



# Novel Transformer Model Based Clustering Method for Standard Cell Design Automation

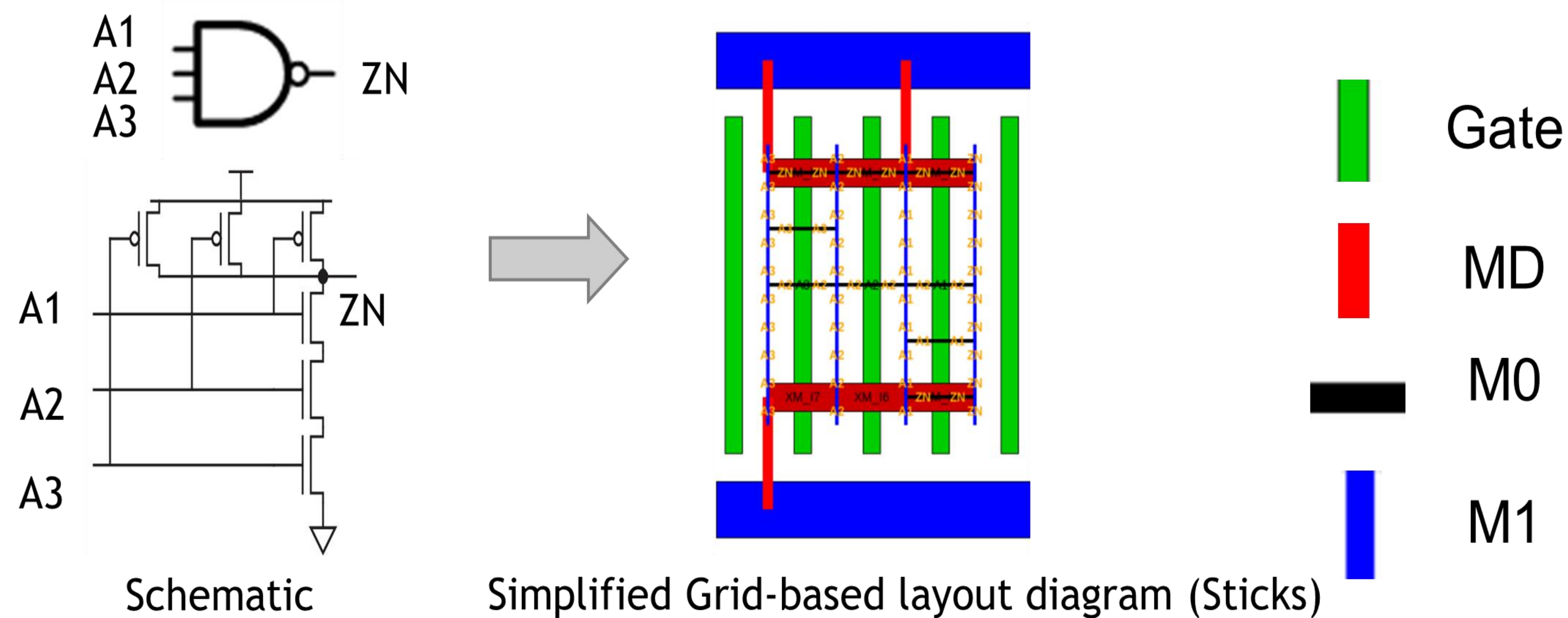
Chia-Tung (Mark) Ho, Ajay Chandna, David Guan, Alvin Ho, Minsoo Kim, Yaguang Li and **Haoxing (Mark) Ren** | ISPD 2024

# OUTLINE

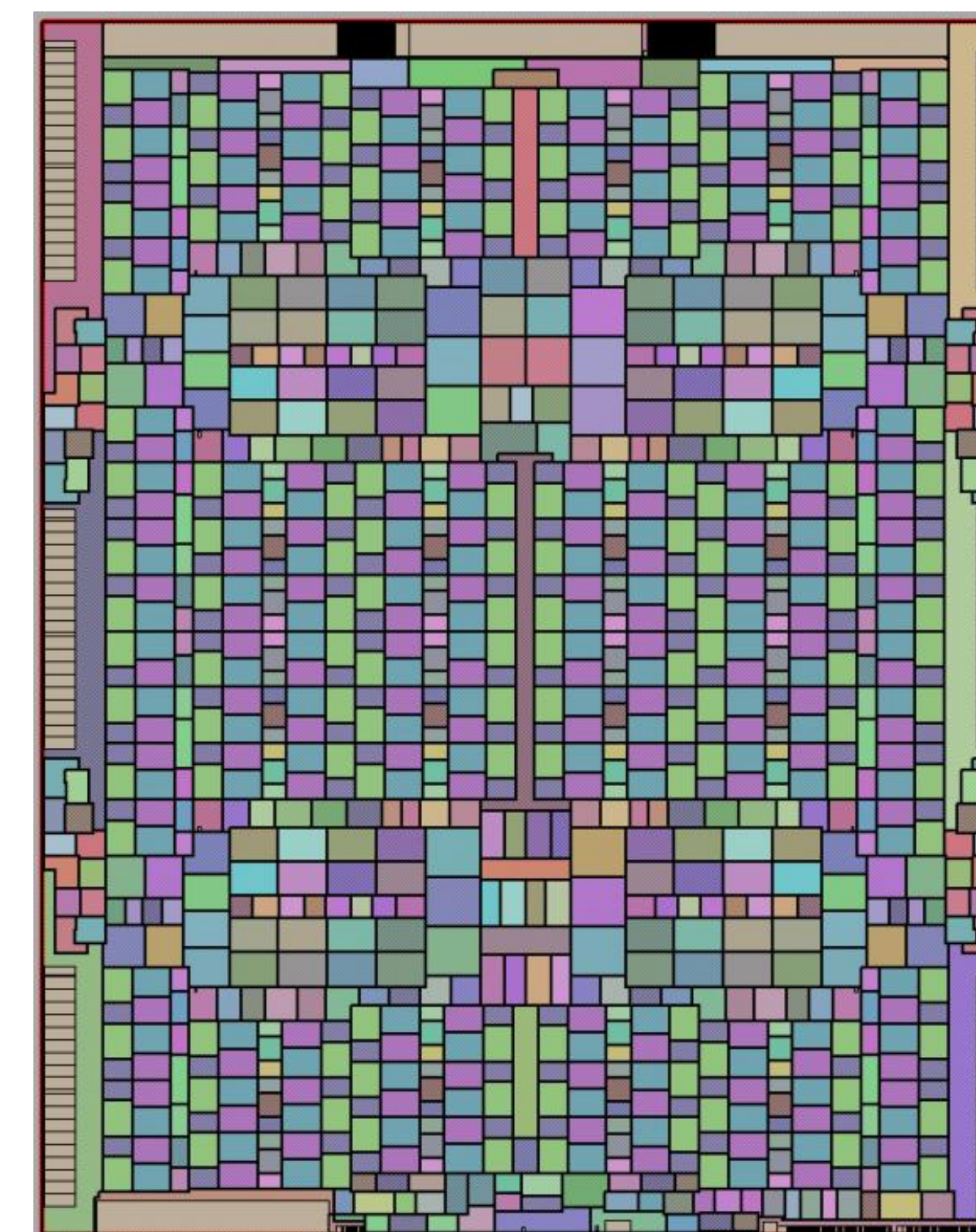
- **Introduction**
- Novel Transformer Model Based Clustering Method
- Experimental Results
- Conclusion

# STANDARD CELL LAYOUT AUTOMATION

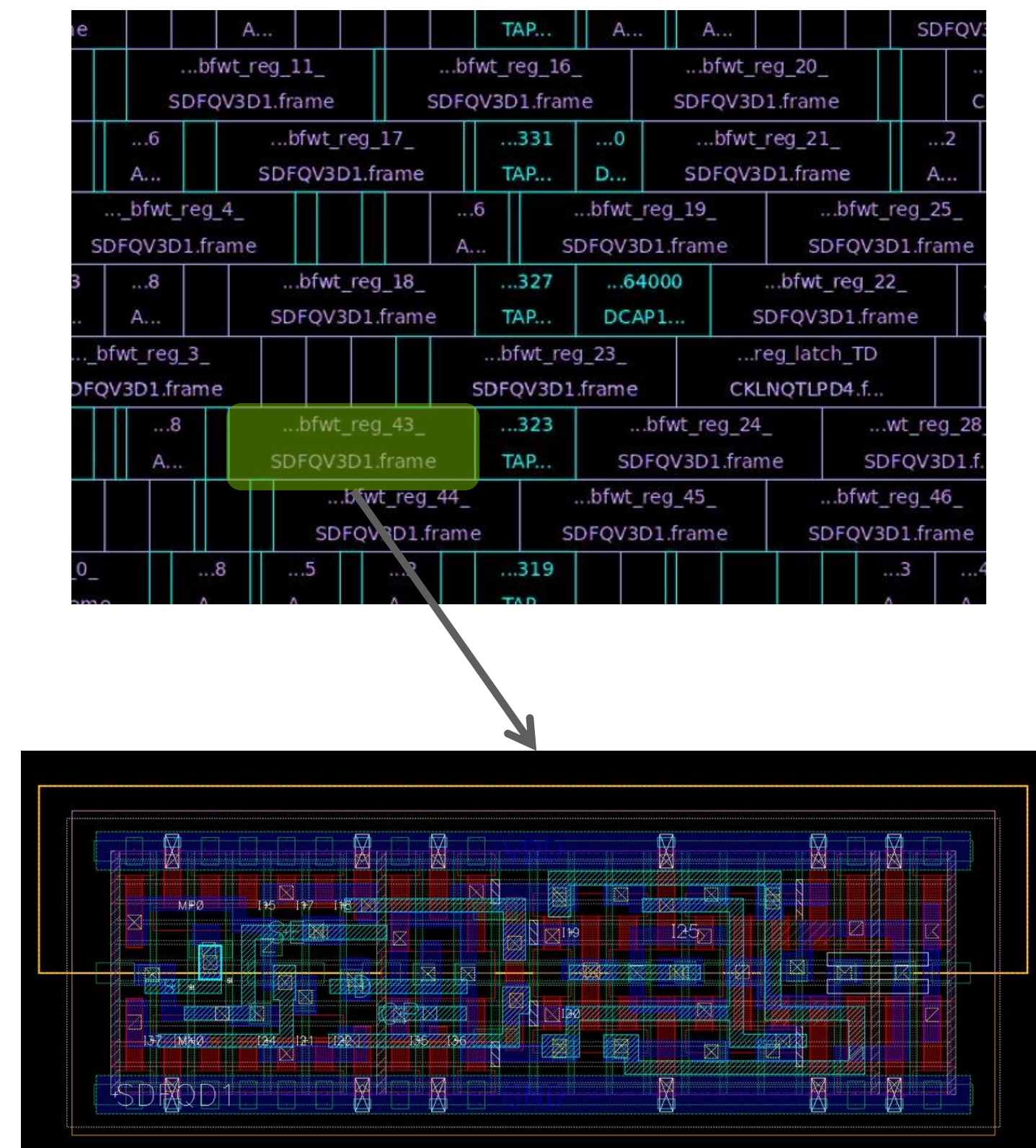
- Standard Cells (STD) are building blocks of digital design layout: AND, NOR, Flip-Flop, Adder, etc
- Months manual design turn around time per library to deliver competitive Power, Performance, and Area (PPA)
- Standard cell layout automation benefits - NVCell (DAC2021, ISPD2023)
  - Productivity: Fast turn around time
  - Performance: Explore more design space
  - Performance: More custom cell design
  - Optimization: Design Technology Co-Optimization



Standard Cell

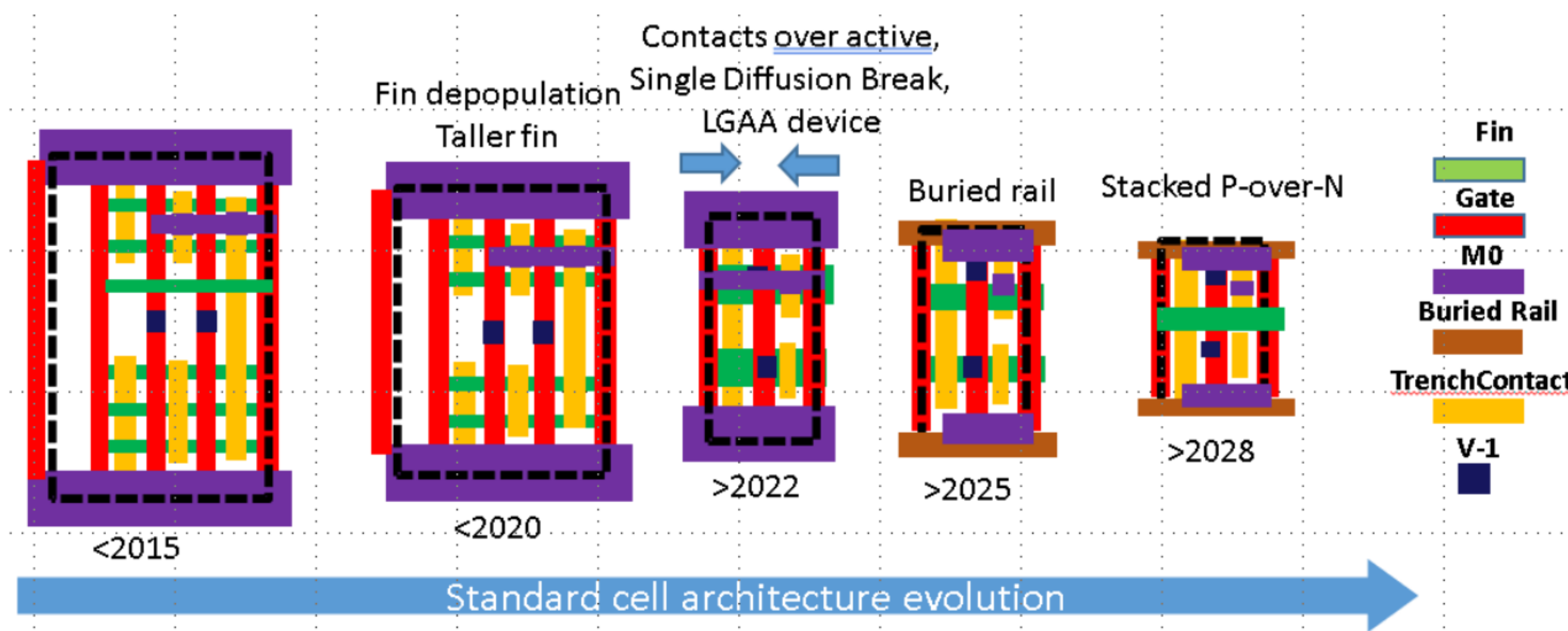


GA100 - 1.7B standard cells

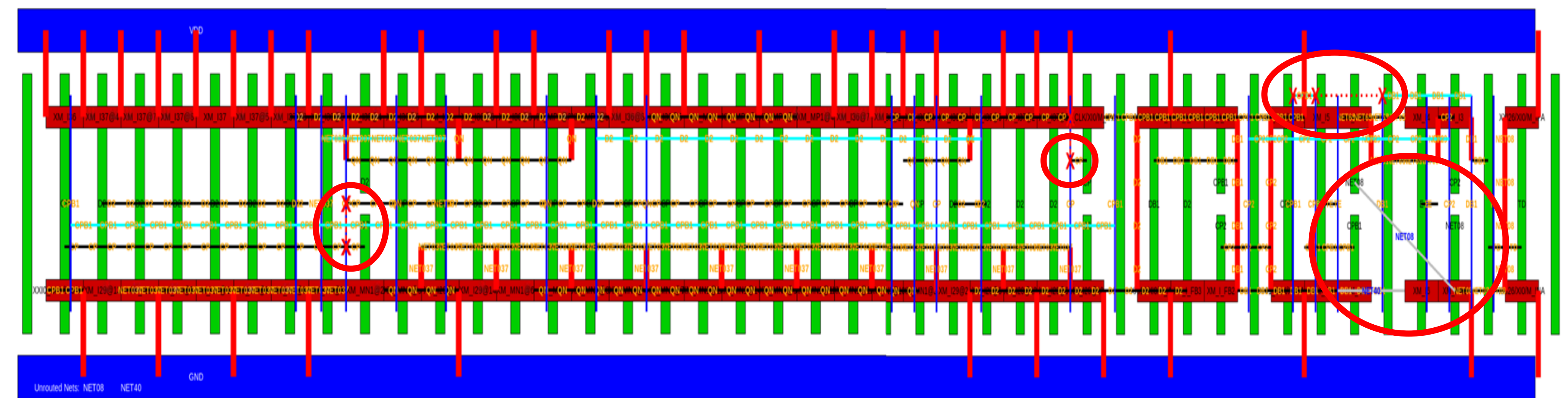


# CHALLENGES: STANDARD CELL LAYOUT AUTOMATION

- Standard cell layout automation challenges as advancing beyond 5nm
  - Limited in-cell routing resource: less routing tracks (i.e., 5 routing tracks)
  - Design rule complexity: Increasing number and complexity of design rules + strict patterning rules
  - Scalability: > hundreds of transistors cell designs
- Better and Efficient standard cell layout automation framework
  - Routability
  - Scalability
  - High-quality PPA
  - How?



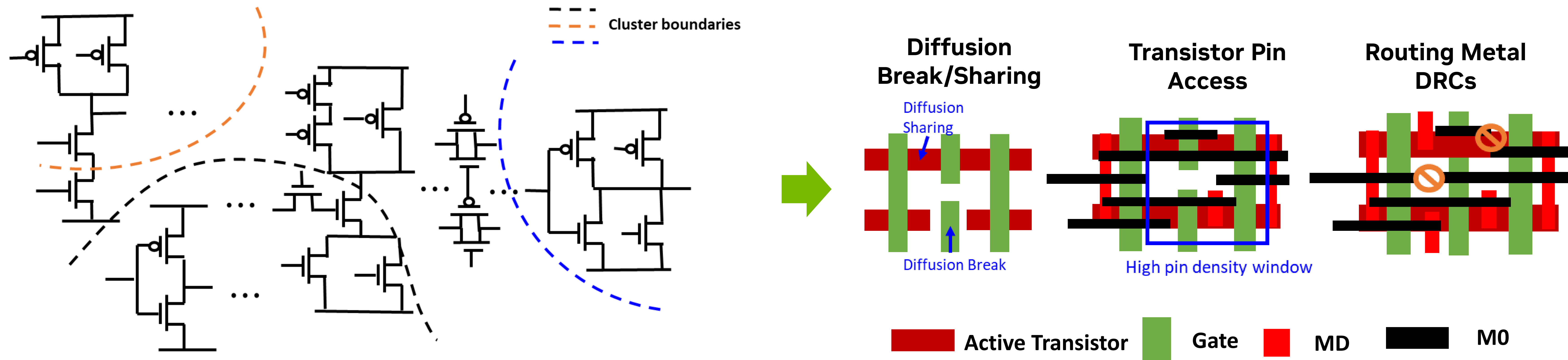
IRDS Roadmap 2022



Routability Challenges of a Latch Design in 5nm in stick format

# LAYOUT-AWARE DEVICE CLUSTERING

- High quality device clustering should consider transistor layout characteristics
  - Diffusion break/sharing
  - Transistor pin access
  - Routing metal DRCs
- **Novel transformer model-based clustering methodology**
  - **Reduce complexity**
  - **Narrow down searching space**
  - **Assist finding routable + optimal layouts faster**

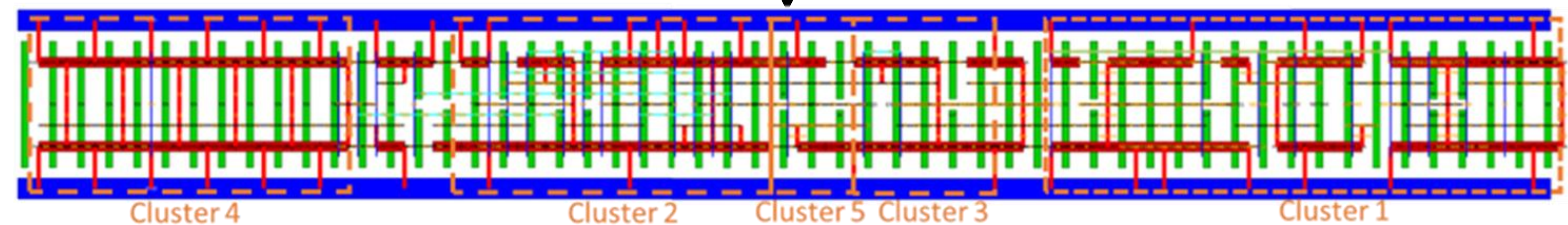
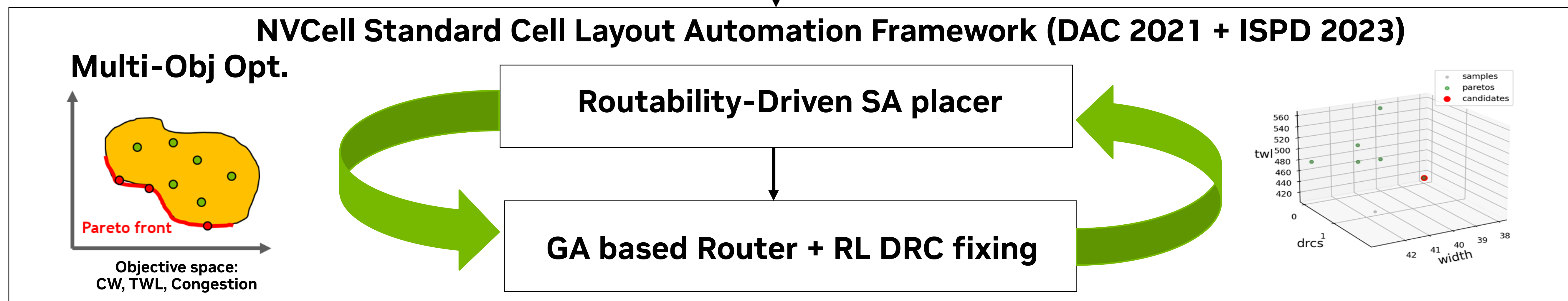
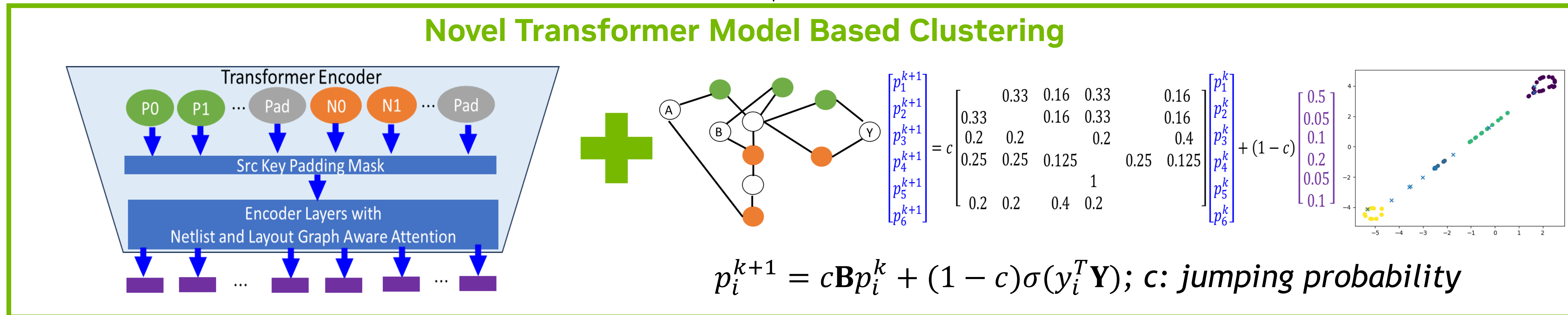
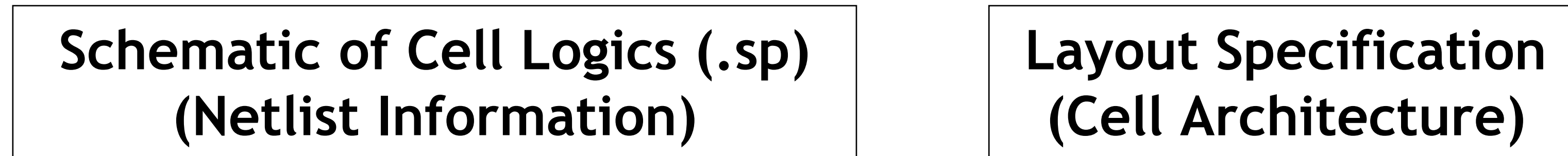


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- Introduction
- **Novel Transformer Model Based Clustering Method**
- Experimental Results
- Conclusion

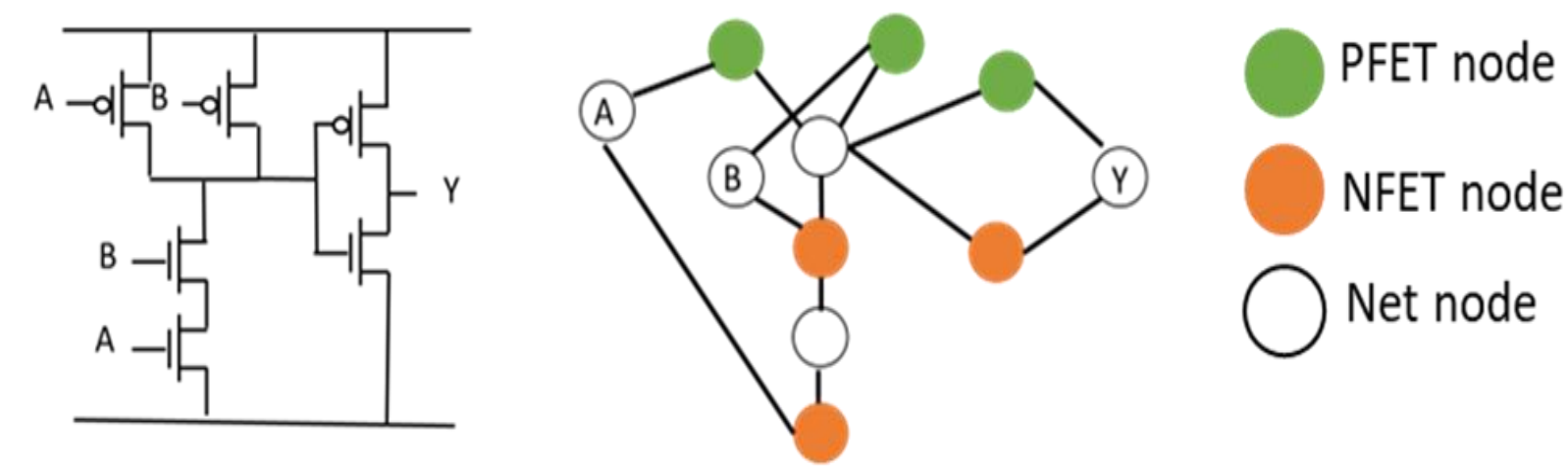
# NOVEL TRANSFORMER MODEL BASED CLUSTERING METHOD

## Framework Overview



# TRANSFORMER ENCODER STRUCTURE

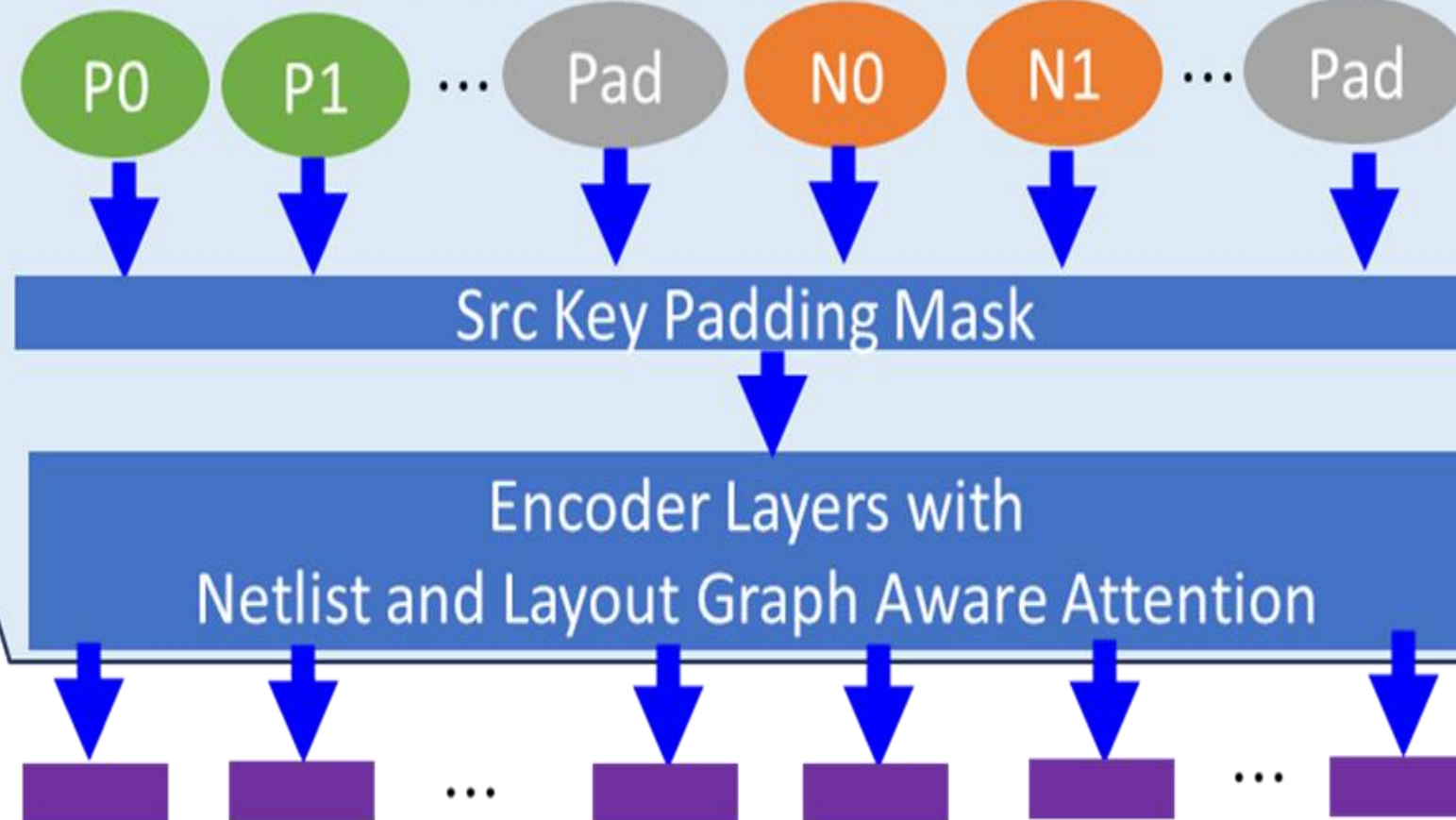
(a) Transformer Encoder Architecture



Netlist logic graph

GINE Network:  
 Extract graph embeddings of devices (tokens)

Transformer Encoder



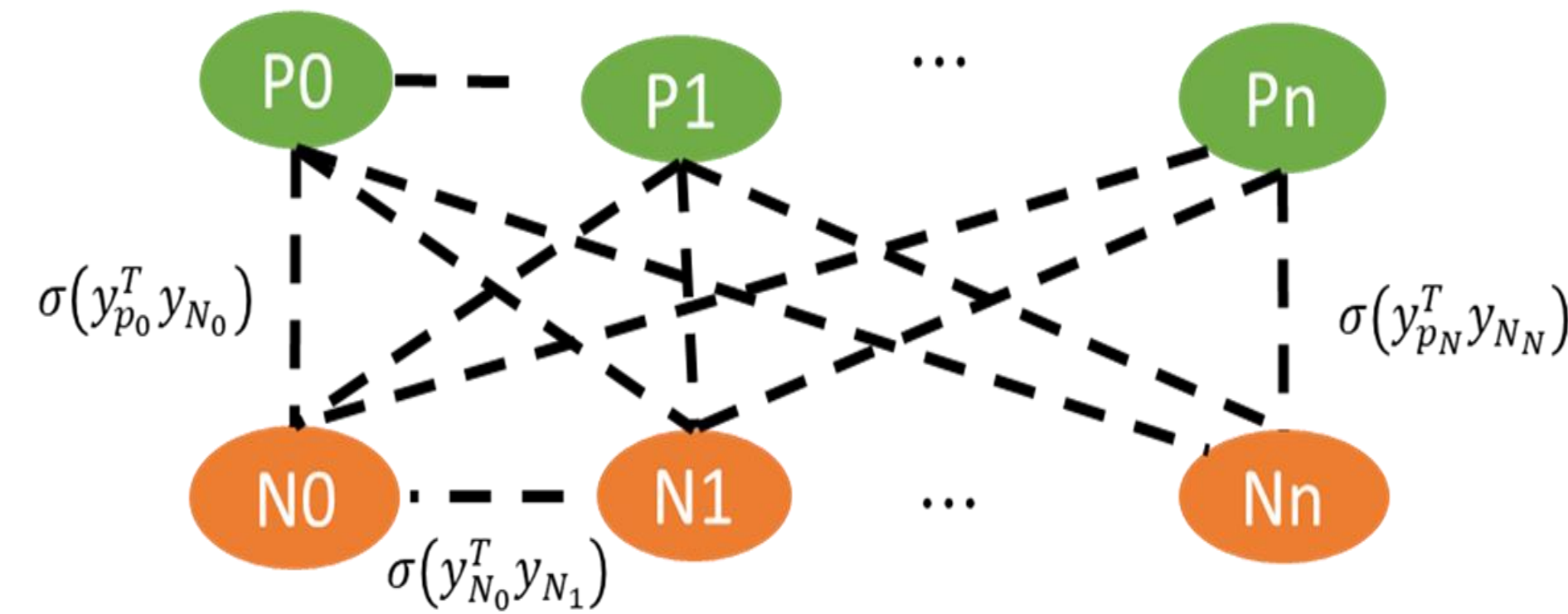
Representative embedding of each device,  $y_v$ .

(b) Training Flow: Similarity loss ( $L_{sim}$ ) from layout graph

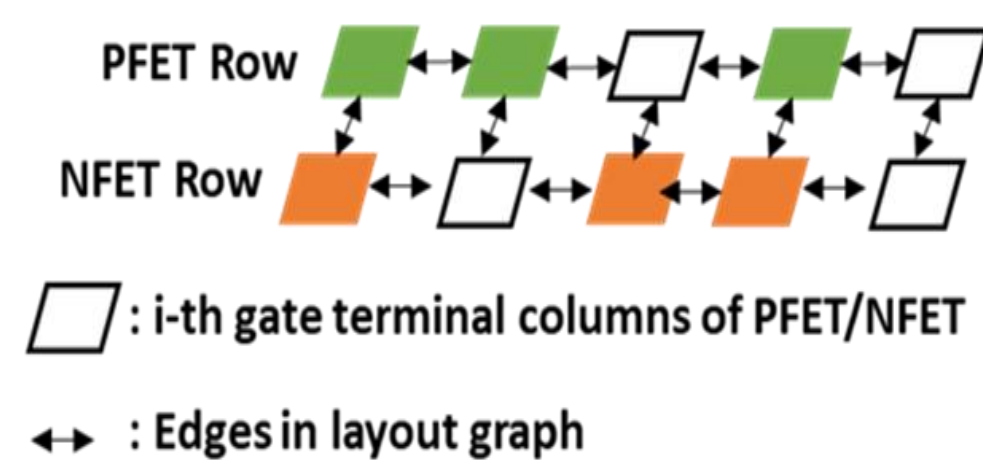
$$L_{sim} = \sum_v \left( - \sum_{u \in N(v)} \log(\sigma(y_v^T y_u)) - \sum_{k \sim rand} \log(\sigma(-y_v^T y_k)) \right)$$

$\sigma(y_v^T y_u)$ : Preferred clustering probability of two devices.

$N_i(v)$ : The neighbor of device  $v$  in the layouts



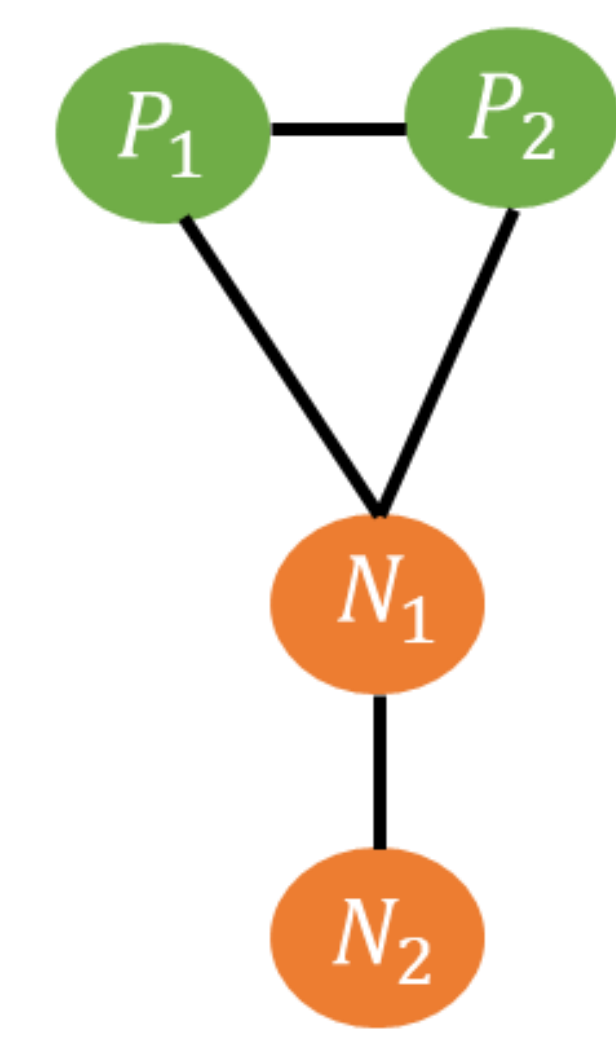
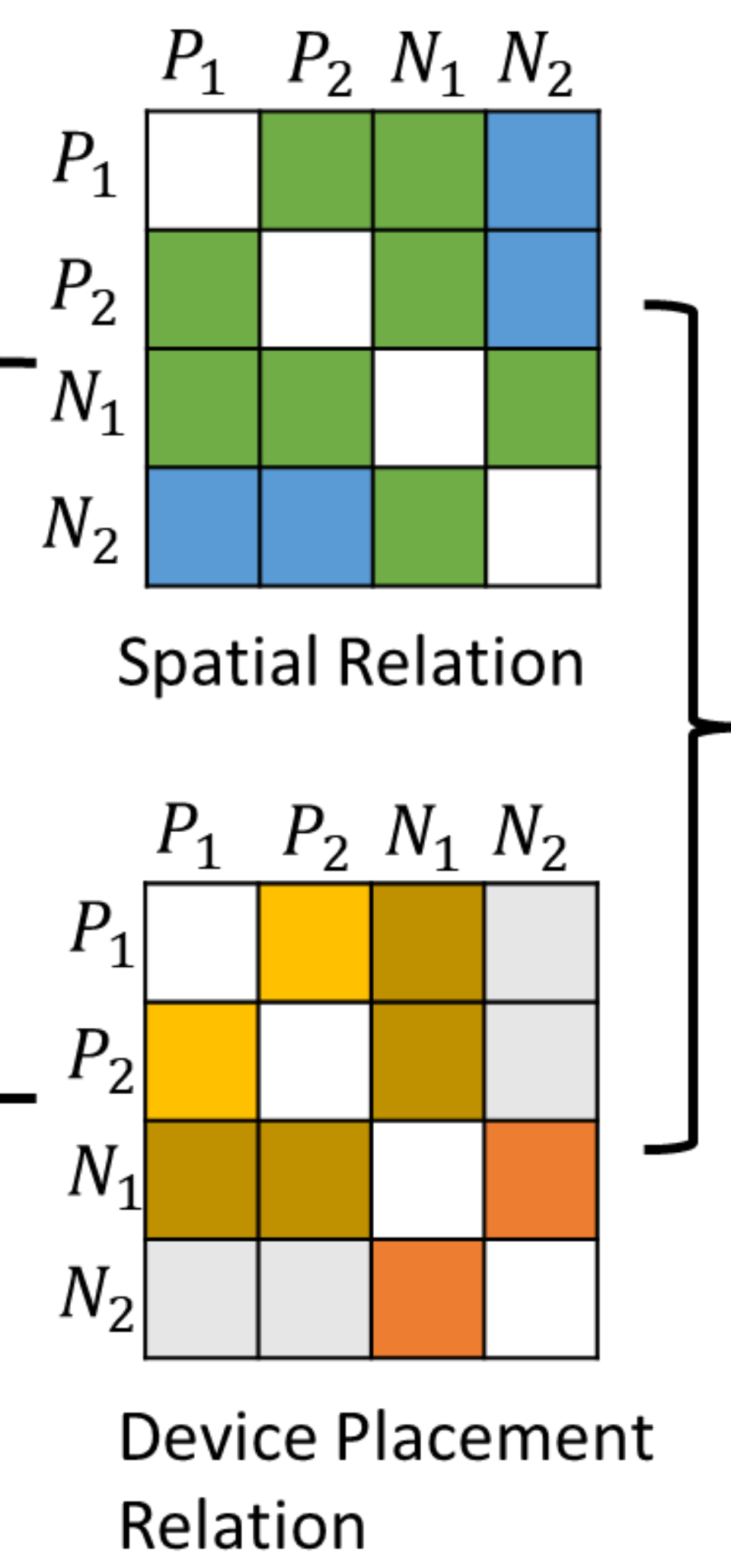
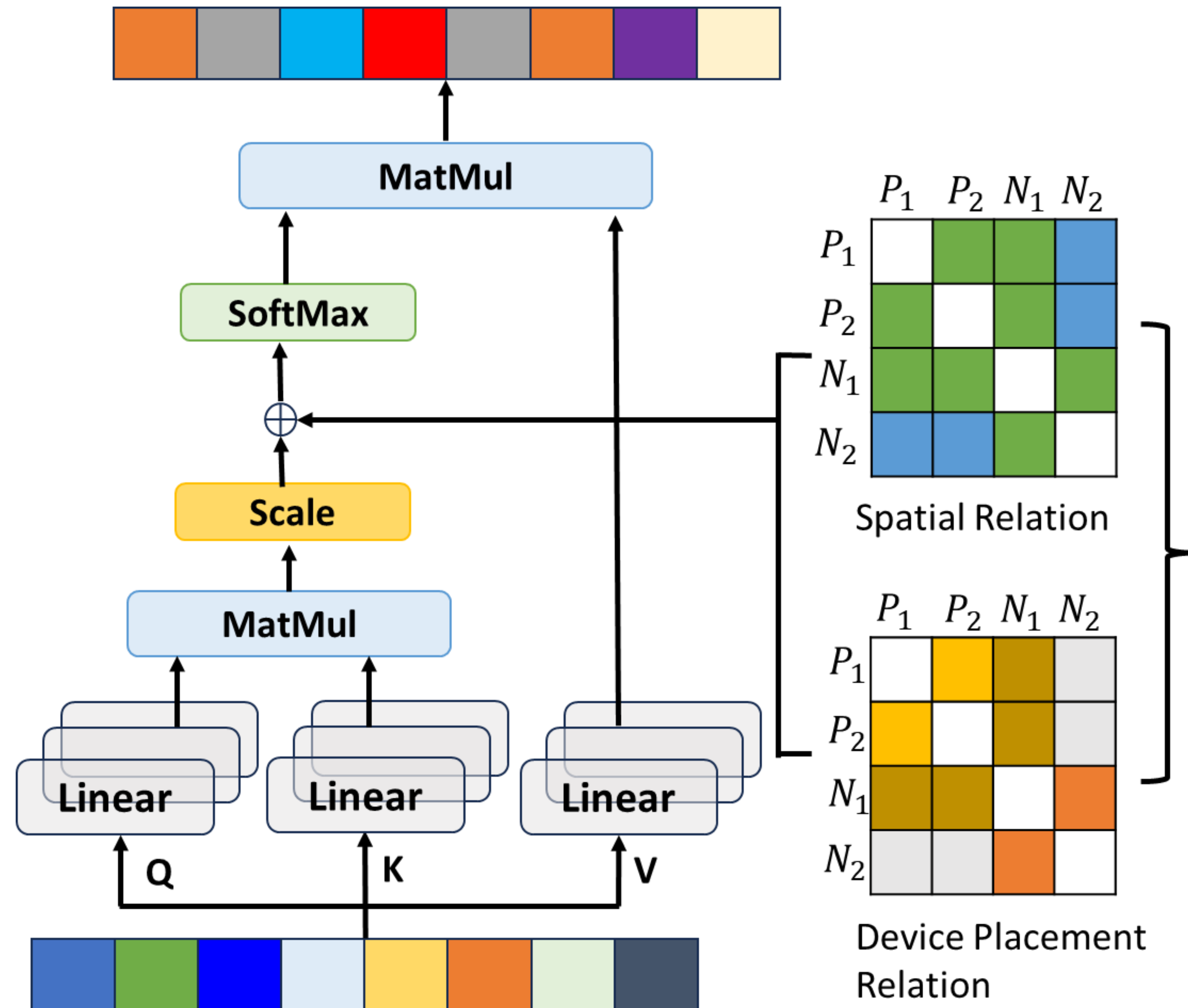
Layout graph (Neighbor columns all connected)



- Goal: Learn the relationship between device pairs in the layout graph
- Netlist logic graph: Topology is from spice netlist
  - Nodes: Nets, devices, and pins
  - Edges: Connections
- Layout graph: Neighbor grids are all connected
  - Column: gate terminal
  - Row: PFET, NFET
- Unsupervised learning from LVS/DRC layouts
- **Global receptive field + Netlist Structure + Device placement relation**



# NETLIST & LAYOUT GRAPH MULTI-HEAD ATTENTION



$$a_{v,u} = \frac{(h_v \mathbf{W}_Q)(h_u \mathbf{W}_K)^T}{\sqrt{d}} + b_{\phi(v,u)} + b_{\kappa(v,u)}$$

Spatial Relation Attn bias      Device Placement Attn bias

- **Spatial Relation bias:** shortest path distance between devices in the netlist logic graph
- **Device Placement bias:** device layout characteristics, such as diffusion sharing, vertical gate/diffusion connect.

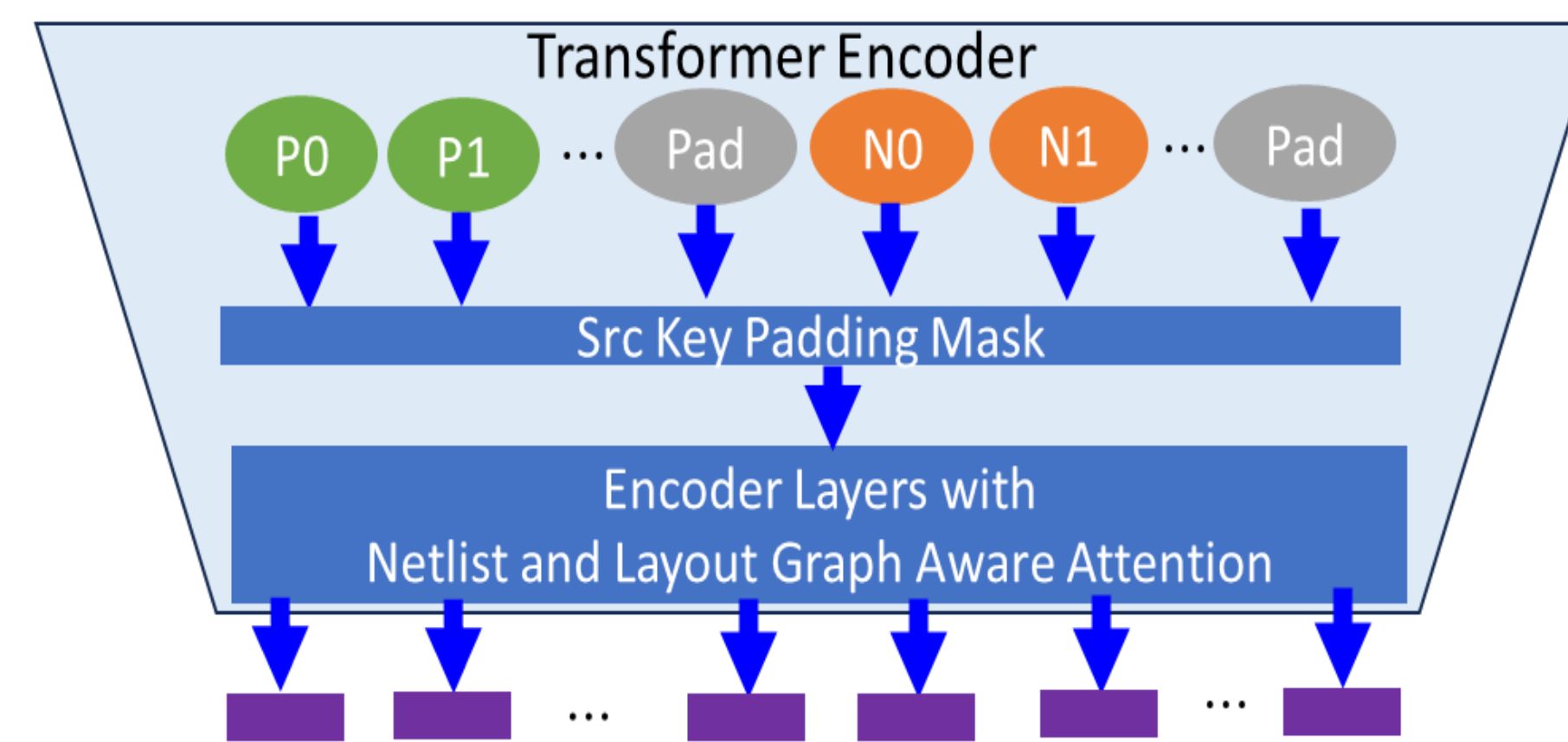
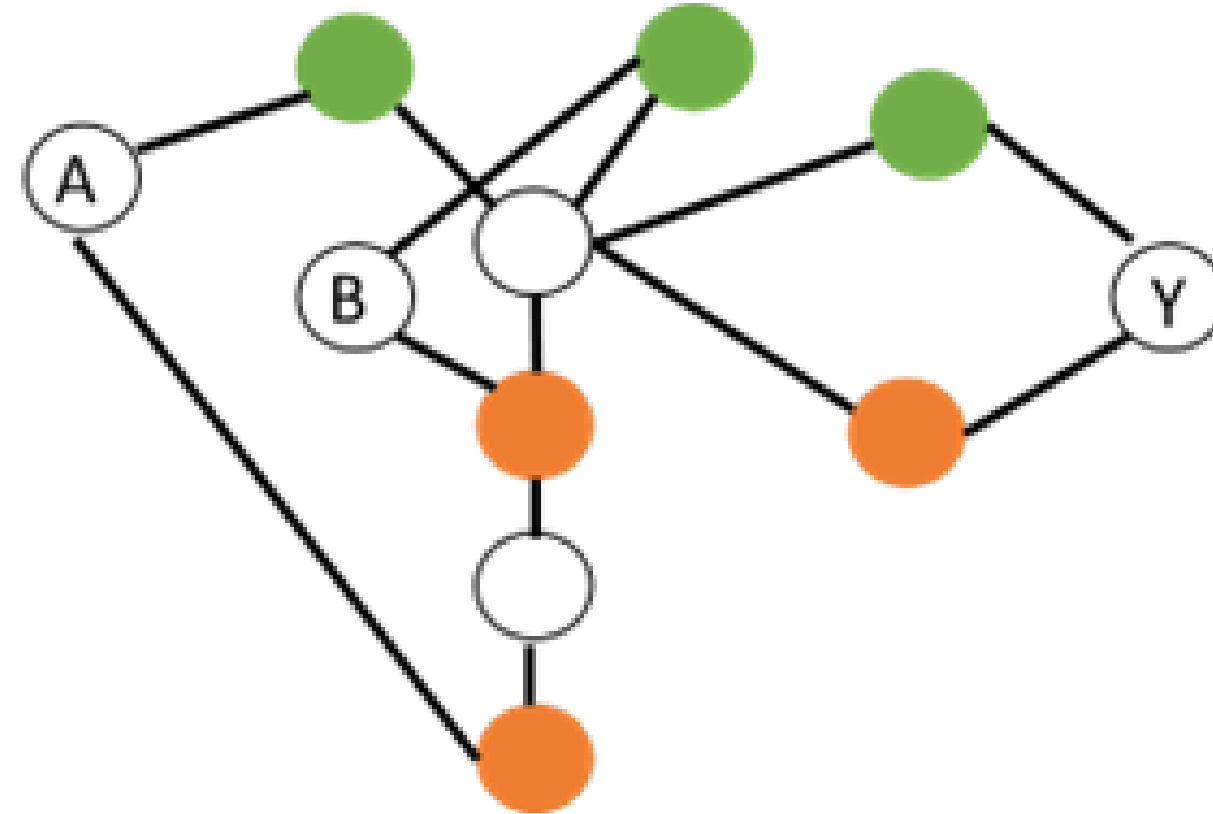
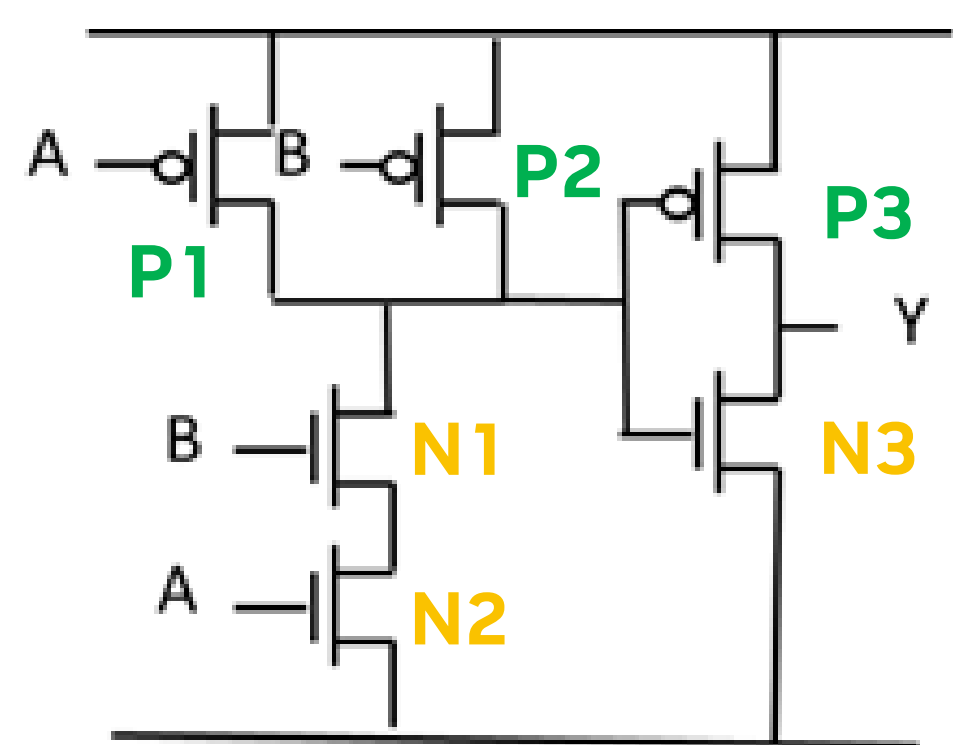
# NETLIST & LAYOUT AWARE PERSONALIZED PAGE RANK VECTOR CLUSTERING

For each device, calculate personalized page rank vector

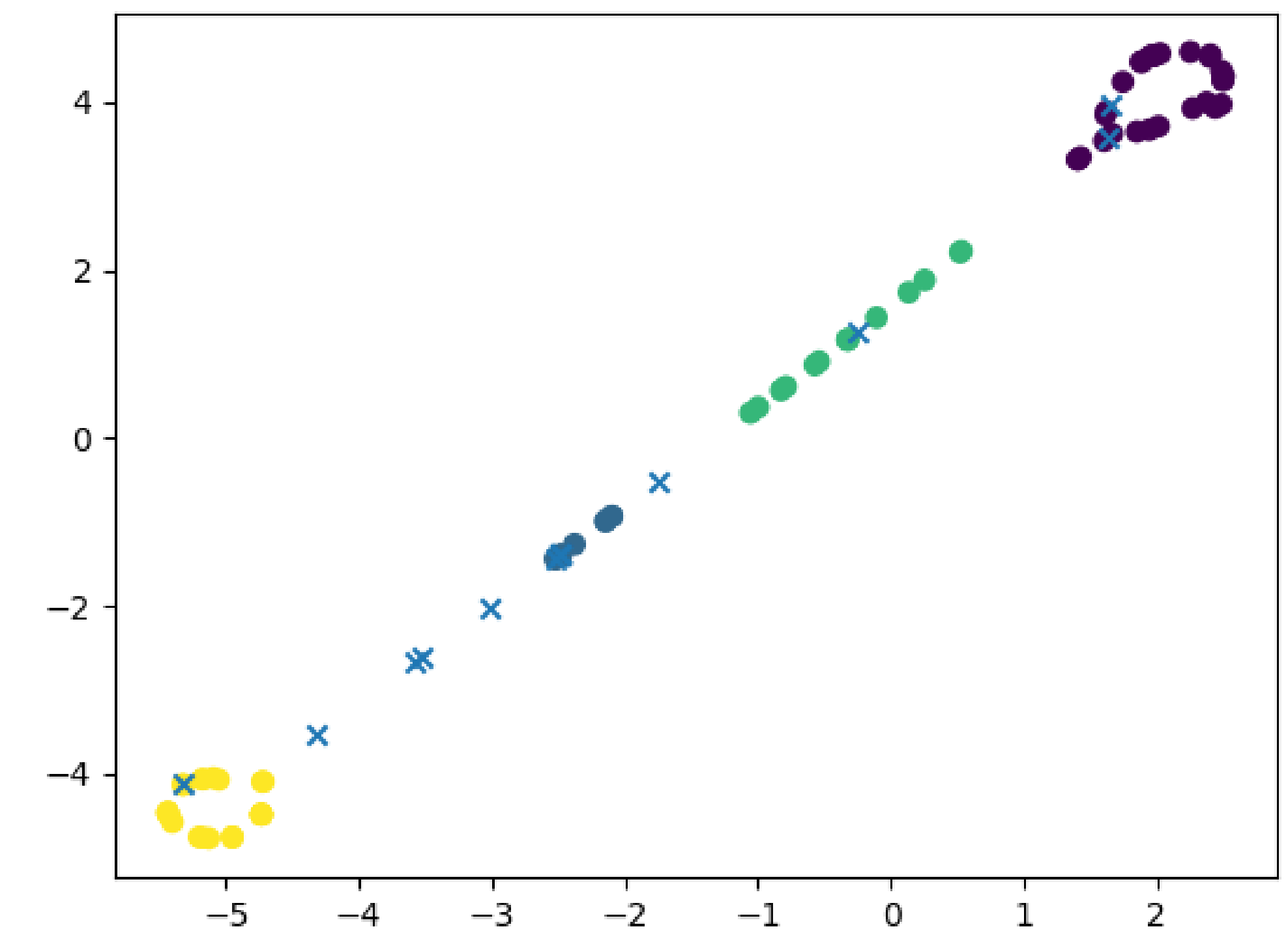
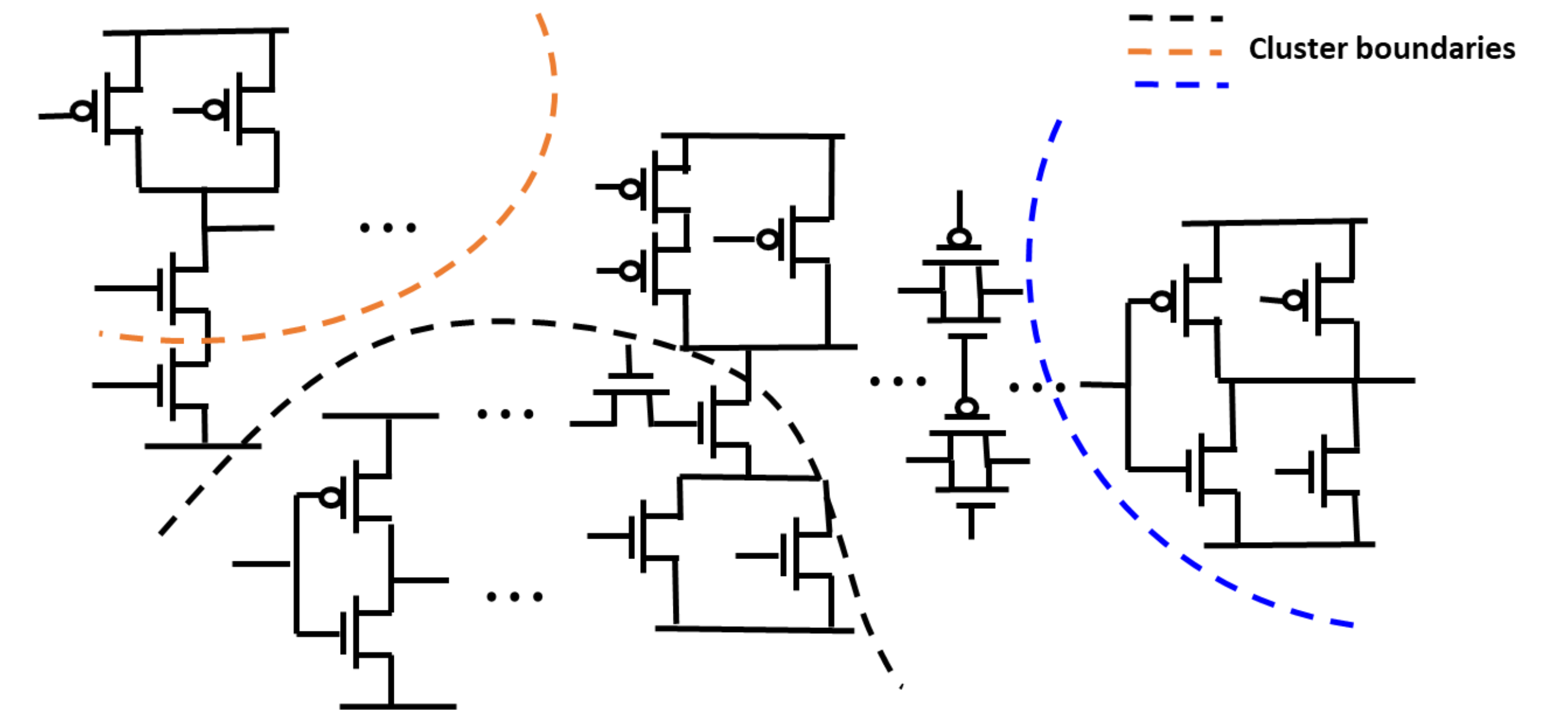
$$p_i^{k+1} = c\mathbf{B}p_i^k + (1 - c)\sigma(y_i^T \mathbf{Y}); c: \text{jumping probability}$$

$$\begin{bmatrix} p_1^{k+1} \\ p_2^{k+1} \\ p_3^{k+1} \\ p_4^{k+1} \\ p_5^{k+1} \\ p_6^{k+1} \end{bmatrix} = c \begin{bmatrix} & 0.33 & 0.16 & 0.33 \\ 0.33 & & 0.16 & 0.33 \\ 0.2 & 0.2 & & 0.2 \\ 0.25 & 0.25 & 0.125 & \\ 0.2 & 0.2 & 0.4 & 1 \\ 0.2 & 0.2 & 0.4 & 0.2 \end{bmatrix} \begin{bmatrix} p_1^k \\ p_2^k \\ p_3^k \\ p_4^k \\ p_5^k \\ p_6^k \end{bmatrix} + (1 - c) \begin{bmatrix} 0.5 \\ 0.05 \\ 0.1 \\ 0.2 \\ 0.05 \\ 0.1 \end{bmatrix}$$

Predicted preference probability vector of i-th device ( $\sigma(y_i^T \mathbf{Y})$ )



DBScan Clustering from  $p_i$

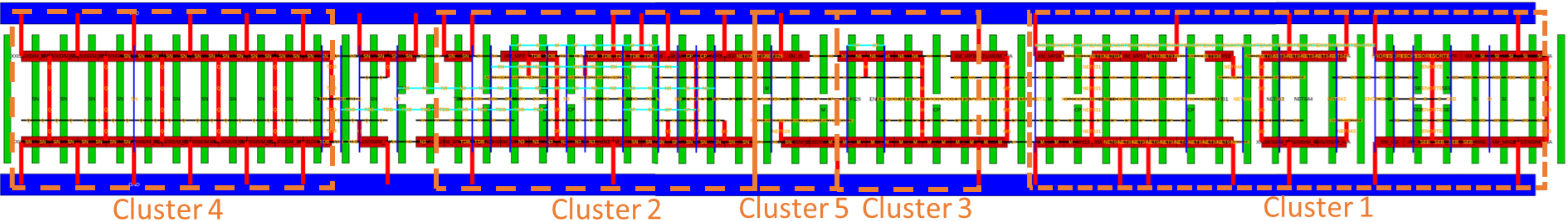


PCA projected cluster result

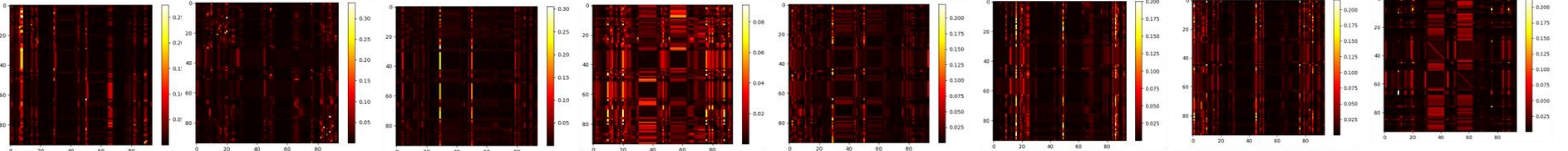
# GENERATED LVS/DRC LAYOUT AFTER CLUSTERING

Generated LVS/DRC Clean Latch Design (~ 100 devices)

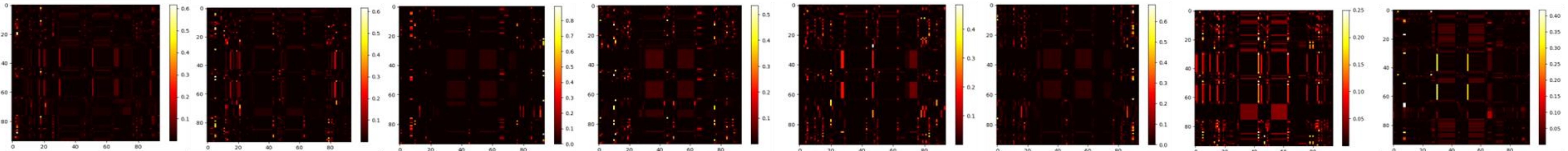
Manual Cell Width = 58 / Generated Cell Width = 56 TWL = 671



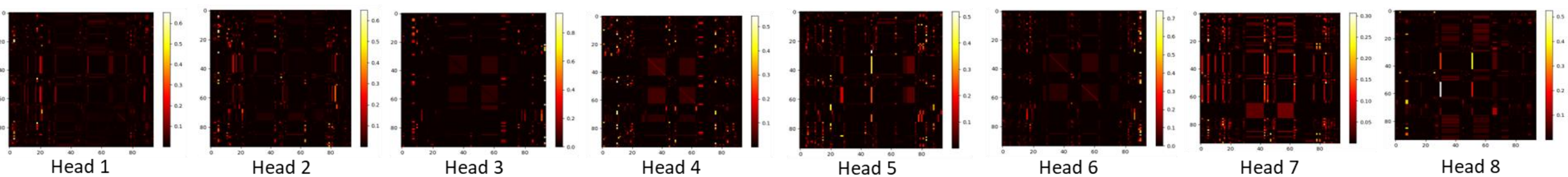
Netlist & Layout Graph Aware Multi-Head Attention Layer 1



Netlist & Layout Graph Aware Multi-Head Attention Layer 2



Netlist & Layout Graph Aware Multi-Head Attention Layer 3

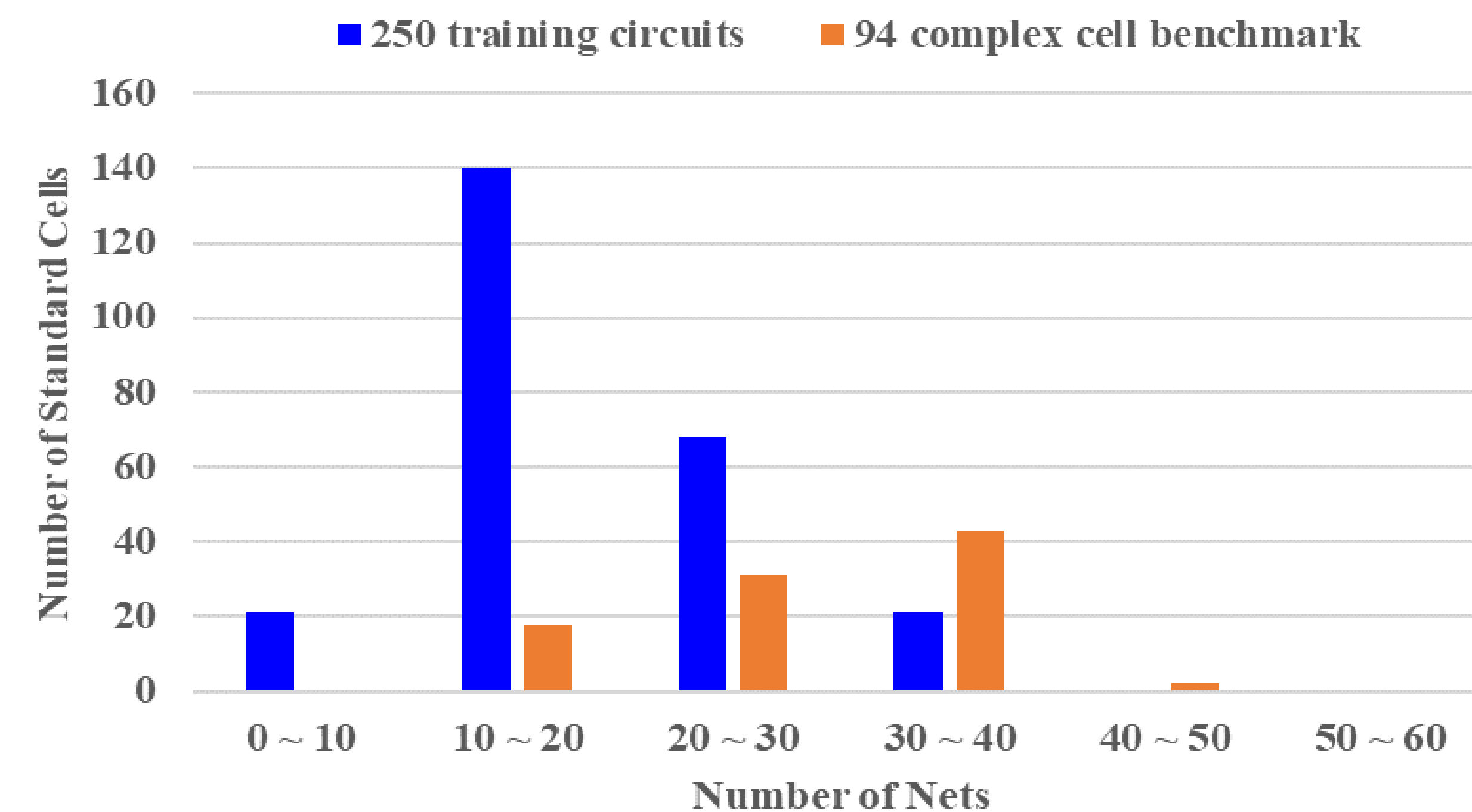
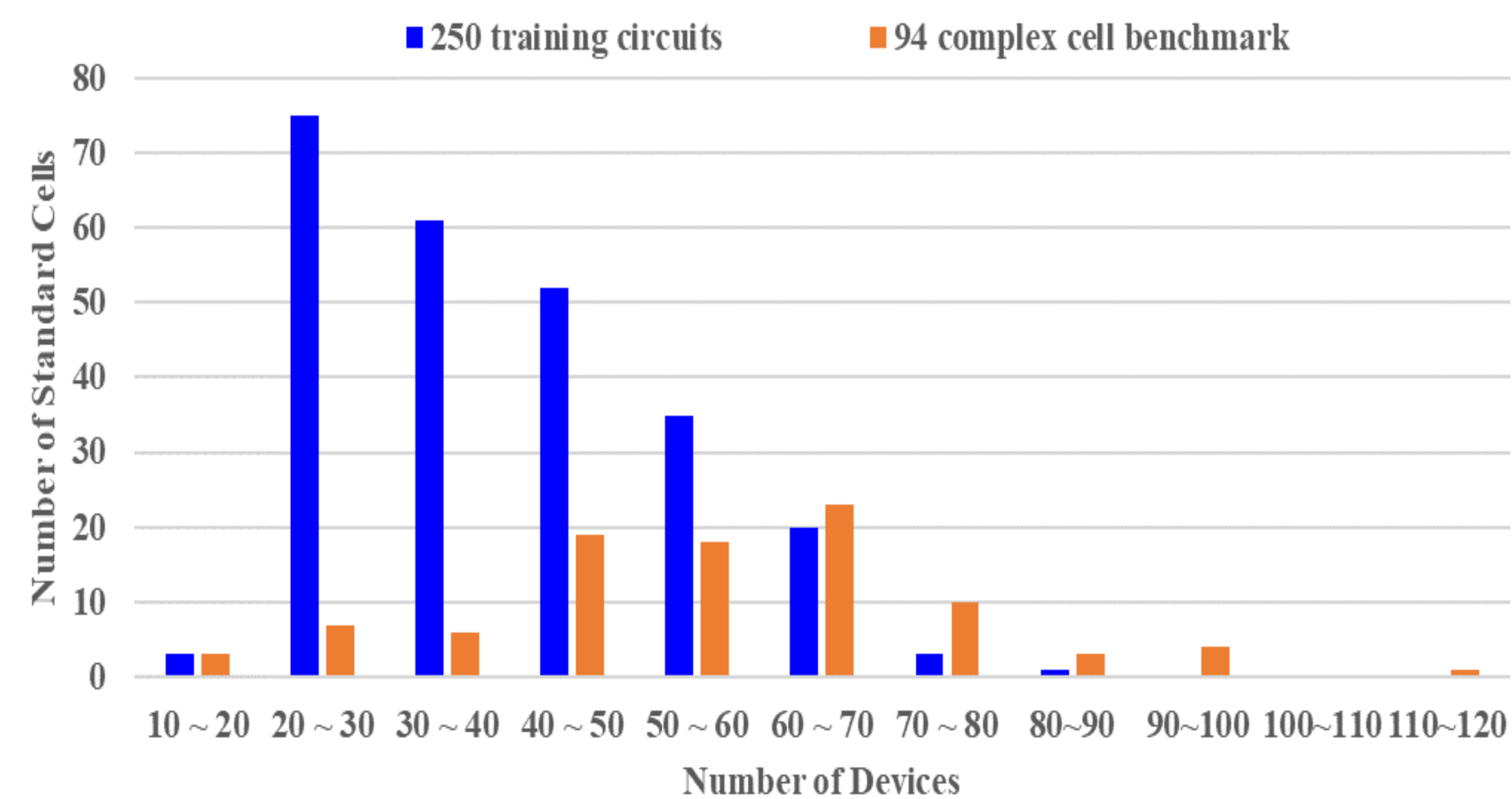


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# Experimental Setup

- Training 250 training circuits set in 5nm library
  - Apply to larger and more complex circuits
  - Apply to different technology nodes
- Experiment I: Clustering Quality Study
- Experiment II: Results of 5nm industrial library
  - 94 complex cell benchmark + Entire cell library
- Experiment III: Results of 3nm (without retraining the model)



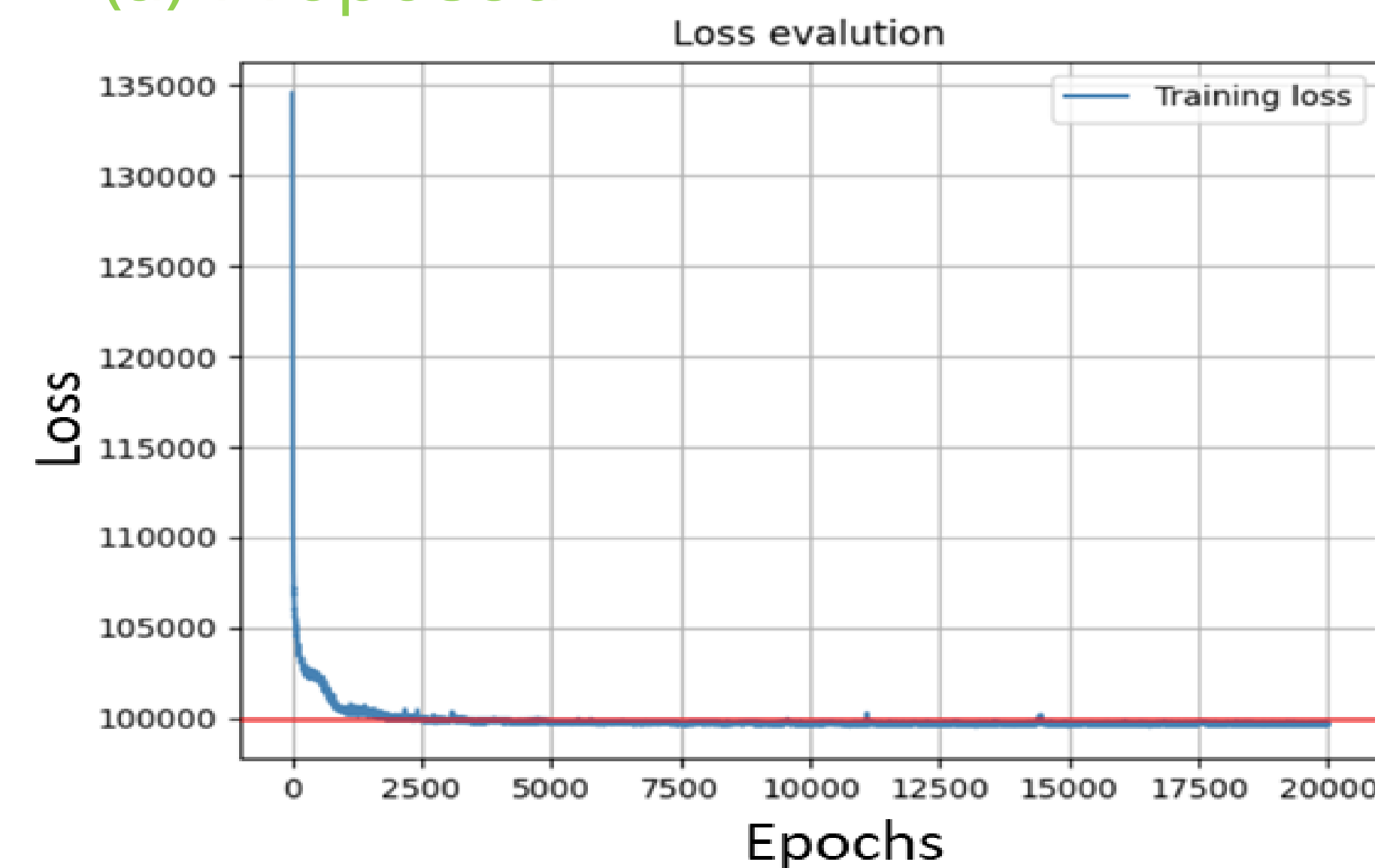
# Clustering Quality Study

- Quality of DBScan clustering method with Different Models and Representative Node Vectors (Rep. Node Vectors)
- Silhouette score (Larger is better): clustering result and the actual LVS/DRC clean layout placement

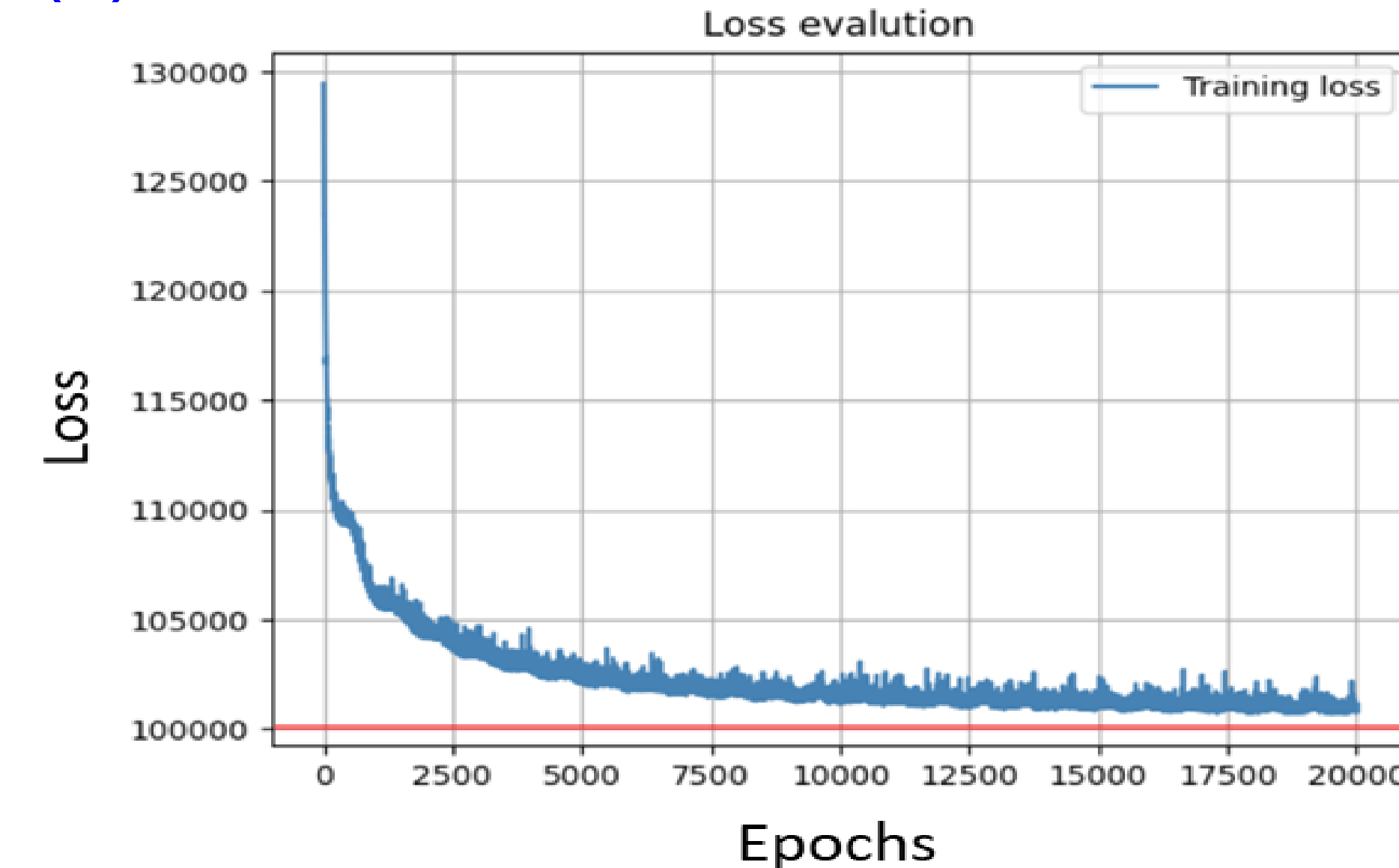
$$\text{Silhouette score} = \frac{(b - a)}{\max(a, b)} ; a = \text{mean intraclass distance} ; b = \text{mean nearest cluster distance}$$

Rep. Node Vectors	Model	Avg. Silhouette	Impr. (%)
Pred. Preference	GINE	0.21	200%
	Transformer based	0.42	50%
PPR with Pred. Preference	N/A	0.22	186%
	GINE	0.37	70%
	<b>Transformer based (proposed)</b>	<b>0.63</b>	-

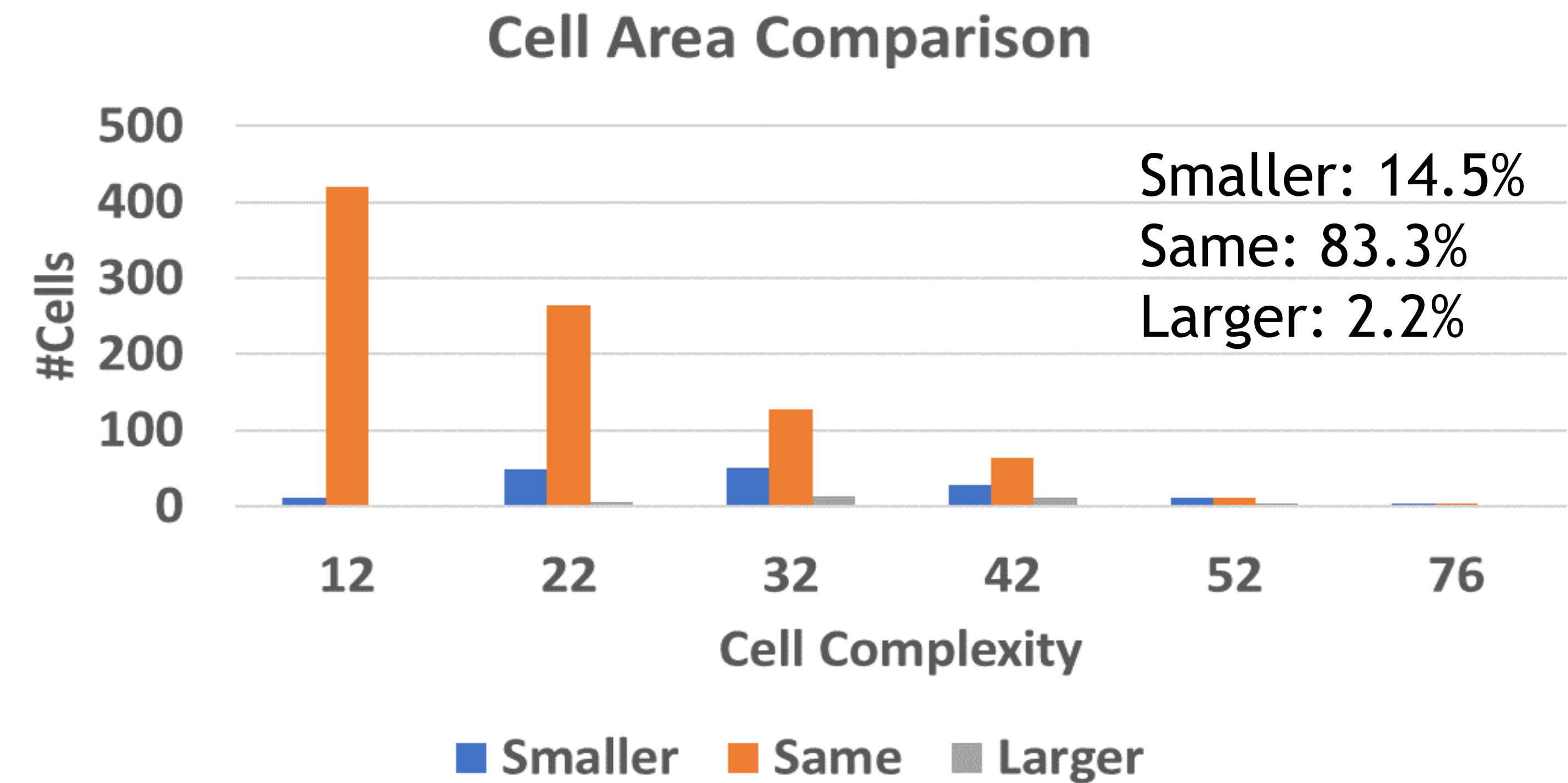
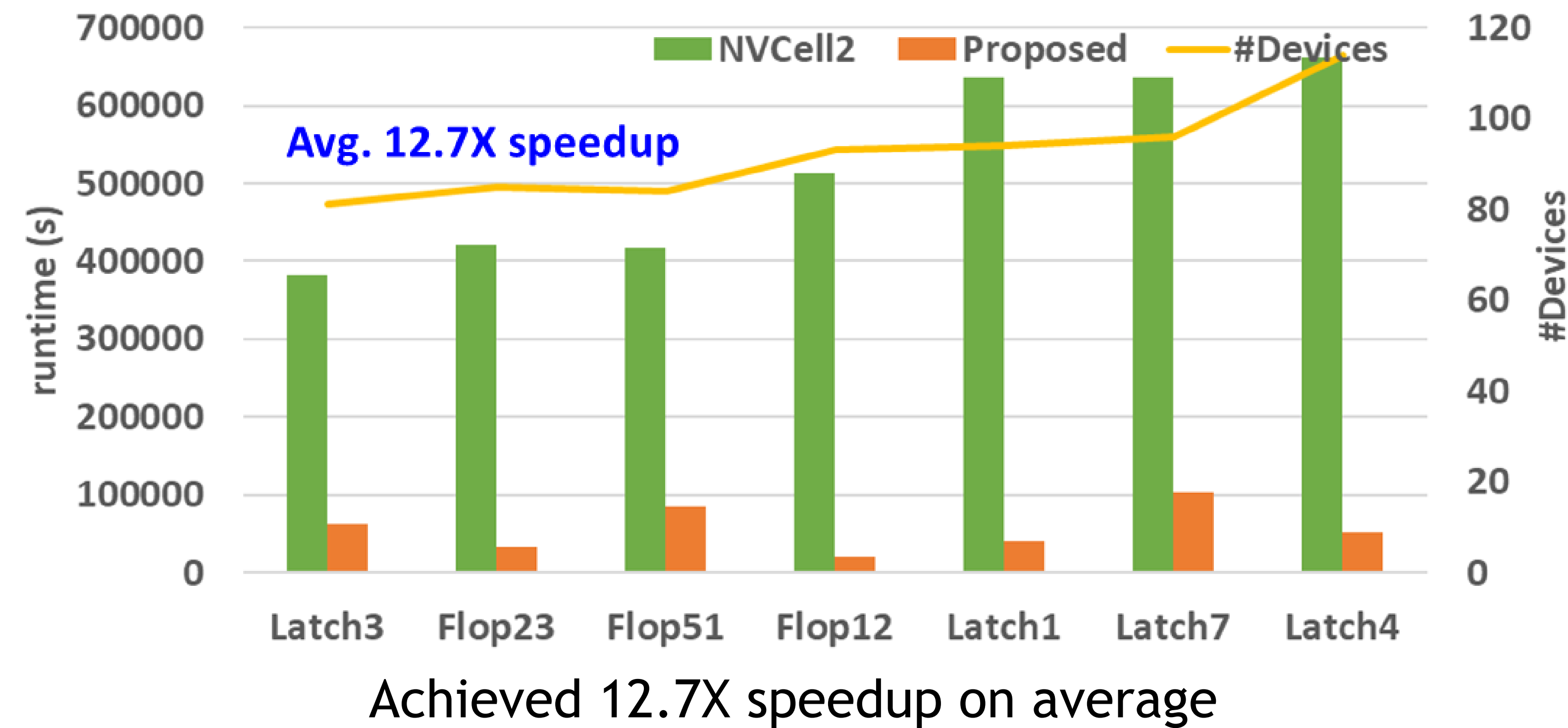
(a) Proposed



(b) PPR with Pred. Preference + GINE



# RESULTS of 5nm



	Success Rate (%)	Cell Width Comparison		
		Smaller	Same	Larger
NVCell (DAC 2021)	0%	N/A	N/A	N/A
NVCell2 (ISPD 2023)	87.2%	22.3%	37.2%	27.7%
Proposed	100%	29.8%	58.5%	11.7%

On a difficult routing benchmark (94 cells)

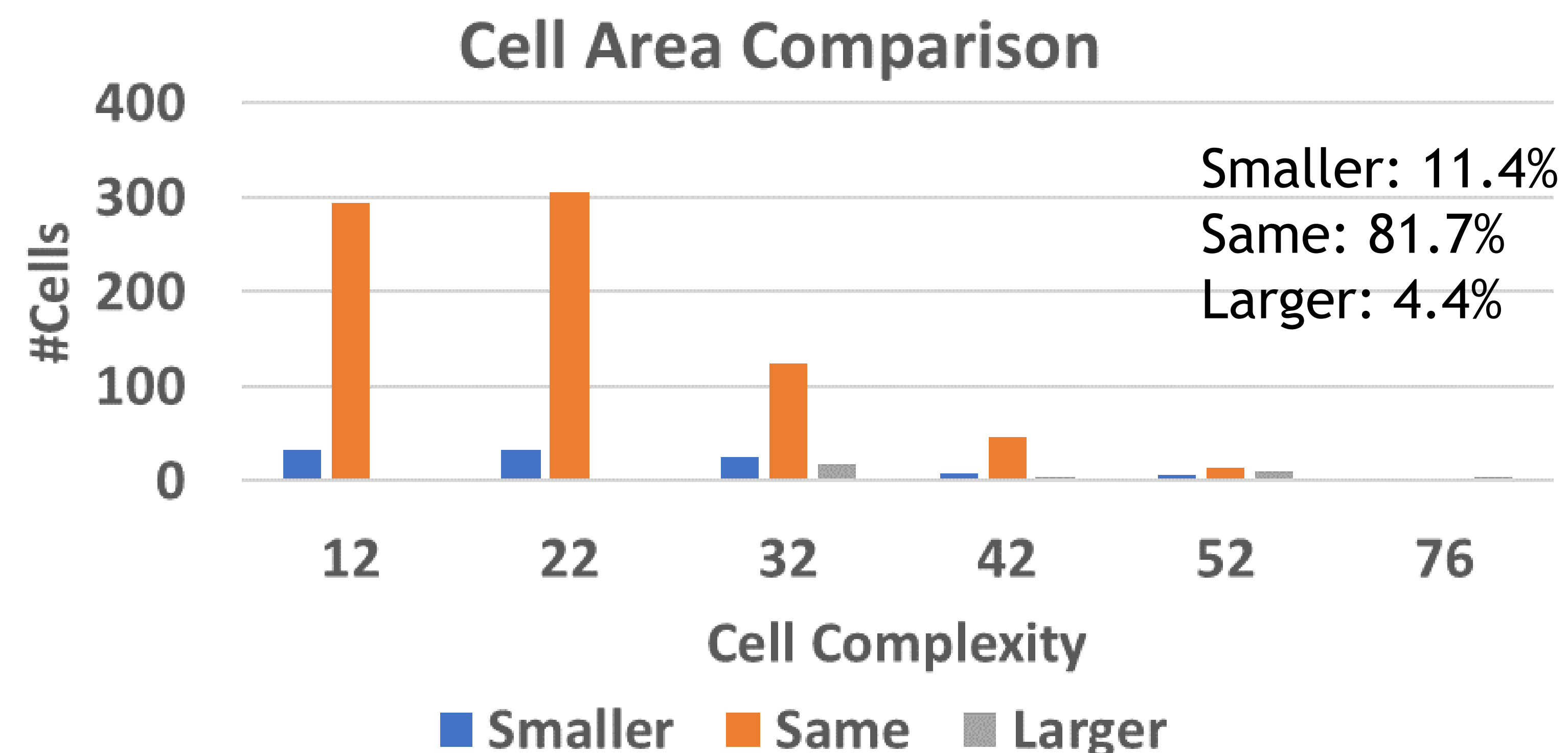
	Success Rate (%)	Cell Width Comparison		
		Smaller	Same	Larger
NVCell (DAC 2021)	91.2%	11.8%	77.6%	1.8%
NVCell2 (ISPD 2023)	98.8%	13.7%	80.1%	4.3%
Proposed	100%	14.5%	83.3%	2.2%

On entire cell library (1078 Cells)

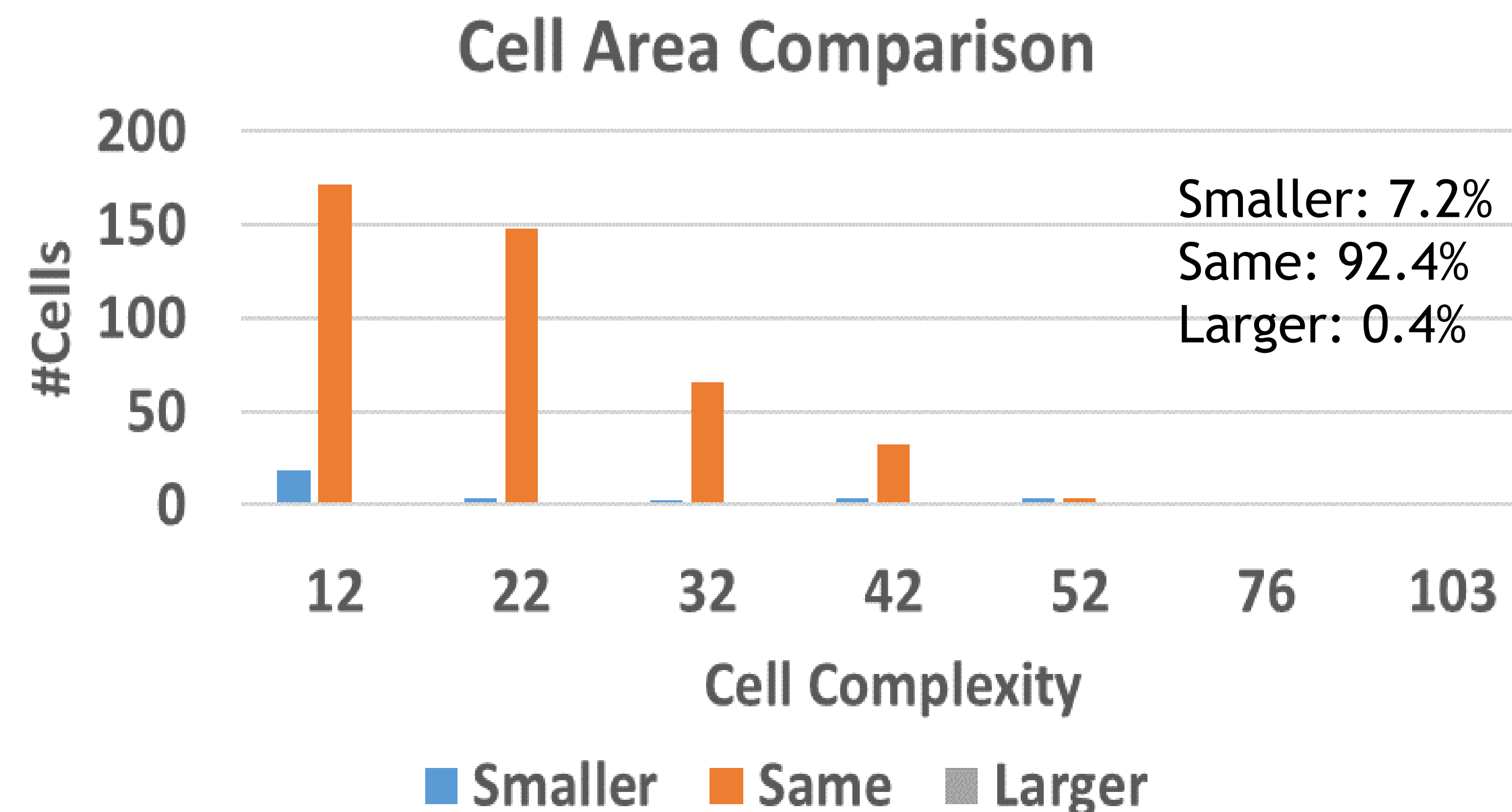
# RESULTS of 3nm

Without Retraining Model

### 5 Routing Tracks Cell Architecture (938 Cells)



### 4 Routing Tracks Cell Architecture (458 Cells)



	Success Rate (%)	Cell Width Comparison		
		Smaller	Same	Larger
Proposed	100%	11.4%	81.7%	4.4%

Total Cell: 938 Cells

	Success Rate (%)	Cell Width Comparison		
		Smaller	Same	Larger
Proposed	100%	7.2%	92.4%	0.4%

Total Cell: 458



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# CONCLUSIONS

- Proposed Novel Transformer Model Based Clustering Method successfully improves the success rate, performance, and area
  - 100% success rate for 5nm
  - 14.5% smaller cell width + 83.3% same cell width
  - Avg. 12.7X speedup on cells with > 80 devices than previous work
- Transferable to different technology nodes
- Competitive PPA result: Power impr. up to 12%, Delay impr. up to 8%, and Area impr. up to 14.29%
- Future works:
  - PPA-driven standard cell layout automation
  - Cluster constraint debugging and optimization for PPA

