PHM frontiers in Korean manufacturing –
success episodes and issues
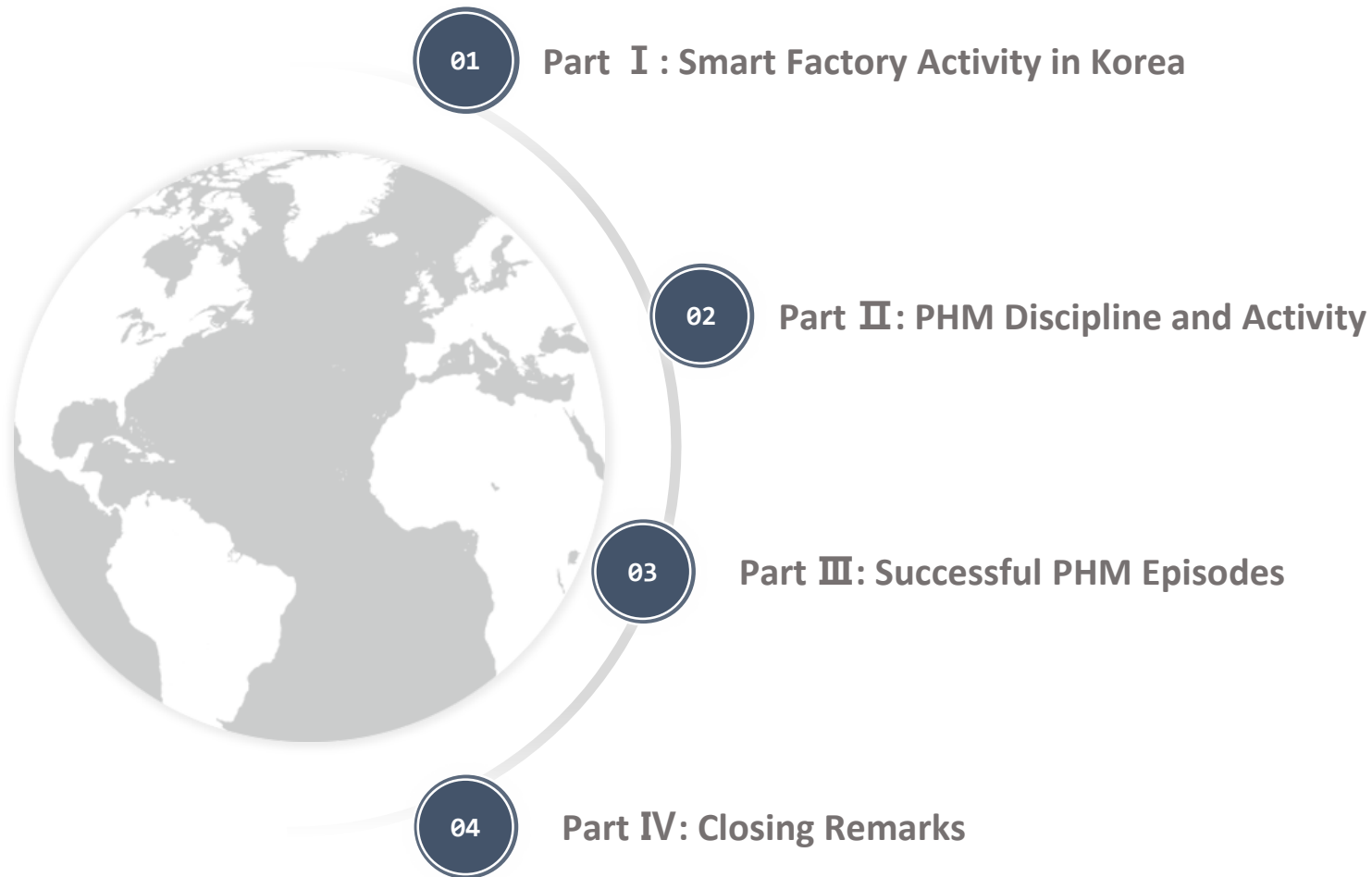
YOUN, Byeng Dong

Professor & CEO

System Health and Risk Management (SHRM) Laboratory (shrm.snu.ac.kr)

Department of Mechanical and Aerospace Engineering

Seoul National University

OnePredict Inc. (onepredict.com)
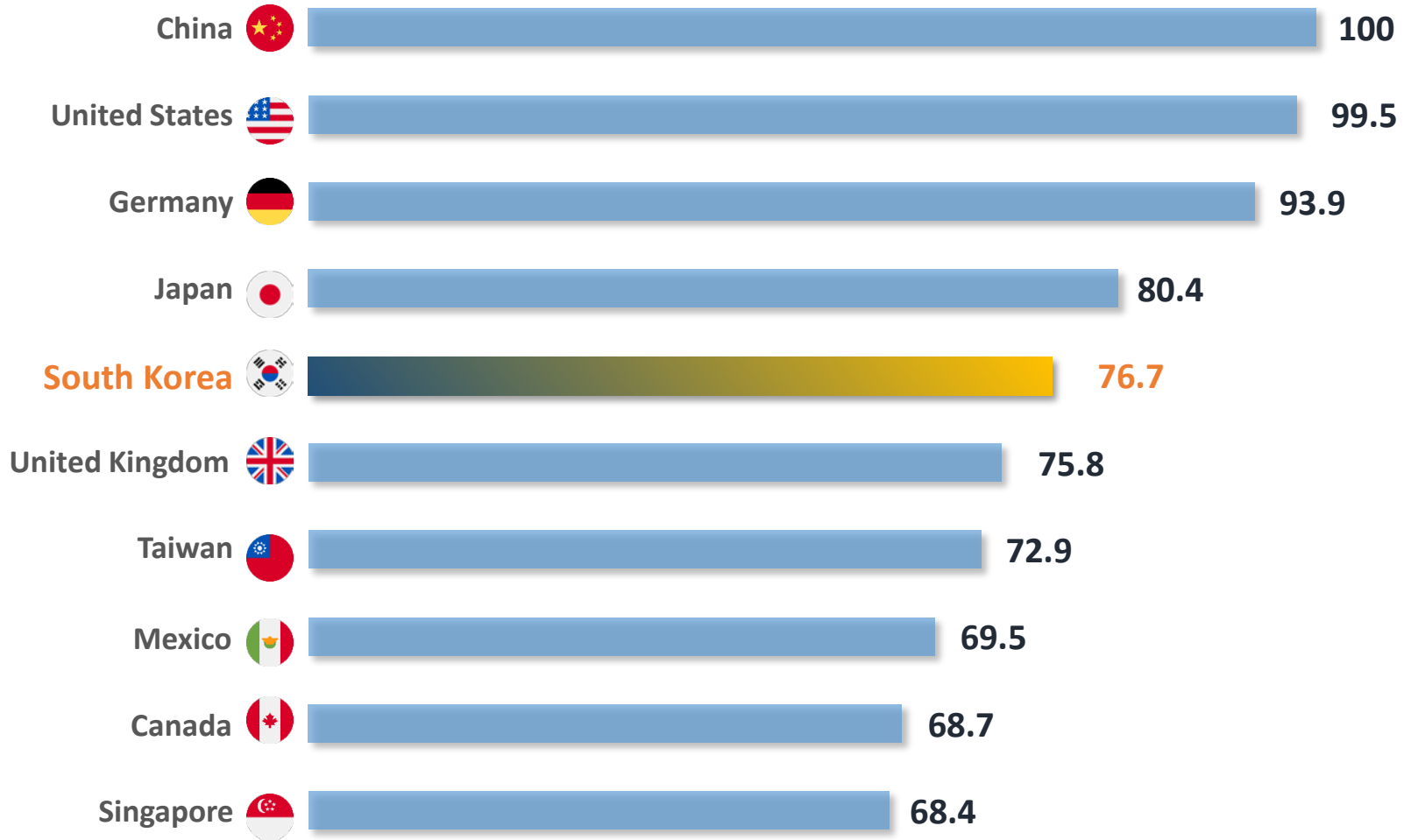
Contents

* PHM: Prognostics and Health Management

Part I
Smart Factory in Korea

Global Manufacturing Competitiveness Index: Country rankings

(100: **High**, 10: **Low**)

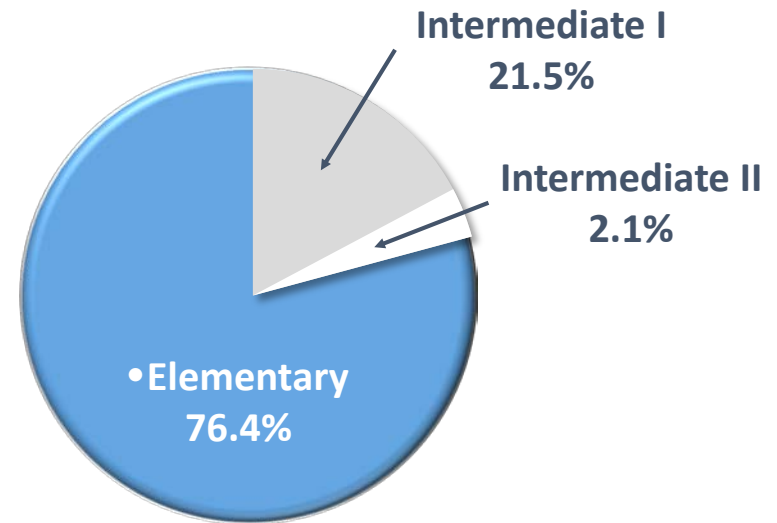| Country	Index
China	100
United States	99.5
Germany	93.9
Japan	80.4
South Korea	76.7
United Kingdom	75.8
Taiwan	72.9
Mexico	69.5
Canada	68.7
Singapore	68.4

Ref: Delotte Touche Limited and US Council on Competitiveness, "2016 Global Manufacturing Competitiveness Index"

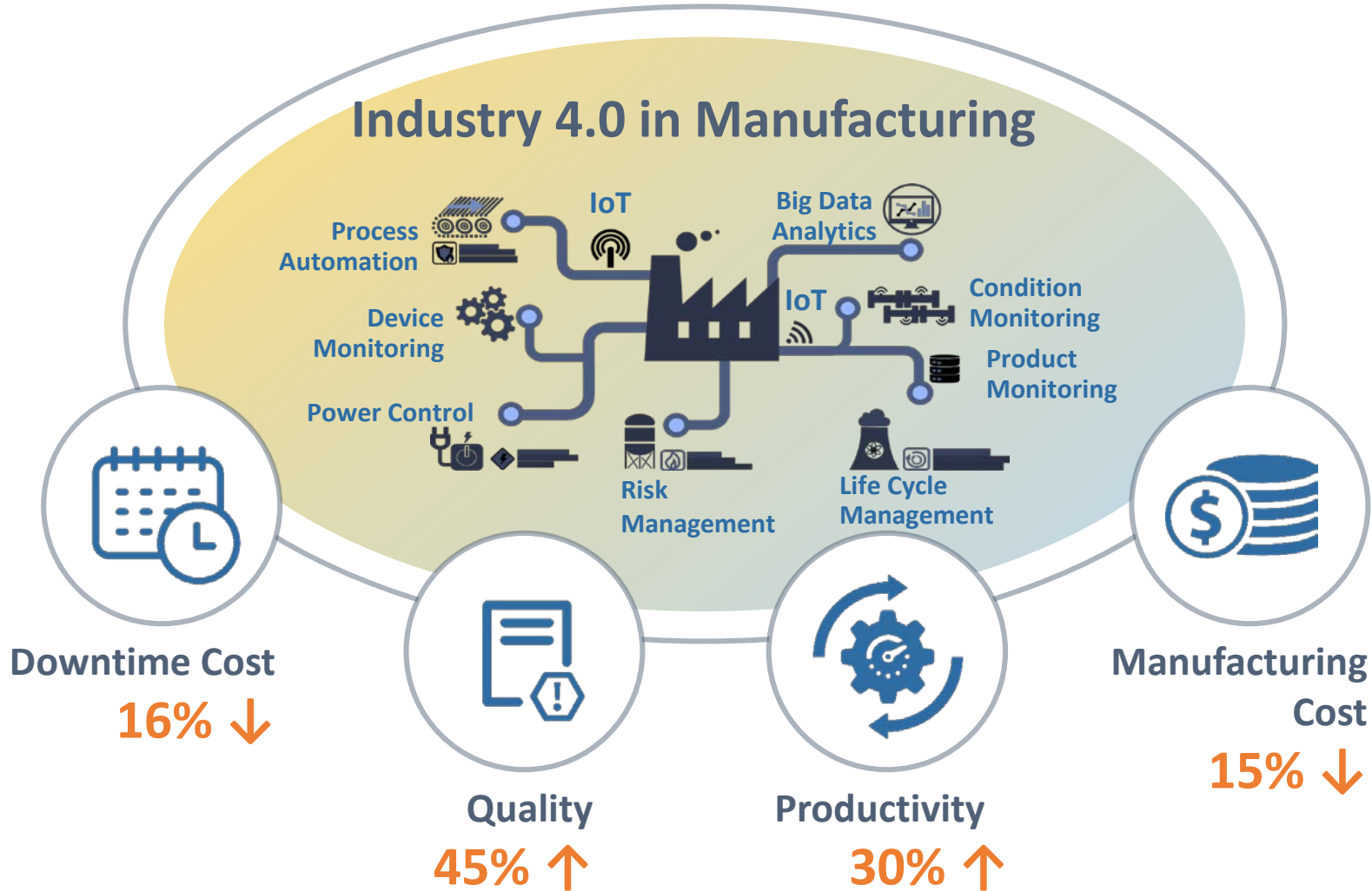# Korea Smart Factory Foundation (KOSF) Newly Launched in 2014

<Number of smart factories supported by the KOST Program>
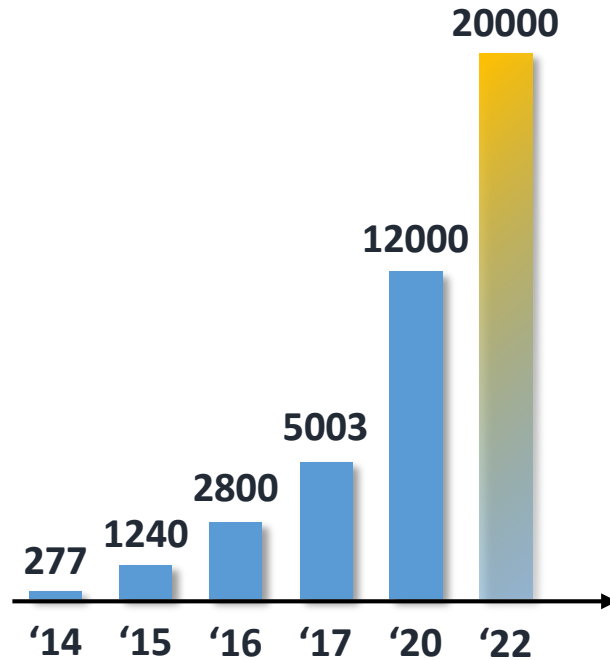
- Number: **18 times** from '14 to '17
- Level: **Elementary** (76.4%)

Bar chart values: 277 ('14), 1240 ('15), 2800 ('16), 5003 ('17), 12000 ('20), 20000 ('22)

Pie chart: Elementary 76.4%, Intermediate I 21.5%, Intermediate II 2.1%
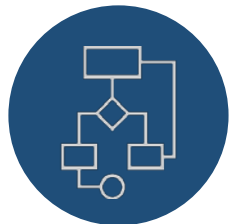
<The level of smart factories in domestic companies>

- Elementary: ERP with data acqn.
- Intermediate I: RT equipment data acqn.
- Intermediate II: RT decision making and control

Ref: '18.04 MOTIE Smart Factory Korea Foundation "2017 Successful Episodes of Smart Factory"

Improvement of Overall Manufacturing Capability
(2800 companies with smart factory, Dec 2017)

Industry 4.0 in Manufacturing

Process Automation · IoT · Big Data Analytics · Device Monitoring · IoT · Condition Monitoring · Product Monitoring · Power Control · Risk Management · Life Cycle Management

Downtime Cost
16% ↓

Quality
45% ↑

Productivity
30% ↑

Manufacturing Cost
15% ↓

Ref: S&T Market Report Vol. 56 2018.02 Smart Factory Industry and Market Trend

Part II

PHM* Discipline and Activity

PHM
Overview

Sensing
Solution

Reasoning
Solution

Diagnostics
Solution

Prognostics
Solution

PHM
Architecture

*PHM – Prognostics and Health Management

Machine data | Physics based | Statistical analysis | Deep learning | IIP(Industrial Information Prognosis) Solution

Awards

| PEMFC | Railway Vehicle | HVAC System | Pulverizer | Bogie System |

| 2014 IEEE PHM Data Challenge | 2014 PHM Society Data Challenge | 2015 PHM Society Data Challenge | 2017 PHMAP Data Challenge | 2017 PHM Society Data Challenge |

PHM Asia Pacific 2017 | phmsociety | IEEE
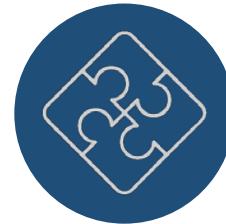
"Five times winner of Global PHM Data Challenges over Various Industrial Sectors"

- **Standard PHM Approaches**

Data-driven | Data-driven + Physics-based (Hybrid)

Data Size / Domain Knowledge

Rule-based | Physics-based
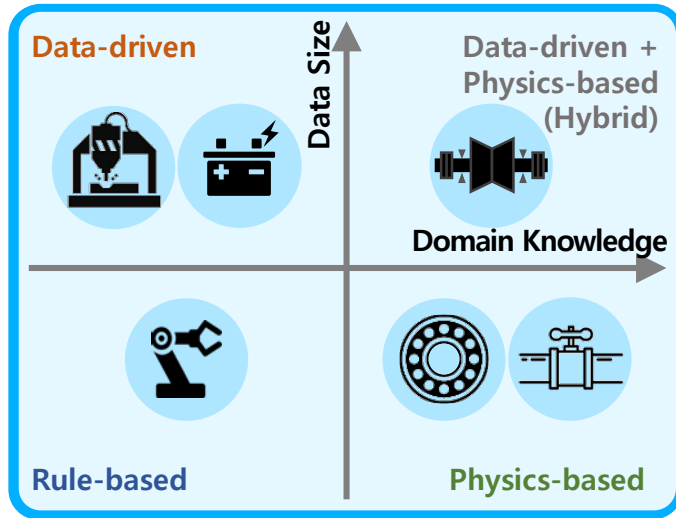
- **6 Core Assets in Manufacturing**

Driving	Power Trans.	Power & Energy

Machining	Hydro-system	Electrical & Electronics

- **Standard PHM Procedure**

Raw Data

Preprocessing: Cleaning → Organization → Filtering, Statistical Modeling → Scaling → Enveloping

Feature Engineering

Health Features

Diagnostics/Prognostics

Health Prediction
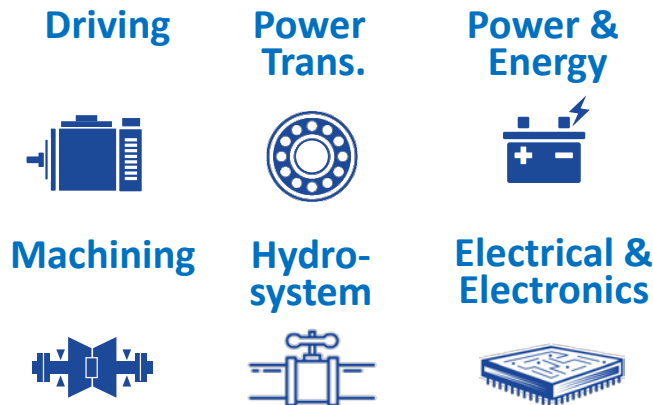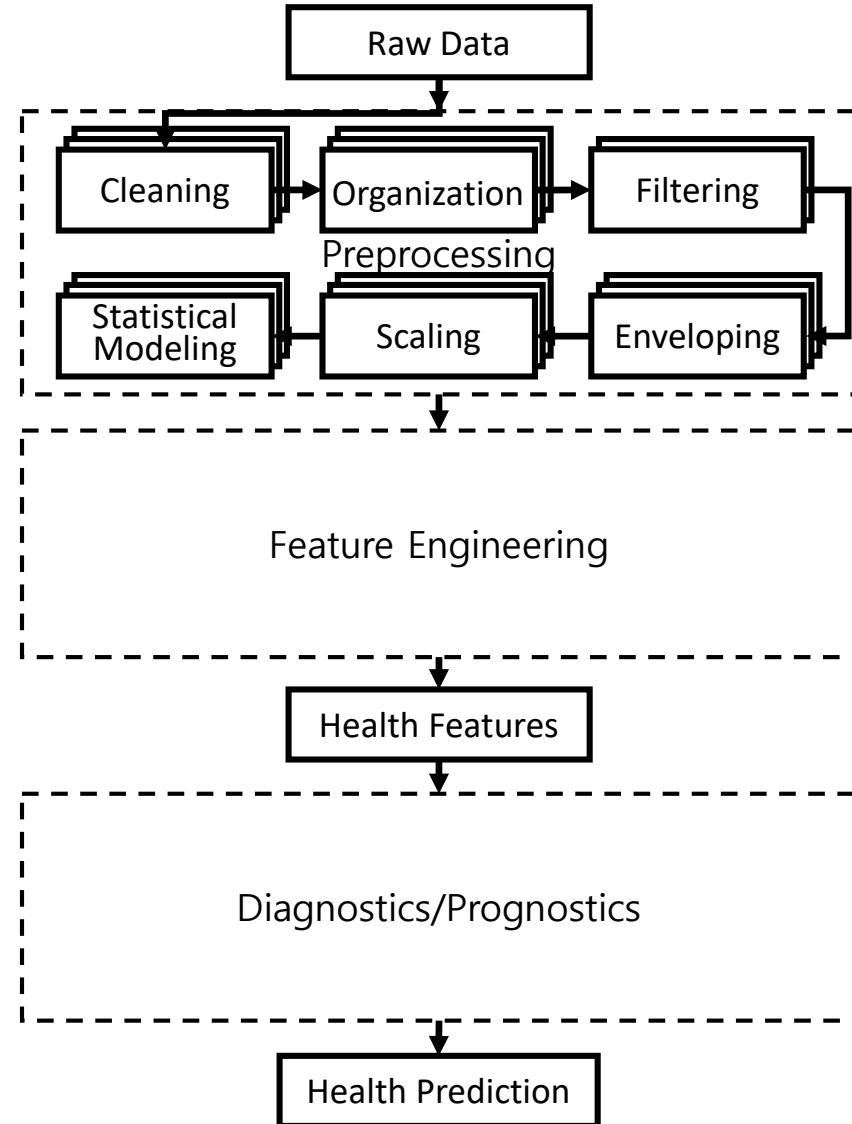
Standard Architecture & MDP* Table for PHM

Exercising Standardization of Prognostics and Health Management (PHM) for Manufacturing Industry

Module	Failure components	Measurement parameters						
		Vibration	Thermography	Oil Analysis	Process Parameter	Performance	Acoustic Monitoring	Electrical Monitoring
Power module	Power supply	D	P	D	-	-	-	D
	Transformer	D	-	M	-	-	M	M
	Energy storage system	-	M	-	-	-	-	M
Hydraulic module	Cylinder	P	M	M	-	-	P	-
	Valve	D	P	-	D	M	M	-
Control module	PLC	-	-	-	-	-	-	D
	Inverter	-	D	-	-	-	-	D
	Switch	-	-	-	-	-	-	D
	Cable	-	-	-	-	D	D	D
Drive module	Motor	M	M	-	M	M	D	M
	LM Guide	D	-	-	-	-	D	-
	Hydraulic supply	M	M	M	M	M	-	-
Transmission Module	Reducer	M	-	M	-	M	D	D
	Ball screw	D	D	-	D	-	-	D
	Chain & Belt	P	-	-	-	-	P	-
	Gear	M	-	M	-	D	D	D
	Bearing	M	M	M	-	-	M	D
Machinig module	Mechanical tool	M	-	-	M	M	D	D
	Electrical tool	-	-	-	-	-	-	-

Standard Architecture

Brochure (w/ MDP table)

http://onepredict.com/blog/newsView.do

*M: Mature
D: Developing
P: Promising

Part III
Successful PHM Episodes

Case Study 1
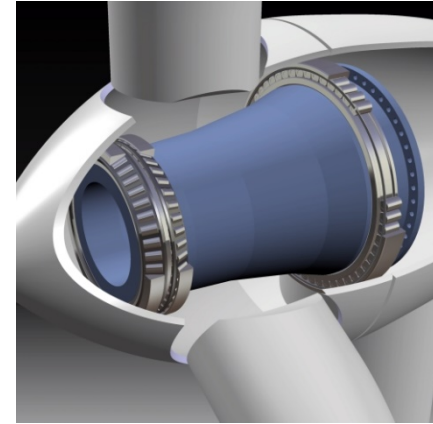Industry Robots

Case Study 2
Industrial Bearing

Case Study 3
Overhead Hoist Transport

Case Study 4
Deep Learning - Steam/Gas Turbine
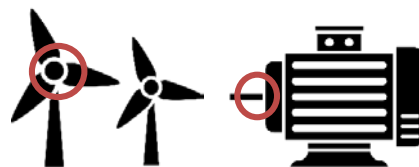
Industrial Bearing
: Rolling-Element Bearing

SCHAEFFLER

SAMSUNG
SAMSUNG HEAVY INDUSTRIES

Case Study 2
Industrial Bearing

GuardiOne
We Predict Things To Come

Industrial Bearings
(custom order)

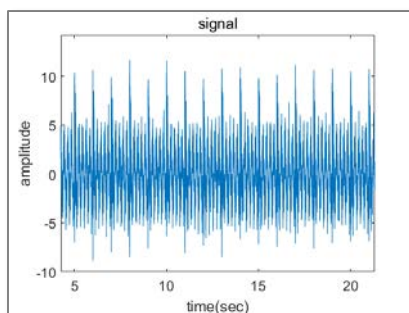Wind Turbine

Motor

Spindle

Pump &
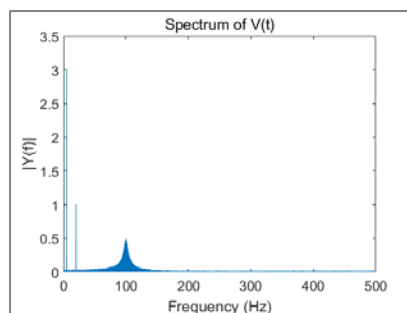Compressor

Robots

1. Sensing

ISO 10816-1 (Vibration measured on Non-Rotating Parts)
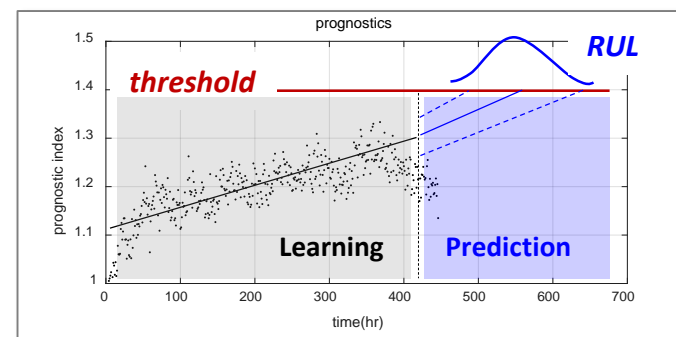
2. Analysis

Waveform analysis

**Spectrum analysis
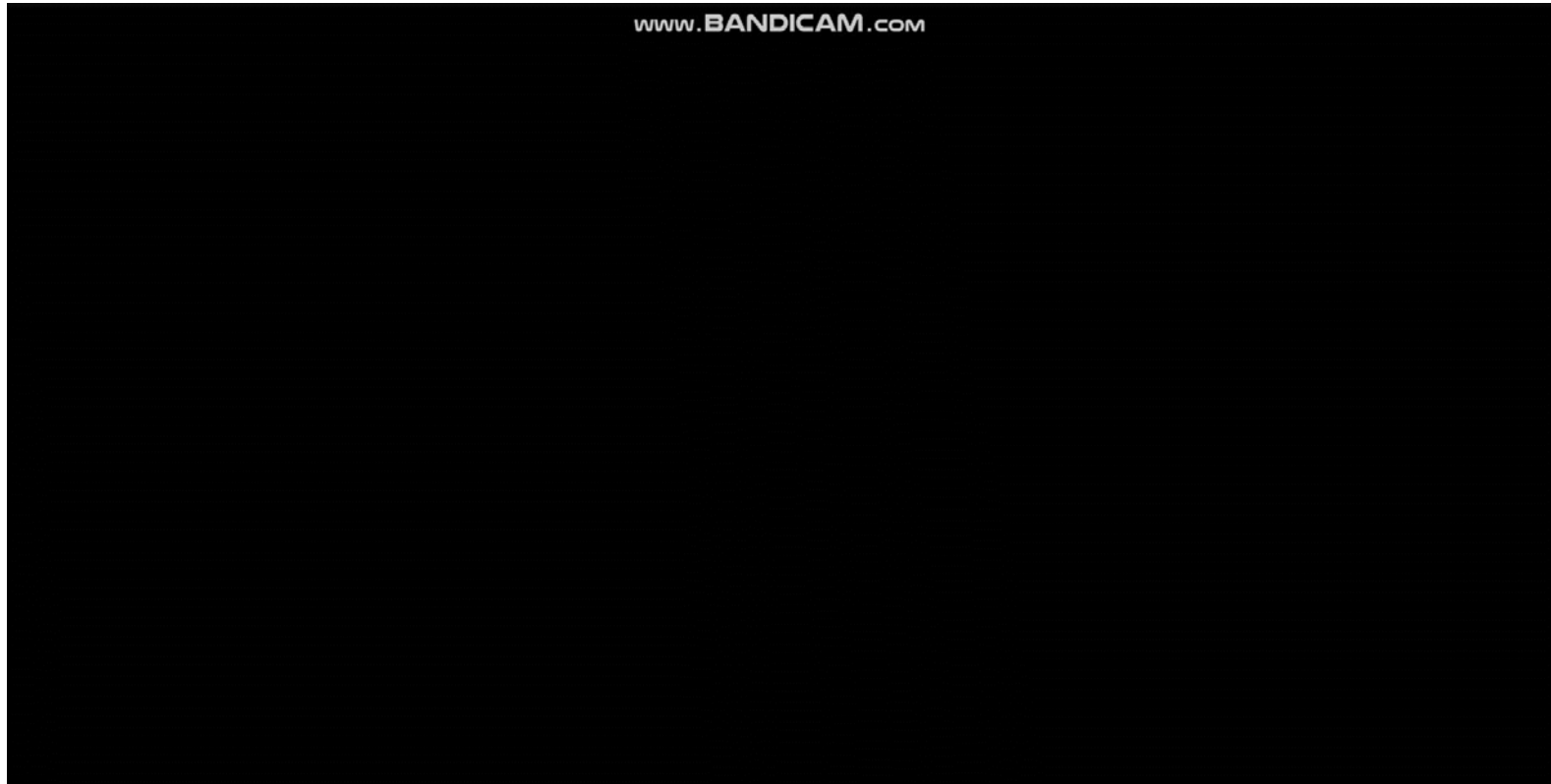Envelope spectrum
& Feature extraction**

3. Diagnosis & Prognosis

RUL

threshold

Learning

Prediction

Prognostic index & RUL Prediction

GuardiOne
We Predict Things To Come

GuardiOne Bearing (Monitoring)

①	Real-time Monitoring of Health Condition	②	Color Image of Health Condition	③	Trend Monitoring of Health Condition	④	Remaining Life Trend Monitoring

"First-ever Commercial Solution for Bearing RUL Prediction"

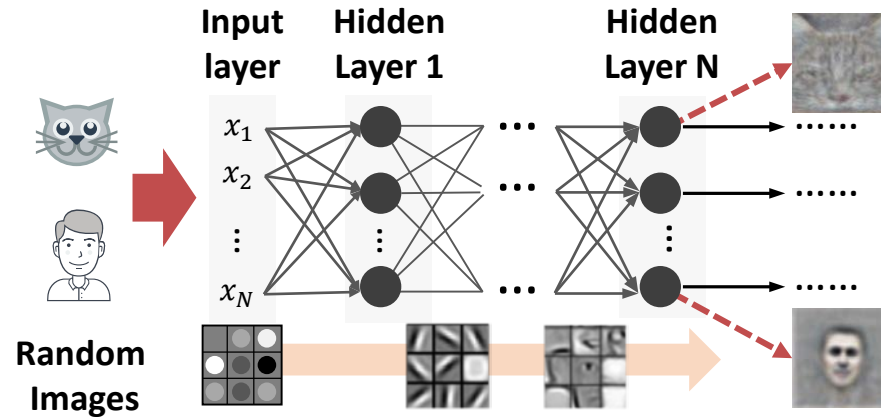# Steam/Gas Turbine
w/ Journal Bearing
(Data-driven, Deep Learning)

Deep Learning

Autonomous machine learning algorithms to extract data features through abstraction of massive data sets

Input layer   **Hidden Layer 1**   **Hidden Layer N**

x_1
x_2
$\vdots$
x_N

Random Images

Popularity of Deep Learning

- Improved computing power
- Enlarged data size
- Advanced DL techniques

Search Trends in Google

Relative Index — Year

World
Korea
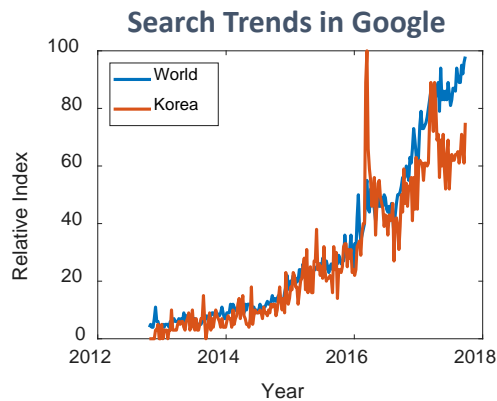
Applications of Deep Learning

Vision Recognition

Voice Recognition

Healthcare

PHM

*R. Zhao et al. (2016), IEEE Tran. Neural Networks and Learning Systems (Submitted); K. Fragkiadaki (2012) Computer Vision-ECCV; Q. V. Le (2012) ICML

Data-driven Approach for Feature Learning[1]

Data Acquisition ▶ **Feature Extraction** ▶ **Feature Selection** ▶ **Feature Learning**

	Domain Knowledge Based	Deep Learning Based
Domain Knowledge	Required	Not Required
System Dependency	Dependent	Independent
Feature Representation	Shallow	Deep
Big Data Learning	Over-fitted Model	Well-fitted Model

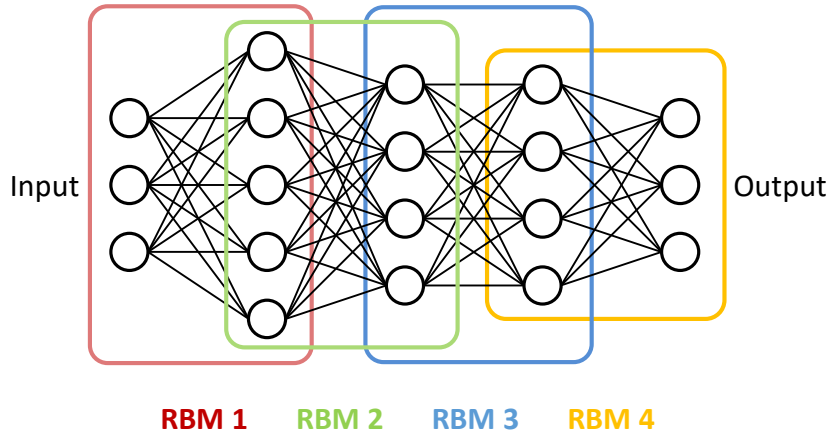## Deep Learning Based Fault Diagnosis[2]

Data Acquisition ▶ **Autonomous Feature Engineering by DL**

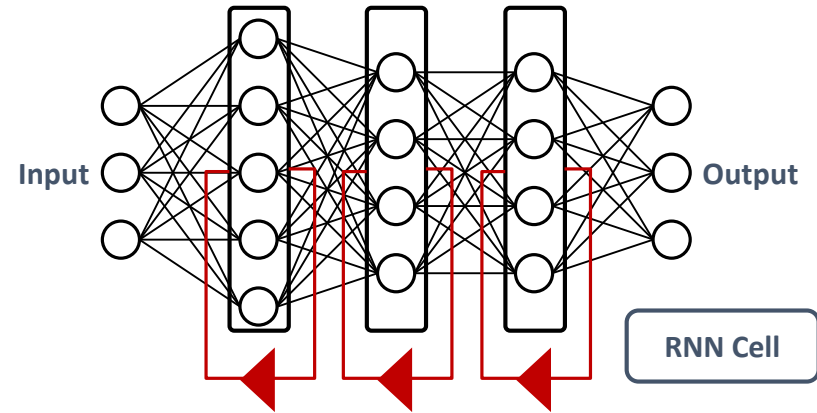| DL Type	Input Data Type	Input Data Labels	Others
DBN	n/a	Unsupervised	Break through in deep learning (2006)
CNN	Vision Data (Images)	Supervised	Parameter sharing, local connectivity
RNN	Sequential Data (Speech)	Supervised	Storing sequential information
AE	n/a	Unsupervised	Representation learning, dimension reduction

*H. Oh et al. (2017), IEEE Tran. Industrial Electronics
** R. Zhao et al. (2016), IEEE Tran. Neural Networks and Learning Systems (Submitted)
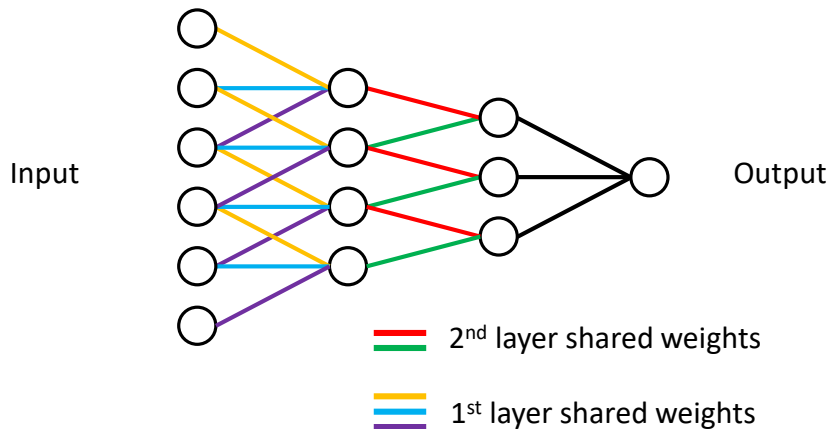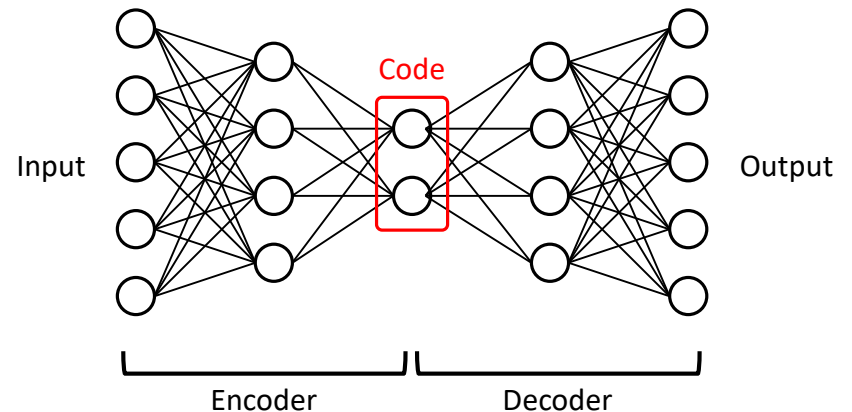
- ## **Deep Learning Algorithms[1)]**

Deep Belief Network

Input

Output

RBM 1 **RBM 2** **RBM 3** **RBM 4**

Recurrent Neural Network

Input

Output

RNN Cell

Convolutional Neural Network

Input

Output

— 2nd layer shared weights

— 1st layer shared weights

Auto Encoder

Input

Code

Output

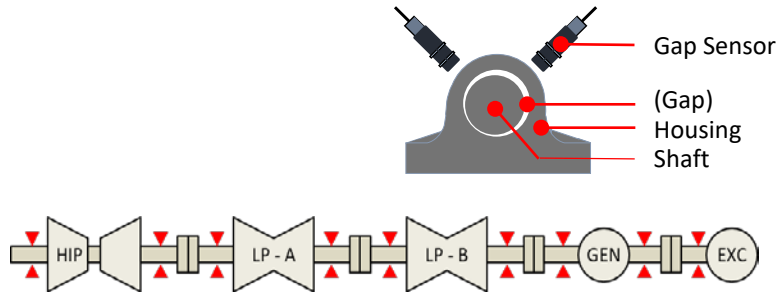Encoder   Decoder

*THE ASIMOV INSTITUTE (http://www.asimovinstitute.org)

• **GuardiOne Turbine-Deep**

1. Sensing

Vibration Data Acquisition

2. Analysis

Omni-directional Regeneration (ODR)

Vibration → Image
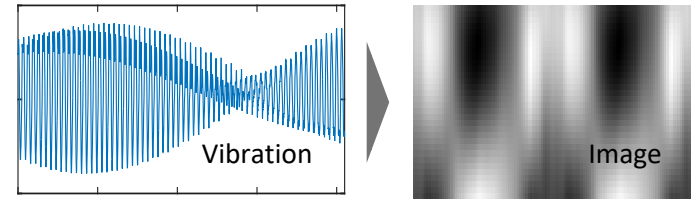
Vib-Imaging Technique

3. Scale-free Turbine Prognostics (Fully validated, **92% prediction accuracy**)
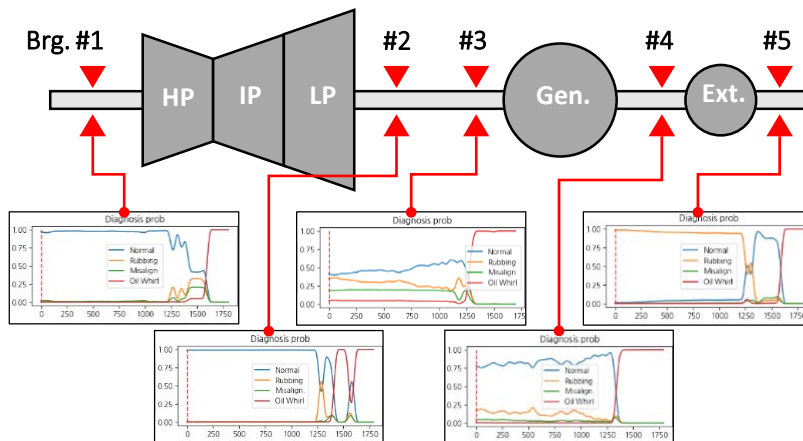
Fault Log		Deep Learning Result				
#	Status	#	Norm.	Rubb.	Misalign.	Oil Whirl
#1	**Normal**	#1	**0.975**	0.010	0.014	0.006
#2	**Normal**	#2	**0.991**	0.005	0.004	0.000
#3	**Normal**	#3	**0.482**	0.288	0.186	0.042
#4	**Normal**	#4	**0.828**	0.135	0.034	0.003
#5	**Rubbing**	#5	0.037	**0.958**	0.005	0.001

VS.

Part IV
Closing Remarks

Industrial Information Prognosis (IIP)

Conventional Business: Raw Material → Product

Raw Material

Product

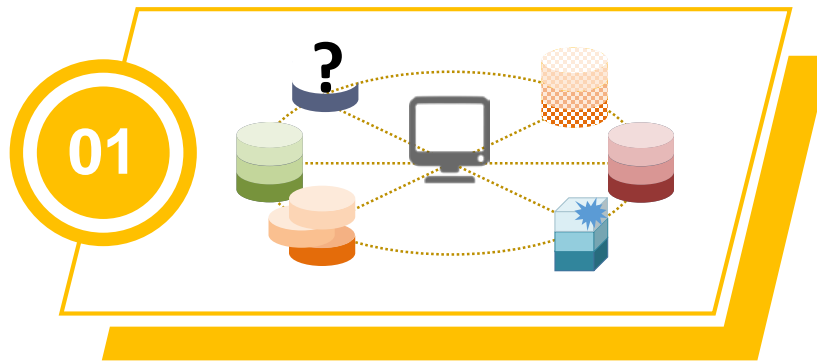**Industrial Raw Data**

Industrial Information

New Business: Industrial Data → Information
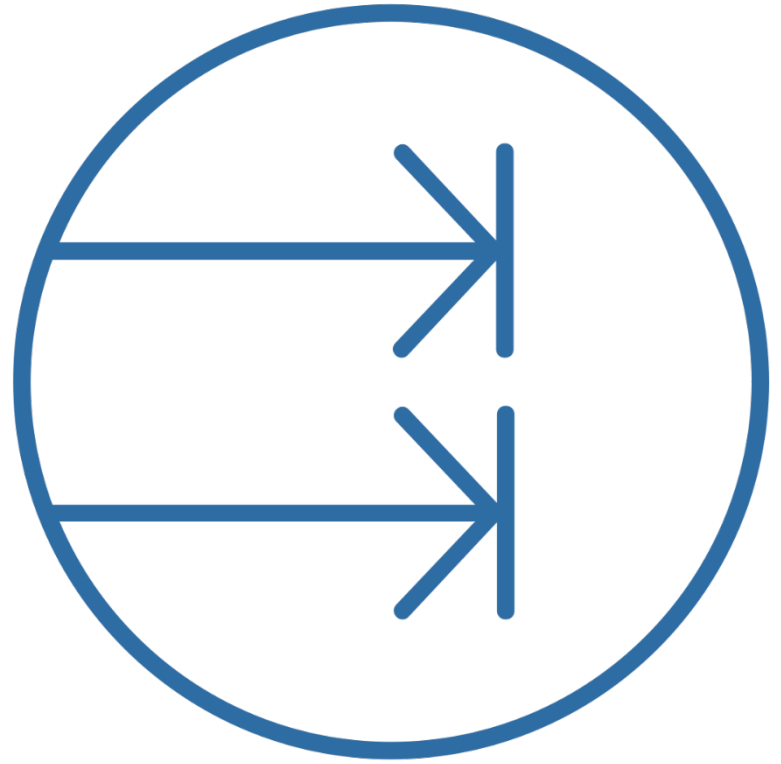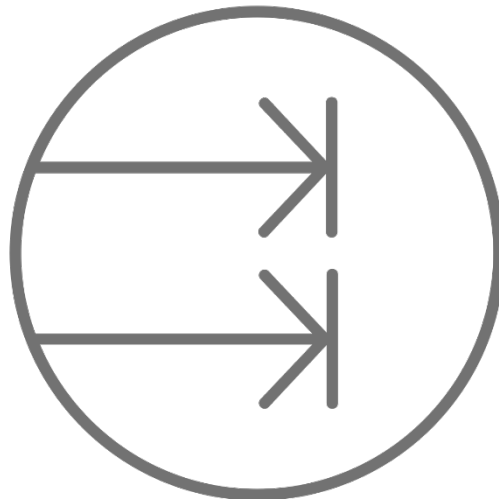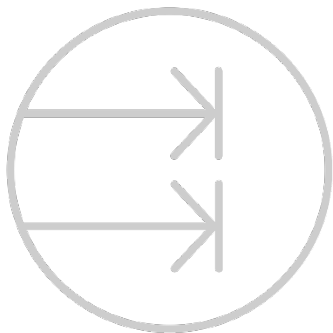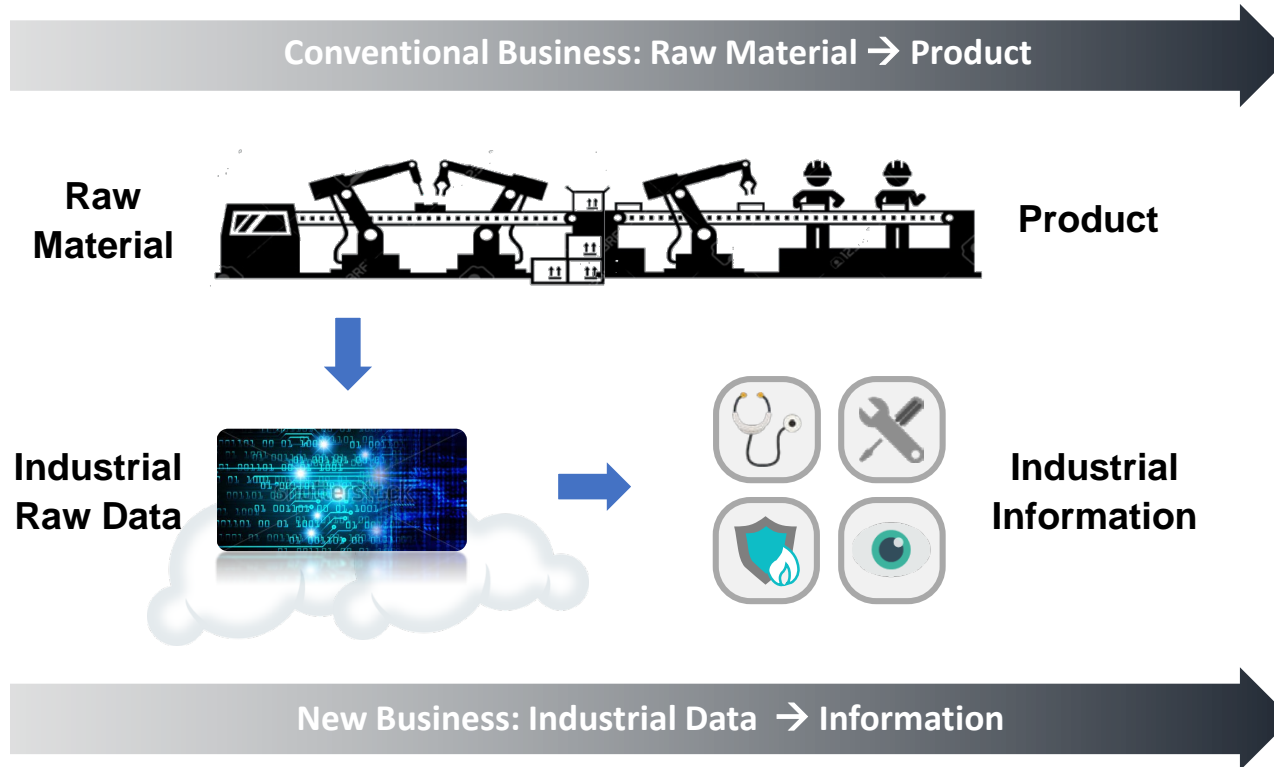
"**Industrial Information** is the one with industrial value, which includes availability, quality, productivity, energy efficiency, safety, etc."
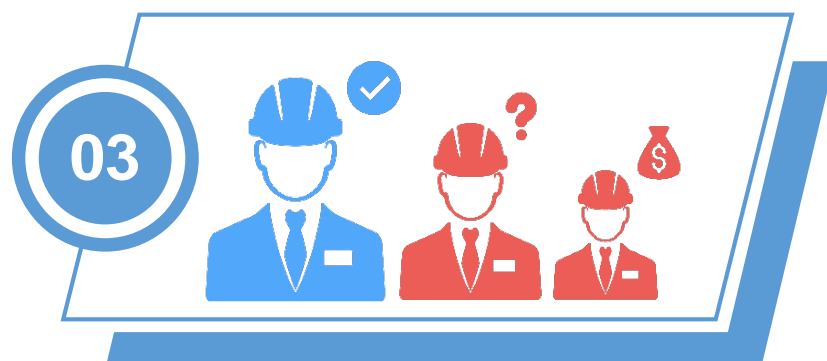
Data Quality
Missing, Unsynchronized, Noisy Data

01

Lack of Labeled Data
Class Imbalance, Labeling Quality

02

Lack of Resources
PHM Experts, Budgets

03

Cyber Security & Data Ownership
Protection of Cloud Network Information

04

THANK YOU FOR LISTENING

ANY QUESTION?