Rapid Layout Pattern Classification

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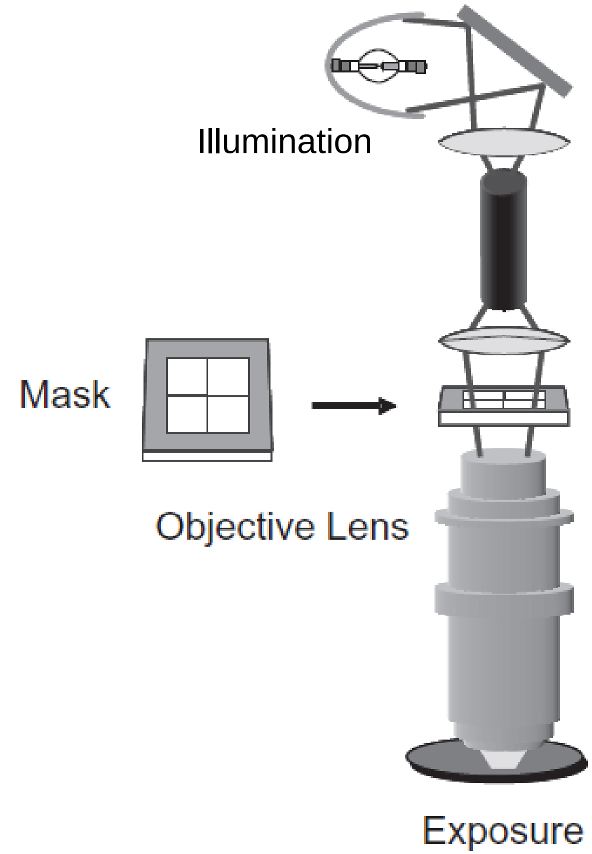
Outline

- Introduction
- Supervised Machine Learning
- Two-Level Hotspot Pattern Classification
- Accuracy and Runtime Enhancement
- Experimental Results and Analysis

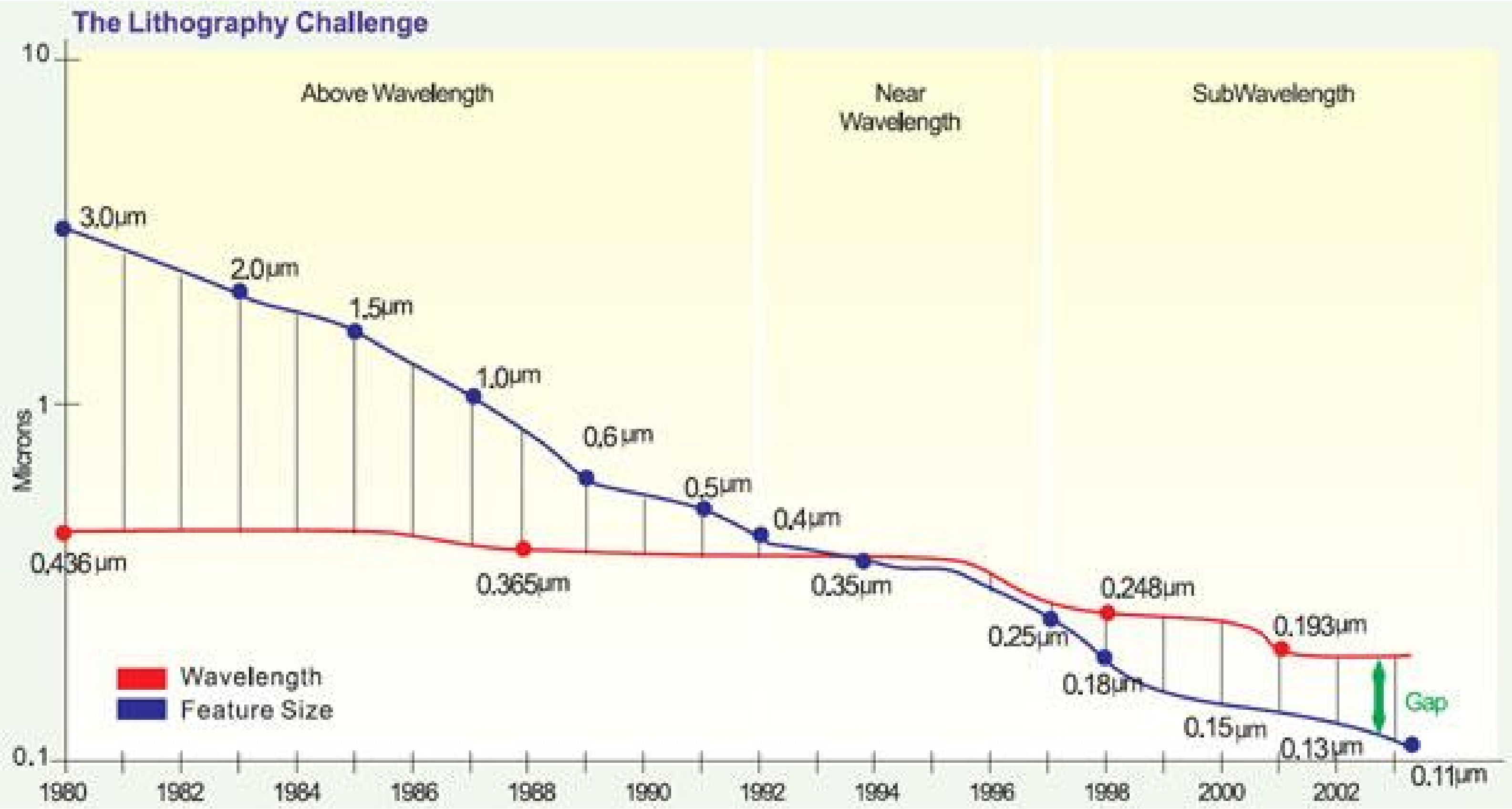
IC Fabrication and Optical Lithography

- Fundamental of IC fabrication: **Optical Lithography**
- Lithography
  - Accounts for about 30% of manufacturing cost.
  - Tends to be the technical limiter for advance in feature size reduction.

Reference: Chris Mack, *Fundamental Principles of Optical Lithography: The Science of Microfabrication,* John Wiley & Sons, 2007.

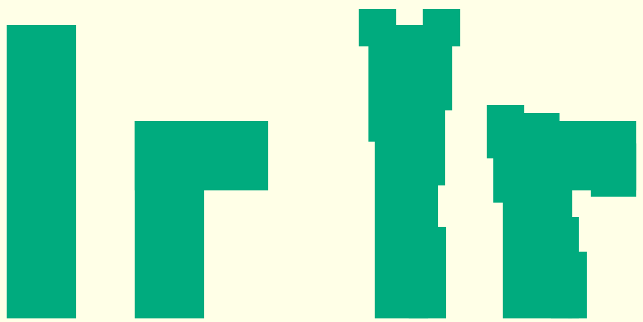


Sub-wavelength Lithography

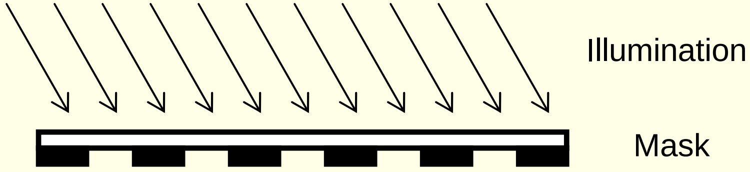


Courtesy of Raghunath Murali (http://www.mirc.gatech.edu/raghu/?p=185&cpage=1)

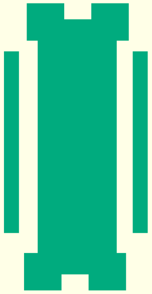
Resolution Enhancement Techniques



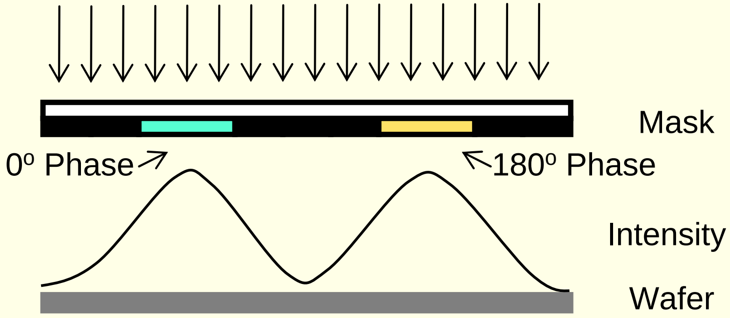
Optical Proximity Correction (OPC)



Off-Axis Illumination (OAI)



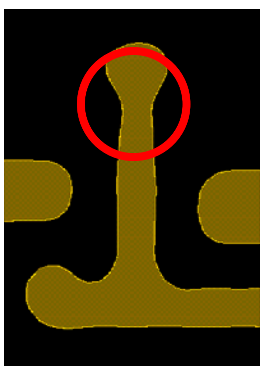
Sub-Resolution Assist Feature (SRAF)

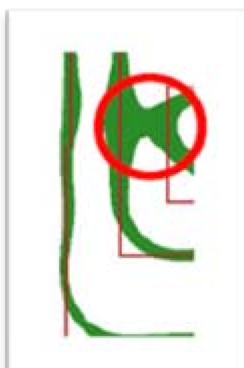


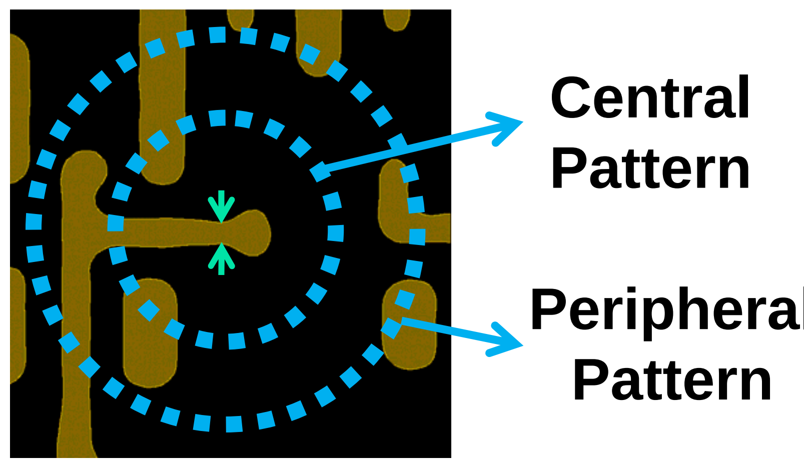
Phase Shift Mask (PSM)

Lithographic Hotspots

- Lithographic hotspots cannot be completely eliminated.
- Studies have shown that hotspots are largely pattern dependent.
- Radius of influence becomes larger. Peripheral patterns can no longer be ignored.


Pinching


Bridging



Physical Verification Tools

- Design Rule Checking
  - One-dimensional geometrical rules are too simple and cannot describe two-dimensional patterns well
  - Checks become overly conservative or result in escaped hotspots
- Model-Based Lithography Simulation
  - Generates accurate printed images and enables robust checking
  - Extremely computationally expensive
  - Requires well-calibrated process models

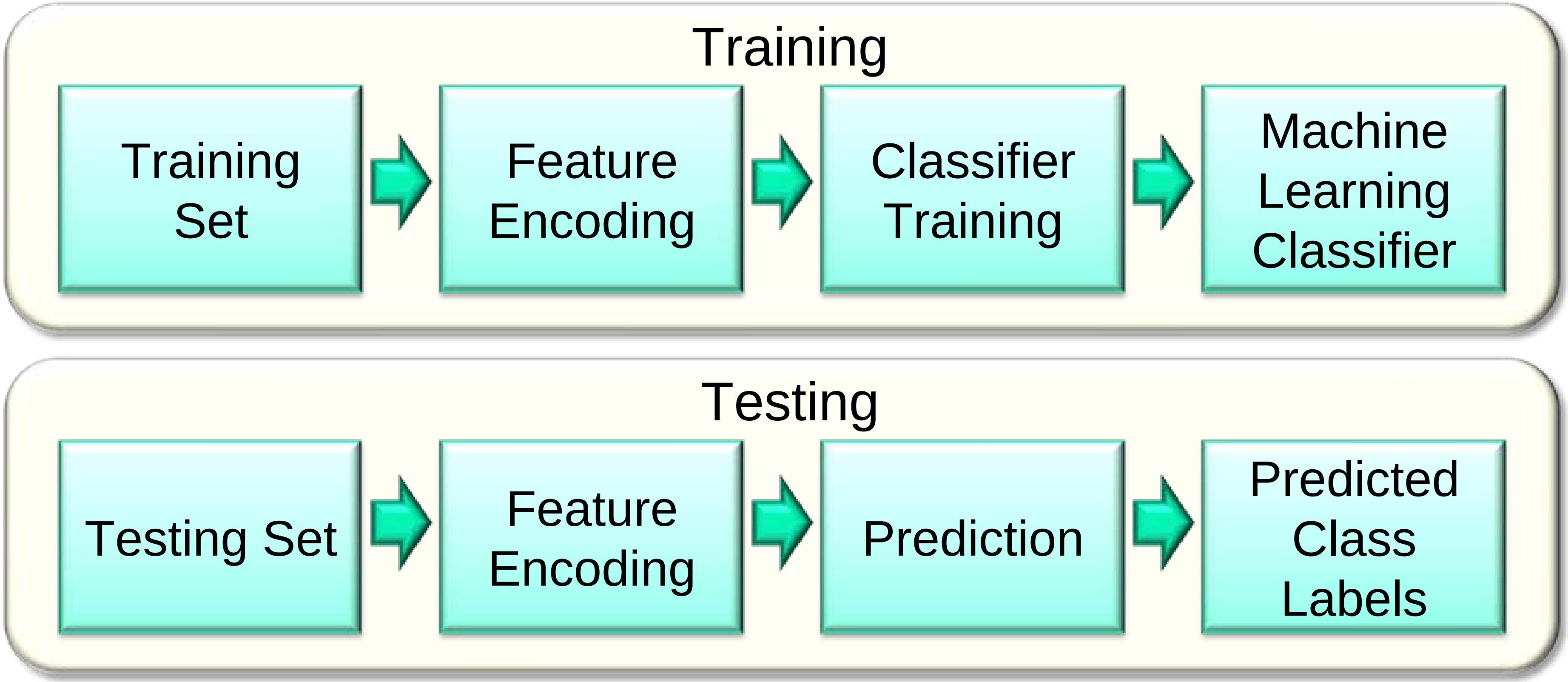
Early Lithographic Hotspot Detection

- Pattern Matching-Based Methods
  - Collect known bad patterns into database, and scan design for occurrences
  - Fast and efficient, but weak in recognizing previously unseen bad patterns
  - References: V. Dai, et al. (SPIE, 2007), H. Yao, et al. (IET-CDS, 2008), J. Ghan, et al. (SPIE, 2009).
- Dual Graph-Based Method
  - Derive graphs from layout geometry to model cumulative effects from patterns in close proximity
  - Reference: A.B. Kahng, et al. (TCAD, 2008).

Early Lithographic Hotspot Detection

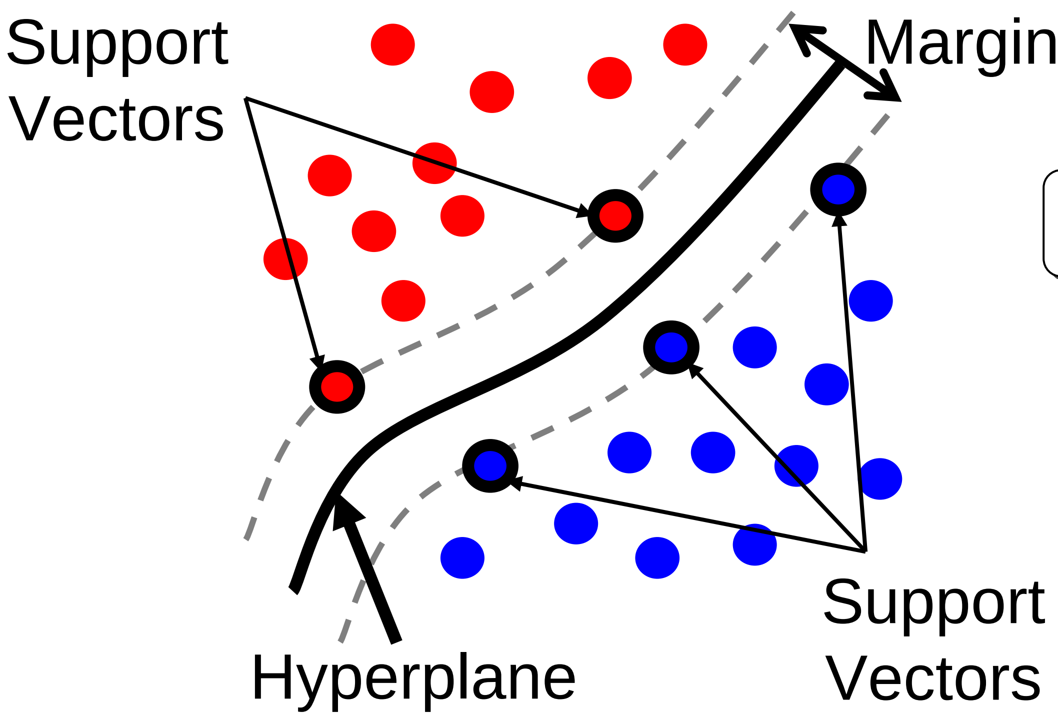
- Machine Learning-Based Methods
  - Construct classification models from known good and bad patterns
  - Capable of making prediction on unseen patterns
  - References: J.-Y. Wuu, et al. (SPIE, 2009), D. Ding, et al. (ICICDT, 2009), D. G. Drmanac, et al. (DAC, 2009).
- We present a rapid two-level hotspot pattern classification flow, utilizing both central and peripheral pattern information.
  - Detailed analysis of classification results is presented.

Supervised Machine Learning



Support Vector Machine (SVM)

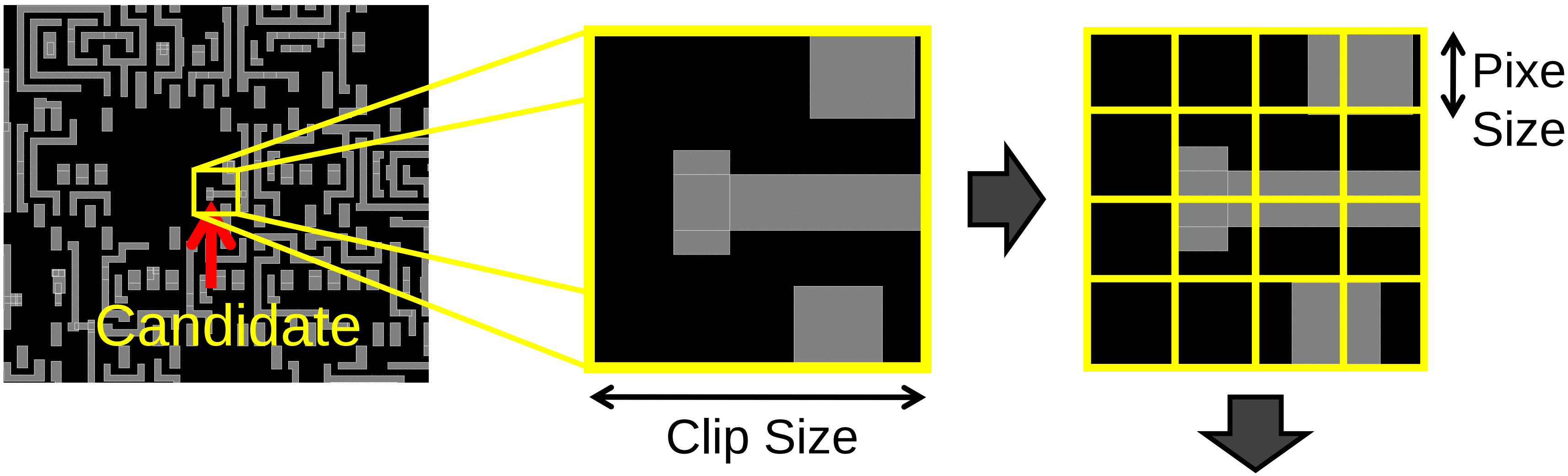
- SVM maps the training data into a higher dimensional space where samples of different classes are separated by a hyperplane.

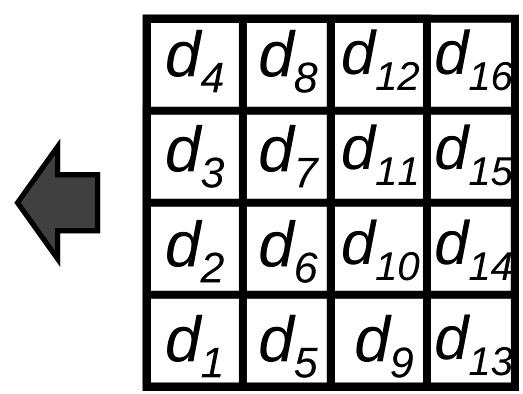


Decision Value:

$$DV(\boldsymbol{x}) = \sum_{i=1}^{k} y_i \alpha_i K(\boldsymbol{x}, \boldsymbol{x}_i) + b$$

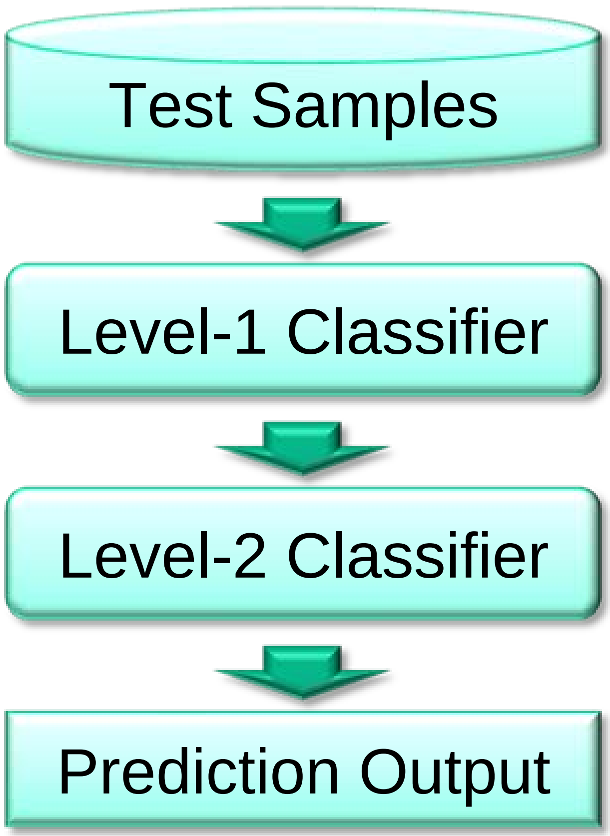
Density-Based Feature Encoding





Feature Vector = $(d_1, d_2, \ldots, d_{16})$

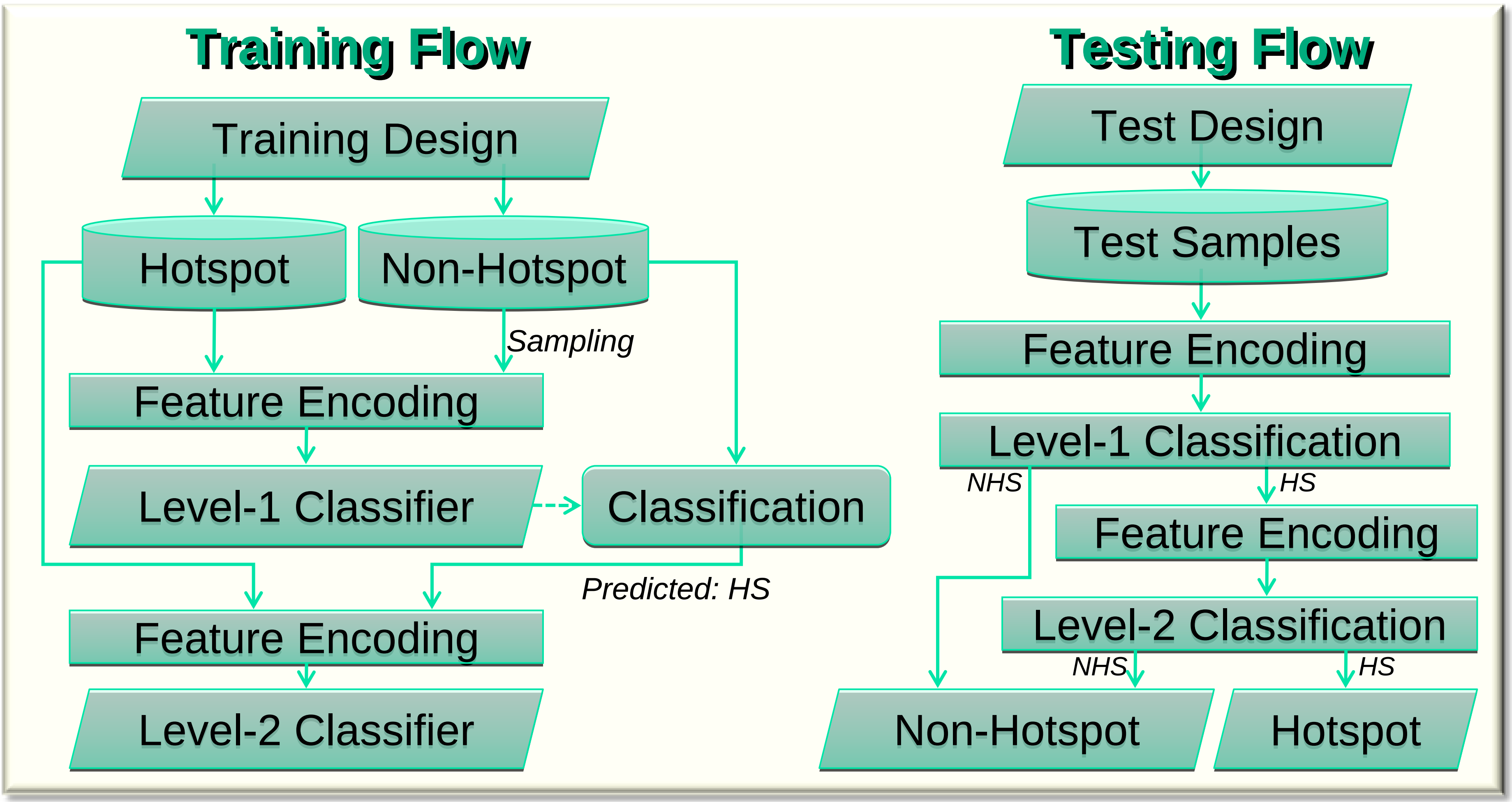
Two-Level Lithographic Hotspot Pattern Classification Flow



Fast filtering using central patterns

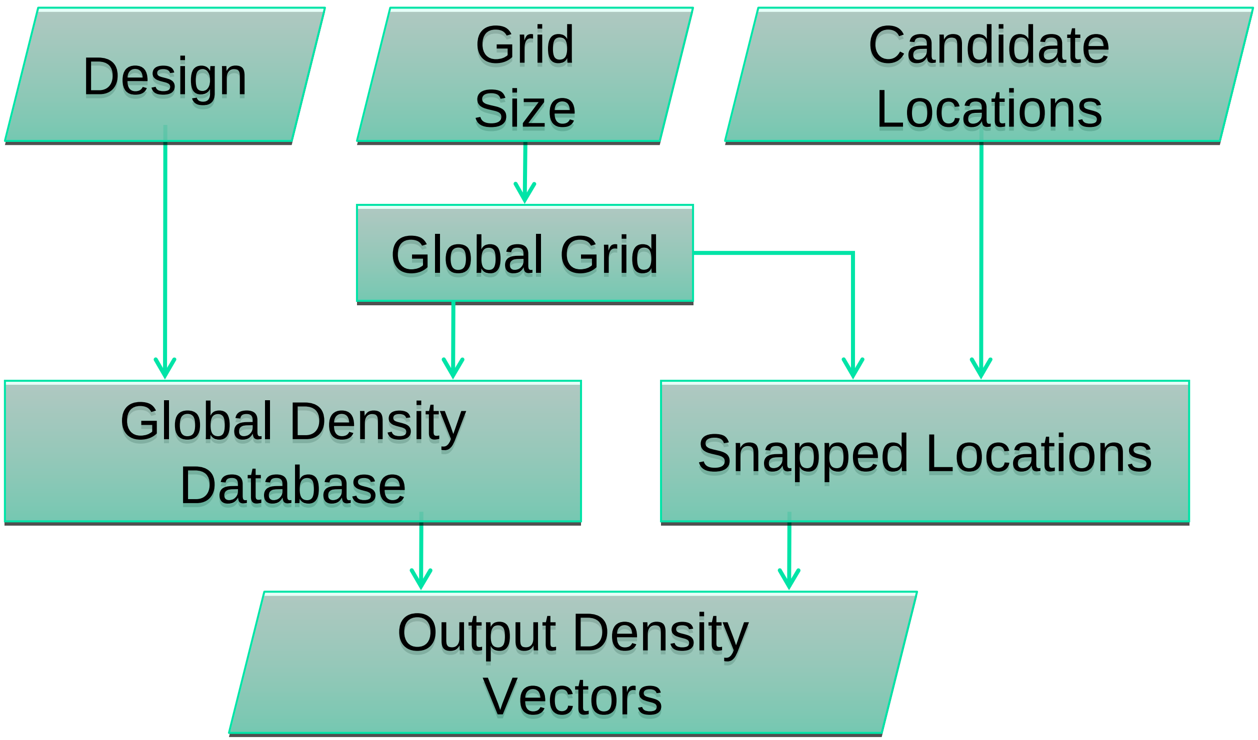
False alarm reduction using central & peripheral patterns

Two-Level Lithographic Hotspot Pattern Classification Flow



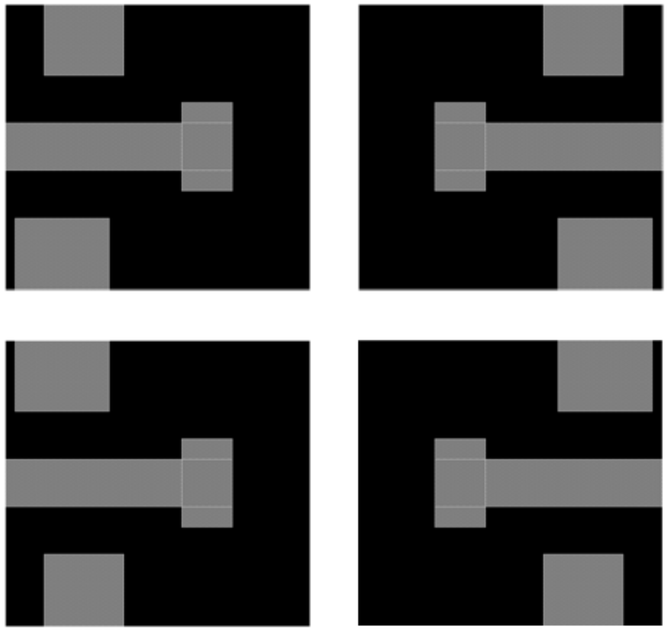
Global Density Pre-Computation

- Align pixel grids and save density computation time.



Pattern Morphing

- Symmetrical variants of a pattern may be equivalent in terms of printability.
- Equivalent variants are created for each training sample.
  - Performed on feature vectors.
  - No modification on original design layout.



Experimental Setup

- Test Cases (Layer: Metal-1)

Test Case	Tech Node	Dimension (mm x mm)	Hotspot Count	Min. Drawn Width/Spacing
T1	45nm	1.00 x 1.00	132	70nm
T2	45nm	0.39 x 0.39	34	70nm
T3	32nm	0.45 x 0.45	45	50nm
T4	32nm	0.30 x 0.30	22	50nm

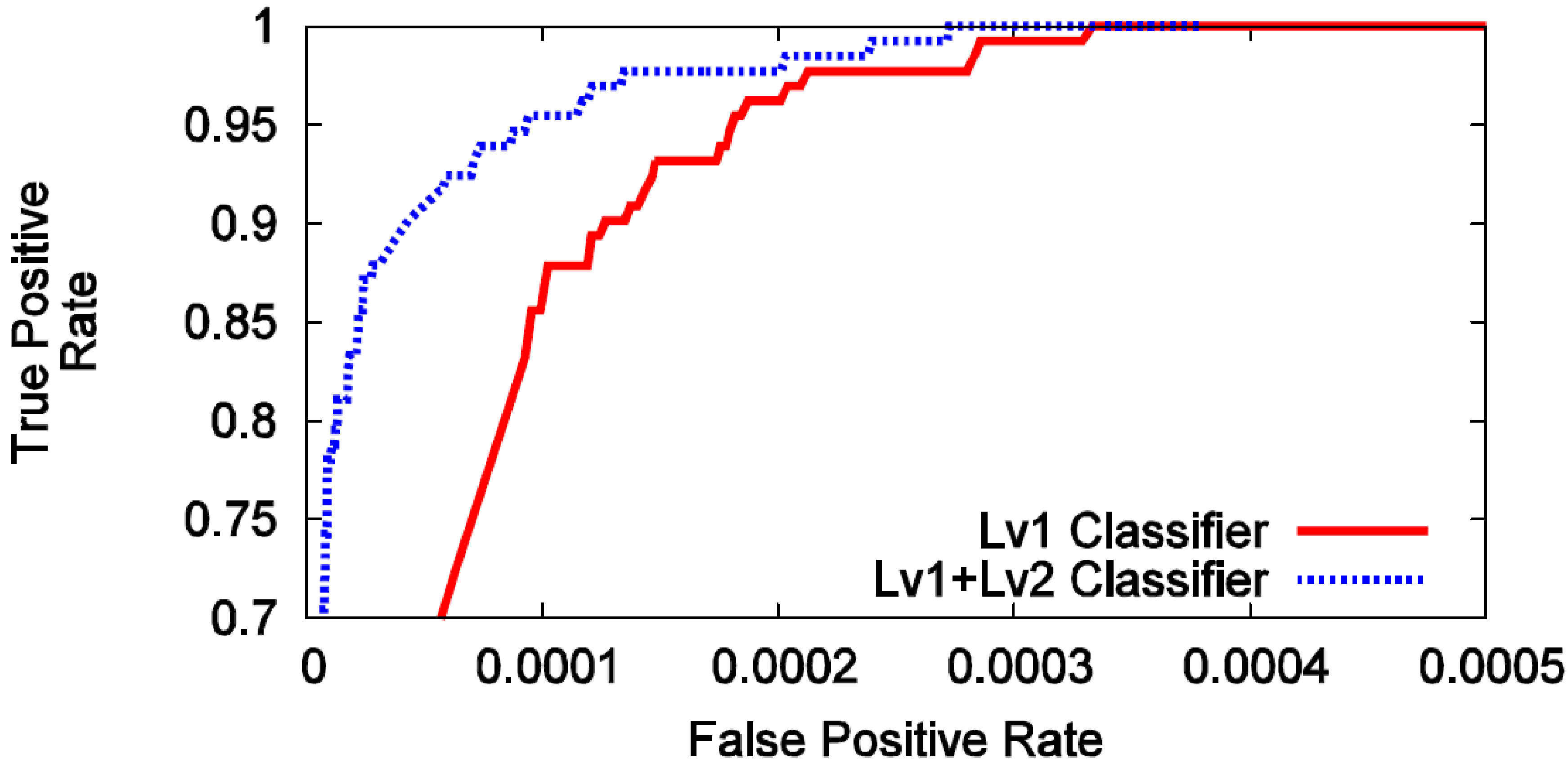
- Hotspot locations verified using *Mentor Graphics Calibre* with real process models and RET recipes
- *LIBSVM* used for classifier construction and pattern classification.

Experimental Results

	Pixel Size	Level-1 Classification				
		Clip Size	TP Count	TP Rate	FP Count	FP Rate
T1	35nm	420nm	132	100%	4583	0.038%
T2	35nm	420nm	33	97.1%	349	0.021%
T3	25nm	300nm	43	95.6%	327	0.034%
T4	25nm	300nm	21	95.5%	162	0.038%
Avg				**97.1%**		**0.033%**

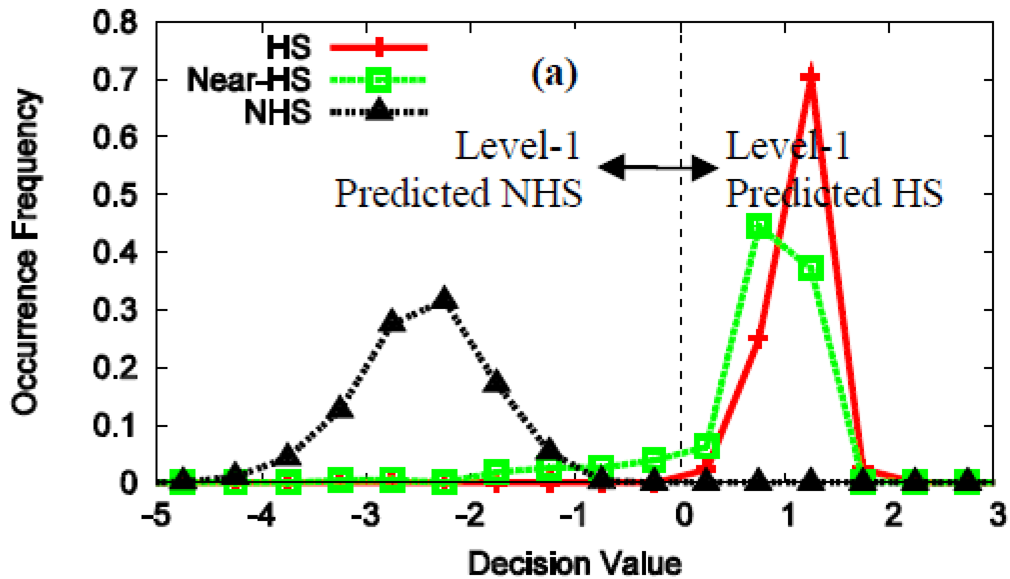
	Pixel Size	Level-1 + Level-2 Classification				
		Clip Size	TP Count	TP Rate	FP Count	FP Rate
T1	35nm	700nm	103	78.0%	140	0.0012%
T2	35nm	700nm	29	85.3%	83	0.005%
T3	25nm	600nm	38	84.4%	183	0.019%
T4	25nm	600nm	18	81.8%	121	0.029%
Avg				**82.4%**		**0.014%**

Level-1 vs. (Level-1 + Level-2) Classification

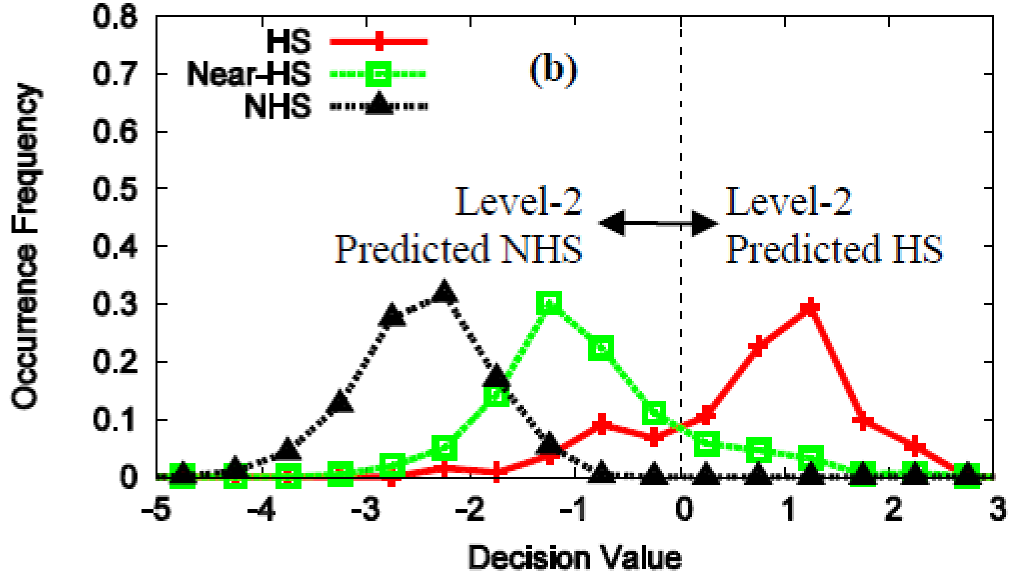


Distribution of Classification Results

Level-1 Classification

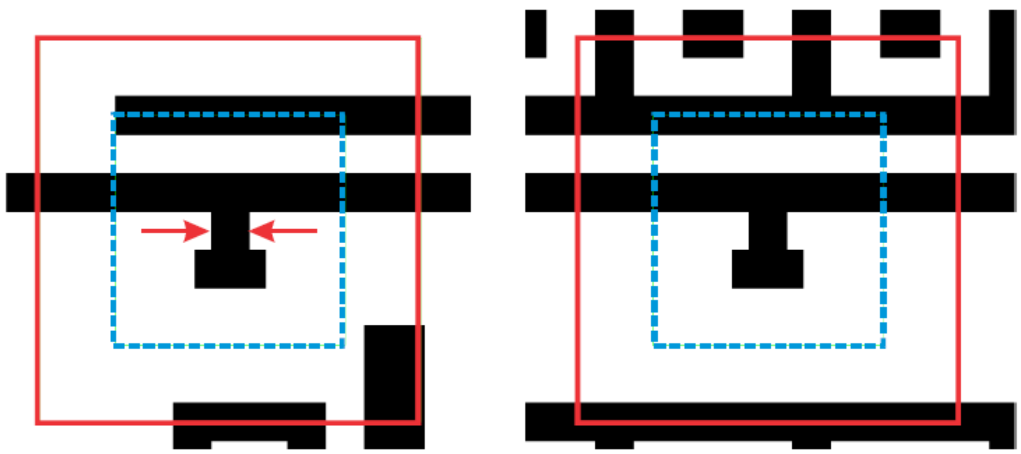


Level-1 + Level-2 Classification



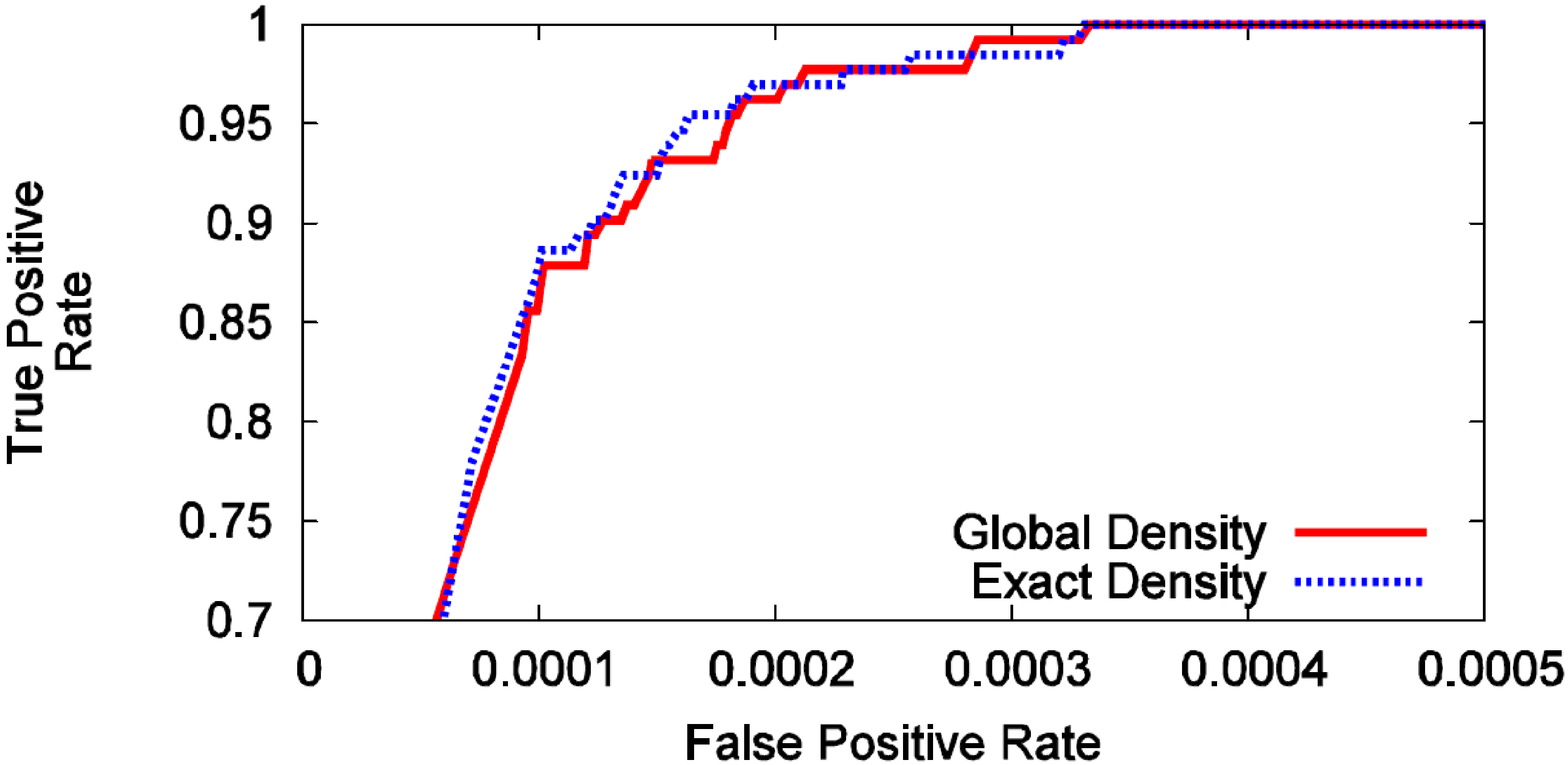
Pattern Examples

- Two layout patterns
  - Undistinguishable for Level-1 Classifier
  - Separated by Level-2 Classifier

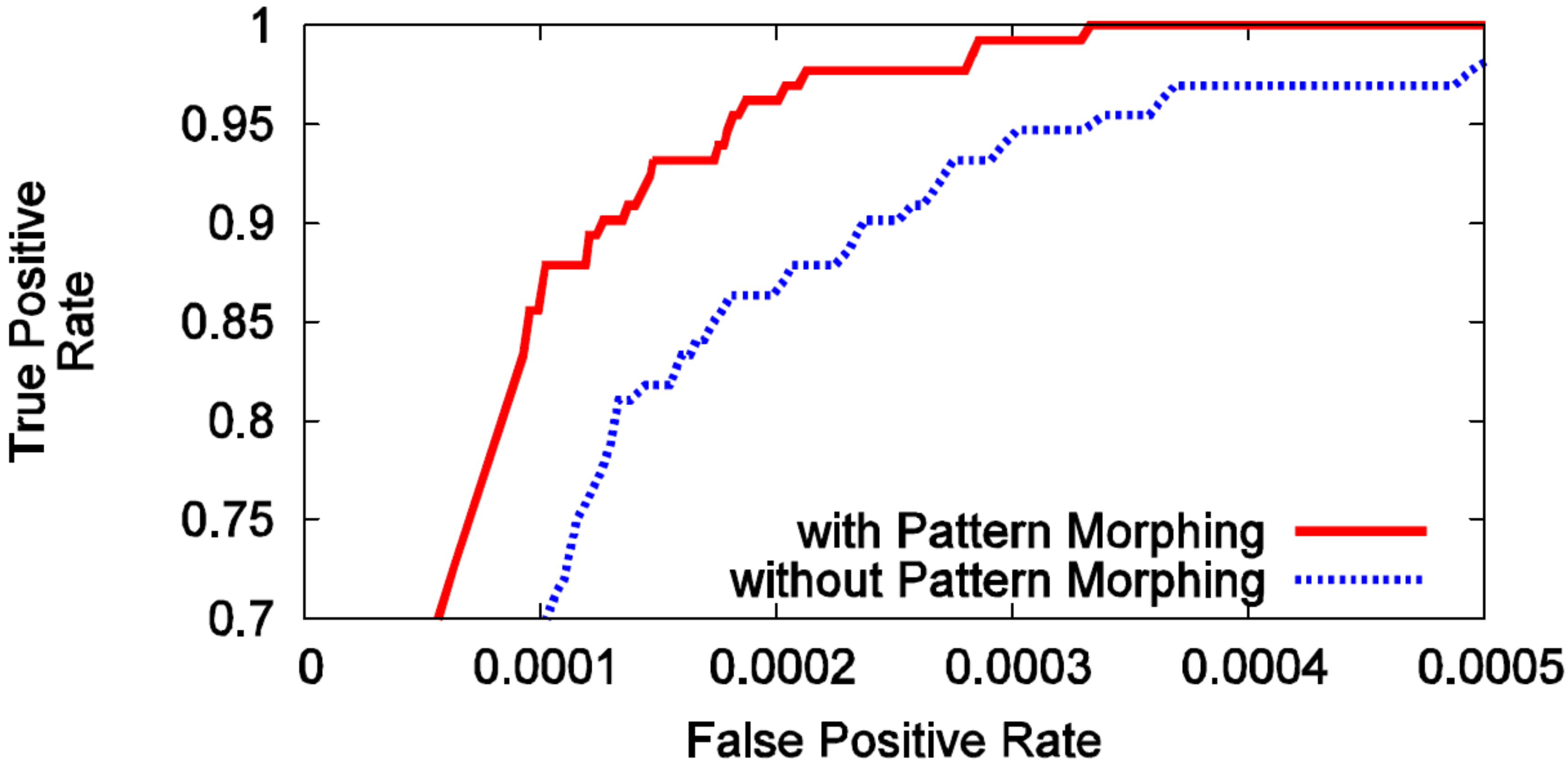


Hotspot　　Non-Hotspot

Effect of Global Density Pre-Computation



Effect of Pattern Morphing



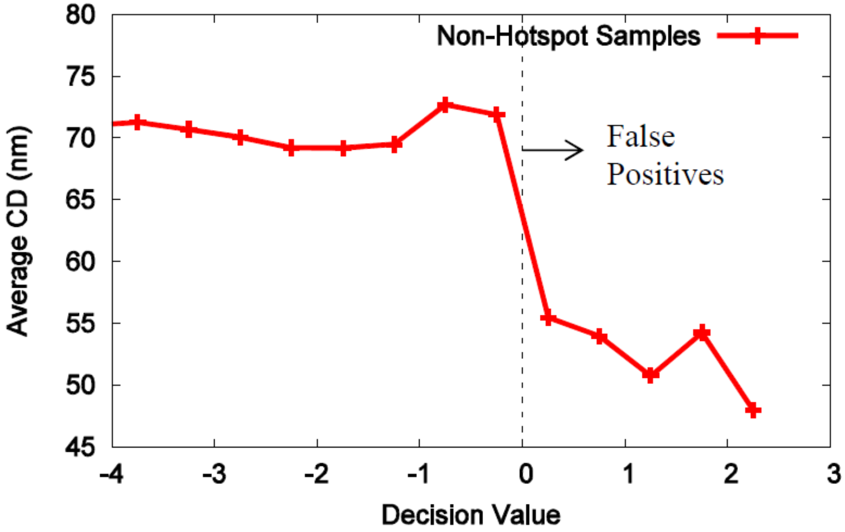
Runtime Information

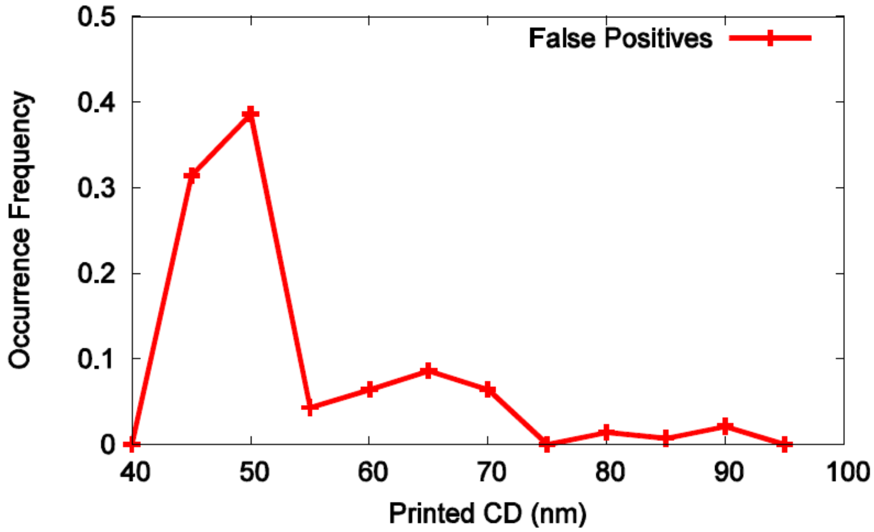
	Sample Location Extraction	Global Density Database	Density Vector Synthesis	Prediction	Total
L2Global	0.1	0.4	0.9	0.4	1.9
[1]	0.1	N/A	147.2	0.4	147.7
Lithography Simulation	N/A				251.1

[1] Jen-Yi Wuu, Fedor G. Pikus, Andres Torres, and Malgorzata Marek-Sadowska, *"Detecting Context Sensitive Hotspots in Standard Cell Libraries*," Proc. SPIE, Vol. 7275, 727515, 2009.

False Positive Analysis

- Analysis shows that most false positives are very close to hotspots.





$$\text{AverageCD}(x) = \frac{\sum_{i=1}^{n} a_i CD_i}{\sum_{i=1}^{n} a_i},$$

$$\text{where } a_i = \begin{cases} 1, \text{if } |DV_i - x| < \delta = 0.25 \\ 0, \quad \text{otherwise} \end{cases}$$

Conclusions

- We presented a two-level lithographic hotspot pattern classification method, based on machine learning techniques.
  - We utilize density-based feature encoding.
  - Accuracy and runtime enhanced by global density pre-computation and pattern morphing.
  - Fast and effective, suitable for early design stages.
- Our method is verified on several 45*nm* and 32*nm* real designs.
- Analysis on classification results shows the false positives are very close to hotspots.