Bilinear Lithography Hotspot Detection

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March 20, 2017

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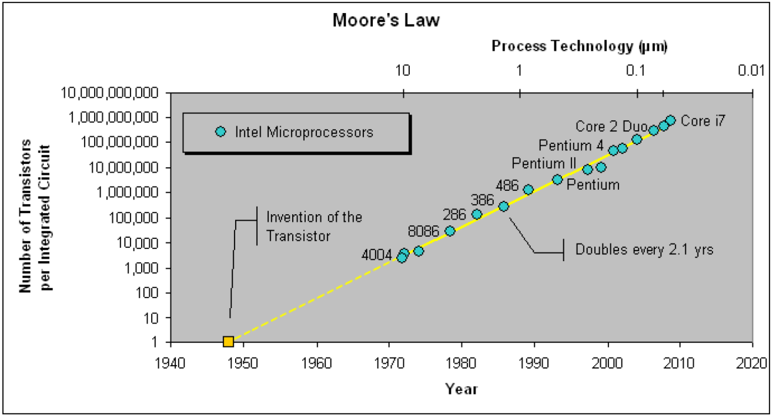
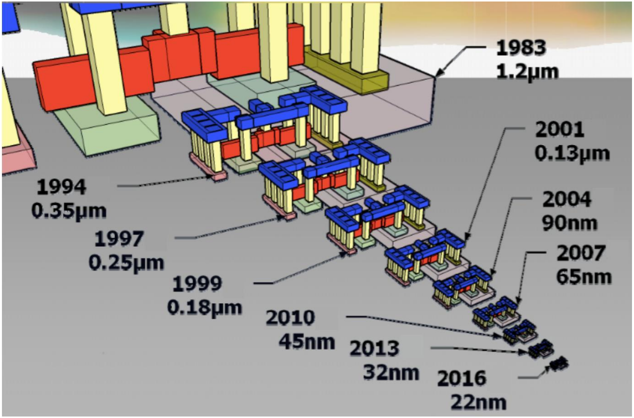
Outline

Outline

Moore's Law to Extreme Scaling

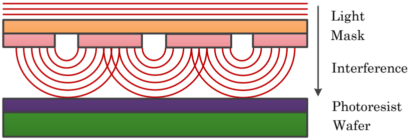


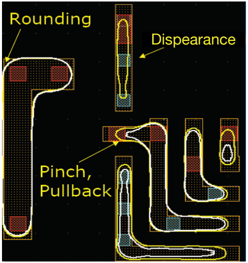
Shrinking Device Feature Size



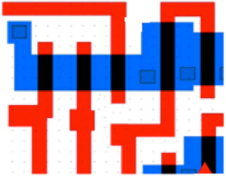
Lithographic Mechanism

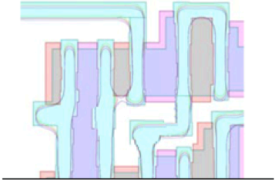
- Light pass through photo masks (mask scale << light wavelength);
- Light diffraction and light interference will happen;
- May cause performance degradation, or even **yield loss**. .

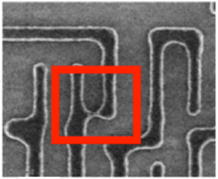




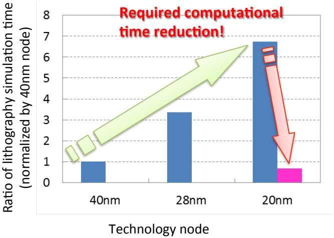
Motivation



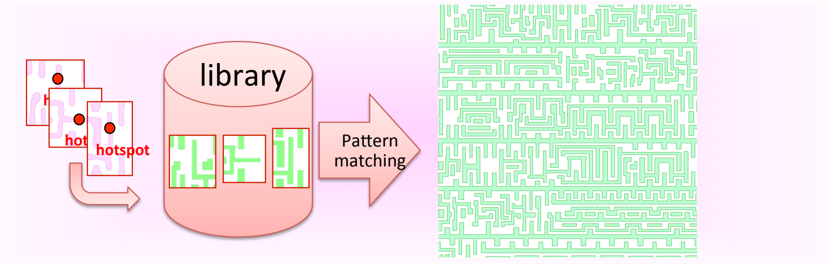




- What you design $\neq$ what you get;
- DFM: MPL, OPC, SRAF;
- Still hotspot: low fidelity patterns;
- Simulations: extremely time intensive.



Pattern Matching based Hotspot Detection



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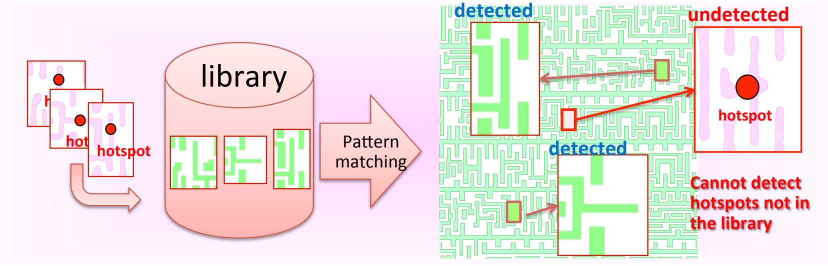

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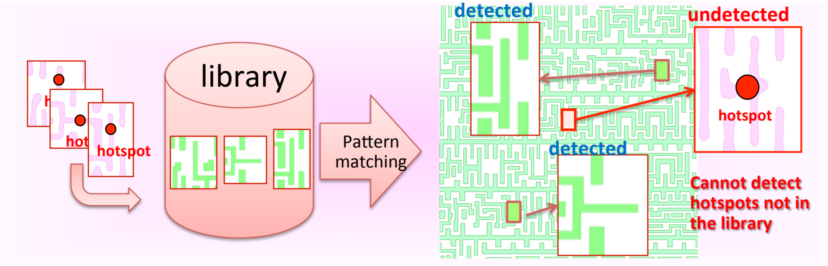
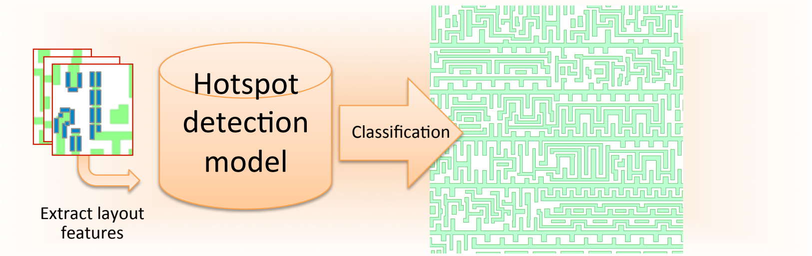


- Fast and reasonably accurate;
- Two-stage filtering, fuzzy pattern matching;
- [Yu+,ICCAD'14][Wen+,TCAD'14];
- Hard to detect unseen pattern.

Machine Learning based Hotspot Detection



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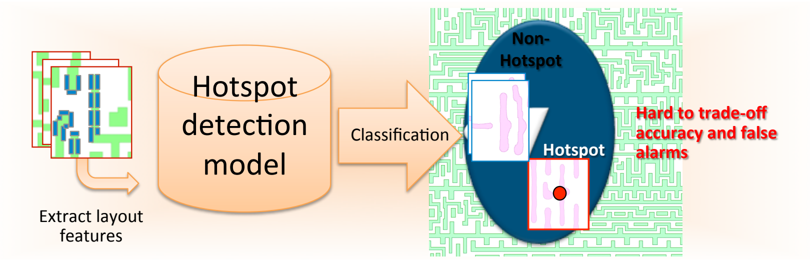

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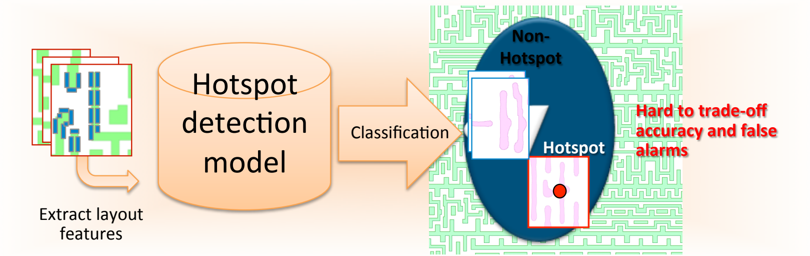

- Can predict new patterns, and are more flexible;
- Support vector machine, boosting, deep neural network...
- [Ding+,ASPDAC'12][Yu+,TCAD'15][Zhang+,ICCAD'16] [Matsunawa+,SPIE'16];
- Hard to balance accuracy and false-alarm.

Rethinking Conventional Methods

- Conventional: vector based feature and learning model;
- Time consuming steps: 1) feature extraction, 2) feature selection;
- Destroying the hidden structural correlations in the layout patterns.

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Matrix based Concentric Sampling (MCCS)

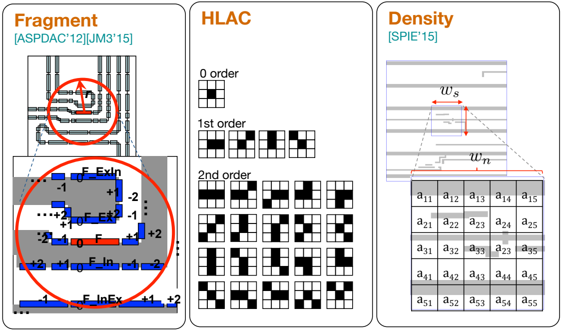
1) Matrix Based: preserve the hidden structural correlations;
2) No feature selection: enable parallel computation;
3) Very simple feature: fast to extract.

Bilinear Lithography Hotspot Detector

1) Matrix based: capture the hidden structural correlations;
2) Low-complexity model: avoid over-fitting;
3) Fast to train.

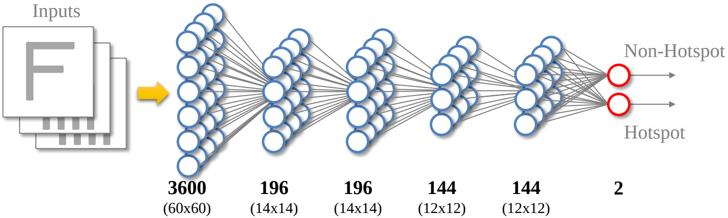
Outline

Geometry based Feature



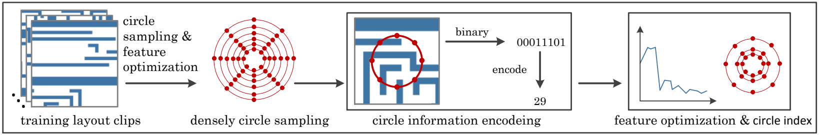
- Hard to be adaptive to different layout designs
- Too many parameters to tune
- Sometimes very complex and may be the cause of over fitting

Deep Learning based Feature



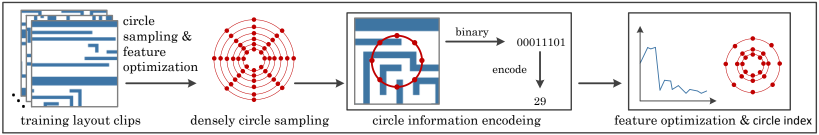
- Network structure from [Matsunawa+,SPIE'16]
- Pros: automatic layout feature extraction; easy to adapt
- Cons: expensive cost in training (may cause even several hours)

Rethinking MCMI



- Maximal Circular Mutual Information (MCMI) [Zhang+,ICCAD'16];
- Preserve the effects of light propagation;
- Searching for the local correlations within each circle.

Rethinking MCMI

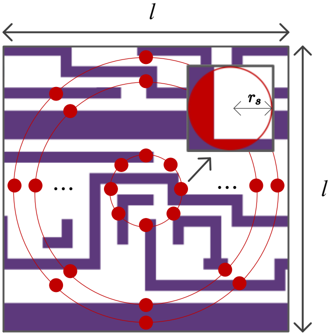


- Maximal Circular Mutual Information (MCMI) [Zhang+,ICCAD'16];
- Preserve the effects of light propagation;
- Searching for the local correlations within each circle.

Questions:

Can we utilize the global correlations among these sampled circles?
Two follow up questions:
1. Can we preserve these correlations using our feature?
2. Can we capture these correlations using our machine learning model?

Matrix based Concentric Circle Sampling (MCCS)



- r_s: is the radius of the sampling area;
- r_{in}: controls the sampling density;
- l: controls the clip size;
- n_p: is the number of points sampled on a circle.

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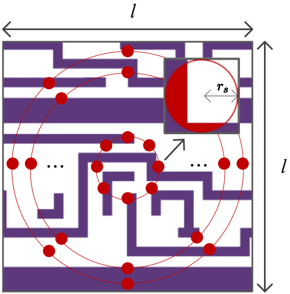
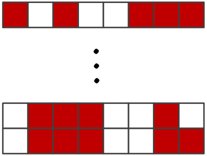
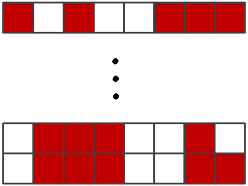




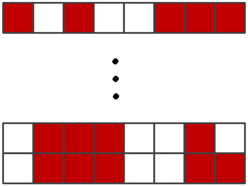
- Points from one circle form a vector;
- Each vector forms one row of the feature matrix;
- Under the condition that $l = 1200nm$, $r_{in} = 60nm$, $n_p = 16$, the dimension of the feature matrix is 33×16 $(33 = 6 + 27)$.

Matrix based Concentric Circle Sampling (MCCS)



- Preserve the hidden structural information;
- Each circle forms a row: light propagation;
- There exist linear combinations among these rows and columns: light diffraction and interference.
- Linear combinations of the rows: correlations among circles;
- Linear combinations of the columns: correlations among lines of points.

Matrix based Concentric Circle Sampling (MCCS)



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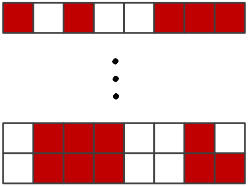

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Outline

Notations

- scalar: x
- vector: $\mathbf{x}$
- matrix: $\mathbf{X}$
- rank r: $\mathbf{X} \in \mathbb{R}^{p \times q}$ and $r \leq \min(p, q)$
- nuclear norm: $||\mathbf{X}||_* = \sum_{i=1}^{n} \sigma_i$
- weighted nuclear norm: $||\mathbf{X}||_{\mathcal{W},*} = \sum_i^n w_i \sigma_i$
- (i, j)=entity: $\mathbf{X}_{i,j}$
- trace: $\mathrm{tr}(\cdot)$
- $(a)_+ = \max(0, a)$
- $\langle A, B \rangle = \sum_{i,j} A_{i,j} \cdot B_{i,j}$
- Frobenius norm: $||\mathbf{X}||_F = \sqrt{\sum_{i,j} X_{i,j}^2}$
- Spectral Elastic Net: $\frac{1}{2}\mathrm{tr}(\mathbf{W}^\top \mathbf{W}) + \lambda ||\mathbf{W}||_*$

Background

- Modern techniques are producing datasets with complex hidden structures;
- These features can be naturally represented as matrices instead of vectors.

- Eg. 1: the two-dimensional digital images, with quantized values of different colors at certain rows and columns of pixels;
- Eg. 2: electroencephalography (EEG) data with voltage fluctuations at multiple channels over a period of time.

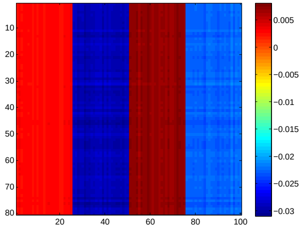
Background

- Most existing learning models are vector based;
- People propose bilinear classifiers that can tackle data in matrix form: [Wolf+,CVPR'07][Pirsiavash+,NIPS'09][Luo+,ICML'15];
- However, these methods have their own drawbacks.

Drawbacks I

- [Wolf+,CVPR'07] uses the sum of k rank-one orthogonal matrices to model the classifier matrix;
- [Pirsiavash+,NIPS'09] assumes the rank of the classifier matrix to be k;
- Both methods describe the correlations of data in different ways, but they require the rank k to be pre-specified.

Drawbacks II



- [Luo+,ICML'15] could determine the rank automatically, however:
- when using the nuclear norm, it assigns same weights to all singular values;
- it aims at capturing the grouping effects (No such effects in our problem) by spectral elastic net term.

Needs for our New Model

- There are several issues for our hotspot detection problem.
- Can we address them?

Needs for our New Model

1. Reduce the impact of outliers;
2. The grouping effects should be discarded;
3. The rank k should be automatically determined;
4. Less weights should be assigned to larger singular values.

Objective Function of our Model

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$$\arg\min_{\mathbf{W},b} \; \lambda||\mathbf{W}||_{\mathcal{W},*} + C\sum_{i}^{n}\{1 - y_i[\mathrm{tr}(\mathbf{W}^{\top}\mathbf{X}_i) + b]\}_{+}. \tag{1}$$

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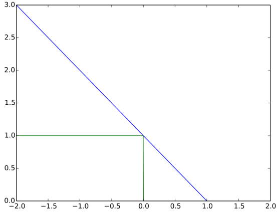

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Resolve Issues

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- We resort to Alternating Direction Method of Multipliers (ADMM) [Boyd+,FTML'11][Goldstein+,SIAM'14].

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Equivalent Objective Function With Auxiliary Variable S

$$\begin{aligned} \arg\min_{\mathbf{W},b,\mathbf{S}} \quad & \lambda||\mathbf{S}||_{\mathcal{W},*} + C\sum_{i}^{n}\{1 - y_i[\mathrm{tr}(\mathbf{W}^\top \mathbf{X}_i) + b]\}_+, \\ \text{s.t.} \quad & \mathbf{S} - \mathbf{W} = 0, \end{aligned} \tag{3}$$

Resolve Issues

Equivalent Objective Function With Auxiliary Variable S

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$$\text{s.t.} \quad \mathbf{S} - \mathbf{W} = 0,$$

- In this way, the original optimization problem is split into two sub-problems with respect to $\{\mathbf{W}, b\}$ and the auxiliary variable $\mathbf{S}$.

Resolve Issues

- Then we apply Augmented Lagrangian Multiplier to develop an efficient ADMM method as follows:

ADMM Formulation

$$
\begin{aligned}
L(\mathbf{W}, b, \mathbf{S}, \mathbf{\Lambda}) =& \lambda ||\mathbf{S}||_{\mathcal{W},*} + C \sum_{i}^{n} \{1 - y_i[\mathrm{tr}(\mathbf{W}^\top \mathbf{X}_i) + b]\}_+ \\
&+ \mathrm{tr}[\mathbf{\Lambda}^\top (\mathbf{S} - \mathbf{W})] + \frac{\rho}{2} ||\mathbf{S} - \mathbf{W}||_F^2,
\end{aligned} \tag{5}
$$

Subproblems

Subproblem 1 to Solve $\mathbf{S}$

$$\arg\min_{\mathbf{S}} \quad \lambda||\mathbf{S}||_{\mathcal{W},*} + \mathrm{tr}(\mathbf{\Lambda}^\top \mathbf{S}) + \frac{\rho}{2}||\mathbf{W} - \mathbf{S}||_F^2. \tag{6}$$

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- We use the shrinkage thresholding method to solve this subproblem.

Subproblems

Subproblem 2 to Solve $(\mathbf{W}, b)$

$$\begin{aligned} \arg\min_{\mathbf{W},b} \quad & C\sum_{i}^{n}\{1 - y_i[\mathrm{tr}(\mathbf{W}^\top \mathbf{X}_i) + b]\}_+ \\ & + \mathrm{tr}[\mathbf{\Lambda}^\top(\mathbf{S} - \mathbf{W})] + \frac{\rho}{2}||\mathbf{S} - \mathbf{W}||_F^2, \end{aligned} \tag{7}$$

- We use the KKT conditions and then the box constraint quadratic programming method to solve this subproblems.

Theoretical Analysis

- We analyze the excessive risk of the proposed classifier theoretically;
- We prove the consistency and correctness of our model;
- Excess risk means the difference between the empirical risk and the expected risk (Definitions in the next slide).

Lemma 1

Lemma 1

The dual norm of the weighted nuclear norm $||\mathbf{W}||_{\mathcal{W},*}$ is

$$||\mathbf{W}||^*_{\mathcal{W},*} = \max_i \frac{1}{w_i} \mathbf{\Sigma}_{ii} \tag{8}$$

where $\mathbf{W} = \mathbf{U\Sigma V}^\top$ through SVD.

* please read the paper for more details of the proof

Theorem 1

With Lemma 1, we can come up with the excessive risk bound for our model:

Theorem 1

With probability at least $1 - \delta$, the excess risk of our method, for each data $\mathbf{X}_i \in \mathbb{R}^{d_1 \times d_2}$, is bounded as

$$R(\hat{\mathbf{W}}) - R(\mathbf{W}^o) \leq \frac{2BL}{\sqrt{n}} \max_i \left(\frac{1}{w_i}\right) \cdot \left(\sqrt{d_1} + \sqrt{d_2}\right) + \sqrt{\frac{\ln(1/\delta)}{2n}}. \tag{9}$$

* please read the paper for more details of the proof

Outline

Experimental Results

- Verified in ICCAD-2012 contest benchmark;
- 2x speed-up in M-CPU(s);
- 19x speed-up in CPU(s);
- Increase detection accuracy from 95.13% to 98.16%.

Table 1: Comparisons with three classical methods

	VCCS-SVM			VCCS-Adaboost			DBF-Adaboost			Ours			
	M-CPU(s)	Accuracy	FA#	M-CPU(s)	Accuracy	FA#	CPU(s)	Accuracy	FA#	CPU(s)	M-CPU(s)	Accuracy	FA#
Case 1	1.09	**100.00%**	**0**	1.37	99.55%	1	7.00	**100%**	**0**	**2.09**	**0.20**	**100.00%**	**0**
Case 2	1.81	94.78%	4	5.44	96.78%	**0**	351.00	98.60%	**0**	**10.70**	**0.33**	**99.40%**	**0**
Case 3	3.26	95.52%	94	4.73	97.62%	4	297.00	97.20%	**0**	**20.56**	**2.34**	**97.78%**	2
Case 4	1.74	80.23%	31	9.45	84.10%	**0**	170.00	87.01%	1	**8.09**	**0.38**	**96.05%**	**0**
Case 5	1.30	95.12%	**0**	2.27	97.56%	**0**	69.00	92.86%	**0**	**5.84**	**0.49**	**97.56%**	**0**
avg.	1.84	93.13%	25.8	4.65	95.12%	1.00	178.80	95.13%	**0.20**	**9.45**	**0.75**	**98.16%**	0.40
ratio	2.46	-	-	6.21	-	-	18.92	-	-	**1.0**	**1.0**	-	-

Experimental Results

- 4x speed-up in CPU(s);
- Increase the accuracy to 98.16%;
- Reduce the false alarms by around 15%.

Table 2: Comparisons with three state-of-the-art hotspot detectors

	TCAD'14			TCAD'15			ICCAD'16			Ours		
	CPU(s)	Accuracy	FA#	CPU(s)	Accuracy	FA#	CPU(s)	Accuracy	FA#	CPU(s)	Accuracy	FA#
Case 1	11	100.00%	1714	38	94.69%	1493	10	**100.00%**	788	**4**	**100.00%**	**783**
Case 2	287	**99.80%**	4058	234	98.20%	11834	103	99.40%	**544**	**17**	99.40%	700
Case 3	417	93.80%	9486	778	91.88%	13850	110	97.51%	**2052**	**49**	**97.78%**	2166
Case 4	102	91.00%	**1120**	356	85.94%	3664	69	**97.74%**	3341	**14**	96.05%	2132
Case 5	49	87.80%	199	20	92.86%	1205	41	95.12%	94	**9**	**97.56%**	**52**
avg.	173.2	94.48%	3315.4	285.2	92.71%	6409.2	66.6	97.95%	1363.8	**18.4**	**98.16%**	**1166.6**
ratio	9.40	-	2.84	15.50	-	5.49	3.62	-	1.17	**1.0**	-	**1.0**

Conclusions

Novel Insights in Hotspot Detection Problem

- Novel matrix feature with hidden structural information preserved;
- Novel Bilinear Machine Learning Model;
- Theoretical analysis proves the correctness and consistency of the model.

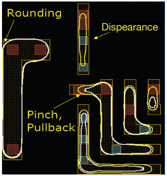
Future Work

- Customized computing system for further speedup
- Transfer learning for further performance improvement

Conclusions

Future Work

- Adjust our methods to new layout designs
- Extend our method to OPC and MPL



We are looking forward to collaboration:

- Industrial benchmarks for HSD
- Industrial benchmarks for OPC, MPL

Thank you

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