From Data to Knowledge

Unlocking the Power of Data for Engineering Applications

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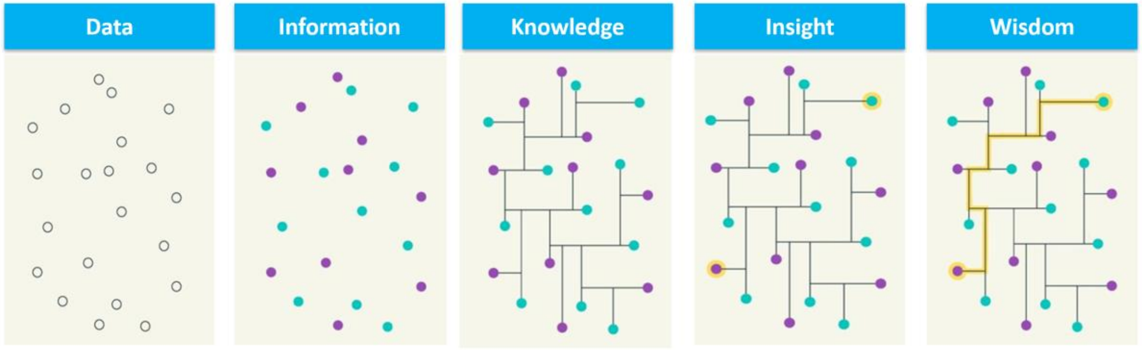
From Data to Wisdom

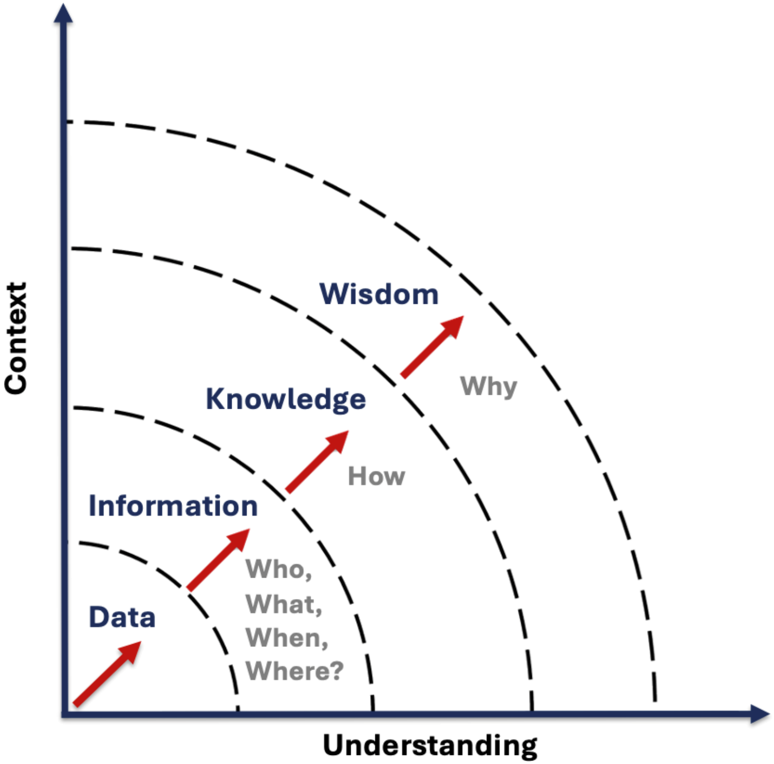
The evolution of data to wisdom is defined by the **DIKW** pyramid [1].



Data is just facts without any context, but when facts are used to understand relationships, it generates **Information**.

That information can be used to understand patterns, it can then help build **Knowledge**.

When knowledge is used to understand principles, it builds **Wisdom**.



[1] Frické, M. (2019). The knowledge pyramid: the DIKW hierarchy. *Knowledge Organization: KO*, *46*(1), 33.

What is Big Data?

No single definition; here is from Wikipedia:

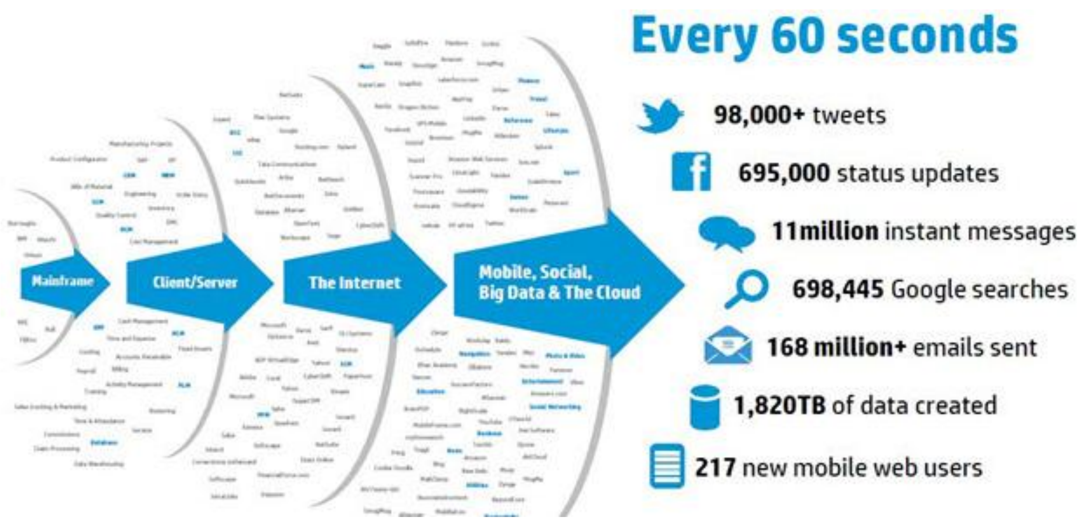
Big data is the term for a collection of data sets so large and complex that it becomes difficult to process using on-hand database management tools or traditional data processing applications.

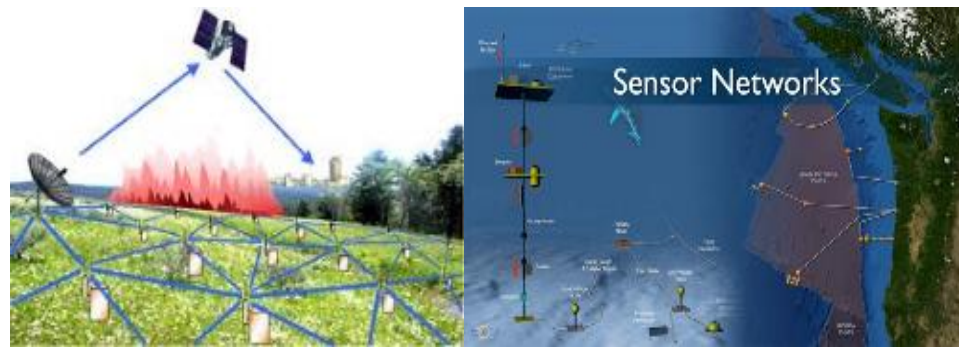
The challenges include **capture**, **curation**, **storage**, **search**, **sharing**, **transfer**, **analysis**, and **visualization**.

The trend to larger data sets is due to the additional information derivable from analysis of a single large set of related data, as compared to separate smaller sets with the same total amount of data, allowing correlations to be found to "spot business trends, determine quality of research, prevent diseases, link legal citations, combat crime, and determine real-time roadway traffic conditions.”

Data that is too large or too complex to be managed using traditional data processing, analysis, and storage techniques.

What is Big Data?





Sensor technology and networks

<u>The 4 V’S of Big Data By IBM</u>

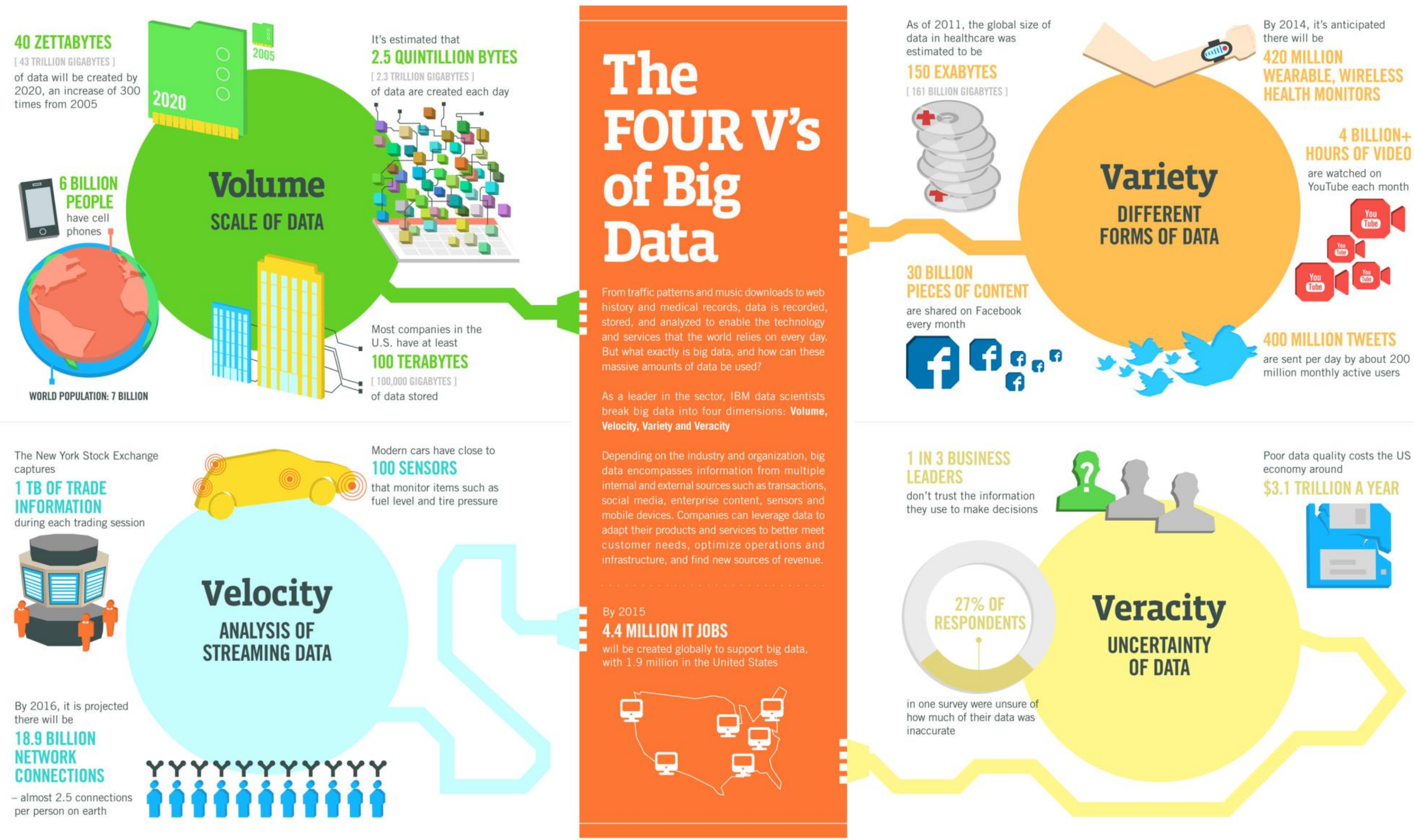
Volume: Large Volume Of Data

Variety: Different formats (Audio, Video, Images, Posts, etc)

Velocity: Speed of Data Processing.

Veracity: To check that the Data is Genuine.

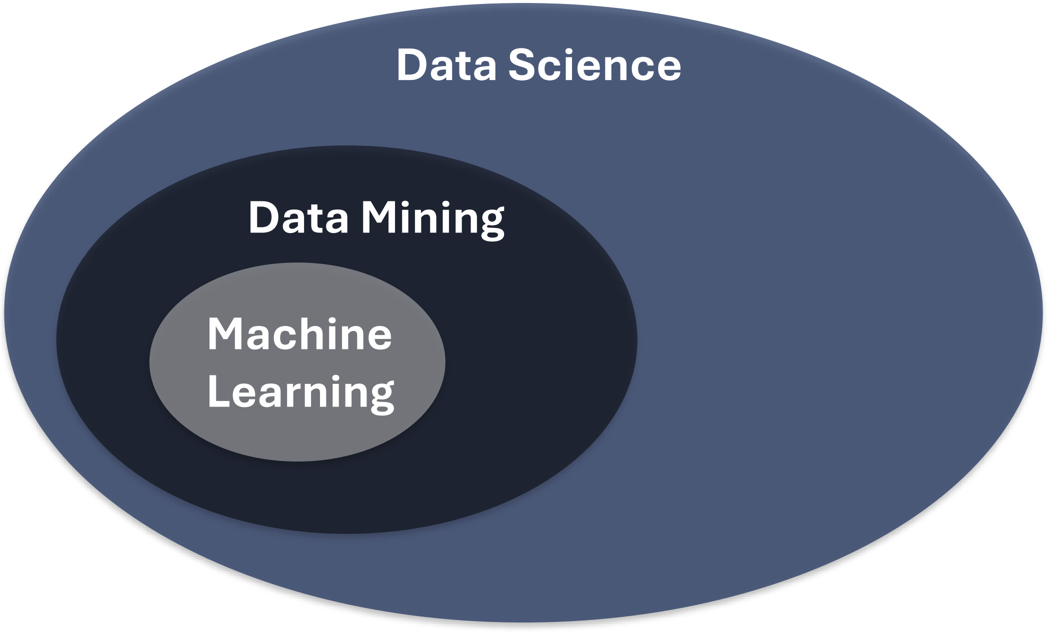
What is Big Data?



Sources: McKinsey Global Institute, Twitter, Cisco, Gartner, EMC, SAS, IBM, MEPTEC, QAS

What is Data Science

Data science is the study of generalizable extraction of knowledge from data [2].

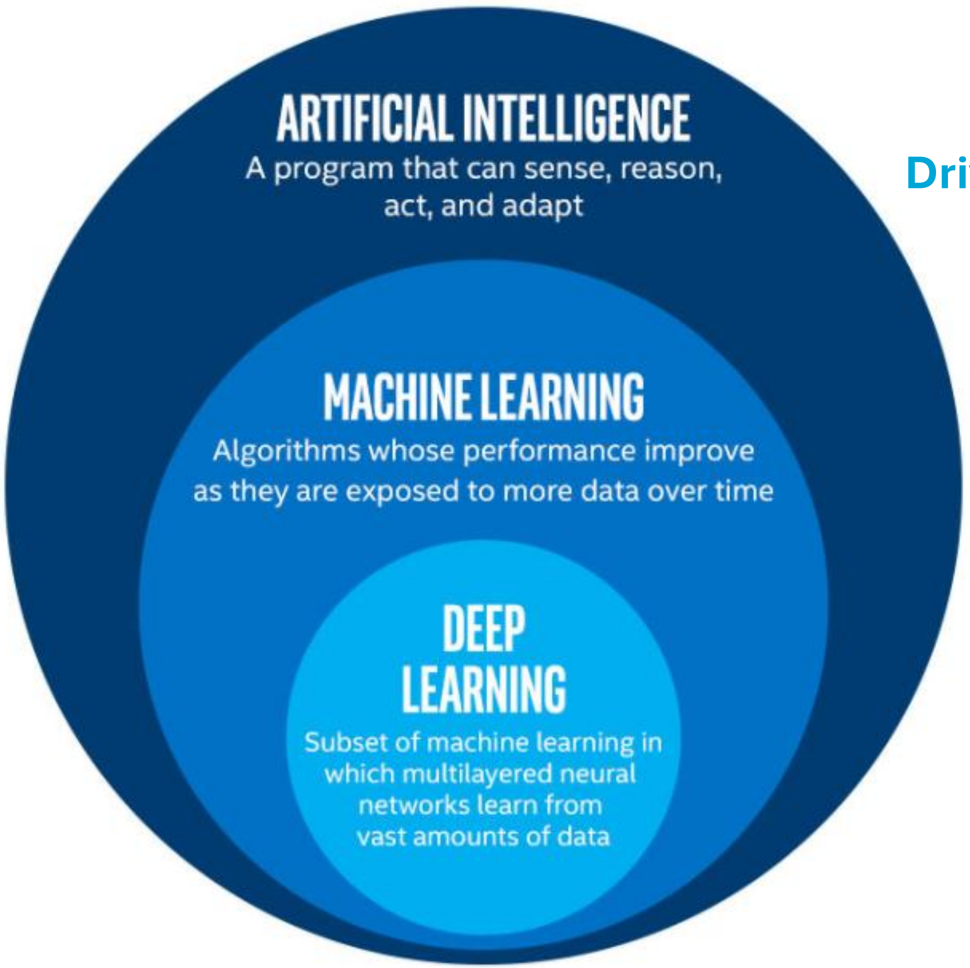


Machine Learning vs. Data mining vs. Data science

[2] Kulin, Merima, Carolina Fortuna, Eli De Poorter, Dirk Deschrijver, and Ingrid Moerman. "Data-Driven Design of Intelligent Wireless Networks: An Overview and Tutorial." Sensors 16, no. 6 (2016): 790.

What is Machine Learning

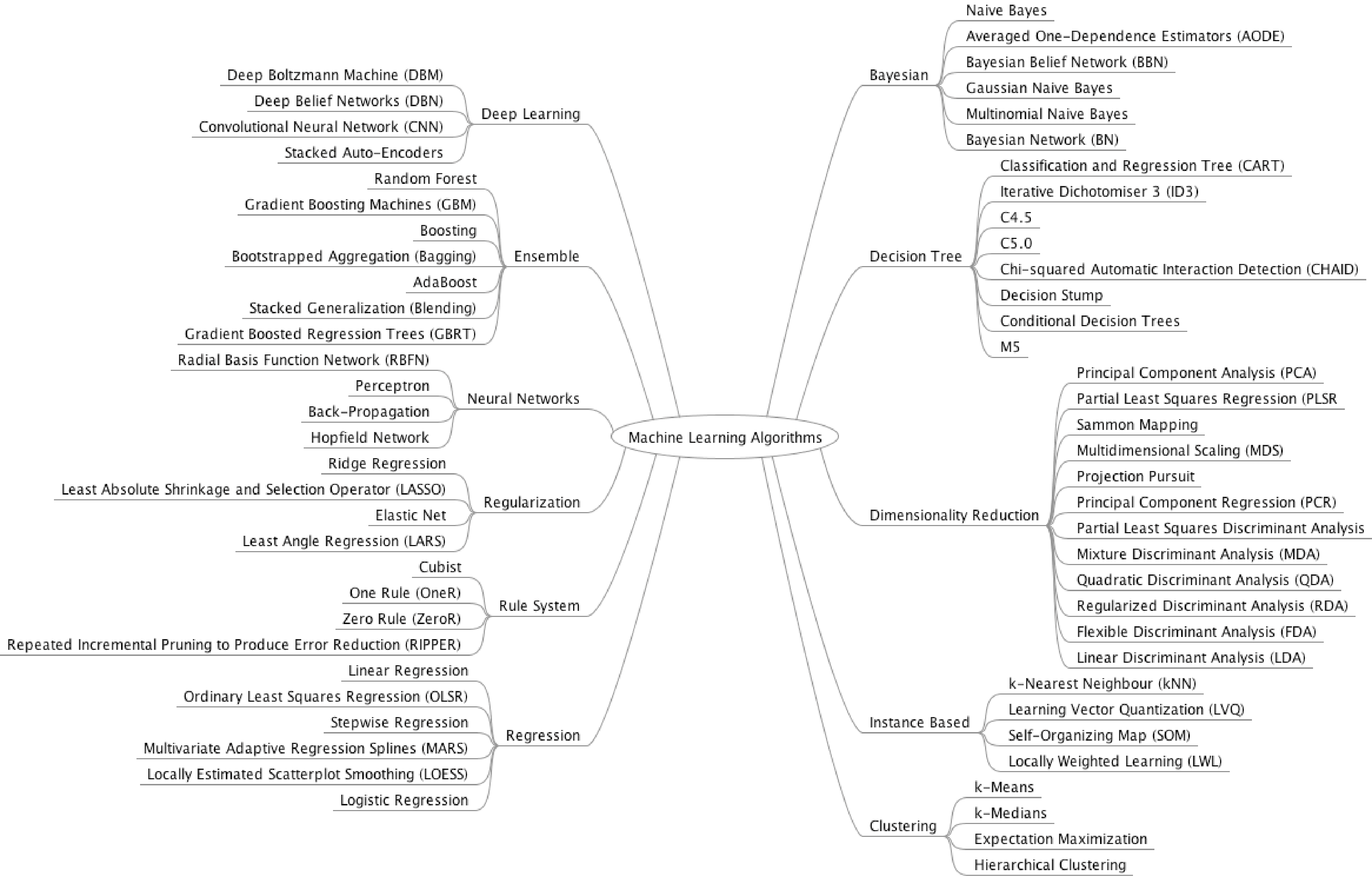
Machine Learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give computers the ability to "learn" (i.e., **progressively improve performance on a specific task**) with **data**, without being explicitly programmed.



Driving Forces

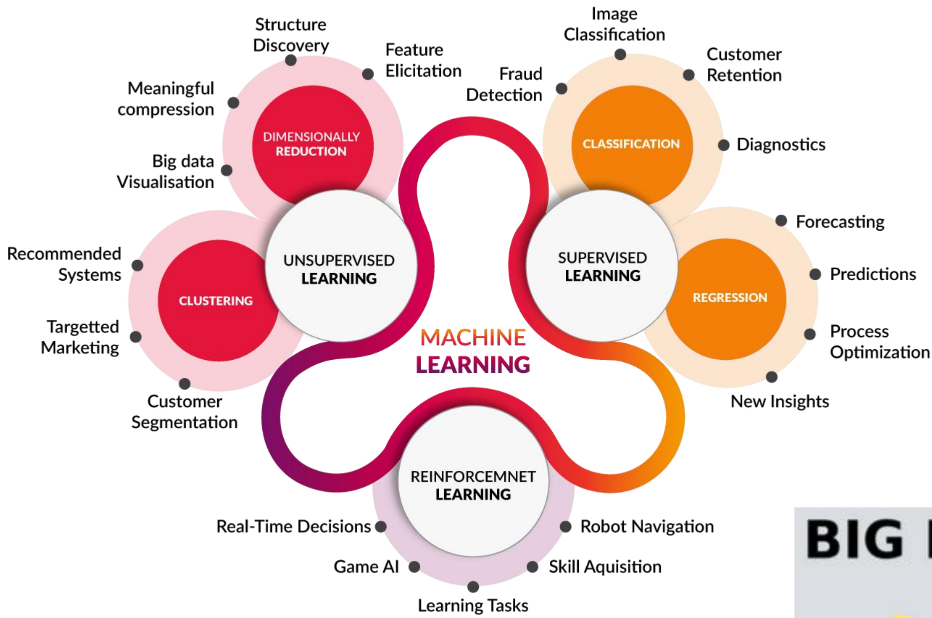
- Explosive growth of data in a great variety of fields
  - Cheaper storage devices with higher capacity
  - Faster communication
  - Better database management systems
- Rapidly increasing computing power

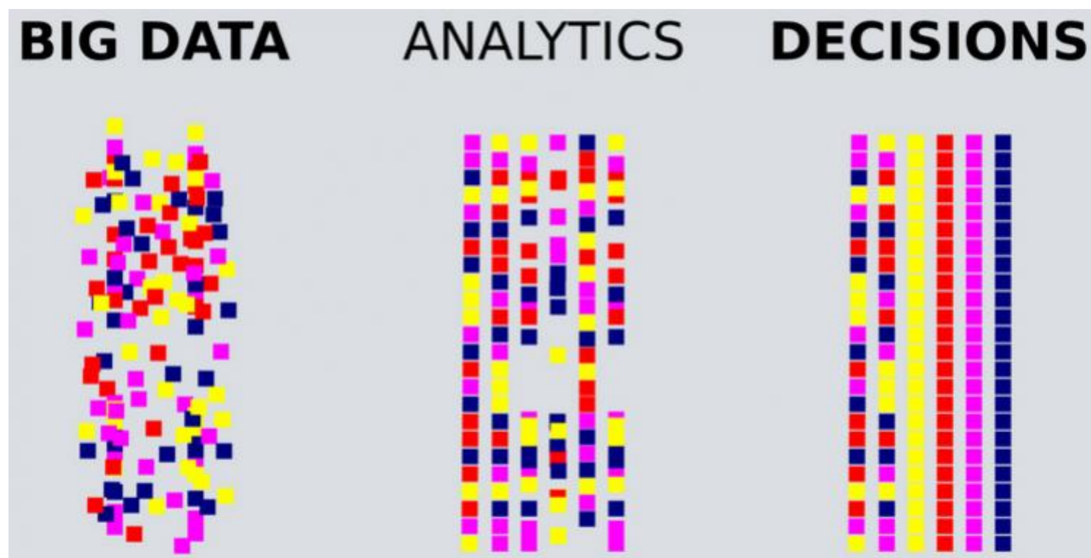
What is Machine Learning



Big Data and Machine Learning

A Marriage Between Giants!





The Ship Data Center

Maersk

Neste

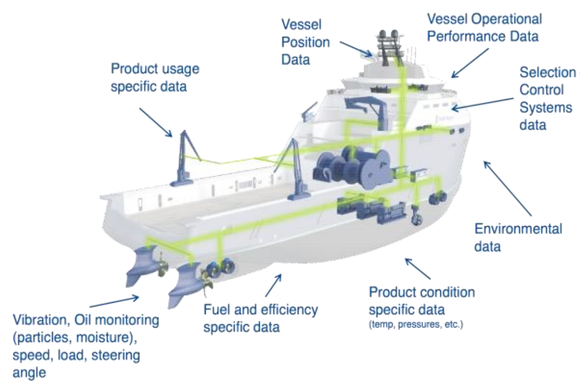
Cosco

MARORKA

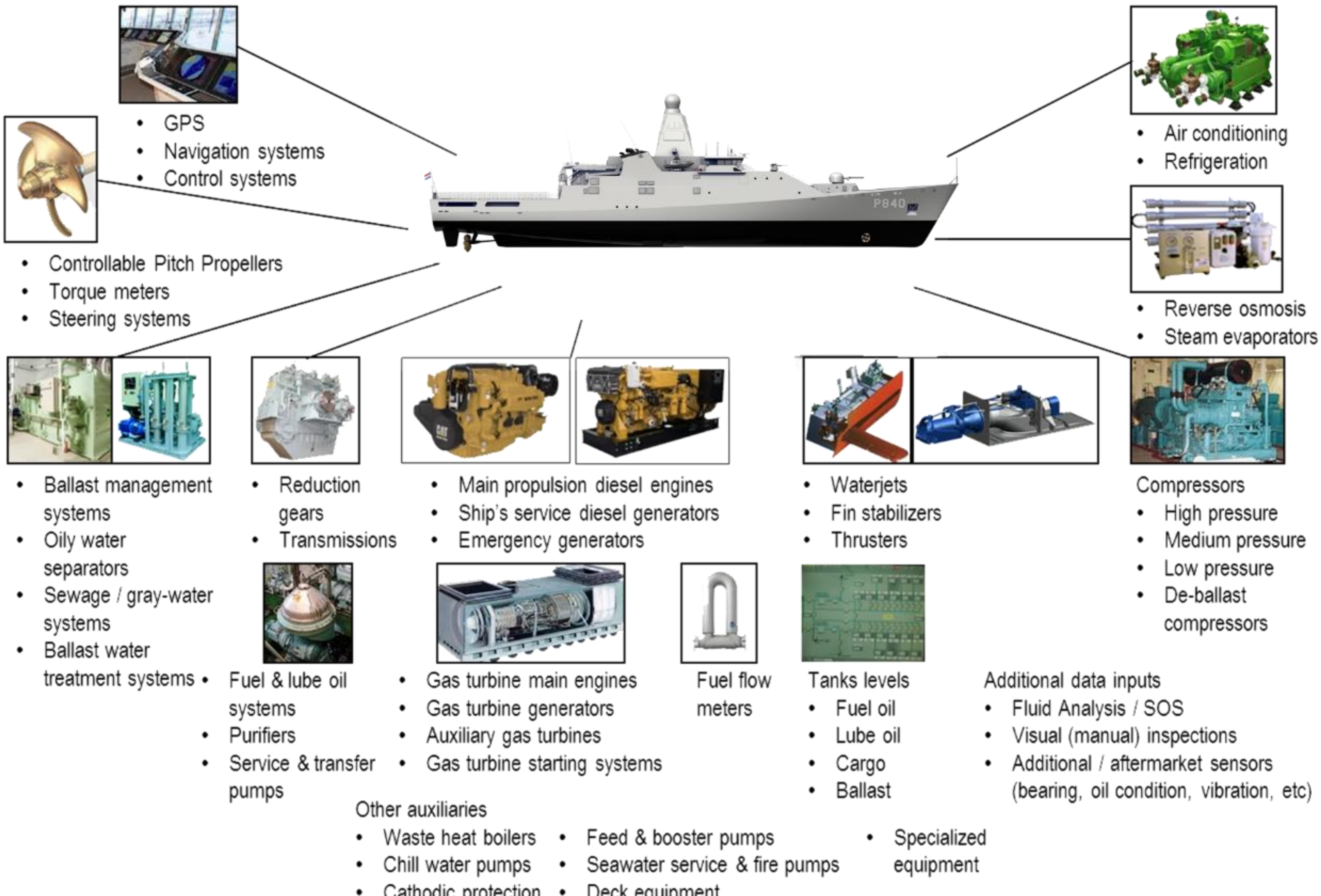
Big Data and Machine Learning

Royston

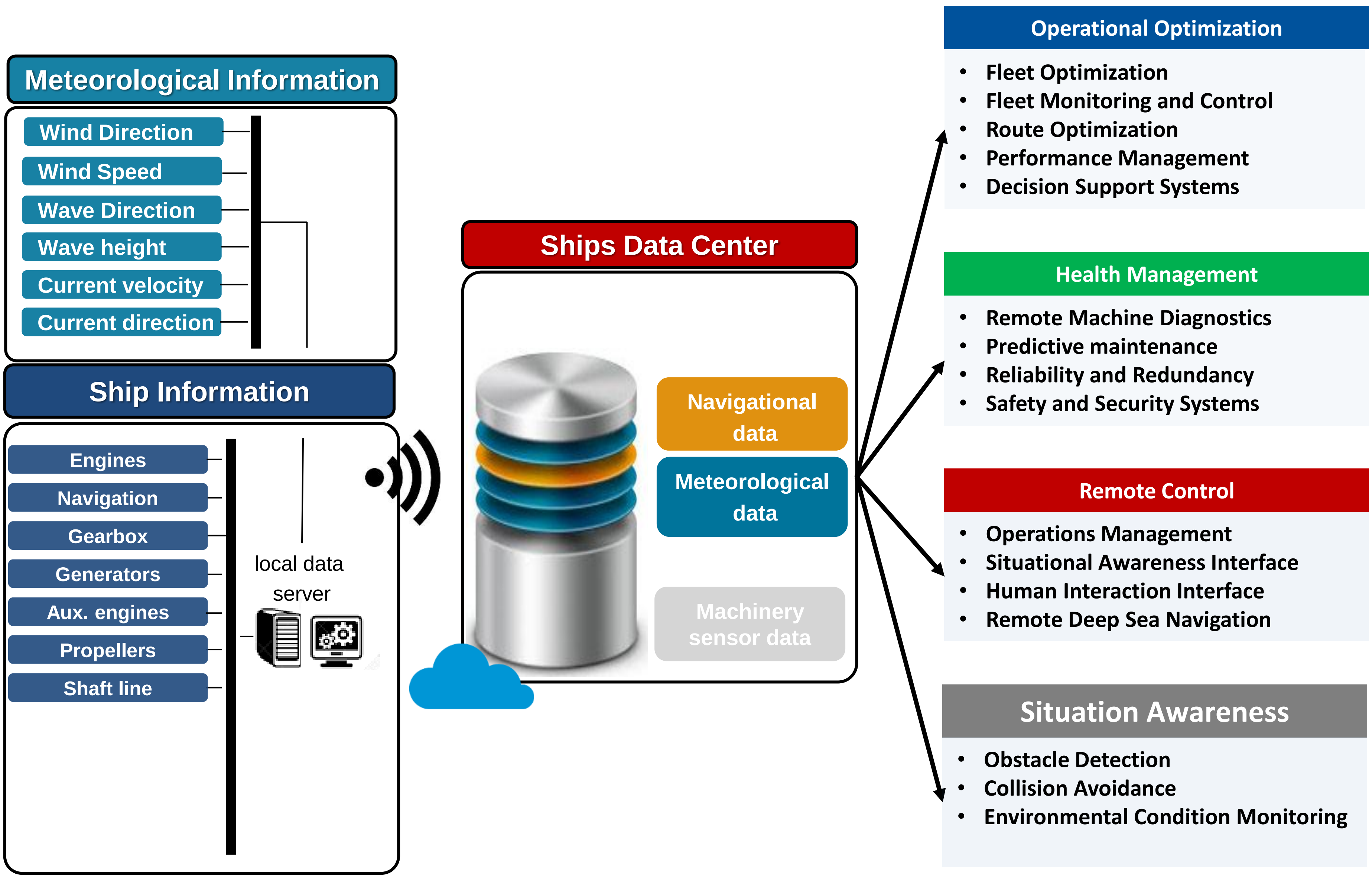
ABS



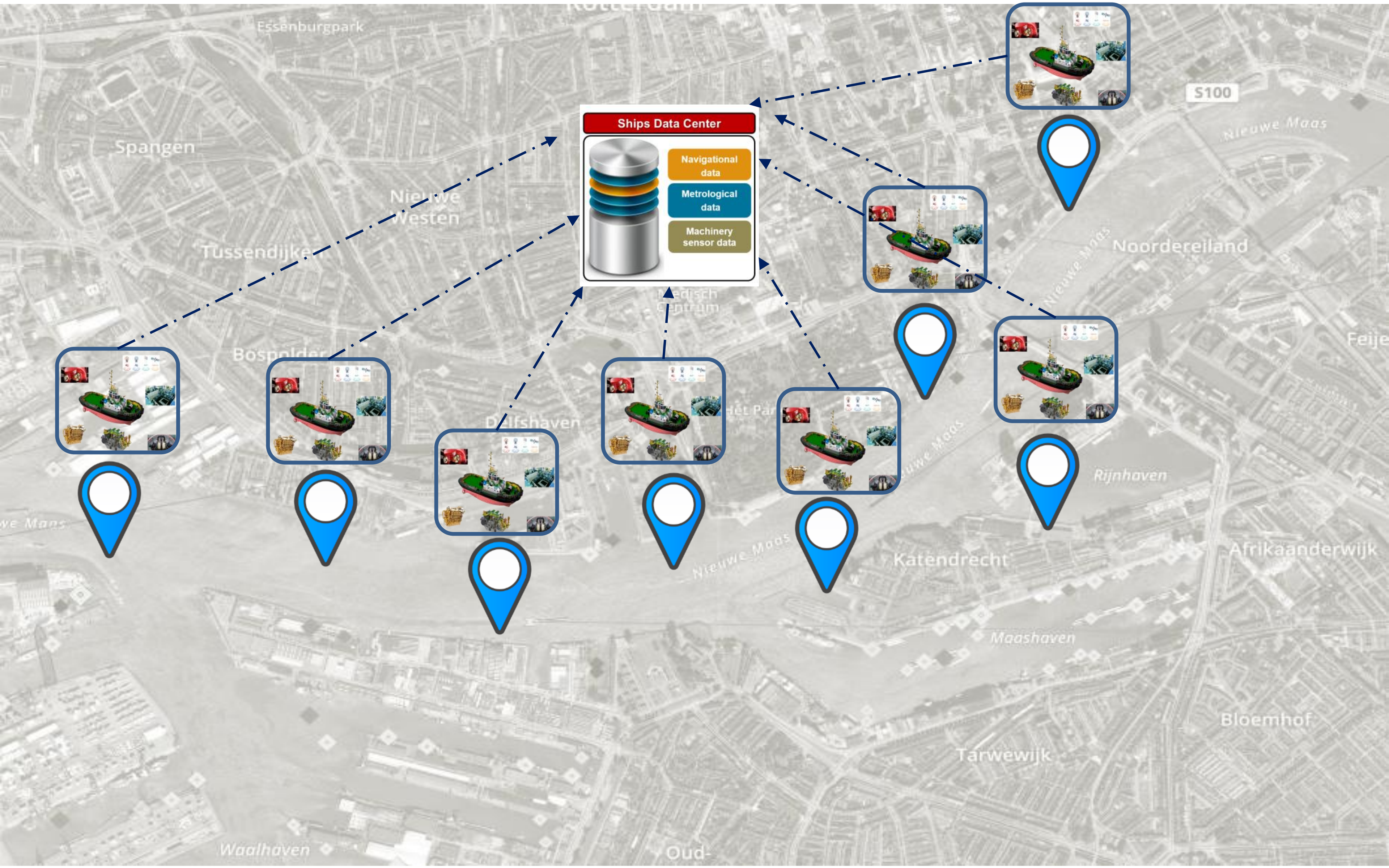
The Ship Data Center



The Ship Data Center



The Ship Data Center



The Ship Data Center

Data-Driven Models

Herbert Alexander Simon: “Learning is any process by which a system improves **performance** from **experience**”.

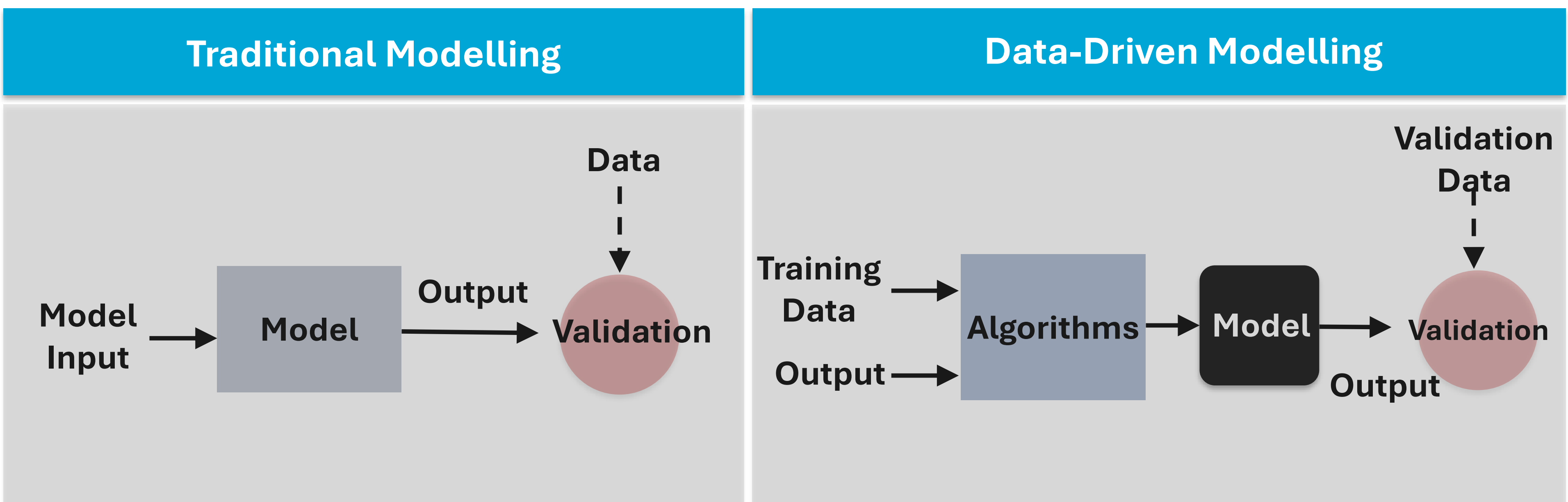
Machine Learning is concerned with computer programs that automatically improve their performance through experience.

Role of Statistics:

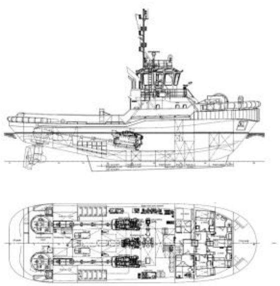
- Inference from a sample

Role of Computer science:

- Efficient algorithms to solve the optimization problem
- Representing and evaluating the model for inference



Data-Driven Models



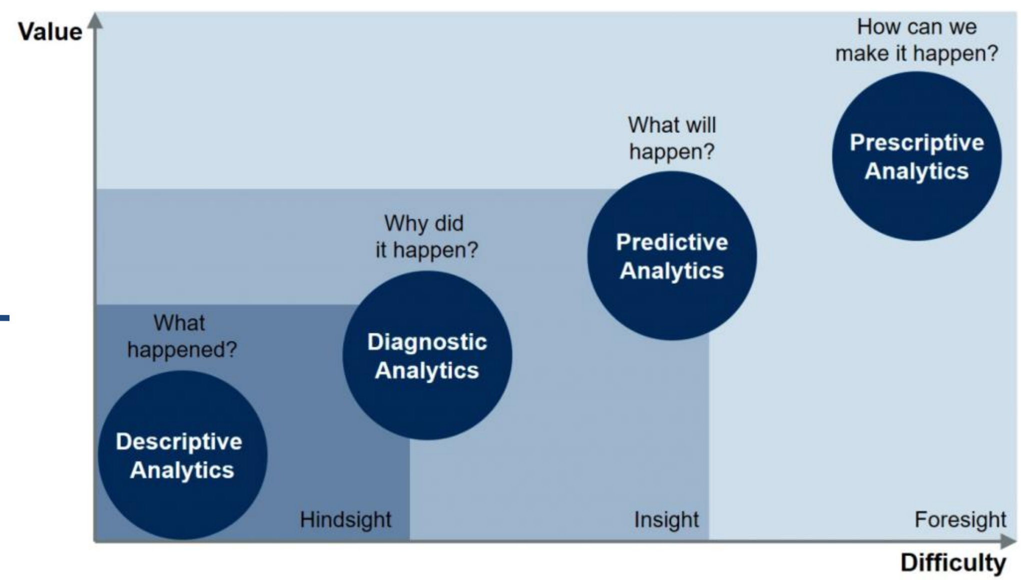
Design

Assembly

Operation

Data & KnowHow

Models

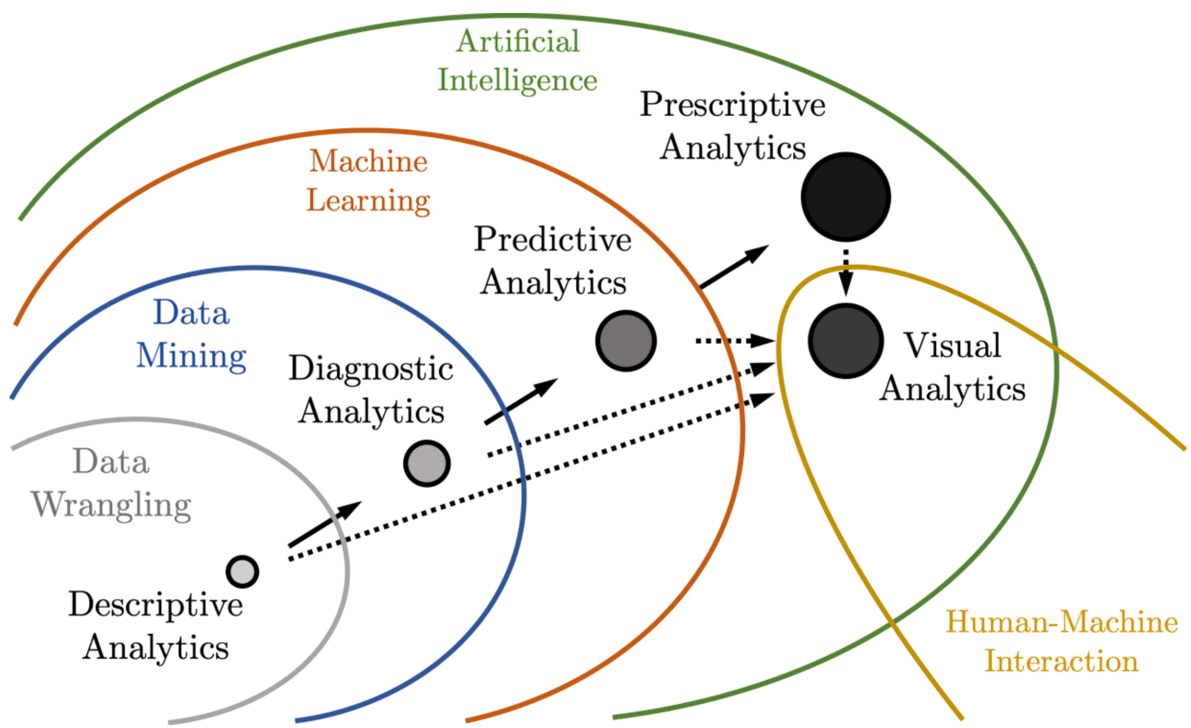


From Predictive to Prescriptive Analytics

While **Descriptive**, **Diagnostic**, and **Predictive** Analytics are quite exploited in research and practice, fewer examples of **Prescriptive** Analytics can be found.

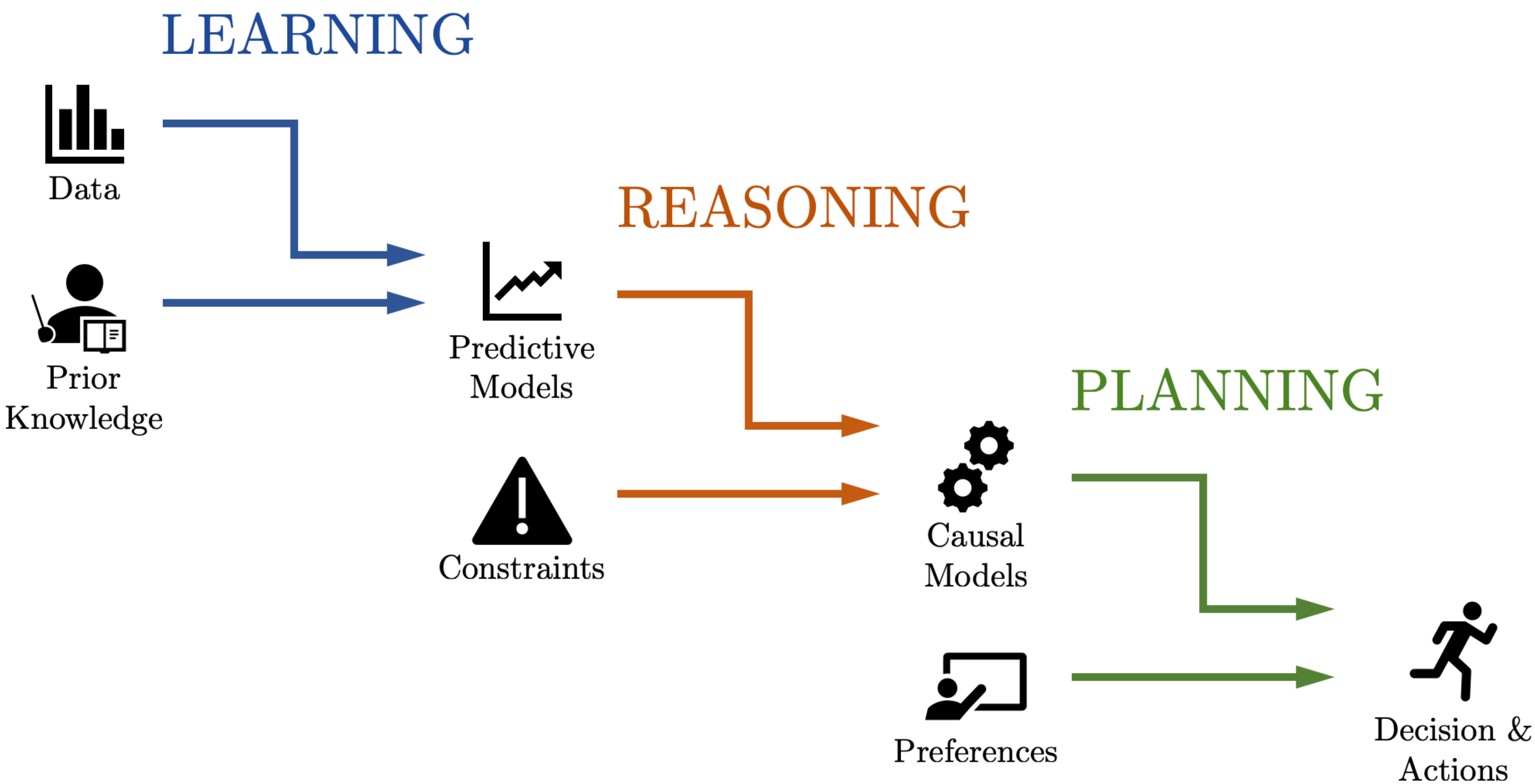
Prescriptive Analytics is the effort to fully automatize the process of taking **decisions** and **actions** starting from the data about the problem with **no human intervention** making specific processes autonomous.

This process is limited by the specific domain which requires that the final decision should be undertaken by a **human operator** who **takes responsibility** for that choice.

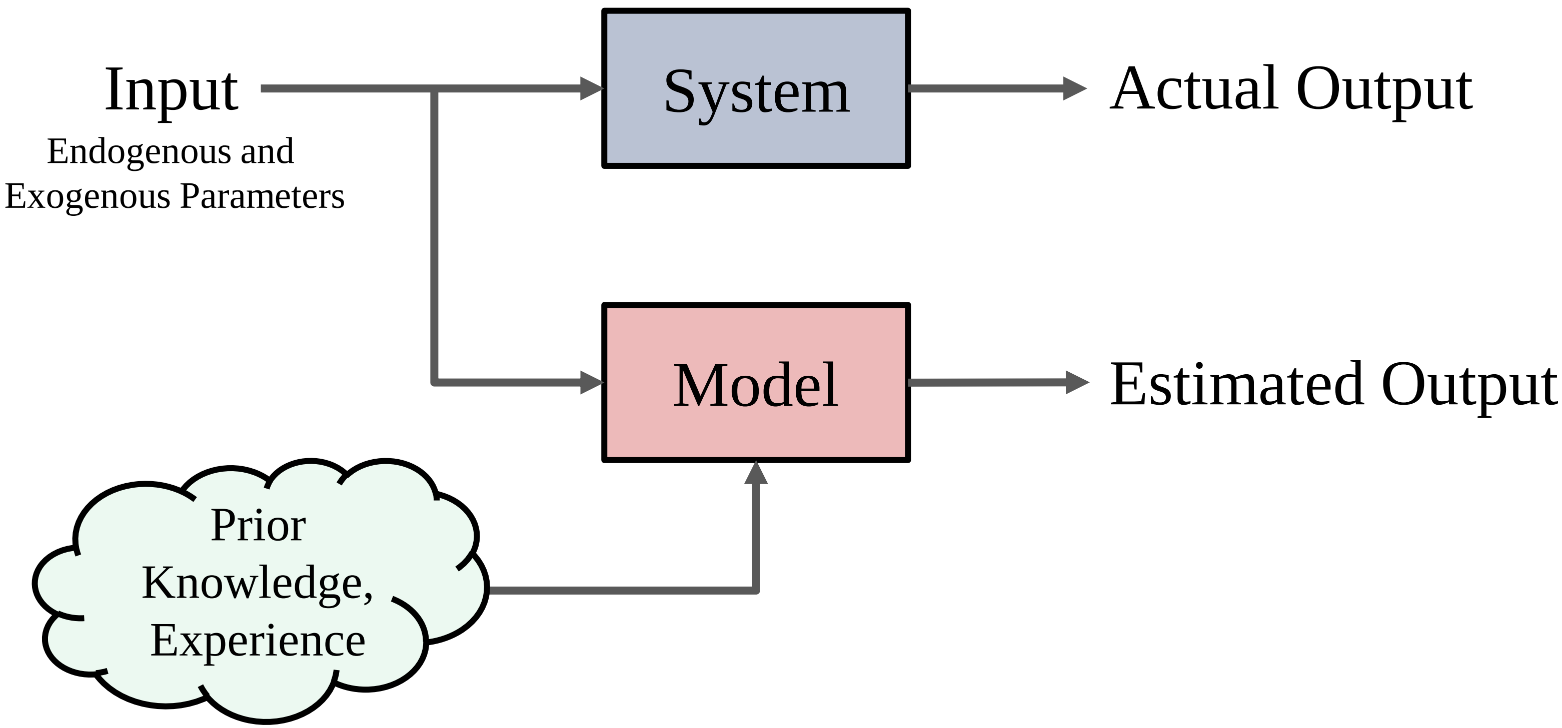


From Predictive to Prescriptive Analytics

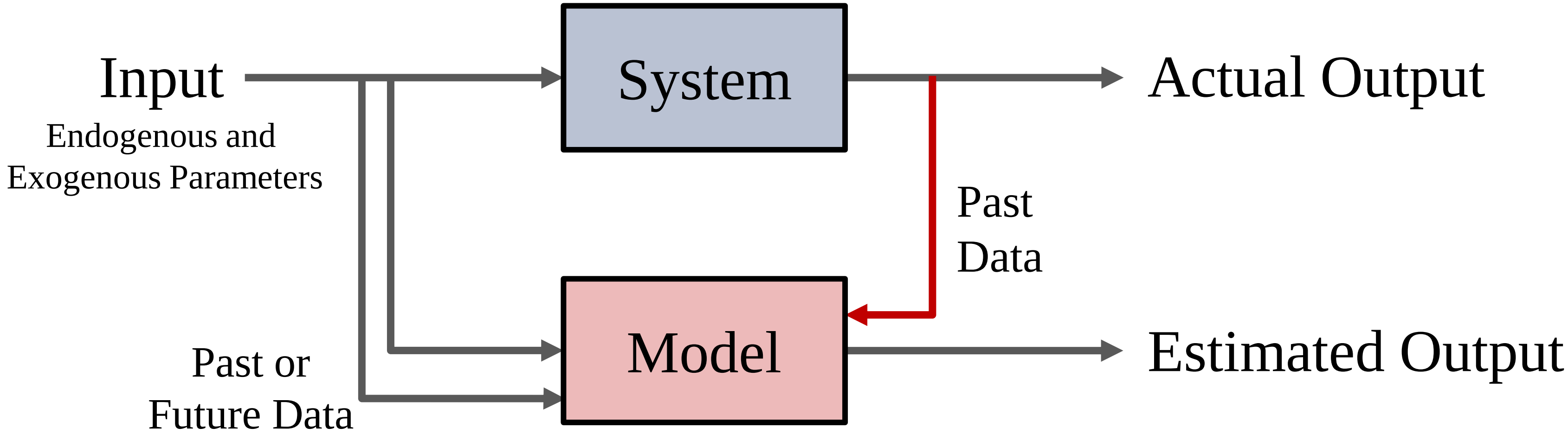
The Staircase Approach: Learning, Reasoning and Planning



White Box Approach



Black Box Approach

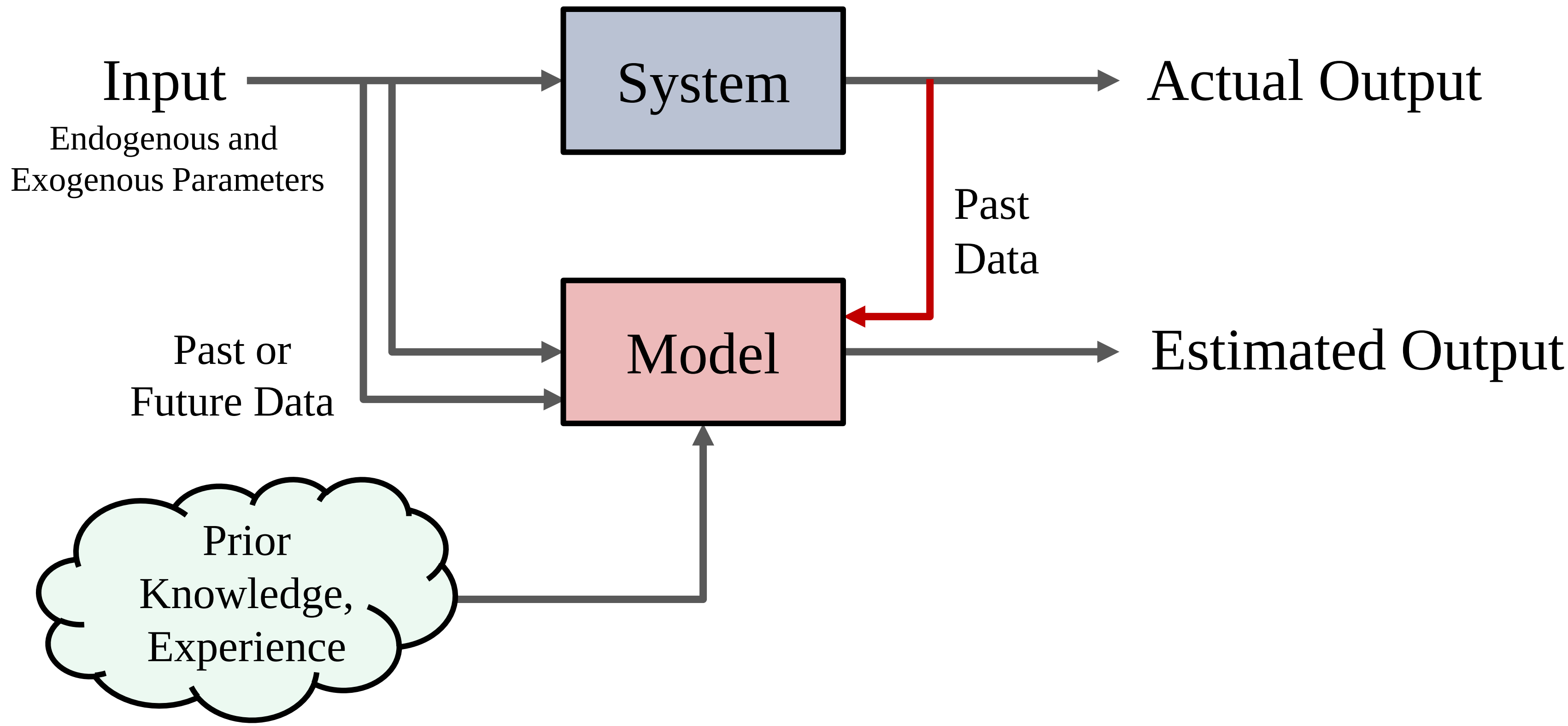


- Black Box Models make use of **statistical inference** procedures based on historical data collection.

- These methods do not require any **a-priory knowledge** of the physical system and allow exploiting even measurements whose role might be important for the calculation of the predicted variables but might not be captured by simple physical models.

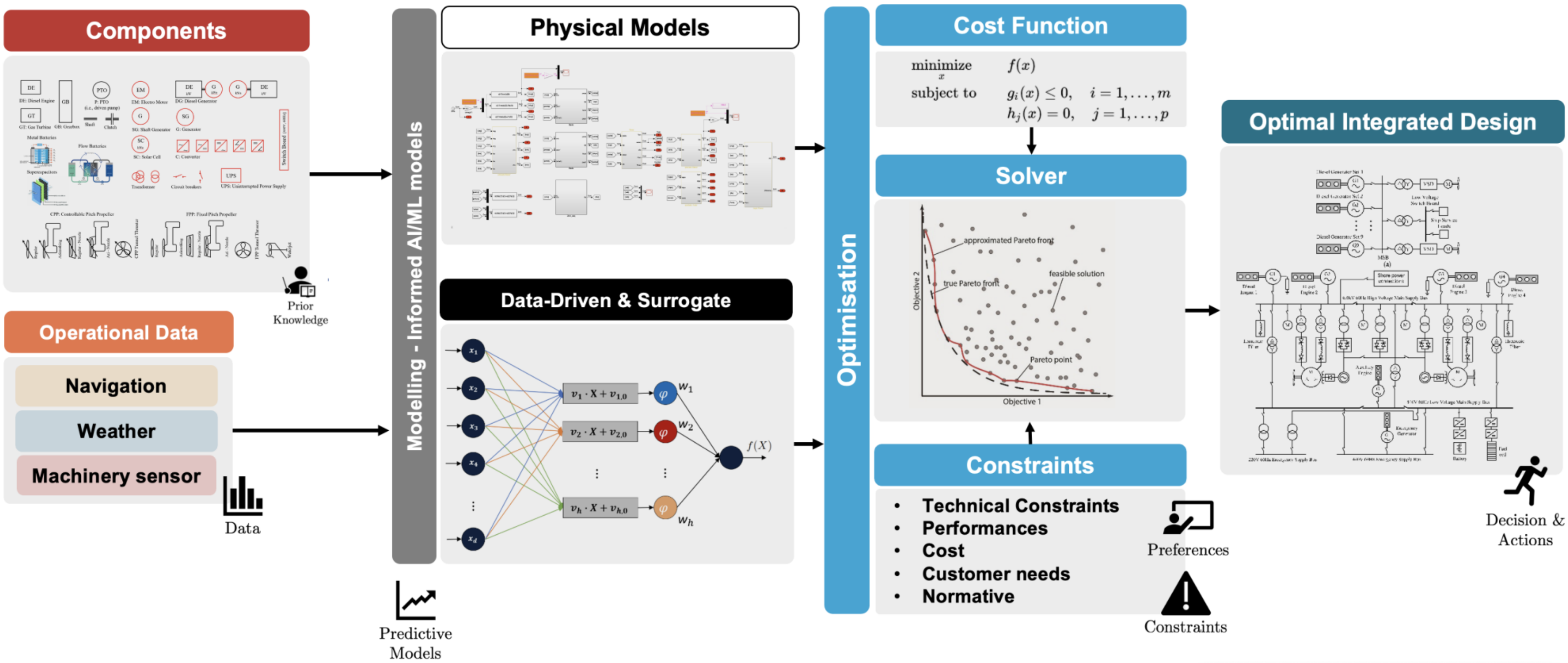
- The model resulting from a black-box approach is not supported by **any physical interpretation** and a **significant amount of data** (both in terms of number of different measured variables and of length of the time series) are required for building reliable models.

Gray Box Approach

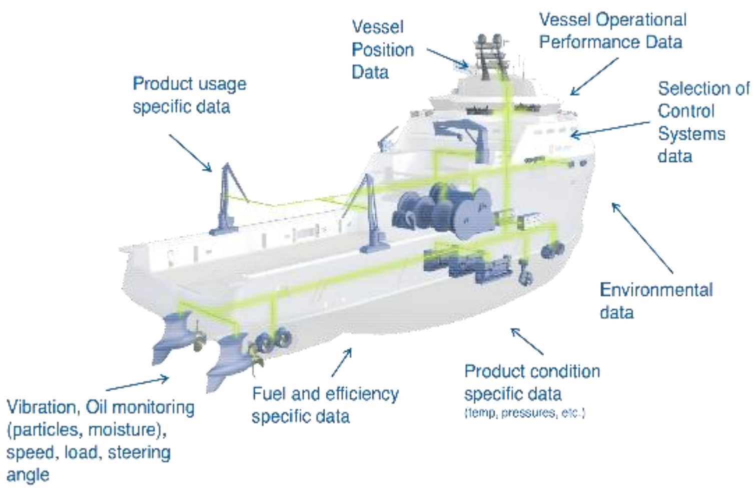


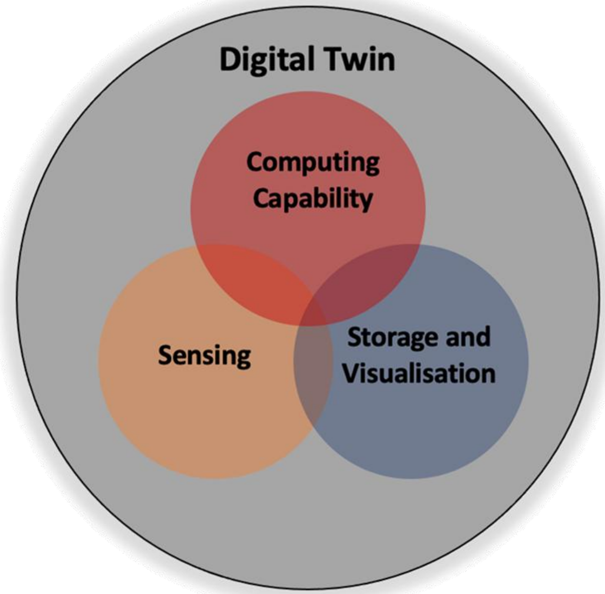
From Predictive to Prescriptive Analytics

Optimal Topology Design

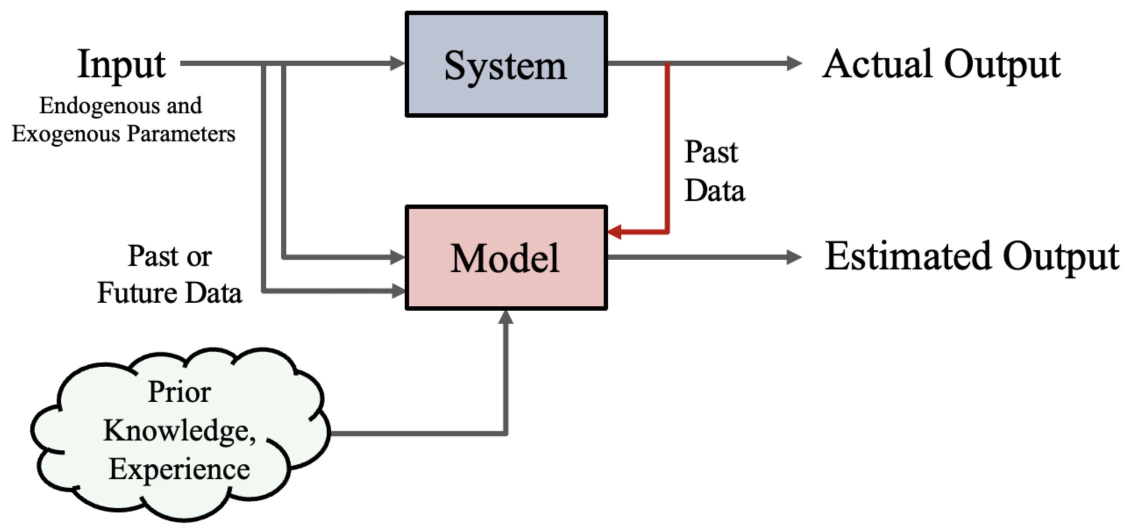


Physics Informed Models

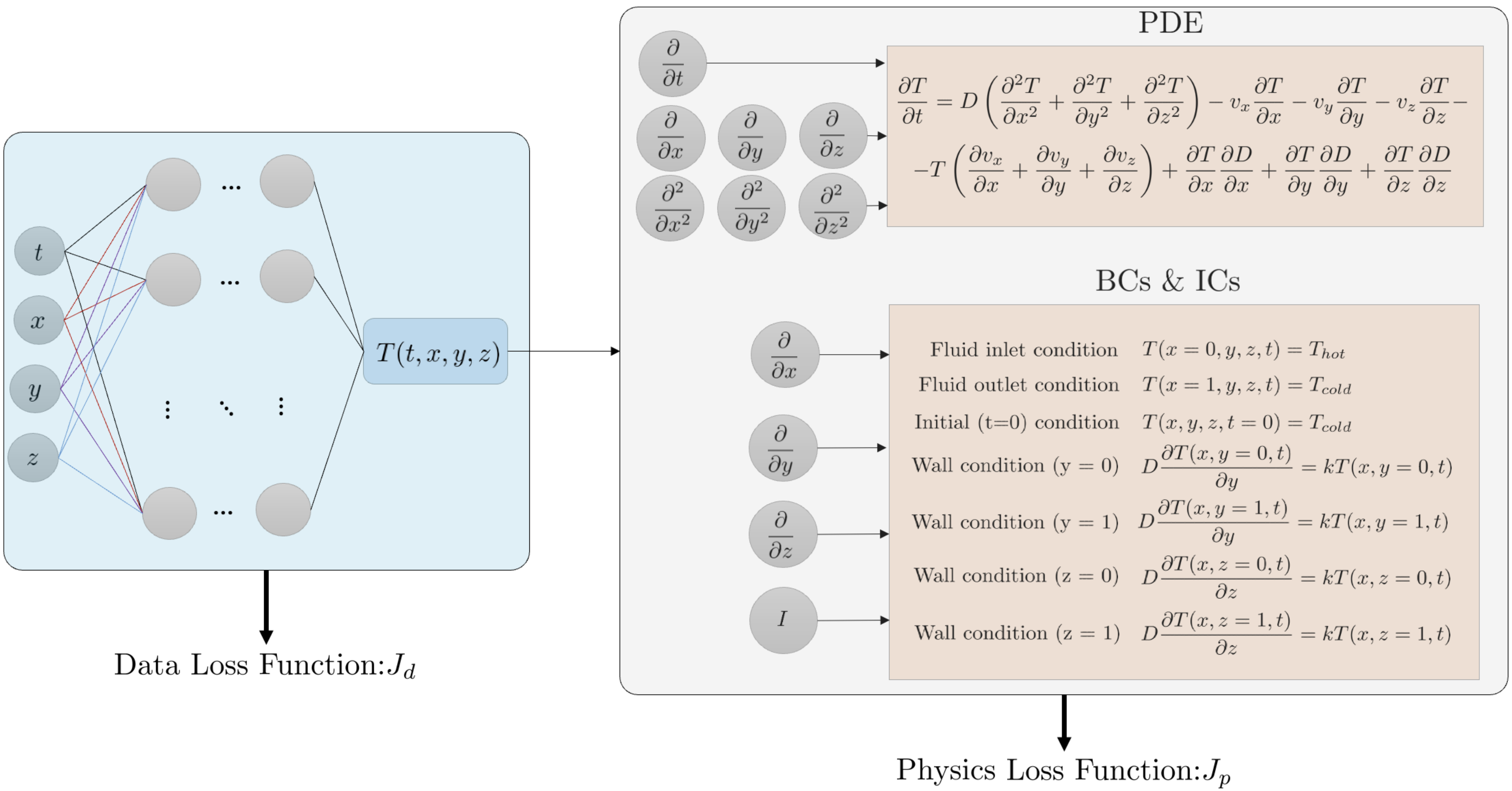




Hybrid Models



Physics Informed Models



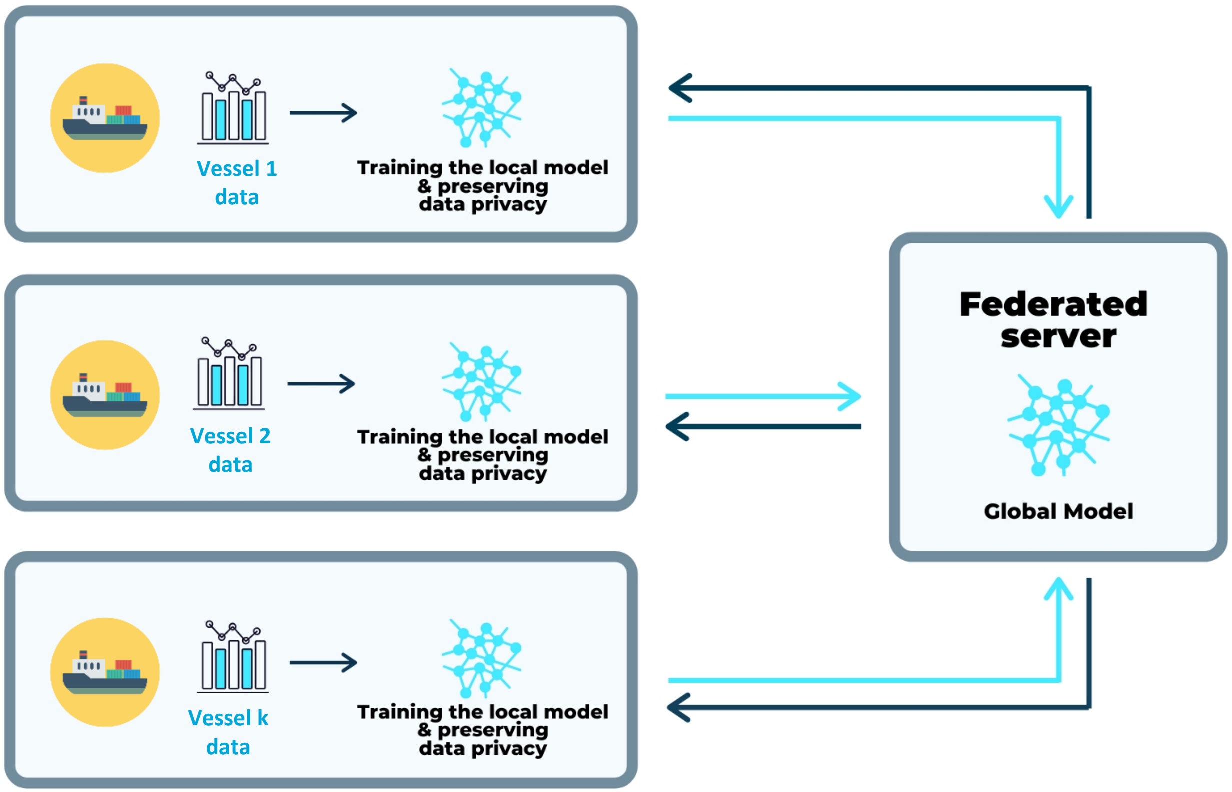
Challenges

Learning with Privacy

Learning from data while preserving the **privacy** of individual observations:

1. Data Preserve privacy is to **corrupt the learning procedure with noise** without destroying the information to extract.

2. Exploit the data in a **federated way**, leaving the data in the hand of the data owner, centralizing only **aggregated information**.



Challenges

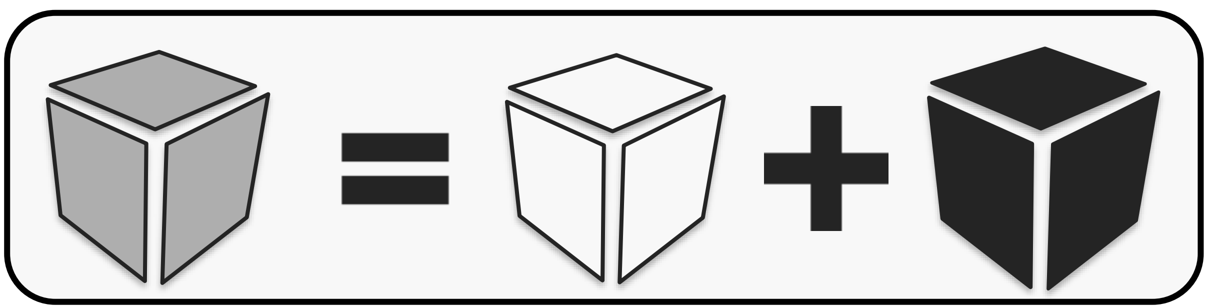
Interpretability and Explainability: the right to explanation

One of the legal bottlenecks hampering the application of advanced analytics to real problems is the “**right to explanation**”.

Such requirement directly collides with the **limitations** of many technologies in terms of **Interpretability** and **Explainability**.

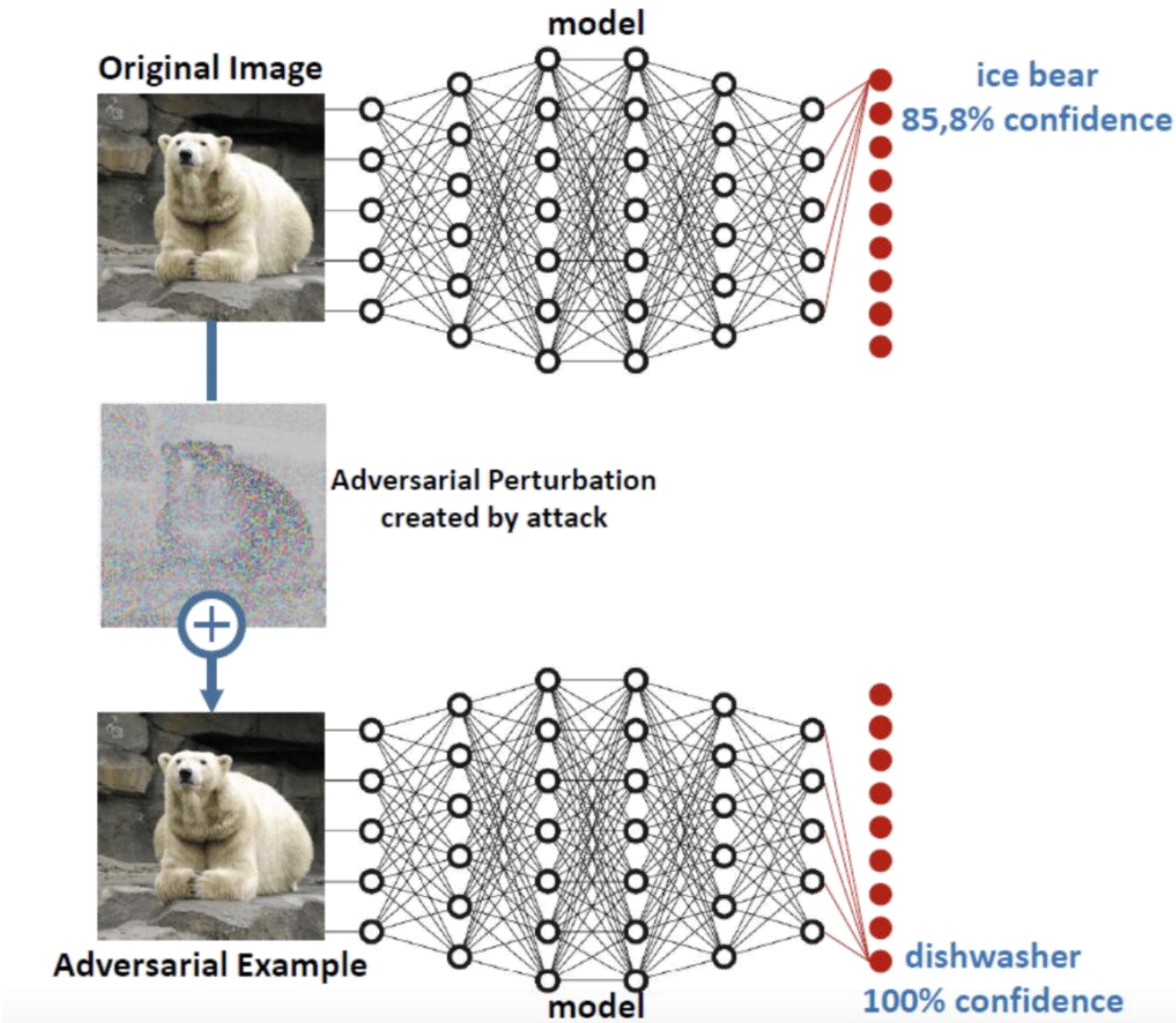
These issues have lately come to the forefront of researchers, primarily due to the widespread development and application of **Deep Learning**.

As they amplify shallow neural networks, **Deep Learning** may become an <u>extreme case of black box models</u>, further reducing their **Interpretability** and **Explainability**.



Challenges

Safety, Security, and Reliability



Case Studies

Hull and Propeller Marine Fouling

Digital Twin Solutions

Induction Motors Bearings Monitoring

Hull and Propeller Marine Fouling

Motivation and Background

A 30% increase in resistance caused by the moderate biological contamination of a 100 000–DWT tanker hull will increase the ship's fuel consumption by up to 12 tons/day, which is the reason for the increase in ship operating costs and emissions [1].

Fuel consumption due to hull fouling may increase as much as 15% at the end of a docking period.
Additional fuel consumption due to propeller fouling may be up to 5-6% [2].

Estimates of increases in fuel consumption from biofilm attached to the hull alone range from 8% to 12%, and from normal propeller fouling range from 6% to 14% [3].

At 24 knots, the propeller polishing at six-month intervals resulted in a fuel savings of five tons per day for each propeller polish, and the hull cleaning resulted in a fuel savings of approximately 12 tons per day [4]

[1] Song, C., & Cui, W. (2020). Review of Underwater Ship Hull Cleaning Technologies. *Journal of Marine Science and Application*, 1-15.

[2] Christian Schack, FORCE Technology (presentation) March 2010.

[3] T. Munk, D. Kane, D. M. Yebra. (2009). The effects of corrosion and fouling on the performance of ocean-going vessels: a naval architectural perspective. Chapter 7 of Advances in marine antifouling coatings and technologies, Materials.

[4] Naval Sea Systems Command, Naval Ships' Technical Manual Chapter 081. (2006). Waterborne Underwater Hull Cleaning of Navy Ships. Revision 5.

Hull and Propeller Marine Fouling

Motivation and Background

As the fouling increases with time the drag on the hull increases, the propeller efficiency reduces and the hull speed decreases.

An increase in engine power is therefore required to maintain the desired speed.

More engine power → more fuel → increase of CO_2 released

Even a 1mm layer of accumulated fouling or calcium deposits on a propeller will significantly increase its roughness, and within 12 months can increase an ISO class I to an ISO class II, or a class II to a III.

Figures indicate a 6 to 12% gain in fuel consumption in polishing a propeller from a class III condition to a class I condition.

Hull and Propeller Marine Fouling

Motivation and Background

Preventive	Predictive	Corrective	Reactive
Coatings	Fatigue Studies	Coatings Repairs	Coatings Repairs
Anodes	Anodes Renewal	Steelwork Repairs	Steelwork Repairs
Inspections	Coatings Renewal	Hull Cleaning	Hull Cleaning
	Propeller Cleaning	Propeller Cleaning	Propeller Cleaning

Planned	Unplanned
Cost Effective	**Cost Inefficient**

Hull and Propeller Marine Fouling

Motivation and Background

Hull Cleaning

Propeller Cleaning

→ **Planned** → Cost Effective

When?

Hull and Propeller Marine Fouling

Motivation and Background

It is challenging to assess Ship performance drop-off due to hull and propeller fouling because factors as wind, waves, currents and prime movers' efficiency are variable.

Safinah Group
360° Coating & Engineering Experts

- Fuel consumption often a disappointment
- Torsion meter provides most accurate and valuable data

No matter the methodology used, the determination of when it is **time to clean the propeller and the hull** is dependent on what performance drop off the **ship operator or Charterer** is **prepared to accept**.

This led to the conclusion that no fixed time parameters for cleaning can be defined.

Hull and Propeller Marine Fouling

Novelty Detection Approaches

Is it possible to predict the clean and not-clean hull condition based on operational data provided from the automation system?

Clean – Label 0

Fouled – Label 1

Suppose to carry out an experimental campaign and to collect data charactering the behavior and performance of the vessel with the label (1= Fouled, 0=clean).

Machine Learning

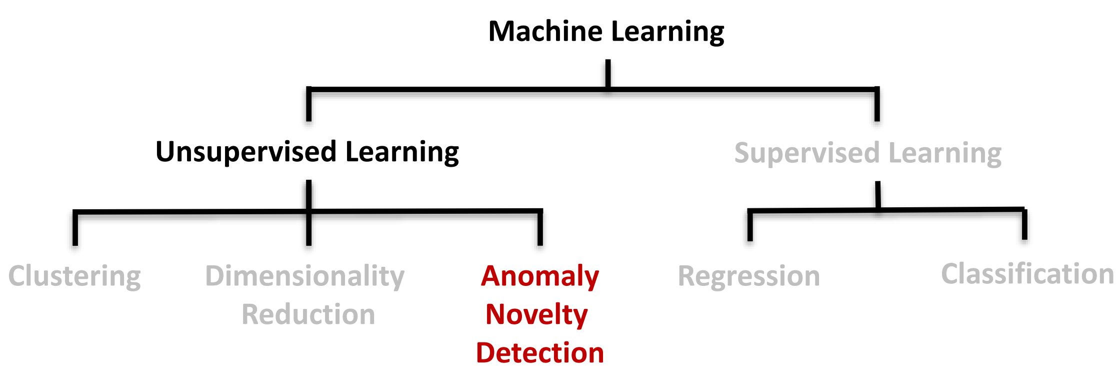
- Unsupervised Learning
  - Clustering
  - Dimensionality Reduction
  - Anomaly Novelty Detection
- **Supervised Learning**
  - Regression
  - **Classification**

Hull and Propeller Marine Fouling

Novelty Detection Approaches

Novelty (outlier) detection methods address the problem of identifying new or unknown data that a data analytics system has not been trained with and was not previously aware of.

An outlier is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism [4].

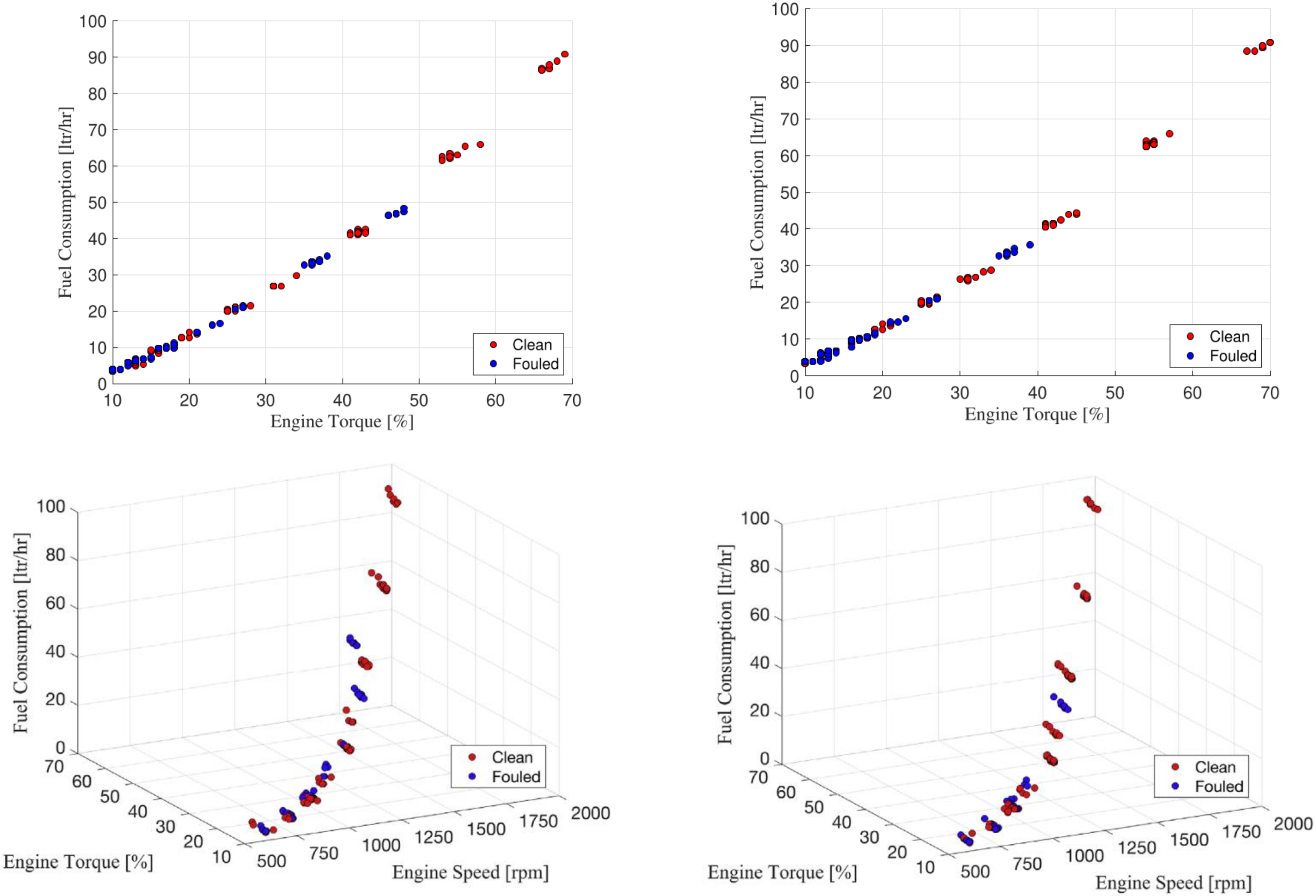


Novelty detection is also referred to as one-class classification because it is trained only on the one class of known data (data from sea trials, in clean hull and propeller conditions).

[4] Hawkins, D. M. (1980). *Identification of outliers* (Vol. 11). London: Chapman and Hall.

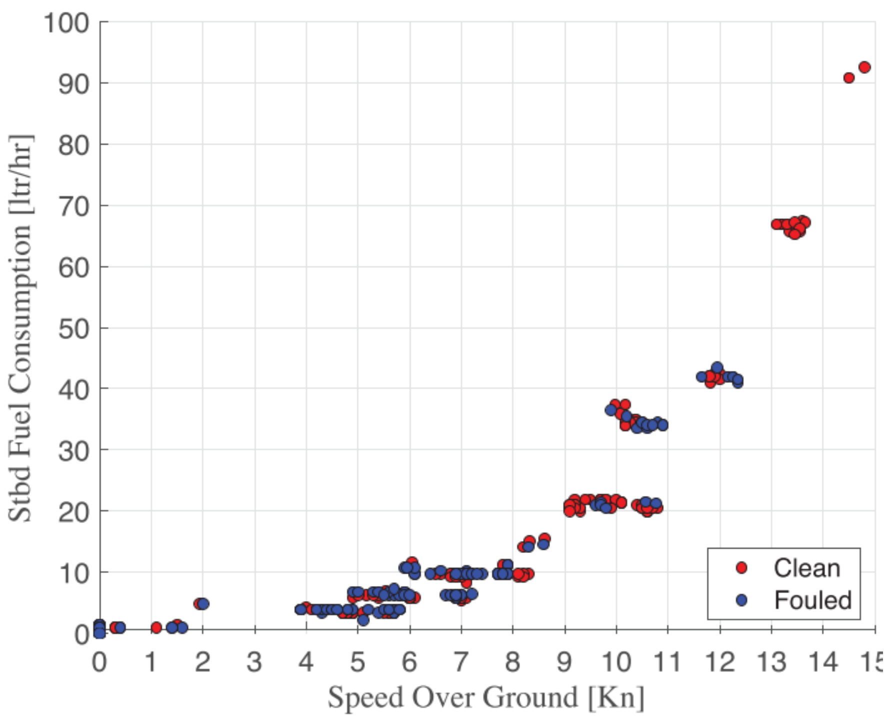
Hull and Propeller Marine Fouling

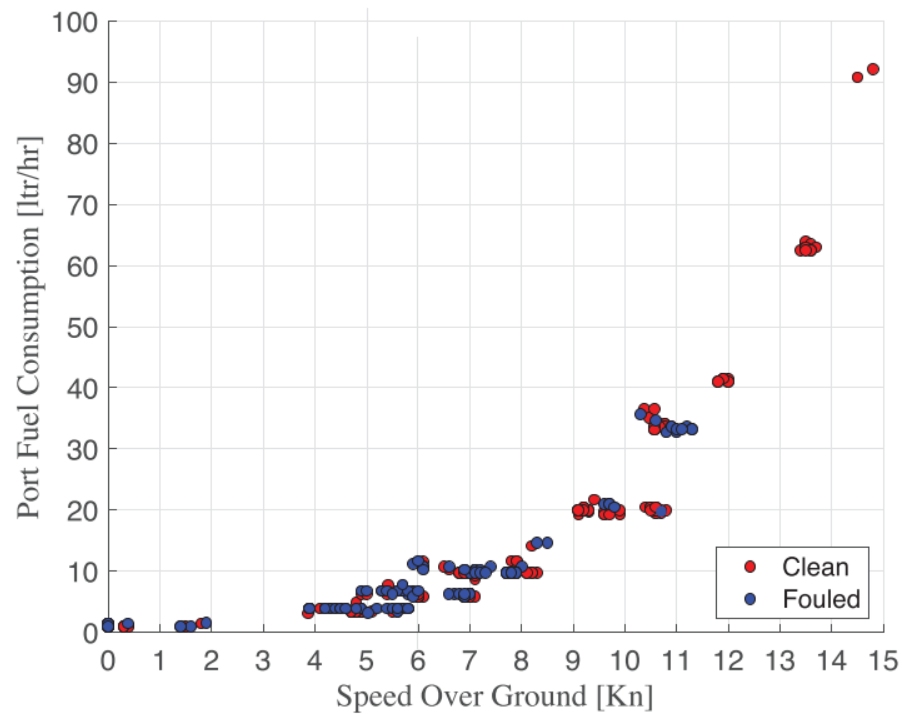
Novelty Detection Approaches



Hull and Propeller Marine Fouling

Novelty Detection Approaches





Hull and Propeller Marine Fouling

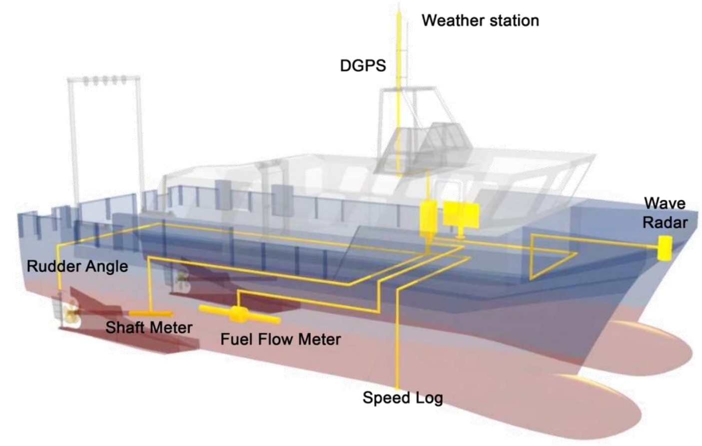
The Prince Royale Vessel

Main particulars of The Princess Royal.

Ship feature	Value	Unit
Length overall	18.9	[m]
Length between Perpendicular	16.45	[m]
Breadth Moulded	7.03	[m]
Displacement (Lightship)	36.94	[t]
Draught (Lightship) (Amid - FP - AP)	1.65–1.6-1.7	[m]
Deadweight	7.32	[t]

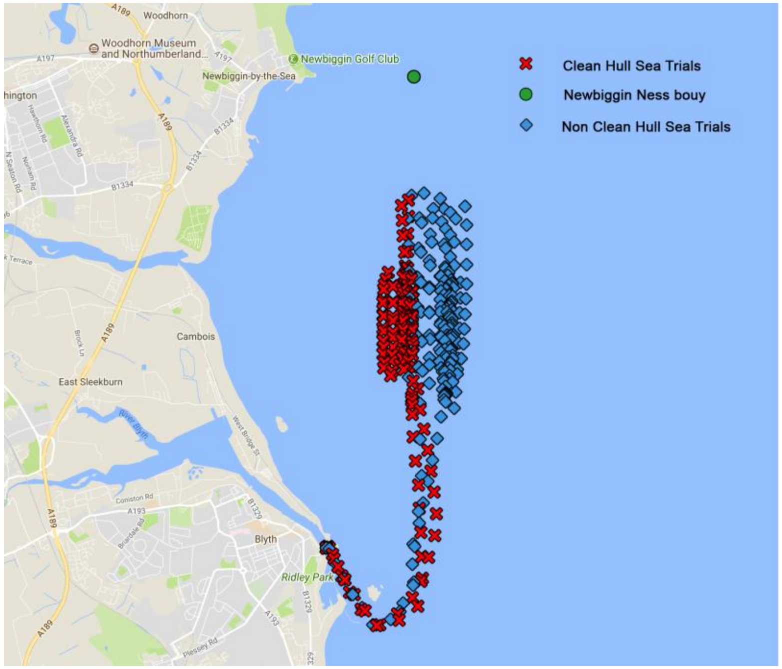
Propeller, engine and gearbox particulars of The Princess Royal.

Propeller particulars	
Number of Propellers	2
Propellers Type	Fixed
Propeller Diameter	0.75 [m]
Number of Blades	5
Engine particulars	
Number of Engines	2
Engine Make and Model	MAN D2676 LE443
Rated Power	537 [kW]
Rated Speed	2300 [rpm]
Rated Fuel Consumption	142 [Ltr/hr]
Gearbox particulars	
Number of Gearbox	2
Reduction Ratio	1.75:1



Trial	Condition
30/03/2017	Clean Hull
27/03/2017	Fouled

Two separate sea trials were carried out six months apart to allow fouling to take place on the hull surface under normal operational conditions.



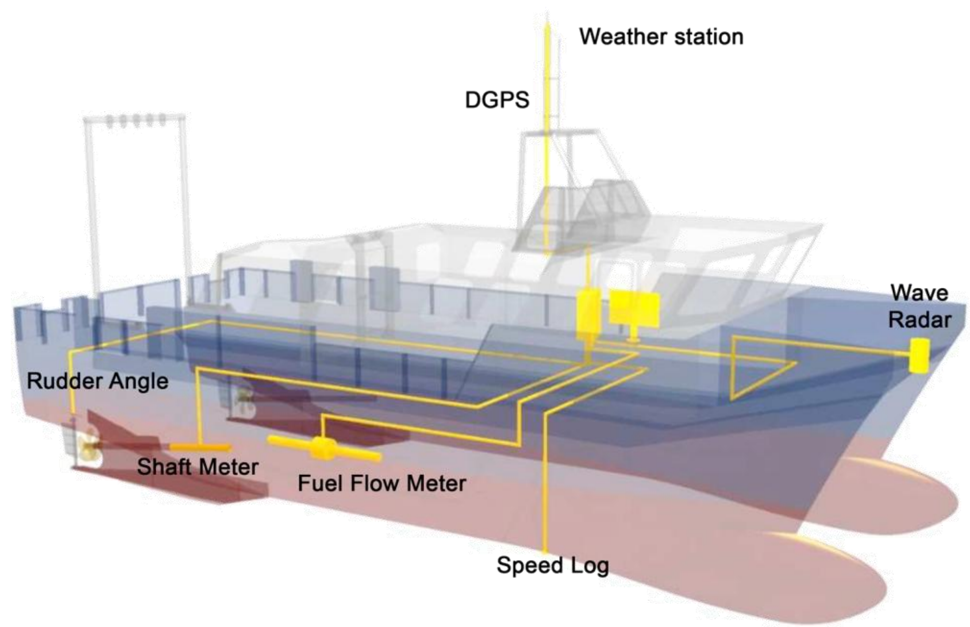
Hull and Propeller Marine Fouling

The Prince Royale Vessel

Measured values available from the monitoring system.

Feature	Variable name	Unit
x_1	Magnetic Heading	[deg]
x_2	True Heading	[deg]
x_3	Latitude	[^{o},$'$, $''$]
x_4	Longitude	[^{o},$'$, $''$]
x_5	Speed through water	[Kn]
x_6	Water Depth	[m]
x_7	Humidity	[%]
x_8	Rudder angle	[deg]
x_9	Course over ground	[deg]
$x_1 0$	Wind Apparent Speed	[m/s]
x_{11}	Wind Apparent Direction	[deg]
x_{12}	Air Temperature	[^oC]
x_{13}	Air Pressure	[mbars]
x_{14}	Relative Humidity	[%]
x_{15}	Coolant Pressure (port)	[bar]
x_{16}	Coolant Temperature (port)	[^oC]
x_{17}	Engine Speed (port)	[rpm]
x_{18}	Engine Torque (port)	[%]
x_{19}	Fuel Delivery Pressure (port)	[bar]
x_{20}	Oil Pressure (port)	[bar]
x_{21}	Oil Temperature (port)	[^oC]
x_{22}	Crankcase Pressure (port)	[bar]
x_{23}	Oil Level (port)	[%]
x_{24}	Fuel Flow (port)	[Ltr/hr]
x_{25}	Fuel Return (port)	[%]
x_{26}	Fuel Supply Pressure (port)	[Ltr]
x_{27}	Fuel Consumption (port)	[Ltr/hr]
x_{28}	Coolant Pressure (starboard)	[bar]
x_{29}	Coolant Temperature (starboard)	[^oC]
x_{31}	Engine Speed (starboard)	[rpm]
x_{32}	Engine Torque (starboard)	[%]
x_{33}	Fuel Delivery Pressure (starboard)	[bar]
x_{34}	Oil Pressure (starboard)	[bar]
x_{35}	Oil Temperature (starboard)	[^oC]
x_{36}	Crankcase Pressure (starboard)	[bar]
x_{37}	Oil Level (starboard)	[%]
x_{38}	Fuel Flow (starboard)	[Ltr/hr]
x_{39}	Fuel Return (starboard)	[%]
x_{40}	Fuel Supply Pressure (starboard)	[bar]
x_{41}	Fuel Consumption (starboard)	[Ltr/hr]

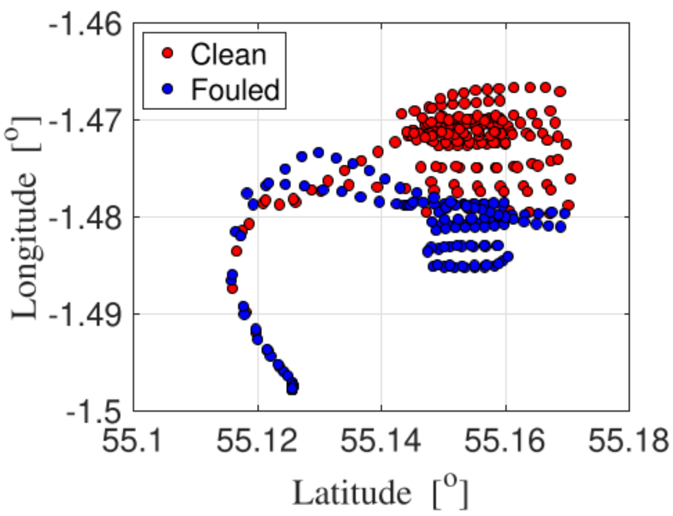
Data logging system

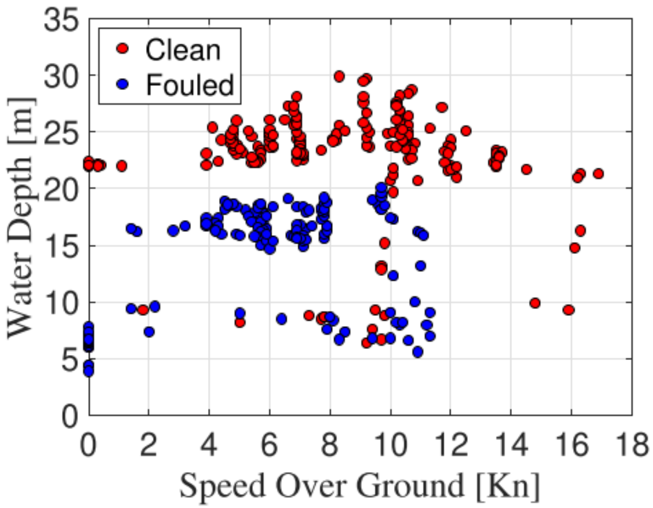


Hull and Propeller Marine Fouling

The Prince Royale Vessel

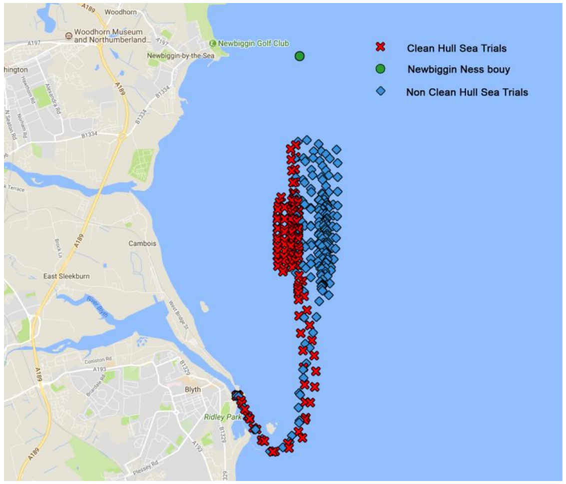
Data Pre-Processing – Some False Friends





Hull and Propeller Marine Fouling

Data Pre-processing - Data fusion

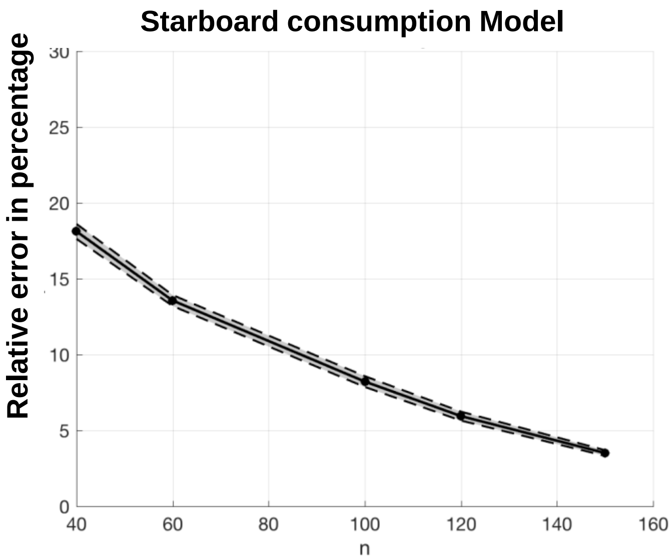


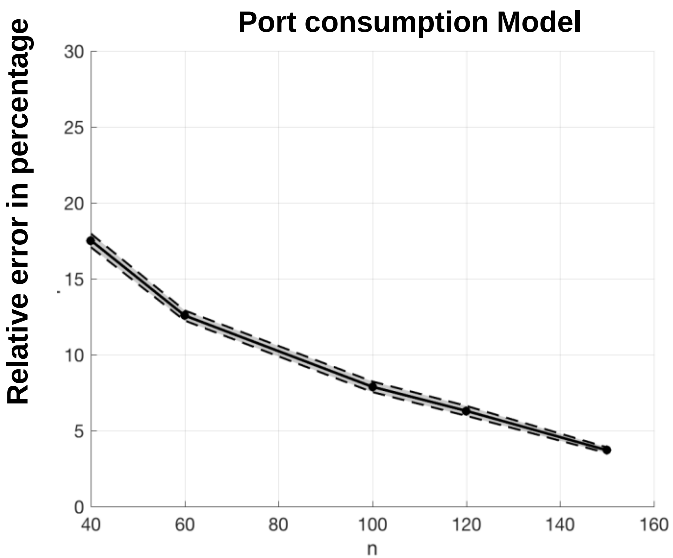
The Importance of the weather

Monitoring System + Weather data

Newbiggin Ness buoy data.

Parameter	Unit
Significant Wave Height	[m]
Wave zero up crossing period	[s]
Wind Wave Significant Wave Height	[m]
Wind Wave Peak Period	[s]
Wind Wave Peak Period Direction	[°]
Swell Significant Wave Height	[m]
Swell Peak Period	[s]
Swell Peak Period Direction	[°]
Sea Surface Elevation	[m]
Sea Temperature	[°C]

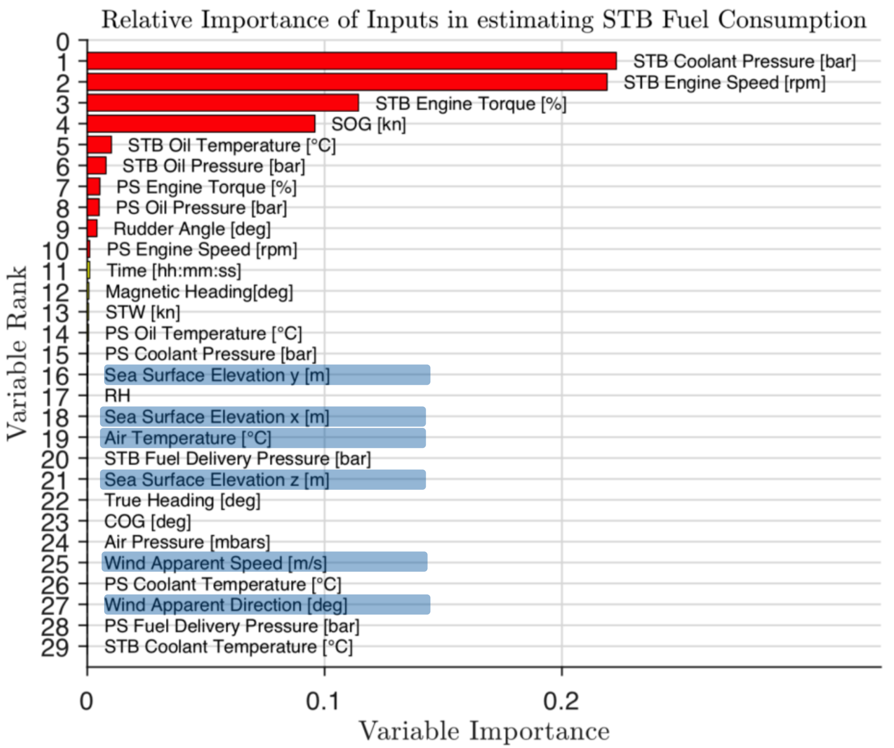




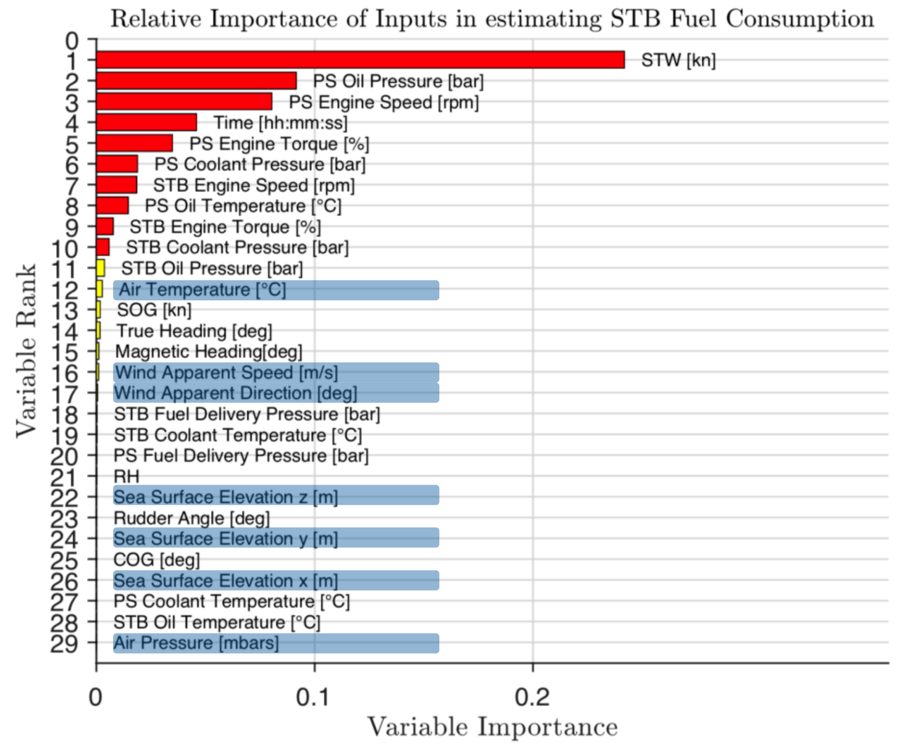
Hull and Propeller Marine Fouling

Data Pre-processing - Data fusion

Starboard consumption Model



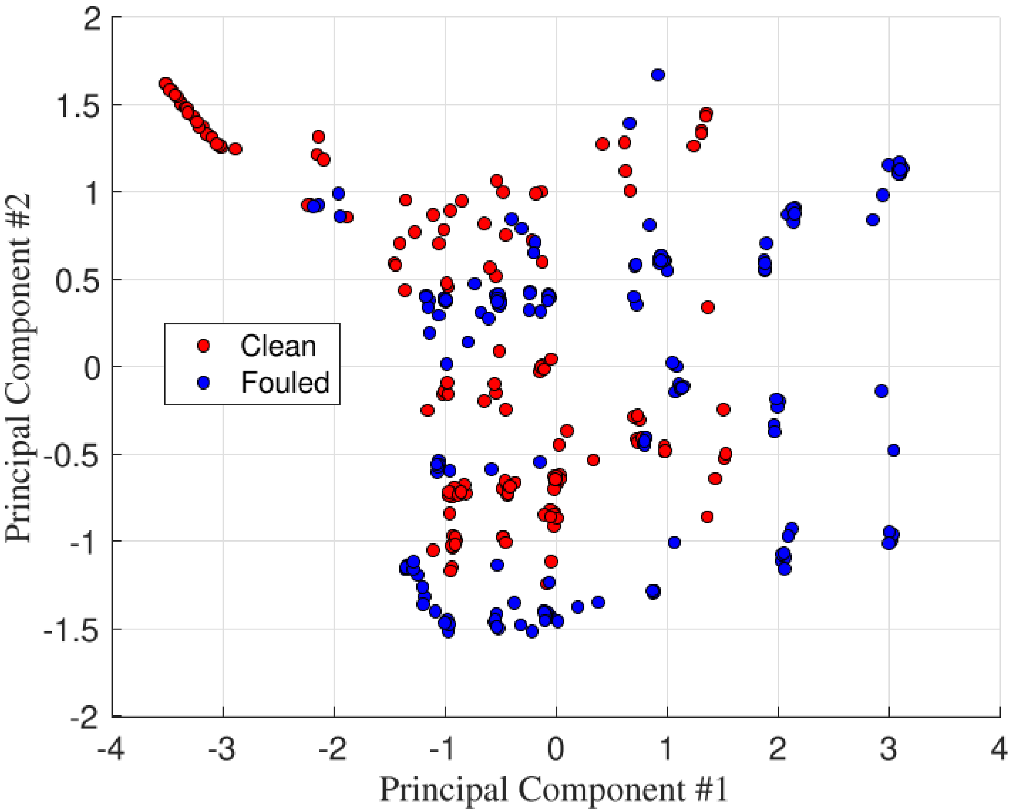
Port consumption Model



Hull and Propeller Marine Fouling

Data Pre-processing - Data fusion

The Failure of Linear Models - PCA



Hull and Propeller Marine Fouling

Measuring the Error

1. Average Misclassifications Rate (AMR) is the mean number of misclassified samples

$$\mathrm{AMR} = \frac{1}{m}\sum_{i=1}^{m} \ell_H\left(f\left(\boldsymbol{x}_i^t\right), y_i^t\right)$$

$$\ell_H(f(\boldsymbol{x}), y) = [f(\boldsymbol{x}) \neq y]$$

2. the Confusion Matrix, which measures four different quantities

$$\mathrm{TN} = \frac{100}{m}\sum_{i=1}^{m}\left[f\left(\boldsymbol{x}_i^t = y_i^t \wedge y_i^t = -1\right]\right.$$

$$\mathrm{TP} = \frac{100}{m}\sum_{i=1}^{m}\left[f\left(\boldsymbol{x}_i^t = y_i^t \wedge y_i^t = +1\right]\right.$$

$$\mathrm{FN} = \frac{100}{m}\sum_{i=1}^{m}\left[f\left(\boldsymbol{x}_i^t \neq y_i^t \wedge y_i^t = -1\right]\right.$$

$$\mathrm{FP} = \frac{100}{m}\sum_{i=1}^{m}\left[f\left(\boldsymbol{x}_i^t \neq y_i^t \wedge y_i^t = +1\right]\right.$$

Hull and Propeller Marine Fouling

Learning Algorithms

Algorithm 1:
One-Class SVM (OCSVM) is a boundary-based anomaly detection method, inspired by SVM, which encloses the inlier class in a minimum volume hypersphere by minimizing a Tikhonov regularization problem, similar to the one reported for the SVM framework.

Like traditional SVMs, OCSVM can also be extended to non-linearly transformed spaces using the **Kernel trick** for distances.

The hyperparameters OCSVM HOCSVM are:
- The kernel, which is usually fixed (Gaussian Kernel)
- Its hyperparameter h_1
- The regularization hyperparameter h_2

Algorithm 2:
The Global KNN (GKNN), inspired by the KNN, was originally introduced as an unsupervised distance-based outlier detection method.

The hyperparameter of GKNN is the number of neighbours to be considered h_1.

Hull and Propeller Marine Fouling

Results

AMR, TP, TN, FP, and FN of the models learned with the different algorithms (OCSVM and GKNN) when $l = 150$ and $\nu \in \{10,20,30\}$.

	ν	AMR	TP	TN	FP	FN
OCSVM	10	0.04 ± 0.01	47.8 ± 1.2	47.8 ± 1.0	2.2 ± 1.0	1.8 ± 1.1
	20	0.04 ± 0.01	48.0 ± 0.9	48.0 ± 1.1	2.0 ± 1.0	2.0 ± 1.0
	30	0.03 ± 0.01	48.4 ± 1.0	48.4 ± 0.9	1.6 ± 1.0	1.4 ± 1.0
GKNN	10	0.05 ± 0.02	47.6 ± 2.3	47.6 ± 1.8	2.4 ± 1.9	2.6 ± 1.9
	20	0.04 ± 0.02	48.2 ± 2.0	48.2 ± 1.9	1.8 ± 2.3	2.2 ± 2.0
	30	0.03 ± 0.01	48.7 ± 1.2	48.7 ± 1.1	1.3 ± 1.0	1.7 ± 0.8

AMR, TP, TN, FP, and FN of the models learned with the different algorithms (OCSVM and GKNN) when $\nu = 30$ and $l \in \{30,70,150\}$.

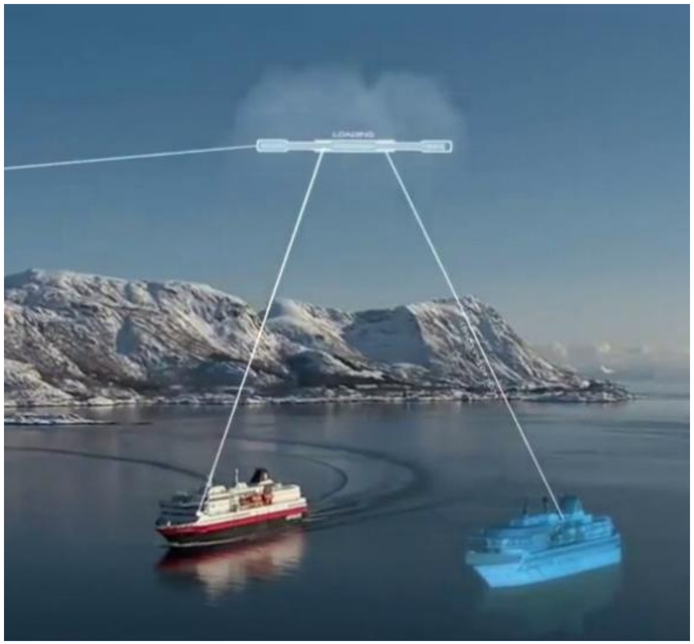
	l	AMR	TP	TN	FP	FN
OCSVM	30	0.22 ± 0.11	39.5 ± 10.8	39.5 ± 11.3	10.5 ± 10.7	11.5 ± 11.5
	70	0.07 ± 0.04	46.4 ± 3.5	46.4 ± 3.6	3.6 ± 3.7	3.4 ± 3.8
	150	0.03 ± 0.01	48.4 ± 1.0	48.4 ± 0.9	1.6 ± 1.0	1.4 ± 1.0
GKNN	30	0.25 ± 0.15	37.9 ± 15.0	37.9 ± 10.5	12.1 ± 14.3	12.9 ± 16.9
	70	0.11 ± 0.06	45.1 ± 6.6	45.1 ± 6.2	4.9 ± 6.0	6.1 ± 6.1
	150	0.03 ± 0.01	48.7 ± 1.2	48.7 ± 1.1	1.3 ± 1.0	1.7 ± 0.8

OCSVM		
x_5	Speed through water [kn]	0.12 ± 0.03
x_{17}	Engine Speed (port) [rpm]	0.07 ± 0.03
x_{30}	Engine Speed (starboard) [rpm]	0.07 ± 0.03
x_{18}	Engine Torque (port) [%]	0.06 ± 0.04
x_{31}	Engine Torque (starboard) [%]	0.06 ± 0.04
GKNN		
x_5	Speed through water [kn]	0.14 ± 0.04
x_{17}	Engine Speed (port) [rpm]	0.08 ± 0.03
x_{18}	Engine Torque (port) [%]	0.07 ± 0.04
x_{30}	Engine Speed (starboard) [rpm]	0.07 ± 0.04
x_{31}	Engine Torque (starboard) [%]	0.06 ± 0.04

Digital Twin Solutions

Motivation and Background

Is it possible to build a data-driven Digital Twin of the ship and use it for estimating the speed loss due to marine fouling?



Data Driven Methods can be applied for predicting the speed, and therefore the speed loss of the ship, able to act as a Digital Twin of the ship itself.

Deep Extreme Learning Machines can be used for estimating the speed loss caused by the marine fouling effects on the ship hull and propeller, leveraging on the large amount of information collected from the on-board monitoring system sensors.

Digital Twin Solutions

Available Vessels and Data

Ship Feature	V1 Value	V1 Unit	V2 Value	V2 Unit
Deadweight	46764	[t]	46067	[t]
Design speed	15	[knots]	15.5	[knots]
Draft (summer SW)	12.18	[m]	12.2	[m]
Length between perpendicular	176.75	[m]	176.83	[m]
Breadth moulded	32.18	[m]	32.20	[m]
Main engines installed power	3840×2	[kW]	8200	[kW]
Auxiliary engines installed power	682×2	[kW]	1176×3	[kW]
Shaft generator power	3200	[kW]		
Exhaust boilers steam generator	750×2	[kg/h]	1130	[kg/h]
Auxiliary boilers steam generator	14000×2	[kg/h]	14000×2	[kg/h]
Fuel consumption	34.7	[mt/day]	31.8	[mt/day]

V1

Date	Event
21/03/2012	Vessel delivery
29/10/2012	Propeller cleaning
30/03/2013	Hull cleaning
01/08/2013	Loss of the LOG speed measurement
17/07/2014	Change from fixed-speed to variable-speed operations

V2

Date	Event
19/04/2014	Propeller polishing
20/12/2014	Hull cleaning
28/08/2015	Hull cleaning and Propeller polishing
28/11/2015	Dry-docking

Variable name	Unit	Variable name	Unit
Timestamp	[t]	Sea depth	[m]
Latitude	[°]	Seawater temperature	[°C]
Longitude	[°]	CPP set point	[°]
Main engines fuel consumption	[kg/h]	CPP feedback	[°]
Auxiliary engines power output	[kg/h]	Fuel density	$[kg/m^3]$
Shaft generator power	[kg/h]	Fuel temperature	[°C]
Propeller shaft power	[kW]	Ambient pressure	[bar]
Propeller speed	[rpm]	Humidity	[]
Ship draft (fore)	[m]	Dew point temperature	[]
Ship draft (aft)	[m]	Shaft torque	[kNm]
Draft port	[m]	Rudder angle	[°]
Draft starboard	[m]	Acceleration x direction	$[m/s^2]$
Relative wind speed	[m/s]	Acceleration y direction	$[m/s^2]$
Relative wind direction	[°]	Acceleration z direction	$[m/s^2]$
GPS heading	[°]	Roll	[°]
Speed over ground	[knots]	Pitch	[°]
Speed through water	[knots]	Yaw	[°]

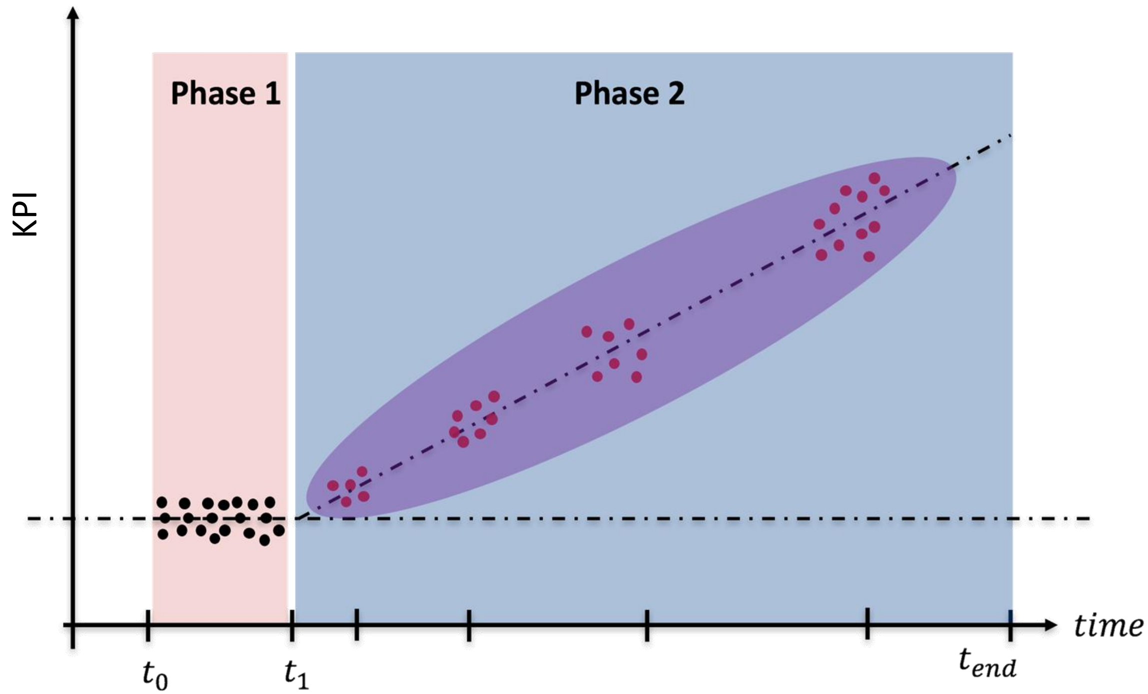
Digital Twin Solutions

Methodology

To this aim, a two-phase approach can be applied:

Phase 1: a data-driven model based Digital Twin is built, leveraging on the large amount of information collected from the on-board monitoring system sensors.

Phase 2: the model developed is applied in order to estimate the speed-loss of the ship and its drift.



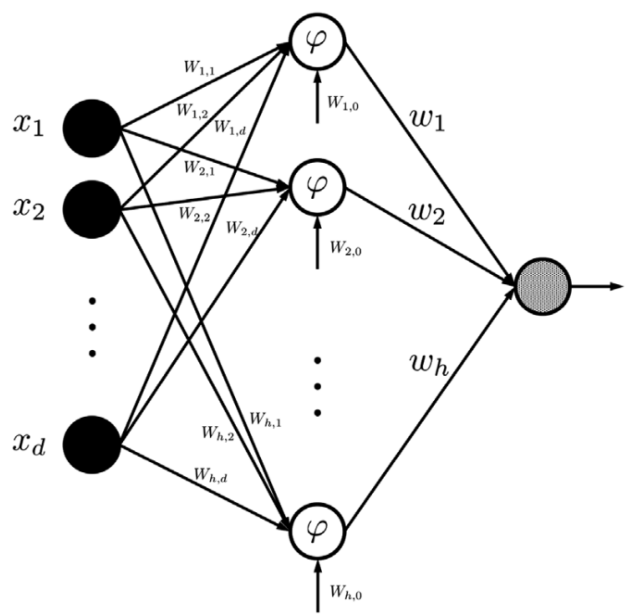
Digital Twin Solutions

Methodology

Phase 1: data-driven model based Digital Twin - Deep Extreme Learning Machines

Deep Extreme Learning Machines are the evolution of the Shallow Extreme Learning Machine for the purpose of creating an algorithm able to both learn new features from the available raw variables and create a regression model.

Shallow Extreme Learning Machine



$$f(x) = \sum_{i=1}^{h} w_i g_i(x)$$

$$g_i(\boldsymbol{x}) = \varphi\left(W_{i,0} + \sum_{j=1}^{d} W_{i,j} x_j\right)$$

Digital Twin Solutions

Methodology

Phase 1: data-driven model based Digital Twin - Deep Extreme Learning Machines

$$f(X) = \sum_{j=1}^{h} \boldsymbol{w}_j g_j(X),$$

w is the output weight vector between the hidden layer and the output layer.

Hidden-layer output corresponding to the input sample X

$$g_j \ : \ \mathbb{R}^d \rightarrow \mathbb{R}, \ \ j \ \in \ \{1, \cdots, h\}$$

$$\mathbf{X} = \{x_1, x_2, \dots x_d\}$$

$$\boldsymbol{v}_1 = \{v_{1,0}, v_{1,1}, v_{1,2}, \dots v_{1,d}\}$$

$$\boldsymbol{v}_2 = \{v_{2,0}, v_{2,1}, v_{2,2}, \dots v_{2,d}\}$$

$$\vdots$$

$$\boldsymbol{v}_j = \{v_{h,0} v_{h,1}, v_{h,2}, \dots v_{h,d}\}$$

Input weights (connecting input neurons to hidden neurons)

$\boldsymbol{v}_j \in \mathbb{R}^d, \quad j \in \{1, \cdots, h\}$

$v_j^0, \quad j \in \{1, \cdots, h\}$ **Bias term**

$\varphi : \mathbb{R} \rightarrow \mathbb{R}$ **Nonlinear activation function**

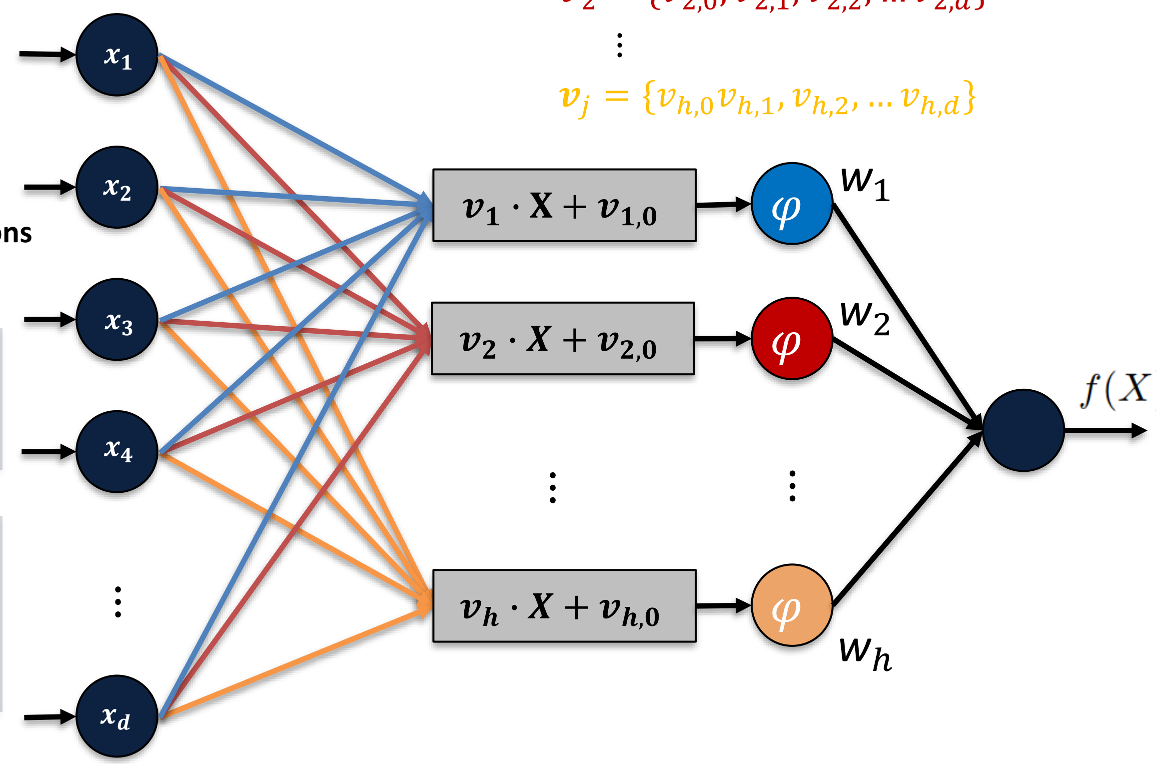
$\boldsymbol{w} \in \mathbb{R}^h$ **Output weights (connecting hidden neurons to output neurons without any bias)**

Neuron's response to an input stimulus:

$$\varphi(\boldsymbol{v}_j \cdot X + v_j^0), \quad j \in \{1, \cdots, h\}$$

Overall output function of the network:

$$f(X) = \sum_{j=1}^{h} w_j \varphi(\boldsymbol{v}_j \cdot X + v_j^0)$$



Digital Twin Solutions

Methodology

Phase 1: data-driven model based Digital Twin - Deep Extreme Learning Machines

$$V=\begin{bmatrix}\varphi(\boldsymbol{v}_1\cdot X_1+v_1^0) & \cdots & \varphi(\boldsymbol{v}_h\cdot X_1+v_h^0)\\ \vdots & \ddots & \vdots \\ \varphi(\boldsymbol{v}_1\cdot X_n+v_1^0) & \cdots & \varphi(\boldsymbol{v}_h\cdot X_n+v_h^0)\end{bmatrix}=\begin{bmatrix}\boldsymbol{\phi}^T(X_1)\\ \vdots \\ \boldsymbol{\phi}^T(X_n)\end{bmatrix}$$

Activation Matrix

$V_{i,j}$ is the activation value of the j-th hidden neuron for the i-th input pattern

The training problem reduces to minimisation of the convex cost

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \|V\boldsymbol{w} - \boldsymbol{y}\|^2$$

A matrix pseudo-inversion yields the unique L_2 solution:

$$\boldsymbol{w}^* = V^+\boldsymbol{y}.$$

The simple, efficient procedure to train an Extreme Learning Machines involves the following steps:

1. Randomly generate hidden node parameters (in or case $\boldsymbol{v}_i$ and bias $\boldsymbol{v}_i^0$) for each hidden neuron
2. Compute the activation matrix V
3. Compute the output weights by solving the pseudo-inverse problem: $\boldsymbol{w}^* = V^+\boldsymbol{y}.$

Regularisation strategies:

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \|V\boldsymbol{w} - \boldsymbol{y}\|^2 + \lambda\|\boldsymbol{w}\|^2 \longrightarrow \boldsymbol{w}^* = (V^TV + \lambda I)^{-1}V^T\boldsymbol{y}$$

Digital Twin Solutions

Methodology

Phase 1: data-driven model based Digital Twin - Deep Extreme Learning Machines

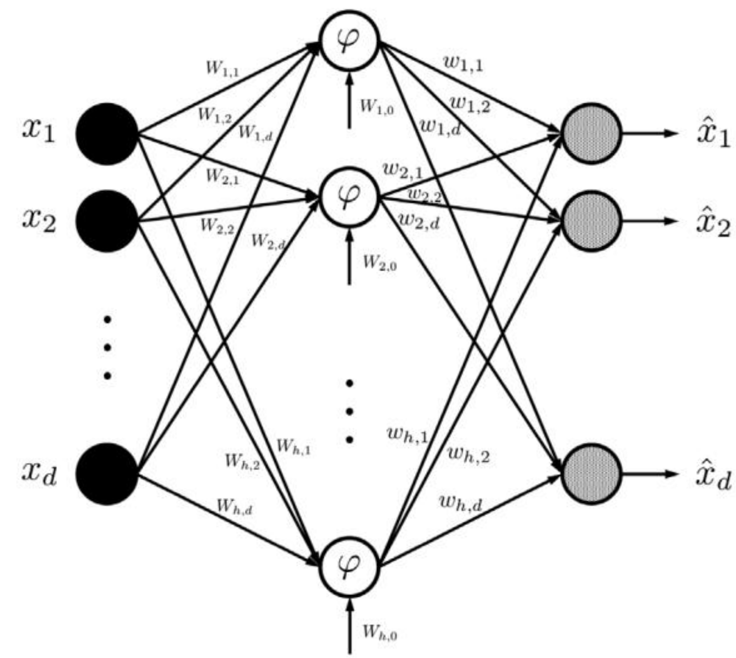
Due to its shallow architecture, feature learning using Shallow Extreme Learning Machine may not be effective even when h (the number of the neuron is large – EXTREME!!).

Since **feature learning** is often useful to improve the accuracy of the final model, multilayer (deep) solutions are usually needed.

Multilayer learning architectures are developed using Extreme Learning Machine-based autoencoder as its building block, which results in a sort of Deep Extreme Learning Machines.

At each layer i of the l layers, each one composed of h_i i∈{1,…,l} neurons, the Deep Extreme Learning Machines tries to reconstruct the input data and the outputs of the previous layer are used as the inputs of the next one.

$$\hat{x}_j = f_j(\boldsymbol{x}) = \sum_{i=1}^{h} w_{i,j}\varphi\left(W_{i,0} + \sum_{j=1}^{d} W_{i,j}x_j\right) = \sum_{i=1}^{h} w_{i,j}\varphi_i(\boldsymbol{x})$$



Deep Extreme Learning Machines

Digital Twin Solutions

Methodology

Phase 2: Speed-loss Estimation

Once the Deep Extreme Learning Machines-based Digital Twin has been built, it is possible to apply it to the rest of the data in order to estimate the expected speed (v_{exp}) and compare it with the measured one (v_{mes}) for the purpose of computing the percentage speed loss SL%.

ISO 19030 procedure

The calculation of the percentage speed loss based on the corrected propulsion power.
The expected speed v_{exp} is computed based on reference, clean-hull data starting from actual measurements of draft (T) and trim (δ):

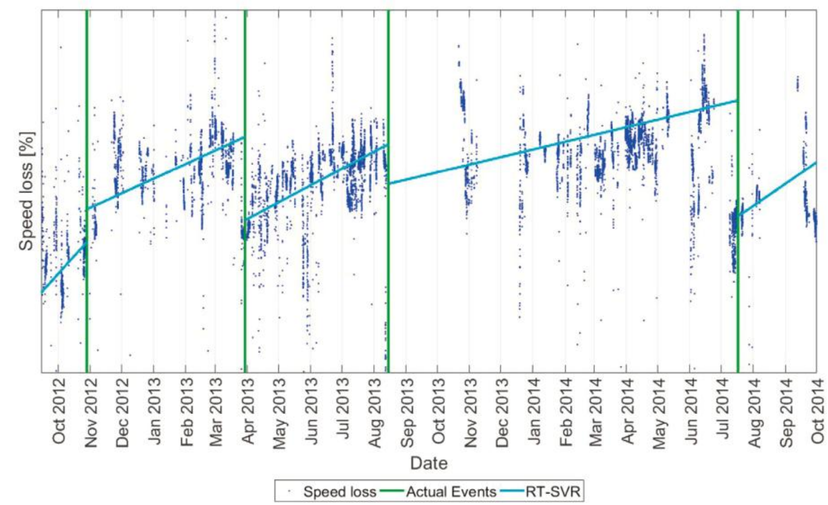
$$v_{exp} = f\left(P_p', T, \delta\right)$$

where P_p' is the corrected power for accounting the effect of the draft, and trim.
This allows to compute the percentage speed loss as:

$$\mathrm{SL}_{\%} = 100\,\frac{v_m - v_{exp}}{v_{exp}}$$

ISO 19030 procedure

Deep Extreme Learning Machines



Digital Twin Solutions

Methodology

Phase 2: Speed-loss Estimation

The result of this process is a **series of values in time** representing the trend of the percentage speed loss.

$$g(t) = at + b \text{ with } a, b \in \mathbb{R}$$

$$a^*, b^* = \arg\min_{a,b \in \mathbb{R}} \sum_{t \in \{t_1, t_2, ...\}} \max[\min[at + b - \mathrm{SL}_{\%}(t), \hat{\epsilon}], \tilde{\epsilon}]$$

The **automatic identification** of changes in time of the **distribution of the percentage speed loss** was carried out, in order to check if those changes were in correspondence to maintenance activities and testify the quality of the estimated speed loss.

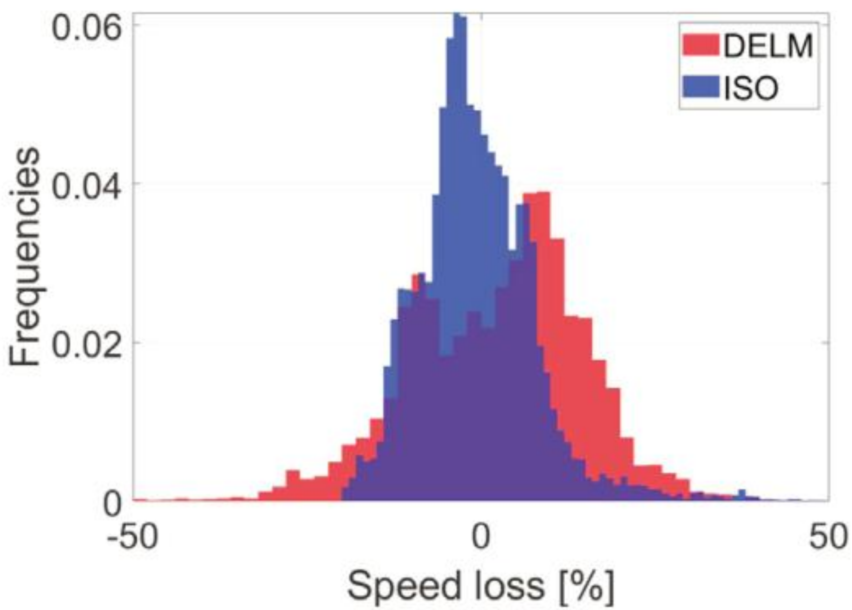
For this purpose, **Kolmogorov–Smirnov** test (Smirnov, 1944) has been adopted.

This nonparametric statistical test can be exploited to check if two different data samples of data are derived from the same probability distribution.

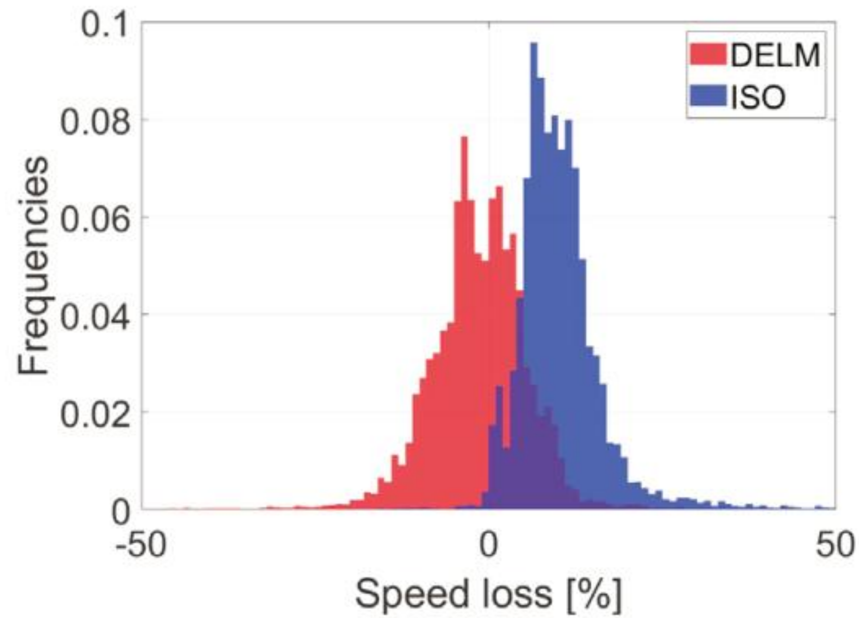
Null Hypothesis: the two samples belong to the same distribution.

Digital Twin Solutions

Results



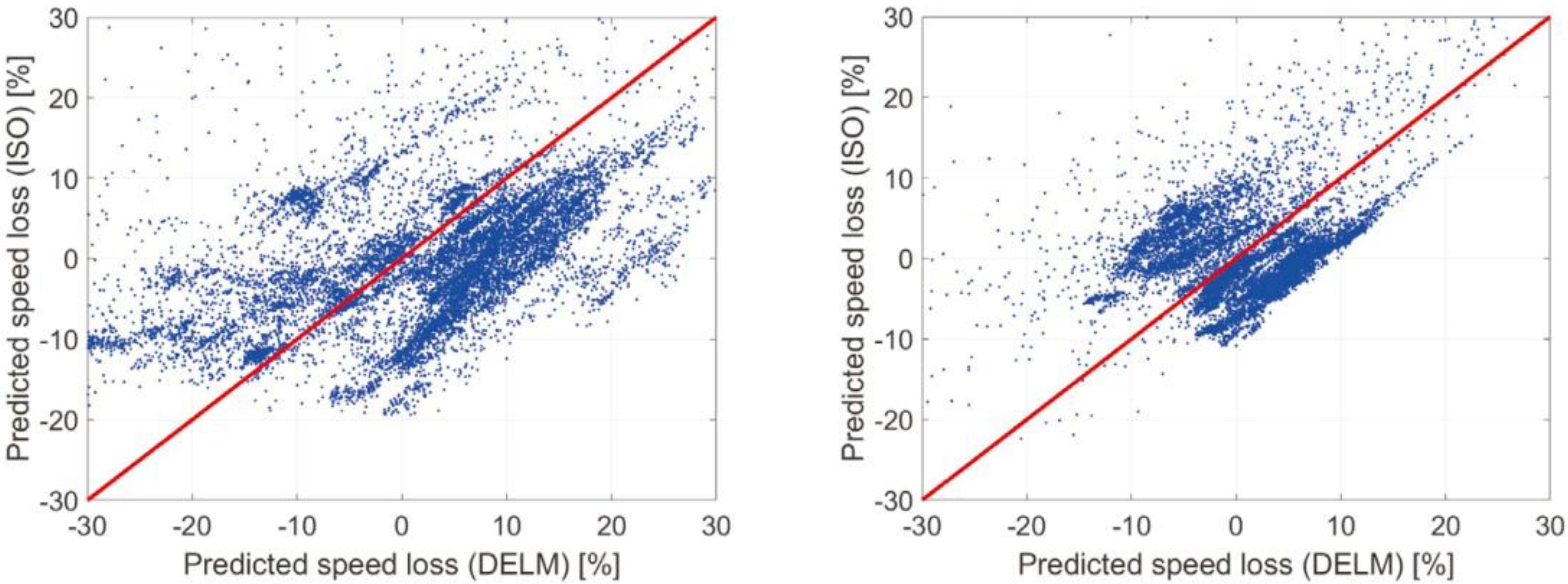
(a) V1



(b) V2

Digital Twin Solutions

Results



(a) V1

(b) V2

Digital Twin Solutions

Results

V1

Date	Event
21/03/2012	Vessel delivery
29/10/2012	Propeller cleaning
30/03/2013	Hull cleaning
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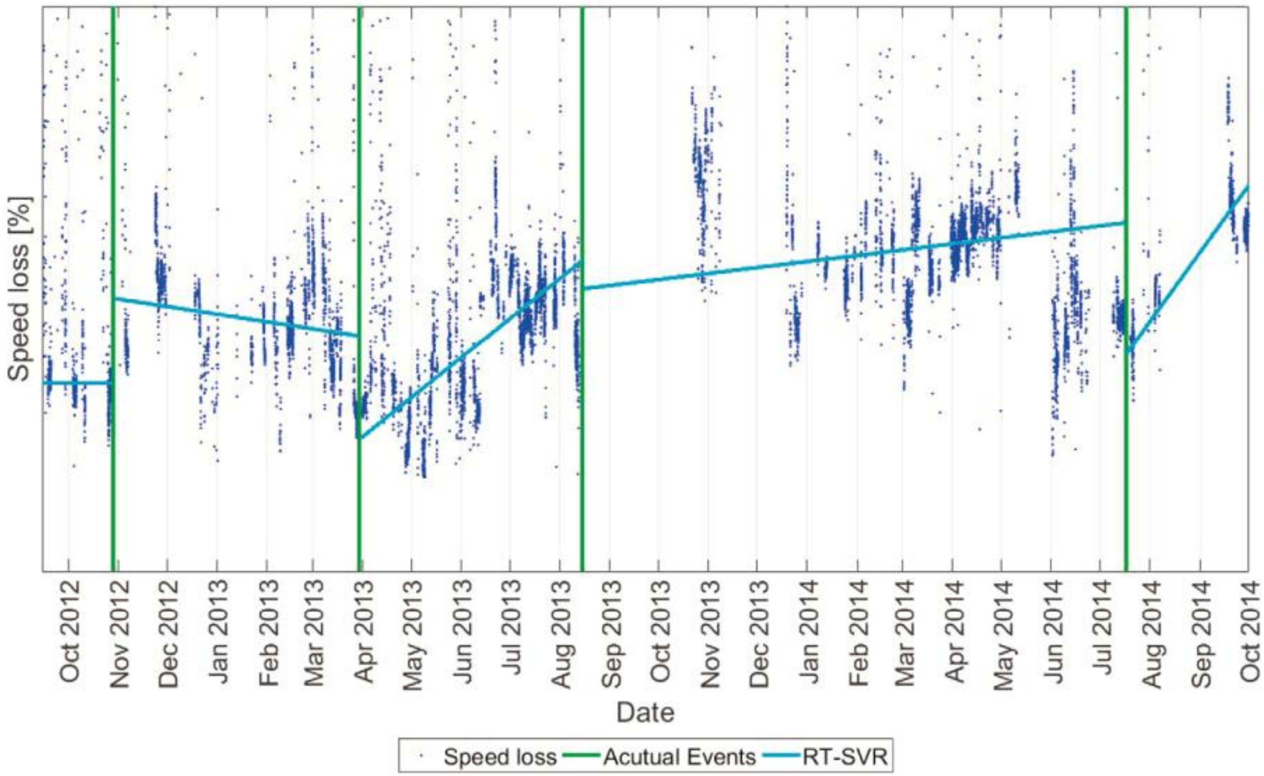
ISO 19030 Procedure



Digital Twin Solutions

Results

V1

Date	Event
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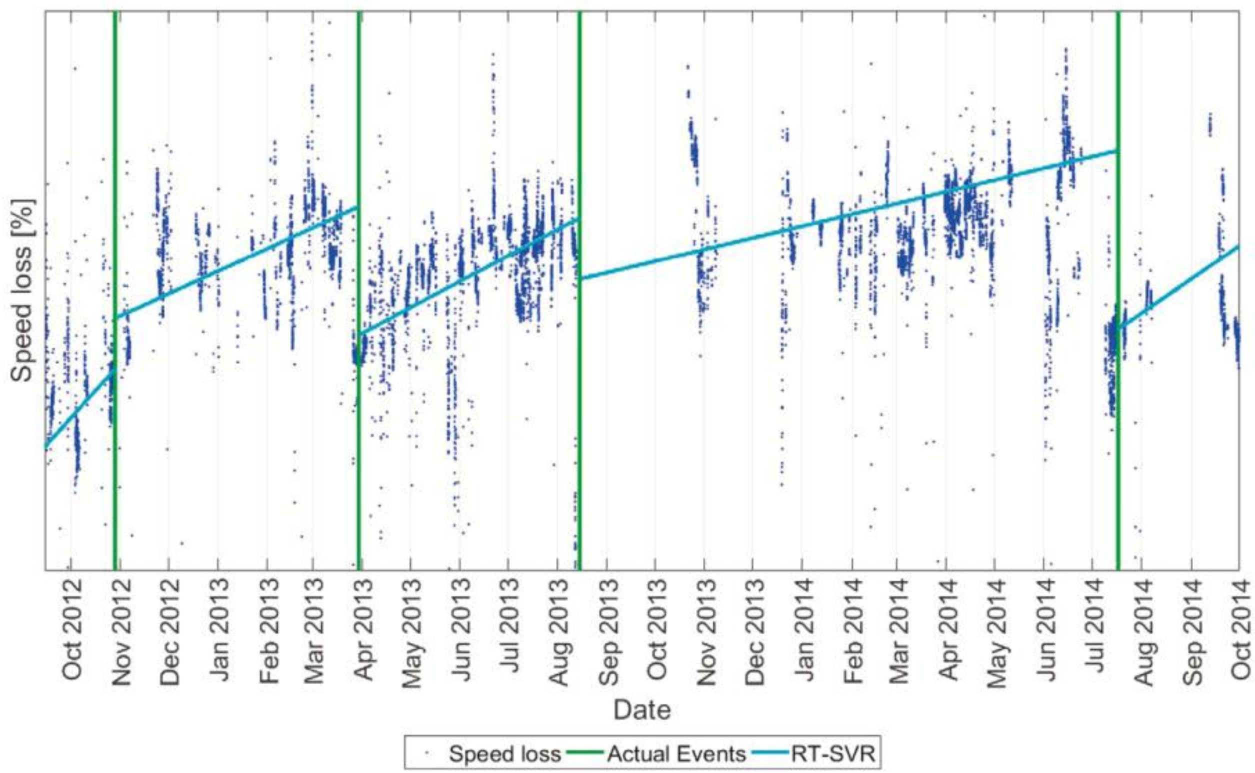
Deep Extreme Learning Machines-based Digital Twin



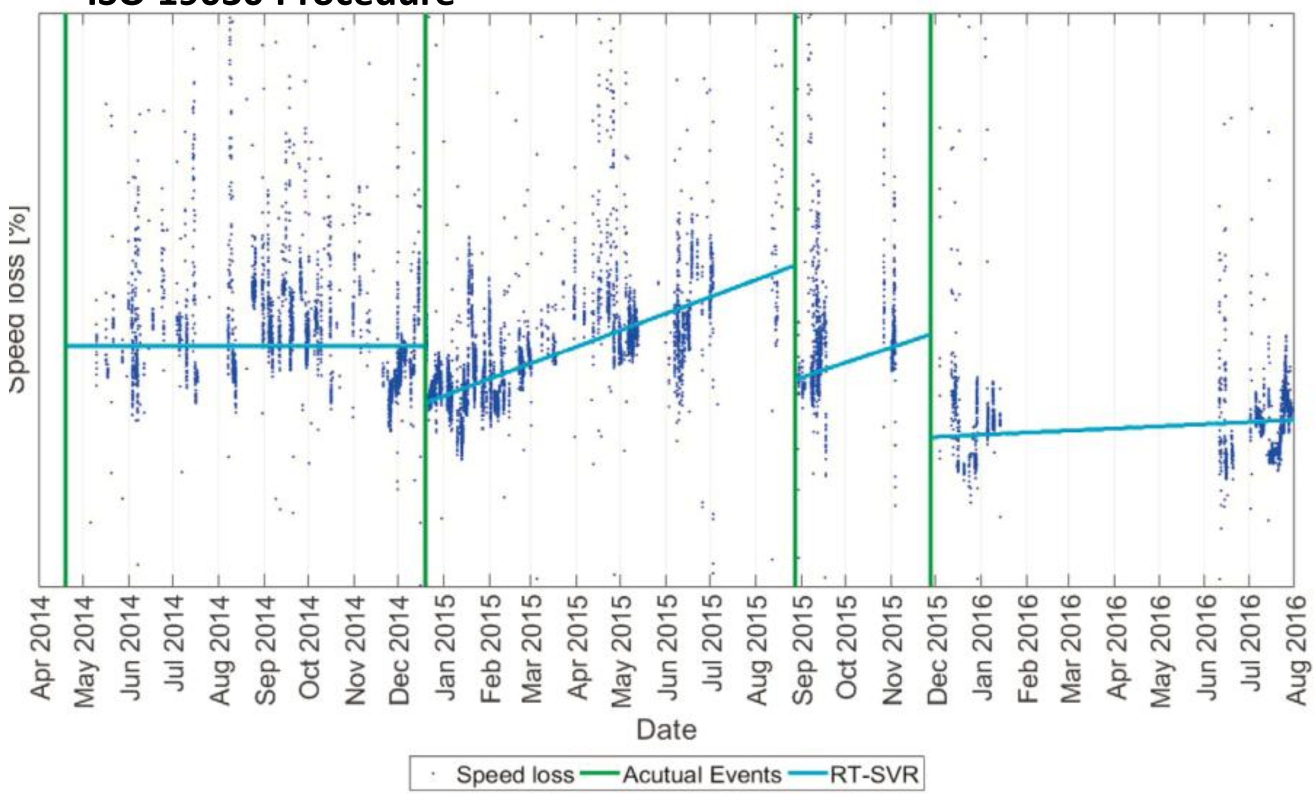
Digital Twin Solutions

Results

V2

Date	Event
19/04/2014	Propeller polishing
20/12/2014	Hull cleaning
28/08/2015	Hull cleaning and Propeller polishing
28/11/2015	Dry-docking

ISO 19030 Procedure



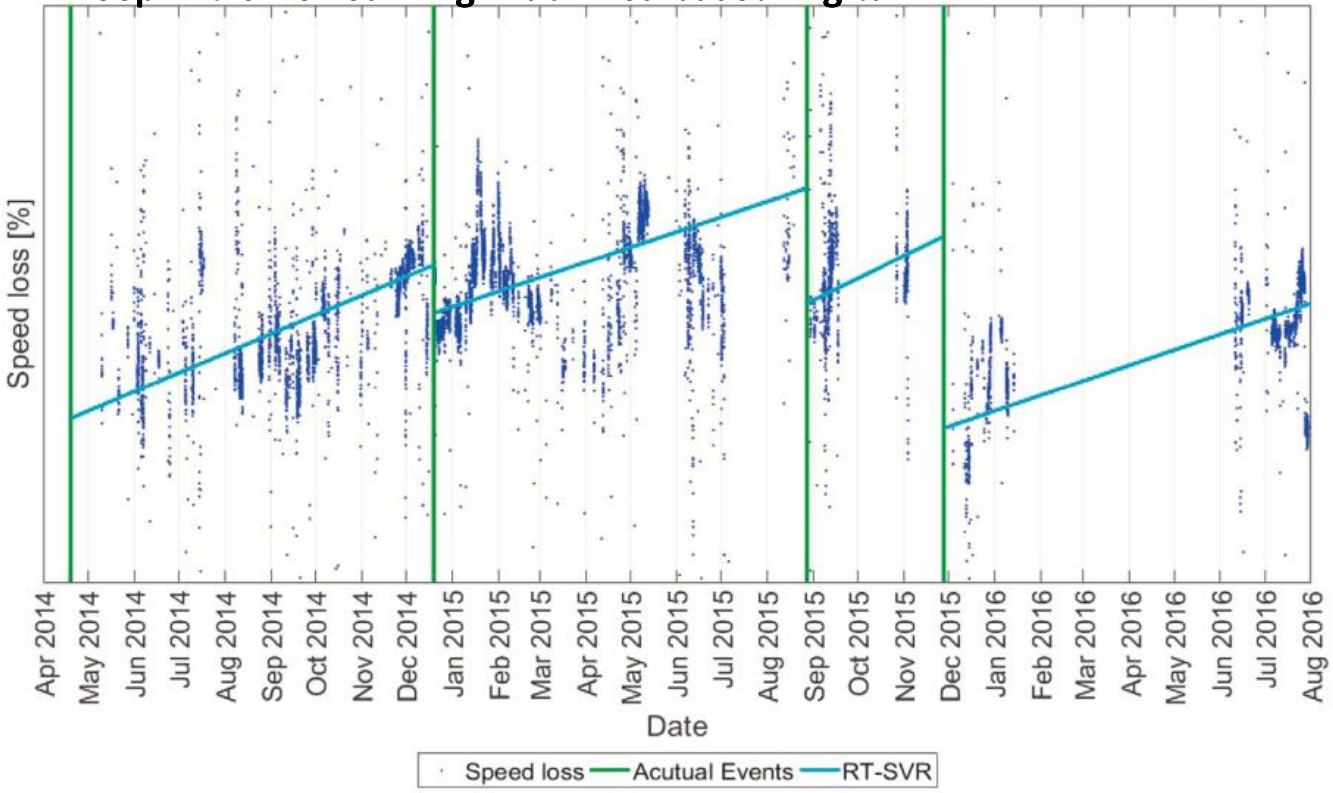
Digital Twin Solutions

Results

V2

Date	Event
19/04/2014	Propeller polishing
20/12/2014	Hull cleaning
28/08/2015	Hull cleaning and Propeller polishing
28/11/2015	Dry-docking

Deep Extreme Learning Machines-based Digital Twin



Digital Twin Solutions

Results

V2

Date	Event
19/04/2014	Propeller polishing
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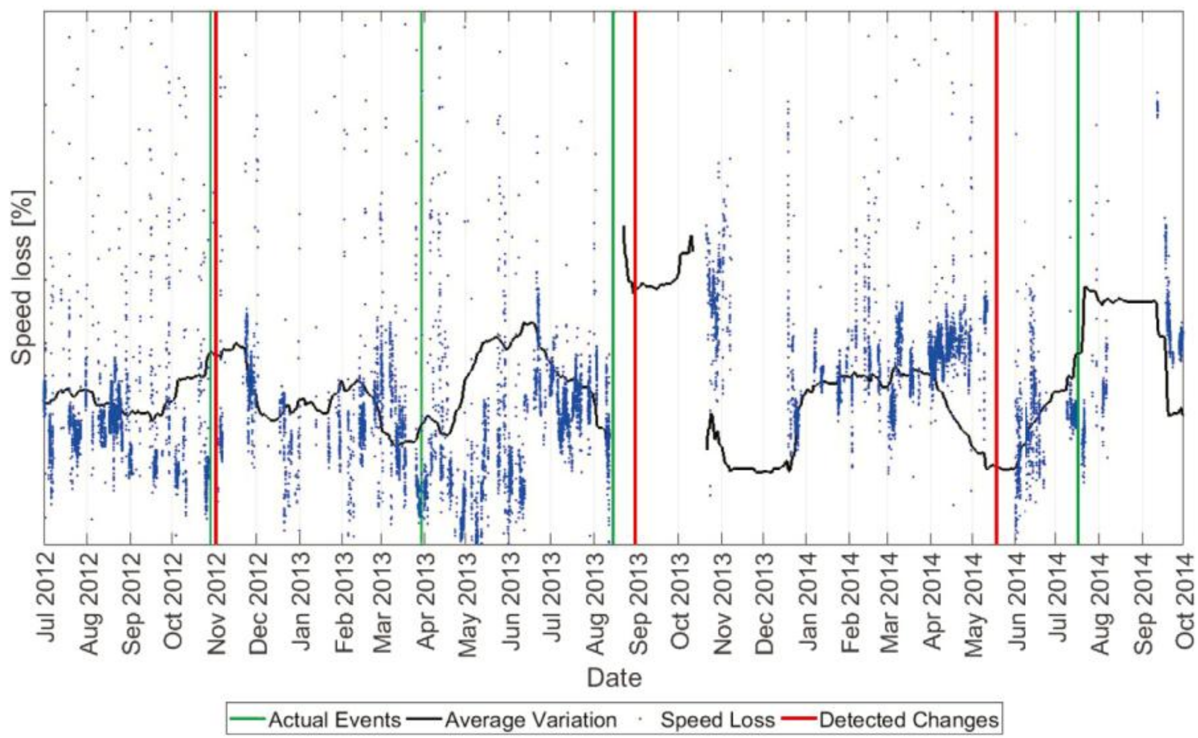
28/11/2015	Dry-docking

Deep Extreme Learning Machines-based Digital Twin



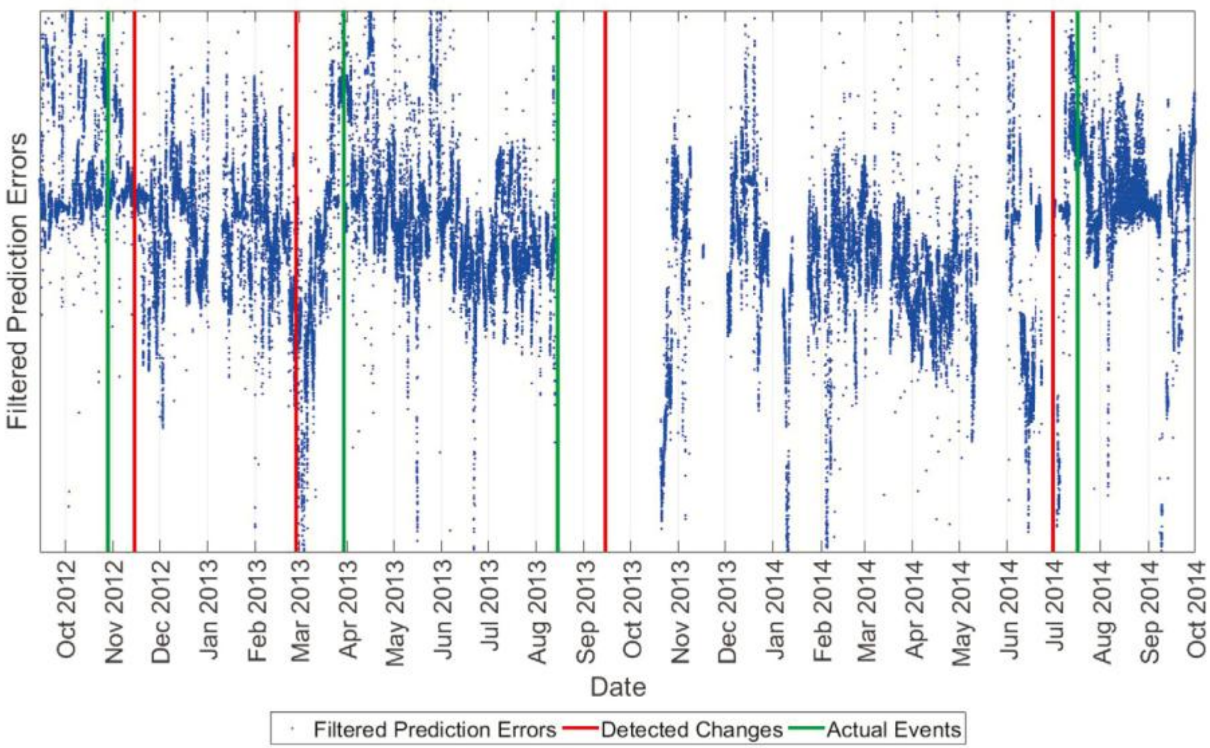
Digital Twin Solutions

Results

V2

Date	Event
19/04/2014	Propeller polishing
20/12/2014	Hull cleaning
28/08/2015	Hull cleaning and Propeller polishing
28/11/2015	Dry-docking

Deep Extreme Learning Machines-based Digital Twin



Digital Twin Solutions

Conclusion

1. The speed loss calculated using the linear robust regression provides an accurate picture of the status of the hull and propeller fouling at a specific point in time.

2. This information could be used effectively to optimize the scheduling of maintenance events, as today, hull and propeller cleaning are performed at fixed intervals, or in correspondence of other maintenance events. In practice, they could be performed more or less often depending on the actual status of the hull and propeller, according to methods based on the minimization of **costs**, fuel **consumption**, and **emissions**.

3. In the future, the proposed method could be exploited also for the evaluation of the effectiveness of different energy-saving solutions, such as the case of a new propeller design or the evaluation of the benefits deriving from the application of sails.

4. The proposed method, will facilitate the verification of the impact of **new technologies** or **vessel components**, thereby allowing to increase the transparency of energy and fuels efficiency technologies by providing a method to **validate fuel savings claims made by the manufacturers and providers**, supporting further uptake in the shipping industry.

Induction Motors Bearings Monitoring

Motivation and Background

Condition Based Maintenance (CBM) allows potential failures early detection and enables to estimate, the time remaining before the failure, and the equipment estimated life in accordance with relevant models/algorithms.

1
DATA ACQUISITION

2
DATA PROCESSING

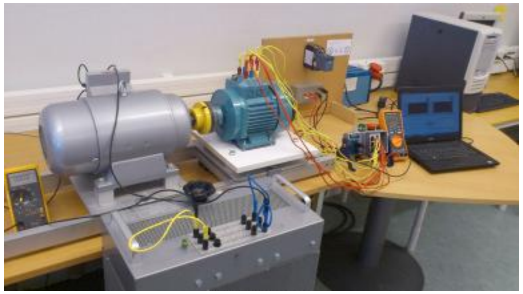
3
MAINTENANCE DECISION-MAKING

1
DATA ACQUISITION

Are data without failure and or performance degradation useful?

Experiments

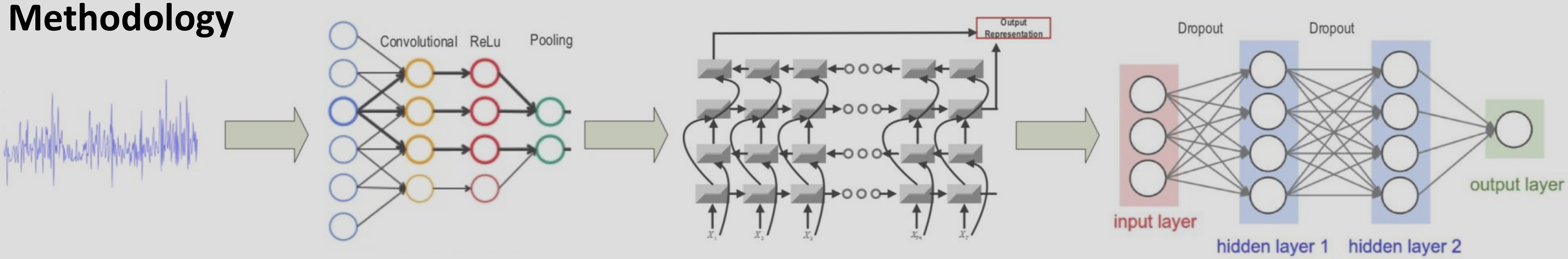
Digital Twin



Induction Motors Bearings Monitoring

Motivation and Background

Methodology



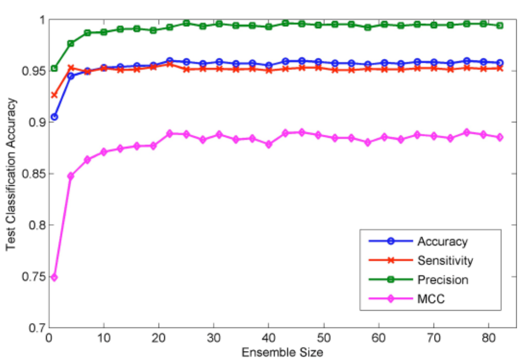
Raw Sensory Data

Local Feature Extractor
Convolutional Neural Network

Temporal Encoder
Deep BI-directional LSTM

Regressor Layer

Results



Publications

ELSEVIER

Applied Soft Computing

Neural networks for load torque monitoring
of an induction motor

Lucia Frosini*, Giovanni Petrecca

What Next?

Induction Motors Bearings Monitoring

Motivation and Background

What Next?

your idea, we have
onboard that
our approach.

what you need

We were thinking more to something like this:

Based on my methodology I would need to install onboard the following:

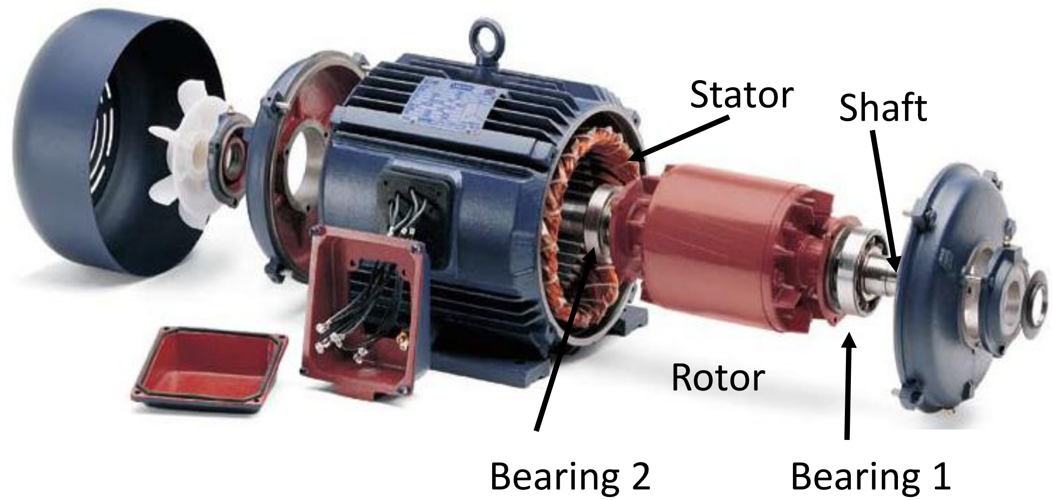
- Temperature sensor
- Torque Sensor
- Speed sensors
- 3-Phase voltage sensor
- 3-Phase current sensor
- Vibration Measurements
- ….
- ….

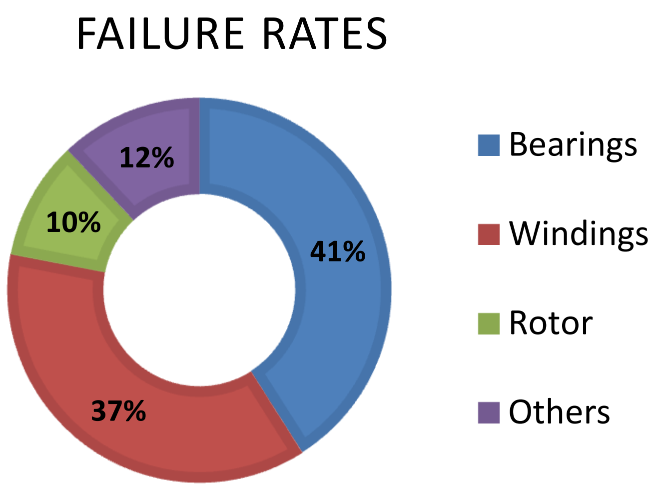
Induction Motors Bearings Monitoring

Motivation and Background

Induction Motors (IMs) are ubiquitous in Industrial Systems:

- Cheap
- Highly efficient
- Requiring **low maintenance** activities





IMs **Bearings** are subject to continuous mechanical stress and produce undesirable vibrations when degraded.

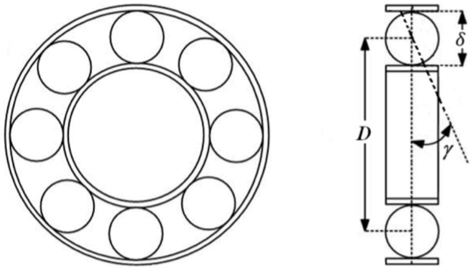
Bearing fault account for the 41% of all IMs failures.

Induction Motors Bearings Monitoring

Motivation and Background

Rolling-Element Bearing related defects can be categorized as:

- Outer bearing race defects
- Inner bearing race defects
- Ball defects
- Train defects.



(b) Bearing characteristic parameters

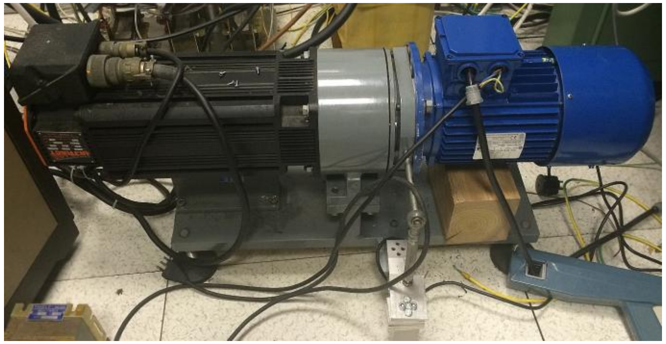
The vibration frequencies to detect these faults can be described by the following relationships:

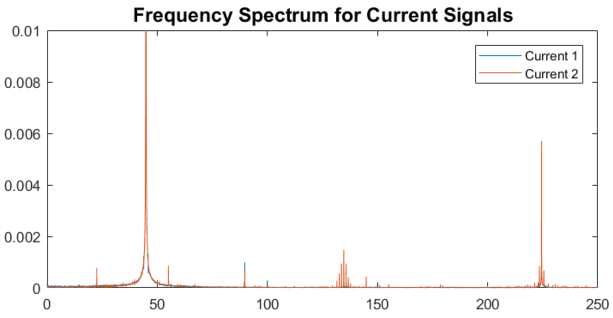
$$f_{od}=\frac{n\cdot f_r}{2}\left(1-\frac{\delta}{D}\cos(\gamma)\right) \quad f_{bd}=\frac{D\cdot f_r}{\delta}\left(1-\frac{\delta^2}{D^2}\cos^2(\gamma)\right) \quad f_{id}=\frac{n\cdot f_r}{2}\left(1+\frac{\delta}{D}\cos(\gamma)\right) \quad f_{tr}=\frac{f_r}{2}\left(1-\frac{\delta}{D}\cos(\gamma)\right)$$

A common approach is to analyse fault features in the **vibration signal** collected with **vibration probes**.

Vibration sensors are not **cheap**, are prone to **faults**, are hard or impossible to install on many systems, and are sensible to **corrosive** and **dusty environments**.

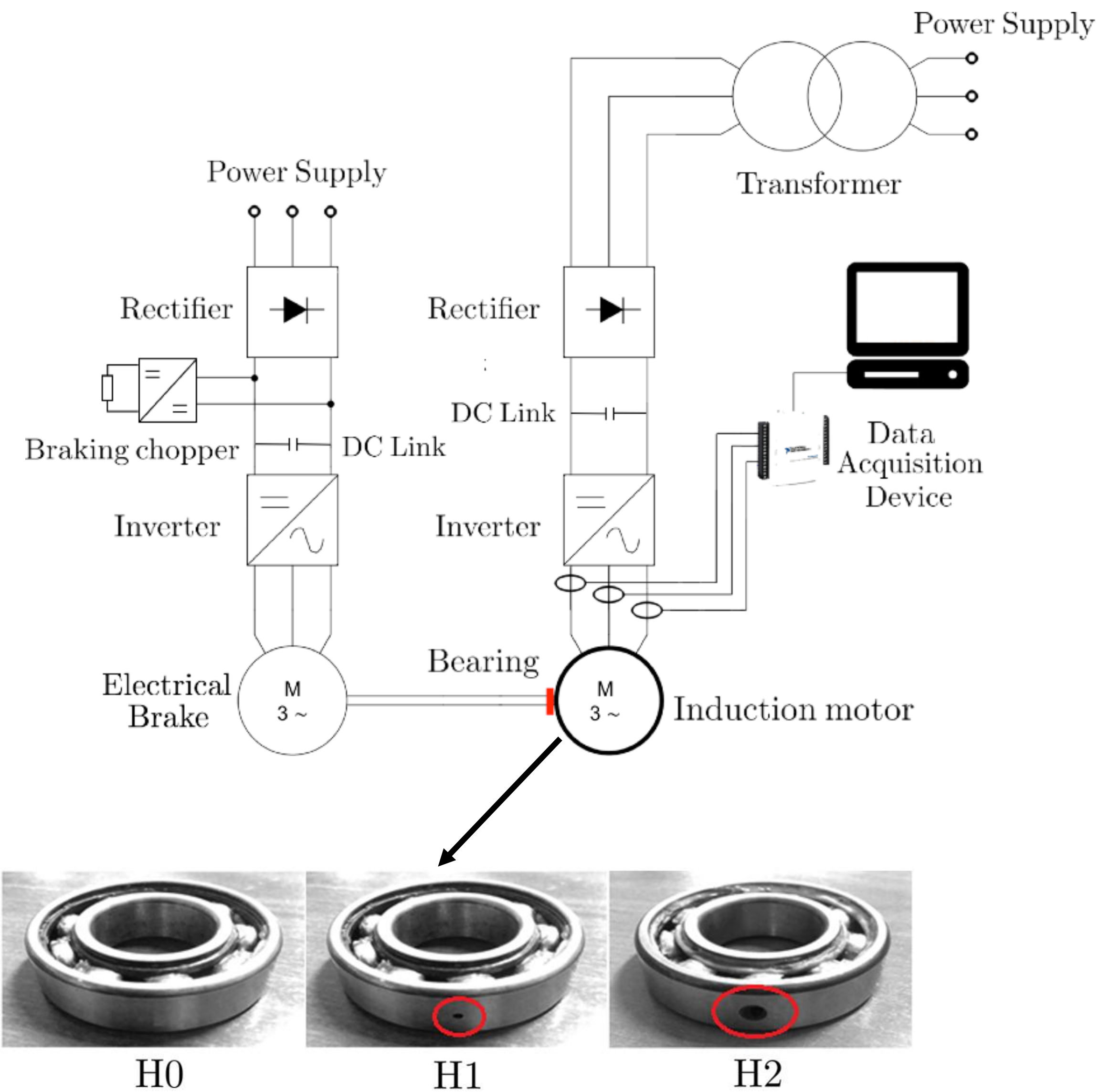
f_{od}: outer race defect frequency
f_{id}: inner race defect frequency
f_{bd}: ball defect frequency
f_{tr}: train defect frequency
f_r: is the shaft rotation frequency
n: rollers number
δ: roller diameter of the bearing
D: pitch diameter of the bearing
γ: contact angle





Induction Motors Bearings Monitoring

Data Acquisition



Induction Motors Bearings Monitoring

Data Acquisition

- Three **identical artificially damaged** bearings have been used:
  - H0 = no damages,
  - H1 = size-1 artificial induced hole (1.6 mm),
  - H2 = size-2 artificial induced hole (5 mm).

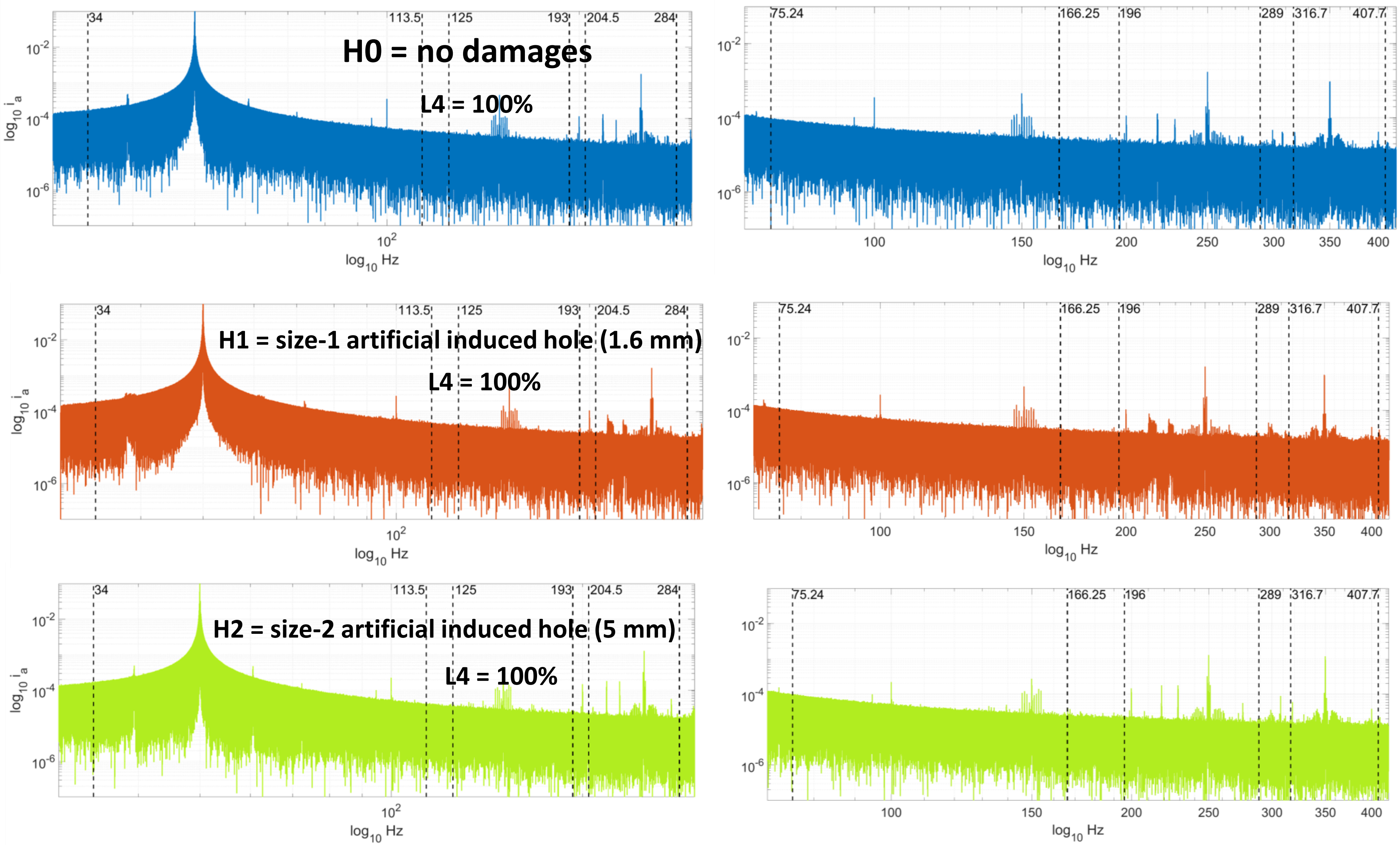
- For each bearing damaged condition, **four different mechanical** conditions have been investigated, applying to the motor shaft different **resistive torques** at the same **rotational speed**.

- Each mechanical condition is identified by the **stator current** percentage of the **rated motor current**:
  - L1 = 25%,
  - L2 = 50%,
  - L3 = 75%,
  - L4 = 100%.

For each experiment, once the steady-state conditions have been reached, the stator currents have been acquired for **30 seconds**.
Experiments have been repeated 30 times for each damage condition, to build a large enough set of experiments.

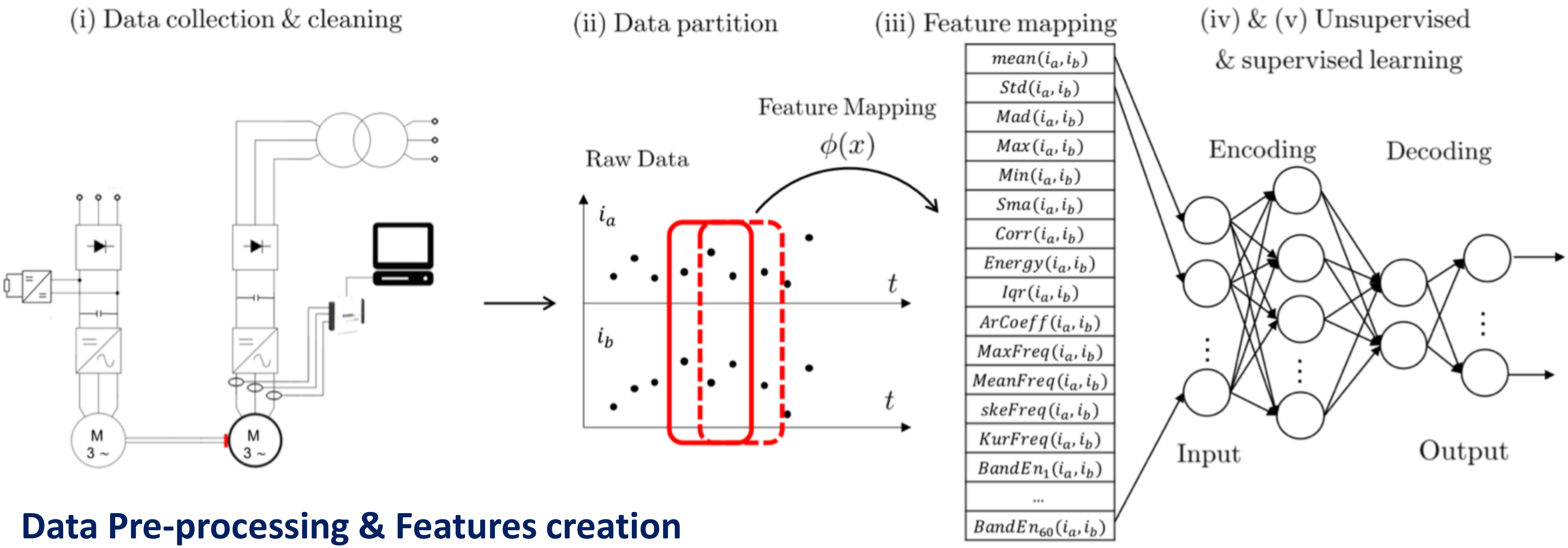
Induction Motors Bearings Monitoring

Methodology



Induction Motors Bearings Monitoring

Methodology



Data Pre-processing & Features creation

The first phase: process of collecting the raw data with an analog to digital converter device **cleaned from the higher noise frequencies.**

The second phase: consists in **segmenting these raw data** in overlapping sliding time windows of **24 s**. This quantity has been selected considering the peculiar characteristic of the studied IM, so to have a window large enough to capture the **behavior of the IM**.

The third phase: extraction from the windowed raw data a series of simple yet informative features, which have been chosen based on previous studies on similar context.

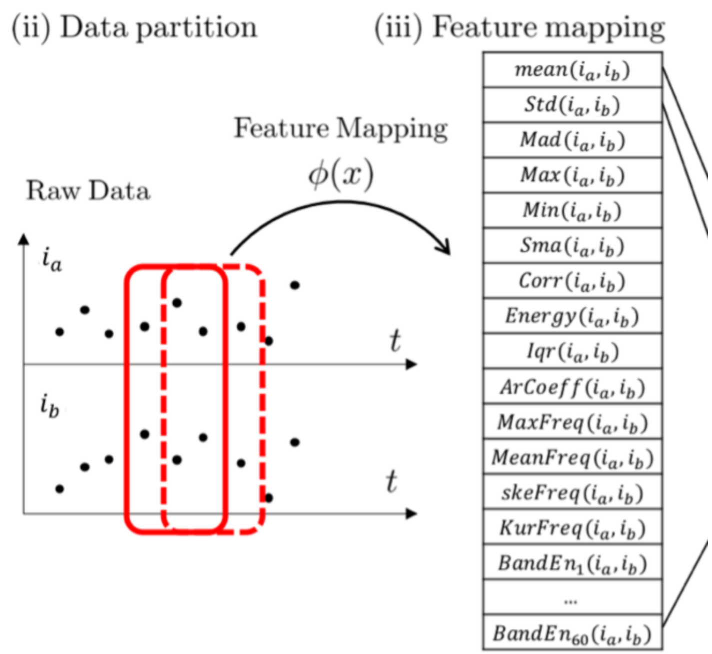
Induction Motors Bearings Monitoring

Methodology

Time Domain
Signal magnitude area of i_a and i_b
Correlation coefficient between i_a and i_b
Average sum of the squares of i_a and i_b
Interquartile range of i_a and i_b
Signal Entropy of i_a and i_b
Autoregression coefficients of i_a and i_b
Mean value of i_a and i_b
Standard deviation of i_a and i_b
Median absolute value of i_a and i_b
Largest values of i_a and i_b
Smallest value of i_a and i_b

Frequency Domain
Largest frequency component of i_a and i_b
Frequency signal average of i_a and i_b
Frequency signal Skeewness of i_a and i_b
Frequency signal Kurtosis of i_a and i_b
Energy at 60 different band frequencies of i_a and i_b

8 features



The result of this **feature mapping** is a sample $\boldsymbol{x} \in \boldsymbol{X} \subseteq R^d$ with d = 155 with associated its label $\boldsymbol{y} \in Y$

$$y_1 \in Y_1 = \{1,2,3\}$$

1 = H0 = no damages
2 = H1 = size-1 artificial induced hole (1.6 mm)
3 = H2 = size-2 artificial induced hole (5 mm)

$$y_2 \in Y_2 \subseteq R$$

L1 = 25%
L2 = 50%
L3 = 75%
L4 = 100%

Induction Motors Bearings Monitoring

Methodology

A total of n = 1400 samples have been collected for solving a **multioutput** (two labels) and **multitasks** problem:

- one label brings to a **classification task**
- one label brings to a **regression one**

Drawbacks

High dimensional feature mapping → **Hard to interpret**

High **dimensional space** and the low number of experiments →

Risk is to **overfit** the available data instead of learning some meaningful information out of them.

Solution

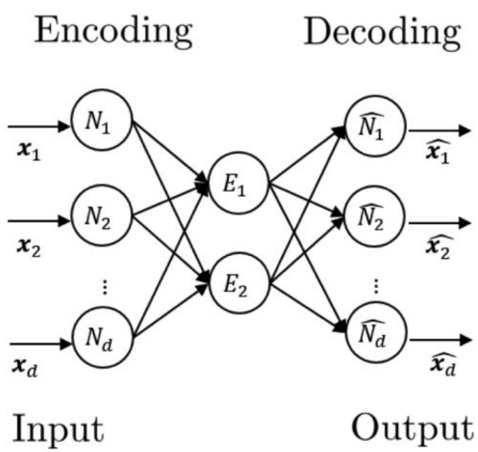
Unsupervised Dimensionality Reduction

Induction Motors Bearings Monitoring

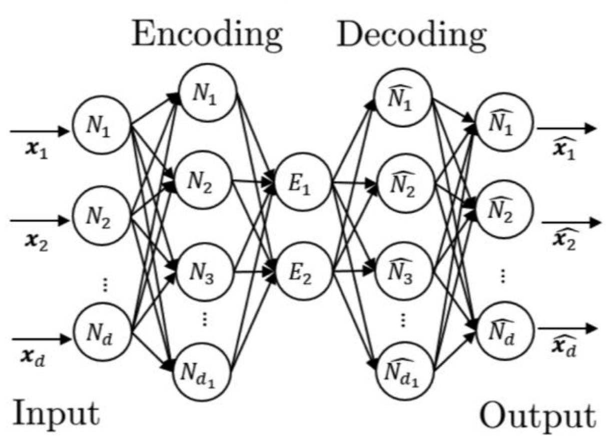
Methodology

The unsupervised learning feature selection process has been developed utilizing SNNs and DNNs.

instead of learning the relationship between the input space X and the output space Y, try to perform an often lower dimensional feature mapping, which is able to explain, in a more informative way, the point sampled from X.



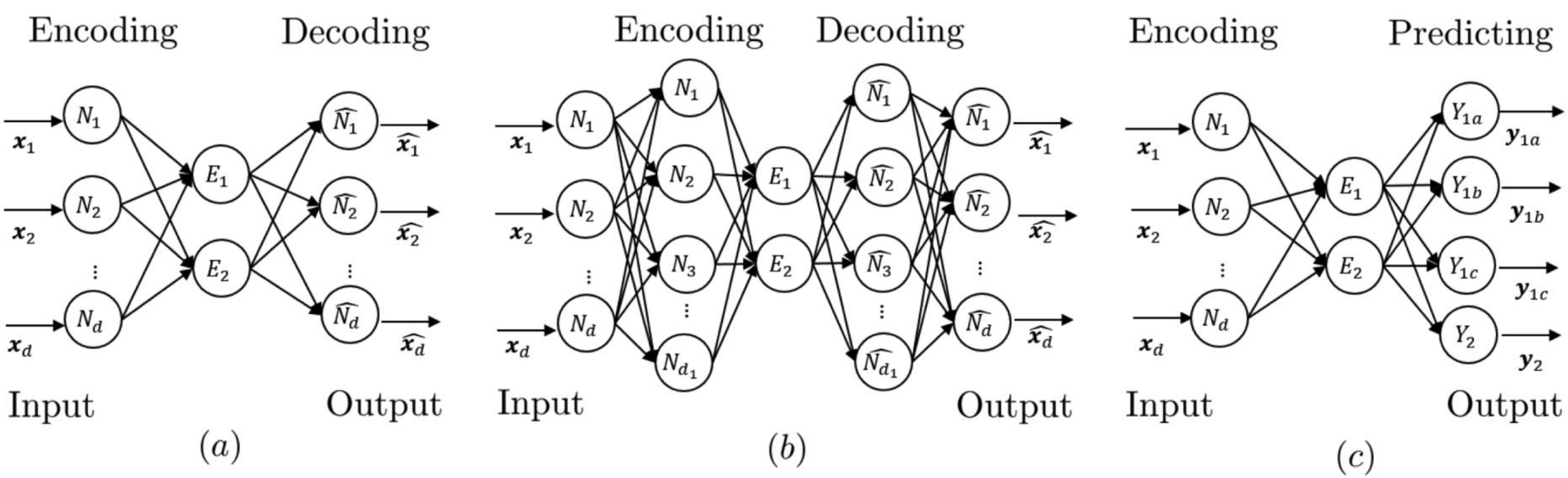
By staking many autoencoders it is possible to obtain a deep autoencoder:



Induction Motors Bearings Monitoring

Methodology

Once the representation has been learned, it is possible to use the deep autoencoder in order to learn the relation between X and Y with the final SNN & DNN architecture



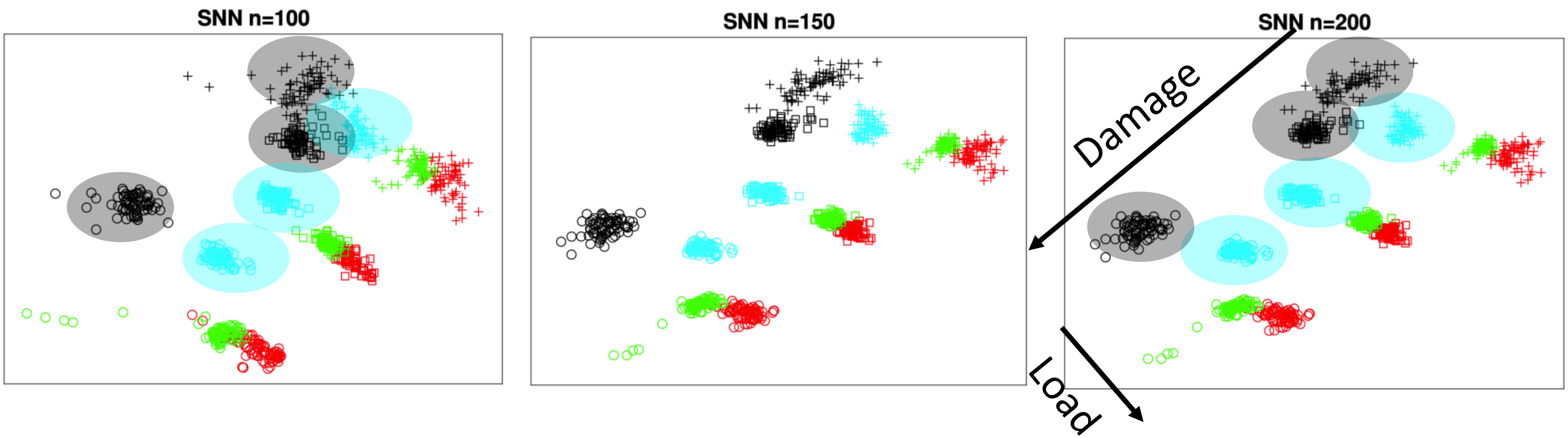
Hyperparameters:

- the activation function (e.g. sigmoidal, hyperbolic tangent, and rectified linear);
- the number of layers;
- the number of neurons for each layer;
- the type of regularizes and magnitude of regularization (e.g. norm of the weights, dropout, and early stopping);
- the loss function (e.g. quadratic and linear);
- the optimizer and optimization time (e.g. stochastic gradient descent and mini-batch gradient descent).

Induction Motors Bearings Monitoring

Results

Projected test point in the two-dimensional space defined by the different networks.
To simulate in a more realistic scenario a reduced amount of labeled samples has been exploited just $n \in \{100, 150, 200\}$



- H0 – L1
- H1 – L1
- H2 – L1
- H0 – L2
- H1 – L2
- H2 – L2
- H0 – L3
- H1 – L3
- H2 – L3
- H0 – L4
- H1 – L4
- H2 – L4

- H0 = no damages
- H1 = size-1 artificial induced hole (1.6 mm)
- H2 = size-2 artificial induced hole (5 mm)

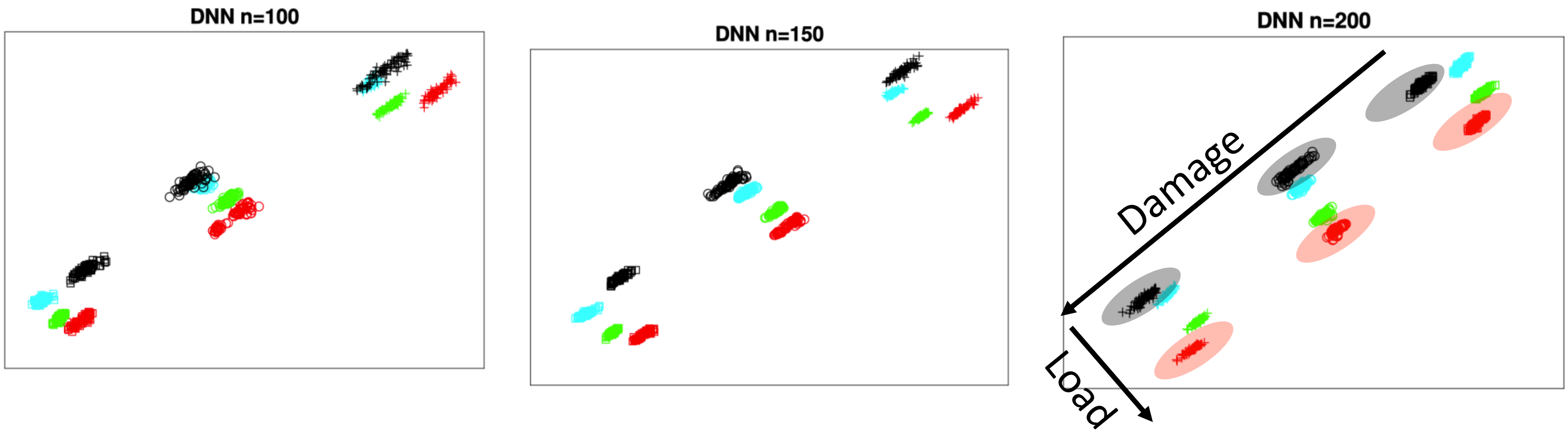
- L1 = 25%
- L2 = 50%
- L3 = 75%
- L4 = 100%

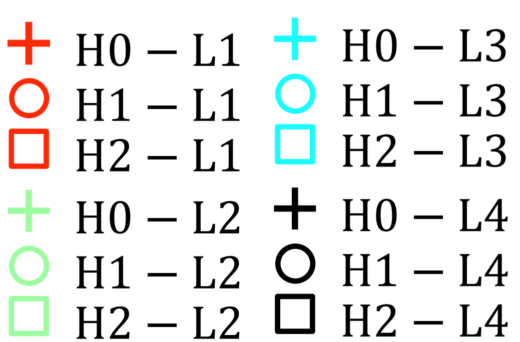
H0 H1 H2

Induction Motors Bearings Monitoring

Results

Clusters based on load and damage conditions





- H0 = no damages
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- L1 = 25%
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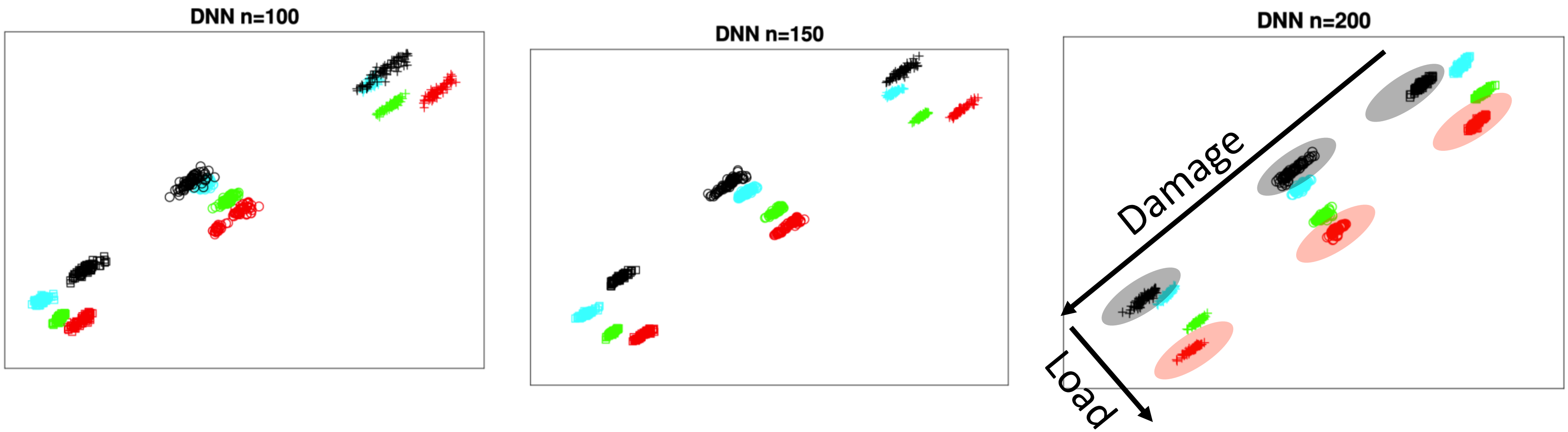
Induction Motors Bearings Monitoring

Results

Clusters based on load and damage conditions



H0 – L1
H1 – L1
H2 – L1
H0 – L2
H1 – L2
H2 – L2
H0 – L3
H1 – L3
H2 – L3
H0 – L4
H1 – L4
H2 – L4

- H0 = no damages
- H1 = size-1 artificial induced hole (1.6 mm)
- H2 = size-2 artificial induced hole (5 mm)

- L1 = 25%
- L2 = 50%
- L3 = 75%
- L4 = 100%

H0 H1 H2

Induction Motors Bearings Monitoring

Conclusion

- DNN and SNN find **compact** and expressive representations of the **bearings damage status**, by grouping the data in separate clusters based on load and damage conditions;
- both in SNN and DNN learned representation groups are ordered by load and entity of the damage;
- DNN provide clearer and more defined clusters with respect to SNN ones, showing higher classification performances even when the number of training samples is extremely limited.

This model:

- USE simply collectable data;
- IS unintrusive;
- IS interpretable;
- HAS good precision;
- IS cheap.

Thank You!