Sogang Univ. BK4 Seminar

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Manufacturing AI Problems and Solutions

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Today

1 Why Industrial AI?

2 Computer vision ML for manufacturing

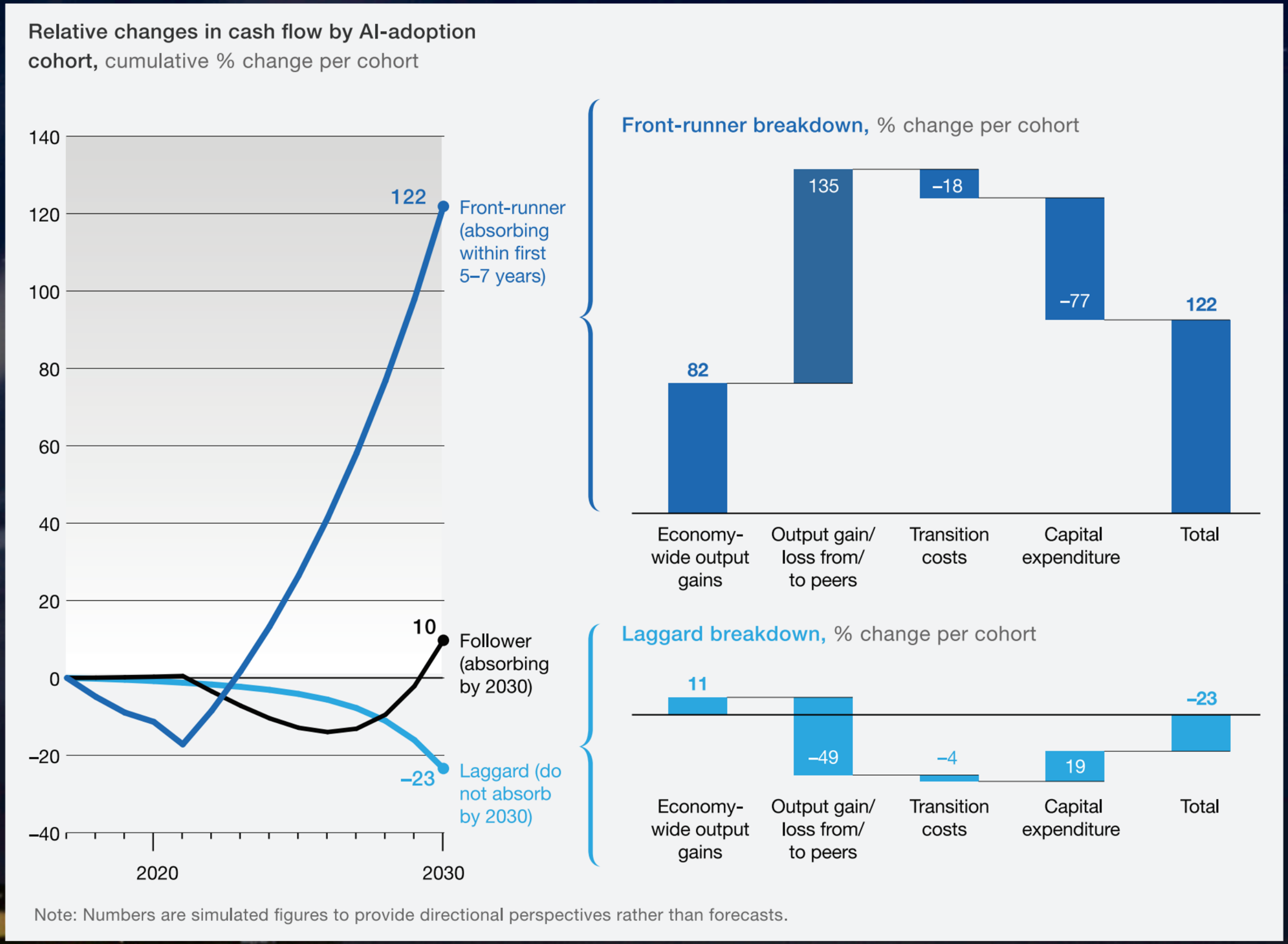
3 Time-series ML for manufacturing

4 Difficulties with time-series ML in manufacturing

5 Gauss Labs success story: Virtual Metrology

"The measure of intelligence is the ability to change."
– **Albert Einstein**

Fast AI adoption and absorption by front-runners can create larger economic gains



* Source: McKinsey Global Institute Analysis (2019)

"The merit of all things lie in their difficulty."
– **Alexandre Dumas** in *The Three Musketeers*

Data-ism

Catch-22

Anna Karenina

Volume	Variety	Velocity
FatData	Shift/drift	Imbalance
Quality	Nonlinearity	Complexity

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Data-ism

Catch-22

Anna Karenina

Investment

Infrastructure

Data Platforms

AI Ops

Transformative and Integrated Use Cases

Return

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"The merit of all things lie in their difficulty."
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Data-ism

Catch-22

Anna Karenina

Every company or sector has its own problems

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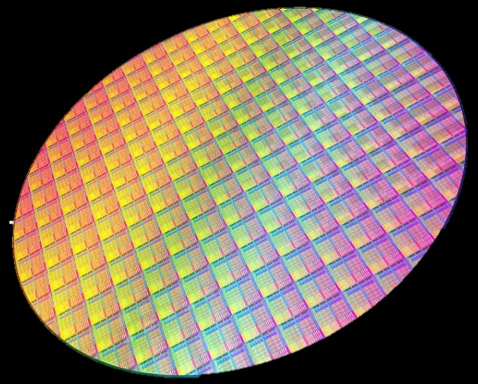
Computer vision and time-series ML in Manufacturing

lots of image data to measure and inspect

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

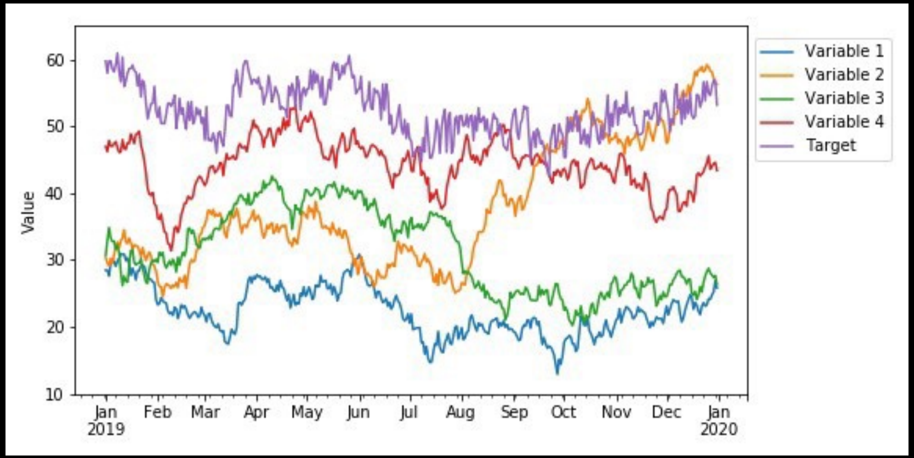
→ Image pattern classification/clustering, image enhancement, image anomaly detection, defect inspection



(almost) all the data coming from manufacturing are time-series data

sensor data, process times, material measurement, equipment maintenance history, *etc.*

→ time-series (TS) prediction/estimation, TS anomaly detection, TS classification



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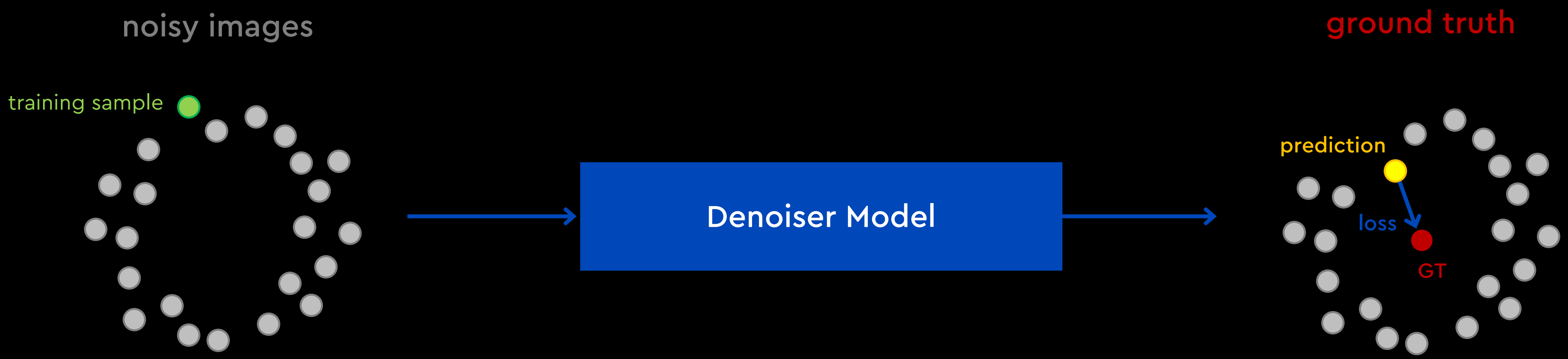
Computer Vision ML for manufacturing

Metrology
Measurement of critical features

Inspection
Anomaly detection, localization and classification

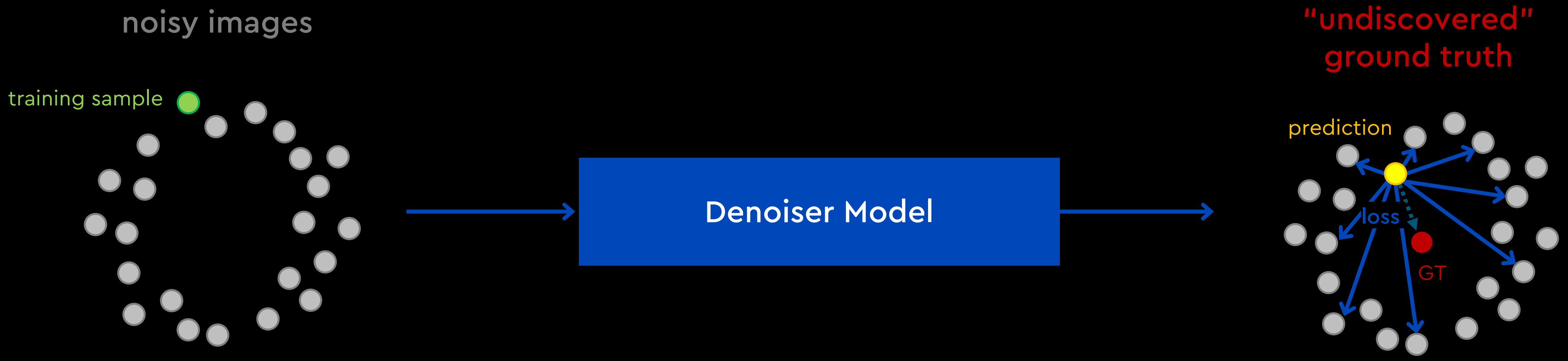
Image courtesy of ASML

Supervised image denoising



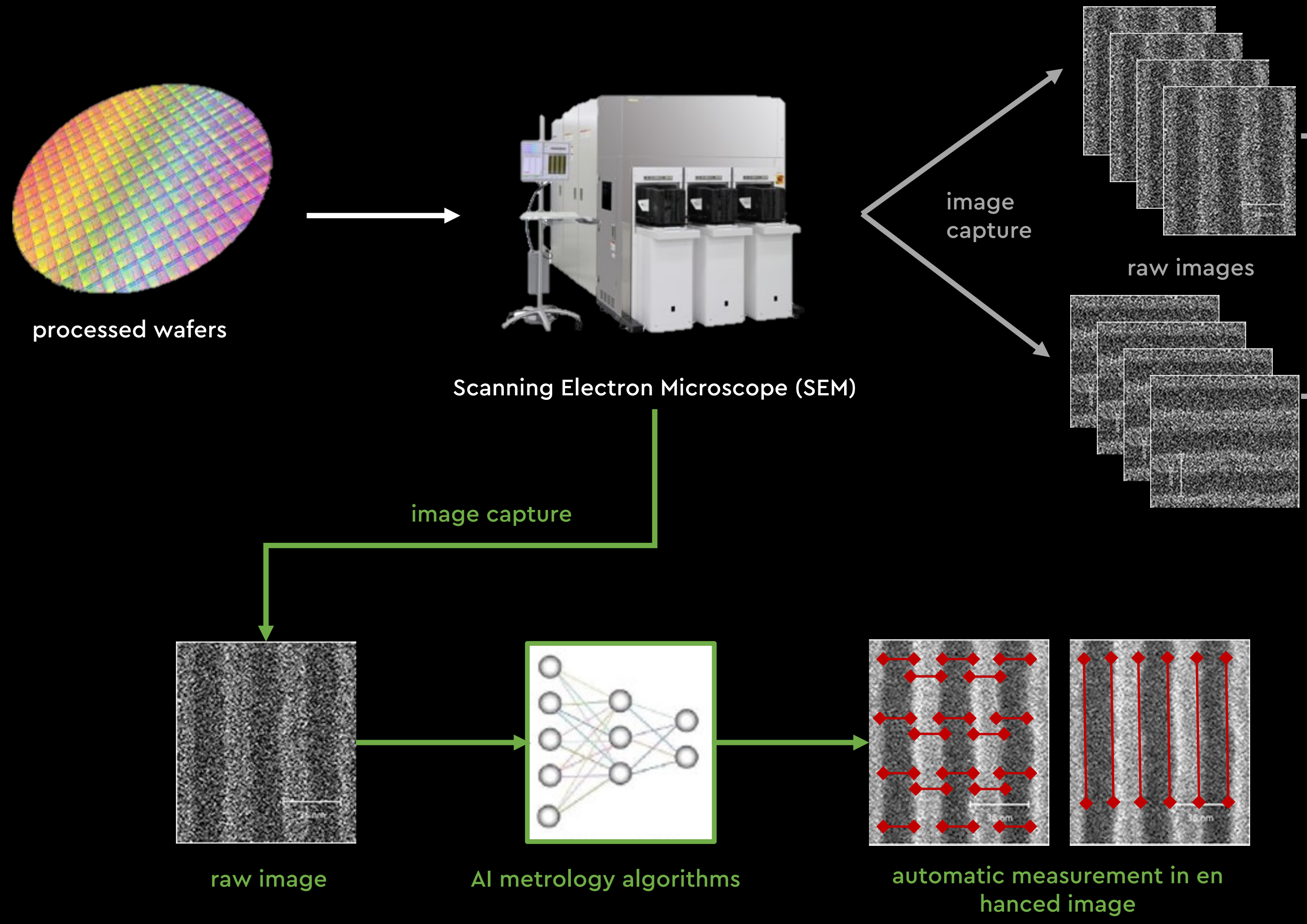
However, it is not possible to acquire ground-truth images from SEM device, in practice.

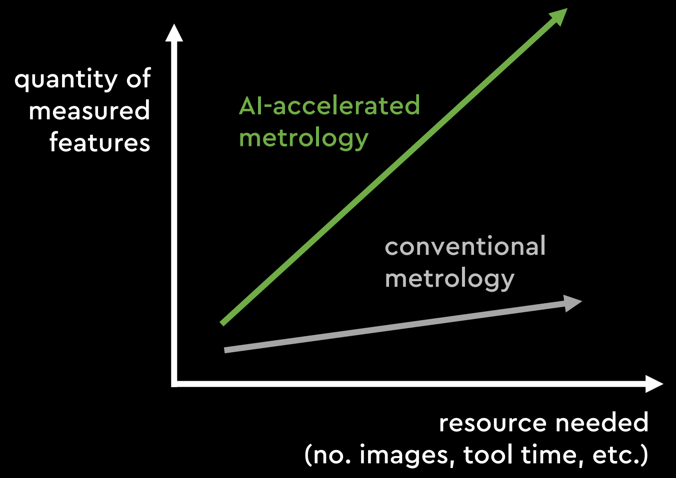
Blind denoising without ground truth



If the mean of the noise is zero, the average of the gradients that model takes is same with the gradient to the ground truth

Automatic measurement for semiconductor manufacturing



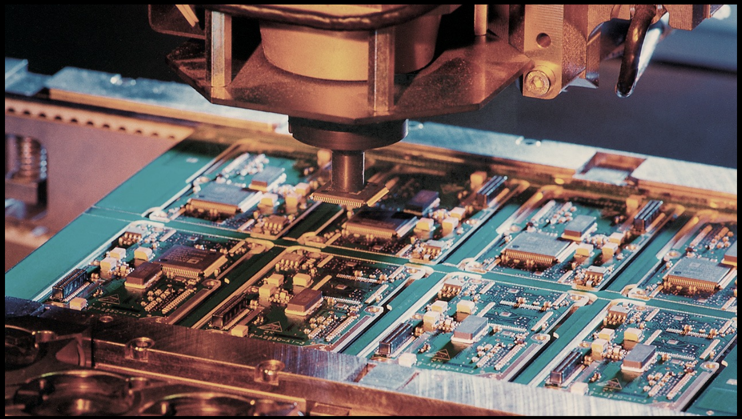


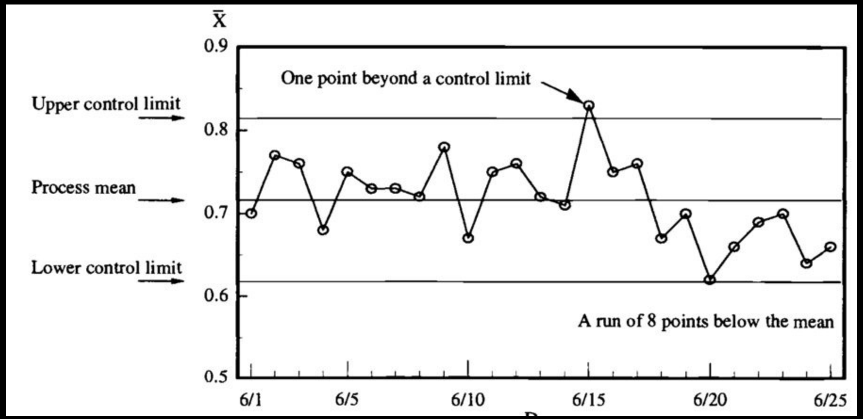
Time-series ML for manufacturing

Why time-series ML?

manufacturing application is about one of the following:

- prediction of time-series values - virtual metrology, yield prediction
- anomaly detection on time-series data - root cause analysis, yield analysis
- classification of time-series values - equipment anomaly alarm generation

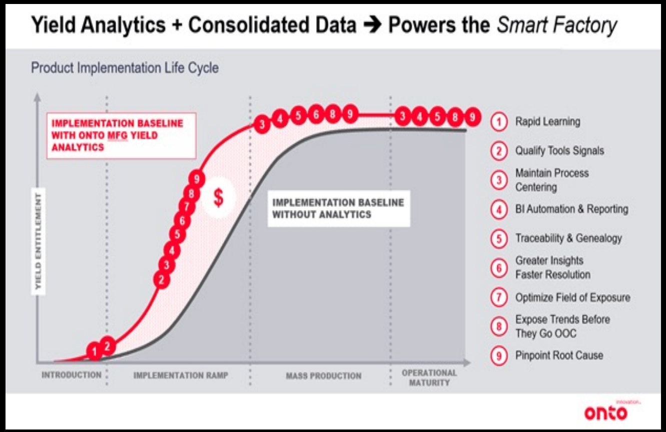


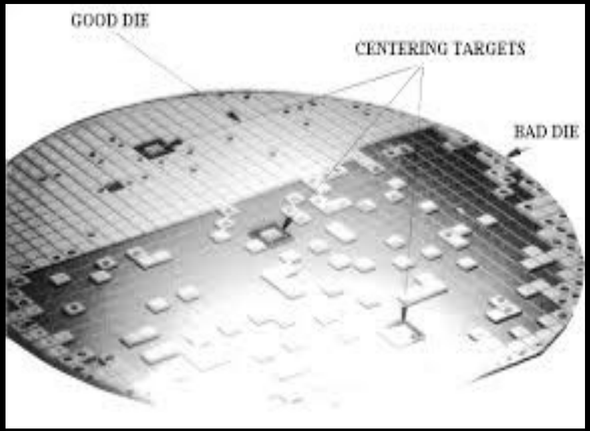


Time-series prediction and estimation

- virtual metrology
  - *measure unmeasured process materials using equipment signals and other information*
  - *impact: save investment on measurement equipment*

- yield prediction
  - *predict yield (# working dies / # total dies) with material measurements from equipment*
  - *impact: better product quality and better profitability*





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Time-series anomaly detection and root cause analysis

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

- **yield analysis**
  - *find responsible equipment for yield drop*
  - *impact: 1% yield improvement brings profit increase of tens of millions of dollars!*

Difficulties with TS ML in manufacturing

Data challenges

- concept drift/shift

  $p\left(x\left(t_k\right), x\left(t_{k-1}\right), \ldots\right)$ *changes over time*

  $p\left(y\left(t_k\right) \mid x\left(t_k\right), x\left(t_{k-1}\right), \ldots, y\left(t_{k-1}\right), y\left(t_{k-2}\right), \ldots\right)$ *changes over time*

- we have fat data, i.e., # features larger than # data

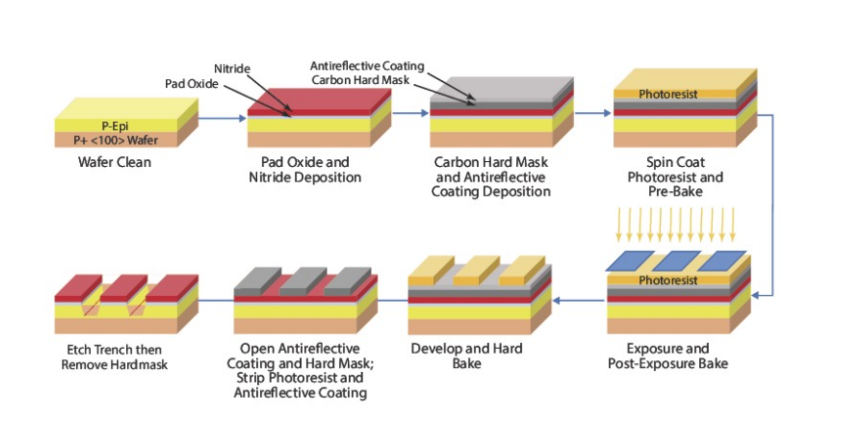
- poor data quality, i.e., lots of missing values or anomalies

- huge volume of data to process, different types of data

Domain knowledge and fully home-grown algorithms

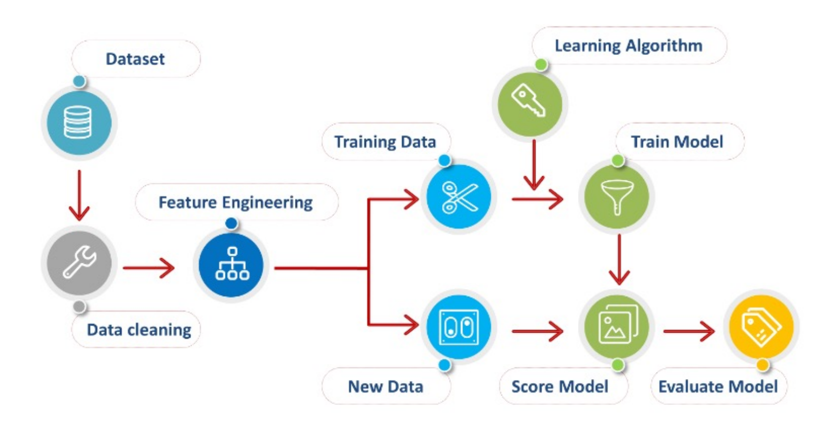
in most cases, domain knowledge is critical!

close collaboration with customers required



off-the-shelf algorithms not working!

developing fully customized algorithms needed



Gauss Labs success story: Virtual Metrology (VM)

What is VM?

in many cases, we cannot measure all processed materials

- measurement equipment is too expensive
- measuring every materials makes production slow inducing low throughput

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

- in semiconductor manufacturing line, average sampling rate is less than 1%

PROBLEM

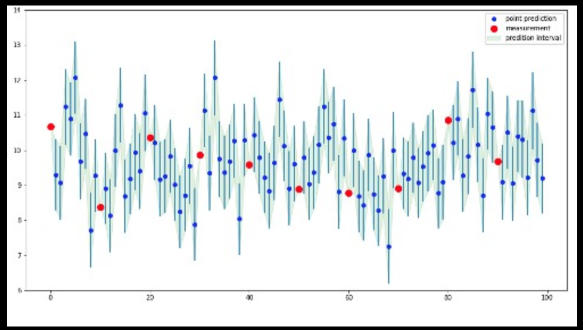
- predict the measurement of unmeasured material using indirect signals
- sensor data, maintenance history, operation data, . . .

process

Sample measurements

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

AI Model
(semi-supervised learning)



10x change made by VM

To the best of our knowledge

- no organization has even been successful with VM

Gauss Labs VM

- uses online learning to cope with data drift/shift
- RMSE comparable to measurement equipment precision
- also predicts uncertainty of predictions - providing prediction reliability information

VM implications

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

Conclusion

supervised and unsupervised ML everywhere in industrial AI applications

lots of challenges

- data challenge, domain knowledge required, need for customizing algorithms

10x changes potentially made via various applications

Impacts

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

Gauss Labs has success stories include

- Virtual Metrology (VM)
- Subnanometer-precision Machine Vision

Who we are

SCAN here
For info

Founded in Silicon Valley and Seoul, Korea, in August 2020

Strategic investment of $55m by SK

Global team of ~45 Gaussians (grow with quality and speed)

Top talents from global companies (16 PhDs)

Mission of innovating industry with trustworthy AI technologies

Reliable, robust, and scalable AI products and solutions for 10x changes

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We normalize AI.