Optimizing Homomorphic Evaluation Circuit with Program Synthesis and Term Rewriting

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Korea University

Seoul National University



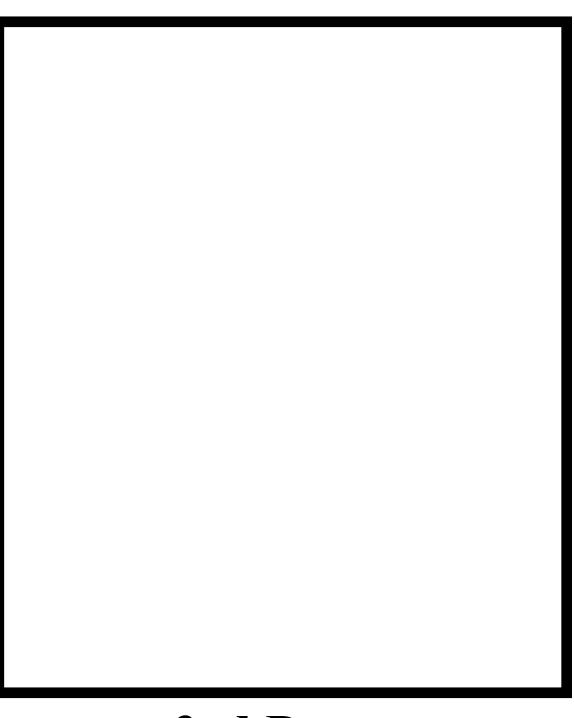




Homomorphic Evaluation(HE) (1/3) **Privacy Preserving Secure Computation**

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





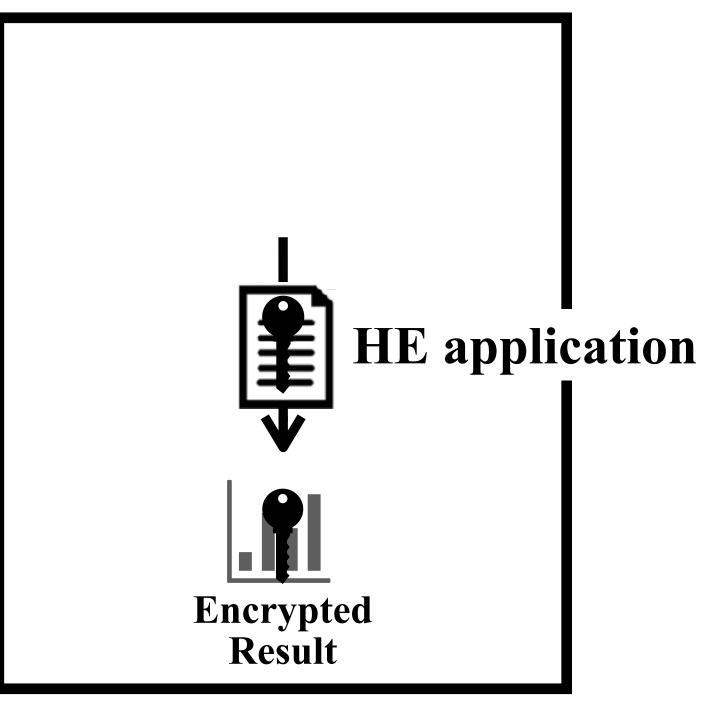
3rd Party

Homomorphic Evaluation(HE) (1/3)

- Allows for computation on encrypted data
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Privacy Preserving Secure Computation



3rd Party

Homomorphic Evaluation(HE) (2/3) **Building HE applications**



Generate/manage keys, hints

Add maintenance operations

Write code in low-level HE instructions



Application



Choose parameters

Track noise level



complicated

requires expertise



HE application

suboptimal



Homomorphic Evaluation(HE) (3/3)

Existing Homomorphic Compiler



Generate/manage keys, hints

Add maintenance operations

Write code in low-level HE instructions



Application

Choose parameters

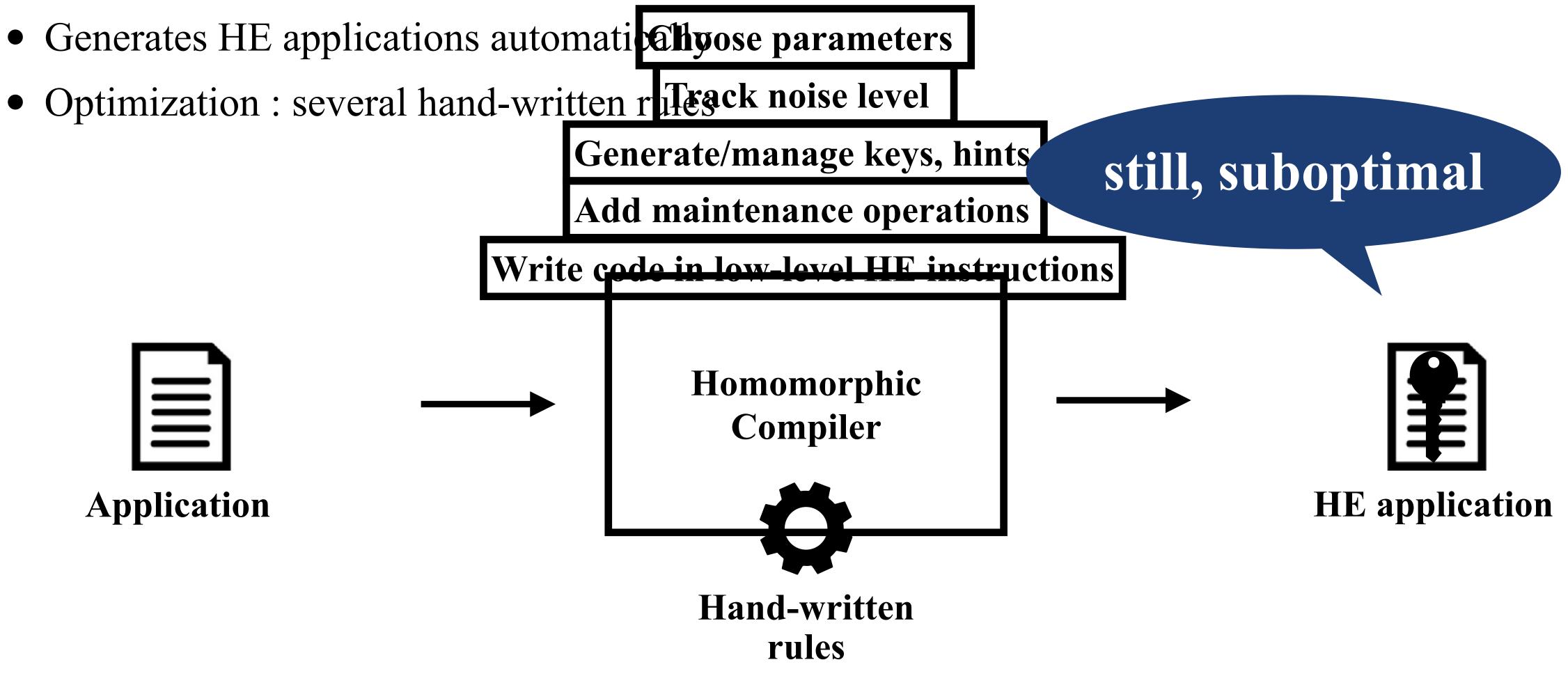
Track noise level





HE application

Homomorphic Evaluation(HE) (3/3) **Existing Homomorphic Compiler**



Homomorphic Evaluation(HE) (2/3)

Code for homomorphic addition of two integers

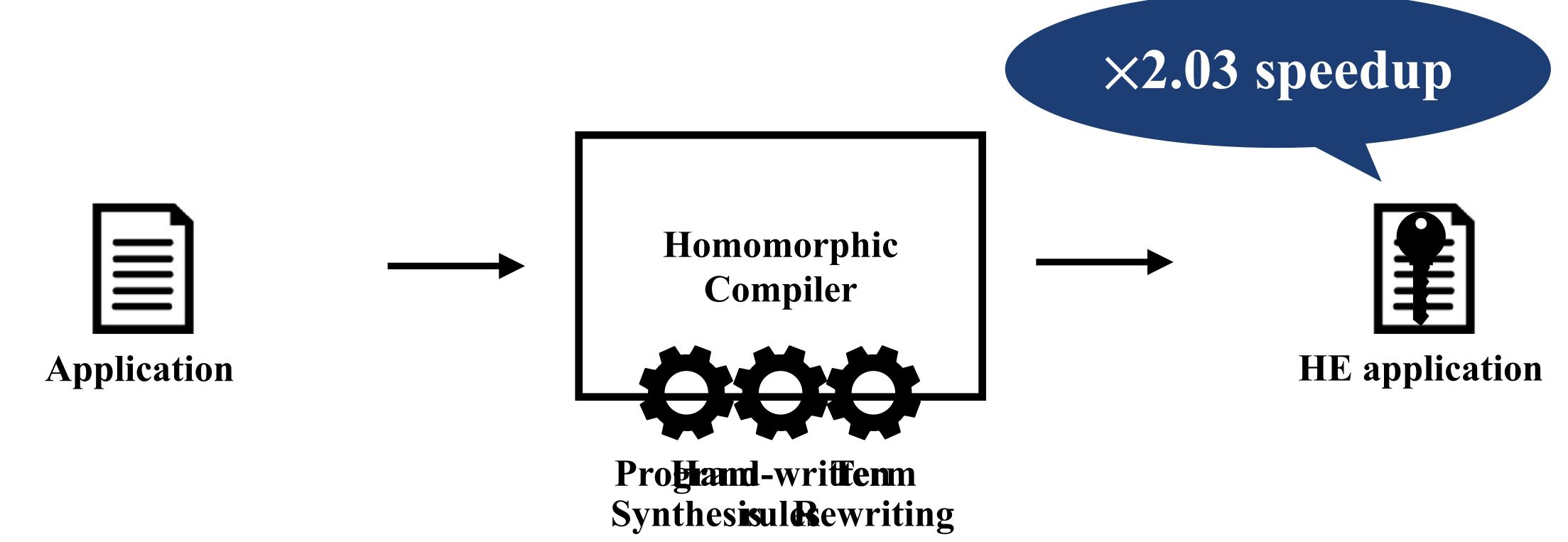
```
#include "FHE.h"
#include "EncryptedArray.h"
#include <NTL/lzz pXFactoring.h>
#include <fstream>
#include <sstream>
#include <sys/time.h>
int main(int argc, char **argv)
   long m=0, p=2, r=1; // Native plaintext space
                      // Computations will be 'modulo p'
                      // Levels
   long L=16;
                      // Columns in key switching matrix
   long c=3;
                      // Hamming weight of secret key
   long w=64;
   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);
                                       Manually written
    ea.encrypt(ct1, publicKey, v1);
   v2.push back(atoi(argv[2]));
    Ctxt ct2(publicKey);
                                       using HElib
    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);
```

Input to Cingulata (a HE compiler)

Our Contributions (1/2)

- Generates HE applications automatically



Automatic, Aggressive HE optimization Framework

Optimization : searchial chander interesting by construction of the search of the sear

Our Contributions (2/2)

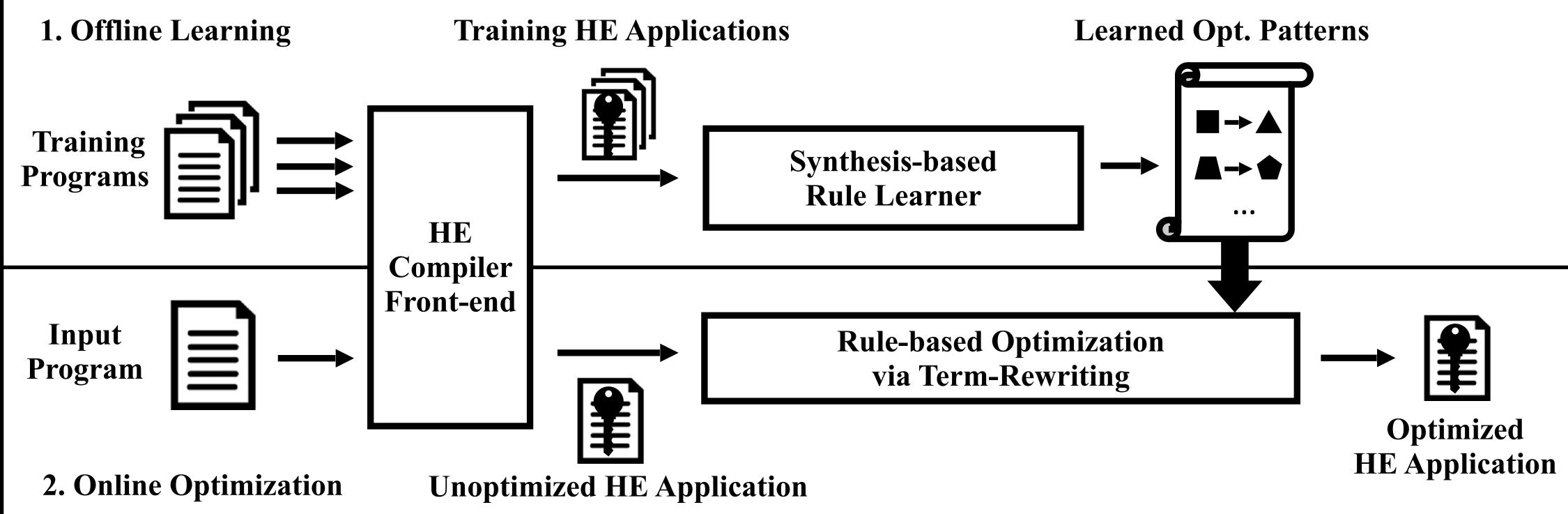
Automatic, Aggressive HE optimization Framework

- 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 19 out of 25 Applications (vs 15)
 - x3.71 Speedup in Maximum (vs x3.0)
 - x2.03 Speedup on Average (vs x1.53)
- Open Tool Available : <u>https://github.com/dklee0501/Lobster</u>



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

 $Enc_p(\mu \in \{0,1\}) = pq + 2r + \mu$ $Dec_p(c) = (c \mod p) \mod 2$ $Dec_p(Enc_p(\mu)) = Dec_p(pq + 2r + \mu) = \mu$ • For ciphertexts $\mu_i \leftarrow Enc_p(\mu_i)$, 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 × in $\mathbb{Z}_2 = \{0,1\}$ are equal to XOR and AND





Performance Hurdle : Growing Noise

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

$$\underline{\mu_1} + \underline{\mu_2} = p(q_1 + q_2) + 2(r_1) + \frac{\mu_1}{\mu_1} \times \underline{\mu_2} = p(pq_1q_2 + \dots) + \frac{\mu_1}{\mu_1} + \frac{\mu_2}{\mu_2} = p(pq_1q_2 + \dots) + \frac{\mu_1}{\mu_2} + \frac{\mu_2}{\mu_1} + \frac{\mu_2}{\mu_2} = p(pq_1q_2 + \dots) + \frac{\mu_1}{\mu_2} + \frac{\mu_2}{\mu_2} + \frac{\mu_2}{\mu_1} + \frac{\mu_2}{\mu_2} = p(pq_1q_2 + \dots) + \frac{\mu_2}{\mu_2} + \frac{\mu_2$$

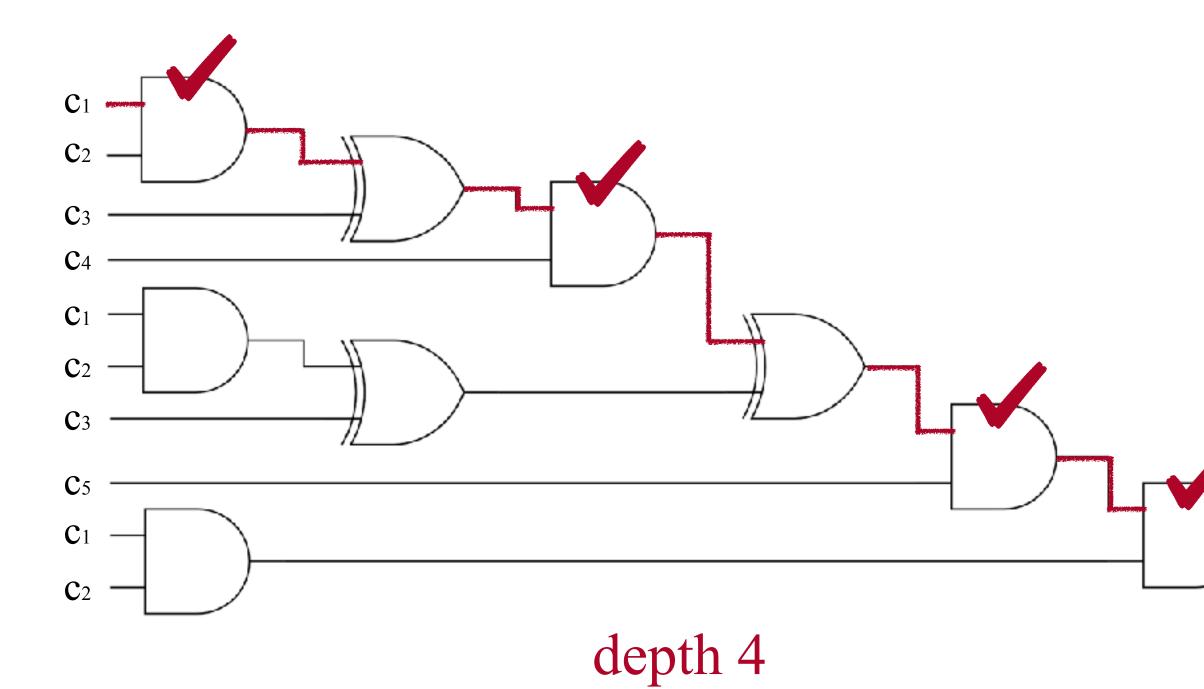
• if (noise > p) then incorrect results

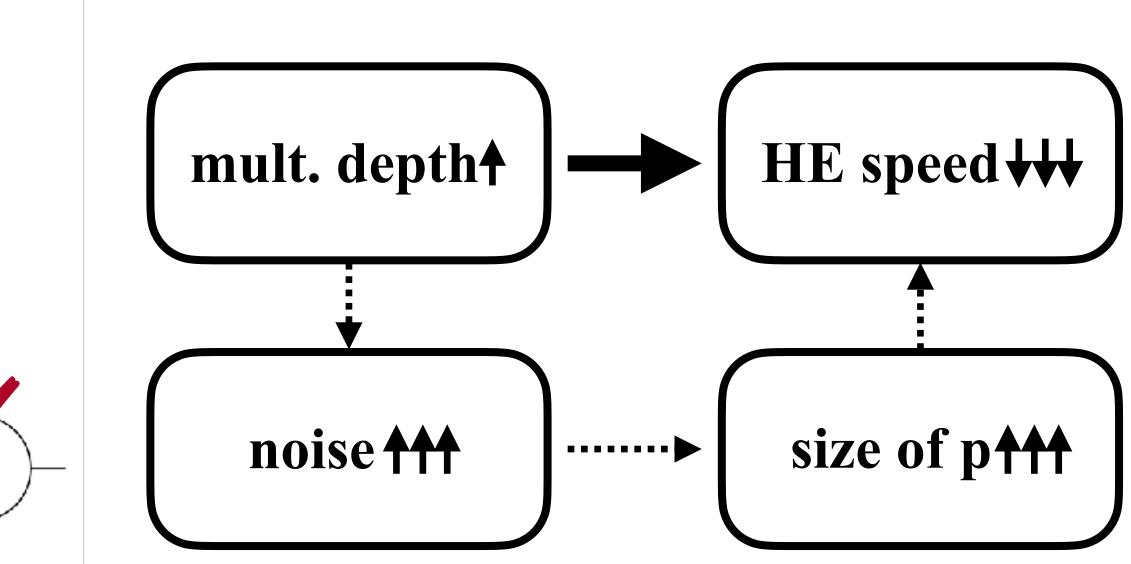
 $r_1 + r_2$) + ($\mu_1 + \mu_2$) double increase $2(2r_1r_2 + r_1\mu_2 + r_2\mu_1)$ + ($\mu_1 \times \mu_2$) quadratic increase noise



Multiplicative Depth : a Decisive Performance Factor

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

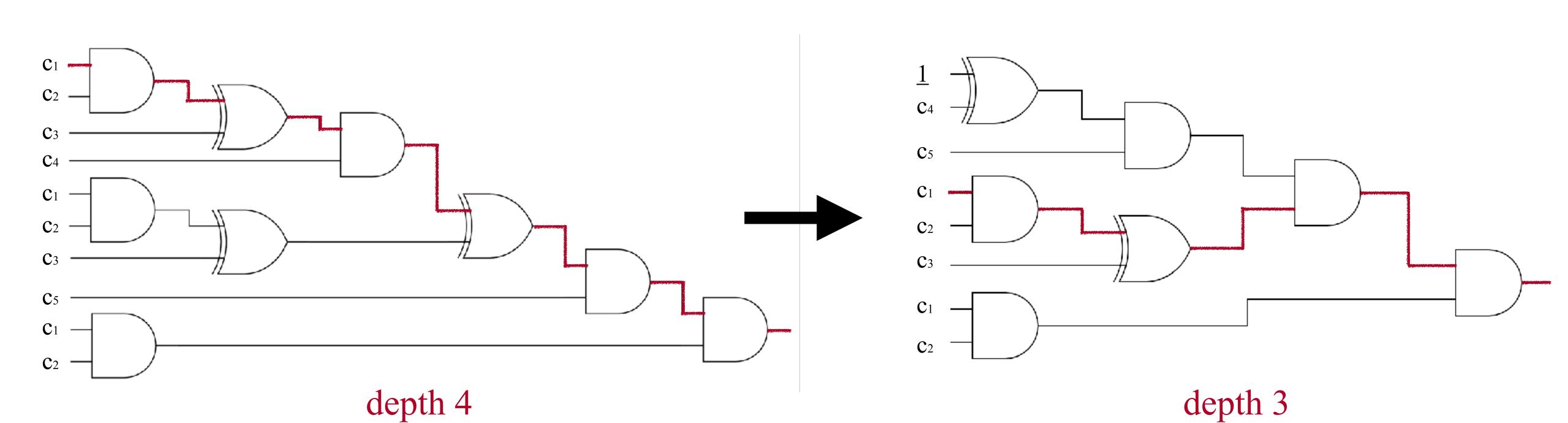


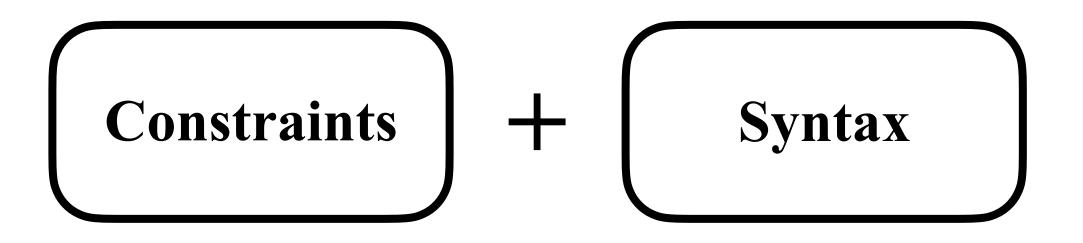


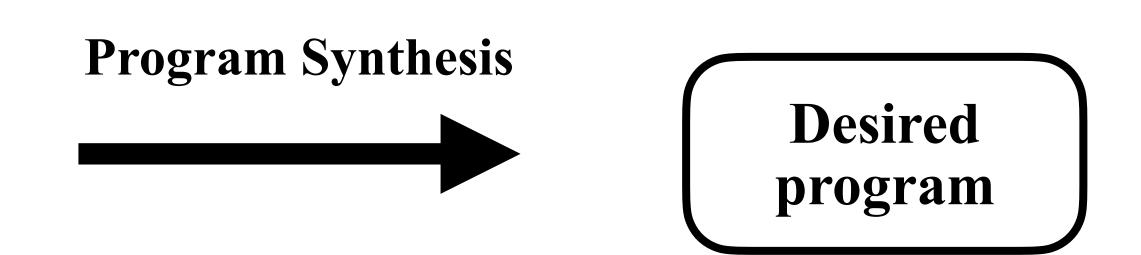


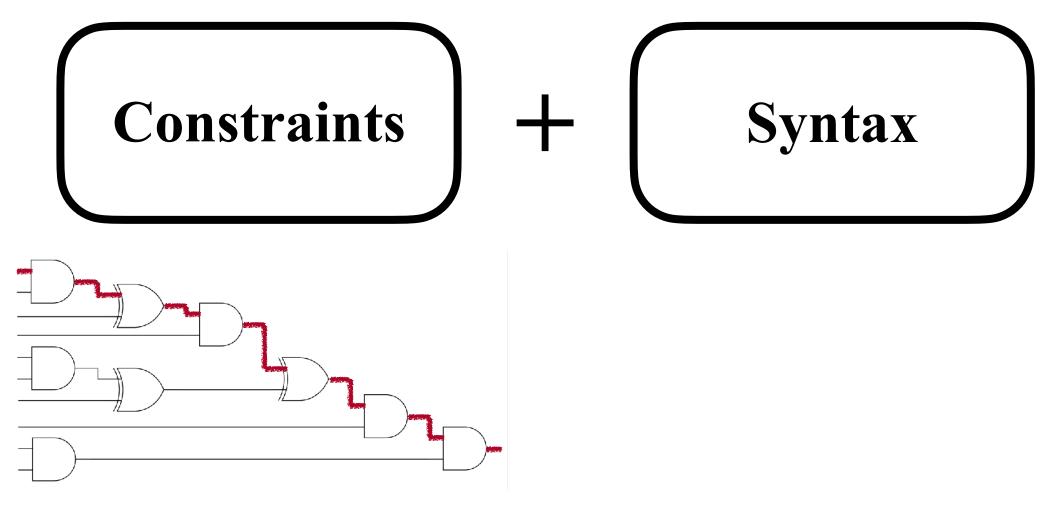
What is HE optimization?

• Finding a new circuit that has smaller mult. depth

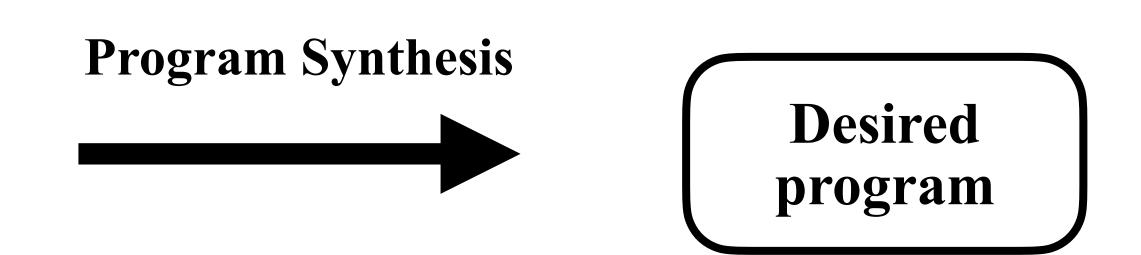


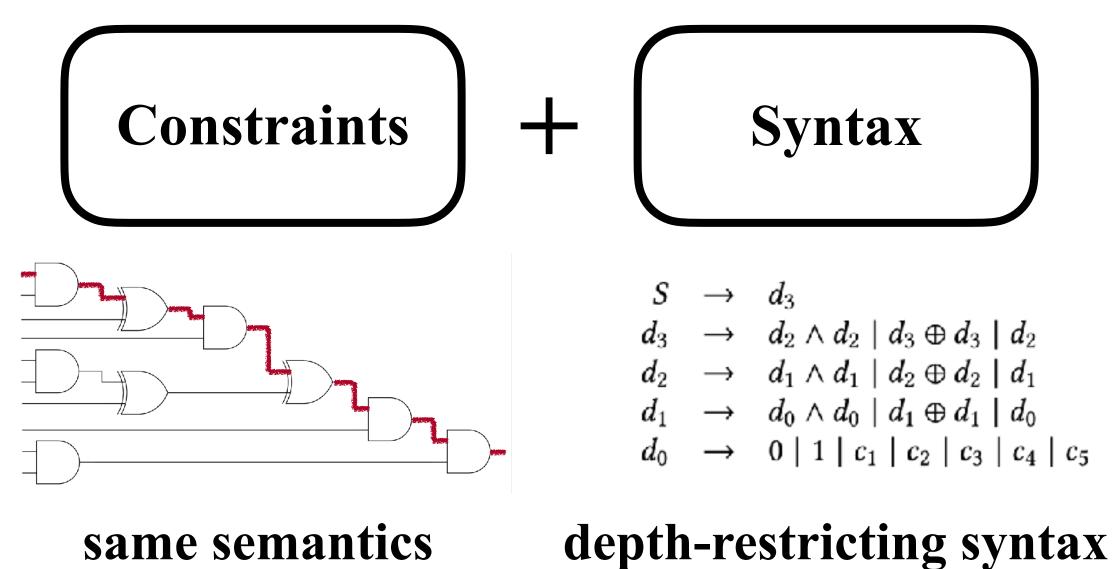


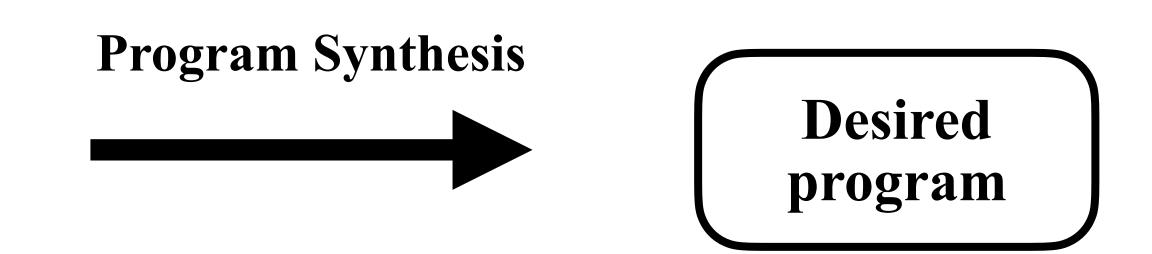


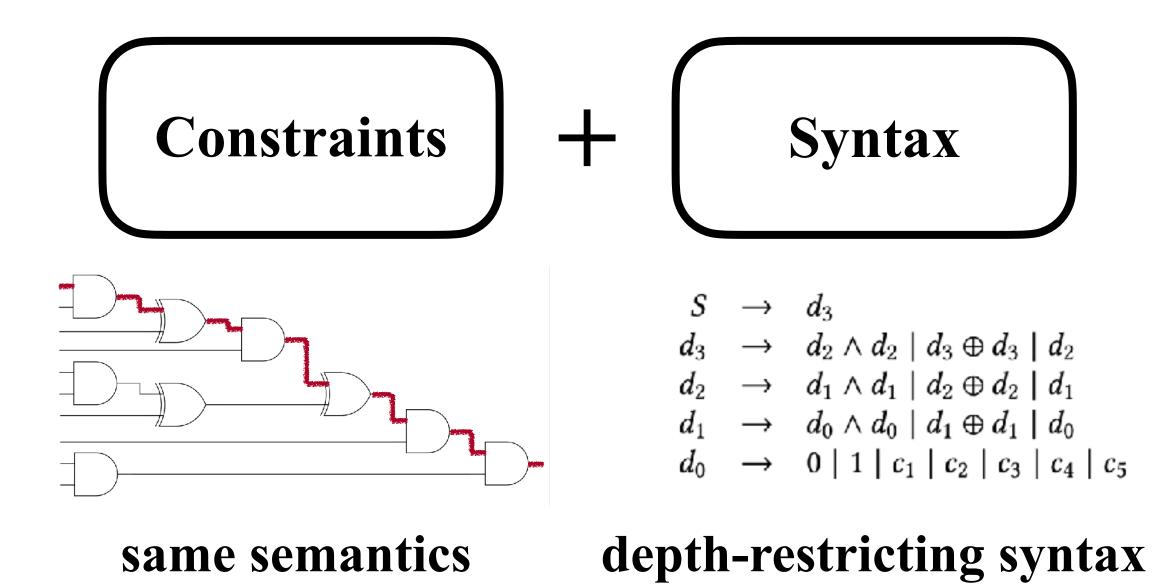


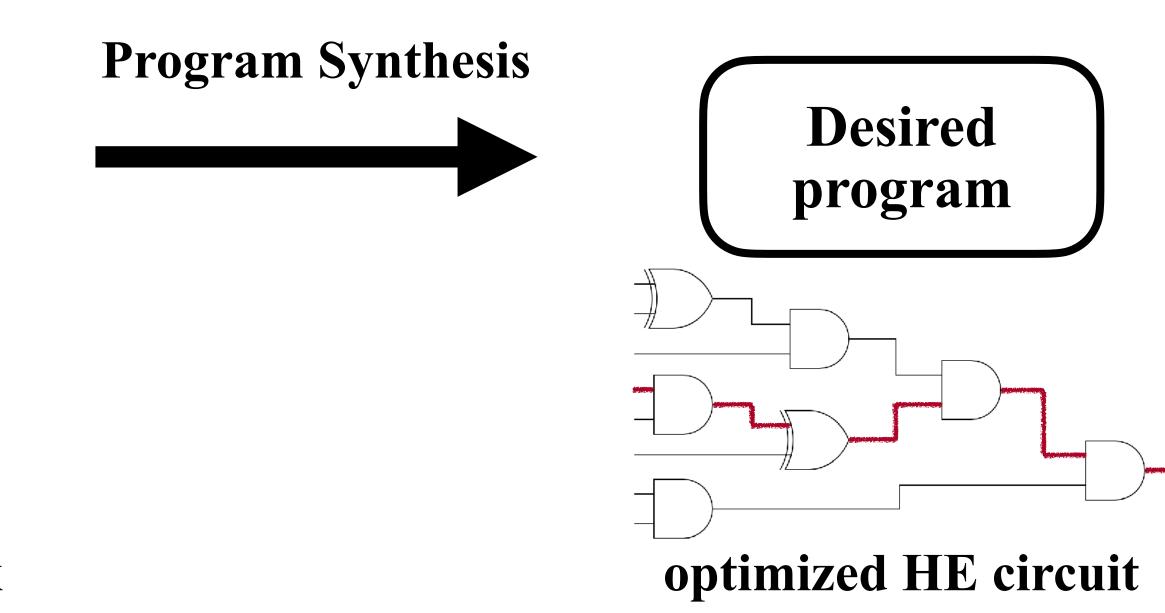
same semantics

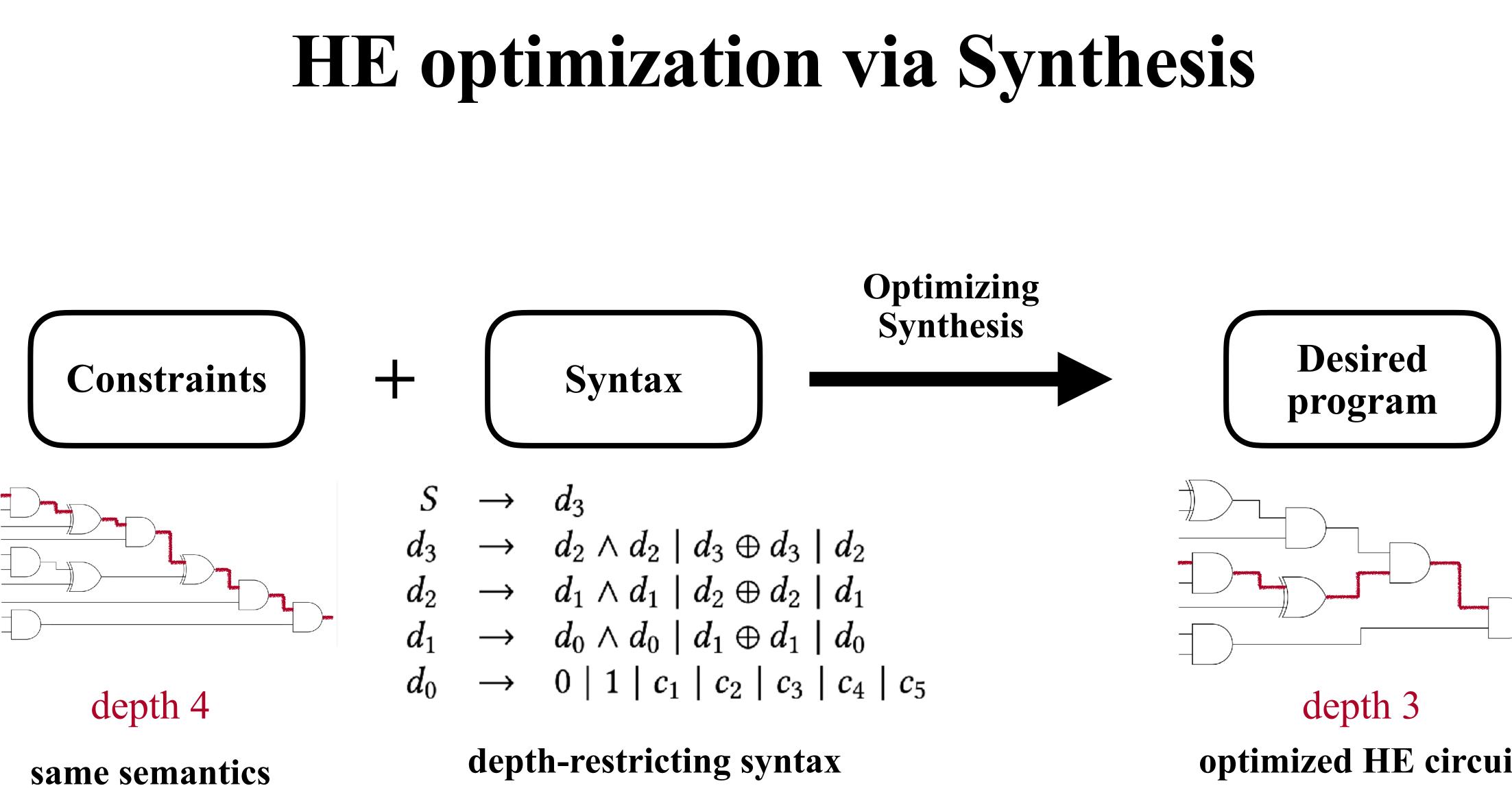






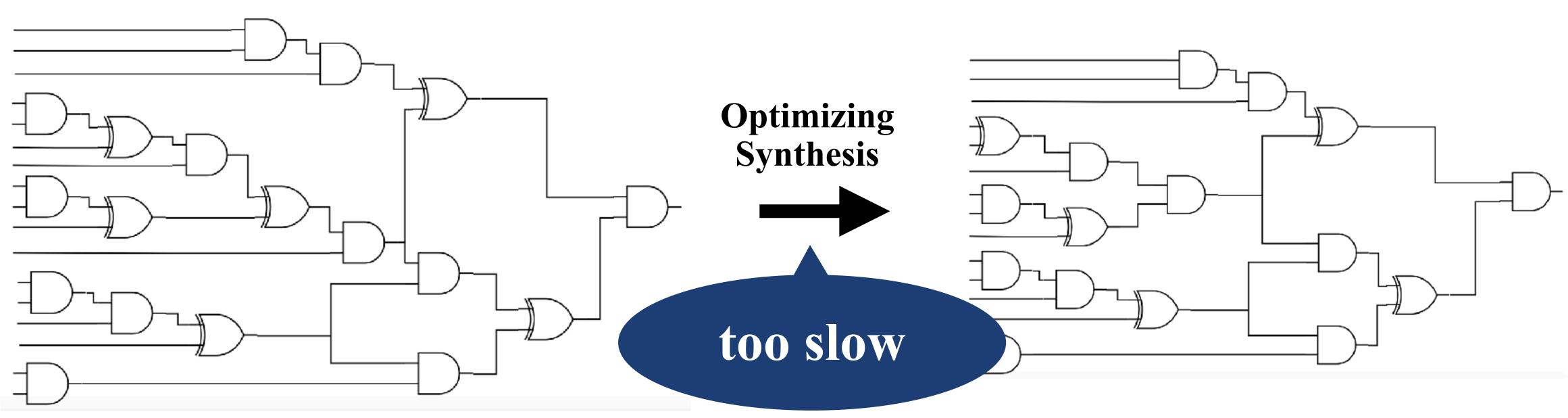


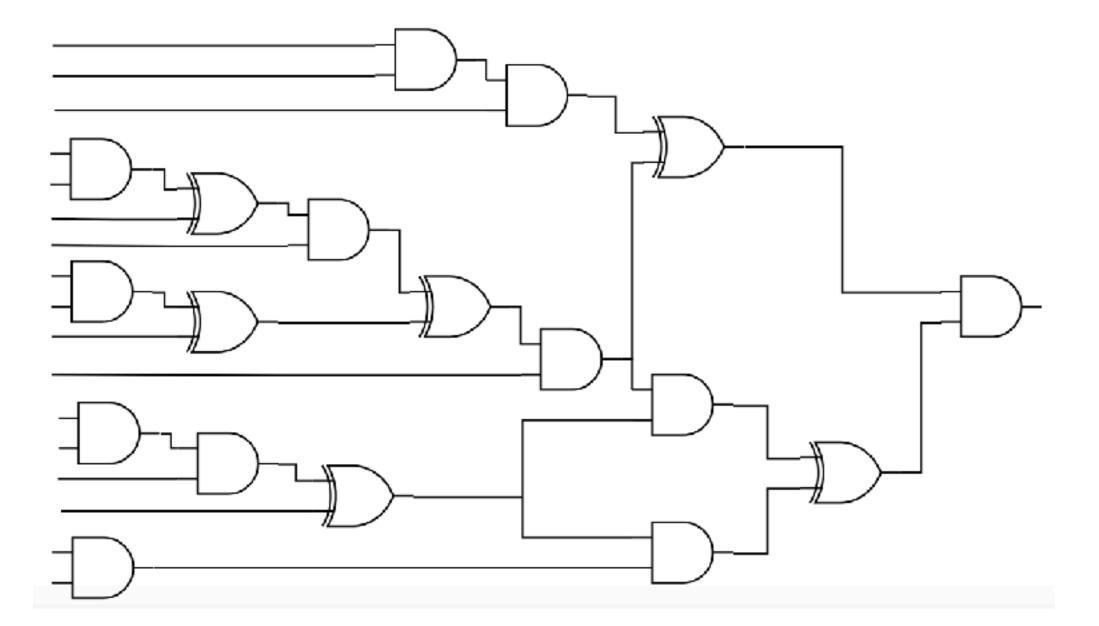


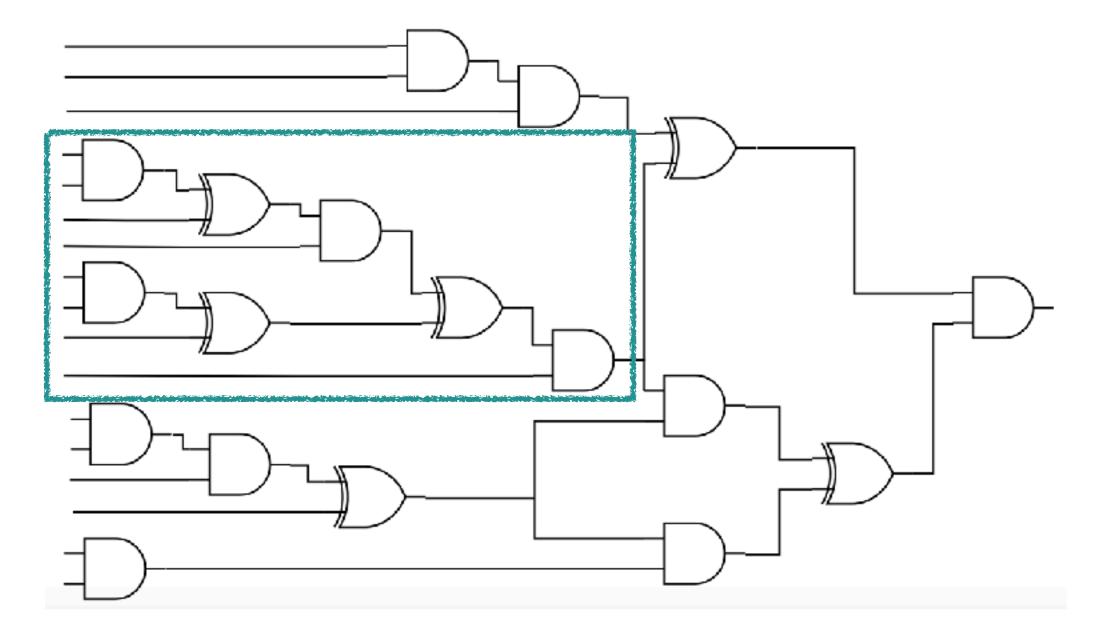


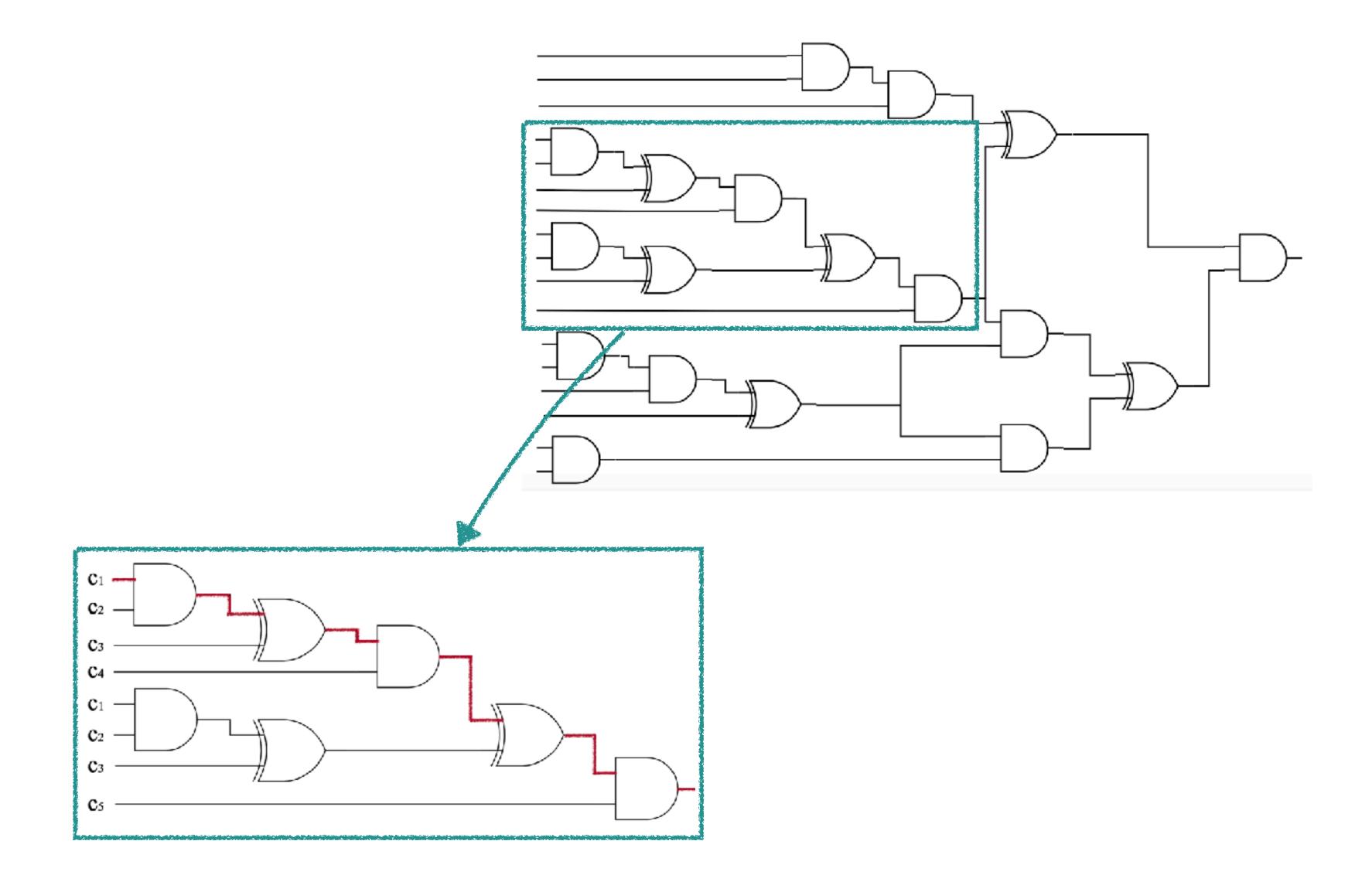
optimized HE circuit

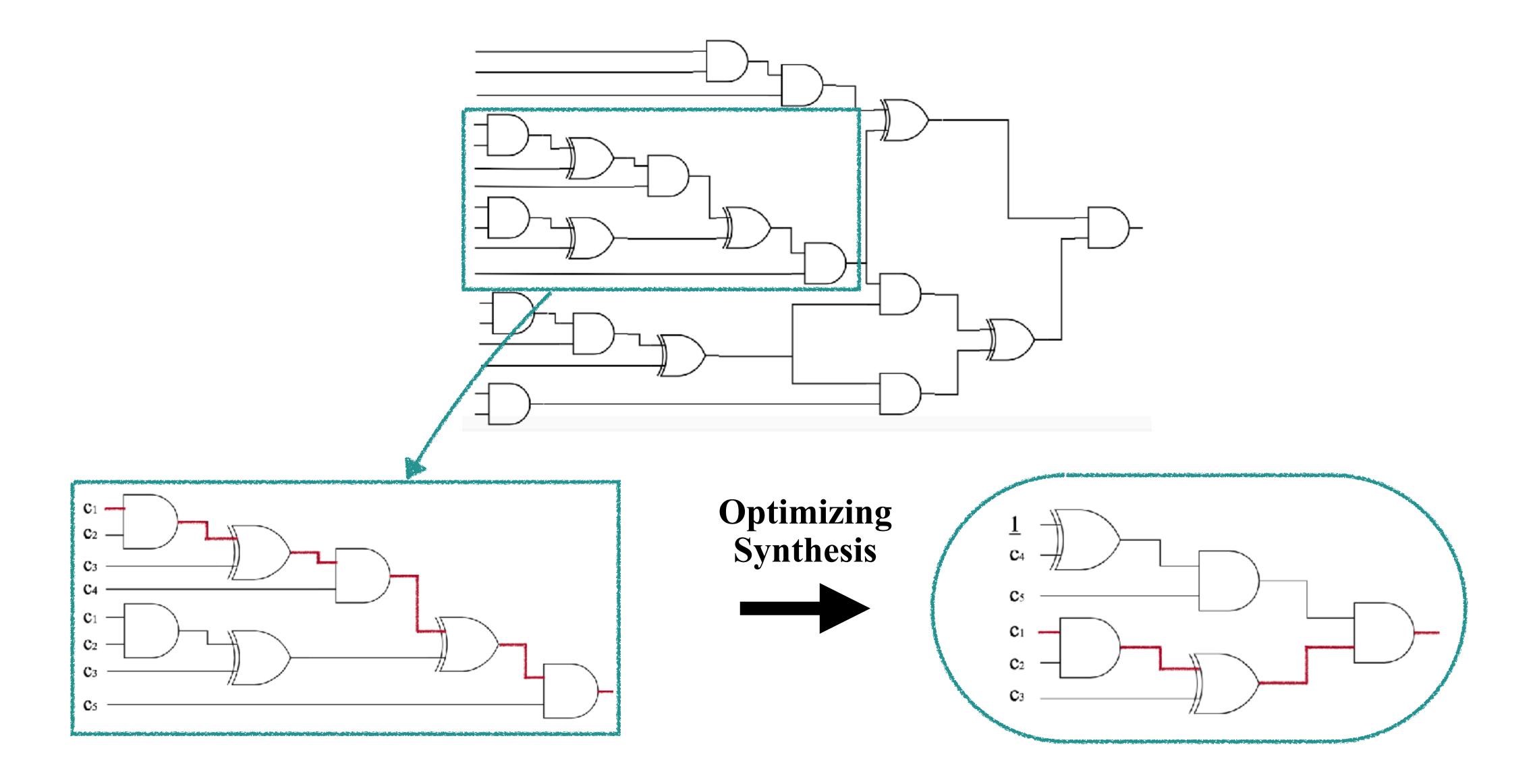
Hurdle : Synthesis Scalability

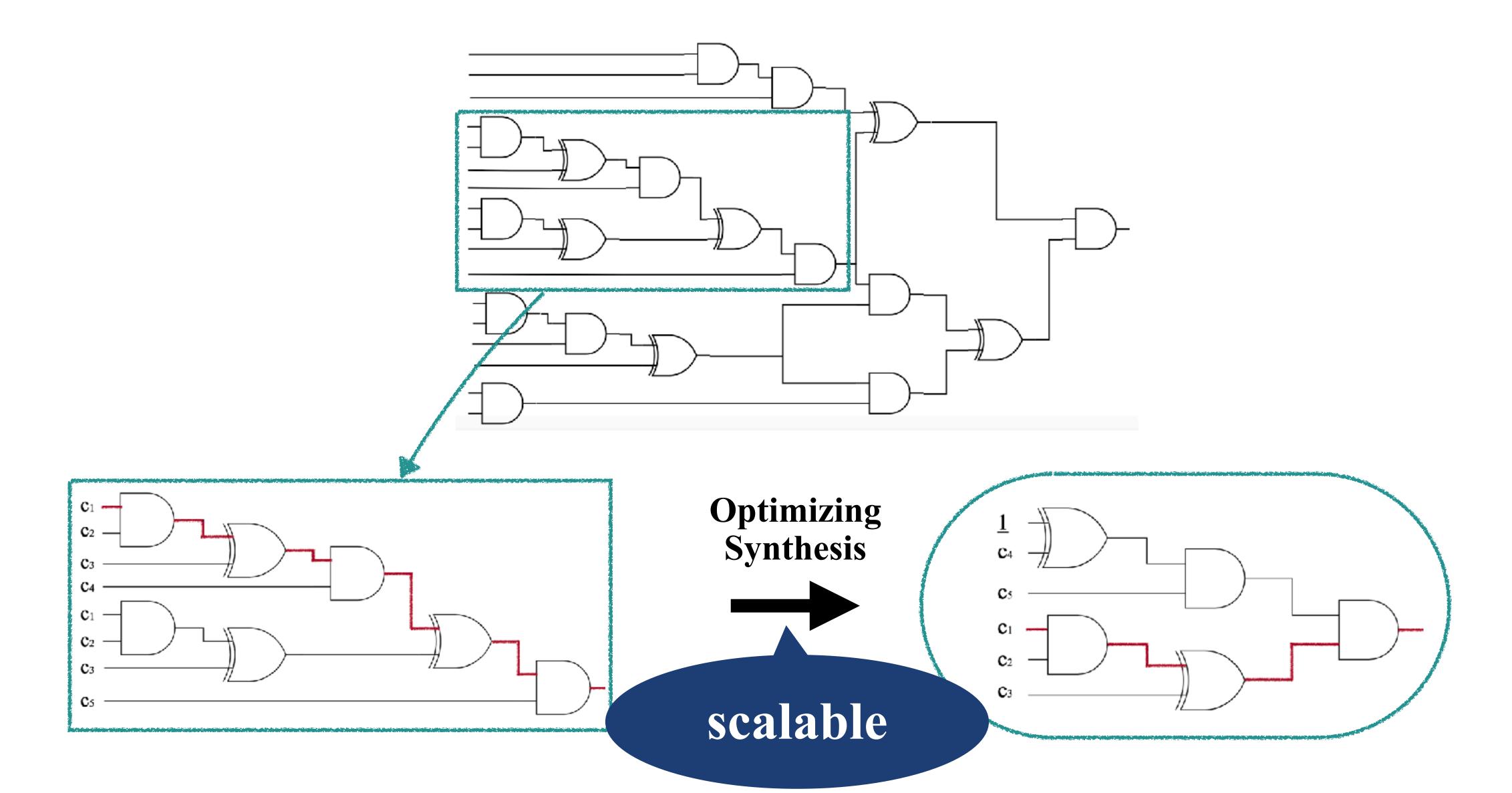


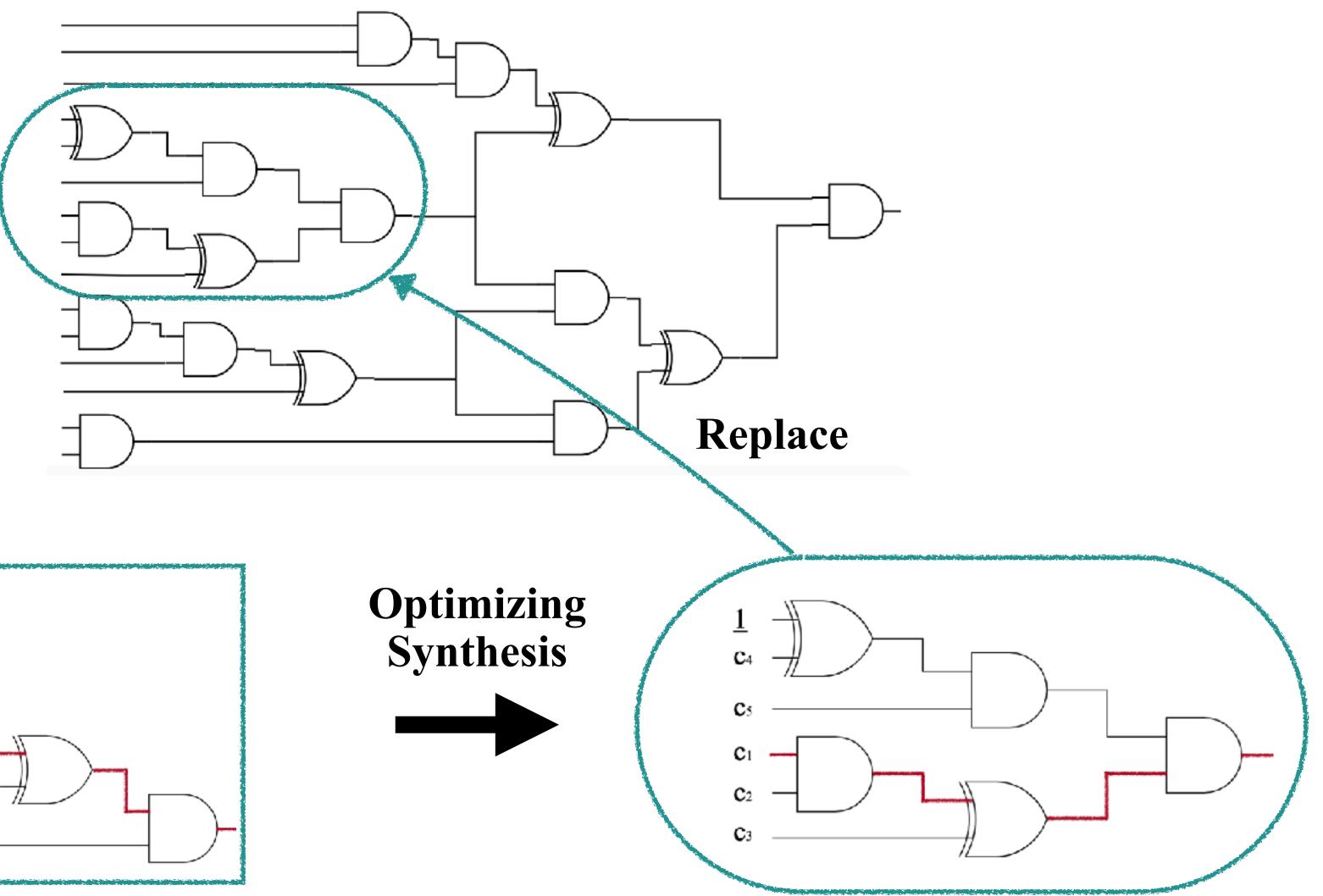


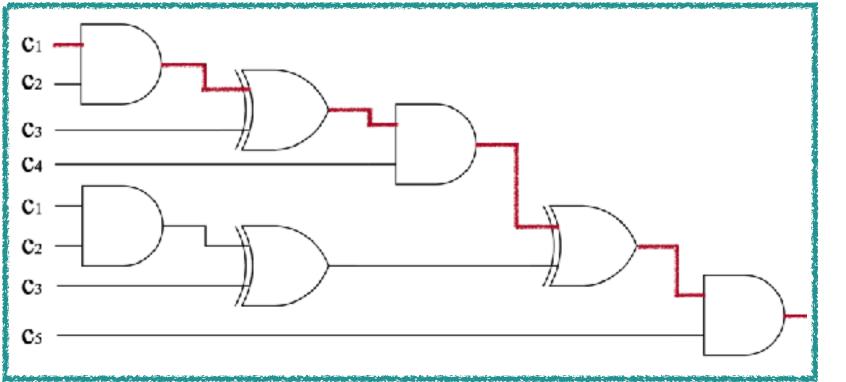












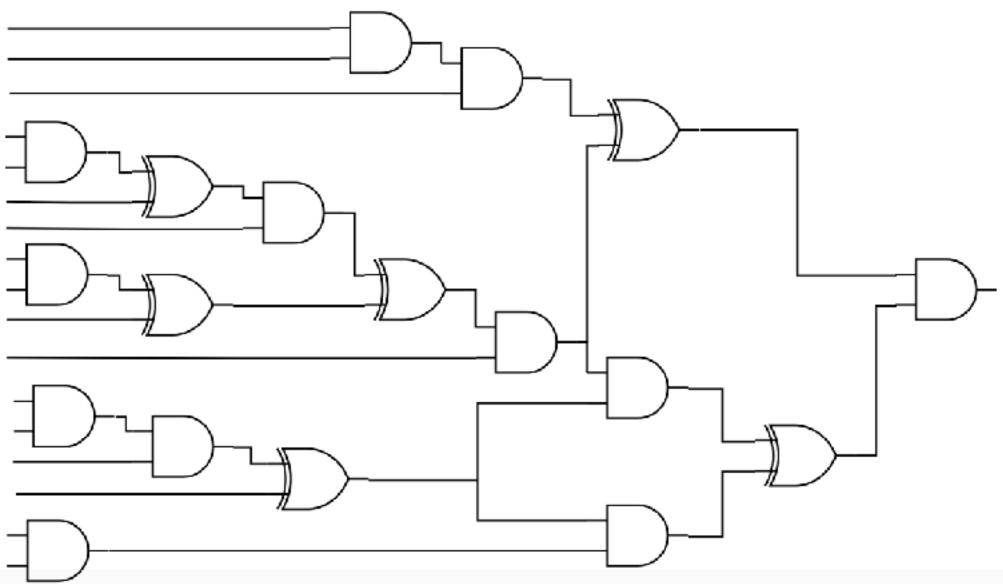
Solution 2: Learning Successful Synthesis Patterns

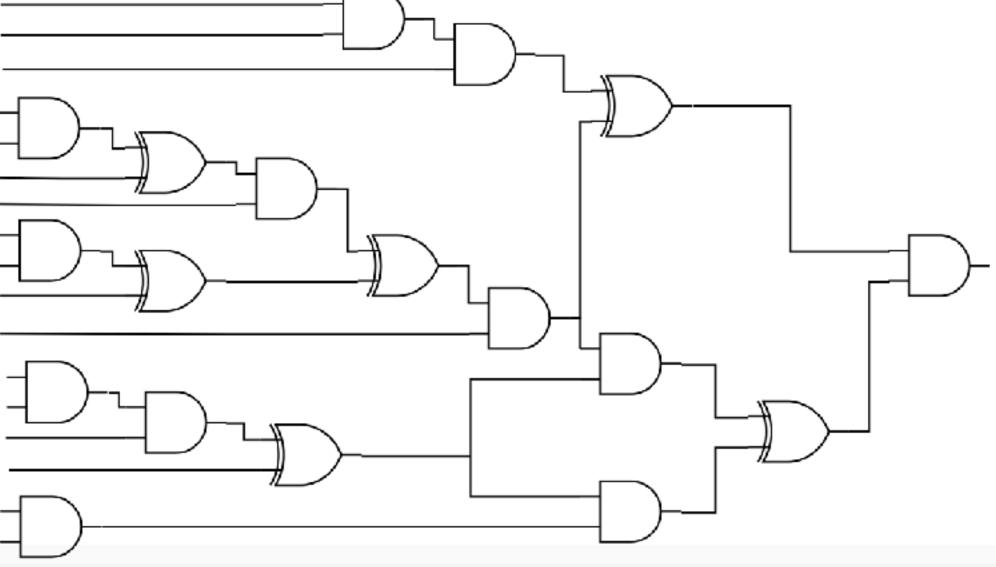
- Offline Learning
 - Collect successful synthesis patterns
- Online Optimization
 - Applying the patterns by term rewriting

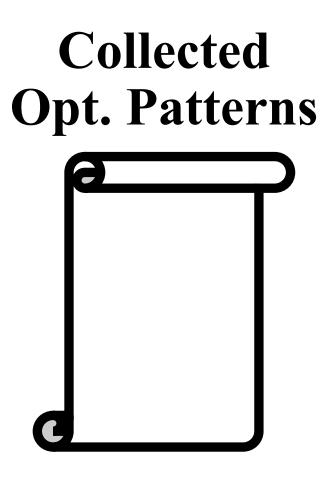


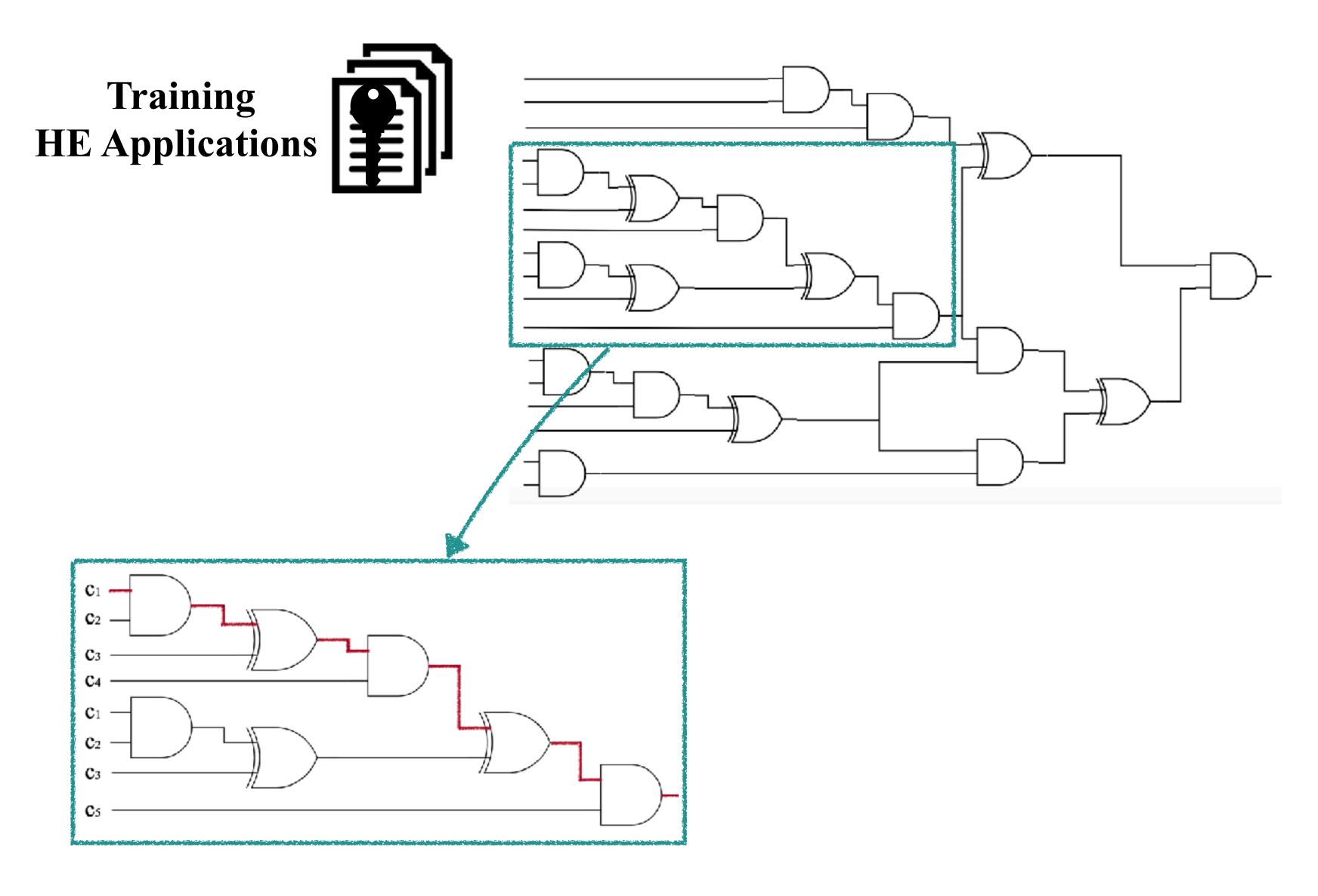
Training **HE Applications**

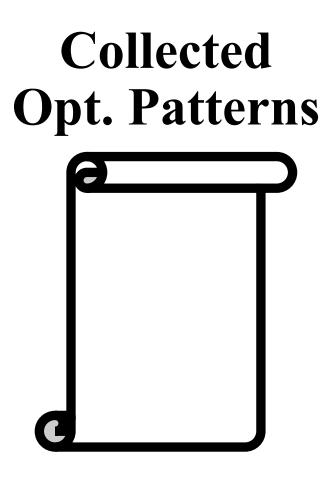


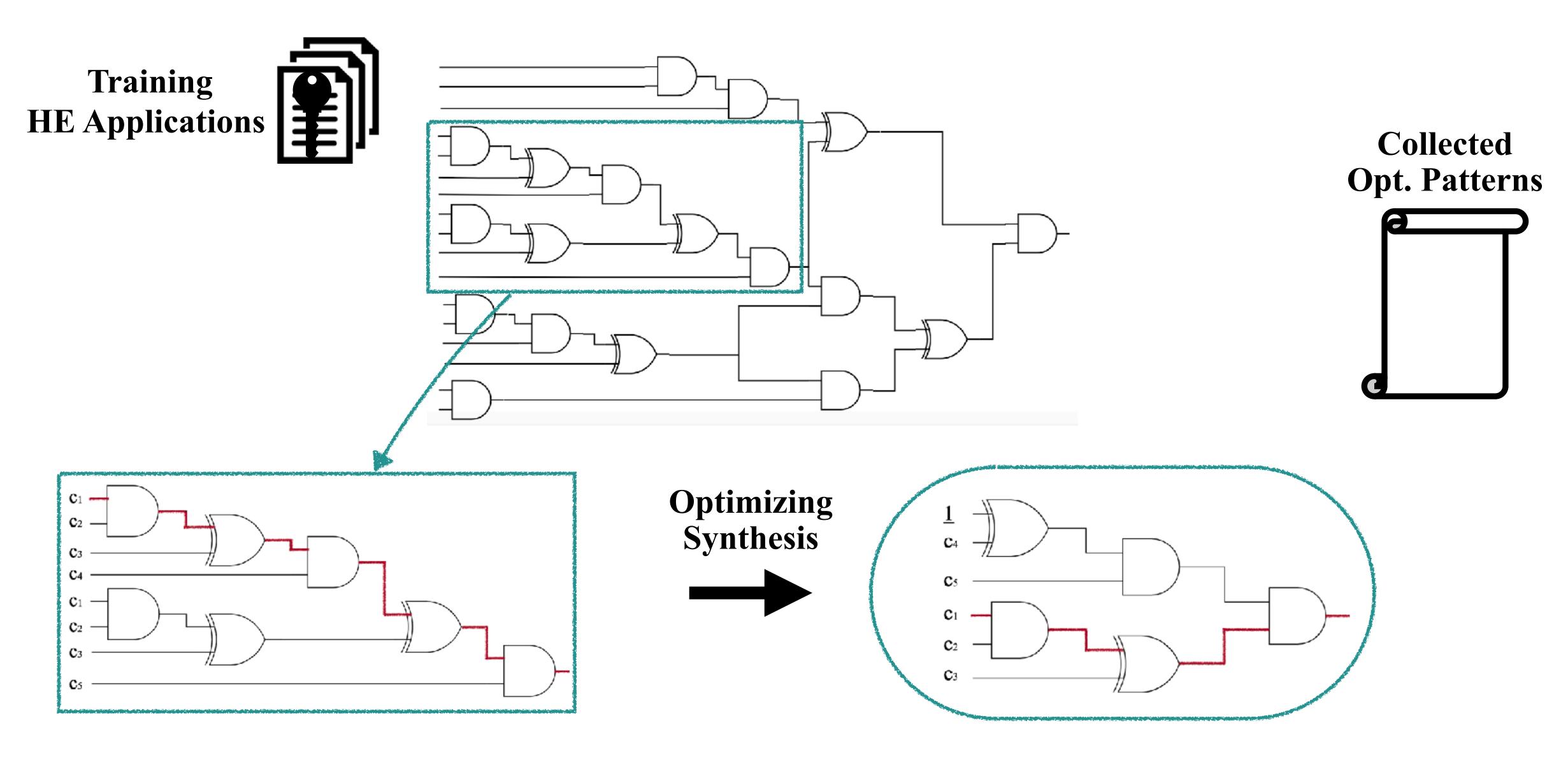


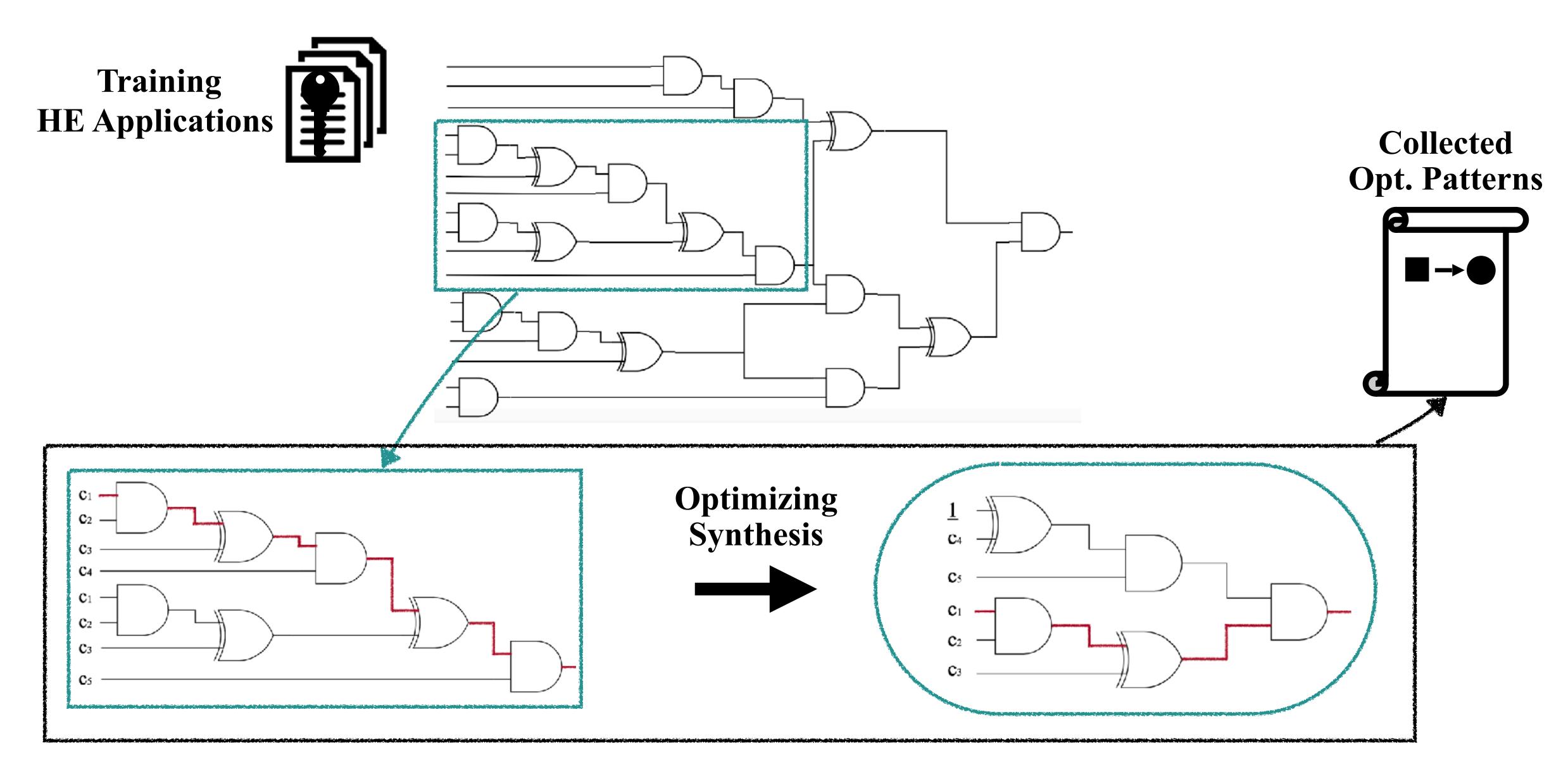


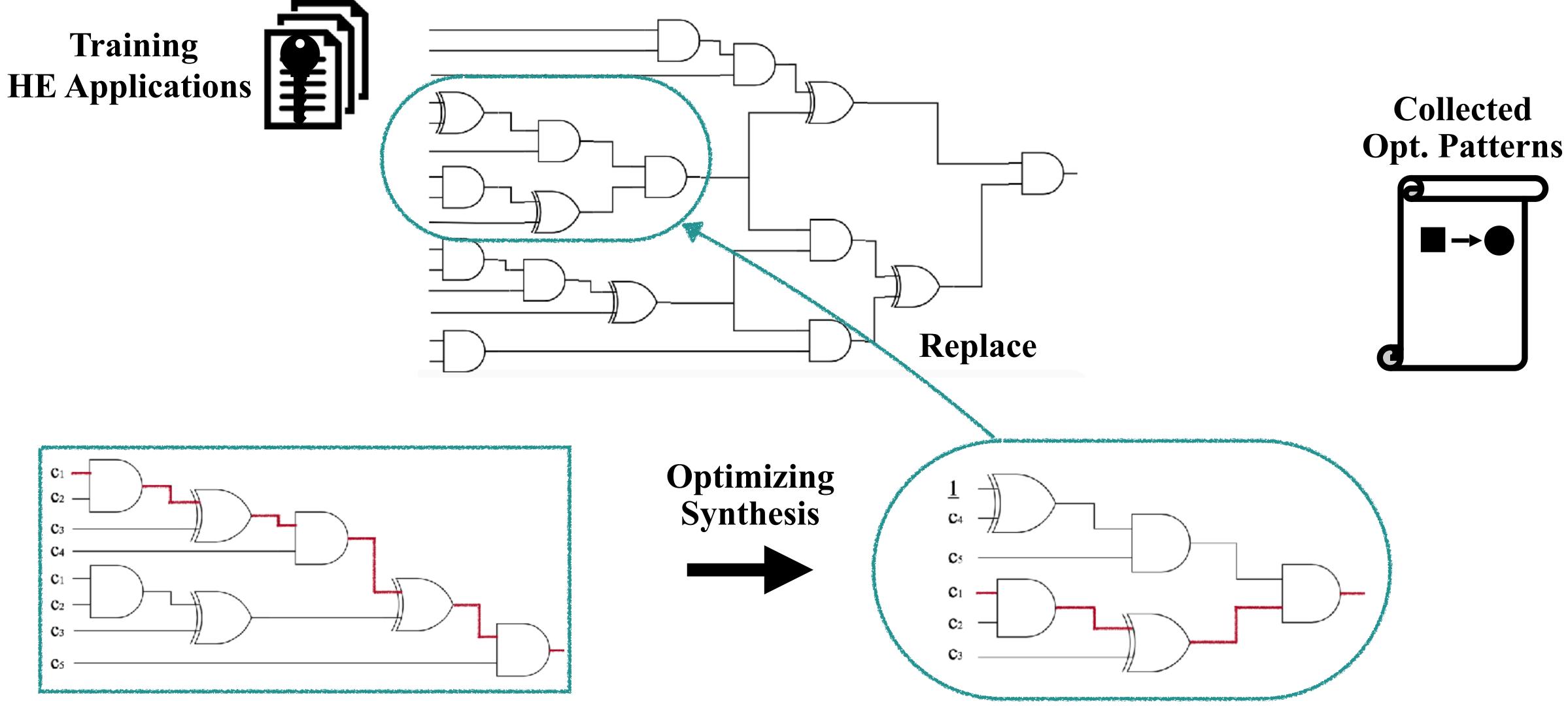


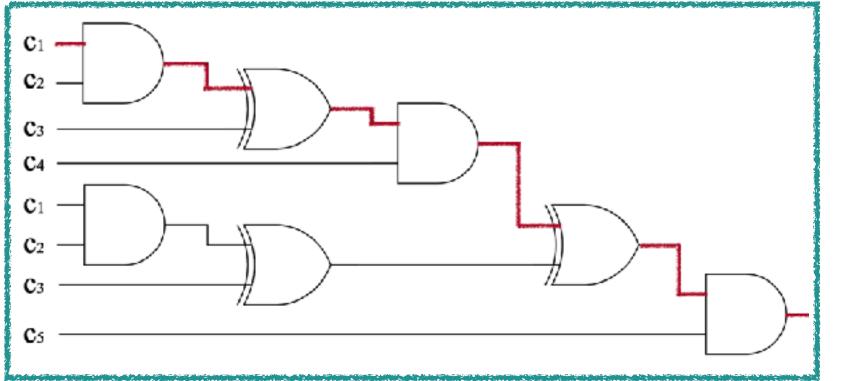


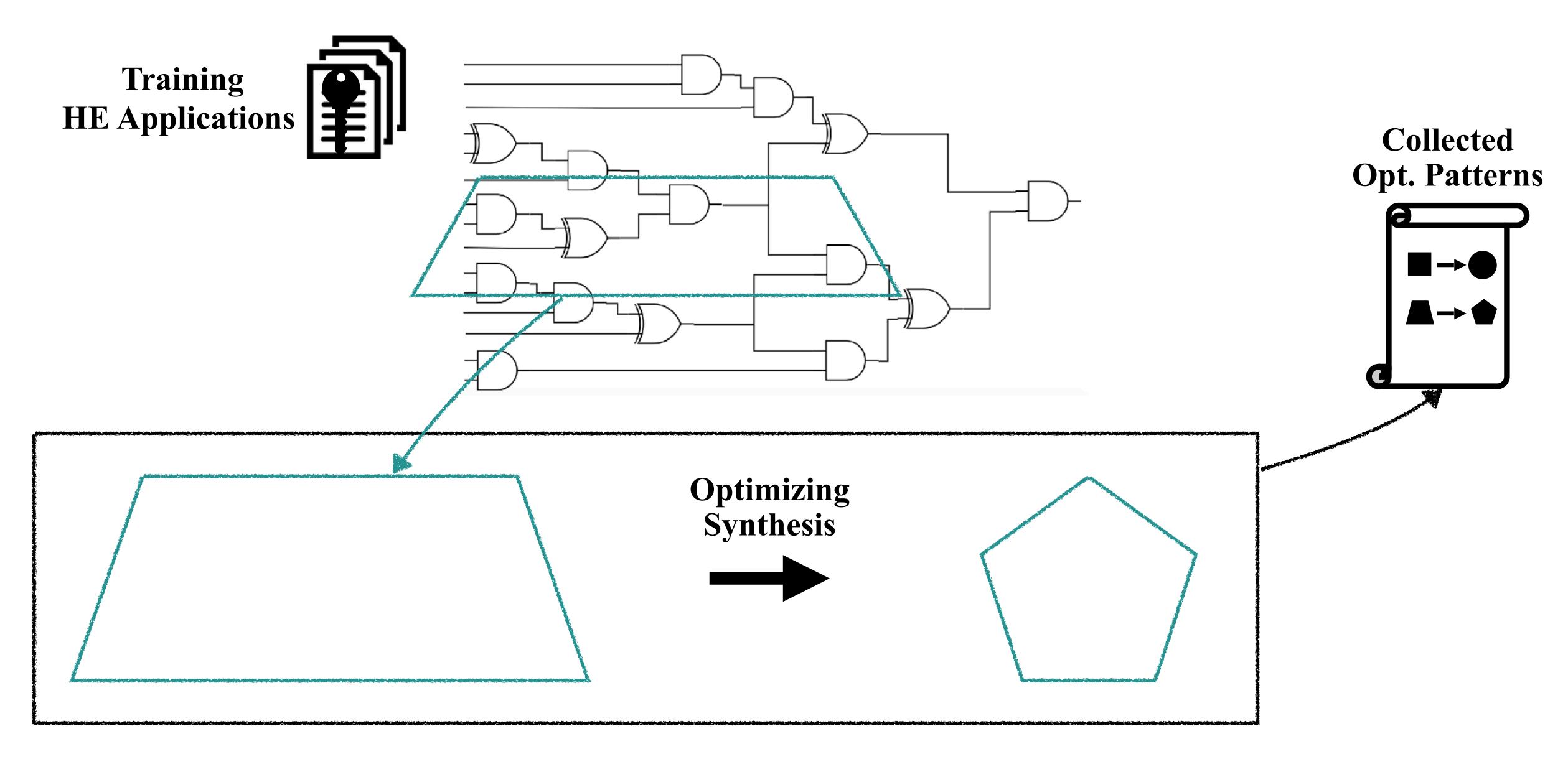




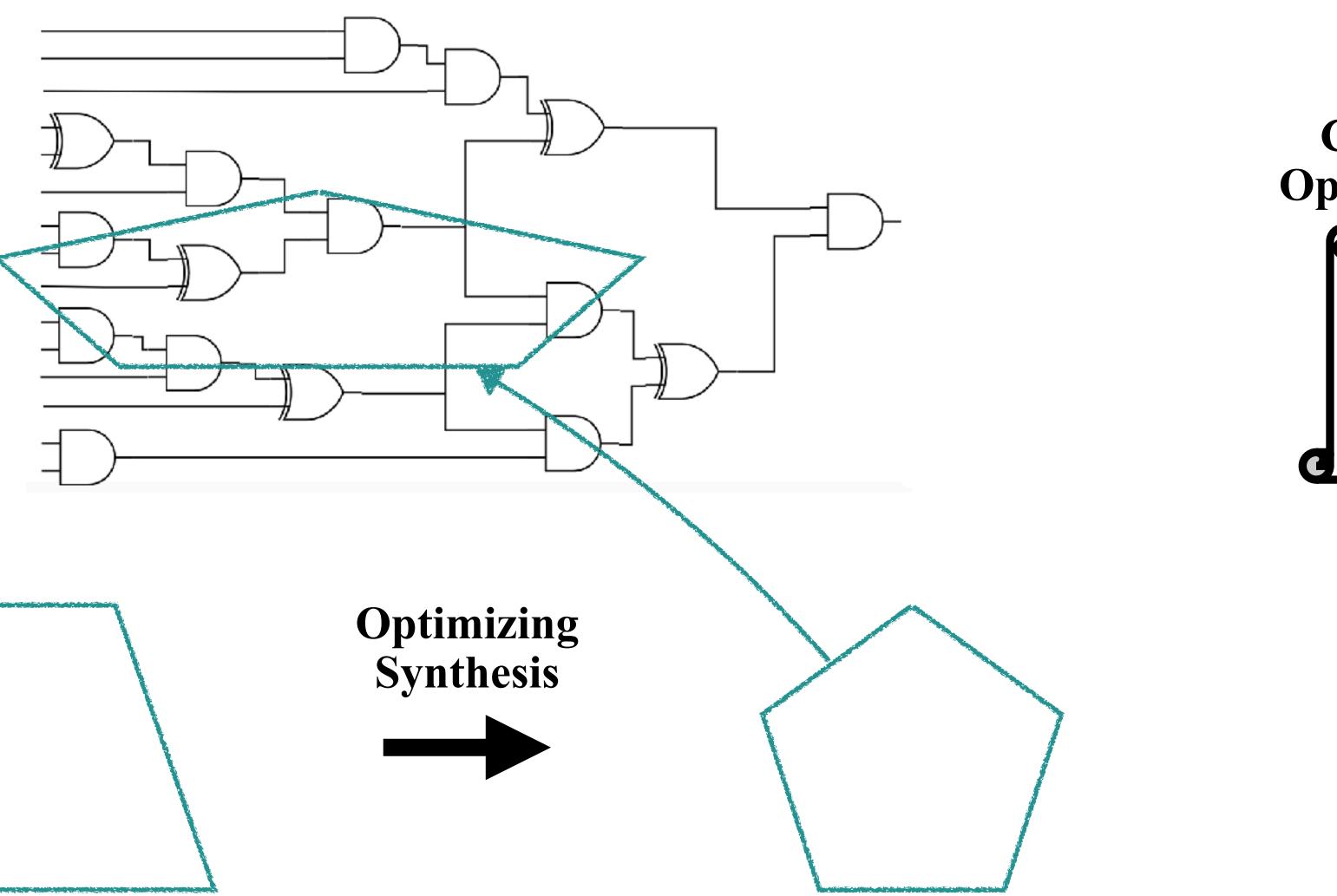


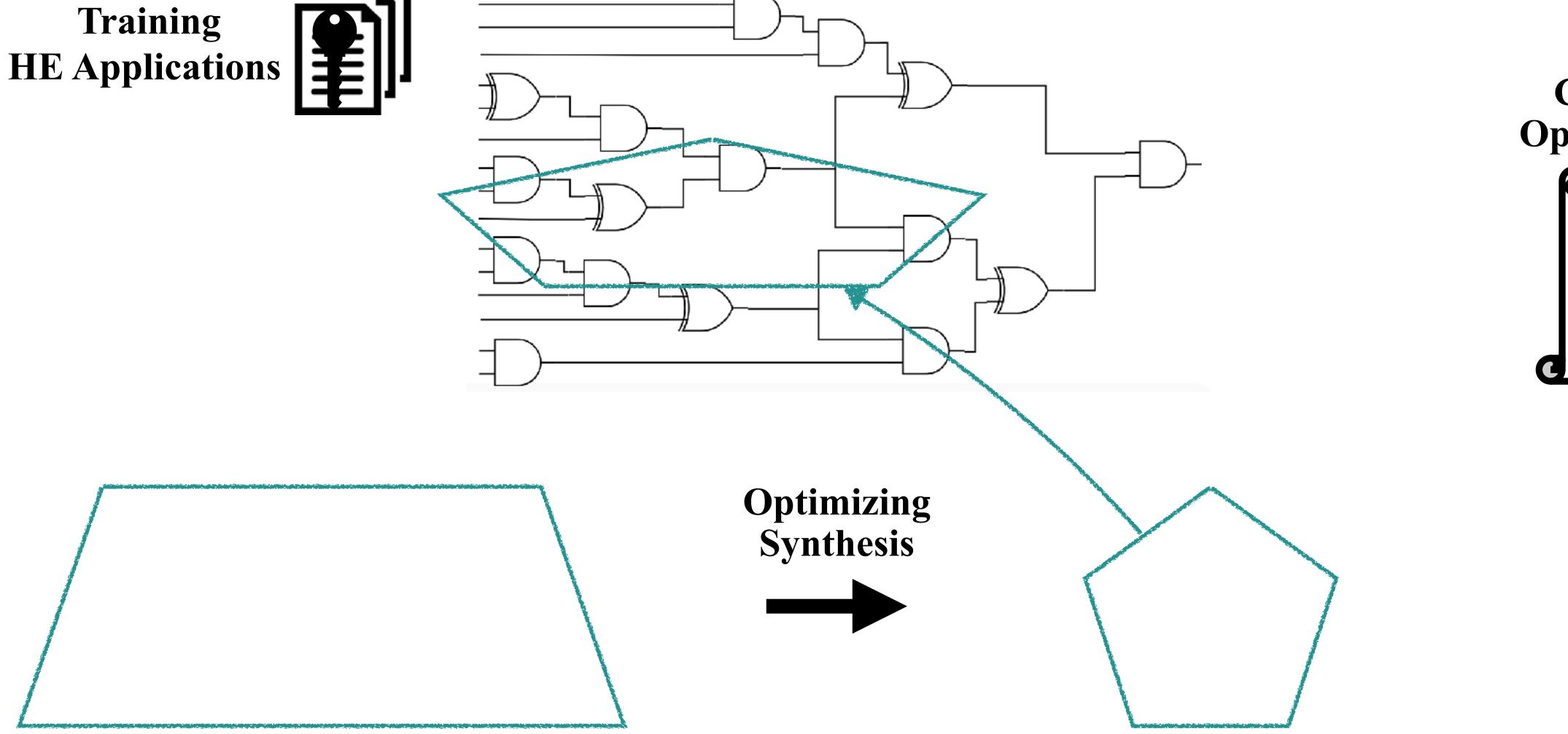


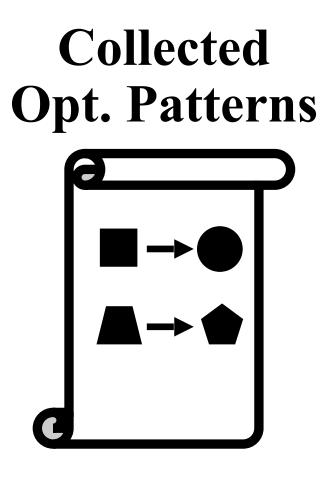


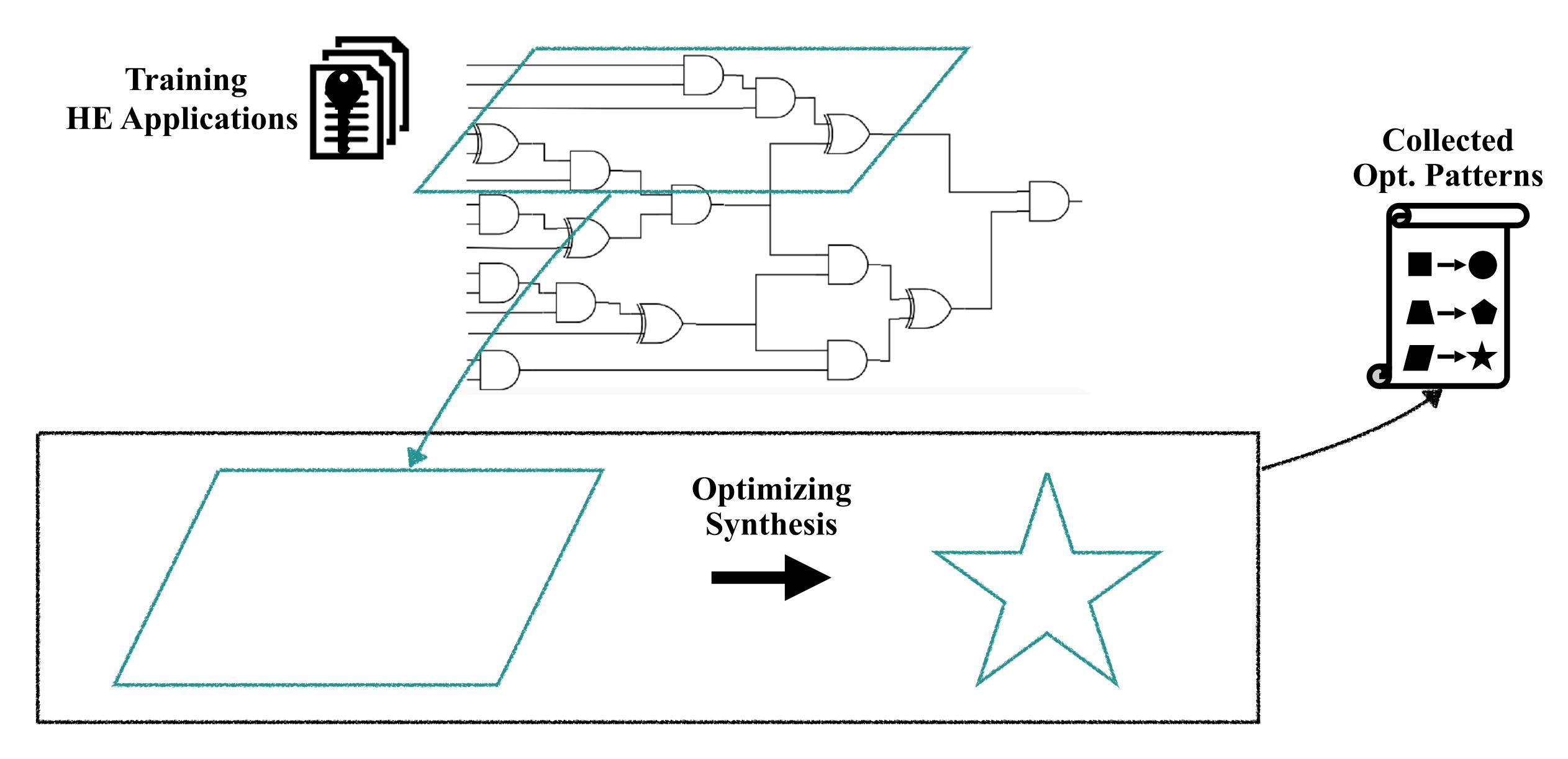


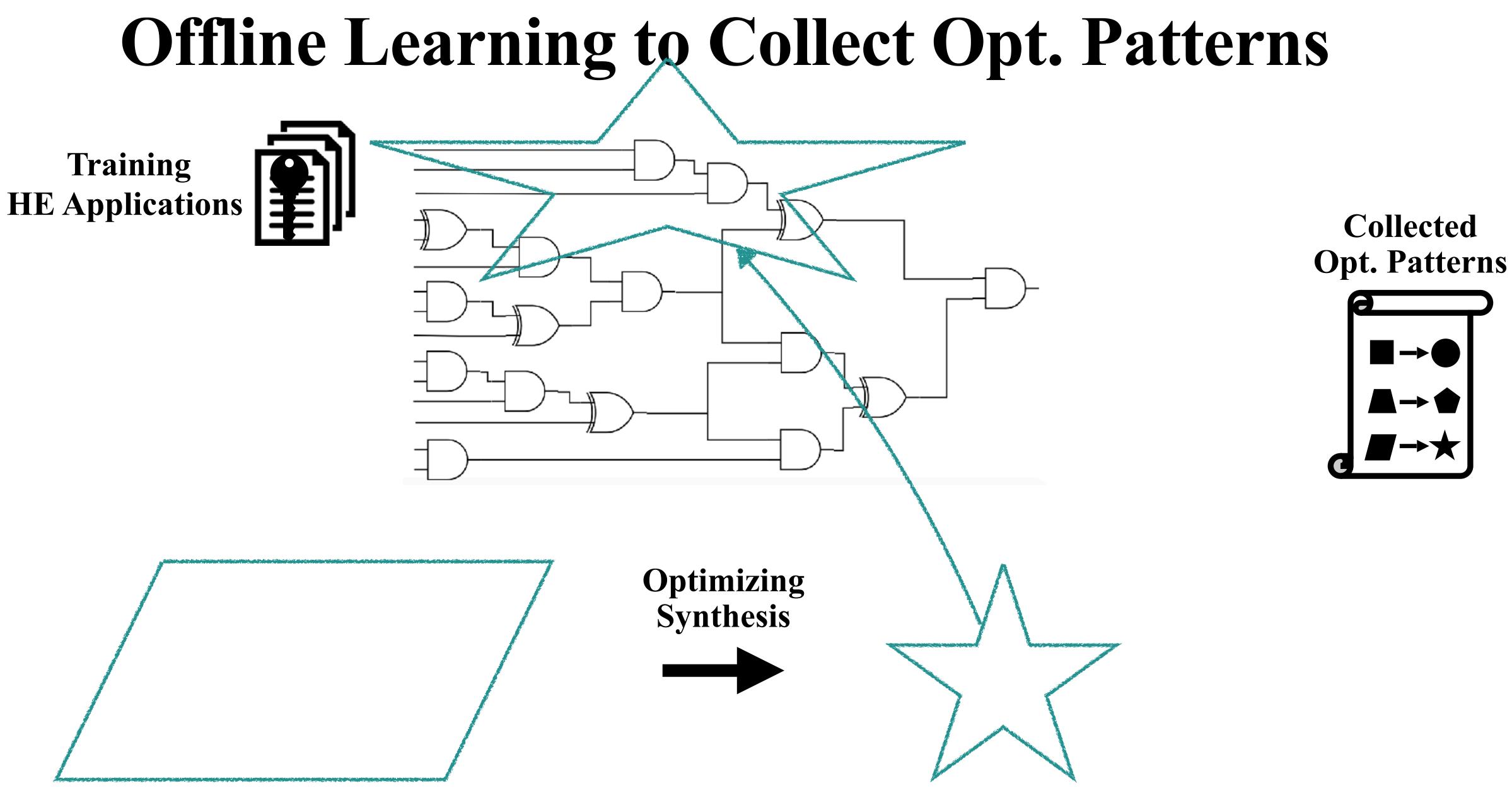


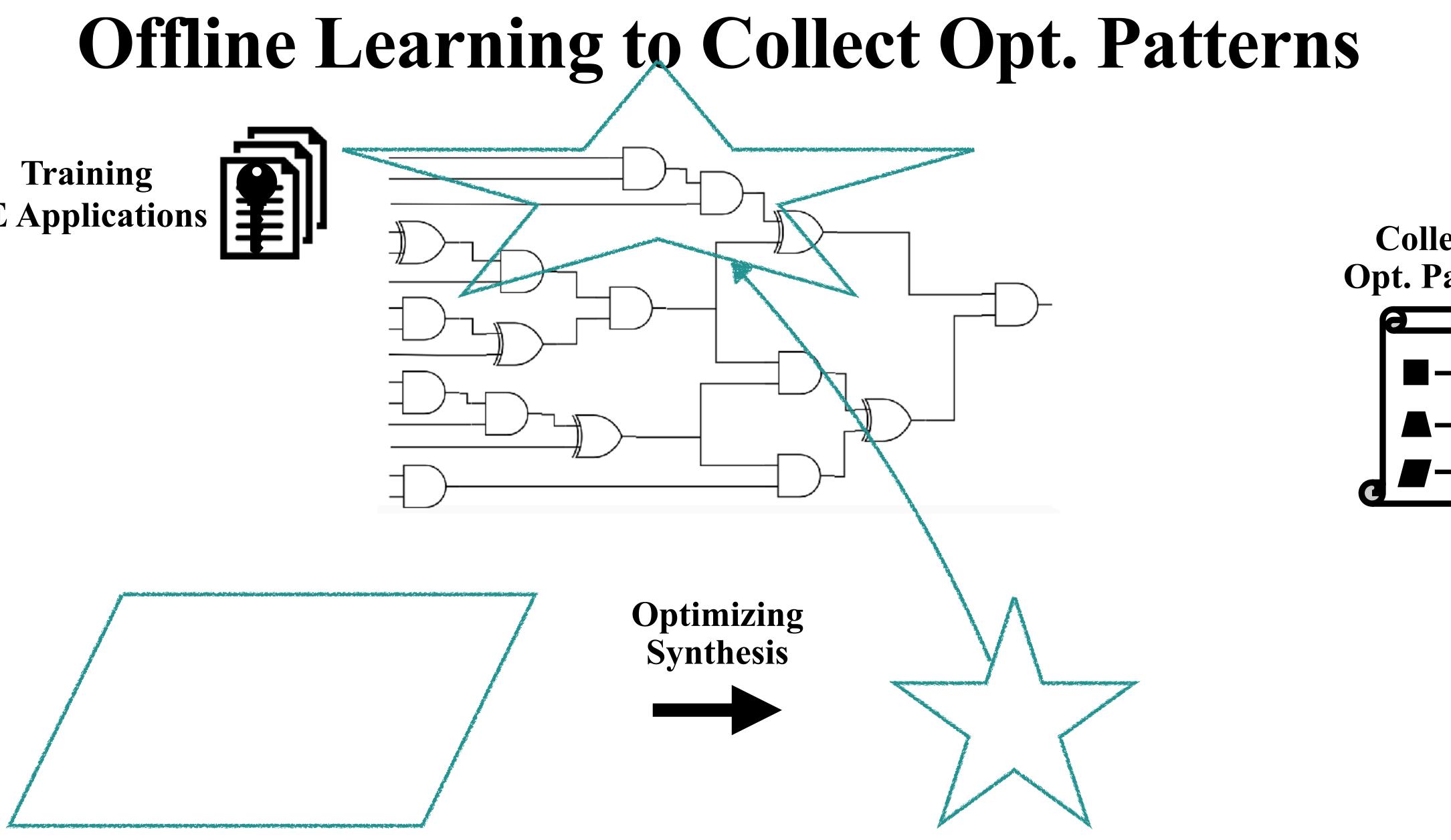


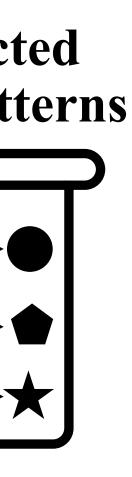








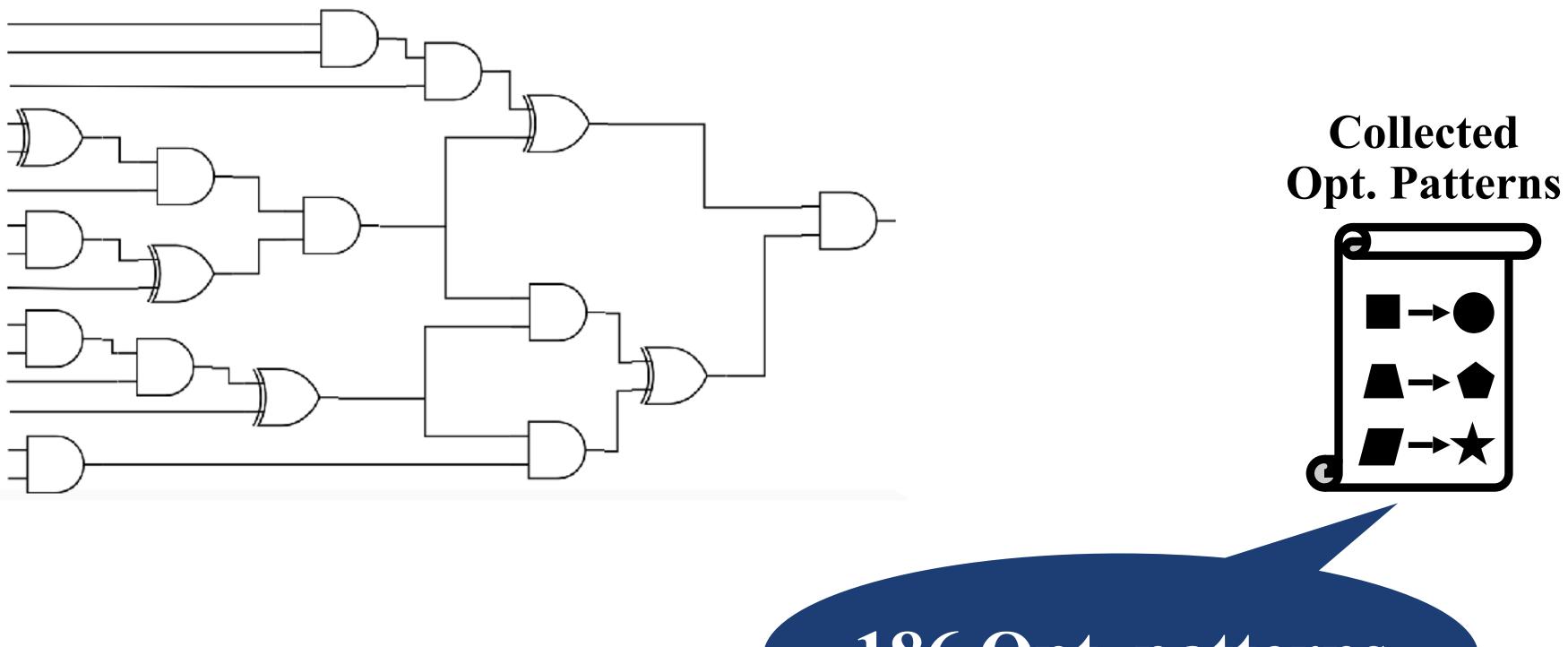




Offline Learning to Collect Opt. Patterns



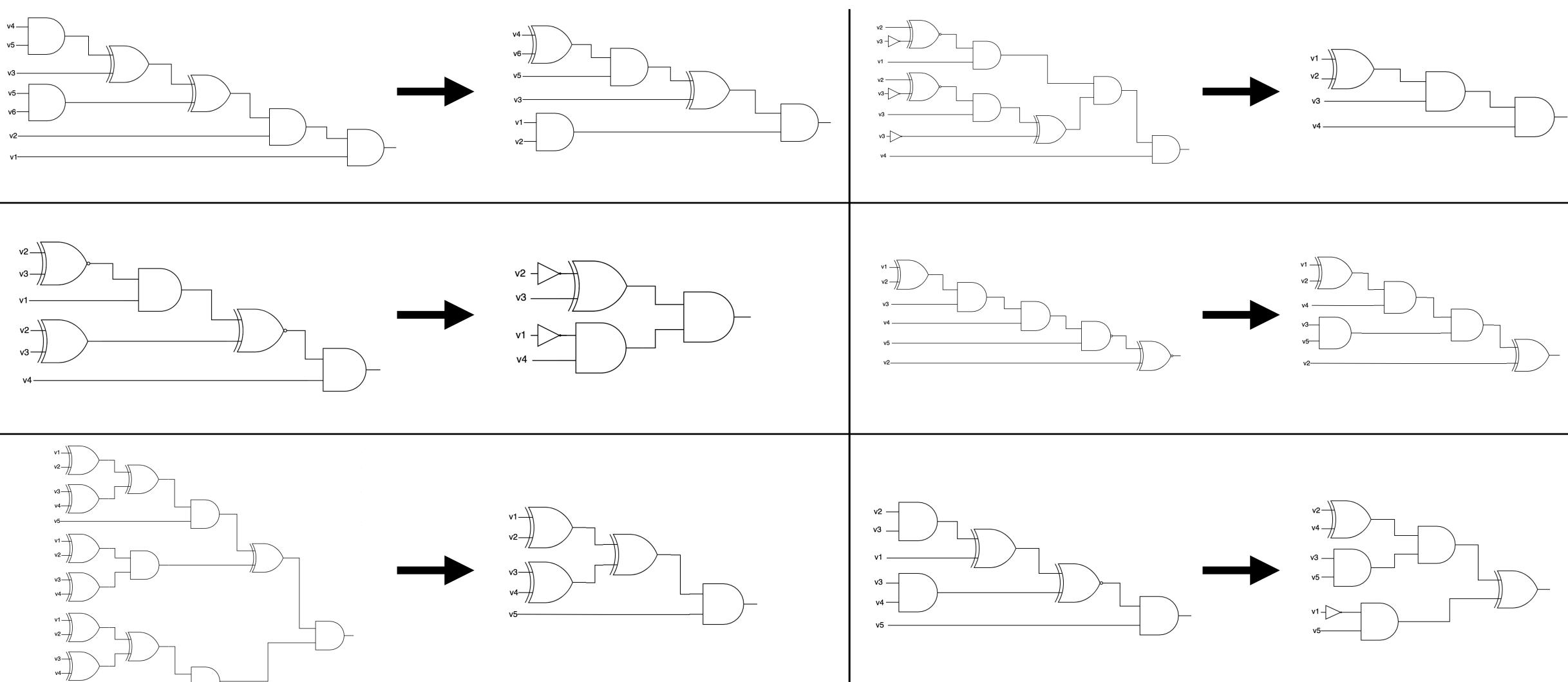


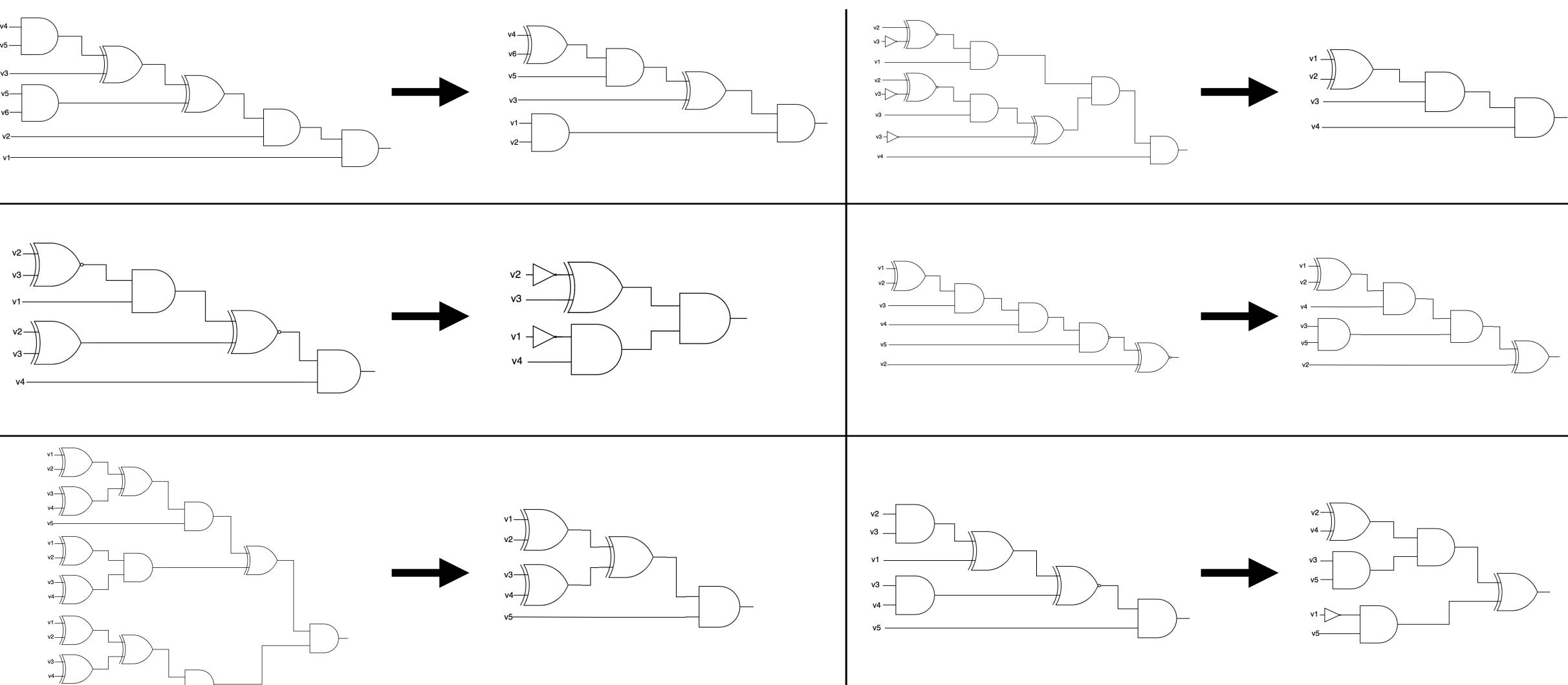


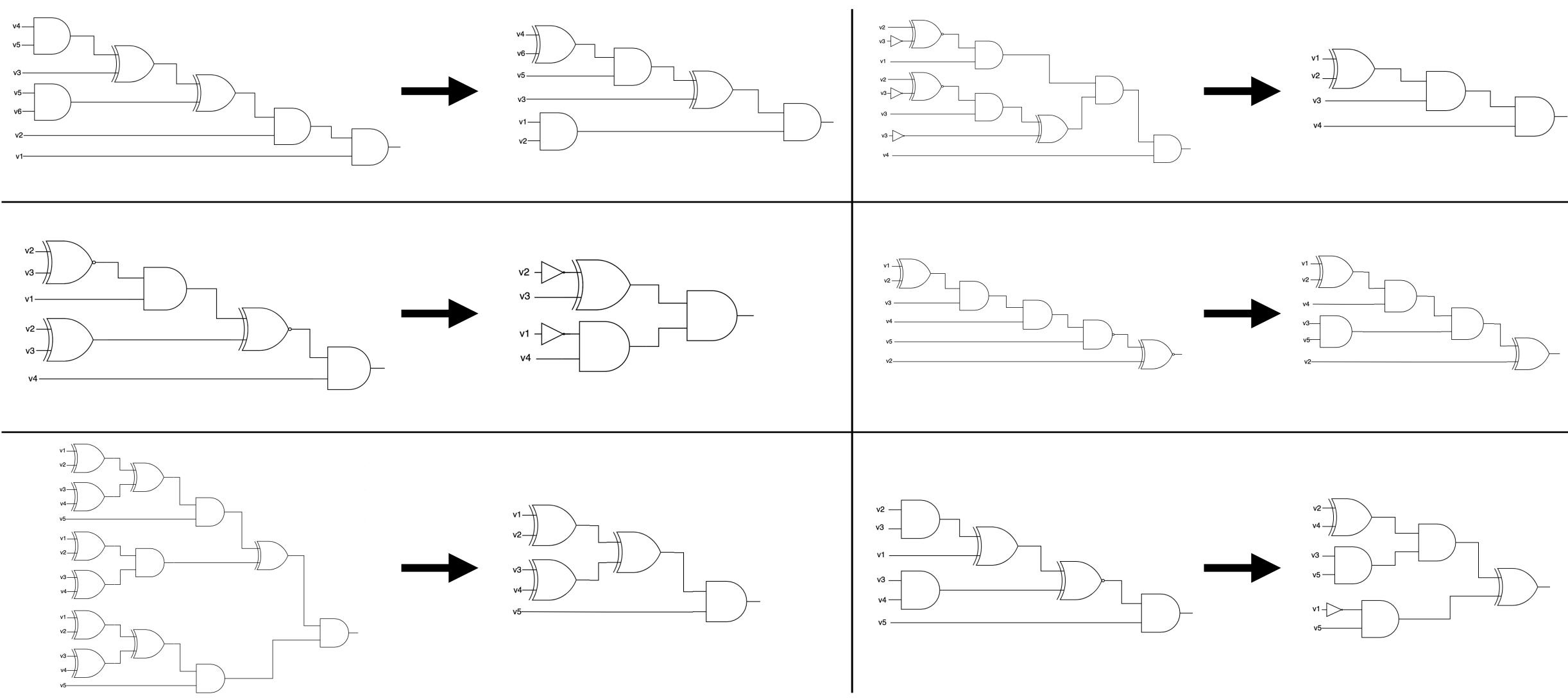
186 Opt. patterns



Learned Optimization Patterns : examples



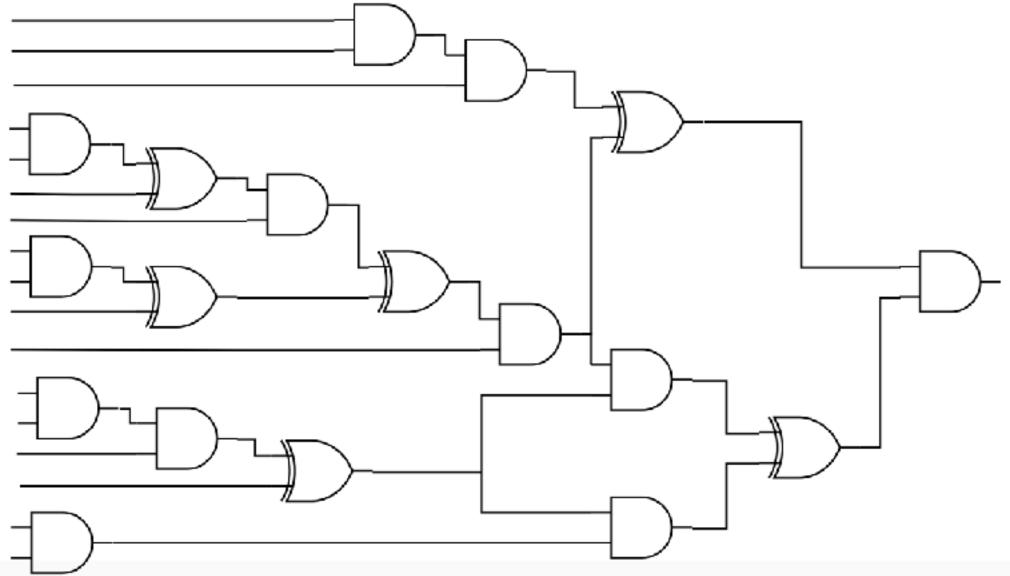


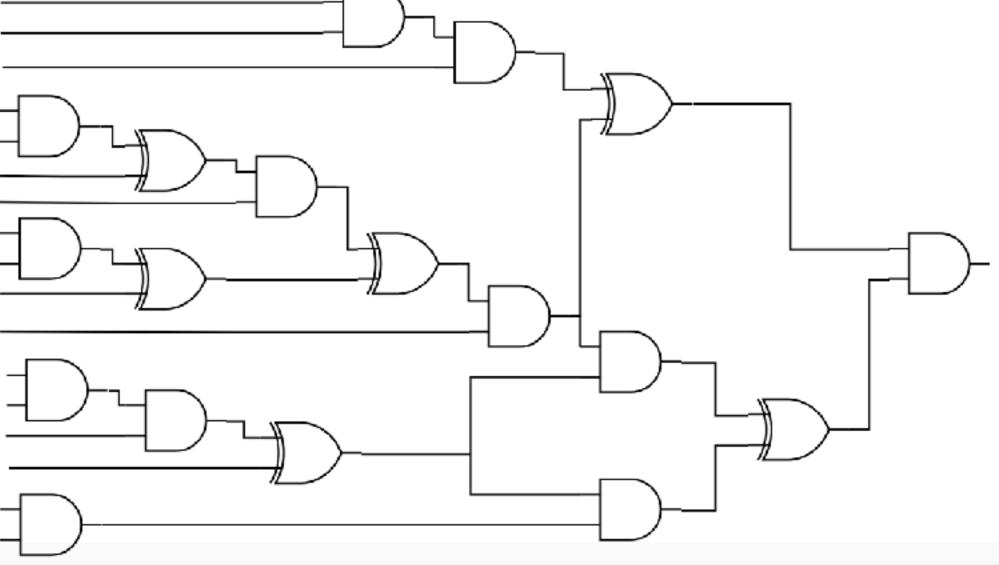


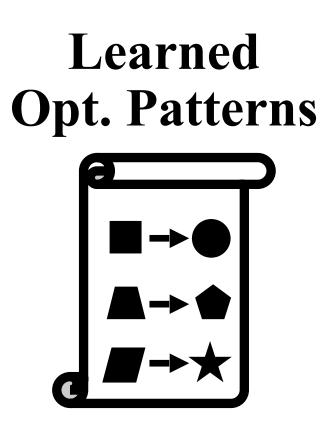
Online Rule-based Optimization

Input **HE application**

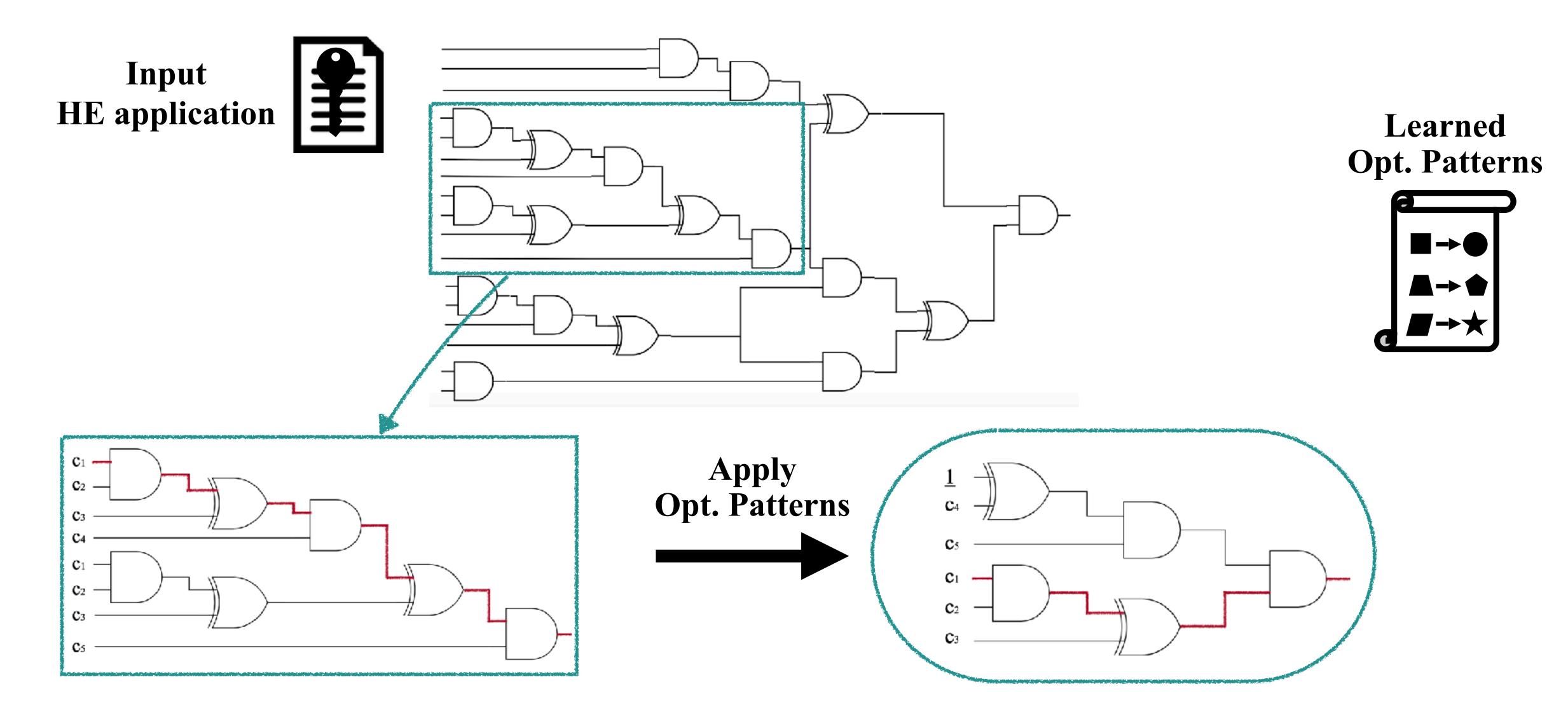




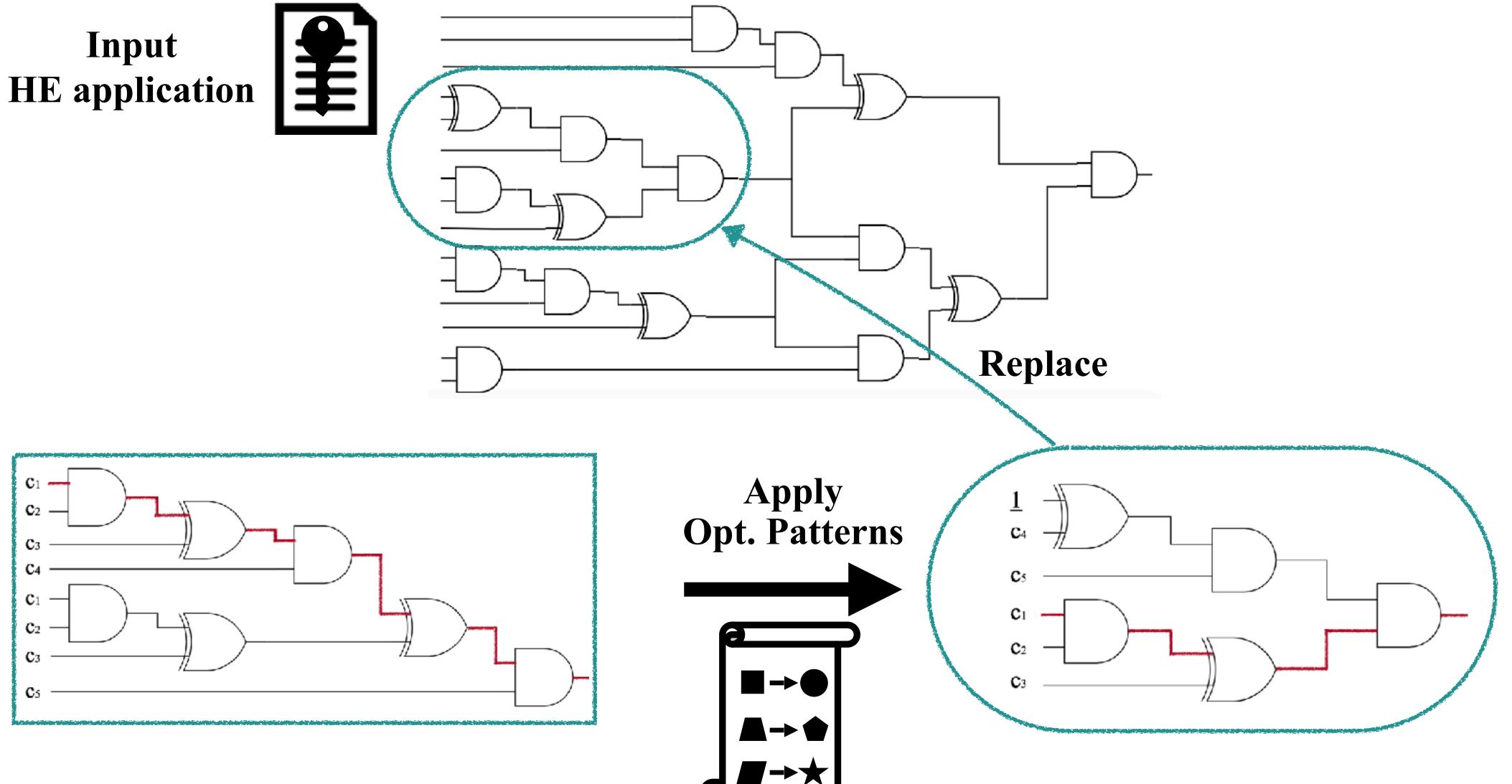


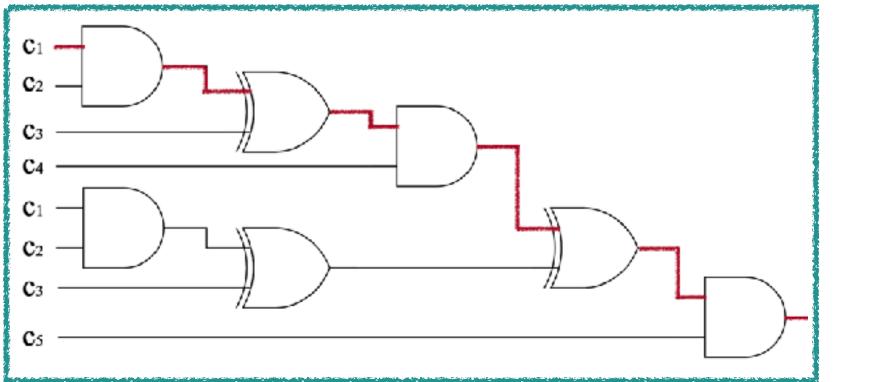


Online Rule-based Optimization

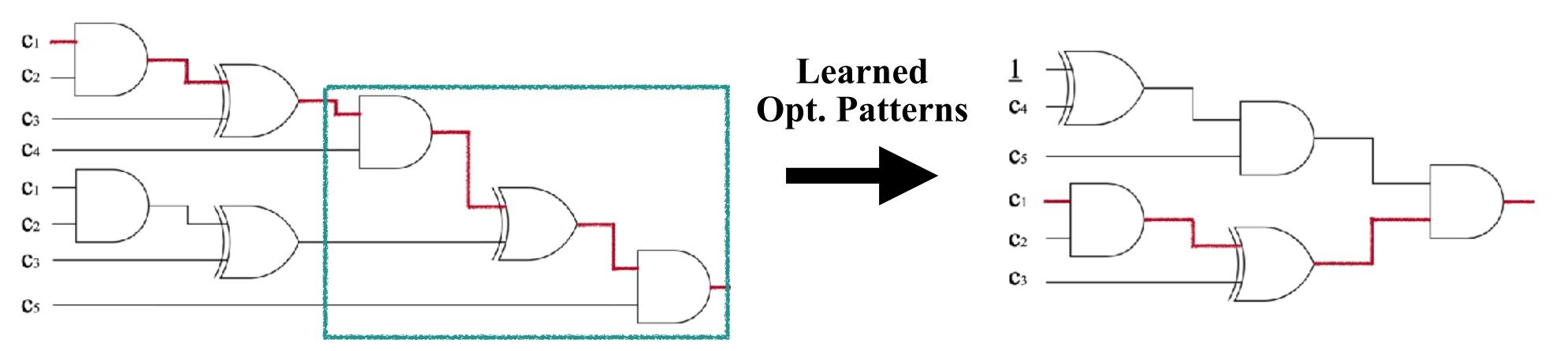


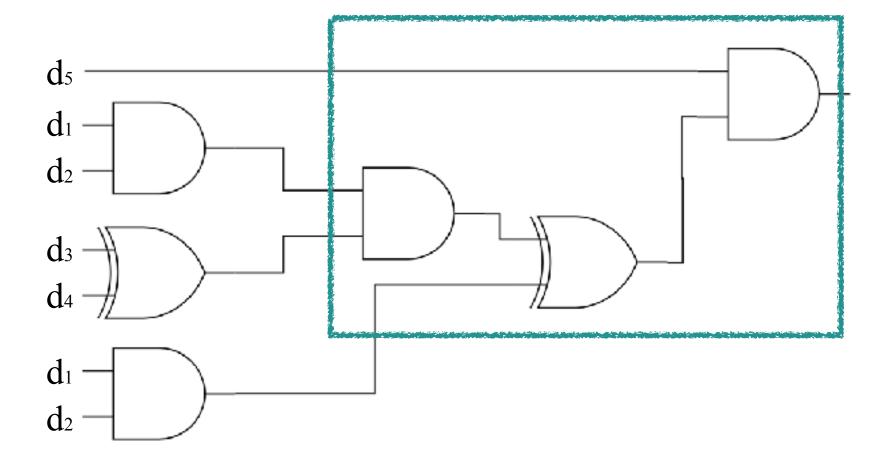
Online Rule-based Optimization



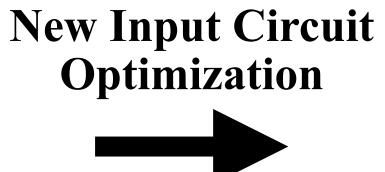


Applying Learned Optimization Patterns (1/2)



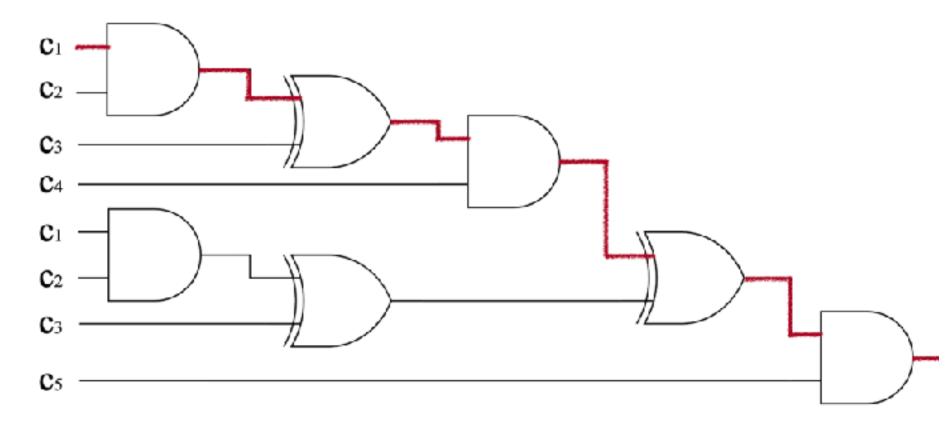


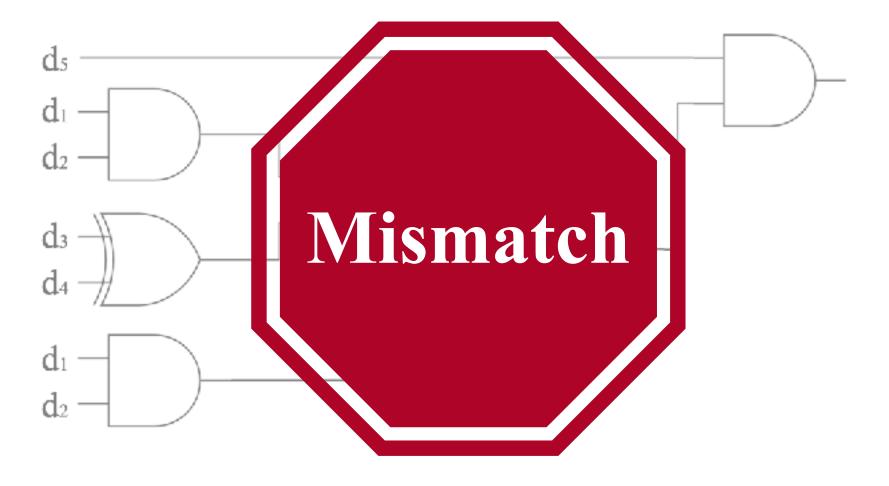
Syntactic Matching is Not Effective



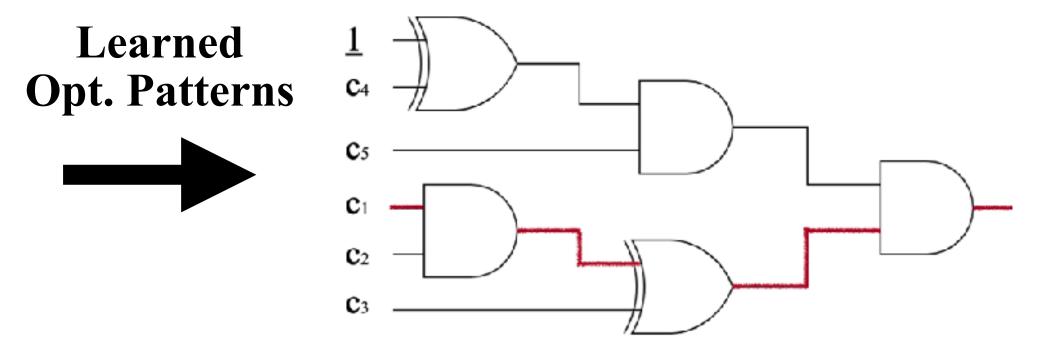


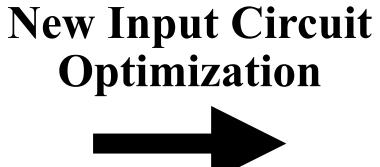
Applying Learned Optimization Patterns (1/2)





Syntactic Matching is Not Effective

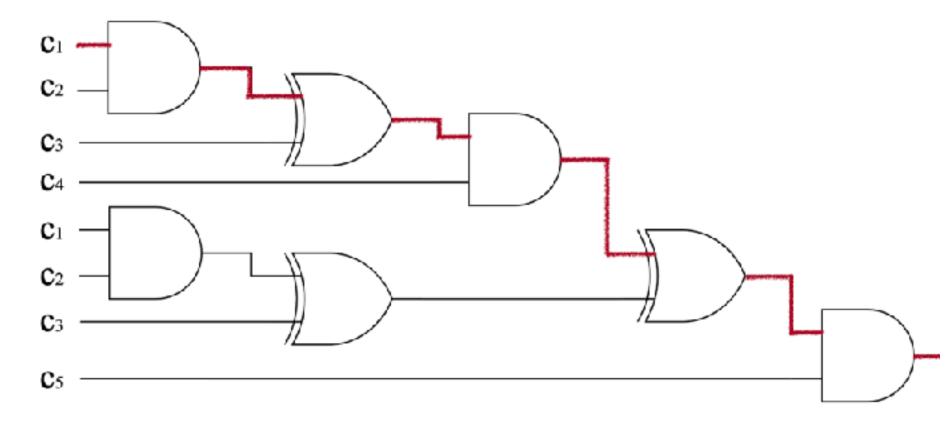


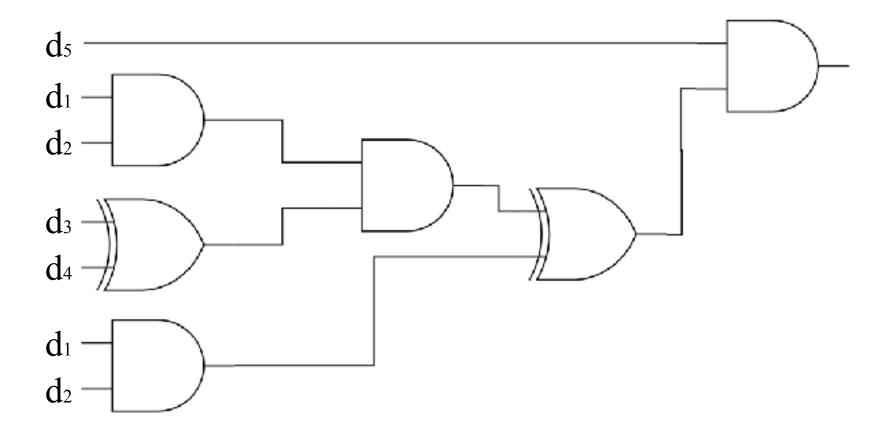


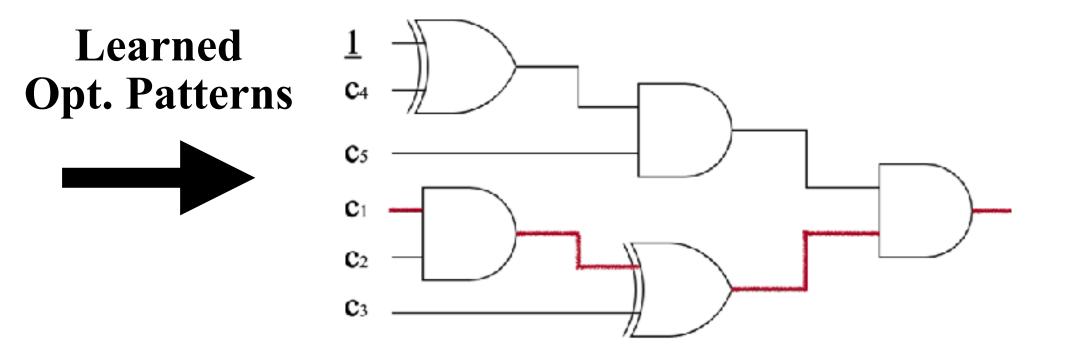


Applying Learned Optimization Patterns (2/2)

Normalization + Equational Matching





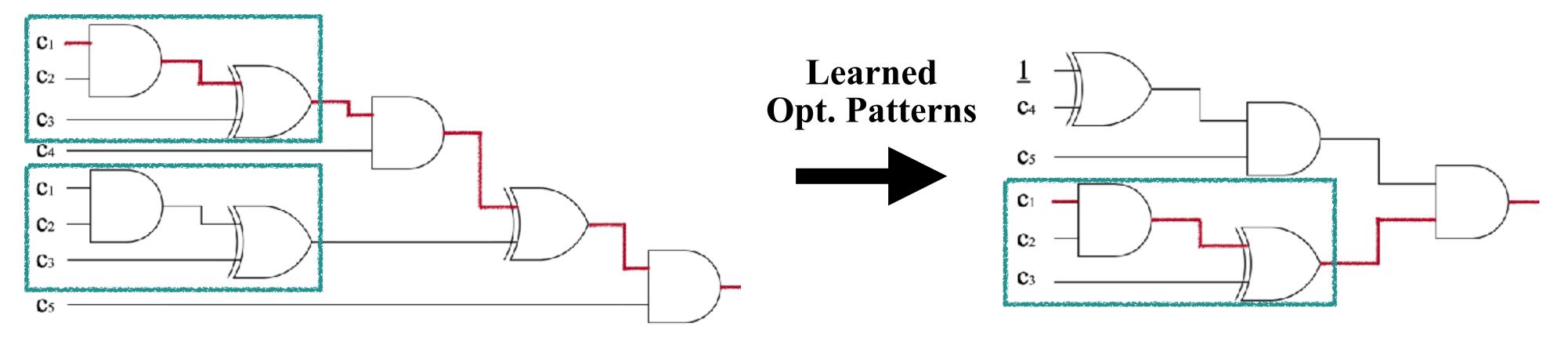


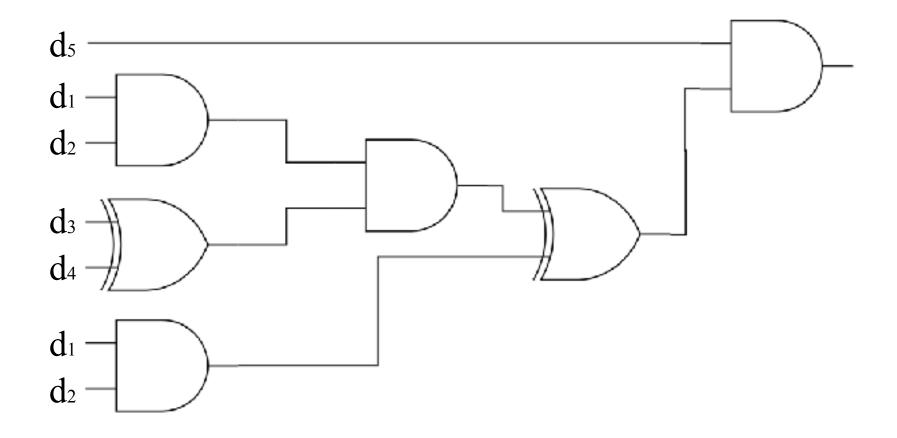


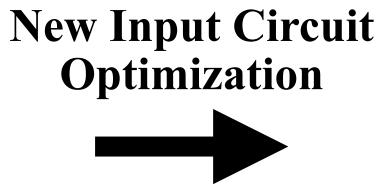


Applying Learned Optimization Patterns (2/2)

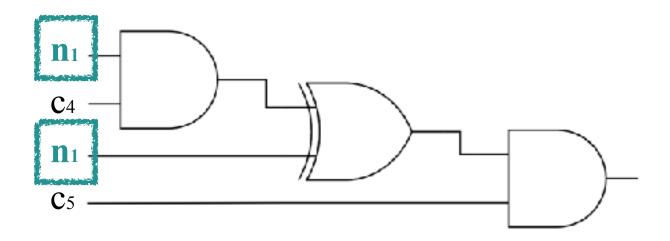
Normalization + Equational Matching

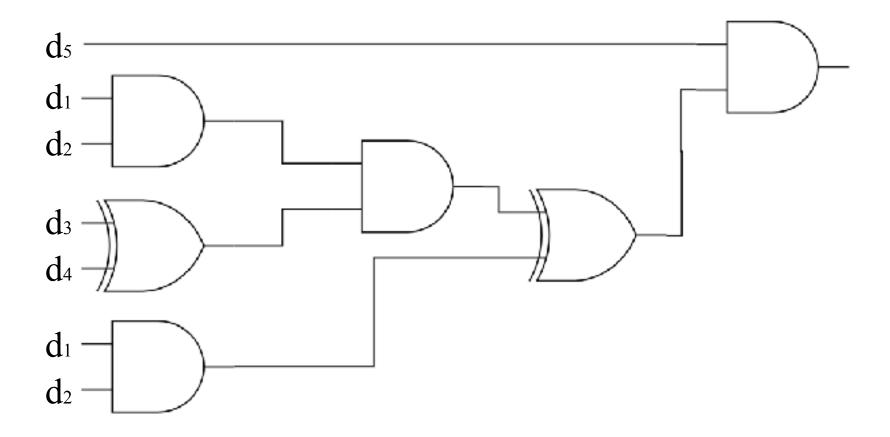




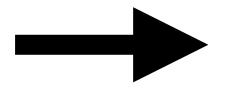


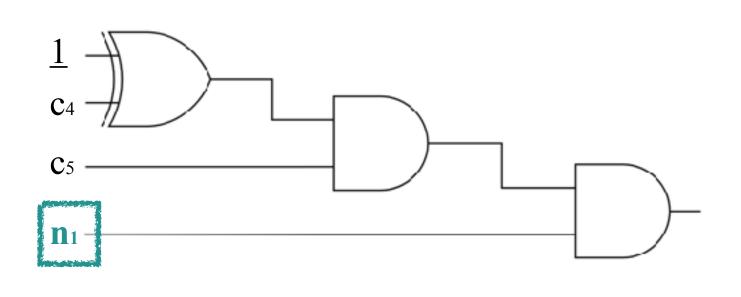


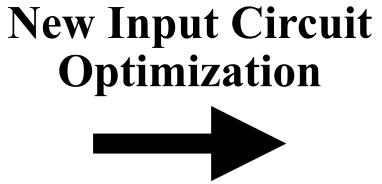




Normalized Opt. Patterns



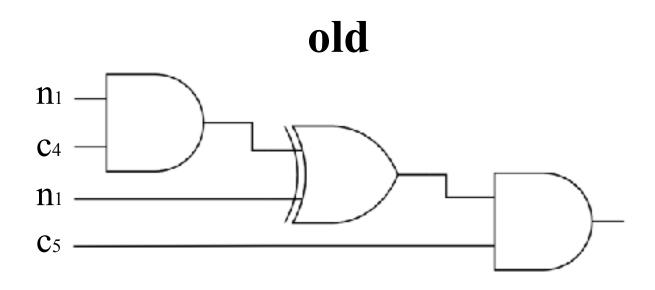


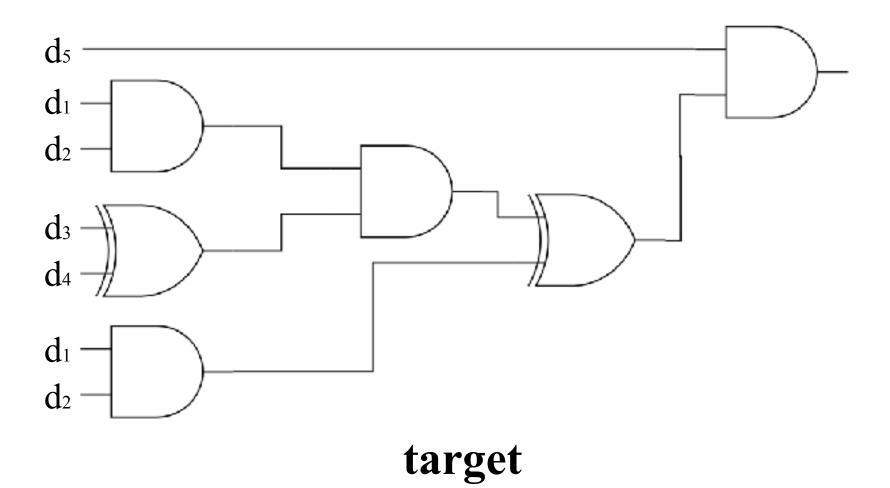




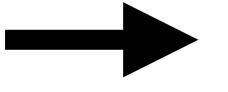
Applying Learned Optimization Patterns (2/2)

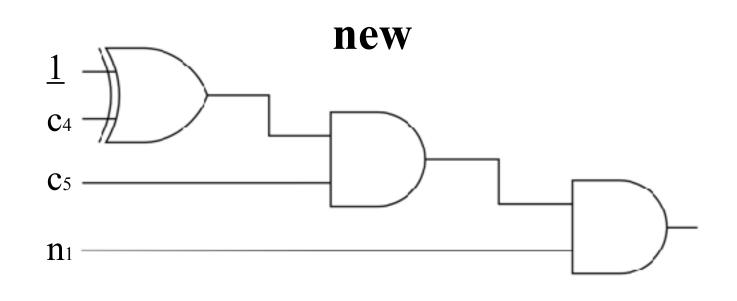
Normalization + Equational Matching

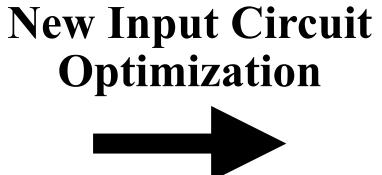






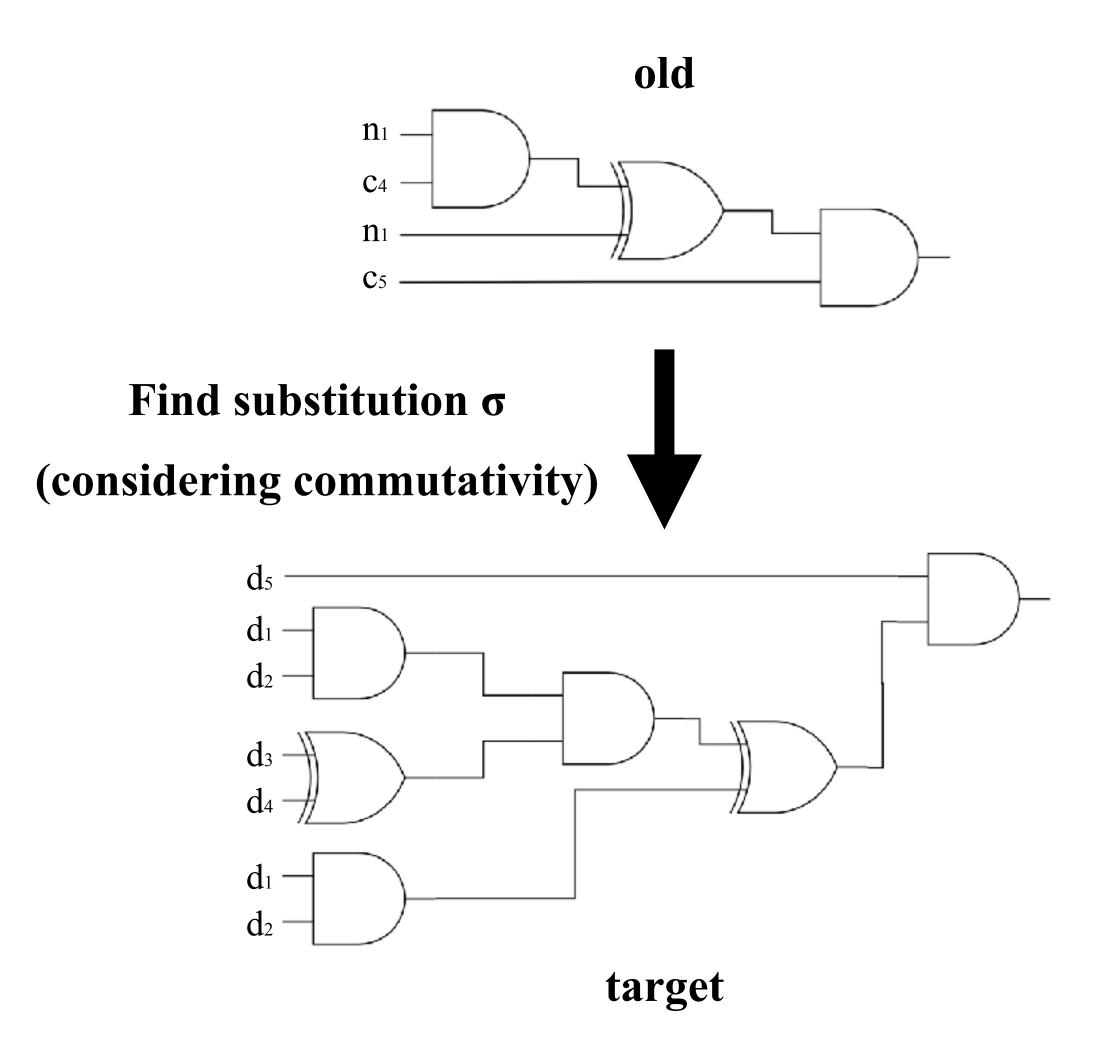




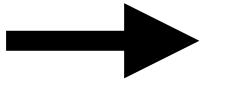


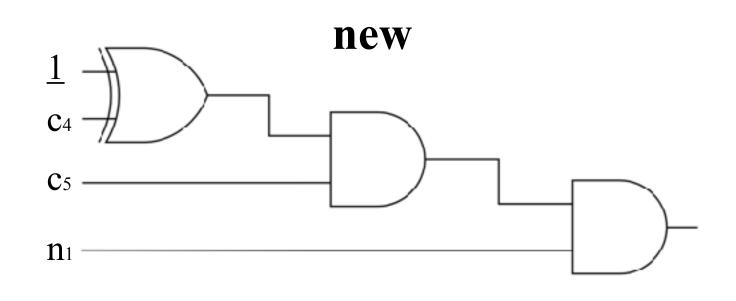
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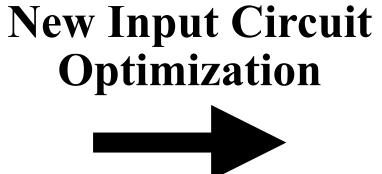
target'



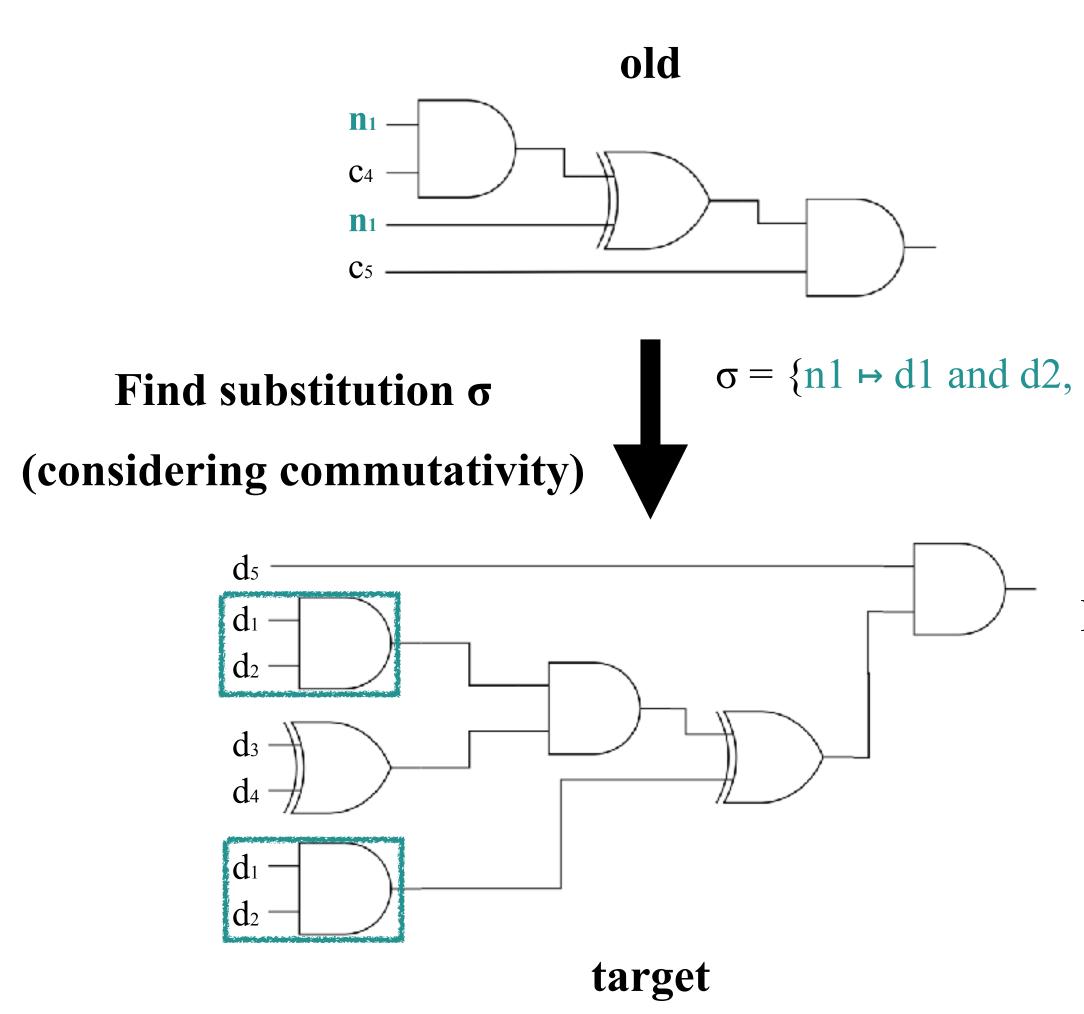




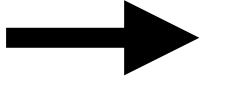


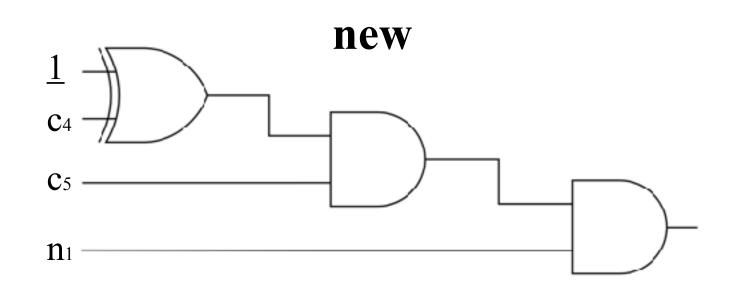


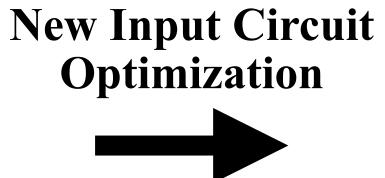
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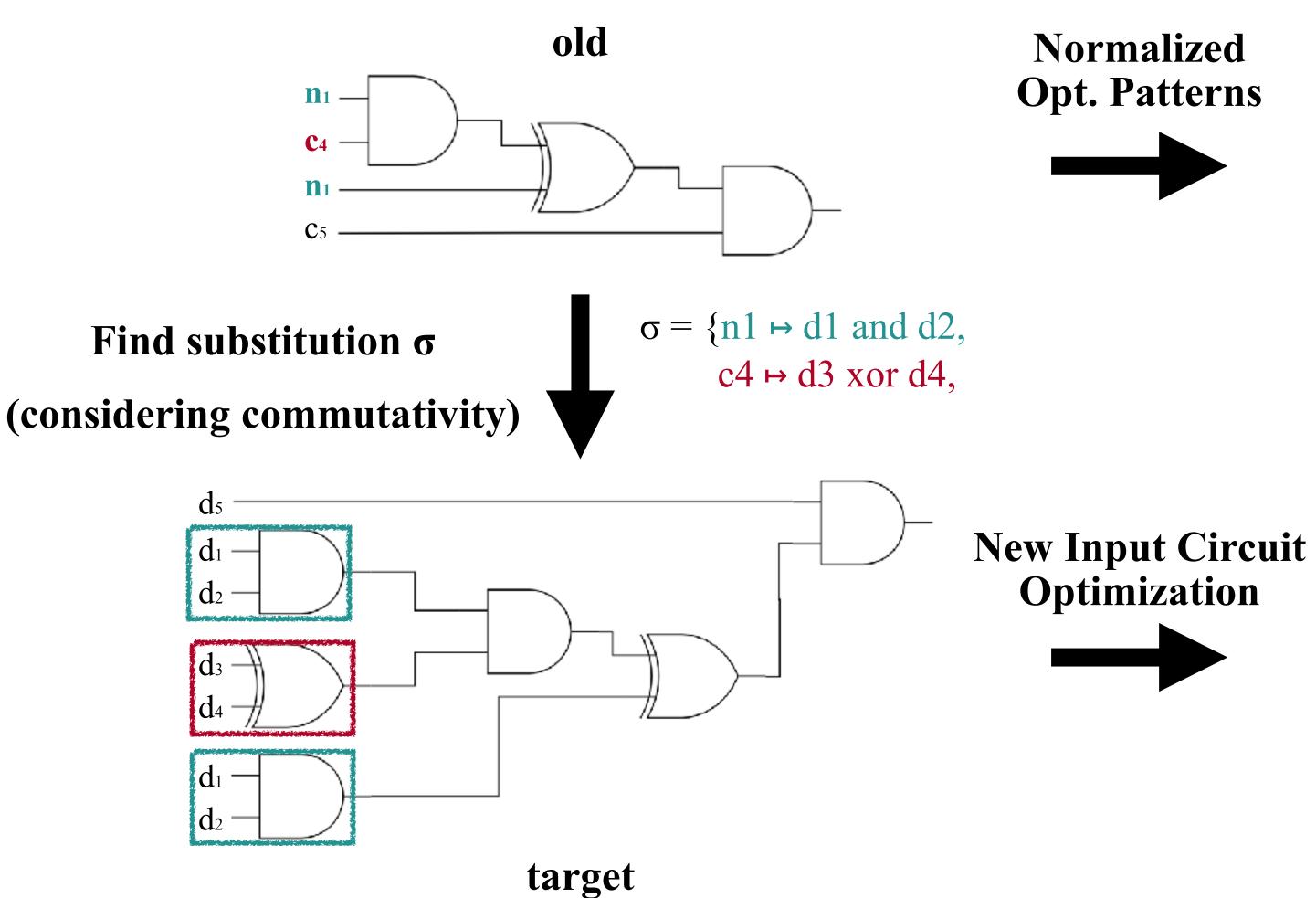




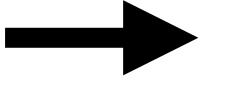


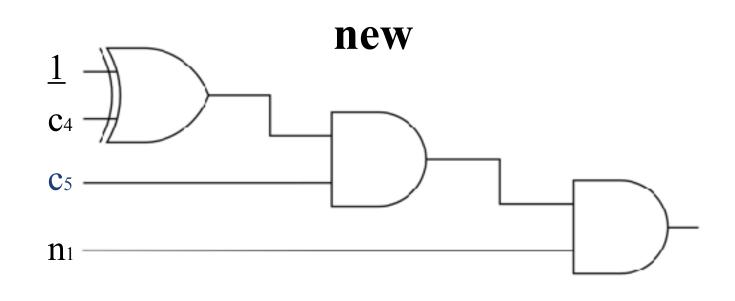


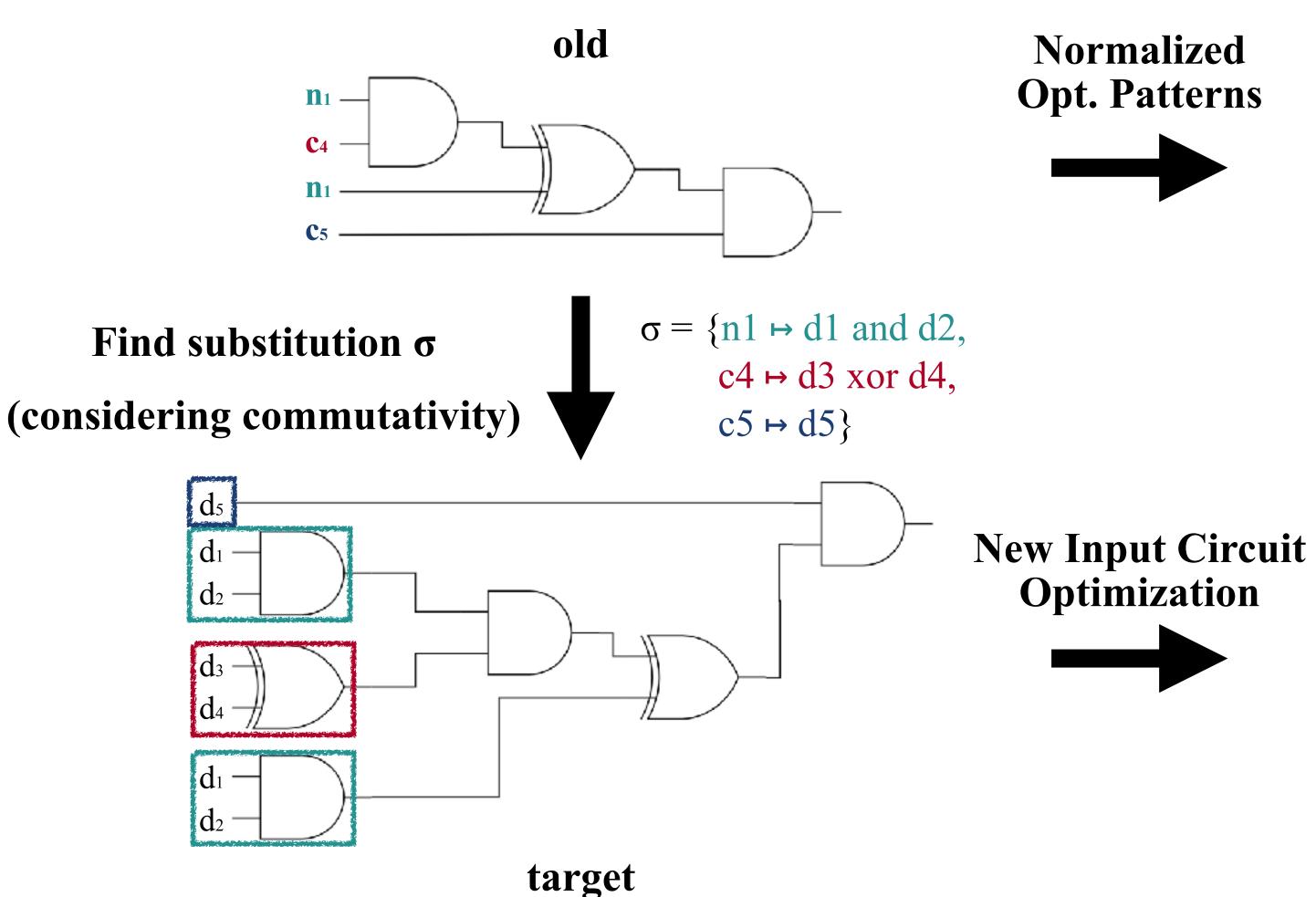
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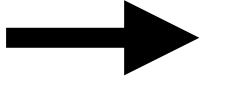


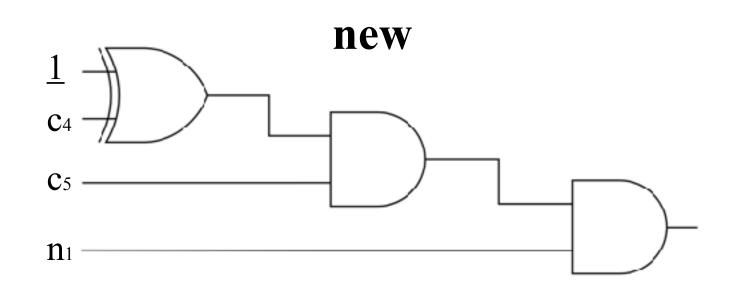




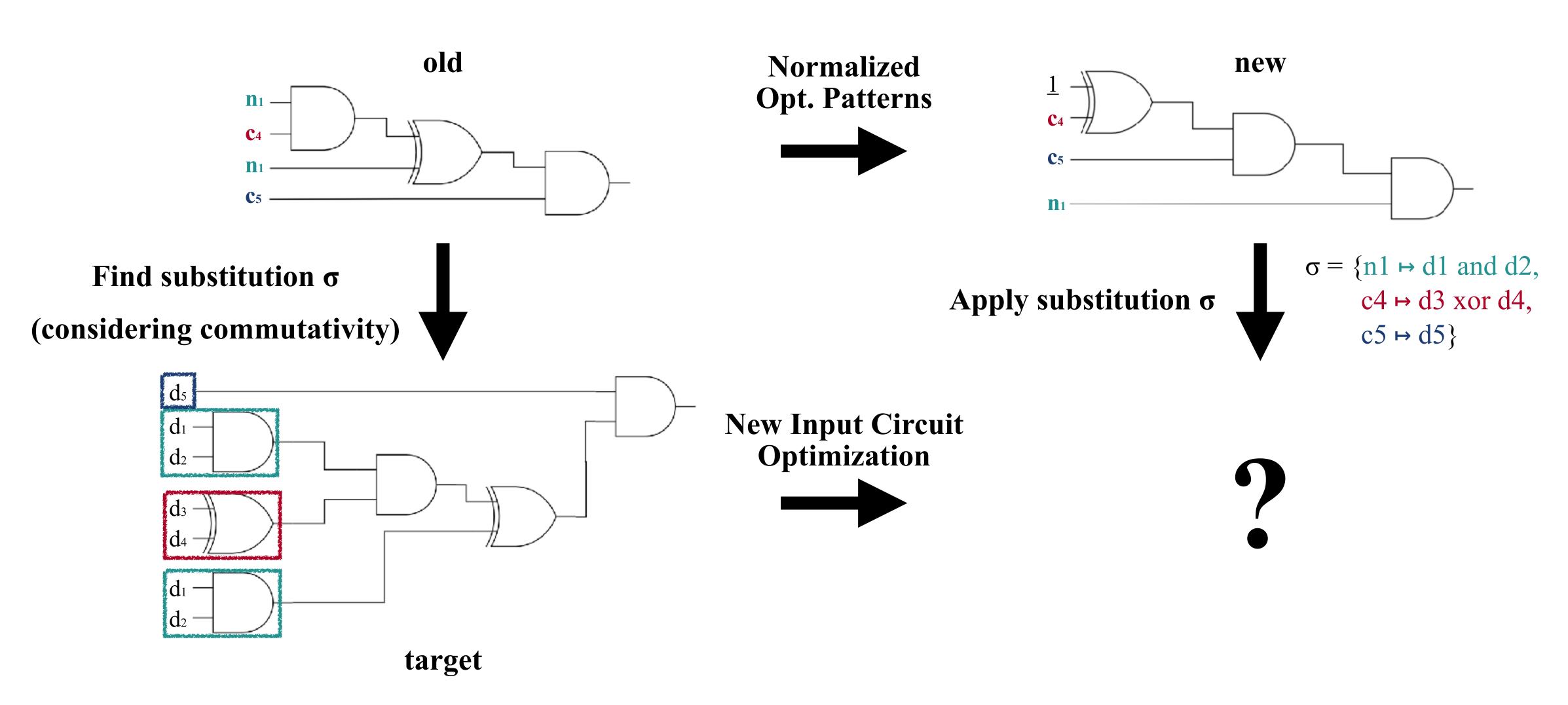






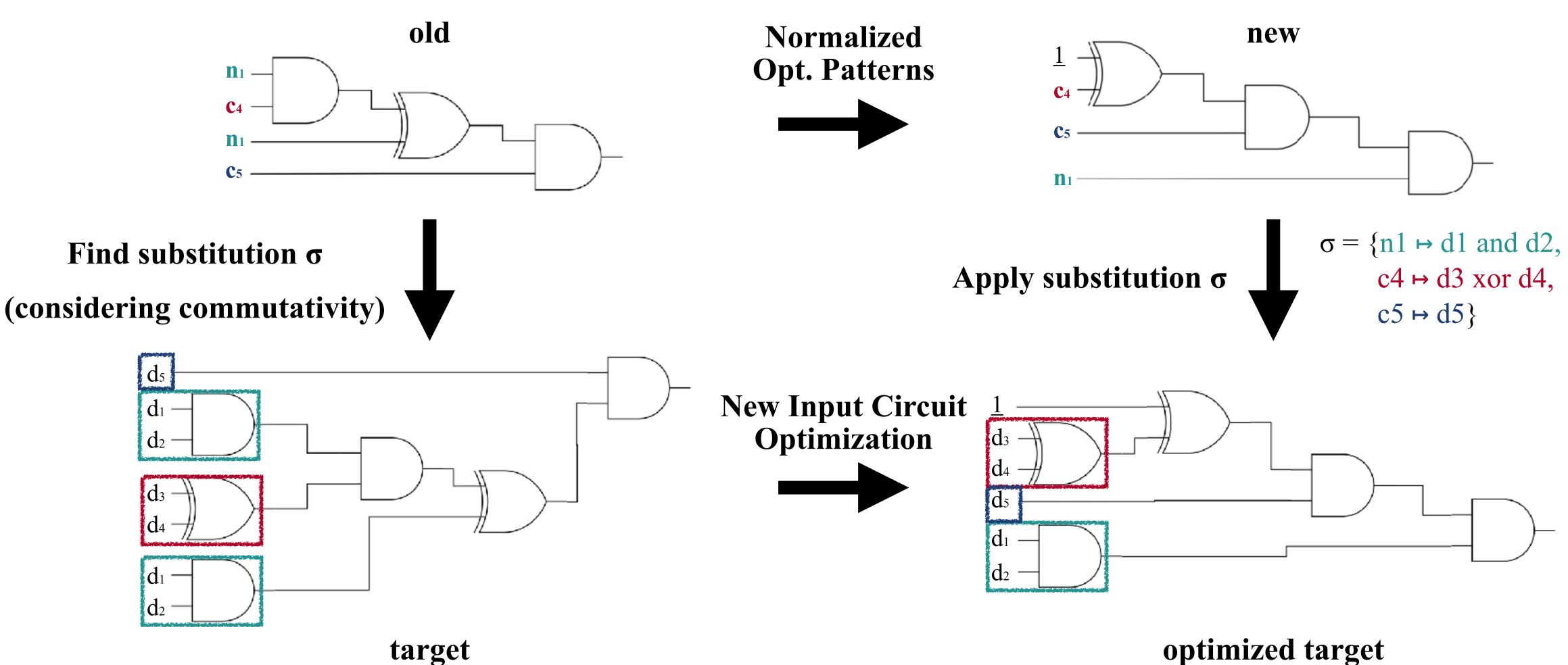


Applying Learned Optimization Patterns (2/2)



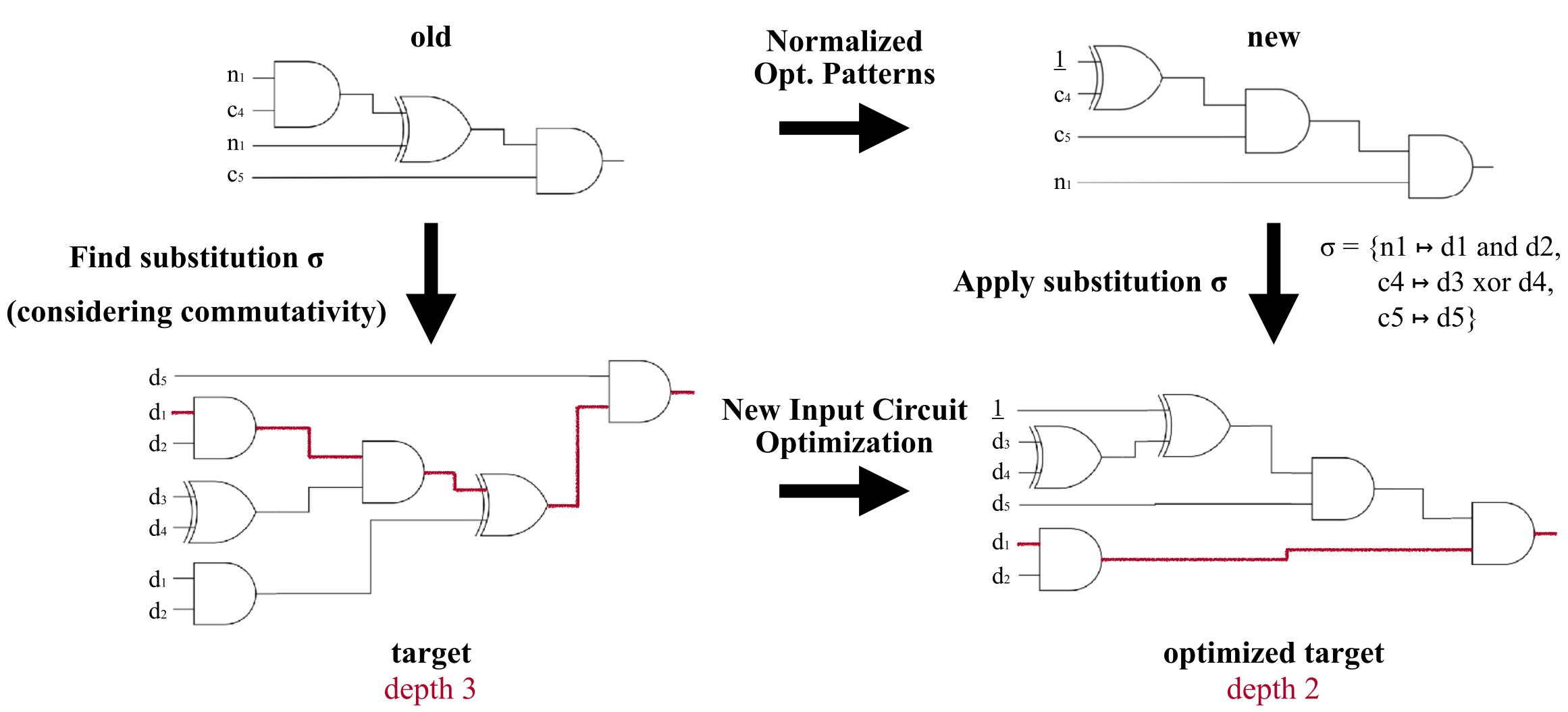
Normalization + Equational Matching

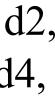
Applying Learned Optimization Patterns (2/2)



Normalization + Equational Matching

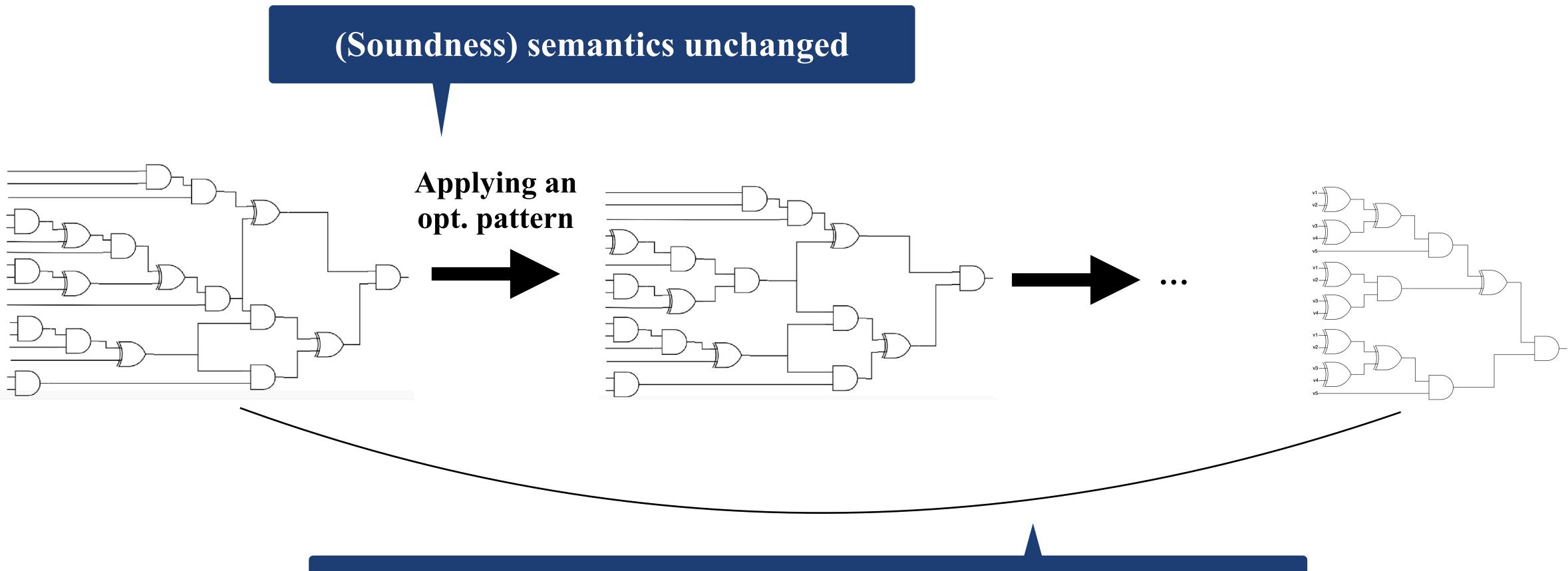








Applying Learned Optimization Patterns



(Termination) finitely many rule applications

Formal properties

Lobster Performance (1/5)

• 25 HE algorithms from 4 sources

- Cingulata benchmarks
- Sorting benchmarks
- Hackers Delight benchmarks
- EPFL benchmarks

12 Homomorphic bitwise operations

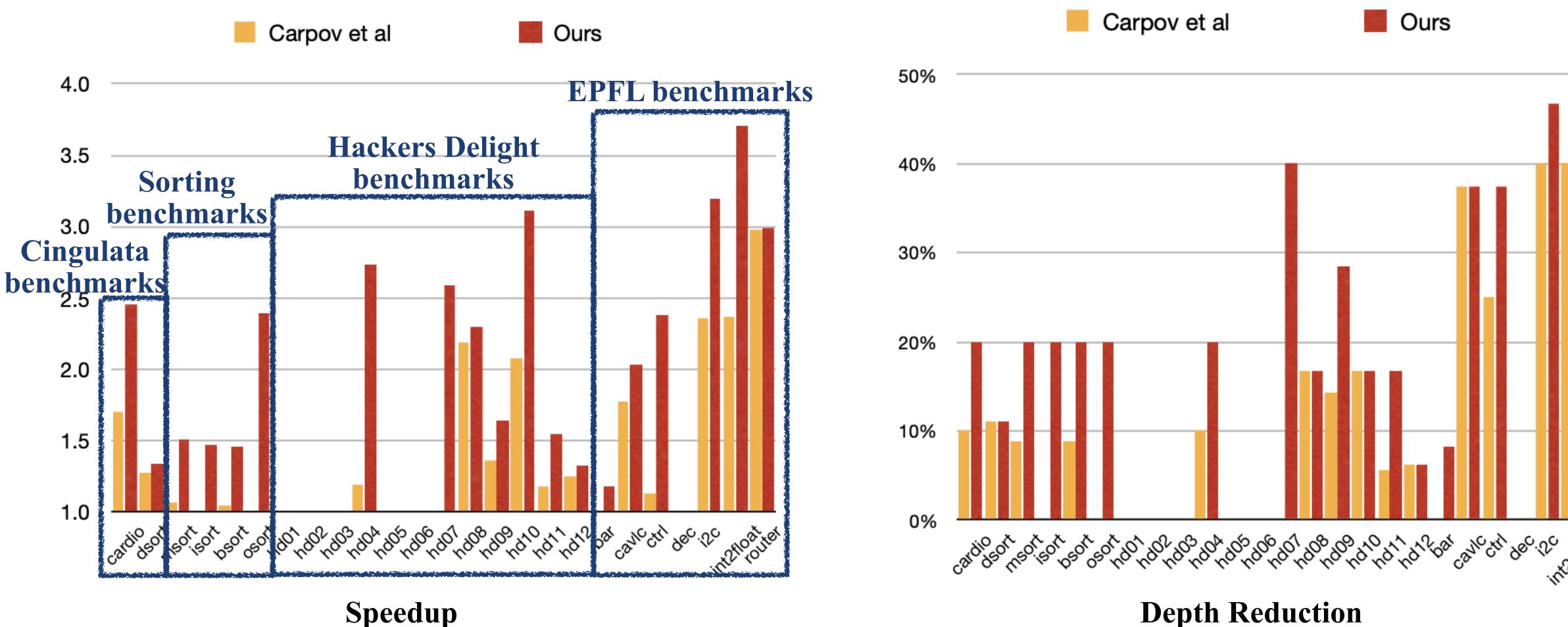
7 EPFL combinational benchmark suite (to test circuit optimizer)

Benchmarks

2 HE friendly algorithms (medical, sorting)

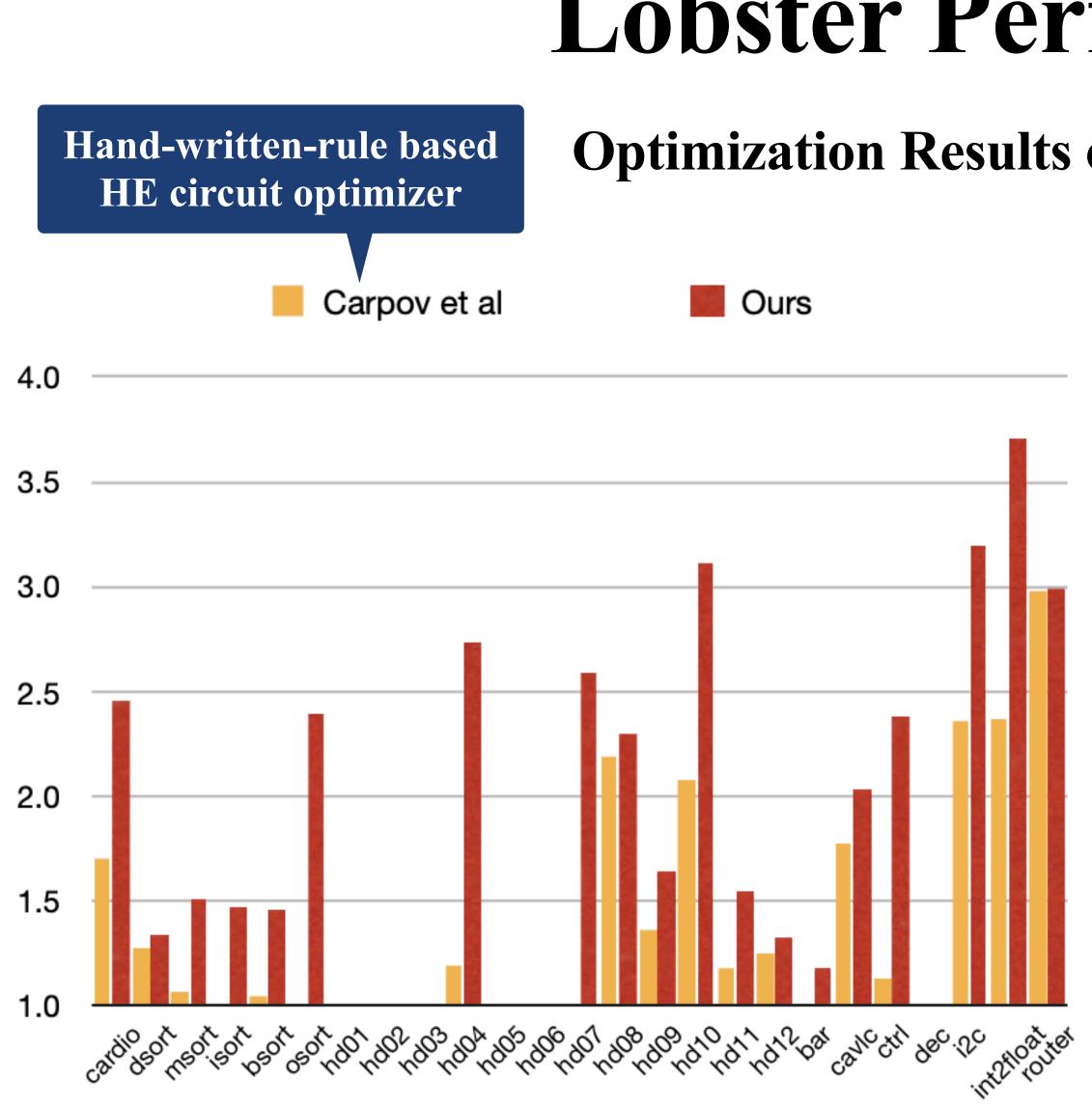
4 privacy-preserving sorting algorithms (merge, insert, bubble, odd-even)





Lobster Performance (2/5)

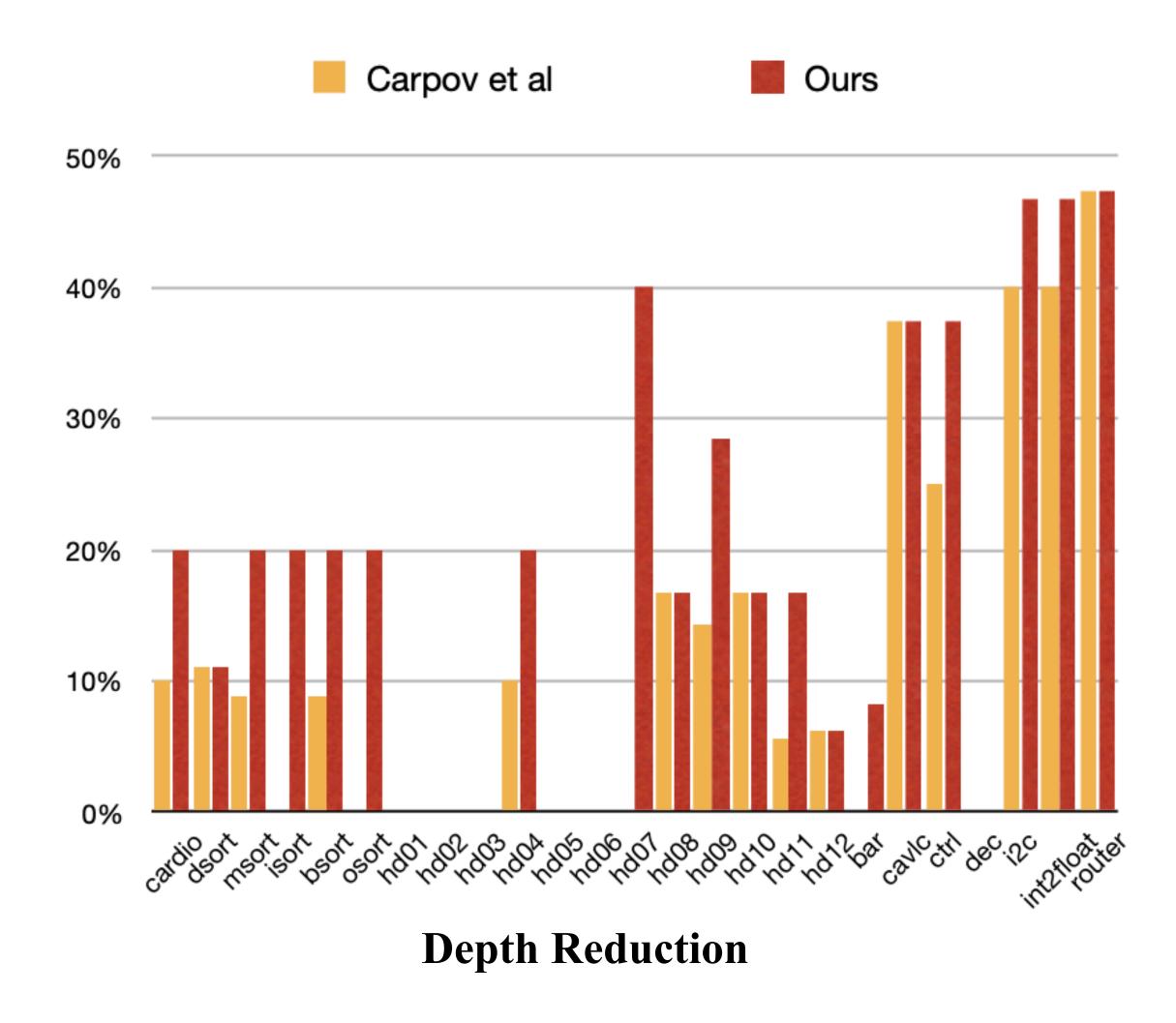


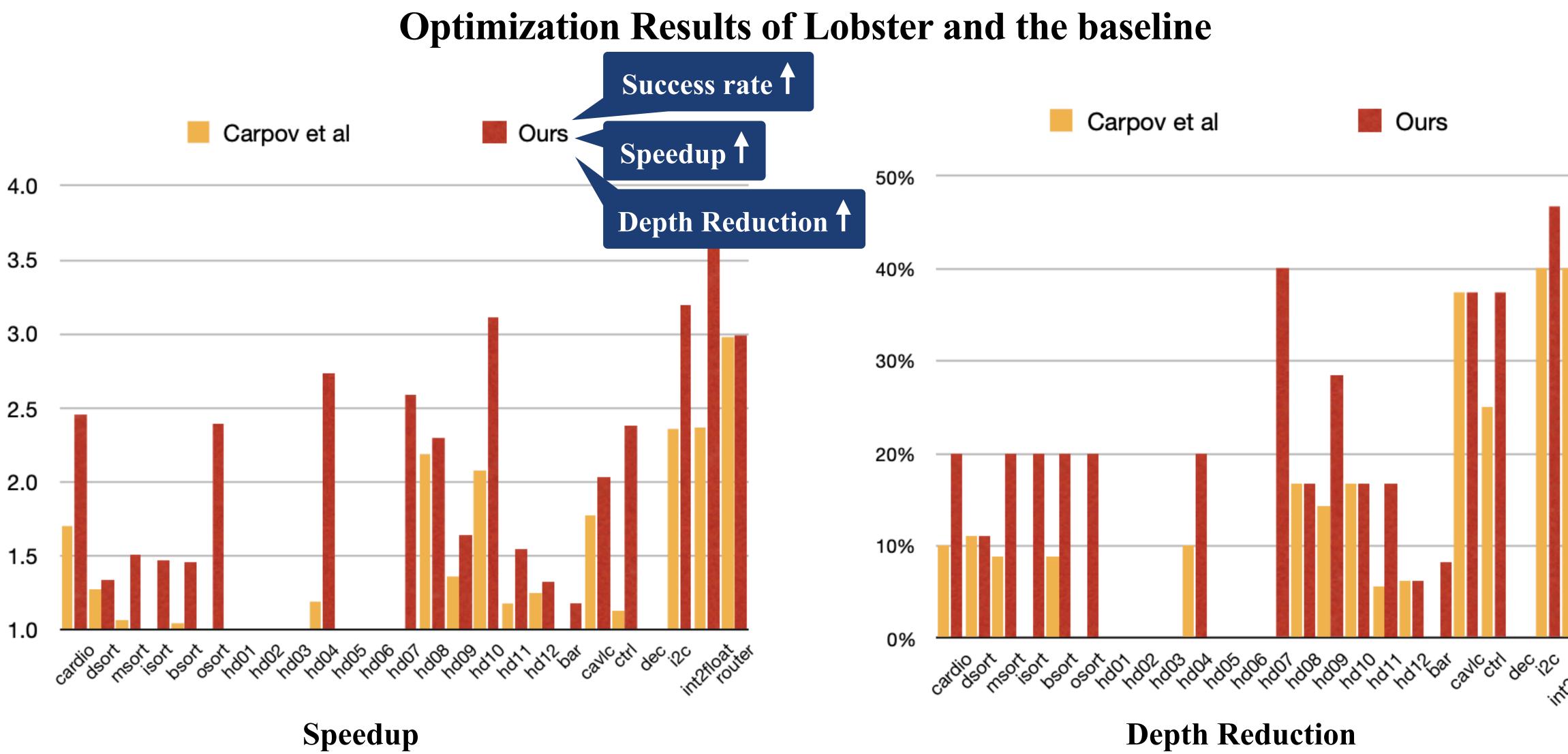


Speedup

Lobster Performance (2/5)

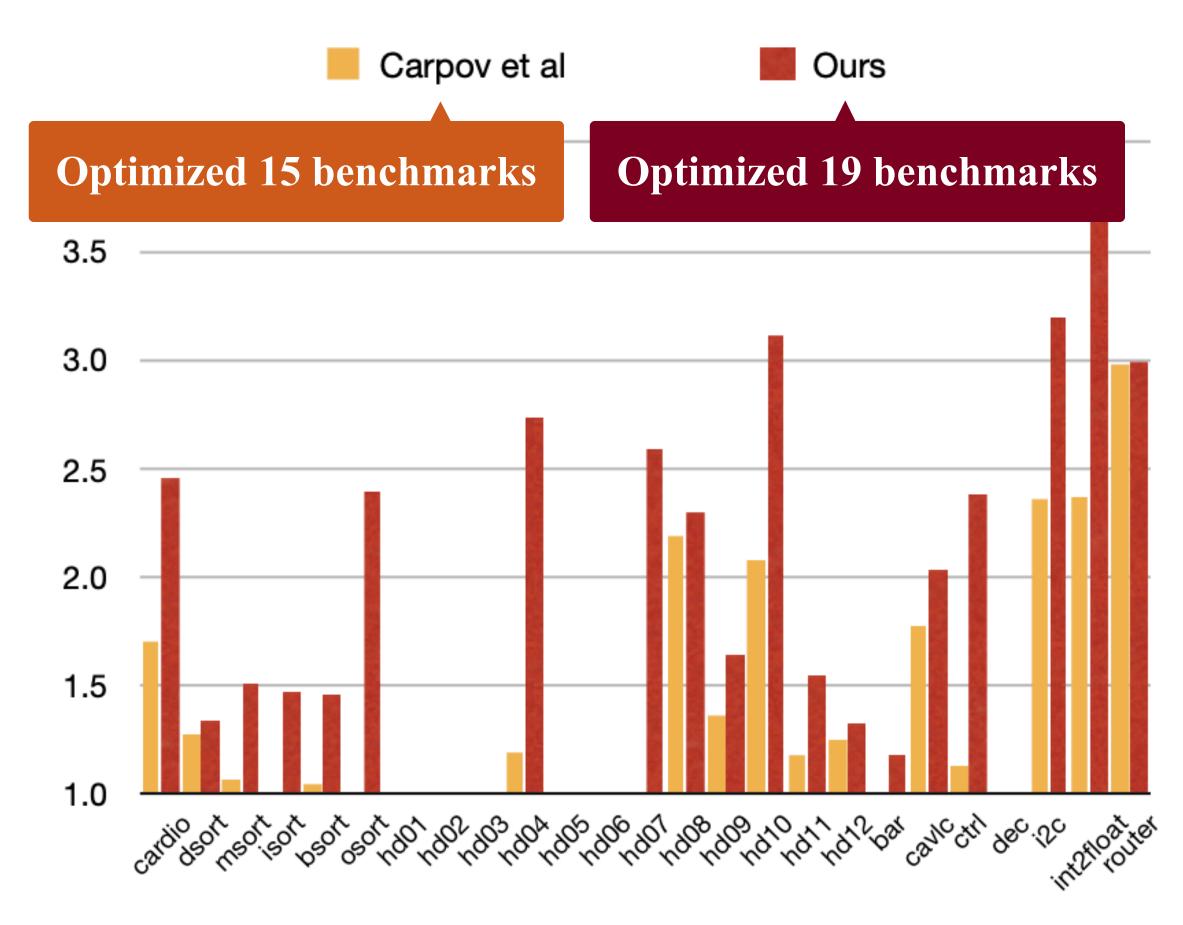
Optimization Results of Lobster and the baseline



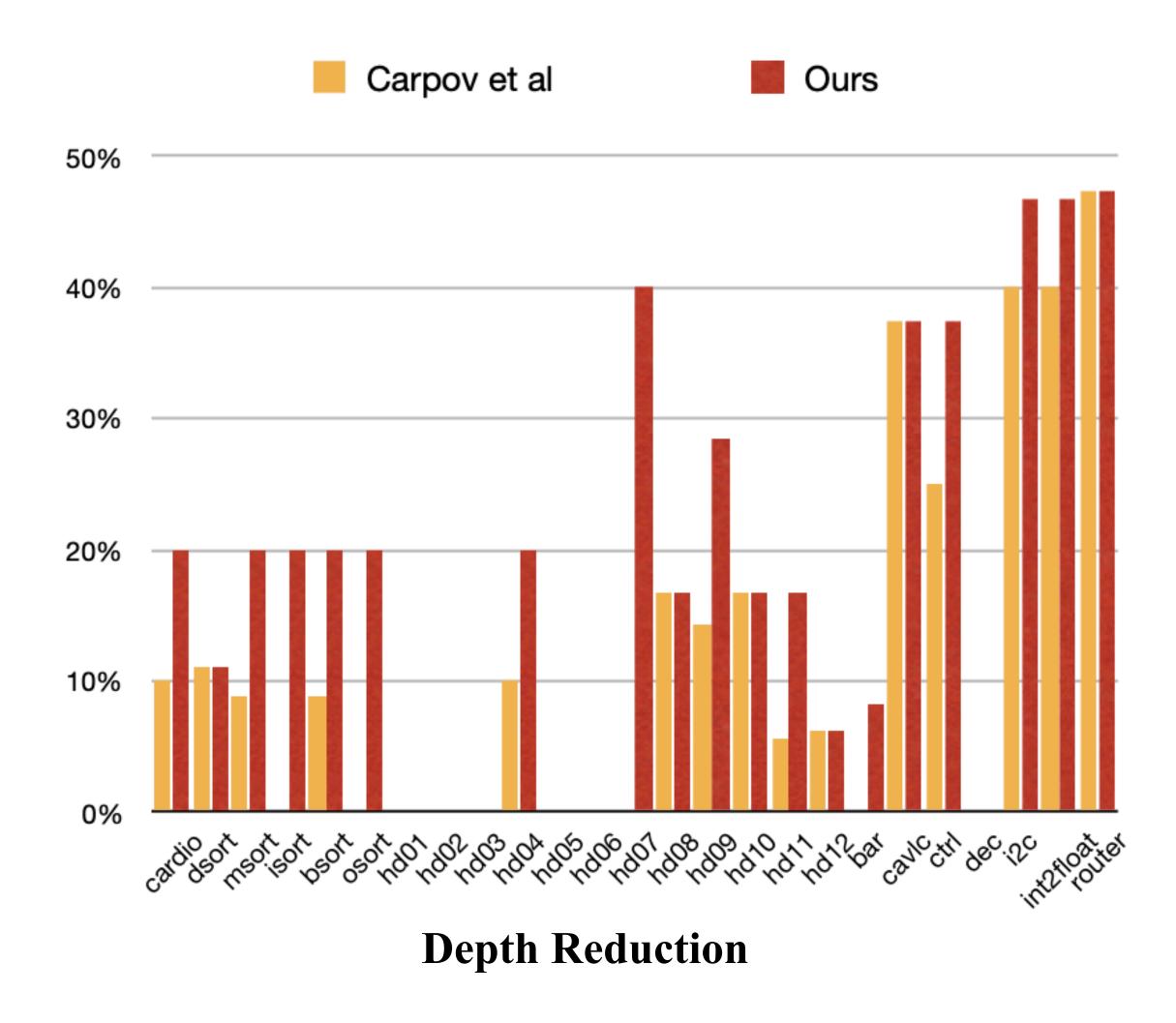


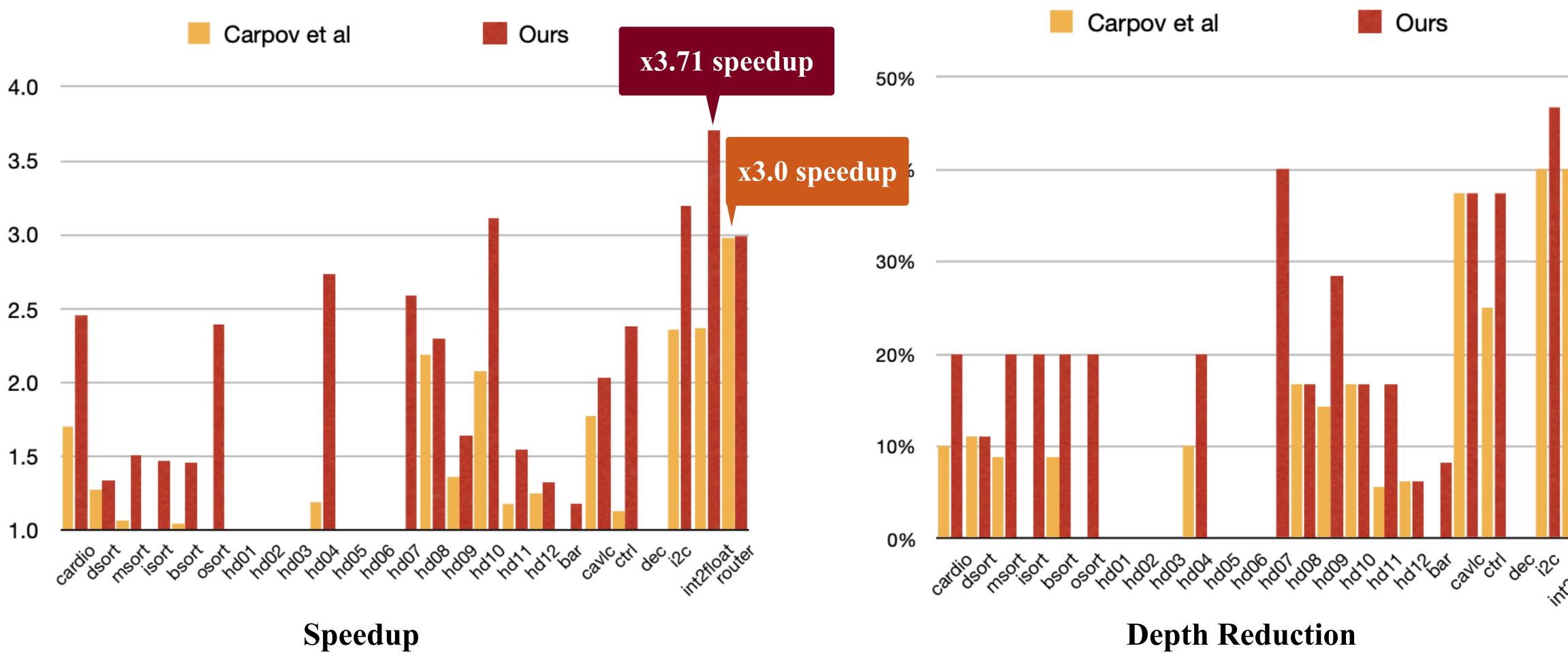






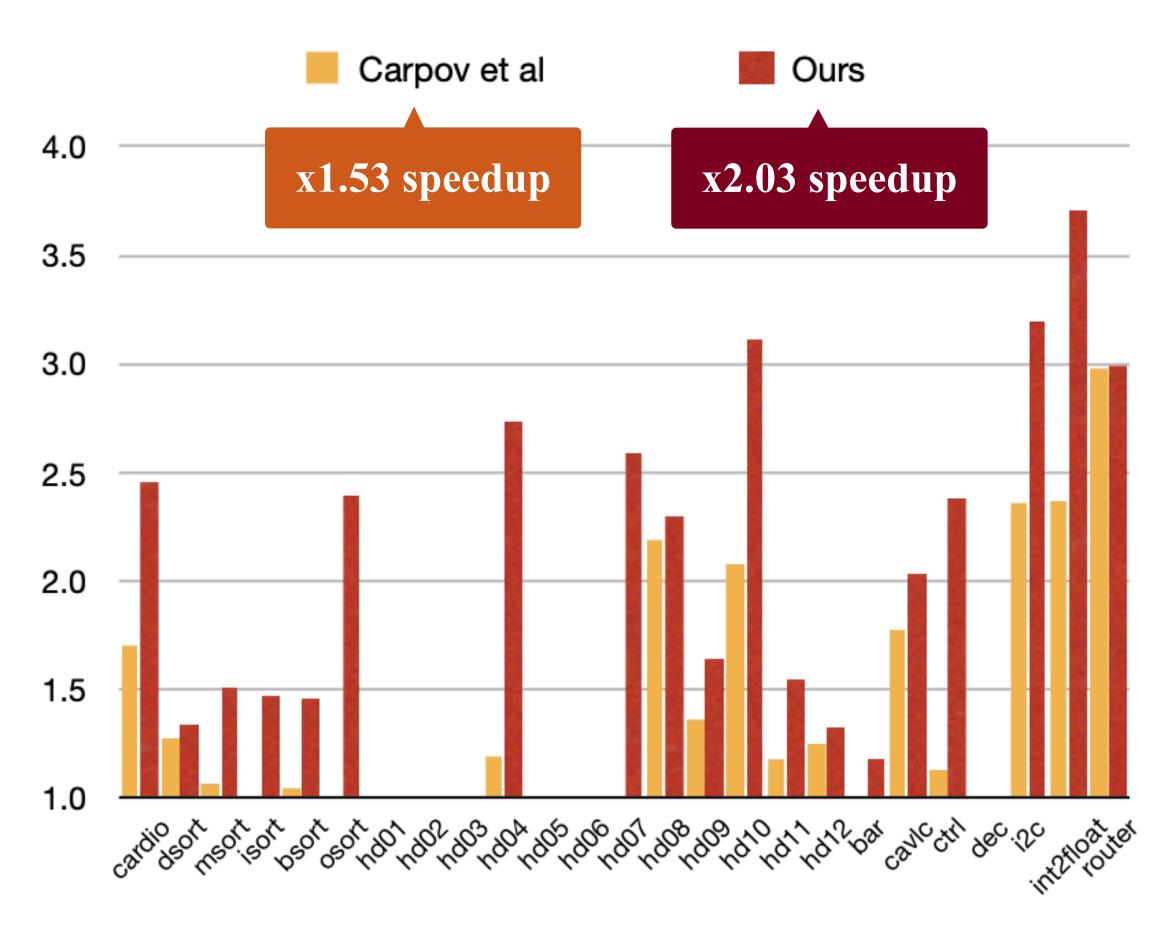
Lobster Performance (2/5)



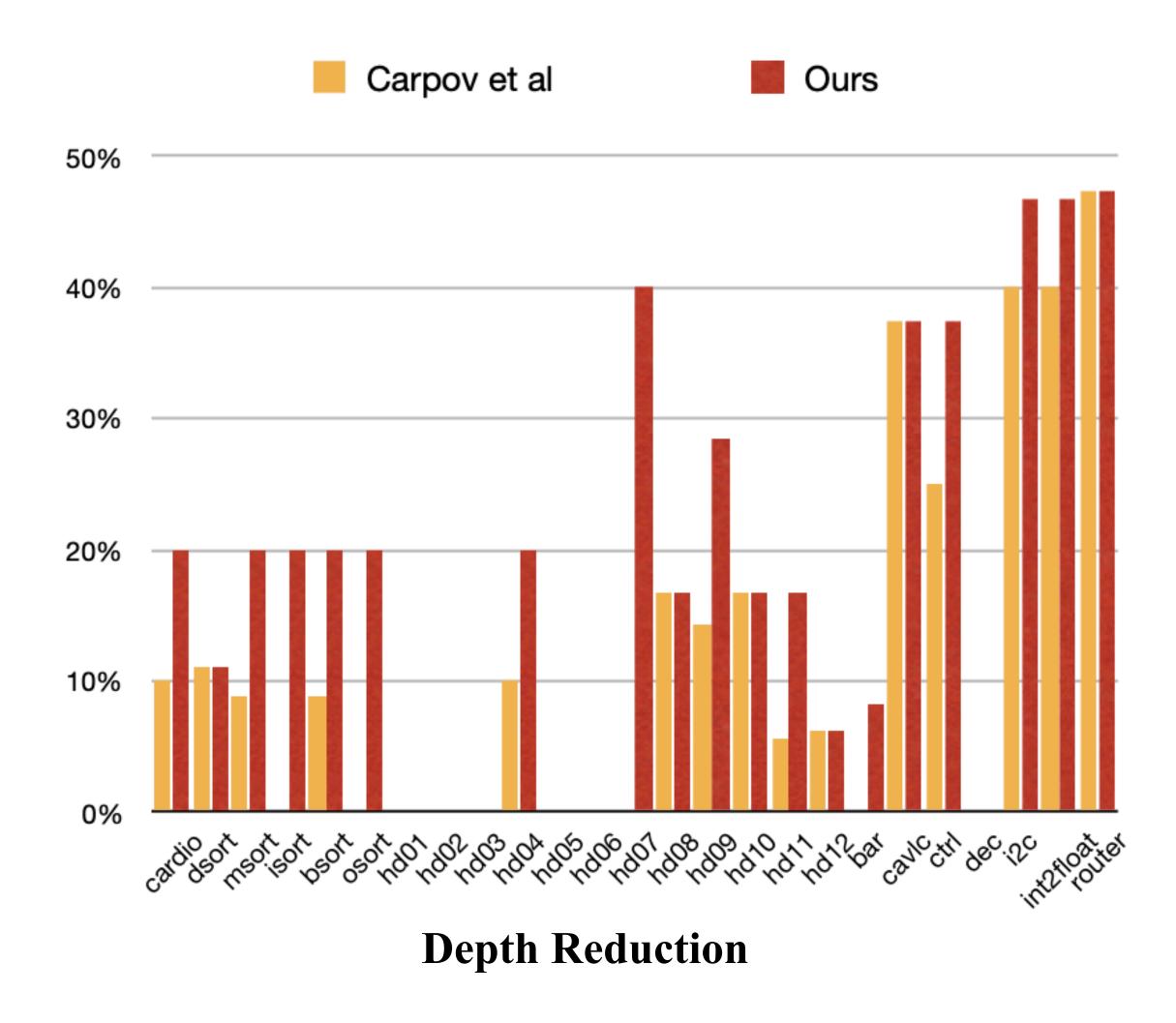


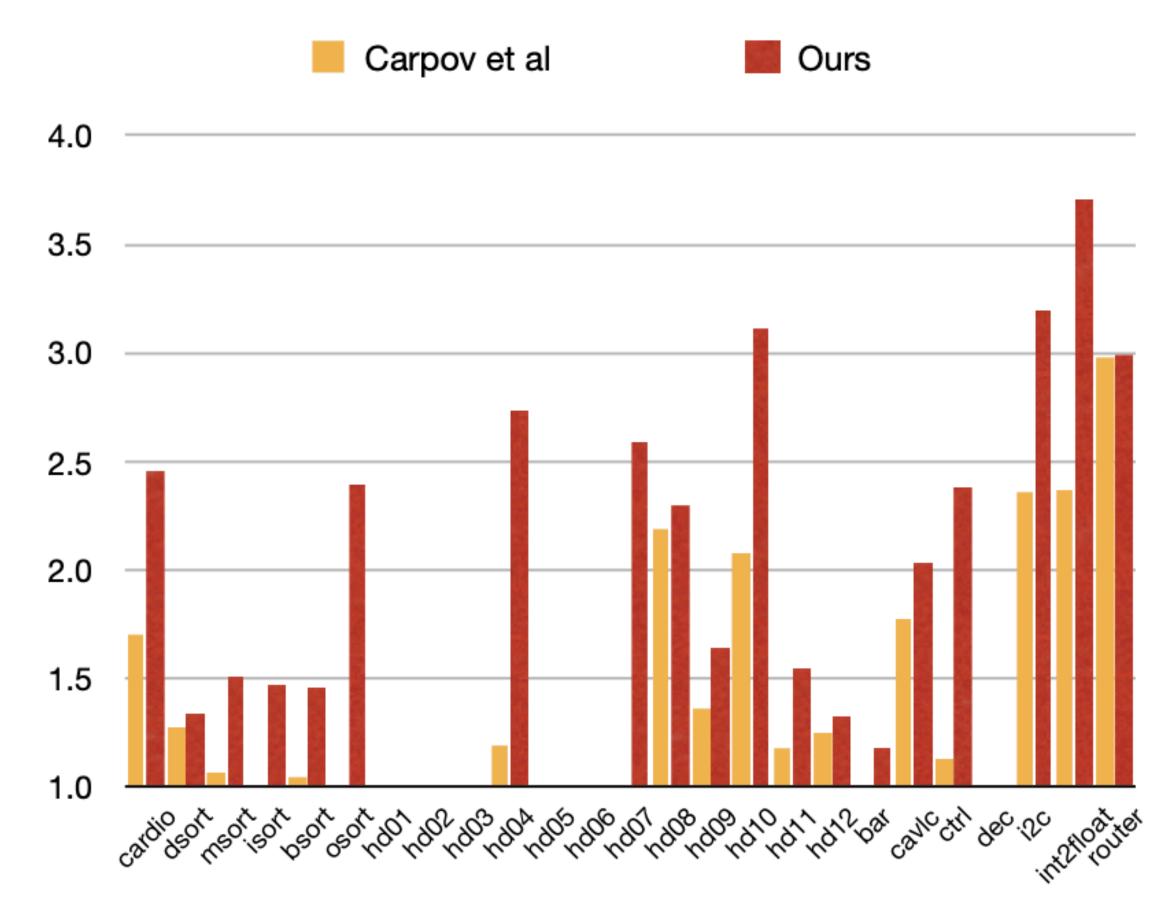




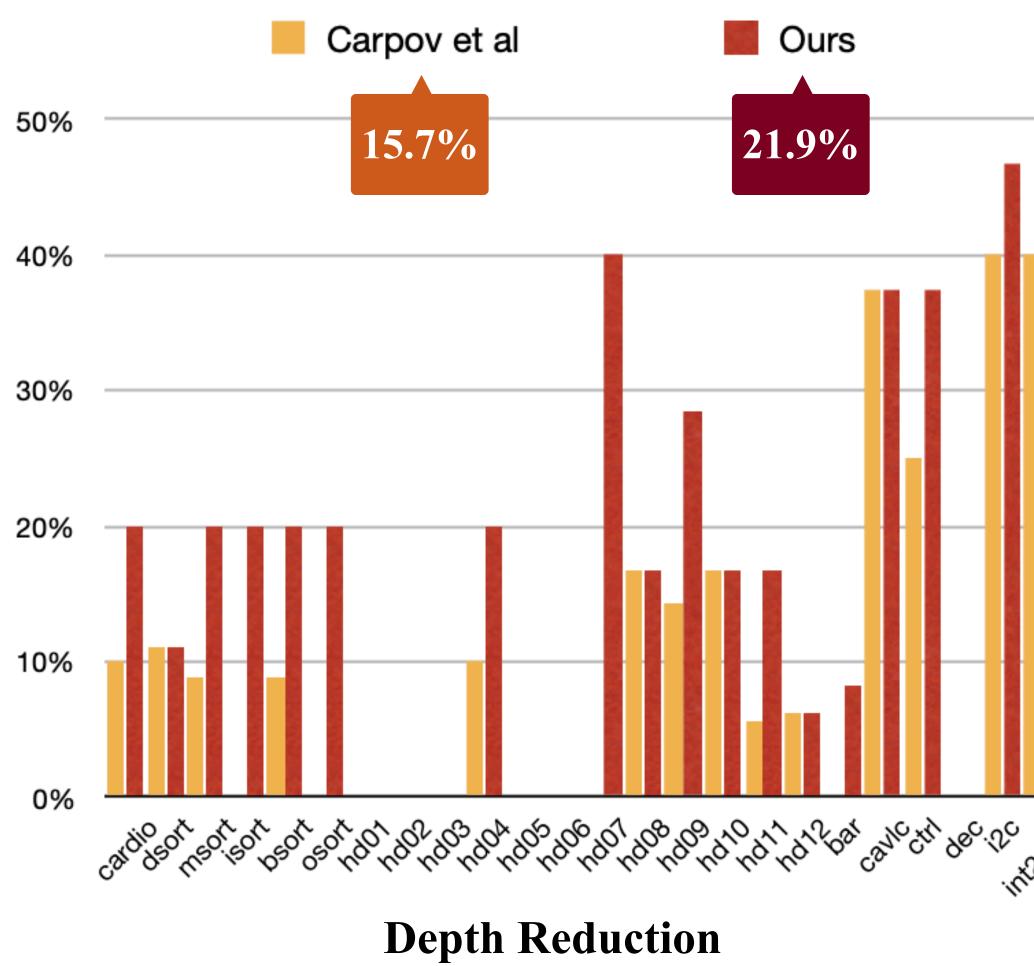


Lobster Performance (2/5)

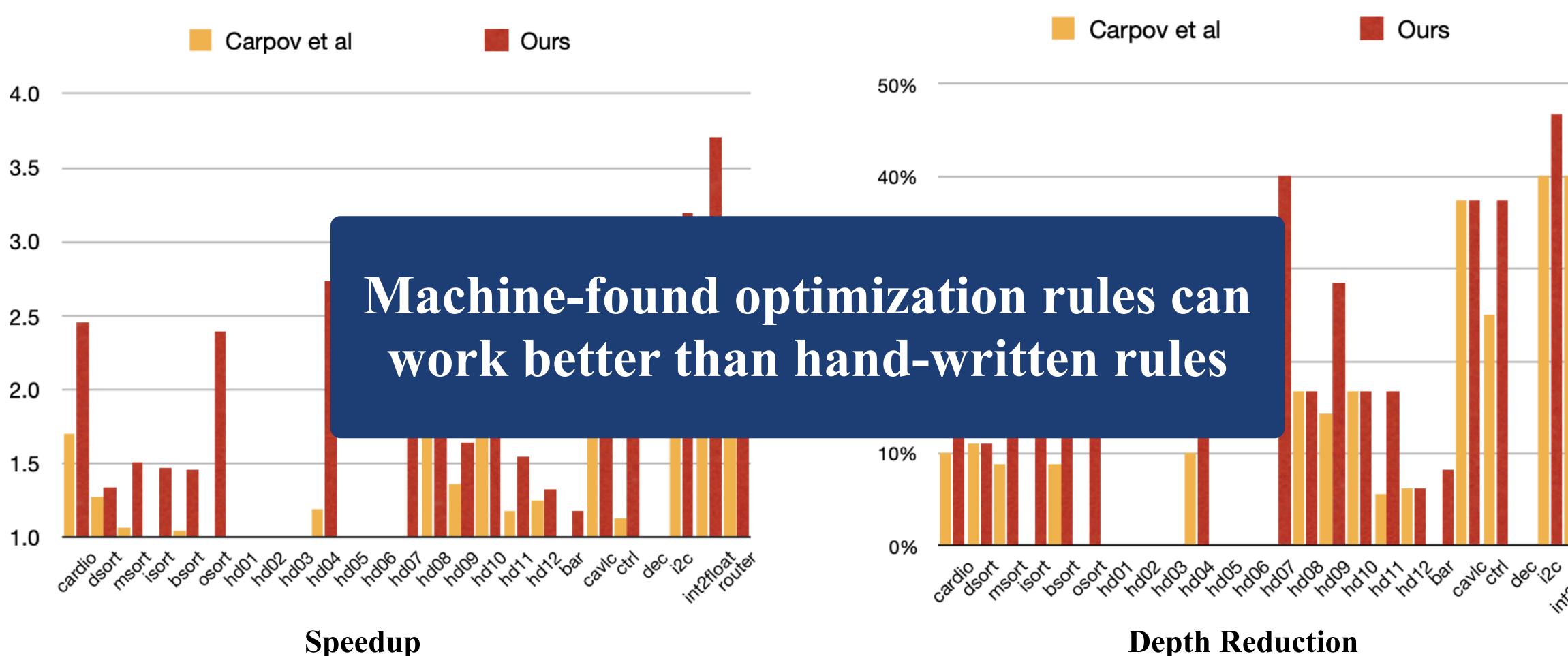




Lobster Performance (2/5)

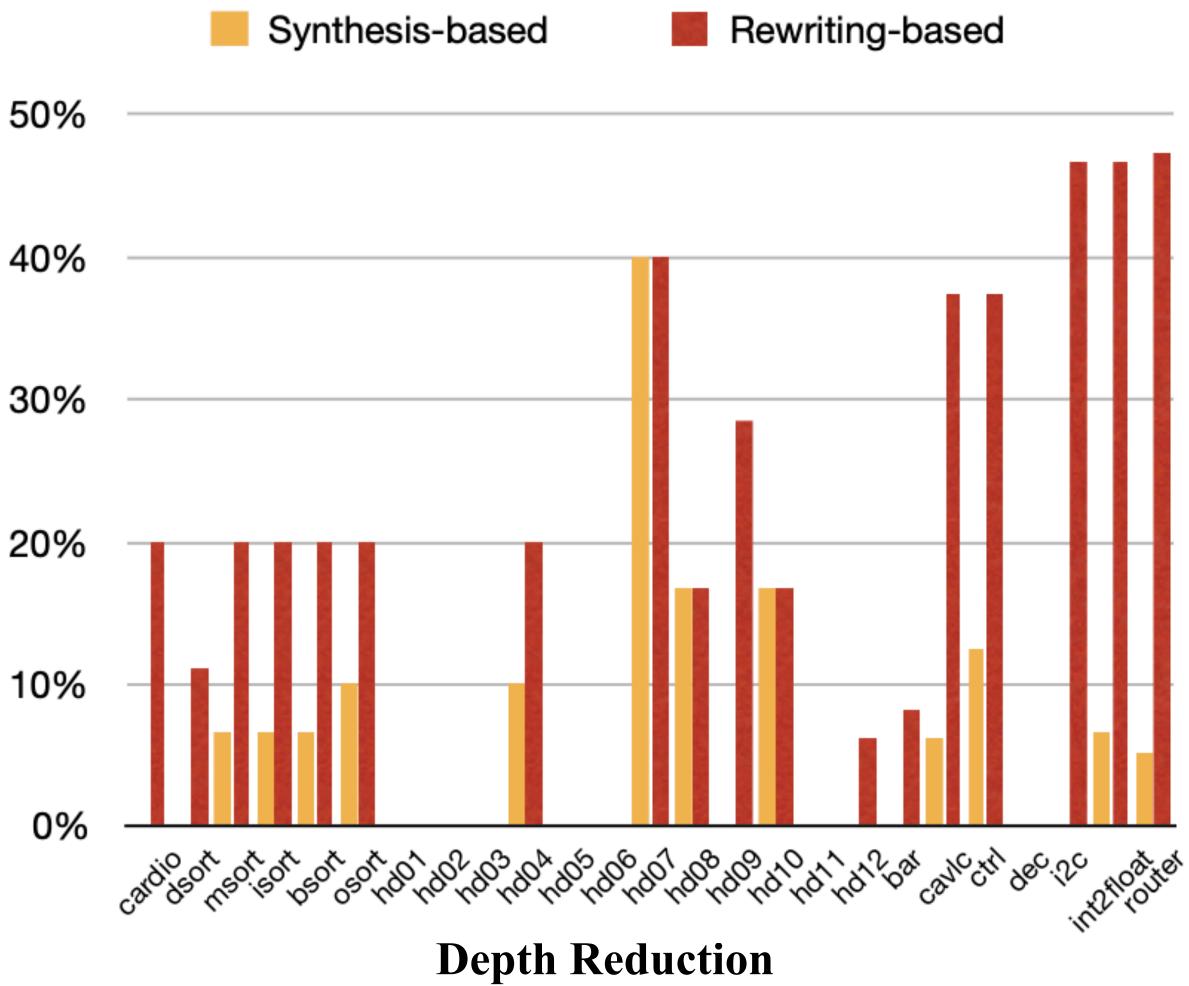




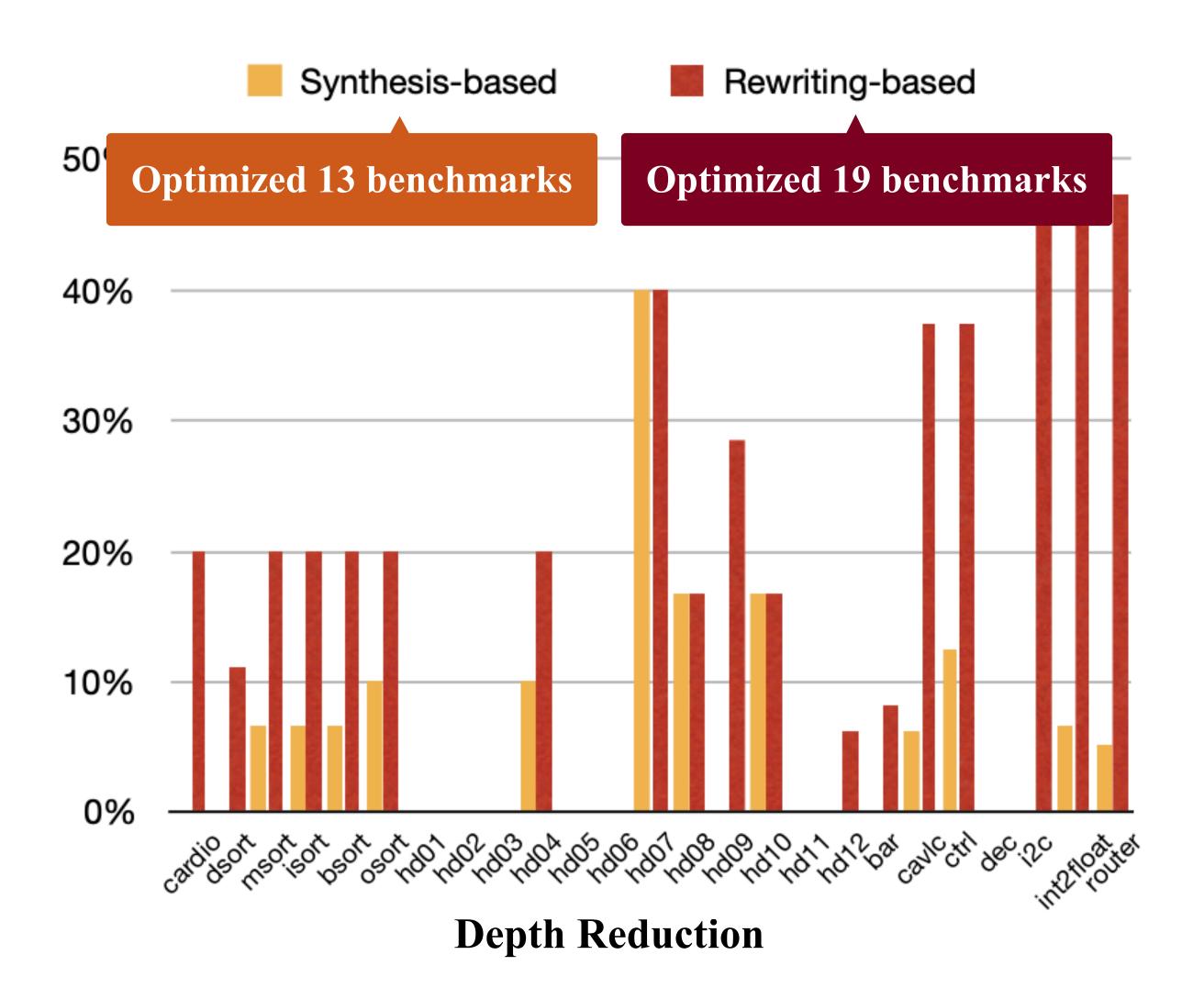


Lobster Performance (2/5)

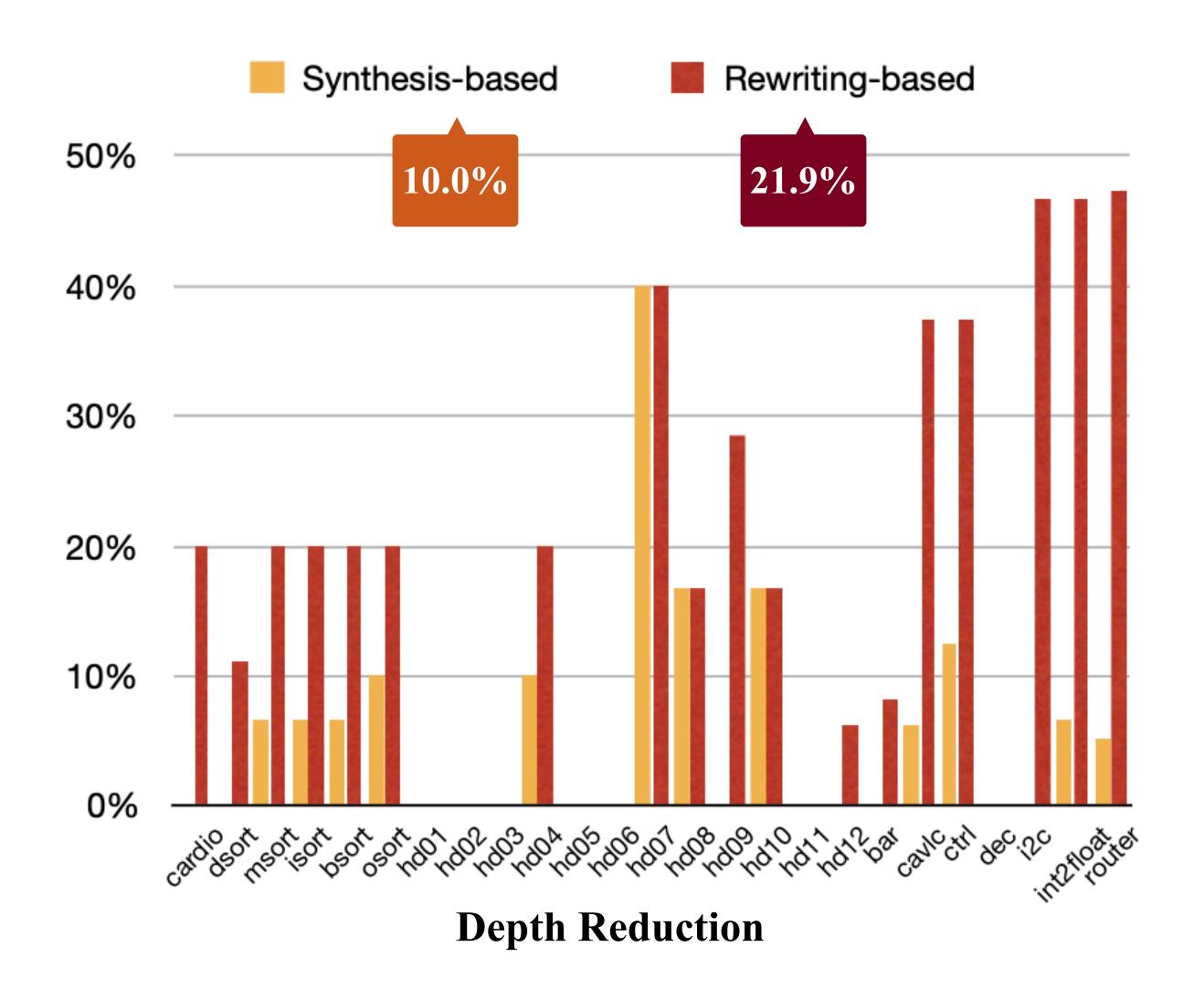




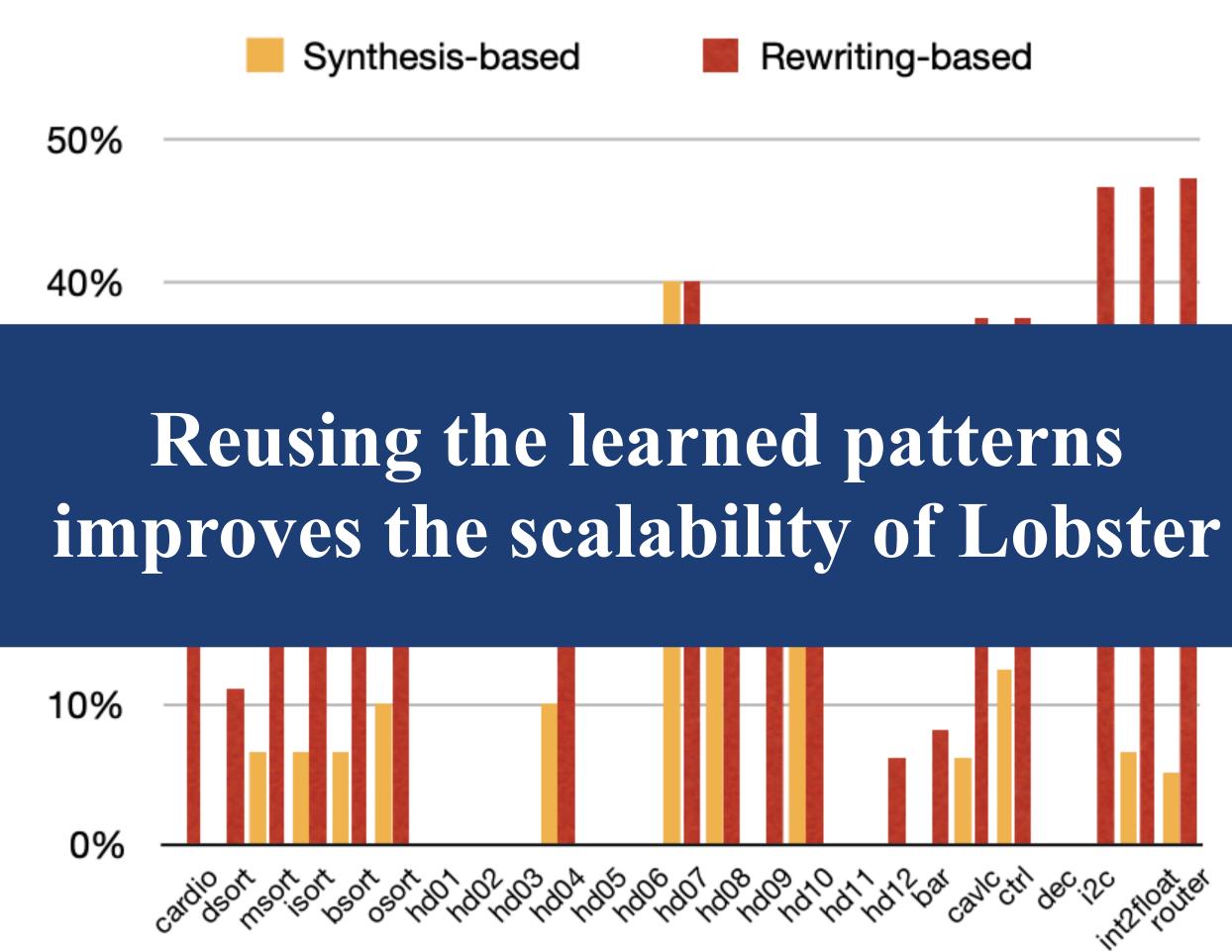




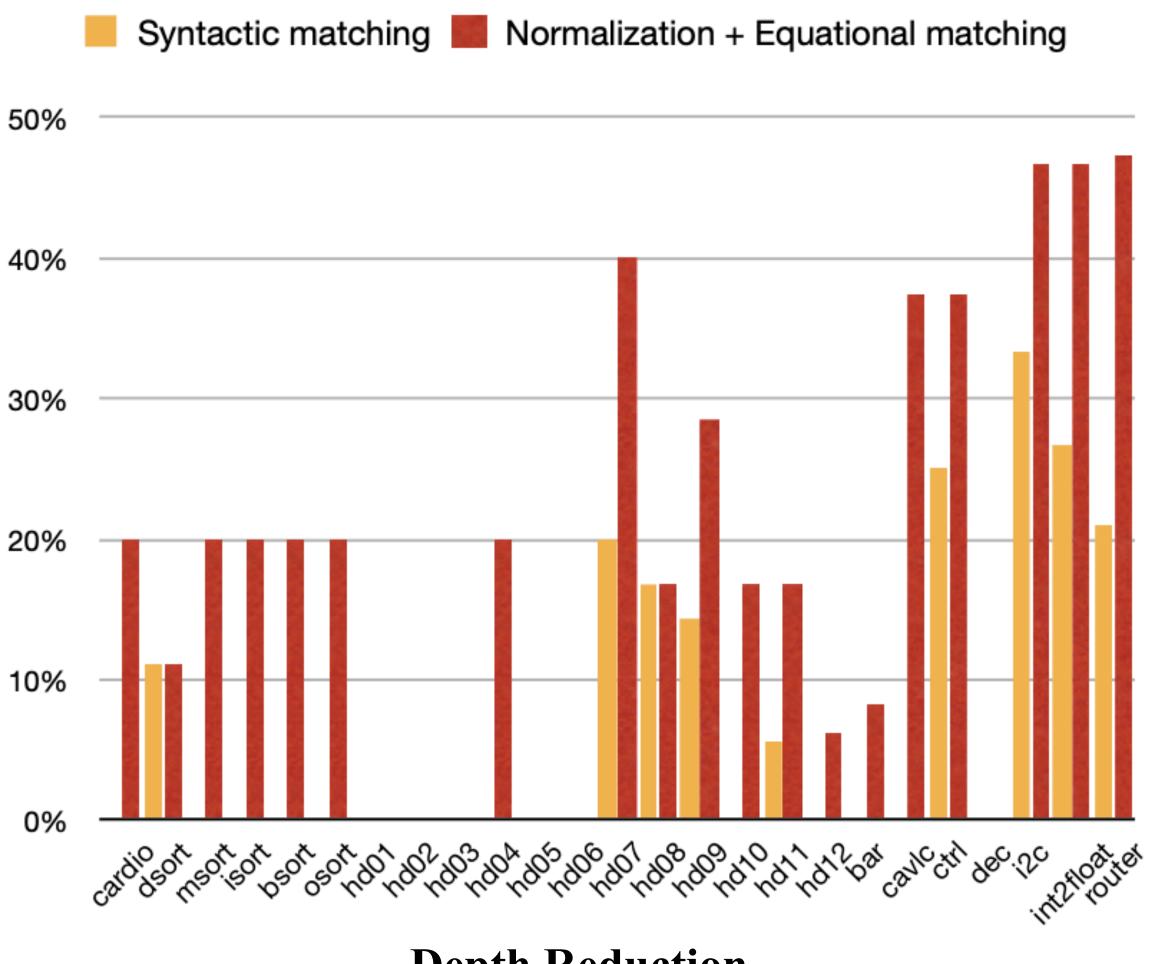




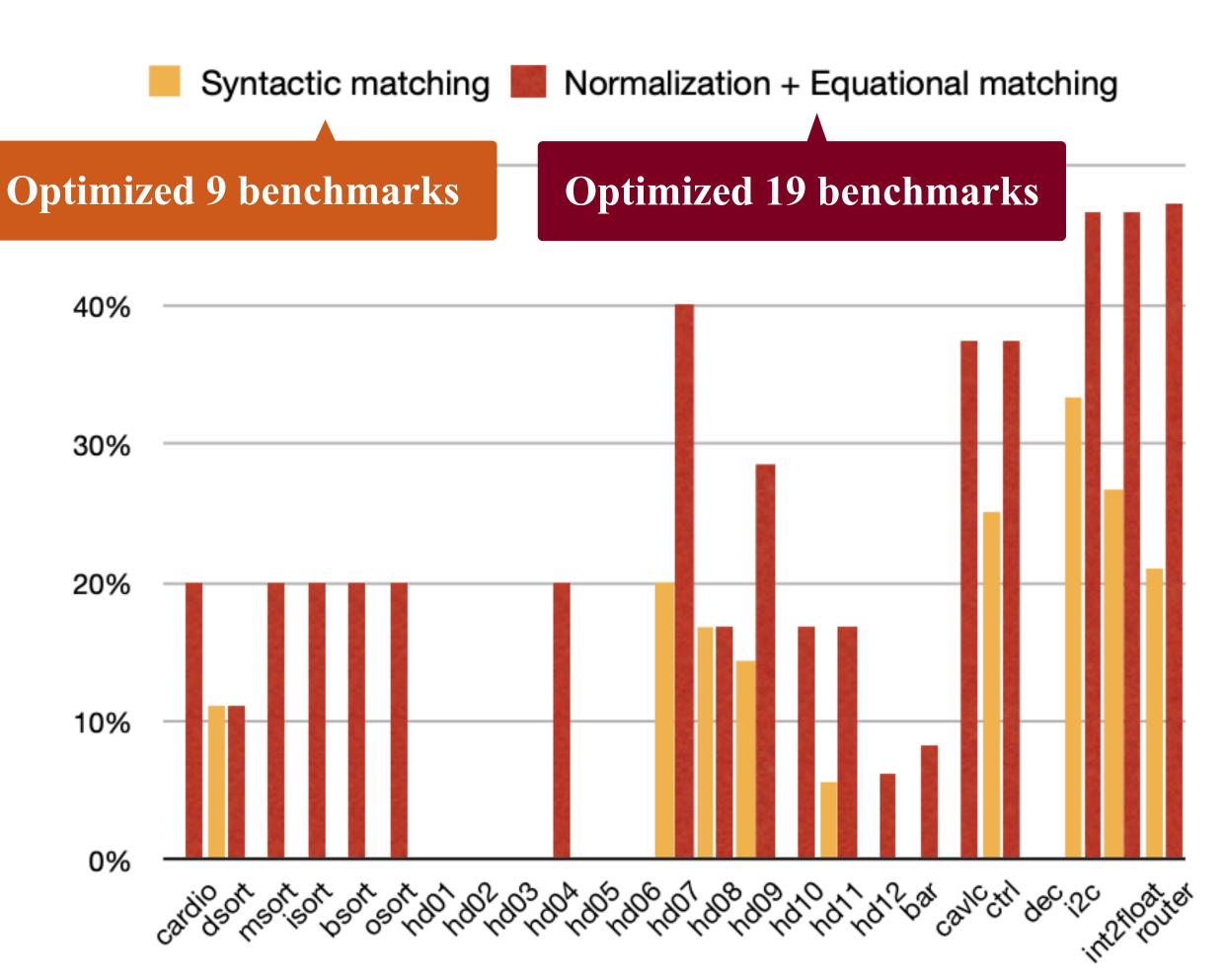




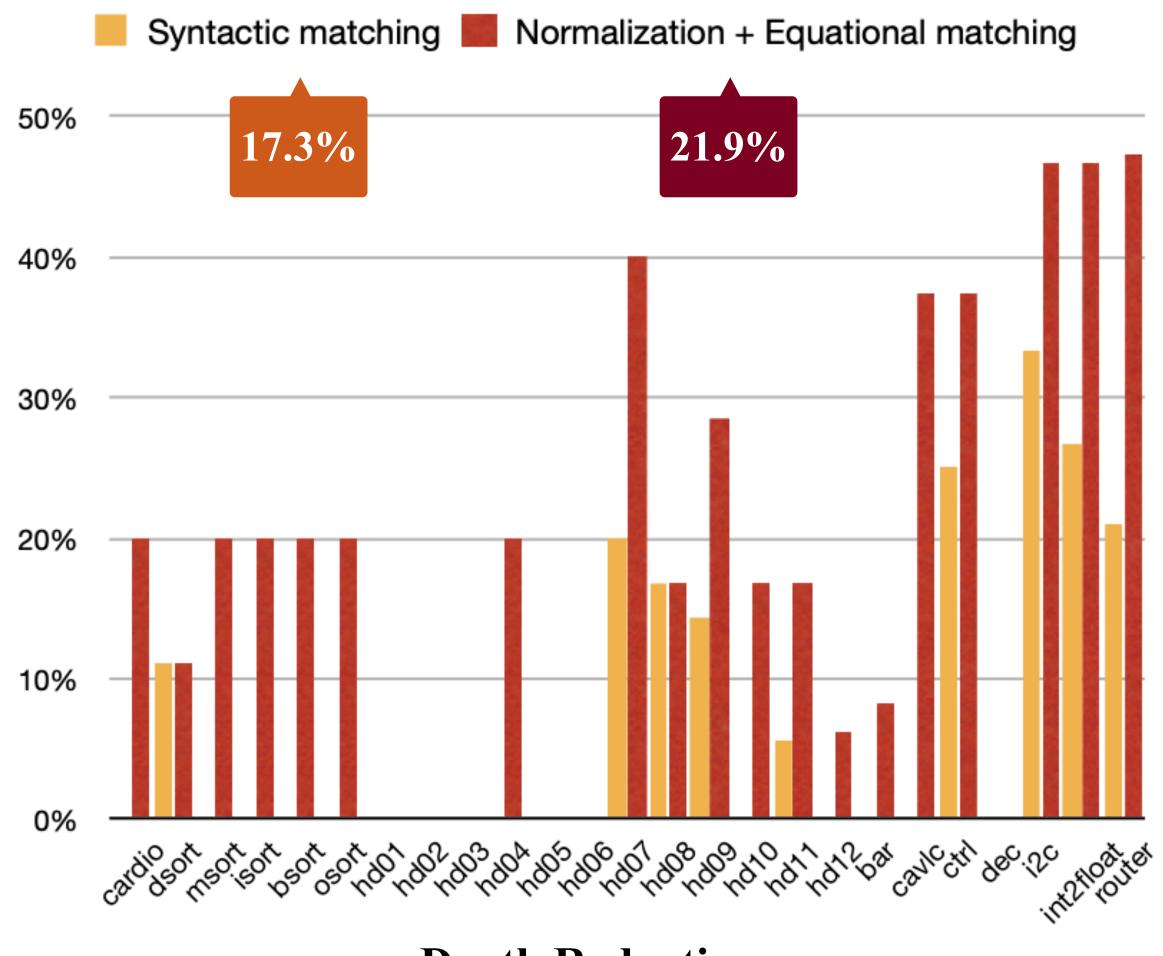








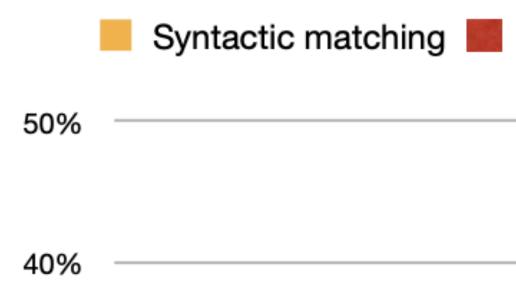




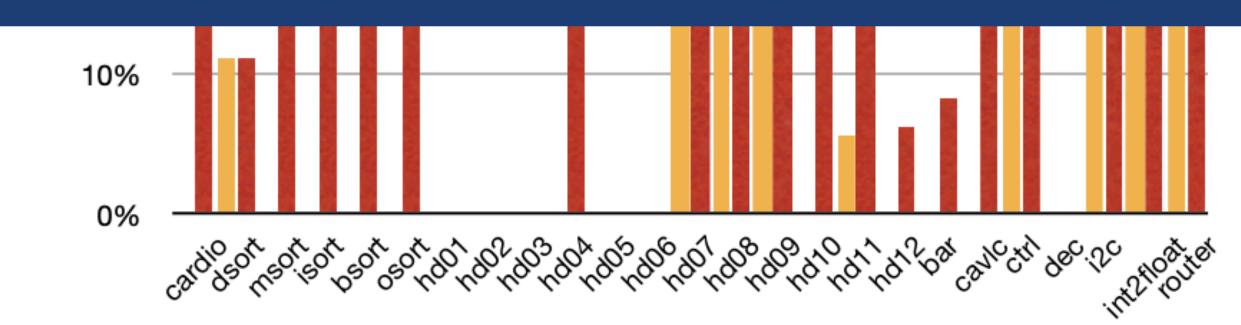


Lobster Performance (4/5)

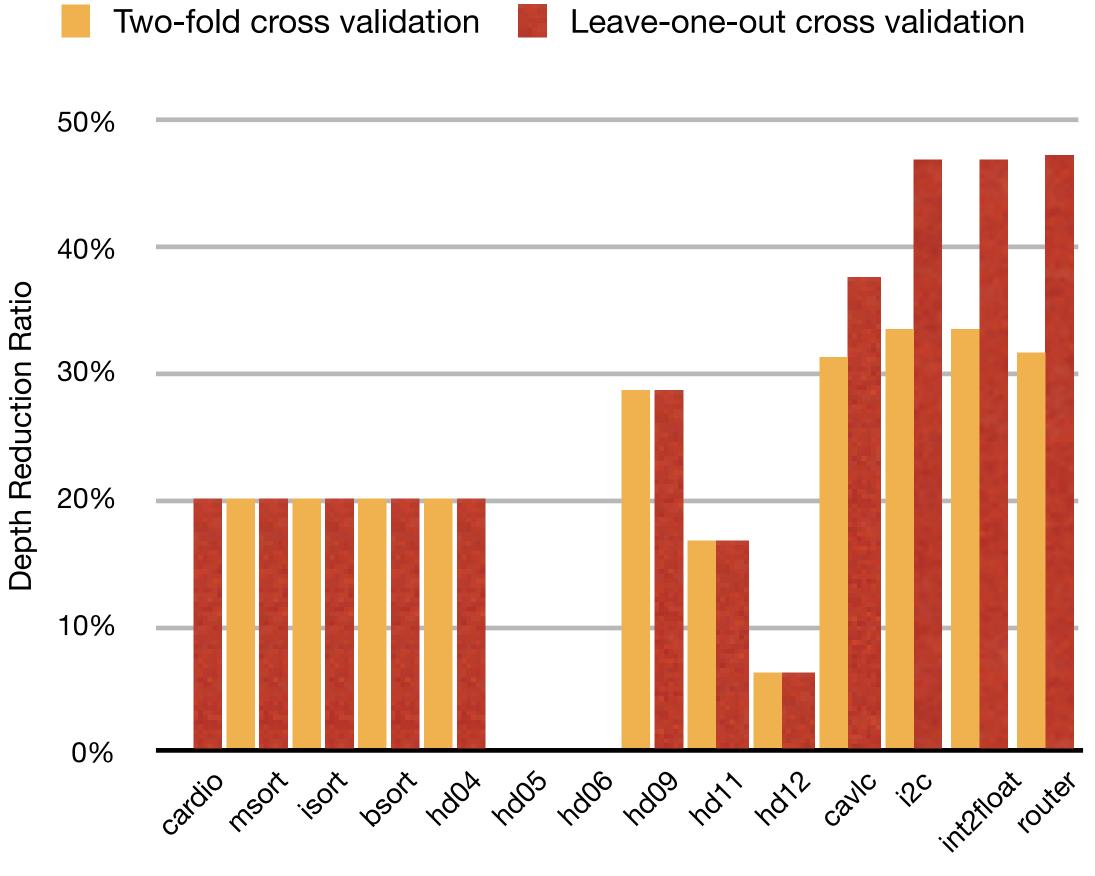
Effectiveness of Equational Term Rewriting



Equational term rewriting allows to flexibly apply the learned patterns

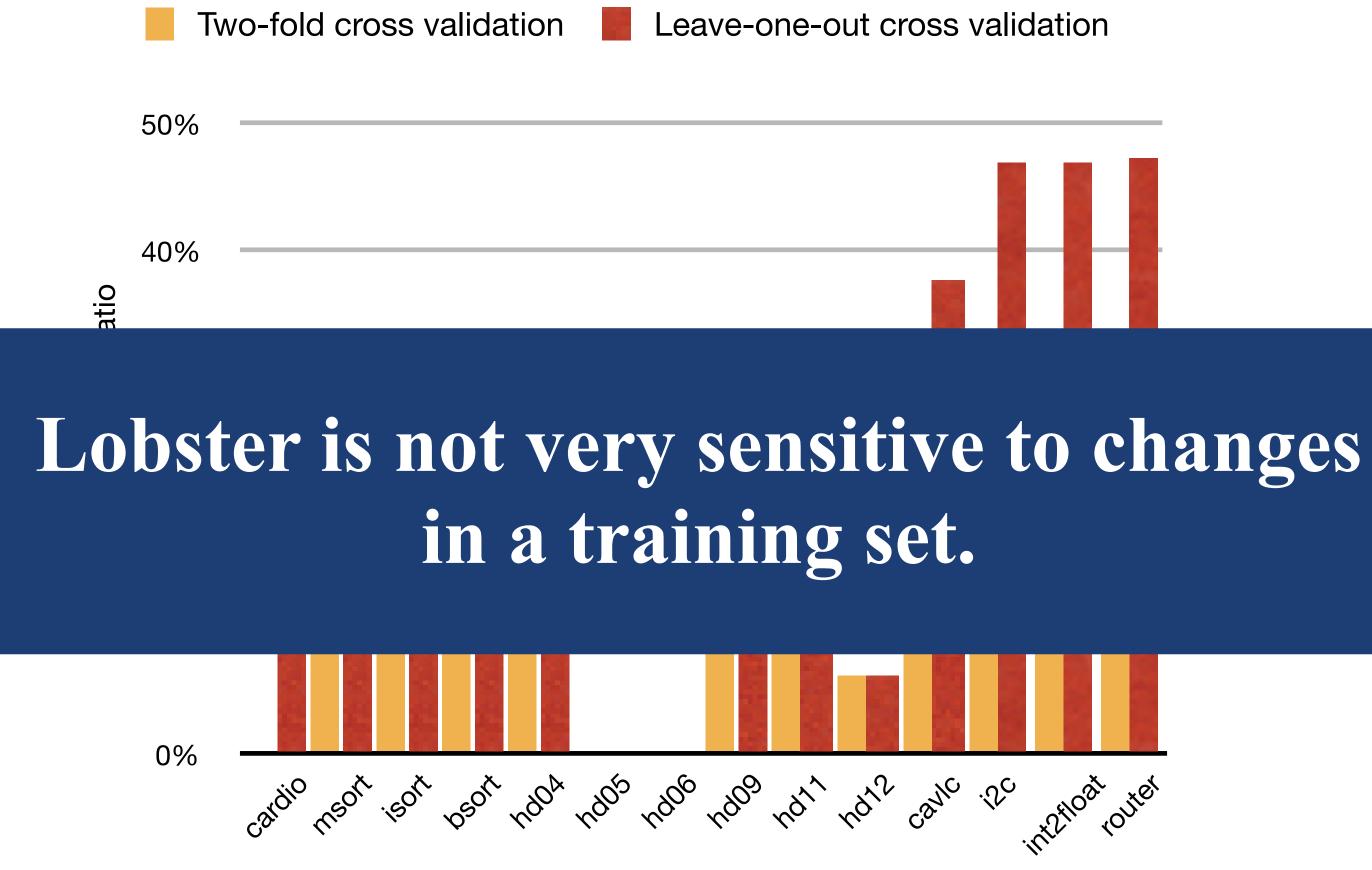


Syntactic matching Normalization + Equational matching





Benchmarks





Benchmarks

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





(:) Thank you!