

# SRAF Insertion via Supervised Dictionary Learning

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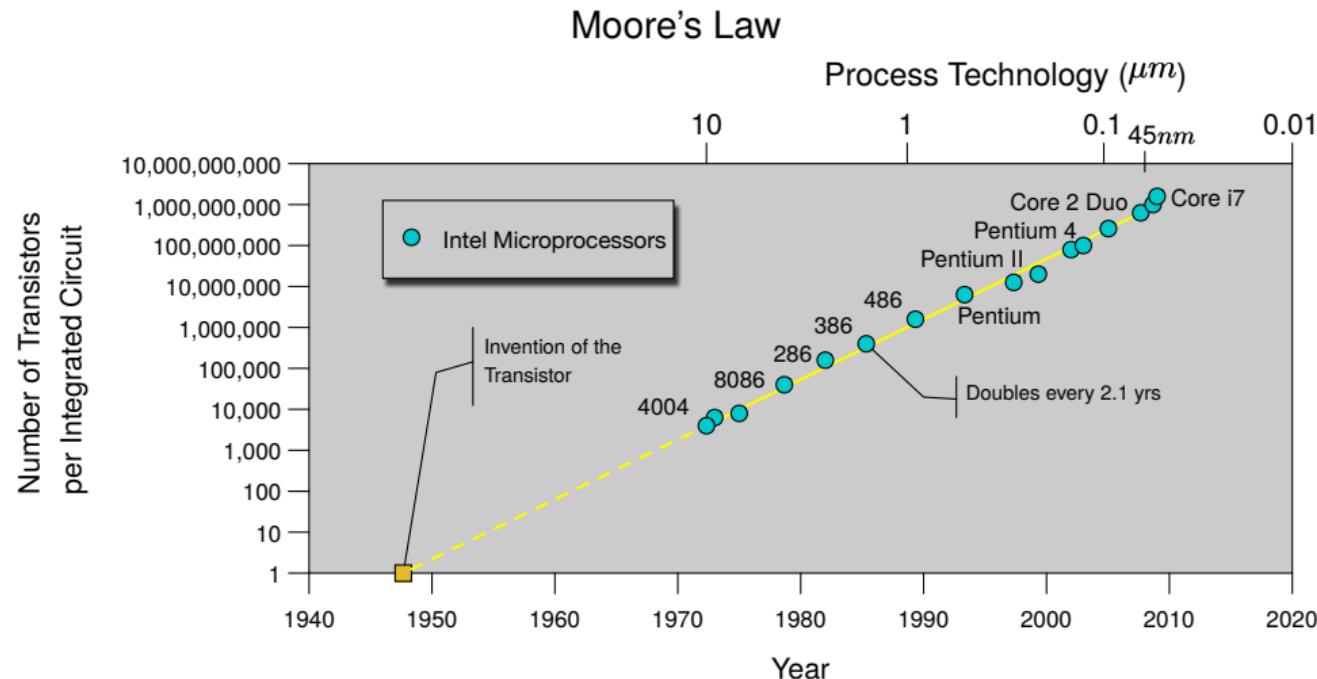
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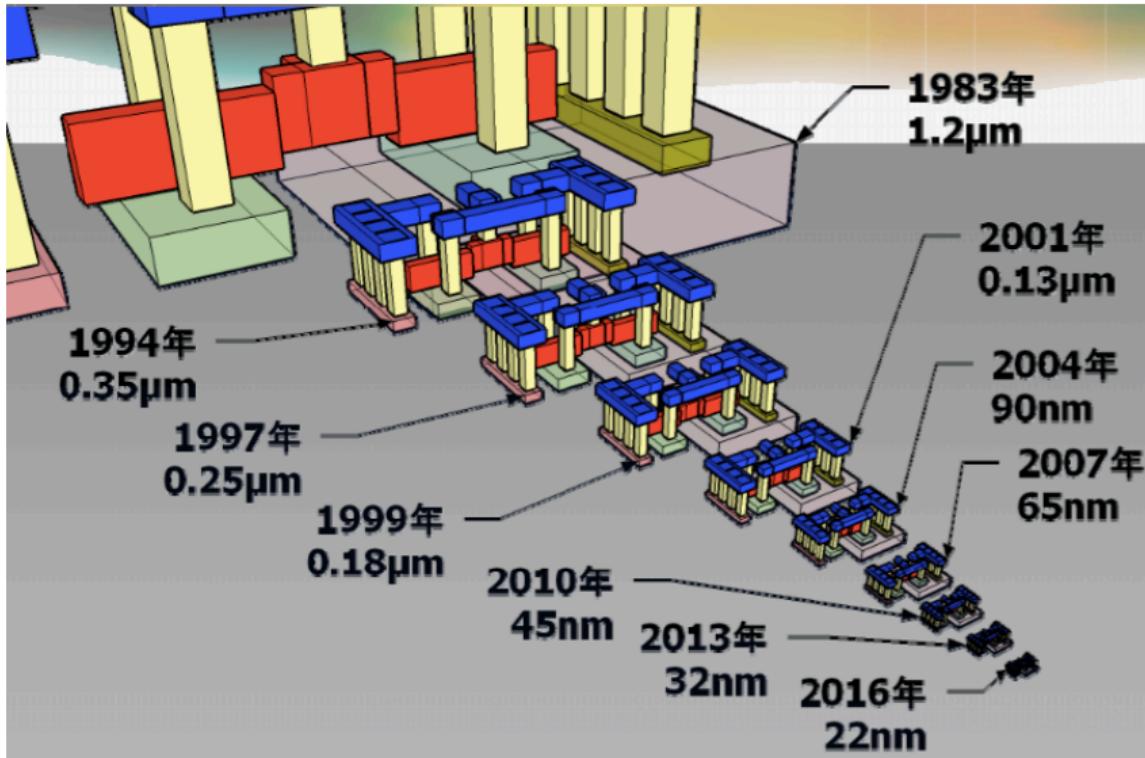


cadence

# Moore's Law to Extreme Scaling

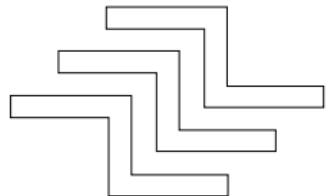


# Nanometer Era of Manufacturing: An Inverter Example



## Optical Proximity Correction (OPC)

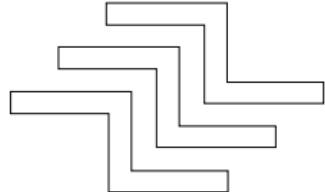
## Design target



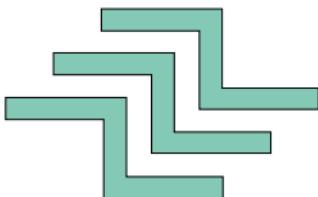
## Optical Proximity Correction (OPC)

## Design target

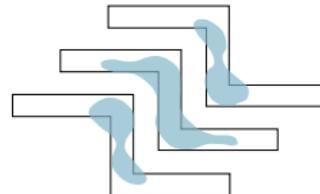
without OPC



## Mask

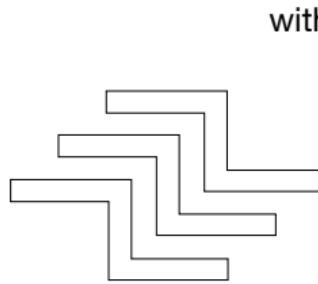


## Wafer



# Optical Proximity Correction (OPC)

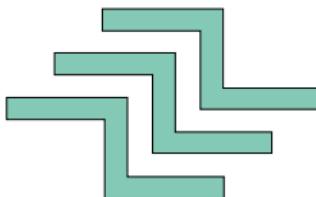
Design target



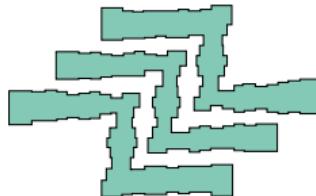
without OPC



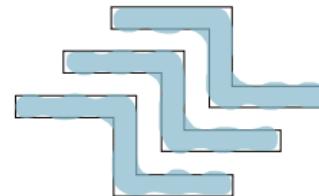
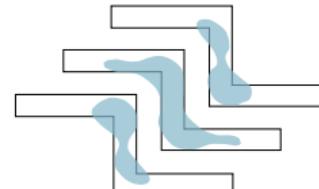
Mask



with OPC

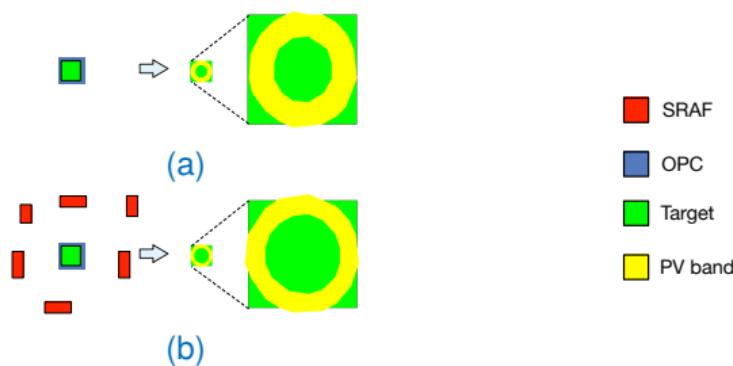


Wafer



# What is SRAF?

- ▶ Patterns deliver light to target features without printing themselves
- ▶ Make isolated features more dense
- ▶ Improve the robustness of the target patterns
- ▶ Rule-based [Jun+, SPIE'15], Model-based [Shang+, Mentor'05], Machine learning model-based [Xu+, ISPD'16]



(a) Printing with OPC only ( $2688 \text{ nm}^2$  PV band area); (b) Printing with both OPC and SRAF ( $2318 \text{ nm}^2$  PV band area).

# Outline

Supervised Feature Revision

SRAF Insertion

Experimental Results

# Outline

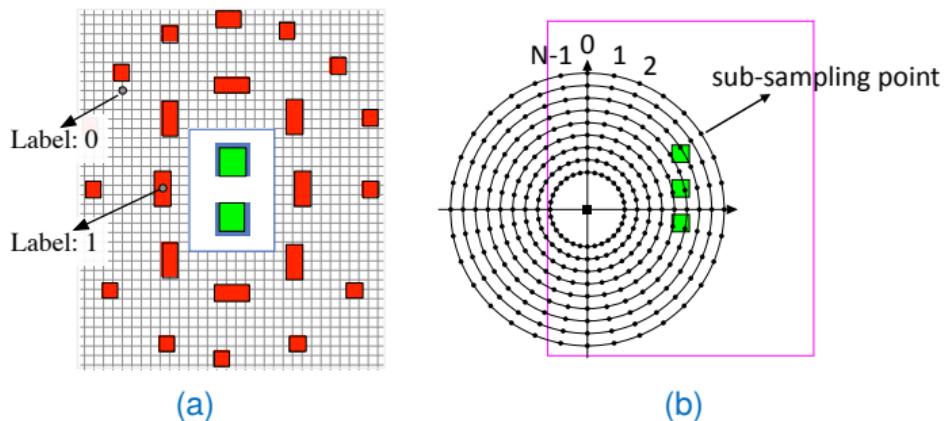
Supervised Feature Revision

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## Concentric Circle Area Sampling

- ▶ Initial feature extraction method in SRAF generation



(a) SRAF label; (b) CCAS feature extraction method in machine learning model-based SRAF generation.

# Introduction to Dictionary Learning

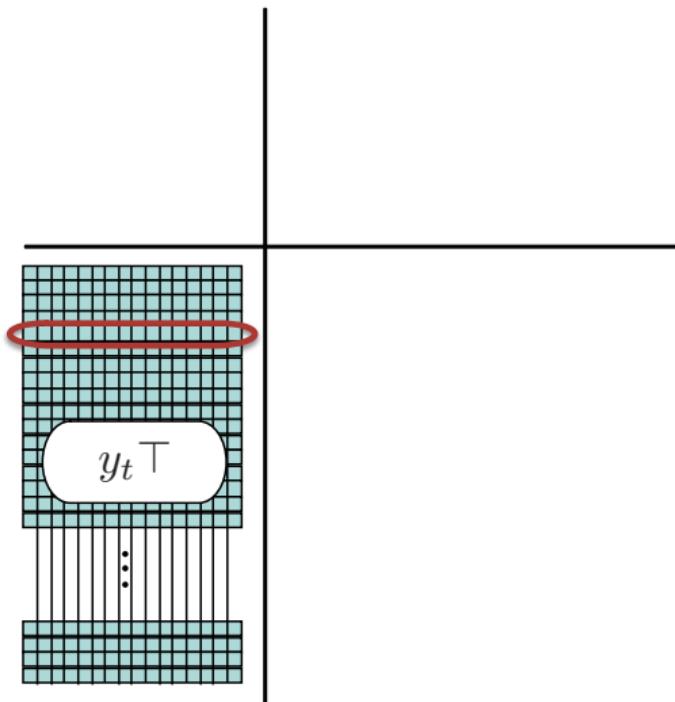
## Overview

Originally, the dictionary learning model is composed of two parts. One is **sparse coding** and the other is **dictionary constructing**. The joint objective function with respect to  $\mathbf{D}$  and  $\mathbf{x}$  is below.

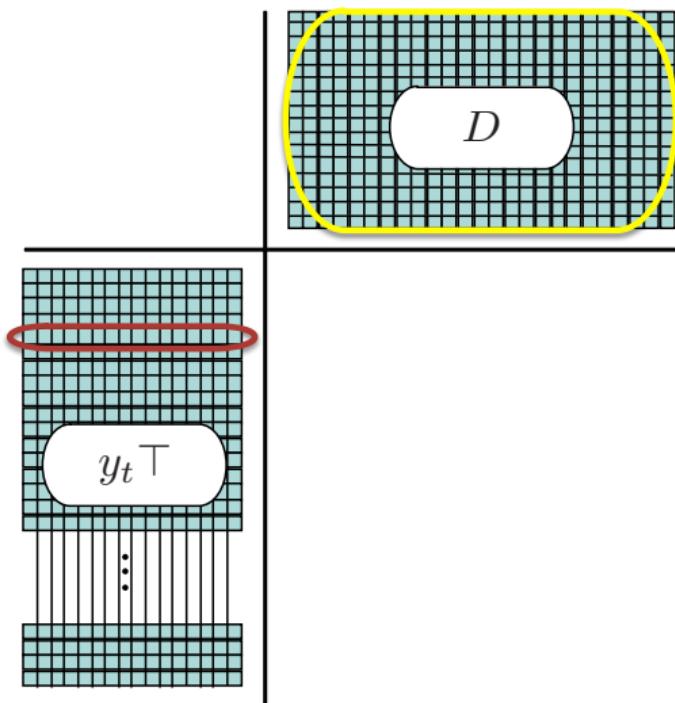
$$\min_{\mathbf{x}, \mathbf{D}} \frac{1}{N} \sum_{t=1}^N \left\{ \frac{1}{2} \|\mathbf{y}_t - \mathbf{D}\mathbf{x}_t\|_2^2 + \lambda \|\mathbf{x}_t\|_p \right\}, \quad (1)$$

- ▶  $\mathbf{y}_t \in \mathbb{R}^{(n)}$ : the  $t$ -th input data vector
- ▶  $D = \{\mathbf{d}_j\}_{j=1}^s, \mathbf{d}_j \in \mathbb{R}^{(n)}$ : the dictionary where every column is called an **atom**.
- ▶  $\mathbf{x}_t \in \mathbb{R}^{(s)}$ : the sparse code
- ▶  $\lambda$ : hyper-parameter
- ▶  $p$ : the norm type of penalty term, e.g.  $l_1$  norm

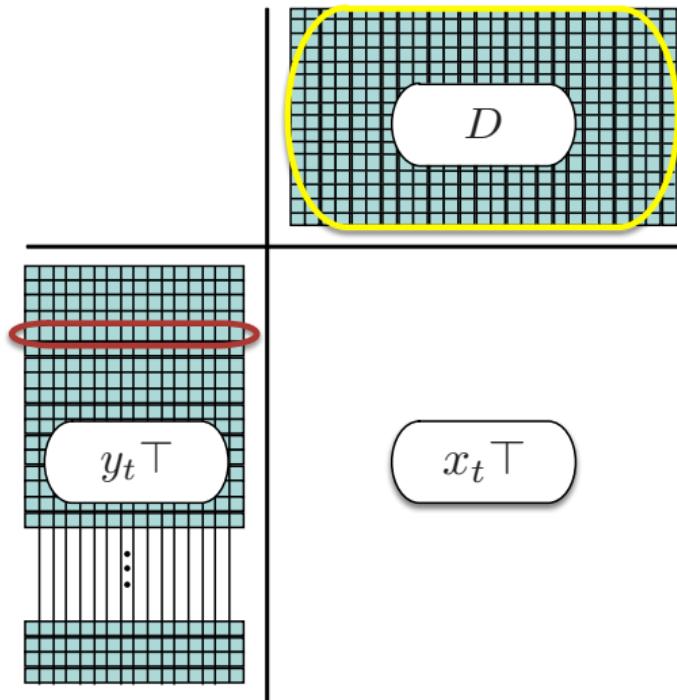
# The Illustration for Dictionary Learning



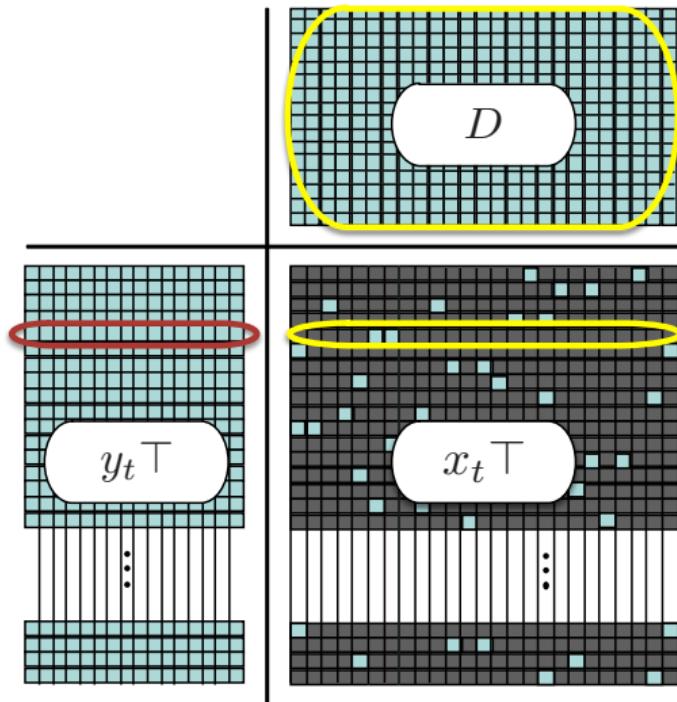
# The Illustration for Dictionary Learning



# The Illustration for Dictionary Learning



# The Illustration for Dictionary Learning



# Online Learning Framework

## Sparse Coding

The subproblem with  $\mathbf{D}$  fixed is convex. The objective function for sparse coding of  $i$ -th training data vector in memory is

$$\mathbf{x}_t \stackrel{\Delta}{=} \arg \min_{\mathbf{x}} \frac{1}{2} \|\mathbf{y}_t - \mathbf{D}\mathbf{x}\|_2^2 + \lambda \|\mathbf{x}\|_p. \quad (2)$$

## Solver Details

- ▶  $p = 0$ :  $l_0$  norm and NP-hard [Mallat+, TIP'93], [Pati+, ACSSC'93]
- ▶  $p = 1$ : LASSO problem [Friedman+, JSS'10], [Beck+, SIIMS'09]

# Online Learning Framework

## Dictionary Constructing

The subproblem with  $\mathbf{x}$  fixed is also convex. The objective function for dictionary constructing is

$$\mathbf{D} \triangleq \arg \min_{\mathbf{D}} \frac{1}{N} \sum_{t=1}^N \frac{1}{2} \|\mathbf{y}_t - \mathbf{D}\mathbf{x}_t\|_2^2 + \lambda \|\mathbf{x}_t\|_p. \quad (3)$$

## Solver Details

- ▶ Block coordinate descent method with warm start
- ▶ Introducing two auxiliary variables  $\mathbf{B}$  and  $\mathbf{C}$  to speed up convergence rate
- ▶ Sequentially updating atoms in a dictionary  $\mathbf{D}$

$$\vec{B}_t \leftarrow \frac{t-1}{t} \vec{B}_{t-1} + \frac{1}{t} \vec{y}_t \vec{x}_t^\top, \quad (4)$$

$$\vec{C}_t \leftarrow \frac{t-1}{t} \vec{C}_{t-1} + \frac{1}{t} \vec{x}_t \vec{x}_t^\top. \quad (5)$$

# Further Exploration: Supervised Dictionary Learning

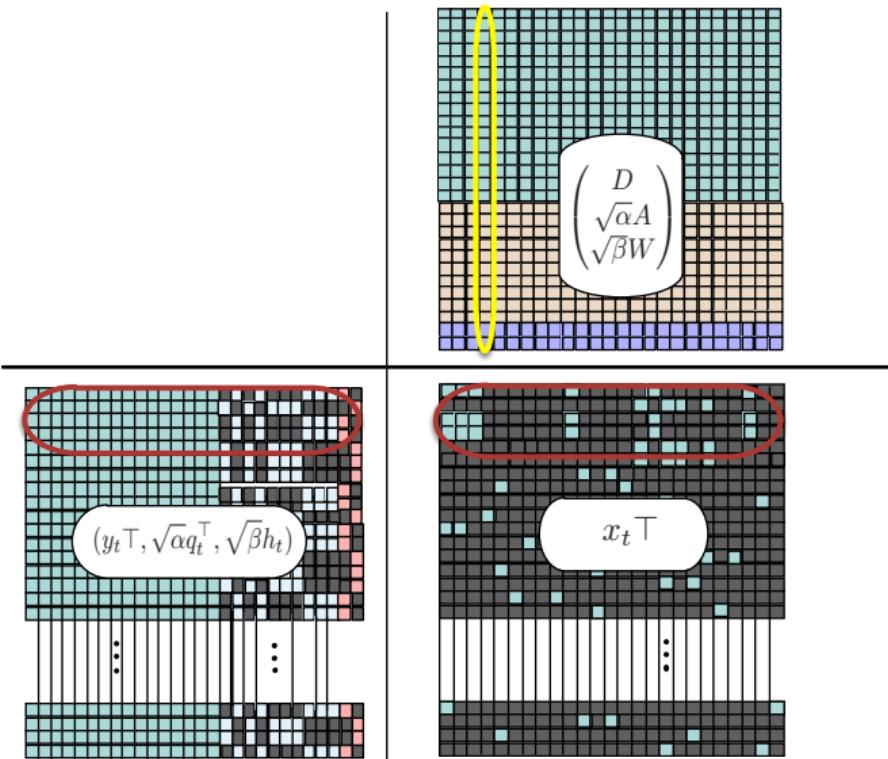
## Exploring Latent Label Information

$$\min_{\mathbf{x}, \mathbf{D}, \mathbf{A}} \frac{1}{N} \sum_{t=1}^N \left\{ \frac{1}{2} \left\| \left( \mathbf{y}_t^\top, \sqrt{\alpha} \mathbf{q}_t^\top \right)^\top - \begin{pmatrix} \mathbf{D} \\ \sqrt{\alpha} \mathbf{A} \end{pmatrix} \mathbf{x}_t \right\|_2^2 + \lambda \|\mathbf{x}_t\|_p \right\}. \quad (6)$$

## Exploiting both Latent and Direct Label Information

$$\min_{\mathbf{x}, \mathbf{D}, \mathbf{A}, \mathbf{W}} \frac{1}{N} \sum_{t=1}^N \left\{ \frac{1}{2} \left\| \left( \mathbf{y}_t^\top, \sqrt{\alpha} \mathbf{q}_t^\top, \sqrt{\beta} h_t \right)^\top - \begin{pmatrix} \mathbf{D} \\ \sqrt{\alpha} \mathbf{A} \\ \sqrt{\beta} \mathbf{W} \end{pmatrix} \mathbf{x}_t \right\|_2^2 + \lambda \|\mathbf{x}_t\|_p \right\}. \quad (7)$$

# The Illustration for Supervised Online Dictionary Learning



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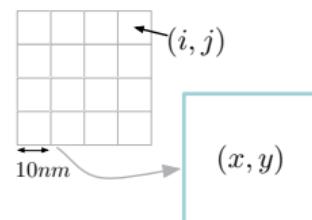
# SRAF Insertion

## Preliminary Work

- ▶ SRAF probability learning for each grid: Logistic regression
- ▶ SRAF grid model construction: Merging

$$c(x, y) = \begin{cases} \sum_{(i,j) \in (x,y)} p(i,j), & \text{if } \exists p(i,j) \geq \text{threshold}, \\ -1, & \text{if all } p(i,j) < \text{threshold}. \end{cases} \quad (8)$$

- ▶  $p(i,j)$ : the probability of a grid with index  $(i,j)$
- ▶  $c(x, y)$ : the summed probability value of merged grid with index  $(x,y)$



SRAF grid model construction.

# SRAF Insertion via ILP

$$\max_{a(x,y)} \sum_{x,y} c(x,y) \cdot a(x,y) \quad (9a)$$

$$\text{s.t. } a(x,y) + a(x-1, y-1) \leq 1, \quad \forall (x,y), \quad (9b)$$

$$a(x,y) + a(x-1, y+1) \leq 1, \quad \forall (x,y), \quad (9c)$$

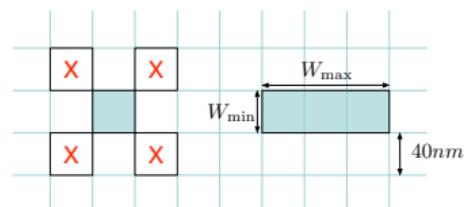
$$a(x,y) + a(x+1, y-1) \leq 1, \quad \forall (x,y), \quad (9d)$$

$$a(x,y) + a(x+1, y+1) \leq 1, \quad \forall (x,y), \quad (9e)$$

$$a(x,y) + a(x,y+1) + a(x,y+2) \\ + a(x,y+3) \leq 3, \quad \forall (x,y), \quad (9f)$$

$$a(x,y) + a(x+1,y) + a(x+2,y) \\ + a(x+3,y) \leq 3, \quad \forall (x,y), \quad (9g)$$

$$a(x,y) \in \{0, 1\}, \quad \forall (x,y). \quad (9h)$$



SRAF insertion design rule  
under the grid model.

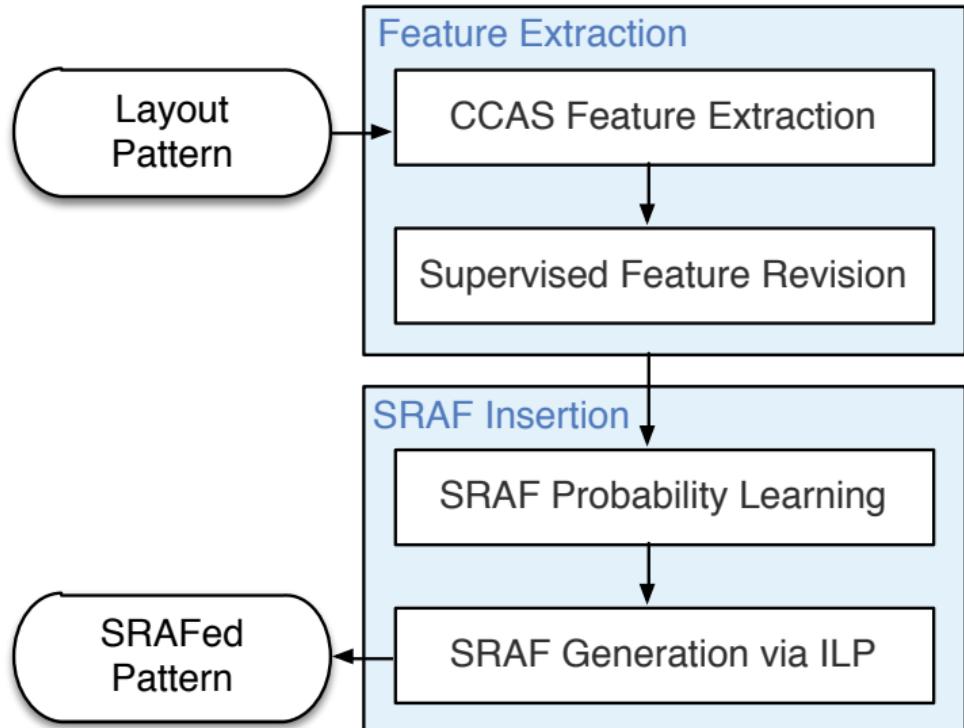
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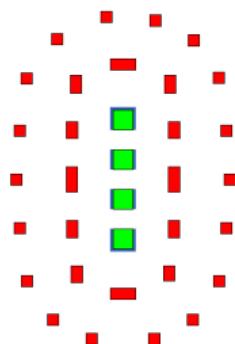
# The Overall Flow



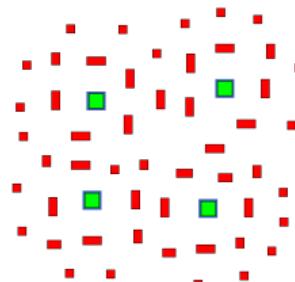
# Experimental Bed

## Benchmark Set

- ▶ The same benchmark set as applied in [Xu+, ISPD'16]
- ▶ 8 dense layouts and 10 sparse layouts with contacts sized 70nm
- ▶ 70nm spacing for dense and  $\geq$  70nm spacing for sparse layouts



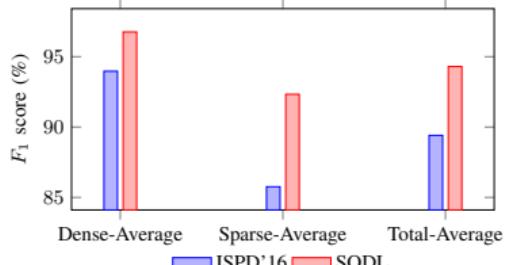
(a)



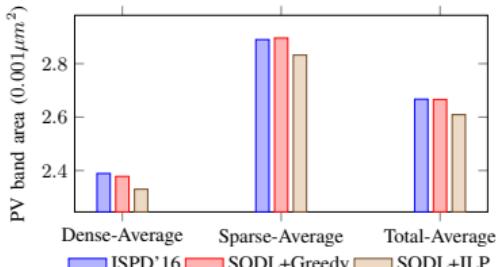
(b)

(a) Dense layout with golden SRAFs; (b) Sparse layout with golden SRAFs.

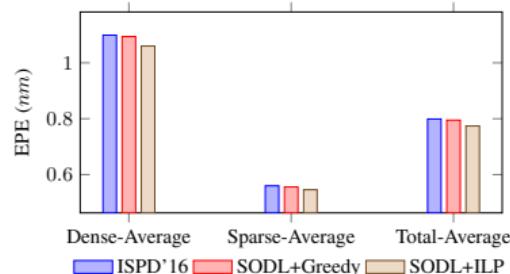
# Results



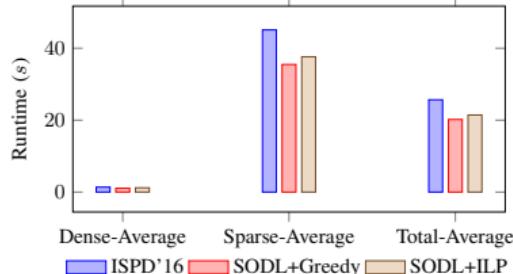
(a)



(b)



(c)



(d)

Lithographic performance comparisons with a state-of-the-art machine learning based SRAF insertion tool.

# Conclusion

## Summary:

- ▶ First introduced the concept of dictionary learning into the layout feature extraction stage and further proposed a supervised online dictionary learning algorithm.
- ▶ ILP for SRAF generation in a global view.
- ▶ Boost  $F_1$  score and enhance lithographic performance with less time overhead.

## Future Work:

- ▶ Speed up SRAF insertion process
- ▶ Consider more SRAF design rules into ILP
- ▶ ...