Educator Hub

Data Science in Semiconductor Memory Manufacturing

Reviewed 2025

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Data Science in memory manufacturing – goal and objectives

Goal

- Participants will gain understanding on source of data and analytical methodologies in semiconductor manufacturing

Objectives

- Identify the different sources of data in semiconductor memory manufacturing
- Understand the different roles and team dynamics of data science in semiconductor manufacturing

Target Audience

- Interns, NCGs (new college grads), and new employees in some technical roles need to understand these concepts
- Examples of critical target audience roles at Micron that utilize these concepts
  - i4.0 Analyst
  - Data Analyst
  - Data Engineer
  - Solution Architect
  - AI Architect
  - Domain Architect
  - Cloud Application Architect
  - Machine Learning Engineer
  - Data Scientist

Pro tip

Everyone interviewing at Micron can use this presentation to prepare for the interview by learning foundational information about memory. Check out the candidate guides for Engineering, Technician and Business roles.

- Micron engineering candidate guide
- Micron technician candidate guide
- Micron business candidate guide

Data Science Big Picture

micron

Industrial Revolution enablers by generation

1st Industrial Revolution

18th Century

Mechanization Steam-based Machines

2nd Industrial Revolution

19th ~ 20th Century

Electrical Energy-based Mass Production

3rd Industrial Revolution

Late 20th Century

Computer and Internet-based Knowledge

Artificial Intelligence Information Technology

Intelligence

Machine Learning

Gen AI (LLM, etc.)

Agentic AI

+

Information

Big Data

IoT

Cloud

We are here

4th Industrial Revolution

Early 21st Century

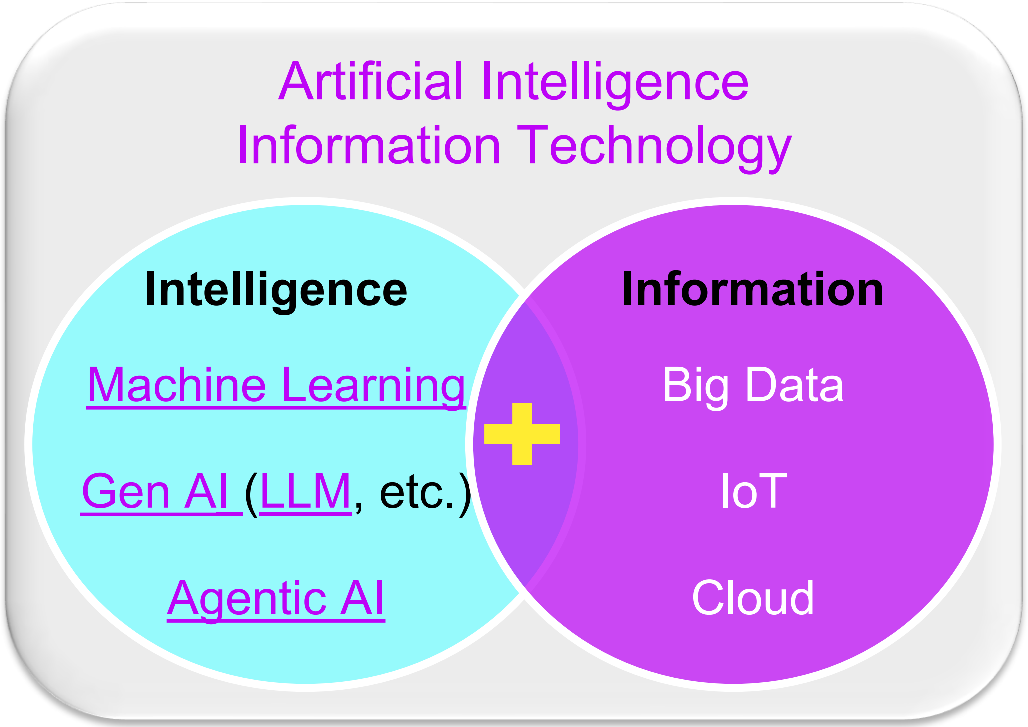
Cyber Physical System to have robots do "cognitive" work

Images created for Micron by Copilot

Key enablers for Big Data and Artificial Intelligence

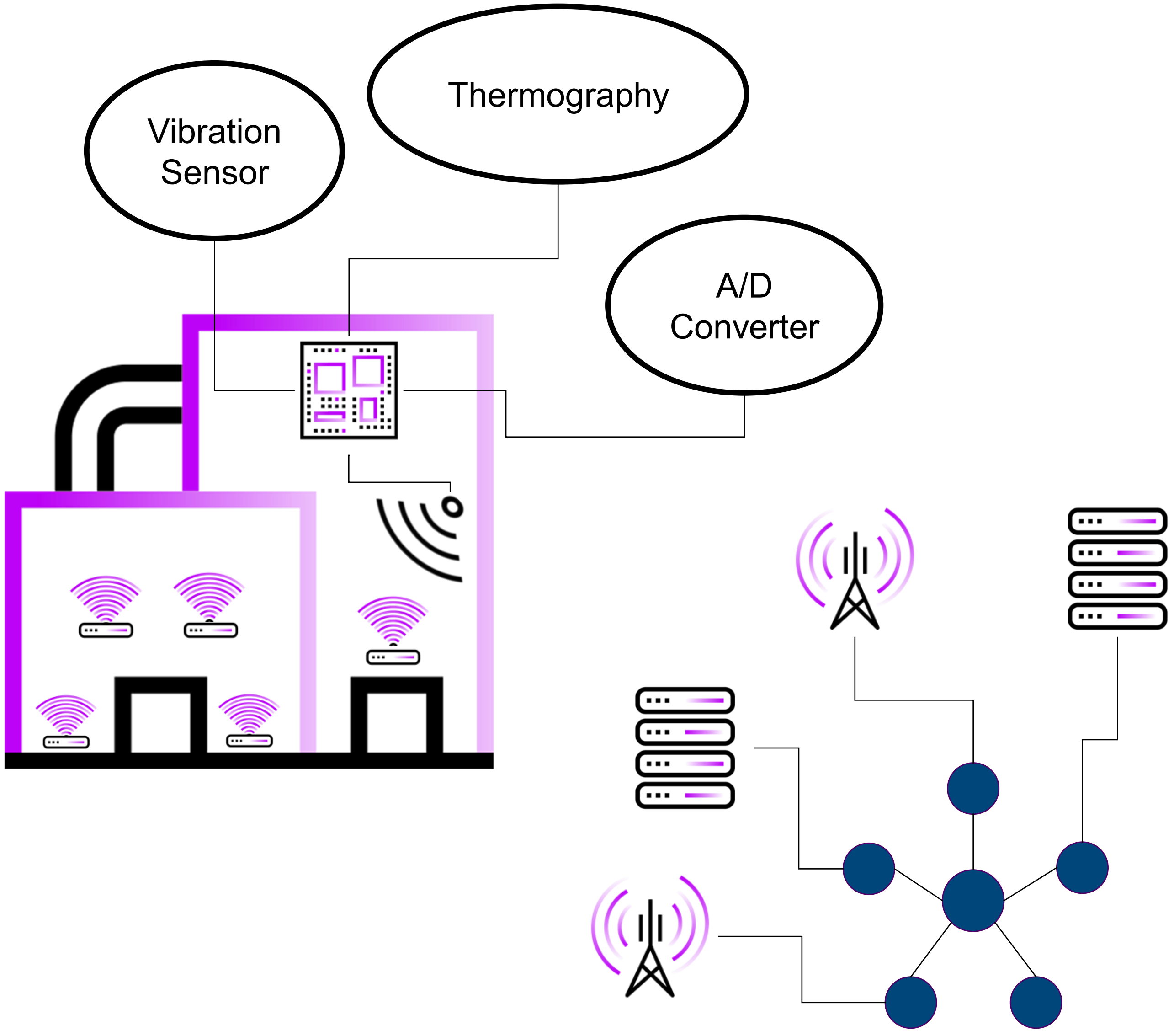
- Massive data collection capability
- Highly scalable computational power and storage
- Sophisticated machine learning algorithms

These key enablers are explored in more depth in the next slides



Massive data collection

- **Intelligent sensors with edge node**
  - With data processing (ML) & transmittance capability
- **5G wireless network**
  - Super high band width for wireless real time communication which is 100X faster than 4G
- **Optical network**
  - Wired network as backbone to support 5G base station
- **Semiconductor industry**
  - Manufacturing equipment and facility also generate massive data every second
  - Opportunity: Big data from decades ago

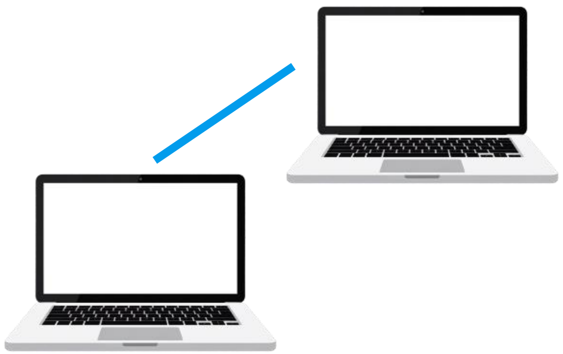


Highly Scalable Computational Power

1950's ~ 1990's
- Mainframe Computer

Mid 1990's
- Personal Computer (Intel/Microsoft/Apple)

Late 1990's to early 2000's
- Internet connects PCs over the world



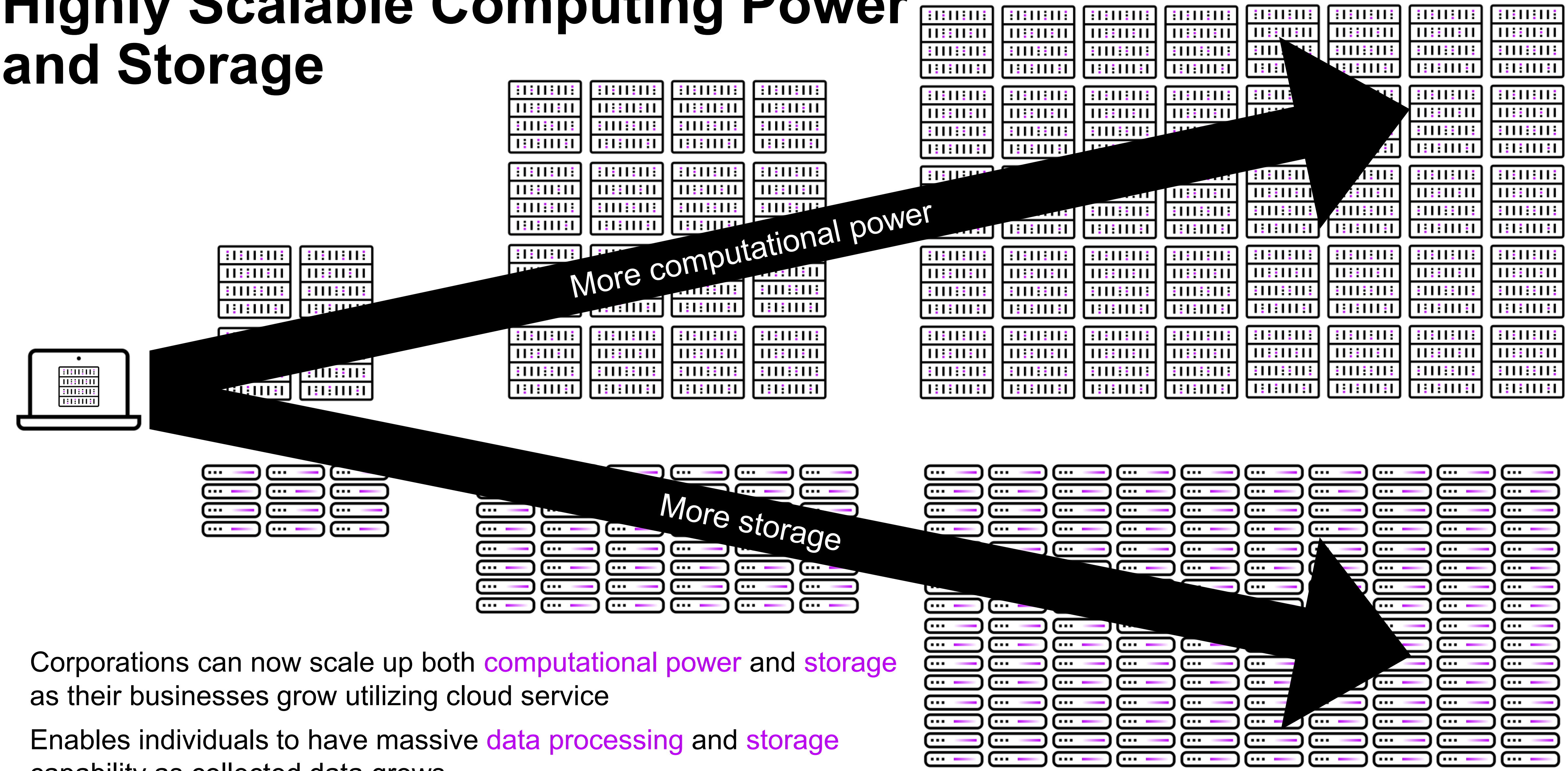
Mid 2000's
- Google's advanced search engine indexes massive internet data
- Cloud technology clusters servers to scale up data processing capability e.g., Hadoop as open source

Early 2010's to current
- Meta (Facebook) and Twitter use cloud technology to build their social network sites
- Amazon provides cloud services

Current
- Non-IT Industries to use scalable computational power
- Digital transformation takes place in manufacturing

Images created for Micron by Copilot

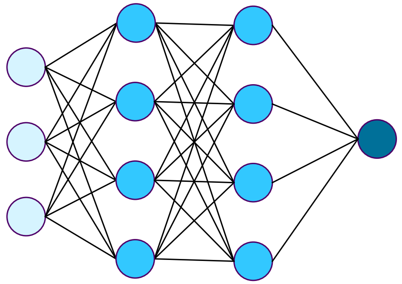
Highly Scalable Computing Power and Storage



- Corporations can now scale up both computational power and storage as their businesses grow utilizing cloud service
- Enables individuals to have massive data processing and storage capability as collected data grows

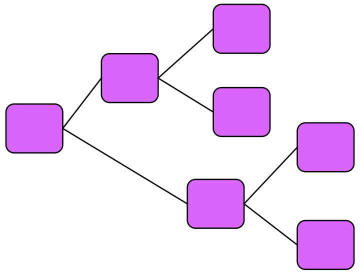
Machine Learning

1950's ~ 1990's
- Neural Network is invented in the 1950's
- A primitive neural network is developed for the United States Postal Service for reading zip codes



Neural Network

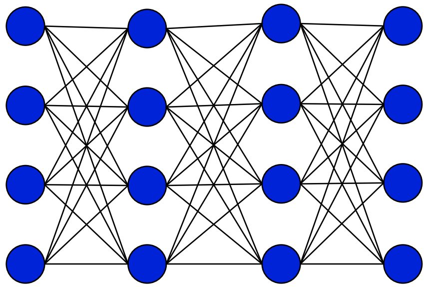
2000's ~ early 2010's
- Decision Tree Algorithm
- Random Forest
- Gradient Boosting Machine
- Feature Selection & Prediction Model 3.7



Decision Tree Algorithm

Current
- Enables nonparametric data analysis
- No prefixed distribution nor prefixed assumption

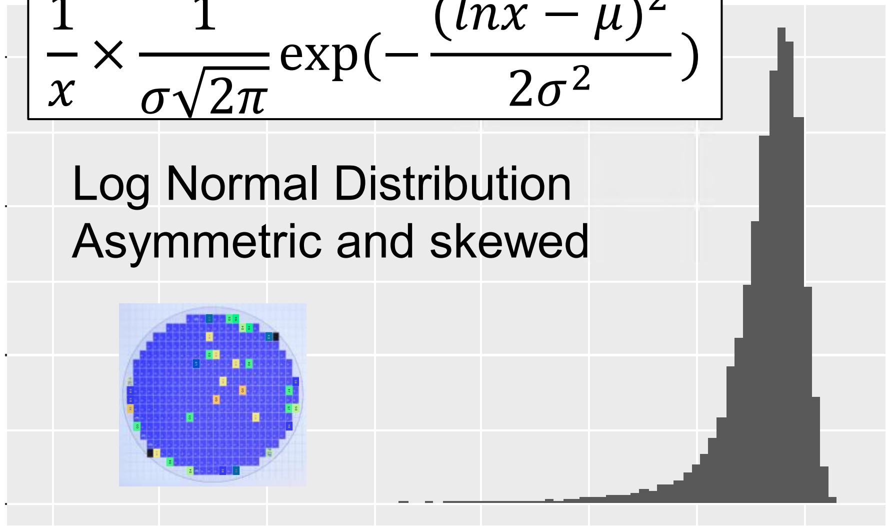
2010's ~
- Neural Network suddenly became mainstream
- Multi-layered Neural Network (a form of Deep Learning)
- Massive but simple matrix computation powered by GPU
- Feature Selection & Prediction (or recognition)



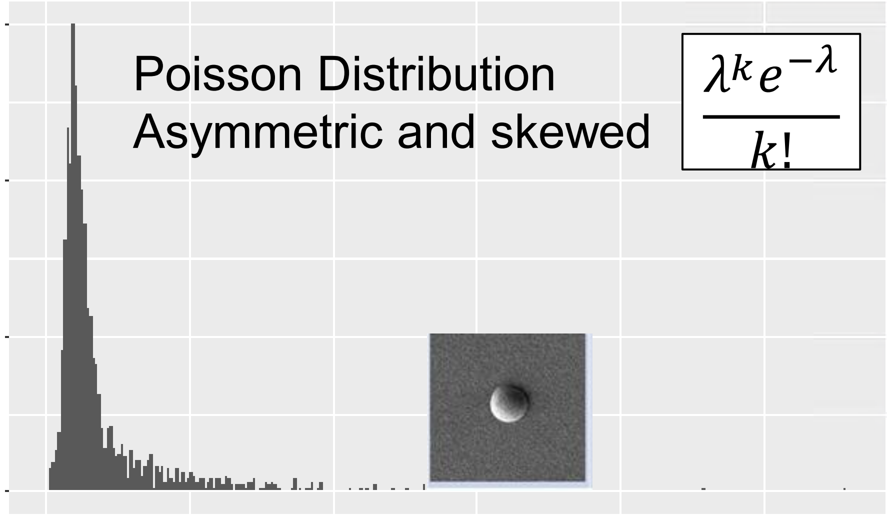
Multi-layered Neural Network

What traditional parametric statistic has been…

$$\frac{1}{x}\times\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(lnx-\mu)^2}{2\sigma^2}\right)$$



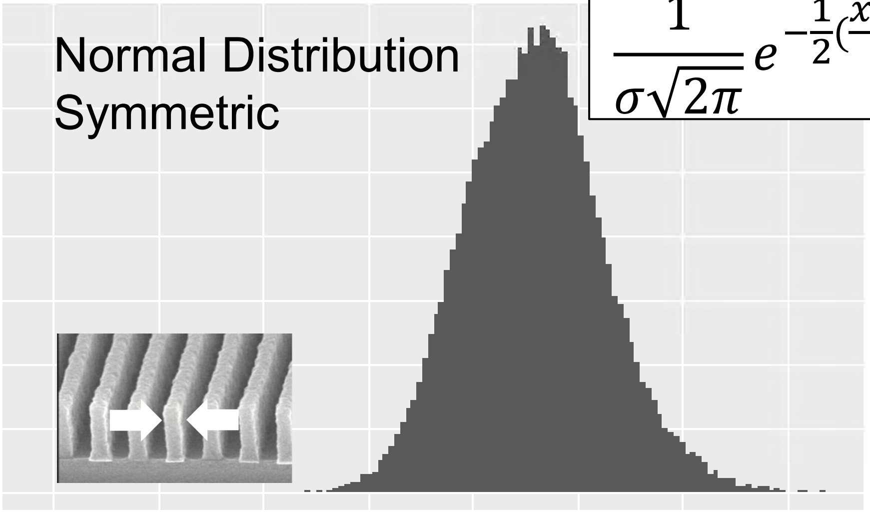
Yield per wafer distribution



$$\frac{\lambda^k e^{-\lambda}}{k!}$$

Particle Count distribution

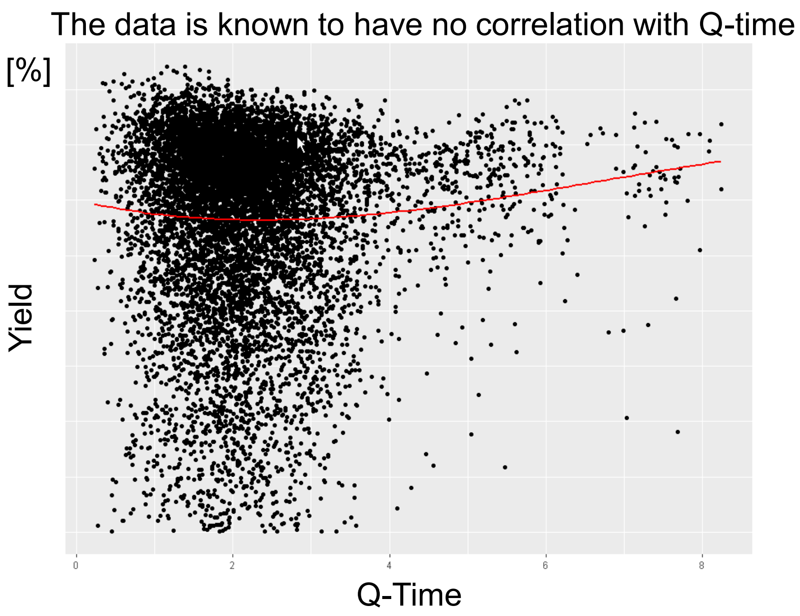
$$\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$$

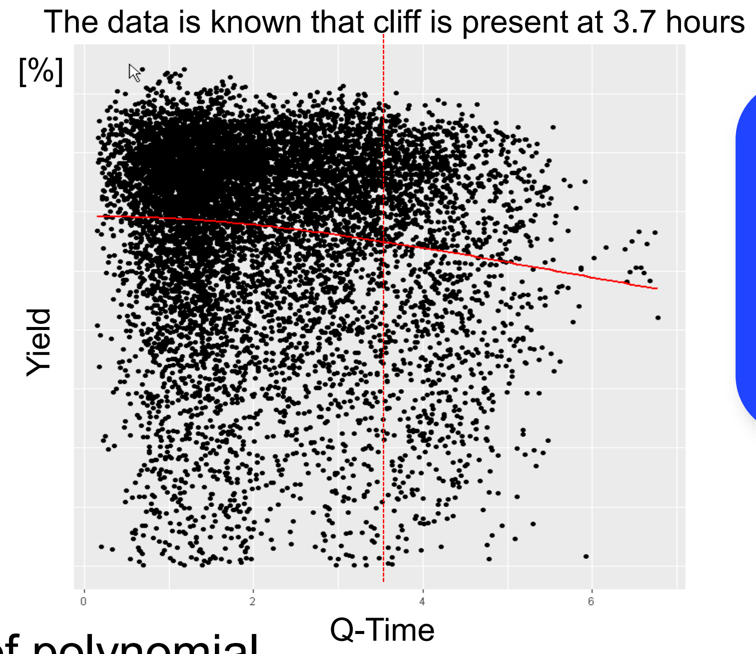


Line Width Measurement distribution

- Statistical distribution varies depending on data type
- Before doing any statistical modeling, one may need to determine which data fits which distribution
- Correlation among different data of different distribution may not be all linear e.g. $y = ax + b$ presuming normal distribution
- But "true" correlation can be anything other than linear
  - e.g. $y = \exp(-ax),\ y = bx^2$, etc.…
- May not be able to discover those relationships if only using $y = ax + b$ as fitting model

Regression model e.g. polynomial

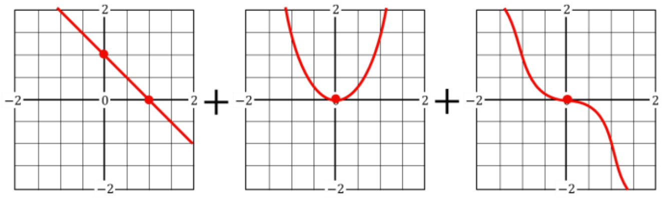




When you use regression model, you presume such physical mechanism

Fitting by 3rd order of polynomial

- At Micron Q-Time refers to the max allowable time interval between two manufacturing process steps. It is a critical control parameter used to prevent degradation in yield
- Queue Time (Q-Time) vs. Yield -> want to find out at which time the yield decays
- Regression model may provide rough idea on correlation
- However, to what extent does this regression model reflect the physical phenomena occurring on the wafer during processing?
- Do we know each term in polynomial regression x, x^2, x^3, x^4?
- Might there be another model that better fits the data or process? E.g., exp(x)



$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \ldots + \beta_n x^n + \mathcal{E}$$

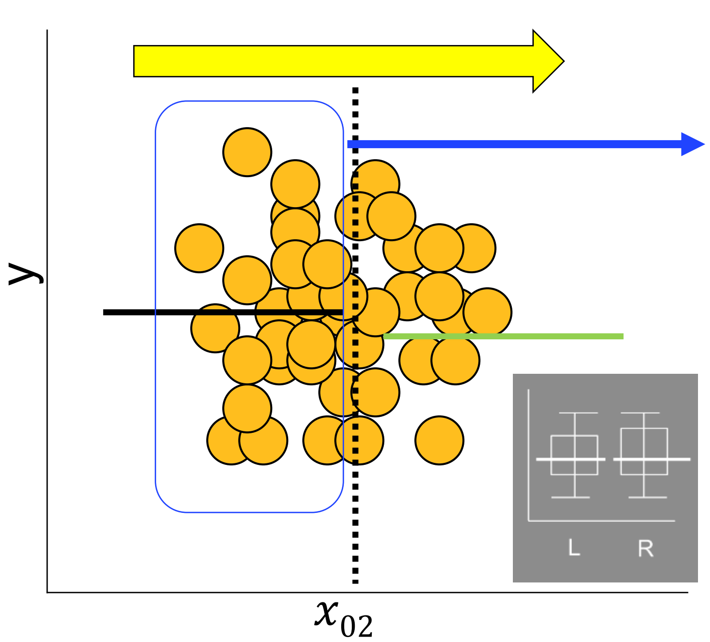
What machine learning does (e.g. ”Random Forest”)

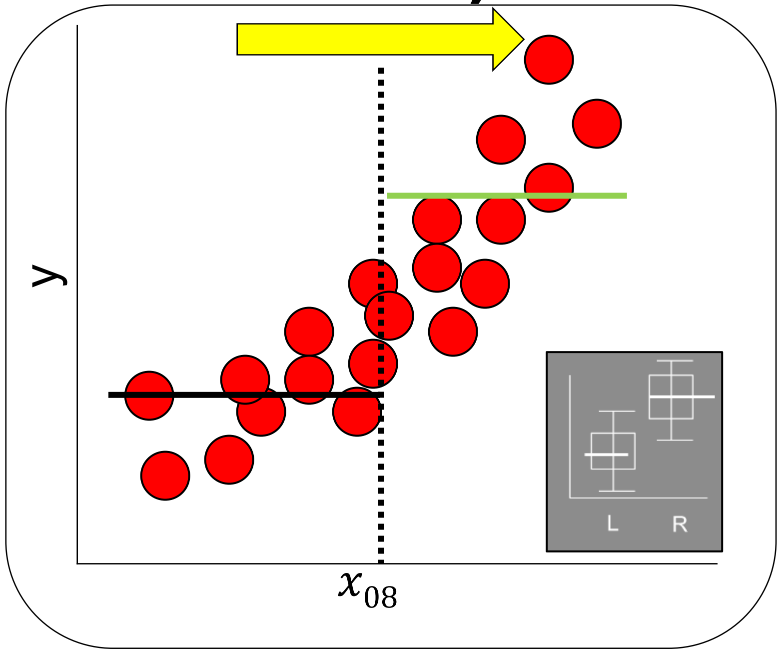
Your Data Sheet to Explore

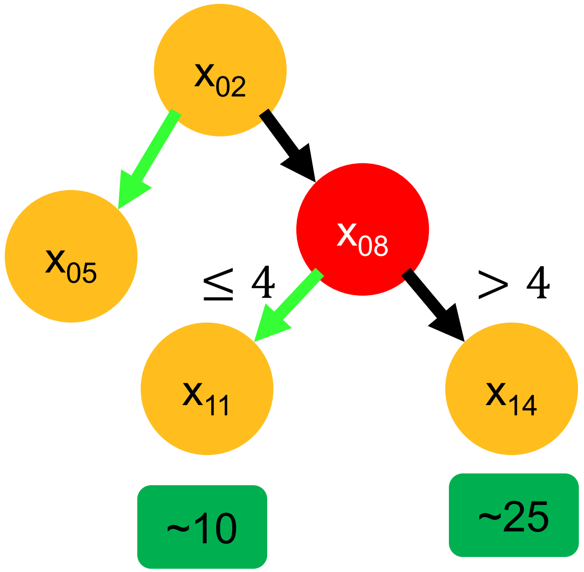
~10

~25

y	x01	x02	x03	x04	x05	x06	x07	x08	x09	x10	x11	x12	x13	x14	x15
7								1							
10								2							
13								3							
16								4							
19								5							
22								6							
25								7							
28								8							
31								9							
34								10							
37								11							
40								12							
43								13							
46								14							
49								15							







[1] Equation: y $= f(x_{01}, x_{02}, x_{03} \ldots \ldots x_i)$, where i is the number of explanatory variables

[2] Randomly select x parameters starting from x_{02}

[3] Change Point Detection – identify the point where the mean gap in y is maximized

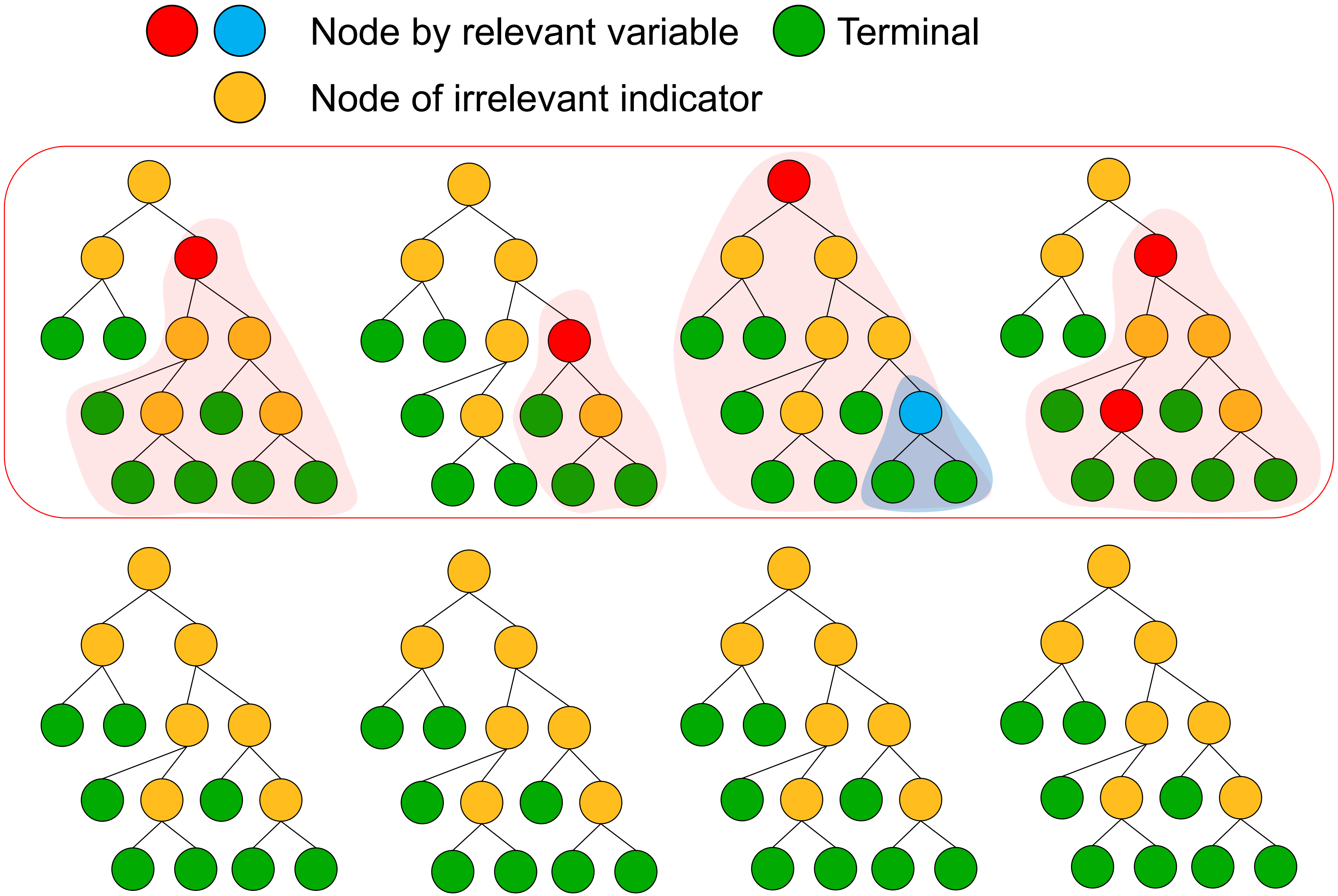
[4] Node Assignment – change point is set as “node” and x data is split into two groups [5] Recursive Splitting - repeat step 3 within each group to find additional nodes

[6] If x_{08} is selected as relevant, then the node based on x_{08} is considered truly predictive

- A truly correlated variable tends to show a relatively large mean gap
- The model may not provide an exact value but provides reliable estimate of mean
- A decision tree that includes x_{08} as a node should demonstrate better predictive performance than one without it

Example continues in next slide

Random Forest to find highly correlated parameter



[7] Repeat [2] to [5] to create multiple trees to form a “forest”

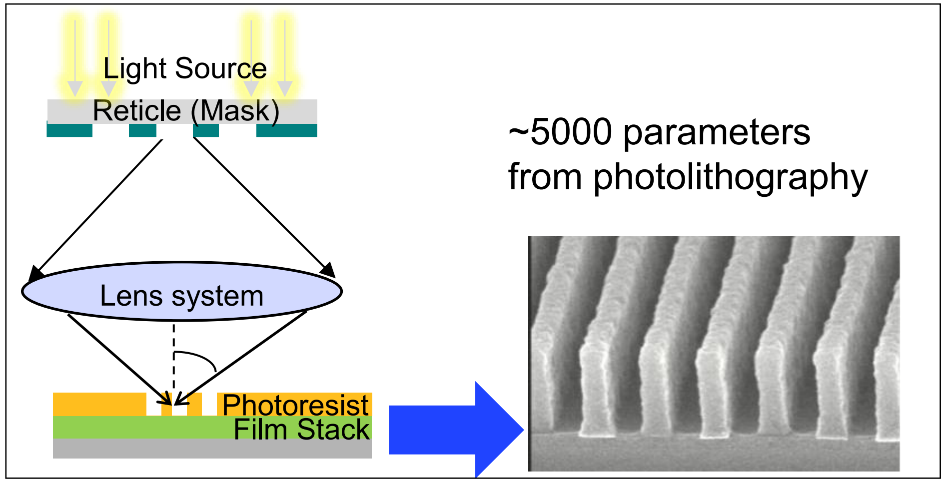
The forest and/or trees with node of relevant variable have better predictability at the terminals on “y”

Key Points

- The flow presumes no assumption on data distribution
- Evaluate all parameters and data points with equal importance
- Requires extensive and repetitive calculations to build the decision tree and reach converge for identifying key parameters
- Dependent on high-performance computing resource

Machine Learning transforms data analysis

- In memory manufacturing, massive number of parameters are controlled and understood
  - $Y = f(X_1, X_2,\ X_3 \ldots \ldots \ldots . X_n)$
  - Where n can be hundreds to thousands per parameter Y of interest
  - n becomes larger and larger as technology node advances



- Break limitation of deterministic modeling
  - Remove subjective interpretation by human
    - Regression model
    - Statistical Distribution of data
    - Physical fundamental formula

$$\nabla \times D = \rho_v$$

$$\nabla \times B = 0$$

$$\nabla \times E = -\frac{\partial B}{\partial t}$$

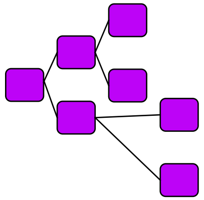
$$\nabla \times H = \frac{\partial D}{\partial t} + J$$

$$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

$$\sum \vec{F} = m\vec{a}$$

$$1N = 1kg \times {}^{m}/_{s^2}$$

$$F_g = G\frac{m_1 m_2}{r^2}$$

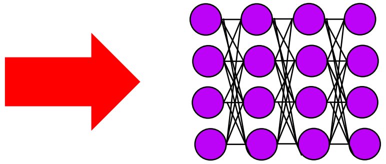


$$dU = Tds - pdV + \sum_i \mu_i dN_i$$

$$dH = Tds + Vdp + \sum_i \mu_i dN_i$$

$$dF = -SdT - pdV + \sum_i \mu_i dN_i$$

$$dG = -SdT + Vdp + \sum_i \mu_i dN_i$$

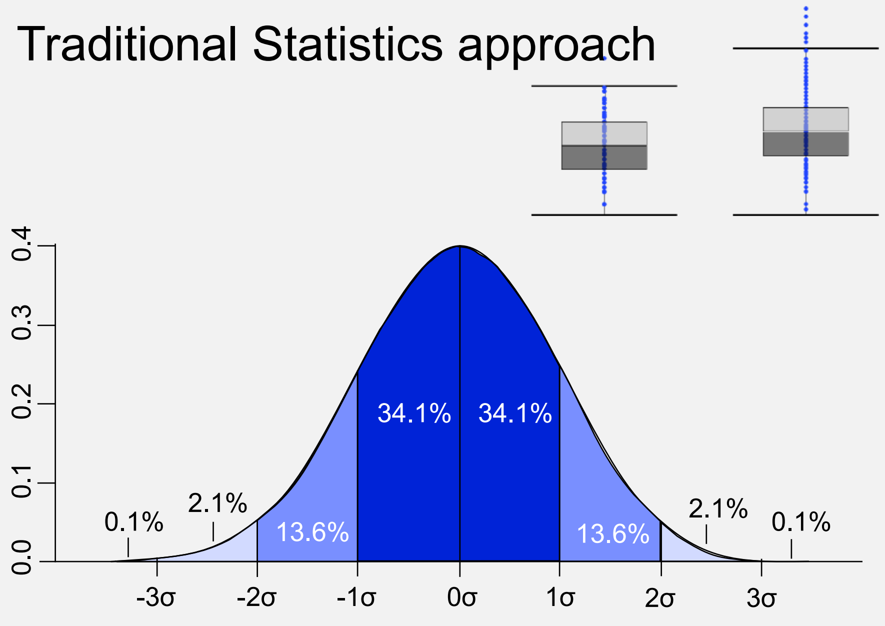


- Explore key features from data
  - Nonparametric approach with no presumed model
  - Focus on feature engineering
  - Use data to explain what is happening

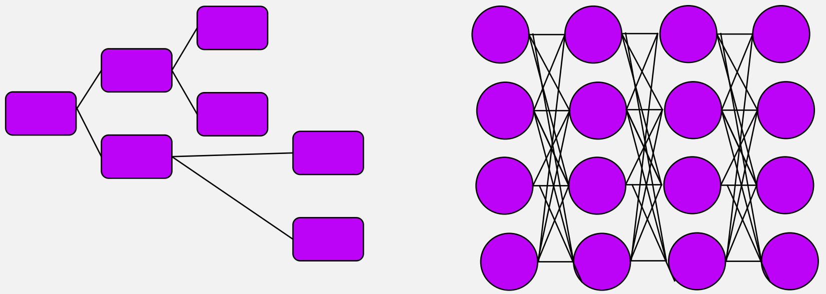
Machine Learning vs. Traditional Statistics

- Expectations for Machine Learning in manufacturing are very high
- However, manufacturing engineers are deeply rooted in p-value based statistical methods
  - p-value ($p < 0.05$) based judgement has long served as backbone for process validations/still common language to make assertive decision in manufacturing
- Yet advanced statistical & nonparametric approach does exist
- Statistical approach and machine learning have been co-existing and utilized in hybrid mode in the field

Traditional Statistics approach



Machine Learning approach



Generative AI (Gen AI)

https://www.micron.com/about/micron-glossary/generative-ai

- **Definition:**
  - Generative AI - commonly known as Gen AI - refers to artificial intelligence systems capable of creating new content—such as text, images, audio, or code—based on patterns learned from existing data.
- **How It Works:**
  - Gen AI models are trained on large datasets using deep learning architectures, often involving transformers and Large Language Models (LLMs) for text-based tasks. These models generate outputs that closely resemble human-created content.
- **Examples:**
  - Text generation
  - Image synthesis
  - Code generation
- **Prompt engineering:**
  - The process by which humans interact with generative AI, crafting, and refining queries to ensure the models understand and respond effectively.
- **Some Gen AI use cases to get started:**
  - Can help write better emails
    - Prompt example: “Rewrite this email for clarity. Use professional tone.”
  - Identifying action items from an email or meeting
    - Prompt example: “List action items from all emails I received in the last week.”
  - Planning a trip
    - Prompt example “I will be traveling for work for 3 weeks to Hiroshima, Japan in March. Provide two weekend itineraries to learn about the culture.”

Data in memory manufacturing


Image created for Micron by Copilot

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Micron delivers a broad portfolio of memory and storage

Memory

High-bandwidth memory (HBM), and graphics memory (GDDR) solutions

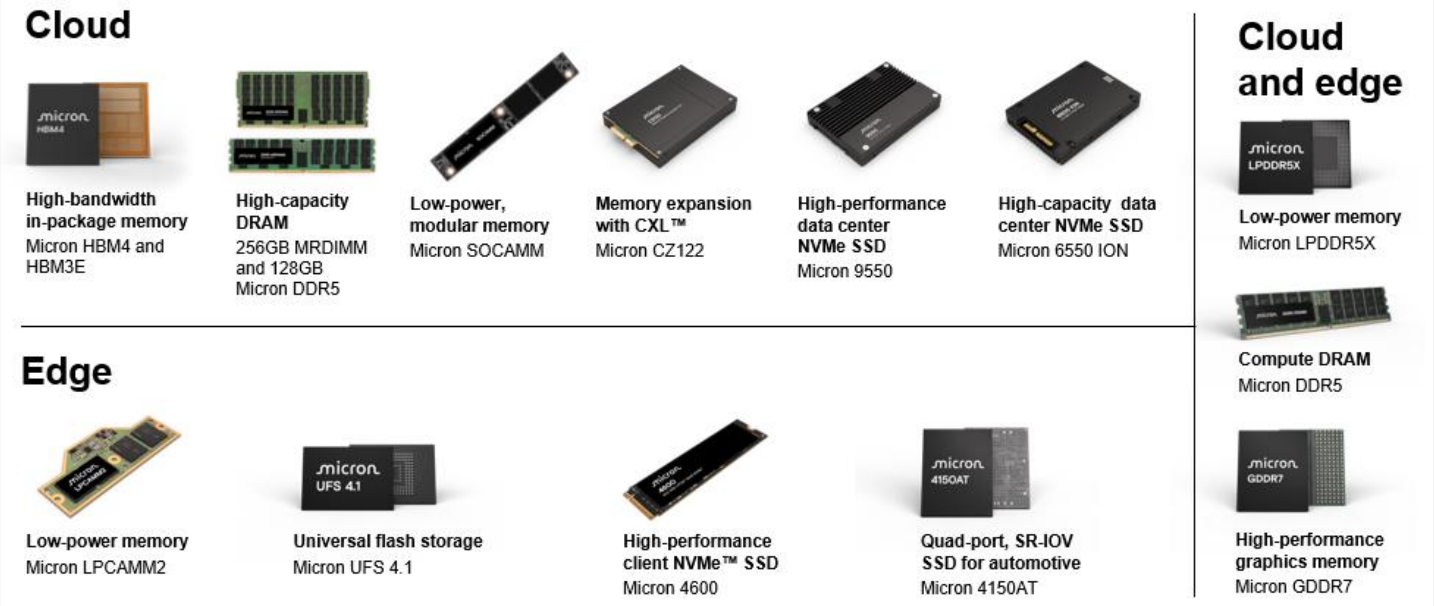
Low-power DRAM and DRAM

Multichip packages (DRAM and NAND)

Storage

Solid-state drives (SSD)

Flash storage (NAND and NOR)

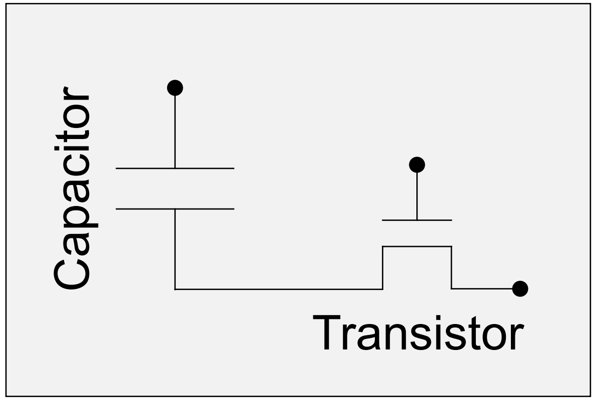


Examples of Micron portfolio products

Let’s explore DRAM Memory

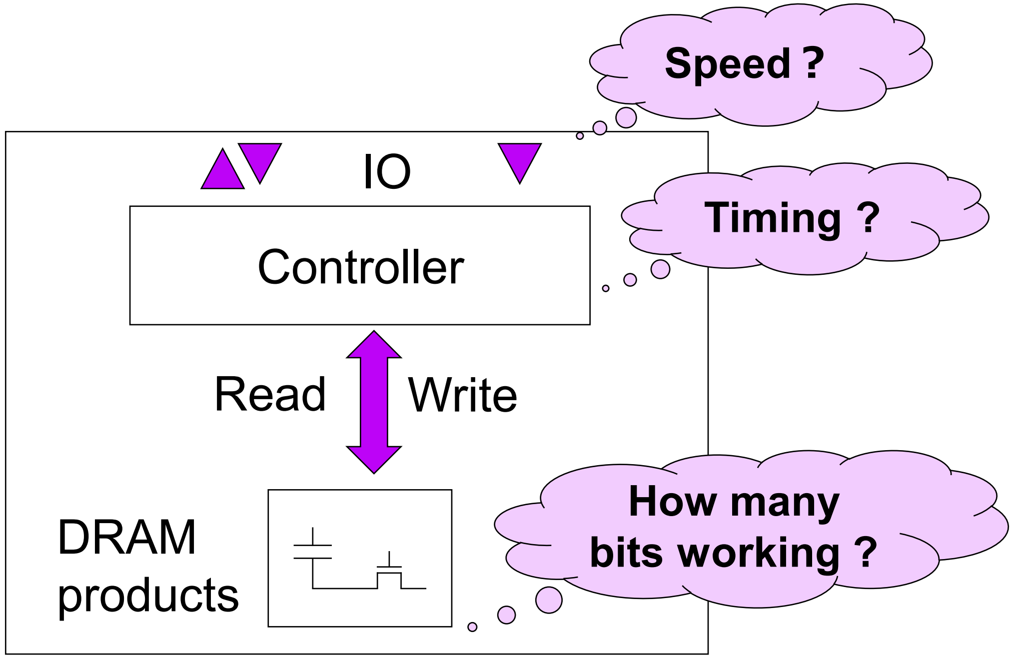
DRAM

- **D**ynamic
- **R**andom
- **A**ccess
- **M**emory



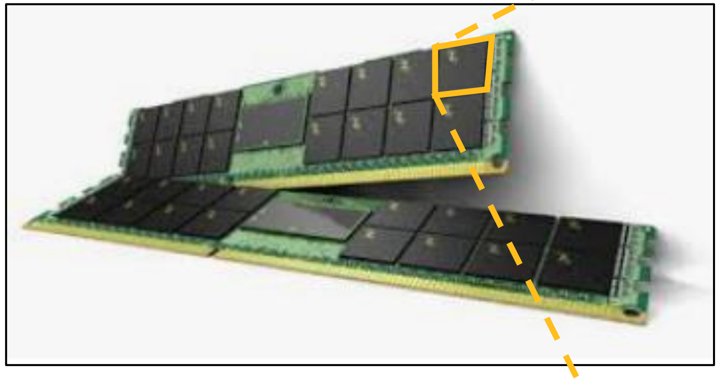
DRAM Memory Cell

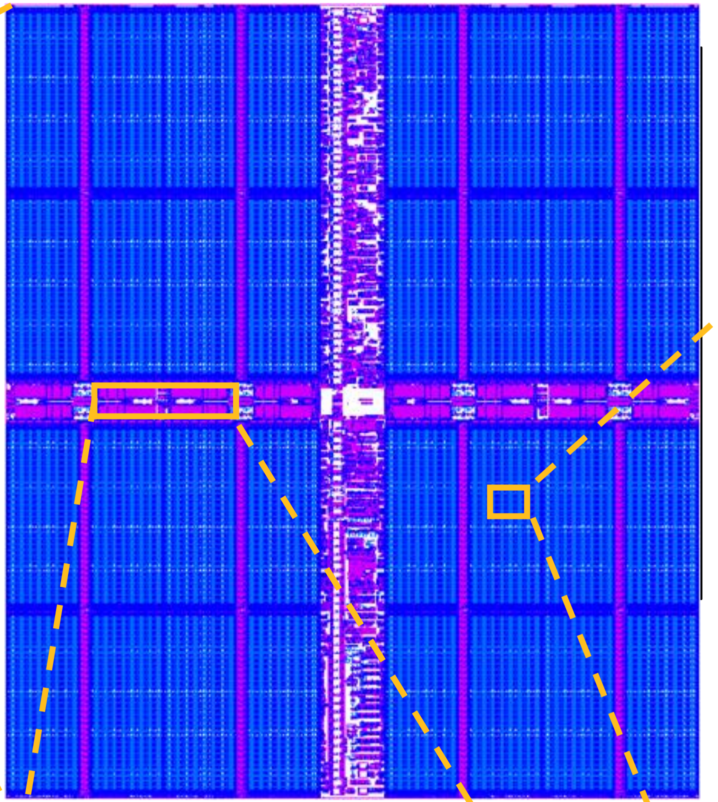
To store 1/0 bit

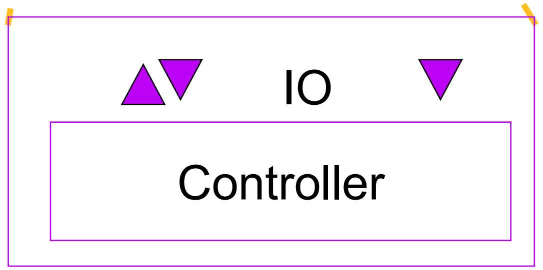


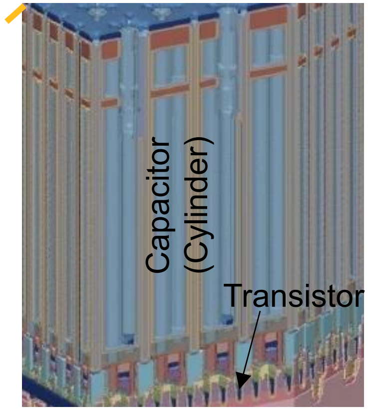
- Billions of DRAM memory cells, each with a transistor and a capacitor, store binary information in the form of a 1 or a 0.
  - The transistor acts as a switch (turns on or turns off) to allow access to the capacitor
  - To store a “0” on the capacitor, 0 volts are sent to the capacitor
  - To store a '1' on the capacitor, a higher voltage is sent to the capacitor (e.g., 1 volt)
- Additional peripheral circuitry reads and writes the binary data to individual cells.
- To learn more about what is semiconductor Memory, types of Memory, and how they work please refer to the Intro to Memory module: https://www.micron.com/educatorhub/courses/intro-to-memory

Where does the data come from within DRAM?

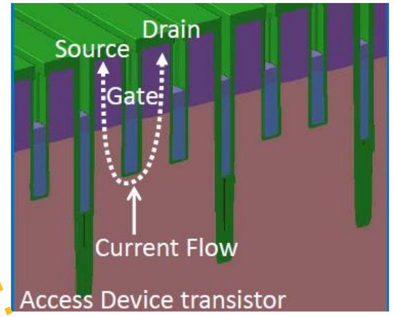


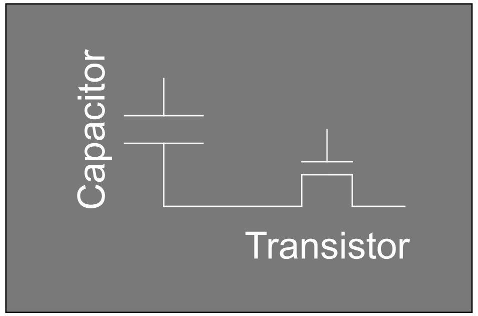




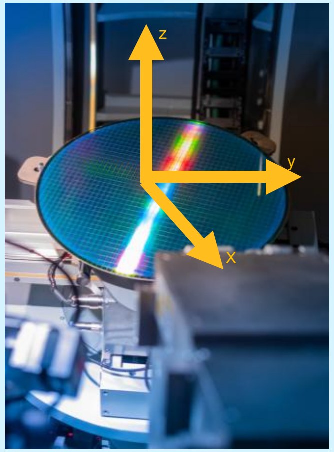


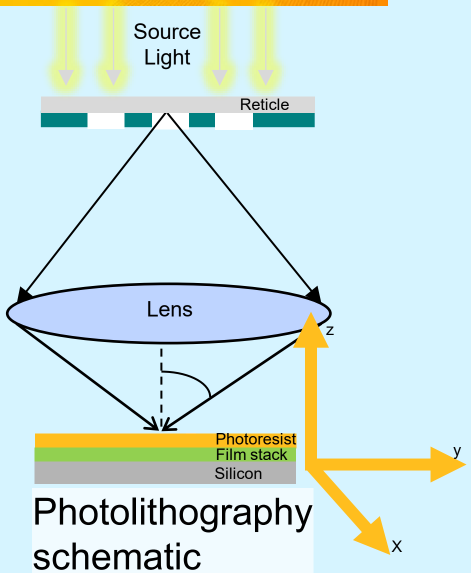
This is a digital composite image, not a real SEM image (Scanning Electron Microscopy).





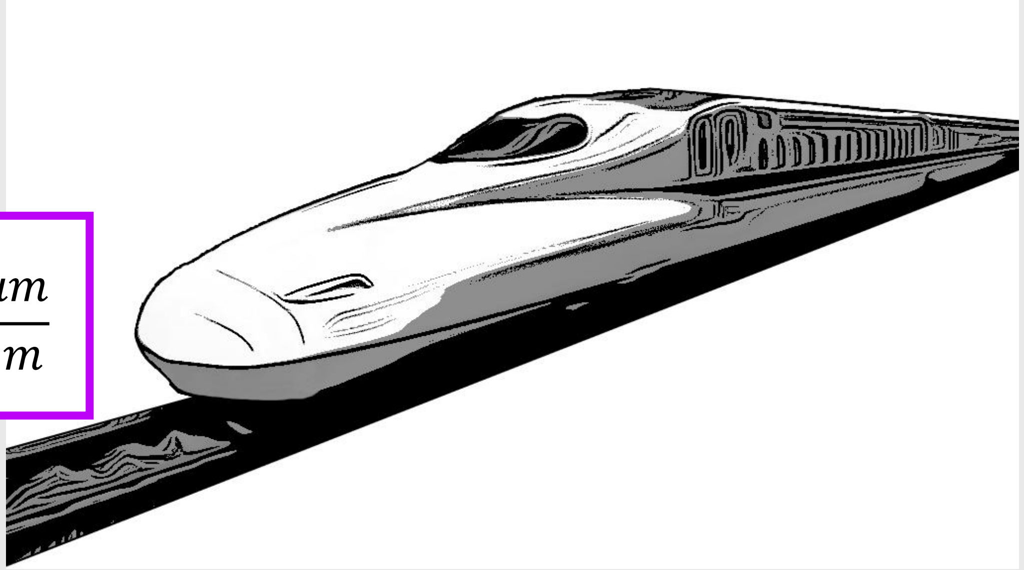
Proportional accuracy





Photolithography schematic

$$\frac{2\ nm}{300\ mm} = \frac{2.6\ um}{400\ m}$$



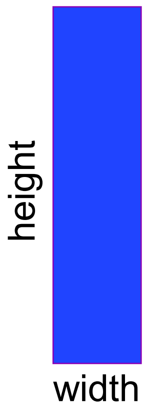
A 400m long bullet train with multiple cars would have to stop within a 2.6μm precision (less than the width of a human hair) at a platform to match the precision of the photolithography tool! (Note: the precision of a real train is a few centimeters).

The 300mm diameter wafer stops within 2nm accuracy in X, Y and Z directions in some photolithography tools, and each layer needs to be aligned precisely (overlay) with prior layers.

Proportional aspect ratio

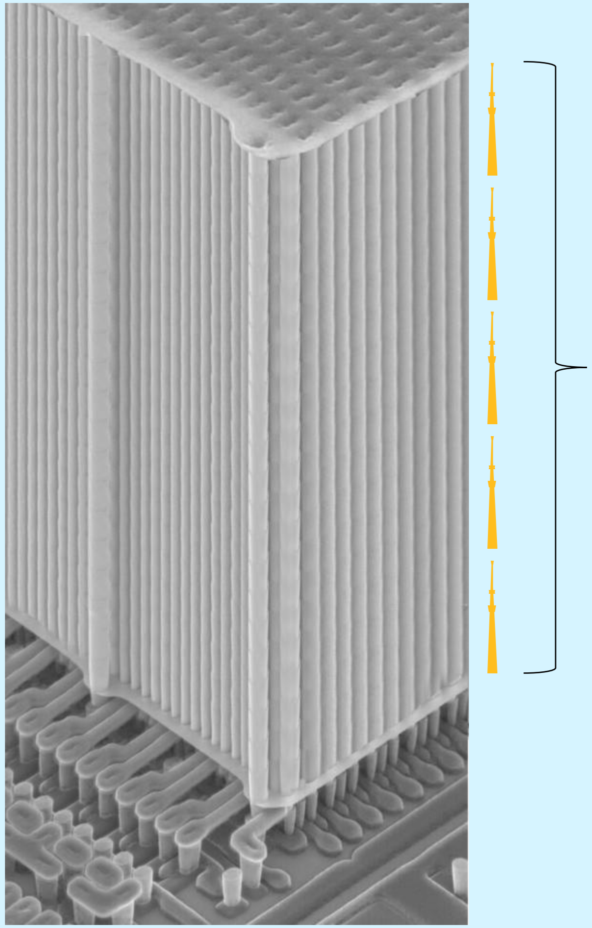
An example from Japan:

Aspect Ratio (AR) = height/width



$$\frac{634\ meters\ (\sim 2080\ feet)}{68\ meters\ (\sim 223\ feet)}$$

AR for the Tokyo Skytree ~ 10

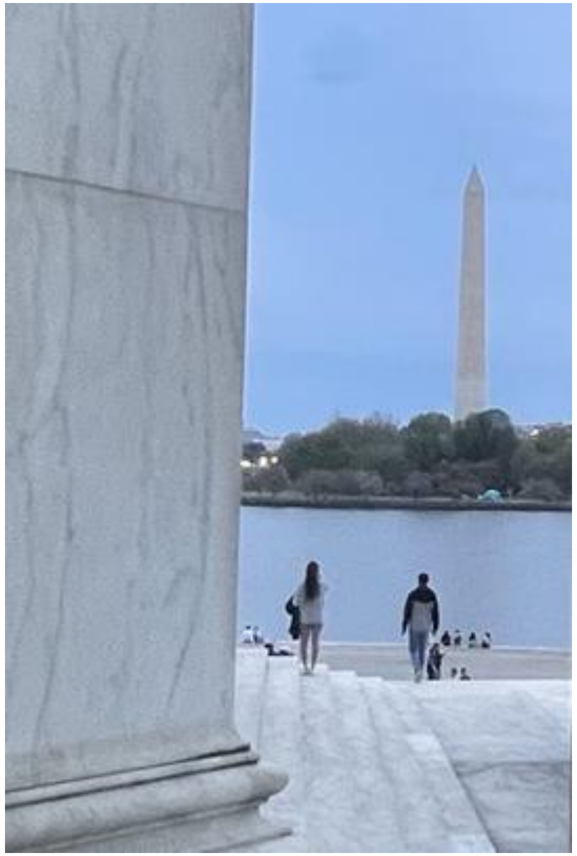


5 Tokyo Skytree buildings!

AR for a DRAM capacitor cylinder ~50!

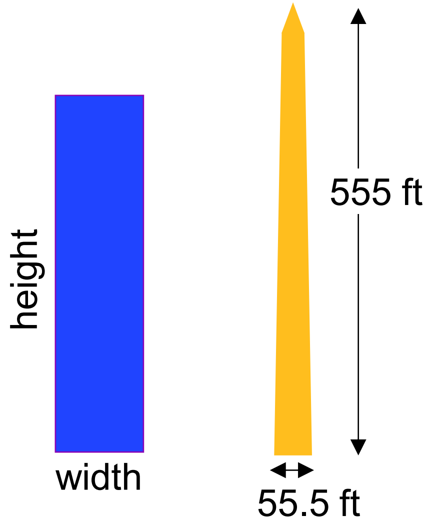
Proportional aspect ratio

An example from
the United States:

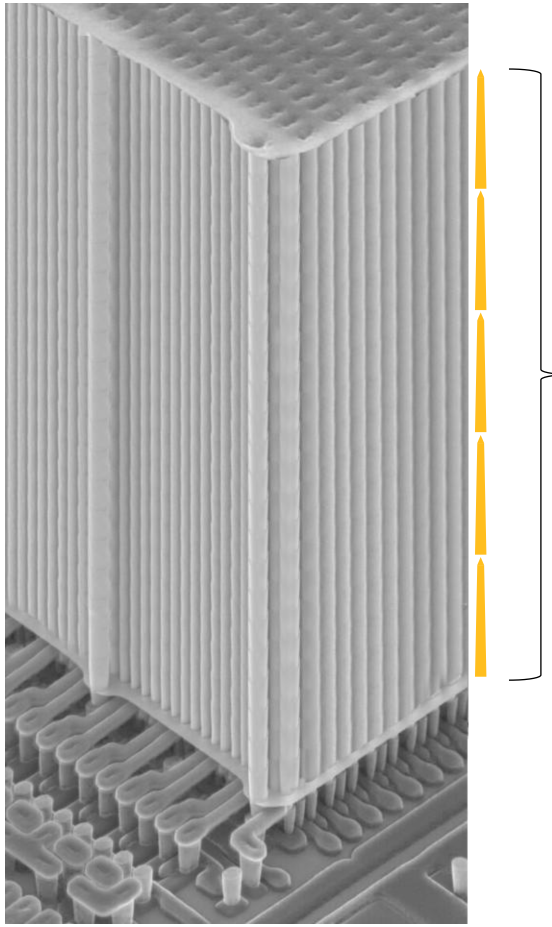


Washington Monument, Washington DC

Aspect Ratio (AR) =
height/width



Aspect ratio
Washington
Monument ~10

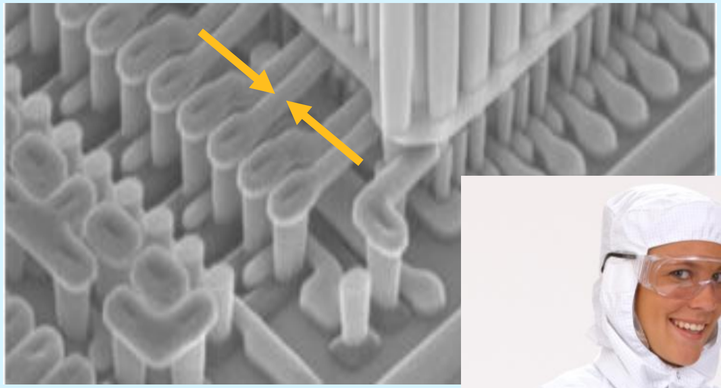


5 Washington
Monuments!

Aspect ratio for DRAM
capacitor cylinder ~50!

How small is the nanometer scale

It is difficult to imagine the nanometer scale. Let's say that a DRAM line width is approximately 15 nm. If we compare the line width to a 300 mm diameter wafer…

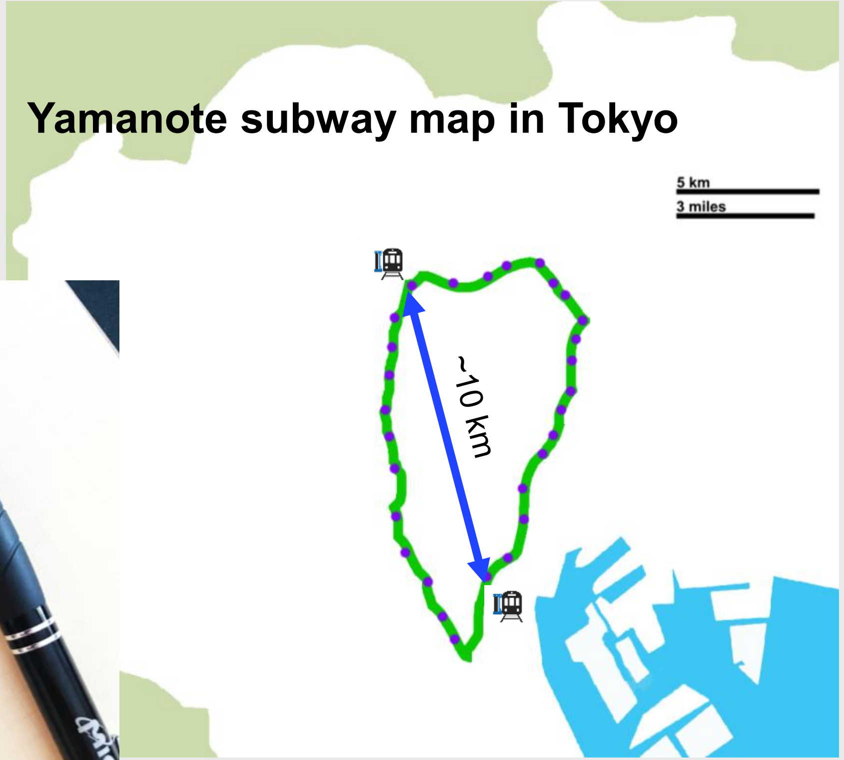


300 mm diameter wafer

$$\frac{15\ nm}{300\ mm} = \frac{0.5\ mm}{10\ km}$$

…that is similar to comparing a 0.5 mm line from a mechanical pencil to 10 kilometers, which is the distance from Shinagawa to Ikebukuro station in Tokyo!

0.5 mm mechanical pencil lead



~10 km (6.2 miles) is the distance from Shinagawa Station to Ikebukuro Station

Data in Semiconductor manufacturing

Prime Data

- Data that has immediate impact to yield & quality of products
- Collected inline & real time during manufacturing
- Semiconductor industry has used “Big Data” for decades
- Here are some examples

Equipment Sensor

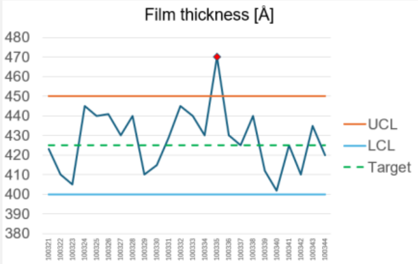
Sensor data collected during wafer processing

Equipment History

- ❑ Which equipment processed a wafer at a specific process step?
- ❑ When was preventive maintenance done on the equipment?

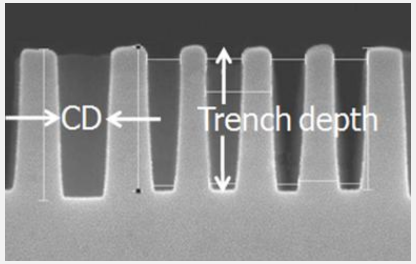
SPC (Statistical Process Control)

Any issues or trends seen in the data?



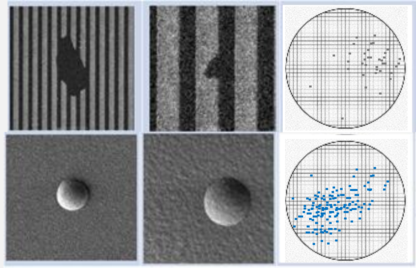
Critical Dimensions

Line & Space, thickness, depth



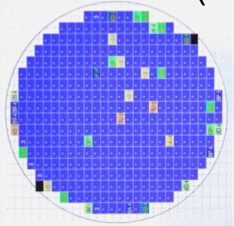
Defects

Number of particles, unwanted shape



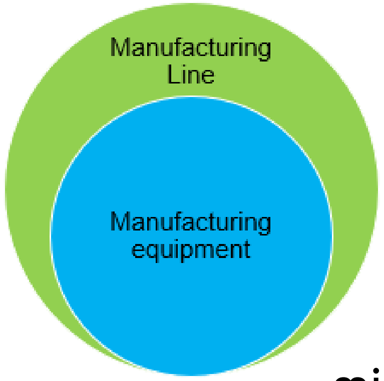
Probe Testing

Wafer Yield: good die / all die
Involves hundreds of tests (and test results) on each die



Parametric Testing

Testing of electrical parameters from the different components of the circuits involves hundreds of tests (and test results) per wafer

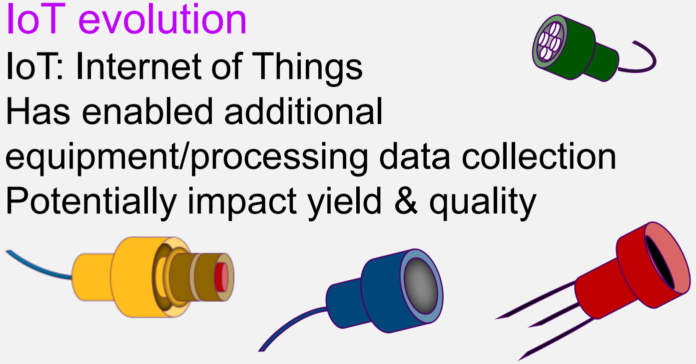


IOT = “Internet of Things”

Other data in Semiconductor manufacturing

Weather
Temperature, humidity, lighting

IoT evolution
IoT: Internet of Things
Has enabled additional equipment/processing data collection
Potentially impact yield & quality

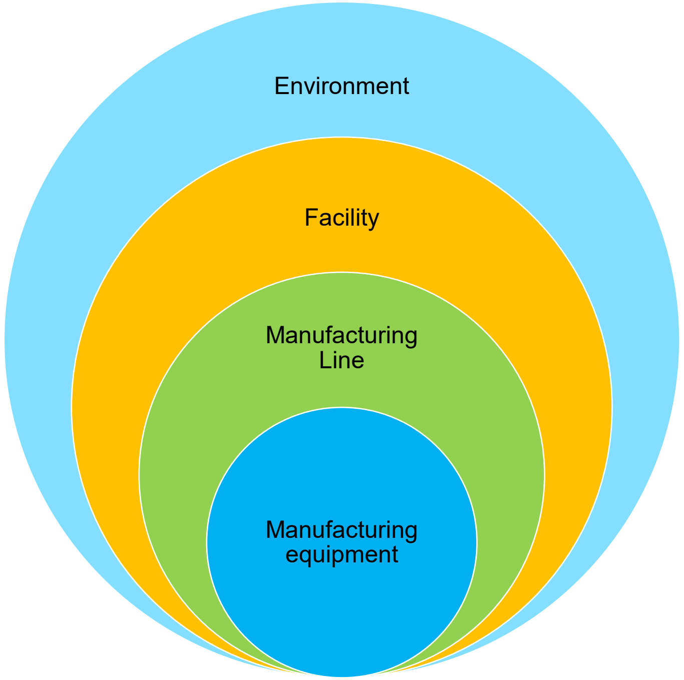


Clean Room Environment
Humidity, temperature, airborne molecular contamination

Equipment Parts
Transport robot
Vacuum pump

Utility
Electrical power supply, gas supply, air condition

Overhead Hoist Transport
Real time location and routing, congestion monitor



Priorities in Memory Manufacturing

Yield

Make it functional

Quality

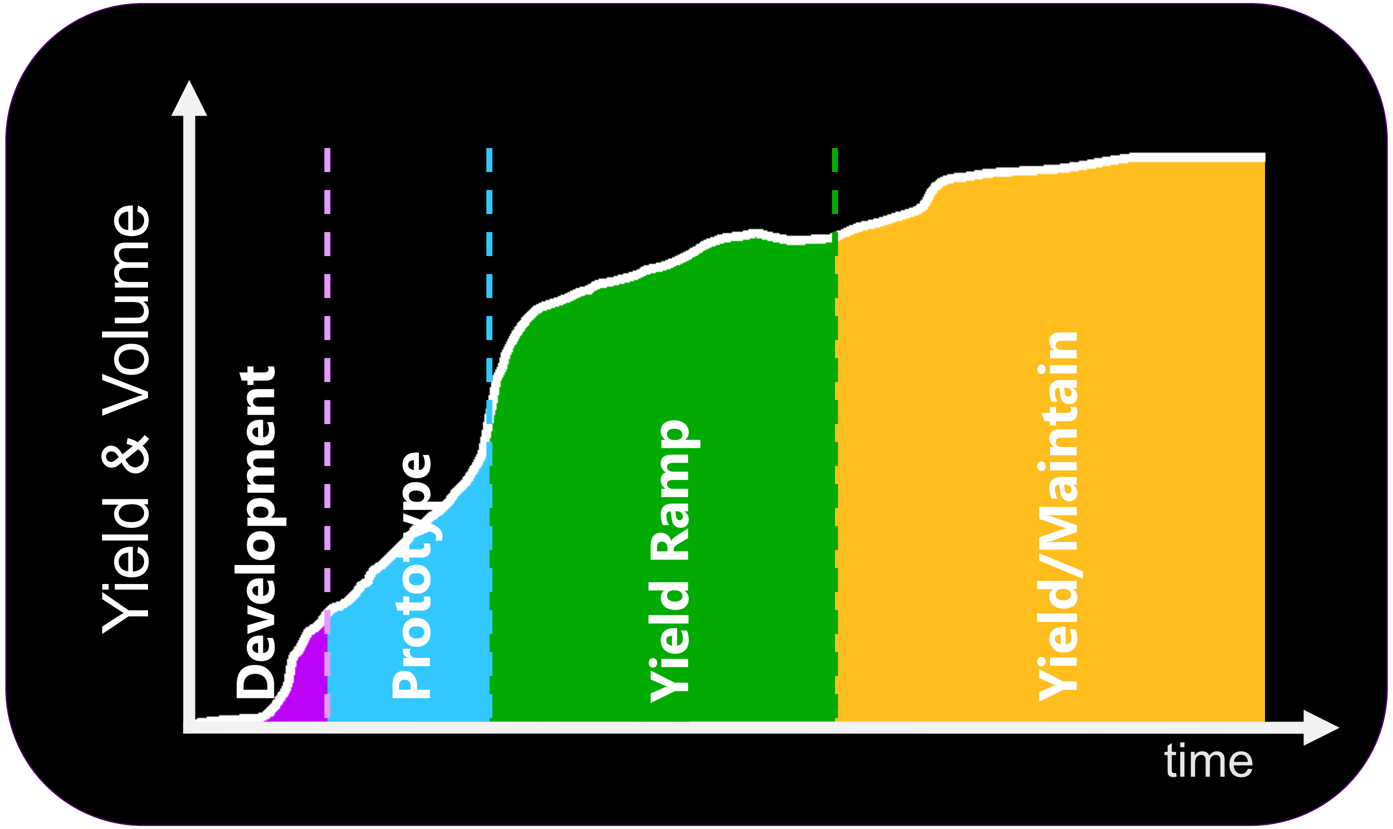
Make better

Cycle Time

Make faster

Cost

Spend less



Data shown in previous slides is analyzed to optimize these key priorities

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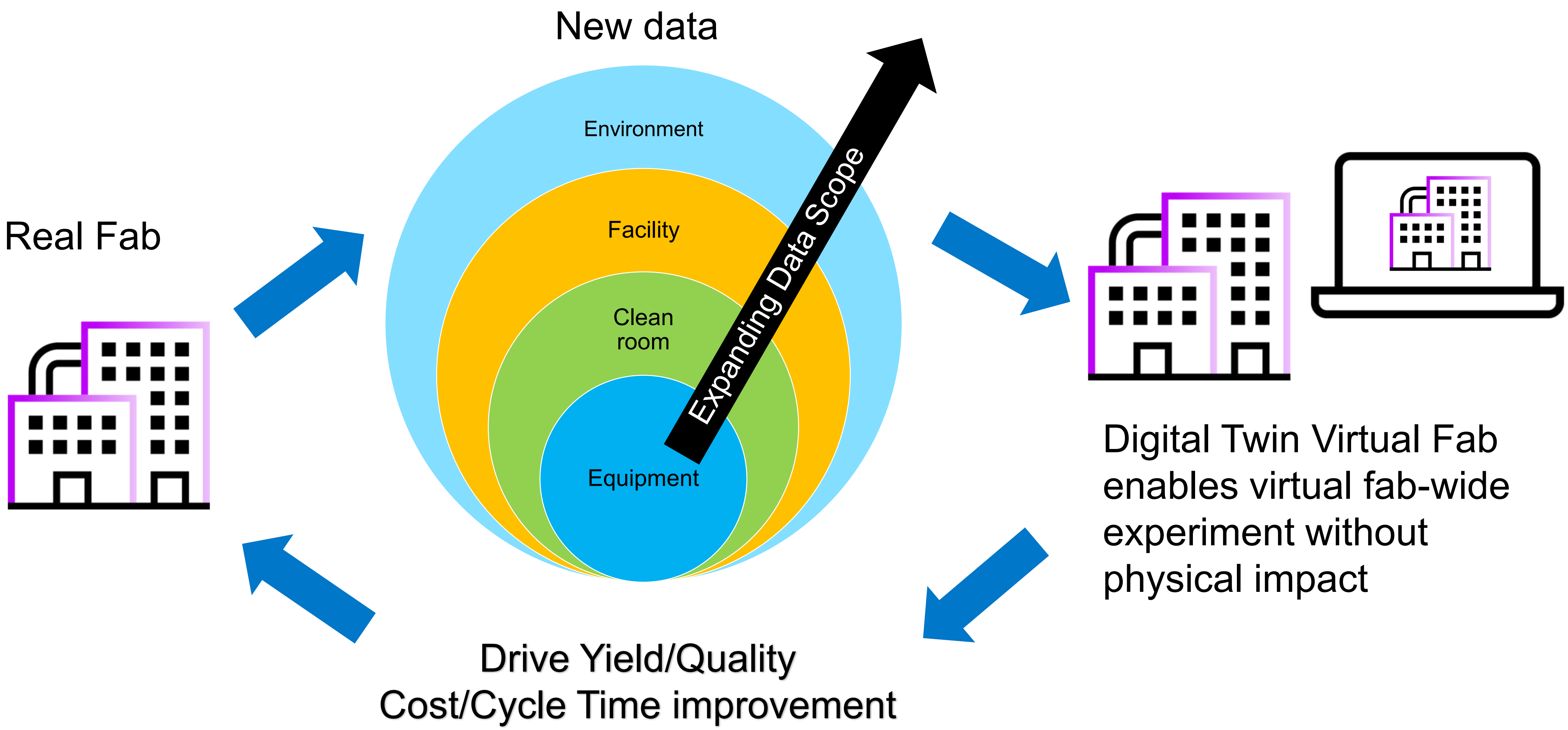
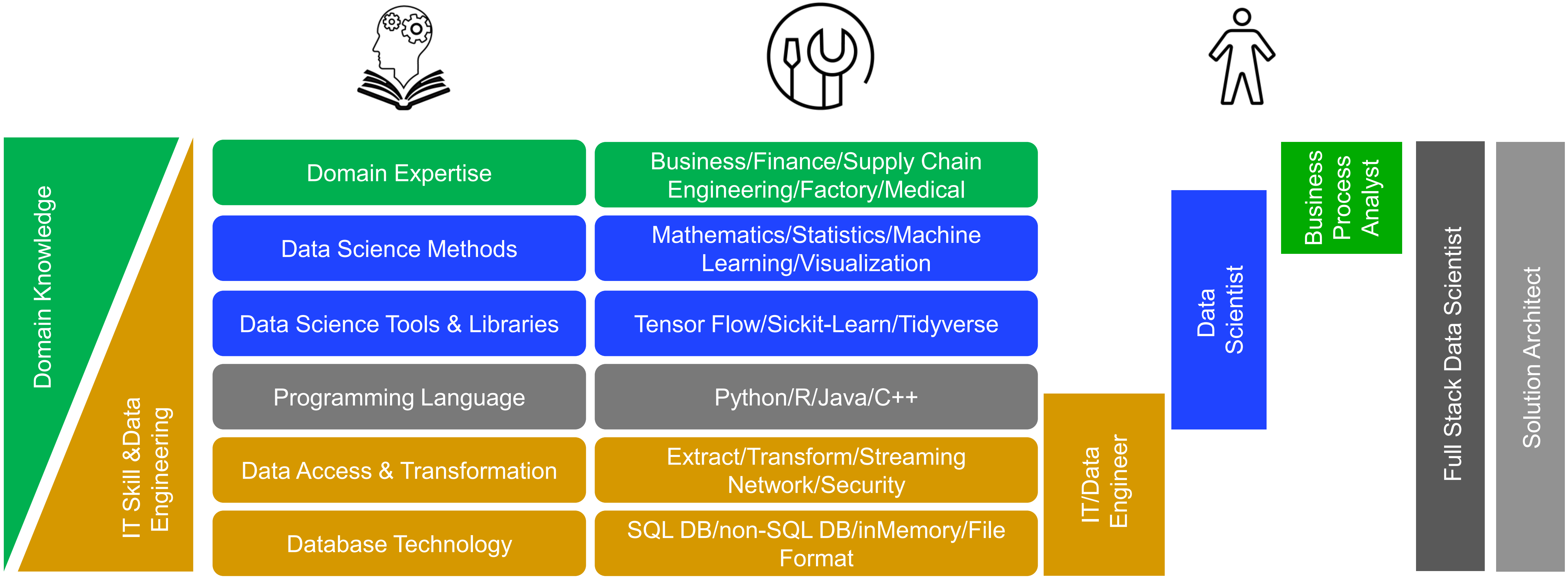
Big Data/AI integration in semiconductor industry



Data Science Roles and Team Dynamics

micron

How Data Science Team is formed



Data Science Knowledge Stack

Data Science Dynamics: Skills/Tools Coverage

Data Engineering

- Database architecture
- API development
- Data streaming
- Relational database
- Data extraction/ data joining

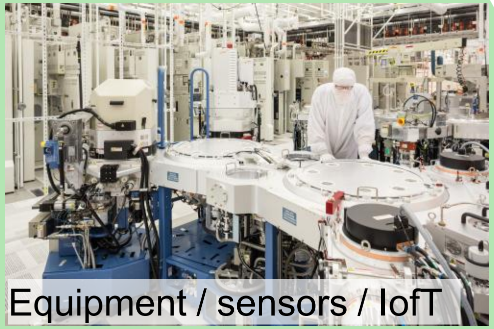
Data Science

- ML coding proficiency Python, R, etc.
- Scikit-Learn
- Tensor Flow
- Data visualization
- Machine learning

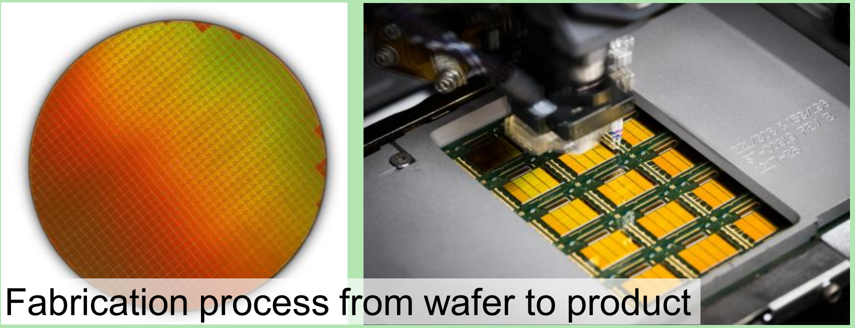
Domain Expertise

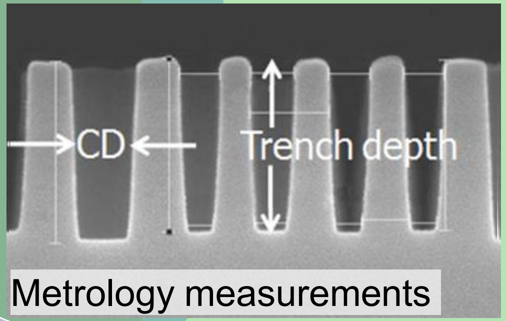

Fab


Equipment

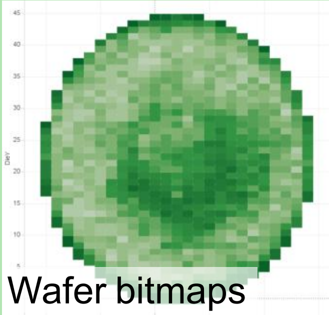

Equipment / sensors / IofT

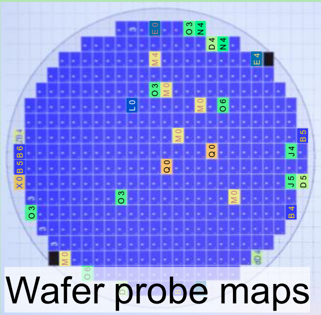

Robots


Fabrication process from wafer to product

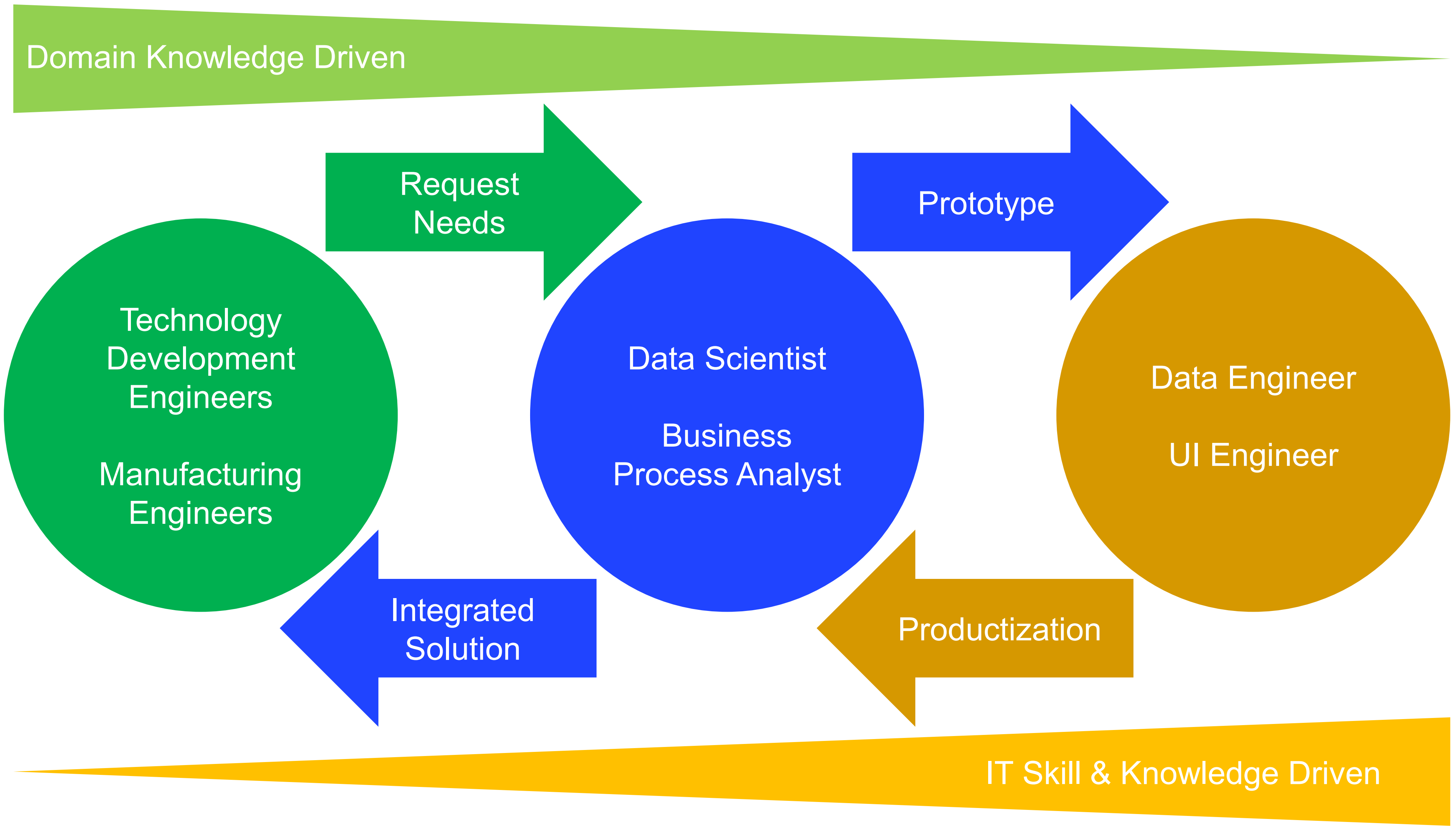


Metrology measurements


Wafer bitmaps


Wafer probe maps

Dynamics of Data Science Project



How Data Science Project is Executed

Prerequisite for Data Science in memory manufacturing

- Can you tell how DRAM memory stores single bit “0/1” information?
  - Hint: Can use Micron Educator Hub to learn more, e.g., Intro to Memory
- Can you tell how DRAM memory is made?
  - Hint: Can use Micron Educator Hub to learn more, e.g., Intro to Fabrication
- Can you tell how small an advanced transistor is?
  - Hint: in the nanometer scale!
- Can you tell why overlay in photolithography is important?
  - Hint: why is alignment between layers important?

Domain knowledge

Prerequisite for Data Science Continued

- Can you explain the difference between mean and median?
  - Hint: what if data distribution is skewed? What if there is excursion point?
- Can you explain difference between supervised and unsupervised learning?
  - Hint: e.g. learning with labeled data for learning and prediction -> supervised y=f(x)
- Can you explain the concept of statistical significance?
  - Hint: t-test, ANOVA, $p<0.05$
- Can you provide examples of IoT?
  - Hint: devices to collect image/sound/temperature, etc.
- Can you provide examples of tools or methods that can be used for data visualization?
  - Hint: scatter plot, histogram, box plot, contour map

Data Science knowledge

Prerequisite for Data Science continued

- Can you develop analytical scripts with Python and/or R?
  - Example: print (‘Hello World’) in Python

- Can you extract data from a database using SQL?
  - Example: “select * from data_table”

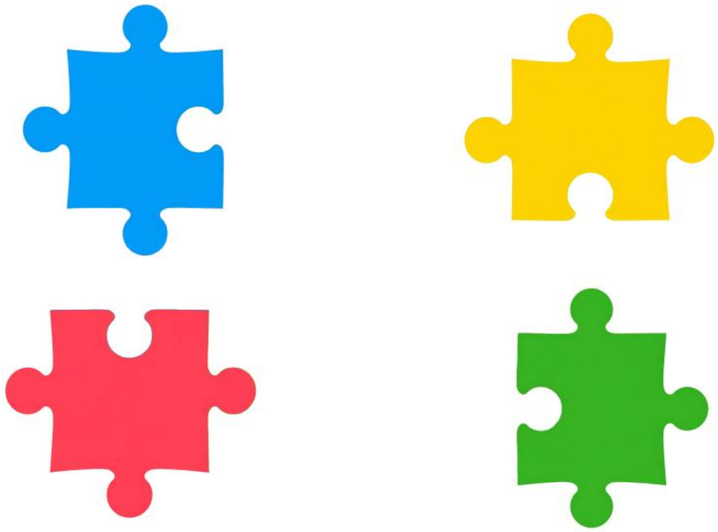
- Can you create an interactive user interface (UI) and what tools can you use to do so?
  - Hint: Tableau, FLASK for more interactive UI

IT skills & knowledge

Integrating Data Science Jigsaw Puzzle Pieces into One

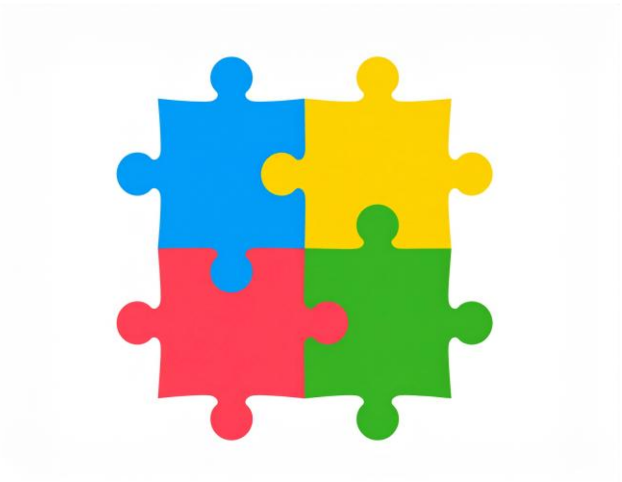
Problem Statement

Algorithm Statistics



Data Sourcing

Visualization User Interface



Integrated DS (Data Science) Solution

Image created for Micron by Adobe Firefly

Case Studies

Image created for Micron by Copilot

Case Study: Wafer Map Analytic

Domain knowledge

- Each memory die on wafer is electrically tested
  - Check every die functionality to ensure it is sellable to customer
- A Wafer Map is generated with the test results. Each die is represented by a rectangle in the wafer map. Colors and codes may be used in the map to represent a good die or a bad die. Bad die are further sub-categorized depending on the specific failing test.
- You may see “signatures” which may help identify what caused the functional failure
- The “signature” may help process engineers diagnose the reason for the failure or root cause
- Highly dimensional data
  - Product ID: specific type of device
  - Lot ID: unique identifier assigned to a group of wafers that are processed together through various stages of fabrication
  - Wafer ID: unique identifier assigned to a wafer in a lot
  - Die location (x,y): specific position of die on wafer
  - VALUE

Wafer Map

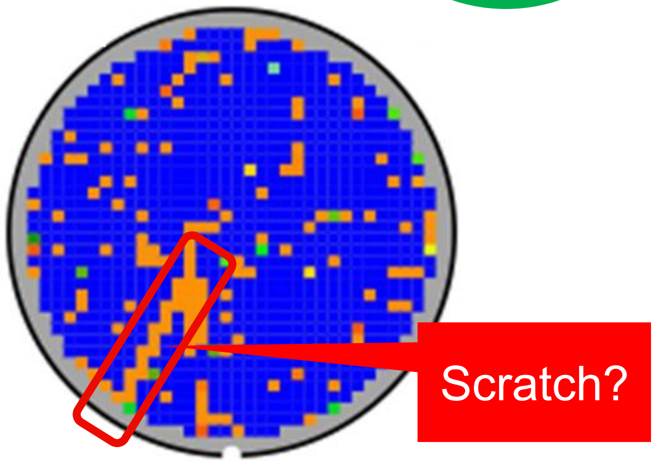


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Image created for Micron by Copilot

Electrical Functional Test Flow

Domain knowledge

Probe Tests -> hundreds of tests to validate capacitors correctly store 1s and 0s: includes data reads and writes

Data to be collected

Test characterization data → Repair → Pass or Failure

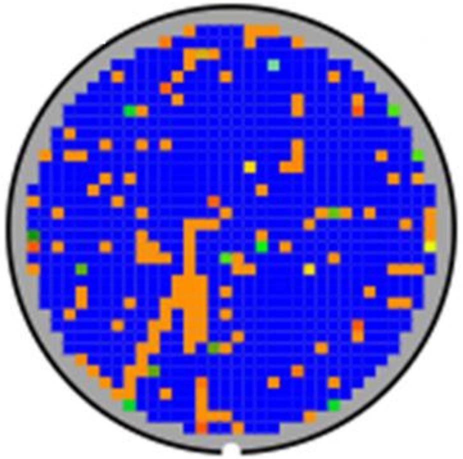
Fails can be categorized into different fail types. Probe test algorithm determines how to ‘Repair’ (implementing ‘redundant’ elements built into the die).

1	1	1	1	1	1	1	1	1
1	1	1	1	0	1	1	1	0
1	1	1	1	0	1	0	1	1
1	1	1	1	1	1	0	1	1
1	1	1	1	1	1	0	1	1
1	1	1	1	1	1	1	1	1

This good redundant column is used to replace the column with two fails

Redundant columns

Tester estimates if the die can be repaired with the existing redundant elements. If the die is found to be repairable then mark as “pass” otherwise, “fail”



Note: Redundant or spare rows and columns are manufactured in each DRAM die to replace non-functioning rows and columns.

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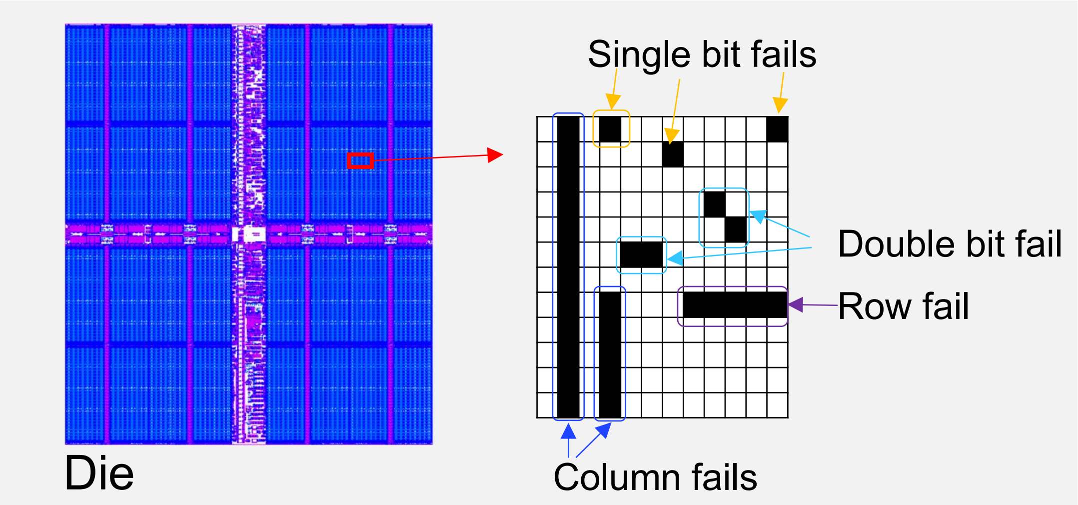
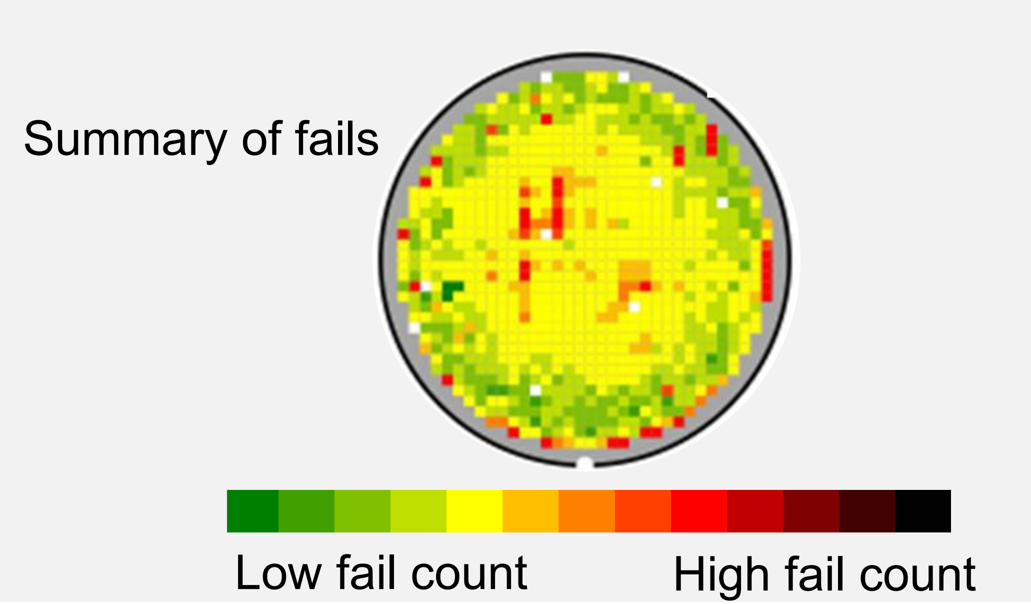
Wafer Map of Probe Test Data: Bit Map

Domain knowledge

- Bit Map
  - Fails can be categorized into different fail types, e.g., single bit, double bit, column/row
  - Fails can also be visualized in a bit map
  - Fail data can be used to determine how to repair using redundant elements built into the die.
  - Data level:
    - Lot level data (5-25 wafers per lot) (e.g., wafer level average)
    - Wafer level data (e.g., fail count per wafer)
    - Die level data (e.g., fail count per die)





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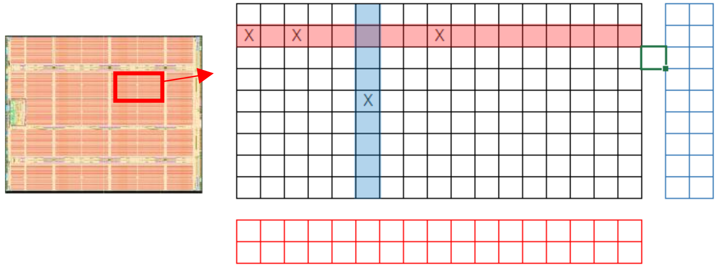
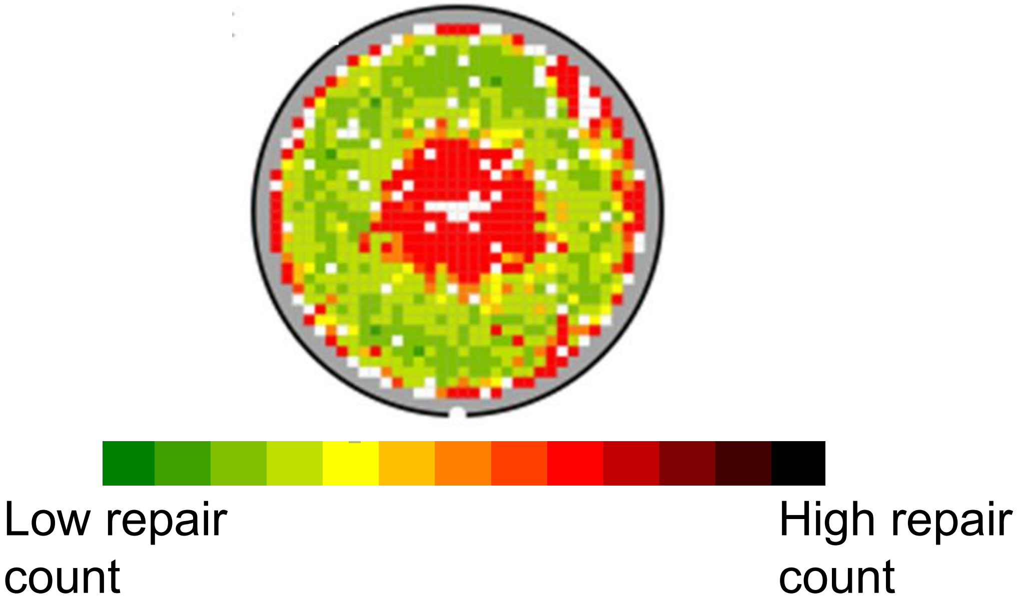
Wafer Map of Probe Test Data: Repair Density

Domain knowledge

- Repair Density
  - How many repair elements were used to repair fails found during testing
  - Data levels:
    - Lot level data (e.g., wafer average repair count)
    - Wafer level data (e.g., die average repair count)
    - Die level data (e.g., repair count per die)



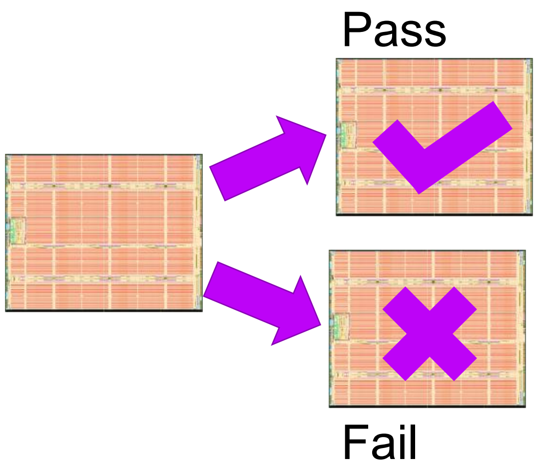


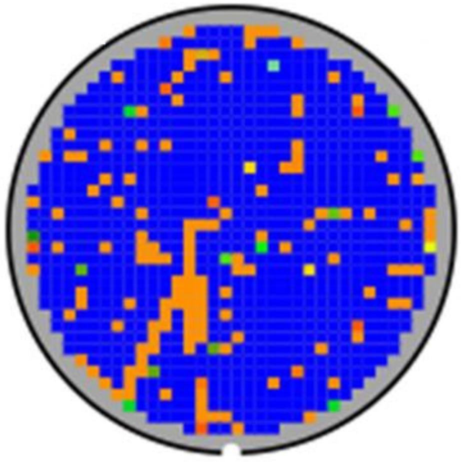
This data has been produced solely for educational purposes and does not represent real Micron data.

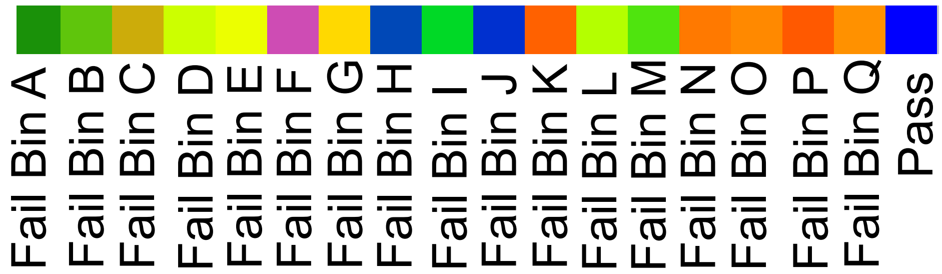
Wafer Map of Probe Test Data: Fail Bin

Domain knowledge

- Fail Bin
  - The probe testing consists of a series of tests, each with specific conditions that test different circuit functionality
  - Each test has a name and an associated color and character
    - For example, if a test finds open contacts that are not repairable, the die fails to Bin O, and the wafer map will show the die in orange color.
  - Data: Symbolic e.g., character/color per die
  - High Level Summary of fail mode of the die

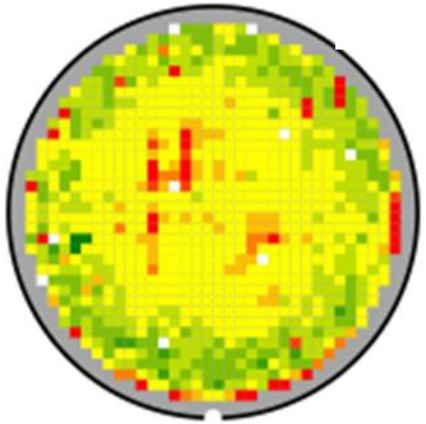




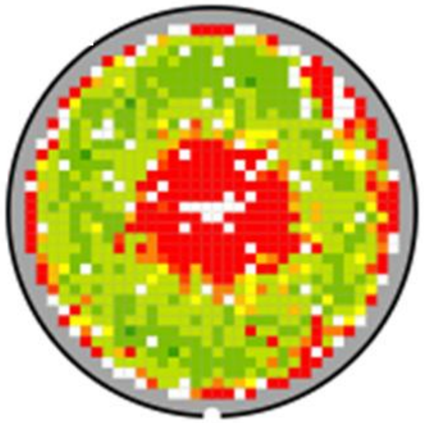


Wafer Map by resolution of the data

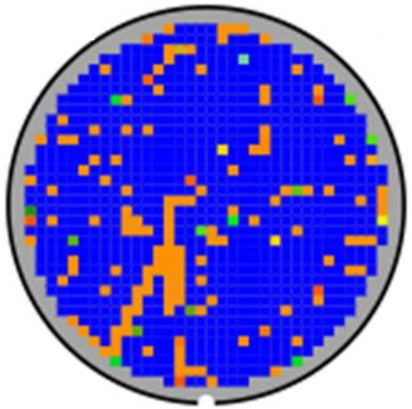
Domain knowledge



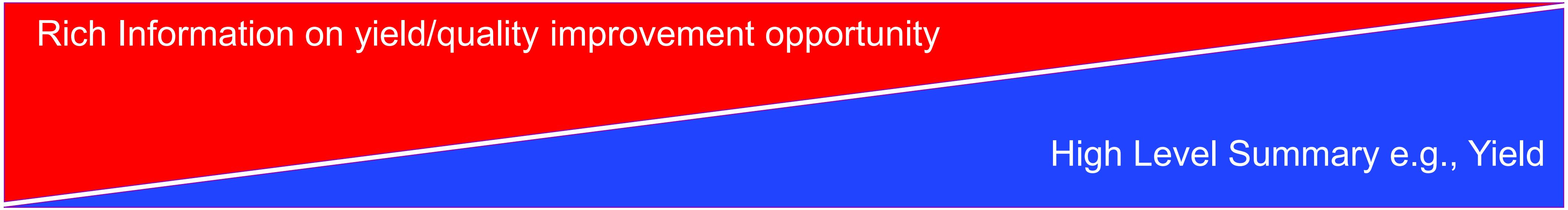
Bit Map



Repair Density



Fail Bin Map



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Problem statement

Problem Statement

- Semiconductor Fabs produce a remarkably high volume of wafer outs daily—often in the hundreds or even thousands.

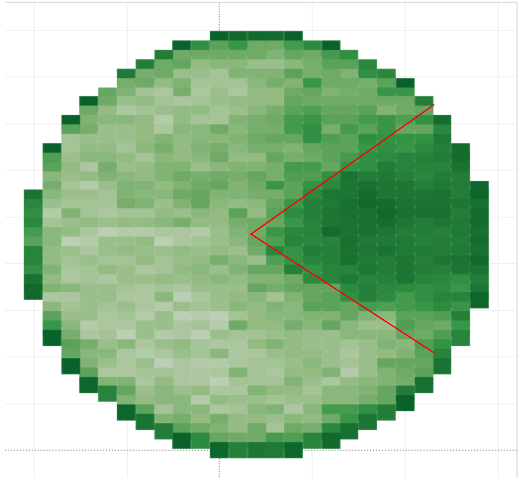
- Within this output, some 'signatures' may emerge, warranting further investigation

- Given time constraints, how would you efficiently classify or group these wafers to enable meaningful analysis?"

Wafer Map Classification by Human

Problem Statement

- A Micron engineer in the Yield Enhancement Group was asked to monitor & summarize bit map of “pizza slice” signature issue every two weeks.
- The engineer has to look at the “wafer map” for hundreds of wafers individually, to find which wafers have such “pizza slice” signature. This takes the engineer about 5 hours every two weeks.



Week 5 – Week 6:	X	High occurrence
Week 7 – Week 8:	✓	Little occurrence
Week 9 – Week 10:	✓	Little occurrence
Week 11 – Week 12:	Δ	Some occurrence

Outcome
- Only three levels (high occurrence, some occurrence, little occurrence)
- The result can be subjective
- Less quantitative
- May not be reproducible if other persons do the same work

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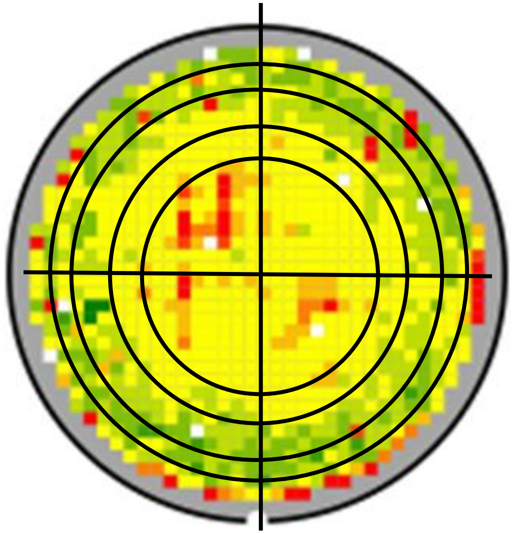
Wafer Map Analysis Data vs. Algorithm

Algorithm
Statistics

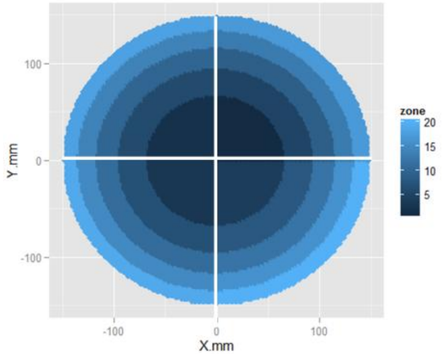
Data	Data Type	Analytic Approach
Bit Map Summary	Numeric	Numeric clustering algorithm e.g. K-mean Expectation Maximize
Repair Density	Numeric	Numeric clustering algorithm e.g. K-mean Expectation Maximize
Pass & Failure	Factorial (character)	Deep Learning Autoencoder Wafer Map to Image

Wafer Map Classification Approach

Algorithm
Statistics



Divide into 20 equal area zones
Radial & Quadrant to capture bit count by wafer region



Wafer Zone definition

LOT_ID	WAFER_ID	Zone1	Zone2	Zone3	Zone4	Zone5	Zone6	Zone7	Zone8	Zone9	Zone10	Zone11	Zone12	Zone13	Zone14	Zone15	Zone16	Zone17	Zone18	Zone19	Zone20
A	1																				
A	2																				
A	3																				
A	4																				
A	5																				
A	6																				
A	7																				
A	8																				
A	9																				
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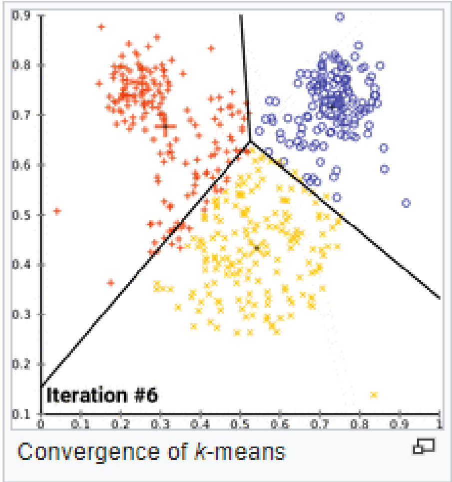
A	23																				
A	24																				
A	25																				
B	1																				
B	2																				
B	3																				
B	4																				
B	5																				
B	6																				

Create Data frame in either Python or R by transforming die level data into aggregated mean value by zone

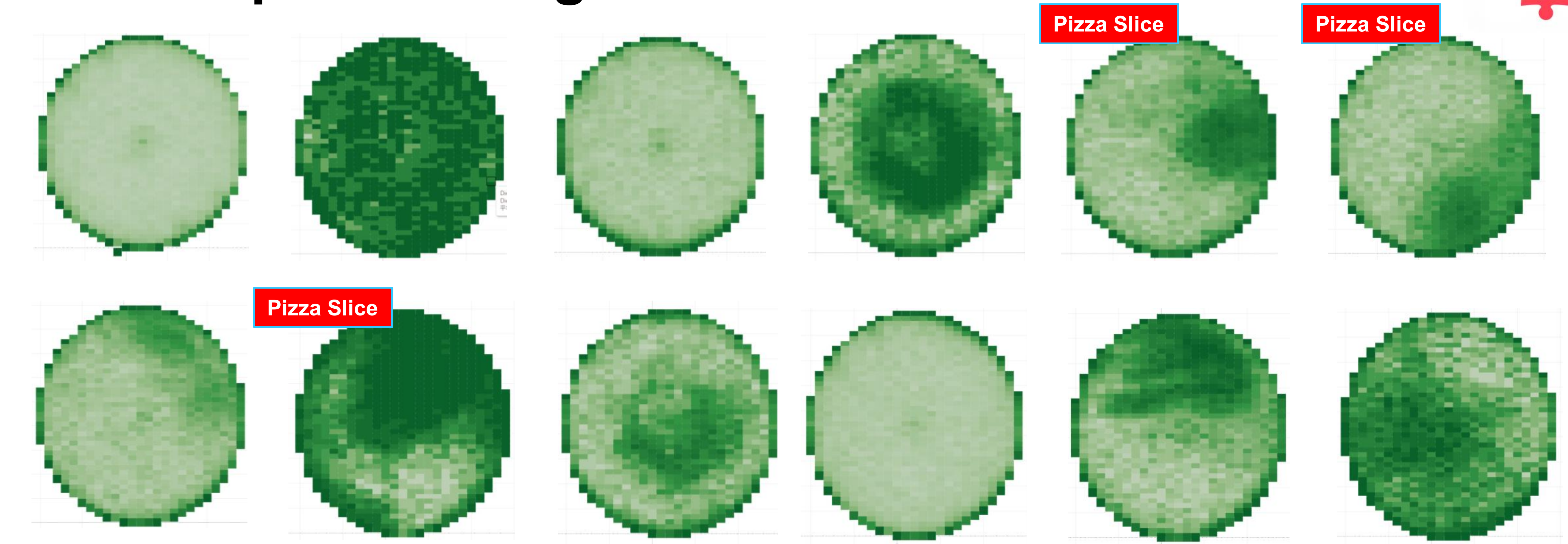


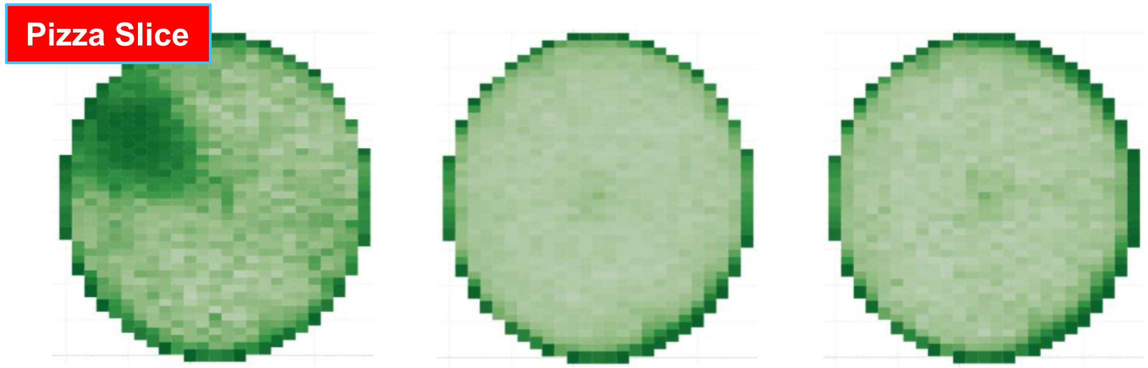
K-mean

Cluster<-kmeans(df[, 3:22], 15)

Wafer Map Clustering

Integrated
DS
Solution





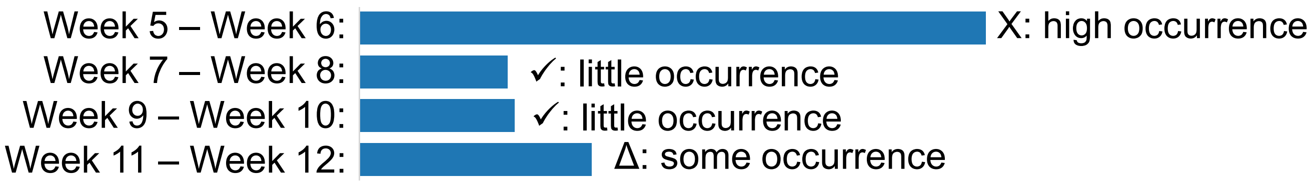
- Classification on 2000 wafers failure mode
- Visual inspection by human: Hours to a day
- By algorithm: 5 min

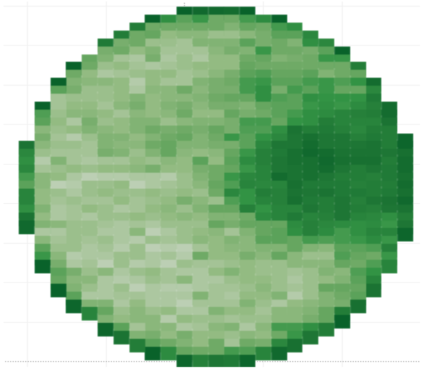
Comparison of human classification vs. algorithm

Integrated DS Solution

Week 5 – Week 6: X
Week 7 – Week 8: ✓
Week 9 – Week 10: ✓
Week 11 – Week 12: Δ

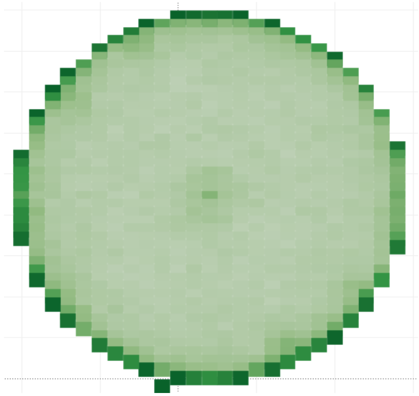
Classification by date by algorithm



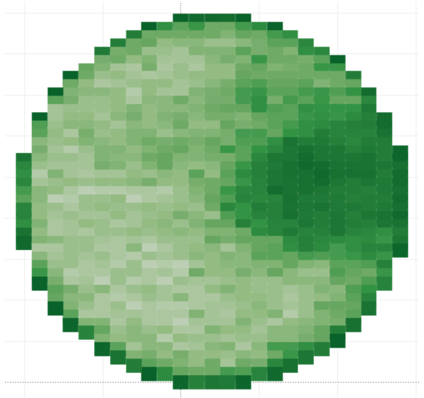


By human eye inspection

Good Cluster

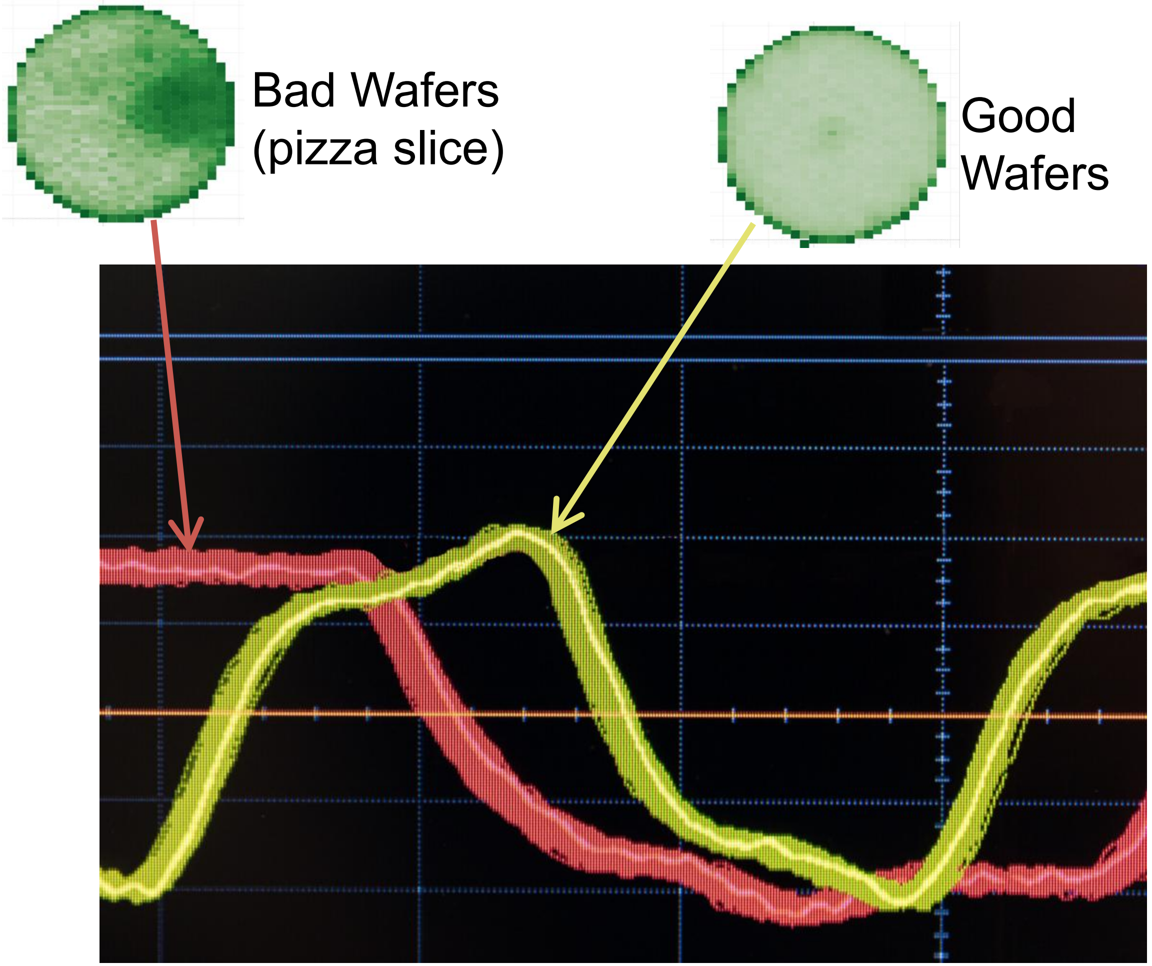


Bad wafers



Clustering algorithm offers reproducible and quantitative analytical results

Further Drilldown



- Subsequent drilldown analysis of manufacturing data revealed a clear distinction between good wafers and those exhibiting 'pizza slice' signature, which were linked to a specific process step and equipment
- This insight guided process engineers to take targeted corrective actions
- With continued investigation, the findings can evolve into prescriptive guidance, offering actionable solutions to resolve the underlying issue.

→ Prescriptive result

Summary on Wafer Map Signature Analysis

- Clustering algorithm automated manual cognitive work by human
- Visually identifies possible root cause of quality degradation
- The outcome is objective, robust and more reproducible than human classification
- With further drilldown the result can be prescriptive and provide actionable results for process engineers to fix the problem

Summary & Conclusion

- Catalyst for Big Data & AI in Smart Manufacturing
  - Enabled by highly scalable computing, advanced machine learning algorithms, and ultra-high bandwidth IoT networks
- Essential Role of Data in Memory Manufacturing
  - Characterized by extremely small, precise dimensions requiring meticulous data handling
- Dynamics of Data Science
  - Domain knowledge is vital for meaningful insights and effective application
- Real-World Application
  - Wafer Map Analytics is reviewed as a case study for improving yield and quality—illustrating typical analytics practices in semiconductor manufacturing

Key Terminology Glossary

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Glossary

Term or acronym	Definition/description
AI	Artificial Intelligence
AR	Aspect Ratio
Big Data	Large and complex data sets that require advanced methods and technologies to store, process, and analyze.
Capacitance	The ability of a system to store an electric charge, measured in farads.
Critical Dimension	The specific width or space between features on a semiconductor wafer that must be controlled precisely during manufacturing.
Data Science	The field of study that combines domain expertise, programming skills, and knowledge of mathematics and statistics to extract meaningful insights from data.
Defect	An imperfection or anomaly in a semiconductor wafer that can affect the performance of the final product.
DRAM Memory Cell	A cell in DRAM that consists of one transistor and one capacitor where the capacitor can store binary information (1/0).
DRAM	Dynamic Random Access Memory, a type of fast memory used in computers and other devices to store data temporarily.
IoT	Internet of Things. A network of physical devices embedded with sensors, software, and other technologies that enable them to collect, exchange, and act on data over the Internet.
Machine Learning	A subset of artificial intelligence that involves the use of algorithms and statistical models to enable computers to perform tasks without explicit instructions.
Parametric Data	Data that is measured and collected based on specific parameters or characteristics.
Probe	The process of testing semiconductor wafers to identify functional and non-functional die.
SQL	Structured Query Language
Transistor	A semiconductor device used to amplify or switch electronic signals and electrical power.
Yield	The number of good die produced divided by the total number of die on a wafer.

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