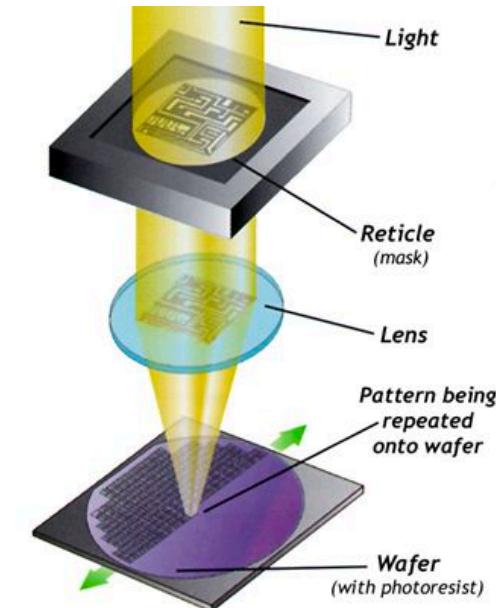
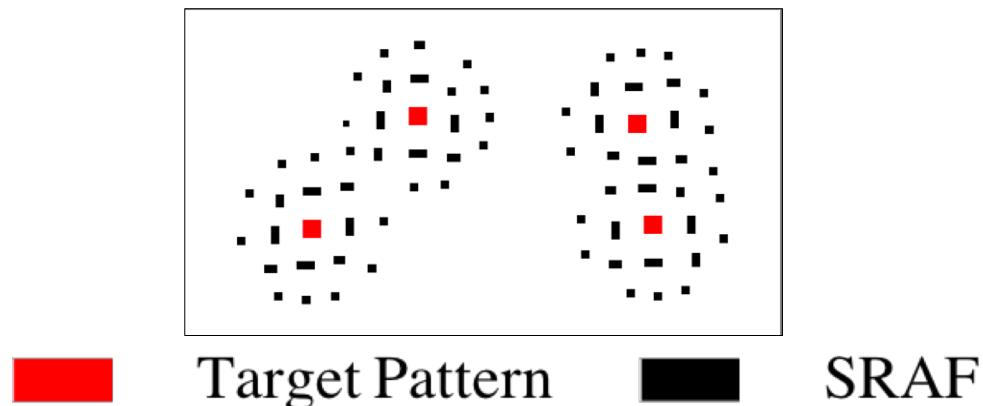

GAN-SRAF: Sub-Resolution Assist Feature Generation using Generative Adversarial Networks

**Mohamed Baker Alawieh, Yibo Lin, Zaiwei Zhang, Meng Li,
Qixing Huang and David Z. Pan**
The University of Texas at Austin

Work funded in part by NSF

Motivation

- ◆ With the IC technology scaling, resolution enhancement techniques are becoming indispensable
- ◆ Sub-Resolution Assist Feature (SRAF) generation is used to improve the lithographic process window of target patterns



Conventional Approaches

- ◆ Rule-Based approaches:
 - › Work well for simple designs with regular patterns
 - › Cannot handle complex shapes
- ◆ Model-Based (MB) approaches:
 - › Achieve high quality results
 - › Suffer from exorbitant computational cost
- ◆ Machine Learning (ML) Based approach:
 - › Achieves results quality similar to MB
 - › Results in 10X reduction in runtime

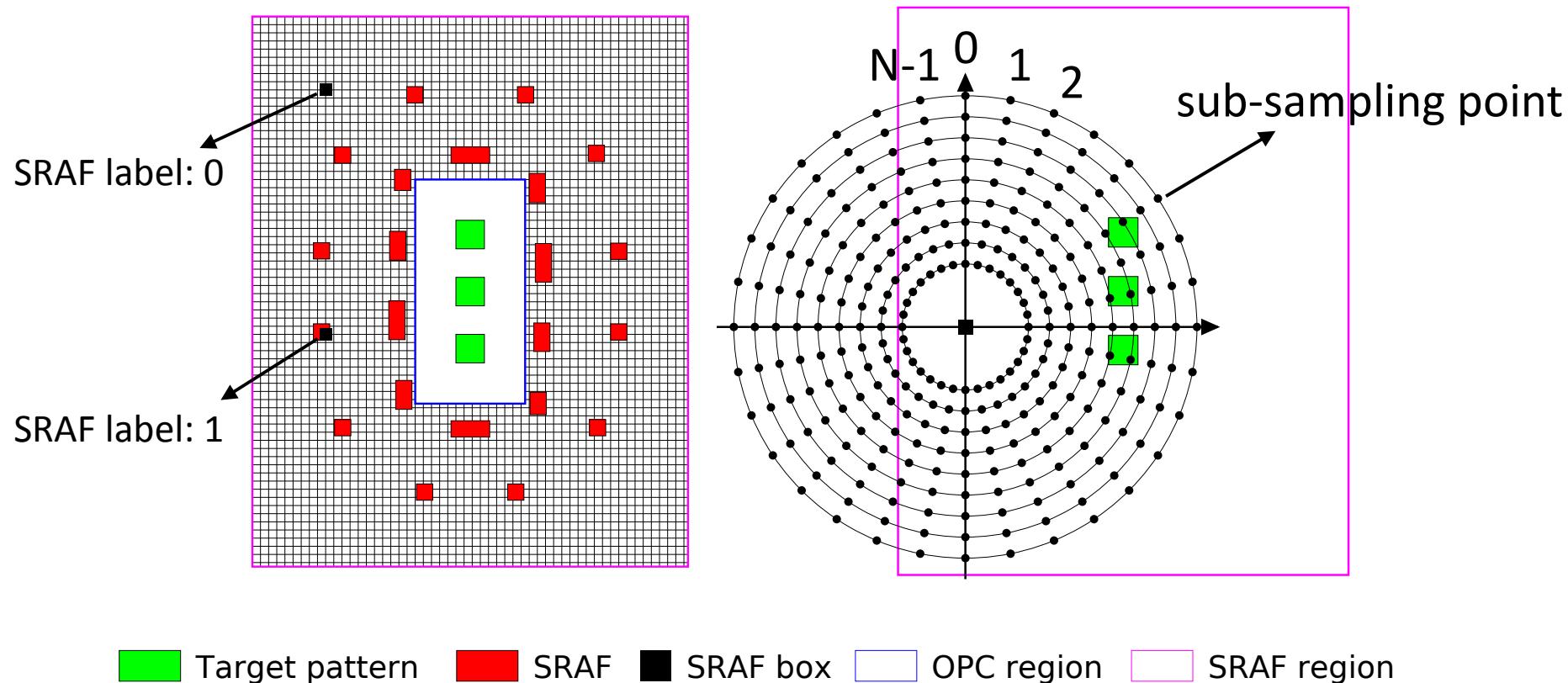
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Can we do better?!

ML Based Approach

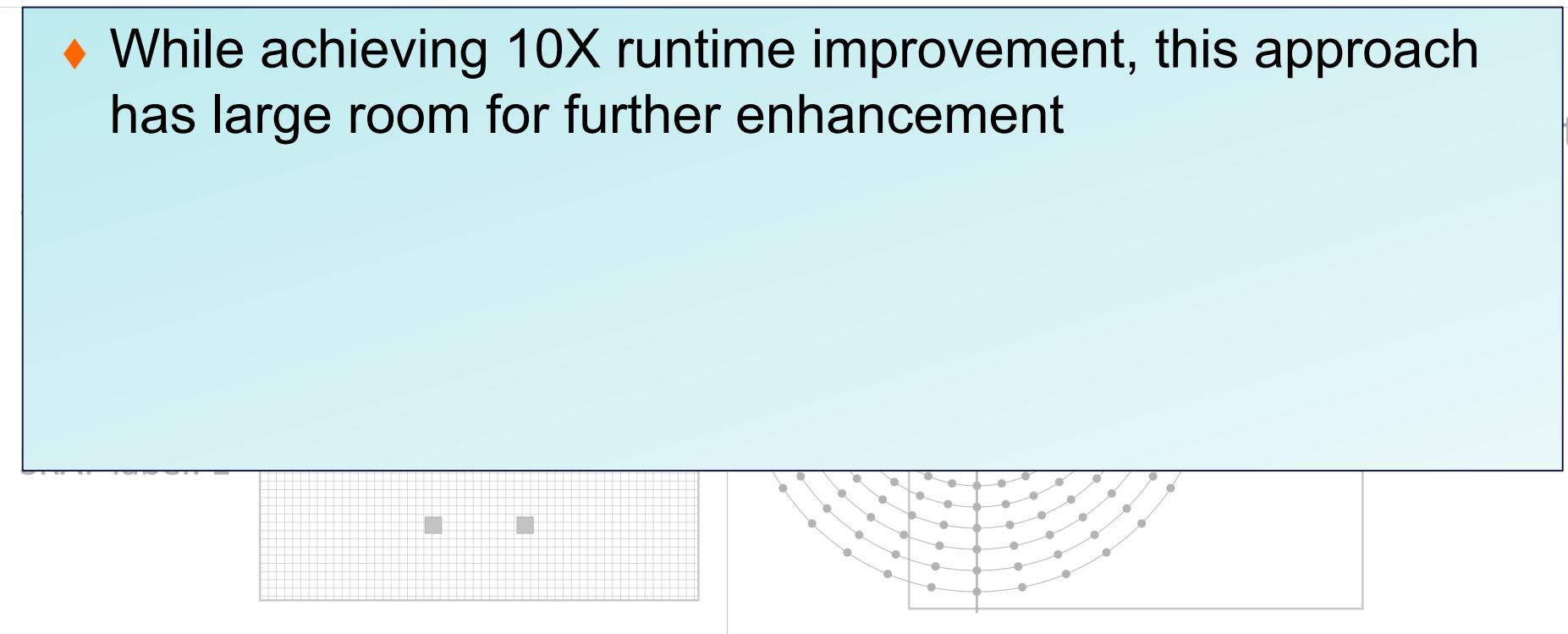
- ◆ Proposes local sampling scheme with a classification model
- ◆ On a 2D grid, the classifier predicts the presence of SRAF in each grid



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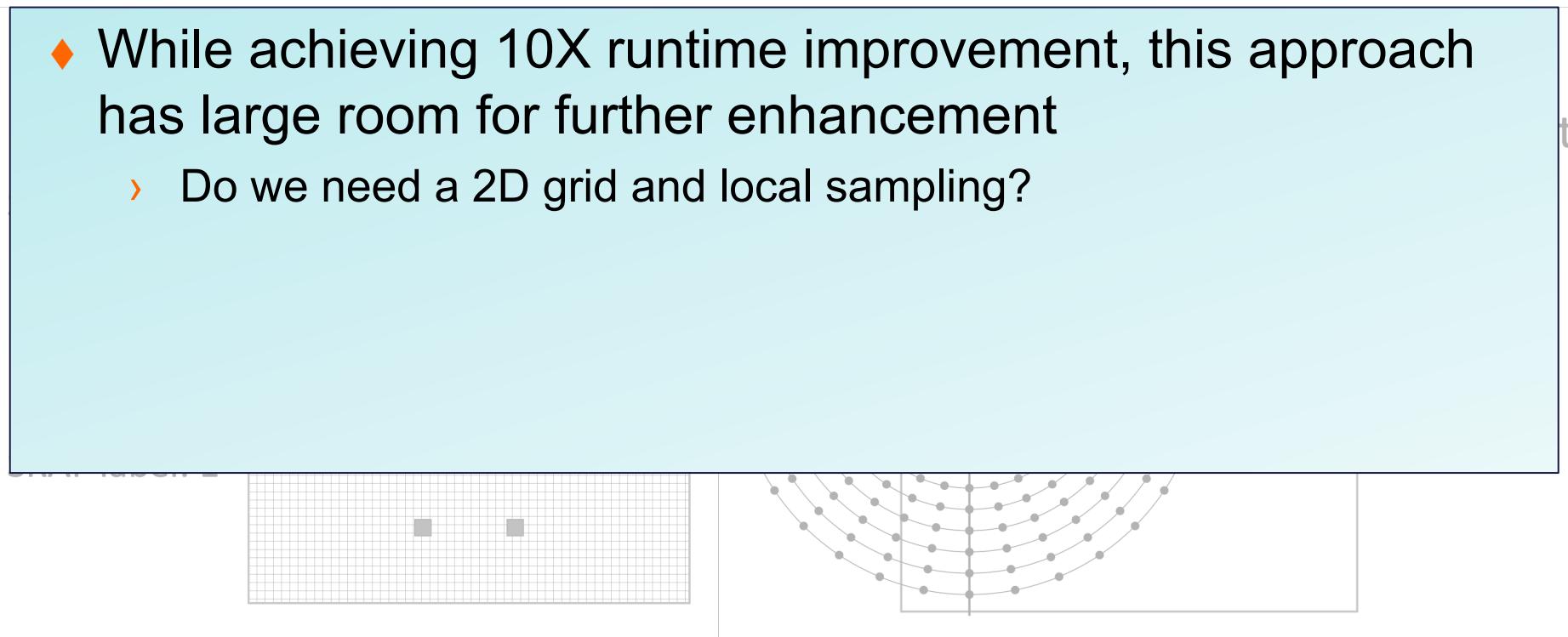
◆ While achieving 10X runtime improvement, this approach has large room for further enhancement



■ Target pattern ■ SRAF ■ SRAF box ■ OPC region ■ SRAF region

ML Based Approach

- ◆ Proposes local sampling scheme with a classification model
- ◆ On a 2D grid, the classifier predicts the presence of SRAF in each grid
 - ◆ While achieving 10X runtime improvement, this approach has large room for further enhancement
 - › Do we need a 2D grid and local sampling?

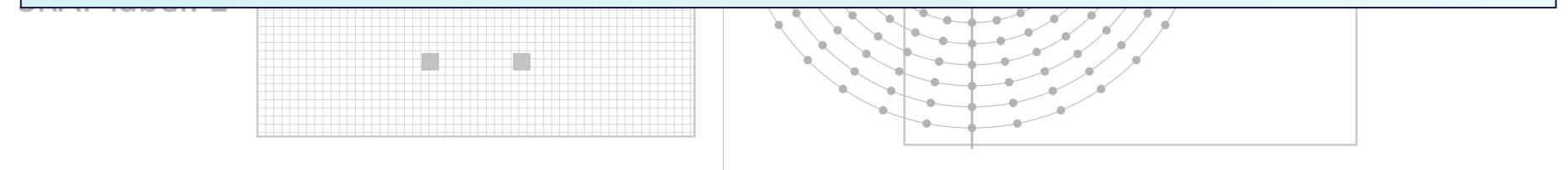


ML Based Approach

- ◆ Proposes local sampling scheme with a classification model
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◆ While achieving 10X runtime improvement, this approach has large room for further enhancement

- › Do we need a 2D grid and local sampling?
- › Can we avoid the feature extraction step?



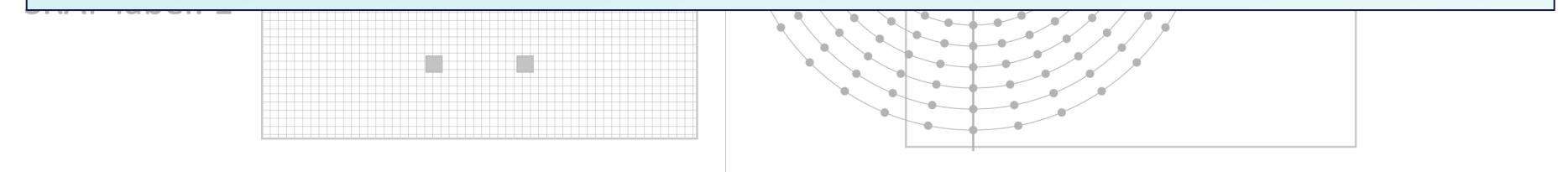
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ML Based Approach

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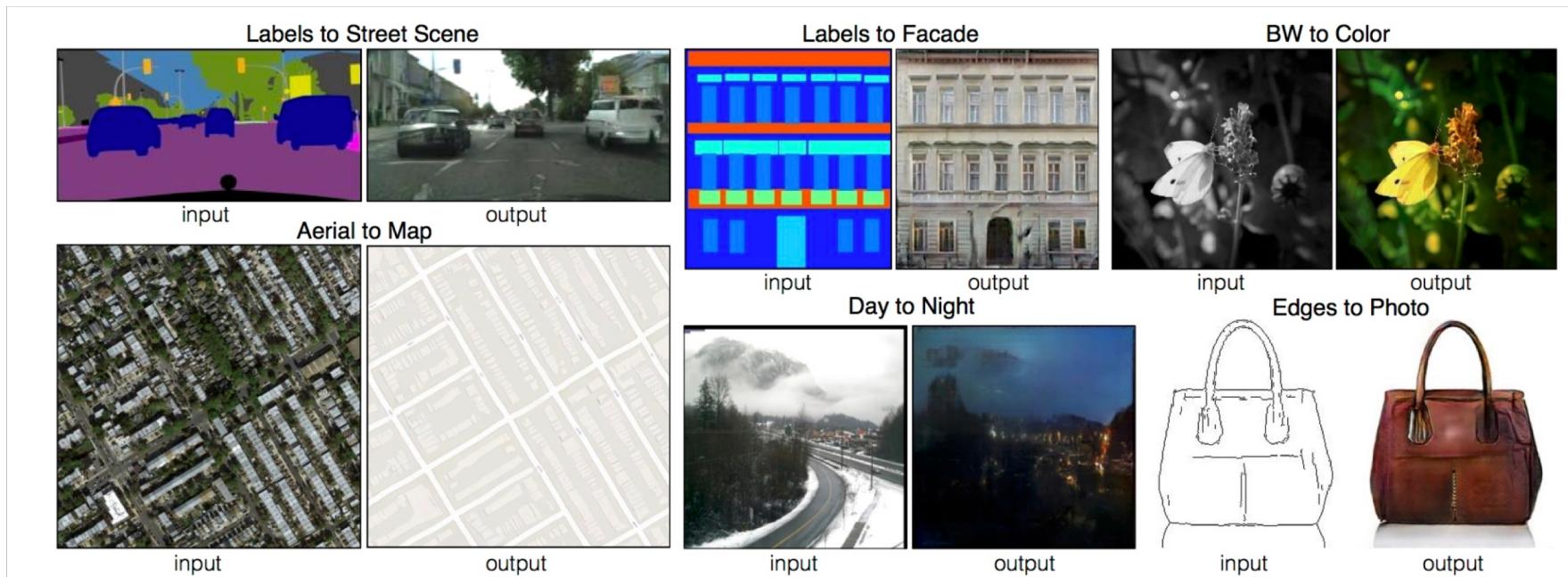
- › Do we need a 2D grid and local sampling?
- › Can we avoid the feature extraction step?
- › Most importantly, with all advancements in Computer Vision, can we recast this problem to leverage these advancement?



■ Target pattern ■ SRAF ■ SRAF box ■ OPC region ■ SRAF region

CGAN for Image Translation

- ◆ GANs have been proposed to produce images similar to those in training data set
- ◆ CGAN, takes as an input a picture in one domain and *translates* it to a new one
 - › During training it sees pairs of matched images

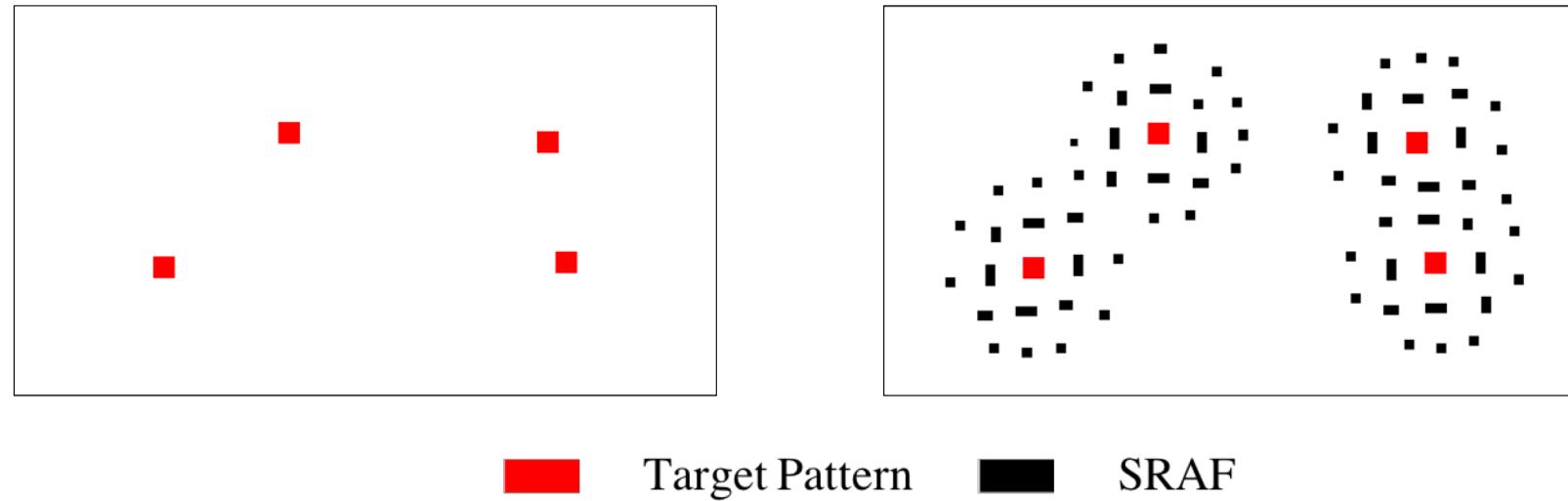


SRAF Generation & Image Translation

- ◆ What does SRAF generation have to do with Image translation?!

SRAF Generation & Image Translation

- ◆ What does SRAF generation have to do with Image translation?!



- ◆ Can we define the problem as translating images from the Target Domain (D_T) to the SRAF Domain (D_S)?

Challenges

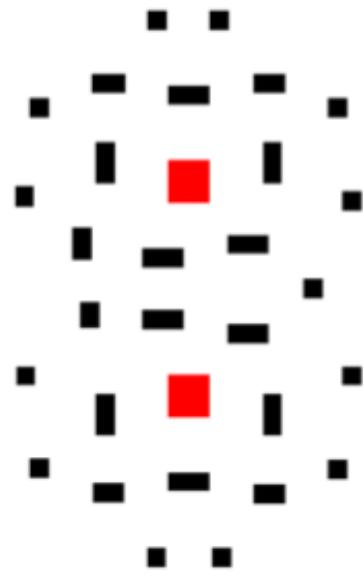
- ◆ Layout images have sharp edges which pose a challenge to GANs
 - › Model is not guaranteed to generate polygon SRAF shapes
 - › Sharp edges can complicate gradient propagation
- ◆ Generated images need ultimately be changed to layout format
 - › Images cannot be directly mapped to ‘GDS’ format
 - › Post-processing step should not be time consuming

Challenges

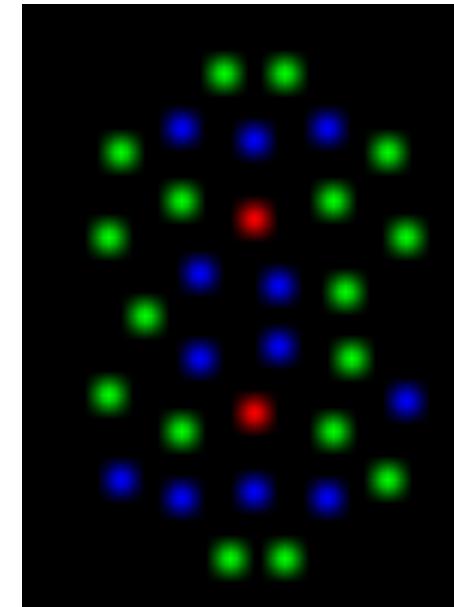
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 - › Post-processing step should not be time consuming
- ◆ *Hence, a proper encoding is needed to address these challenges!*

Mult-Channel Heatmap Encoding

- ◆ Key Idea: encode each type of object on a separate channel in the image
 - › Channel index carries object description (type, size,...)
 - › Excitations on the channel carry objects location



Original Layout



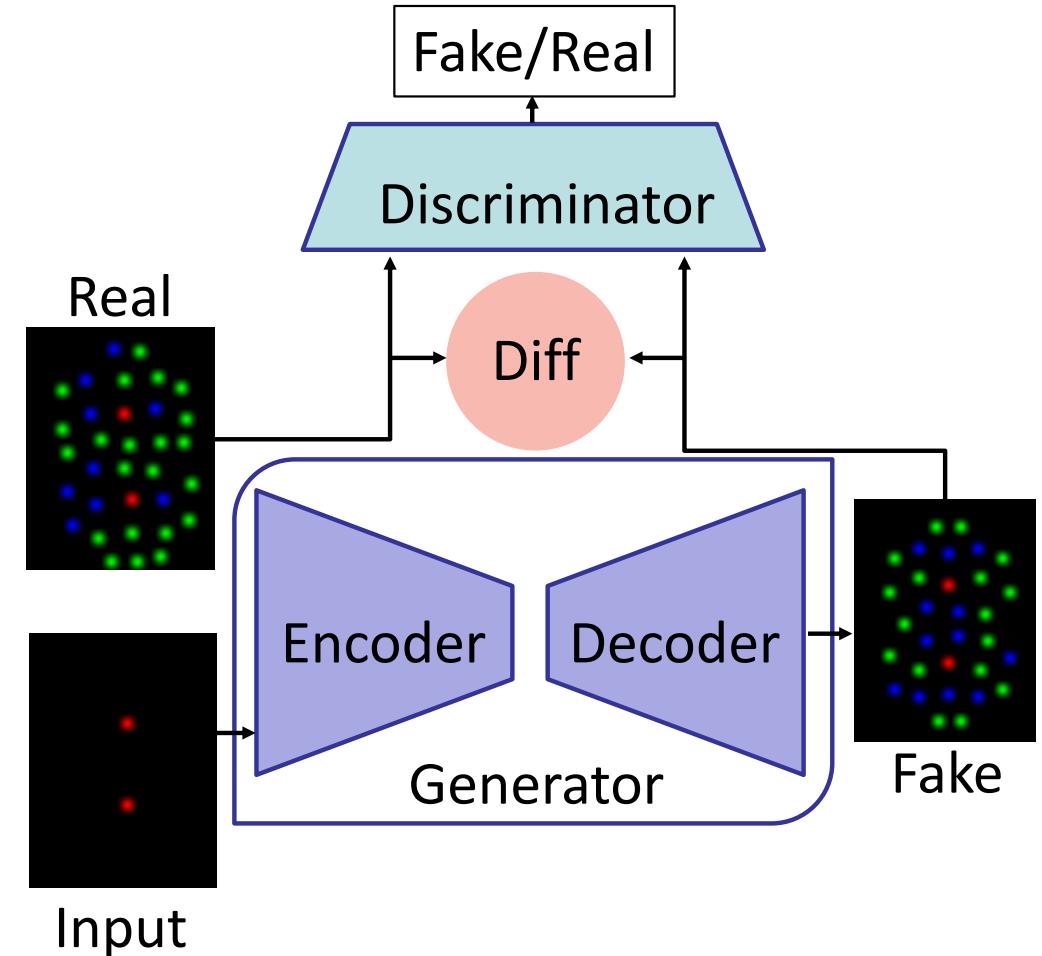
Encoded Layout

Challenges Revisited

- ◆ Layout images have sharp edges which pose a challenge to GANs
 - › Model is not guaranteed to generate polygon SRAF shapes
 - › **Polygon shapes are not needed, the objective of model is to predict locations on different channels**
 - › Sharp edges can complicate gradient propagation
 - › **No sharp edges in encoded image**
- ◆ Generated images need ultimately be changed to layout format
 - › Images cannot be directly mapped to ‘GDS’ format
 - › **Decoding is straight forward, it suffices to detect excitation location on each channel to get full GDS information**

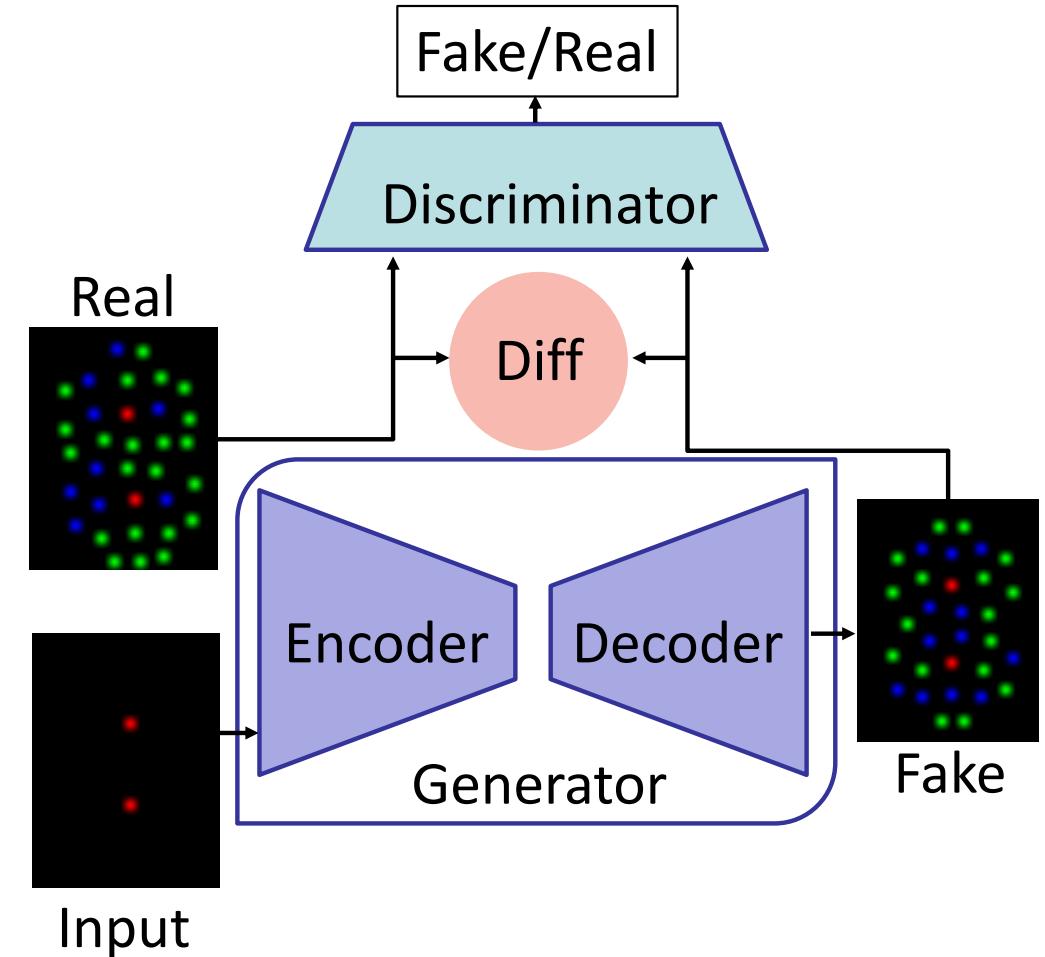
CGAN Approach

- ◆ Generator:
 - Trained to produce images in D_S based on input from D_T
 - Tries to fool the Discriminator
- ◆ Discriminator:
 - Trained to detect ‘fakes’ generated by the Generator
- ◆ The two networks are jointly trained until convergence



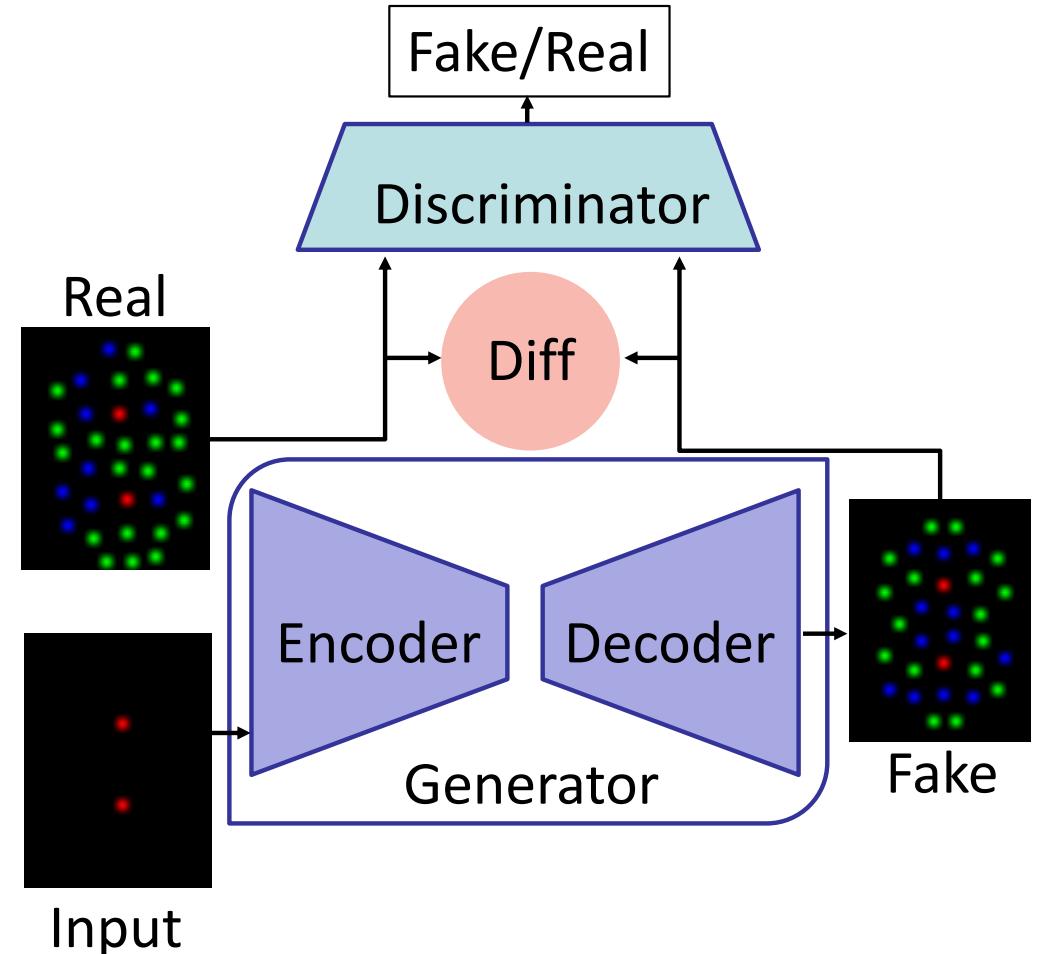
CGAN Approach

- ◆ Generator:
 - › Encoder: Downsampling
 - › Decoder: Upsampling



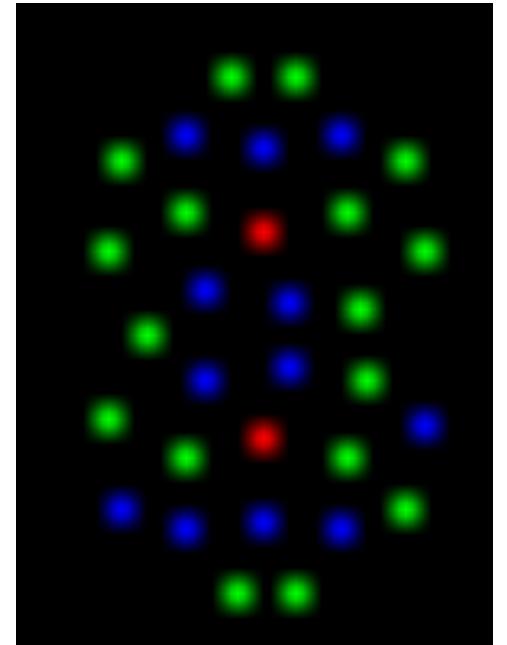
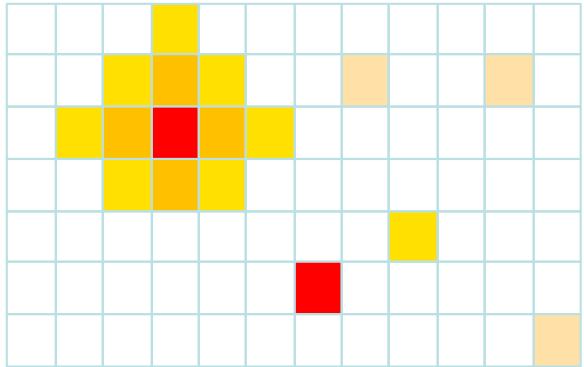
CGAN Approach

- ◆ Generator:
 - Encoder: Downsampling
 - Decoder: Upsampling
- ◆ Discriminator:
 - CNN trained as a classifier
- ◆ After training, only the generator is used



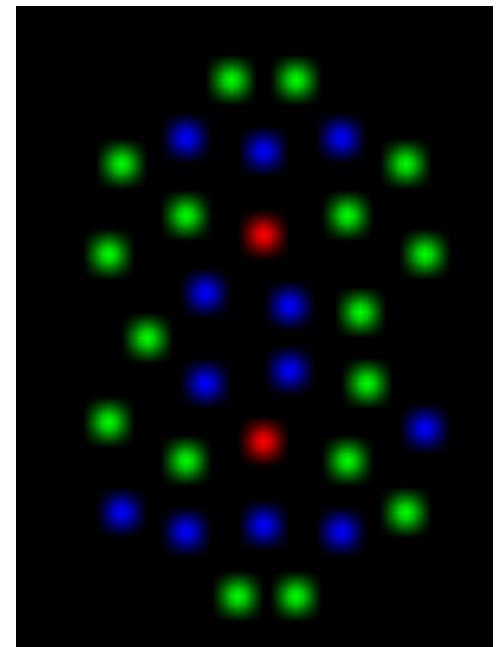
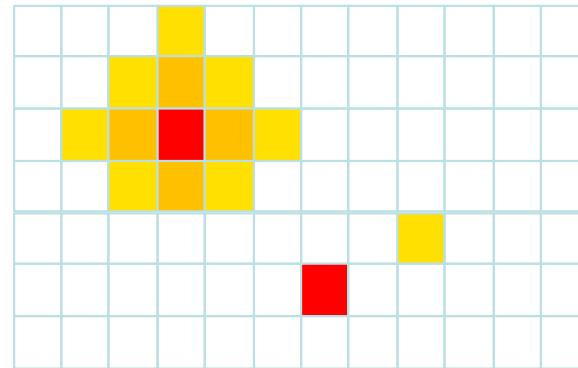
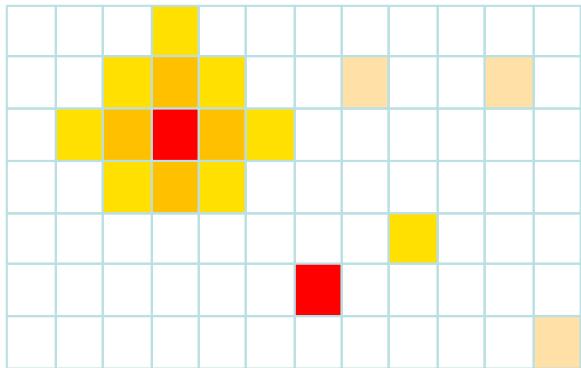
Results Decoding

- ◆ Decoding the generated layout images consists of two steps:
 - › Thresholding & Excitation detection



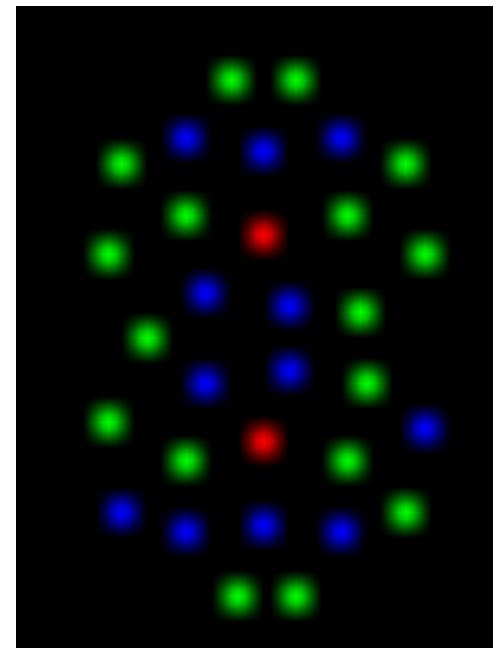
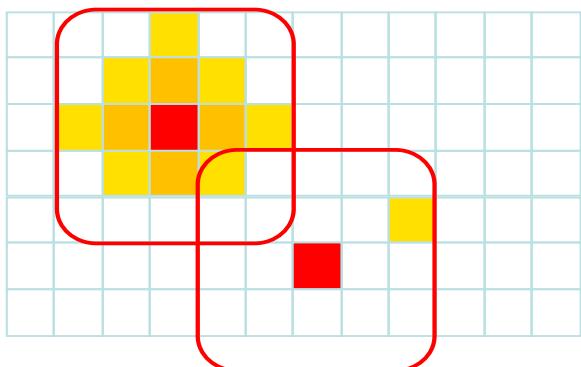
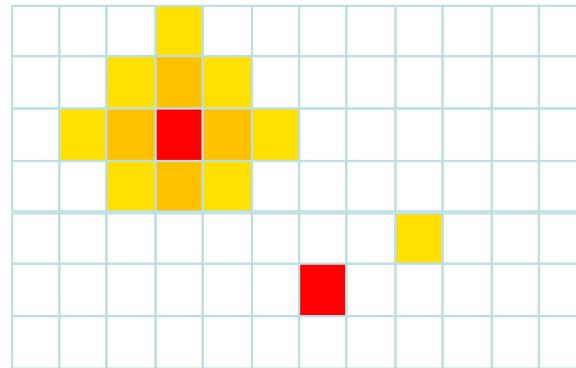
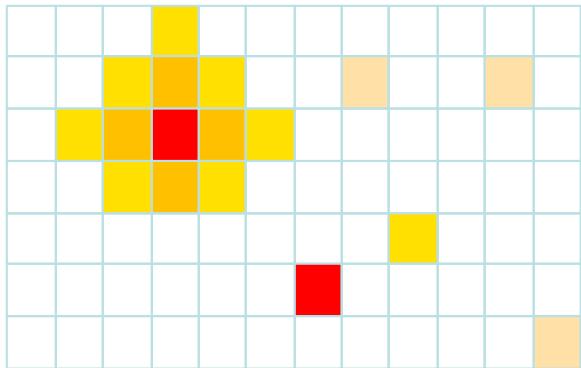
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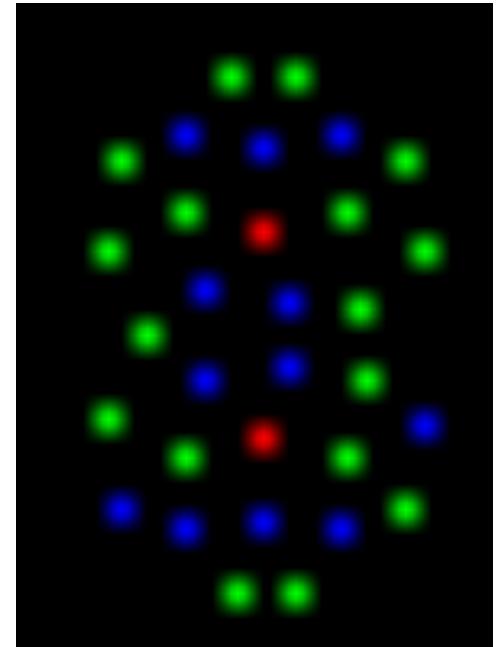
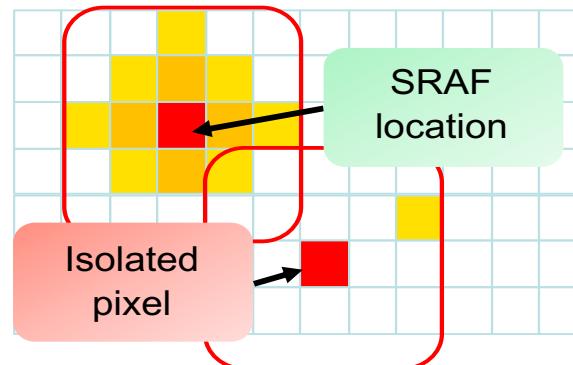
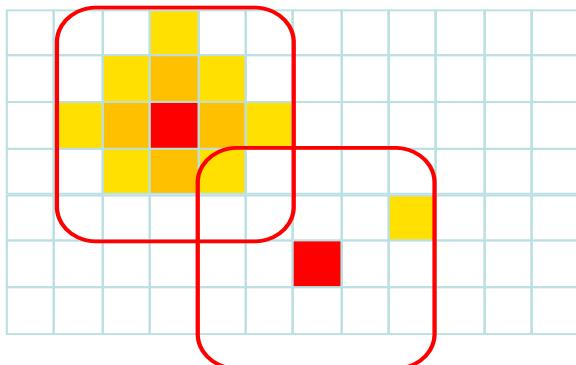
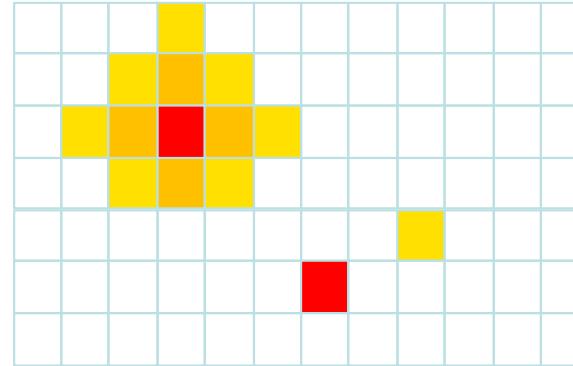
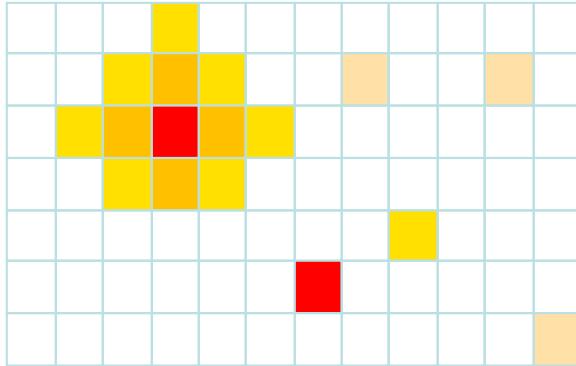
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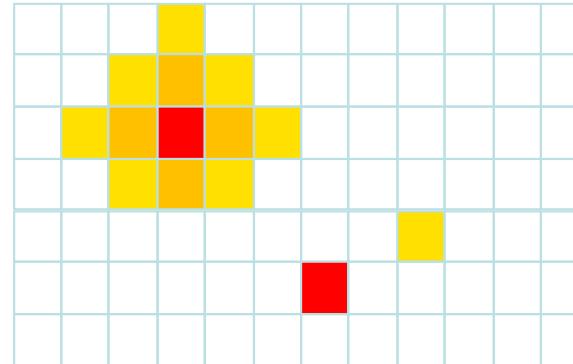
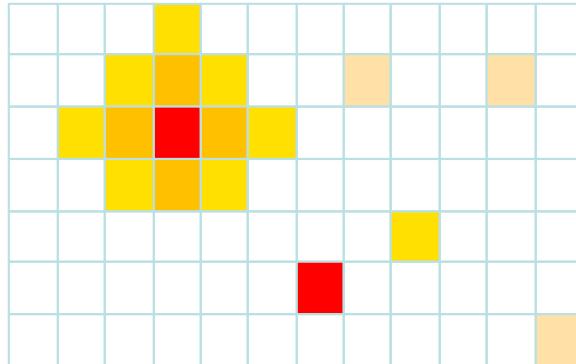
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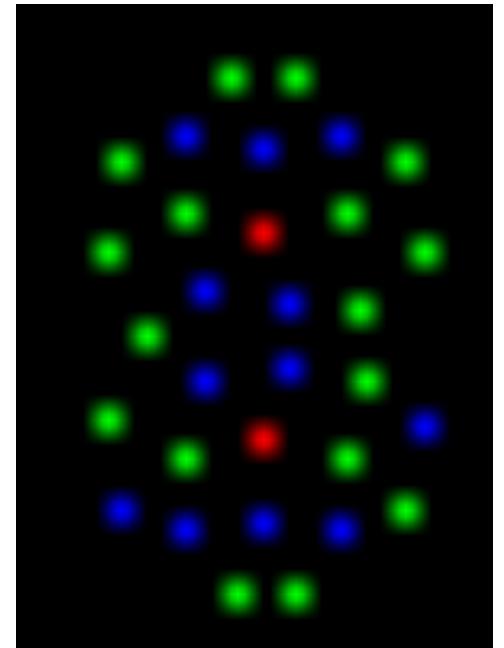
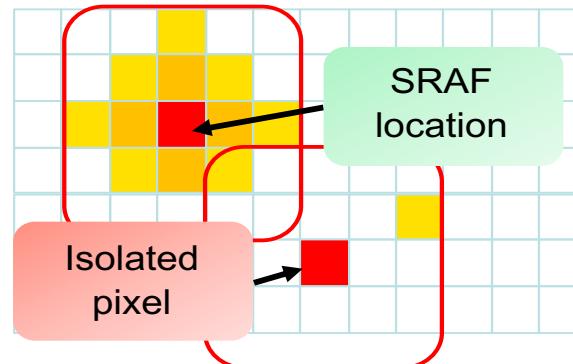
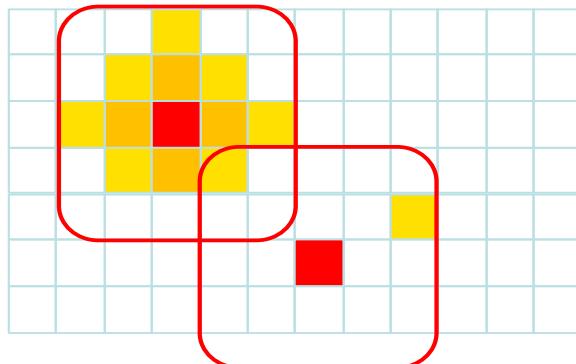


Results Decoding

- ♦ Decoding the generated layout images consists of two steps:
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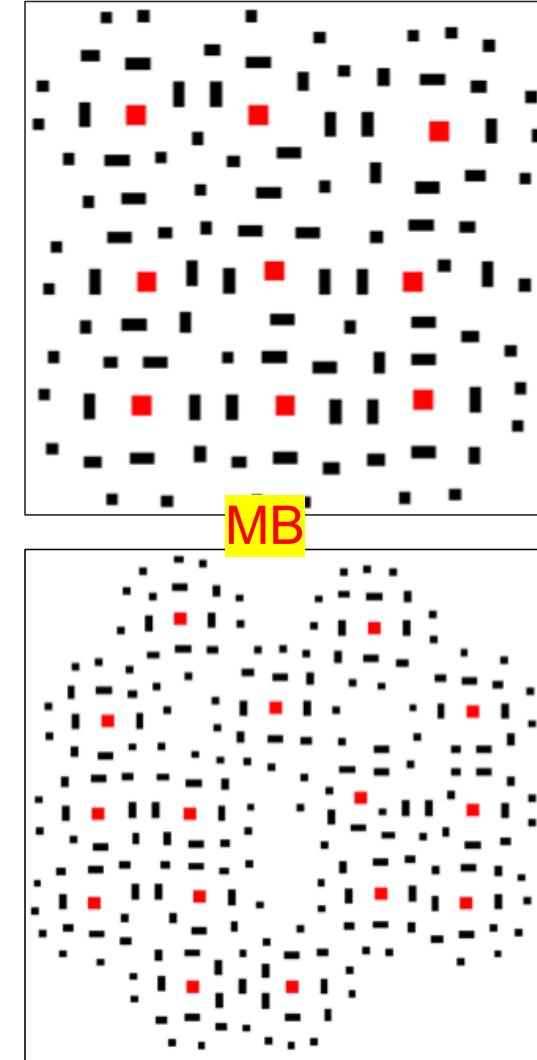


Decoding scheme is fast → GPU accelerated



Sample Results

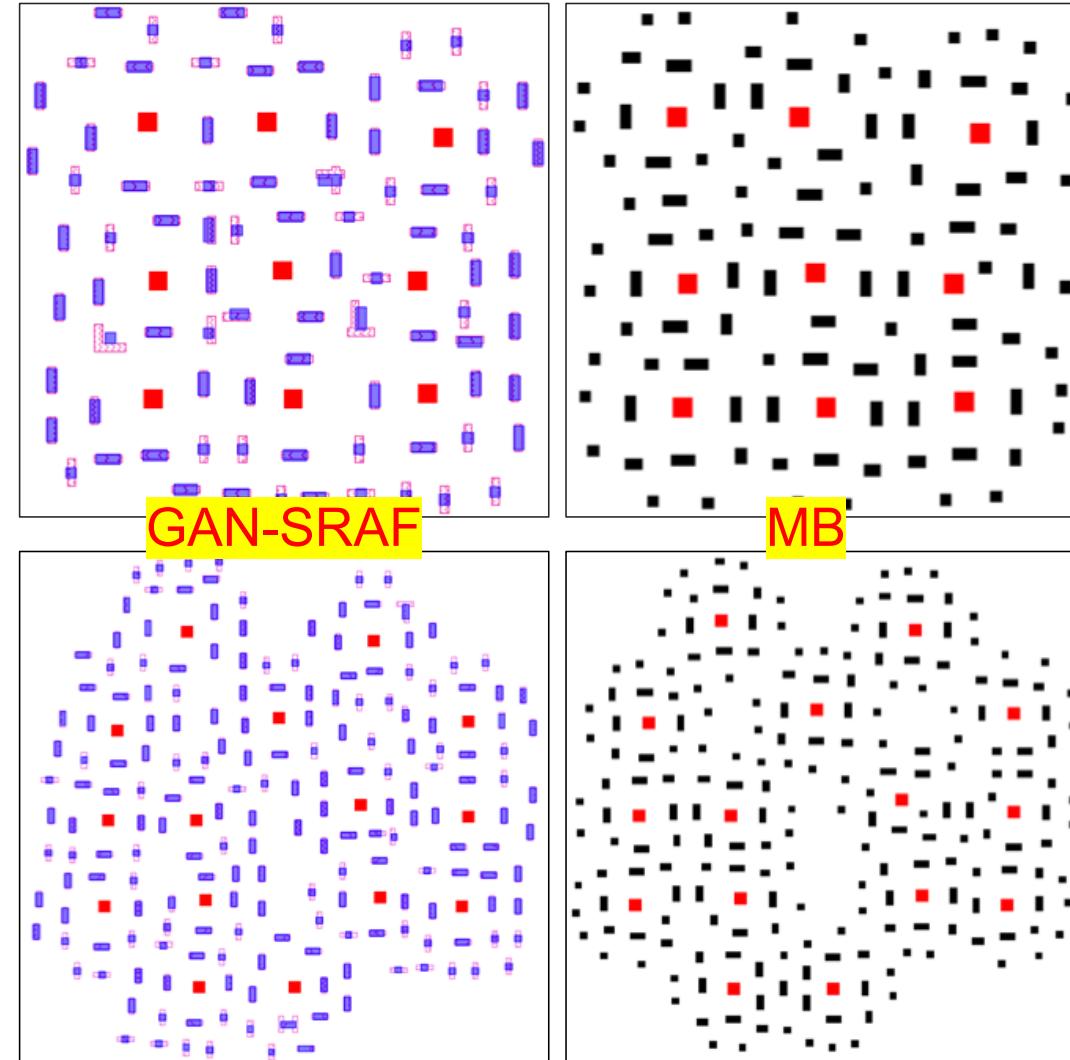
- LS_SVM: Xu et al, ISPD'16, TCAD'17
- MB: Model-Based Approach - Calibre



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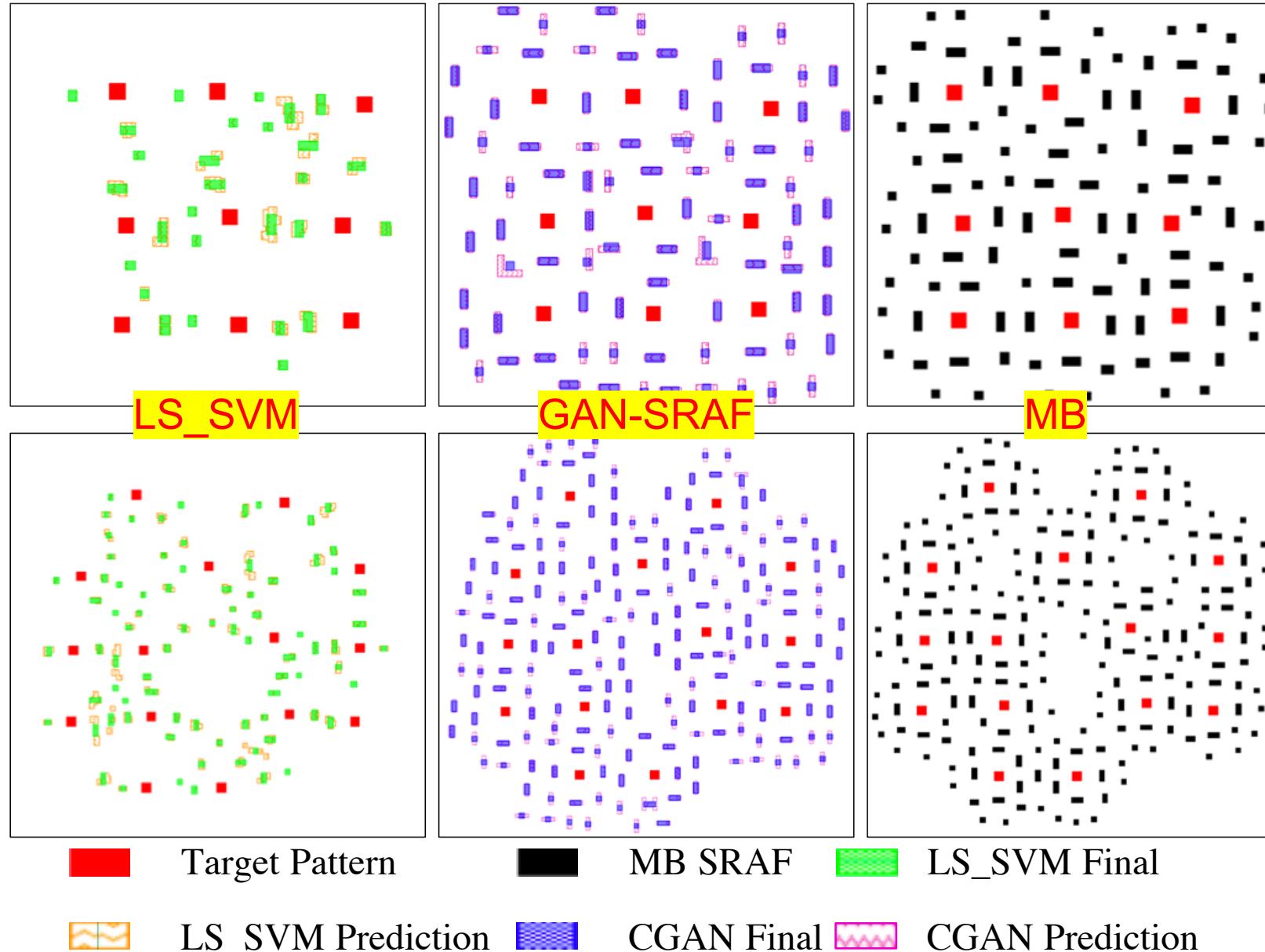
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A post processing
legalization step is applied



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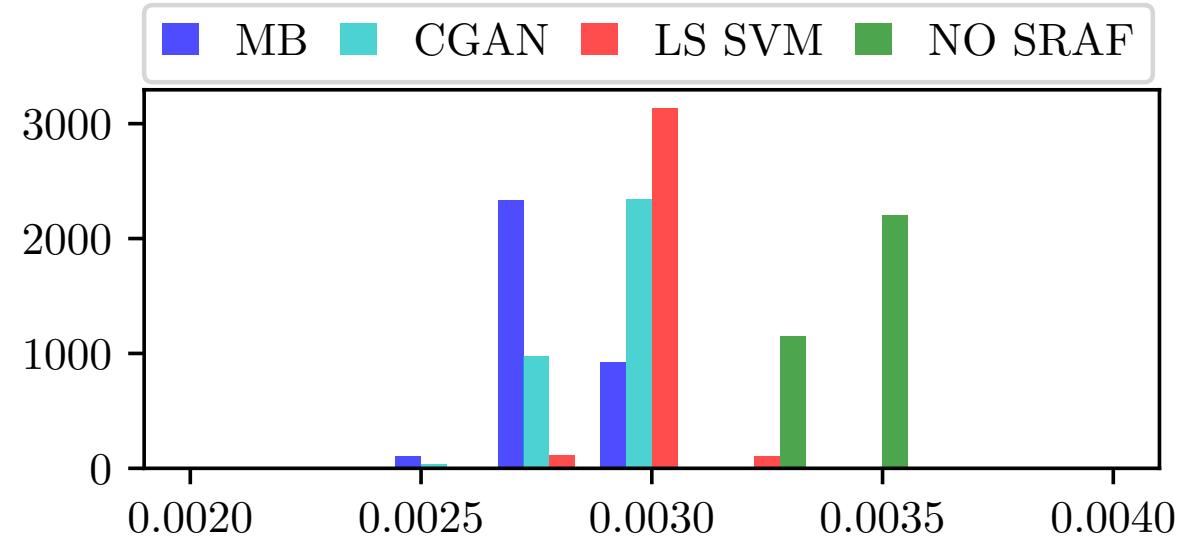
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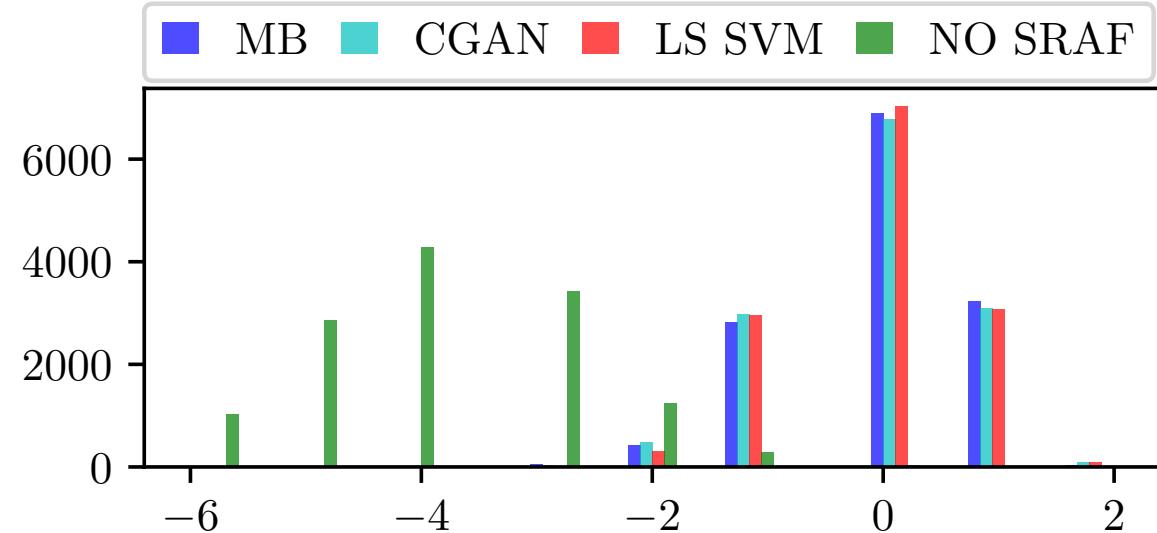
Lithography Compliance Checks

- LS SVM: Xu et al, ISPD'16, TCAD'17
- MB: Model-Based Approach - Calibre

Histogram of PV (μm^2)



Histogram of EPE (nm)



Comparison Summary

	No SRAF	MB	LS_SVM	CGAN
PV Band (μm^2)	0.00335	0.002845	0.00301	0.00291
EPE (nm)	3.9287	0.5270	0.5066	0.541
Run time (s)	-	6910	700	48

- ◆ The proposed CGAN based approach can achieve comparable results with LS_SVM and MB with **14.6X** and **144X** reduction in runtime

Conclusions

- ◆ GAN-SRAF, a novel SRAF generation framework, is presented featuring:
 - › Novel problem formulation as image translation
 - › Smart heatmap encoding scheme and GPU accelerated decoding
- ◆ Results demonstrate significant speedup when compared to ML and MB
 - › *While achieving comparable lithography performance*



Thank You!