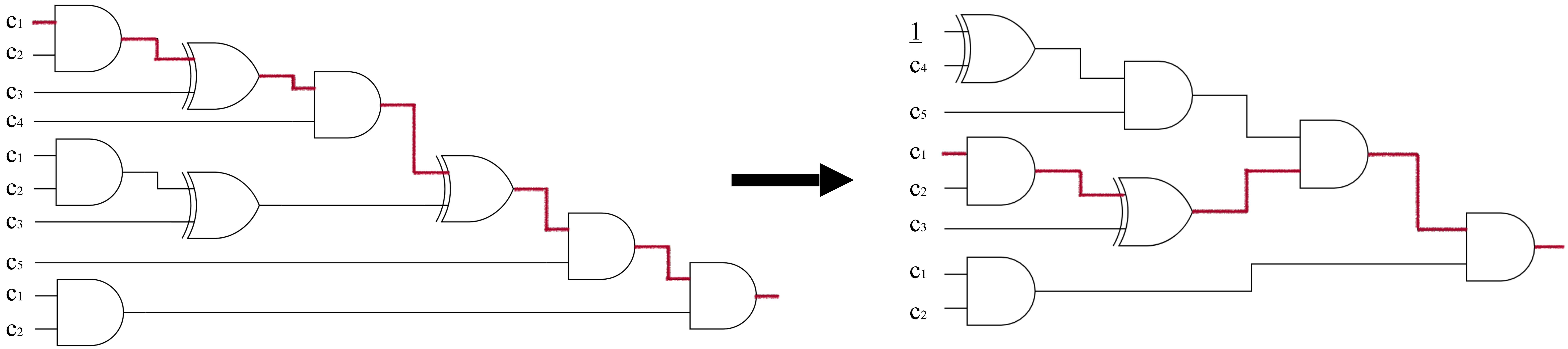
depth 4





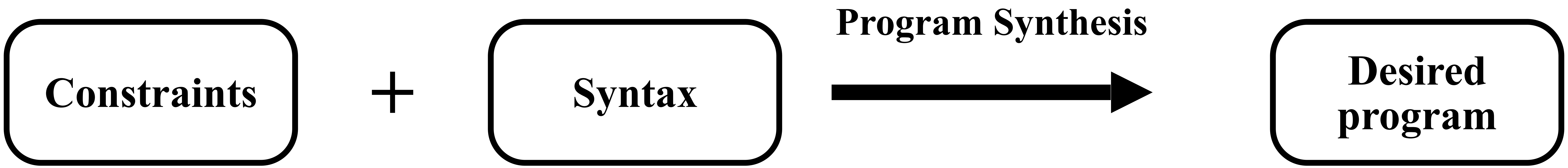
What is HE optimization?

- Finding a new circuit that has smaller mult. depth



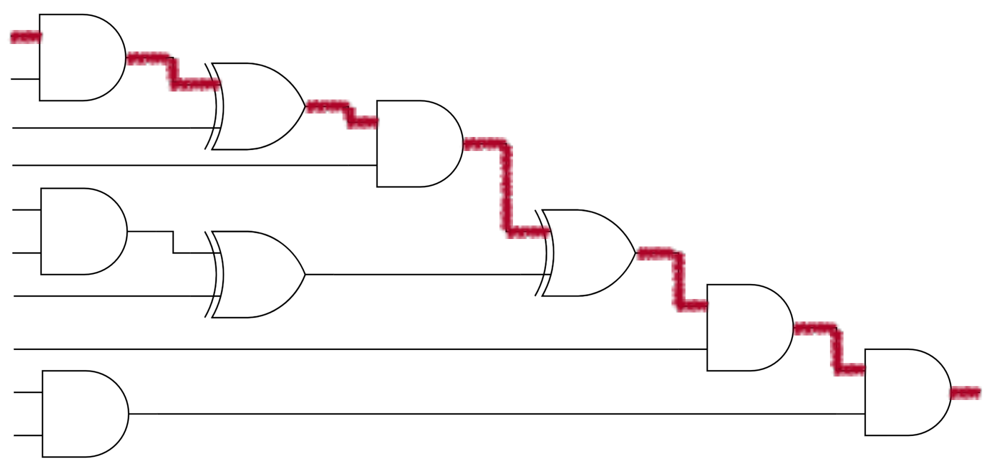
depth 4 depth 3

HE optimization via Synthesis



HE optimization via Synthesis

Constraints + Syntax —Program Synthesis→ Desired program

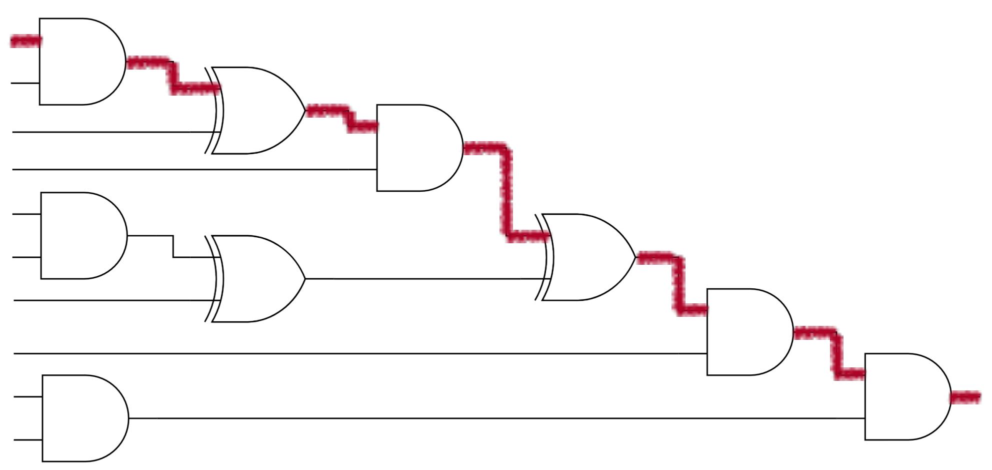


depth 4

same semantics

HE optimization via Synthesis

Constraints + **Syntax** —**Program Synthesis**→ **Desired program**



depth 4

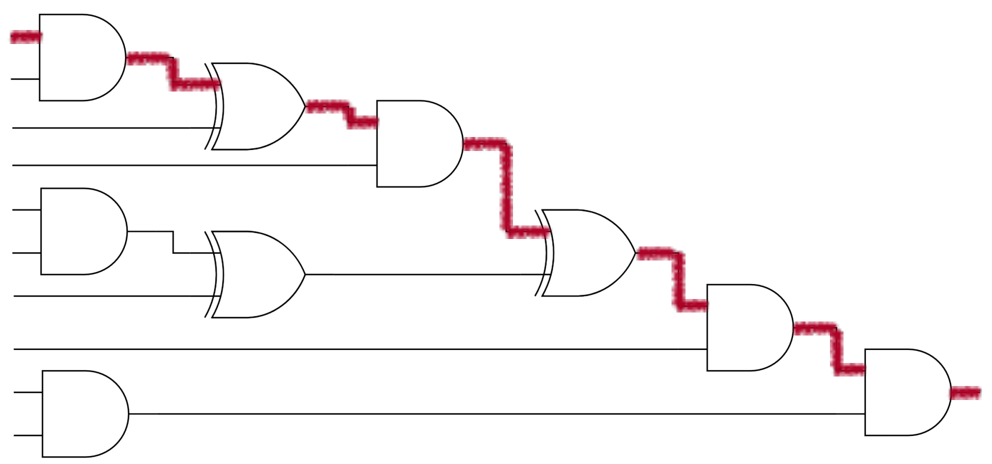
same semantics

$$
\begin{aligned}
S &\rightarrow d_3 \\
d_3 &\rightarrow d_2 \wedge d_2 \mid d_3 \oplus d_3 \mid d_2 \\
d_2 &\rightarrow d_1 \wedge d_1 \mid d_2 \oplus d_2 \mid d_1 \\
d_1 &\rightarrow d_0 \wedge d_0 \mid d_1 \oplus d_1 \mid d_0 \\
d_0 &\rightarrow 0 \mid 1 \mid c_1 \mid c_2 \mid c_3 \mid c_4 \mid c_5
\end{aligned}
$$

depth-restricting syntax

HE optimization via Synthesis

Constraints + **Syntax** —Program Synthesis→ **Desired program**



depth 4

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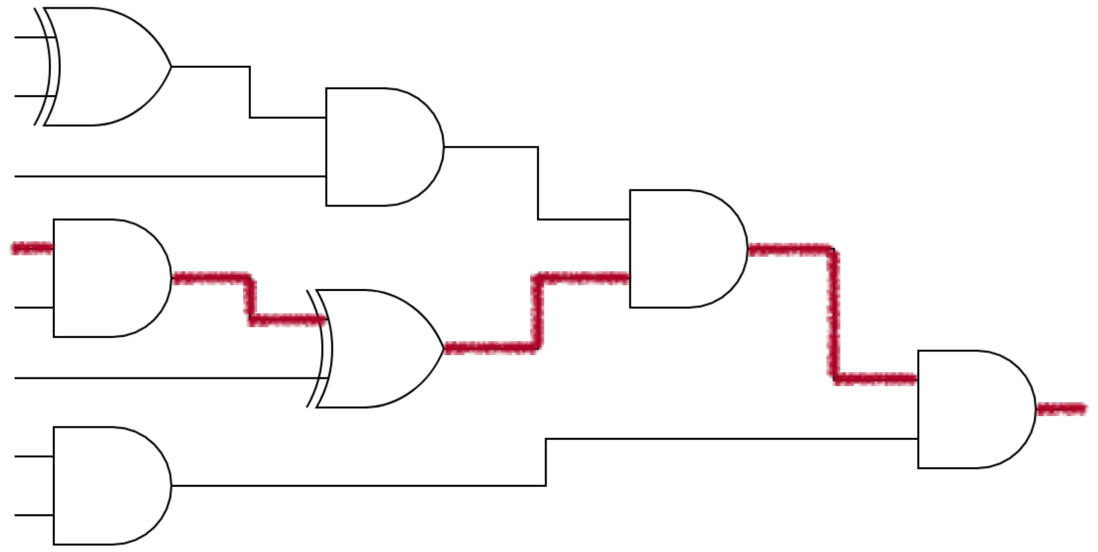
depth-restricting syntax

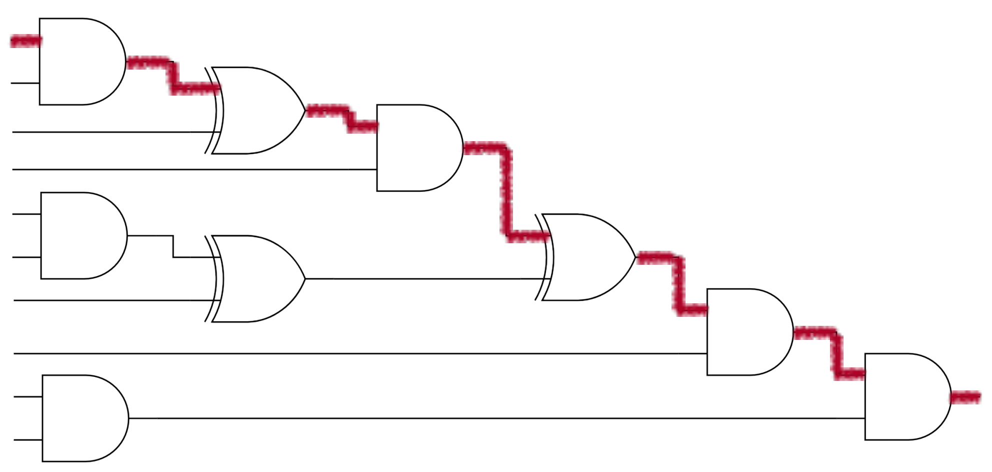


depth 3

optimized HE circuit

HE optimization via Synthesis

Constraints + **Syntax** → (Optimizing Synthesis) → **Desired program**



depth 4

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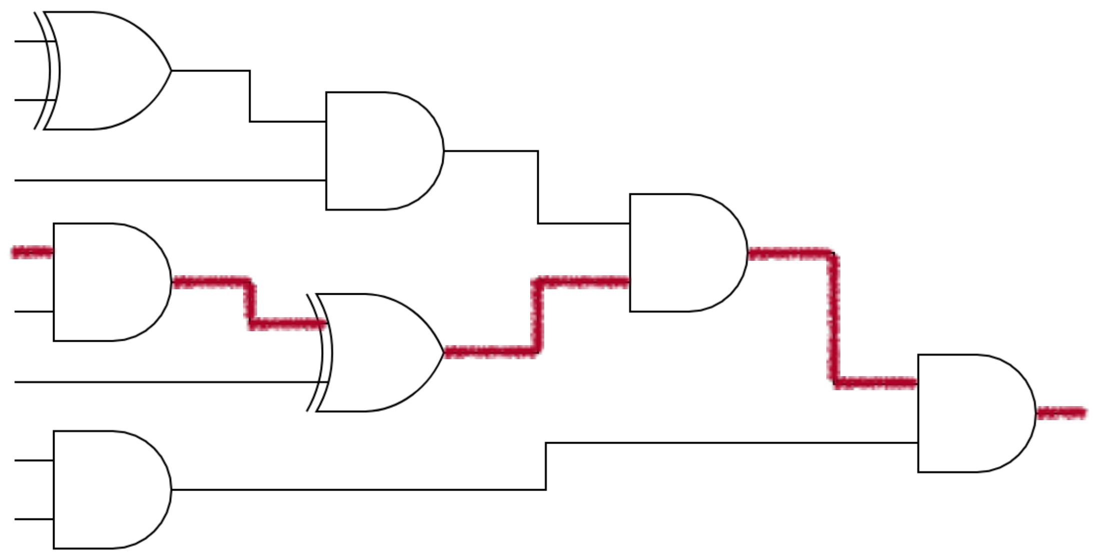
\end{aligned}
$$

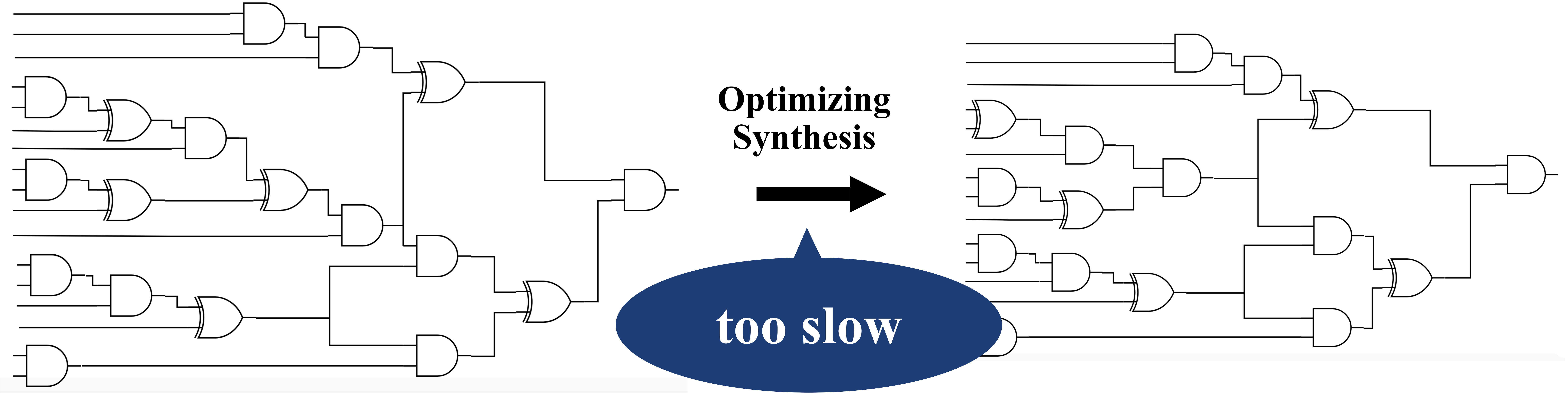
depth-restricting syntax



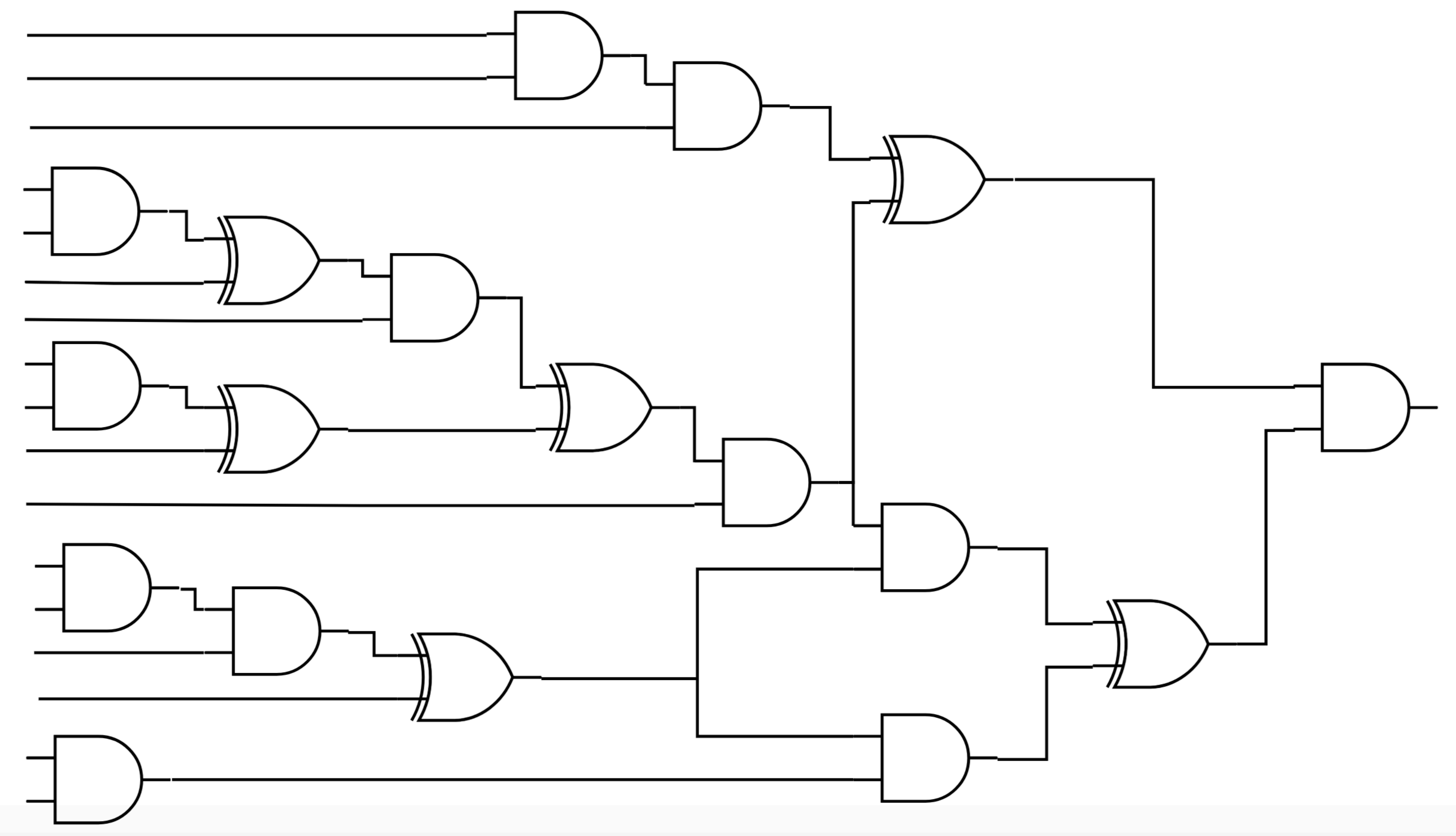
depth 3

optimized HE circuit

Hurdle : Synthesis Scalability



Solution1 : Synthesis via Localization



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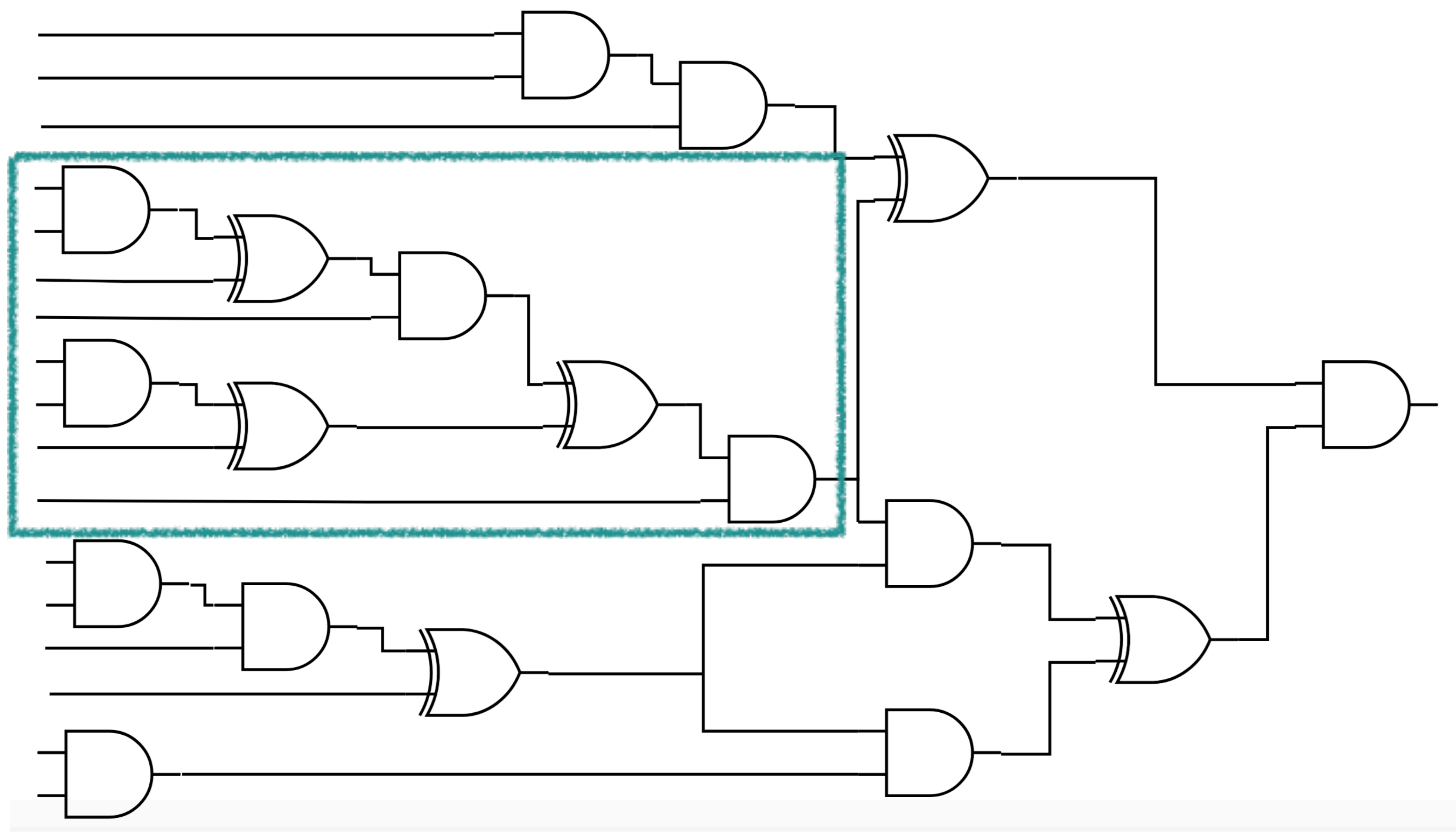

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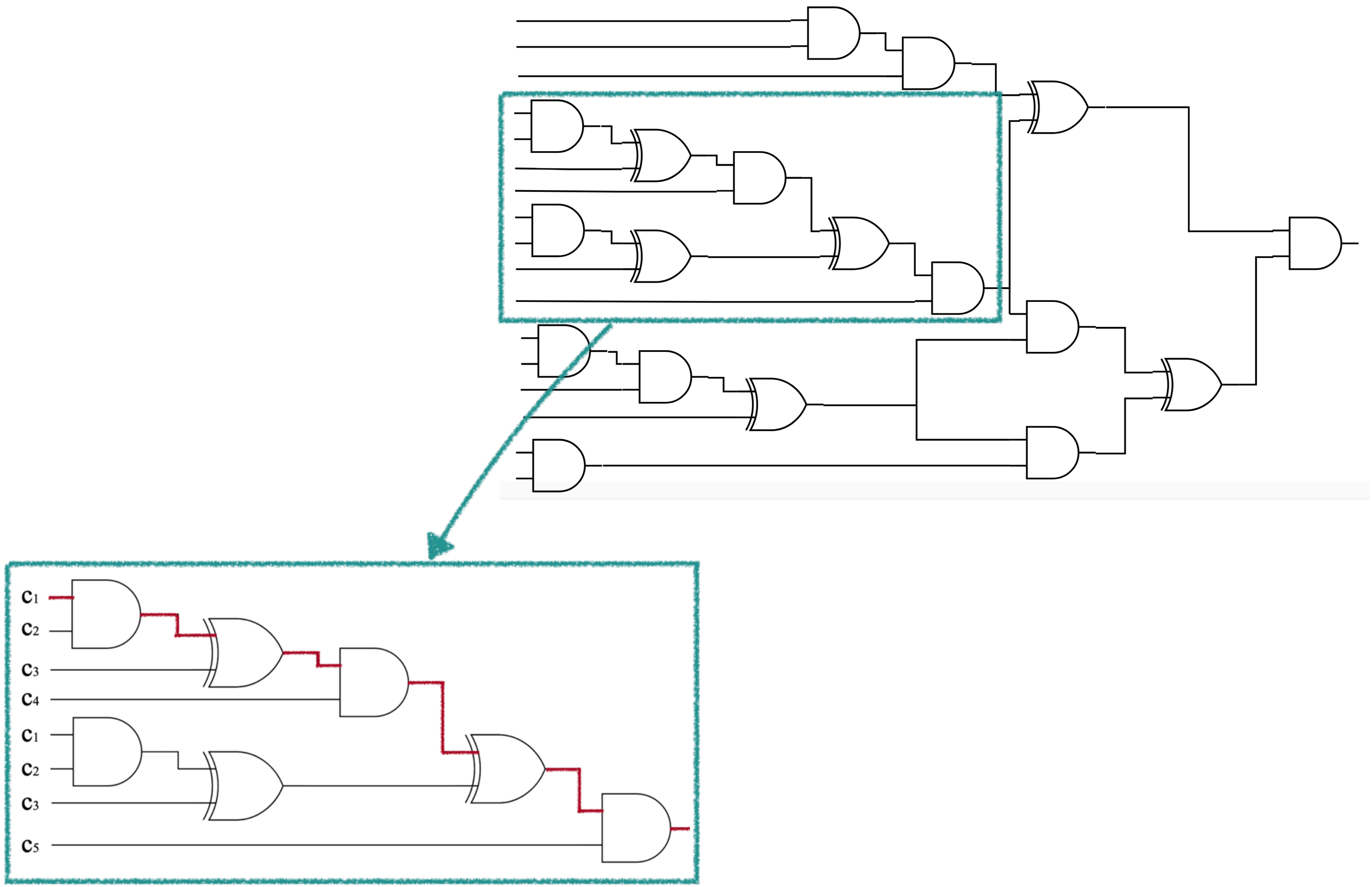

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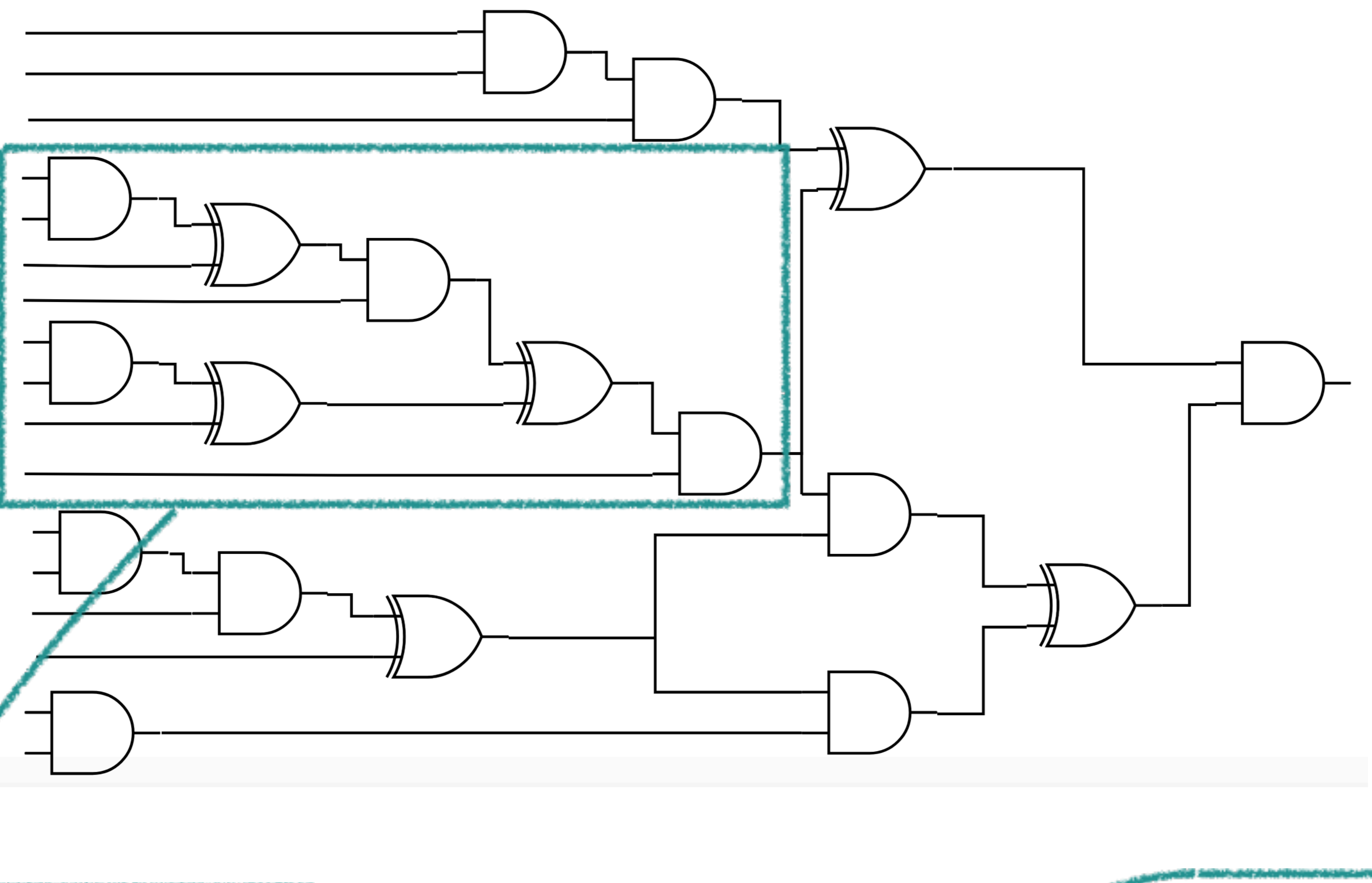
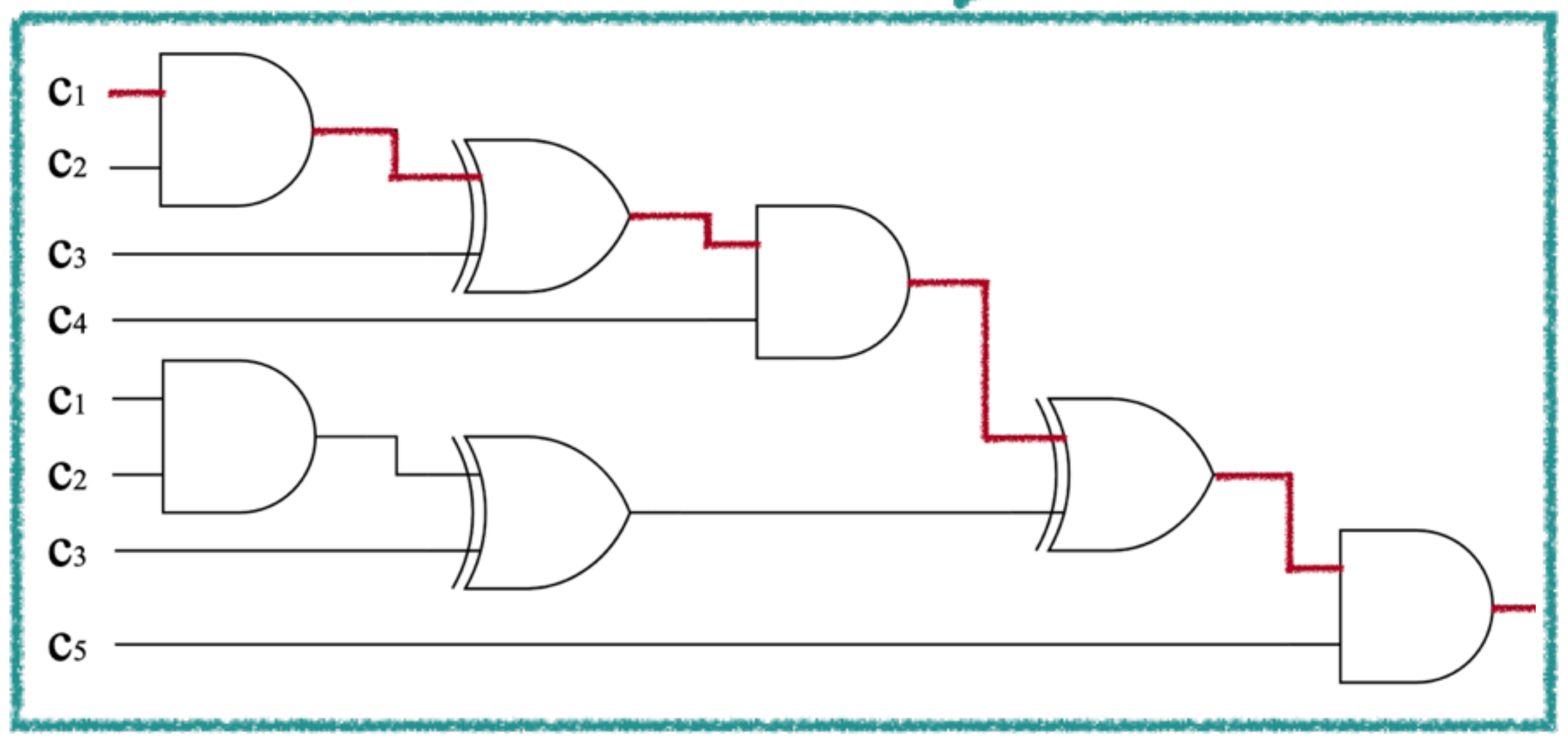
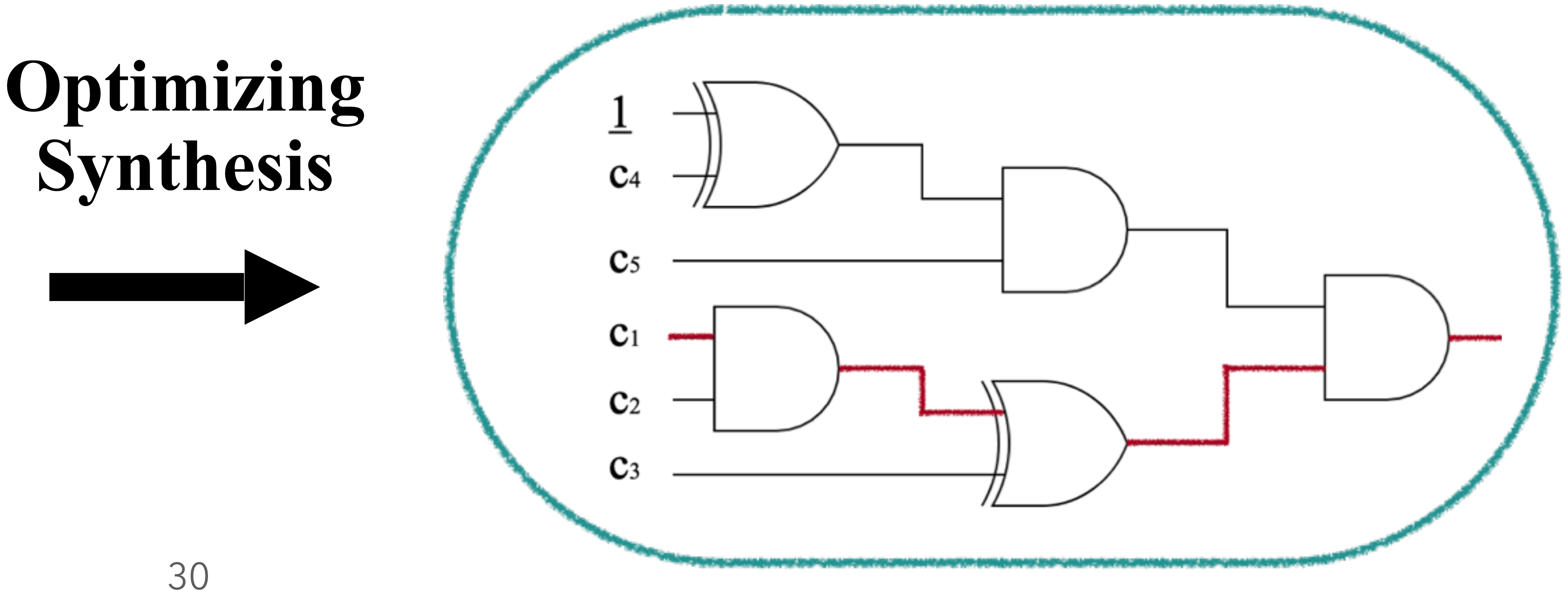




Optimizing Synthesis



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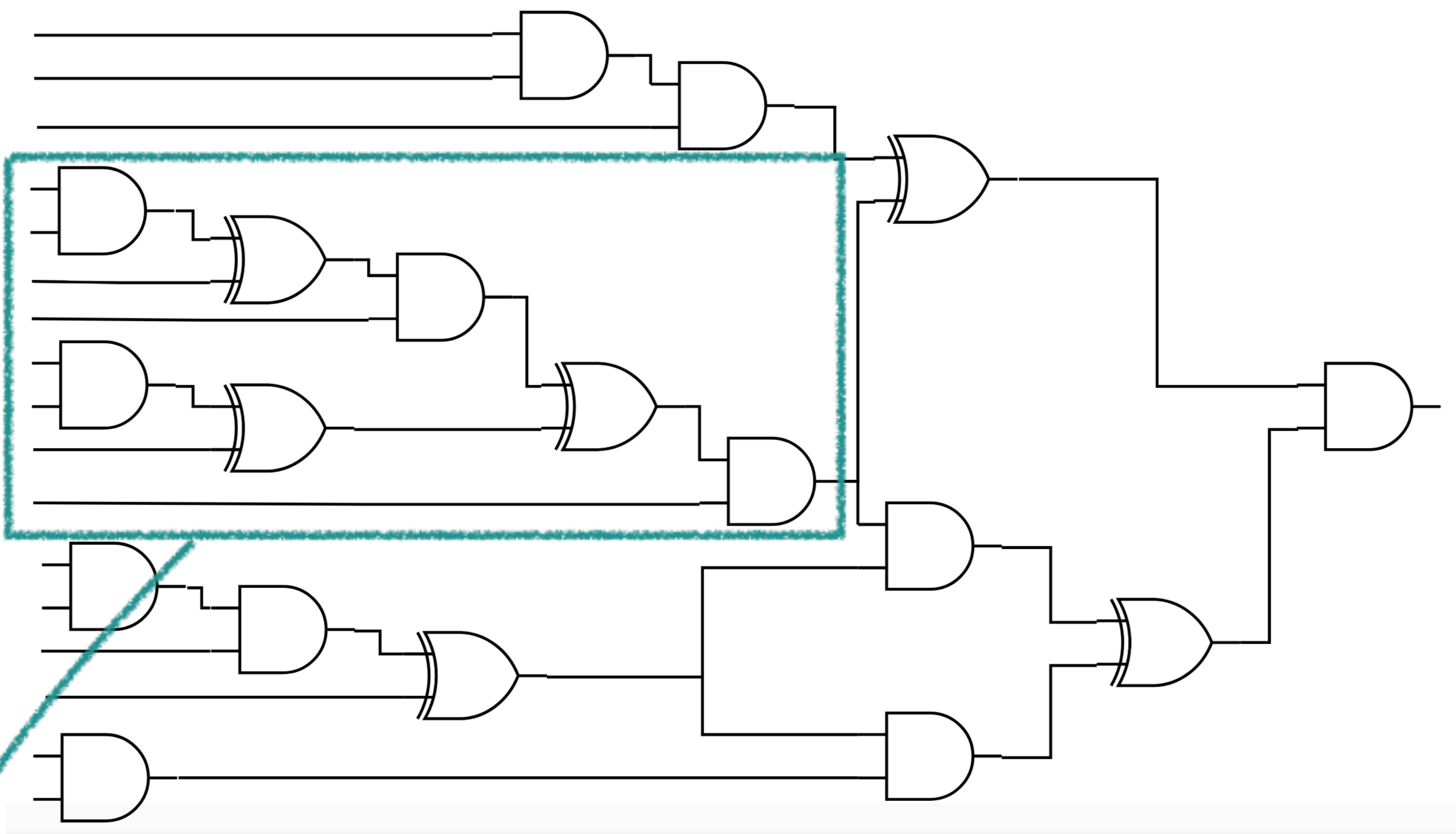

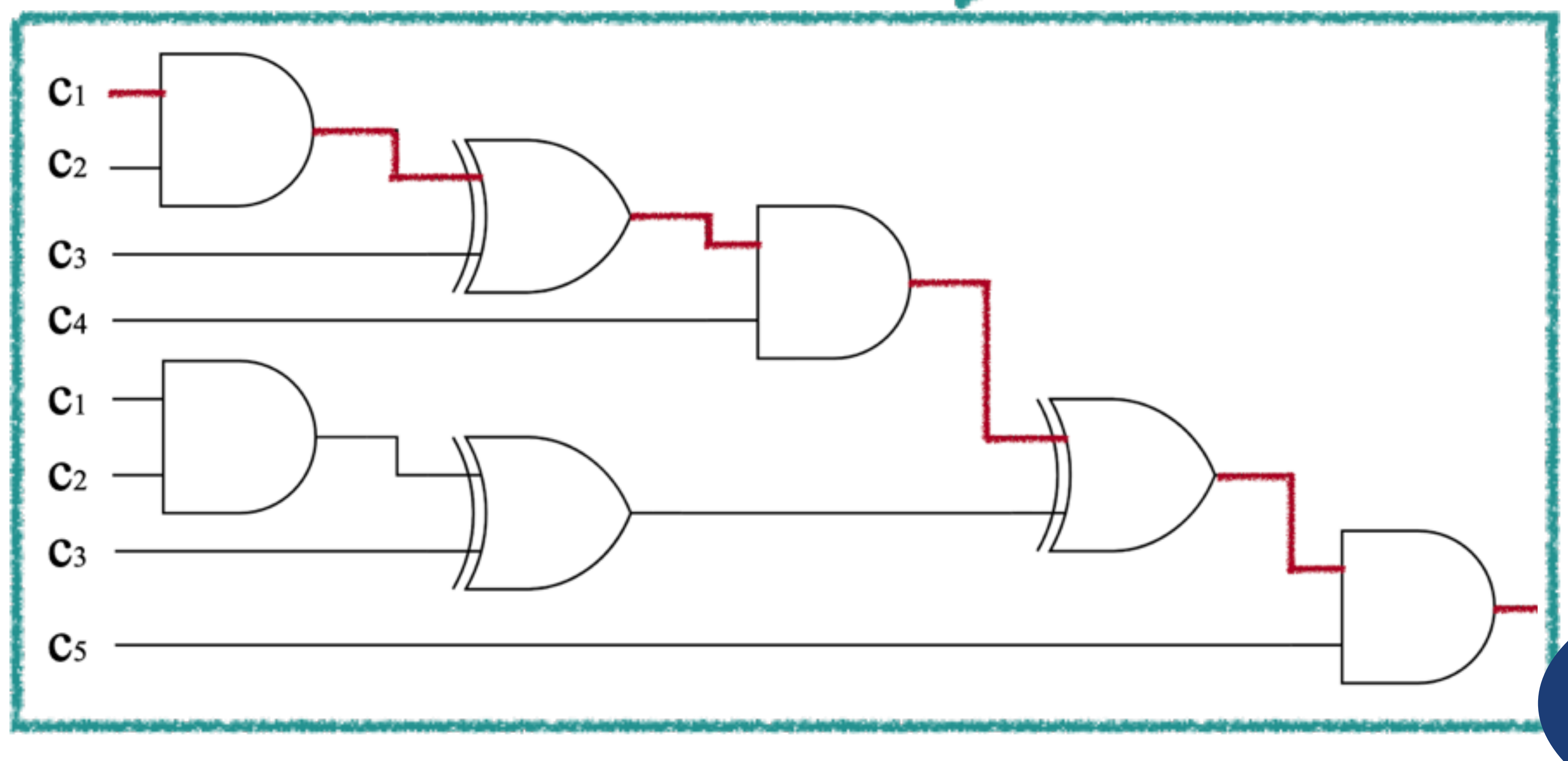

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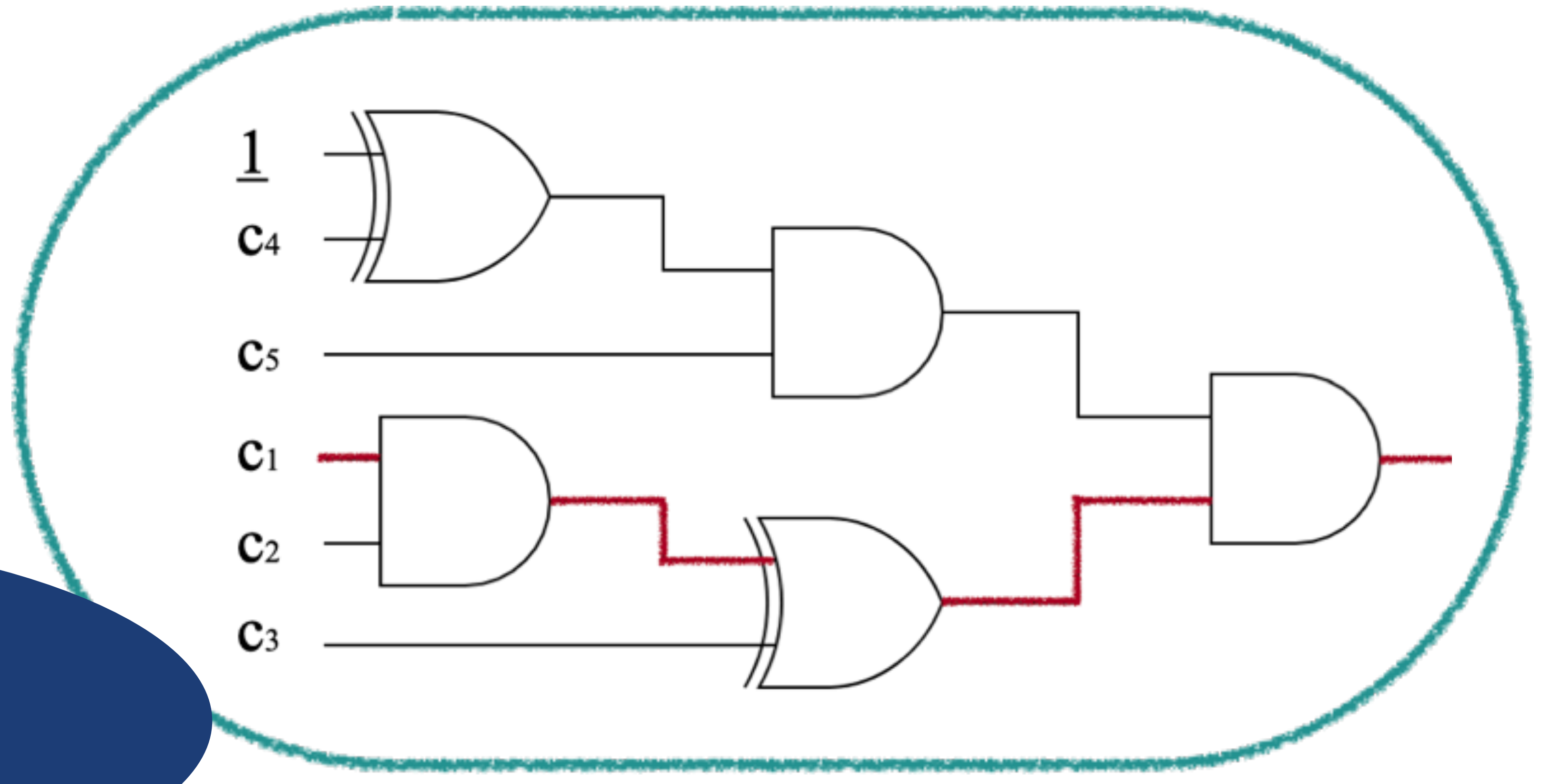
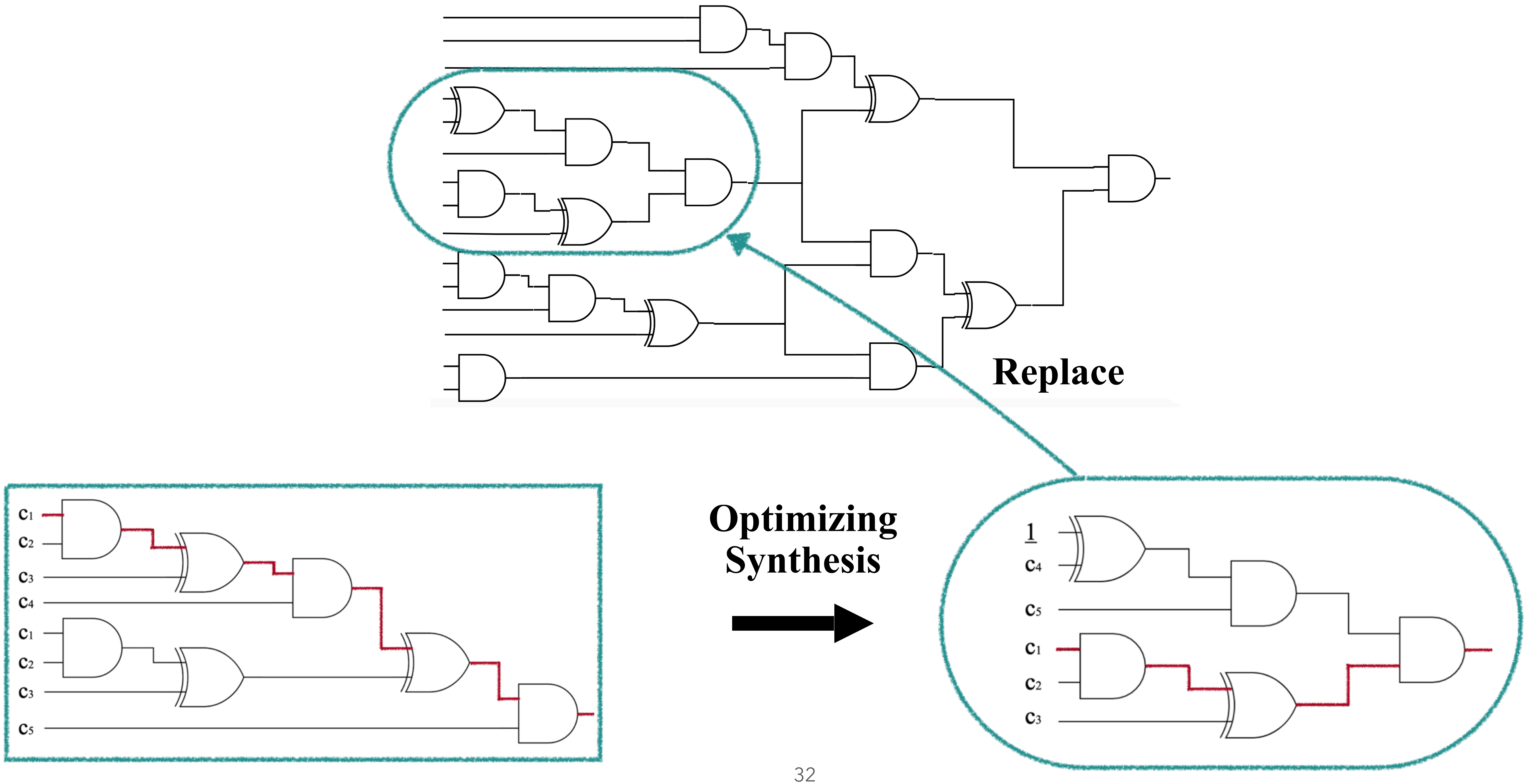


scalable

Solution1 : Synthesis via Localization



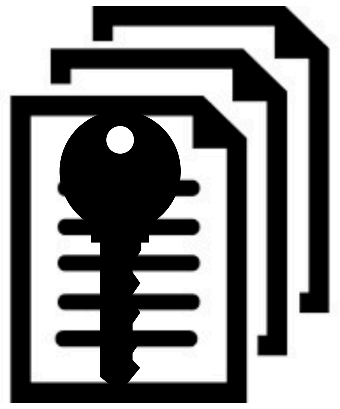
Solution 2: Learning Successful Synthesis Patterns

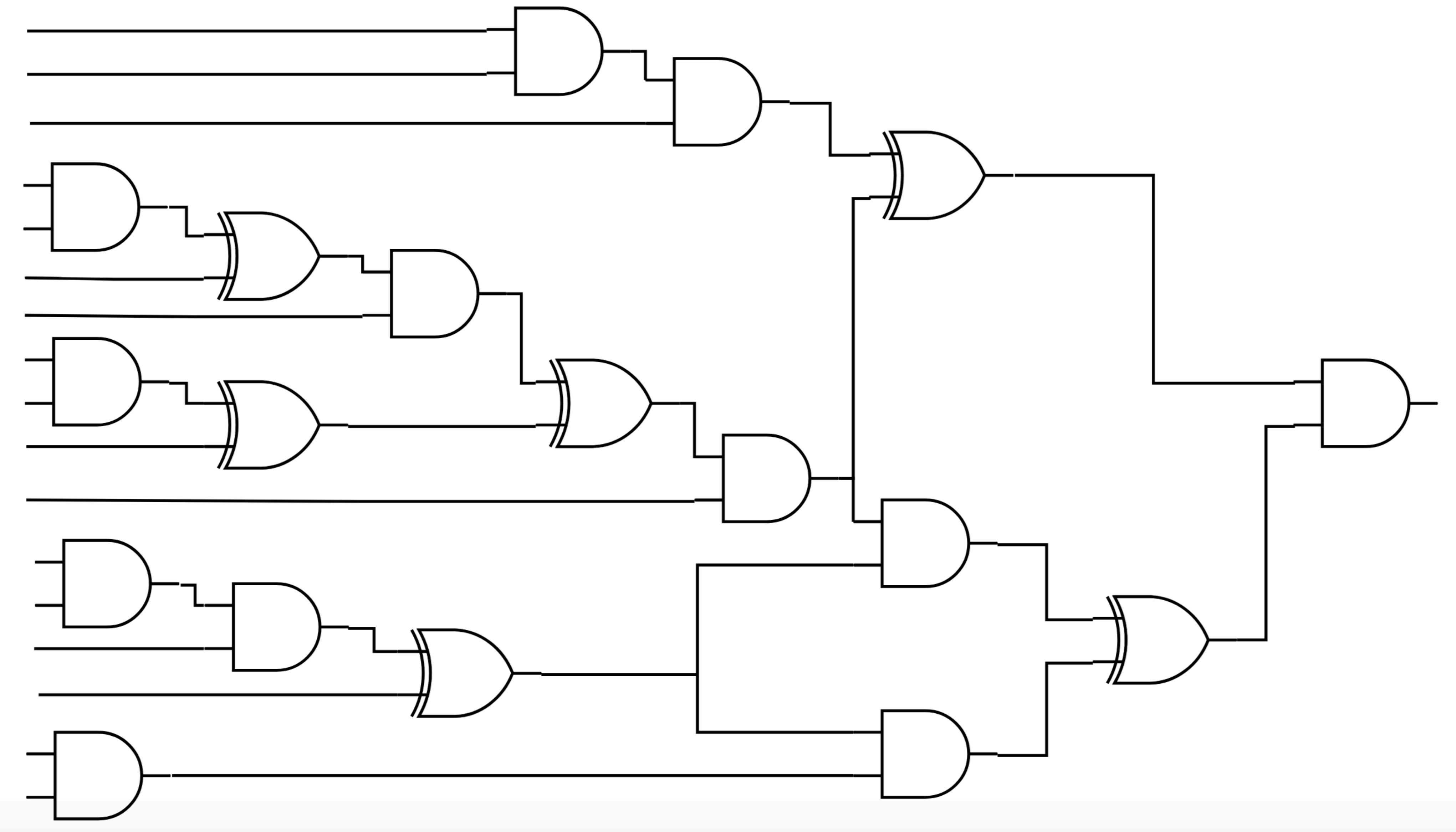
- Offline Learning
  - Collect successful synthesis patterns

- Online Optimization
  - Applying the patterns by term rewriting

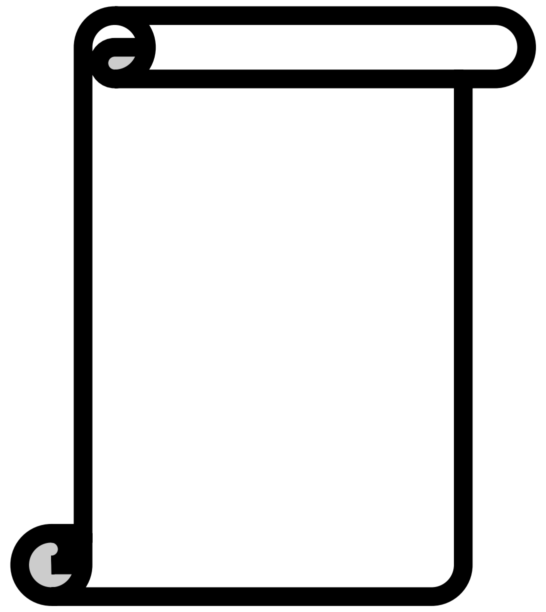
Offline Learning to Collect Opt. Patterns

Training
HE Applications





Collected
Opt. Patterns



Offline Learning to Collect Opt. Patterns

Training
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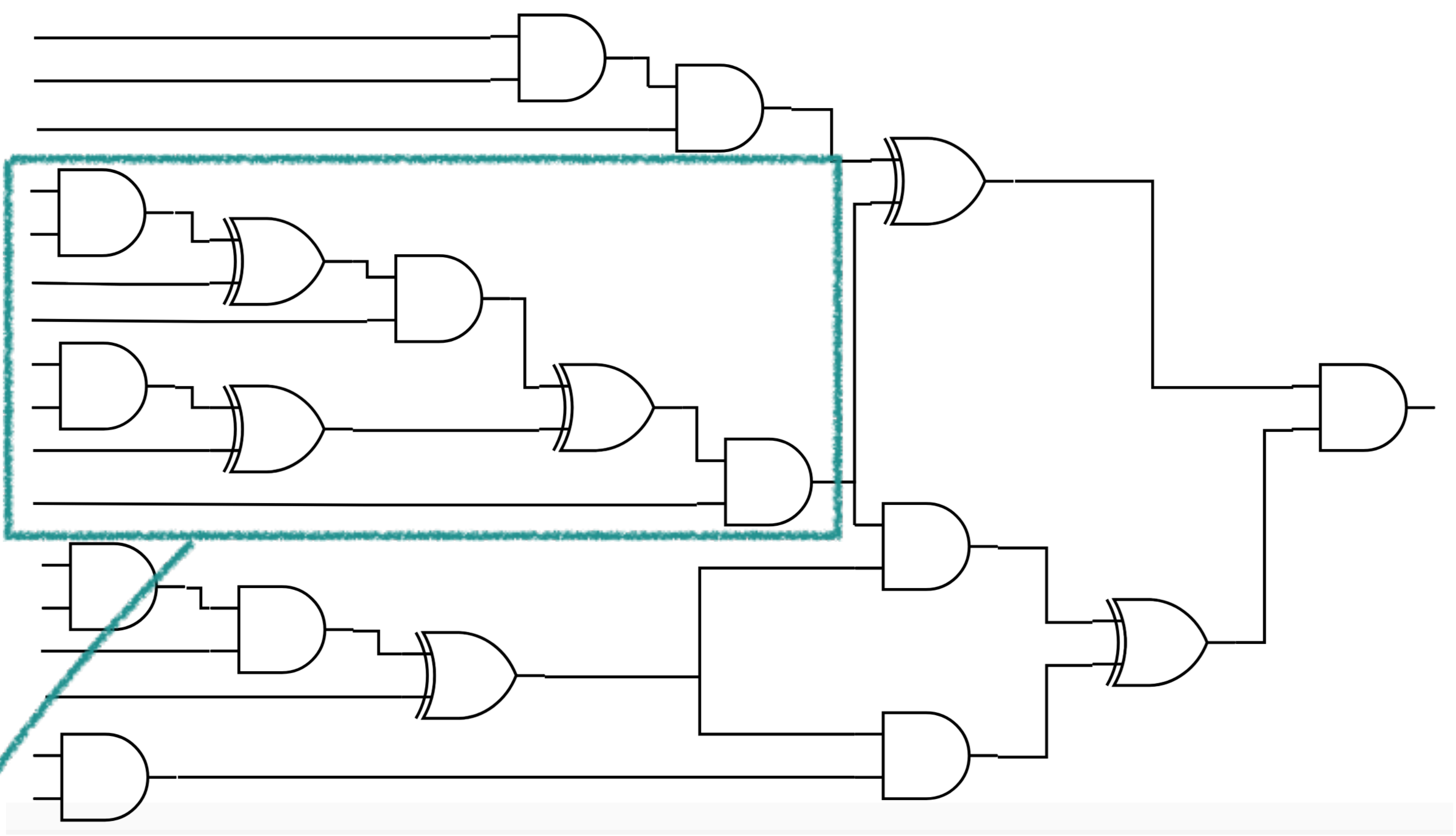

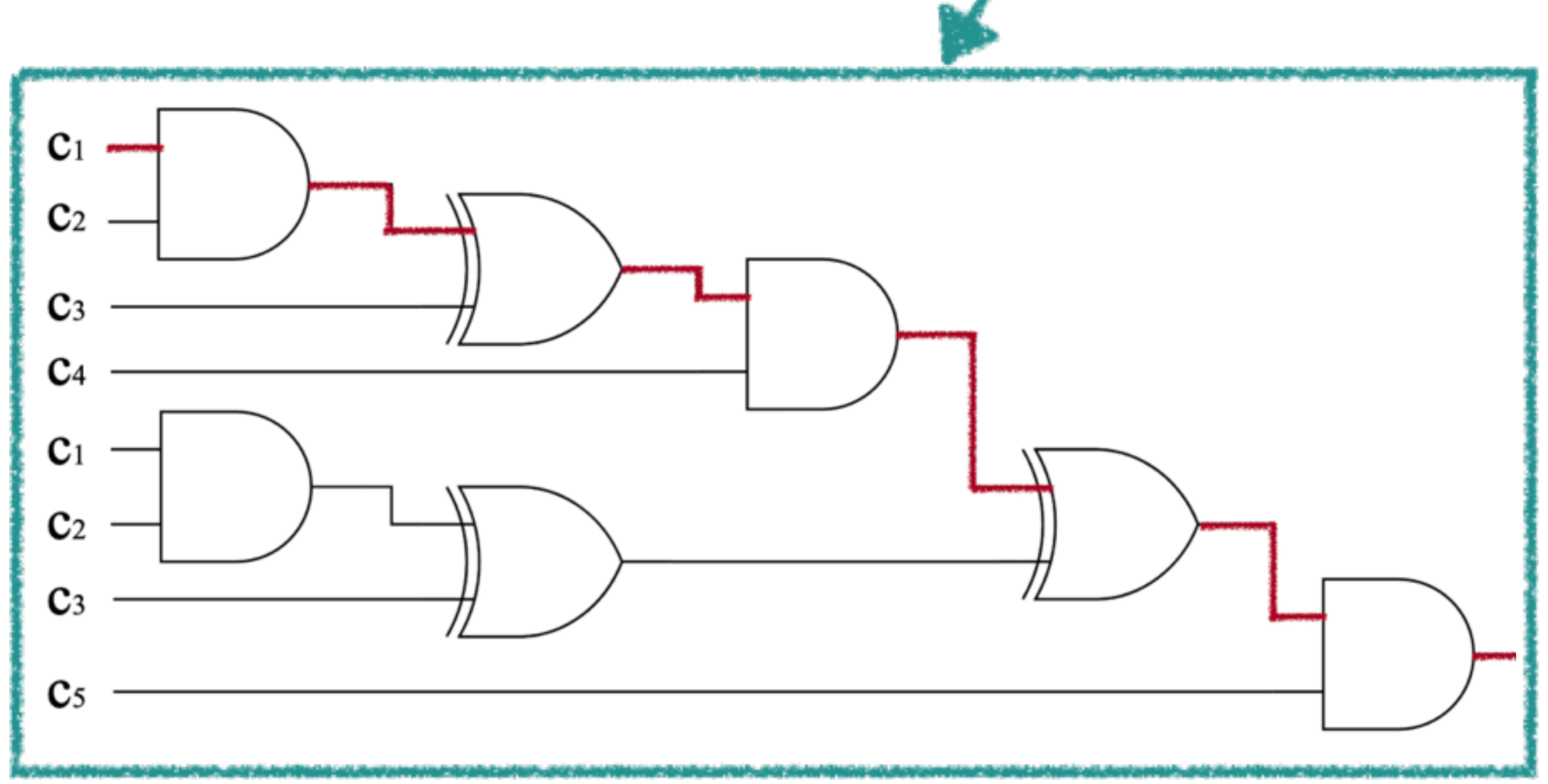

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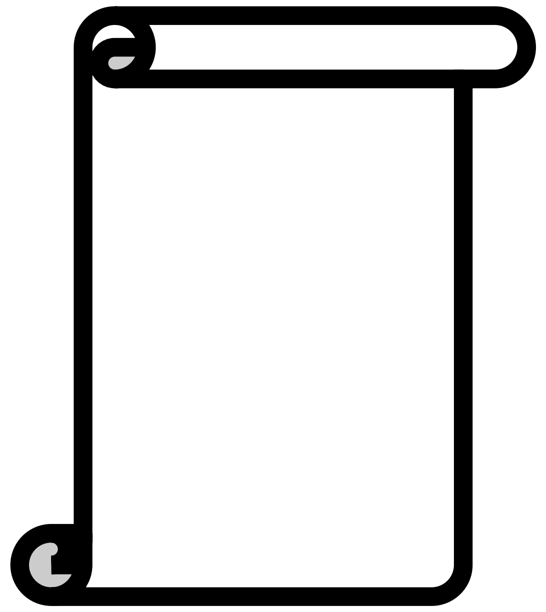
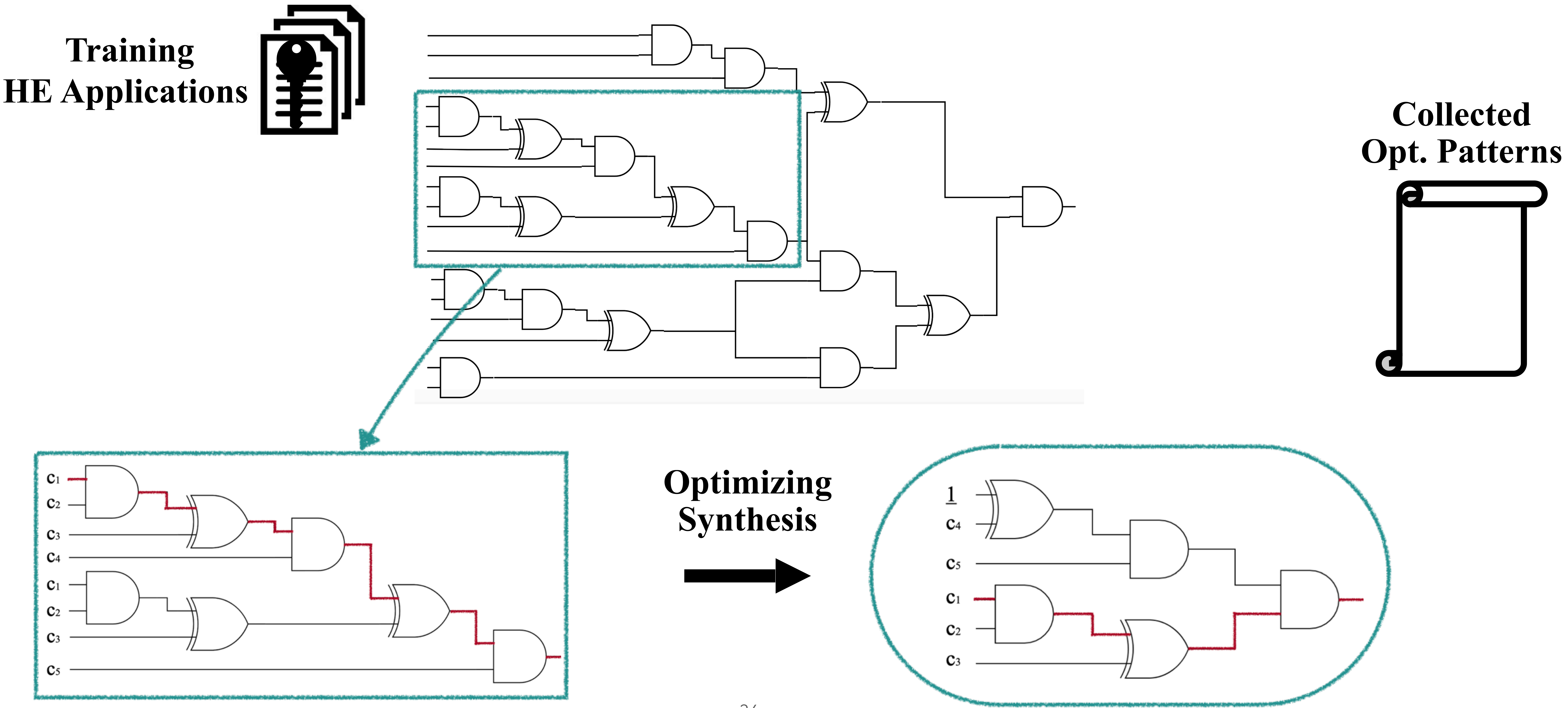


Offline Learning to Collect Opt. Patterns



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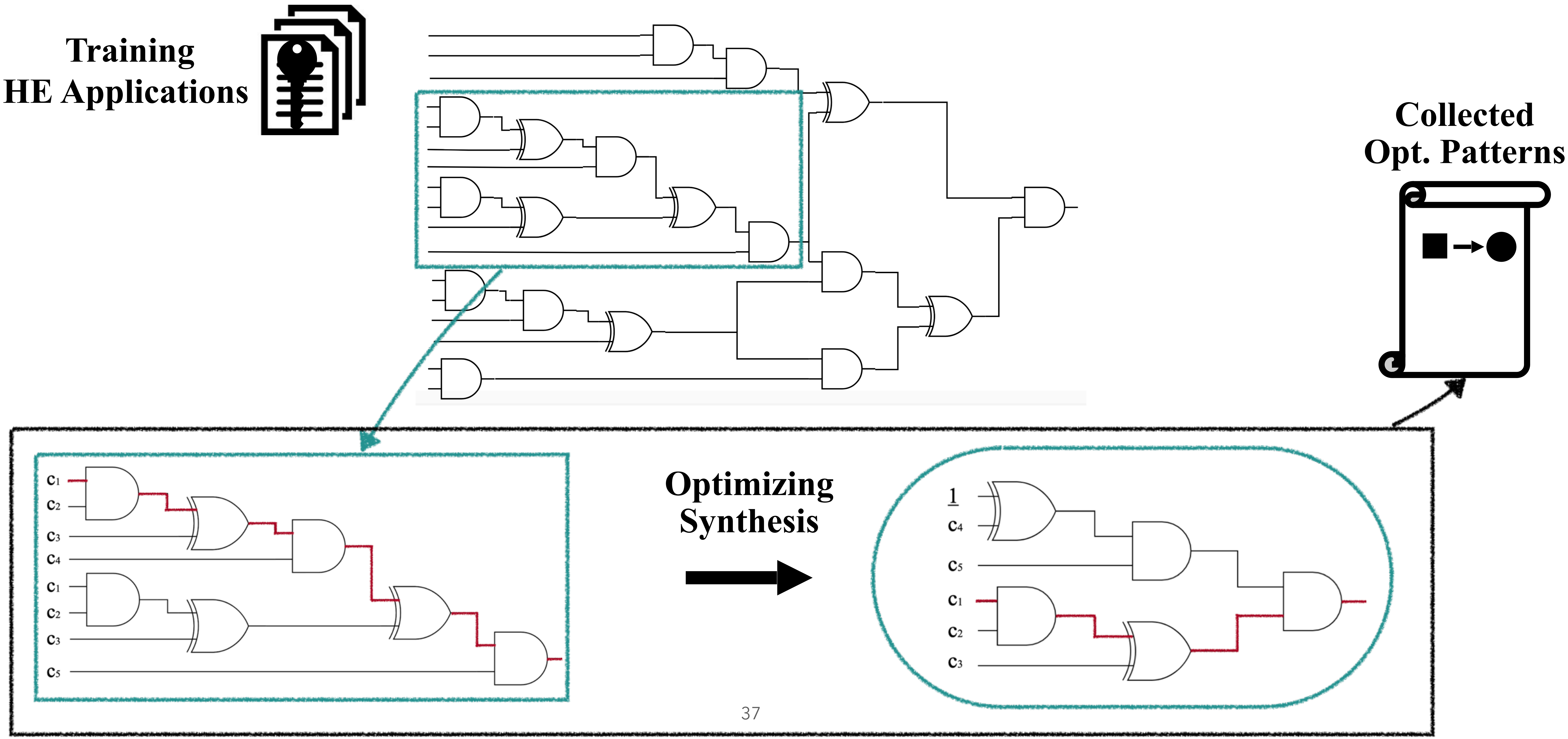

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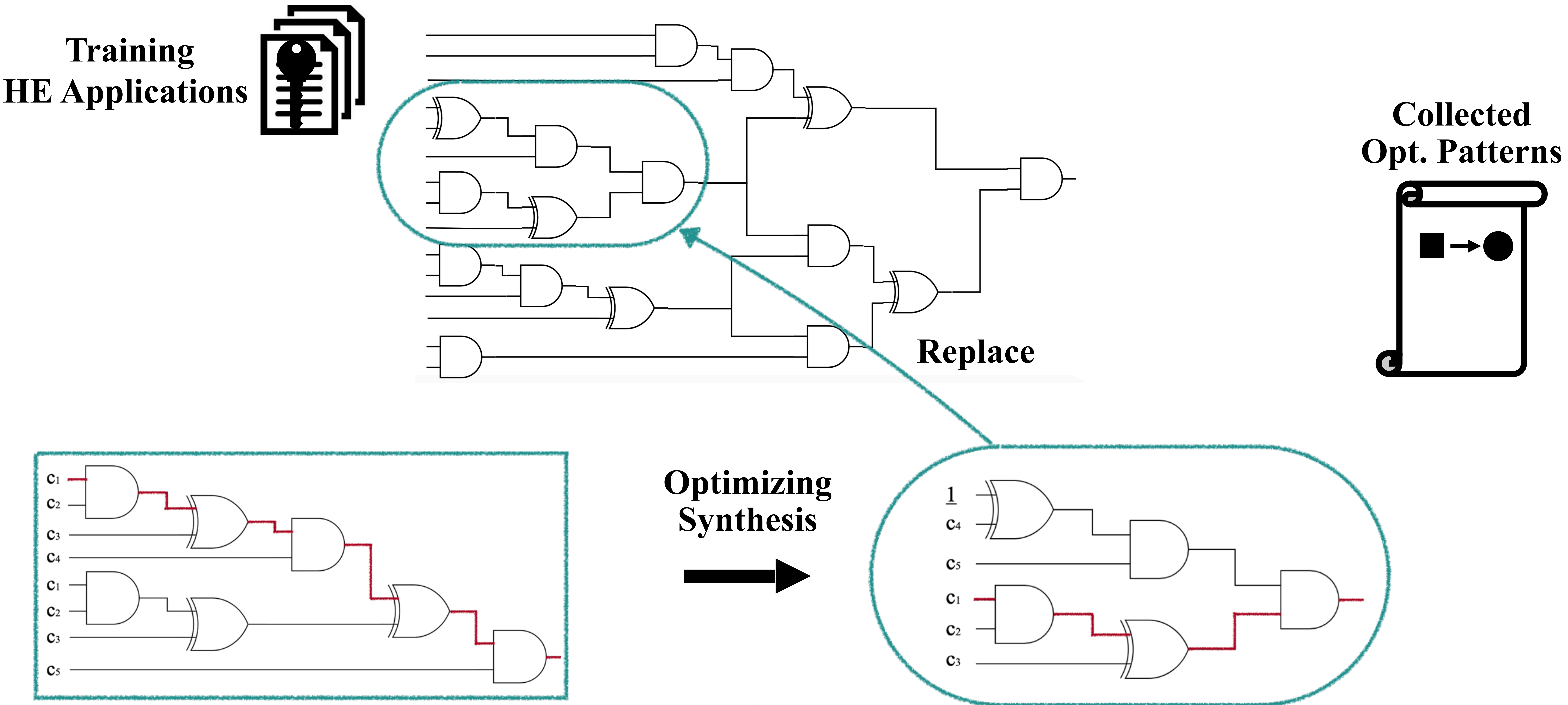

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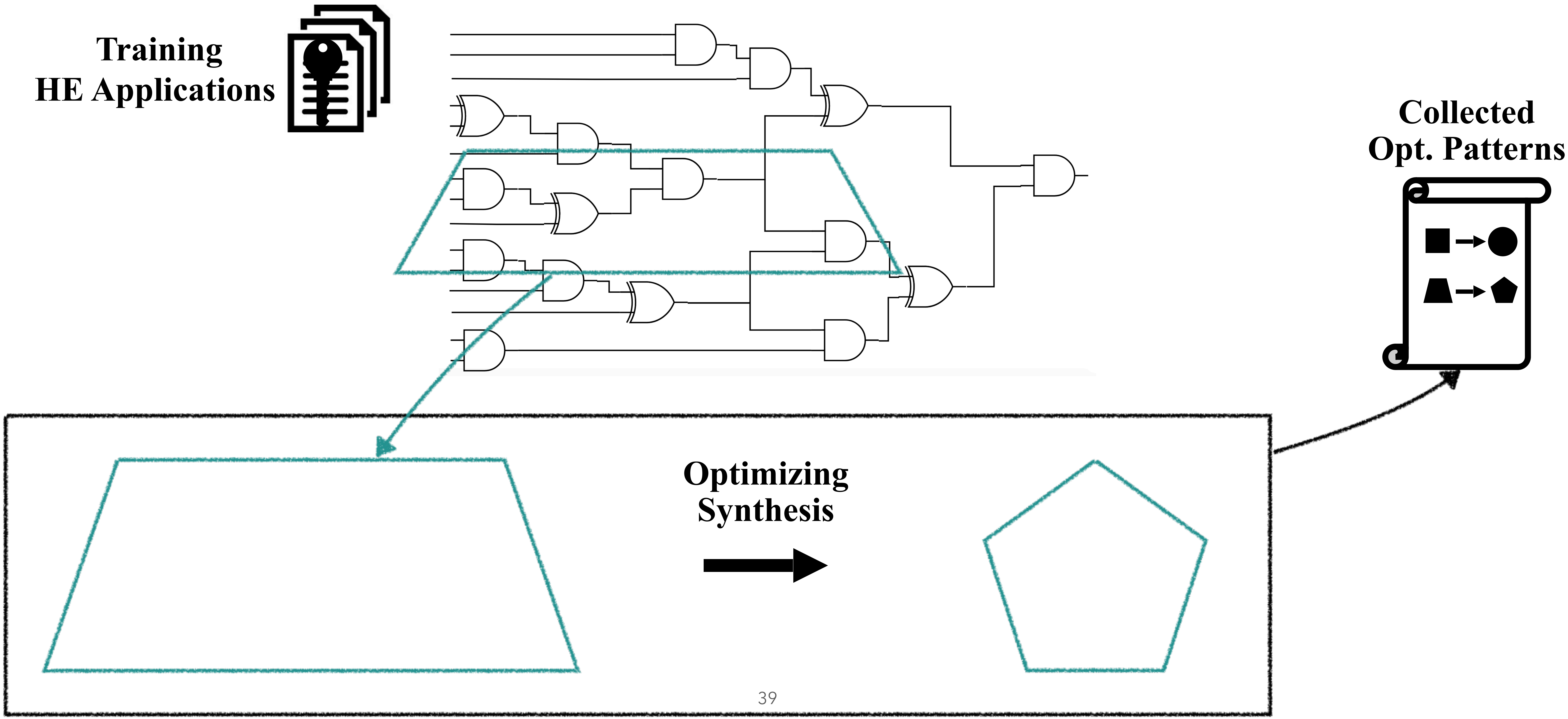

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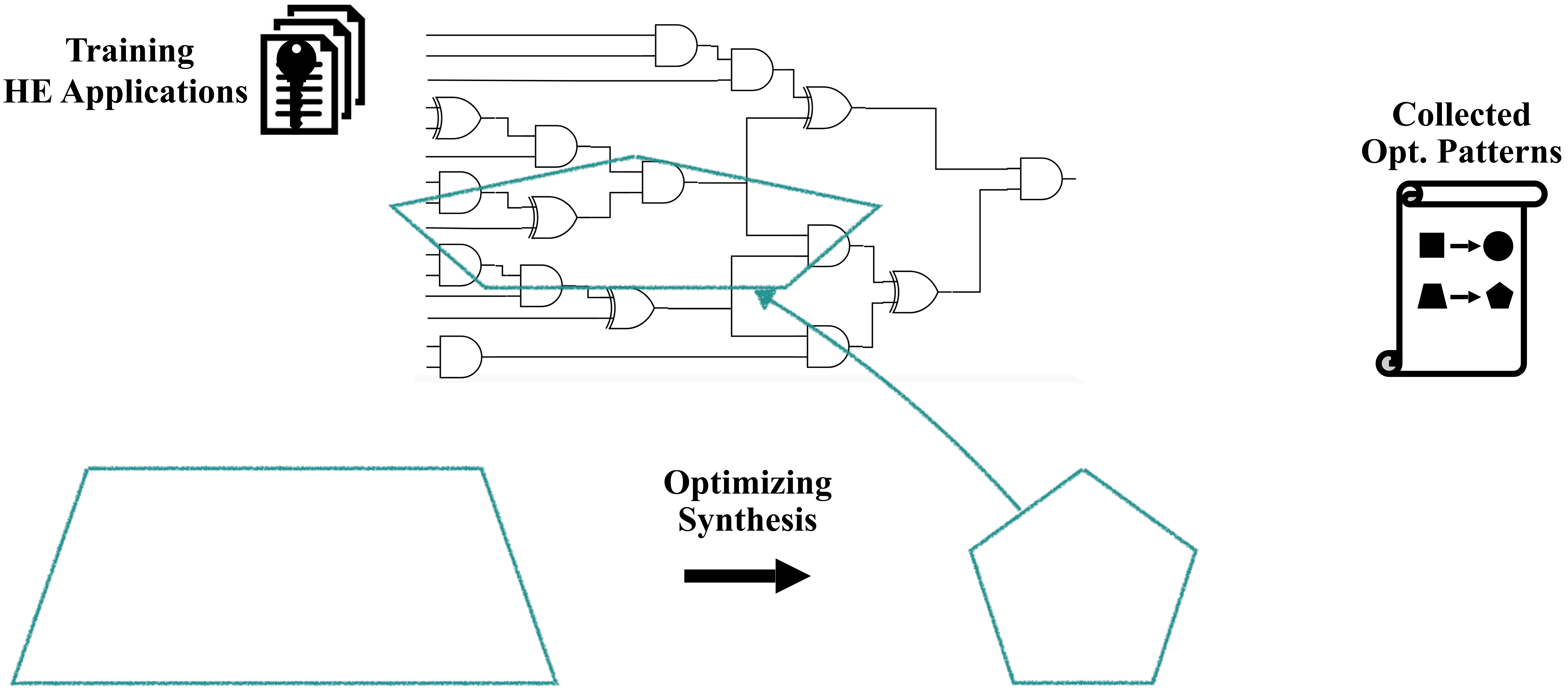
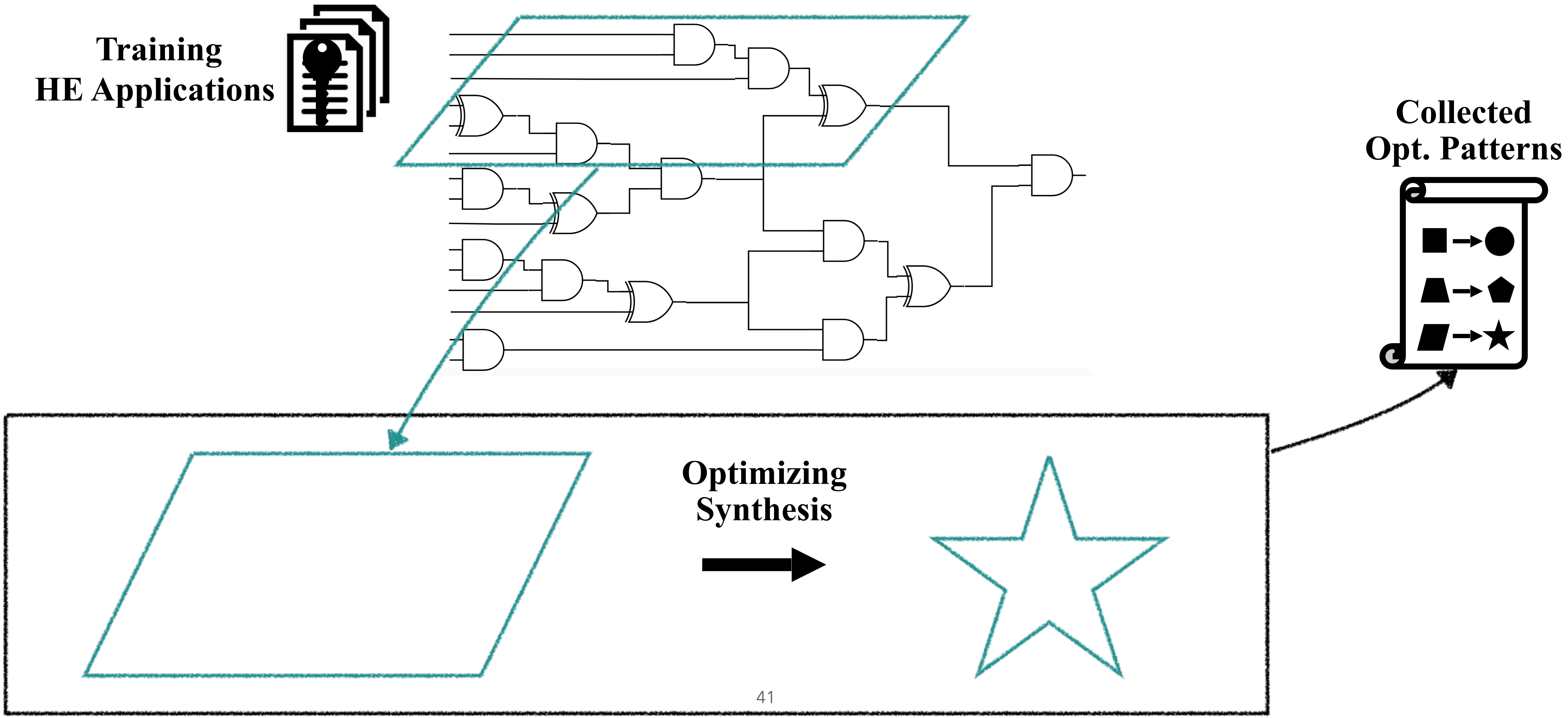
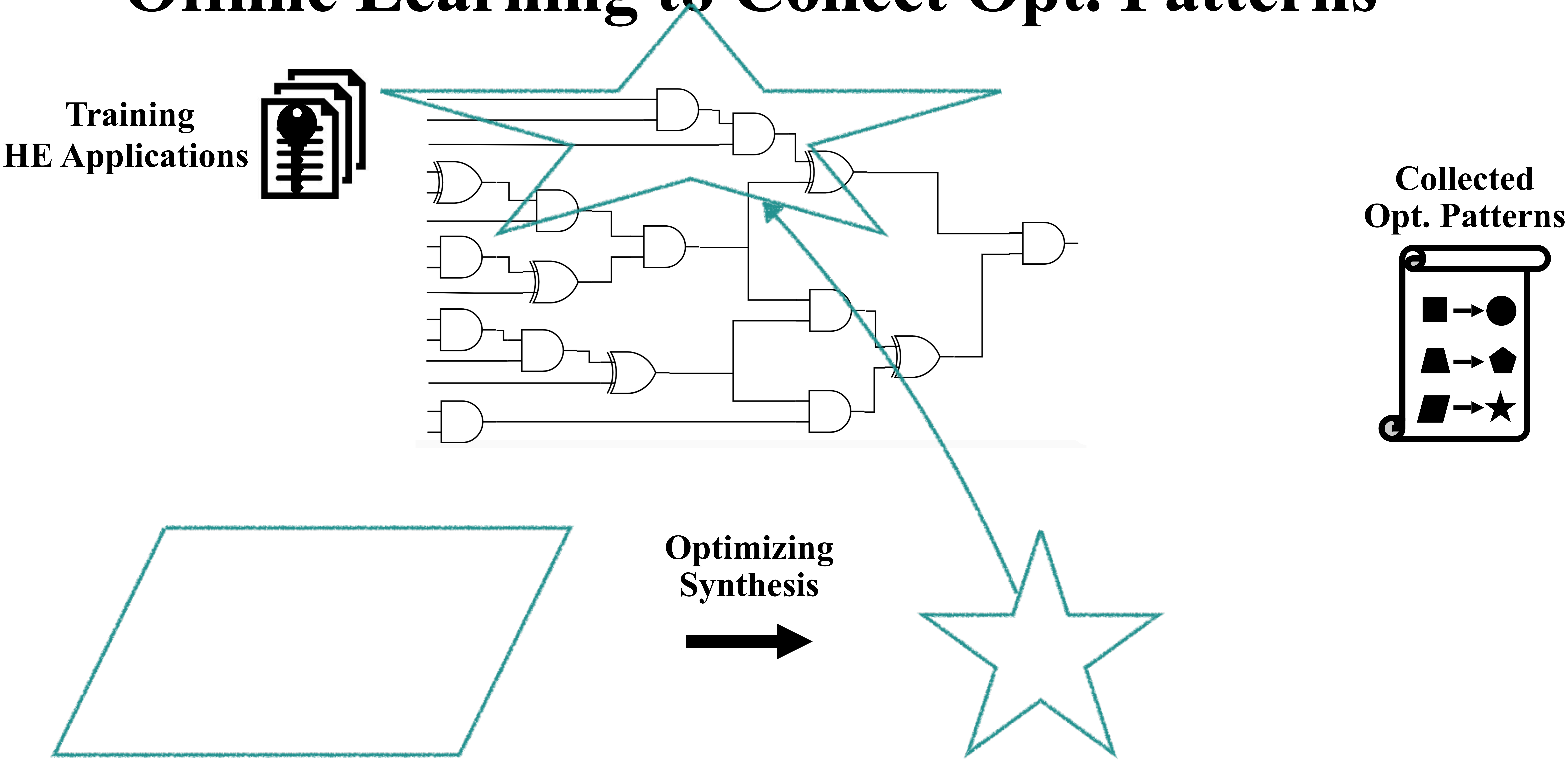


Offline Learning to Collect Opt. Patterns

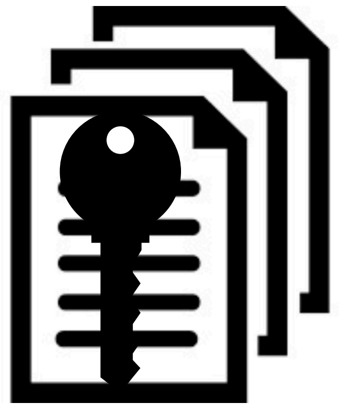


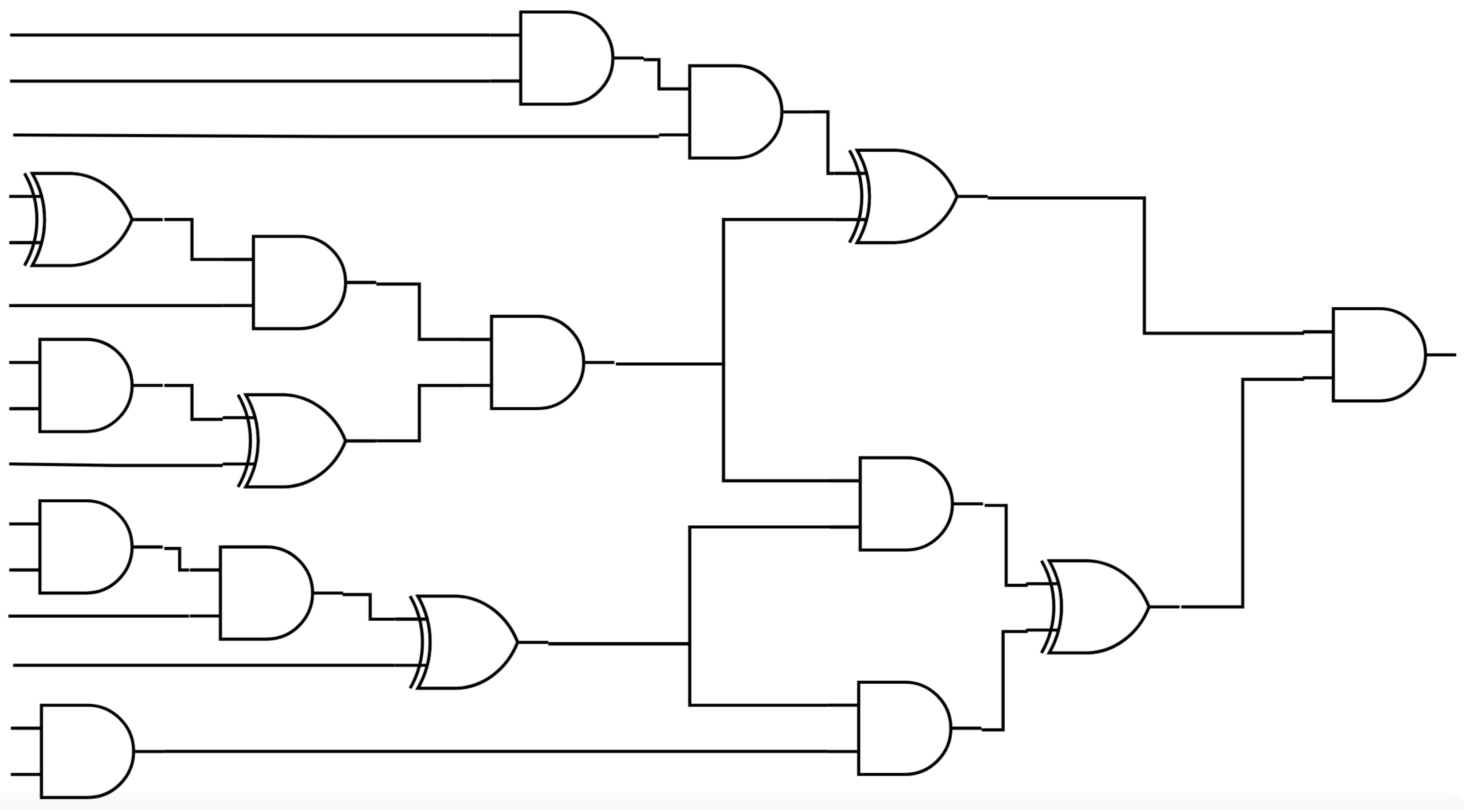
Offline Learning to Collect Opt. Patterns



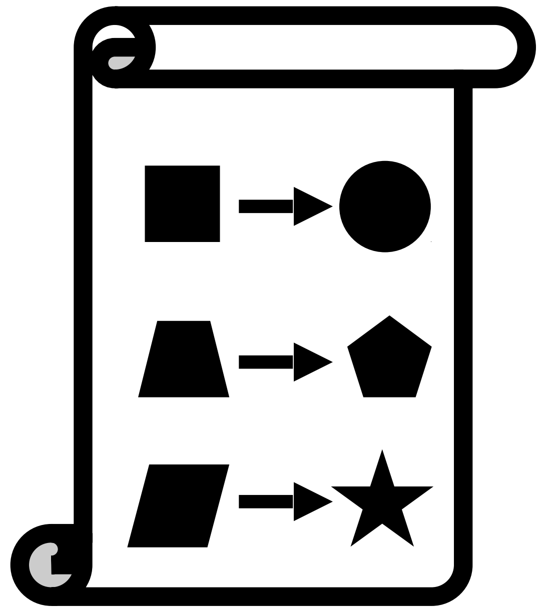
Offline Learning to Collect Opt. Patterns

Training
HE Applications



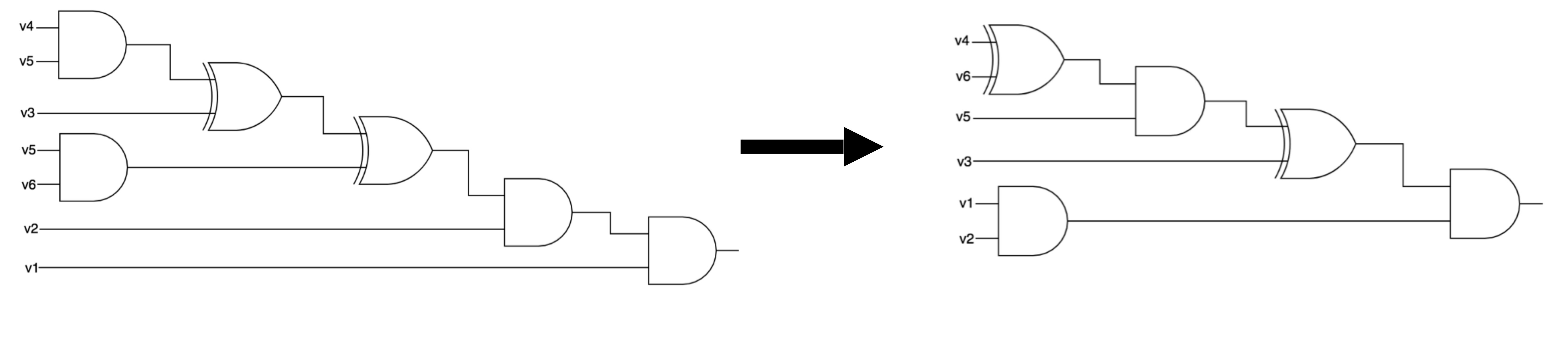


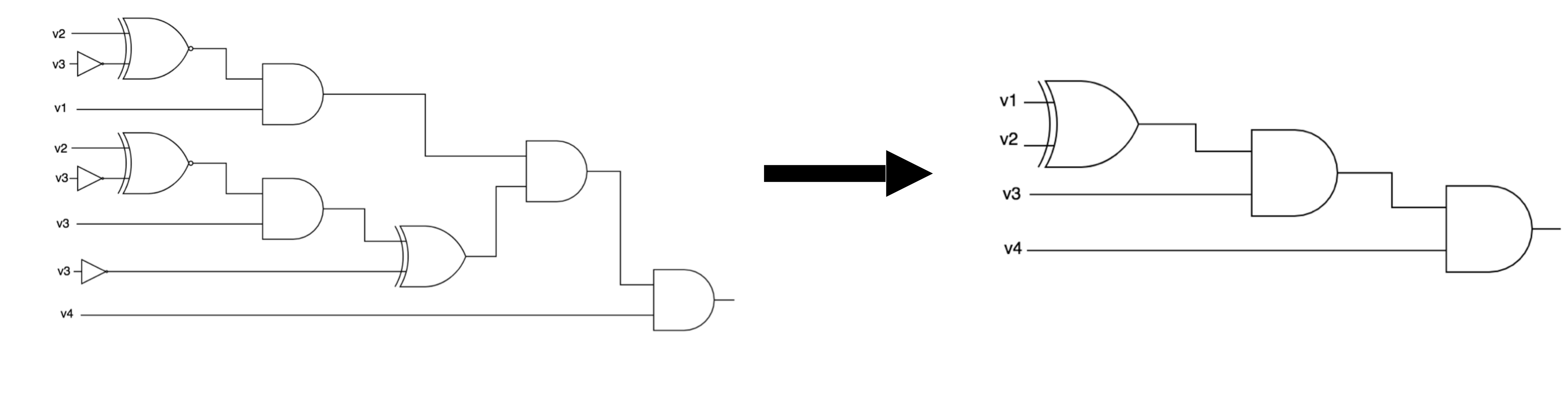
Collected
Opt. Patterns

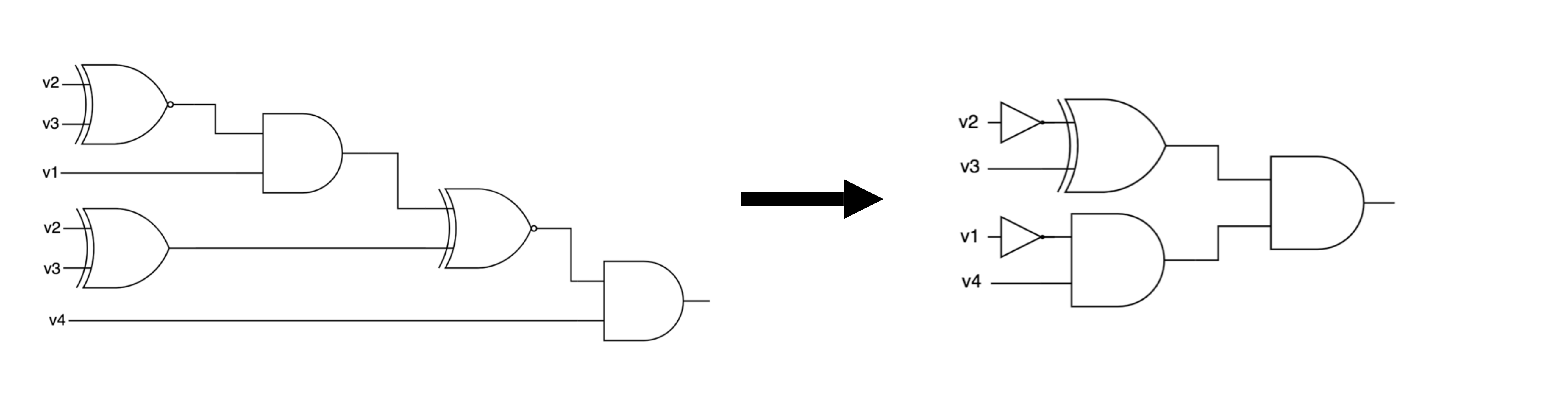


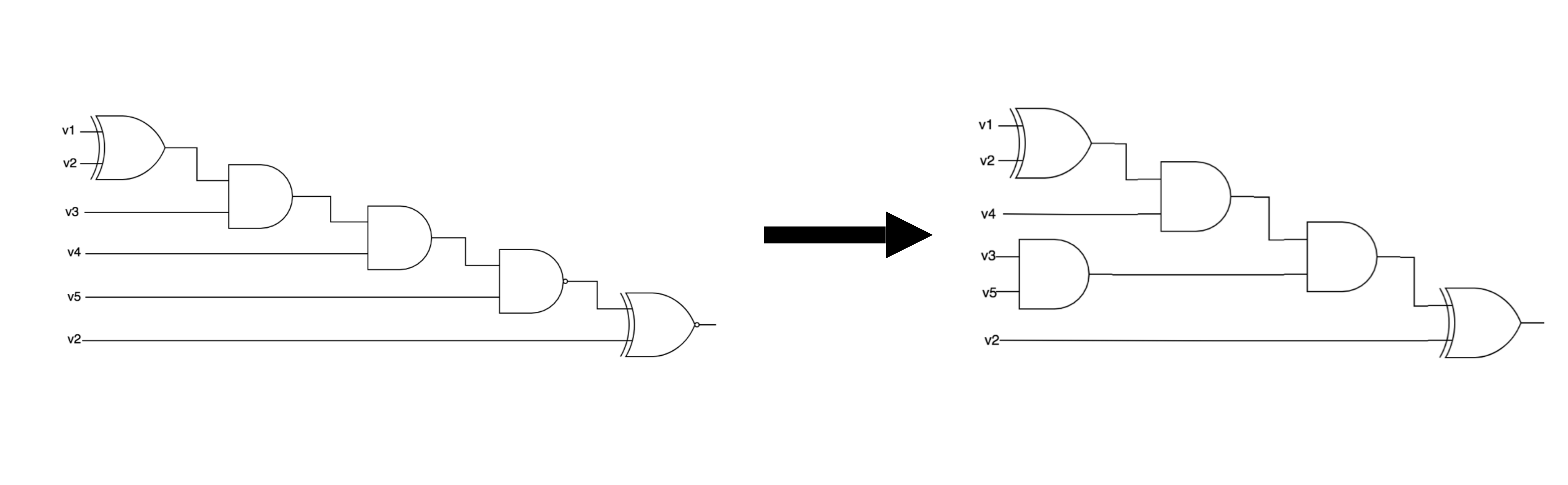
400 Opt.
patterns

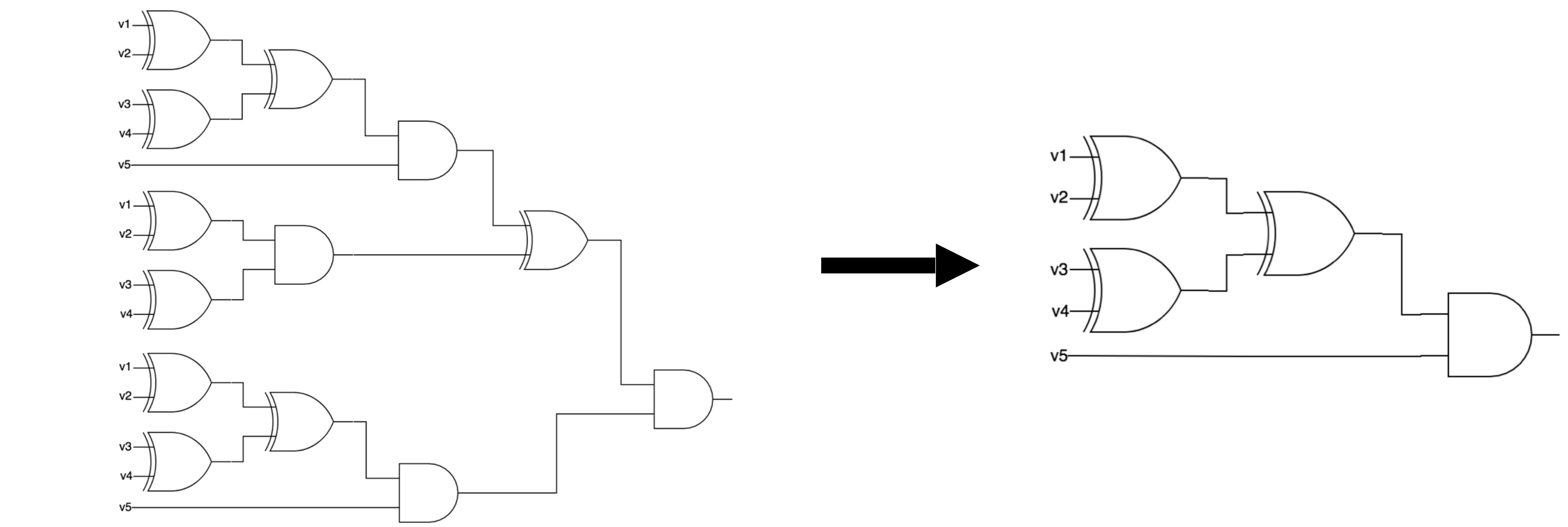
Learned Optimization Patterns : examples

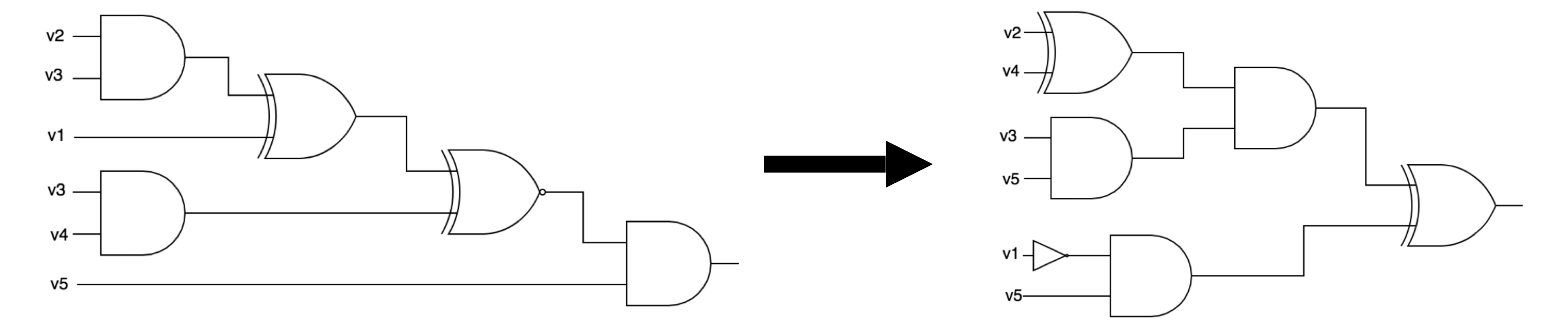






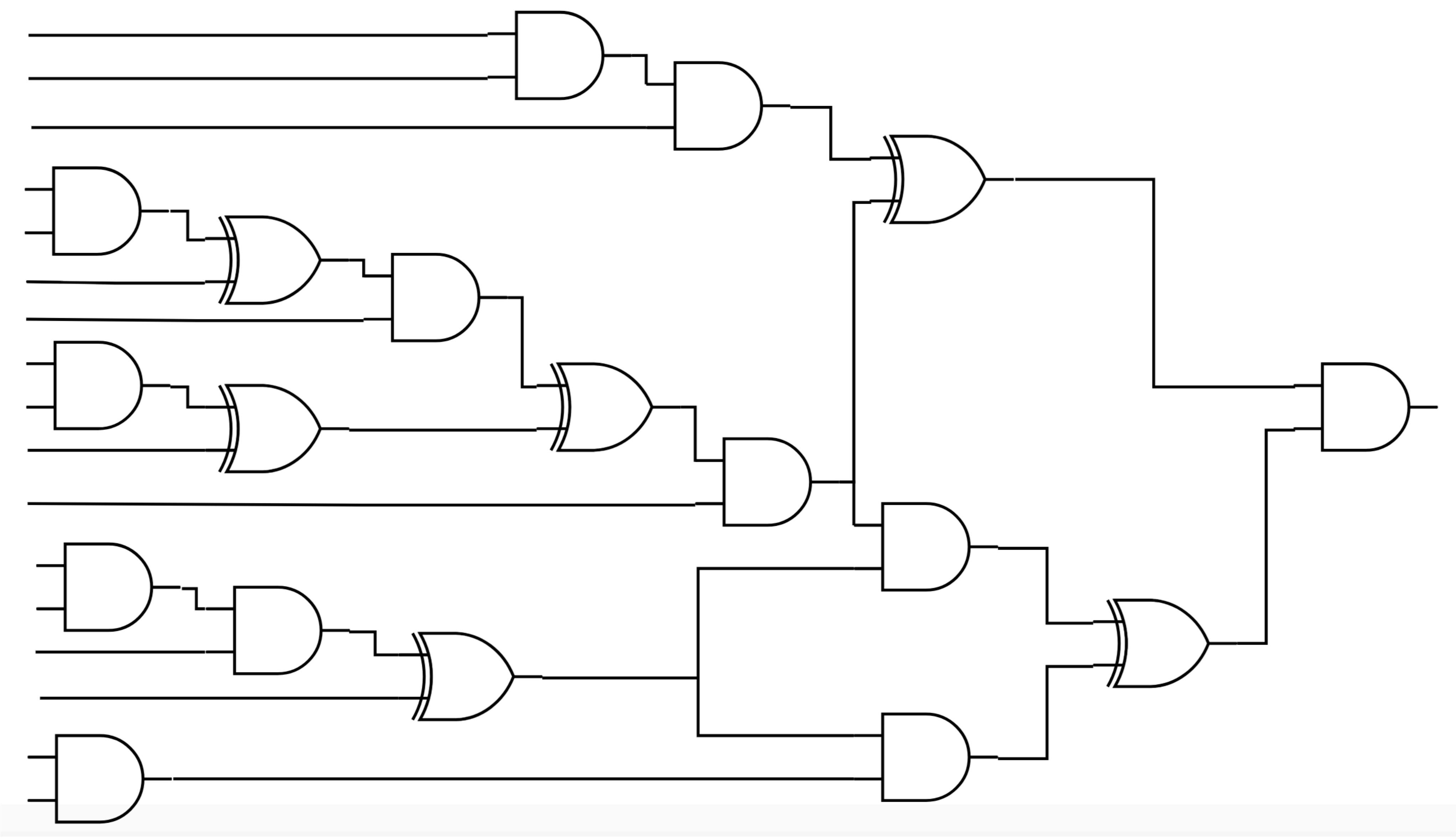




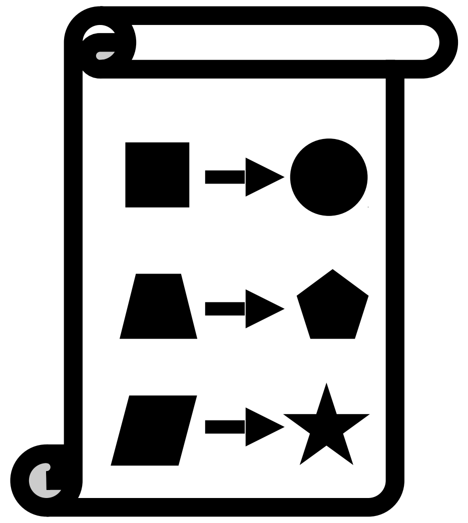


Online Rule-based Optimization

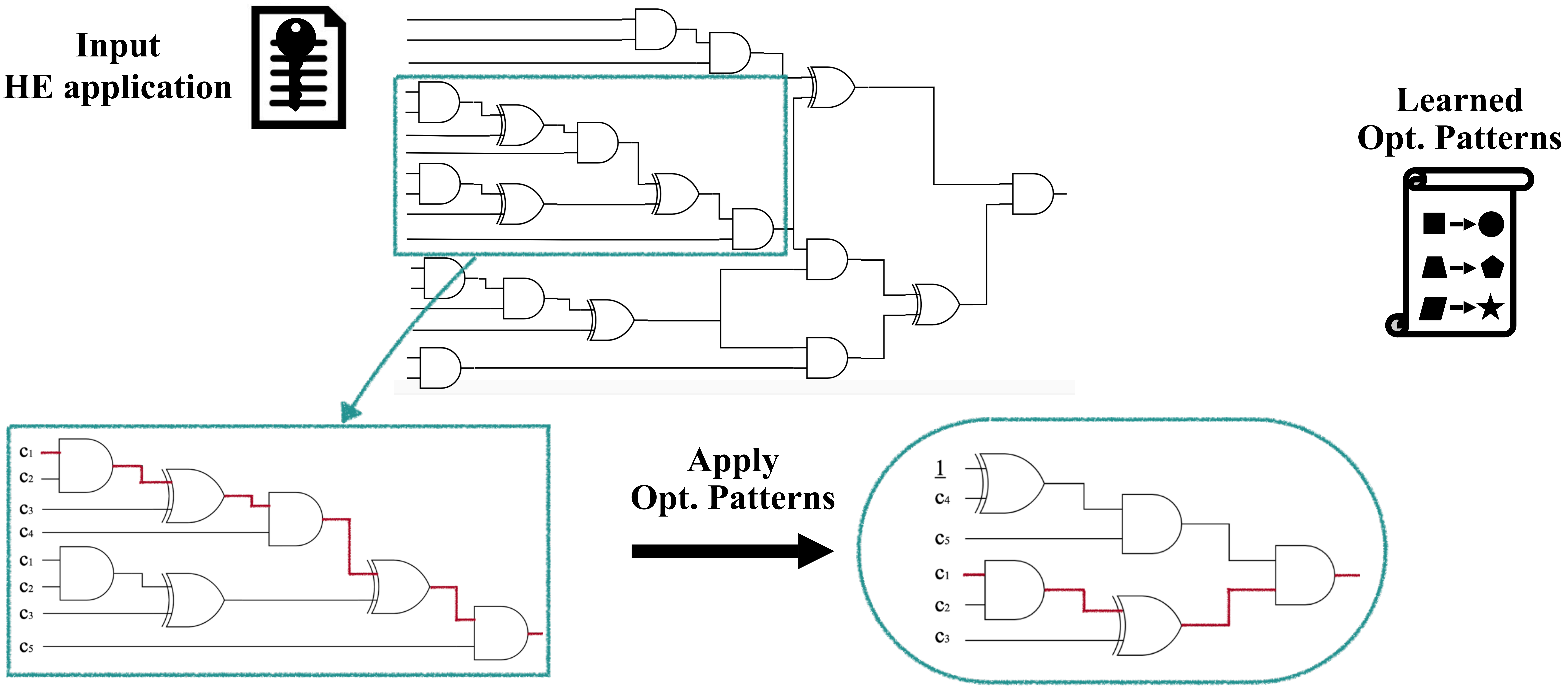
Input
HE application



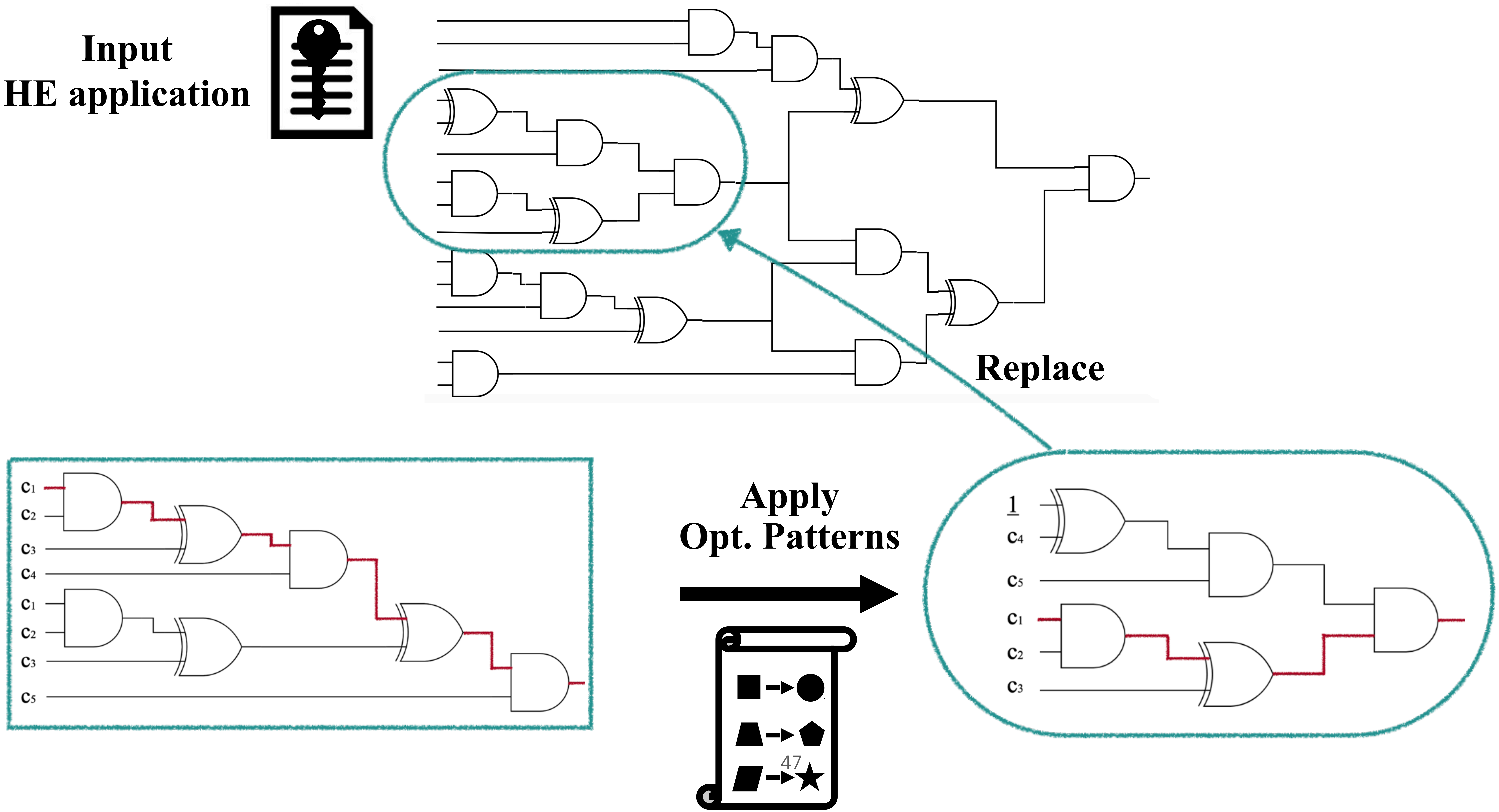
Learned
Opt. Patterns



Online Rule-based Optimization

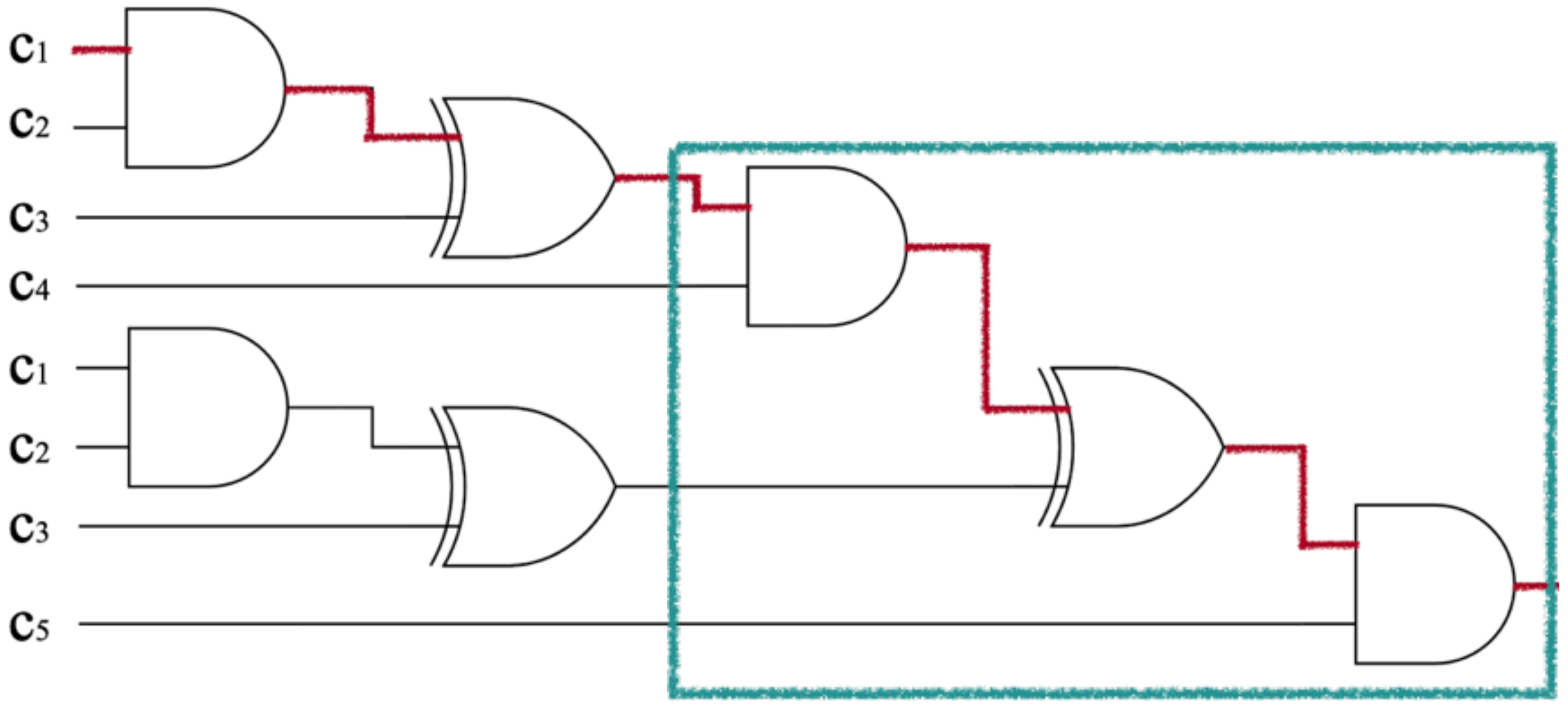


Online Rule-based Optimization

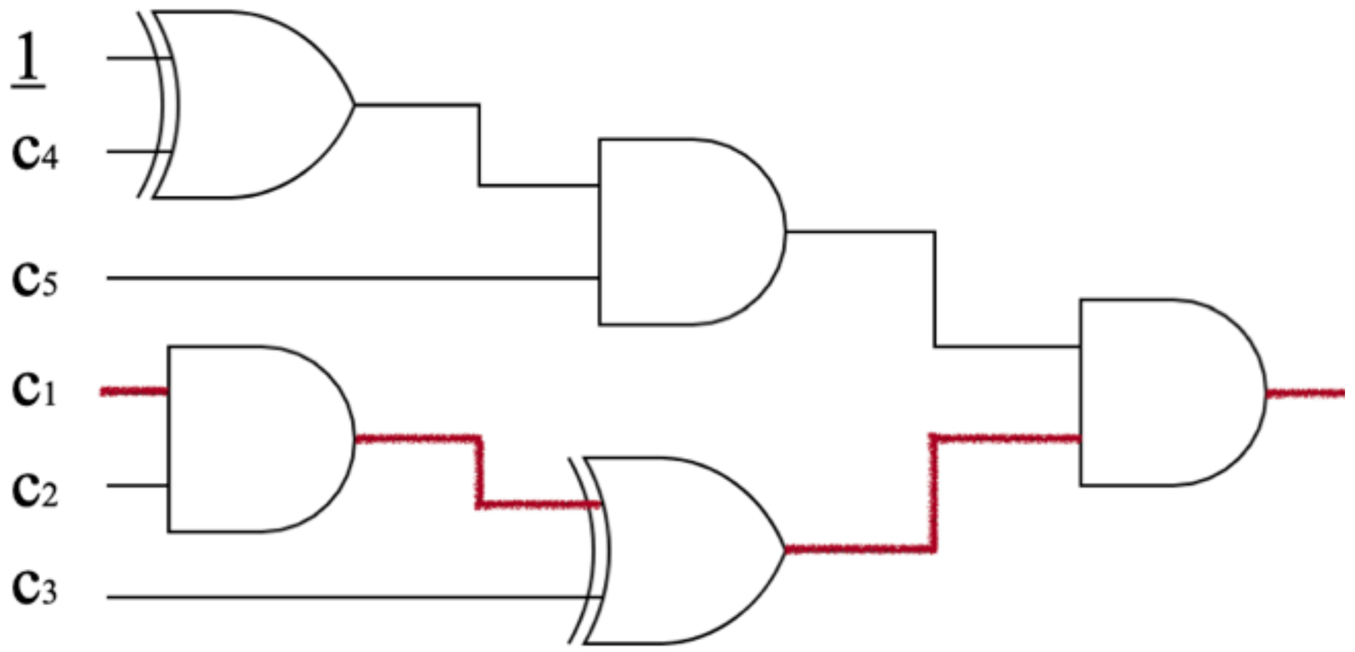


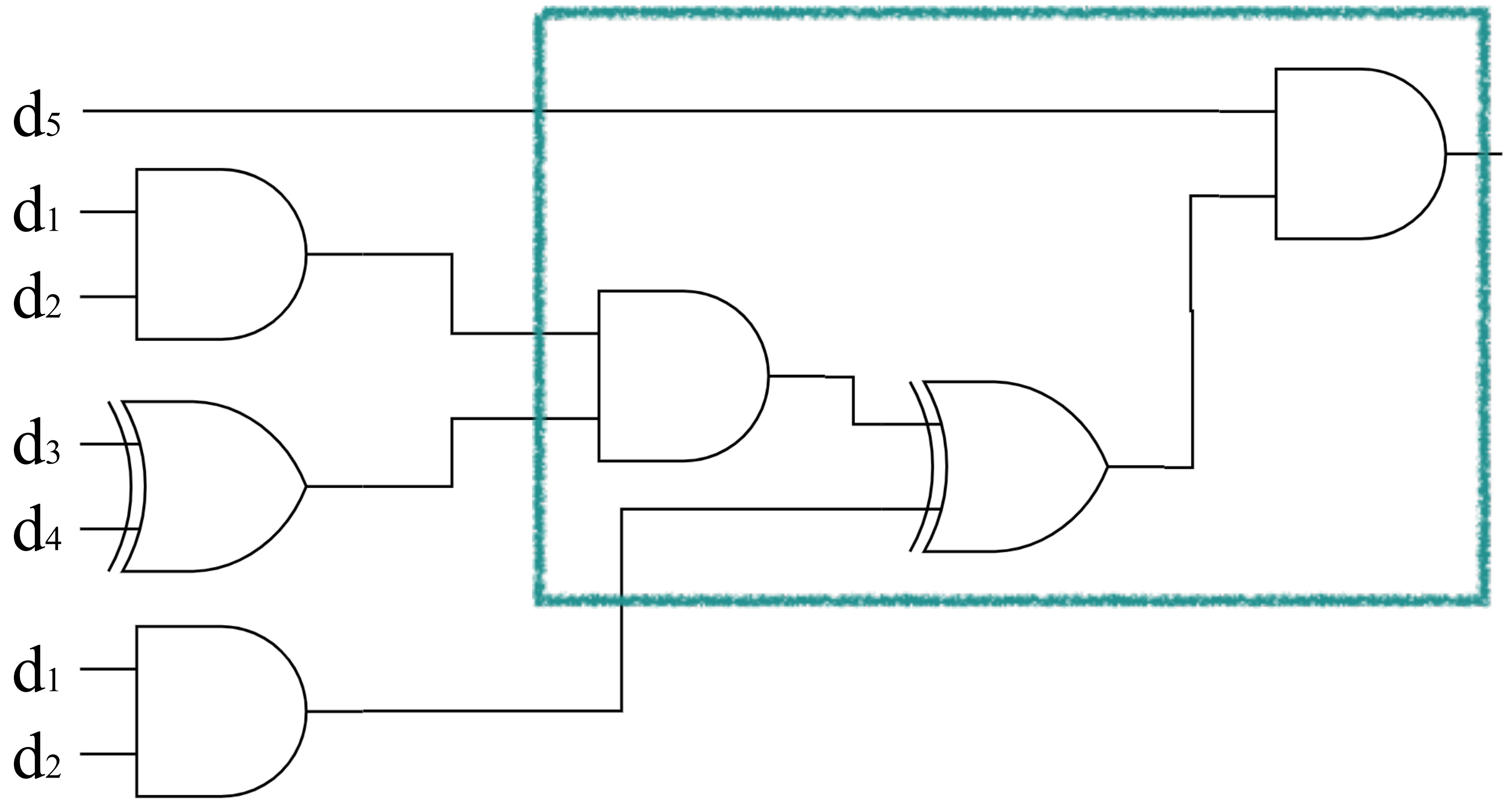
Applying Learned Optimization Patterns (1/2)

Syntactic Matching is Not Effective



Learned Opt. Patterns →



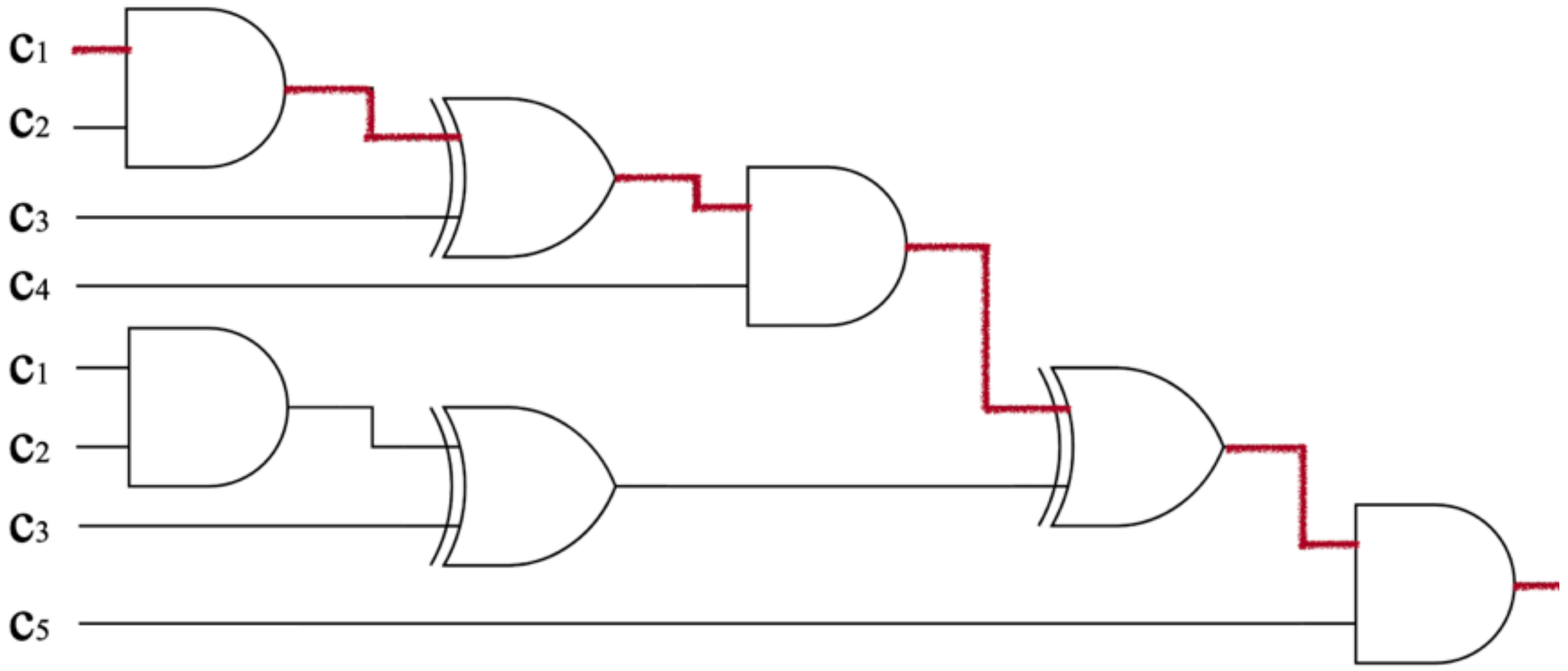


New Input Circuit Optimization →

?

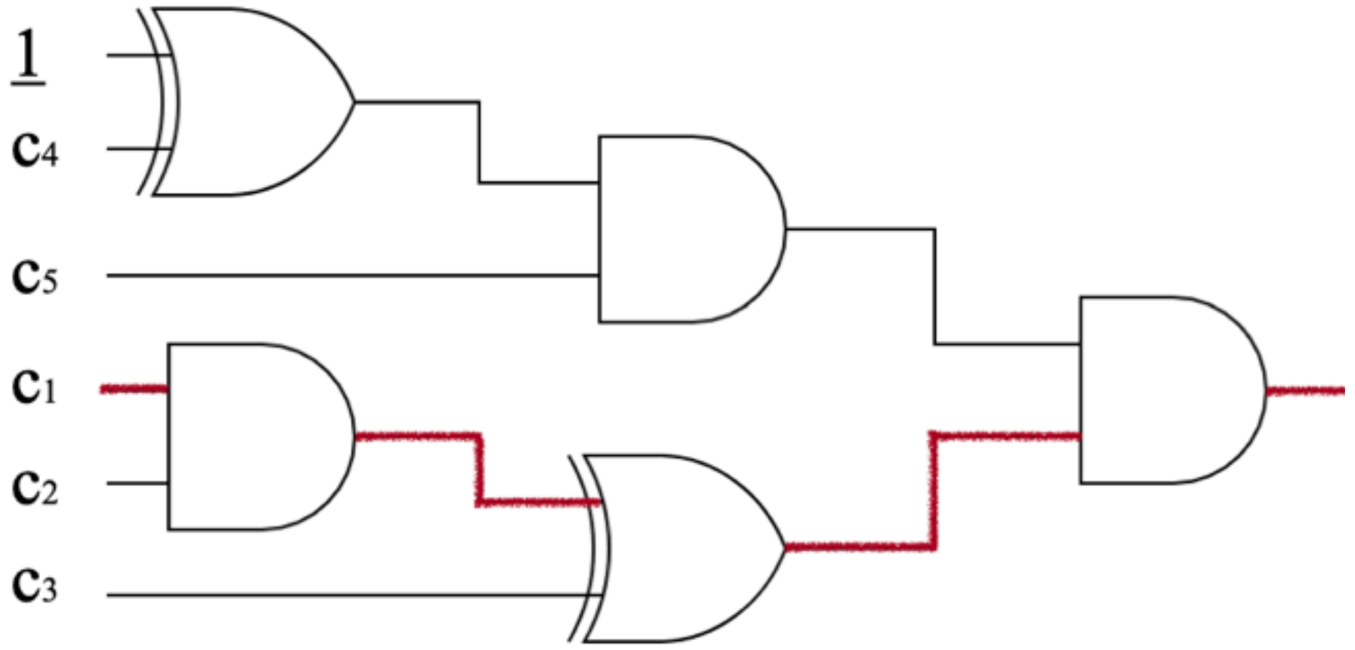
Applying Learned Optimization Patterns (1/2)

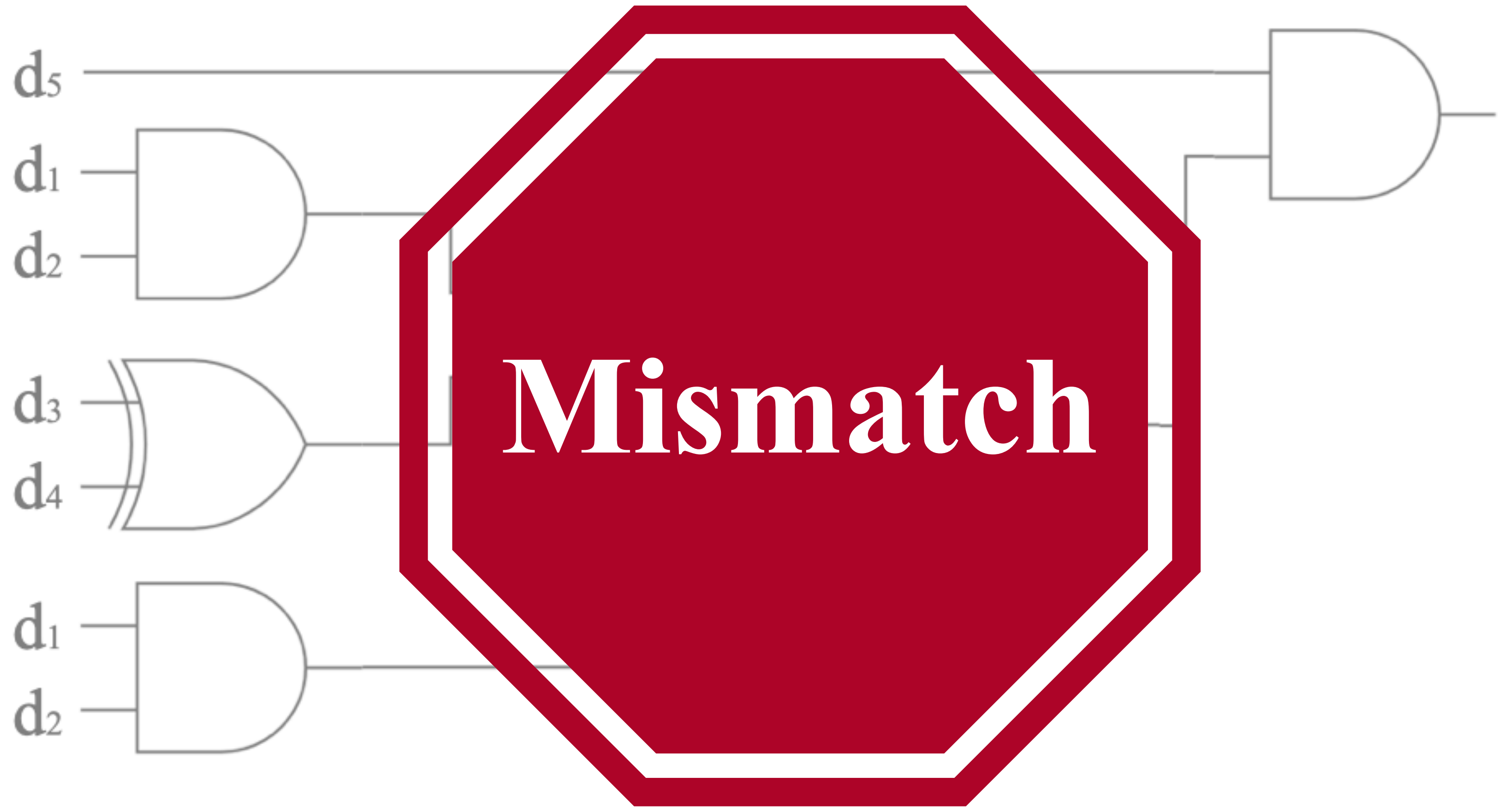
Syntactic Matching is Not Effective



Learned Opt. Patterns

→





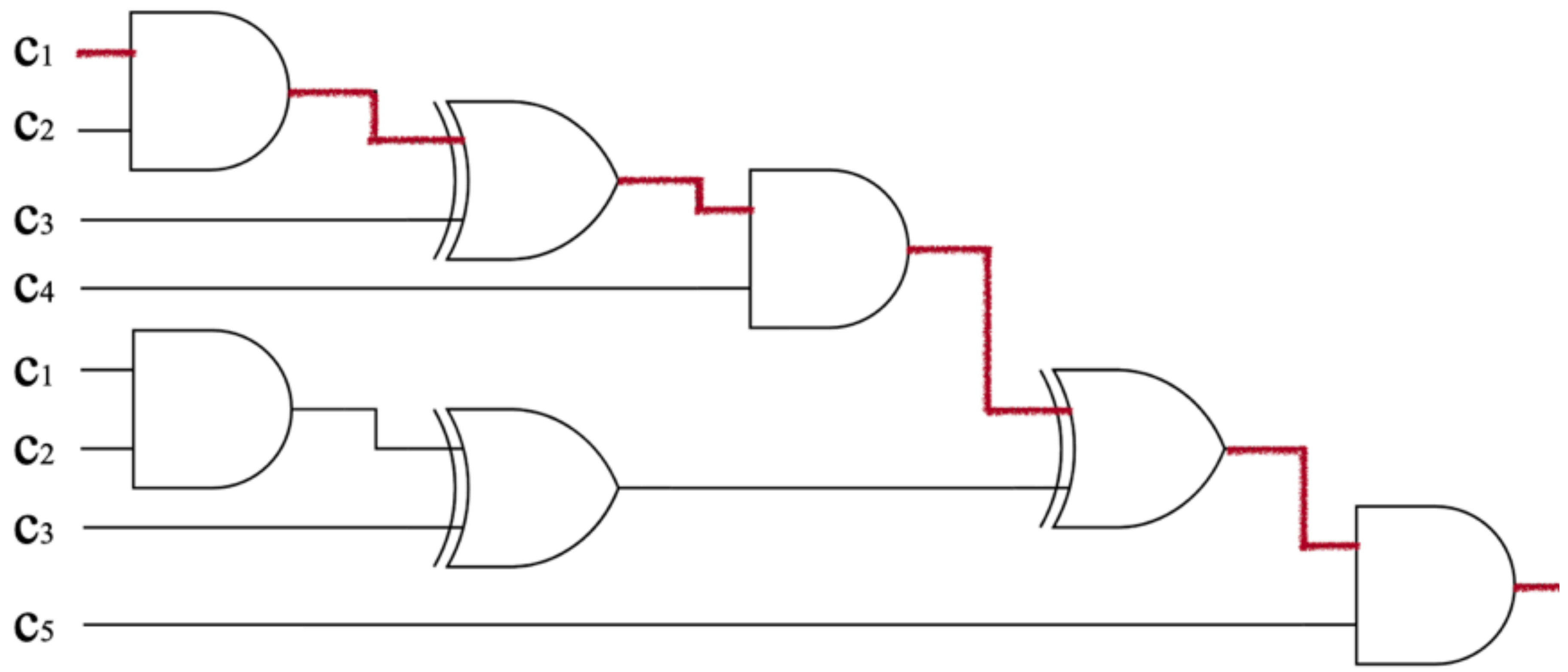
New Input Circuit Optimization

→

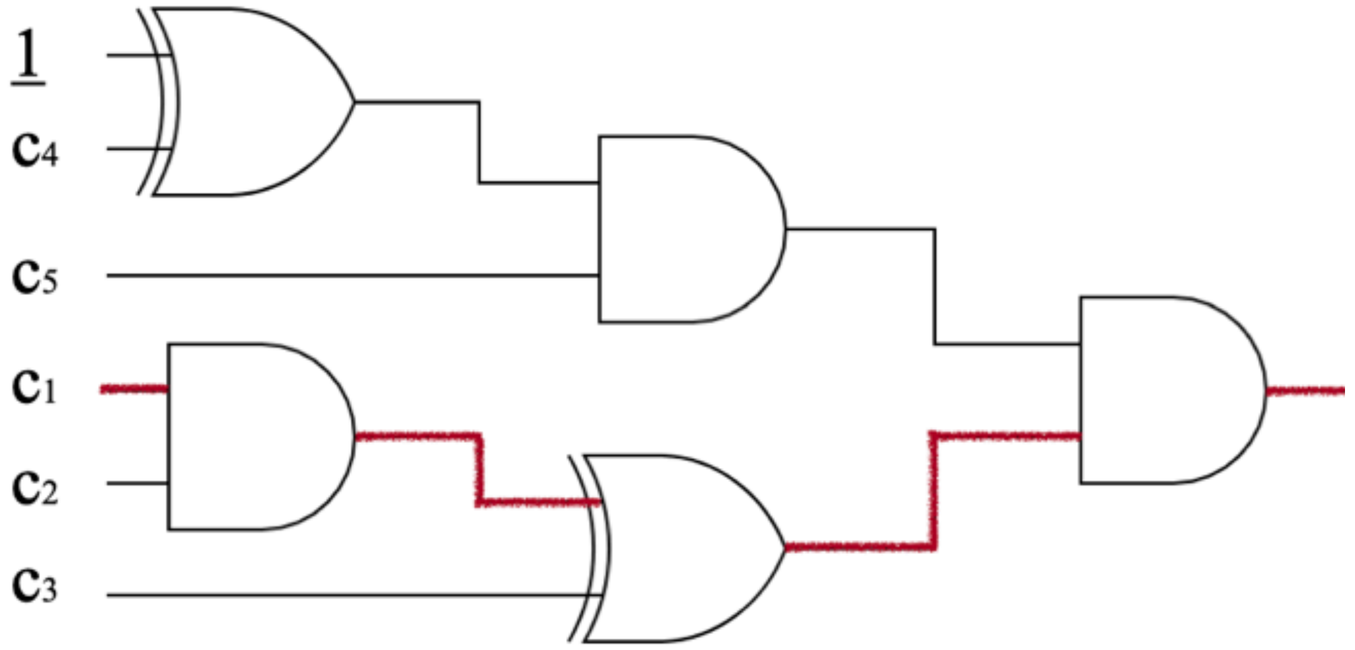
?

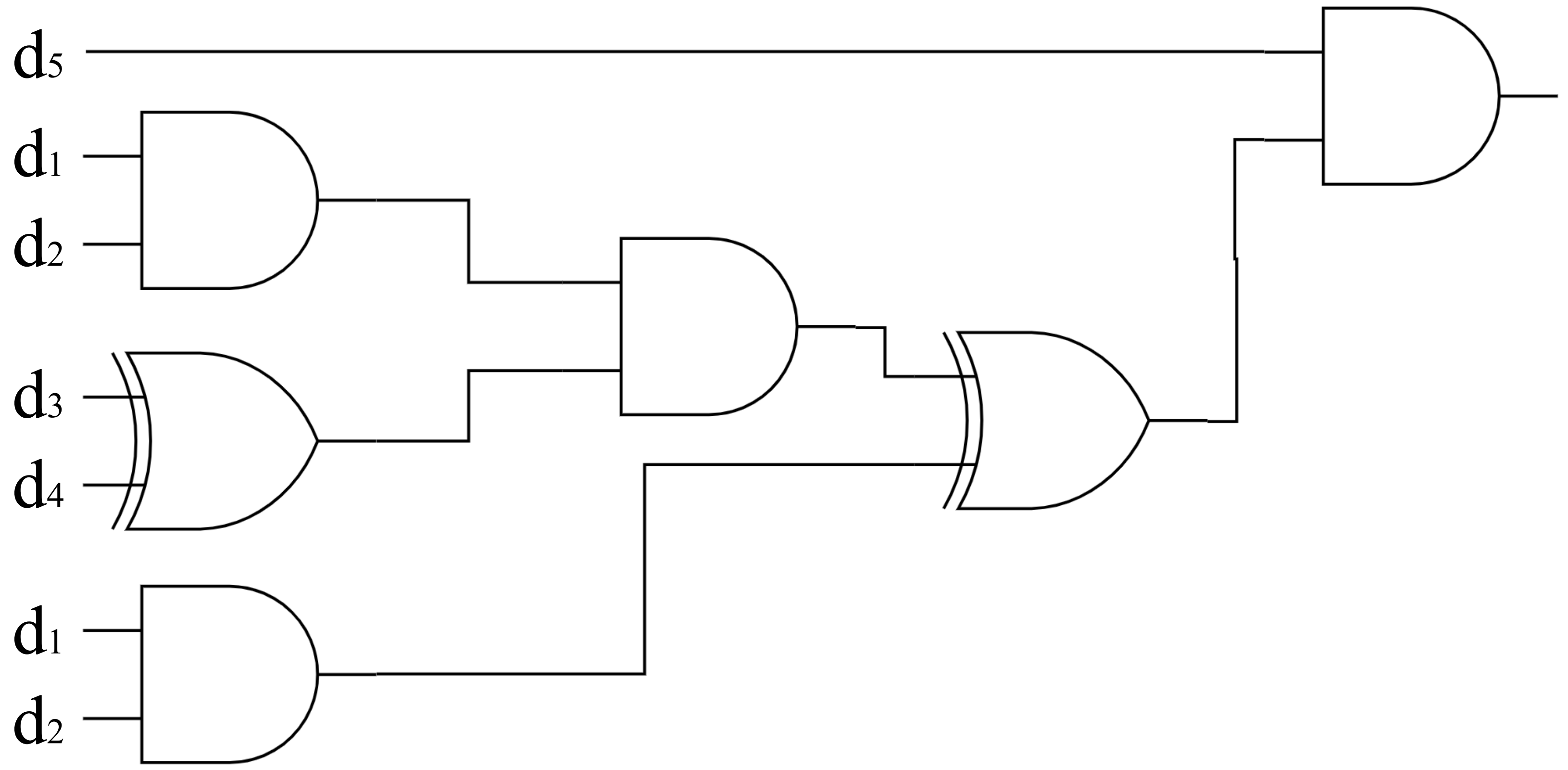
Applying Learned Optimization Patterns (2/2)

Normalization + Equational Matching



Learned Opt. Patterns



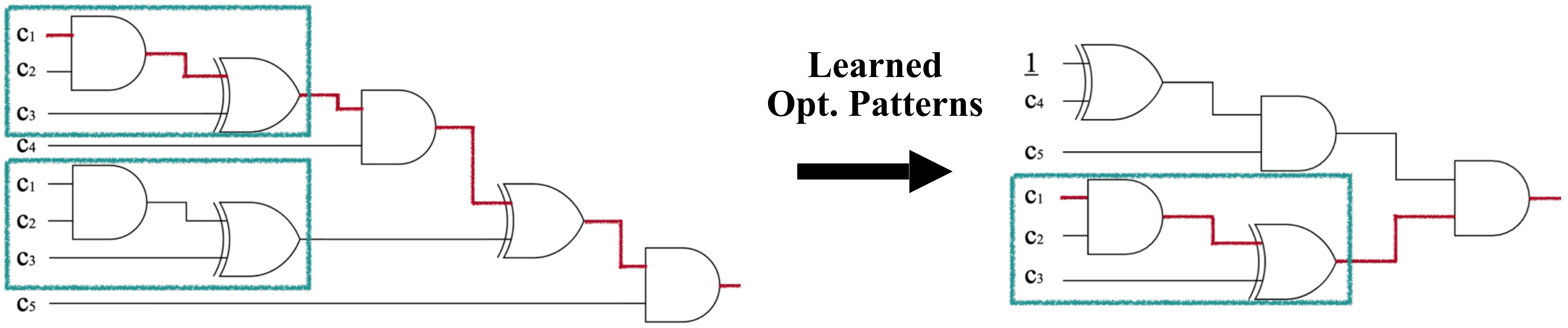


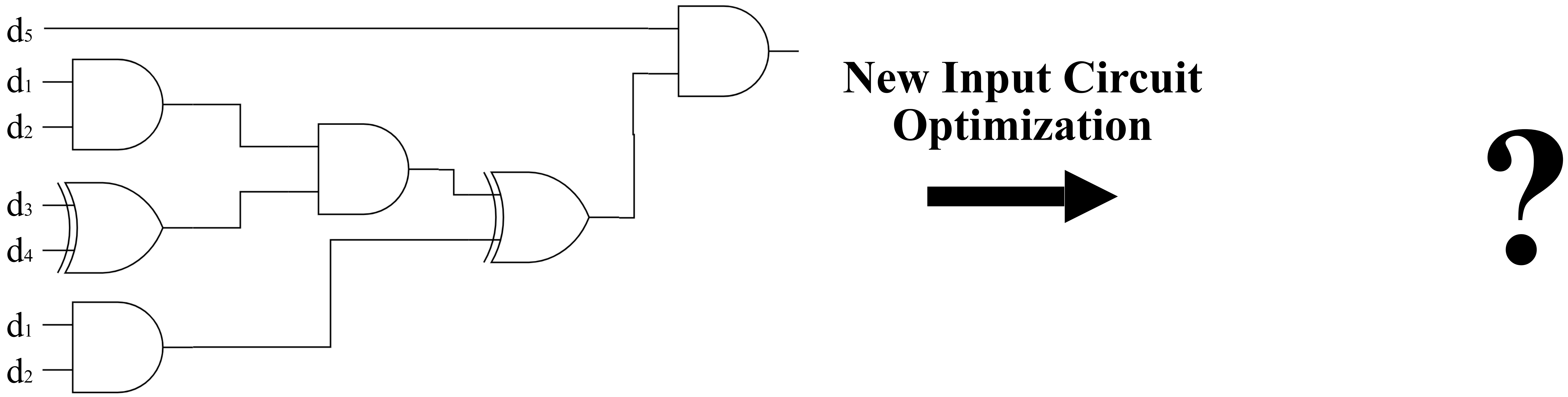
New Input Circuit Optimization

?

Applying Learned Optimization Patterns (2/2)

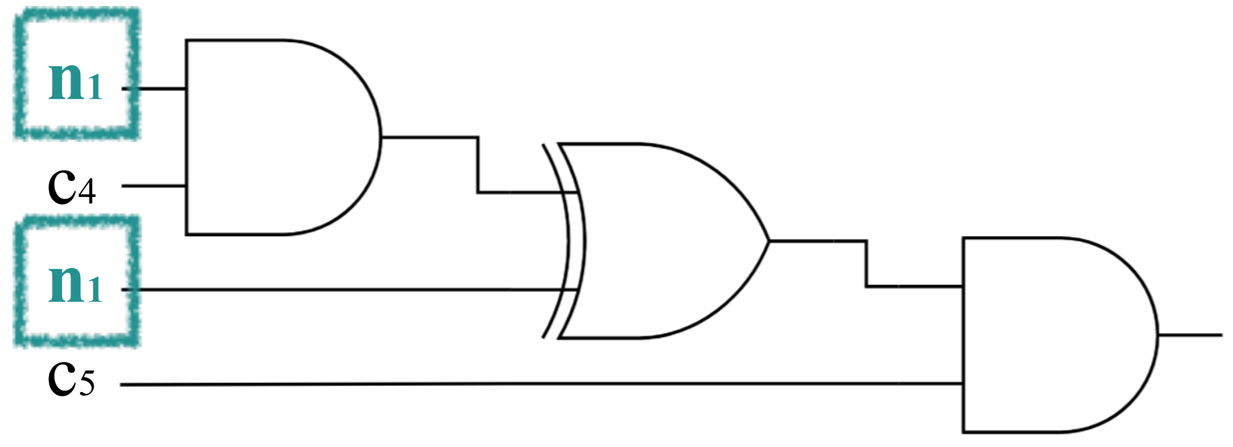
Normalization + Equational Matching



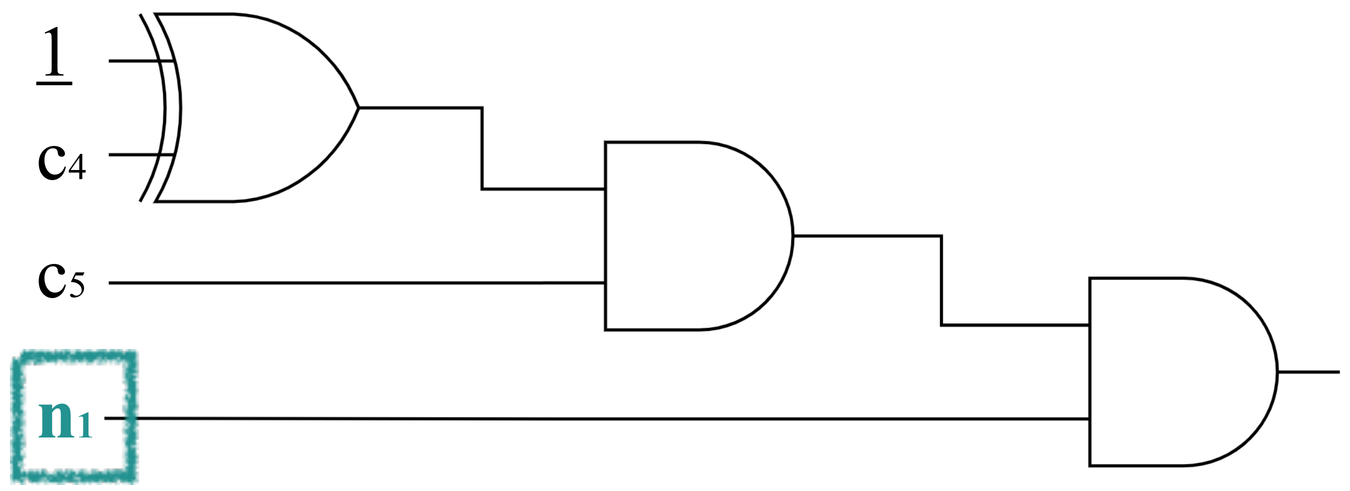


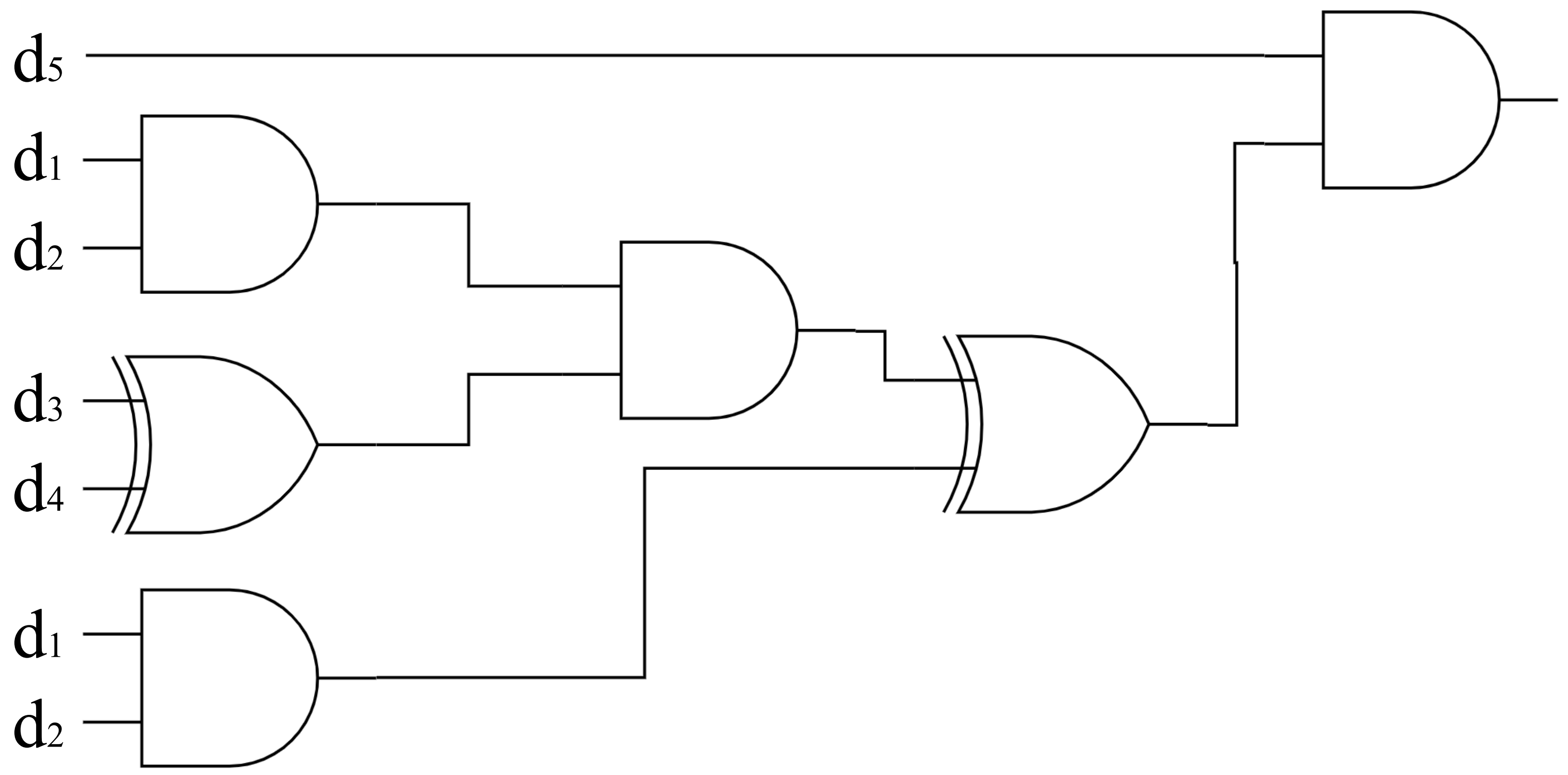
Applying Learned Optimization Patterns (2/2)

Normalization + Equational Matching



Normalized Opt. Patterns





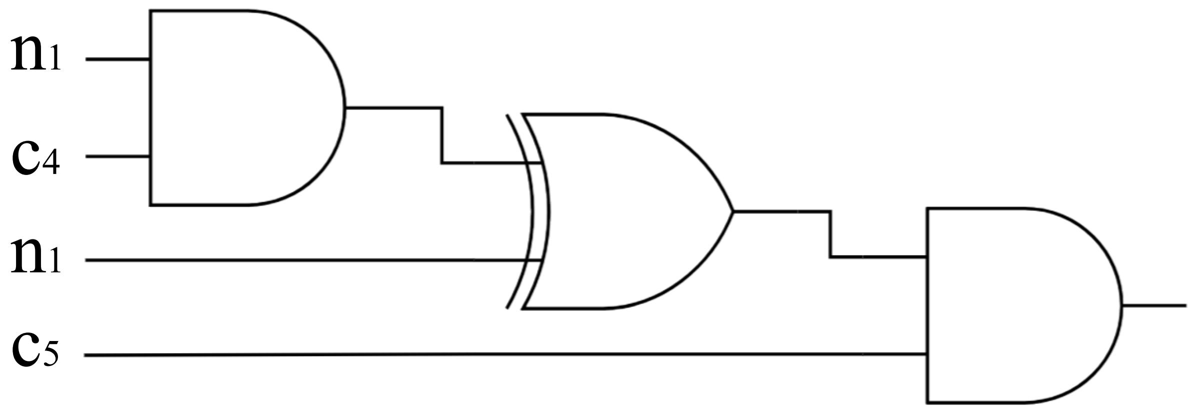
New Input Circuit Optimization

?

Applying Learned Optimization Patterns (2/2)

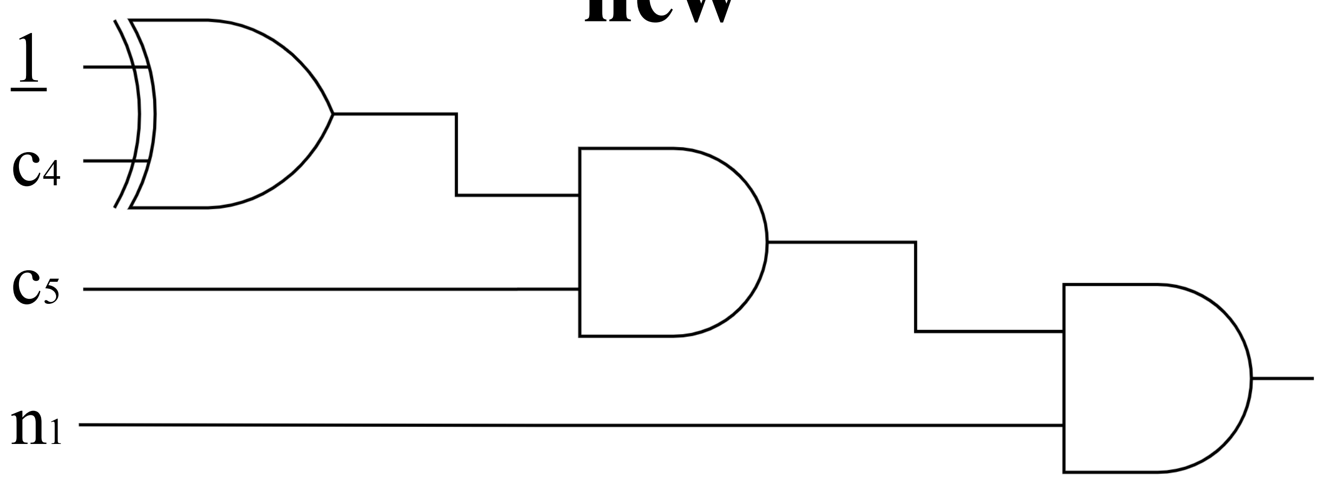
Normalization + Equational Matching

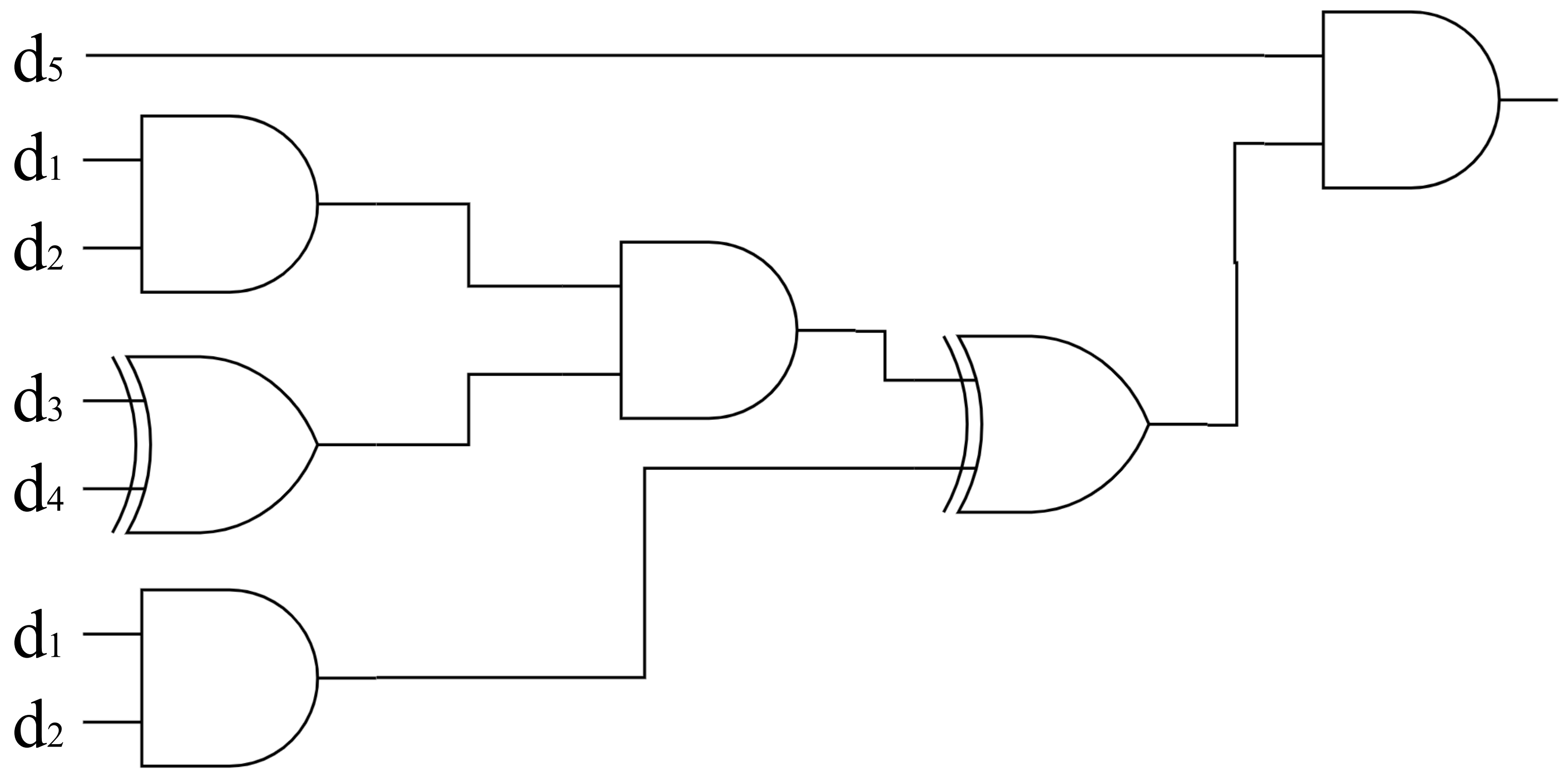
old



Normalized Opt. Patterns

new





target

New Input Circuit Optimization

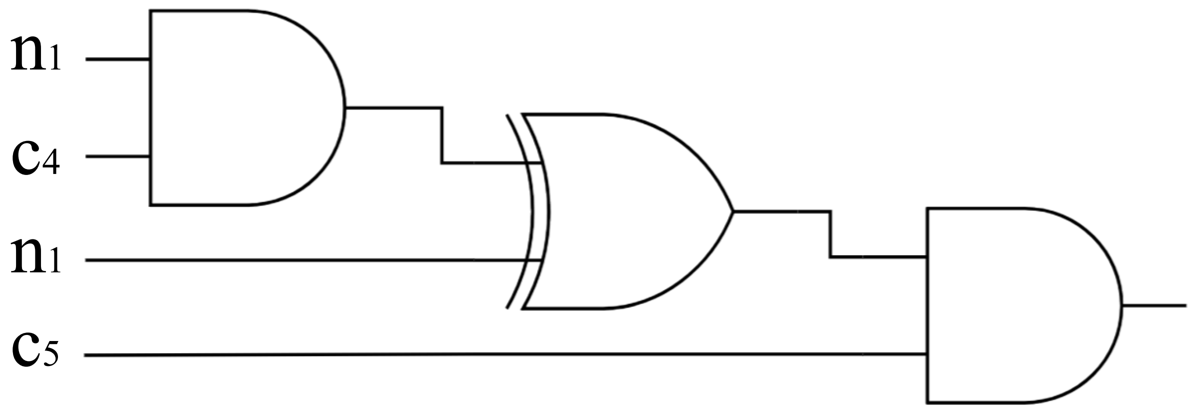
?

target'

Applying Learned Optimization Patterns (2/2)

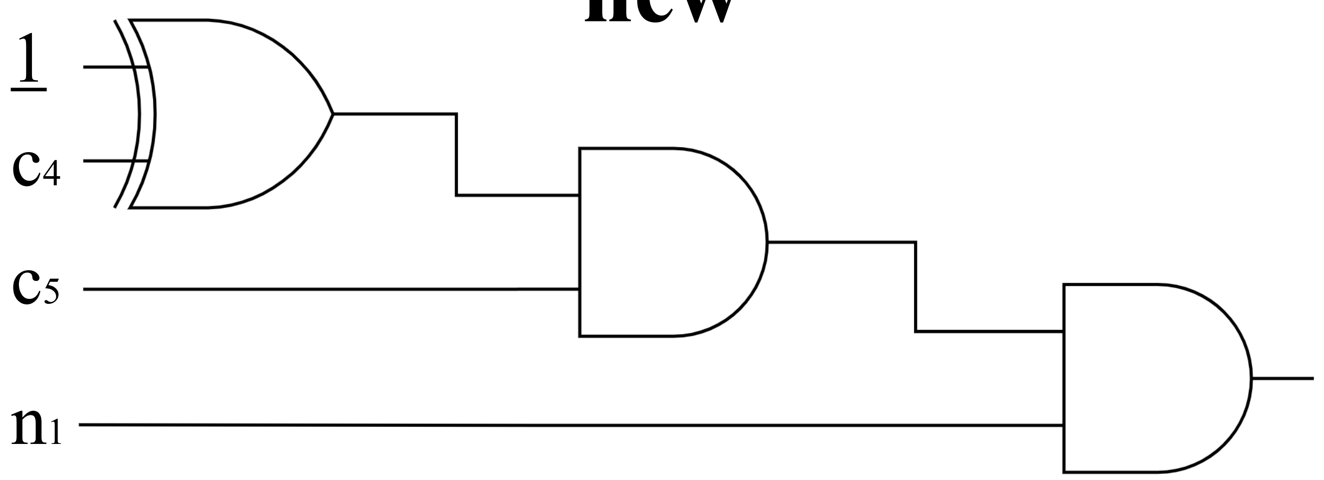
Normalization + Equational Matching

old



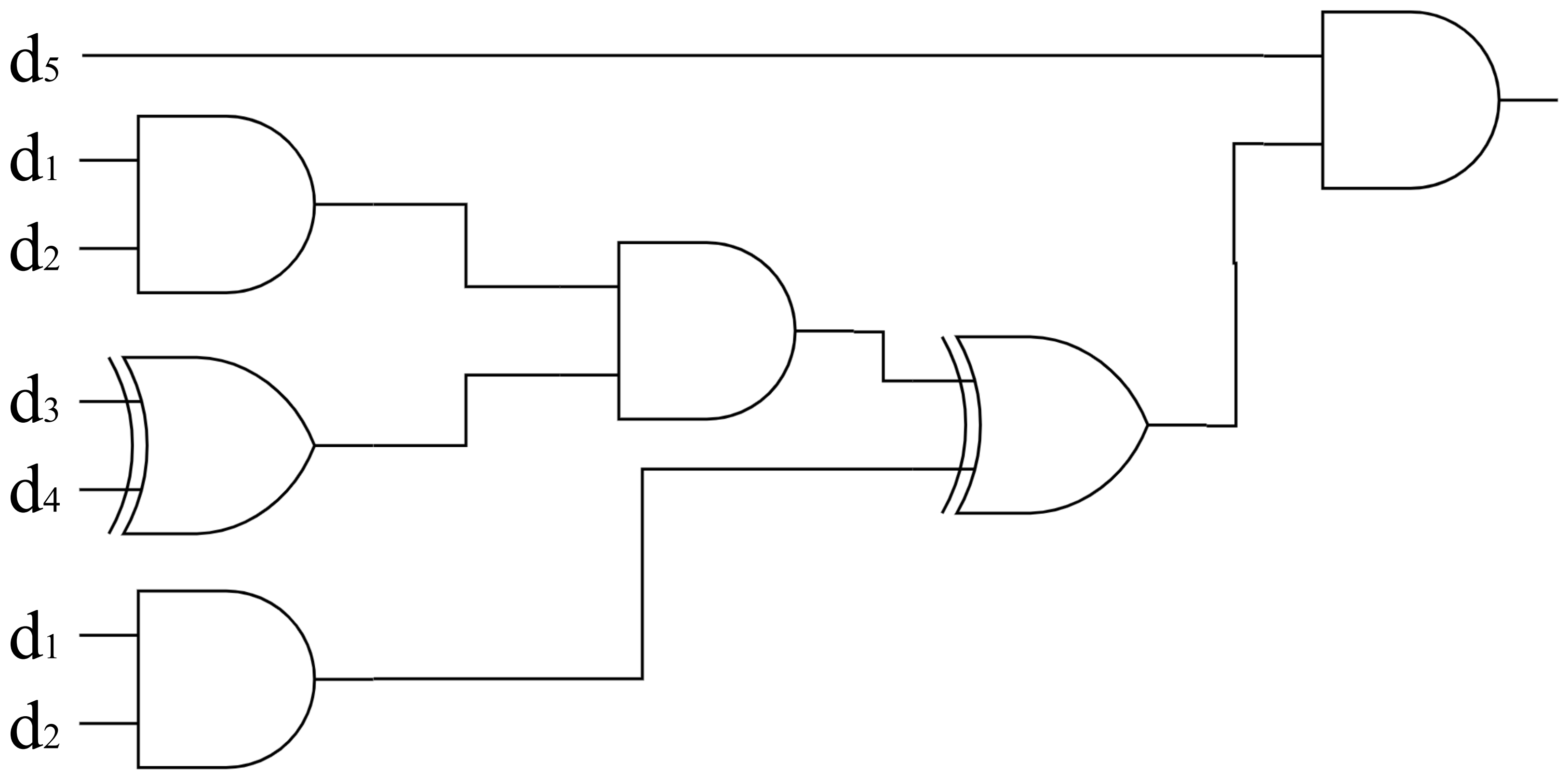
Normalized Opt. Patterns

new



Find substitution σ

(considering commutativity)



target

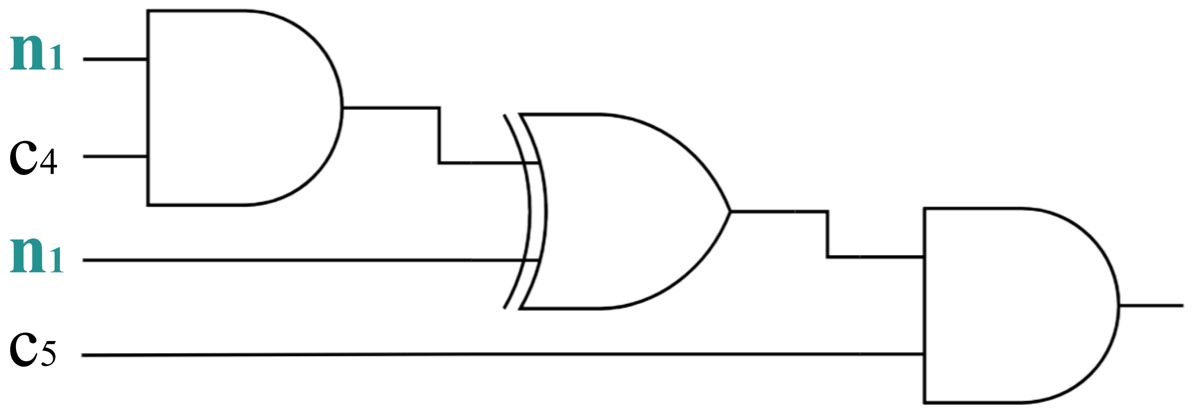
New Input Circuit Optimization

?

Applying Learned Optimization Patterns (2/2)

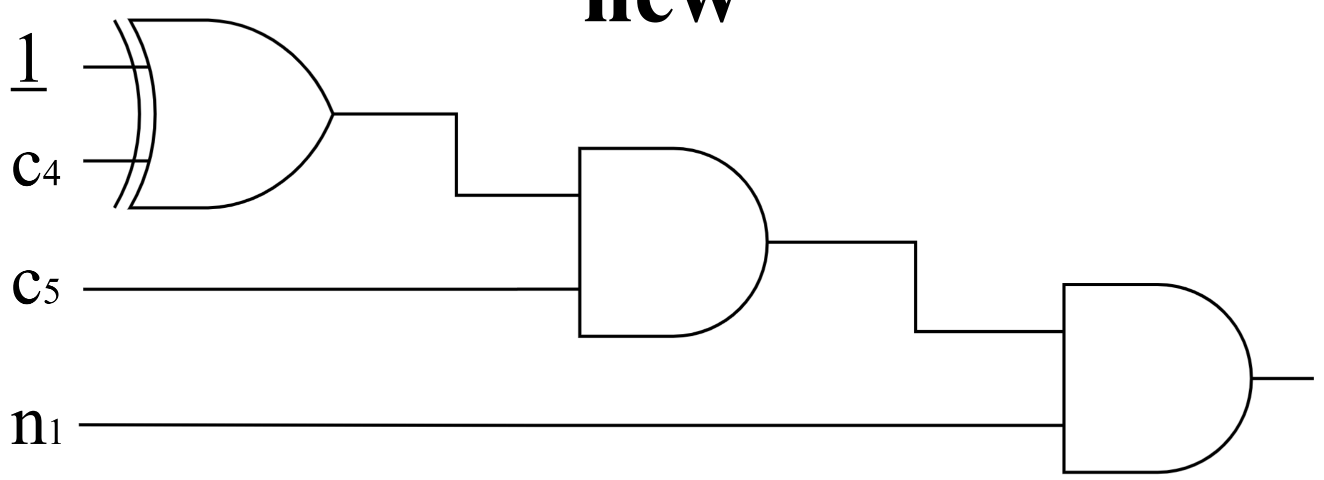
Normalization + Equational Matching

old



Normalized Opt. Patterns

new



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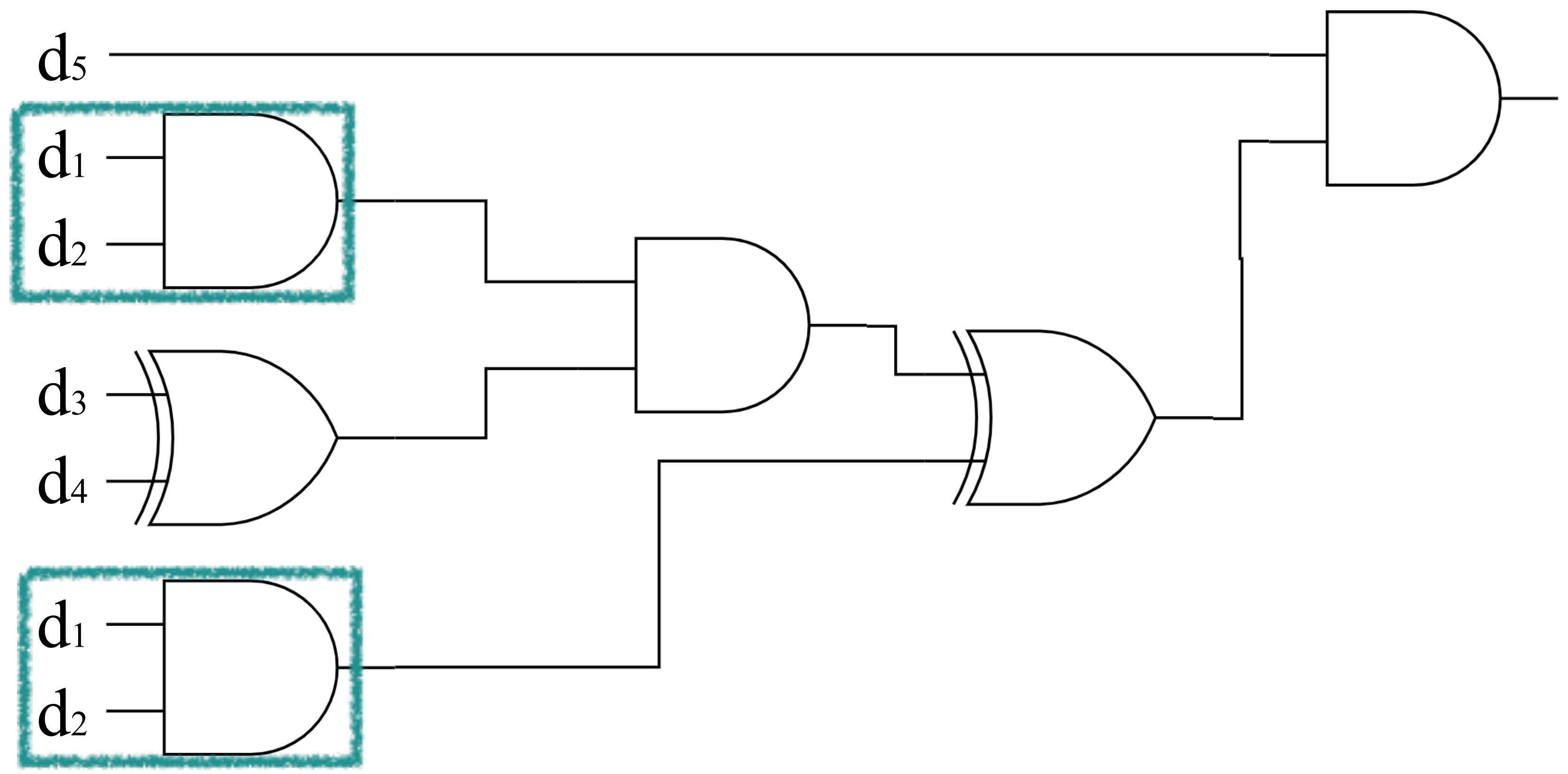


target

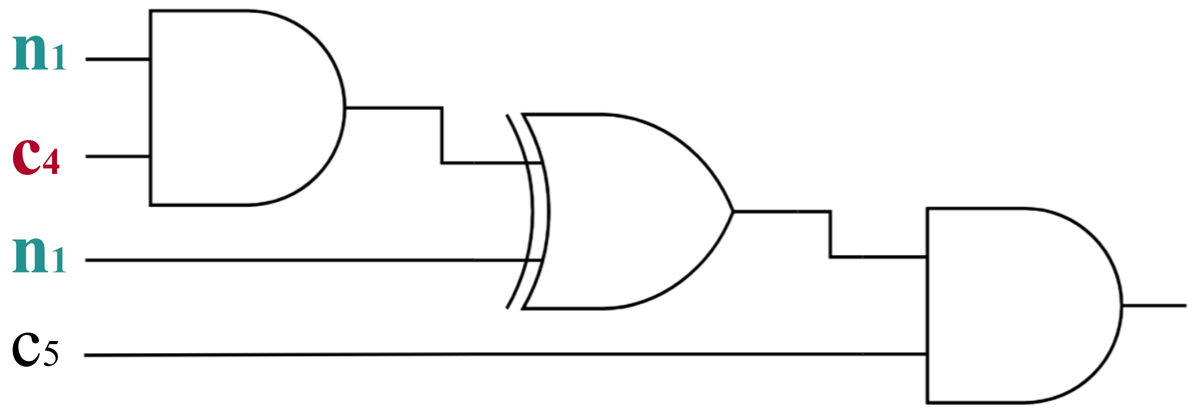
New Input Circuit Optimization

?

Applying Learned Optimization Patterns (2/2)

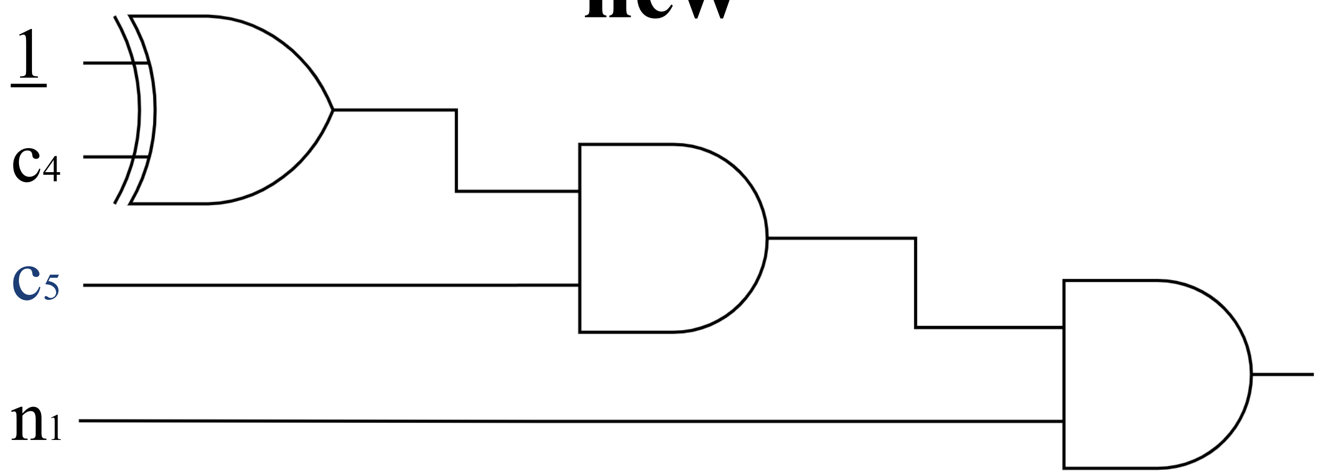
Normalization + Equational Matching

old



Normalized Opt. Patterns

new



Find substitution σ

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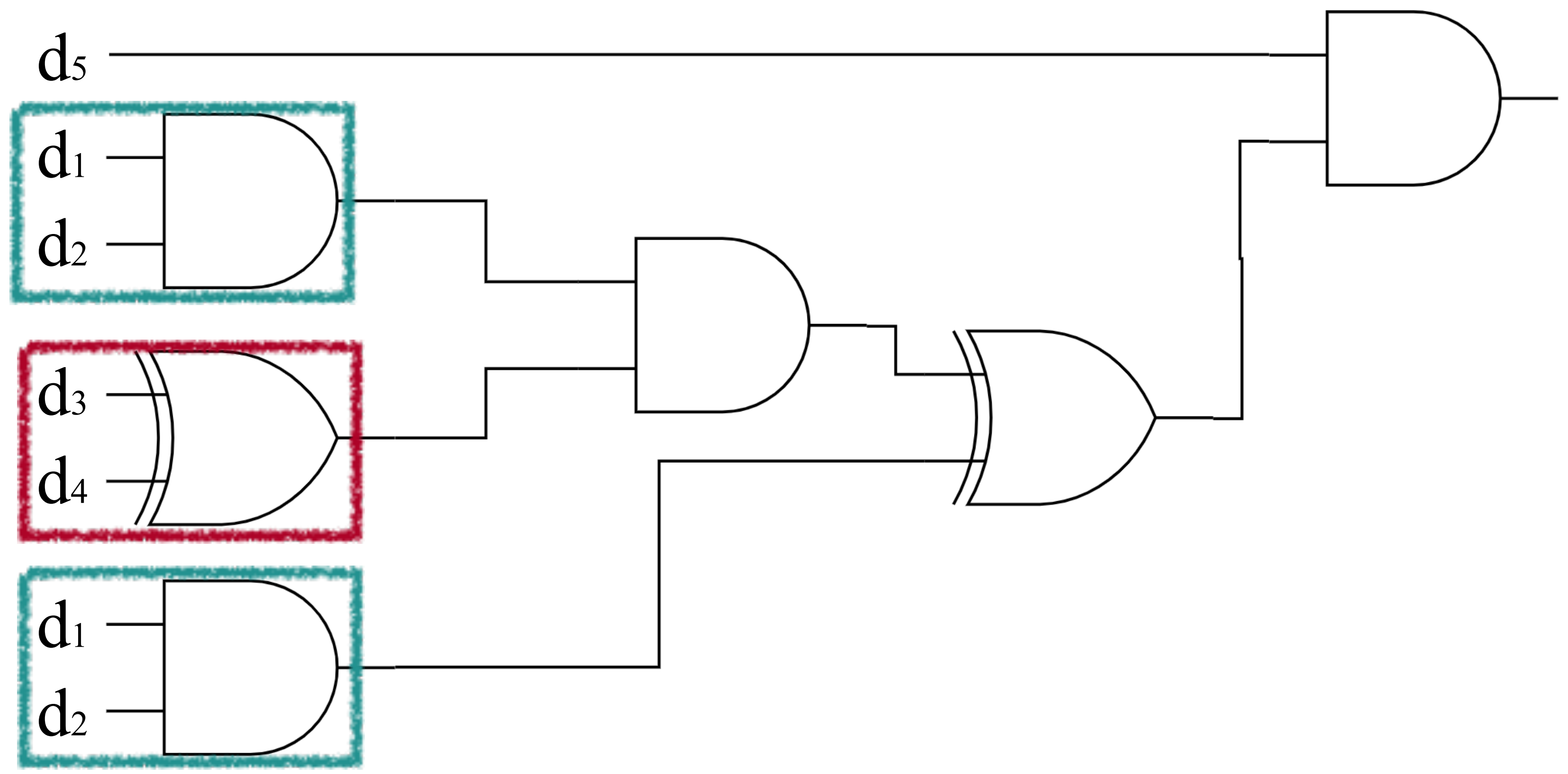
σ = {n1 ↦ d1 and d2,
c4 ↦ d3 xor d4,



target

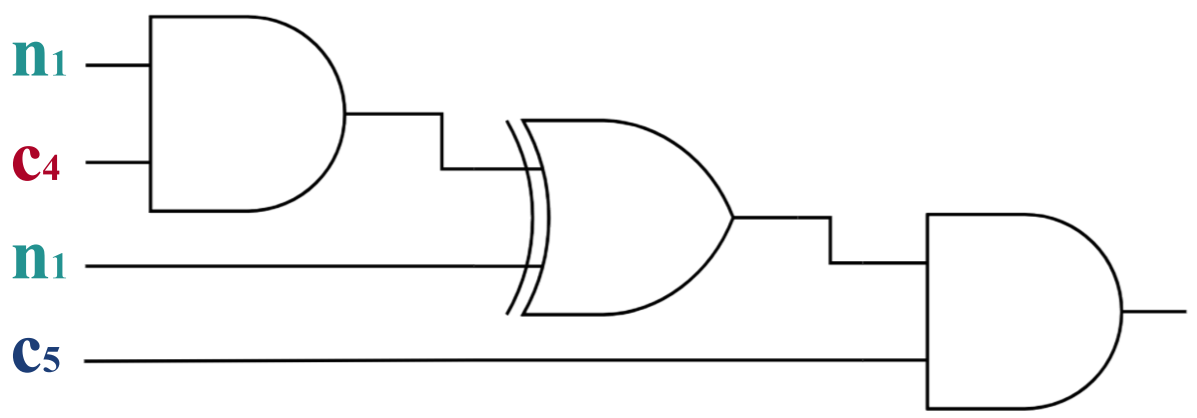
New Input Circuit Optimization

?

Applying Learned Optimization Patterns (2/2)

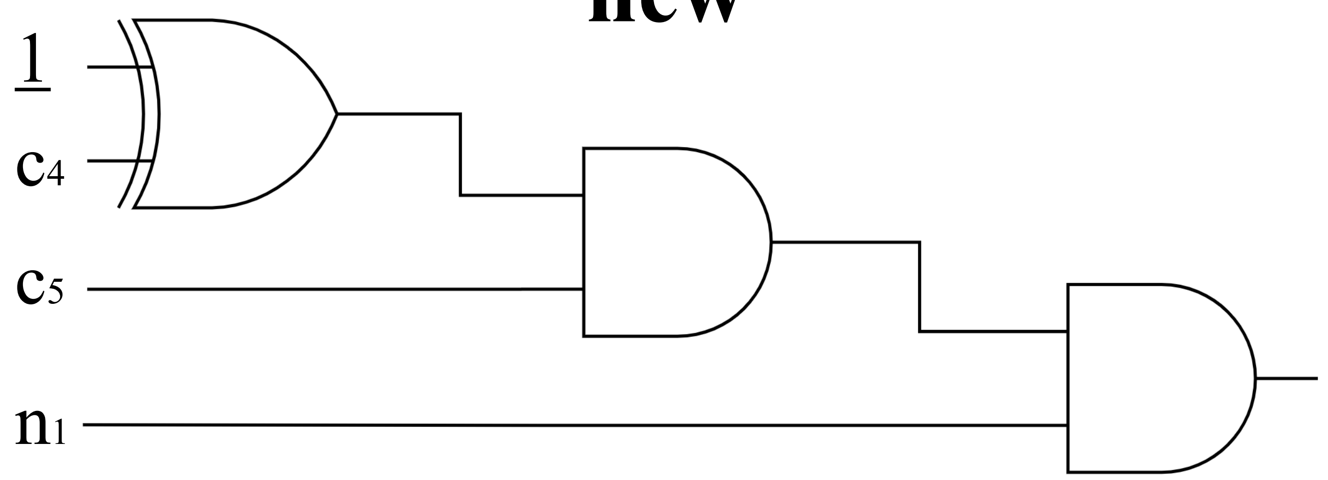
Normalization + Equational Matching

old



Normalized
Opt. Patterns

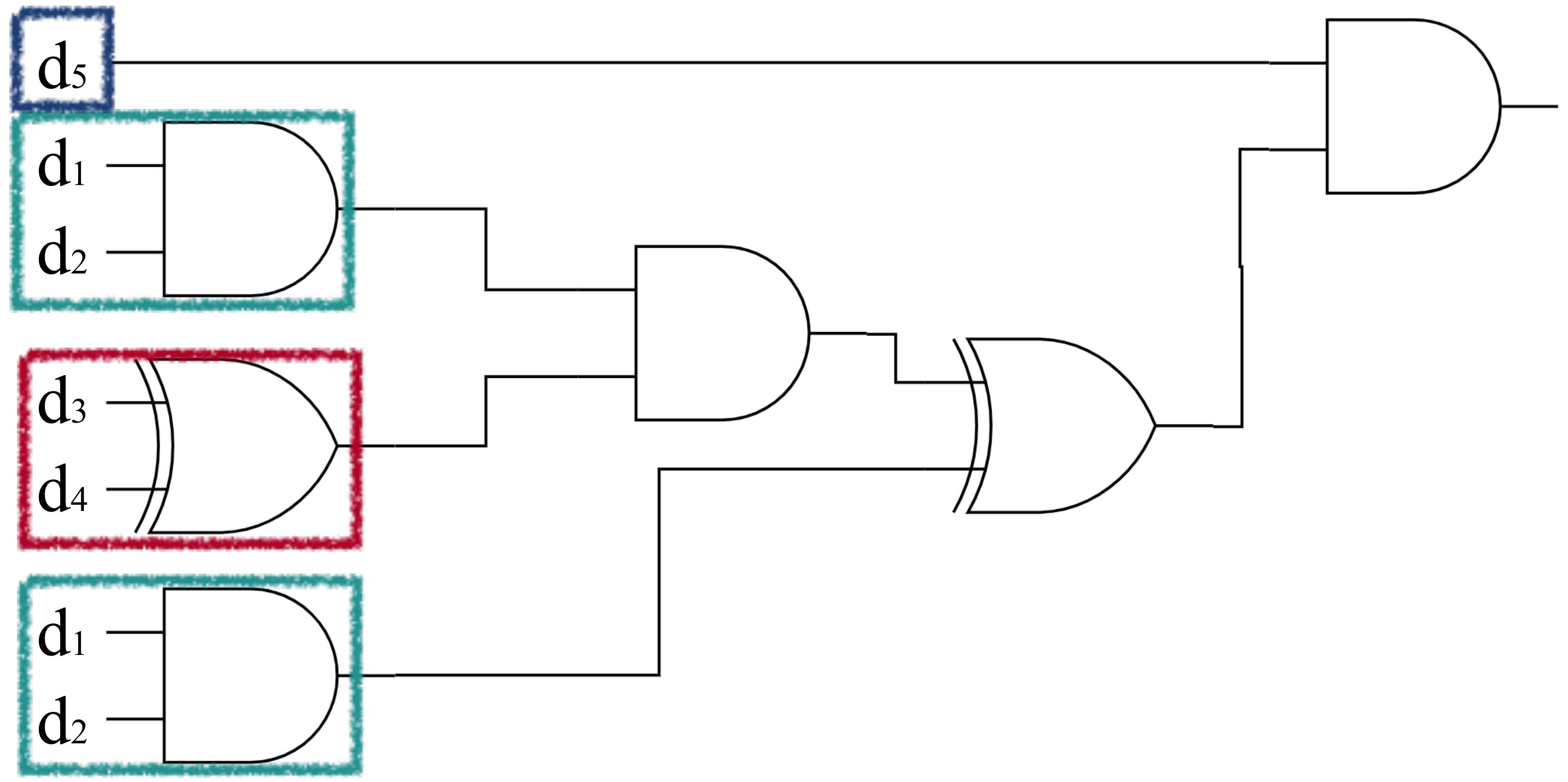
new



Find substitution σ

(considering commutativity)

σ = {n1 ↦ d1 and d2,
c4 ↦ d3 xor d4,
c5 ↦ d5}



target

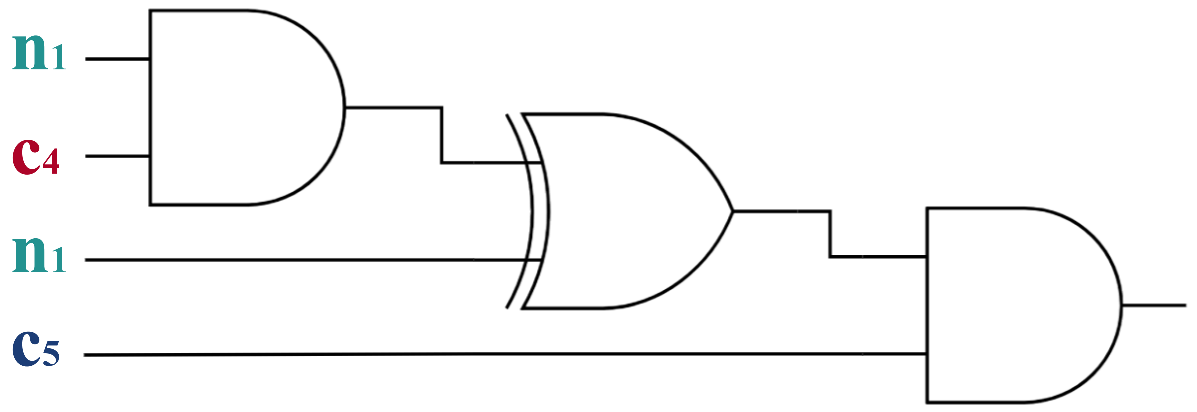
New Input Circuit
Optimization

?

Applying Learned Optimization Patterns (2/2)

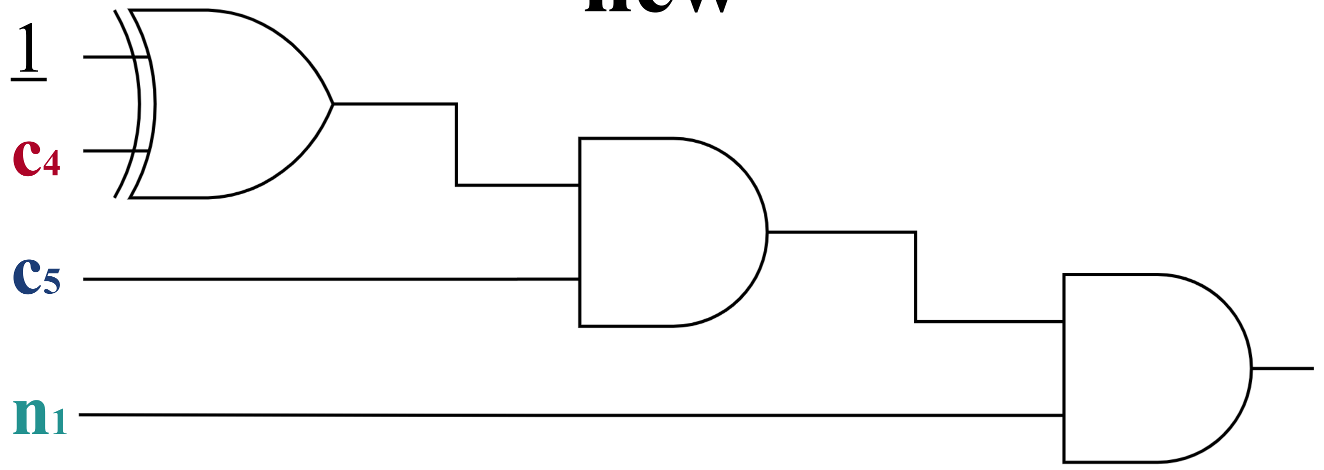
Normalization + Equational Matching

old



Normalized Opt. Patterns

new

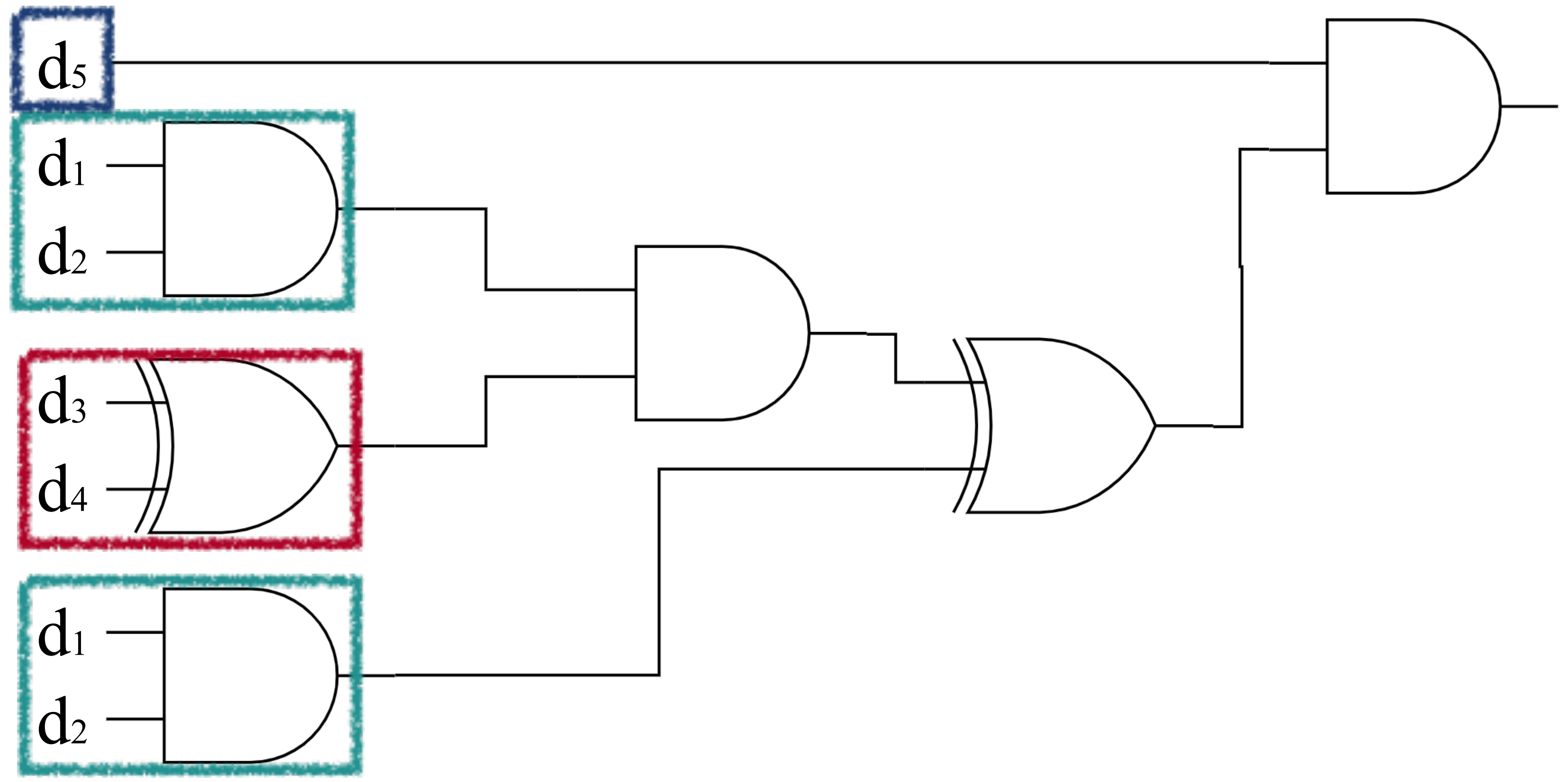


Find substitution σ

(considering commutativity)

Apply substitution σ

σ = {n1 ↦ d1 and d2,
c4 ↦ d3 xor d4,
c5 ↦ d5}



target

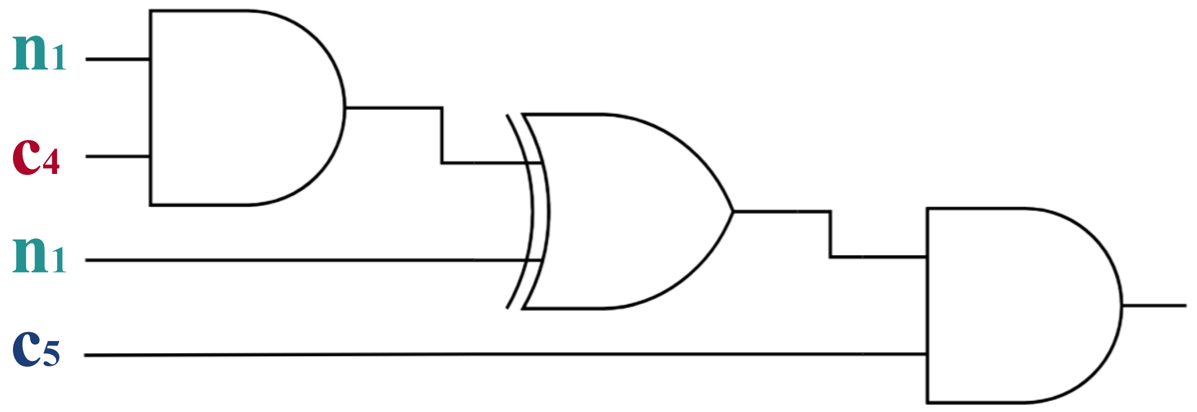
New Input Circuit Optimization

?

Applying Learned Optimization Patterns (2/2)

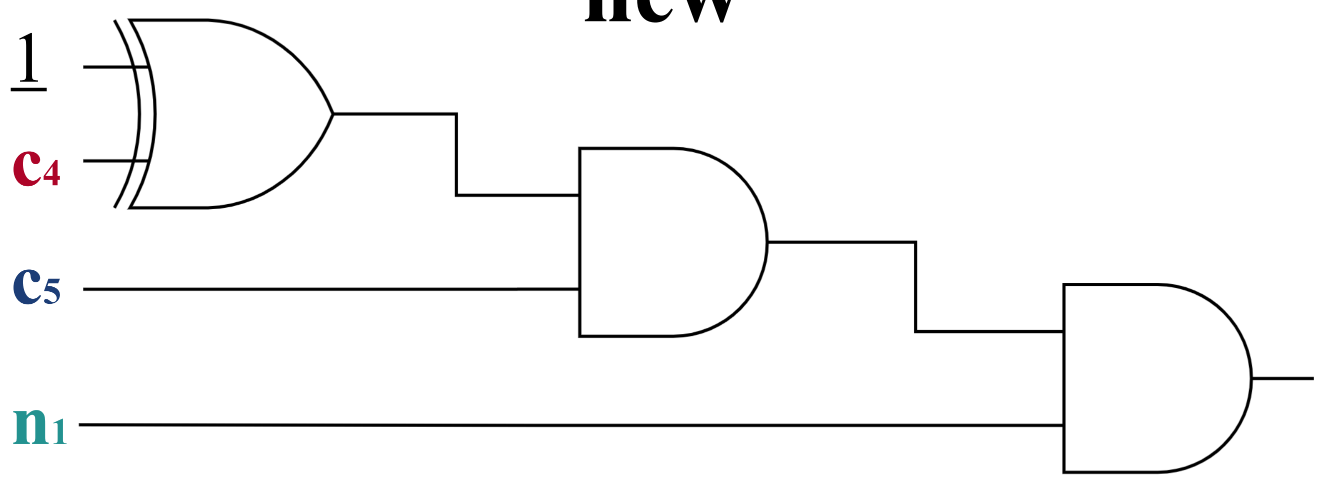
Normalization + Equational Matching

old



Normalized Opt. Patterns →

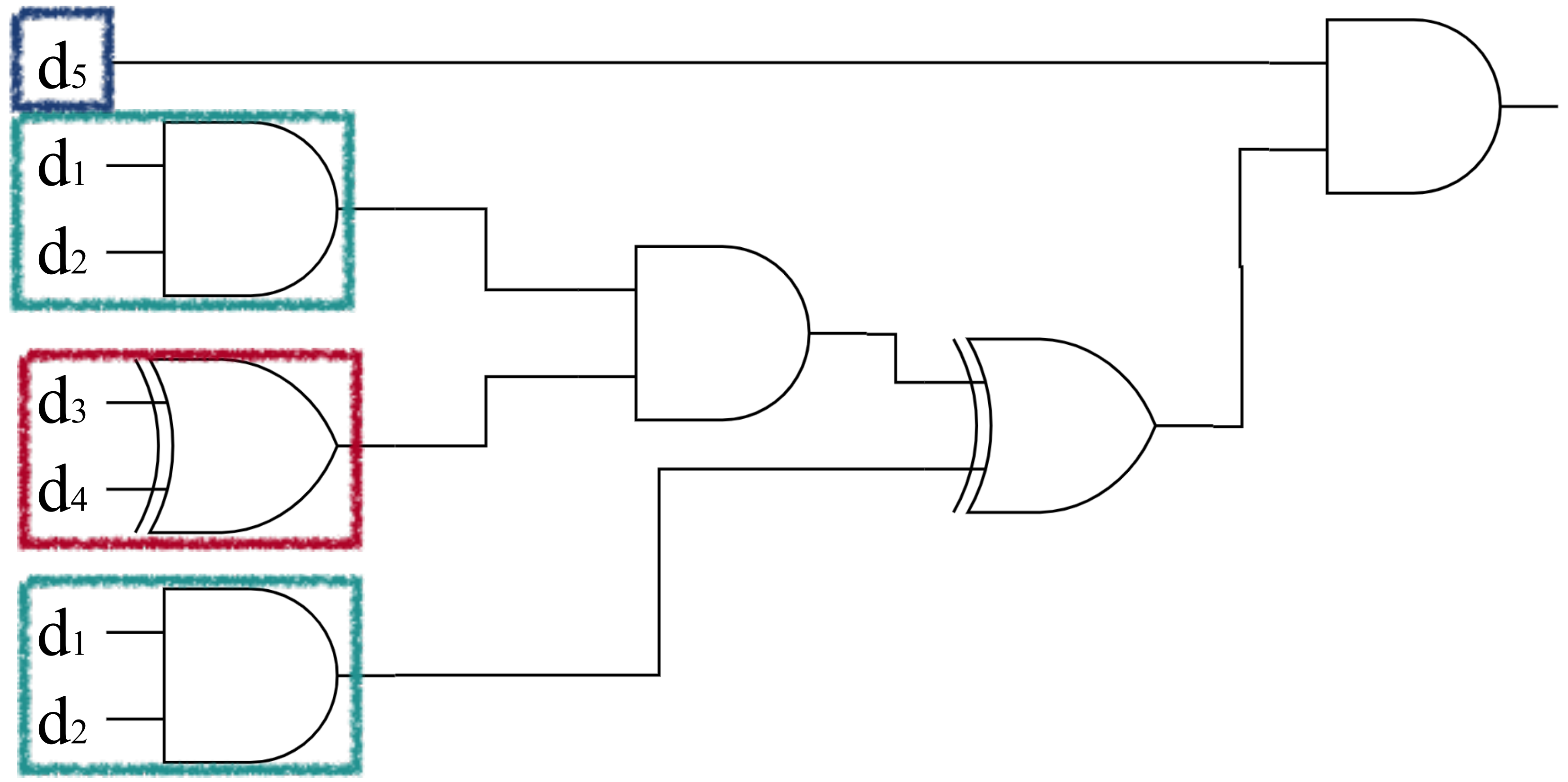
new



Find substitution σ (considering commutativity)

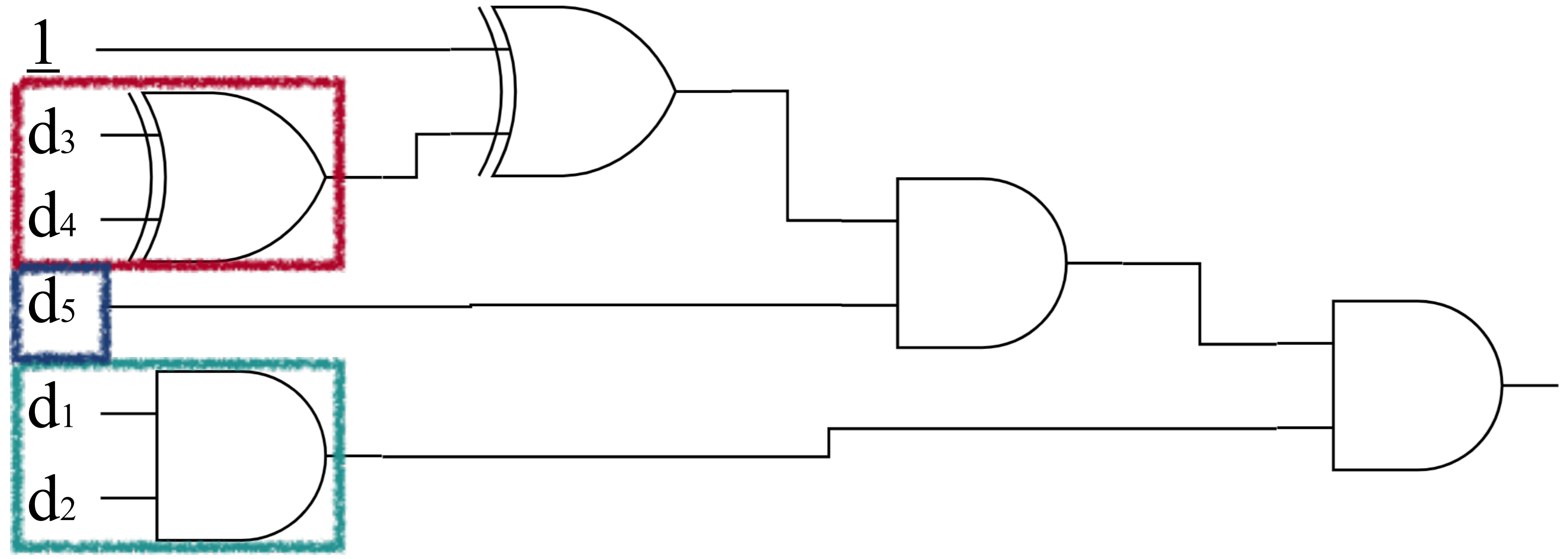
Apply substitution σ

σ = {n1 ↦ d1 and d2,
c4 ↦ d3 xor d4,
c5 ↦ d5}



target

New Input Circuit Optimization →

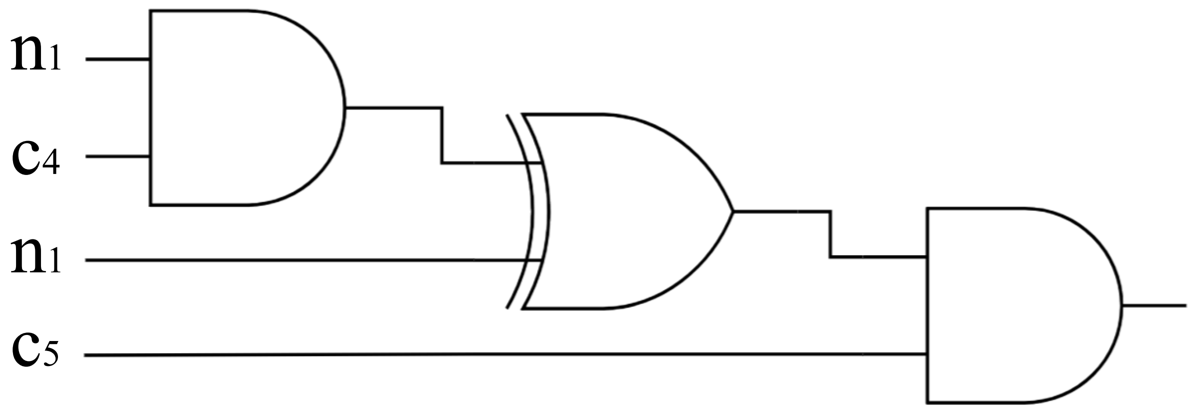


optimized target

Applying Learned Optimization Patterns (2/2)

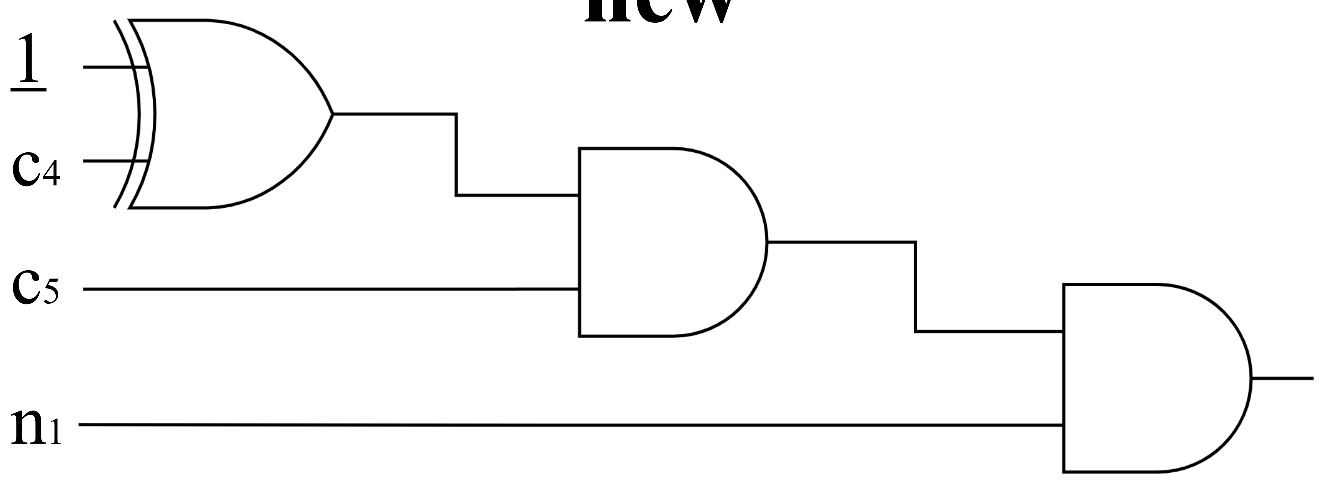
Normalization + Equational Matching

old



Normalized Opt. Patterns

new

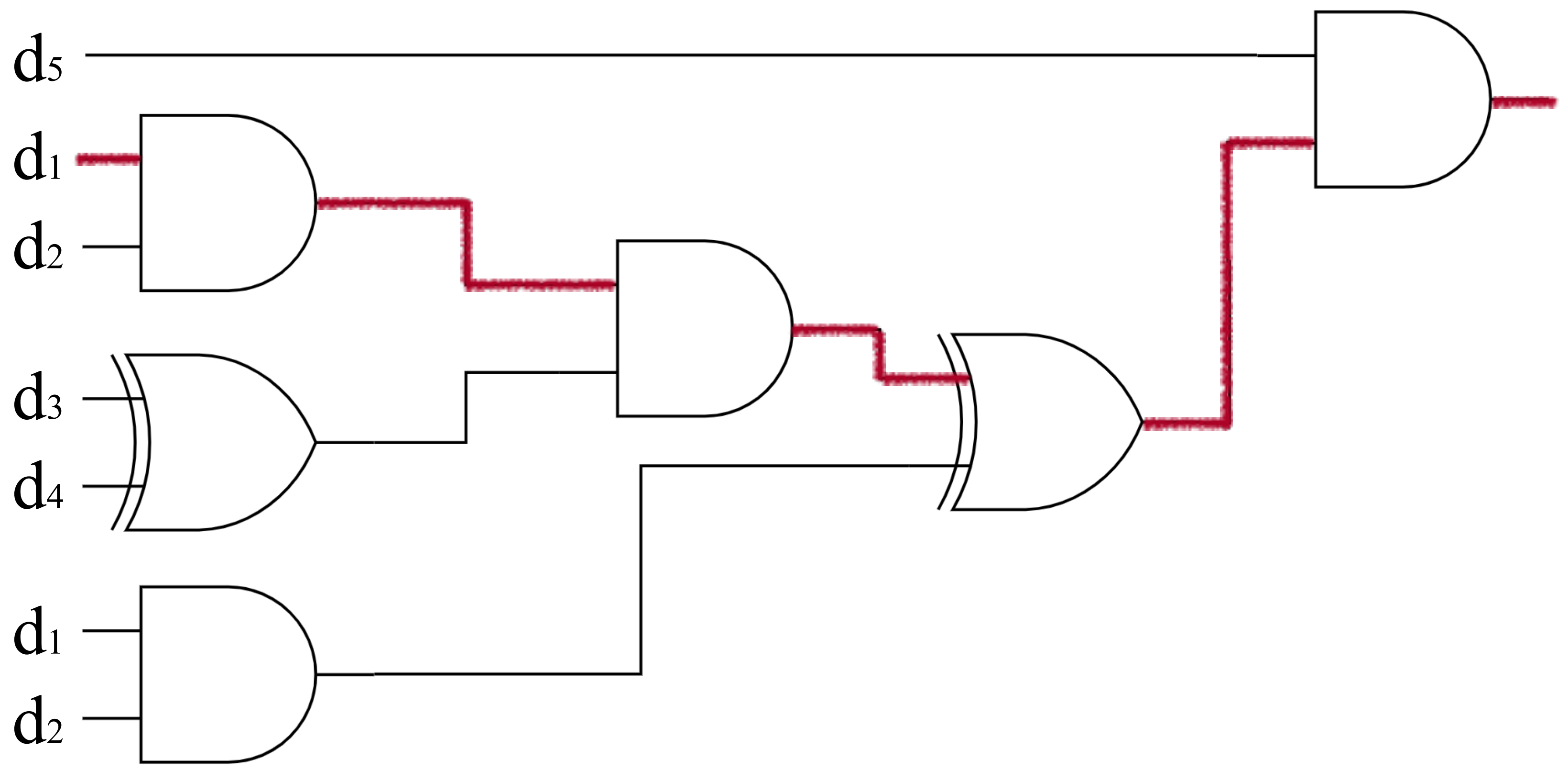


Find substitution σ

(considering commutativity)

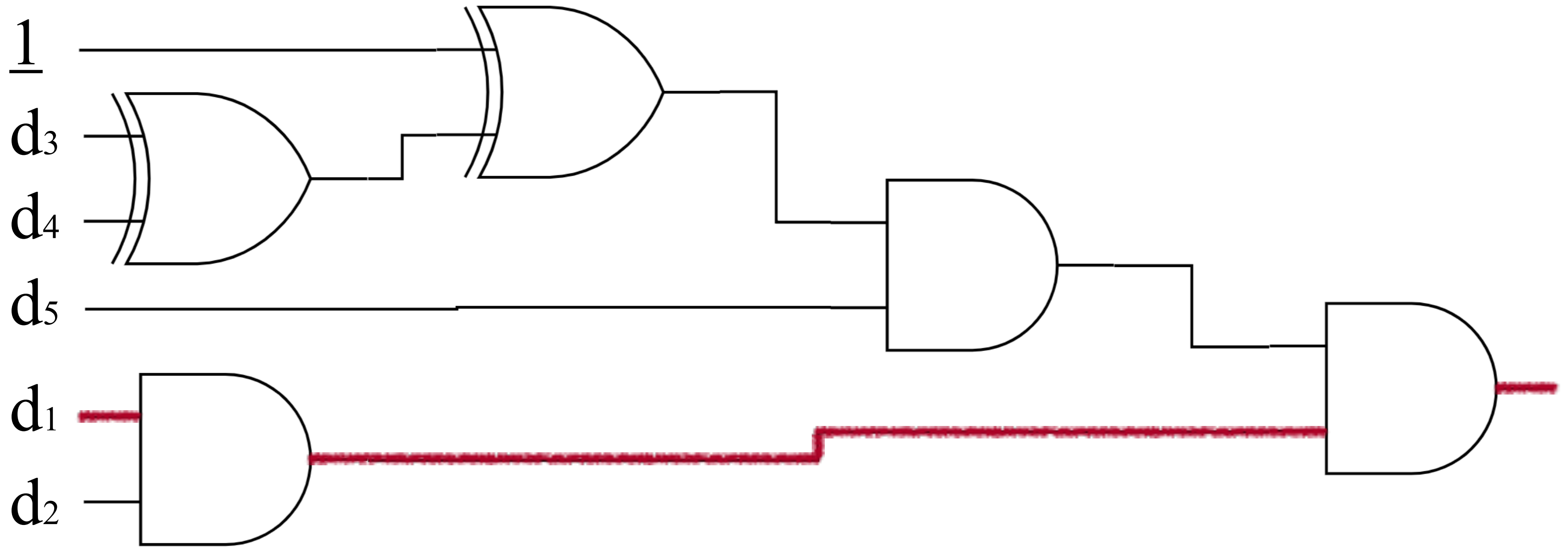
Apply substitution σ

$\sigma = \{n1 \mapsto d1 \text{ and } d2,$
$c4 \mapsto d3 \text{ xor } d4,$
$c5 \mapsto d5\}$



target
depth 3

New Input Circuit Optimization

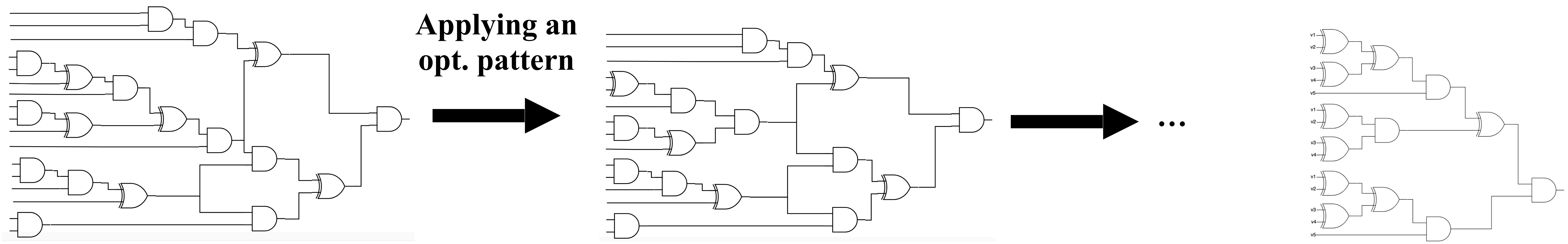


optimized target
depth 2

Applying Learned Optimization Patterns

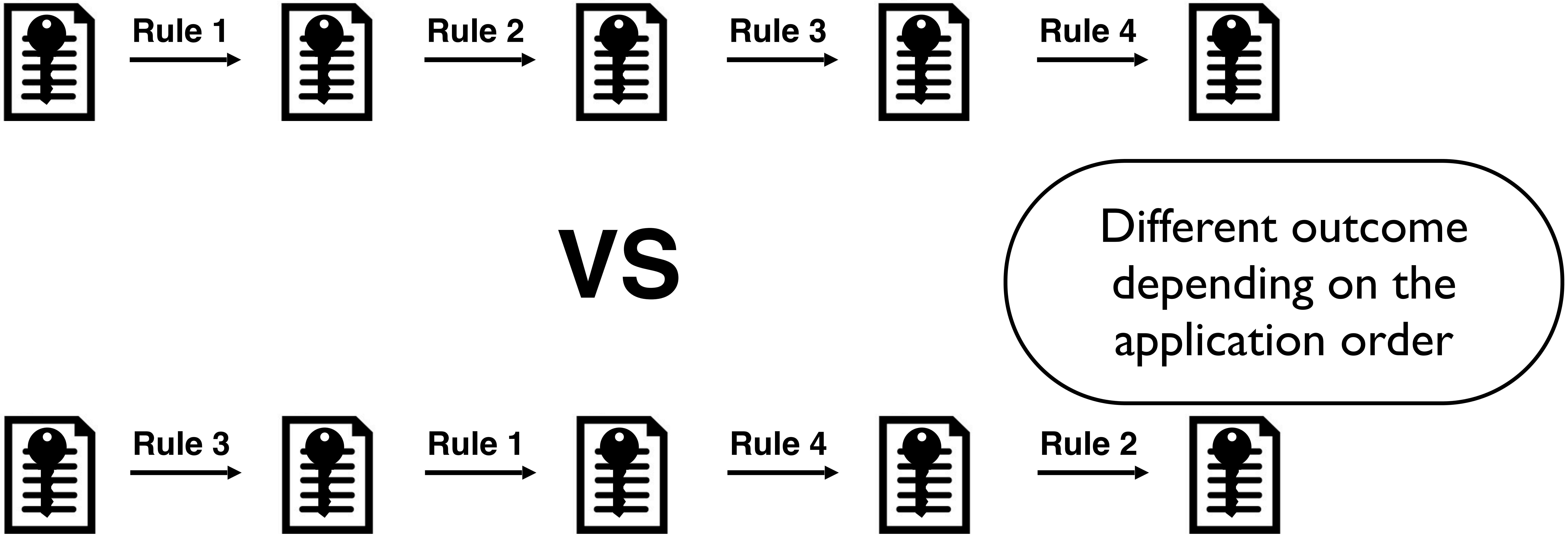
Formal properties

(Soundness) semantics unchanged



(Termination) finitely many rule applications

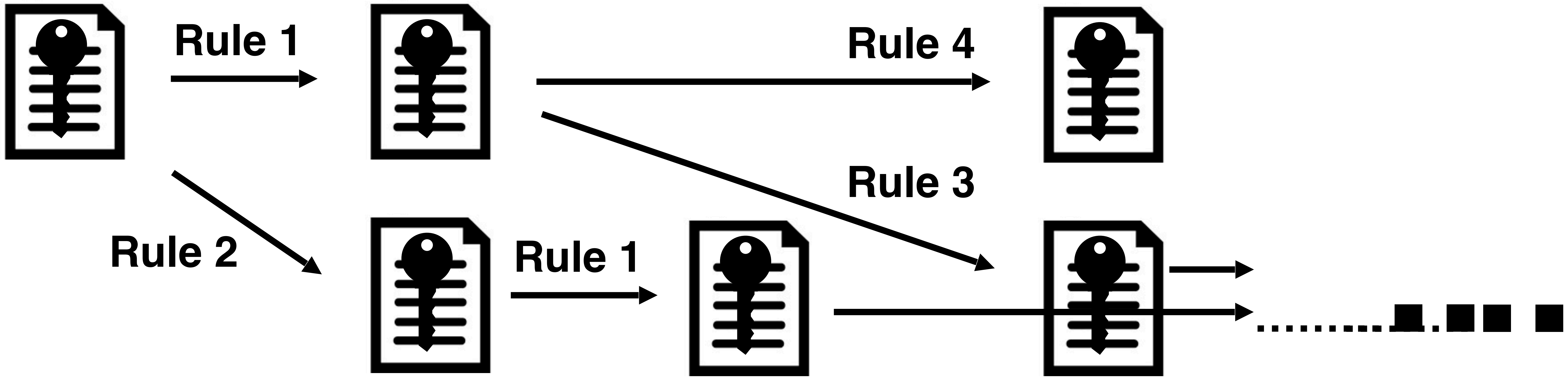
Phase-Ordering Problem



Existing Solutions

- Using a pre-defined application order (e.g., LLVM optimization passes)

- Backtracking (i.e., maintaining top-k candidates)



Equality Saturation

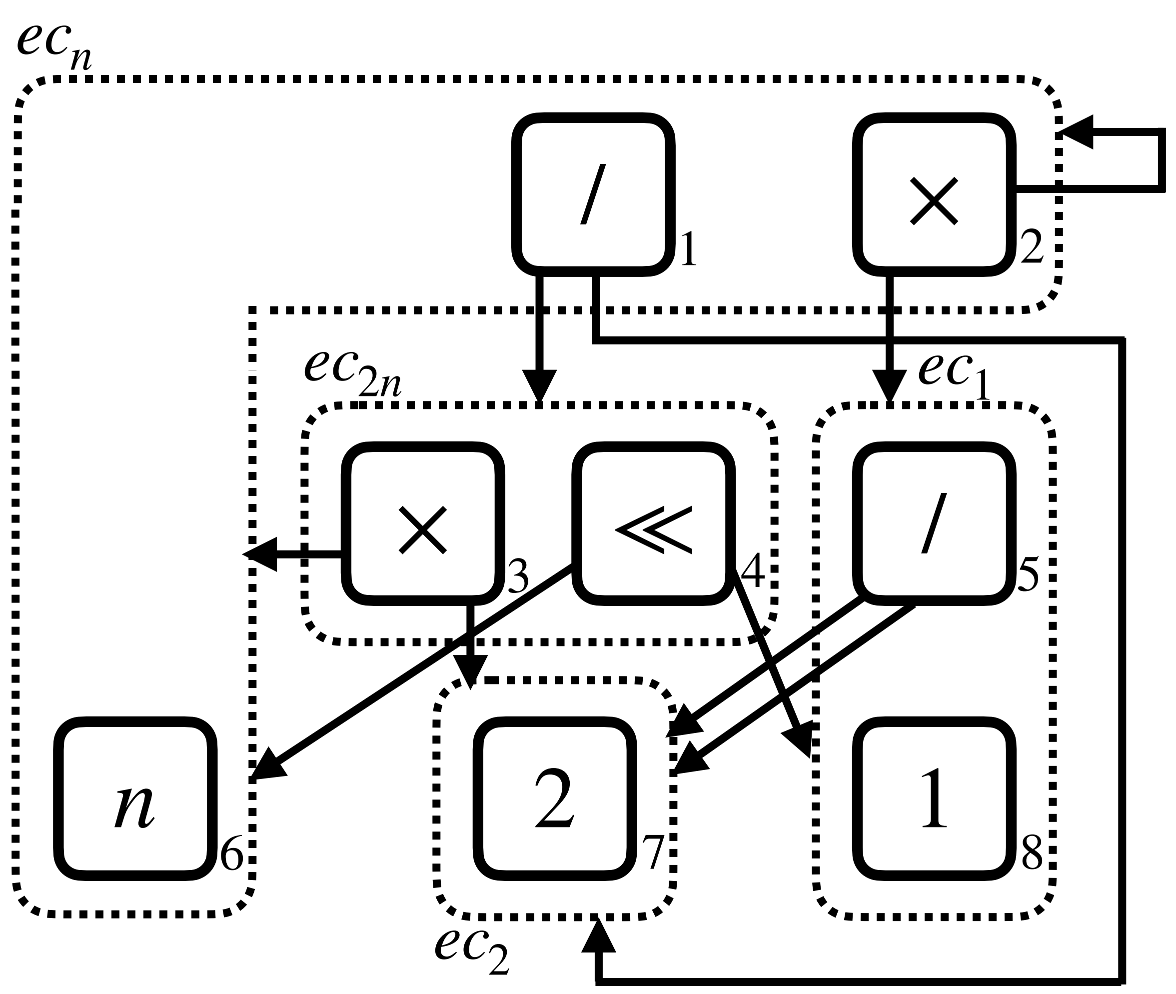
- A solution to the phase ordering problem

- Obtains results of all possible orderings and extract the best one among them

- Enabled by ***E-graph***, a very efficient data structure

E-Graph

- E-graph = e-nodes + e-classes
  - E-classes = set of e-nodes
  - E-node = a node whose children are e-classes



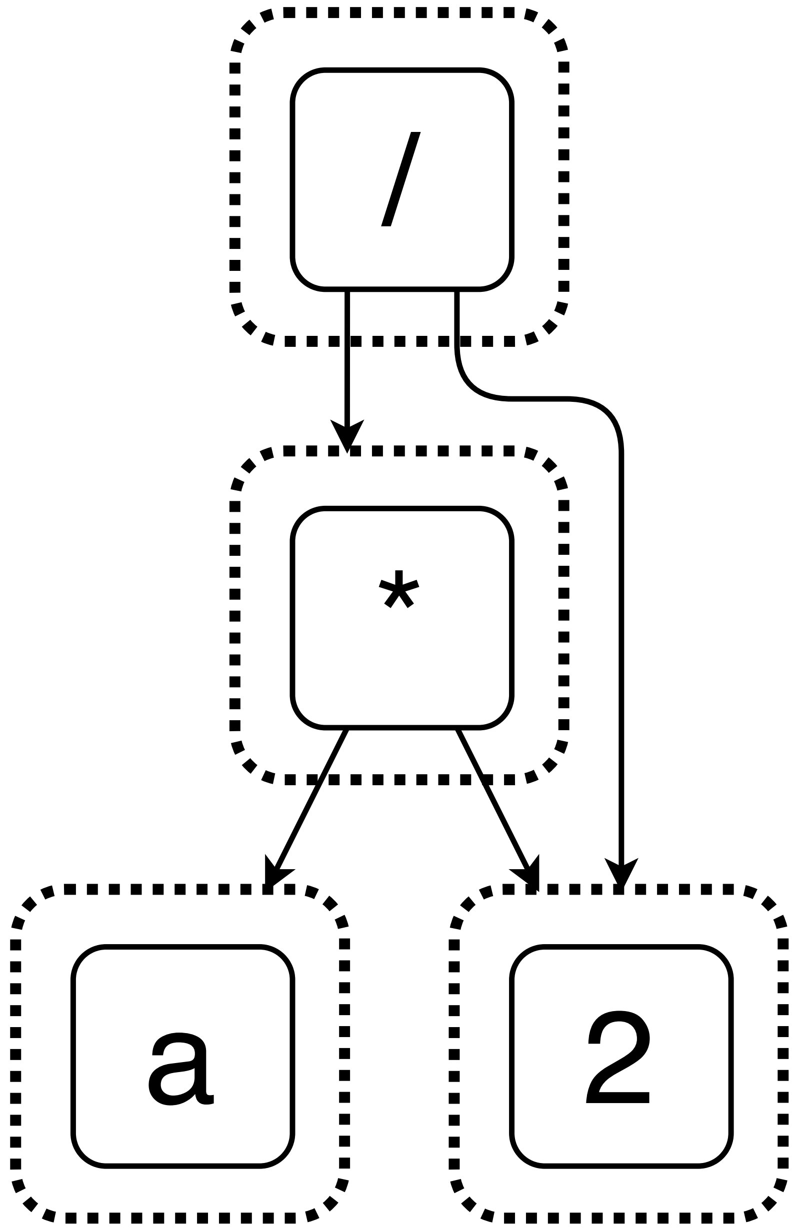
- Meaning
  - E-node (bold): expressions with sub-expressions represented by children e-classes
  - E-class (doted): semantically equivalent e-nodes

Example

- Optimizing $(a \times 2)/2$ using the following rules:

(1) $x \times 2 \rightarrow x \ll 1$ (2) $(x \times y)/z \rightarrow x \times (y/z)$

(3) $x/x \rightarrow 1$ (4) $1 \times x \rightarrow x$



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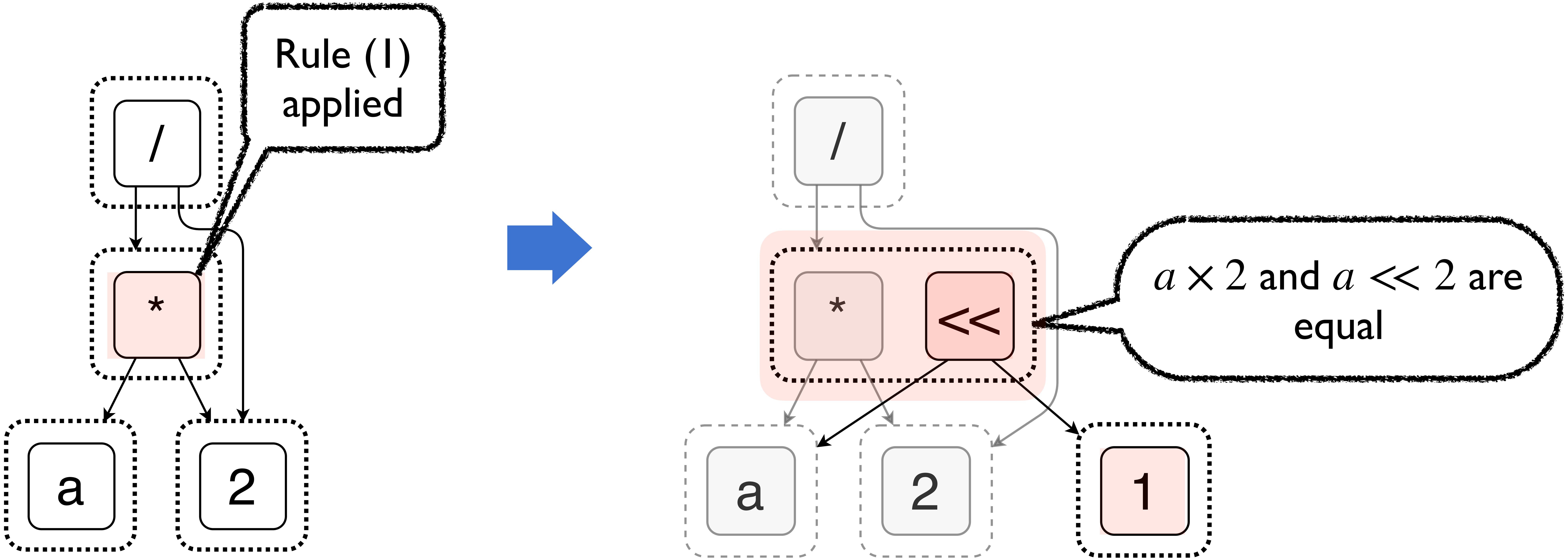

Example

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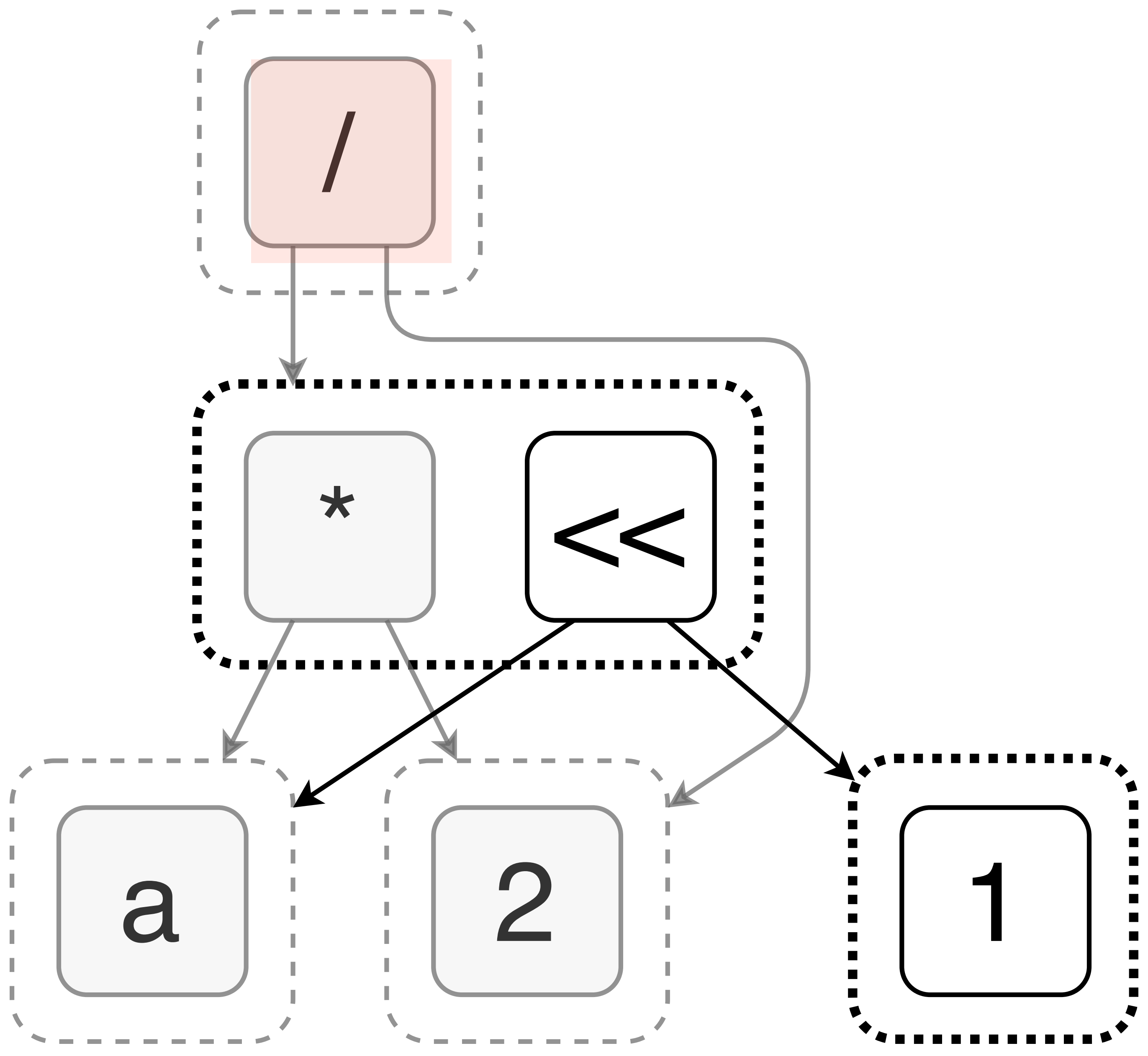

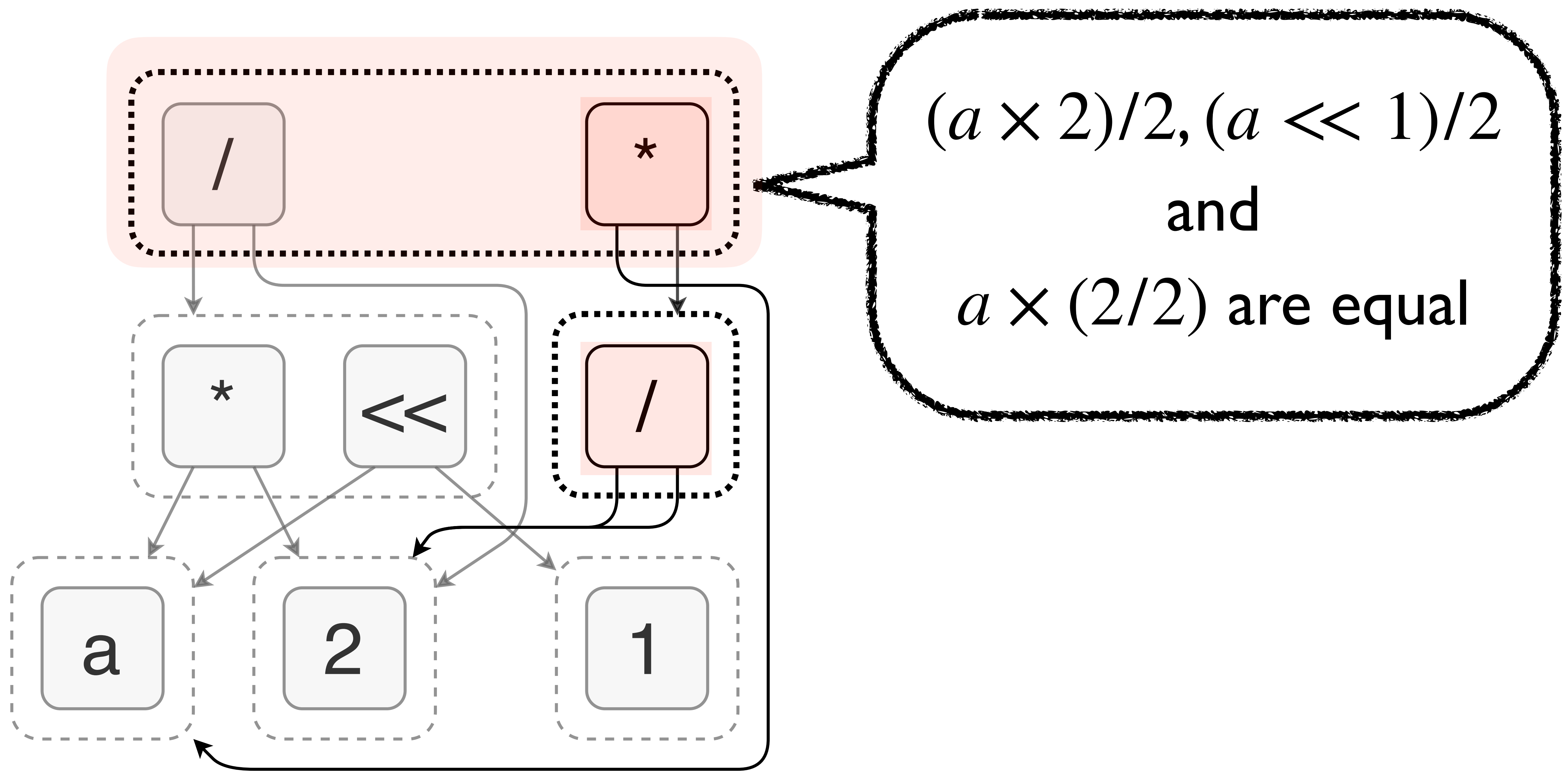

Example

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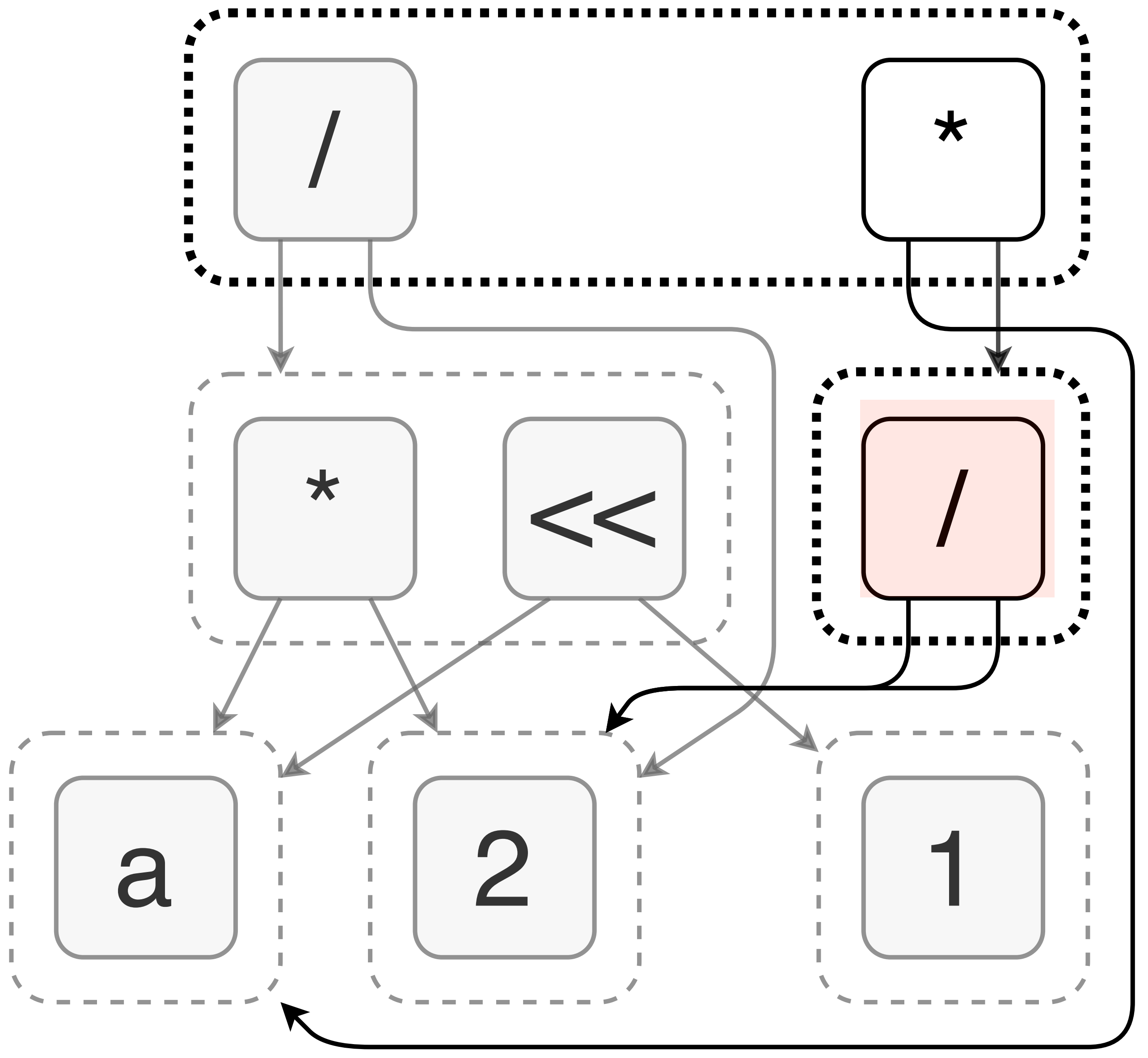

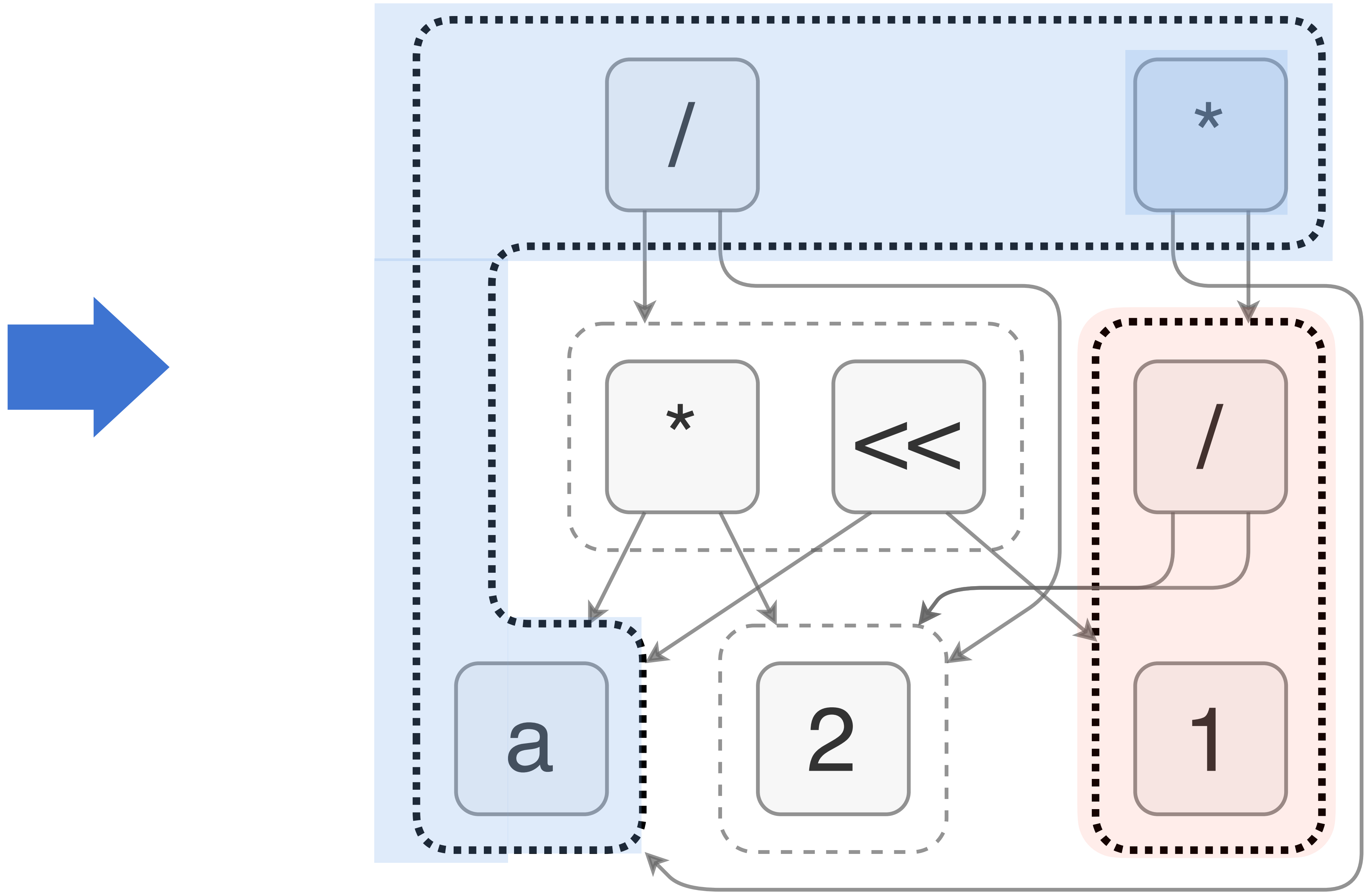

Example

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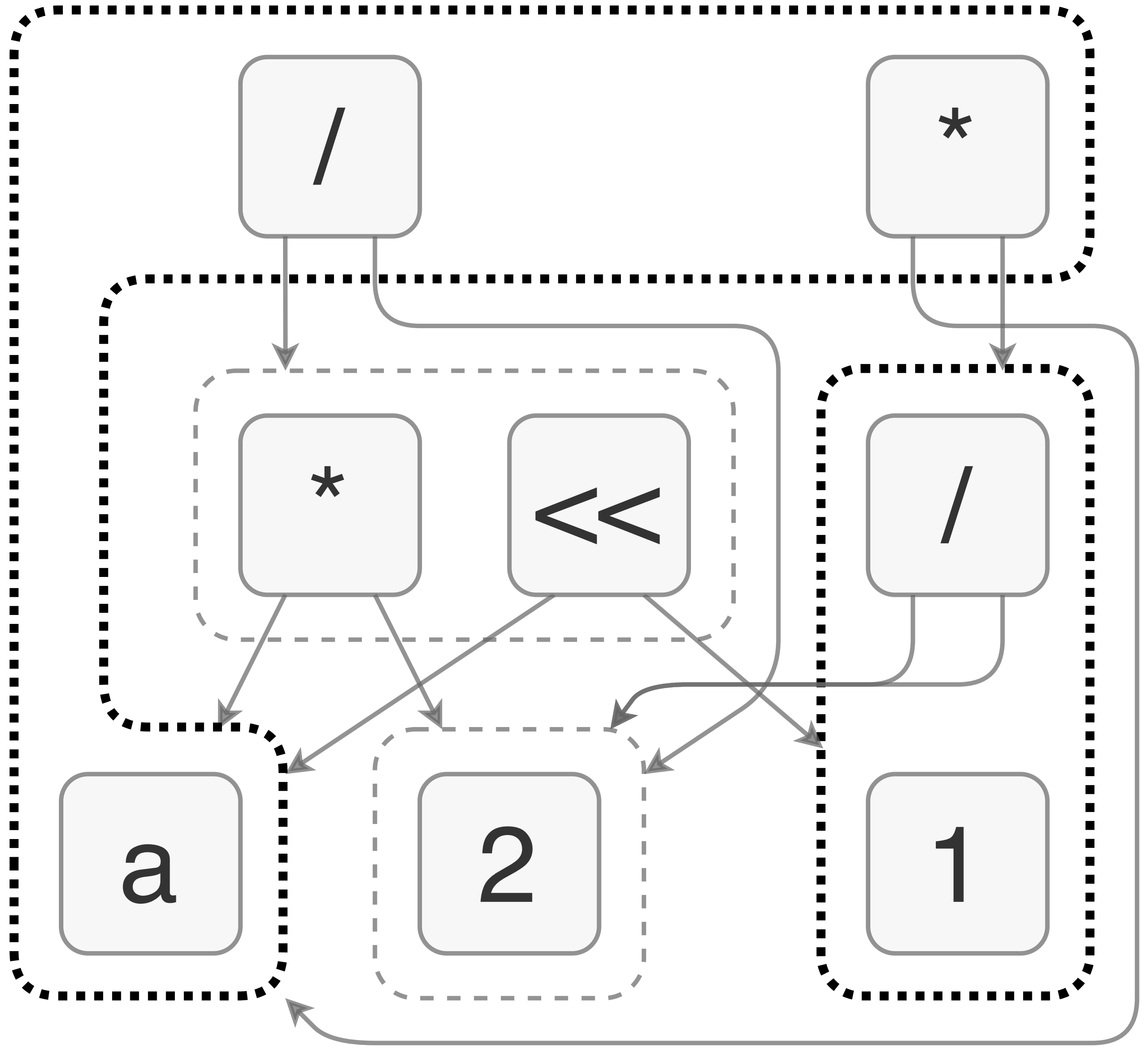
  (1) $x \times 2 \rightarrow x \ll 1$ (2) $(x \times y)/z \rightarrow x \times (y/z)$

  (3) $x/x \rightarrow 1$ (4) $1 \times x \rightarrow x$

- More rule application can't change the graph

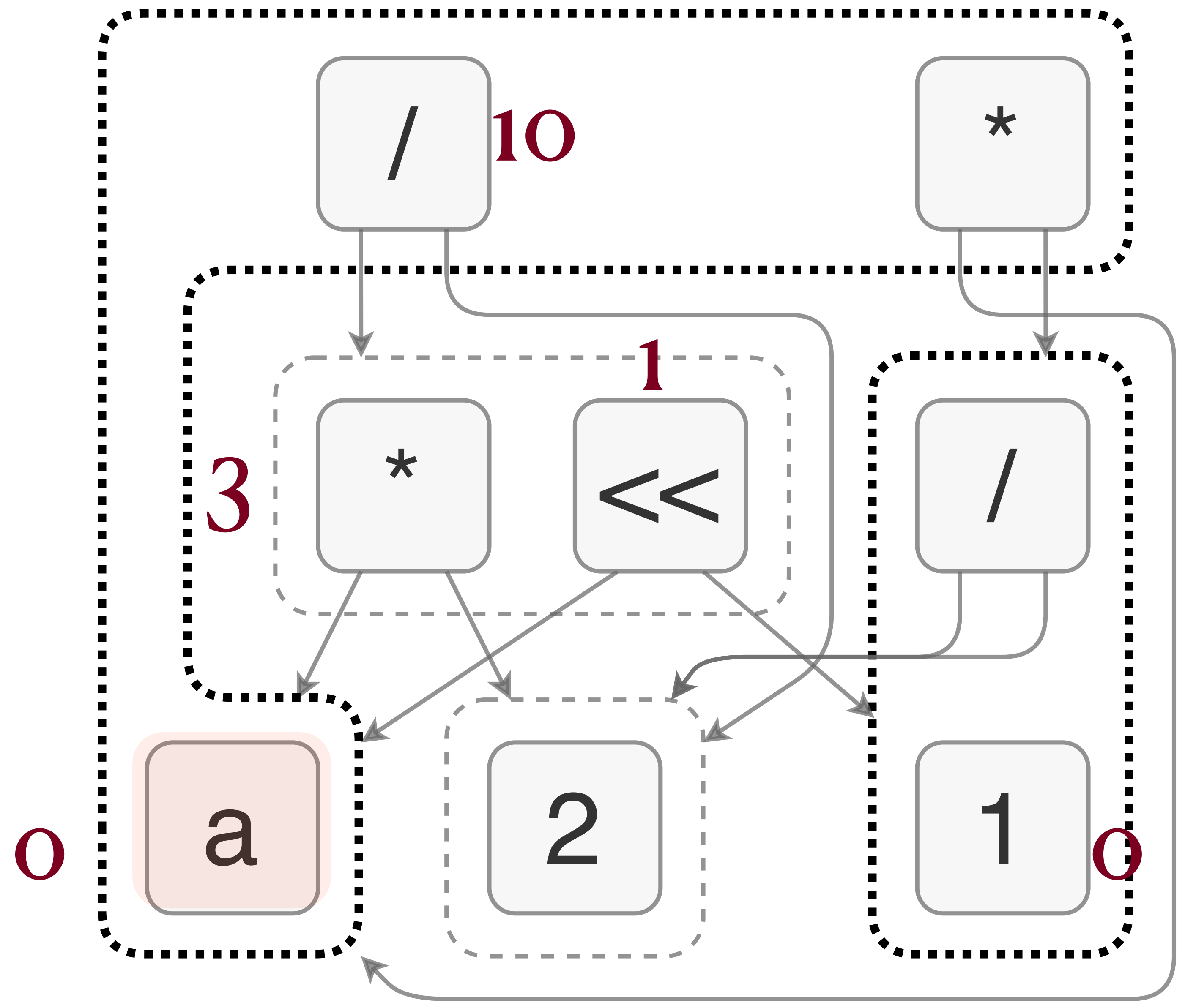
  — *Saturation!*

  - Exprs represented by the root node's e-class is *all* exprs obtainable by applying the rules in *all* possible orders



Extracting an Optimal Solution

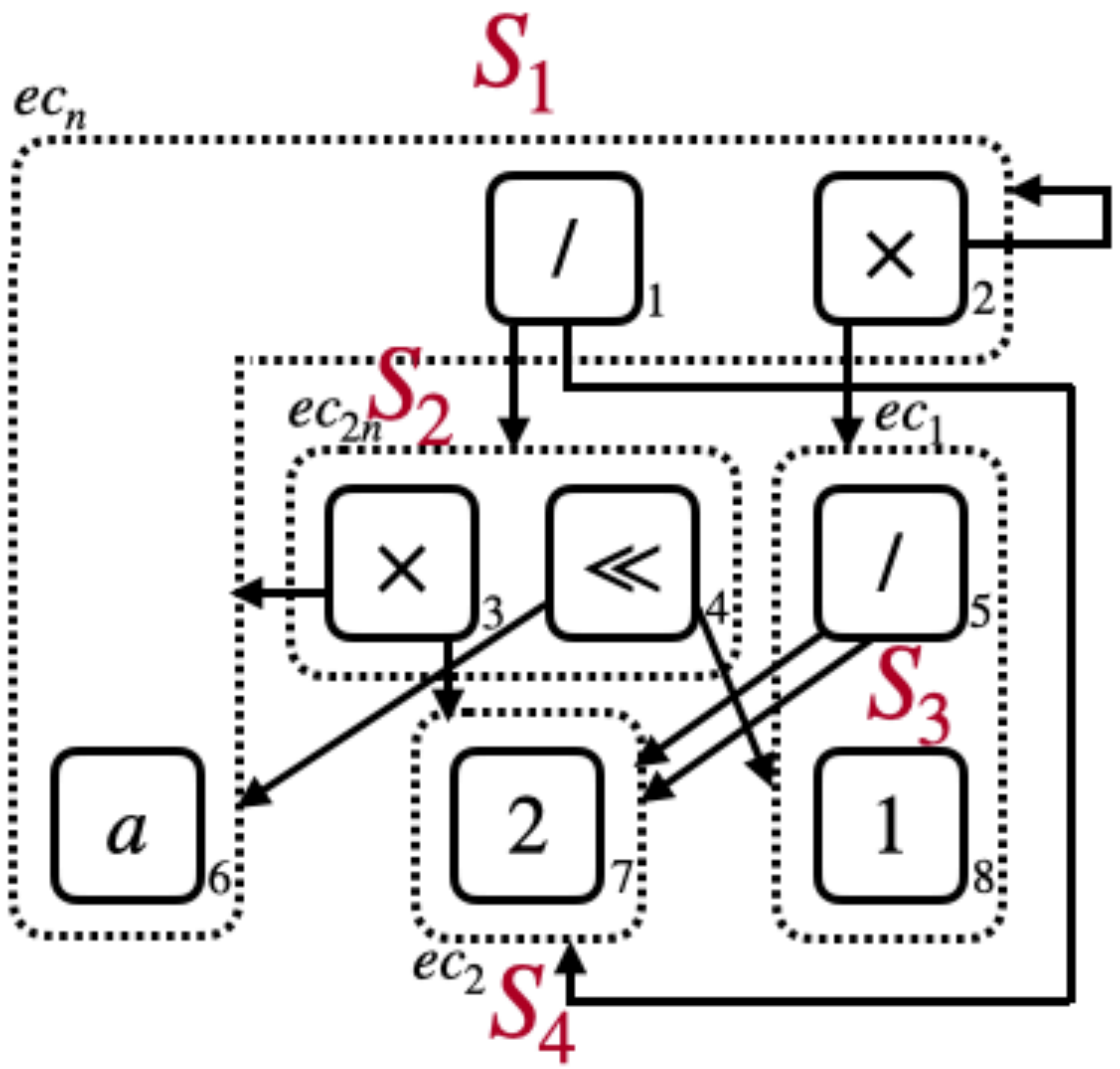
- Extract an expression of the best score after saturation†
  - e.g., greedy method using scores assigned for each kind of e-node
  - By integer linear programing in more complicated cases



† Termination is not always guaranteed

Fundamental Meaning of Equality Saturation

- E-graph ≅ Grammar representing semantically equivalent exprs
  - (E-class ≅ non-terminal, E-node ≅ production rule)
- Equality saturation = **grammar induction**



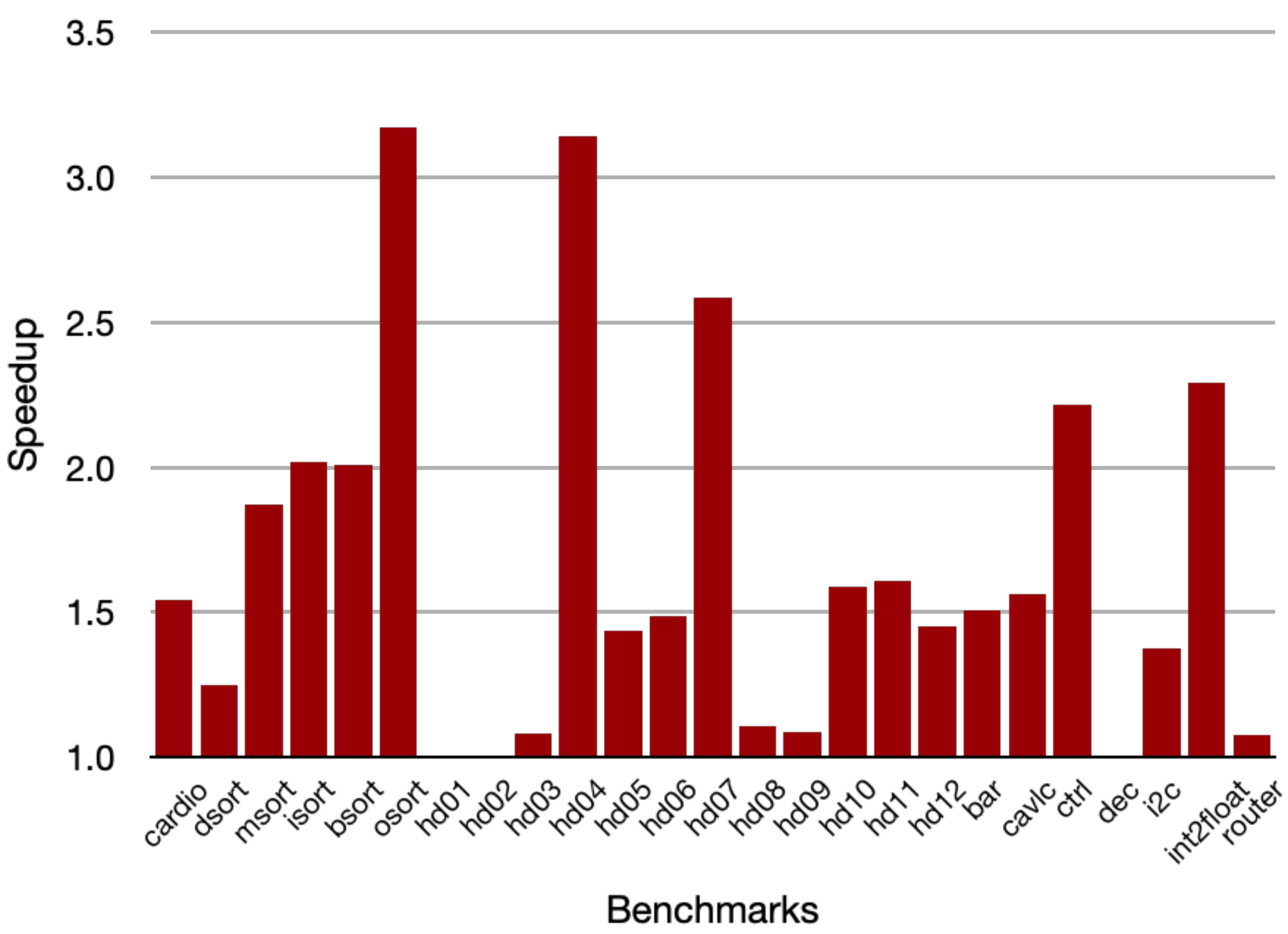
$$
\begin{aligned}
S_1 &\rightarrow S_2 \,/\, S_4 \\
&\;\;|\;\; S_1 * S_3 \\
&\;\;|\;\; a \\
S_2 &\rightarrow S_1 \ll S_3 \\
&\;\;|\;\; S_1 * S_4 \\
S_3 &\rightarrow S_4 \,/\, S_4 \\
&\;\;|\;\; 1 \\
S_4 &\rightarrow 2
\end{aligned}
$$

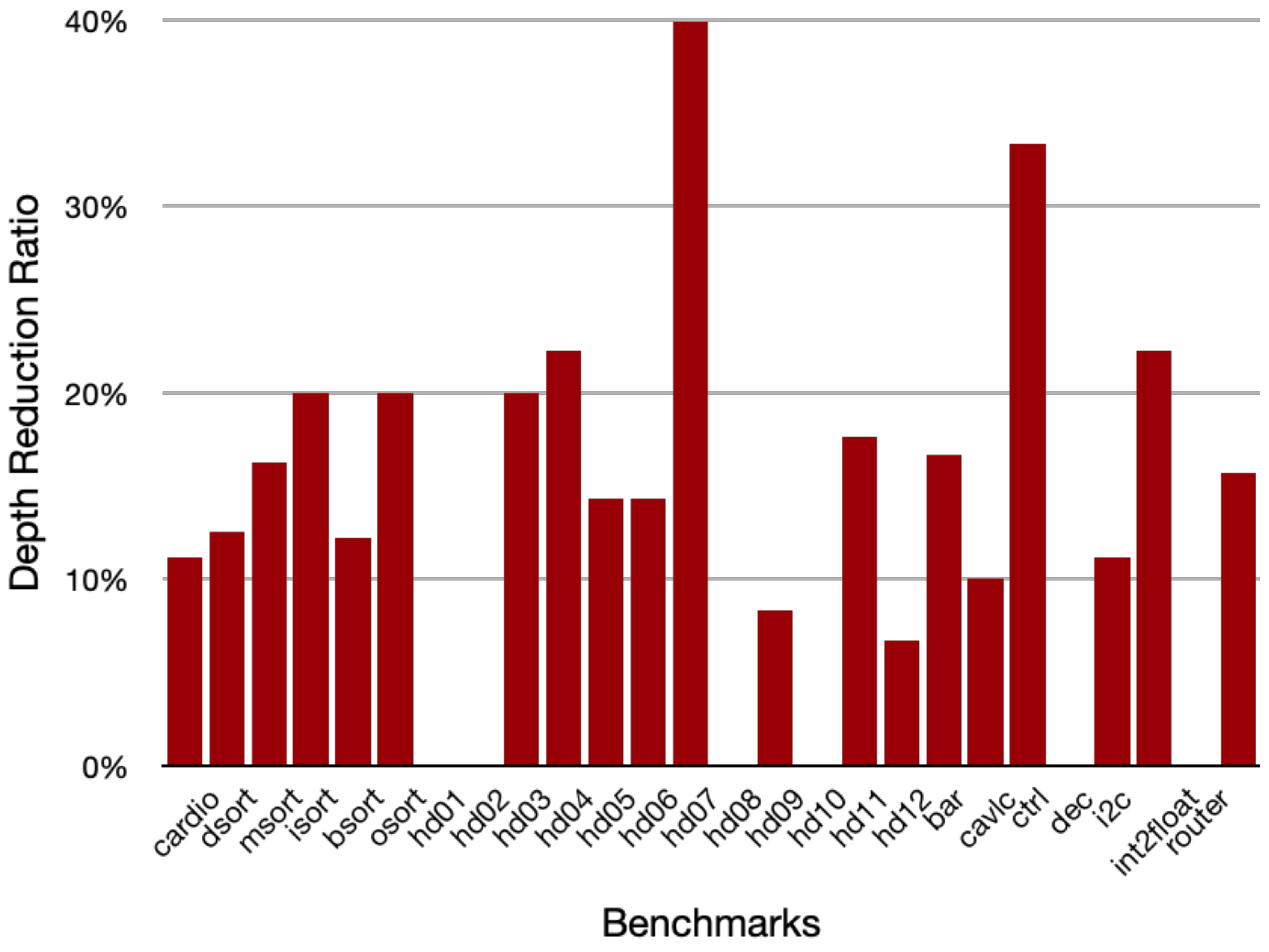
Evaluation

- 25 HE algorithms from 4 sources
  - Cingulata benchmarks
  - Sorting benchmarks
  - Hackers Delight benchmarks
  - EPFL benchmarks
- Baseline tool: Cingulata
  - A HE compiler using optimization rules written by domain experts

Lobster Performance

- Achieved an average of 2x, up to 3.1x faster performance compared to Cingulata (with up to a 40% reduction in multiplication depth)

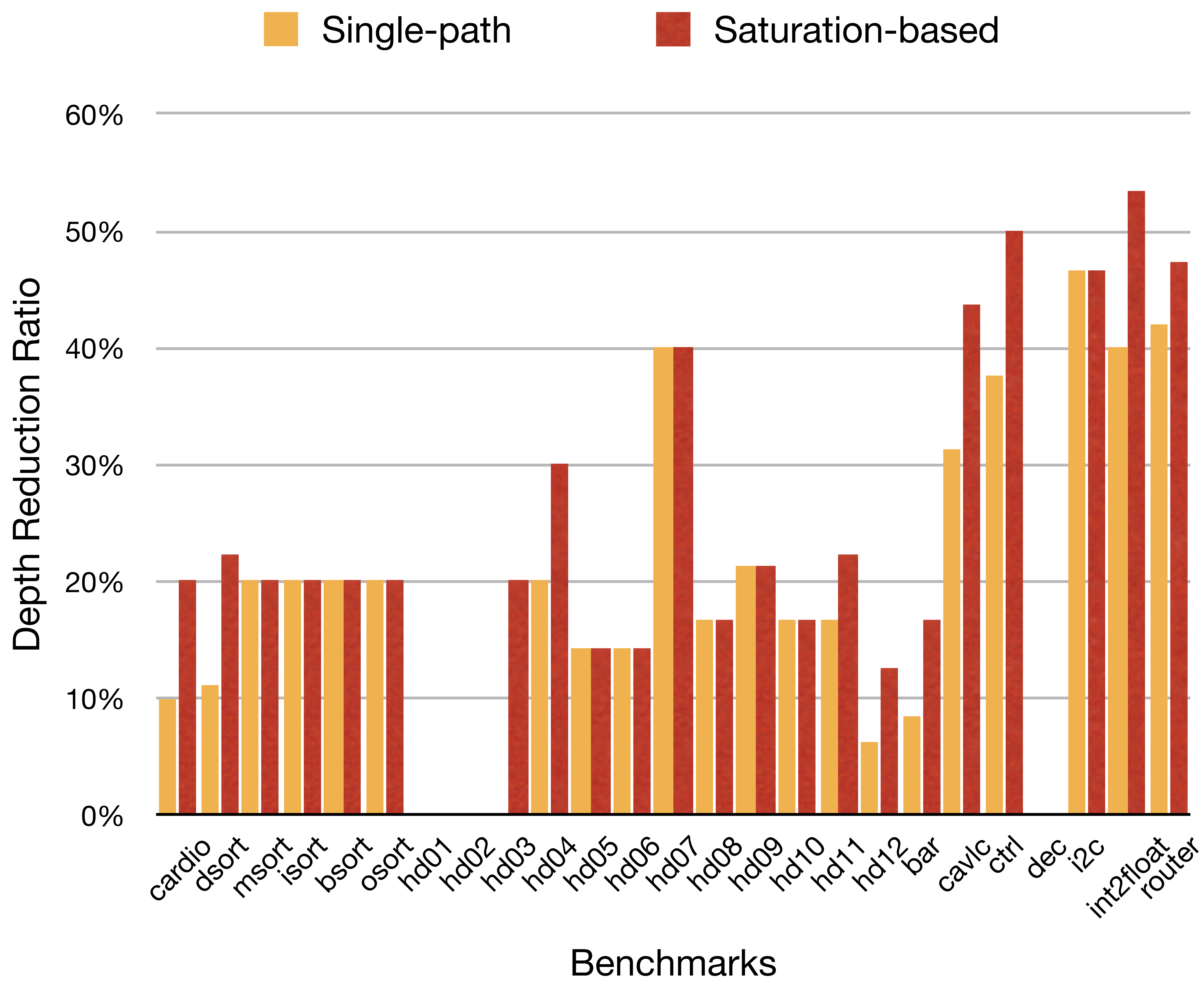




Efficacy of Equality Saturation

Success rate↑ : 19 → 22 in the number of successfully optimized programs

- Execution time: x2.03 → x2.26
- Reduction in multiplicative depth: 21.9% → 25.1%



Contents

- Case 1 : Optimizing compiler for homomorphic encryption

- **Case 2: Deobfuscation of bit-manipulating code**
  - Jaehyung Lee and Woosuk Lee, *Simplifying Mixed Boolean-Arithmetic Obfuscation by Program Synthesis and Term Rewriting*, **ACM CCS 2023**
  - Jaehyung Lee, Seoksu Lee, Eunsun Cho and Woosuk Lee, *Simplifying Mixed Boolean-Arithmetic Obfuscation by Program Synthesis and Equality Saturation*, **IEEE TDSC (Submitted)**

- Lessons from the two cases

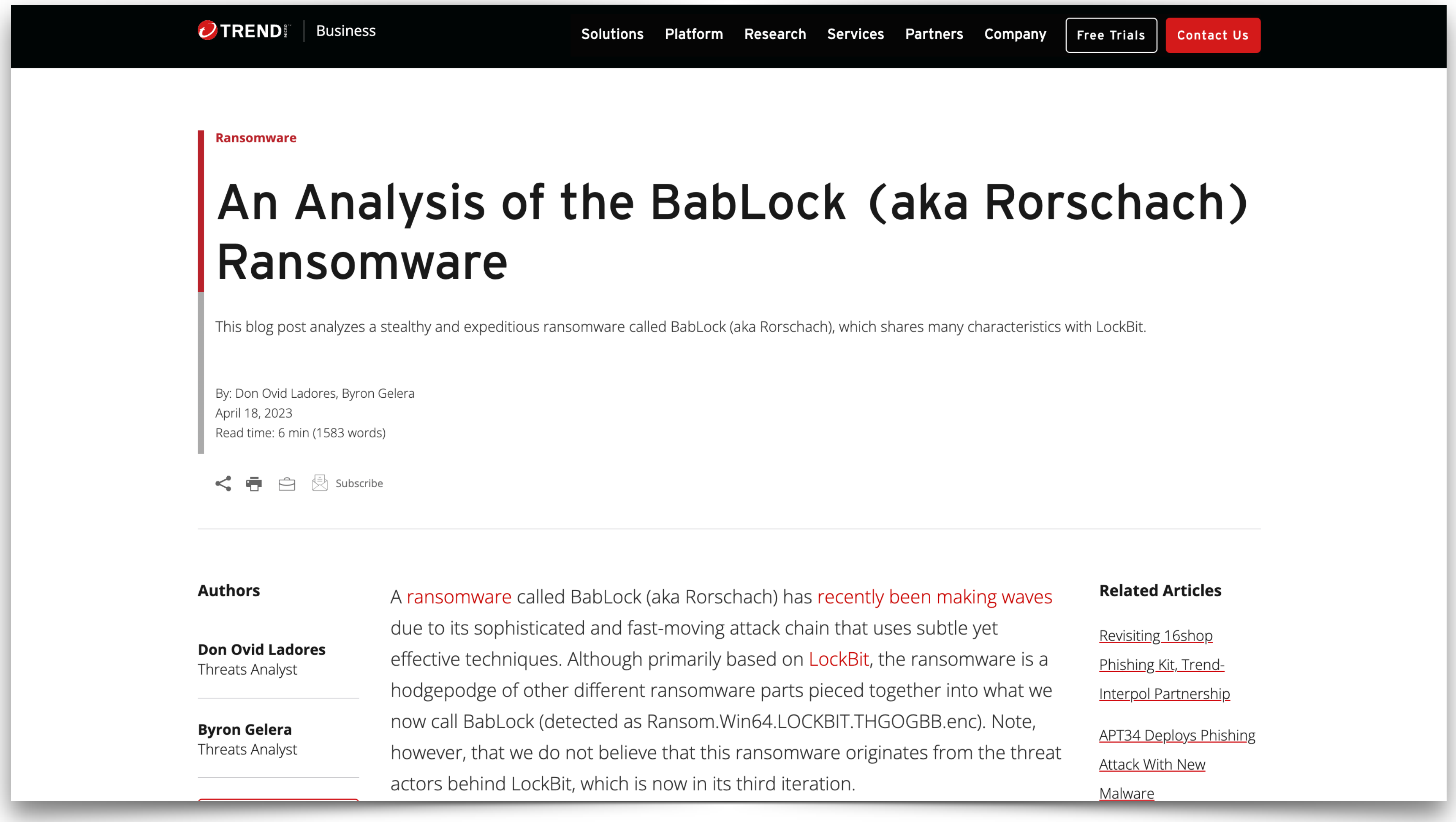
- Core technology: high-performance program synthesis

Mixed Boolean Arithmetic (MBA)

- Program expressions with logical operators (AND, OR, XOR…) and bitwise arithmetic operators (+,-,*,/,%,…)
  - e.g., $8458(x \vee y \wedge z)^3\,((xy) \wedge x \vee t) + x + 9(x \vee y)yz^3$
- MBA obfuscation: transforming arbitrary bitwise expressions into highly complex MBA expressions while maintaining their meaning

Popular MBA Obfuscation

- The cost of obfuscation and executing obfuscated code is low.
  - Only basic operations are added, and the execution flow remains unchanged (no additional calls to user/system functions, etc.)
- Theoretical foundation: any bitwise expressions can be obfuscated in infinitely many ways. Deobfuscation is NP-hard
- Widely adopted by various tools
  - Code obfuscation(Tigress, VMProtect)
  - DRM(Irdeto)
  - Being used for malware



Previous Approaches for MBA Deobfuscation

- **Term Rewriting** : SSPAM [Eyrolles et al. 2016]

Cannot handle a wide range of MBA obfuscation rules

- **Program Synthesis** : Syntia [Blazytko et al. 2017], QSynth [David et al. 2020], Xyntia [Menguy et al. 2021]

No Guarantee of Correctness

- **Neural Network Inference** : NeuReduce [Feng et al. 2020]

Unscalable

- **Algebraic Methods** : MBA-Solver [Xu et al. 2021], SiMBA [Reichenwallner et al. 2022]

Limited to a specific class of MBA expressions

Our Goal

- Term Rewriting : “Rewrite with fi…

To overcome the limitations, we should achieve :

- **Soundness** : Guarantee of correctness
- **Generality** : Covers arbitrary MBA expression
- **Flexibility** : Regardless of obfuscation rules
- **Scalability** : Covers huge MBA expression

  - **MBA-Solver** [Xu et al. 2021], **SiMBA** [Reichenwallner et al. 2022]

Limited to specific set of transformations (linear)

Program Synthesis-Based MBA Deobfuscation

Constraints + **Grammar** —**Synthesize**→ **Result**

(((((~ e) + 1) & (~ ((((- e) - 1) | (- a)) + (((- e) - 1) & (- a))))) + (((~ e) + 1) & (~ ((((- e) - 1) | (- a)) + (((- e) - 1) & (- a)))))) - (((~ e) + 1) ^ ((((- e) - 1) | (- a)) + (((- e) - 1) & (- a))))) …

$$
\begin{aligned}
S &\rightarrow\ !S \mid S \oplus S \mid S \wedge S \\
&\mid\ S \vee S \mid -S \mid S + S \\
&\mid\ S \times S \mid S - S \mid S >> S \\
&\mid\ S << S \mid V \mid C \\
V &\rightarrow \texttt{b} \mid \texttt{e} \mid \cdots \\
C &\rightarrow \texttt{0x00} \mid \texttt{0x01} \mid \cdots
\end{aligned}
$$

1 + a

Same semantics **Syntax** **Deobfuscated expression**

Can cover arbitrary MBA Exprs

Challenge : Scalability

(((((~ e) + 1) & (~ ((((- e) - 1) | (- a)) + (((- e) - 1) & (- a))))) + (((~ e) + 1) & (~ ((((- e) - 1) | (- a)) + (((- e) - 1) & (- a)))))) - (((~ e) + 1) ^ ((((- e) - 1) | (- a)) + (((- e) - 1) & (- a))))) …

Synthesize → 1 + a

Too Slow! 😡

size of obfuscated expression ⬆ -> deobfuscation performance ⬇

Solution 1: Synthesis via Localization

- Sub-expressions are chosen for replacement

((((- e) & (~ (((~ e) | (- a)) + ((~ e) & (- a))))) +
((- e) & (~ (((~ e) | (- a)) + ((~ e) & (- a)))))) …
(v1 & ((v2 * v3) & (v2 - v1)))
…

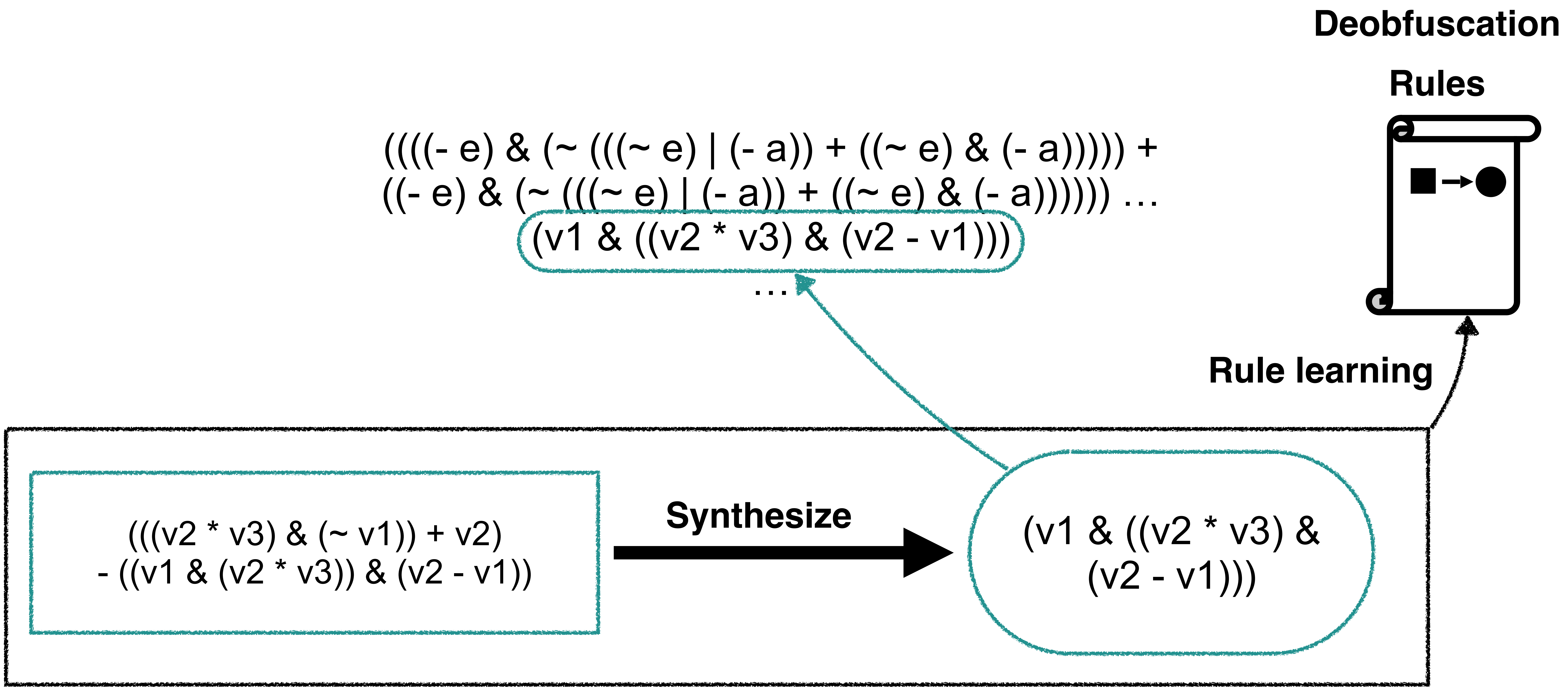
(((v2 * v3) & (~ v1)) + v2)
- ((v1 & (v2 * v3)) & (v2 - v1))

Synthesize

(v1 & ((v2 * v3) &
(v2 - v1)))

Scalable 🙂

Solution 2: Learning Successful Synthesis Patterns



Comparison to the HE Optimization

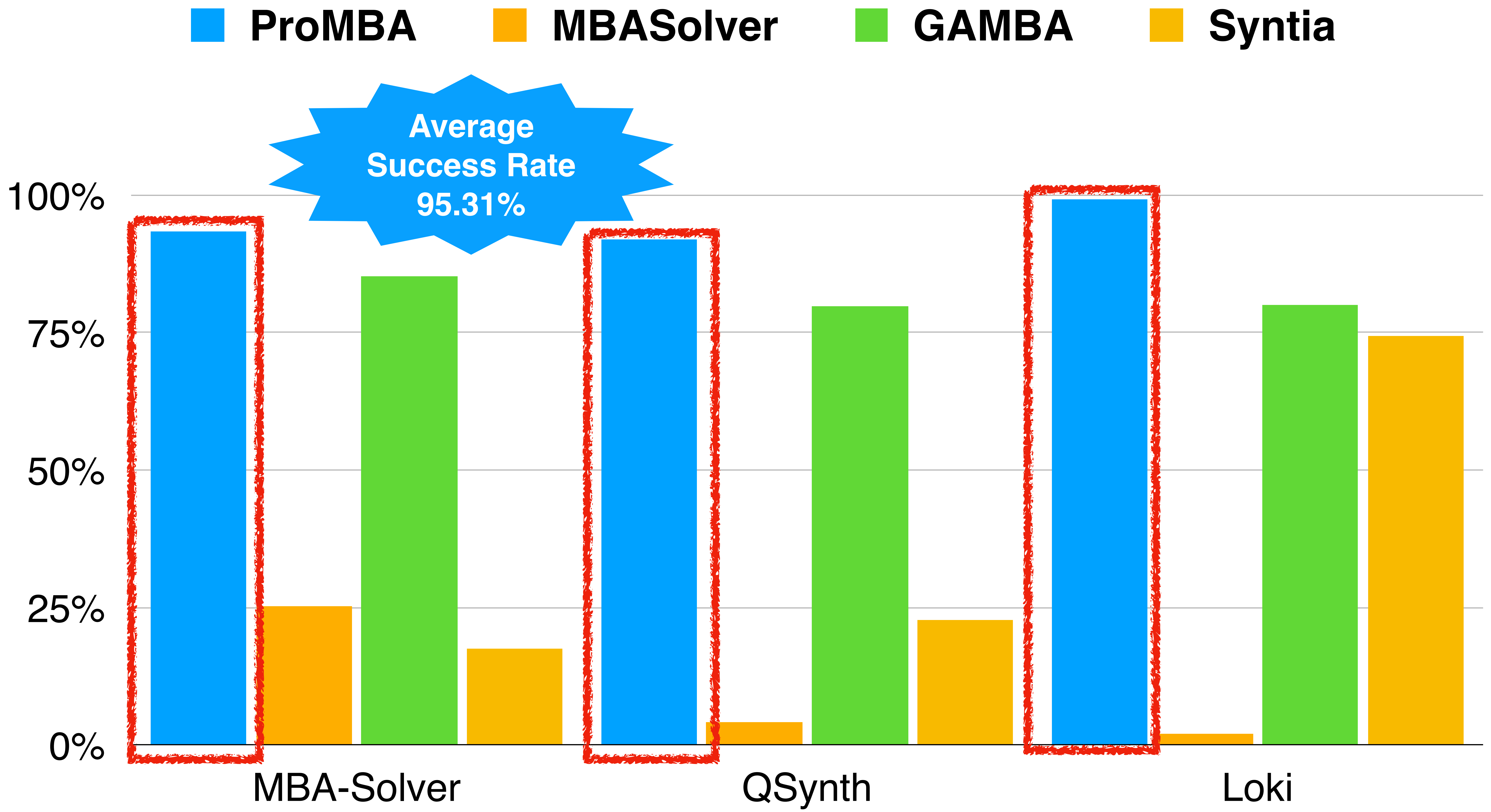
- **Commons** : Synthesis via localization → Learning rules → Term rewriting + Equality saturation
- **Major Diffs** : Learning and applying rules directly online (without offline learning)
  - Rules used in MBA obfuscation are highly diverse, making offline-learned rules ineffective for deobfuscating new MBA expressions.
  - Advances in program synthesis have enabled faster rule synthesis.
- **Others**: using algebraic methods for certain types of MBA expressions (linear MBA), selecting target subexpressions for replacement, etc.

Evaluation

- ProMBA: performs term rewriting first and then equality saturation
- 4000 MBA obfuscated expressions from prior work
  - From three categories with different sizes, from small to large
- Baseline tools
  - MBASolver [PLDI '22] : Algebraic method. Correctness guarantee
  - Syntia [USENIX '17] : Heuristics. No correctness guarantee
  - GAMBA [WORMA'23] : Algebraic + heuristics. Correctness guarantee
- Success: (1) size of deobfuscated result $\leq$ size of original expression, (2) deobfuscated result has the same meaning as the original one

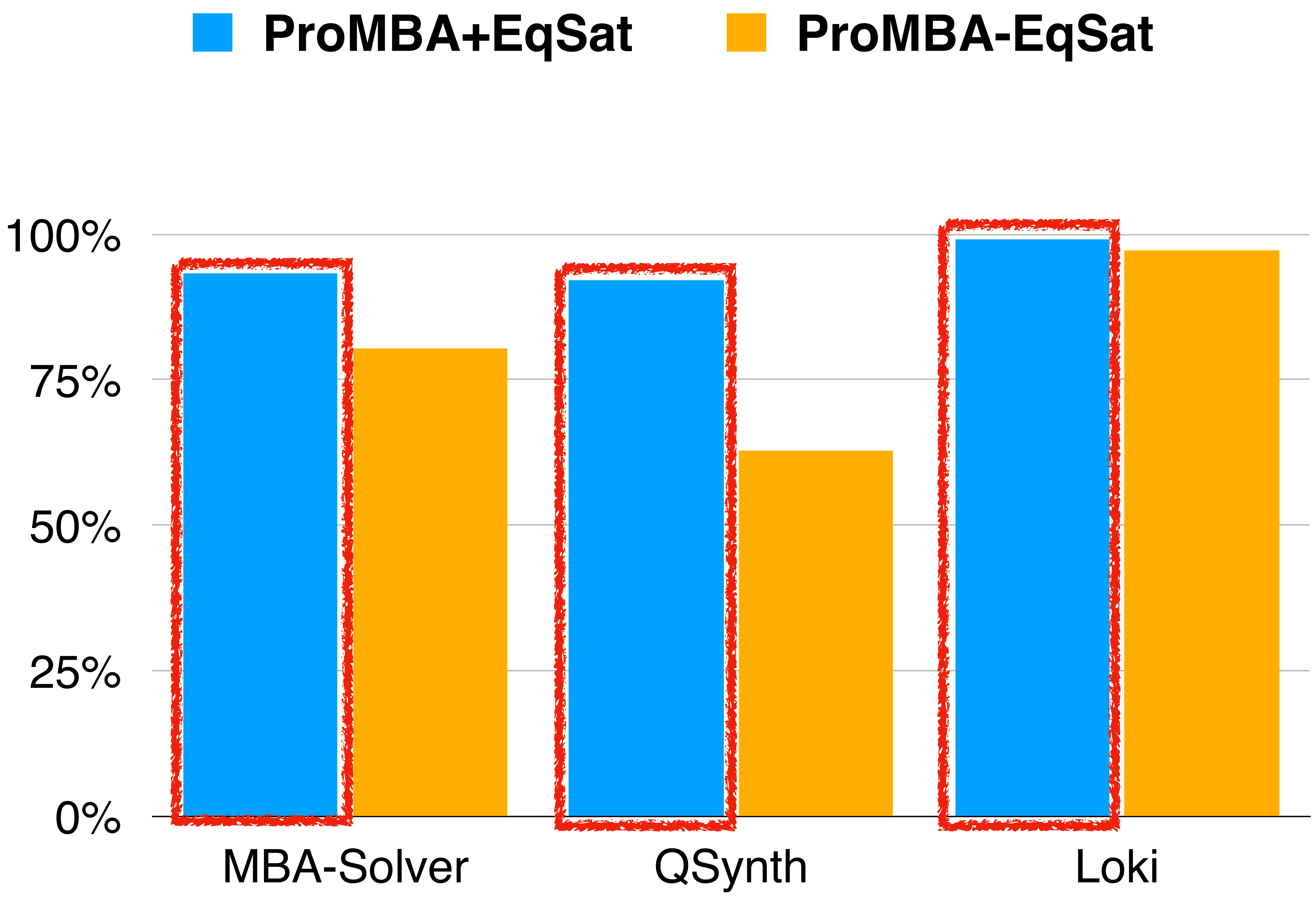
Results

- An average deobfuscation success rate of 95.3%, significantly outperforming other tools (13%, 82.5%, 39.4%)



Efficacy of Equality Saturation

- Increased success rate: 84% → 95%
- Reduced average size of deobfuscated results : 9.4 → 7.9 (in AST nodes)



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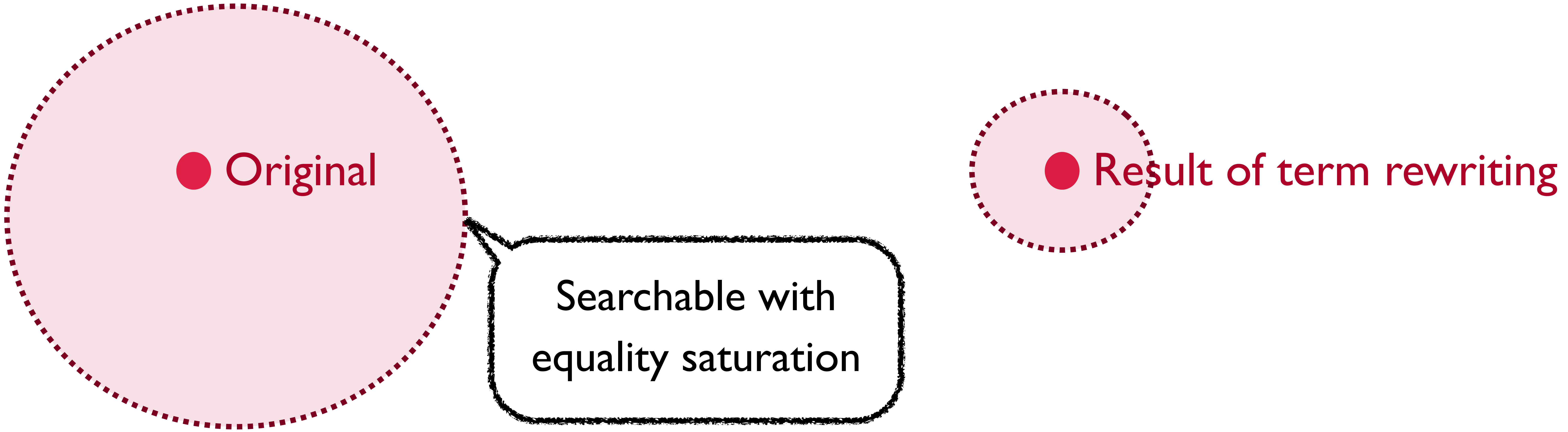
- Case 1 : Optimizing compiler for homomorphic encryption
- Case 2: Deobfuscation of bit-manipulating code
- **Lessons from the two cases**
- Core technology: high-performance program synthesis

Lesson 1 : Both Term Rewriting and Equality Saturation are Necessary (1/2)

- Equality saturation is for overcoming the phase-ordering problem, the limitation of term rewriting. But, equality saturation alone is insufficient.
- The main issue is its high computational cost.
- In the case of homomorphic encryption optimization
    - EqSat alone causes OOM (256GB) for large circuits (depths > 25)
    - Even smaller circuits may not reach saturation within 12 hours
- For MBA deobfuscation — lower success rate (92% → 61.8%) when with equality saturation alone (with early termination to avoid high cost)

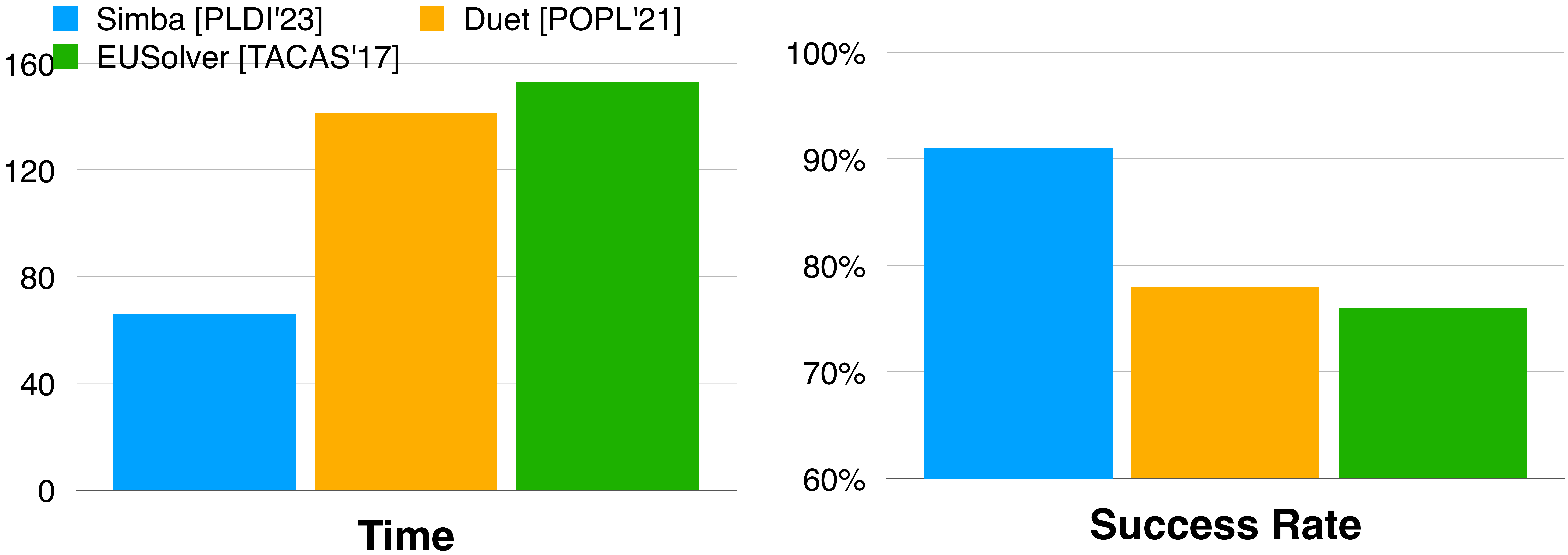
Lesson 1 : Both Term Rewriting and Equality Saturation are Necessary (2/2)

- The larger the original expression and the more rules there are, the greater the search space and computational cost
- It is beneficial to do term rewriting first and then equality saturation.
  - Reducing the size of the original expression decreases the search space and provides direction to the exploration process.



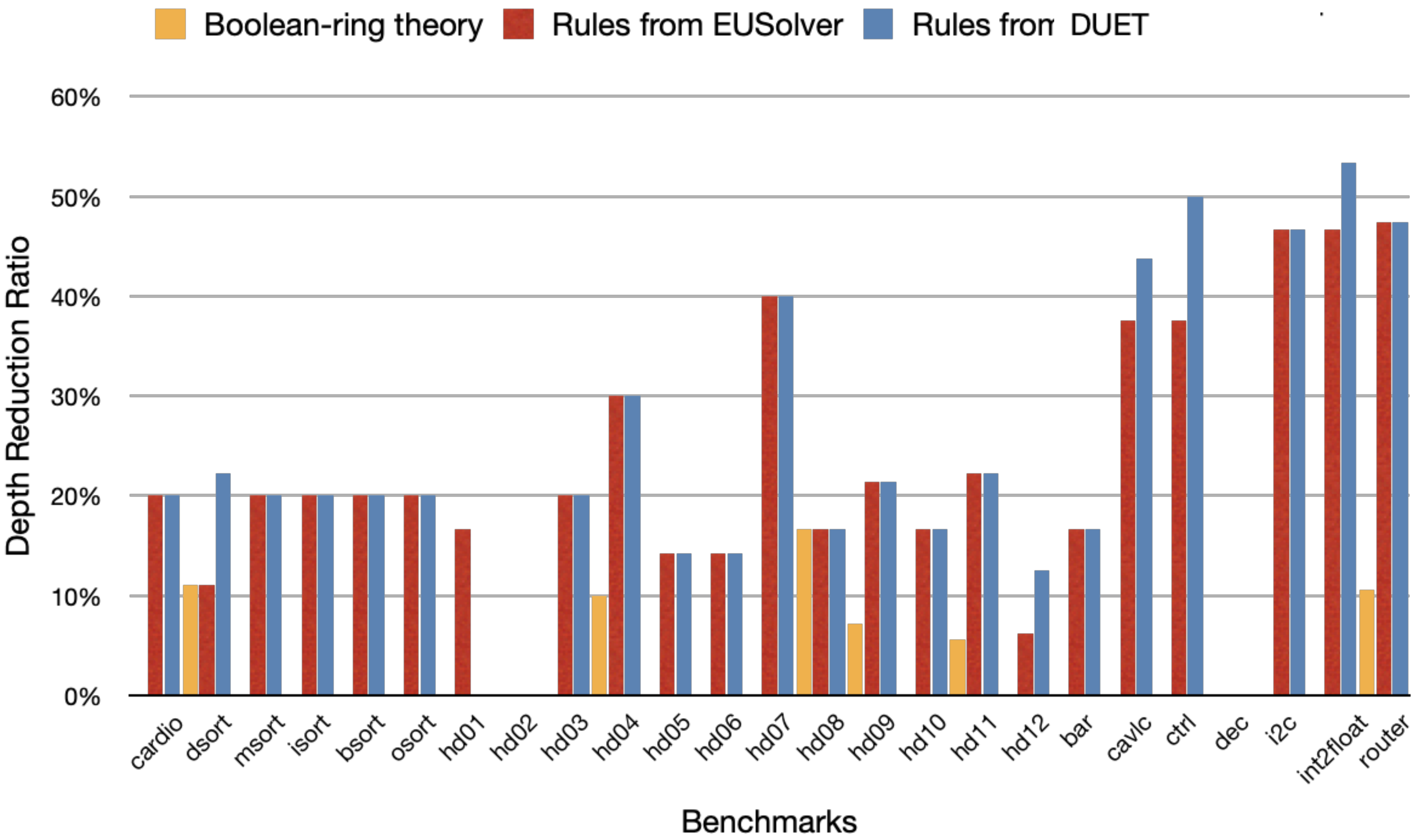
Lesson 2 : Performance of Synthesis is key (1/2)

- Rules discovered by a better synthesizer lead to better optimization
  - Performance : Simba > Duet > EUSolver
- Case of MBA



Lesson 2 : Performance of Synthesis is key (2/2)

- Case of HE optimization



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- Case 1 : Optimizing compiler for homomorphic encryption

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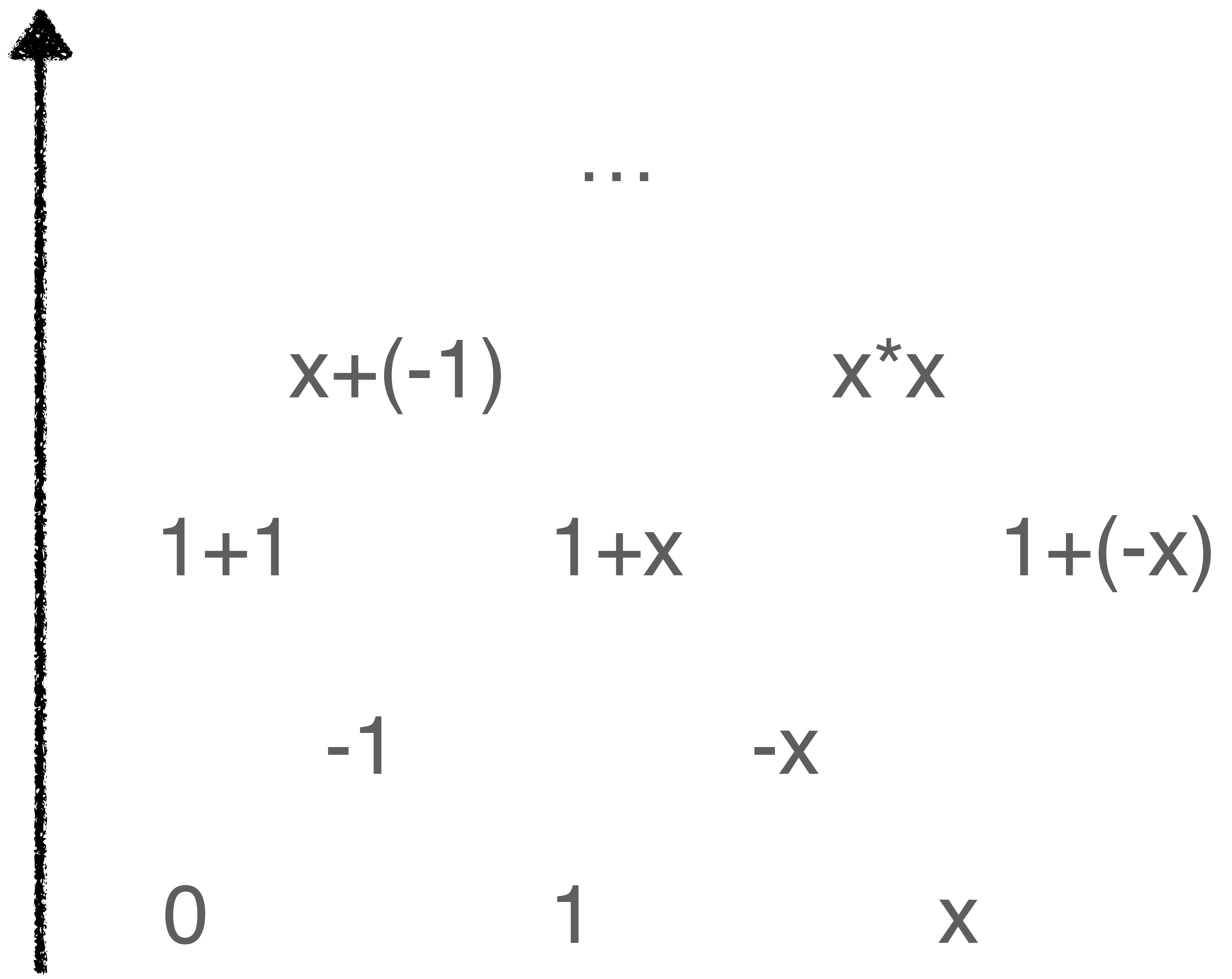
- **Core technology: high-performance program synthesis**
    - Yongho Yoon, Woosuk Lee, and Kwangkeun Yi, Inductive Program Synthesis via Iterative Forward-Backward Abstract Interpretation. **ACM PLDI 2023**

Two Synthesis Strategies — Bottom-Up



$$
\begin{aligned}
E \quad \rightarrow \quad & 0 \\
| \quad & 1 \\
| \quad & x \\
| \quad & E + E \\
| \quad & E * E \\
| \quad & -E
\end{aligned}
$$

Two Synthesis Strategies — Top-Down

0 1 x E+E E*E -E

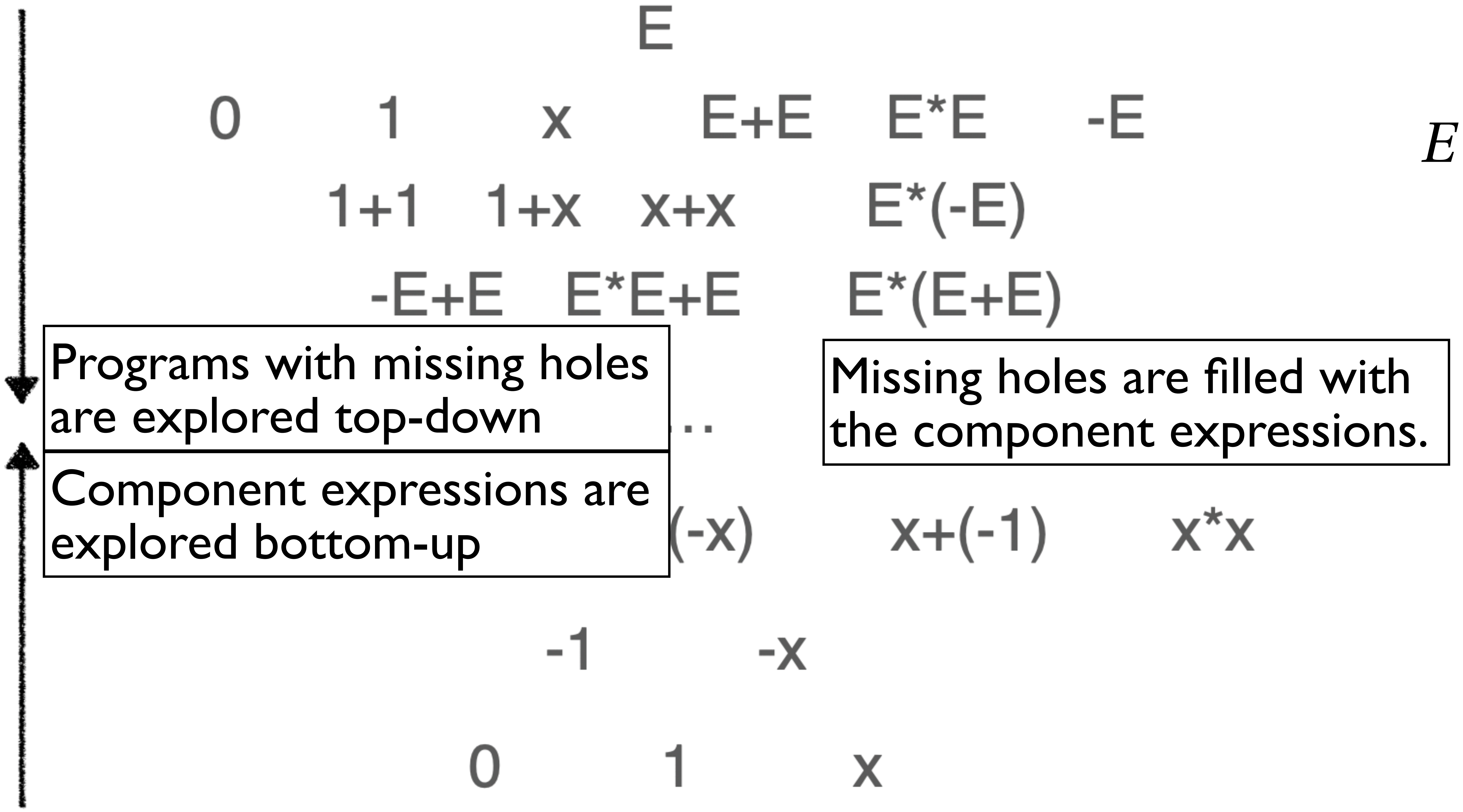
1+1 1+x x+x E*(-E)

-E+E E*E+E E*(E+E)

…

$$
\begin{aligned}
E \quad \rightarrow \quad & 0 \\
| \quad & 1 \\
| \quad & x \\
| \quad & E + E \\
| \quad & E * E \\
| \quad & -E
\end{aligned}
$$

Bidirectional Synthesis



$$
\begin{array}{rcl}
E & \rightarrow & 0 \\
 & | & 1 \\
 & | & x \\
 & | & E + E \\
 & | & E * E \\
 & | & -E
\end{array}
$$

*(POPL'21) Woosuk Lee, "Combining the Top-Down Propagation and Bottom-Up Enumeration for Inductive Program Synthesis"

Synthesis + Static Analysis

- Can prune infeasible program candidates
  - "Infeasible" = partial program that can never satisfy the given spec no matter how we fill in the holes
  - The more component expressions, the higher impact of the pruning
- "**Fairly precise"** static analysis for pruning infeasible candidates
  - Input: spec(input-output examples) and an incomplete partial program
  - Output: "May be feasible" or "Infeasible"

Example

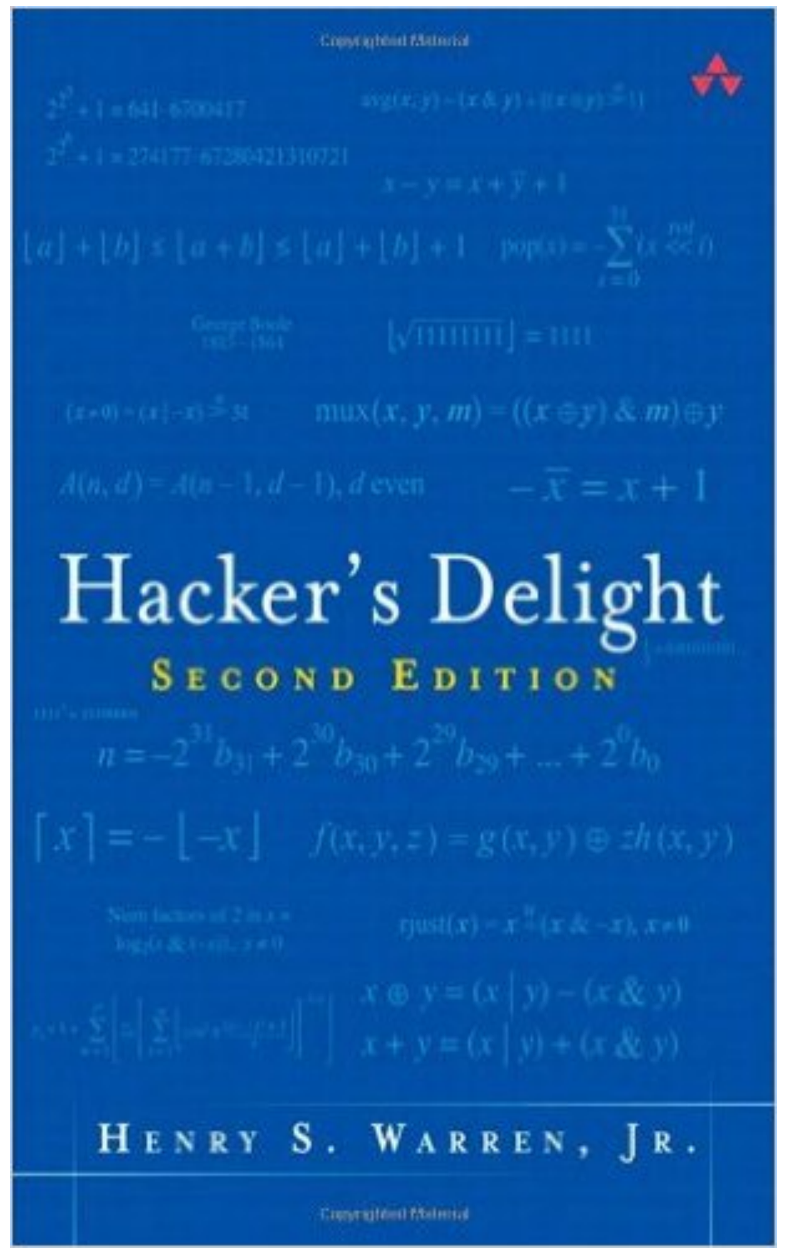
- Goal: turn off all bits from the first bit to the rightmost 0 from a given bitvector
- Target function f(x: BitVec) : BitVec.
- Syntactic constraint:

$$
\begin{array}{lll}
S & \rightarrow & x \mid 0001_2 \\
 & \mid & S \wedge S \mid S \vee S \mid S \oplus S \\
 & \mid & S + S \mid S \times S \mid S/S \mid S >> S \\
 & & \ldots
\end{array}
$$

input bit-vector and bit-vector literals

bitwise logical binary operators

bitwise arithmetic binary operators



- Semantic constraint : $f(1011_2) = 0011_2$
- Solution: $f(x) = ((x + 0001_2) \oplus x) >> 0001_2$

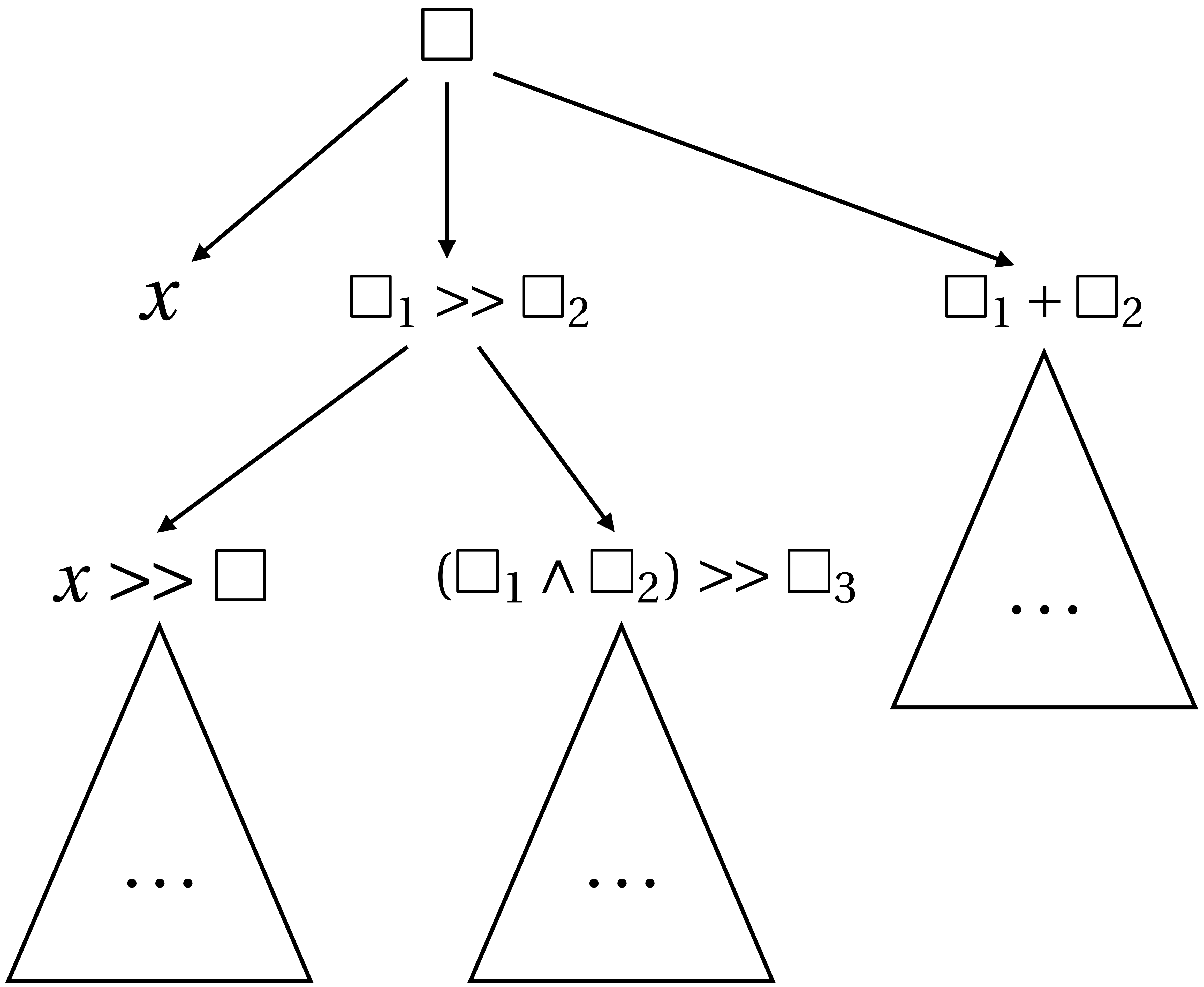
Example

Syntactic Spec

$$
\begin{array}{lll}
S & \rightarrow & x \mid 0001_2 \\
 & \mid & S \wedge S \mid S \vee S \mid S \oplus S \\
 & \mid & S + S \mid S \times S \mid S / S \mid S >> S
\end{array}
$$

Semantic Spec

$$f(1011_2) = 0011_2$$



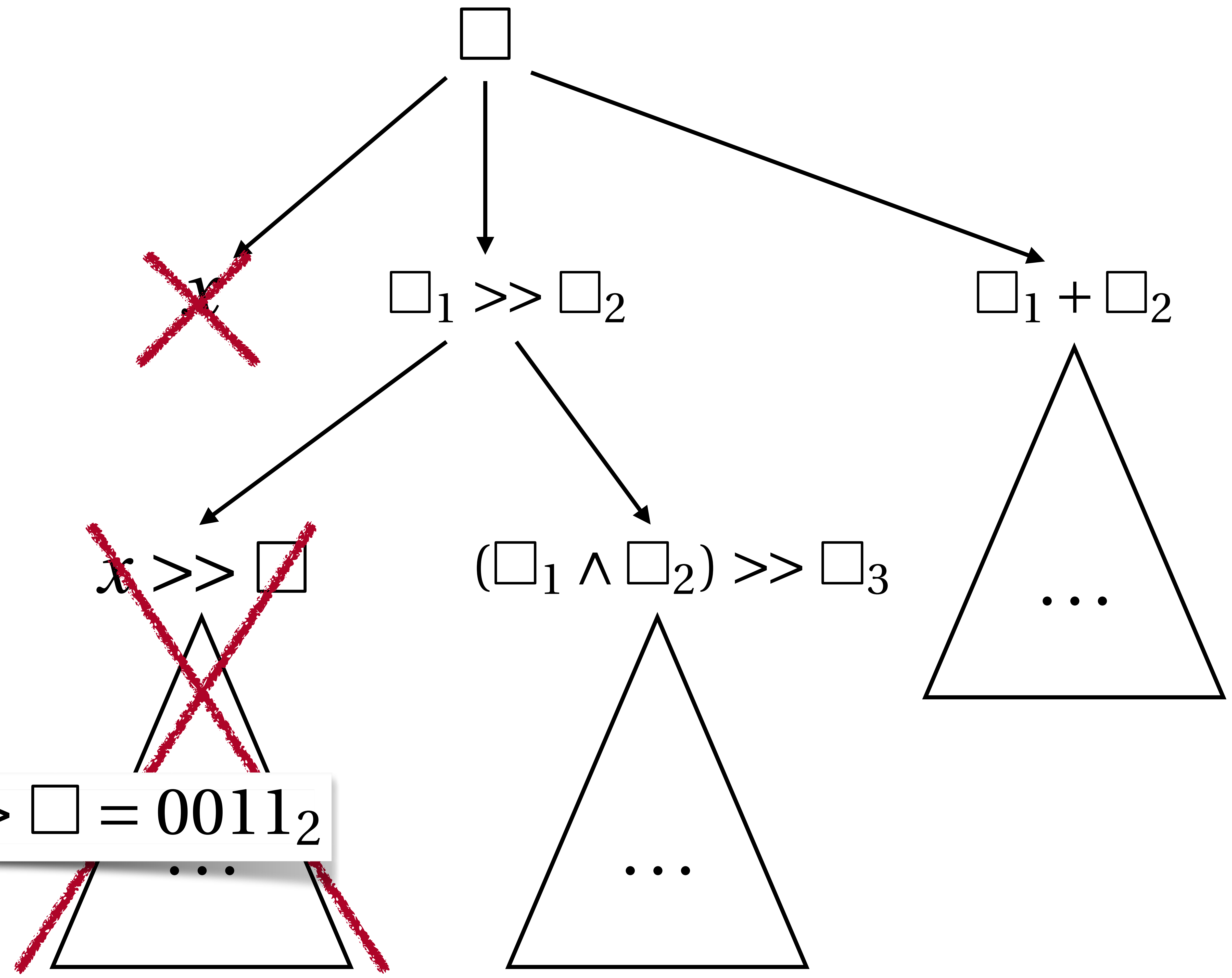
Example

Syntactic Spec

$$
\begin{aligned}
S \quad \rightarrow \quad & x \mid 0001_2 \\
\mid \quad & S \wedge S \mid S \vee S \mid S \oplus S \\
\mid \quad & S + S \mid S \times S \mid S / S \mid S >> S
\end{aligned}
$$

Semantic Spec

$f(1011_2) = 0011_2$



$$\nexists \square . f(1011_2) = 1011_2 >> \square = 0011_2$$

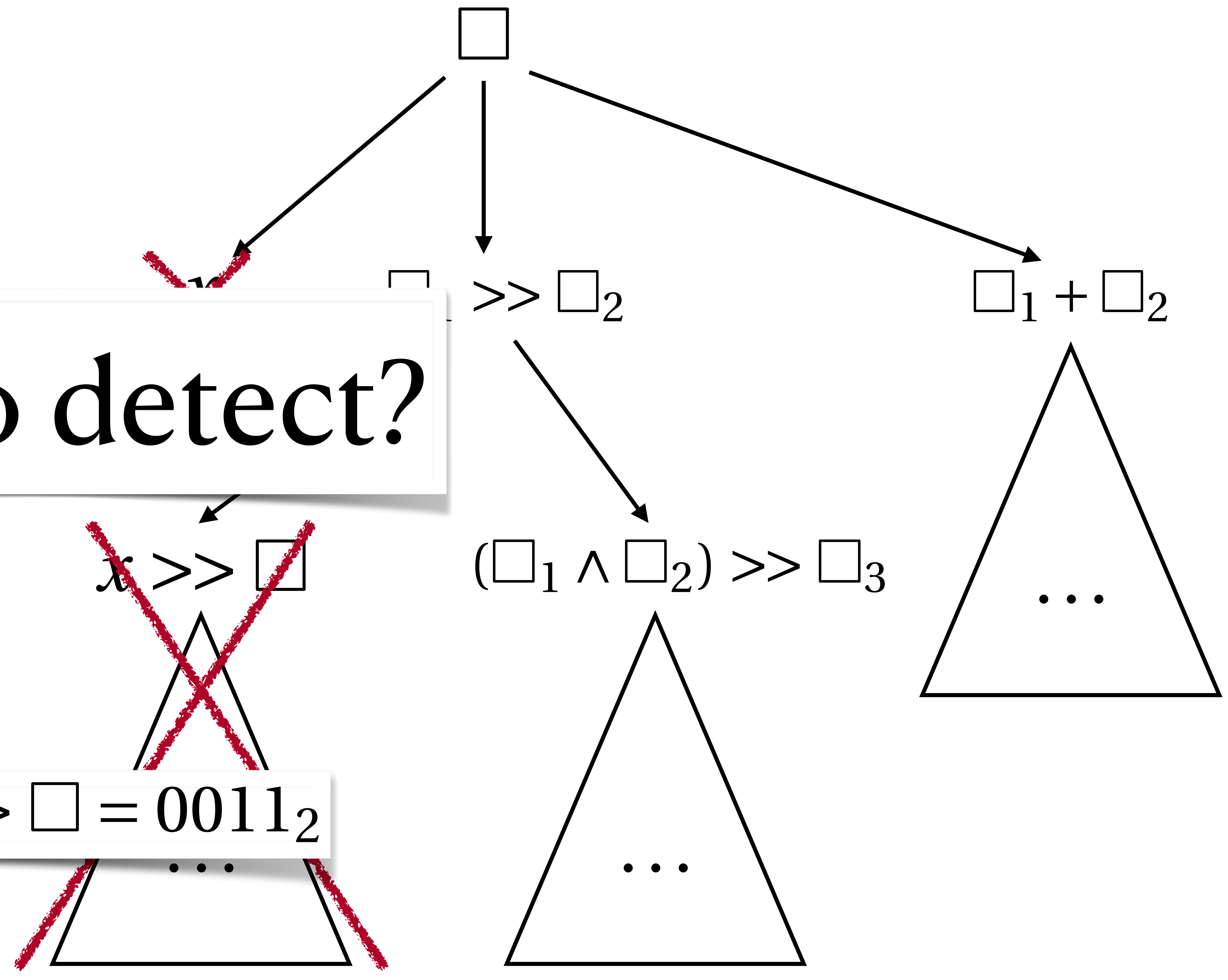
Example

Syntactic Spec

$$
\begin{array}{rcl}
S & \rightarrow & x \mid 0001_2 \\
 & \mid & S \land S \mid S \lor S \mid S \oplus S \\
 & \mid & S + S \mid S \times S \mid S / S \mid S >> S
\end{array}
$$

Semantic Spec

$$f(1011_2) = 0011_2$$

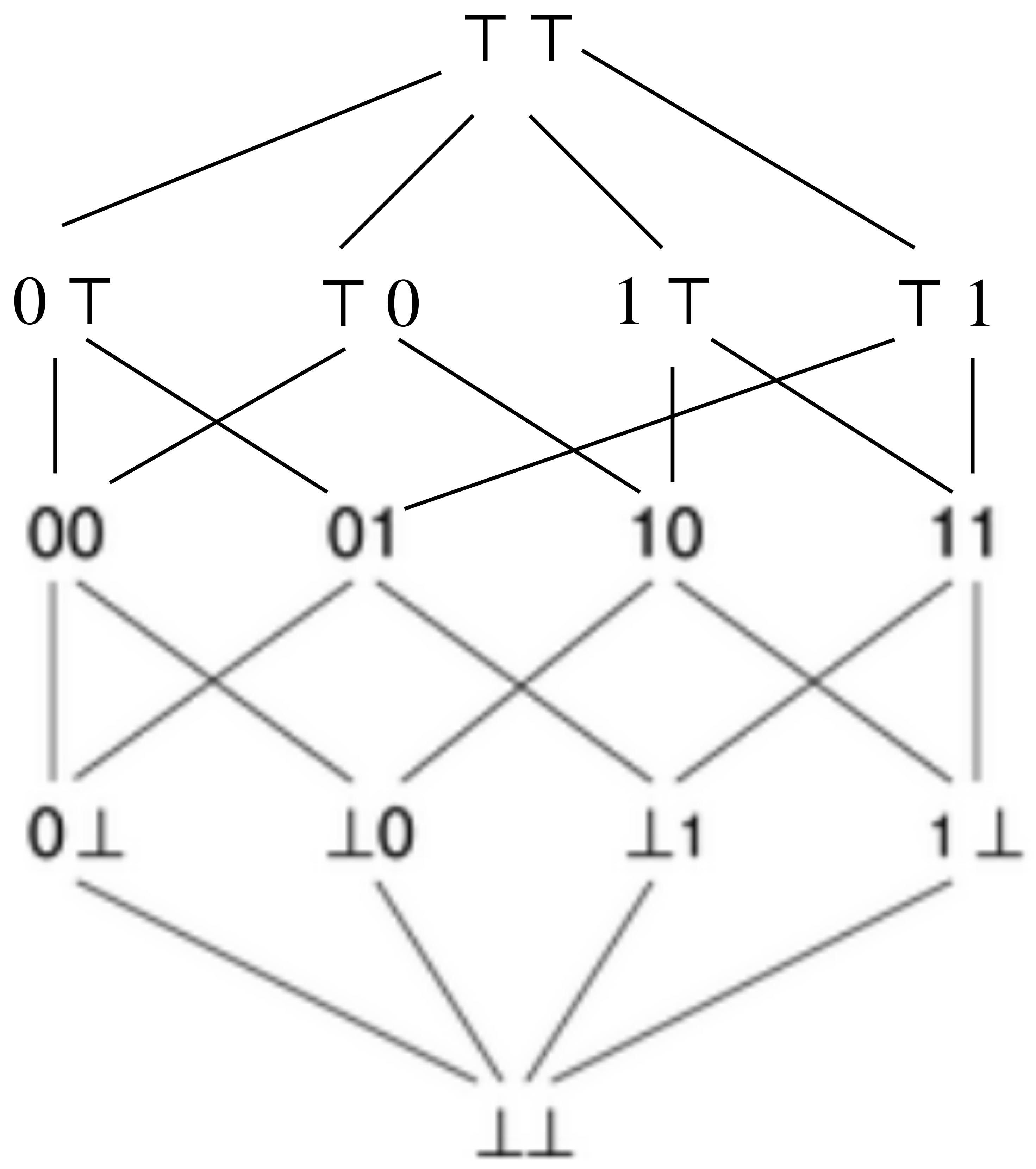


How to detect?

$$\nexists \Box . f(1011_2) = 1011_2 >> \Box = 0011_2$$

Static Analysis

- Simulation of program execution with “abstract" values instead of concrete ones
  - Abstraction = over-approximation (e.g., concrete : {0, 2, 6} → abstract : even)
- Bitfield abstract domain
  - Each bit is represented by $\{0, 1, \bot, \top\}$
  - $\top$: unknown, $\bot$: no value
- e.g., $\top 01 \top$ represents a set $\{0010_2, 0011_2, 1010_2, 1011_2\}$
- Abstract operators (denoted with #)
  - e.g., $1\top 10 \wedge^{\#} 00\top\top = 00\top 0$



Using Forward Analysis

Checking only output feasibility

Semantic Spec

$f(1011_2) = 0011_2$

Candidate Partial Program

$f(x) = x \lor \square$

Forward

$$
\begin{aligned}
x &\mapsto 1011 \\
\square &\mapsto \top\top\top\top
\end{aligned}
$$

Using Forward Analysis

Checking only output feasibility

Semantic Spec

$f(1011_2) = 0011_2$

Candidate Partial Program

$f(x) = x \vee \square$

Forward

$$\begin{aligned} x &\mapsto 1011 \\ \square &\mapsto \top\top\top\top \\ x \vee \square &\mapsto 1\top 11 \not\sqsupseteq 0011 \end{aligned}$$

Infeasible output

Limitation of Forward Analysis

Checking only output feasibility

Semantic Spec

$f(1011_2) = 0011_2$

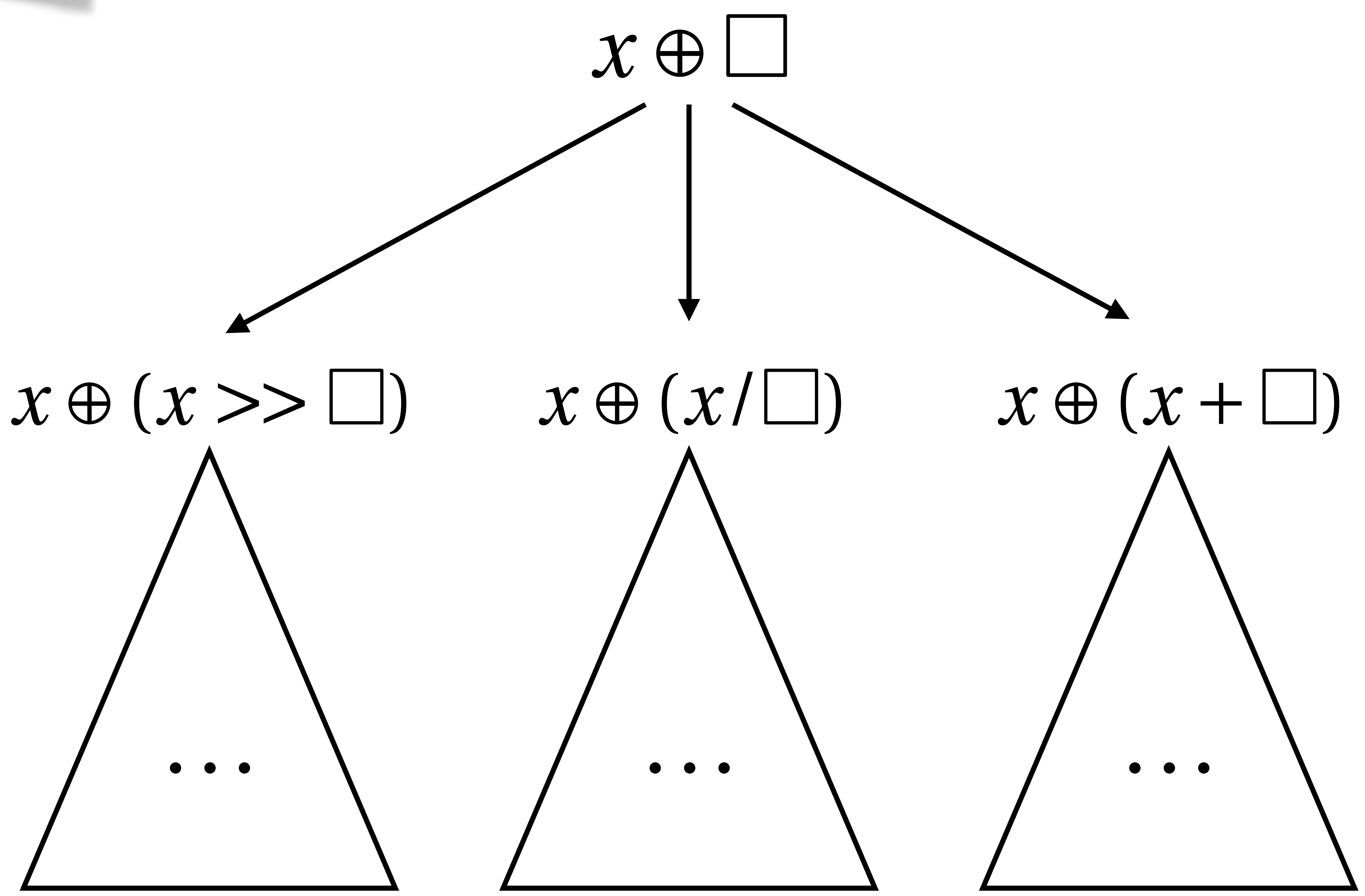
Candidate Partial Program

$f(x) = x \oplus \square$

Forward

$$
\begin{aligned}
x &\mapsto 1011 \\
\square &\mapsto \top\top\top\top \\
x \oplus \square &\mapsto \top\top\top\top \;\sqsupseteq 0011
\end{aligned}
$$

Nothing to do



Need: Backward Analysis Too

Output feasibility + Hole Precondition

Semantic Spec

$f(1011_2) = 0011_2$

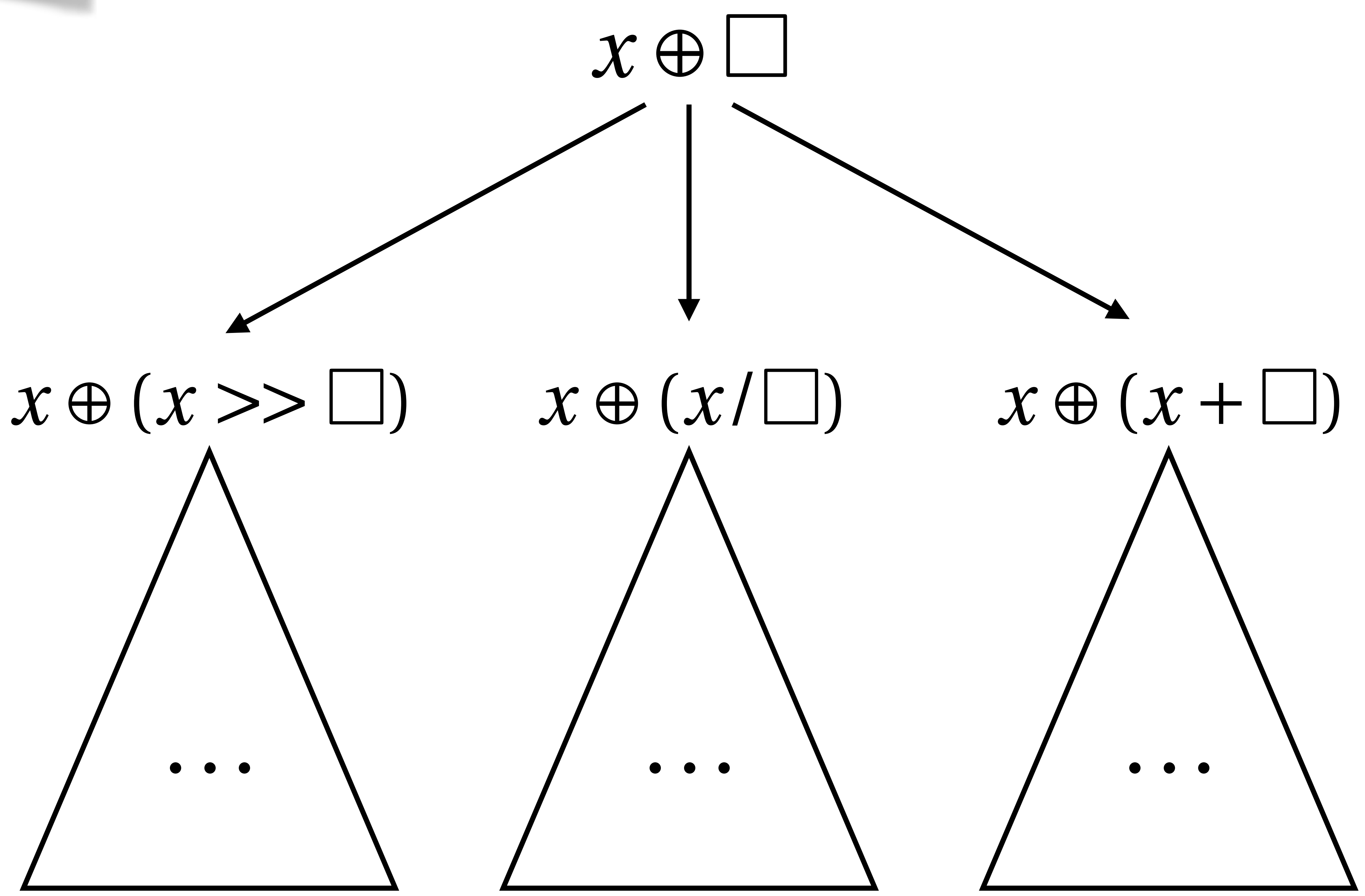
Candidate Partial Program

$f(x) = x \oplus \square$

Forward

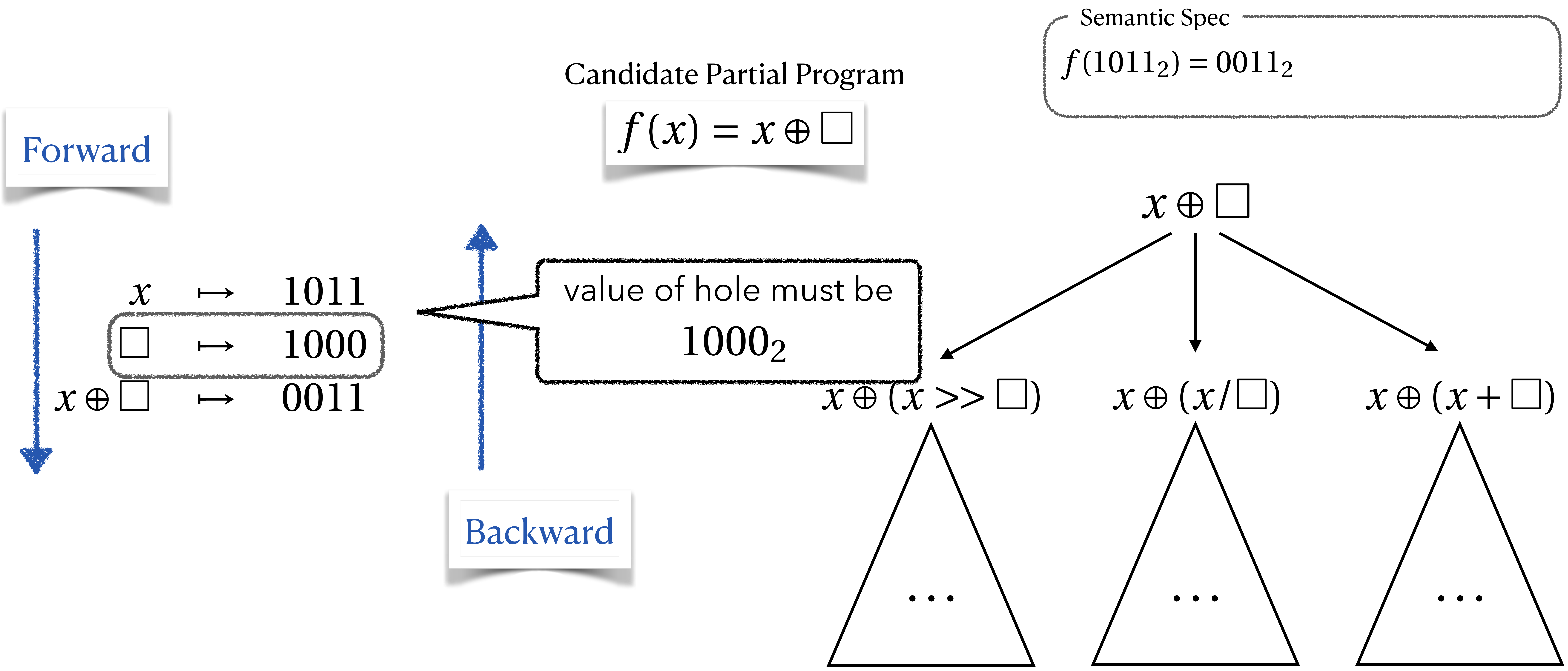
$$x \mapsto 1011$$
$$\square \mapsto \top\top\top\top$$
$$x \oplus \square \mapsto 0011$$

Backward



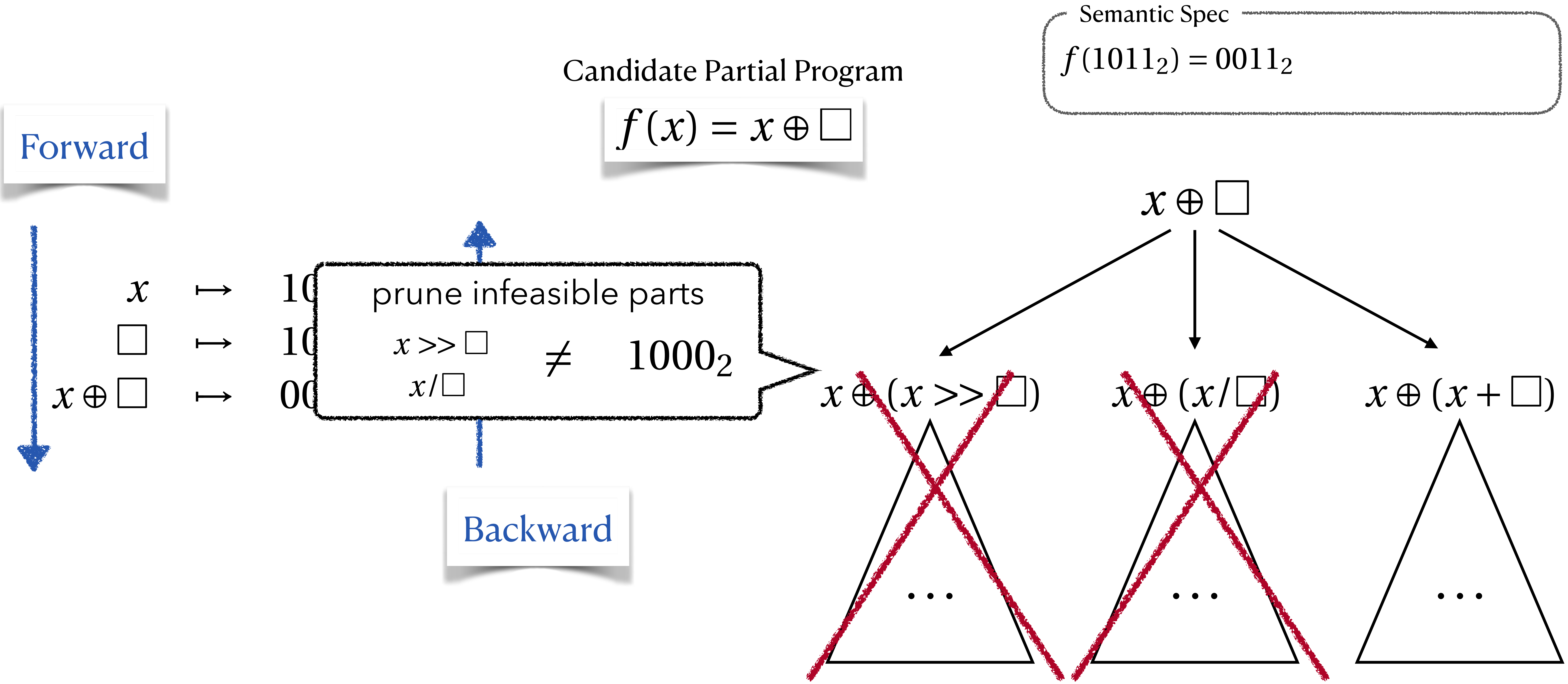
Need: Backward Analysis Too

Output feasibility + Hole Precondition



Need: Backward Analysis Too

Output feasibility + Hole Precondition

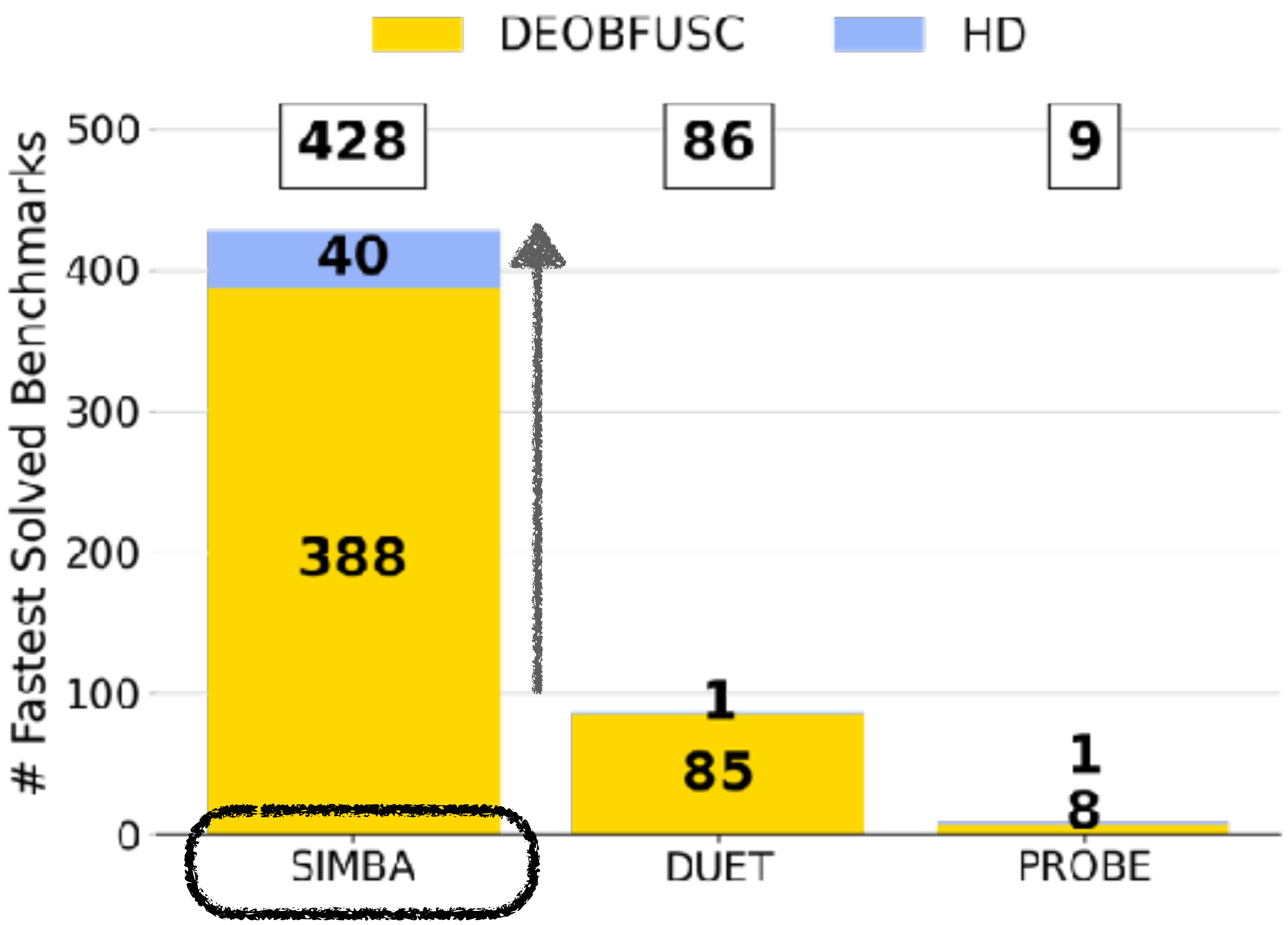


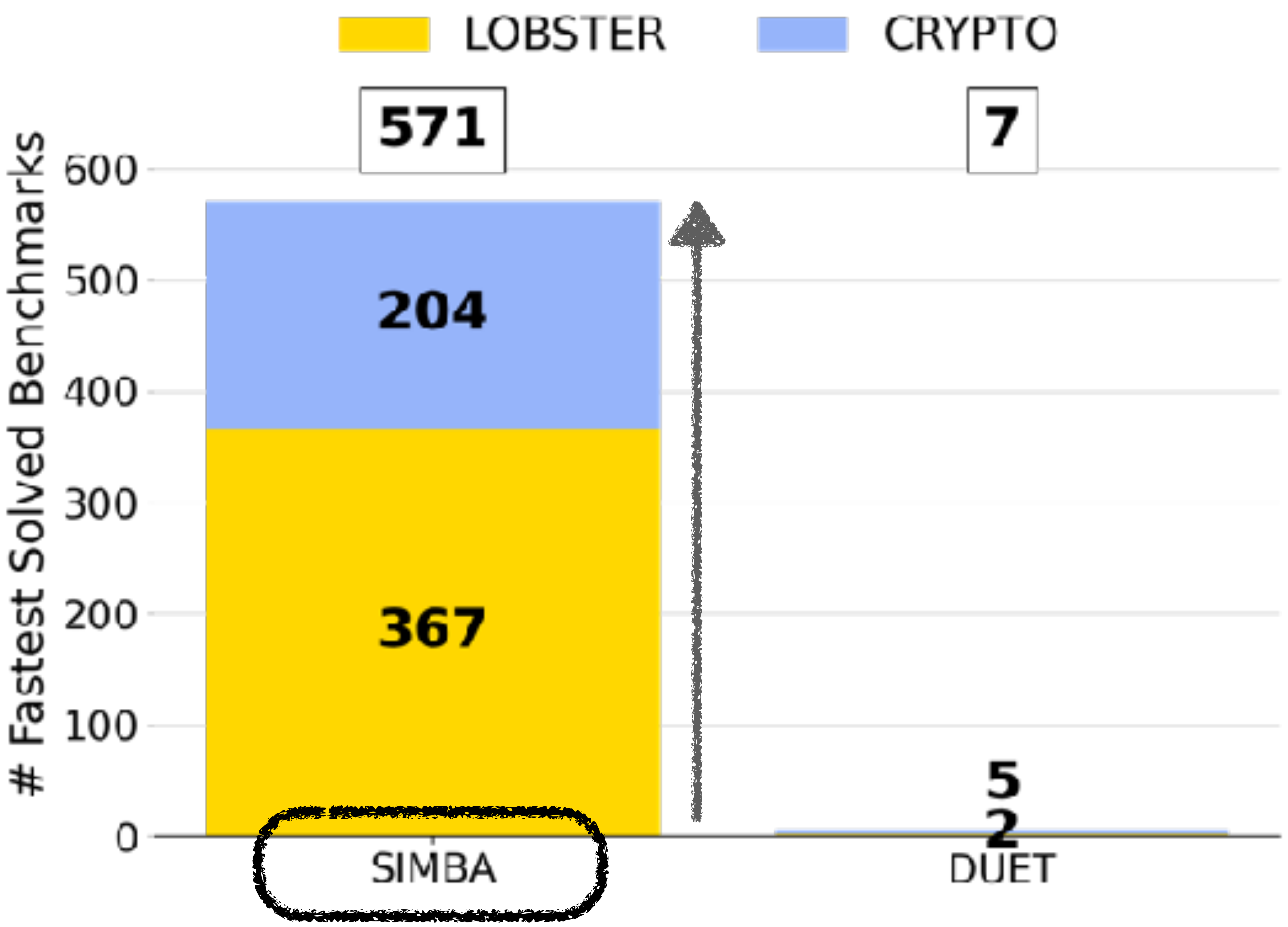
Evaluation

- Our tool: **Simba**
- Benchmark: 1,125 synthesis tasks from 4 sources
  - HD: 44 from hacker's delight
  - Deobfsc: 500 from the program deobfuscation tasks in prior work
  - Lobster: 369 from optimizing homomorphic evaluation circuits
  - Crypto: 212 from generating circuits resilient to side-channel attacks
- Baseline tools
  - **duet**: Woosuk Lee, "Combining the Top-Down Propagation and Bottom-Up Enumeration for Inductive Program Synthesis", POPL'21
  - **probe**: Barke et al., Just-in-Time Learning for Bottom-Up Enumerative Synthesis, OOPSLA'20

Results

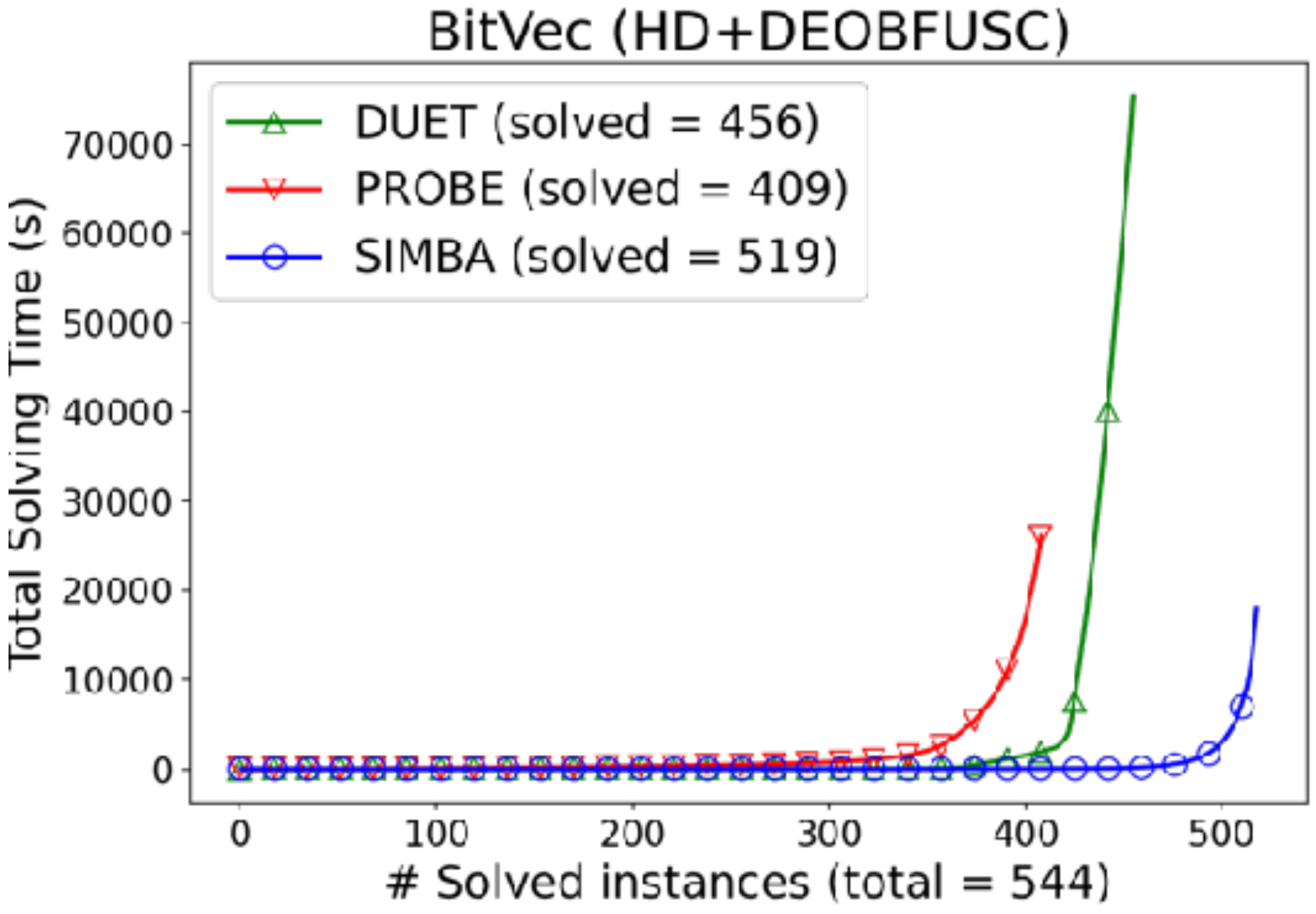
- Siginificantly outperforms the baseline tools

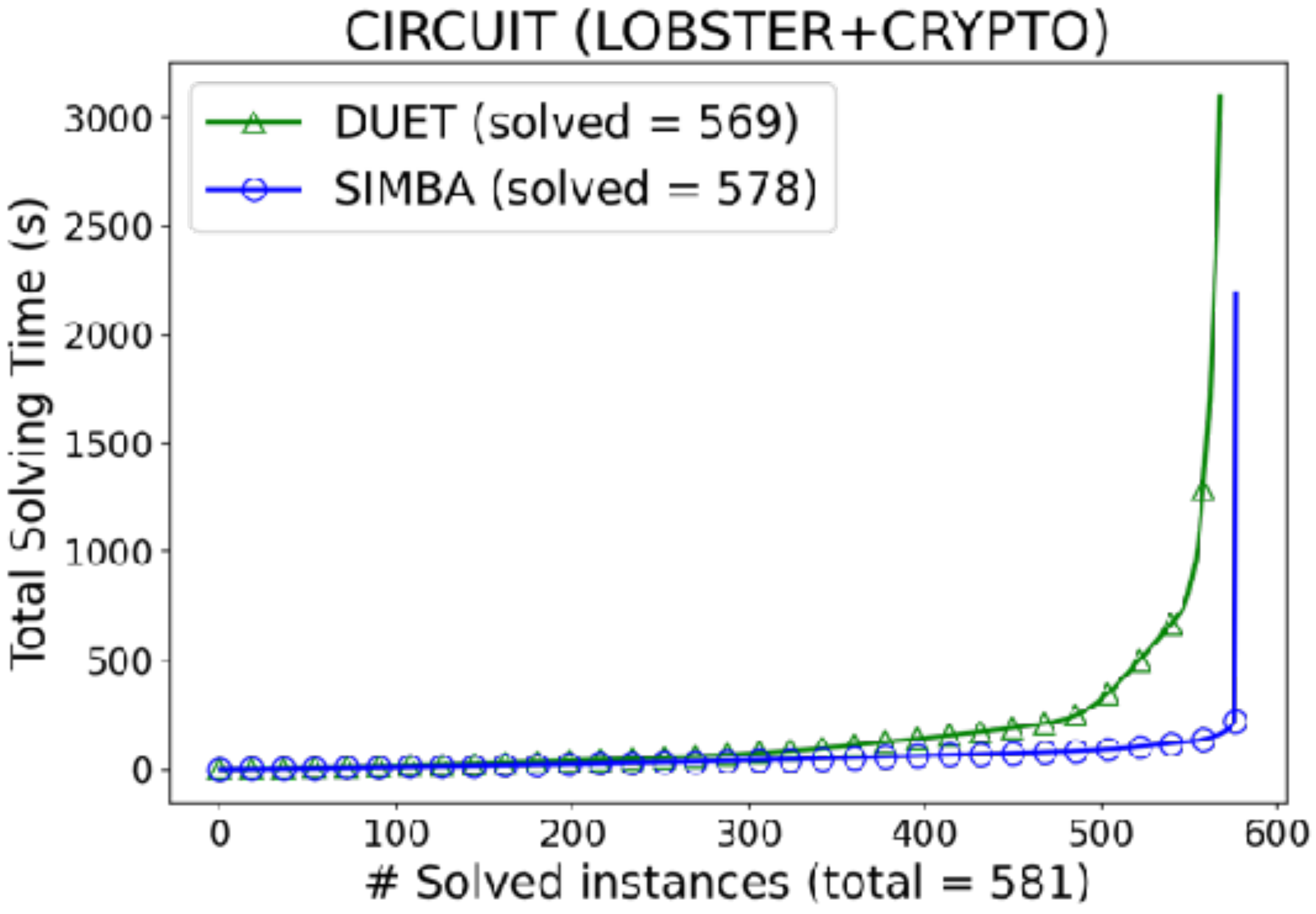




Results

- Siginificantly outperforms the baseline tools





Conclusion

- By using advanced search algorithms
  - program synthesis, term rewriting, and equality saturation
  - and by leveraging the high performance of modern computers
- In certain cases
  - Low-level languages
  - e.g., Boolean circuits and bitwise integers
- We can achieve better optimization than domain experts
  - By discovering new optimization rules
  - and sophisticated rule application orders that yield (nearly)optimal results