Gaussian Mixture 2021:
Time-series learning and its applications in manufacturing fields

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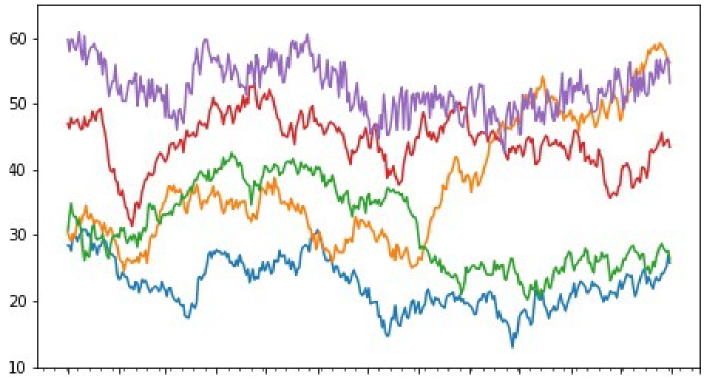
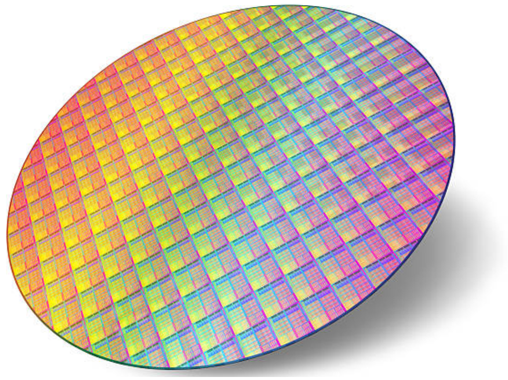
Today

- Why time-series machine learning for manufacturing AI?
- Time-series machine learning (ML)
  - what is time-series?
  - supervised and unsupervised learnings
- Difficulties with time-series ML in manufacturing
  - data challenge
  - domain knowledge critical, off-the-shelf algorithm not working
- Time-series ML applications
  - virtual metrology (VM), yield prediction and analysis, root cause analysis
- Gauss Labs success story: Virtual Metrology
  - 10x changes possible!

Why time-series ML?

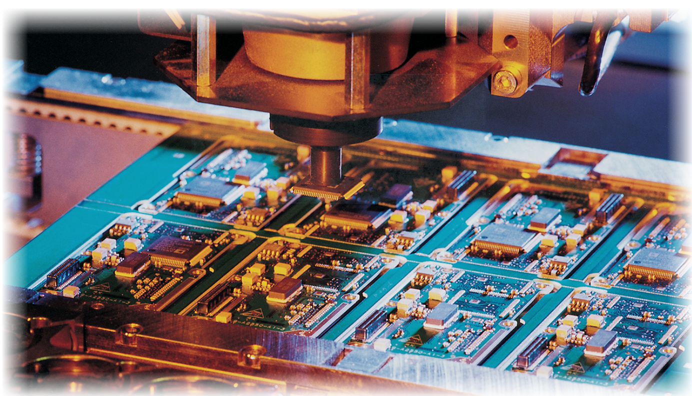
- *(almost) all the data coming from manufacturing environment are time-series data*
  - sensor data, process times, material measurement, equipment maintenance history, images, *etc.*
- sheer amount of time-series data is huge
  - peta-scale data per day in semiconductor manufacturing lines

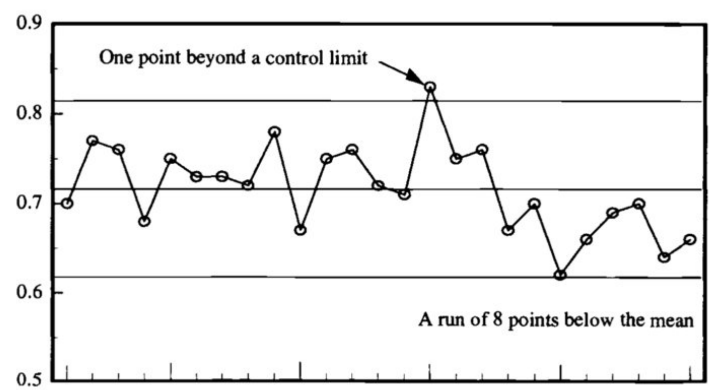




Why time-series ML?

- 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
  - process control with feedback - advanced process control
  - metrology and inspection - automatic features measurement and defect inspection
  - process time estimation or prediction - planning, scheduling, dispatching





ML techniques for time-series data

Time-series data

- definition of times-series:

$$x : T \to \mathbf{R}^n \text{ where } T = \{\ldots, t_{-2}, t_{-1}, t_0, t_1, t_2, \ldots\} \subseteq \mathbf{R}$$

- example: material measurements: when $n = 3$

$$x(t) = \left[\begin{array}{c} \text{average\_thickness}(t) \\ \text{refractory\_index}(t) \\ \text{image\_feature\_size}(t) \end{array}\right]$$

- for supervised learning, we define two time series

$$x : T \to \mathbf{R}^n \text{ and } y : T \to \mathbf{R}^m$$

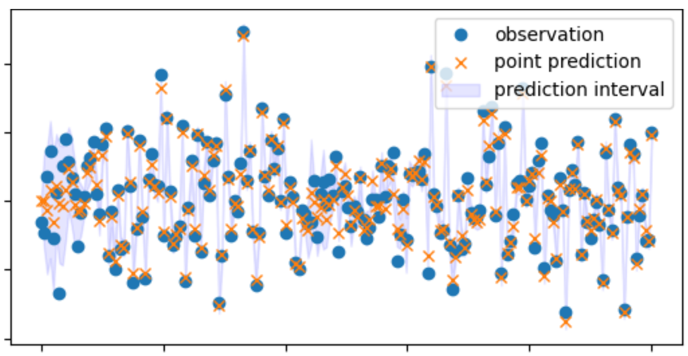
Supervised and unsupervised learning for time-series

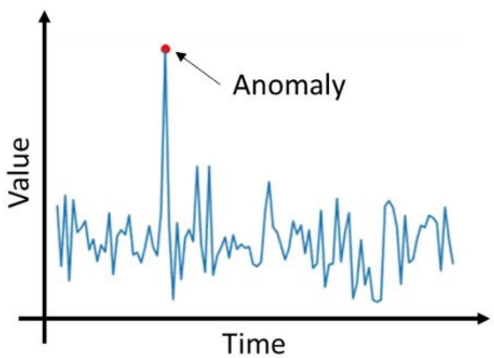
- supervised time-series learning

$$\begin{array}{ll} \text{predict} & y(t_k) \\ \text{given} & x(t_k), x(t_{k-1}), \ldots \text{ and } y(t_{k-1}), y(t_{k-2}), \ldots \end{array}$$

- unsupervised time-series anomaly detection
  - find time segment that is considerably different from the rest

$$\begin{array}{ll} \text{find} & k^* \\ \text{such that} & x(t_k)|_{k=k^*}^{k^*+l} \text{ is significantly different from } x(t_k)|_{k=-\infty}^{\infty} \end{array}$$

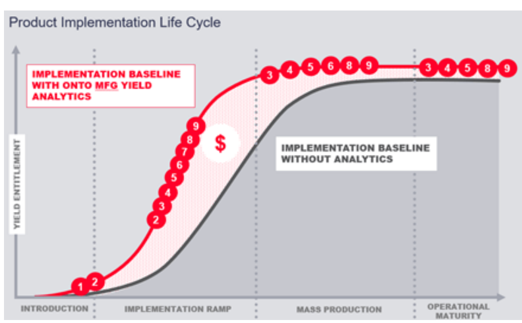


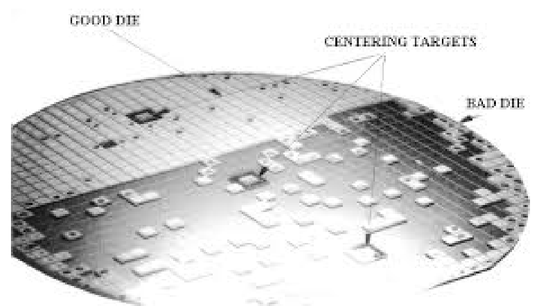


Time-series ML applications

Prediction of time-series values

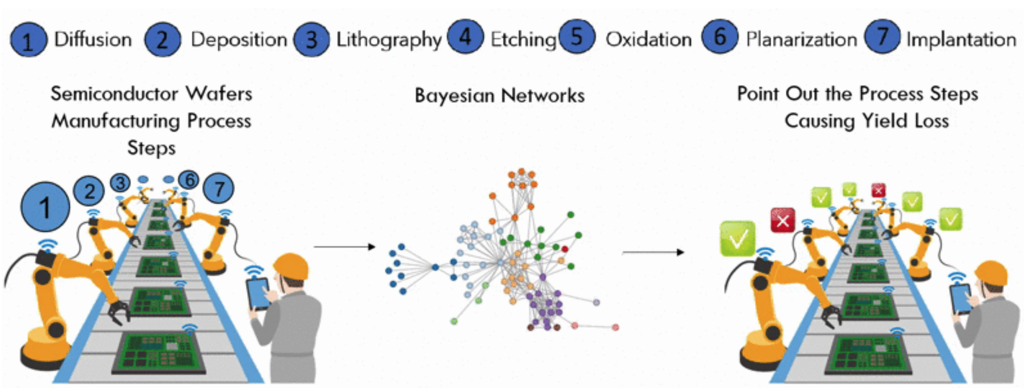
- virtual metrology
  - measure unmeasured process materials using equipment signals and other information
  - supervised learning
    - $x(t_k)$: sensor signals, $y(t_k)$: measurement
- yield prediction
  - predict yield (# working dies / # total dies) with material measurements from equipments
  - supervised learning
    - $x(t_k)$: material measurement in process, $y(t_k)$: yield





Anomaly detection on time-series data

- equipment alarm root cause analysis
  - when alarm goes off, find responsible equipment
  - anomaly detection
    - $x_e(t_k)$: processed material measurement for equipment e
- yield analysis
  - find responsible equipment for yield drop



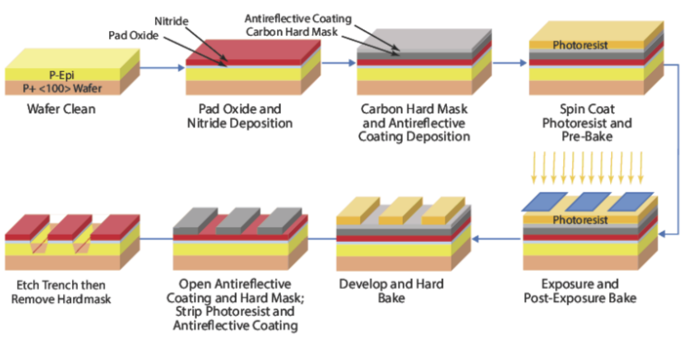
Difficulties with time-series ML in manufacturing

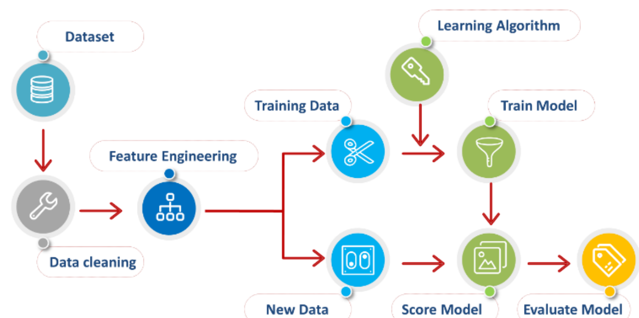
Data challenge

- concept drift/shift exist:
  - $p(x(t_k), x(t_{k-1}), \ldots)$ changes over time
  - $p(y(t_k)|x(t_k), x(t_{k-1}), \ldots, y(t_{k-1}), y(t_{k-2}), \ldots)$ changes over time
- hence, we have fat data, $i.e.$, # features far larger than # data
- (sometimes) poor data quality, $e.g.$, lots of missing values and incorrectly measured values
- huge volume of data to process, different types of data, high process speed demanded!

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

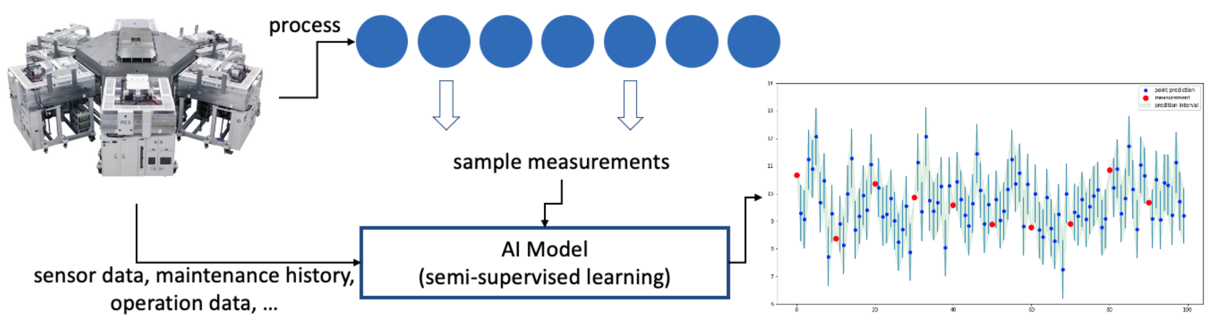




Gauss Labs success story: Virtual Metrology (VM)

What is VM?

- in many cases, we cannot measure all processed materials for fundamental reasons
  - measurement equipment is too expensive
  - measuring every materials hinders production speed inducing low throughput
- thus, we do sampling (with very low smapling rate)
  - in semiconductor manufacturing line, avarage sampling rate is less than 1%
- problem: *predict the measurement of unmeasured material* using indirect signals such as sensor data, maintenance history, operation data, . . .



10x change VM makes

- background (to our best knowledge)
  - no org. has even been successful with VM (due to data challenge)

- Gauss Labs VM
  - uses *fully customized* online learning to cope with data drift/shift
  - *RMSE error 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 for time-series occur everywhere in industrial AI applications

- lots of challenges
  - data challenge, domain knowledge required, need for customizing algorithms

- *10x changes potentially made via various applications*
  - Gauss Labs has success stories include
    * Virtual Metrology (VM)
    * Subnanometer-precision Machine Vision