

# **A New Lithography Hotspot Detection Framework Based on AdaBoost Classifier and Simplified Feature Extraction**

Tetsuaki Matsunawa<sup>1</sup>, Jhih-Rong Gao<sup>2</sup>, Bei Yu<sup>2</sup> and David Z. Pan<sup>2</sup>

<sup>1</sup>Toshiba Corporation

<sup>2</sup>The University of Texas at Austin

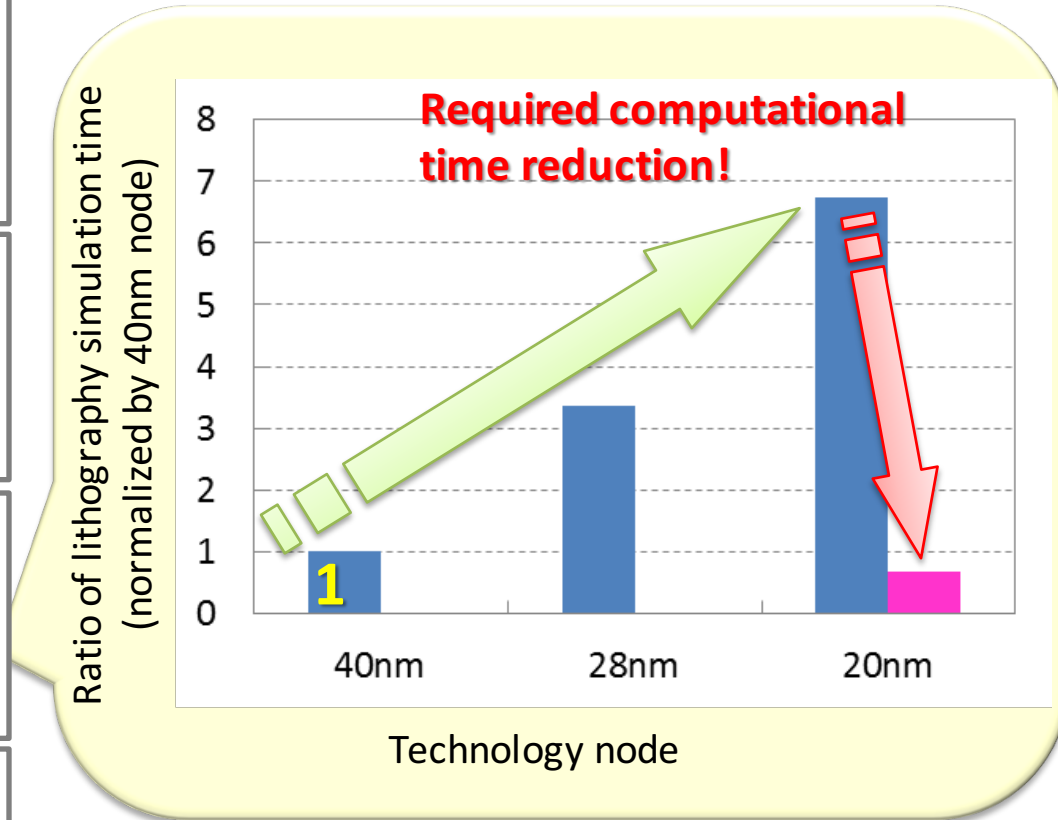
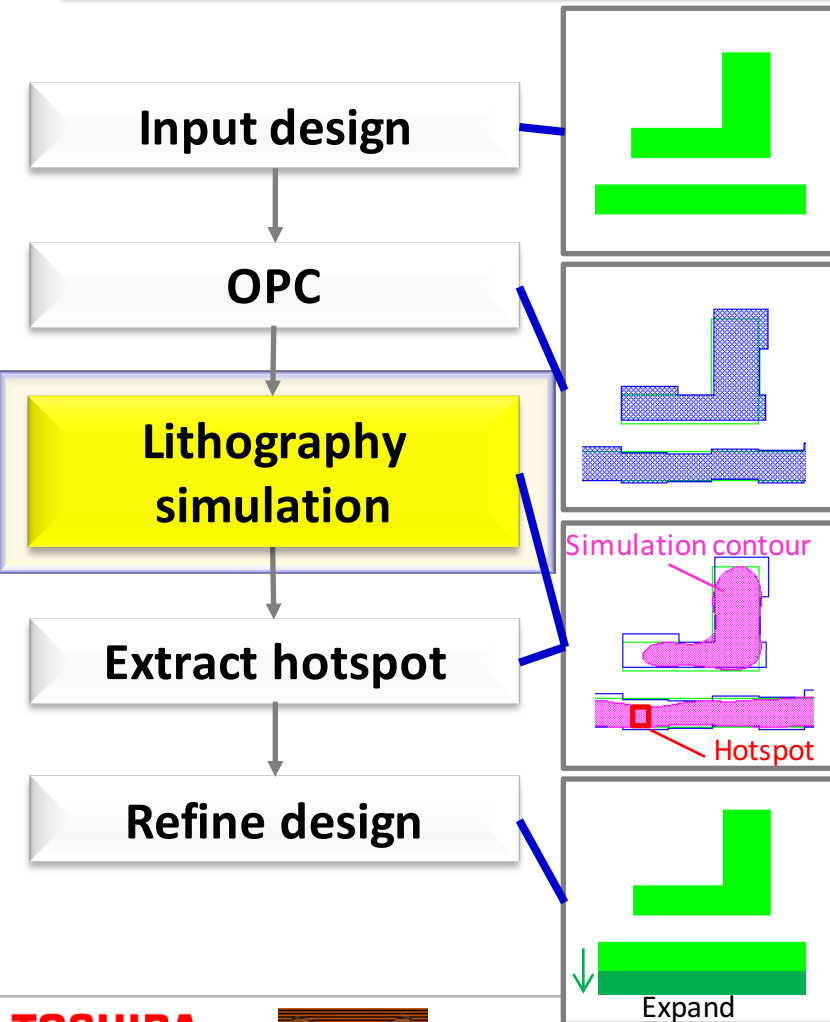
# Outline

---

- **Background**
- **Simplified Feature Extraction**
- **AdaBoost Classifier**
- **Experimental results**
- **Conclusion**

# Hotspot detection

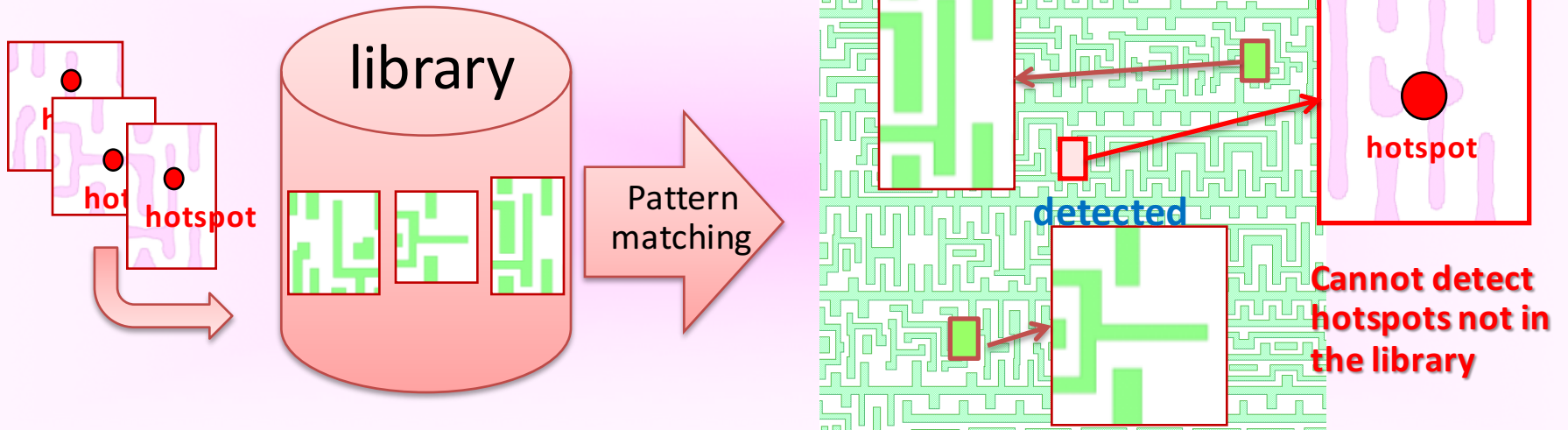
- Issue: Lithography simulation is time consuming
- Goal: High accurate hotspot detection in short runtime



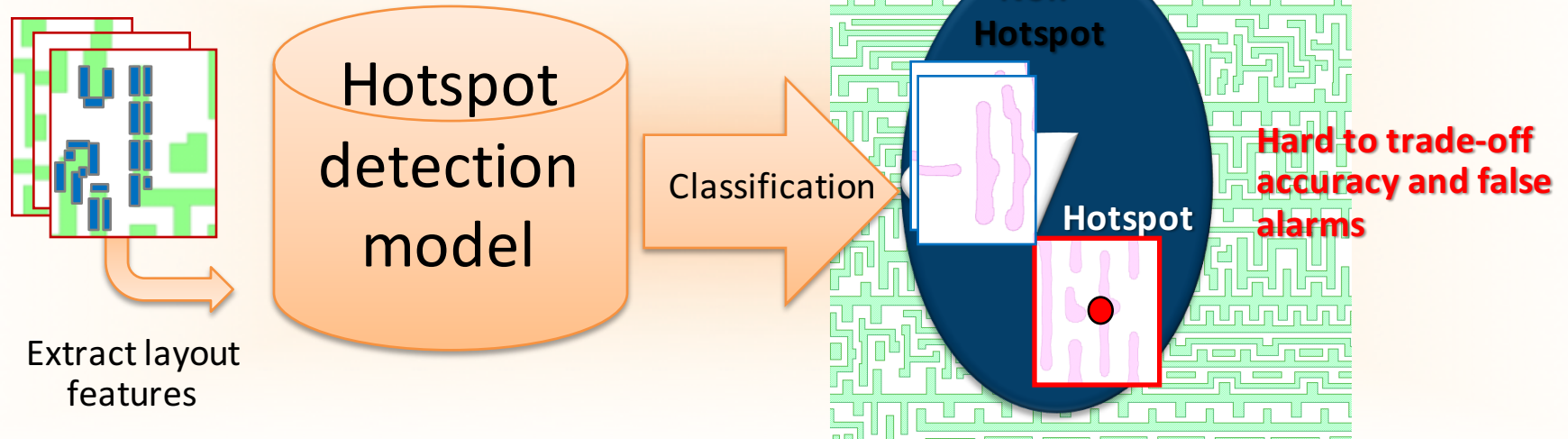
Simulation-based hotspot detection is the most widely used technique

# Two major simulation-less approaches

## Pattern Matching



## Machine Learning

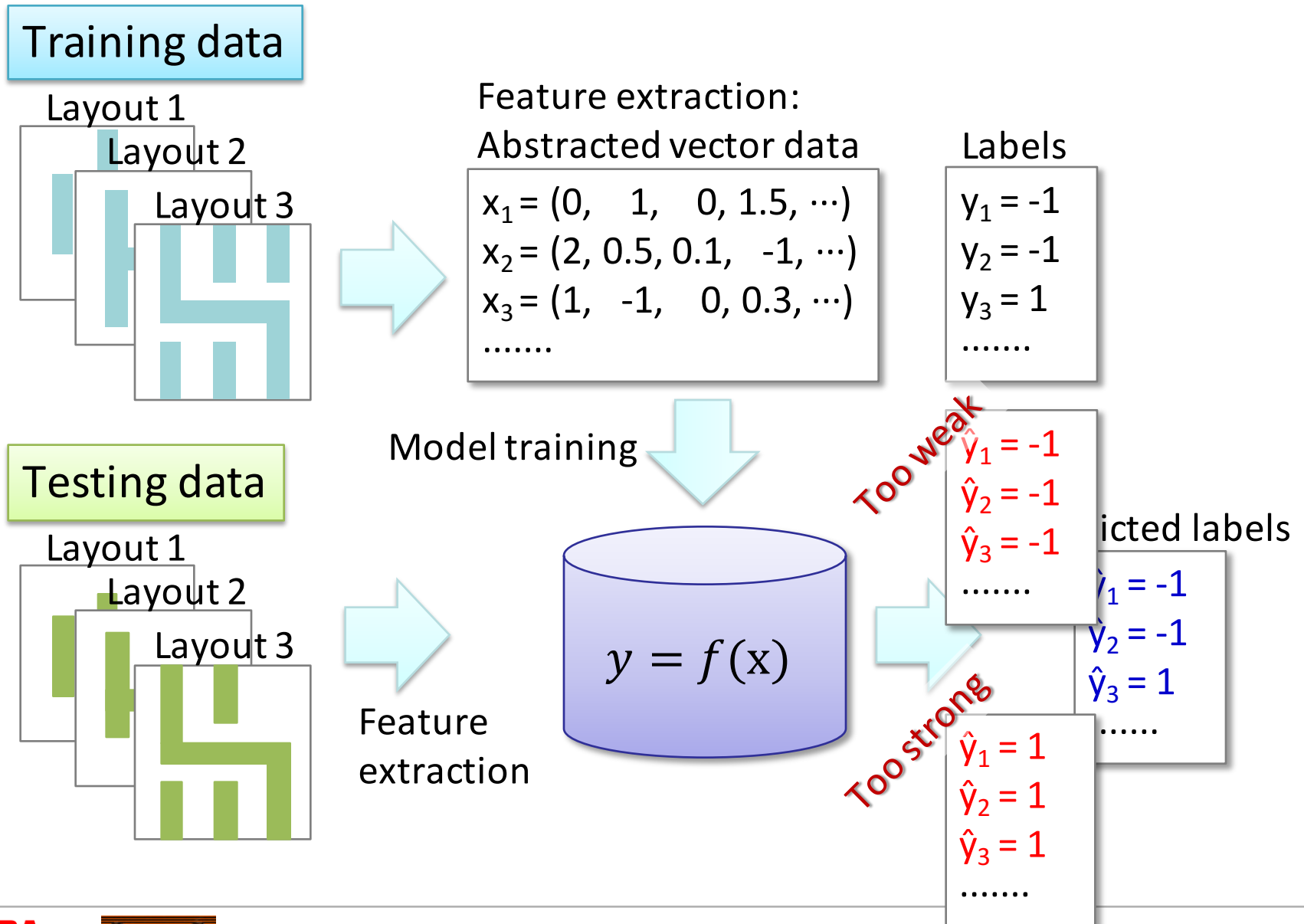


# Issues of conventional methods

---

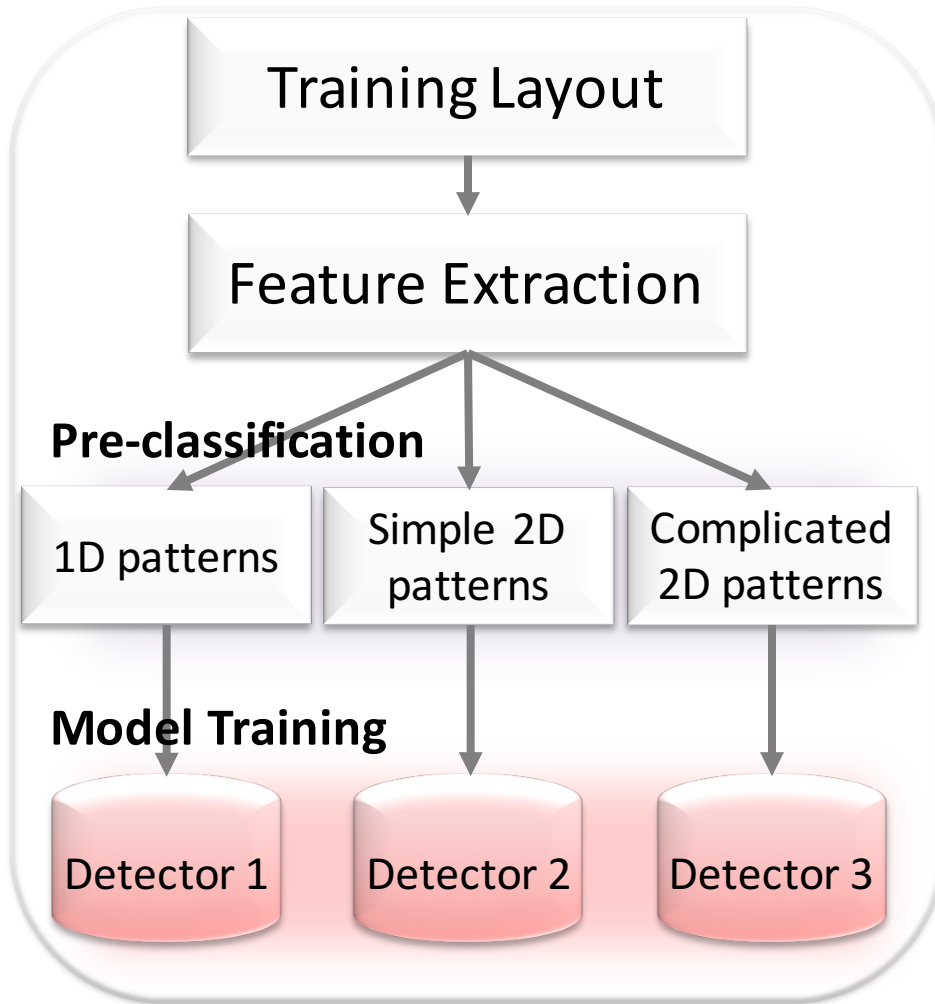
- **Lithography Simulation-based**
  - Time consuming
  
- **Pattern Matching-based**
  - Cannot detect unknown hotspot
  
- **Machine Learning-based**
  - Trade off relation between accuracy and false-alarm

# Machine learning based hotspot detection

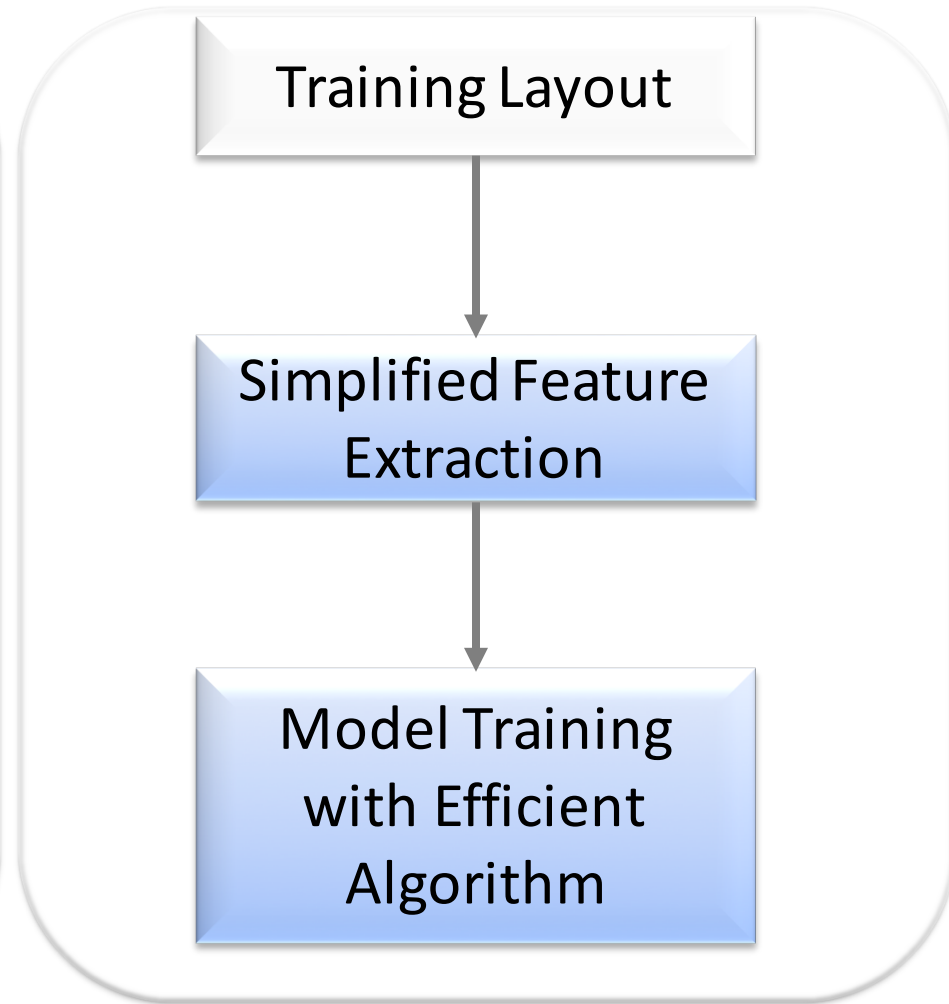


# New hotspot detection framework

## State-of-the-art approach



## Our framework



# Outline

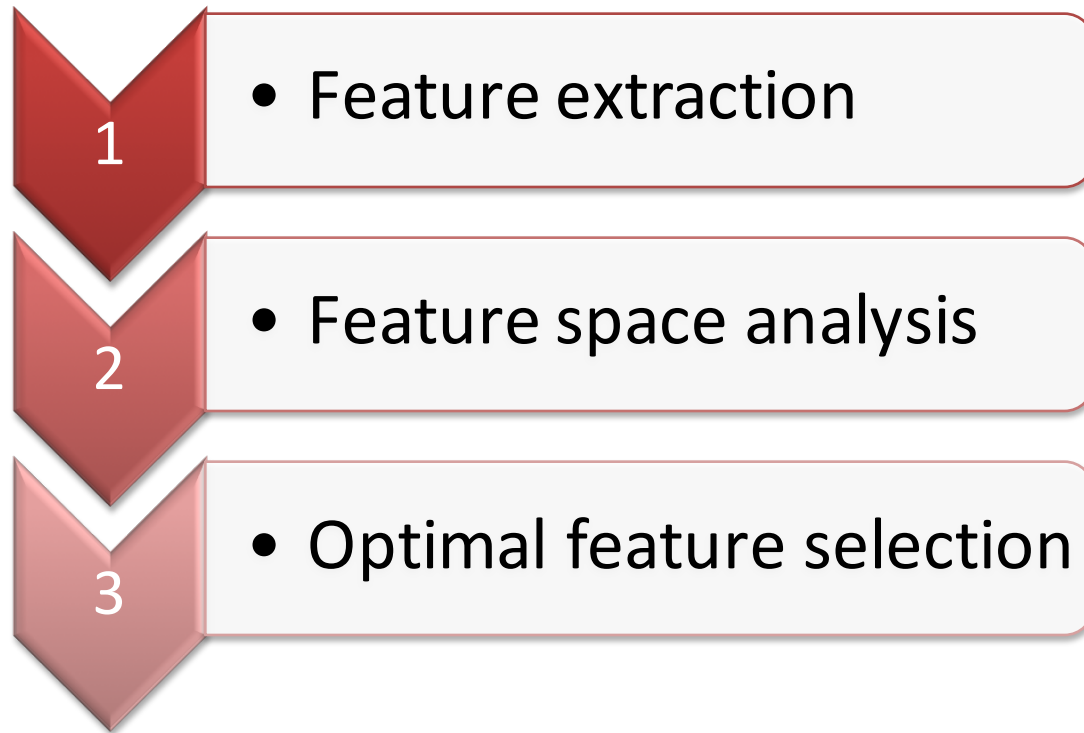
---

- Background
- **Simplified Feature Extraction**
- AdaBoost Classifier
- Experimental results
- Conclusion



# What is a “Simplified Feature”

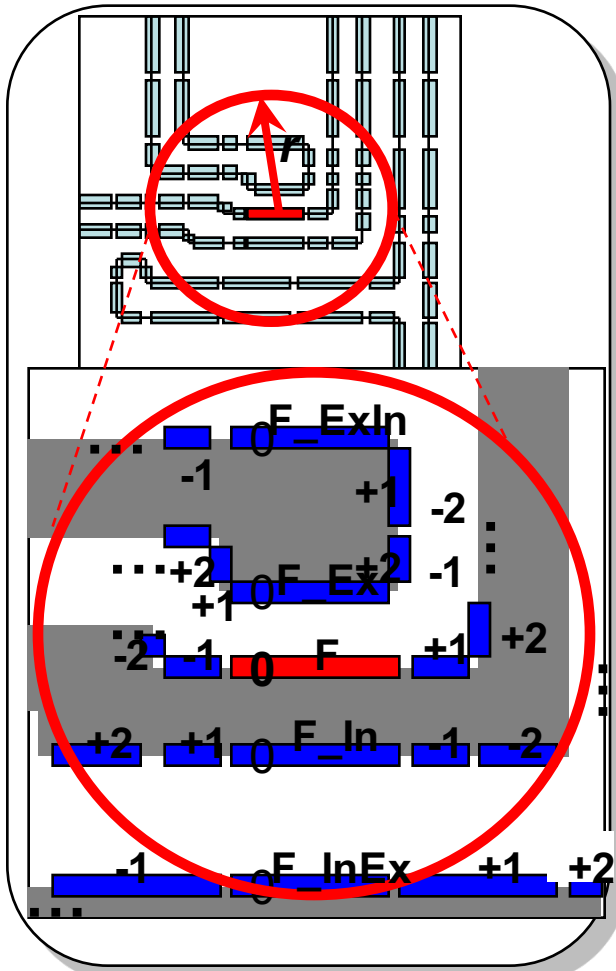
- Optimized layout feature to make model training easier



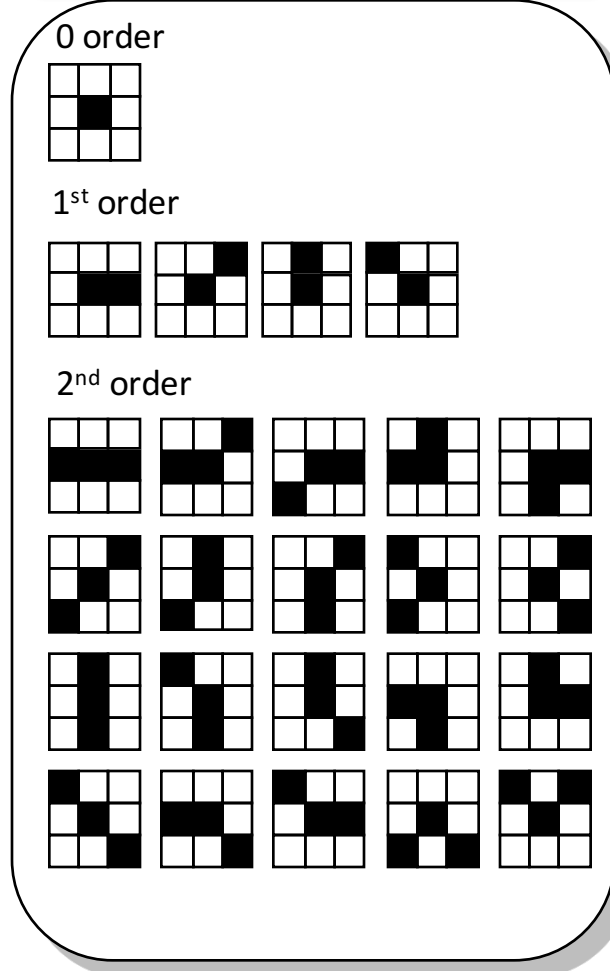
Optimized layout feature  
and parameters

# Layout features

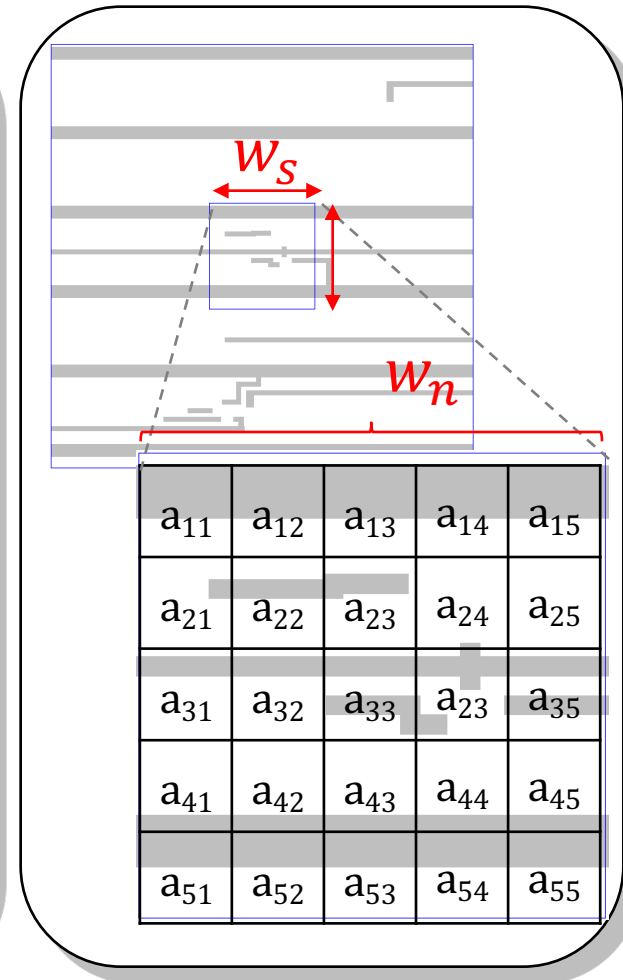
## Fragmentation-based



## Higher order local auto-correlation

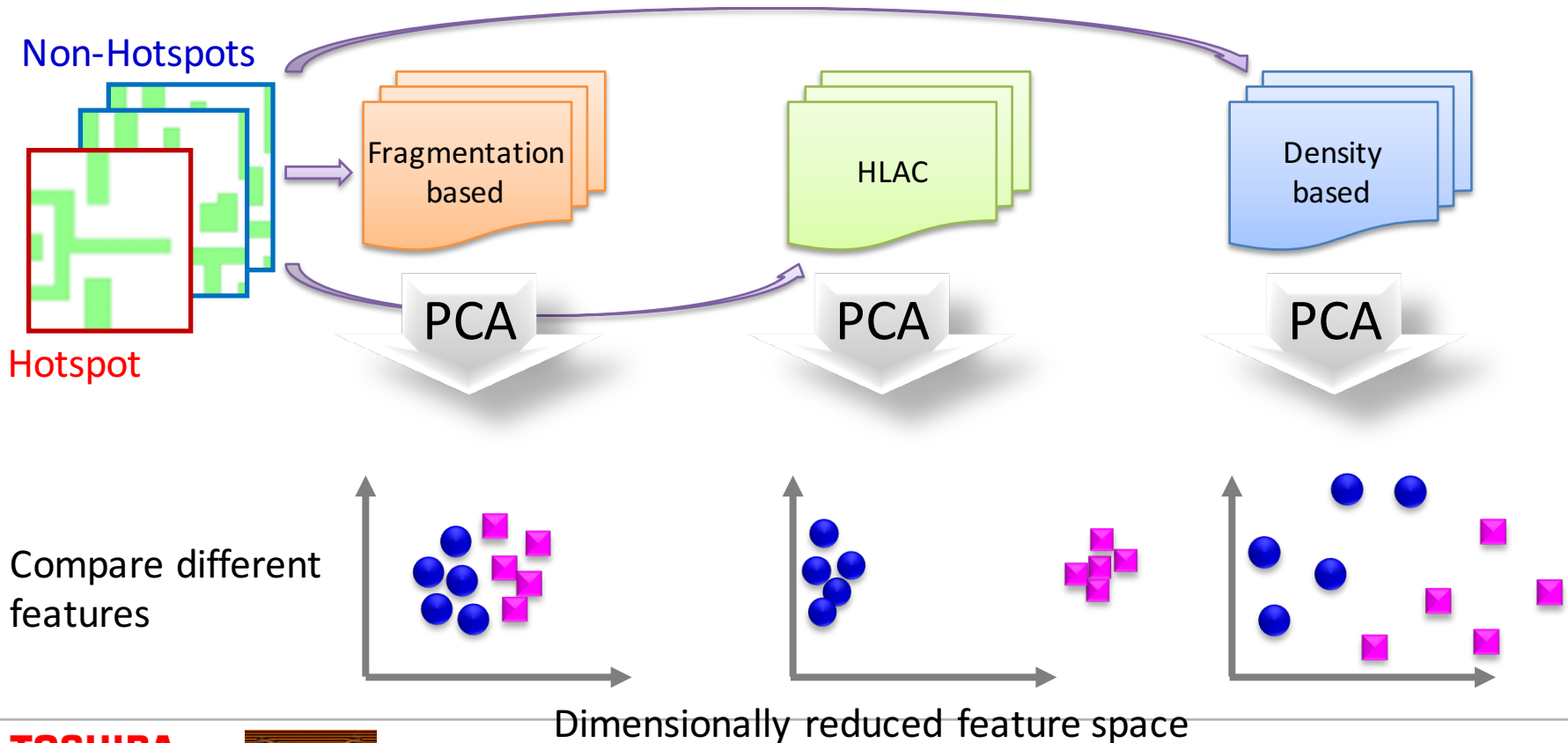


## Density-based



# Feature space analysis

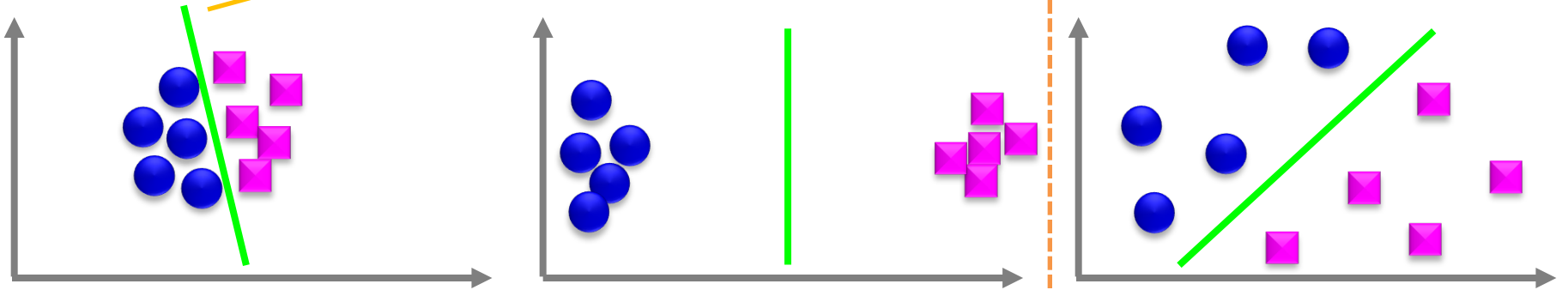
- **Principal Component Analysis (PCA)**
  - Dimensionality reduction based on orthogonal transformation
- **Mahalanobis Distance**
  - Normalized Euclidean distance



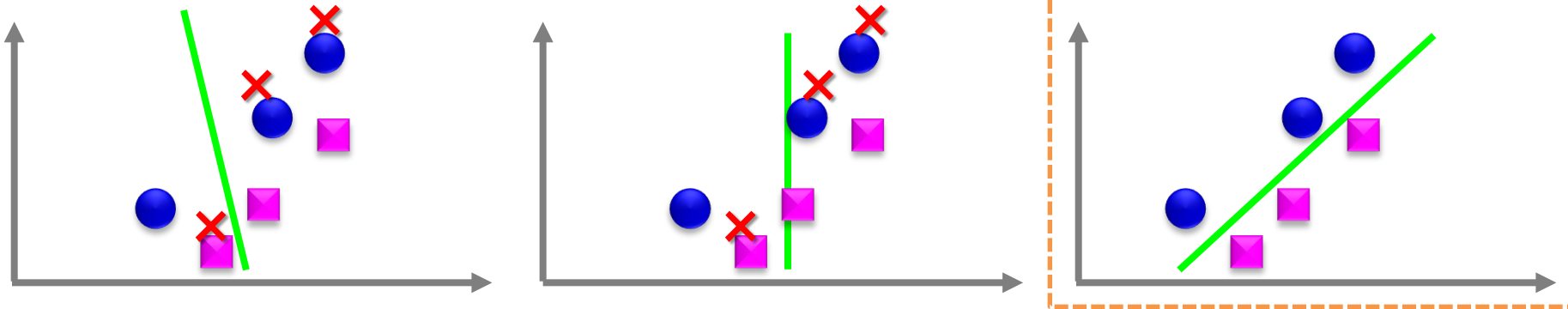
# Feature space analysis for generalization capability

Training

Decision boundary



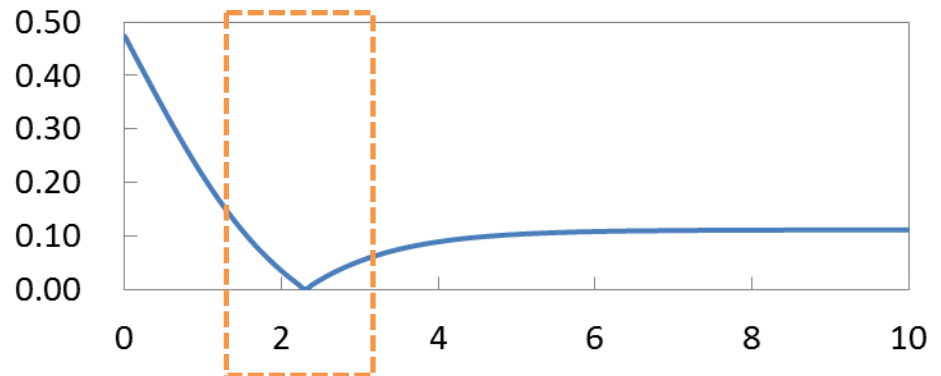
Testing



Feature space index

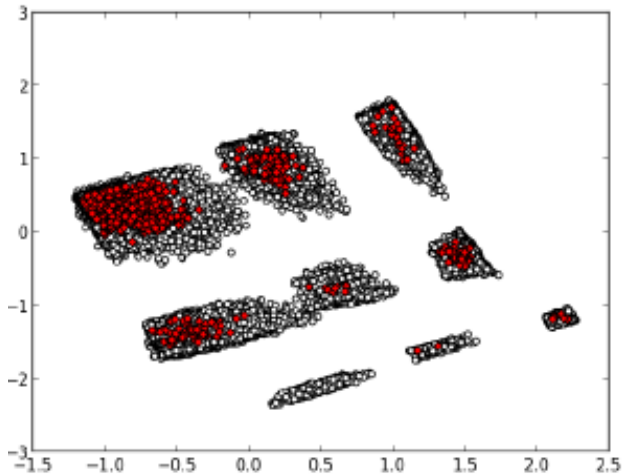
$$H = \left| 1 - \frac{1}{\alpha + \exp(D_m)} \right|$$

Mahalanobis distance between Hotspots and Non-Hotspots

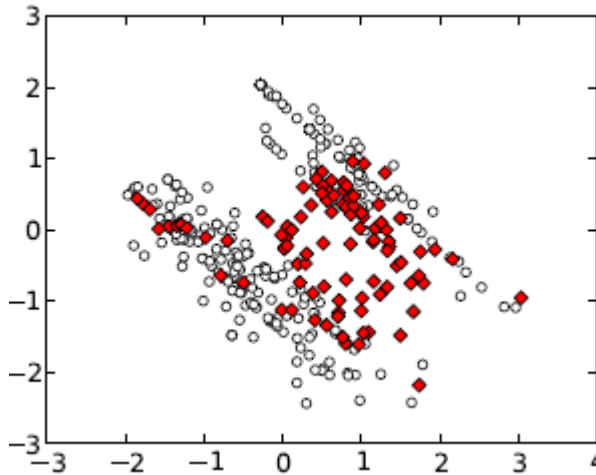


# Comparison of different features

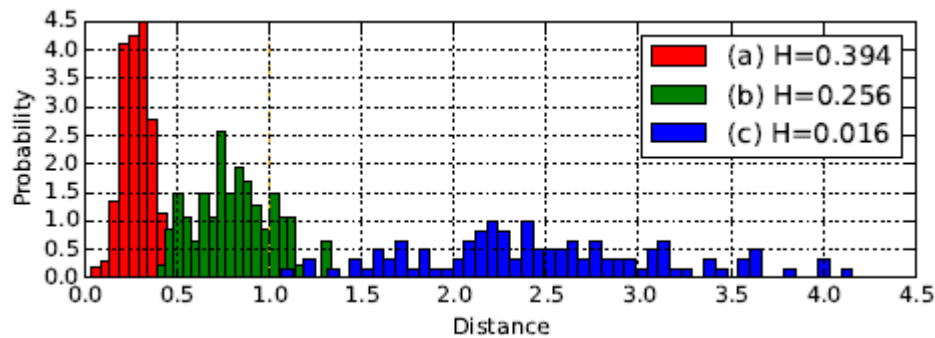
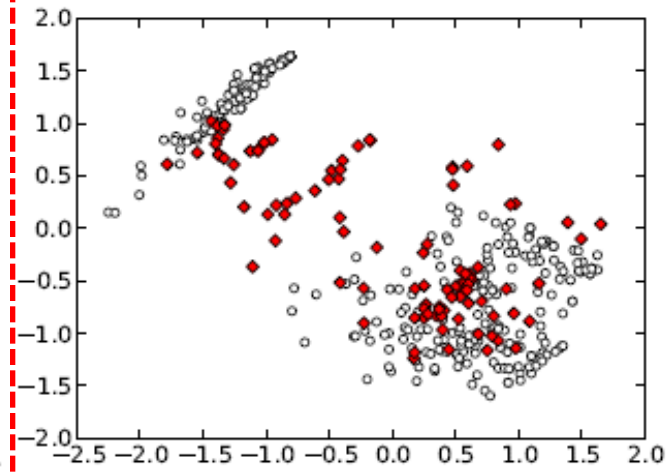
Fragmentation-based



Higher order local auto-correlation



Density-based



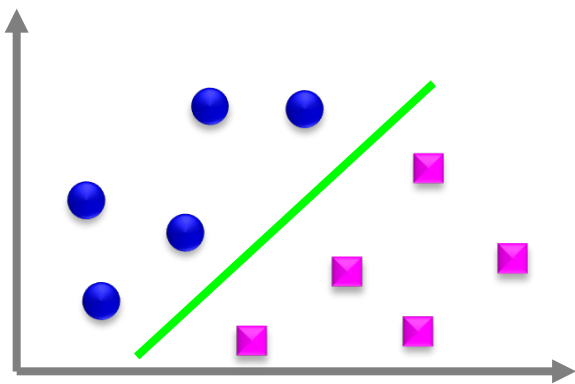
# Outline

---

- Background
- Simplified Feature Extraction
- **AdaBoost Classifier**
- Experimental results
- Conclusion

# Machine learning algorithms

## LR (Logistic Regression)

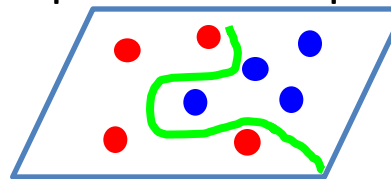


$$y(\mathbf{x}) = \sigma(\mathbf{w}^T \mathbf{x})$$

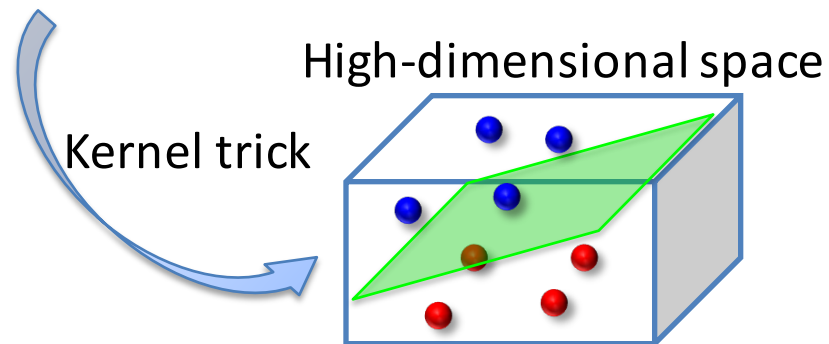
$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$

## SVM (Support Vector Machine)

Input feature space



High-dimensional space



# How to learn hotspot features

---

## Why AdaBoost algorithm?

Hotspot detection is extremely complicated multiclass-classification problem

- Hotspot has many defect mode

Conventional method is hard to generalize all variations of hotspot features

- Accuracy limitation because of too many factors of hotspot

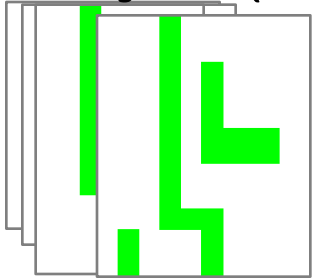
AdaBoost can simultaneously learn many factors of hotspot

- Utilize boosting algorithm in conjunction with several classifiers



# AdaBoost Classifier

Input layout (features)



Calibrate final classifier

$$Y_M(\mathbf{x}) = \text{sign} \left( \sum_m^M a_m y_m(\mathbf{x}) \right)$$

$\mathbf{x}$ : feature vector  
 $a_m$ : weight  
 $M$ : #of base classifier

Set model

Learn layout features in each classifier

$y_1(\mathbf{x})$

Classifier for  
"Narrow"  
mode

$y_2(\mathbf{x})$

Classifier for  
"Open"  
mode

$y_3(\mathbf{x})$

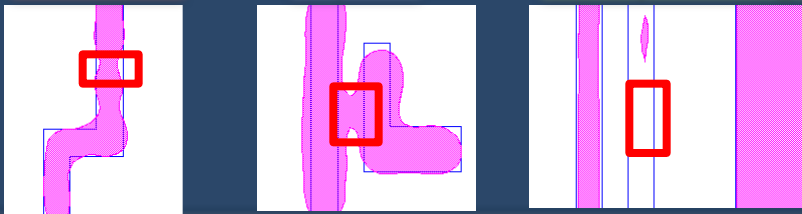
Classifier for  
"Not printing"  
mode

Hotspot

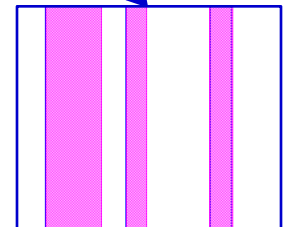
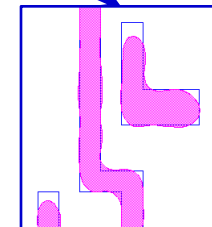
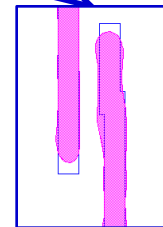
Narrow

Open

Not printing



Non-Hotspot



Generalize final classifier in conjunction with base classifiers corresponding to many defect modes

# Outline

---

- Background
- Simplified Feature Extraction
- AdaBoost Classifier
- **Experimental results**
- Conclusion

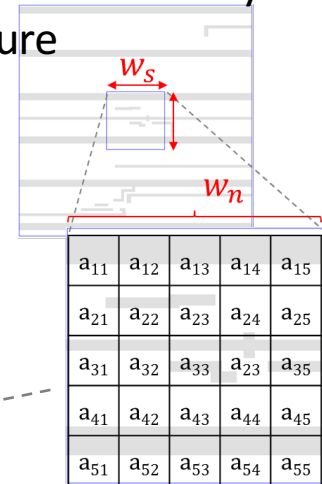
# Detection model training

## ➤ ICCAD 2012 Benchmark Problem3\*

\*[http://cad\\_contest.cs.nctu.edu.tw/CAD-contest-at-ICCAD2012/problems/p3/p3.html](http://cad_contest.cs.nctu.edu.tw/CAD-contest-at-ICCAD2012/problems/p3/p3.html)

Data	Size(KB)	#of HS	#of NHS
	Train/Predict	Train/Predict	Train/Predict
Benchmark1	918 / 1112	99 / 226	340 / 319
Benchmark2	31655 / 28043	174 / 498	5285 / 4145
Benchmark3	29933 / 33333	909 / 1808	4643 / 3541
Benchmark4	12320 / 10072	95 / 177	4451 / 3386
Benchmark5	5726 / 4893	26 / 41	2716 / 2111

Simplified density-based feature



Training layout



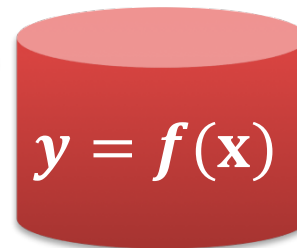
Testing layout



Optimization & Feature extraction



Model training



Feature extraction



Prediction

# Comparison experiments

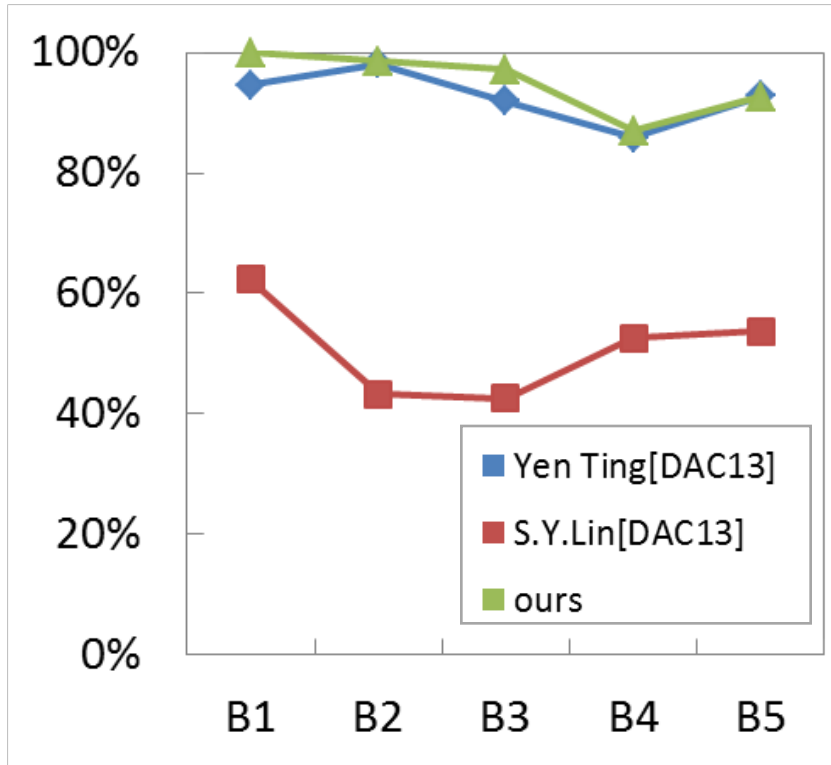
---

- Comparison with related detection methods:
  - [1] **Topological classification and critical feature extraction**, Yen Ting et. al., (DAC'13)
  - [2] **Fuzzy matching model**, S. Y. Lin et. al., (DAC'13)
  
- Comparison of different algorithms:
  - **Logistic Regression** and **Support Vector Machine**

# Comparison with state-of-the-art methods

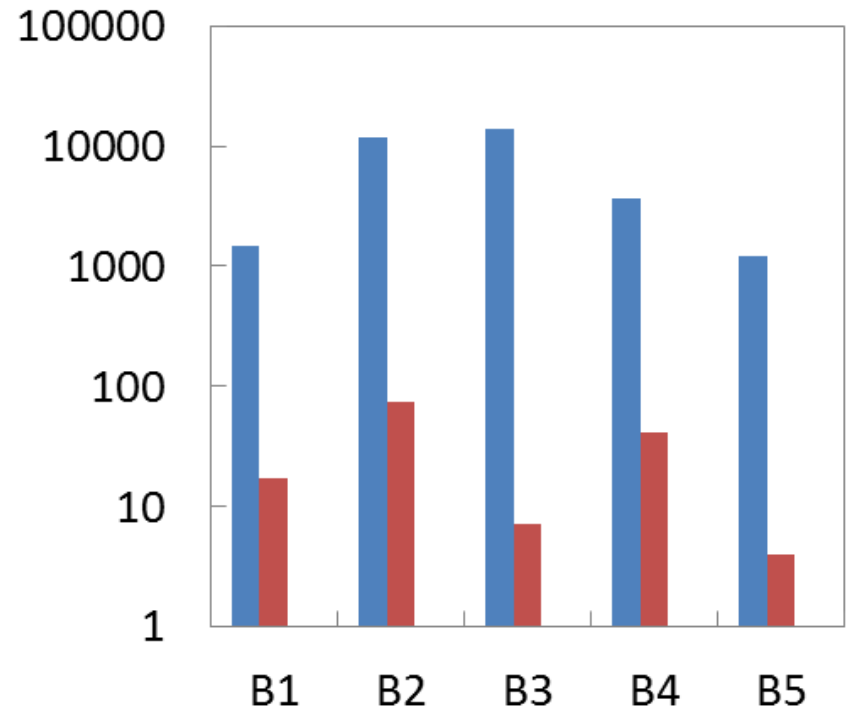
## Detection Accuracy

(#correctly detected hotspots/#total hotspots)



## False Alarm

(#of falsely detected patterns as hotspots)

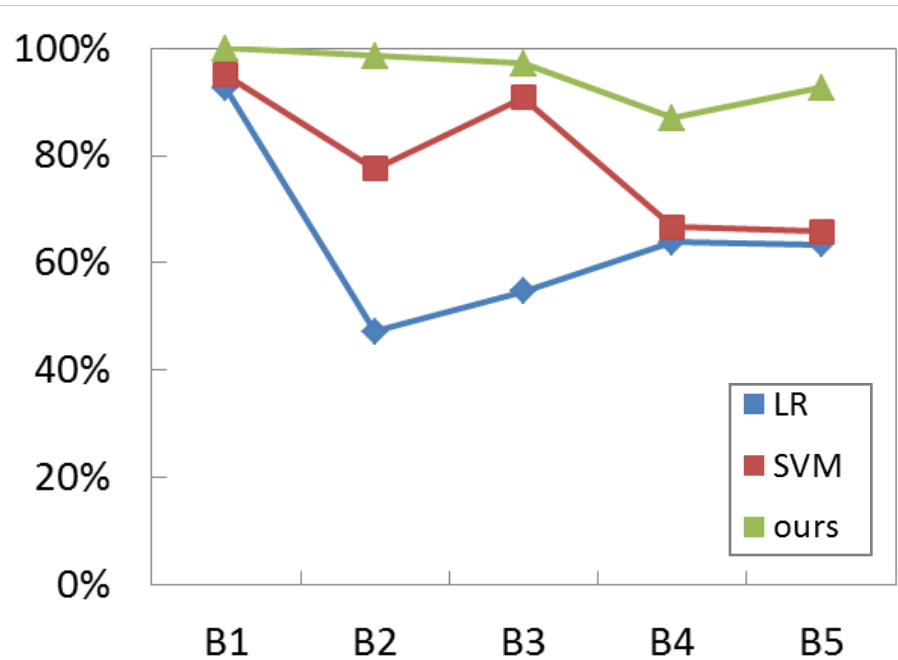


Average **95%** accuracy with almost **0** false alarm

# Comparison of different algorithms

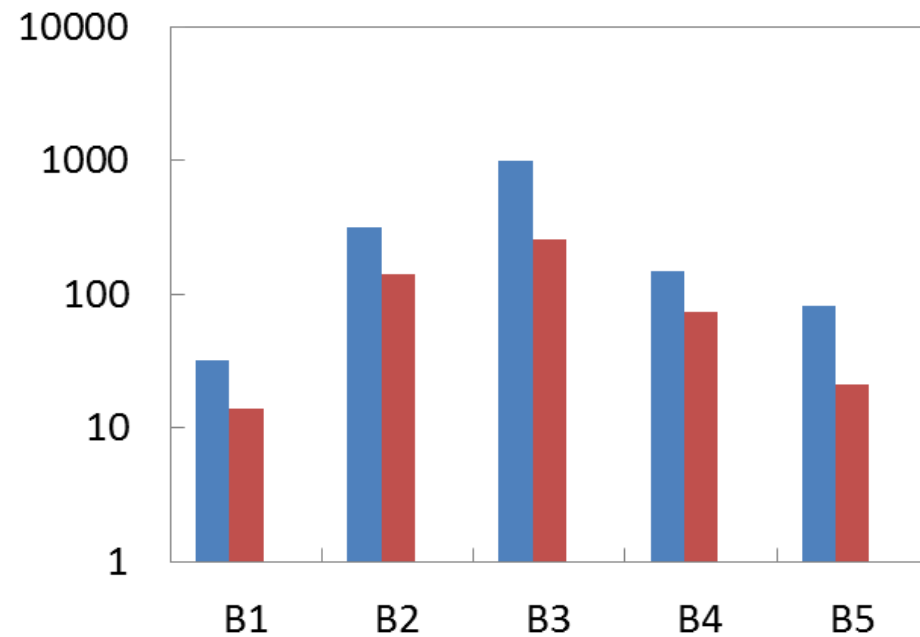
## Detection Accuracy

(#correctly detected hotspots/#total hotspots)



## False Alarm

(#of falsely detected patterns as hotspots)



Average **95%** accuracy with almost **0** false alarm

# Conclusion

---

- **Toshiba** and **UTDA** developed a new hotspot detection framework.
- Our method utilizes **AdaBoost** classifier and **simplified feature extraction** method.
- Experimental results show that our method can achieve over **95% accuracy** with almost **0 false-alarm**.