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Mask Synthesis using Machine Learning Software & Hardware for EUV Lithography

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Outline

- **Motivation**
  - Inspiring stories of machine learning (ML)
  - Rapid advances in ML software & hardware
  - Mask synthesis (MS) is a form of reinforcement learning (RL) from ML point of view
- **Proposed MS flow on ML platforms**
  - Architecture design
  - Differentiation from other approaches
- **Lithography models for 3D mask, imaging & resist processes**
  - Implementation considerations for ML frameworks
  - Modeling challenges & status
- **Proof-of-concept evaluation**
  - Lithography models generation & quality evaluation
  - Mask synthesis evaluation
- **Conclusion**

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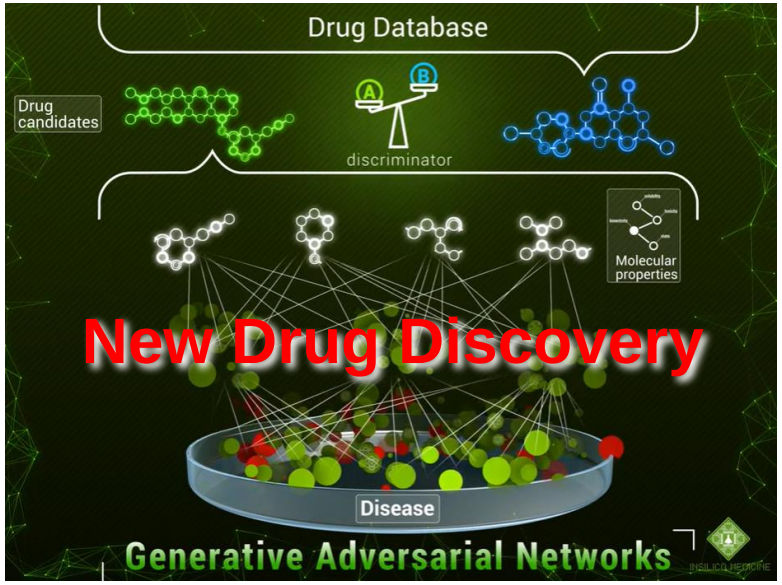
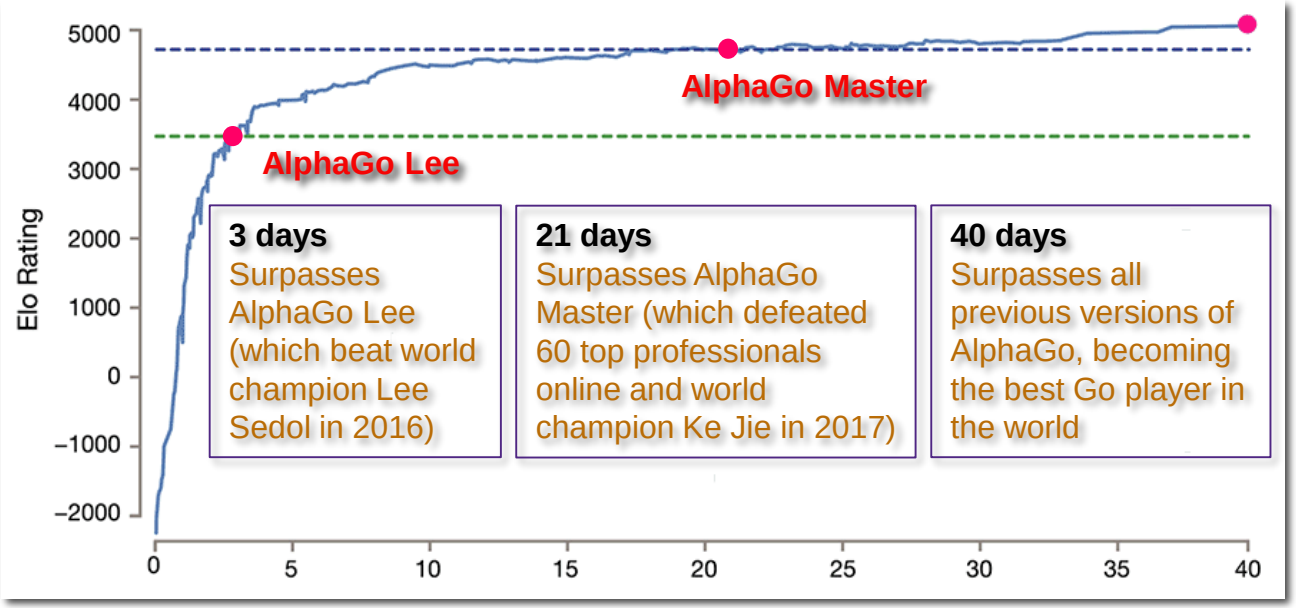
Inspiring stories of ML



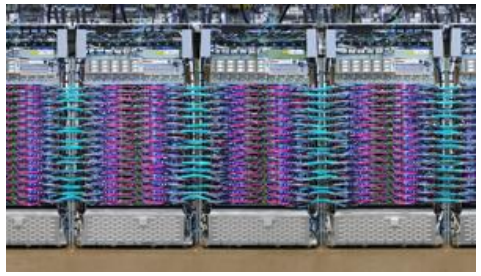


Rapid advances in ML software & hardware

- Software libraries
  - Actively developed and frequently updated by industry heavyweights
  - Openly released to the public, easily accessible for all types of users
  - Built-in support for hardware acceleration (e.g., GPU)

TensorFlow PyTorch mxnet Microsoft Cognitive Toolkit aka.ms/CognitiveToolkit Microsoft

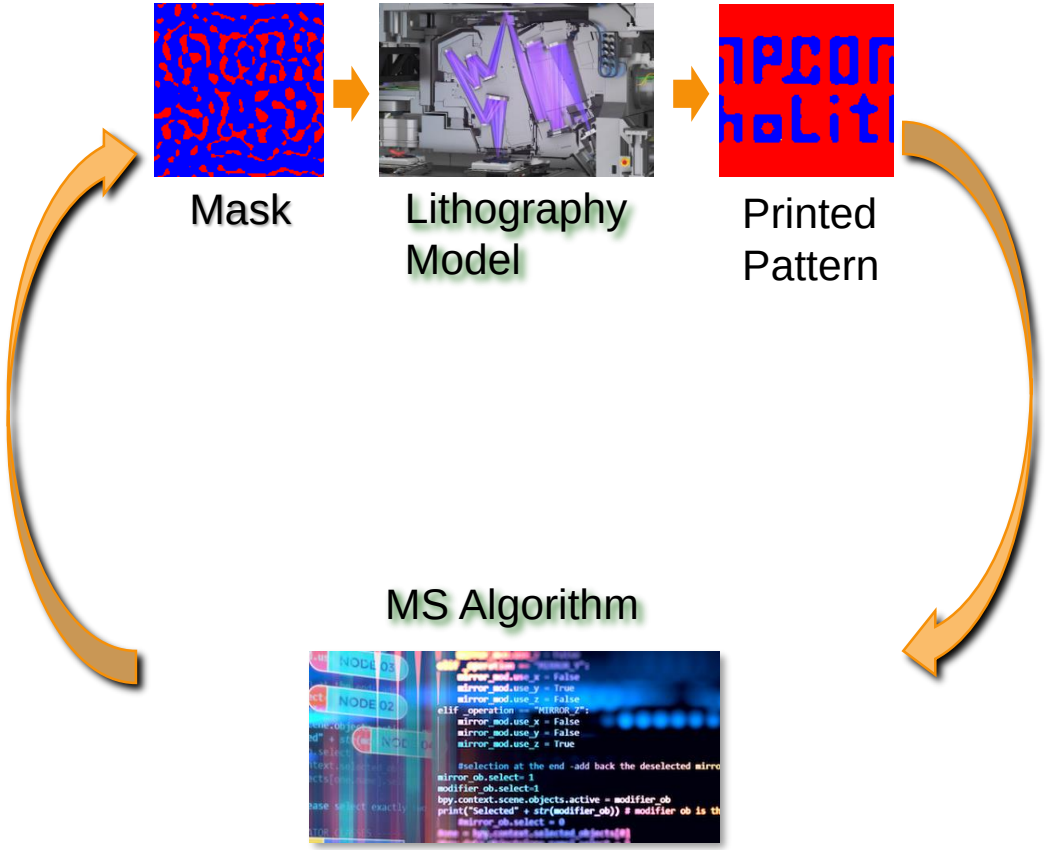
- Hardware devices
  - Significant speedup in ML model training and inference
  - Active development by established companies and young startups



Analogy between mask synthesis and reinforcement learning

Reinforcement Learning (RL)

Mask Synthesis (MS)



Mask synthesis can be regarded as a form of reinforcement learning from ML point of view

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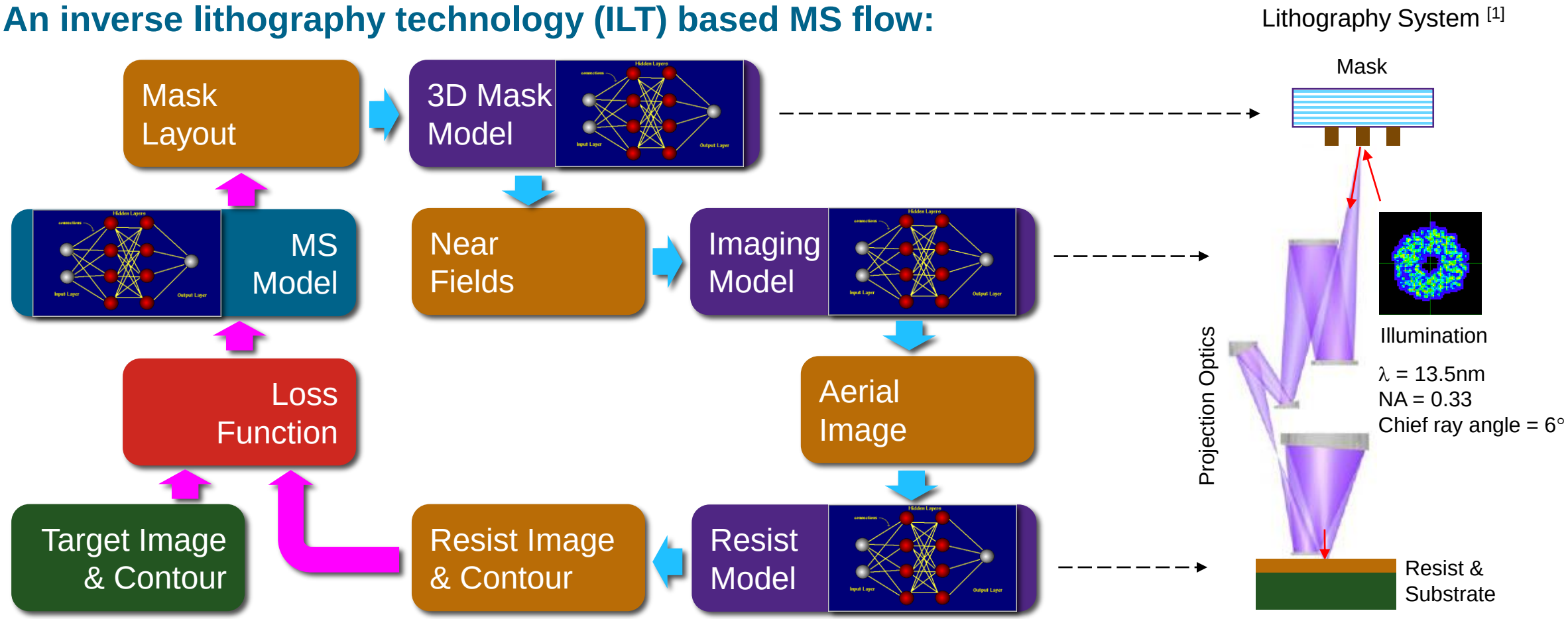
Mask synthesis (MS) on machine learning (ML) platforms

- **An inverse lithography technology (ILT) based MS flow:**



- **The objective of this work is to implement & run the MS flow entirely in an ML framework (e.g., TensorFlow) with GPU acceleration**

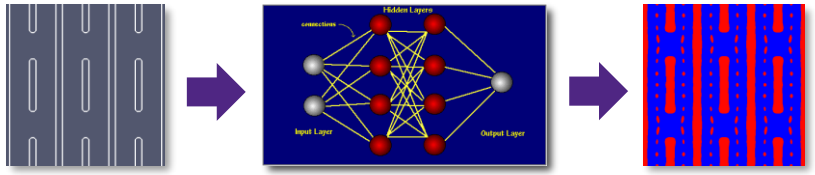
[1] Jan van Schoot et al, “High-numerical aperture extreme ultraviolet scanner for 8-nm lithography and beyond,” J. Micro/Nanolith. MEMS MOEMS 16(4), 041010 (2017)

Differentiation #1: platforms

- **Proprietary special-purpose platforms**
  - Proprietary mask synthesis tools are commercially available
- **Open general-purpose platforms**
  - This work seeks a solution that runs entirely on off-the-shelf open ML platforms
  - Potential benefits:
    - Take advantage of the latest advances in ML software and hardware
    - Save development effort and allow developers to focus more on domain-specific components (i.e., ML-based 3D mask, imaging and resist models, etc.)

TensorFlow PyTorch mxnet Microsoft Cognitive Toolkit aka.ms/CognitiveToolkit Microsoft

Differentiation #2: ML approaches



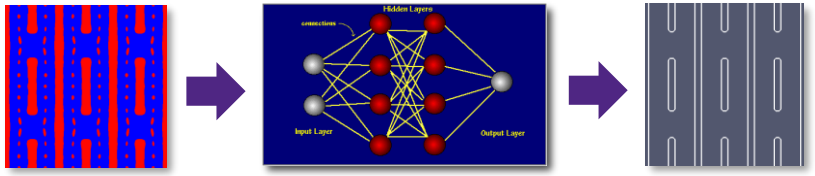
Wafer target (input) | ML mask synthesis model | Optimized mask (output)

- **Supervised learning (SL)**
  - ML-based OPC/ILT solutions using supervised learning approach have been reported
    - The ML-OPC/ILT model is a mapping function from input to output
    - A conventional OPC/ILT tool is required to generate training samples (i.e., OPC/ILT input-output pairs)
    - An ML framework (e.g., TensorFlow) is used to train the ML-OPC/ILT model on these samples
- **Reinforcement learning (RL)**
  - This work seeks a solution that optimizes the mask directly using an ML framework
    - No need for a separate OPC/ILT tool to generate training samples
  - Analogy to reinforcement learning
    - Agent = mask synthesis model
    - Environment = lithography system

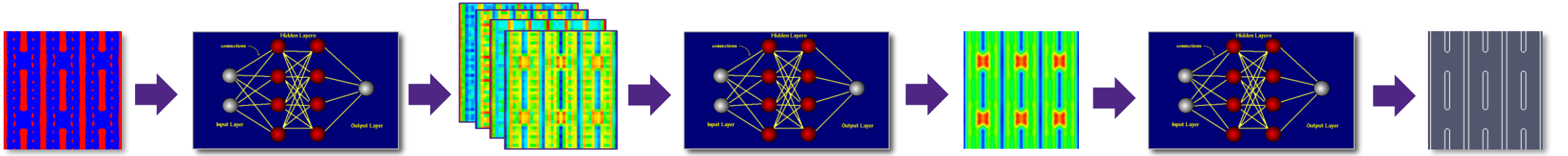
Differentiation #3: lithography models

Two approaches to implement lithography models in ML frameworks:

- **Lumped end-to-end lithography model**



- **Separable & interchangeable lithography models**



  – A more natural way to model the physical and chemical processes in lithography
  – Can readily take into account process conditions (e.g., dose, focus, slit location) w/o having to re-train the entire model.

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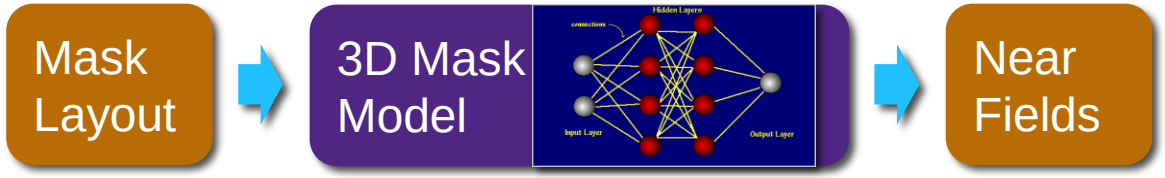
3D mask model for electromagnetic field (EMF) diffraction

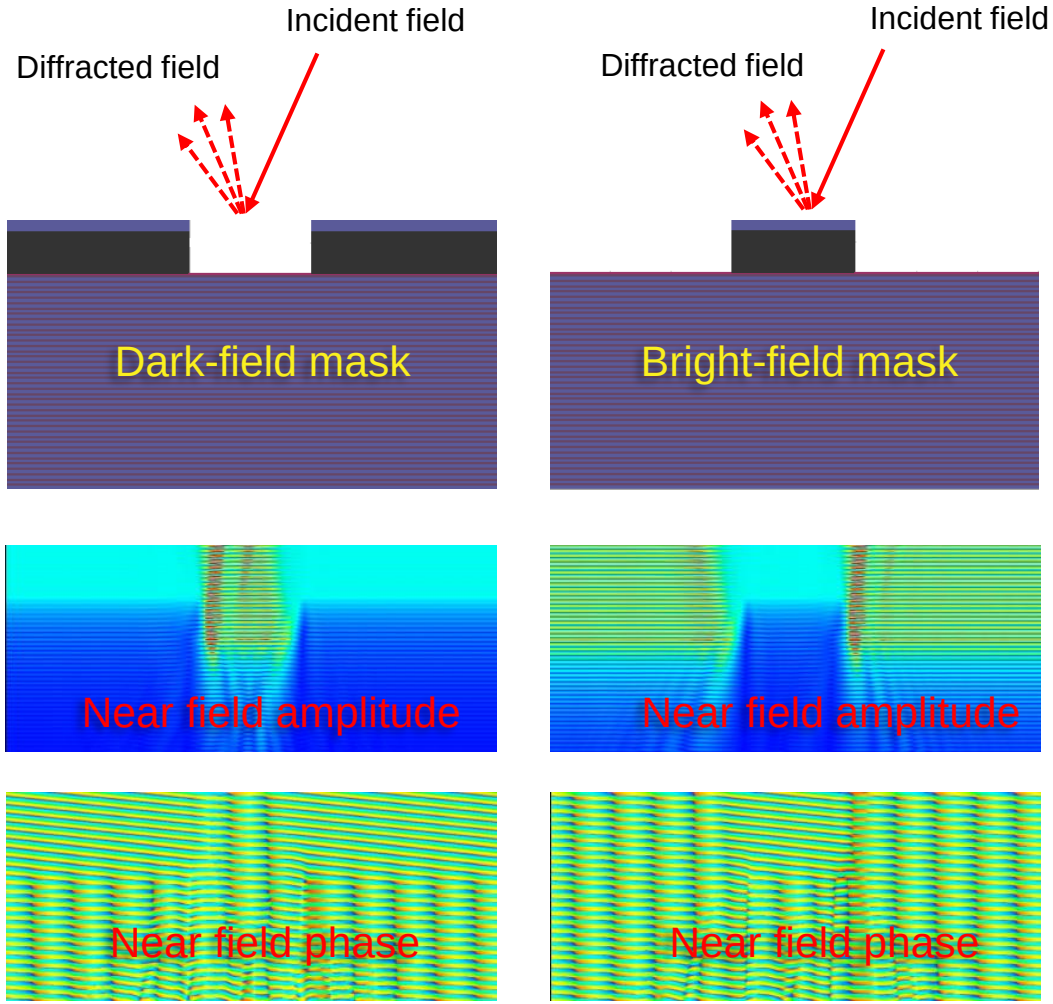
- Governed by Maxwell's equations

$$\nabla \times \vec{E} = -\frac{\partial \vec{B}}{\partial t} \qquad \nabla \times \vec{H} = \vec{J} + \frac{\partial \vec{D}}{\partial t}$$

- Can be solved rigorously using numerical methods such as FDTD and RCWA (a.k.a. waveguide) methods [2]

- Approximated and implemented as a neural network (NN) in this work

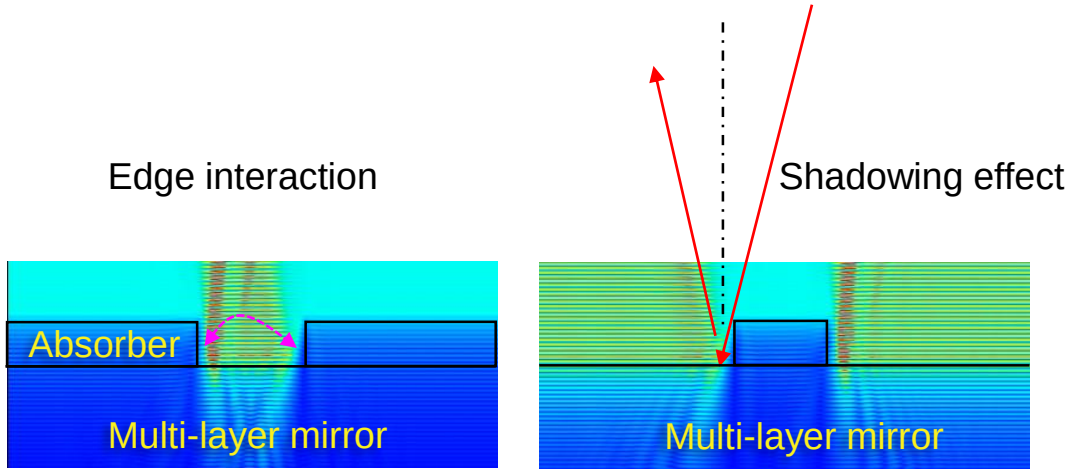


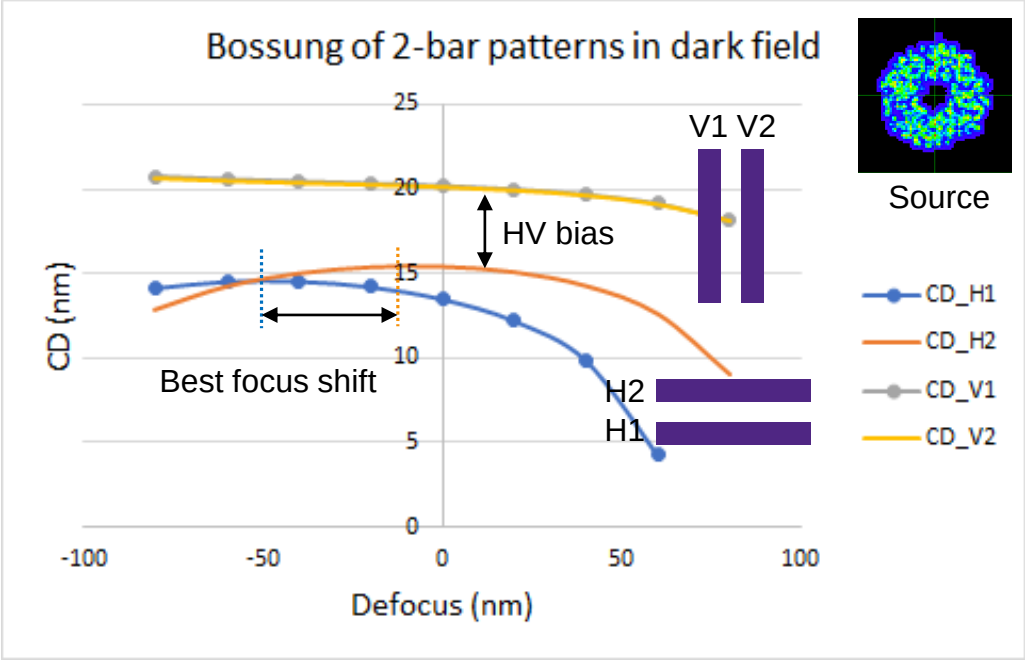


[2] Andreas Erdmann et al, "Rigorous mask modeling using waveguide and FDTD methods: an assessment for typical hyper-NA imaging problems," Proc. SPIE 6283 (19 May 2006)

3D mask modeling challenges

- 3D mask effects:
  - Shadowing effect due to oblique chief ray angle
  - Strong interaction between absorber edges
- They lead to complex pattern-dependent wafer printing behaviors [3-4]
  - CD bias between horizontal and vertical L/S patterns
  - CD variations through exposure slit
  - Complicated thru-focus CD variations (a.k.a. best focus shift)
  - …
- It is important for the NN-based 3D mask model to accurately capture these effects
  - Evaluations to be shown in later slides

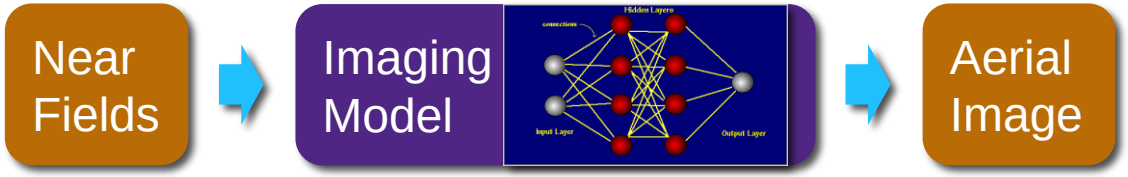


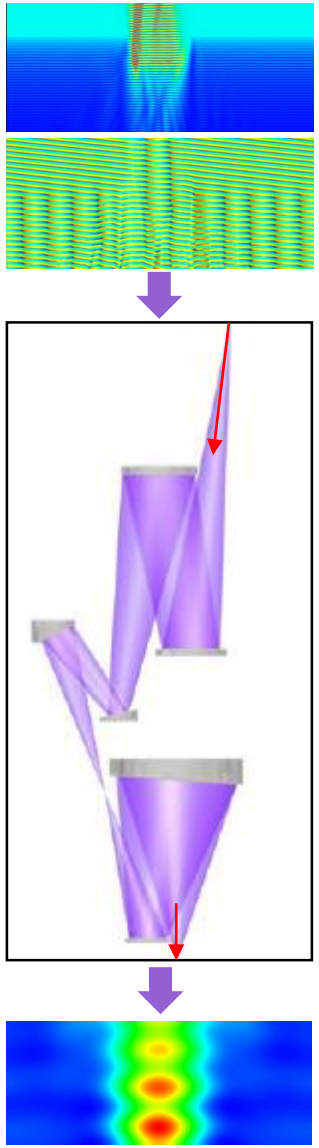


[3] Peng Liu et al, "Fast 3D thick mask model for full-chip EUVL simulations," Proc. SPIE 8679, Extreme Ultraviolet (EUV) Lithography IV, 86790W (1 April 2013)
[4] Renzo Capelli et al,"Scanner arc illumination and impact on EUV photomasks and scanner imaging ," Proc. SPIE 9231, 30th European Mask and Lithography Conference, 923109 (17 October 2014)

Imaging model for projection optics

- Electromagnetic field (EMF) propagation through projection optics
  - Input: mask near-field amplitude & phase
  - Output: aerial image in resist
- The aerial image can be computed using Abbe or Hopkins imaging theory [5-6]
  - With extensions to include high-NA & wafer film stack effects [7-8]
- Can be directly implemented as a neural network (NN) model in an ML framework

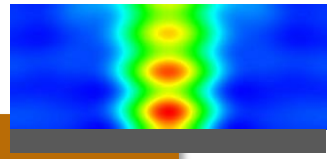




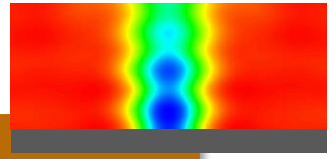
[5] Max Born and Emil Wolf, “Principle of Optics,” Cambridge University Press, 7th Ed. 1999
[6] Joseph Goodman, “Introduction to Fourier Optics,” 2nd ed, 1996.
[7] Michael S Yeung "Modeling High Numerical Aperture Optical Lithography", Proc. SPIE 0922, Optical/Laser Microlithography, (1 January 1988)
[8] Donis G. Flagello and Tomas D. Milster "Three-dimensional modeling of high-numerical-aperture imaging in thin films", Proc. SPIE 1625 (1 June 1992)

Resist model for resist processes

- Resist processes:



Resist exposure
- Initial acid generation



Post-exposure bake
- Acid / base diffusion & neutralization
- De-protection reaction
- Mechanical deformation

Resist development
- Developer diffusion & dissolution reaction with resist
- Mechanical deformation

- Described (approximately) by a series of partial differential equations [9-10]

$$\frac{\partial[PAG]}{\partial t} = -C \cdot I \cdot [PAG]$$

$$[H] = 1 - [PAG]$$

$$\frac{\partial[M]}{\partial t} = -k_a \cdot [H] \cdot [M]$$

$$\frac{\partial[H]}{\partial t} = -k_Q \cdot [Q] \cdot [H] + D_H \nabla^2 [H]$$

$$\frac{\partial[Q]}{\partial t} = -k_Q \cdot [Q] \cdot [H] + D_Q \nabla^2 [Q]$$

$$\frac{\partial A}{\partial t} = -k_A AC$$

$$\frac{\partial B}{\partial t} = k_B AC + \nabla(D_B \nabla B)$$

$$\frac{\partial C}{\partial t} = -k_C AC + \nabla(D_C \nabla C)$$

$$f_i = \partial \sigma_{ij} / \partial x_j$$

$$\sigma_{ij} = 2\mu\varepsilon_{ij} + \lambda\varepsilon_{kk}\delta_{ij}$$

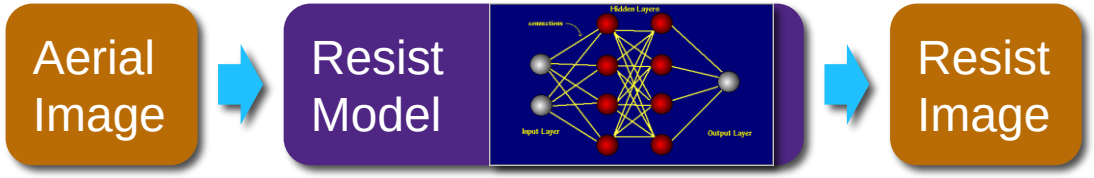
$$\varepsilon_{ij} = \frac{1}{2}\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right)$$

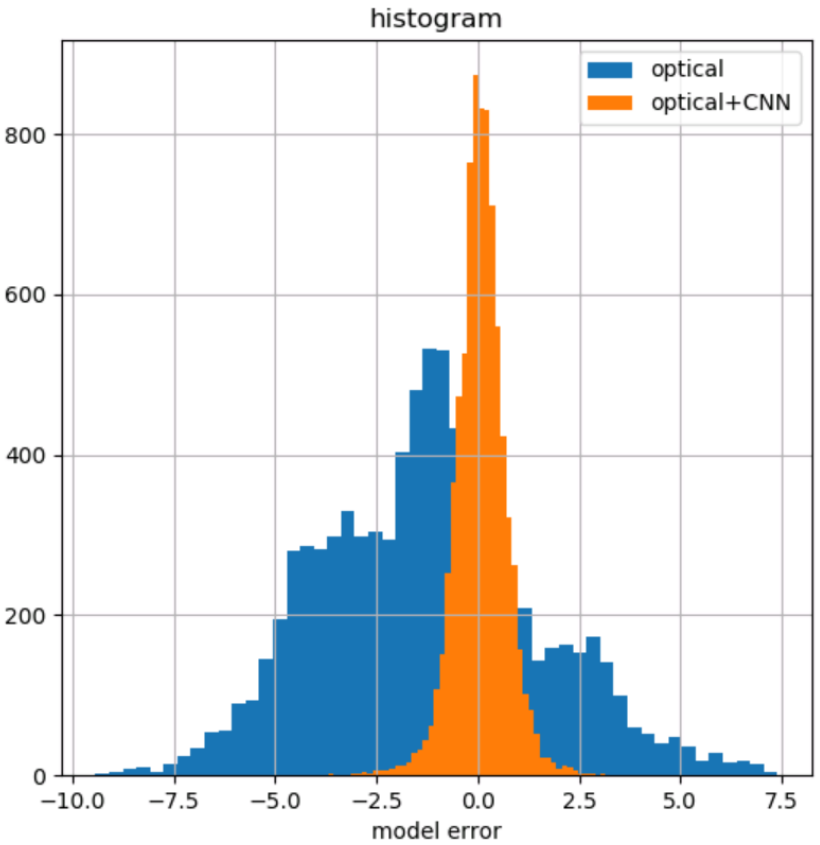
- Can be approximated and implemented as a neural network (NN)

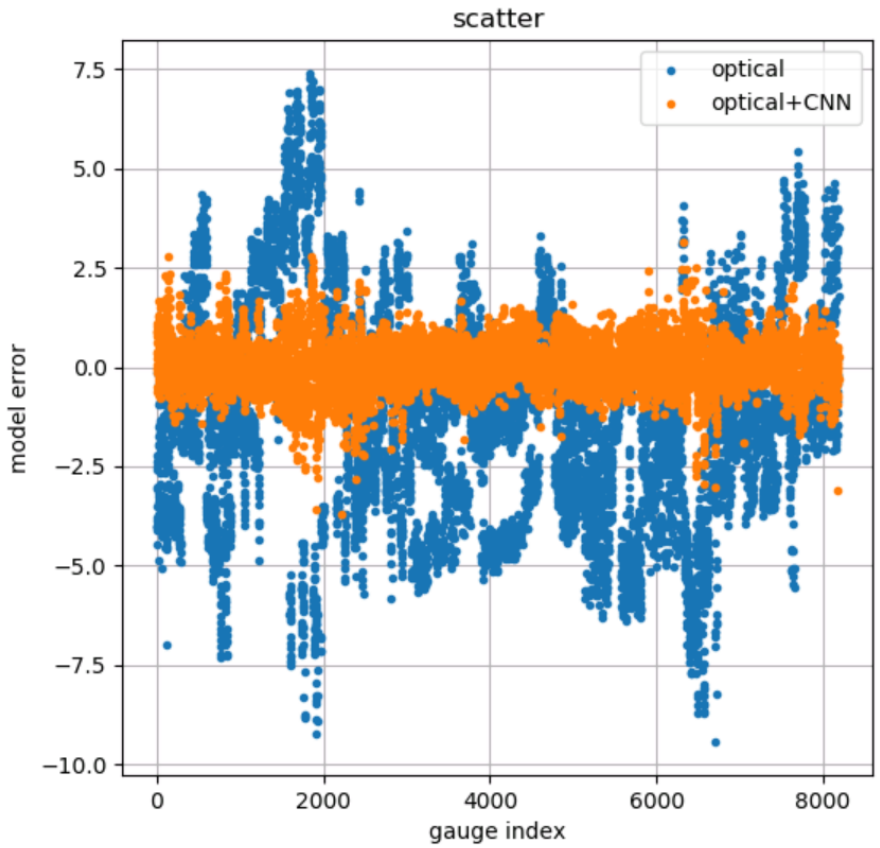
[9] Andreas Erdmann et al, "Comparison of simulation approaches for chemically amplified resists," Proc. SPIE 4404, Lithography for Semiconductor Manufacturing II, (26 April 2001)
[10] Peng Liu et al, "A physical resist shrinkage model for full-chip lithography simulations", Proc. SPIE 9779, Advances in Patterning Materials and Processes XXXIII, 97790Y (25 March 2016)

NN-based resist modeling status

- NN-based resist models have been developed and shown very encouraging results







A CNN-based EUV resist model evaluation

Data info:

- Total ~ 8,000 CD gauges
- ML training: 80% random sampled

Model	RMS	Range
Optical	2.97	16.8
Optical + CNN	0.62	6.9

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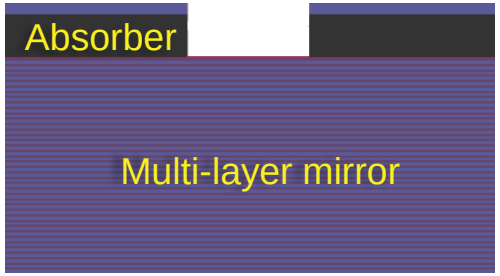
Overview of lithography models generation for this evaluation

- 3D mask model:
  - Approximated & implemented as a neural network (NN) in TensorFlow
  - Constructed based on human knowledge as well as machine learning
- Imaging model:
  - Exact implementation of the imaging theory in TensorFlow
  - No training required
- Resist model:
  - A constant-threshold (CT) resist model is used in this evaluation
    - Instead of a full NN-based resist model
  - For the benefit of simplicity and focusing on 3D mask model quality evaluation

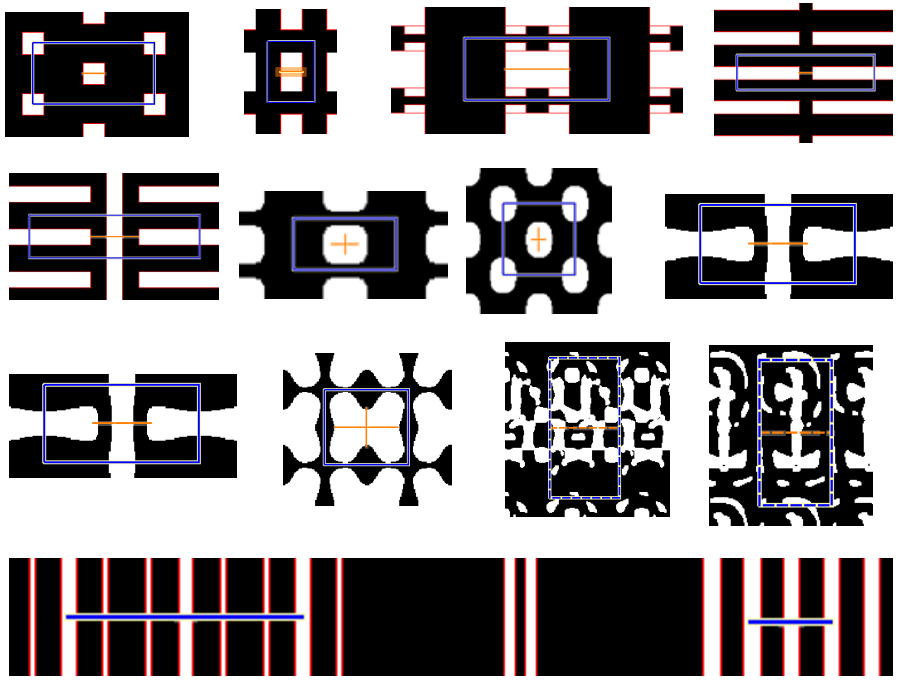
Generation of a toy NN-based 3D mask model

- Physics-based hybrid ML architecture:
  - Consists of a primary NN and a secondary NN
  - The primary NN captures the main 3D mask effects
    - Constructed based on human knowledge about the main effects of EMF diffraction processes
    - Directly coded in TensorFlow w/o training
  - The secondary NN is designed for residual effects
    - Feature vectors & mapping functions are learnt from training samples by machine
- Training of the secondary NN using TensorFlow:
  - Data generated by RCWA rigorous 3D mask model
  - Training/validation patterns: ~900/200 (random split)
  - Testing patterns: ~1000
    - Not seen in training/validation
    - Used only in model quality evaluation

Mask topography

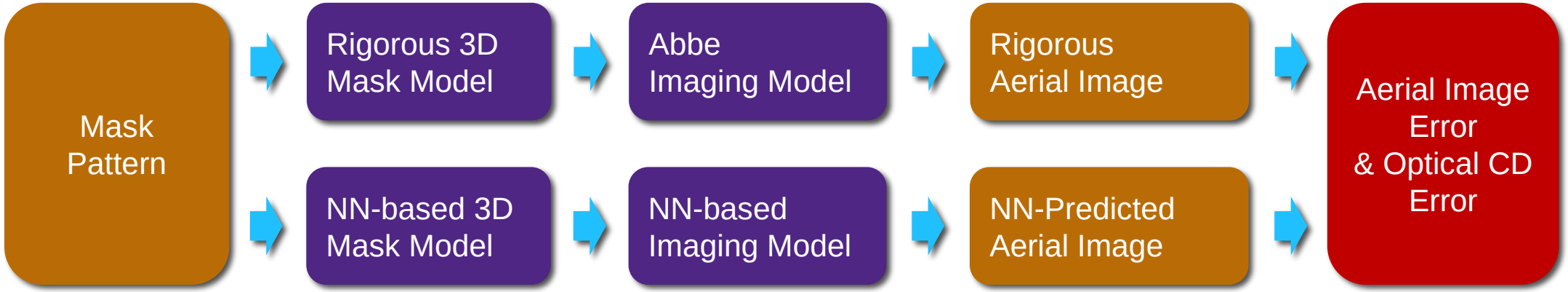


Pattern examples (in dark field):

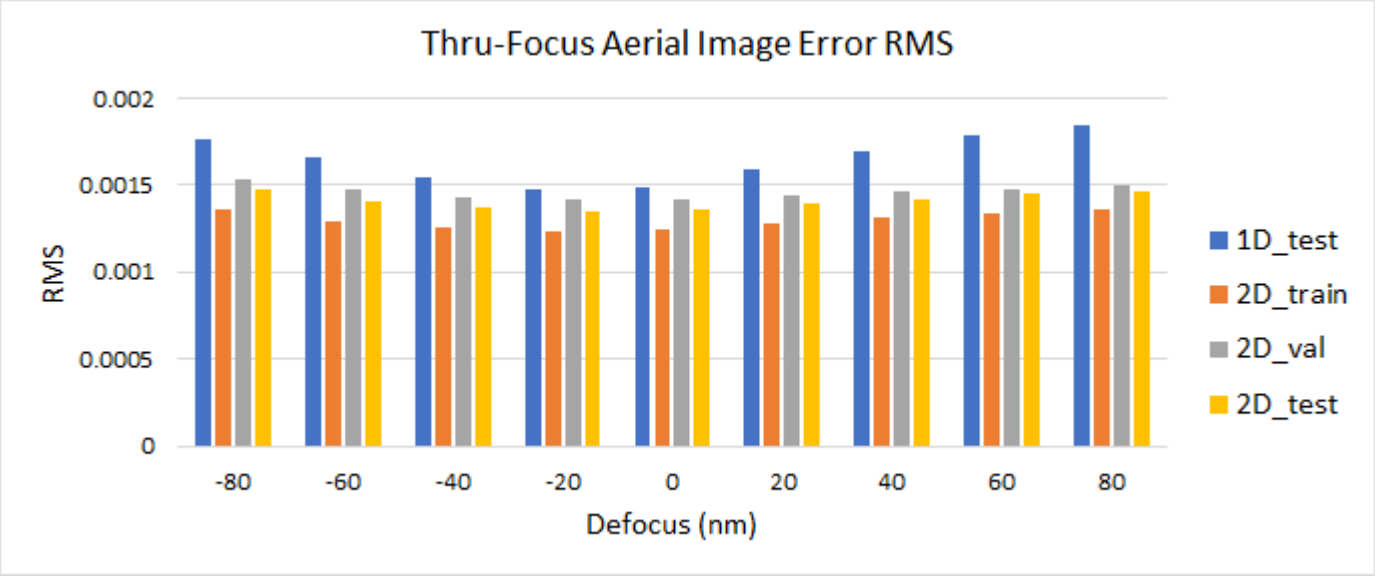


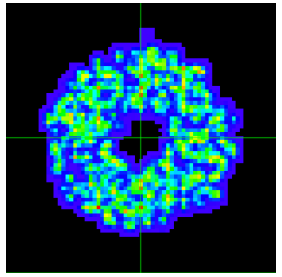
Model quality evaluation: Aerial image error thru focus

- Evaluation flow:



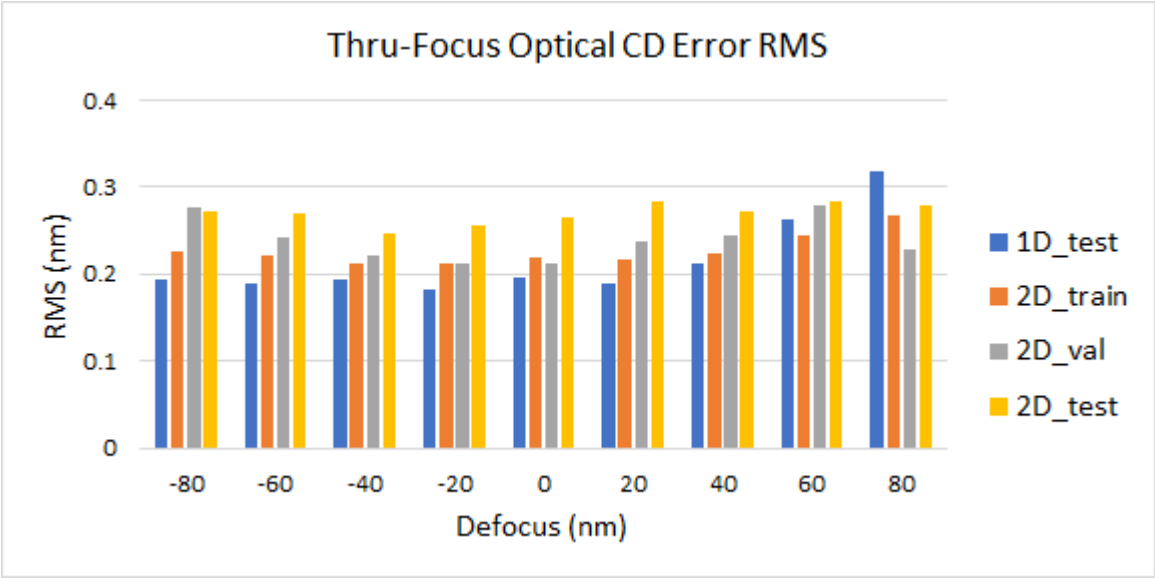
- Aerial image error:

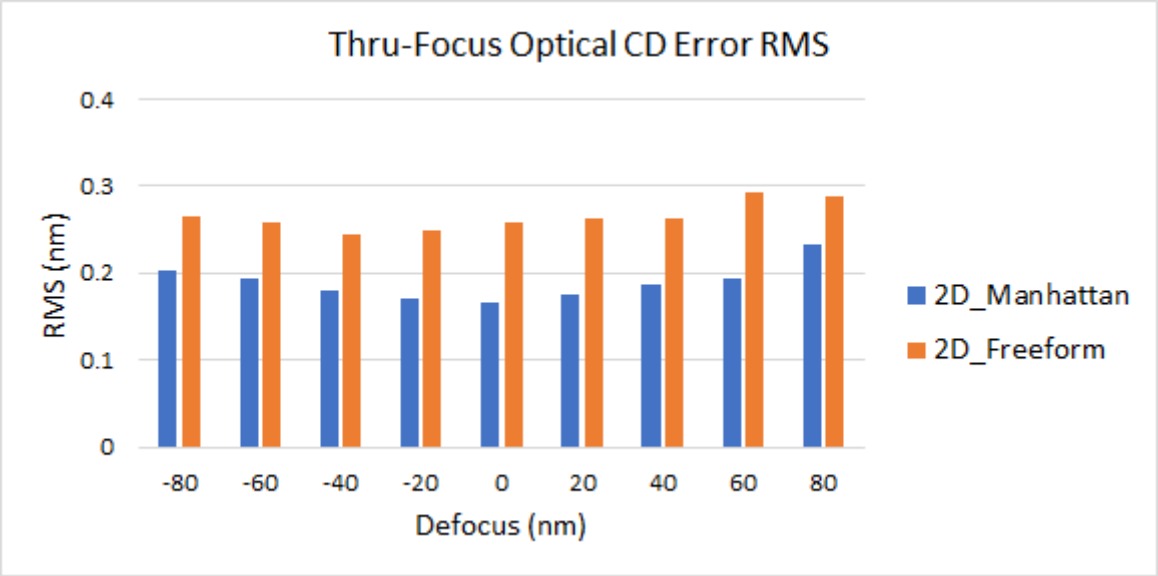


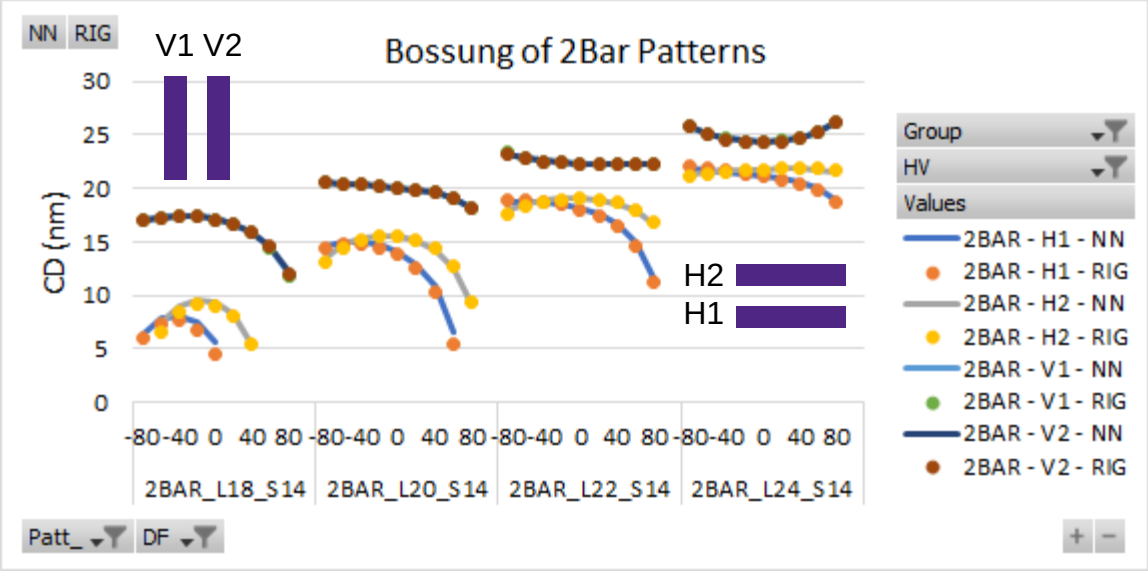


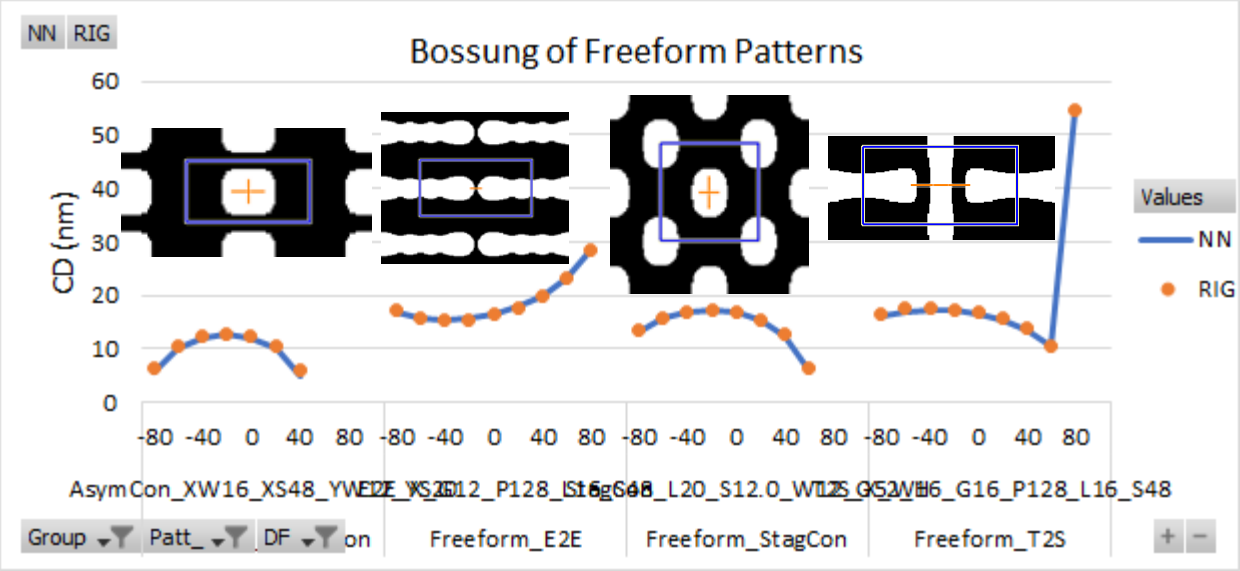
Illumination Source

Model quality evaluation: Optical CD error thru focus

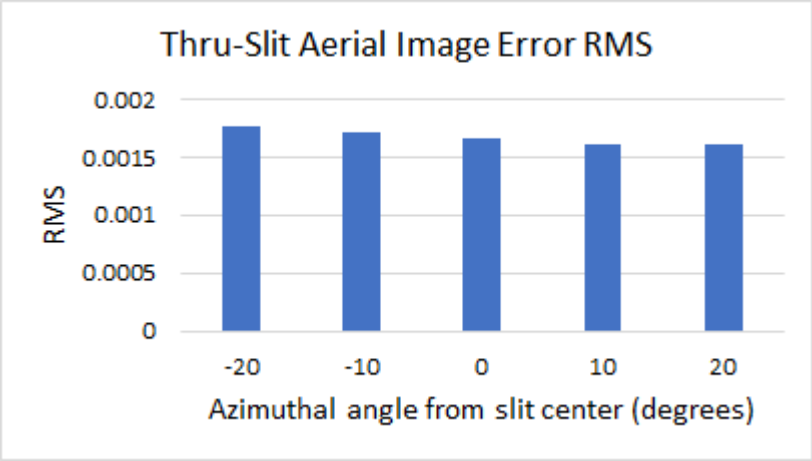


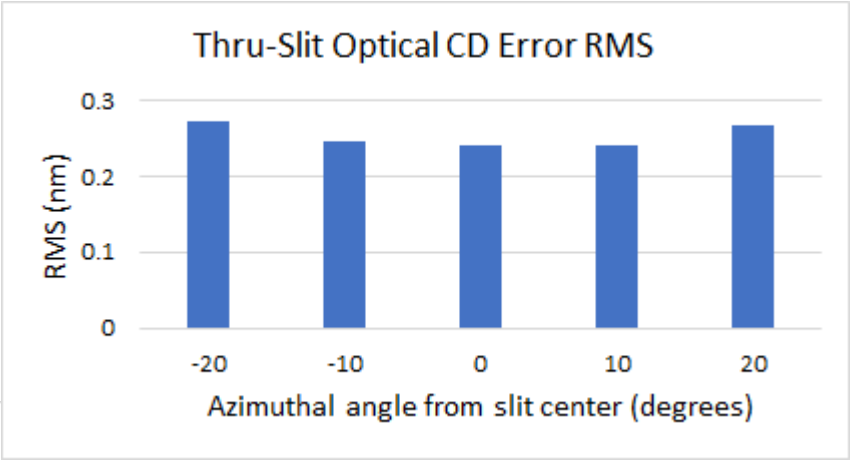


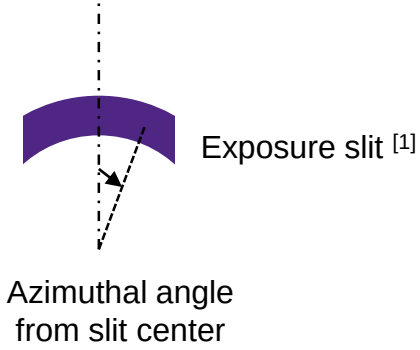


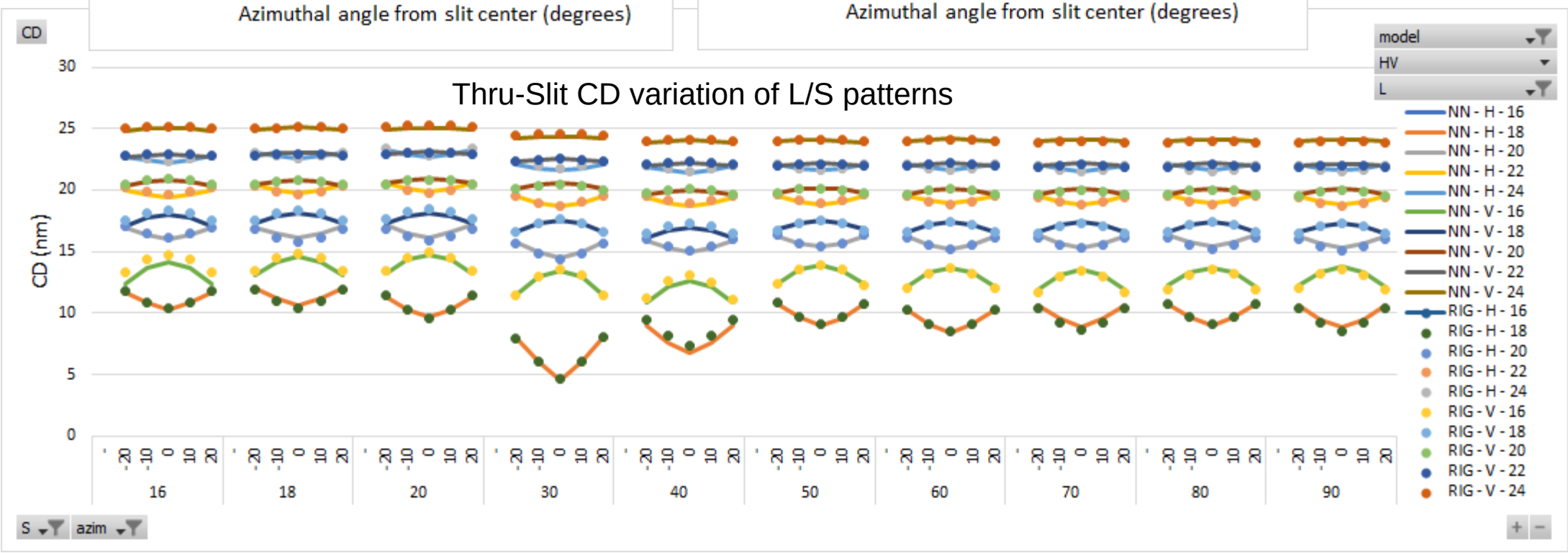


Model quality evaluation: Aerial image & CD error thru slit



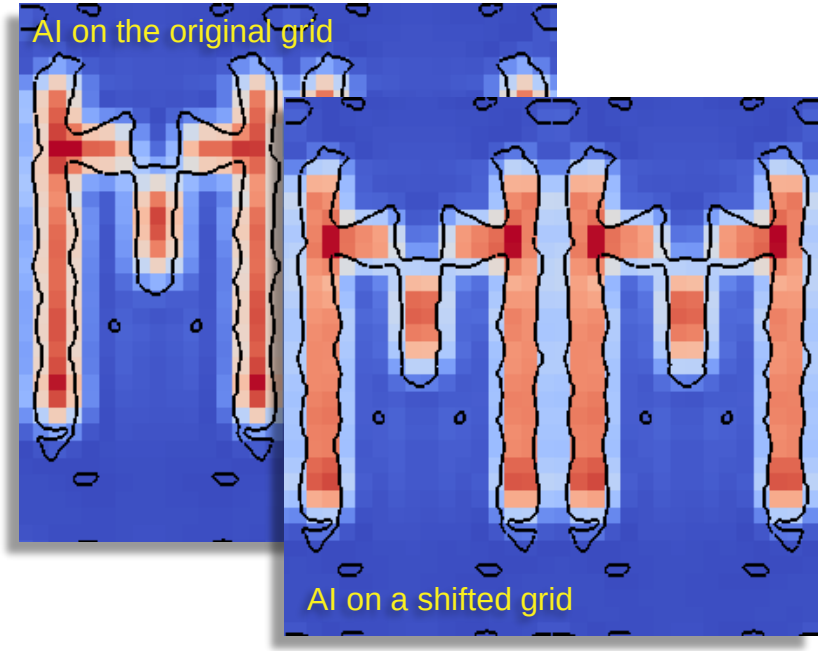




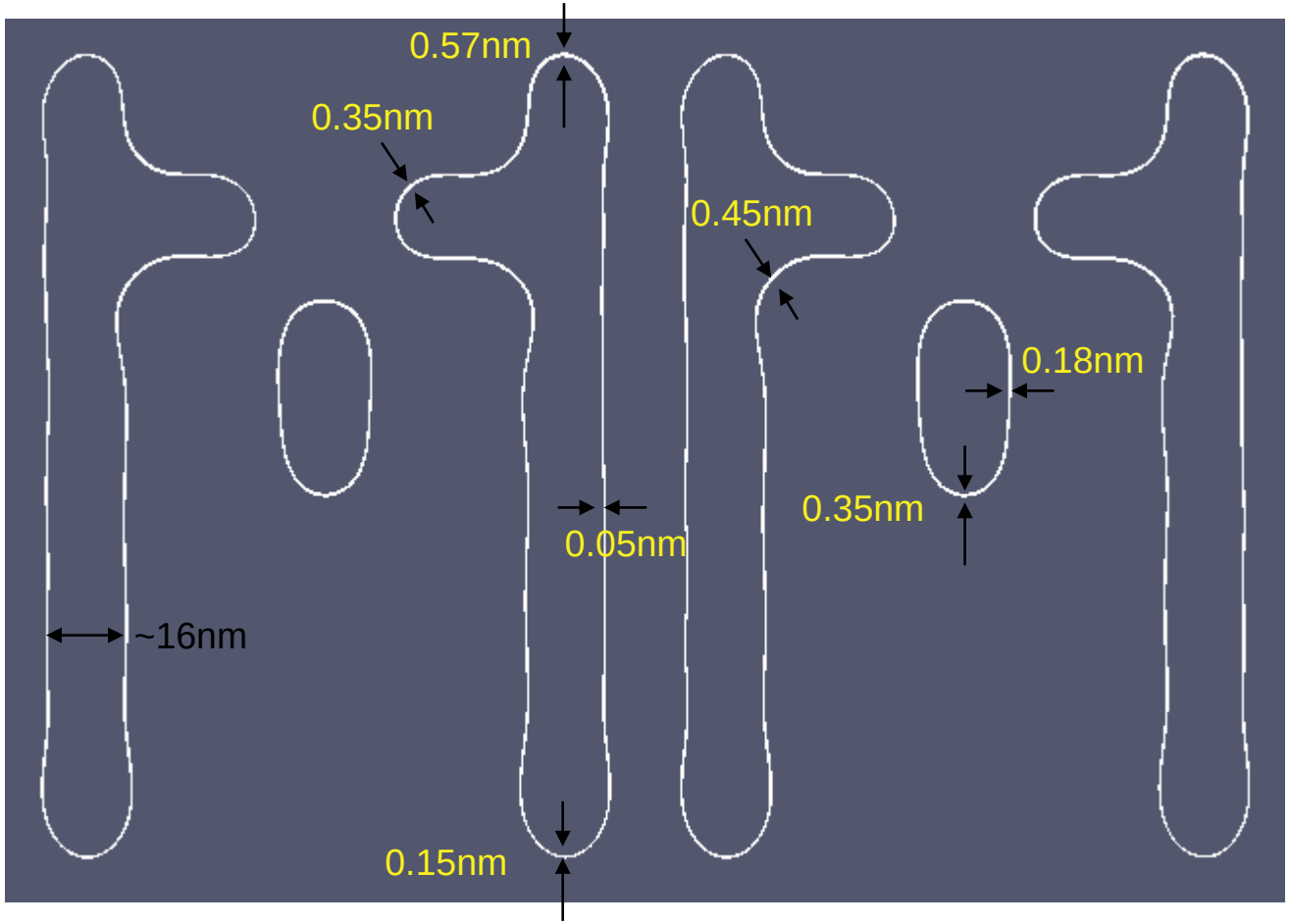


Model quality evaluation: Shift variance band (SVB)

- Testing procedure:
  - 8 sampling grids were setup
    - Sampling pitch = 8nm
    - Each shifted by 1nm from previous one in both x and y
  - Mask field and aerial image (AI) were computed for each sampling grid and optical contours from all sampling grids were overlaid



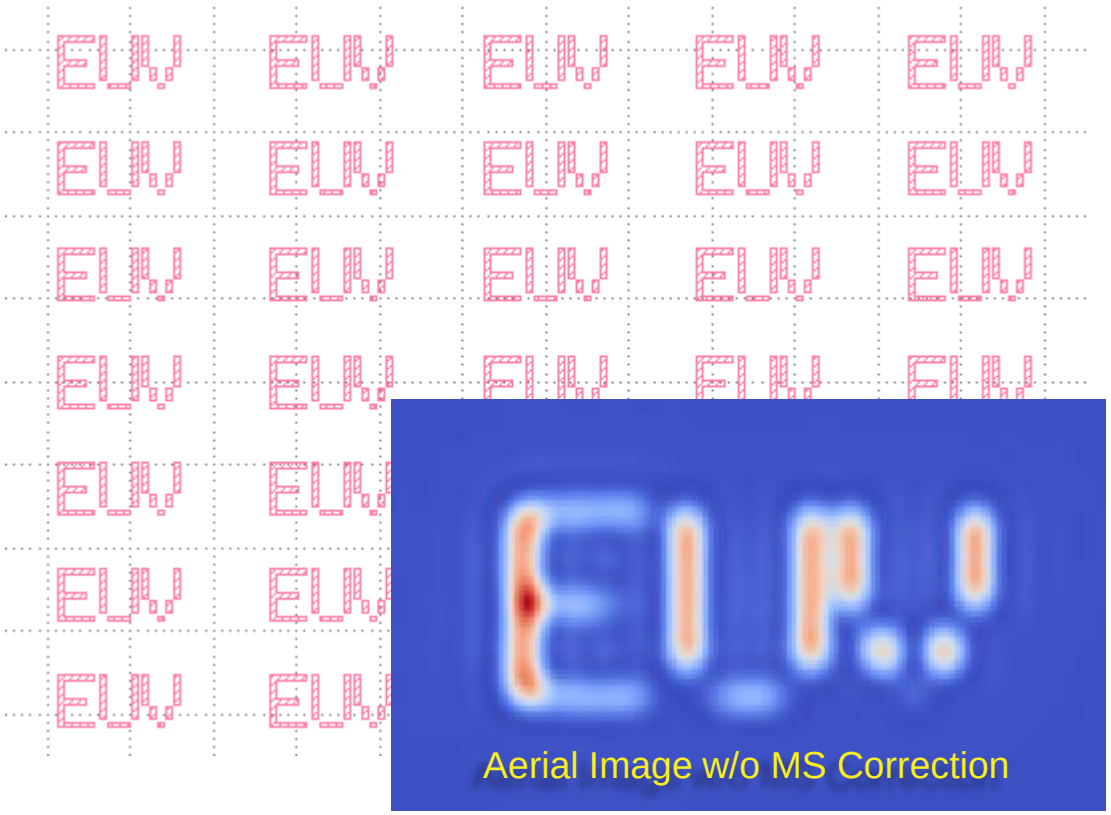
Black contours: mask pattern
Color background: aerial image (AI)



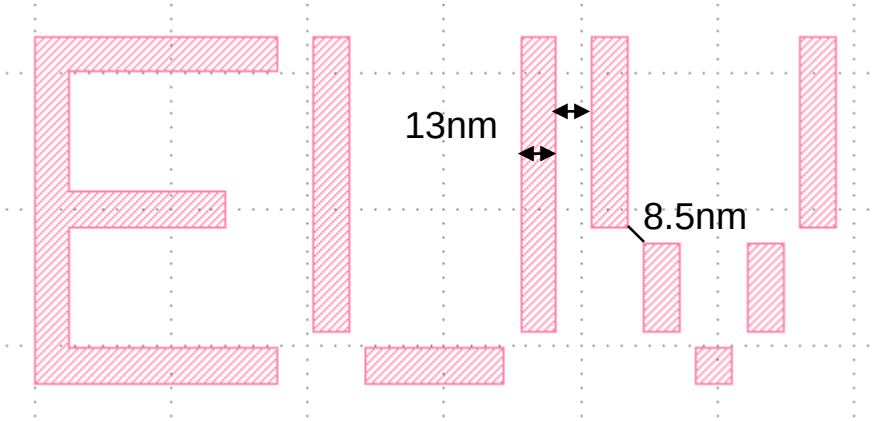
- Sampled SVB: 0.05 - 0.57nm
- Almost entirely contributed by the secondary NN

A toy target pattern for mask synthesis (MS) testing

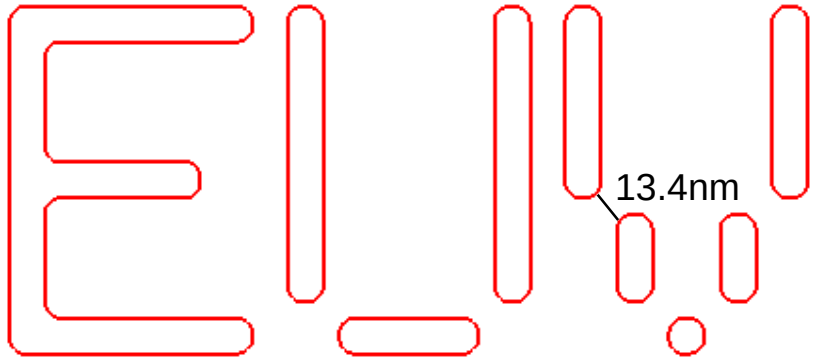
- Designed to print a repeating pattern resembles the word “EUV”
- 13nm minimum line & space (k_1 ~ 0.318)
- Dark-field imaging



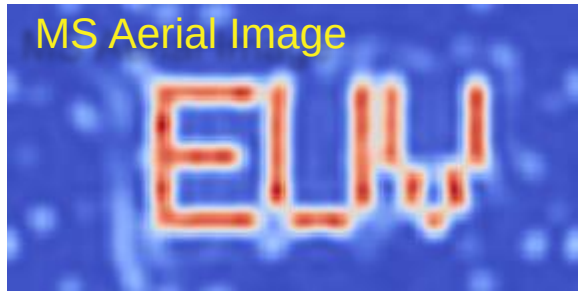
Original target GDS

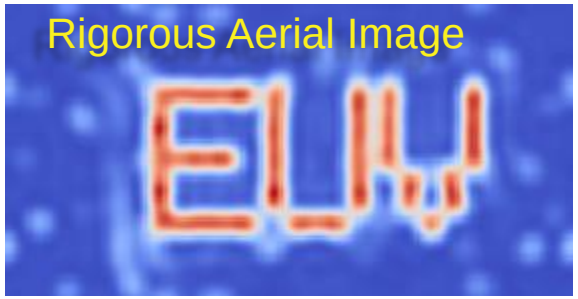


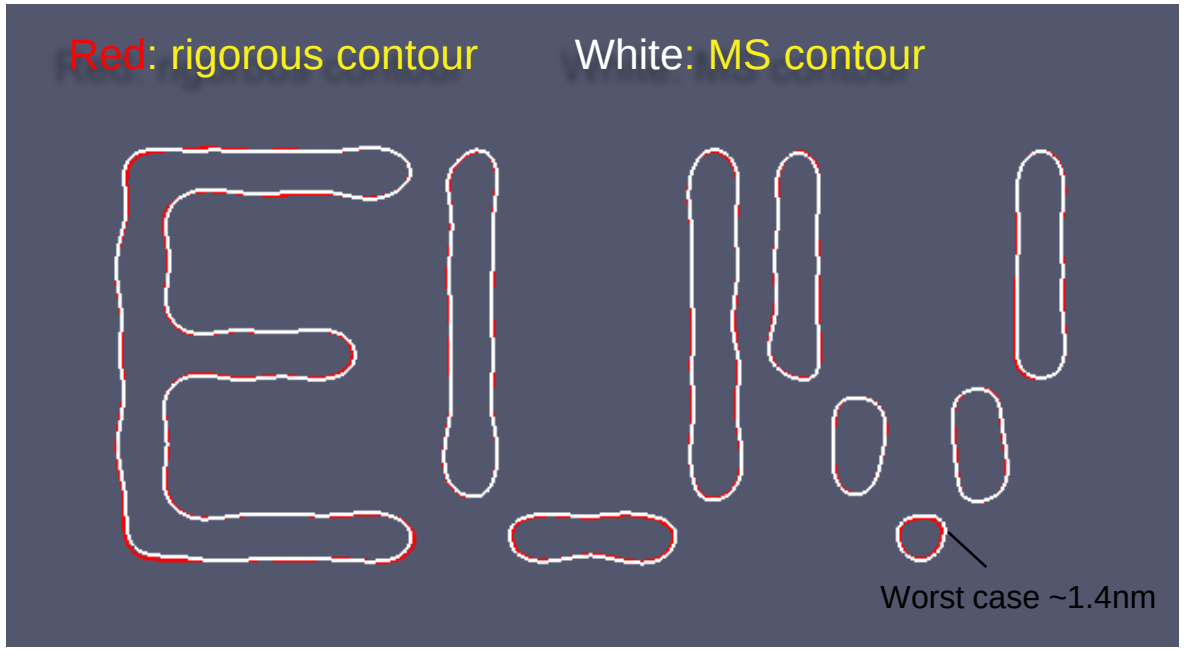
Modified target with corner rounding



MS correction results & rigorous verification



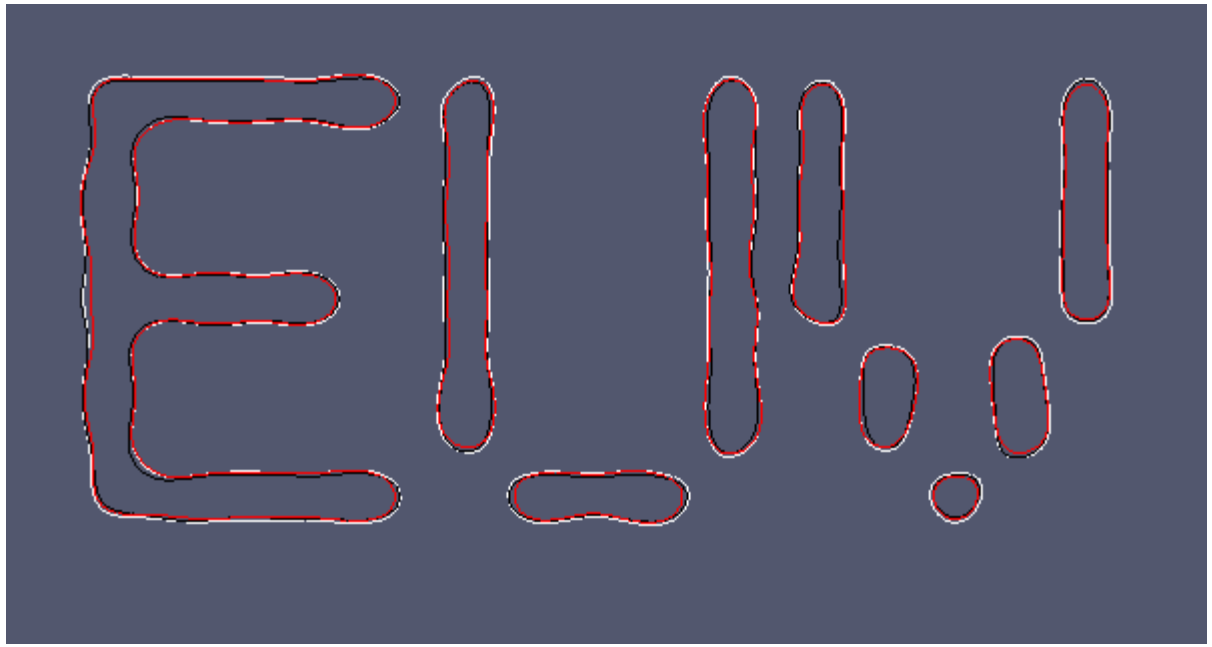




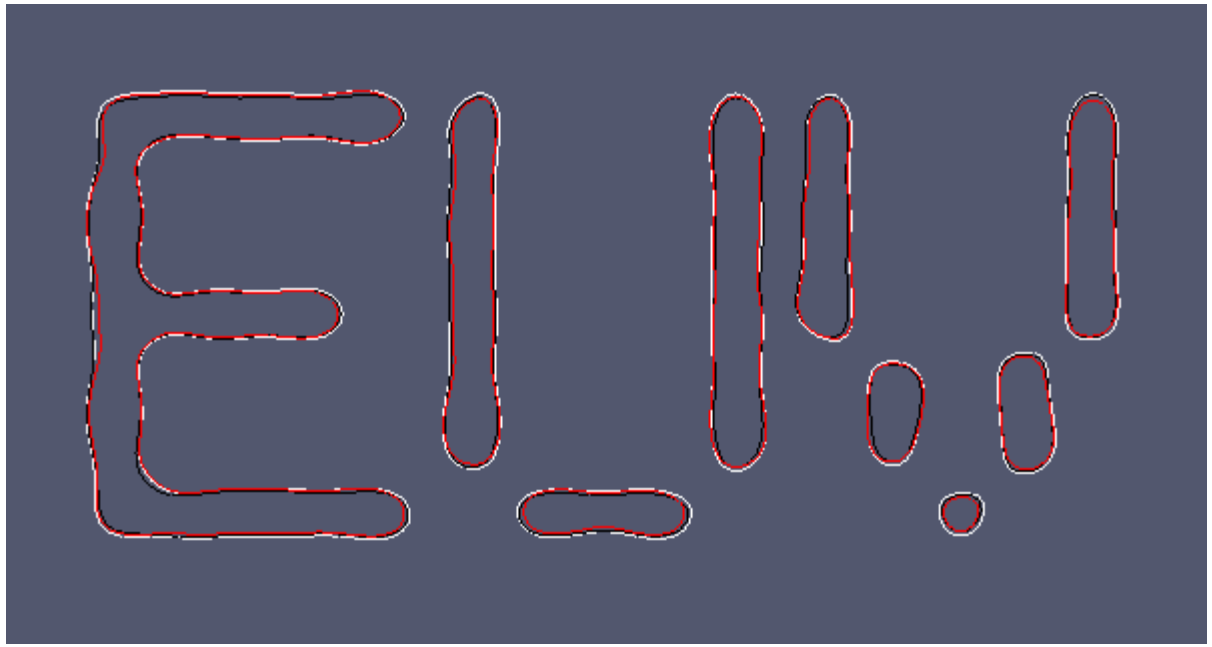
Noticeable contour differences in some areas

Effects of focus variation (±40nm)

MS Prediction



Rigorous verification

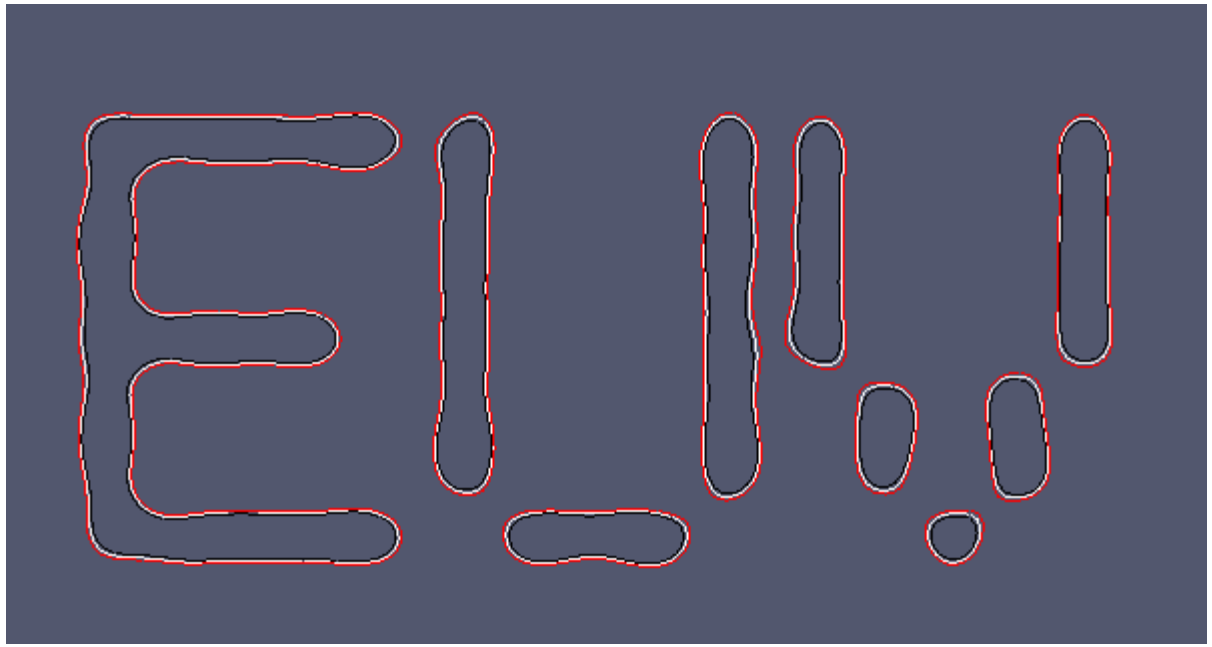


White: nominal
Black: -40nm defocus
Red: +40nm defocus

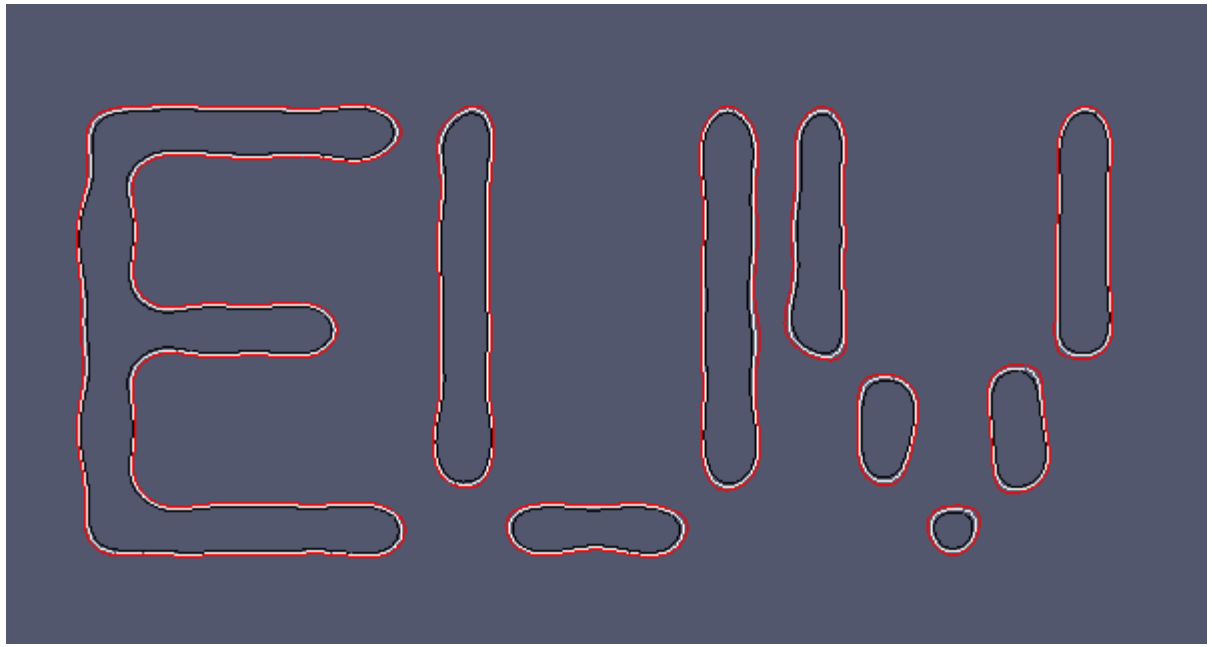
The trend is captured well in MS prediction

Effects of exposure dose variation (±5%)

MS Prediction



Rigorous verification



White: nominal
Black: -5% dose
Red: +5% dose

The trend is captured well in MS prediction

Conclusion

- **A new standalone mask synthesis flow was demonstrated in this work**
  - It ran entirely on an open general-purpose machine learning (ML) software & hardware platform
  - The lithography processes were simulated by separable & interchangeable NN-based lithography models
  - The mask was optimized via reinforcement learning (RL)
  - The proposed flow worked and produced masks that printed as intended
- **This work also showed the need for 3D mask model accuracy improvement, especially for complex freeform masks**
  - The generation/training of the toy mask 3D model in this work was quite crude
    - Limited pattern coverage, simple training samples selection scheme (i.e., random), no architecture or hyper-parameter tuning, etc.
  - Abundant opportunities for improvement

Acknowledgement

- Wolfgang Hoppe, Makoto Miyagi and Peter Brooker
  - for assistance in the rigorous 3D mask simulations
- Rich Wu
  - for providing the resist model data

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Thank You