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北京大学高能效计算与应用中心
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Layout Symmetry Annotation for Analog Circuits with Graph Neural Networks

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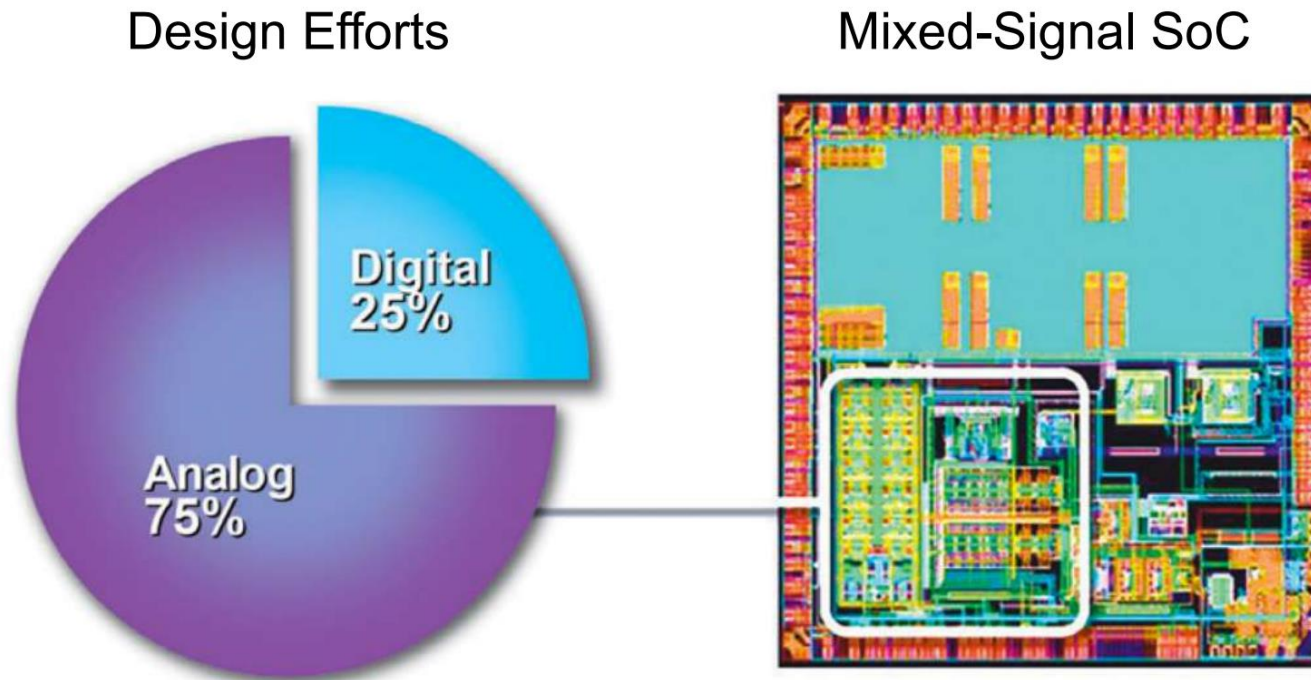
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Outline

- Introduction and Problem Formulation
- SymDetect: Our Proposed Framework
- Experimental Results
- Conclusions and Future Work

Analog Layout Automation

- Analog/mixed signal IC design still relies heavily on manual design

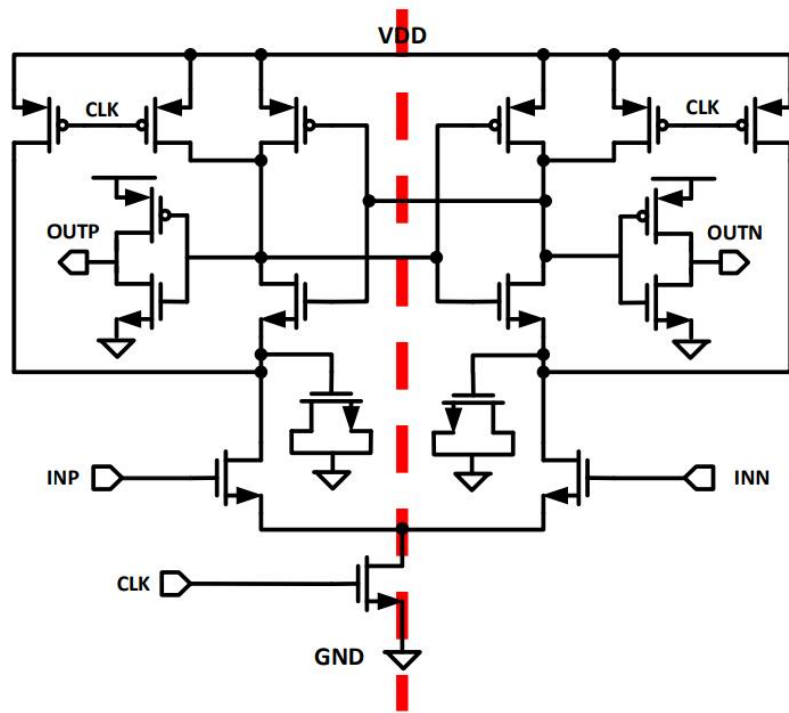


- Automatic constraint annotation is a critical step to existing analog layout automation tools, such as ALIGN [DAC'19, Kunal+], MAGICAL [ICCAD'19, Xu+]

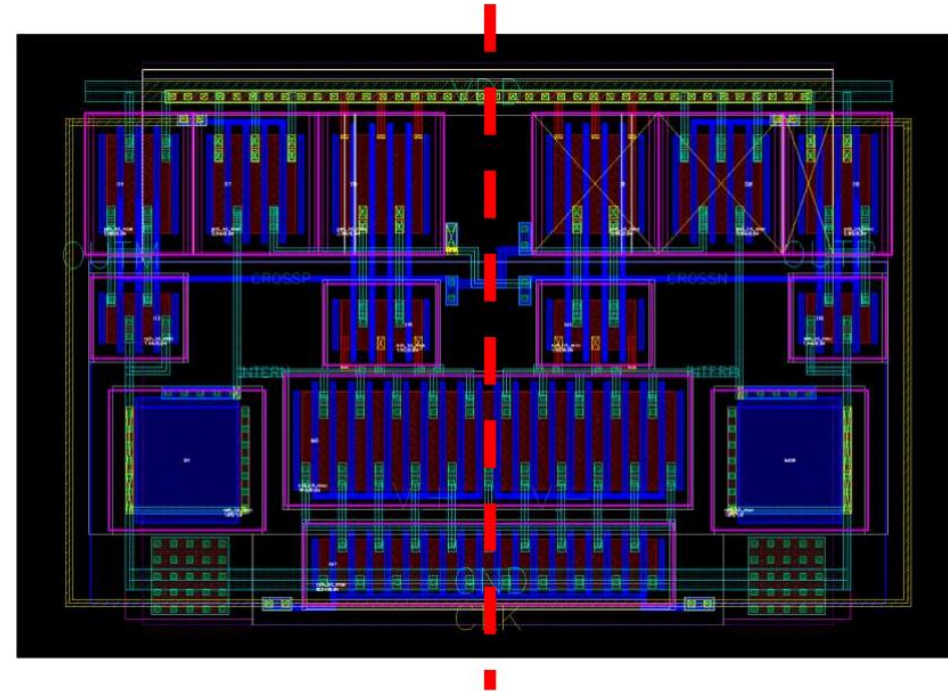
Symmetry Constraint Annotation

➤ Symmetry Constraint

- Symmetry constraint is one of the substantial and representative constraints for layout design



Comparator Schematic



Comparator Layout

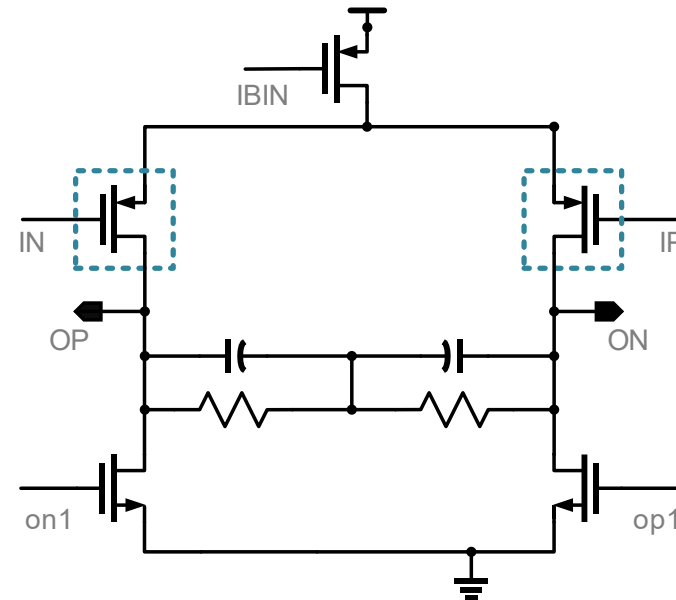
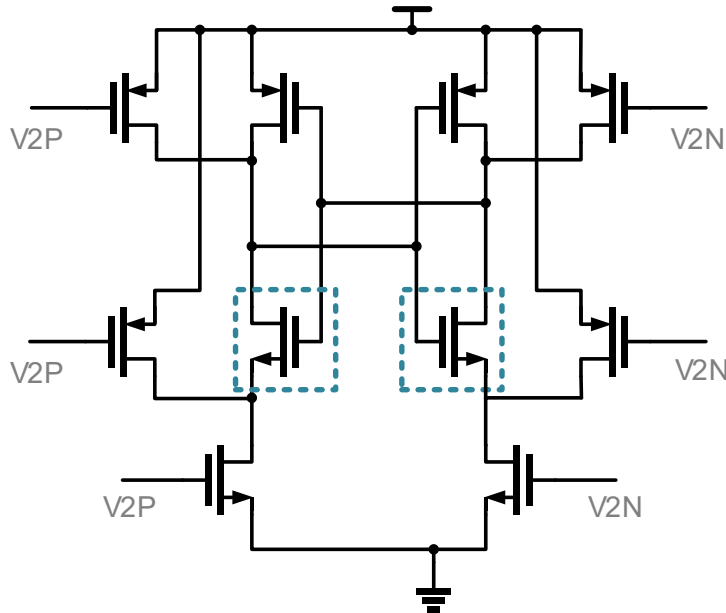
Prior Works and Challenges

- Categorized into two major types
 - Circuit analysis
 - Graph matching
- Circuit analysis
 - Traditional circuit analysis [ICCAD'93, Charbon+]
- Graph matching
 - Analog constraints extraction based on the signal flow analysis [ASICON'05, Zhou+]
 - S3DET: detecting symmetry constraint by [ASPDAC'11, Liu+]

Prior Works and Challenges

Challenges

- The performance highly-correlated to empirical parameters
- The surrounding structures of symmetry constraints varies considerably
- No incorporation of designer expertise



Graph Neural Networks (GNNs)

■ Graph Neural Networks

- Graph neural networks are powerful in modeling implicit features of graph structure data
- Analog circuits → hypergraphs

■ Transductive and inductive settings

- Transductive

GCN [ICLR'17, Kipf+]

- Inductive

GraphSage [NeurIPS'17, Hamilton+]

- Transductive and inductive

GAT [ICLR'18, Velickovic+]

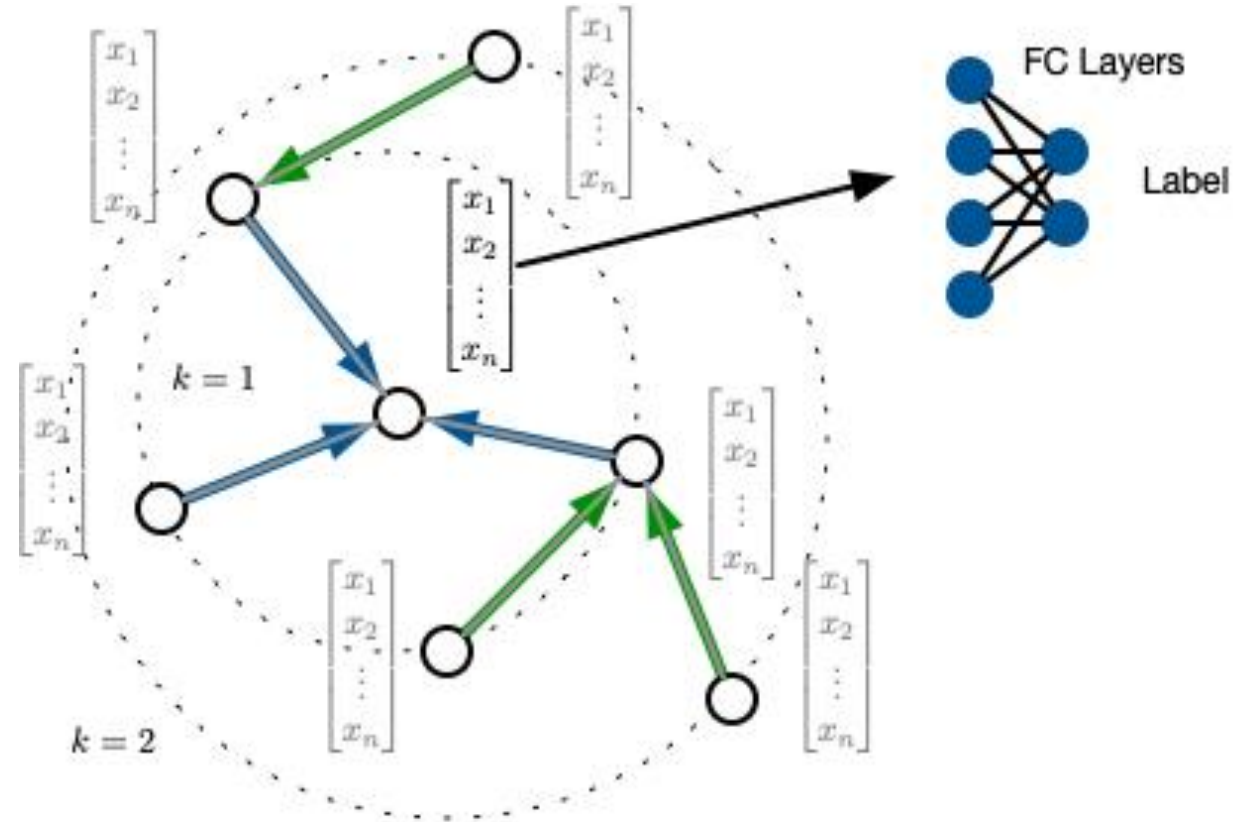
GNNs: Node Embedding

Node Embedding

- Map each node in a graph into a low-dimensional space
- Capture the insight from local graph structure and node features

Sample and aggregation scheme

- Compute node embeddings by sampling neighbor nodes and aggregating their embeddings



Problem Formulation

Input

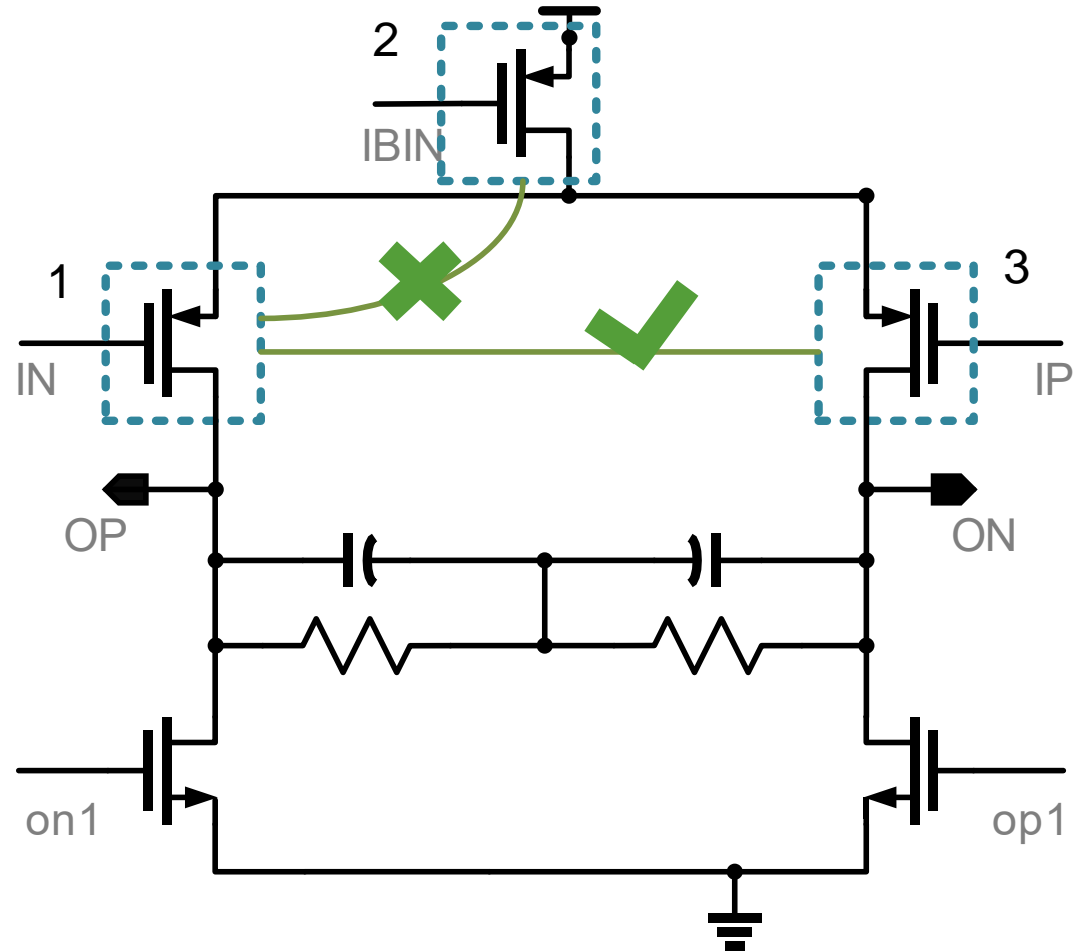
- netlist
- labeled symmetry pairs

Output

- For a new circuit
to predict symmetry pairs

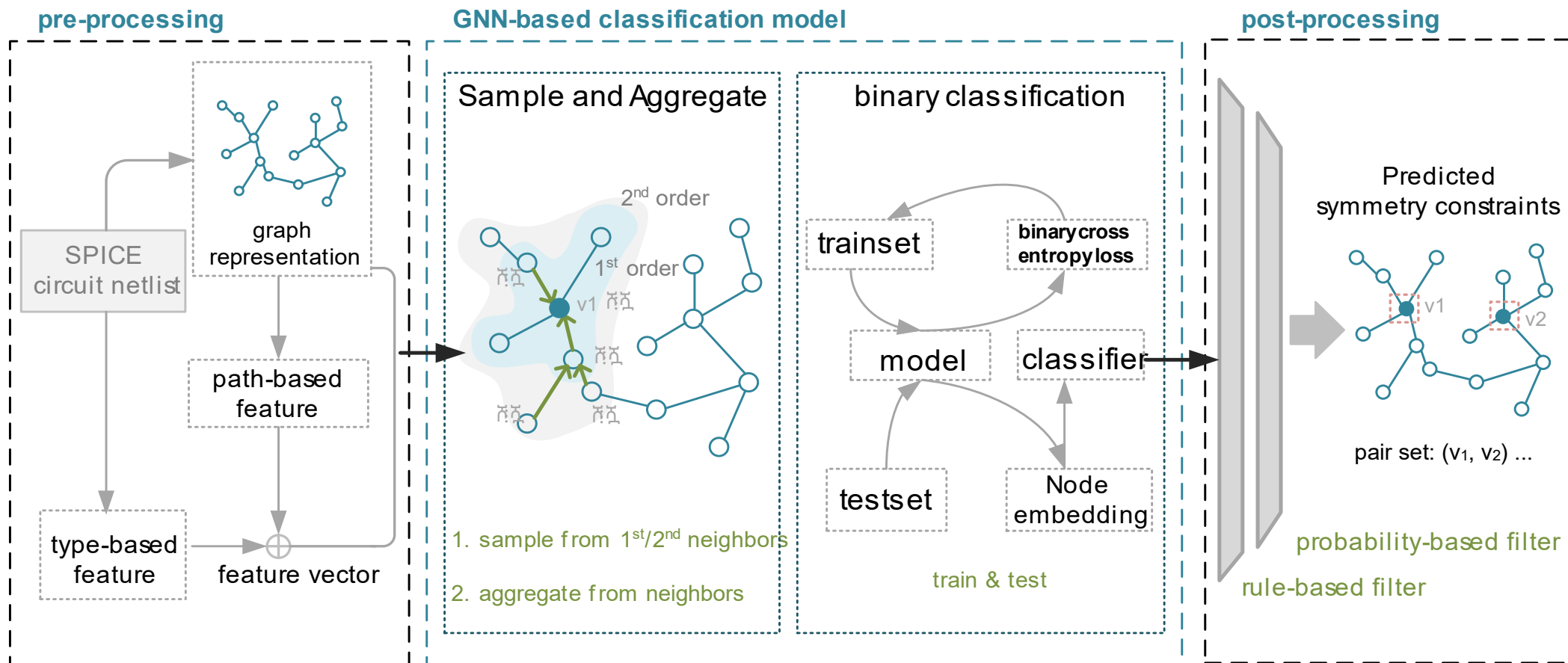
Objective

- to build a model with:
maximum annotation accuracy



SymDetect: Overall Flow

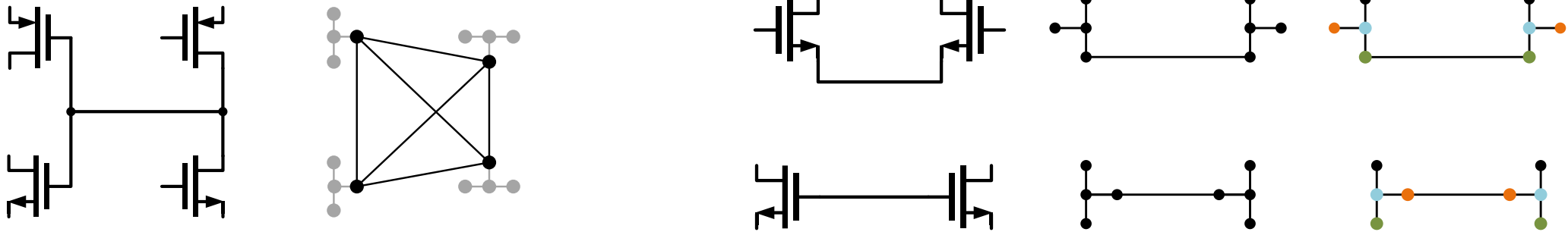
Overall Flow of SymDetect



SymDetect: Graph Representation

Graph Representation

- Both **device instances** and **device pins** are recognized as **graph nodes**
- Edges connecting pin nodes with their corresponding device nodes
- The pin nodes form a clique if sharing the same net



SymDetect: Feature Extraction

Feature extraction

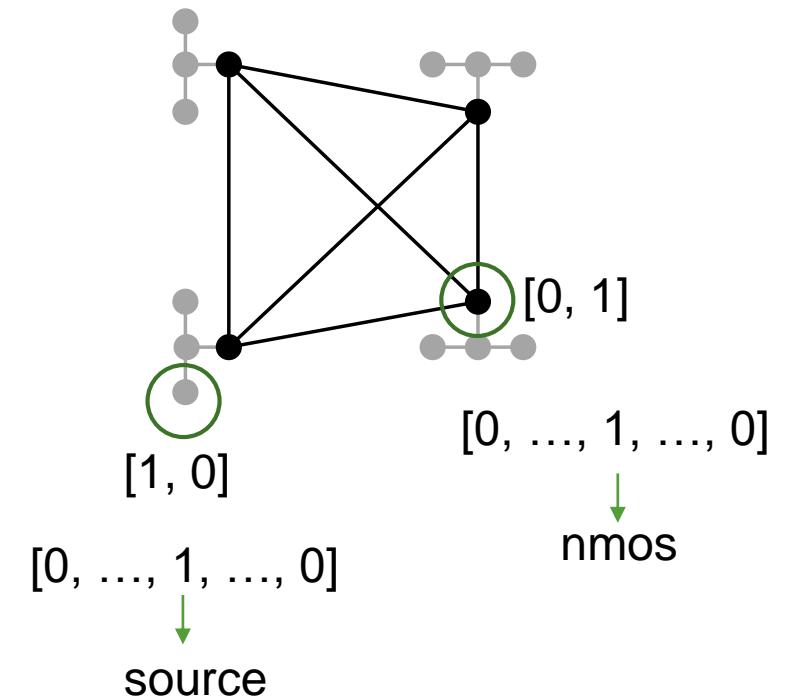
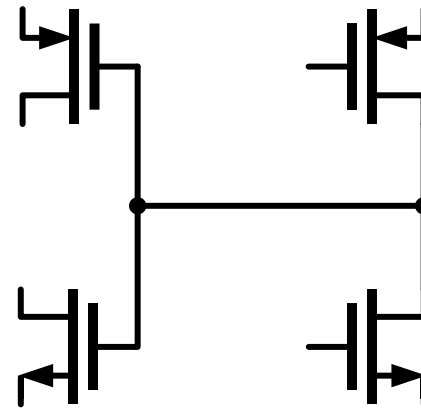
- Type-based feature
- Path-based feature

Type-based feature

- Type information as part of node feature
- A 2-dimension vector to indicate whether a node is a device or a pin
[0, 1] for a device, [1, 0] for a pin
- A 13-dimension **one-hot vector**

device types: capacitor, resistor, diode, NMOS, PMOS, IO

pin types: source, drain, gate, substrate, passive, cathode of a diode, anode of a diode



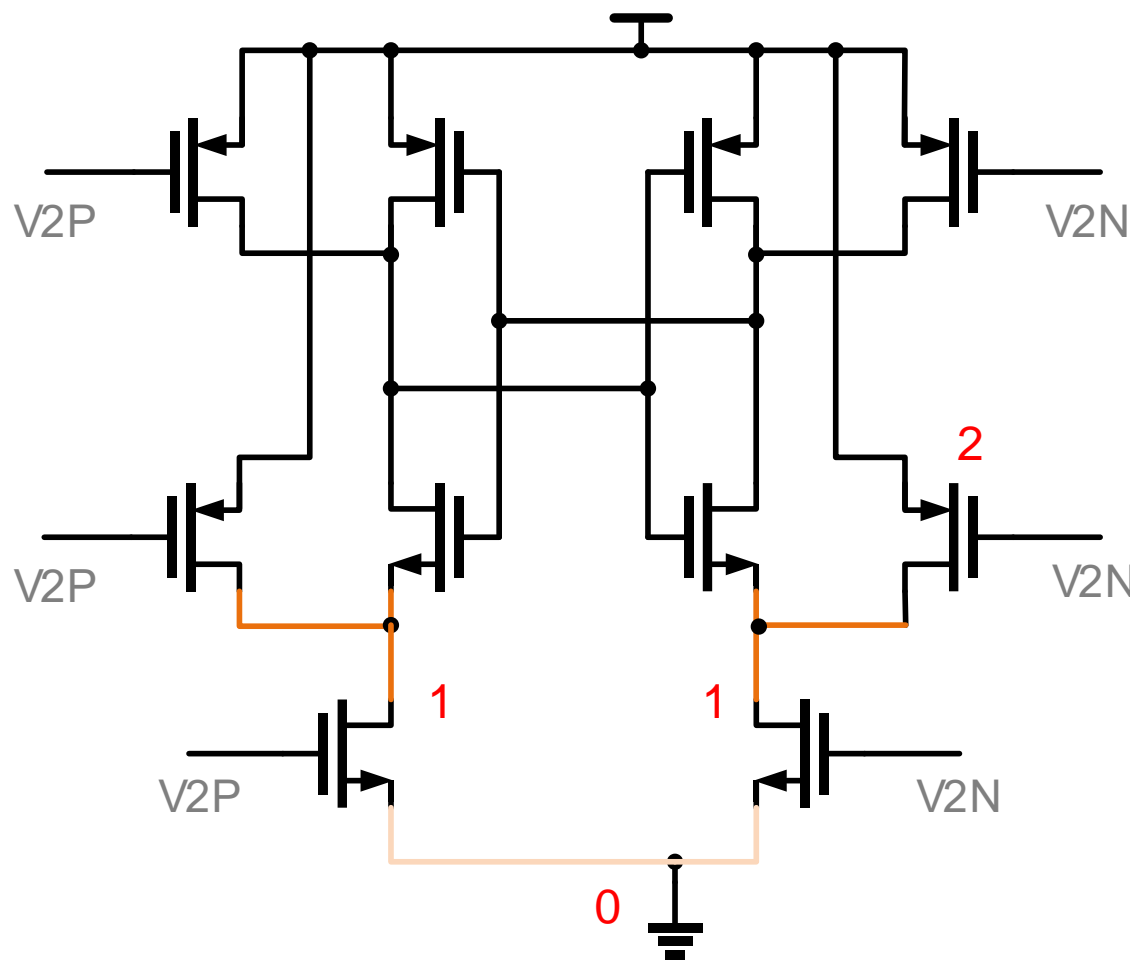
SymDetect: Feature Extraction

Feature Extraction

- Type-based feature
- Path-based feature

Path-based feature

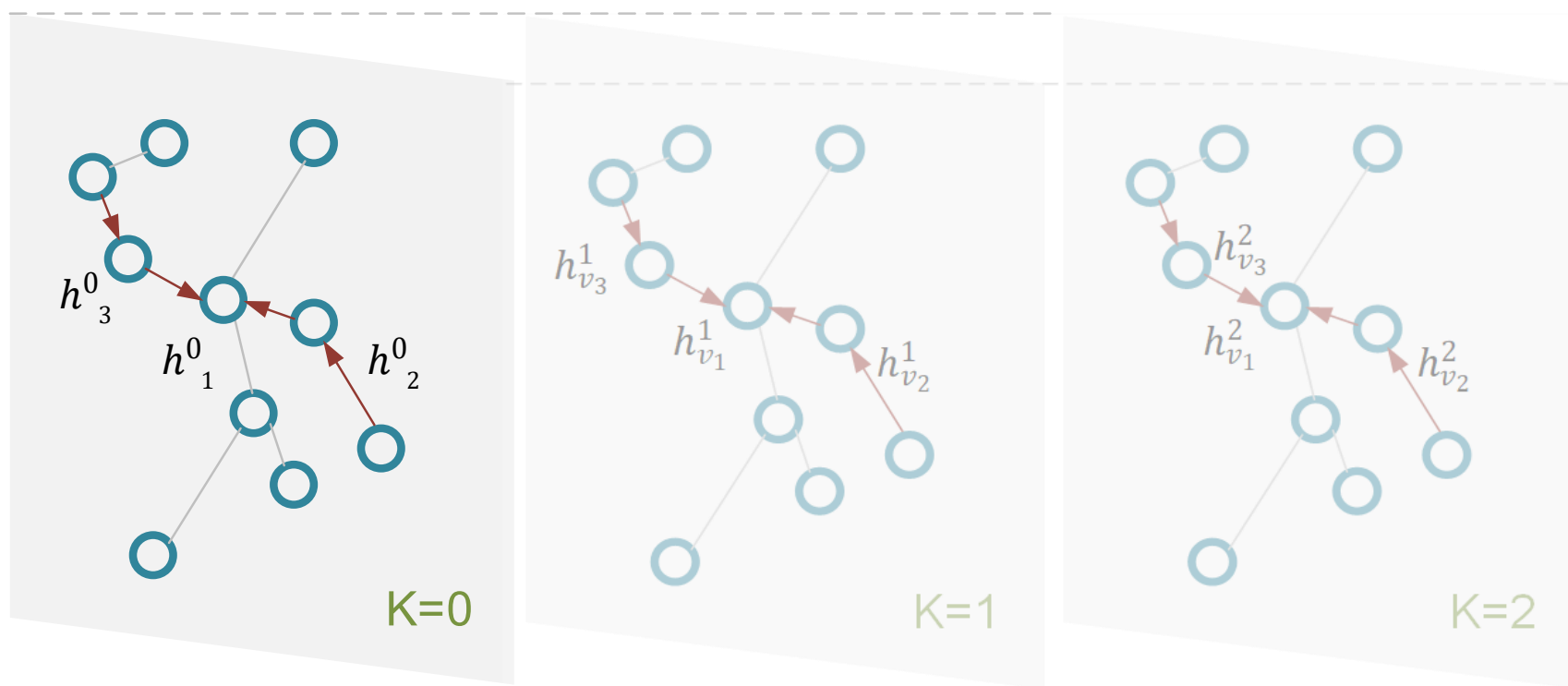
- Characterize the global position of each node by computing the length of VSS/GND-sourced paths



SymDetect: Sample and Aggregate Model

► Sage

- Sample from neighborhood

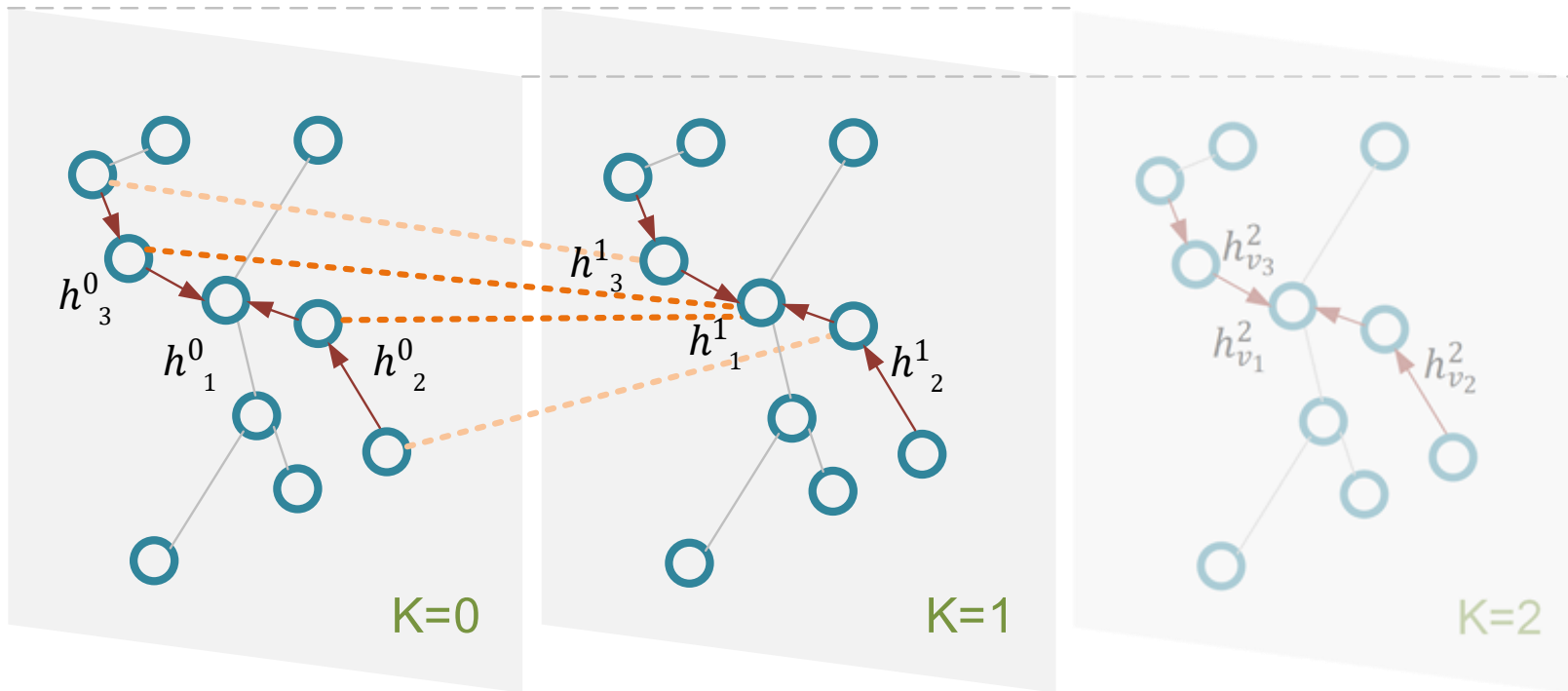


SymDetect: Sample and Aggregate Model

➤ Sage

- Aggregate by aggregator function

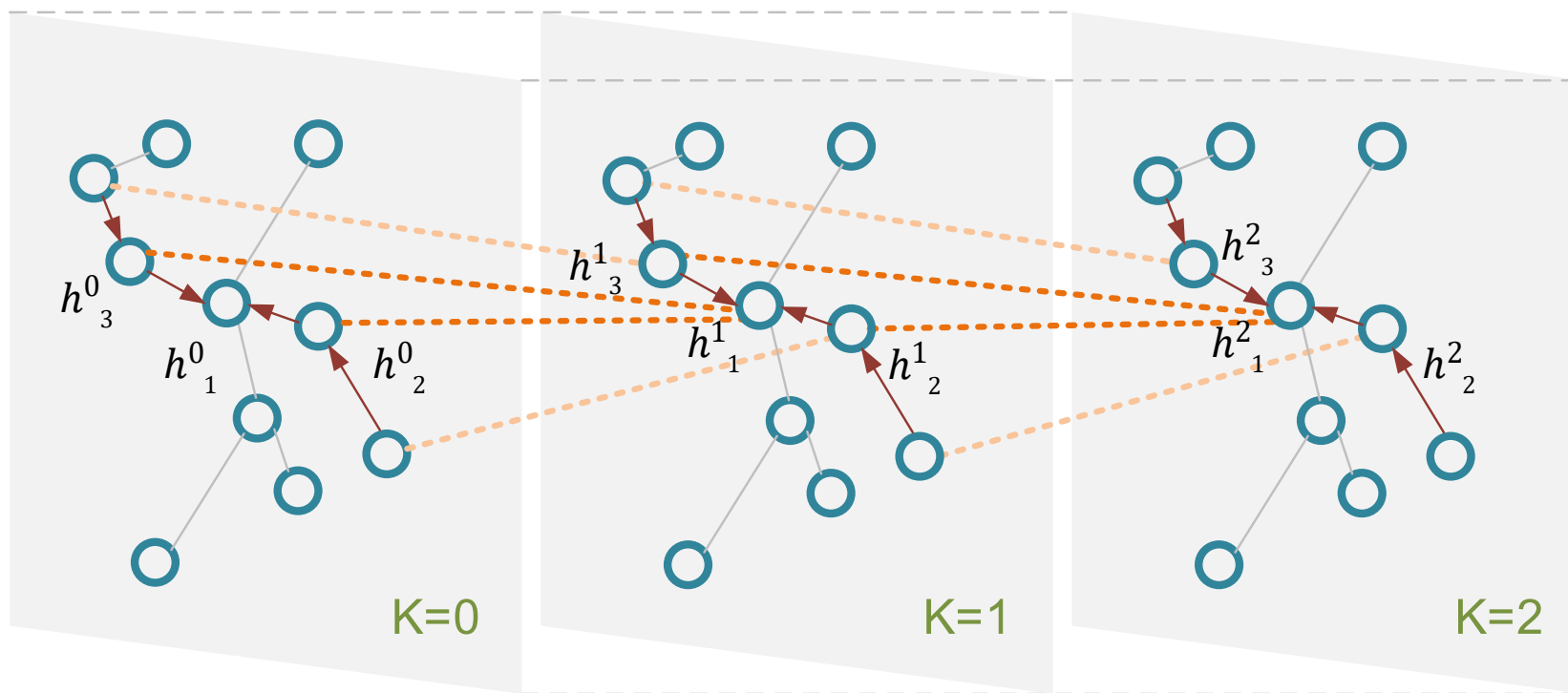
- $$h_v^k = \sigma(W \cdot \{h_v^{\{k-1\}} \oplus \text{MEAN}(h_u^{\{k-1\}}, \forall u \in N(v))\})$$



SymDetect: Sample and Aggregate Model

► Sage

- Take aggregation depth $K=2$



SymDetect: Binary Classification

► Binary Classification

- We designate a **label** y for each node pair (v_1, v_2)
1 for symmetric, 0 for non-symmetric
- We calculate the probability of label $y = 1$ by **bilinear scoring function**:

$$prob = \sigma(z_1^T W z_2)$$

where $\sigma(\cdot)$ is an activation function, z_1 and z_2 are node embeddings

- We apply binary **cross entropy loss** to train our GNN model:

$$loss = -\frac{1}{N} \sum_{i=1}^N y_i \cdot \log(prob_i) + (1 - y_i) \cdot \log(1 - prob_i)$$

SymDetect: Post Processing

➤ Post Processing

- To reduce false alarms

➤ Rule-based filter

- The **sizes and types** of two symmetric nodes are supposed to be identical

➤ Probability-based filter

- A device node appears in no more than one symmetry pair
- The filter sorts all candidate pairs by predicted probabilities
- Pick the pair with **higher probability**

Experimental Setup

► Baseline methods

- S³DET [ASPDAC'20, Liu+]
- signal flow analysis (SFA) [ICCAD'19, Xu+]

► Dataset statistics

Datasets	Circuits	Nodes	Edges	Valid pairs	Pos/Neg
S ³ -leaf	10	1378	9149	1522	89/1433
ALIGN-leaf	5	580	2134	576	48/528
OTA	5	684	3422	750	45/705

Experimental Setup

► Evaluation metric

- We adopt: *true positive rate*(TPR), *false positive rate*(FPR), and *F1-score* and *ROC*

- $TPR = \frac{TP}{P}$

- $FPR = \frac{FP}{N}$

- $F1 - score = \frac{2TP}{2TP+FN+FP}$

- *ROC* plots the TPR against the FPR

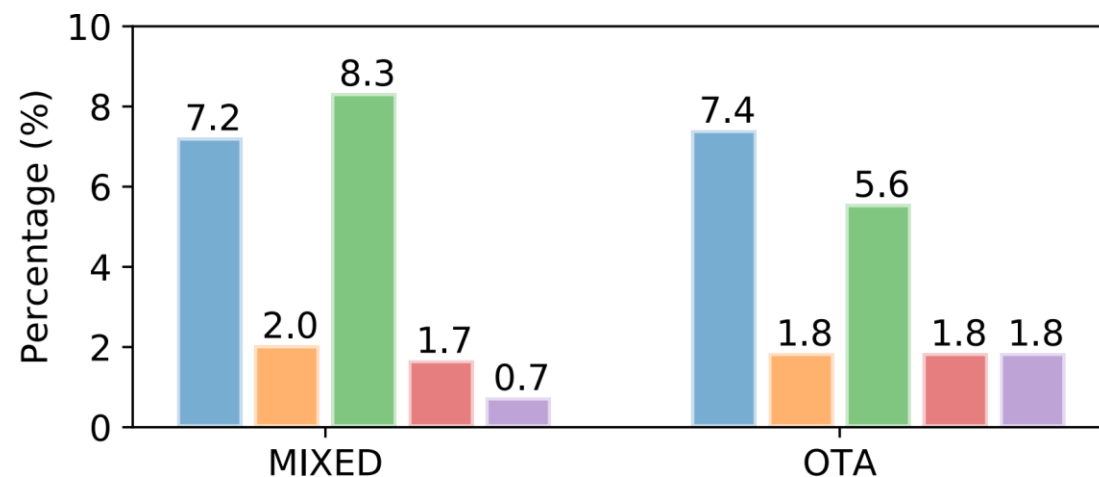
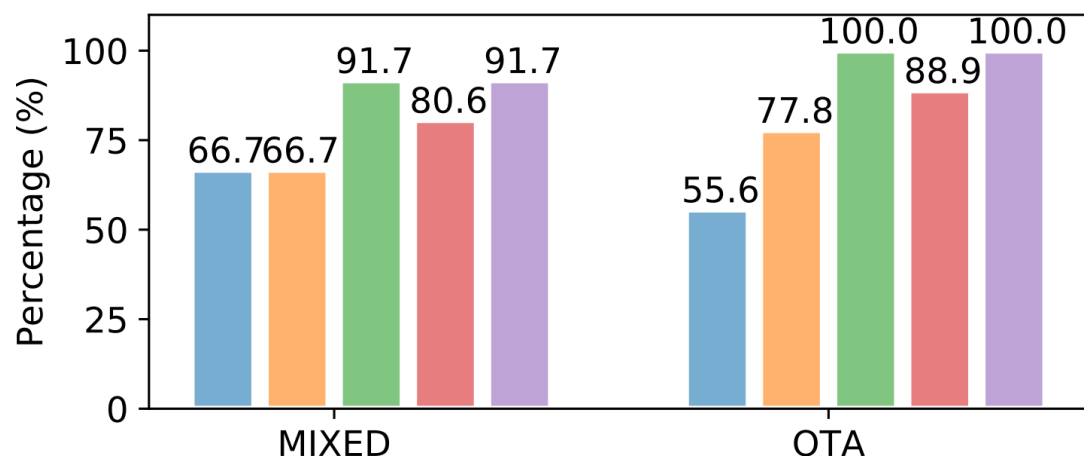
true\predicted	positive	negative
positive	TP	FN
negative	FP	TN

confusion matrix

Experimental Results

Experimental Results

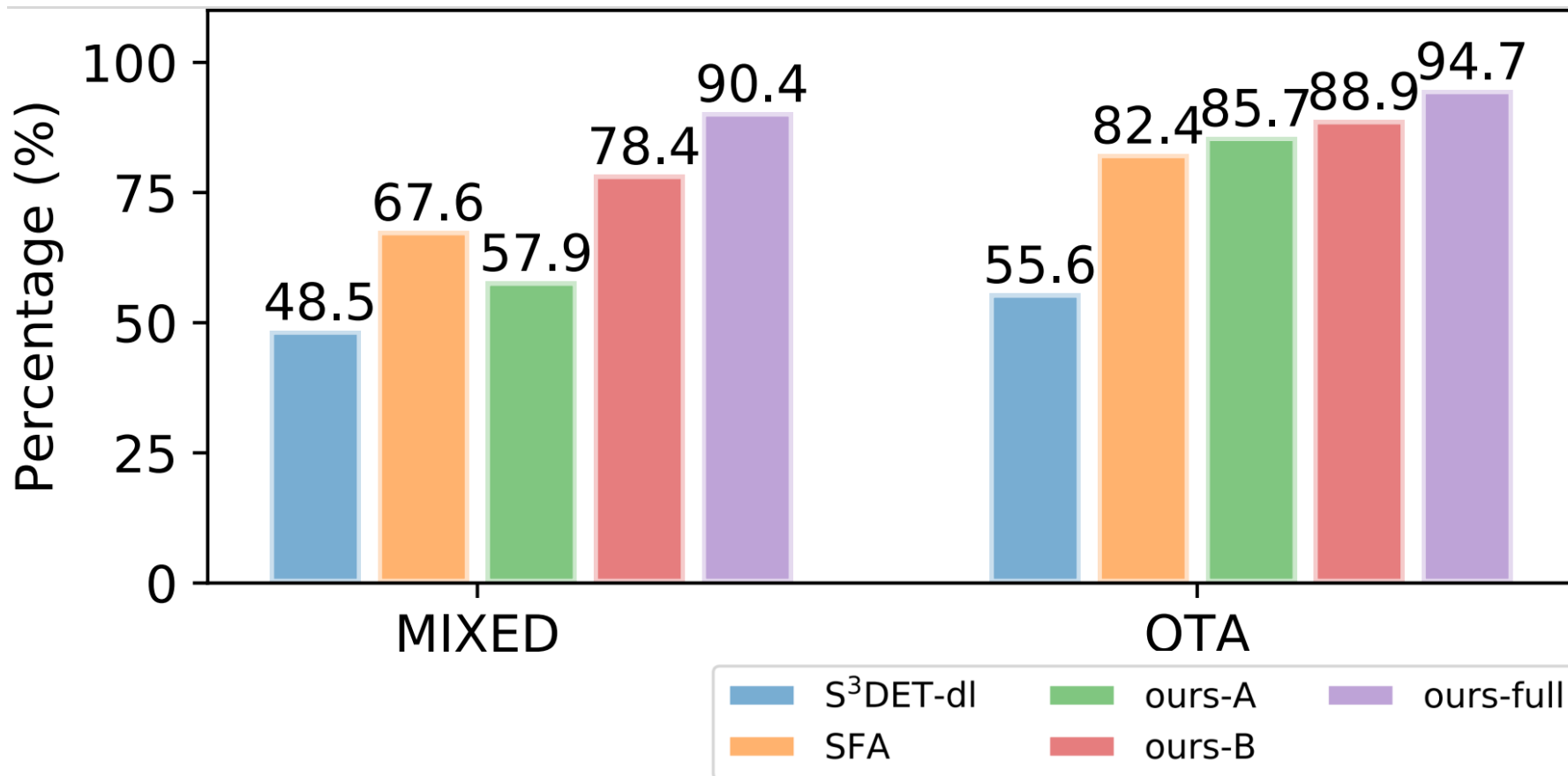
— TPR and FPR:



Experimental Results

Experimental Results

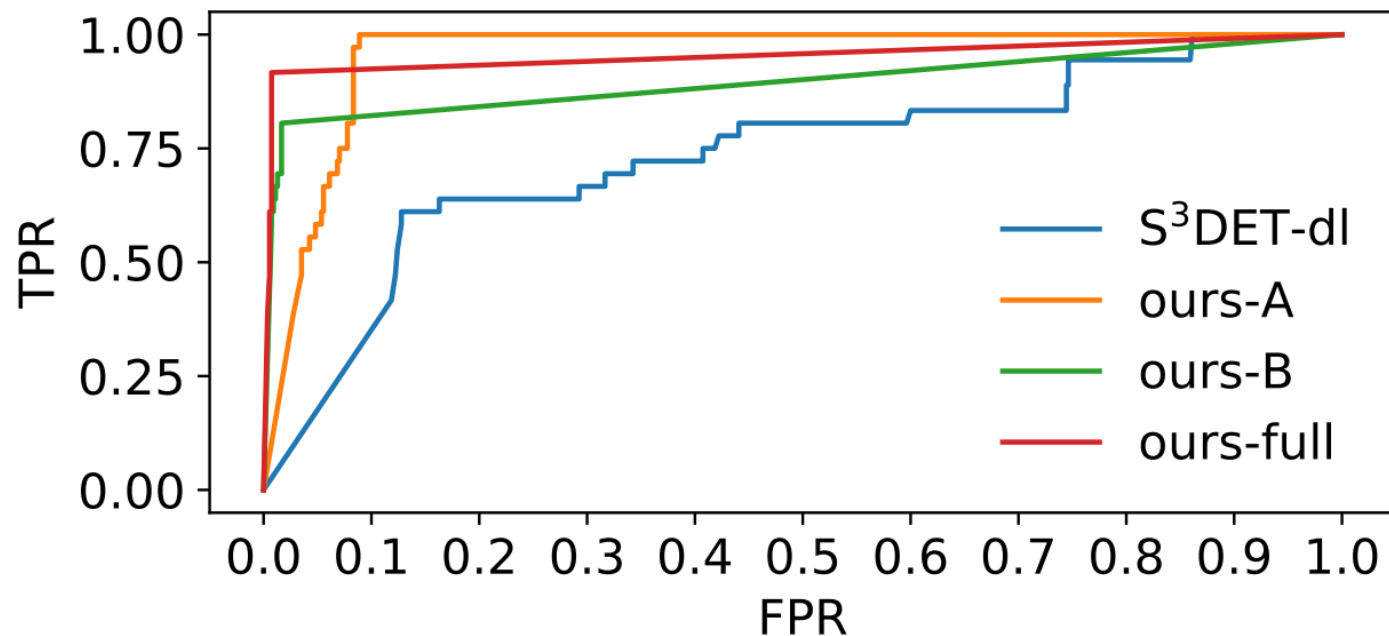
— F1-score:



Experimental Results

Experimental Results

— ROC:



— Runtime:

- The one-shot training time costs less than 2 minutes
- The inference time per circuit (about 0.1s) is comparable to the other two approaches

Conclusions and Future Work

➤ Conclusions

- A **graph learning based** framework for layout symmetry annotation in analog circuits
- Node feature extraction from **both local information** (device/pin type) and **global graph structure** (path length from VSS/GND)
- A training technique to learn the node similarity from the **imbalanced data**
- The proposed approach **outperforms** previous symmetry annotation

➤ Future work

- Extend our GNN-based approach to **system symmetry constraint**
- We can also include **other constraints** such as matching constraint or shielding constraint



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Thanks!
Questions are welcome

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