

"L'avenir est comme le reste il n'est
plus ce qu'il était'

Paul Valery, "Notre Destin et Les Lettres", 1937)"

Yan Borodovsky

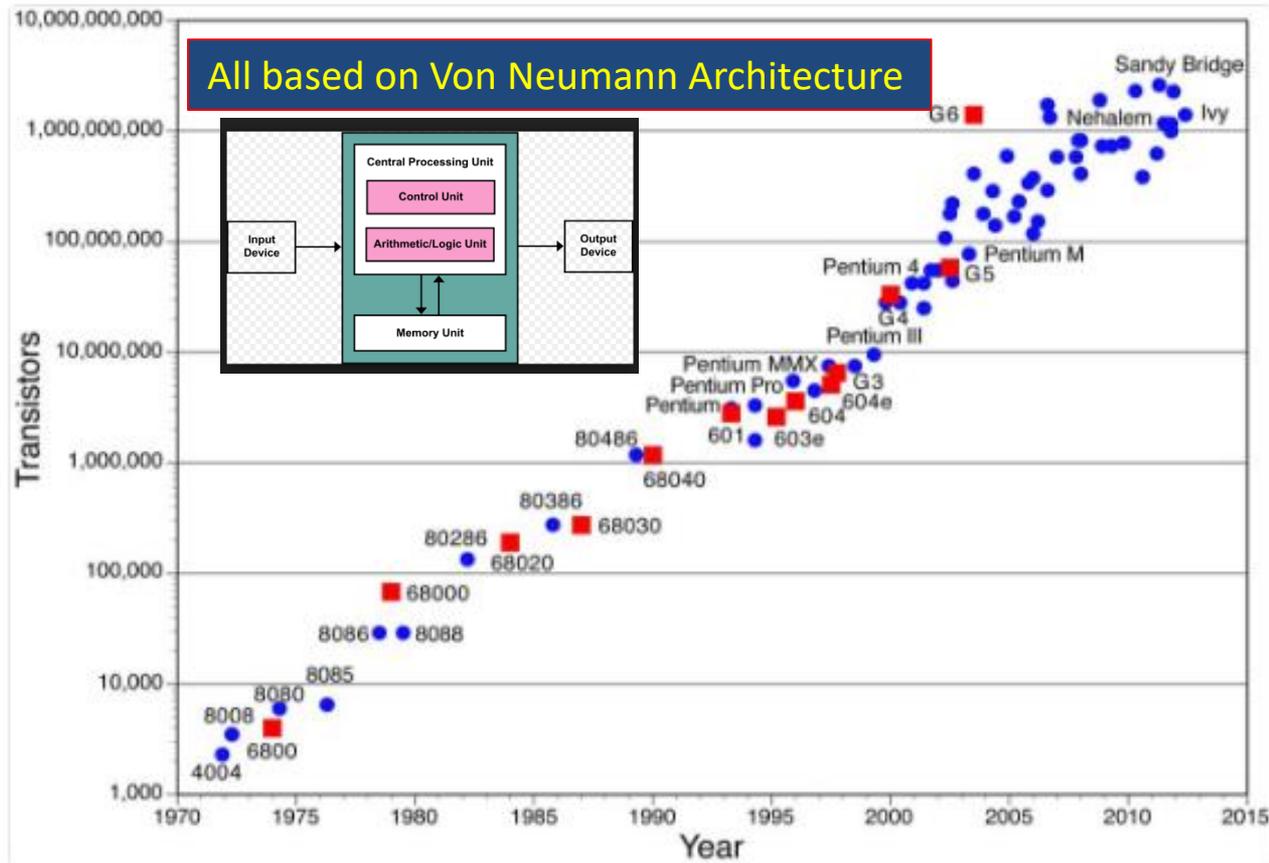
SPIE Fellow

The Future isn't what is used to be

Yan Borodovsky

SPIE Fellow

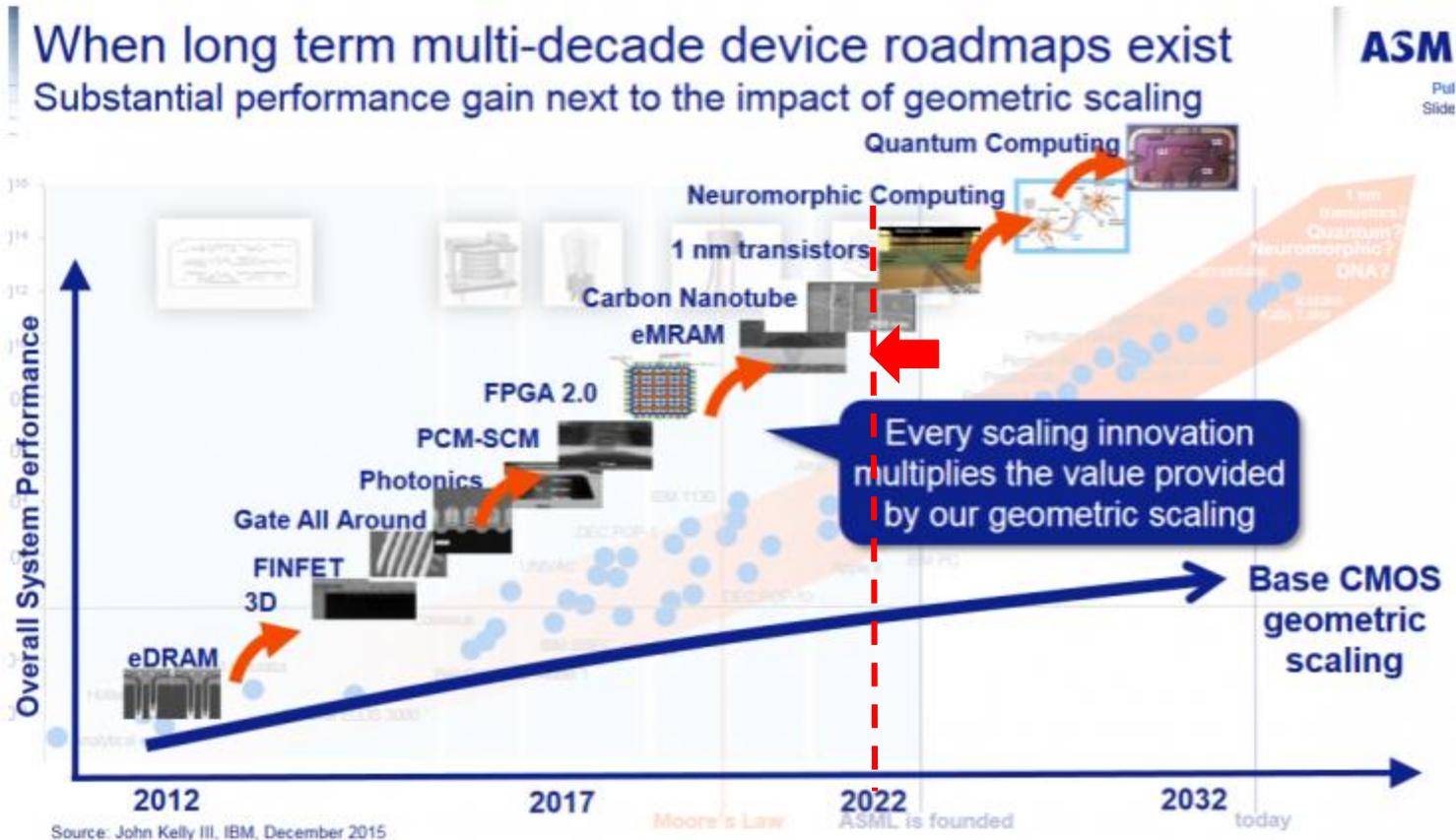
Moore's Law that used to be...



Moore's law Graph Source: **"What lies beneath? 50 years of enabling Moore's Law"**,
Mike Czerniak, Solid State Technology , Nov. 17, 2015

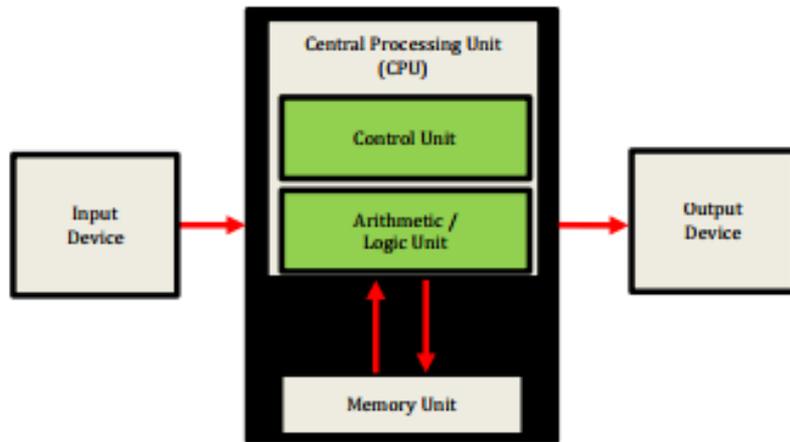
Moore's Law to be

Von Neumann AND Non-Von Neumann



2022-2024 Computing Platforms

von Neumann Architecture



Neuromorphic Architecture

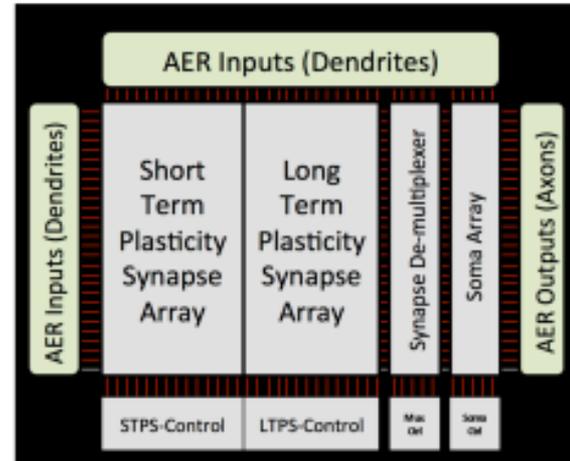


Figure 1. Comparison of high-level conventional and neuromorphic computer architectures. The so-called “von Neumann bottleneck” is the data path between the CPU and the memory unit. In contrast, a neural network based architecture combines synapses and neurons into a fine grain distributed structure that scales both memory (synapse) and compute (soma) elements as the systems increase in scale and capability, thus avoiding the bottleneck between computing and memory.

Source: “Neuromorphic Computing: From Materials to Systems Architecture”

Report of a Roundtable Convened to Consider Neuromorphic Computing Basic Research Needs, October 29-30, Gaithersburg, MD, USA, US DOE, Office of Science

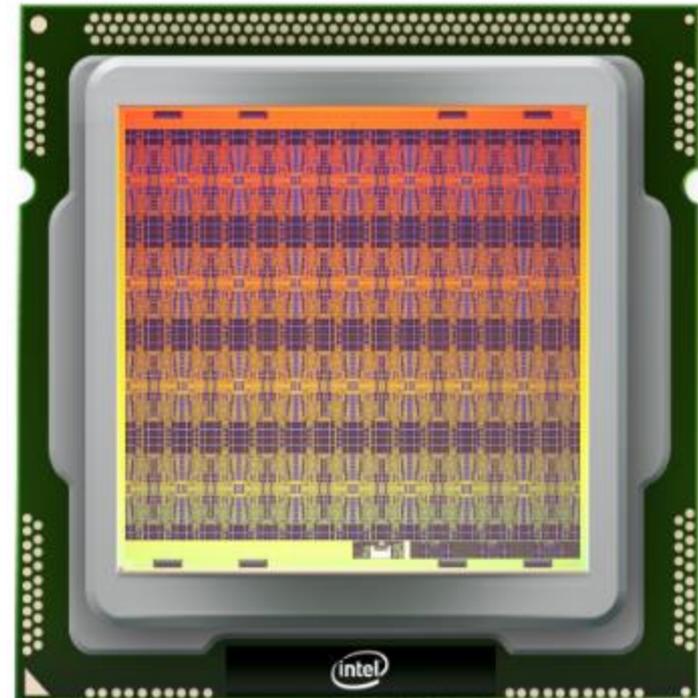
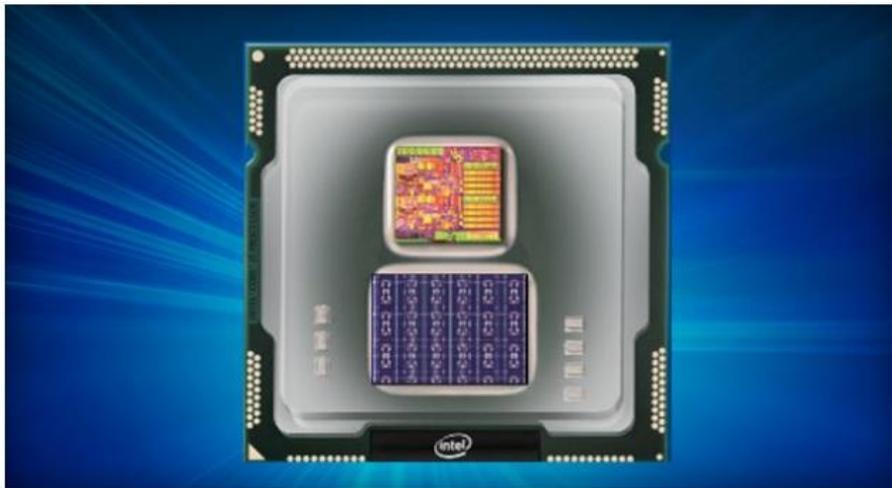
https://science.energy.gov/~media/bes/pdf/reports/2016/NCFMtSA_rpt.pdf

Von Neumann AND Non-Von Neumann already here

Intel Unveils Neuromorphic, Self-Learning Chip Codenamed Loihi

By Joel Hruska on September 27, 2017 at 9:18 am | 14 Comments

1.1K shares



Loihi simulates a total of 130,000 neurons and 130 million synapses, all capable of communicating with each other... comparable to some small insects. For example, a common fruit fly, an insect studied for AI research, has about 250,000 neurons and 10 million synapses. ...human brain - 100 billion neurons,

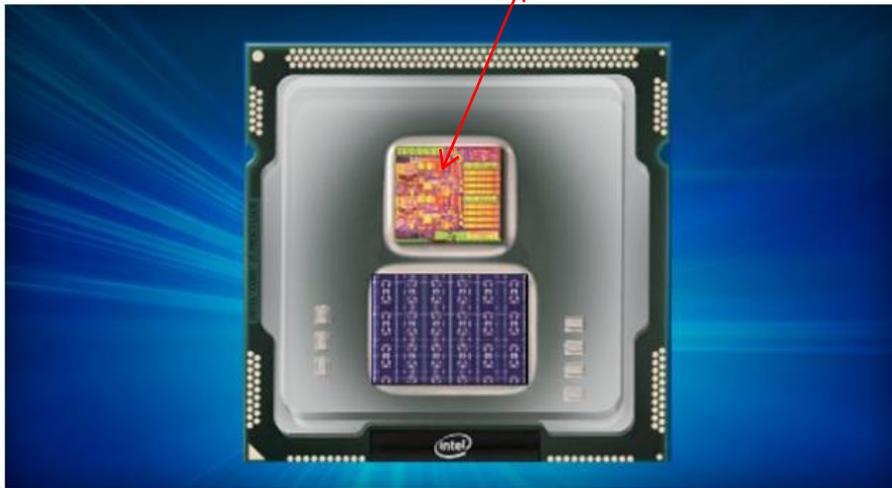
<https://www.extremetech.com/computing/256467-intel-unveils-new-neuromorphic-self-learning-chip-codenamed-loihi>

Von Neumann AND Non-Von Neumann already here

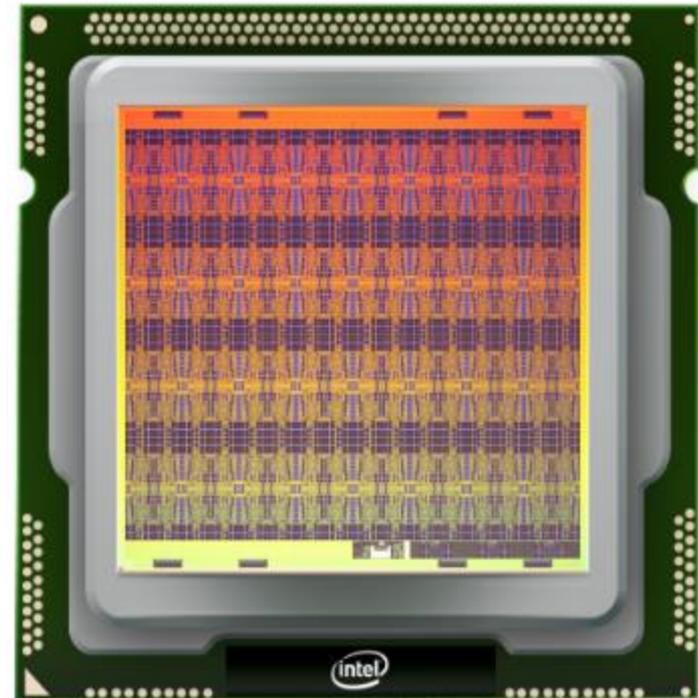
Intel Unveils Neuromorphic, Self-Learning Chip Codenamed Loihi

By Joel Hruska on September 27, 2017 at 9:18 am | 14 Comments

This is Control Programming Unit
>50% area is defect intolerant



This is Neuromorphic Part and
it is (or will be) defect tolerant



Loihi simulates a total of 130,000 neurons and 130 million synapses, all capable of communicating with each other... comparable to some small insects. For example, a common fruit fly, an insect studied for AI research, has about 250,000 neurons and 10 million synapses. ...human brain - 100 billion neurons,

<https://www.extremetech.com/computing/256467-intel-unveils-new-neuromorphic-self-learning-chip-codenamed-loihi>

Big 2017 Story – EUV Ecosystem status gives enough confidence to customers to place multiple tools orders

ASML

Public
Slide 16
January 17, 2018

EUV shipments ramp in support of customers' production plans

Customers

show commitment to insert EUV in volume manufacturing by ordering systems

- 4 EUV systems shipped in Q4, 5 recognized in revenue
- Of the 12 EUV shipments planned in 2017, we shipped 10 during the year, 1 shipment is in progress, 1 shipment planned in January 2018
- 10 orders received, EUV backlog increased to 28
- Planned shipments of 22 systems in 2018, back-end loaded, and plan at least 30 systems in 2019

ASML

commits to securing system performance, shipments and support required for volume manufacturing

For volume manufacturing of logic and memory, ASML remains committed to deliver:

- Throughput of >125 wafers per hour
- Availability of >90% on average
- Shipments on time in sufficient volume
- Ability to support a growing installed base

Source: https://staticwww.asml.com/doclib/investor/financial_results/2018/asml_20180107_presentation.pdf

Foundries – 7nm (+, ++) EUV

ASML

Public
Slide 17
July 19, 2017

EUV layer adoption - logic 7nm example
Addressing majority of critical layers at initial insertion

Layer	
Active	Initial EUV layer
Gate	Other candidate EUV layer
LI	Initial EUV layer
Contact	Initial EUV layer
Metal 0	Initial EUV layer
Via 0	Initial EUV layer
Metal 1	Initial EUV layer
Via 1	Initial EUV layer
Metal 2	Initial EUV layer
Via 2	Initial EUV layer
Metal 3	Initial EUV layer
Via 3	Other candidate EUV layer
Metal 4	Other candidate EUV layer
Via 4	Other candidate EUV layer
Metal 5	Other candidate EUV layer

Initial EUV layers
Other candidate EUV layers

Metal layers
patterning
types



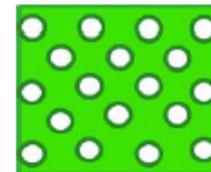
2D pattern
(1 EUV exposure)

or



1D pattern
(1 ArFi spacer exposure
+ 1 EUV cut exposure)

Via / Contact
example



(1 EUV exposure)

Source: ASML 2017 Second-Quarter Results Webcast Presentation

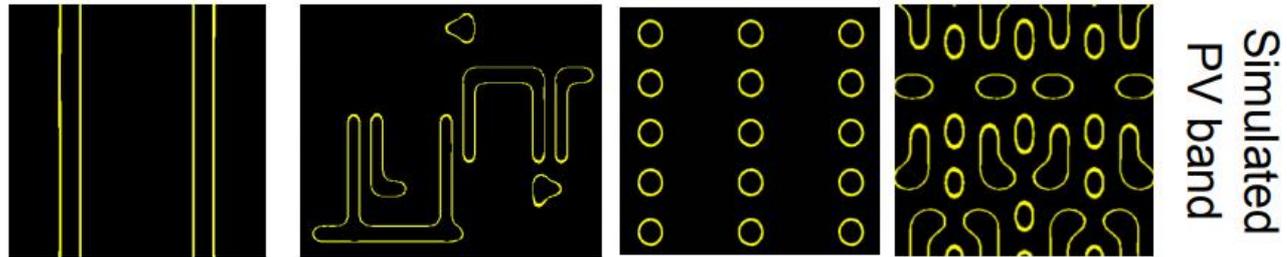
Stochastic Patterning Failures must be eliminated for EUV HVM



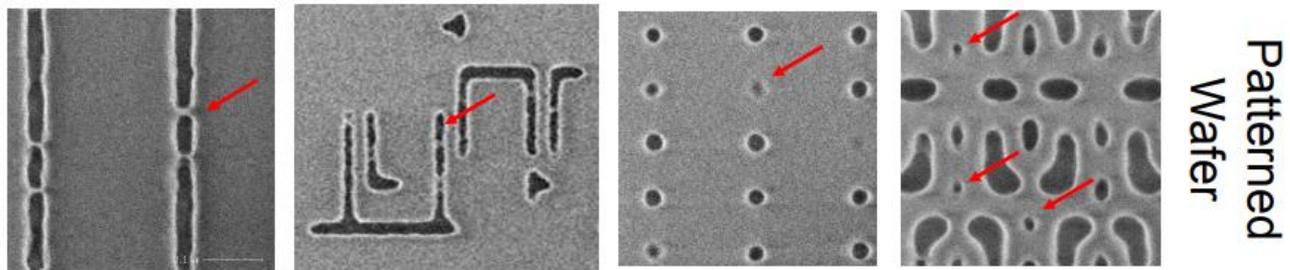
Stochastic Printability Failures

Examples from a Logic 10 nm node Local-Interconnect layer

OPC calibration says OK, but ...



Printing Failures happen



We attribute those issues to the stochastic effects in EUV.

Oct 27, 2014
Washington, D.C.

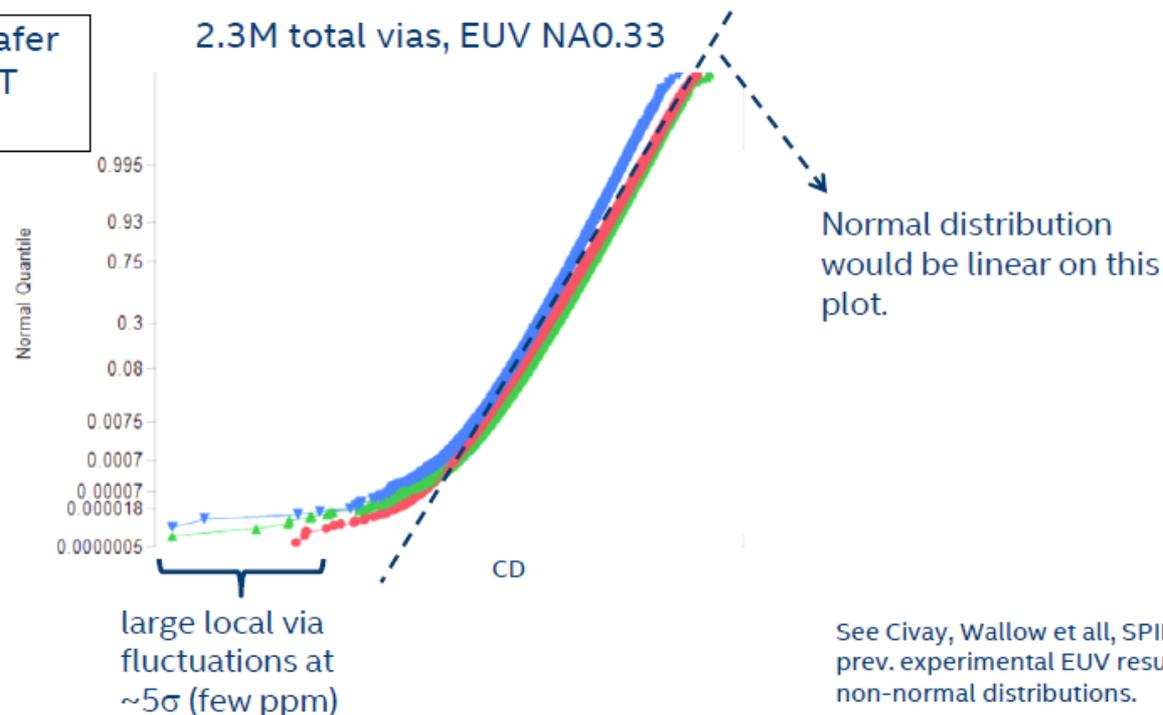
2014 International Symposium on Extreme Ultraviolet Lithography

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With 10B Via/Cuts per chip 5 σ process will kill every chip – zero yield

2.3M measured vias: Non-normal CD distribution.

Actual in-fab on-wafer measured vias, NOT simulated results.



Via Patterning with EUV

Stochastic requirements for vias

Required failure rate for 99% die yield

26X32mm die

	HP_{min} (nm)	Via count	Fail. rate	
<i>NA = 0.33 Illum. quad with $\sigma=0.2$</i>	26	0.18×10^{11}	55×10^{-14}	$\sim 7 \sigma$
<i>0.33 NA Limit</i> 	18	0.39×10^{11}	26×10^{-14}	
<i>0.55NA Limit</i> 	11	1.03×10^{11}	10×10^{-14}	
<i>YB 2/26/2018</i>	8	1.95×10^{11}	5×10^{-14}	$\sim 8 \sigma$

Measuring and Modeling Stochastic Limitations in EUV Resists

P. Naulleau,
W. Chao, O. Kostko, F. Ogletree, Berkeley Lab
S. Bhattaria, A. Neureuther, UC Berkeley



Photon Shot Noise AND Resist Inhomogeneity produce Stochastic Noise in Litho Channel

Modeling Via stochastics: resist conditions

Baseline Chemically Amplified Resist used in subsequent slides:

Esize = 79 mJ/cm²

E0 = 15.7 mJ/cm²

QE = 3

PAG = 0.2/nm³

Quencher = 0.085/nm³

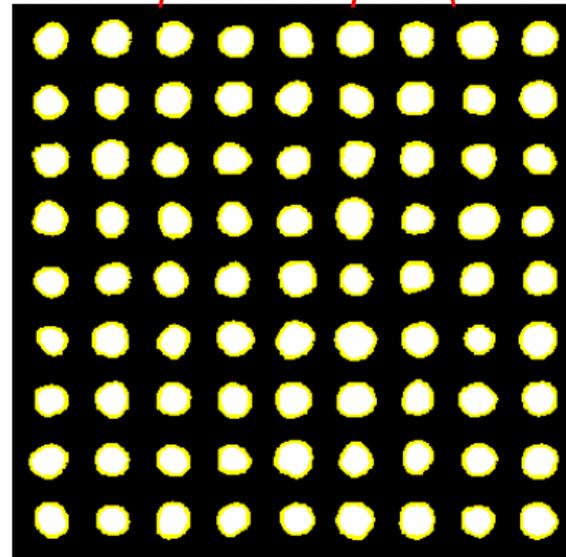
Protecting groups = 2/nm³

Absorptivity = 4.2/um

Thickness = 35 nm

Acid diffusion range = 12 nm

*16-nm HP contacts ; NA = 0.33
Illum. - optimized quad ($\sigma=0.1$)*



Developed resist

Measuring and Modeling Stochastic Limitations in EUV Resists

P. Naulleau,

W. Chao, O. Kostko, F. Ogletree, Berkeley Lab

S. Bhattaria, A. Neureuther, UC Berkeley



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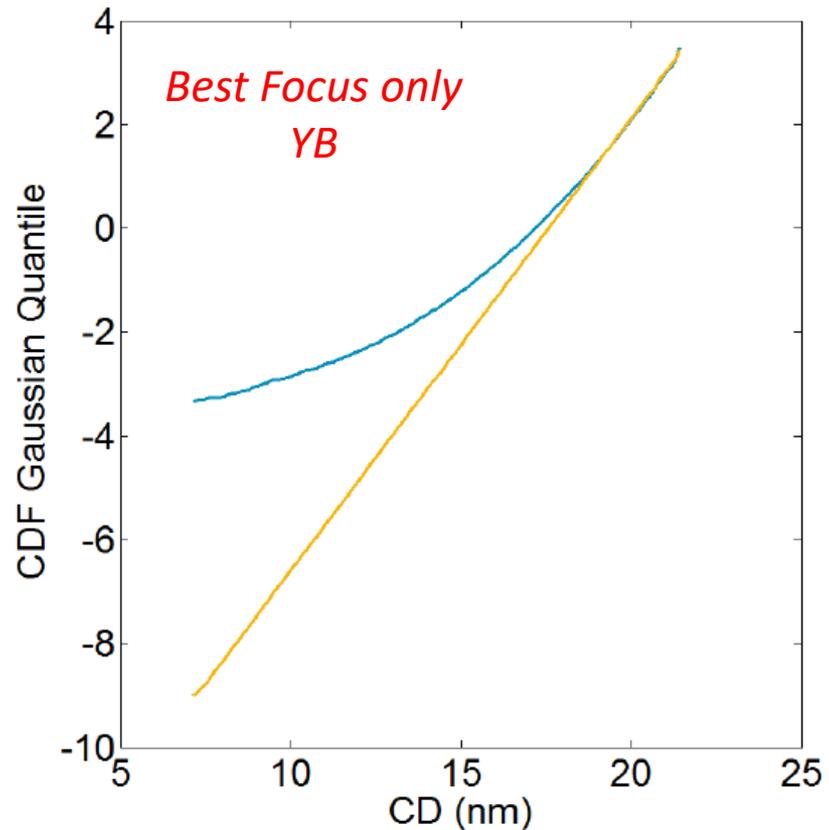
Photopolymer Japan, Chiba, Japan, June 26 - 29, 2017

Stochastic Noise in the Channel is Significant - parts per several millions

CDF shows large variations at 4σ frequency

CDF of stochastic resist model

Gaussian CDF



Via Patterning with EUV

Stochastic requirements for vias

Required failure rate for 99% die yield

26X32mm die

<i>Year</i>	<i>Node</i>	<i>EUV</i>	<i>HP_{min} (nm)</i>	<i>Via count</i>	<i>Fail. rate</i>
2019	~7nm	1X	26	0.18 x 10 ¹¹	55 x 10 ⁻¹⁴ → ~7 σ
2020	5nm	2X	18	0.39 x 10 ¹¹	26 x 10 ⁻¹⁴
2022	3nm	3X	11	1.03 x 10 ¹¹	10 x 10 ⁻¹⁴
2026	1.5nm	?	8	1.95 x 10 ¹¹	5 x 10 ⁻¹⁴ → ~8 σ

YB

Measuring and Modeling Stochastic Limitations in EUV Resists

P. Naulleau,
W. Chao, O. Kostko, F. Ogletree, *Berkeley Lab*
S. Bhattaria, A. Neureuther, *UC Berkeley*



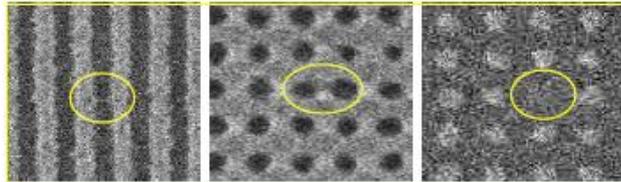
EUV RESIST PERFORMANCE

LOW DOSE IS ACHIEVED, BUT LIMITED BY STOCHASTICS



Feature	32nm pitch dense line-space / Vertical		32nm pitch dense line-space / Vertical		26nm pitch dense line-space / Horizontal		36nm pitch regular dense contacts	38nm pitch regular dense pillars
	CAR	NCAR	CAR	NCAR	CAR	NCAR	CAR	NCAR
SEM top-down image @ BE/BF								
Dose mj/cm ²	30.5	31.4	21	20.9	39	37.3	31	30
LWR/LCDU nm	4.7	4.6	5.4	5.2	4.5	4.2	3.5	3.9

Challenge #1:
Stochastic Failures



Source:

EUV DEVELOPMENTS AT IMEC

DANILO DE SIMONE, PETER DE BISSCHOP, IVAN POLLENTIER, WAIKIN LI, EMILY GALLAGHER, VICKY PHILIPSEN, VINCENT WIAUX, RYOUNG-HAN KIM, ERIC HENDRICKX, GEERT VANDENBERGHE, KURT RONSE, [GREG MCINTYRE](#)

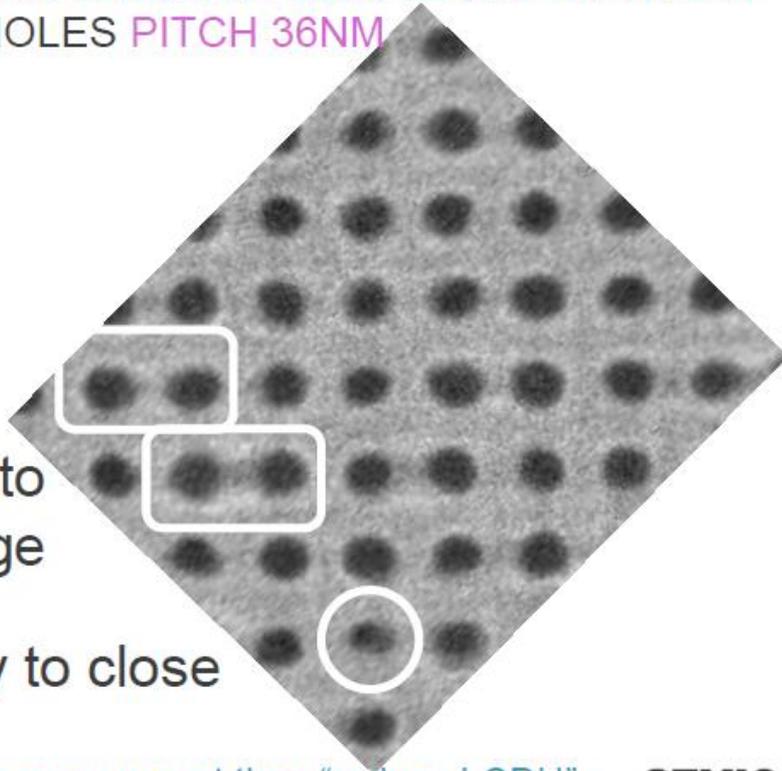
ON BEHALF OF IMEC PATTERNING

15 JUNE 2017, EUVL WORKSHOP, BERKELEY, CA

Features Patterned with NXE 3300
NA=0.33

Stochastic Nanofailures

BUT, (AGAIN) NANO FAILURES ARE MORE IMPORTANT
DENSE REGULAR CONTACT HOLES PITCH 36NM



CHs with tendency to merge

CH with tendency to close

>To get rid of nano failures is more urgent than "reduce LCDU"<

imec

16

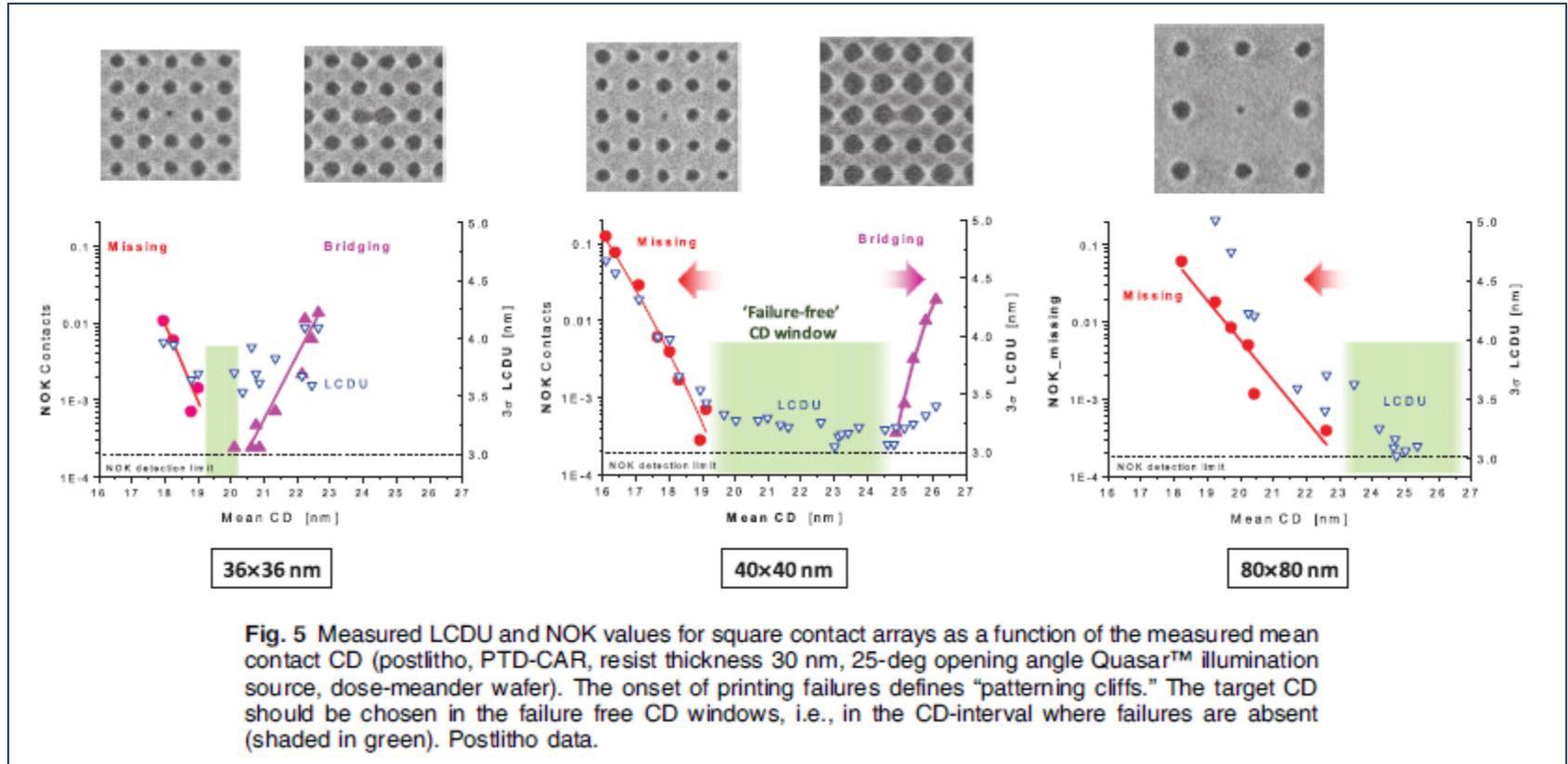
D. DE SIMONE

SEMICON
EUROPA

14-17 NOV 2017
MUNICH
GERMANY

Yield and Stochastic Failures

5nm Node



Source: Peter De Bisschop, “Stochastic effects in EUV lithography: random, local CD variability, and printing failures,” J. Micro/Nanolith. MEMS MOEMS 16(4), 041013 (2017), doi: 10.1117/1.JMM.16.4.041013.

Defectivity Intolerance of Von Neumann Computing will eventually result in end of viable area scaling.

Patterning Holy Grail

Moore's Law = Density+Cost Per Transistor

$$CPT_{n+1/n} = \text{Wafer Cost}_{n+1/n} * \text{AreaScale}_{n+1/n}$$

(Assuming equivalent yield)

Wafer Cost	Area Scale	CPT
1.1	0.55	0.6
1.2	0.50	0.6
1.3	0.46	0.6
1.4	0.43	0.6
1.5	0.40	0.6

5nm Node and below will be progressively defect prone due to impact of Stochastic effects in EUV Litho. Defects ↑ = Yield ↓



~50% of Wafer Cost is Patterning now

$$CPT_{n+1/n} = 2 * \text{PatternCost}_{n+1/n} * \text{AreaScale}_{n+1/n}$$

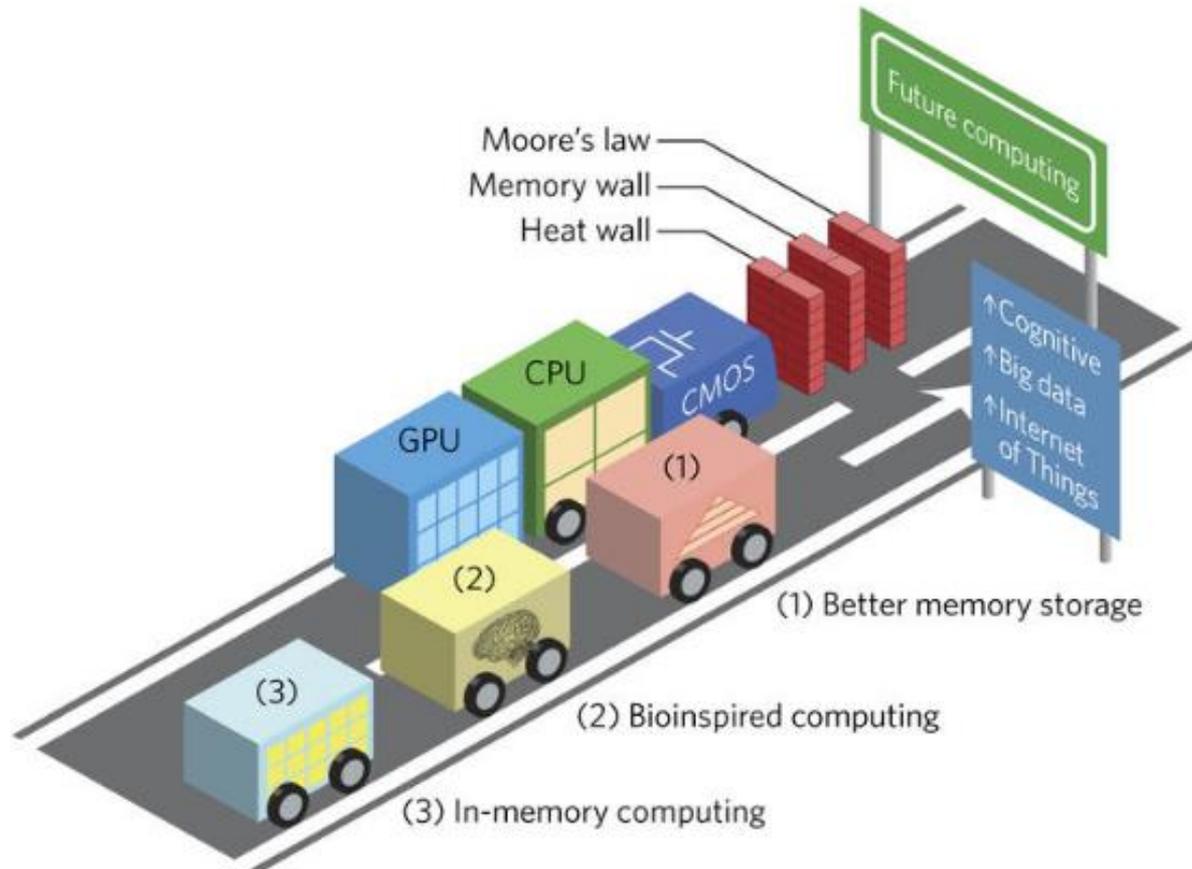
Lowest PatterningCost*AreaScale solution is Litho Holy Grail.



Y. Borodovsky, *Alternative Lithographic Technologies VII, Conference*
9423, 23 February 2015, San Jose, CA, USA

17

Bioinspired Computing will be a vehicle to get Through Defect Limiting Moore's Law Wall



Source

“The future of electronics based on memristive systems”

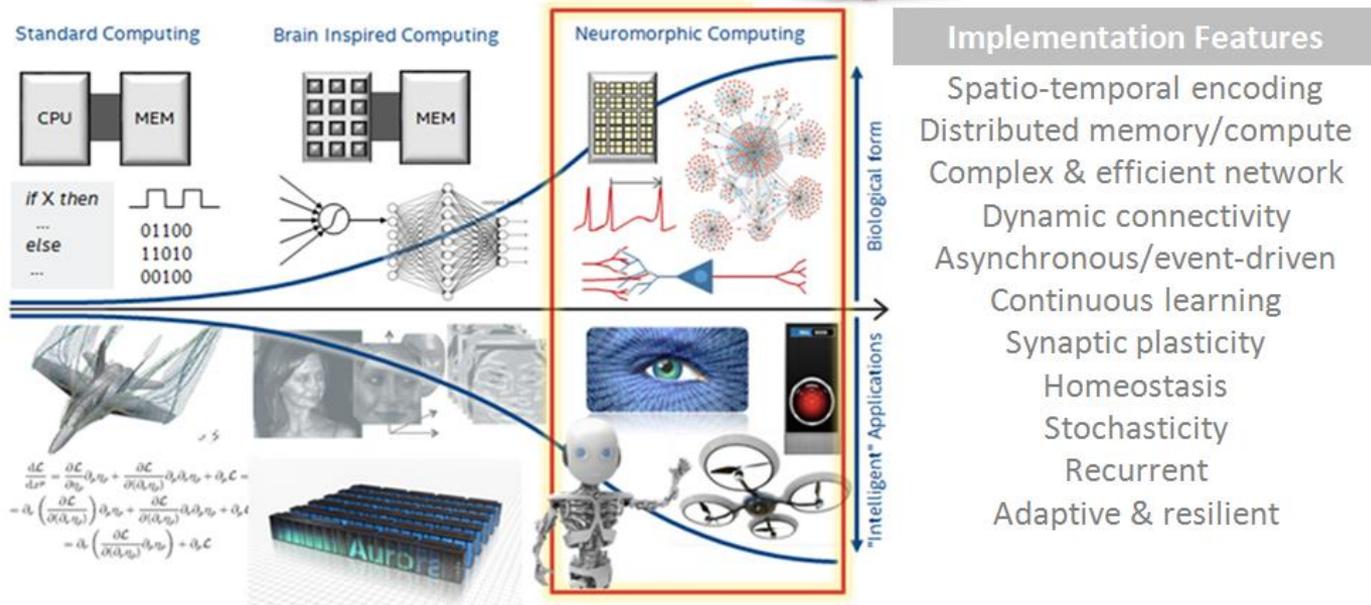
Mohammed A. Zidan, John Paul Strachan & Wei D. Lu

Nature Electronics **1**, 22–29 (2018), doi:10.1038/s41928-017-0006-8

Beyond von Neumann Computing – Opportunity for further scaling with 10^x defect density

Efficient & Scalable Neuromorphic Systems

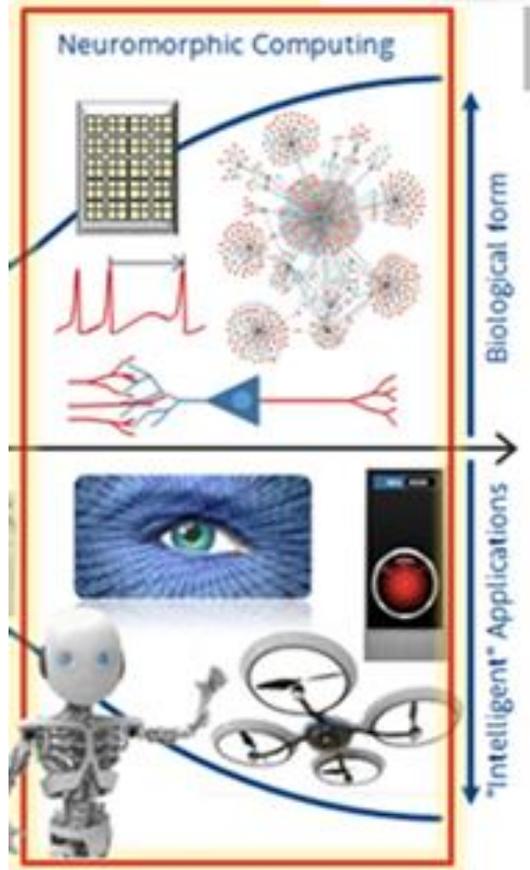
Neuromorphic Circuit – circuit that in its structure mimics organization of the brain



Exploit integration, spike timing, sparsity, plasticity & resiliency

“Challenges and Opportunities for Efficient & Scalable Neuromorphic Systems”, Vivek De, Intel, DAC54, 6/18-22/2017. Austin, TX USA

Bioinspired Computing might be a vehicle to get Through Defect Limiting Moore's Law Wall



Neuromorphic Circuit mimic in its structure organization of the brain

Figures 1 illustrate the quantitative data for the neuromorphic model of AND, NAND, OR, NOR, XOR and XNOR gates. The graph shows the relationship between R_p and probability (assurance) of reaching the correct solution, which is the supposed output of logic functions f . The stochastic perturbations ξ are modeled as uniformly distributed discrete random noise. For $R_p \in [0, 0.4]$, the correct output f for AND, NAND, NOR and OR gates is achieved within $\sim 100\%$ requiring 400 iterations. In contrast, gates XOR and XNOR achieve the correct f from 80% to 100% requiring ~ 450 iterations. As R_p increases, the required number of iterations to achieve stability increases. Figure 1.b illustrates the number of iterations for the network to evolve to a stable state for different R_p .

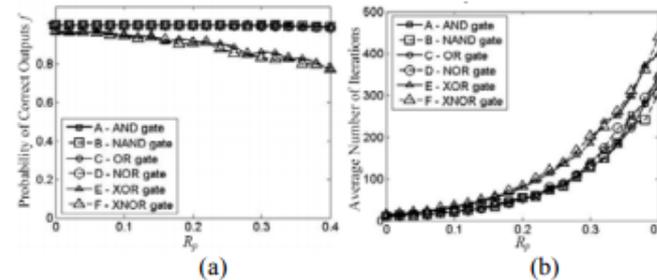


Figure 1. Fault-tolerance of the neuromorphic model of elementary logic gates in the presence of disturbances for $R_p \in [0, 0.4]$ (5000 runs)

The superposition of inherent noise, interference and other disturbances are considered as stochastic perturbations ξ . We use the perturbed-to-unperturbed ratio R_p which characterizes the *strength* of the ξ . In general, ξ is a mapping of all ξ_i which are hardware-dependent. Continuous and discrete distributions of random ξ_i result in probability functions $\chi(\xi_i)$ as well as distribution functions. Normal, binomial, hypergeometric, Poisson and other distributions affect ξ .

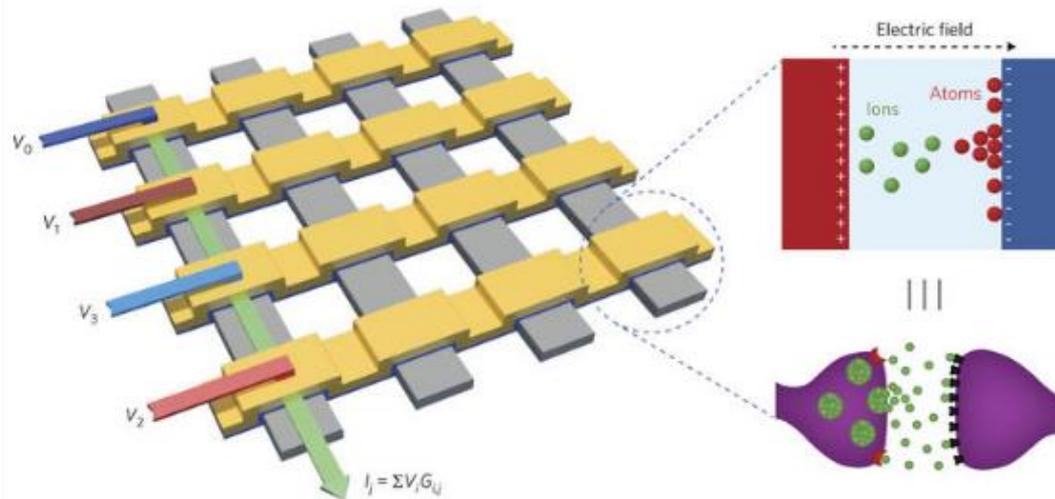
We simplify the analysis by using $R_p \in [0, 1]$.

For an ideal unperturbed model $R_p=0$, while for a completely faulty cell, $R_p=1$.

Neuromorphic Logic Networks and Robust Stochastic Computing Under Large Perturbations and Uncertainties

RRAMs, Spin-Torque and other technologies are actively pursued as neuromorphic computing fundamental building blocks

→ Hardware implementation of artificial neural networks in a memristor crossbar.



A memristor is formed at each crosspoint and can be used to simultaneously store data and process information. In this approach, vector-matrix multiplication can be obtained through Ohm's law and Kirchhoff's law through a simple read operation. In addition, the internal dynamics of memristors can be utilized to faithfully emulate underlying processes in biological synapses. V_i , voltage applied at row i ; I_j , current through column j ; $G_{i,j}$, conductance of the memristor at the intersection of row i and column j .

The future of electronics based on memristive systems”

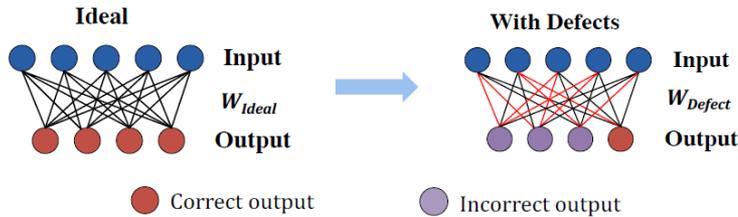
Mohammed A. Zidan, John Paul Strachan & Wei D. Lu

Nature Electronics **1**, 22–29 (2018), doi:10.1038/s41928-017-0006-8

Neuromorphic computing as enabler to break through next Moore's Law Wall

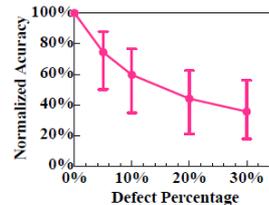
Impact of Memristor Defects

- An illustration of the defects on neural network



- Impact of the defects

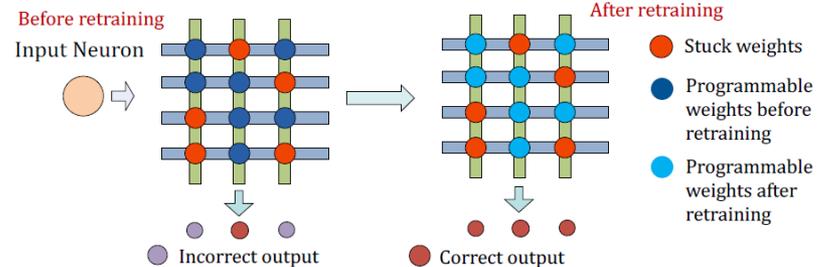
- Two-layer network for MNIST recognition
- Large accuracy degradation:
59.7% at 10% defects, 44.2% at 20% defects



6

Rescue: The Network Retraining

- Tune the network for the self rescue



- Two major considerations in the retraining

- Weight initialization:



- Weight updating:

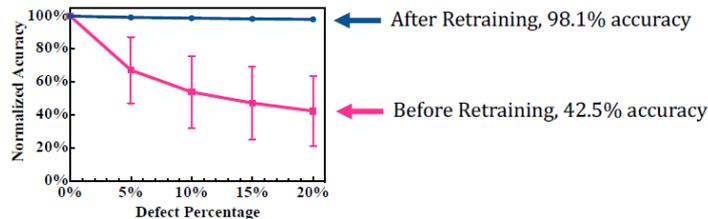
$$\Delta w_{ij}(\text{defect}) = 0$$

The amount of weight that each synapse needs to be updated in backpropagation

8

Evaluations: Robustness of the Retraining

- Feed-forward neural networks for MNIST recognition
 - Recognition accuracy before and after retraining

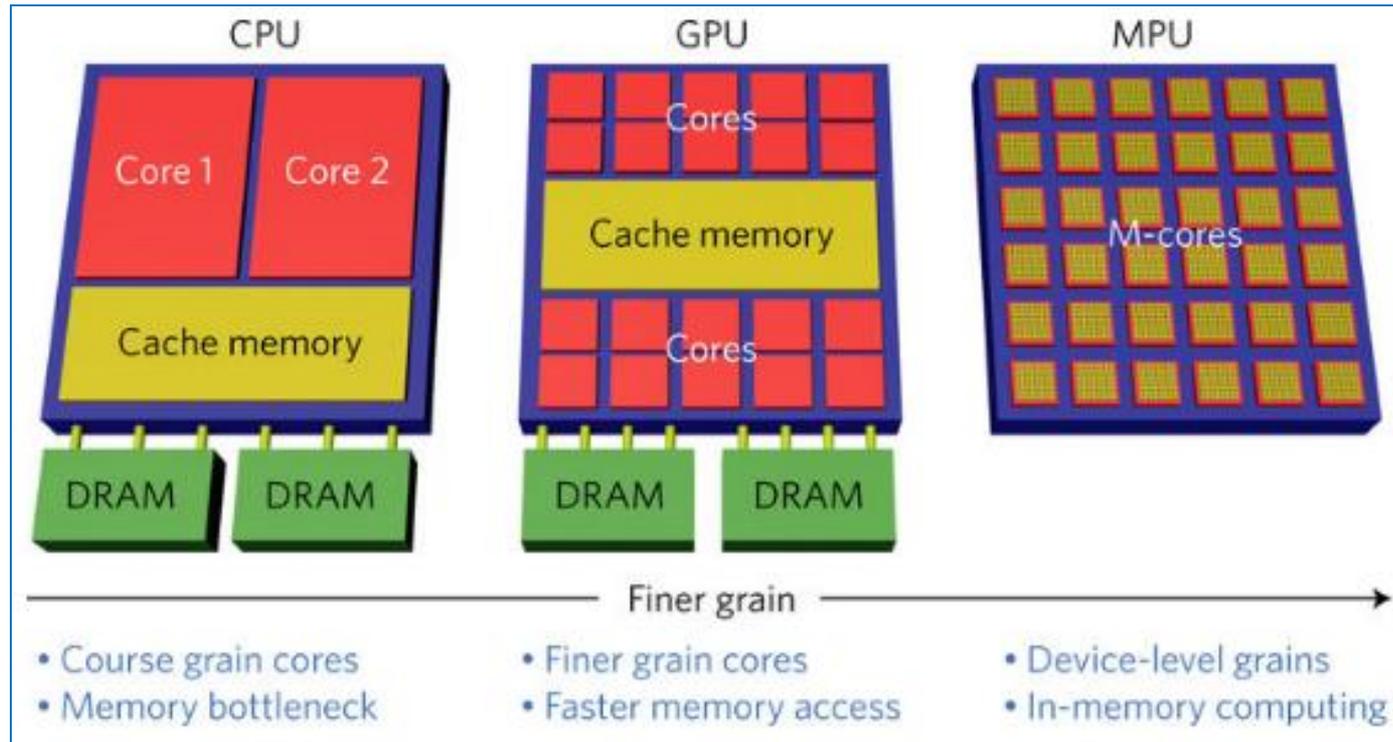


Source: Prof. Chenchen Liu Presentation at DAC 17
“Rescuing Memristor-based Neuromorphic Design with High Defects”

Chenchen Liu, * Miao Hu, * John Paul Strachan and † Hai (Helen) Li; Clarkson University*Hewlett-Packard Labs †Duke University

Full Paper: DAC '17, June 18-22, 2017, Austin, TX, USA
 c 2017 ACM. ISBN 978-1-4503-4927-7/17/06... \$15.00
 DOI: <http://dx.doi.org/10.1145/3061639.3062310>

Proposed MPU Architecture



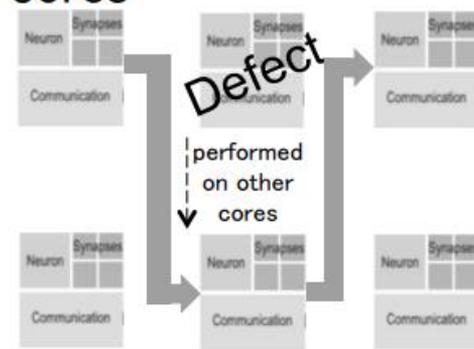
Source: “The future of electronics based on memristive systems”
Mohammed A. Zidan, John Paul Strachan & Wei D. Lu
Nature Electronics **1**, 22–29 (2018),doi:10.1038/s41928-017-0006-8

Proposed MPU Architecture shall support defect prone IC scaling

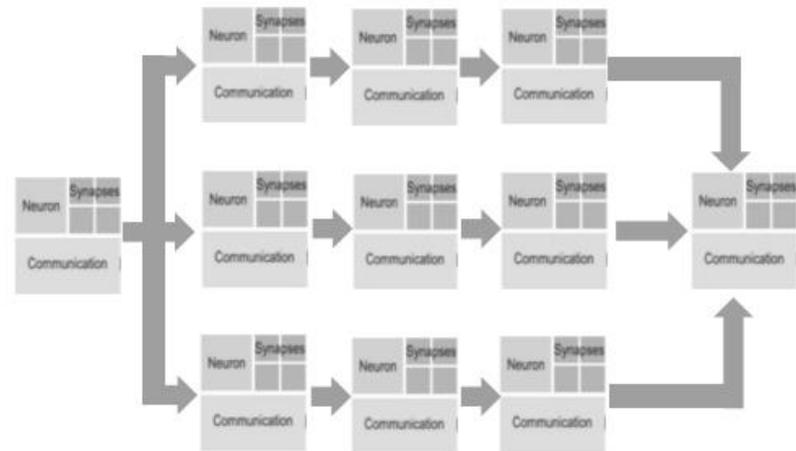


High defect tolerance And reliability

- Defect tolerance – Treatment at the defective core is performed on other cores



- Reliability – The majority voting system can be configured by programming



From ¹¹ “Neuromorphic device for Automotive” by Yoshifumi Sakamoto, Engineering and Cognitive Innovation, IBM Japan, LTD, email: sakay@jp.ibm.com

Putting it all in Perspective

Von Neumann Computing will eventually hit scaling wall as defectivity required to support it will reach $< 10^{-14}$ /die features for overall 10^{-2} /cm² defects per wafer/per print.

Neuromorphic Computing can tolerate up to $4 \cdot 10^{-1}$ defects per network.

Multiple technologies that were under development and commercialization efforts for >10 years but were not adopted for Logic will become viable alternatives to EUV to drive parts density and cost as per Moore's Law

NanoImprint for Logic

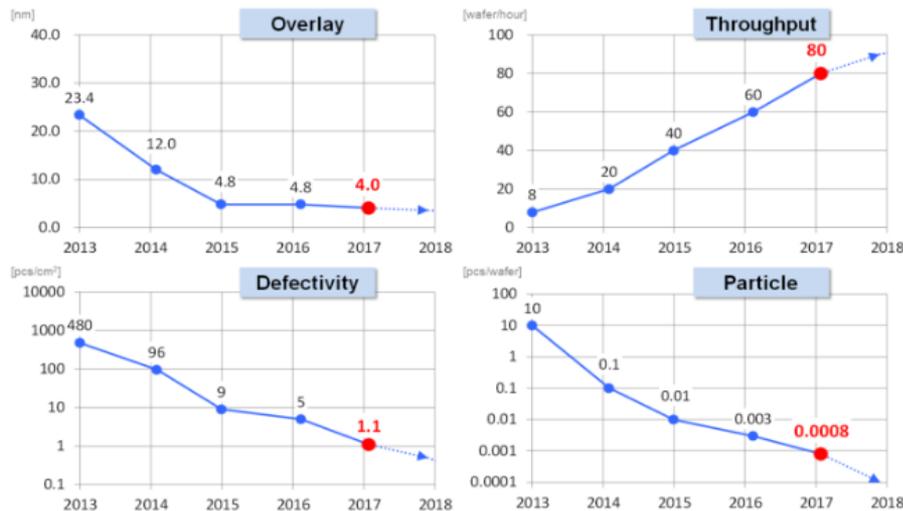


Figure 1. Historical overview of defectivity, particle generation, overlay and throughput, starting in 2013.

From "A review of nanoimprint lithography for high-volume semiconductor device manufacturing" by Douglas J. Resnick/Jin Choi, Advanced Optical Technologies, Volume 6, Issue 3-4, 2017

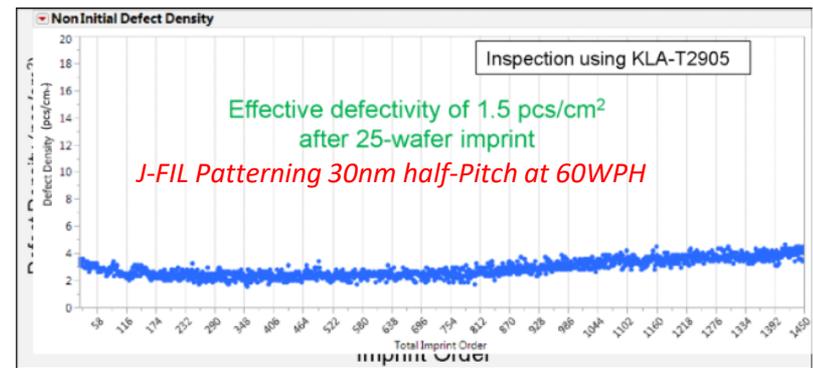


Figure 10. Defect density across a 25 wafer run. Overall defectivity increased by 1.5 defects/cm².

NIL – OK to support Neuromorphic parts manufacturing now?

How will it scale during next 10 years?

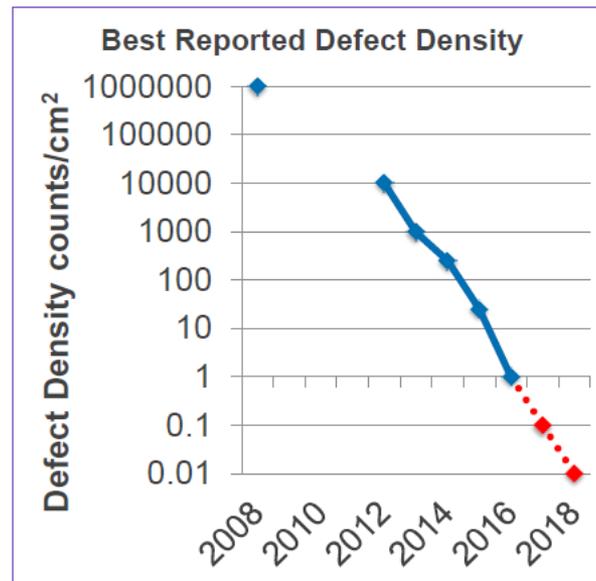
DSA Defectivity – OK to support Neuromorphic Products now?

DSA Defectivity

Source: "DSA: How far have we come and how much further is left to go?" Darron Jurajda, Brewer Science, 2016

Defectivity Industry Milestones

- 2008 – 0.01% or 10^6 cm^{-2}
- 2012 – $>10,000 \text{ cm}^{-2}$
- 2013 – Process monitor data first reported, 979 cm^{-2}
- 2014 – $\sim 200 \text{ cm}^{-2}$ (LiNe flow), 270 cm^{-2} (LETI contacts)
- 2015 – 24 cm^{-2} (LiNe flow golden performance)
- 2016 – $\sim 0 \text{ cm}^{-2}$ (LETI, hole open yield, 0.01 mm^2 inspection area)
- Two more orders of magnitude needed to hit industry target of $0.01 \text{ defects cm}^{-2}$



**SEMICON
TAIWAN**

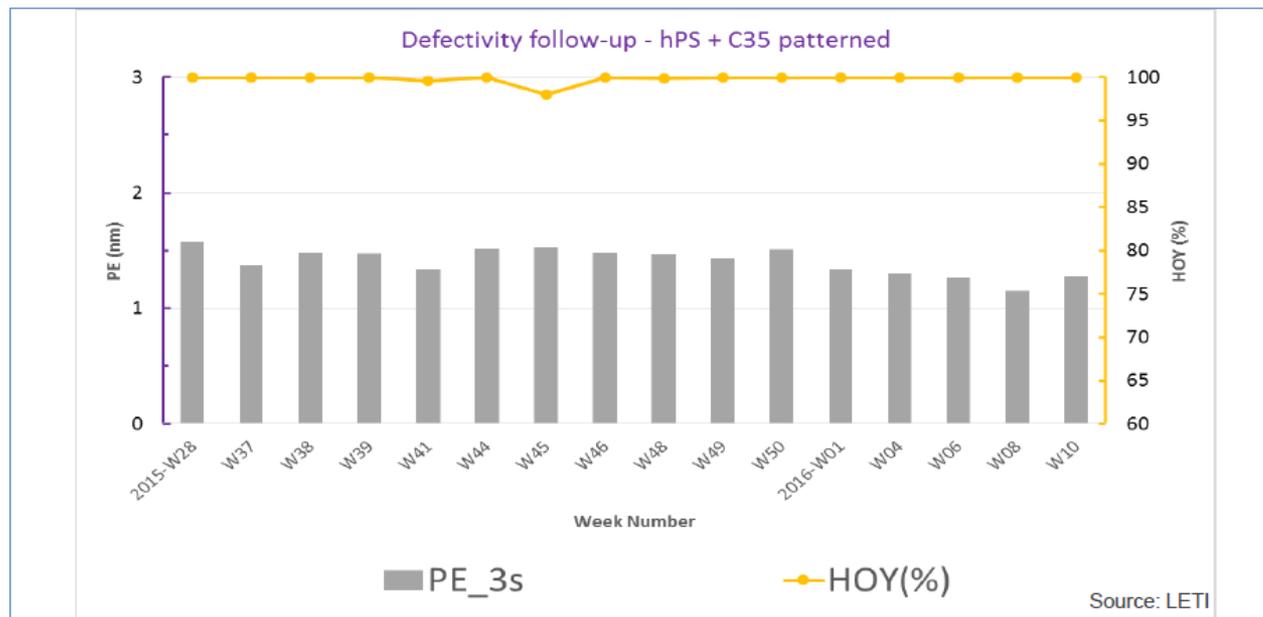
Tada, et. al., Macromolecules, 41, 9267-9276, (2008)
Benchera, et. al, SPIE 2012
Caoa, et. al, SPIE 2013

Gronheid, et. al, SPIE 2014
Argoud, et. al, SPIE 2014
Pathangi, et. al, SPIE 2015

semi

DSA Defectivity– OK to support Neuromorphic Products now?

DSA Pattern Placement and Hole Open Yield



Consistent placement error (PE) and hole open yield (HOY) week to week



Source: "DSA: How far have we come and how much further is left to go?"

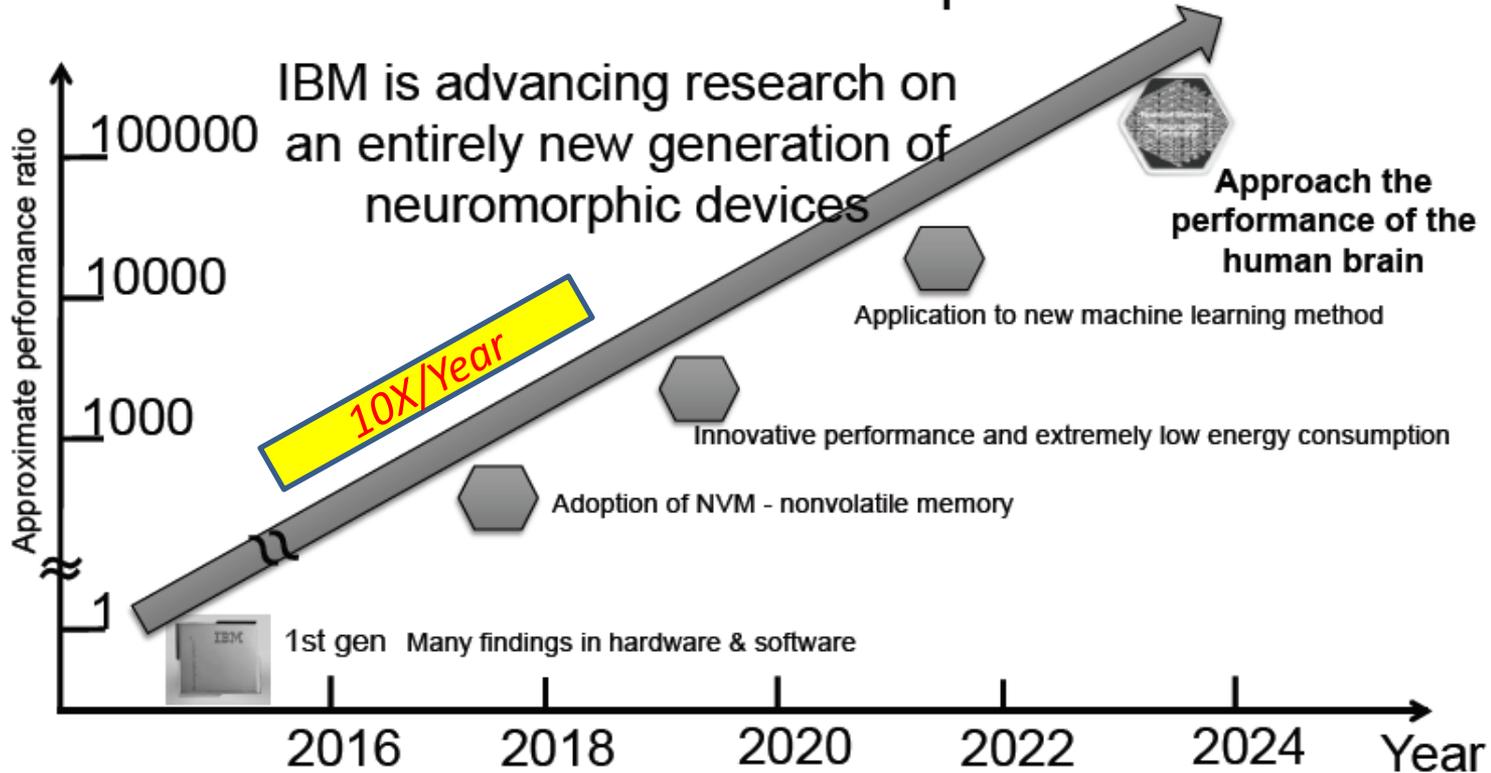


Darron Jurajda, Brewer Science, 2016

2024 - WOW!



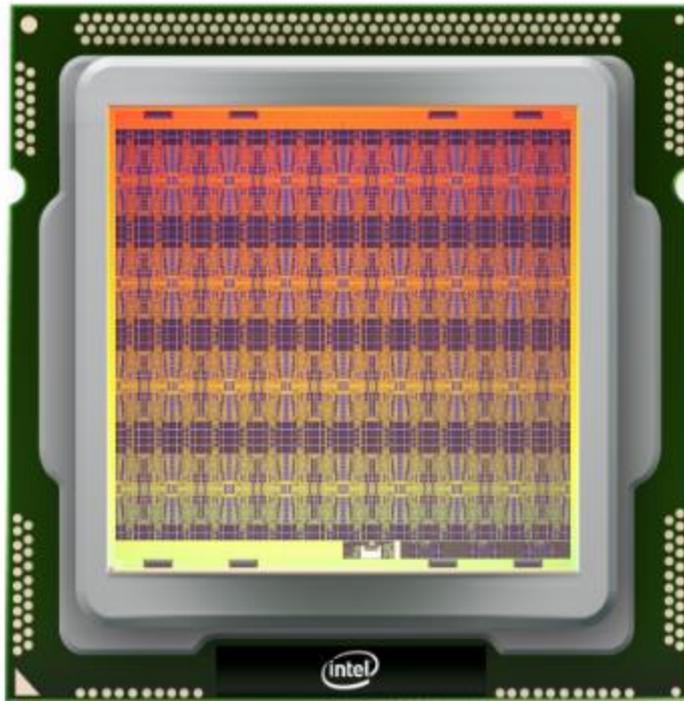
Conclusion – The future of Neuromorphic devices



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From “Neuromorphic device for Automotive” by Yoshifumi Sakamoto, Engineering and Cognitive Innovation, IBM Japan, LTD, email: sakay@jp.ibm.com

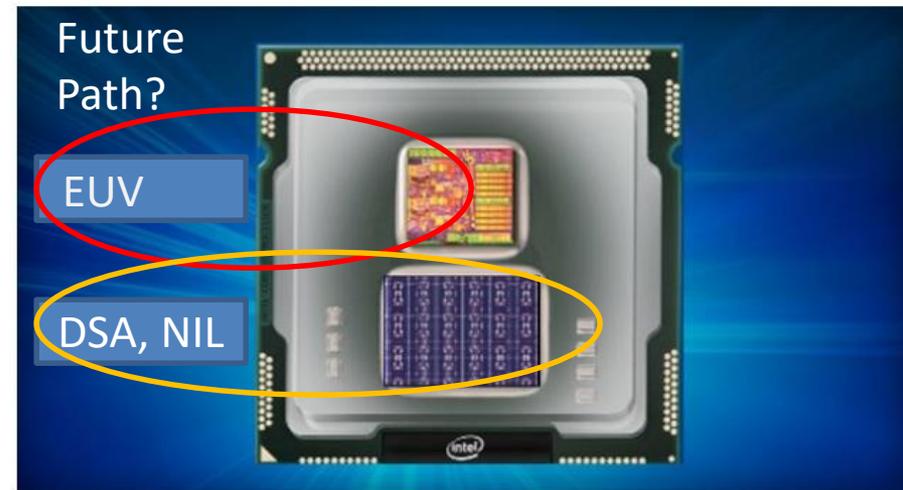
Defects – If you cannot beat them – Join them



Intel Unveils Neuromorphic, Self-Learning Chip Codenamed Loihi

By Joel Hruska on September 27, 2017 at 9:18 am | 14 Comments

1.1K shares f t G+ r Y



Loihi simulates a total of 130,000 neurons and 130 million synapses, all capable of communicating with each other... comparable to some small insects. For example, a common fruit fly, an insect studied for AI research, has about 250,000 neurons and 10 million synapses. ...human brain - 100 billion neurons,

<https://www.extremetech.com/computing/256467-intel-unveils-new-neuromorphic-self-learning-chip-codenamed-loihi>

CPU – Defect Intolerant – Traditional Litho
NMU- Defect Tolerant – Minimal Cost Litho

Defects: If you cannot beat them – join them

Von Neumann Computing will eventually hit scaling wall as defectivity requirements will reach $< 10^{-14}$ /chip features for overall 0.01/cm² defects/layer on a wafer.

Neuromorphic Computing can tolerate up to $4 \cdot 10^{-1}$ defects per network.

Neuromorphic Computing defect tolerance will enable continuation of Moore's Law by augmenting Von Neumann Control parts on the same 2 chip part.

Neuromorphic Computing is expected to be Artificial Intelligence workhorse.

IDC forecasts Global Revenue for Cognitive and AI Systems going from \$18B in 2017 to \$46B in 2020 and Global Cognitive and AI Systems Spending annual growth rate (CAGR) of 54.4% through 2020 . *Word of caution: AI is at the top of Gartner Hype Cycle now.*

Collaboration between Technologists and Computer Architects is needed to create compelling computing products that take advantage of defect tolerant manufacturing.

Directed Self Assembly and NanoImprint Lithography are in a good position to support Neuromorphic Computing parts patterning to provide necessary means to enable Moore's Law beyond capabilities of conventional Lithography

Thank you for
your attention!

Time for
Questions

Presentation Format

- Most of the information to be presented are from my previous public talks approved by my former employer, Intel, for external presentation and publications. Those foils will be copied “as is” and will have Intel logo, colored background and information on where and when those were presented.
- Foils made for this presentation will be on simple white background and will have no Intel logo.
- Multiple foils will be using materials presented or published by others during 2015-2018 and will have its source shown on the foil. My additions to those, if any, will be in italic red.