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

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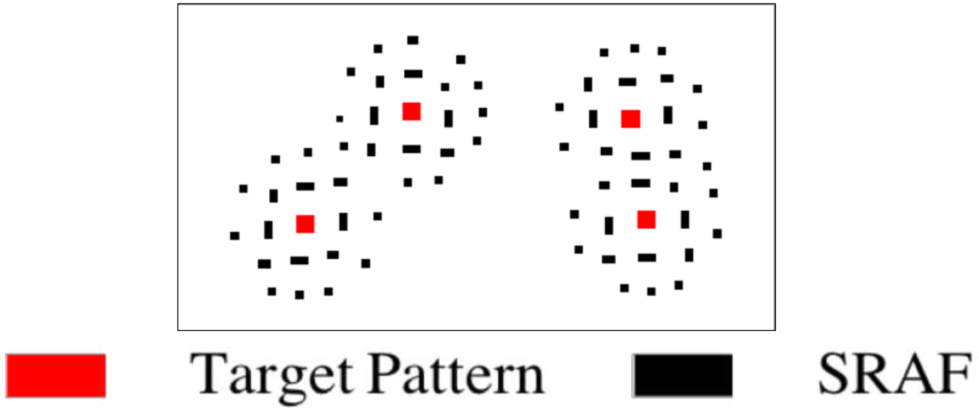
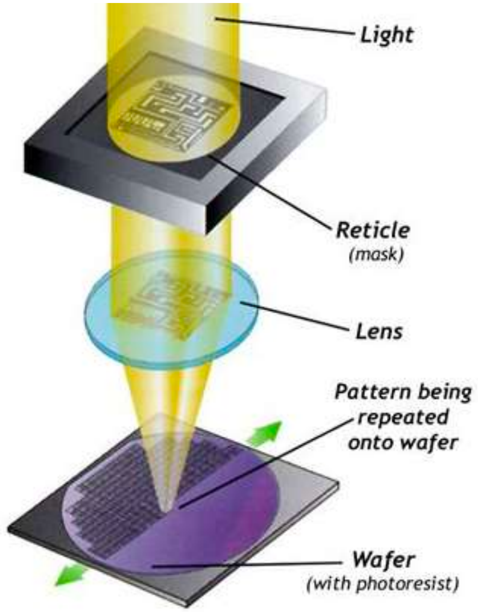
Motivation

- 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





https://slideplayer.com/slide/9416386/

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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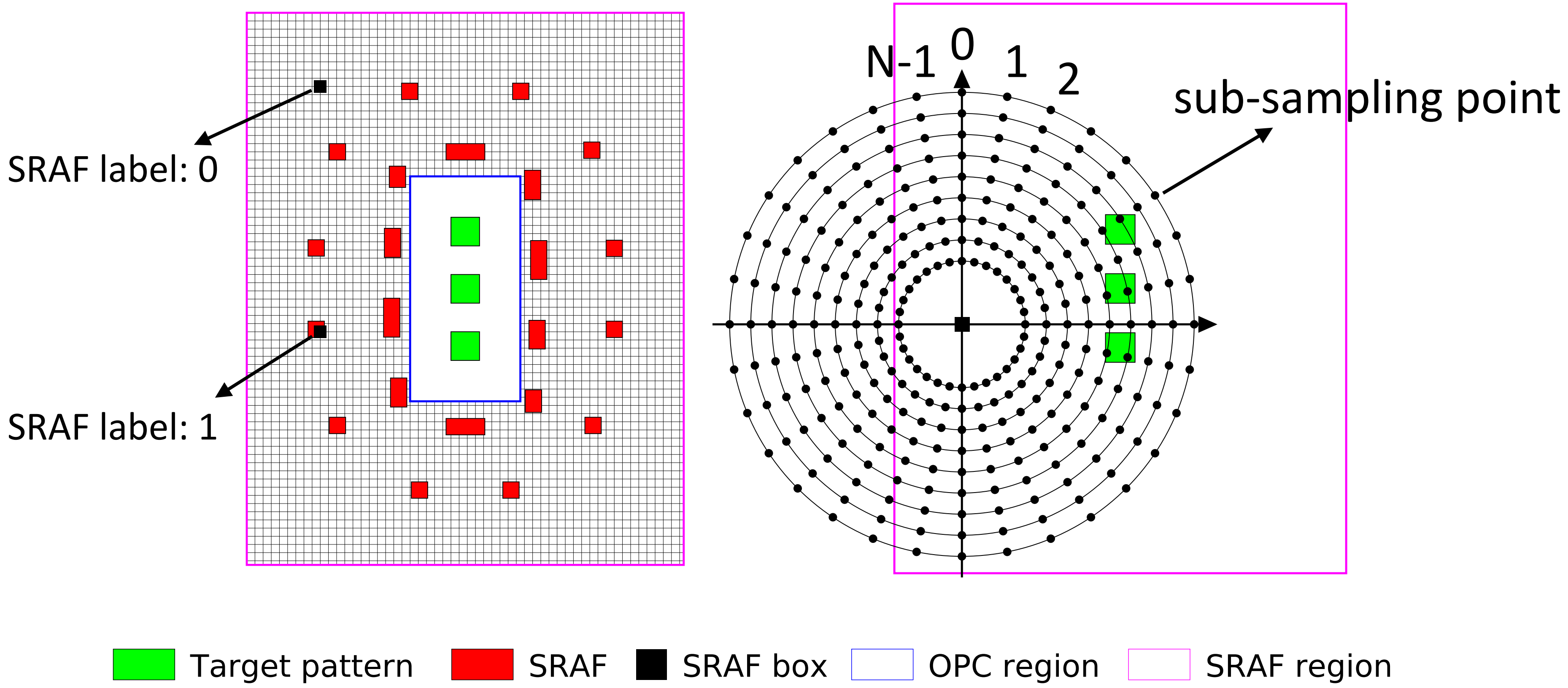
<u>Can we do better?!</u>

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



[Xu et al, ISPD’16, TCAD’17]

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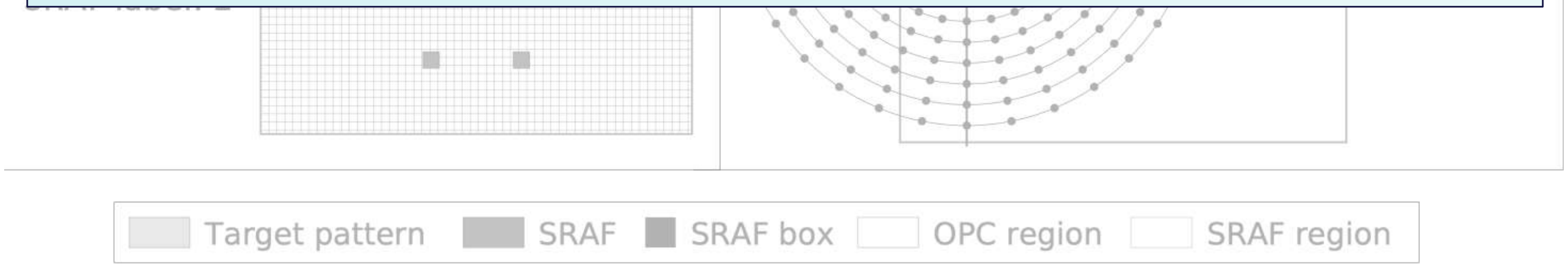
- While achieving 10X runtime improvement, this approach has large room for further enhancement



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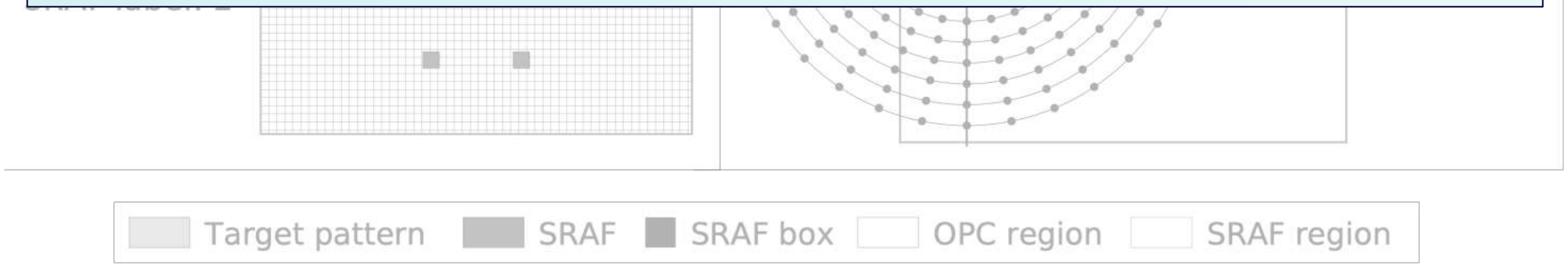

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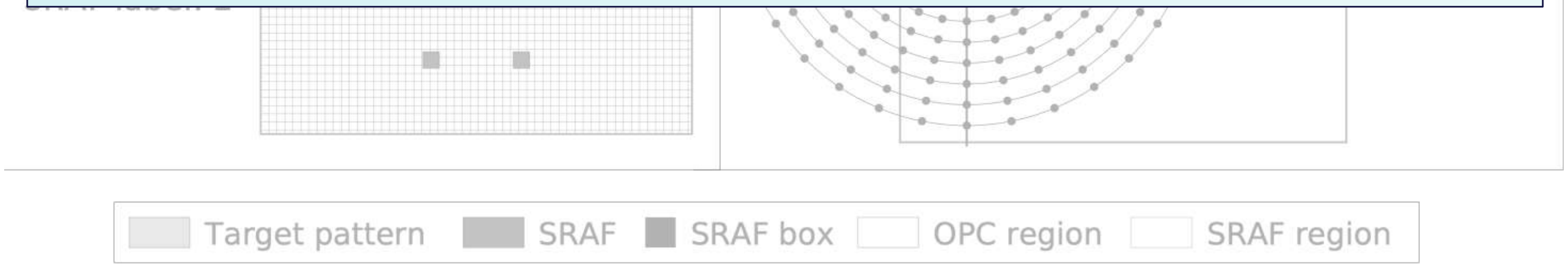

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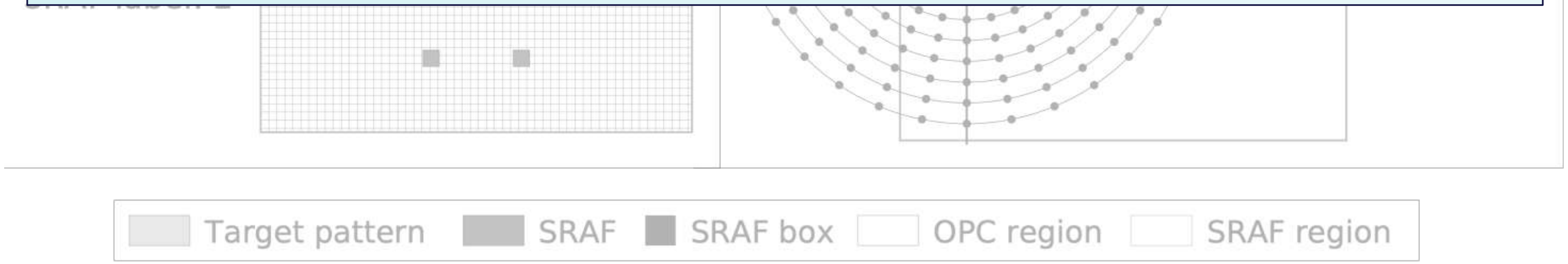
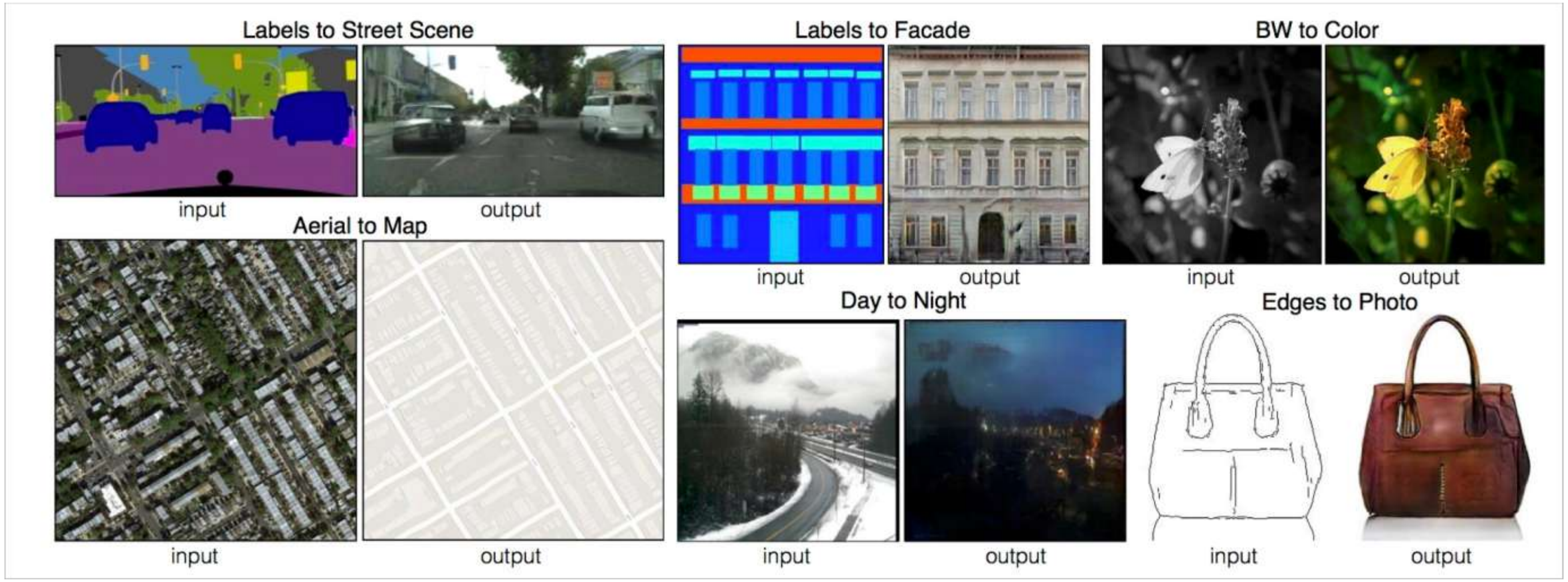
  - Do we need a 2D grid and local sampling?
  - Can we avoid the feature extraction step?
  - Most importantly, with all advancements in Computer Vision, can we recast this problem to leverage these advancement?



[Xu et al, ISPD’16, TCAD’17]

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



[Isola et al, CVPR'18]

SRAF Generation & Image Translation

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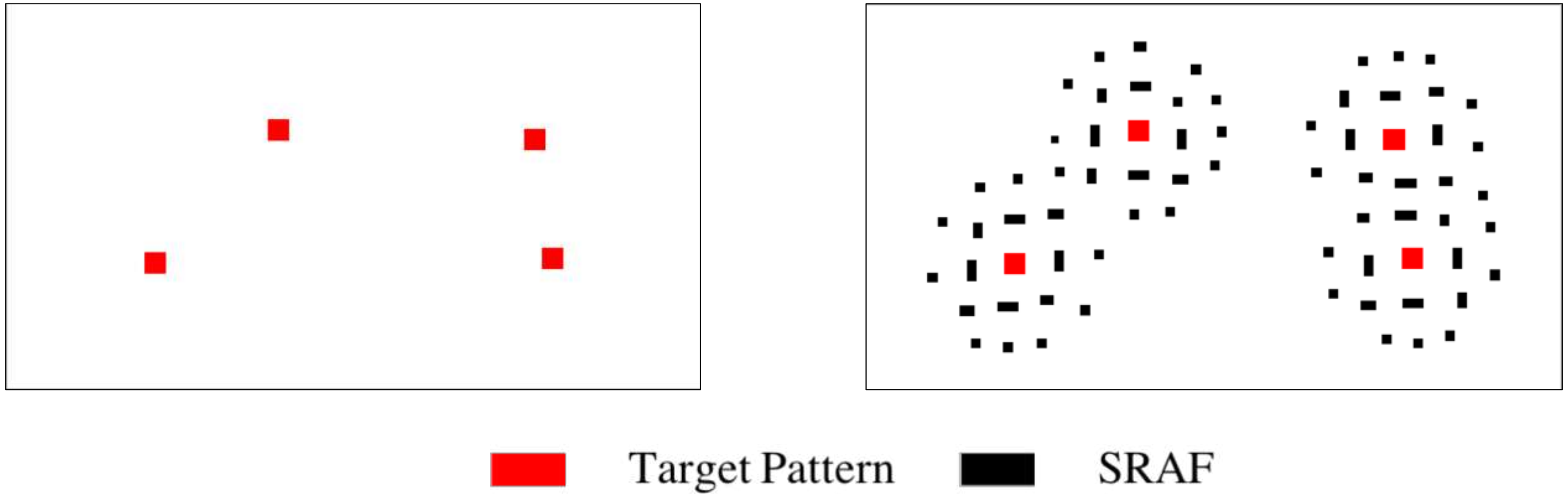

- Can we define the problem as translating images from the Target Domain (D_T) to the SRAF Domain (D_S)?

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

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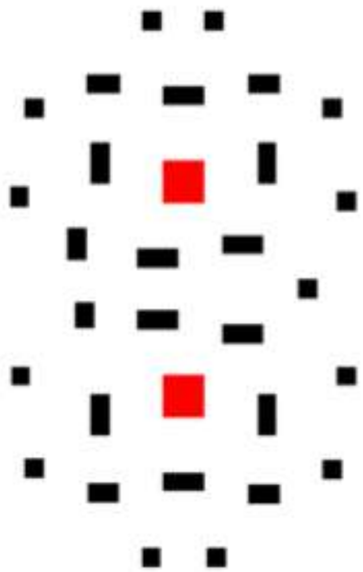
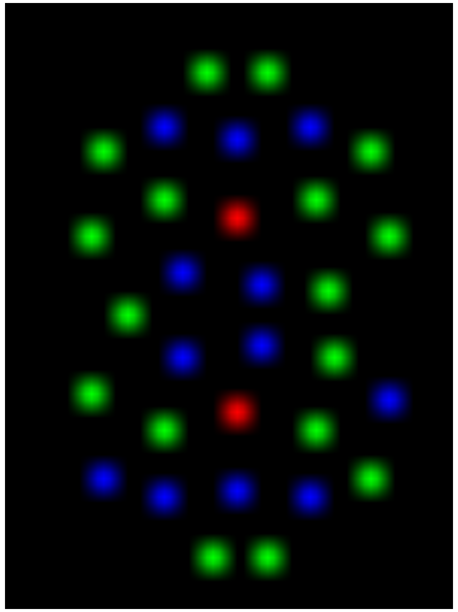
  - Post-processing step should not be time consuming
- *Hence, a proper encoding is needed to address these challenges!*

Multi-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



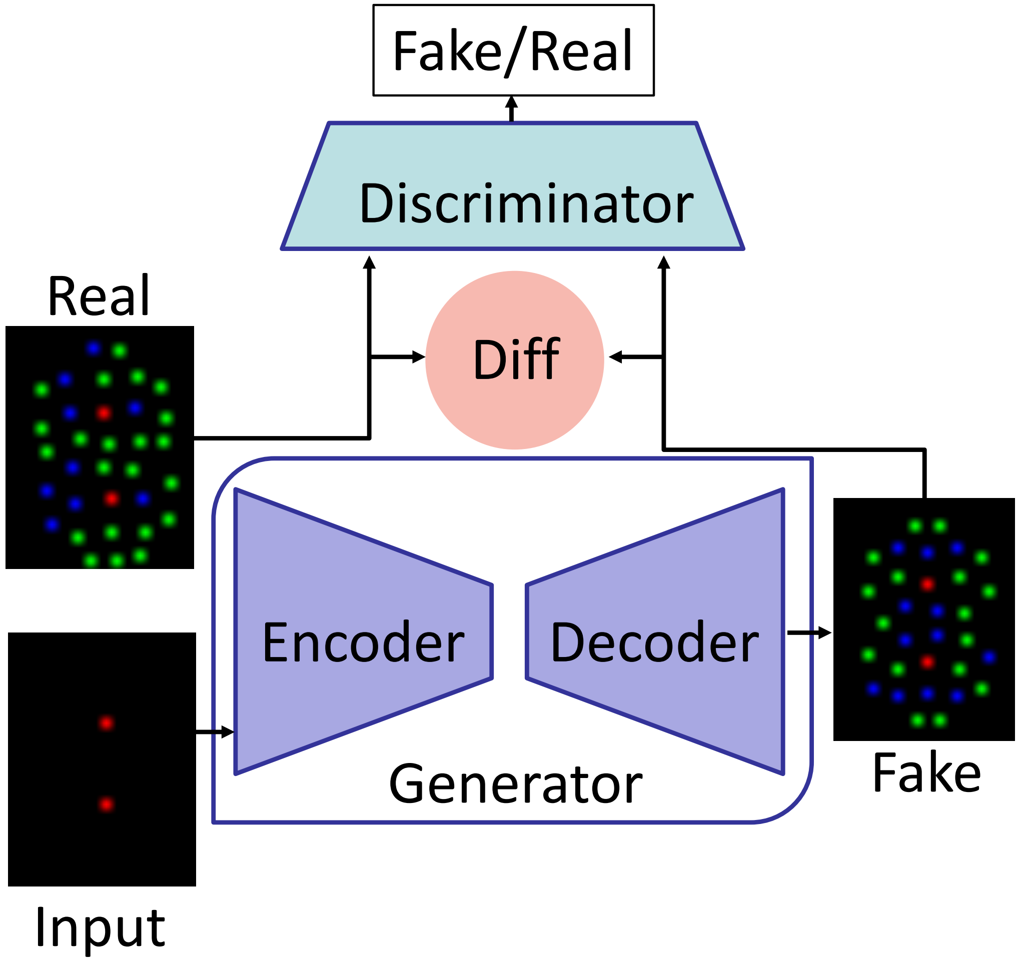
Encoded Layout

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

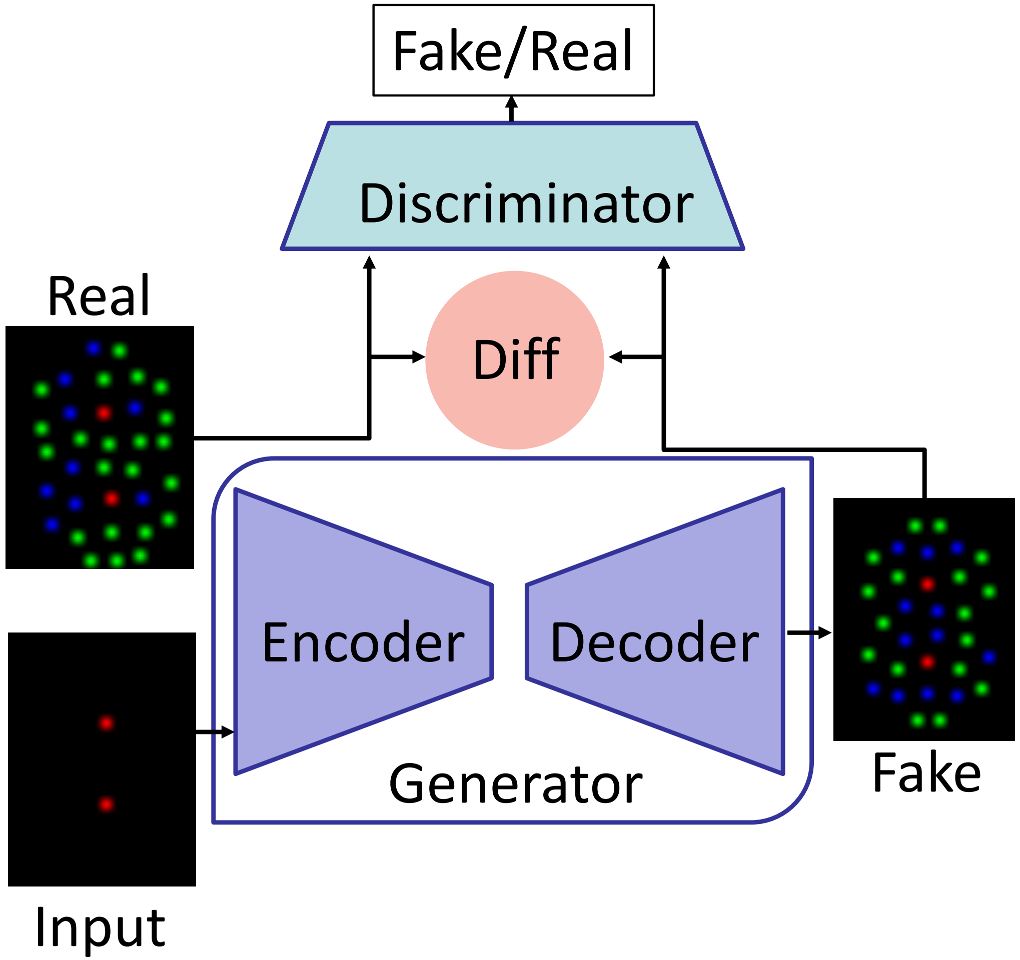
CGAN Approach

- 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



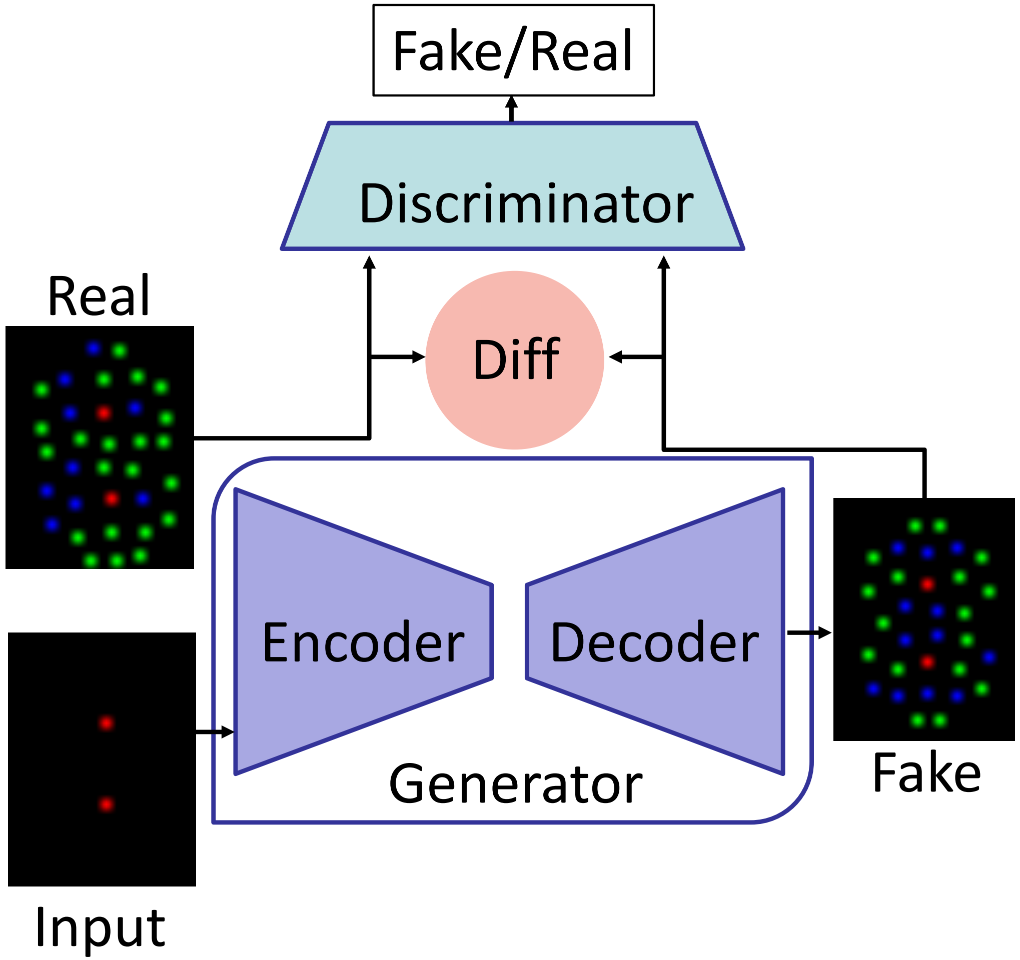
CGAN Approach

- Generator:
  - Encoder: Downsampling
  - Decoder: Upsampling



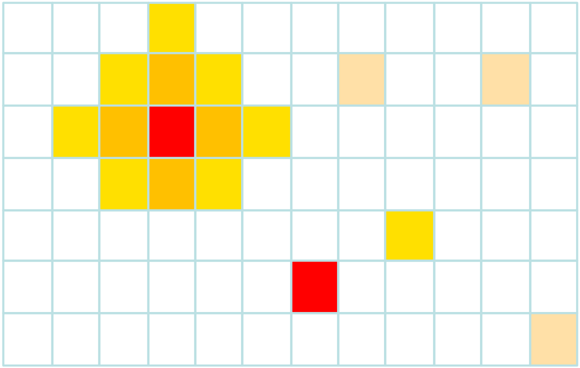
CGAN Approach

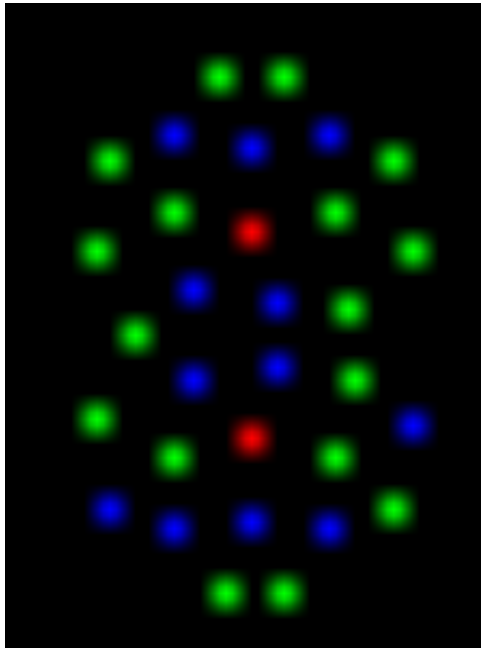
- Generator:
  - Encoder: Downsampling
  - Decoder: Upsampling
- Discriminator:
  - CNN trained as a classifier
- After training, only the generator is used



Results Decoding

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





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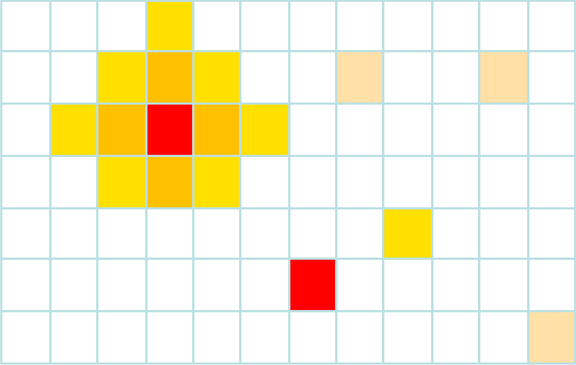

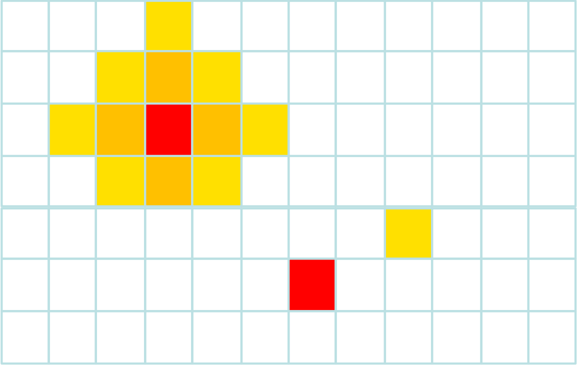

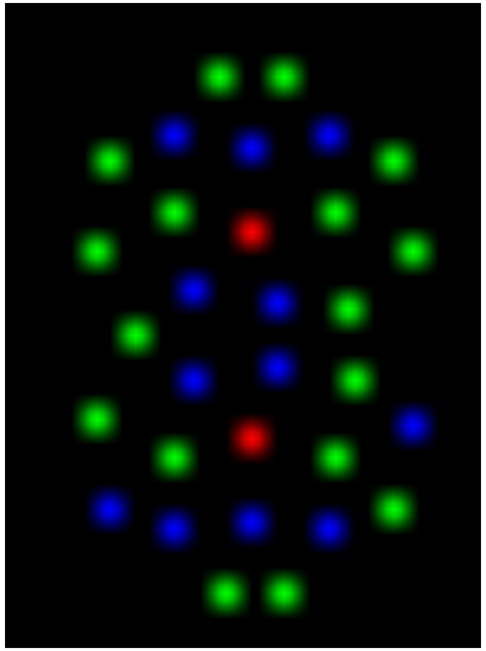

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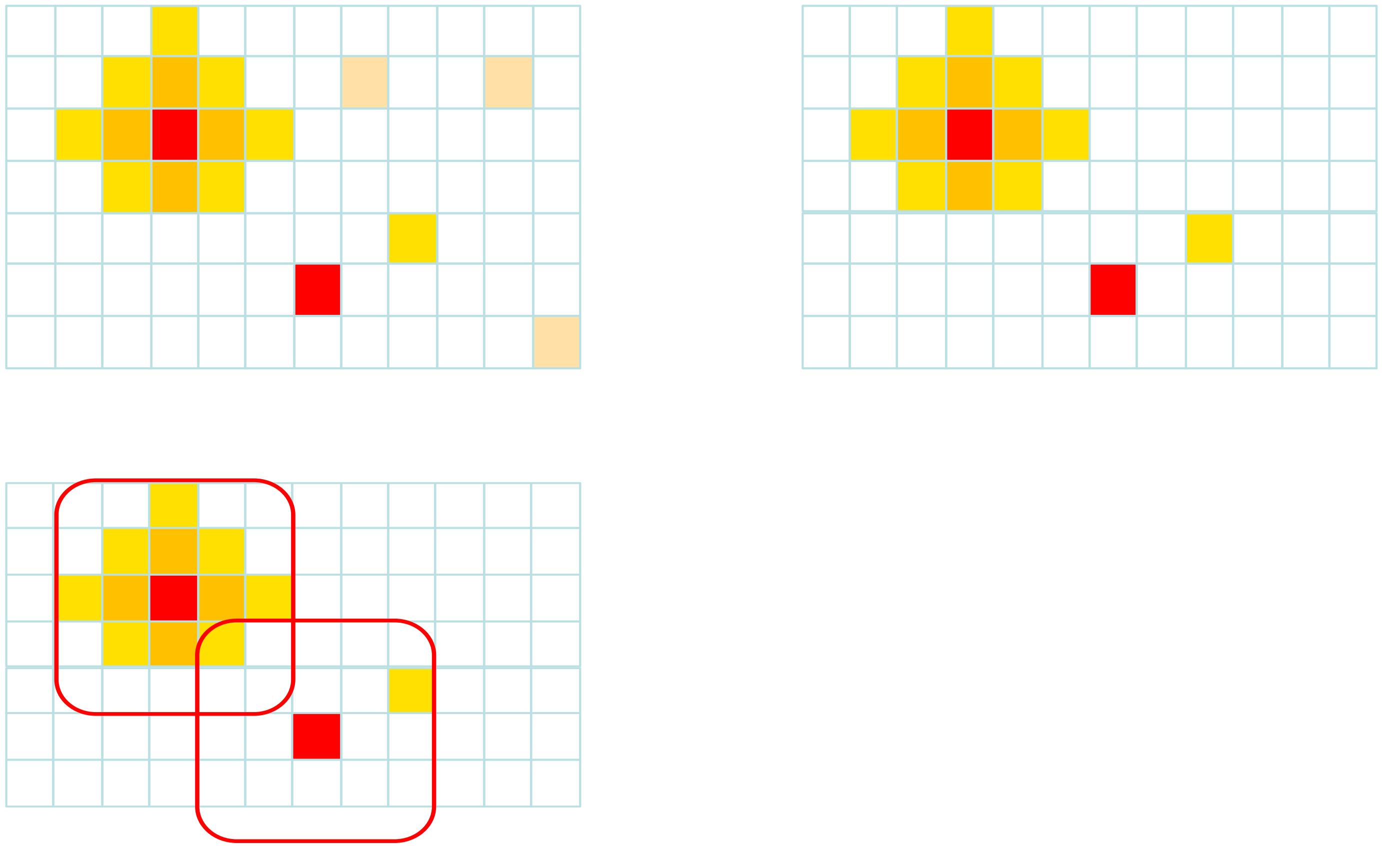

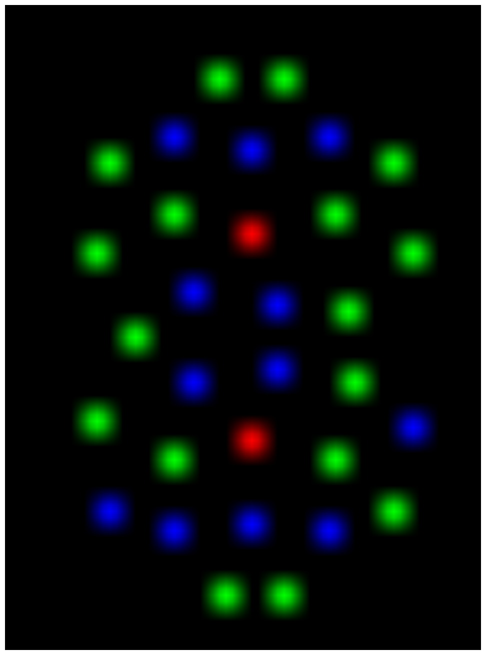

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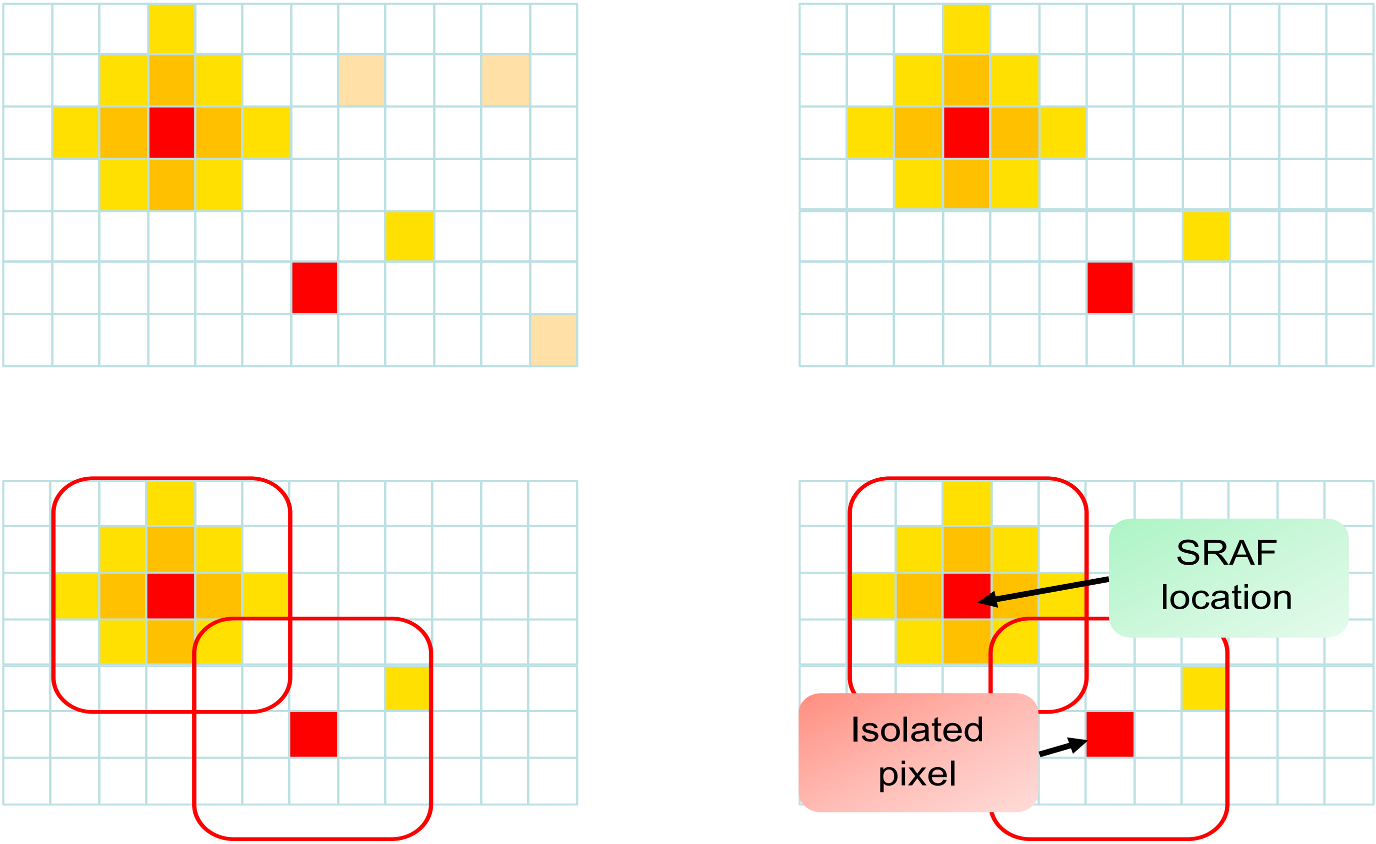

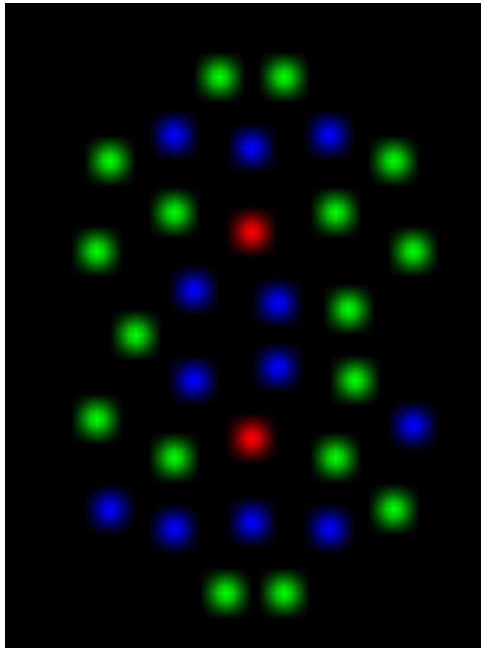

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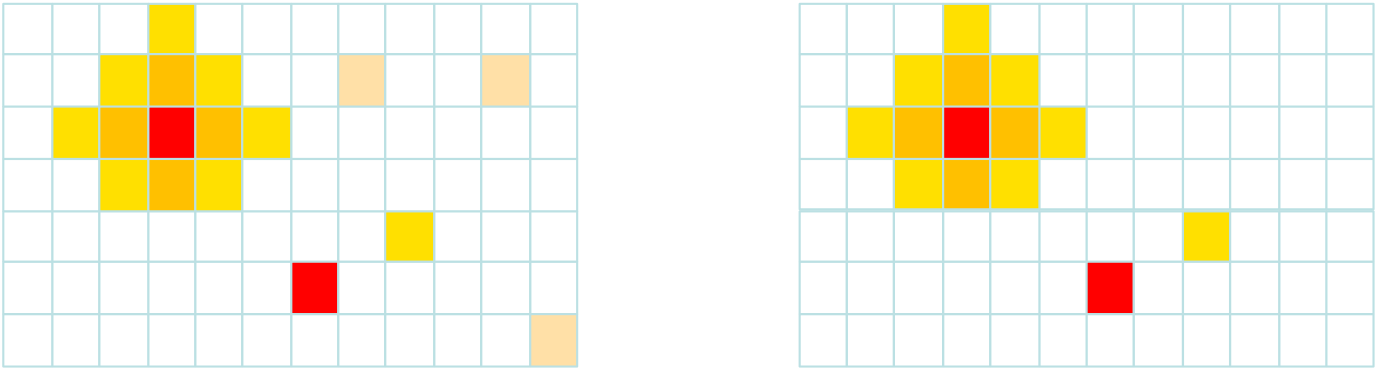
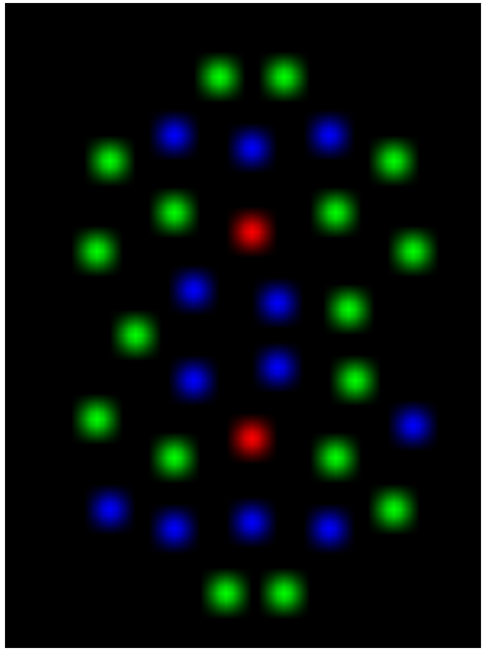
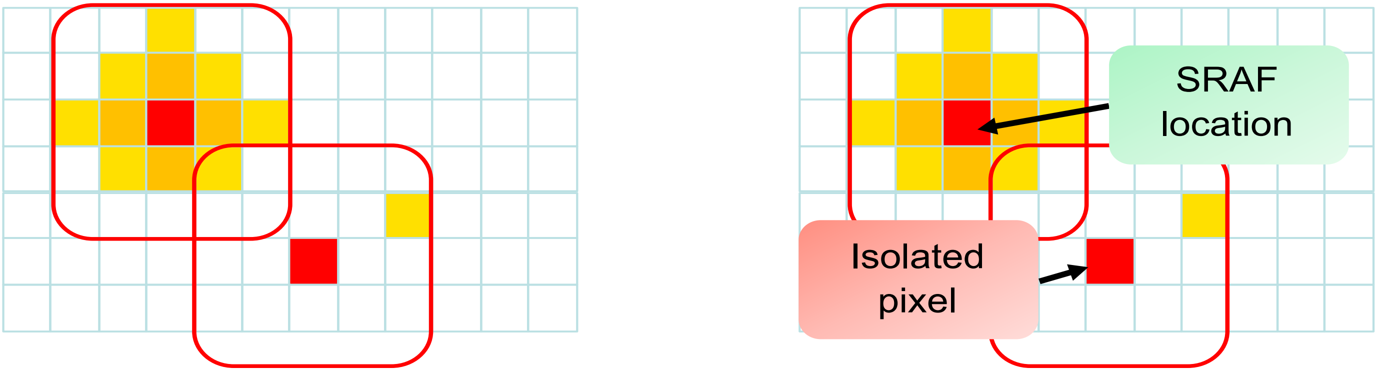


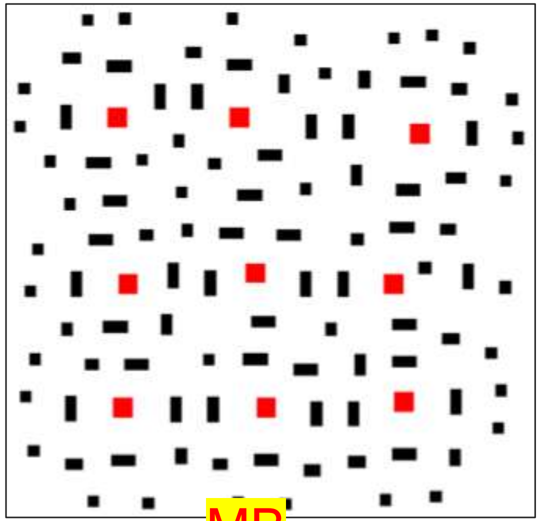


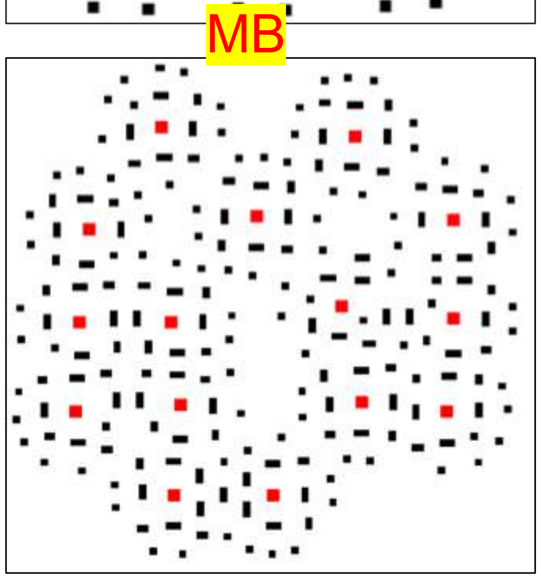
Decoding scheme is fast → GPU accelerated



Sample Results

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





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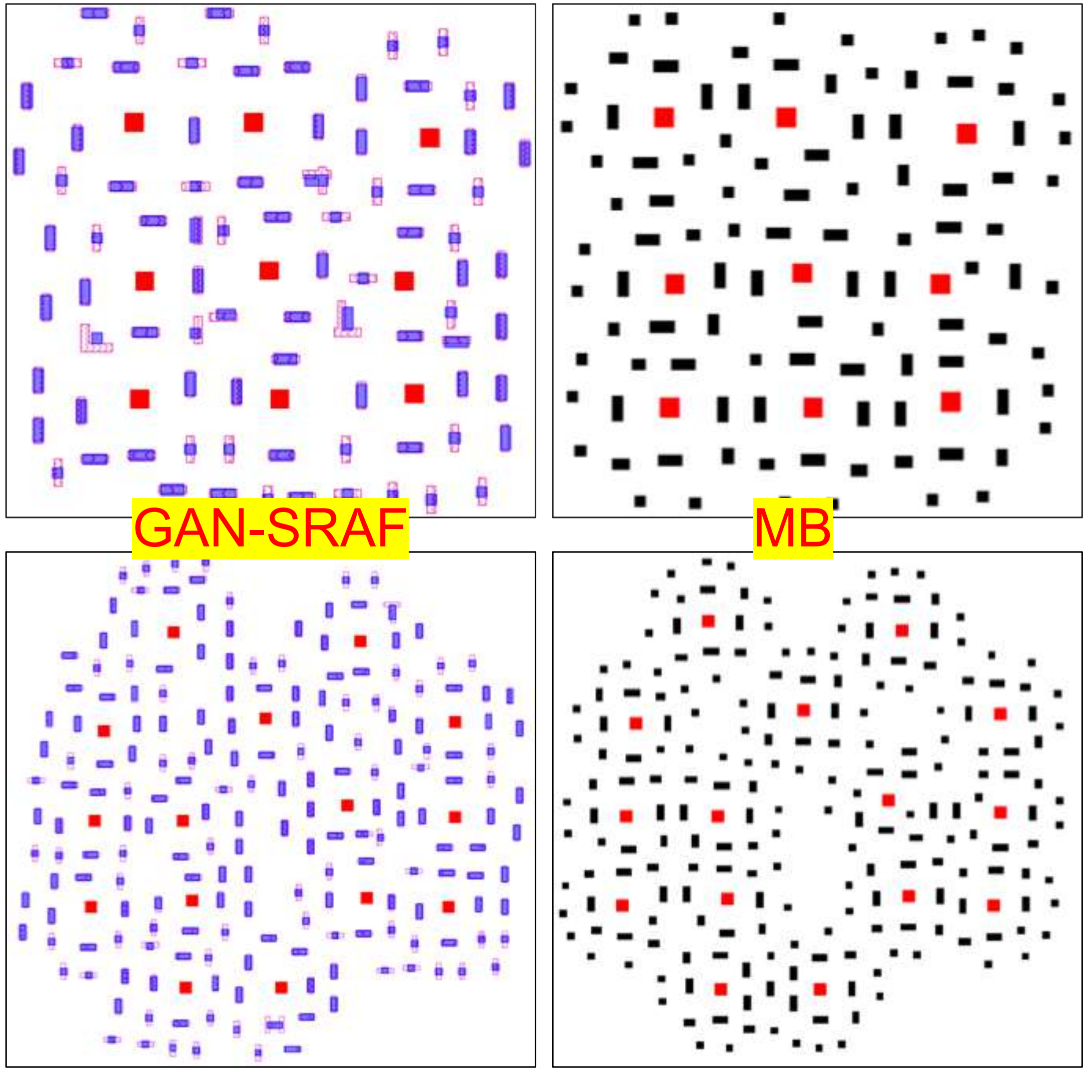
A post processing legalization step is applied



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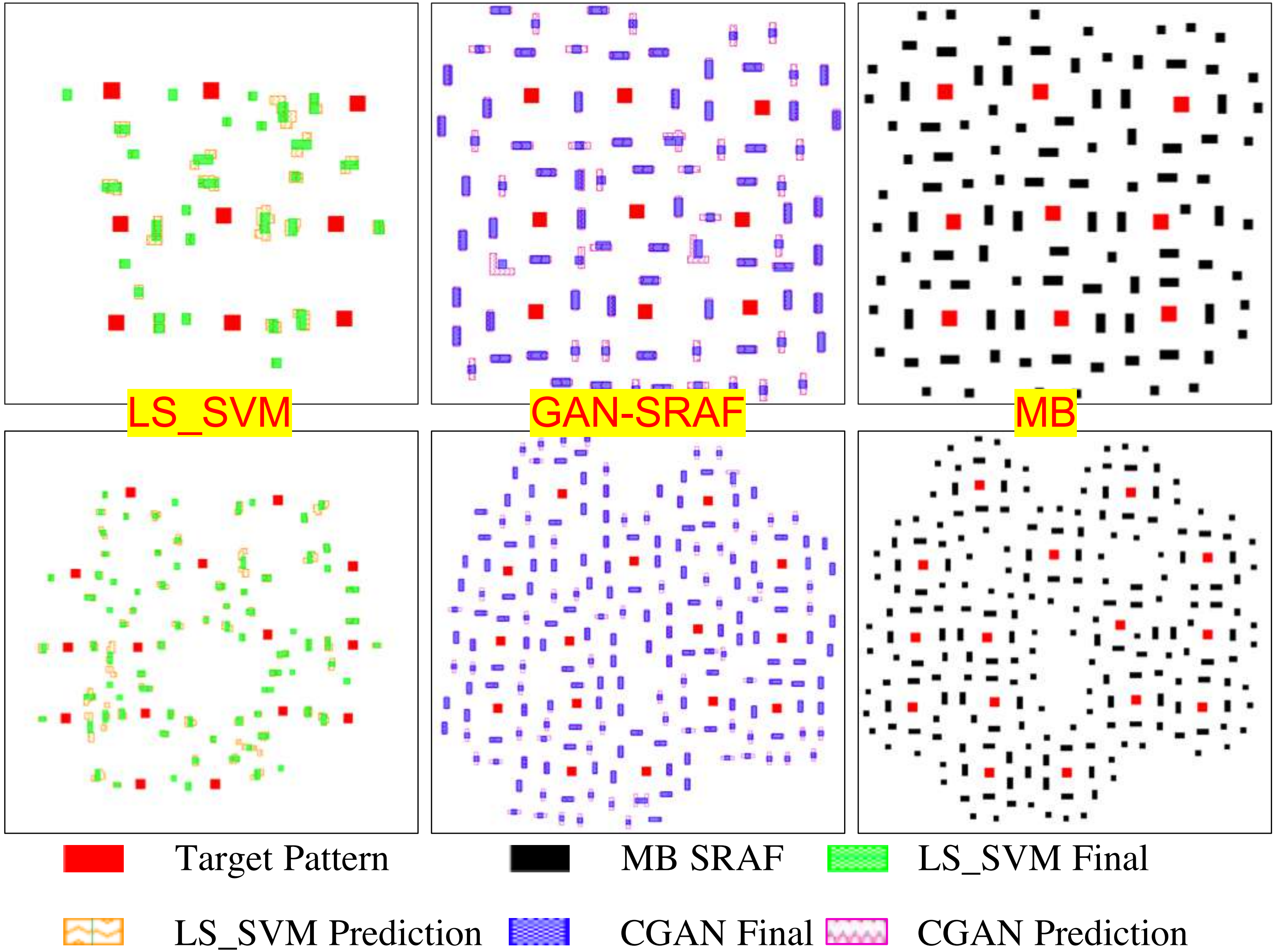
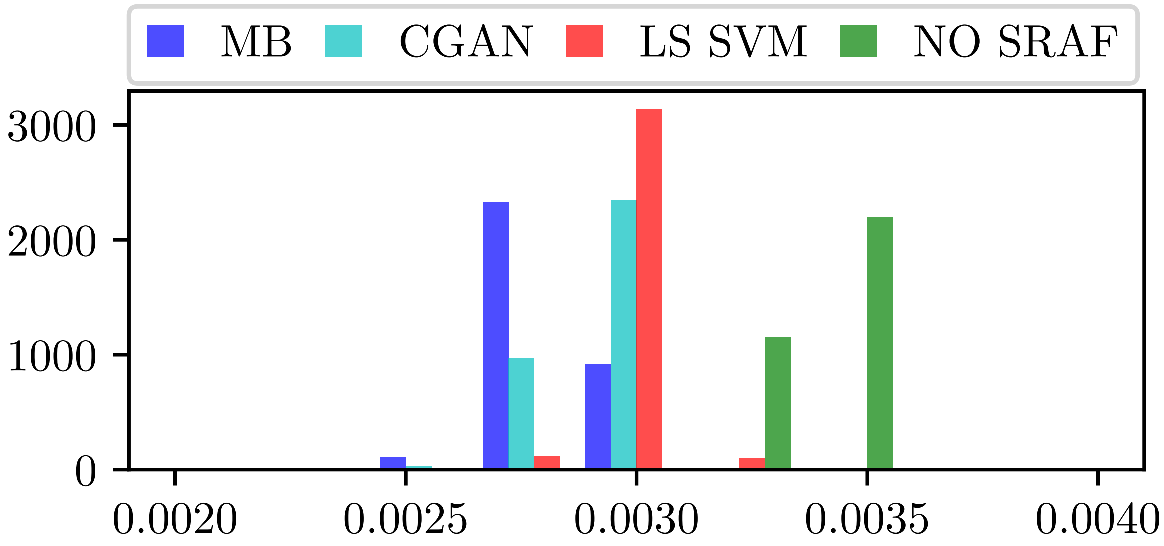


Lithography Compliance Checks

Histogram of PV (um^2)



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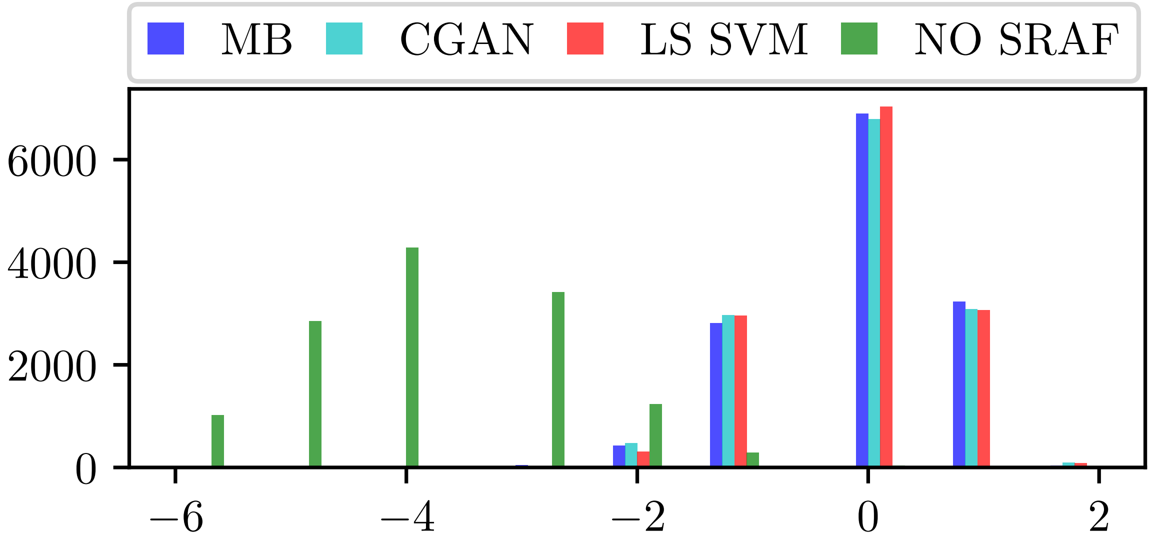
Histogram of EPE (nm)



Comparison Summary

	No SRAF	MB	LS_SVM	CGAN
PV Band (um^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!