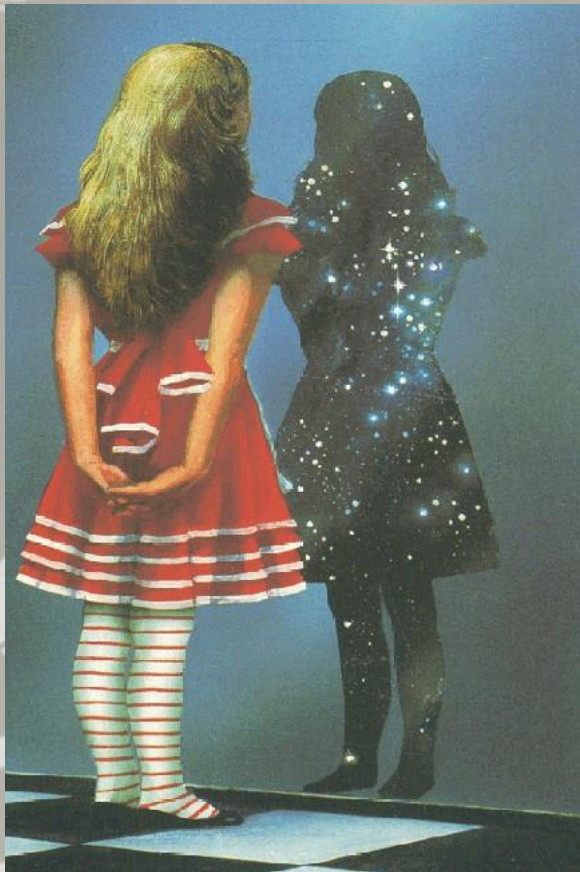


Industrial Artificial Intelligence The Driving Force of manufacturing



Professor Diego Galar
Head of Maintenance &
Reliability, Tecnalia
Lulea *University* of technology

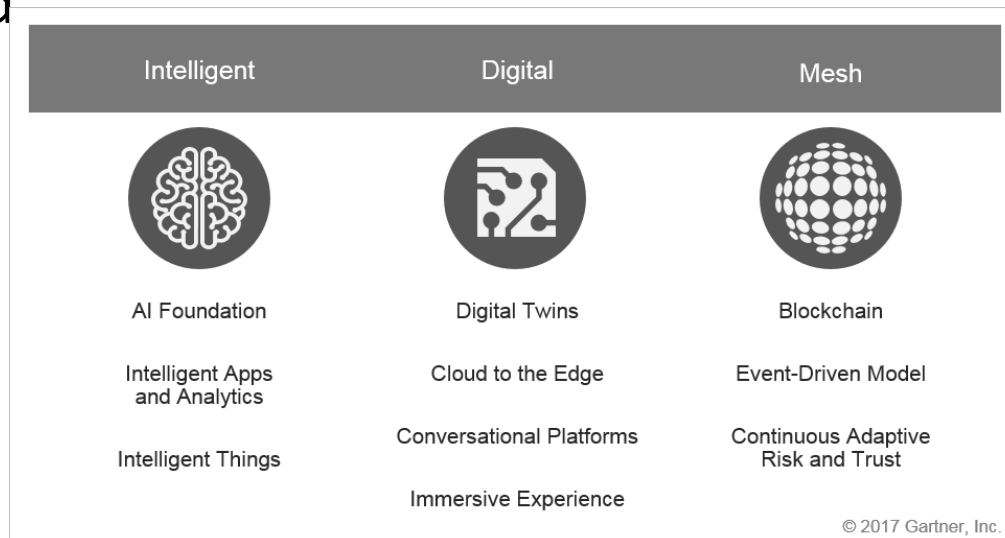
Ongoing industrial evolution

Digitalisation

- Integration of digital technologies into industrial context the **digitization** of everything that can be digitized

Industry 4.0

- Enabling industry to achieve Operational Excellence, through digitalised services



Manufacturing already generates more data than any other sector*

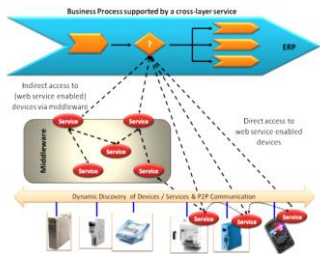


Measurement in Petabytes
1 Discrete manufacturing
constitutes 1072 petabytes;
process manufacturing 740
petabytes

* Source: IDC; McKinsey Global Institute analysis 2010

ICT-enabled Intelligent Manufacturing

- ICT is a key enabler for improving manufacturing systems at three levels:



Smart Factories

- Goal:**
More automation, better control & optimisation of factory processes
- Means:**
Software, lasers & intelligent devices embedded in machines & factory infrastructure

Factory productivity

- Less waste
- Less energy use
- Faster time-to-market
- Better quality

Virtual Factories

- Goal:**
To manage supply chains; to create value by integrating products & services
- Means:**
Software to holistically interconnect & manage distributed factory assets; new business models & value propositions

Supply-chain productivity

- High-value products
- Keep jobs in Europe
- Process transparency
- IPR security
- Lower CO2 footprint

Digital Factories

- Goal:**
To “see” the product before it is produced
- Means:**
Software for the digital representation & test of products & processes prior to their manufacture & use

Design productivity

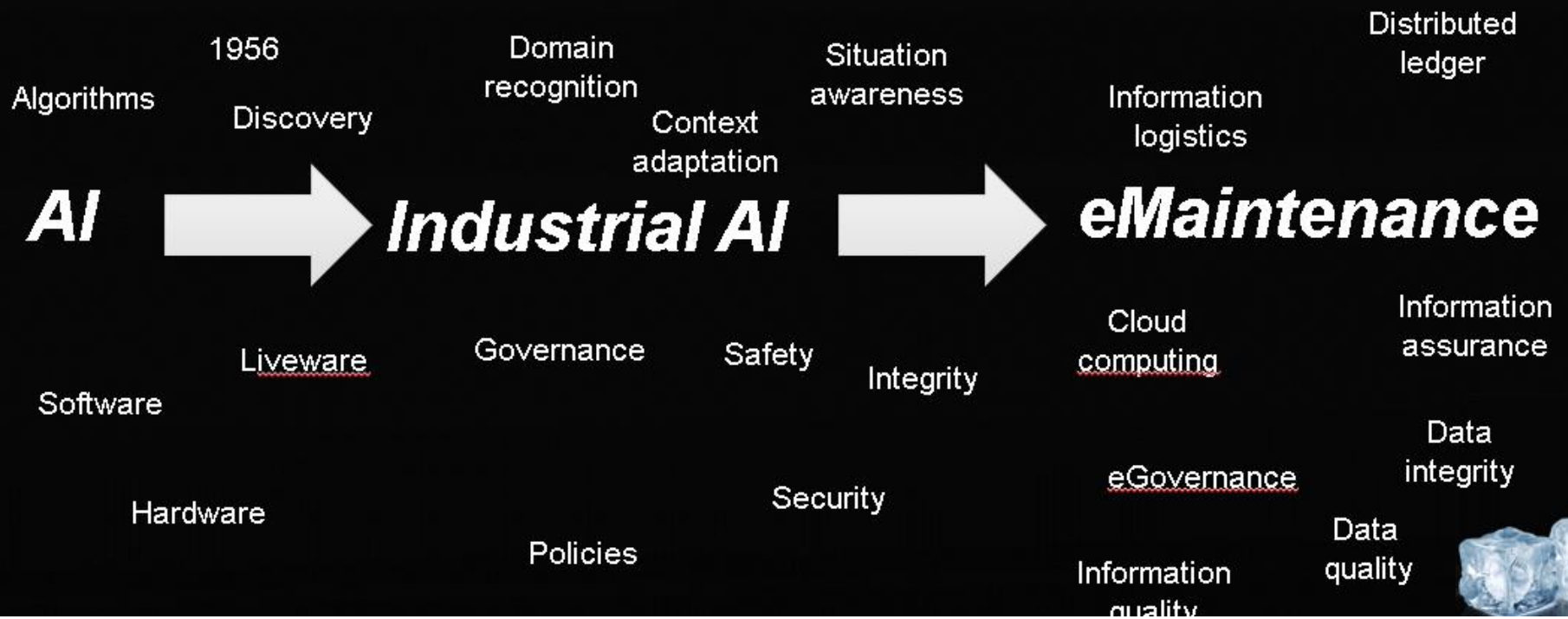
- Reduce design errors
- Better & efficient products
- Less waste + rework
- Faster time-to-market



Industry is going digital

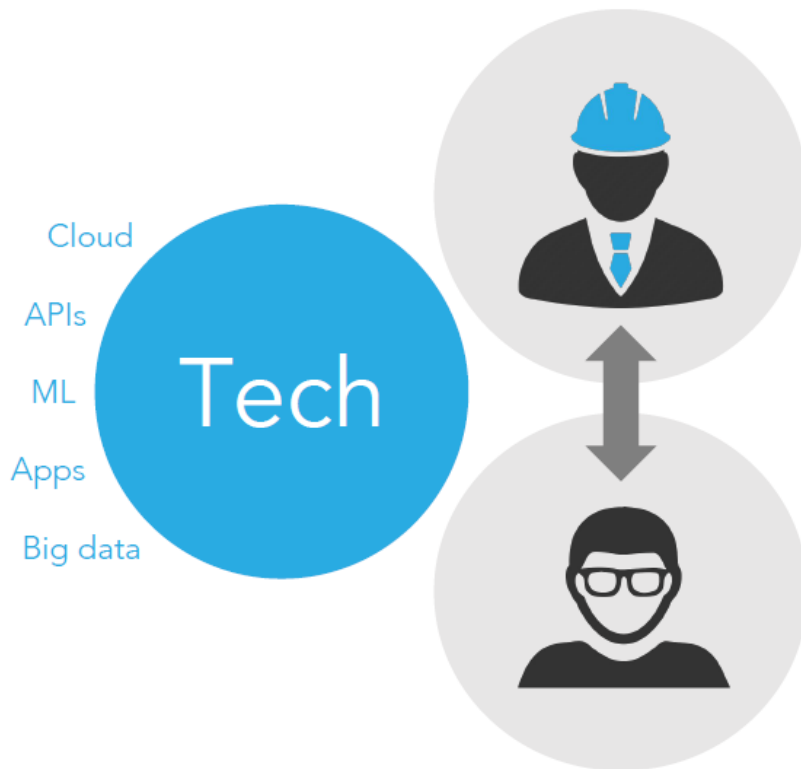


SCIENCE²CONCEPTUALISATION²MATERIALISATION

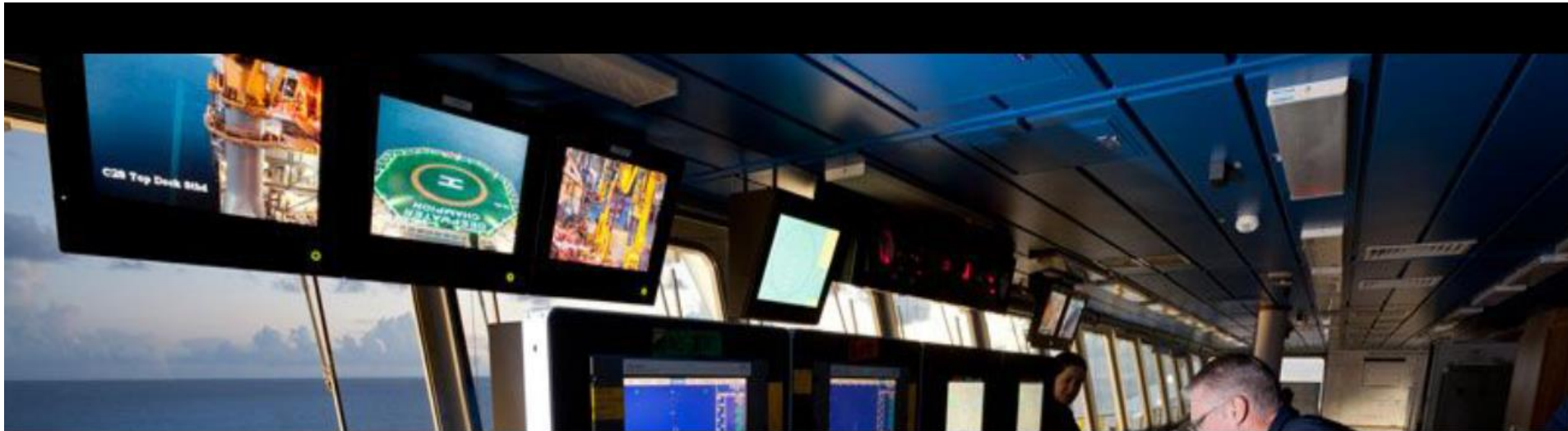


Data science and AI in industry and transport ..the transformation

Digital transformation enables design thinking in data science
and design thinking enables digital transformation



Digitalisation should equip
data scientists and engineers
to cocreate a solution

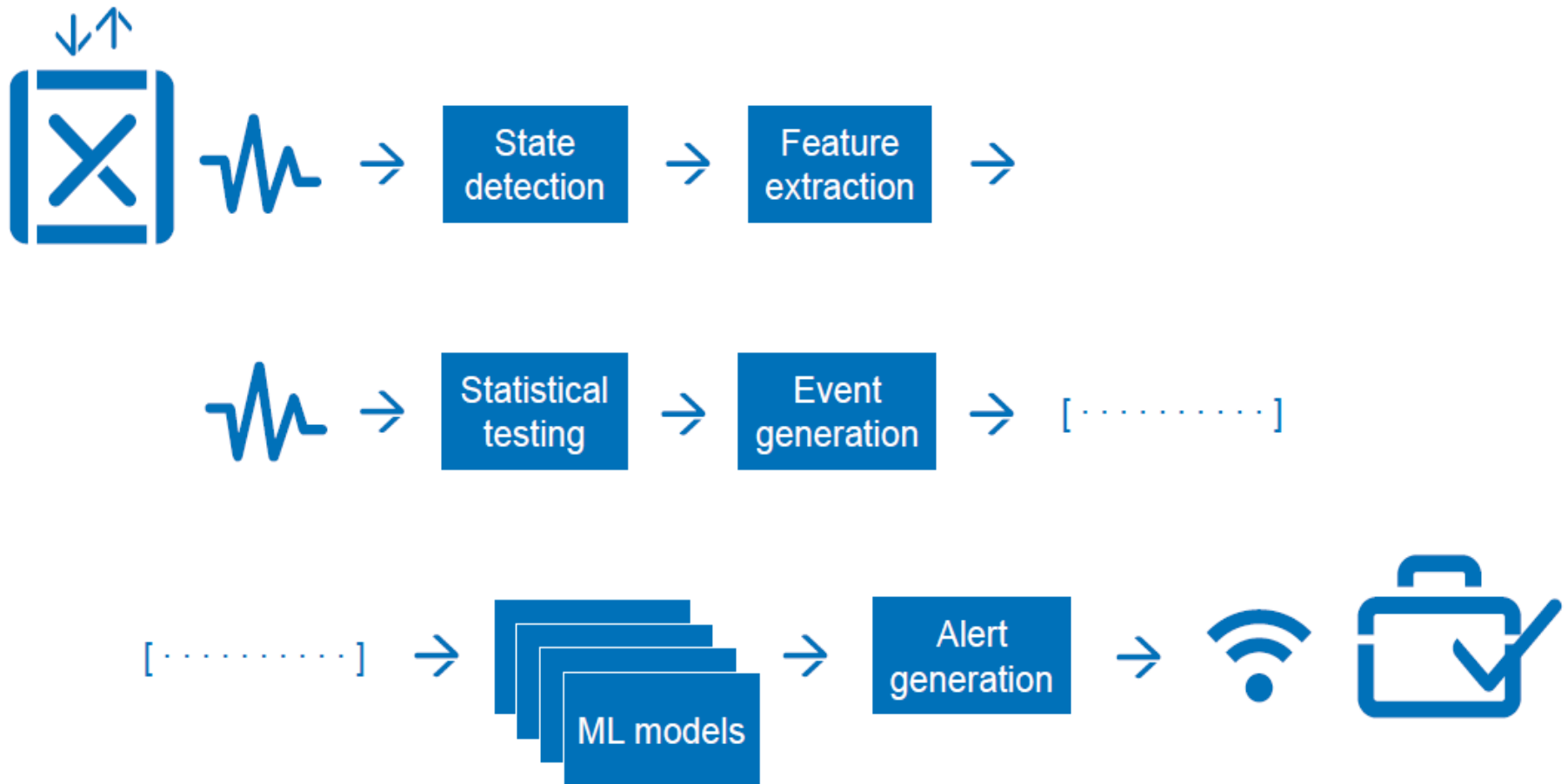


Data science in heavy-asset industries must aim to augment operators' way of working with additional information so that they can prevent unplanned downtime



The traditional way.....

Data refining pipeline



Type of Anomaly

- Point Anomalies
- Contextual Anomalies
- Collective Anomalies

FALSE

FALSE
POSITIVE

NEGATIVE

Black swans and the swan song

Achilles heel of diagnosis and prognosis

Enemies of digitization....



Black Swan Events

- **Rarity**—It is an *outlier*, as it lies outside the realm of regular expectations, because nothing in the past can convincingly point to its possibility.
- **Extreme impact**—It carries an extreme impact.
- **Retrospective (though not prospective) predictability**—In spite of its outlier status, human nature makes us concoct explanations for its occurrence *after* the fact, making it explainable and predictable.



The term "Swan Song" comes from a belief dating back to 3rd century B.C. that the Mute Swan is silent its entire life until it sings one beautiful song right before it dies.



Risk perspective

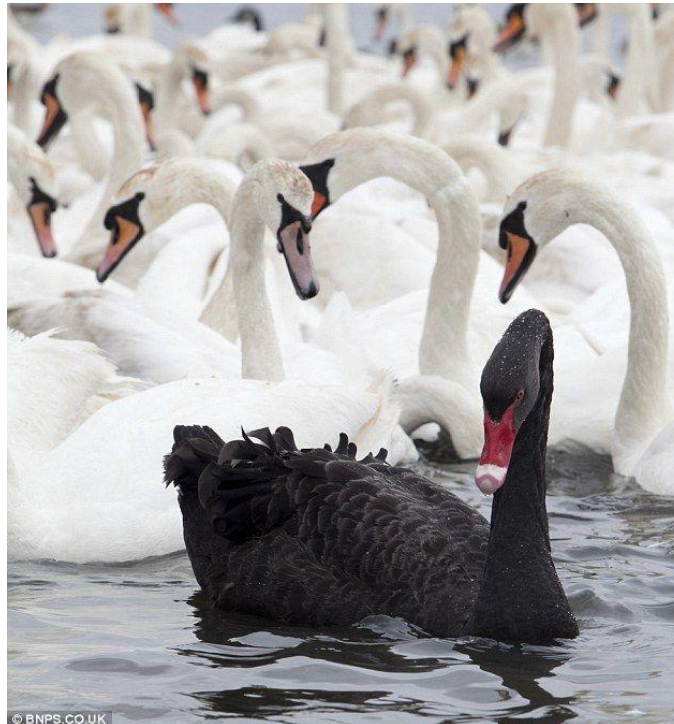
Probability-based
Historical data

+

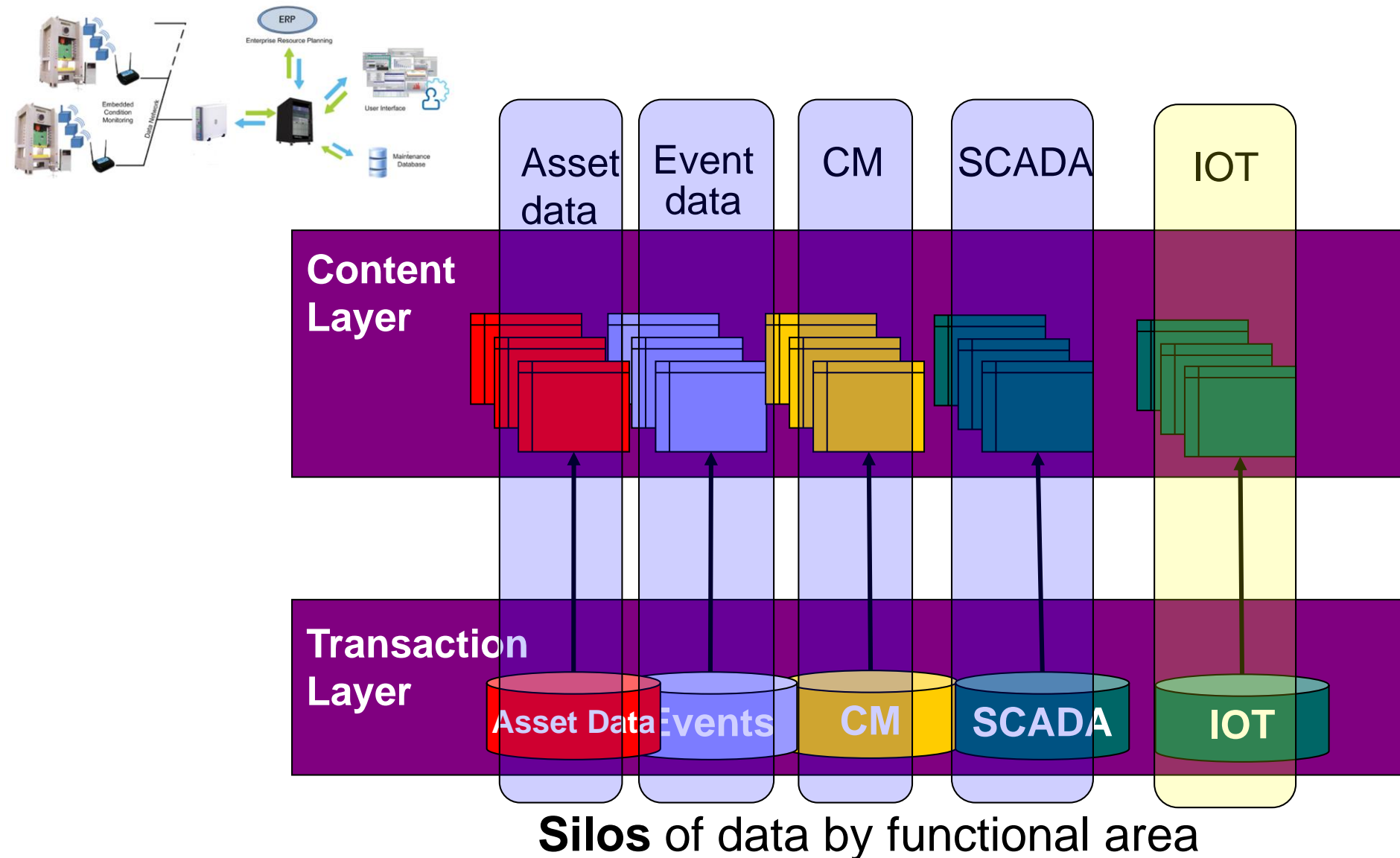
Knowledge
dimension

+

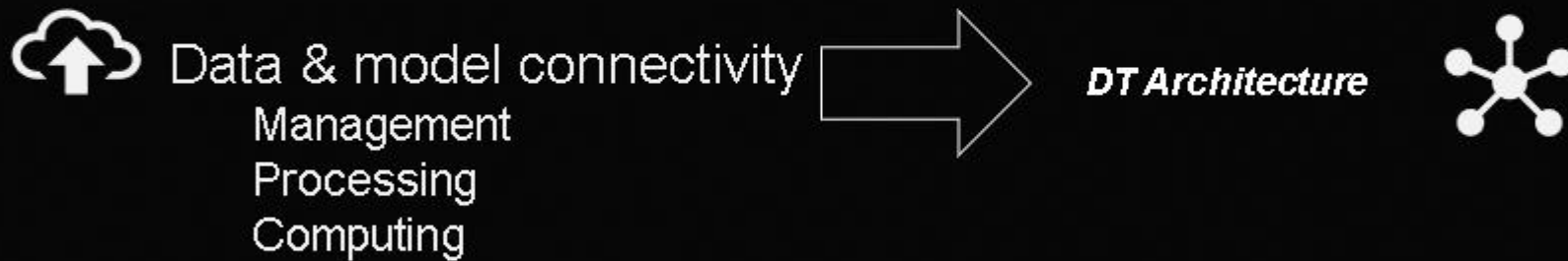
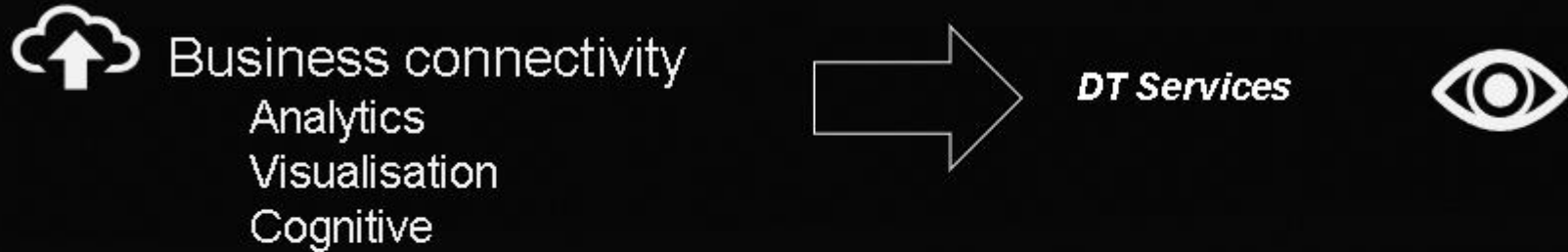
Surprises



Unified data format: What connections are needed?



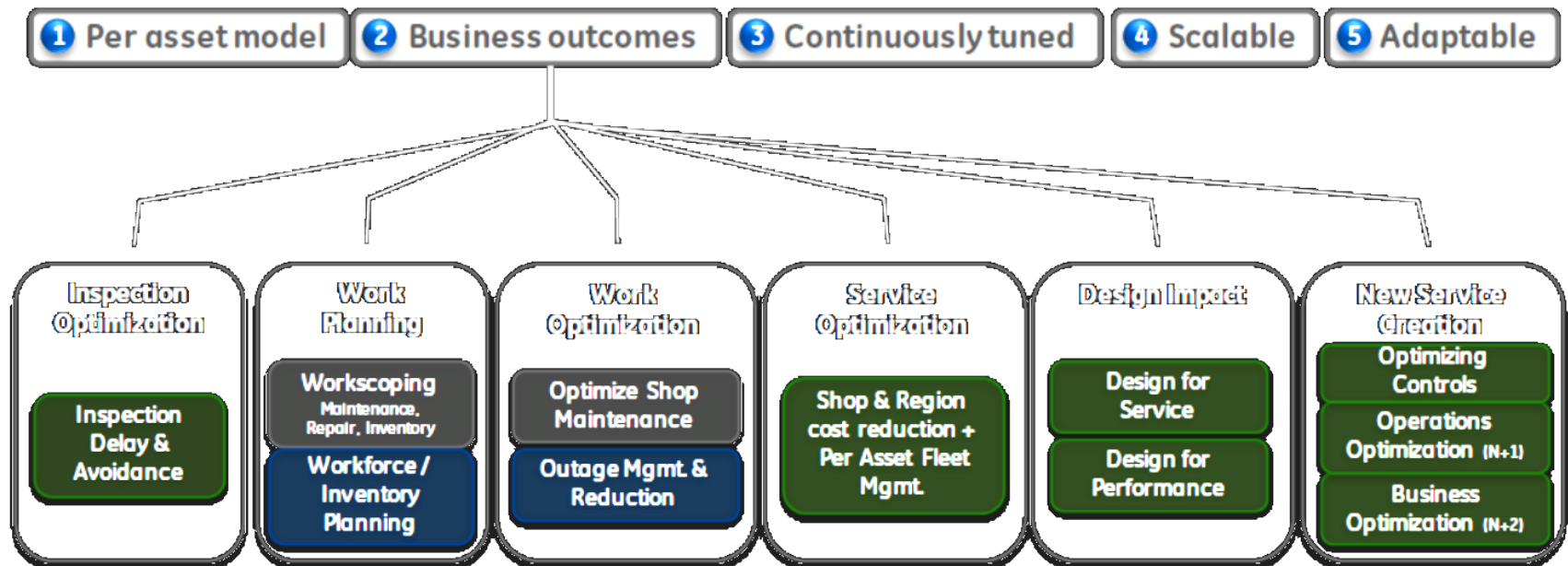
MATERIALISATION OF CYBER-PHYSICAL ENVIRONMENT (DIGITAL TWIN)



Digital Twin – Definition



Engineering models that continuously increase insights into each asset to deliver specific business outcomes





Some Representative Twins

Lifing
Models

Anomaly
Models

Domain
Models

Operations
Models

INPUTS

Atmospheric
Data



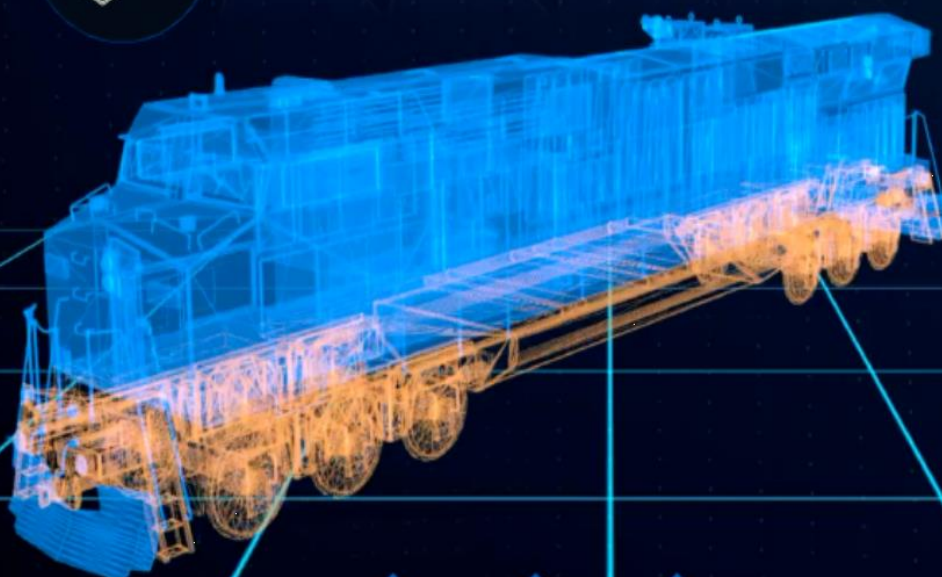
Operational
Data



Inspection &
Repair



Site Events



OUTCOMES

Business
Optimization

Operations
Optimization

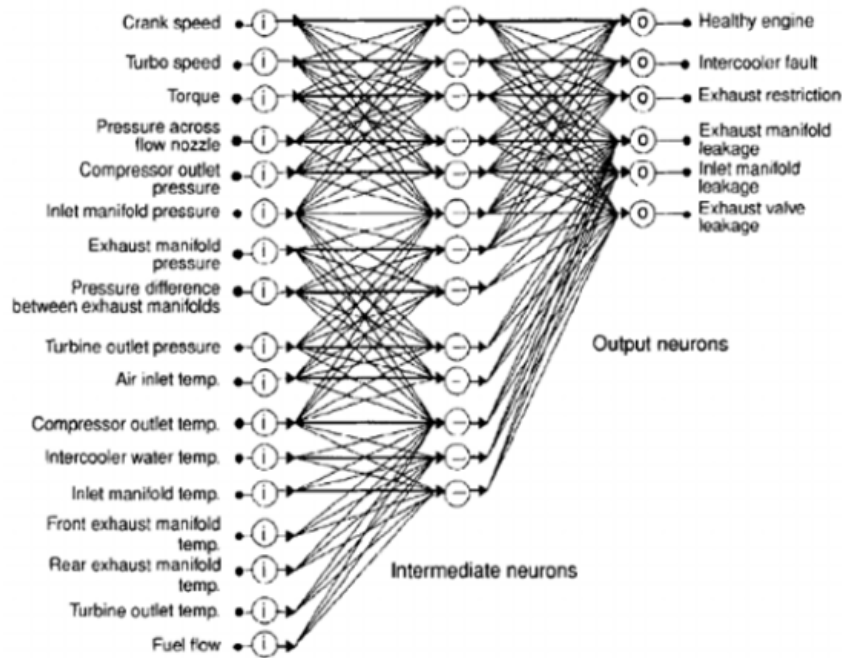
Asset
Performance
Management

Advance
Controls/Edge
Computing

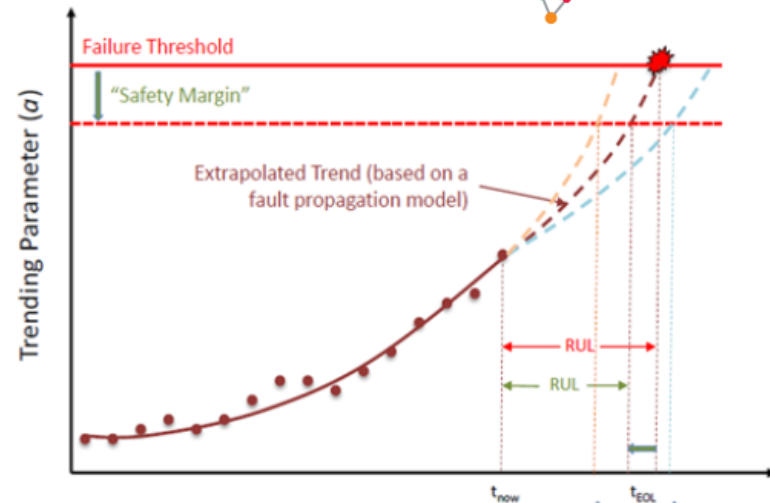
Reliability Capacity Emissions

CUSTOMER KPIs

Digital twin 1.0

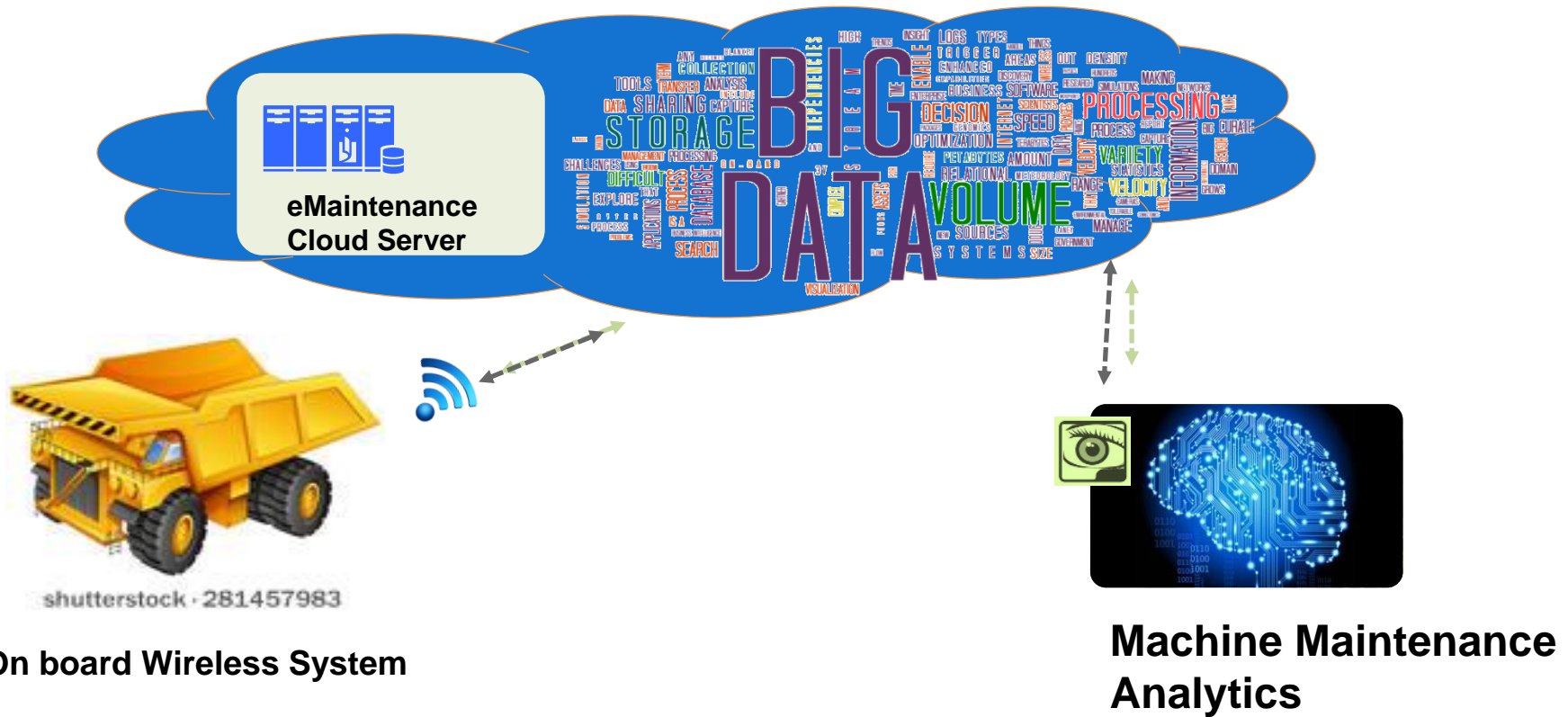


Diagnostics



Prognostics

Digital twin 1.0



Data

Information

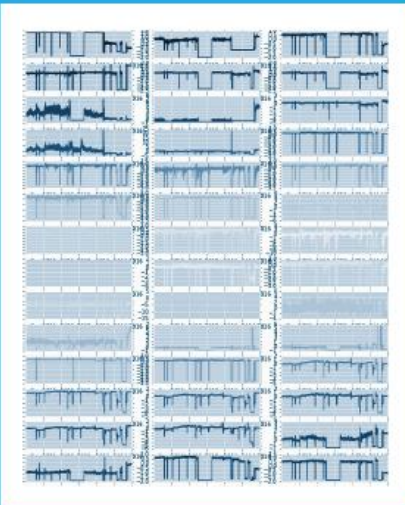
Knowledge

Everything is normality.....

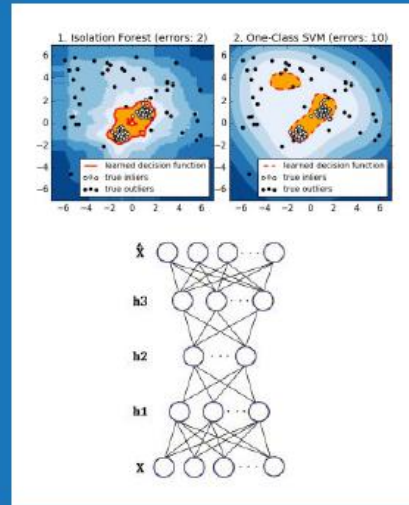
Smarter: Anomaly detection



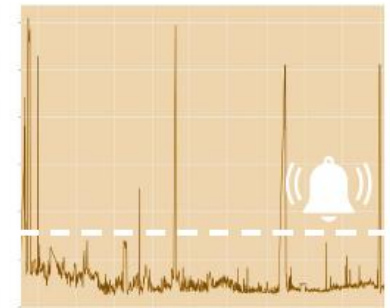
100+ sensors and derived sensors



> 99 % normal behaviour








One virtual sensor of "normality"



Deploy model,
connect to live data,
send notifications

Digital twin made with OT

Do you have IoT in your plant?

Devices	Connections	History	Analytics	Presentation
 <p>Control loops & processes</p> <p>Smart instruments, valves, etc.</p> <p>Not-so-smart instruments, valves, etc.</p> <p>Augmented by context</p>	 <p>Field Networks</p> <p>Fieldbus</p> <p>HART</p> <hr/> <p>DCS/PLC</p> <p>OPC</p> <p>xml</p> <p>Historian</p> <p>AMS</p> <p>ODBC/SQL</p> <hr/> <p>Business/Cloud</p> <p>Gateways</p> <p>MQTT</p>	 <p>Plant-based historians</p> <p>Laboratory information management systems</p> <p>Computerized maintenance management</p> <p>Vendor data</p>	 <p>Offline analysis</p> <p>Home-grown tools</p> <p>Platforms with limited tools</p> <p>Vendor solutions</p>	 <p>Solution-dependent tools</p> <p>Back to DCS or HMI</p> <p>Display anywhere</p>

What about IT systems?

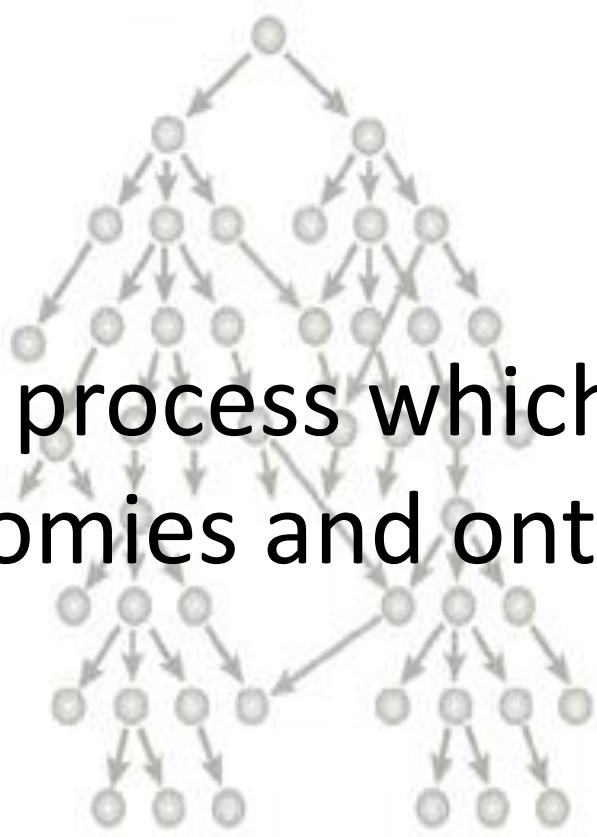


a Simple hierarchy



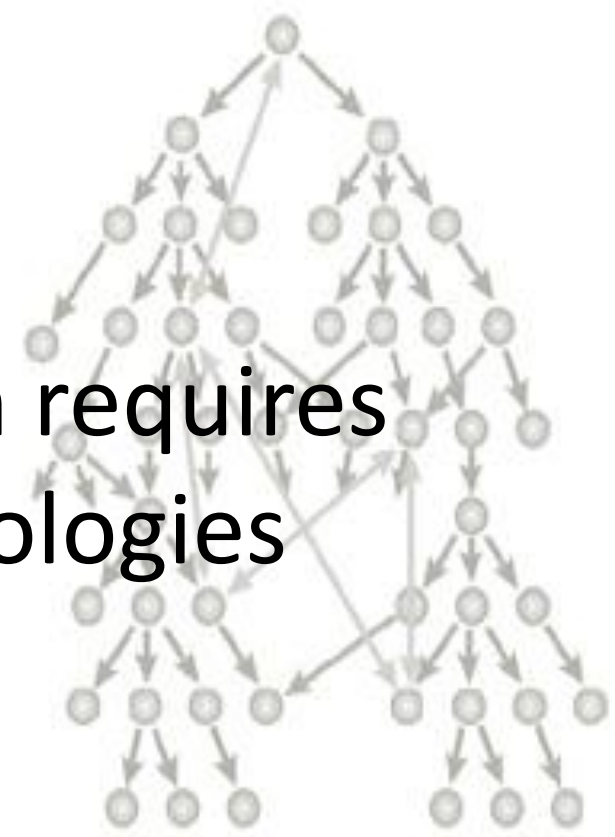
→ Rule: is instance of
Directed rule:
1 parent

b Directed acyclic graph = DAG



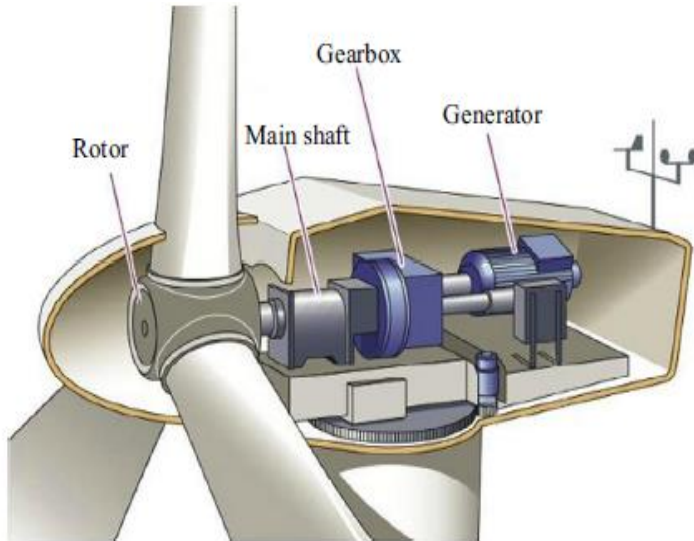
→ Rule: signals to
Directed rule:
>1 parent

c Graph

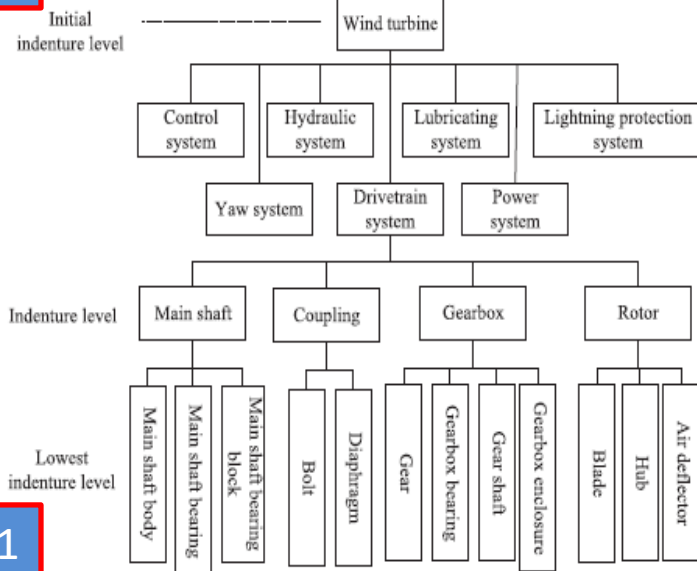


↔ Rule: is next to
Undirected rule:
parents are equivalent
to children

A fusion process which requires taxonomies and ontologies

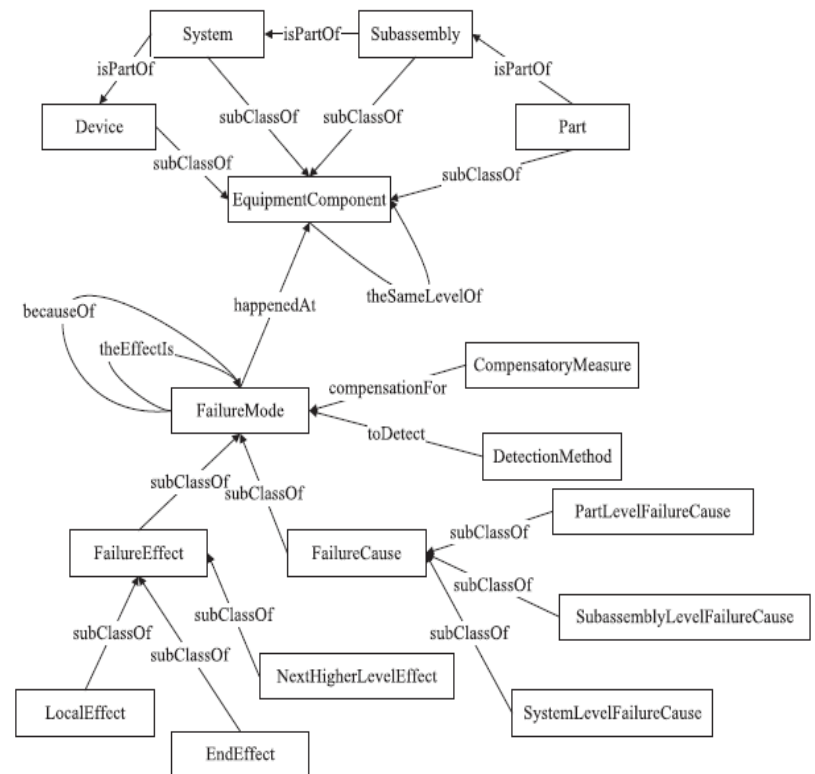


1



1

2



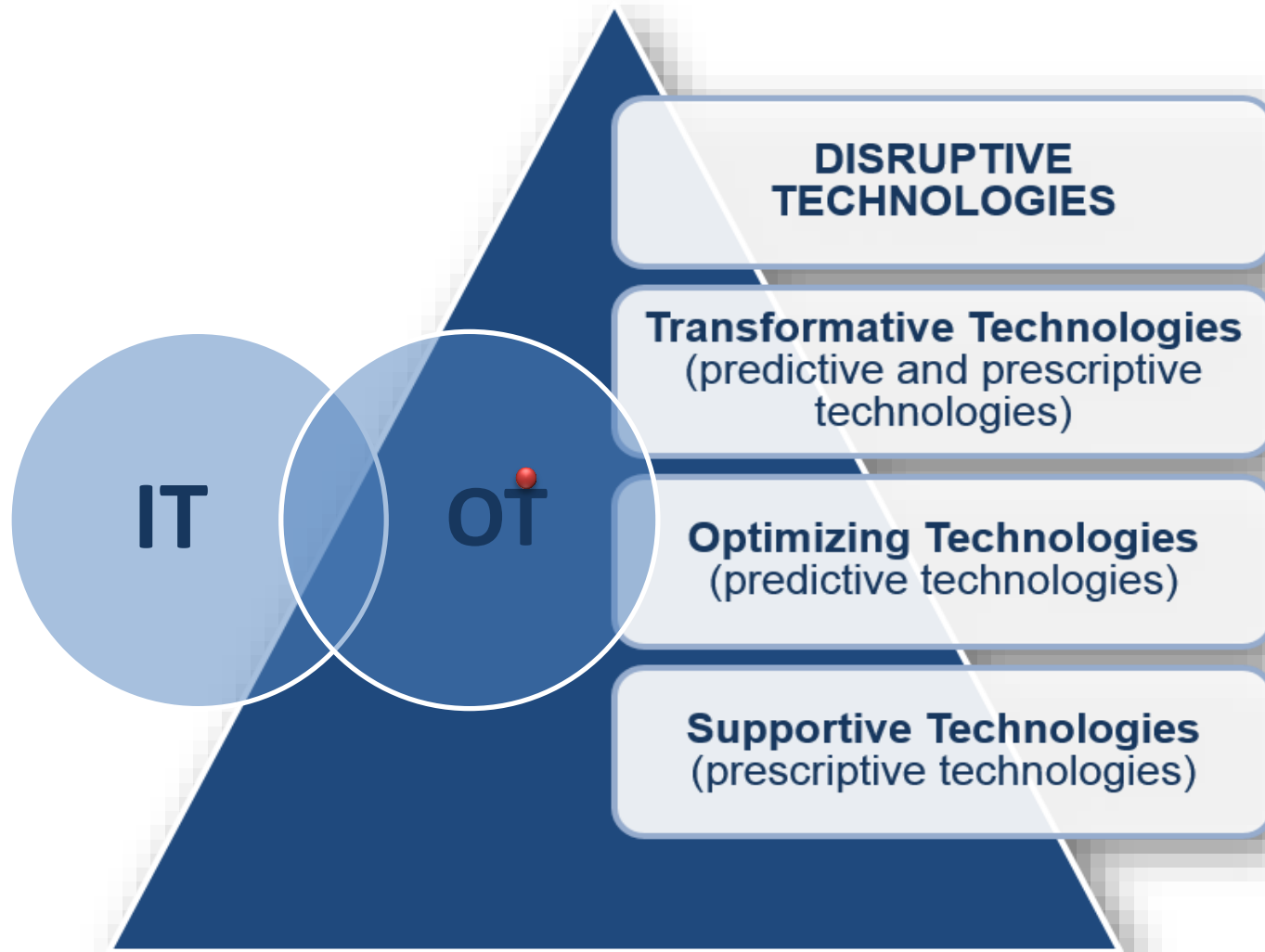
Rule-1

$\text{FailureMode}(\text{?x}) \wedge \text{hasHappened}(\text{?x}, \text{true}) \wedge \text{Device}(\text{?y}) \wedge$
 $\text{happenedAt}(\text{?x}, \text{?y}) \wedge \text{FailureMode}(\text{?z}) \wedge \text{theEndEffectIs}(\text{?z},$
 $\text{?x}) \wedge \text{FailureMode}(\text{?a}) \wedge \text{theHighEffectIs}(\text{?z},$
 $\text{?a}) \wedge \text{theDirectFailureCauses}(\text{?x}, \text{?a}) \wedge \text{hasHappened}(\text{?a}, \text{true})$

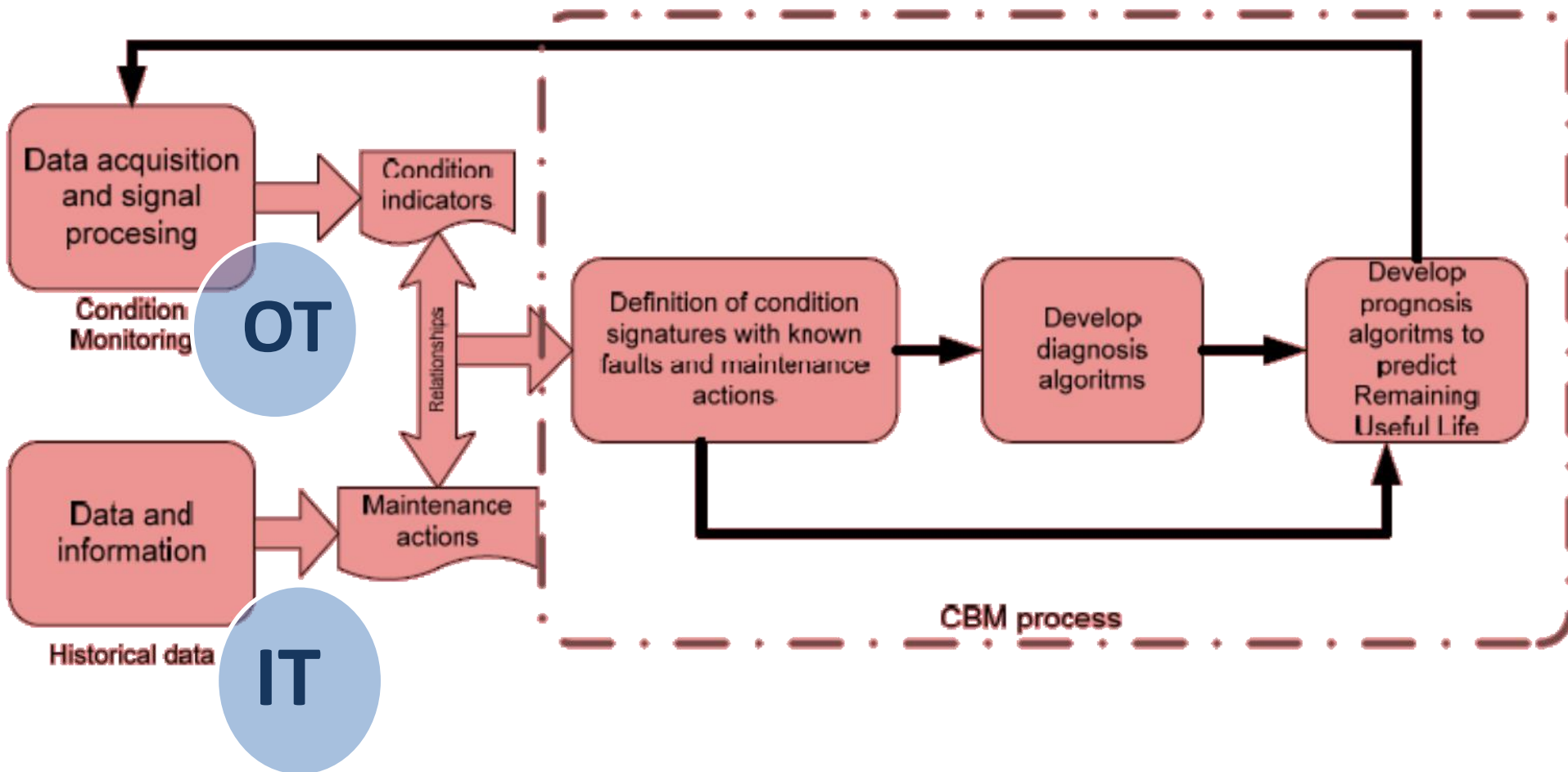
2

TRANSFORMATIVE MAINTENANCE SOLUTIONS

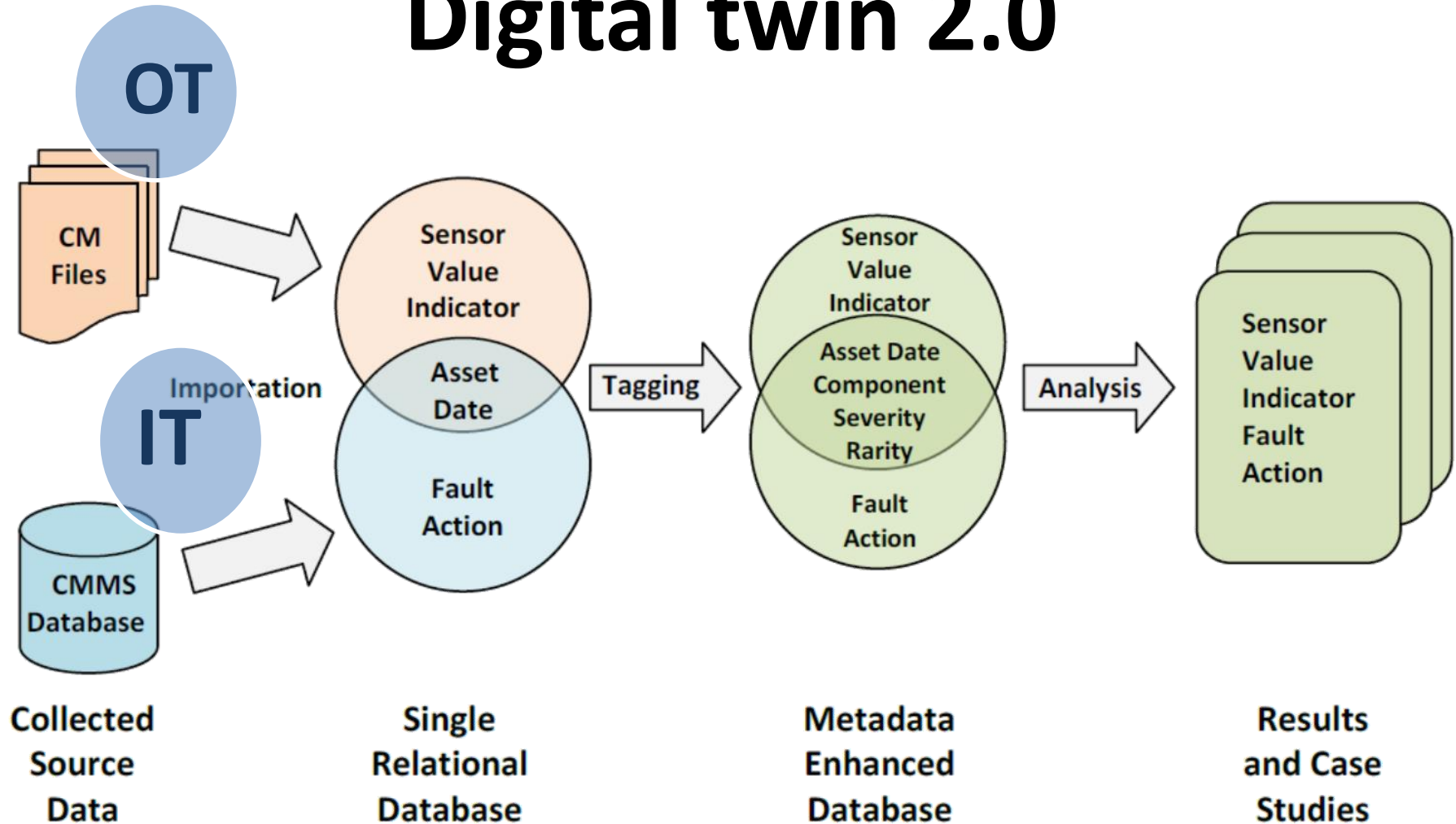
Integration & Application of Technologies

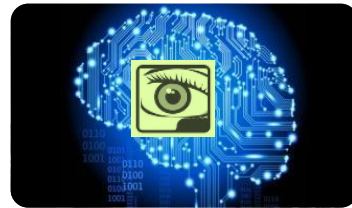
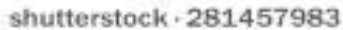


A necessary merging process

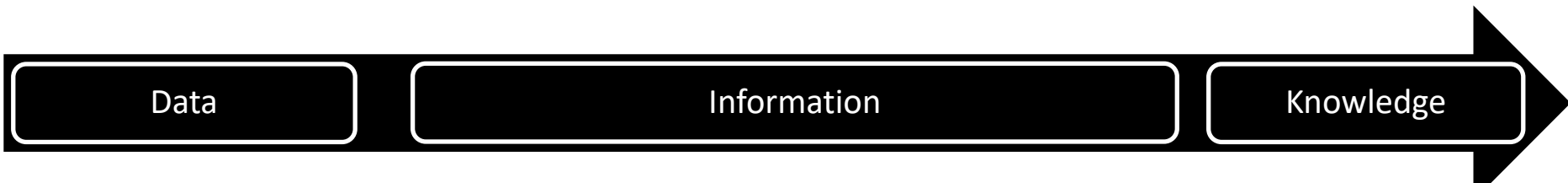


Digital twin 2.0



[illegible]

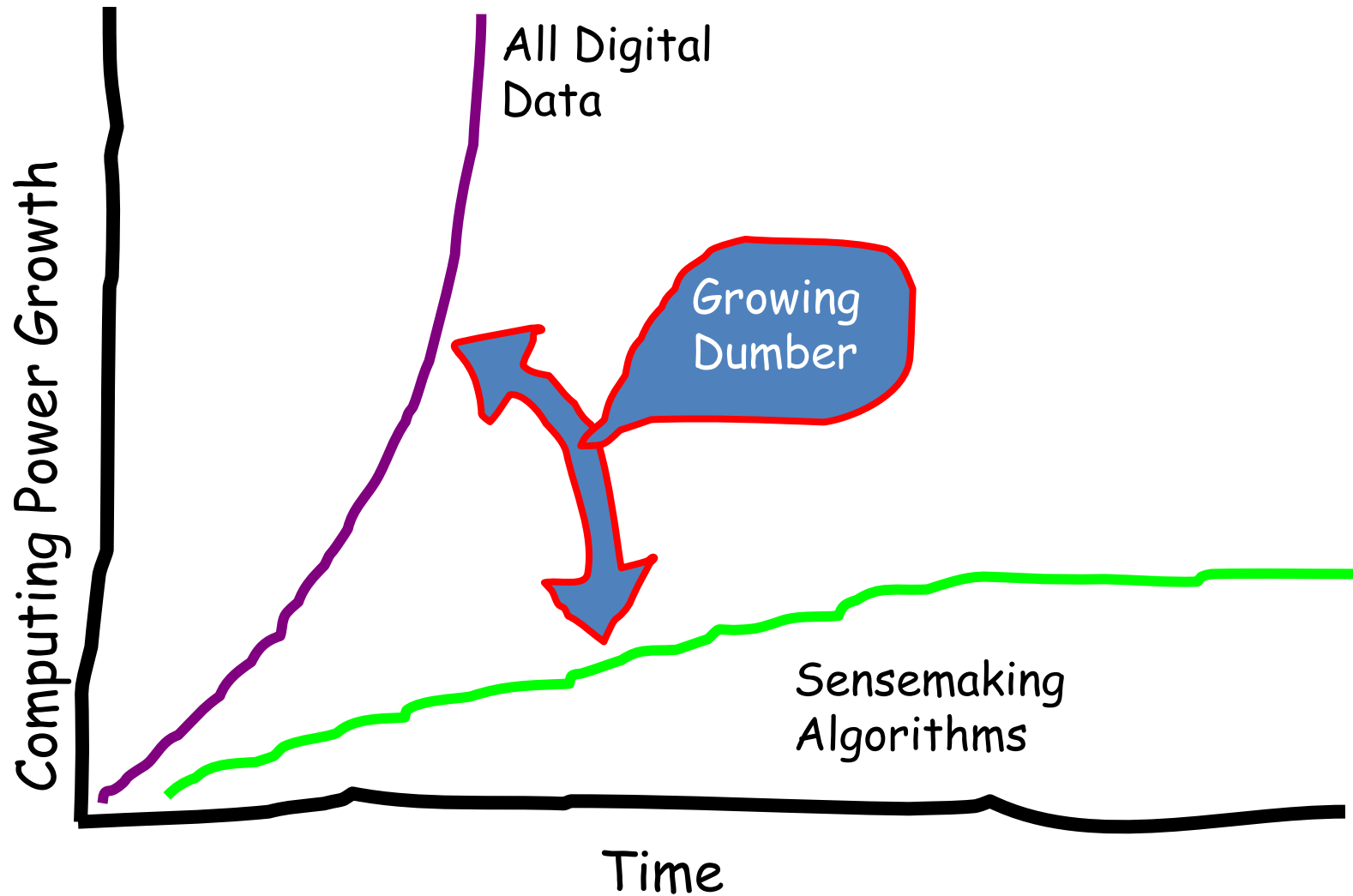
Technical services



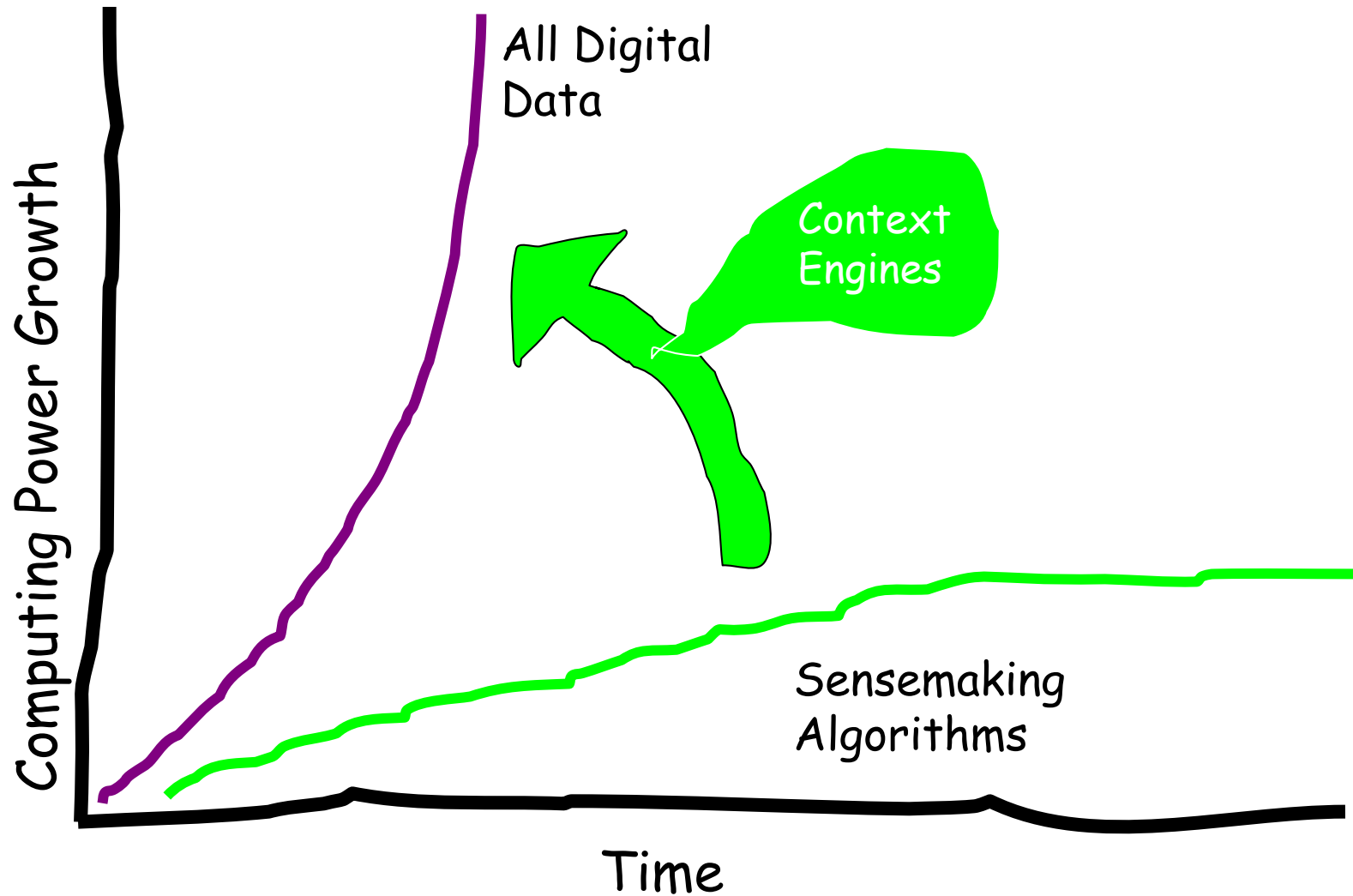


The need for sensemaking analytics

Trend: Organizations are Getting Dumber



The Way Forward



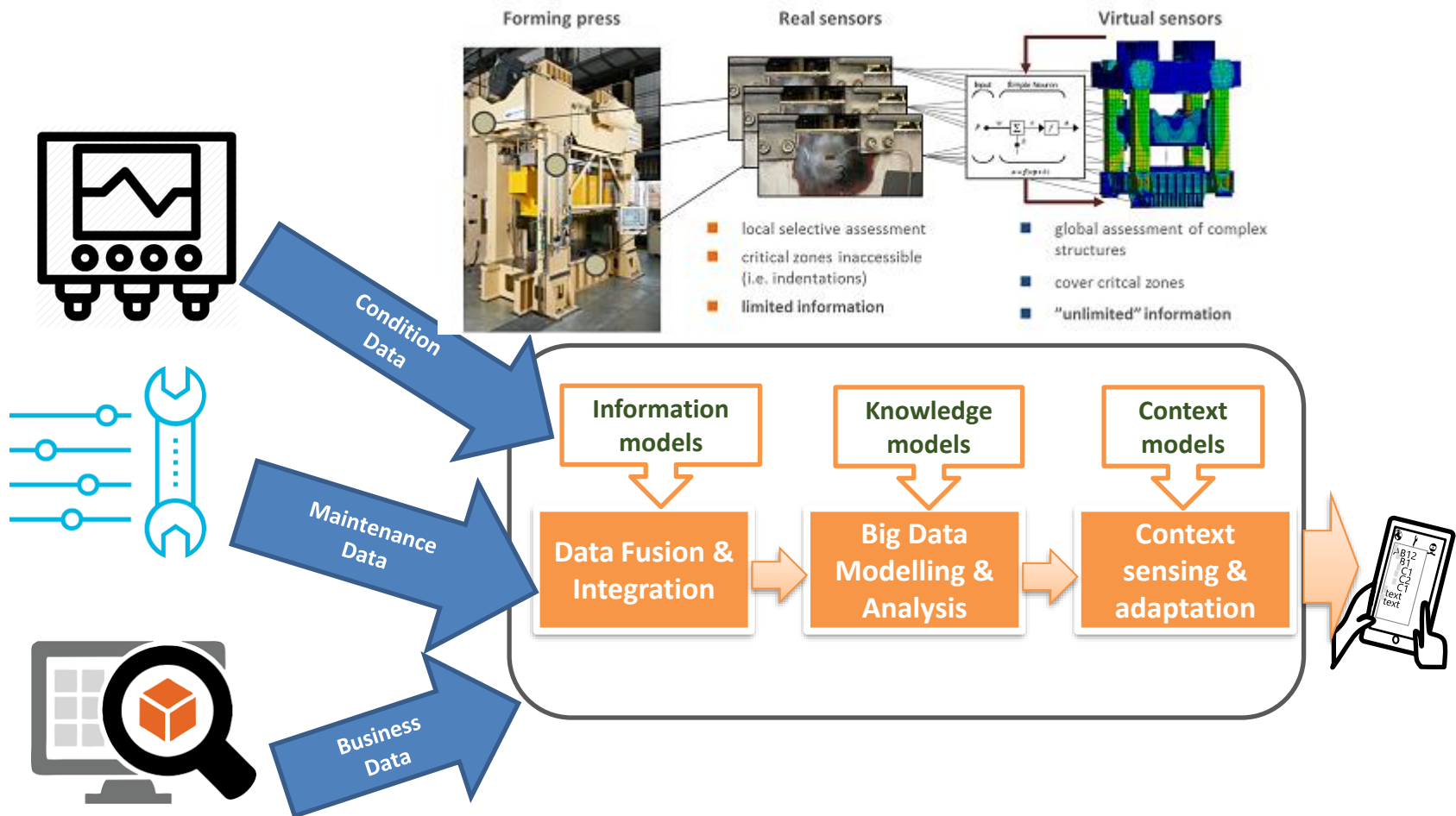
What is context awareness?

- “An application’s ability to adapt to **changing circumstances and respond according to the context of use**”
- Issues in context awareness system implementing
 - How is context represented?
 - How frequently does context information have to be consulted?
 - What are the minimal services an environment needs to provide to make context awareness feasible?
 - ...



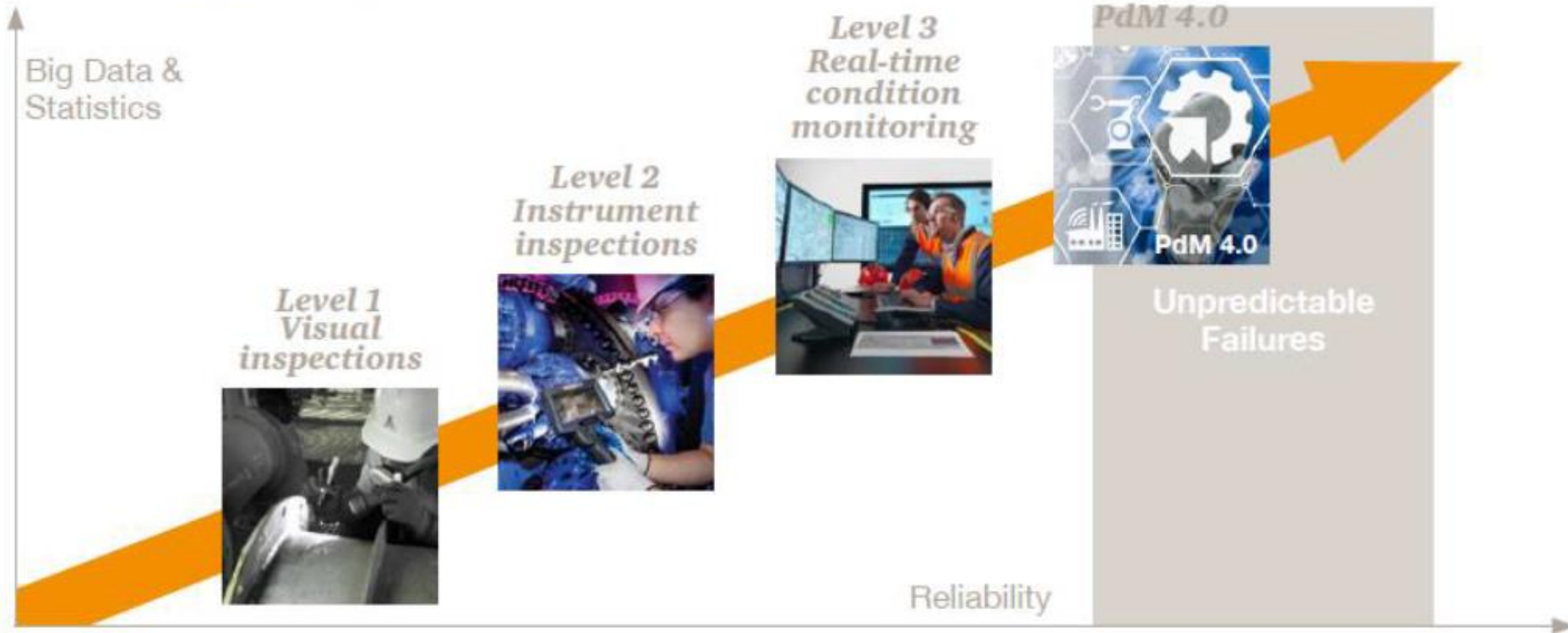
Context-aware Maintenance Decision Support Solution

Digital twin 2.1



PdM Maturity

PdM Maturity Matrix



DETECTION, ISOLATION & PROGNOSIS

Detection

Through sensors, Models etc

Isolation

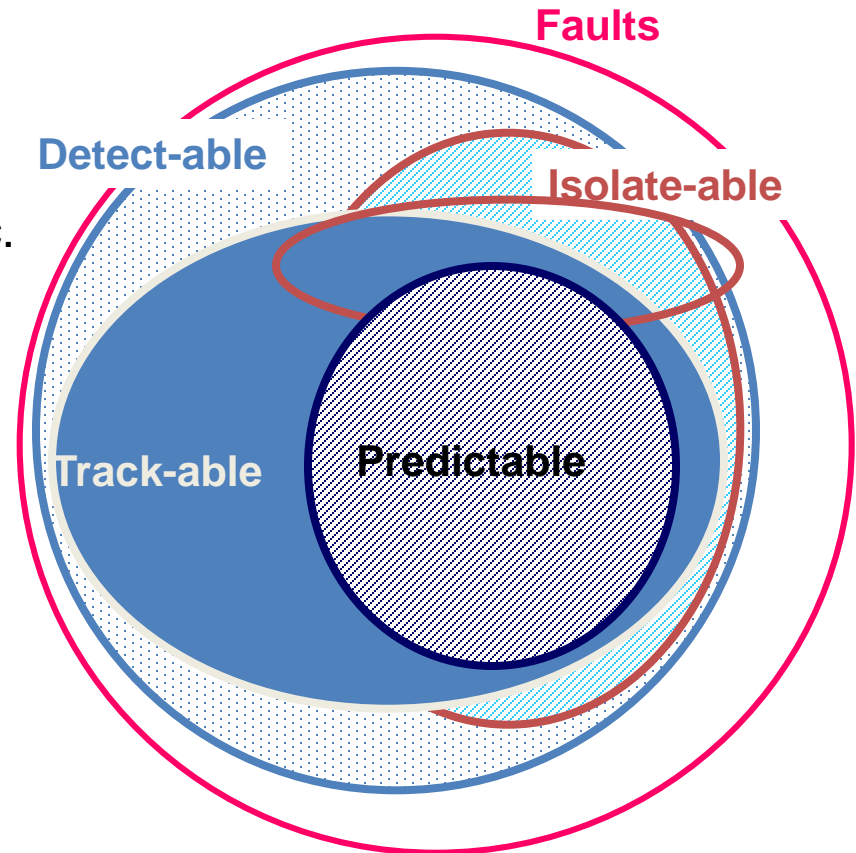
Information fusion from sensors, Models etc.

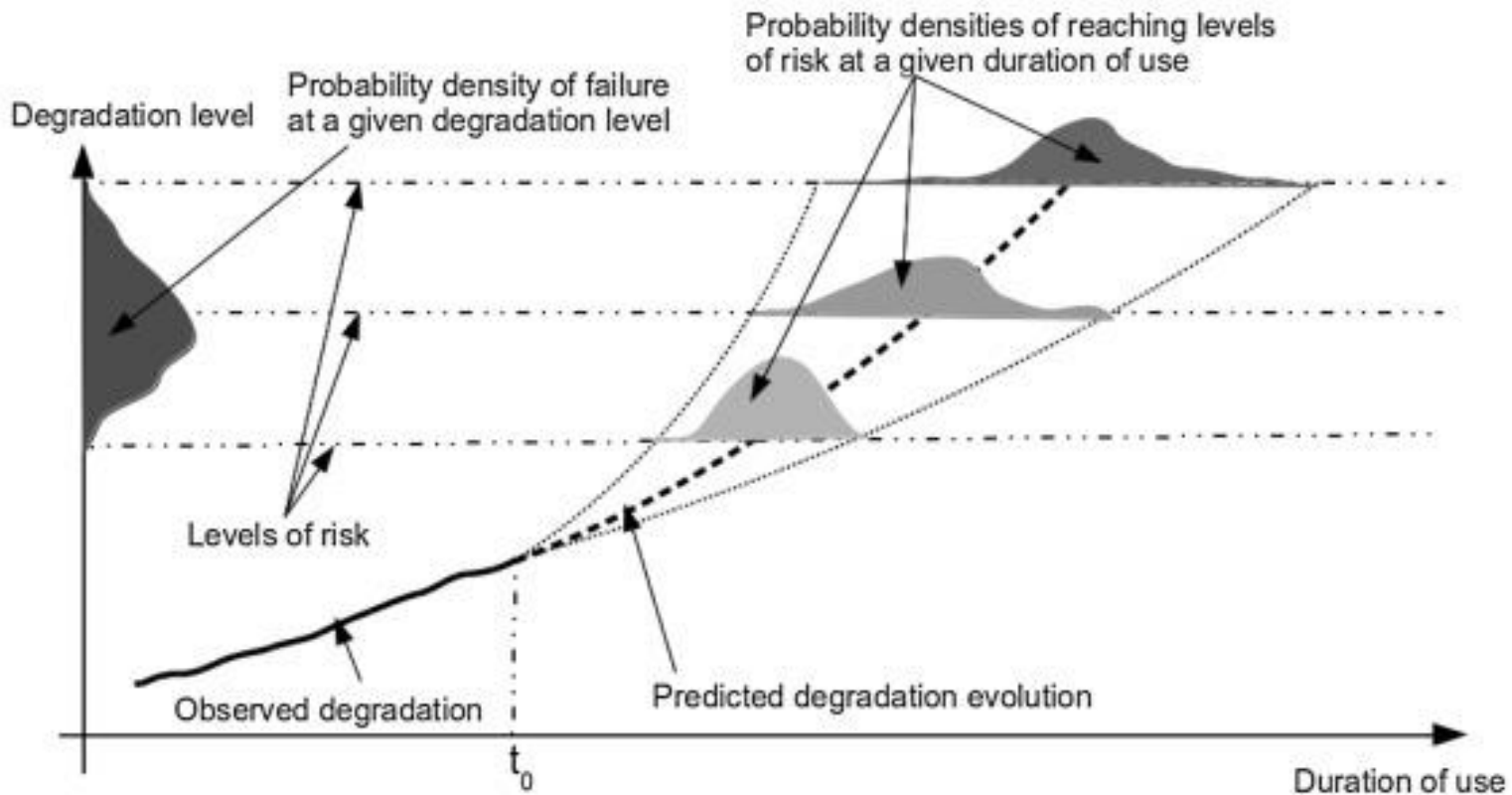
Tracking/Trending

Processed PHM data

Prediction/Prognosis

Based on tracking/trending, & lifing models





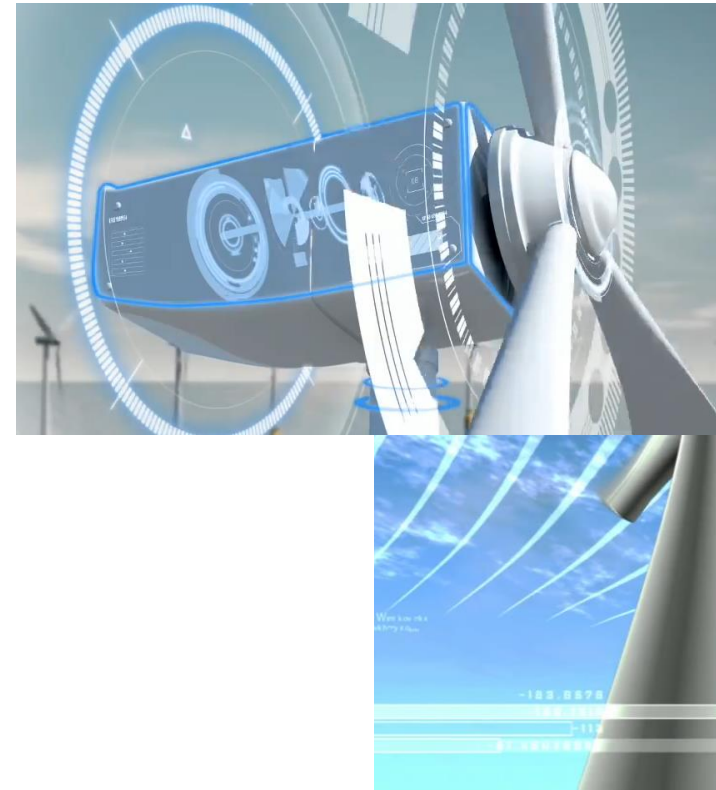
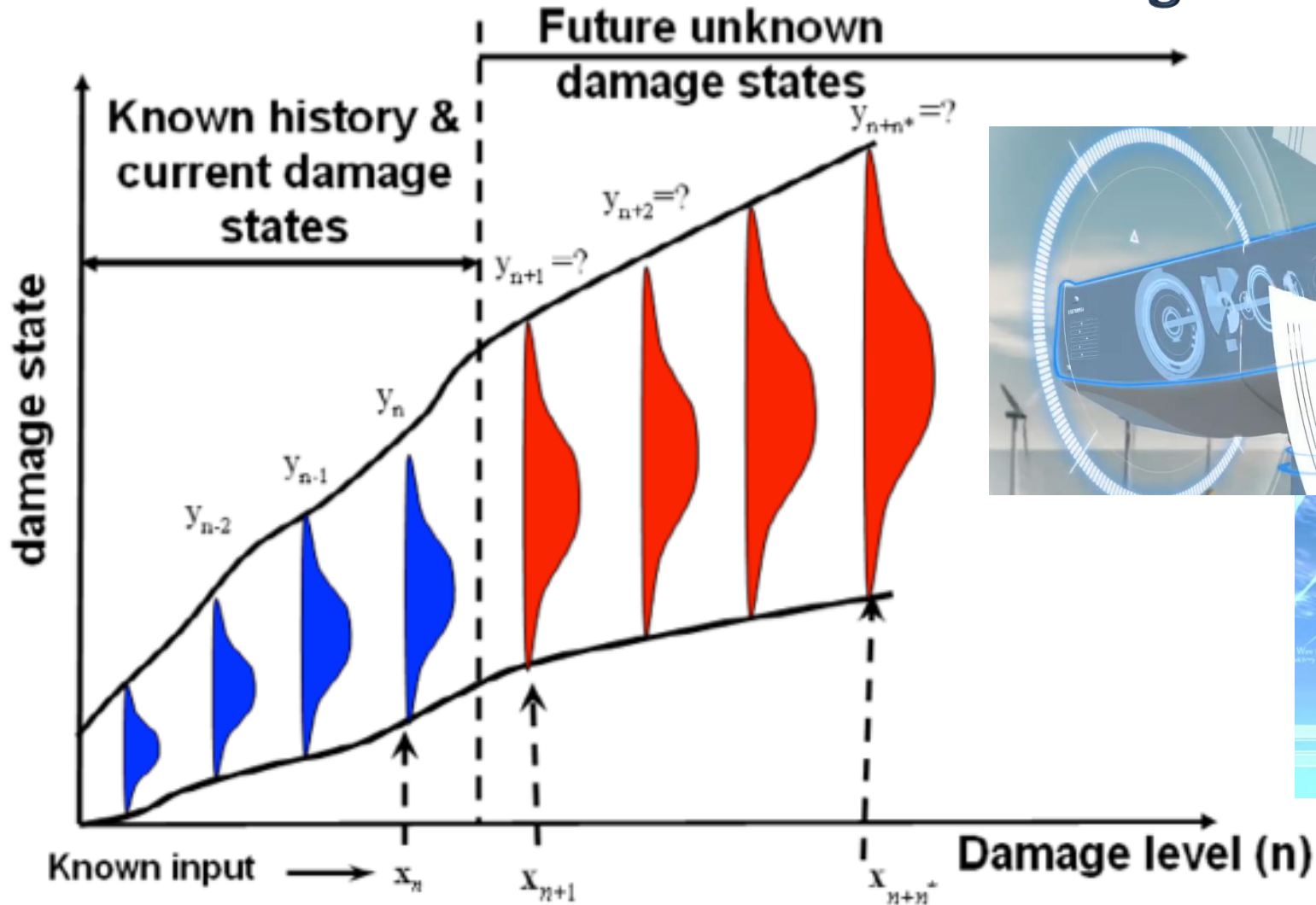
1. In the absence of direct “stressors, loading meters” how can we infer the best (descriptors/features) to capture future damage dimensions?
2. How can we accurately predict the progression of a specific failure mode? Considering that multiple failure modes may occur at any time in a complex equipment, system?
3. Given the numerous sources of uncertainty, how do we assign confidence associated with the predictions?

The background image shows a complex industrial robotic assembly line. Several robotic arms are visible, some in the foreground and others further back, working on various components. The scene is brightly lit, typical of a factory floor. Overlaid on this image is the text 'Data science... Narrow vision and mistakes' in a large, bold, black font. The text is centered and occupies the middle portion of the image. The overall tone is professional and technical.

Data science... Narrow vision and mistakes

Prognosis when ignorant.....?

Remember the unknown stages



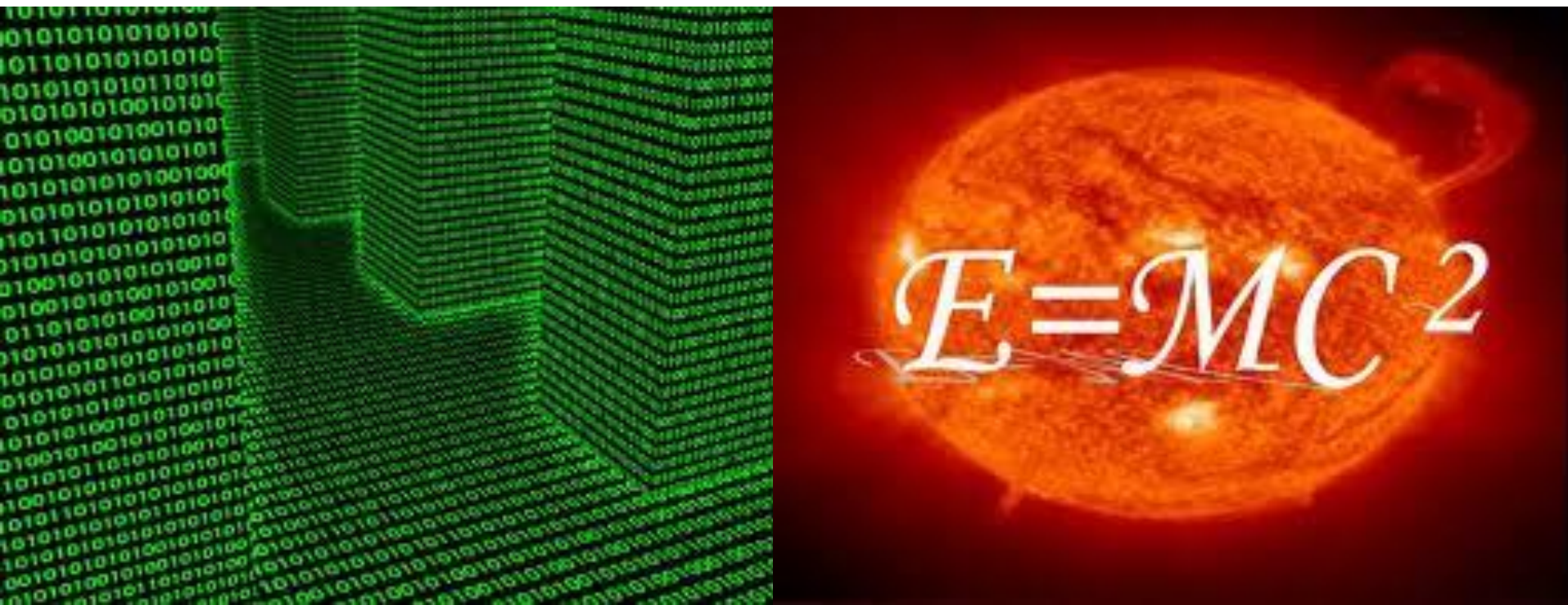
Black Swan Losses

- Loss Distribution
 - Tail events are rare – very little data
 - Typically strong model assumptions



Data driven or model based?

Data-Based or Physics-Based
Models? – That is the question!

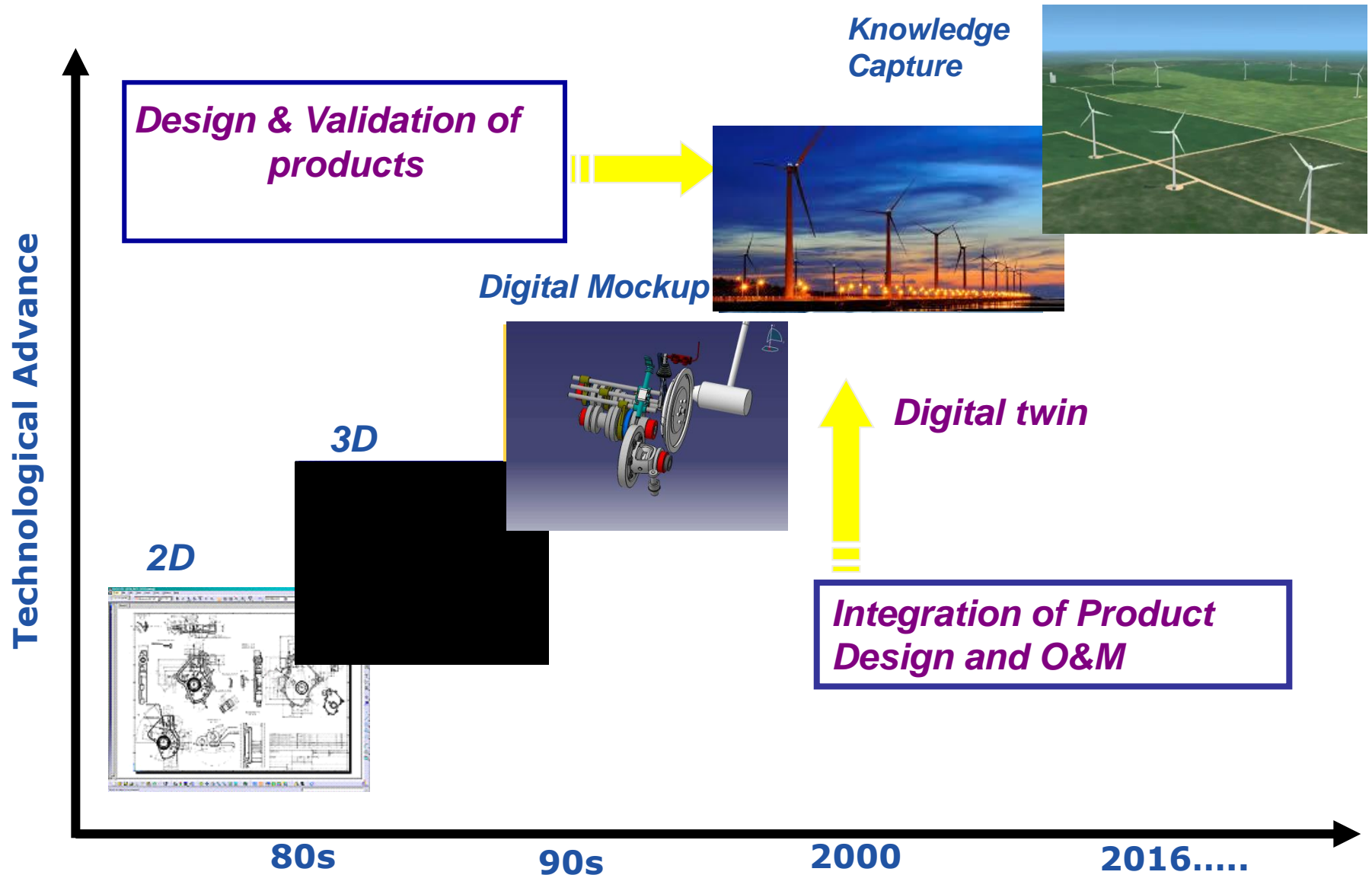


Hybrid models

- Combine knowledge about the physical process and information from sensor readings to enhance prognostics capabilities.
- Integration of measured data and physics can lead to a reduction of uncertainty (e.g. adjust predictions from model using observed data).
- Integration can be implemented at different levels of the PHM process:
 - Online model parameters updating.
 - Model predictions correction based on observed data.
 - Measure current damage level and propagate.
 - Build empirical degradation models from data.



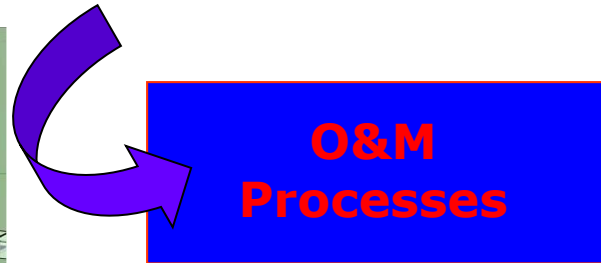
Evolution of the Process



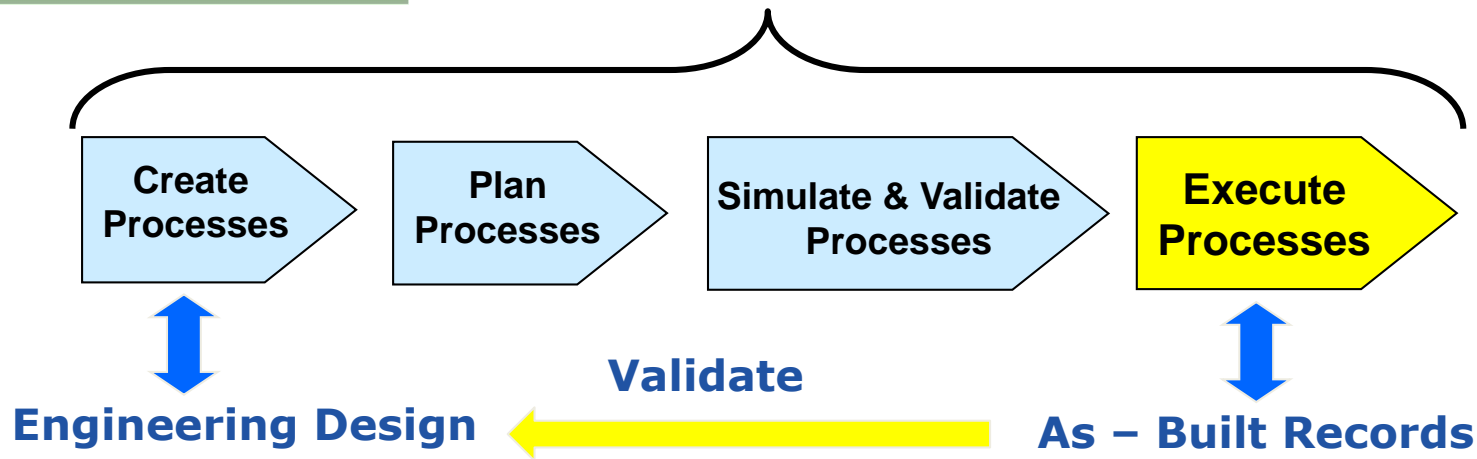
PLM and digital twins

← Product Lifecycle Processes →

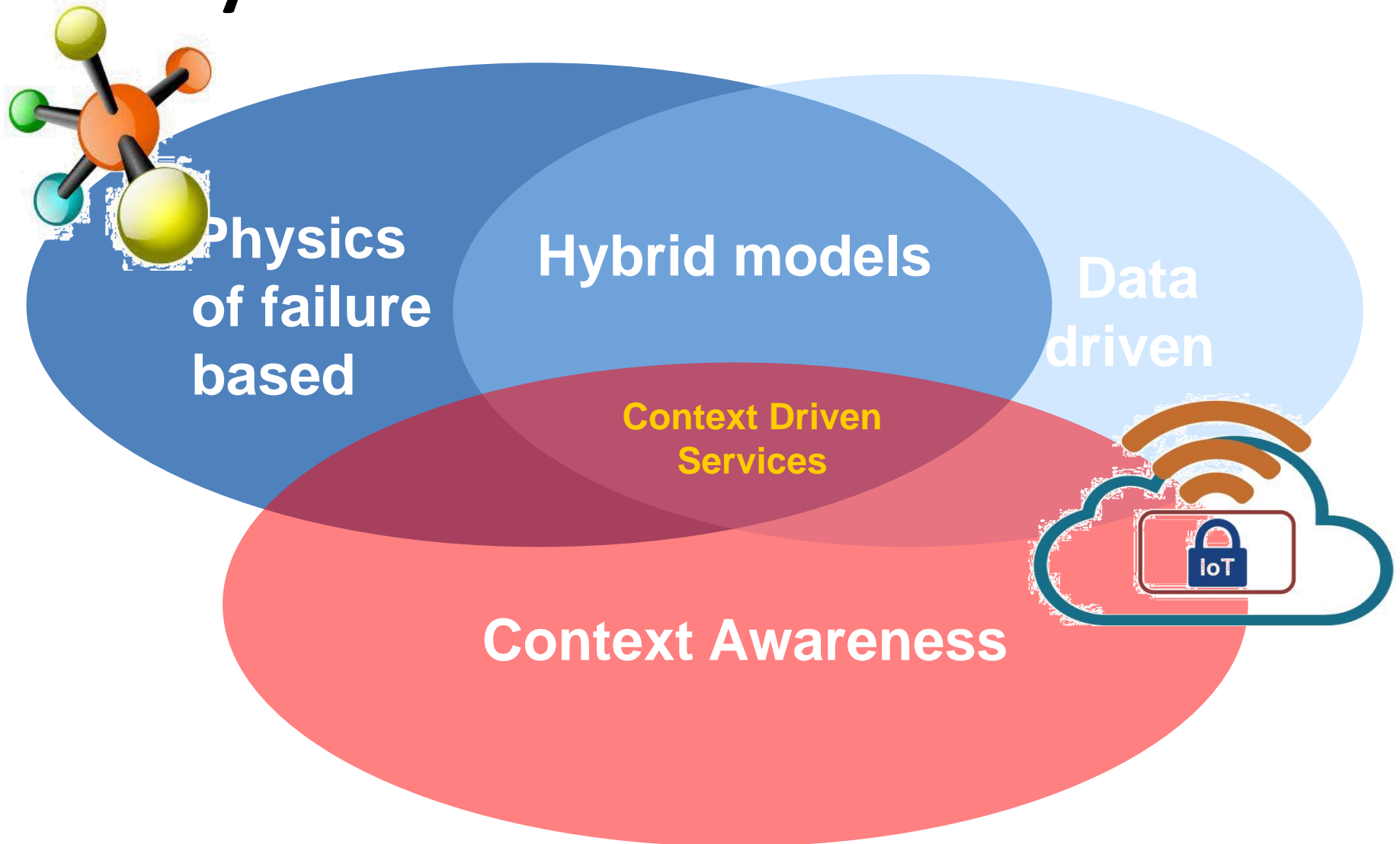
Design → Build → Operate → Maintain



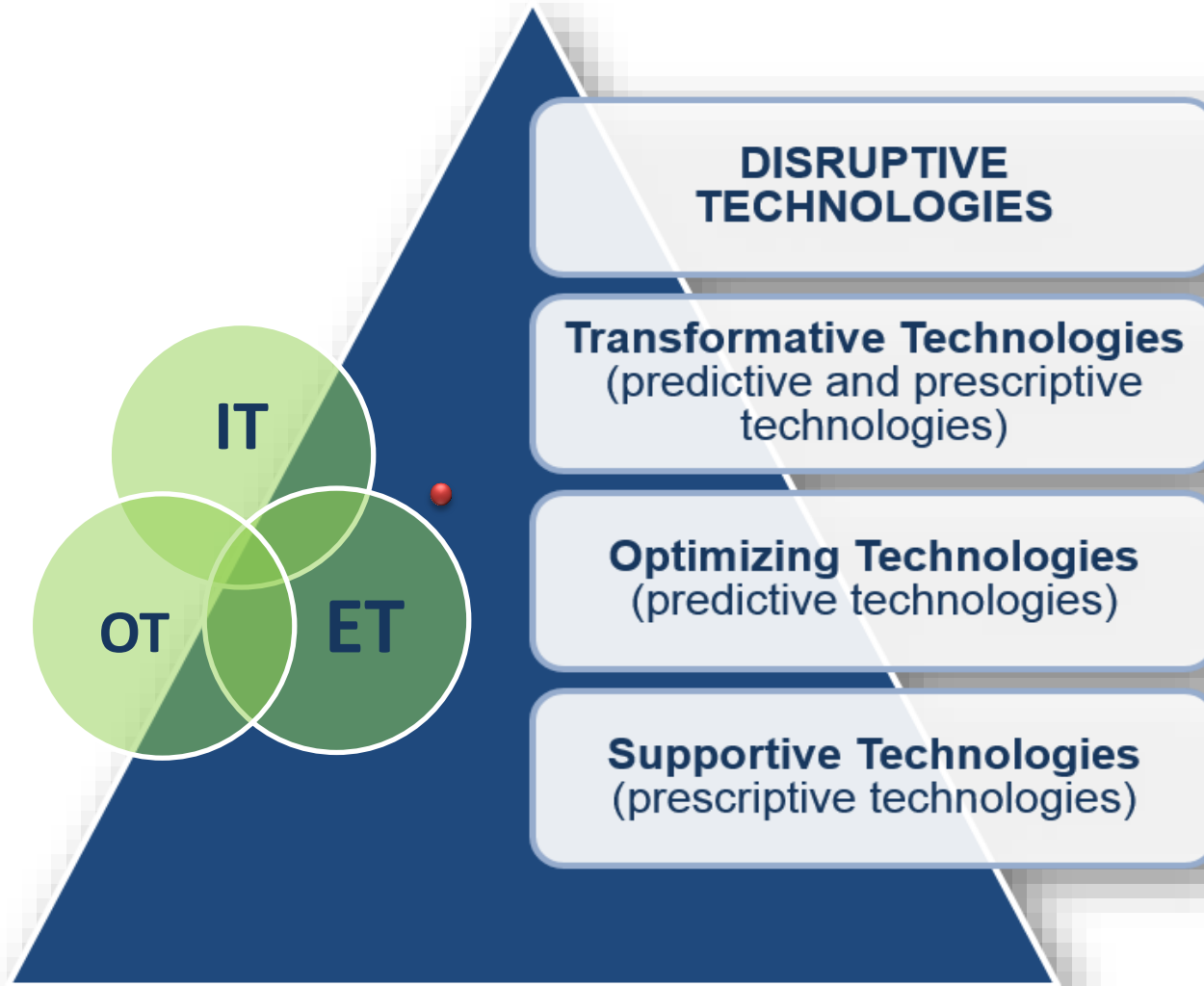
Digital Twin Solutions



Hybrid & Context Driven Services



Digital twin 3.0



Methodology



Rolling stock



HVAC

Identify failure modes of Equipment units, Subunits, Components and Parts based on the Taxonomy

Analyze failure effects / causes

Classify failure effects by severity

Perform criticality calculations

Rank failure mode criticality

Determine critical items

Identify means of failure detection, isolation and compensating provisions

Document the analysis. Summarize uncorrectable design areas, identify special controls necessary to mitigate risk.

Make recommendations

Follow up on corrective action implementation / effectiveness

Taxonomy

FMECA Analysis
(failure mode
identification)

Relate available
variable with failure
modes

Identification of possible modeling
methods for failure identification

Critical system, sub-system,
component identification

Diganosis/Progonosis

Condition
Monitoring

Maintenance
Planning

Identification of the **system** for the
analysis

Survey for the functionality of the system

Identification of the Equipment units,
Subunits, Components and Parts

Complete Taxonomy creation

Identify the measurements for the detection
of failures

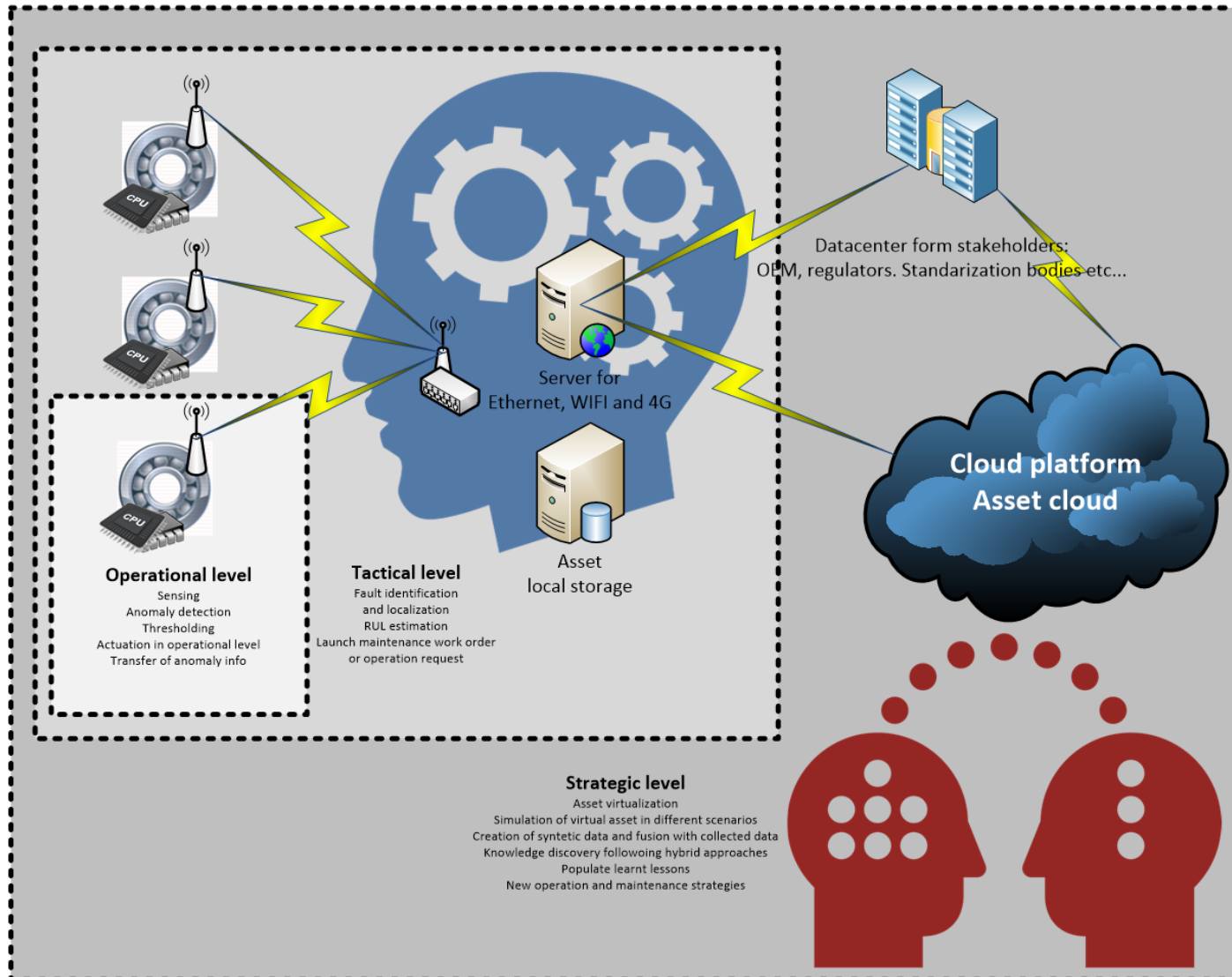
Identify the available variables and
parameters in the system

Exploration of possible data extraction form
variables

Sensitivity analysis for the detection of failure
modes from available variables

Analysis of indirect monitoring of failure
modes through variables

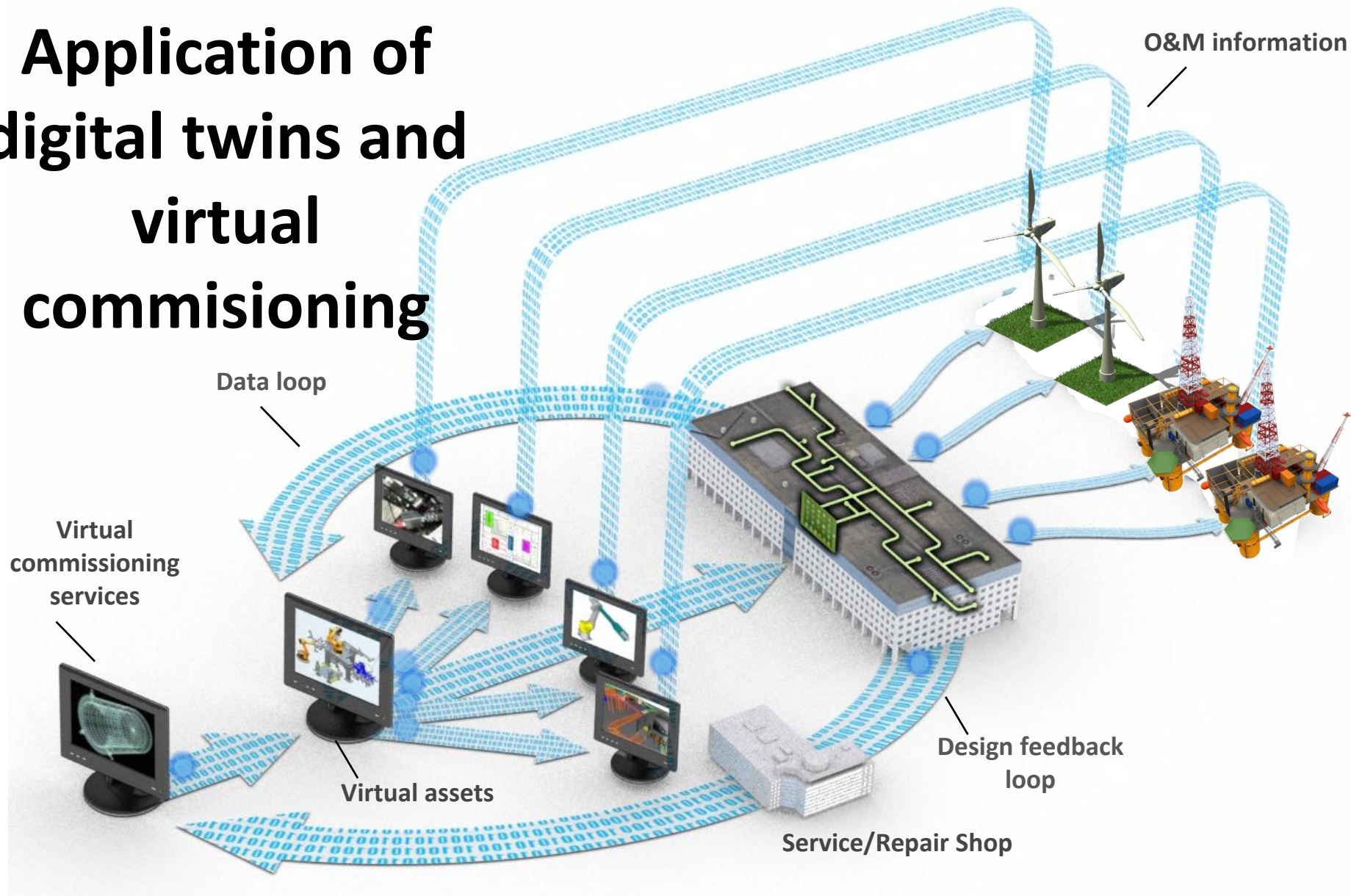
Are digital twins 1.0 and 2.0 useless????



**What do we
expect
from hybrid
digital
twins?**



Application of digital twins and virtual commissioning



Types of data analytics

Descriptive Analytics

Group historical
data according to
their similarity

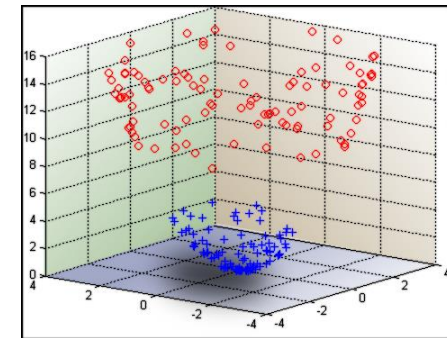
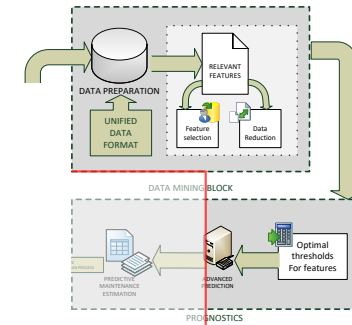
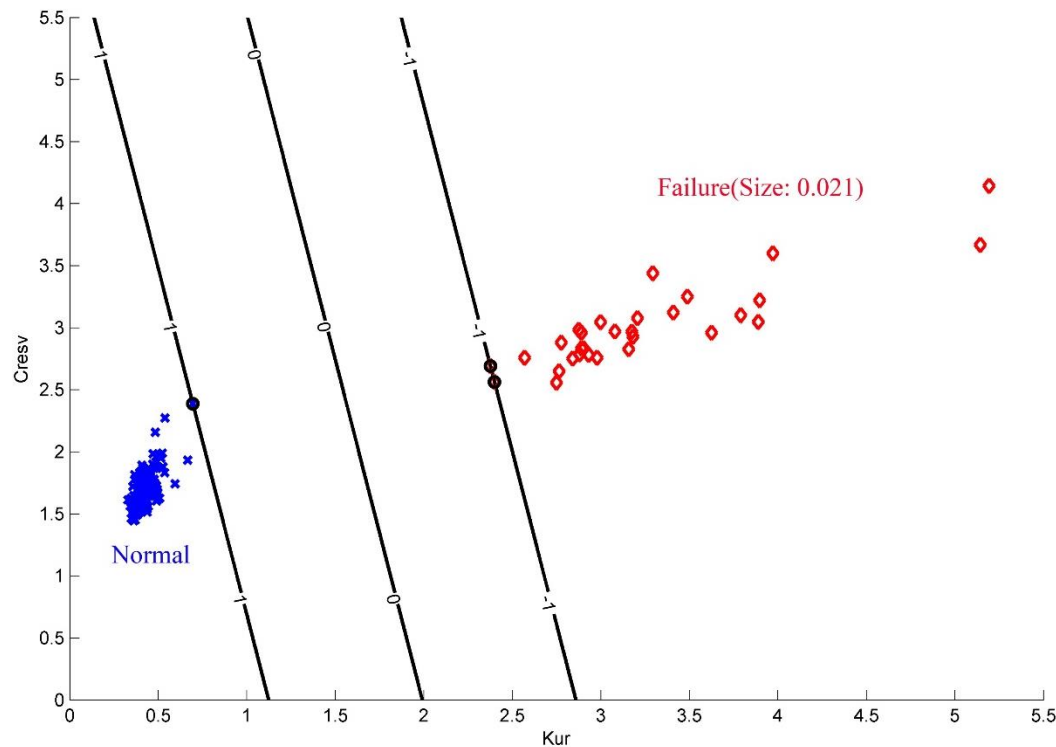
Reports
Mapping

Diagnostic Analytics

Determine cause
of successes and
failures

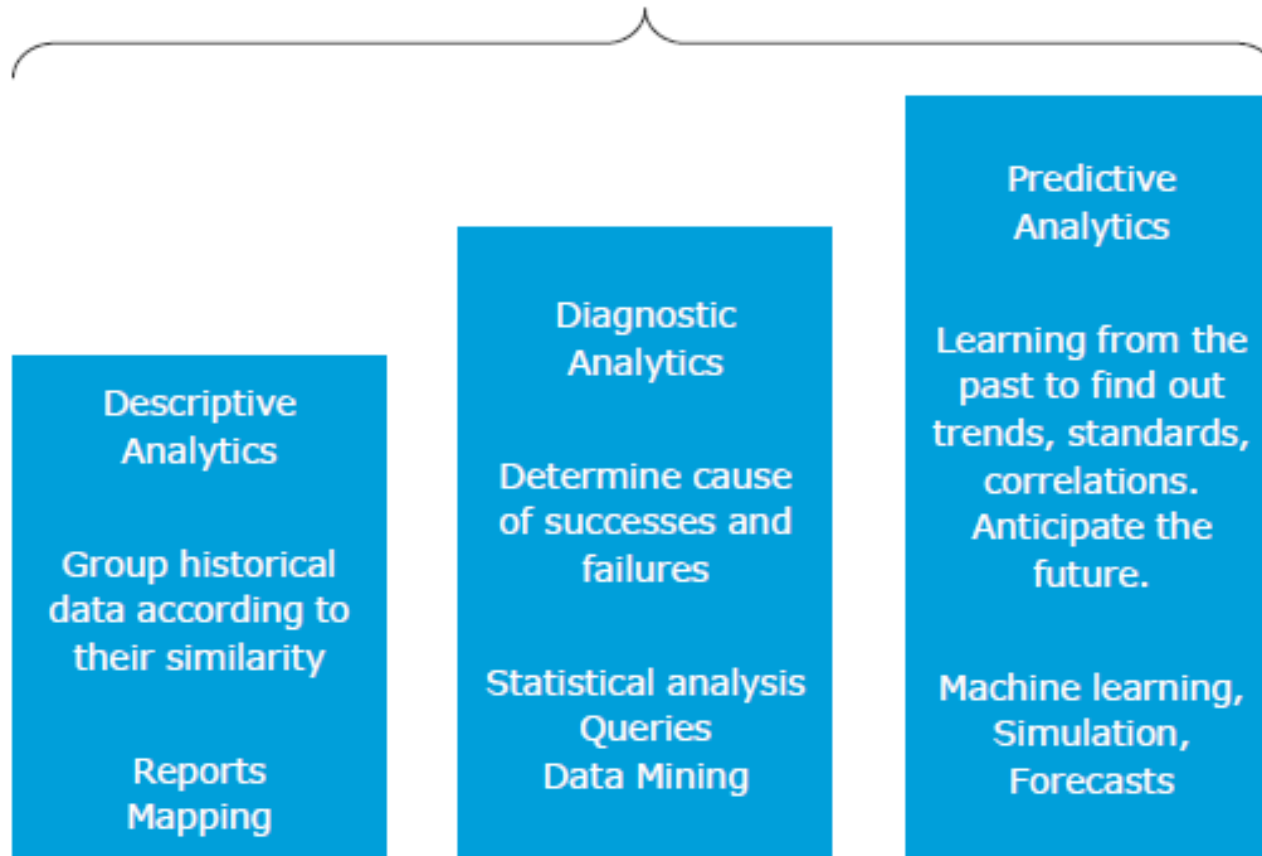
Statistical analysis
Queries
Data Mining

Descriptive/ Diagnostic analytics

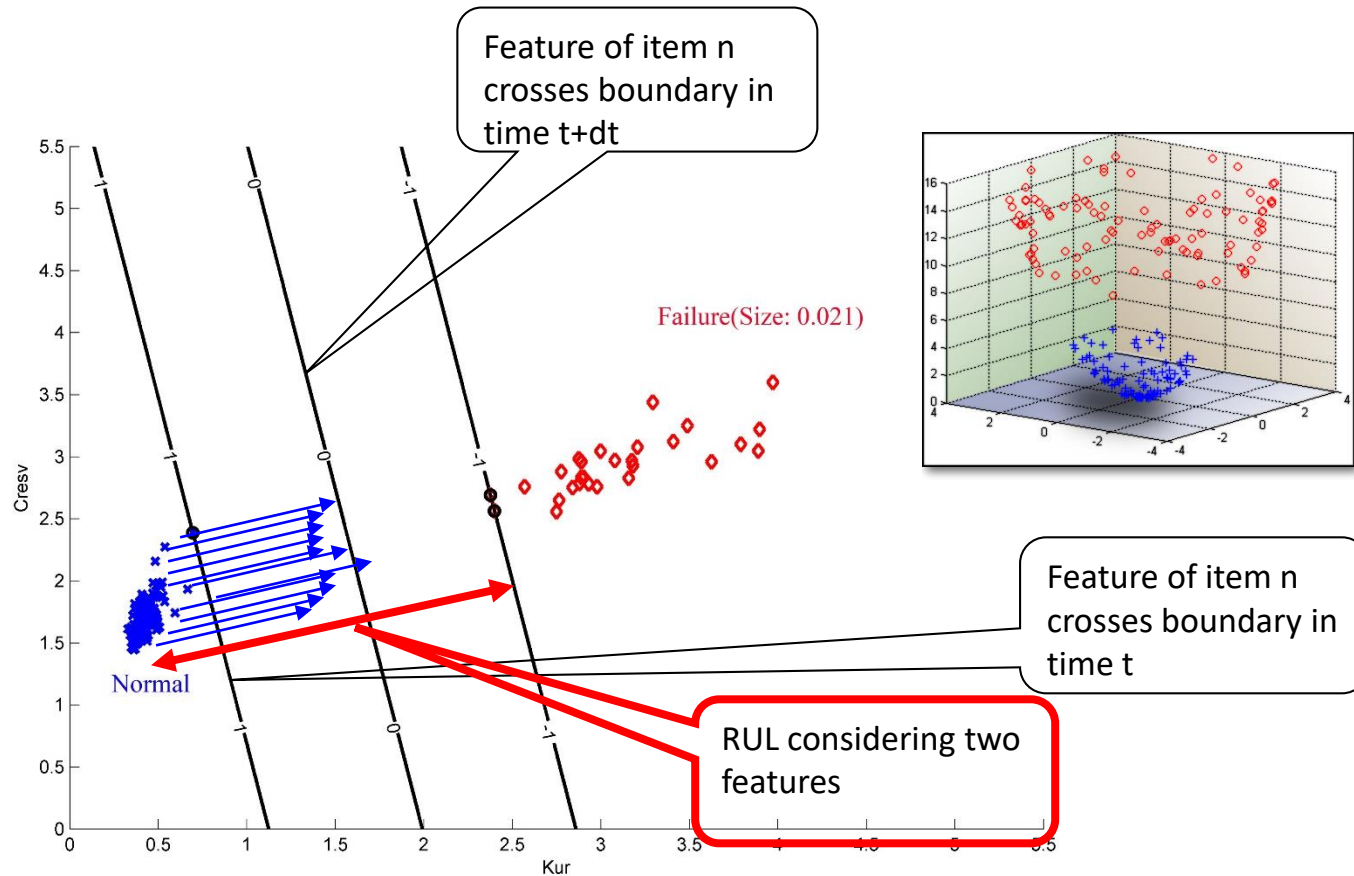


Types of data analytics

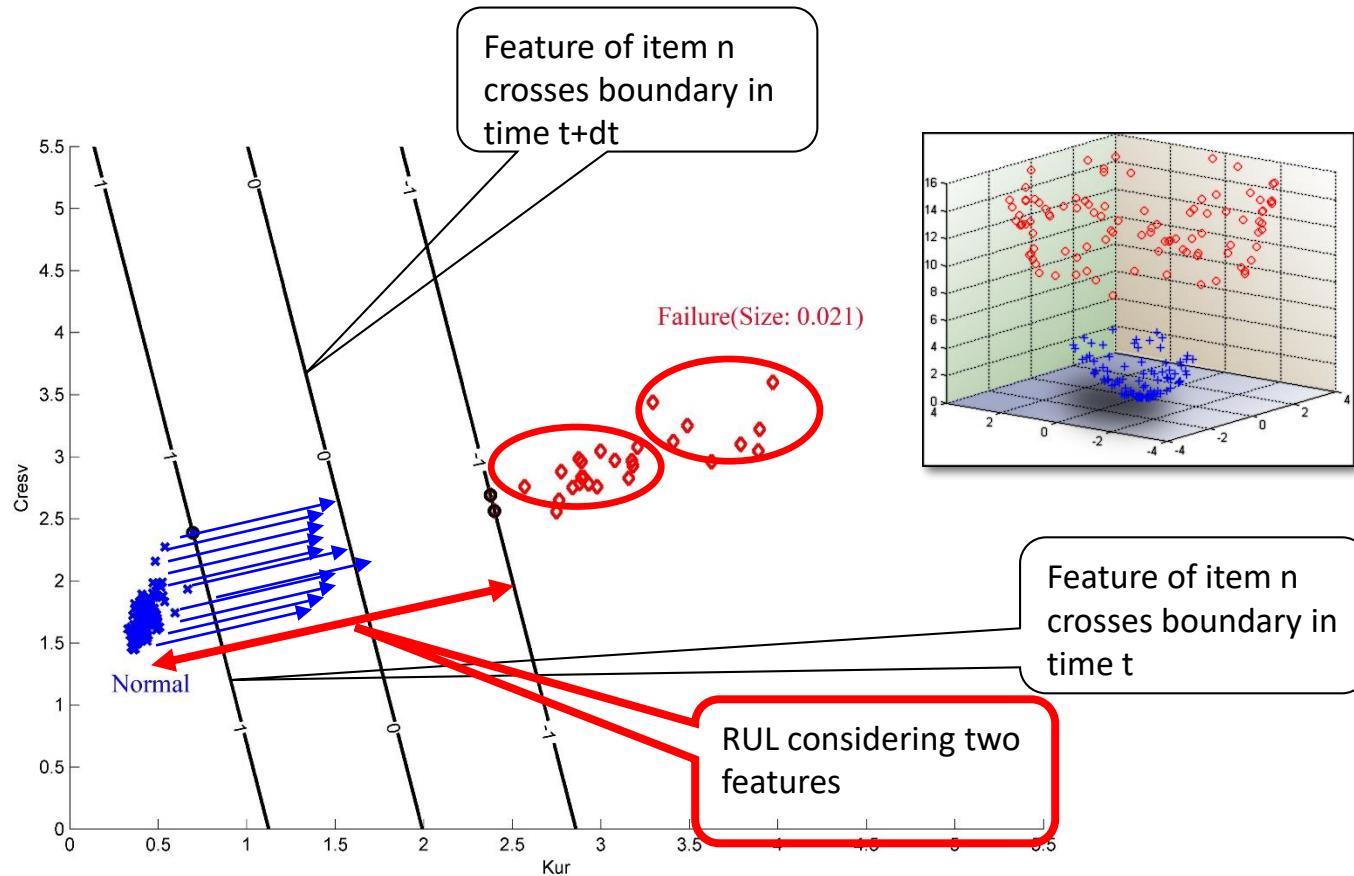
To Educate and Inform



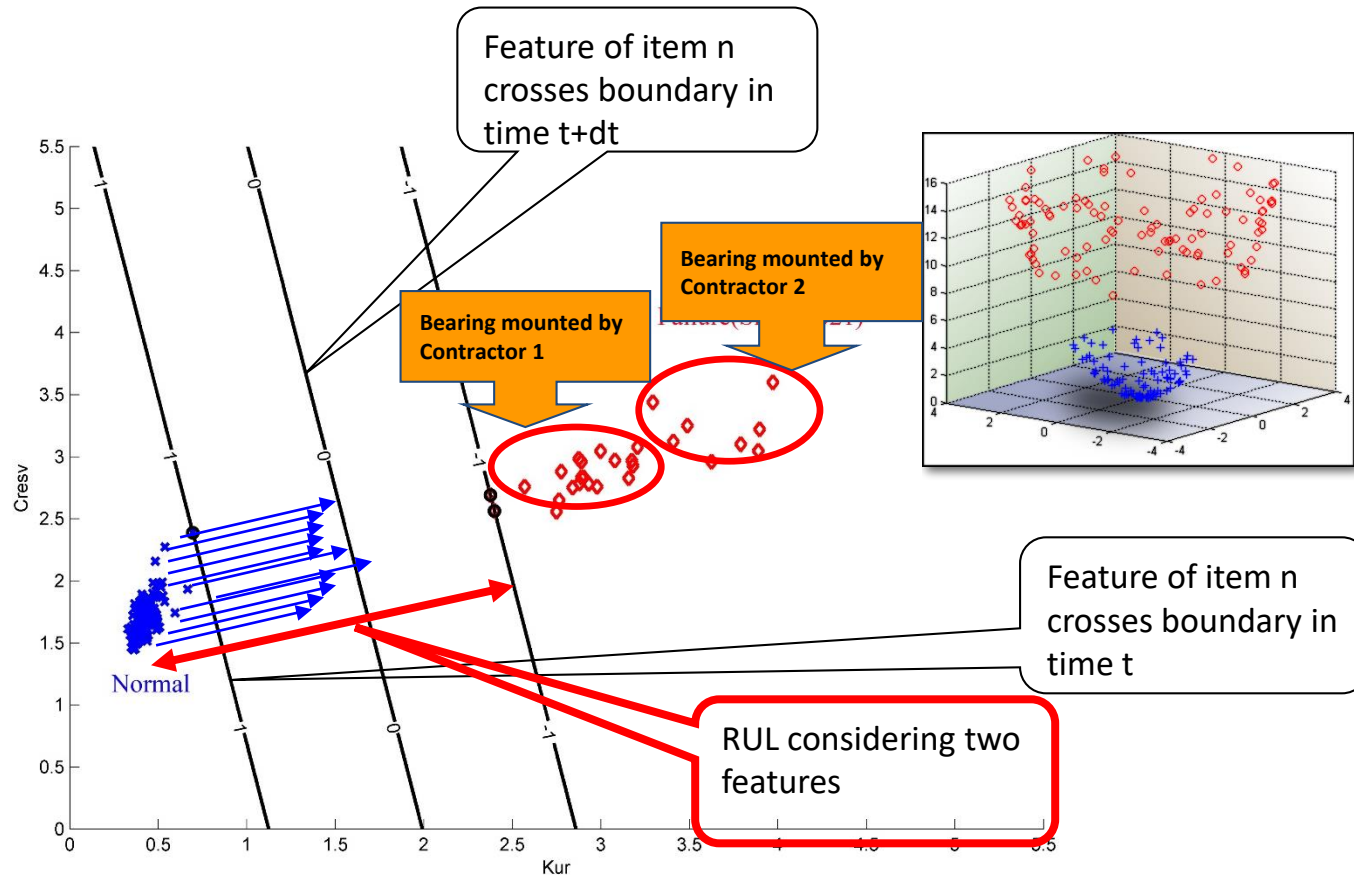
Predictive analytics: RUL prediction and simulation of scenarios



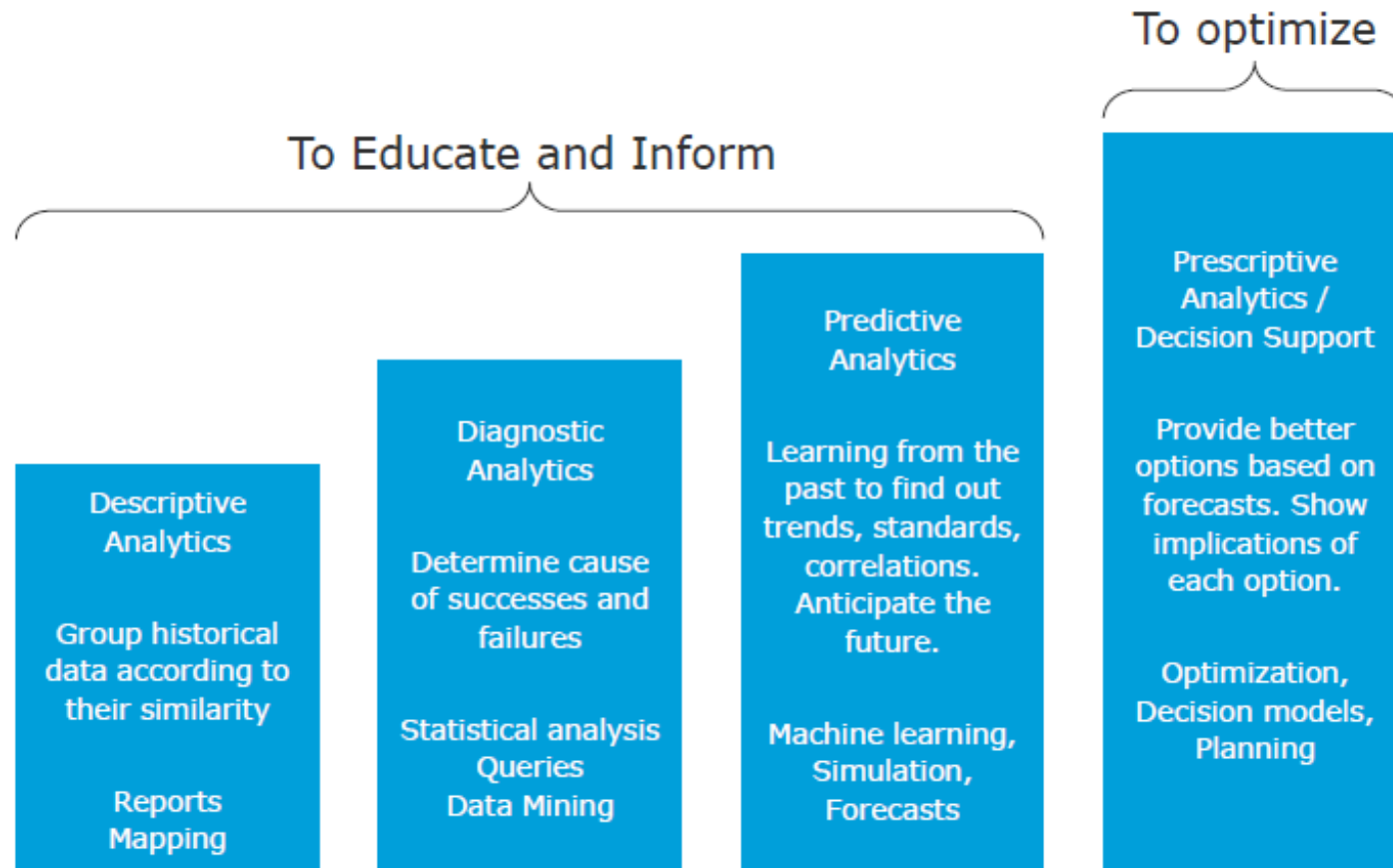
Predictive analytics: RUL prediction and simulation of scenarios



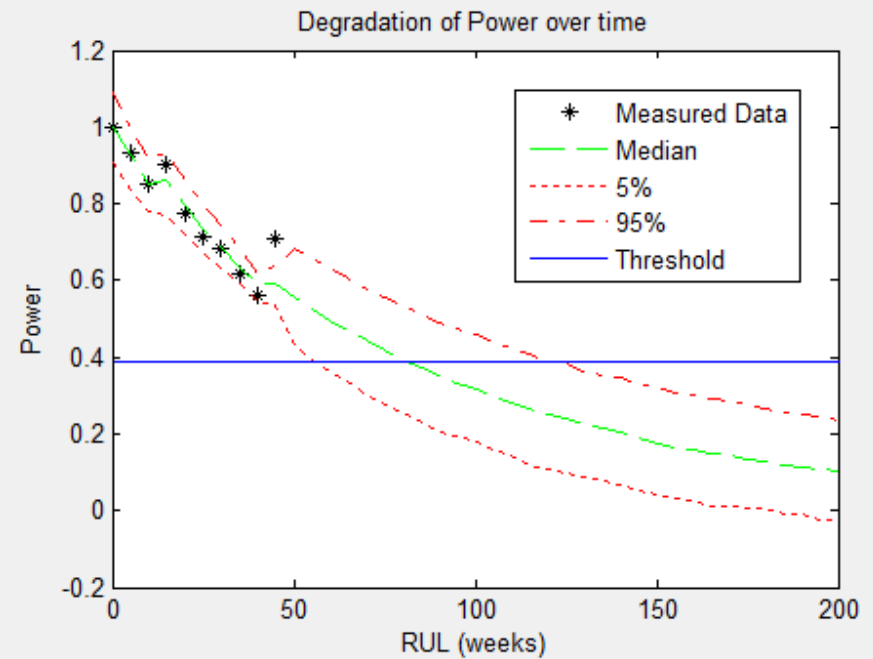
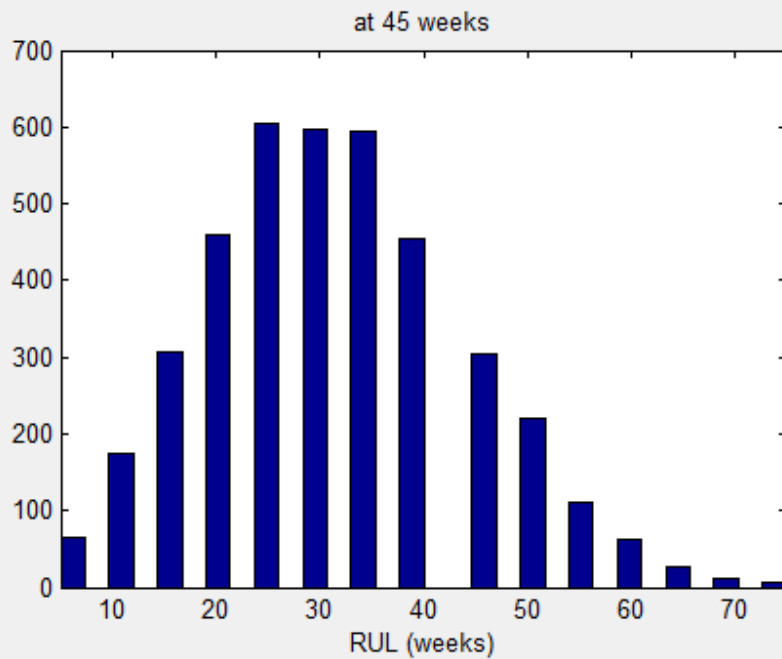
Predictive analytics: RUL prediction and simulation of scenarios



Types of data analytics



Prognosis information: Particle filter considering context



Types of data analytics



- **Digital twins and Hybrid models** are needed for virtual commissioning to deliver O&M services and kill black swans and listen the swan song
- O&M based on Data driven solutions can lead to **catastrophic failures**
- **Cognitive analytics is the logical sequence of prescription**
- **Digital twin 4.0 will consider evolutionary models and normality dynamics**



Thanks!!

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