

# Optimizing Homomorphic Evaluation Circuit with Program Synthesis and Term Rewriting

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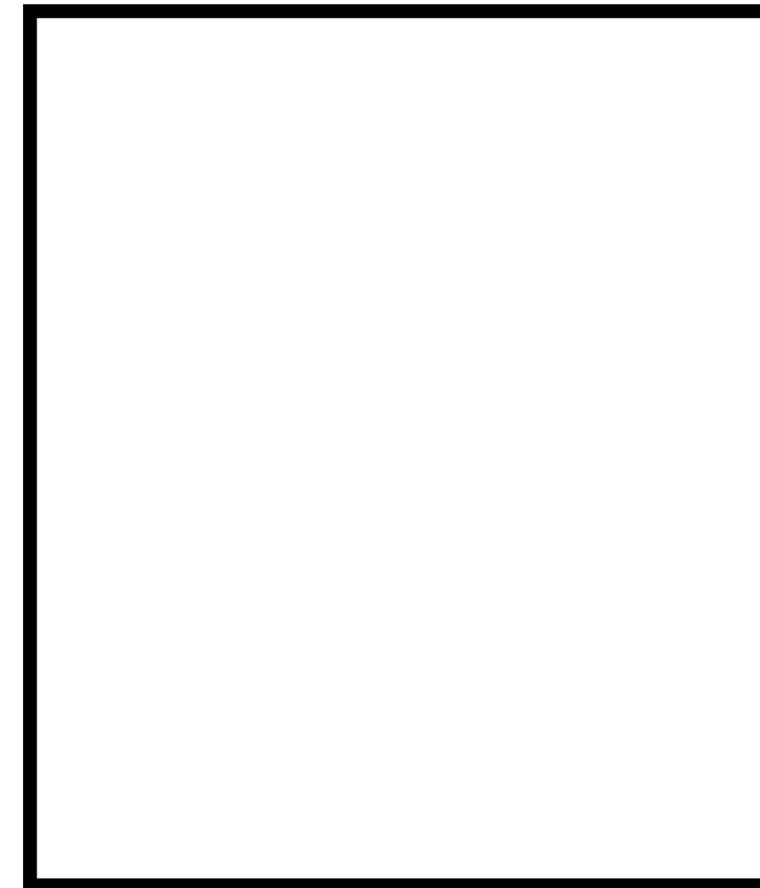
# References

- *Optimizing Homomorphic Evaluation Circuits by Program Synthesis and Term Rewriting*,  
**PLDI 2020**: Proceedings of the 41st ACM SIGPLAN Conference on Programming Language Design and Implementation
- *Optimizing Homomorphic Evaluation Circuits by Program Synthesis, Term Rewriting, and Time-bounded Exhaustive Search*,  
**TOPLAS**: ACM Transactions on Programming Languages and Systems (under review)

# Homomorphic Evaluation(HE) (1/3)

## Privacy Preserving Secure Computation

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

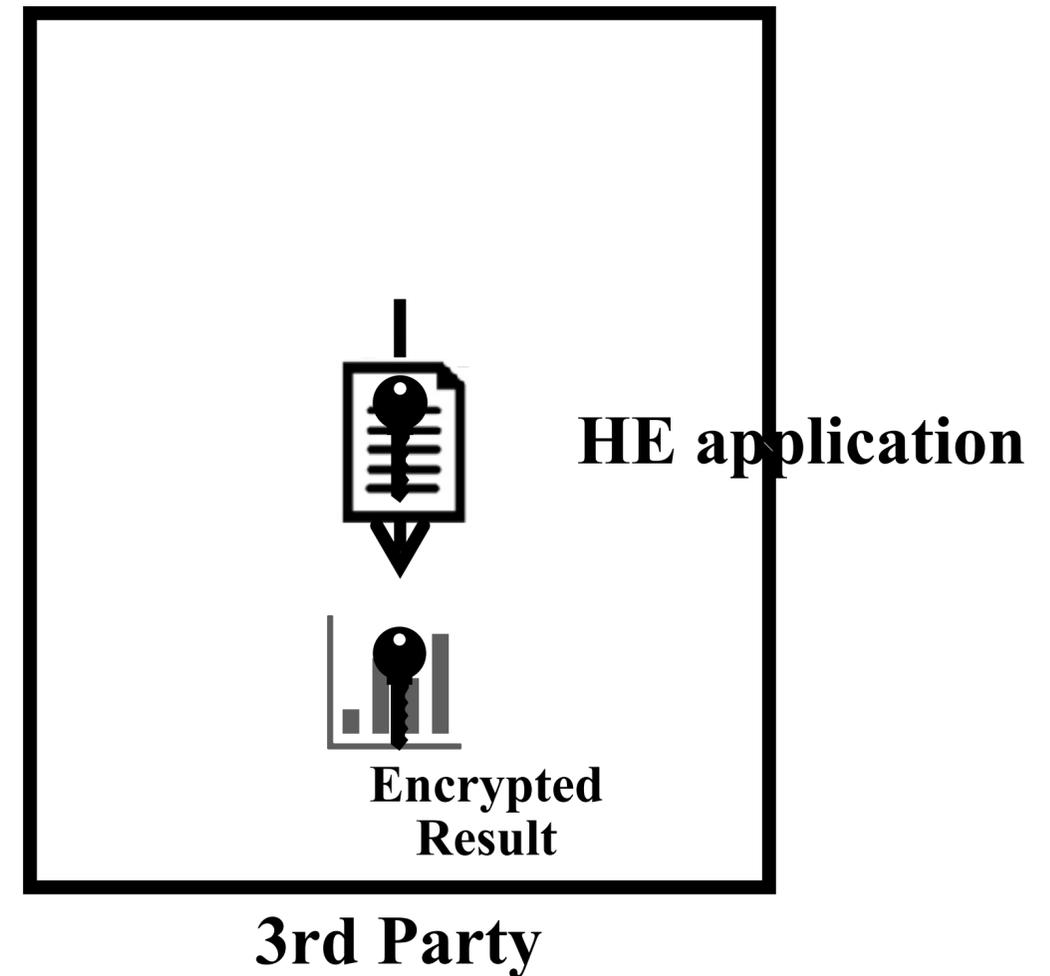


3rd Party

# Homomorphic Evaluation(HE) (1/3)

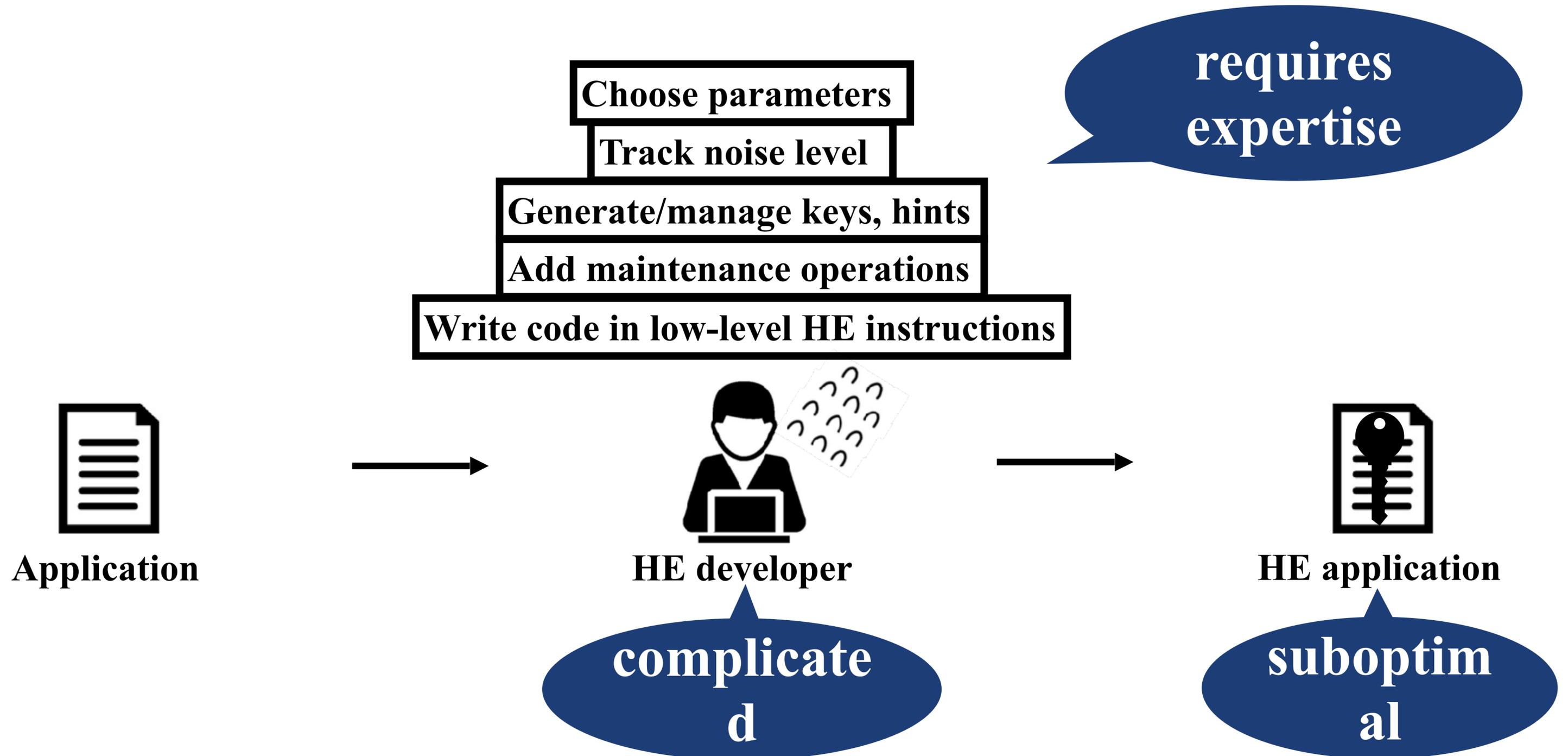
## Privacy Preserving Secure Computation

- Allows for computation on encrypted data
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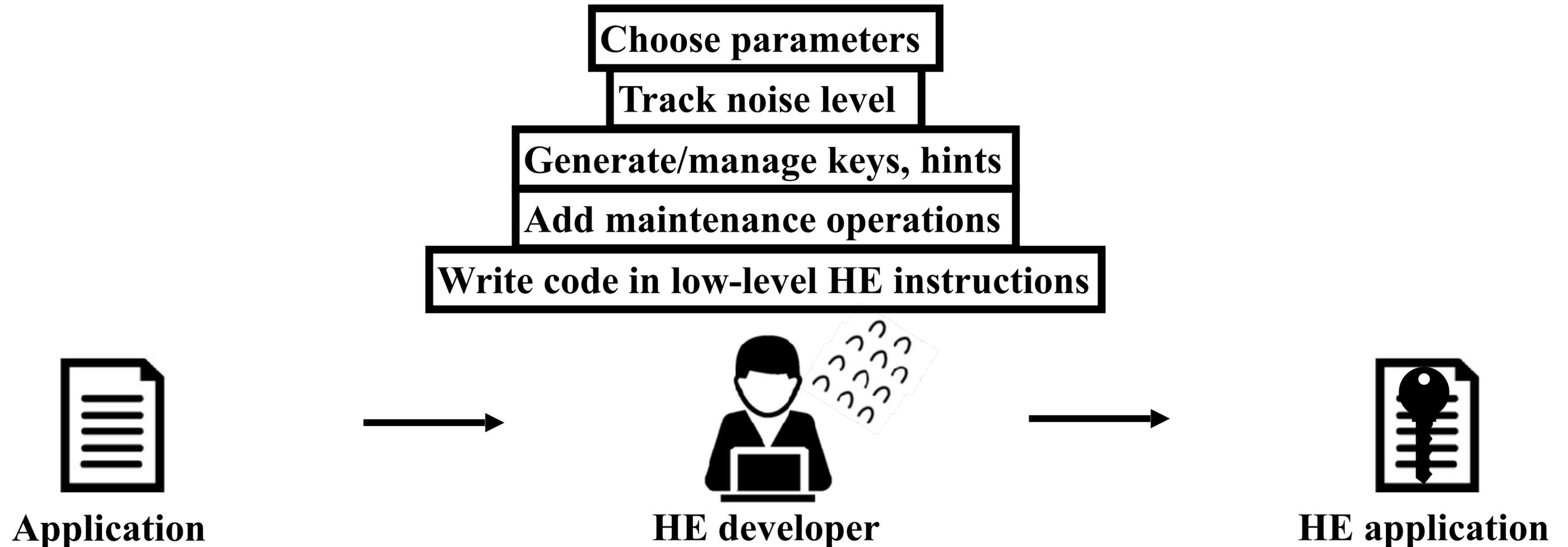
# Homomorphic Evaluation(HE) (2/3)

Building HE applications



# Homomorphic Evaluation(HE) (3/3)

Existing Homomorphic Compiler



# Homomorphic Evaluation(HE) (3/3)

## Existing Homomorphic Compiler

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

Choose parameters

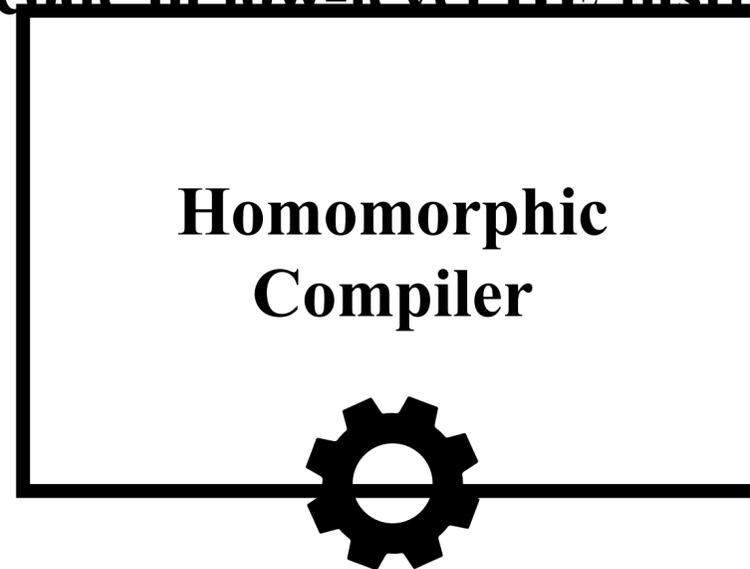
Track noise level

Generate/manage keys, hints

Add maintenance operations

Write code in low-level HE instructions

still,  
suboptimal



HE application

# Homomorphic Evaluation(HE) (2/3)

## Code for homomorphic addition of two integers

```
#include "FHE.h"
#include "EncryptedArray.h"
#include <NTL/lzz_pXFactoring.h>
#include <fstream>
#include <sstream>
#include <sys/time.h>

int main(int argc, char **argv)
{
    long m=0, p=2, r=1; // Native plaintext space
                        // Computations will be 'modulo p'
    long L=16;         // Levels
    long c=3;          // Columns in key switching matrix
    long w=64;         // Hamming weight of secret key
    long d=0;
    long security = 128;
    ZZx G;
    m = FindM(security,L,c,p, d, 0, 0);
    FHEcontext context(m, p, r);
    buildModChain(context, L, c);
    FHESecKey secretKey(context);
    const FHEPubKey& publicKey = secretKey;
    G = context.alMod.getFactorsOverZZ()[0];
    secretKey.GenSecKey(w);
    addSome1DMatrices(secretKey);
    EncryptedArray ea(context, G);
    vector<long> v1;
    v1.push_back(atoi(argv[1]));
    Ctxt ct1(publicKey);
    ea.encrypt(ct1, publicKey, v1);
    v2.push_back(atoi(argv[2]));
    Ctxt ct2(publicKey);
    ea.encrypt(ct2, publicKey, v2);
    Ctxt ctSum = ct1;
    ctSum += ct2;
```

```
#include <iostream>
#include <fstream>
#include <integer.hxx>

int main()
{
    Integer8 a, b, c;

    cin >> a;
    cin >> b;
    c = a + b;

    cout << c;
    FINALIZE_CIRCUIT(blif_name);
}
```

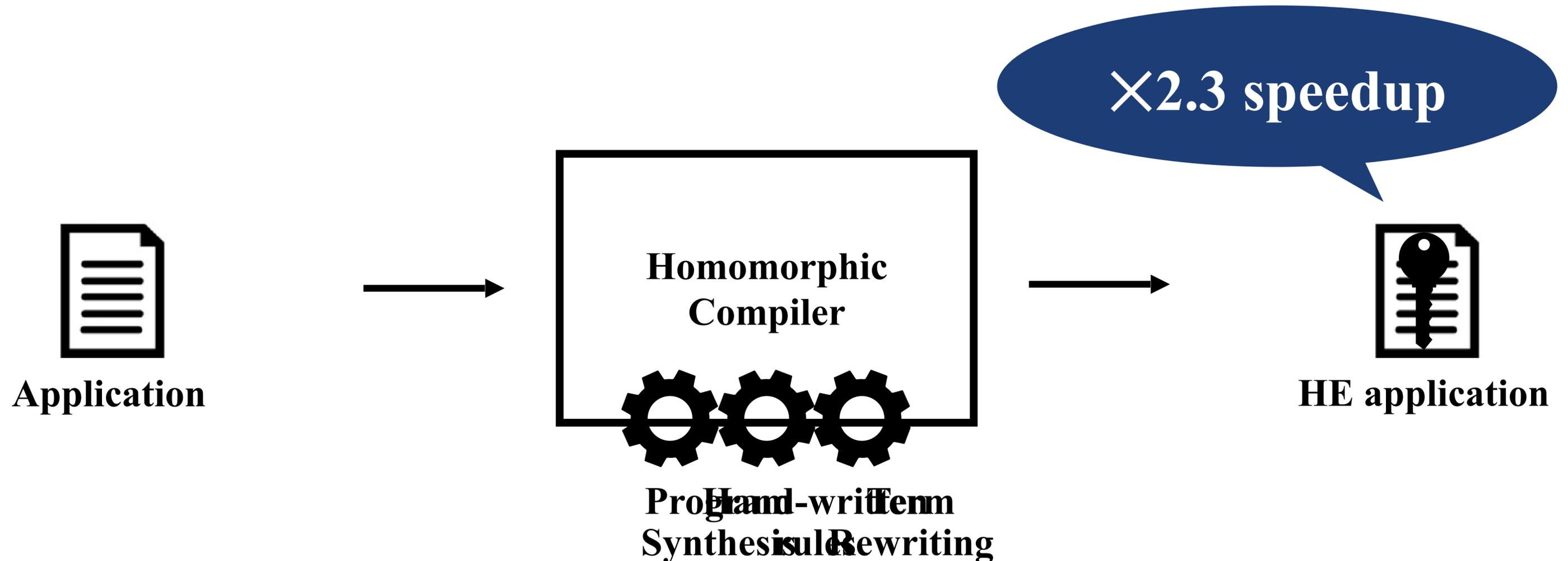
Manually written  
using HElib

Input to Cingulata  
(a HE compiler)

# Our Contributions (1/2)

## Automatic, Aggressive HE optimization Framework

- Generates HE applications automatically
- Optimization : search for new rules by program synthesis + applying by term rewriting



# Our Contributions (2/2)

## Automatic, Aggressive HE optimization Framework

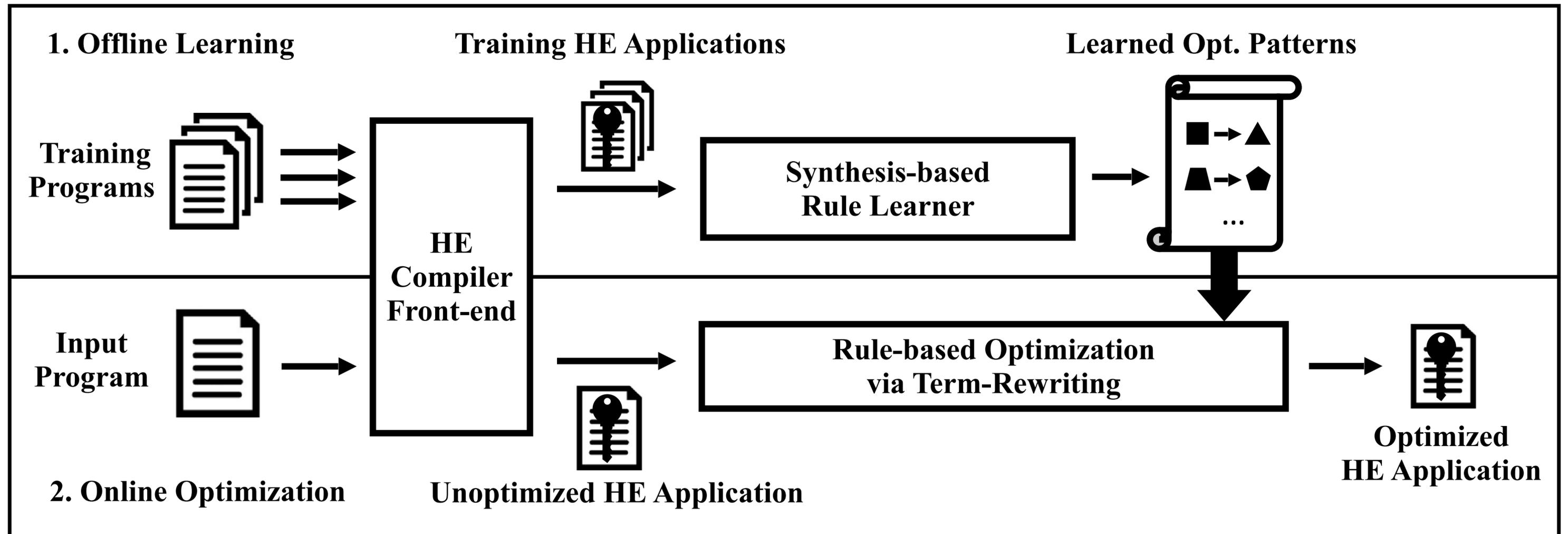
- Learning Optimization Patterns by Program Synthesis
- Applying Learned Patterns by Term Rewriting
- Theorem : Semantic Preservation & Termination Guaranteed
- Performance (vs state-of-the-art HE Optimizer)
  - Optimized 22 out of 25 Applications (vs 15)
  - x5.43 Speedup in Maximum (vs x3.0)
  - x2.26 Speedup on Average (vs x1.53)
- Open Tool Available : <https://github.com/dklee0501/Lobster>



# Our Lobster

Learning to Optimize Boolean circuit using Synthesis and Term Rewriting

- 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

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

$$Dec_p(c) = \underline{(c \bmod p)} \underline{\bmod 2}$$

$$Dec_p(Enc_p(\mu)) = Dec_p(\cancel{pq} + \cancel{2r} + \mu) = \mu$$

- 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

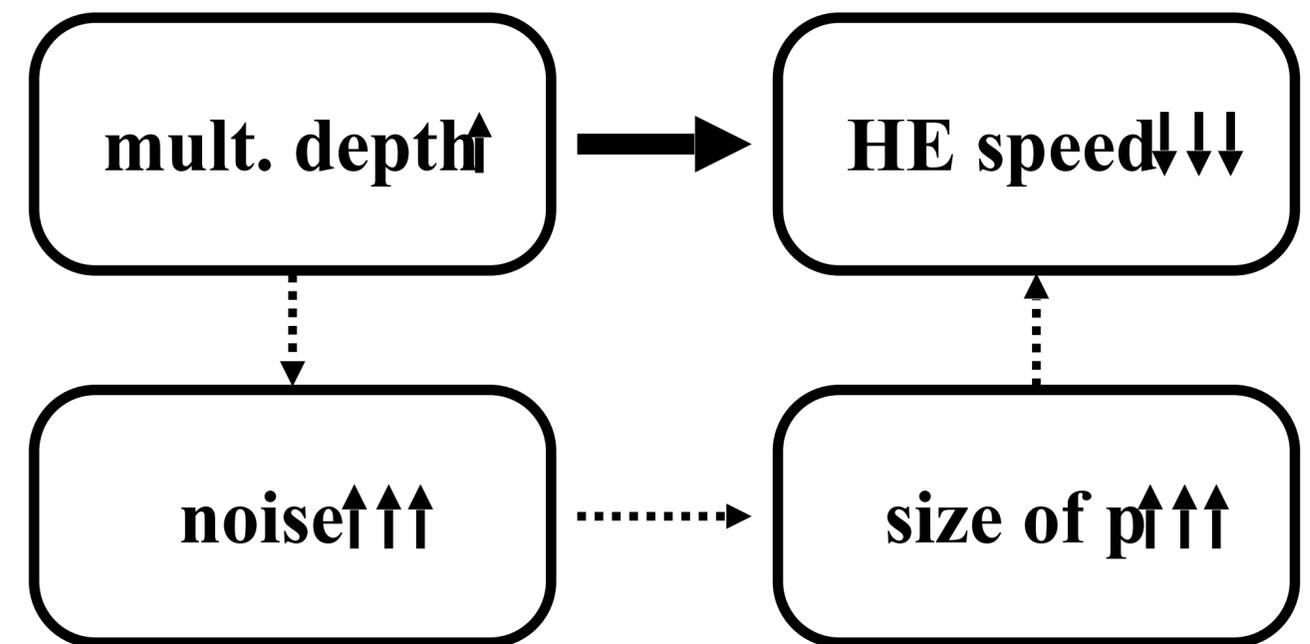
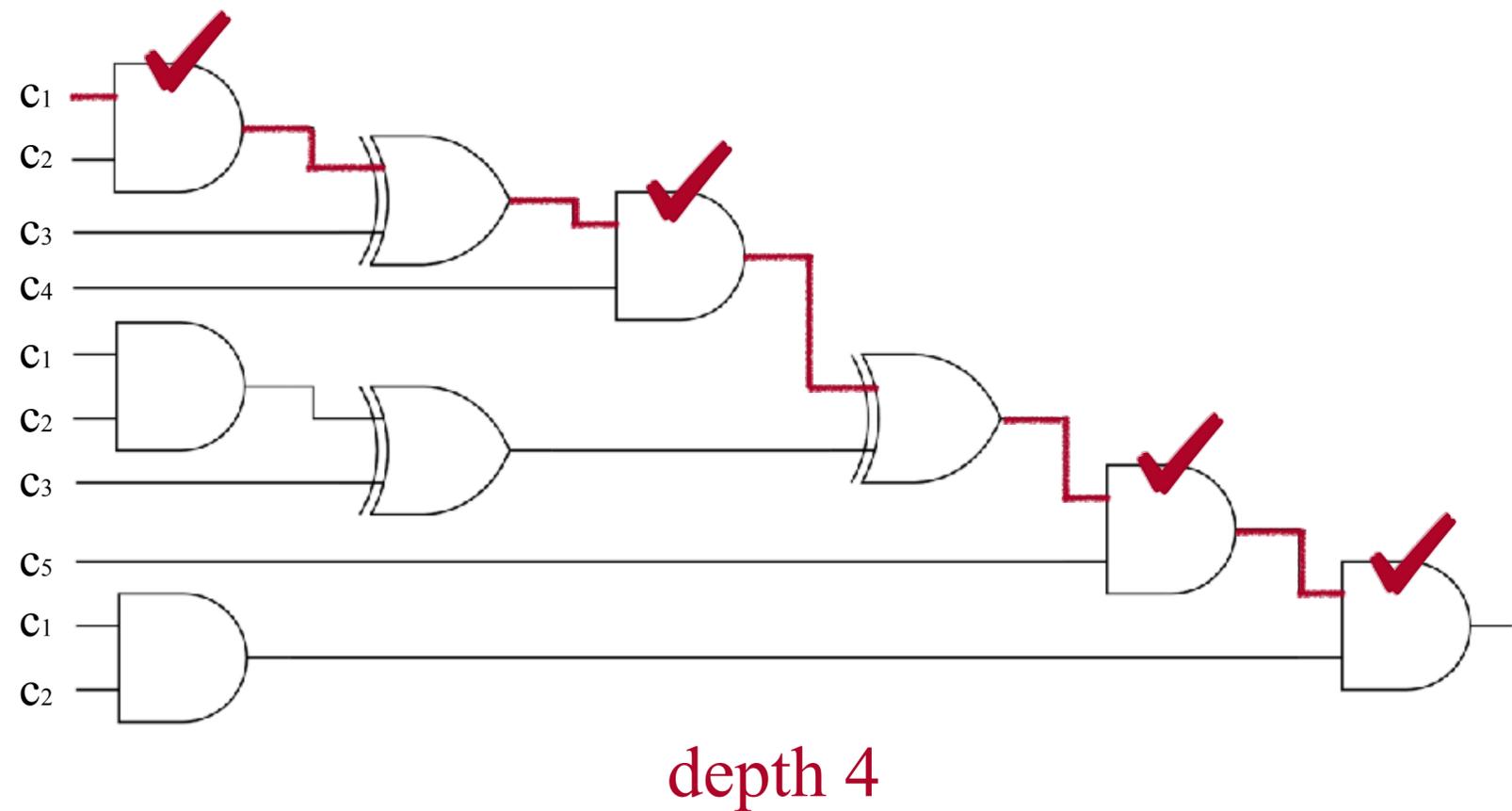
- Noise increases during homomorphic operations.
- For  $\underline{\mu}_i = pq_i + 2r_i + \mu_i$

$$\begin{aligned}\underline{\mu}_1 + \underline{\mu}_2 &= p(q_1 + q_2) + \boxed{2(r_1 + r_2) + (\mu_1 + \mu_2)} \text{ double increase} \\ \underline{\mu}_1 \times \underline{\mu}_2 &= p(pq_1q_2 + \dots) + \boxed{2(2r_1r_2 + r_1\mu_2 + r_2\mu_1) + (\mu_1 \times \mu_2)} \text{ quadratic increase} \\ &\qquad \qquad \qquad \text{noise}\end{aligned}$$

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

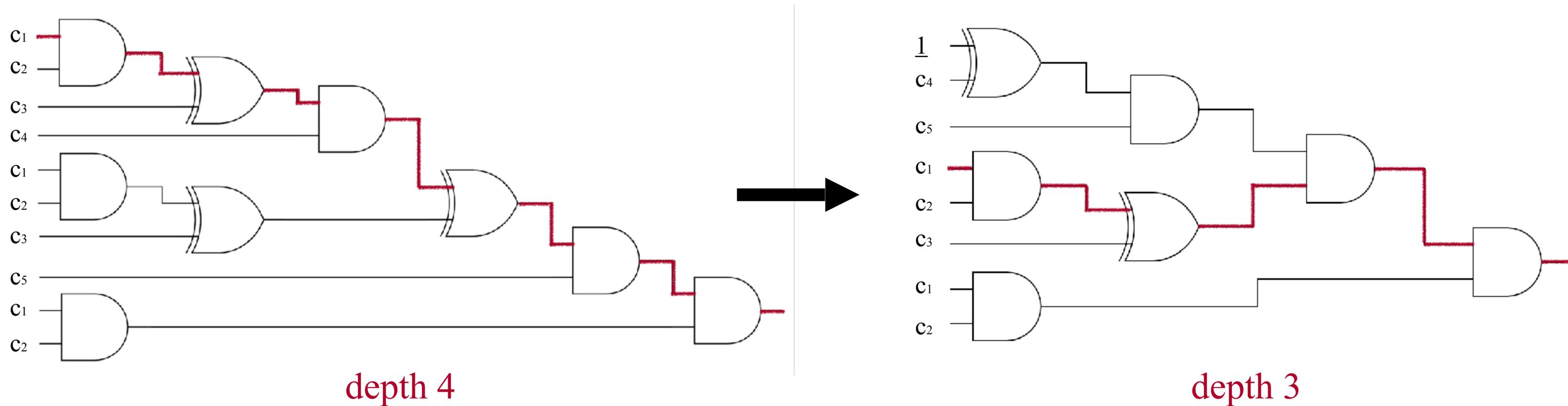
# Multiplicative Depth : a Decisive Performance Factor

- Multiplicative depth : the maximum number of sequential multiplications from input to output

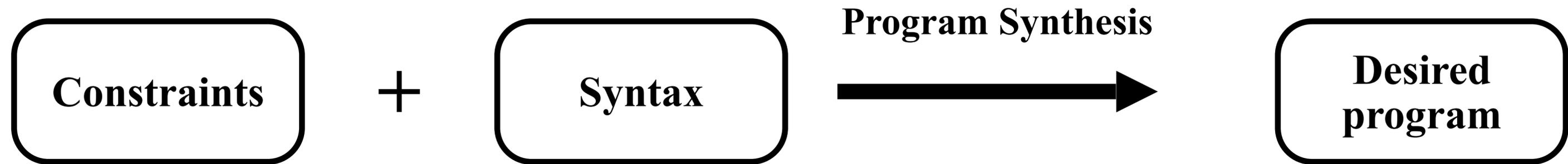


# What is HE optimization?

- Finding a new circuit that has smaller mult. depth



# HE optimization via Synthesis



# HE optimization via Synthesis

Constraints

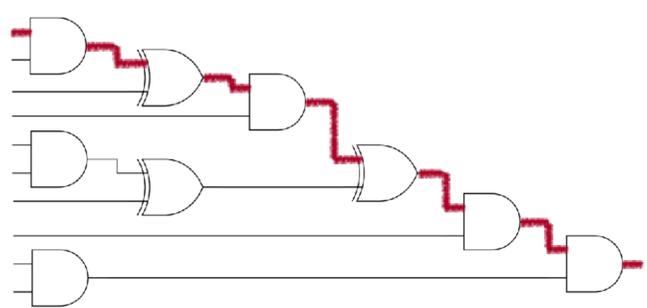
+

Syntax

Program Synthesis



Desired program



depth 4

same semantics

# HE optimization via Synthesis

Constraints

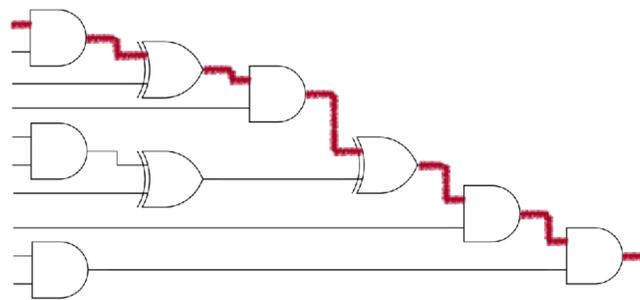
+

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

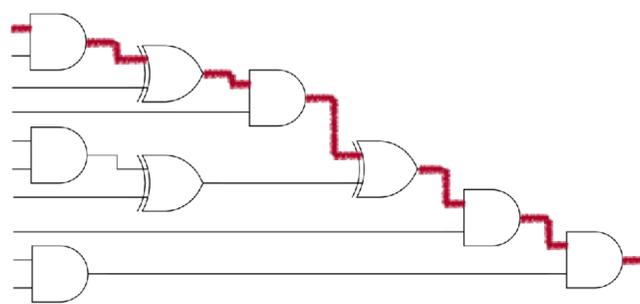
+

Syntax

Program Synthesis



Desired program

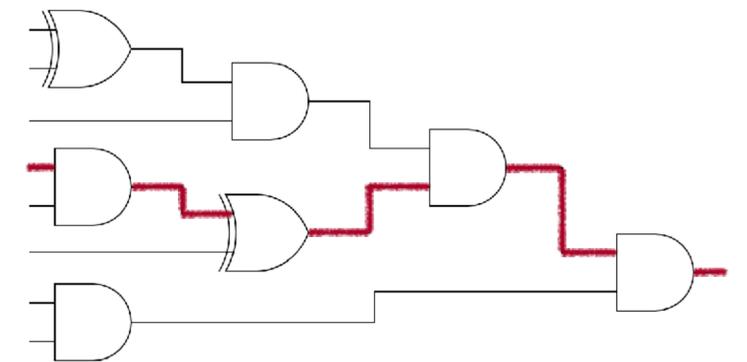


depth 4

same semantics

$S \rightarrow d_3$   
 $d_3 \rightarrow d_2 \wedge d_2 \mid d_3 \oplus d_3 \mid d_2$   
 $d_2 \rightarrow d_1 \wedge d_1 \mid d_2 \oplus d_2 \mid d_1$   
 $d_1 \rightarrow d_0 \wedge d_0 \mid d_1 \oplus d_1 \mid d_0$   
 $d_0 \rightarrow 0 \mid 1 \mid c_1 \mid c_2 \mid c_3 \mid c_4 \mid c_5$

depth-restricting syntax



depth 3

optimized HE circuit

# HE optimization via Synthesis

Constraints

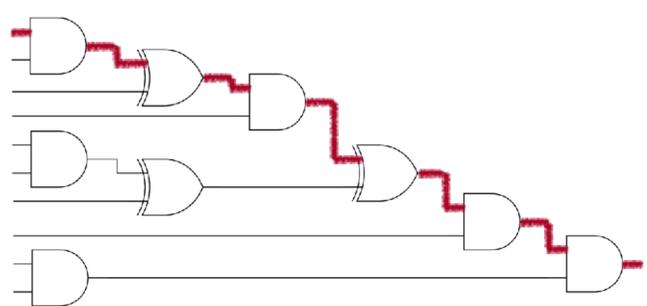
+

Syntax

Optimizing  
Synthesis



Desired  
program

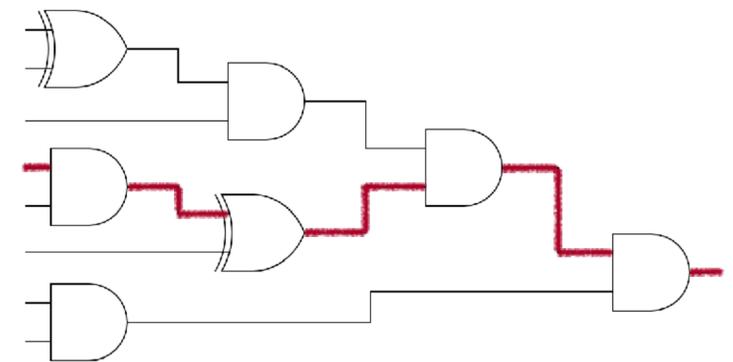


depth 4

same semantics

$S \rightarrow d_3$   
 $d_3 \rightarrow d_2 \wedge d_2 \mid d_3 \oplus d_3 \mid d_2$   
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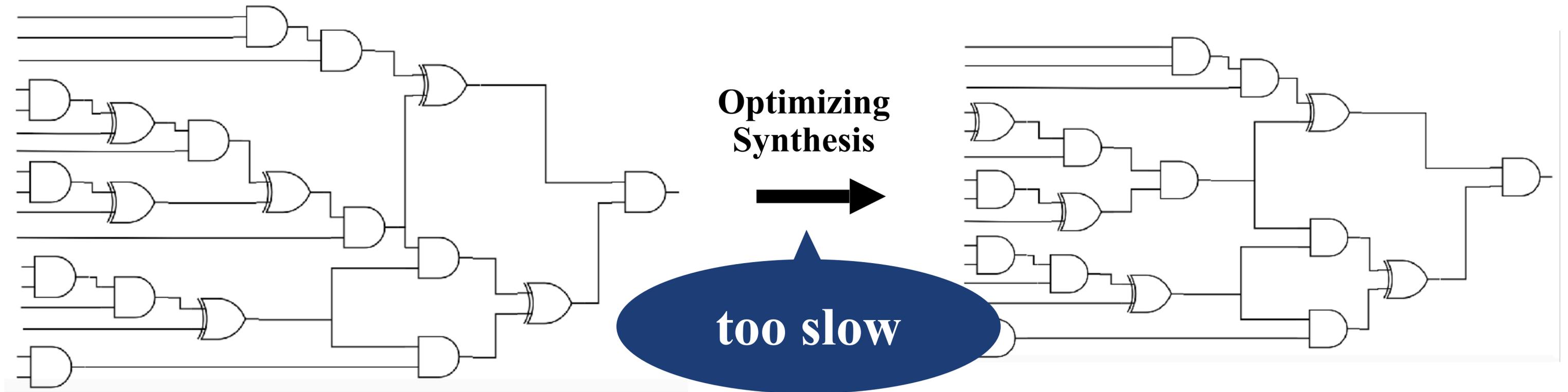
depth-restricting syntax



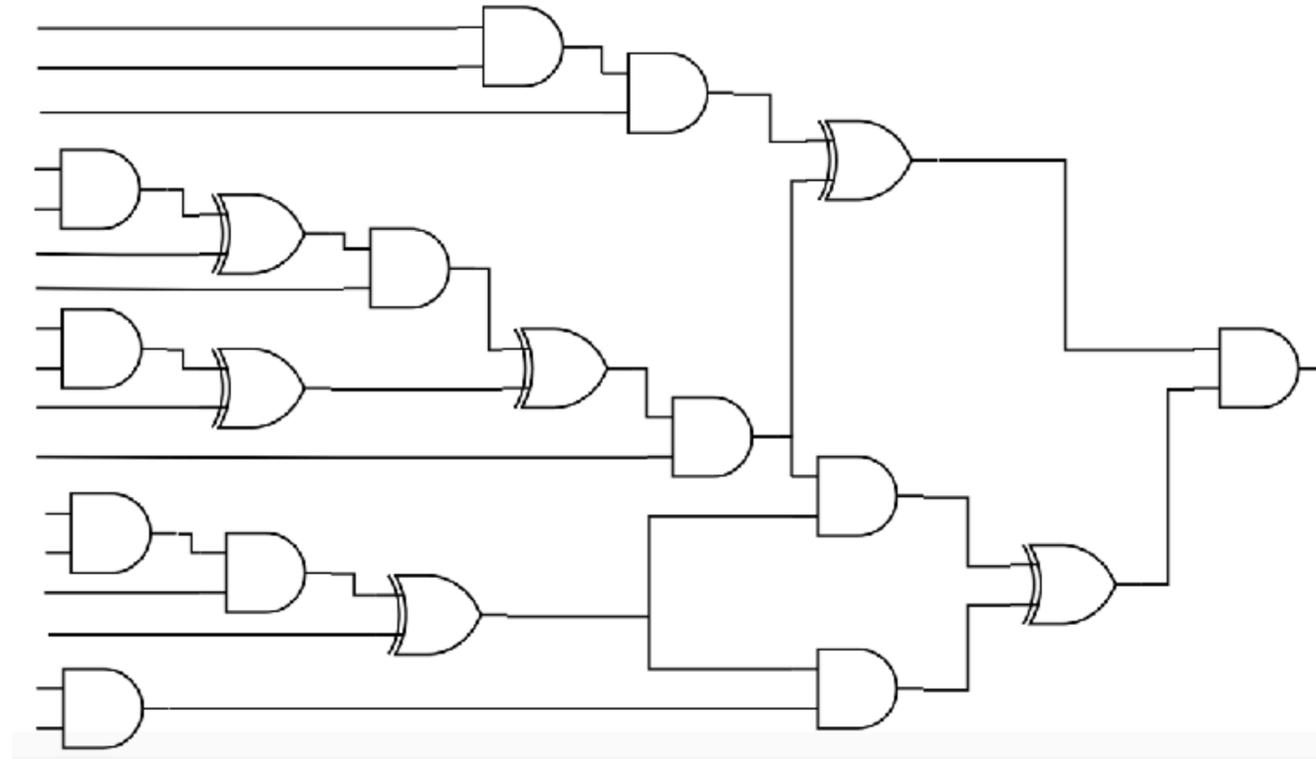
depth 3

optimized HE circuit

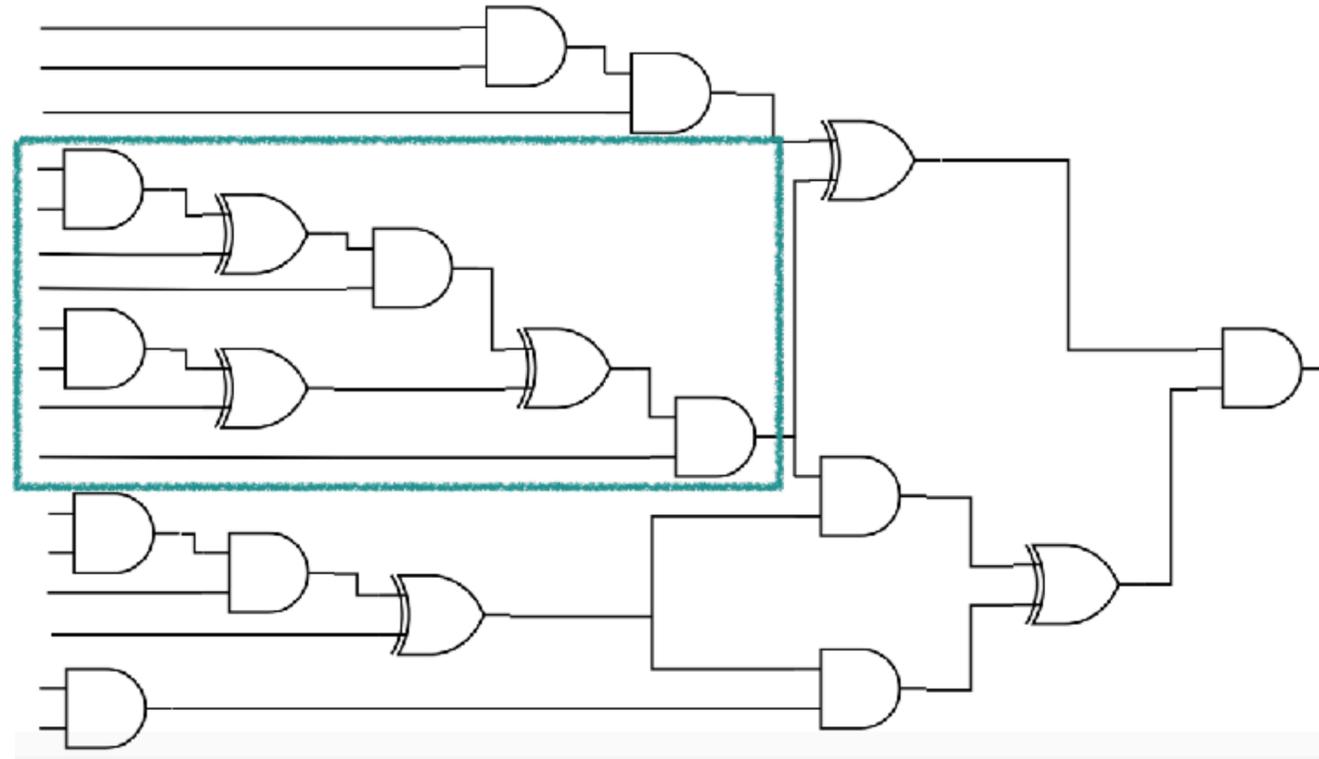
# Hurdle : Synthesis Scalability



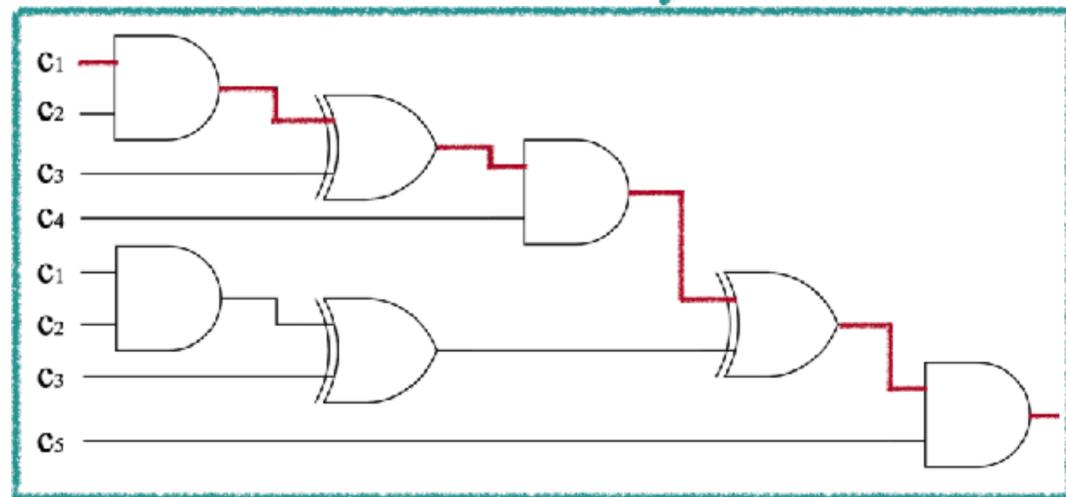
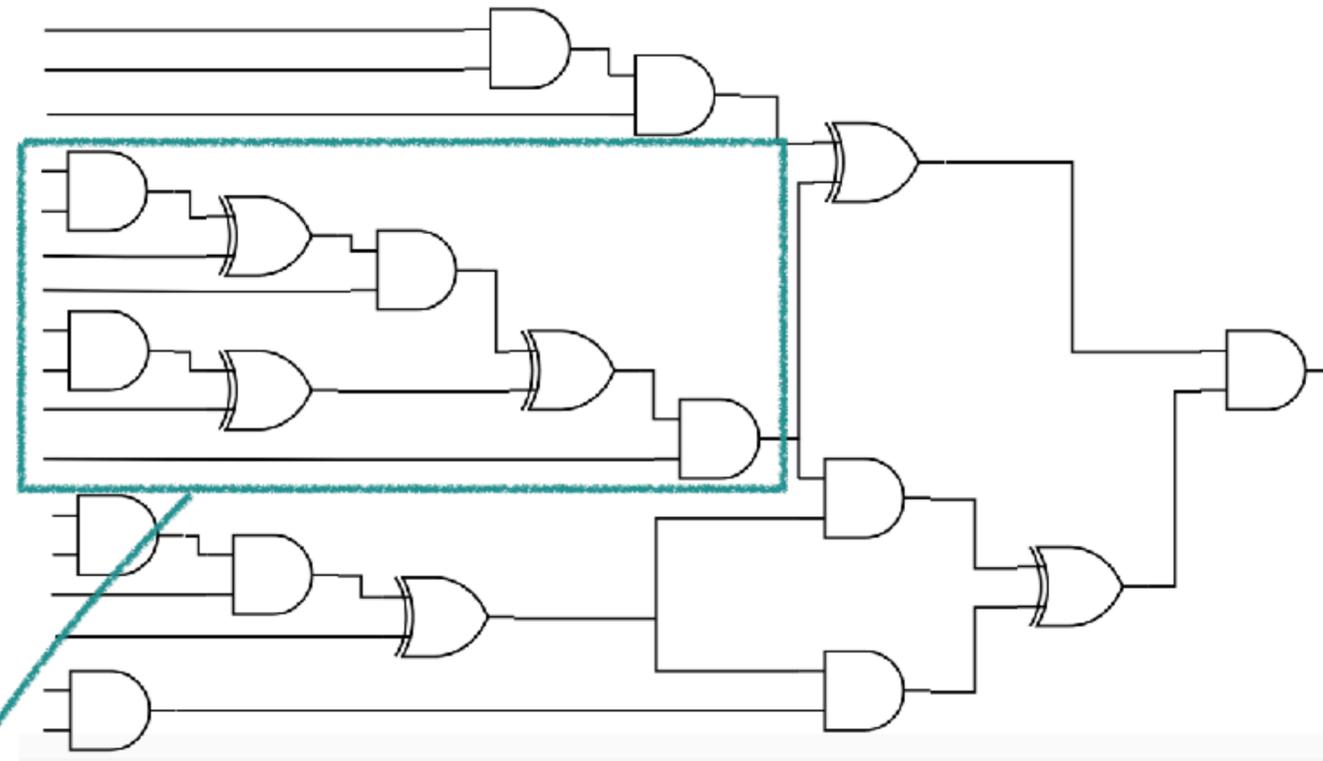
# Solution1 : Synthesis via Localization



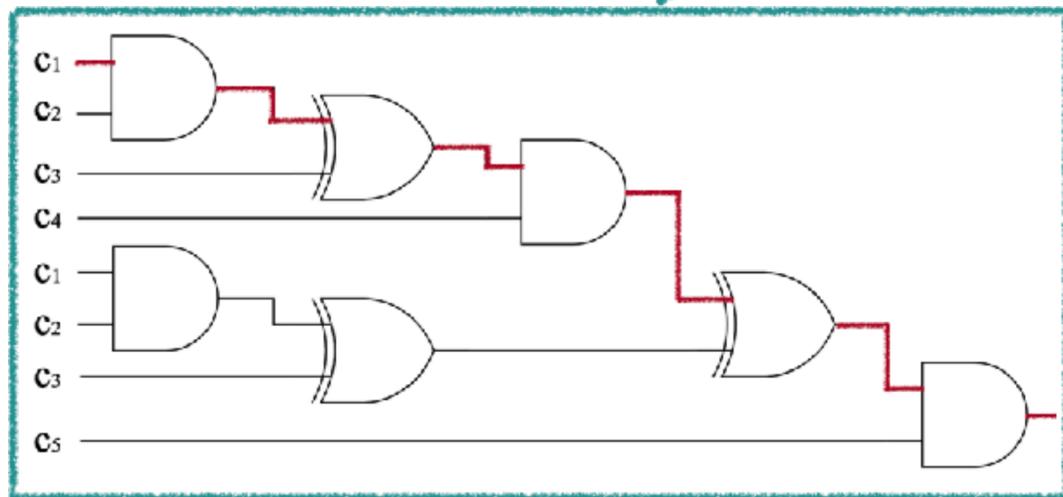
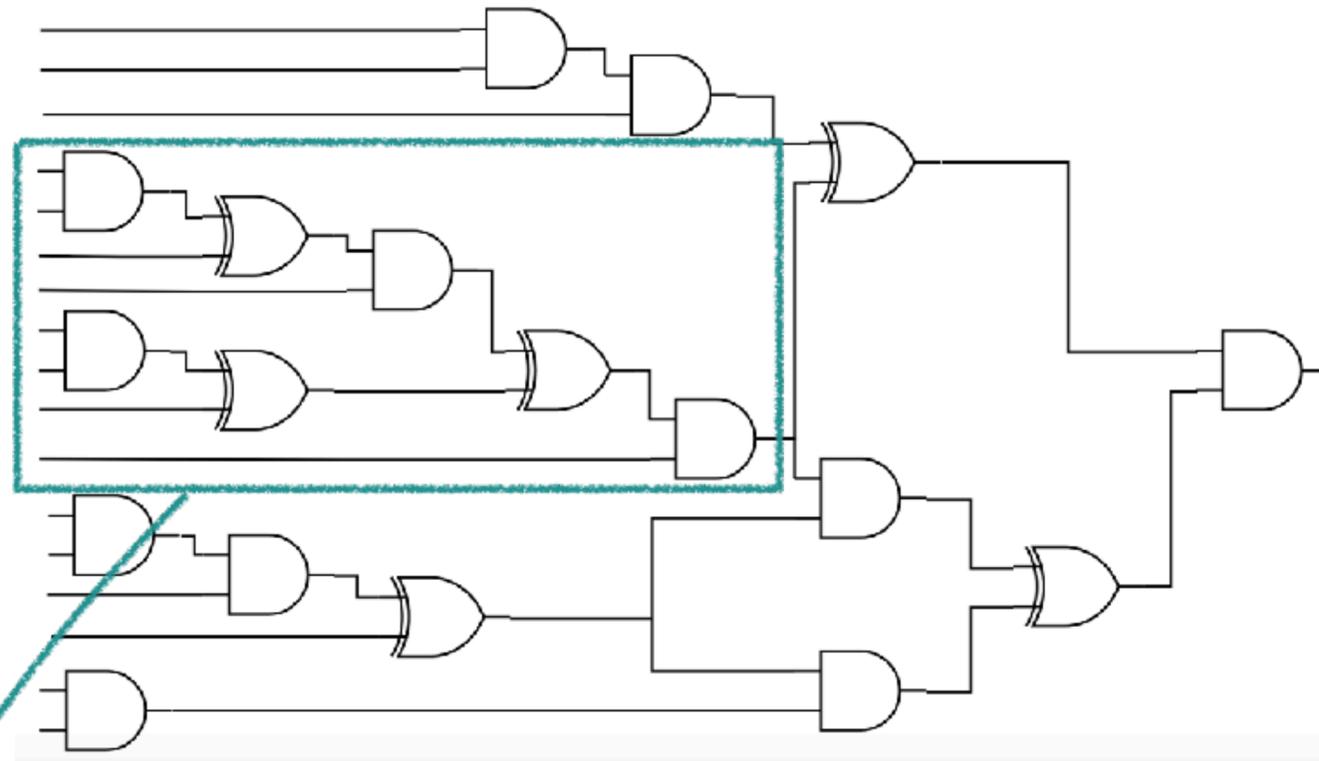
# Solution1 : Synthesis via Localization



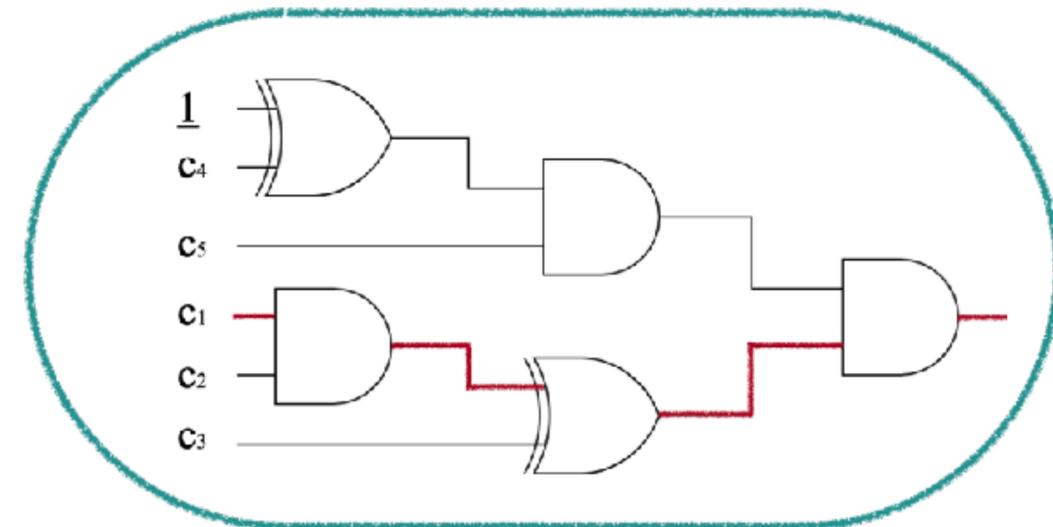
# Solution1 : Synthesis via Localization



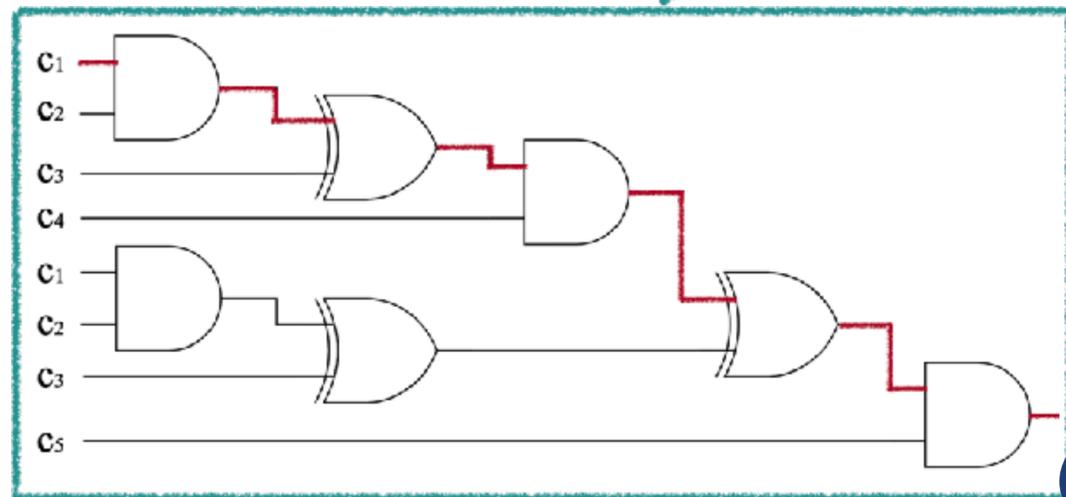
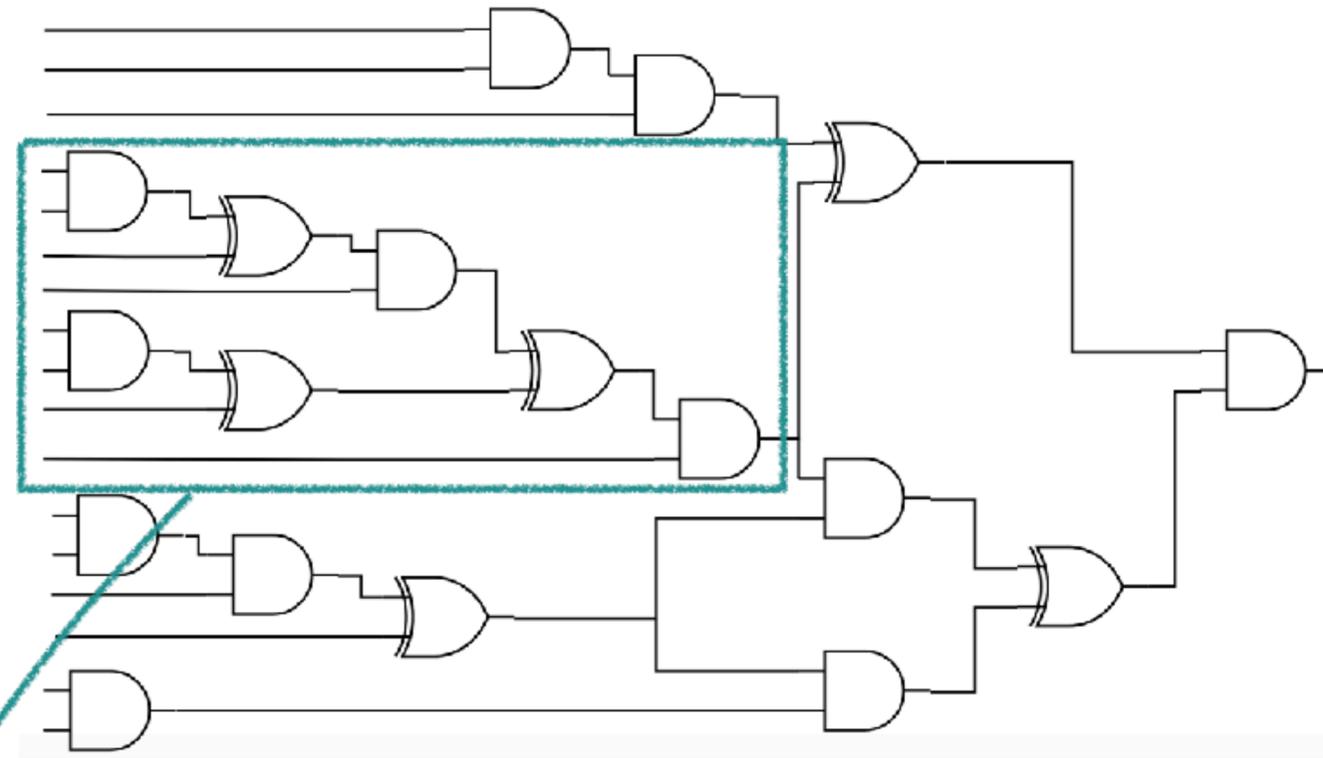
# Solution1 : Synthesis via Localization



**Optimizing  
Synthesis**



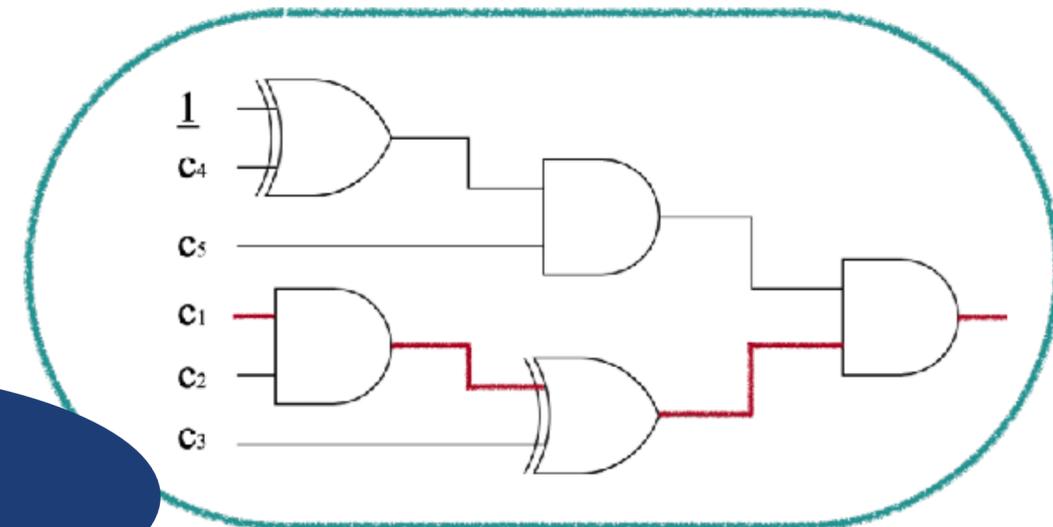
# Solution1 : Synthesis via Localization



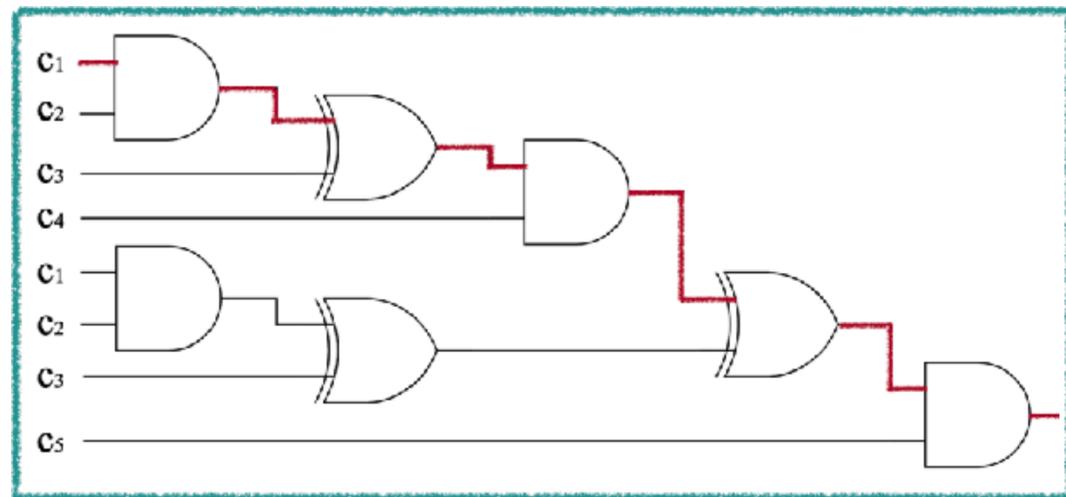
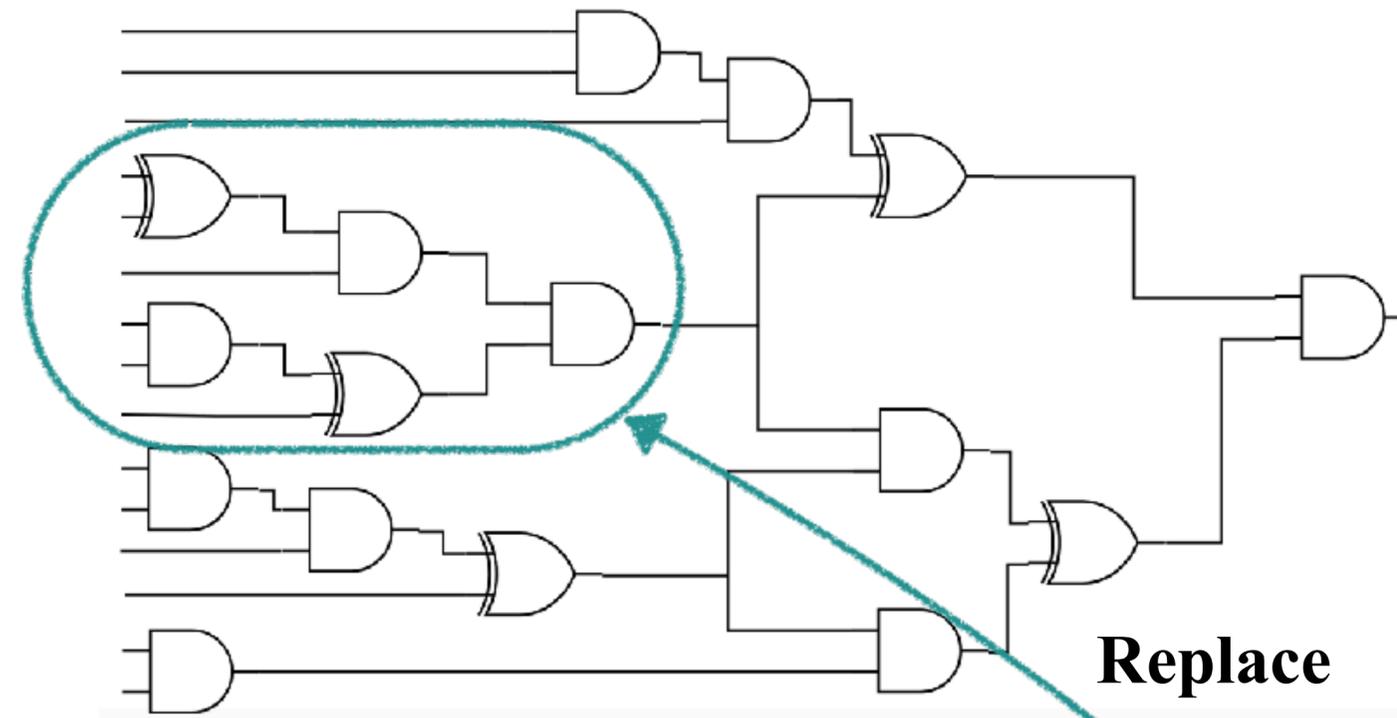
Optimizing  
Synthesis



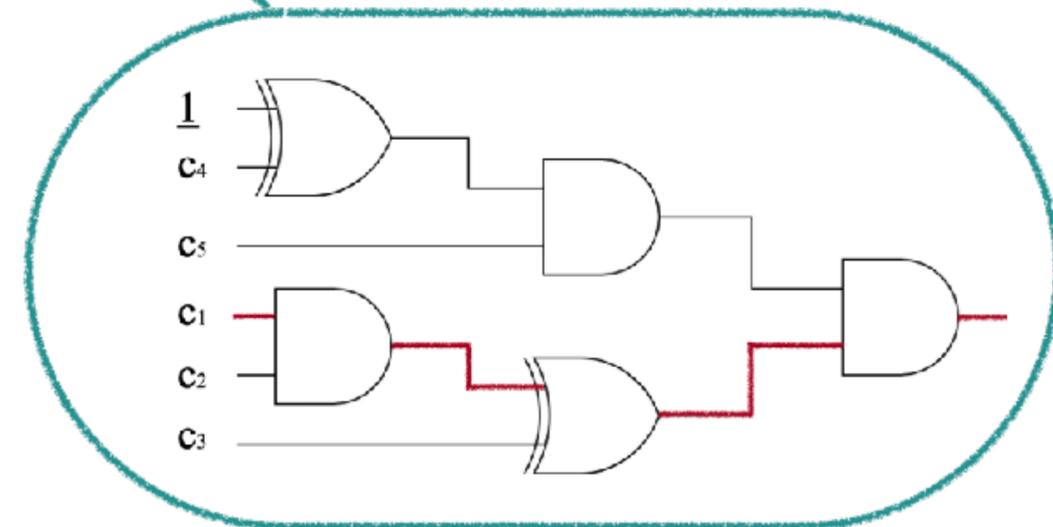
scalable



# Solution1 : Synthesis via Localization



Optimizing  
Synthesis

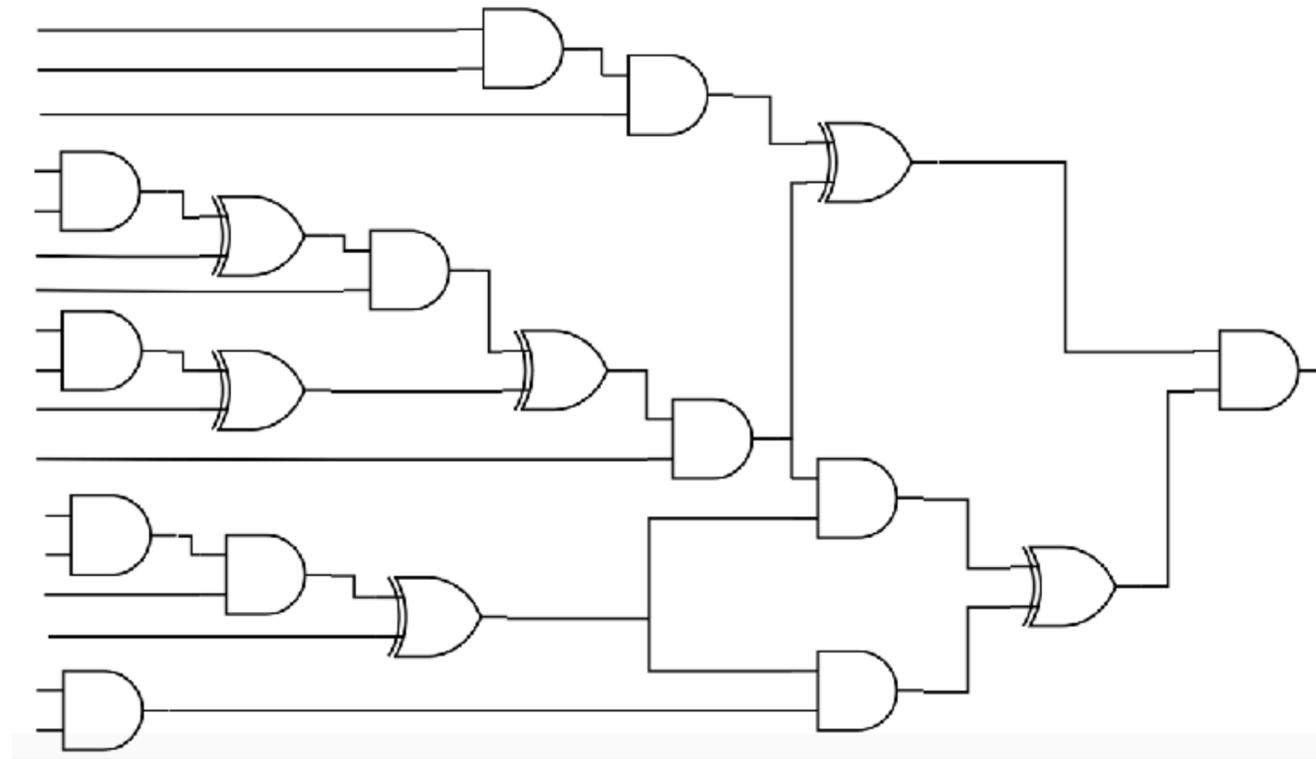


# Solution 2: Learning Successful Synthesis Patterns

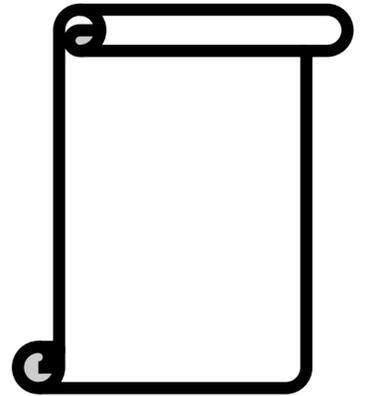
- Offline Learning
  - Collect successful synthesis patterns
- Online Optimization
  - Applying the patterns by term rewriting

# Offline Learning to Collect Opt. Patterns

Training  
HE Applications

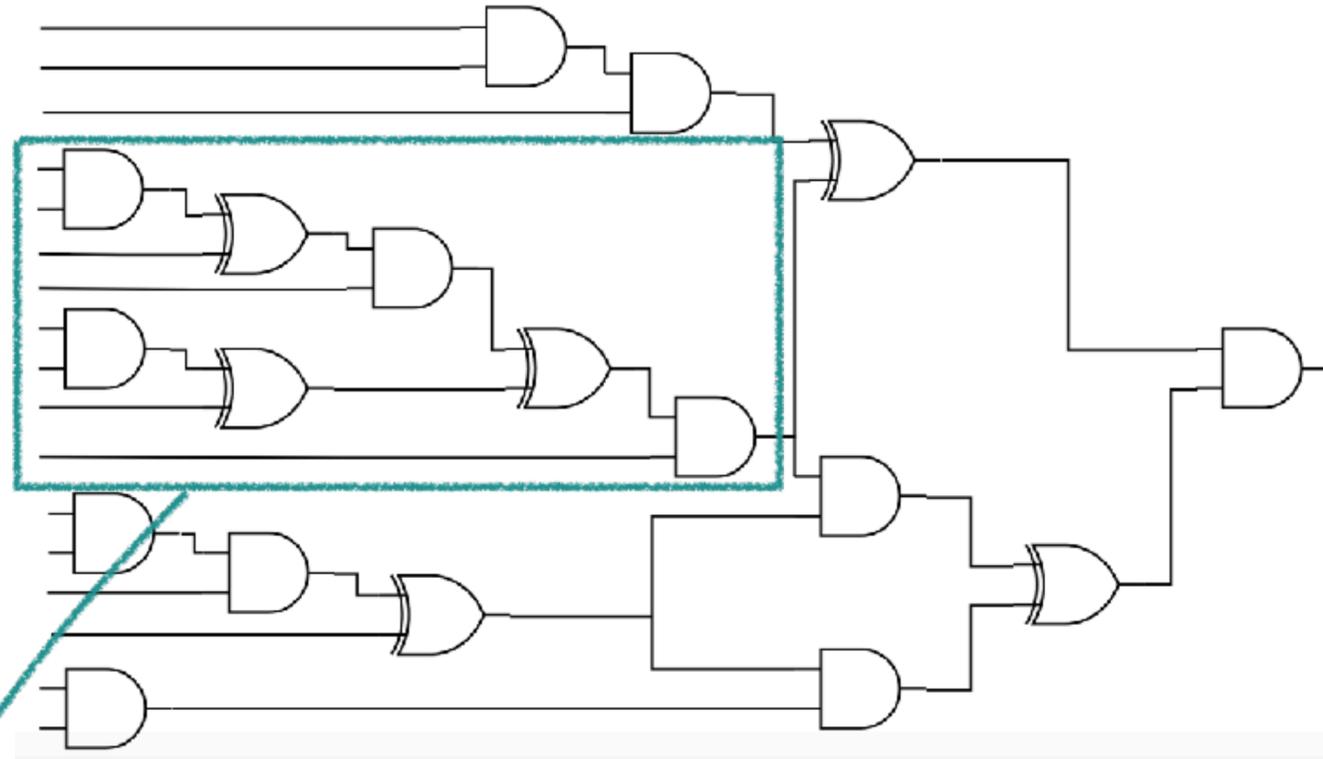


Collected  
Opt. Patterns

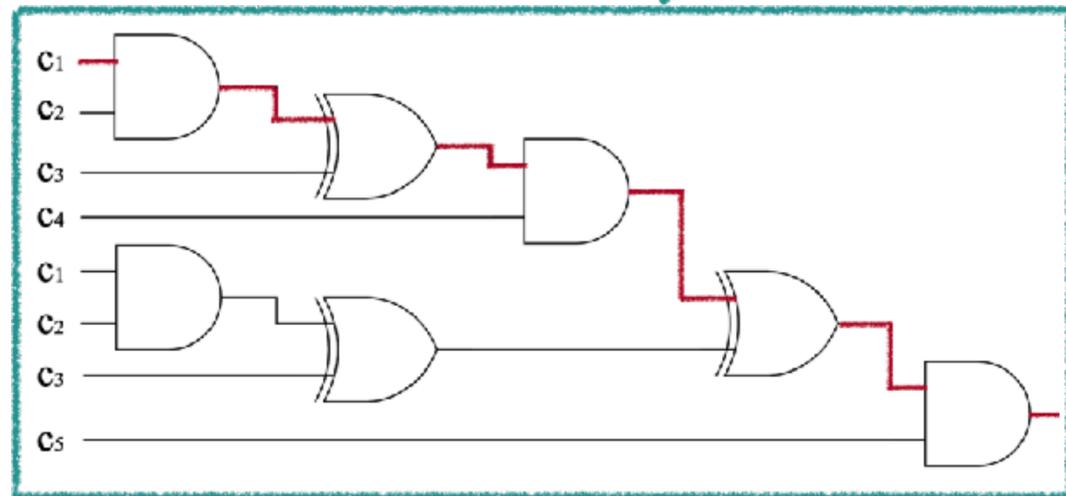
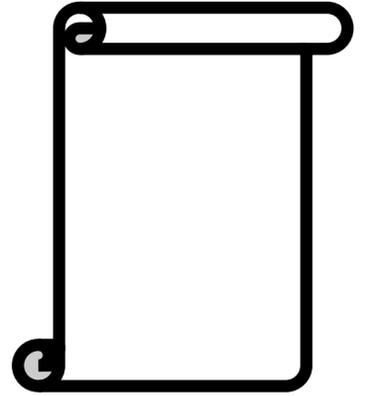


# Offline Learning to Collect Opt. Patterns

Training  
HE Applications

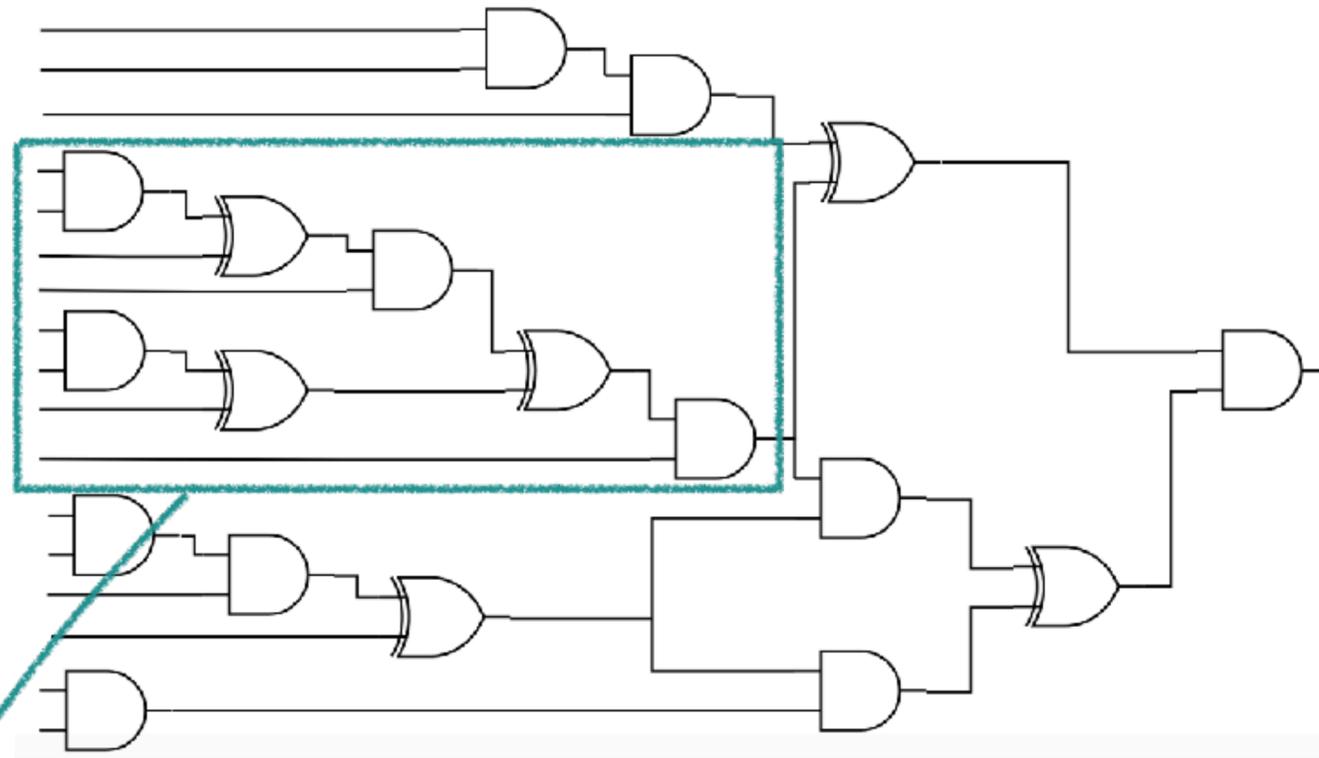


Collected  
Opt. Patterns

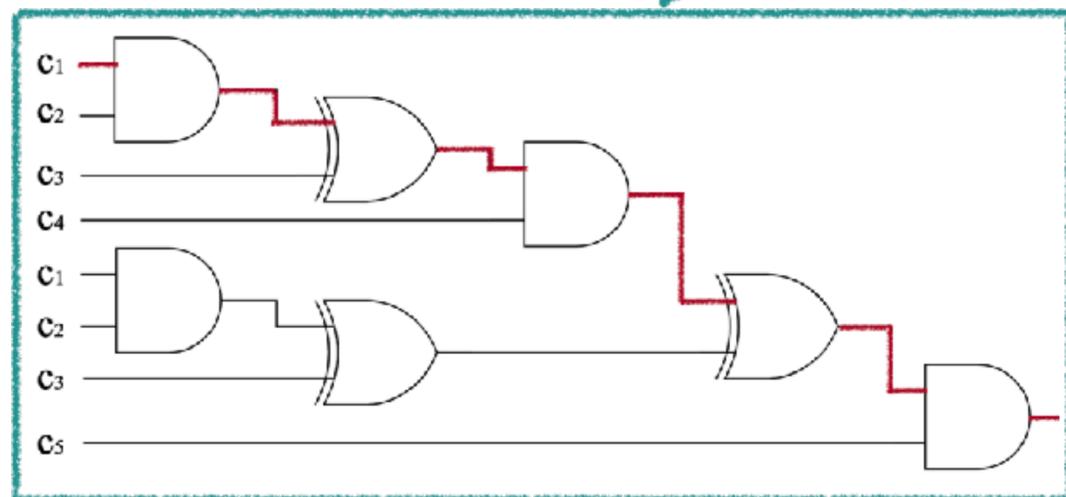
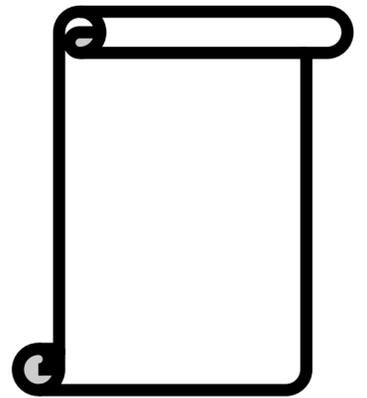


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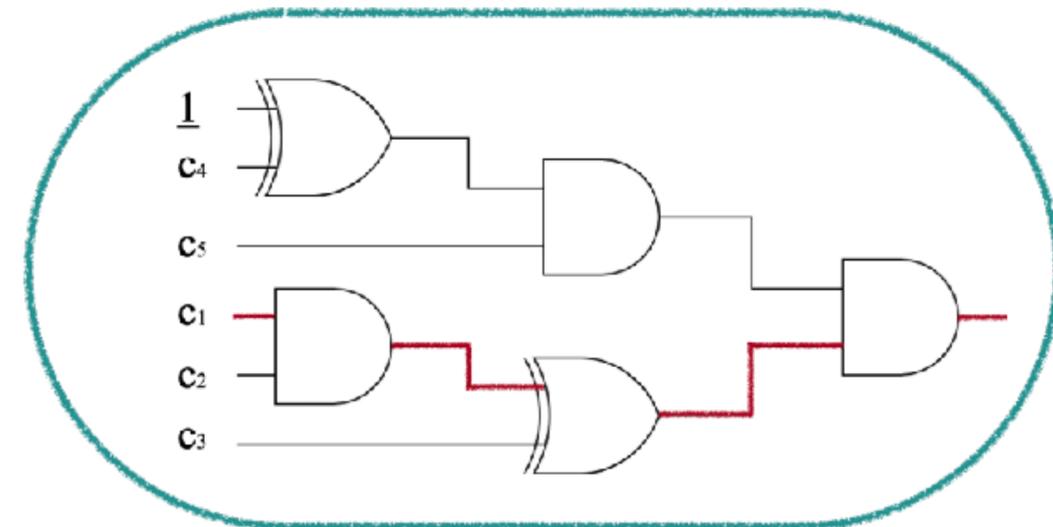
Training  
HE Applications



Collected  
Opt. Patterns

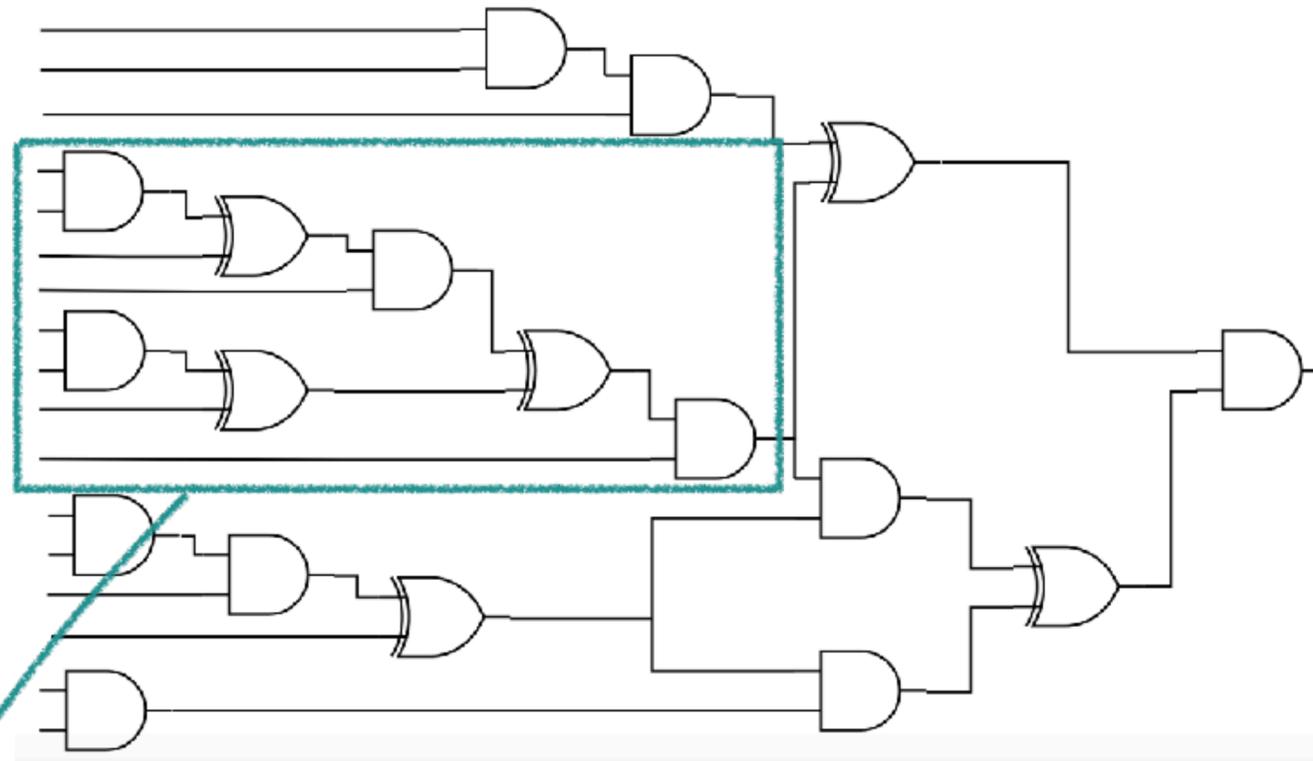


Optimizing  
Synthesis

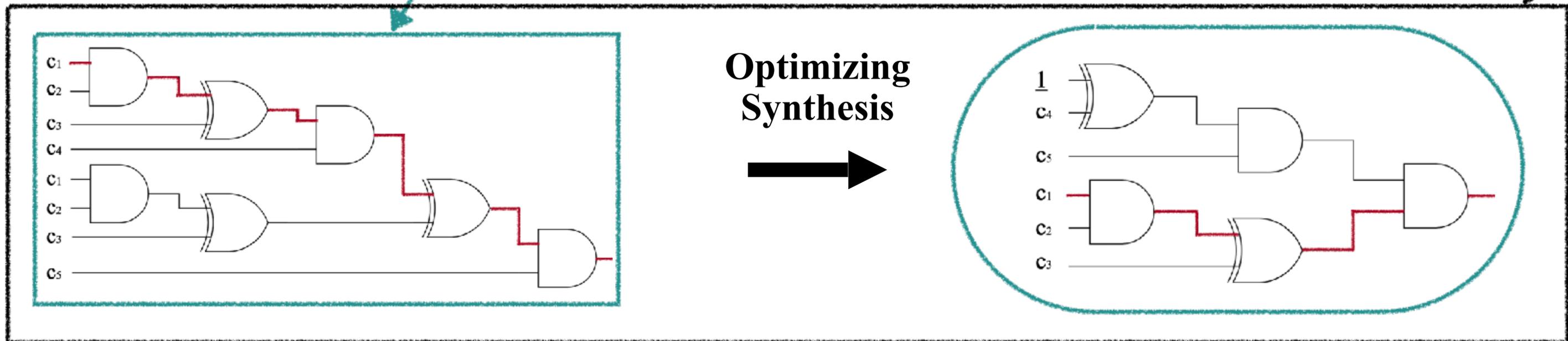
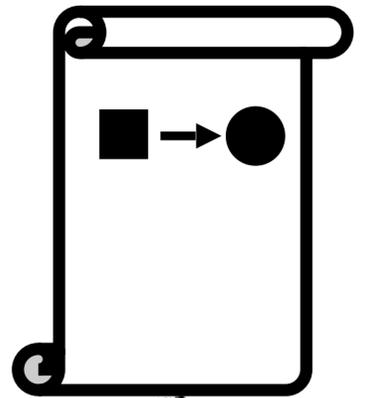


# Offline Learning to Collect Opt. Patterns

Training  
HE Applications

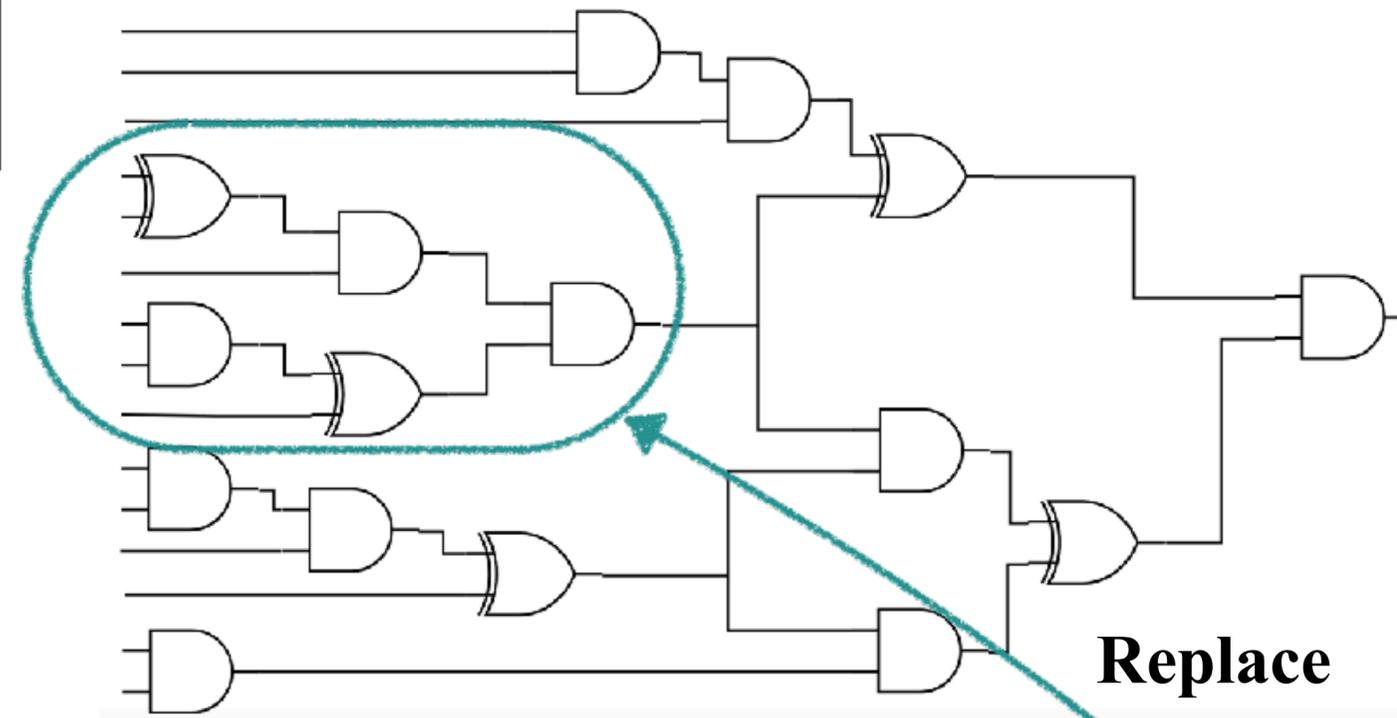


Collected  
Opt. Patterns

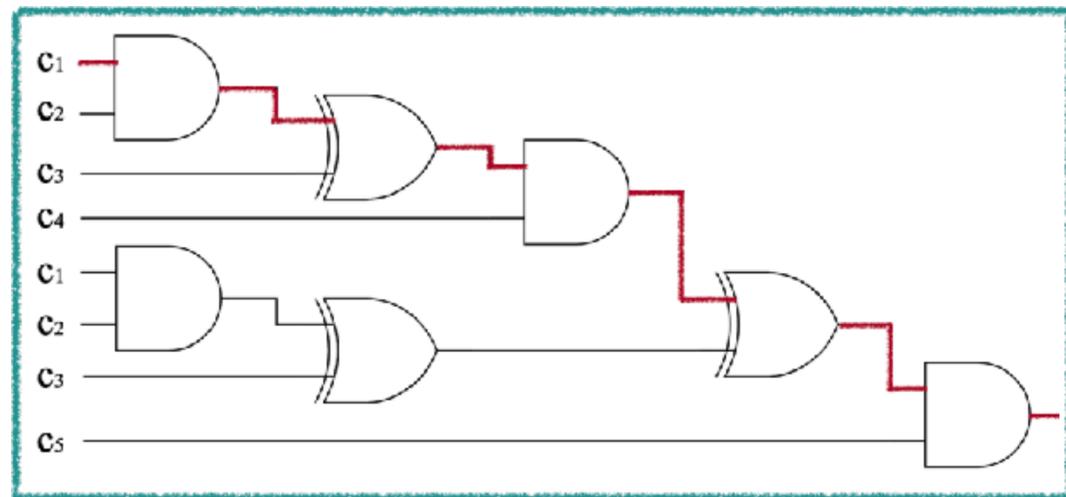
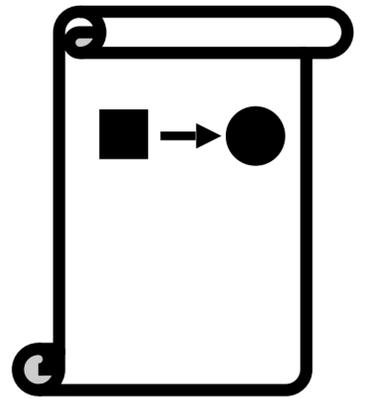


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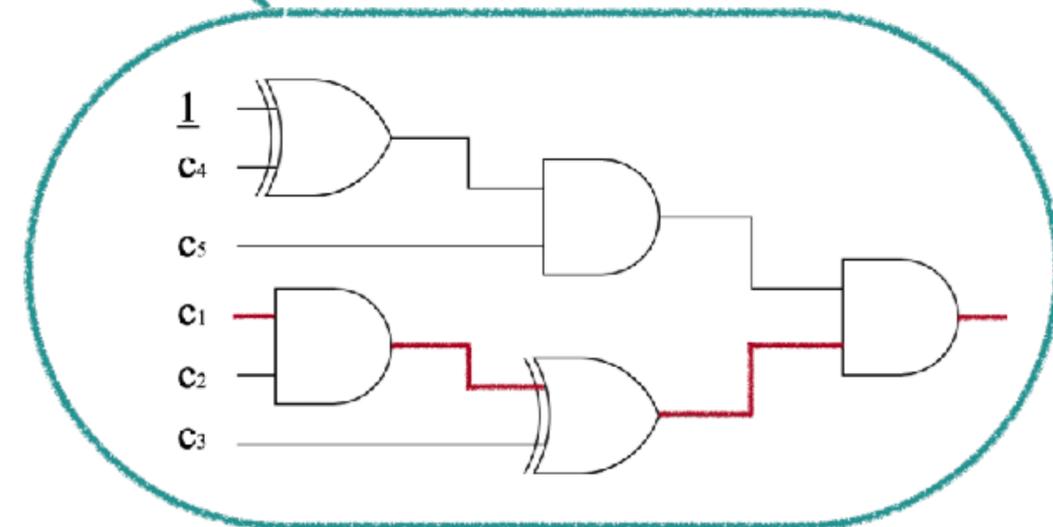
Training  
HE Applications



Collected  
Opt. Patterns

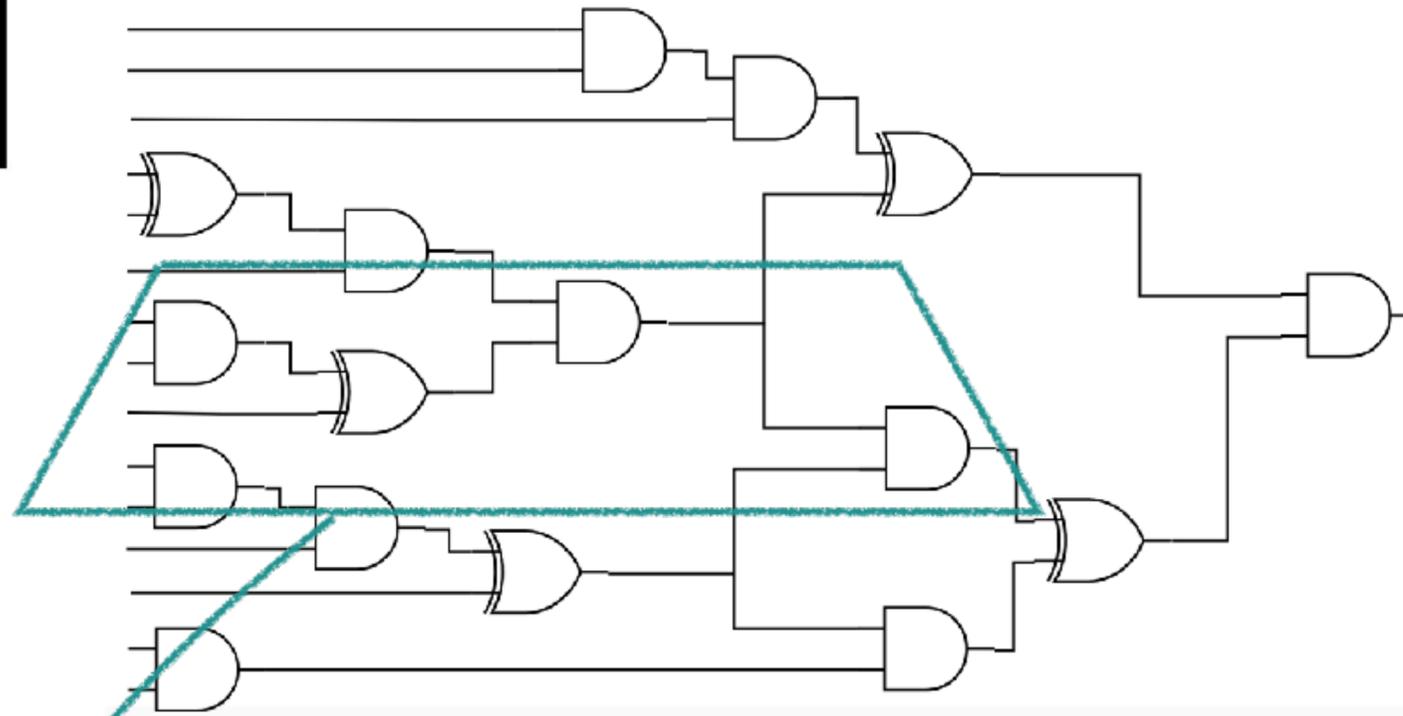


Optimizing  
Synthesis

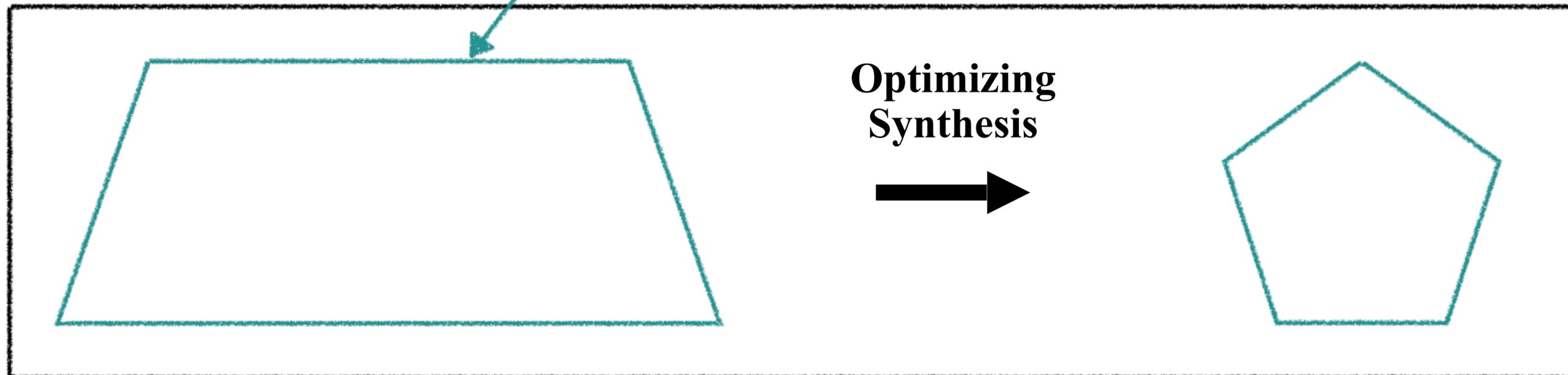
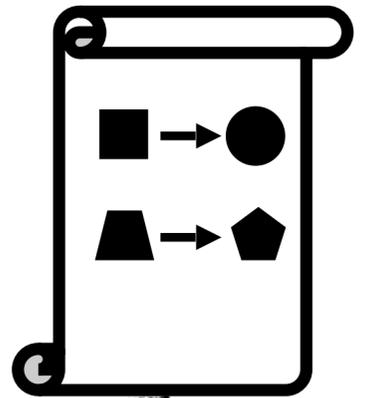


# Offline Learning to Collect Opt. Patterns

Training  
HE Applications

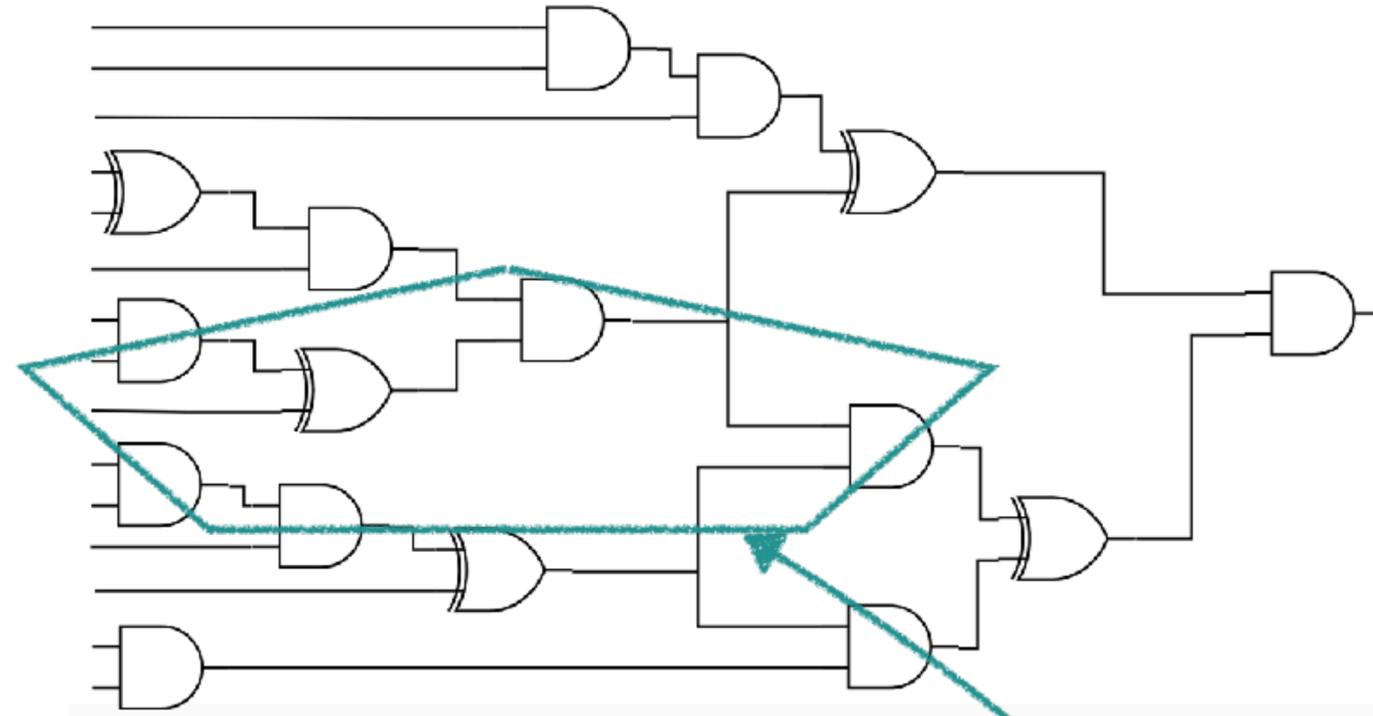


Collected  
Opt. Patterns

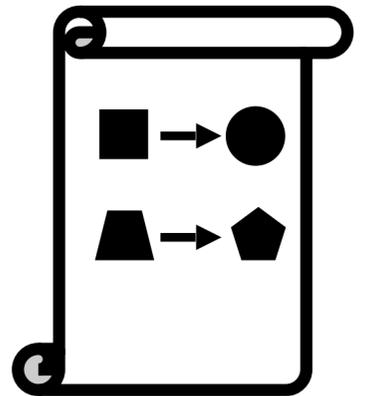


# Offline Learning to Collect Opt. Patterns

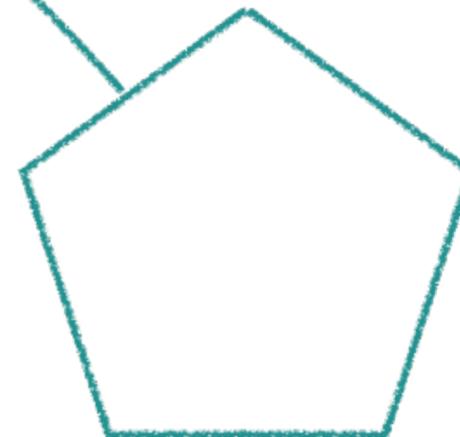
Training  
HE Applications



Collected  
Opt. Patterns

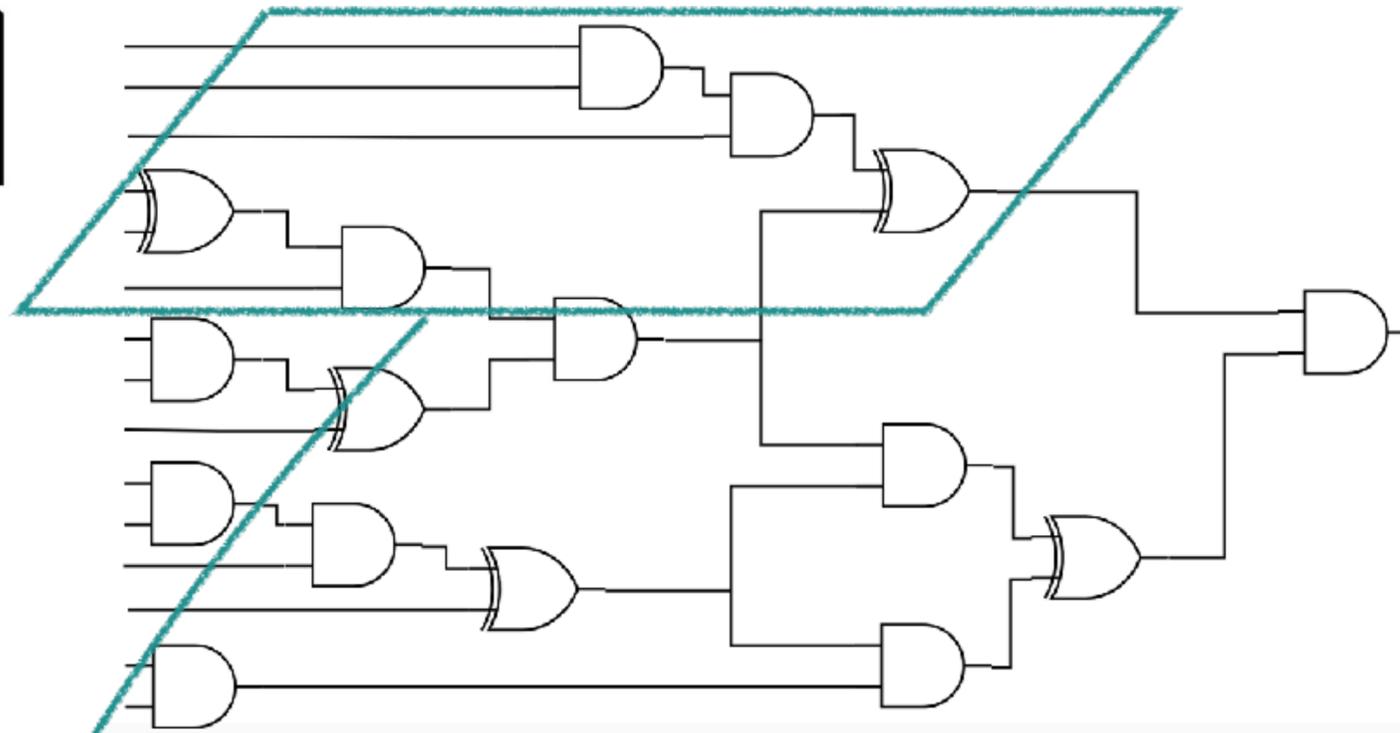


Optimizing  
Synthesis

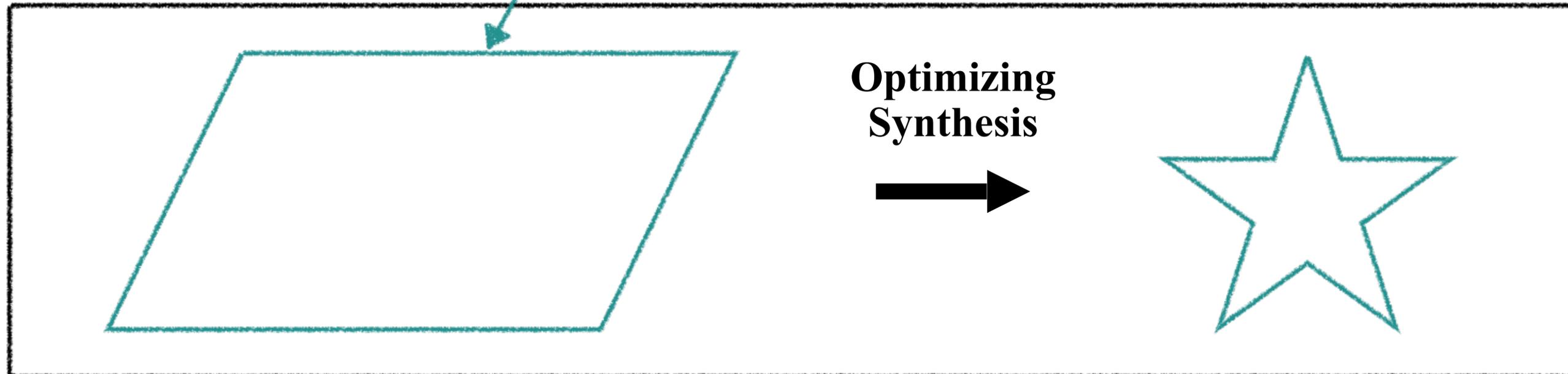
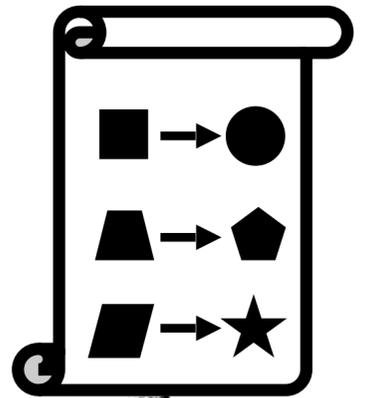


# Offline Learning to Collect Opt. Patterns

Training  
HE Applications

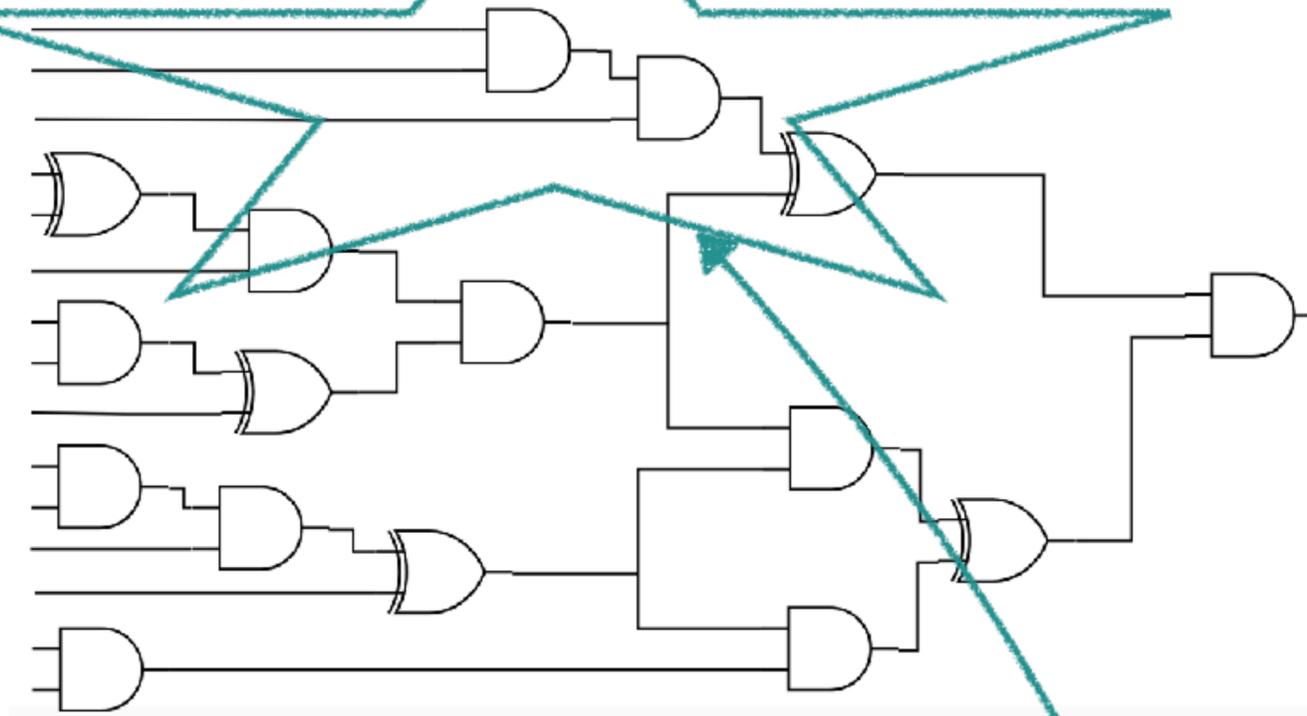


Collected  
Opt. Patterns

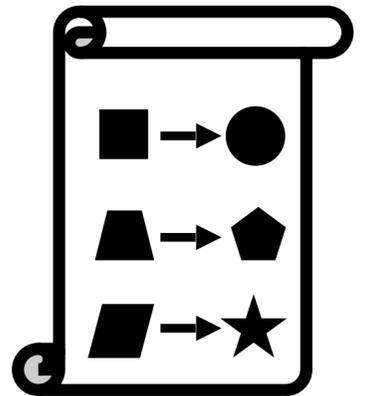


# Offline Learning to Collect Opt. Patterns

Training  
HE Applications



Collected  
Opt. Patterns

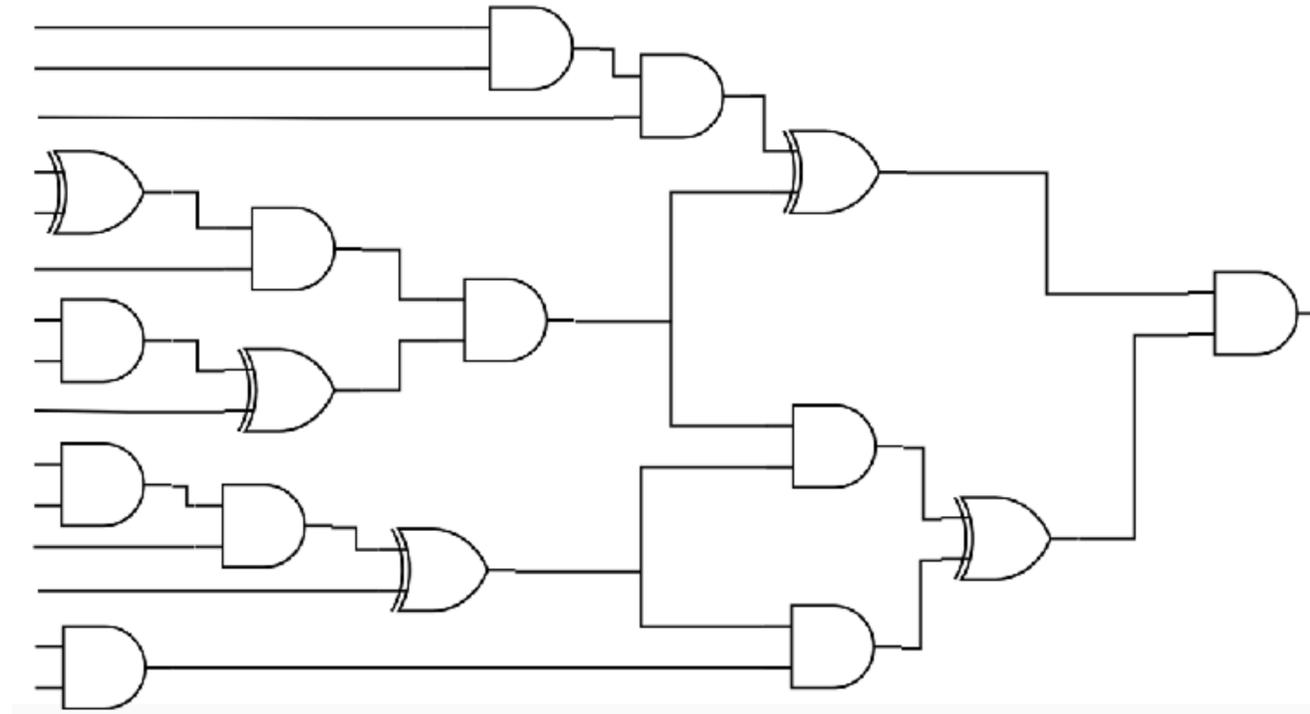


Optimizing  
Synthesis

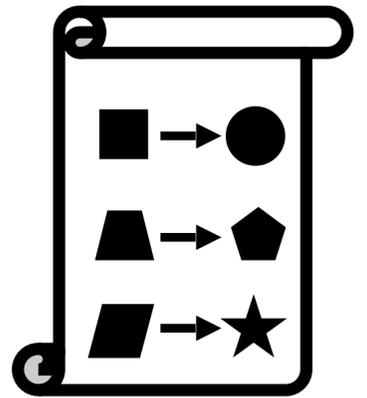


# Offline Learning to Collect Opt. Patterns

Training  
HE Applications

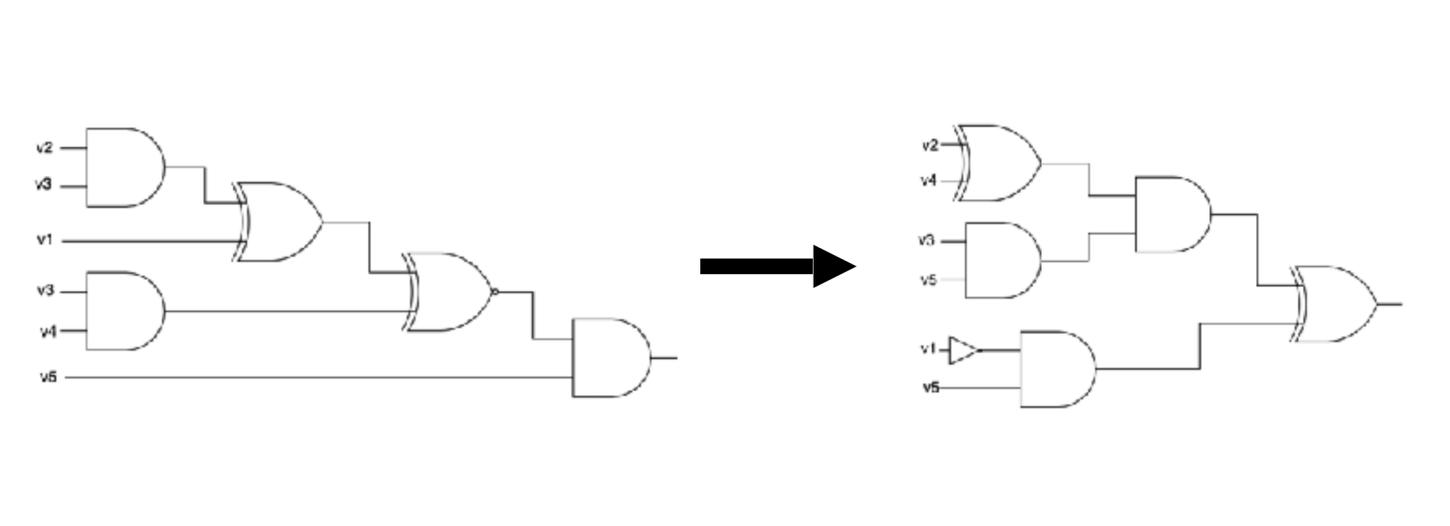
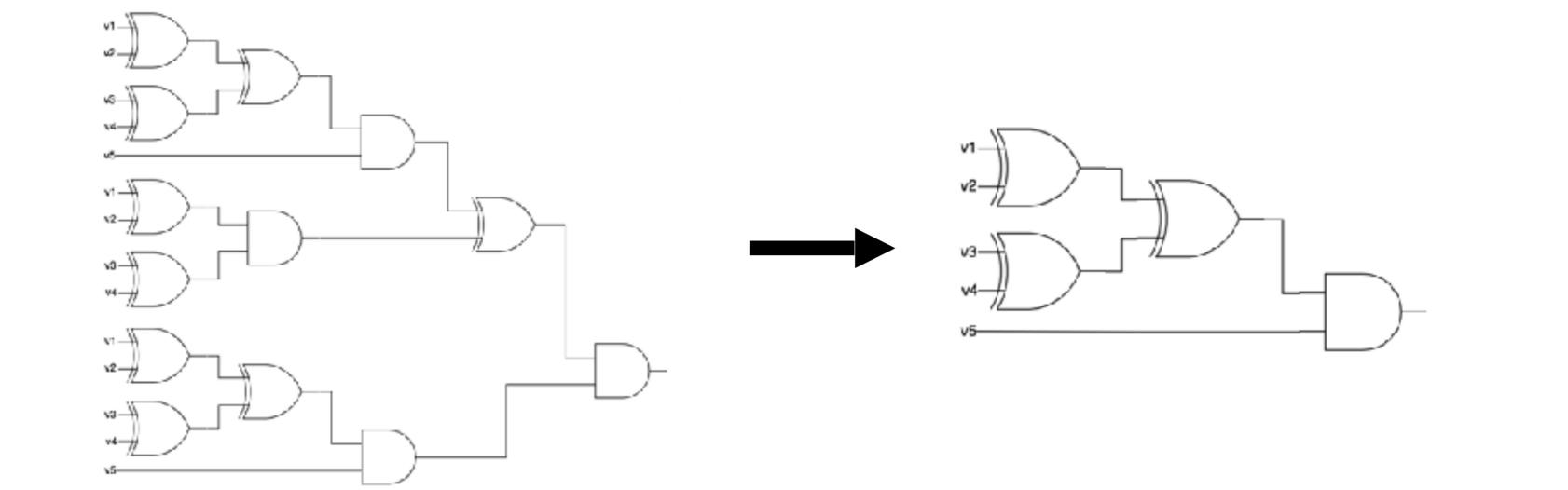
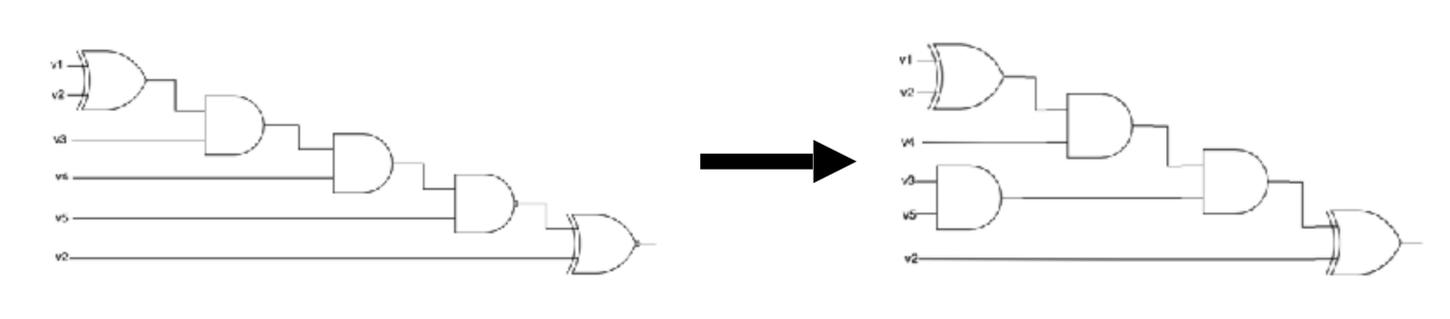
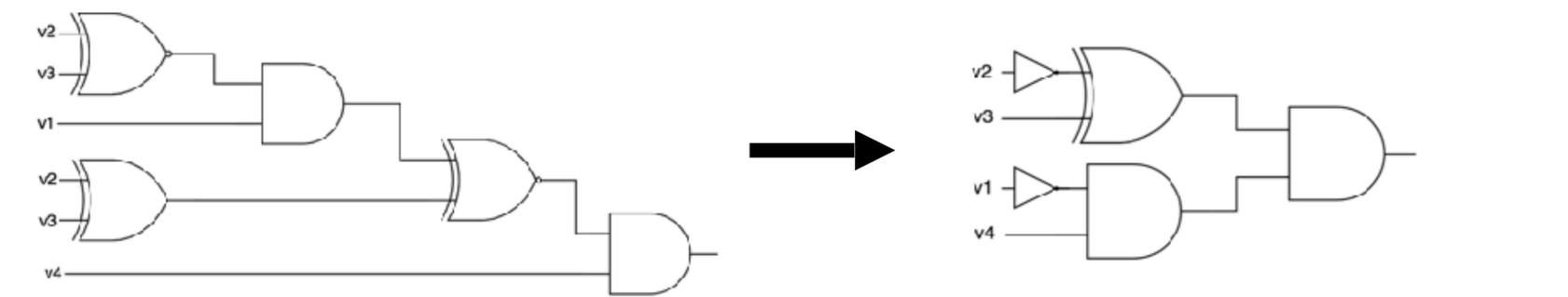
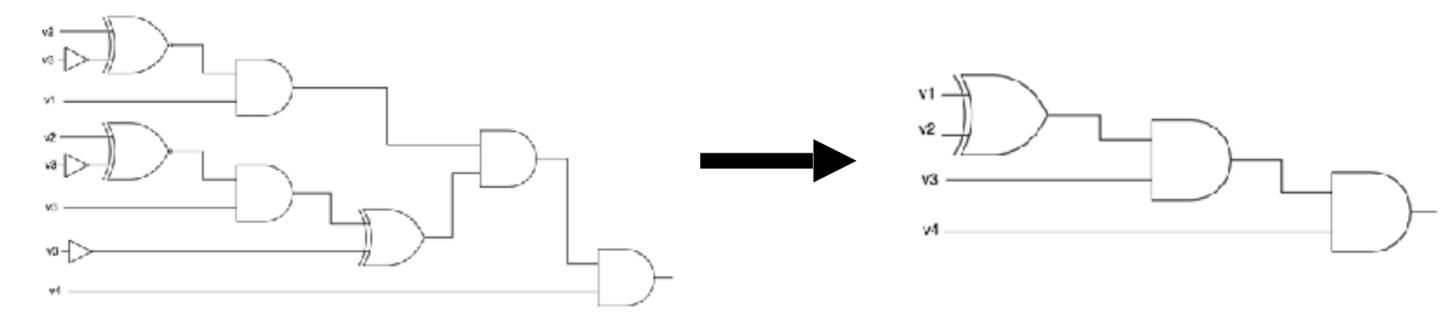
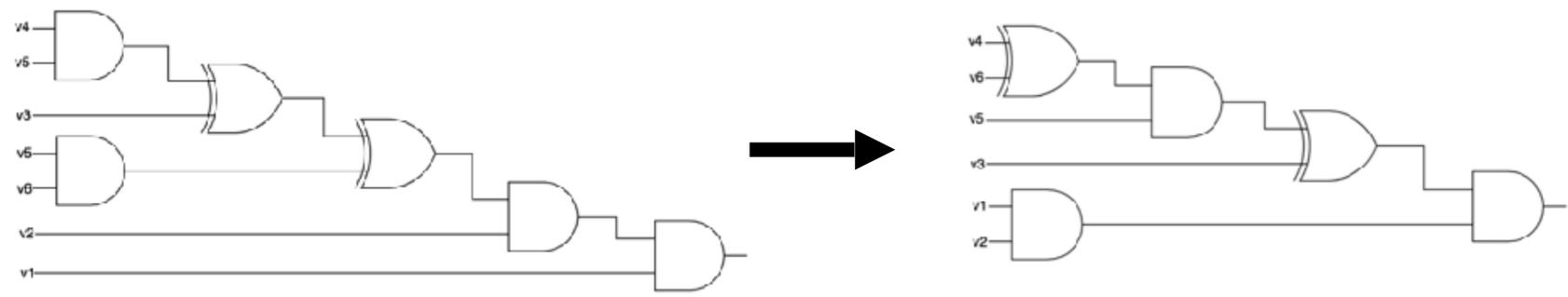


Collected  
Opt. Patterns



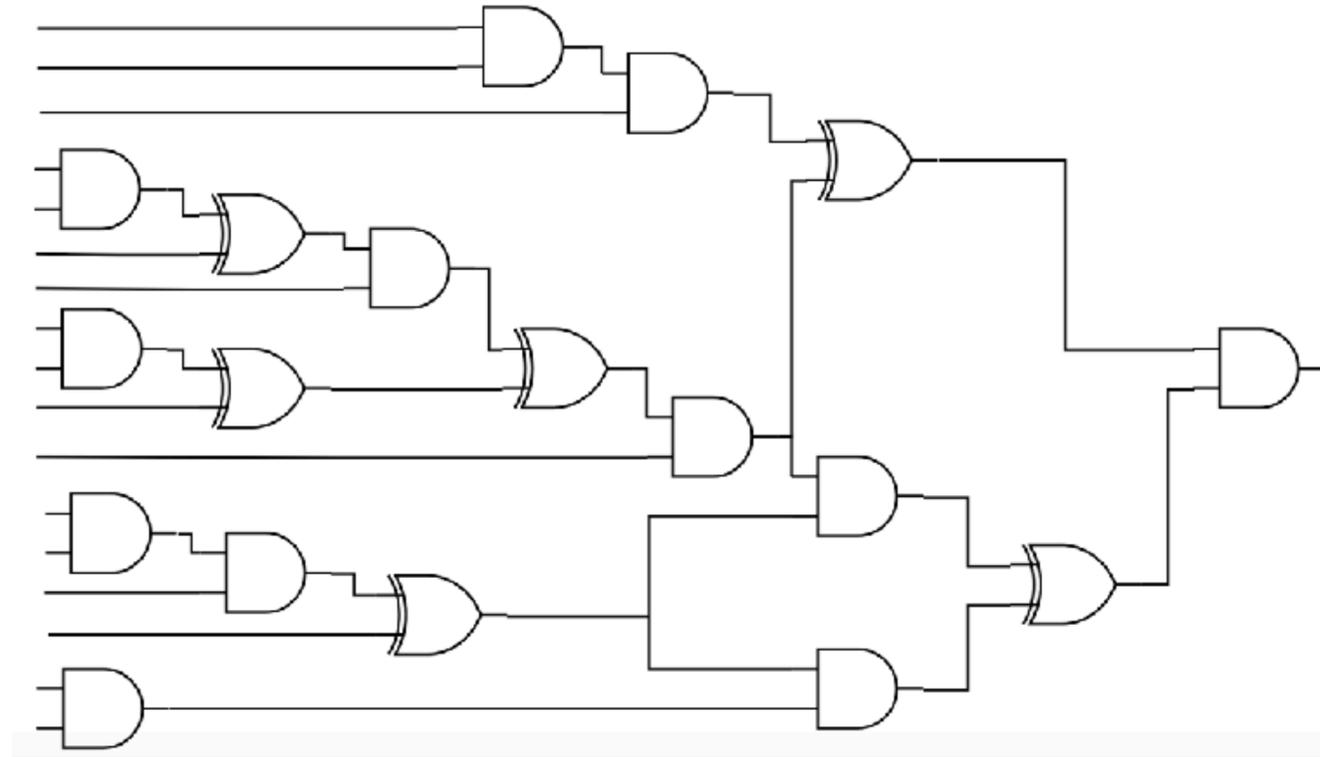
186 Opt.  
patterns

# Learned Optimization Patterns : examples

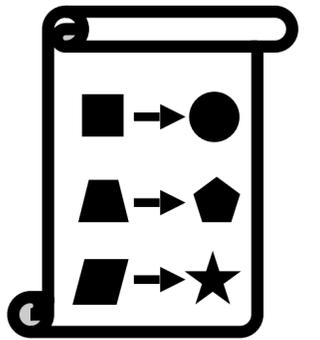


# Online Rule-based Optimization

Input  
HE application

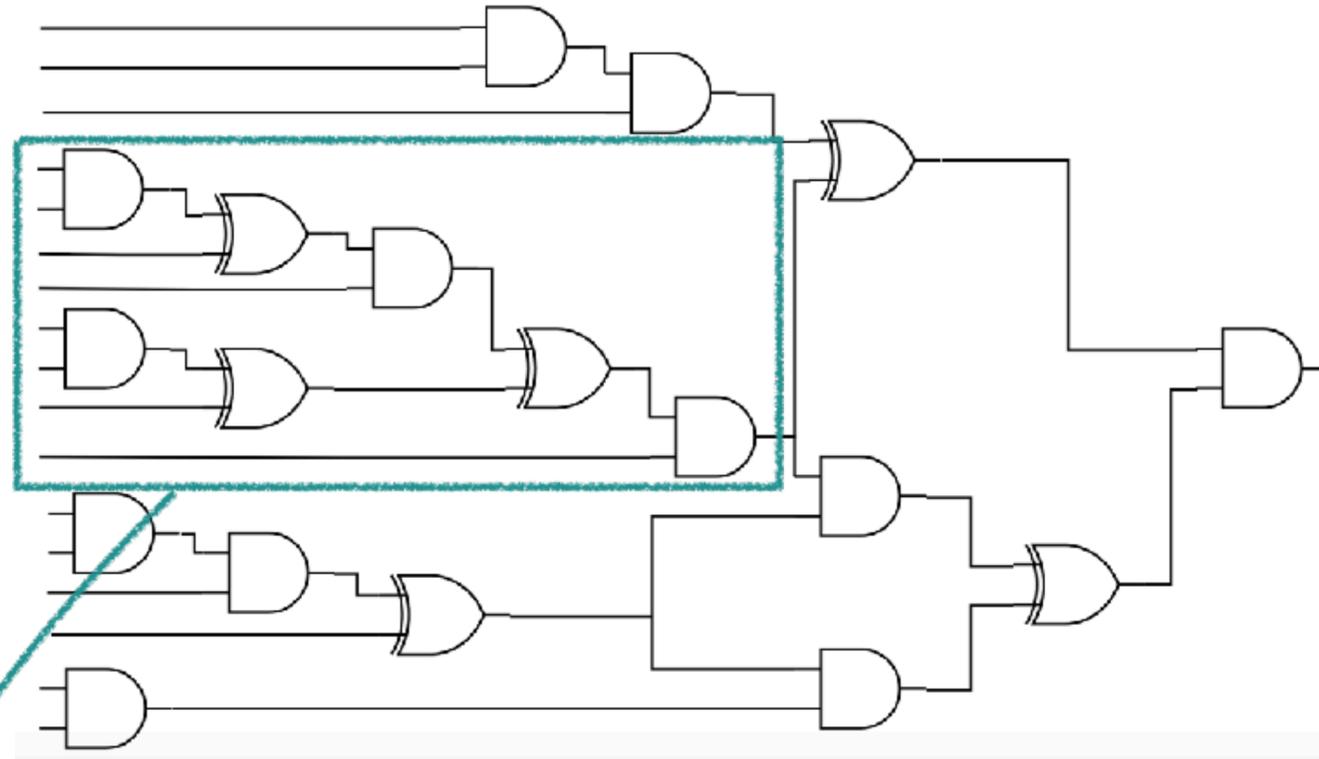


Learned  
Opt. Patterns

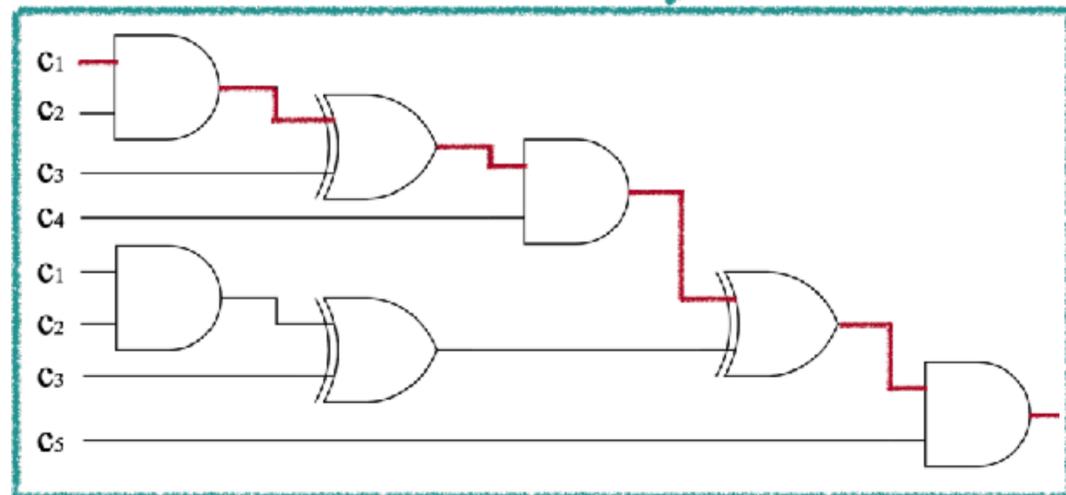
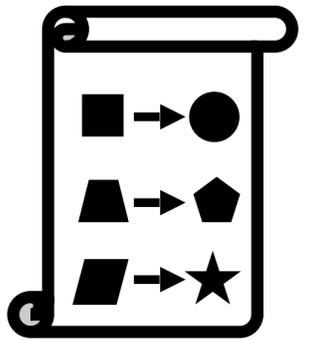


# Online Rule-based Optimization

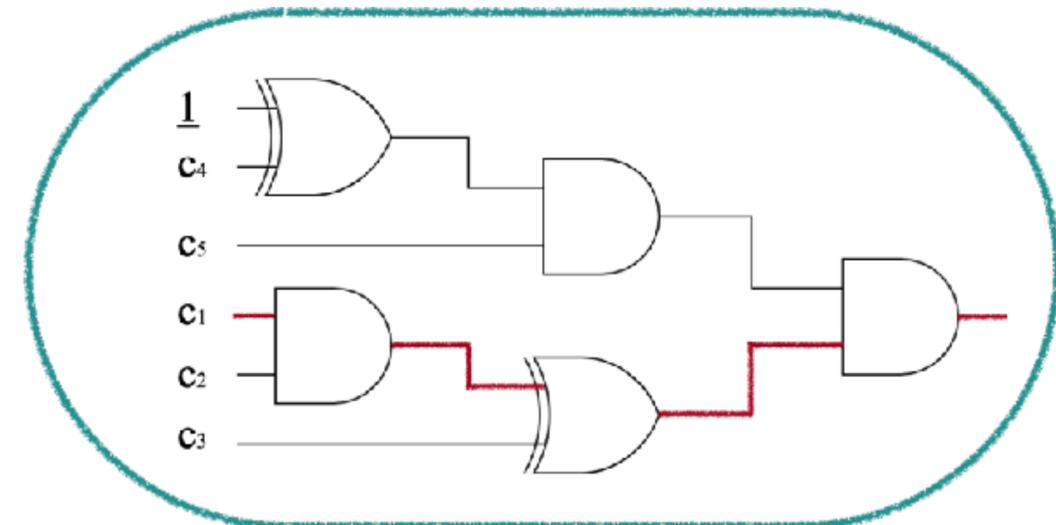
Input  
HE application



Learned  
Opt. Patterns

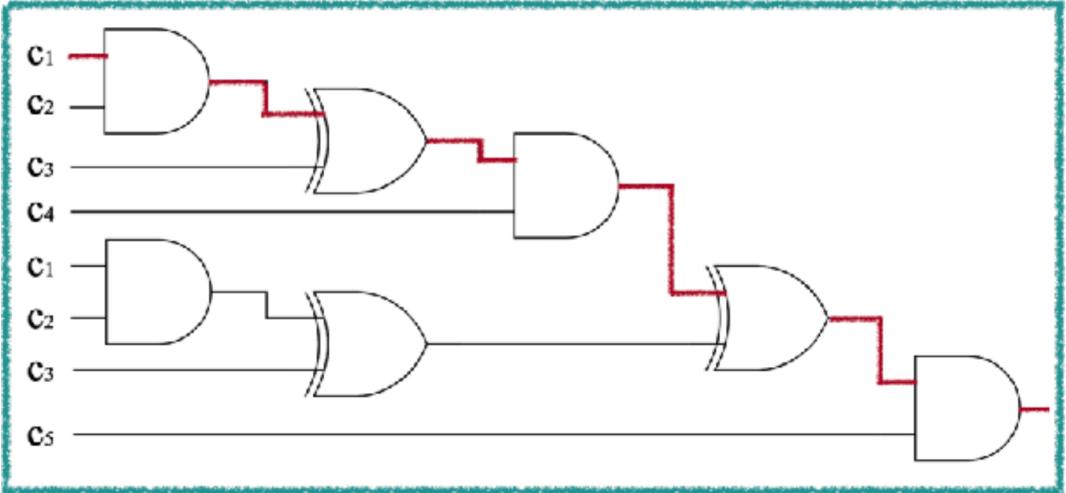
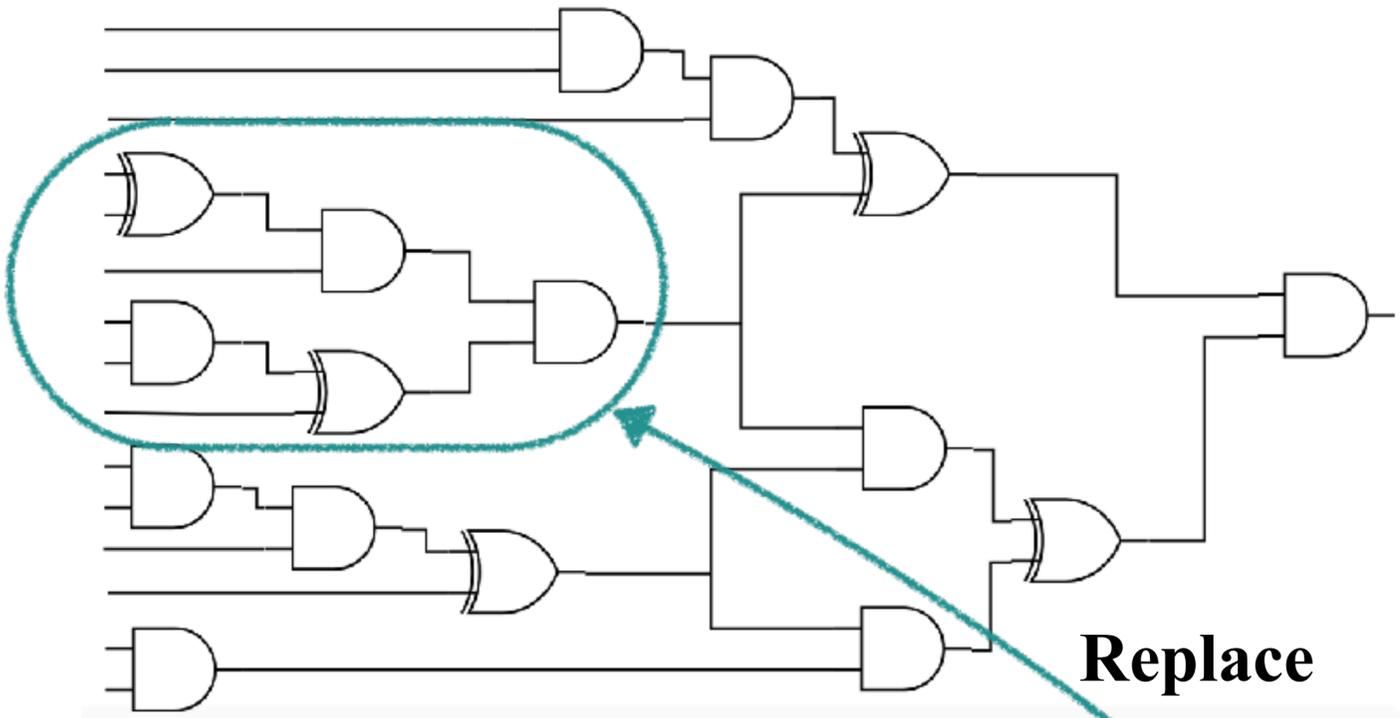


Apply  
Opt. Patterns

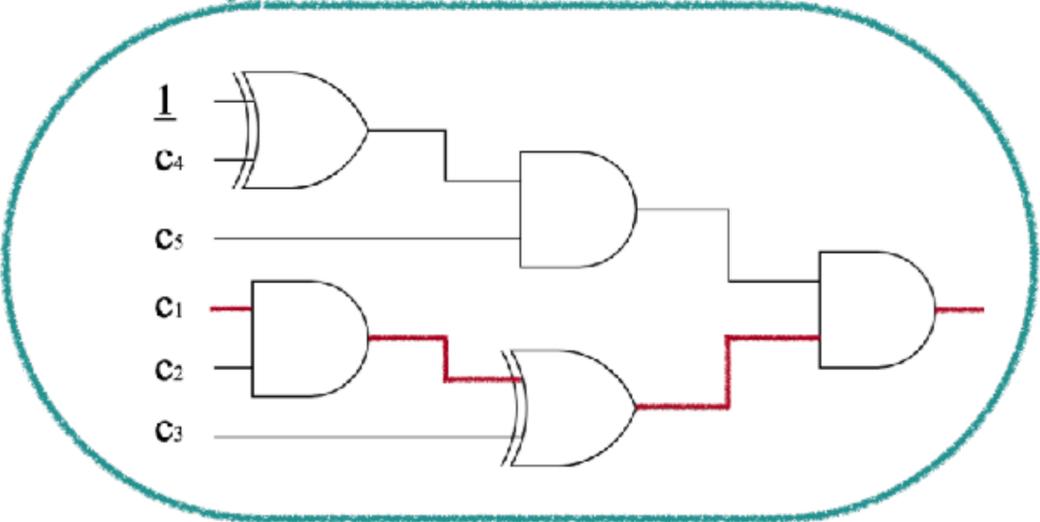
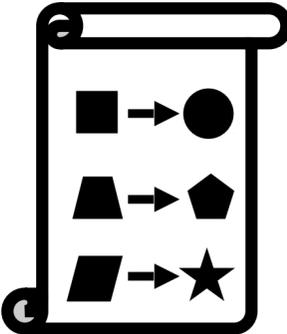


# Online Rule-based Optimization

Input  
HE application

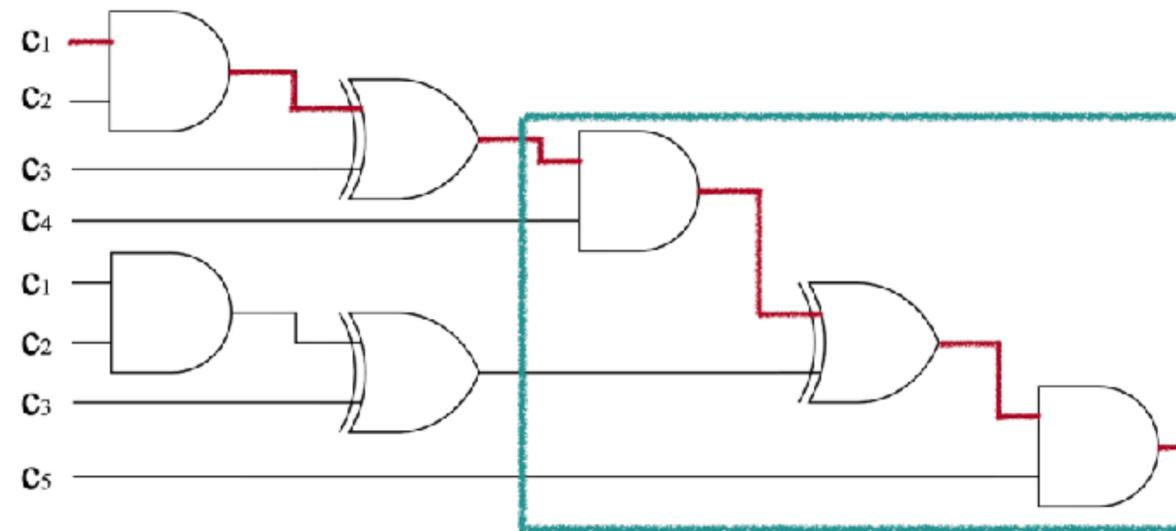


Apply  
Opt. Patterns

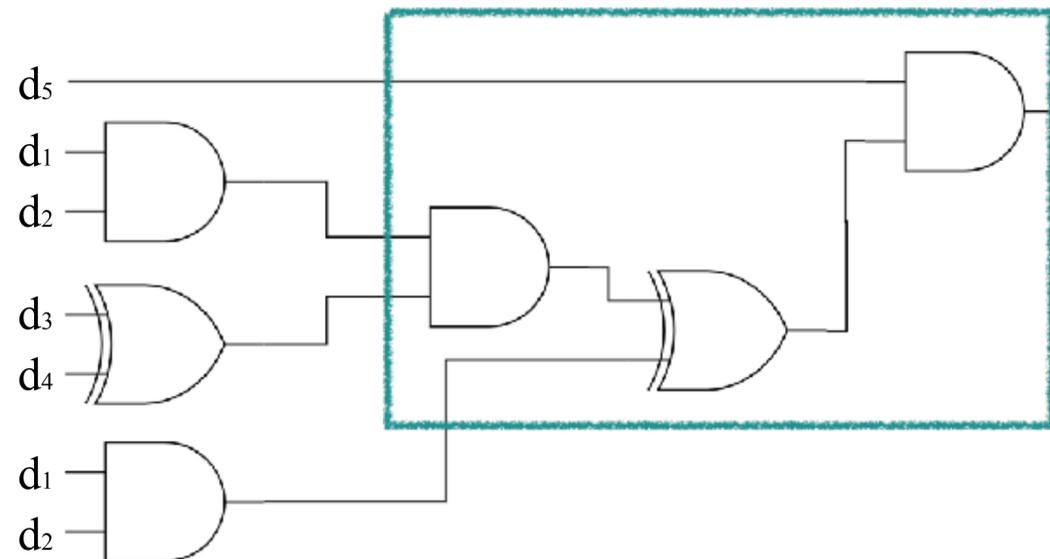
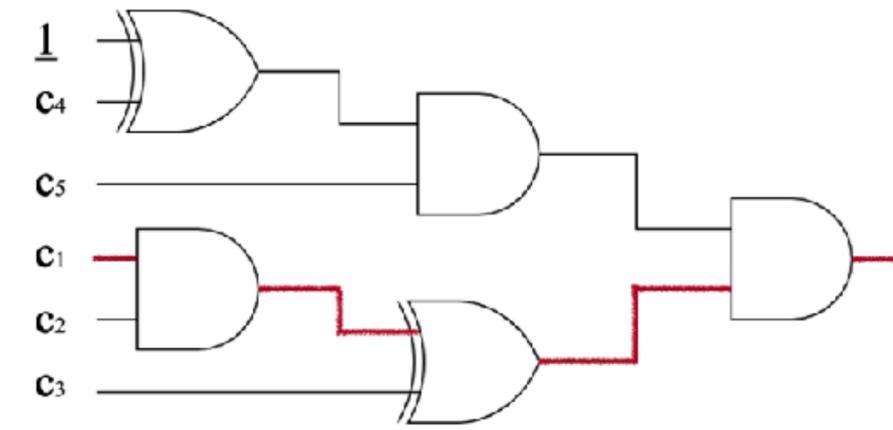


# Applying Learned Optimization Patterns (1/2)

## Syntactic Matching is Not Effective



Learned  
Opt. Patterns

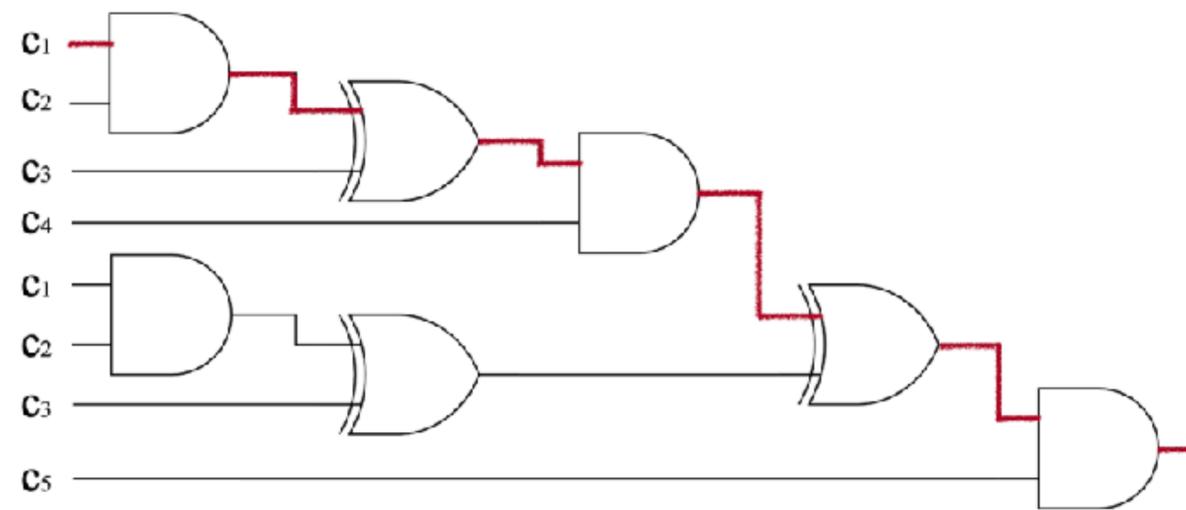


New Input Circuit  
Optimization

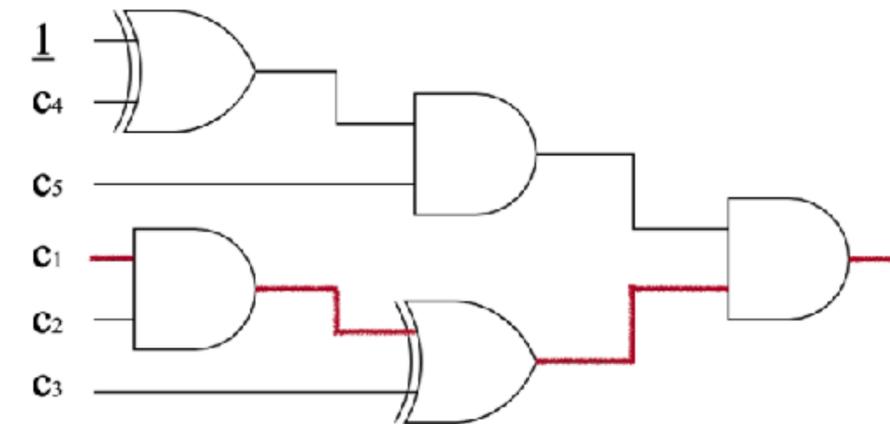


# Applying Learned Optimization Patterns (1/2)

Syntactic Matching is Not Effective



Learned  
Opt. Patterns

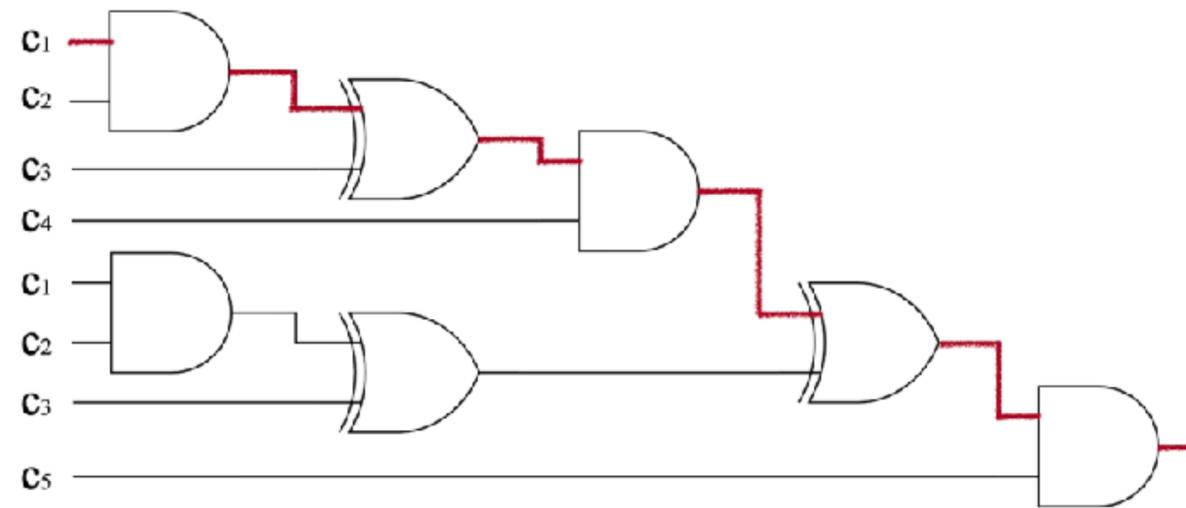


New Input Circuit  
Optimization

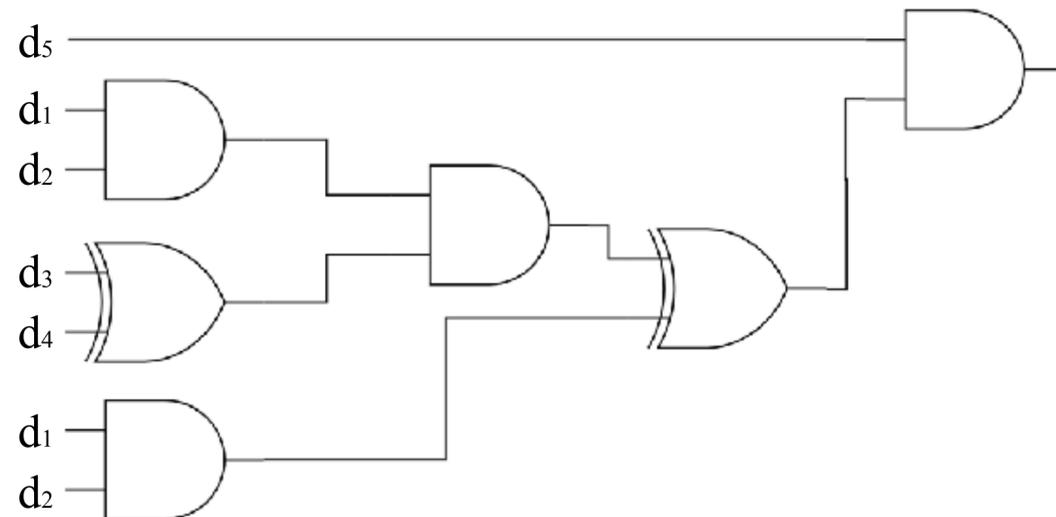
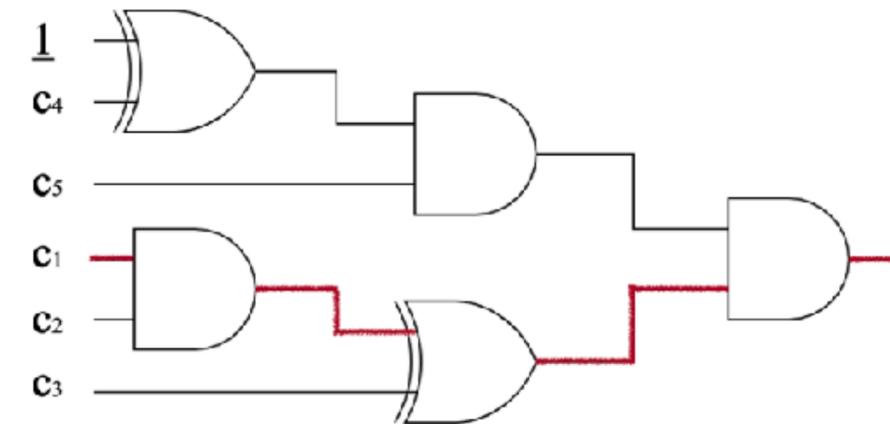


# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching



Learned  
Opt. Patterns

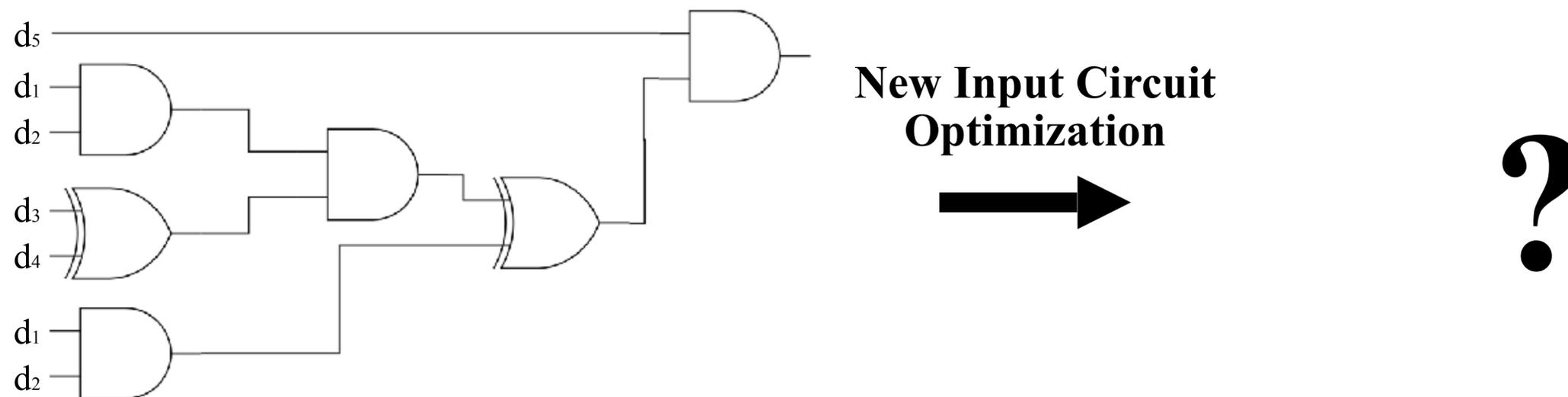
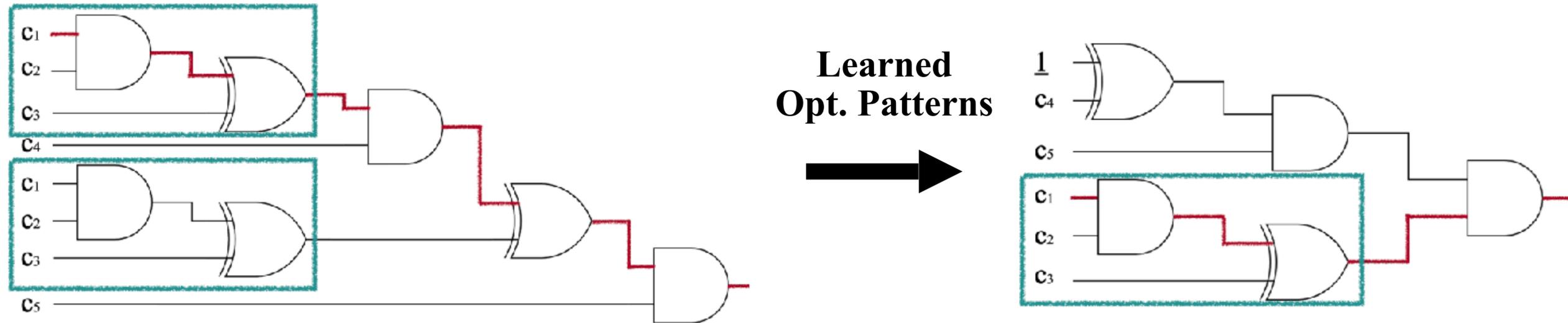


New Input Circuit  
Optimization



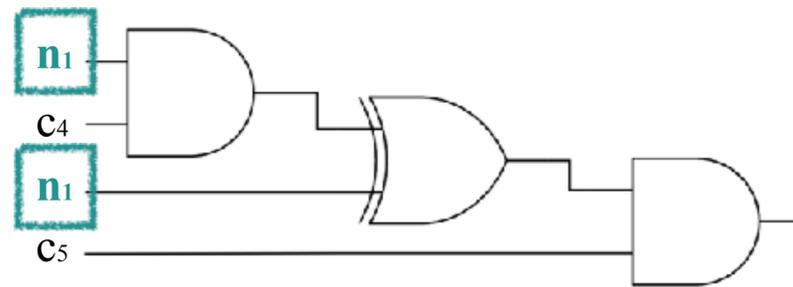
# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching

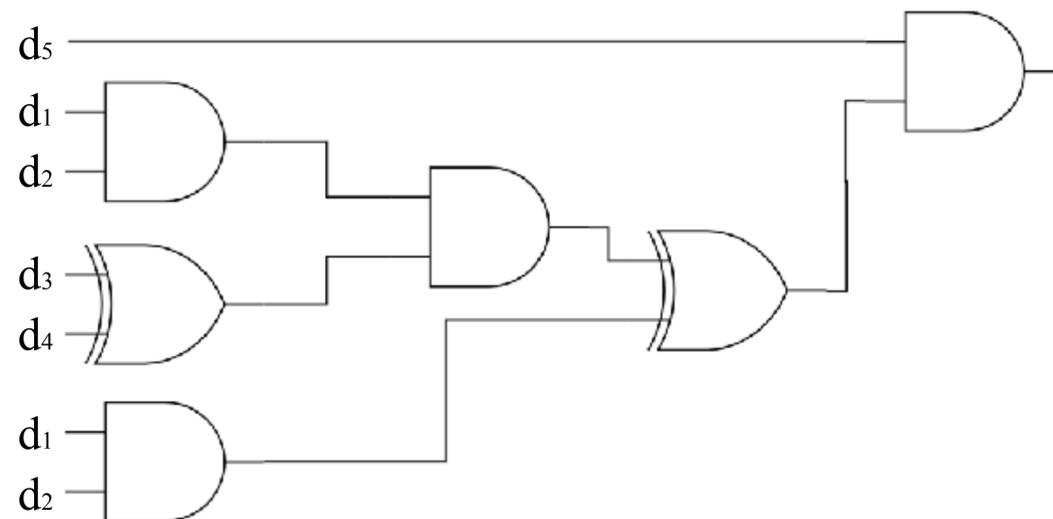
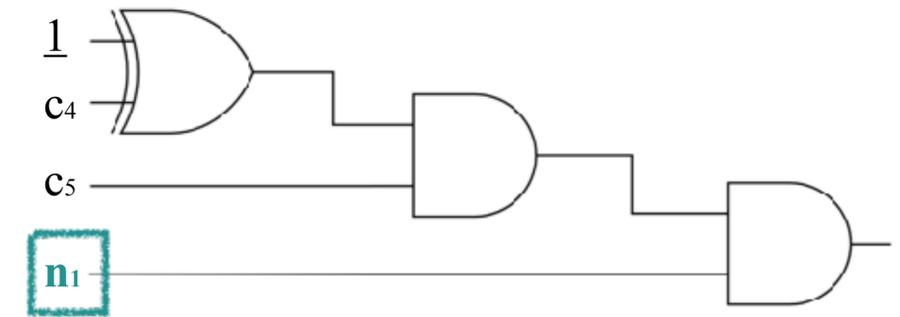


# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching



Normalized  
Opt. Patterns

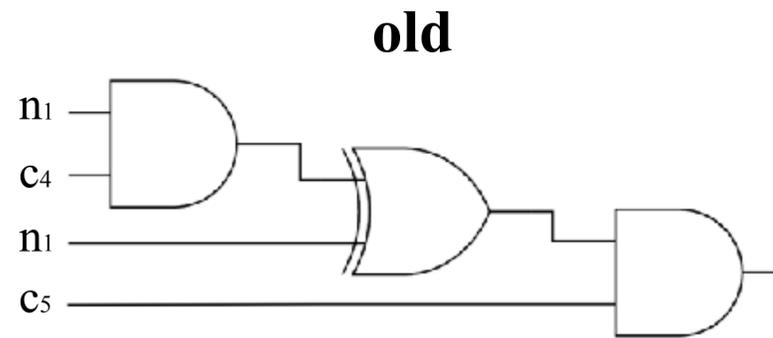


New Input Circuit  
Optimization

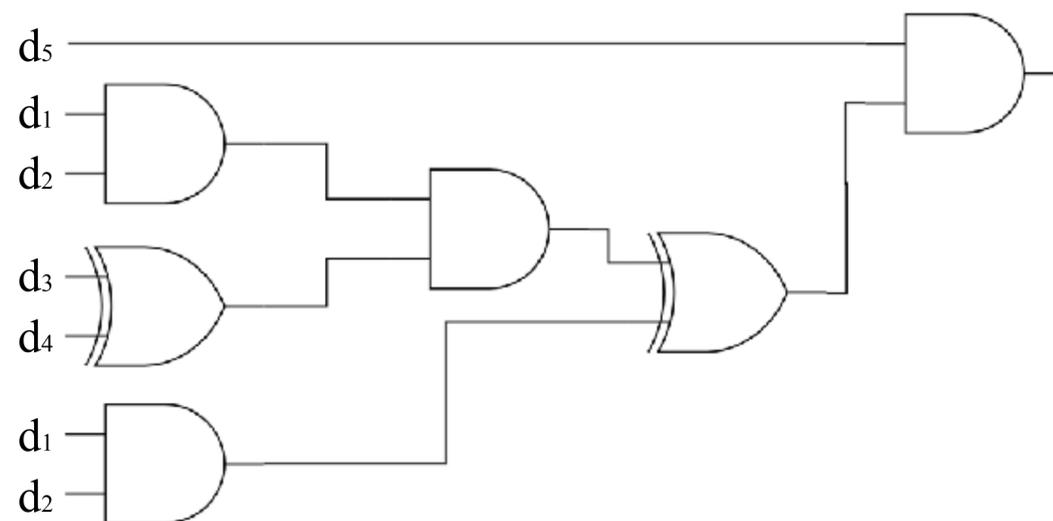
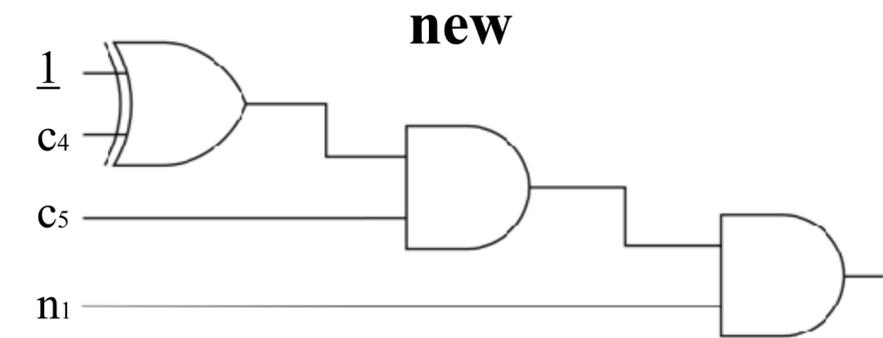


# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching



Normalized  
Opt. Patterns



New Input Circuit  
Optimization



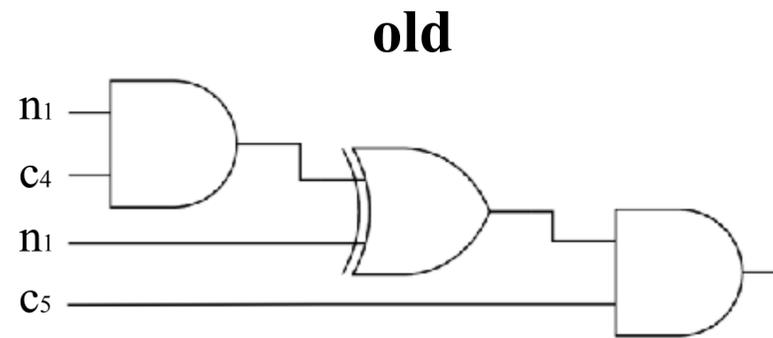
?

target

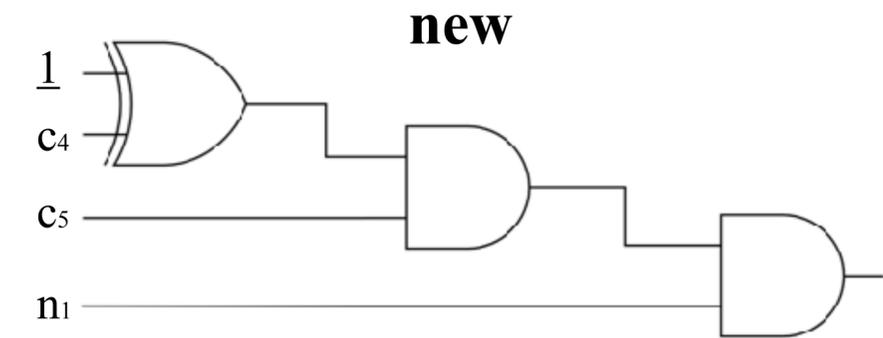
target'

# Applying Learned Optimization Patterns (2/2)

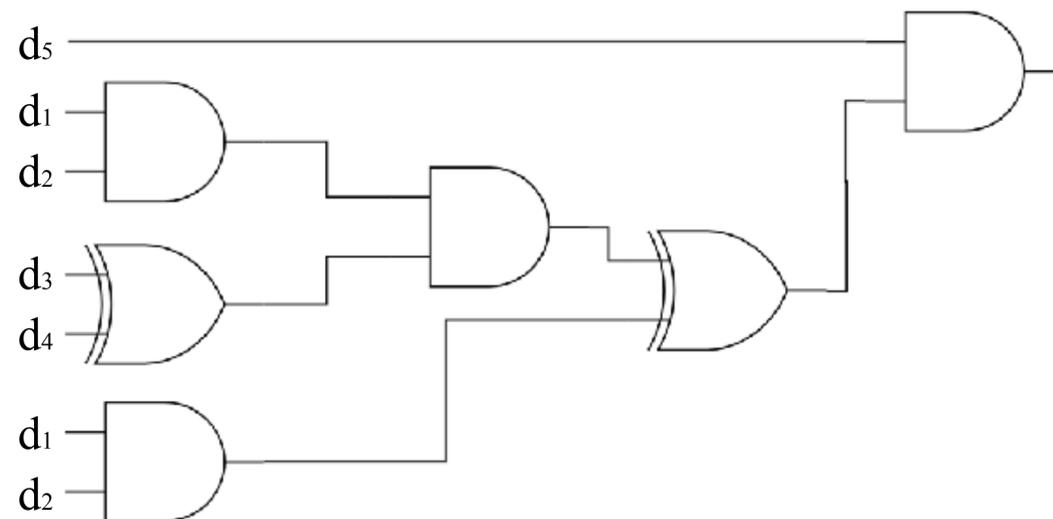
## Normalization + Equational Matching



Normalized  
Opt. Patterns



Find substitution  $\sigma$   
(considering commutativity)



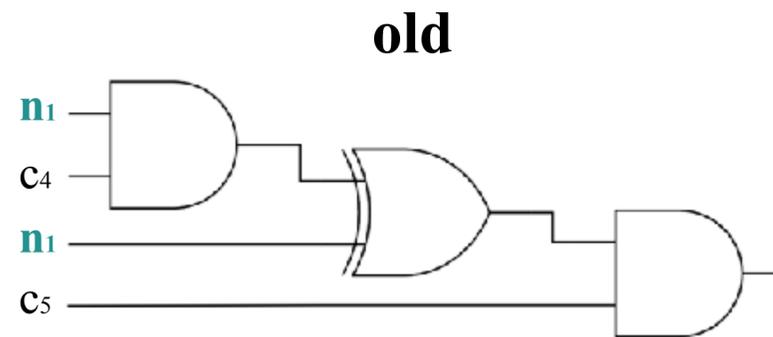
**target**

New Input Circuit  
Optimization

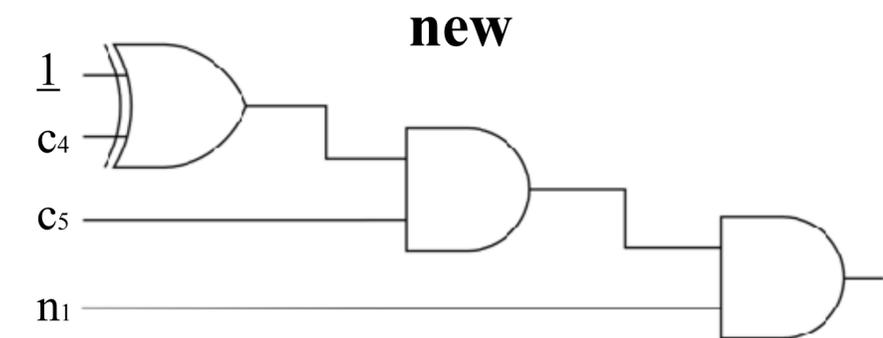


# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching



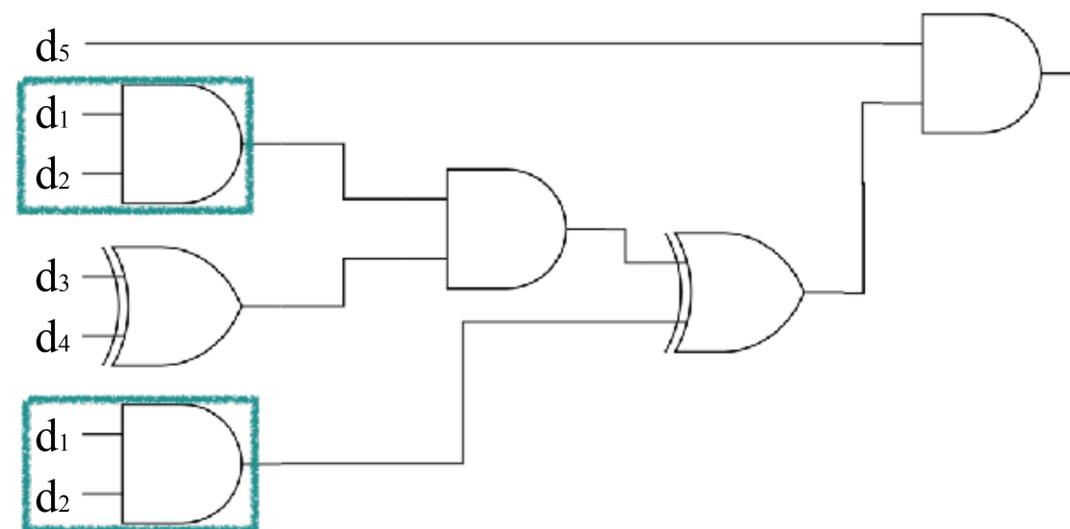
Normalized  
Opt. Patterns



Find substitution  $\sigma$   
(considering commutativity)



$$\sigma = \{n_1 \mapsto d_1 \text{ and } d_2,\}$$



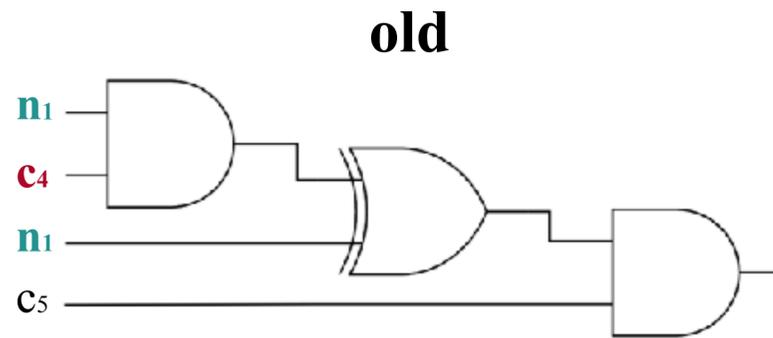
**target**

New Input Circuit  
Optimization

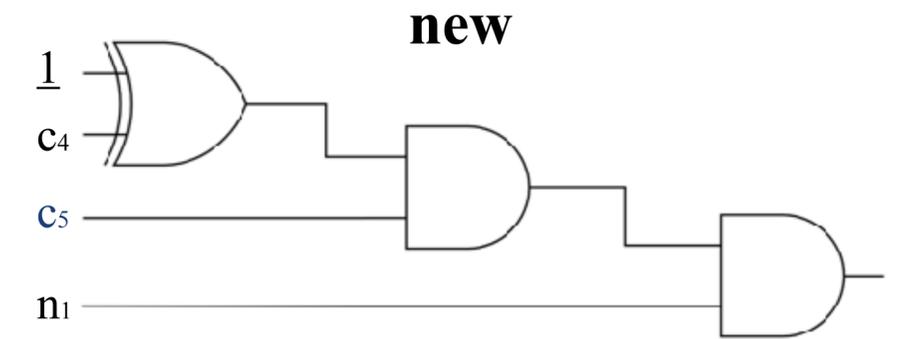


# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching



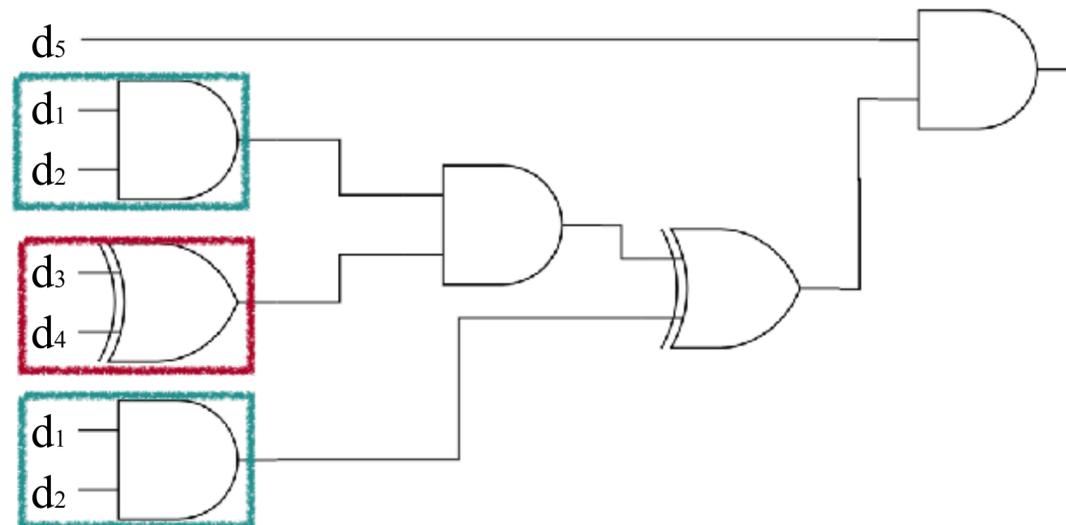
Normalized  
Opt. Patterns



Find substitution  $\sigma$   
(considering commutativity)



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



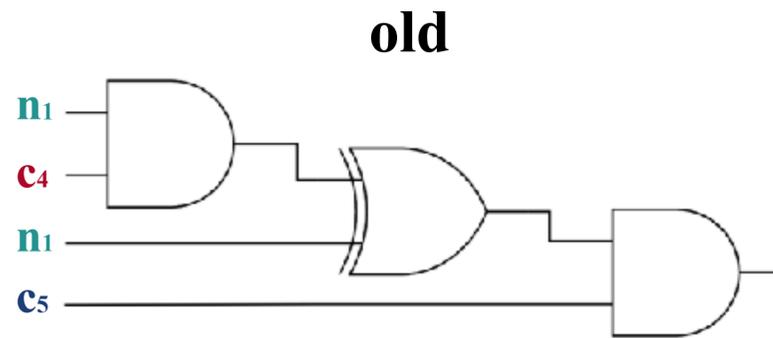
**target**

New Input Circuit  
Optimization

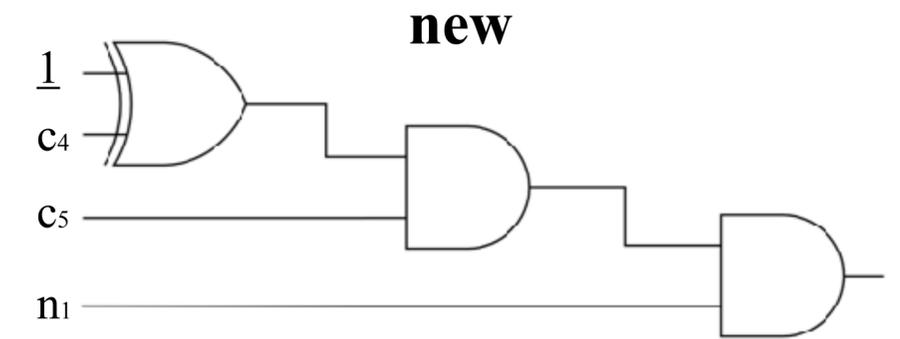


# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching

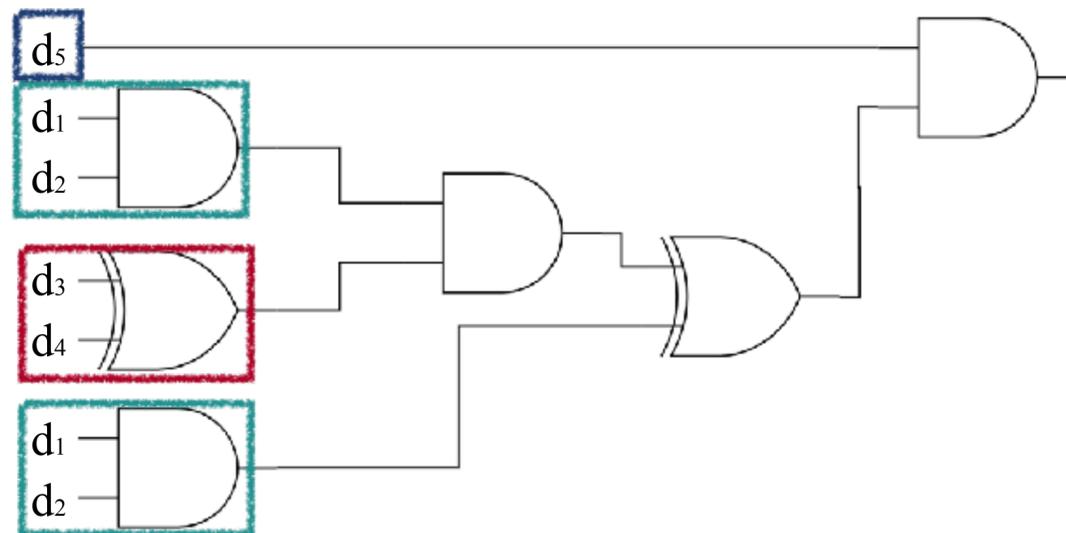


Normalized  
Opt. Patterns



Find substitution  $\sigma$   
(considering commutativity)

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



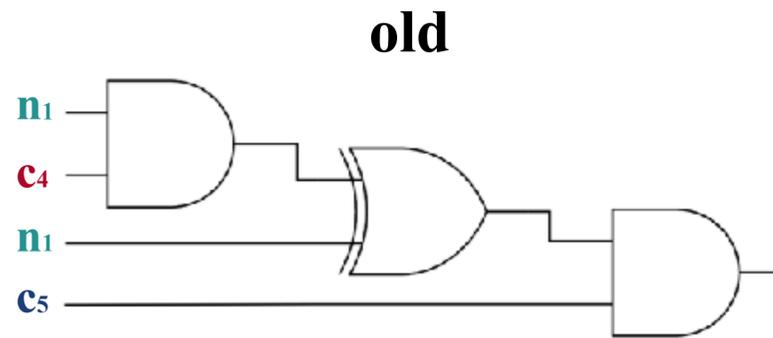
target

New Input Circuit  
Optimization

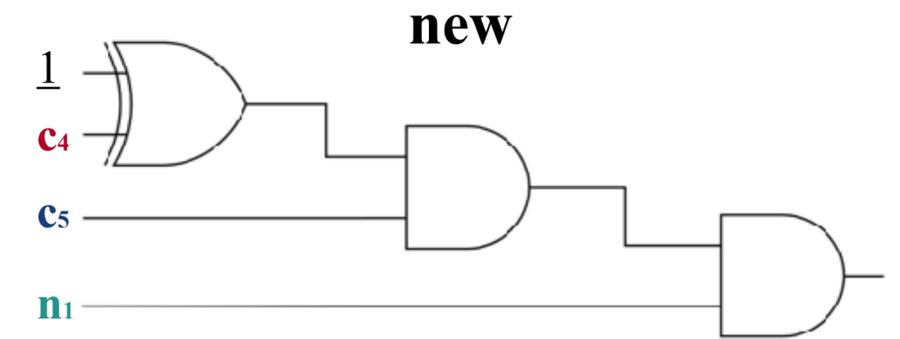


# Applying Learned Optimization Patterns (2/2)

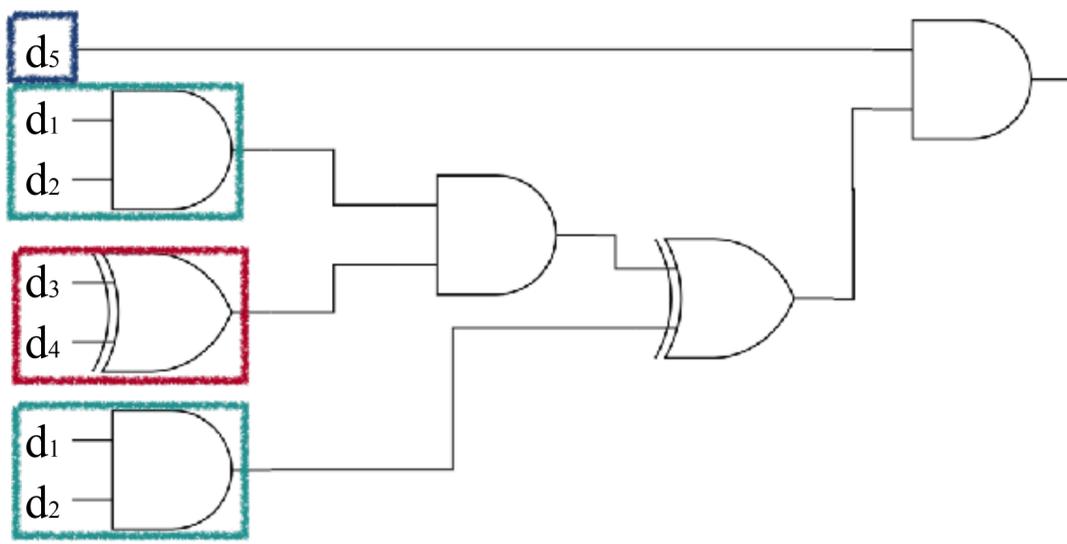
## Normalization + Equational Matching



Normalized  
Opt. Patterns

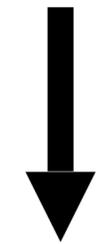


Find substitution  $\sigma$   
(considering commutativity)



target

Apply substitution  $\sigma$



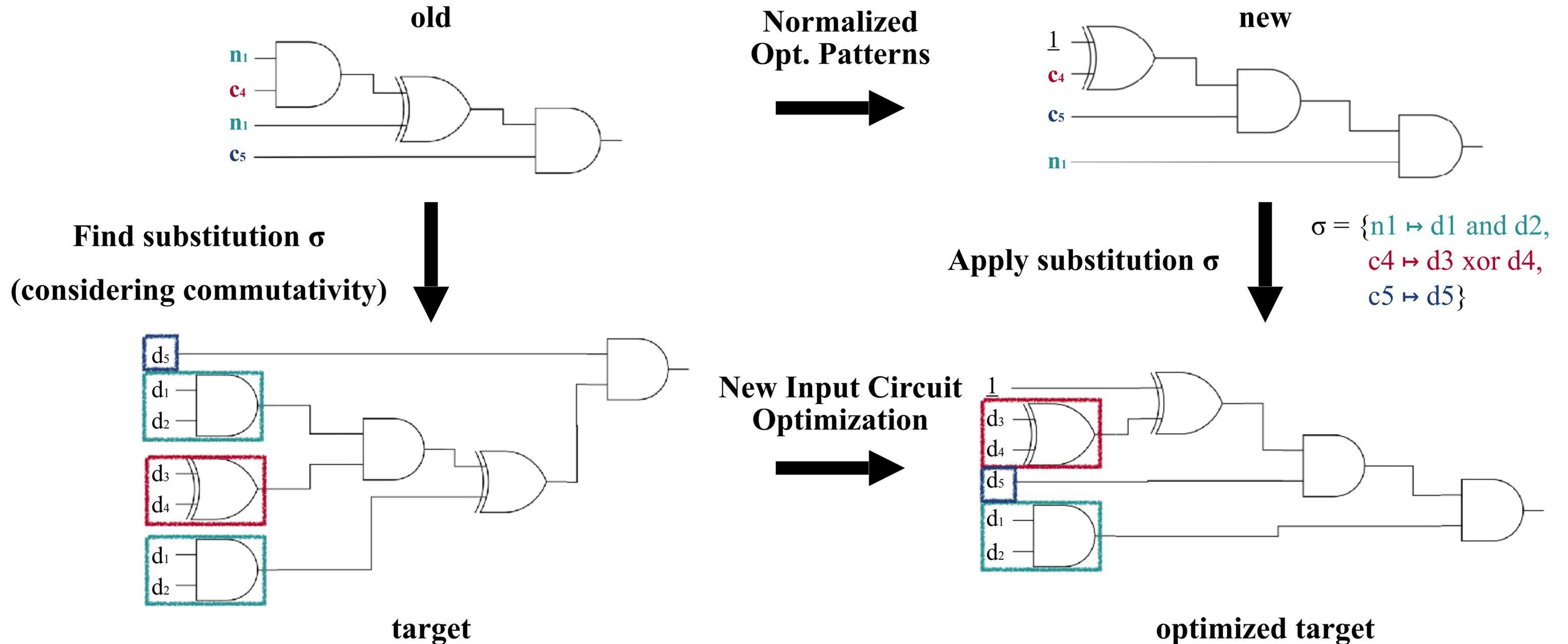
$\sigma = \{n1 \mapsto d1 \text{ and } d2,$   
 $c4 \mapsto d3 \text{ xor } d4,$   
 $c5 \mapsto d5\}$

New Input Circuit  
Optimization



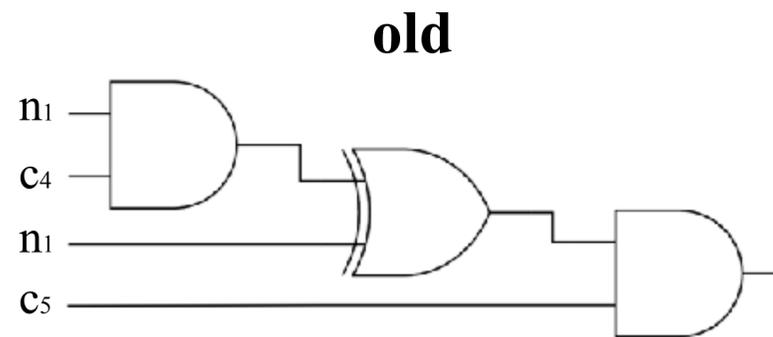
# Applying Learned Optimization Patterns (2/2)

## Normalization + Equational Matching

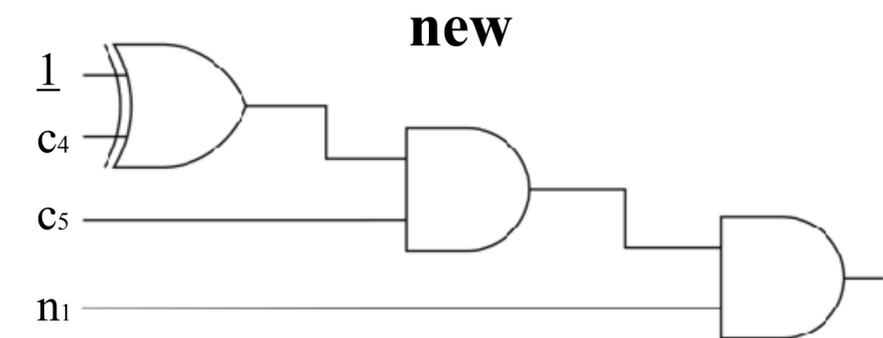


# Applying Learned Optimization Patterns (2/2)

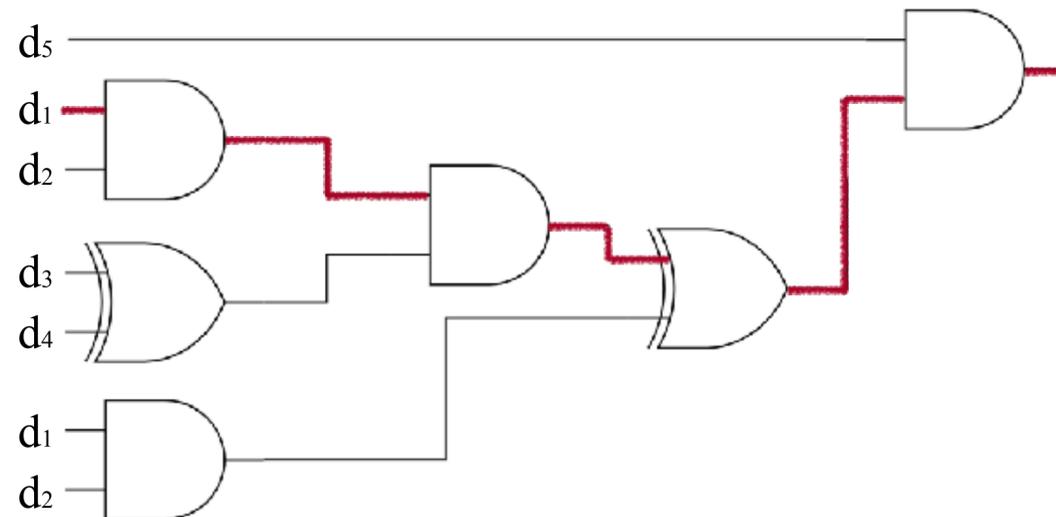
## Normalization + Equational Matching



Normalized  
Opt. Patterns



Find substitution  $\sigma$   
(considering commutativity)



target  
depth 3

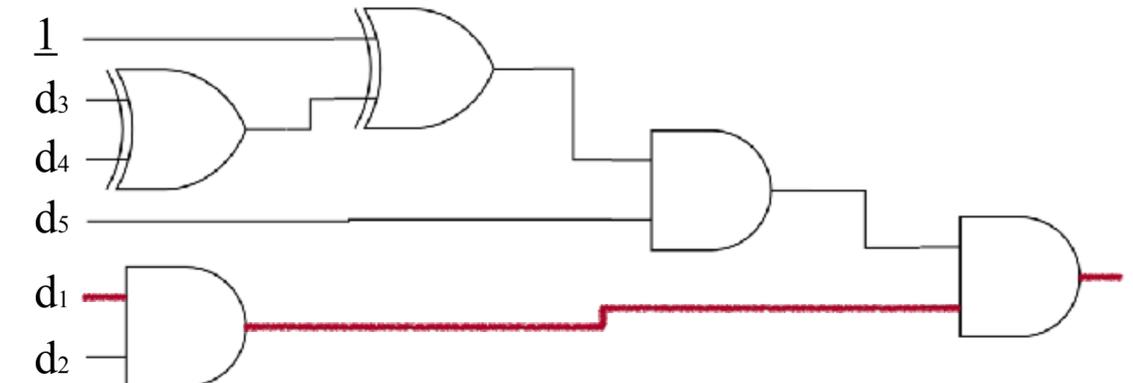
New Input Circuit  
Optimization



Apply substitution  $\sigma$



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

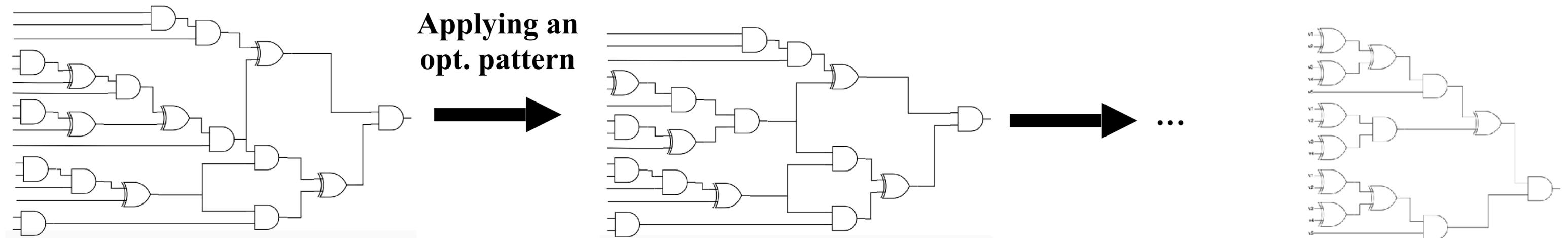


optimized target  
depth 2

# Applying Learned Optimization Patterns

Formal properties

(Soundness) semantics unchanged



(Termination) finitely many rule applications



# Exhaustive Search with E-graphs

- Idea: Apply the rewrite rules in all possible orders and store all the results
- Example
  - Optimizing a given circuit:  $((x_1 \wedge x_2) \wedge (x_2 \oplus x_3)) \wedge x_3$
  - Usable rewrite rules:

$$\text{rule (1) : } ((v_1 \wedge v_2) \wedge v_3) \wedge v_4 \longrightarrow ((v_1 \wedge v_2) \wedge v_4) \wedge ((v_2 \oplus v_4) \oplus v_3)$$

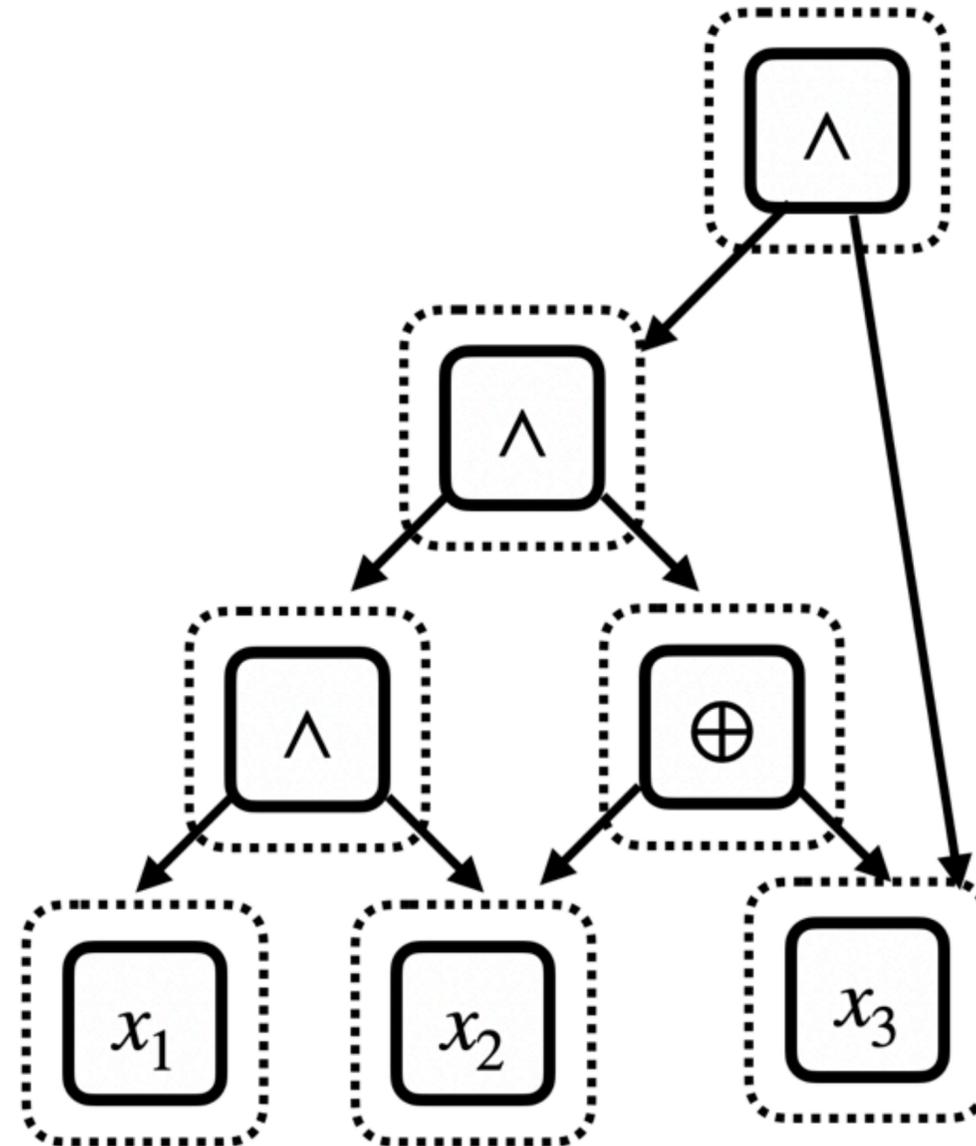
$$\text{rule (2) : } ((v_1 \wedge v_2) \wedge v_3) \wedge v_4 \longrightarrow (v_1 \wedge v_2) \wedge (v_3 \wedge v_4)$$

$$\text{rule (3) : } (v_1 \oplus v_1) \longrightarrow 0$$

$$\text{rule (4) : } (v_1 \wedge 0) \longrightarrow 0$$

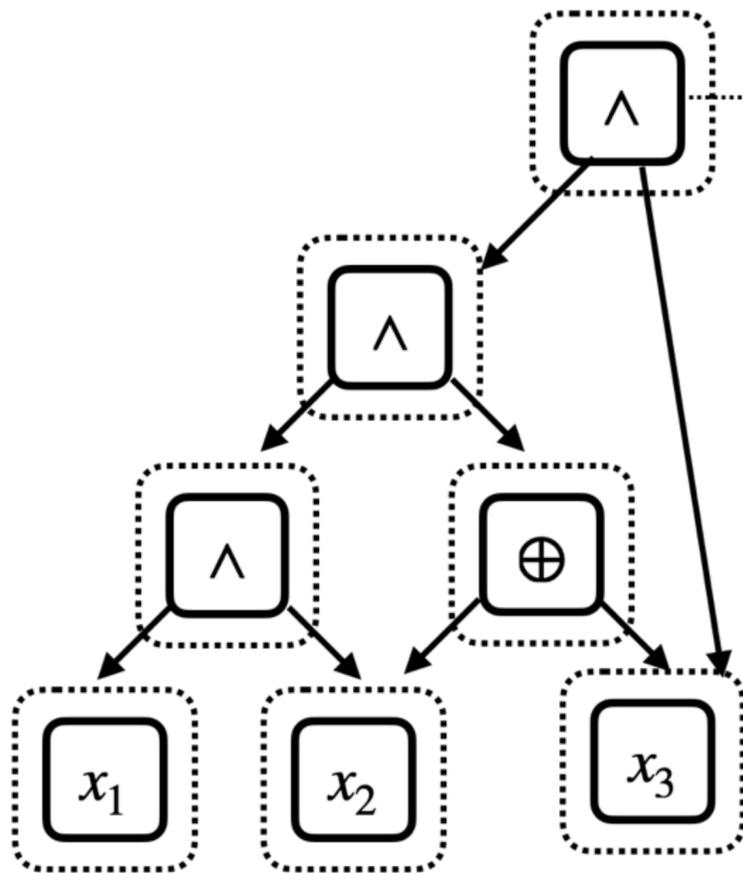
# Exhaustive Search with E-graphs

$$\text{root} : ((x_1 \wedge x_2) \wedge (x_2 \oplus x_3)) \wedge x_3$$



# Exhaustive Search with E-graphs

$root : ((x_1 \wedge x_2) \wedge (x_2 \oplus x_3)) \wedge x_3$



rewritable by rule (1)

rewritable by rule (2)

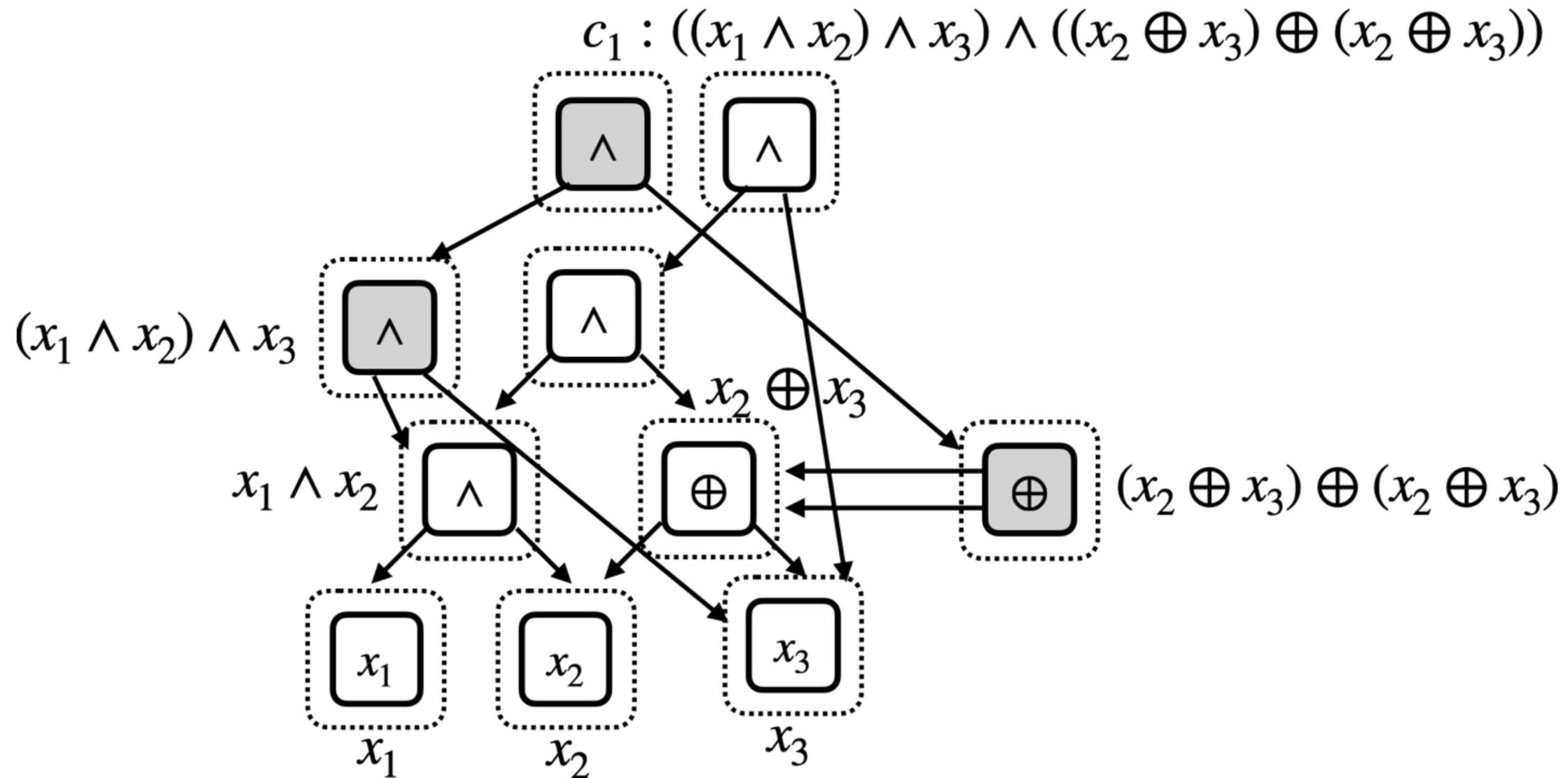
$ematch(root)$

$c_1 : ((x_1 \wedge x_2) \wedge x_3) \wedge ((x_2 \oplus x_3) \oplus (x_2 \oplus x_3))$

$c_2 : (x_1 \wedge x_2) \wedge ((x_2 \oplus x_3) \wedge x_3)$

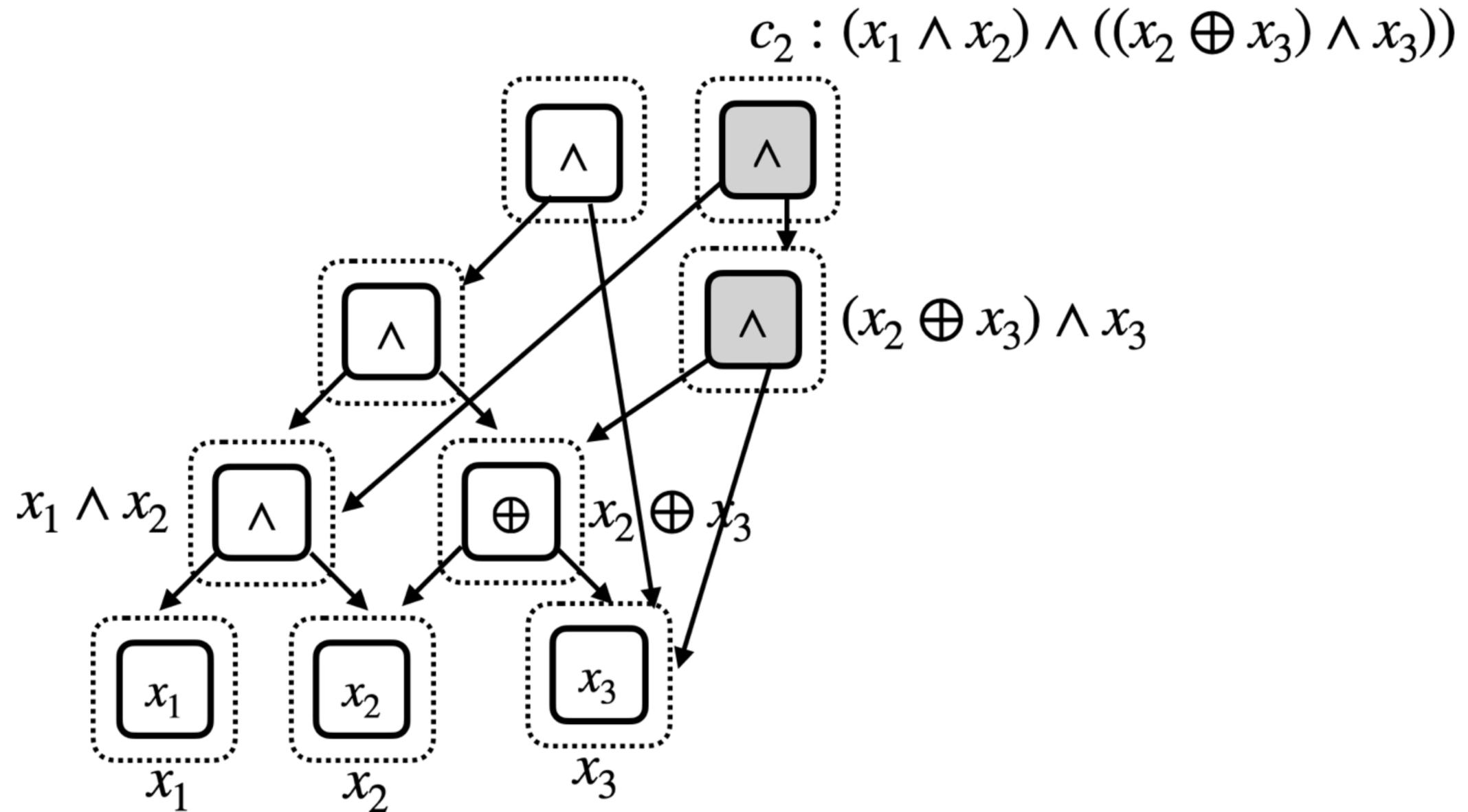
# Exhaustive Search with E-graphs

- Applying rule (1) (shaded: newly added)



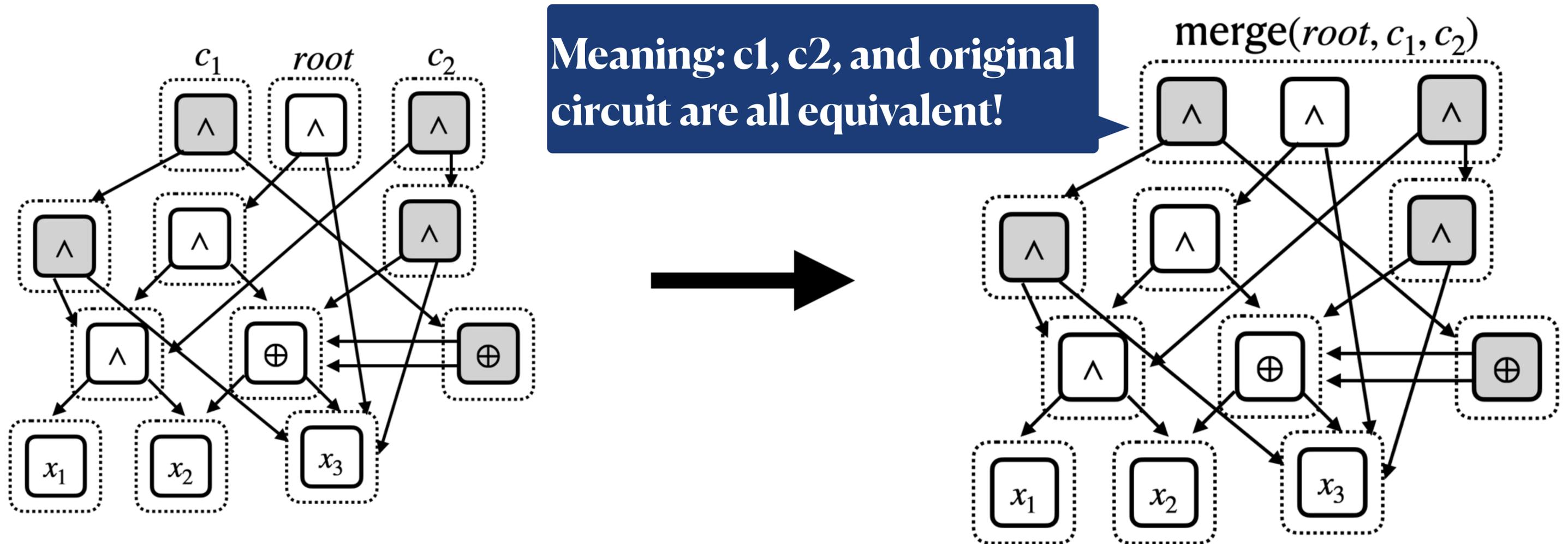
# Exhaustive Search with E-graphs

- Applying rule (2)



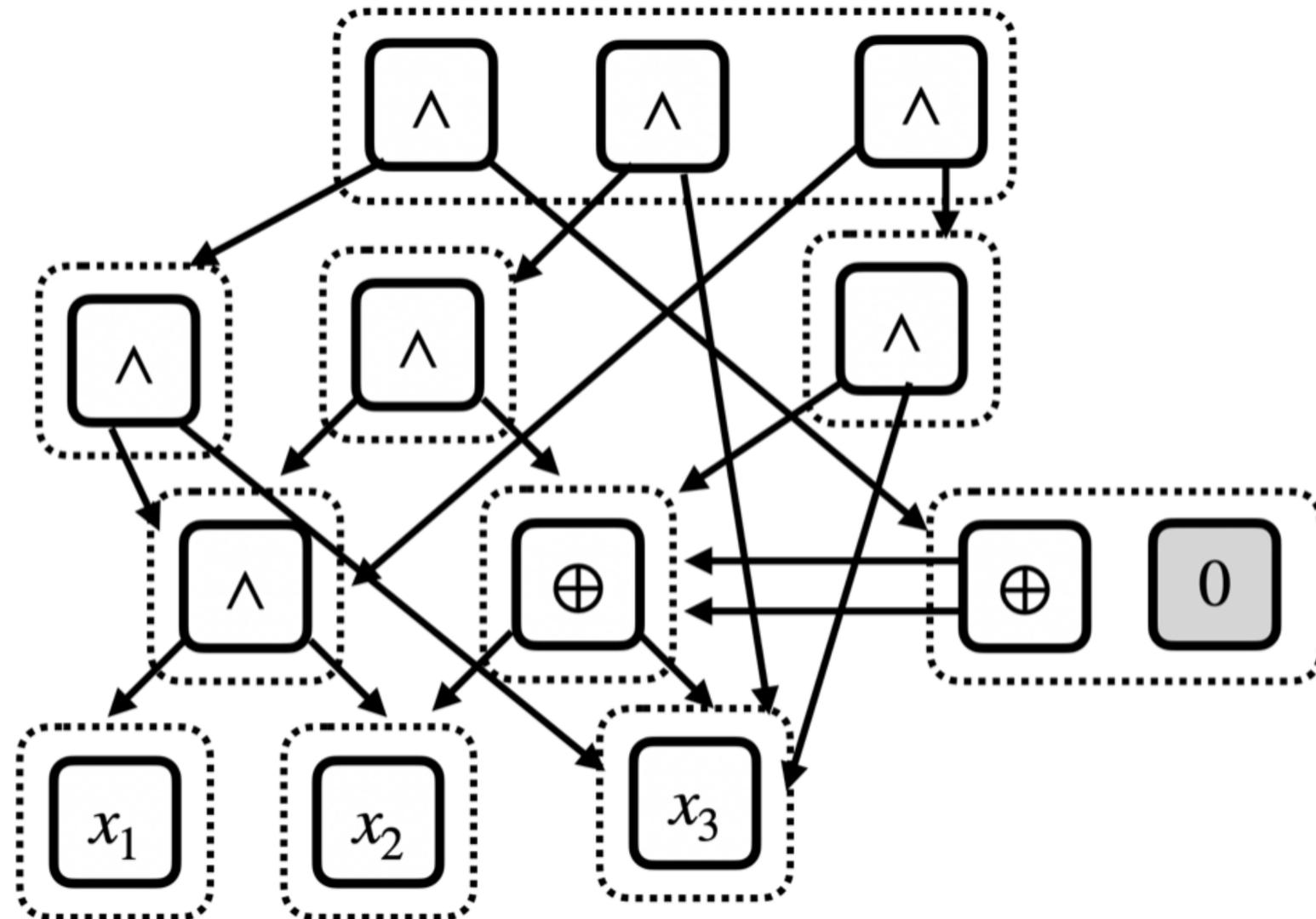
# Exhaustive Search with E-graphs

- Merging the results of applying rules (1) and (2)



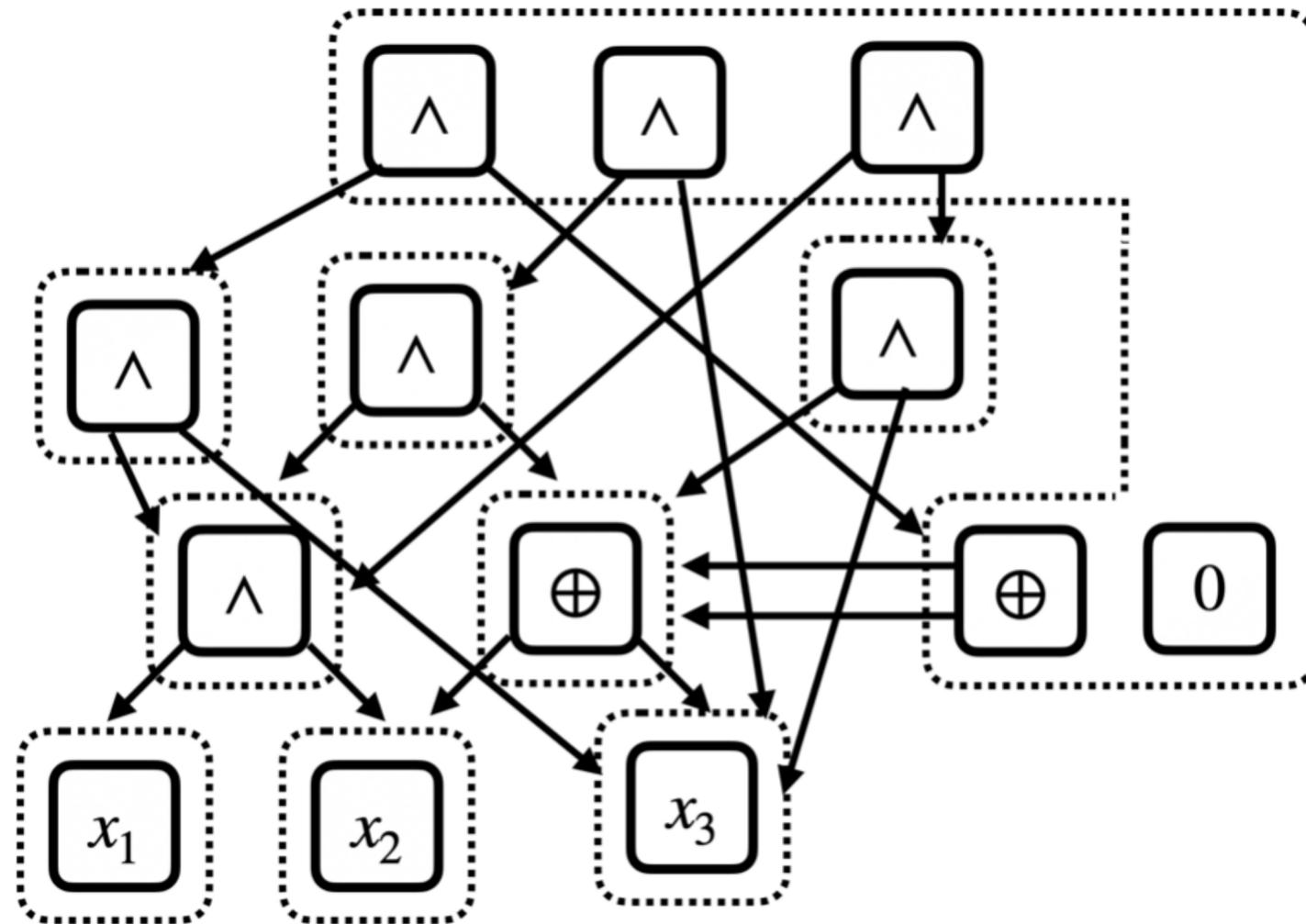
# Exhaustive Search with E-graphs

- Applying rule (3)  $(v_1 \oplus v_1) \rightarrow 0$  and merging



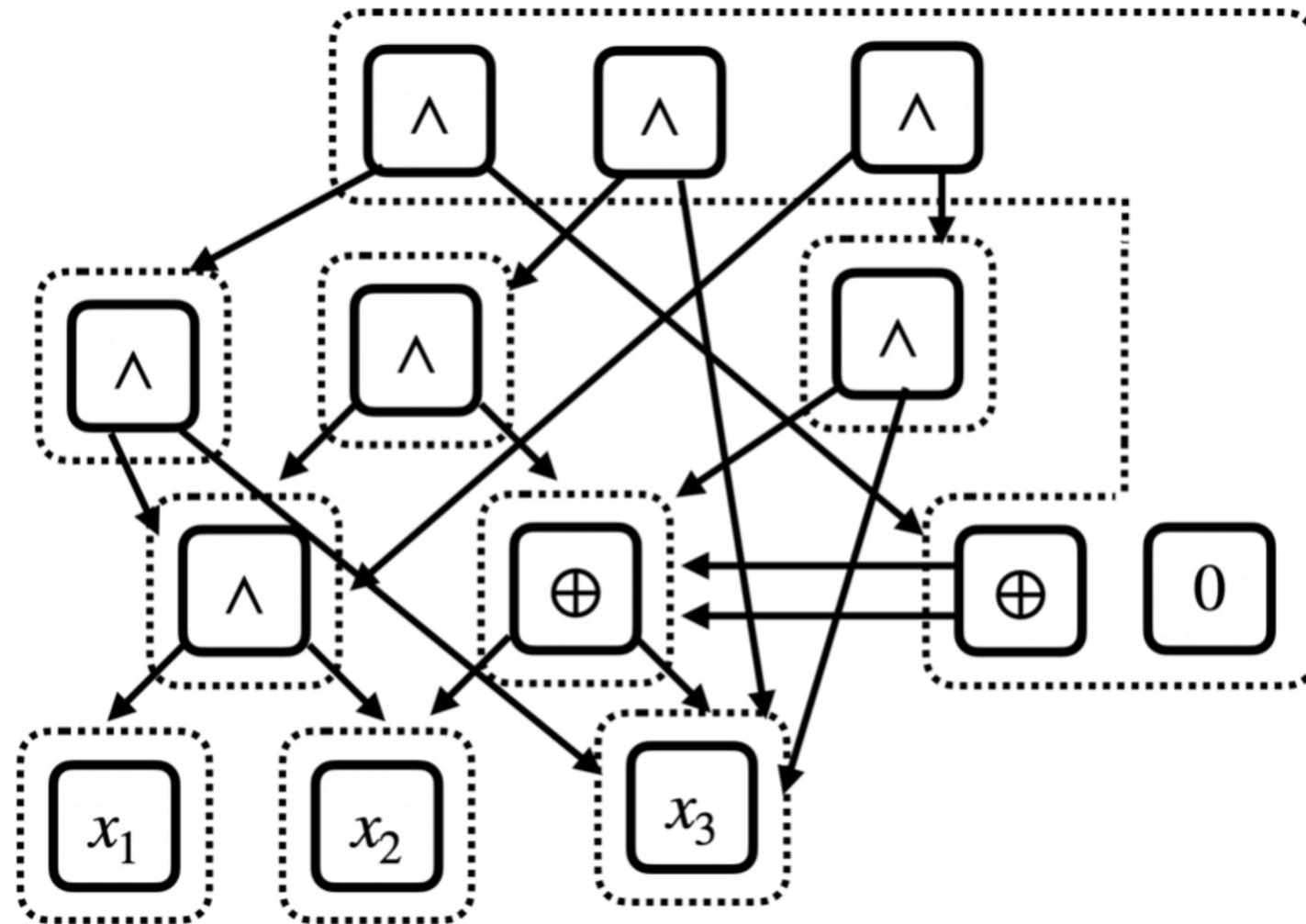
# Exhaustive Search with E-graphs

- Applying rule (4)  $(v_1 \wedge 0) \rightarrow 0$  and merging



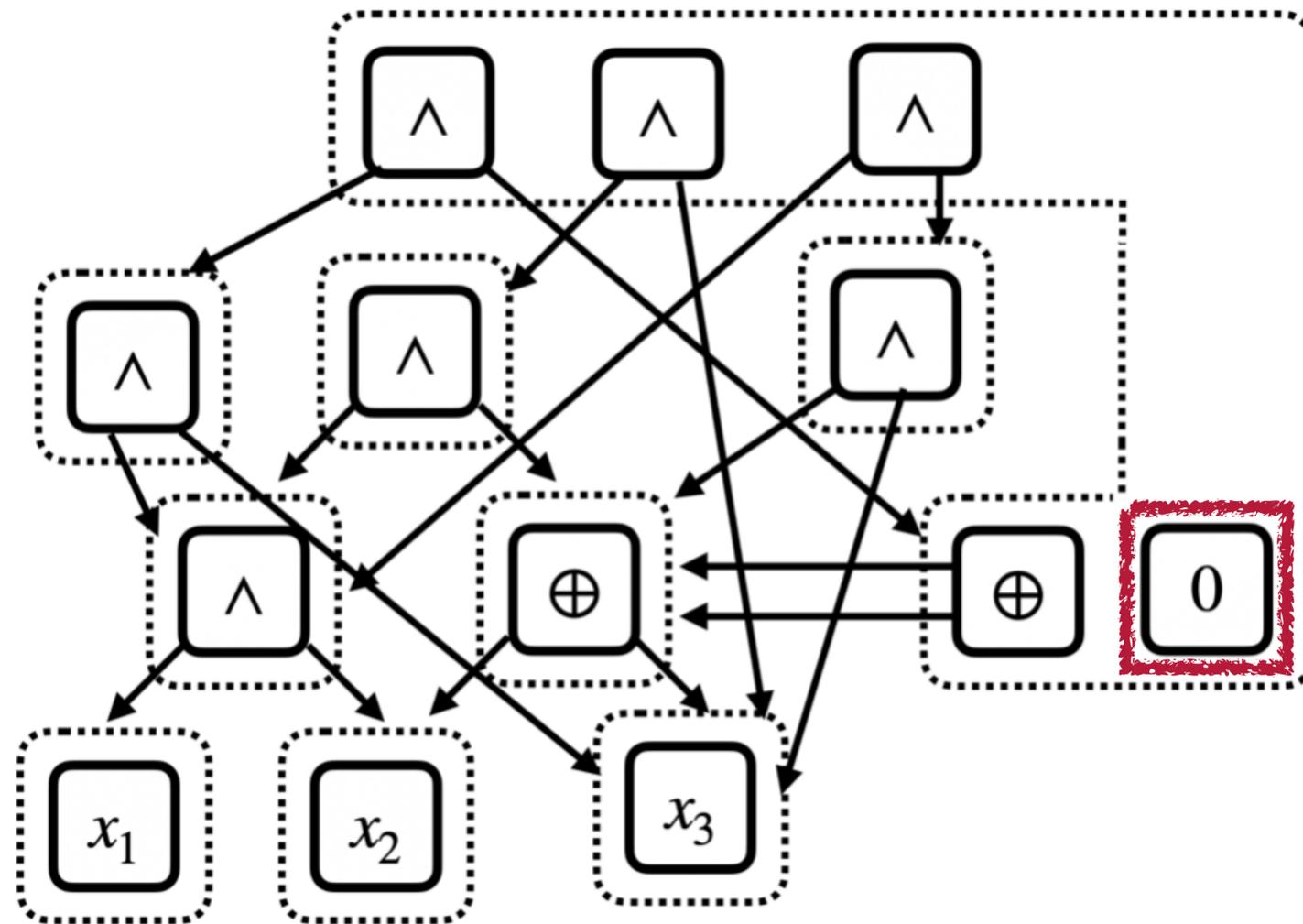
# Exhaustive Search with E-graphs

- Applying any rule doesn't change the e-graph => **saturated!**



# Exhaustive Search with E-graphs

- Pick the best result: **0**



# Rewriting vs. Exhaustive search (aka equality saturation)

- Rewriting: scalable but may find a sub-optimal result
- Equality saturation: unscalable but guaranteed to find an optimal result<sup>†</sup>
- We use the rewriting method for large circuits and equality saturation for small circuits.

<sup>†</sup> egg: Fast and Extensible Equality Saturation, ACM POPL 2021

# Lobster Performance (1/4)

## Benchmarks

- 25 HE algorithms from 4 sources
  - Cingulata benchmarks
  - Sorting benchmarks
  - Hackers Delight benchmarks
  - EPFL benchmarks

**2 HE friendly algorithms  
(medical, sorting)**

**4 privacy-preserving sorting  
algorithms  
(merge, insert, bubble, odd-even)**

**12 Homomorphic  
bitwise operations**

**7 EPFL combinational benchmark suite  
(to test circuit optimizer)**

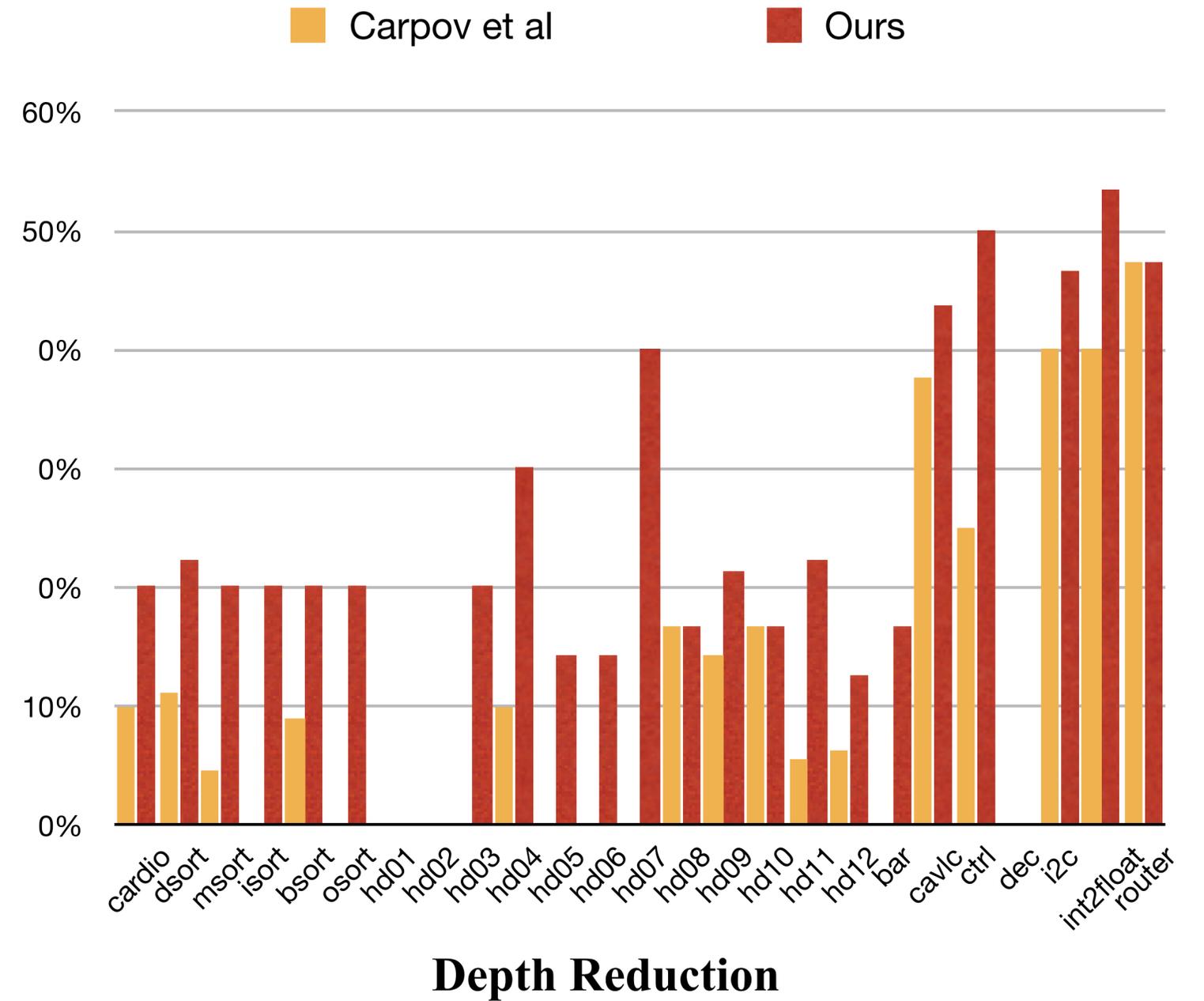
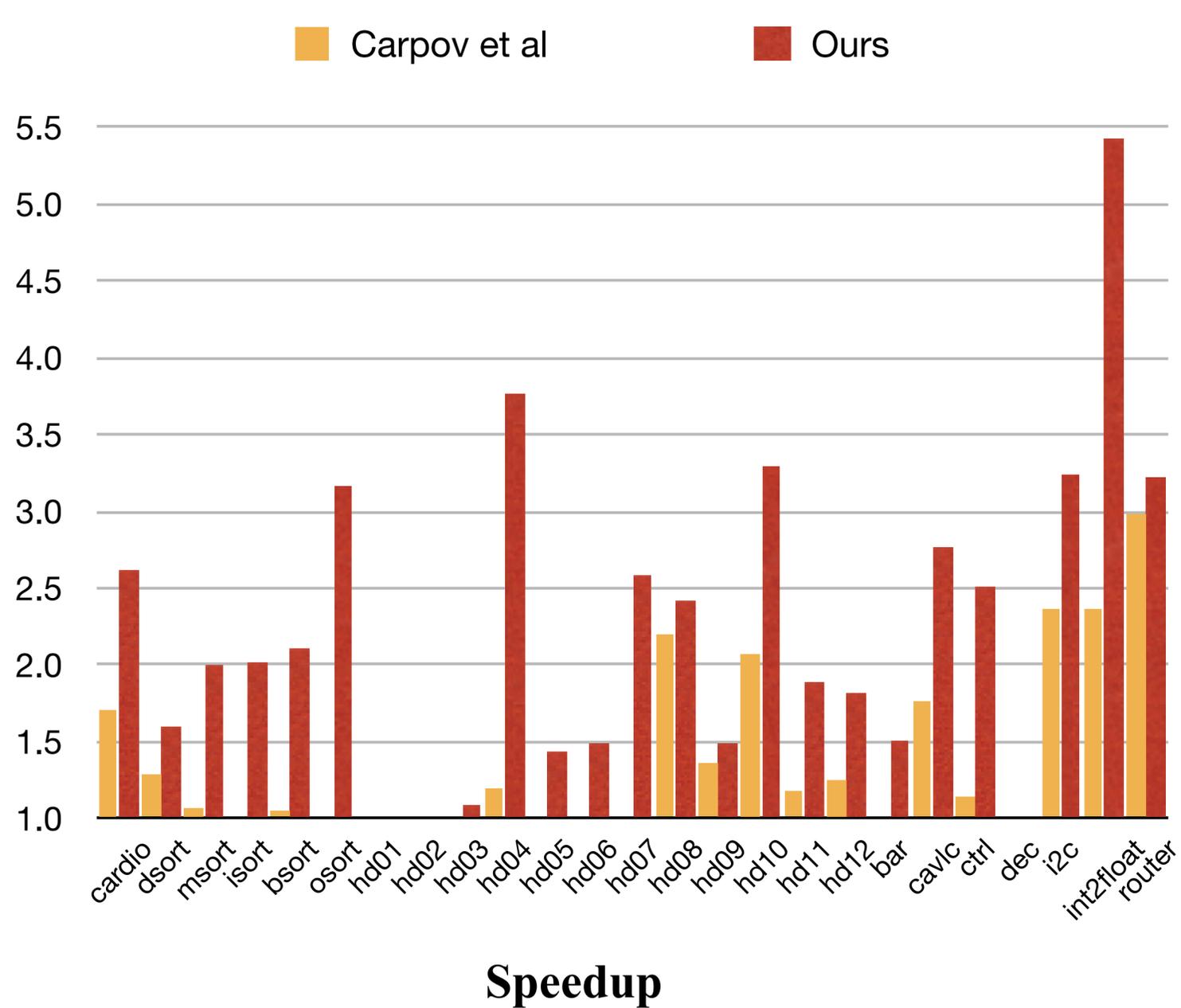
# Lobster Performance (1/4)

## Benchmarks

Name	Description	×Depth	#AND	Size
cardio	medical diagnostic algorithm [16]	10	109	318
dsort	FHE-friendly direct sort [17]	9	708	1464
msort	merge sort [17]	45	810	1525
isort	insertion sort [17]	45	810	1525
bsort	bubble sort [17]	45	810	1525
osort	oddeven sort [17]	25	702	1343
hd-01	isolate the rightmost 1-bit [35]	6	87	118
hd-02	absolute value [35]	6	76	229
hd-03	floor of average of two integers (a clever impl.) [35]	5	27	64
hd-04	floor of average of two integers (a naive impl.) [52]	10	75	159
hd-05	max of two integers [35]	7	121	295
hd-06	min of two integers [35]	7	121	295
hd-07	turn off the rightmost contiguous string of 1-bits [35]	5	17	32
hd-08	determine if an integer is a power of 2 [35]	6	18	37
hd-09	round up to the next highest power of 2 [35]	14	134	236
hd-10	find first 0-byte [52]	6	35	73
hd-11	the longest length of contiguous string of 1-bits [52]	18	391	652
hd-12	number of leading 0-bits [52]	16	116	232
bar	barrel shifter [1]	12	3141	5710
cavlc	coding-cavlc [1]	16	655	1219
ctrl	ALU control unit [1]	8	107	180
dec	decoder [1]	3	304	312
i2c	i2c controller [1]	15	1157	1987
int2float	int to float converter [1]	15	213	386
router	lookahead XY router [1]	19	170	277

# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



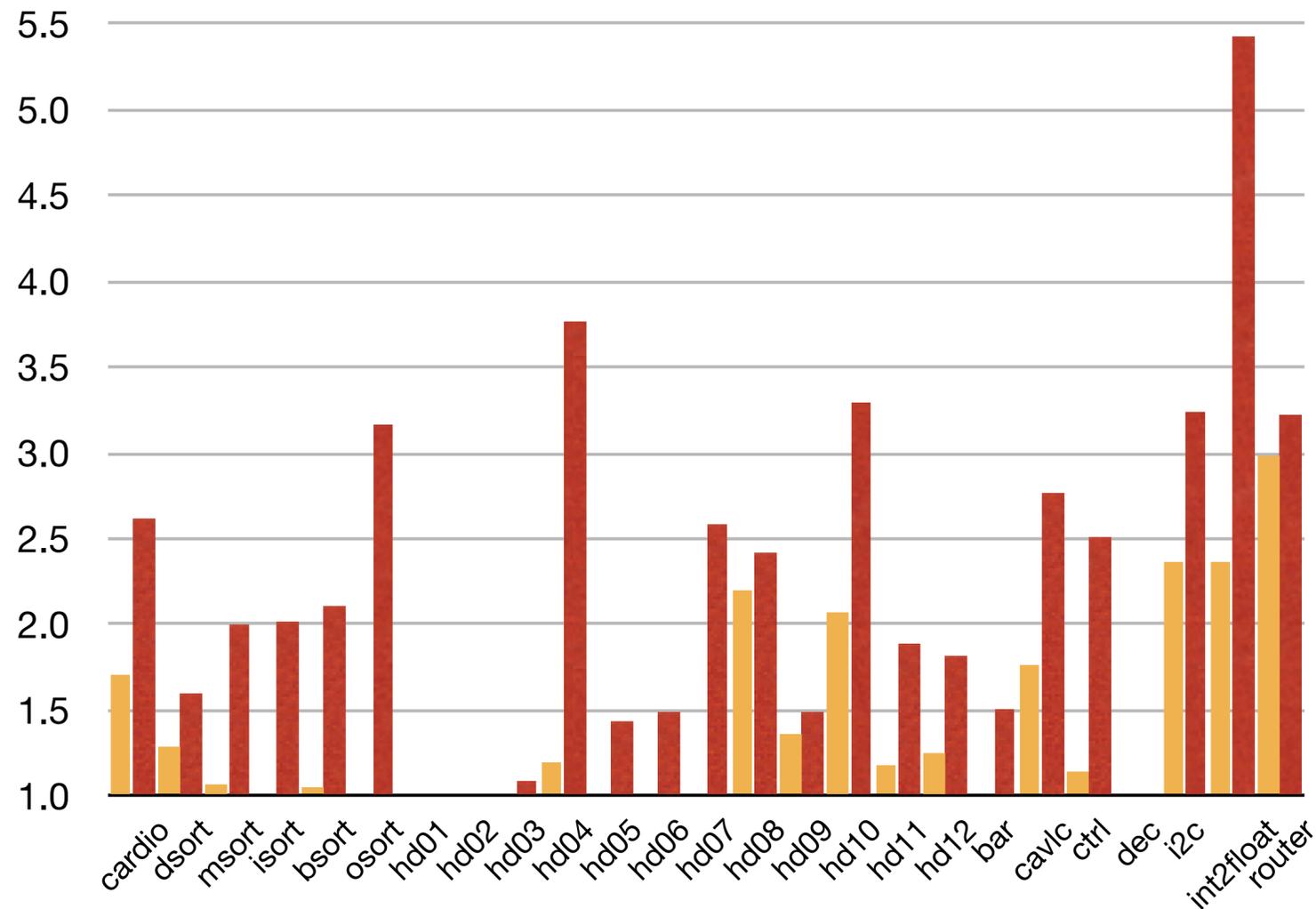
# Lobster Performance (2/4)

Hand-written-rule based  
HE circuit optimizer

## Optimization Results of Lobster and the baseline

Carpov et al

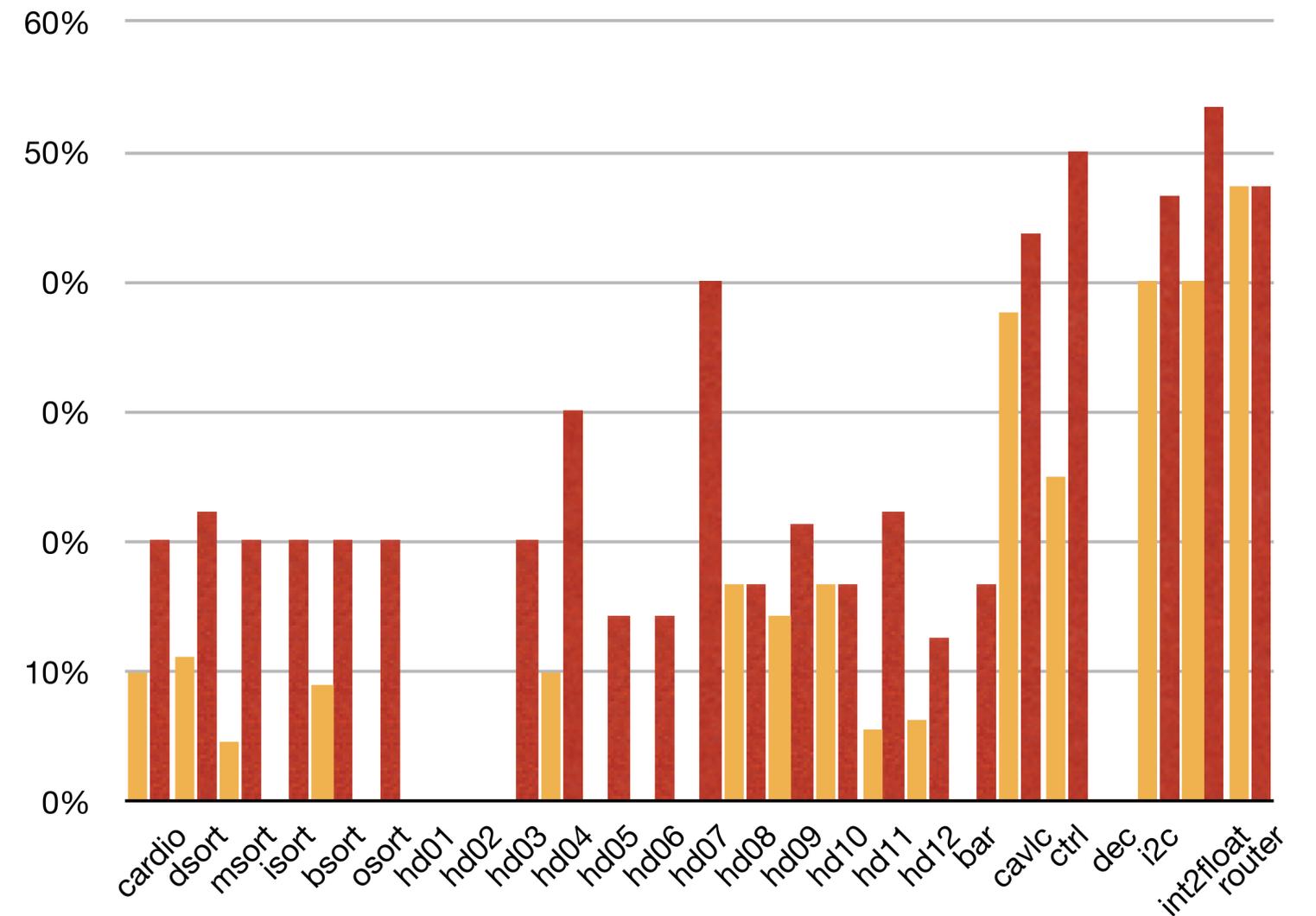
Ours



Speedup

Carpov et al

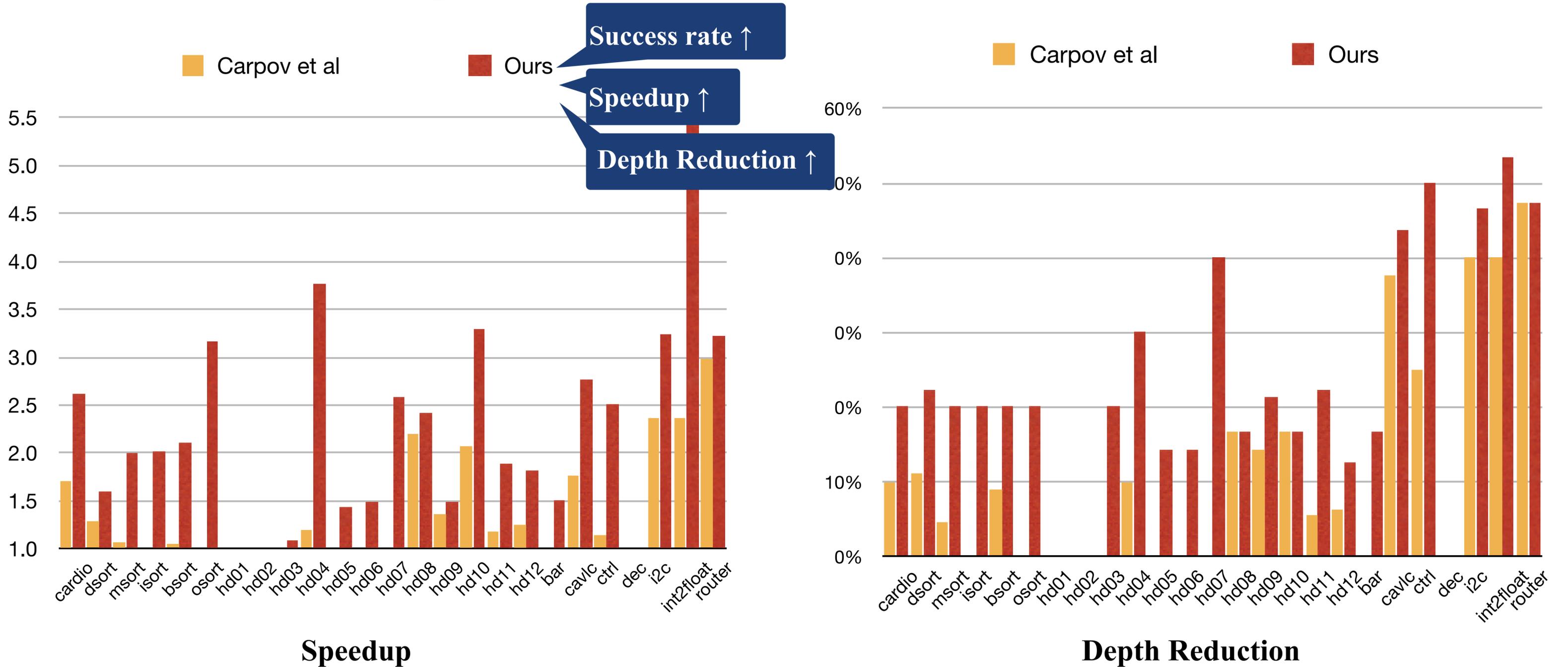
Ours



Depth Reduction

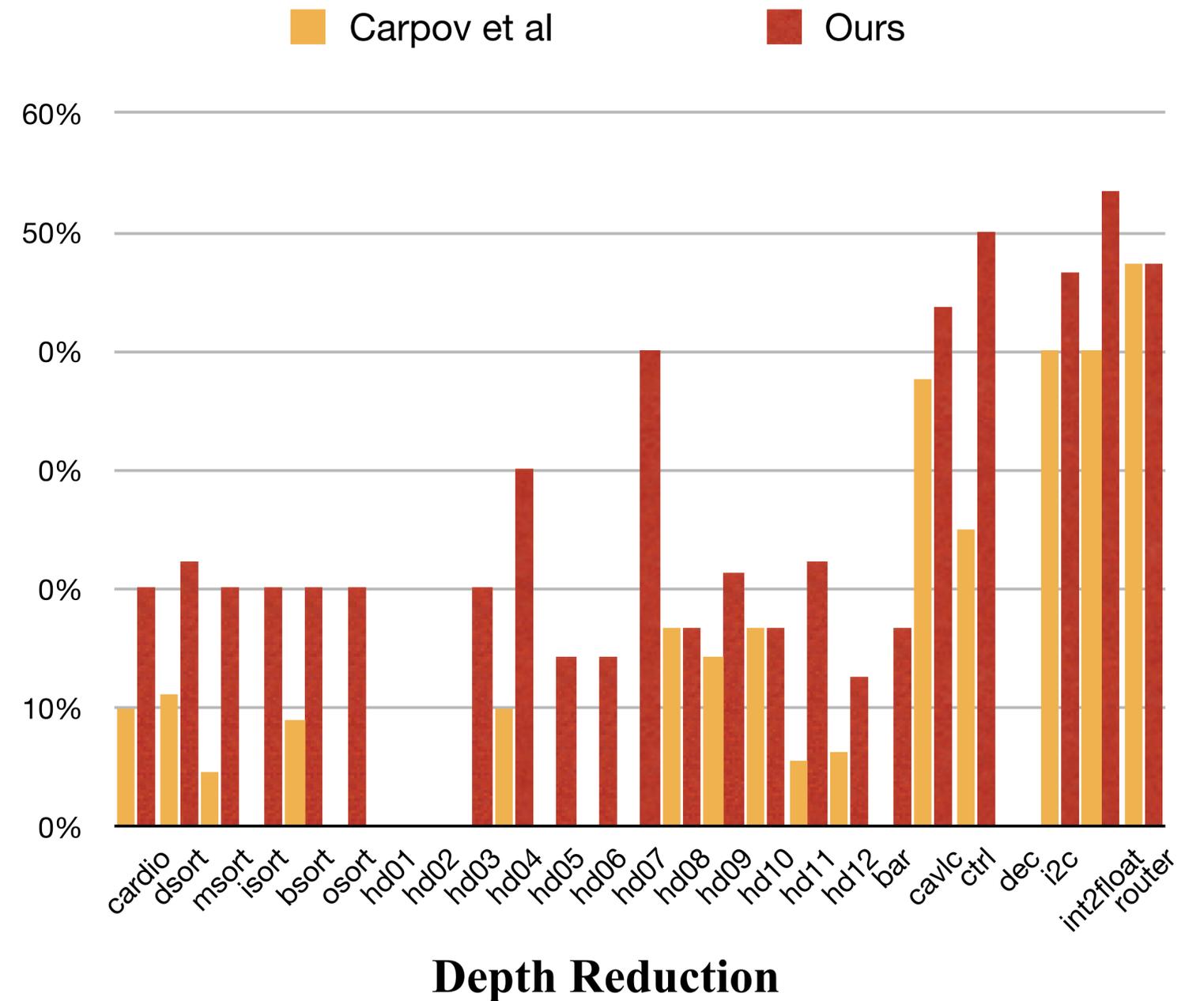
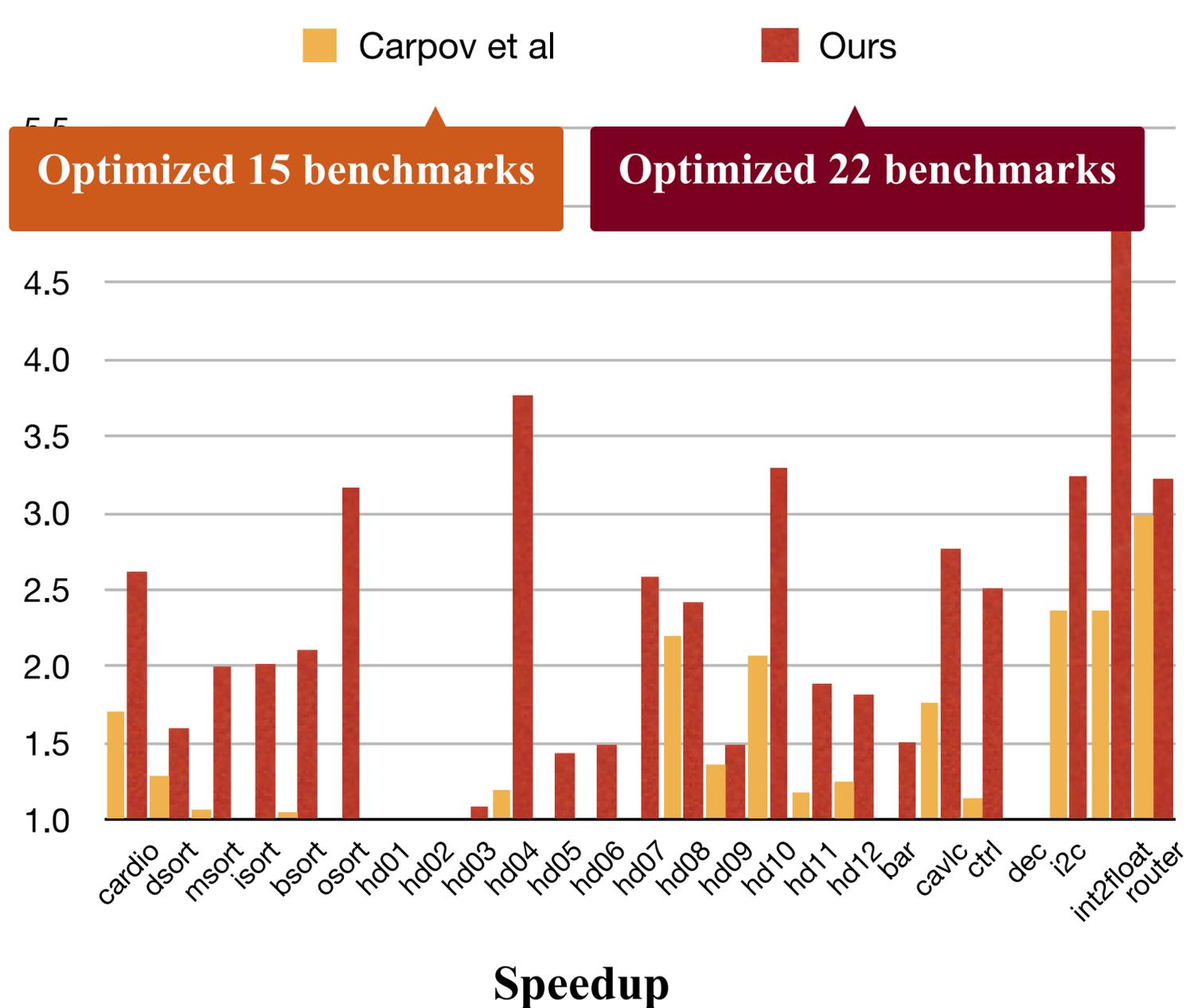
# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



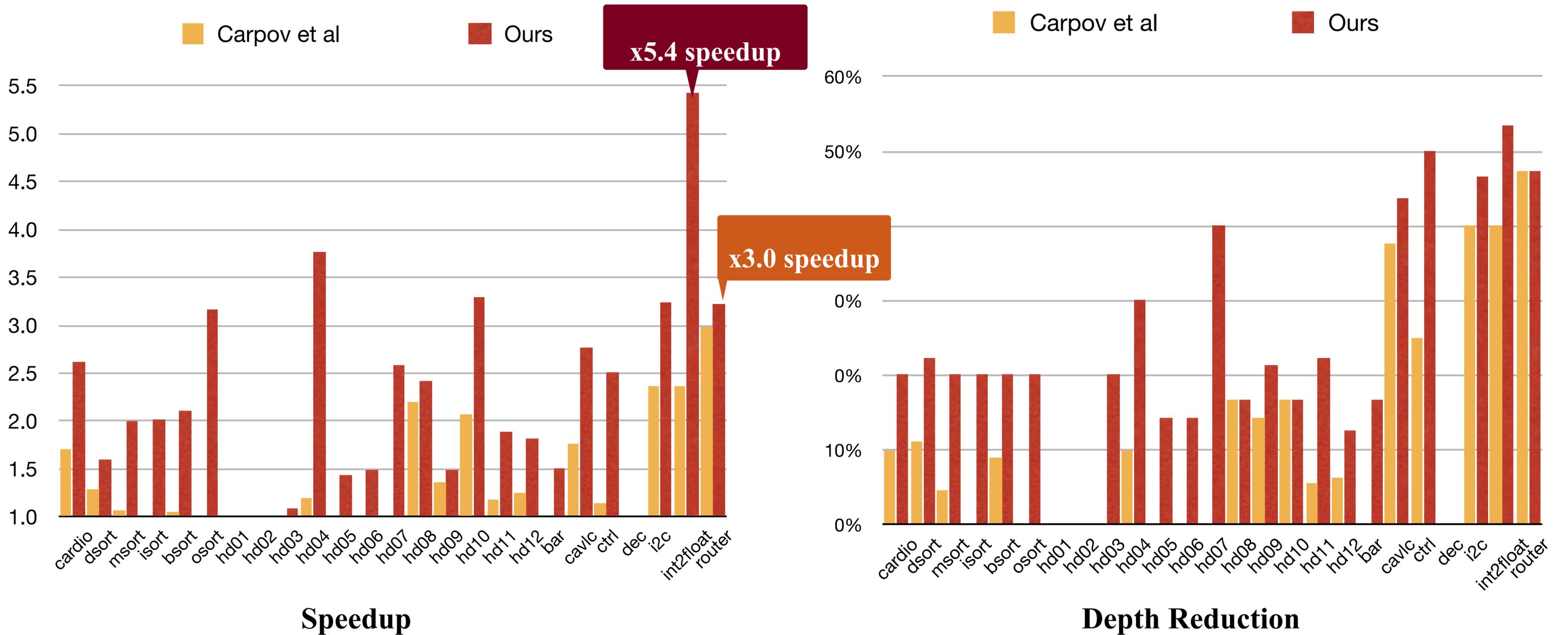
# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



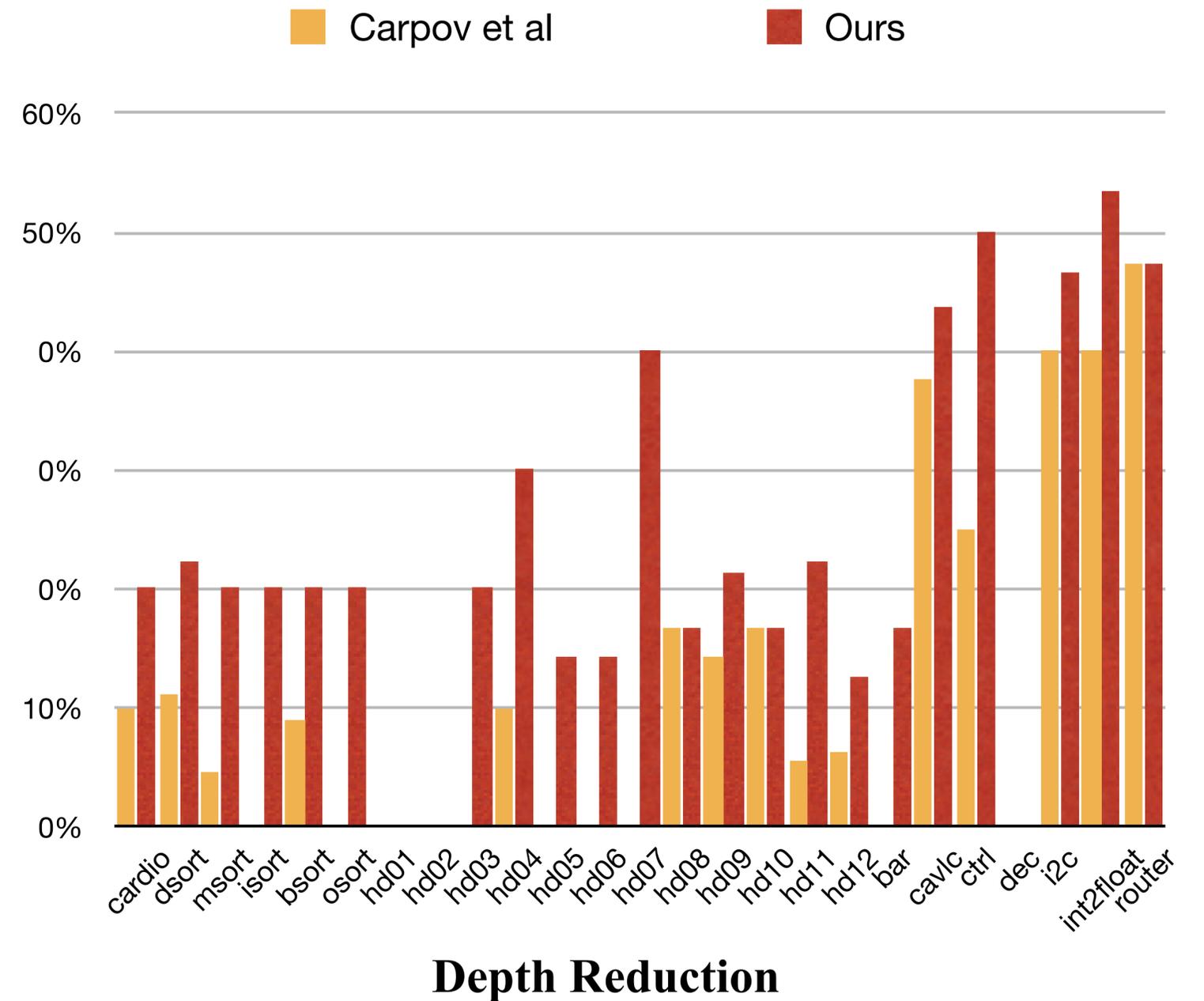
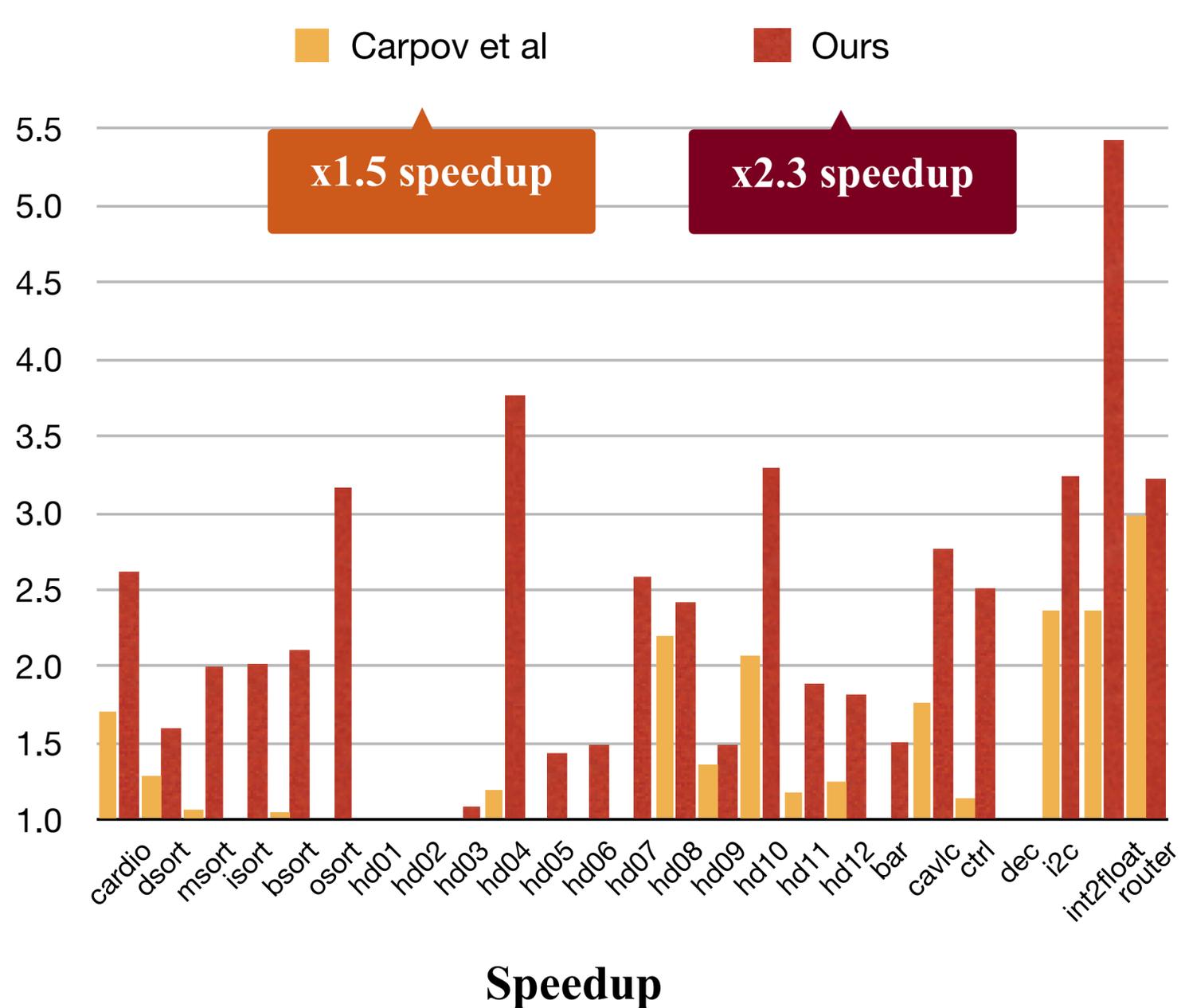
# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



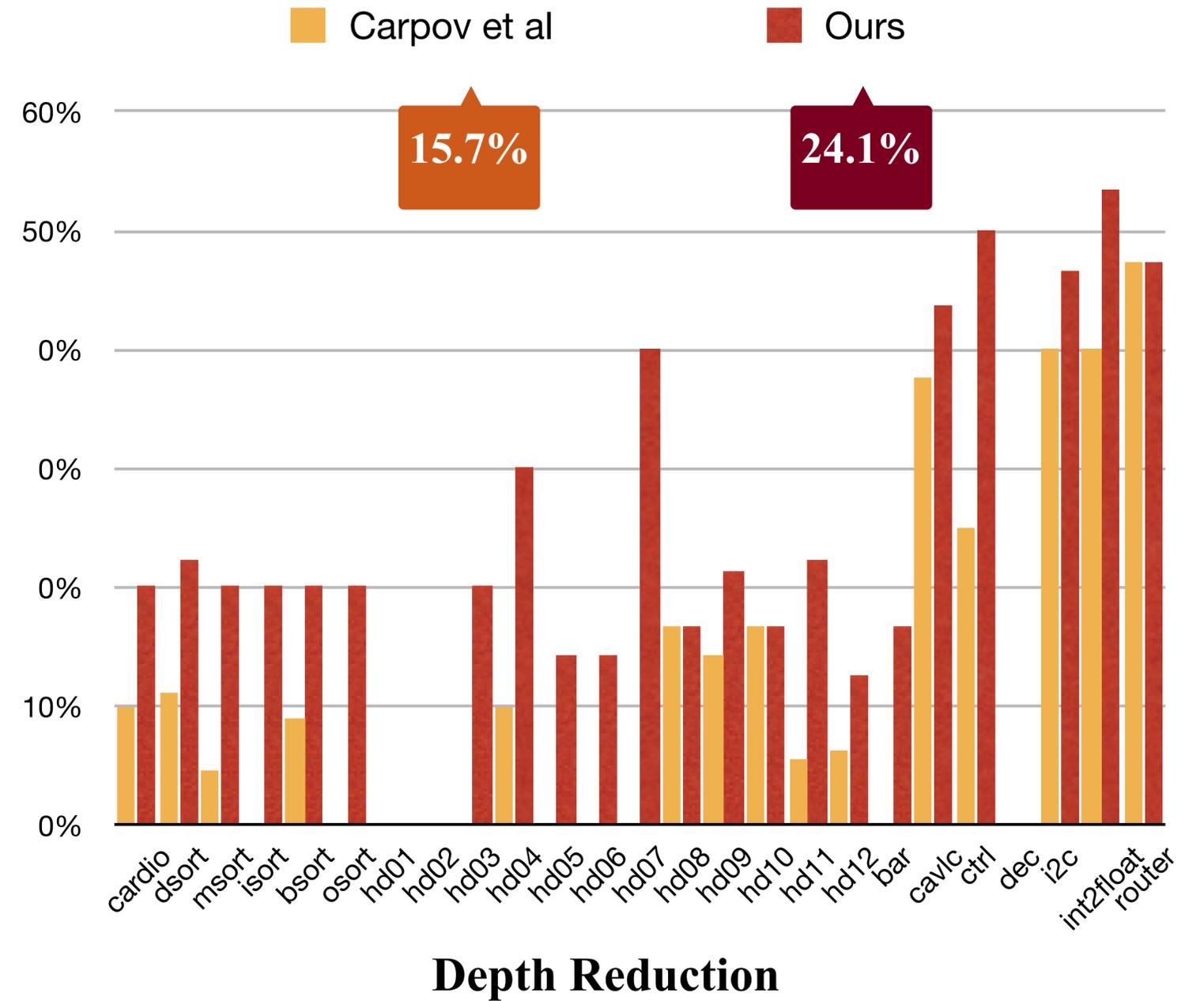
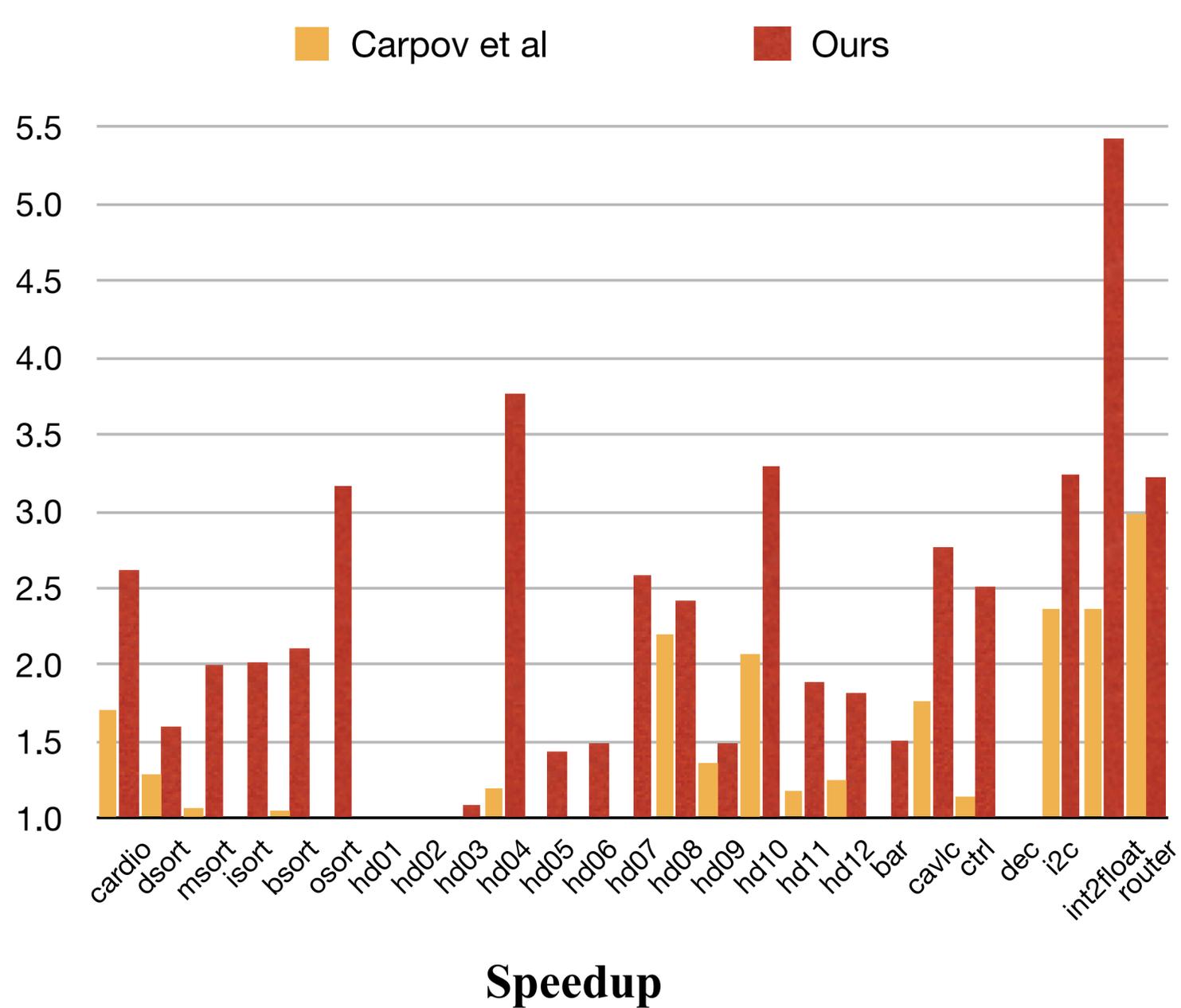
# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



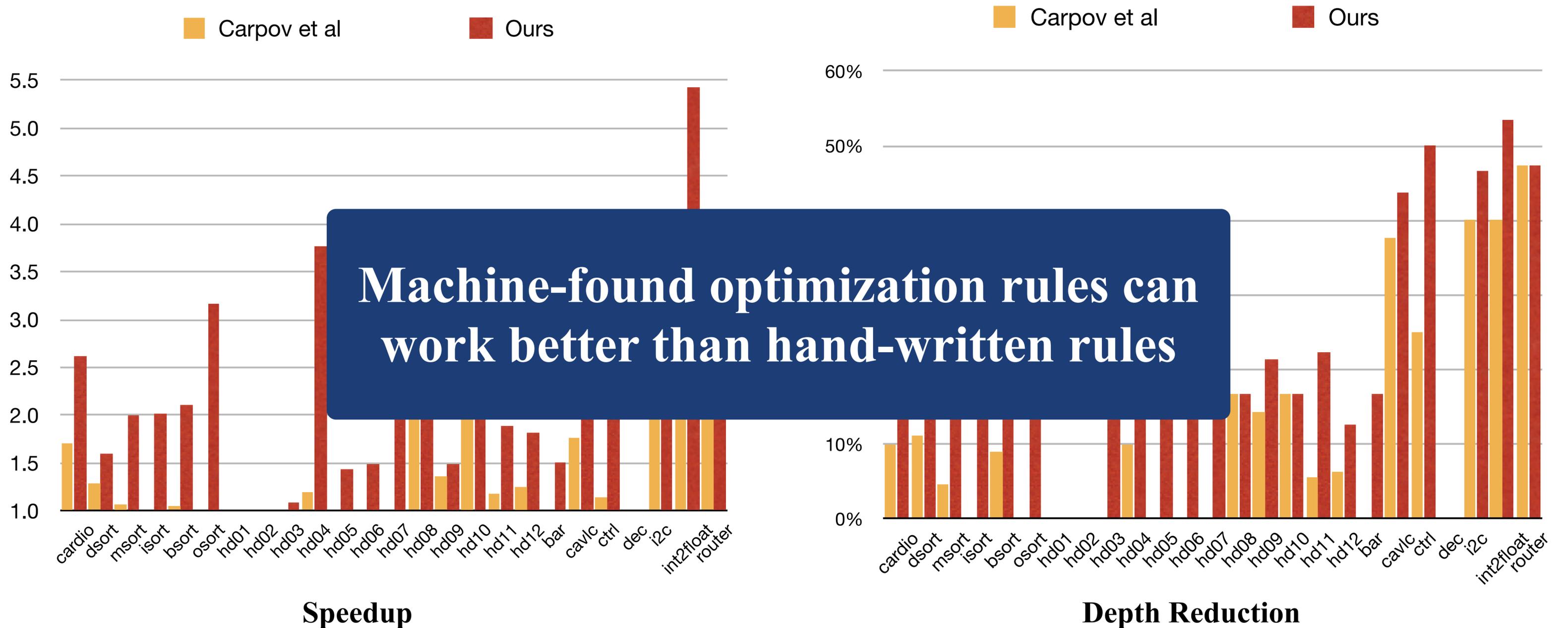
# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



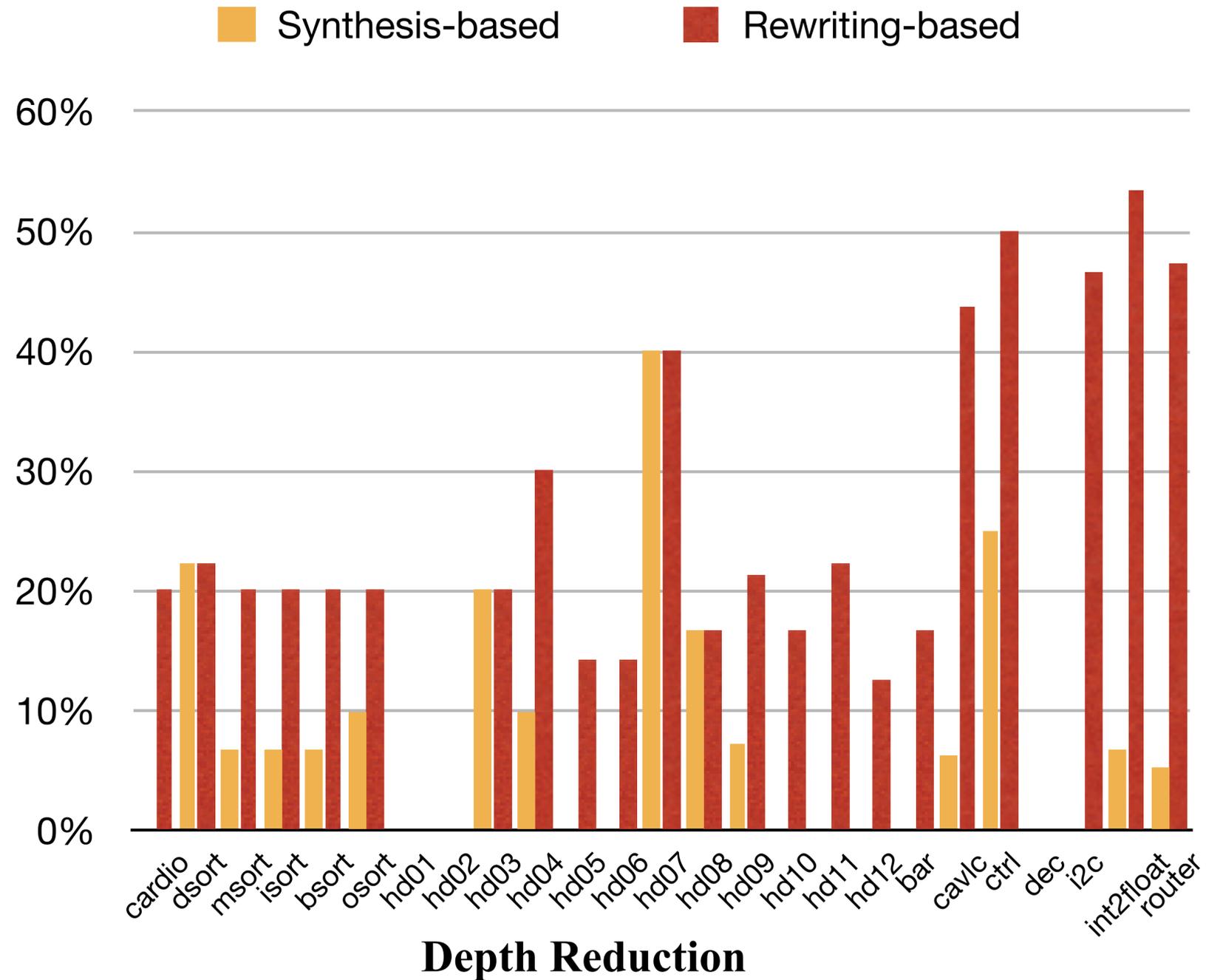
# Lobster Performance (2/4)

## Optimization Results of Lobster and the baseline



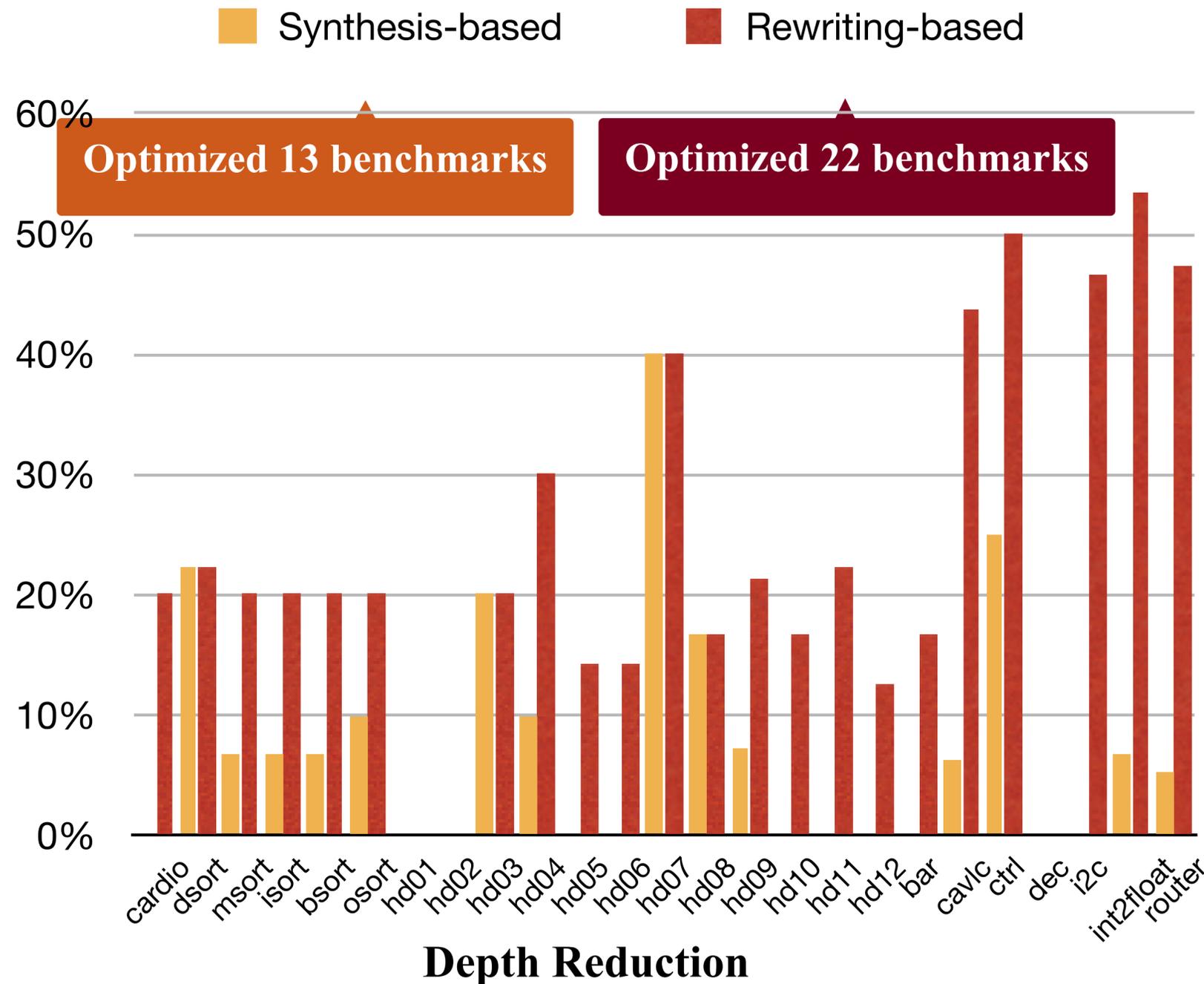
# Lobster Performance (3/4)

## Efficacy of Reusing Learned Optimization Patterns



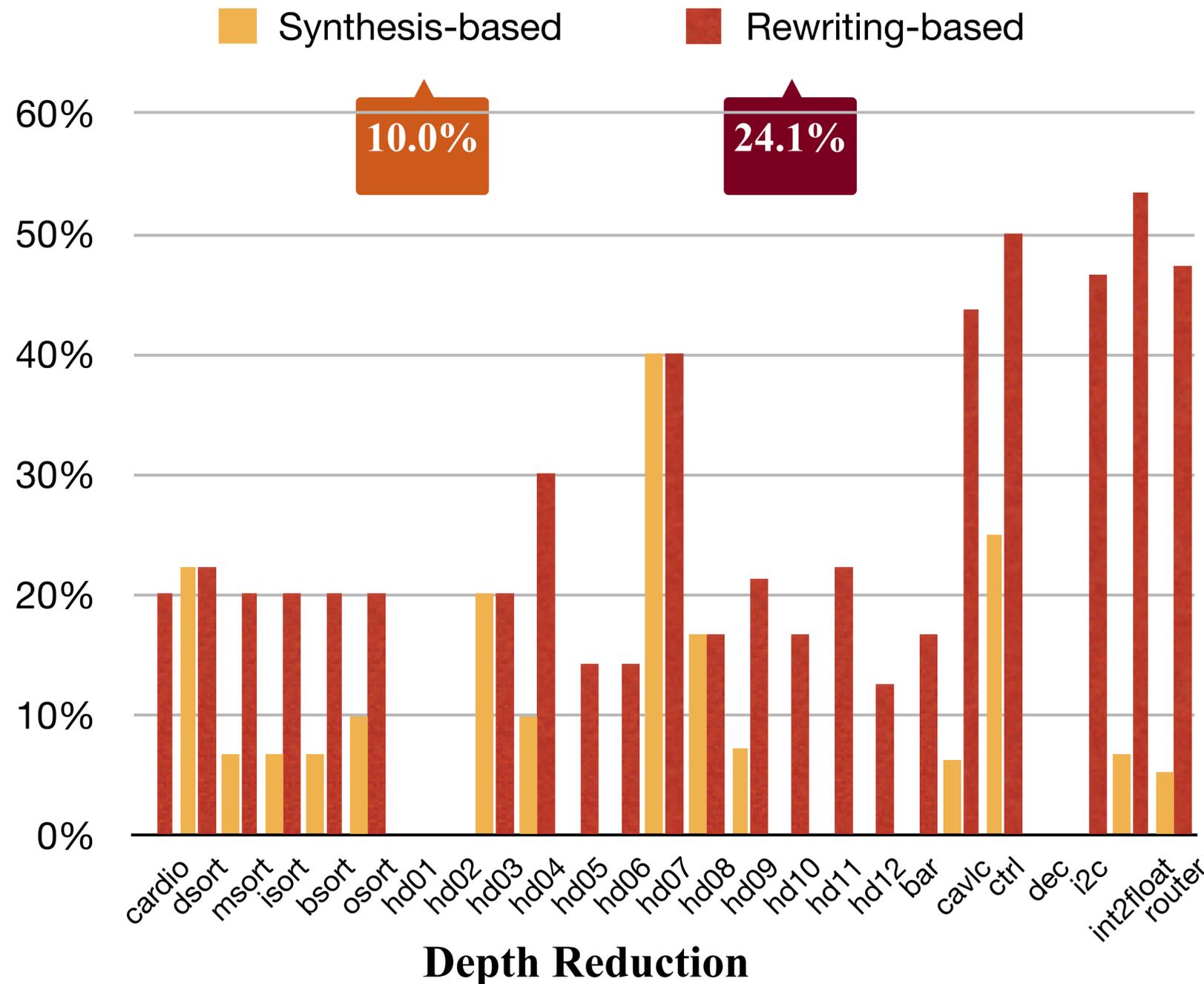
# Lobster Performance (3/4)

## Efficacy of Reusing Learned Optimization Patterns



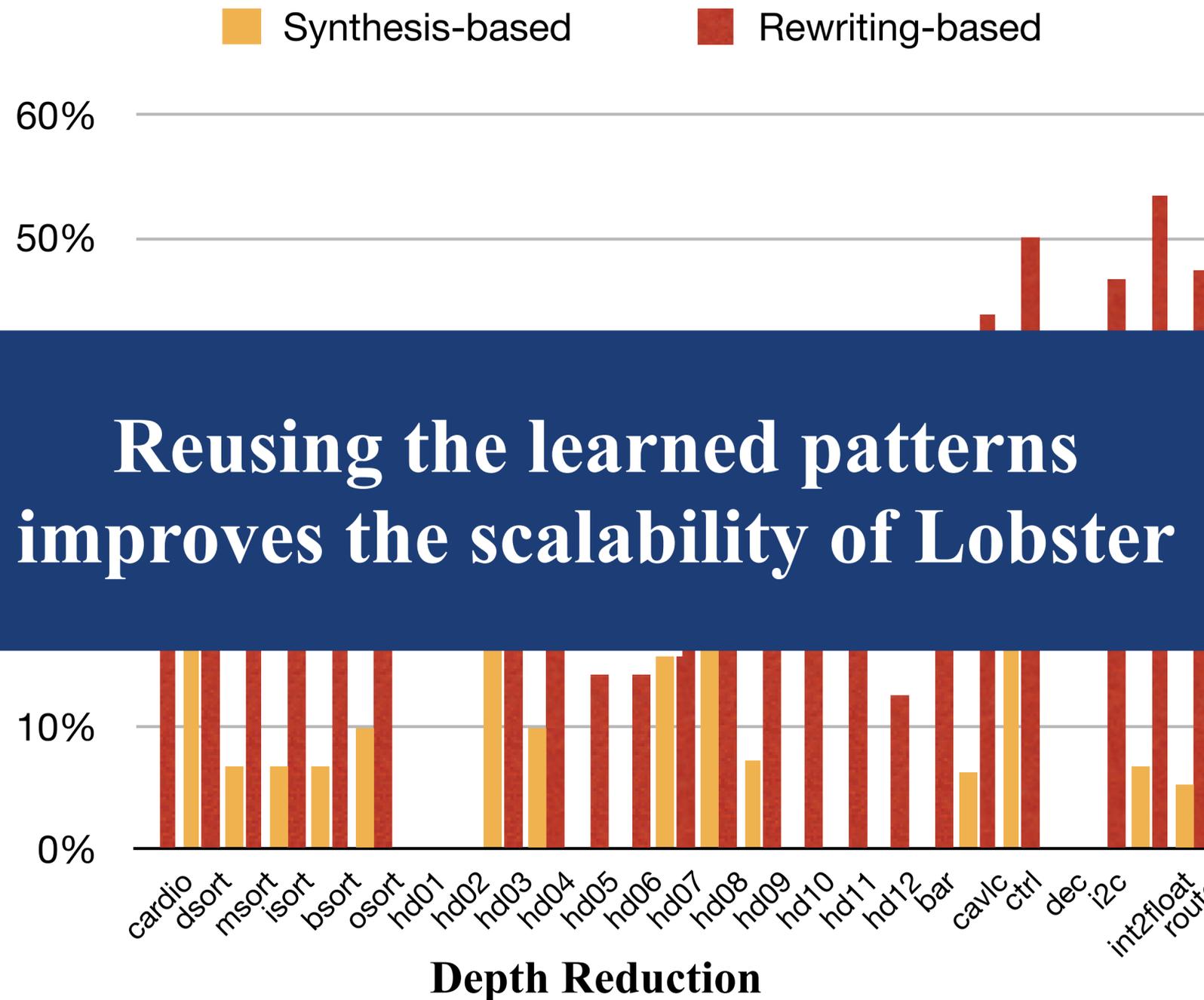
# Lobster Performance (3/4)

## Efficacy of Reusing Learned Optimization Patterns



# Lobster Performance (3/4)

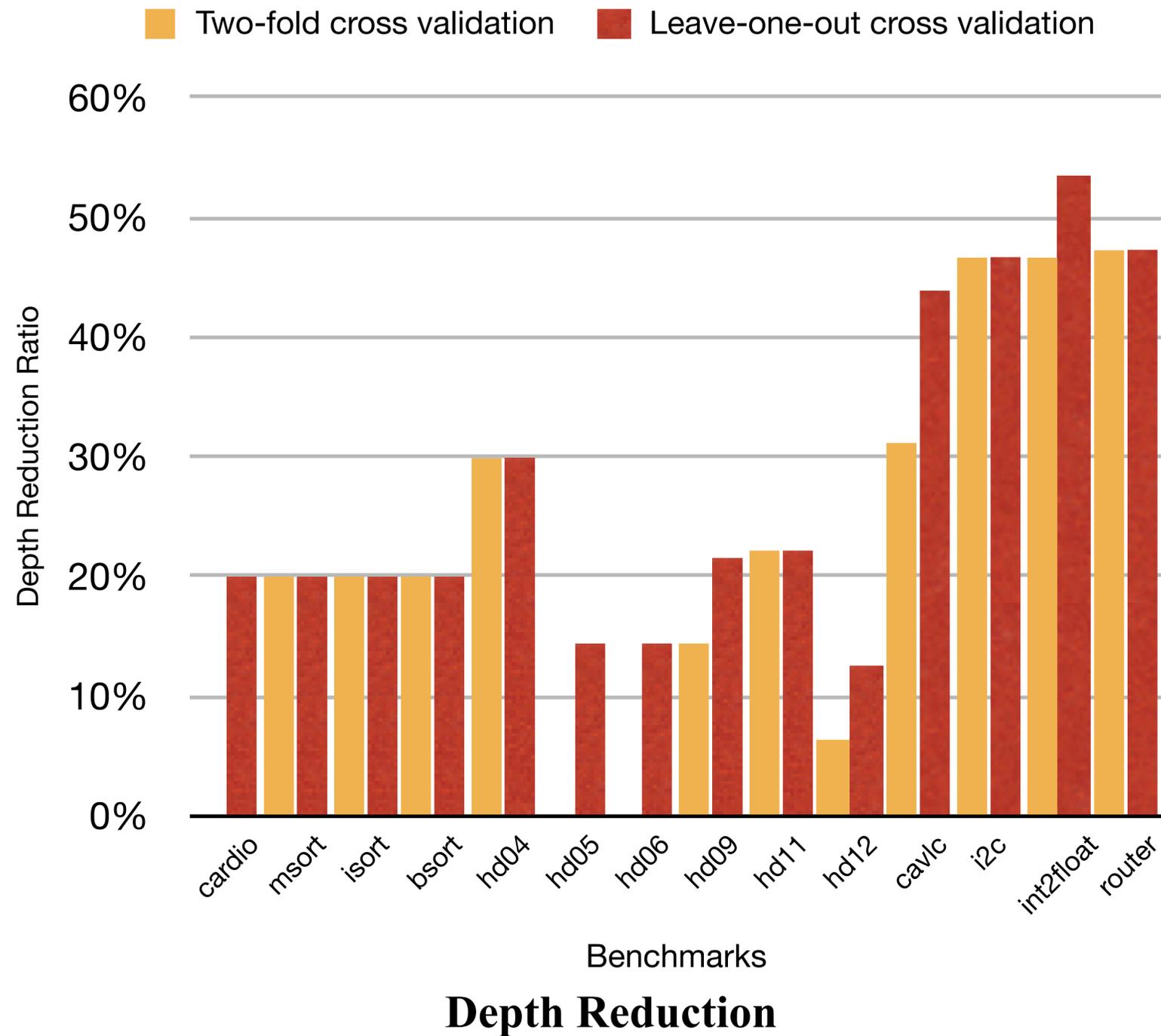
## Efficacy of Reusing Learned Optimization Patterns



Reusing the learned patterns improves the scalability of Lobster

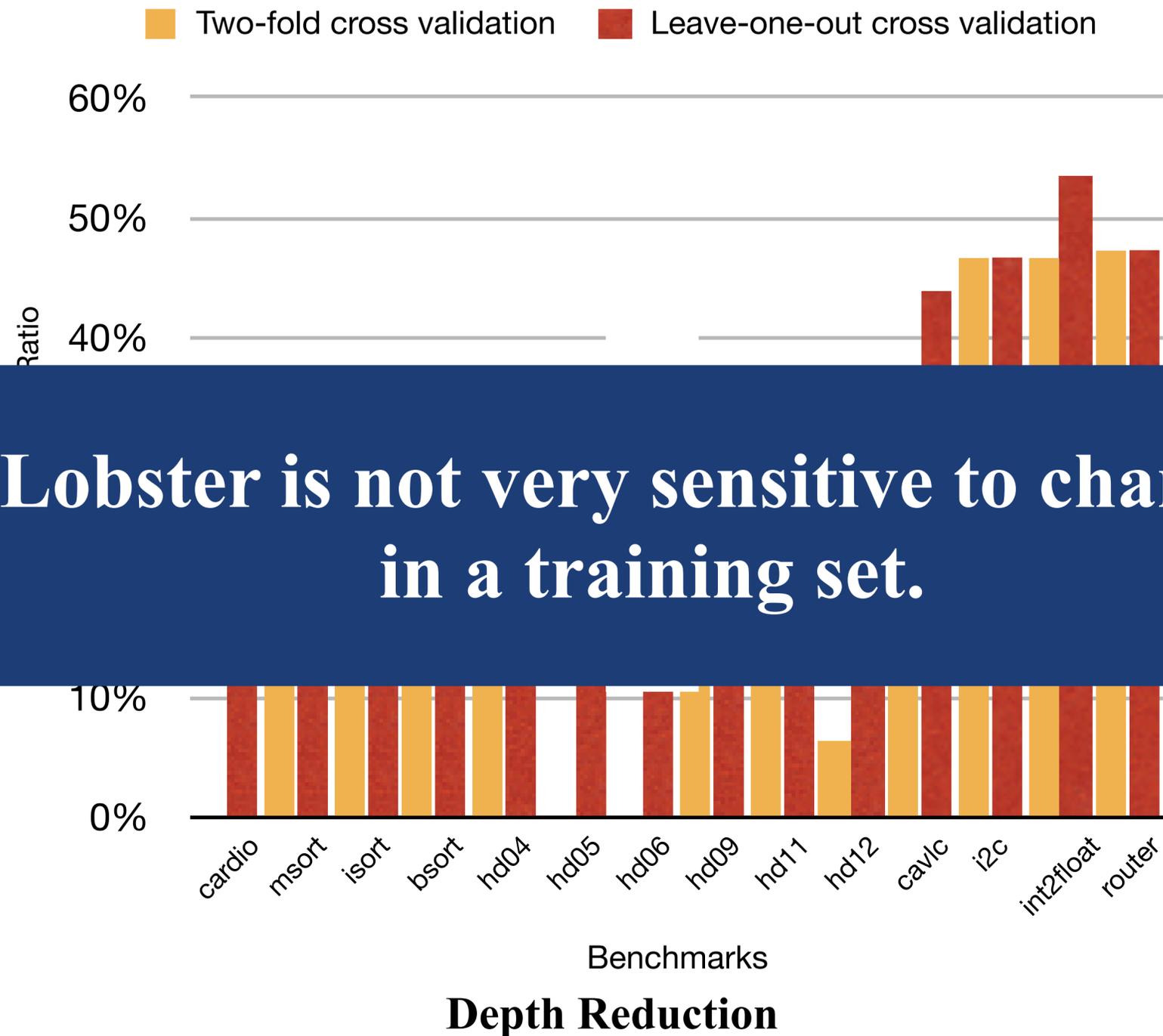
# Lobster Performance (4/4)

## Effectiveness of Equational Term Rewriting



# Lobster Performance (4/4)

## Effectiveness of Equational Term Rewriting



# Related Work

- Hardware synthesis (e.g., ABC)
  - For decreasing circuit area and circuit depth (latency), not for multiplicative depth reduction
- General-purpose FHE compilers (e.g., Cingulata, Ramparts, Alchemy)
  - Optimization rules are hand-written, which requires manual efforts and often sub-optimal.
- Domain-specific FHE compilers (e.g., CHET)
  - Optimizations specialized for specific tasks (e.g., secure neural-network inference)
- Synthesis-based program optimization (e.g., STROKE, Optgen, Souper)
  - Optimization rules are also automatically learned, and applied via *syntactic* matching
  - We use *equational* matching to maximize generalization.

# In the Paper...

- Detailed description of synthesis via localization
- Formalized Equational Term Rewriting
- Detailed description of experiment results



**Thank you!**