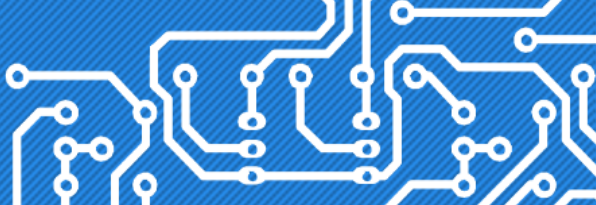


International Symposium on Physical Design



HeLO: A Heterogeneous Logic Optimization Framework by Hierarchical Clustering and Graph Learning

Yuan Pu, Fangzhou Liu, Zhuolun He, Keren Zhu, Rongliang Fu,
Ziyi Wang, Tsung-Yi Ho, Bei Yu

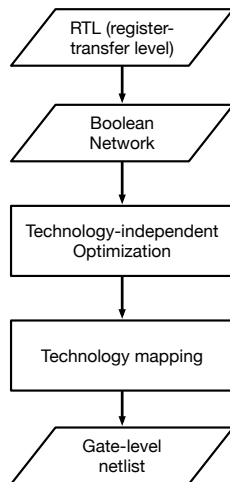
Department of Computer Science and Engineering
The Chinese University of Hong Kong



- ① Introduction
- ② Motivation
- ③ Proposed Algorithm
- ④ Experimental Results

Introduction

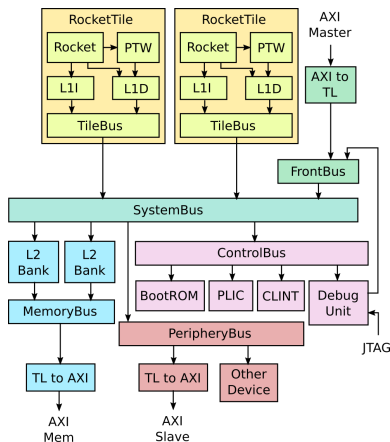
- RTL design: a high-level design abstraction modelling digital circuits.
- Boolean network: directed acyclic graph (DAG).
 - directed acyclic graph, node for Boolean function (AND, OR, ect.) and edge for wire.
 - DAG types:
 - and-inverter graph (**AIG**): AND gates and inverter on the edge.
 - majority-inverter graph (**MIG**): 3-input majority node.
 - **XAG**, **XMG**, etc.
 - Technology-independent logic optimization:
 - minimize node count (area) and depth (critical path).
 - multi-level optimization strategy: rewrite, rebalance.
 - Trade-off for node count and depth.
 - Metric: node-depth product (NDP).



Heterogeneous Logic Optimization: Motivation

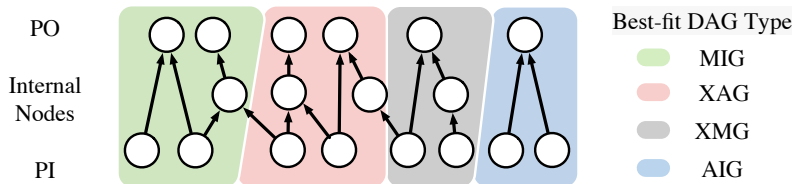
- Modern VLSI designs such as SoC, CPU \Rightarrow consists of modules with various structures and functionalities
- Different modules \Rightarrow different optimization strategies/scripts for logic optimization \Rightarrow Optimal PPA.

Rocket SoC Diagram.



Heterogeneous Logic Optimization: Introduction

- Represent different circuit portions by different DAG types; Optimize separately (by corresponding optimization strategy).
- Motivations:
 - Different DAG types → different expressive power for specific structures/functionalities.
 - Different DAG types → different optimization algorithms desired.
 - Conclusion: Different DAG types → different logic optimization results.
- Example: **MIG** effectively represents carry operators, thus leading to better optimization result for arithmetic designs.



Previous Work for Hetero Logic Optimization

- MixSyn¹:
 - Detect AND/OR and XOR components in a circuit.
 - Render optimization separately.
 - Drawbacks: Hard to extend to other gate types.
- LSOacle²:
 - min-cut circuit partition (k-way partition) into sub-circuits.
 - CNN to predict best-fit DAG type for subcircuit (treating the Karnaugh-map of subcircuit as image).
 - Render logic optimization for each sub-circuit, based on predicted DAG type.

¹Luca Amarú, Pierre-Emmanuel Gaillardon, and Giovanni De Micheli (2013). “MIXSyn: An efficient logic synthesis methodology for mixed XOR-AND/OR dominated circuits”. In: *Proc. ASPDAC*, pp. 133–138.

²Walter Lau Neto, Max Austin, et al. (2019). “LSOacle: A logic synthesis framework driven by artificial intelligence”. In: *Proc. ICCAD*, pp. 1–6.

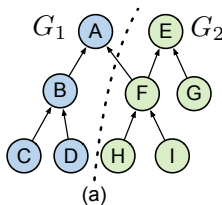
- partitions consist of logic components with varying structures and functions → hard to determine best-fit DAG type.
- Treat best-fit DAG type prediction as an image classification task → lacks utilization of topological information.

Motivation

- **O1:** When two sub-circuits exhibit **similarities** in their structures or functionalities, they often select the same DAG type for optimal results.
- Explanation:
 - Efficacy of different DAG types varies with specific Boolean functions and topological structures.
 - Circuits with similar functions or topologies opt for the same DAG type to maximize expressive power and optimization outcomes.

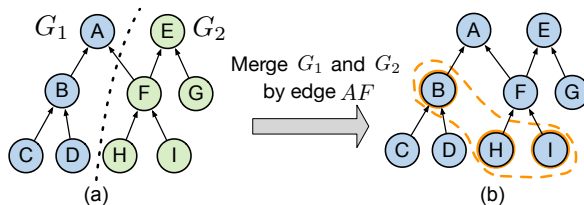
Observation 2

- **O2:** If two interconnected sub-circuits are functionally or structurally similar, merging them into a single circuit and performing logic optimization often yields better results than optimizing each separately.
- Explanation:
 - Multi-level optimization algorithms : cut-based.
 - Merging two circuits \rightarrow new cut choices generated at intersection \rightarrow enlarging the solution space.



Observation 2

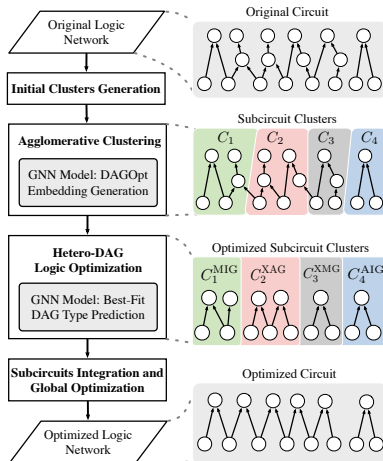
- **O2:** If two interconnected sub-circuits are functionally or structurally similar, merging them into a single circuit and performing logic optimization often yields better results than optimizing each separately.
- Explanation:
 - Multi-level optimization algorithms : cut-based.
 - Merging two circuits \rightarrow new cut choices generated at intersection \rightarrow enlarging the solution space.



Proposed Algorithm

Main techniques:

- **Agglomerative clustering:** allocate structurally/functionally similar logic components into the same sub-circuit.
- **GNN model:**
 - Generate structural-functional embeddings for sub-circuits.
 - Determine best-fit DAG type.
- **Hetero-DAG logic optimization:**
 - Support four DAG types: AIG, MIG, XMG, XAG.
 - Optimization: script provided by LSOacle.



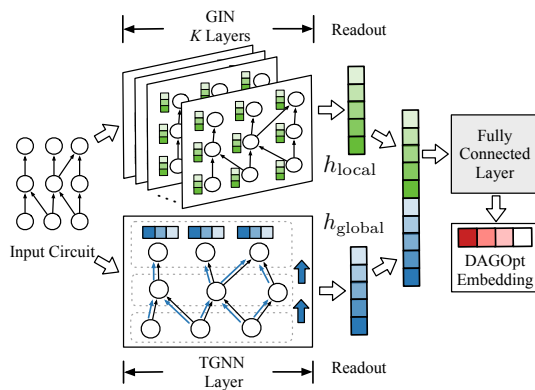
- partitions consist of logic components with varying structures and functions → hard to determine best-fit DAG type.
- **Solution: Agglomerative clustering.**
- Treat best-fit DAG type prediction as an image classification task → lacks utilization of topological information.
- **Solution: GNN for determining best-fit DAG type.**

- Purpose:
 - Quantify the structural and functional similarities across various circuits.
 - Used for agglomerative clustering.
- Construction embedding e^c for a circuit c :
 - Represent c into AIG, MIG, XMG, XAG.
 - Render logic optimization on the four representations and obtain corresponding node-depth product (NDP).
 - Compile the NDP values into a normalized vector.
- Two structurally/functionally similar sub-circuits \rightarrow similar DAGOpt embeddings.

$$e^c = \frac{(\text{NDP}^{\text{AIG}}, \text{NDP}^{\text{MIG}}, \text{NDP}^{\text{XMG}}, \text{NDP}^{\text{XAG}})}{\sum_{t \in \{\text{AIG}, \text{MIG}, \text{XMG}, \text{XAG}\}} \text{NDP}^t}. \quad (1)$$

Customized GNN Model

- graph isomorphism model (GIN):
 - Map structurally similar sub-graphs to similar embeddings.
 - Capture local structural information.
 - Read out (mean) node embeddings into h_{local} .
- topological graph neural network(TGNN):
 - Message passing following topological order.
 - Readout (mean) node embeddings of POs (exclude POs of small connected components) into h_{global} .
 - Mimic logic simulation, capture global structural and functional information.



Steps:

- step 1: Initial cluster generation: treat each fanin cone of PO as an initial cluster.
- step 2: Pre-trained GNN \rightarrow generate DAGOpt embedding for each initial cluster, as its coordinate.
- step 3: **Merge** two connected clusters with the most similar embedding into one sub-circuit.
- step 4: Repeat step 3 until some termination condition.

Reasons for choosing PO fanin cone as initial cluster:

- Fanin cone of a PO encompasses every potential cut for its nodes \rightarrow preserving complete cut-based structural information.
- Logic function at PO only depends on the logic outputs of all leave nodes in the PO fanin cone \rightarrow preserving independent functional information.

Illustration of Agglomerative Clustering

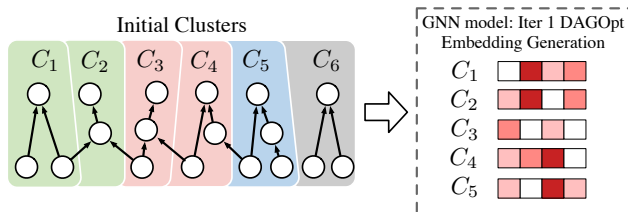


Illustration of Agglomerative Clustering

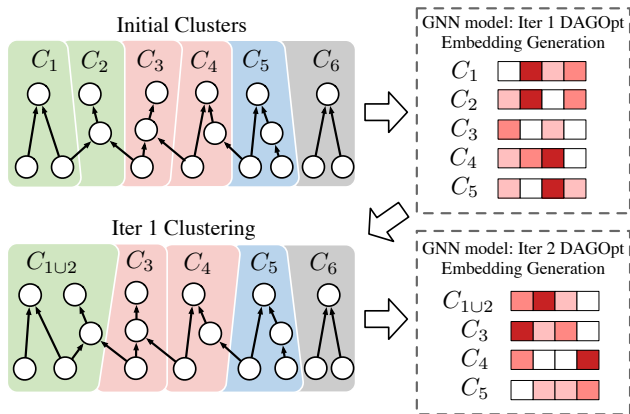
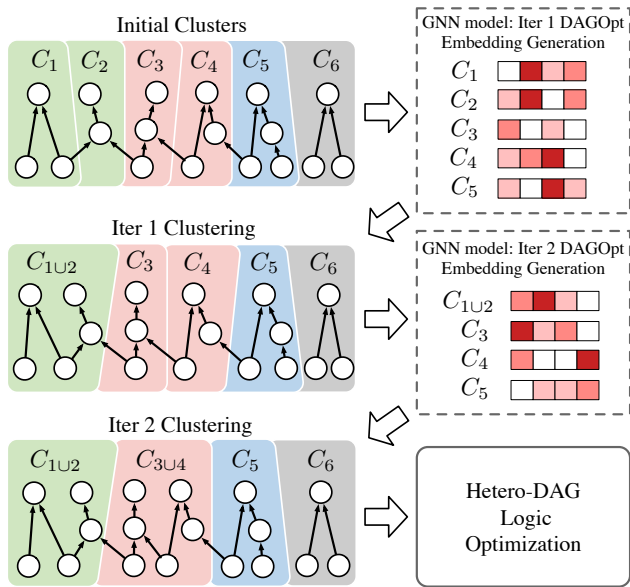


Illustration of Agglomerative Clustering



- Best-fit DAG type prediction:
 - Pre-trained GNN \rightarrow generate DAGOpt embedding e^c .
 - DAG type corresponding to smallest value in $e^c \rightarrow$ best-fit DAG type.
- Optimization: optimize each sub-circuit by predicted DAG type, using script provided by LSOacle.
- Integration: Convert sub-circuits into MIGs (with no change of node count and depth).
 - MIGs \supset AIGs: setting one input of 3-majority gate to 1 \rightarrow AND gate.
 - MIGs \supset XMG.
 - MIGs \supset XAG: setting one input of 3-majority gate to 1, invert two input edges \rightarrow XOR gate.
- Global optimize: rewrite.

Experimental Results

- 5714 sub-circuits selected from EPFL, ISCAS'89 benchmark suites and OpenCores.
- Script of LSOracle to obtain the DAGOpt embedding of each sub-circuit, as ground truth.
- Distribution of sub-circuits favoring AIG, MIG, XMG, and XAG as the best-fit DAG type $\rightarrow 0.52 : 0.28 : 0.16 : 0.30$.
- Note: some circuits might have more than one best-fit DAG types.

Evaluation of prediction accuracy:

- Training/testing split ratio: 80:20.
- Accuracy for best-fit DAG type prediction: 79.99%.

Evaluation of hetero-DAG optimization:

- Baseline: ABC³, FlowTune⁴, Mockturtle⁵, LSOacle.
- Both **technology-independent logic optimization** and **technology mapping**.
- pdk: ASAP7.

³Robert Brayton and Alan Mishchenko (2010). “ABC: An academic industrial-strength verification tool”. In: *Proc. CAV*, pp. 24–40.

⁴Walter Lau Neto, Yingjie Li, et al. (2022). “FlowTune: End-to-end Automatic Logic Optimization Exploration via Domain-specific Multi-armed Bandit”. In: *IEEE TCAD*.

⁵Mathias Soeken et al. (2018). “The EPFL logic synthesis libraries”. In: *arXiv preprint arXiv:1805.05121*.

Technology-Independent Logic Optimization Results

Table: Technology-independent logic toptimization result. NDP denotes the product of node count and depth.

Circuit	Original			ABC (30*resyn)			Flowtune			Mockturtle			LSOracle			HeLO (ours)		
	#nodes	depth	NDP	#nodes	depth	NDP	#nodes	depth	NDP	#nodes	depth	NDP	#nodes	depth	NDP	#nodes	depth	NDP
pico-rv	18139	31	562309	15775	30	473250	14641	52	761332	20036	21	420756	18838	21	395598	19268	18	346824
chip_bridge	58789	31	1822459	57733	26	1501058	56377	23	1296671	59237	19	1125503	59538	19	1131222	58317	19	1108023
s38417	8568	28	239904	7842	24	188208	7730	22	170060	9016	18	162288	9028	18	162504	9522	16	152352
fpu	66522	33	2195226	58477	31	1812787	56731	33	1872123	66889	23	1538447	67248	22	1401752	68099	20	1361980
aes_core	21522	26	559572	19822	20	396440	19302	22	424644	20825	21	437325	21561	27	582147	21867	18	393606
des_perf	72720	16	1163520	72394	16	1158304	65593	16	905488	70176	15	1052640	70176	15	1052640	70176	15	1052640
ethernet	69763	41	2860283	66443	34	2259062	65684	31	2036204	70226	25	1755650	68482	24	1643568	71896	20	1437920
dyn_node	3926	27	106002	3620	24	86880	3596	22	79112	3979	19	75601	4191	21	88011	4034	18	72612
DMA	4295	20	85900	3450	17	58650	3301	19	62719	4348	15	65220	4208	17	71536	4342	15	65130
vga_lcd	105828	22	2328216	103583	21	2175243	103191	21	2167011	107657	16	1722512	108465	16	1735440	101534	17	1726078
fpga_bridge	318195	42	13364190	315998	37	11691926	301337	36	10848132	340217	26	8845642	325698	27	8793846	324356	24	7784544
i2c	1342	20	26840	1047	14	14658	1009	11	11099	1417	9	12753	1387	11	15257	1385	8	11080
mem_ctrl	46836	114	5339304	43608	104	4535232	36366	81	2945646	51762	69	3571578	52123	68	3544364	56592	61	3452112
normalize	1.000	1.000	1.000	0.967	0.882	0.860	0.911	0.863	0.769	1.037	0.656	0.678	1.018	0.678	0.673	1.019	0.596	0.619

- Node-depth product (NDP) of HeLO is reduced by 38.9%, 24.3%, 9.6% and 8.7%, compared with the result of ABC(30*resyn), FlowTune, Mockturtle and LSOracle.

Technology Mapping Result

Table: ASIC technology mapping result using the ASAP7 PDK. Area is in μm^2 and delay is in ps . ADP denotes the product of delay and area.

Circuit	Original			ABC (30*resyn)			Flowtune			Mockturtle			LSOracle			HeLO (ours)		
	area	delay	ADP	area	delay	ADP	area	delay	ADP	area	delay	ADP	area	delay	ADP	area	delay	ADP
pico-rv	775.5	439.1	340492.0	779.2	434.5	338563.3	764.3	680.6	520193.6	841.5	312.9	263316.0	778.2	312.9	243503.0	831.6	290.0	241153.0
chip_bridge	3016.0	310.1	935394.0	3097.2	325.8	1008896.6	3010.2	308.3	928117.2	2988.2	294.2	879253.0	3038.9	294.2	894162.0	3028.2	263.9	799010.0
s38417	418.6	280.3	117319.0	415.4	304.4	126459.9	415.8	302.0	125572.7	415.7	283.0	117648.0	432.3	267.8	115776.0	416.2	266.7	111016.0
fpu	3115.4	466.5	1453351.0	3134.1	467.5	1465111.8	3101.4	523.3	1622869.6	3111.5	455.9	1418551.0	3062.2	452.2	1384682.0	3127.9	324.8	1016029.0
aes_core	1032.6	280.0	289164.0	1019.9	293.6	299428.1	941.5	320.3	301562.5	1033.1	277.5	286670.0	1001.5	291.2	291683.0	1061.0	251.0	266276.0
des_perf	3325.8	242.2	805408.0	3647.0	265.4	968020.6	3114.1	267.8	833899.1	3457.8	232.8	804807.0	3457.8	232.8	804807.0	3457.8	232.8	804807.0
ethernet	3476.7	384.6	1337324.0	3424.2	470.4	1610860.5	3495.8	465.4	1627101.5	3486.5	309.6	1079382.0	3366.8	306.5	1031939.0	3407.0	289.4	985948.0
dyn_node	204.4	293.2	59925.0	198.7	317.8	63156.4	203.9	286.7	58450.0	201.7	266.3	53703.0	212.0	251.5	53321.0	205.5	231.7	47610.0
DMA	182.6	196.9	35963.6	178.7	198.1	35394.3	179.1	212.4	38041.2	185.3	206.9	38350.3	186.1	196.7	36611.9	185.8	196.7	36556.3
vga_lcd	6125.5	300.0	1837402.0	5374.8	262.4	1410242.6	5491.7	306.7	1684097.0	5896.3	237.8	1401913.8	5751.7	237.8	1367531.3	5627.5	259.5	1460459.2
fpga_bridge	17049.5	584.6	9967166.9	16578.4	499.6	8281754.7	15978.7	580.2	9271167.1	17053.6	331.0	5644403.8	16760.3	356.9	5982606.9	16385.7	340.9	5585048.8
i2c	57.7	247.3	14278.5	50.4	230.0	11597.4	50.9	161.1	8201.7	59.5	131.7	7840.7	59.7	133.0	7940.7	60.2	131.7	7931.6
mem_ctrl	2282.5	1559.8	3560243.5	2165.5	1496.9	3241553.5	1850.2	1191.1	2203815.5	2333.1	1086.0	2533863.3	2340.3	1086.0	2541704.5	2395.2	1021.3	2446214.2
normalize	1.000	1.000	1.000	0.976	0.997	0.909	0.940	1.004	0.926	1.000	0.792	0.700	0.985	0.791	0.711	0.979	0.734	0.665

- Area-delay product (ADP) of HeLO is reduced by 36.6%, 39.2%, 5.2% and 6.9%, compared with the result of ABC, FlowTune, Mockturtle and LSOracle.

Runtime Comparison

Table: Runtime analysis of ABC, Flowtune, Mockturtle, LSOacle and HeLO for logic optimization. The unit of the runtime is second (s).

Circuit	ABC (30*resyn)	Flowtune	Mockturtle	LSOacle	HeLO (ours)
pico-rv	15	324	29	113	57
chip_bridge	62	541	792	1616	262
s38417	7	81	3	56	30
fpu	86	665	28	633	480
aes_core	23	166	41	120	63
des_perf	121	530	93	680	70
ethernet	70	1007	1276	5106	803
dyn_node	3	20	23	18	12
DMA	3	24	2	28	59
vga_lcd	128	9174	3002	12460	3254
fpga_bridge	3032	9160	72461	70789	47611
i2c	1	12	7	11	21
mem_ctrl	56	876	61	414	337
Normalize.	0.068	0.426	1.467	1.735	1.000

- ABC: very fast; only provide AIG optimization; least effective optimization result.
- FlowTune: multi-armed bandit exploration, slower than ABC.
- Mockturtle: slow for optimizing whole large Boolean Network.
- LSOacle: slow for enumerating each DAG-type optimization for each sub-circuit.

THANK YOU!