

# Deep Learning-Driven Simultaneous Layout Decomposition and Mask Optimization

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# Outline

Introduction

Algorithm

Experimental Results

Conclusion



# Outline

Introduction

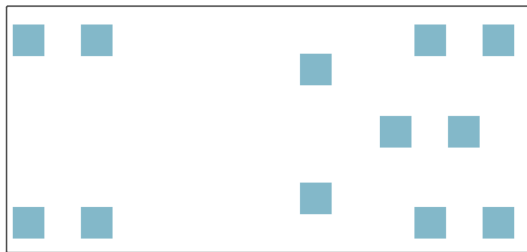
Algorithm

Experimental Results

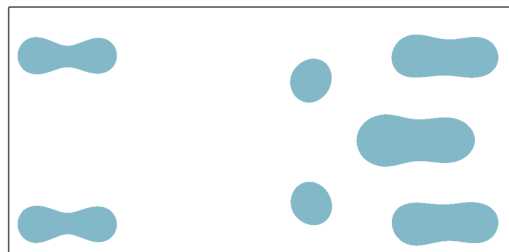
Conclusion



# Optical Proximity Effect



Target



Result

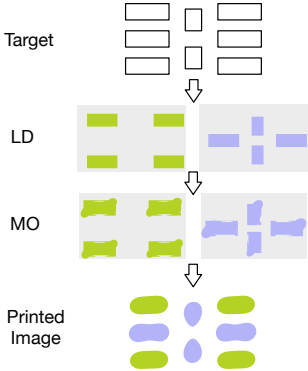
► Resolution enhancement Technologies (RETs):

- OPC
- MPL

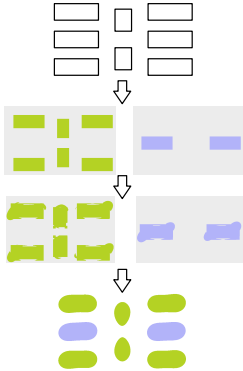


# Layout Decomposition for Mask Optimization

- ▶ Different decomposition results converge to divergent printability



#EPE Violation = 3

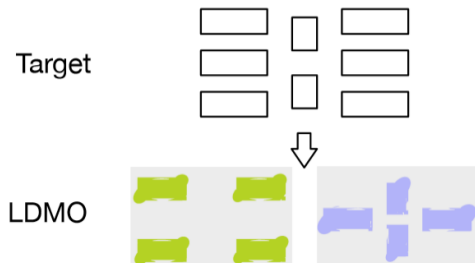
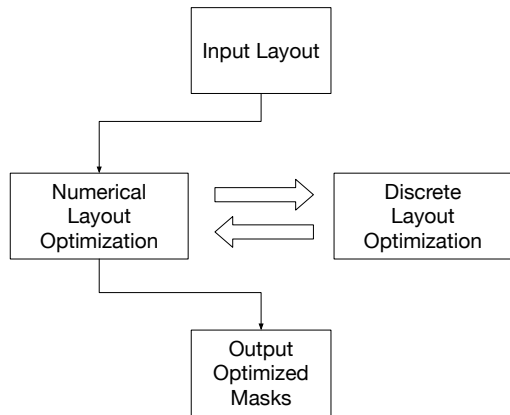


#EPE Violation = 1



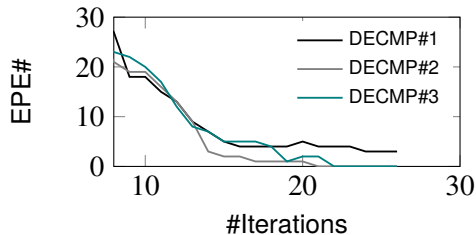
# Option for Decomposition Selection

- **Solution:** Collaboration of LD and MO in a unified framework [Ma+,ICCAD'17].

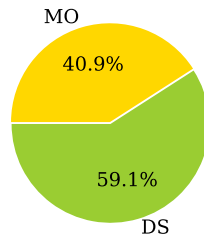


# Issues

- ▶ **Not Accurate:** Greedy pruning.
- ▶ **Not Efficient:** OPC suffers from large computational complexity.



Decomposition convergence of EPE



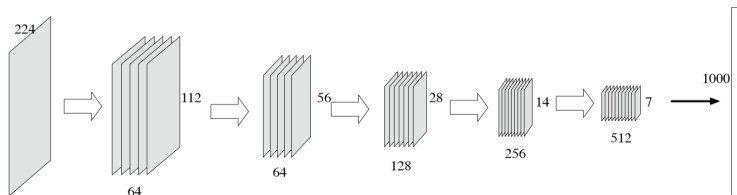
Runtime break down





# Motivation

- ▶ Powerful convolutional neural network (CNN)
  - Build mapping relationship automatically.
  - Large amount of data required.



- ▶ CNN application in EDA field:
  - Routing predicting [Xie+, ICCAD'18]
  - Hotspot detection [Yang+, TCAD'18]
  - Resist modeling [Lin+, TCAD'18]
- ▶ How about integrating CNN for decomposition selection?



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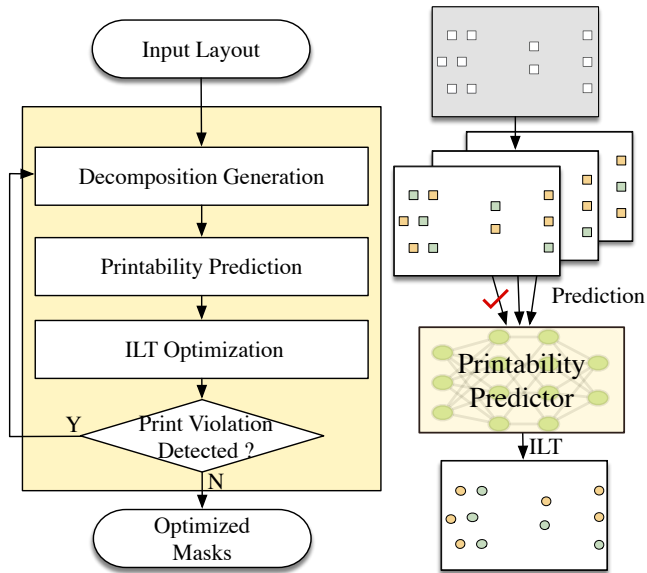
**Algorithm**

Experimental Results

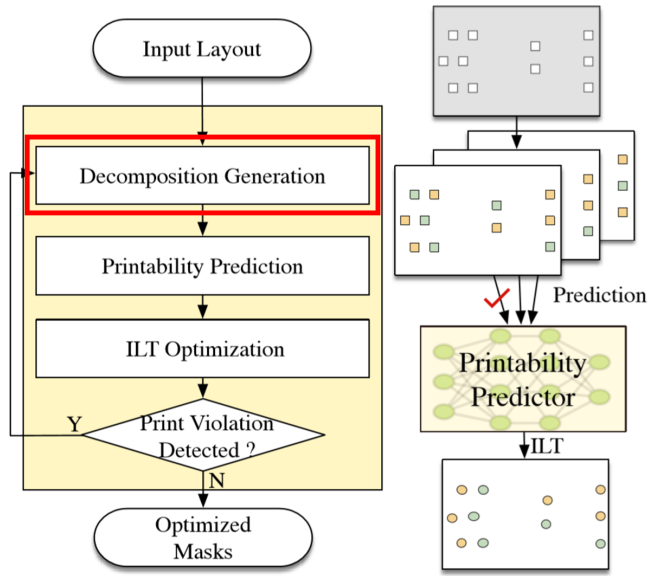
Conclusion



# Forward Optimization Flow



# Decomposition Generation

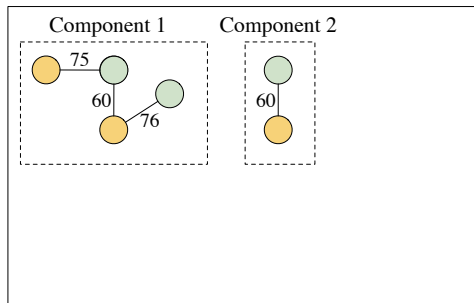
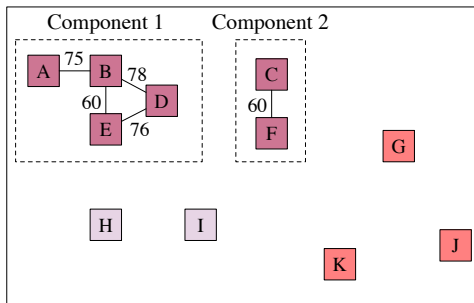


# Decomposition Generation

- Classify patterns & build minimal spanning tree

$$\mathcal{E} \in \begin{cases} \mathcal{S}_P, & \text{if } d \leq n_{min}, \\ \mathcal{V}_P, & \text{if } n_{min} < d \leq n_{max}, \\ \mathcal{N}_P, & \text{if } n_{max} < d. \end{cases}$$

■  $\mathcal{S}_P$  ■  $\mathcal{N}_P$  ■  $\mathcal{V}_P$

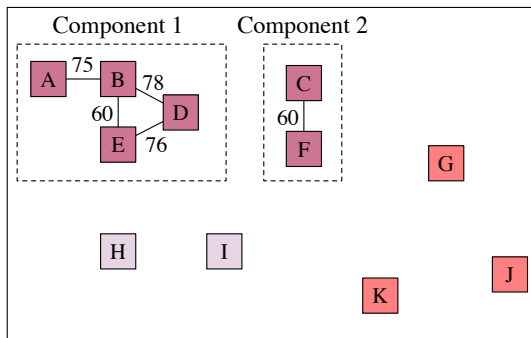


# Decomposition Generation

## ► n-wise arrays

- $\mathcal{S}_P$  and  $\mathcal{V}_P$  with three-wise
- $\mathcal{N}_P$  with two-wise

■  $\mathcal{S}_P$ 
■  $\mathcal{N}_P$ 
■  $\mathcal{V}_P$



<i>Arrs1</i>	$\mathcal{S}_P$		$\mathcal{V}_P$		<i>Arrs2</i>	$\mathcal{N}_P$		
	B	F	H	I		G	J	K
#1	1	0	0	1	#1	0	1	0
#2	1	1	1	1	#2	0	0	1
#3	0	0	1	1	#3	1	1	1
#4	0	0	0	0	#4	1	0	0
#5	0	1	1	0				
#6	1	1	0	0				
#7	1	0	1	0				
#8	0	1	0	1				



# Decomposition Generation

## ► n-wise arrays

- Relax combination strength
- Complete combination of  $n$  factors

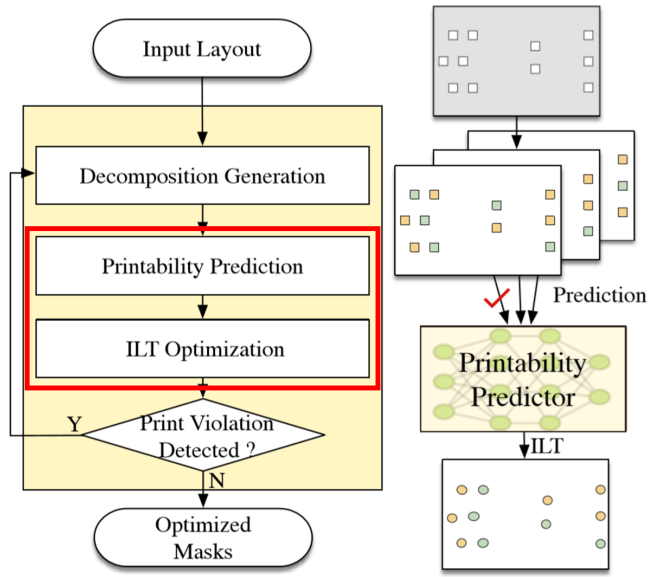
	factor1	factor2	factor3	factor4
#1	1	0	0	1
#2	1	1	1	1
#3	0	0	1	1
#4	0	0	0	0
#5	0	1	1	0
#6	1	1	0	0
#7	1	0	1	0
#8	0	1	0	1

Any **three** columns contain complete combination from 000 to 111

Three-wise arrays



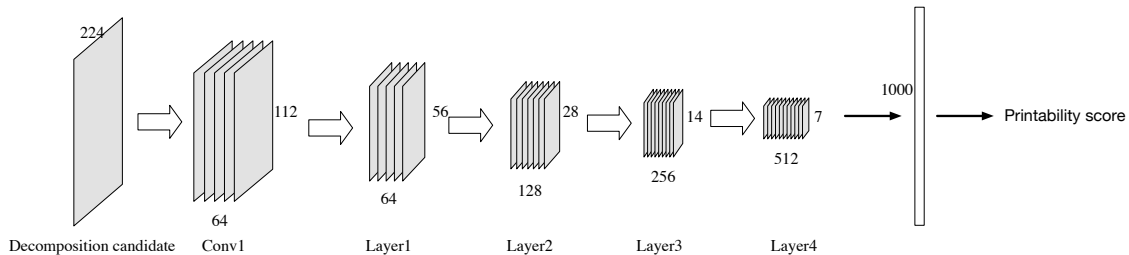
# Printability Prediction & Mask Optimization





# Printability Prediction & Mask Optimization

- ▶ Select the best decomposition candidate for OPC engine

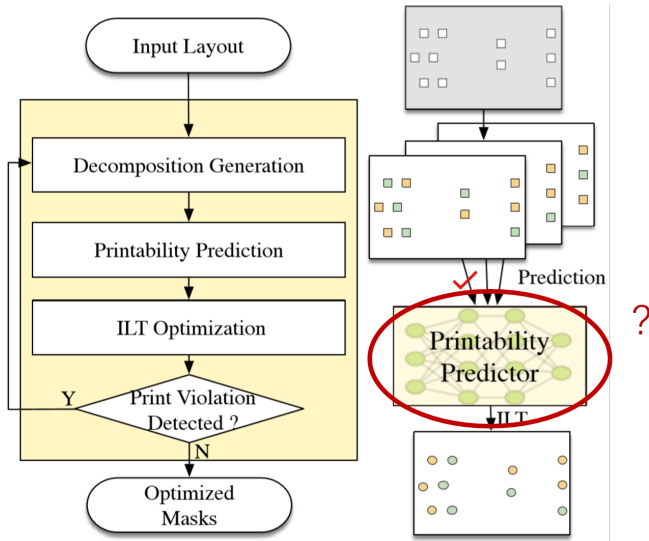


$$\text{Printability score} = \alpha \times \#EPE + \beta \times \text{L2 Error} + \gamma \times \#Print \text{ Violation}$$



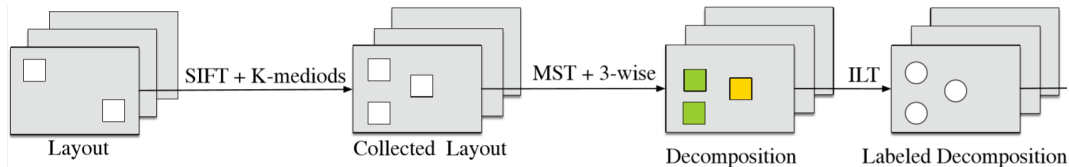
# How to Sample Data?

- ▶ Sample typical data for train



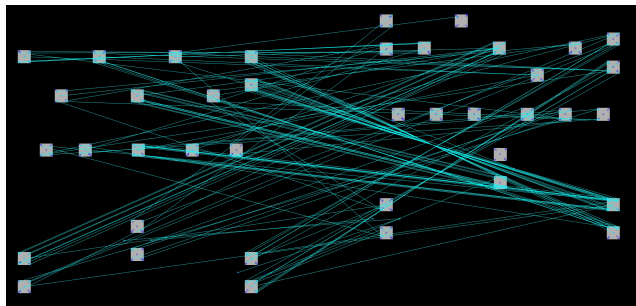
# How to Sample Data?

- ▶ Layout sampling
- ▶ Decomposition sampling
  - Similar to decomposition generation stage
- ▶ Get printability score



# Layout Sampling

- ▶ Calculate point distance
  - Match points
  - Euclidean distance as matched points distance
- ▶ Calculate layout distance
  - Sum up matched points as layout distance
- ▶ Cluster layouts



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Algorithm

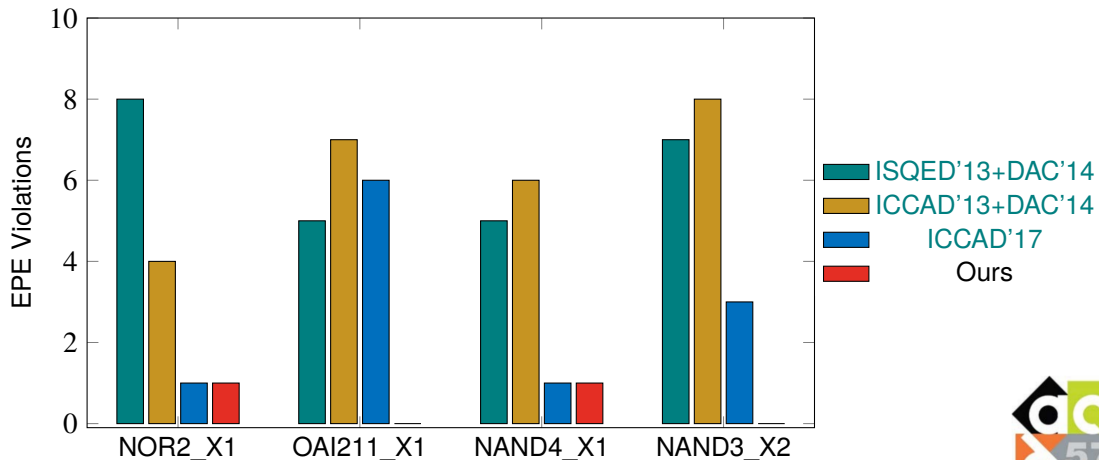
**Experimental Results**

Conclusion



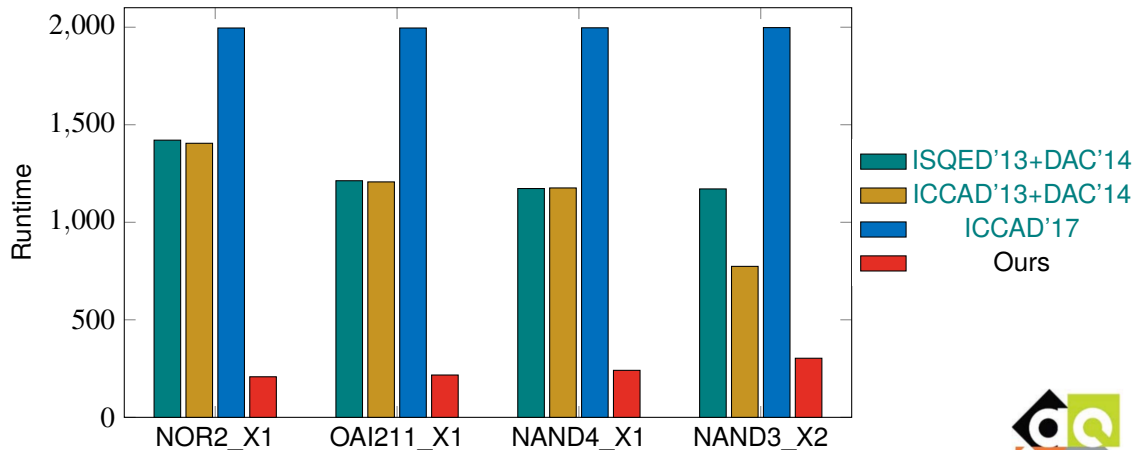
# Comparison on EPE violations

- ▶ Outperform state-of-the-art.
- ▶ Reduce 68.0% EPE violations on average.



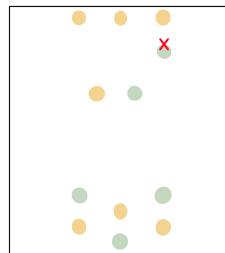
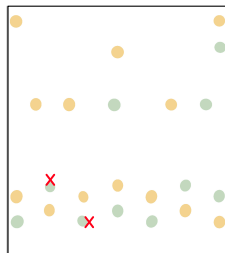
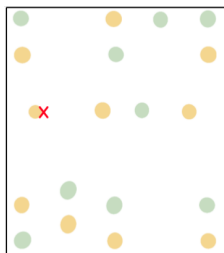
# Comparison on Runtime

- ▶ About 4X speed up.

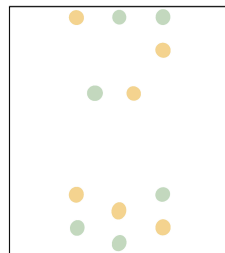
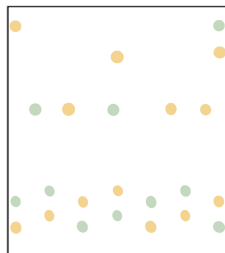
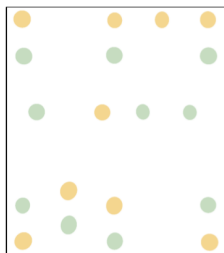


# Optimization results

ICCAD'17



Ours



AOI211\_X1

NAND3\_X2

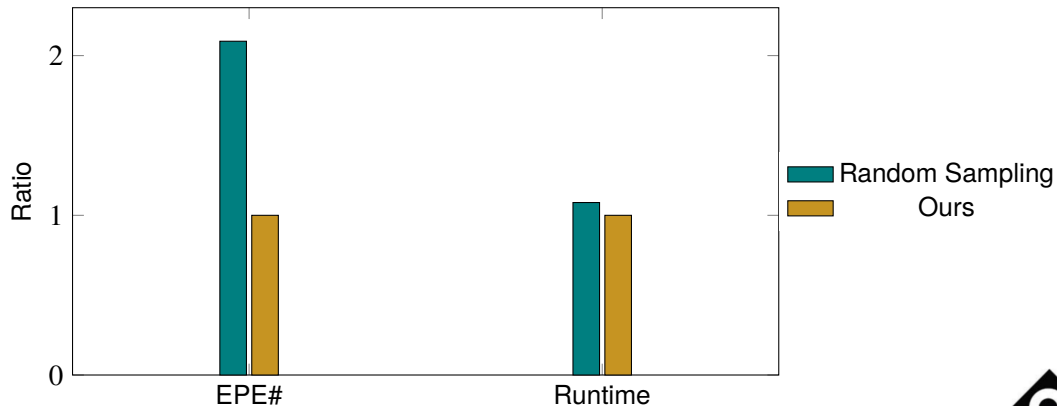
BUF\_X1





# Comparison with Random Sampling

- ▶ Reduce half of EPE violations.



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# Conclusion

- ▶ Deep learning based layout decomposition and mask optimization framework.
  - Decomposition generation approach.
  - Decomposition printability estimation.
- ▶ A set of sampling strategies.
- ▶ Experimental results demonstrate the effectiveness and efficiency.



# Thank You

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