Samsung Flash Design Team Invited Seminar

Jun 27, 2024

Industrial AI & its applications in manufacturing

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Today

1 why Industrial AI?

2 computer vision ML in manufacturing

3 time-series ML in manufacturing

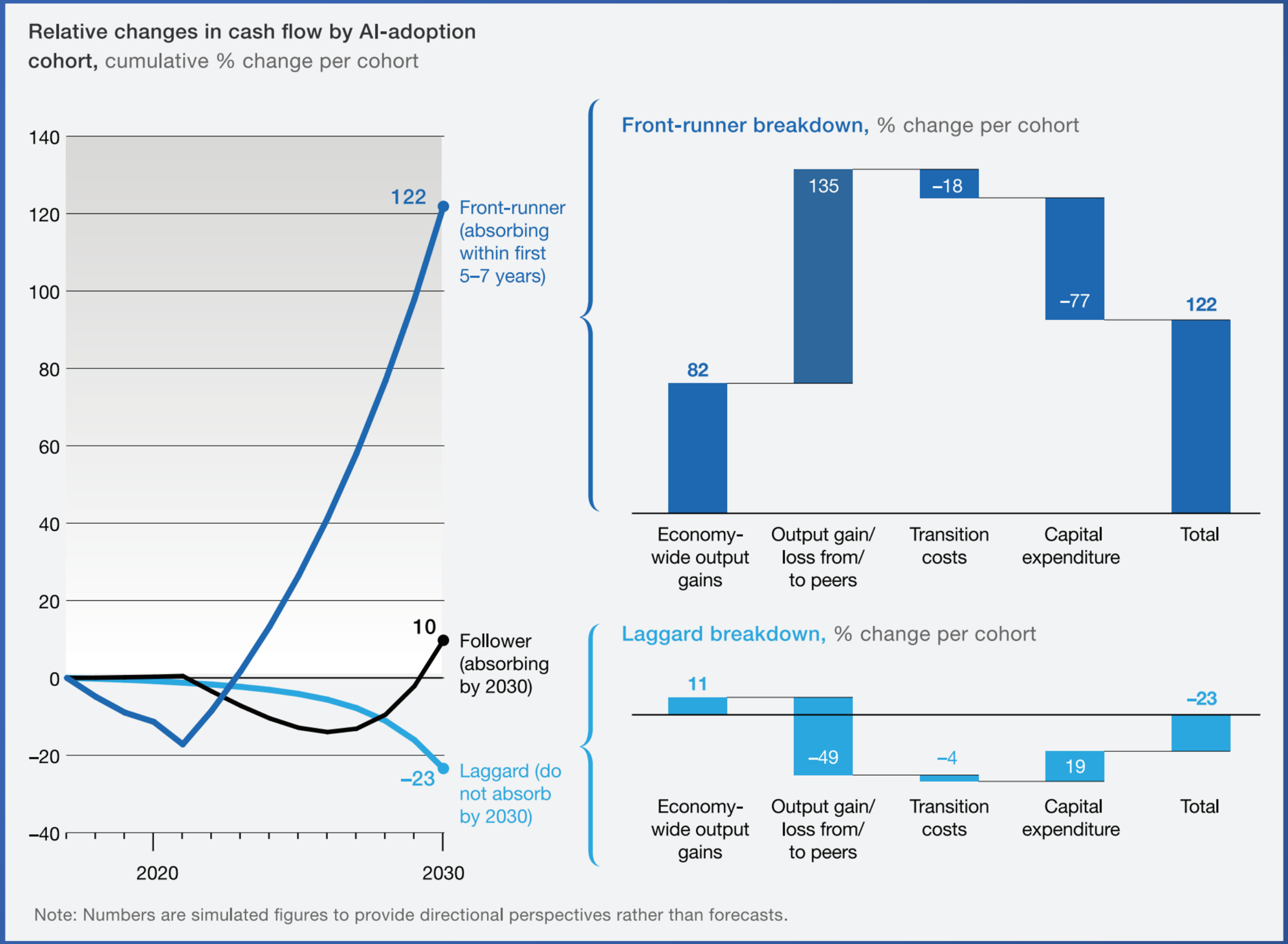
4 AI challenges for manufacturing

5 Virtual Metrology - manufacturing AI success story

Why Industrial AI?

Fast AI adoption creates LARGER economic gains

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



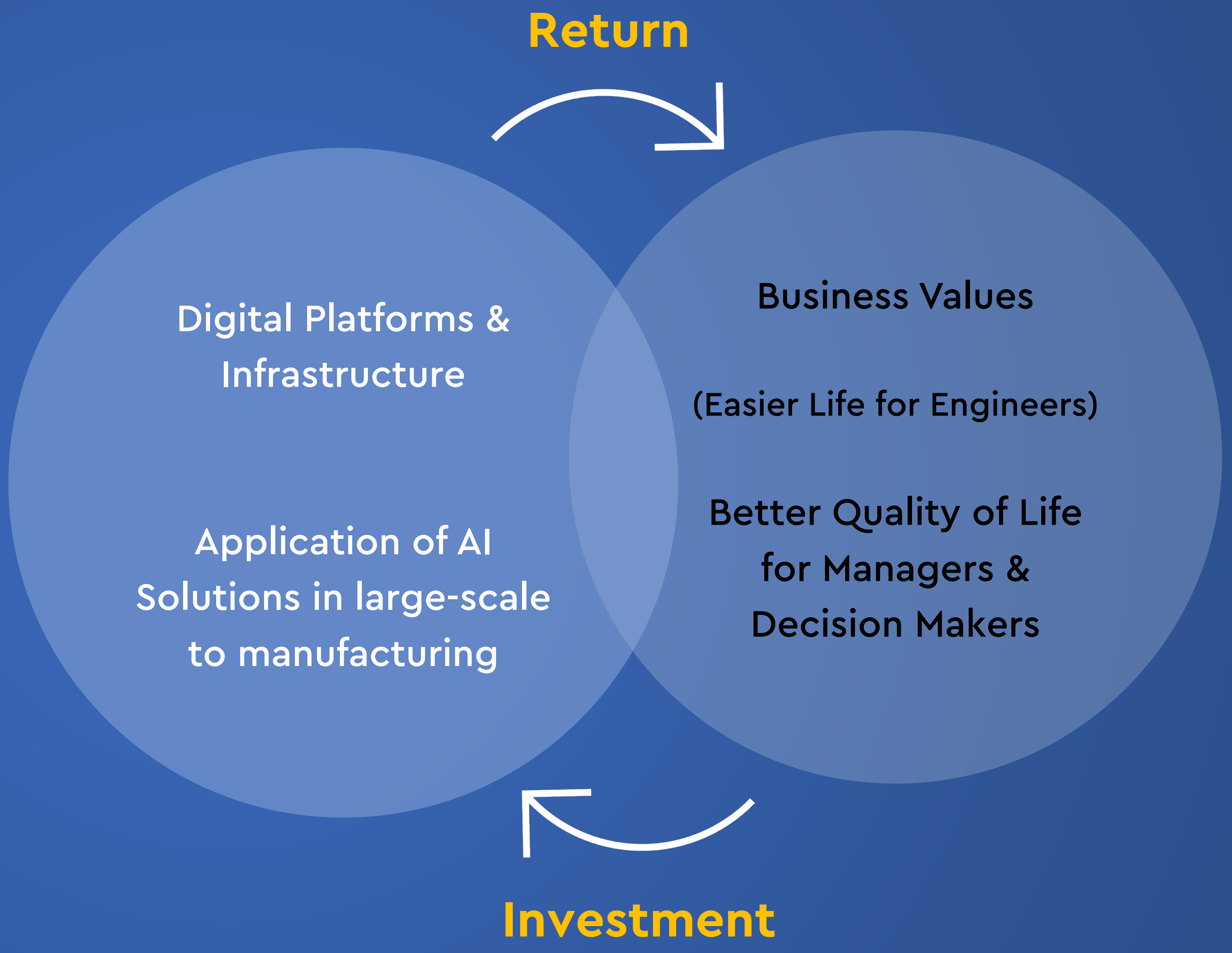
* Source: McKinsey Global Institute Analysis (2019)

Characteristics of Industrial AI

Virtuous (or vicious) Cycle

Data-centric AI

Data Characteristics



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

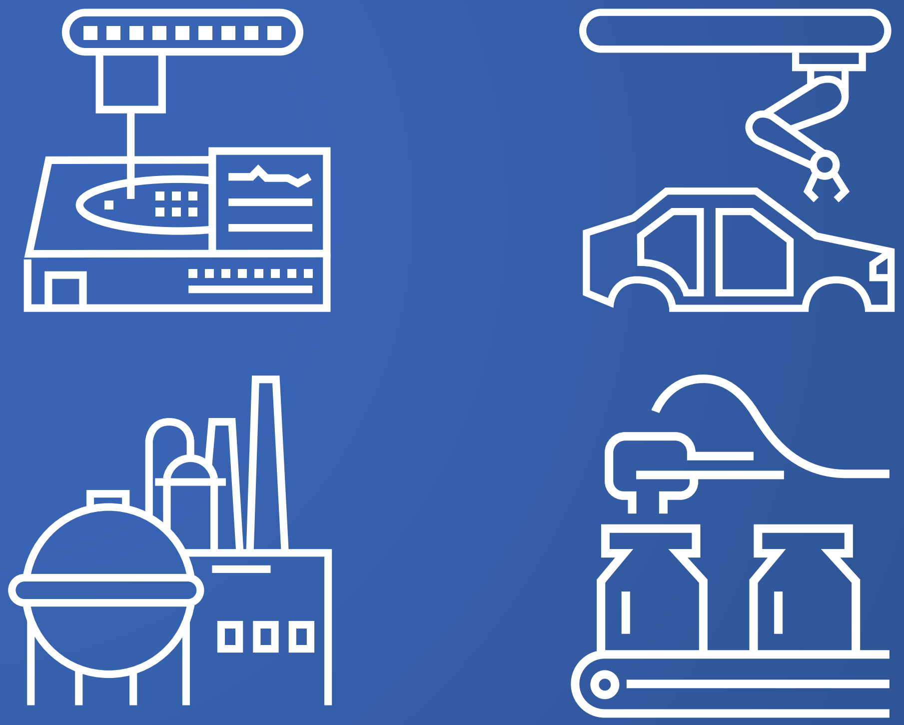
Data-centric AI

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

Virtuous (or vicious) Cycle

Data-centric AI

Data Characteristics



Every company or sector has its own problems

Virtuous (or vicious) Cycle

Data-centric AI

Data Characteristics

Opportunities vs Difficulties

Semiconductor is Great starting point for industrial AI

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

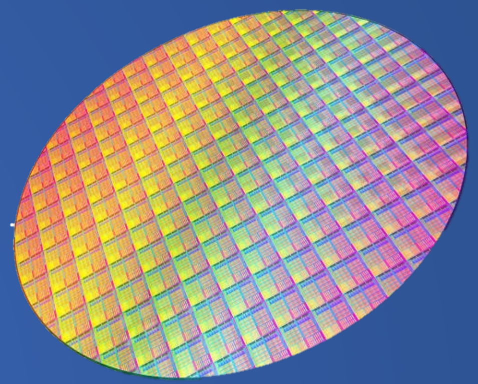
Diverse and sophisticated pro cesses, ideal for expanding to new customers & sectors

Huge impact even within the sector itself

Computer Vision in Manufacturing

Computer vision and time-series ML in Manufacturing

Huge amount of image data to measure and inspect



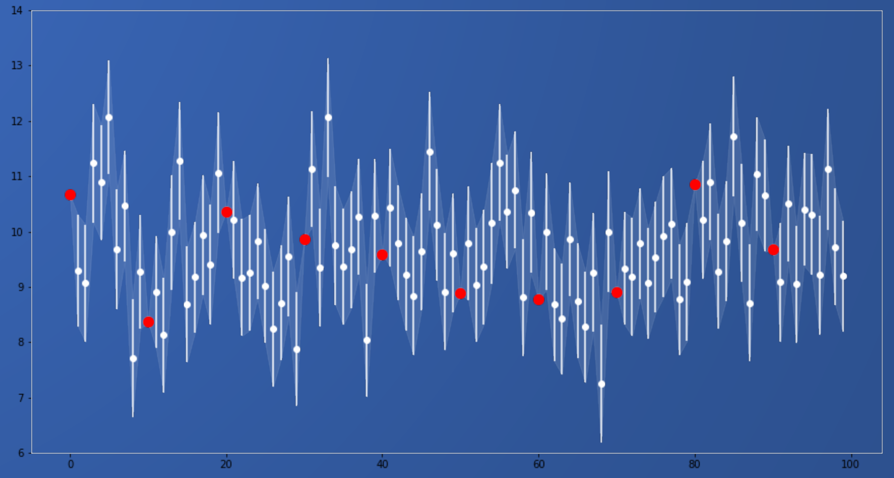
Scanning electron microscope (SEM) images, transmission electron microscope (TEM) images, etc.

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

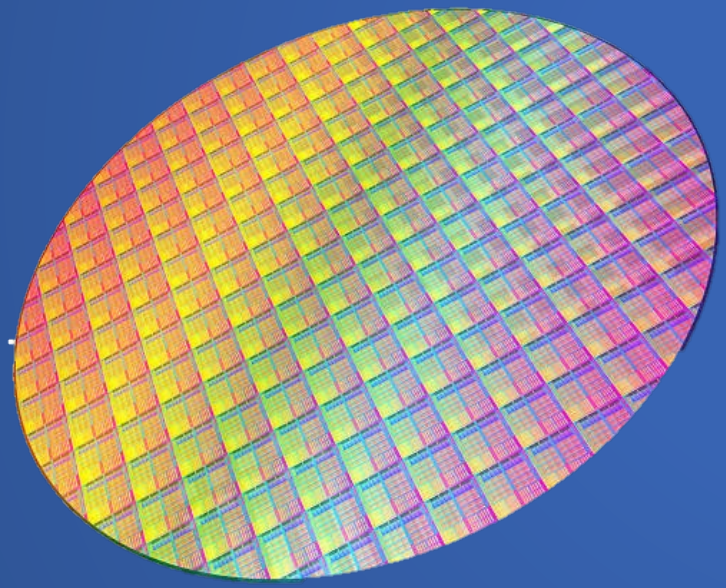
Almost all data coming from manufacturing - time-series data

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

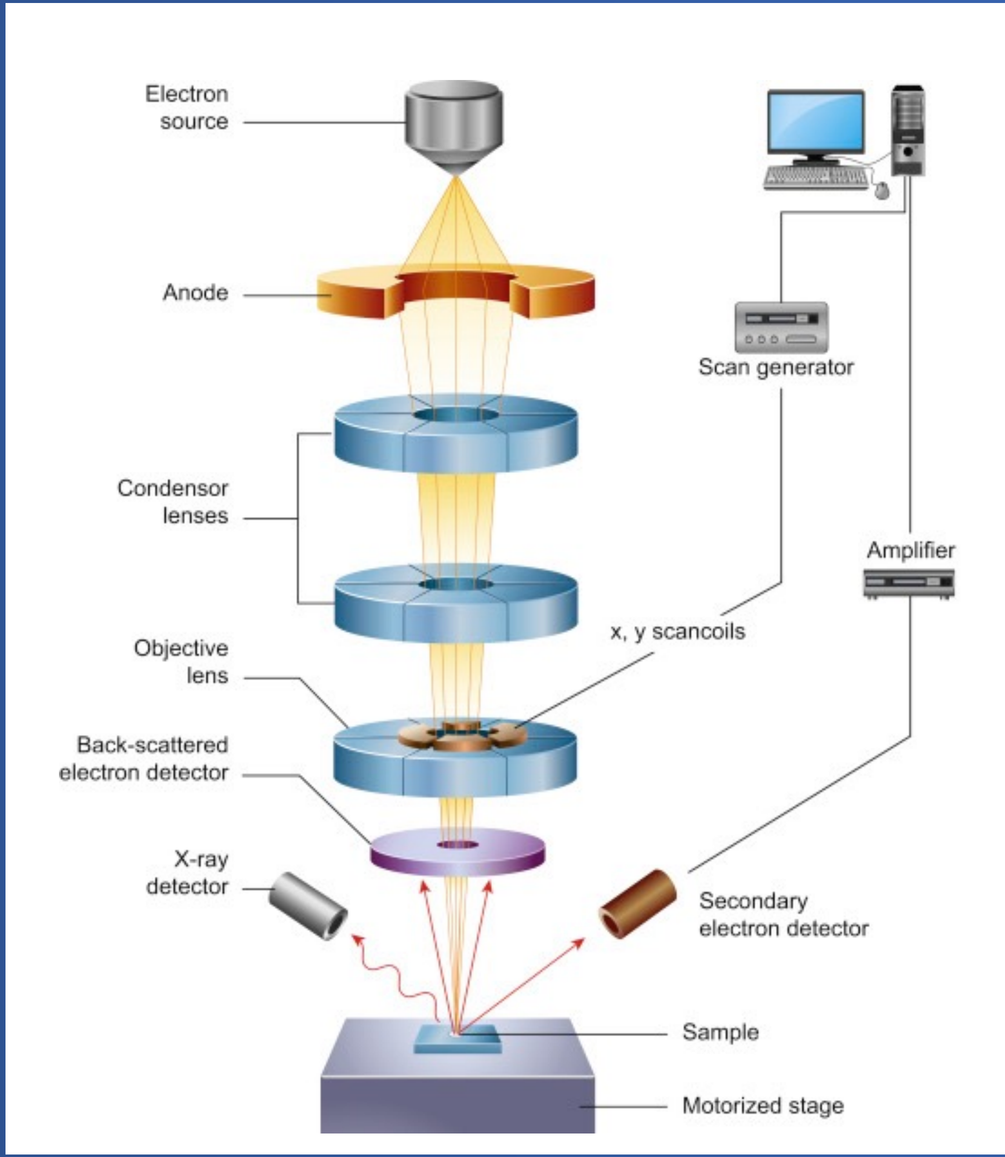
Inspection

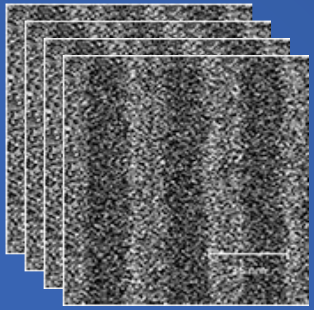
Defect Inspection

Defect localization and classification

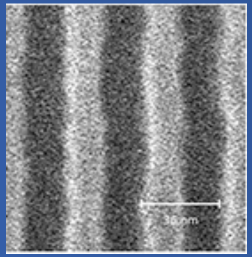
Image courtesy of ASML

Scanning Electron Microscope





raw images



average of multiple images

Image restoration

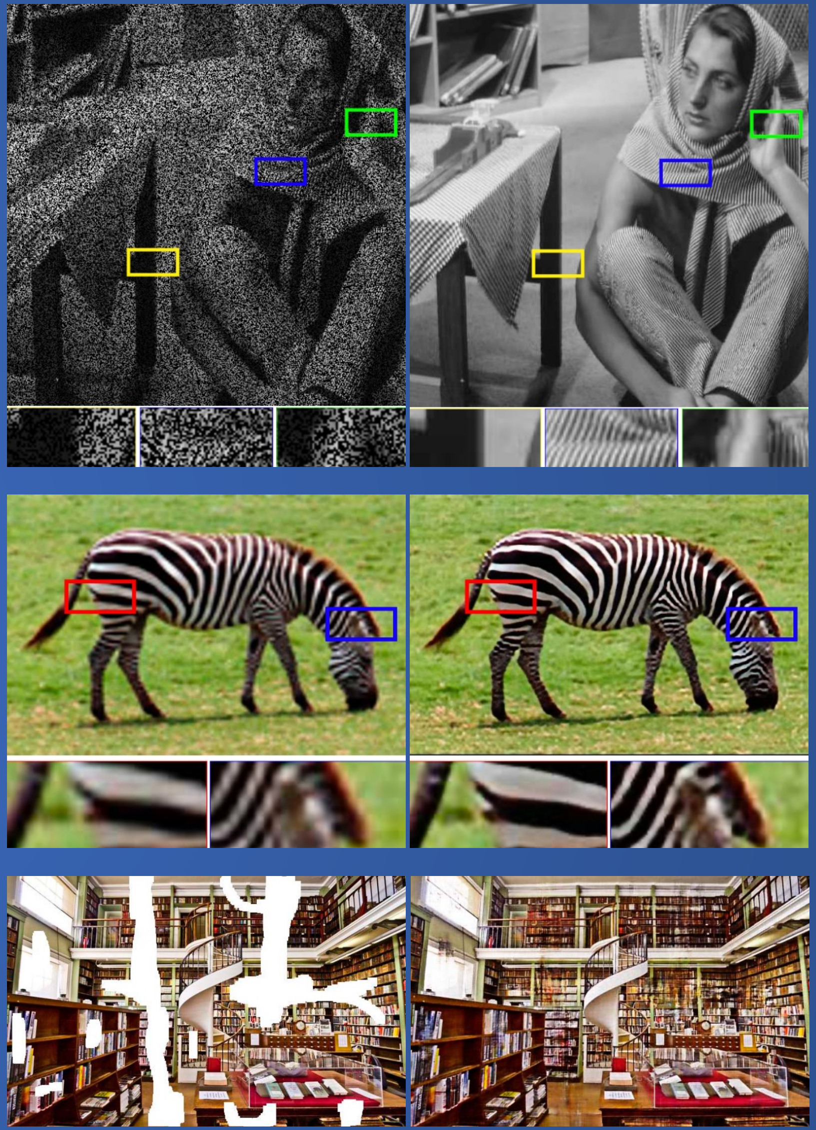
Inverse problem of image corruption

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

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

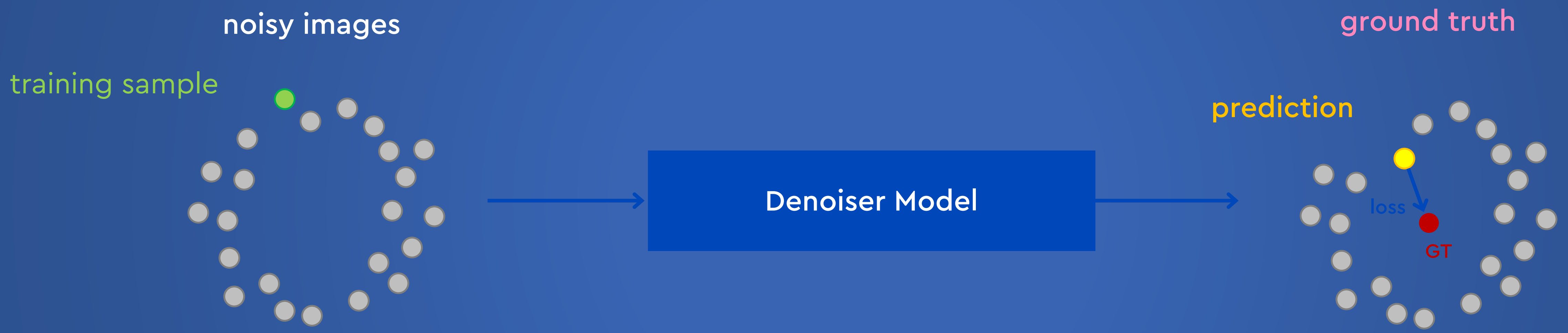
$f(\cdot)$ & corresponding solutions

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



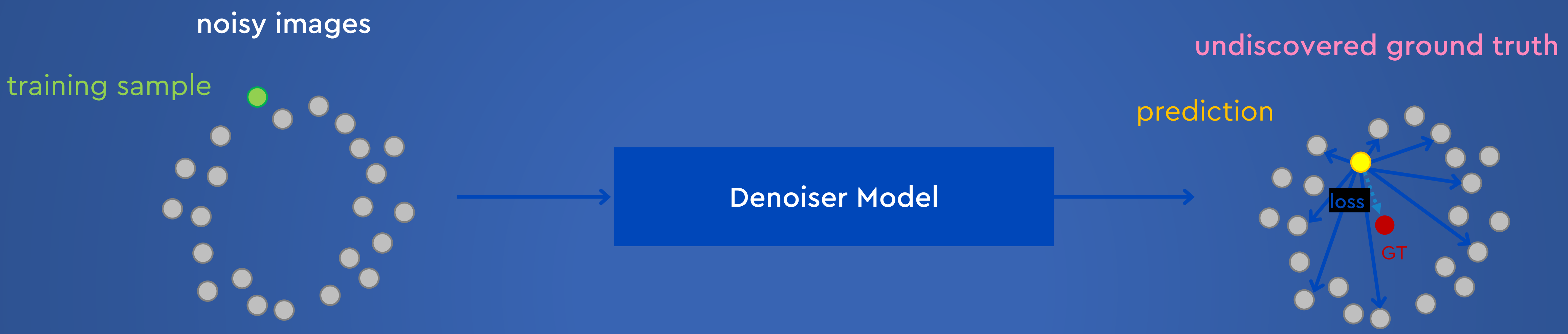
Dmitry Ulyanov et al. Deep Image Prior. CVPR, 2018

Supervised image denoising



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

Blind denoising without ground truth



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!

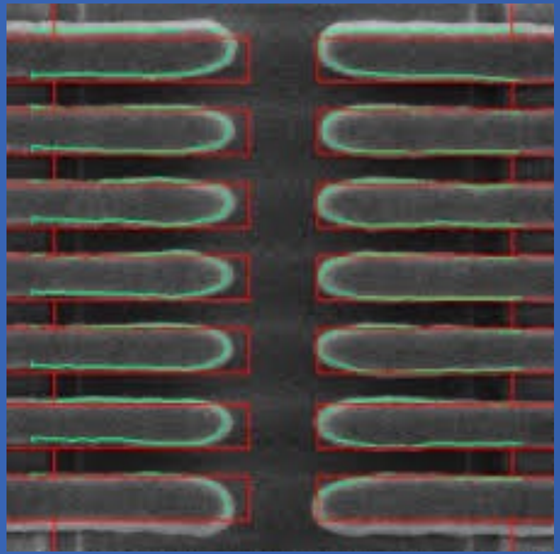
Metrology based on segmentation and pattern recognition

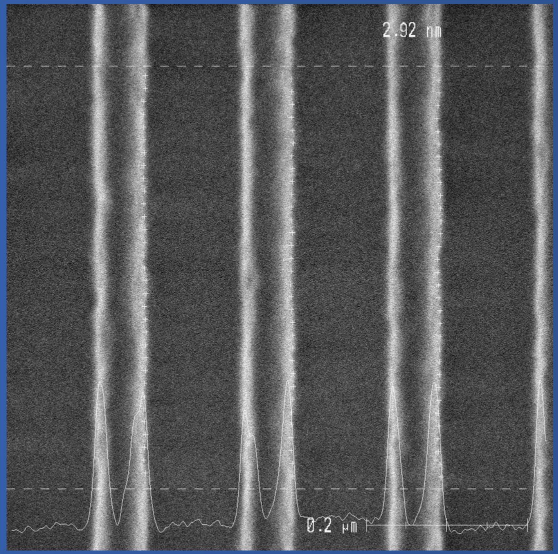
Investment

Automatic measurement of critical dimensions

Approaches

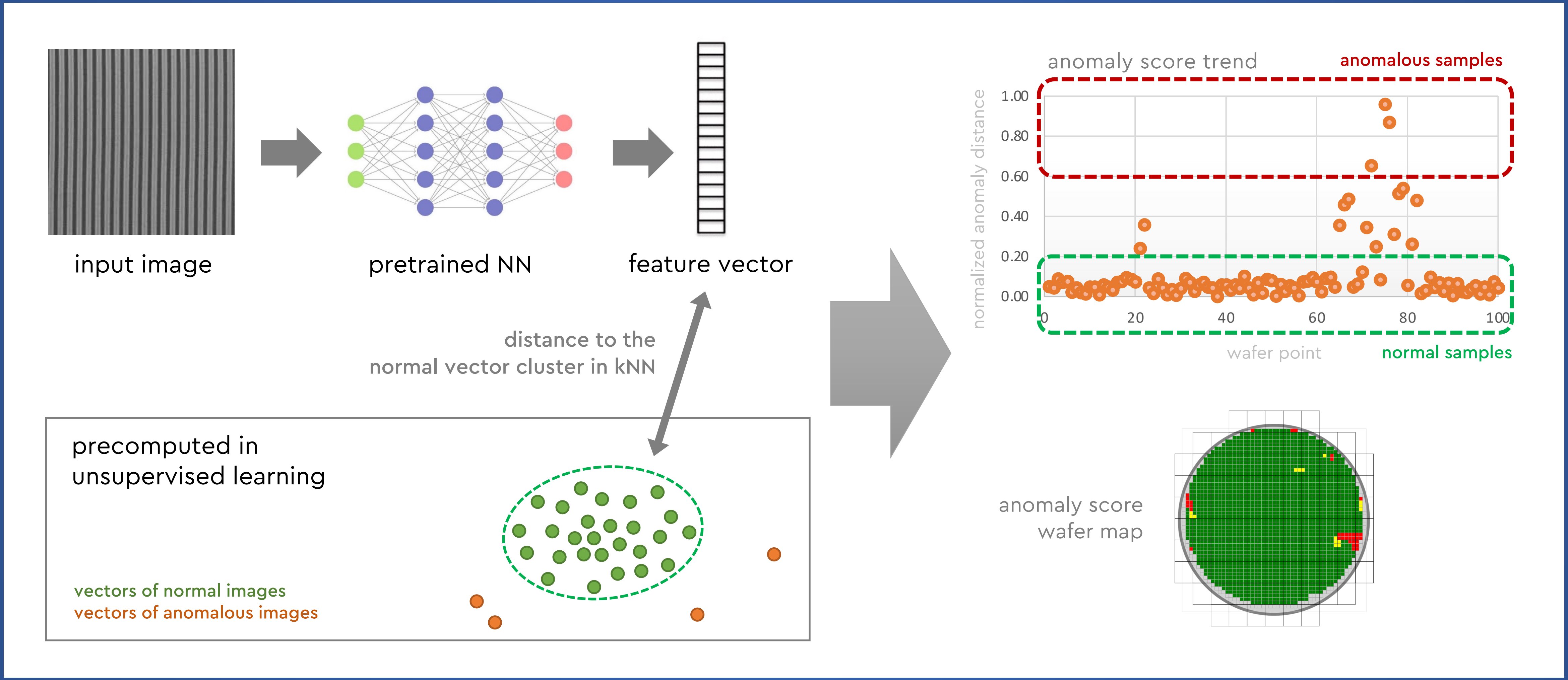
- Texture segmentation
- Repetitive pattern recognition
- Automatic measurement



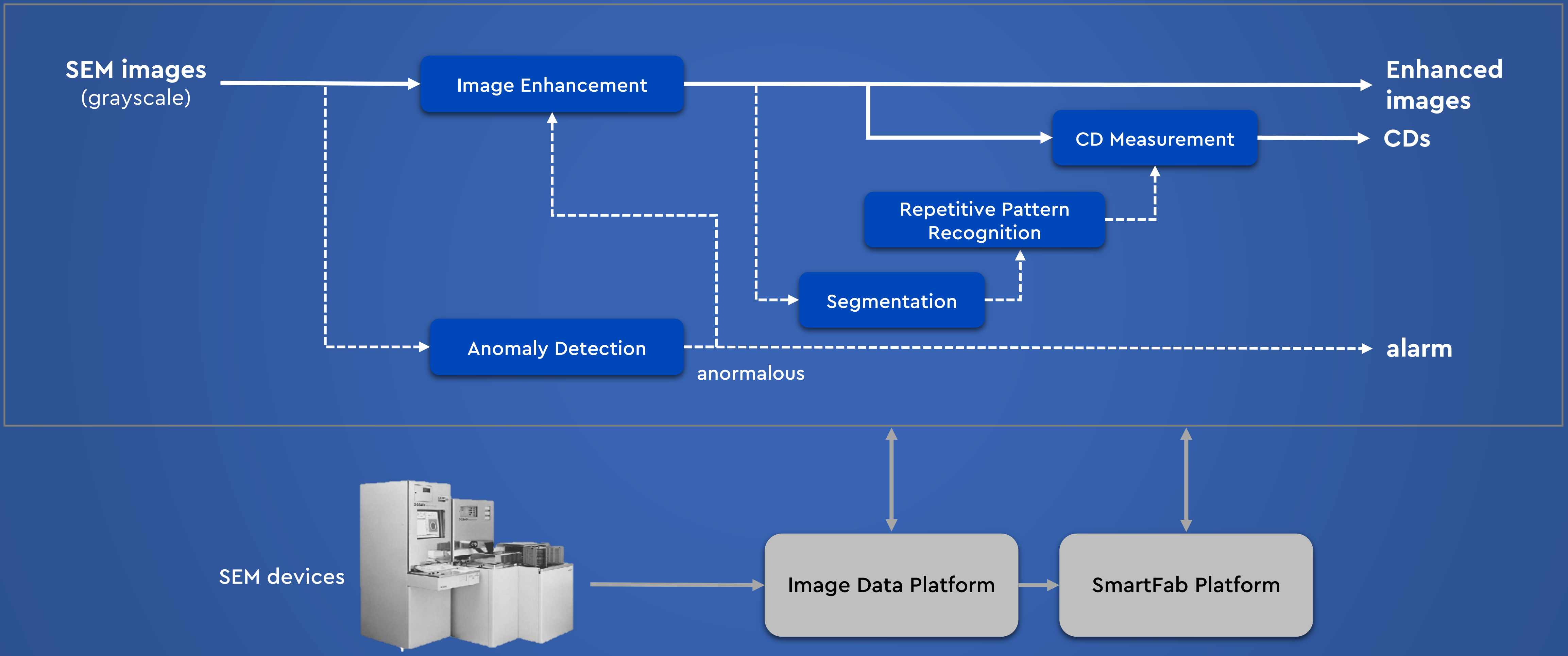


Extremely challenging!
<0.1 nm measurement precision guaranteed

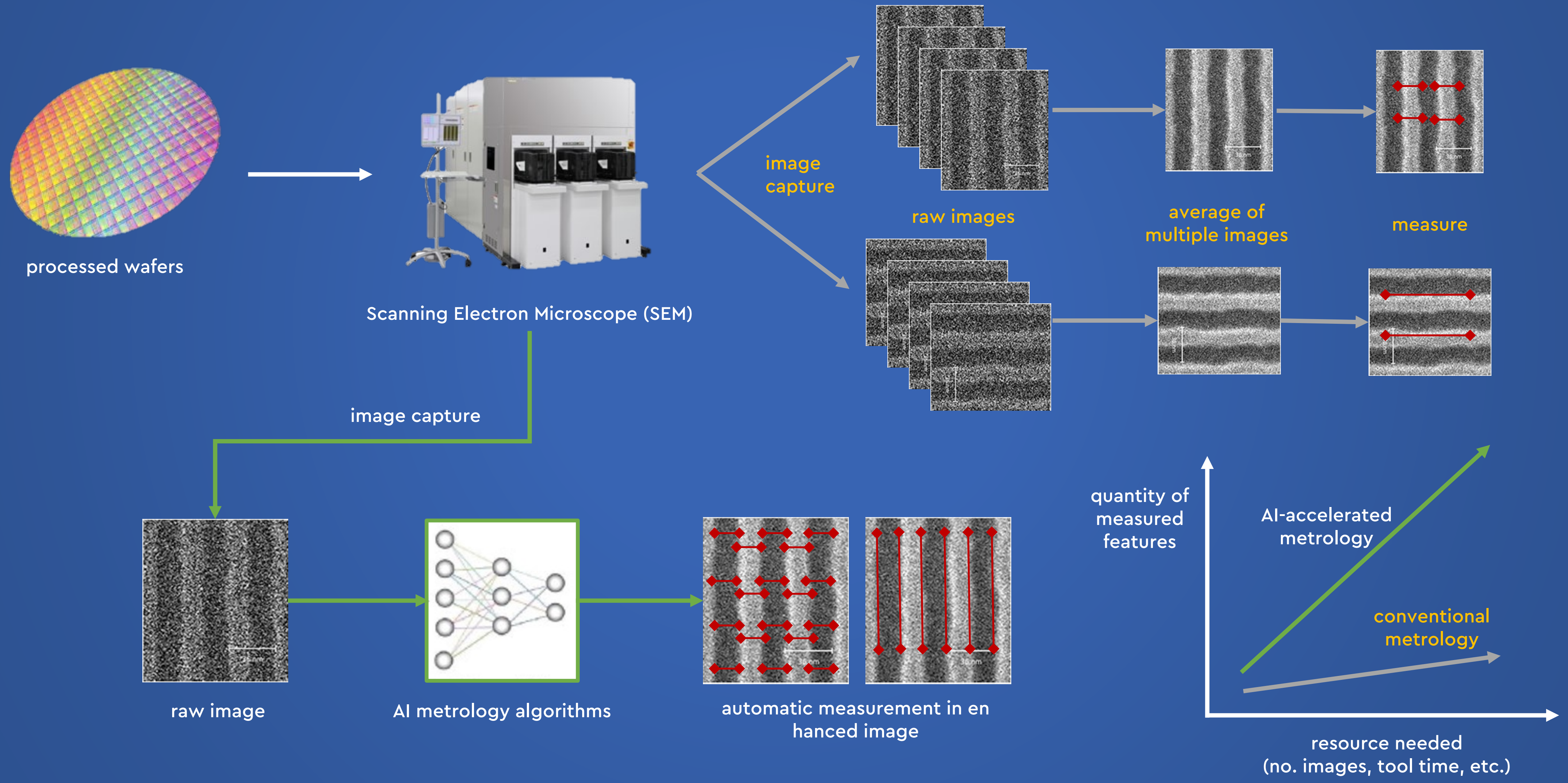
Anomaly detection in unsupervised learning



AI-accelerated metrology system



Automatic measurement for semiconductor manufacturing

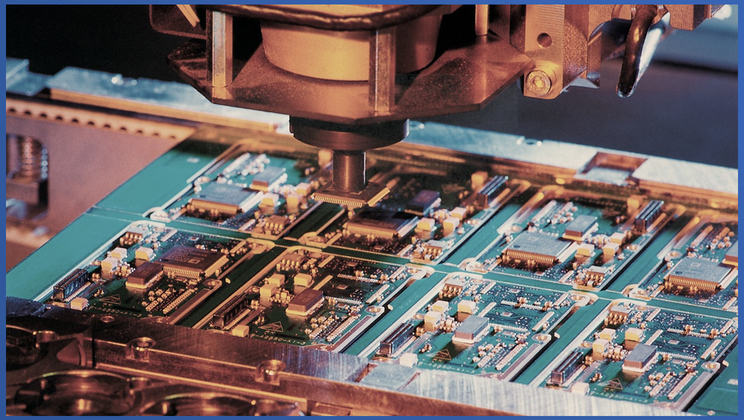


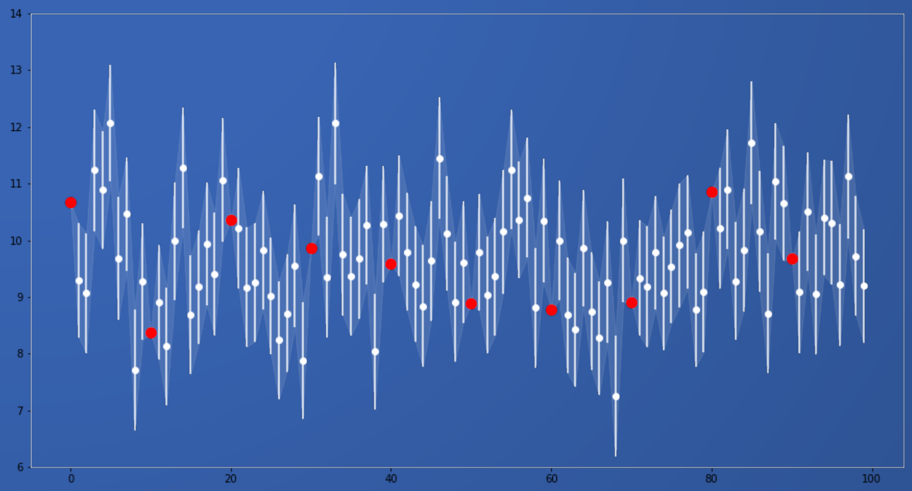
Time-series ML

Why time-series (TS) 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





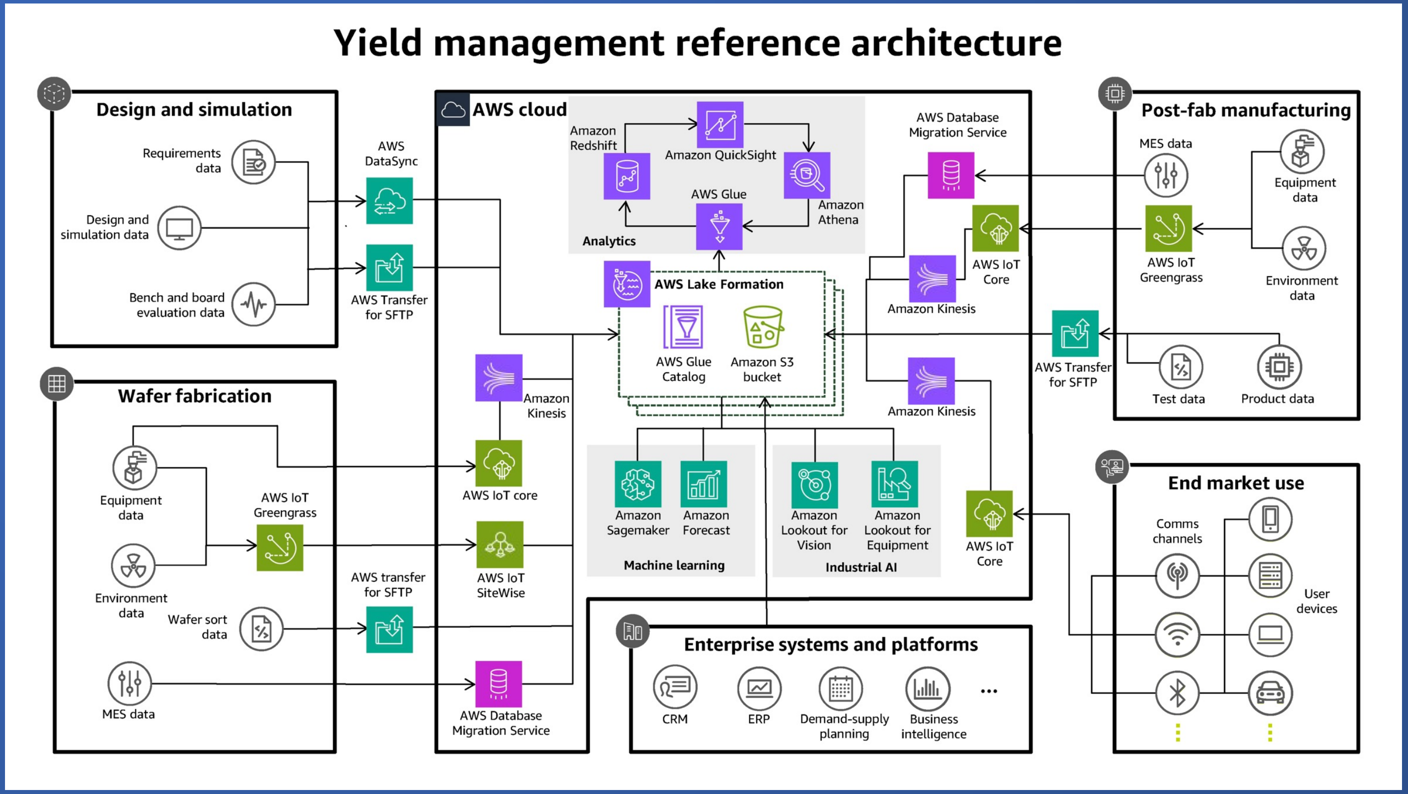
Difficulty & Advantage of TS ML

- *extremely difficult problems to solve*
- *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 & application-tailored algorithms required*

TS prediction & estimation

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

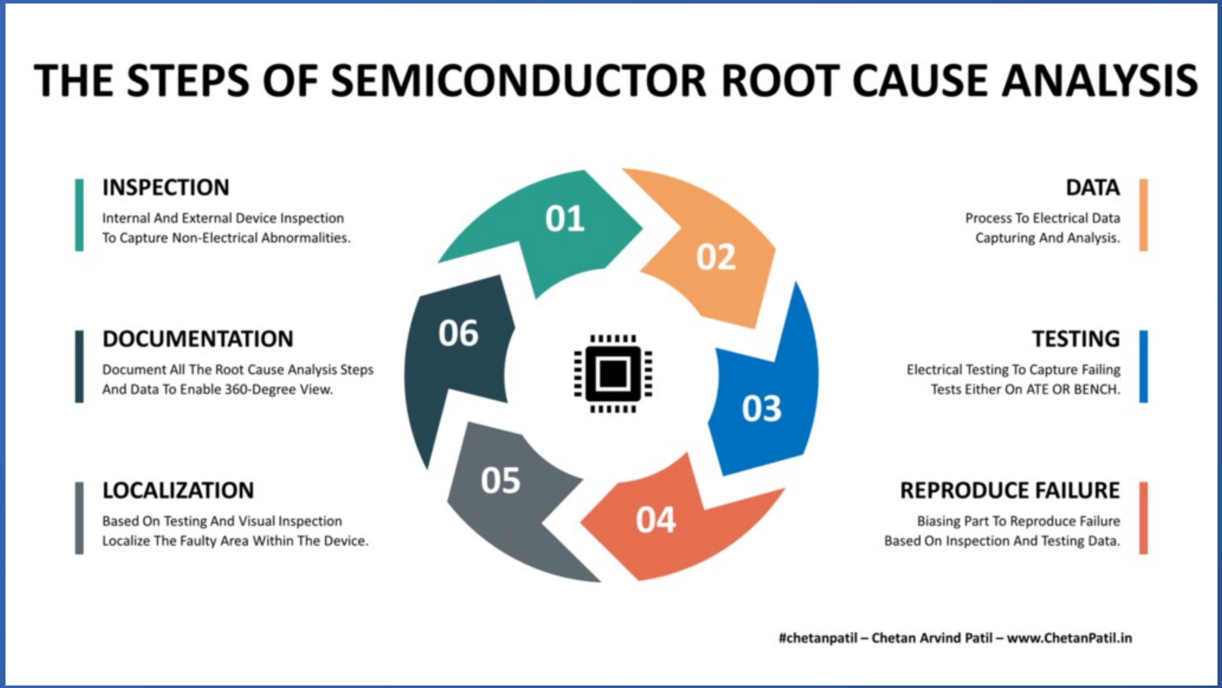
- yield prediction
  - *predict yield before final tests*
  - *better product quality & profit*



Root cause analysis & recommendation system

- equipment alarm root cause analysis
  - *when alarm goes off, find responsible equipment and root causes, where to look*
  - *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*



Virtual Metrology

What is VM?

cannot measure all processed wafers

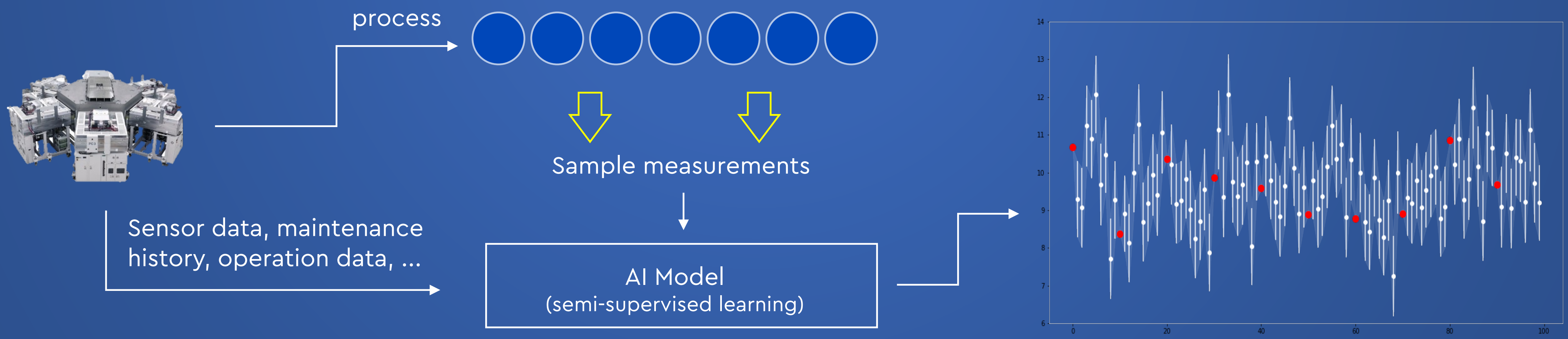
- measurement equipment too expensive
- full measuring hurts throughput
- Not enough space for all measurement equipment

then what? do sampling (with very low sampling rate)

- average sampling rate is less than 5%

PROBLEM

- predict the measurement of unmeasured material using indirect signals
- measure without measuring
- sensor data, maintenance history, operation data, . . .



Data challenges

- covariate shift & concept drift

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

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

- fat data, *i.e.*, # features way larger than # data

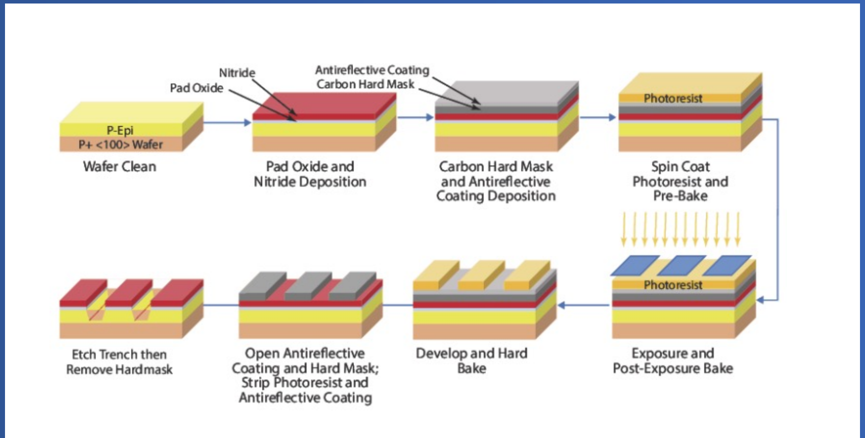
- poor data quality; missing values, anomalies, wrong formats

- huge volume of data to process

Domain knowledge & fully home-grown models

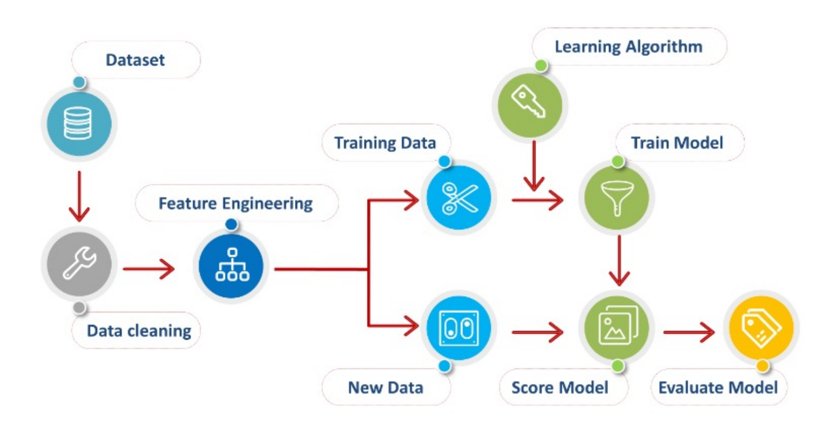
in most cases,
domain knowledge is critical!

close collaboration with customers required



off-the-shelf algorithms
not working!

developing fully customized algorithms needed



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

- 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

Speaker's Recommendations

Recommendations for Maximum Impact via Industrial AI

- Goal of projects
  - North star – Yield Improvement, Process Quality, Making Engr's lives easier
  - Hard problem – scheduling and optimization

- Be strategic!
  - Learn from others – lots of successes/failures of industrial AI
  - Ball park estimation for ROI – efforts, time, expertise, data
  - Reusability, common technology
  - Utilities vs technical excellency / uniqueness vs common technology
  - home-grown vs off-the-shelf

Recommendations for Maximum Impact via Industrial AI

- Remember
  - data, data, data! – readiness, quality, procurement, pre-processing, DB
  - NEVER underestimate domain knowledge/expertise

    – data do NOT tell you everything
  - exploratory data analysis (EDA)
  - do NOT over-optimize your algorithms – ML is (almost) all about trials-&-errors
  - overfitting/generalization/concept drift/shift - way more important than you could ever imagine
  - DevOps, MLOps, Agile dev, software development/engineering

Thank You