# Prognosis, Diagnosis and Maintenance Decision Support Systems: A mathematical approach

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Lulea University of technology


# Big data in industry

## The revolution of maintenance analytics

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# Industrial data a late but powerful entry

*12+ TBs* of tweet data every day

*30 billion* RFID tags today (1.3B in 2005)

*4.6 billion* camera phones world wide

*? TBs* of data every day

*25+ TBs* of log data every day

*100s of millions of GPS enabled* devices sold annually

*76 million* smart meters in 2009… 200M by 2014

*2+ billion* people on the Web by end 2011

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**An increasingly sensor-enabled and instrumented business environment generates HUGE volumes of data with MACHINE SPEED characteristics…**

**1 BILLION lines of code**

**EACH engine generating 10 TB every 30 minutes!**

# Scale of Industrial Internet (of Things IIoT)

Social media versus electric generating power source

## 2012 Twitter Usage

**80** Gigabytes per day

*enabling social connections*

**vs.**

## Gas Turbine Compressor Blade Monitoring potential*

**588** Gigabytes per day

*enabling capital asset productivity*

Data volume potential is 7x greater from a gas turbine than current Twitter usage

imagination at work



* Note: Assumes operational gas turbines (generating units only) >50MW are equipped with Blade Health Monitoring capabilities

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# Big Data is mostly machine generated data

Volume | Velocity | Variety | Variability

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# The IBM idea of Internet of things for maintenance

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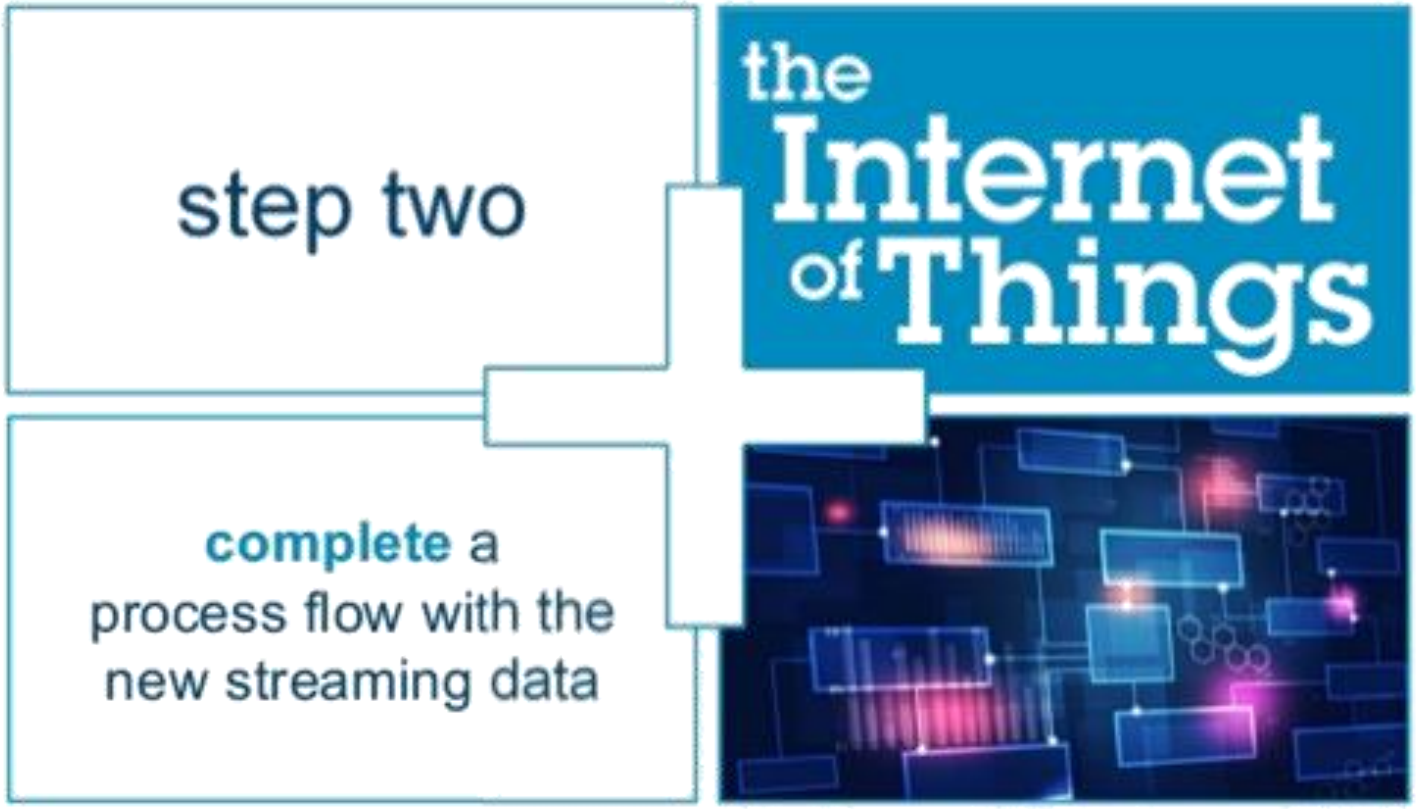
# The IBM idea of Internet of things for maintenance



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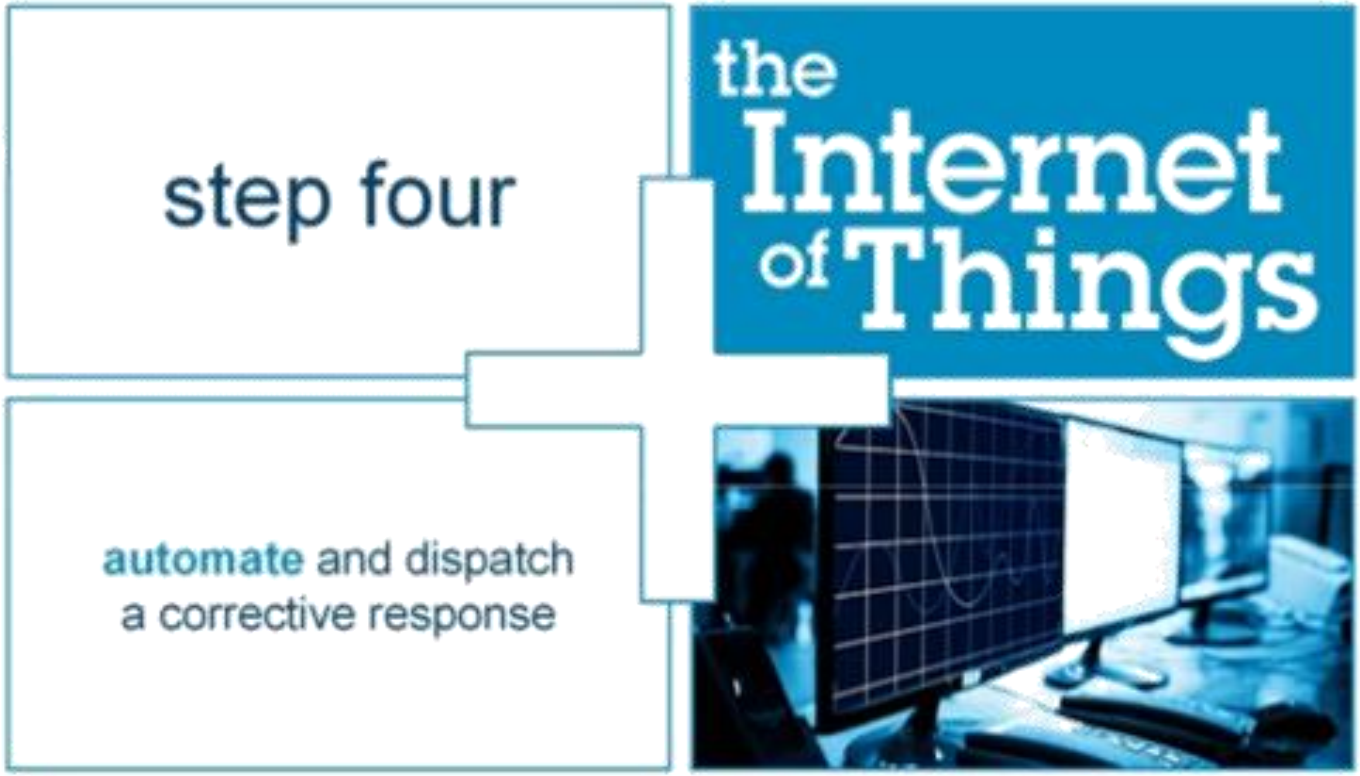

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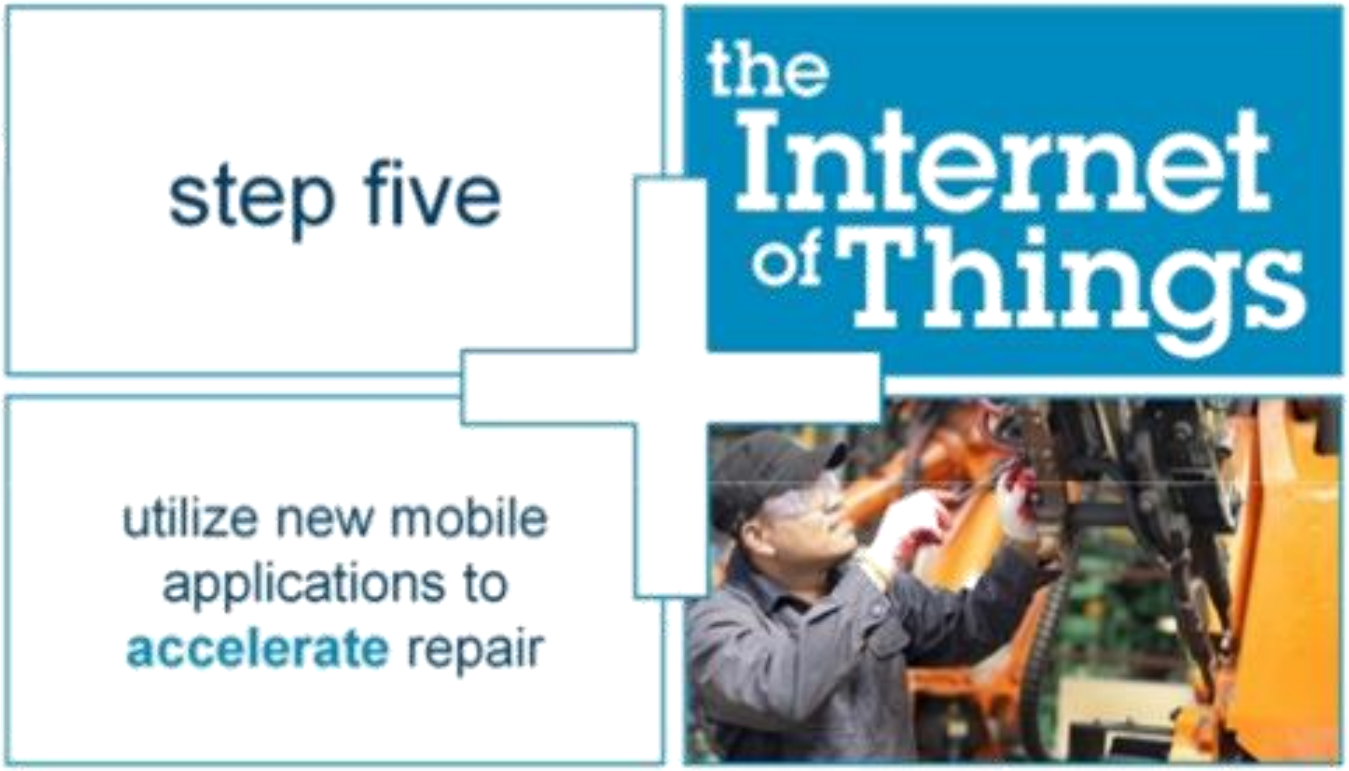


# ICT and Business goals

## The asset management connection

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# Asset Management?

- Only way to fully meet high level of operational performance objectives at the lowest cost to the facility
- Enables Risk Management for consistent performance
- Provides complete objective data for process improvement

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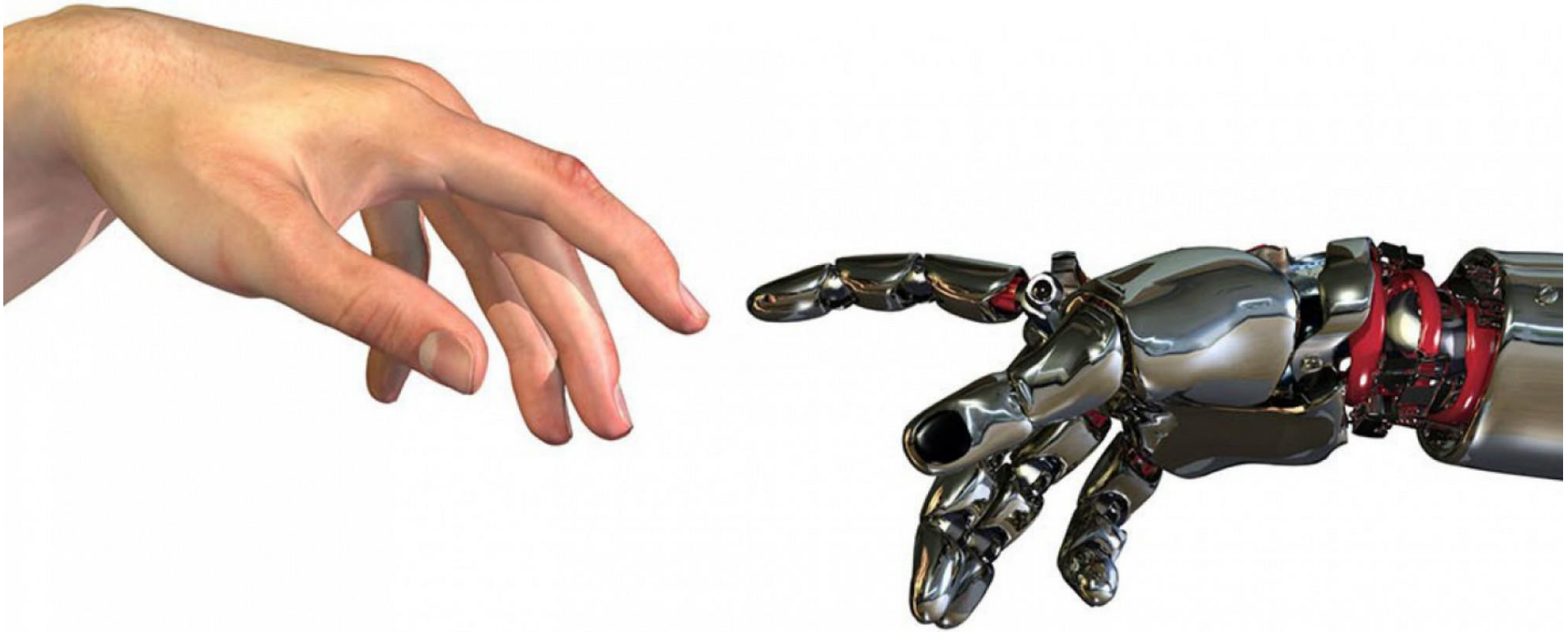
# SMARTness related to maintenance?



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# Smarter Assets
enable
new business models
based on **RISK**

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# Understanding of Risk

Corporate Risk Register

Risk Appetite

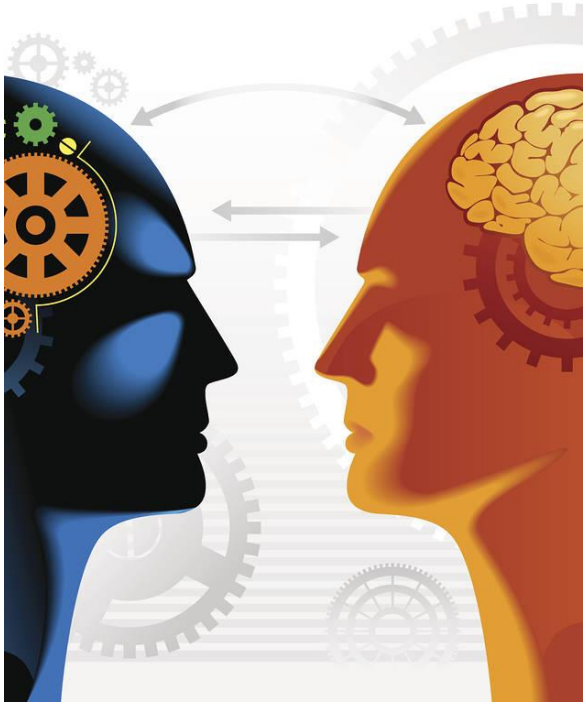
Service Risk

Asset Risk

Criticality

Resilience

Reliability



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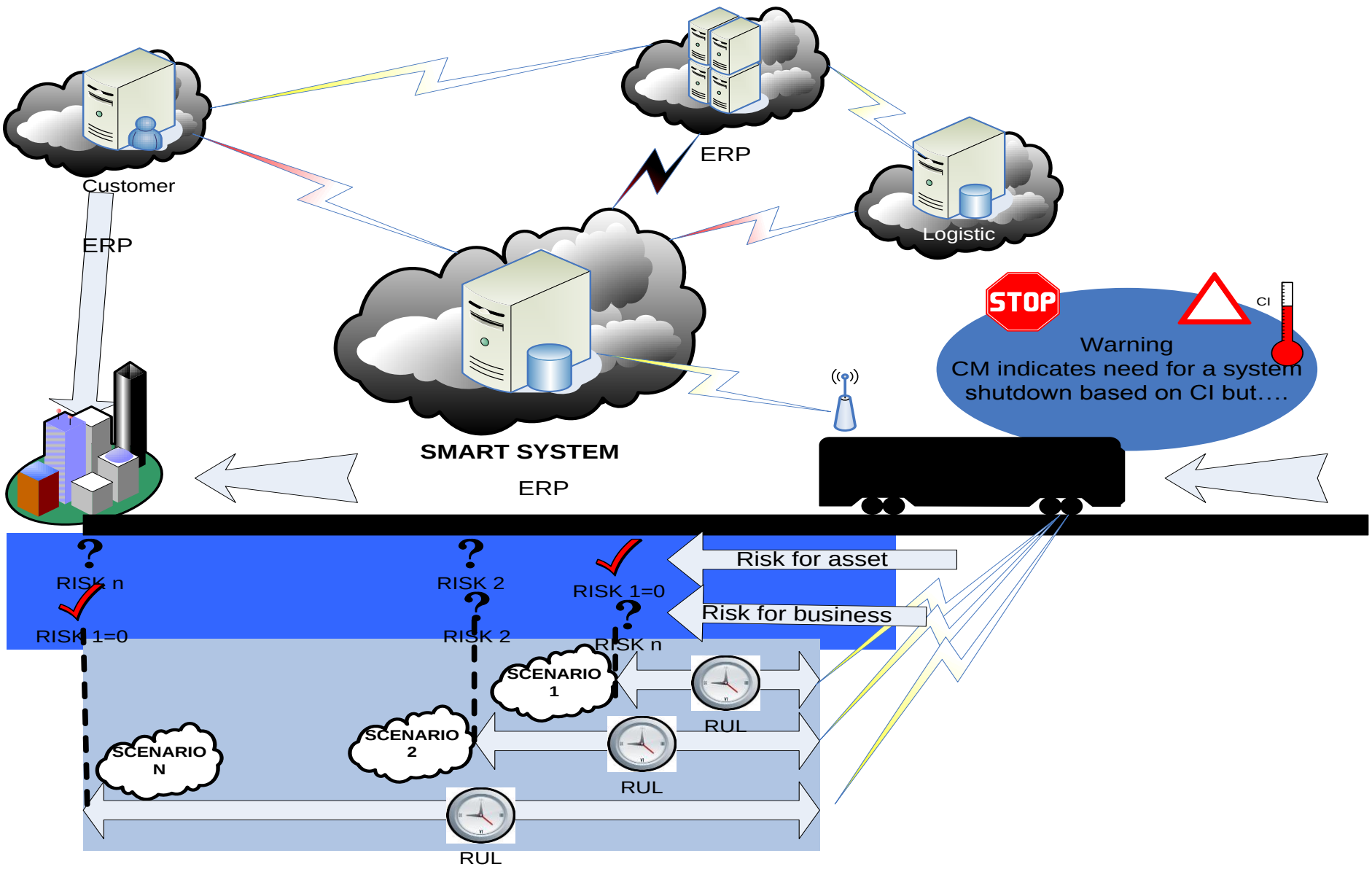
# But...What is Risk?



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# How should these SMART assets be?

## Instrument the assets

**A billion transistors per human being on the planet**

## Interconnect them

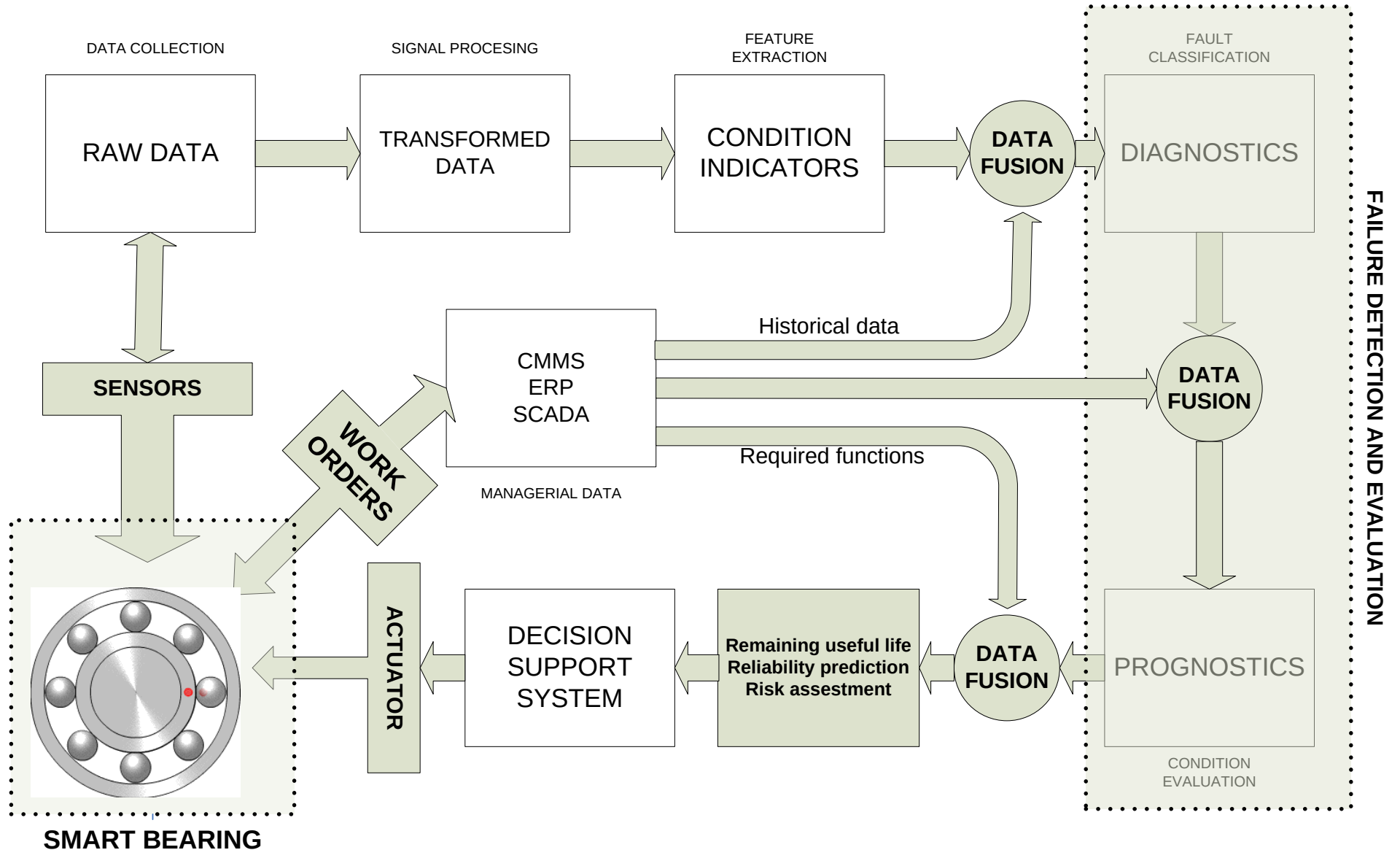
**A trillion devices all giving off data – the ‘internet of things’**

## Make them intelligent

**New analytics tools assessing this ocean of data**

# A SMART bearing proposal…..

SCADA Supervisory Control And Data Acquisition
ERP Enterprise Resource Planning
CMMS Computer Maintenance Management Software



# A revolution based on SMART objects

# The collective mind with distributed intelligence

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# A Smart bearing is so much more than just a bearing!

Detect wheel damage

Operation planning

Error detection in boggie

Position of the car

Load in the car

Maintenance planning

LKAB

Detect rail damage

TRAFIKVERKET

Continuous scanning of rail

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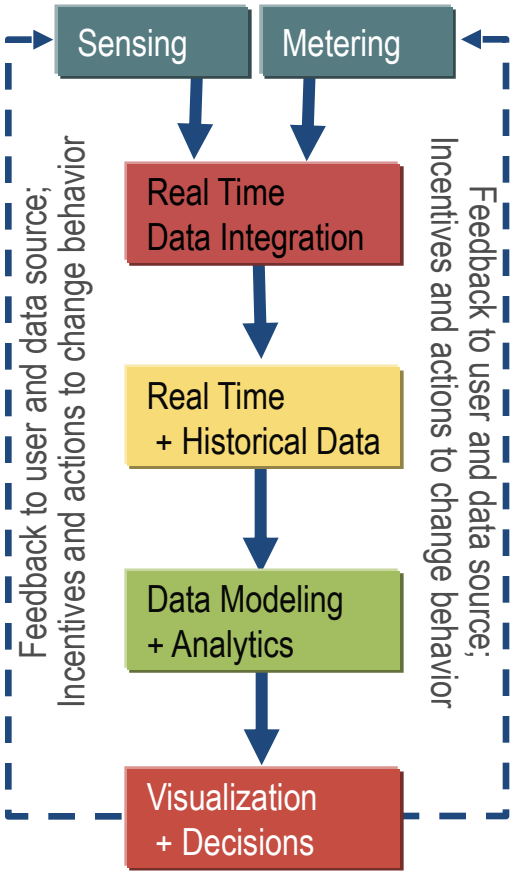
# What does it mean to become Smarter?

Our world is becoming
INSTRUMENTED

Our world is becoming
INTERCONNECTED

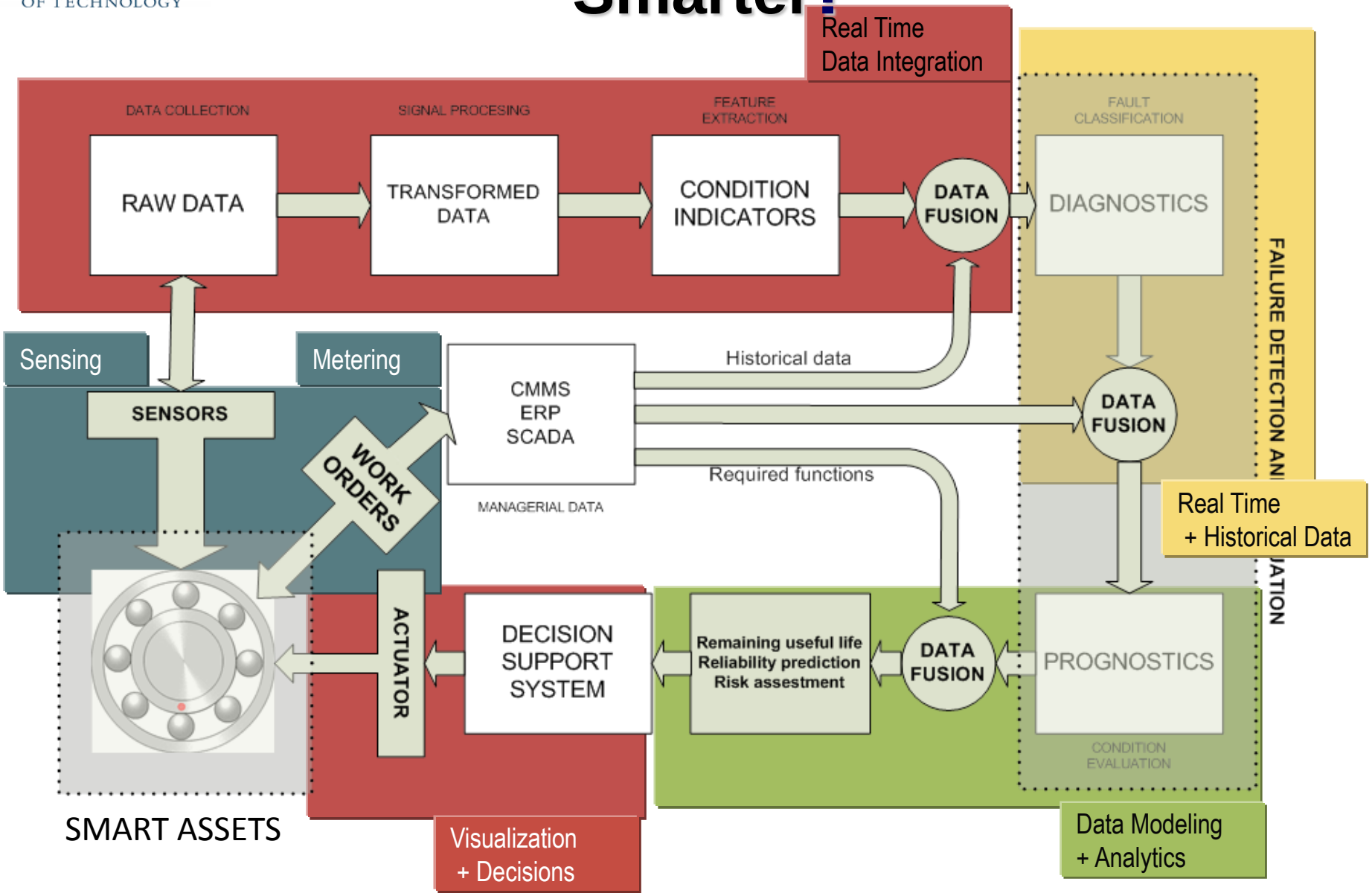
Virtually all things are becoming
INTELLIGENT

Measuring, Monitoring, Modeling and Managing




- Data collection
- Data Integration
- Comparison of historical data, with newly collected data
- Data modeling and analytics to create insights to optimize smarter decisions

# What does it mean to become Smarter?



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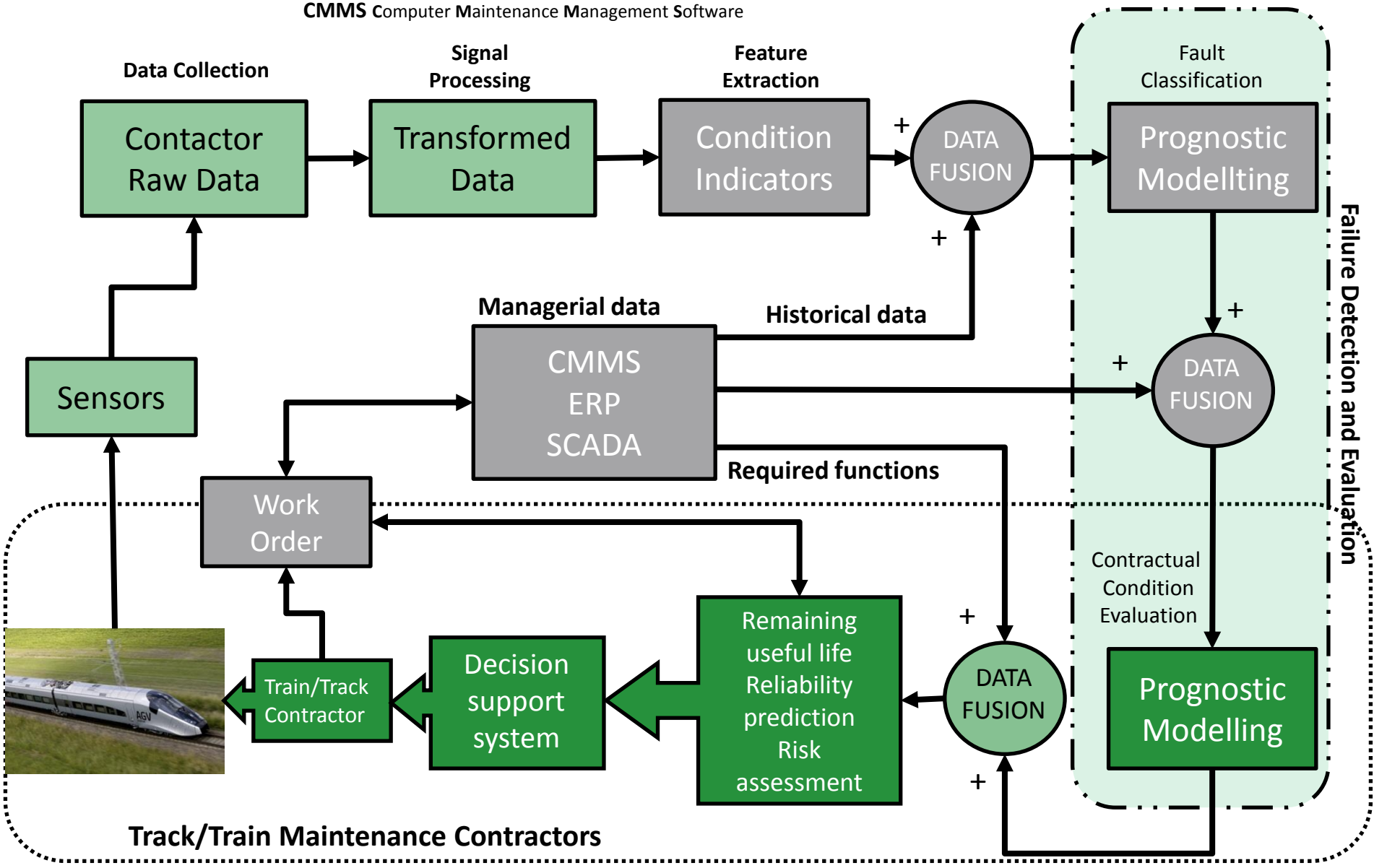
**SCADA** **S**upervisory **C**ontrol **A**nd **D**ata **A**cquisition
**ERP** **E**nterprise **R**esource **P**lanning
**CMMS** **C**omputer **M**aintenance **M**anagement **S**oftware




# Data science…in maintenance
# Narrow vision and mistakes

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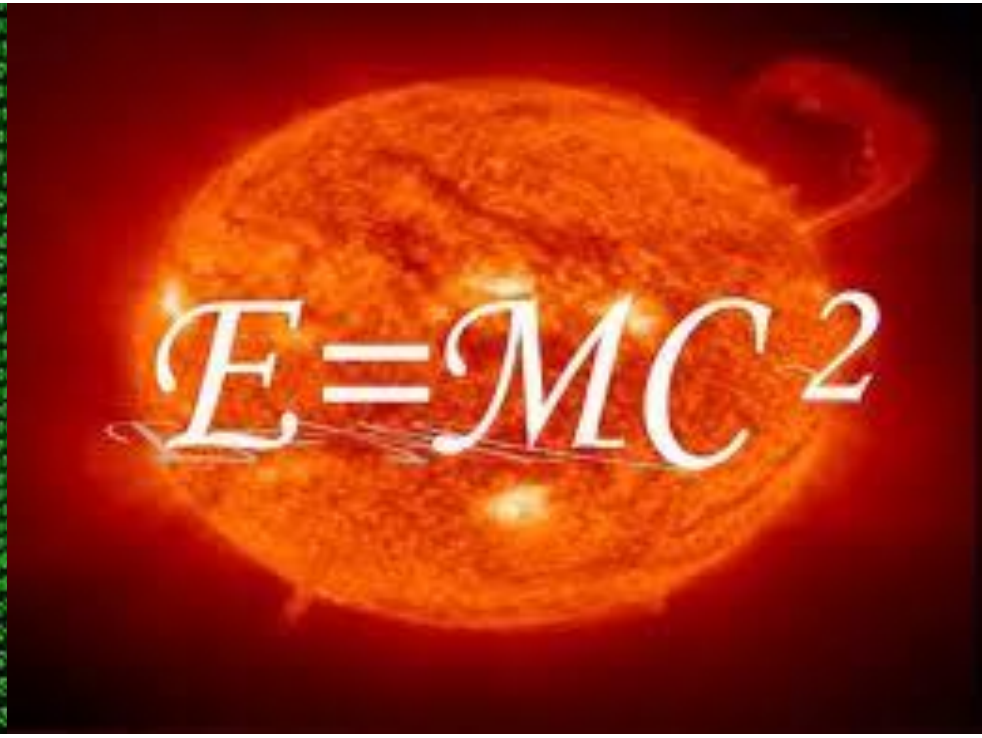
# Diagnosis and Prognosis methods

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

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/DeleteSavedProgram 0.0070 1.0440 0.0160 0.0180
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/GetFolderContents 0.0040 0.0290 0.0480 0.0560
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/GetSavedProgramsFolderContents 0.0030 2.0190 0.0290 0.0340 0.0450
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# To These

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# Value when analyzing data at mass scale

- As observations increase in frequency
  - Each individual observation is worth less
  - …as the set of all observations becomes more valuable
- *Big Data* is the accumulation and analytical processes that uses this data for business value

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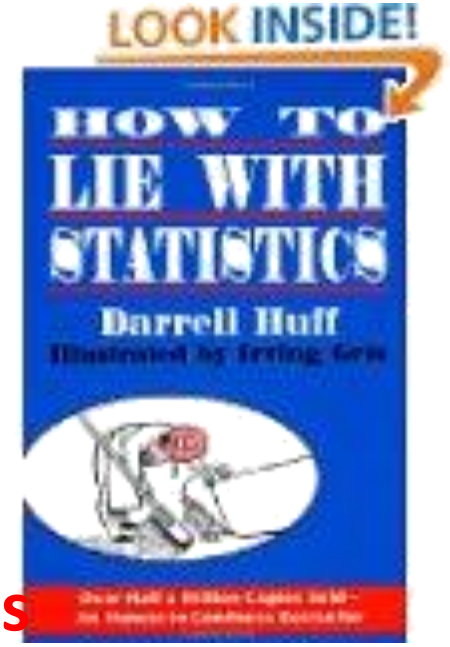
# Let us be careful bigger = smarter?




- Yes!
  - tolerate errors
  - **discover the long tail and corner cases**
  - machine learning works much better
- But!
  - more data, more error (e.g., semantic heterogeneity)
  - with enough data you can prove anything
  - still need humans to ask right questions, lack of analytics

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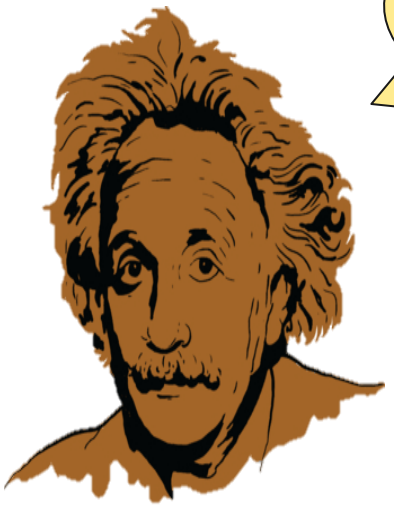
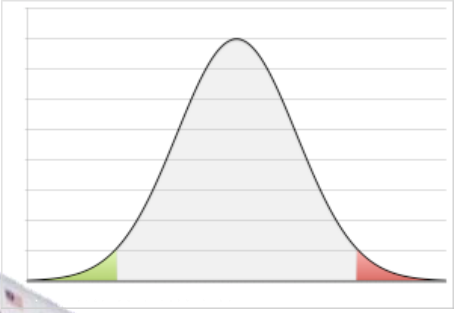
# But Remember…



Not everything that can be counted… counts,
Not everything that counts… can be counted

The only thing that interferes with my ability to learn is…

My Education



**AND…even with all this data**

**We can't find many answers**

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# Black Swan Losses

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

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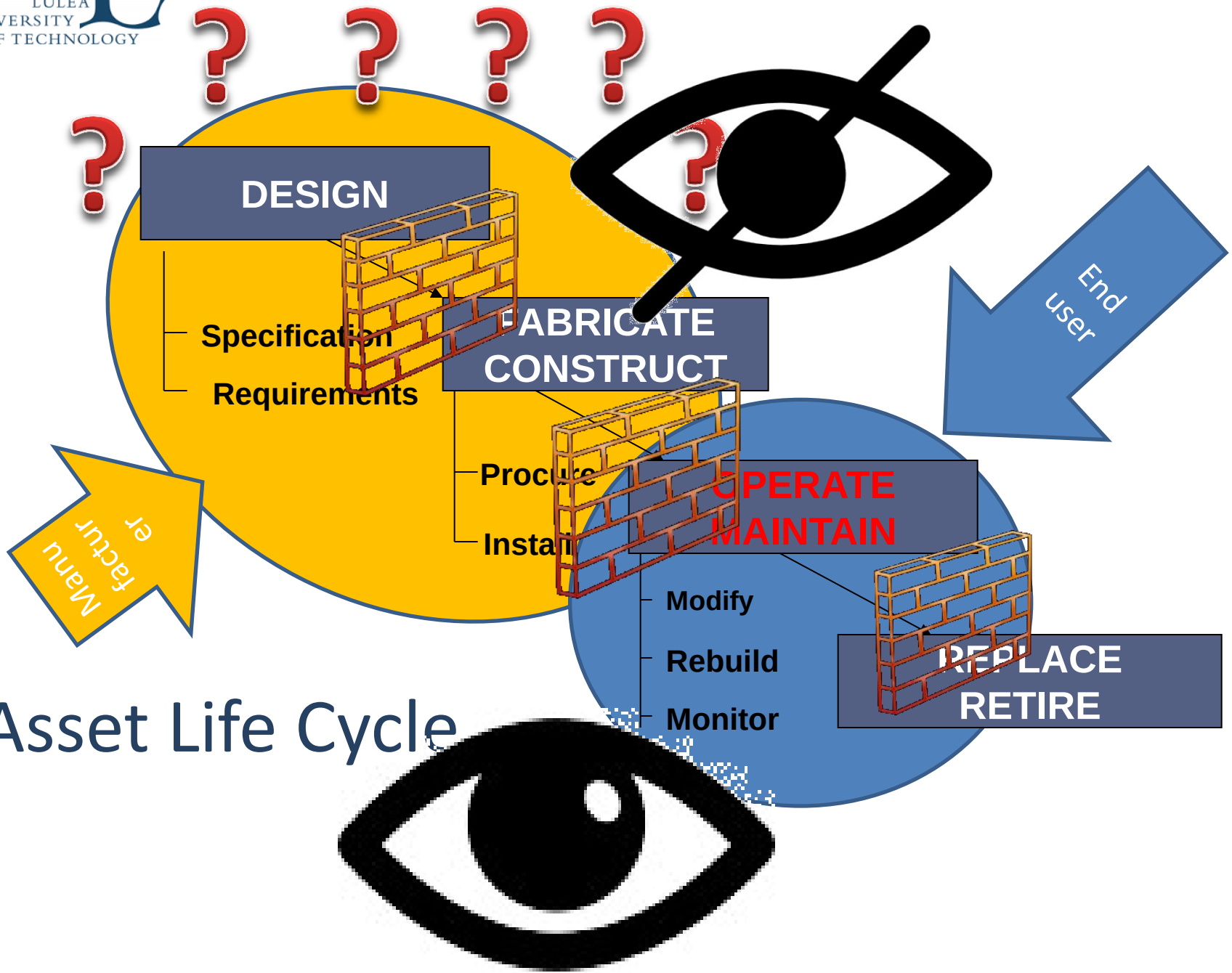
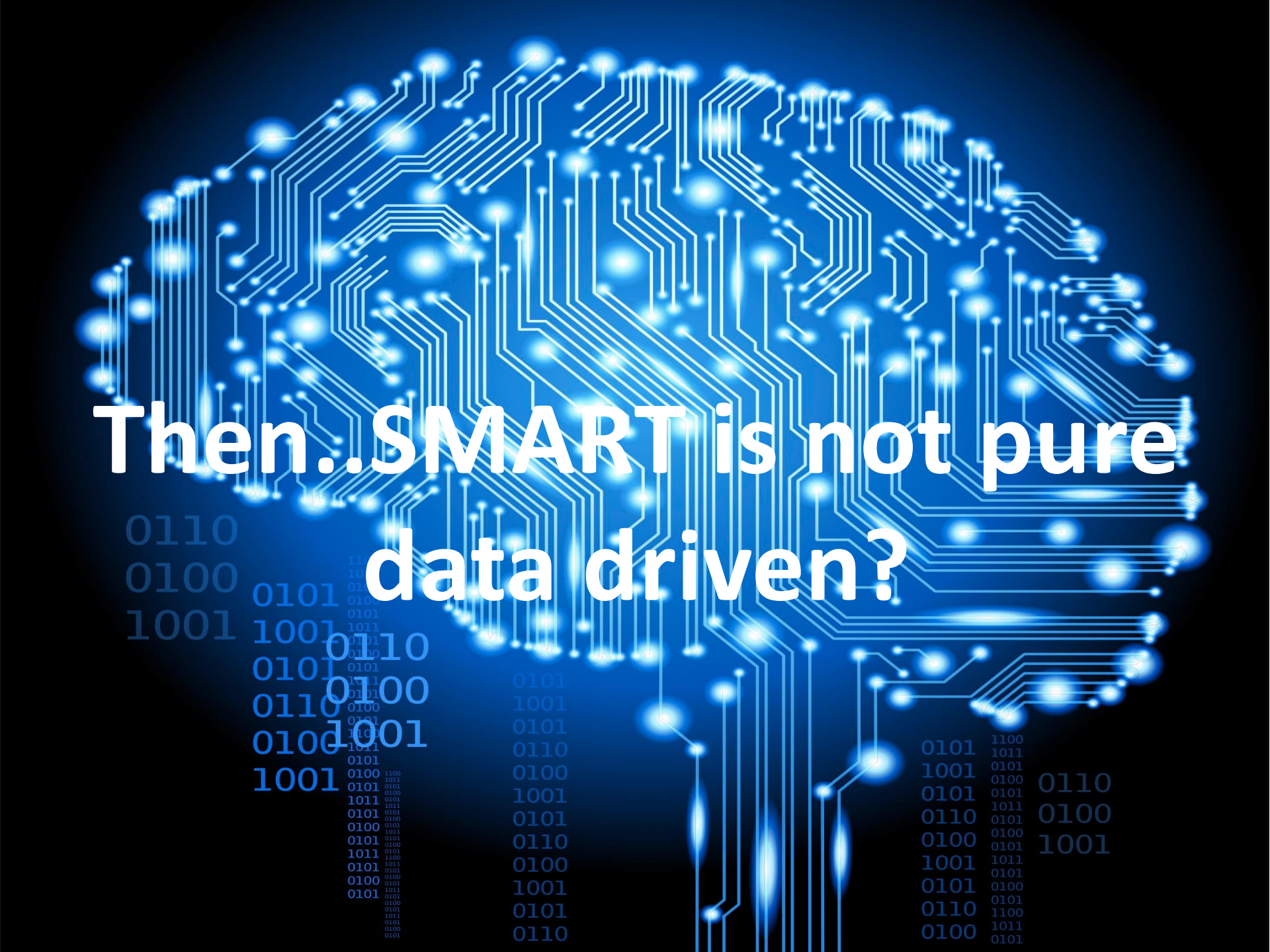
# Asset Life Cycle




Then..SMART is not pure data driven?

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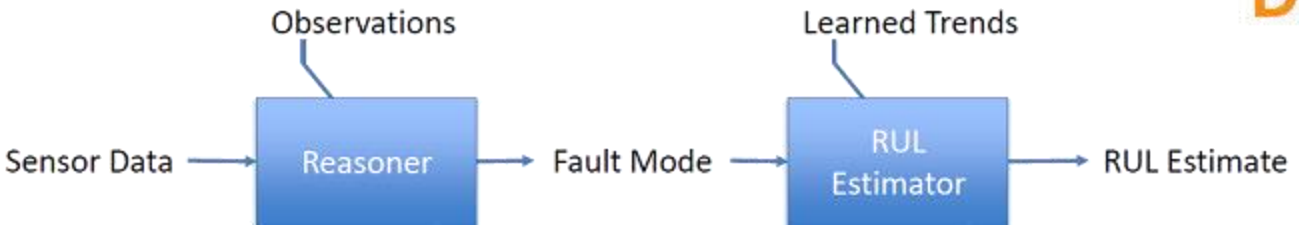
# Data driven methods


- Fit mathematical model to observations (trending)
  - No guaranty that extrapolation will be meaningful
- Collect statistics of failures as a function of current state
  - Requires volumes of data and is difficult to know when you have enough

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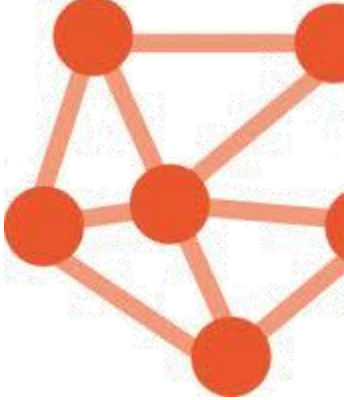
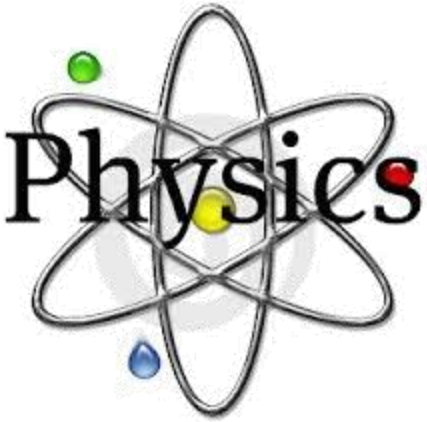


# Physical based methods

- Physics of Failure Model Driven
  - Capture physical basis of failure in model that relates the forces that cause damage to their effect
    - Requires a detailed understanding of the problem
- Many Implementations Are a Combination of Both



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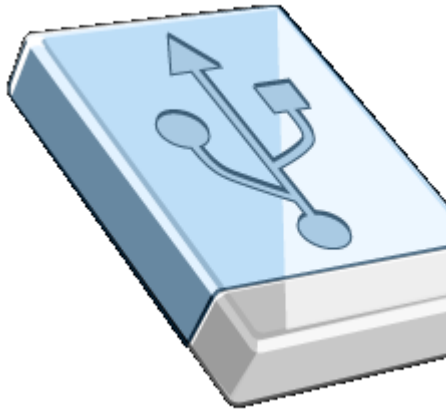
# Source of knowledge

- FMEA / FMECA
  - What the failure modes are
  - Effects (and Criticality) – which failure modes to go after
- Fault Tree Analysis
  - Propagation Models
- Designers / Reliability Engineers
  - System knowledge and insight
  - Expected / nominal behavior of the system
- Seeded Failure Testing / Accelerated Life Testing
  - Data (and lots of it if you're lucky)
  - Failure signatures
  - Effects of environmental conditions
- Fielded Systems
  - Sensors measurements
  - Maintenance logs



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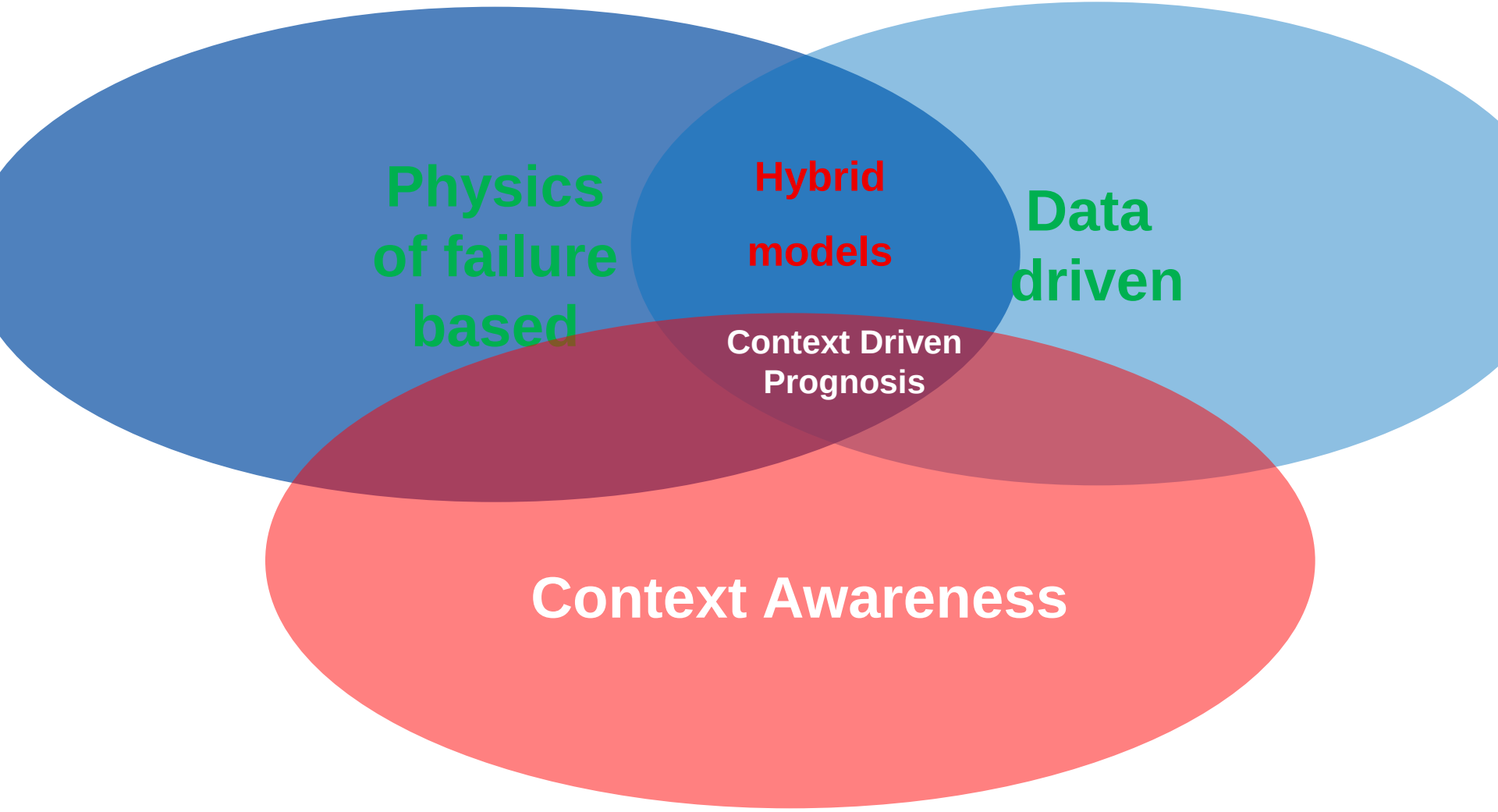
# Context Driven Diagnosis /Prognosis



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# What is context?

"Any information that can be used to characterize the **situation of entities that are considered relevant** to the interaction between a user and an application"

Dey et al.

"A pattern of behavior or relations among variables that are outside of the subjects of design manipulation and potentially affect user behavior and system performance"

Sato

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# 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?
  - ...

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# What are the challenges?


1. Lack of recommendations about **the functional needs** of the context.

2. **The gap** which still exists between fundamental researches on context representation and actual context-awareness prototypes.
   - No organization of context is used even if recommended in the studies.

3. The difficulties in building efficient computerized systems for context processing:
   1. Open systems: MIMOSA, OSA CBM, RAIL TOPOMODEL
   2. Technologies: Cloud computing

# Contextual variables

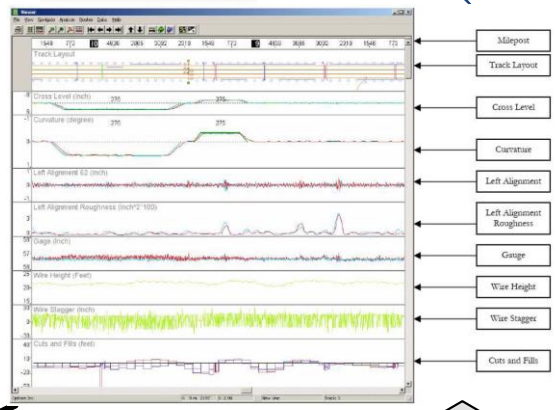
CM data about Infra coming from rolling stock

WO reported by Maintenance

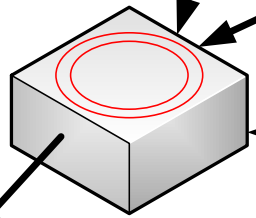
| WO XXXXX |
|---|
| **Asset code: XXXX** |
| **Railtrack / Location** |
| Date: XXXX |
| Location: XXXX |
| Technician: XXXX |
| **Failure mode detected: Rough track** |

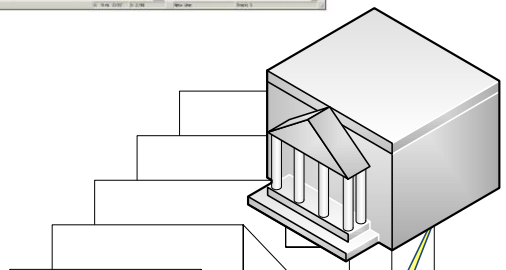
CMMS

CM track side

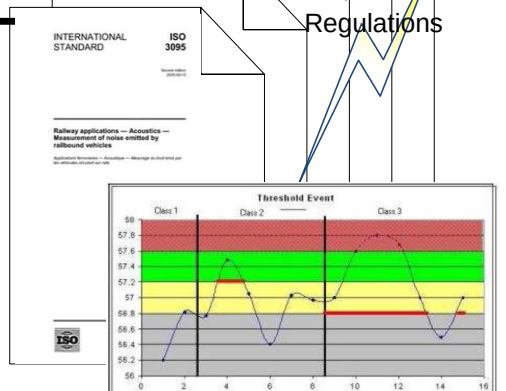



| Metadata |
|---|
| **Asset code: XXXX** |
| **Railtrack / Location** |
| Date: XXXX |
| Location: XXXX |
| Technician: XXXX |
| **Failure mode existing: Rough track** |
| **Frequency: Common** |
| **Gauge reading: XXXXX** |
| **Severity: Unacceptable** |
| **Performed actions: XXXXXX** |





Regulations



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# SMART infrastructure in railway: Fusion of IM and Operators info.....including WOs

Condition indicators from track side

**Off line information provided by measurement vehicles**

**DATA REPOSITORIES And INFORMATION FUSION**

Condition indicators from real time data collection like: **load, vibration, temperature**

**On line information**

On board data collection

Vehicle as moving sensor

GPS

Track information

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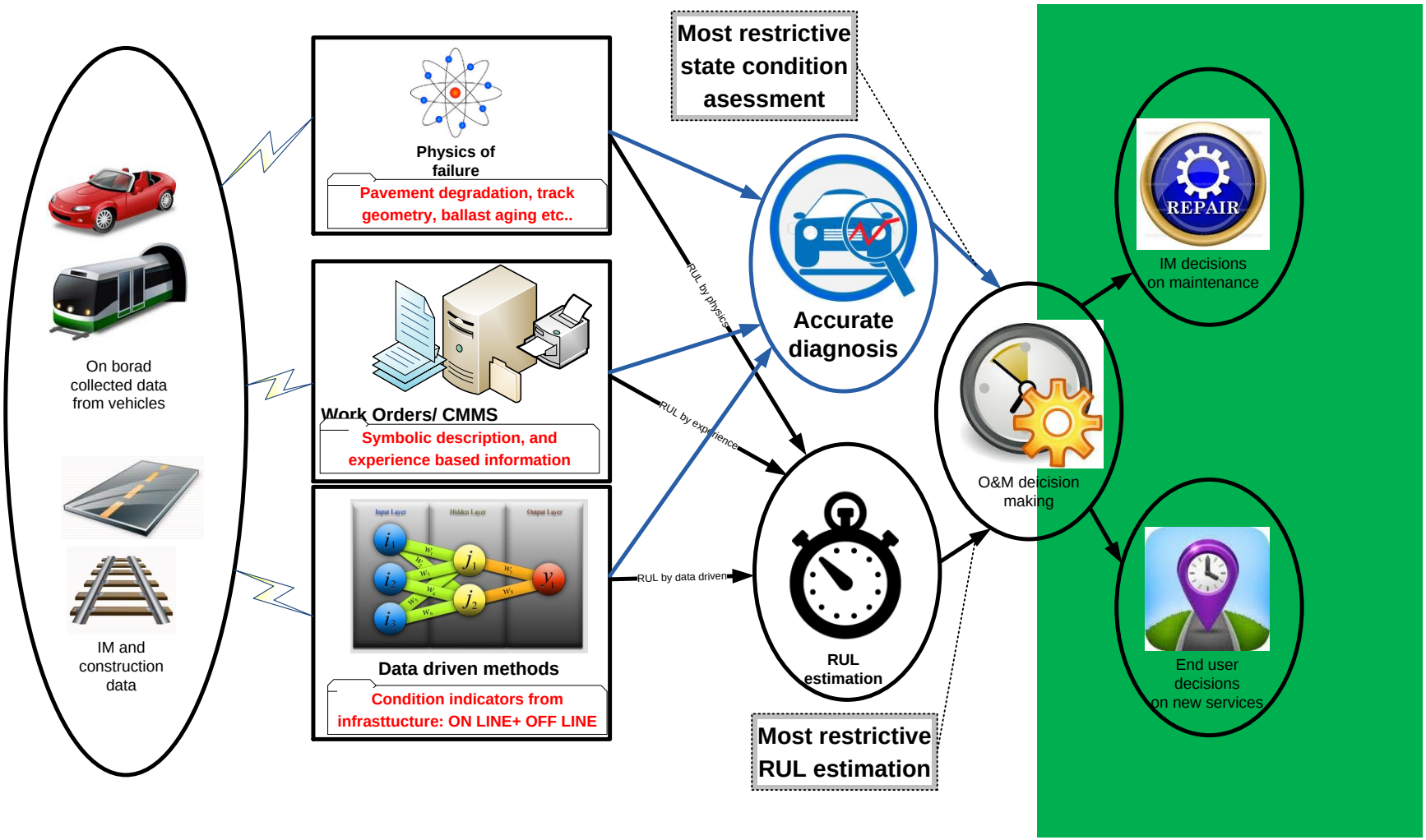
# Diagnosis and Prognosis, enablers for new business models



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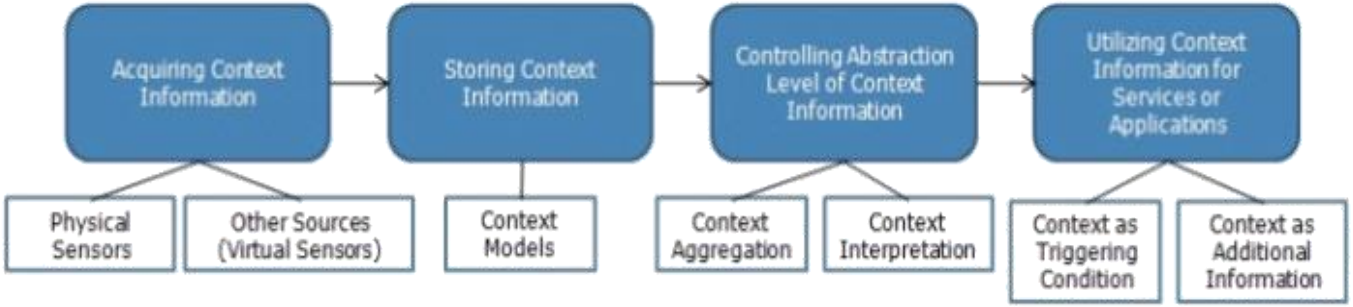
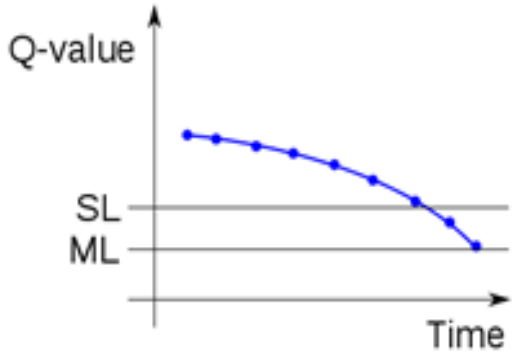
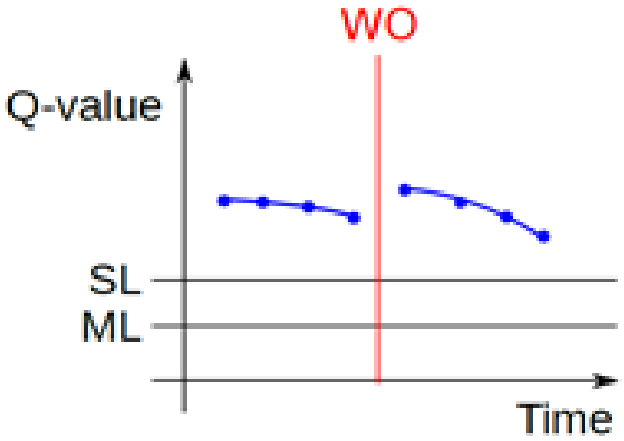
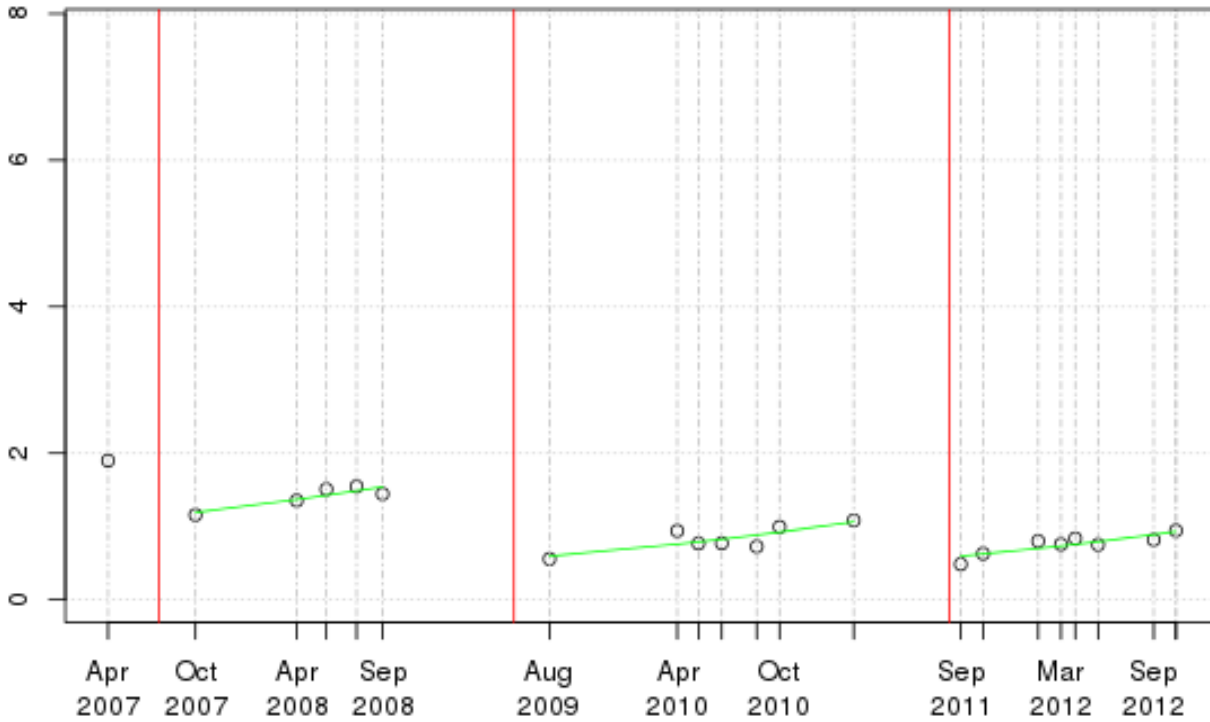
# A success story of context: Railway



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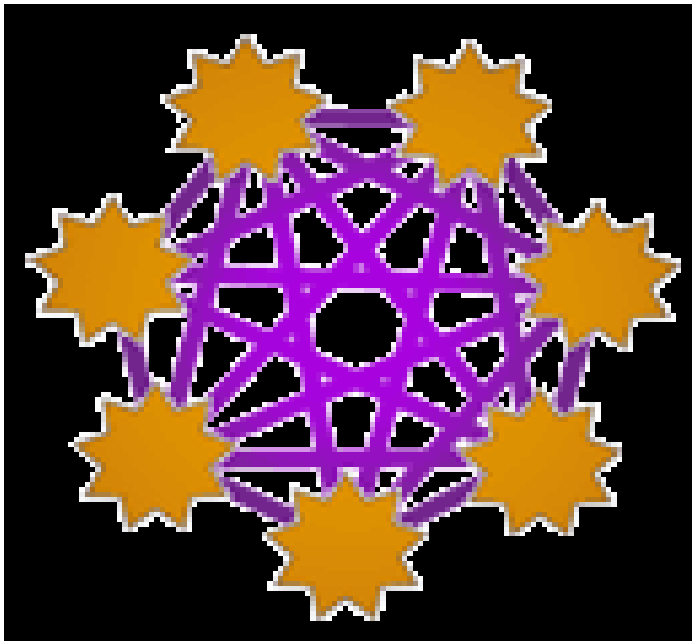
# Diagnosis

Fault detection + Fault identification



**Anomaly detection + Clustering / Classification**

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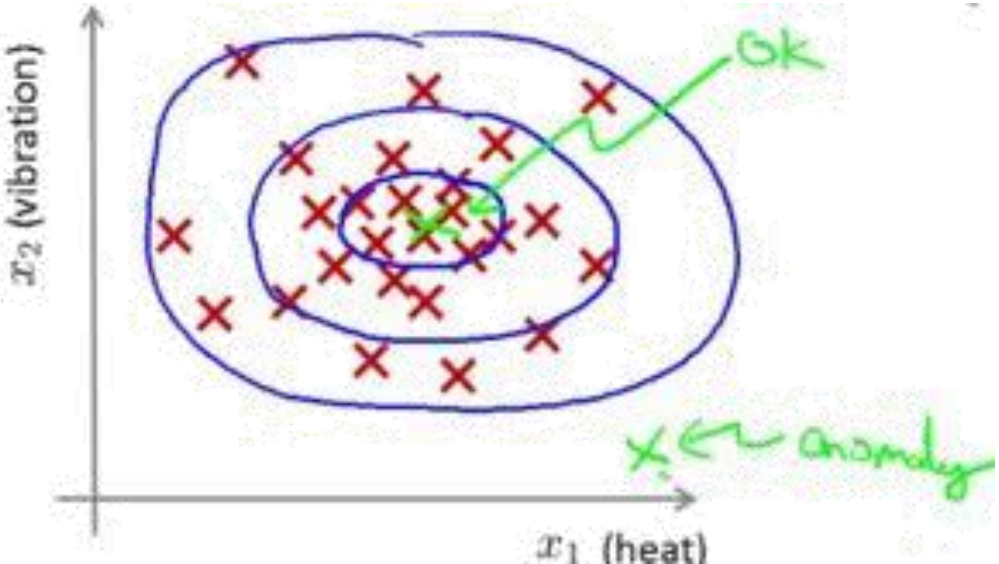
# What are Anomalies?

- Anomaly is a pattern in the data that does not conform to the **expected behavior**
- Also referred to as outliers, exceptions, peculiarities, surprise, etc.



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# Type of Anomaly

- Point Anomalies
- Contextual Anomalies
- Collective Anomalies

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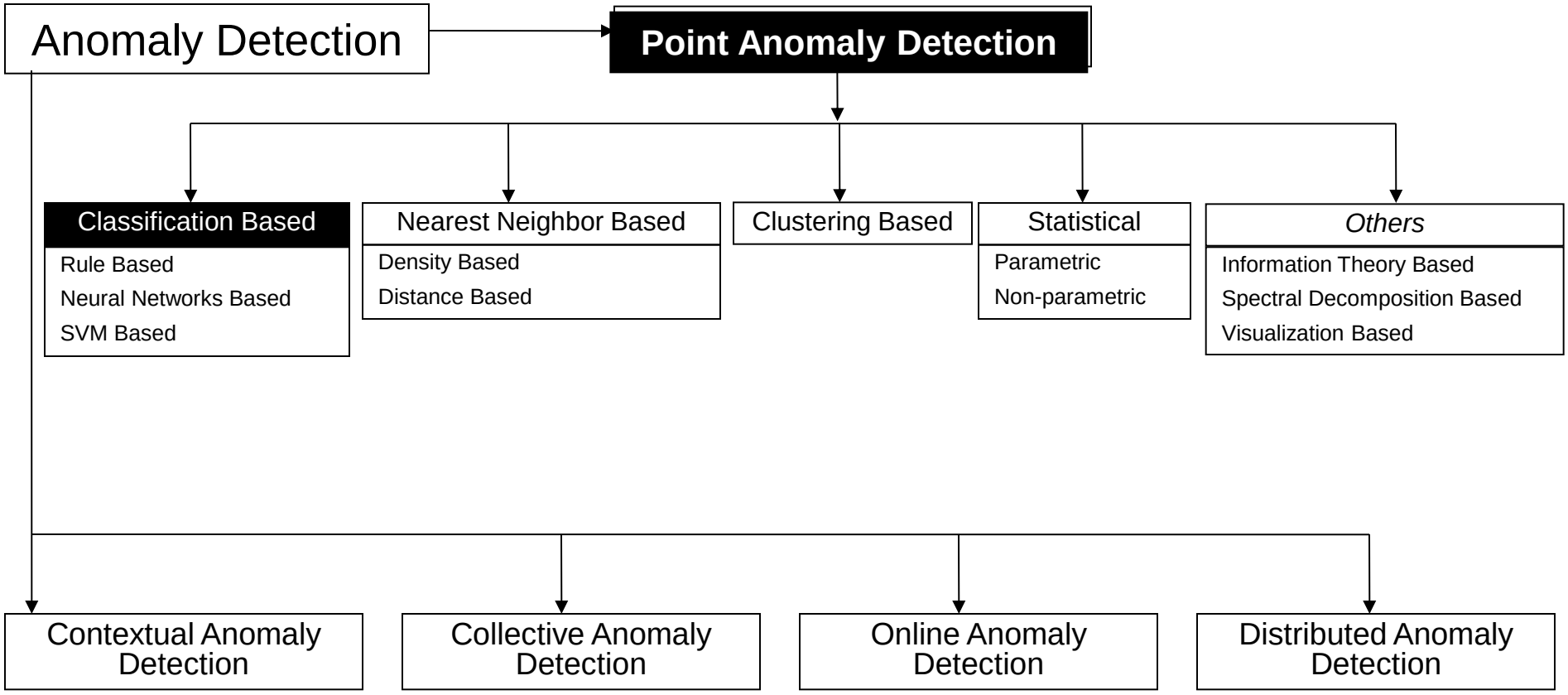
# Available techniques



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# Prognosis or the chrystal ball

# DETECTION, ISOLATION & PROGNOSIS

**Detection**

Through sensors, Models etc

**Isolation**

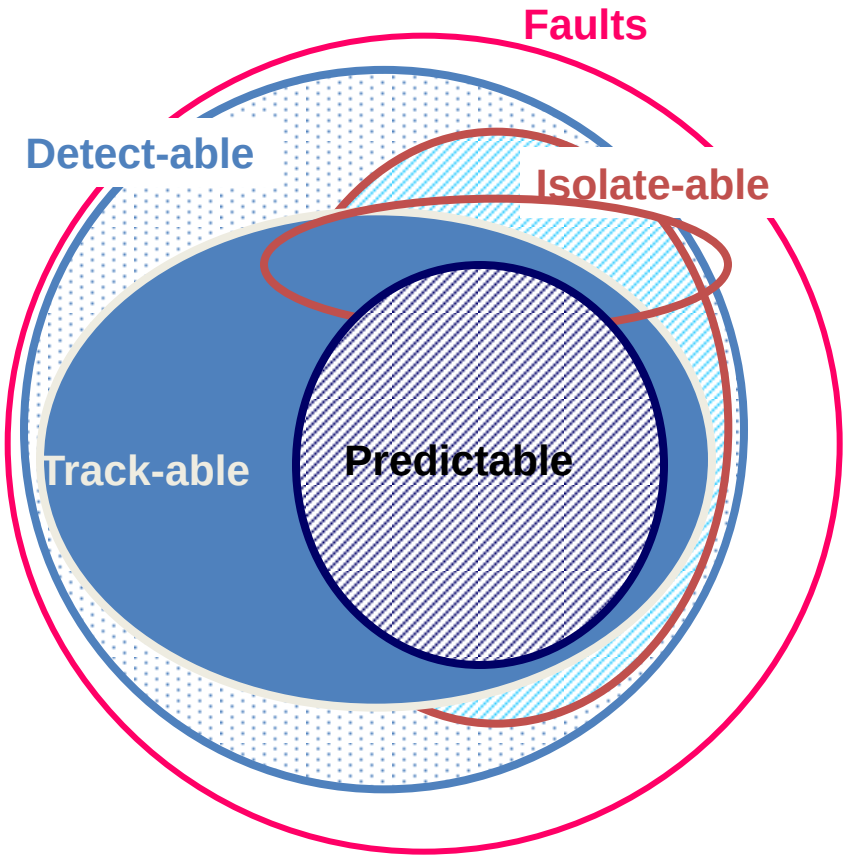
Information fusion from sensors, Models etc.

**Tracking/Trending**

Processed PHM data

**Prediction/Prognosis**

Based on tracking/trending, & lifing models



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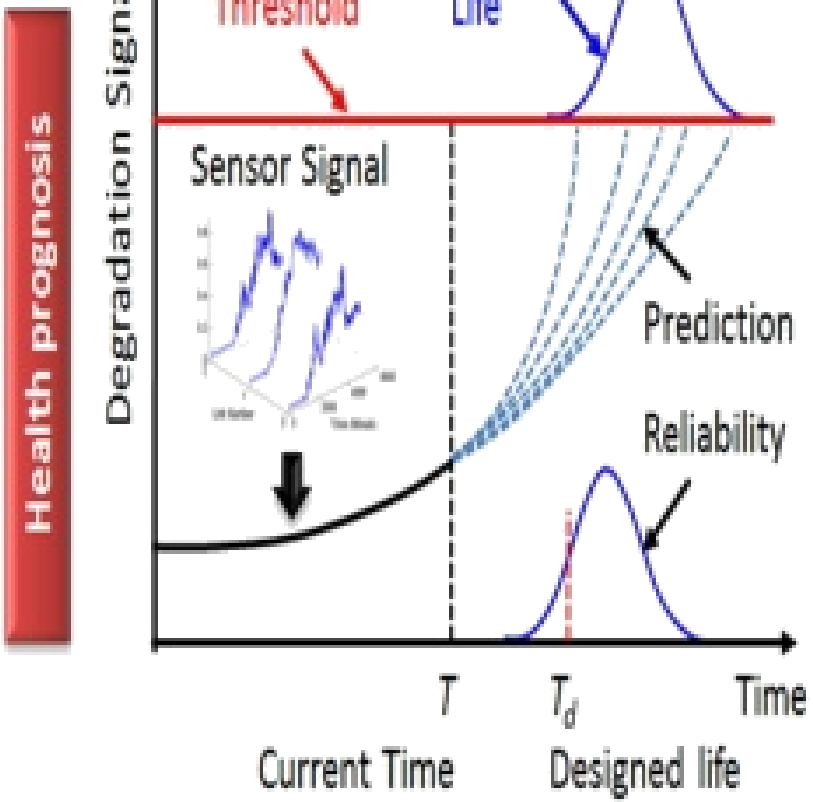
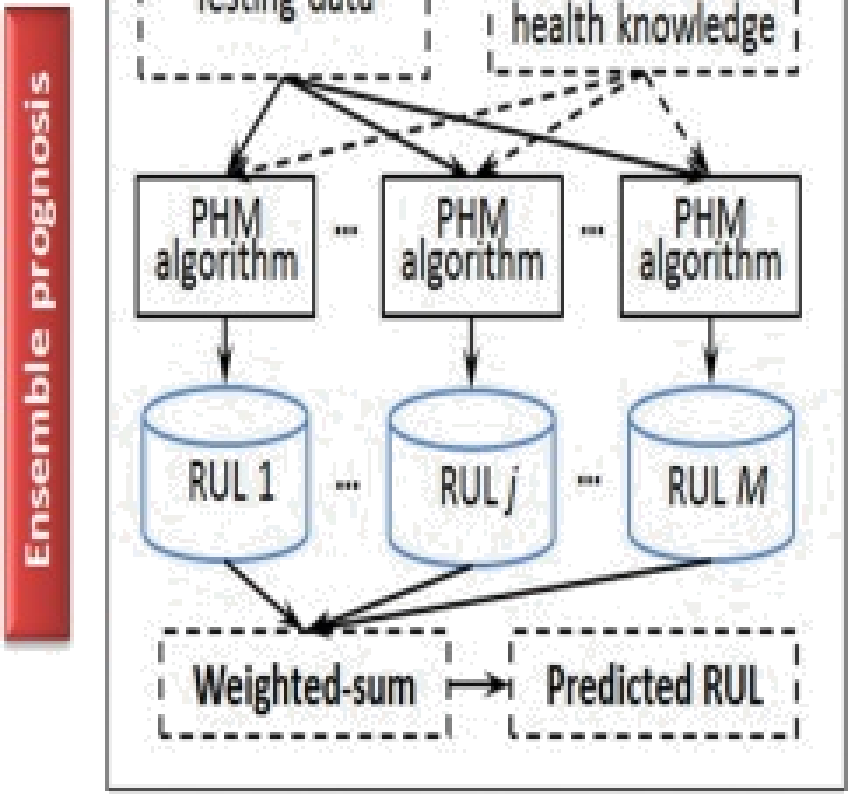
# Uncertainty in RUL is a fact



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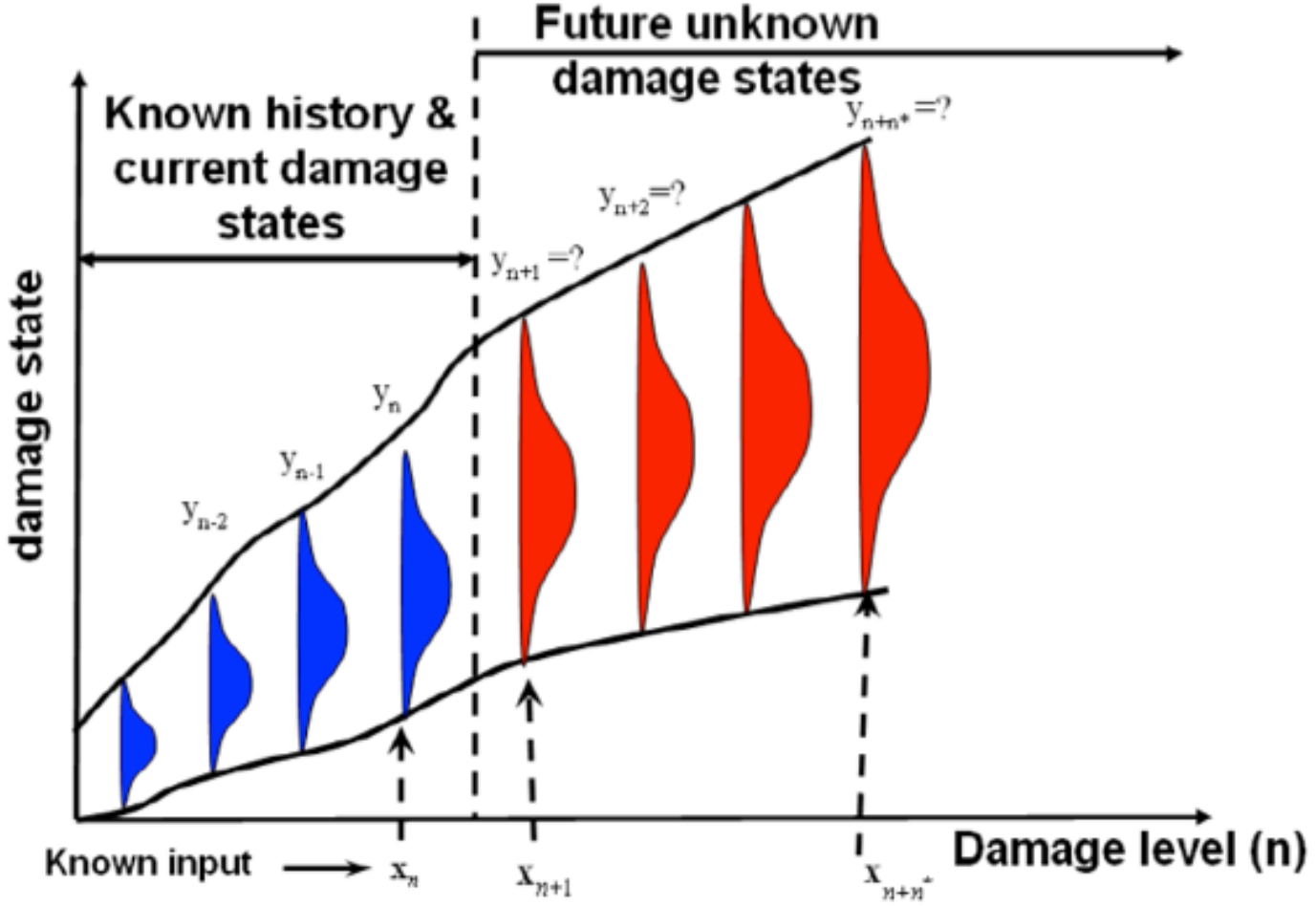
# Lack of data influences the prediction

## Don´t understimate physical models…



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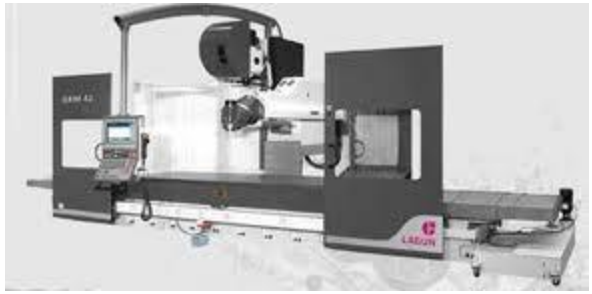
# Machine tools..a complex asset



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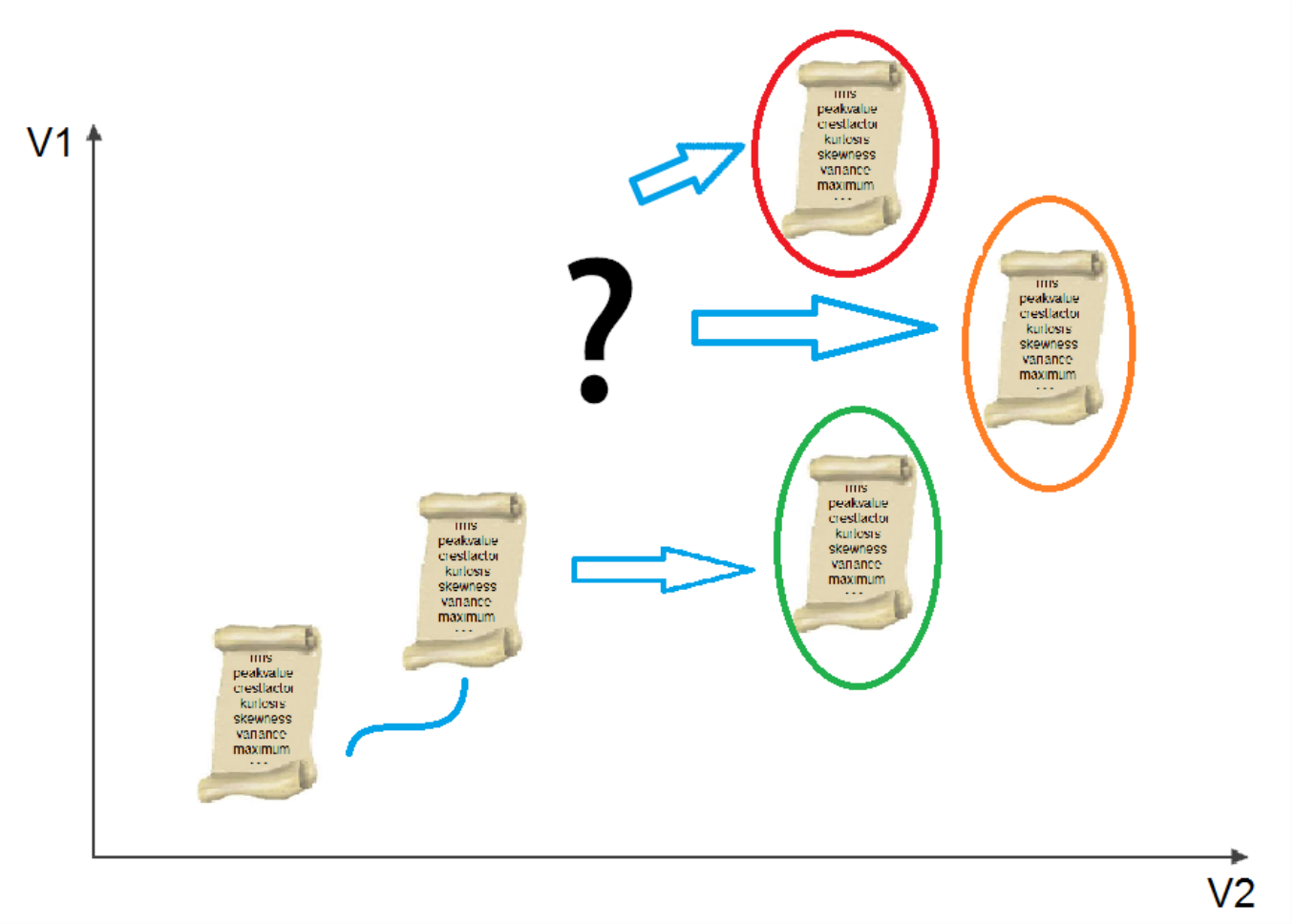
# Prognostics: Fingerprint trajectories



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# Diagnosis, prognosis and then the maintenance decision…
# What special analytics we need?

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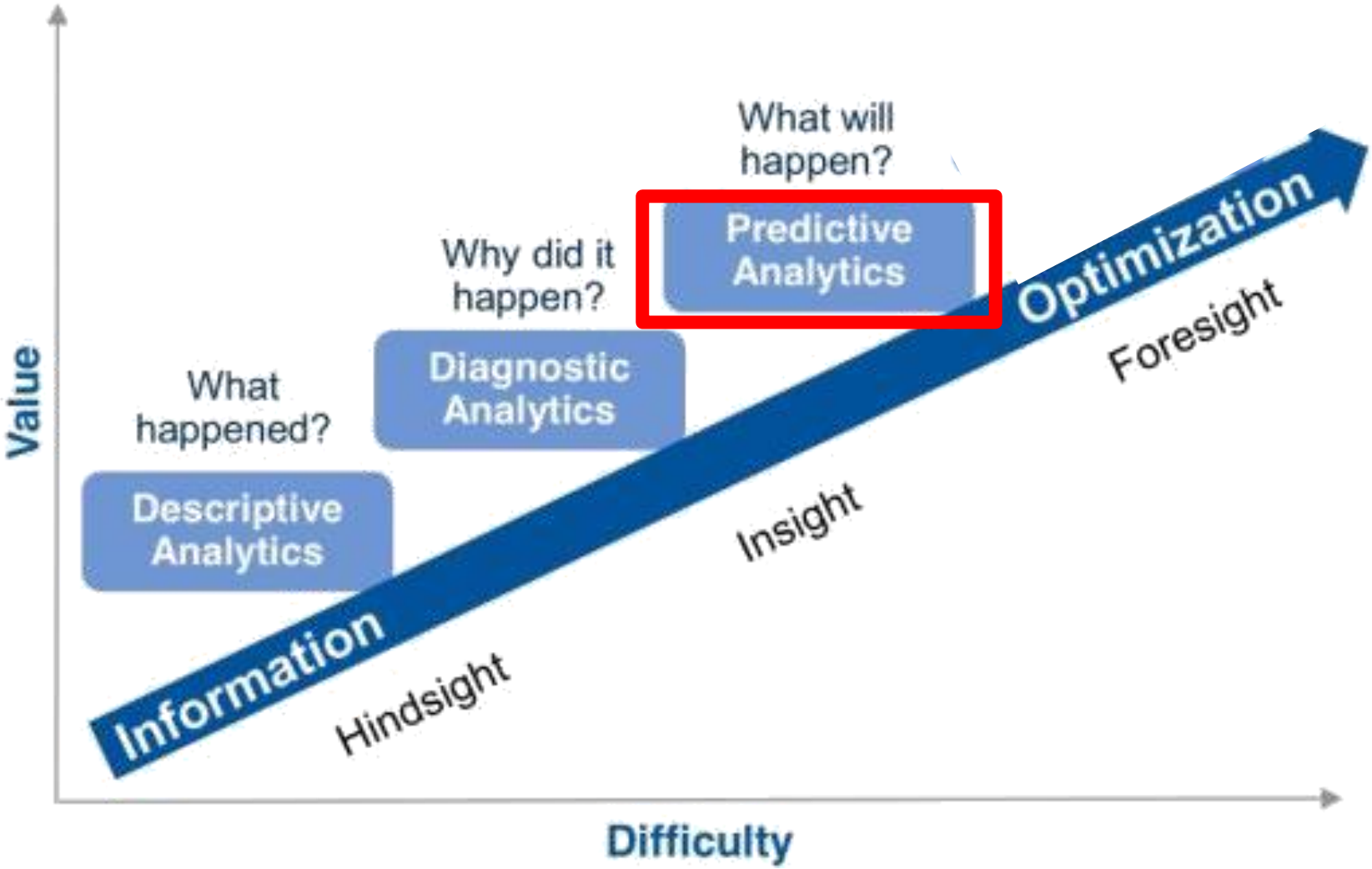
# Prediction is not the ultimate goal



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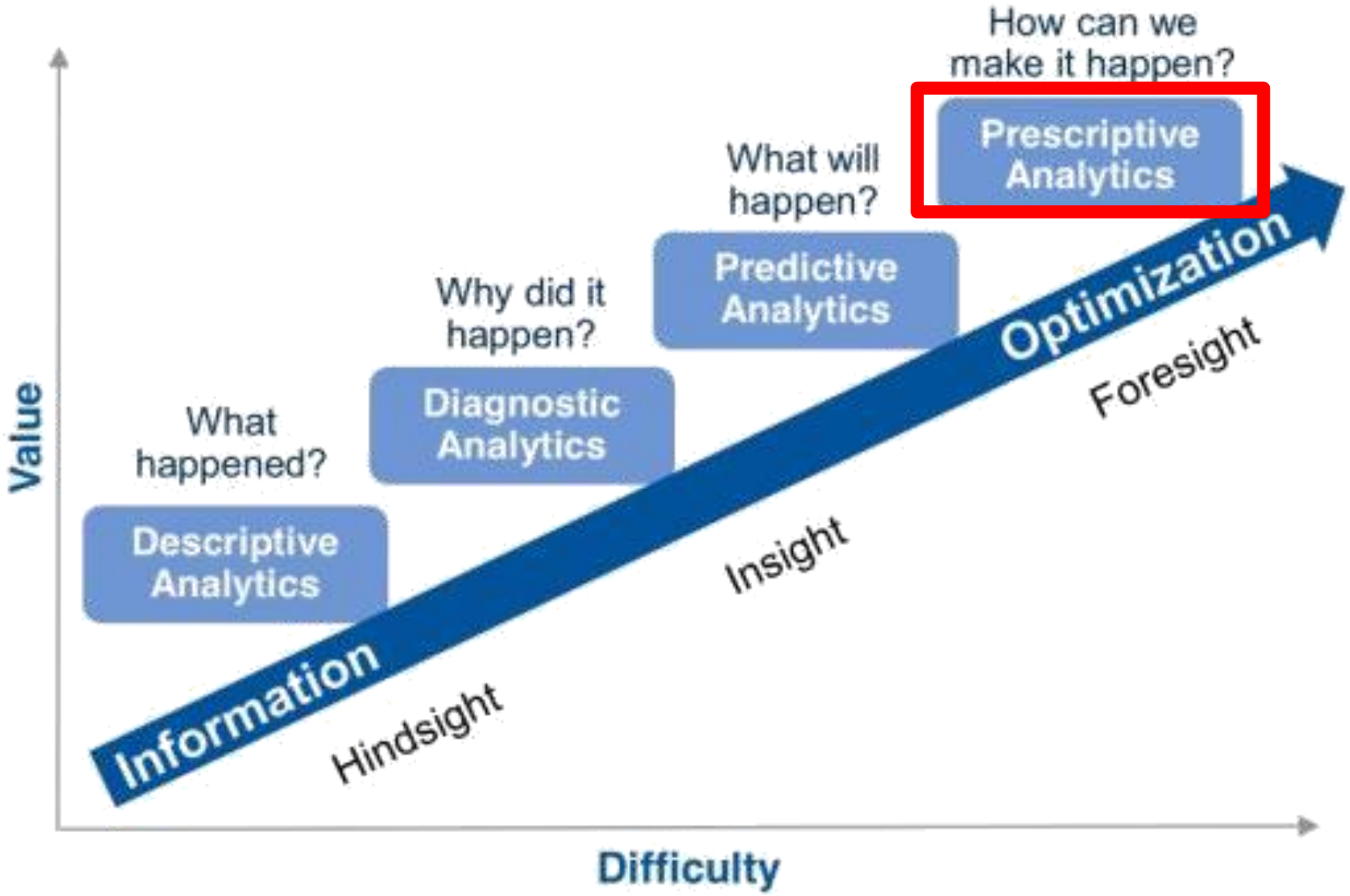
# The reaction is our expectation



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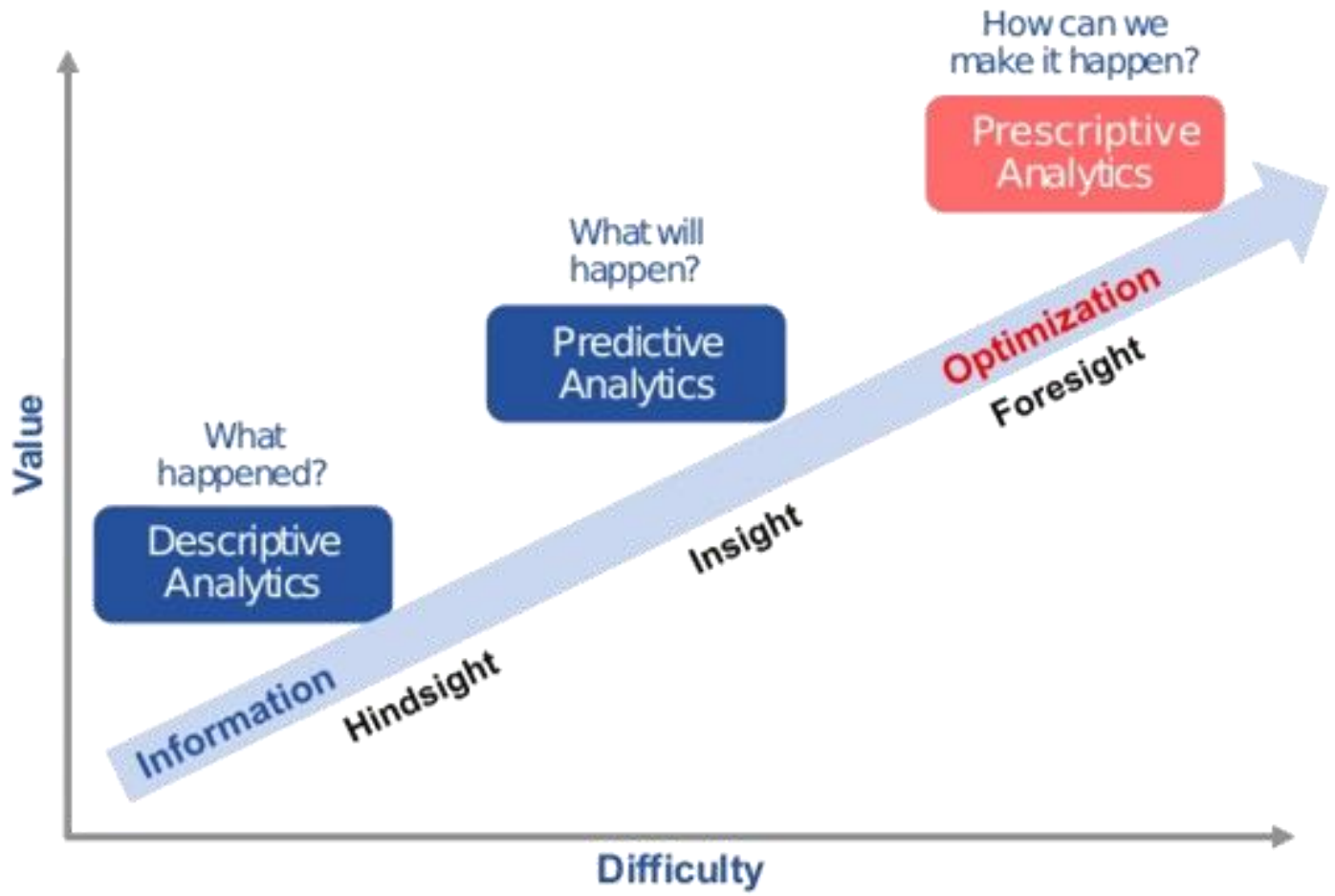
# SMARTness is about prescription

Prescriptive Analytics delivers largest value



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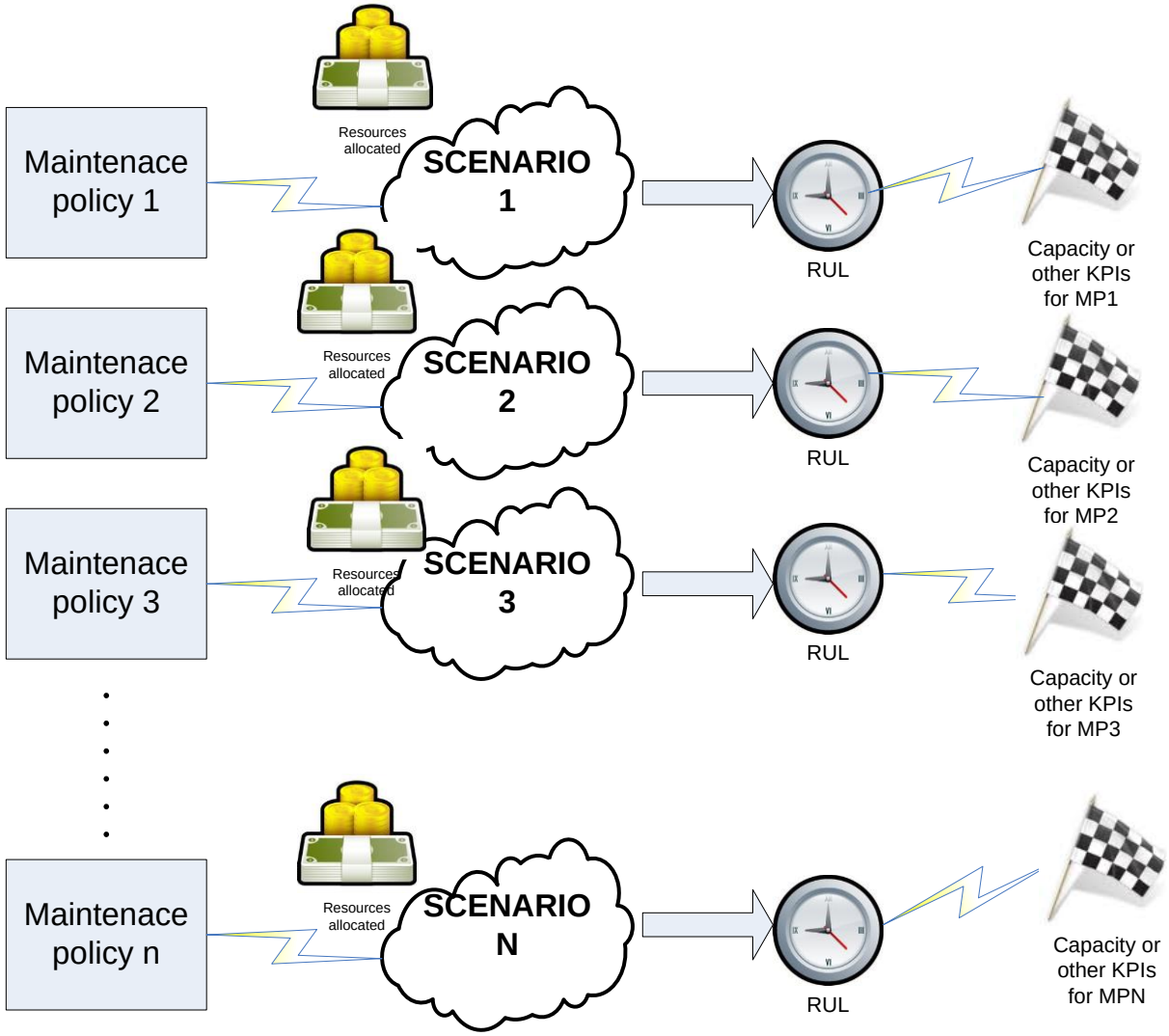
# SMARTness and prescription require simulation

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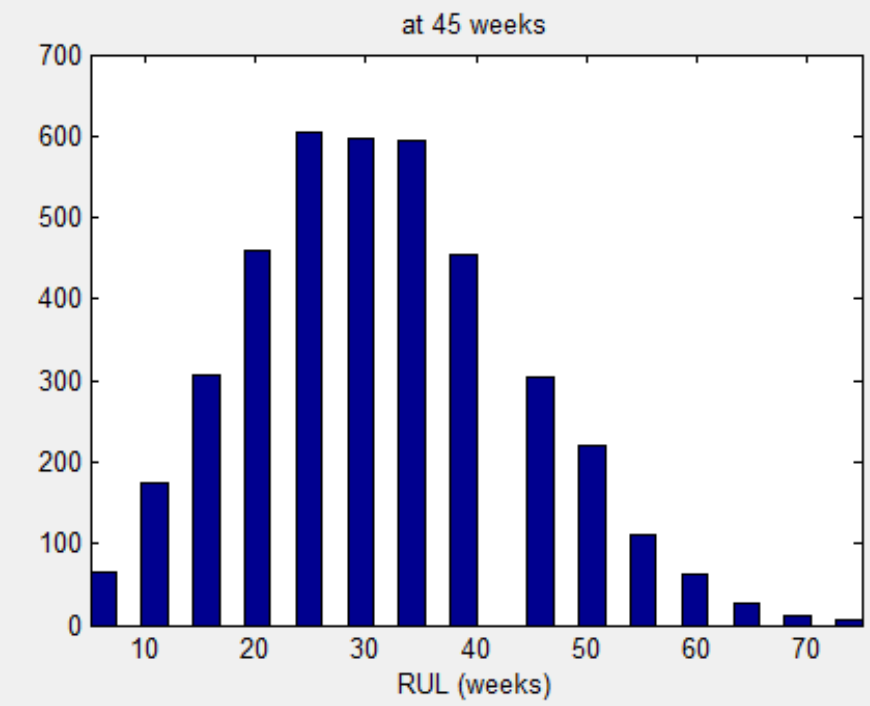
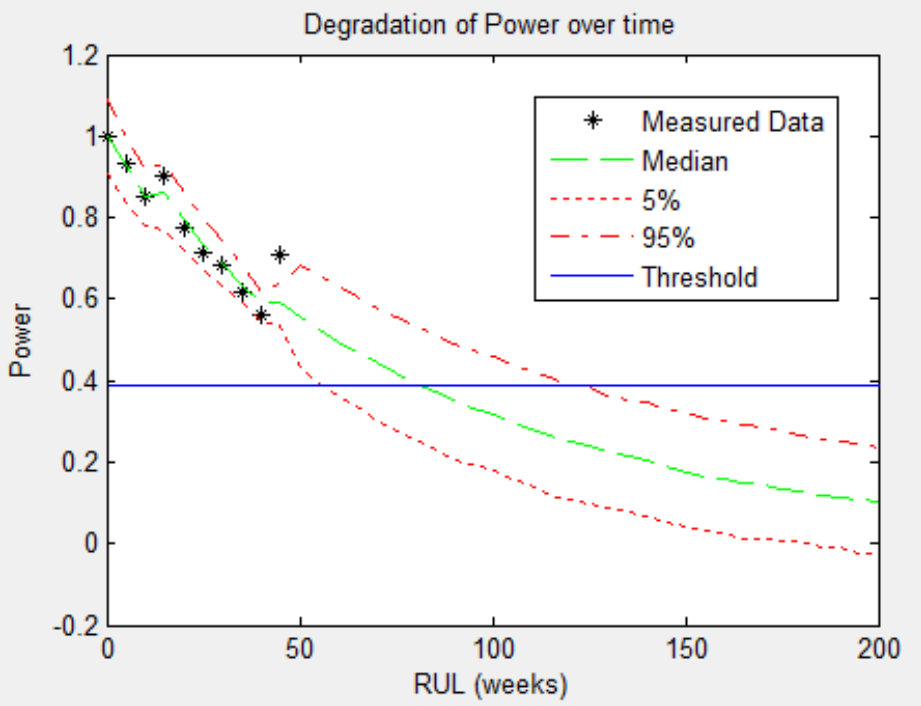
# Prognosis information: the first step for the prescription



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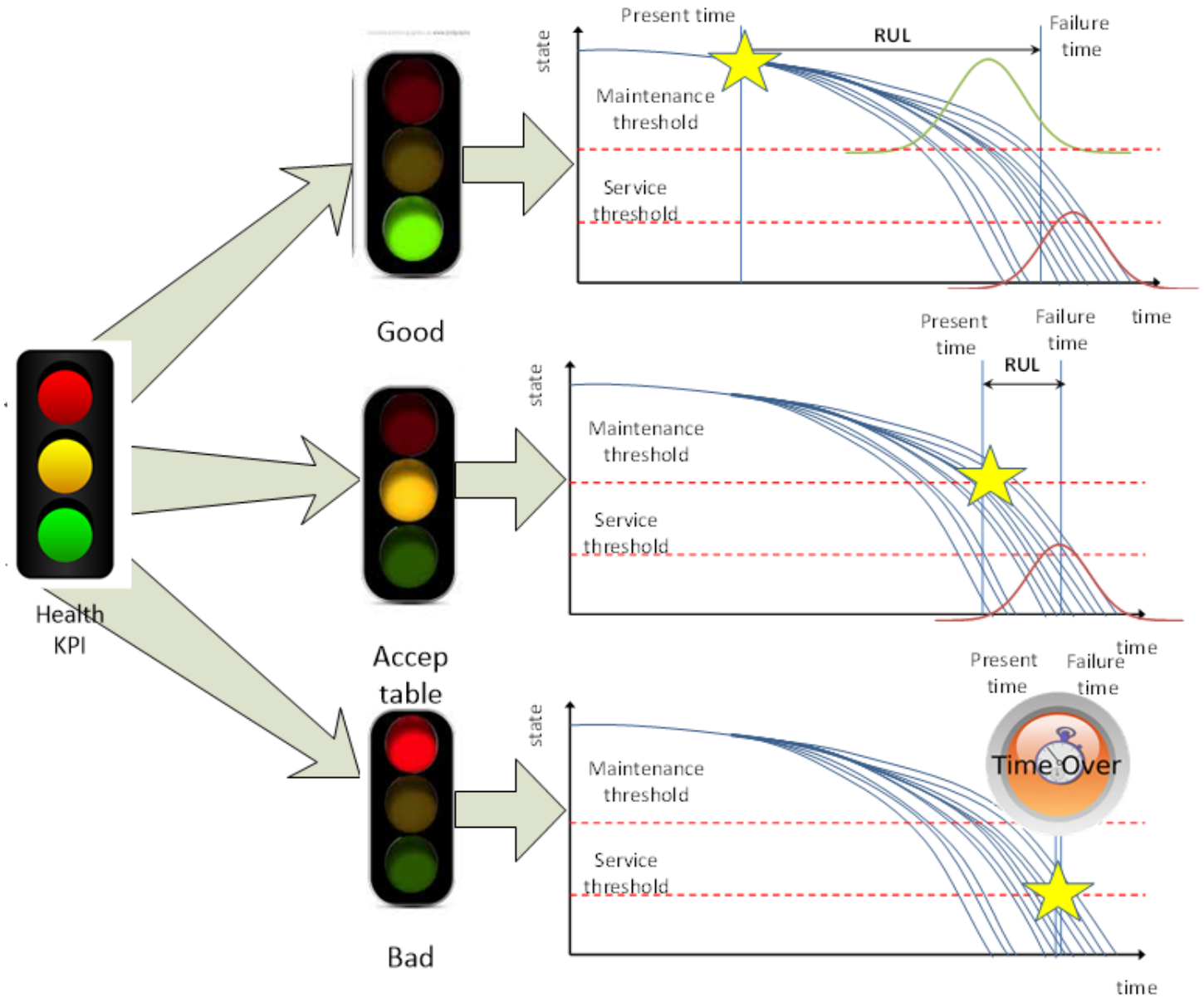
# MA based on RUL



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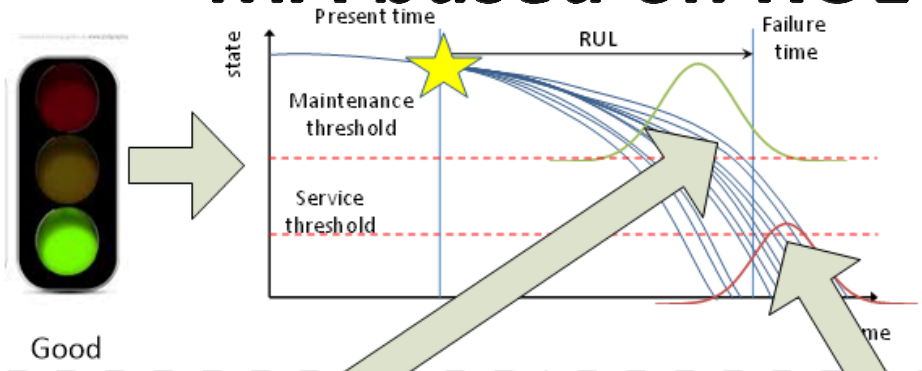
# MA based on RUL




RUL to reach maintenance thresholds

RUL to reach service level

RUL to maint. SOFT OPERATION

RUL to maint. MEDIUM OPERATION

RUL to maint. HARSH OPERATION

RUL to service SOFT OPERATION

RUL to service MEDIUM OPERATION

RUL to service HARSH OPERATION

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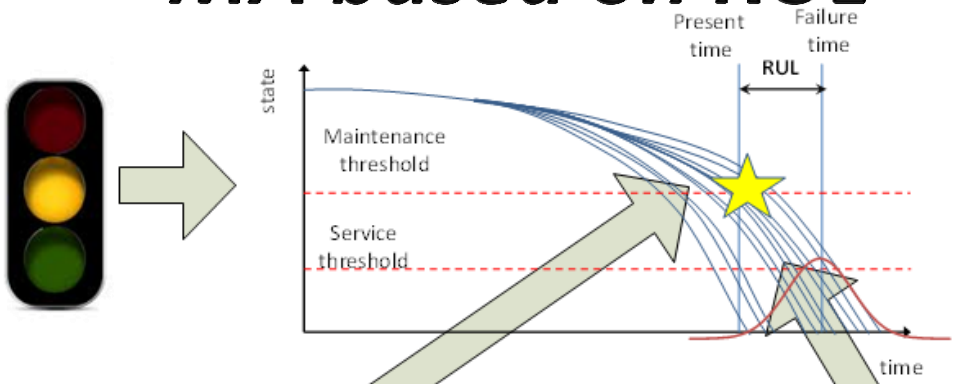
# MA based on RUL




Maintenance intervention

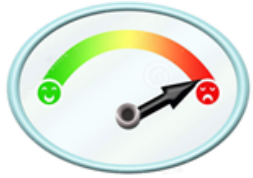
Corrective Maintenance action

Preventive Maintenance action

RUL to reach service level

RUL to service SOFT OPERATION

RUL to service MEDIUM OPERATION



RUL to service HARSH OPERATION

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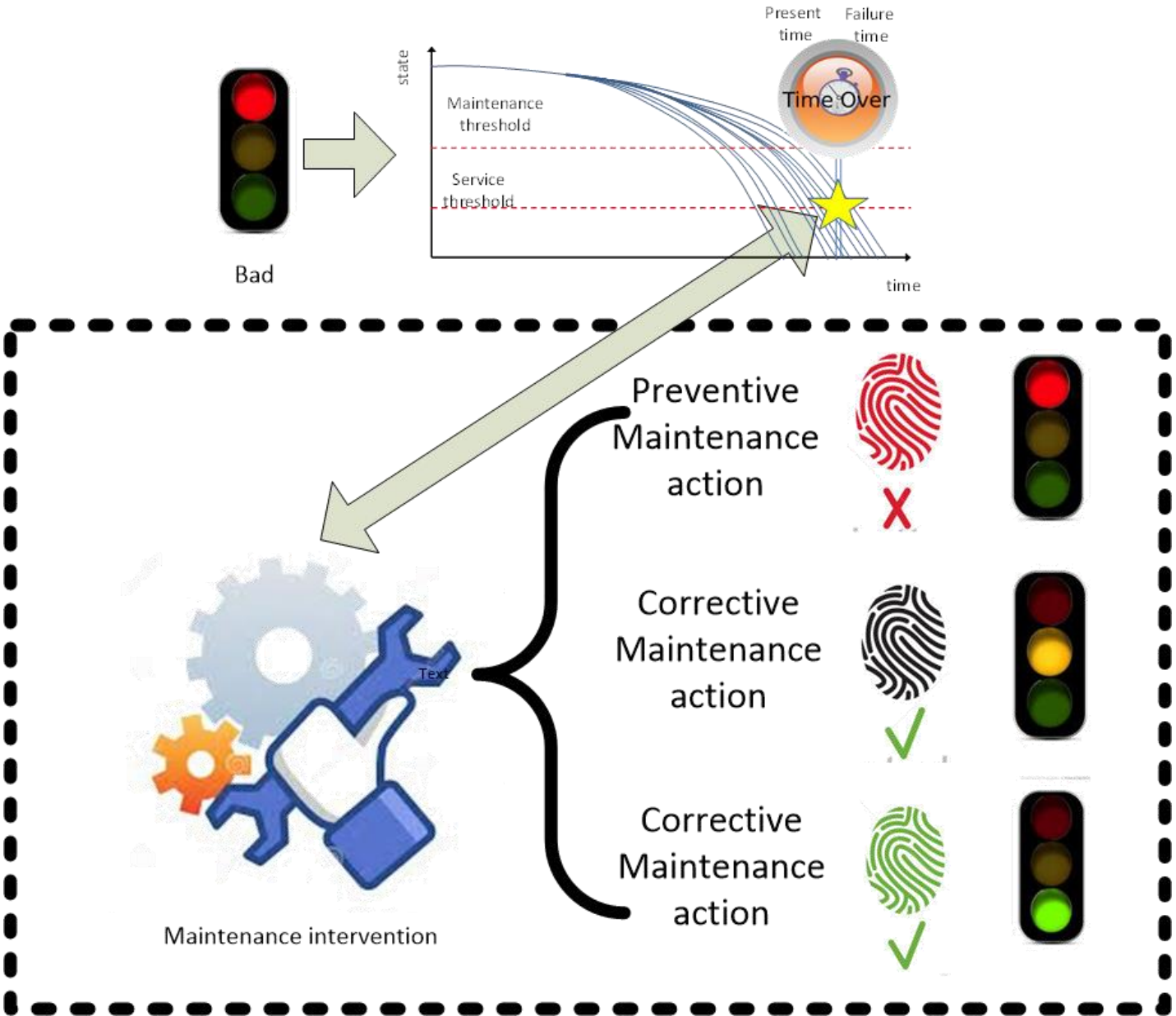
# MA based on RUL



# In summary…..

- Risk is the enabler of SMARTness
- The nature of the data and granularity is still a challenge to perform maintenance analytics
- Data drive approaches cannot provide predictions or prescription based on events very seldon happened
- Maintenance analytics has overcome prediction going for prescription

Thank you for your Attention!!!

Any Questions?