

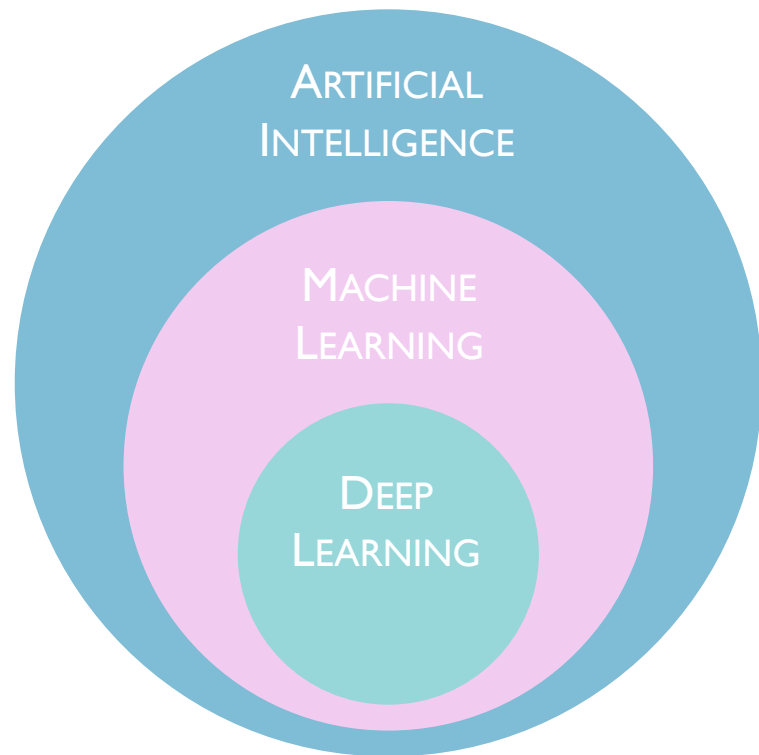


# mmeC

## MACHINE LEARNING APPLICATION FOR METROLOGY AND PROCESS CONTROL

PHILIPPE LERAY, SANDIP HALDER, DORIN CERBU, ROEL WUYTS, WILFRIED VERACHTERT

# MACHINE INTELLIGENCE



- Reasoning
- Generic Goals
- Concept Building
- Language Building
- Pattern Recognition
- ...

Tuning model parameters based on available data = "learning"

- Pattern Recognition
- Feature Extraction
- ...

Using neural networks as machine learning model

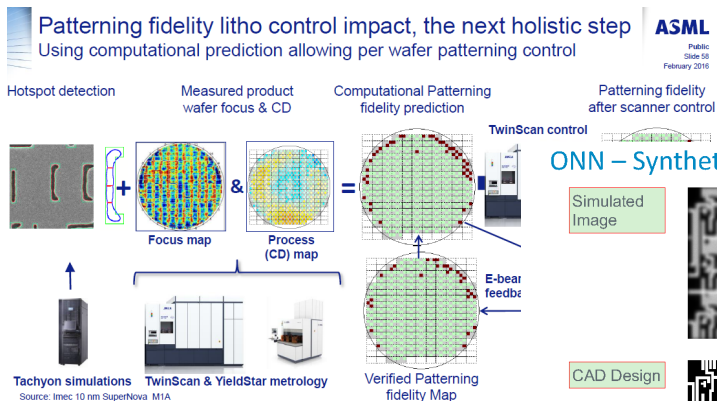
- Multilayer Perceptron
- Convolutional Neural Networks (CNN)
- Long Short Term Memory (LSTM)
- ...

**Machine Learning**  
is a subset of general  
**Artificial Intelligence**

**Deep Learning**  
is a technique to do  
**Machine Learning**

# THIS IS HAPPENING IN OUR INDUSTRY

## SOFTWARE INCLUSIVE OF SIMULATION/EMULATION



ASML  
Public  
Slide 58  
February 2016

## SEMICONDUCTOR ENGINEERING

Home > Manufacturing, Packaging & Materials > Fabs Meet Machine Learning

MANUFACTURING, PACKAGING & MATERIALS

## Fabs Meet Machine Learning

95 Shares

D2S' CEO sounds off on the impact of deep learning, EUV and other manufacturing advancements.

JULY 19TH, 2018 - BY: MARK LAPEDUS

**SE: Is deep learning being used in semiconductor manufacturing?**

**Fujimura D2S CEO:** It's happening fast, but it's in the beginning stages. I don't think there is any question that deep learning is already impacting the semiconductor manufacturing sector.

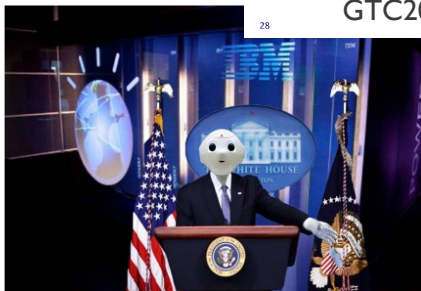
## Metrology Time Machine: What's After Tom

### Cognitive Computing

- The wave after IoT/Cloud
- Watson is 5 years old
  - Won Jeopardy in 2001
  - Now it's working with Doctors to solve cancer
  - It is a decision making tool
    - *Not a replacement for decision makers*

### Watson knows what ...

you don't know,  
what you forgot,  
or forgot that you forgot.



<https://www.nvidia.com/en-us/gtc/>  
GTC2018

(Synthetic image is generated from incoherent simulation based on known PSF and shot noise to add to simulate the sensor noise.)

KLUG TENSOR

In his presentation, **Applied Materials** president and CEO Gary Dickerson will explain how the rapid increase in data generation, combined with A.I. and machine learning, creates the need for new system architectures and compute models in the years ahead.

<https://www.globenewswire.com/news-release/2017/09/21/1126089/0/en/Applied-Materials-Focuses-on-Enabling-Artificial-Intelligence-Era-at-2017-Analyst-Day.html>

# MACHINE LEARNING ON METROLOGY DATA



## VALUE

- REDUCED TIME SPENT @ METROLOGY
- IMPROVE YIELD

## REDUCED TIME SPENT @ METROLOGY

- PREDICT BAD WAFER → STOP EARLY
- PREDICT BAD/GOOD DIES  
→ SELECT THE PARTS TO BE MEASURED

## IMPROVE YIELD

- CORRECT ERRORS IN LATER PROCESS STEPS

## FEATURE REDUCTION

- REDUCE THE AMOUNT OF DATA FROM METROLOGY TOOLS TO BE PROCESSED
- REDUCE USELESS MEASUREMENTS

## DATA ANALYSIS ON METROLOGY TOOLS

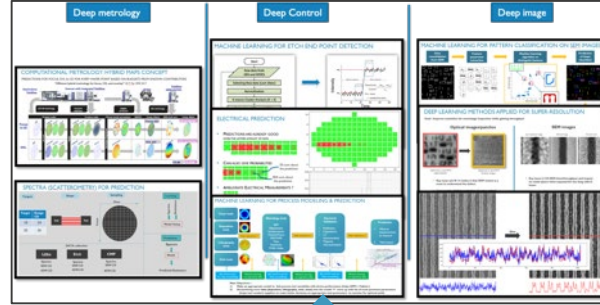
- ASSESS METROLOGY TOOL ERRORS



# MACHINE LEARNING AT IMEC

## ML applications: Deep metrology, deep control, deep image

1. ML for sampling
2. ML for prediction
3. ML for process control
4. ML for tool maintenance
5. ML for image enhancement



## APPLICATIONS & ALGORITHMS

HW

DATA

Data structuring, Access control,  
Federated model

HW based ML

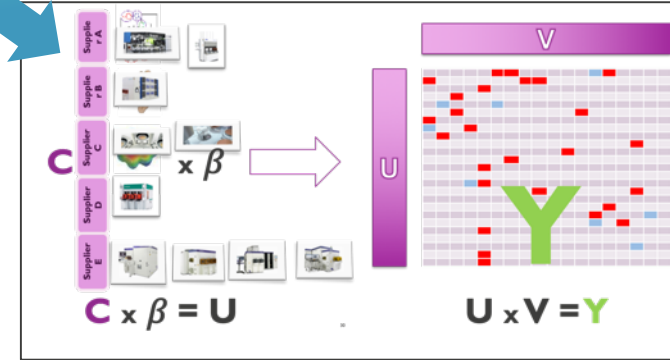
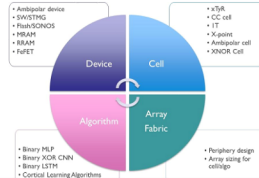
### IMEC MACHINE LEARNING RESEARCH PROGRAM ONE-SLIDE SUMMARY

#### Mission

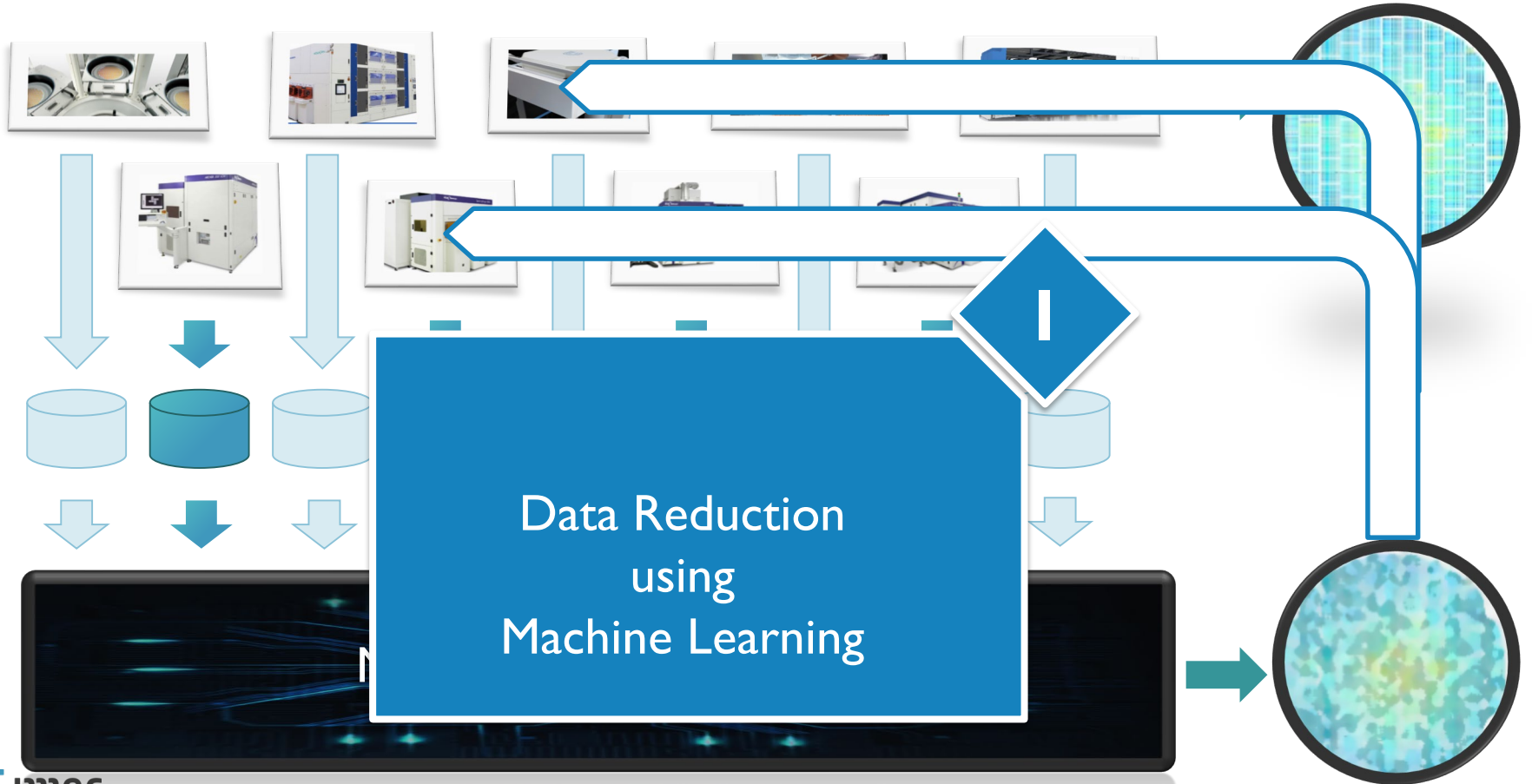
- Combine algorithm and architecture optimization with semiconductor technology elements to enable high power implementation of machine learning for classification and time series prediction.

#### Structure

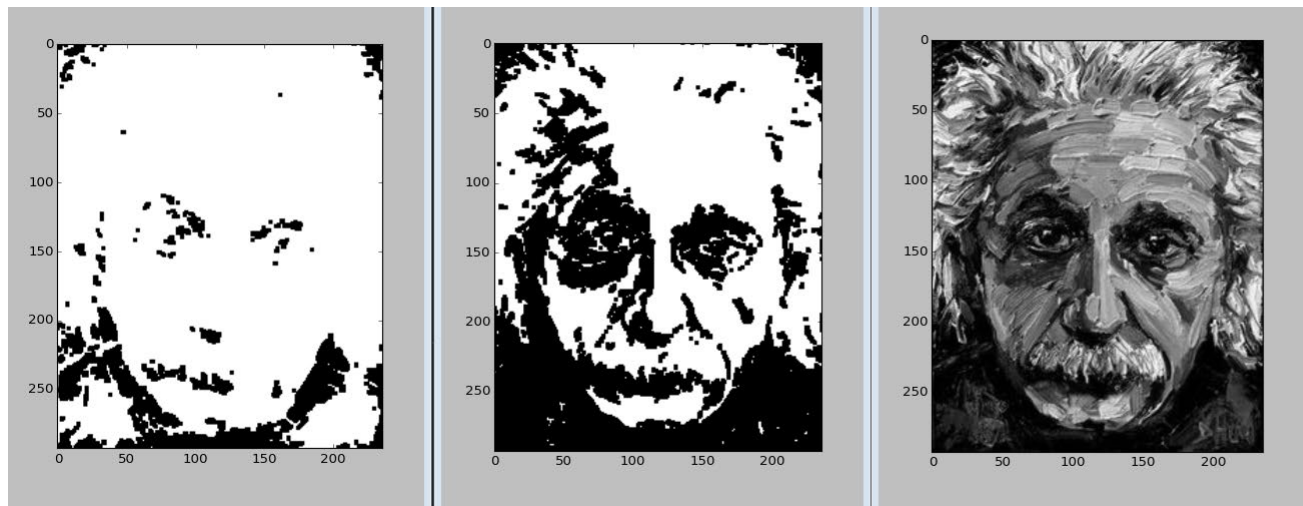
- Algorithmic optimizations
- Digital implementation and architecture
- Analog computational memory
- Technology optimization for machine learning
- Demonstration



# MACHINE LEARNING ON METROLOGY DATA – GUIDANCE

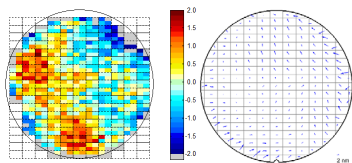


# MACHINE LEARNING FOR SMART METROLOGY

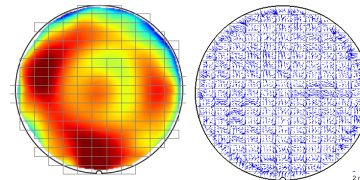


Can we go  
further to predict  
electrical impact ?

(just impact not yield )



Balanced sampling  
to optimize throughput  
without compromising on  
information quality

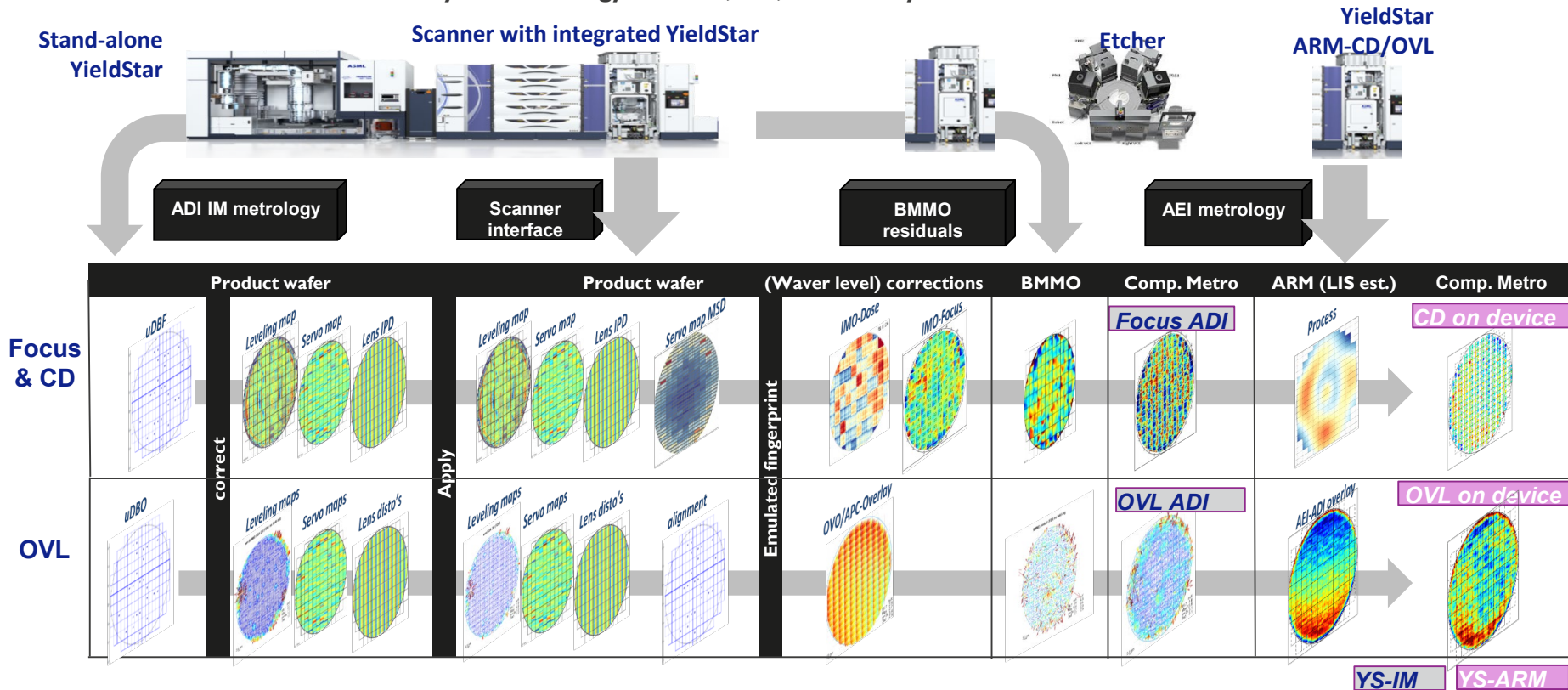


- Measure less but in a smart way so that full wafer behavior can be predicted accurately
- Use ML models to reduce sampling and determine sampling spatial density to get the correct complete picture

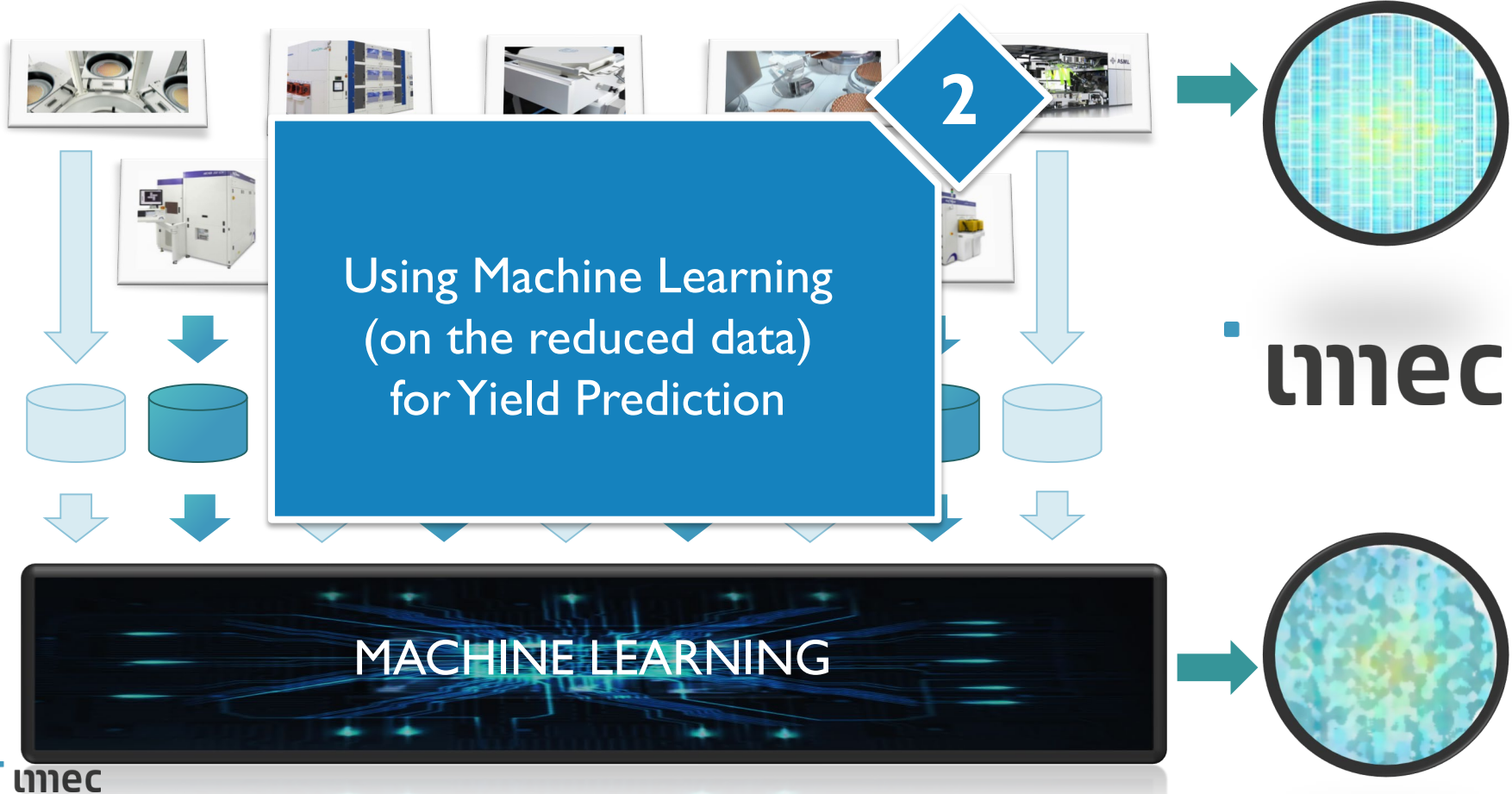
# COMPUTATIONAL METROLOGY: HYBRID MAPS CONCEPT

PREDICTIONS FOR FOCUS, OVL & CD FOR EVERY WAFER POINT BASED ON BUDGETS FROM KNOWN CONTRIBUTORS

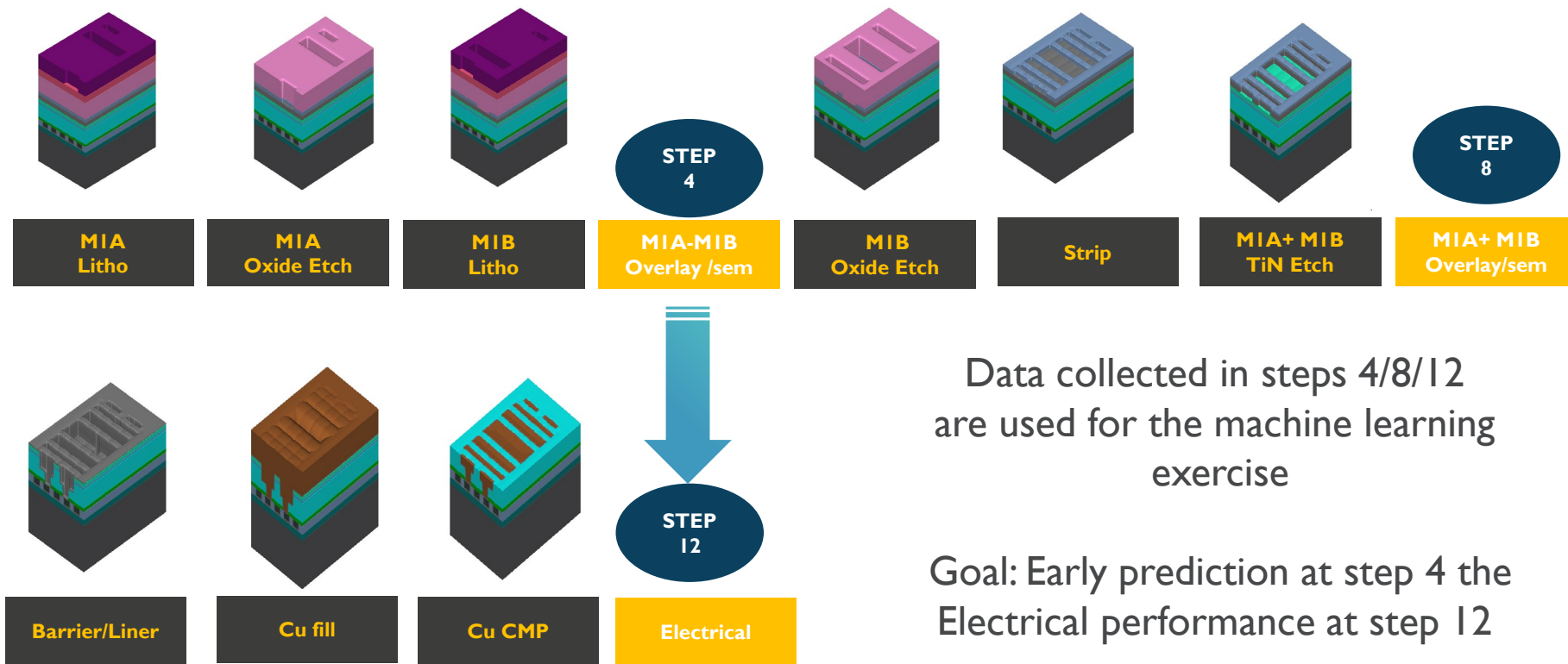
“Efficient hybrid metrology for focus, CD, and overlay” W.T.Tel. SPIE 2017



# MACHINE LEARNING ON METROLOGY DATA – PREDICTIVE

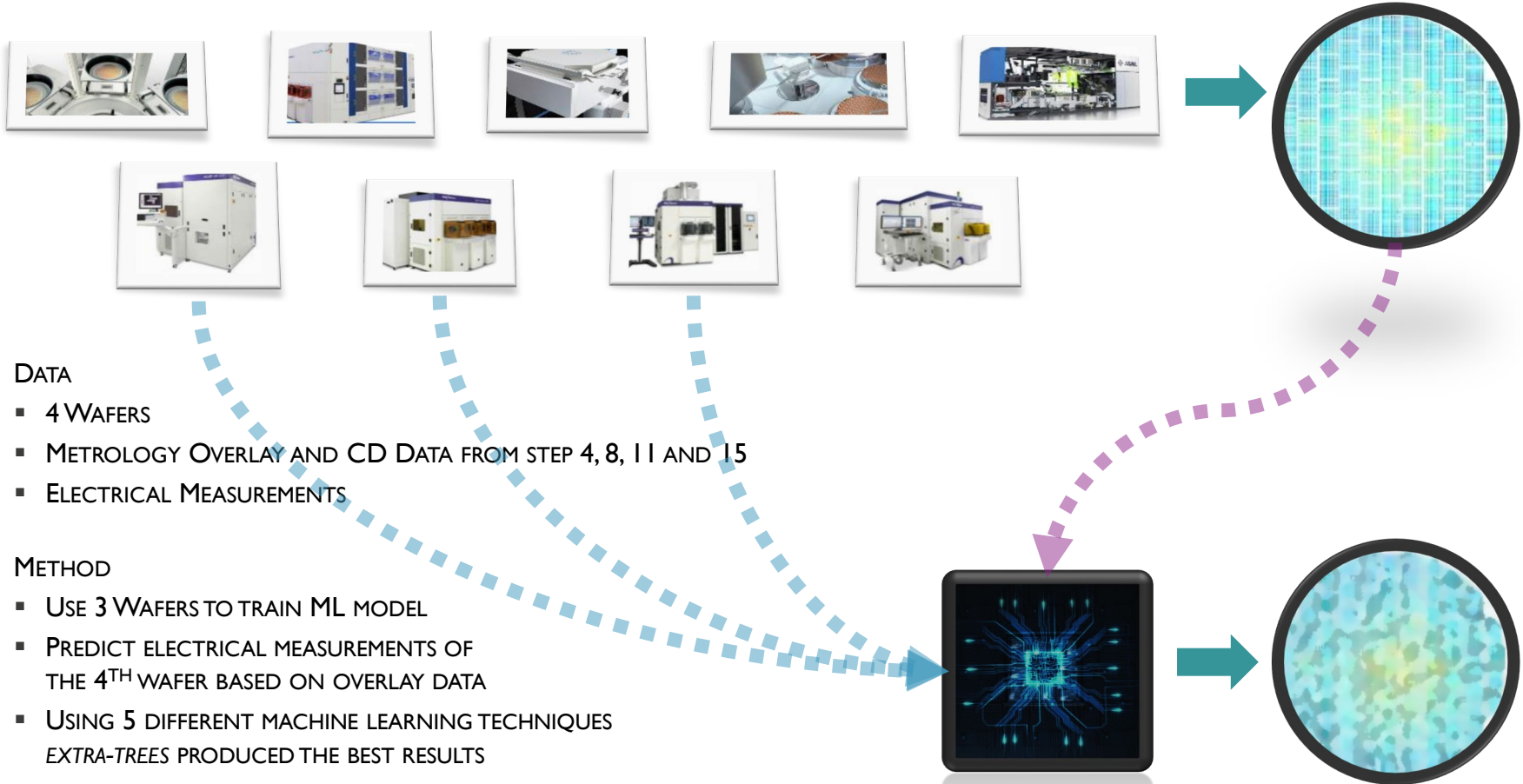


# FEASIBILITY STUDY – PROCESS FLOW AND MEASUREMENTS





# FEASIBILITY STUDY

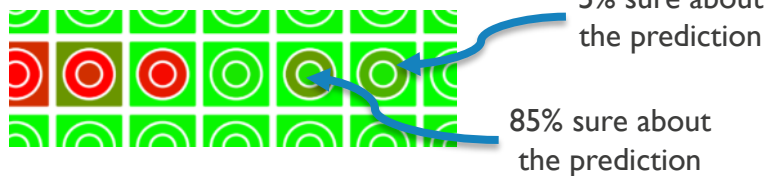


# PRELIMINARY RESULTS

- PREDICTIONS ARE ALREADY GOOD  
GIVEN THE LIMITED AMOUNT OF DATA



- CAN ALSO GIVE PROBABILITIES



- AMELIORATE ELECTRICAL MEASUREMENTS ?

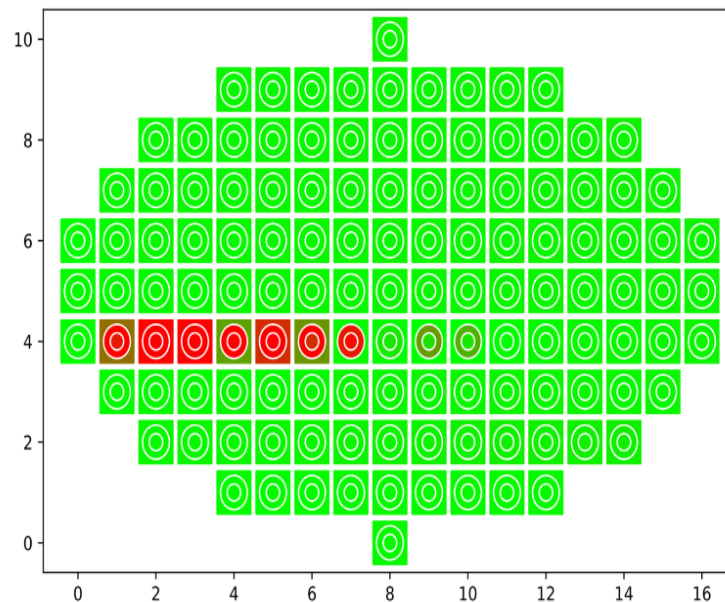
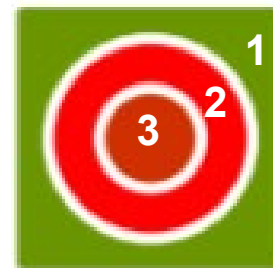


(1) REAL ELECTRICAL  
MEASUREMENTS

PREDICTED ELECTRICAL  
MEASUREMENTS

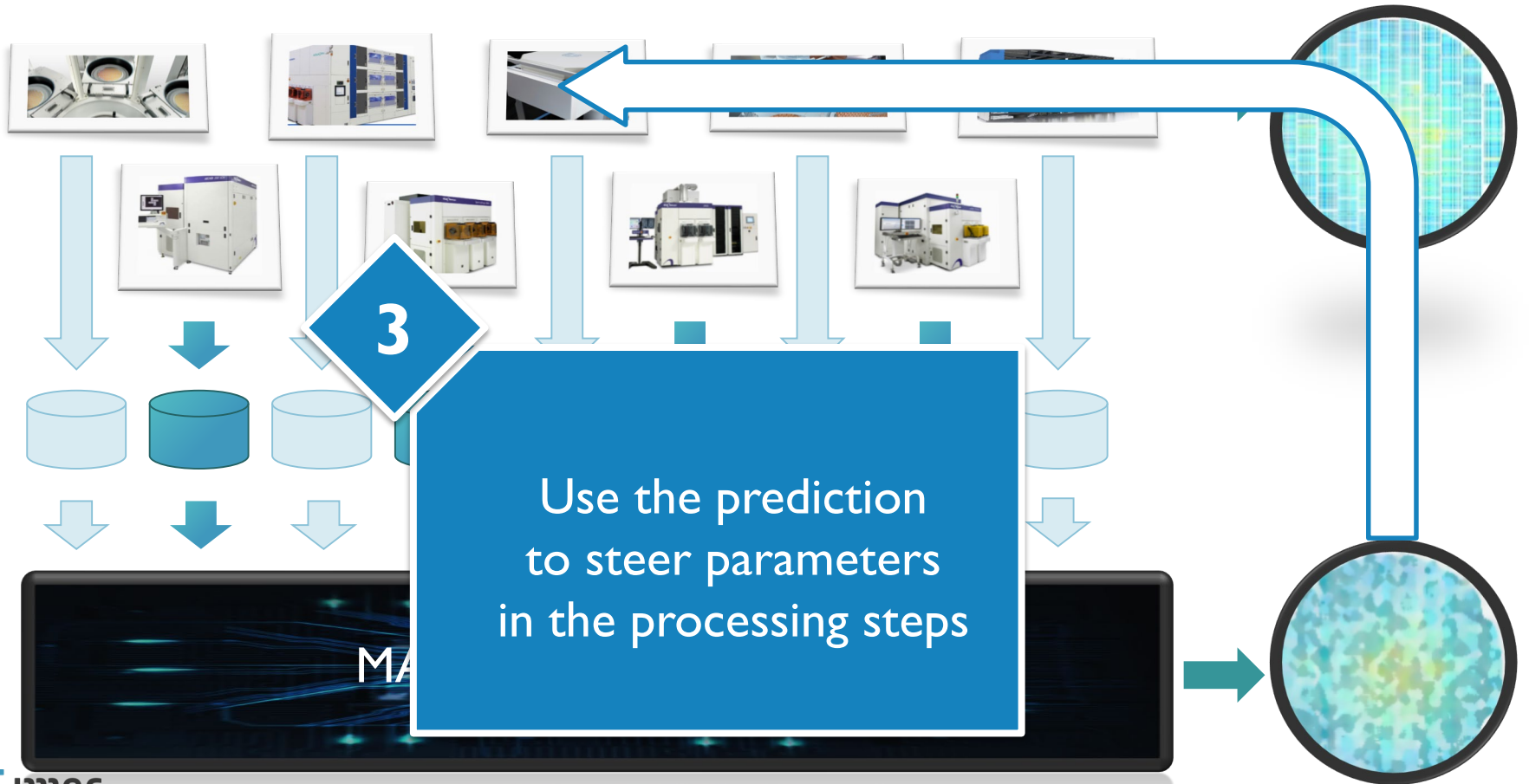
(2) AFTER STEP 4

(3) AFTER STEP 8

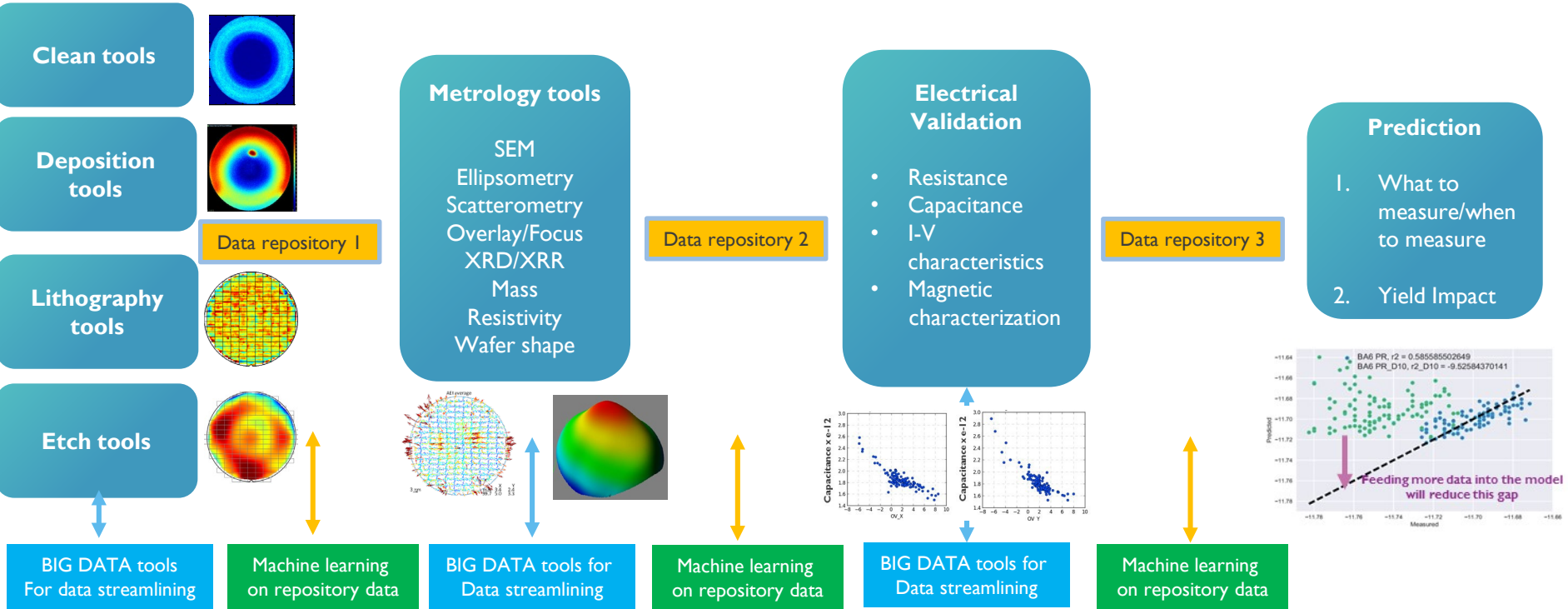




# MACHINE LEARNING ON METROLOGY DATA – PROCESS CONTROL



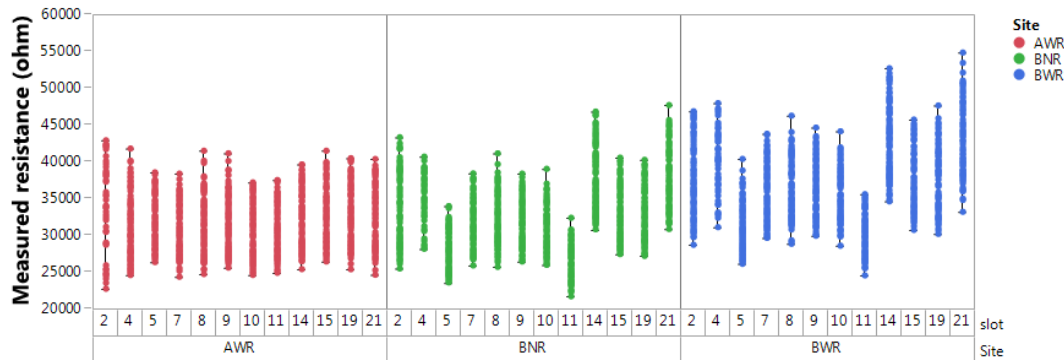
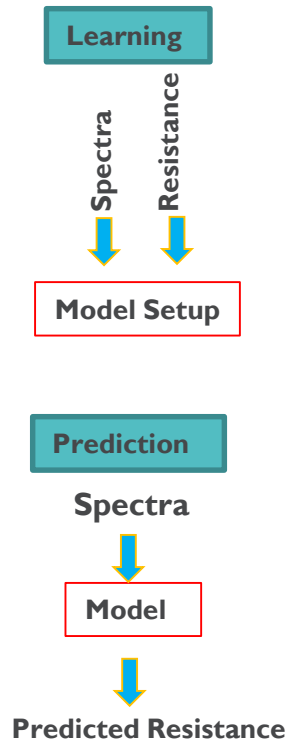
# MACHINE LEARNING FOR PROCESS MODELING & PREDICTION



- 1) **Make an appropriate model to link process tool variability with device performance**
- 2) **Streamlining more data (deposition, lithography, etch, clean) into the model → come up with list of most pertinent parameters**

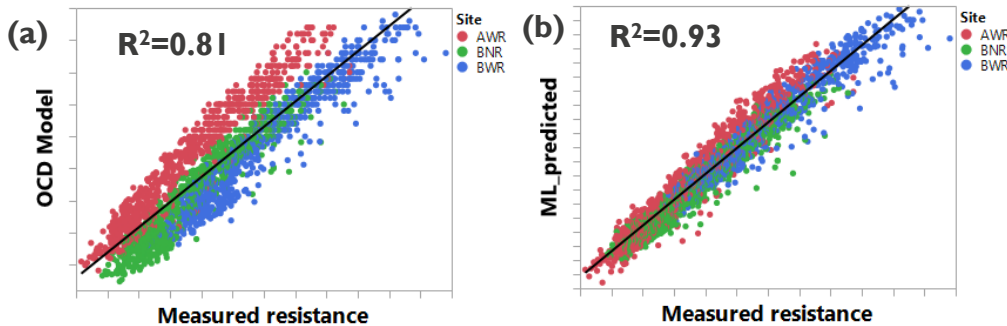
# PREDICTING LINE RESISTANCE FROM OCD SPECTRA

## OCD MODEL VS MACHINE LEARNING



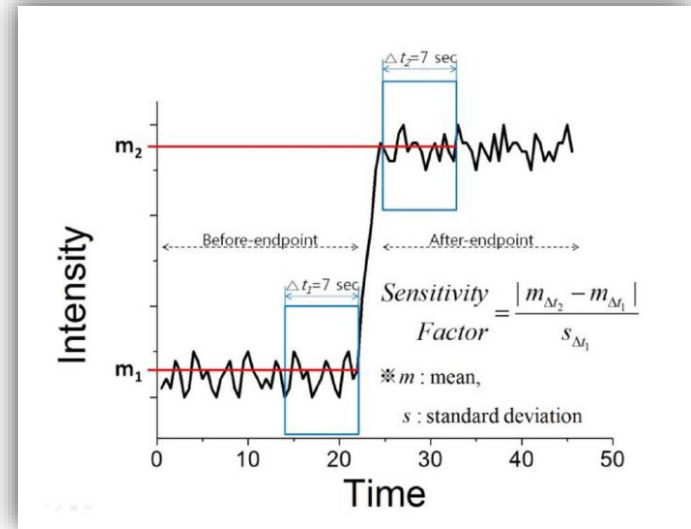
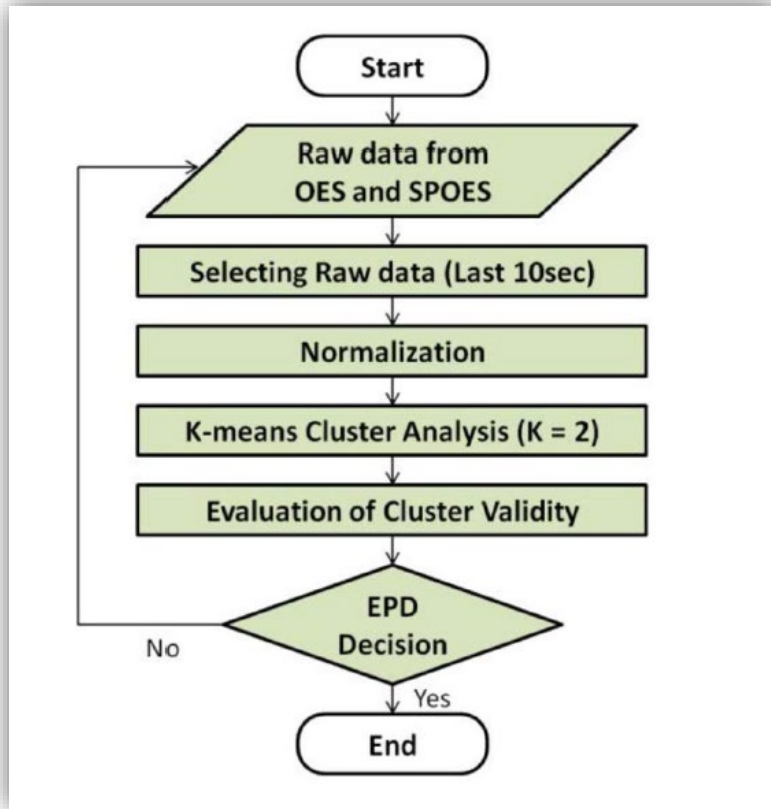
Wafers highlighted are used in training set

#	wafer#	DoE
1	2	M1A FEM
2	4	M1B FEM
3	5	Etch v1
4	7	POR
5	8	POR
6	9	POG OVL
7	10	POR
8	11	Etch v1
9	14	Etch v2
10	15	POR
11	19	POR
12	21	Etch v2



- Machine learning +OCD spectra improves the correlation between measured and predicted line resistance.
- The differentiation between targets reduces. All data on the same linear fit.

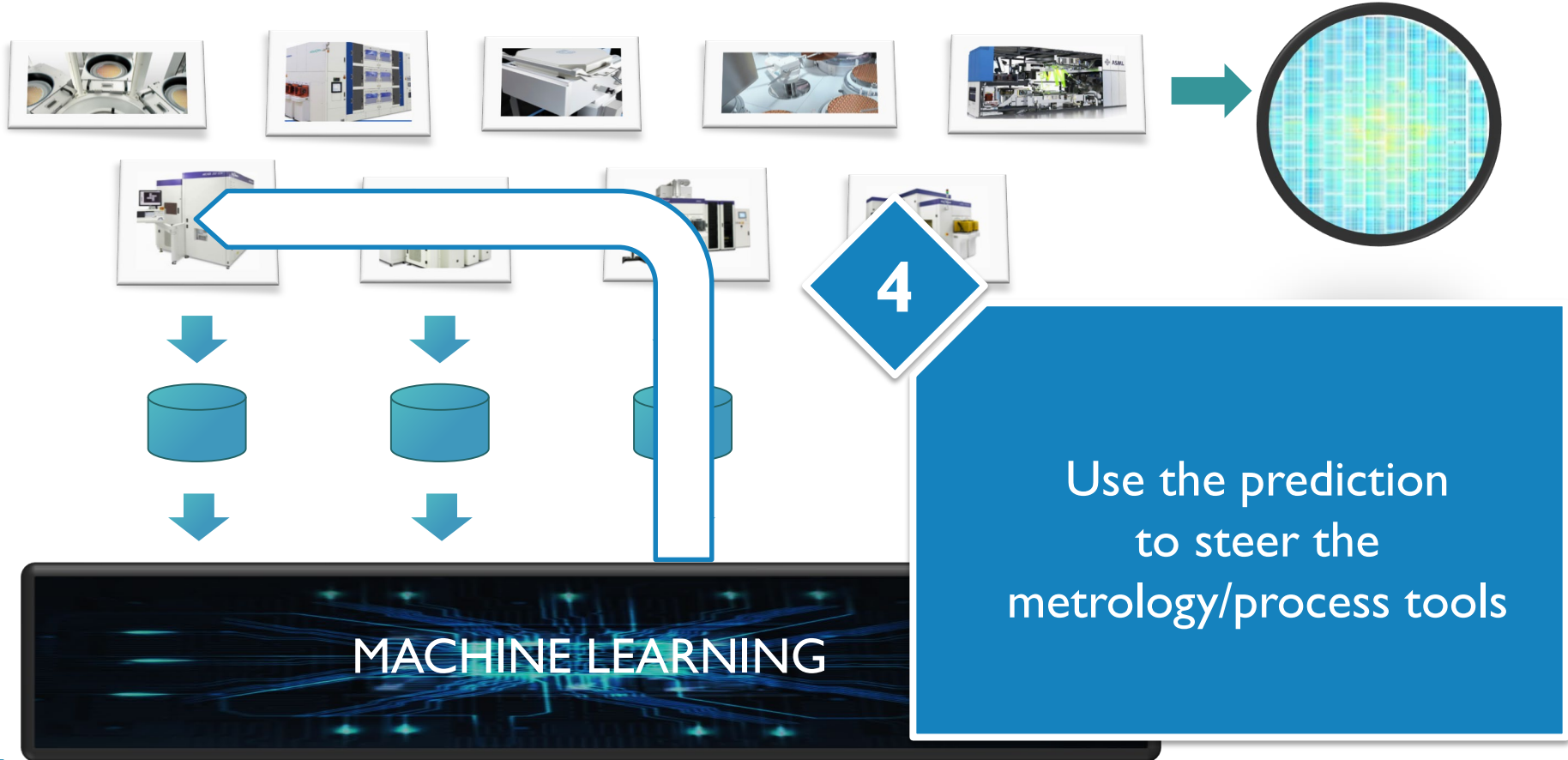
# MACHINE LEARNING FOR ETCH END POINT DETECTION



## Goals:

- 1) Improvement of the end point detection of etch tools
- 2) Check the impact on electrical properties with better EPD
- 3) Show improvement in the whole process flow

# MACHINE LEARNING ON METROLOGY DATA – TOOL MAINTENANCE



# MACHINE LEARNING TO DETECT HW FAULT

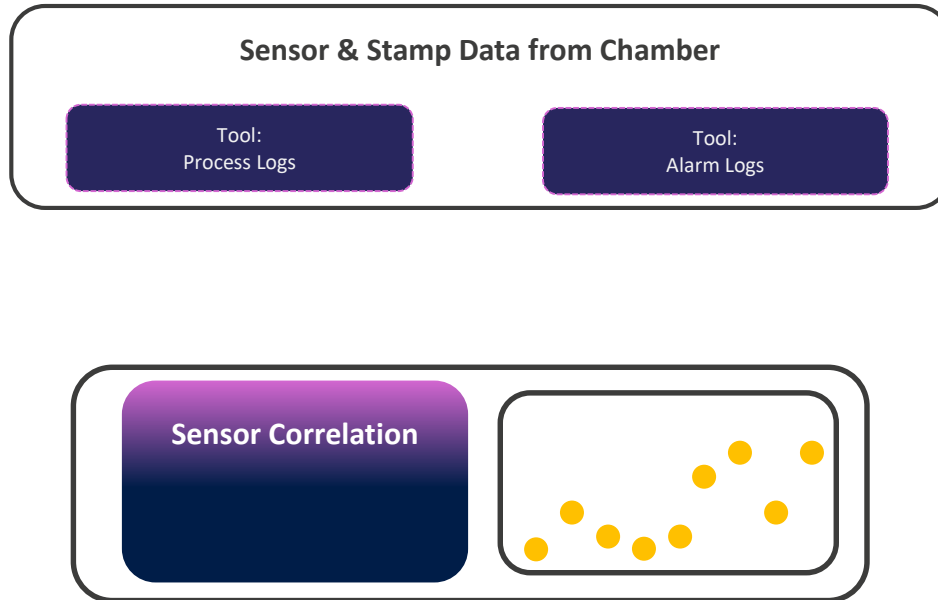
## UNBIASED DATA COLLECTION (RAW) FROM THE TOOL

### Problem Description:

Part has a lifetime before chamber experiences severe problem

Nominal lifetime is expected to be higher

Product mix and applications being etched can have an influence on the lifetime.



**Determine correlation**

**What are the parameters that have an influence on the sensor data?**

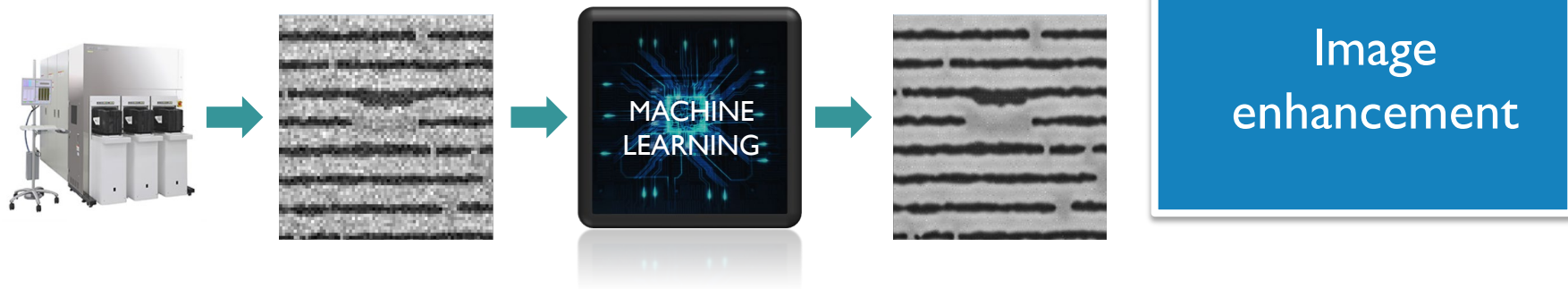
**Correlation to:**

- Etch parameters
- Etch recipe and lot type
- chamber conditions

# MACHINE LEARNING ON IMAGES

## ENHANCE METROLOGY CAPABILITIES

5



- Machine learning based classification algorithms on Review SEM image
  - Better use of Review SEM images
  - better guide LMC
- Demonstrated capability of DeepNN for SEM images processing
  - Strong correlation of CD from inferred images and CD of original images
  - Defect structure is preserved in the generated image
  - Methodology enables ~16x faster CD-SEM image acquisition for further defect inspection
  - Weak correlation for LVR as high frequency details are not preserved
- Machine learning SEM image denoiser
  - Enable increase of signal to noise ratio in generated images

# MACHINE LEARNING FOR PATTERN CLASSIFICATION ON SEM IMAGES

Data  
consolidation  
from SEM



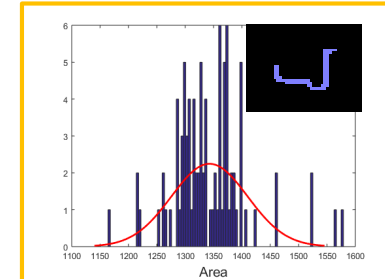
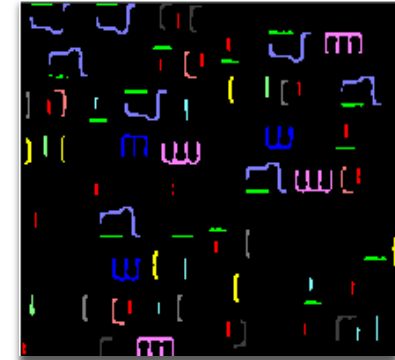
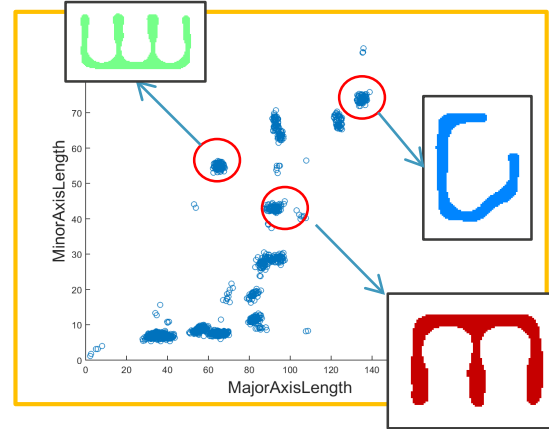
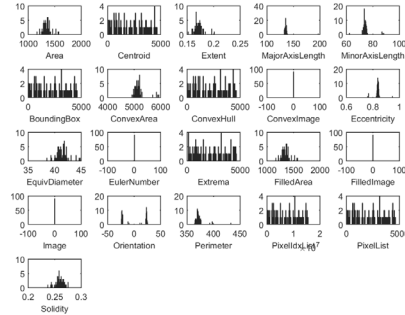
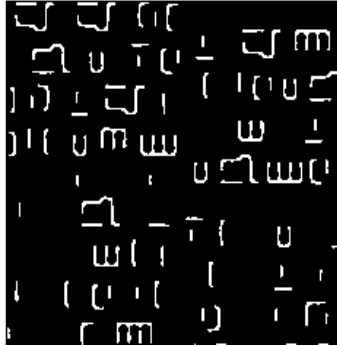
Feature  
parameter  
extraction



Machine learning  
algorithm to  
distinguish features



Prediction  
of shape  
class/label



Main objectives:-

1. Review-SEM images remain under-utilized – only used for defect verification but not for metrology. Analyze review-SEM images with machine learning approaches to gather much more efficiently process and tool variations and stochastic effects.
2. Come up with machine learning based classification algorithms to better guide LMC



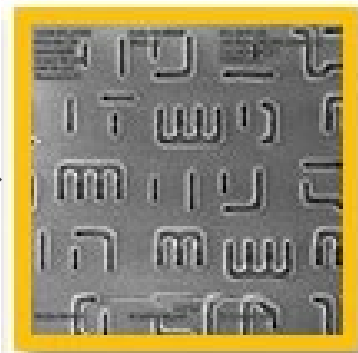
# DEEP LEARNING METHODS APPLIED FOR SUPER-RESOLUTION

Goal : Improve resolution for metrology/ inspection while gaining throughput

## Optical images/patches



Supernova 2, post M1A  
(optical patch)

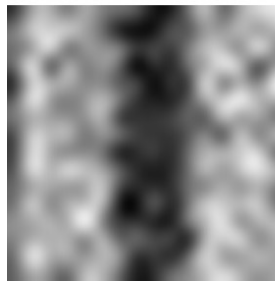


Supernova 2, post M1A  
(E-beam image)

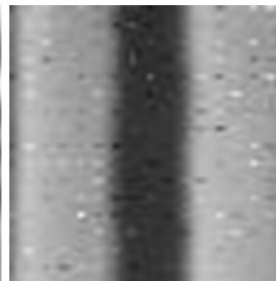
- Key issue sub N-14 nodes is that **SEM** review is a must to understand the defect.
- Can we get a higher resolution of some optical patches to understand the location of the defect and use it for improving classification

## SEM images

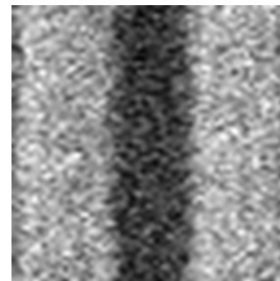
Low resolution image



Inferred image



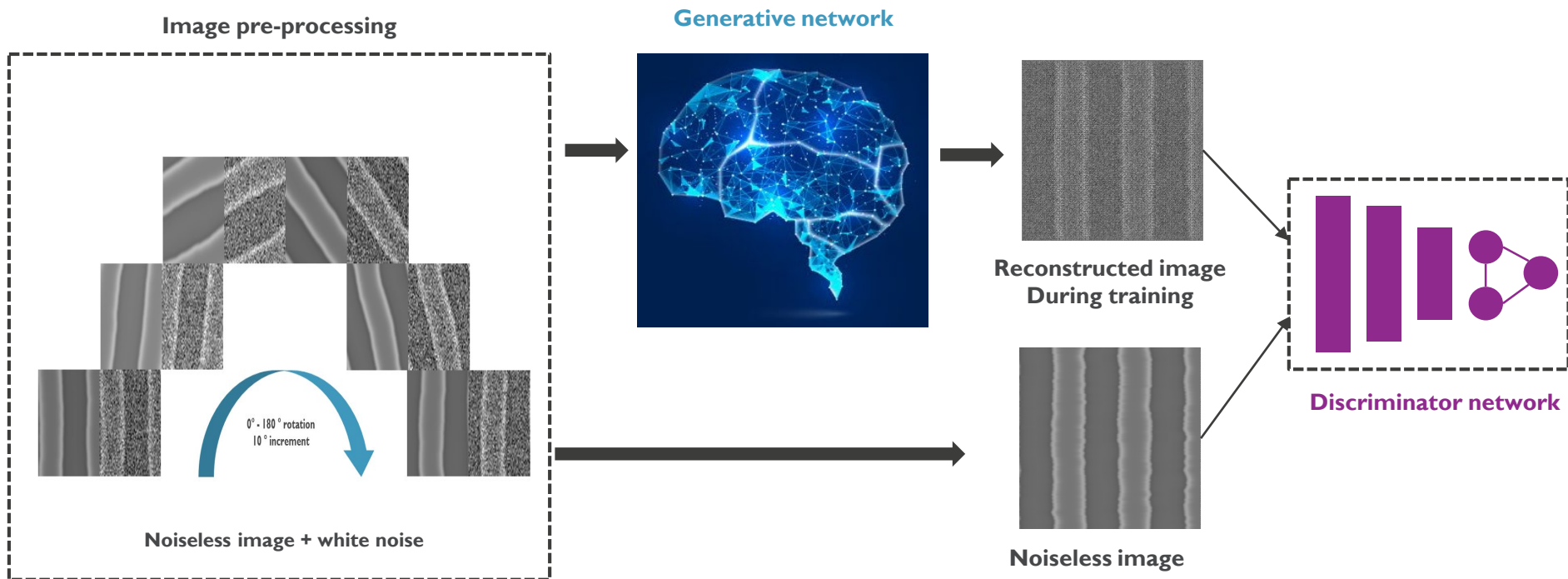
Ground truth



- Key issue is **CD-SEM** time/throughput and impact on resist layers when exposed for too long with E-beam
- Can we get a higher resolution **CD-SEM** e-beam image by scanning with bigger pixel size or less number of frames

# NOISE REDUCTION USING DEEP LEARNING

## EMPLOYING GENERATIVE-ADVERSARIAL-NETWORKS



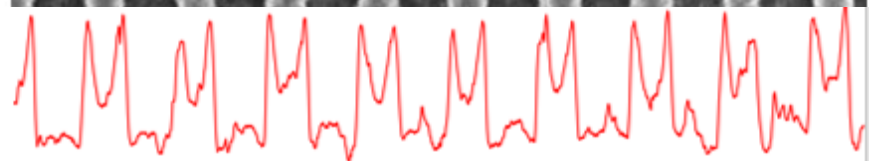
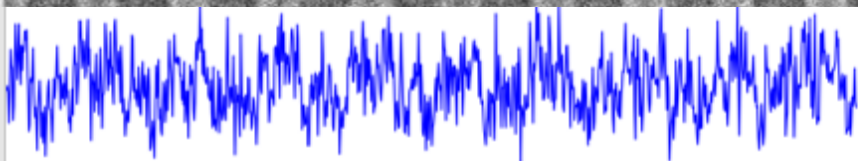
Forward flow of information and network architecture

Generation pairs of synthetic and noisy images

~30K images used for training

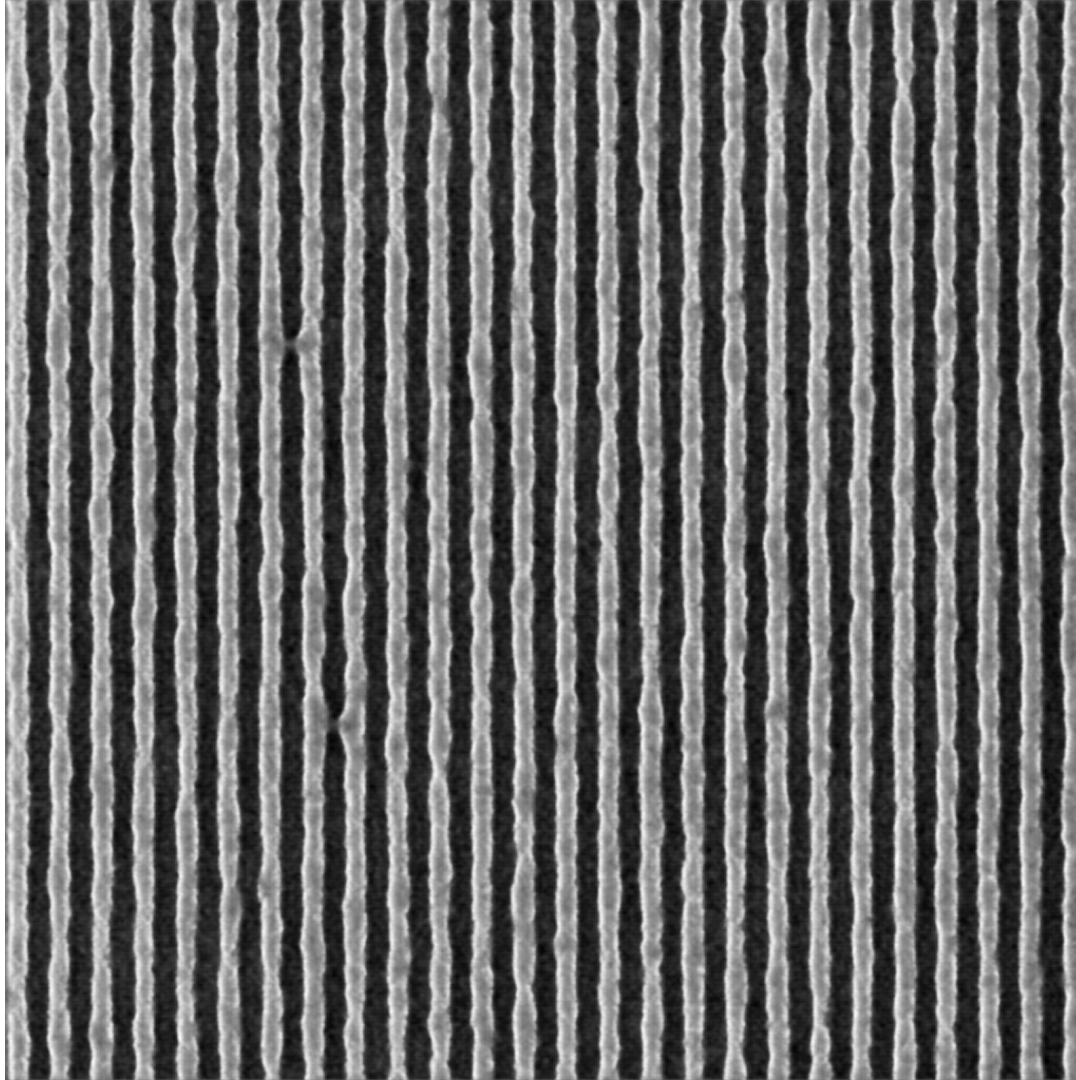
SMART FILTER

filter



# EUV Litho

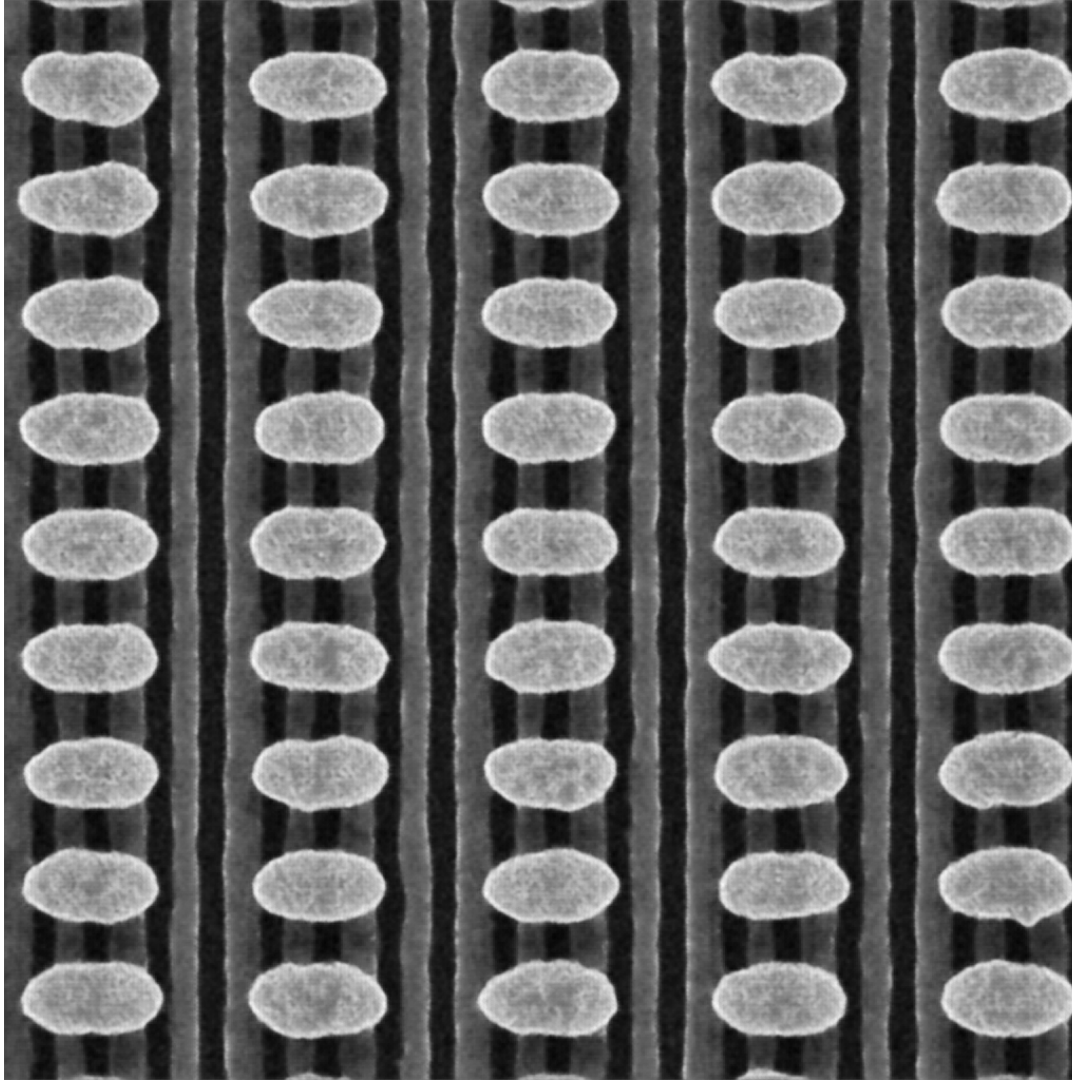
Defect can be  
enhanced and  
facilitate its  
detection





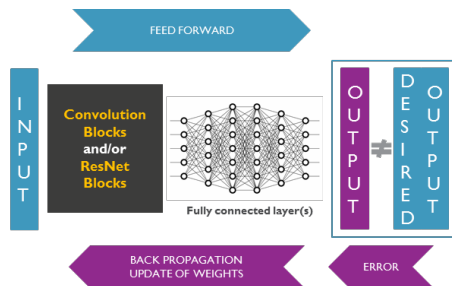
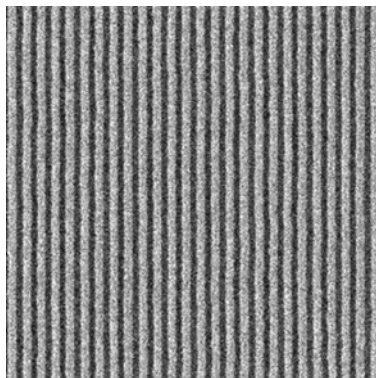
## Block on SAQP

Contrast of  
lines under  
blocks has  
changed

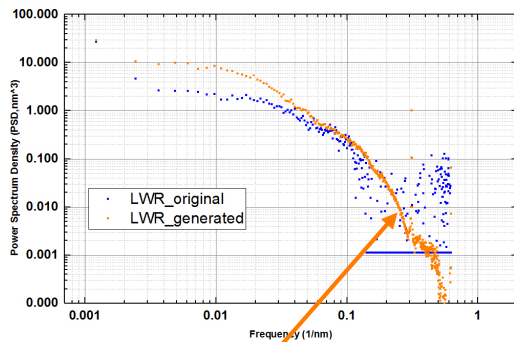
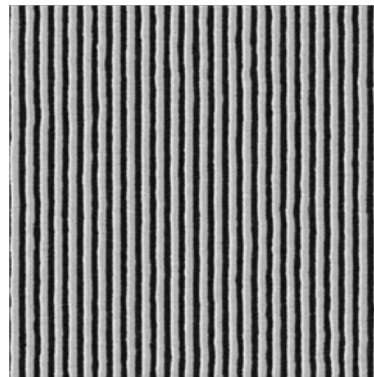


# DEEP LEARNING ENABLED IMAGE PROCESSING

Low resolution input image



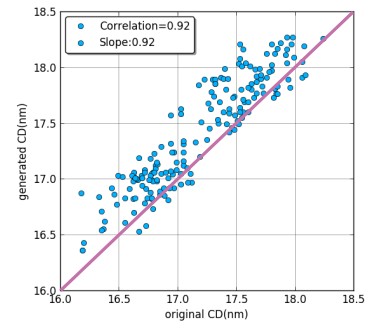
High resolution generated image



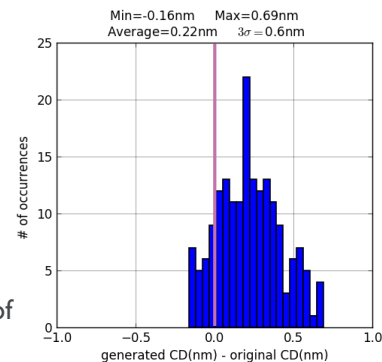
Breaching the noise plateau

Machine learning assisted metrology:

1. Resolution enhancement of CDSEM images
2. Smart filter - deep learning powered SEM image denoiser. Deep learning enabled increase of signal to noise ratio in generated images
3. Machine learning assisted image fusion for contrast enhancement of SEM images



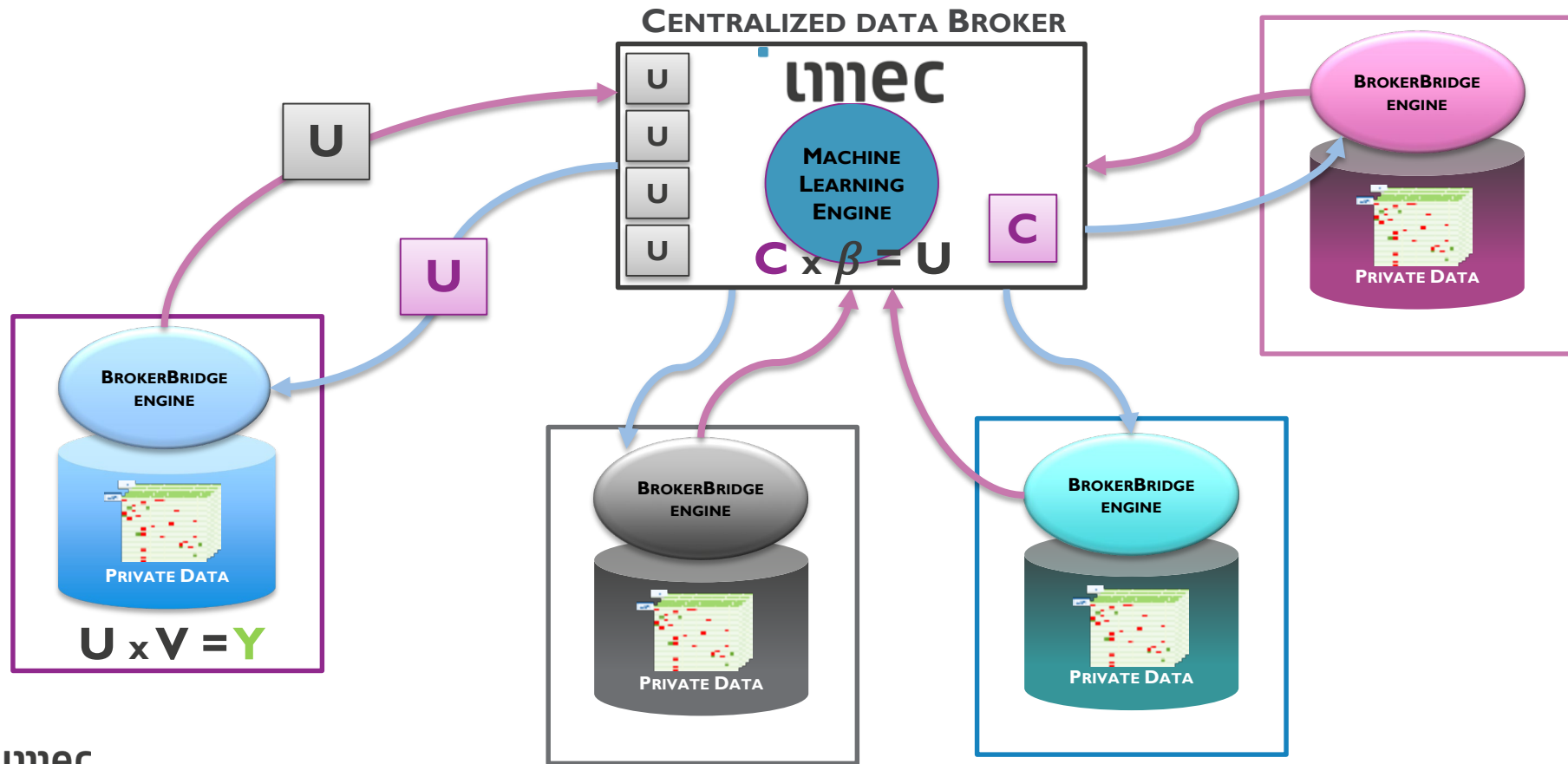
Strong correlation of measured line CD



Small residuals < 1 nm

# 6 PRIVACY PRESERVING MULTIPARTY MACHINE LEARNING

- In our industry, machine learning activities are investigated in silo
  - Because some of the data contains IP (Supplier or chip makers)
  - Because the algorithm implementation might generate money for the one developing the solution
- But it prevents us to use machine learning to its maximum efficiency
  - Core knowledge of different parties is not sharable (between suppliers or between chip makers and suppliers)
  - If the community could collaborate with their data and their knowledge AND preserving their intellectual properties, machine learning could reach a new level





BUT ...

## HOW TO TEACH THE MACHINE?

- <https://www.bbc.com/news/science-environment-47267081>

Science & Environment

### **AAAS: Machine learning 'causing science crisis'**

By Pallab Ghosh  
Science correspondent, BBC News, Washington

- <https://www.techtimes.com/articles/229660/20180608/mit-creates-worlds-first-psychopath-ai-fed-with-gruesome-reddit-content.htm>

### **MIT Creates World's First Psychopath AI, Fed With Gruesome Reddit Content**

8 June 2018, 7:48 am EDT By [Alexandra Burlacu](#) Tech Times

- Biased learning sets lead to wrong conclusions
- The outcome of machine learning must be verified by engineers to verify the physical meaning of the “intelligent” analysis

# CONCLUSION

## SO FAR...

- Machine learning algorithm can be useful, it is happening and it is a huge opportunity
- It helps extracting low intensity signals out of noise
- Final results (i.e. electrical, maintenance) can be predicted earlier
- Tool performance can be improved
- Metrology sampling can be optimized
- More information can be extracted from images (increase resolution, reduce noise)
- Privacy Preserving Multiparty Machine learning could be the next step for efficient use of machine learning
- But...
  - The artificial “intelligence” is not there yet
  - A machine can learn only as well as its teacher
  - Artificial “intelligence” does not exclude organic “intelligence”. Engineers knowledge needs to be included



embracing a better life