

Data Efficient Lithography Modeling with Residual Neural Networks and Transfer Learning

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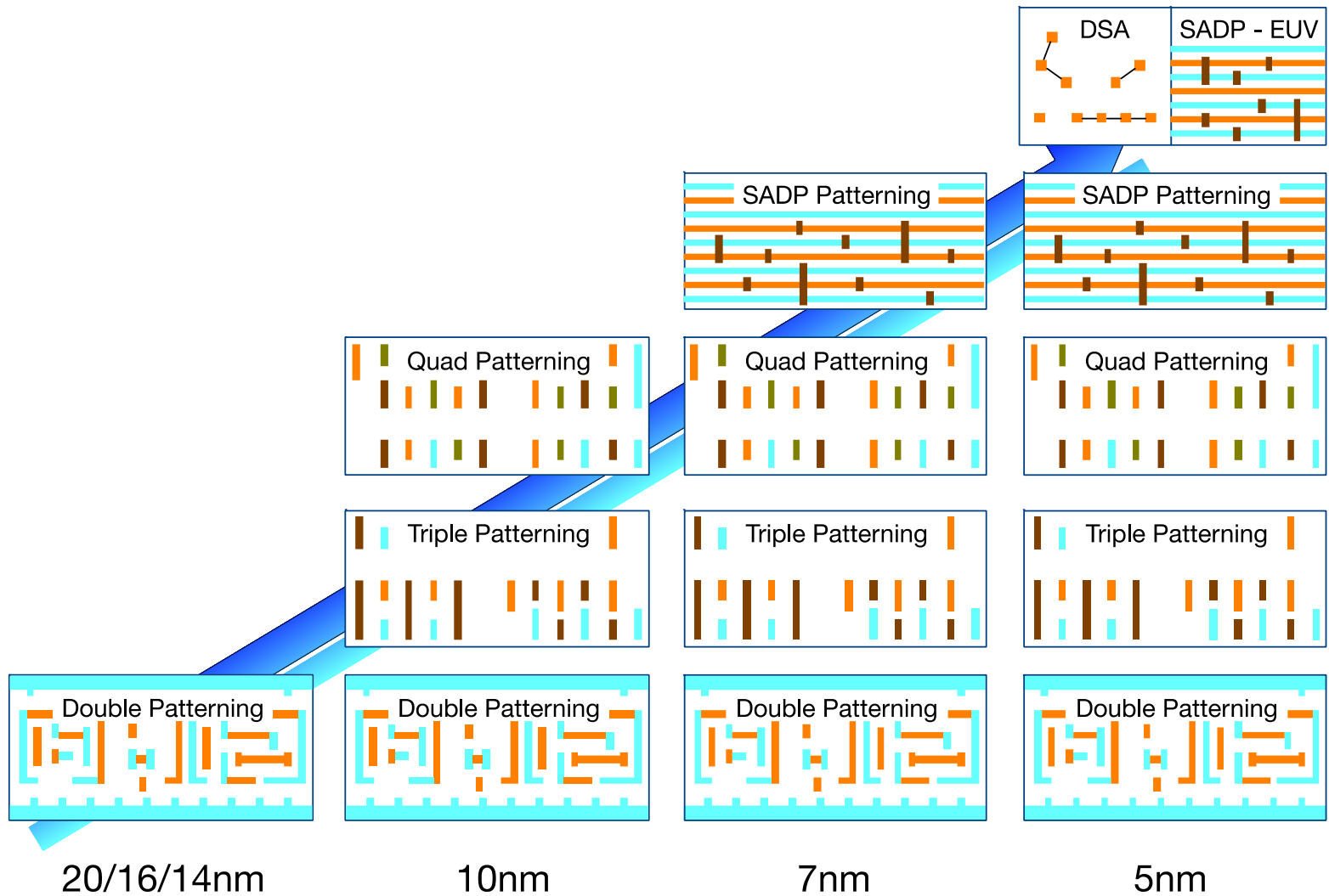
²Toshiba Memory Corporation

<http://yibolin.com>

Outline

- Introduction
- Problem Formulation
- Related Work
- Data Efficient Lithography Modeling
- Experiment Results
- Conclusion

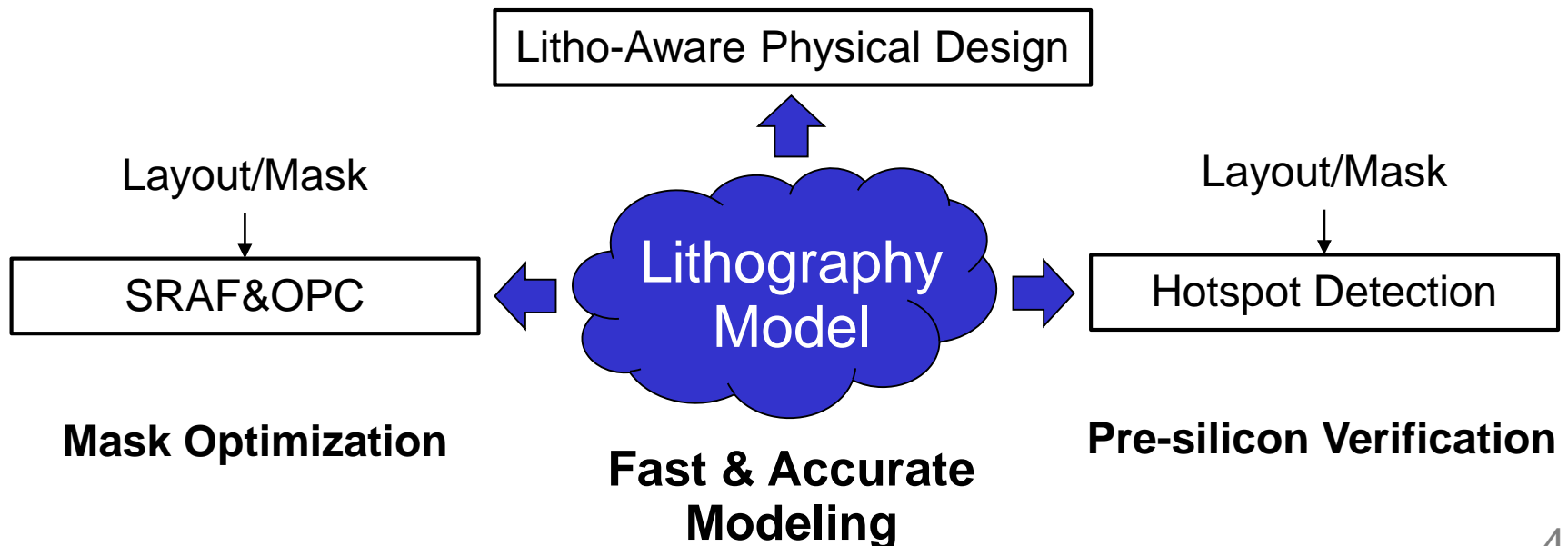
Advanced Lithography with Scaling

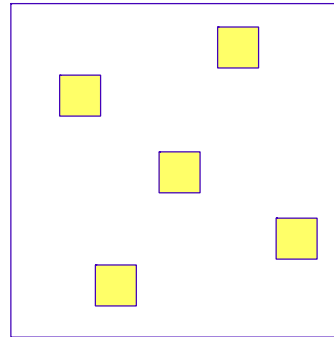
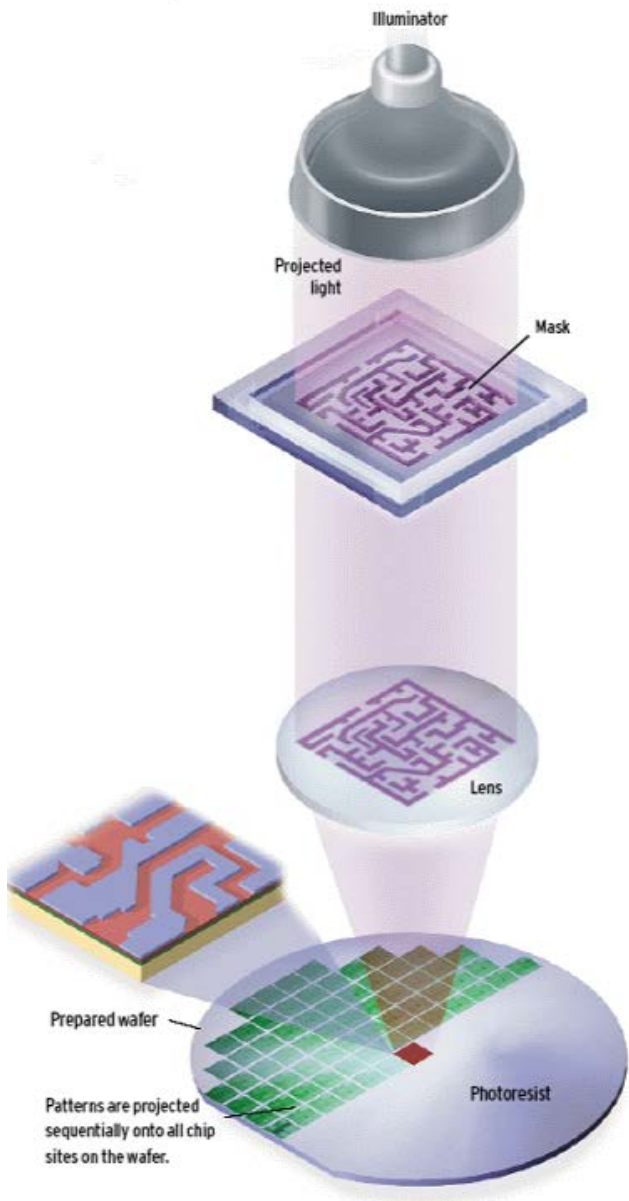


[Courtesy Mentor Graphics]

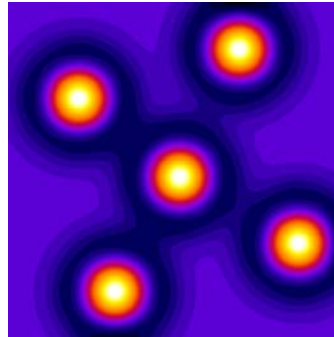
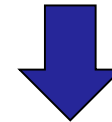
Design and Manufacturing Challenges

- Design Closure
 - Lithography aware physical design
 - Reduce turn-around time
- Manufacturing/yield Closure
 - Pre-silicon verification, e.g., hotspot detection
 - Fast and effective mask optimization, e.g., SRAF, OPC

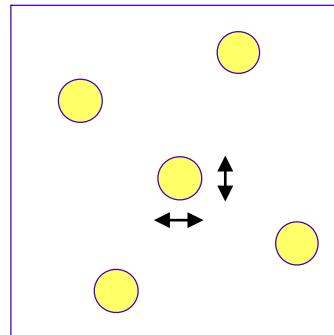
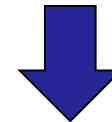




Contact Mask



Aerial Image
(Light intensity map)



Resist Pattern

Modeling Photoresist

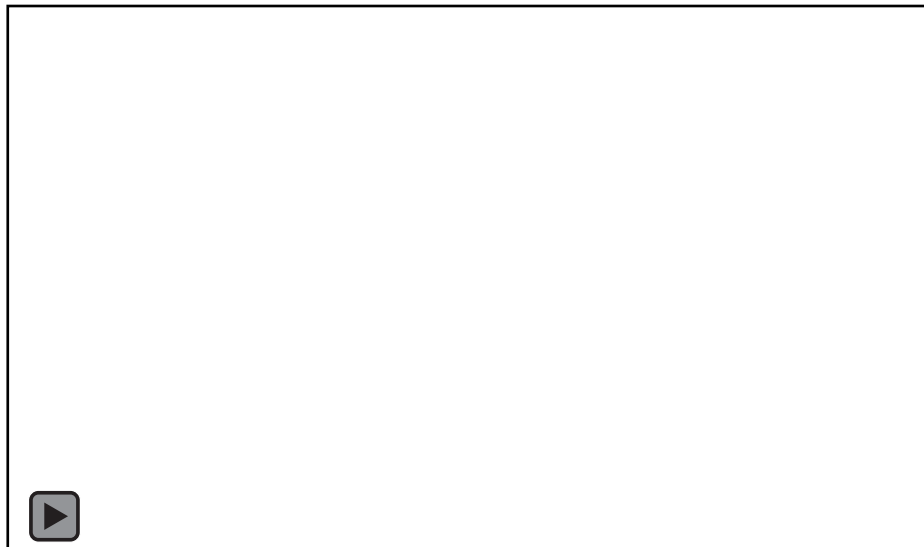
Intensity



x



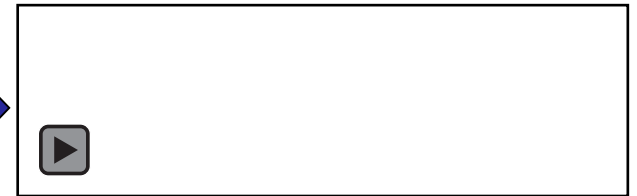
Resist model
 $f: X \rightarrow Y$



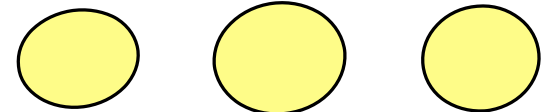
y



Predicted Pattern

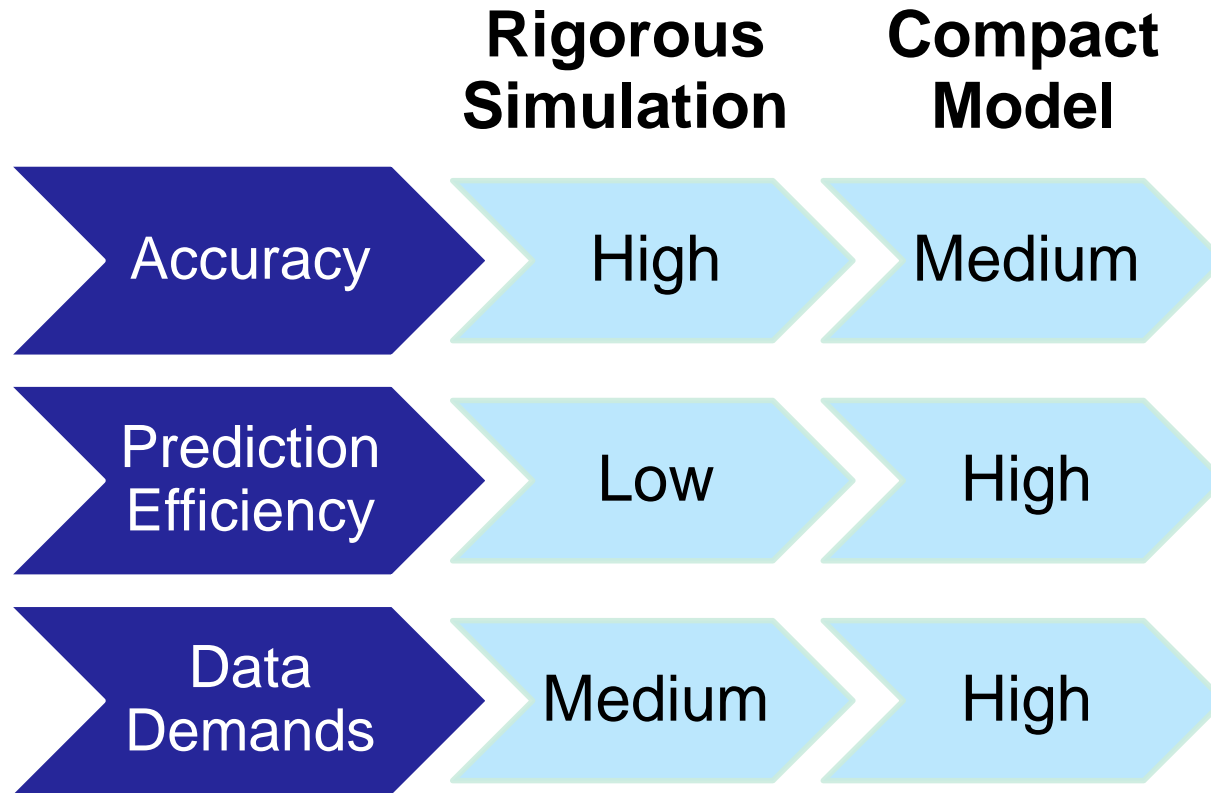


Match CD



Actual Pattern

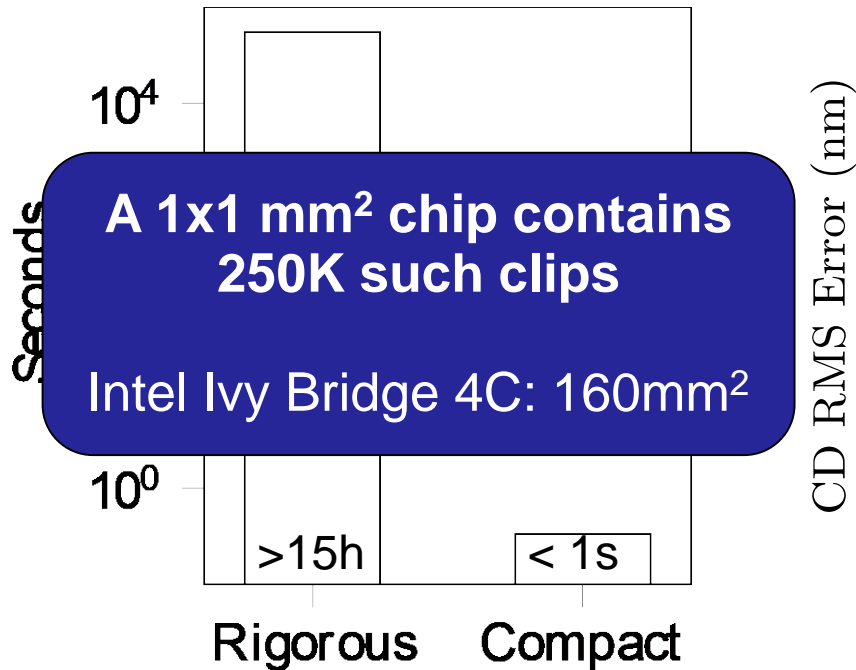
Challenges in Lithography Modeling



Rigorous simulation: physics-level simulation, e.g., Synopsys Sentaurus Lithography
Compact model: e.g., Mentor Graphics Calibre, machine learning models

Prediction Efficiency

For 1K 2x2 μm^2 clips



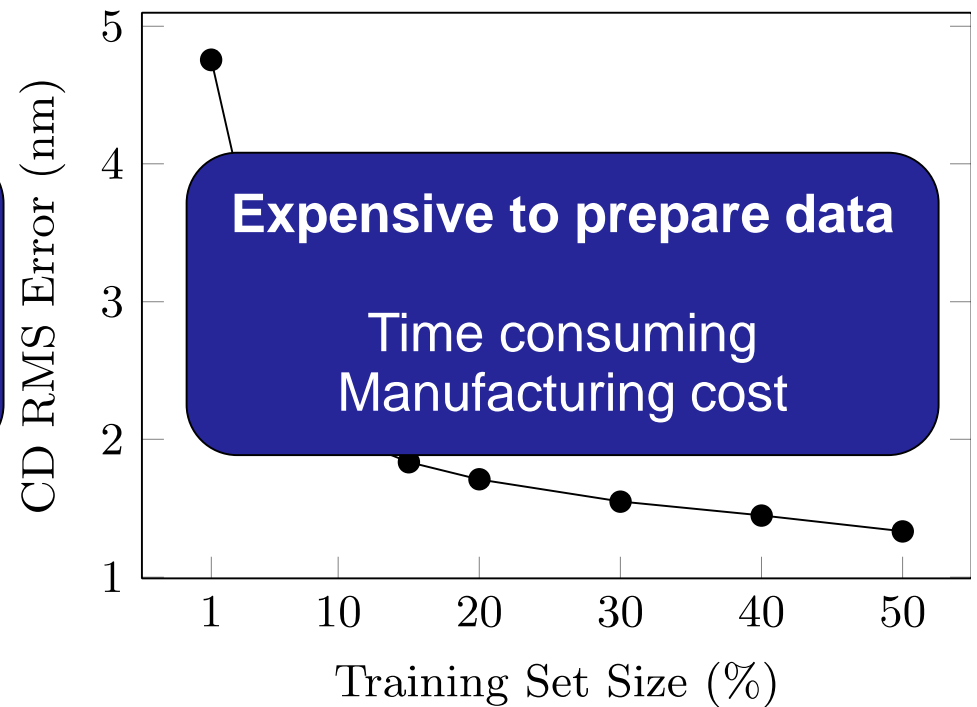
A 1x1 mm^2 chip contains 250K such clips
Intel Ivy Bridge 4C: 160 mm^2



Data Demanding

Compact Model

High target accuracy \rightarrow
Require **big training data**



Expensive to prepare data
Time consuming
Manufacturing cost

Previous Study on ML-based Modeling

Convolutional neural networks

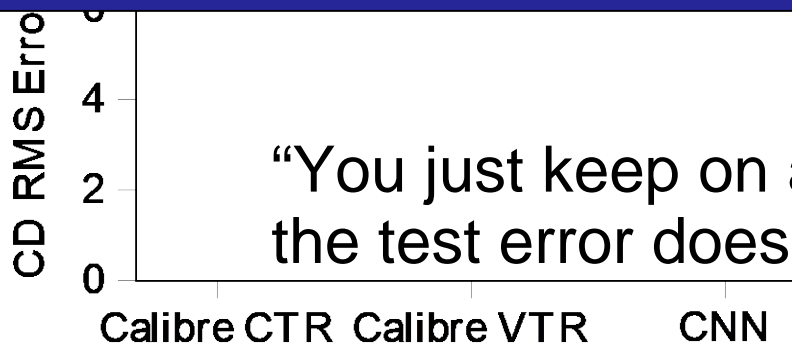
- [Watanabe+, SPIE'17]
- Task: threshold prediction
- 3 convolutional layers
- 2 fully connected layers

Artificial neural networks

- [Shim+, SPIE'17]
- Task: resist height prediction
- 5 hidden layers

Neural networks are getting **deeper** for higher accuracy

AlexNet-8, VGG-19, ResNet-101, ResNet-1202



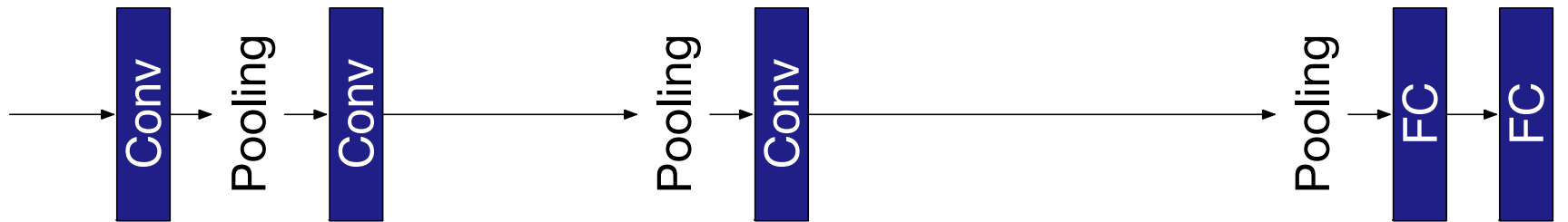
“You just keep on adding layers, until the test error doesn’t improve anymore.”

– Yoshua Bengio

Pitfalls in Deeper Neural Networks

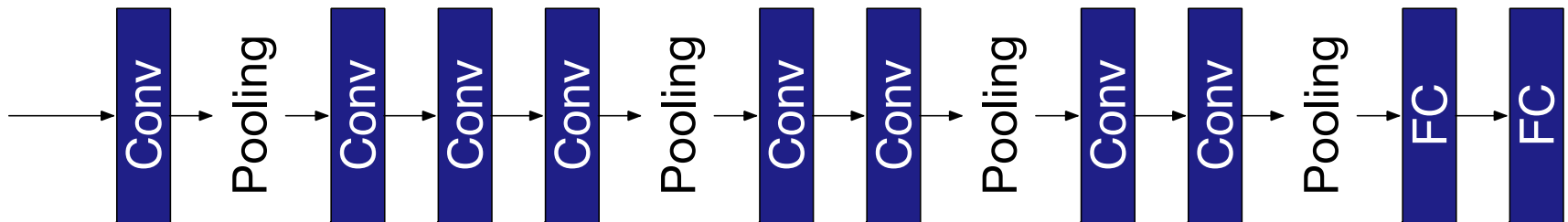
- Larger model capacity

CNN-5



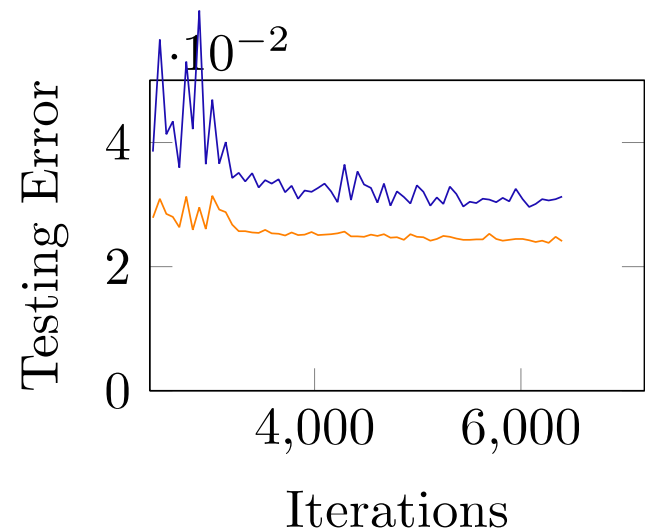
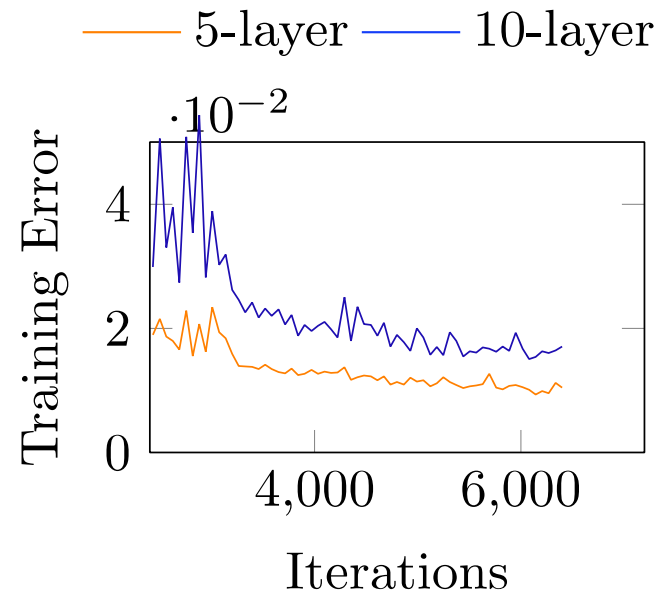
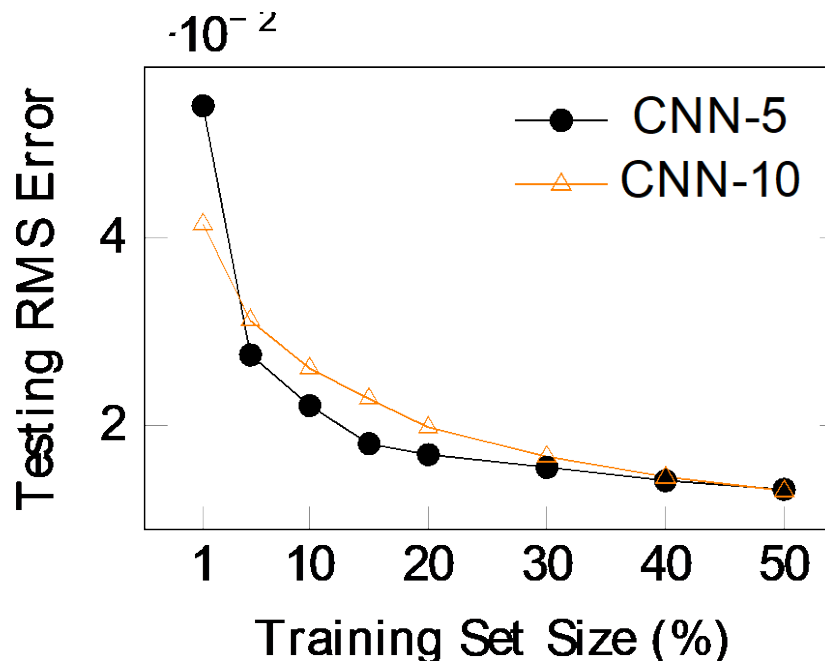
[Watanabe+, SPIE'17]

CNN-10



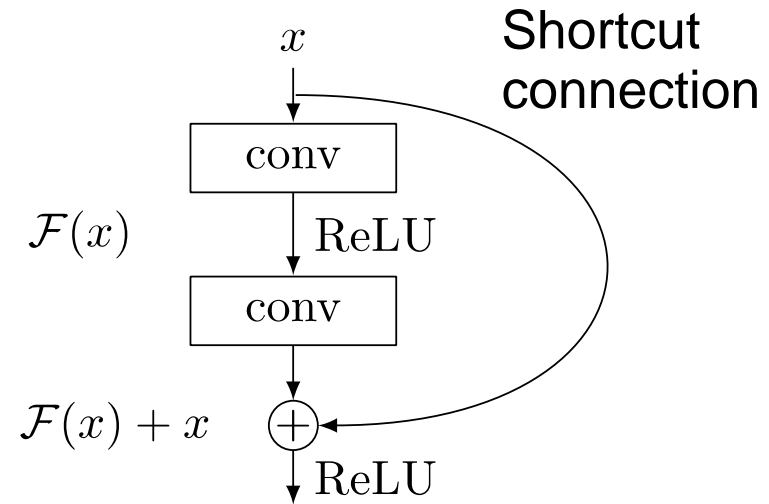
Pitfalls in Deeper Neural Networks

- Larger model capacity
- Gradient vanishing

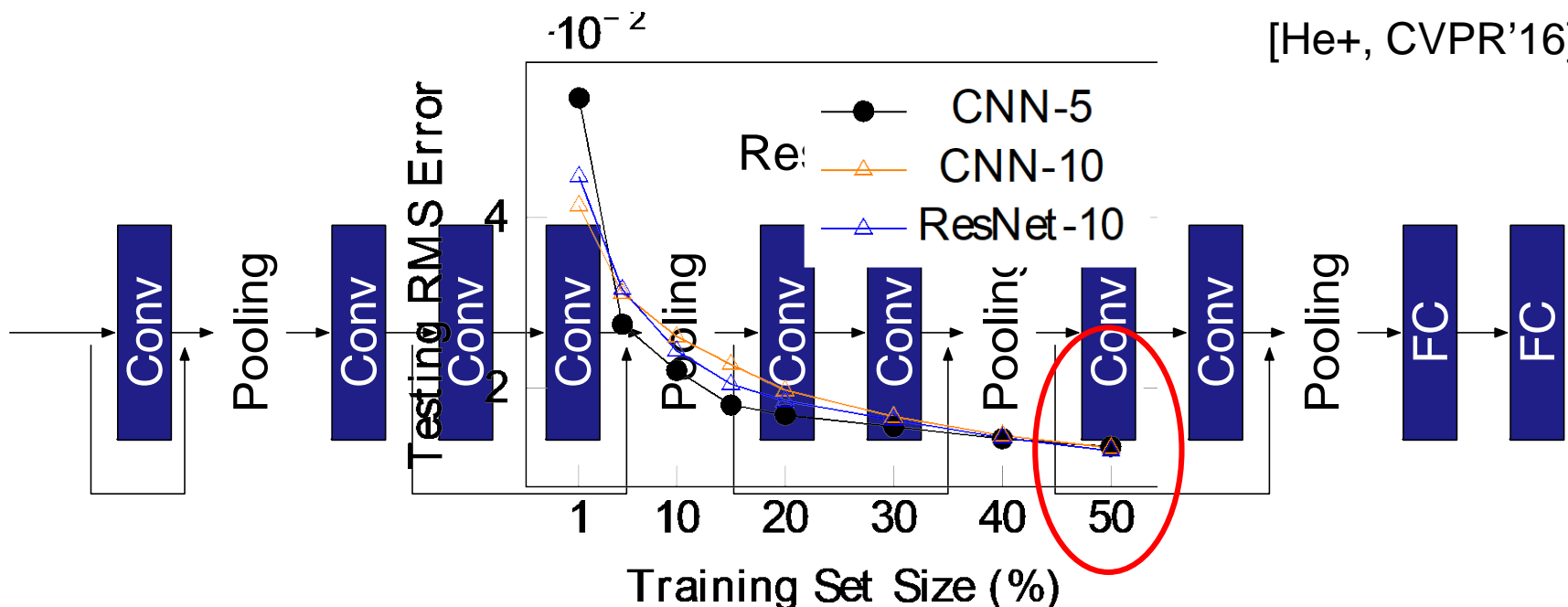


Pitfalls in Deeper Neural Networks

- Larger model capacity
- Gradient vanishing
 - ResNet
- Overfitting
- Require **MORE** data



[He+, CVPR'16]



Do We Have Big Data?

- Yes, but **old data**
- Different design rules
- Different manufacturing configurations

Can We Use Old Data?

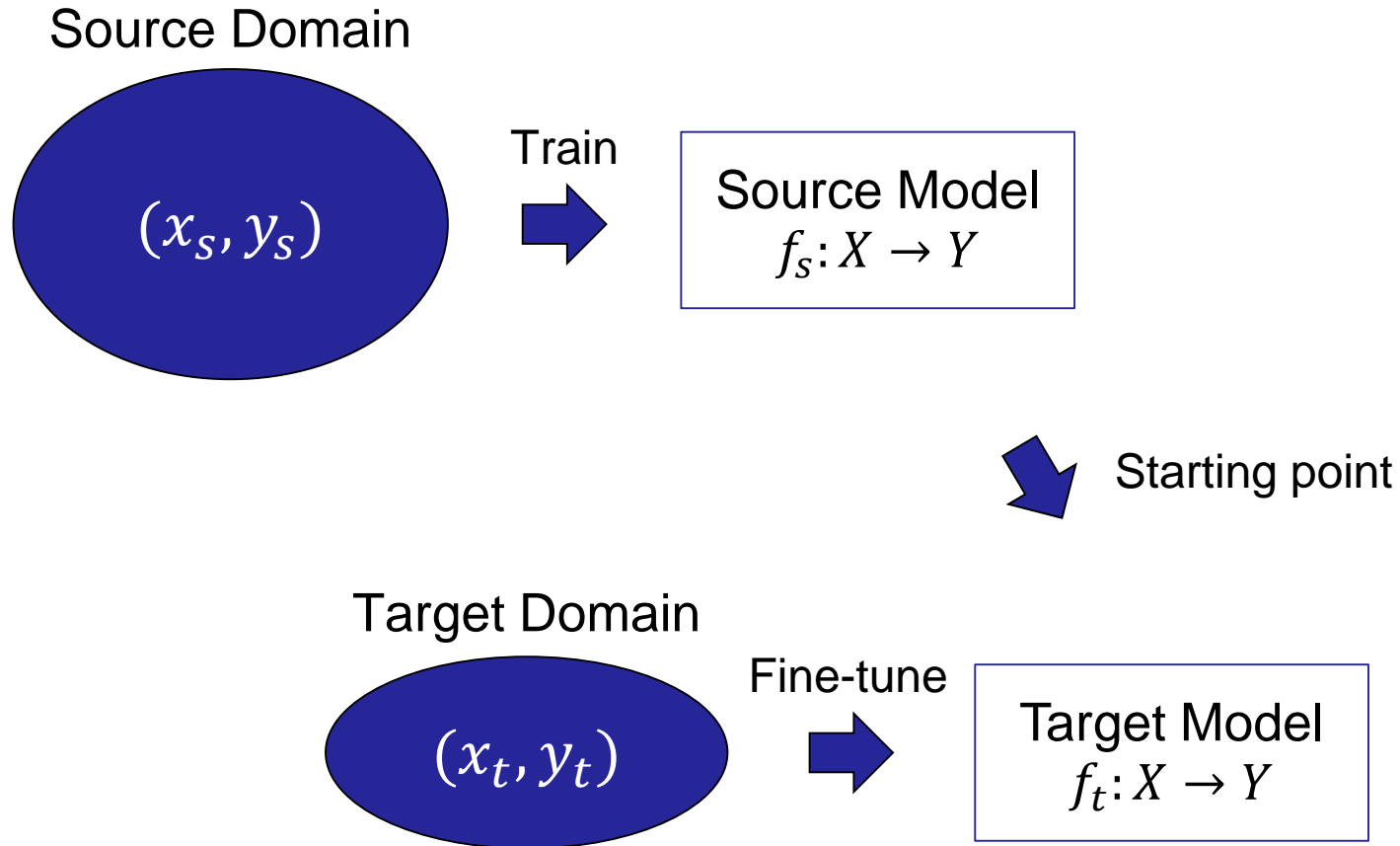
- It depends...
- How different the old data is from the new data?
- Worth trying

Our customer has a new chip to synthesize. It is quite different from the previous one.

Sure, let's first try the previous recipe.

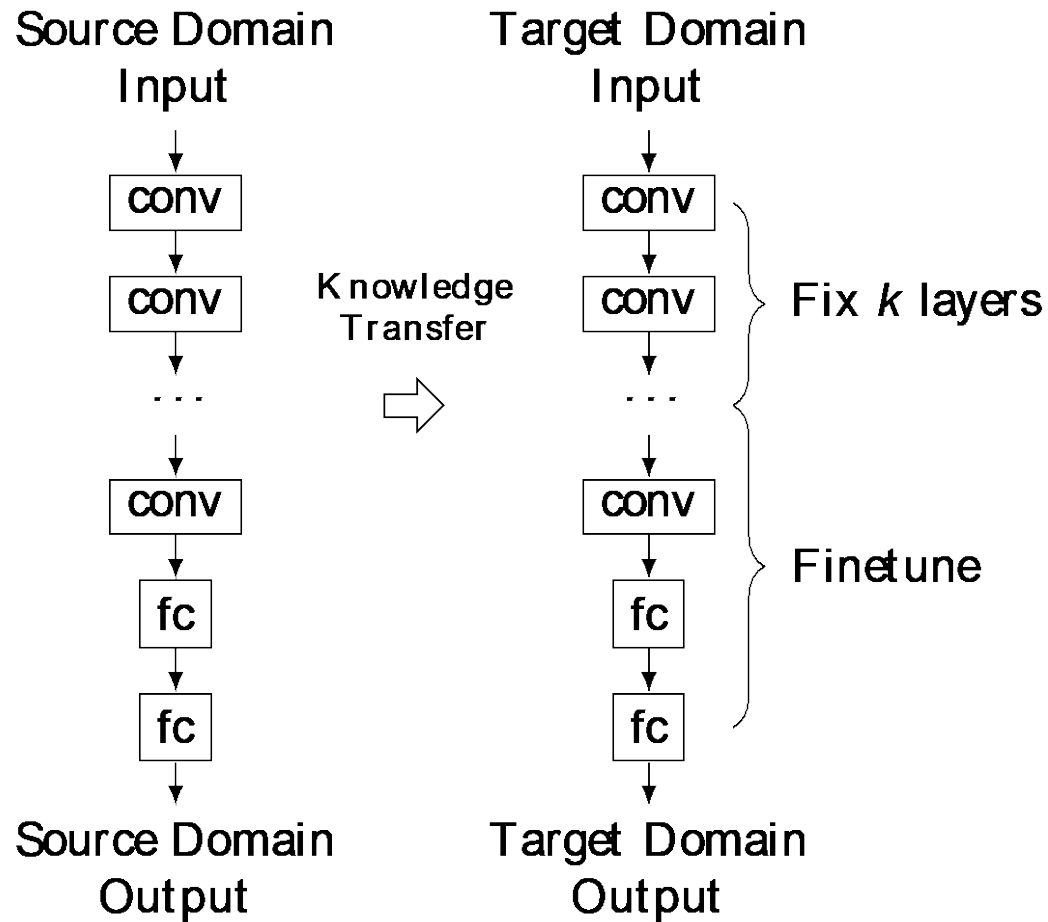


Transfer Learning from Source to Target



Transfer Learning from Source to Target

TF_k Scheme



Technology Transition from N10 to N7

Contact Layer Design Rules [Liebmann, SPIE'15]		
	N10	N7
Patterning	LELE	LELELE

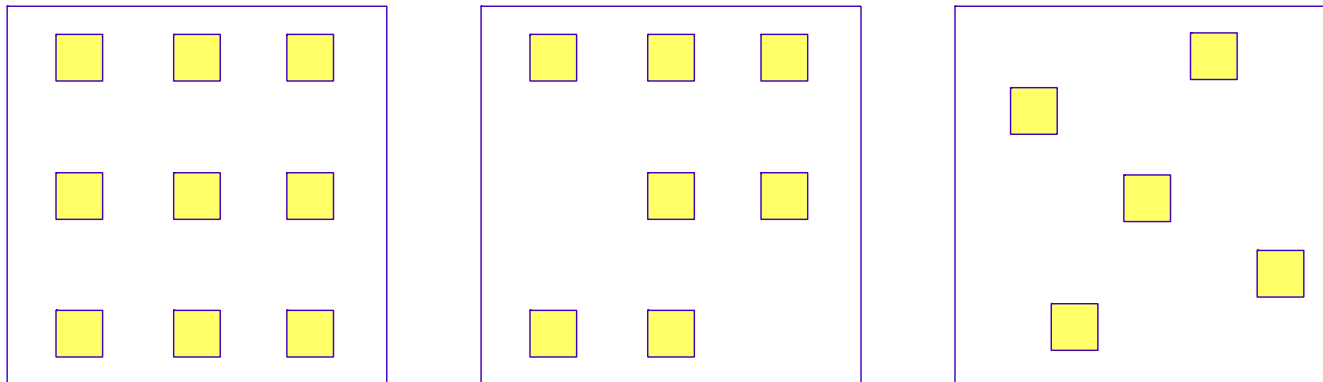
	N10	N7 _a	N7 _b
Design Rule	A	B	B
Optical Source	A	B	B
Resist Material	A	A	B



Different dissolution slopes

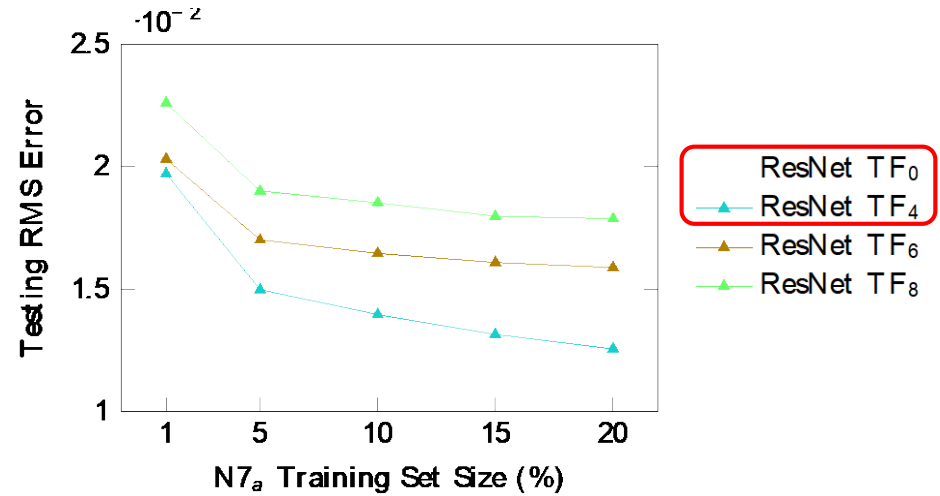
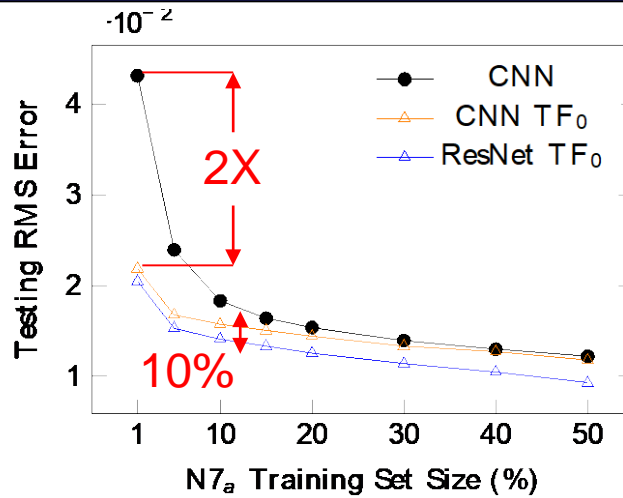
Technology Transition from N10 to N7

- Python 2.7
- Tensorflow 1.2.1
- GeForce GTX 1080
- SRAF, OPC, Aerial image: Mentor Graphics Calibre
- Rigorous simulation: Synopsys Sentaurus Lithography
- Average 10 trials of different random seeds
- ~30K clips for each N10 and N7 dataset

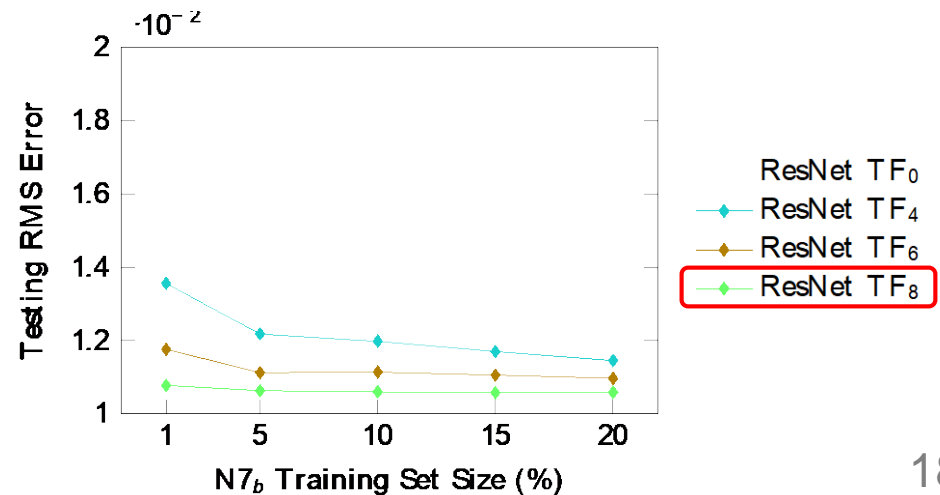
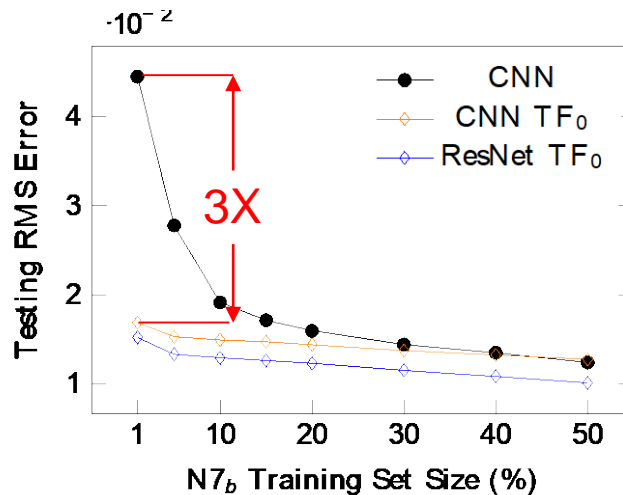


Explore Knowledge Transfer

From N10 to N7

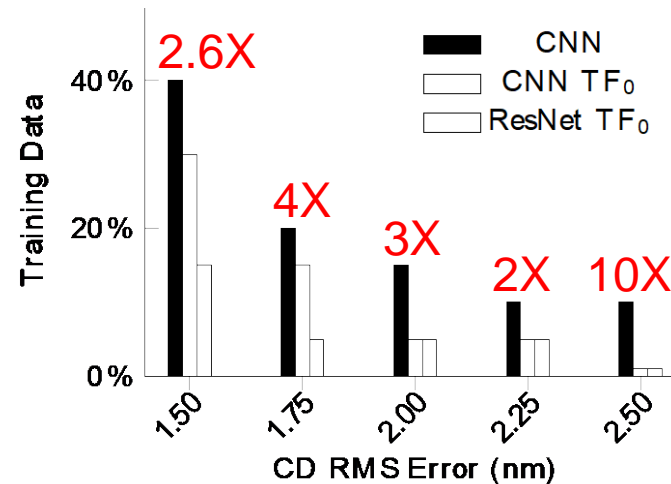


From N7_a to N7_b



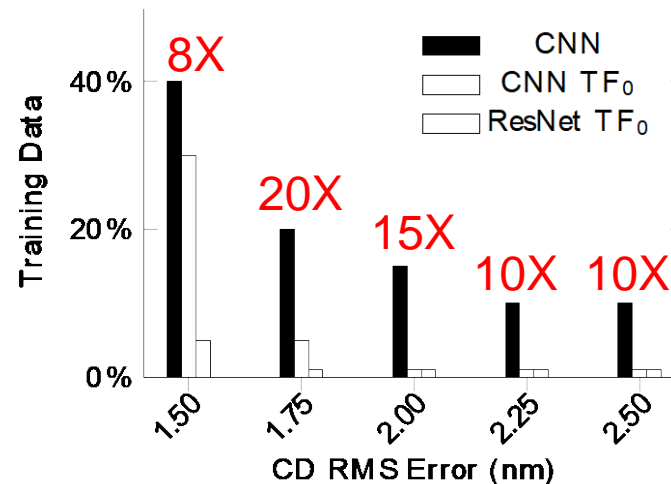
Data Reduction from Knowledge Transfer

From N10 to N7_b



2~10X reduction
on training data

From N7_a to N7_b



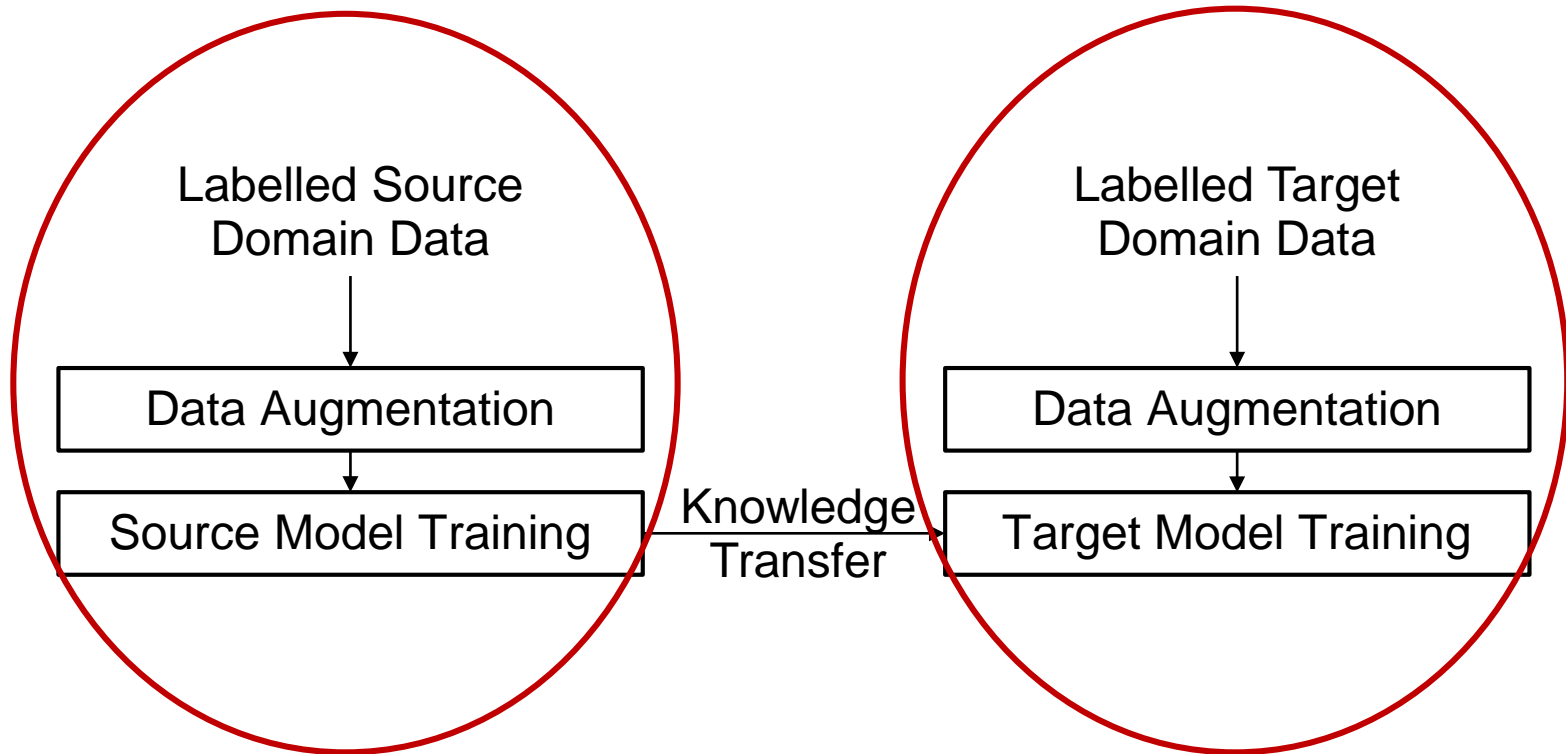
8~20X reduction
on training data

Explore Knowledge Transfer

	N10→N7_b	N7_a→N7_b
Dataset Similarity	Medium	High
Knowledge Transfer	Medium	High
Data Reduction	2~10X	8~20X

- Improve data efficiency
- Less cost for data preparation
- Less turn-around time
- Prototyped by Toshiba Memory Corp.

Conclusion



- Transfer learning & ResNet
- Improve data efficiency
- 2~10X reduction of training data
- Reduce turn-around time
- Increase modeling accuracy



Future Directions

	Transfer Learning	Active Learning	Semi-supervised Learning
Labelled Old Data	✓		
Labelled New Data	✓		✓
Label Querying		✓	

ML is more than classification/regression
Better understanding about data



Thanks