VLSI Mask Optimization: From Shallow To Deep Learning

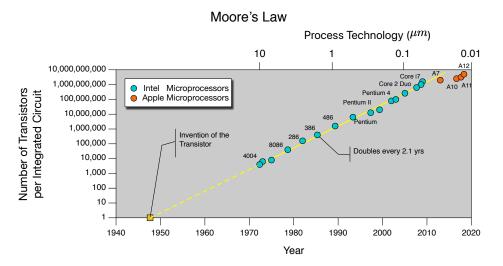
Haoyu Yang¹, Wei Zhong², Yuzhe Ma¹, Hao Geng¹, Ran Chen¹, Wanli Chen¹, Bei Yu¹

¹The Chinese University of Hong Kong ²Dalian University of Technology

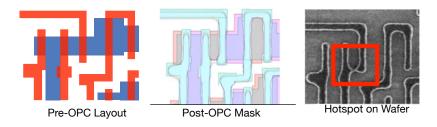




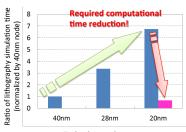
Moore's Law to Extreme Scaling



Challenge 1: Failure (Hotspot) Detection



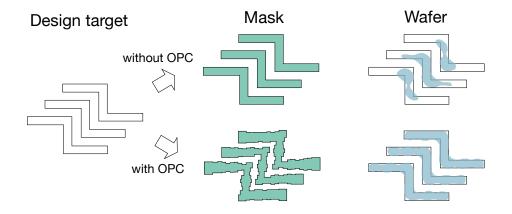
- RET: OPC, SRAF, MPL
- Still hotspot: low fidelity patterns
- Simulations: extremely CPU intensive



Technology node



Challenge 2: Optical Proximity Correction (OPC)





Why Deep Learning?

Feature Crafting v.s. Feature Learning

Although prior knowledge is considered during manually feature design, information loss is inevitable.

Feature learned from mass dataset is more reliable.

Scalability

With shrinking down circuit feature size, mask layout becomes more complicated. Deep learning has the potential to handle ultra-large-scale instances while traditional machine learning may suffer from performance degradation.

Mature Libraries











Outline

Hotspot Detection via Machine Learning

OPC via Machine Learning

Heterogeneous OPC





Outline

Hotspot Detection via Machine Learning

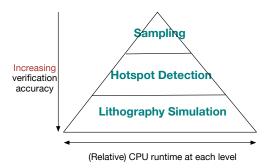
OPC via Machine Learning

Heterogeneous OPC





Hotspot Detection Hierarchy



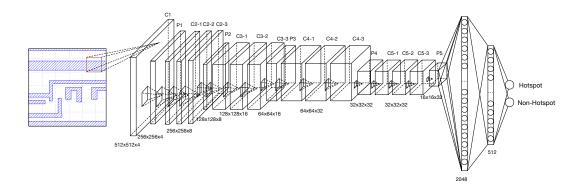


- Sampling (DRC Checking): scan and rule check each region
- Hotspot Detection: verify the sampled regions and report potential hotspots
- Lithography Simulation: final verification on the reported hotspots



Early Study of DNN-based Hotspot Detector*

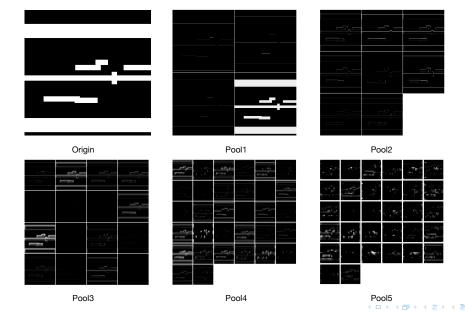
- Total 21 layers with 13 convolution layers and 5 pooling layers.
- A ReLU is applied after each convolution layer.



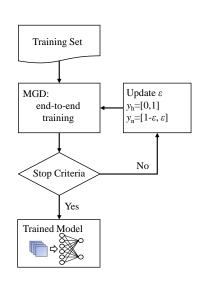
^{*}Haoyu Yang, Luyang Luo, et al. (2017). "Imbalance aware lithography hotspot detection: a deep learning approach". In: JM3 16.3, p. 033504. 4 日 5 4 例 5 4 图 5 4 图 5 图

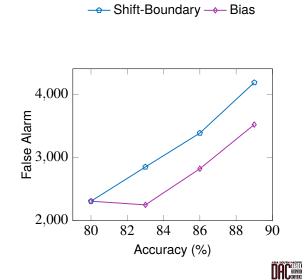


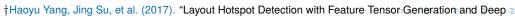
What Does Deep Learning Learn?



The Biased Learning Algorithm [DAC'17]†







Optimizing AUC [ASPDAC'19]‡

The AUC objective:

$$\mathcal{L}_{\Phi}(f) = \frac{1}{N_{+}N_{-}} \sum_{i=1}^{N_{+}} \sum_{j=1}^{N_{-}} \Phi\left(f\left(\mathbf{x}_{i}^{+}\right) - f\left(\mathbf{x}_{j}^{-}\right)\right).$$

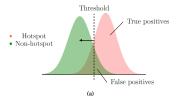
Approximation candidates:

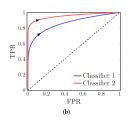
PSL
$$\Phi_{PSL}(z) = (1 - z)^2$$

PHL
$$\Phi_{\text{PHL}}(z) = \max(1-z,0)$$

PLL
$$\Phi_{\text{PLL}}(z) = \log(1 + \exp(-\beta z))$$

$$\mathsf{R} \ \Phi_{\mathsf{R}^*}(z) = \left\{ \begin{array}{ll} -(z-\gamma)^p, & \text{if } z > \gamma \\ 0, & \text{otherwise} \end{array} \right.$$

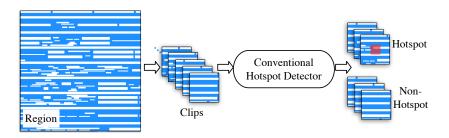




[‡]Wei Ye et al. (2019). "LithoROC: lithography hotspot detection with explicit ROC optimization". In: *Proc. ASPDAC*, pp. 292–298.



Conventional Clip based Solution

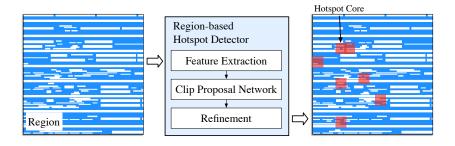


- A binary classification problem.
- Scan over whole region.
- Single stage detector.
- Scanning is time consuming and single stage is not robust to false alarm.





Region based approach [DAC'19]



- Learning what and where is hotspot at same time.
- Classification Problem -> Classification & Regression Problem.



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Heterogeneous OPC





OPC Previous Work

Classic OPC

Model/Rule-based OPC

```
[Cobb+,SPIE'02][Kuang+,DATE'15]
[Awad+,DAC'16][Su+,ICCAD'16]
```

- 1. Fragmentation of shape edges;
- 2. Move fragments for better printability.
- Inverse Lithography

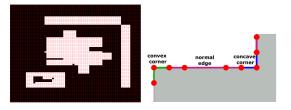
```
[Pang+,SPIE'05][Gao+,DAC'14]
[Poonawala+,TIP'07][Ma+,ICCAD'17]
```

- Efficient model that maps mask to aerial image;
- Continuously update mask through descending the gradient of contour error.

Machine Learning OPC

[Matsunawa+,JM3'16][Choi+,SPIE'16] [Xu+,ISPD'16][Shim+,APCCAS'16]

- Edge fragmentation;
- Feature extraction;
- Model training.



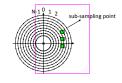




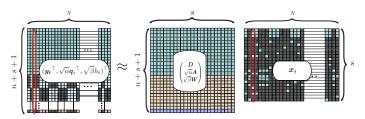
Machine Learning-based SRAF Insertion

SRAF Insertion with Machine Learning [ISPD'16]¶





Tackling Robustness with Dictionary Learning [ASPDAC'19]

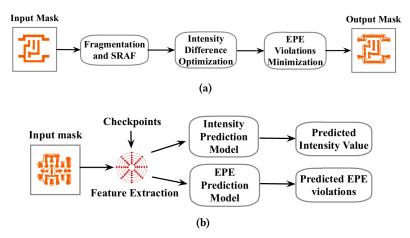


[¶]Xiaoqing Xu et al. (2016). "A machine learning based framework for sub-resolution assist feature generation". In: *Proc. ISPD*, pp. 161–168.

| Hao Geng et al. (2019). "SRAF Insertion via Supervised Dictionary Learning". In: *Proc. ASPDAC*, pp. 406–411.



Machine Learning Assists Model-based OPC [ASPDAC'19]**

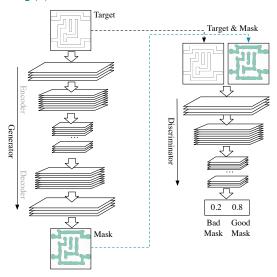


Replace lithography simulation (slow) with machine learning-based EPE predictor (fast) in OPC iterations.

^{**}Bentian Jiang et al. (2019). "A fast machine learning-based mask printability predictor for OPC acceleration". In: *Proc. ASPDAC*, pp. 412–419.



GAN-OPC [DAC'18]††



Better starting points for legacy OPC engine and reduce iteration count.

††Haoyu Yang, Shuhe Li, et al. (2018). "GAN-OPC: Mask Optimization with Lithography-guided Generative Adversarial Nets". In: *Proc. DAC*, 131:1–131:6.

Outline

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OPC via Machine Learning

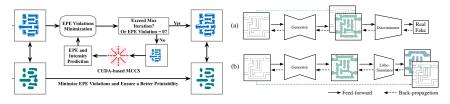
Heterogeneous OPC



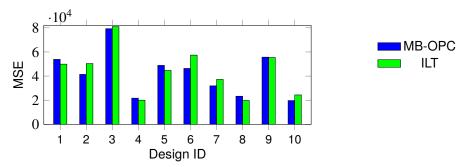


An Observation of Previous OPC Solutions

Machine learning solutions rely on legacy OPC engines



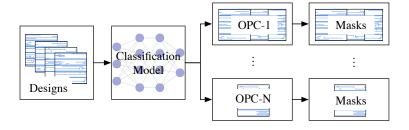
Legacy OPC engines exhibit different performance on different designs







A Design of Heterogeneous OPC Framework

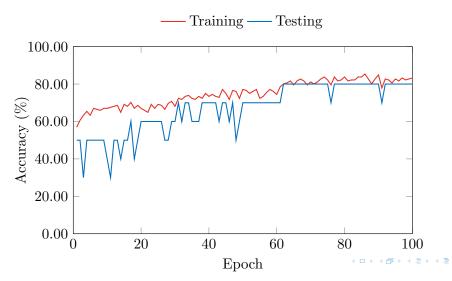


We design a classification model that can determine the best OPC engine for a given design at trivial cost.



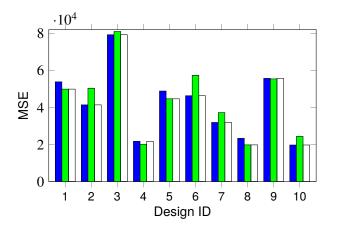
Training on Artificial Designs

- Training data comes from GAN-OPC and is labeled according to results of MB-OPC and ILT.
- Test on 10 designs from ICCAD 2013 CAD Contest.





Experimental Results





Several Benefits

- Does not require extremely high prediction accuracy of the classification model.
- Take advantages of different OPC solutions on different designs.





Conclusion and Discussion

So Far:

- Recent progress of deterministic machine learning model for hotspot detection
- State-of-the-art machine learning solutions for OPC and SRAF insertion
- A heterogeneous OPC framework guided by a classification engine

Future:

- Manufacturability issues.
- Classification challenge when more than two OPC engines are available.

