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Recent Advances of Industrial AI for Smart and Resilient Industrial Systems

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Outline

1. Trends of Data Centric Systems and Unmet Needs
2. Trends of AI and Industrial AI Systems
3. Some Examples
4. Training of New Breed of Industrial AI Engineers

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1. Trends of Data Centric Systems and Unmet Needs

2. Trends of AI and Industrial AI Systems

3. Some Examples

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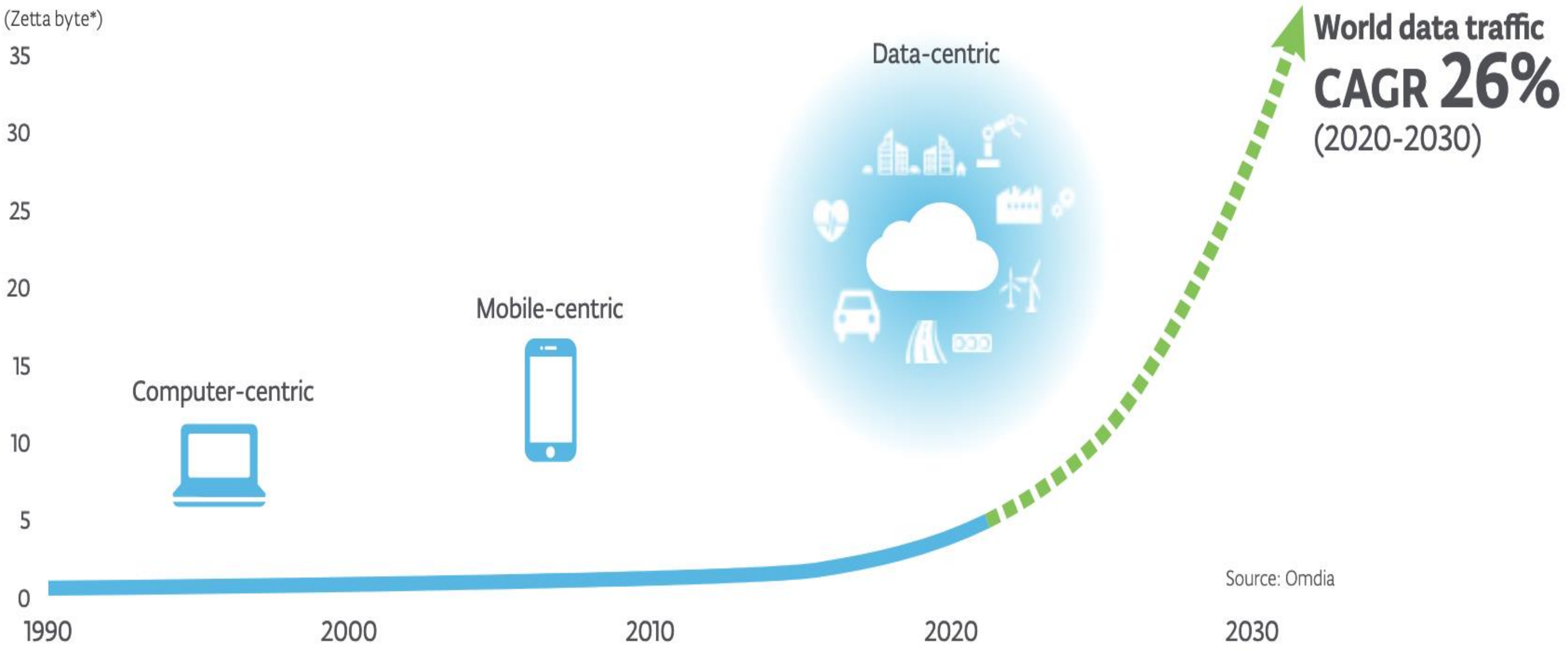
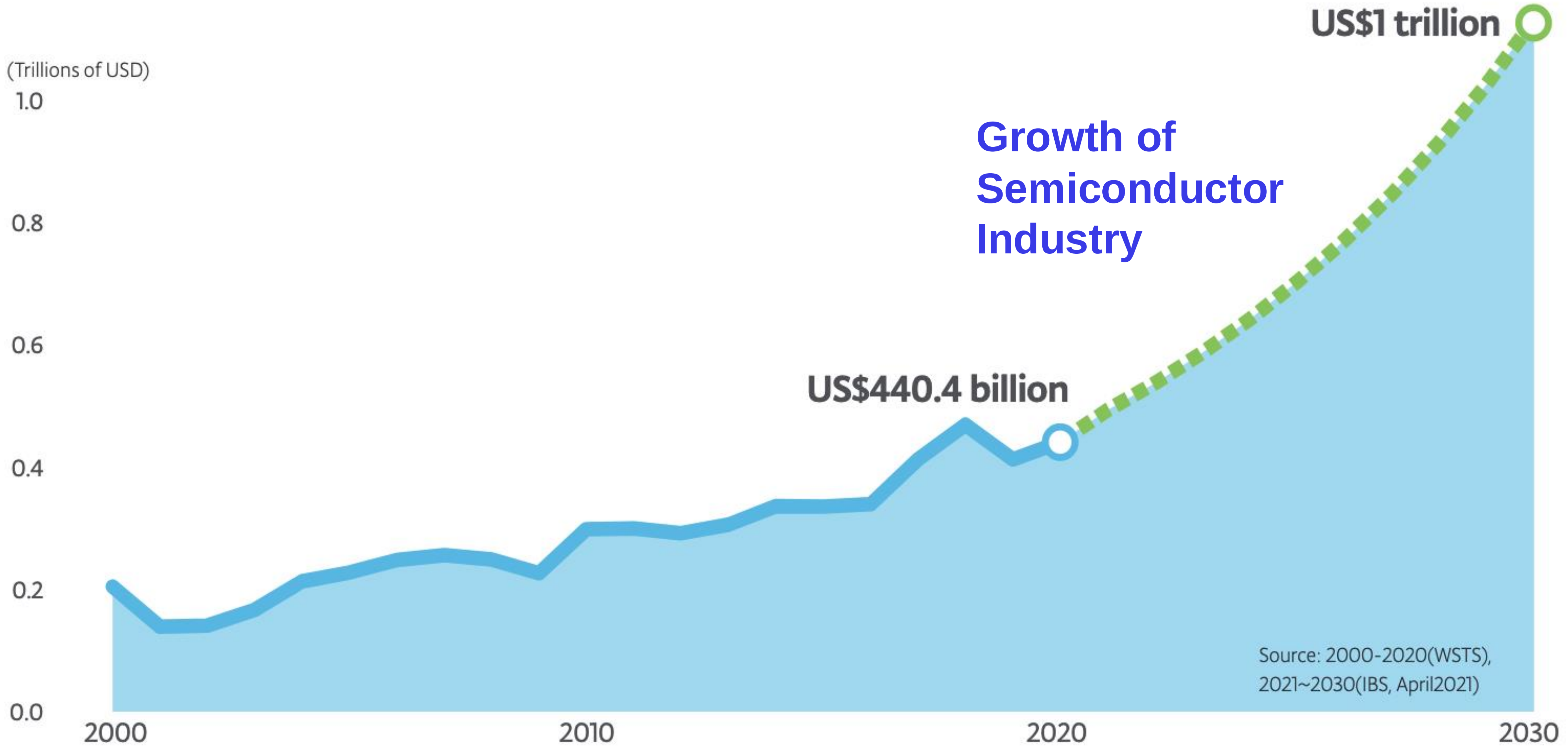
Trends of Connected Systems and Data Driven Economy



*Zettabyte: 1Zettabyte = 1021byte, 1Zettabyte is said to be "the number of sand grains on sandy beaches around the world"

Growth of Semiconductor Industry



Reference: Tokyo Electron Ltd. (TEL)

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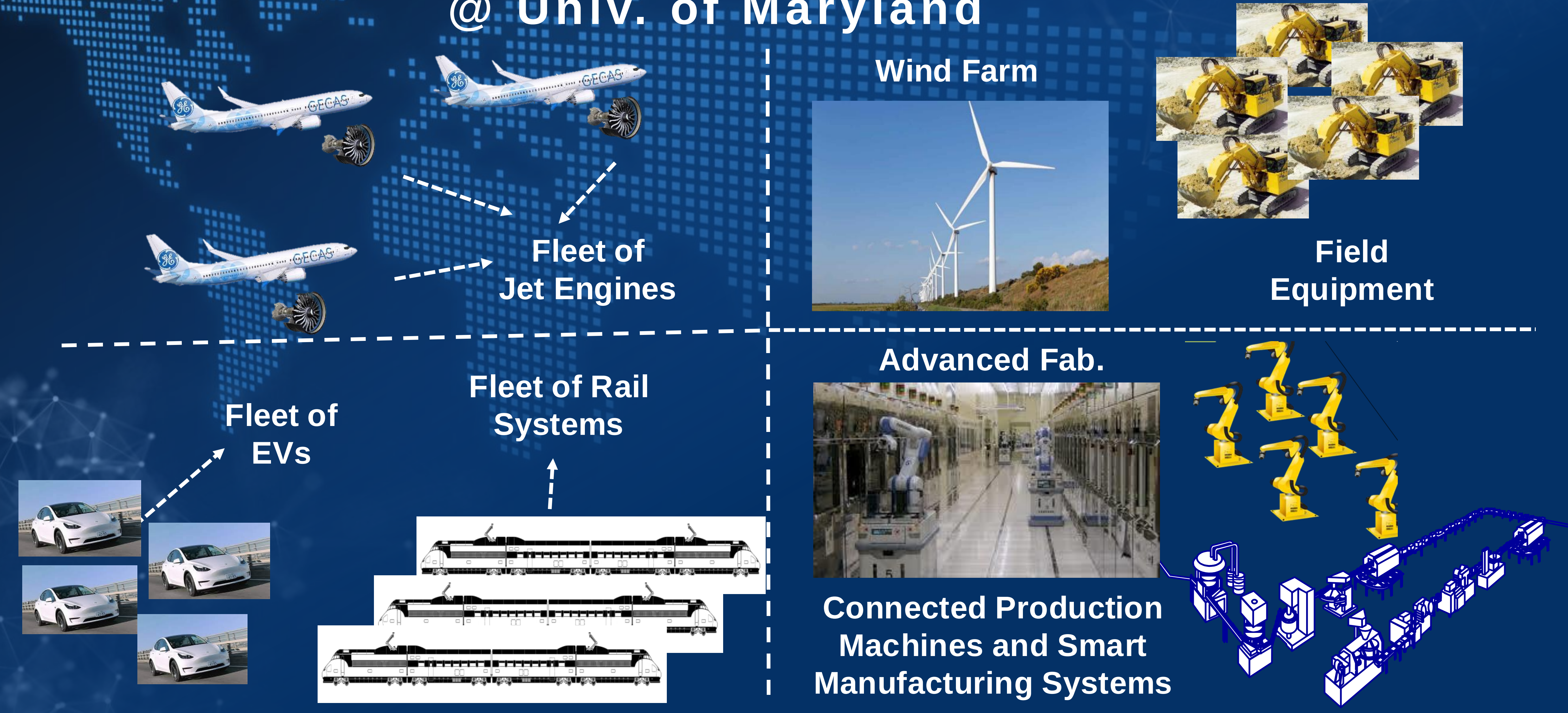
Industrial AI and Data-Centric Metrology for Highly Connected and Complex Industrial System @ Univ. of Maryland



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Challenges and Needs of AI in Complex Industrial System

	Visible	Invisible
Avoid	Utilize New Knowledge/ Technologies For Value-added Improvement	Value Creation using Smarter Information For Unknown Knowledge
Solve	Problem Solving Through Continuous Improvement and Standard Work	Utilize New Methods/ Techniques to Solve The Unknown Problems

Jay Lee, Book on Industrial AI, Springer, 2020

Data and Modeling Issues in Complex Industrial Systems

Data Usability

High

- Uncertain Quality (Drifted or Shifted)
- Comprehensive
- Background Recorded

- Good Quality
- Comprehensive
- Background Recorded

Low

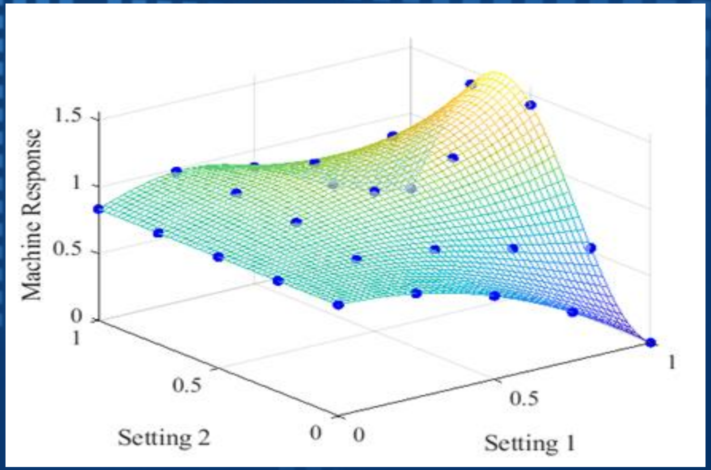
- Bad Quality
- Broken (Not comprehensive)
- Background Missing

- Good Quality
- Broken (Not comprehensive)
- Background Missing

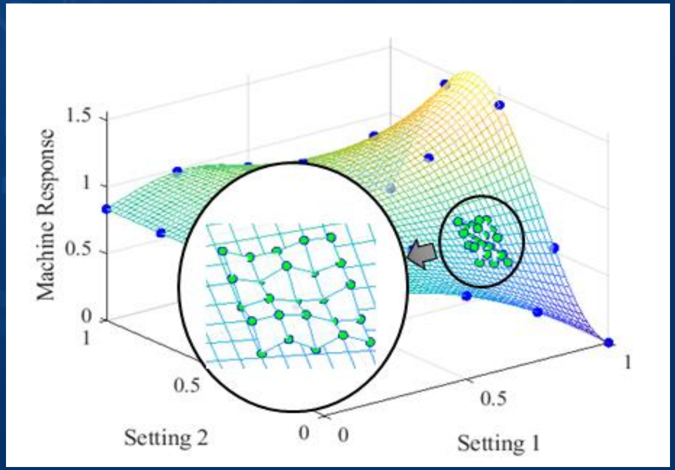
Low **High**

Data Usefulness

Reference Source



Target Source



Source	Reference Source	Target Source
Data Quantity	✓ High Volume	✓ Low Volume
Data Quality	✓ High quality	✓ Dynamic ✓ Time-restricted ✓ Drifted / Shifted ✓ Noisy
Data Representativeness	✓ Comprehensive	✓ Local ✓ High variation
Data Availability	✓ High availability	✓ Low availability

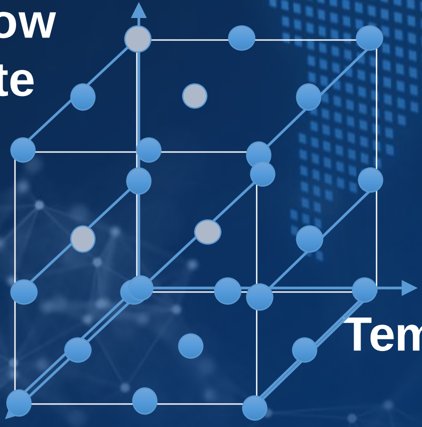
Need Better Data Representation Methodology

Limited Data Scenario

- Difficult for modeling
- Usually need data augmentation strategy to generate more data
- Whole data space is not fully explored

Traditional DOE methods

Flow rate

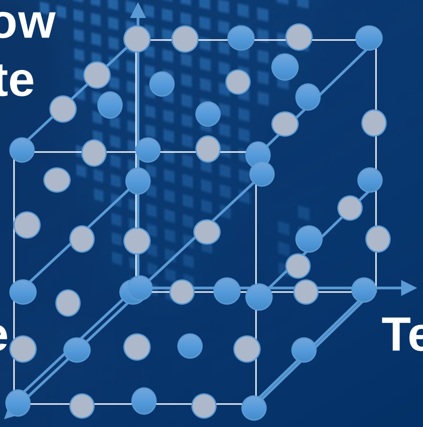


Temperature

Pressure

Sampling methods

Flow rate



Temperature

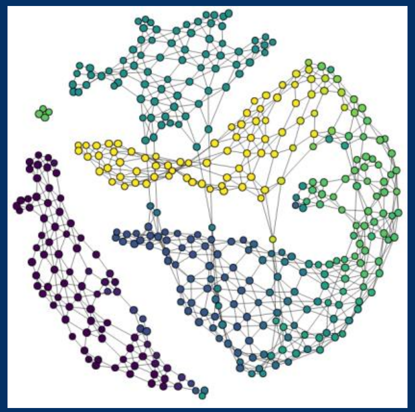
Pressure

High Volume Data Scenario

- High model complexity
- Labeling would be demanding work for user
- Computation expensive

clustering methods

Topological Data Analysis

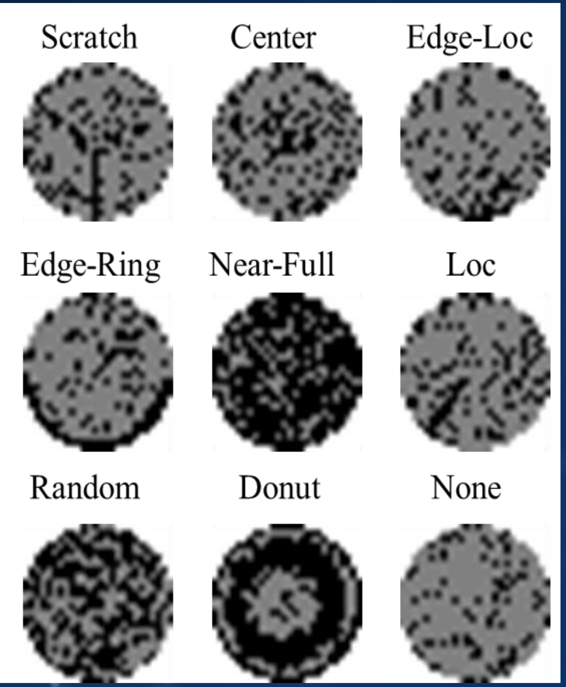


Low Complexity/Quantity

High Complexity/Quantity

Example: Data Representation using Topological Data Analysis (TDA)

TSMC WM-118K Dataset (810,000)



Data Generation
- Preprocessing
- Feature Extraction

Graph Construction
- Construct graph by graph-based TDA

Initialization
- Selected data from nodes of graph

Modeling
- Develop an adaptive model to evaluate the data space

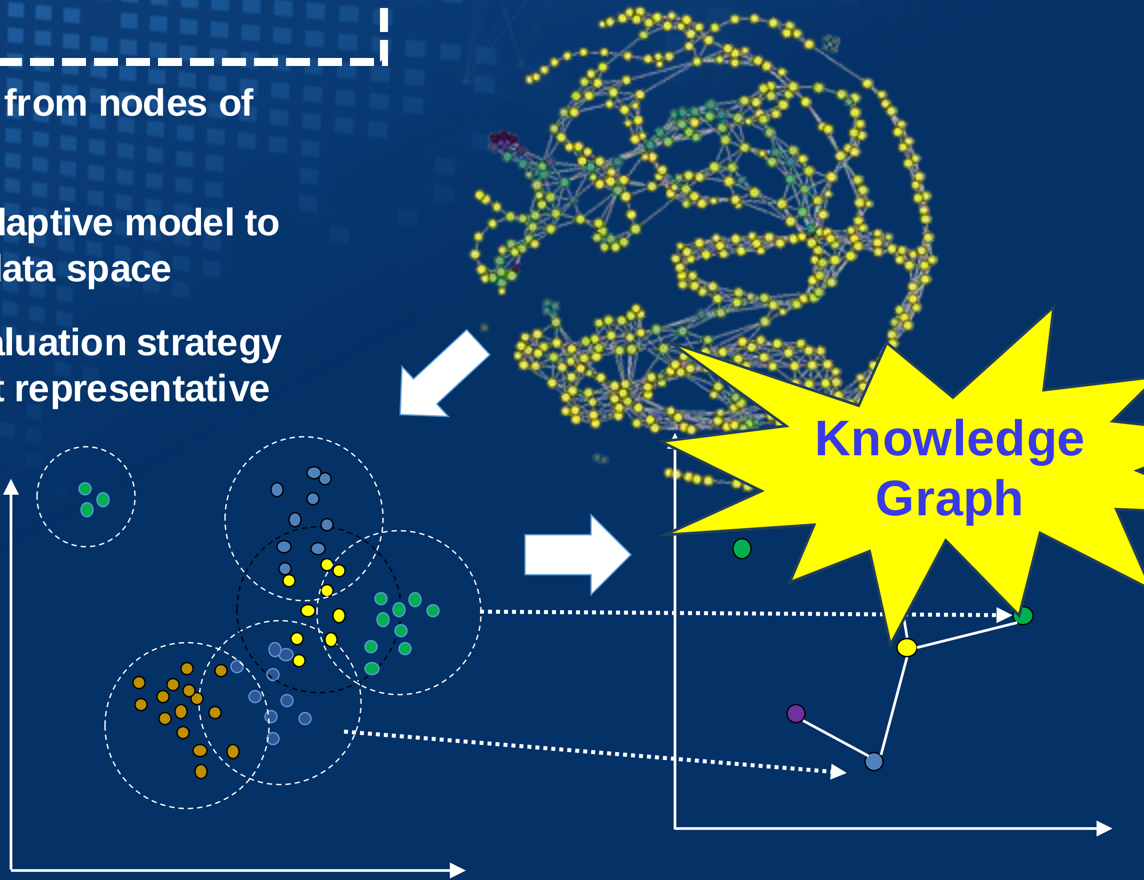
Evaluation
- Design an evaluation strategy to decide next representative data

New Representative Data

Result

Constructed by only labeled data (170,000)

Node color is represented by mixture proportion of each class



Ref:https://en.wikipedia.org/wiki/Wafer_testing#/media/File:Wafer_prober_service_configuration.jpg

Hsu, Jia, Li, Lee, A Novel Quality Clustering Methodology on Fab-Wide Wafer Map Images in Semiconductor Manufacturing ASME 2022 17th International Manufacturing Science and Engineering Conference.

Outline

1. Trends of Data Centric Systems and Unmet Needs
2. **Trends of AI, Industrial AI Systems**
3. Some Examples in Semiconductor Manufacturing
4. Training of New Breed of Industrial AI Engineers

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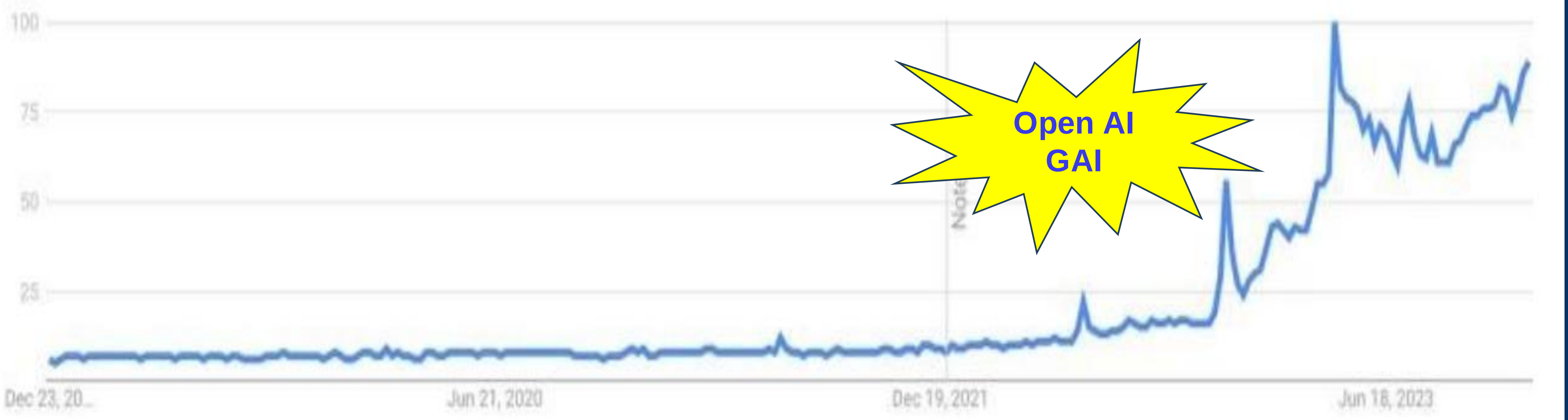
AI Has Been Gaining Amazing Attention since 2022

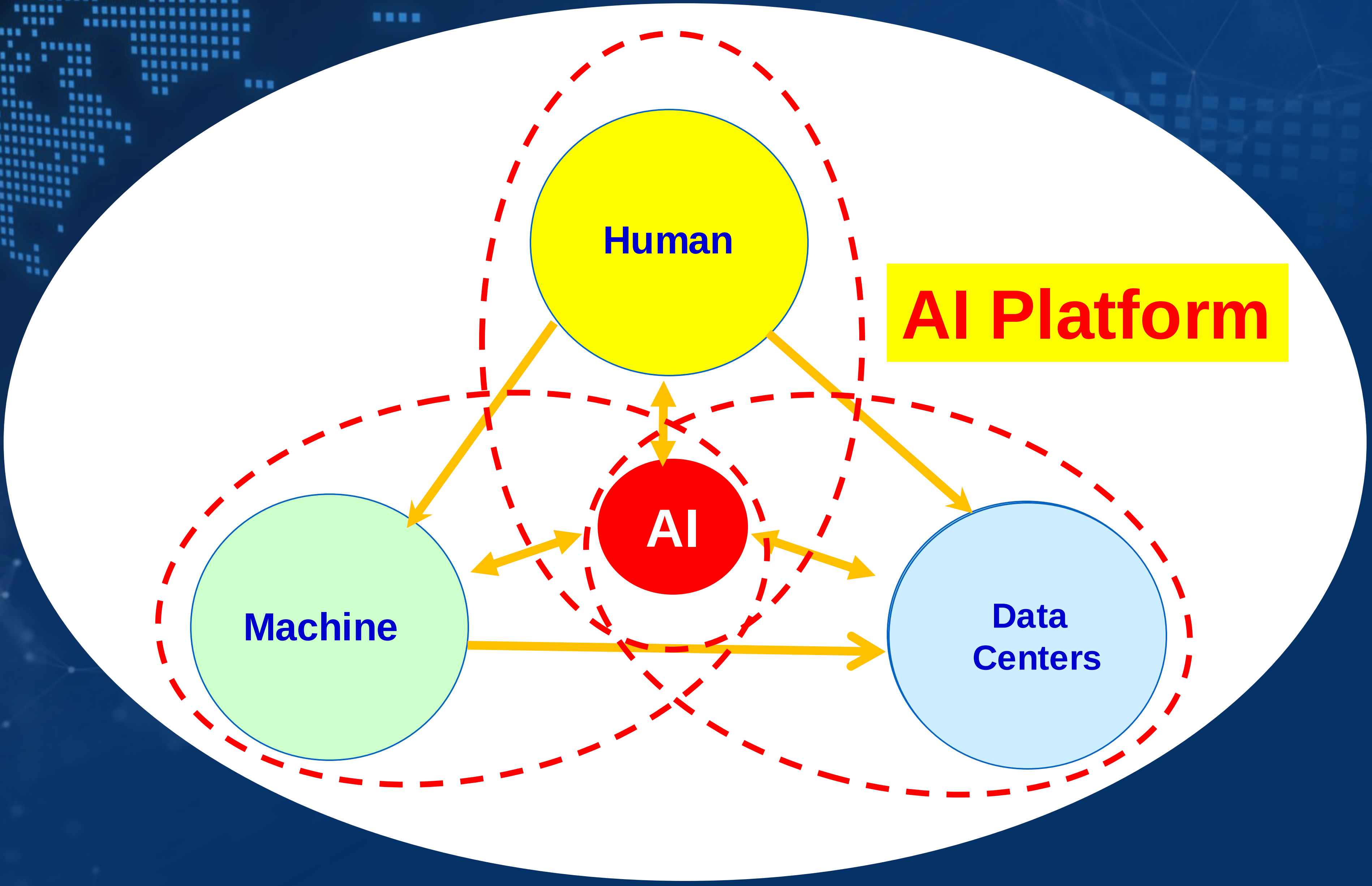
Level of Attention



$16.7 B **$26.9 B** **$50 B**

NVIDIA Revenue **NVIDIA Valuation >$ 3T**

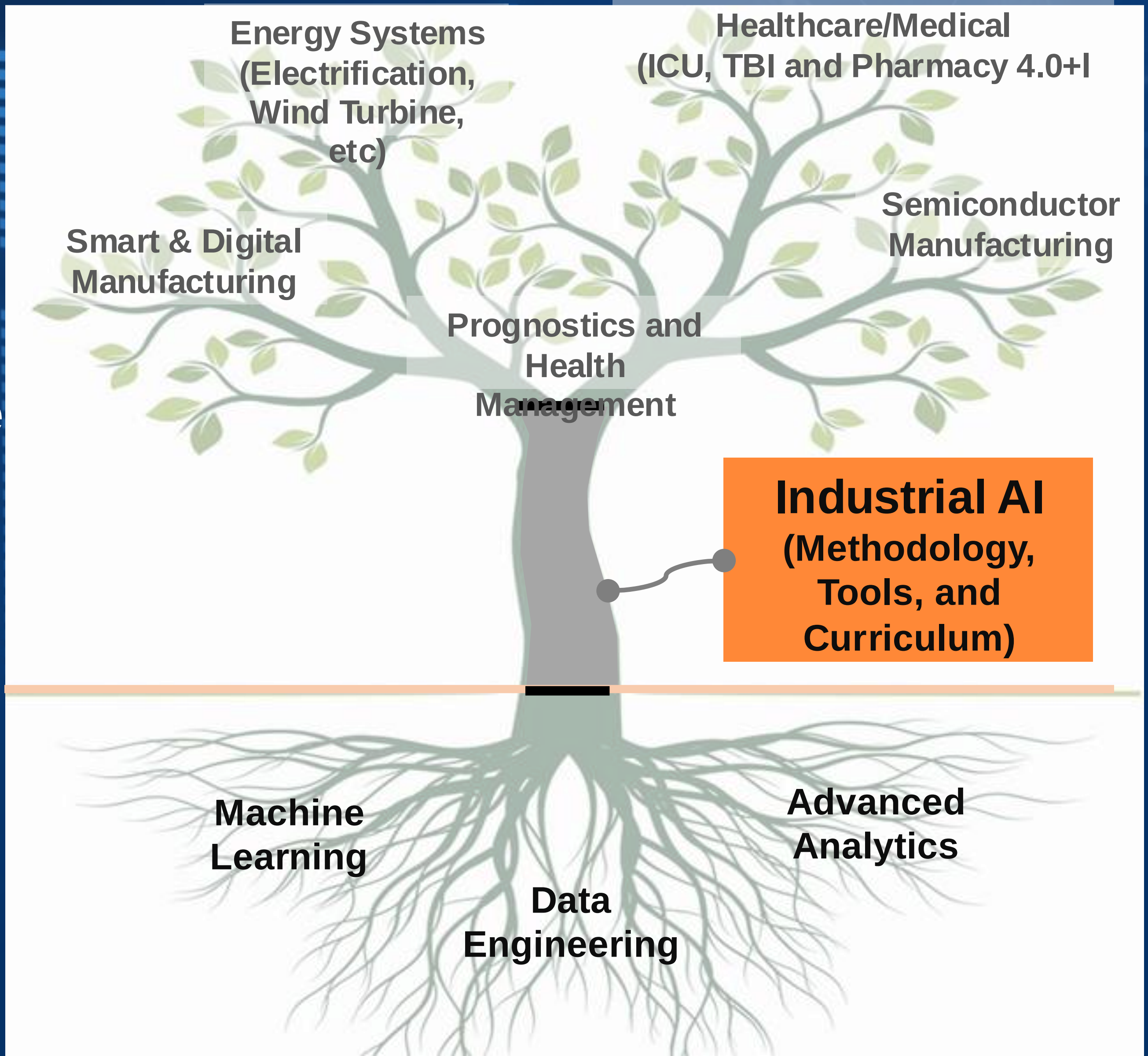
Evolving Role of AI from Algorithm to Platform, and to Agent



Industrial AI

►**Industrial AI**

is a *systematic discipline* which focuses on developing, validating and deploying various machine learning algorithms systemically and rapidly for industrial applications with sustainable performance.



Domain

+

Discipline

+

Data

Overview of Industrial AI Systems

Industrial AI

1. **Manufacturing AI**
   - **Semiconductor**
   - Machine Tools
   - Industrial Robots
   - Production Quality
2. **New Energy AI**
   - Wind Turbine
   - Power Supplies
   - EV Battery
   - Oil & Gas
3. **Transportation AI**
   - Automotive
   - High-speed Trains
   - Aviation
   - Marine Vessels
4. **Healthcare AI**
   - Rehabilitation
   - Neurocritical Care
   - Sports Medicine
   - Chronic Care

Target Systems

1. **Component**

2. **Unit**

3. **Fleet**

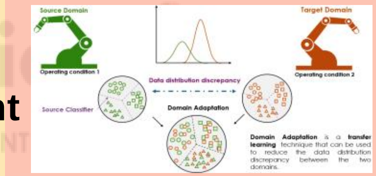
Traditional Machine Learning

1. **Signal Process & Feature Extraction**
2. **Physics-Based Model**
3. **Data-Driven Model**
4. **Deep Learning**
5. **Health Assessment**
6. **Health Diagnosis**
7. **Predictive Maintenance**
8. **Remaining Useful Life**
9. **Failure Modes and Effects Analysis**

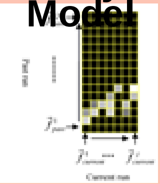
Non-Traditional Machine Learning

1. **Topological Data Analysis**

2. **Domain Adaptation & Transfer Learning**



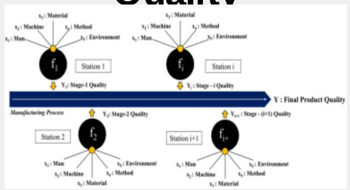
3. **Similarity-Based Model**



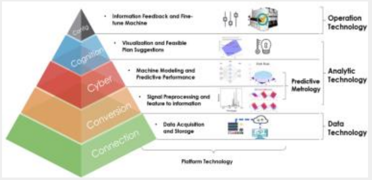
4. **Surrogate Model**
5. **Just-in-time Model**
6. **Industrial Large Knowledge Model**

Methodology Platform

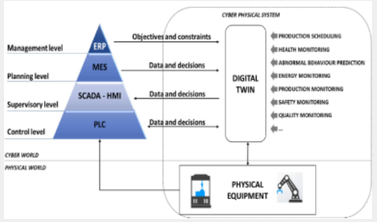
1. **Stream-of-Quality**



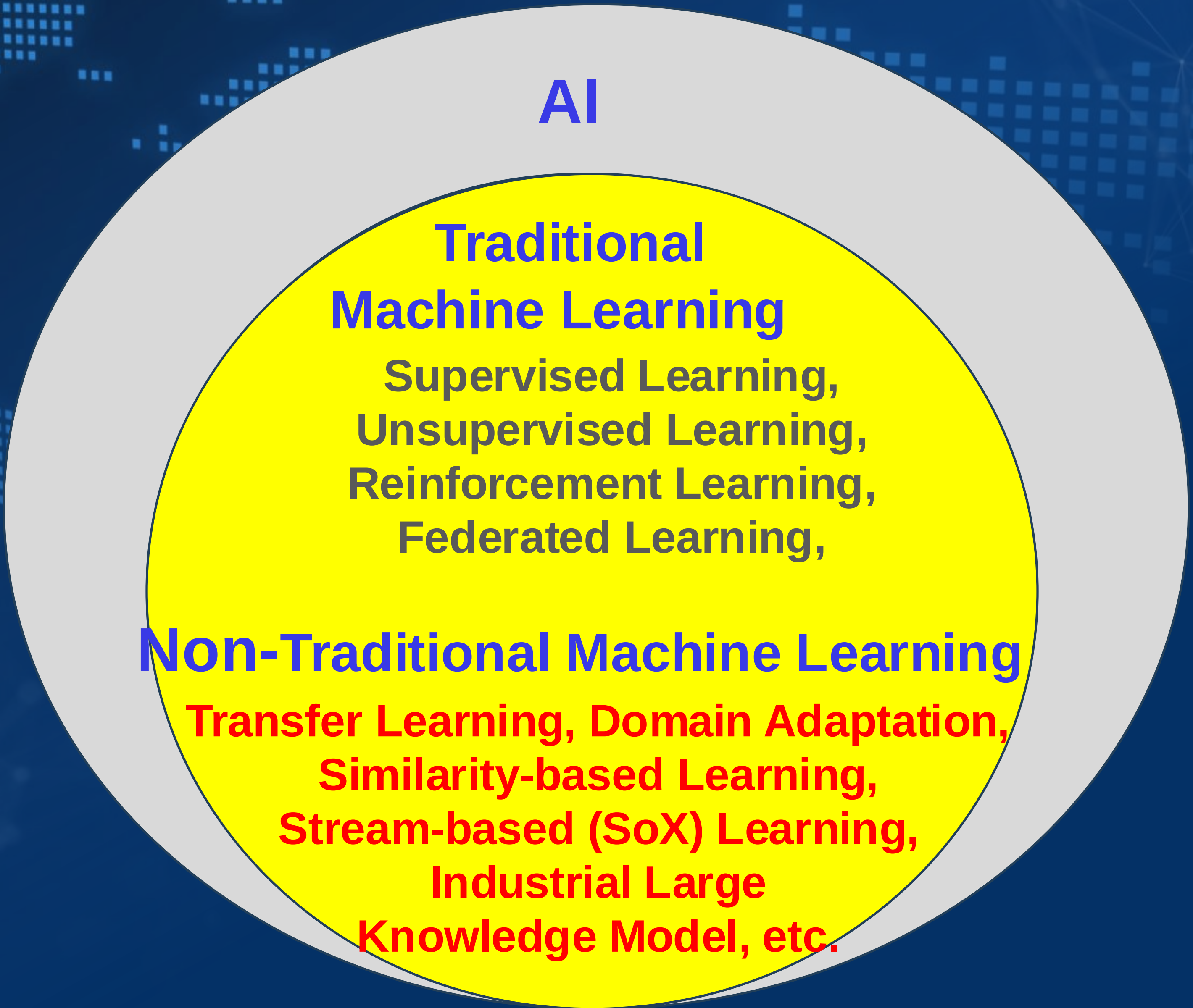
2. **5C-level Cyber-Physical System**



3. **Digital Twin**



Traditional Machine Learning vs. Non-Traditional Machine Learning



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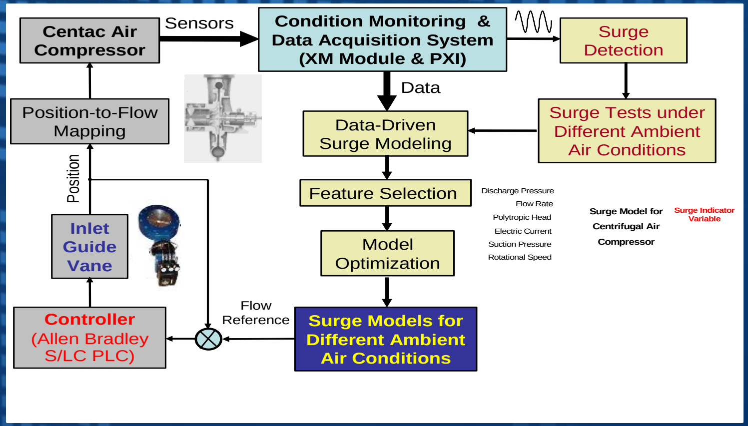
Traditional Machine Learning Methods and Algorithms for Industrial Systems

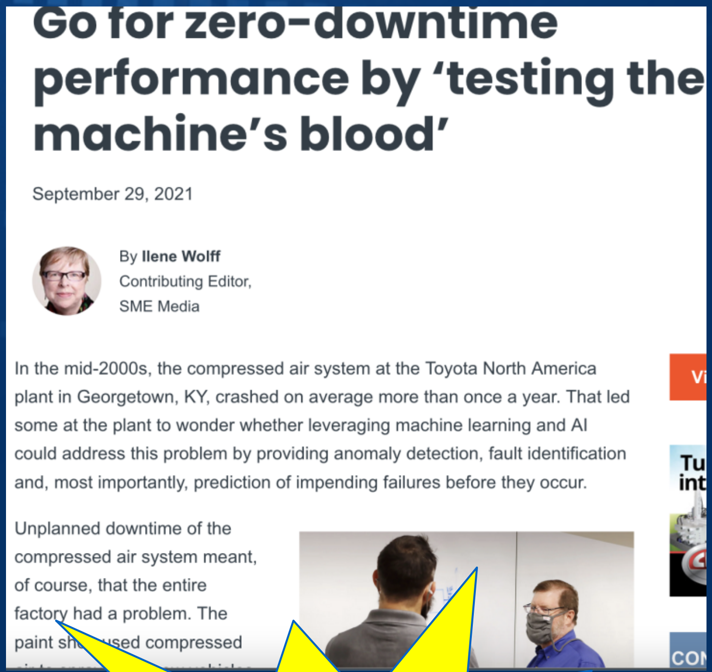
	Machine Learning Methods	Algorithms
Fault Detection	One-Class Detection	Control Charts (Statistical Process Control); One-Class Support Vector Machine; PCA - T^2; SOM-MQE; GMM-L2
	Binary Classification	Naïve Bayes; Logistic Regression; Decision Trees; Support Vector Machine; (Deep) Neural Networks; Fuzzy Inference Systems; Self-Organizing Map
Fault Diagnosis	Binary/ Multi-class Classification	
Health Assessment	Supervised Regression	Linear Regression; General Linear Regression; Gaussian Process Regression; (Deep) Neural Networks
	Unsupervised Regression	Parametric Method; Hidden Markov Model; Kalman Filters / Particle Filters; Factor Analysis; Principal Component Analysis
Remaining Useful Life Prediction	Supervised Prediction	Linear Regression; General Linear Regression; Gaussian Process Regression; (Deep) Neural Networks
	Unsupervised Prediction	Kalman Filters / Particle Filters; Stochastic Process Model; Similarity Based Model; Survival / Hazard Analysis (Cox Model)

Zero Downtime Compressor at Toyota Georgetown, KY

AI for Compressor Surge Prediction

PCA + SVM





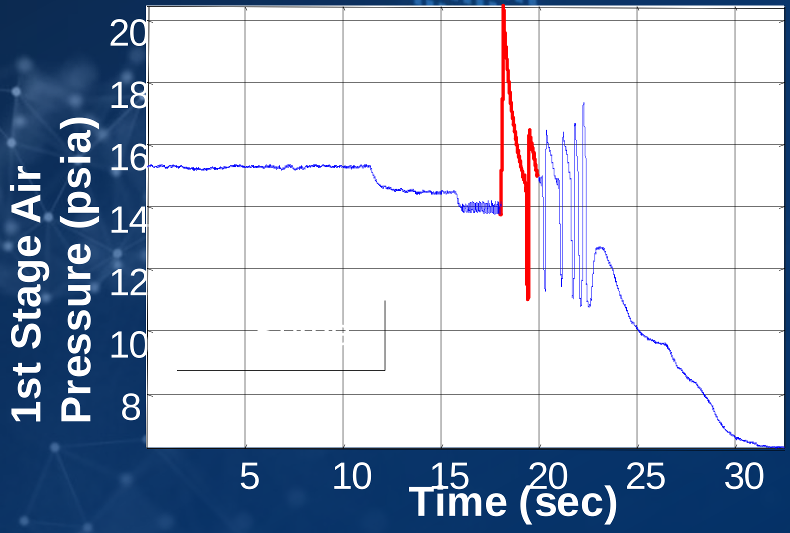
Go for zero-downtime performance by 'testing the machine's blood'

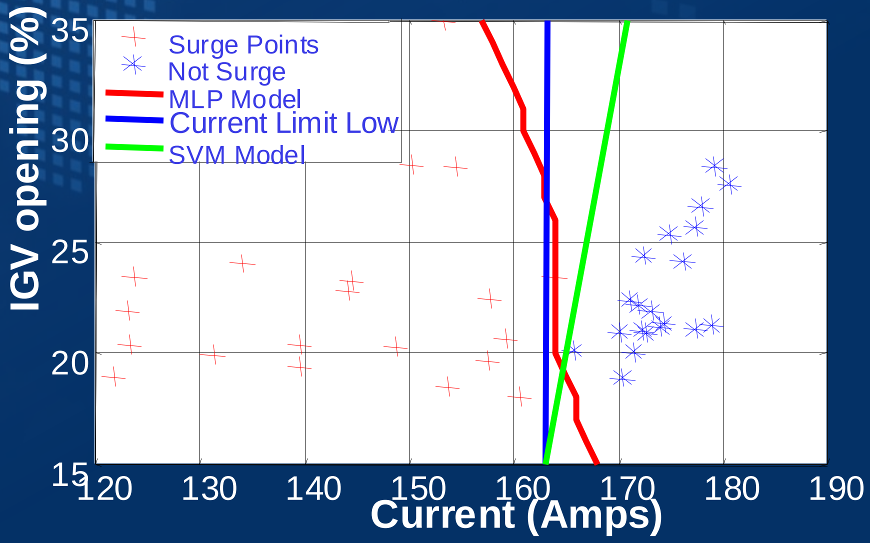
September 29, 2021

By Ilene Wolff
Contributing Editor,
SME Media

In the mid-2000s, the compressed air system at the Toyota North America plant in Georgetown, KY, crashed on average more than once a year. That led some at the plant to wonder whether leveraging machine learning and AI could address this problem by providing anomaly detection, fault identification and, most importantly, prediction of impending failures before they occur.

Unplanned downtime of the compressed air system meant, of course, that the entire factory had a problem. The paint shop used compressed





Zero Downtime
No failure
since 2006

https://www.sme.org/technologies/articles/2021/september/go-for-zero-downtime-performance-by-testing-the-machines-blood/

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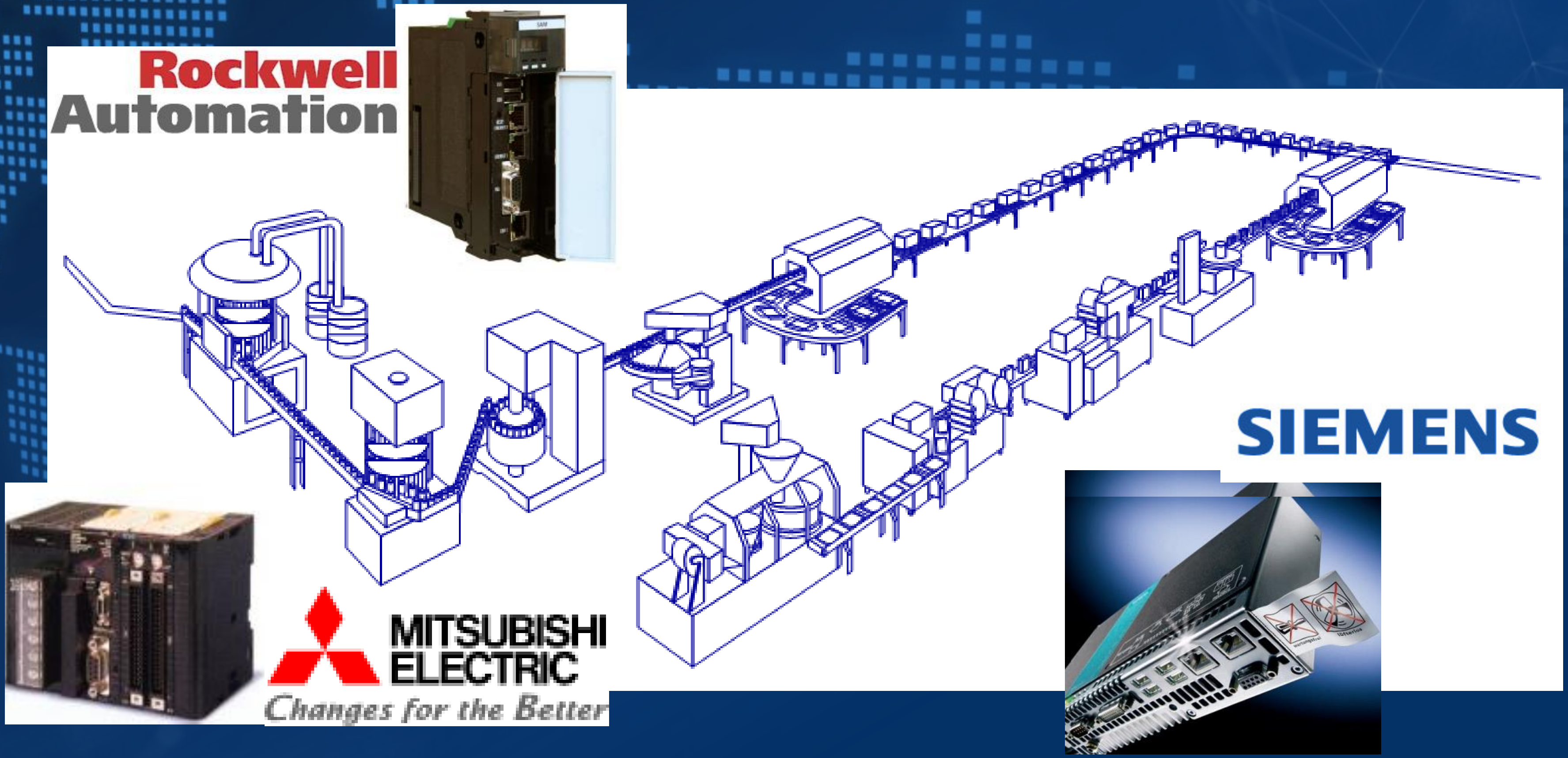
Embedded AI for Production Systems



Reconfigurable AI Augmented PLC Systems

Enable Zero-Breakdown Productivity

AI-Augmented Uptime Improvement for P&G (2007-11)

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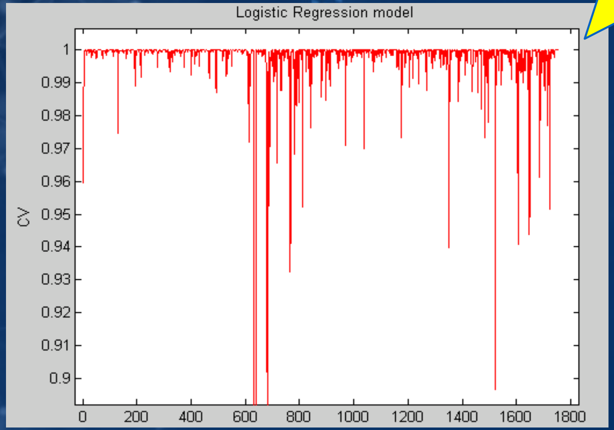
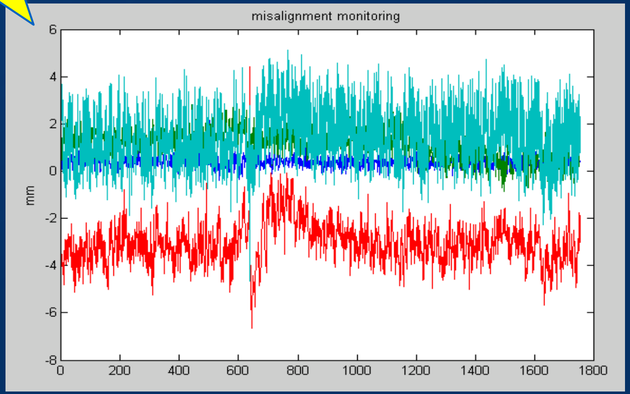
2012 NSF I/UCRC
Economic Impact Report

$450 M
Saving/Year





Real-Time Performance

Process Quality Monitoring

AI Augmented Machine Tool Health Monitoring Technology Demonstrated in 2018 and Commercialized Today

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Mazak

IMTS2018
International Manufacturing Technology Show
September 10 - 15, 2018 · McCormick Place · Chicago

Mazak
Discovery Week
Oct. 2023

Non-Traditional Machine Learning— Transfer Learning

» The most optimum way of learning is to utilize the pre-acquired knowledge as the basis of intended learning plan.

» In machine learning application, the exchanging knowledge across different tasks is named as transfer learning.

» In industrial applications, providing the data under different operating and health conditions is not straightforward.

Transfer Learning

Data is available

Operating condition 1
- Temperature
- Load
- Pressure
- Rotating speed
- …

Operating condition 2
- Temperature
- Load
- Pressure
- Rotating speed
- …

Data is not available

Domain Adaptation

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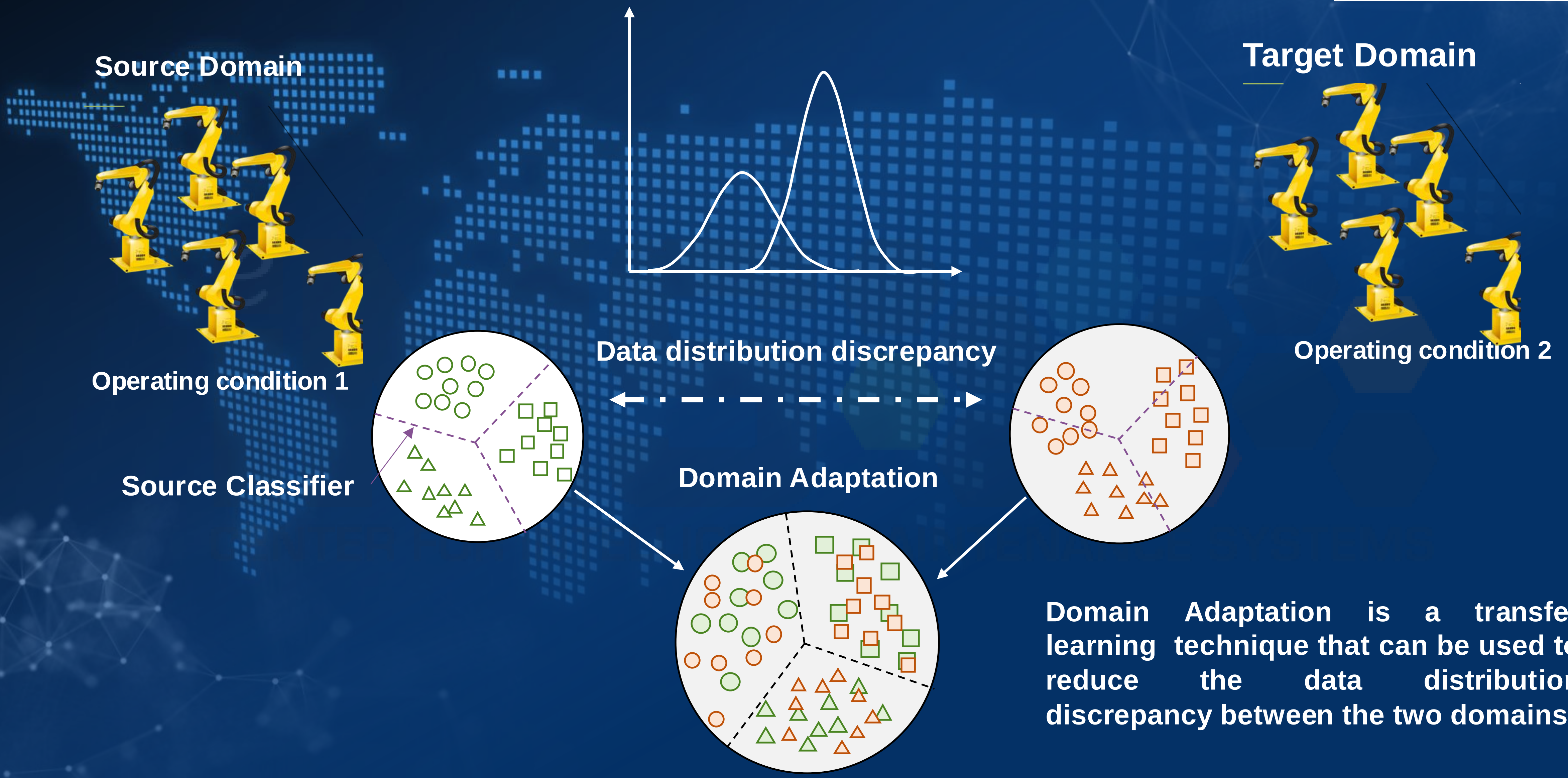
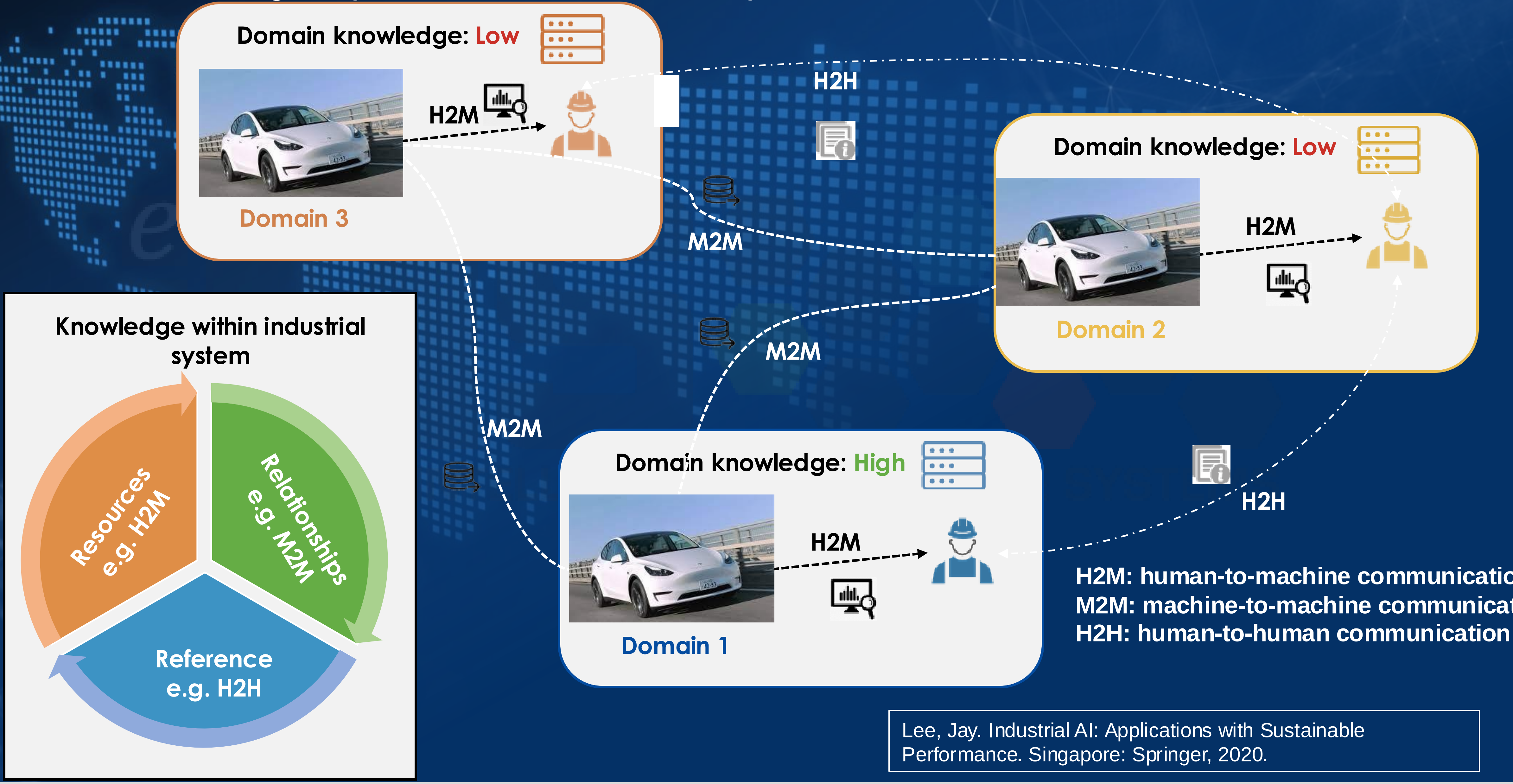


Domain Adaptation is a transfer learning technique that can be used to reduce the data distribution discrepancy between the two domains.

Integrated Machine Learning for Highly Connected Systems



Lee, Jay. Industrial AI: Applications with Sustainable Performance. Singapore: Springer, 2020.

Tesla Full Self-Driving (FSD) Beta V12 (released on 8/26/2023)

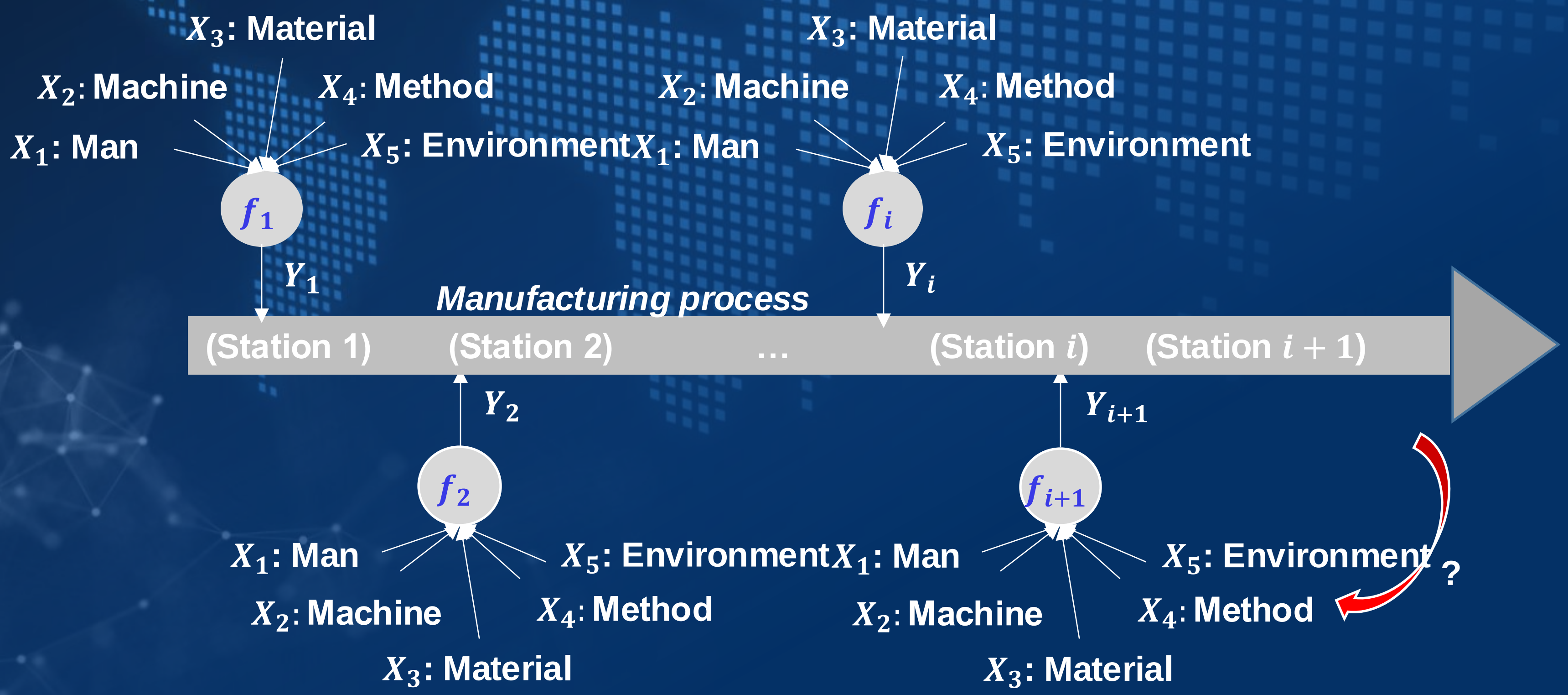
- Musk highlighted that FSD V12 relies entirely on artificial intelligence and neural networks to drive, with no traditional code. He stated “there are no heuristics, no lines of code” to explicitly tell the car how to handle situations like traffic lights or turns. Instead, the system has been trained on large volumes of driving footage to learn proper driving behavior.
- Reduced 90% of the code with better performance.

Non-Traditional Machine Learning

Stream-of-X (SoX) Methodology

Stream of Quality™ (SoQ™) is a traceable systematic methodology for connected quality.

- It can collect the manufacturing information of a product during its production processes.
- The data of each station can be labeled with a time stamp and saved in an immutable block. Then the product quality data forms an information stream and can be stored in structured block chain.
- It can be used to describe the product, trace the entire production process and analyze the root cause of quality issues.



Y_j: Quality

X_i: Process factor

$Y_i = f_i(X_1, X_2, X_3, X_4, X_5, Y_{i-1})$

$Y = g(Y_1, Y_2, \ldots, Y_n)$

Lee, J., Stream-of-Quality (SoQ) methodology for industrial Internet-based manufacturing system, https://www.sciencedirect.com/science/article/abs/pii/S2213846322001912

Digital Twin of Manufacturing Systems

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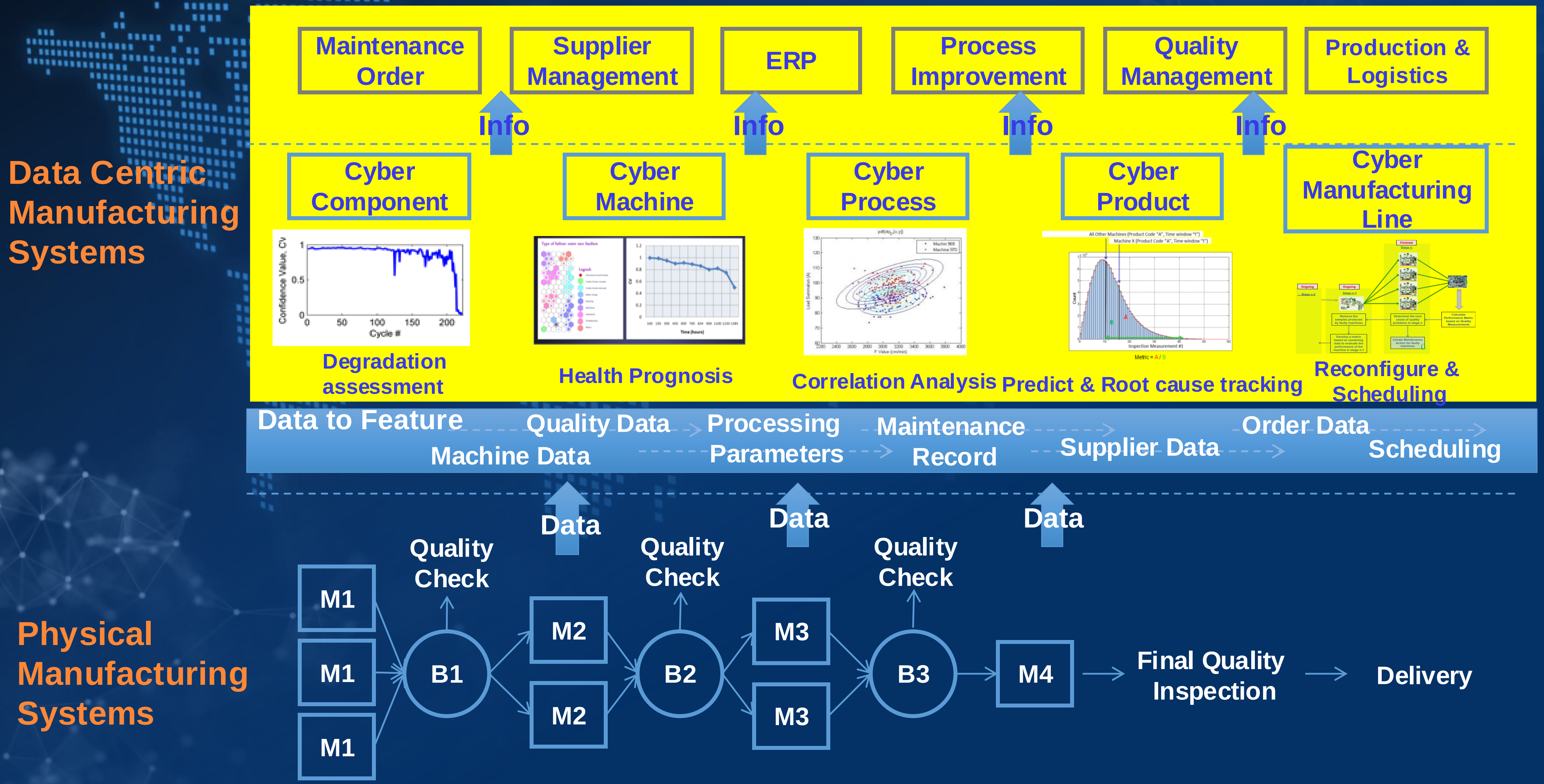
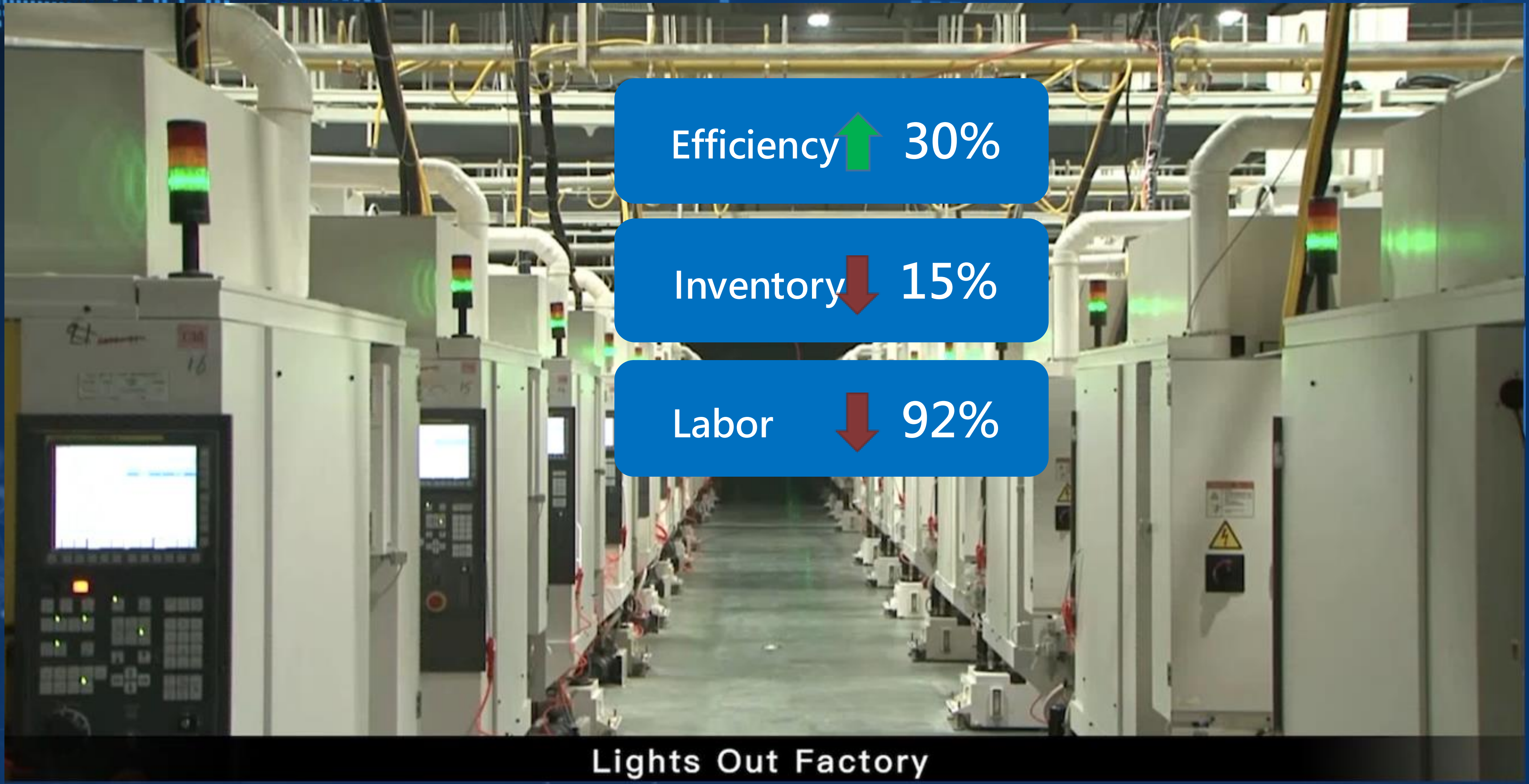
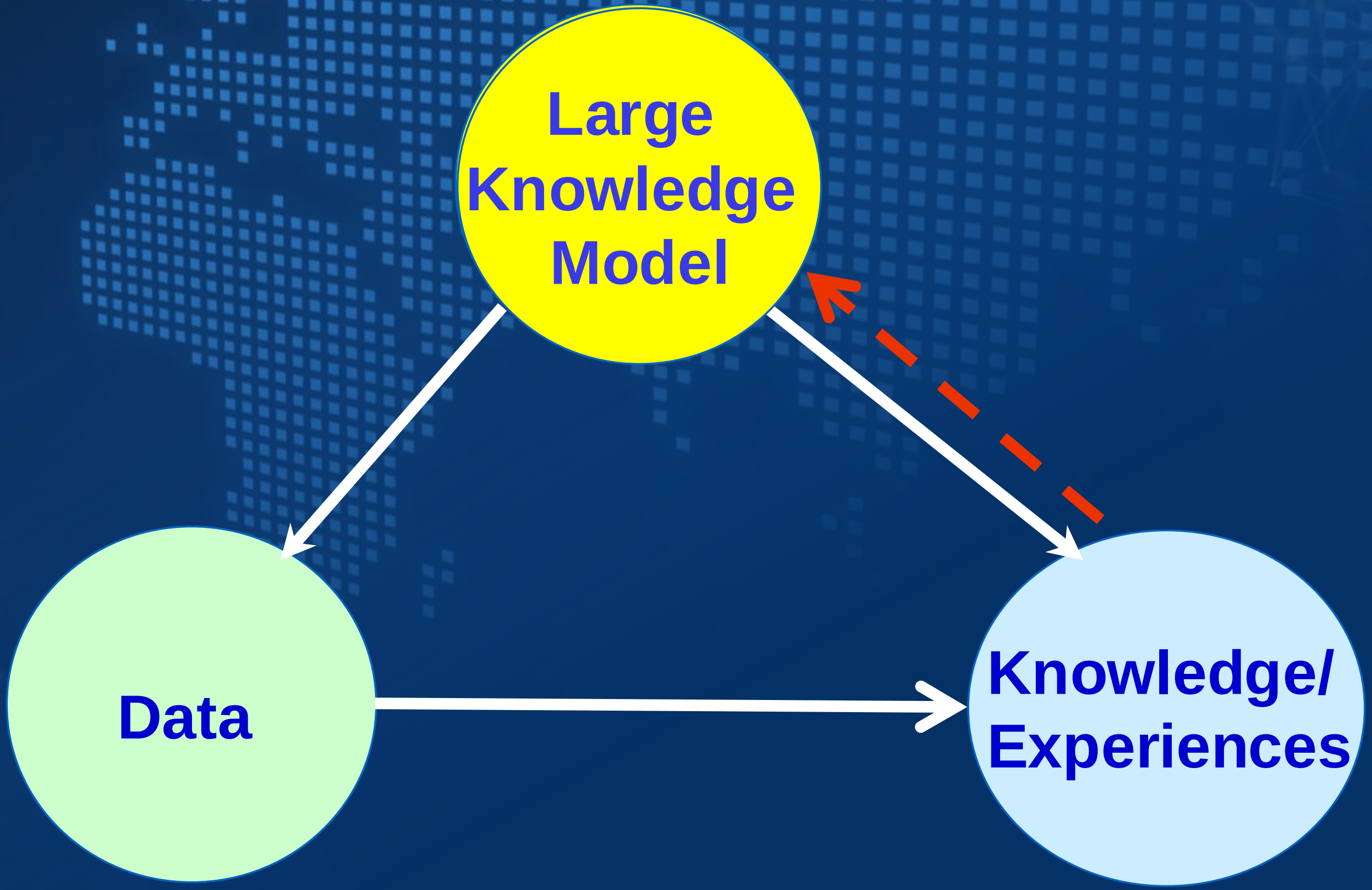


Foxconn World Economic Forum (WEF) Lighthouse Factory Award



Domain, Data, and Large Knowledge Model



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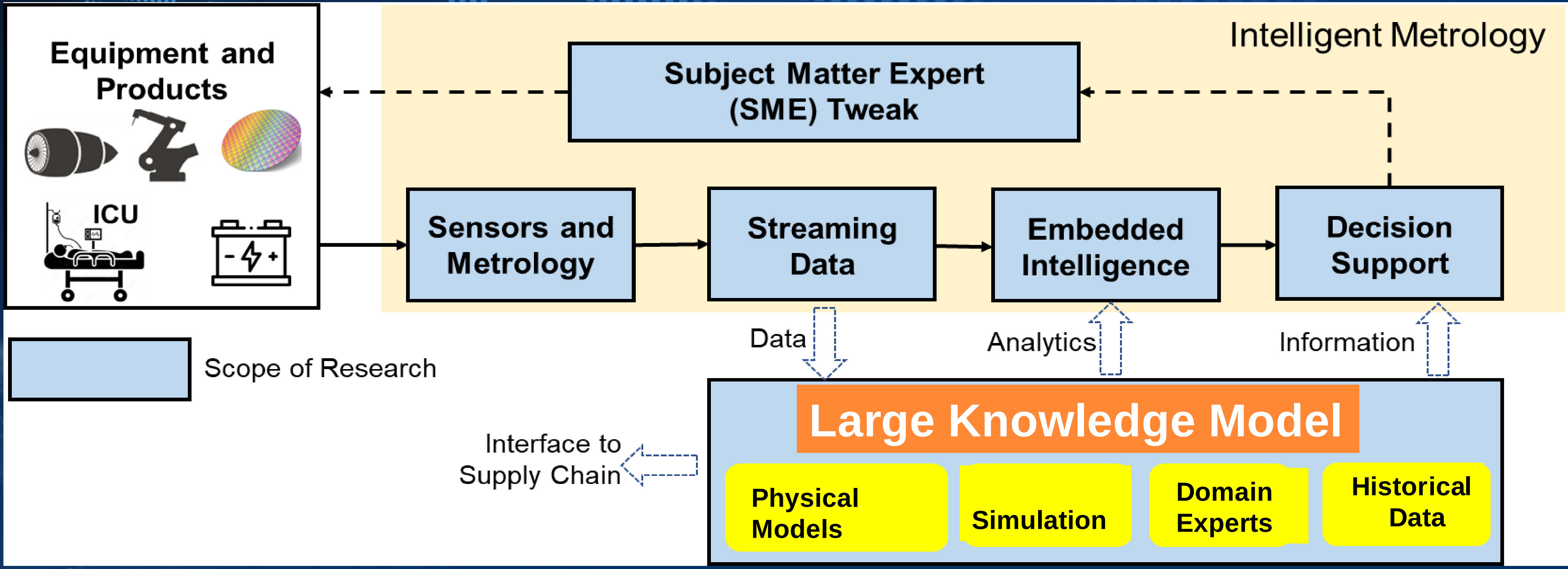
Industrial Large Knowledge Model for Data-Rich Complex Industrial Systems



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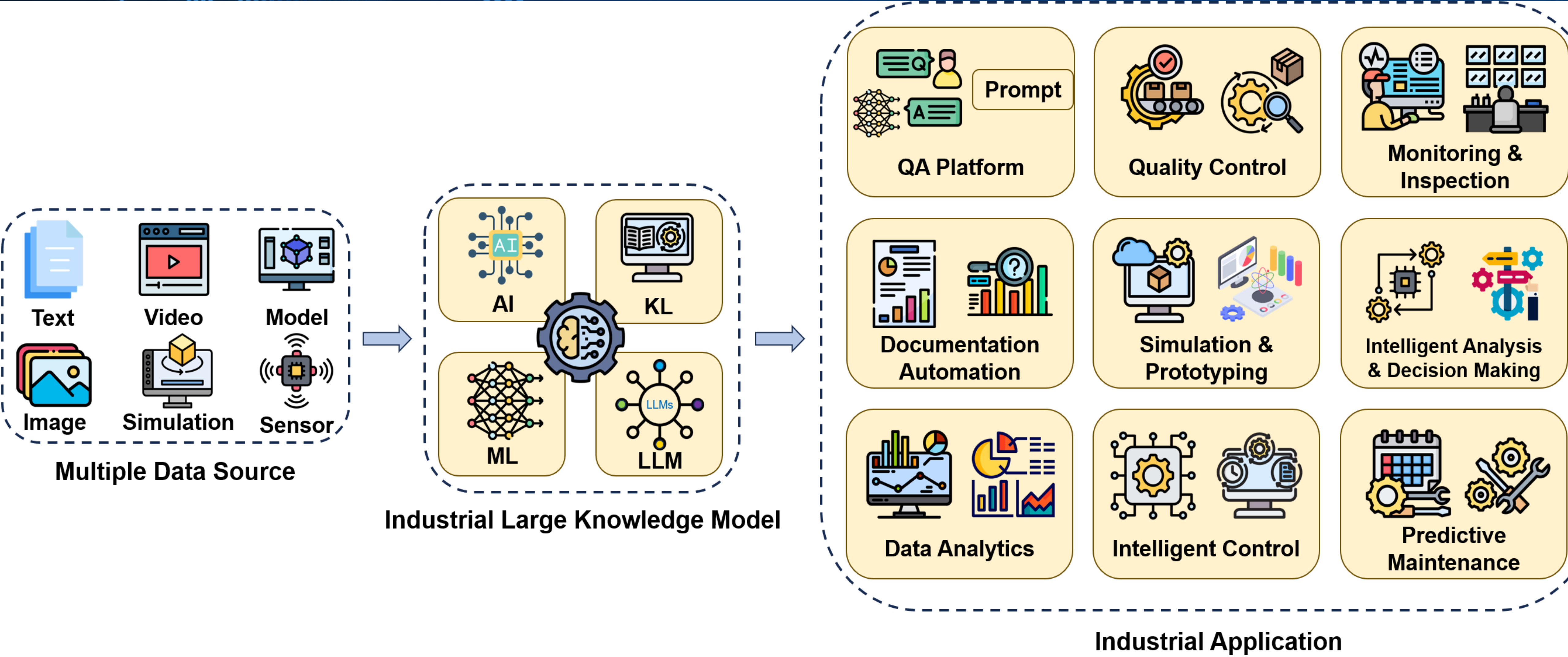
Industrial Generative AI (IGAI) – Industrial Large (Domain) Knowledge Model



Jay Lee, A Unified Industrial Large Knowledge Model Framework in Smart Manufacturing, Dec. 2023
https://arxiv.org/pdf/2312.14428.pdf

Large Language Models (LLMs) vs. Large Knowledge Models (LKMs)

- **Large Language Model (LLMs):**

  LLMs like ChatGPT, are trained on vast datasets of text. They excel in understanding and generating human language, making them adept at tasks like natural language processing, conversation, and text generation. However, their knowledge is often general and not specialized.

- **Large Knowledge Model (LKMs):**

  LKMs are designed to process and understand large volumes of domain-specific knowledge (May have different types of data, especially machine sensor data). They are tailored for specific industries or applications, incorporating detailed, expert-level understanding of particular fields.

LLMs vs. LKMs in Industrial AI

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	LLMs	LKMs
Data Handling and Privacy	Potential concerns with data security, as they often require sending data to third-party servers (Like OpenAI) for processing	Offer greater control over data privacy, as they can be hosted within a company's secure environment
Domain-Specific Knowledge	Knowledge is general may lack deep, industry-specific insights	Specialized provide in-depth, technical knowledge relevant to specific industries
Integration and Customization	Need additional resources for integration and customization to fit specific industrial requirements	Easily tailored and integrated into existing systems, aligning closely with industry-specific needs
Scalability and Maintenance	Highly scalable but necessitates external updates and maintenance	Scalability and updates are managed internally, offering more control by the company but requiring dedicated resources
Real-Time Decision Making	Limited in handling real-time, complex industrial decisions due to their generic training	Better suited for real-time decision-making in industrial settings, leveraging specific industry data

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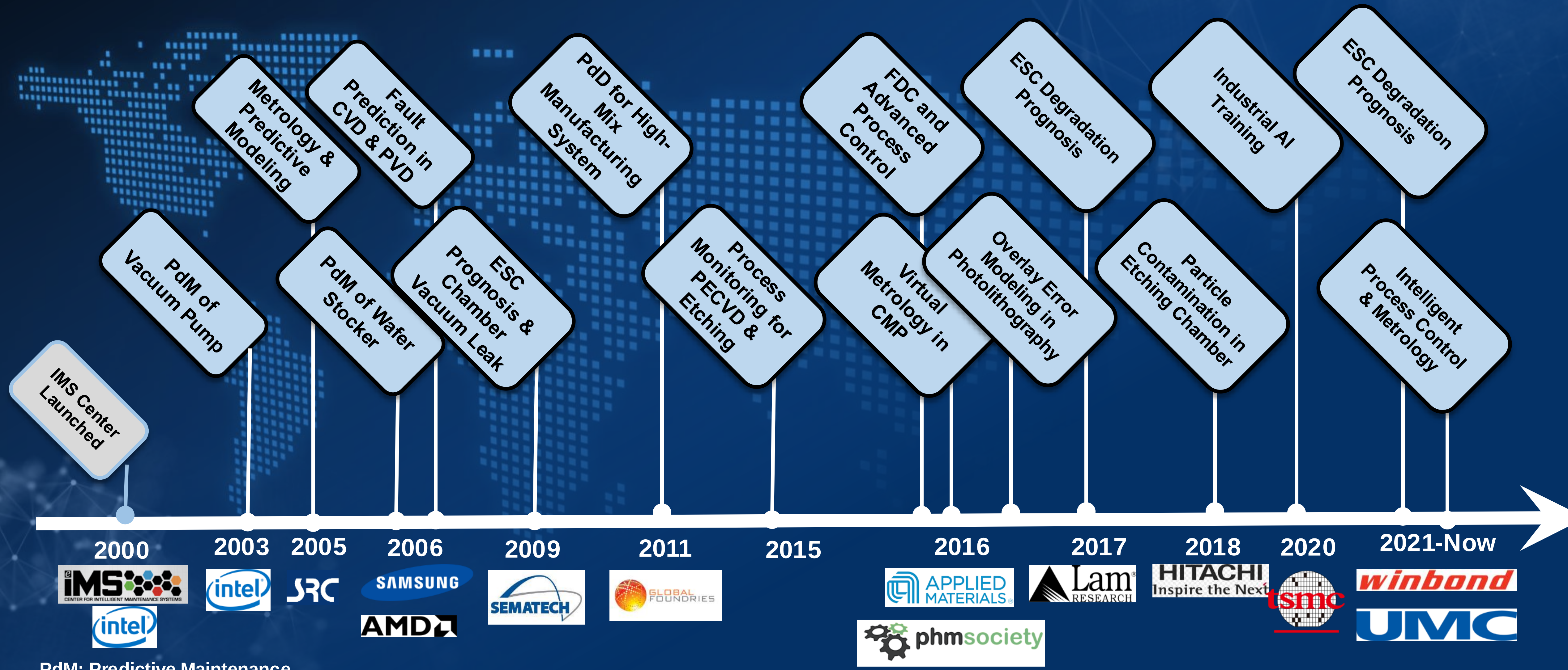
2. Trends of AI and Industrial AI Systems
3. **Some Examples**
4. Training of New Breed of Industrial AI Engineers

History of Our Semiconductor Research



PdM: Predictive Maintenance
ESC: Electrostatic Chuck
PECVD: Plasma Enhanced Chemical Vapor Deposition
CMP: Chemical Mechanical Polishing
FDC: Fault Detection & Classification
PVD: Physical Vapor Deposition

Chamber Difference Quantification using Traditional PCA

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Goal:

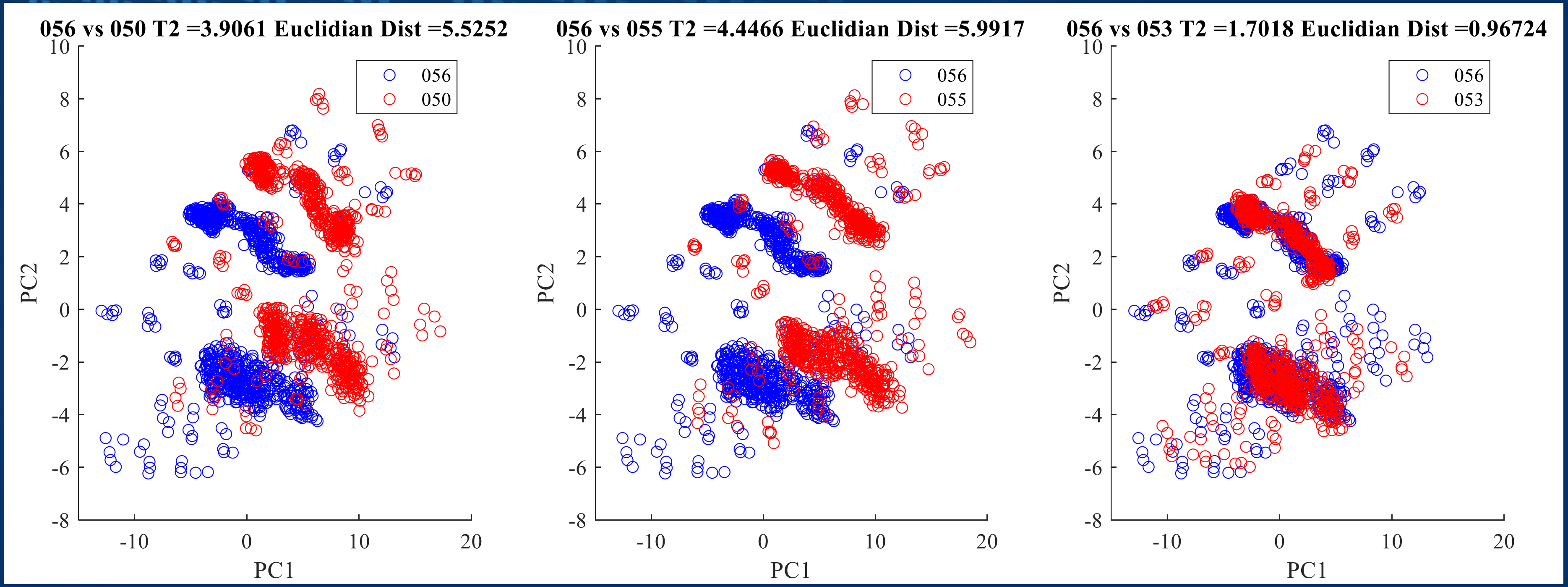
To compare the difference and measure the distance between different machines based on the machine fingerprints (the PCs of IE features under different machine offset settings or DG configurations).

Steps:

1. Extract statistic features of sensors
2. Conduct sensitivity analysis and select features
3. Perform PCA on selected feature matrix of all 870 experiments (first 5 PCs are selected)
4. Calculate averaged T^2 and Euclidian distance as discrepancy measurement
5. Visualize PC of different machines

Result:

Machine 1 (056) is compared with 2 055),3 (055),and 4 (053)



Data Centric Metrology for Semiconductor Manufacturing

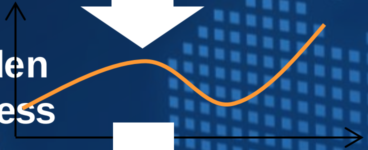
Different Machine

Process Discrepancy

Product Yield Variation

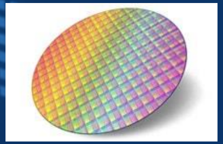
Golden Machine

Target Machine

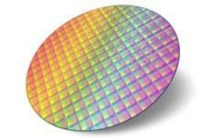


Golden Process

Target Process



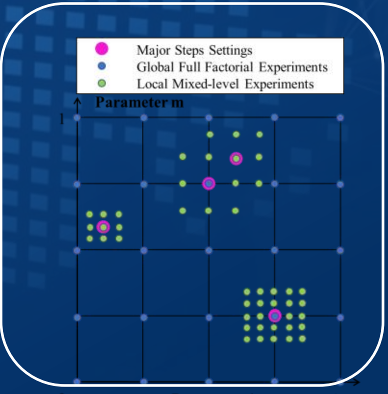
Golden Wafer Product



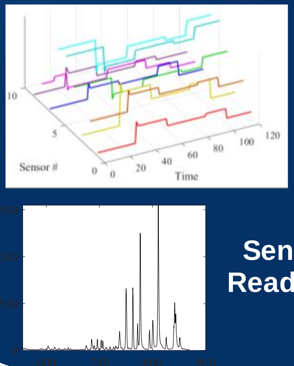
Target Wafer Product

A systematic process-data-driven approach which caliberates the target machine input parameters to compensate machine responses discrepancy from the golden machine.

DOE



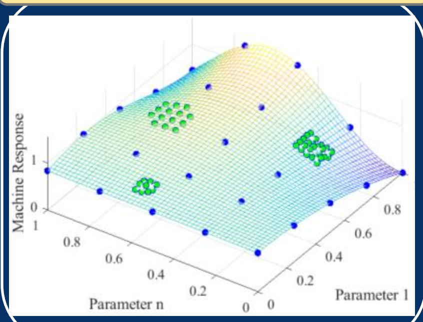
Process Monitoring



Sensor Readings

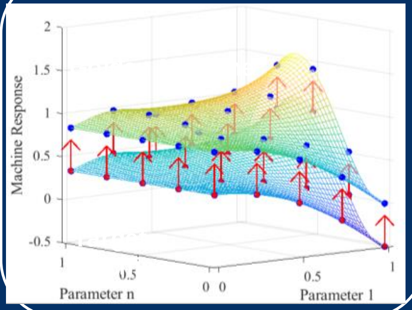
OES

Data-driven Modeling



Build Models for Process

Machine Calibration



Compensate Parameter Offset

- Chamber matching is the common practice to increase production consistency and yield by controlling the machine process based on feedback from product metrology.
- Machine calibration is the common practice to adjust machines to have identical performance by assigning global offsets on machine settings.
- Chamber matching and machine calibration could significantly improve production yield of the etching process.

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Current NIST Award
Digital Twin - Enabled Yield Enhancement Methodology for Semiconductor Manufacturing by Using Stream-of-Quality Analytics

Overall Objectives: This proposal aims to model the complex process-to-process (i.e., CMP-Litho-Etch) interaction and investigate its impact on product yield (i.e., uniformity, CD, e-test) by developing novel SoQ analytics. The established SoQ will be further utilized to perform root-cause analysis and inter-process control for yield enhancement.

Research Tasks	AMAT	UC & UMD
	• Simulation/Production/Yield Data • Fab-Wide Digital Twin Integration Framework Design • Semiconductor Domain Experts	• Stream of Quality (SoQ) Analytics • SoQ Based Root Cause Analysis • Model validation and enahncement

Expected Deliverables:
1) Novel SoQ analytics that can model complex process-to-process interaction in semiconductor manufacturing
2) Root Cause Identification based on the SoQ analytics
3) Knowledge graph (data-driven ontology) for root-cause analysis (Optional)
4) Novel digital twin framework design for fab-wide VM model integration and management
5) New public data for the entire research community

Prognostics and Health Management for Commercial Jet Engine Fleet

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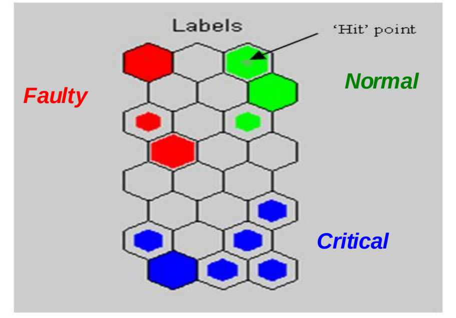
Feature Extraction and Signal Processing

Detect variations and jumps in parameters such as Exhaust Gas Temperature (EGT), spool rotational speed, pressure, etc.

Health Assessment using Self Organizing Map (SOM)



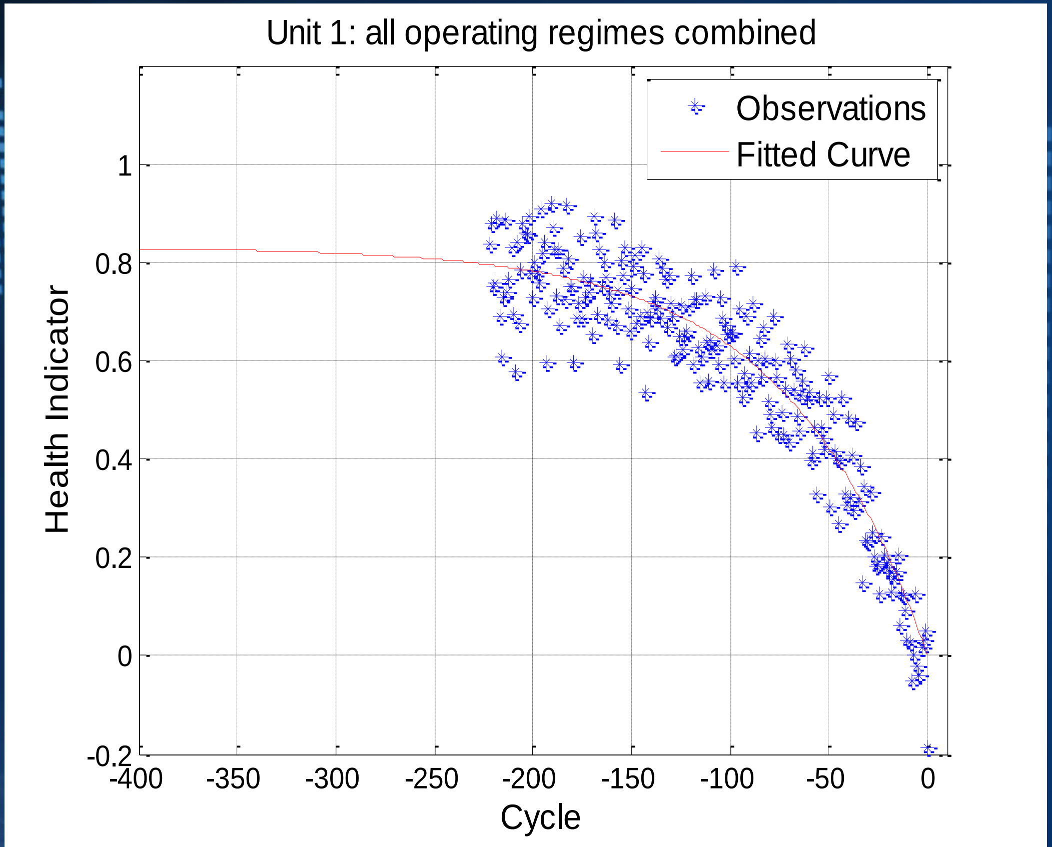
Phase I Deliverables

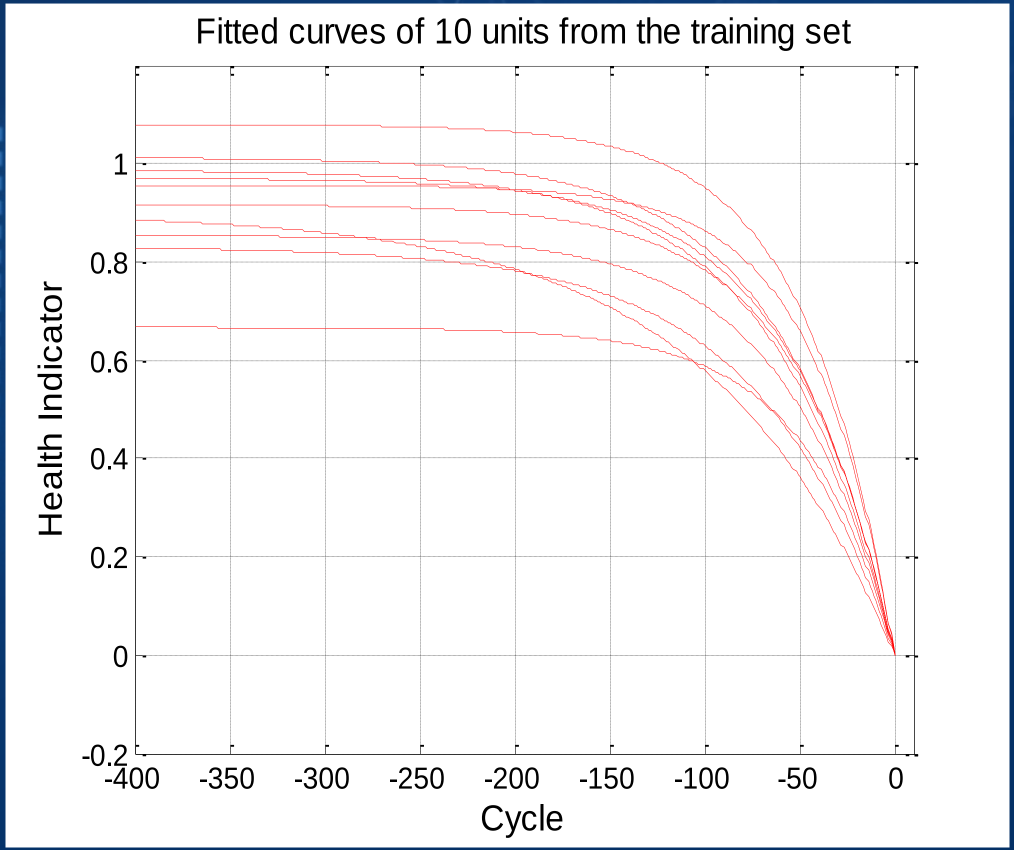
- Improved anomaly detection
- Precision classification of anomalies
- Earlier fault prediction

Value

Deliver Competitive Value to Airlines and Customers

Library of Degradation Patterns

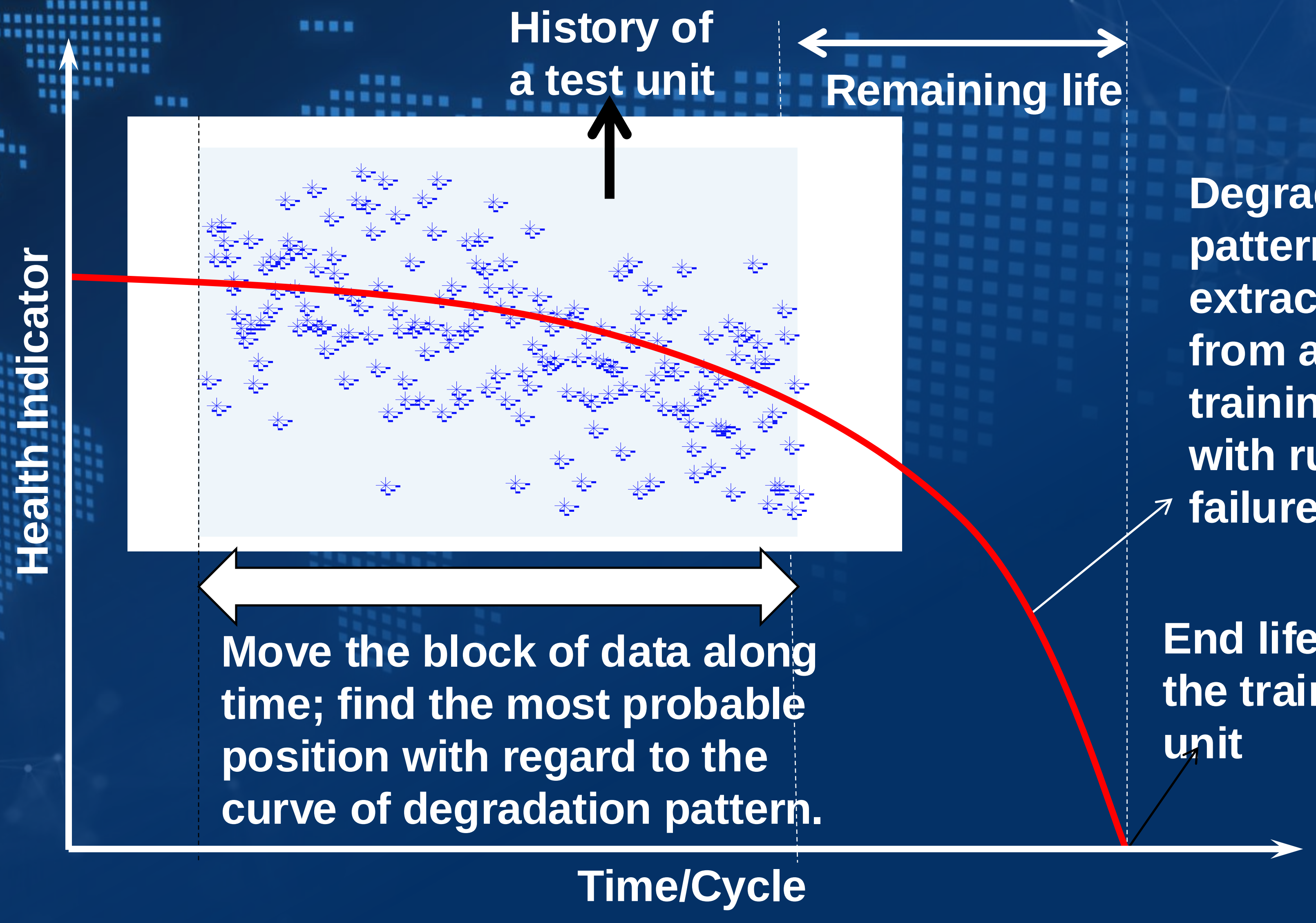




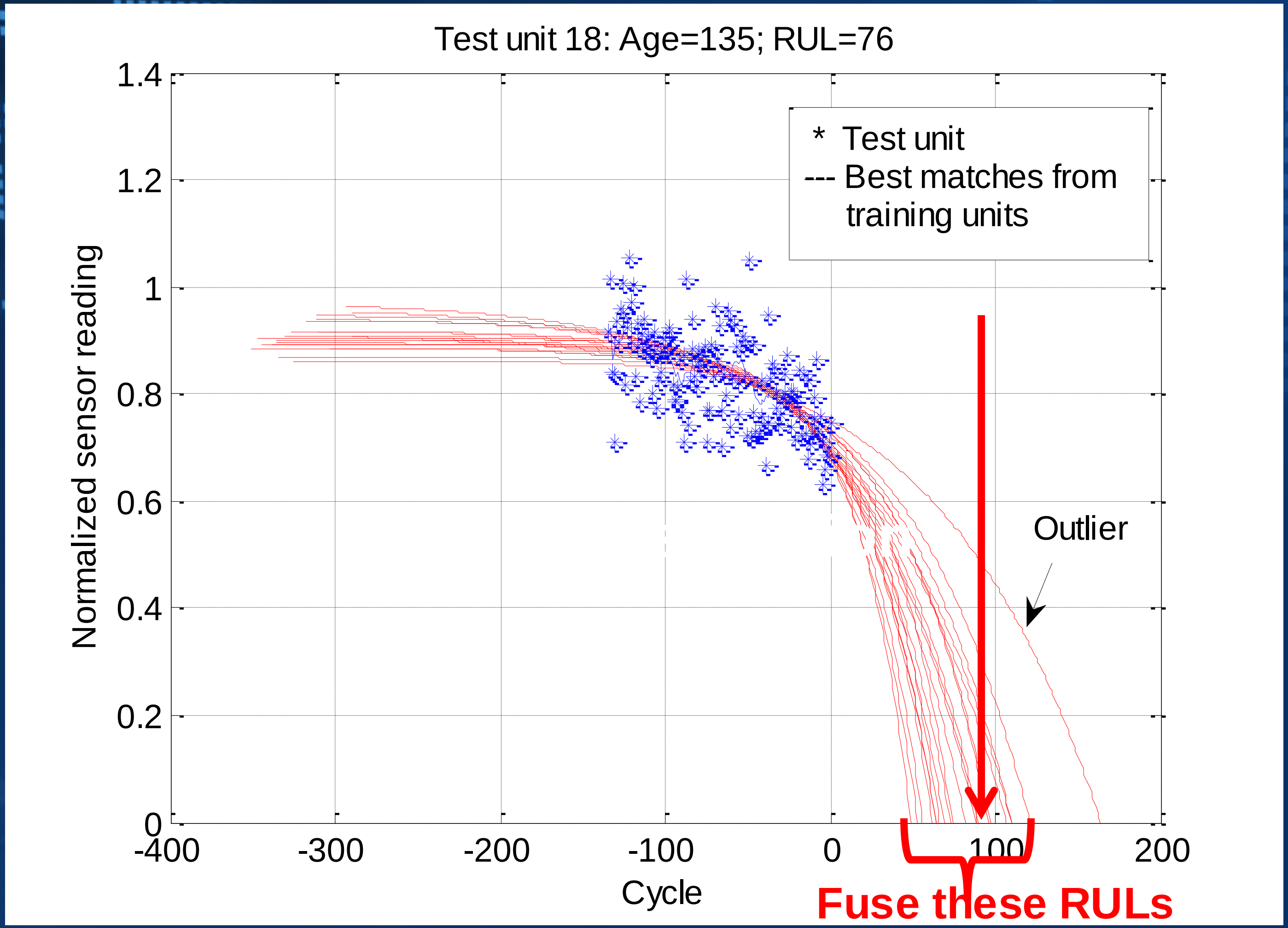
- **Fit an exponential degradation curve for each training unit**
- **Create a library of degradation patterns/models**

Ref: NASA PHM Data Challenge, 2008

Similarity Methodology (Fleet-Based System)



Remaining Useful Life (RUL) Fusion



Candidates: Rank by distance score; cut at 25% increase of the smallest score

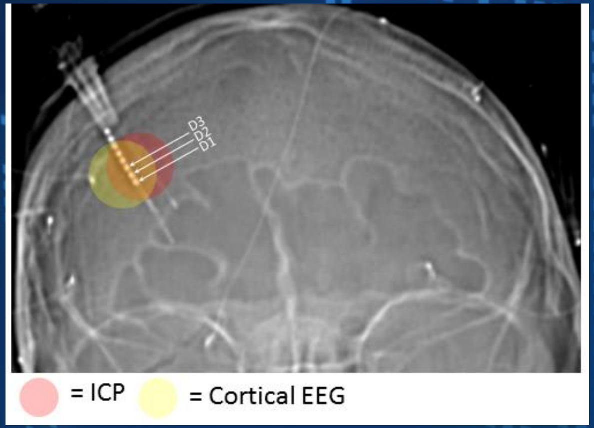
Remove outliers

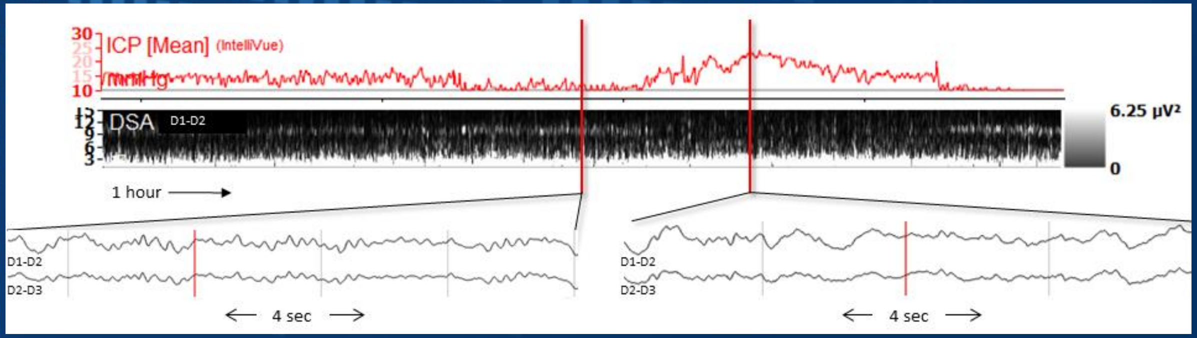
AI-Augmented Analytics for ICU

Traumatic Brain Injury (TBI)

Objectives: To determine whether ICP elevations are associated with the presence of ischemic changes in the Electroencephalography (EEG) recorded at the cortex and on the scalp

Dataset: 104 (Traumatic Brain Injury)TBI patients with ICP and EEG waveform data in unsynchronized 120Hz(ICP) and 256Hz(EEG)





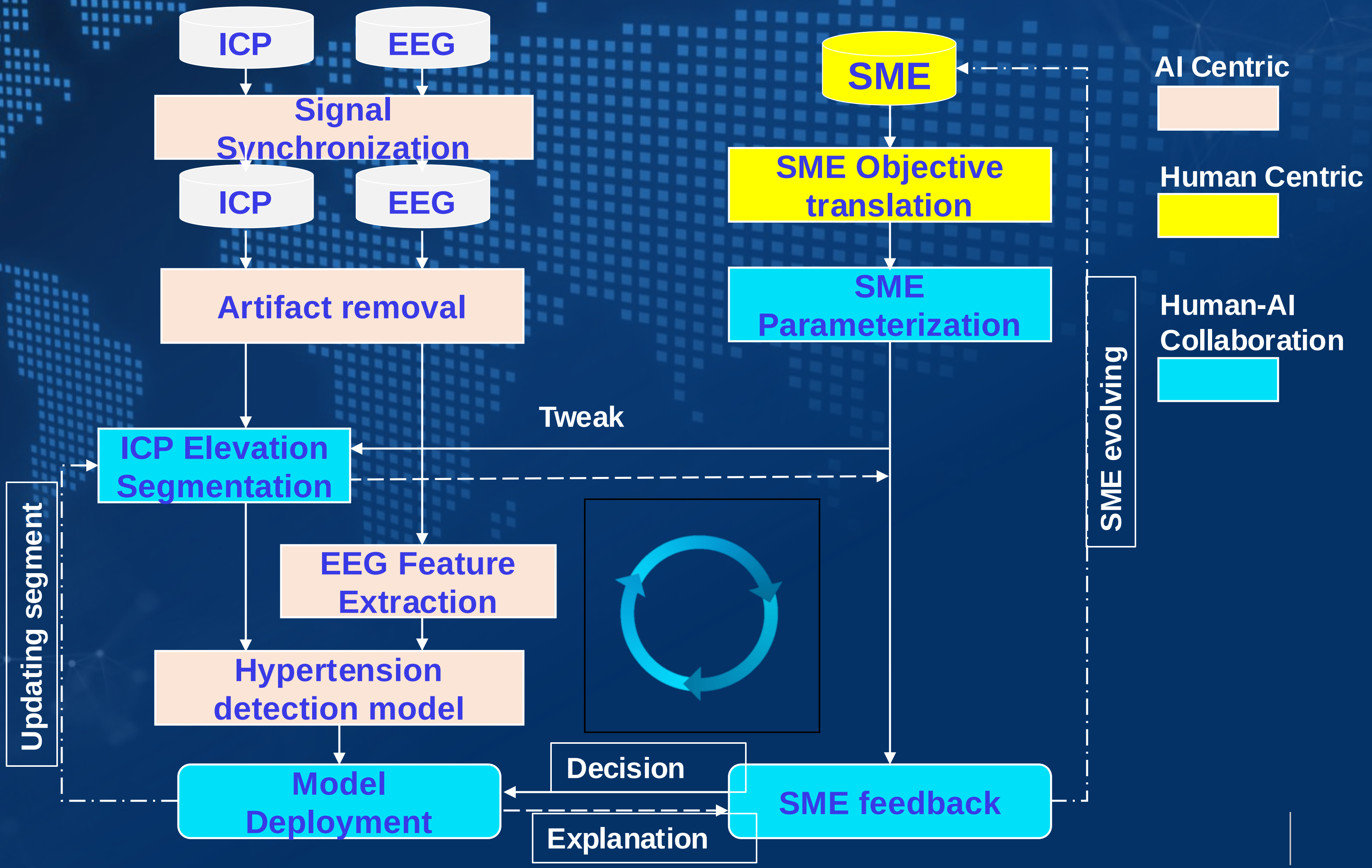
Mixture of delta and high theta frequencies are seen

attenuation of the faster frequencies and enhanced higher amplitude delta frequency

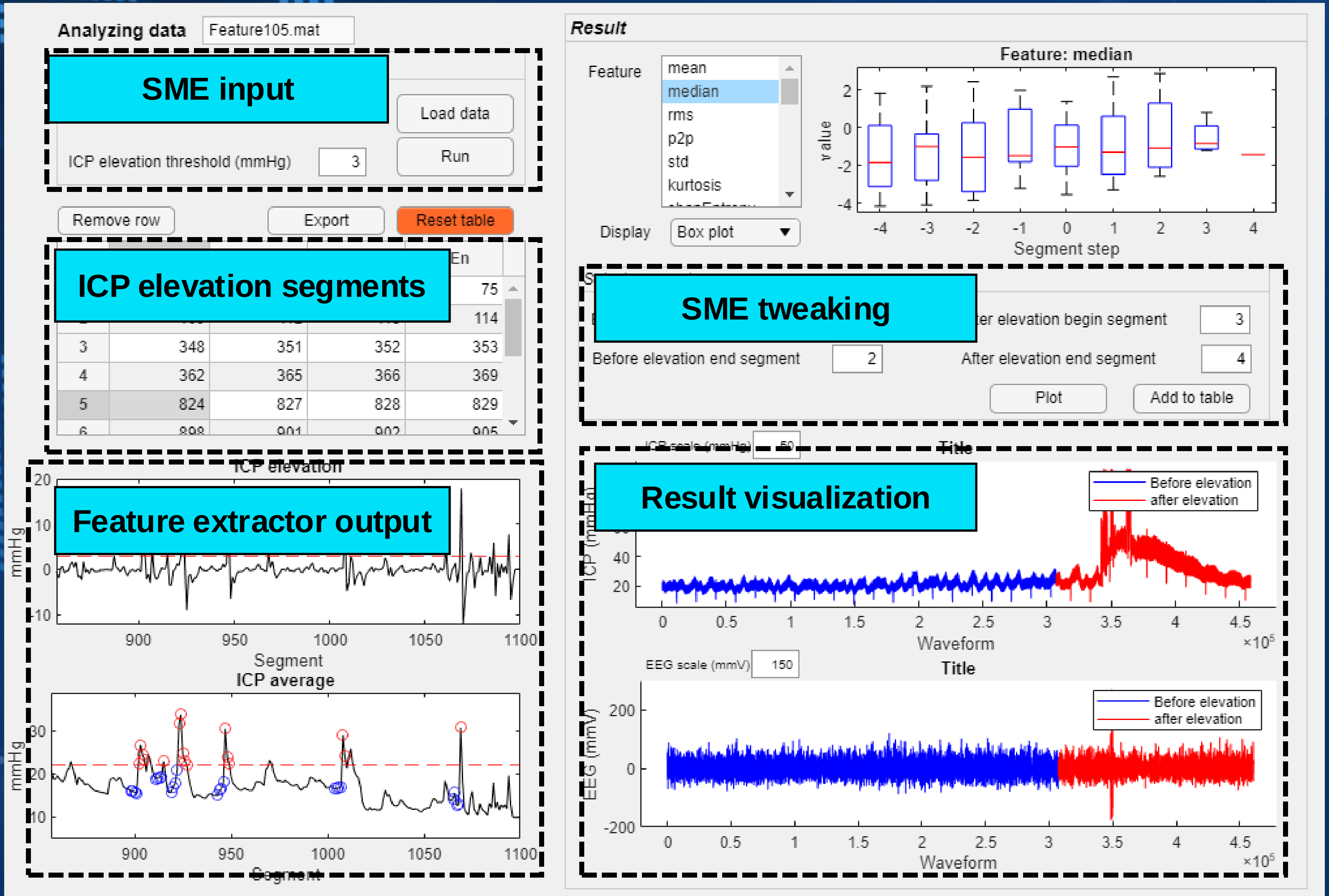
Challenges:

- **Pattern changes on EEG along with ICP elevation is observable by Human Expert but hard to auto-detect by machine learning model due to high variances and unexpected artifact/noises**
- **The relationship between ischemic changes EEG and ICP elevation is intermittent and inconsistent**
- **Patterns among different patients are different.**

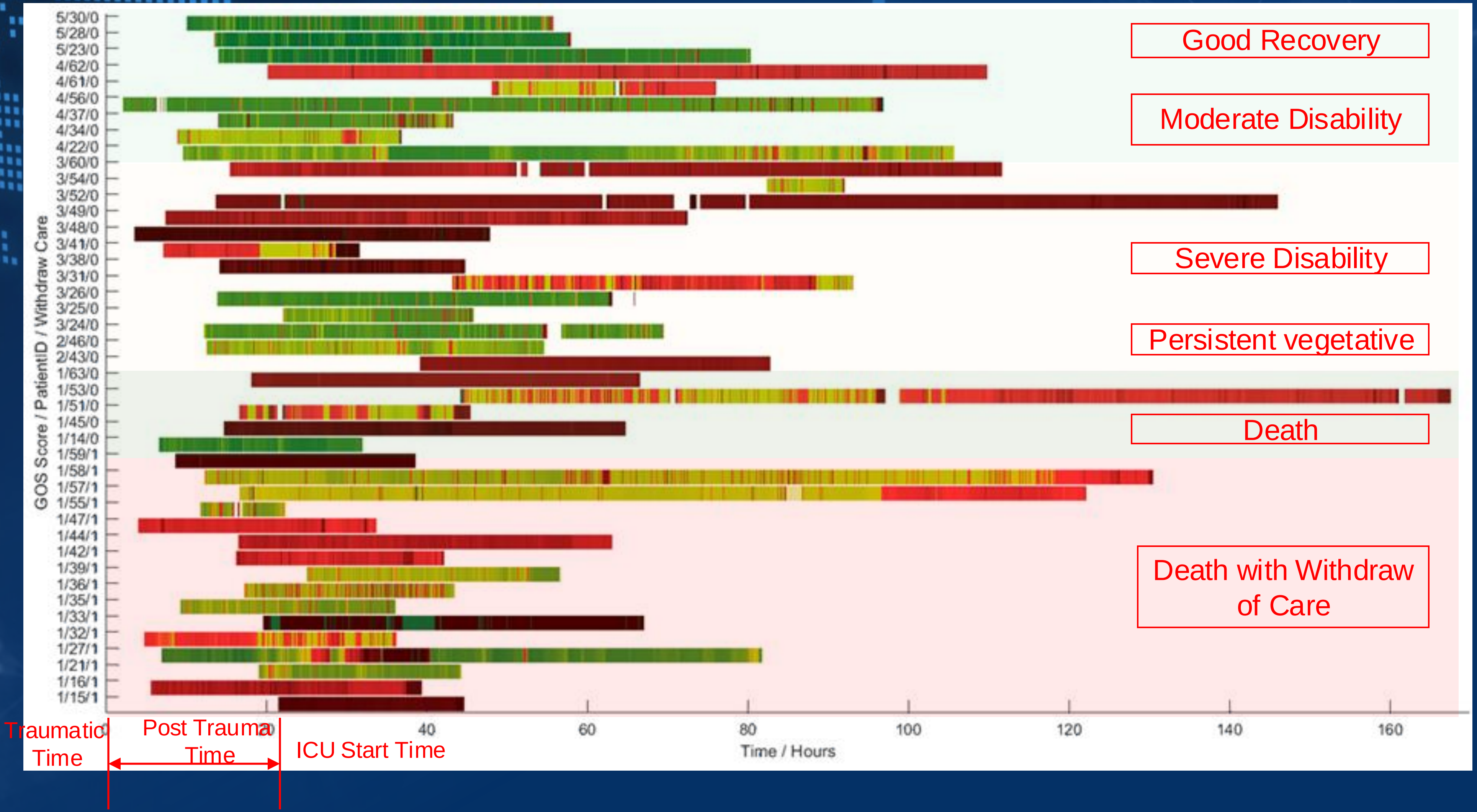
Domain-Augmented Human-AI Integration



ICP Elevation Segmentation- Human AI interaction UI



Health Assessment Results Summary of 43 ICU Patients



REVIEW ARTICLE

Front. Neurol., 28 August 2020 | https://doi.org/10.3389/fneur.2020.00959

Intracranial Pressure Monitoring Signals After Traumatic Brain Injury: A Narrative Overview and Conceptual Data Science Framework

Honghao Dai[1,2], Xiaodong Jia[1,2], Laura Pahren[1,2], Jay Lee[1,2] and Brandon Foreman[3*]

Outline

1. Trends of Data Centric Systems and Unmet Needs

2. Trends of AI and Industrial AI Systems

3. Some Examples

4. Training of New Breed of Industrial AI Engineers

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SPECIAL COMPETITIVE STUDIES PROJECT

Memo to the President on U.S. Leadership in Advanced Manufacturing

2-2-2 AND NATSEC TECH BY SCSP
JUN 18

Key convergence technologies that are definitive for advanced manufacturing competitiveness include:

- **Industrial AI.** Thanks to its early lead in deploying generative AI, the United States appears well-positioned for AI deployment in the physical world. At present, much of the progress has been self-organizing: America is home to a variety of innovative startups and Fortune 500 companies that are either building or deploying industrial AI solutions in innovative ways. Yet, the United States is being substantially out-organized on a national level. This is especially reflected from a data perspective because the United States lacks large-scale national programs that encourage sharing of critical data sets needed to train industrial AI models across the private and public sectors.

2. **Organize: Close Gaps in the Manufacturing Innovation Ecosystem.** Facilitate a coordination and strengthen key federal m programs.

- *Scale and Reimagine the Manufacturing* The United States should redouble its support for its core manufacturing technology innovation programs, bringing resourcing for manufacturers more in line wit spending by other industrialized nations.
- *Create a Data Foundry Network for Industrial AI.* A networked public-private partnership could serve as a trusted hub for companies to share necessary datasets to train sophisticated industrial AI models.
- *Establish a White House Office of Manufacturing.* A White House-level office would enhance policy coordination and bring urgency to the advanced manufacturing agenda.

U.S. Needs to Lead and Excel Industrial AI with Speed and Scale.

Current Challenges of AI Talents

1. Hard to Find

2. Can’t Afford

3. Hard to Keep

4P Approach for AI Learning Enterprise

Level 4 Professional-based Learning

Level 3 Project-Based Learning

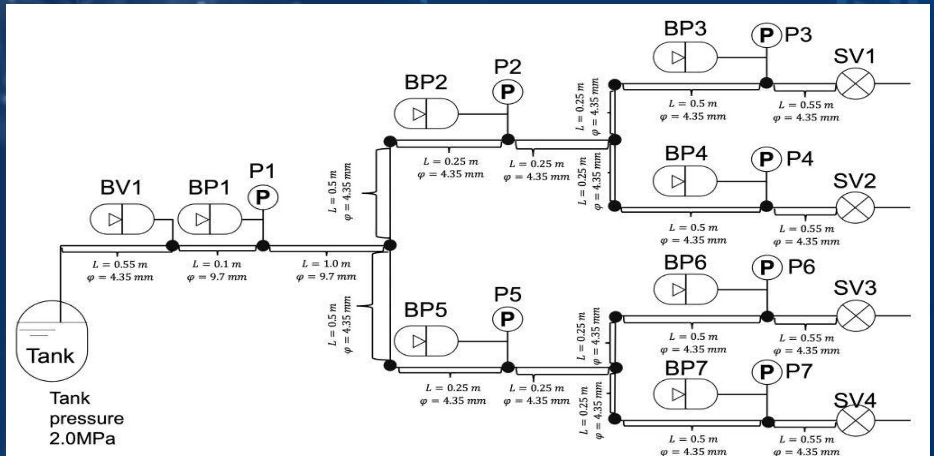
Level 2 Practice-based Learning

Level 1 Principle-Based Learning

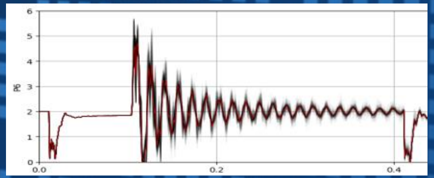
Ref: Jay Lee, Industrial AI Book, Springer, 2020

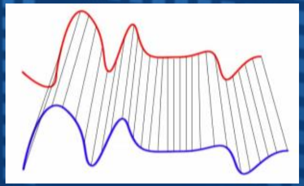
PHM AP Data Challenge 2023

9/11-14, 2023

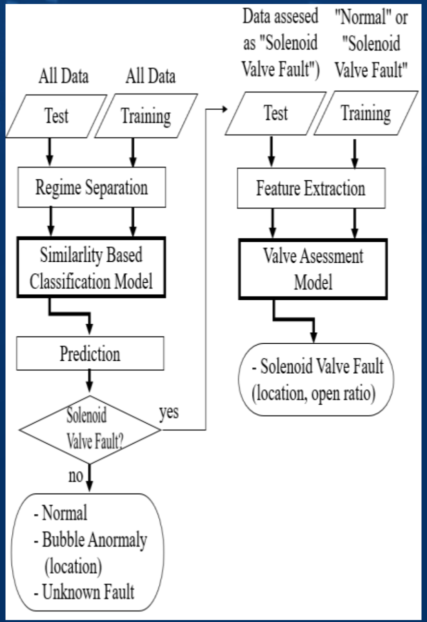


Approach





Dynamic Time Warping



Final Evaluation Result

Team	Score
LB	100.00%
vibrationsensor	99.94%
SK	99.86%
Team Tsubasa	99.05%
KYU	97.26%
Kalle Anka PHM	93.77%
LDM	93.08%
MIDAS Wolverines	92.98%
Team HSNR	82.48%
propulsion	82.22%
JANUS	82.02%
CUMT	80.48%
DataCrunchers	79.33%
HEU-Zheng	76.87%
Bubu	76.44%
Jiaxiang	76.05%
maedatakafumi	74.40%
P-DX AI	73.39%
Young	72.15%
tcs research	71.90%
MORI	71.09%
e-kagaku	61.49%
YUFC	60.48%
Escape	60.12%
Industrial AI	56.13%

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Takanobu MINAMI

KOMATSU

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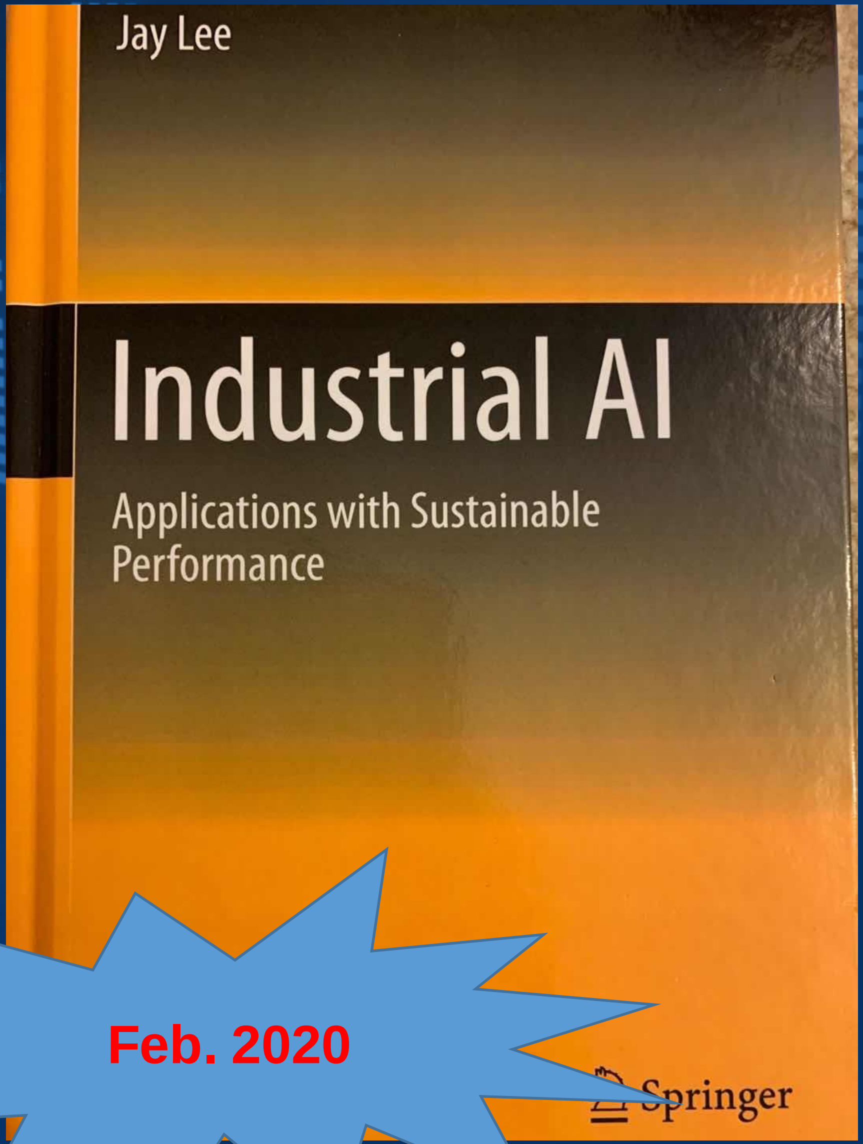
“Industrial AI” Book



Feb. 2020

Thank You

More Information See

www.iaicenter.com

Contact: leejay@umd.edu

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