VLSI Layout Hotspot Detection Based on Discriminative Feature Extraction

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Oct 28, 2016

Outline

Problem Background

Conventional Methods

Our Method

Results

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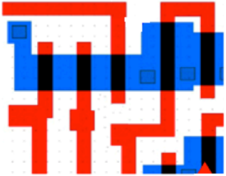
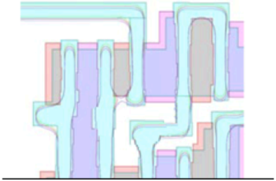
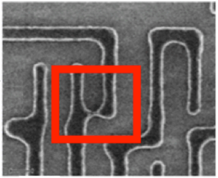
Lithography Hotspot Detection Background







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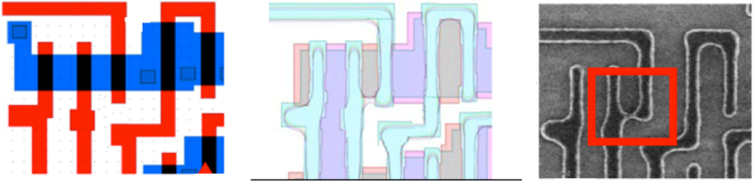

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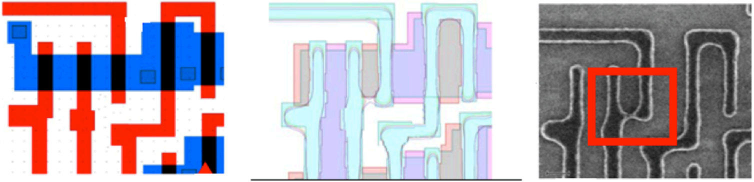

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- DFM: OPC, RET, MPL

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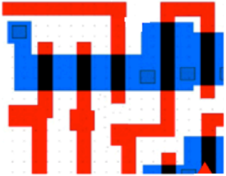
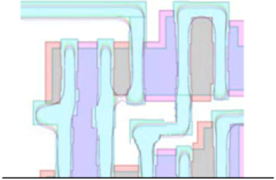
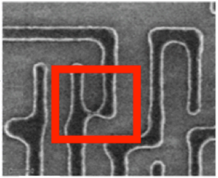

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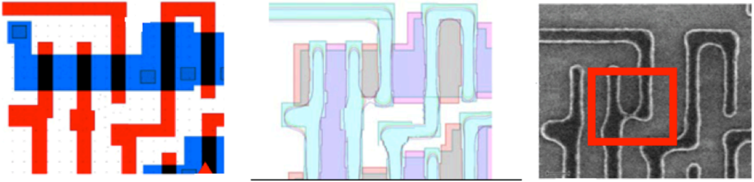

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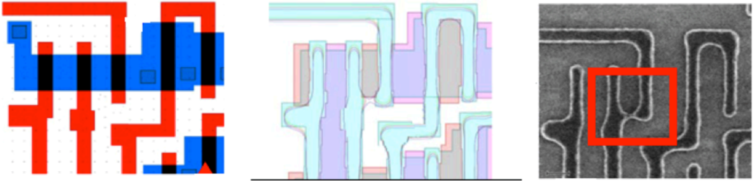

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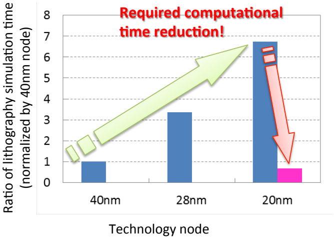

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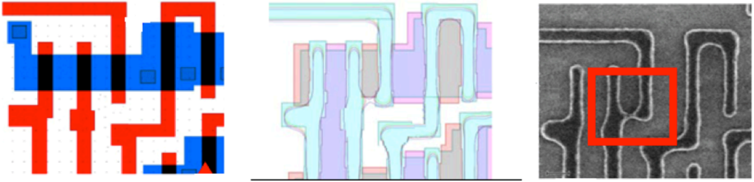

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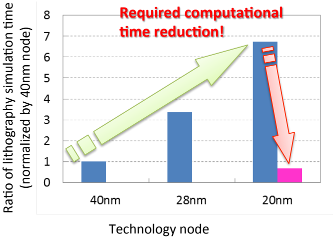

- Pattern Matching or Machine Leaning?

Key Issue in Hotspot Detection?

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- The first problem in machine learning based hotspot detection is?
- Definitely layout pattern feature extraction.
- We need discriminative pattern information to detect hotspot.

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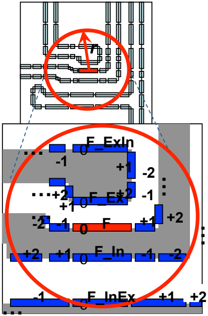
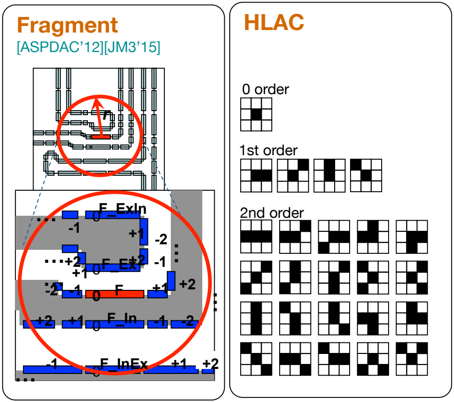
Conventional Feature Extraction

Fragment

[ASPDAC'12][JM3'15]

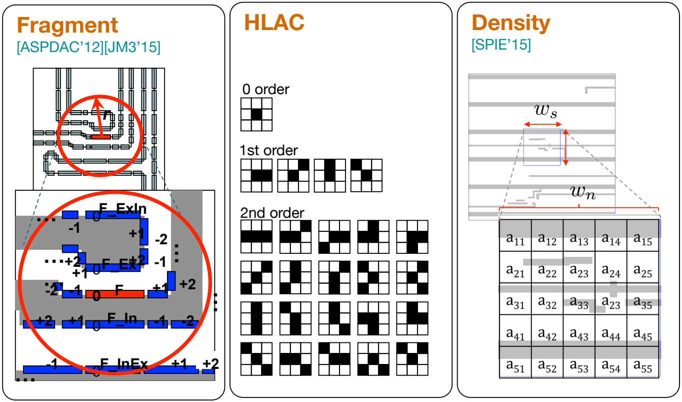


Conventional Feature Extraction



- Fragment feature is very complicated, which leads to over-fitting.

Conventional Feature Extraction



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- High order local correlation (HLAC) is only efficient in some image processing task.

Conventional Feature Extraction

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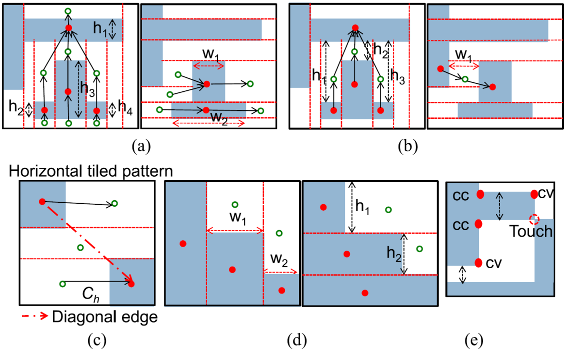
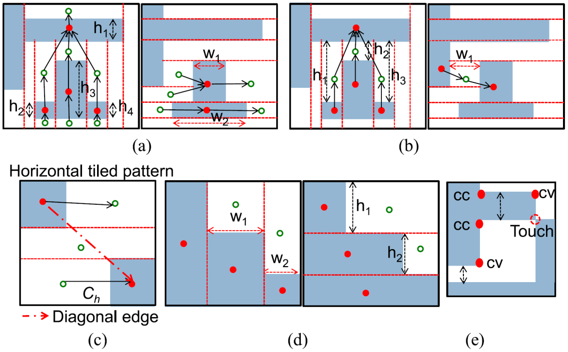
- High order local correlation (HLAC) is only efficient in some image processing task.
- Density based feature loses some important pattern information.

Feature in [TCAD'15]



- (a) Internal feature

Feature in [TCAD'15]



- (a) Internal feature
- (b) External feature

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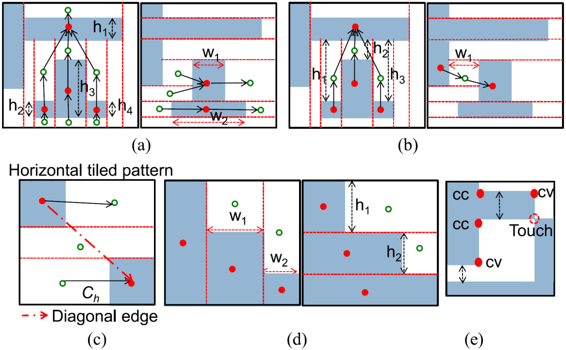

- (a) Internal feature
- (b) External feature
- (c) Diagonal feature

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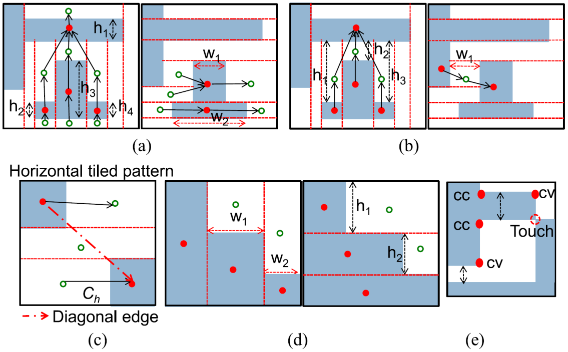

- (a) Internal feature
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- (d) Segment feature

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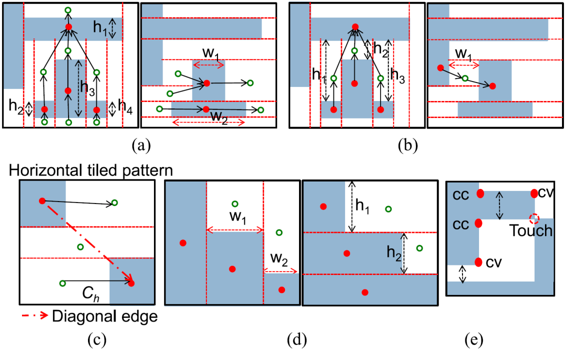

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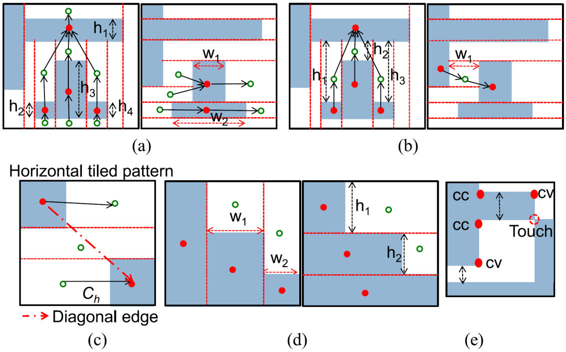

- (a) Internal feature
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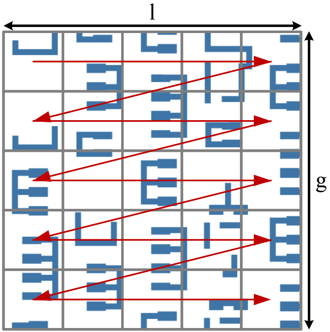
- (d) Segment feature

- Pros: easy and fast to extract.
- Cons: still complicated, hard to detect new patterns.

Density based Feature [SPIE'15]



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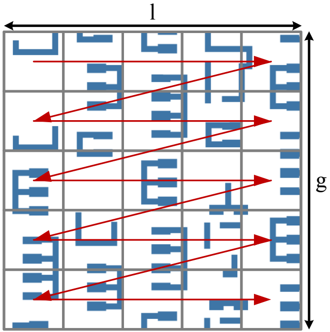

- Side length l, grid number g.

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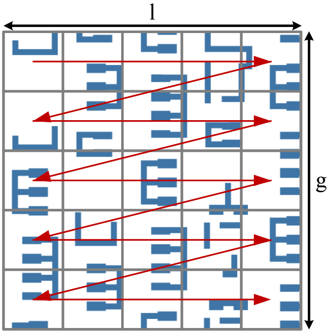

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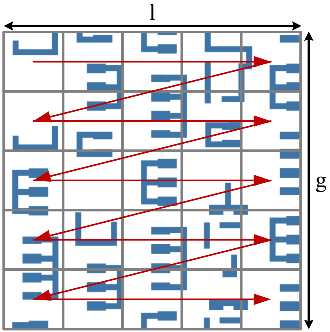

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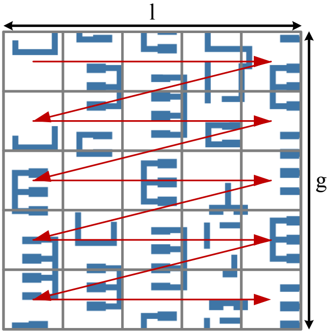

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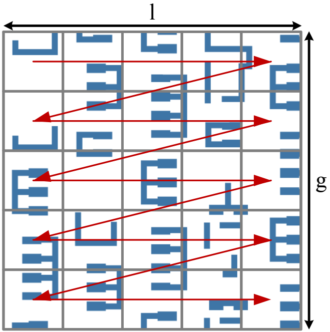

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- Cons: Severe layout pattern information loss.

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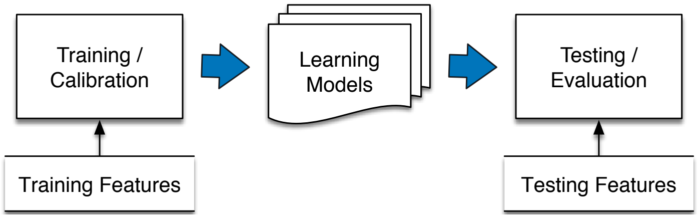
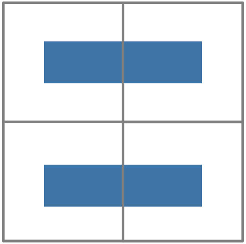
Learning Framework



- Training stage $\rightarrow$ models.
- Testing stage
- Learning models: Decision-tree, ANN, SVM...

Major Drawbacks of Conventional Density Based



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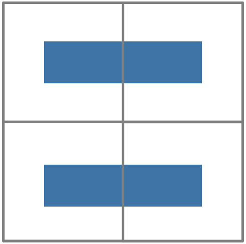

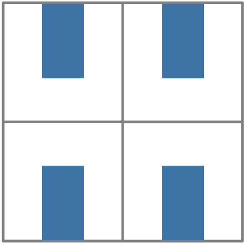

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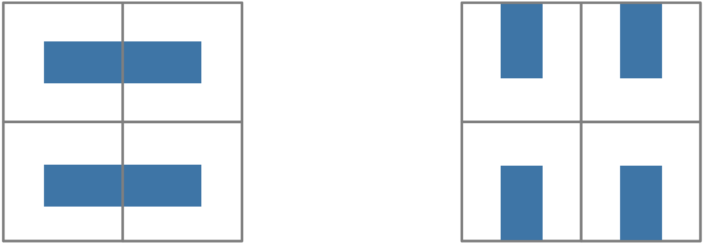

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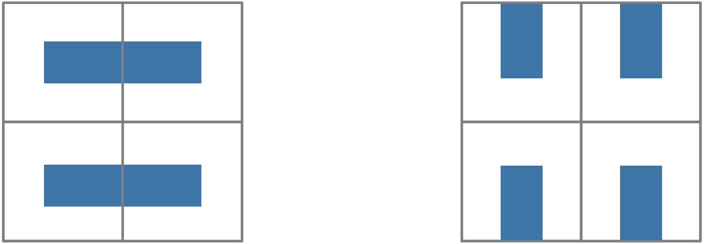
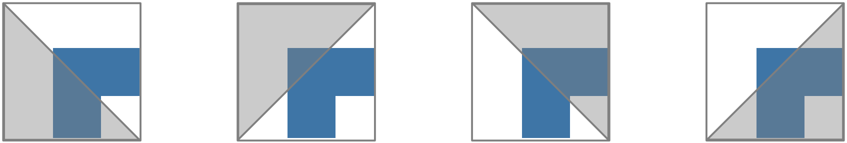


- For both patterns, we can only get the same feature vector.
- However, their contributions to the hotspot formation are different.

Local Grid Density Differential (LGDD)



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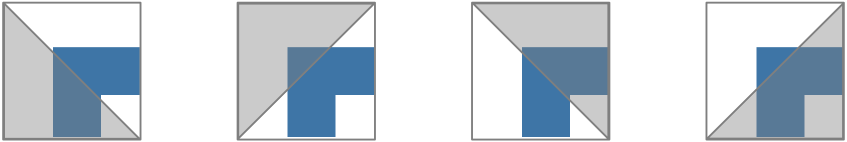

- locally average the density value of a specific area in a grid.

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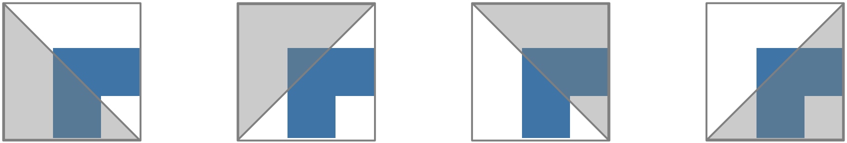
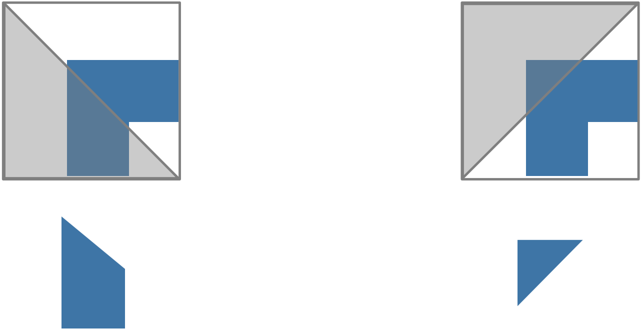


- locally average the density value of a specific area in a grid.
- We apply triangle area in this paper.

Examples of LGDD



- The area value of the blue region in the shadow part.

Definitions for Evaluations

- Accuracy: The rate of correctly predicted hotspots among the set of actual hotspots.
- Extra: The number of falsely detected hotspots.

Effect of LGDD

- Performance comparison between LGDD and conventional density based feature.

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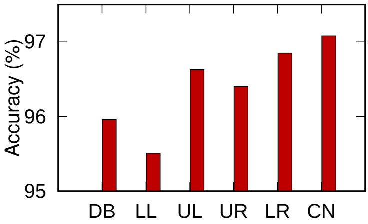

- The impact on accuracy.

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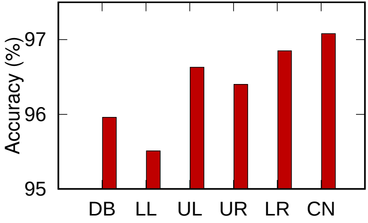
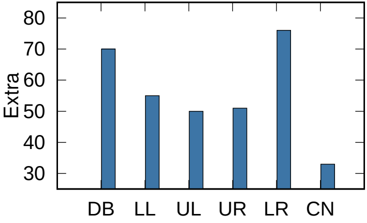
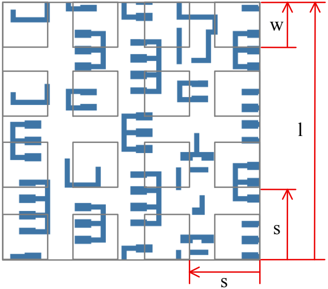




- The impact on accuracy.
- The impact on extra.

Stride Analysis



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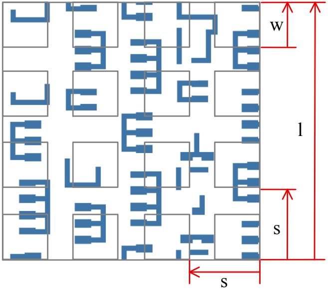

- Stride is the spacing between two adjacent grids (horizontally and vertically).

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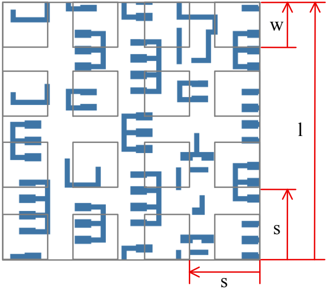

- Stride is the spacing between two adjacent grids (horizontally and vertically).
- Density based feature is a special case with $w = s$ in our stride analysis.

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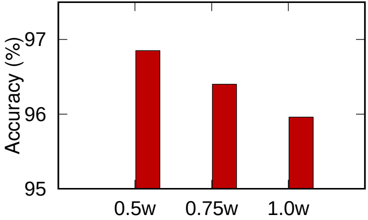

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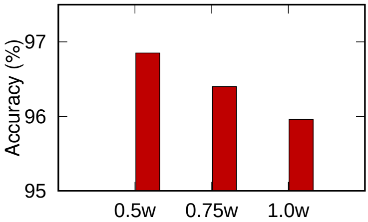
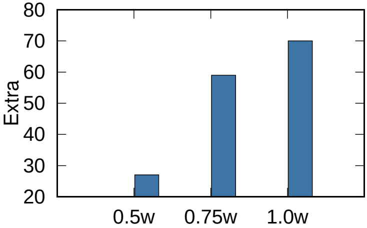


- The impact on accuracy.



- The impact on extra.

- The performance raises when shrinking the stride.
- However, after a threshold, the smaller of the stride, the worse of the performance.

Learning Model

Adaboost classifier

Require: $\mathbf{X} = (\mathbf{x_1}, ..., \mathbf{x_n})$, $\mathbf{Y} = (y_1, ..., y_n)$, T.

for $i \leftarrow 1$ to n **do**:

  $D_1(i) = \frac{1}{n}$;

for $t \leftarrow 1$ to T **do**:

  $h_t \leftarrow$ base classifier with small error ϵ_t;

  $\epsilon_t \leftarrow P(h_t(\mathbf{x_i}) \neq y_i) = \sum_{i=1}^{n} D_t(i) I(h_t(\mathbf{x_i}) \neq y_i)$;

  $\alpha_t \leftarrow \frac{1}{2}\log(\frac{1-\epsilon_t}{\epsilon_t})$;

  $Z_t \leftarrow 2[\epsilon_t(1-\epsilon_t)]^{\frac{1}{2}}$;

  for $i \leftarrow 1$ to n **do**:

    $D_{t+1}(i) \leftarrow \dfrac{D_t(i) exp(-\alpha_t y_t h_t(\mathbf{x_i}))}{Z_t}$;

$f \leftarrow \text{sign}(\sum_{t=1}^{T} \alpha_t h_t)$;

return f

- Decision-Tree as weak learner, more details in the paper.

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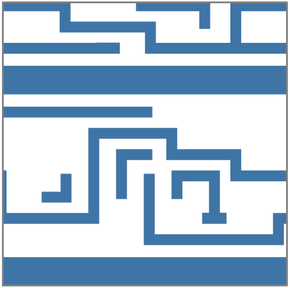
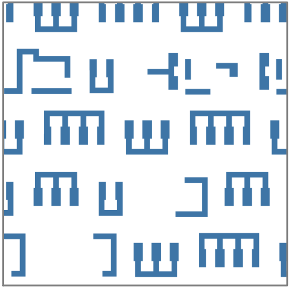
Benchmark Examples





- ICCAD benchmark.
- Industrial benchmark.

Effect of Our Methods

Table: Comparison with conventional density based method

	Density Based		Our Proposed	
	Extra#	Accuracy	Extra#	Accuracy
ICCAD-1	**0**	99.50%	2	**100.00%**
ICCAD-2	**0**	97.18%	**0**	**98.80%**
ICCAD-3	**0**	97.50%	1	**97.78%**
ICCAD-4	4	82.49%	5	**83.05%**
ICCAD-5	**0**	**95.12%**	**0**	**95.12%**
Industry	70	95.96%	**26**	**97.53%**
Average	12.3	94.63%	**5.6**	**95.38%**

- Consider both LGDD and stride analysis.
- Increase accuracy from 94.63% to 95.38%.
- Reduce the extra number from 12.3 to 6.

End

Thanks and Questions?