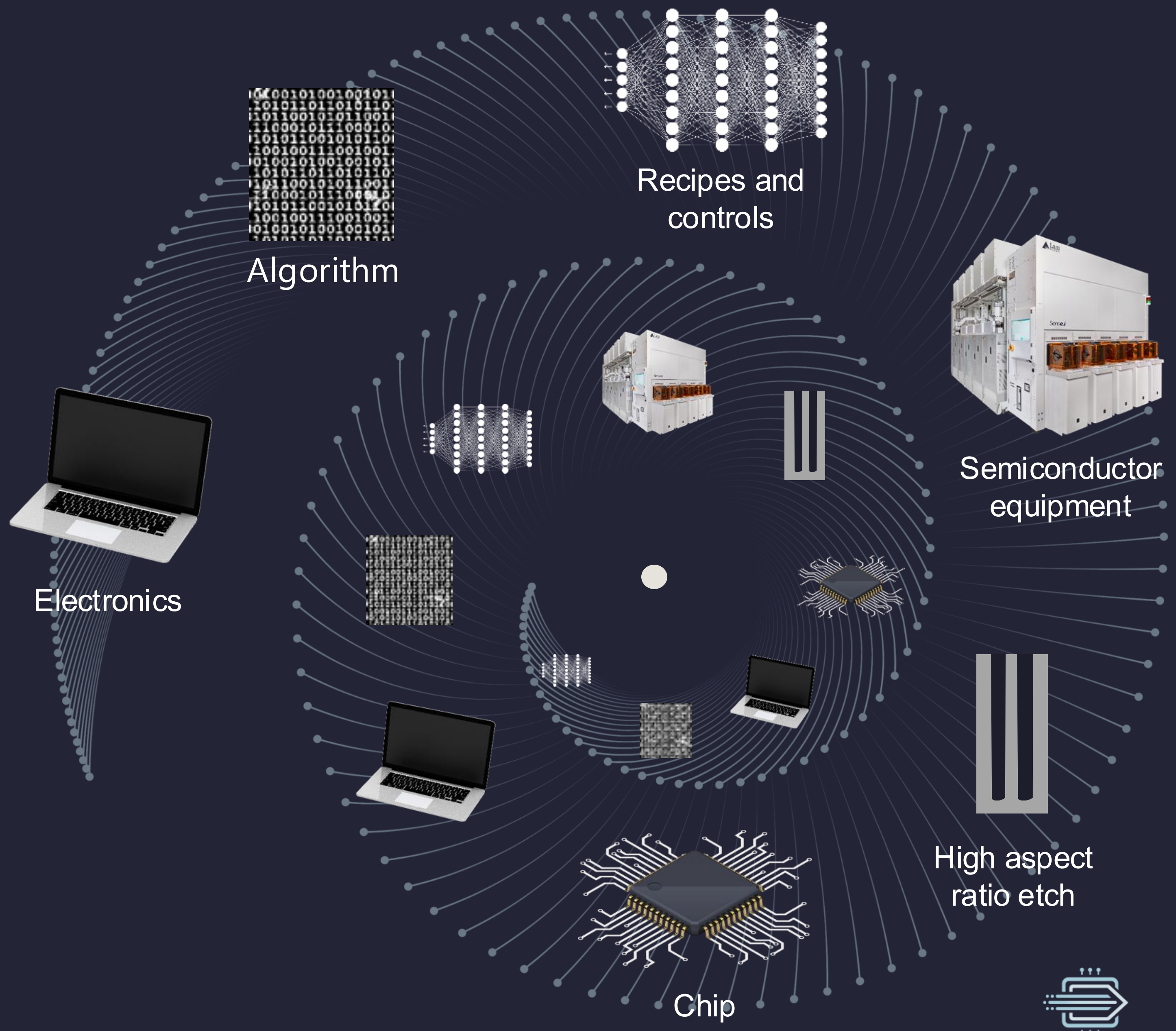
What goes around comes around: Using AI to make AI

Richard A. Gottscho, Ph.D.

President, SemiSan LLC
Former Exec VP and CTO of Lam Research



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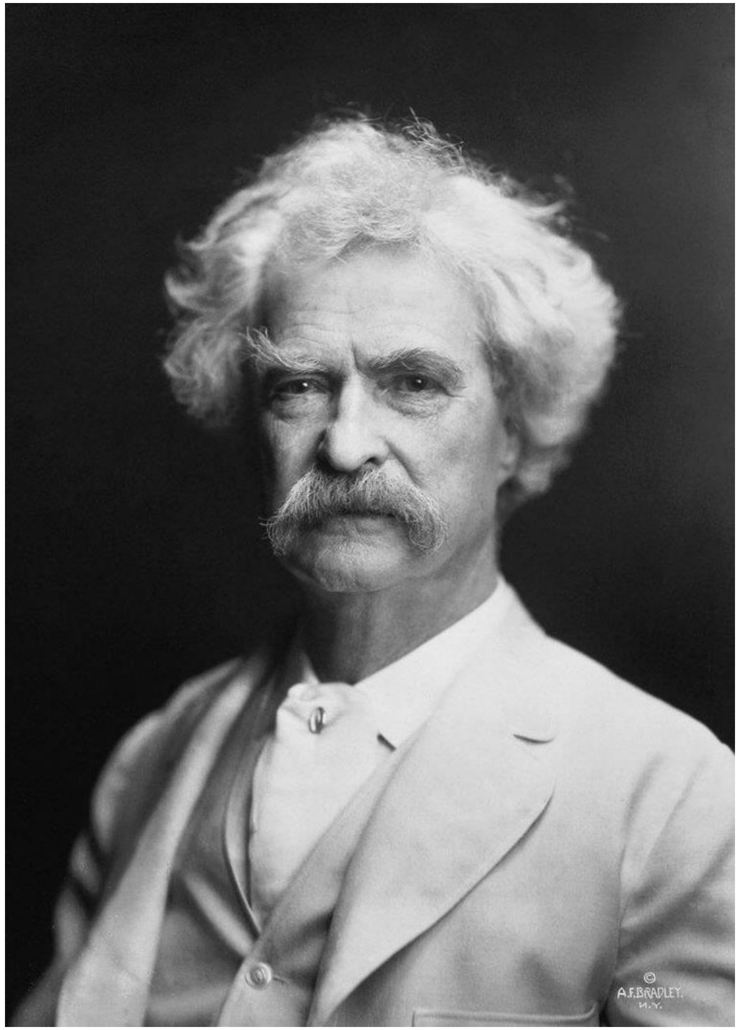
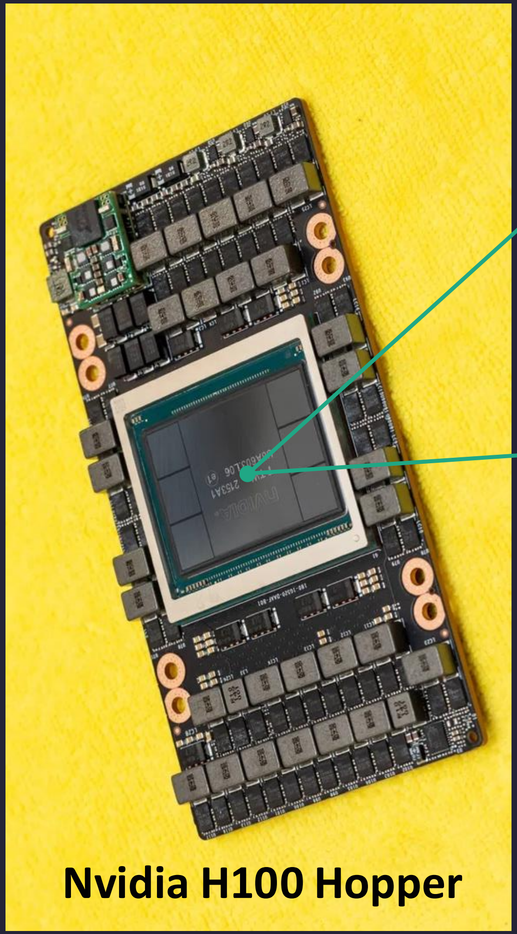


It ain't what you don't know that gets you into trouble. It's what you know for sure that just ain't so.

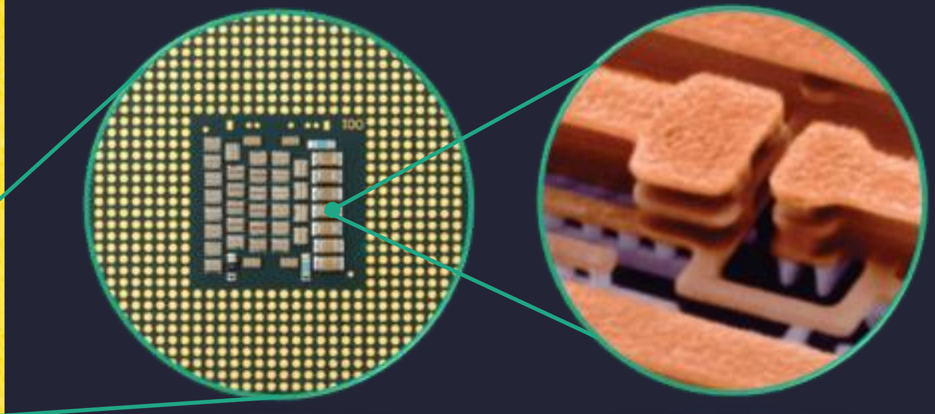
Mark Twain 1835-1910
American writer and humorist

SEMISAN

Inside every AI system are chips…



Nvidia H100 Hopper



At the heart of every electronic product is a complex microchip

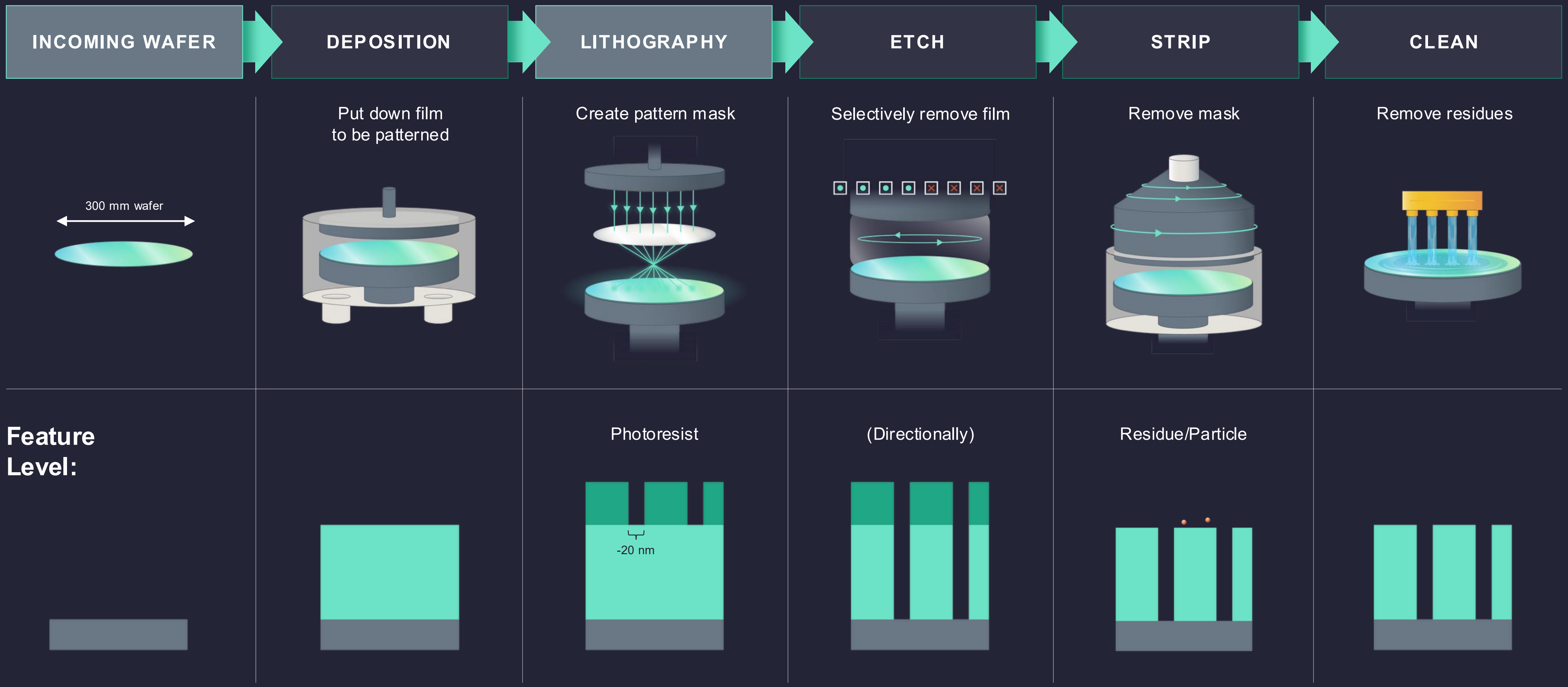
Each chip contains billions of transistors that require advanced technologies to create

Lam's equipment is used to manufacture these semiconductor devices with as many as 1000 process steps

Innovative people, designing and developing the process

Lam wafer fabrication equipment is behind virtually every chip on the market.

How chips are made



INCOMING WAFER	DEPOSITION	LITHOGRAPHY	ETCH	STRIP	CLEAN
	Put down film to be patterned	Create pattern mask	Selectively remove film	Remove mask	Remove residues
Feature Level:		Photoresist	(Directionally)	Residue/Particle	

Applied Materials: How do you make a semiconductor
Micron: The Hidden Steps of Semiconductor Manufacturing

Wafer fab equipment enables semiconductor industry

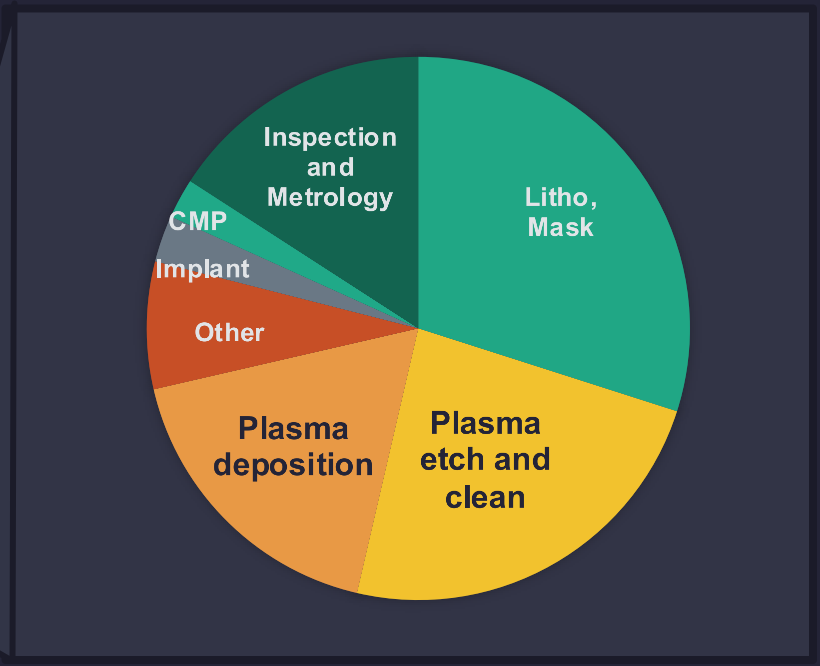
2024

Electronics
~$3.7 Trillion

Semiconductors
~$588 Billion

Wafer fab equipment
~$120 Billion

WFE segments



2024 WFE ranking

1	**Applied Materials**
2	**ASML**
3	**Tokyo Electron**
4	**Lam Research**
5	**KLA**

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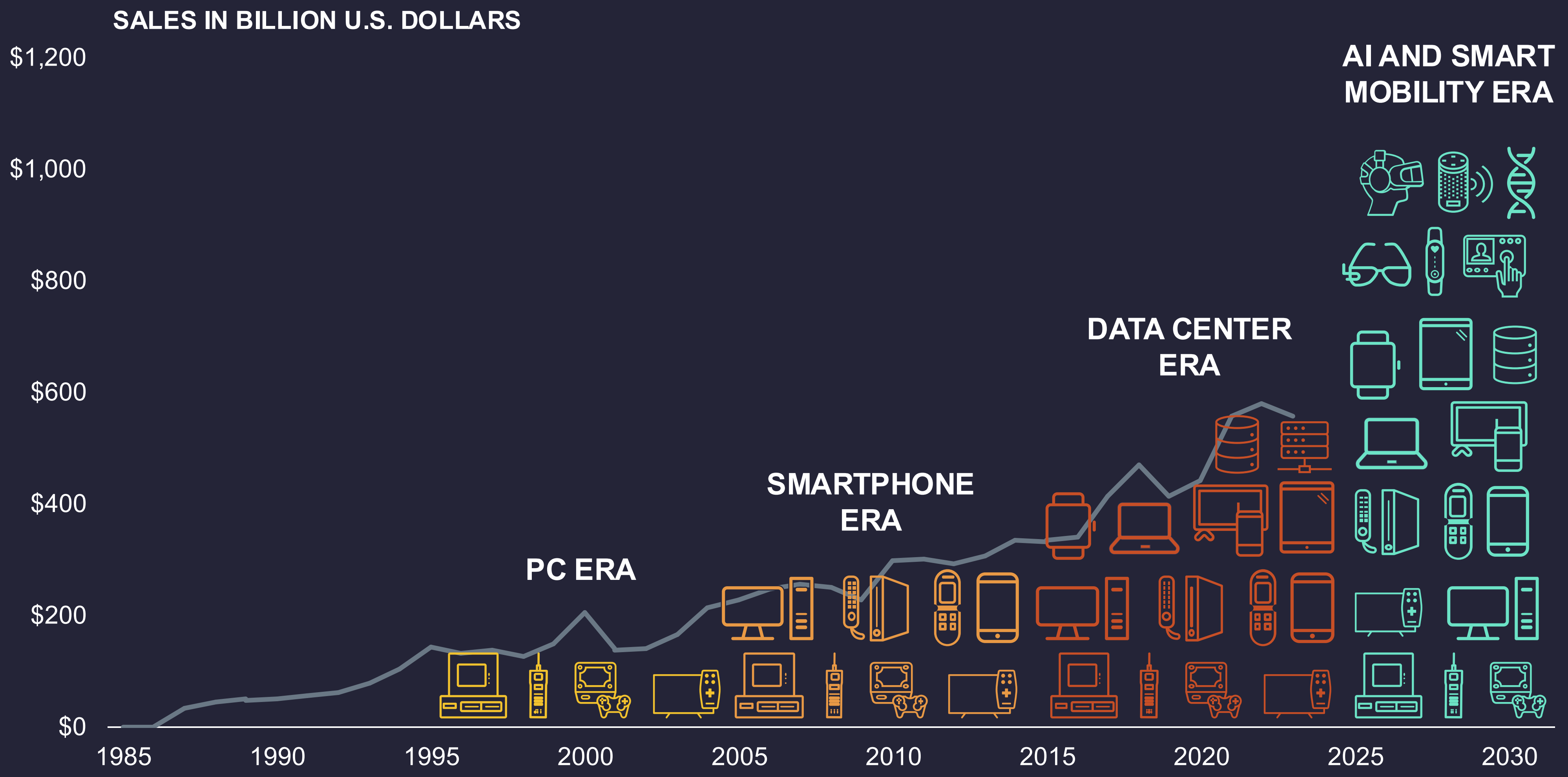
Data sources: WSTS, Gartner, VLSI, Lam Research internal

$1 trillion semiconductor industry:

A multitude of drivers to amplify industry growth



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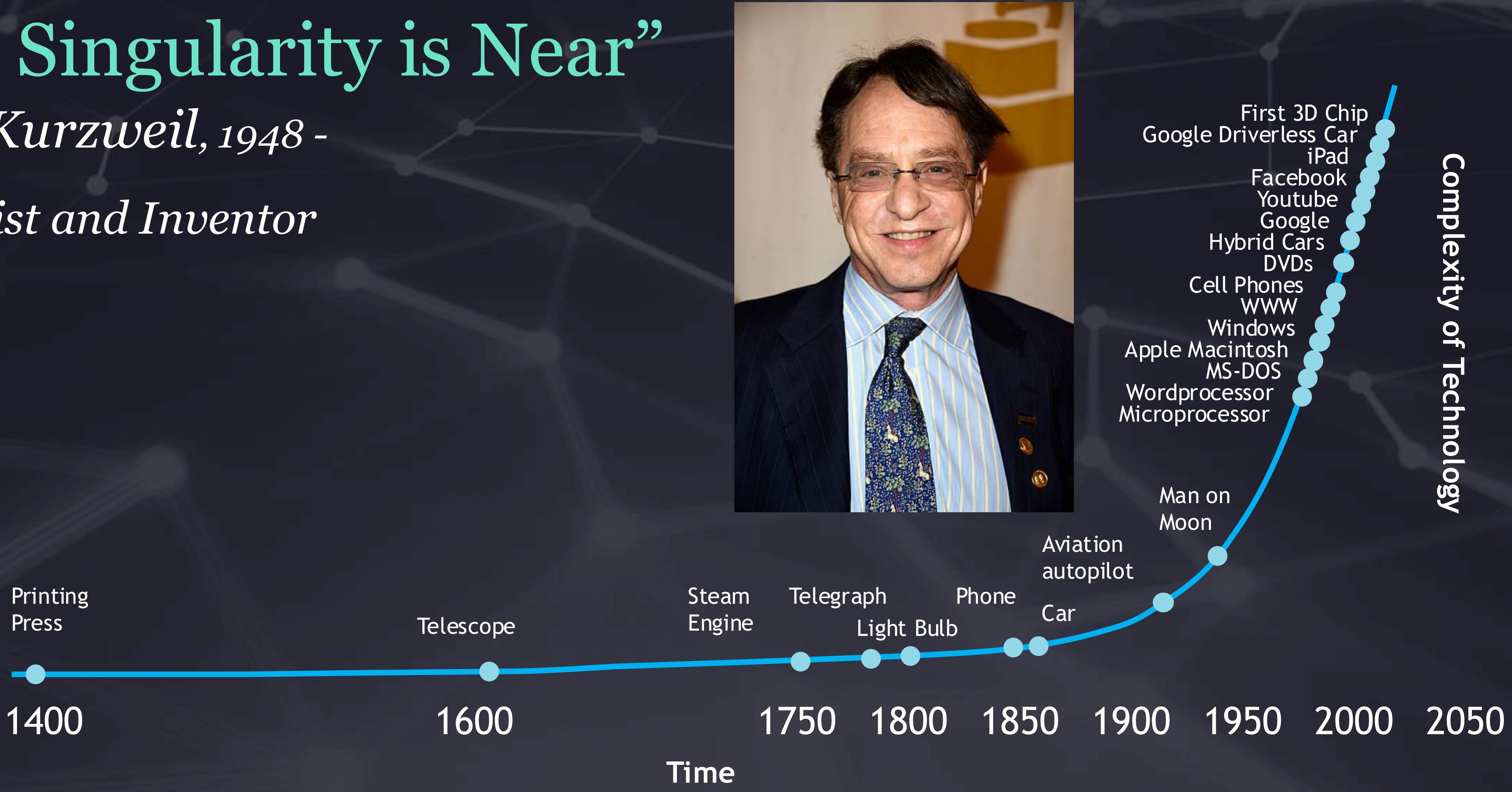
“The Singularity is Near”

Ray Kurzweil, 1948 -

Futurist and Inventor



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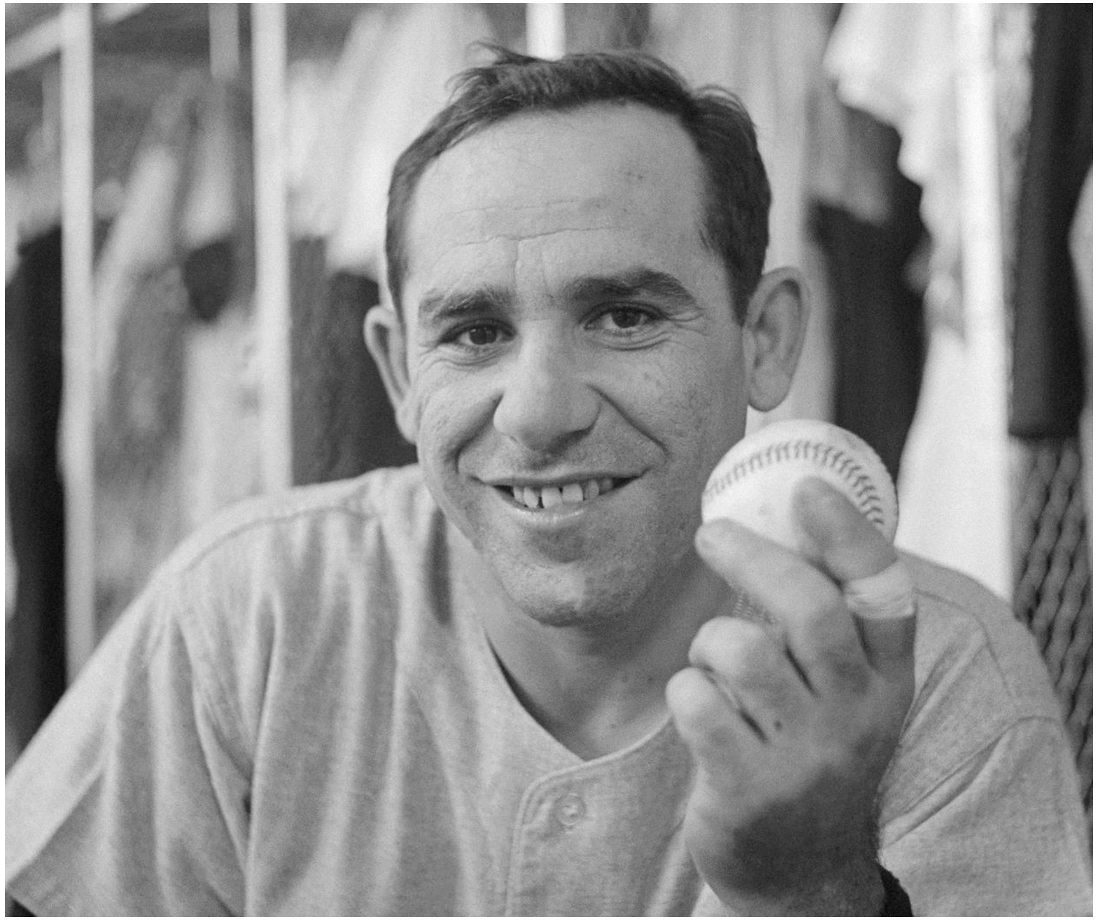
“The future ain’t what it used to be”



Yogi Berra, 1925-2015

NY Yankee

The *Semiverse* is Lam's vision for a new digital ecosystem: a seamlessly integrated digital and physical network created to foster creativity and problem solving through unprecedented global collaboration.

Tim Archer, Lam President & CEO,
Accelerating through the Semiverse, imec International Technology Forum, May 2022

Semiverse for *10,000x lower cost*

Virtualization *leverages* (<u>not replaces!</u>) investment in physical assets and real experiments

Virtual experimentation saves time, money, and resources (per recipe)

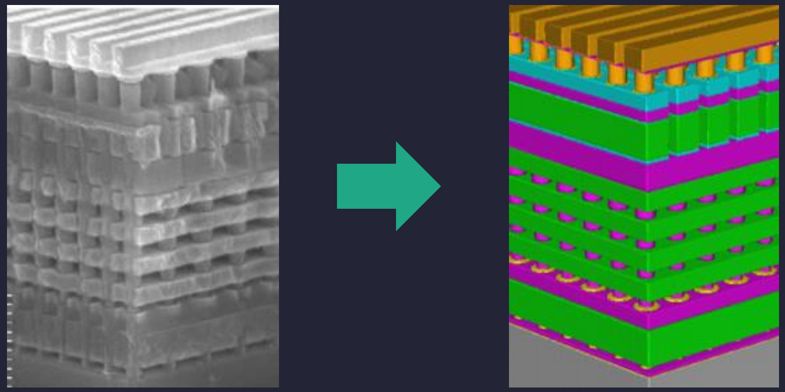
- Real experiments - $1000, 0.5 days
- Simulated experiments - $0.11, 8 mins
- Emulated simulations - $3e-07, 0.0013 s

Virtual experimentation can be ubiquitous and an effective workforce training tool

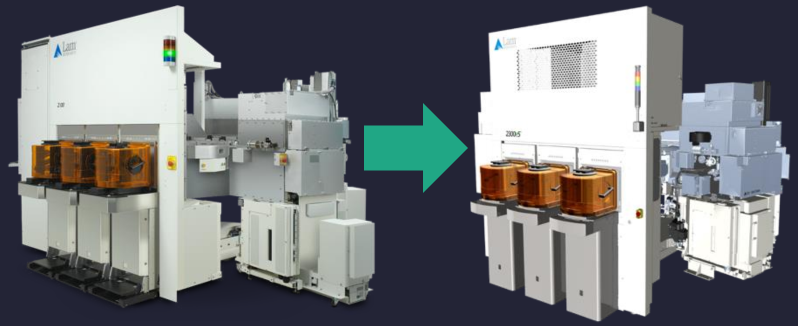
Barriers

- ***Business model***
- ***Some invention required***
- ***Data sharing/ownership concerns***

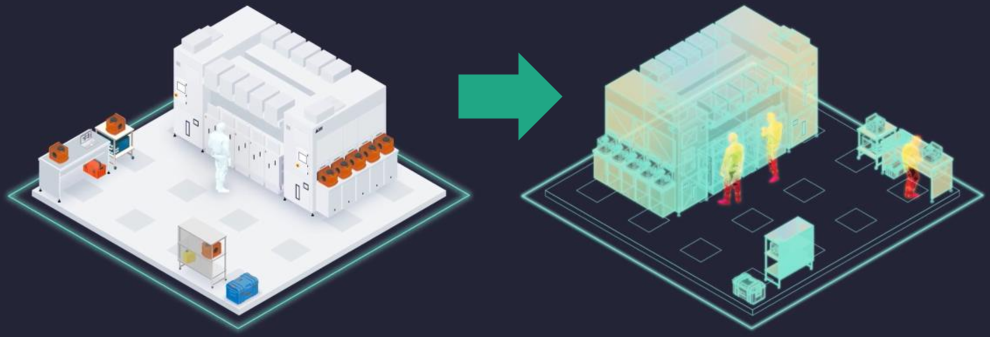
Virtual process:



Virtual tool:

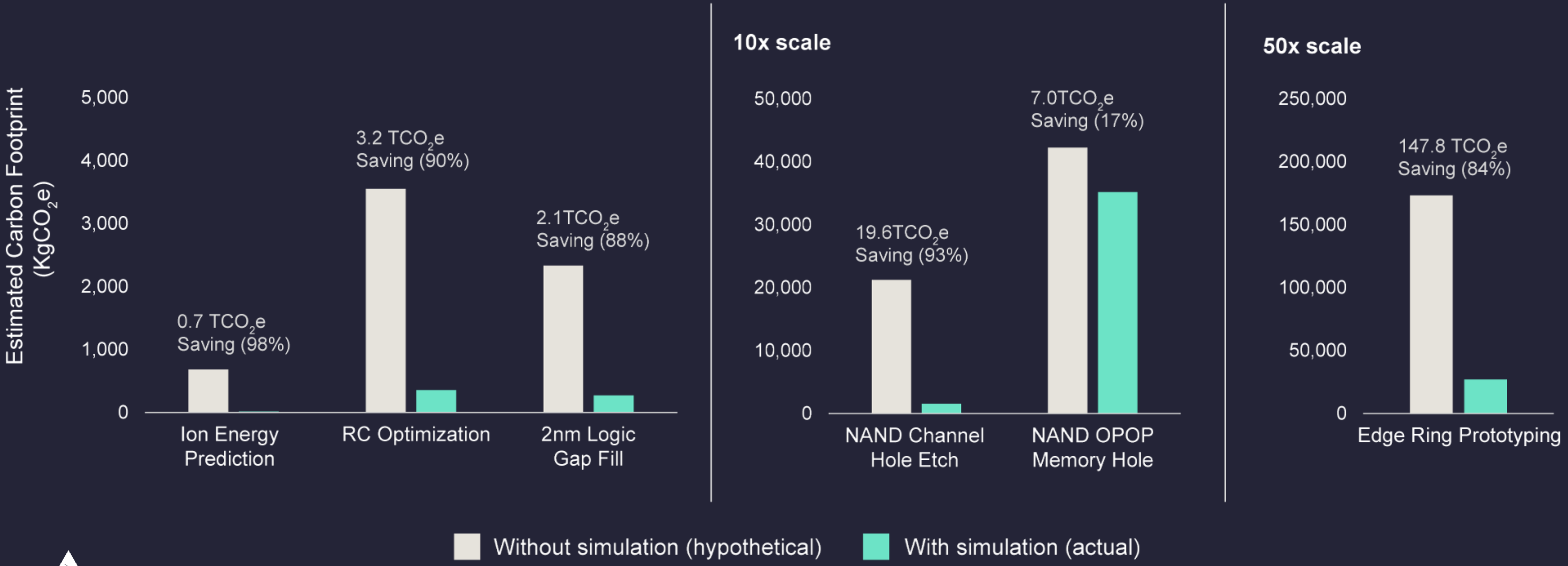


Virtual fab:



The Semiverse is GREENer

Every experiment investigated showed lower CO_2 equivalent from simulation



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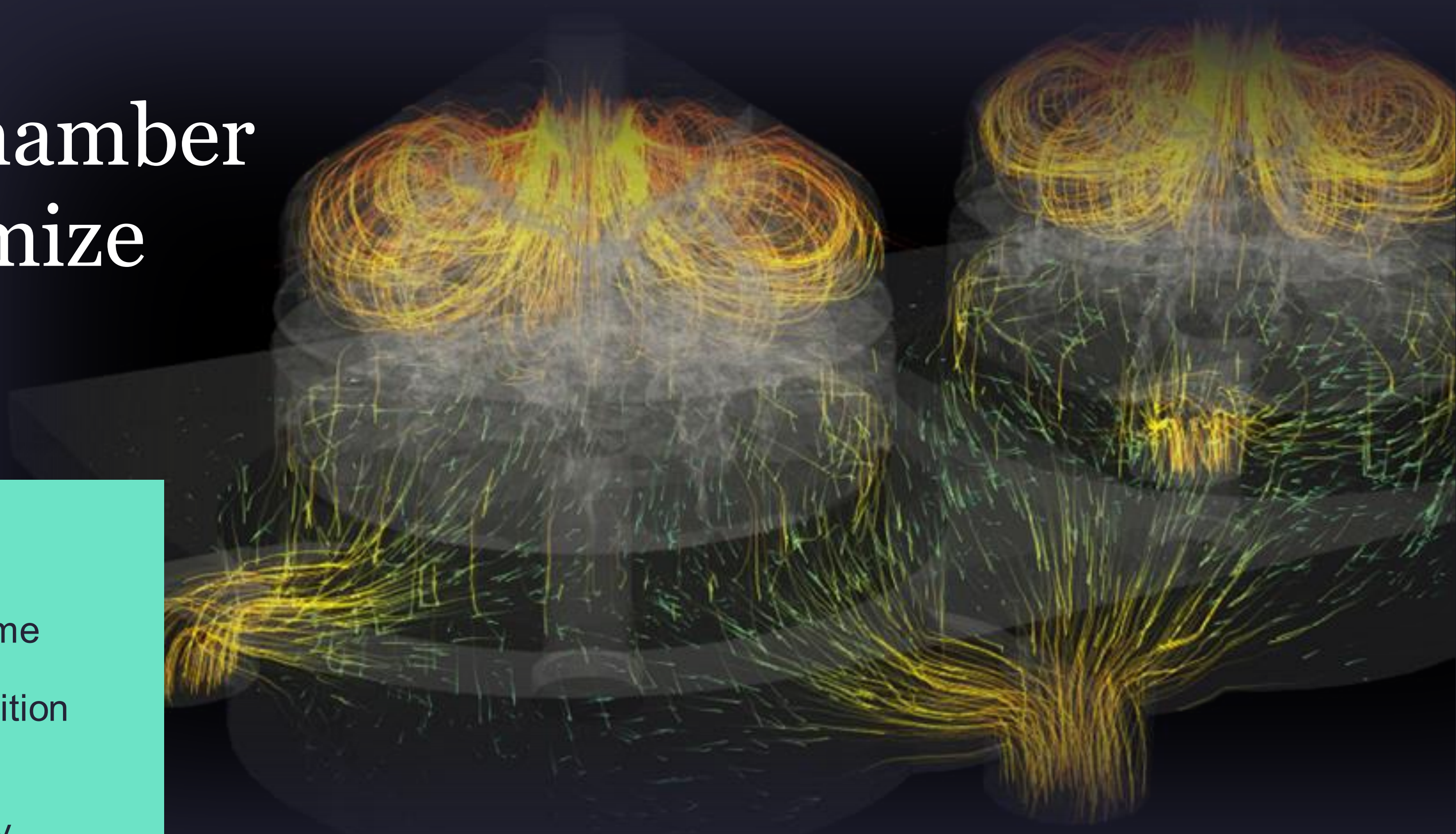
IEEE TRANSACTIONS ON SEMICONDUCTOR MANUFACTURING, VOL. 37, NO. 4, NOVEMBER 2024

Reactor-scale twin

Simulate operating conditions in the chamber to predict and optimize process behaviors

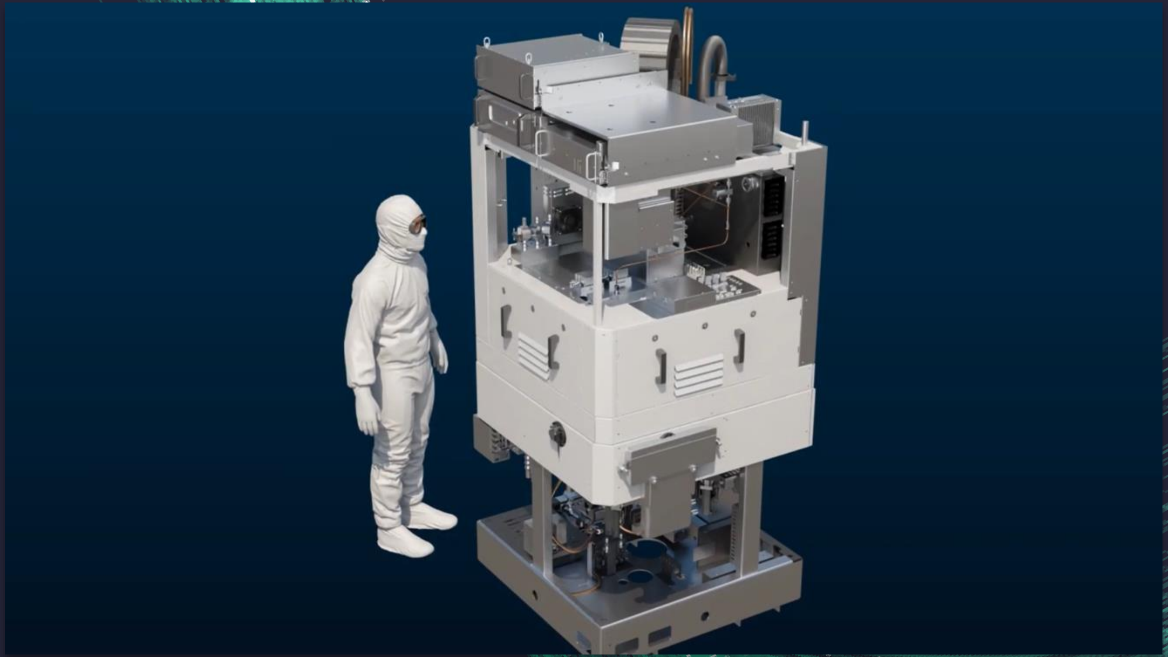


The power of transformation

- ⊕ Reduce product development cycle time
- ⊕ Accurately estimate the etch or deposition rate on the entire wafer surface
- ♻ Less waste with enhanced productivity

Equipment-scale twin

Improving first time right from design through install

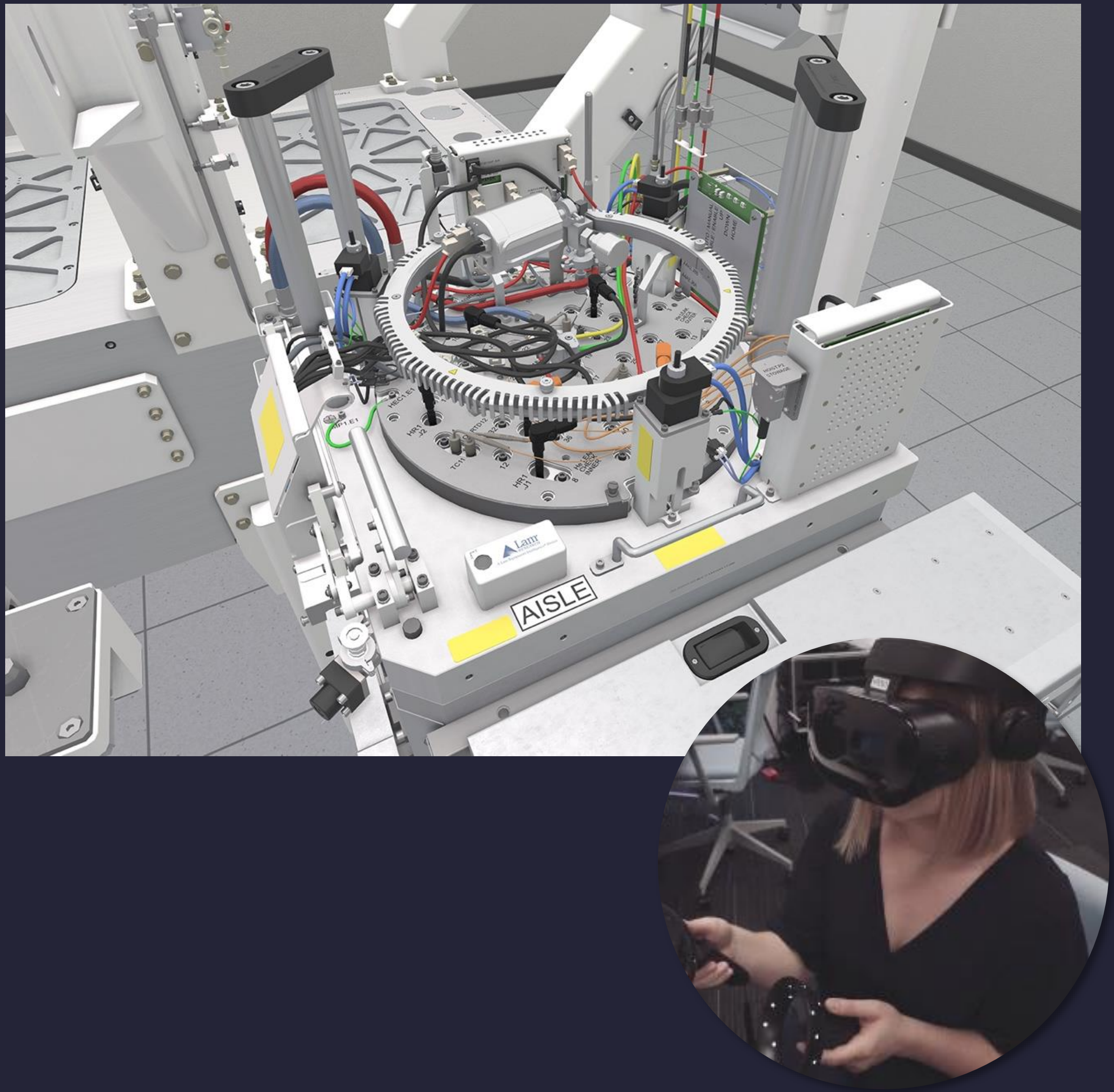


The power of transformation

- ⊕ Virtual design, build, test, and verification – find issues before physical build
- ⊕ Design for manufacturing and serviceability
- ♻ Less waste from fewer hardware iterations

Equipment-scale twin

Building equipment expertise faster and more effectively



The power of transformation

- Provides faster more complete learning for engineering workforce
- Allows more frequent refresher training and content updates
- Enable earlier access to new product training

Equipment-scale twin

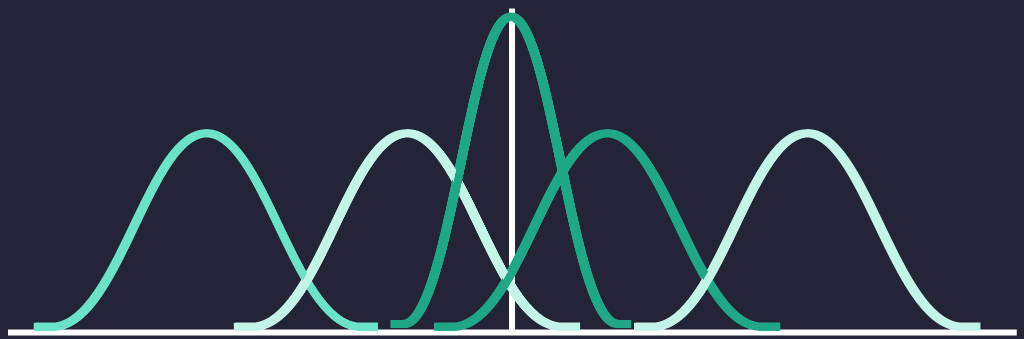
Reducing tool downtime with AI and AR enabled troubleshooting

The power of transformation

- AI identifies problem and prescribes fix using data and learning from various sources
- Minimizes engineering service labor and cost

Fab-scale twins

Using machine learning to achieve yield faster with chamber matching and fleet optimization

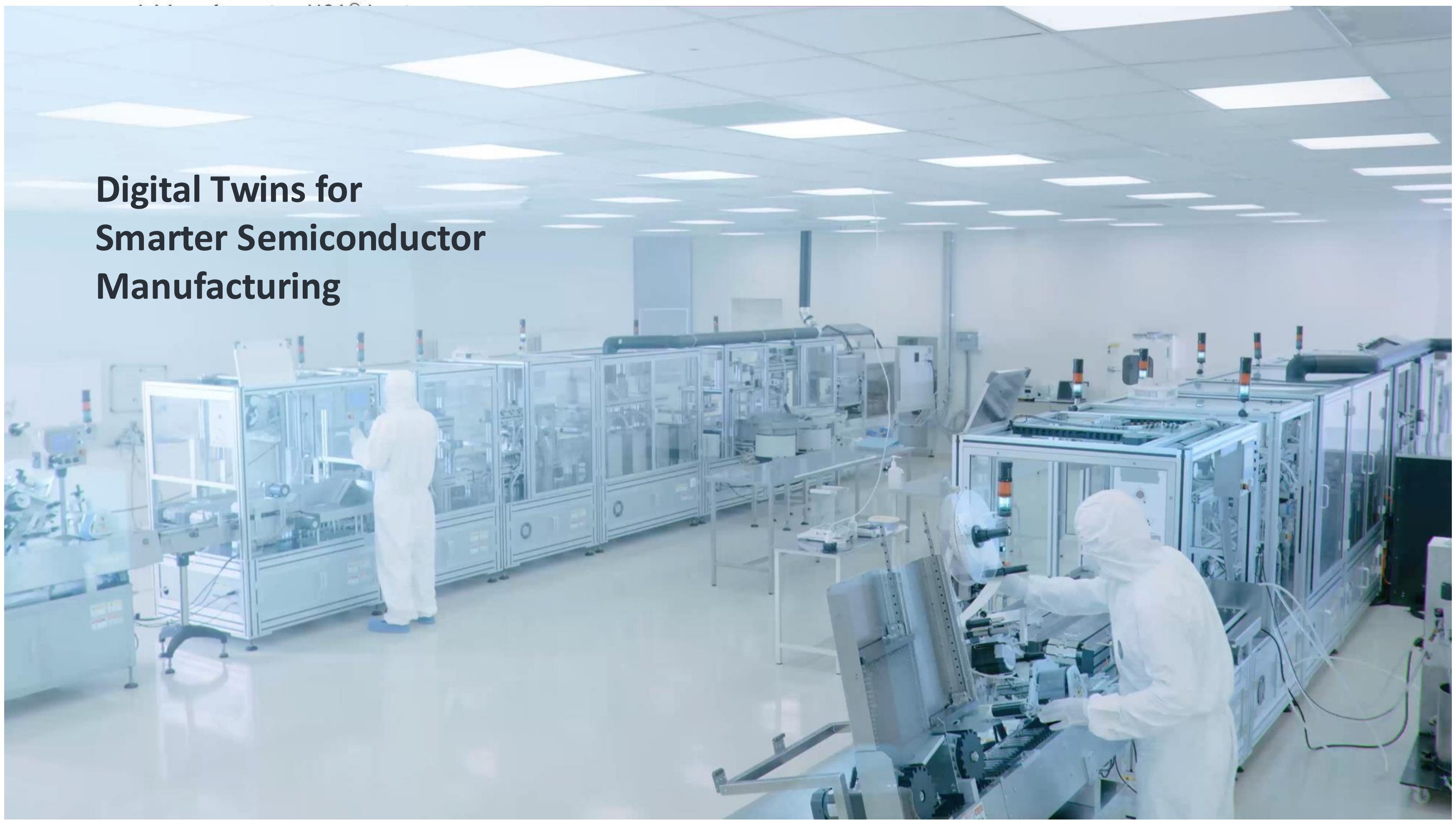


The power of transformation

- Accelerate chamber matching during install, shortening time to tool qualification
- Minimizes fleet performance variability
- Reduces engineering service labor

Semiconductor Manufacturing and Advanced Research with Twins

https://www.smartusatwins.org/



Digital Twins for Smarter Semiconductor Manufacturing

Ask ChatGPT

Please provide a summary of the state-of-the-art in the use of machine learning to optimize semiconductor chip manufacturing

Thought for 13 seconds…

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Machine learning (ML) has rapidly been adopted across semiconductor manufacturing, transitioning from traditional rule-based control to data-driven, adaptive systems. State-of-the-art ML methods now permeate every facet of semiconductor chip manufacturing—from virtual metrology and yield enhancement to recipe tuning, scheduling, and design automation.

Ongoing advancements in explainability, federated training, and quantum-inspired algorithms are poised to drive the next wave of efficiency, quality, and agility in semiconductor fabs.

References included in further reading list at end of this presentation

SEMISAN

Some Pertinent References

- E.A Rietman and E.R. Lory, “Use of neural networks in modeling semiconductor manufacturing processes: an example for plasma etch modeling.” Semiconductor Manufacturing, IEEE Transactions on Semiconductor Manufacturing 6(4):343 – 347 (1993)

- Anirudh et al., "2022 Review of Data-Driven Plasma Science," IEEE Trans. Plasma Sci., vol. 51, no. 7, July 2023.
  - Plasma science is entering a transformative data-driven era
  - Core technologies:
    - Surrogate modeling & Physics-Informed Neural Networks (PINNs)
    - Workflow automation, visualization, and uncertainty quantification

- Y.-L. Chen *et al.*, “Exploring Machine Learning for Semiconductor Process Optimization: A Systematic Review.” Jul. 16, 2024. doi: 10.36227/techrxiv.172114788.85190557/v1
  - Optimize semiconductor manufacturing
  - Literature survey identifying 58 publications

- A. D. Bonzanini, K. Shao, D. B. Graves, S. Hamaguchi, and A. Mesbah, “Foundations of machine learning for low-temperature plasmas: methods and case studies,” *Plasma Sources Science and Technology*, vol. 32, no. 2, Feb. 2023, doi: 10.1088/1361-6595/acb28c.

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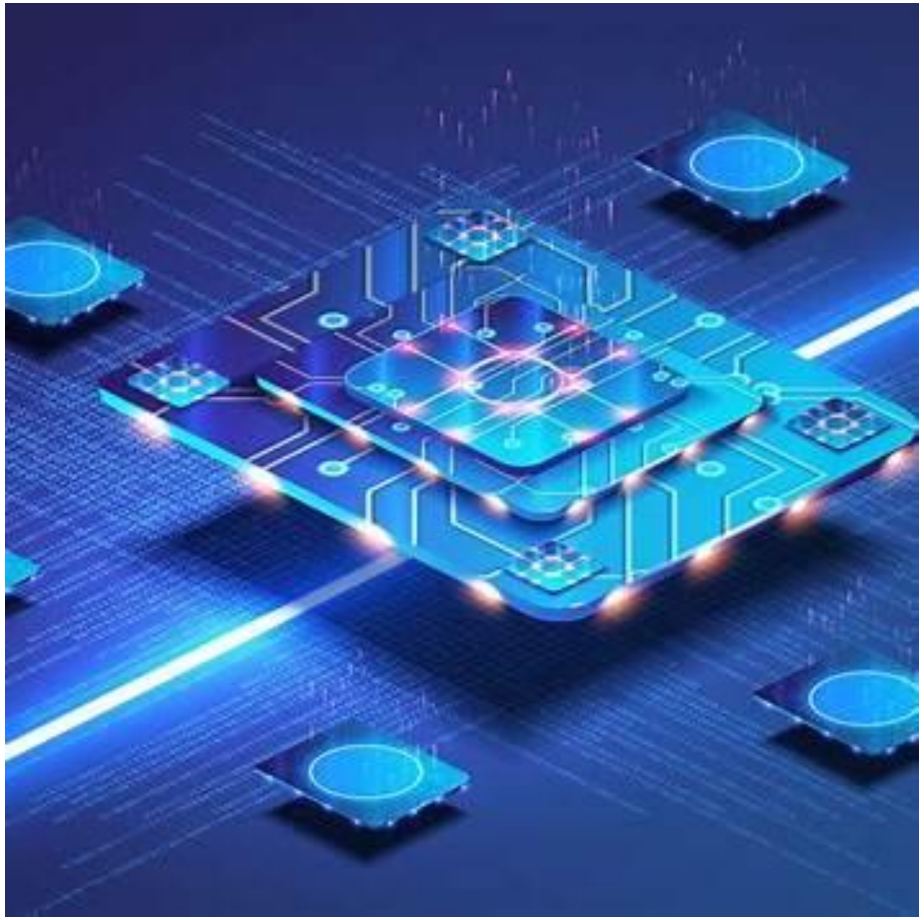
Manufacturing leads the way with lots of cheap data

- For a typical fleet of tools
  - 100 sensors, 200 chambers
  - 2000 status variables
  - 100’s of process steps
  - 5 Hz frequency
- How much data per fleet?
  - 5000 features extracted per wafer run
  - 100 million feature data points per day
  - 5-10 billion raw data points per day

AI in Chip Design

- **Automated Floor-planning & Placement**
  - Placing blocks (compute, memory, I/O) optimally.
  - Google's DeepMind-trained AI delivers better layouts for TPU chips in <24 hours
- **Generative EDA Tools**
  - ML models to explore countless design variants and optimize multi-objective trade-offs (power, timing, area).
  - Synopsys' DSO.ai applies ML to chip design workflows; Cadence's Cerebrus uses reinforcement learning for automatic optimization of placement, routing, and power use
- **Physics-aware & Antenna Modeling**
  - Co-design circuits with electromagnetic properties in mind.
  - Achieves faster and better designs for RF/wireless amplifiers—often beyond human capability



iln.ieee.org+12spectrum.ieee.org+12ece.engin.umich.edu+1

https://www.aegissofttech.com/insights/ai-in-semiconductor-industry/?utm_source=chatgpt.com

https://engineering.princeton.edu/news/2025/01/06/ai-slashes-cost-and-time-chip-design-not-all?utm_source=chatgpt.com

Why can’t we design a process like we design a chip?

SPEC

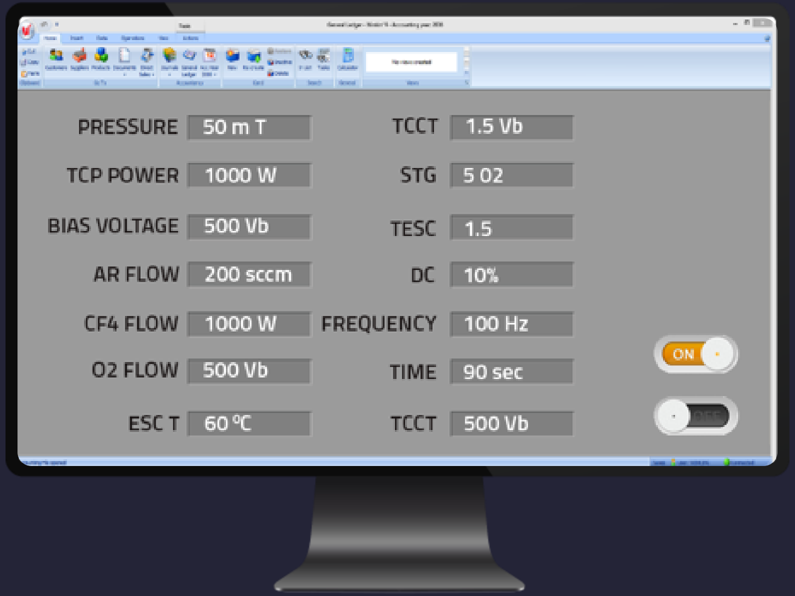
CD 50

PROFILE 80º

SELECTIVITY 20:1

ETCH DEPTH 50

RECIPE



PRESSURE 50 m T

TCP POWER 1000 W

BIAS VOLTAGE 500 Vb

AR FLOW 200 sccm

CF4 FLOW 1000 W

O2 FLOW 500 Vb

ESC T 60 ºC

TCCT 1.5 Vb

STG 5 02

TESC 1.5

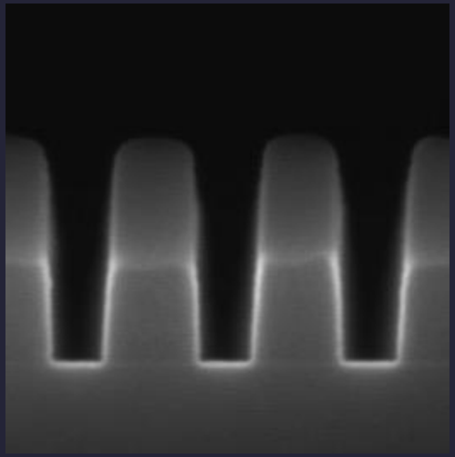
DC 10%

FREQUENCY 100 Hz

TIME 90 sec

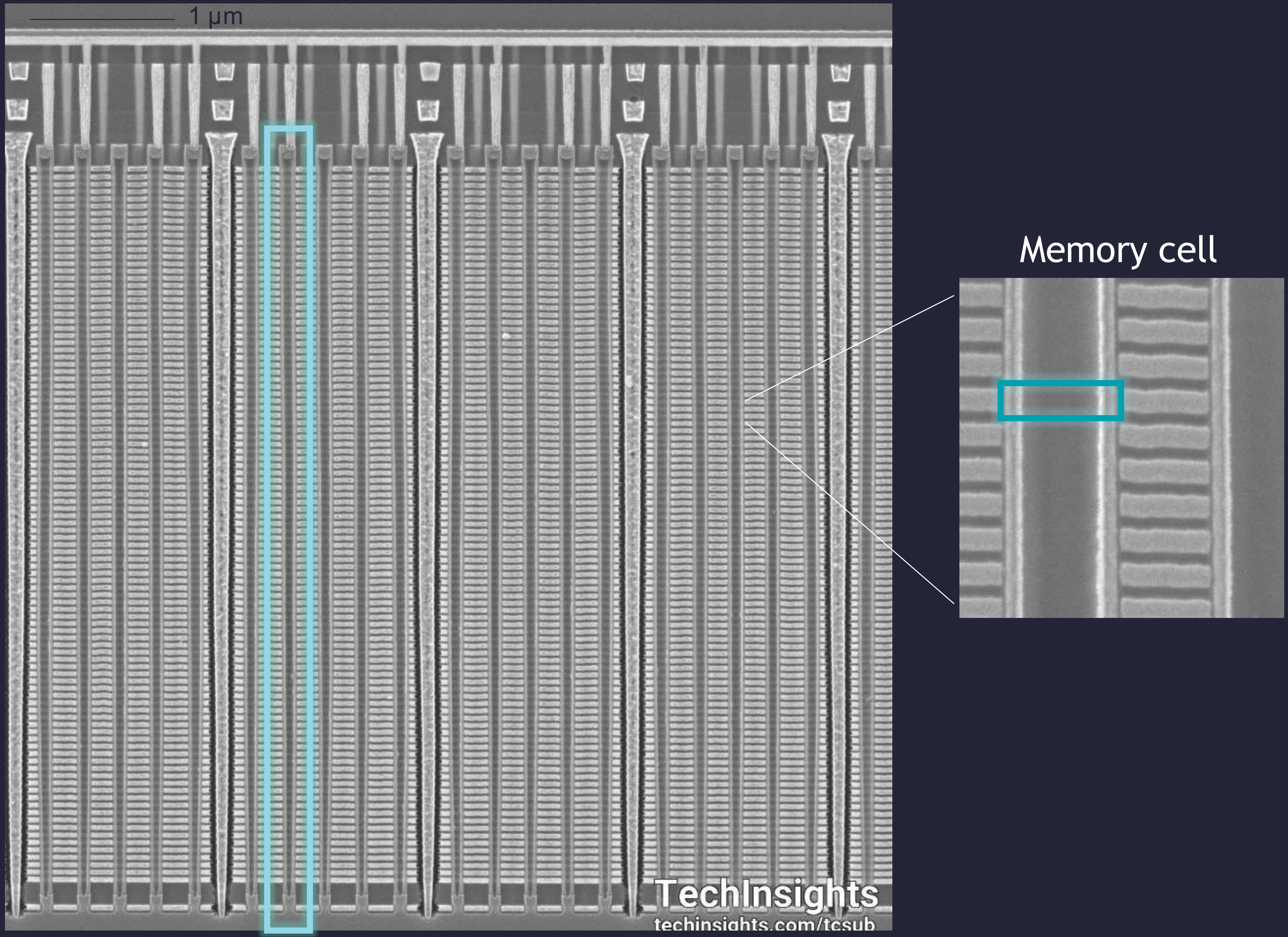
TCCT 500 Vb

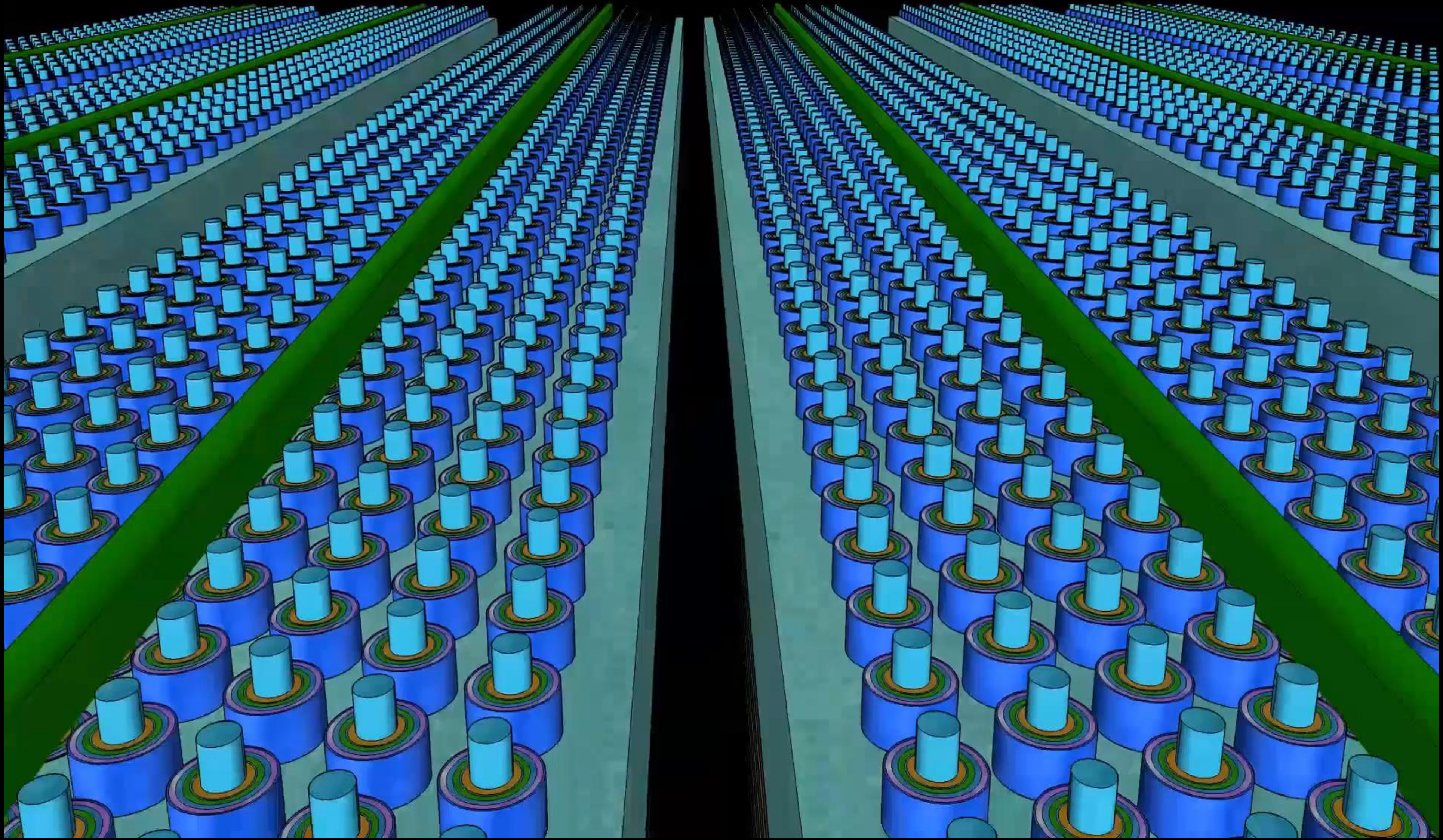
RESULT



Consider memory hole etch in 3D NAND

SEM of 3D NAND Samsung 92L, 256Gb, TLC, Tech Insights

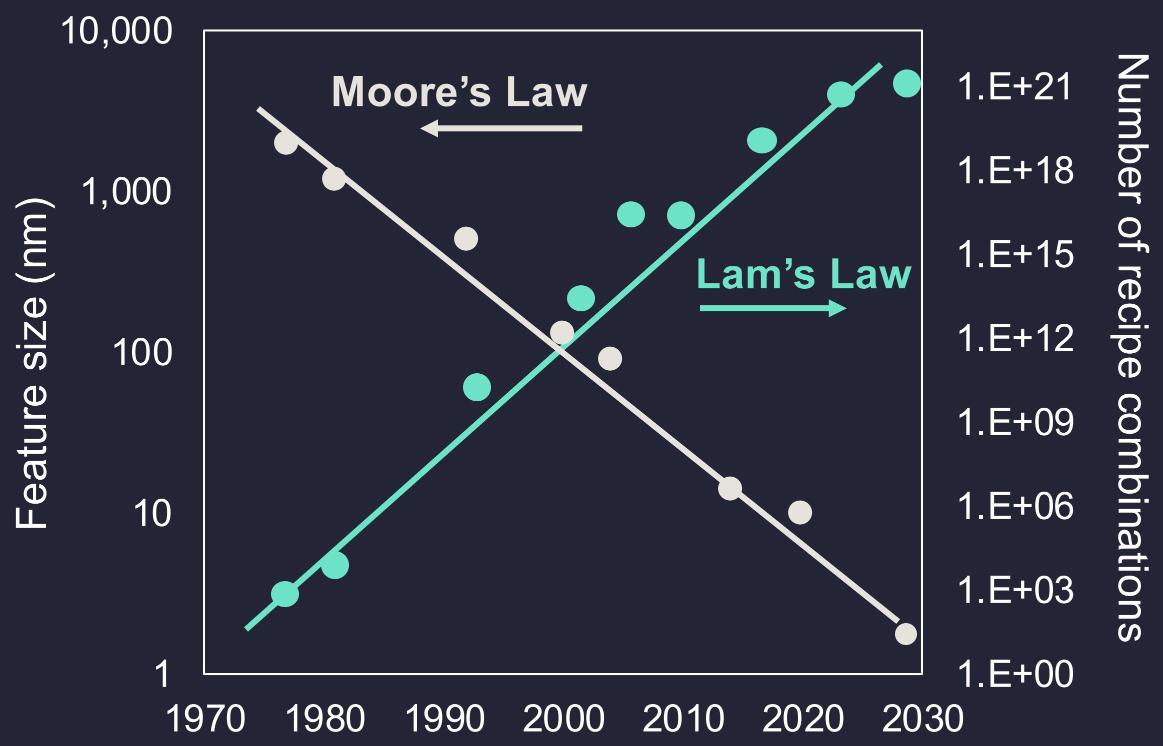




Why not just use a *big data* approach?

Simply put, it costs too much and takes too long

Little data world but *big* dimensional space



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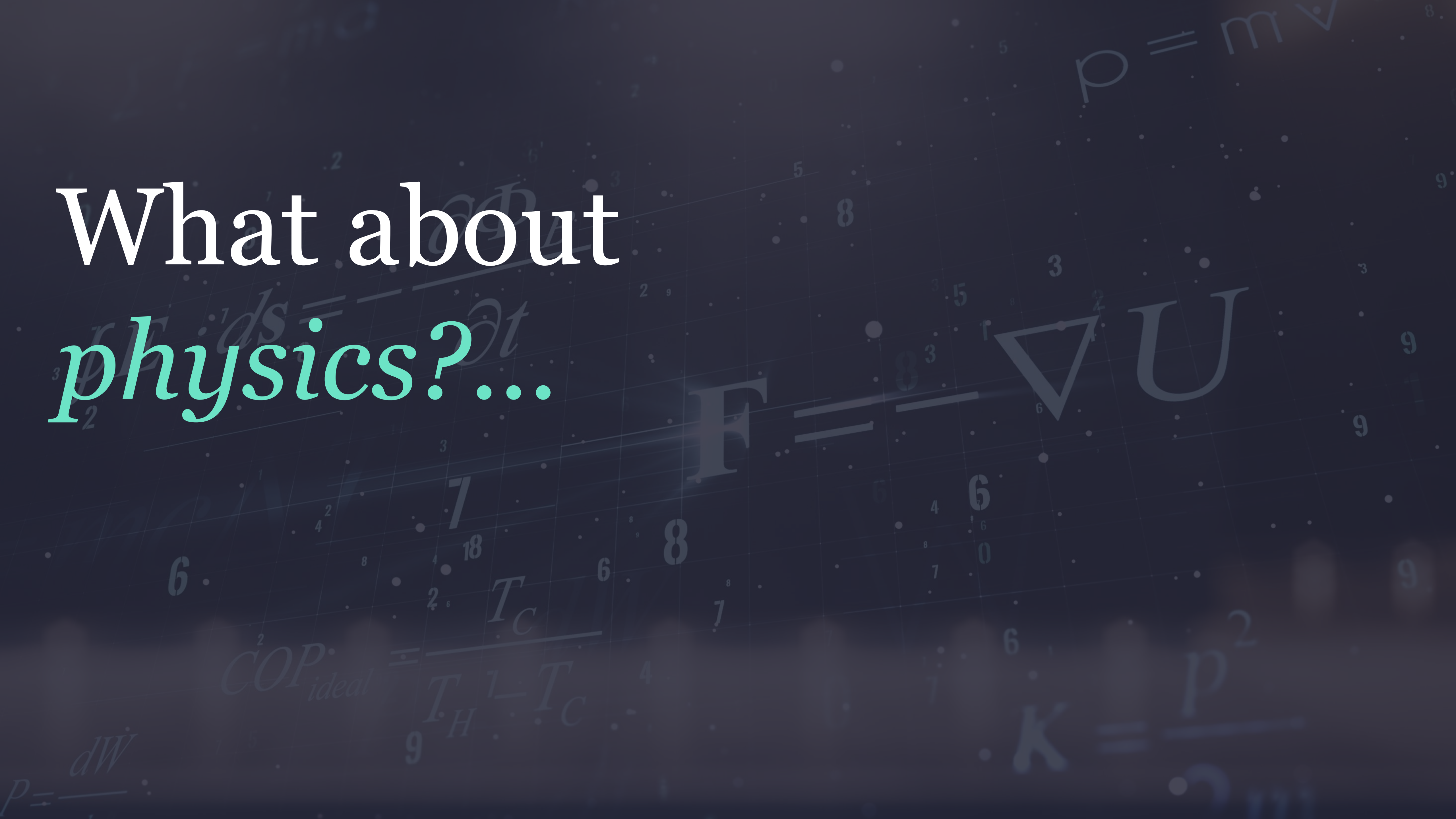
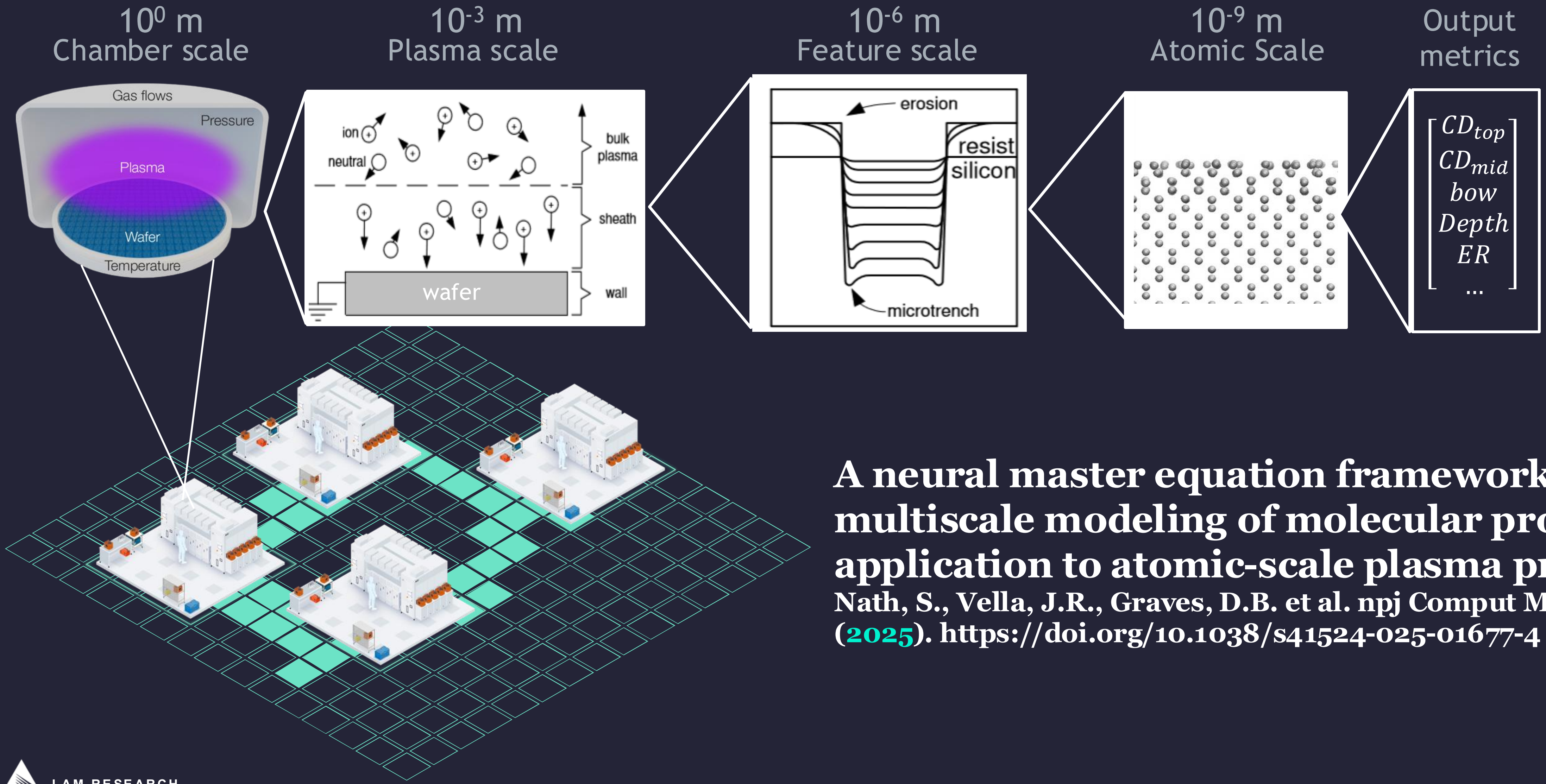
What about *physics?...*



Scales that span at least nine orders of magnitude



A neural master equation framework for multiscale modeling of molecular processes: application to atomic-scale plasma processes

Nath, S., Vella, J.R., Graves, D.B. et al. npj Comput Mater 11, 231 (2025). https://doi.org/10.1038/s41524-025-01677-4

Complexity Reduction and Semi-Empiricism

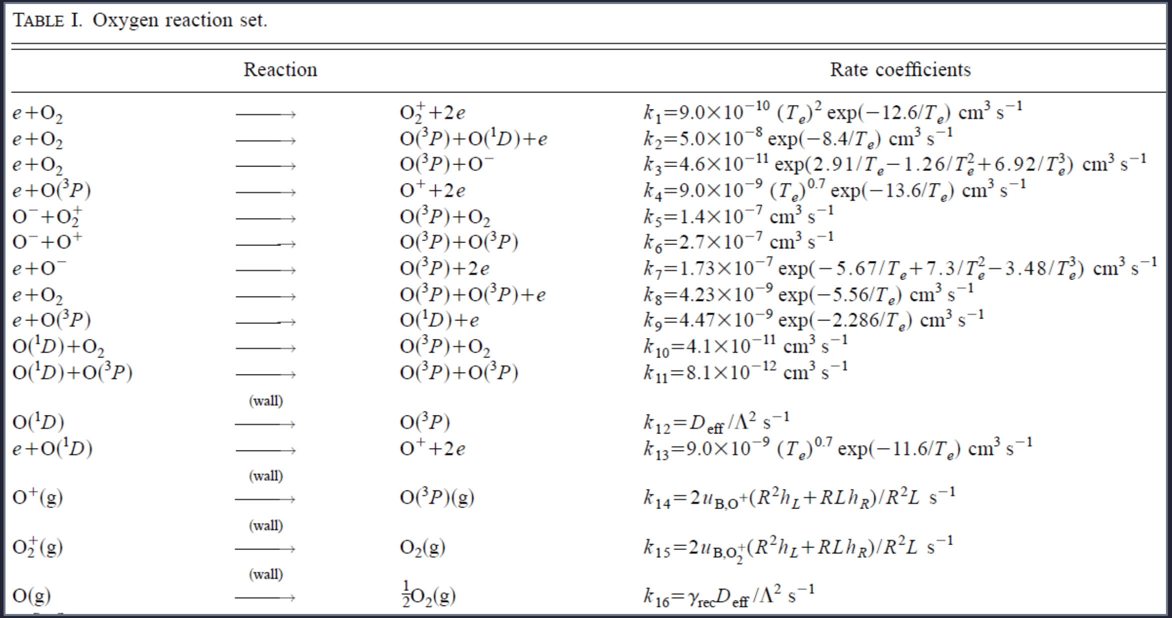
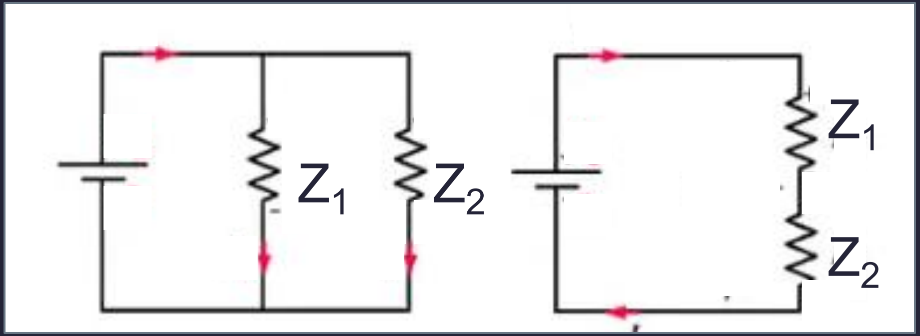


TABLE I. Oxygen reaction set.

Reaction			Rate coefficients
$e+O_2$	$\longrightarrow$	O_2^++2e	$k_1=9.0\times10^{-10}\ (T_e)^2 \exp(-12.6/T_e)\ \text{cm}^3\ \text{s}^{-1}$
$e+O_2$	$\longrightarrow$	$O(^3P)+O(^1D)+e$	$k_2=5.0\times10^{-8} \exp(-8.4/T_e)\ \text{cm}^3\ \text{s}^{-1}$
$e+O_2$	$\longrightarrow$	$O(^3P)+O^-$	$k_3=4.6\times10^{-11} \exp(2.91/T_e-1.26/T_e^2+6.92/T_e^3)\ \text{cm}^3\ \text{s}^{-1}$
$e+O(^3P)$	$\longrightarrow$	O^++2e	$k_4=9.0\times10^{-9}\ (T_e)^{0.7} \exp(-13.6/T_e)\ \text{cm}^3\ \text{s}^{-1}$
$O^-+O_2^+$	$\longrightarrow$	$O(^3P)+O_2$	$k_5=1.4\times10^{-7}\ \text{cm}^3\ \text{s}^{-1}$
O^-+O^+	$\longrightarrow$	$O(^3P)+O(^3P)$	$k_6=2.7\times10^{-7}\ \text{cm}^3\ \text{s}^{-1}$
$e+O^-$	$\longrightarrow$	$O(^3P)+2e$	$k_7=1.73\times10^{-7} \exp(-5.67/T_e+7.3/T_e^2-3.48/T_e^3)\ \text{cm}^3\ \text{s}^{-1}$
$e+O_2$	$\longrightarrow$	$O(^3P)+O(^3P)+e$	$k_8=4.23\times10^{-9} \exp(-5.56/T_e)\ \text{cm}^3\ \text{s}^{-1}$
$e+O(^3P)$	$\longrightarrow$	$O(^1D)+e$	$k_9=4.47\times10^{-9} \exp(-2.286/T_e)\ \text{cm}^3\ \text{s}^{-1}$
$O(^1D)+O_2$	$\longrightarrow$	$O(^3P)+O_2$	$k_{10}=4.1\times10^{-11}\ \text{cm}^3\ \text{s}^{-1}$
$O(^1D)+O(^3P)$	$\longrightarrow$	$O(^3P)+O(^3P)$	$k_{11}=8.1\times10^{-12}\ \text{cm}^3\ \text{s}^{-1}$
$O(^1D)$	$\xrightarrow{\text{(wall)}}$	$O(^3P)$	$k_{12}=D_{\text{eff}}/\Lambda^2\ \text{s}^{-1}$
$e+O(^1D)$	$\longrightarrow$	O^++2e	$k_{13}=9.0\times10^{-9}\ (T_e)^{0.7} \exp(-11.6/T_e)\ \text{cm}^3\ \text{s}^{-1}$
$O^+(g)$	$\xrightarrow{\text{(wall)}}$	$O(^3P)(g)$	$k_{14}=2u_{B,O^+}(R^2h_L+RLh_R)/R^2L\ \text{s}^{-1}$
$O_2^+(g)$	$\xrightarrow{\text{(wall)}}$	$O_2(g)$	$k_{15}=2u_{B,O_2^+}(R^2h_L+RLh_R)/R^2L\ \text{s}^{-1}$
$O(g)$	$\xrightarrow{\text{(wall)}}$	$\frac{1}{2}O_2(g)$	$k_{16}=\gamma_{\text{rec}}D_{\text{eff}}/\Lambda^2\ \text{s}^{-1}$

PARALLEL **SERIES**



$$\frac{1}{Z_{eff}} = \frac{1}{Z_1} + \frac{1}{Z_2}$$

$$Z_{eff} = Z_1 + Z_2$$

$Z_{eff} \sim Z_1$
When $Z_2 >> Z_1$

$Z_{eff} \sim Z_2$
When $Z_2 >> Z_1$

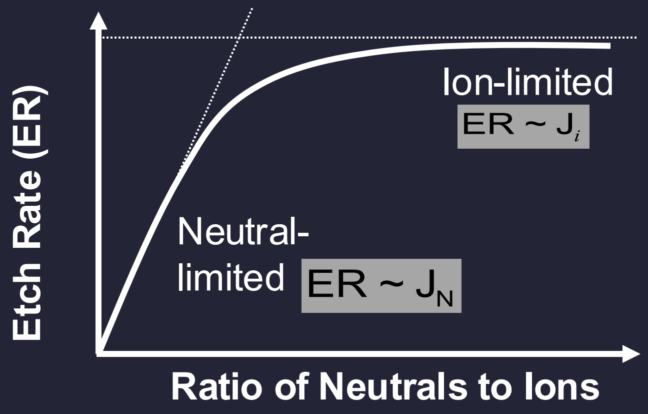
Where Z ≡ chemical impedance ~1/keff

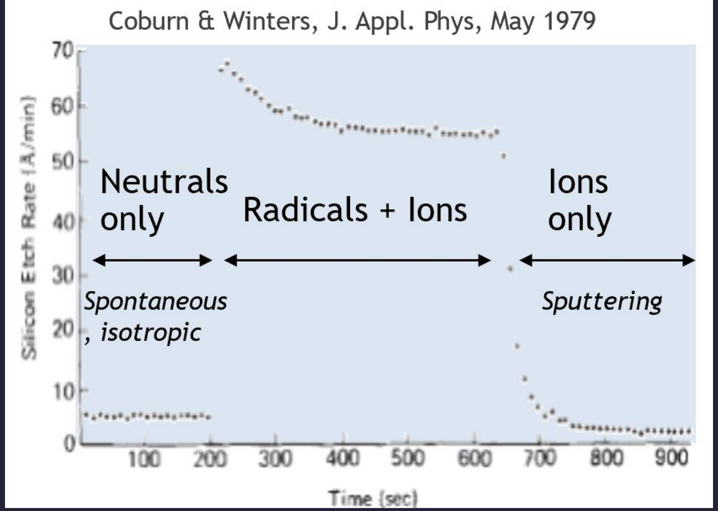
Source: Lee and Lieberman, global model, 1994

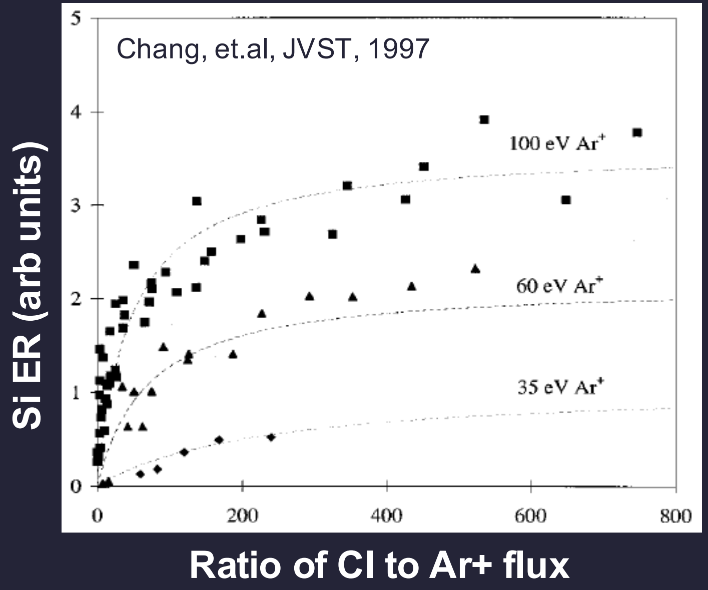
Basic Plasma Etch Mechanism: Ion-Neutral Synergy

$$\text{Etch Rate} \approx \frac{1}{\dfrac{U_O}{\left(\varepsilon_i^{1/2}-\varepsilon_{th}^{1/2}\right)_i \cdot J_i}+\dfrac{1}{\nu \cdot S_0 \cdot J_N}}$$

Ion Energy ↗ Ion Flux ↑ Neutral Flux ↑

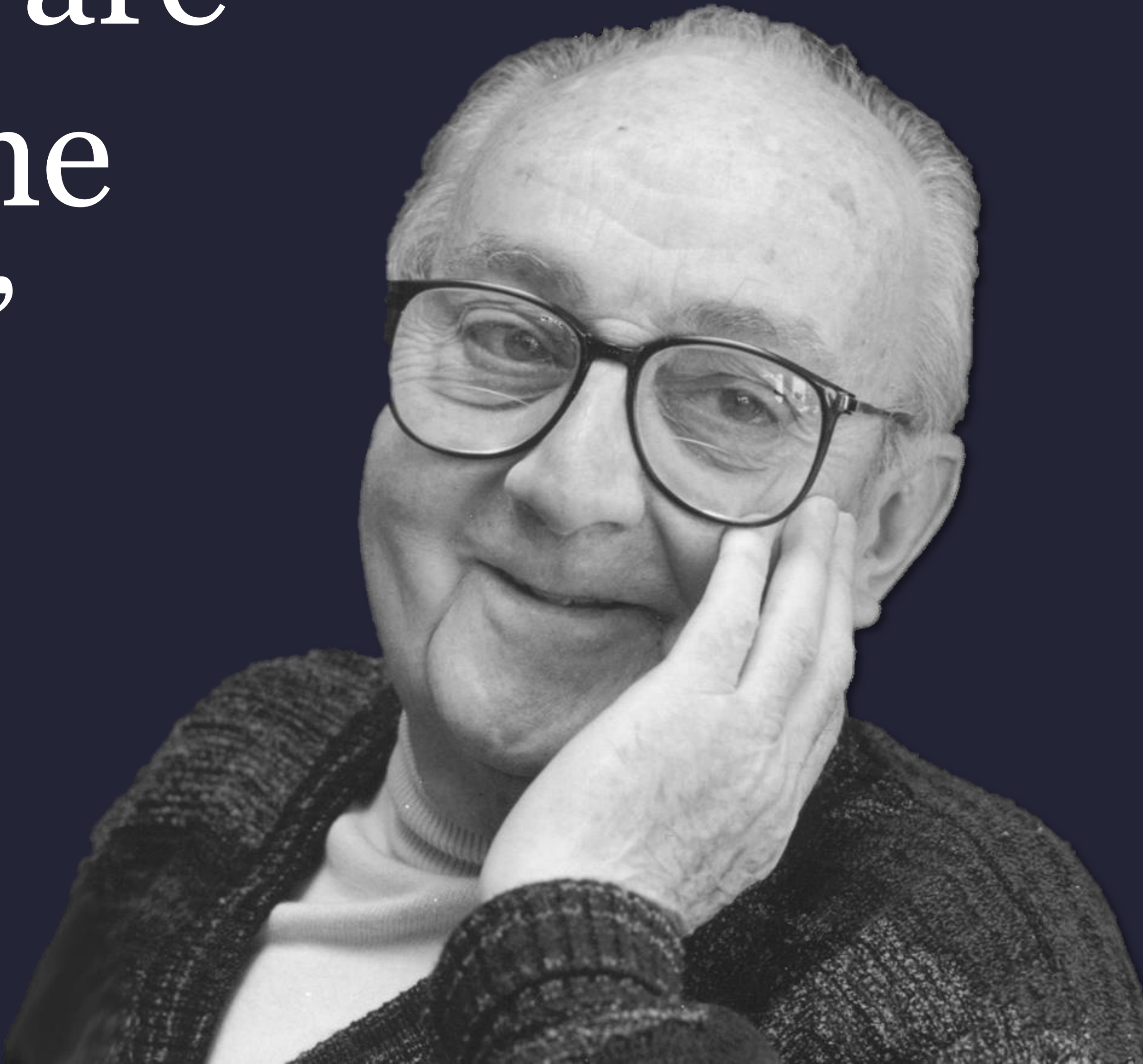



Coburn & Winters, J. Appl. Phys, May 1979


Chang, et.al, JVST, 1997

“All models are wrong, some are useful.”

George Box, 1976

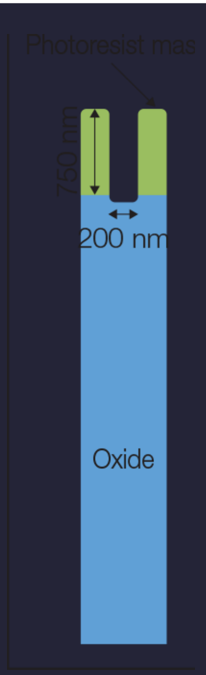


LAM RESEARCH

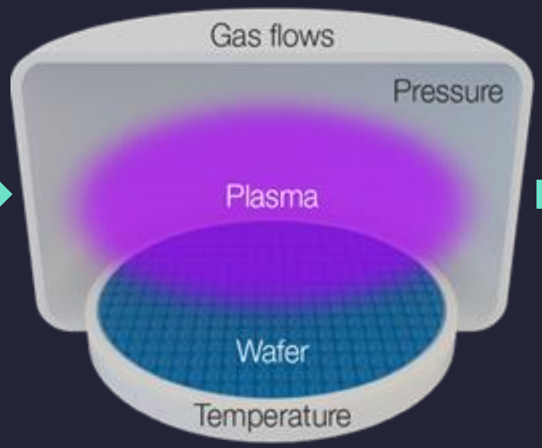
Let’s play a “game” to benchmark models (and Humans)

A virtual plasma etch process twin

INCOMING | **RECIPE** → **SIMULATOR** → **OUTPUT** | **TARGET** | **OTHER PROFILES**



Pressure
Plasma power1
Plasma power2
Ar flow
Gas 1
Gas 2
Gas 3
Duty cycle
Pulse frequency
Temperature

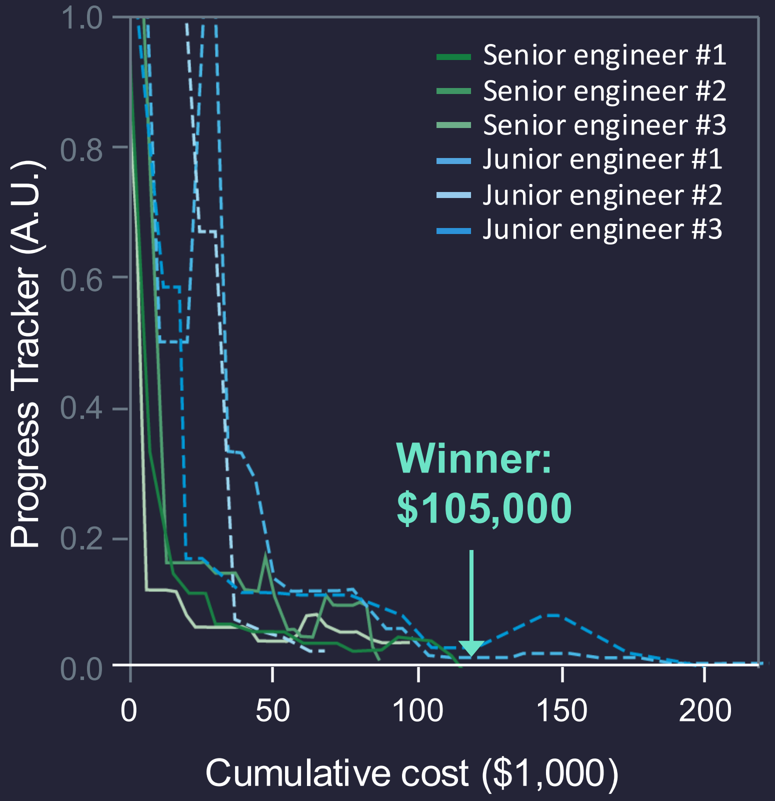


Etch depth
Etch rate
Mask remain
Top CD
Delta CD
Bow CD

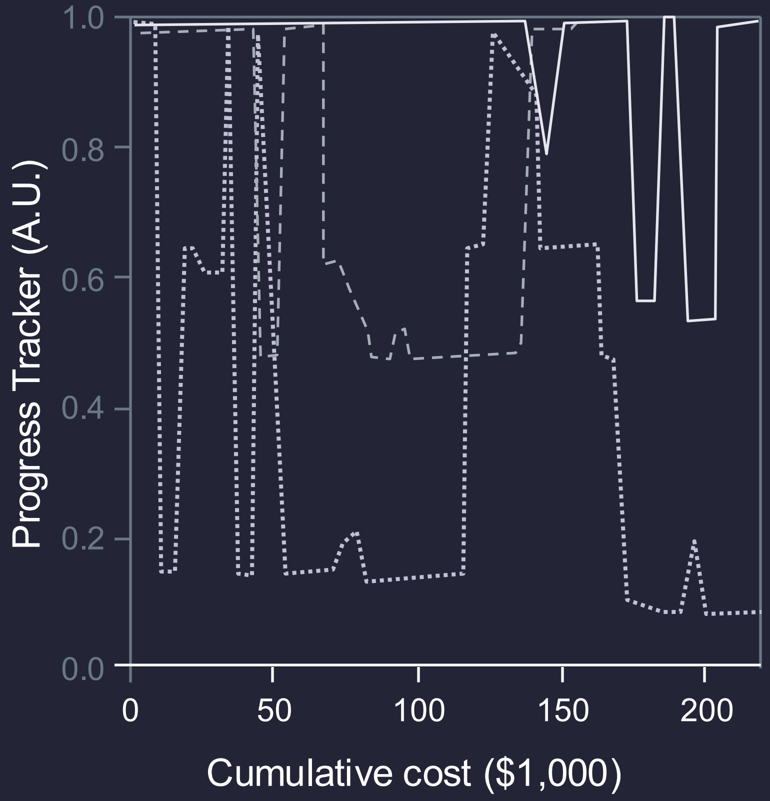
Kanarik, K.J., Osowiecki, W.T., Lu, Y.(. *et al.* Human–machine collaboration for improving semiconductor process development. *Nature* **616**, 707–711 (2023). https://doi.org/10.1038/s41586-023-05773-7

Machine alone was no match for expert engineer

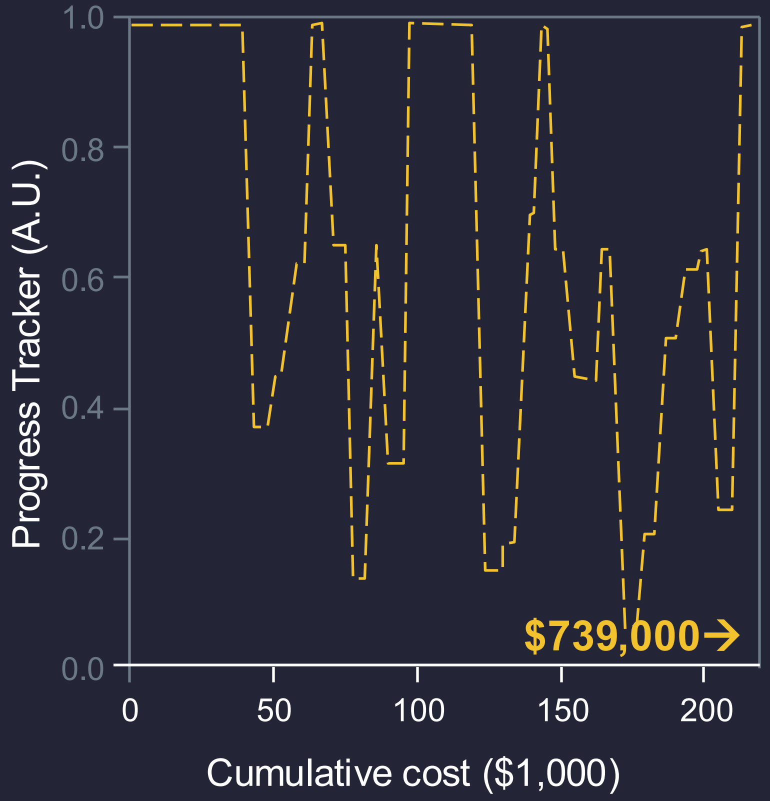
Process engineers



Inexperienced humans



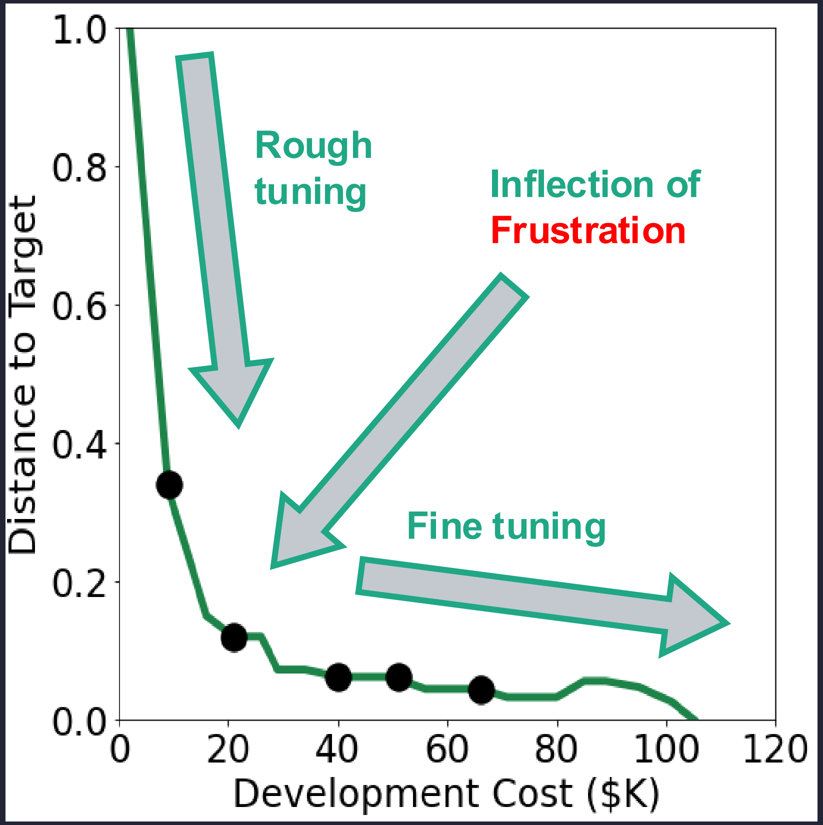
Computer algorithm



Source: Kanarik et al, Nature, 2023

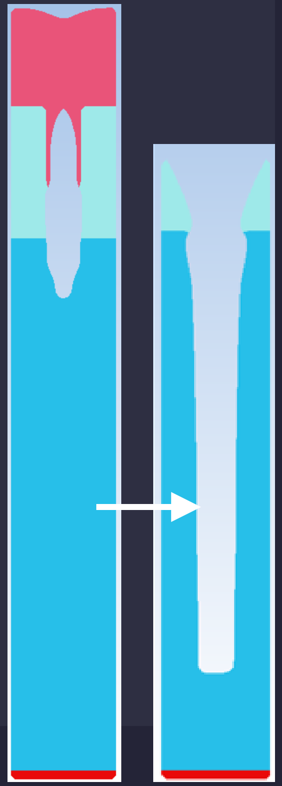
Human learning curve consists of rough and fine tuning

Expert trajectory



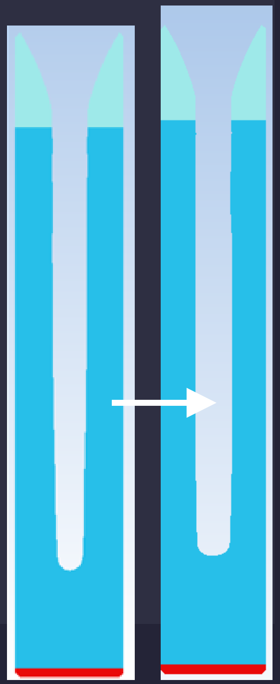
Rough-tuning stage

- Baseline from experience
- Domain knowledge and physical intuition are valuable
- Fulfilling, rapid progress *toward* solution



Fine-tuning stage

- Close to spec
- Physical intuition and domain knowledge less useful
- Frustrating, low-productivity path to solution



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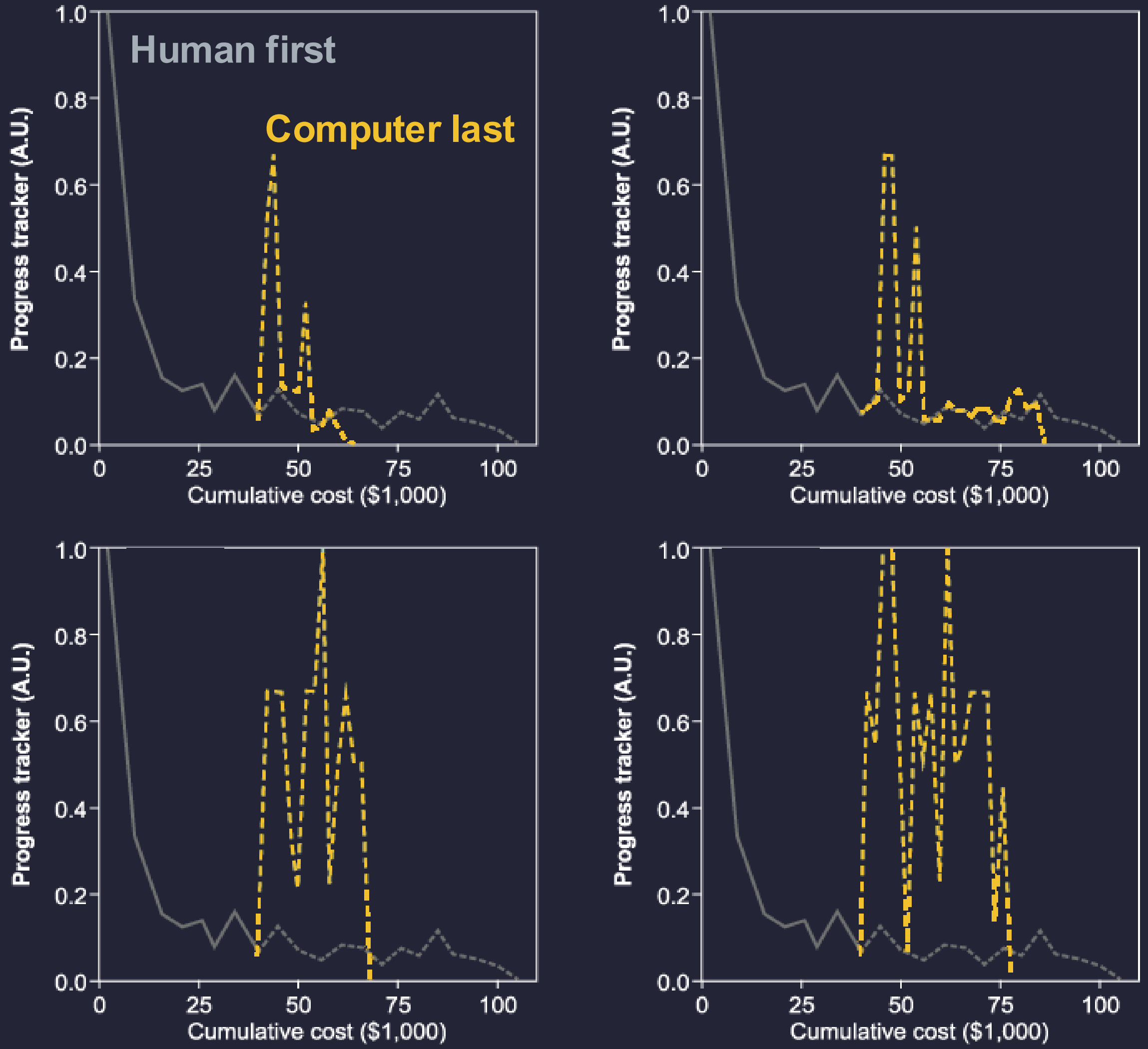
Human-machine collaboration yields cost and time savings

Expert trajectory

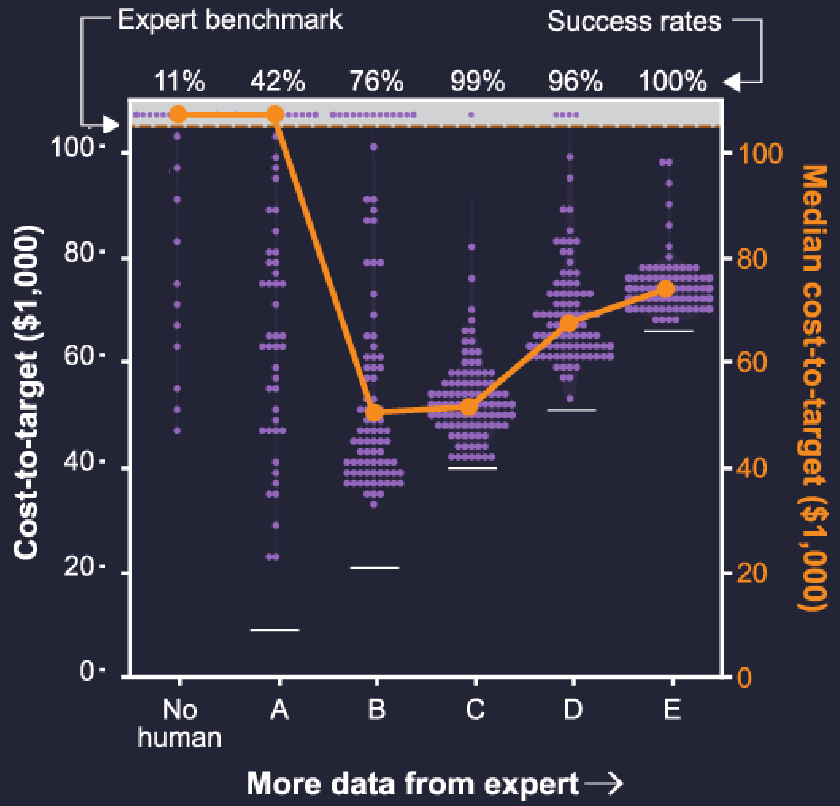
99% success rate



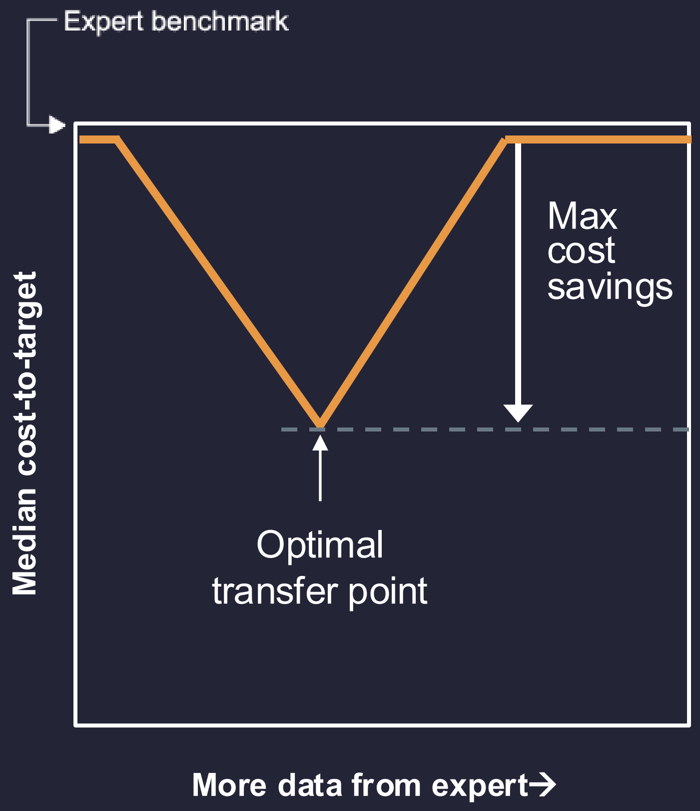
Success rate: % meeting target at lower cost than expert
Source: Kanarik et al, Nature, 2023

Optimal transfer leverages human investment

Experimental V-curve



Schematic



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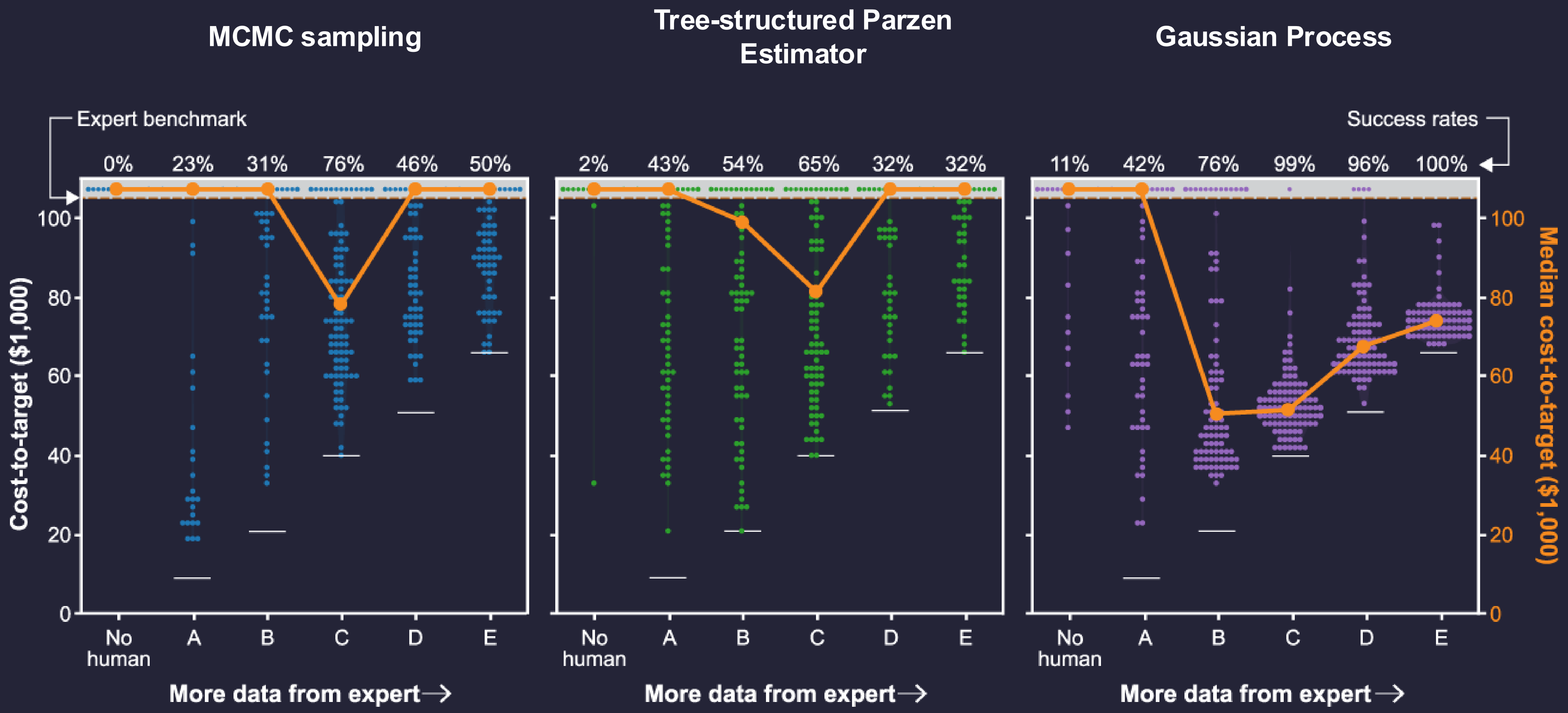
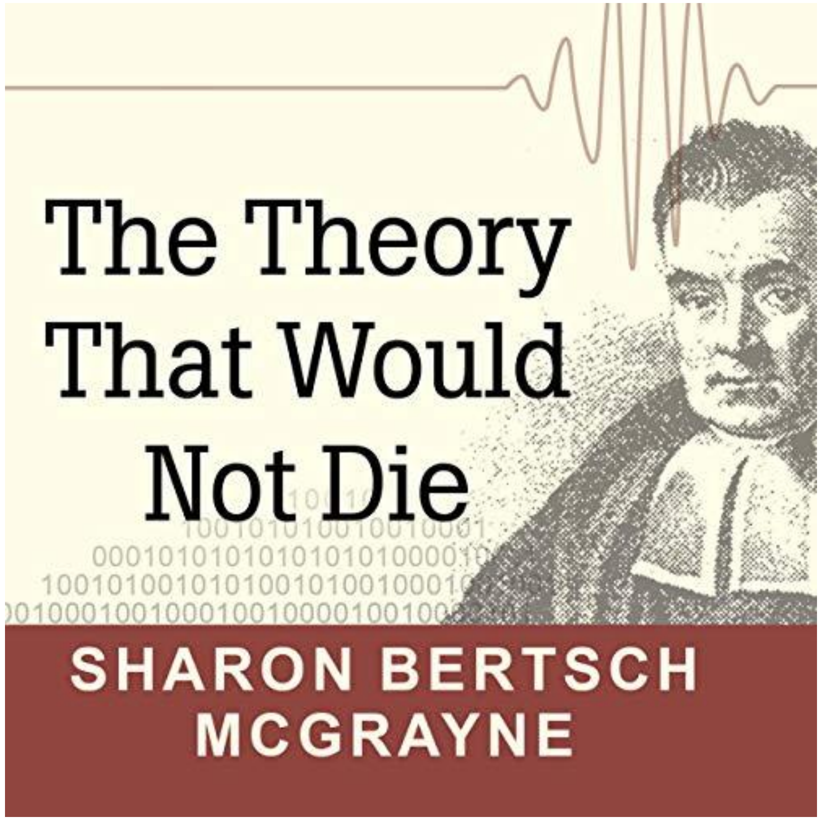
Source: Kanarik et al, Nature, 2023

Bayesian Optimization Algorithm Comparison



And the winner is…



How Bayes' Rule Cracked the Enigma Code, Hunted Down Russian Submarines, and Emerged Triumphant from Two Centuries of Controversy

Bayesian Optimization using a Gaussian Process

Görtler, et al., "A Visual Exploration of Gaussian Processes", Distill, 2019.
https://distill.pub/2019/visual-exploration-gaussian-processes/

Eric J. Ma, An Attempt At Demystifying Bayesian Deep Learning
https://ericmjl.github.io/bayesian-deep-learning-demystified/#/IntroductionSlide

An Attempt At Demystifying Bayesian Deep Learning
Eric J. Ma

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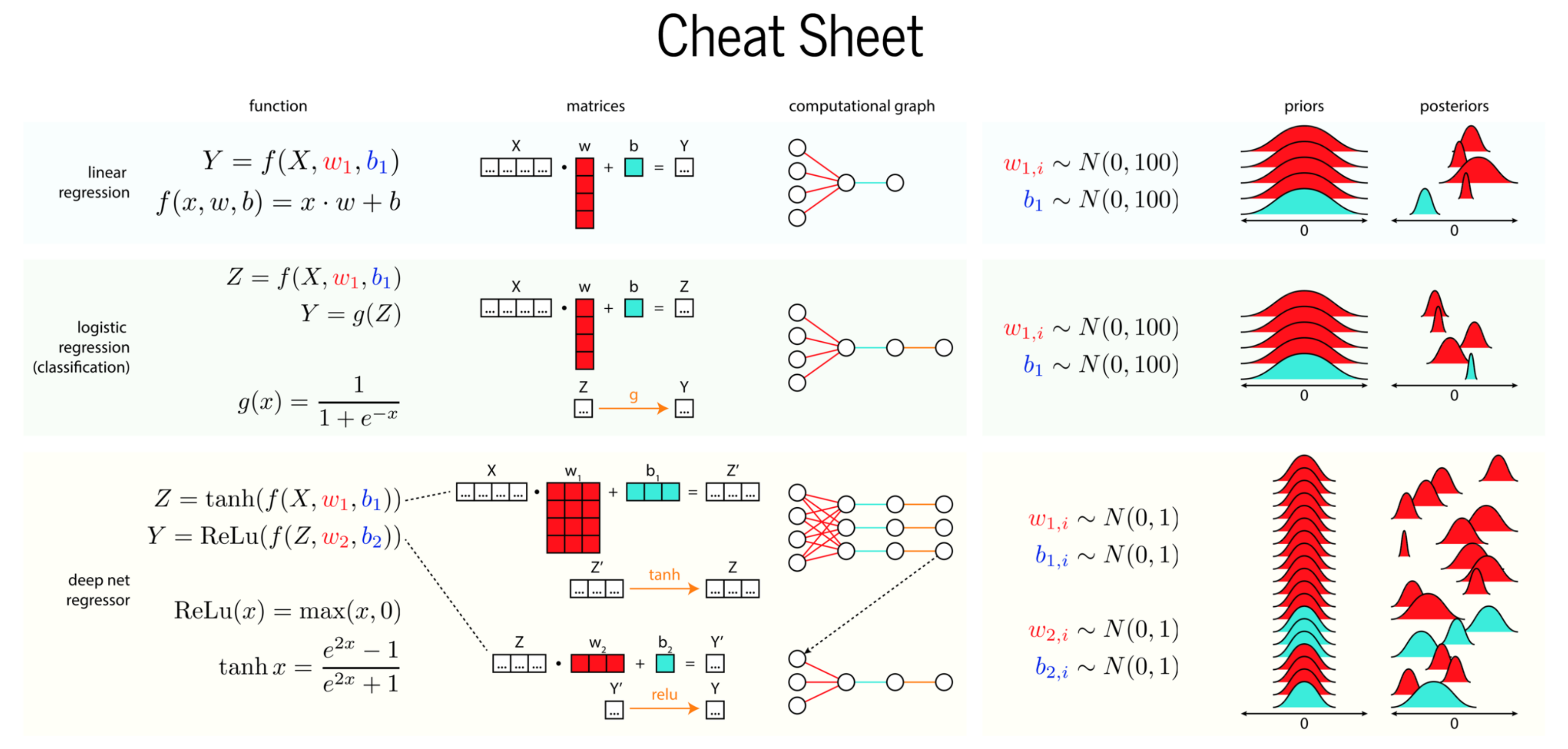


Cheat Sheet

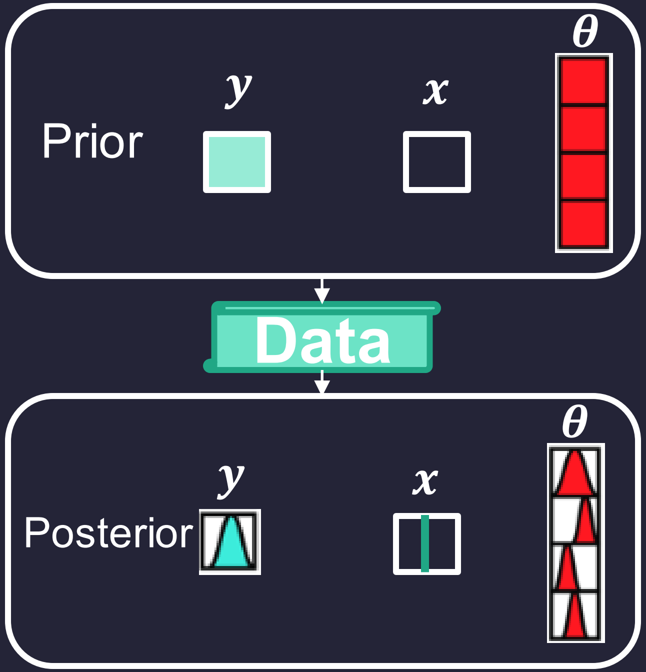
	function	priors
linear regression	$Y = f(X, w_1, b_1)$ $f(x, w, b) = x \cdot w + b$	$w_{1,i} \sim N(0, 100)$ $b_1 \sim N(0, 100)$
logistic regression (classification)	$Z = f(X, w_1, b_1)$ $Y = g(Z)$ $g(x) = \frac{1}{1 + e^{-x}}$	$w_{1,i} \sim N(0, 100)$ $b_1 \sim N(0, 100)$
deep net regressor	$Z = \tanh(f(X, w_1, b_1))$ $Y = \mathrm{ReLu}(f(Z, w_2, b_2))$ $\mathrm{ReLu}(x) = \max(x, 0)$ $\tanh x = \frac{e^{2x} - 1}{e^{2x} + 1}$	$w_{1,i} \sim N(0, 1)$ $b_{1,i} \sim N(0, 1)$ $w_{2,i} \sim N(0, 1)$ $b_{2,i} \sim N(0, 1)$

Source: ericmjl/bayesian-deep-learning-demystified

Bayesian Optimization

Bayes theorem: $p(\boldsymbol{\theta}|D) = \dfrac{p(\boldsymbol{\theta})p(D|\boldsymbol{\theta})}{p(D)}$

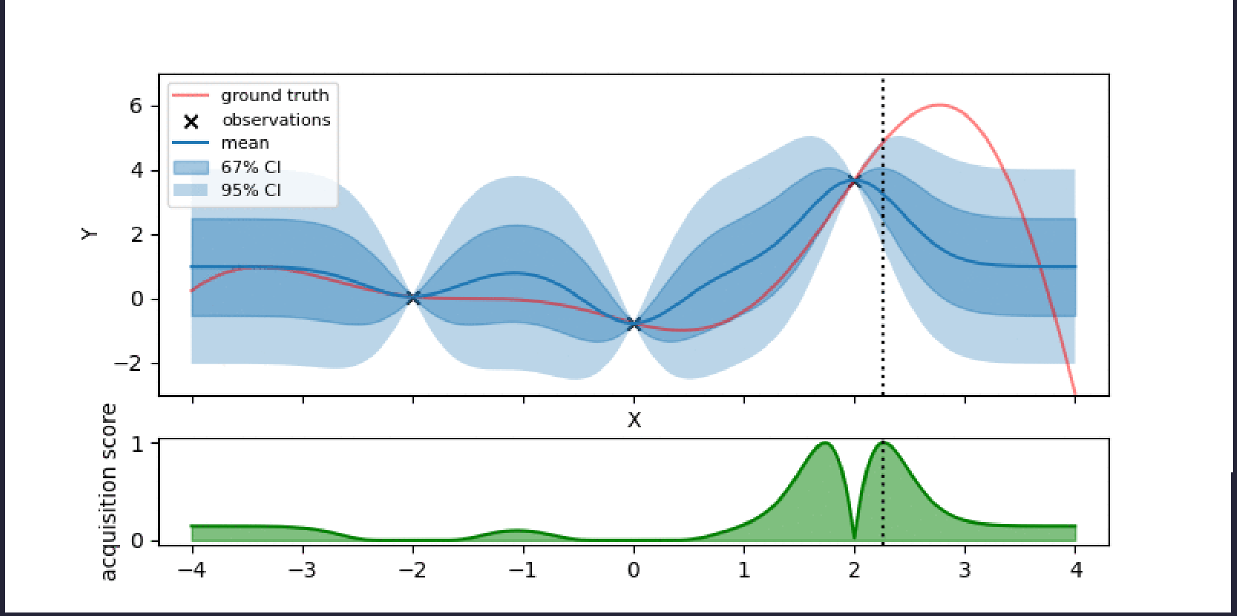
Surrogate: $\overset{\text{Metrology}}{\boldsymbol{y}} = f(\overset{\text{Recipe}}{\boldsymbol{x}}, \overset{\text{Model parameters}}{\boldsymbol{\theta}}) + \boldsymbol{\varepsilon} \leftarrow \text{Noise}$



Prior $\boldsymbol{y}$ $\boldsymbol{x}$ $\boldsymbol{\theta}$

Data

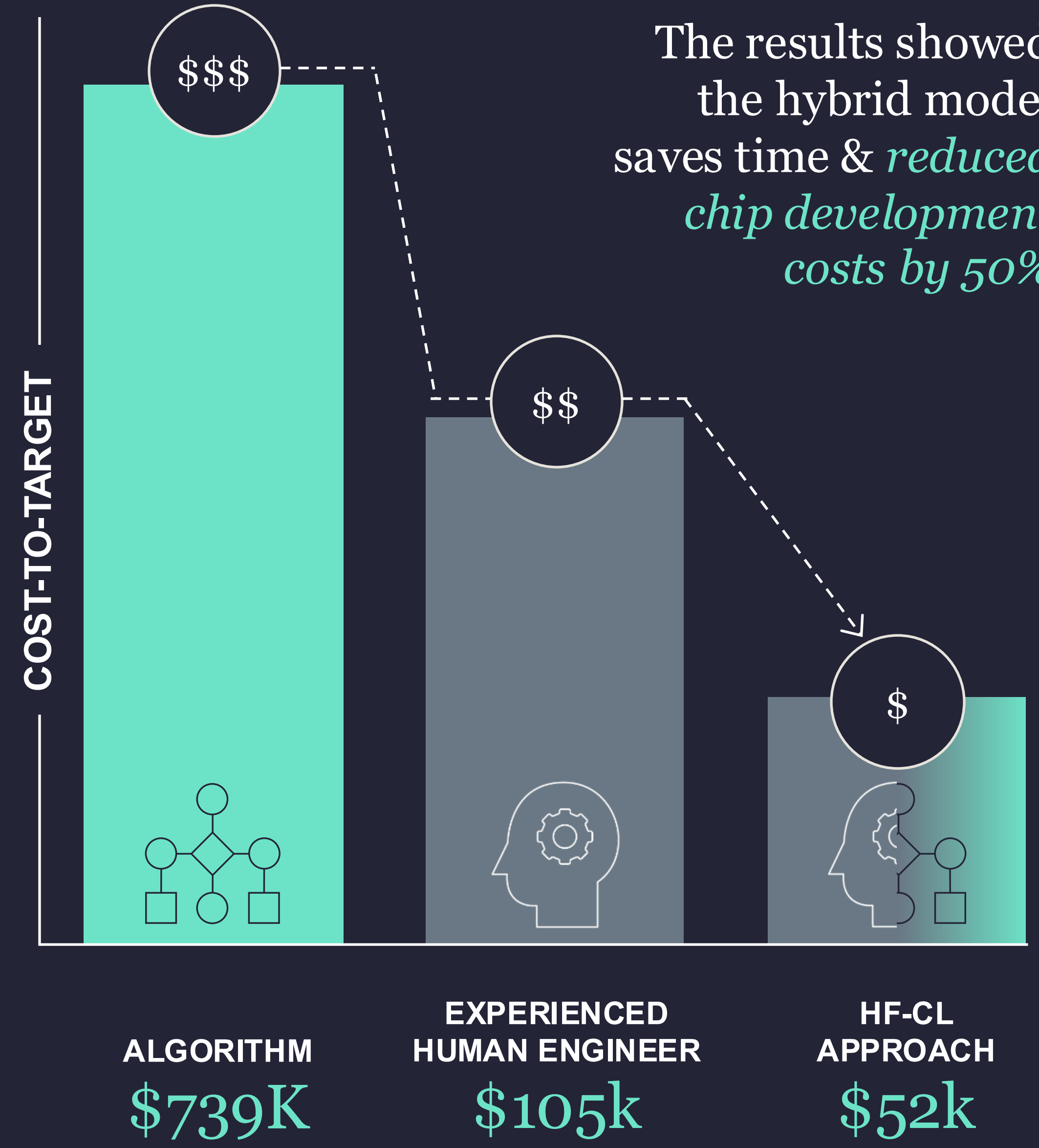
Posterior $\boldsymbol{y}$ $\boldsymbol{x}$ $\boldsymbol{\theta}$



- Bayesian Optimization is a widely adopted ML/AI framework for optimization and inverse design where performance evaluation is costly
  - Bayesian inference allows one to characterize epistemic uncertainty
  - BO makes cost-efficient decisions for next experiment based on evidence collected from existing data and remaining uncertainty of model
  - BO updates the model and experiment decision based on new data

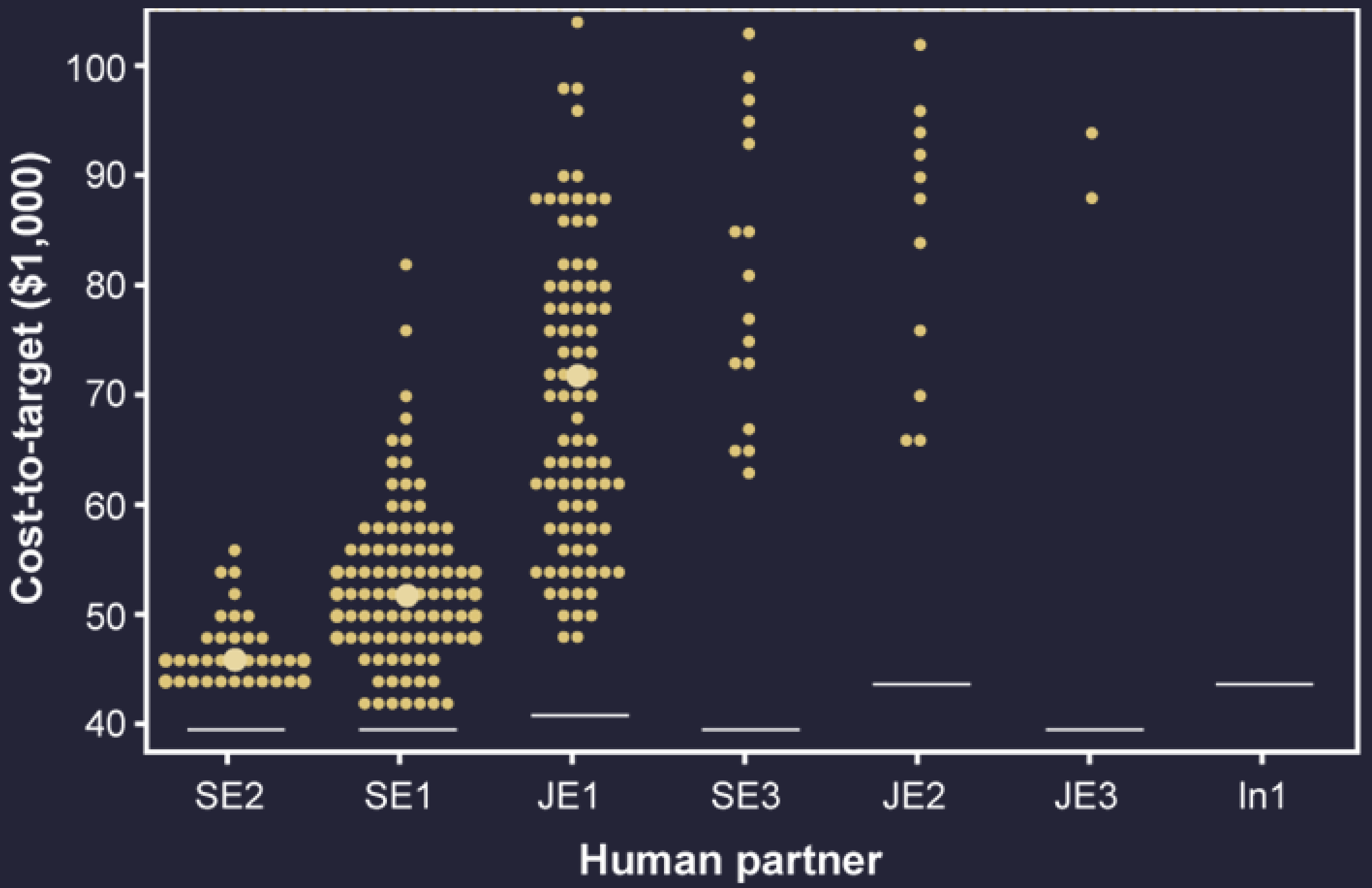
Hybrid approach wins

Human-first, machine-last saves countless hours and millions of dollars



The results showed the hybrid model saves time & *reduced chip development costs by 50%*

Computer should partner with an experienced engineer



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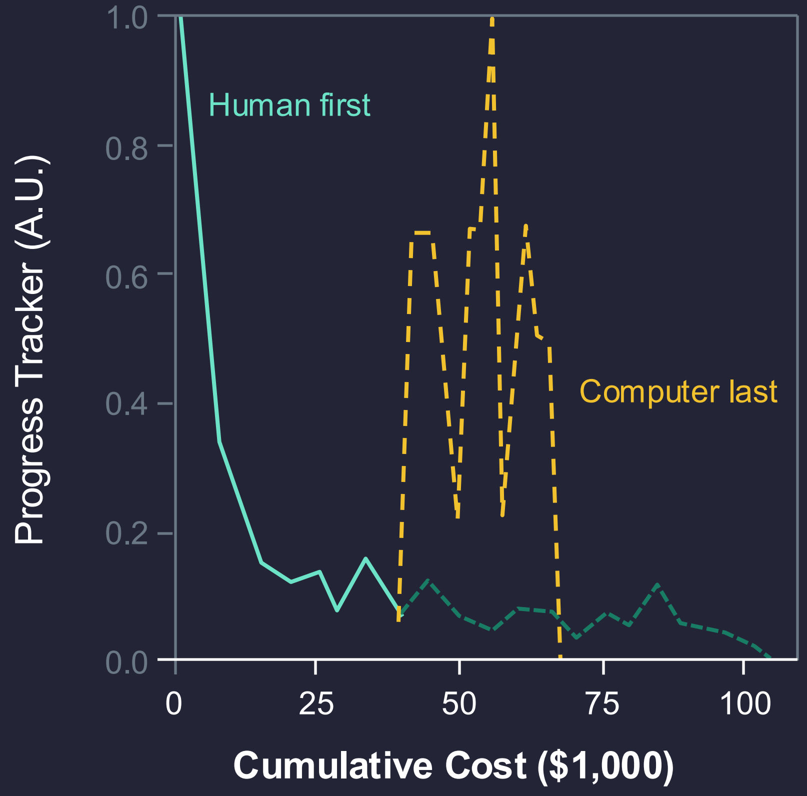
Source: Kanarik et al, Nature, 2023

Algorithm behaves differently than process engineer



Source: Kanarik et al., Nature, 2023

Parameter 1	Parameter 2	Parameter 3	Parameter 4	Parameter 5	Parameter 6	Parameter 7	Parameter 8
1148.6	68.5	4026	90.7	33.9	20.9	220.0	50.9
1165.2	66.5	3594	198.7	33.3	22.3	231.0	58.4
1166.8	67.1	3480	167.6	32.6	21.3	226.1	58.2
1149.3	68.3	3842	109.2	30.7	17.9	252.7	58.3
1160.1	60.5	3110	181.0	27.2	17.8	204.5	58.1
1158.0	60.0	3103	156.8	27.0	17.8	202.9	58.0
1143.9	68.6	3550	90.1	33.4	16.1	180.0	59.5
1137.1	67.3	3715	96.7	34.1	17.4	180.6	59.5
1160.5	67.7	3830	169.9	30.2	18.0	199.4	57.0
1170.7	67.0	3728	196.3	29.2	17.5	195.7	56.3
1161.6	67.2	3687	181.9	30.2	17.7	194.5	56.0

There is high value learning from virtual worlds that *are not* precisely predictive

Few-Shot Test-Time Optimization Without Retraining for Semiconductor Recipe Generation and Beyond

http://arxiv.org/abs/2505.16060

Shangding Gu1∗, Donghao Ying1, Ming Jin2, Yu Joe Lu3, Jun Wang 4, Javad Lavaei 1, Costas Spanos1 (May 2025)

We validate MFL on semiconductor plasma etching tasks, where it achieves target recipe generation in just five iterations, significantly outperforming both Bayesian optimization and human experts.

1UC Berkeley 2Virginia Tech 3Lam Research 4UCL

Physics Informed Machine Learning

Fewer experiments needed

Improved extrapolation

Ensure physics is obeyed!

Physics-Informed Gaussian Processes for Bayesian Optimization

- Additive Models (Data + Physics Residuals)
  - $f(x) = f_{physics}(x) + f_{residual}(x)$
  - $f_{physics}(x)$: physics-based model (PDE, surrogate, empirical)
  - $f_{residual}(x)$: GP correction
  - Train GP on $y - f_{physics}(x)$
  - Total prediction = physics model + GP-predicted residual
- Informed Kernels
  - Embed constraints: periodicity, conservation laws, symmetries
  - Example: Periodic kernel: $k(x,x') = \sigma^2 \exp(-2 \sin^2(\pi|x-x'|/p)/l^2)$
  - Learn a composite kernel that combines a physics-informed part and a flexible part.
- Physics-Based Priors
  - Default GP: $\mu(x) = 0$
  - Replace with $\mu(x) = f_{physics}(x)$
- Physics-Informed Acquisition Functions
  - Guide exploration to physics-interesting areas
  - Feasibility-aware acquisition

Three Approaches to Physics-Informed ML

	Physics-Informed Neural Networks (PINNs)	**Physics-Informed Gaussian Processes (PIGPs)**	**Physics-Informed Neural Operators (PINOs)**
Physics incorporation	Penalize PDE residuals in loss function	Embed physics in prior mean/kernels or residuals	Embed PDE constraints into operator learning
Uncertainty quantification	No (unless Bayesian PINNs)	Yes	Not standard
Data requirement	Moderate to high	Low	High
Strengths	Handles complex nonlinear PDEs, flexible	Excellent in data-scarce regimes, principled uncertainty	Learns solution operators across PDE families
Computation	Optimization (can be costly, especially with stiff PDEs)	GP regression (scales poorly with data size)	Requires large training data + compute

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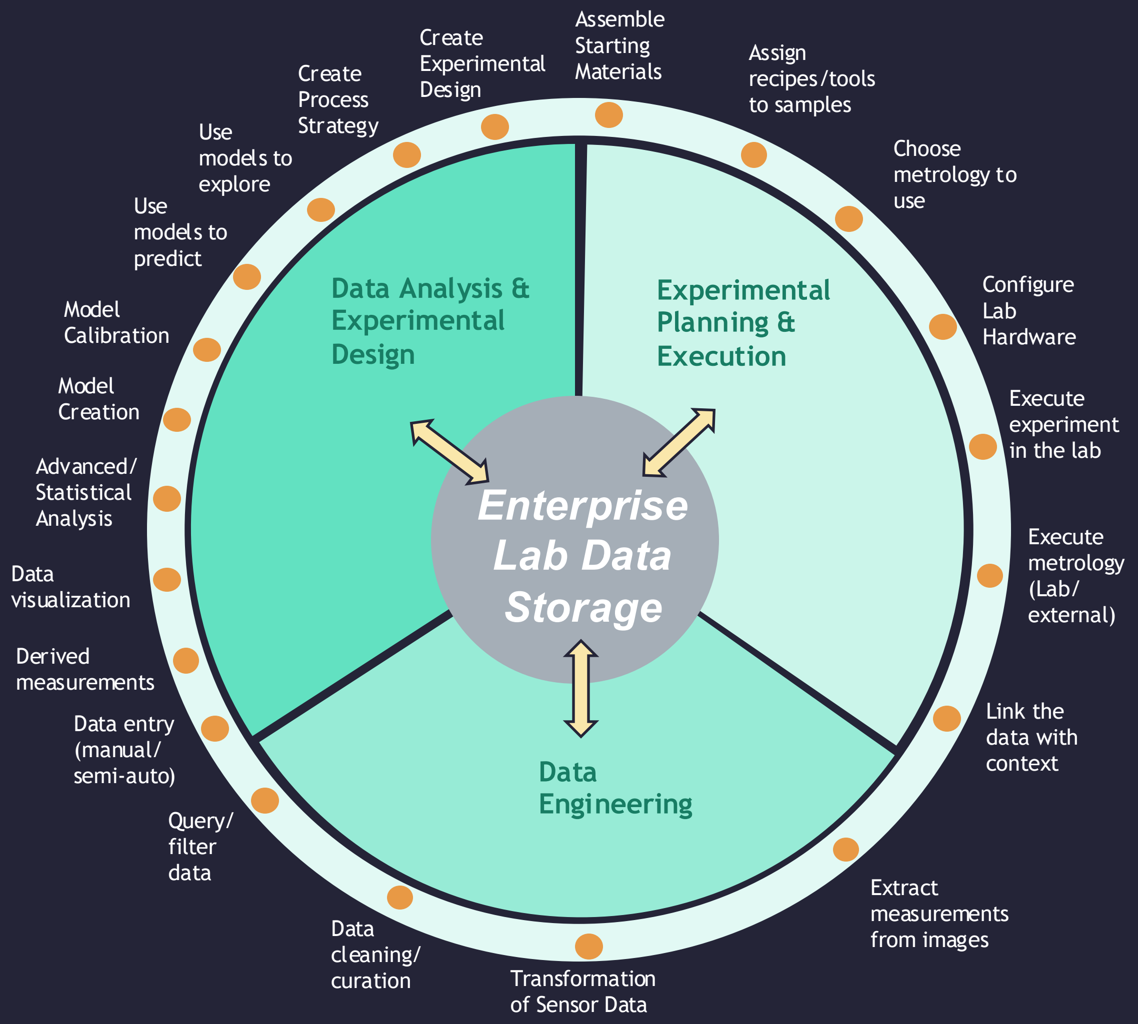
Virtual Process Development

Transform process development through digitalization, automation, simulation & data analysis



- Process Development is not one monolithic workflow. It is many different paths through a variety of different activities. Catering to these varied workflows requires a holistic strategy.
- The activities largely reside in three disciplines, with specific requirements, and must be connected through enterprise-scale storage of experimental process data.
- Modernizing and automating physical experimental activities in the lab is key to delivering the contextual data to the data store
- Image analysis and flexible platforms for data science, machine learning and advanced analytics are critical for data engineering.
- Connecting platforms and systems to create efficient, friction-free workflows = Virtual Process Development

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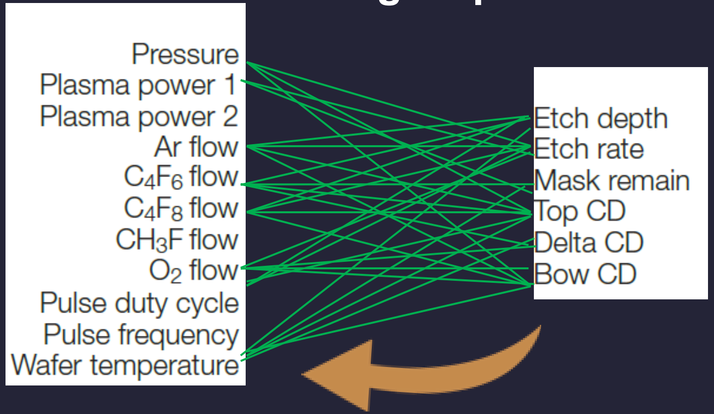
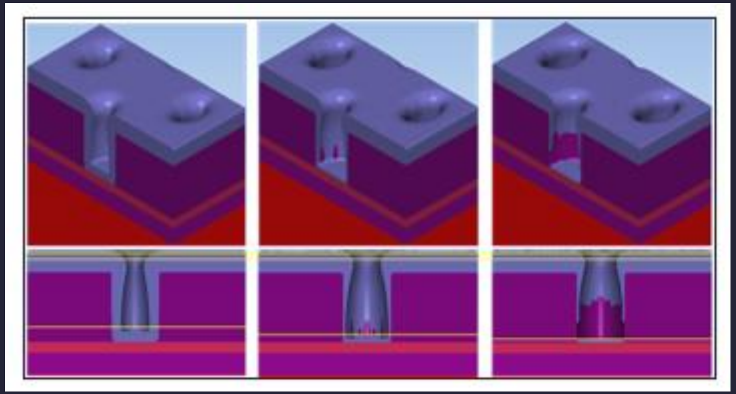
Virtual Process Development – Physics and Data

Predictive

Inverse Design Optimization



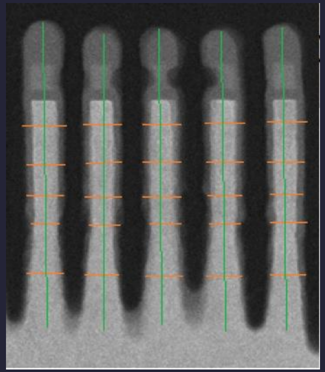
Mechanistic Unit Process Models



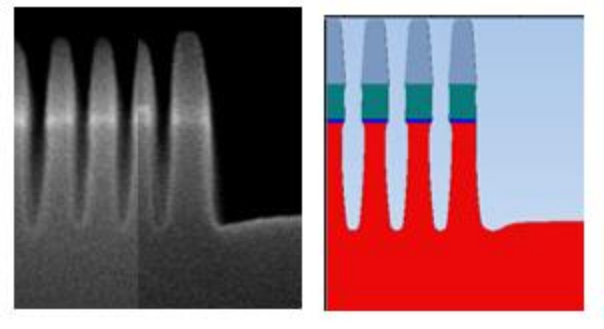
Data-driven

Physics-Based

Image Measurement



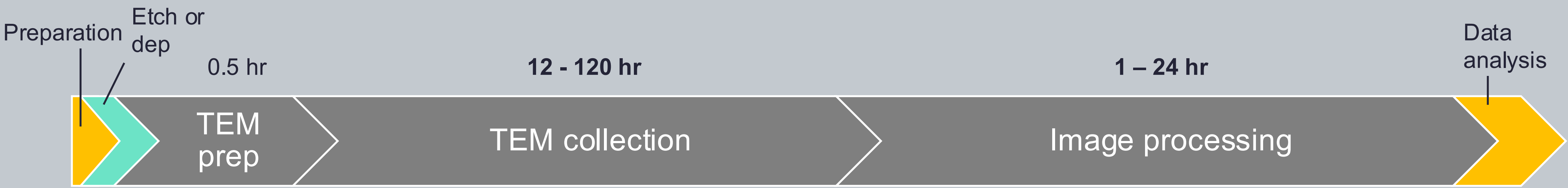
Automated Model Calibration



Analytical

Real-time profile metrology for *100x* cycle time reduction

Metrology for high aspect ratio solution development costly, time-consuming, and destructive


Preparation

Etch or dep

0.5 hr

TEM prep

12 - 120 hr

TEM collection

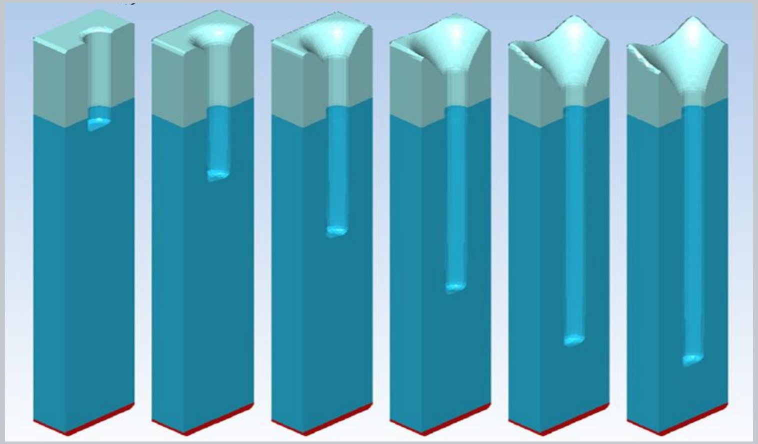
1 – 24 hr

Image processing

Data analysis

Real-time metrology offers 100x cycle time reduction

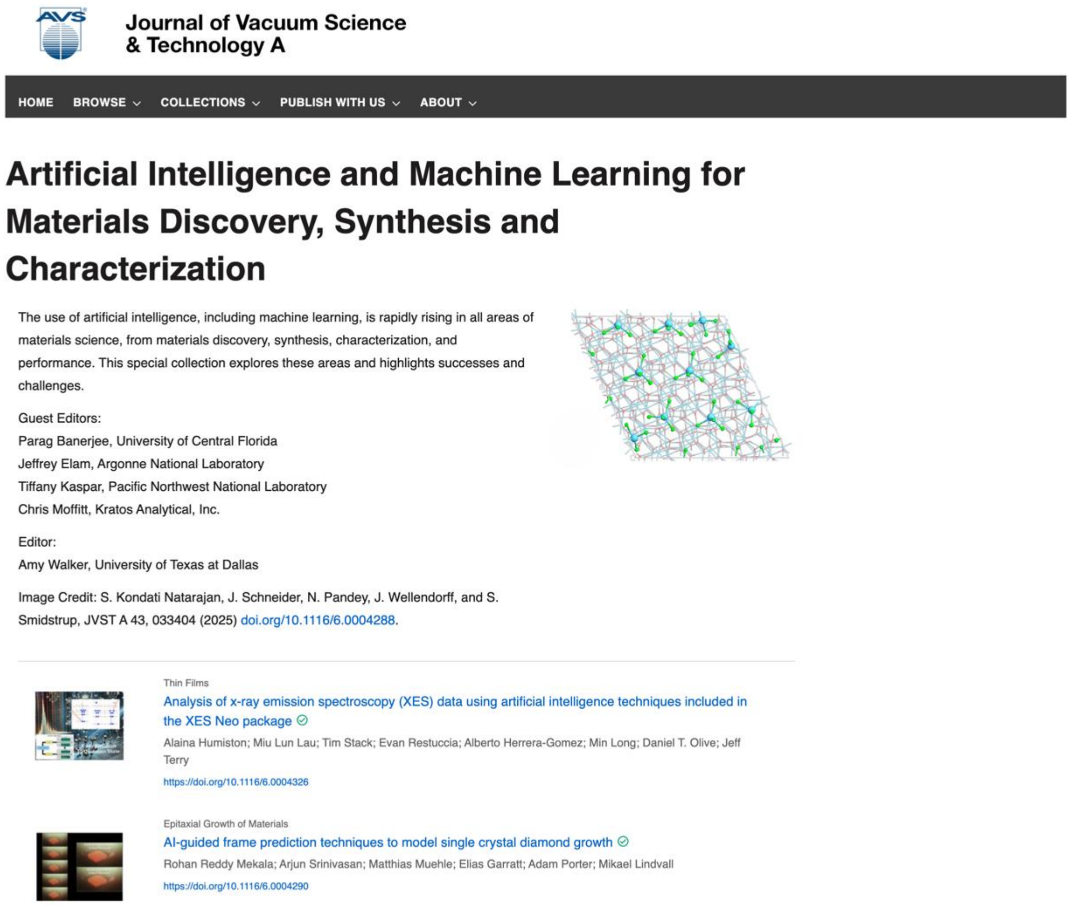

1 cycle



Barriers: Business model and some invention required

New Materials Development

- DFT/AI predictions of stability and transition states
- Synthesis has been a bottleneck, but…
    - Combinatorial techniques combined with automation and *autonomy* is revolutionizing the pace of new materials innovation
- Process integration and device fabrication remain bottlenecks



Journal of Vacuum Science
& Technology A

Artificial Intelligence and Machine Learning for Materials Discovery, Synthesis and Characterization

The use of artificial intelligence, including machine learning, is rapidly rising in all areas of materials science, from materials discovery, synthesis, characterization, and performance. This special collection explores these areas and highlights successes and challenges.

Guest Editors:
Parag Banerjee, University of Central Florida
Jeffrey Elam, Argonne National Laboratory
Tiffany Kaspar, Pacific Northwest National Laboratory
Chris Moffitt, Kratos Analytical, Inc.

Editor:
Amy Walker, University of Texas at Dallas

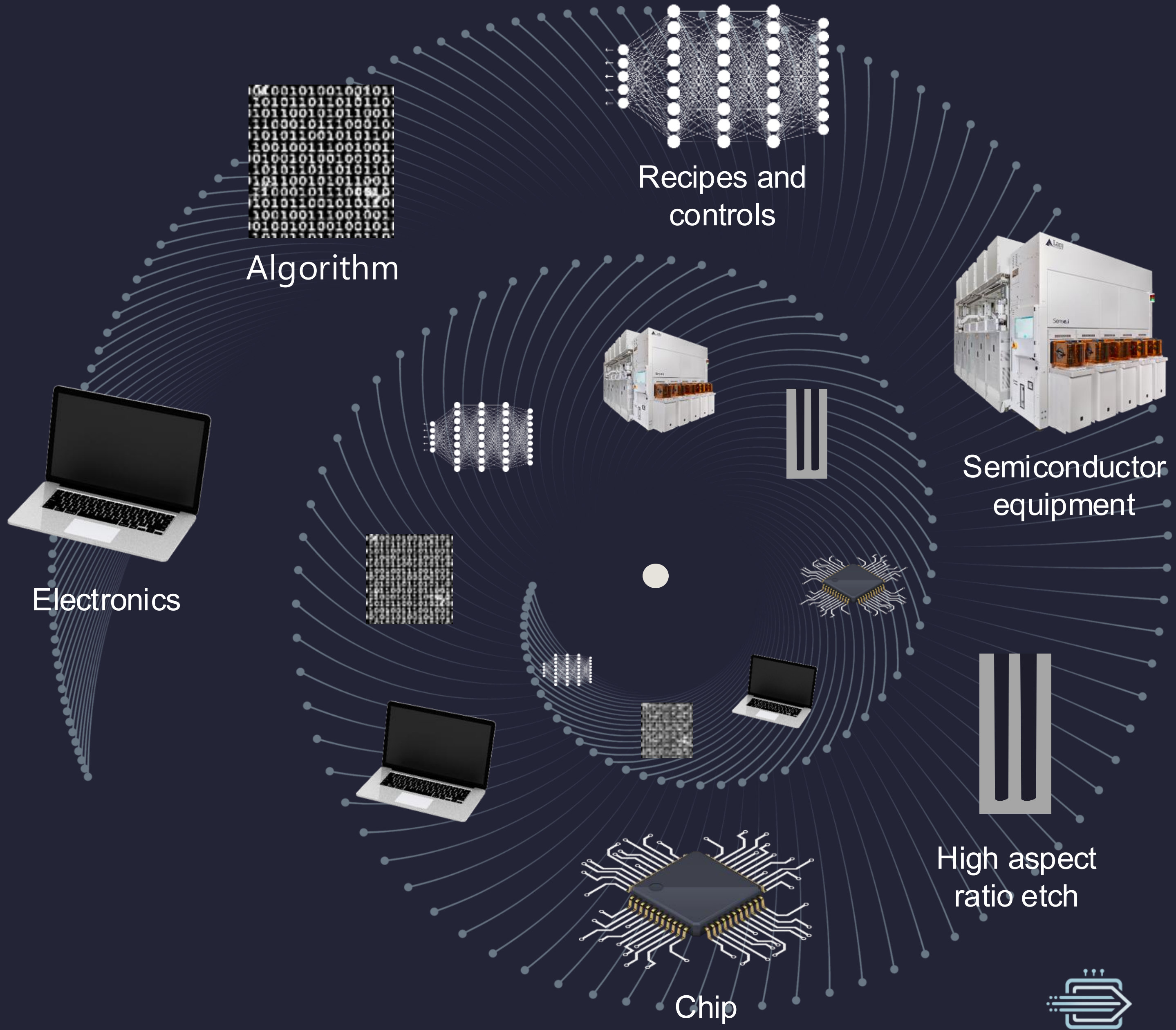
Image Credit: S. Kondati Natarajan, J. Schneider, N. Pandey, J. Wellendorff, and S. Smidstrup, JVST A 43, 033404 (2025) doi.org/10.1116/6.0004288.

Thin Films
Analysis of x-ray emission spectroscopy (XES) data using artificial intelligence techniques included in the XES Neo package ✓
Alaina Humiston; Miu Lun Lau; Tim Stack; Evan Restuccia; Alberto Herrera-Gomez; Min Long; Daniel T. Olive; Jeff Terry
https://doi.org/10.1116/6.0004326

Epitaxial Growth of Materials
AI-guided frame prediction techniques to model single crystal diamond growth ✓
Rohan Reddy Mekala; Arjun Srinivasan; Matthias Muehle; Elias Garratt; Adam Porter; Mikael Lindvall
https://doi.org/10.1116/6.0004290

Focus	Count
Synthesis	I
Characterization/Analysis	IIII
Monitoring/Control	IIII
Discovery	I

What goes around comes around faster and better



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Further reading

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