Norwegian University of Science and Technology

"Learning strategies for digital twins used in maintenance, repair and operations"

(Trial lecture)

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23rd January 2024

Outline

- Introduction and background
  - Industry 4.0
  - Digital twin (DT)
  - Main elements of DT
- Learning strategies in Digital twin
- Qualification of DT
- Case study
- Summary

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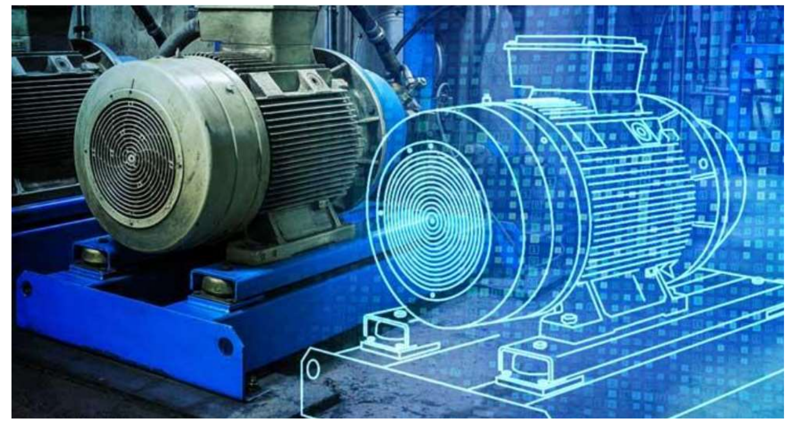
Introduction and background

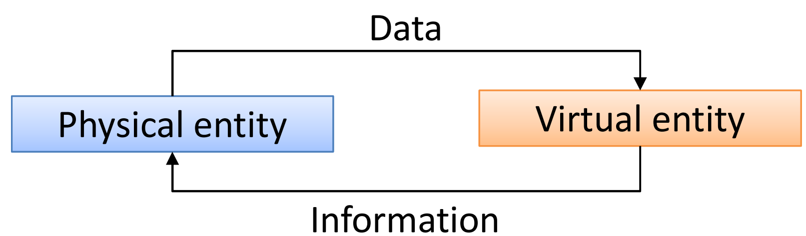
- Industry 4.0
- Maintenance, repair, operations
- Reduction of unplanned downtime, equipment failures, maintenance cost
- More effective maintenance planning and minimization of production interruptions
- Digital twin technology

https://tractian.com/en/blog/maintenance-industry-4-role-management-software

Introduction and background

- Digital twin is *a virtual representation of a physical asset/system/process/product that is updated through the continuous exchange of information between the virtual system and its physical counterpart*.
- Michael Grieves and John Vickers, NASA, 2002
- Visualization, monitoring, diagnostics, prognostics, optimization
  - Minimize risk of accidents
  - Remote monitoring of assets
  - Reduce downtime and maintenance costs
  - Root cause analysis
  - Optimize new designs based on historical data
  - Supporting real-time decision-making



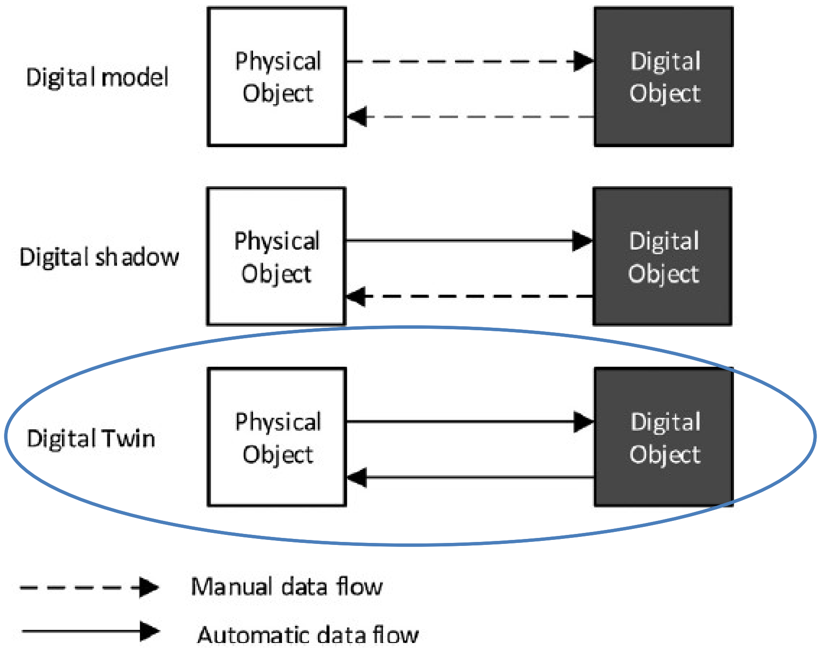


Reyes Yanes, Abraham, Rabiya Abbasi, Pablo Martinez, and Rafiq Ahmad. 2022. “Digital Twinning of Hydroponic Grow Beds in Intelligent Aquaponic Systems.” *Sensors 2022, Vol. 22, Page 7393* 22 (19): 7393
https://www.reliableplant.com/Read/31897/digital-twins-ai

Introduction and background

Main characteristic of digital twin

- ✓ **Synchronization** or **flow of information** between the physical and virtual system
- ✓ **Ability to adapt to changes in their counterpart** to provide modelling results in **real-time**

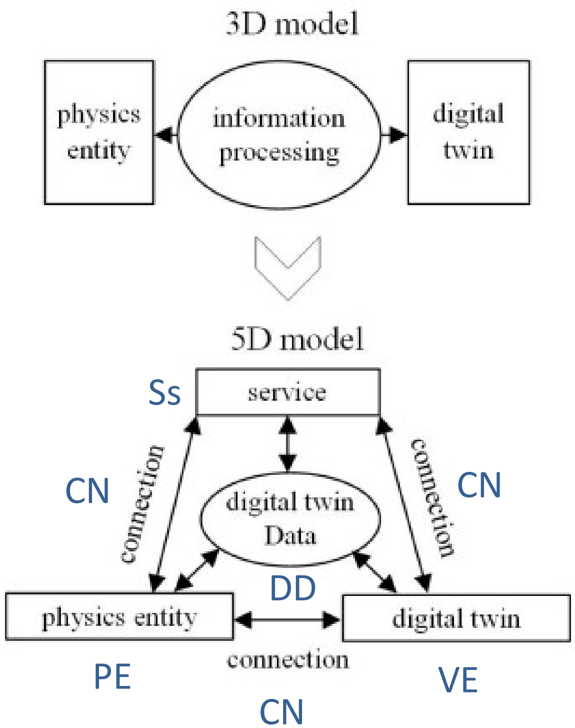


Errandonea, Itxaro, Sergio Beltrán, and Saioa Arrizabalaga. 2020. “Digital Twin for Maintenance: A Literature Review.” *Computers in Industry* 123 (December): 103316

Introduction and background

Main elements of digital twin

- ✓ Physical entity model (PE)
  - Functional subsystems, sensory devices
- ✓ Virtual model (VE)
  - Geometries, physical properties, behaviors, rules
- ✓ DT services (Ss)
  - Services for PE and VE, calibration, validation
- ✓ DT data (DD)
  - Data from PE and VE, fused data
- ✓ DT connections (CN)
  - Data transmission channels, interconnections



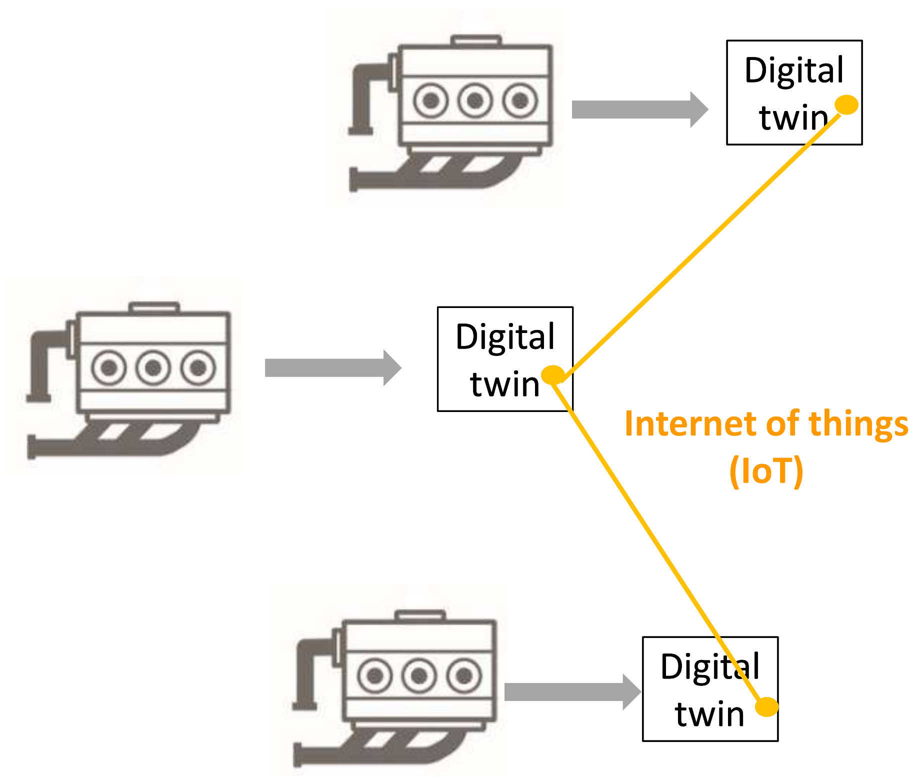
$$M_{DT} = (PE, VE, Ss, DD, CN)$$

Xie, Jinghai, Jia Guo, Mi Sun, Dongyu Su, Wei Li, Siyuan Chen, and Shaorong Wang. 2022. "A Digital Twin Five-Dimensional Structural Model Construction Method Suitable for Active Distribution Network." *2022 2nd International Conference on Electrical Engineering and Mechatronics Technology, ICEEMT 2022*, 418–26

Introduction and background

Different types of digital twin

- ✓ **Component twins**
- ✓ **Asset twins**
- ✓ **System twins**
- ✓ **Process twins**



https://se.mathworks.com

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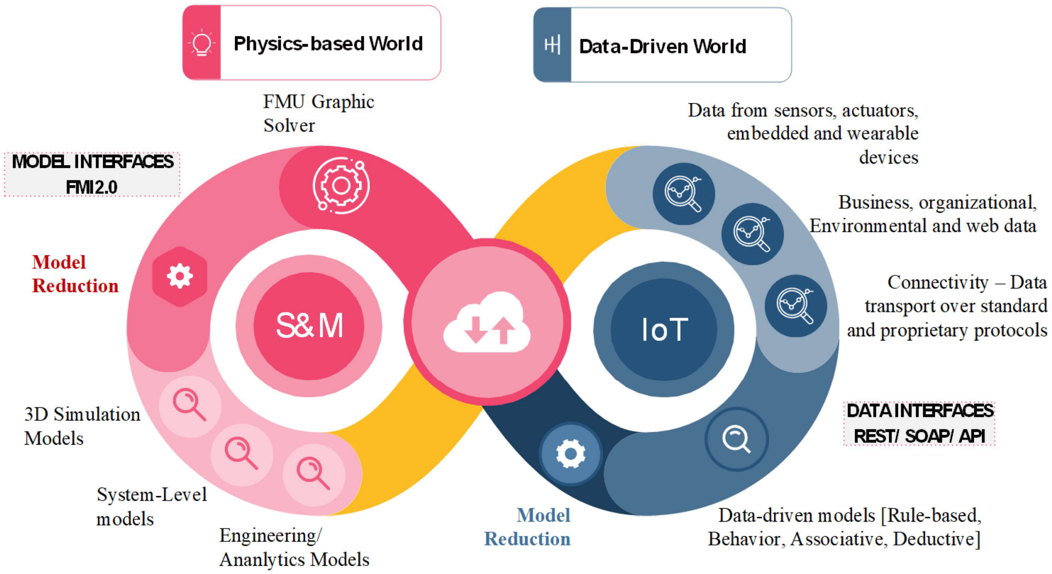
Learning strategies in DT

✓ Virtual model (VE)
  - Geometries
  - physical properties
  - behaviors
  - Rules

✓ **Digital twin** can **learn** from **rule models**, **behavior models**, and to some extent **physics-based models**



Chakraborti, Ananda, Henri Vainio, Kari T. Koskinen, and Juha Lammi. 2023. “A Graph-Based Model Reduction Method for Digital Twins.” *Machines 2023, Vol. 11, Page 733* 11 (7): 733.

NTNU

Learning strategies in DT

✓ Virtual model (VE)

- Geometries
- physical properties
- behaviors
- Rules

Rule models

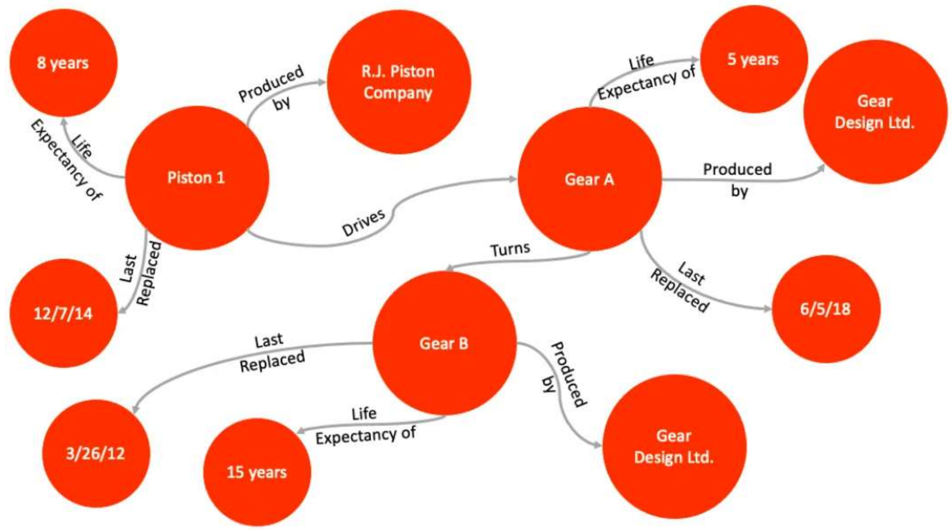
- To define the constraints, guidelines, and operational rules
- “what-if” analysis, “if-then” statements
- Knowledge-graph
- Machine learning (e.g., Natural language processing)
- Requires data from maintenance reports and manuals

Pros

- Easy to track the dependencies and interactions for simple systems
- Transparent and interpretable
- Does not require large data to be trained

Cons

- Largely depend on data quality
- Design new rule-based models when it comes to different languages
- Challenging for complex systems and complex rules



https://www.ontotext.com/blog/knowledge-graphs-in-manufacturing/

Learning strategies in DT

- ✓ Virtual model (VE)
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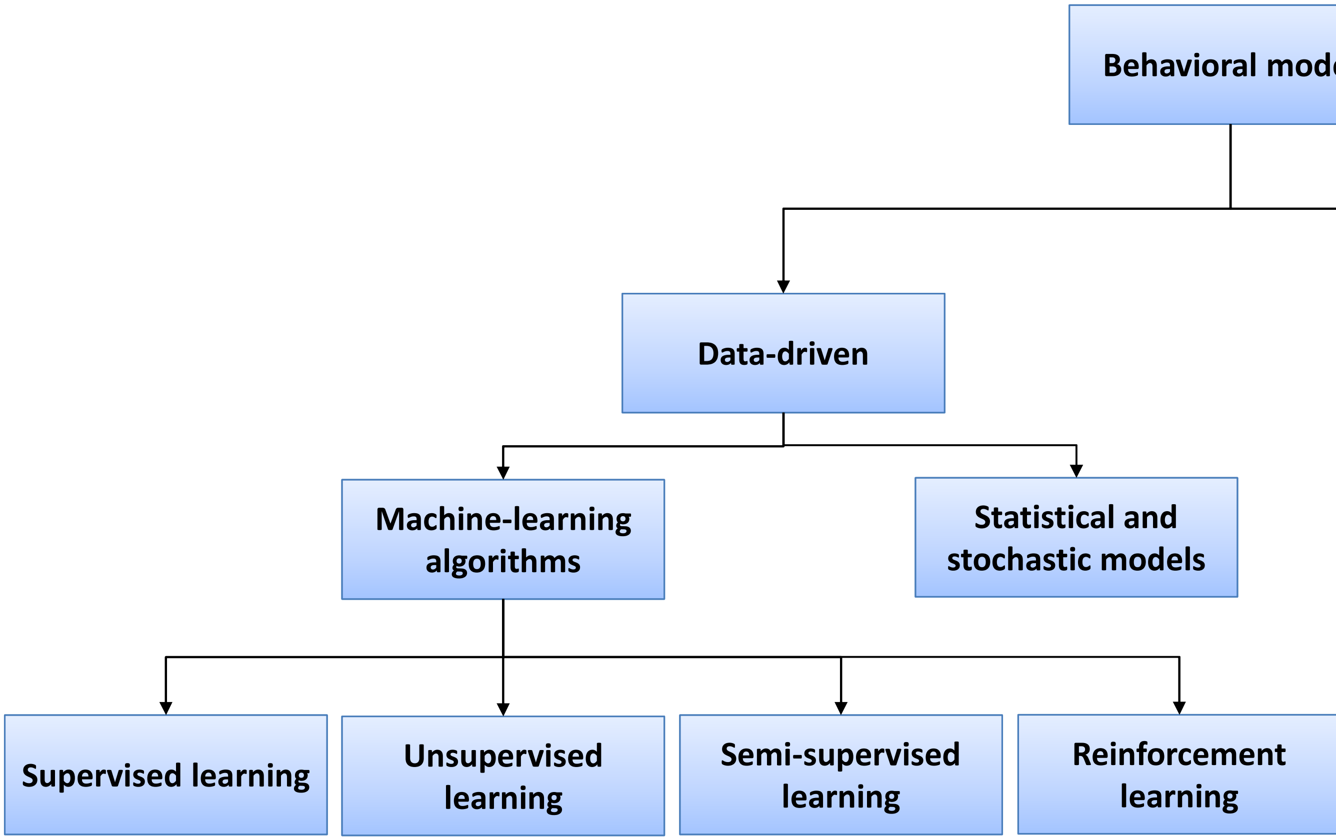
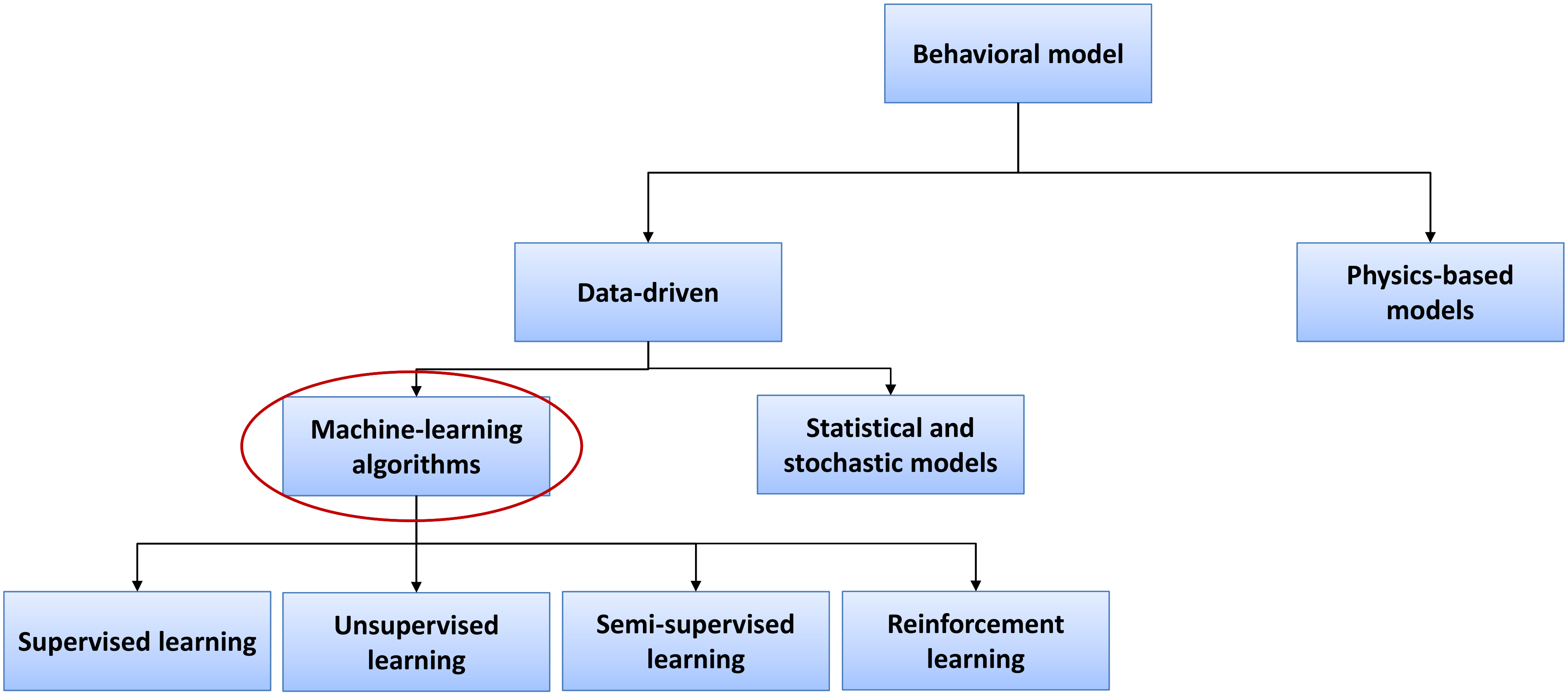
  - physical properties
  - behaviors
  - Rules

Learning strategies in DT



Learning strategies in DT



Machine Learning (ML) algorithms

- **Support vector machine (SVM)**
  - Supervised learning
  - Labeled data
  - Classification and regression

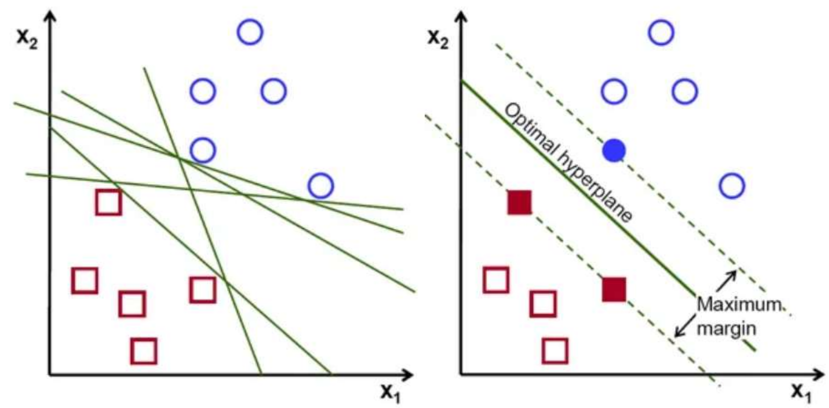
$$Features = [x_1, x_2, \dots, x_n]$$

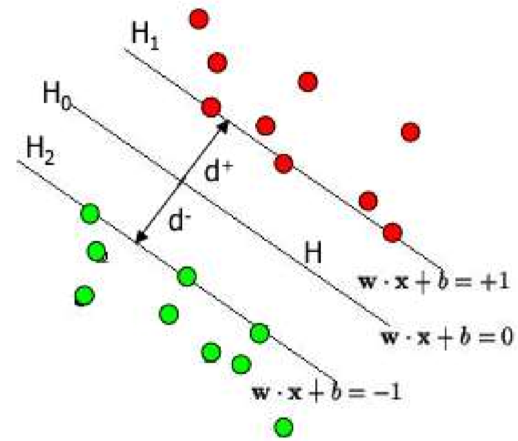
$$y = health\ status = \begin{Bmatrix} y = 1, healthy \\ y = 0, faulty \end{Bmatrix}$$

$$w^T . x + b = 0$$

$$w^T . x + b \geq 0 \quad for\ d_i = +1$$

$$w^T . x + b \leq 0 \quad for\ d_i = -1$$

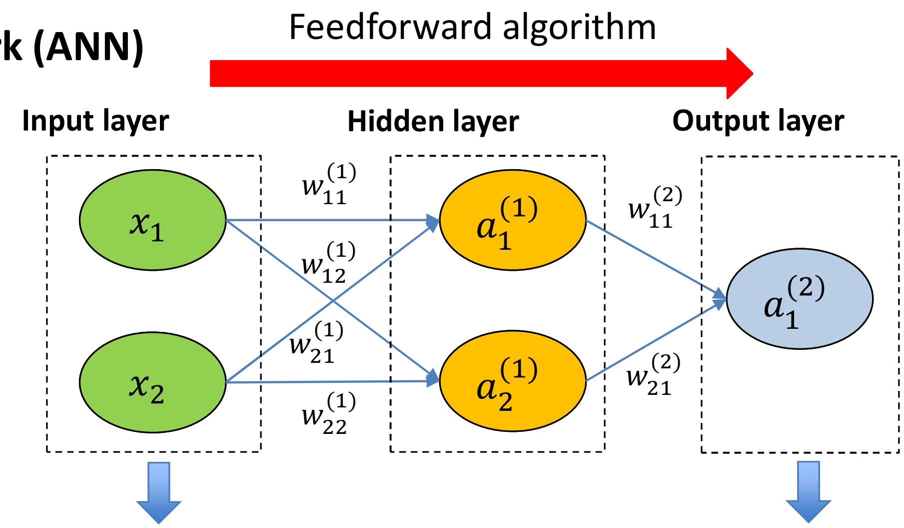




Nalepa, Jakub, and Michal Kawulok. 2018. "Selecting Training Sets for Support Vector Machines: A Review." *Artificial Intelligence Review 2018 52:2* 52 (2): 857–900

Machine learning (ML)

- **Artificial Neural Network (ANN)**
  - Layers and nodes
  - Weights and biases
  - Feedforward algorithm
  - Back propagation algorithm



$$Loss\ function = MSE = \frac{1}{2}\left(a_1^{(2)} - y_{\text{true}}\right)^2$$

$$z_1^{(1)} = w_{11}^{(1)}.x_1 + w_{21}^{(1)}.x_2 + b_1^{(1)}$$

$$z_2^{(1)} = w_{12}^{(1)}.x_1 + w_{22}^{(1)}.x_2 + b_2^{(1)}$$

$$a_1^{(1)} = \emptyset(z_1^{(1)})$$

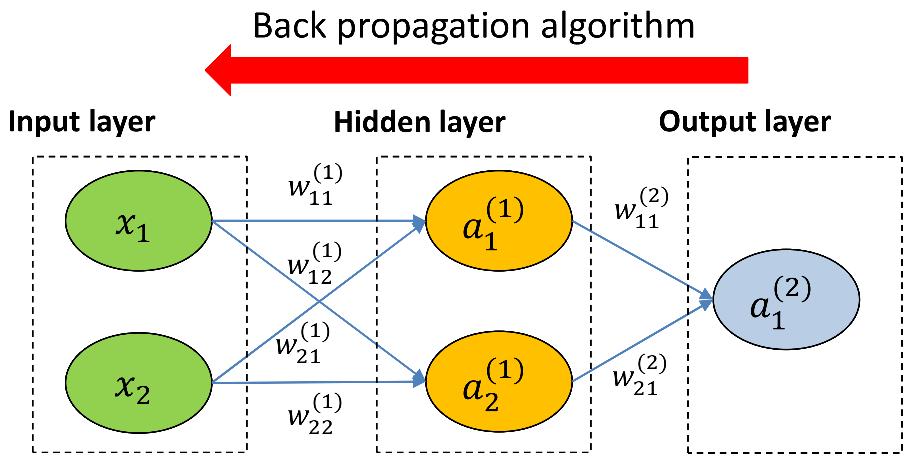
$$a_2^{(1)} = \emptyset(z_2^{(1)})$$

$$z_1^{(2)} = w_{11}^{(2)}.a_1^{(1)} + w_{21}^{(2)}.a_2^{(1)} + b_1^{(2)}$$

$$a_1^{(2)} = \emptyset(z_1^{(2)})$$

$$\emptyset(k) = RELU(k) = \max(0, k)$$

Machine learning (ML)



$$\delta_1^{(2)} = \left(a_1^{(2)} - y_{true}\right).\acute{\emptyset}(z_1^{(2)})$$

$$\frac{\partial L}{\partial w_{ij}^{(2)}} = a_i^{(1)}.\delta_1^{(2)}$$

$$\frac{\partial L}{\partial b_1^2} = \delta_1^{(2)}$$

$$\delta_1^{(1)} = \begin{cases} \delta_1^{(2)}.w_{11}^{(2)} & if\, z_1^{(1)} > 0 \\ 0 & otherwise \end{cases}$$

$$\delta_2^{(1)} = \begin{cases} \delta_1^{(2)}.w_{21}^{(2)} & if\, z_2^{(1)} > 0 \\ 0 & otherwise \end{cases}$$

$$\frac{\partial L}{\partial w_{ij}^{(1)}} = x_i.\delta_j^{(1)} \qquad \frac{\partial L}{\partial b_j} = \delta_j^{(1)}$$

Update/adjust weights and biases

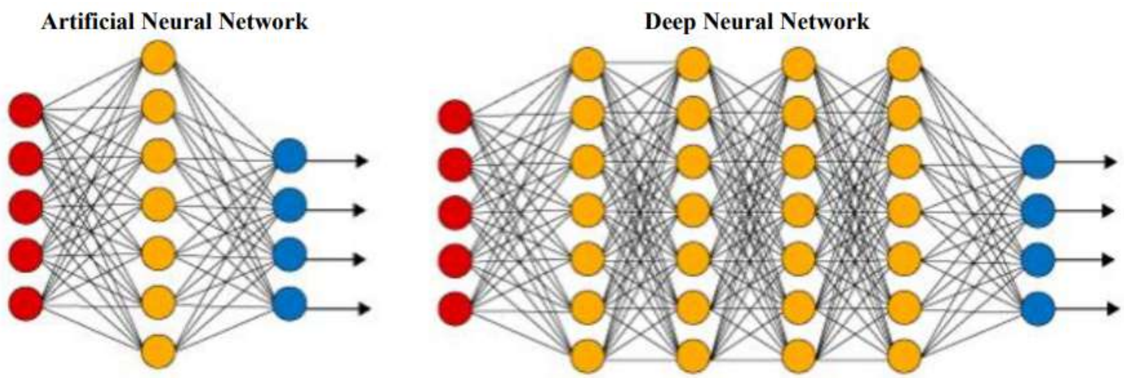
$$w_{ij}^{(l)} = w_{ij}^{(l)} - \alpha \frac{\partial L}{\partial w_{ij}^{(l)}}$$

$$b_j^{(l)} = b_j^{(l)} - \alpha \frac{\partial L}{\partial b_j^{(l)}}$$

Emmert-Streib, Frank, Zhen Yang, Han Feng, Shailesh Tripathi, and Matthias Dehmer. 2020. “An Introductory Review of Deep Learning for Prediction Models With Big Data.” *Frontiers in Artificial Intelligence* 3 (February): 507091. https://doi.org/10.3389/FRAI.2020.00004/BIBTEX

Machine learning (ML)

- **Deep Neural Network (DNN)**
  - **More hidden layers, more complexity**



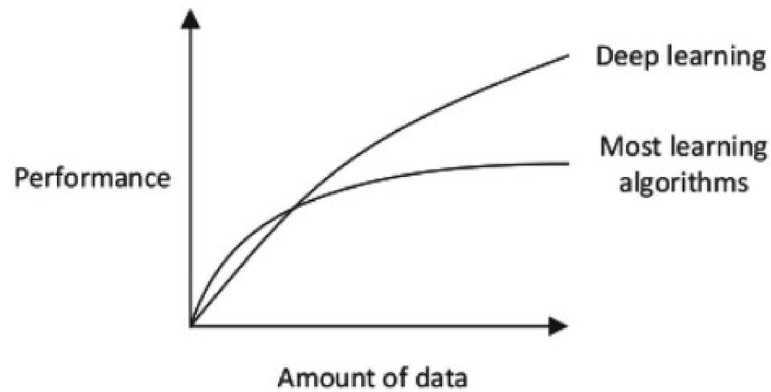
Mostafa, Bossy M, Noha E El-Attar, Samy A Abd-Elhafeez, and Wael A Awad. 2021. “Machine and Deep Learning Approaches in Genome: Review Article.” *Alfarama Journal of Basic & Applied Sciences* 2 (1): 105–13

Challenges

1. What is the optimal number of hidden layers and nodes? What to include as input nodes?
2. Finding optimal parameters (weights, biases)
3. Uncertainty caused by measurement errors from sensors

Solutions

1. Using MSE and measuring function complexity to find the number of hidden nodes
2. Self-adaptation algorithm, Combined genetic and differential evolution algorithm
3. Probabilistic NN, bootstrapping



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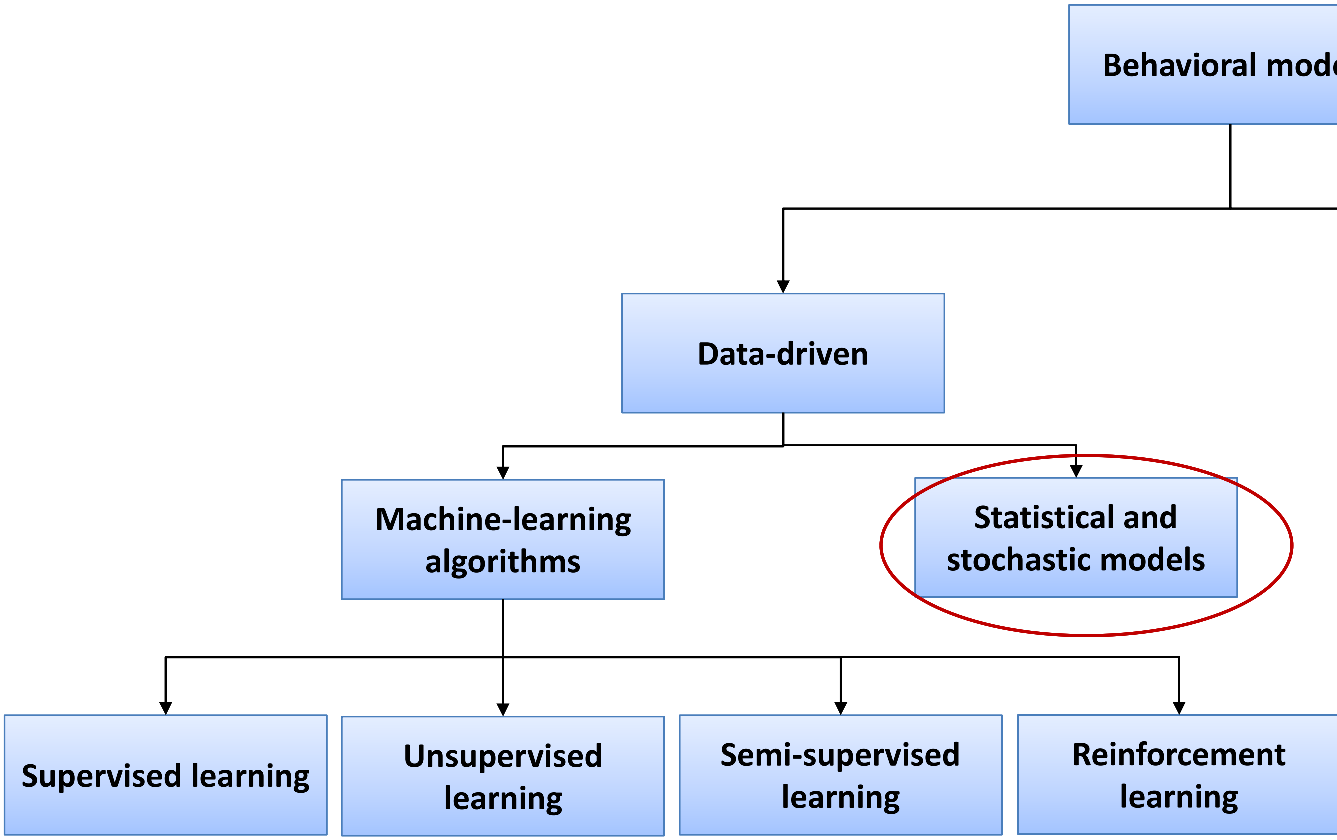
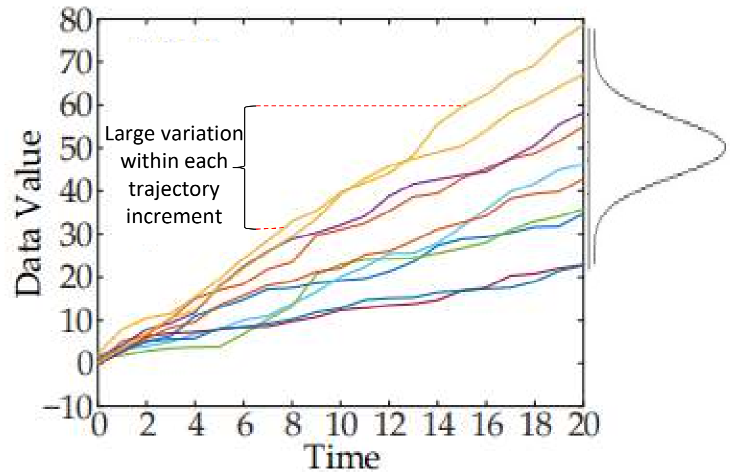
Learning strategies in DT



Stochastic approaches

- **Gamma process**
  - Independent and non-negative increments
  - Monotonically increasing or decreasing degradation
  - Fatigue, corrosion, crack growth
  - $G(t+u) - G(u)$ and $G(s+v) - G(v)$ are independent for $t+u > u \geq s+v > v$
  - $G(t+u) - G(u) \sim Gamma(\alpha(t+u) - \alpha(u), \beta)$
  - $F_{T_c}^{G}(t) = P\{T_c \leq t\} = P\{G(t) \geq c\} = \frac{\Gamma(\alpha t, cu)}{\Gamma(\alpha t)}$



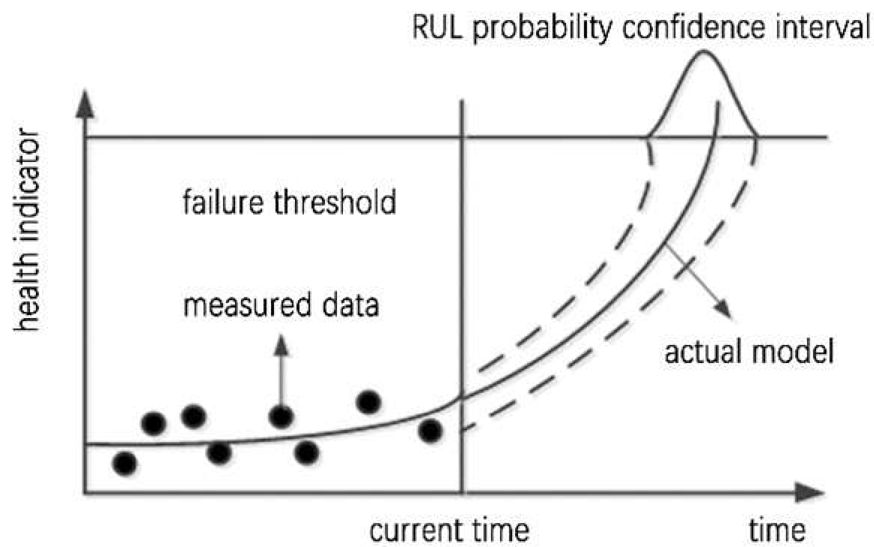
Degradation trajectories of Gamma process, Unit to unit variability

Rodríguez-Picón, Luis Alberto, Luis Carlos Méndez-González, Iván Juan Carlos Pérez-Olguín, and Jesús Israel Hernández-Hernández. 2023. "A Gamma Process with Three Sources of Variability." *Symmetry 2023, Vol. 15, Page 162* 15 (1): 162

hang, Zongyi, Dianrong Gao, Tianyuan Guan, Yingna Liang, Jianhua Zhao, Liwen Wang, and Jie Tang. 2023. "A Reliability Evaluation Method for Gamma Processes with Multiple Random Effects

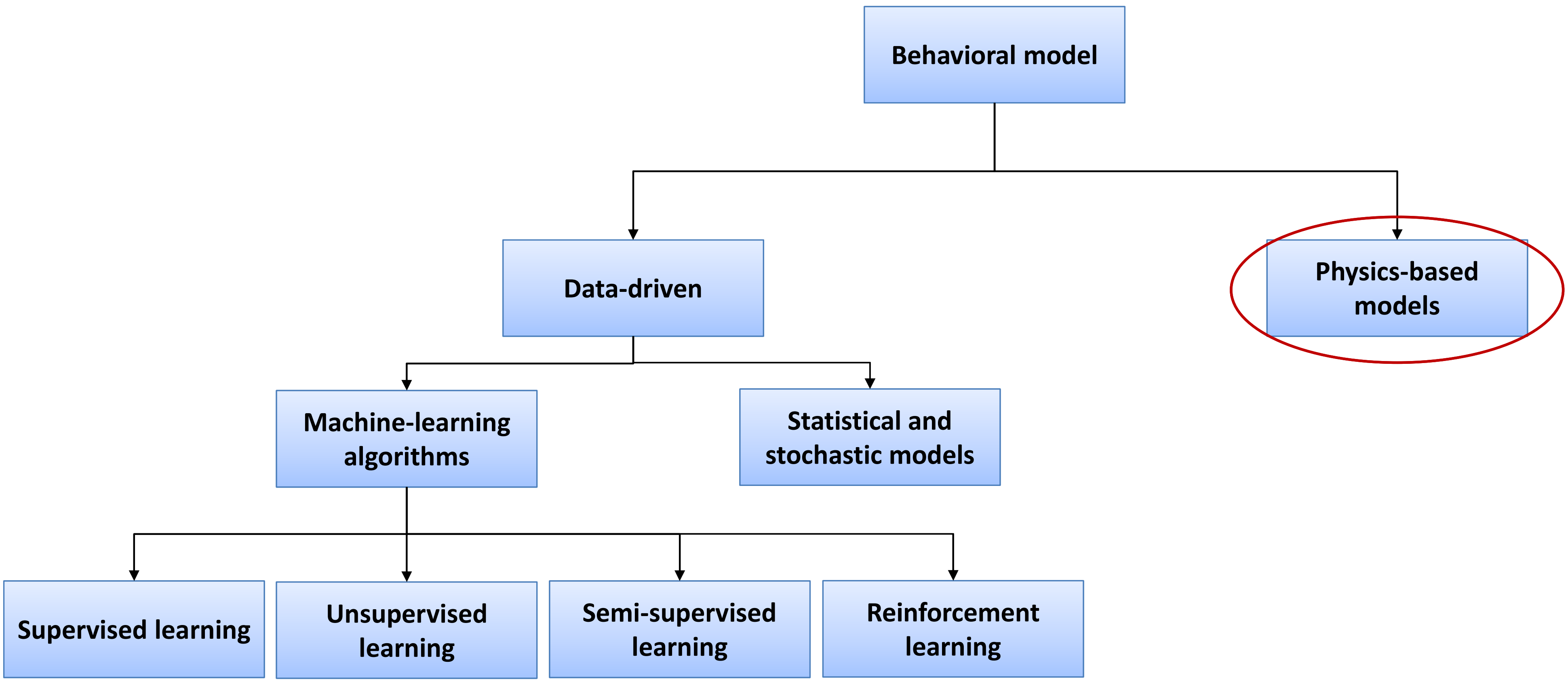
Stochastic approaches

- **Wiener process**
  - Non-monotonic degradation process
  - Independent increments following a Normal distribution
  - $\{Y(t), t \geq 0\}$
  - $\mathrm{Y}(t) = y_0 + \nu t + \sigma_B B(t)$
  - First passage time (FPT) distribution: Inverse Gaussian (IG) distribution
  - $T_L \sim IG(\mu, \lambda)$, where $\mu = \frac{L - y_0}{\nu}$ and $\lambda = \frac{(L - y_0)^2}{\sigma_B^2}$
  - $f_T(t; \mu, \lambda) = \sqrt{\frac{\lambda}{2\pi t^3}} \exp(-\frac{\lambda(t-\mu)^2}{2\mu^2 t})$



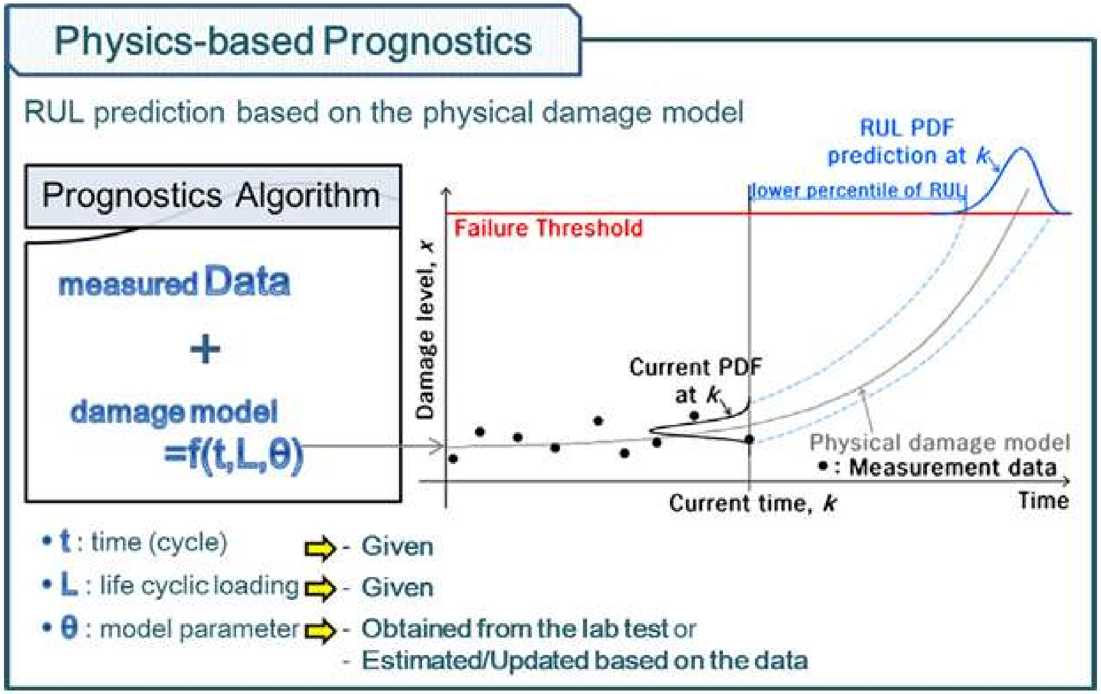
ghui Meng, Yiqiang Chen, and Zhenwei Zhou. 2022. "Segmental Degradation RUL Prediction of IGBT Based on Combinatorial Prediction Algorithms - IEEE Access %." 2022

Learning strategies in DT



Learning strategies in DT

- Computational fluid dynamics (CFD)
- Paris' law
- Finite element analysis (FEA)



Challenges

- Model complexity increases, number of parameters increases, parameters estimation becomes difficult.
- Correlation between parameters
- Noise and bias in sensor signals

Solutions

- Identifying equivalent parameters from a simpler model (not always possible)
- Sensitivity analysis, statistical methods, …
- Denoising in signal processing

An, Dawn, Nam H. Kim, and Joo Ho Choi. 2015. "Practical Options for Selecting Data-Driven or Physics-Based Prognostics Algorithms with Reviews." *Reliability Engineering & System Safety* 133 (January): 223–36

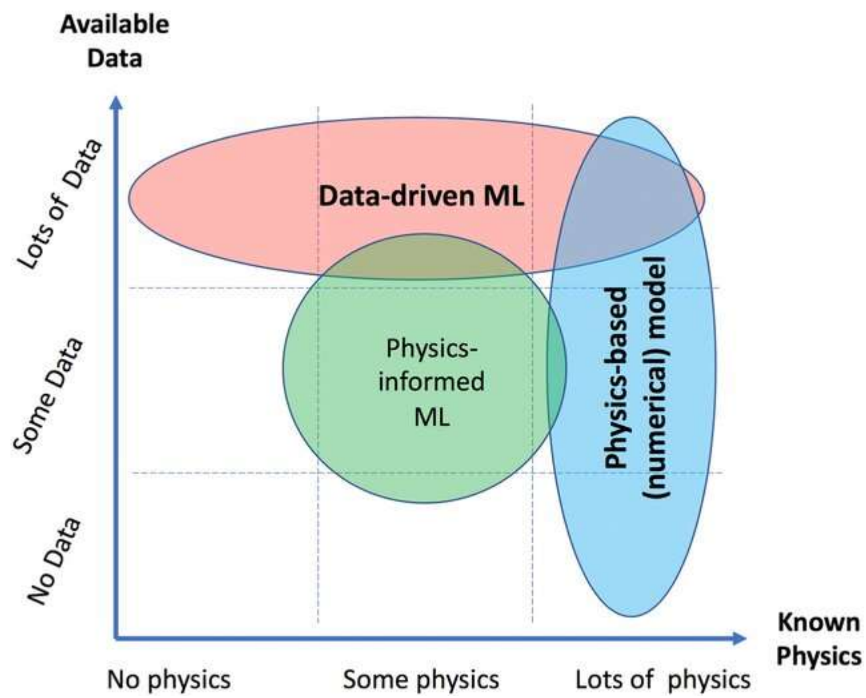
Learning strategies in DT

Comparison

Physics-based	Data-driven
Solid foundations based on physics, first principles and reasoning (high interpretability)	Black box (less interpretability)
Generalizes well to systems with similar physics	Poor generalization on unseen problems
Less data is required	Lots of data for training
Less biases	Bias in data is reflected in prediction
Not suitable for very complex systems with lots of parameters	Multidimensional analysis of complex systems
Causal relationships provide insight and understanding	Correlations, not causality
Model has universal validity-predict any point covered by the model	Difficult to predict extreme/critical condition

Learning strategies in DT

- Physics-Informed Neural Network (PINN)
- Incorporates physical principles into the learning process
- Accurately model physical systems even with limited data



Tartakovsky, A. M., C. Ortiz Marrero, Paris Perdikaris, G. D. Tartakovsky, and D. Barajas-Solano. 2020. "Physics-Informed Deep Neural Networks for Learning Parameters and Constitutive Relationships in Subsurface Flow Problems." *Water Resources Research* 56 (5)

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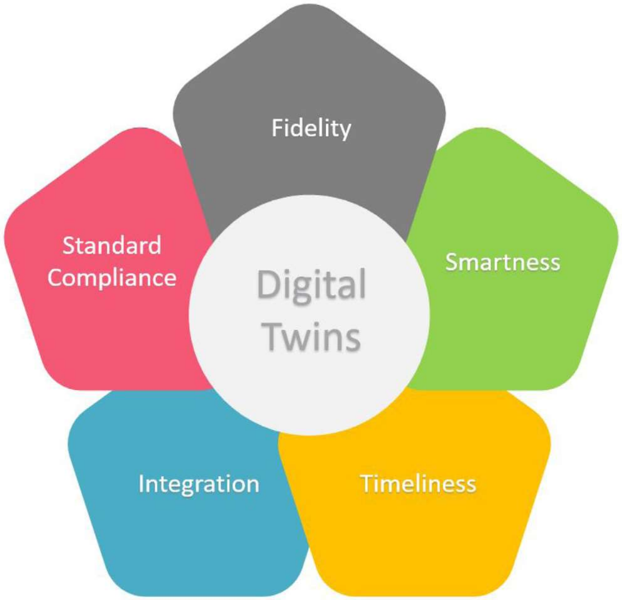
Qualification of digital twin

- Fidelity:
  - Quantity of input parameters
  - Precision of the outcome
- Smartness
  - Descriptive
  - Diagnostic
  - Prognostic
  - Decision-making
- Timeliness
  - Ability of the DT to accurately and quickly reflect to changes or updates of the physical system
- Integration
  - level of a DT connected both internally and externally
- Standard compliance
  - ability of DT to follow the established standards, guidelines, and best practices



Liu, Jie, Xingheng Liu, Jørn Vatn, and Shen Yin. 2023. "A Generic Framework for Qualifications of Digital Twins in Maintenance." *Journal of Automation and Intelligence* 2 (4): 196–203

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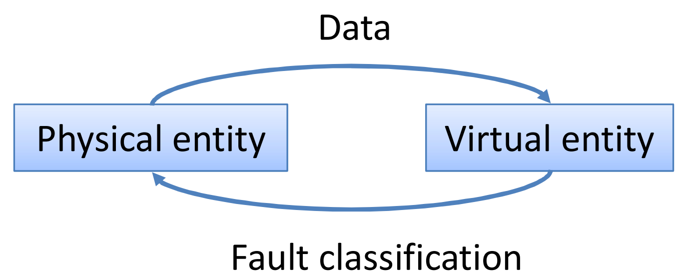
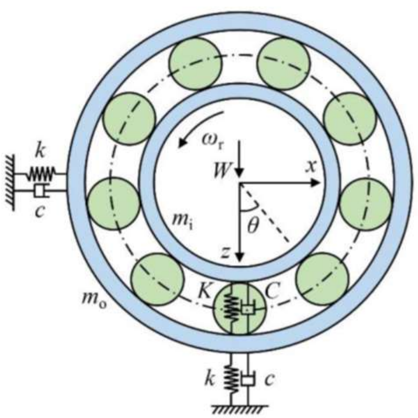
Case study

Digital Twin Enabled Domain Adversarial Graph Networks for Bearing Fault Diagnosis (Feng et al. 2023)

1. Limited pre-existing data
2. Dynamic simulation of operating conditions by digital twin
3. A graph convolutional network-based transfer learning to transfer knowledge from simulated data (DT) to measurement data for fault detection of bearings



Construction of Digital Twin



x_i , x_o: Horizontal translational displacement

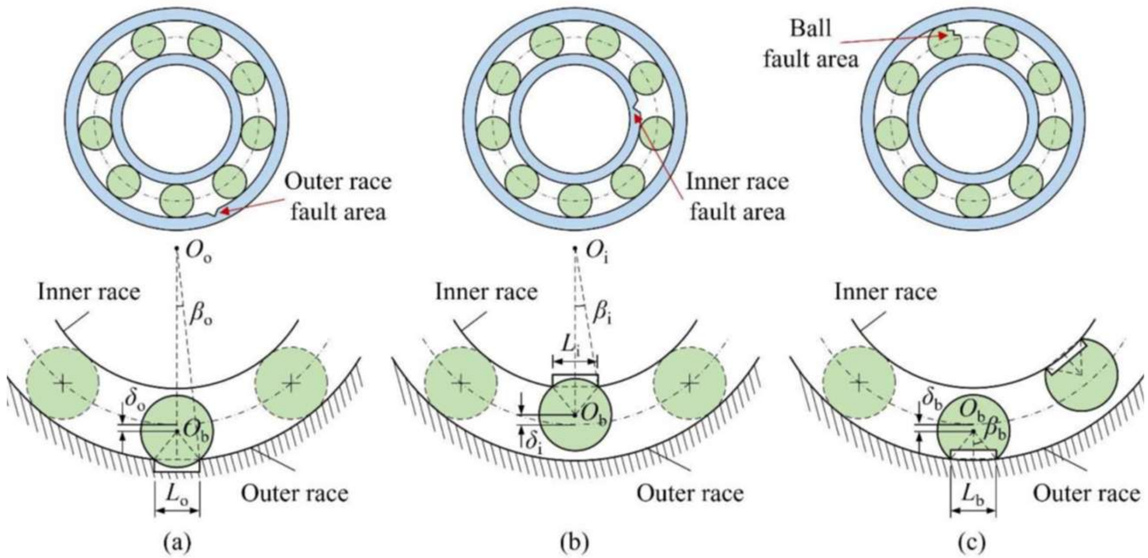
z_i , z_o: Vertical translational displacement

Nonlinear dynamic model of roller bearing

Case study

1. Determine rotating speed
2. Model contact forces
3. Angular position calculation
4. Incorporate contact damping forces
5. Formulate kinetic differential equations
6. Numerically solve the equations

Dynamic physics-based model



Schematic of localized faults

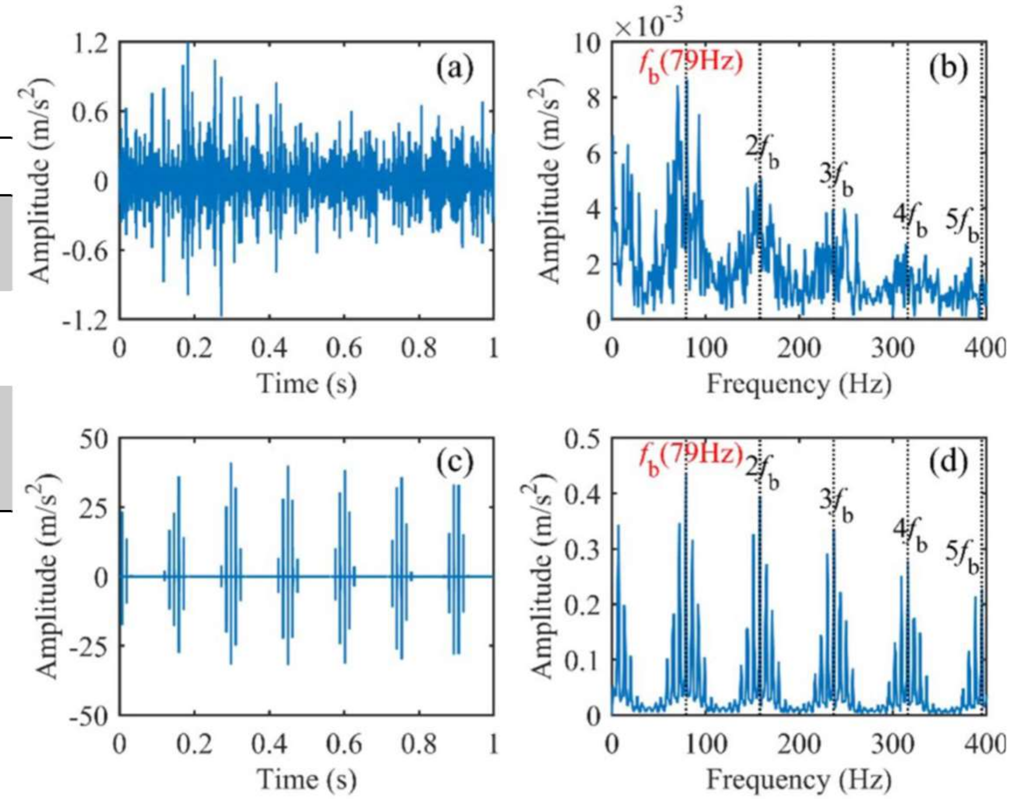
Case study

Bearing fault frequencies

Fault condition	Characteristic frequency
Ball pass frequency outer race (BPFO)	$f_o = \frac{N}{2}(1 - \frac{d}{D}\cos\alpha)\, f_r = 3.5848\, f_r$
Ball pass frequency inner race (BPFI)	$f_i = \frac{N}{2}(1 + \frac{d}{D}\cos\alpha)\, f_r = 5.4152\, f_r$
Ball spin frequency (BSF)	$f_b = \frac{D}{d}\left[1 - \left(\frac{d}{D}\cos\alpha\right)^2\right] f_r = 4.7135\, f_r$

$$f_r = rotating\ frequency = \frac{Rotating\ speed(rpm)}{60} = \frac{1005}{60} = 16.75$$

DT model is highly effective in reproducing vibration response of bearings with various faults



Comparison of measured signal and simulated signal under rolling ball fault: (a) waveform of the measured signal, (b) envelope spectrum of the measured signal, (c) waveform of the simulated signal, (d) envelope spectrum of the simulated signal.

Case study

Train the neural network model for fault diagnosis

1.Task Orientation

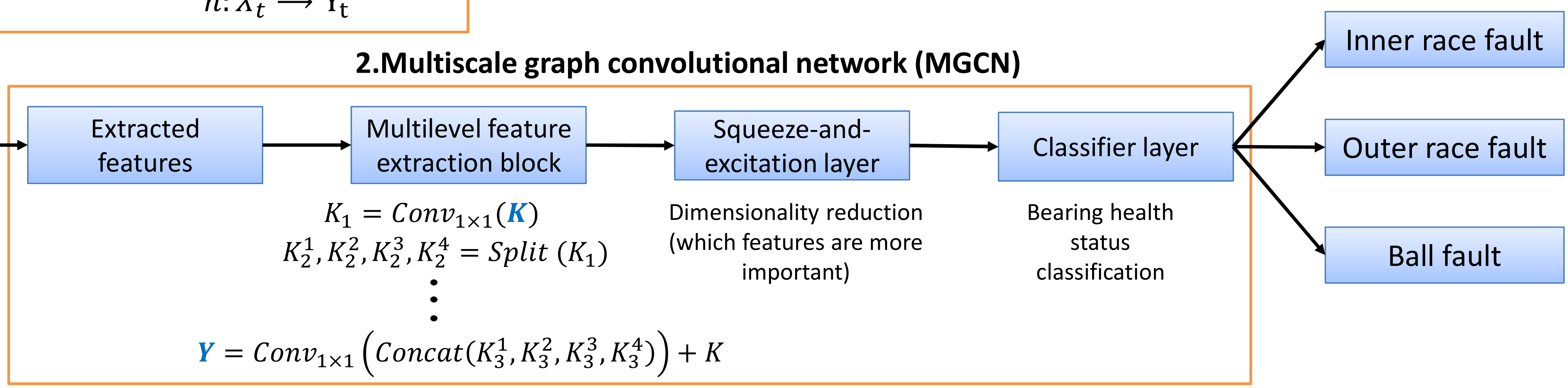
Source domain : $D_s = X_s$

$Y_s = (x_i^s)\,,\,(y_i^s)_{i=1}^{n_s}$

Target domain : $D_t = X_t = (x_j^t)_{j=1}^{n_t}$

$h: X_t \longrightarrow \mathrm{Y_t}$

2.Multiscale graph convolutional network (MGCN)



Case study

Classification loss which is composed of 3 loss functions:

1. **Cross entropy loss (L_{CE})**: measure of dissimilarity between the true label and the predicted label
2. **Maximum metric discrepancy (MMD) loss (L_{MMD})**: to capture the difference between the probability distributions of the source domain and the target domain
3. **Domain adversarial loss (L_{DA})**: To distinguish the data originating from source domain and target domain
4. $Total\ loss = L_{sum} = L_{CE} + \kappa L_{MMD} + \eta L_{DA}$

$Case\ A: Simulated\ data \longrightarrow Measured\ data$

$Case\ B: Measured\ data \longrightarrow Simulated\ data$

Approach	Accuracy $A \longrightarrow B(\%)$	Accuracy $B \longrightarrow A(\%)$
WDCNN	83.96 ± 7.76	68.03 ± 0.55
CNN-MMD	70.90 ± 9.08	68.50 ± 3.40
CNN-Coral	71.83 ± 6.93	60.14 ± 8.88
DAGCN	94.57 ± 1.46	81.33 ± 5.65
DDTLN	92.66 ± 0.84	76.80 ± 5.53
DT-DAGN	$\mathbf{100.00 \pm 0.00}$	$\mathbf{91.20 \pm 2.29}$

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Summary

- Digital twin helps us in real-time decision-making, controlling assets remotely, optimizing new designs based on historical data, ….
- Synchronization between the physical and virtual entities and ability to adapt to changes are the two main characteristics of digital twin
- Physics-based models and machine-learning algorithms are widely used in developing digital twins
- Physics-informed data-driven techniques

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Thank you!