Online Learning and Feature Optimization in Lithography Hotspot Detection

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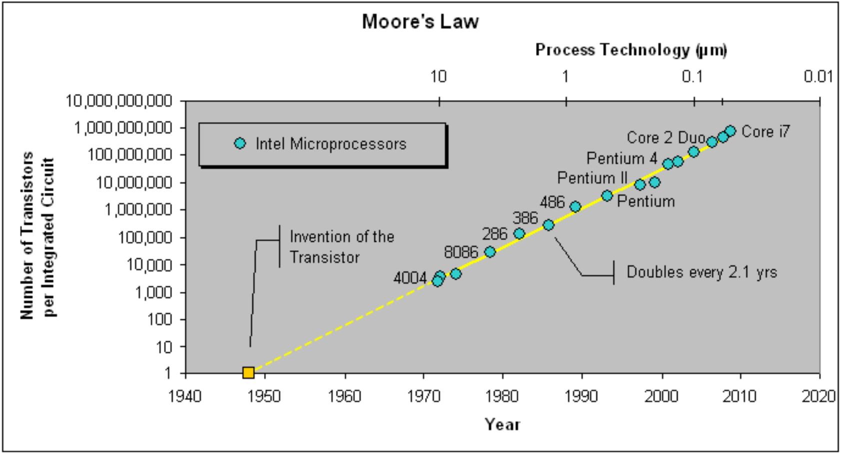
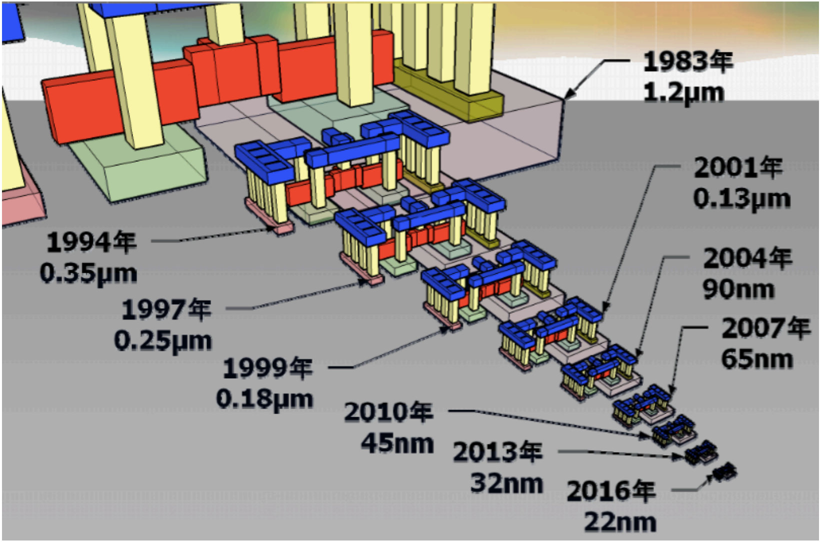
Outline

Outline

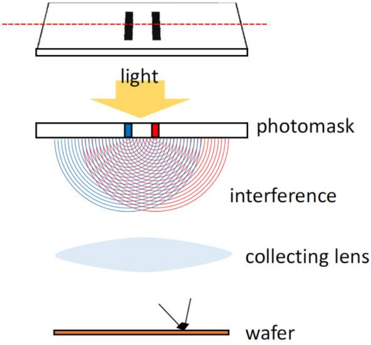
Moore’s Law to Extreme Scaling

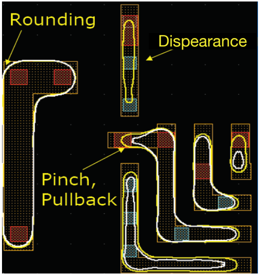



1983年
1.2μm
2001年
0.13μm
2004年
90nm
2007年
65nm
1994年
0.35μm
1997年
0.25μm
1999年
0.18μm
2010年
45nm
2013年
32nm
2016年
22nm

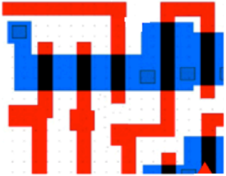
Lithographic Mechanism

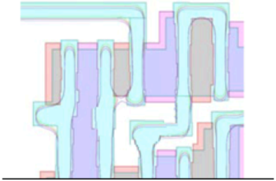
- light diffraction when through photomask
- May cause performance degradation, or even **yield loss**
- What you see $\neq$ what you get

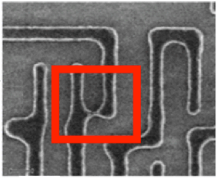




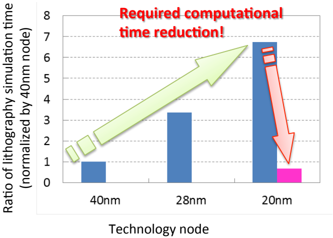
Lithography Hotspot Detection



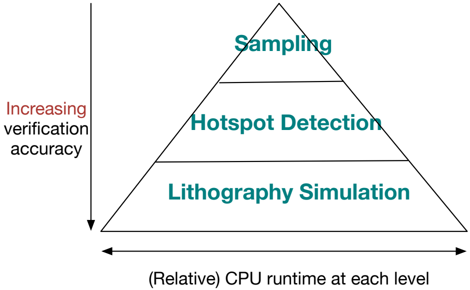


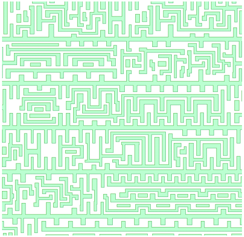


- RET: OPC, SRAF, MPL
- Still hotspot: low fidelity patterns
- Simulations: extremely CPU intensive



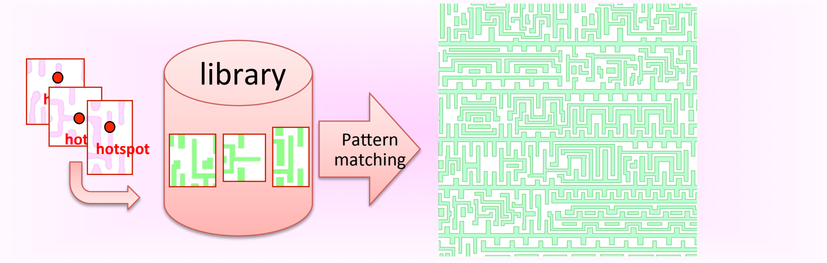
Layout Verification Hierarchy





- **Sampling**:
  scan and rule check each region
- **Hotspot Detection**:
  verify the sampled regions and report potential hotspots
- **Lithography Simulation**:
  final verification on the reported hotspots

Pattern Matching based Hotspot Detection



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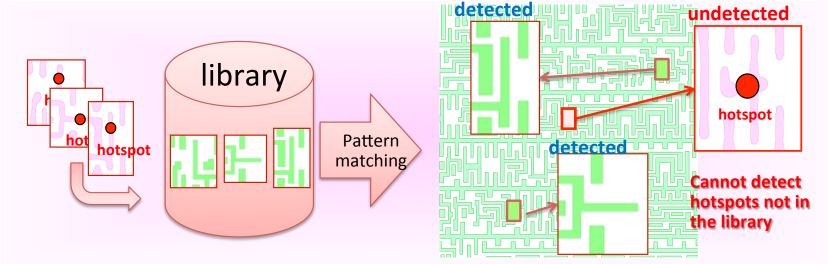
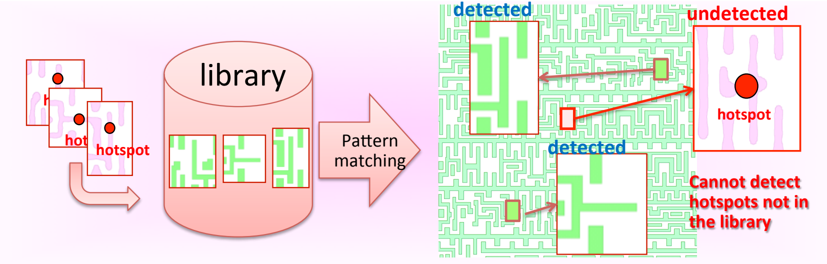
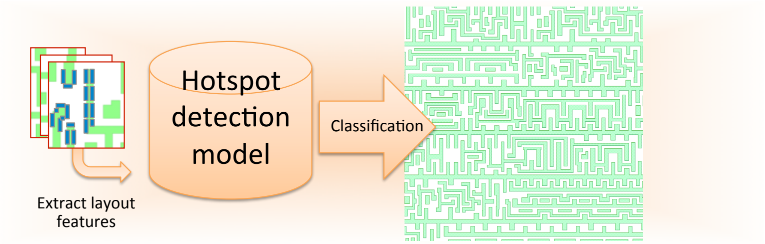


Pattern Matching based Hotspot Detection

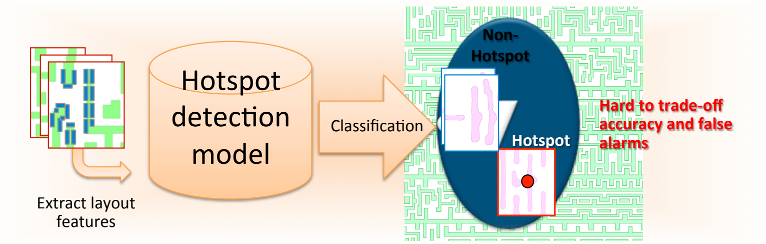


- Fast and accurate
- [Yu+,ICCAD'14] [Nosato+,JM3'14] [Su+,TCAD'15]
- Fuzzy pattern matching [Wen+,TCAD'14]
- Hard to detect non-seen pattern

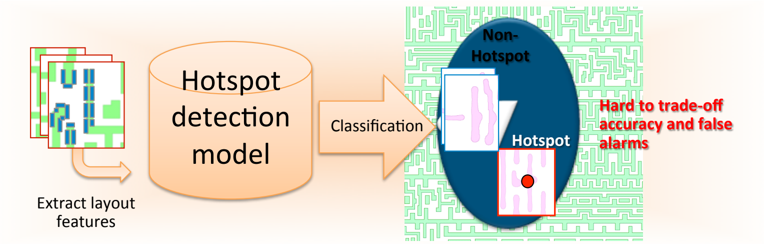
Machine Learning based Hotspot Detection



Machine Learning based Hotspot Detection



Machine Learning based Hotspot Detection



- Predict new patterns
- Decision-tree, ANN, SVM, Boosting ...
- [Drmanac+,DAC'09] [Ding+,TCAD'12] [Yu+,JM3'15] [Matsunawa+,SPIE'15] [Yu+,TCAD'15]
- Hard to balance accuracy and false-alarm

Rethinking Performance Metrics

- **Accuracy**: The rate of correctly predicted hotspots among the set of actual hotspots.
- **False Alarm**: The number of incorrectly predicted non-hotspots.
- **Detection Runtime**: CPU runtime of hotspot detection.

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- ~~**Detection Runtime**: CPU runtime of hotspot detection.~~

Rethinking Performance Metrics

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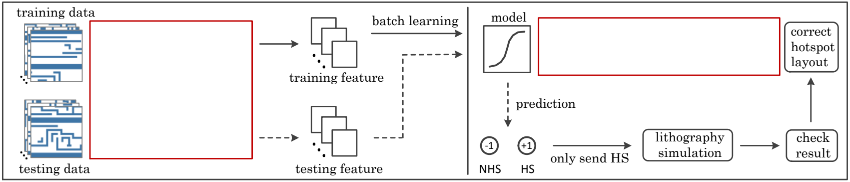
- ~~**Detection Runtime**: CPU runtime of hotspot detection.~~

Overall Detection and Simulation Time (ODST)

Includes: (1) Detection runtime; (2) Lithography simulation time for hotspots in testing.

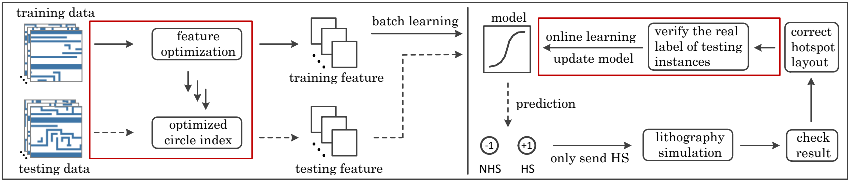
*Transfer false alarm into equivelent lithography simulation time.

Rethinking Hotspot Detection Framework



- Conventional framework: supervised learning.
- Two stages: training and testing.
- Testing hotspot (HS) is verified by litho simulator.

Rethinking Hotspot Detection Framework



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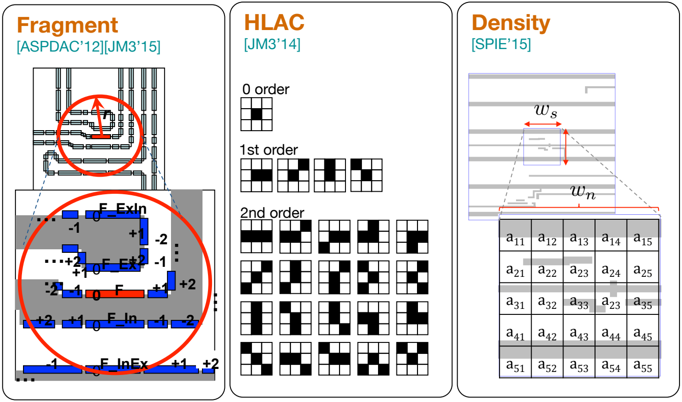
Proposed New Framework:

- Feature optimization.
- Online model learning.

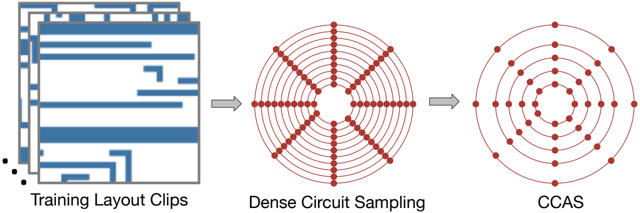
Outline

Conventional Feature Extraction



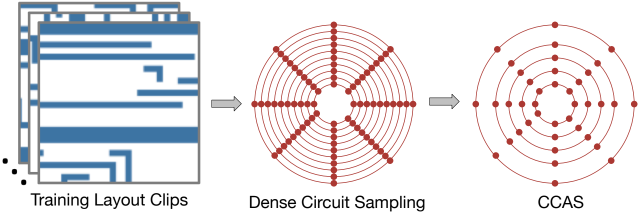
- Hard to be adaptive to different layout designs
- Too many parameters to tune
- Sometimes very complex and may cause over fitting

Rethinking CCAS



- Concentric Circle Area Sampling (CCAS) [Matsunawa+,JM3'16].
- Capture the affects of light diffraction.
- Simple rule to select circles from dense samples.

Rethinking CCAS



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- Capture the affects of light diffraction.
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Question:

Can we find **correlation** between circles and hotspots, and select circles samrtly?

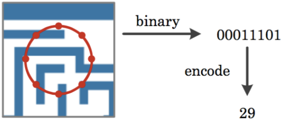
Rethinking CCAS

Measure correlation between circle and the hotspot.

Mutual Information

$$I(C_i; Y) = \sum_{c_i \in C} \sum_{y \in Y} p(c_i, y) \log \frac{p(c_i, y)}{p(c_i)p(y)}$$

- c_i: one encoded decimal number in circle $\mathcal{C}$
- $p(c_i)$: probability of c_i
- y: each classification label
- $p(y)$: probability of y



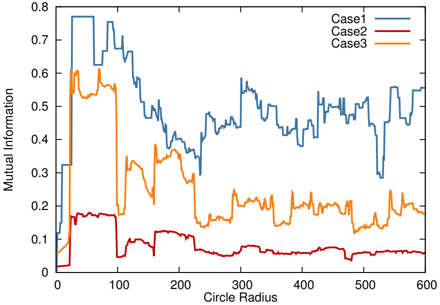
Decimal number encoding

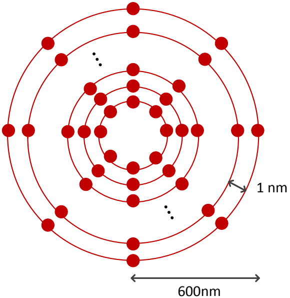
Smart CCAS Circle Selection

Higer Mutual Information

More correlation between circle and label variable.

- Mutual information curve can be drawn based on training data
- We donot want to sample circles too dense

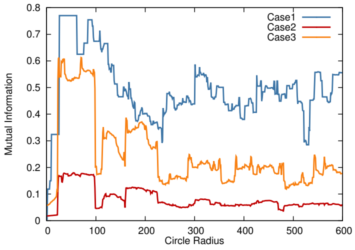




Smart CCAS Circle Selection

Mathematical Formulation

$$
\begin{aligned}
\max \quad & \mathbf{v}^\mathsf{T}\mathbf{w} \\
\text{s.t.} \quad & v_i = I(C_i;Y), && \forall v_i \in \mathbf{v}, \\
& ||w_i||_0 = n_c, && \forall\, i,\ w_i \in \{0,1\}, \\
& |i-j| \geq d, && \forall\, i \neq j,\ w_i = w_j = 1
\end{aligned}
$$



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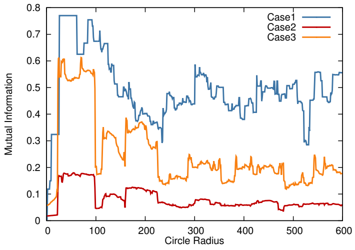
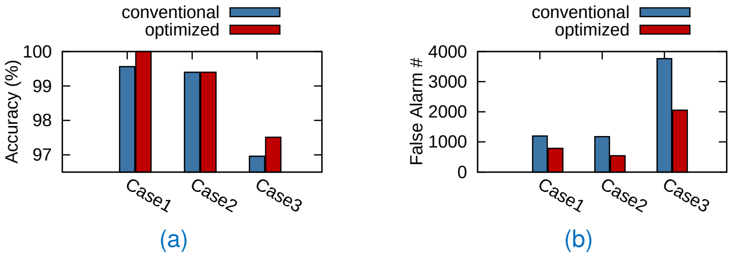


Optimally Solved by Dynamic Programming

$$D[i,j] = \max\{v[i] + D[i-d, j-1], D[i-1,j]\}\}$$

Performance of Feature Optimization

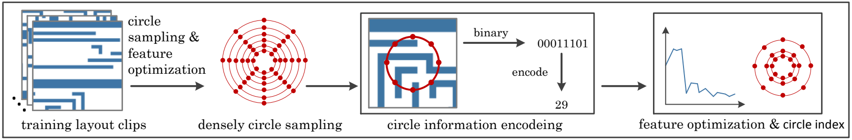
- Smart Circle Selection v.s. Conventional CCAS.



(a) The impact on accuracy; (b) The impact on false alarm.

Review of the Feature Optimization Framework

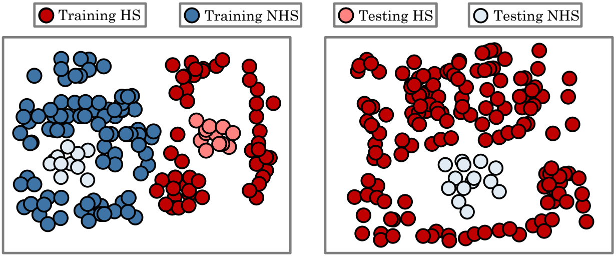
- Firstly, we densely sample the circles from the training data.
- Secondly, we optimally select circles by DP algorithm.
- Thirdly, we use the obtained circle index to extract features.



Outline

Motivation of Online Hotspot Detection

- In (a), all testing hotspots and non-hotspots can be correctly detected.
- But in (b), all testing non-hotspots become false alarms.



(a) (b)

Algorithm Flow of Smboost

Smooth Boosting [Servedio, JMLR'03]

Require: $\{(x_1, y_1), \ldots, (x_m, y_m)\}, \gamma, \theta = \frac{\gamma}{2+\gamma}, T.$

for $i \leftarrow 1$ to n **do**
  $M_1(i) \leftarrow 1;$
  $N_0(i) \leftarrow 0;$
end for
for $t \leftarrow 1$ to T **do**
  Run weak classifier to get h_t such that $\frac{1}{2}\sum_{j=1}^{n} M_t(j)|h_t(x_j) - y_j| \leq \frac{1}{2} - \gamma;$
  for $j \leftarrow 1$ to n **do**
    $N_t(j) \leftarrow N_{t-1}(j) + y_j h_t(x_j) - \theta;$
  end for
  for $j \leftarrow 1$ to n **do**
    $M_{t+1}(j) \leftarrow \min\{1.0, (1-\gamma)^{\frac{N_t(j)}{2}}\};$
  end for
end for
return $f \leftarrow \text{sign}(\frac{1}{T}\sum_{t=1}^{T} h_t);$

Algorithm Flow of Online Smboost

- Extend conventional smboost to the online scenario.

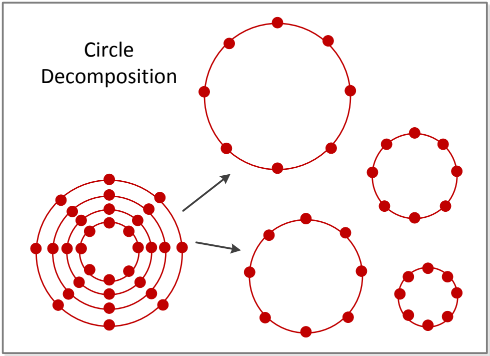
Online Smooth Boosting

Require: Streaming instance (x, y), batch smboost classifier.

1: $M_1 \leftarrow 1, N_0 \leftarrow 0$;
2: **for** $t \leftarrow 1$ to T **do**
3: online update $h_t(x, y)$;
4: $N_t \leftarrow N_{t-1} + yh_t(x) - \theta$;
5: $M_{t+1} \leftarrow \min\{1.0, (1-\gamma)^{\frac{N_t}{2}}\}$;
6: **end for**
7: **return** $f \leftarrow$sign$(\frac{1}{T}\sum_{t=1}^{T} h_t)$;

Online Weak Classifier

- Use Naive Bayes (NB) as weak classifier [Chen+,ICML'12].
- NB is a lossless [Oza, ICSMC'05] online weak classifier.
- Modify NB to work better with our proposed feature.



Outline

Comparison with [Matsunawa+,SPIE'15]

- Verified in ICCAD-2012 contest benchmark
- 4x speed-up due to the simple feature.
- Increase detection accuracy from 95.13% to 97.95%.

	[Matsunawa+,SPIE'15]			batch		
	FA#	CPU(s)	Accuracy	FA#	CPU(s)	Accuracy
Case1	**0**	**7**	**100.00%**	**0**	**7**	**100.00%**
Case2	**0**	351	98.60%	**0**	**53**	**99.40%**
Case3	**0**	297	97.20%	3	**66**	**97.51%**
Case4	1	170	87.01%	**0**	**49**	**97.74%**
Case5	**0**	69	92.86%	**0**	**27**	**95.12%**
avg.	**0.2**	178.8	95.13%	0.6	**40.4**	**97.95%**
ratio	-	4.43	0.97	-	**1.0**	**1.0%**

Comparisons with [Wen+,TCAD'14] [Yu+,TCAD'15]

- *ODST = Overall Detection and Simulation Time*
- Increase detection accuracy by at least 3.47% on average.
- Improve the performance of ODST by at least 58.80% on average.

	[Wen+,TCAD'14]		[Yu+,TCAD'15]		batch	
	ODST(s)	Accuracy	ODST(s)	Accuracy	ODST(s)	Accuracy
Case1	17151	100.00%	14968	94.69%	**7890**	**100.00%**
Case2	40867	**99.80%**	118574	98.20%	**5572**	99.40%
Case3	95277	93.80%	139278	91.88%	**20660**	**97.51%**
Case4	**11302**	91.00%	36996	85.94%	33526	**97.74%**
Case5	2039	87.80%	12070	92.86%	**1005**	**95.12%**
avg.	33327.2	94.48%	64377.2	92.71%	**13730.6**	**97.95%**
ratio	2.43	0.96	4.69	0.95	**1.0**	**1.0**

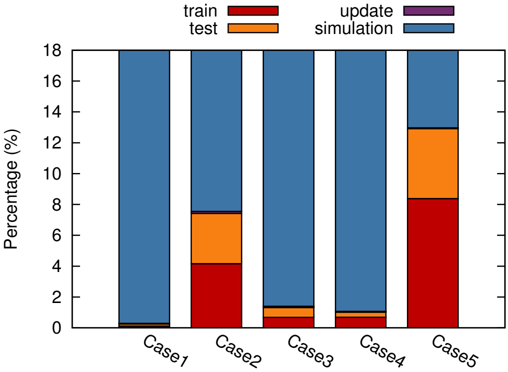
Batch Learning v.s. Online Learning

- Further improve the detection accuracy from 97.95% to 98.45%.
- Further reduce ODST by 26.1%.

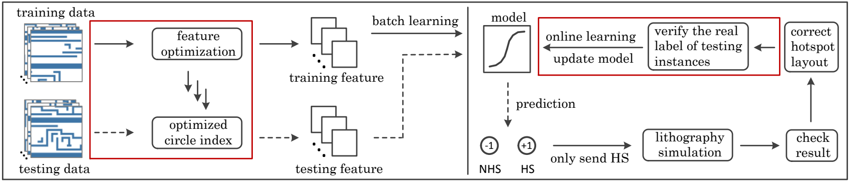
	batch				online			
	FA#	CPU(s)	ODST(s)	Acccuracy	FA#	CPU(s)	ODST(s)	Accuracy
Case1	788	10	7890	**100.00%**	**704**	13	**7050**	**100.00%**
Case2	544	132	5572	**99.40%**	**308**	152	**3251**	**99.40%**
Case3	2052	140	20660	97.51%	**1819**	180	**18379**	**97.57%**
Case4	3341	116	33526	**97.74%**	**2096**	158	**21148**	**97.74%**
Case5	94	76	1005	95.12%	**82**	78	**910**	**97.56%**
avg.	1363.8	94.8	13730.6	97.95%	**1008.8**	116.4	**10147.6**	**98.45%**
ratio	-	-	1.35	0.99	-	-	**1.0**	**1.0**

Runtime Breakdown for ICCAD Benchmark

- Online updating is only a small portion of the whole detection flow.
- False alarms of Case 2 and Case 5 are dramatically reduced.



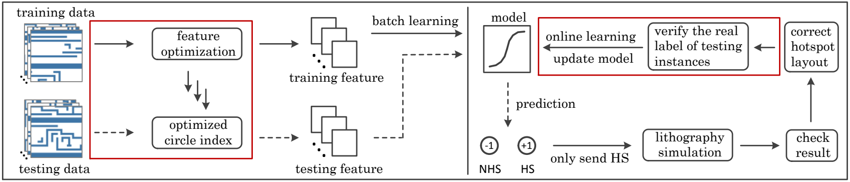
Conclusion



A New Hotspot Detection Framework

- New performance metric: runtime & performance trade-off
- Feature optimization based on mutual information
- Online learning

Conclusion



A New Hotspot Detection Framework

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Future work

- Further improve the accuracy
- Hardware or parallel speedup of hotspot detector

Thank You

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