tecnalia

MEMBER OF BASQUE RESEARCH & TECHNOLOGY ALLIANCE

LULEÅ UNIVERSITY OF TECHNOLOGY

Digital Twins Issues and challenges

Prof. Diego Galar

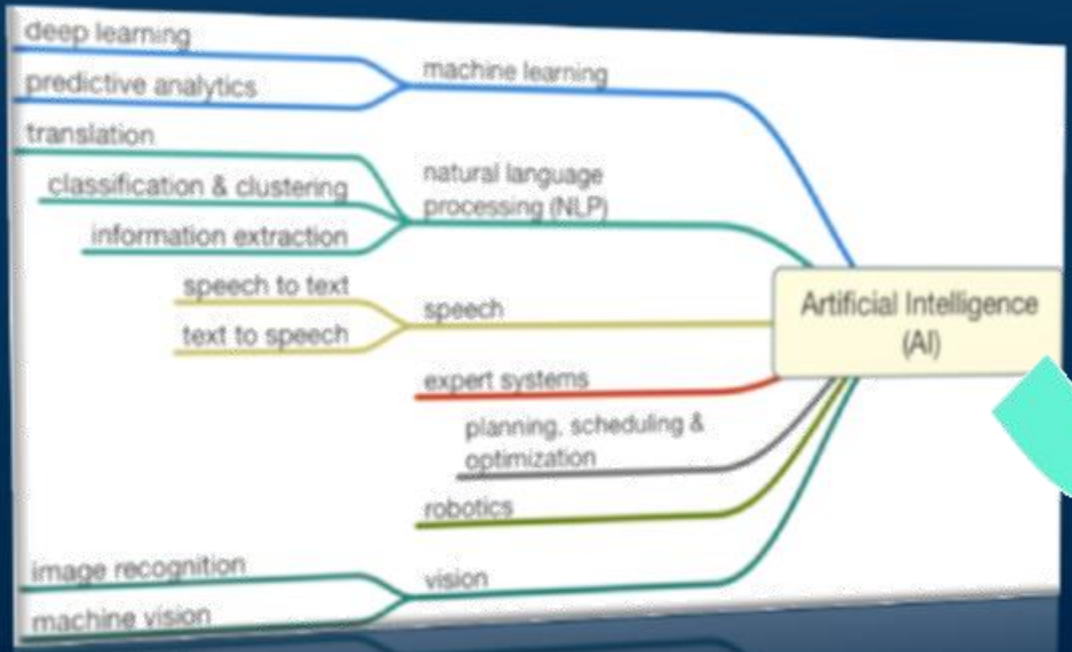
Maintenance and Relaibility, Tecnalia

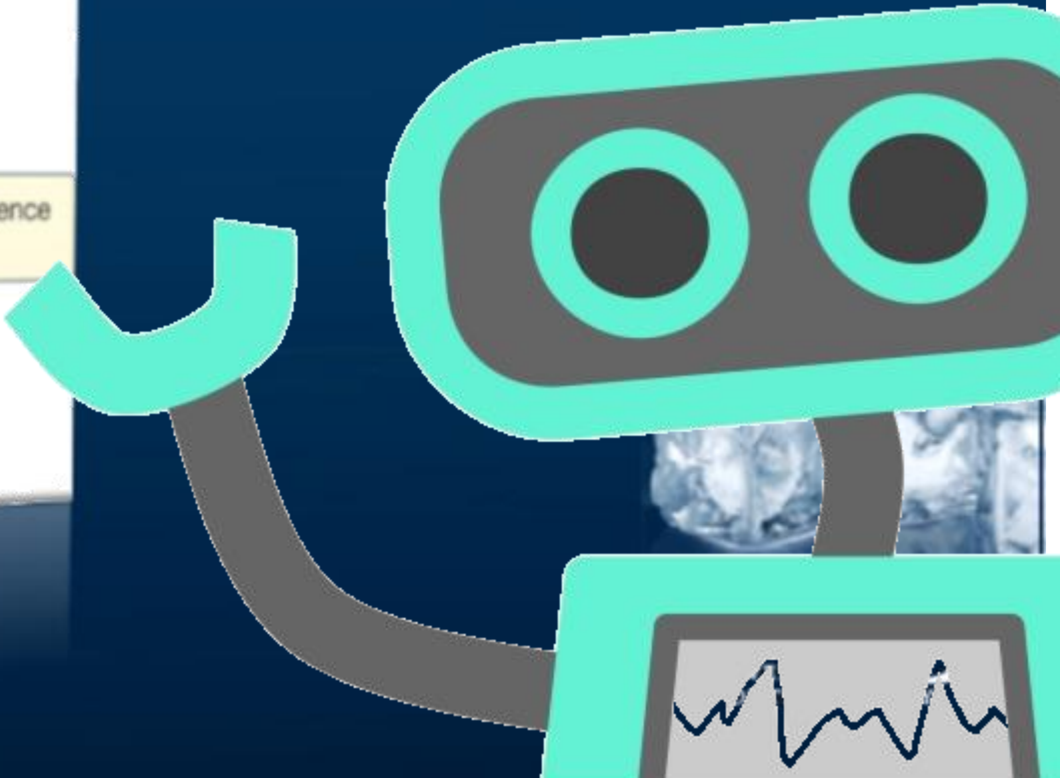
Division of Operation and Maintenance Engineering

Lulea University of Technology

AI DEFINITION

Artificial intelligence (AI) is the ability of a computer or computer-controlled system to perform tasks commonly associated with intelligent beings.





INDUSTRIAL AI

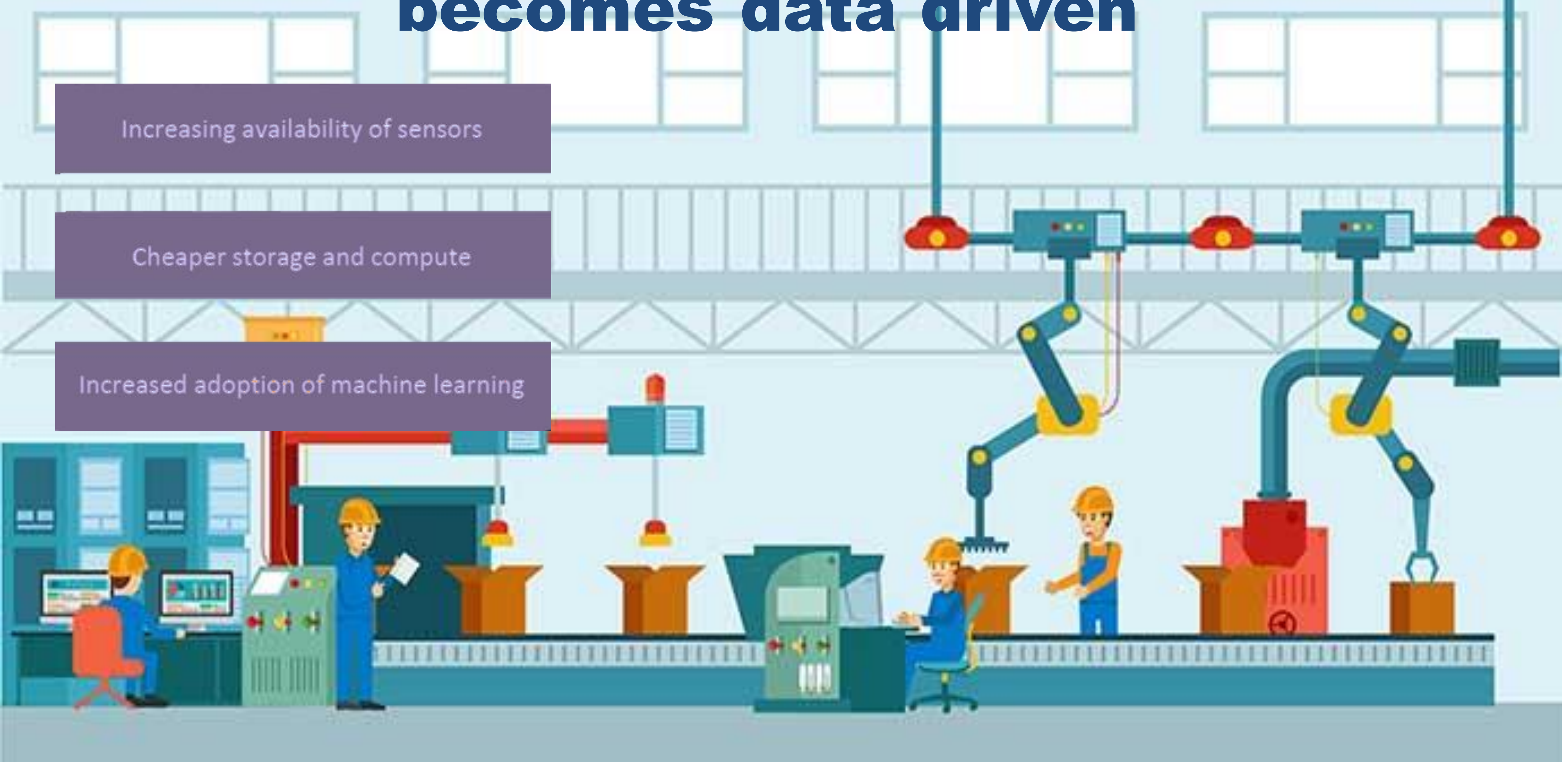
Industrial AI is the application of technologies to address industrial pain-points for customer value creation, productivity improvement, and insight discovery

Equipment in industry needs AI since becomes data driven

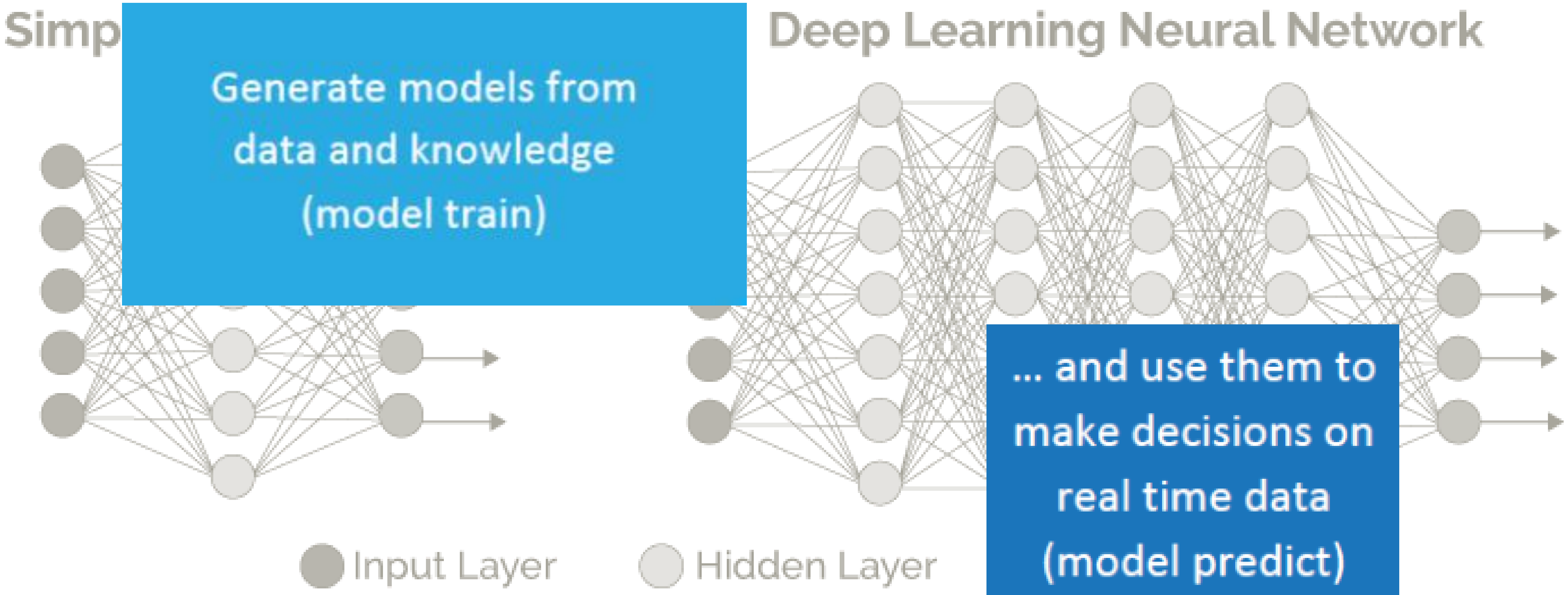
Increasing availability of sensors

Cheaper storage and compute

Increased adoption of machine learning



Data driven methods are well known for long



Generate models from data and knowledge (model train)

... and use them to make decisions on real time data (model predict)

Scale up and populate..
The Achilles heel

"Through 2020, 80% of AI projects will remain alchemy, run by wizards whose talents will not scale in the organization."

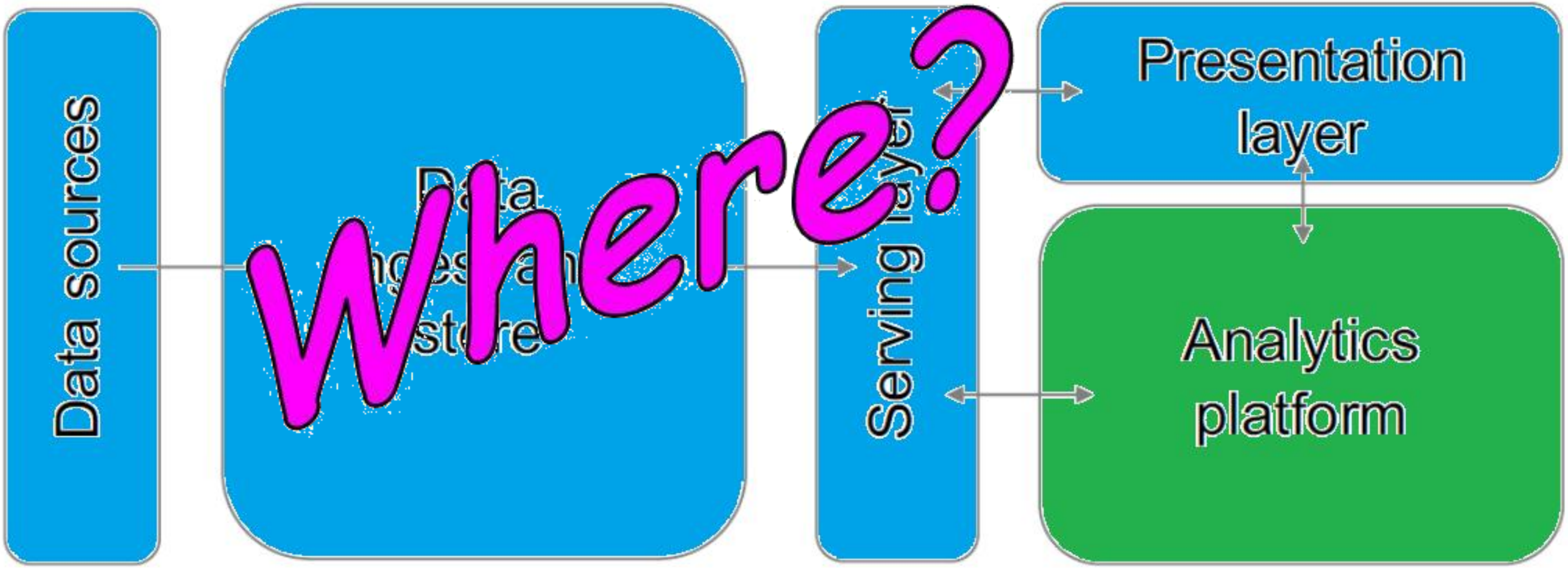
– GARTNER

Why scaling is difficult?

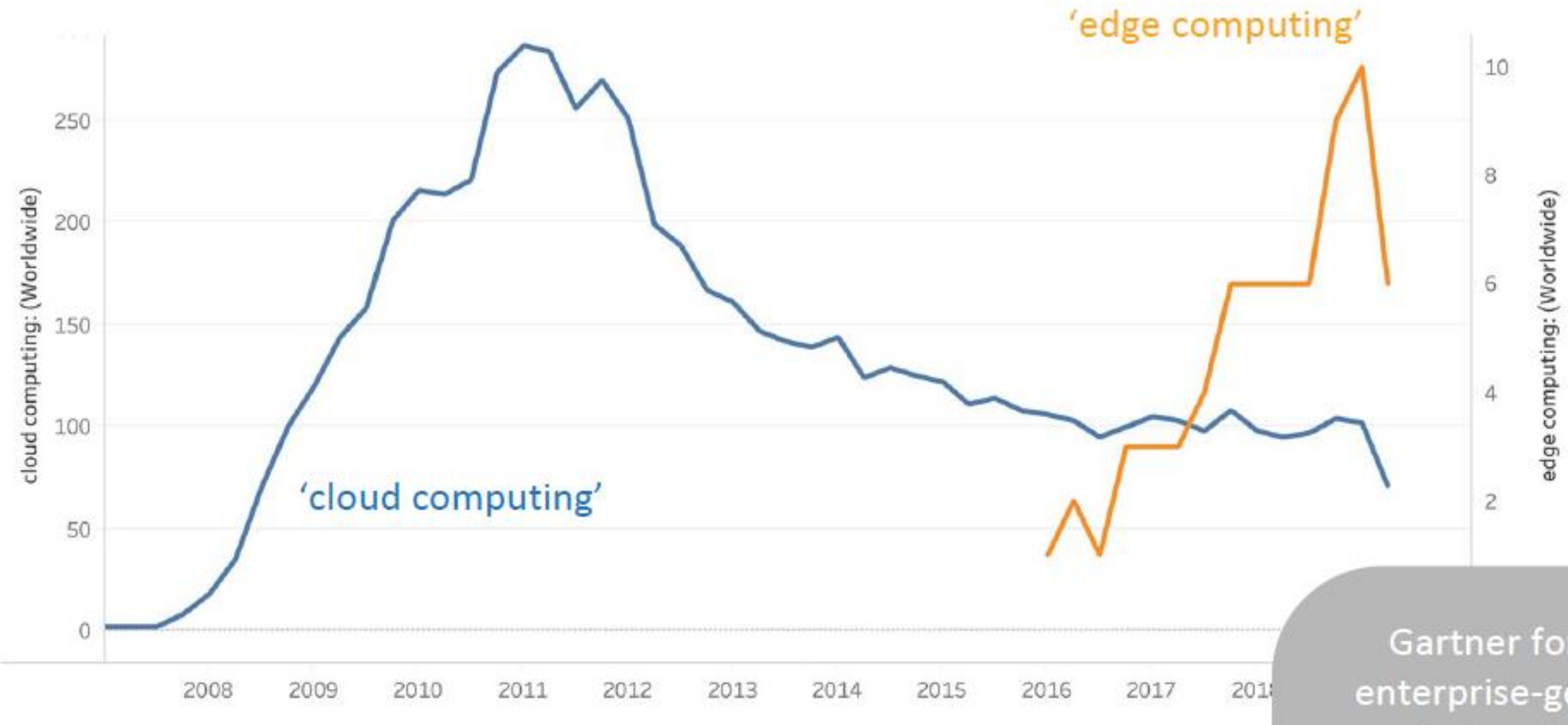
The infrastructure

Where?
CLOUD
Data Centers
Thousands
FOG
Nodes
Millions
EDGE
Devices
Billions
CREDITCARD
0000000000

Conceptual view of AI platform

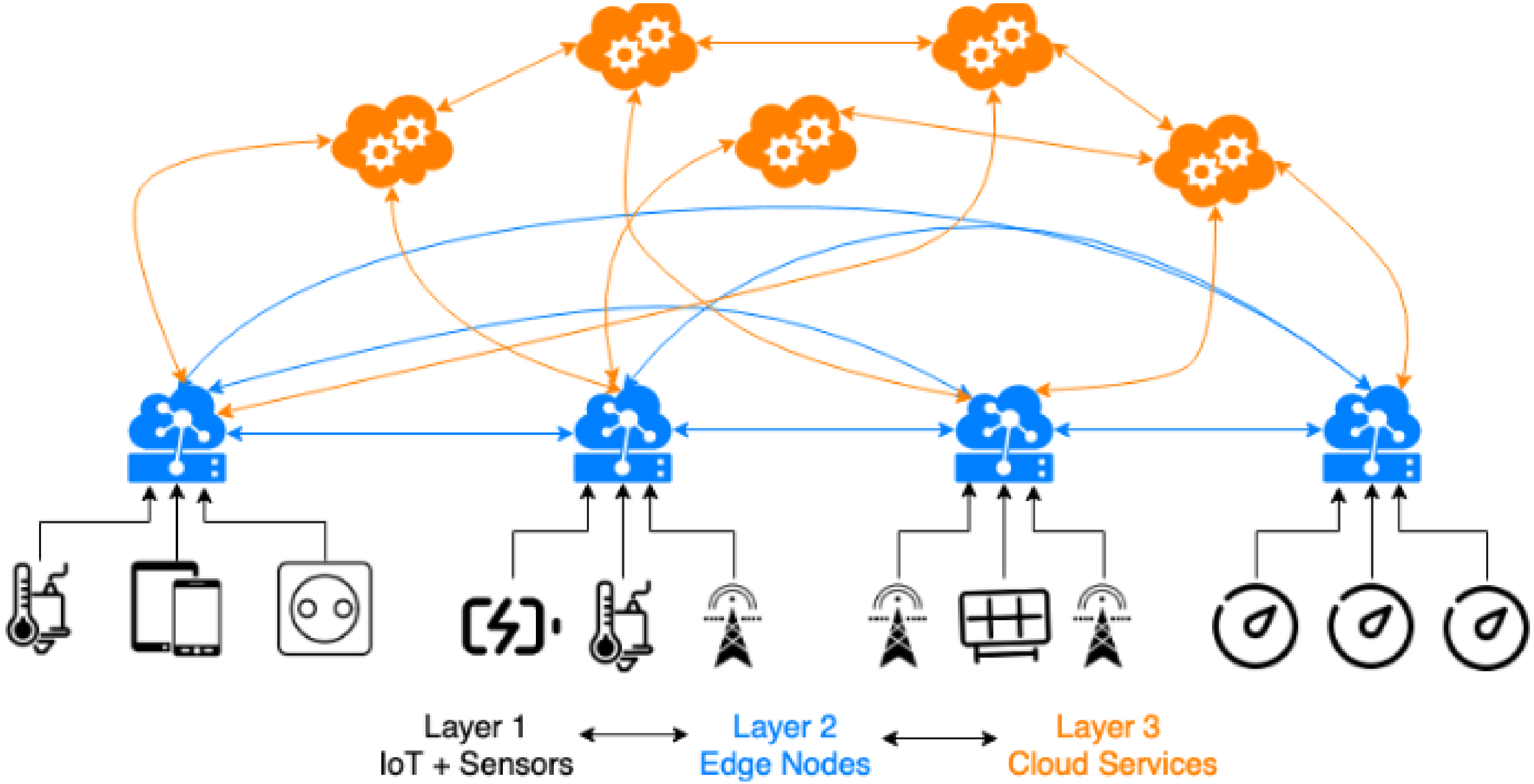


Edge computing is on the rise in many industries



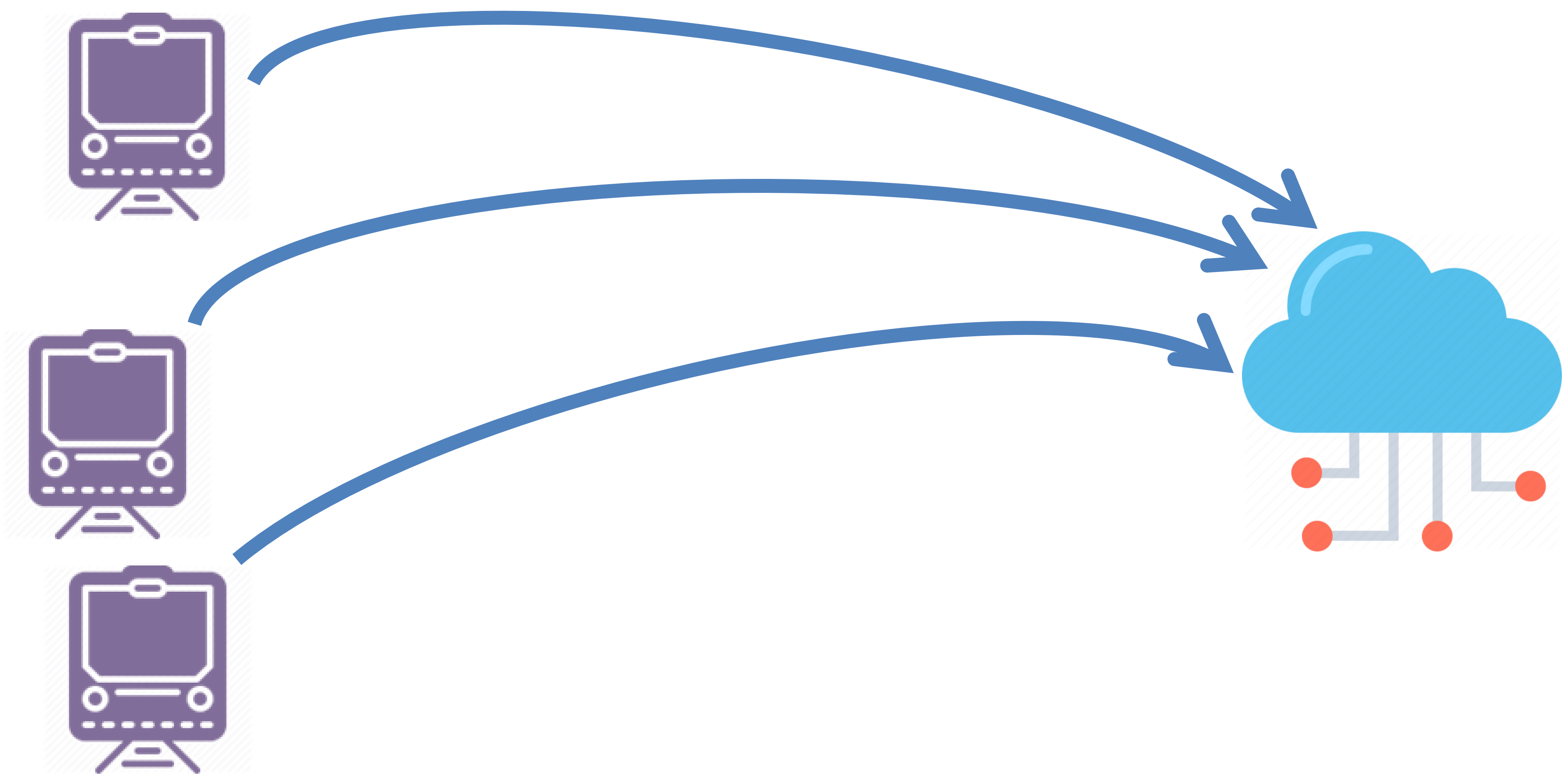
Gartner forecasts that 75% of enterprise-generated data will be created and processed at the edge by 2022

Multiple layer Edge computing architecture

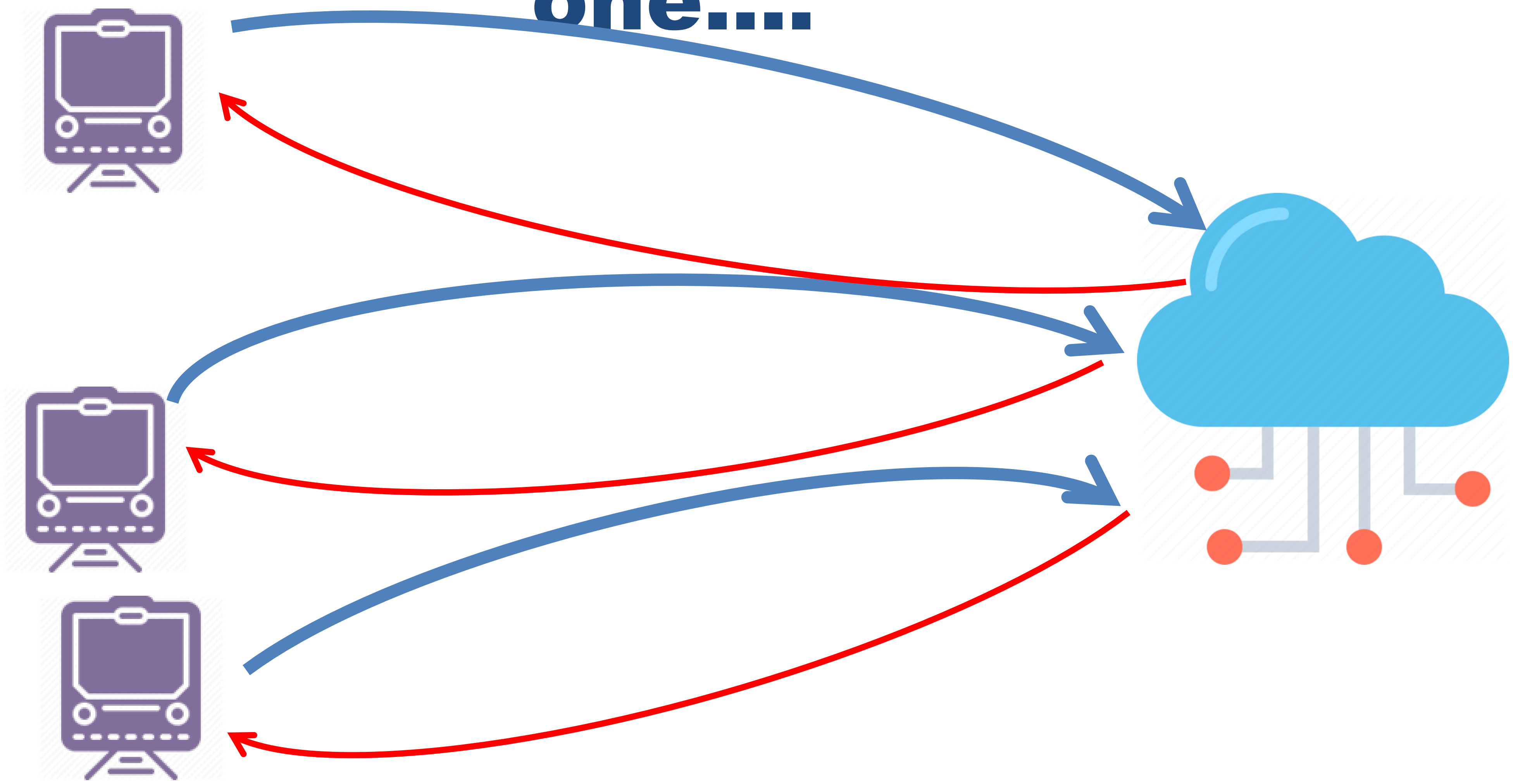


Edge agents versus cloud centralized

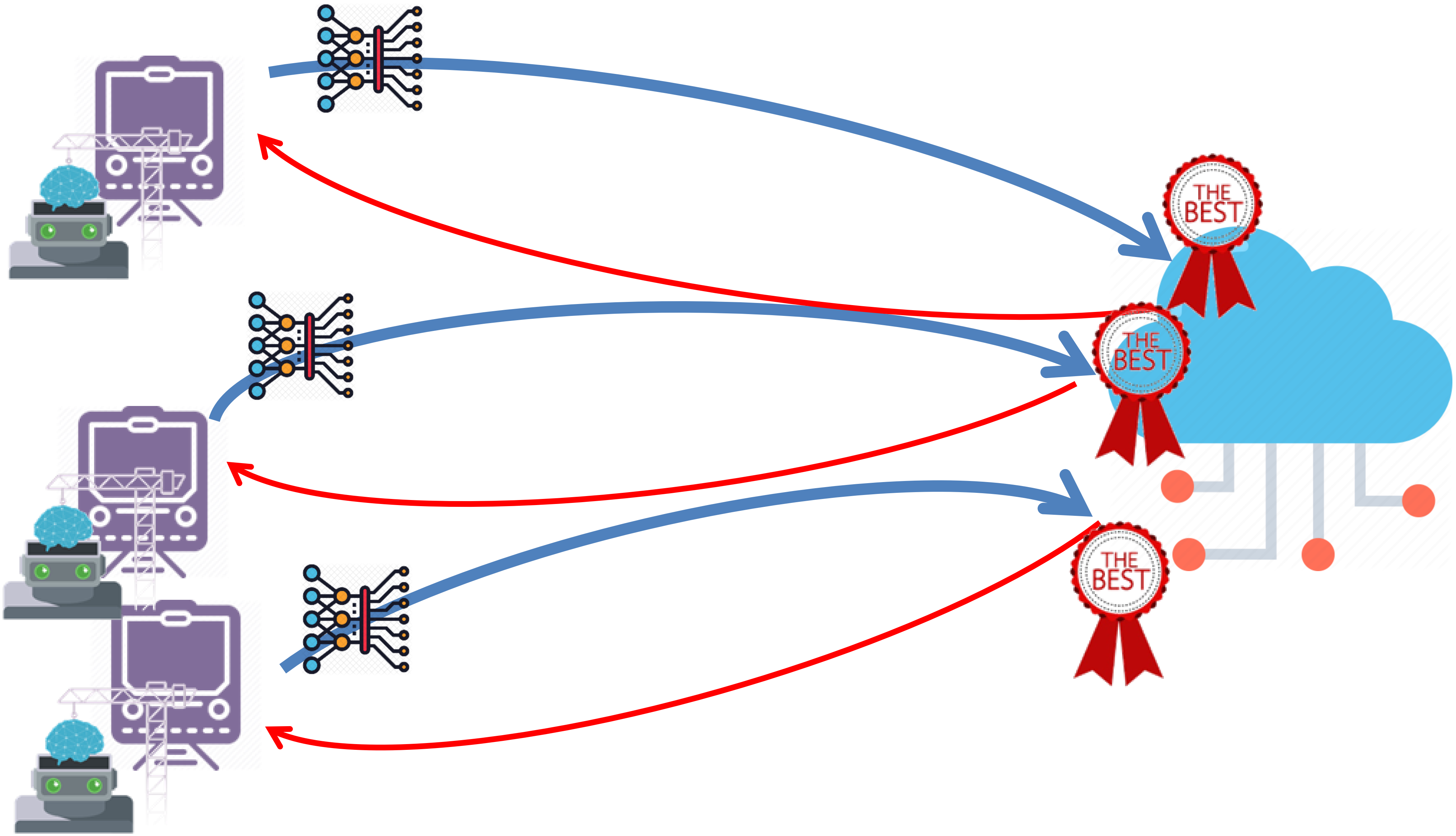
Traditional way, we transfer everything to cloud



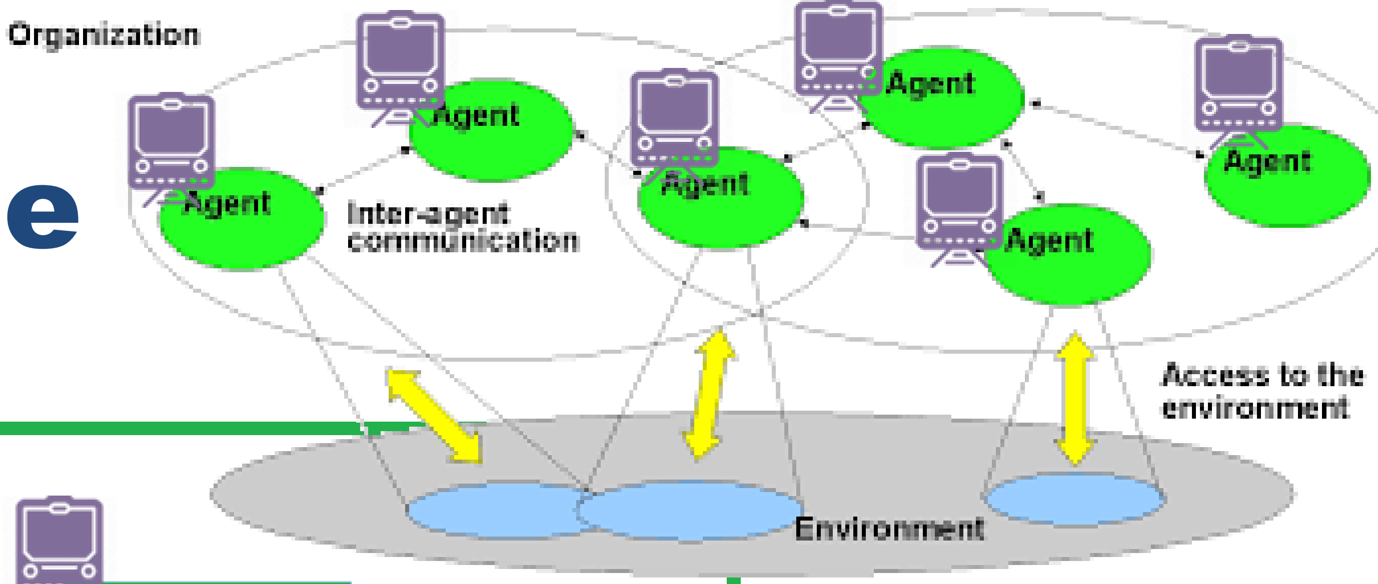
The cloud provides the services one by one....

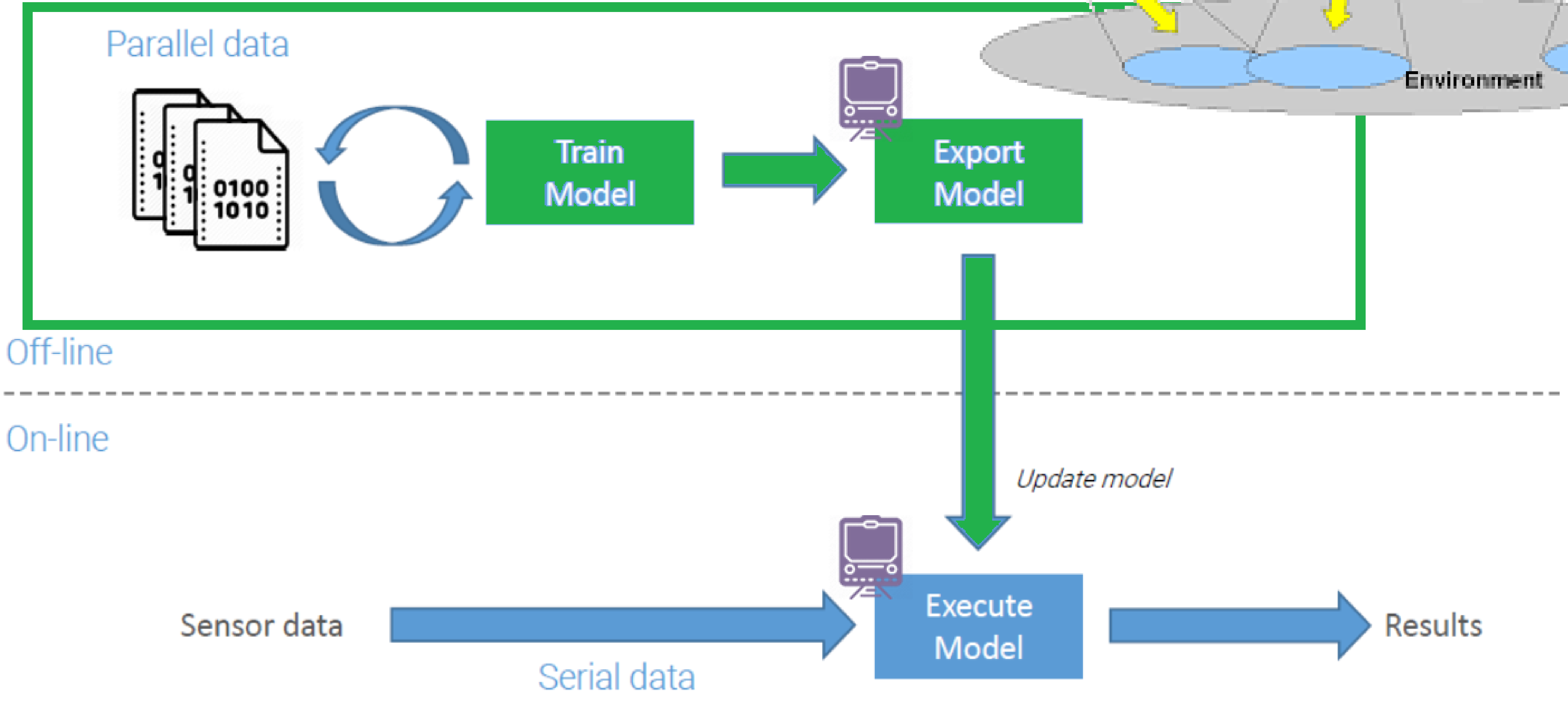


With Multi agent for large fleet



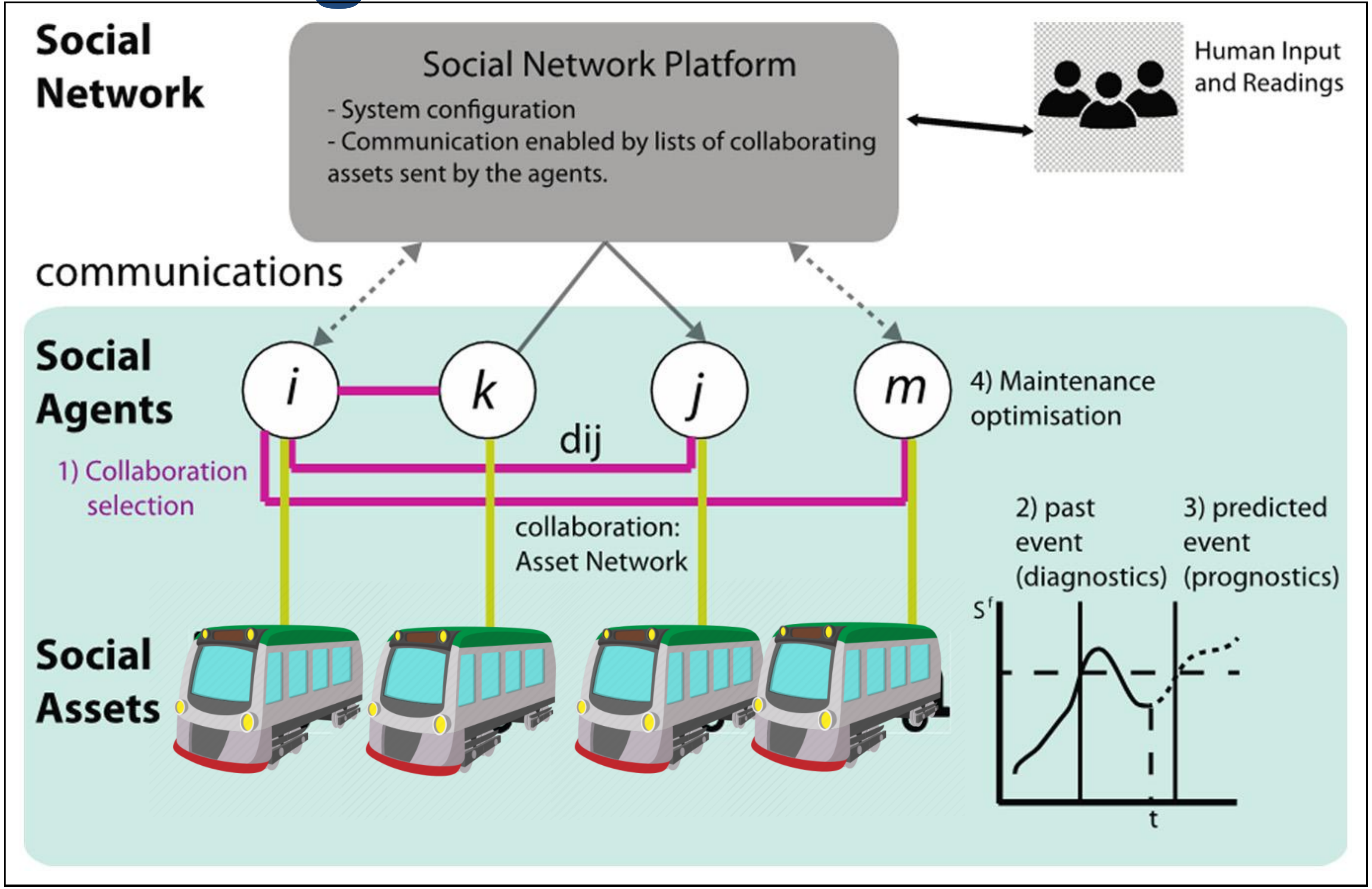
AI workflow @edge





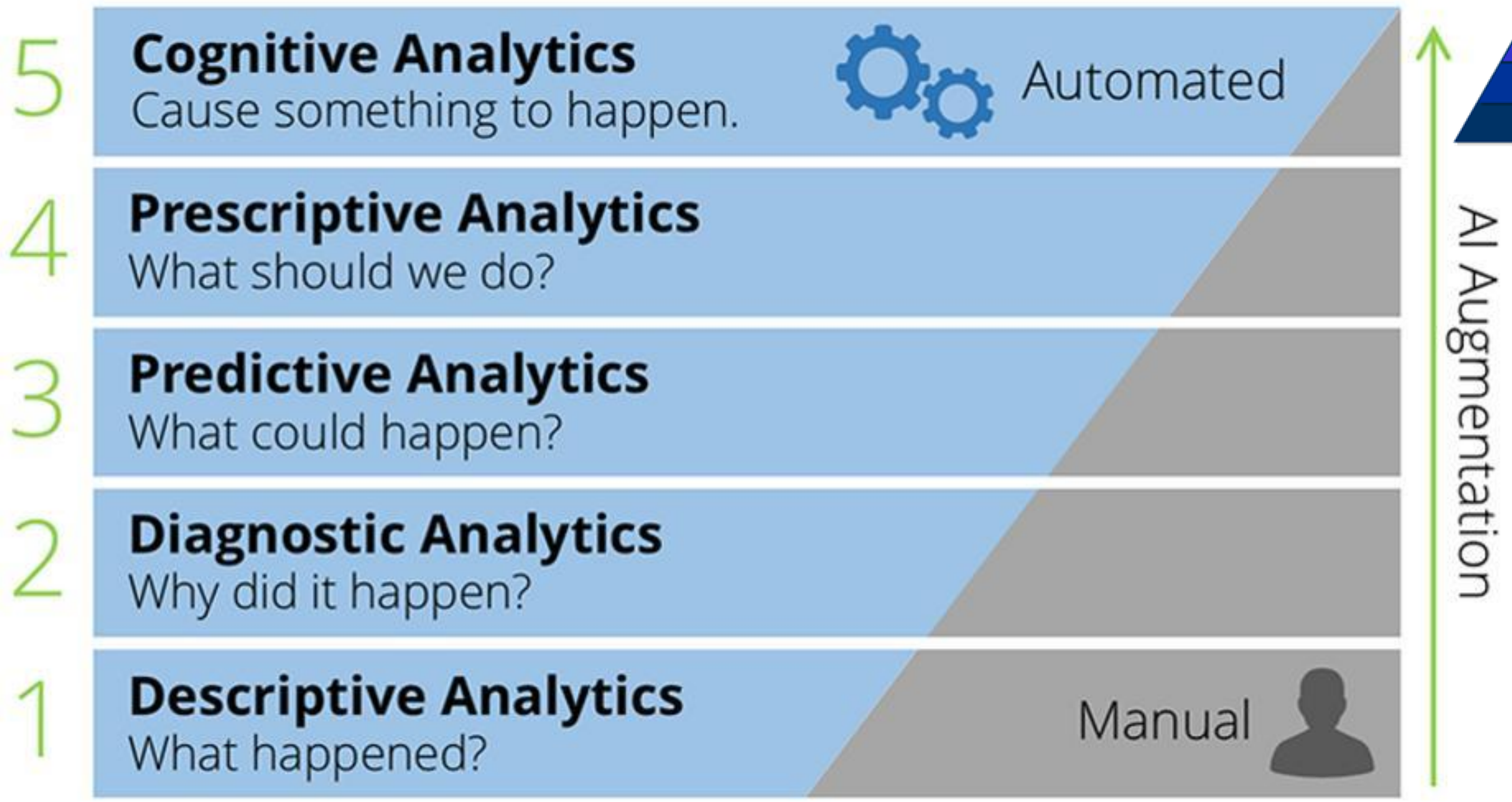
Human confused? Let us machine talk

Social agents: The middleware



The analytics

Analytics and expectations also change



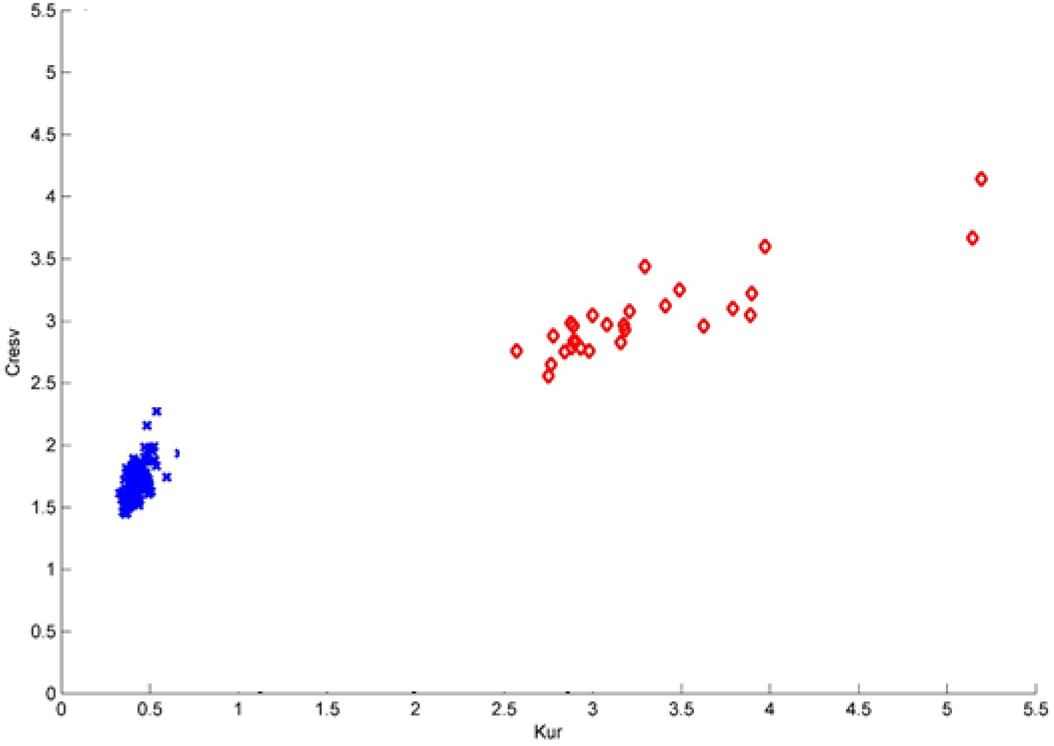
Types of data analytics

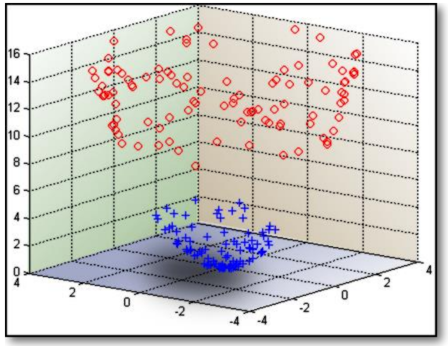
Descriptive Analytics

Group historical data according to their similarity

Reports
Mapping

Descriptive analytics





The challenge in Descriptive analytics

Types of data analytics

Descriptive Analytics

Group historical data according to their similarity

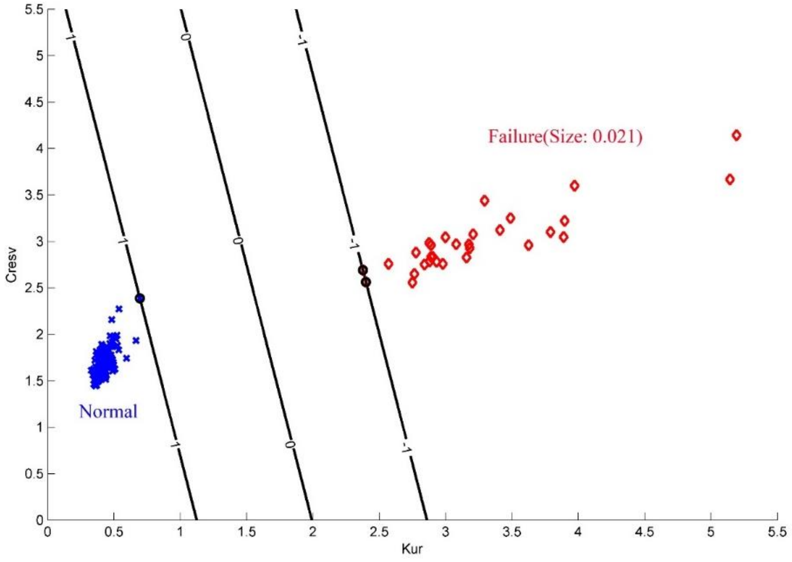
Reports
Mapping

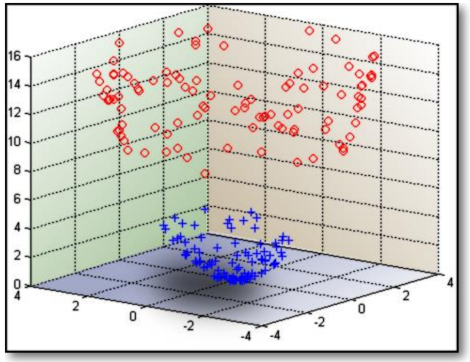
Diagnostic Analytics

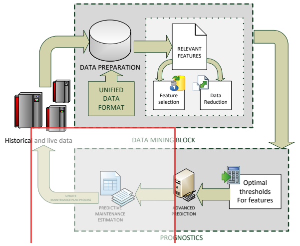
Determine cause of successes and failures

Statistical analysis
Queries
Data Mining

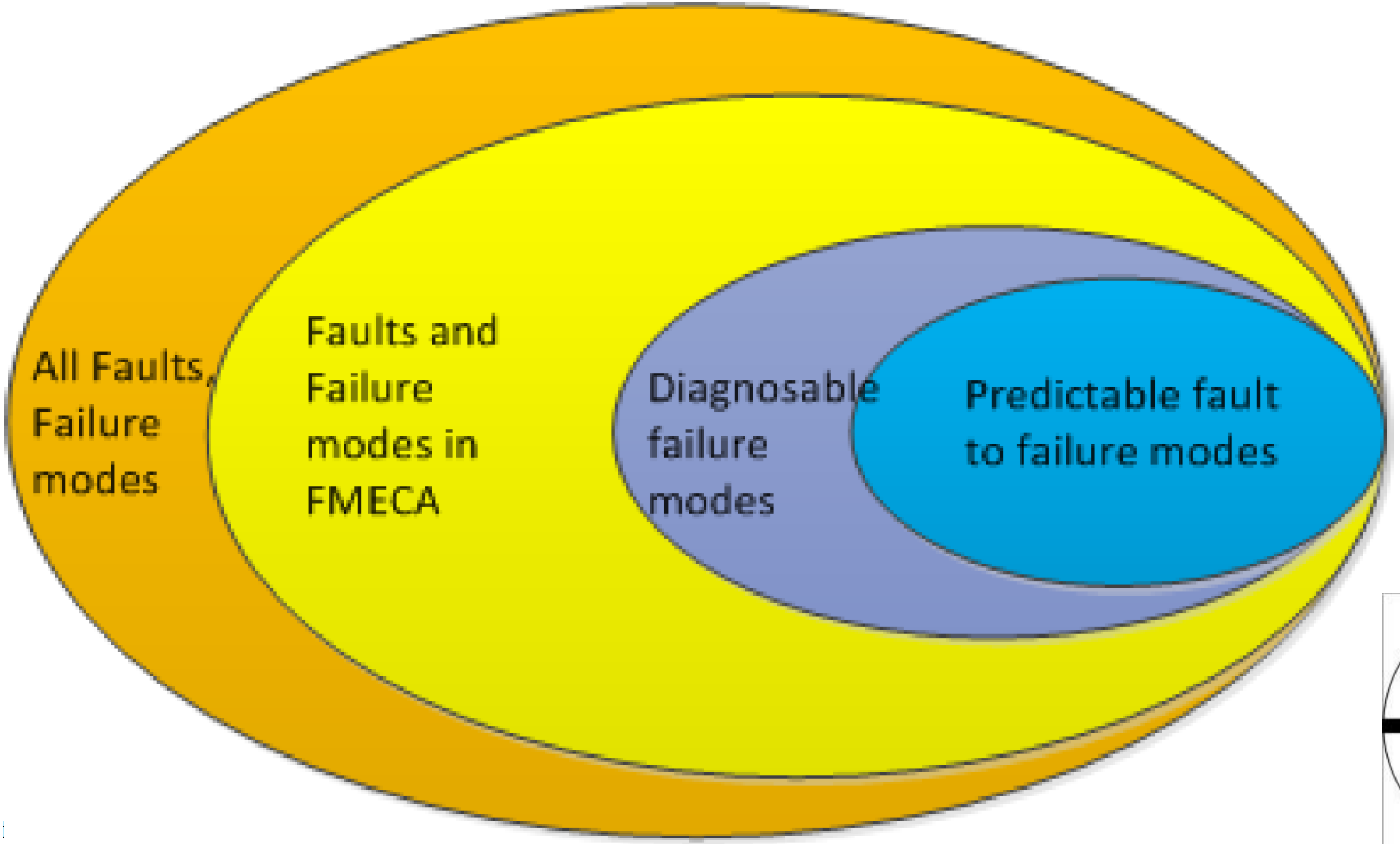
Diagnostic analytics







The challenge in Diagnostics analytics



“Black Swan Event: An event or occurrence that deviates beyond what is normally expected of a situation and that would be extremely difficult to predict.”

Black Swan Losses

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

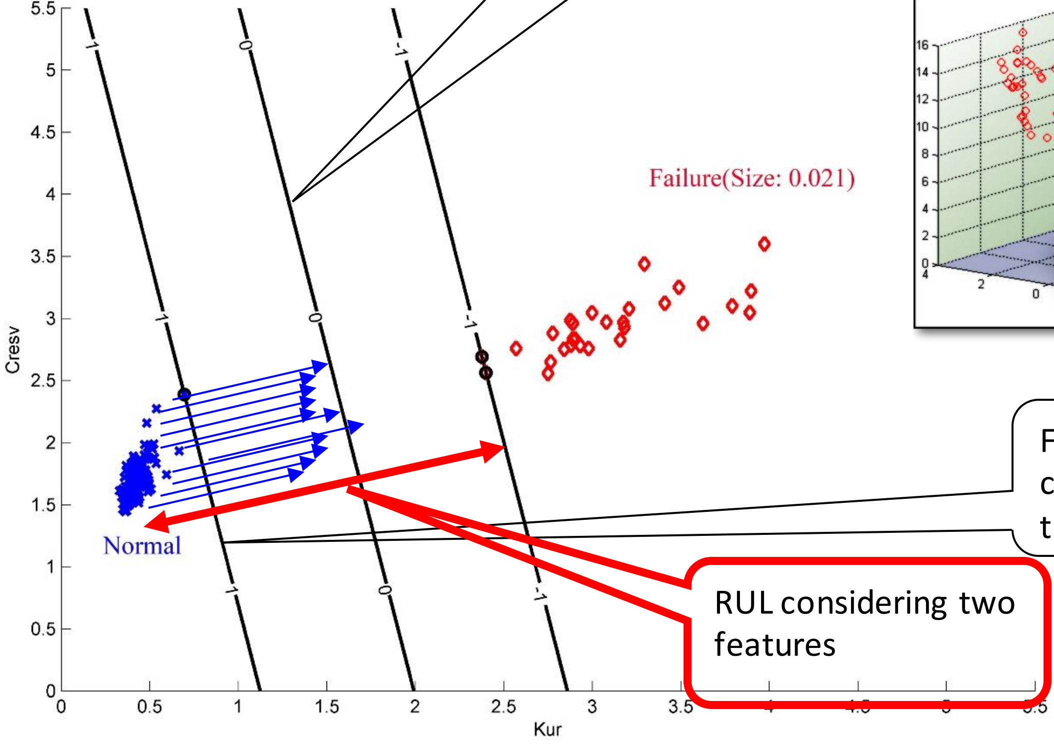
Types of data analytics

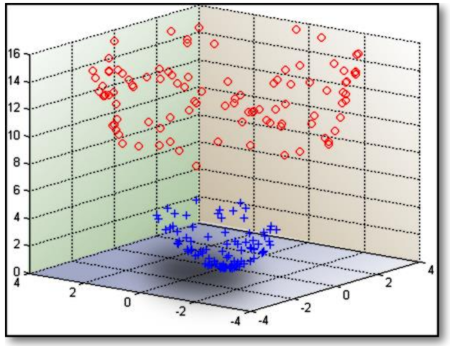
To Educate and Inform

Descriptive Analytics	Diagnostic Analytics	Predictive Analytics
Group historical data according to their similarity	Determine cause of successes and failures	Learning from the past to find out trends, standards, correlations. Anticipate the future.
Reports Mapping	Statistical analysis Queries Data Mining	Machine learning, Simulation, Forecasts

Predictive analytics:RUL prediction

Feature of item n crosses boundary in time t+dt





Feature of item n crosses boundary in time t

RUL considering two features

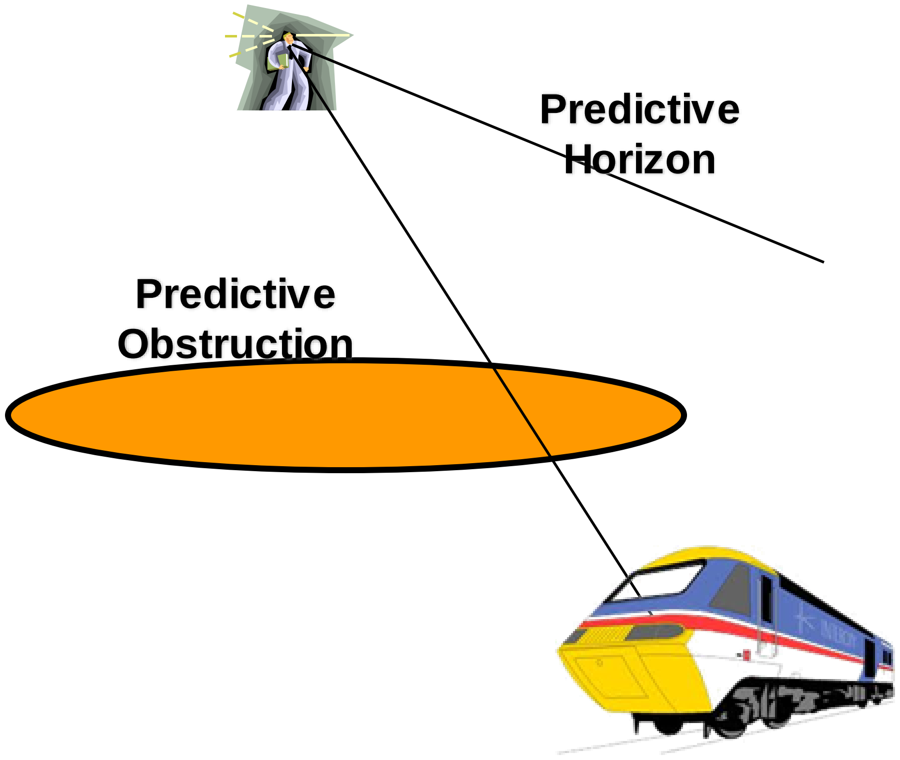
Prognostic Horizon
How Far Do You Want to See Into the Future?

Choose One

- **Detect Train Just Before it Hits You,**

or

- **Detect Train Far Enough in Advance to Take The "Right" Evasive Action**



The picture of Dorian Gray
The challenge in predictive analytics

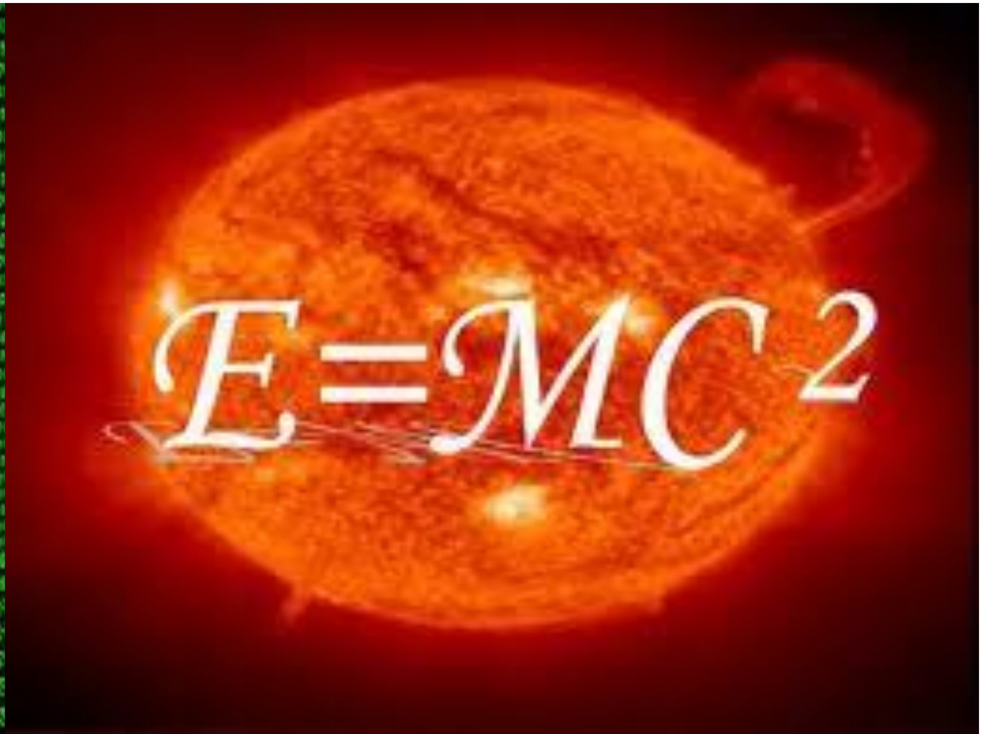
Huge gap between data science and O&M

"I need to deploy models into live business environments."

"I need strong, transparent insights to improve my daily decisions."

Data driven or model based?

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



Types of data analytics

To optimize

To Educate and Inform

Descriptive Analytics

Group historical data according to their similarity

Reports
Mapping

Diagnostic Analytics

Determine cause of successes and failures

Statistical analysis
Queries
Data Mining

Predictive Analytics

Learning from the past to find out trends, standards, correlations. Anticipate the future.

Machine learning, Simulation, Forecasts

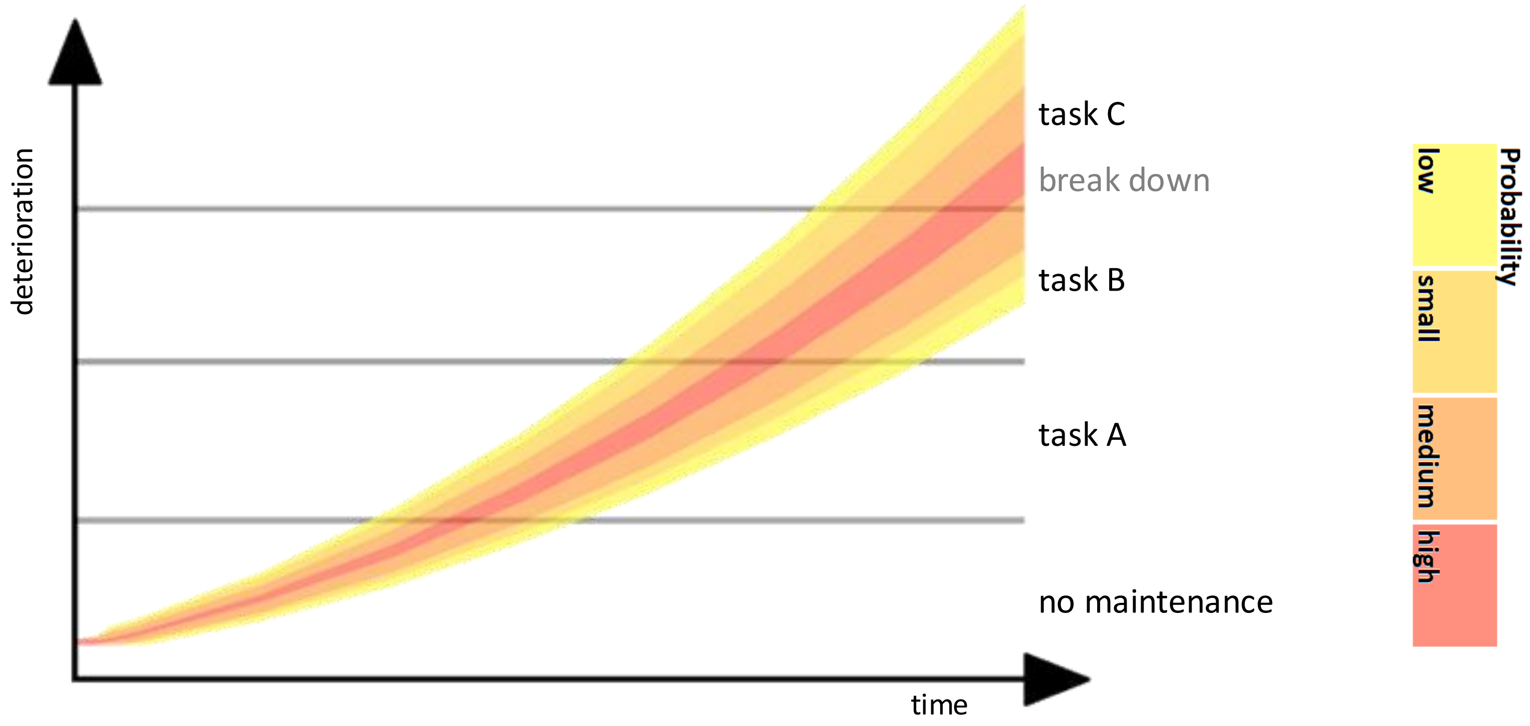
Prescriptive Analytics / Decision Support

Provide better options based on forecasts. Show implications of each option.

Optimization, Decision models, Planning

Prescriptive analytics:RUL prediction and simulation of scenarios

Maintenainers demand: Operational recommendations with RUL estimations characterised via deterioration process, probability model, possible tasks



Can you predict and track the root cause of chaos?

HOW MACHINES LEARN

Text, images, speech & videos

- 350M photos/day
- 4.5B likes/day
- 3.5B Google searches/day
- 304 M active Amazon users

Feed Back Type

- Search relevance
- Likes
- Clicks
- Product reviews
- Tagging
- Rating

Consumer Internet: Discrete, High Events

Sensor time series, text & images

- 173000+ monitored assets
- 250M/samples/day- CCGT plant
- 3 Trips/year for GT
- 29 Events/1M flights for a/c engines
- 1 Inspection/Year

Feed Back Type

- Inspection results
- Failure events
- Domain knowledge
- Feedback loop slow

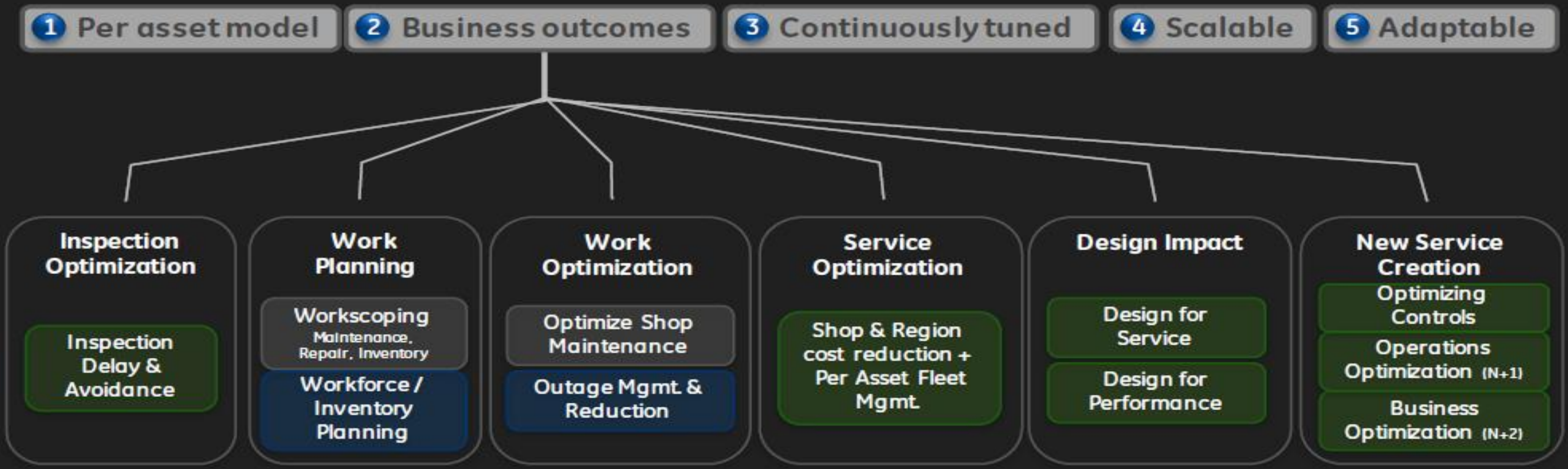
Industrial Internet: Continuous, Low Events

Industrial Data & Feedback Loop are Different

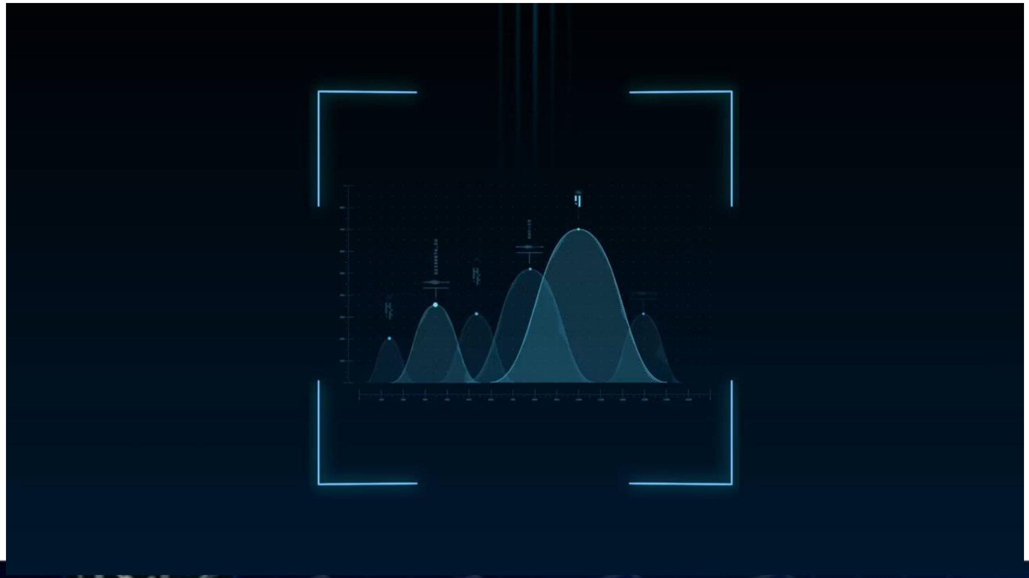
LULEÅ UNIVERSITY OF TECHNOLOGY

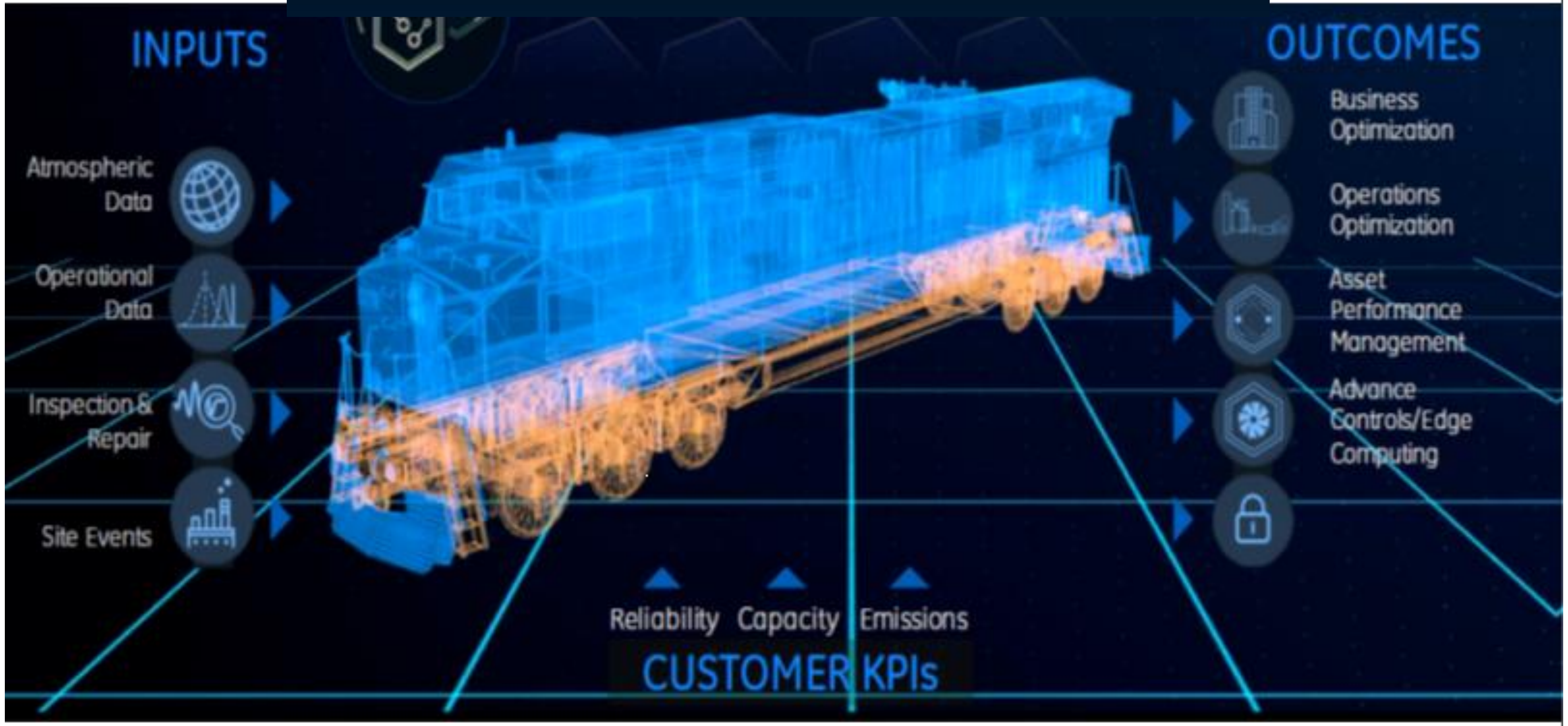
The method, let us twin reality

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

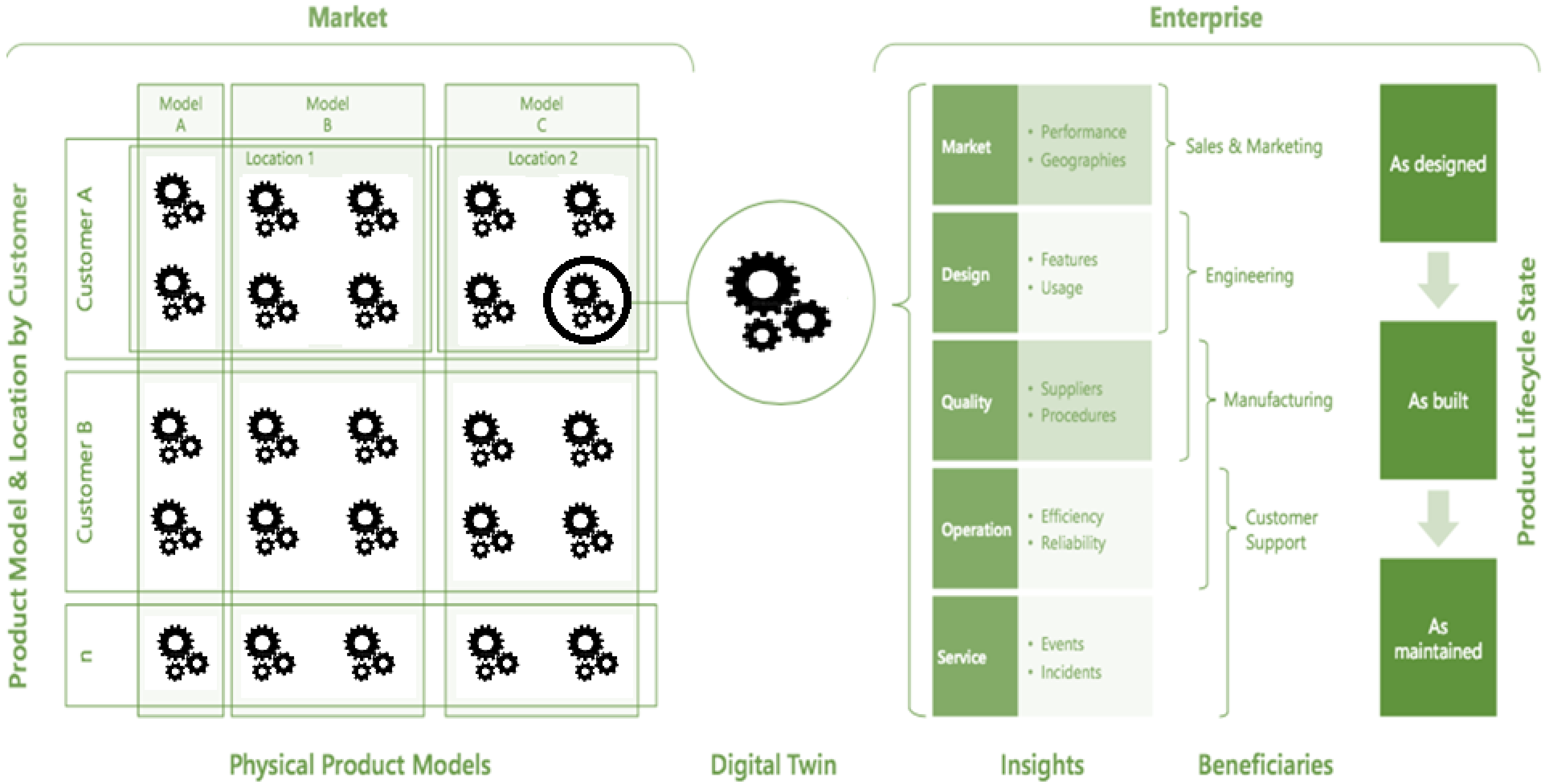


The twin as a service provider

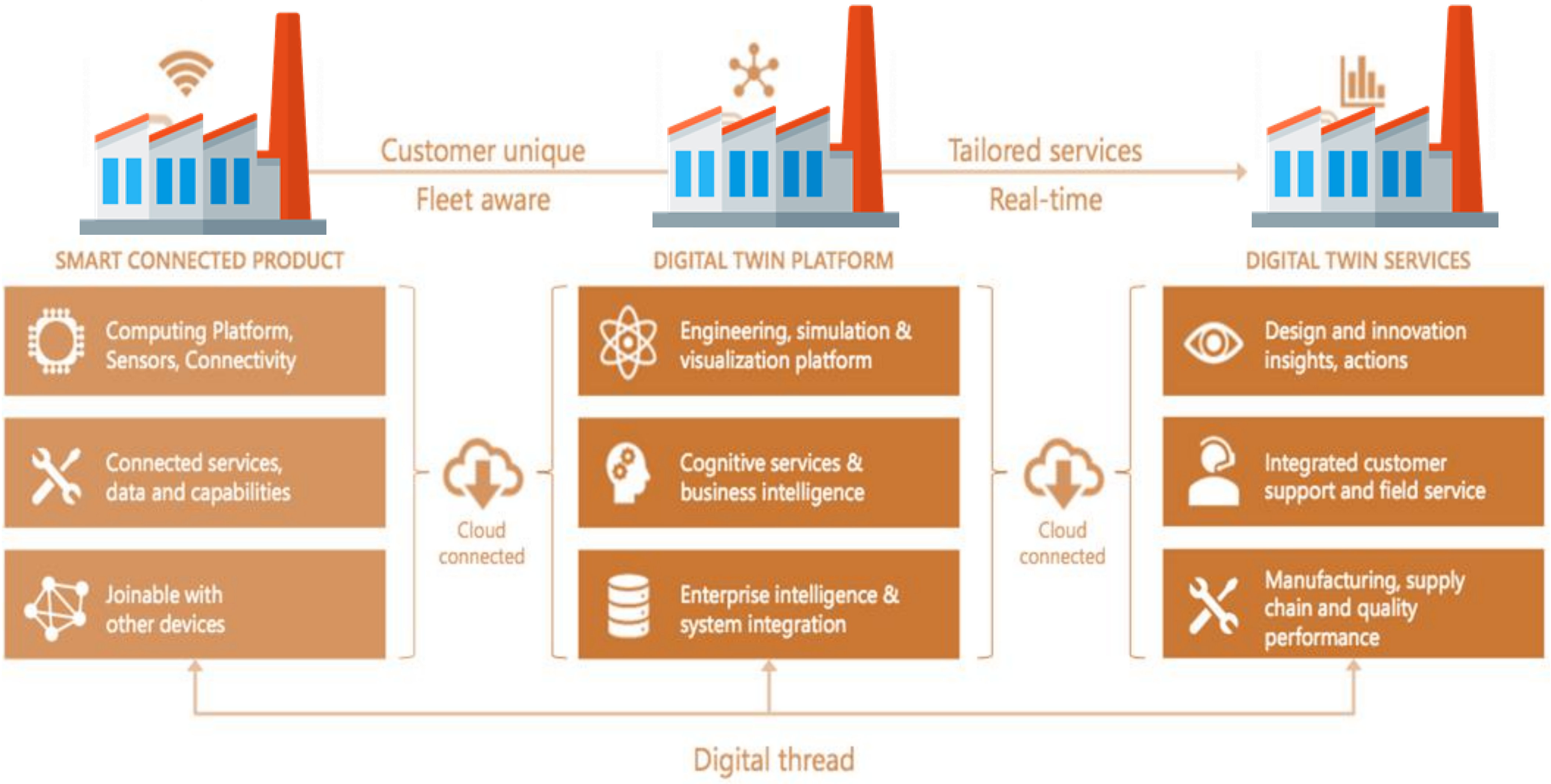




Digital Twin: A virtual instance of a customer's smart connected physical product

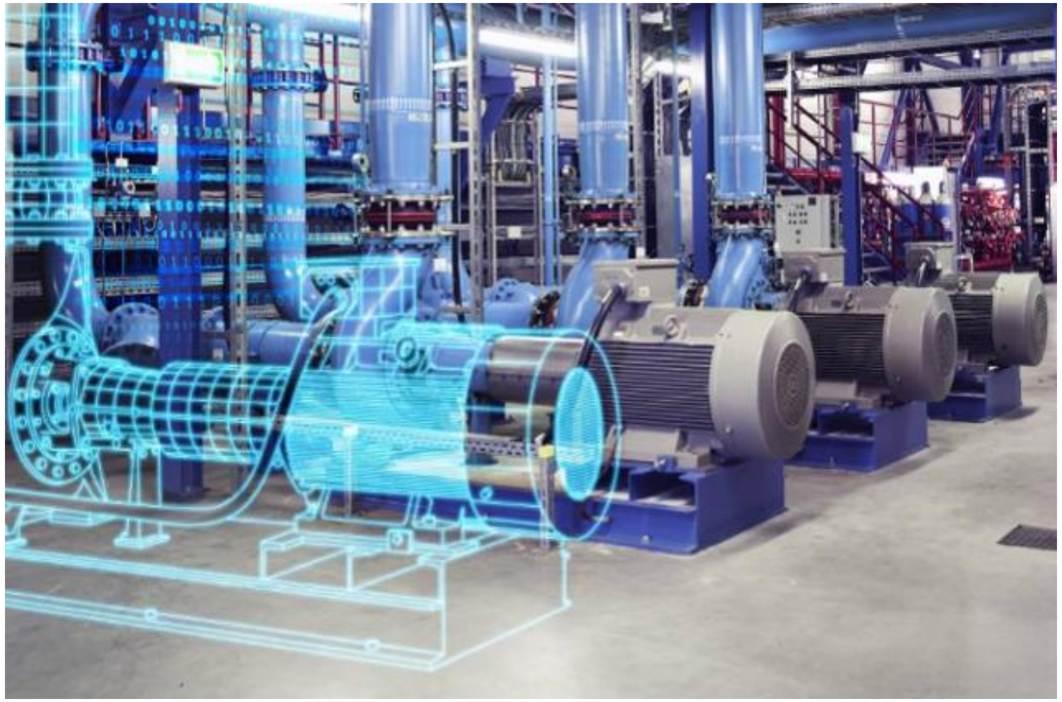


Digital Twin Solution Architecture



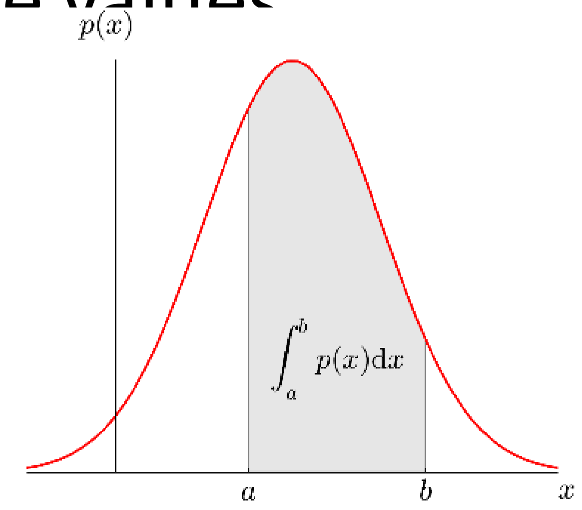
Digital twin

- The digital twin refers to a digital ***replica*** of physical assets, processes and systems that can be used in real-time for control and decision purposes
  - Computerized mathematical model (what we have done over years)
  - Real-time, thanks to IoT
- **In contrast to a physical asset, the digital twin can immediately perform forecasting**



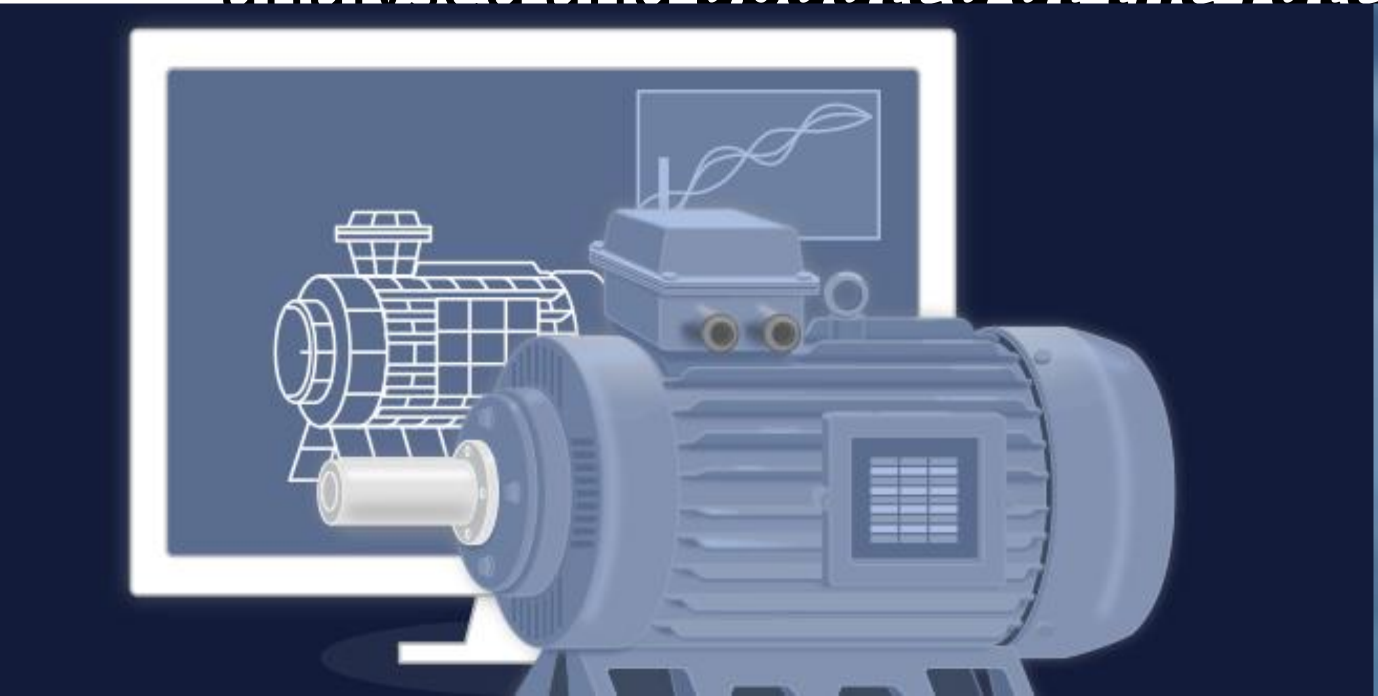
Stochastic digital twin

- A stochastic digital twin is a computerized model of the ***stochastic behavior*** of a system where
  - the model is updated in real-time
    - based on sensor information and other information
    - accessed via the internet and the use of cloud computing resources
- What-if inquiries result in ***pdf***'s rather than single values

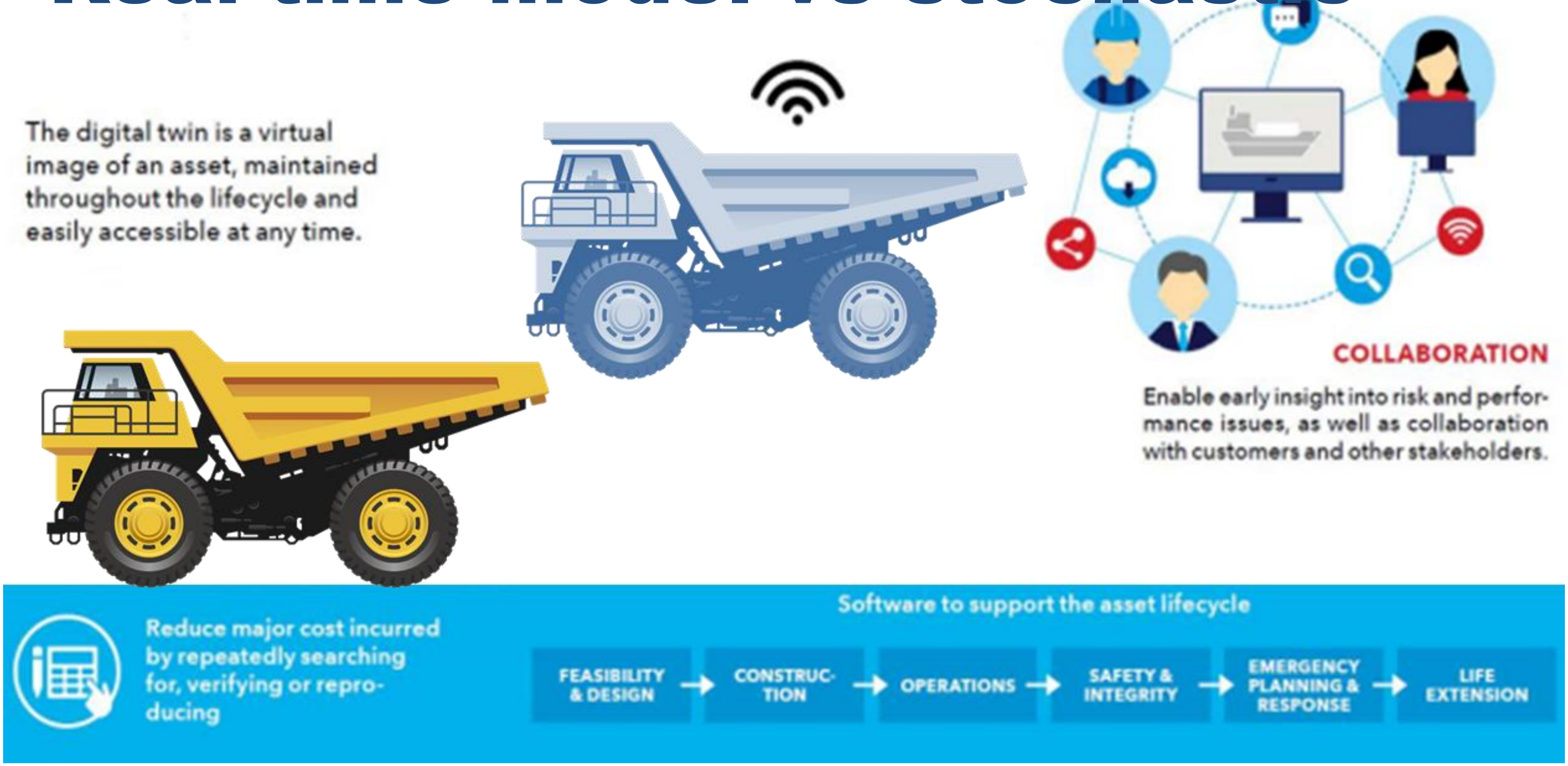


Real-time model

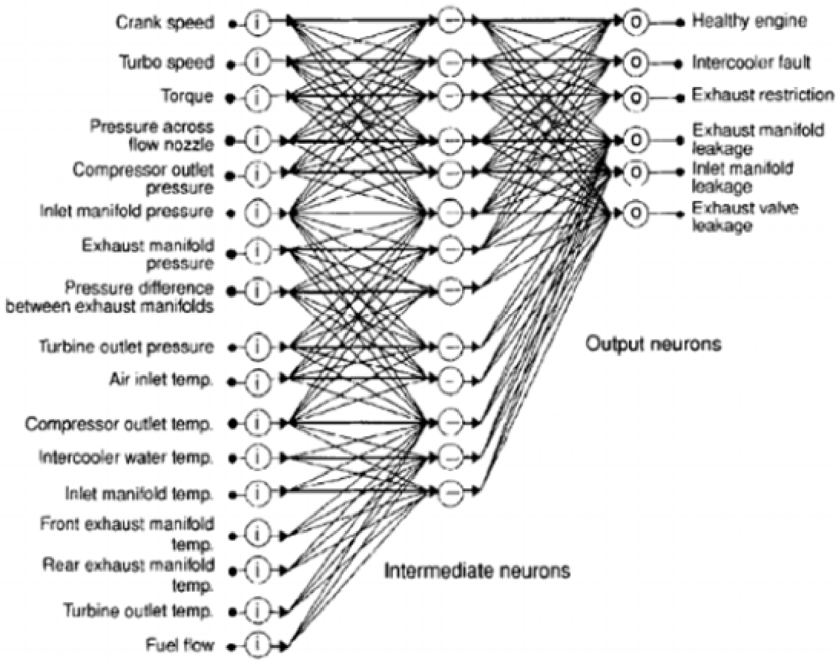
- A real-time model is a model where it is possible to obtain values of system performance and system states in ***real-time***
- With real-time we mean that data referring to a system is analysed and ***updated at the rate at which it is received***

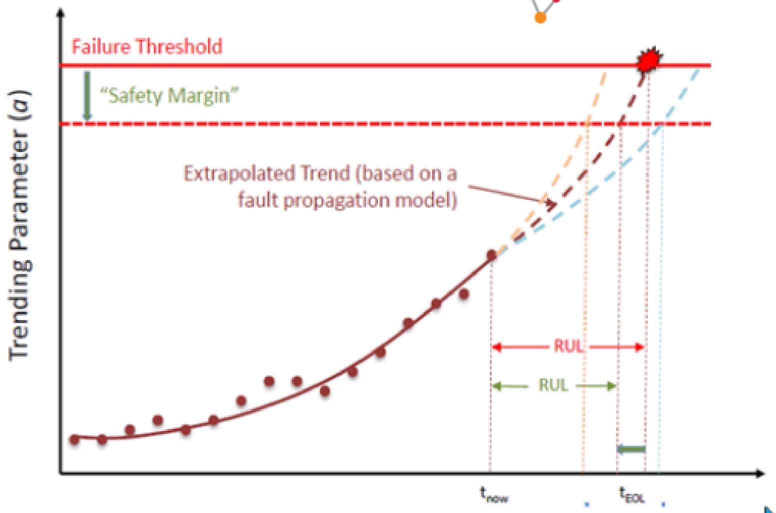


Real-time model vs stochastic



Digital twin 1.0

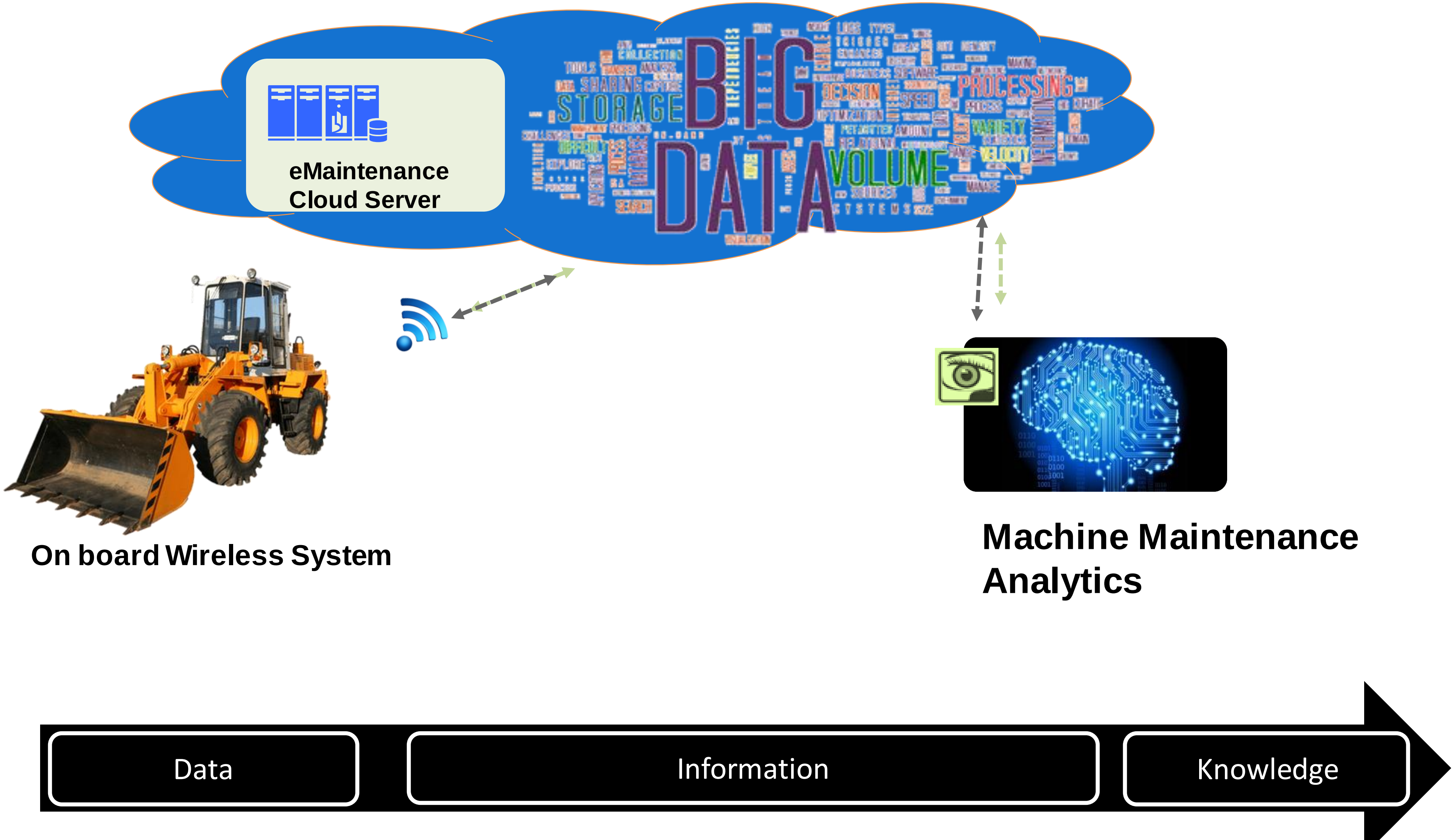




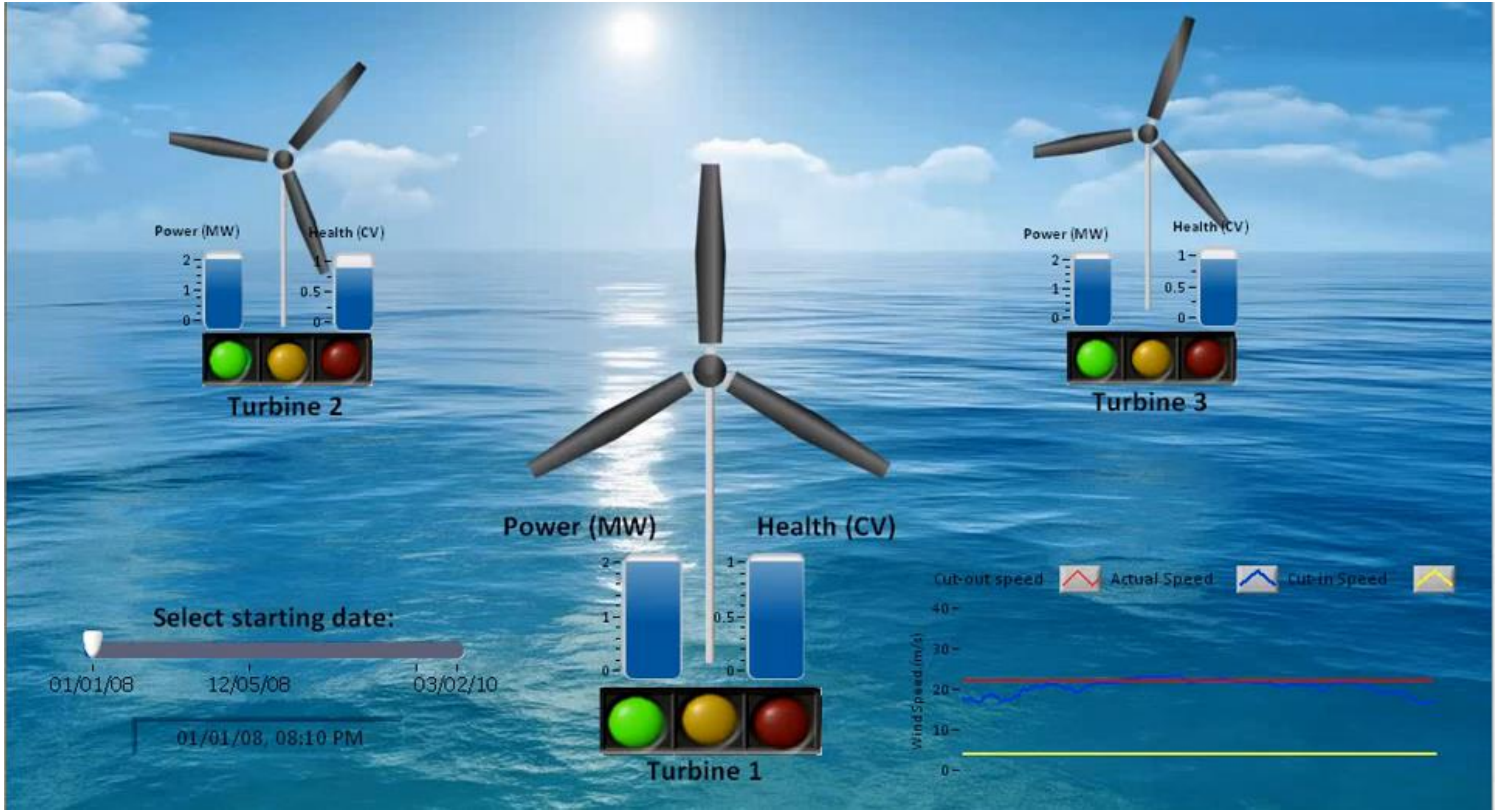
Diagnostics

Prognostics

Digital twin 1.0

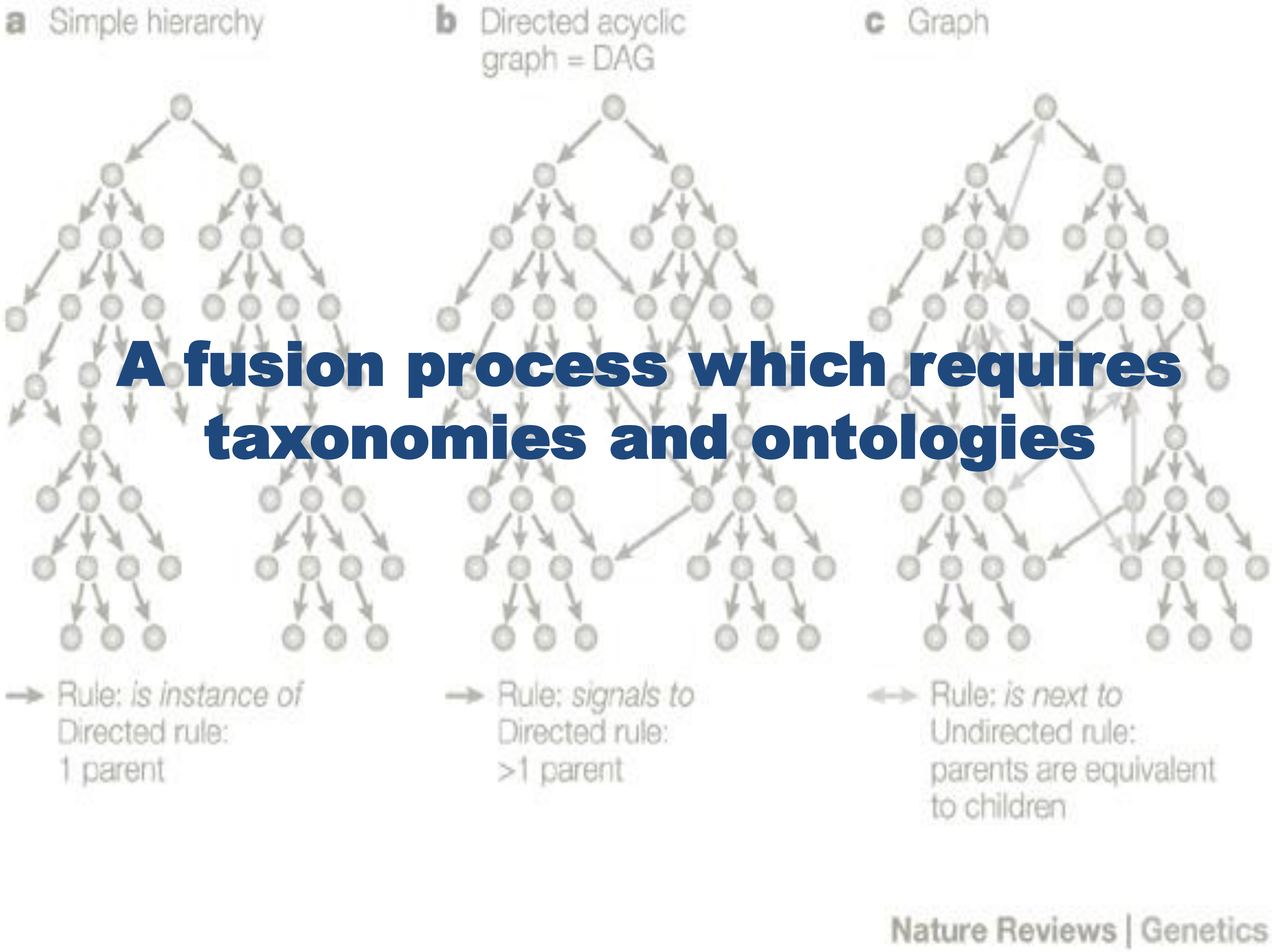


Twin based purely on OT

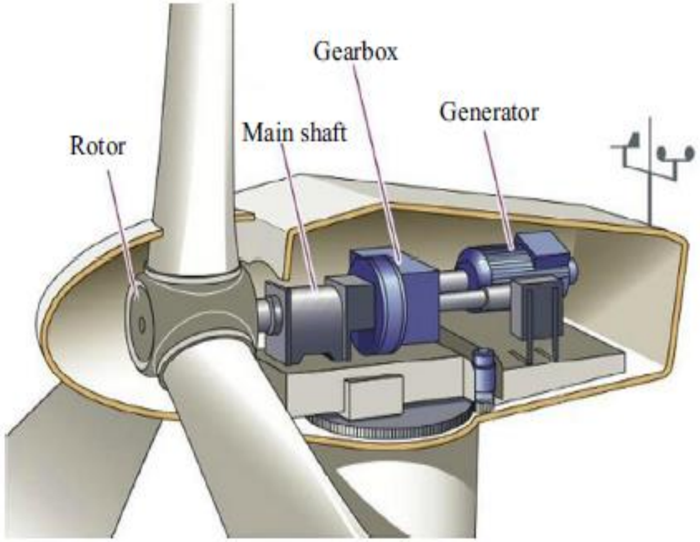


What about IT systems?

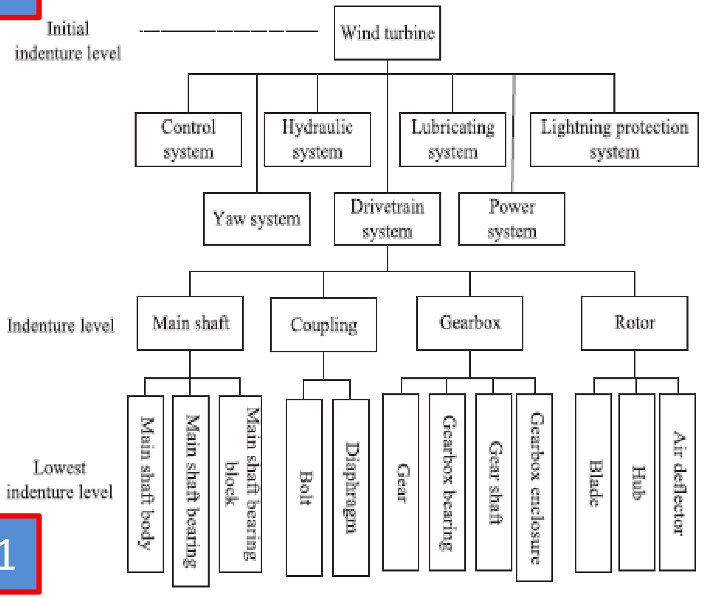
A fusion process which requires taxonomies and ontologies



Taxonomies and ontologies

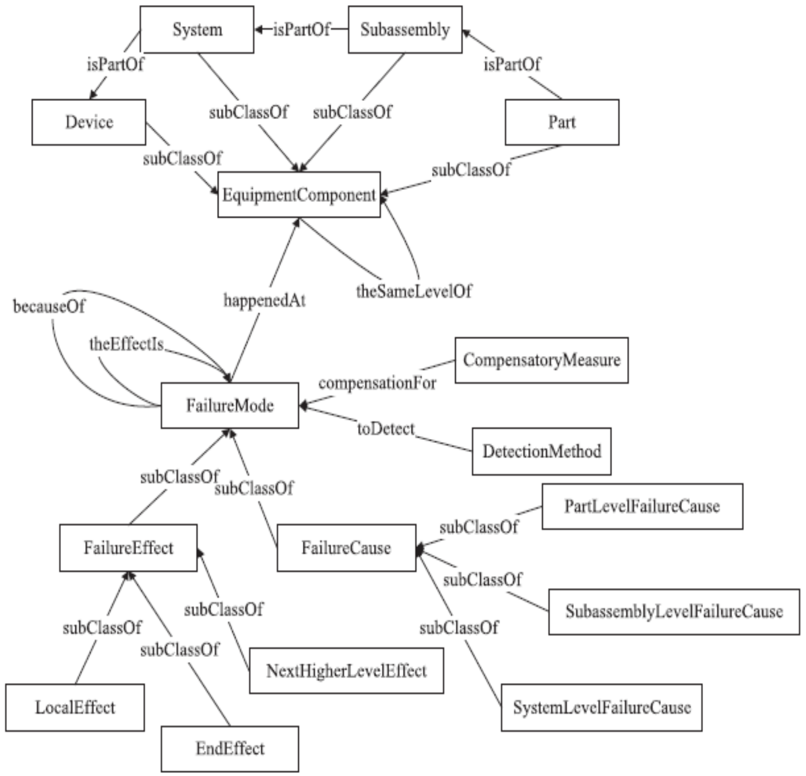


1



1

2

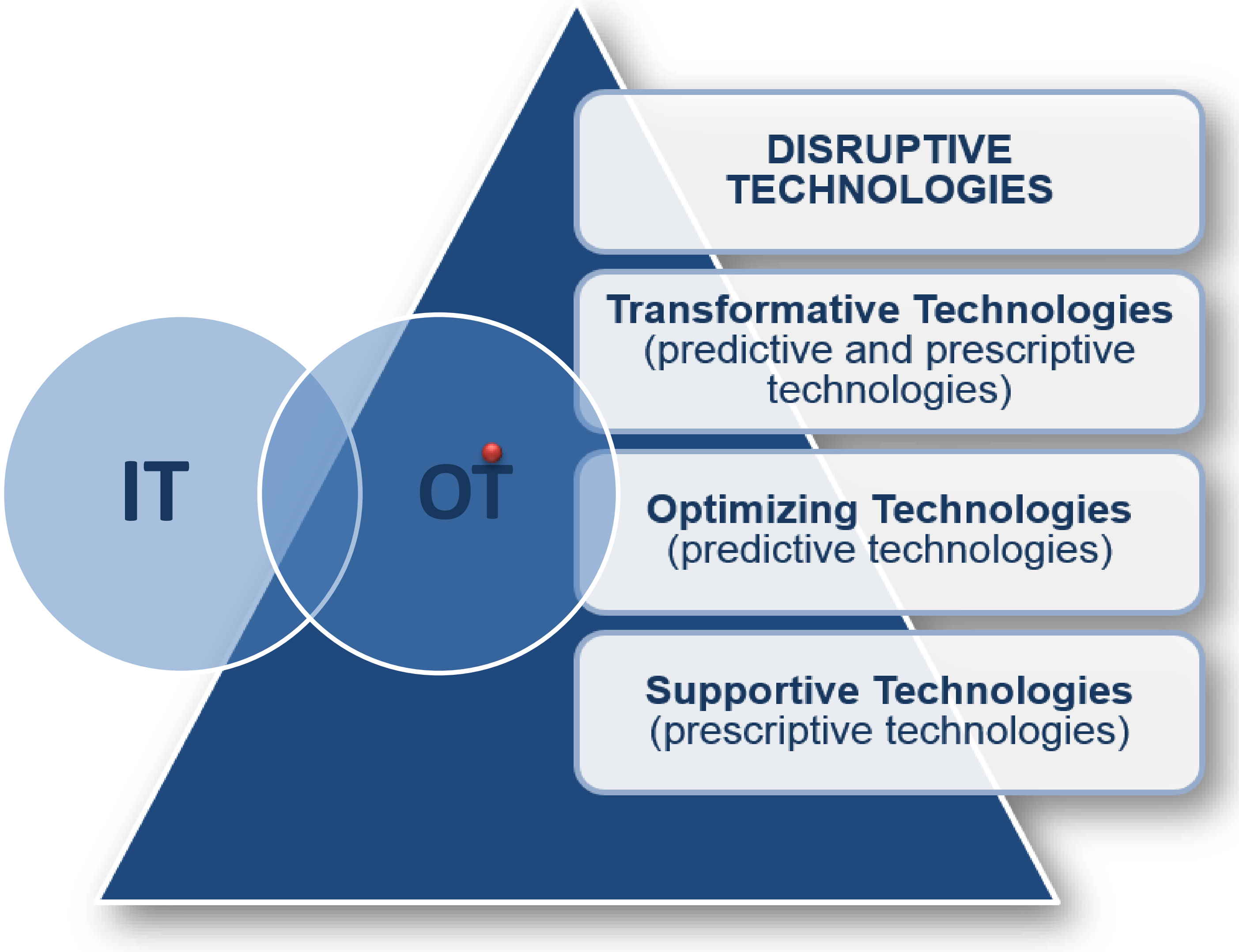


Rule-1

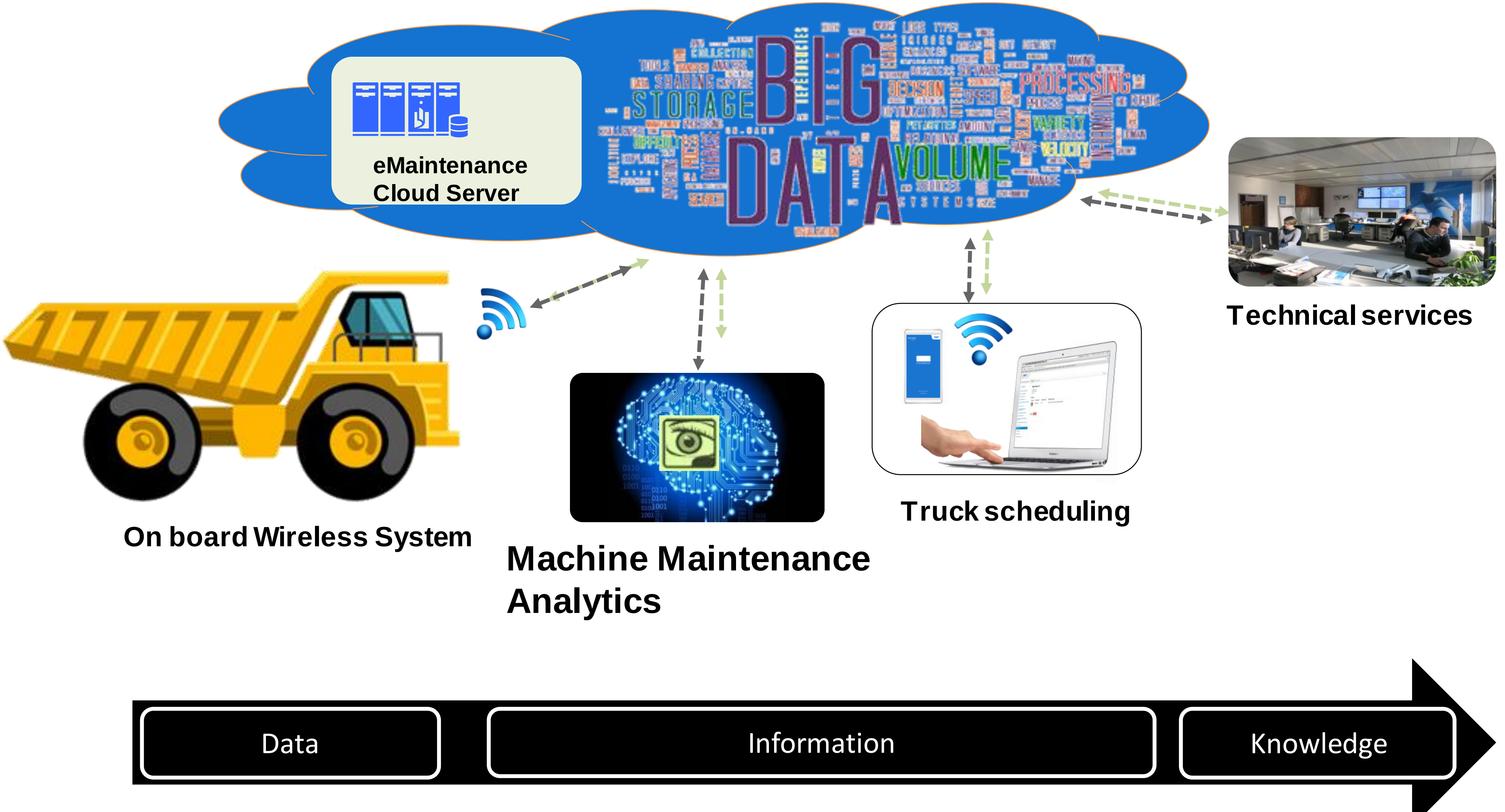
FailureMode(?x) ^ hasHappened(?x, true) ^ Device(?y) ^ happenedAt(?x, ?y) ^ FailureMode(?z) ^ theEndFffectIs(?z, ?x) ^ FailureMode(?a) ^ theHighEffectIs(?z, ?a)?theDirectFailureCauseIs(?x, ?a) ^ hasHappened(?a, true)

2

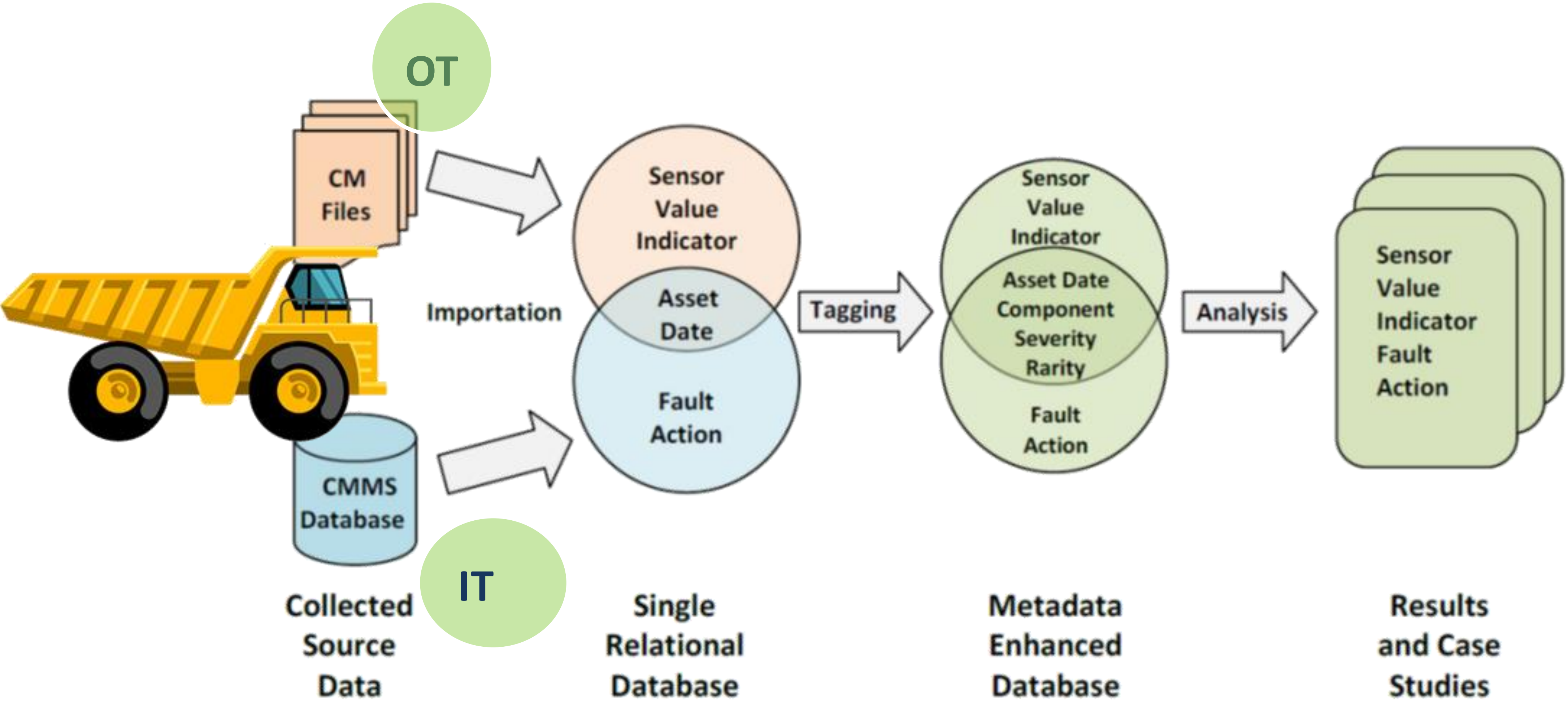
TRANSFORMATIVE MAINTENANCE SOLUTIONS
Integration & Application of Technologies



Digital twin 2.0



Digital twin 2.0



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.X

What can I see in my data?

Now casting

1) What has happened

2) What is happening

Forecasting

3) What will happen in the future

4) When will it happen

Health index calculation

Remaining useful life prediction

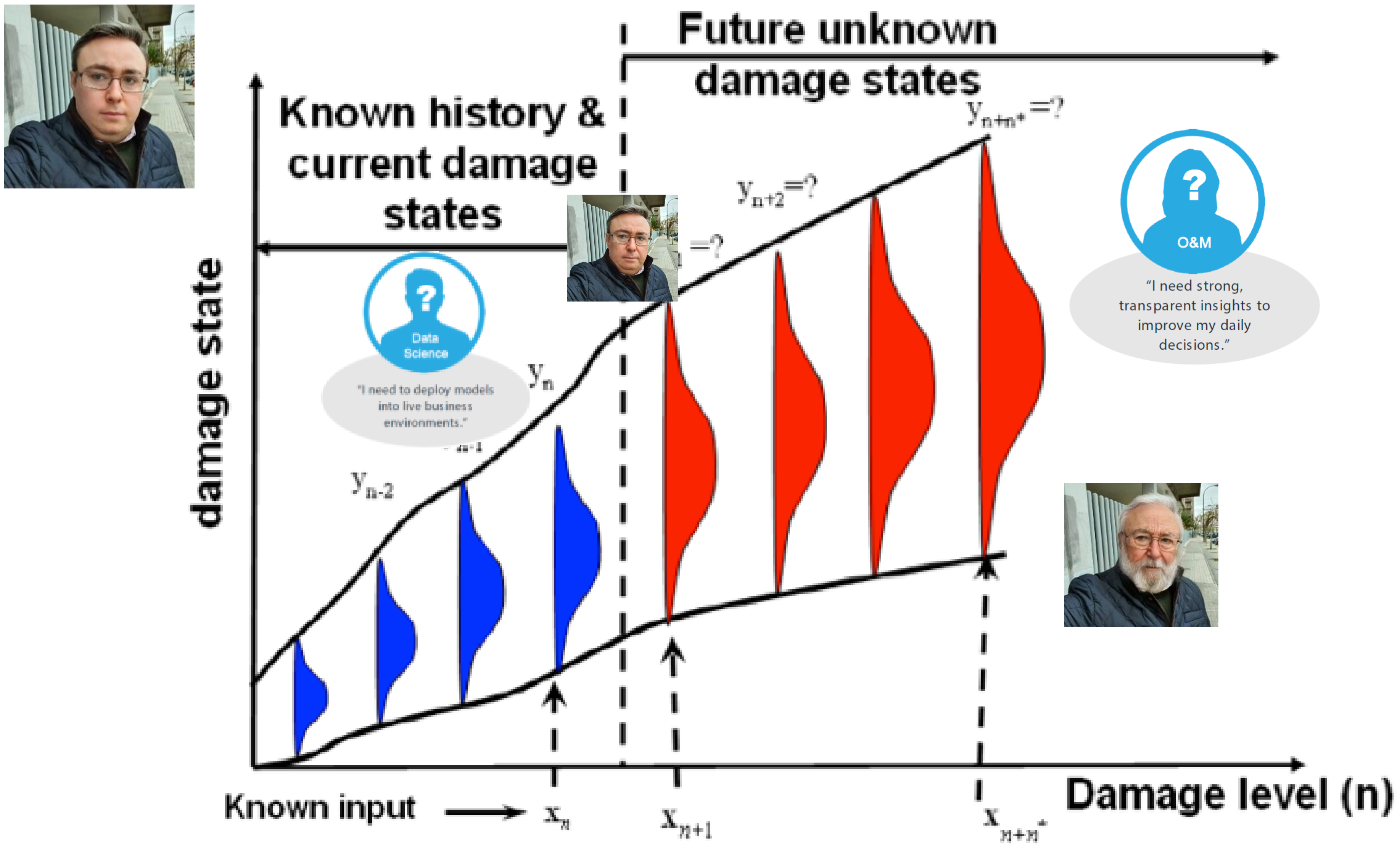
Maintenance, when needed

Domain knowledge and AI, both needed

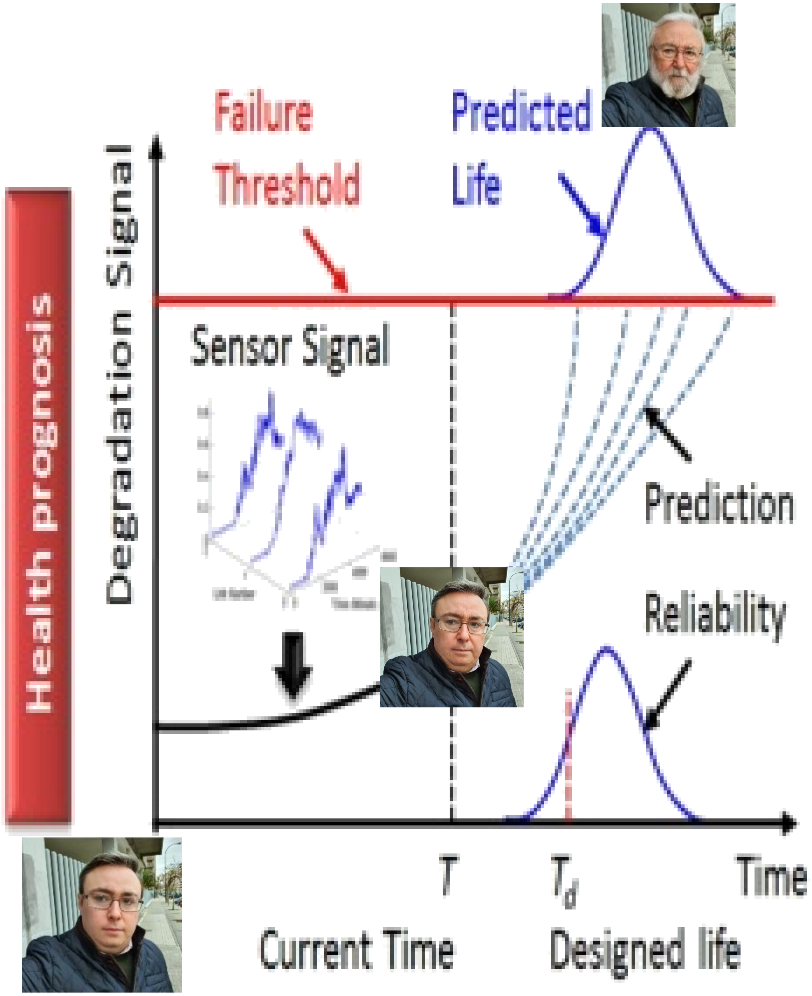
Predicting the future.....

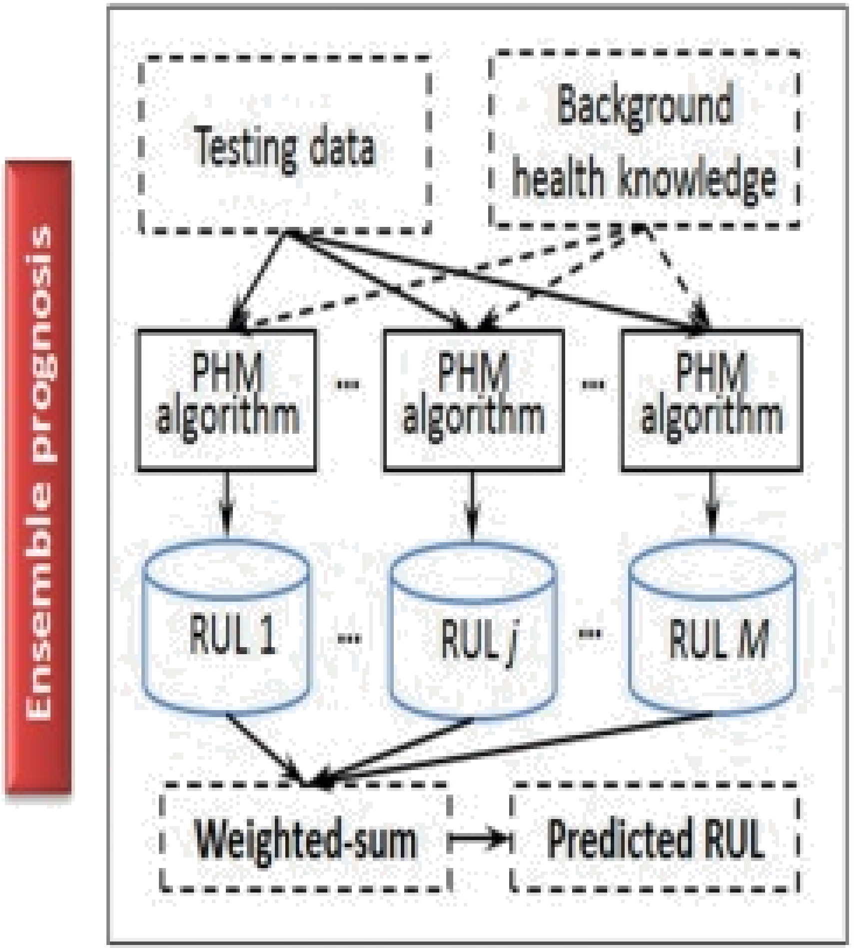
Or predicting the past.....

Domain knowledge and physics sometimes is not in the data



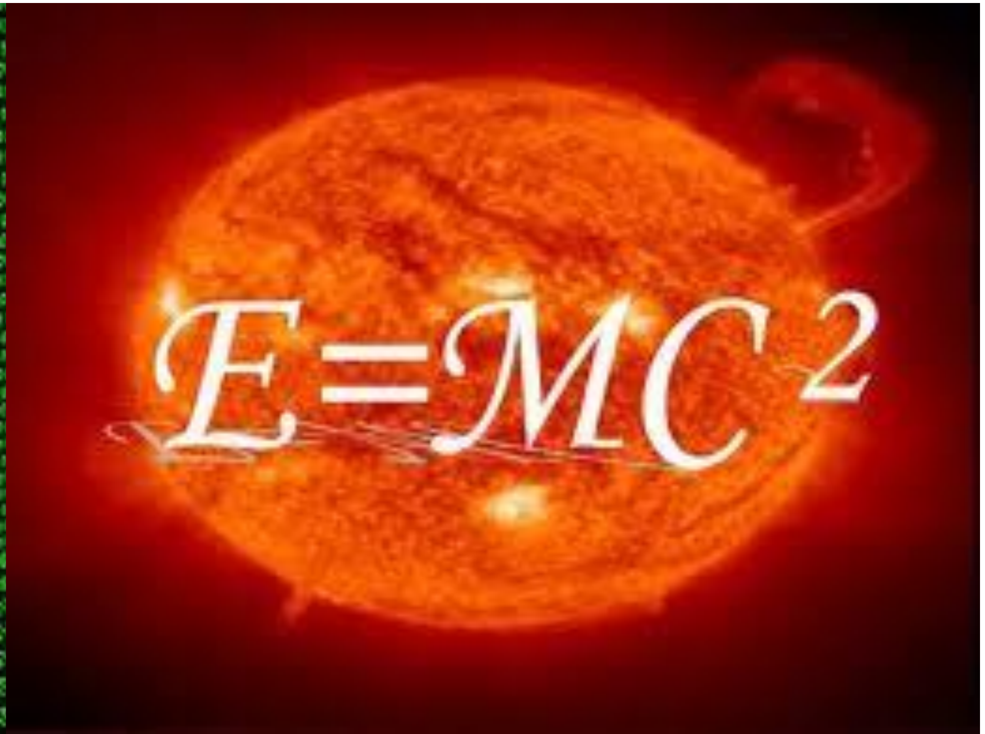
And the Uncertainty in RUL minimized with physics, maximized with data





Data driven or model based?

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



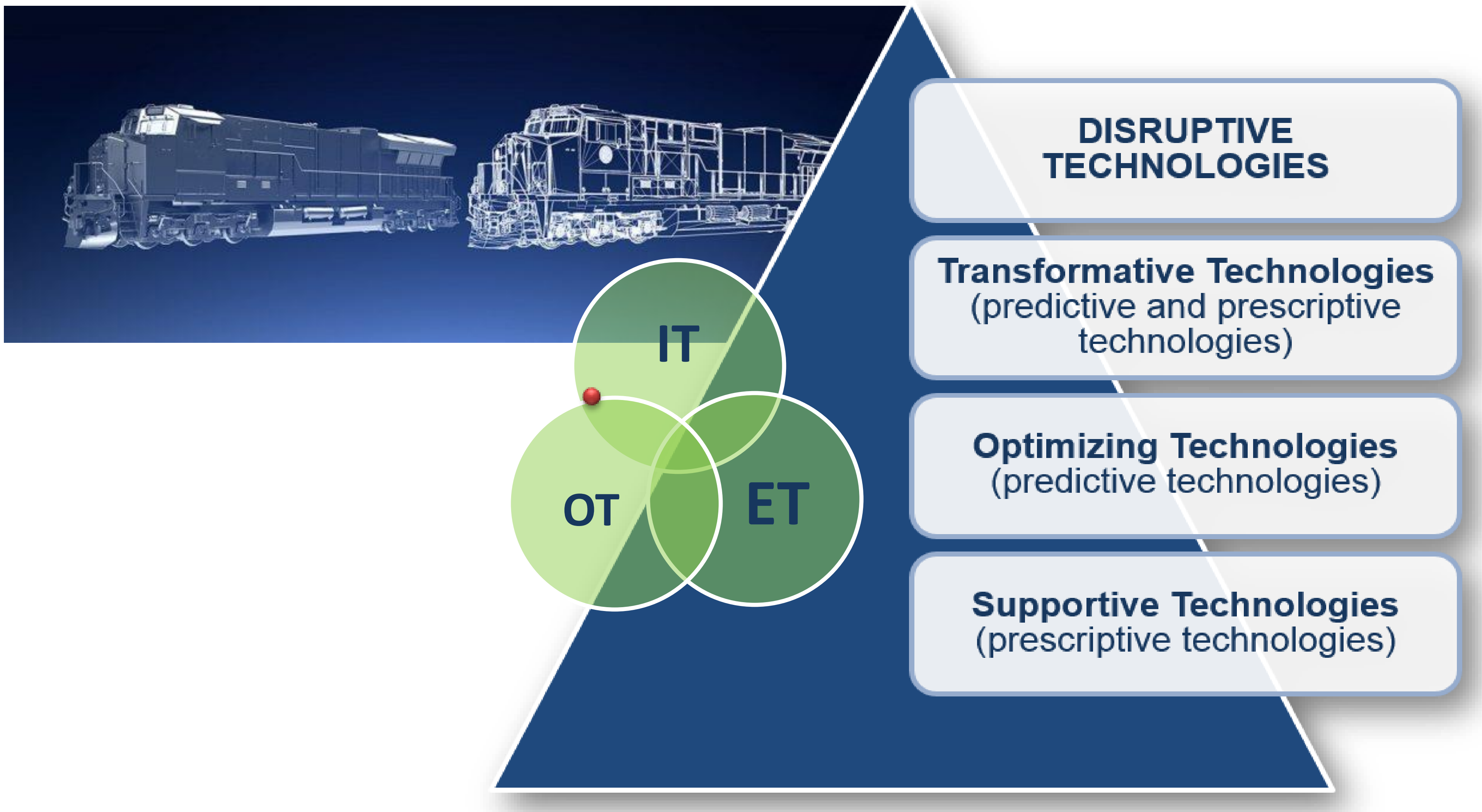
Hybrid models

- 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).

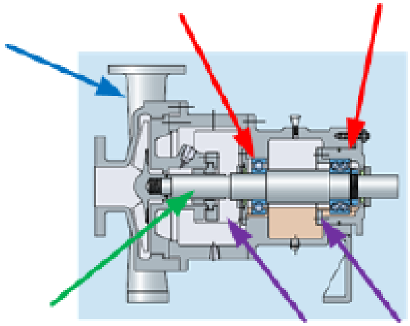
- Integration can be implemented at different levels of the PHM process:
  - Online model parameters updating.
  - Model predictions correction based on observed data.
  - Measure current damage level and propagate.
  - Build empirical degradation models from data.

Digital twin 3.0



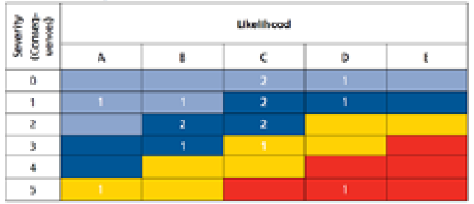
The process of twin 3.0 building

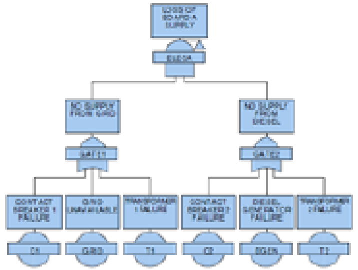
The asset (machine, equipment, electronics, system, structure, etc.



Defining taxonomy of parts within the asset

FMECA identifying monitored failure modes and parts taxonomy





Articulation of Failure Physics

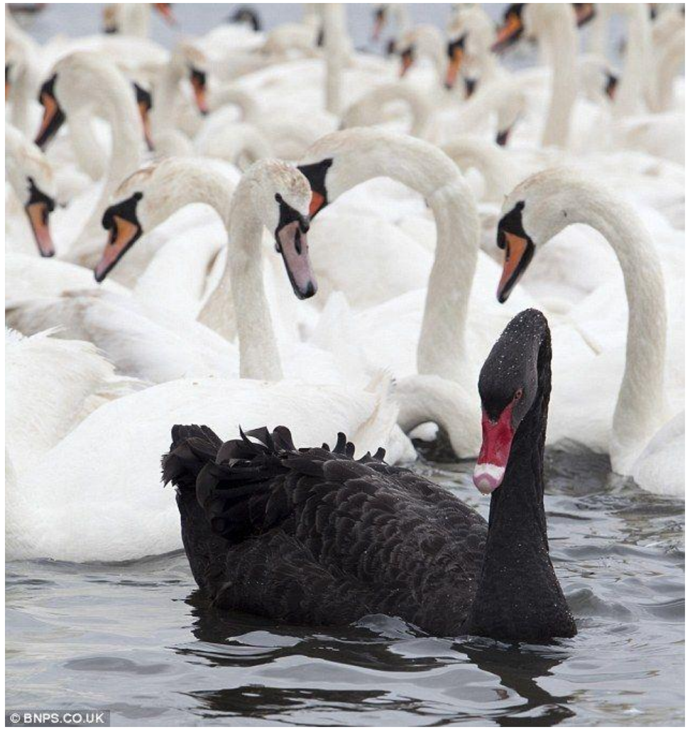
Can you predict and track the root cause of chaos?

Black Swan Losses

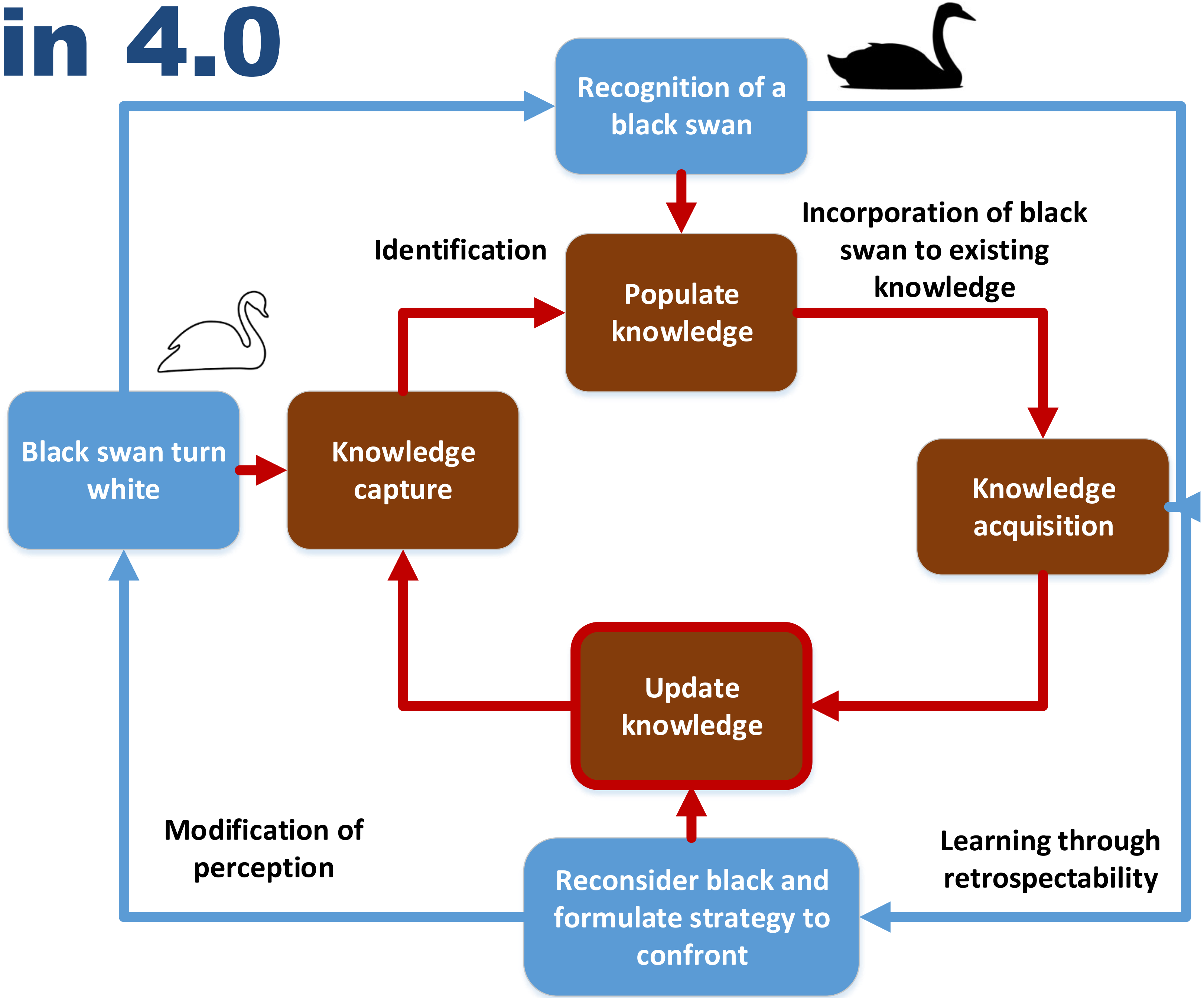
- Loss Distribution
  - Tail events are rare – very little data
  - Typically strong model assumptions

All the knowledge together

Probability-based Historical data + Knowledge dimension + Surprises

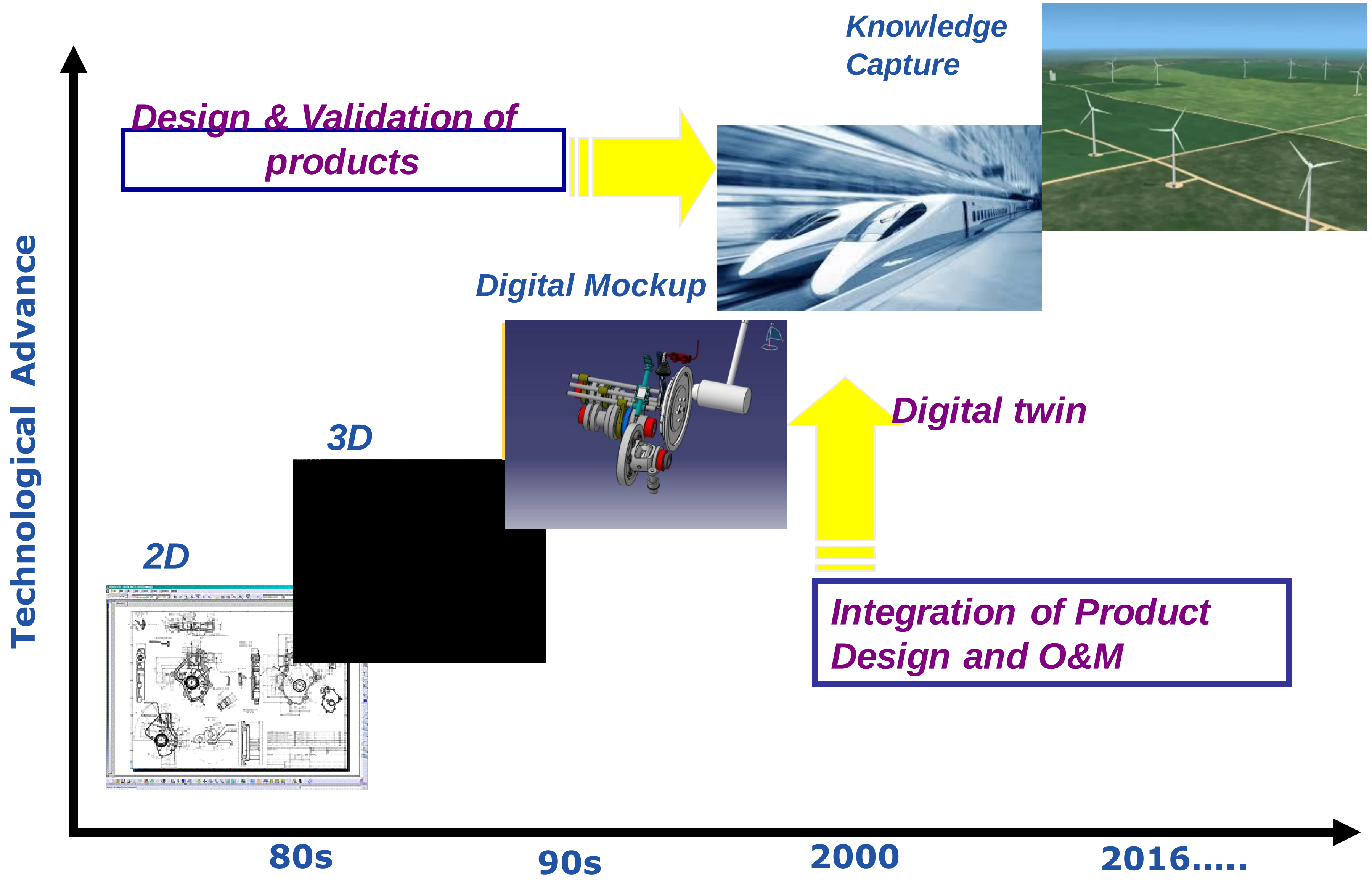


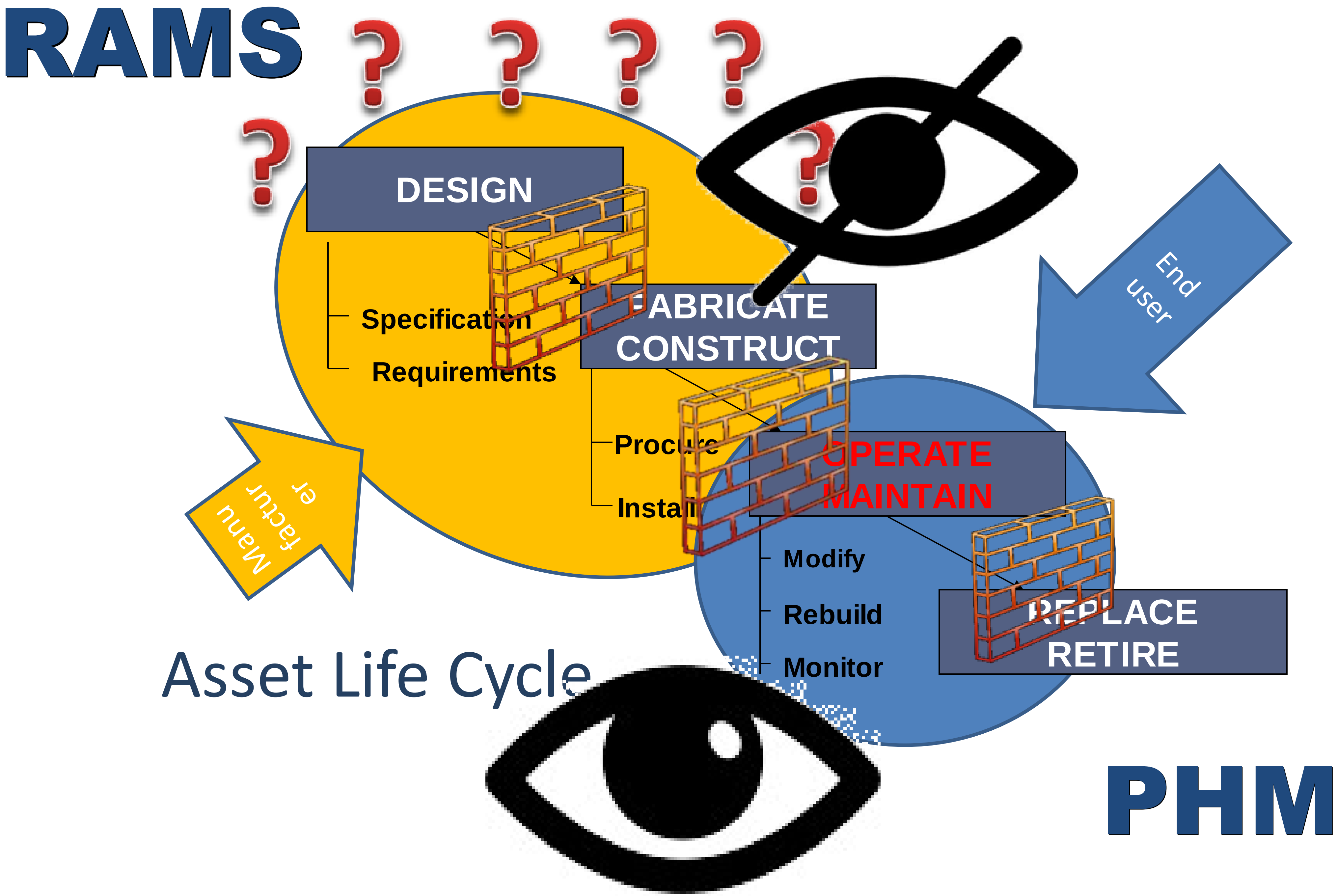
Digital Twin 4.0



Black Swan KD

Evolution of the Process




RAMS
DESIGN
Specification
Requirements
FABRICATE
CONSTRUCT
Procure
Install
OPERATE
MAINTAIN
Modify
Rebuild
Monitor
REPLACE
RETIRE
End user
Manufacturer
Asset Life Cycle
PHM

PLM and digital twins

Product Lifecycle Processes

Design → Build → Operate → Maintain

O&M Processes

Digital Wind Solutions

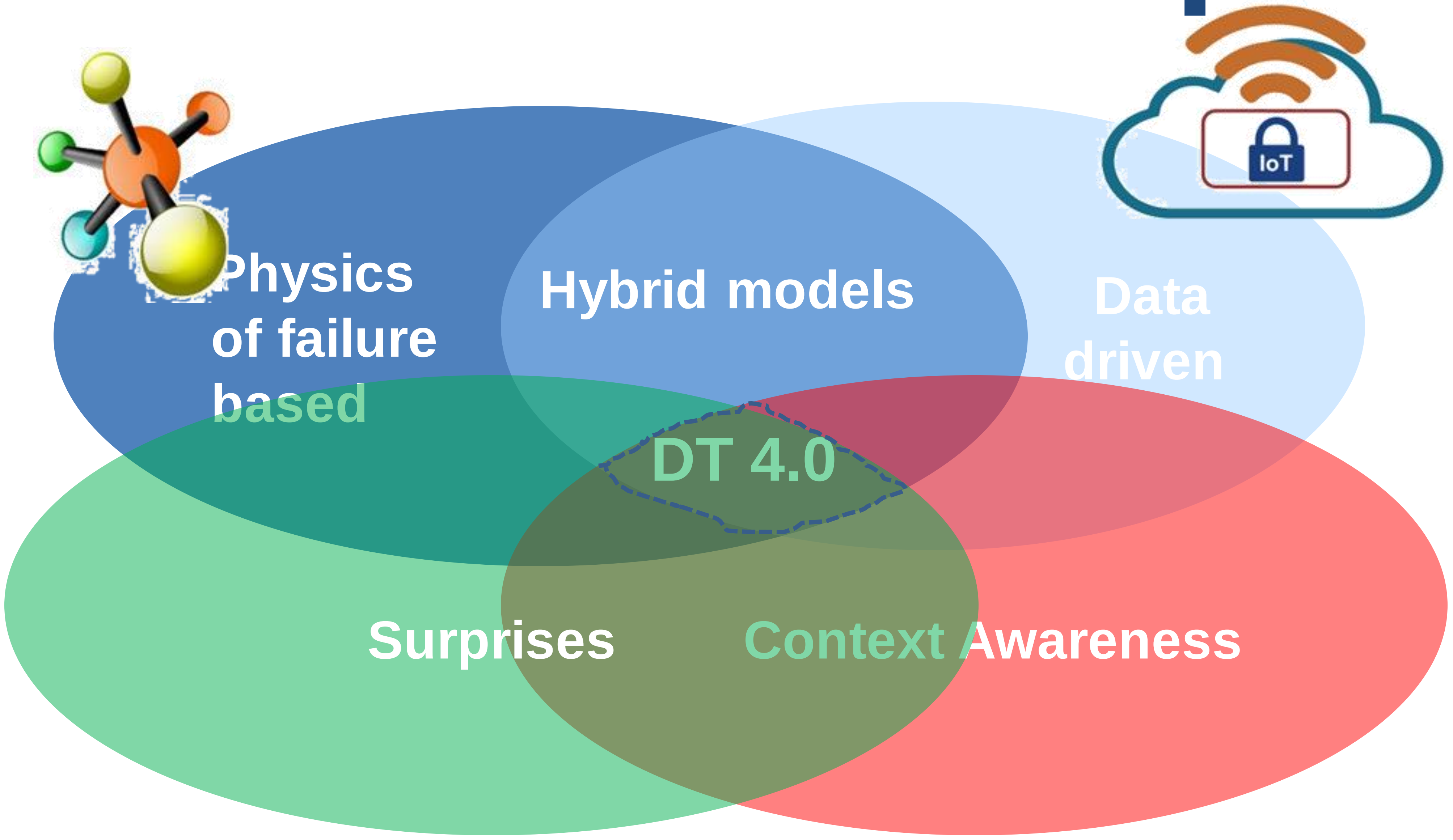
Create Processes → Plan Processes → Simulate & Validate Processes → Execute Processes

Engineering Design

Validate

As – Built Records

The DT 4.0 concept



Types of data analytics

To Educate and Inform

Descriptive Analytics

Group historical data according to their similarity

Reports
Mapping

Diagnostic Analytics

Determine cause of successes and failures

Statistical analysis
Queries
Data Mining

Predictive Analytics

Learning from the past to find out trends, standards, correlations. Anticipate the future.

Machine learning, Simulation, Forecasts

To optimize

Prescriptive Analytics / Decision Support

Provide better options based on forecasts. Show implications of each option.

Optimization, Decision models, Planning

To decide

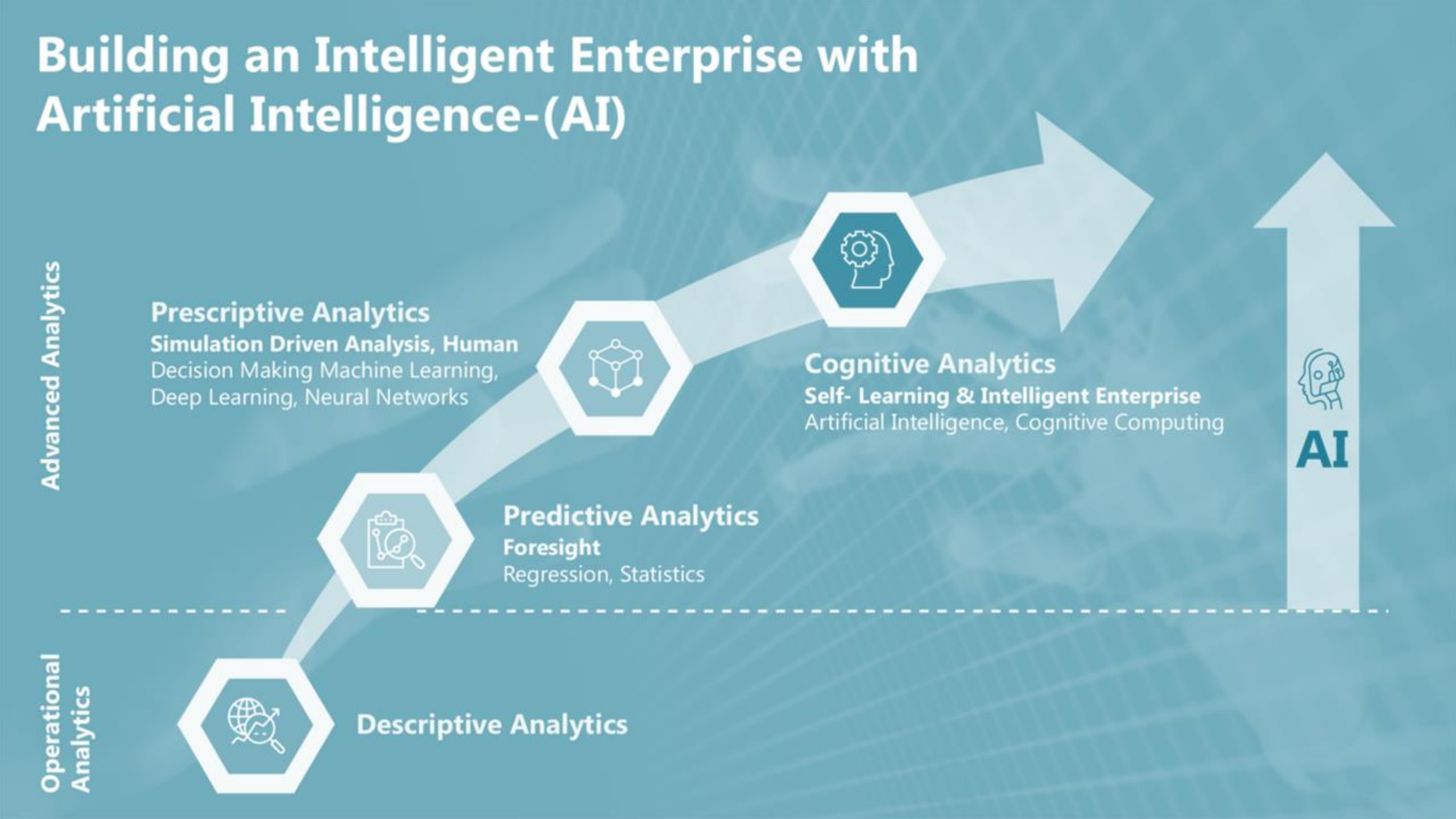
Cognitive Analytics / Intelligent Autonomous Actions

AI systems that learns from actions, finding correlations, and learn from outcomes. Autonomous operations.

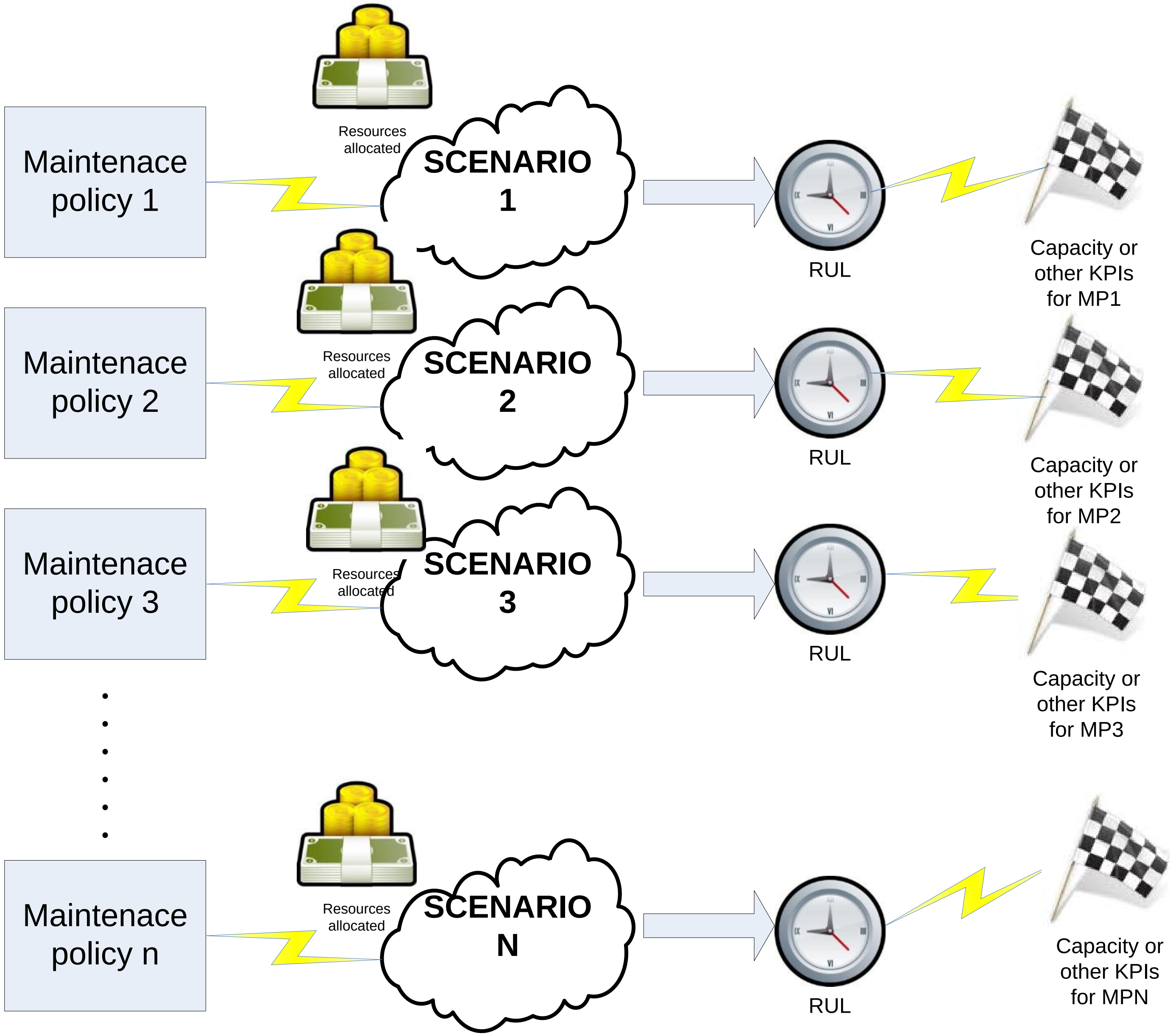
Artificial Intelligence

Reduced human intervention

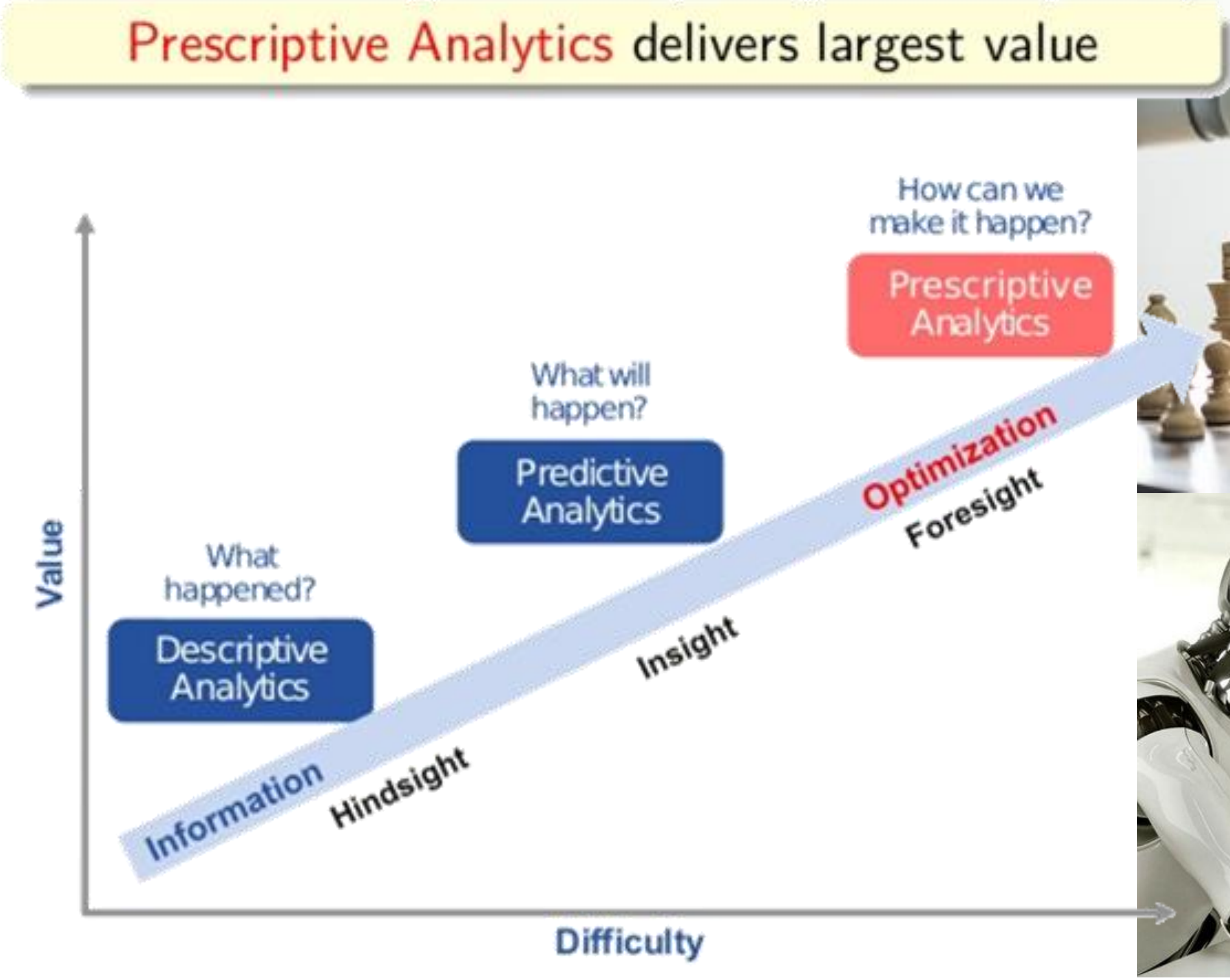
Take direct action


Building an Intelligent Enterprise with Artificial Intelligence-(AI)
Advanced Analytics
Operational Analytics
Prescriptive Analytics
Simulation Driven Analysis, Human
Decision Making Machine Learning, Deep Learning, Neural Networks
Cognitive Analytics
Self- Learning & Intelligent Enterprise
Artificial Intelligence, Cognitive Computing
AI
Predictive Analytics
Foresight
Regression, Statistics
Descriptive Analytics

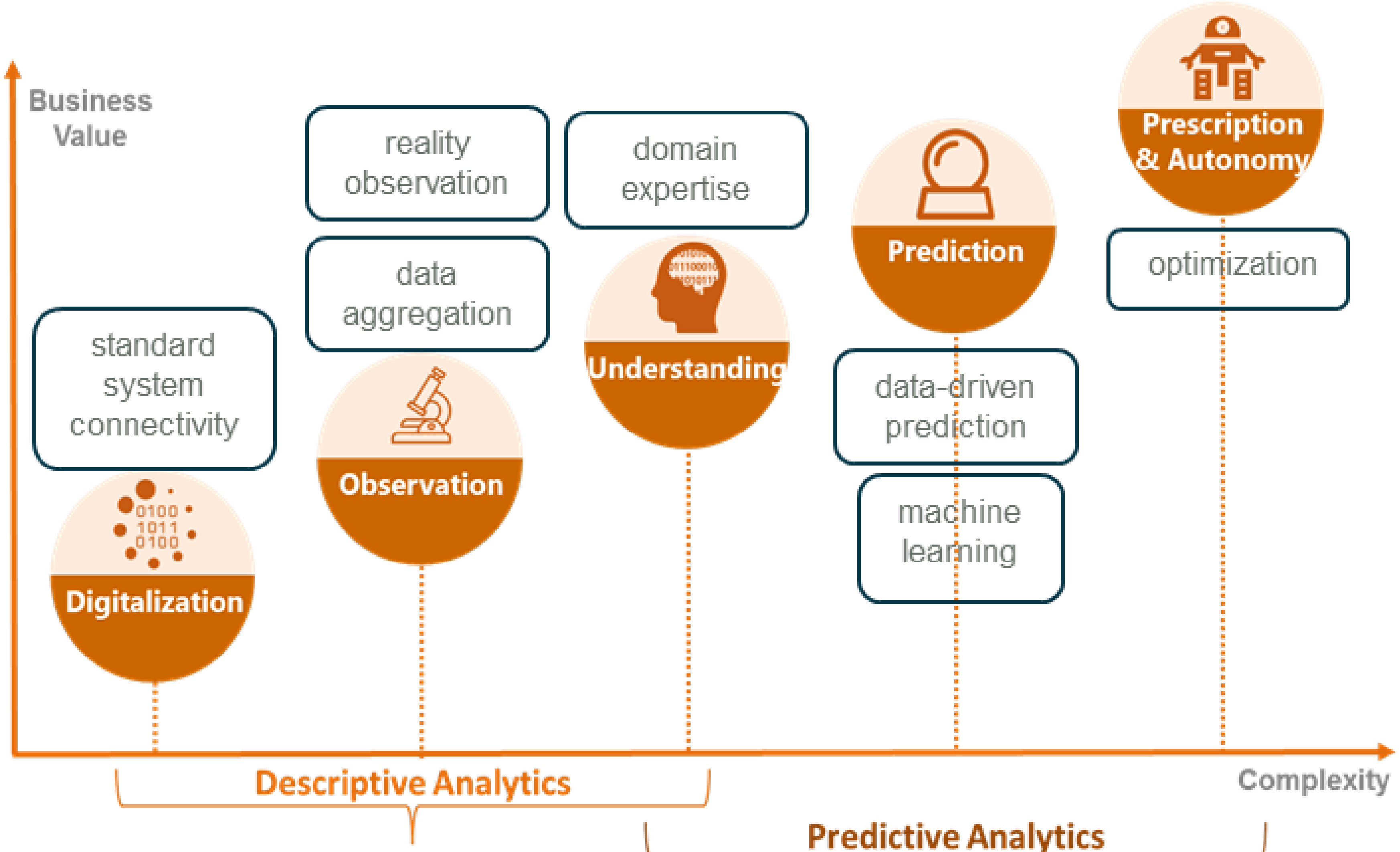
Simulation of maintenance policies and different RUL calculation



How many scenarios you can think of?



Maturity in the classical approach



In dark factory and unmanned assets maintenace crew out of the loop

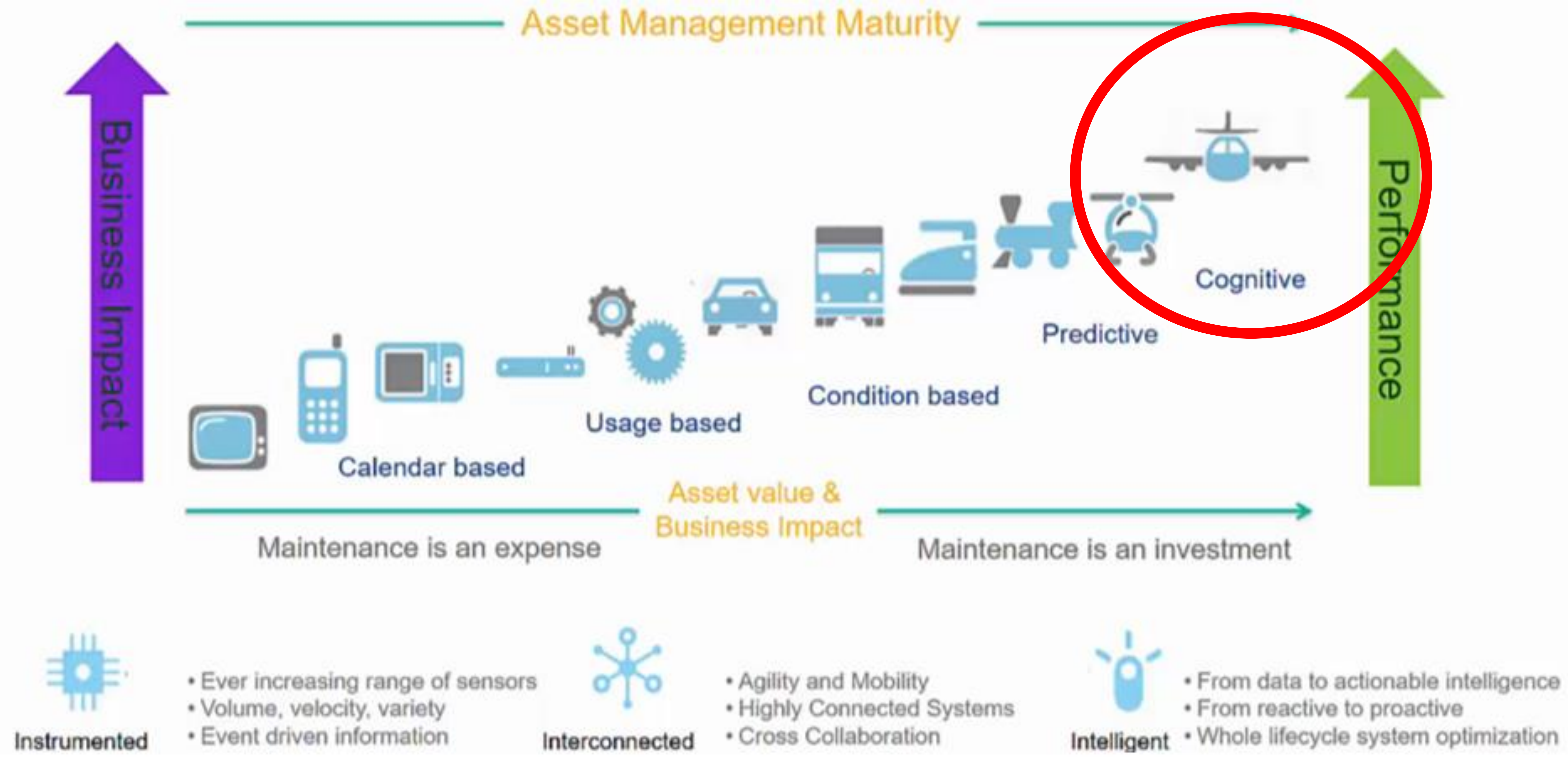
- Context is dynamic
- Prescriptions cannot be taken manually
- Humans cannot keep up with data complexity
- Industrial AI must take over with cognition

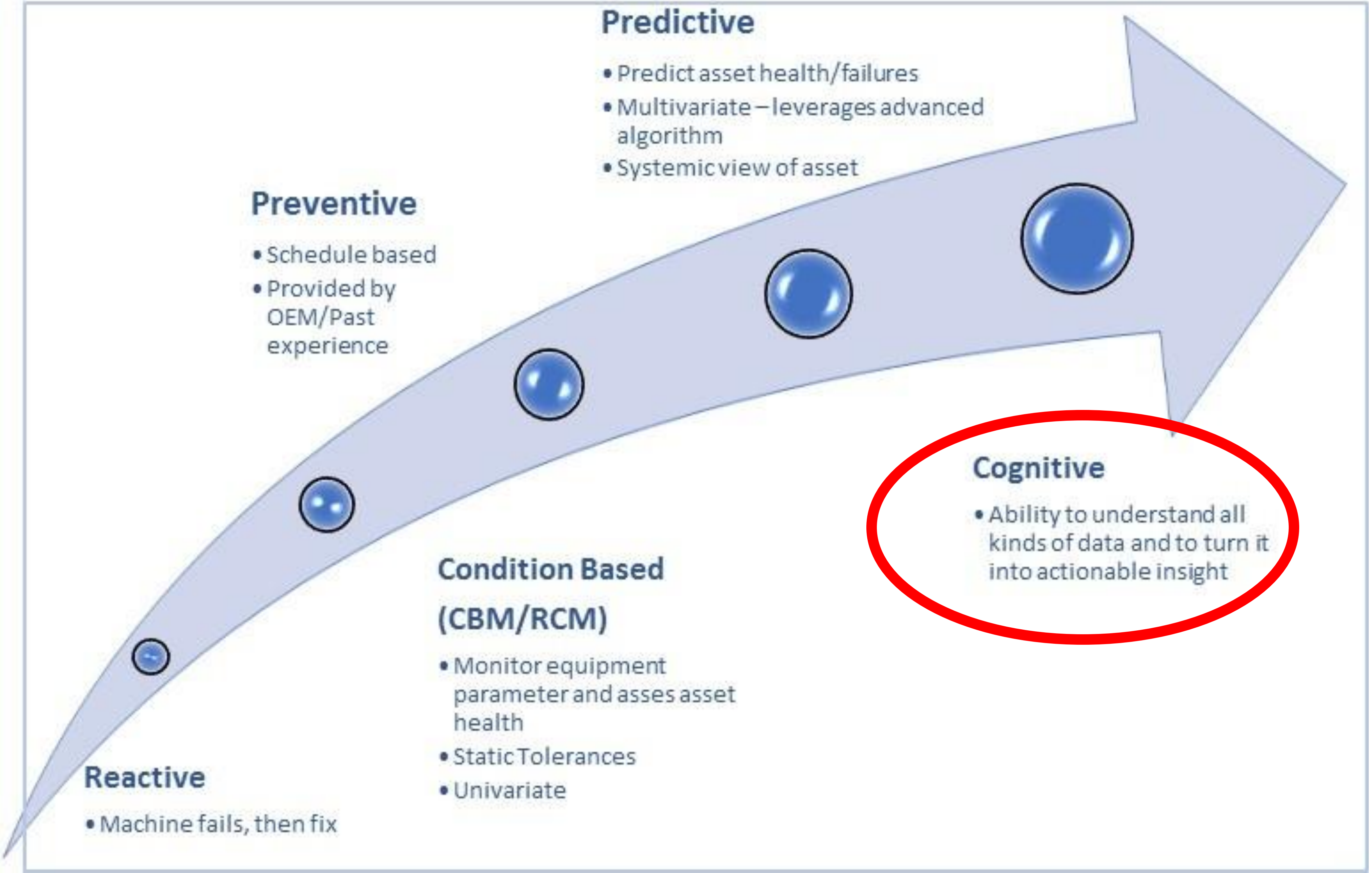
Terror Management Theory

Terror management

- Core premise: basic existential dilemma
  - Desire for life
  - Awareness that death is inevitable

Cognitive assets will self preserve



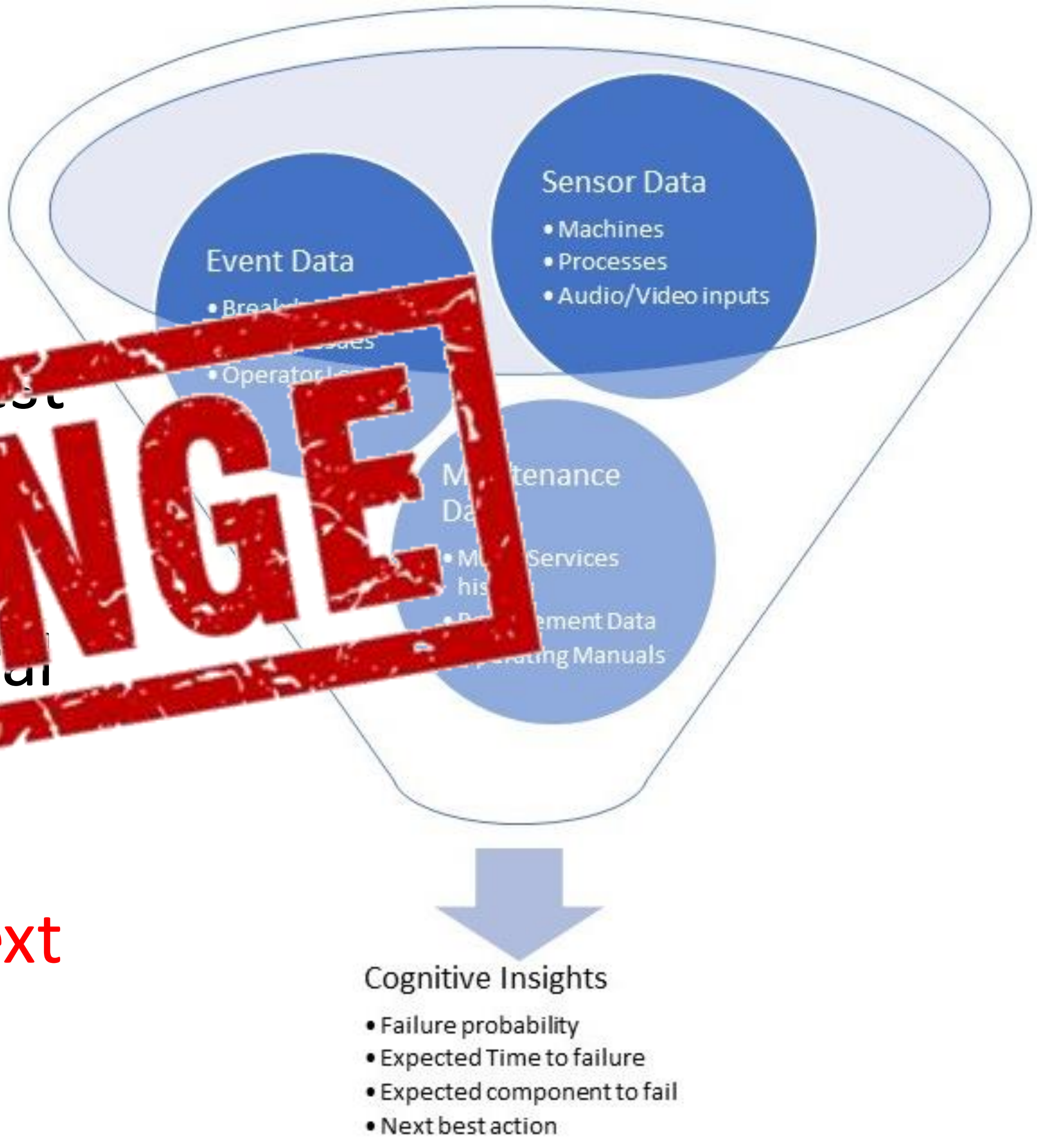

Predictive
• Predict asset health/failures
• Multivariate – leverages advanced algorithm
• Systemic view of asset
Preventive
• Schedule based
• Provided by OEM/Past experience
Cognitive
• Ability to understand all kinds of data and to turn it into actionable insight
Condition Based (CBM/RCM)
• Monitor equipment parameter and asses asset health
• Static Tolerances
• Univariate
Reactive
• Machine fails, then fix

Cognitive Maintenance is a further upgrade on predictive maintenance, as it enables us to ingest all kinds of data

- Structured
- Unstructured (audio/video/natural language)

and obtain a better informed insight and superior recommendation on next best action.

CHALLENGE



Terror management

1

Gather the data

- Instrument your equipment/assets to collect data
- Gather preexisting data

2

Visualize the patterns

- Visualize your data in meaningful dashboards
- Start to see patterns
- Build with Bluemix

3

Advance to analytics & digitization

- Gain insights from the data, produce models, predict recommendations
- Streamline business processes

4

Infuse with cognitive

- Refine models with cognitive machine learning
- Use other cognitive functions to improve engagement

Prereq off-load

Value

Vision

Concluding remarks

- M2M is not possible due to lack of standards
- Multiagent and federated learning are good starting point for the facebook of the machines
- Machines may not talk but DTs can
- In unmanned and unattended assets social network can provide added value services and reduce need for humans

Thanks

diego.galar@ltu.se
diego.galar@tecnalia.com