SAIT AIRC Invited Seminar - I

Apr 24, 2024

Industrial AI & its applications in manufacturing

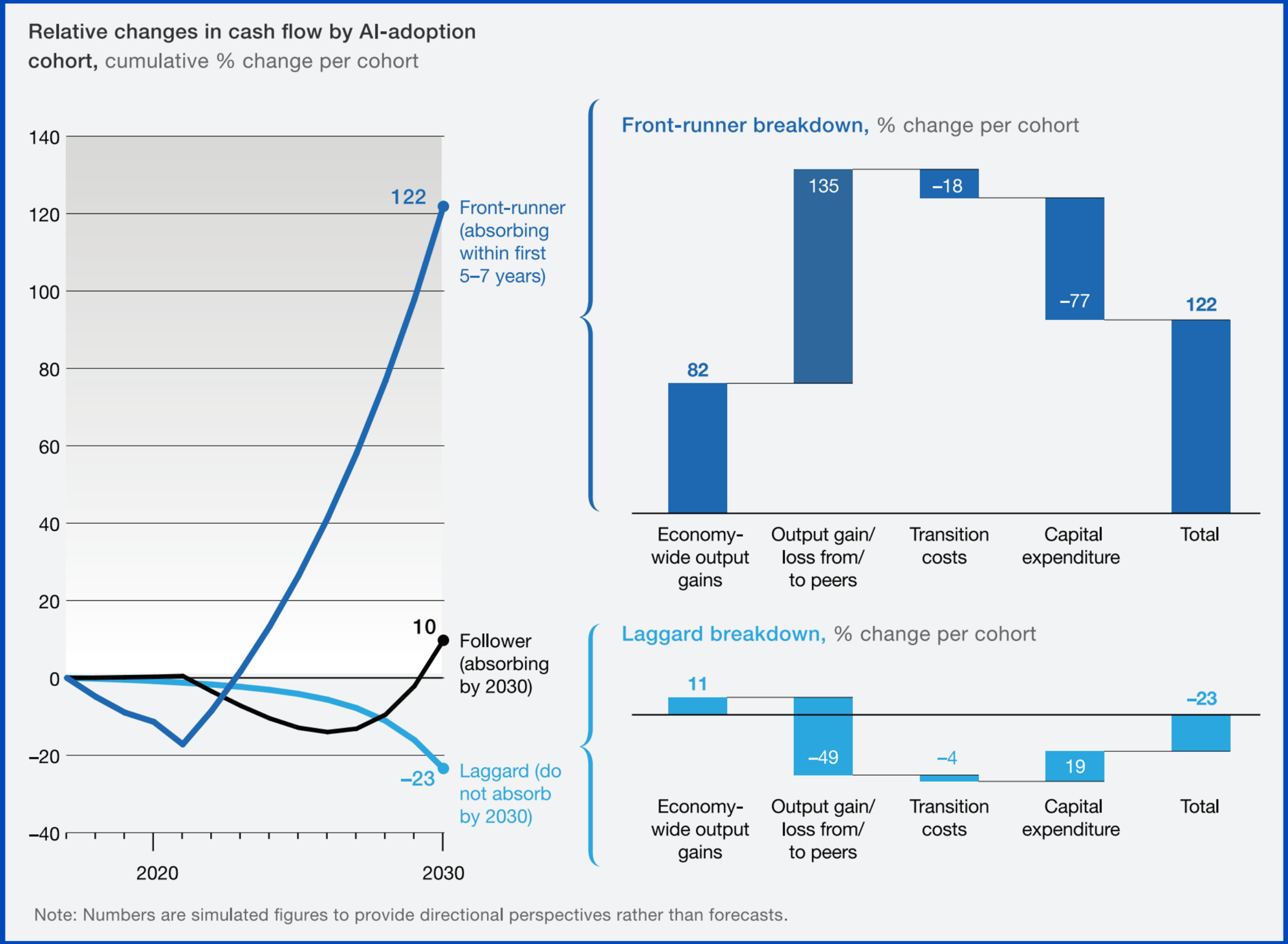
Sunghee Yun
Co-founder / VP - AI Technology & Product Strategy

Today

Why Industrial AI?

Fast AI adoption creates LARGER economic gains

- change in cash flow by 2030
    - front-runner - +122%
    - follower - +10 %
    - laggard - -23%

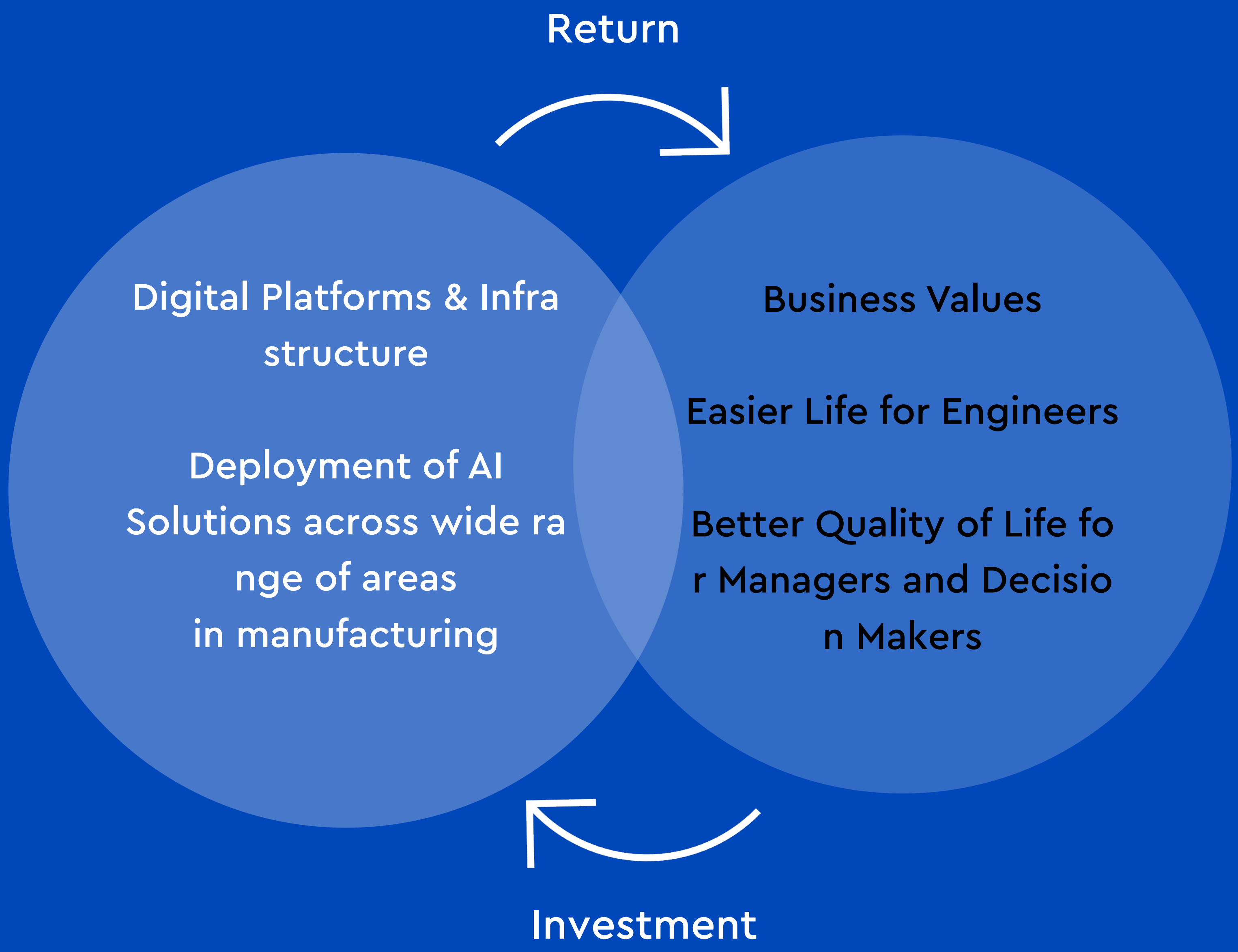


* Source: McKinsey Global Institute Analysis (2019)

Data Characteristics

Virtuous (or Vicious) Cycle

Data-centric AI



"We need 1,000 models for 1,000 problems" – Andrew Ng

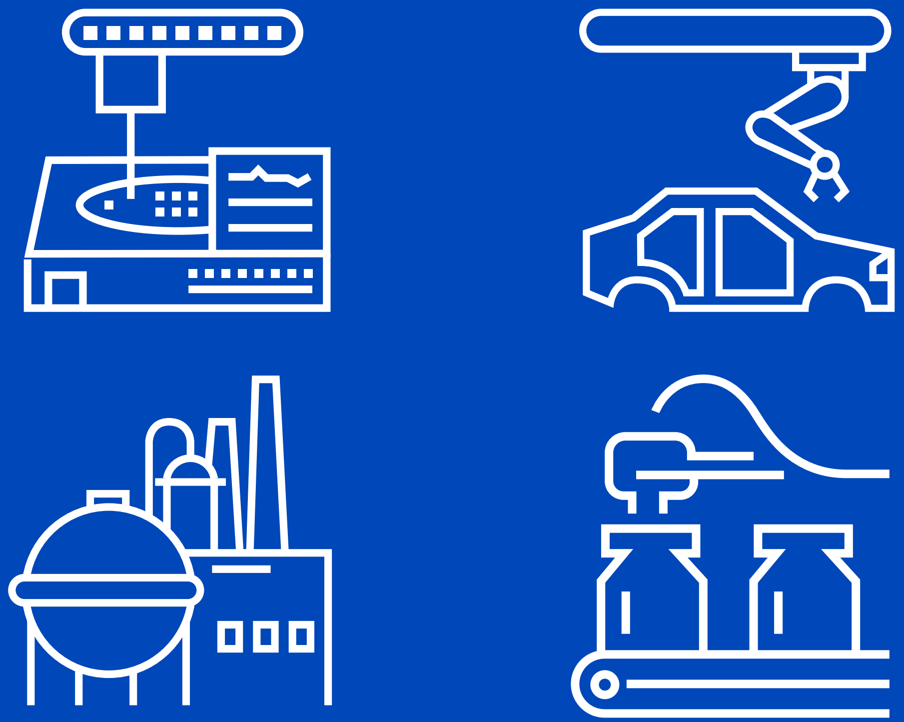
Data-centric AI

Discipline of systematically engineering the data used to build an AI system

Data Characteristics

Virtuous (or Vicious) Cycle

Data-centric AI



Every company or sector has its own problems

Semiconductor is Great Starting Point!

Semiconductor Fab

Modern MEGA fab has

- ~1,000 process equipement
- ~100 metrology equipment
- ~1,000 wafers per day, per equipment
- ~1,000 processes per wafer
- 3-6-month cycle time

Servers and Systems

Equipment Sensor Data
(~1M parameters, ~1Tb/day)

Metrology Image Data
(~1M images, ~10 Tb/day)

Manufacturing Execution Data
(~10M events, ~10 Gb/day)

Why Semiconductor?

Data availability from advanced digitalization

Diverse and sophisticated processes, ideal for expanding to new customers & sectors

Huge impact even within the sector itself

Difficulties

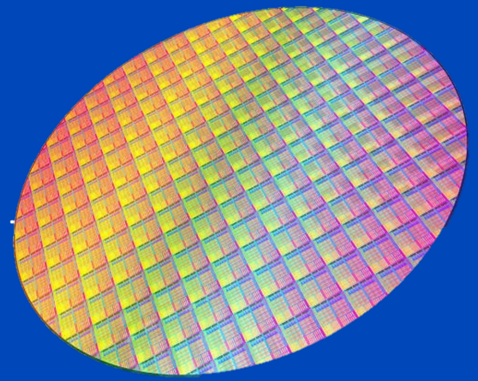
Data Characteristics

Virtuous (or Vicious) Cycle

Data-centric AI

Computer vision and time-series ML in Manufacturing

Huge amount of image data to measure and inspect



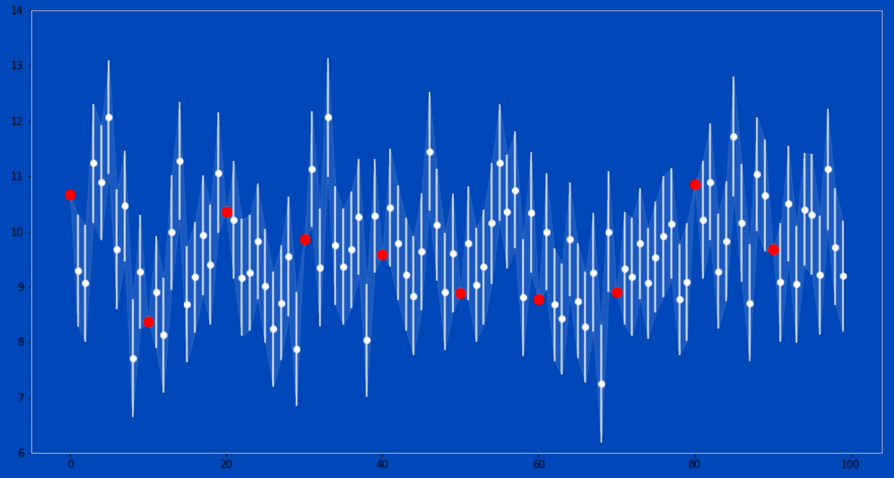
Scanning electron microscope (SEM) images, transmission electron microscope (TEM) images, etc.

→ pattern classification, defect inspection, anomaly detection, etc.

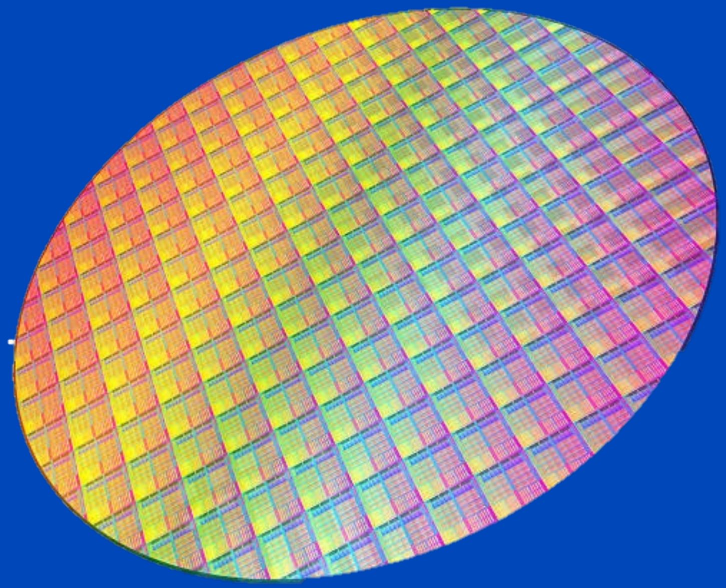
Almost all data coming from manufacturing - time-series data

sensor data, process times, measurement, *MES* data

→ time-series ML – semi-supervised learning, (variational) Bayesian inference, anomaly detection



Computer Vision ML for manufacturing



Metrology

Measurement of critical features

Inspection

Defect Inspection
Defect localization and classification

Image courtesy of ASML

Scanning Electron Microscope

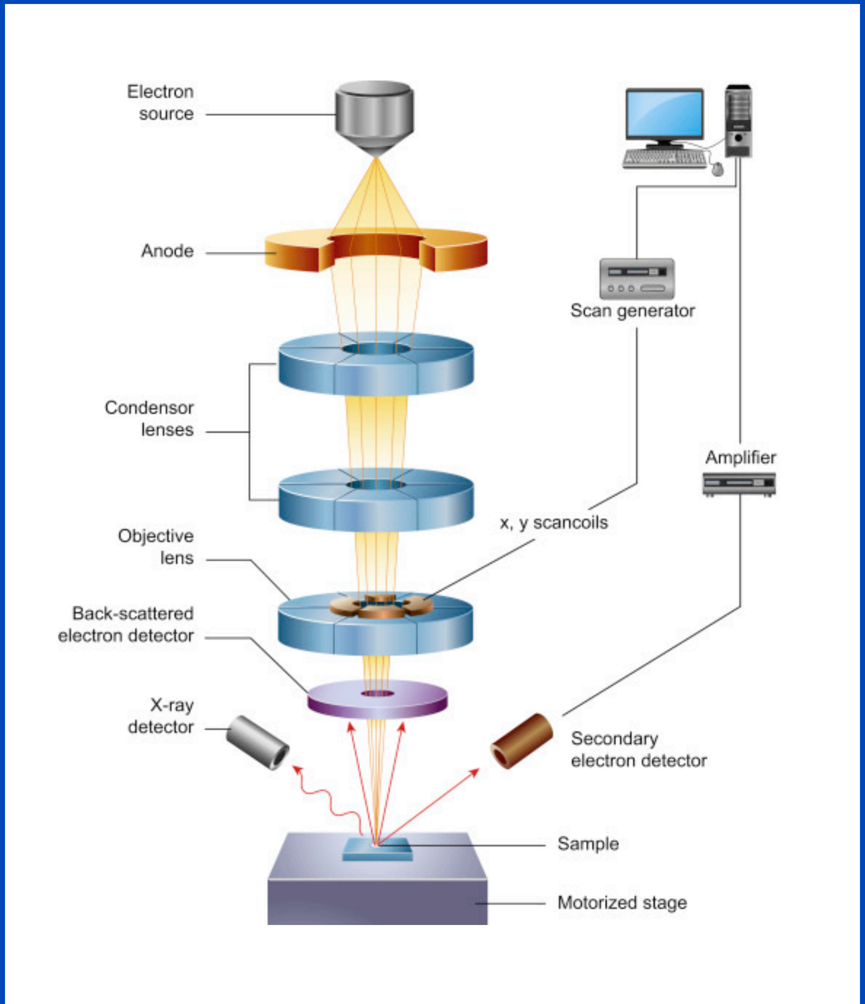
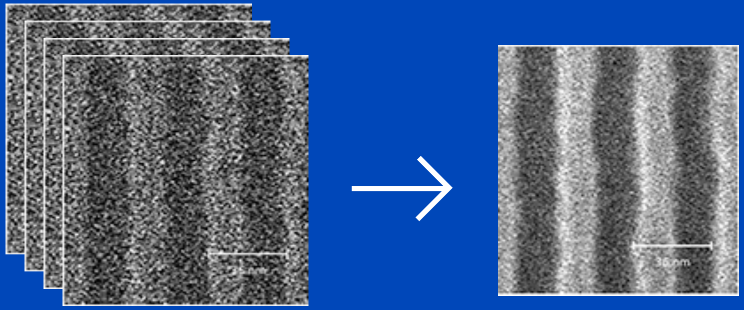


Image courtesy of https://www.sciencedirect.com/science/article/pii/B978008100040300002X



raw images

average of multiple images

Shot Noise Image courtesy of https://en.wikipedia.org/wiki/Shot_noise

Image restoration

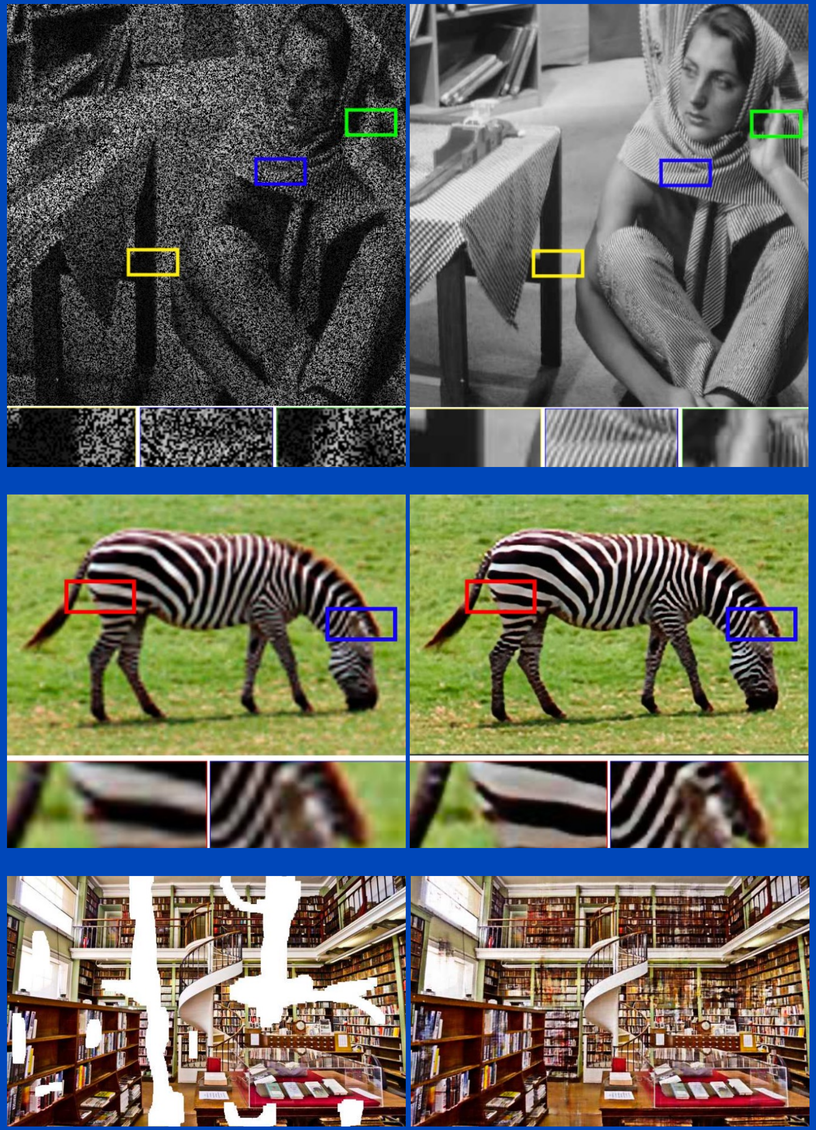
Inverse problem of image corruption

$$x = f(y) + n$$

- y: clean image
- x: corrupted image
- n: noise

$f(\cdot)$ & corresponding solutions

- Noising: Identity function → Denoising
- Downsampling → Super-resolution
- Missing pixels → Inpainting



Dmitry Ulyanov et al. Deep Image Prior. CVPR, 2018

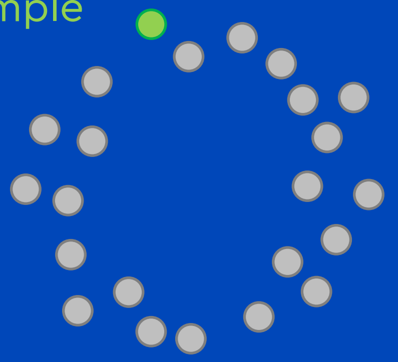
Supervised image denoising

However, NOT possible to acquire ground-truth in practice.

Blind denoising without ground truth

noisy images

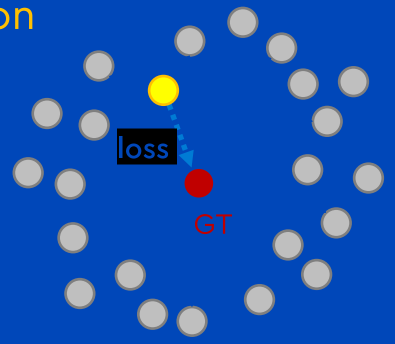
training sample



Denoiser Model

undiscovered ground truth

prediction



assuming mean of noise zero, averages of gradients, or equivalently, gradients of averages, surrogates for ground truth

Information containment perspective, noise generating filter does not erase perfectly groud truth!

J. Lehtinen, et al. Noise2Noise: Learning Image Restoration without Clean Data. ICML, 2018.

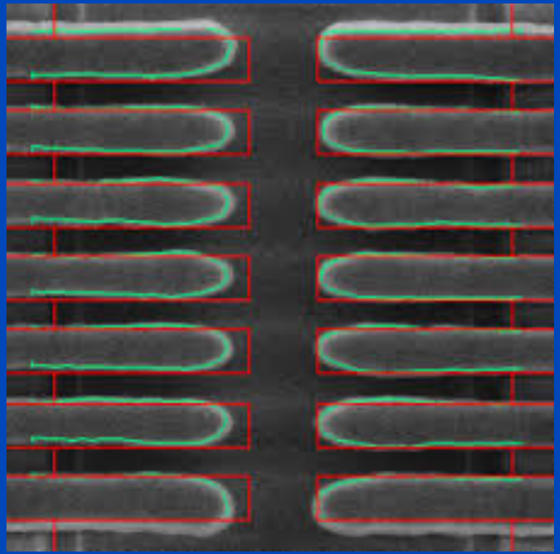
Metrology based on segmentation and pattern recognition

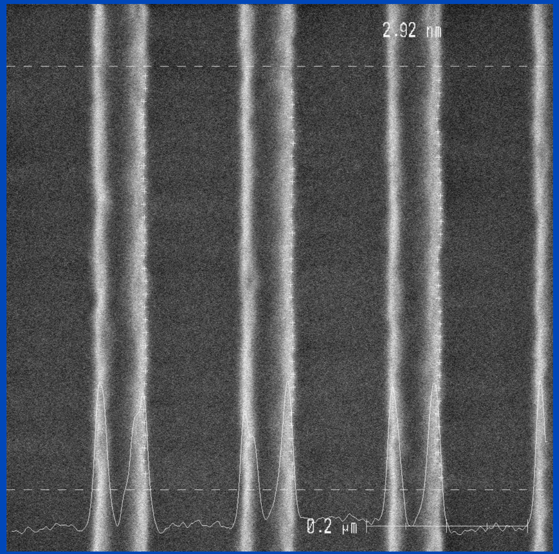
Investment

Automatic measurement of critical dimensions

Approaches

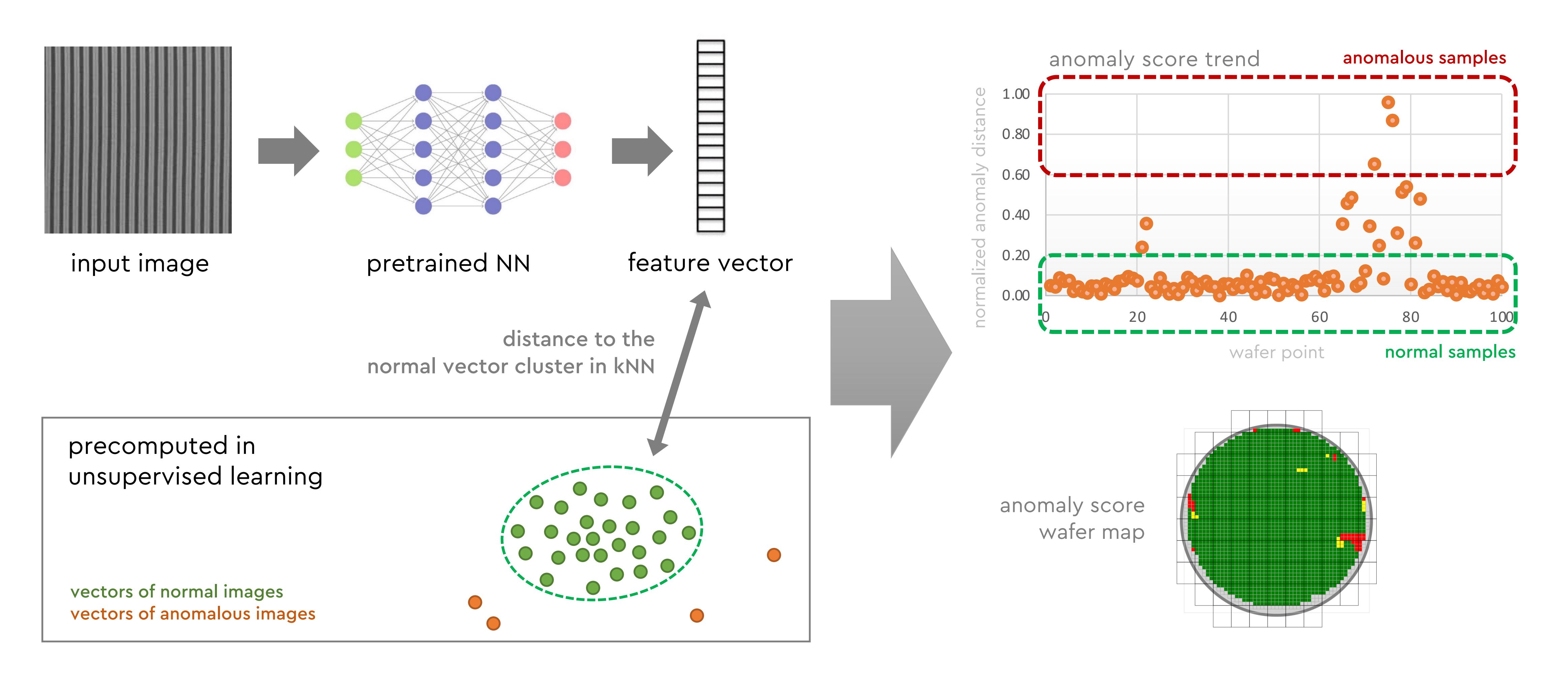
- Texture segmentation
- Repetitive pattern recognition
- Automatic measurement



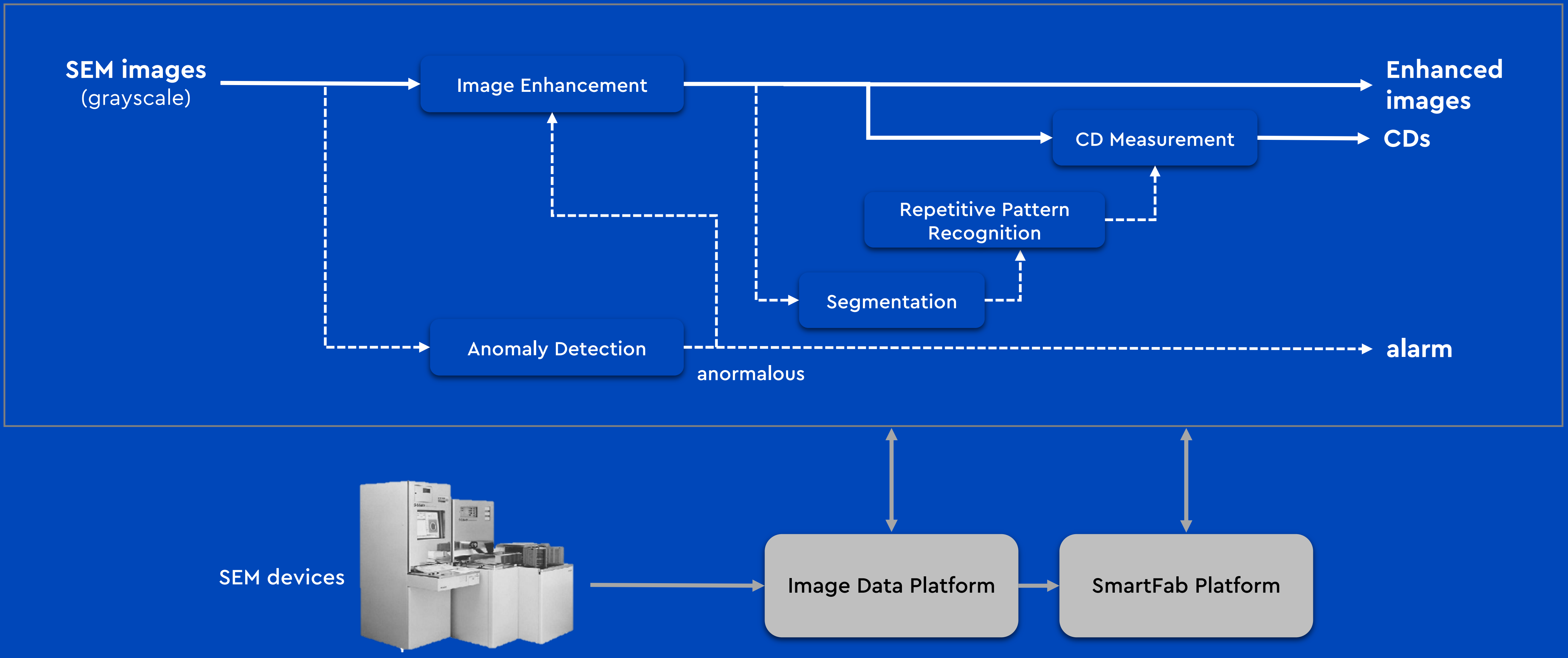


Extremely challenging!
<0.1 nm measurement precision guaranteed

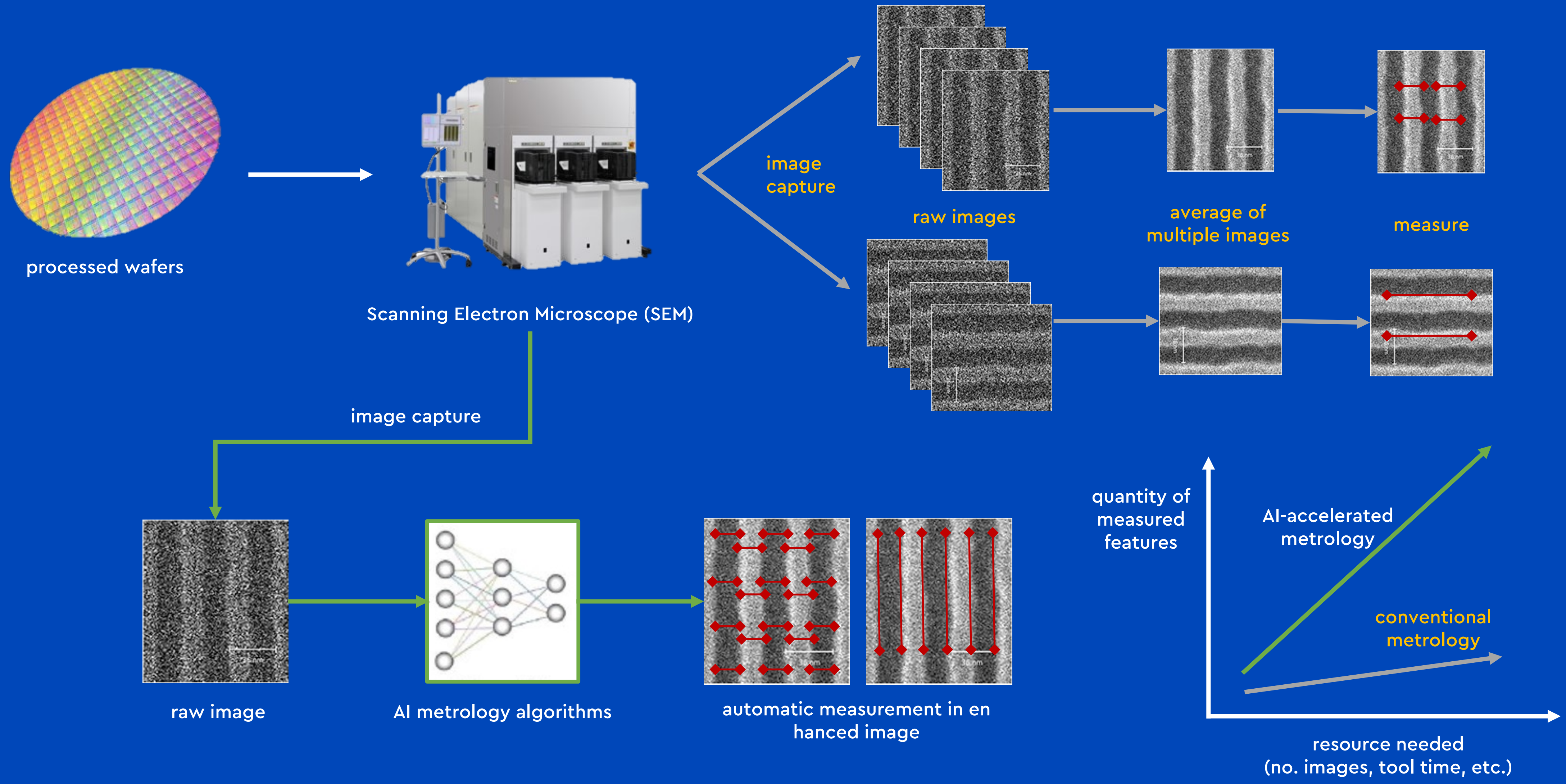
Anomaly detection in unsupervised learning



AI-accelerated metrology system



Automatic measurement for semiconductor manufacturing

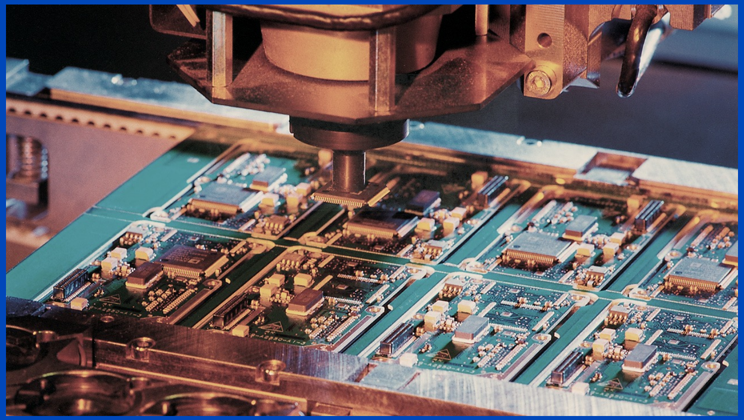


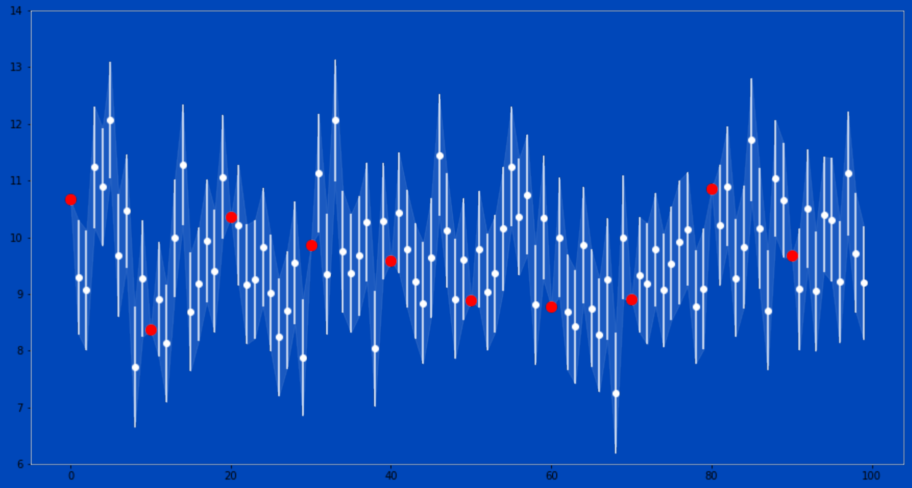
Time-series ML for manufacturing

Why time-series ML?

manufacturing application is about one of the followings:

- estimation of TS values - virtual metrology, yield prediction
- classification of TS values – predictive maintenance, recommendation system
- anomaly detection on TS - root cause analysis, root cause analysis for yield drop





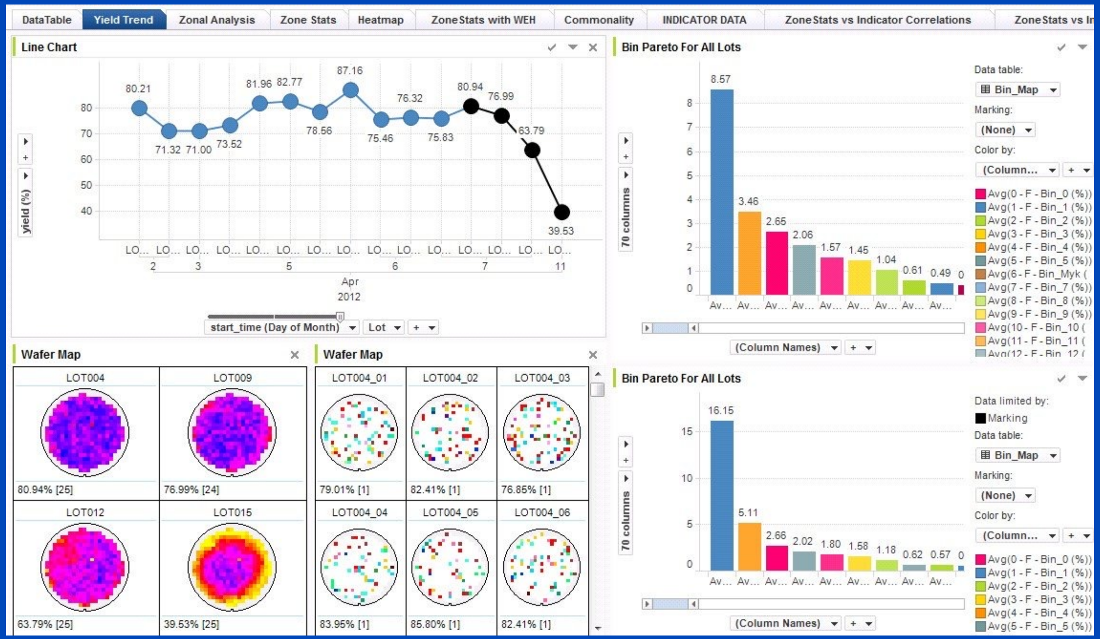
Difficulty & Advantage of TS ML

- *extremely difficult problems to solve*
- *(thus) not many researchers are interested*
    - *everyone's crazy about LLM, NLP, & CV*
- *all academic papers deal with easy (or synthesized) data*
- *almost no definition can exist for time-series data*
- *NONE of algorithms in papers worked*
- *100% home-grown data-specific application-tailored algorithms required*

Time-series prediction & estimation

- **virtual metrology**
  - *measure unmeasured processed materials using equipment sensor signals*
  - *business impacts*
    - *save investment on equipment, improve feedback control, SPC, yield improvement*

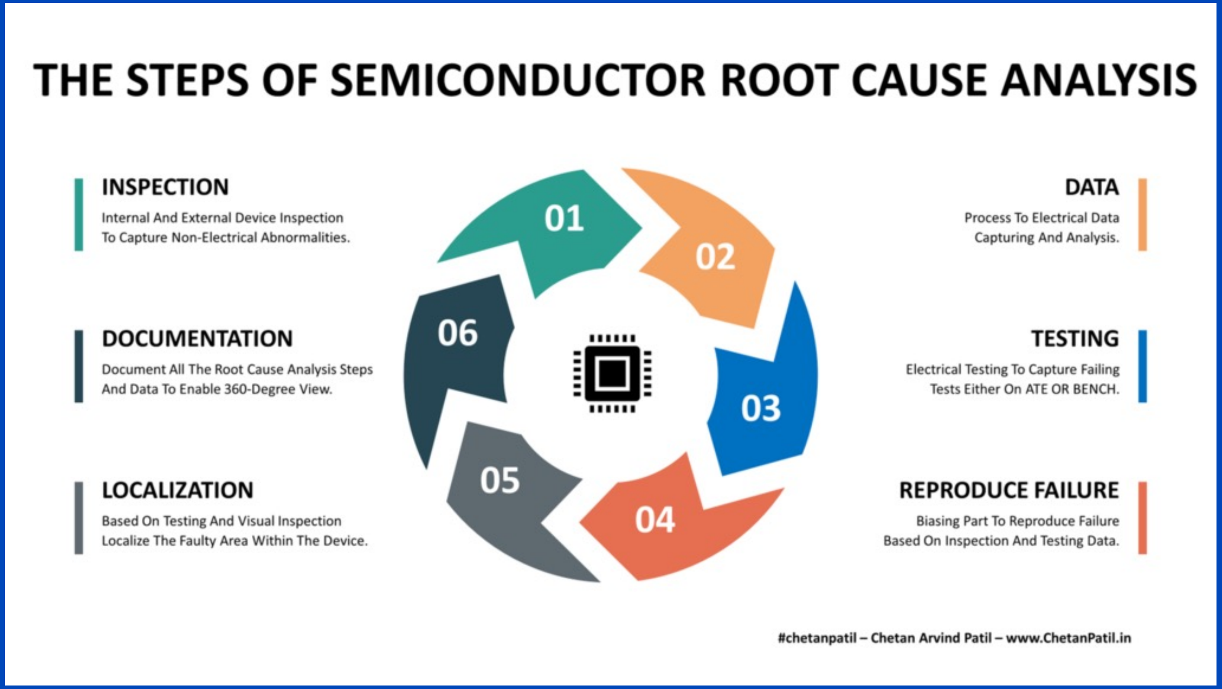
- **yield prediction**
  - *predict yield without waiting for fabrication to be finished*
    - *prevent wafer from being wasted*
  - *better product quality and larger profit, business impact*



Root cause analysis & recommendation system

- equipment alarm root cause analysis
  - *when alarm goes off, find responsible equipment and root causes*
  - *reduce equipment downtime, make process engineers' lives easier*

- recommendation system
  - *when things go wrong, provide recommendation for finding root cause*
  - *recommendation steps to following based on history data*



Difficulties of Time-series ML

Data challenges

- covariate shift & concept drift

$\mathrm{Prob}(x_{t_k}, x_{t_{k-1}}, x_{t_{k-2}}, \ldots)$ *changes over time*

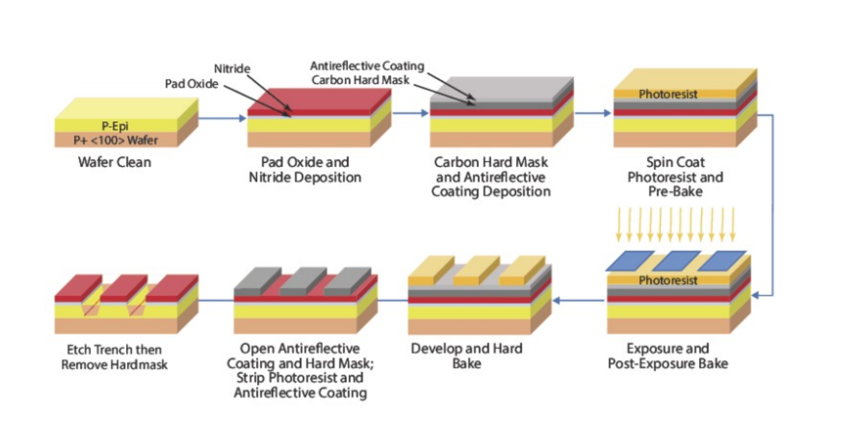
$\mathrm{Prob}(y_{t_k} | y_{t_{k-1}}, y_{t_{k-2}}, \ldots, x_{t_k}, x_{t_{k-1}}, x_{t_{k-2}}, \ldots)$ *changes over time*

- fat data, *i.e.*, # features way larger than # data
- poor data quality; missing values, anomalies, wrong formats
- huge volume of data to process

Domain knowledge and fully home-grown algorithms

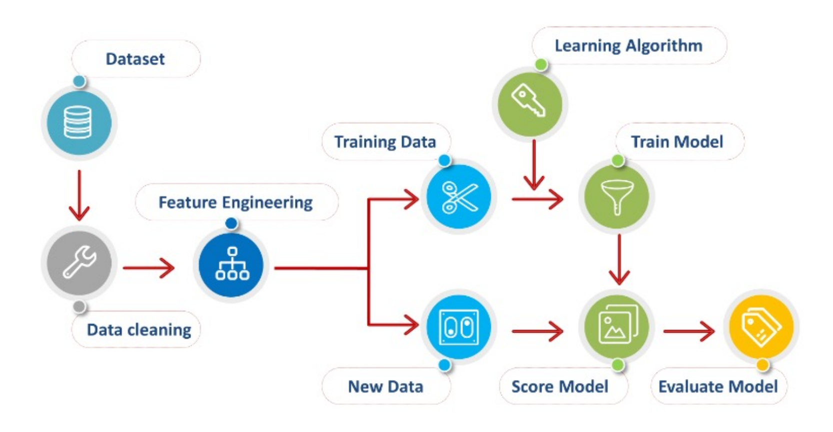
in most cases,
domain knowledge is critical!

close collaboration with customers required



off-the-shelf algorithms
not working!

developing fully customized algorithms needed



Virtual Metrology (VM)

What is VM?

in many cases, we cannot measure all processed materials

- measurement equipment too expensive
- full measuring hurts throughput

thus, we do sampling (with very low sampling rate)

- average sampling rate is less than 5%

PROBLEM

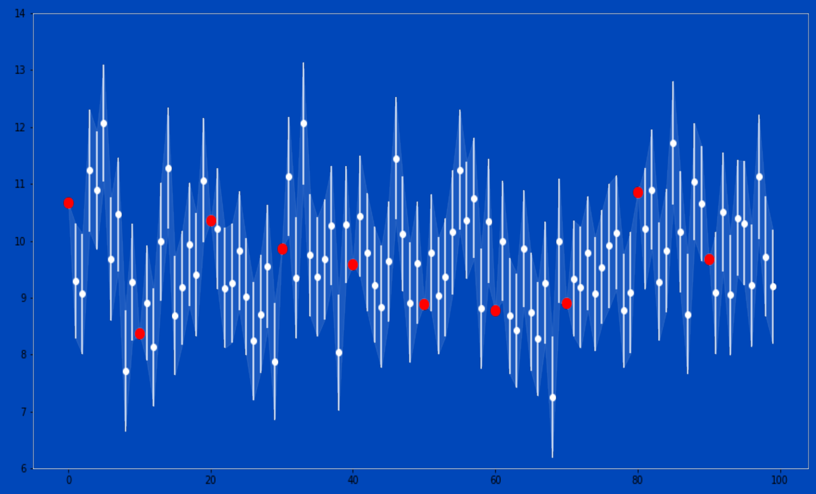
- predict the measurement of unmeasured material using indirect signals
- sensor data, maintenance history, operation data, . . .

process

Sample measurements

Sensor data, maintenance history, operation data, ...

AI Model
(semi-supervised learning)



Business Impact made by VM

To the best of our knowledge

- no organization has even been *(this)* successful with VM

VM

- uses home-grown AI model to address with data drift/shift problems
- error comparable to measurement equipment precision
- provide credibility intervals of predictions - reliability information

VM implications

- virtually measuring ALL wafers – equivalent to investing on 100x measurement equipment
- enables optimal re-allocation of limited measurement resources

Conclusion

supervised / unsupervised / semi-supervised AIs required everywhere in industrial sectors

lots of agonizing challenges

huge changes potentially made via various applications

Impacts

- Tens of Millions of dollars by 1% yield increase
- 100x measurement equipment save by VM

THANK YOU

sunghee.yun@erudio.bio
linkedin.com/in/sungheeyun