DeePattern: Layout Pattern Generation with Transforming Convolutional Auto-Encoder

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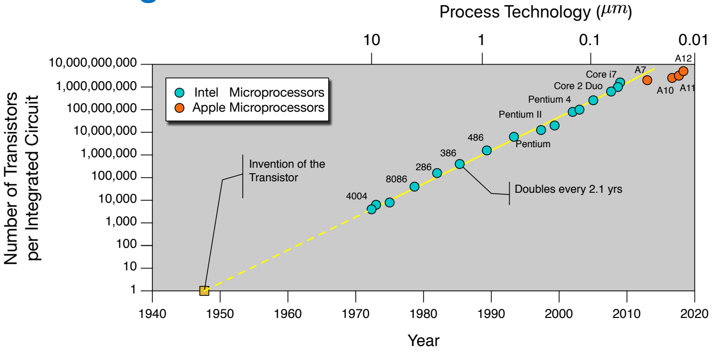
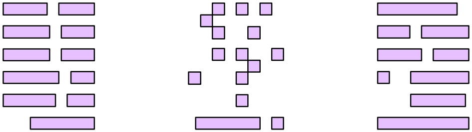
EUV Brings Challenges in DFM



- Hotspot detection and fix∗
- Early technology node development
- Design rule, OPC recipe development, ...

∗Harry J Levinson and Timothy A Brunner (2018). "Current challenges and opportunities for EUV lithography". In: *Proc. SPIE*. vol. 10809.

Related Works



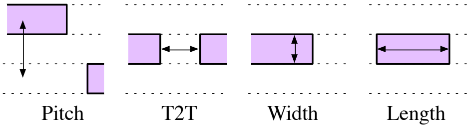
(a) (b) (c)

- Transferring from previous technology node (not applicable for large technology node gap†)
- Randomly placing patterns according to certain constraints (limited diversity)
- Generative machine learning models (violating design rules)

†Linda Zhuang et al. (2016). “A novel methodology of process weak-point identification to accelerate process development and yield ramp-up”. In: *Proc. ICSICT*, pp. 852–855.

Pattern Generation Challenges

Satisfying design rules



Coverage of the design space

- The complexity of a pattern in x and y directions (denoted as c_x and c_y) are defined as the number of scan lines subtracted by one along x-axis and y-axis, respectively.
- The diversity of a pattern library is given by the Shannon Entropy of the pattern complexity sampled from the library,

$$\mathrm{H} = -\sum_i \sum_j P(c_{xi}, c_{yj}) \log P(c_{xi}, c_{yj}),$$

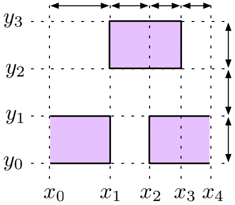
where $P(c_{xi}, c_{yj})$ is the probability of a pattern sampled from the library has complexities of c_{xi} and c_{yj} in x and y directions respectively.

Layout Pattern Generation

Problem (Pattern Generation)

Given a set of layout design rules, the objective of pattern generation is to generate a pattern library such that the pattern diversity and the number of unique DRC-clean patterns in the library is maximized.

Problem Simplification with Squish Patterns

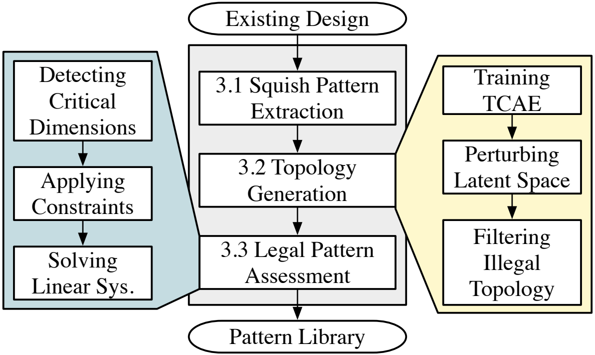


$$\boldsymbol{T} = \begin{bmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 \end{bmatrix}$$

$$\boldsymbol{\delta}_x = \begin{bmatrix} x_1 - x_0 & x_2 - x_1 & x_3 - x_2 & x_4 - x_3 \end{bmatrix}$$

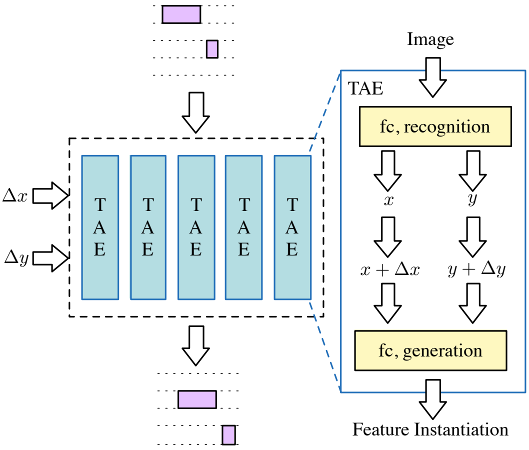
$$\boldsymbol{\delta}_y = \begin{bmatrix} y_1 - y_0 & y_2 - y_1 & y_3 - y_2 \end{bmatrix}$$

The Overall Flow



With the help of squish patterns, the problem becomes generating legal topologies and solving associated δ_xs and δ_ys that are much easier than directly generating DRC-clean patterns.

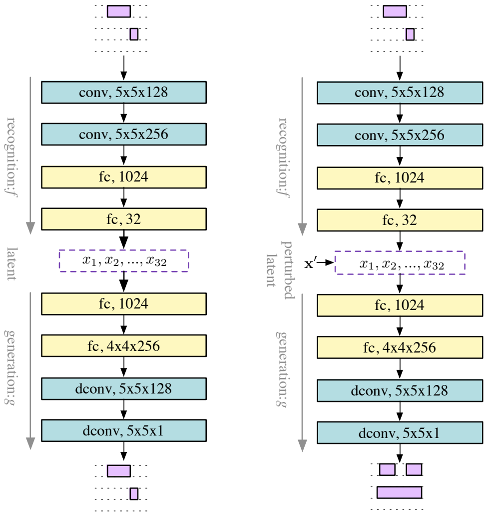
Transforming Auto-Encoders (TAEs)‡



- Originally targets to learning image features that are robust to certain transformations of in-image objects.
- Allow transformations without destroying the object itself.
- Transformations are limited to a coordinate system.

‡DL-ICANN2011-Hinton.

Topology Generation with TCAE



Input pattern to latent space,

$$\boldsymbol{l} = f(\boldsymbol{T}; \boldsymbol{W}_f)$$

Topology reconstruction,

$$\boldsymbol{T}' = g(\boldsymbol{l} + \Delta \boldsymbol{l}; \boldsymbol{W}_g)$$

Training objective:

$$\min_{\boldsymbol{W}_f, \boldsymbol{W}_g} ||\boldsymbol{T} - \boldsymbol{T}'||, \text{ s.t. } \Delta \boldsymbol{l} = \boldsymbol{0}$$

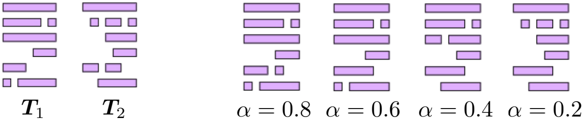
TCAE-Combine

- Generalization from existing topologies

$$\boldsymbol{T}_g = g\left(\sum_i \alpha_i f(\boldsymbol{T}_i)\right),$$

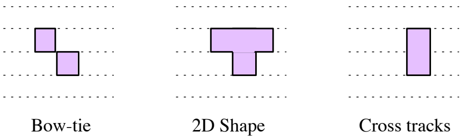
where $0 < \alpha_i < 1, \forall i$ are combination coefficients and satisfy $\sum_i \alpha_i = 1$.

- Sample results



TCAE-Random

- Feature Sensitivity
  Let $\boldsymbol{l} = \begin{bmatrix} l_1 & l_2 & \dots & l_n \end{bmatrix}^\top$ be the output of the layer associated with the latent vector space. The sensitivity s_i of a latent vector node l_i is defined as the probability of reconstructed pattern being invalid when a perturbation $\Delta l_i \in [-t, t]$ is added up on l_i with everything else unchanged.
- Filter illegal topologies



- Sample perturbation vectors from $\mathcal{N}(0, \frac{1}{s_i})$.

Legal Pattern Assessment

Creating DRC constraints for legal δ_xs and δ_ys,

$$
\begin{aligned}
y_{i+1} - y_i &= \frac{p}{2}, & \forall i, \\
x_i - x_j &= t_{\min}, & \forall (i,j) \in \mathcal{C}_{T2T}, \\
x_i - x_j &= l_{\min}, & \forall (i,j) \in \mathcal{C}_{W}, \\
x_{i+1} - x_i &> 0, & \forall i, \\
x_{\max} - x_0 &= d_x, \\
y_{\max} - y_0 &= d_y.
\end{aligned}
$$

Experiments

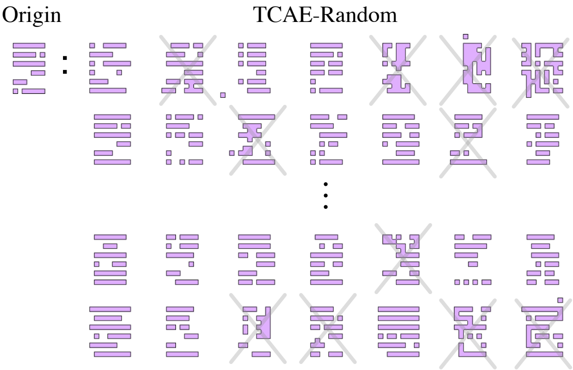
Understanding Features in TCAE

Transformations	Reconstructed Topologies
Extend or pull back line-ends	
Create or destroy shapes	
Control shape directions	

Experiments

TCAE-Random Examples

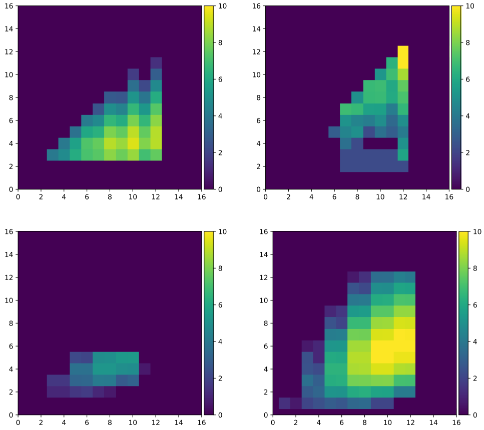
Contribution of Gaussian perturbation on topology reconstruction. 1000 topologies (∼400 legal) are created from one topology randomly picked from the existing pattern library.



Experiments

Comparison with State-of-the-Art

Method	Pattern #	H
Existing Design	-	3.101
Industry Tool	55408	1.642
DCGAN	1	0
TCAE-Combine	1738	2.665
TCAE-Random	**286898**	**3.337**



(a) Existing layout pattern dataset. (b) Industrial layout generator; (c) TCAE-Combine; (d) TCAE-Random.

Conclusion

- Address the pattern library requirements in DFM flows/researches under advanced technology nodes.
- Propose a TCAE framework that can capture layout design rule characteristics.
- We show auto-learned features contribute to layout space locally or globally.
- The experimental results show that our framework outperforms a state-of-the-art industrial layout generation tool in terms of pattern library diversity.

Thank You